

NISTIR 8271 DRAFT SUPPLEMENT

Face Recognition Vendor Test (FRVT) Part 2: Identification

Patrick Grother
Mei Ngan
Kayee Hanaoka
*Information Access Division
Information Technology Laboratory*

This document is a draft supplement of [NIST Interagency Report 8271](#)

2021/03/04

NISTIR 8271 DRAFT SUPPLEMENT

Face Recognition Vendor Test (FRVT) Part 2: Identification

Patrick Grother
Mei Ngan
Kayee Hanaoka
*Information Access Division
Information Technology Laboratory*

This document is a draft supplement of [NIST Interagency Report 8271](#)

February 2021



U.S. Department of Commerce
Wynn Coggins, Acting Secretary

National Institute of Standards and Technology
James Altoff, Under Secretary of Commerce for Standards and Technology and Director, acting

RELEASE NOTES

2021-02-08: The fourth draft of the update to [NIST Interagency Report 8271](#):

- ▷ We have added results for eight algorithms submitted by eight developers: Cyberlink, Dermalog, Imagus, Paravision, Sensetime, Trueface, Vigilant Solutions, and X-Forward AI. With the exception of Trueface, all of these developers have participated previously.
- ▷ We anticipate updating this report again in the first week of March 2021.
- ▷ The main [results page](#) has been revised with tabs for the investigative and lights-out identification tables, and a new tab dedicated to speed and resource consumption.
- ▷ The report cards (example [here](#)) hyperlinked from the [results page](#) have been revised to improve content and format.

2020-12-14: The third draft of the update to [NIST Interagency Report 8271](#):

- ▷ We have added results for fifteen algorithms submitted by thirteen developers. The four first-time participants are: Acer, Akurat Satu Indonesia, Canon, and Xforward AI Technology. The ten returning developers are: AllGoVision, Cyberlink Corp, Dahua Technology, Deepglint, Guangzhou Pixel Solutions, IIT Vision, Innovatrics, Rank One Computing, Scanovate, Sensetime Group, Synesis, and VisionLabs.
- ▷ We have added two new datasets to the evaluation: First a set of “visa-border” photos, representing search of an airport immigration lane photo against a database of closely ISO standard portraits; second a “visa-kiosk” set representing search of a photo collected in a registered traveller kiosk against the same ISO portrait gallery. The images are described in section 2.1.
- ▷ As in previous reports, we include results for searching mugshots against a mugshot gallery containing a single image of each of 12 million people. However we have suspending running searches against a gallery in which multiple lifetime photos per person are present, because this is computationally expensive. We retain a $N = 3$ million search test dedicated to ageing in which mugshots taken up to 18 years after the first photograph are searched - see Table 5.
- ▷ Tables containing computational resource information, Table 2 . . . , now include duration of the finalization step, in which search algorithms can, at their option, build fast-search data structures.
- ▷ We have linked revised per-algorithm PDF report cards from the main [results page](#).
- ▷ We have regenerated all figures and tables to drop algorithms submitted before June 2018. Results for prior algorithms appear in [archived editions](#) of this report.
- ▷ Going forward, we anticipate producing more frequent updates to this report. Developers may submit one algorithm to this evaluation every four calendar months.

2020-03-24: The second draft of the update to [NIST Interagency Report 8271](#):

- ▷ Adds results for three algorithms from three developers, Dermalog, Innovatrics, and Synesis.
- ▷ Adds Table 5 on ageing showing the increase in false negative rates with time elapsed between two photos. Some of the results were contained in graphs in prior editions of this report, but the table adds results for some newly submitted algorithms.
- ▷ Adjusts frontal mugshot results (for recent and lifetime consolidated galleries) to include the effect of removing some images that should not have been included in image test sets. These images were mostly profile views, images of tattoos containing faces, images of faces on tee shirts, and images of photographs on walls behind the intended subject. This affects many tables and reduces false negative identification rates for all algorithms. The reduction is larger for “recent” enrollments than for “lifetime consolidated” ones with the consequence that accuracy on recent images is now superior.

2020-02-26: The first draft of the update to [NIST Interagency Report 8271](#):

- ▷ Adds results for 38 algorithms from 31 different developers, eleven of whom are entirely new to the 1:N track of FRVT. These are Allgovision, Cyberlink, Deepsea Tencent, Farbar F8, Imperial College London, Intsys MSU, Kedacom, Kneron, Pixelall, and Scanovate.

DISCLAIMER

Specific hardware and software products identified in this report were used in order to perform the evaluations described in this document. In no case does identification of any commercial product, trade name, or vendor, imply recommendation or endorsement by the National Institute of Standards and Technology, nor does it imply that the products and equipment identified are necessarily the best available for the purpose.

INSTITUTIONAL REVIEW BOARD

The National Institute of Standards and Technology's Research Protections Office reviewed the protocol for this project and determined it is not human subjects research as defined in Department of Commerce Regulations, 15 CFR 27, also known as the Common Rule for the Protection of Human Subjects (45 CFR 46, Subpart A).

ACKNOWLEDGMENTS

The authors are grateful for the support and collaboration of the the Department of Homeland Security's Science & Technology Directorate (S&T), Office of Biometric Identity Management (OBIM), and Customs and Border Protection (CBP).

Additionally, the authors are grateful to staff in the NIST Biometrics Research Laboratory for infrastructure supporting rapid evaluation of algorithms.

Executive Summary

This document is a draft revision of the September 2019 report [NIST Interagency Report 8271](#). That report gave extensive documentation of face recognition applied to mugshots. This report extends that by adding more two more challenging datasets containing images with serious departures from canonical frontal image standards. The report also adds results for algorithms submitted to NIST since in 2019 and 2020. The algorithms, which implement one-to-many identification of faces appearing in two-dimensional images, are prototypes from the research and development laboratories of mostly commercial suppliers, and are submitted to NIST as compiled black-box libraries implementing a NIST-specified C++ test interface. The report therefore does not describe how algorithms operate. The report lists accuracy results alongside developer names and will therefore be useful for comparison of face recognition algorithms and assessment of absolute capability. The report is accompanied by a [webpage](#) with sortable results.

The evaluation uses six datasets: frontal mugshots, profile view mugshots, desktop webcam photos, visa-like immigration application photos, immigration lane photos, and registered traveler kiosk photos. These datasets are sequestered at NIST, meaning that developers do not have access to them for training or testing. This aspect is important because face recognition algorithms are very often deployed without the developer having access to the customers image data. A possible exception to this would be in a cloud-based application where the operational image data is uploaded to a cloud operated by a face recognition developer.

The major result in NIST IR 8271 was that massive gains in accuracy have been achieved in the years 2013 to 2018 and these far exceed improvements made in the prior period, 2010 to 2013. While the industry gains were broad - at least 30 developers' algorithms outperformed the most accurate algorithm from late 2013, there remains a wide range of capability. While this report shows accuracy gains only over the period 2018-2020, the most accurate algorithm reported here is substantially more accurate than anything reported in NIST IR 8271. This is evidence that face recognition development continues apace, and that FRVT reports are but a snapshot of contemporary capability.

From discussion with developers, the accuracy gains stem from the adoption of deep convolutional neural networks. As such, face recognition has undergone an industrial revolution, with algorithms increasingly tolerant of poorly illuminated and other low quality images, and poorly posed subjects. One related result is that a few algorithms correctly match side-view photographs to galleries of frontal photos, with search accuracy approaching that of the best c. 2010 algorithms operating on purely frontal images. The capability to recognize under a 90-degree change in viewpoint - pose invariance - has been a long-sought milestone in face recognition research.

With good quality portrait photos, the most accurate algorithms will find matching entries, when present, in galleries containing 12 million individuals, with rank one miss rates of approaching 0.1%. The remaining errors are in large part attributable to long-run ageing, facial injury and poor image quality. Given this impressive achievement - close to perfect recognition - an advocate might claim that cooperative face recognition is a solved problem, a statement that can be refuted with the following context and caveats:

- ▷ **Mugshots vs. less constrained captures:** The low error rates reported here are attained using mostly excellent cooperative live-capture mugshot images collected with an attendant present. Recognition in other circumstances, particularly those without a dedicated photographic environment and human or automated quality control checks, will lead to declines in accuracy. This is documented here for side-view images, poorer quality webcam images, and, particularly, for newly introduced ATM-style kiosk photos that were not originally intended for automated face recognition. In this case, recognition error rates are much higher, often in excess of 20% even with the more accurate algorithms which variously remain intolerant of face cropping (at image edge) and of large downward head pitch.
- ▷ **Algorithm accuracy spectrum:** Recognition accuracy is very strongly dependent on the algorithm and, more

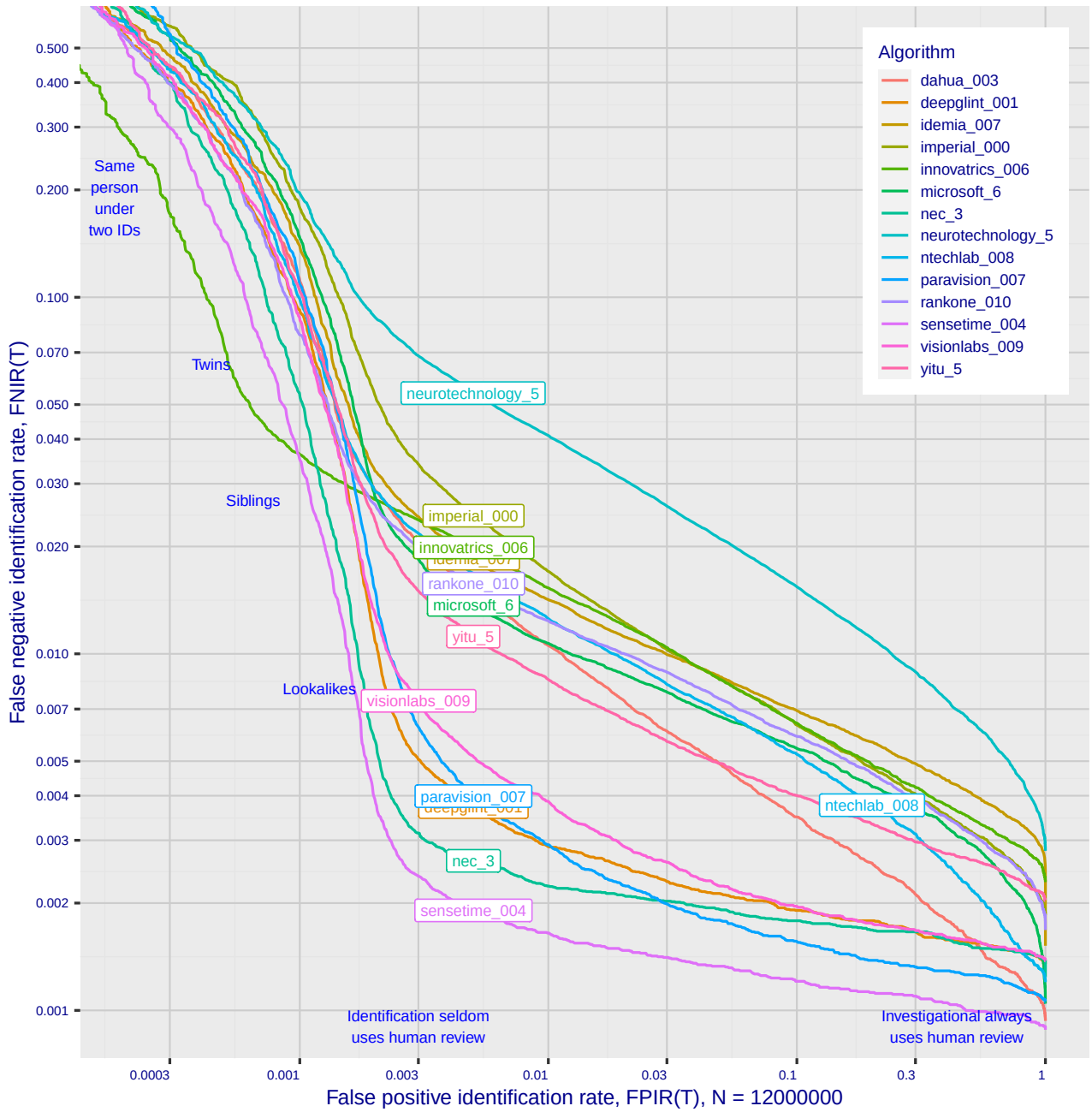


Figure 1: Identification miss rates across the false positive range. $N = 12$ million individuals are enrolled with one recent image.

generally, on the developer of the algorithm. False negative error rates in a particular scenario range from a few tenths of one percent to beyond fifty percent. This is tabulated exhaustively later: For example Table 8 shows accuracy across datasets. Figure 1 here compares algorithms on mugshot searches in a consolidated gallery of 12 million subjects and 12 million photos. Many algorithms do not achieve the low error rates noted above, and while many of those may still be useful and valuable to end-users, only the most accurate excel on poor quality images and those collected long after the initial enrollment sample.

- ▷ **Versioning:** While results for up to ten algorithms from each developer are reported here, the intra-provider accuracy variations are usually smaller than the inter-provider variations. That said different versions give an

order of magnitude fewer misses. Some developers demonstrate speed-accuracy tradeoffs¹. See Figs. 18, 19.

- ▷ **Low similarity scores:** In thousands of mugshot cases the correct gallery image is returned at rank 1 but its similarity score is nevertheless low, below some operationally required score threshold. This is not so important when face recognition is used for “lead generation” in investigational applications because human reviewers are specifically required to review potentially long candidate lists and the threshold is effectively 0. In applications where search volumes are higher and labor is not available to review the results from searches, a higher threshold must be applied. This reduces the length of candidate lists and false positive identification rates at the expense of increased false negative miss rates. The tradeoff between the two error rates is reported extensively later.
- ▷ **Population size:** As the number of enrolled subjects grows, some mates are displaced from rank one, decreasing accuracy. As tabulated later for N up to 12 million, false negative rates generally rise slowly with population size. This enables use of face recognition in very large populations. However in most positive and negative identification applications², a score threshold is set to limit the rate at which non-mate searches produce false positives. This has the consequence that some mated searches will report the mate below threshold, i.e. a miss, even if it is at rank 1. The utility of this is that many non-mated searches will return no candidate identities at all. As the error-tradeoff characteristic shows, investigational miss rates on the right side are very low but then rise steadily (in the center region) as threshold is increased to support “lights-out” applications, and ultimately rise quickly (left side) as discussed below. Thus, if we demand that just one in one thousand non-mate searches produce any false positives, the most accurate algorithms there (Sensetime-004 and NEC-3) would fail on between 3 and 5% of mated searches. Even though the graph shows results for the most accurate algorithms, all but two would fail to find the mate in more than 8% of mated searches. While the two most accurate algorithms produce a relatively flat error tradeoff until the threshold is raised to limit false positives to about 1 in 400 non-mated searches³

Thereafter, as the threshold is raised to further reduce false positives, miss rates rise rapidly. This means that low false positive identification rates are inaccessible with these algorithms, a result that does not apply for ten-finger identification algorithms. The rapid rise occurs because the lower mate scores are mixed with very high non-mate scores, the low scores from poor image quality and ageing, the high non-mates from the presence of lookalikes persons (doppelgangers), twins (discussed next) and, ultimately, the presence of a few unconsolidated subjects i.e. persons present under multiple IDs.

- ▷ **False negatives from ageing:** A large source of error in long-run applications where subjects are not re-enrolled on a set schedule is ageing. Changes in facial appearance increase with the time elapsed between photographs. These will depress similarity scores and eventually cause false negatives. All faces age and while this usually proceeds in a graceful and progressive manner, drug use can accelerate this [28]. Elective surgery may be effective in delaying it although this has not been formally quantified with face recognition. As ageing is essentially unavoidable, it can only be mitigated by scheduled re-capture, as in passport re-issuance. To quantify ageing effects, we used the more accurate algorithms to enroll the earliest image of 3.1 million adults and then search with 10.3 million newer photos taken up to 18 years after the the initial enrollment photo. Figure 2 puts ageing into context by contrasting it with the increase in false negatives that occurs when the number of individuals in

¹For example, NEC-0 prepares templates much faster than NEC-2 but gives twenty times more misses. Dermalog-5 executes a template search much more quickly than Dermalog-6 but is also much less accurate.

²In a positive identification application such as a registered traveler system, a user is making an implicit claim to be enrolled in the system - most users will be. In a negative application, such as with deportees, the implicit claim is that the subject is not enrolled - most will not be.

³The gallery size here is 12 million people, one image per person. Given 331 201 non-mated searches, an exhaustive implementation of one-too-many search would execute almost 4 trillion comparisons. At a false positive identification rate of 0.0025 the number of false positives is, to first order, 828 corresponding to single-comparison false match rate of $828 / 4 \text{ trillion} = 2.1 \cdot 10^{-10}$ i.e. about 1 in 5 billion. Strictly this FMR computation is meaningful only for algorithms that implement 1:N search using N 1:1 comparisons, which is not always the case.

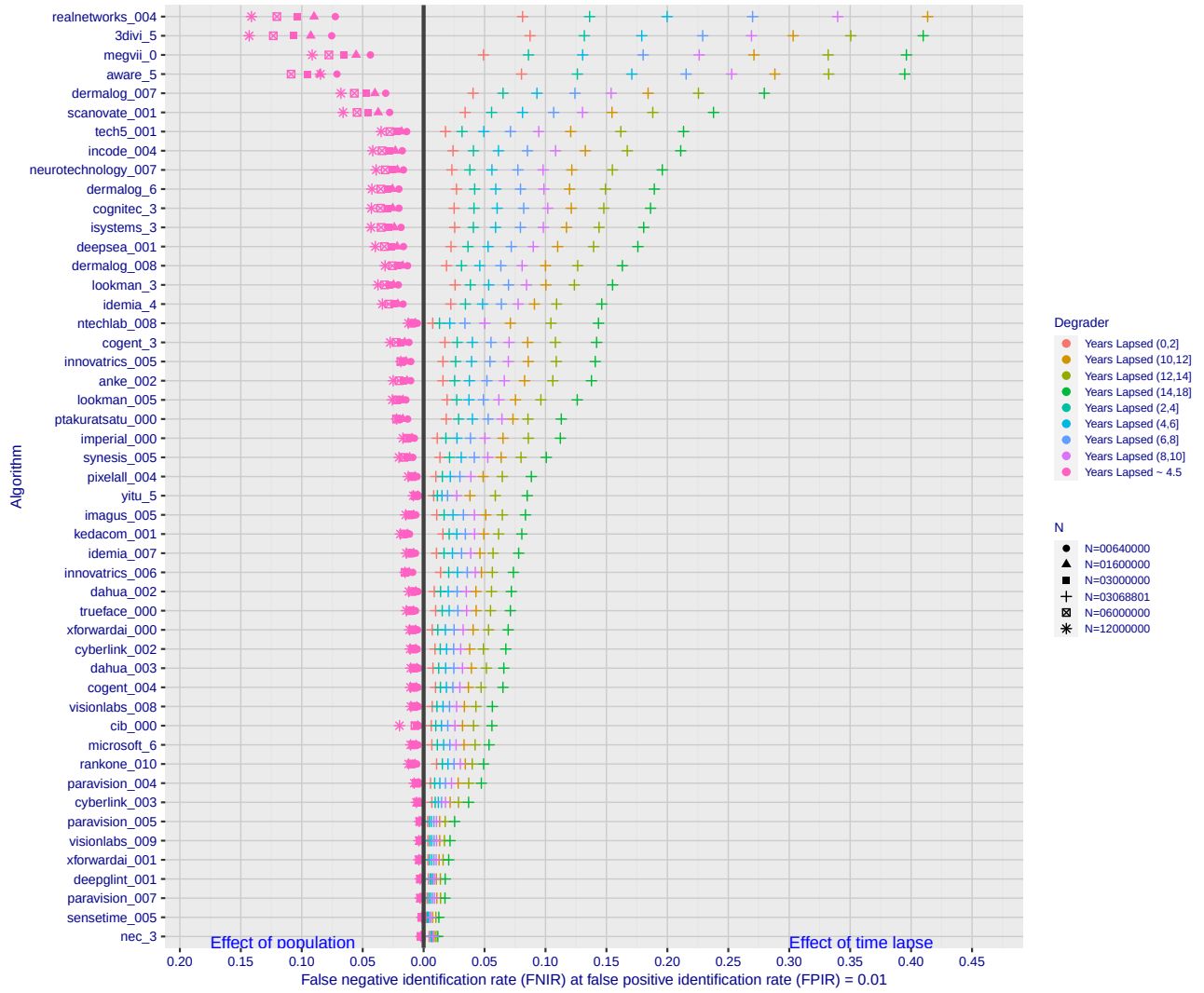


Figure 2: Identification miss rates as a function of enrolled population size, N , and time-lapse, ΔT .

an enrollment database becomes larger and the chance of a false positive increases such that higher thresholds may become necessary⁴.

The Figure shows, from top to bottom, increases in false negative identification rates (FNIR) with the algorithm being tested. This applies to increases due to N on the left side, and increases due to ageing on the right side. The relative spacing of the dots shows that for all algorithms the dependency of FNIR on N (up to 12 million) is considerably less than on ΔT (up to 18 years).

In the inset table, accuracy is seen to degrade progressively with time, as mate scores decline and non-mates displace mates from rank 1 position. More accurate algorithms tend to be less sensitive to ageing. The more accurate algorithms give fewer errors after 18 years of ageing than middle tier algorithms give after four. Note also we do not quantify an ageing rate - more formal methods [2] borrowed from the longitudinal analysis literature have been published for doing so (given suitable repeated measures data). See Figures 60, 79 and 88.

▷ **False positives from twins:** By enrolling 640 000 mugshots, adding photos of one twin, and then searching photos

⁴Some algorithms implement strategies to automatically adjust scores to account for increased population size. This relieves the system owner of having to increase thresholds as N increases.

of those subjects and their twin the inset figure shows, for one typical algorithm, the similarity is generally greater when searching twins against themselves (A) than when searching twins against their sibling (B) but very often still above even stringent thresholds i.e. those corresponding to one in one thousand searches producing a false positive. Thus twins will very often produce a high-scoring non-match on a candidate list and a false alarm in an online identification system. The plot of Fig. 3 shows that fraternal twins are sometimes correctly rejected at those thresholds - including most different sex twins (at center). Figure ?? shows substantially similar behavior for all algorithms tested. In an investigative search, a twin would typically appear at rank 1, or rank 2 if their sibling happened to also be the gallery. Twins (and triplets etc.) constituted 3.3% of all live births [17] in recent years⁵, and because that number is higher today than when the individuals in current adult databases were born, the false positives that arise from twins are now, and will increasingly be, an operational problem. Relative to the United States, twins are born with considerable regional variation. For example they are much less common in East Asia, and much more common in Sub-Saharan Africa [21]. The presence of twins in the mugshot database is inevitable given its size, around 12.3 million people. As this is not an insignificant sample of the domestic United States population, people with other familial ties will be present also. The data was collected over an extended period and because location information is not available, we are unable to estimate the proportion of the domestic population that is present in the dataset. However, if we assume twins are neither more or less disposed to arrest than the general population, we can estimate that hundreds of thousands of individuals in the dataset are twins. This will affect false positive rates because we randomly set aside 331 201 individuals for nonmate searches, and some proportion of those will be twins with siblings in the gallery.

- ▷ **Database integrity:** An operational error rate should be added to all false negative rates in this report reflecting the proportion of images in a real database that are un-matchable. Such anomalies arise from images that: do not contain a face; include multiple persons; cannot be decoded; are rotated by 90° or 180°; depict a face on clothing; and others introduced by a long tail of various clerical errors. While the mugshot trials in this report have been constructed to minimize such effects, they are a real problem in actual operations.

This report is being updated continuously as new algorithms are submitted to FRVT, and run on new datasets. Participation in the [one-to-many identification track](#) requires a developer to first demonstrate high accuracy in the [one-to-one verification track](#) of FRVT.

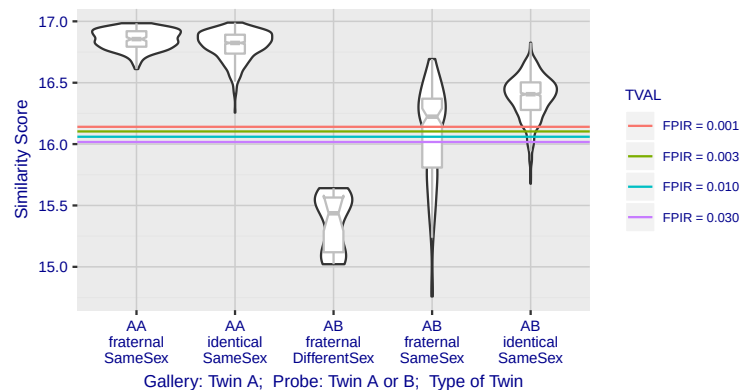


Figure 3: Intra- and inter-twin scores

⁵See the CDC's National Vital Statistics Report for 2017: <https://www.cdc.gov/nchs/data/nvsr/nvsr67/nvsr67.08-508.pdf>

Scope and Context

Audience: This report is intended for developers, integrators, end users, policy makers and others who have some familiarity with biometrics applications. The methods and metrics documented here will be of interest to organizations engaged in tests of face recognition algorithms. Some of these have been incorporated in the ISO/IEC 19795 Part 1 Biometric Testing and Reporting Framework standard, now nearing [publication](#).

Prior benchmarks: Automated face recognition accuracy has improved massively in the two decades since initial commercialization of the various technologies. NIST has tracked that improvement through its conduct of regular independent, free, open, and public evaluations. These have fostered improvements in the state of the art. This report serves as an update to the [NIST Interagency Report 8271](#) on performance of face identification algorithms, published in September 2019.

Demographics: In December 2019, NIST published a first report on demographic dependencies in face recognition, [NIST Interagency Report 8280](#) that documented age, sex and race differentials in one-to-one and one-to-many false positive and false negative rates.

Scope: NIST IR 8271 documented recognition results for four databases containing in excess of 30.2 million still photographs of 14.4 million individuals. That constituted the largest public and independent evaluation of face recognition ever conducted. It includes results for accuracy, speed, investigative vs. identification applications, scalability to large populations, use of multiple images per person, images of cooperative and non-cooperative subjects.

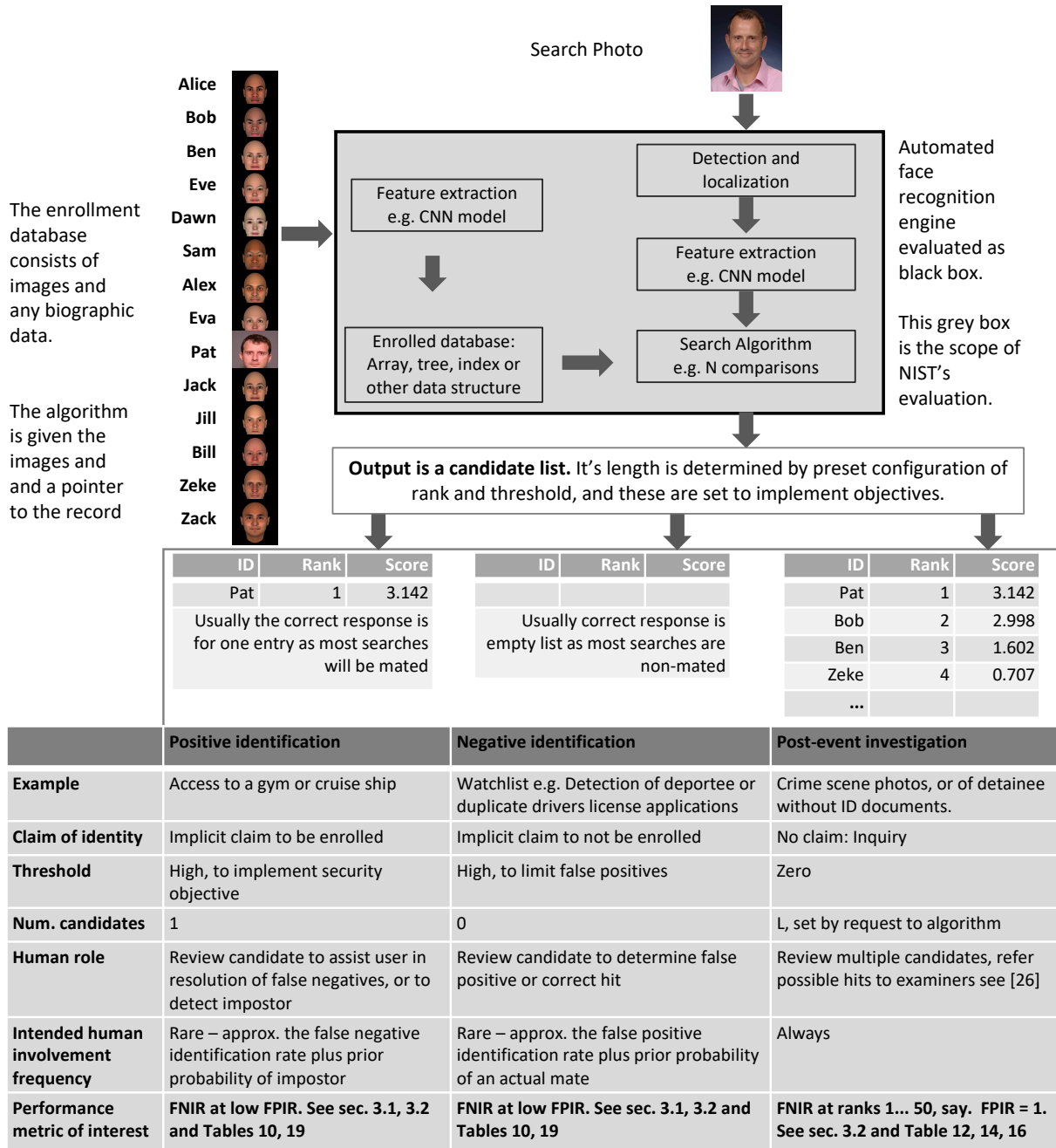
The report also includes results for ageing, recognition of twins, and recognition of profile-view images against frontal galleries. It otherwise does not address causes of recognition failure, neither image-specific problems nor subject-specific factors including demographics. Separate reports on demographic dependencies in face recognition will be published in the future. Additionally out of scope are: performance of live [human-in-the-loop transactional systems](#) like automated border control gates; human recognition accuracy as used in forensic applications; and recognition of persons in video sequences (which NIST evaluated separately [9]). Some of those applications share core matching technologies that *are* tested in this report.

Images: Five kinds of images are employed; these are either compared with images of the same kind, or against others from different capture environments as follows. The primary dataset is a set of law enforcement mugshot images (Fig. 5) which are enrolled and then searched with three kinds of images: other mugshots (i.e. within-domain); profile-view photographs (90 degree cross-view); and lower quality webcam images (Fig. 6) collected in similar detention operations (cross-domain). Additionally we compare high quality visa-like photos collected in immigration offices, with: medium quality border crossing images collected in primary immigration lanes; poor quality images collected in ATM-like registered traveller kiosks.

Participation and industry coverage: The report includes performance figures for prototype algorithms from the research laboratories of commercial developers and a few universities. This represents a substantial majority of the face recognition industry, but only a tiny minority of the academic community. Participation was open worldwide. While there is no charge for participation, developers incur some software engineering expense in implementing their algorithms behind the NIST application programming interface (API). The test is a black-box test where the function of the algorithm, and the intellectual property associated with it, is hidden inside pre-compiled libraries.

Recent technology development: Most face recognition research with deep convolutional neural networks (CNNs) has been aimed at achieving invariance to pose, illumination and expression variations that characterize photojournalism and social media images. The initial research [18, 22] employed large numbers of images of relatively few ($\sim 10^4$) individuals to learn invariance. Inevitably much larger populations ($\sim 10^7$) were employed for training [11, 20] but the benchmark, Labeled Faces in the Wild with (essentially) an equal error rate metric [12], represents an easy task,

one-to-one verification at very high false match rates. While a larger scale identification benchmark duly followed, Megaface [15], its primary metric, rank one hit rate, contrasts with the high threshold discrimination task required in most large-population applications of face recognition, namely credential de-duplication, and background checks. There, identification in galleries containing up to 10^8 individuals must be performed using a) very few images per individual and b) stringent thresholds to afford very low false positive identification rates. This track of FRVT was launched to measure the capability of the new technologies, including in these two cases. FRVT has included open-set identification tests since 2002, reporting both false negative and positive identification rates [7].



Performance metrics for applications: This report documents the performance of one-to-many face recognition algorithms. The word “performance” here refers to recognition accuracy and computational resource usage, as measured

by executing those algorithms on massive sequestered datasets.

This report includes extensive tabulation of recognition error rates germane to the main use-cases for face search technology. The Figure below, inspired by the Figure 1 in [23] differentiates different applications of the technology. The last row directs readers to the main tables relevant to those applications, respectively threshold-based and rank-based metrics that are special cases of the metrics given in section 3. The terms negative identification and positive identification are taken from the [ISO/IEC 2382-37:2017](#) standardized biometrics vocabulary.

The algorithms are specifically configured for these applications by setting thresholds and candidate list lengths. Both rank-based metrics and threshold-based metrics include tradeoffs. In investigation, overall accuracy will be reduced if labor is only available to review a few candidates from the automated system. Note that when a fixed number of candidates are returned, the false positive identification rate of the automated face recognition engine will be 100%, because a probe image of anyone not enrolled will still return candidates. In identification applications where false positives must be limited to satisfy reviewer labor availability or a security objective, higher false negative rates are implied. This report includes extensive quantification of this threshold-based tradeoff. See Sec. 3

Template diversity: The FRVT is designed to evaluate black-box technologies with the consequence that the templates that hold features extracted from face images are entirely proprietary opaque binary data that embed considerable intellectual property of the developer. Despite migration to CNN-based technologies there is no consensus on the optimal feature vector dimension. This is evidenced by template sizes ranging from below 100 bytes to more than four kilobytes. This diversity of approaches, suggests there is no prospect of a standard template something that would require a common feature set to be extracted from faces. Interoperability in automated face recognition remains solidly based on images and documentary standards for those, in particular the ICAO portrait [27] specification deriving from the ISO/IEC 19794-5 Token frontal [24] standard, which are similar to certain ANSI/NIST Type 10 [26] formats.

Training: The algorithms submitted to NIST have been developed using image datasets that developers do not disclose. The development will often include application of machine learning techniques and will additionally involve iterative training and testing cycles. NIST itself does not perform any training and does not refine or alter the algorithm in any way. Thus the model, data files, and libraries that define an algorithm are fixed for the duration of the tests. This reflects typical operational reality where recognition software, once installed, is fixed and constant until upgraded. This situation persists because on-site training of algorithms on customer data is atypical essentially because training is not a turnkey process.

Automated search and human review: Virtually all applications using automated face search require human review of the outputs at some frequency: Always for investigational applications; rarely in positive identification applications, after rejection (false or otherwise); and rarely in negative identification applications, after an alarm (false or otherwise). The human role is usually to compare a reference image with the query image or the live-subject if present, to render either a definitive decision on “exclusion” (different subjects), or “identification” (same subject), or a declaration that one or both images have “no value” and that no decision can be made. Note that automated face recognition algorithms are not built to do exclusion - low scores from a face comparison arise from different faces *and* poor quality images of the same face.

Human reviewers make recognition errors [5, 19, 25] and are sensitive to image acquisition and quality. Accurate human review is supported by high resolution - as specified in the Type 50, 51 acquisition profiles of the ANSI/NIST Type 10 record [26], and by multiple non-frontal views as specified in the same standard. These often afford views of the ear. Organizations involved in image collection should consider supporting human adjudication by collecting high-resolution frontal and non-frontal views, preparing low resolution versions for automated face recognition [24], and retaining both for any subsequent resolution of candidate matches. Along these lines, the [ISO/IEC Joint Technical](#)

Committee 1 subcommittee 37 on biometrics has just initiated projects on image quality assessment and face-aware capture.

This publication is available free of charge from: <https://doi.org/10.6028/NIST.IR.8271>

Release Notes

FRVT Activities: Since February 2017, NIST has been evaluating one-to-one verification algorithms on an ongoing basis. NIST then restarted FRVT's one-to-many track in February 2018, inviting participants to send up to prototype algorithms. Both tracks allows developers to submit updated algorithms to NIST at any time but no more frequently than four calendar months. This more closely aligns development and evaluation schedules. Results are posted to the web within a few weeks of submission. Details and full report are linked from the [Ongoing FRVT site](#).

FRVT Reports: The results of the FRVT appear in the series NIST Interagency Reports tabulated below. The reports were developed separately and released on different schedules. In prior years NIST has mostly reported FRVT results as a single report; this had the disadvantage that results from completed sub-studies were not published until all other studies were complete.

Date	Link	Title	No.
2014-03-20	PDF	FRVT Performance of Automated Age Estimation Algorithms	7995
2015-04-20	PDF	Face Recognition Vendor Test (FRVT) Performance of Automated Gender Classification Algorithms	8052
2014-05-21	PDF	FRVT Performance of face identification algorithms	8009
2017-03-07	PDF	Face In Video Evaluation (FIVE) Face Recognition of Non-Cooperative Subjects	8173
2017-11-23	PDF	The 2017 IARPA Face Recognition Prize Challenge (FRPC)	8197
2018-11-27	PDF	Face Recognition Vendor Test - Part 2: Identification	8271
2019-09-11	PDF	Face Recognition Vendor Test - Part 2: Identification	8271
2019-12-11	PDF	Face Recognition Vendor Test - Part 3: Demographic Effects	8280
2020-01-03	WWW	Face Recognition Vendor Test (FRVT) - Part 1 Verification	Draft

Details appear on pages linked from <https://www.nist.gov/programs-projects/face-projects>.

Appendices: This report is accompanied by appendices which present exhaustive results on a per-algorithm basis. These are machine-generated and are included because the authors believe that visualization of such data is broadly informative and vital to understanding the context of the report.

Typesetting: Virtually all of the tabulated content in this report was produced automatically. This involved the use of scripting tools to generate directly type-settable L^AT_EX content. This improves timeliness, flexibility, maintainability, and reduces transcription errors.

Graphics: Many of the Figures in this report were produced using the [ggplot2](#) package running under [R](#), the capabilities of which extend beyond those evident in this document.

Contents

Release Notes	1
Disclaimer	3
Institutional Review Board	3
Acknowledgments	3
Executive Summary	4
Scope and Context	9
Release Notes	13
1 Introduction	15
2 Evaluation datasets	16
3 Performance metrics	22
4 Results	38
Appendices	66
A Accuracy on large-population FRVT 2018 mugshots	66
B Effect of time-lapse: Accuracy after face ageing	111
C Effect of enrolling multiple images	198
D Accuracy with poor quality webcam images	205
E Accuracy for profile-view to frontal recognition	215
F Search duration	219
G Gallery Insertion Timing	226

1 Introduction

One-to-many identification represents the largest market for face recognition technology. Algorithms are used across the world in a diverse range of biometric applications: detection of duplicates in databases, detection of fraudulent applications for credentials such as passports and driving licenses, token-less access control, surveillance, social media tagging, lookalike discovery, criminal investigation, and forensic clustering.

This report contains a breadth of performance measurements relevant to many applications. Performance here refers to accuracy and resource consumption. In most applications, the core accuracy of a facial recognition algorithm is the most important performance variable. Resource consumption will be important also as it drives the amount of hardware, power, and cooling necessary to accommodate high volume workflows. Algorithms consume processing time, they require computer memory, and their static template data requires storage space. This report documents these variables.

1.1 Open-set searches

FRVT tested open-set identification algorithms. Real-world applications are almost always “open-set”, meaning that some searches have an enrolled mate, but some do not. For example, some subjects have truly not been issued a visa or drivers license before; some law enforcement searches are from first-time arrestees⁶. In an “open-set” application, algorithms make no prior assumption about whether or not to return a high-scoring result, and for a mated search, the ideal behaviour is that the search produces the correct mate at high score and first rank. For a non-mate search, the ideal behavior is that the search produces zero high-scoring candidates.

Many academic benchmarks execute only closed-set searches. The proportion of mates found in the rank one position is the default accuracy metric. This hit rate metric ignores the score with which a mate is found; weak hits count as much as strong hits. This ignores the real-world imperative that in many applications it is necessary to elevate a threshold to reduce the number of false positives.

⁶Operationally closed-set applications are rare because it is usually not the case that all searches have an enrolled mate. One counter-example, however, is a cruise ship in which all passengers are enrolled and all searches should produce exactly one identity. Another example is forensic identification of dental records from an aircraft crash.

2 Evaluation datasets

This report documents accuracy for four kinds of images - mugshots, webcam, profiles and wild - as described in the following sections.

2.1 Immigration-related images

This report includes benchmark tests sharing a common enrollment of high quality frontal portrait images collected while subject make applications for various immigration benefits. We then search that with two kinds of images, webcam images collected during in-bound immigration and also images collected from registered travelers using a ATM-style kiosk. These are described below and depicted in Figure 4.

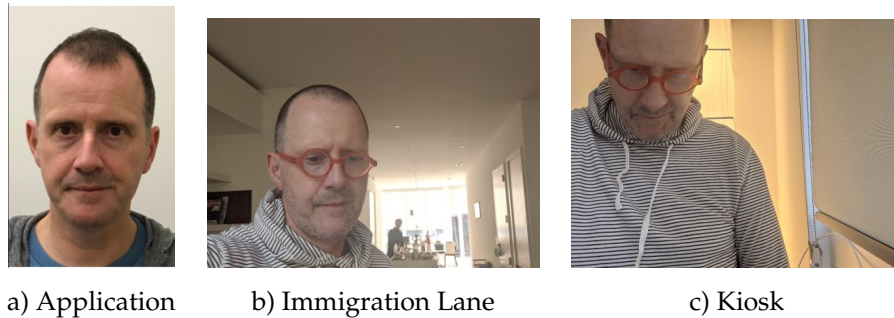


Figure 4: Example photos.

- ▷ **Application reference photos:** The images are collected in an attended interview setting using dedicated capture equipment and lighting. The images, at size 300x300 pixels, are smaller than normally indicated by ISO. The images are all high-quality frontal portraits collected in immigration offices and with a white background. As such, potential quality related drivers of high false match rates (such as blur) can be expected to be absent. The images are encoded as ISO/IEC 10918-1 i.e. JPEG. Older images had a compression ration of about 16:1, while newer images, since 2010, are more lightly compressed at 4:1. When these images are provided as input into the algorithm, they are labeled with the type “iso”. This report enrols 1 600 000 application images, one per person.
- ▷ **Border crossing photos:** Most images are have width 320 and height 240 pixels. They are JPEG compressed at 16:1 i.e. filesize just below 15KB. The images present challenges for face recognition in that subjects often exhibit non-zero yaw and pitch (associated with the rotational degrees of freedom of the camera mount), low contrast (due to varying and intense background lights), and poor spatial resolution (due to inexpensive cameras). There are often subjects standing in the background, usually at very low resolution (see Figure 4b). In such cases, algorithms should detect all faces and determine which is the largest and most centered. When these images are provided as input into the algorithm, they are labeled with the type “wild”.
- ▷ **Kiosk photos:** These photos were collected from subjects whose attention was focused on interaction with an immigration kiosk. They images were not intended for use with automated face recognition. The camera is situated above a display which the user touches, and is triggered either without directing the subject to look at it, or without waiting for the subject to comply. The images are therefore characterized by pitch-down pose, sometimes exceeding 45 degrees, as in Figure 4c. Yaw-angle variation is mild, with most images close to frontal. The images

have width 320 pixels and height 240 pixels and therefore tall individuals are sometimes cropped. This is often just above the eyes and can occur at the nose or mouth. Conversely, short individuals are sometimes cropped such that only the top part of the face is visible. In a quite small number of cases, there other subjects standing just behind the primary subject such that algorithms should detect all faces and determine which is the largest and most centered. Background ceiling lighting is often visible and this sometimes leads to under-exposure of the face. When these images are provided as input into the algorithm, they are labeled with the type “wild”.

2.2 Law enforcement images

The main mugshot dataset used is referred to as the FRVT 2018 set. This set was collected over the period 2002 to 2017 in routine United States law enforcement operations. This set yields three subsets

- ▷ **Mugshots:** Mugshots comprise about 86% of the database. They have reasonable compliance with the ANSI/NIST ITL1-2011 Type 10 standard’s subject acquisition profiles levels 10-20 for frontal images [26]. The most common departure from the standard’s requirements is the presence of mild pose variations around frontal - the images of Figure 5 are typical. The images vary in size, with many being 480x600 pixels with JPEG compression applied to produce filesizes of between 18 and 36KB with many images outside this range, implying that about 0.5 bits are being encoded per pixel. When these images are provided as input into the algorithm, they are labeled with the type “mugshot”. Example images appear in Fig. 5

NIST Interagency Report 8238 includes a comparison of this set of mugshots with the smaller and easier sets of mugshots used in tests run in 2010 and 2014.

- ▷ **Profile images:** Profile-view images have been collected in law enforcement for more than 100 years, as human capability is improved with orthogonal information. The profile images used in this report were collected during the same session as the frontal mugshot photograph, in the same standardized photographic setup. These would not therefore be used with automated face recognition. A small subset, 200 000 images, were set aside for testing. When these images are provided as input into the algorithm, they are labeled with the type “wild”. Example images appear in Fig. 7
- ▷ **Webcam images:** The remaining 14% of the images were collected using an inexpensive webcam attached to a flexible operator-directed mount. These images are all of size 240x240 pixels, that are in considerable violation of most quality-related clauses of all face recognition standards. As evident in the figure, the most common defects are non-frontal pose (associated with the rotational degrees of freedom of the camera mount), low contrast (due to varying and intense background lights), and poor spatial resolution (due to inexpensive camera optics) - see examples in Fig 6. The images are overly JPEG compressed, to between 4 and 7KB, implying that only 0.5 to 1 bits are being encoded per color pixel. When these images are provided as input into the algorithm, they are labeled with the type “wild”. Example images appear in Fig. 6

These are drawn from NIST Special Database 32 which may be downloaded [here](#).

These images were partitioned in galleries and probesets for the various experiment listed in Table 1.

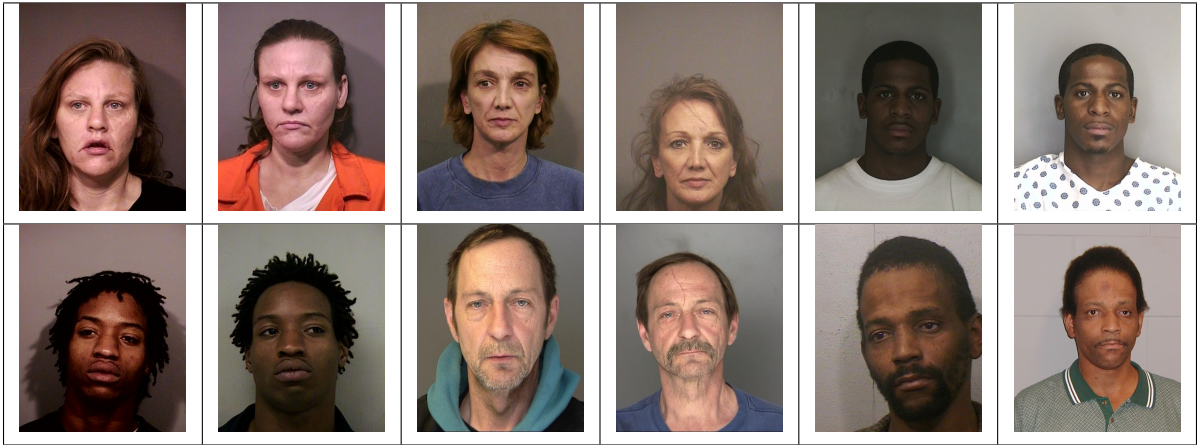


Figure 5: Six mated mugshot pairs representative of the FRVT-2014 (LEO) and FRVT-2018 datasets. The images are collected live, i.e. not scanned from paper. Image source: NIST Special Database 32 the Multiple Encounter Deceased Subjects dataset.



Figure 6: Twelve webcam images representative of probes against the FRVT-2018 mugshot gallery. The first eight images are four mated pairs. Such images present challenges to recognition including pose, non-uniform illumination, low contrast, compression, cropping, and low spatial sampling rate. Image source: NIST Special Database 32 the Multiple Encounter Deceased Subjects dataset.

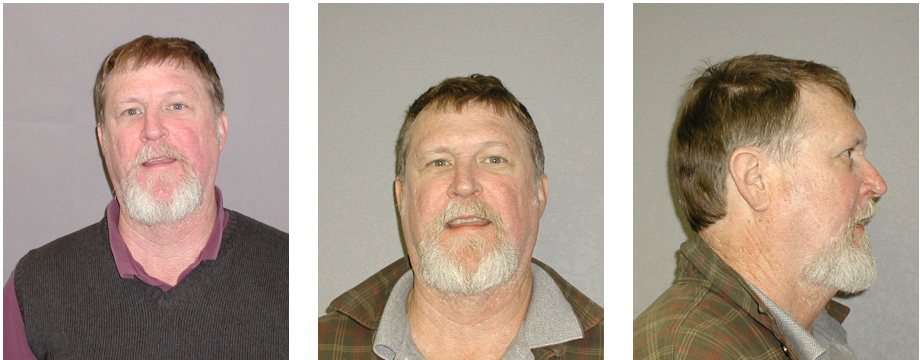


Figure 7: **[Profile views]** The three images are a frontal enrollment, subsequent frontal probe, and same-session ninety degree profile view. While collection of both frontal and profile views has been typical in law enforcement for more than a century, the recognition of profile to frontal views has essentially been impossible. However, reasonably high accuracy results is now possible - see section E.

This publication is available free of charge from: <https://doi.org/10.6028/NIST.IR.8271>

Image				
Encounter	1	...	$K_i - 1$	K_i
Capture Time	T_1	...	T_{K_i-1}	T_{K_i}
Role RECENT	Not used	Not used	Enrolled	Search
Role LIFETIME	Enrolled	Enrolled	Enrolled	Search

Figure 8: Depiction of the “recent” and “lifetime” enrollment types. Image source: NIST Special Database 32

2.3 Enrollment strategies

Many operational applications include collection and enrollment of biometric data from subjects on more than one occasion. This might be done on a regular basis, as might occur in credential (re-)issuance, or irregularly, as might happen in a criminal recidivist situation [4]. The number of images per person will depend on the application area. In civil identity credentialing (e.g. passports, driver’s licenses), the images will be acquired approximately uniformly over time (e.g. ten years for a passport). While the distribution of dates for such images of a person might be assumed uniform, a number of factors might undermine this assumption⁷. In criminal applications, the number of images would depend on the number of arrests. The distribution of dates for arrest records for a person (i.e. the recidivism distribution) has been modeled using the exponential distribution but is recognized to be more complicated⁸.

In any case, the 2010 NIST evaluation of face recognition showed that considerable accuracy benefits accrue with retention and use of *all* historical images [6].

To this end, the FRVT API document provides $K \geq 1$ images of an individual to the enrollment software. The software is tasked with producing a single proprietary undocumented “black-box” template⁹ from the K images. This affords the algorithm an ability to generate a *model* of the individual, rather than to simply extract features from each image on a sequential basis.

As depicted in Figure 8, the i -th individual in the FRVT 2018 dataset has K_i images. These are labelled as x_k for $k = 1 \dots K_i$ in chronological order of capture date. To measure the utility of having multiple enrollment images, this report evaluates three kinds of enrollment:

- ▷ **Recent:** Only the second most recent image, x_{K_i-1} is enrolled. This strategy of enrollment mimics the operational policy of retaining the imagery from the most recent encounter. This might be done operationally to ameliorate the effects of face ageing. Obviously retaining only the most recent image should only be done if the identity of the person is trusted to be correct. For example, in an access control situation retention of the most recent successful *authentication* image would be hazardous if it could be a false positive.
- ▷ **Lifetime-consolidated:** All but the most recent image are enrolled, $x_1 \dots x_{K_i-1}$. This subject-centric strategy might be adopted if quality variations exist where an older image might be more suitable for matching, despite the ageing effect.

⁷For example, a person might skip applying for a passport for one cycle, letting it expire. In addition, a person might submit identical images (from the same photography session) to consecutive passport applications at five year intervals.

⁸A number of distributions have been considered to model recidivism, see for example [3].

⁹There are no formal face template standards. Template standards only exist for fingerprint minutiae - see ISO/IEC 19794-2:2011.

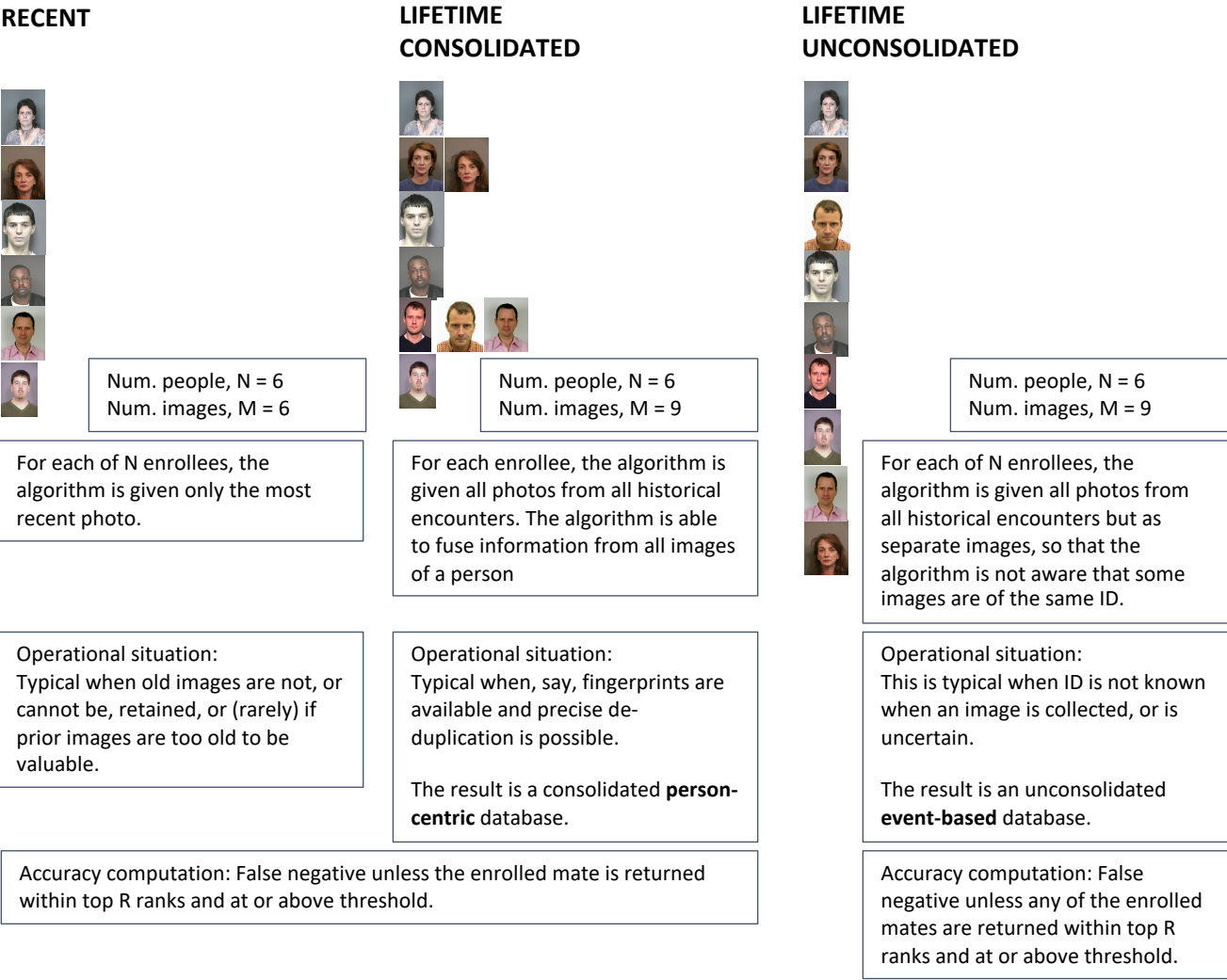


Figure 9: Enrollment strategies. The figure shows the three kinds of enrollment databases examined in this report. Image source: NIST Special Database 32

ENROLLMENT					SEARCH			
TYPE SEE		POPULATION			MATE		NON-MATE	
SECTION 2.3		FILTER	N-SUBJECTS	N-IMAGES	N-SUBJECTS	N-IMAGES	N-SUBJECTS	N-IMAGES
Mugshot trials from enrollmt of single images								
1	RECENT	NATURAL	640 000	640 000	154 549	154 549	331 254	331 254
2	RECENT	NATURAL	1 600 000	1 600 000				
3	RECENT	NATURAL	3 000 000	3 000 000				
4	RECENT	NATURAL	6 000 000	6 000 000				
5	RECENT	NATURAL	12 000 000	12 000 000				
Cross-domain								
13	MUGSHOTS AS ON ROW 2				82 106 WEBCAM	82 106 WEBCAM	331 254 WEBCAM	331 254 WEBCAM
Cross-view								
14	MUGSHOTS AS ON ROW 2				100 000 PROFILE	100 000 PROFILE	100 000 PROFILE	100 000 PROFILE
Mugshot ageing								
17	OLDEST	NATURAL	3 068 801	3 068 801	2 853 221	10 951 064	0	0
Visa-border								
18	PRIOR	NATURAL	1 600 000 VISA	1 600 000 VISA	80 000 BORDER	80 000 BORDER	80 000 BORDER	80 000 BORDER
19	VISA AS ON ROW 18				21 016 BORDER	21 016 BORDER	21 016 BORDER	21 016 BORDER

Table 1: **Enrollment and search sets.** Each row summarizes one identification trial. Unless stated otherwise, all entries refer to mugshot images. The term “natural” means that subjects were selected without heed to demographics, i.e. in the distribution native to this dataset. The probe images were collected in a different calendar year to the enrollment image. Missing values in rows 2-12 are the same as in row 1.

- ▷ **Lifetime-unconsolidated:** Again all but the most recent image are enrolled $x_1 \dots x_{K_i-1}$ but now separately, with different identifiers, such that the algorithm is not aware that the images are from the same face. This kind of event- or encounter-centric enrollment is very common when operational constraints preclude reliable consolidation of the historical encounters into a single identity. This aspect also prevents the recognition algorithm from a) building a holistic model of identity (as is common in speaker recognition systems) and b) implementing fusion, for example template-level fusion of feature vectors, or post-search score-level fusion. The result is that searches will typically yield more than one image of a person in the top ranks. This has consequences for appropriate metrics, as detailed in section 3.2.1

NIST first evaluated this kind of enrollment in mid 2018, and the results tables include some comparison of accuracy available from all three enrollment styles.

In all cases, the most recent image, x_{K_i} , is reserved as the search image. For the 1.6 million subject enrollment partition of the FRVT 2018 data, $1 \leq K_i \leq 33$ with $K_i = 1$ in 80.1% of the individuals, $K_i = 2$ in 13.4%, $K_i = 3$ in 3.7%, $K_i = 4$ in 1.4%, $K_i = 5$ in 0.6%, $K_i = 6$ in 0.3%, and $K_i > 6$ is 0.2% for everyone else. This distribution is substantially dependent on United States recidivism rates.

We did not evaluate the case of retaining only the highest quality image, since automated quality assessment is out of scope for this report. We do not anticipate that such strategies will prove beneficial when the quality assessment apparatus is imperfect and unvalidated.

3 Performance metrics

This section gives specific definitions for accuracy and timing metrics. Tests of open-set biometric algorithms must quantify frequency of two error conditions:

- ▷ **False positives:** Type I errors occur when search data from a person who has never been seen before is incorrectly associated with one or more enrollees' data.
- ▷ **Misses:** Type II errors arise when a search of an enrolled person's biometric does not return the correct identity.

Many practitioners prefer to talk about "hit rates" instead of "miss rates" - the first is simply one minus the other as detailed below. Sections 3.1 and 3.2 define metrics for the Type I and Type II performance variables.

Additionally, because recognition algorithms sometimes fail to produce a template from an image, or fail to execute a one-to-many search, the occurrence of such events must be recorded. Further because algorithms might elect to not produce a template from, for example, a poor quality image, these failure rates must be combined with the recognition error rates to support algorithm comparison. This is addressed in section 3.5.

Finally, section 3.7 discusses measurement of computation duration, and section 3.8 addresses the uncertainty associated with various measurements. Template size measurement is included with the results.

3.1 Quantifying false positives

It is typical for a search to be conducted into an enrolled population of N identities, and for the algorithm to be configured to return the closest L candidate identities. These candidates are ranked by their score, in descending order, with all scores required to be greater than or equal to zero. A human analyst might examine either all L candidates, or just the top $R \leq L$ identities, or only those with score greater than threshold, T . The workload associated with such examination is discussed later, in 3.6.

False alarm performance is quantified in two related ways. These express how many searches produces false positives, and then, how many false positives are produced in a search.

False positive identification rate: The first quantity, FPIR, is the proportion of non-mate searches that produce an adverse outcome:

$$\text{FPIR}(N, T) = \frac{\text{Num. non-mate searches where one or more enrolled candidates are returned with score at or above threshold}}{\text{Num. non-mate searches attempted.}} \quad (1)$$

Under this definition, FPIR can be computed from the highest non-mate candidate produced in a search - it is not necessary to consider candidates at rank 2 and above. FPIR is the primary measure of Type I errors in this report.

Selectivity: However, note that in any given search, several non-mate may be returned above threshold. In order to quantify such events, a second quantity, selectivity (SEL), is defined as the *number* of non-mates returned on a candidate list, averaged over all searches.

$$\text{SEL}(N, T) = \frac{\text{Num. non-mate enrolled candidates returned with score at or above threshold}}{\text{Num. non-mate searches attempted.}} \quad (2)$$

where $0 \leq \text{SEL}(N, T) \leq L$. Both of these metrics are useful operationally. FPIR is useful for targeting how often an

adverse false positive outcome can occur, while SEL as a number is related to workload associated with adjudicating candidate lists. The relationship between the two quantities is complicated - it depends on whether an algorithm concentrates the false alarms in the results of a few searches or whether it disburses them across many. This was detailed in FRVT 2014, NISTIR 8009. It has not yet been detailed in FRVT 2018.

3.2 Quantifying hits and misses

If L candidates are returned in a search, a shorter candidate list can be prepared by taking the top $R \leq L$ candidates for which the score is above some threshold, $T \geq 0$. This reduction of the candidate list is done because thresholds may be applied, and only short lists might be reviewed (according to policy or labor availability, for example). It is useful then to state accuracy in terms of R and T , so we define a “miss rate” with the general name **false negative identification rate** (FNIR), as follows:

$$\text{FNIR}(N, R, T) = \frac{\text{Num. mate searches with enrolled mate found outside top } R \text{ ranks or score below threshold}}{\text{Num. mate searches attempted.}} \quad (3)$$

This formulation is simple for evaluation in that it does not distinguish between causes of misses. Thus a mate that is not reported on a candidate list is treated the same as a miss arising from face finding failure, algorithm intolerance of poor quality, or software crashes. Thus if the algorithm fails to produce a candidate list, either because the search failed, or because a search template was not made, the result is regarded as a miss, adding to FNIR.

Hit rates, and true positive identification rates: While FNIR states the “miss rate” as how often the correct candidate is either not above threshold or not at good rank, many communities prefer to talk of “hit rates”. This is simply the **true positive identification rate** (TPIR) which is the complement of FNIR giving a positive statement of how often mated searches are successful:

$$\text{TPIR}(N, R, T) = 1 - \text{FNIR}(N, R, T) \quad (4)$$

This report does not report true positive “hit” rates, preferring false negative miss rates for two reasons. First, costs rise linearly with error rates. For example, if we double FNIR in an access control system, then we double user inconvenience and delay. If we express that as decrease of TPIR from, say 98.5% to 97%, then we mentally have to invert the scale to see a doubling in costs. More subtly, readers don’t perceive differences in numbers near 100% well, becoming inured to the “high nineties” effect where numbers close to 100 are perceived indifferently.

Reliability is a corresponding term, typically being identical to TPIR, and often cited in automated (fingerprint) identification system (AFIS) evaluations.

An important special case is the **cumulative match characteristic** (CMC) which summarizes accuracy of mated-searches only. It ignores similarity scores by relaxing the threshold requirement, and just reports the fraction of mated searches returning the mate at rank R or better.

$$\text{CMC}(N, R) = 1 - \text{FNIR}(N, R, 0) \quad (5)$$

We primarily cite the complement of this quantity, $\text{FNIR}(N, R, 0)$, the fraction of mates *not* in the top R ranks.

The **rank one hit rate** is the fraction of mated searches yielding the correct candidate at best rank, i.e. $\text{CMC}(N, 1)$. While this quantity is the most common summary indicator of an algorithm’s efficacy, it is not dependent on similarity scores, so it does not distinguish between strong (high scoring) and weak hits. It also ignores that an adjudicating reviewer is often willing to look at many candidates.

3.2.1 False negative rates for unconsolidated galleries

As detailed in section 2.3 a common type of gallery, here referred to as the lifetime unconsolidate type, is populated with all images of an individual without any association between them. That is, the gallery construction algorithm is not provided with any ID labels that would support processing of a person's images jointly. This contrasts with the lifetime consolidate type where an algorithm may explicitly fuse features from multiple images of a person, or select a best image. In such cases, where the number of enrolled images is a random variable, we define two false negative rates as follows.

The first demands that the algorithm place any of the K_i mates in the top $R \geq 1$ ranks. The proportion of searches for which this does not occur forms a false negative identification rate:

$$\text{FNIR}_{\text{any}}(N, R, T) = 1 - \frac{\text{Num. mate searches where any enrolled mate is found in the top } R \text{ ranks and at-or-above threshold}}{\text{Num. mate searches attempted.}} \quad (6)$$

The second demands that the algorithm place all K_i mates in the top $R \geq K_i$ ranks. The proportion of searches for which this does not occur forms a false negative identification rate:

$$\text{FNIR}_{\text{all}}(N, R, T) = 1 - \frac{\text{Num. mate searches where all enrolled mates are found in the top } R \text{ ranks and at-or-above threshold}}{\text{Num. mate searches attempted.}} \quad (7)$$

Placing all mates in the top ranks is a more difficult task than correctly retrieving any image, so it holds that: $\text{FNIR}_{\text{all}} \geq \text{FNIR}_{\text{any}}$. This is evident in the results presented for November 2018 algorithms in Tables starting at ??.

The information retrieval community might prefer to compute and plot *precision* and *recall*; this is a valid approach, but we advance the two metrics above because they relate to our normal definition of consolidated FNIR, and they cover the two extreme use-cases of wanting any hit vs. all hits.

3.3 DET interpretation

In biometrics, a false negative occurs when an algorithm fails to match two samples of one person – a Type II error. Correspondingly, a false positive occurs when samples from two persons are improperly associated – a Type I error.

Matches are declared by a biometric system when the native comparison score from the recognition algorithm meets some threshold. Comparison scores can be either similarity scores, in which case higher values indicate that the samples are more likely to come from the same person, or dissimilarity scores, in which case higher values indicate different people. Similarity scores are traditionally computed by fingerprint and face recognition algorithms, while dissimilarities are used in iris recognition. In some cases, the dissimilarity score is a distance possessing metric properties. In any case, scores can be either mate scores, coming from a comparison of one person's samples, or nonmate scores, coming from comparison of different persons' samples.

The words "genuine" or "authentic" are synonyms for mate, and the word "impostor" is used as a synonym for non-mate. The words "mate" and "nonmate" are traditionally used in identification applications (such as law enforcement search, or background checks) while genuine and impostor are used in verification applications (such as access control).

An error tradeoff characteristic represents the tradeoff between Type II and Type I classification errors. For identification this plots false negative vs. false positive identification rates i.e. FNIR vs. FPIR parametrically with T. Such plots

are often called detection error tradeoff (DET) characteristics or receiver operating characteristic (ROC). These serve the same function – to show error tradeoff – but differ, for example, in plotting the complement of an error rate (e.g. TPIR = 1 – FNIR) and in transforming the axes, most commonly using logarithms, to show multiple decades of FPIR. More rarely, the function might be the inverse of the Gaussian cumulative distribution function.

The slides of Figures 10 through 15 discuss presentation and interpretation of DETs used in this document for reporting face identification accuracy. Further detail is provided in formal biometrics testing standards, see the various parts of ISO/IEC 19795 Biometrics Testing and Reporting. More terms, including and beyond those to do with accuracy, appear in ISO/IEC 2382-37 Information technology – Vocabulary – Part 37: Harmonized biometric vocabulary.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

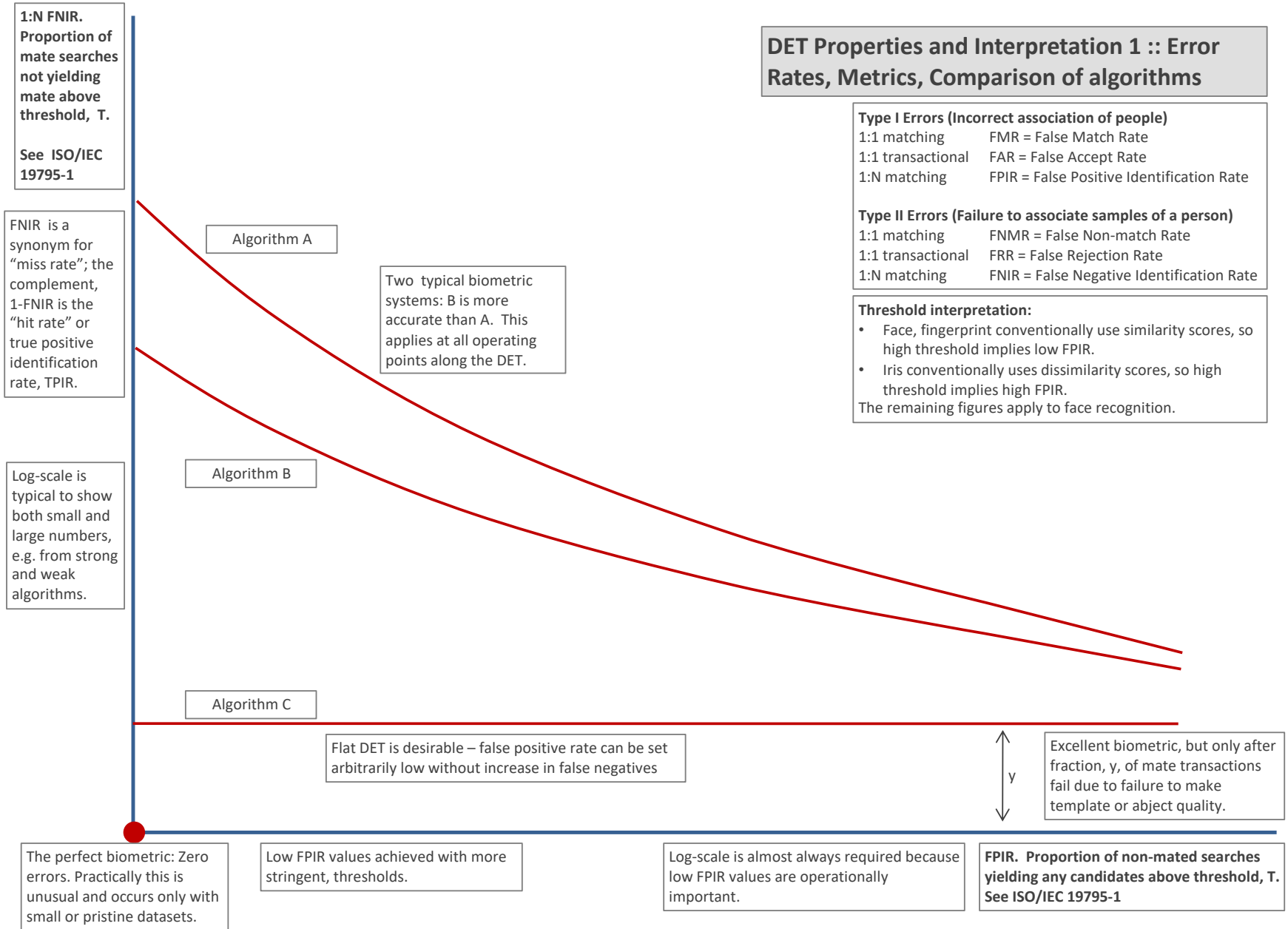
T = 0 → Investigation
T > 0 → Identification

Figure 10: DET as the primary performance reporting mechanism.

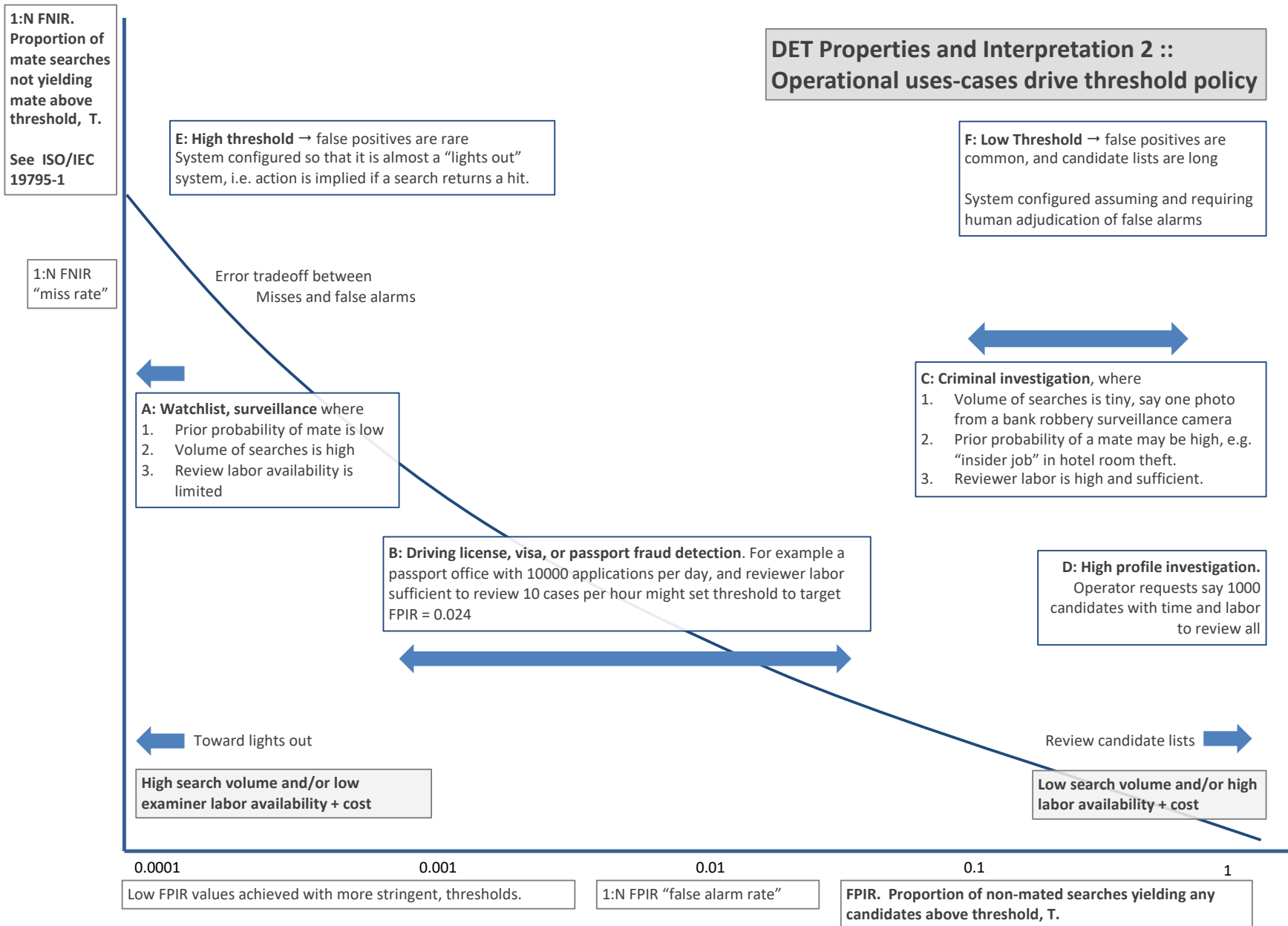


Figure 11: DET as the primary performance reporting mechanism.

2021/03/04
11:49:04

FNIR(N, R, T) =
FPIR(N, T) =

False neg. identification rate
False pos. identification rate

N = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

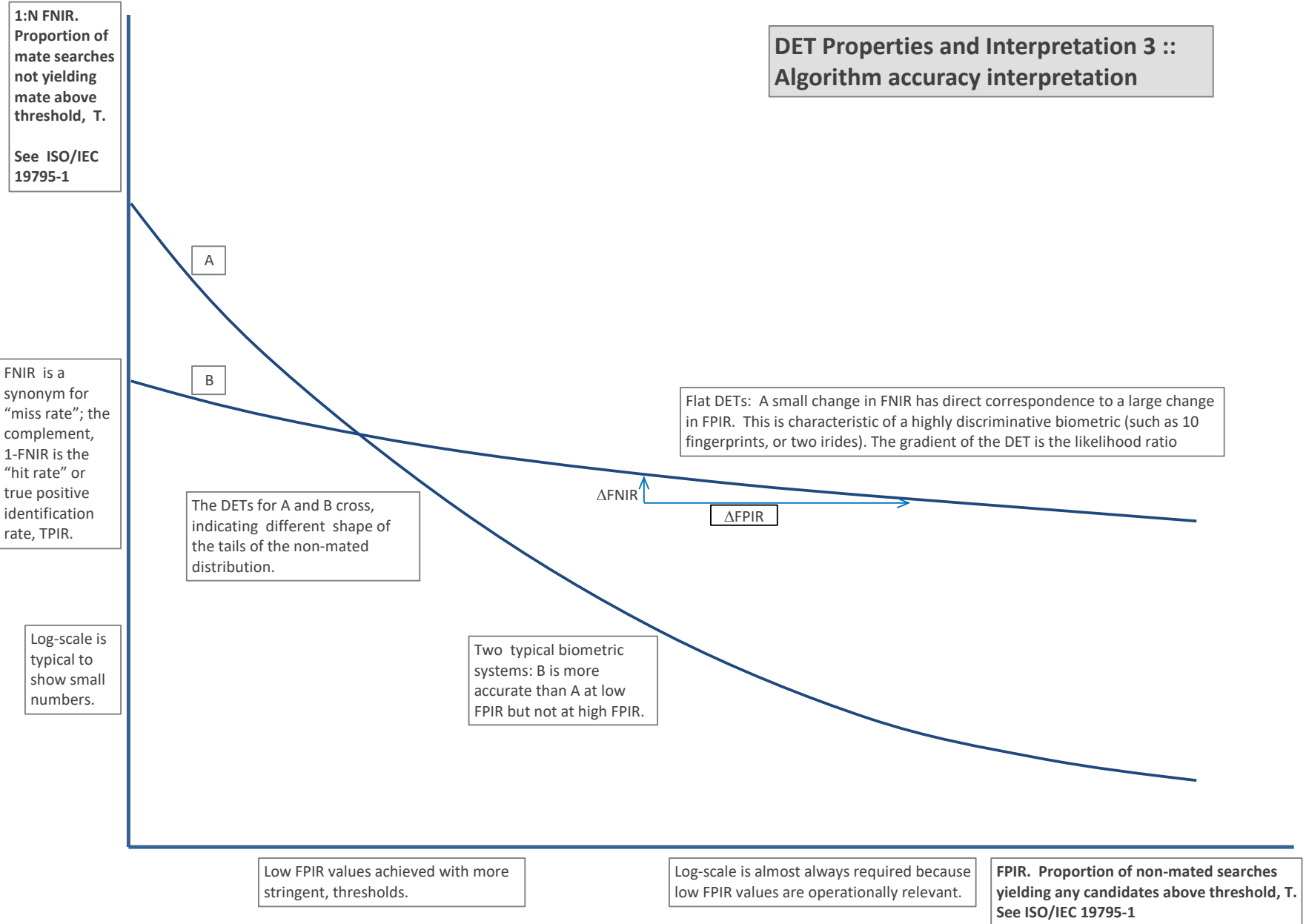


Figure 12: DET as the primary performance reporting mechanism.

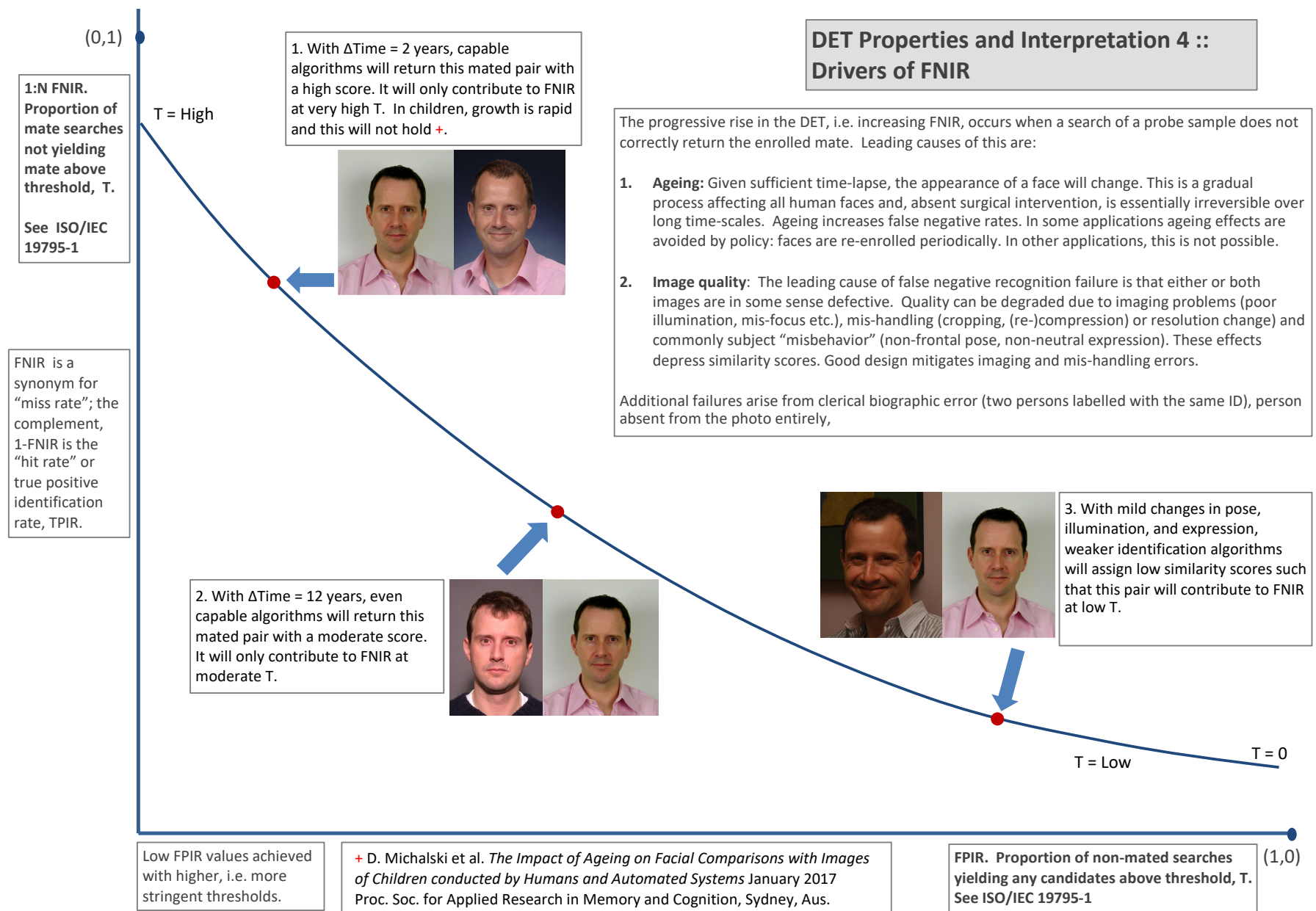


Figure 13: DET as the primary performance reporting mechanism.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

1:N FNIR.
Proportion of
mate searches
not yielding
mate above
threshold, T.

See ISO/IEC
19795-1

FNIR is a
synonym for
“miss rate”; the
complement,
1-FNIR is the
“hit rate” or
true positive
identification
rate, TPIR.

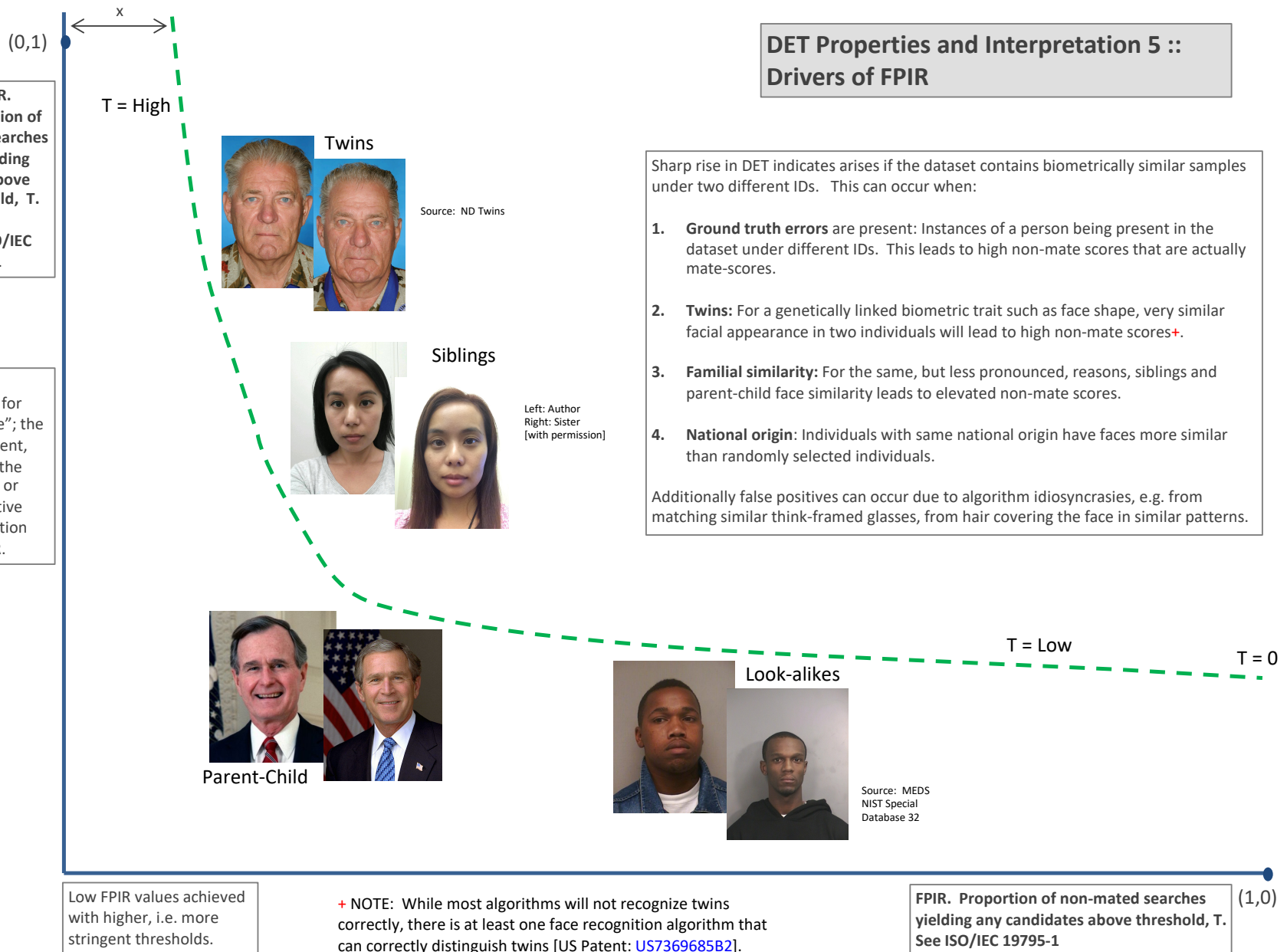


Figure 14: DET as the primary performance reporting mechanism.

2021/03/04
11:49:04

FNIR(N, R, T) =
FPIR(N, T) =

False neg. identification rate
False pos. identification rate

N = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

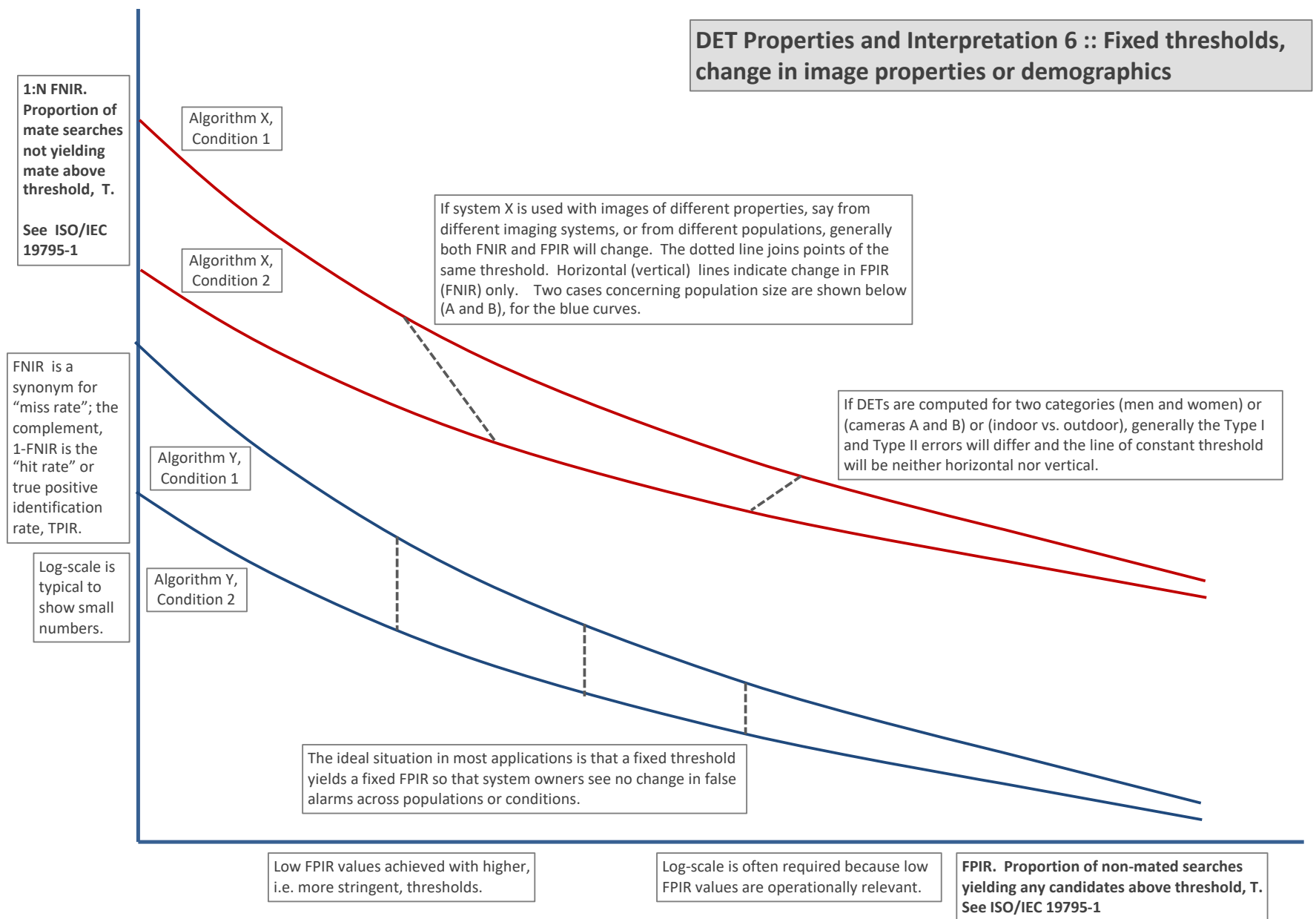


Figure 15: DET as the primary performance reporting mechanism.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

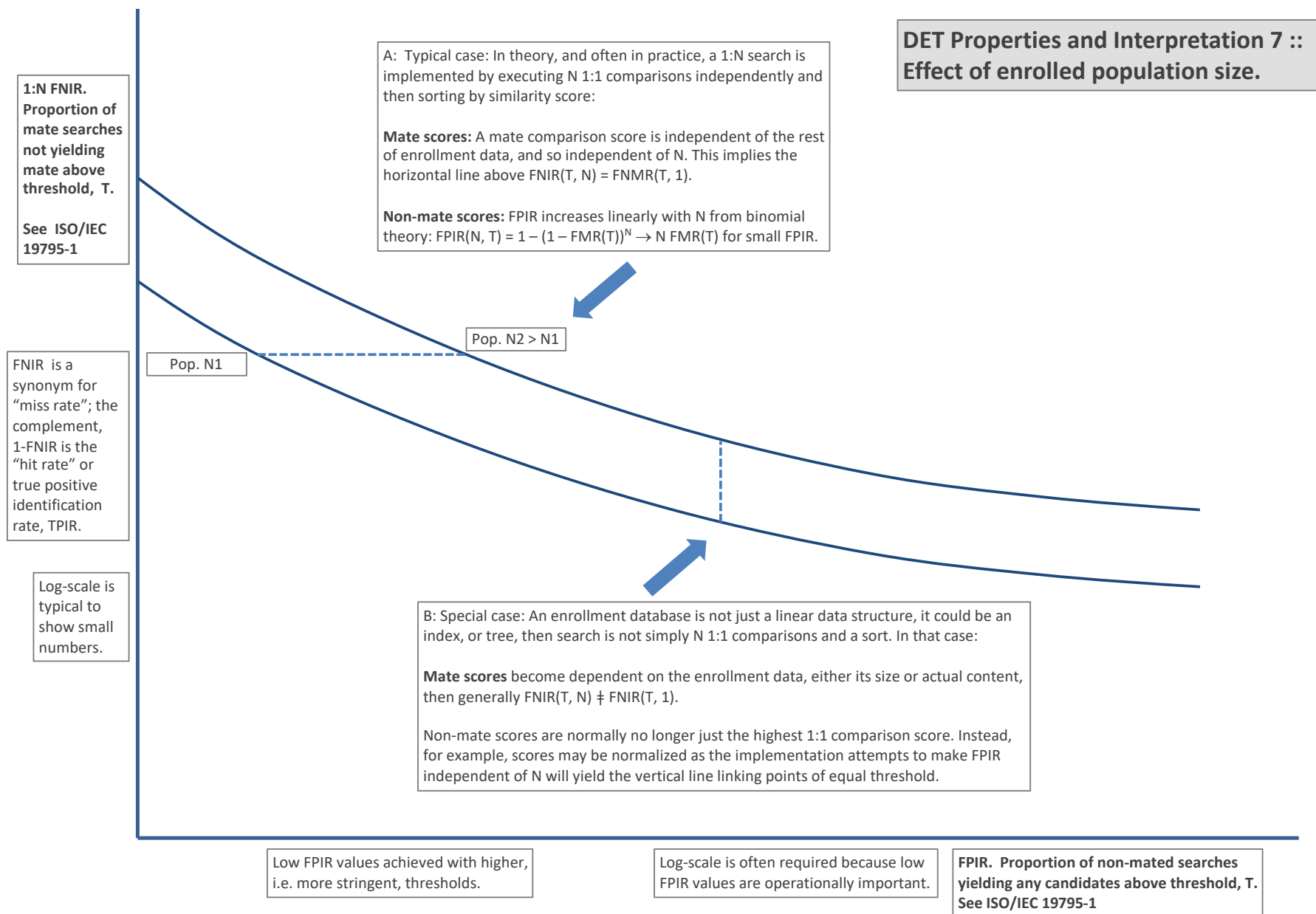
T = 0 → Investigation
T > 0 → Identification

Figure 16: DET as the primary performance reporting mechanism.

2021/03/04
11:49:04
FNIR(N, R, T) =
FPIR(N, T) =
False neg. identification rate
False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

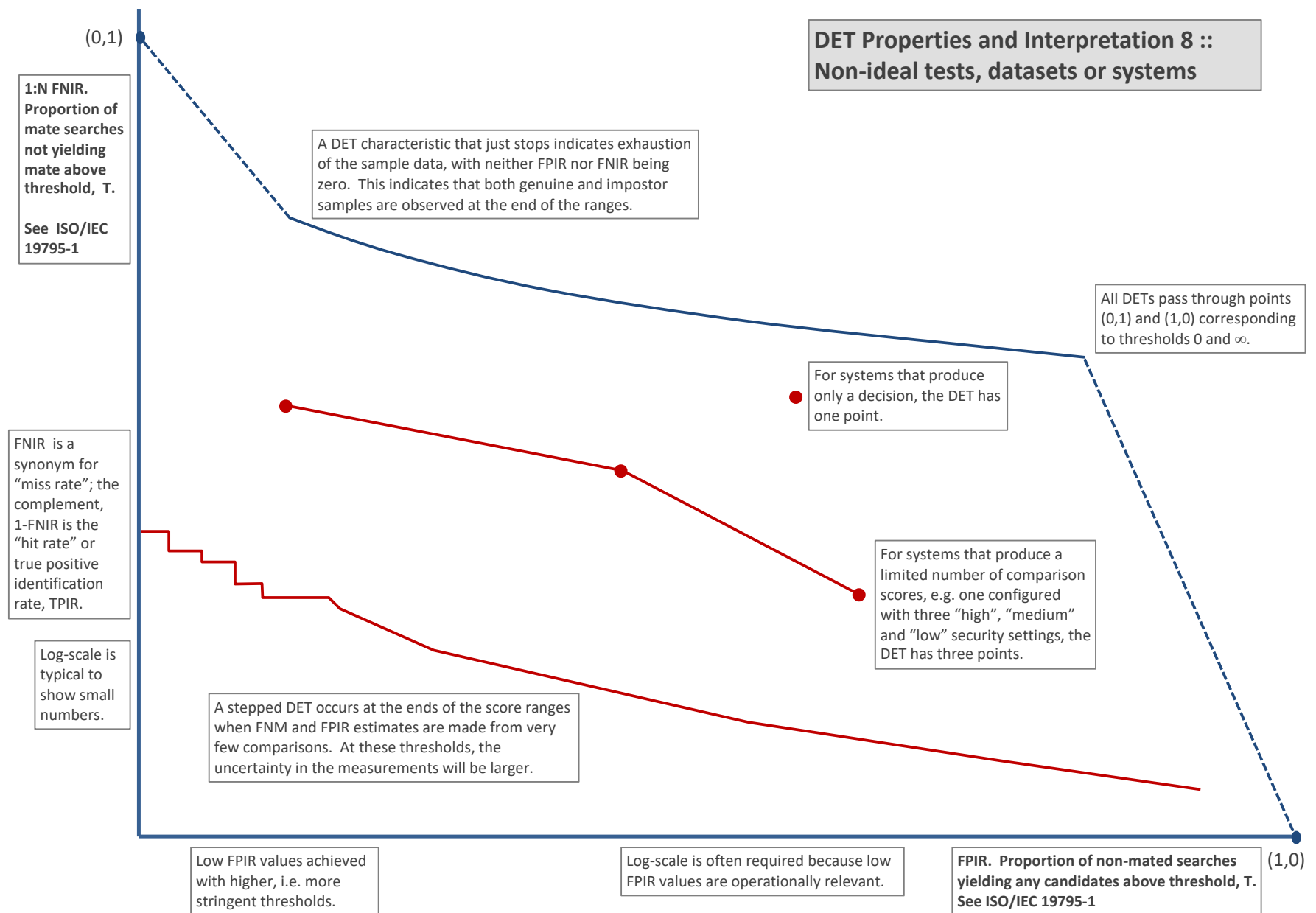


Figure 17: DET as the primary performance reporting mechanism.

3.4 Best practice testing requires execution of searches with and without mates

FRVT embeds 1:N searches of two kinds: Those for which there is an enrolled mate, and those for which there is not. The respective numbers for these types of searches appear in Table 1. However, it is common to conduct only mated searches¹⁰. The cumulative match characteristic is computed from candidate lists produced in mated searches. Even if the CMC is the only metric of interest, the actual trials executed in a test should nevertheless include searches for which no mate exists. As detailed in Table 1 the FRVT reserved disjoint populations of subjects for executing true non-mate searches.

3.5 Failure to extract features

During enrollment some algorithms fail to convert a face image to a template. The proportion of failures is the failure-to-enroll rate, denoted by FTE. Similarly, some search images are not converted to templates. The corresponding proportion is termed failure-to-extract, denoted by FTX.

We do not report FTX because we assume that the same underlying algorithm is used for template generation for enrollment and search.

Failure to extract rates are incorporated into FNIR and FPIR measurements as follows.

- ▷ **Enrollment templates:** Any failed enrollment is regarded as producing a zero length template. Algorithms are required by the API [10] to transparently process zero length templates. The effect of template generation failure on search accuracy depends on whether subsequent searches are mated, or non-mated: Mated searches will fail giving elevated FNIR; non-mated searches will not produce false positives so, to first order, FPIR will be reduced by a factor of $1 - \text{FTE}$.
- ▷ **Search templates and 1:N search:** In cases where the algorithm fails to produce a search template from input imagery, the result is taken to be a candidate list whose entries have no hypothesized identities and zero score. The effect of template generation failure on search accuracy depends on whether searches are mated, or non-mated: Mated searches will fail giving elevated FNIR; Non-mated searches will not produce false positives, so FPIR will be reduced. Thus given a measurement of false negative and positive rates made over only those where failures-to-extract did not occur, those rates - call them $\text{FNIR}^\dagger$ and $\text{FPIR}^\dagger$ - could be adjusted by an explicit measurement of FTX as follows

$$\text{FNIR} = \text{FTX} + (1 - \text{FTX})\text{FNIR}^\dagger \quad (8)$$

$$\text{FPIR} = (1 - \text{FTX})\text{FPIR}^\dagger \quad (9)$$

This approach is the correct treatment for positive-identification applications such as access control where cooperative users are enrolled and make attempts at recognition. This approach is not appropriate to negative identification applications, such as visa fraud detection, in which hostile individuals may attempt to evade detection by submitting poor quality samples. In those cases, template generation failures should be investigated as though a false alarm had occurred.

¹⁰For example, the [Megaface benchmark](#). This is bad practice for several reasons: First, if a developer knows, or can reasonably assume, that a mate always exists, then unrealistic gaming of the test is possible. A second reason is that it does not put FPIR on equal footing with FNIR and that matters because in most applications, not all searches have mates - not everyone has been previously enrolled in a driving license issuance or a criminal justice system - so addressing between-class separation becomes necessary.

3.6 Fixed length candidate lists, threshold independent workload

Suppose an automated face identification algorithm returns L candidates, and a human reviewer is retained to examine up to R candidates, where $R \leq L$ might be set by policy, preference or labor availability. For now, assume also that the reviewer is not provided with, or ignores, similarity scores, and thresholds are not applied. Given the algorithm typically places mates at low (good) ranks, the number of candidates a reviewer can be expected to review can be derived as follows. Note that the reviewer will:

- ▷ Always inspect the first ranked image Frac. reviewed = 1
- ▷ Then inspect those candidates where mate not confirmed at rank 1 Frac. reviewed = 1-CMC(1)
- ▷ Then inspect those candidates where mate not confirmed at rank 1 or 2 Frac. reviewed = 1-CMC(2)

etc. Thus if the reviewer will stop after a maximum of R candidates, the expected number of candidate reviews is

$$M(R) = 1 + (1 - CMC(1)) + (1 - CMC(2)) + \dots + (1 - CMC(R-1)) \quad (10)$$

$$= R - \sum_{r=1}^{R-1} CMC(r) \quad (11)$$

A recognition algorithm that front-loads the cumulative match characteristic will offer reduced workload for the reviewer. This workload is defined only over the searches for which a mate exists. In the cases where there truly is no mate, the reviewer would review all R candidates. Thus, if the proportion of searches for which a mate does exist is β , which in the law enforcement context would be the recidivism rate [3], the full expression for workload becomes:

$$M(R) = \beta \left(R - \sum_{r=1}^{R-1} CMC(r) \right) + (1 - \beta)R \quad (12)$$

$$= R - \beta \sum_{r=1}^{R-1} CMC(r) \quad (13)$$

3.7 Timing measurement

Algorithms were submitted to NIST as implementations of the application programming interface(API) specified by NIST in the Evaluation Plan [10]. The API includes functions for initialization, template generation, finalization, search, gallery insert, and gallery delete. Two template generation functions are required, one for the preparation of an enrollment template, and one for a search template.

In NIST's test harness, all functions were wrapped by calls to the C++ `std::chrono::high resolution clock` which on the dedicated timing machine counts 1ns clock ticks. Precision is somewhat worse than that however.

3.8 Uncertainty estimation

3.8.1 Random error

This study leverages operational datasets for measurement of recognition error rates. This affords several advantages. First, large numbers of searches are conducted (see Table 1) giving precision to the measurements. Moreover, for the two mugshot datasets, these do not involve reuse of individuals so binomial statistics can be expected to apply to recognition error counts. In that case, an observed count of a particular recognition outcome (i.e. a false negative or false positive) in M trials will sustain 95% confidence that the actual error rate is no larger than some value.

As an example, the minimum number of mugshot searches conducted in this report is $M = 154\,549$, and for an observed FNIR around 0.002, the measurement supports a conclusion that the actual FNIR is no higher than 0.00228 at 99% confidence level. On the false positive side, we tabulate FNIR at FPIR values as low as 0.001. Given estimates based on 331 254 non-mate trials, the actual FPIR values will be below 0.00115 at 99% confidence. In conclusion, large scale evaluation, without reuse of subjects, supports tight uncertainty bounds on the measured error rates.

3.8.2 Systematic error

The FRVT 2018 dataset includes anomalies discovered as a result of inspecting images involved in recognition failures from the most accurate algorithms. Two kinds of failure occur: False negatives (which, for the purpose here, include failures to make templates) and false positives.

False negative errors: We reviewed 600 false negative pairs for which either or both of the leading two algorithms did not put the correct mate in the top 50 candidates. Given 154 549 searches, this number represents 0.39% of the total, resulting in FNIR ~ 0.0039 . Of the 600 pairs:

- ▷ **A: Poor quality:** About 20% of the pairs included images of very low quality, often greyscale, low resolution, blurred, low contrast, partially cropped, interlaced, or noisy scans of paper images. Additionally, in a few cases, the face is injured or occluded by bandages or heavy cosmetics.
- ▷ **B: Ground truth identity label bugs:** About 15% of the pairs are not actually mated. We only assigned this outcome when a pair is clearly not mated.
- ▷ **C: Profile views:** About 35% included an image of a profile (side) view of the face, or, more rarely, an image that was rotated 90 degrees in-plane (roll).
- ▷ **D: Tattoos:** About 30% included an image of a tattoo that contained a face image. These arise from mis-labelling in the parent dataset metadata.
- ▷ **E: Ageing:** There is considerable time-lapse between the two captures.

All these estimates are approximate. Of these, the tattoo and mislabeled images can never be matched. These constitute an accuracy floor in the sample implying that FNIR cannot be below 0.0018¹¹. The profile-views, low-quality images, and images with considerable ageing can, in principle, be successfully matched - indeed some algorithms do so - so are not part of the accuracy floor.

¹¹This value is the sum of two partial false negative rates: $\text{FNIR}_B = 0.15 * 0.0039$ plus $\text{FNIR}_D = 0.3 * 0.0039$

For the microsoft-4 algorithm the lowest miss rate from (recent entry in Table 17) is $\text{FNIR}(640\,000, 50, 0) = 0.0018$. This is close to the value estimated from the inspection of misses. It is below the 0.0039 figure because the algorithm does match some profile and poor quality images, that the yitu-2 algorithm does not.

For many tables (e.g. Table 17), the FNIR values obtained for the FRVT-2018 mugshots could be corrected by reducing them by 0.0018. The best values would then be indistinct from zero. The results in this report *were not* adjusted to account for this systematic error.

False positive errors: As shown in Figure 1 and discussed in Figure 14 many of the DET characteristics in this report exhibit a pronounced turn upward at low false positive rates. The shape can be caused by identity labelling errors in the ground truth of a dataset, specifically persons present in the database under two IDs such that some proportion of non-mate pairs are actually mated. To look for such possibilities, we merged the highest 1000 non-mate pairs produced by three different algorithms which resulted in 1839 unique pairs. This constitutes 0.56% of all non-mate searches. We assert that it is *very* difficult for human reviewers to assign the pairs into the following three categories: twins; doppelgangers; or ground-truth errors (instances of the same person under two IDs). Given this difficulty we made no attempt to correct any possible ground truth errors except by removing 57 pairs in the following categories:

- ▷ **A: Profile views:** Thirteen pairs included one or two profile-view images. As described in Figure 159, these can cause false positives.
- ▷ **B: Same-session photographs:** For twelve pairs, the images were identical or trivially altered (e.g. cropped) versions of the same photo. These were present under a different ID likely due to some clerical or procedural mistake.
- ▷ **C: Tattoos of faces:** There were fourteen instances of tattoo photographs that contained faces causing false matches.
- ▷ **D: T-shirt faces:** There were six instances of T-shirt photographs (of Bob Marley and Che Guevara) being detected instead of the face and causing false positives.
- ▷ **E: Background faces:** There were twelve instances of one subject appearing in the background of two otherwise correct portrait photos.

Note we did not remove any images where there was a chance that the pair was actually a different person.

In any case, the results in this report have not been adjusted for this systematic error.

4 Results

This section gives extensive results for algorithms submitted to FRVT 2018. Three page “report cards” for each algorithm are contained in a [separate supplement](#). Performance metrics were described in section 3. The main results are summarized in tabular form with more exhaustive data included as DET, CMC and related graphs in appendices as follows:

- ▷ The three tables 2-4 list algorithms alongside full developer names, acceptance date, size of the provided configuration data, template size and generation time, and search duration data.
 - The **template generation duration** is most important to applications that require fast response. For example, an eGate taking more than two seconds to produce a template might be unacceptable. Note that GPUs may be of utility in expediting this operation for some algorithms, though at additional expense. Two additional factors should be considered^{12,13}.
 - The **search duration** is the time taken for a search of a search template into a gallery of N enrollment templates. This performance variable, together with the volume of searches, is influential on the amount of hardware needed to sustain an operational deployment. This is measured here with the algorithm running on a single core of a contemporary CPU. Search is most simply implemented as N computations of a distance metric followed by a sort operation to find the closest enrollments. However, considerable optimization of this process is possible, up to and including fast-search algorithms that, by various means, avoid computation of all N distances.
 - The **template size** is the size of the extracted feature vector (or vectors) and any needed header information. Large template sizes may be influential on bus or network bandwidth, storage requirements, and on search duration. While the template itself is an opaque data blob, the feature dimensionality might be estimated by assuming a four-bytes-per-float encoding. There is a wide range of encodings. For the more accurate algorithm, sizes range from 256 bytes to about 2KB bytes, indicating essentially no consensus on face modeling and template design.
 - The **template size multiplier** column shows how, given k input images, the size of the template grows. Most implementations internally extract features from each image and concatenate them, and implement some score-level fusion logic during search. Other implementations, including many of the most accurate algorithms, produce templates whose size does not grow with k . This could be achieved via selection of the best quality image - but this is not optimal in handling ageing where the oldest image could be the best quality. Another mechanism would be feature-level fusion where information is fused from all k inputs. In any case, as a black-box test, the fusion scheme is proprietary and unknown.
 - The size of the **configuration data** is the total size of all files resident in a vendor-provided directory that contains arbitrary read-only files such as parameters, recognition models (e.g. caffe). Generally a large value for this quantity may prohibit the use of the algorithm on a resource-constrained device.

¹²The FRVT 2018 API prohibited threading, so some gains from parallelism may be available on multiple-cores or multiple processors, if the feature extraction code could be distributed across them.

¹³Note also that factors of two or more may be realizable by exploiting modern vector processing instructions on CPUs. It is not clear in our measurements whether all developers exploited Intel’s AVX2 instructions, for example. Our machine was so equipped, but we insisted that the same compiled library should also run on older machines lacking that instruction. The more sophisticated implementations may have detected AVX2 presence and branched accordingly. The less sophisticated may be defaulted to the reduced instruction set. Readers should see the FRVT 2018 API document for the specific chip details.

▷ Tables 17-18 report core rank-based accuracy for mugshot images. The population size is limited to $N = 1.6$ million identities because this is the largest gallery size on which all algorithms were executed. Notable observations from these tables are as follows:

- **Accuracy gains since 2018:** NIST Interagency Report 8238 documented massive gains over those reported in the FRVT 2014 report, NIST Interagency Report 8009. Further gains are documented in this report. Comparing the most accurate algorithm in November 2018, NEC-3, the value of $\text{FNIR}(N, L, T)$ reduced from 0.0031 to 0.0024 for the Sensetime-004 algorithm with $N = 12$ million recent images. The tables show broader gains: many developers have made advances since 2018 with between two and five-fold reduction in errors.
- **Wide range in accuracy:** The rank-1 miss rates vary from $\text{FNIR}(N, 1, 0) = 0.0012$ for sensetime-004 up to about 0.5 for the very fast but inaccurate microfocus-x algorithms. Among the developers who are superior to NEC in 2013, the range is from 0.002 to 0.035 for camvi-3. This large accuracy range is consistent with the buyer-beware maxim, and indicates that face recognition software is far from being commoditized.

▷ Tables 20-21 report threshold-based error rates, $\text{FNIR}(N, L, T)$, for $N = 1.6$ million for mugshot-mugshot accuracy on FRVT 2014, FRVT 2018, and also (in pink) mugshot-webcam accuracy using FRVT 2018 enrollments. Notable observations from these tables are as follows:

- **Order of magnitude accuracy gains since 2014:** As with rank-based results, the gains in accuracy are substantial, though somewhat reduced. At $\text{FPIR} = 0.01$, the best improvement over NEC in 2014 is a 27 fold reduction in FNIR using the NEC.2 algorithm. At $\text{FPIR} = 0.001$, the largest gain is a six-fold reduction in FNIR via the NEC.3 algorithm.
- **Broad gains across the industry:** About 19 companies realize accuracy better than the NEC benchmark from 2014. This is somewhat lower than the 28 developers who succeeded on the rank-1 metric. This may be due to the ubiquity of, and emphasis on, the rank-1 metric in many published algorithm development papers.
- **Webcam images:** Searches of webcam images give $\text{FNIR}(N, T)$ values around 2 to 3 times higher than mugshot searches. Notably the leading developers with mugshots are approximately the same with poorer quality webcams. But some developers e.g. Camvi, Megvii, TongYi, and Neurotechnology do improve their relative rankings on webcams, perhaps indicating their algorithms were tailored to less constrained images.

▷ Tables 13, 15, 16 and show, respectively, high-threshold, rank 1, and rank 50 FNIR values for all algorithms performing searches into five different gallery sizes, $N = 640\,000$, $N = 1\,600\,000$, $N = 3\,000\,000$, $N = 6\,000\,000$ and $12\,000\,000$. The $\text{FPIR} = 0.001$ table is included to inform high-volume duplicate detection applications. The Rank-1 table is included as a primary accuracy indicator. The Rank-50 table is included to inform agencies who routinely produce 50 candidates for human-review. The notable results are:

- **Slow growth in rank-based miss rates:** $\text{FNIR}(N, R)$ generally grows as a power law, aN^b . From the straight lines of many graphs of Figure 20 this is clearly a reasonable model for most, but not all, algorithms. The coefficient a can be interpreted as FNIR in a gallery of size 1. The more important coefficient b indicates scalability, and often, $b \ll 1$, implies very benign growth in FNIR . The coefficients of the models appear in the Tables 15 and 16.
- **Slow growth in threshold-based miss rates:** $\text{FNIR}(N, T)$ also generally grows as a power law, aN^b except at the high threshold values corresponding to low FPIR values. This is visible in the plots of Figure 36 which

show straight lines except for $FPIR = 0.001$, which increase more rapidly with N above 3 000 000. Each trace in those figures shows $FNIR(N, T)$ at fixed $FPIR$ with both N and T varying. Thus at large N , it is usually necessary to elevate T to maintain fixed $FPIR$. This causes increased $FNIR$. Why that would no-longer obey a power-law is not known. However, if we expect large galleries to contain individuals with familial relations to the non-mate search images - in the most extreme case, twins - then suppression of false positives becomes more difficult. This is discussed in the Figures starting at Fig. 10

- ▷ Figure ?? shows false positives from twins against their enrolled siblings, broken out by type of twin: fraternal or identical. The Figure is based on the enrollment of 104 single images on one of a pair of twins, and then the search of 2354 second images. Note that the dataset is heavily skewed towards identical twins which is not representative of the true population. There is also a skew towards same sex fraternal twin pairs compared to different sex fraternal twin pairs again not representative of the true population.

The notable results are:

- For all algorithms tested, the 1087 mated searches (Twin A vs. Twin A) produce scores almost always above typical operational thresholds, with (not shown) matches at rank 1. The images are of good quality, so this is the result expected from the rest of this report.
- For the 1066 identical twin searches (AB), almost all produce the twin at rank 1, with a few producing the mate at further down the candidate lists rank and low score.
- For the 169 fraternal searches (AB) from same sex pairs, most algorithms give a large number of very high scores, implying false positives at all thresholds. However, there are long tails containing lower scores that are correctly below threshold. In general, scores that are higher in this distribution are all rank 1 whereas the lower scores have much higher ranks.
- (Not shown) Of the 169, there are 24 fraternal searches (AB) involving different sex twins. Here most algorithms correctly report scores well below the lowest threshold, and usually not on the candidate list at all.

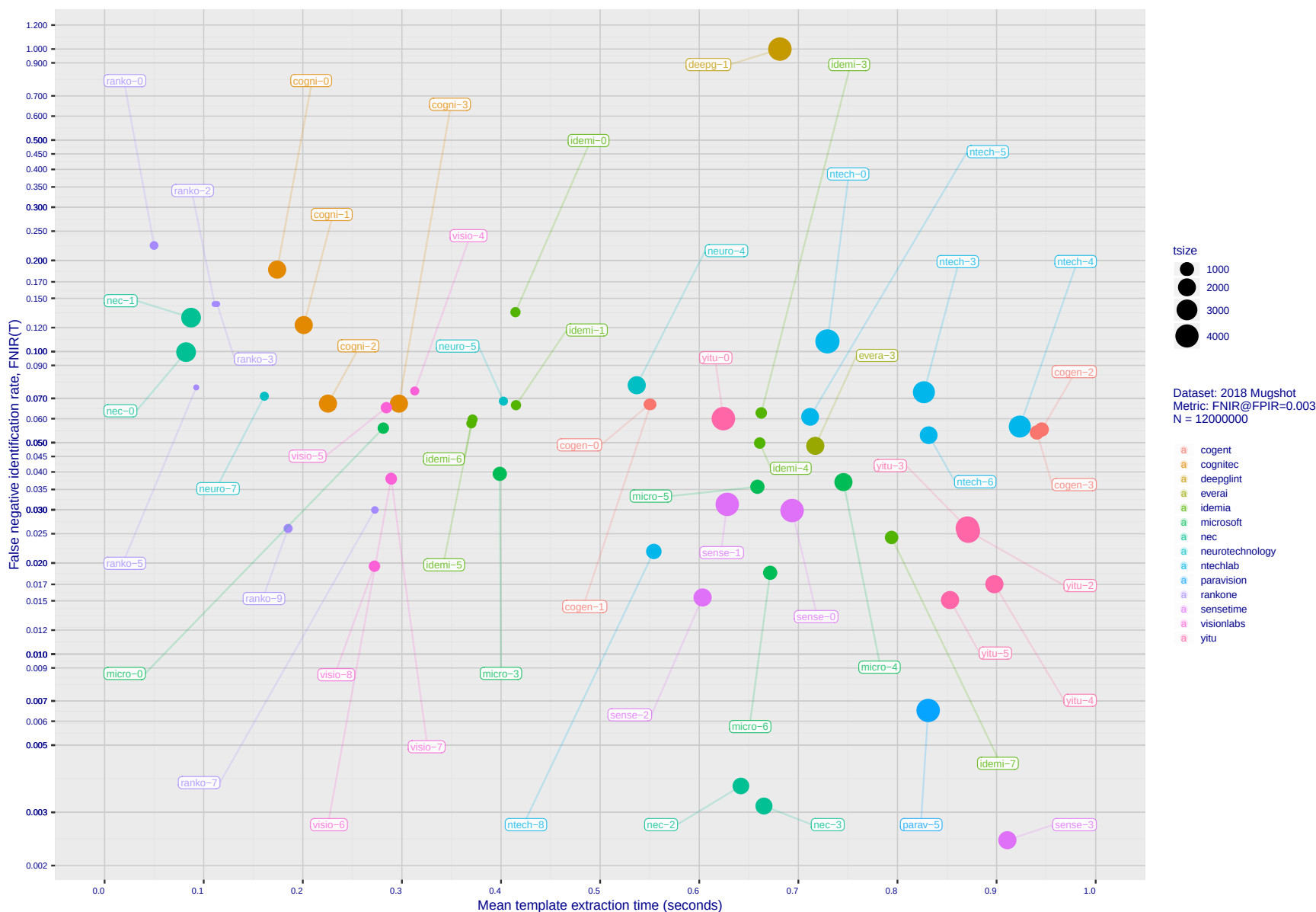


Figure 18: [Mugshot Dataset] Speed-accuracy tradeoff. For developers of the more accurate algorithms the plot shows the tradeoff of high-threshold recognition miss-rates, $FNIR(N, N, T)$ for $FPIR(N, T) = 0.003$, and template generation time. Developers are coded by color. Template size is encoded by the size of the circle. Some labels are quite distant from the respective point, to avoid superposing text. Without any other influences, the assumption would be that taking time to localize the face, and extract features, would lead to better accuracy. The most notable result, for NEC, is that their slower algorithms are much more accurate than the version that extract features in fewer than 90 milliseconds.

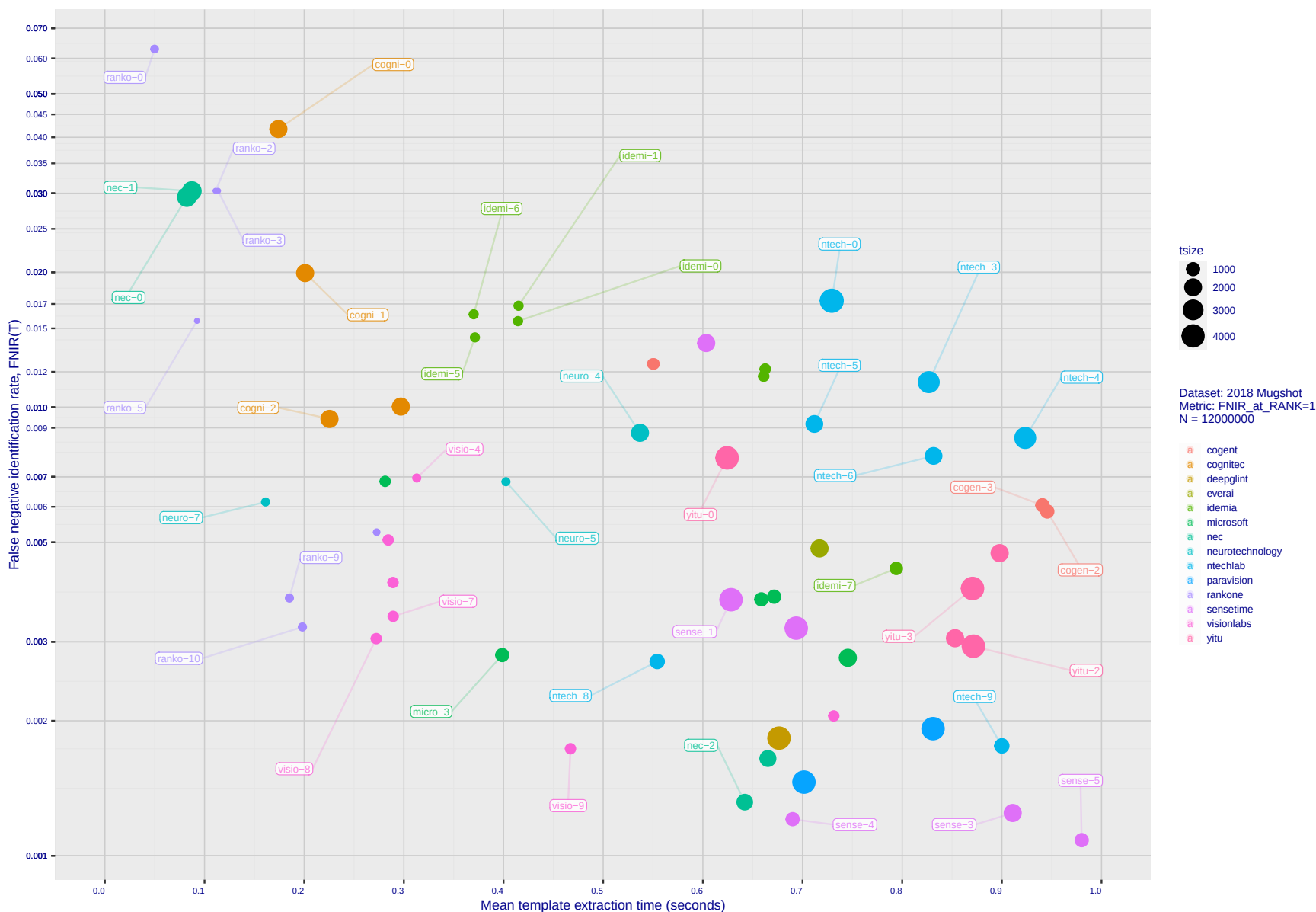


Figure 19: **[Mugshot Dataset] Speed-accuracy tradeoff.** For developers of the more accurate algorithms the plot shows the tradeoff of rank-one recognition miss-rates, $FNIR(N, 1, 0)$, and template generation time. Developers are coded by color. Template size is encoded by the size of the circle. Some labels are quite distant from the respective point, to avoid superposing text. Without any other influences, the assumption would be that taking time to localize the face, and extract features, would lead to better accuracy. This occurs for NEC with their slower algorithm being much accurate than the version that extract features in fewer than 90 milliseconds.

2021/03/04
11:49:04FNIR(N, R, T) =
FPR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

	DEVELOPER FULL NAME	SHORT NAME	SEQ. NUM.	VALIDATION DATE	CONFIG ¹ DATA (MB)	LIB ¹ DATA (MB)	TEMPLATE GENERATION			FINALIZE ² TIME (S)	SEARCH DURATION ⁵ MILLISEC					POWER LAW (μs)
							SIZE (B)	MULT ³	TIME (MS) ⁴		L=1 N=1.6M	L=50 N=1.6M	L=50 N=3M	L=50 N=6M	L=50 N=12M	
1	3Divi	3divi	5	2018-10-26	186	51	¹³¹ 4096	k	⁷⁶ 638	⁹⁷ 28	⁽⁶⁴⁾ 538	⁽⁶⁴⁾ 537	⁽⁵⁷⁾ 1377	⁽⁵⁵⁾ 2614	⁽⁵²⁾ 5530	⁸³ 0.07N ^{1.1}
2	3Divi	3divi	6	2018-10-26	187	51	²⁸ 528	k	⁷⁷ 640	¹⁸ 5	⁽¹¹⁾ 33	⁽¹²⁾ 33	-	-	-	-
3	Acer Incorporated	acer	000	2020-08-12	35	67	²² 512	-	¹⁴ 198	¹¹ 4	⁽⁴⁷⁾ 295	⁽⁴⁸⁾ 295	⁽³⁷⁾ 623	⁽⁴⁹⁾ 2302	⁽⁴⁵⁾ 4915	¹⁰⁷ 0.00N ^{1.3}
4	Akurat Satu Indonesia	ptakuratsatu	000	2020-10-23	0	572	³⁰ 538	-	¹³⁶ 905	¹³⁸ 28633	⁽⁶⁾ 15	⁽⁶⁾ 16	⁽⁶⁾ 17	⁽⁵⁾ 17	⁽⁵⁾ 17	^{6827.74} N ^{0.1}
5	Alchera Inc	alchera	2	2018-10-30	7	14	⁸² 2048	k	⁶ 114	¹²² 63	⁽¹¹⁷⁾ 2923	⁽¹²⁰⁾ 2929	-	-	-	-
6	Alchera Inc	alchera	3	2018-10-30	251	14	⁸⁹ 2048	k	⁶² 531	¹²³ 63	⁽¹¹⁸⁾ 2955	⁽¹²¹⁾ 2956	⁽¹⁰³⁾ 6546	⁽¹⁰⁴⁾ 15013	⁽¹⁰⁵⁾ 35262	¹⁰² 0.10N ^{1.2}
7	Alivia / Innovation Sys	isystems	3	2018-10-30	350	784	⁹⁹ 2048	1	¹²³ 825	⁷⁶ 16	⁽⁵³⁾ 385	⁽⁵⁴⁾ 389	⁽⁴⁴⁾ 979	⁽⁴⁴⁾ 1822	⁽⁶⁸⁾ 9348	¹⁰⁸ 0.00N ^{1.3}
8	AllGoVision	allgovision	000	2019-07-30	168	150	⁹¹ 2048	k	⁴² 404	³⁶ 12	⁽¹²⁰⁾ 3226	⁽¹²³⁾ 3193	⁽¹⁰¹⁾ 6129	⁽¹⁰¹⁾ 12449	⁽¹⁰²⁾ 25835	⁴² 1.40N ^{1.0}
9	AllGoVision	allgovision	001	2020-07-14	283	126	⁹⁰ 2048	-	¹¹² 777	⁴² 13	⁽¹¹⁹⁾ 3174	⁽¹²²⁾ 3183	⁽¹⁰⁰⁾ 6073	⁽⁹⁹⁾ 12284	⁽¹⁰¹⁾ 25701	⁴⁰ 1.42N ^{1.0}
10	Anke Investments	anke	0	2018-10-30	779	27	¹¹⁸ 2072	k	⁴⁷ 429	⁷⁴ 16	⁽⁷⁴⁾ 675	⁽⁷⁶⁾ 748	⁽⁶²⁾ 1483	⁽⁶¹⁾ 2968	⁽⁵⁶⁾ 6148	⁶⁰ 0.21N ^{1.1}
11	Anke Investments	anke	1	2018-10-30	779	27	¹¹² 2072	k	⁴⁸ 430	⁸⁸ 15	⁽⁷⁰⁾ 707	⁽⁸¹⁾ 769	-	-	-	-
12	Anke Investments	anke	002	2019-06-27	341	401	¹⁰⁸ 2056	k	⁷² 623	⁴⁸ 13	⁽⁷³⁾ 624	⁽⁷³⁾ 682	⁽⁵⁵⁾ 1306	⁽⁵¹⁾ 2403	⁽⁴⁹⁾ 5082	³⁶ 0.30N ^{1.0}
13	Aware	aware	5	2018-10-30	368	27	¹²² 3100	k	¹¹⁷ 792	¹⁰⁶ 34	⁽¹⁵⁾ 95	⁽¹⁸⁾ 98	⁽¹⁶⁾ 203	⁽¹⁵⁾ 371	⁽¹³⁾ 252	¹³ 4.13N ^{0.7}
14	Aware	aware	6	2018-10-30	368	27	² 124	k	¹¹⁶ 789	² 2	⁽²⁷⁾ 158	⁽²⁷⁾ 162	-	-	-	-
15	Ayonix	ayonix	1	2018-10-29	74	2	⁴³ 1036	k	² 12	³¹ 11	⁽⁴³⁾ 279	⁽⁴⁴⁾ 279	-	-	-	-
16	Ayonix	ayonix	2	2018-10-30	74	2	⁴³ 1036	1	¹ 11	⁵³ 14	⁽⁴³⁾ 279	⁽⁴³⁾ 276	⁽³⁰⁾ 535	⁽²⁹⁾ 1087	⁽³⁰⁾ 2284	⁴⁸ 0.11N ^{1.0}
17	Camvi Technologies	camvitech	4	2018-10-30	233	220	³⁸ 1024	1	⁹¹ 686	¹⁰⁴ 51	⁽¹²⁾ 33	⁽¹¹⁾ 32	⁽¹⁰⁾ 38	⁽⁹⁾ 40	⁽⁸⁾ 48	^{8492.66} N ^{0.1}
18	Camvi Technologies	camvitech	5	2018-10-30	257	220	³⁷ 1024	1	¹⁰⁸ 751	¹⁰² 51	⁽¹⁰⁾ 31	⁽⁹⁾ 30	-	-	-	-
19	Canon Inc	cib	000	2020-10-19	426	127	¹⁴⁰ 8196	-	⁸⁶ 674	¹²⁸ 113	⁽¹²¹⁾ 3589	⁽¹²⁵⁾ 3604	⁽¹⁰⁴⁾ 6738	⁽¹⁰²⁾ 13495	⁽¹⁰³⁾ 27114	²⁰ 2.33N ^{1.0}
20	Cognitec Systems GmbH	cognitec	2	2018-10-30	463	26	¹⁰² 2052	k	¹⁷ 225	⁹² 27	⁽¹⁰⁸⁾ 1733	⁽¹¹⁰⁾ 1763	⁽⁹²⁾ 3660	⁽⁹⁰⁾ 7279	⁽⁹⁰⁾ 13895	³⁹ 0.83N ^{1.0}
21	Cognitec Systems GmbH	cognitec	3	2018-10-30	465	26	¹⁰⁴ 2052	k	²⁷ 297	⁷² 16	⁽¹⁰⁷⁾ 1719	⁽¹¹¹⁾ 1791	⁽⁹¹⁾ 3638	⁽⁸⁹⁾ 7277	⁽⁹³⁾ 14904	⁵⁴ 0.66N ^{1.0}
22	Cyberlink Corp	cyberlink	000	2019-06-12	217	93	¹⁰⁵ 2052	1	⁸⁰ 654	¹⁰⁰ 30	⁽⁷⁶⁾ 696	⁽⁷⁵⁾ 701	⁽⁵⁸⁾ 1379	⁽⁵⁶⁾ 2639	⁽⁵⁸⁾ 6214	⁵⁰ 0.28N ^{1.0}
23	Cyberlink Corp	cyberlink	001	2019-10-07	459	102	¹⁰⁶ 2052	1	⁴⁵ 423	⁹⁸ 28	⁽⁷⁷⁾ 698	⁽⁷⁴⁾ 700	⁽⁵⁶⁾ 1350	⁽⁸²⁾ 5524	⁽⁸⁵⁾ 12031	¹⁰⁶ 0.00N ^{1.3}
24	Cyberlink Corp	cyberlink	002	2020-07-31	333	109	¹³⁶ 4140	-	¹⁰⁴ 724	¹²⁹ 6875	⁽¹⁰²⁾ 1353	⁽¹²⁴⁾ 3198	⁽¹⁰²⁾ 6138	⁽⁹⁸⁾ 12205	⁽⁸⁸⁾ 13106	¹⁵ 16.71N ^{0.8}
25	Cyberlink Corp	cyberlink	003	2021-01-05	333	100	¹³⁸ 6212	-	⁹³ 691	¹⁰⁹ 35	⁽⁶⁰⁾ 488	⁽⁷⁶⁾ 723	⁽⁶⁰⁾ 1415	⁽⁵⁹⁾ 2886	⁽⁵³⁾ 5643	⁶⁹ 0.12N ^{1.1}
26	Dahua Technology Co Ltd	dahua	0	2018-10-29	276	167	⁸² 2048	k	³⁷ 374	⁸⁸ 22	-	⁽⁴⁰⁾ 258	-	-	-	-
27	Dahua Technology Co Ltd	dahua	1	2018-10-29	276	167	⁷³ 2048	k	³³ 369	⁹⁴ 28	-	⁽³⁹⁾ 257	⁽³⁵⁾ 602	⁽³³⁾ 1202	⁽³⁶⁾ 3007	⁹² 0.02N ^{1.2}
28	Dahua Technology Co Ltd	dahua	002	2019-12-02	607	137	⁸³ 2048	k	⁹⁰ 685	⁸⁵ 19	⁽³⁶⁾ 243	⁽⁴¹⁾ 269	⁽⁵¹⁾ 1189	⁽⁶⁰⁾ 2950	⁽⁶¹⁾ 6732	¹¹² 0.00N ^{1.5}
29	Dahua Technology Co Ltd	dahua	003	2020-11-18	889	154	⁶⁴ 2048	-	¹⁰³ 723	⁷⁹ 18	⁽⁴⁹⁾ 283	⁽³⁸⁾ 249	⁽²⁹⁾ 468	⁽²⁸⁾ 935	⁽²⁸⁾ 1871	²¹ 0.16N ^{1.0}
30	Deepglint	deepglint	001	2019-11-15	448	265	¹³⁰ 4096	-	⁸⁸ 676	¹⁰⁷ 35	⁽⁷⁵⁾ 677	⁽¹⁰⁵⁾ 1495	⁽⁶⁶⁾ 1724	⁽⁵⁷⁾ 2747	⁽⁵⁹⁾ 6246	¹⁴ 25.27N ^{0.8}
31	Dermalog	dermalog	5	2018-10-26	0	440	³ 128	1	⁶¹ 528	¹²⁸ 3155	⁽¹⁾ 0	⁽¹⁾ 0	⁽¹⁾ 0	⁽¹⁾ 0	⁽¹⁾ 0	⁶ 66.21N ^{0.2}
32	Dermalog	dermalog	6	2018-10-26	0	453	⁸ 256	1	⁵⁷ 507	³ 2	⁽²⁴⁾ 142	⁽²⁴⁾ 144	⁽²⁰⁾ 269	⁽¹⁹⁾ 531	⁽¹⁹⁾ 1294	⁵⁵ 0.05N ^{1.0}
33	Dermalog	dermalog	007	2020-02-12	0	424	⁴ 128	1	⁴⁴ 410	¹ 1	⁽¹⁸⁾ 98	⁽¹⁶⁾ 96	⁽¹⁸⁾ 218	⁽¹⁶⁾ 429	⁽¹⁷⁾ 1013	⁷⁶ 0.01N ^{1.1}
34	Dermalog	dermalog	008	2021-01-25	0	531	²⁴ 512	-	³⁵ 370	¹³ 4	⁽⁴⁸⁾ 335	⁽³⁵⁾ 246	⁽²⁸⁾ 462	⁽²⁷⁾ 924	⁽²⁷⁾ 1849	²⁴ 0.15N ^{1.0}
35	FarBar Inc	f8	001	2019-10-03	266	19	⁷⁷ 2048	k	¹²⁰ 810	⁵¹ 14	-	-	-	-	-	-
36	Gorilla Technology	gorilla	2	2018-10-29	91	1252	⁴⁷ 1132	k	³⁰ 338	⁸⁰ 24	⁽²⁵⁾ 145	⁽²⁵⁾ 146	⁽²¹⁾ 293	⁽²⁰⁾ 612	⁽²³⁾ 1509	⁷⁴ 0.02N ^{1.1}
37	Gorilla Technology	gorilla	3	2018-10-26	94	1252	¹¹⁶ 2156	k	⁶⁴ 559	¹³³ 12020	-	⁽¹¹⁴⁾ 2047	-	-	-	-
38	Gorilla Technology	gorilla	004	2020-01-06	182	1244	¹¹⁷ 2192	k	³⁹ 388	¹¹¹ 41	⁽⁴⁶⁾ 286	⁽⁴⁷⁾ 285	⁽⁵²⁾ 1191	⁽⁵²⁾ 2416	⁽⁴⁸⁾ 5036	¹⁰⁵ 0.00N ^{1.3}
39	Gorilla Technology	gorilla	005	2021-02-22	306	1420	¹³⁹ 6288	-	⁵⁵ 483	¹³⁵ 78	⁽⁸²⁾ 802	⁽⁸²⁾ 799	⁽⁶³⁾ 1514	⁽⁶⁸⁾ 4454	⁽⁶⁴⁾ 8820	⁹⁴ 0.05N ^{1.2}
40	Guangzhou Pixel Solutions Co Ltd	pixelall	002	2019-07-01	0	165	¹²⁰ 2560	k	¹² 190	⁶⁵ 15	⁽¹⁰⁰⁾ 1296	⁽¹⁰²⁾ 1334	⁽⁸⁰⁾ 2526	⁽⁷⁹⁾ 5136	⁽⁸⁰⁾ 11045	⁴⁹ 0.52N ^{1.0}
41	Guangzhou Pixel Solutions Co Ltd	pixelall	003	2019-11-05	0	690	¹¹⁸ 2560	k	⁹⁷ 703	⁸⁹ 22	⁽⁹⁷⁾ 1273	⁽⁹⁹⁾ 1307	⁽⁷⁷⁾ 2474	⁽⁷⁶⁾ 5198	⁽⁸¹⁾ 11141	⁵⁶ 0.46N ^{1.0}
42	Guangzhou Pixel Solutions Co Ltd	pixelall	004	2020-07-02	0	538	¹¹⁹ 2560	k	⁴⁹ 449	⁷⁸ 17	⁽⁹⁶⁾ 1259	⁽⁹⁸⁾ 1300	⁽⁷⁸⁾ 2465	⁽⁸¹⁾ 5492	⁽⁸²⁾ 11443	⁶⁴ 0.34N ^{1.1}
43	Hengrui AI Technology	hr	000	2021-02-10	501	392	⁸⁷ 2048	-	¹³⁵ 905	⁶¹ 15	⁽⁴⁴⁾ 282	⁽⁴²⁾ 276	⁽³²⁾ 539	⁽³⁸⁾ 3177	⁽³⁸⁾ 3177	⁸⁶ 0.03N ^{1.1}
44	Hikvision Research Institute	hikvision	5	2018-10-29	593	9	⁵¹ 1408	1	⁶⁹ 607	⁷¹ 16	⁽⁸⁷⁾ 883	⁽⁸⁸⁾ 895	⁽⁶⁸⁾ 1908	⁽⁶⁴⁾ 3792	⁽⁶⁹⁾ 9387	⁸⁴ 0.10N ^{1.1}
45	Hikvision Research Institute	hikvision	6	2018-10-29	593	9	⁵⁰ 1408	1	⁶⁷ 598	⁷⁵ 16	⁽⁸⁹⁾ 871	⁽⁸⁷⁾ 877	-	-	-	-
46	Idemia	idemia	5	2018-10-29	417	48	¹⁹ 352	1	³⁶ 371	¹⁷ 5	⁽²¹⁾ 137	⁽²²⁾ 138	⁽²⁶⁾ 437	⁽²⁴⁾ 724	⁽²⁴⁾ 1630	⁹⁹ 0.01N ^{1.2}
47	Idemia	idemia	6	2018-10-29	417	48	¹⁸ 352	1	³⁴ 370	¹⁶ 4	⁽²²⁾ 137	⁽²¹⁾ 138	⁽²⁷⁾ 442	⁽²⁶⁾ 827	⁽²⁵⁾ 1646	¹⁰¹ 0.01N ^{1.2}
48	Idemia	idemia	007	2020-01-17	738	113	³⁵ 860	1	¹¹⁸ 794	⁵² 14	⁽²⁶⁾ 151	⁽²⁶⁾ 152	⁽³⁹⁾ 683	⁽³⁷⁾ 1481	⁽³⁷⁾ 3022	¹¹⁰ 0.00N ^{1.4}
49	Imagus Technology Pty Ltd	imagus	005	2021-01-15	222	311	⁷² 2048	-	¹¹⁵ 786	⁵⁰ 14	⁽³⁸⁾ 236	⁽⁴⁹⁾ 313	⁽³⁸⁾ 651	⁽³⁶⁾ 1361	⁽³¹⁾ 2461	⁸² 0.03N ^{1.1}
50	Imperial College London	imperial	000	2019-08-28	461	15	⁷⁶ 2048	1	⁶⁵ 577	⁴¹ 13	⁽⁵⁰⁾ 360	⁽⁵³⁾ 379	⁽⁶⁴⁾ 1626	⁽⁶⁶⁾ 4057	⁽⁷⁸⁾ 10291	¹¹³ 0.00N ^{1.5}
51	Incode Technologies Inc	incode	2	2018-10-29	71	31	⁶² 2048	1	²⁴ 289	⁷⁰ 15	⁽⁵⁸⁾ 411	⁽⁵⁵⁾ 404	-	-	-	-
52	Incode Technologies Inc	incode	3	2018-10-29	133	31	⁹⁶ 2048	1	⁹⁵ 697	⁶⁰ 15	⁽⁵⁷⁾ 408	⁽⁵⁸⁾ 412	⁽⁴¹⁾ 847	⁽³⁸⁾ 1608	⁽⁴³⁾ 4486	⁷⁸ 0.05N ^{1.1}

Notes	
1	Configuration size does not capture static data present in libraries. Libraries are included but the size also includes any ancillary libraries for image processing (e.g. openCV) or numerical computation (e.g. blas).
2	Finalization is the processing of converting N = 1600000 templates into a searchable data structure operation which can be a simple copy, or the building of an index or tree, for example. The duration of the operation may be data dependent, and may not be linear in the number of input templates.
3	This multiplier expresses the increase in template size when k images are passed to the template generation function.
4	All durations are measured on Intel®Xeon®CPU E5-2630 v4 @ 2.20GHz processors. Estimates are made by wrapping the API function call in calls to std::chrono::high_resolution_clock which on the machine in (3) counts 1ns clock ticks. Precision is somewhat worse than that however.
5	Search durations are measured as in the prior note. The power-law model in the final column mostly fits the empirical results in Figure 160. However in certain cases the model is not correct and should not be used numerically.

Table 2: Summary of algorithms and properties included in this report. The blue superscripts give ranking for the quantity in that column. Missing search durations, denoted by “-”, are absent because those runs were not executed, usually because we did not run on the larger galleries. Caution: The power-law model is sometimes an incorrect model. It is included here only to show broad sublinear behavior, which is flagged in green. The models should not be used for prediction.

2021/03/04
11:49:04FN(R/N, T) =
FPR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

	Developer	Short	Seq.	Validation	Config ¹	Lib ¹	Template Generation			Finalize ²	Search Duration ⁵ Millisec						Power Law
	Full Name	Name	Num.	Date	Data (MB)	Data (MB)	Size (B)	Mult ³	Time (ms) ⁴	Time (s)	L=1	L=50	L=50	L=50	L=50	Power Law	
										N=1.6M	N=1.6M	N=1.6M	N=3M	N=6M	N=12M	(μs)	
53	Incode Technologies Inc	incode	004	2019-06-24	254	50	⁹⁸ 2048	1	⁵⁴ 475	³⁴ 12	(⁵¹)365	(⁵²)378	(⁶¹)1482	(³⁹)1660	(³⁵)2954	⁶² 0.12N ^{1.1}	
54	Innovatrics	innovatrics	4	2018-10-30	0	400	⁴⁶ 1076	k	⁴⁰ 399	¹³⁰ 10902	(⁵)8	(³)8	(⁴)11	(²)9	(⁴)13	¹⁰ 668.38N ^{0.2}	
55	Innovatrics	innovatrics	005	2019-09-30	0	455	²⁹ 538	1	¹²⁴ 827	¹³² 11897	(³)8	(⁴)8	(³)9	(⁴)9	(³)9	² 4055.65N ^{0.1}	
56	Innovatrics	innovatrics	006	2020-10-05	0	488	³¹ 538	-	¹²² 818	¹³⁶ 14052	(⁴)8	(⁵)9	(²)9	(³)9	(²)9	¹ 4220.00N ^{0.1}	
57	IrexAI	irex	000	2021-02-09	724	46	¹²¹ 3080	-	¹²⁷ 844	⁸⁴ 19	(⁷²)616	(⁷⁰)600	(⁴⁸)1120	(⁵⁴)2477	(⁵⁴)5863	⁶⁵ 0.13N ^{1.1}	
58	Kedacom International Pte	kedacom	001	2019-09-16	239	36	¹⁷ 292	1	⁵⁸ 507	⁴ 2	(⁸⁰)764	(⁷⁹)760	(⁶⁹)1940	(⁶²)2983	(⁶⁰)6623	⁵² 0.31N ^{1.0}	
59	Kneron	kneron	000	2020-03-03	366	13	⁹² 2048	k	⁶⁰ 523	⁴⁵ 13	(¹¹⁵)2535	(¹¹⁸)2506	(⁹⁸)4752	(⁹⁶)9696	(¹⁰⁰)20926	⁵³ 0.95N ^{1.0}	
60	Lomonosov Moscow State University	intsysmsu	000	2019-08-19	375	168	⁸⁰ 2048	1	⁷⁰ 614	⁴⁶ 13	(⁵⁹)430	(⁶⁰)431	(⁴³)860	(⁴⁰)1730	(⁵¹)5353	⁹⁰ 0.03N ^{1.1}	
61	Lookman Electroplast Industries	lookman	3	2018-10-28	203	24	¹⁶ 292	1	²⁹ 336	¹⁰ 3	(⁷⁹)739	(⁷⁷)745	(⁵⁹)1394	(⁵⁸)2817	(⁶²)8286	⁷² 0.13N ^{1.1}	
62	Lookman Electroplast Industries	lookman	4	2018-10-28	184	24	³⁵ 548	1	²⁸ 320	¹⁵ 4	(⁸⁸)981	(⁸⁹)998	-	-	-	-	
63	Lookman Electroplast Industries	lookman	005	2019-09-16	239	36	³² 548	1	⁵⁶ 506	¹² 4	(⁸⁹)1005	(⁹⁰)1008	(⁸¹)2597	(⁸⁰)5446	(⁶⁵)8939	⁷⁰ 0.19N ^{1.1}	
64	Megvii/Face++	megvii	1	2018-10-28	1703	41	¹²⁴ 4096	1	⁷⁴ 631	¹⁰⁵ 32	(⁶⁵)552	(⁶⁸)561	(⁵⁴)1222	(⁵⁰)2321	(⁵⁵)5968	⁷⁷ 0.08N ^{1.1}	
65	Megvii/Face++	megvii	2	2018-10-28	1735	42	¹²⁵ 4096	1	⁷⁵ 635	¹⁰³ 31	(⁶⁶)553	(⁶⁶)558	-	-	-	-	
66	MicroFocus	microfocus	5	2018-10-29	94	26	¹² 256	k	²¹ 262	⁷ 2	(³²)182	(³¹)186	(²⁴)354	(²³)708	(²¹)1425	²⁸ 0.11N ^{1.0}	
67	MicroFocus	microfocus	6	2018-10-29	94	26	¹⁰ 256	k	²⁰ 262	⁹ 2	(³³)183	(³⁰)186	-	-	-	-	
68	Microsoft	microsoft	5	2018-10-29	381	155	³⁹ 1024	1	⁸¹ 658	³² 11	(¹⁰⁵)1606	(¹⁰⁷)1673	(⁸⁸)3076	(⁸⁶)6302	(⁸⁹)13160	³⁵ 0.79N ^{1.0}	
69	Microsoft	microsoft	6	2018-10-29	478	155	³⁶ 1024	1	⁸⁴ 671	⁶⁴ 15	(¹⁰⁶)1642	(¹⁰⁶)1618	(⁹³)3710	(⁸⁷)6401	(⁸⁷)12892	⁴⁵ 0.68N ^{1.0}	
70	N-Tech Lab	ntech	5	2018-10-30	1685	113	⁶¹ 1940	k	¹⁰¹ 711	¹²⁰ 55	(³⁸)243	(³⁷)246	(³¹)538	(³⁰)1100	(³³)2867	⁸⁷ 0.02N ^{1.1}	
71	N-Tech Lab	ntech	6	2018-10-30	1686	117	⁶² 1940	k	¹²⁶ 831	¹²¹ 63	(³⁷)243	(³⁶)246	(³³)546	(³¹)1104	(³⁴)2873	⁸⁹ 0.02N ^{1.1}	
72	N-Tech Lab	ntechlab	007	2019-06-25	2450	51	¹²³ 3348	k	¹¹⁹ 795	¹²⁴ 73	(⁵⁴)393	(⁵⁹)427	(⁴⁰)780	(⁴³)1768	(⁴⁰)3499	⁵¹ 0.16N ^{1.0}	
73	N-Tech Lab	ntechlab	008	2020-01-06	1111	51	⁴⁹ 1300	k	⁶³ 554	¹¹⁰ 36	(³¹)179	(²⁸)184	(²³)341	(²²)683	(²⁰)1395	²⁶ 0.11N ^{1.0}	
74	N-Tech Lab	ntechlab	009	2021-03-01	1208	42	⁴⁸ 1300	-	¹³⁴ 899	¹⁰⁸ 35	(³⁰)178	(²⁹)184	(²²)336	(²¹)676	(²⁸)1704	⁶³ 0.05N ^{1.1}	
75	NEC	nec	2	2018-10-30	705	35	⁵⁷ 1616	k	⁷⁸ 642	⁸¹ 18	(⁵⁵)405	(⁵⁷)409	(⁴⁶)1072	(⁴¹)1755	(⁴²)4255	⁷⁹ 0.06N ^{1.1}	
76	NEC	nec	3	2018-10-30	774	110	⁵⁸ 1712	k	⁸² 665	⁸⁶ 21	(²)7	(²)7	(⁵)14	(⁸)40	(¹⁰)82	⁹⁵ 0.00N ^{1.2}	
77	Neurotechnology	neurotech	5	2018-10-30	266	53	¹¹ 256	k	⁴¹ 402	⁸ 2	(⁸³)835	(⁸⁴)839	(⁶⁵)1690	(⁶³)3219	(⁶⁸)8955	⁶⁶ 0.19N ^{1.1}	
78	Neurotechnology	neurotech	6	2018-10-30	564	53	¹³ 256	k	¹⁰⁵ 726	⁶ 2	(⁸⁴)839	(⁸⁵)842	-	-	-	-	
79	Neurotechnology	neurotech	007	2019-10-03	57	51	⁹ 256	k	⁷ 161	⁵ 2	(⁹¹)1118	(⁹²)1110	(⁷²)2143	(⁶⁷)4397	(⁶⁷)9045	³⁴ 0.55N ^{1.0}	
80	Newland Computer Co Ltd	newland	2	2018-10-30	96	27	⁶ 2048	-	¹²⁹ 855	⁶⁶ 15	(¹³¹)8741	(¹³⁶)8854	(¹¹⁴)17892	(¹¹²)39356	-	⁷⁵ 1.32N ^{1.1}	
81	Noblis	noblis	1	2018-10-30	114	176	⁷¹ 2048	1	¹⁵ 206	⁶² 15	(⁹⁸)1273	(⁹⁷)1272	-	-	-	-	
82	Noblis	noblis	2	2018-10-30	153	176	¹³² 6144	1	⁵⁹ 517	¹¹³ 43	(¹¹⁴)2513	(¹¹⁹)2522	(⁹⁹)5649	(¹⁰⁰)12432	(¹⁰⁶)44262	¹⁰³ 0.04N ^{1.3}	
83	Paravision (EverAI)	everai	2	2018-10-30	224	304	⁹⁶ 2048	1	³² 366	¹⁰¹ 30	(⁴¹)278	(⁴⁶)283	-	-	-	-	
84	Paravision (EverAI)	everai	3	2018-10-30	438	304	⁷⁰ 2048	1	¹⁰² 717	⁹⁶ 28	(⁴⁰)278	(⁴⁵)281	(³⁴)572	(³²)1146	(²⁹)2278	⁴⁶ 0.12N ^{1.0}	
85	Paravision (EverAI)	everai-paravision	004	2019-06-19	527	128	¹²⁹ 4096	1	⁸⁵ 672	¹¹⁶ 45	(⁶⁷)559	(⁶⁷)559	(⁸²)2611	(⁸⁸)6445	(⁹¹)14519	¹¹¹ 0.00N ^{1.5}	
86	Paravision (EverAI)	paravision	005	2019-12-11	543	154	¹²⁸ 4096	1	¹²⁵ 830	¹¹⁸ 48	(⁶⁸)561	(⁶⁹)564	(⁴⁵)1056	(⁴⁷)2298	(⁴⁶)4966	⁶¹ 0.16N ^{1.1}	
87	Paravision (EverAI)	paravision	007	2021-02-01	529	235	¹²⁷ 4096	-	⁹⁶ 701	¹¹⁹ 48	(⁶⁹)569	(⁶⁵)558	(⁴⁷)1086	(⁴⁵)2111	(⁴¹)4254	¹⁷ 1.11N ^{0.9}	
88	Quantasoft	quantasoft	1	2018-10-30	276	452	⁸⁶ 2048	k	³⁸ 385	¹⁹ 6	(¹³²)15422	(¹³⁷)14858	(¹¹²)14717	-	(⁹⁷)18323	-	
89	Rank One Computing	rankone	4	2018-10-09	0	101	³ 85	k	³ 36	²⁰ 7	(¹⁹)101	(¹⁹)101	(¹⁵)190	-	-	¹⁹ 0.07N ^{1.0}	
90	Rank One Computing	rankone	5	2018-10-24	0	101	⁵ 133	k	⁴ 92	²¹ 7	(²³)140	(²³)144	(¹⁹)266	(¹⁸)525	(¹⁸)1049	¹⁸ 0.11N ^{1.0}	
91	Rank One Computing	rankone	006	2019-06-03	0	133	⁷ 165	k	¹⁹ 245	²⁴ 8	-	-	-	-	-	-	
92	Rank One Computing	rankone	007	2019-11-12	0	137	⁶ 165	k	²² 272	²³ 7	(²⁰)116	(²⁰)115	(¹⁷)215	(¹⁷)439	(¹⁶)877	²⁷ 0.07N ^{1.0}	
93	Rank One Computing	rankone	009	2020-06-26	0	105	¹⁴ 260	k	¹¹ 185	³⁰ 11	(¹⁶)95	(¹⁷)96	(¹⁴)181	(¹⁴)362	(¹⁵)727	²³ 0.06N ^{1.0}	
94	Rank One Computing	rankone	010	2020-11-05	0	135	¹⁵ 261	-	¹³ 198	²⁷ 10	(¹⁷)95	(¹⁵)95	(¹³)178	(¹³)357	(¹⁴)714	²² 0.06N ^{1.0}	
95	Realnetworks Inc	realnetworks	2	2018-10-30	105	104	¹³³ 4104	k	¹⁸ 241	⁹⁵ 28	(¹¹⁰)2008	(¹¹⁵)2048	(⁹⁵)4194	(⁹⁴)8642	(⁹⁴)15035	³⁰ 0.18N ^{1.0}	
96	Realnetworks Inc	realnetworks	003	2019-06-12	93	102	⁵⁹ 1848	k	¹⁰ 173	⁴⁰ 13	(⁹³)1145	(⁹³)1132	(⁷¹)2142	(⁷⁷)5241	(⁷⁹)10495	⁶⁸ 0.21N ^{1.1}	
97	Realnetworks Inc	realnetworks	004	2019-10-17	94	102	⁶⁰ 1848	1	⁹ 171	²⁹ 11	(⁹²)1143	(⁹⁴)1137	(⁷³)2149	(⁷²)4740	(⁷⁴)9693	⁵⁹ 0.36N ^{1.0}	
98	Remark Holdings	remarkai	0	2018-10-30	187	847	⁶⁰ 2048	k	⁶⁶ 593	⁵⁵ 14	(¹²⁰)5685	(¹³¹)5723	-	-	-	-	
99	Remark Holdings	remarkai	000	2019-06-12	234	1092	⁹⁴ 2048	k	⁷⁹ 650	³⁹ 12	(¹²⁷)5776	(¹³⁰)5703	(¹⁰⁸)11604	(¹¹¹)32133	(¹¹²)91436	¹⁰⁴ 0.05N ^{1.3}	
100	Remark Holdings	remarkai	1	2018-10-30	187	847	⁶⁰ 2048	k	⁴⁶ 427	⁵⁹ 14	(¹²⁵)5680	(¹³²)5761	(¹¹¹)12475	(¹¹⁰)28726	(¹¹¹)59618	⁹⁶ 0.37N ^{1.2}	
101	Scanovate Ltd	scanovate	000	2020-01-15	250	446	⁸¹ 2048	1	⁹⁸ 705	⁵⁷ 14	(¹⁰⁴)1419	(¹⁰⁴)1412	(⁸⁷)3008	(⁹⁷)11616	(⁸⁴)12012	⁹⁷ 0.10N ^{1.2}	
102	Scanovate Ltd	scanovate	001	2020-09-10	250	446	⁶⁰ 2048	-	⁸⁷ 675	⁴⁴ 13	(¹⁰¹)1321	(¹⁰¹)1320	(⁷⁸)2502	(⁷⁴)5047	(⁷⁶)10163	³¹ 0.65N ^{1.0}	
103	Sensetime Group	sensetime	0	2018													

Notes

- Configuration size does not capture static data present in libraries. Libraries are included but the size also includes any ancillary libraries for image processing (e.g. openCV) or numerical computation (e.g. blas).
- Finalization is the processing of converting N = 1600000 templates into a searchable data structure operation which can be a simple copy, or the building of an index or tree,

	DEVELOPER	SHORT	SEQ.	VALIDATION	CONFIG ¹	LIB ¹	TEMPLATE GENERATION			FINALIZE ²	SEARCH DURATION ⁵ MILLISEC					POWER LAW
							SIZE (B)	MULT ³	TIME (MS) ⁴		L=1	L=50	L=50	L=50	L=50	
	FULL NAME	NAME	NUM.	DATE	DATA (MB)	DATA (MB)					N=1.6M	N=1.6M	N=3M	N=6M	N=12M	(μs)
105	Sensetime Group	sensetime	002	2019-06-03	523	6	¹⁰⁹ 2056	k	⁶⁸ 603	⁸⁰ 18	⁽⁴⁹⁾ 359	⁽⁵¹⁾ 370	⁽⁶⁷⁾ 1897	⁽⁶⁹⁾ 4508	⁽⁷¹⁾ 9543	¹¹⁴ 0.00 $N^{1.5}$
106	Sensetime Group	sensetime	003	2019-12-02	769	76	¹¹⁰ 2056	1	¹³⁷ 910	⁸³ 19	⁽¹²⁴⁾ 4885	⁽¹²⁹⁾ 4989	⁽¹¹⁰⁾ 12325	⁽¹⁰⁸⁾ 24712	⁽¹⁰⁸⁾ 49445	⁸¹ 0.67 $N^{1.1}$
107	Sensetime Group	sensetime	004	2020-08-10	456	29	⁴⁰ 1032	-	⁹² 690	³⁸ 12	⁽¹¹³⁾ 2490	⁽¹¹⁷⁾ 2477	⁽⁹⁷⁾ 4654	⁽⁹⁹⁾ 9402	⁽⁹⁹⁾ 19651	³³ 1.22 $N^{1.0}$
108	Sensetime Group	sensetime	005	2020-12-17	631	39	⁴¹ 1032	-	¹⁴¹ 980	²⁸ 11	⁽¹¹²⁾ 2459	⁽¹²⁶⁾ 3939	⁽¹⁰⁵⁾ 7398	⁽¹⁰³⁾ 14768	⁽⁹⁸⁾ 19016	¹⁶ 14.03 $N^{0.9}$
109	Shaman Software	shaman	6	2018-10-26	0	200	⁷⁸ 2048	k	⁹⁷ 706	⁵⁶ 14	⁽⁷¹⁾ 603	⁽⁷¹⁾ 612	-	-	-	-
110	Shaman Software	shaman	7	2018-10-26	0	200	⁹³ 2048	k	¹⁰⁰ 707	⁵⁸ 14	⁽⁷⁰⁾ 602	⁽⁷²⁾ 614	⁽⁵⁰⁾ 1187	⁽⁵³⁾ 2448	⁽⁵⁰⁾ 5083	⁴⁷ 0.25 $N^{1.0}$
111	Shanghai Yitu Technology	yitu	4	2018-10-30	2119	136	¹¹³ 2070	1	¹³³ 897	¹¹⁵ 45	⁽⁹⁹⁾ 1288	⁽⁹⁶⁾ 1203	⁽⁷³⁾ 2440	⁽⁷⁸⁾ 5241	⁽⁷³⁾ 9671	⁴¹ 0.52 $N^{1.0}$
112	Shanghai Yitu Technology	yitu	5	2018-10-30	2043	136	¹¹² 2070	1	¹²⁸ 853	¹¹⁴ 44	⁽⁹⁵⁾ 1237	⁽⁹⁵⁾ 1199	⁽⁷⁹⁾ 2513	⁽⁷³⁾ 5013	⁽⁷²⁾ 9620	⁴¹ 0.55 $N^{1.0}$
113	Smlart	smlart	4	2018-10-30	65	89	²⁰ 512	k	⁸ 167	¹⁴ 4	⁽¹³⁸⁾ 16137	⁽¹³⁸⁾ 15633	-	-	-	-
114	Smlart	smlart	5	2018-10-30	562	89	⁹⁷ 2048	k	⁵⁶ 450	⁵⁴ 14	-	-	-	-	-	-
115	Synesis	synesis	3	2018-10-30	237	150	¹²⁶ 4096	k	⁵⁹⁹ 99	²⁹ 29	⁽⁸¹⁾ 789	⁽⁸³⁾ 801	⁽⁷⁰⁾ 1941	⁽⁶⁹⁾ 3888	⁽⁶³⁾ 8810	⁸⁸ 0.07 $N^{1.1}$
116	Synesis	synesis	003	2019-07-04	143	17	⁸⁸ 2048	k	¹⁶ 211	³⁵ 12	⁽⁶²⁾ 507	⁽⁶³⁾ 502	⁽⁷⁴⁾ 2297	⁽⁷⁰⁾ 4564	⁽⁷⁰⁾ 9452	¹⁰⁸ 0.00 $N^{1.4}$
117	Synesis	synesis	005	2020-09-08	494	24	¹³⁴ 4104	-	¹¹⁰ 756	⁹⁰ 24	⁽⁸⁶⁾ 877	⁽⁸⁶⁾ 865	⁽⁸⁹⁾ 3182	⁽⁷¹⁾ 4658	⁽⁷⁵⁾ 9750	⁹⁸ 0.06 $N^{1.2}$
118	Tech5 SA	tech5	001	2019-08-19	1394	116	⁵² 1536	k	¹³² 887	²⁶ 10	⁽⁵²⁾ 383	⁽⁸⁰⁾ 766	⁽⁸⁴⁾ 2767	⁽⁸⁵⁾ 6149	⁽⁵⁷⁾ 6178	⁸⁰ 0.12 $N^{1.1}$
119	Tencent Deepsea Lab	deepsea	001	2019-07-29	250	323	⁷⁹ 2048	1	¹⁰⁷ 737	³⁷ 12	⁽⁹⁰⁾ 1021	⁽⁹¹⁾ 1020	⁽⁸⁵⁾ 2774	⁽⁸³⁾ 5767	⁽⁸⁶⁾ 12341	¹⁰⁰ 0.06 $N^{1.2}$
120	Tevian	tevia	5	2018-10-30	773	15	⁷⁴ 2048	1	⁴³ 405	⁶³ 15	⁽⁵⁶⁾ 405	⁽⁵⁶⁾ 408	⁽⁴²⁾ 854	⁽⁴²⁾ 1757	⁽³⁹⁾ 3380	⁵⁸ 0.14 $N^{1.0}$
121	Thales	cogent	2	2018-10-30	681	39	⁴⁴ 1043	k	¹⁹³ 945	⁹³ 27	⁽¹¹¹⁾ 2017	⁽¹¹⁶⁾ 2144	⁽⁹⁶⁾ 4298	⁽⁹³⁾ 8472	⁽⁹⁶⁾ 16429	³⁵ 1.08 $N^{1.0}$
122	Thales	cogent	3	2018-10-30	681	39	⁴⁵ 1043	k	¹³⁸ 940	²⁵ 9	⁽⁹⁴⁾ 1230	⁽¹⁰⁰⁾ 1311	⁽⁸³⁾ 2687	⁽⁷⁹⁾ 5398	⁽⁷⁷⁾ 10184	³⁸ 0.62 $N^{1.0}$
123	Thales	cogent	004	2021-02-10	1376	59	¹⁰⁷ 2053	-	¹⁴⁰ 947	⁴⁹ 14	⁽¹¹⁶⁾ 2903	⁽¹¹²⁾ 1911	⁽⁹⁰⁾ 3566	⁽⁹¹⁾ 7498	⁽⁹⁵⁾ 16370	⁵⁷ 0.64 $N^{1.0}$
124	TigerIT Americas LLC	tiger	2	2018-10-29	416	518	¹⁰⁰ 2052	k	⁵¹ 461	⁶⁷ 15	⁽¹⁰⁹⁾ 1816	⁽¹¹³⁾ 1921	⁽⁹⁴⁾ 3833	⁽⁹²⁾ 7526	⁽⁹²⁾ 14820	⁴⁵ 0.83 $N^{1.0}$
125	TigerIT Americas LLC	tiger	3	2018-10-30	416	518	¹⁰¹ 2052	k	⁵² 461	¹⁴⁰ 37431	⁽³⁴⁾ 191	⁽³²⁾ 189	-	-	-	-
126	Toshiba	toshiba	0	2018-10-30	961	105	⁵⁶ 1548	k	¹³¹ 876	³³ 12	⁽¹³⁰⁾ 6153	⁽¹³³⁾ 6236	⁽¹⁰⁹⁾ 12221	⁽¹⁰⁹⁾ 25355	⁽¹⁰⁹⁾ 49448	⁹³ 0.36 $N^{1.2}$
127	Toshiba	toshiba	1	2018-10-30	961	105	¹¹¹ 2060	k	¹³⁸ 875	¹⁴¹ 44701	⁽¹²⁹⁾ 6007	⁽¹³⁴⁾ 6355	-	-	-	-
128	Trueface.ai	trueface	000	2021-01-27	247	119	⁶³ 2000	-	³¹ 363	⁴³ 13	⁽³⁹⁾ 271	⁽⁵⁰⁾ 327	⁽³⁶⁾ 614	⁽³⁴⁾ 1239	⁽³²⁾ 2678	³⁷ 0.15 $N^{1.0}$
129	Vigilant Solutions	vigilant	5	2018-10-30	335	122	⁵⁵ 1544	k	¹¹¹ 762	⁸² 19	-	⁽¹⁰⁹⁾ 1720	-	-	-	-
130	Vigilant Solutions	vigilant	6	2018-10-30	337	122	⁵⁴ 1544	k	¹²² 816	⁸⁷ 21	-	⁽¹⁰⁸⁾ 1713	-	-	-	-
131	Vigilant Solutions	vigilantsolutions	007	2021-01-08	340	51	⁵³ 1544	-	⁷¹ 616	⁷⁷ 16	⁽¹⁰³⁾ 1354	⁽¹⁰³⁾ 1352	⁽⁸⁶⁾ 2911	⁽⁸⁴⁾ 5966	⁽⁸³⁾ 11466	⁶⁷ 0.27 $N^{1.1}$
132	Visidon	visidon	1	2018-10-30	166	42	¹⁰³ 2052	k	⁸³ 667	⁶⁹ 15	⁽¹²²⁾ 4370	⁽¹²⁸⁾ 4472	⁽¹⁰⁶⁾ 8454	⁽¹⁰⁵⁾ 17262	⁽¹⁰⁴⁾ 34288	²⁹ 2.40 $N^{1.0}$
133	VisionLabs	visionlabs	6	2018-10-30	360	17	²¹ 512	1	²⁶ 289	¹³⁷ 20290	⁽¹³⁾ 36	⁽¹³⁾ 36	⁽¹¹⁾ 39	⁽¹⁰⁾ 44	⁽⁹⁾ 53	⁹ 3211.93 $N^{0.2}$
134	VisionLabs	visionlabs	7	2018-10-30	360	17	²² 512	1	²⁵ 289	¹³⁹ 34666	⁽¹⁴⁾ 63	⁽¹⁴⁾ 63	⁽¹²⁾ 72	⁽¹²⁾ 80	⁽¹¹⁾ 115	¹¹ 2076.32 $N^{0.2}$
135	VisionLabs	visionlabs	008	2019-06-18	348	17	²⁷ 512	1	²³ 272	¹³⁴ 12747	⁽⁸⁾ 23	⁽⁷⁾ 24	⁽⁷⁾ 26	⁽⁶⁾ 29	⁽⁶⁾ 33	⁷ 2539.61 $N^{0.2}$
136	VisionLabs	visionlabs	009	2020-08-04	689	20	²⁶ 512	-	⁵³ 467	¹³⁵ 13245	⁽⁹⁾ 23	⁽⁸⁾ 29	⁽⁸⁾ 34	⁽¹¹⁾ 61	⁽¹²⁾ 145	¹² 8.88 $N^{0.6}$
137	VisionLabs	visionlabs	010	2021-02-05	1042	20	²⁸ 512	-	¹⁰⁶ 731	¹³¹ 11837	⁽⁷⁾ 21	⁽¹⁰⁾ 32	⁽⁹⁾ 36	⁽⁷⁾ 39	⁽⁷⁾ 43	⁸ 3183.79 $N^{0.2}$
138	Vocord	vocord	5	2018-10-30	1035	185	³⁴ 768	k	¹¹³ 780	²⁷ 7	⁽²⁸⁾ 158	⁽³³⁾ 204	⁽²⁵⁾ 383	⁽²⁵⁾ 767	⁽²²⁾ 1466	²⁵ 0.12 $N^{1.0}$
139	Vocord	vocord	6	2018-10-30	1035	185	¹⁴¹ 10240	k	¹¹⁴ 785	¹²⁷ 243	⁽²⁹⁾ 170	⁽³⁴⁾ 216	-	-	-	-
140	Xforward AI Technology	xforwardai	000	2020-07-24	236	171	⁸⁴ 2048	-	¹⁰⁹ 753	⁴⁷ 13	⁽¹²³⁾ 4603	⁽¹³⁵⁾ 7647	⁽¹¹³⁾ 15723	⁽¹⁰⁷⁾ 23900	⁽¹¹⁰⁾ 53729	⁸⁵ 0.56 $N^{1.1}$
141	Xforward AI Technology	xforwardai	001	2021-01-21	332	50	⁷⁵ 2048	-	⁸⁹ 677	⁷⁵ 16	⁽¹²⁸⁾ 5887	⁽¹²⁷⁾ 4384	⁽¹⁰⁷⁾ 8798	⁽¹⁰⁶⁾ 18553	⁽¹⁰⁷⁾ 48993	⁹¹ 0.32 $N^{1.1}$

Notes

1 Configuration size does not capture static data present in libraries. Libraries are included but the size also includes any ancillary libraries for image processing (e.g. openCV) or numerical computation (e.g. blas).

2 Finalization is the processing of converting N = 1600000 templates into a searchable data structure an operation which can be a simple copy, or the building of an index or tree, for example. The duration of the operation may be data dependent, and may not be linear in the number of input templates.

3 This multiplier expresses the increase in template size when k images are passed to the template generation function.

4 All durations are measured on Intel®Xeon®CPU E5-2630 v4 @ 2.20GHz processors. Estimates are made by wrapping the API function call in calls to std::chrono::high_resolution_clock which on the machine in (3) counts 1ns clock ticks. Precision is somewhat worse than that however.

5 Search durations are measured as in the prior note. The power-law model in the final column mostly fits the empirical results in Figure 160. However in certain cases the model is not correct and should not be used numerically.

Table 4: Summary of algorithms and properties included in this report. The blue superscripts give ranking for the quantity in that column. Missing search durations, denoted by “-”, are absent because those runs were not executed, usually because we did not run on the larger galleries. Caution: The power-law model is sometimes an incorrect model. It is included here only to show broad sublinear behavior, which is flagged in green. The models should not be used for prediction.

2021/03/04
11:49:04FNIR(N, R, T) =
FPR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

MISS RATES		INVESTIGATION, FNIR(N, R = 1, T = 0)								IDENTIFICATION, FNIR(N, R = L, T ≥ 0) FOR FPIR = 0.001							
#	ALGORITHM	(0, 2]	(2, 4]	(4, 6]	(6, 8]	(8, 10]	(10, 12]	(12, 14]	(14, 18]	(0, 2]	(2, 4]	(4, 6]	(6, 8]	(8, 10]	(10, 12]	(12, 14]	(14, 18]
1	3DIVI-005	⁸⁶ 0.0207	⁸⁵ 0.0304	⁸⁵ 0.0415	⁸⁵ 0.0533	⁸⁵ 0.0646	⁸⁵ 0.0735	⁸⁵ 0.0884	⁸⁶ 0.1148	⁸⁹ 0.1580	⁸⁸ 0.2316	⁸⁶ 0.3033	⁸⁶ 0.3740	⁸⁶ 0.4285	⁸⁶ 0.4742	⁸⁷ 0.5329	⁸⁵ 0.5975
2	ANKE-000	⁸³ 0.0162	⁸³ 0.0245	⁸³ 0.0333	⁸³ 0.0428	⁸³ 0.0515	⁸³ 0.0615	⁸³ 0.0780	⁸² 0.1028	⁸⁴ 0.1132	⁸⁴ 0.1761	⁸⁴ 0.2402	⁸⁴ 0.3057	⁸³ 0.3640	⁸³ 0.4200	⁸³ 0.4928	⁸³ 0.5680
3	ANKE-002	³⁹ 0.0055	⁴⁰ 0.0074	⁴¹ 0.0090	⁴⁰ 0.0103	³⁹ 0.0116	⁴⁰ 0.0135	³⁹ 0.0162	³⁸ 0.0202	⁴⁴ 0.0329	⁴⁴ 0.0560	⁴⁶ 0.0843	⁴⁷ 0.1169	⁴⁷ 0.1481	⁴⁷ 0.1820	⁴⁷ 0.2280	⁴⁶ 0.2831
4	AWARE-005	⁹⁴ 0.0328	⁹⁴ 0.0519	⁹⁴ 0.0712	⁹² 0.0910	⁹² 0.1078	⁹² 0.1235	⁹² 0.1457	⁹² 0.1831	⁹⁴ 0.3605	⁹⁵ 0.4949	⁹⁵ 0.5948	⁹⁹ 0.6783	⁹⁸ 0.7393	⁹⁵ 0.7905	⁹⁸ 0.8408	⁹⁶ 0.8831
5	AWARE-006	⁹⁸ 0.0702	⁹⁸ 0.1110	⁹⁸ 0.1502	⁹⁸ 0.1899	⁹⁸ 0.2253	⁹⁸ 0.2614	⁹⁸ 0.3045	⁹⁶ 0.3659								
6	AYONIX-002	¹⁰¹ 0.3360	¹⁰² 0.4389	¹⁰² 0.5144	¹⁰² 0.5814	¹⁰² 0.6340	¹⁰² 0.6818	¹⁰² 0.7297	¹⁰² 0.7774	⁹⁷ 0.8288	⁹⁸ 0.9013	⁹⁸ 0.9375	⁹⁸ 0.9603	⁹⁸ 0.9744	⁹⁹ 0.9837	⁹⁹ 0.9893	⁹⁹ 0.9927
7	CAMVI-004	⁹⁷ 0.0623	⁹⁷ 0.0944	⁹⁷ 0.1243	⁹⁷ 0.1548	⁹⁶ 0.1812	⁹⁶ 0.2056	⁹⁶ 0.2344	⁹⁶ 0.2672	⁷⁹ 0.0810	⁷⁹ 0.1267	⁷⁶ 0.1721	⁷⁶ 0.2203	⁷⁶ 0.2619	⁷⁴ 0.3040	⁷³ 0.3543	⁷⁰ 0.4124
8	CAMVI-005	⁹⁹ 0.0849	⁹⁹ 0.1255	⁹⁹ 0.1631	⁹⁹ 0.1989	⁹⁹ 0.2298	⁹⁸ 0.2585	⁹⁷ 0.2915	⁹⁷ 0.3246								
9	CIB-000	⁷ 0.0022	⁸ 0.0030	⁹ 0.0037	⁹ 0.0044	¹⁰ 0.0049	¹⁰ 0.0057	¹⁰ 0.0069	¹⁰ 0.0062	¹⁶ 0.0139	¹⁷ 0.0240	¹⁸ 0.0373	¹⁹ 0.0525	¹⁹ 0.0689	¹⁷ 0.0859	¹⁷ 0.1109	¹⁷ 0.1454
10	COGENT-000	⁷⁹ 0.0128	⁷⁸ 0.0184	⁸⁰ 0.0250	⁸¹ 0.0327	⁸⁰ 0.0407	⁷⁹ 0.0488	⁷⁸ 0.0611	⁷⁷ 0.0794	⁶⁶ 0.0559	⁶⁷ 0.0923	⁶⁶ 0.1342	⁶⁵ 0.1812	⁶⁵ 0.2243	⁶⁵ 0.2675	⁶² 0.3240	⁶⁷ 0.3992
11	COGENT-001	⁷⁸ 0.0128	⁷⁹ 0.0184	⁸¹ 0.0250	⁸⁰ 0.0327	⁸¹ 0.0407	⁸⁰ 0.0488	⁷⁹ 0.0611	⁷⁸ 0.0794	⁶⁷ 0.0559	⁶⁸ 0.0923	⁶⁵ 0.1342	⁶⁵ 0.1812	⁶⁴ 0.2243	⁶⁴ 0.2675	⁶³ 0.3240	⁶⁶ 0.3992
12	COGENT-002	⁵⁷ 0.0081	⁵⁴ 0.0105	⁵⁴ 0.0123	⁵⁴ 0.0137	⁵¹ 0.0157	⁵¹ 0.0175	⁴⁹ 0.0215	⁴⁹ 0.0280	⁵⁸ 0.0499	⁵⁷ 0.0827	⁵⁶ 0.1207	⁵⁶ 0.1639	⁵⁶ 0.2037	⁵⁶ 0.2432	⁵⁶ 0.2972	⁵⁷ 0.3638
13	COGENT-003	⁵⁹ 0.0082	⁵⁵ 0.0108	⁵⁵ 0.0128	⁵⁵ 0.0145	⁵⁵ 0.0168	⁵² 0.0191	⁵³ 0.0239	⁵³ 0.0312	⁶⁸ 0.0582	⁶⁹ 0.0971	⁶⁹ 0.1407	⁶⁹ 0.1918	⁶⁹ 0.2380	⁷⁰ 0.2836	⁷¹ 0.3440	⁷² 0.4207
14	COGENT-004	⁴⁸ 0.0066	⁴³ 0.0080	³⁹ 0.0085	³⁹ 0.0080	²¹ 0.0083	²¹ 0.0092	²² 0.0106	²⁶ 0.0130	⁵² 0.0410	⁵⁴ 0.0720	⁵⁴ 0.1099	⁵⁴ 0.1539	⁵³ 0.1974	⁵³ 0.2443	⁵³ 0.3043	⁵⁹ 0.3757
15	COGNITEC-000	⁹³ 0.0265	⁹¹ 0.0423	⁹¹ 0.0588	⁹¹ 0.0757	⁹⁰ 0.0894	⁹⁰ 0.1014	⁹⁰ 0.1169	⁸⁹ 0.1381	⁸⁸ 0.1522	⁸⁷ 0.2330	⁸⁷ 0.3051	⁸⁷ 0.3751	⁸⁶ 0.4300	⁸⁶ 0.4779	⁸⁶ 0.5307	⁸⁴ 0.5913
16	COGNITEC-001	⁸¹ 0.0149	⁸² 0.0228	⁸³ 0.0312	⁸³ 0.0399	⁸² 0.0479	⁸² 0.0546	⁸¹ 0.0656	⁷⁹ 0.0806	⁸¹ 0.0963	⁸¹ 0.1562	⁸¹ 0.2157	⁸¹ 0.2771	⁸⁰ 0.3287	⁸⁰ 0.3771	⁸⁰ 0.4343	⁷⁹ 0.4959
17	COGNITEC-002	⁶⁵ 0.0101	⁶⁸ 0.0138	⁶⁹ 0.0170	⁶⁹ 0.0201	⁶⁹ 0.0237	⁶⁸ 0.0264	⁶⁶ 0.0309	⁶⁵ 0.0389	⁶¹ 0.0517	⁶¹ 0.0879	⁶¹ 0.1269	⁶² 0.1707	⁶⁰ 0.2098	⁵⁹ 0.2463	⁵⁵ 0.2919	⁵⁵ 0.3535
18	COGNITEC-003	⁶⁶ 0.0104	⁶⁹ 0.0140	⁷⁰ 0.0174	⁷⁰ 0.0205	⁷⁰ 0.0238	⁶⁹ 0.0266	⁶⁷ 0.0311	⁶⁷ 0.0401	⁶⁰ 0.0504	⁵⁹ 0.0855	⁵⁸ 0.1235	⁵⁸ 0.1662	⁵⁷ 0.2045	⁵⁴ 0.2403	⁵⁴ 0.2854	⁵³ 0.3451
19	CYBERLINK-002	⁴⁰ 0.0055	³⁶ 0.0068	³¹ 0.0075	²⁵ 0.0078	²² 0.0084	²² 0.0094	²³ 0.0107	²¹ 0.0114	²³ 0.0180	²⁴ 0.0302	²⁴ 0.0460	²² 0.0643	²⁴ 0.0837	²⁵ 0.1058	²⁴ 0.1370	²⁴ 0.1787
20	CYBERLINK-003	²⁵ 0.0041	²⁴ 0.0052	¹⁷ 0.0057	¹⁶ 0.0058	¹⁶ 0.0061	¹⁶ 0.0068	¹³ 0.0078	¹⁶ 0.0078	¹¹ 0.0109	¹¹ 0.0175	¹² 0.0259	¹² 0.0356	¹² 0.0468	¹² 0.0594	¹² 0.0787	¹³ 0.1072
21	DAHUA-002	²¹ 0.0035	¹⁸ 0.0047	¹⁸ 0.0058	¹⁷ 0.0067	¹⁸ 0.0074	¹⁷ 0.0082	¹⁹ 0.0100	¹⁹ 0.0108	²¹ 0.0169	²³ 0.0294	²² 0.0449	²¹ 0.0635	²¹ 0.0817	²¹ 0.1013	²¹ 0.1291	²⁰ 0.1638
22	DAHUA-003	¹² 0.0026	¹² 0.0036	¹² 0.0043	¹² 0.0050	¹² 0.0055	¹² 0.0062	¹⁵ 0.0080	¹³ 0.0073	²⁰ 0.0160	²¹ 0.0280	²⁰ 0.0432	²⁰ 0.0615	²⁰ 0.0794	²⁰ 0.0987	²⁰ 0.1270	¹⁹ 0.1587
23	DEEPLINT-001	¹⁰ 0.0024	⁹ 0.0032	⁸ 0.0037	⁷ 0.0040	⁷ 0.0043	⁸ 0.0049	⁸ 0.0060	⁸ 0.0052	⁷ 0.0058	⁵ 0.0087	⁶ 0.0119	⁶ 0.0155	⁶ 0.0199	⁶ 0.0249	⁶ 0.0338	⁶ 0.0463
24	DEEPEA-001	³⁸ 0.0081	³⁸ 0.0116	⁶¹ 0.0149	⁶¹ 0.0182	⁶⁴ 0.0216	⁶² 0.0260	⁶⁹ 0.0332	⁶⁹ 0.0432	³⁵ 0.0458	³⁵ 0.0752	³³ 0.1086	³² 0.1460	³² 0.1812	³² 0.2186	³² 0.2663	³² 0.3213
25	DERMALOG-006	⁷⁰ 0.0113	⁷⁰ 0.0142	⁶⁶ 0.0163	⁶⁵ 0.0183	⁶² 0.0200	⁶¹ 0.0218	⁶⁰ 0.0251	⁵⁸ 0.0329	⁶⁴ 0.0545	⁶² 0.0889	⁶² 0.1271	⁶¹ 0.1697	⁵⁹ 0.2090	⁵⁹ 0.2498	⁵⁸ 0.3028	⁵⁸ 0.3670
26	DERMALOG-007	⁷⁶ 0.0125	⁷⁶ 0.0170	⁷⁸ 0.0214	⁷⁸ 0.0264	⁷³ 0.0309	⁷⁴ 0.0356	⁷⁵ 0.0432	⁷³ 0.0579	⁸⁰ 0.0910	⁸⁰ 0.1453	⁸⁰ 0.2009	⁸⁰ 0.2602	⁸⁰ 0.3134	⁷⁹ 0.3649	⁷⁹ 0.4289	⁸⁰ 0.5007
27	DERMALOG-008	⁴² 0.0057	⁴² 0.0077	⁴³ 0.0095	⁴³ 0.0110	⁴⁴ 0.0128	⁴⁵ 0.0148	⁴⁵ 0.0180	⁴⁵ 0.0223	⁵⁹ 0.0501	⁵⁸ 0.0850	⁵⁹ 0.1247	⁶⁰ 0.1692	⁶¹ 0.2105	⁶⁰ 0.2541	⁶⁰ 0.3102	⁶⁰ 0.3762
28	GORILLA-002	⁸⁸ 0.0213	⁸⁹ 0.0359	⁹⁰ 0.0528	⁹⁰ 0.0716	⁹¹ 0.0895	⁹¹ 0.1088	⁹¹ 0.1367	⁹¹ 0.1765	⁹¹ 0.1828	⁹² 0.2787	⁹² 0.3654	⁹² 0.4485	⁹² 0.5168	⁹⁰ 0.5823	⁹⁰ 0.6508	⁹⁰ 0.7180
29	IDEMIA-003	⁶⁹ 0.0110	⁷⁴ 0.0151	⁷⁴ 0.0196	⁷⁴ 0.0238	⁷² 0.0281	⁷² 0.0313	⁷² 0.0368	⁷¹ 0.0504	⁷⁵ 0.0717	⁷⁴ 0.1147	⁷⁴ 0.1614	⁷⁴ 0.2113	⁷² 0.2553	⁷² 0.2976	⁷² 0.3537	⁷³ 0.4334
30	IDEMIA-004	⁶⁸ 0.0107	⁷² 0.0148	⁷³ 0.0192	⁷² 0.0233	⁷¹ 0.0277	⁷¹ 0.0312	⁷¹ 0.0367	⁷² 0.0512	⁴⁸ 0.0373	⁴⁵ 0.0587	⁴⁴ 0.0833	⁴⁴ 0.1100	⁴⁸ 0.1340	⁴⁴ 0.1580	³⁹ 0.1911	³⁹ 0.2482
31	IDEMIA-005	⁷² 0.0118	⁷⁵ 0.0167	⁷⁸ 0.0218	⁷⁷ 0.0270	⁷⁶ 0.0317	⁷⁵ 0.0357	⁷⁴ 0.0425	⁷⁴ 0.0579	⁵⁴ 0.0440	⁵³ 0.0689	⁵⁰ 0.0964	⁴⁹ 0.1254	⁴⁸ 0.1513	⁴⁶ 0.1762	⁴² 0.2113	⁴³ 0.2698
32	IDEMIA-006	⁷⁵ 0.0124	⁷⁷ 0.0171	⁷⁷ 0.0218	⁷⁶ 0.0263	⁷⁴ 0.0302	⁷³ 0.0321	⁷⁰ 0.0356	⁷⁰ 0.0471	⁵¹ 0.0409	⁴⁹ 0.0620	⁴⁷ 0.0850	⁴³ 0.1097	⁴¹ 0.1309	³⁹ 0.1486	³⁴ 0.1738	³³ 0.2200
33	IDEMIA-007	³⁶ 0.0050	³⁸ 0.0071	³⁹ 0.0089	⁴¹ 0.0106	⁴² 0.0124	⁴² 0.0142	⁴² 0.0171	⁴³ 0.0220	²⁷ 0.0202	²⁷ 0.0335	²⁵ 0.0491	²⁴ 0.0663	²² 0.0825	²¹ 0.0999	¹⁹ 0.1240	²¹ 0.1645
34	IMAGUS-005	²³ 0.0039	²³ 0.0052	²¹ 0.0061	¹⁸ 0.0067	²⁰ 0.0077	²⁰ 0.0088	²⁰ 0.0103	²⁰ 0.0109	³⁰ 0.0212	³⁰ 0.0357	³¹ 0.0539	³² 0.0755	³⁰ 0.0967	²⁸ 0.1183	²⁵ 0.1485	²⁷ 0.1893
35	IMPERIAL-000	²⁴ 0.0040	²⁷ 0.0054	²⁶ 0.0067	²⁶ 0.0079	³¹ 0.0093	³² 0.0112	³¹ 0.0139	³³ 0.0178	⁴¹ 0.0286	⁴³ 0.0503	⁴³ 0.0779	⁴⁵ 0.1116	⁴⁶ 0.1455	⁴⁸ 0.1844	⁵⁰ 0.2341	⁴⁹ 0.2951
36	INCODE-003	⁸² 0.0155	⁸⁴ 0.0247	⁸⁴ 0.0348	⁸⁴ 0.0463	⁸⁴ 0.05751											

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

MISS RATES		INVESTIGATION, FNIR(N, R = 1, T = 0)								IDENTIFICATION, FNIR(N, R = L, T ≥ 0) FOR FPIR = 0.001							
#	ALGORITHM	(0, 2]	(2, 4]	(4, 6]	(6, 8]	(8, 10]	(10, 12]	(12, 14]	(14, 18]	(0, 2]	(2, 4]	(4, 6]	(6, 8]	(8, 10]	(10, 12]	(12, 14]	(14, 18]
45	LOOKMAN-005	⁷⁴ 0.0118	⁶⁸ 0.0134	⁸⁸ 0.0142	⁵⁴ 0.0144	⁵⁰ 0.0150	⁵⁰ 0.0160	⁴³ 0.0176	⁴¹ 0.0213	⁴³ 0.0310	⁴¹ 0.0480	³⁸ 0.0698	³⁸ 0.0954	³⁸ 0.1216	³⁸ 0.1491	³⁸ 0.1890	³⁸ 0.2381
46	MICROFOCUS-005	¹⁰³ 0.4269	¹⁰³ 0.5527	¹⁰³ 0.6355	¹⁰³ 0.7024	¹⁰³ 0.7503	¹⁰³ 0.7876	¹⁰³ 0.8234	¹⁰⁴ 0.8601	⁹⁸ 0.8338	⁹⁹ 0.9113	⁹⁹ 0.9468	⁹⁹ 0.9667	⁹⁹ 0.9771	⁹⁸ 0.9836	⁹⁸ 0.9880	⁹⁸ 0.9924
47	MICROSOFT-003	¹⁹ 0.0034	²² 0.0050	²³ 0.0064	²⁶ 0.0078	²⁹ 0.0092	²⁹ 0.0107	³⁰ 0.0135	³¹ 0.0166	⁴² 0.0288	⁴² 0.0503	⁴² 0.0763	⁴² 0.1067	⁴⁵ 0.1359	⁴⁴ 0.1680	⁴³ 0.2116	⁴¹ 0.2644
48	MICROSOFT-004	¹⁶ 0.0032	¹⁹ 0.0047	¹⁹ 0.0060	²² 0.0075	²⁵ 0.0087	²⁹ 0.0103	²⁹ 0.0131	²⁹ 0.0159	³⁹ 0.0268	⁴⁰ 0.0470	⁴¹ 0.0716	⁴⁰ 0.1007	⁴⁰ 0.1291	⁴³ 0.1610	⁴¹ 0.2052	⁴⁰ 0.2590
49	MICROSOFT-005	¹⁵ 0.0031	¹⁹ 0.0047	²⁵ 0.0066	³⁴ 0.0084	³⁴ 0.0103	³⁸ 0.0131	⁴¹ 0.0164	³⁵ 0.0185	³⁴ 0.0243	³⁹ 0.0432	³⁹ 0.0658	³⁶ 0.0913	³⁷ 0.1172	³⁵ 0.1476	³⁷ 0.1874	³⁷ 0.2272
50	MICROSOFT-006	¹⁷ 0.0032	²¹ 0.0049	²⁴ 0.0065	³² 0.0081	³³ 0.0096	³³ 0.0117	³⁵ 0.0144	³⁰ 0.0160	¹⁵ 0.0134	¹⁵ 0.0233	¹⁶ 0.0346	¹⁴ 0.0462	¹³ 0.0578	¹⁴ 0.0713	¹⁴ 0.0903	¹⁴ 0.1156
51	NEC-000	⁸⁹ 0.0195	⁸⁹ 0.0316	⁸⁸ 0.0445	⁸⁷ 0.0581	⁸⁶ 0.0699	⁸⁷ 0.0817	⁸⁷ 0.0998	⁸⁶ 0.1237	⁷⁷ 0.0759	⁷⁷ 0.1245	⁷⁷ 0.1729	⁷⁷ 0.2240	⁷⁷ 0.2671	⁷⁶ 0.3117	⁷⁴ 0.3639	⁷⁴ 0.4348
52	NEC-001	⁹² 0.0246	⁹⁰ 0.0382	⁸⁸ 0.0524	⁸⁸ 0.0672	⁸⁹ 0.0793	⁸⁹ 0.0904	⁸⁸ 0.1076	⁸⁶ 0.1317	⁸² 0.1019	⁸² 0.1623	⁸² 0.2214	⁸² 0.2834	⁸² 0.3341	⁸² 0.3844	⁸² 0.4440	⁸¹ 0.5183
53	NEC-002	¹⁸ 0.0033	¹⁵ 0.0041	¹¹ 0.0043	¹⁰ 0.0044	⁸ 0.0045	⁷ 0.0049	⁷ 0.0056	⁵ 0.0041	¹⁰ 0.0066	⁶ 0.0090	⁵ 0.0111	⁵ 0.0131	⁴ 0.0149	⁴ 0.0171	⁵ 0.0207	⁵ 0.0267
54	NEC-003	²² 0.0036	¹⁶ 0.0046	¹⁵ 0.0051	¹⁵ 0.0055	¹⁵ 0.0059	¹⁵ 0.0067	¹² 0.0077	¹⁴ 0.0073	⁴ 0.0056	⁴ 0.0076	⁴ 0.0091	³ 0.0105	³ 0.0119	³ 0.0137	² 0.0162	² 0.0209
55	NEUROTECHNOLOGY-003	⁸⁹ 0.0234	⁸⁹ 0.0379	⁹⁰ 0.0549	⁸⁹ 0.0682	⁸⁸ 0.0720	⁸⁶ 0.0747	⁸⁶ 0.0886	⁸⁴ 0.1066	⁹⁶ 0.6802	⁹⁶ 0.8187	⁹⁷ 0.8920	⁹⁷ 0.9355	⁹⁷ 0.9594	⁹⁷ 0.9738	⁹⁷ 0.9828	⁹⁷ 0.9885
56	NEUROTECHNOLOGY-004	⁶⁹ 0.0104	⁶⁹ 0.0134	⁶⁴ 0.0156	⁶¹ 0.0173	⁶⁰ 0.0195	⁶⁰ 0.0212	⁵⁹ 0.0245	⁶⁰ 0.0320	⁷¹ 0.0642	⁷⁰ 0.1015	⁷⁰ 0.1426	⁶⁸ 0.1881	⁶⁷ 0.2299	⁶⁶ 0.2722	⁶⁵ 0.3269	⁶⁵ 0.3943
57	NEUROTECHNOLOGY-005	⁶⁹ 0.0089	⁶⁹ 0.0116	⁵⁶ 0.0136	⁵⁶ 0.0152	⁵⁷ 0.0173	⁵⁴ 0.0196	⁵⁴ 0.0233	⁶³ 0.0306	⁶⁰ 0.0556	⁶⁰ 0.0913	⁶³ 0.1315	⁶³ 0.1766	⁶³ 0.2192	⁶² 0.2617	⁶¹ 0.3174	⁶¹ 0.3843
58	NEUROTECHNOLOGY-007	⁵⁴ 0.0078	⁵³ 0.0103	⁵² 0.0124	⁵³ 0.0140	⁵² 0.0161	⁵² 0.0185	⁵¹ 0.0225	⁶⁰ 0.0290	⁷⁰ 0.0641	⁷⁰ 0.1069	⁷⁰ 0.1546	⁷³ 0.2075	⁷⁴ 0.2572	⁷⁵ 0.3081	⁷⁶ 0.3713	⁷⁶ 0.4421
59	NOBLIS-002	¹⁰⁰ 0.1520	¹⁰⁰ 0.2419	¹⁰⁰ 0.3296	¹⁰¹ 0.4114	¹⁰¹ 0.4856	¹⁰¹ 0.5528	¹⁰⁰ 0.6061	¹⁰¹ 0.6532	¹⁰⁰ 0.9984	¹⁰⁰ 0.9996	¹⁰⁰ 0.9998	¹⁰⁰ 0.9999	¹⁰⁰ 0.9999	¹⁰⁰ 1.0000	¹⁰⁰ 1.0000	¹⁰⁰ 1.0000
60	NTECHLAB-003	⁵³ 0.0078	⁶⁴ 0.0131	⁷⁵ 0.0202	⁷⁶ 0.0295	⁷⁹ 0.0405	⁸¹ 0.0543	⁸² 0.0761	⁸² 0.1035	⁵⁷ 0.0491	⁶¹ 0.0881	⁶⁸ 0.1384	⁷¹ 0.1985	⁷⁵ 0.2594	⁷⁸ 0.3270	⁷⁸ 0.4065	⁷⁸ 0.4891
61	NTECHLAB-004	⁵⁰ 0.0068	⁵⁶ 0.0110	⁶⁷ 0.0167	⁷⁴ 0.0239	⁷⁷ 0.0330	⁷⁷ 0.0447	⁸⁰ 0.0641	⁸¹ 0.0891	⁵⁰ 0.0379	⁵⁴ 0.0688	⁵⁸ 0.1108	⁵⁹ 0.1629	⁶² 0.2192	⁷¹ 0.2846	⁷⁵ 0.3657	⁷⁵ 0.4524
62	NTECHLAB-006	⁴¹ 0.0056	⁵⁹ 0.0095	⁶⁰ 0.0148	⁷¹ 0.0218	⁷³ 0.0301	⁷⁶ 0.0413	⁷⁶ 0.0591	⁸⁰ 0.0814	⁴⁶ 0.0349	⁵⁸ 0.0636	⁵⁸ 0.1023	⁵³ 0.1506	⁵⁵ 0.2024	⁶¹ 0.2617	⁶⁸ 0.3374	⁷¹ 0.4185
63	NTECHLAB-007	²² 0.0044	²³ 0.0066	⁴⁰ 0.0089	⁴⁷ 0.0118	⁴⁹ 0.0150	⁵⁶ 0.0189	⁶¹ 0.0255	⁶³ 0.0342	³⁶ 0.0256	³⁸ 0.0450	⁴⁰ 0.0705	⁴¹ 0.1012	⁴² 0.1334	⁴⁵ 0.1692	⁴⁴ 0.2170	⁴⁴ 0.2752
64	NTECHLAB-008	¹¹ 0.0025	¹⁴ 0.0038	¹⁶ 0.0052	²¹ 0.0074	³⁵ 0.0104	⁴³ 0.0146	⁵⁷ 0.0236	⁶² 0.0348	¹⁷ 0.0143	¹⁹ 0.0267	²³ 0.0459	²⁸ 0.0733	³² 0.1062	³⁴ 0.1469	⁴⁰ 0.2044	⁴² 0.2698
65	PARAVISION-002	⁴³ 0.0058	⁴³ 0.0083	⁴⁹ 0.0111	⁵¹ 0.0137	⁵⁴ 0.0162	⁵⁴ 0.0187	⁵³ 0.0229	⁵³ 0.0295								
66	PARAVISION-003	³⁰ 0.0048	³⁴ 0.0067	⁴² 0.0090	⁴³ 0.0109	⁴³ 0.0128	⁴⁴ 0.0148	⁴² 0.0178	⁴⁷ 0.0219	⁴⁷ 0.0354	⁴⁸ 0.0618	⁴⁹ 0.0931	⁵⁰ 0.1290	⁵¹ 0.1625	⁵¹ 0.1964	⁵¹ 0.2408	⁴⁸ 0.2924
67	PARAVISION-004	⁹ 0.0024	¹⁰ 0.0032	¹⁰ 0.0040	¹¹ 0.0047	¹¹ 0.0053	¹¹ 0.0061	¹¹ 0.0073	¹² 0.0072	¹² 0.0118	¹⁴ 0.0209	¹⁵ 0.0327	¹⁵ 0.0465	¹⁵ 0.0613	¹⁵ 0.0779	¹⁵ 0.1008	¹⁵ 0.1285
68	PARAVISION-005	⁶ 0.0021	⁷ 0.0028	⁸ 0.0035	⁸ 0.0041	⁹ 0.0046	⁹ 0.0054	⁹ 0.0067	¹⁰ 0.0070	⁶ 0.0057	⁸ 0.0093	⁸ 0.0144	⁹ 0.0207	¹⁰ 0.0278	¹⁰ 0.0368	¹¹ 0.0508	¹¹ 0.0715
69	PARAVISION-007	² 0.0019	³ 0.0025	³ 0.0029	⁴ 0.0033	⁴ 0.0036	⁴ 0.0042	⁴ 0.0049	⁵ 0.0030	⁵ 0.0057	⁵ 0.0094	⁵ 0.0144	⁶ 0.0206	⁹ 0.0275	⁹ 0.0357	⁹ 0.0485	⁹ 0.0652
70	PIXELALL-002	⁶⁹ 0.0085	⁶¹ 0.0119	⁵⁹ 0.0147	⁶⁰ 0.0172	⁶¹ 0.0198	⁶² 0.0225	⁶² 0.0270	⁶³ 0.0349	⁸⁵ 0.1193	⁸⁷ 0.1900	⁸⁸ 0.2601	⁸⁵ 0.3332	⁸⁵ 0.3955	⁸⁵ 0.4565	⁸⁵ 0.5268	⁸⁶ 0.6030
71	PIXELALL-003	³⁵ 0.0050	³² 0.0063	²⁹ 0.0072	²⁴ 0.0077	²³ 0.0085	²³ 0.0095	²⁵ 0.0113	²² 0.0119	³⁵ 0.0248	³⁸ 0.0418	³⁸ 0.0622	³⁵ 0.0861	³⁵ 0.1104	³² 0.1364	³² 0.1723	³¹ 0.2167
72	PIXELALL-004	³⁴ 0.0049	³⁰ 0.0063	³⁰ 0.0072	²⁷ 0.0079	²⁶ 0.0089	²⁵ 0.0103	²⁶ 0.0127	²⁵ 0.0146	²⁵ 0.0211	³¹ 0.0360	³¹ 0.0553	³⁴ 0.0792	³¹ 0.1045	³¹ 0.1317	³¹ 0.1700	³⁴ 0.2246
73	PTAKURATSU-000	⁴⁴ 0.0061	³⁵ 0.0082	⁴⁶ 0.0097	⁴⁴ 0.0109	⁴⁰ 0.0120	³⁹ 0.0131	³⁸ 0.0146	³⁵ 0.0180	⁴⁹ 0.0375	⁴⁹ 0.0596	⁴⁸ 0.0842	⁴⁶ 0.1116	⁴⁴ 0.1357	⁴¹ 0.1553	³⁵ 0.1820	³⁹ 0.2326
74	RANKONE-002	⁸⁹ 0.0212	⁸⁶ 0.0313	⁸⁶ 0.0431	⁸⁶ 0.0562	⁸⁷ 0.0712	⁸⁹ 0.0881	⁸⁹ 0.1130	⁸³ 0.1543	⁸³ 0.1111	⁸³ 0.1707	⁸³ 0.2305	⁸³ 0.2968	⁸⁴ 0.3646	⁸⁴ 0.4345	⁸⁴ 0.5172	⁸⁵ 0.6110
75	RANKONE-004	⁹⁶ 0.0424	⁹⁶ 0.0643	⁹⁵ 0.0875	⁹⁵ 0.1127	⁹⁵ 0.1364	⁹⁵ 0.1579	⁹⁵ 0.1914	⁹² 0.2378	⁹² 0.1855	⁹¹ 0.2681	⁹¹ 0.3431	⁸⁹ 0.4155	⁸⁹ 0.4785	⁸⁸ 0.5350	⁸⁸ 0.5980	⁸⁸ 0.6722
76	RANKONE-005	⁸⁰ 0.0136	⁸¹ 0.0192	⁷⁹ 0.0246	⁷⁹ 0.0303	⁷⁸ 0.0362	⁷⁷ 0.0422	⁷⁶ 0.0521	⁷⁶ 0.0694	⁶⁹ 0.0582	⁶⁴ 0.0910	⁶⁰ 0.1260	⁵⁷ 0.1645	⁵⁴ 0.2005	⁵³ 0.2353	⁵³ 0.2816	⁵⁴ 0.3522
77	RANKONE-007	⁵⁹ 0.0078	⁵² 0.0099	⁵⁰ 0.0113	⁴⁸ 0.0123	⁴⁸ 0.0139	⁴⁹ 0.0156	⁴⁷ 0.0191	⁴⁶ 0.0242	³³ 0.0242	³³ 0.0376	³² 0.0542	³⁰ 0.0737	²⁹ 0.0935	²⁸ 0.1130	²⁶ 0.1416	²⁶ 0.1811
78	RANKONE-009	³⁸ 0.0054	³⁹ 0.0072	³⁷ 0.0085	³⁸ 0.0098	³⁸ 0.0113	³⁶ 0.0130	⁴¹ 0.0169	⁴⁴ 0.0220	²⁹ 0.0208	²⁹ 0.0345	²⁸ 0.0504	²⁷ 0.0706	²⁸ 0.0930	²⁹ 0.1174	³⁰ 0.1504	²⁹ 0.2002
79	RANKONE-010	⁷⁹ 0.0047	⁸⁰ 0.0061	⁷⁹ 0.0070	⁷⁵ 0.0076	⁷⁴ 0.0087	⁷³ 0.0098	⁷² 0.0113	⁷² 0.0120	²² 0.0177	²⁹ 0.0269	²⁷ 0.0368	¹⁷ 0.0479	¹⁴ 0.0590	¹³ 0.0688	¹³ 0.0803	¹² 0.0991
80	REALNETWORKS-002	⁹⁸ 0.0381	⁹⁶ 0.0687	⁹⁶ 0.1062	⁹⁶ 0.1495	⁹⁷ 9											

MISS RATES		INVESTIGATION, FNIR(N, R = 1, T = 0)								IDENTIFICATION, FNIR(N, R = L, T ≥ 0) FOR FPIR = 0.001							
#	ALGORITHM	(0, 2]	(2, 4]	(4, 6]	(6, 8]	(8, 10]	(10, 12]	(12, 14]	(14, 18]	(0, 2]	(2, 4]	(4, 6]	(6, 8]	(8, 10]	(10, 12]	(12, 14]	(14, 18]
89	SYNOPSIS-003	⁷⁷ 0.0125	⁷³ 0.0151	⁷¹ 0.0174	⁶⁸ 0.0199	⁶⁷ 0.0223	⁶³ 0.0240	⁶³ 0.0279	⁵⁰ 0.0331	⁷³ 0.0658	⁷¹ 0.1052	⁷¹ 0.1483	⁷⁰ 0.1968	⁷⁰ 0.2399	⁶⁹ 0.2834	⁶⁹ 0.3405	⁶⁸ 0.4046
90	SYNOPSIS-005	²⁹ 0.0044	²⁷ 0.0058	²⁷ 0.0070	³⁰ 0.0080	²⁸ 0.0091	²⁷ 0.0103	²⁷ 0.0125	²⁸ 0.0152	³⁸ 0.0262	³⁷ 0.0444	³⁷ 0.0666	³⁷ 0.0923	³⁶ 0.1156	³³ 0.1399	³³ 0.1736	³² 0.2185
91	TECH5-001	⁴⁷ 0.0061	⁵⁰ 0.0093	⁵⁴ 0.0128	⁵⁹ 0.0171	⁶⁵ 0.0221	⁷⁰ 0.0289	⁷³ 0.0412	⁷³ 0.0560	⁷⁴ 0.0660	⁷⁵ 0.1156	⁷⁸ 0.1733	⁷⁸ 0.2385	⁷⁸ 0.2998	⁷⁹ 0.3629	⁸¹ 0.4424	⁸² 0.5284
92	TOSHIBA-001	⁶¹ 0.0086	⁶² 0.0119	⁶² 0.0150	⁶² 0.0178	⁶³ 0.0209	⁶⁴ 0.0241	⁶⁴ 0.0292	⁶⁴ 0.0365								
93	TRUEFACE-000	²⁶ 0.0043	²⁶ 0.0057	²⁶ 0.0061	¹⁸ 0.0067	¹⁷ 0.0073	¹⁸ 0.0084	¹⁸ 0.0097	¹⁹ 0.0099	²⁶ 0.0200	²⁸ 0.0338	²⁹ 0.0504	²⁸ 0.0705	²⁷ 0.0904	²⁷ 0.1112	²⁵ 0.1401	²⁵ 0.1792
94	VISIONLABS-004	³² 0.0048	³⁷ 0.0069	⁴¹ 0.0091	⁴⁶ 0.0111	⁴⁶ 0.0130	⁴⁷ 0.0152	⁴⁶ 0.0187	⁴⁷ 0.0242	⁶³ 0.0540	⁶⁶ 0.0916	⁶⁷ 0.1358	⁶⁸ 0.1855	⁶⁸ 0.2303	⁶⁷ 0.2745	⁶⁶ 0.3312	⁶² 0.3913
95	VISIONLABS-005	²⁸ 0.0044	²⁹ 0.0063	³⁴ 0.0081	³⁷ 0.0095	³⁷ 0.0109	³⁵ 0.0125	³⁶ 0.0151	³⁷ 0.0187	⁵⁶ 0.0479	⁵⁶ 0.0812	⁵⁷ 0.1212	⁵⁸ 0.1664	⁵⁸ 0.2078	⁵⁸ 0.2473	⁵⁷ 0.2999	⁵⁶ 0.3577
96	VISIONLABS-006	²⁰ 0.0035	²⁰ 0.0048	²² 0.0061	²⁰ 0.0069	¹⁹ 0.0077	¹⁹ 0.0087	²¹ 0.0105	²⁴ 0.0120	⁴⁰ 0.0273	³⁹ 0.0465	³⁹ 0.0702	³⁹ 0.0970	³⁸ 0.1228	³⁶ 0.1486	³⁶ 0.1847	³⁶ 0.2295
97	VISIONLABS-008	¹⁴ 0.0028	¹³ 0.0037	¹⁴ 0.0047	¹⁴ 0.0053	¹⁴ 0.0058	¹⁴ 0.0067	¹⁶ 0.0081	¹⁷ 0.0085	¹⁸ 0.0143	¹⁸ 0.0241	¹⁹ 0.0373	¹⁸ 0.0519	¹⁸ 0.0677	¹⁶ 0.0850	¹⁶ 0.1104	¹⁶ 0.1444
98	VISIONLABS-009	⁴ 0.0020	⁴ 0.0026	⁴ 0.0030	⁸ 0.0034	⁵ 0.0038	⁵ 0.0044	⁶ 0.0052	⁷ 0.0046	⁹ 0.0065	¹⁰ 0.0105	¹⁰ 0.0156	¹⁰ 0.0217	¹¹ 0.0289	¹¹ 0.0368	¹⁰ 0.0499	¹⁰ 0.0681
99	XFORWARD-000	¹⁵ 0.0027	¹¹ 0.0034	¹³ 0.0044	¹³ 0.0052	¹³ 0.0058	¹⁵ 0.0067	¹⁴ 0.0079	¹⁵ 0.0076	¹⁹ 0.0157	²² 0.0281	²¹ 0.0443	²² 0.0635	²³ 0.0834	²⁴ 0.1050	²³ 0.1330	²³ 0.1714
100	XFORWARD-001	⁸ 0.0023	⁸ 0.0028	⁹ 0.0034	⁶ 0.0037	⁶ 0.0039	⁶ 0.0045	⁵ 0.0052	⁶ 0.0043	⁸ 0.0060	⁹ 0.0096	⁸ 0.0144	⁹ 0.0200	⁸ 0.0260	⁸ 0.0334	⁸ 0.0435	⁸ 0.0586
101	YITU-002	⁴⁹ 0.0066	⁴⁶ 0.0083	⁴⁴ 0.0094	³⁹ 0.0101	⁴¹ 0.0121	⁴⁶ 0.0150	⁵⁰ 0.0223	⁵⁹ 0.0328	²⁴ 0.0189	²⁵ 0.0317	²⁶ 0.0494	³¹ 0.0750	³¹ 0.1066	³⁹ 0.1494	⁴⁵ 0.2171	⁵⁰ 0.2958
102	YITU-003	⁵² 0.0072	⁴⁹ 0.0089	⁴⁷ 0.0100	⁴² 0.0107	⁴³ 0.0125	⁴⁸ 0.0153	⁵² 0.0226	⁶⁰ 0.0334	²⁵ 0.0194	²⁶ 0.0321	²⁷ 0.0500	³¹ 0.0756	³⁴ 0.1071	⁴⁰ 0.1500	⁴⁶ 0.2177	⁵¹ 0.2964
103	YITU-004	⁴⁵ 0.0061	⁴¹ 0.0075	³⁵ 0.0081	³¹ 0.0081	³⁰ 0.0092	³⁰ 0.0107	³⁸ 0.0154	⁴⁰ 0.0207	¹⁴ 0.0125	¹³ 0.0204	¹⁴ 0.0314	¹⁶ 0.0469	¹⁷ 0.0671	¹⁹ 0.0955	²⁸ 0.1421	³⁰ 0.2006
104	YITU-005	⁵⁰ 0.0067	⁴⁴ 0.0080	³⁸ 0.0087	³⁵ 0.0085	³² 0.0094	³¹ 0.0108	³⁷ 0.0151	³⁹ 0.0204	¹³ 0.0124	¹² 0.0198	¹³ 0.0308	¹³ 0.0462	¹⁶ 0.0667	¹⁸ 0.0953	²⁷ 0.1418	²⁹ 0.1930

Table 7: Accuracy for the FRVT 2018 mugshot sets under ageing. The second row shows the time lapse between gallery and subsequent probe images, in years. The first two columns identify the algorithm. The next 8 values give rank-based FNIR with $R = 1$, $T = 0$ and $FPIR = 1$. All these are relevant to investigational uses where candidates from all searches would need human review. The second 8 values give threshold-based FNIR with $T \geq 0$, $FPIR = 0.001$ and no rank criterion. The shaded cells indicate the three most accurate algorithms for that elapsed time. The gallery size is 3068801. The total number of searches is 10951064.

2021/03/04
11:49:04
FNIR(N, R, T) =
FPIR(N, T) =
False neg. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

		INVESTIGATION MODE					IDENTIFICATION MODE					FAILURE TO EXTRACT				
		RANK ONE MISS RATE, FNIR(N, 0, 1)					HIGH T → FPIR = 0.001, FNIR(N, T, L)					FEATURES				
		N=1.6M					N=1.6M									
#	ALGORITHM	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK
1	3DIVI-003	¹⁹⁸ 0.083	¹⁹⁴ 0.206		¹⁰² 0.141	¹⁰⁹ 0.474	¹⁷⁵ 0.400	¹⁷³ 0.626		¹⁰³ 0.605	⁸⁸ 0.821	0.002	0.005			
2	3DIVI-004	¹⁴⁰ 0.018	¹⁴⁸ 0.062		⁸⁷ 0.035	⁹⁰ 0.279	¹⁴⁹ 0.169	¹⁵⁵ 0.343		⁸⁸ 0.277	⁶⁹ 0.607	0.002	0.005			
3	3DIVI-005	¹⁴¹ 0.018	¹⁴⁷ 0.062	¹¹⁴ 0.930	¹¹⁸ 0.821	⁹¹ 0.279	¹⁴⁶ 0.166	¹⁵³ 0.339	⁸⁹ 0.996	¹⁰⁷ 0.864	⁶⁸ 0.597	0.002	0.005	0.442		
4	3DIVI-006	¹⁵¹ 0.024	¹⁵⁵ 0.074		⁸⁹ 0.047	⁹⁸ 0.312	¹⁴⁸ 0.168	¹⁵⁴ 0.342		⁸⁹ 0.283	⁷² 0.615	0.002	0.005			
5	ACER-000	¹²⁰ 0.011	¹¹² 0.036	⁹⁸ 0.827	⁷⁶ 0.025	⁷⁷ 0.209	¹³⁹ 0.146	¹³³ 0.246	⁵⁶ 0.981	⁸⁴ 0.201	⁵⁹ 0.490	0.000	0.000	0.042		
6	ALCHERA-000	¹³⁶ 0.016	¹³⁵ 0.047	¹⁰⁵ 0.870	⁸⁸ 0.046	⁹⁵ 0.292	¹³⁶ 0.138	¹²¹ 0.216	¹⁰³ 0.999	⁸¹ 0.176	⁵⁴ 0.803	0.006	0.014	0.328		
7	ALCHERA-001	²⁰³ 0.987	¹⁹⁸ 1.000		¹²⁰ 1.000	¹⁵³ 1.000	²⁰¹ 0.999	¹⁹⁴ 1.000		¹³⁷ 1.000	¹²¹ 1.000	0.006	0.013	0.324		
8	ALCHERA-002	¹⁷⁹ 0.095	¹⁷¹ 0.166	¹²⁷ 0.954	¹¹⁵ 0.668	¹⁰⁵ 0.446	¹⁸² 0.486	¹⁷¹ 0.591	¹²¹ 1.000	¹⁰⁶ 0.827	⁸⁵ 0.811	0.001	0.002	0.106		
9	ALCHERA-003	¹¹⁷ 0.010	¹¹⁰ 0.035	⁷⁶ 0.741	⁶⁹ 0.016	⁷⁵ 0.206	¹⁴⁰ 0.155	¹³⁰ 0.239	¹¹¹ 0.999	⁸⁰ 0.172	⁵⁶ 0.464	0.001	0.002	0.106		
10	ALLGOVISION-000	¹²³ 0.011	¹⁰⁷ 0.033	¹⁰⁷ 0.894	⁷³ 0.021	⁹² 0.282	¹¹⁶ 0.088	¹¹⁰ 0.166	⁶⁸ 0.990	⁶⁷ 0.117	⁶⁴ 0.526	0.002	0.003	0.122		
11	ALLGOVISION-001	¹⁰⁹ 0.009	¹²⁰ 0.038	⁶⁶ 0.661	⁷² 0.021	⁸⁶ 0.241	¹²¹ 0.102	¹²¹ 0.221	⁶² 0.986	⁷⁵ 0.150	⁶⁰ 0.491	0.001	0.001	0.042		
12	ANKE-000	¹³¹ 0.013	¹¹⁶ 0.038	¹¹⁷ 0.931	¹²³ 1.000	²⁰¹ 1.000	¹²⁶ 0.117	¹²³ 0.220	⁷³ 0.994	¹⁸² 1.000	¹⁶⁵ 1.000	0.000	0.001	0.080		
13	ANKE-001	¹³² 0.013	¹¹⁵ 0.038	¹²² 0.946	¹⁹³ 1.000	¹³⁶ 1.000	¹³⁰ 0.119	¹²² 0.220	⁷⁷ 0.994	¹¹⁸ 1.000	¹⁴² 1.000	0.000	0.001	0.080		
14	ANKE-002	⁴⁹ 0.003	⁵⁰ 0.016	⁴⁹ 0.522	³⁴ 0.005	⁴⁴ 0.119	⁵⁴ 0.032	⁴⁴ 0.079	³⁴ 0.948	³⁵ 0.034	²⁸ 0.245	0.001	0.001	0.049		
15	AWARE-003	¹⁵⁷ 0.031	¹⁶⁰ 0.090	¹⁵⁹ 0.966	¹⁰⁶ 0.316	⁹⁴ 0.290	¹⁵⁴ 0.128	¹⁴⁷ 0.298	⁶⁴ 0.984	⁹⁶ 0.428	⁶⁵ 0.530	0.004	0.003	0.874		
16	AWARE-004	¹⁷³ 0.068	¹⁷³ 0.176	¹⁴⁶ 0.976	¹⁰⁸ 0.122	¹⁰³ 0.414	¹⁶² 0.269	¹⁶⁷ 0.509	¹²⁴ 1.000	⁹⁴ 0.397	⁸⁶ 0.816	0.003	0.003	0.776		
17	AWARE-005	¹⁵⁸ 0.031	¹⁴⁹ 0.067	¹⁴⁷ 0.978	⁹⁸ 0.048	⁹⁷ 0.308	¹⁷⁰ 0.364	¹³⁴ 0.253	¹²⁷ 1.000	⁸⁷ 0.255	⁹⁵ 0.916	0.001	0.002	0.189		
18	AWARE-006	¹⁷⁵ 0.070	¹⁶⁷ 0.128	¹⁴⁹ 0.983	⁹⁹ 0.111	¹⁰⁴ 0.421	¹⁶³ 0.276	¹⁵⁸ 0.398	¹¹⁹ 0.999	⁹² 0.368	⁸⁹ 0.749	0.001	0.002	0.189		
19	AYONIX-000	¹⁹⁸ 0.450	¹⁹³ 0.685	¹⁵⁸ 0.996	¹¹⁴ 0.607	¹¹⁷ 0.867	¹⁹⁰ 0.811	¹⁸⁸ 0.939	⁹⁴ 0.998	¹¹¹ 0.954	¹⁰³ 0.982	0.010	0.031	0.939		
20	AYONIX-001	¹⁹⁴ 0.341	¹⁸⁸ 0.527	¹⁵⁴ 0.993	¹¹⁷ 0.994	¹¹⁴ 0.778	¹⁹² 0.824	¹⁸³ 0.920	¹¹⁷ 0.999	¹¹⁵ 0.999	¹⁰⁰ 0.969	0.010	0.031	0.939		
21	AYONIX-002	¹⁹³ 0.341	¹⁸⁹ 0.527	¹⁵³ 0.993	¹¹¹ 0.464	¹¹⁵ 0.778	¹⁹¹ 0.824	¹⁸⁴ 0.920	¹¹⁵ 0.999	¹⁰⁸ 0.915	¹⁰¹ 0.969	0.010	0.031	0.939		
22	CAMVI-003	¹⁶⁹ 0.052	¹⁶¹ 0.090	¹⁰⁸ 0.911	⁵⁶ 0.093	¹⁰³ 0.360	¹⁰¹ 0.071	⁸⁹ 0.132	⁴² 0.970	⁶⁶ 0.114	³¹ 0.402	0.006	0.013	0.675		
23	CAMVI-004	¹⁶⁷ 0.047	¹⁵⁶ 0.077	⁷⁸ 0.744	⁹⁵ 0.072	⁹⁶ 0.296	¹⁰² 0.072	⁹¹ 0.136	¹¹³ 0.999	⁶⁵ 0.100	⁸² 0.787	0.000	0.000	0.000		
24	CAMVI-005	¹⁷² 0.065	¹⁶⁵ 0.103	⁸⁰ 0.746	⁹⁷ 0.098	⁹⁹ 0.341	¹²⁰ 0.099	¹¹⁷ 0.179	¹²² 1.000	⁷⁶ 0.156	¹¹⁰ 0.999	0.000	0.000	0.000		
25	CIB-000	¹⁶ 0.002	⁷ 0.008	¹⁰ 0.100	⁵ 0.002	² 0.069	¹⁹ 0.012	²⁰ 0.045	¹³¹ 1.000	¹⁸ 0.017	⁸³ 0.894	0.000	0.000	0.000		
26	COGENT-000	¹¹⁹ 0.010	¹³² 0.046	¹³⁷ 0.965			⁸¹ 0.053	⁹² 0.140	⁸² 0.995			0.000	0.000	0.000		
27	COGENT-001	¹¹⁸ 0.010	¹³³ 0.046	¹³⁸ 0.965			⁸⁰ 0.053	⁹³ 0.140	⁸³ 0.995			0.000	0.000	0.000		
28	COGENT-002	⁶¹ 0.004	⁷² 0.020	¹¹² 0.925			⁶⁸ 0.044	⁶² 0.098	⁹³ 0.998			0.000	0.000	0.000		
29	COGENT-003	⁶³ 0.004	⁷⁶ 0.021	¹²¹ 0.939			⁷² 0.046	⁵⁸ 0.095	⁹⁵ 0.998			0.000	0.000	0.000		
30	COGENT-004	³⁰ 0.002	³² 0.013	¹¹¹ 0.922	²⁹ 0.004	⁴⁰ 0.113	⁵⁵ 0.033	²⁴ 0.051	⁹¹ 0.997	²¹ 0.022	⁵⁵ 0.456	0.000	0.000	0.000		
31	COGNITEC-000	¹⁵³ 0.025	¹⁴³ 0.059	¹³⁵ 0.964			¹⁴⁴ 0.161	¹⁴⁸ 0.303	⁷⁰ 0.992			0.003	0.002	0.924		
32	COGNITEC-001	¹²⁴ 0.012	¹⁰⁹ 0.034	¹³⁰ 0.958			¹²² 0.102	¹²⁸ 0.230	¹⁸² 1.000			0.003	0.002	0.924		
33	COGNITEC-002	⁸⁶ 0.006	⁹⁶ 0.025	¹²⁴ 0.949			⁸² 0.053	¹¹⁶ 0.178	¹³² 1.000			0.003	0.002	0.924		
34	COGNITEC-003	⁹⁰ 0.006	⁹⁵ 0.025	¹¹⁶ 0.930			⁷⁹ 0.053	¹⁰⁸ 0.162	¹³⁵ 1.000			0.004	0.002	0.878		
35	CYBERLINK-000	⁶⁵ 0.004	⁷¹ 0.020	⁷⁴ 0.717	⁵² 0.007	⁵⁴ 0.134	⁸⁸ 0.056	⁷⁴ 0.116	⁸⁵ 0.995	⁵⁸ 0.063	⁴⁵ 0.339	0.001	0.001	0.063		
36	CYBERLINK-001	³⁹ 0.004	⁶⁰ 0.018	⁷⁵ 0.731	⁴⁷ 0.007	⁵³ 0.133	⁸³ 0.054	⁷¹ 0.109	⁸¹ 0.995	⁵² 0.062	⁷³ 0.652	0.000	0.000	0.040		
37	CYBERLINK-002	⁴⁶ 0.003	²⁴ 0.012	⁵⁹ 0.577	²⁶ 0.004	³⁴ 0.107	²⁵ 0.015	²⁷ 0.053	⁶⁵ 0.988	²² 0.024	³⁴ 0.288	0.001	0.000	0.042		
38	CYBERLINK-003	¹⁷ 0.002	¹¹ 0.009	⁴¹ 0.474	¹⁴ 0.003	¹² 0.082	¹⁴ 0.008	¹⁶ 0.035	⁴⁴ 0.972	¹³ 0.012	⁴⁷ 0.368	0.000	0.000	0.039		
39	DAHUA-000	¹¹³ 0.009	⁹⁸ 0.026				¹¹² 0.086	⁸⁰ 0.135				0.004	0.003			
40	DAHUA-001	⁹⁴ 0.007	⁹⁰ 0.024	⁷³ 0.703			¹⁰⁴ 0.073	⁸² 0.122	⁵⁴ 0.980			0.002	0.002	0.346		
41	DAHUA-002	²⁶ 0.002	²³ 0.012	²⁵ 0.304	¹³ 0.003	¹³ 0.084	²⁶ 0.015	²² 0.046	¹² 0.638	¹⁷ 0.017	¹³ 0.159	0.001	0.000	0.099		
42	DAHUA-003	⁷ 0.001	⁵ 0.007	¹⁸ 0.206	⁴ 0.002	⁵ 0.073	²² 0.014	¹⁹ 0.041	¹⁰ 0.579	¹⁴ 0.013	⁹ 0.134	0.000	0.000	0.000		
43	DEEPLINT-001	¹² 0.001	⁴ 0.007	¹⁷ 0.200	¹¹ 0.002	⁶ 0.073	⁷ 0.003	⁴ 0.014	¹²⁰ 1.000	³ 0.006	¹² 0.159	0.000	0.000	0.038		
44	DEEPLINT-001	⁷⁰ 0.004	⁴⁸ 0.016	⁹⁶ 0.814	⁵⁸ 0.010	⁵⁹ 0.140	⁷¹ 0.046	⁶⁴ 0.101	⁶¹ 0.985	⁵⁹ 0.077	⁴³ 0.326	0.000	0.001	0.047		
45	DERMALOG-003	¹⁸³ 0.126	¹⁷⁶ 0.217		¹⁰⁶ 0.296	¹¹⁰ 0.560	¹⁸¹ 0.482	¹⁷⁵ 0.655		¹⁰⁸ 0.677	⁹¹ 0.870	0.002	0.002	0.103		
46	DERMALOG-004	¹⁸² 0.125	¹⁷⁵ 0.215	¹¹³ 0.930	¹⁰¹ 0.135	¹⁰⁶ 0.467	¹⁸⁰ 0.480	¹⁷⁶ 0.657	⁸⁶ 0.995	¹⁰² 0.603	⁹⁰ 0.856	0.001	0.002	0.107		

Table 8: **Miss rates by dataset:** At left, rank 1 miss rates relevant to investigations; at right, with threshold set to target FPIR = 0.01 for higher volume, low prior, uses. Yellow indicates most accurate algorithm. Throughout blue superscripts indicate the rank of the algorithm for that column.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 $\rightarrow$ Investigation
T > 0 $\rightarrow$ Identification

		INVESTIGATION MODE					IDENTIFICATION MODE					FAILURE TO EXTRACT				
		RANK ONE MISS RATE, FNIR(N, 0, 1)					HIGH T $\rightarrow$ FPIR = 0.001, FNIR(N, T, L)					FEATURES				
		N=1.6M					N=1.6M									
#	ALGORITHM	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK
47	DERMLOG-005	¹³⁵ 0.015	¹¹⁴ 0.037	⁷² 0.701	¹⁰⁵ 0.242	¹⁰² 0.384	¹¹⁵ 0.088	¹⁰¹ 0.154	⁶⁷ 0.990	⁹⁰ 0.300	⁷¹ 0.614	0.001	0.002	0.102		
48	DERMLOG-006	¹⁰⁴ 0.008	⁹⁴ 0.024	⁶⁴ 0.619	⁵⁹ 0.010	⁶³ 0.155	⁷⁸ 0.052	⁶⁶ 0.105	⁵⁸ 0.981	⁵⁰ 0.059	⁴⁴ 0.318	0.003	0.006	0.181		
49	DERMLOG-007	¹¹² 0.009	⁹⁹ 0.027	⁶⁸ 0.675	⁶⁶ 0.014	⁶⁶ 0.170	¹¹³ 0.086	⁹⁹ 0.152	⁶⁸ 0.990	⁶⁴ 0.099	⁶⁸ 0.557	0.001	0.002	0.102		
50	DERMLOG-008	⁵⁰ 0.003	⁴¹ 0.015	⁴⁸ 0.516	⁴⁸ 0.007	⁵⁸ 0.139	⁷⁰ 0.045	⁵⁵ 0.094	¹⁴¹ 1.000	⁴⁷ 0.057	⁹⁹ 0.940	0.000	0.000	0.002		
51	EYDEA-003	¹⁷⁷ 0.080	¹⁶⁹ 0.148	¹³³ 0.960	⁹⁸ 0.101	¹⁰¹ 0.379	¹²² 0.388	¹⁶⁹ 0.543	⁷⁸ 0.994	¹⁰⁸ 0.570	⁸³ 0.792	0.001	0.003	0.161		
52	F8-001	¹²⁸ 0.012	⁶⁷ 0.669	¹⁴³ 1.000	¹⁹⁰ 1.000		¹⁴⁵ 0.166		¹⁰² 0.998			0.004	1.000	0.158		
53	GLORY-000	¹⁸⁷ 0.178	¹⁸² 0.320	¹⁵⁷ 0.994	¹⁰⁴ 0.228	¹¹² 0.678	¹⁷¹ 0.367	¹⁷⁰ 0.547	⁸¹ 0.995	⁹⁸ 0.453	⁸⁷ 0.839	0.011	0.013	0.985		
54	GLORY-001	¹⁸⁴ 0.127	¹⁷⁹ 0.267	¹⁵² 0.992	¹⁰³ 0.178	¹¹¹ 0.594	¹⁶⁴ 0.305	¹⁶⁸ 0.537	⁷¹ 0.993	⁹⁵ 0.408	⁸⁷ 0.819	0.011	0.013	0.988		
55	GORILLA-001	¹⁷⁰ 0.060	¹⁶² 0.095	¹¹⁹ 0.936			¹⁷⁶ 0.406	¹⁶³ 0.453	¹⁴⁷ 1.000			0.001	0.001	0.069		
56	GORILLA-002	¹⁴⁷ 0.020	¹²⁹ 0.044	⁸¹ 0.753			¹⁵² 0.188	¹⁴¹ 0.268	¹³⁷ 1.000			0.001	0.001	0.069		
57	GORILLA-003	¹⁵⁹ 0.036	¹⁵¹ 0.070	⁹⁷ 0.821			¹⁶⁶ 0.318	¹⁶² 0.434	¹⁷¹ 1.000			0.001	0.001	0.069		
58	GORILLA-004	⁹¹ 0.006	⁹¹ 0.024	⁷¹ 0.697	⁶² 0.012	⁶⁴ 0.162	¹¹⁸ 0.089	¹⁰⁷ 0.160	⁵⁶ 0.959	⁷² 0.135	⁵⁴ 0.438	0.000	0.001	0.042		
59	GORILLA-005	⁵⁴ 0.003	⁶¹ 0.018	¹⁹ 0.209	⁴⁸ 0.006	⁴⁶ 0.124	⁹² 0.058	⁹⁵ 0.142	¹³ 0.700	⁶³ 0.088	⁴¹ 0.315	0.000	0.000	0.040		
60	HIK-003	¹²⁵ 0.012	¹⁰² 0.027	⁷⁰ 0.689			¹²³ 0.103	¹⁰³ 0.158	⁴⁰ 0.969			0.000	0.000	0.048		
61	HIK-004	¹²² 0.011	¹⁰⁰ 0.027	⁷⁷ 0.743			¹¹⁹ 0.099	¹⁰⁰ 0.153	⁴⁶ 0.976			0.000	0.000	0.048		
62	HIK-005	⁷⁴ 0.005	⁵² 0.017	⁵³ 0.535	⁴⁹ 0.007	³⁸ 0.111	⁶⁸ 0.044	⁴³ 0.077	¹¹⁸ 0.999			0.000	0.000	0.000		
63	HIK-006	⁷⁵ 0.005	⁵¹ 0.017	⁵⁴ 0.535			⁷³ 0.047	⁴⁷ 0.086	¹⁴³ 1.000			0.000	0.000	0.000		
64	HR-000	¹⁵ 0.001	¹⁶ 0.010	⁷ 0.064	³ 0.002	¹ 0.057	³ 0.002	³ 0.013	¹ 0.133	¹ 0.005	¹ 0.099	0.001	0.000	0.042		
65	IDEMIA-003	⁹⁷ 0.007	¹⁰⁸ 0.034	¹²⁸ 0.958	⁷⁰ 0.018	⁷⁹ 0.210	⁷⁴ 0.047	¹⁰⁹ 0.165	⁶⁹ 0.123	⁸⁰ 0.766		0.000	0.000	0.041		
66	IDEMIA-004	⁹³ 0.007	¹⁰⁶ 0.032	¹²³ 0.947	⁷¹ 0.018	⁷⁸ 0.210	⁶¹ 0.037	⁷⁸ 0.118	⁴⁵ 0.973	⁶⁸ 0.123	⁸¹ 0.766	0.000	0.000	0.041		
67	IDEMIA-005	¹⁰³ 0.008	¹²¹ 0.039	¹²⁶ 0.954	⁷⁴ 0.021	⁸² 0.217	⁶⁷ 0.044	⁹⁸ 0.150	⁴⁹ 0.978	⁷⁰ 0.130	⁹² 0.879	0.000	0.000	0.041		
68	IDEMIA-006	¹¹⁵ 0.010	¹⁵³ 0.072	¹⁴¹ 0.969	⁷⁸ 0.030	⁸⁸ 0.253	⁶⁴ 0.043	¹²⁶ 0.226	⁵⁷ 0.982	⁷⁴ 0.144	⁷⁷ 0.733	0.000	0.000	0.041		
69	IDEMIA-007	⁴⁵ 0.003	⁴⁵ 0.015	¹⁷⁶ 1.000	⁴³ 0.006	⁸⁰ 0.131	³¹ 0.018	²⁸ 0.055	¹⁶⁹ 1.000	⁴³ 0.052	¹⁸² 1.000	0.000	0.000	0.040		
70	IMAGUS-002	¹⁹⁰ 0.220	¹⁸⁰ 0.301	¹⁵¹ 0.988			¹⁸⁸ 0.749	¹⁸⁰ 0.816	¹⁴⁸ 1.000			0.004	0.008	0.550		
71	IMAGUS-003	¹⁹⁵ 0.356	¹⁸⁶ 0.513	¹⁵⁵ 0.993			¹⁸⁹ 0.807	¹⁸² 0.909	¹³¹ 1.000			0.004	0.008	0.550		
72	IMAGUS-005	²⁸ 0.002	²⁵ 0.012	²⁶ 0.319	⁴¹ 0.006	⁵² 0.132	³⁴ 0.018	³⁵ 0.066	²⁴ 0.838	²⁴ 0.029	²⁵ 0.231	0.000	0.000	0.000		
73	IMPERIAL-000	⁴² 0.002	⁴² 0.015	²⁴ 0.280	³⁸ 0.004	²³ 0.097	⁴⁶ 0.026	³⁷ 0.068	¹⁰⁶ 0.999	³⁸ 0.042	²⁸ 0.245	0.000	0.000	0.000		
74	INCODE-000	¹⁶⁸ 0.049	¹⁶⁴ 0.100	¹²⁵ 0.951			¹⁶⁵ 0.310	¹⁶⁰ 0.420	⁹⁸ 0.998			0.001	0.004	0.173		
75	INCODE-001	¹³⁸ 0.017	¹³⁴ 0.046	⁸² 0.762			¹³⁵ 0.212	¹⁴⁴ 0.296	¹³⁸ 1.000			0.001	0.004	0.173		
76	INCODE-002	¹⁴² 0.018	¹³⁶ 0.048	¹⁰⁰ 0.843			¹⁵¹ 0.184	¹⁴² 0.269	⁷² 0.993			0.000	0.001	0.066		
77	INCODE-003	¹³⁰ 0.013	¹²³ 0.040	⁸³ 0.764			¹⁴⁷ 0.167	¹⁵⁸ 0.264	¹¹⁶ 0.999			0.000	0.001	0.066		
78	INCODE-004	⁶⁰ 0.004	⁵⁸ 0.017	⁴² 0.475	⁵⁶ 0.008	⁵⁶ 0.135	⁸⁵ 0.054	⁸¹ 0.120	⁷⁸ 0.995	⁵⁴ 0.063	³⁹ 0.313	0.000	0.001	0.066		
79	INNOVATRICS-002	¹⁶⁶ 0.045	¹⁵⁴ 0.074	¹⁰³ 0.853			¹⁶⁰ 0.234	¹⁴⁹ 0.310	¹⁴² 1.000			0.000	0.001	0.046		
80	INNOVATRICS-003	¹⁵⁴ 0.026	¹³⁹ 0.055	¹⁰² 0.845			¹⁵⁶ 0.221	¹⁴⁵ 0.297	¹²⁵ 1.000			0.000	0.001	0.046		
81	INNOVATRICS-004	¹²⁹ 0.012	¹²⁵ 0.040	¹²⁵ 0.958			¹³⁵ 0.132	¹²⁵ 0.222	⁵² 0.980			0.000	0.001	0.046		
82	INNOVATRICS-005	⁴³ 0.002	³⁸ 0.014	³⁸ 0.407	³¹ 0.005	³⁵ 0.109	⁵⁶ 0.034	⁵⁰ 0.089	²¹ 0.846	⁴¹ 0.047	³⁶ 0.251	0.000	0.001	0.041		
83	INNOVATRICS-006	⁴⁴ 0.002	³³ 0.013	⁴⁵ 0.510	²² 0.004	²⁰ 0.094	⁴³ 0.025	⁷⁰ 0.107	³⁰ 0.899	²⁵ 0.029	²¹ 0.198	0.000	0.001	0.040		
84	INTSYSMSU-000	¹⁸⁵ 0.146	⁸⁹ 0.023	⁵⁸ 0.562	⁹⁴ 0.072	⁵¹ 0.132	¹⁹⁹ 0.998	¹⁹³ 1.000	¹²⁸ 1.000	¹¹⁴ 0.999	¹¹¹ 0.999	0.000	0.000	0.050		
85	IREX-000	⁷¹ 0.004	¹² 0.010	⁶⁹ 0.681	¹⁰ 0.002	¹⁰ 0.082	⁵¹ 0.028	³¹ 0.060	³⁸ 0.957	³⁹ 0.044	¹⁵ 0.170	0.000	0.000	0.042		
86	ISYSTEMS-002	⁹² 0.006	⁹⁷ 0.026	¹⁰¹ 0.844			¹⁰⁷ 0.078	⁸⁵ 0.126	⁹² 0.998			0.002	0.002	0.142		
87	ISYSTEMS-003	⁸¹ 0.005	⁸⁶ 0.023	⁵⁰ 0.791			⁷⁵ 0.059	⁶⁹ 0.107	¹²⁵ 1.000			0.002	0.002	0.142		
88	KEDACOM-001	¹⁰⁰ 0.008	¹¹¹ 0.036	¹⁴³ 0.972	⁸³ 0.034	⁸³ 0.237	⁴¹ 0.023	⁴⁰ 0.072	⁶¹ 0.986	⁴⁶ 0.055	³⁷ 0.305	0.000	0.000	0.000		
89	KNERON-000	⁸⁷ 0.006	¹⁰¹ 0.027	⁵⁶ 0.552	⁷⁹ 0.028	⁷³ 0.195						0.000	0.000	0.000		
90	LOOKMAN-003	¹⁰⁸ 0.009	¹¹⁹ 0.038		⁸⁶ 0.035	⁸⁵ 0.239	⁶⁶ 0.044	⁷³ 0.112		⁶² 0.084	⁴⁶ 0.355	0.000	0.000			
91	LOOKMAN-004	¹¹⁰ 0.009	¹²² 0.039	¹⁴⁵ 0.973			⁶⁹ 0.045	⁶⁸ 0.105	⁴⁷ 0.977			0.000	0.000	0.000		
92	LOOKMAN-005	¹⁰² 0.008	¹¹³ 0.036	¹⁴⁴ 0.972	⁸⁵ 0.035	⁸⁴ 0.237	⁵³ 0.030	⁴⁶ 0.086	⁵⁰ 0.978	⁵³ 0.062	³⁸ 0.308	0.000	0.000	0.000		

Table 9: **Miss rates by dataset:** At left, rank 1 miss rates relevant to investigations; at right, with threshold set to target FPIR = 0.01 for higher volume, low prior, uses. Yellow indicates most accurate algorithm. Throughout blue superscripts indicate the rank of the algorithm for that column.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 $\rightarrow$ Investigation
T > 0 $\rightarrow$ Identification

		INVESTIGATION MODE				IDENTIFICATION MODE				FAILURE TO EXTRACT				
		RANK ONE MISS RATE, FNIR(N, 0, 1)				HIGH T $\rightarrow$ FPIR = 0.001, FNIR(N, T, L)				FEATURES				
		N=1.6M				N=1.6M								
#	ALGORITHM	MUGSHOT	WEBCAM	PROFILE	KIOSK	MUGSHOT	WEBCAM	PROFILE	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK
93	MEGVII-001	¹²⁶ 0.012	⁵⁷ 0.017		¹²² 1.000	¹⁰⁵ 0.072	⁶¹ 0.097			0.002	0.000			
94	MEGVII-002	¹²⁷ 0.012	⁵⁹ 0.017	³⁰ 0.450	¹⁶⁰ 1.000	¹⁰⁶ 0.077	⁶⁰ 0.096	¹⁰¹ 0.998		0.002	0.000	0.033		
95	MICROFOCUS-003	²⁰³ 0.594	¹⁹⁶ 0.781		¹¹⁷ 0.708	¹⁹⁶ 0.931	¹⁹² 0.979			¹¹³ 0.982	¹⁰⁹ 0.991	0.001	0.005	
96	MICROFOCUS-004	²⁰⁰ 0.576	¹⁹⁵ 0.758		¹¹⁶ 0.701	¹⁹⁴ 0.904	¹⁹⁰ 0.975			¹¹² 0.974	¹⁰⁷ 0.989	0.001	0.005	
97	MICROFOCUS-005	¹⁹⁶ 0.424	¹⁹² 0.601		¹¹³ 0.494	¹⁹³ 0.777	¹⁸⁸ 0.835	¹⁸⁸ 0.928		¹¹⁰ 0.935	¹⁰⁸ 0.985	0.001	0.005	
98	MICROFOCUS-006	¹⁹⁷ 0.427	¹⁹¹ 0.583		¹¹² 0.490	¹⁹⁷ 0.782	¹⁹⁷ 0.978	¹⁸⁵ 0.923		¹⁰⁹ 0.923	¹⁰⁵ 0.971	0.001	0.005	
99	MICROSOFT-003	¹⁸ 0.002	²⁷ 0.012		²⁶ 0.004	³⁶ 0.109	⁵⁰ 0.028	⁸³ 0.091		³⁶ 0.036	²⁹ 0.233	0.000	0.001	
100	MICROSOFT-004	¹⁴ 0.001	²⁶ 0.012		²⁰ 0.004	³⁷ 0.109	⁴⁷ 0.026	⁴⁸ 0.087		³³ 0.033	²³ 0.222	0.000	0.001	
101	MICROSOFT-005	²⁷ 0.002	²¹ 0.011	¹³ 0.144	¹⁶ 0.003	²⁴ 0.099	⁴⁸ 0.026	³⁶ 0.070	¹¹ 0.587	²³ 0.027	¹⁷ 0.180	0.000	0.001	0.049
102	MICROSOFT-006	²⁹ 0.002	²² 0.011	¹⁵ 0.150	²⁴ 0.004	²⁵ 0.100	¹⁸ 0.012	¹⁷ 0.037	⁴ 0.386	³⁰ 0.032	¹⁶ 0.178	0.000	0.001	0.049
103	NEC-000	¹³⁹ 0.017	¹²⁷ 0.041	¹³⁵ 0.959	⁷⁵ 0.025	⁸⁷ 0.243	¹⁰⁸ 0.079	⁹⁰ 0.140	⁵¹ 0.979		⁵⁶ 0.474	0.001	0.002	0.890
104	NEC-001	¹⁴⁸ 0.021	¹⁴⁰ 0.056	¹⁴⁰ 0.967	⁸² 0.033	⁸⁹ 0.277	¹²⁵ 0.106	¹¹⁵ 0.197	⁶³ 0.986	⁷¹ 0.133	⁵⁷ 0.468	0.005	0.003	0.934
105	NEC-002	⁴ 0.001	¹⁰ 0.009	³⁴ 0.363	¹⁹ 0.003	⁴² 0.117	⁶ 0.003	⁷ 0.020	¹¹⁴ 0.999	⁶ 0.008	⁷⁵ 0.676	0.000	0.001	0.041
106	NEC-003	¹⁰ 0.001	¹⁷ 0.010	³³ 0.352	²³ 0.004	⁴⁵ 0.120	⁵ 0.002	⁶ 0.017	²¹ 0.824	⁹ 0.008	⁷⁴ 0.668	0.000	0.001	0.041
107	NEUROTECHNOLOGY-003	¹⁴⁰ 0.022	¹²⁸ 0.042	¹³⁴ 0.961		¹⁸⁷ 0.636	¹⁴¹ 0.266	¹⁹⁷ 1.000				0.000	0.001	0.131
108	NEUROTECHNOLOGY-004	⁸³ 0.006	⁷⁰ 0.020	¹⁴² 0.970		⁹⁷ 0.063	⁷⁸ 0.117	⁷⁵ 0.994				0.000	0.001	0.131
109	NEUROTECHNOLOGY-005	⁶⁹ 0.004	⁹³ 0.024	¹⁰⁶ 0.893		⁸⁶ 0.054	⁸⁷ 0.130	⁹⁶ 0.998				0.000	0.000	0.030
110	NEUROTECHNOLOGY-006	¹⁴³ 0.018	¹³¹ 0.045	⁶³ 0.606		¹⁶¹ 0.249	¹⁵⁰ 0.418					0.000	0.000	
111	NEUROTECHNOLOGY-007	⁶⁴ 0.004	⁷⁵ 0.021	⁸⁹ 0.796	⁵⁷ 0.009	⁷⁰ 0.180	⁹⁷ 0.062	¹¹³ 0.173	¹³⁰ 1.000	⁹¹ 0.339	¹⁸¹ 1.000	0.001	0.001	0.041
112	NEWLAND-002	¹⁷⁶ 0.079	¹⁶⁶ 0.117	¹¹⁸ 0.936		¹⁷⁸ 0.438	¹⁶⁴ 0.466	¹⁰⁸ 0.999				0.007	0.012	0.200
113	NOBLIS-001	¹⁹² 0.249	¹⁸⁷ 0.522	¹⁵⁶ 0.993		²⁰² 1.000	¹⁹⁹ 1.000	¹⁴⁶ 1.000				0.000	0.000	0.000
114	NOBLIS-002	¹⁸⁰ 0.179	¹⁸⁴ 0.392	¹⁴⁸ 0.982		¹⁹⁸ 0.997	²⁰⁵ 1.000	¹³² 1.000				0.000	0.000	0.000
115	NTECHLAB-003	⁸⁸ 0.006	⁸³ 0.023	⁴³ 0.504		⁸⁸ 0.054	⁷⁶ 0.118	²³ 0.837				0.000	0.000	0.040
116	NTECHLAB-004	⁷⁶ 0.005	⁶⁶ 0.019	⁴⁴ 0.506	⁵⁴ 0.008	⁴⁹ 0.129	⁶² 0.041	⁶⁷ 0.105	²² 0.833	⁴⁵ 0.053	³³ 0.263	0.000	0.000	0.040
117	NTECHLAB-005	⁷⁶ 0.005	⁶² 0.018	³⁵ 0.367	³⁵ 0.008	⁴³ 0.118	⁶³ 0.042	⁶⁸ 0.102	¹⁸ 0.771	⁸⁷ 0.073	³⁵ 0.294	0.000	0.000	0.040
118	NTECHLAB-006	⁶⁸ 0.004	⁵⁵ 0.017	³² 0.347	⁵¹ 0.007	⁴⁸ 0.113	⁵⁹ 0.037	⁵⁶ 0.094	¹⁷ 0.754	⁴⁸ 0.057	³² 0.260	0.000	0.000	0.040
119	NTECHLAB-007	⁴⁷ 0.003	²⁸ 0.012	²⁷ 0.326	³¹ 0.004	²⁵ 0.107	⁴¹ 0.026	³⁶ 0.067	¹⁶ 0.750	³¹ 0.032	²⁴ 0.223	0.000	0.000	0.042
120	NTECHLAB-008	²⁰ 0.002	¹³ 0.010	¹⁶ 0.157	¹⁸ 0.003	¹⁴ 0.084	²³ 0.014	²¹ 0.045	⁹ 0.529	³⁴ 0.033	¹⁹ 0.183	0.000	0.000	0.044
121	NTECHLAB-009	⁸ 0.001			⁶ 0.002	⁰ 0.074	¹² 0.005			¹⁵ 0.015	¹⁰ 0.142	0.000	0.000	0.041
122	PARAVISION-000	¹⁴⁴ 0.019	¹¹⁸ 0.038	⁵² 0.534	¹¹⁰ 0.423	¹⁰⁵ 0.529	¹¹⁷ 0.089	¹¹¹ 0.170	¹¹⁰ 0.999	⁹⁹ 0.470	⁹⁸ 0.926	0.000	0.000	0.000
123	PARAVISION-001	⁶² 0.004	⁷⁵ 0.020	²⁸ 0.329	¹⁰⁹ 0.414	¹⁰⁸ 0.484	⁷⁶ 0.049	⁸⁶ 0.128	¹⁰⁵ 0.999	⁹⁷ 0.444	⁷⁶ 0.739	0.000	0.000	0.000
124	PARAVISION-002	⁶⁷ 0.004	⁷⁸ 0.022	³⁰ 0.335	⁶⁷ 0.015	⁶⁸ 0.175	⁷⁶ 0.050	⁷⁰ 0.119	⁵⁸ 0.983	⁶⁰ 0.080	⁶¹ 0.497	0.000	0.000	0.032
125	PARAVISION-003	⁵³ 0.003	⁶⁷ 0.019	²³ 0.252	⁶⁵ 0.015	⁶⁷ 0.167	⁵⁷ 0.035	⁵⁶ 0.096	⁷⁶ 0.994	⁴⁹ 0.058	³⁶ 0.296	0.000	0.000	0.032
126	PARAVISION-004	¹⁹ 0.002	¹⁹ 0.010	¹¹ 0.104	⁴⁰ 0.006	³⁷ 0.112	¹⁷ 0.010	¹⁸ 0.038	¹⁴⁹ 1.000	¹⁹ 0.018	⁹⁴ 0.908	0.000	0.000	0.032
127	PARAVISION-005	¹⁵ 0.002	¹⁴ 0.010	⁷ 0.079	⁴⁸ 0.007	²¹ 0.106	⁷ 0.004	⁸ 0.024	⁵³ 0.980	¹² 0.011	⁷ 0.132	0.000	0.000	0.038
128	PARAVISION-007	⁶ 0.001	⁶ 0.008	³ 0.066	³⁶ 0.005	²⁷ 0.101	⁸ 0.004	⁹ 0.025	¹⁴⁸ 1.000	¹¹ 0.009	¹⁴⁵ 1.000	0.000	0.000	0.000
129	PIXELALL-002	⁷⁵ 0.005	⁸⁰ 0.022	⁹⁴ 0.810	⁶¹ 0.011	⁷¹ 0.187	¹²⁴ 0.105	¹⁵⁷ 0.388	¹⁴⁴ 1.000	¹⁰¹ 0.602	¹²⁷ 1.000	0.000	0.000	0.000
130	PIXELALL-003	³⁴ 0.002	³⁷ 0.014	⁴⁷ 0.515	⁴⁴ 0.006	⁶¹ 0.151	³⁸ 0.022	⁴¹ 0.073	¹²³ 1.000	³⁷ 0.037	⁶⁶ 0.554	0.000	0.000	0.000
131	PIXELALL-004	³² 0.002	⁴⁰ 0.015	⁵⁰ 0.523	³⁸ 0.005	⁶² 0.152	³³ 0.018	⁴⁵ 0.079	¹³⁴ 1.000	⁴² 0.051	¹⁰⁸ 0.994	0.000	0.000	0.000
132	PTAKURATSATU-000	⁵² 0.003	⁵⁴ 0.017	⁶² 0.605	³⁷ 0.005	³⁶ 0.105	⁵⁸ 0.037	⁴⁴ 0.124	³² 0.924	⁴⁰ 0.046	²⁶ 0.232	0.000	0.001	0.039
133	QUANTASOFT-001	¹⁸⁹ 0.218	¹⁹⁴ 0.727				¹⁸⁸ 0.639					0.000	0.000	
134	RANKONE-002	¹⁴⁵ 0.019	¹⁵² 0.071				¹²⁸ 0.118	¹³⁶ 0.261				0.000	0.000	
135	RANKONE-003	¹⁴⁶ 0.019	¹⁵⁰ 0.068				¹²⁹ 0.118	¹³⁵ 0.255				0.000	0.000	
136	RANKONE-004	¹⁶⁵ 0.041	¹⁶⁸ 0.141				¹⁵³ 0.193	¹⁶¹ 0.426				0.000	0.000	
137	RANKONE-005	¹¹⁴ 0.009	¹²⁶ 0.041	¹⁵⁶ 0.986			⁹¹ 0.059	¹¹⁴ 0.173	⁹² 0.998			0.000	0.000	0.489
138	RANKONE-006	⁸⁰ 0.005		⁹¹ 0.797			⁶⁰ 0.037	⁴⁸ 0.977				0.002		0.167

Table 10: **Miss rates by dataset:** At left, rank 1 miss rates relevant to investigations; at right, with threshold set to target FPIR = 0.01 for higher volume, low prior, uses. Yellow indicates most accurate algorithm. Throughout blue superscripts indicate the rank of the algorithm for that column.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 $\rightarrow$ Investigation
T > 0 $\rightarrow$ Identification

		INVESTIGATION MODE					IDENTIFICATION MODE					FAILURE TO EXTRACT				
		RANK ONE MISS RATE, FNIR(N, 0, 1)					HIGH T → FPIR = 0.001, FNIR(N, T, L)					FEATURES				
		N=1.6M					N=1.6M									
#	ALGORITHM	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK
139	RANKONE-007	⁵⁶ 0.003	⁶⁵ 0.019	⁸⁸ 0.796			⁴⁰ 0.022	⁵⁷ 0.095	³⁹ 0.967			0.001	0.001	0.102		
140	RANKONE-009	⁴⁰ 0.002	³⁰ 0.013	⁸⁵ 0.549	³⁹ 0.006	⁵⁸ 0.134	³⁰ 0.018	⁴² 0.076	⁴¹ 0.969	⁵¹ 0.062	⁴⁴ 0.328	0.000	0.000	0.000		
141	RANKONE-010	³⁵ 0.002	¹⁵ 0.010	³⁶ 0.374	³⁹ 0.005	⁴⁸ 0.126	²¹ 0.014	³⁸ 0.058	²⁰ 0.802	⁴⁴ 0.052	³¹ 0.259	0.000	0.000	0.000		
142	REALNETWORKS-000	¹⁶³ 0.040	¹⁵⁹ 0.078				¹⁵⁸ 0.234	¹⁵⁹ 0.319				0.001	0.000			
143	REALNETWORKS-001	¹⁶⁴ 0.040	¹⁵⁸ 0.078				¹⁵⁹ 0.234	¹⁵¹ 0.319				0.001	0.000			
144	REALNETWORKS-002	¹⁶⁰ 0.039	¹⁵⁷ 0.078				¹⁵⁹ 0.231	¹⁵⁰ 0.315				0.001	0.000			
145	REALNETWORKS-003	¹⁵² 0.024	¹⁴⁶ 0.062	⁸⁵ 0.771	⁸¹ 0.031	⁷⁶ 0.209	¹⁴⁷ 0.159	¹³⁹ 0.266	¹⁰⁰ 0.998	⁷⁸ 0.164	⁶² 0.500	0.001	0.000	0.009		
146	REALNETWORKS-004	¹⁵⁰ 0.024	¹⁴⁴ 0.059	⁹⁰ 0.797	⁸⁹ 0.031	⁸¹ 0.213	¹⁴² 0.158	¹³⁹ 0.263	¹¹² 0.999	⁷⁹ 0.170	⁷⁰ 0.613	0.001	0.000	0.009		
147	REMARKAI-000	⁸⁸ 0.003	⁶³ 0.018	⁶⁵ 0.660	⁵⁸ 0.008	⁶⁰ 0.148	⁸⁹ 0.055	⁸⁰ 0.120	¹⁰⁹ 0.999	⁵⁶ 0.069	⁷⁶ 0.717	0.000	0.000	0.000		
148	REMARKAI-000	¹⁰⁷ 0.009	¹⁰⁵ 0.030				¹³⁵ 0.128	¹²⁸ 0.203				0.000	0.001			
149	REMARKAI-002	¹⁰⁵ 0.008	¹⁰⁴ 0.029	⁹² 0.802			¹³² 0.124	¹¹⁸ 0.196	⁶⁹ 0.991			0.000	0.001	0.017		
150	SCANOVATE-000	⁷⁹ 0.005	¹³⁰ 0.045	⁵⁷ 0.560	⁸⁴ 0.035	⁸⁰ 0.211	¹⁰⁰ 0.067	¹³² 0.240	²⁹ 0.893	⁸⁵ 0.215	⁵⁰ 0.400	0.000	0.001	0.057		
151	SCANOVATE-001	⁸² 0.005	¹²⁴ 0.040	⁸¹ 0.585	⁷⁹ 0.031	⁶⁹ 0.178	¹⁰⁶ 0.081	¹²² 0.227	³¹ 0.911	⁸² 0.192	⁵³ 0.404	0.000	0.001	0.044		
152	SENSETIME-000	³⁸ 0.002	⁴⁷ 0.016	⁵¹ 0.528			³⁸ 0.021	³¹ 0.063	²⁰² 1.000			0.004	0.000	0.042		
153	SENSETIME-001	³⁹ 0.002	⁴⁶ 0.016				³⁹ 0.022	³⁴ 0.064				0.004	0.000			
154	SENSETIME-002	¹³³ 0.014	⁶⁸ 0.020	³⁷ 0.384	⁶⁰ 0.011	²⁹ 0.104	²⁴ 0.015	¹³ 0.028	⁷⁴ 0.994	²⁹ 0.032	⁶³ 0.523	0.009	0.000	0.040		
155	SENSETIME-003	³ 0.001	² 0.007	¹⁴ 0.150	¹² 0.003	¹⁶ 0.091	² 0.002	⁷ 0.012	⁷ 0.477	⁷ 0.008	⁸ 0.133	0.000	0.000	0.041		
156	SENSETIME-004	² 0.001	³ 0.007	⁶ 0.072	⁹ 0.002	¹⁵ 0.084	¹ 0.002	² 0.013	³ 0.229	² 0.006	⁵ 0.113	0.000	0.000	0.041		
157	SENSETIME-005	¹ 0.001	¹ 0.006	¹ 0.059	⁸ 0.002	⁹ 0.082	¹ 0.002	² 0.014	² 0.173	⁴ 0.007	² 0.104	0.000	0.000	0.041		
158	SHAMAN-003	¹⁸⁰ 0.124	¹⁷² 0.172				¹⁷⁸ 0.451	¹⁷² 0.597				0.020	0.011			
159	SHAMAN-004	¹⁹¹ 0.222	¹⁸¹ 0.319				¹⁸⁸ 0.615	¹⁷⁸ 0.754				0.020	0.011			
160	SHAMAN-006	¹⁶² 0.040	¹⁴² 0.058	¹²⁰ 0.938			¹³⁷ 0.141	¹²⁹ 0.237	⁴³ 0.972			0.020	0.011	0.869		
161	SHAMAN-007	¹⁶¹ 0.040	¹⁴¹ 0.057				¹³⁸ 0.141	¹³¹ 0.240				0.020	0.010			
162	SIAT-001	²² 0.002	¹⁸³ 0.333		³⁰ 0.004	²⁵ 0.099	²⁵ 0.018	¹⁵⁸ 0.365		²⁷ 0.031		0.000	0.000			
163	SIAT-002	²³ 0.002	¹⁸⁵ 0.446		¹⁰⁸ 0.348	²⁸ 0.102	³⁷ 0.022	¹⁶⁸ 0.478		⁹³ 0.372	⁹⁷ 0.923	0.000	0.000			
164	SMILART-004	²⁰² 0.965	¹⁹⁷ 0.974				¹⁹⁶ 0.968	¹⁹¹ 0.976				0.011	0.013			
165	SMILART-005											0.011	0.013			
166	SYNESIS-003	¹⁸⁶ 0.170	¹⁷⁷ 0.235				¹⁸⁸ 0.582	¹⁷⁴ 0.646				0.006	0.015			
167	SYNESIS-003	¹³⁷ 0.016	⁸⁷ 0.023	⁹⁹ 0.827	⁶⁴ 0.013	⁵⁸ 0.136	⁹⁸ 0.065	⁸¹ 0.123	³⁷ 0.960	⁵⁸ 0.075	⁴⁰ 0.314	0.000	0.001	0.063		
168	SYNESIS-005	¹⁰⁶ 0.009	³¹ 0.013	⁷⁹ 0.744	¹⁹ 0.003	¹⁹ 0.092	⁴² 0.025	³⁹ 0.072	⁵⁹ 0.984	³² 0.032	²² 0.214	0.001	0.000	0.135		
169	TECH5-001	⁶⁶ 0.004	⁵³ 0.017	⁶⁰ 0.584	⁴⁶ 0.007	³⁵ 0.107	⁸⁹ 0.057	¹⁵⁹ 0.935	¹⁵⁰ 1.000	⁸⁶ 0.244	¹⁰⁹ 0.994	0.000	0.000	0.006		
170	TEVIAN-003	¹³⁴ 0.015	¹³⁹ 0.052				¹⁵⁹ 0.177	¹⁴⁶ 0.298				0.001	0.002			
171	TEVIAN-004	¹²¹ 0.011	¹¹⁷ 0.038				¹²² 0.117	¹¹⁵ 0.176				0.001	0.002			
172	TEVIAN-005	⁹⁹ 0.007	¹⁰³ 0.028	⁴⁰ 0.467			¹¹⁴ 0.087	⁸⁶ 0.144	³⁸ 0.962			0.001	0.002	0.116		
173	TIGER-000	¹⁷¹ 0.062	¹⁶³ 0.095				¹⁷⁴ 0.390	¹⁶⁶ 0.500				0.000	0.000			
174	TIGER-002	⁸⁴ 0.006	⁸⁵ 0.023	⁴⁶ 0.514			¹¹⁰ 0.086	¹⁰⁸ 0.158	¹⁰⁷ 0.999			0.000	0.000	0.056		
175	TIGER-003	⁸⁵ 0.006	⁸⁴ 0.023				¹¹¹ 0.086	¹⁰⁴ 0.158				0.000	0.000			
176	TONGYITRANS-000	⁹⁵ 0.007	⁸² 0.022				¹⁰⁵ 0.074	⁷² 0.112				0.003	0.001			
177	TONGYITRANS-001	⁹⁶ 0.007	⁸¹ 0.022				⁹⁸ 0.066	⁶³ 0.101				0.003	0.001			
178	TOSHIBA-000	⁷² 0.004	⁷⁷ 0.022	⁸⁴ 0.766			⁹⁸ 0.062	⁷⁷ 0.118	⁸⁴ 0.995			0.000	0.000	0.070		
179	TOSHIBA-001	⁷⁷ 0.005	⁷⁹ 0.022				⁹¹ 0.058	⁵⁴ 0.092				0.000	0.000			
180	TRUEFACE-000	⁵⁵ 0.003	³⁴ 0.014	²² 0.230	⁵⁰ 0.007	¹⁸ 0.092	³² 0.018	³² 0.062	²⁶ 0.882	²⁶ 0.030	²⁰ 0.188	0.001	0.001	0.047		
181	VD-000	¹⁹⁹ 0.474	¹⁹⁰ 0.551				¹⁹⁴ 0.917	¹⁸⁸ 0.946				0.011	0.013			
182	VD-001	¹⁵⁶ 0.028	¹³⁸ 0.053				¹⁵⁴ 0.201	¹⁴³ 0.281				0.005	0.001			
183	VIGILANTSOLUTIONS-003	¹⁷⁴ 0.069	¹⁷⁰ 0.151	¹³¹ 0.958			¹⁷⁷ 0.408	¹⁷² 0.660	¹⁰⁴ 0.999			0.000	0.001	0.127		
184	VIGILANTSOLUTIONS-004	¹⁸¹ 0.125	¹⁷⁸ 0.244	¹³⁶ 0.965			¹⁸⁸ 0.549	¹⁸¹ 0.817	⁸⁸ 0.996			0.000	0.001	0.127		

Table 11: **Miss rates by dataset:** At left, rank 1 miss rates relevant to investigations; at right, with threshold set to target FPIR = 0.01 for higher volume, low prior, uses. Yellow indicates most accurate algorithm. Throughout blue superscripts indicate the rank of the algorithm for that column.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 $\rightarrow$ Investigation
T > 0 $\rightarrow$ Identification

		INVESTIGATION MODE					IDENTIFICATION MODE					FAILURE TO EXTRACT				
		RANK ONE MISS RATE, FNIR(N, 0, 1)					HIGH T → FPIR = 0.001, FNIR(N, T, L)					FEATURES				
		N=1.6M					N=1.6M									
#	ALGORITHM	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK
185	VIGILANTSOLUTIONS-005	¹¹¹ 0.009		¹⁰⁹ 0.920			¹⁷³ 0.388		¹⁴³ 1.000			0.000	0.001	0.127		
186	VIGILANTSOLUTIONS-006	¹¹⁶ 0.010		¹¹⁰ 0.921			¹⁶⁸ 0.353		¹³⁶ 1.000			0.000	0.001	0.127		
187	VIGILANTSOLUTIONS-007	⁵⁷ 0.003	⁵⁶ 0.017	¹¹³ 0.925	⁶⁵ 0.013	⁶⁷ 0.175	⁵² 0.028	⁴⁶ 0.088	⁸⁷ 0.996	⁶¹ 0.081	⁴⁹ 0.391	0.000	0.001	0.127		
188	VISIONLABS-004	⁴⁸ 0.003	⁶⁹ 0.020	³¹ 0.343			⁹⁰ 0.058	¹⁰⁶ 0.159	²⁸ 0.890			0.001	0.001	0.046		
189	VISIONLABS-005	⁴¹ 0.002	⁶⁴ 0.019	²⁹ 0.334			⁷⁷ 0.050	⁹⁷ 0.147	²⁷ 0.888			0.001	0.001	0.046		
190	VISIONLABS-006	²⁴ 0.002	⁴⁴ 0.015	²¹ 0.211	²⁵ 0.004	²² 0.096	⁴⁹ 0.027	³² 0.090	¹³ 0.672			0.001	0.001	0.051		
191	VISIONLABS-007	²¹ 0.002	⁴³ 0.015	²⁰ 0.211	²¹ 0.004	²¹ 0.095	⁴⁸ 0.027	³¹ 0.090	¹⁴ 0.672	²⁵ 0.031	¹⁹ 0.185	0.001	0.001	0.051		
192	VISIONLABS-008	³¹ 0.002	³⁵ 0.014	¹² 0.141	⁷ 0.002	⁸ 0.081	²⁰ 0.013	²⁵ 0.051	⁸ 0.481	¹⁶ 0.017	¹¹ 0.151	0.001	0.000	0.075		
193	VISIONLABS-009	⁵ 0.001	⁸ 0.008	⁹ 0.091	² 0.001	⁴ 0.071	¹⁰ 0.005	¹⁰ 0.025	¹⁹ 0.799	¹⁰ 0.008	⁴ 0.113	0.000	0.000	0.060		
194	VISIONLABS-010	¹¹ 0.001	²⁰ 0.010	⁵ 0.069	¹ 0.001	³ 0.069	¹³ 0.005	¹² 0.027		⁵ 0.008	³ 0.109	0.000	0.000	0.040		
195	VOCORD-003	⁸⁹ 0.006	⁹² 0.024	⁸⁷ 0.804	⁹³ 0.061	⁷² 0.188	¹³¹ 0.122	¹⁰² 0.155	⁹⁸ 0.998	⁷⁷ 0.157	⁵⁴ 0.404	0.001	0.011	0.425		
196	VOCORD-004	¹⁰¹ 0.008	⁷⁴ 0.021	⁸⁰ 0.792	⁶³ 0.012	⁴⁸ 0.127	¹⁶⁹ 0.355	¹¹² 0.173	¹²⁹ 1.000	⁸³ 0.193	¹⁰⁶ 0.991	0.000	0.000	0.000		
197	VOCORD-005	³⁸ 0.007	³⁸ 0.023	⁸⁵ 0.812	⁹¹ 0.055	⁷⁴ 0.206	¹⁴¹ 0.158	⁸⁶ 0.130	⁹⁰ 0.997	⁷³ 0.138	⁴⁶ 0.381	0.001	0.009	0.554		
198	VOCORD-006	²⁰⁴ 1.000	²⁰¹ 1.000	¹⁶³ 1.000	¹²¹ 1.000	¹⁵⁸ 1.000	²⁰³ 1.000	²⁰⁰ 1.000	¹⁵⁴ 1.000	¹⁷⁹ 1.000	¹⁶² 1.000	0.001	0.009	0.554		
199	XFORWARD-000	³⁶ 0.002	³⁶ 0.014	⁸ 0.089	²⁷ 0.004	¹⁹ 0.094	²⁷ 0.015	²⁸ 0.053	⁵ 0.440	²⁰ 0.021	¹⁴ 0.169	0.000	0.000	0.000		
200	XFORWARD-001	³³ 0.002	²⁹ 0.013	⁴ 0.067	¹⁵ 0.003	¹¹ 0.082	¹¹ 0.005	¹⁴ 0.028	⁶ 0.448	⁸ 0.008	⁶ 0.123	0.000	0.000	0.000		
201	YISHENG-001	¹⁵⁵ 0.027	¹⁴⁵ 0.060		⁹² 0.058	⁹³ 0.287	¹⁶⁷ 0.346	¹⁷⁵ 0.808		¹⁰⁴ 0.666	⁹⁶ 0.919	0.002	0.005			
202	YITU-002	²⁵ 0.002	¹⁸ 0.010				²⁰ 0.018	²¹ 0.049				0.000	0.000			
203	YITU-003	⁵¹ 0.003	⁴⁹ 0.016				³⁵ 0.019	²⁶ 0.052				0.003	0.001			
204	YITU-004	⁹ 0.001	⁸ 0.008	¹⁰⁴ 0.866			¹⁵ 0.010	¹¹ 0.027	³³ 0.936			0.000	0.000	0.000		
205	YITU-005	³⁷ 0.002	³⁹ 0.014				¹⁶ 0.010	¹⁵ 0.032				0.003	0.001			

Table 12: **Miss rates by dataset:** At left, rank 1 miss rates relevant to investigations; at right, with threshold set to target FPIR = 0.01 for higher volume, low prior, uses. Yellow indicates most accurate algorithm. Throughout blue superscripts indicate the rank of the algorithm for that column.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

MISSES BELOW THRESHOLD, T		ENROL MOST RECENT				
FNIR(N, T > 0, R > L)		DATASET: FRVT 2018				
#	ALGORITHM	N=0.64M	N=1.6M	N=3.0M	N=6.0M	N=12.0M
1	3DIVI-005	¹⁴⁶ 0.1358	¹⁴⁶ 0.1664	¹²⁷ 0.1915	¹²² 0.2370	¹¹⁸ 0.3054
2	ACER-000	¹⁴⁰ 0.1185	¹³⁹ 0.1455	¹²² 0.1714	¹¹⁶ 0.2074	¹¹¹ 0.2537
3	ALCHERA-003	¹³⁸ 0.1176	¹³⁸ 0.1553	¹²³ 0.1853	¹²⁵ 0.2409	¹²⁵ 0.3553
4	ALLGOVISION-000	¹¹⁵ 0.0688	¹¹⁶ 0.0881	¹⁰⁴ 0.1084	¹⁰⁰ 0.1389	⁹¹ 0.2129
5	ALLGOVISION-001	¹²¹ 0.0785	¹²¹ 0.1017	¹¹¹ 0.1218	¹⁰⁸ 0.1584	⁹⁸ 0.2273
6	ANKE-000	¹²⁷ 0.0942	¹²⁸ 0.1169	¹¹⁶ 0.1404	¹¹³ 0.1776	¹¹² 0.2559
7	ANKE-002	⁵⁴ 0.0229	⁵⁴ 0.0318	⁵⁴ 0.0406	³⁵ 0.0605	⁴⁵ 0.1466
8	AWARE-003	¹³⁵ 0.1098	¹³⁴ 0.1283	¹¹⁷ 0.1447	¹¹² 0.1768	¹⁰³ 0.2364
9	AWARE-005	¹⁷¹ 0.3389	¹⁷³ 0.3643	¹³⁴ 0.3993	¹³¹ 0.4526	¹¹⁰ 0.2531
10	AYONIX-002	¹⁹¹ 0.7862	¹⁹¹ 0.8242	¹³⁹ 0.8508	¹³⁵ 0.8704	¹³³ 0.8939
11	CAMVI-004	⁷⁶ 0.0367	¹⁰² 0.0716	⁹⁹ 0.0983	¹²⁵ 0.2508	¹¹⁵ 0.2701
12	CIB-000	¹⁵ 0.0086	¹⁵ 0.0125	¹⁹ 0.0160	²⁵ 0.0303	³⁶ 0.1251
13	COGENT-000	⁹³ 0.0430	⁸¹ 0.0527	⁸⁰ 0.0695	⁸⁶ 0.1133	⁸⁰ 0.1960
14	COGENT-001	⁹² 0.0430	⁸⁰ 0.0527	⁸² 0.0695	⁸⁵ 0.1133	⁸¹ 0.1960
15	COGENT-002	⁶⁴ 0.0322	⁶⁸ 0.0444	⁶⁸ 0.0610	⁸³ 0.1116	⁹³ 0.2180
16	COGENT-003	⁶⁵ 0.0328	⁷² 0.0463	⁷⁹ 0.0683	⁹³ 0.1294	¹⁰⁵ 0.2445
17	COGENT-004	³³ 0.0210	³⁸ 0.0331	⁶³ 0.0527	⁸⁸ 0.1138	⁹⁰ 0.2119
18	COGNITEC-000	¹⁴⁸ 0.1377	¹⁴⁴ 0.1606	¹²⁸ 0.1870	¹¹⁸ 0.2176	¹¹⁷ 0.2831
19	COGNITEC-001	¹²³ 0.0807	¹²⁴ 0.1017	¹¹⁰ 0.1214	¹⁰⁴ 0.1513	⁹⁶ 0.2238
20	COGNITEC-002	⁸⁶ 0.0406	⁸² 0.0531	⁷⁵ 0.0666	⁷¹ 0.0935	⁷⁶ 0.1874
21	COGNITEC-003	⁸⁴ 0.0400	⁷⁸ 0.0526	⁷¹ 0.0650	⁶⁷ 0.0895	⁶⁹ 0.1772
22	CYBERLINK-000	⁸⁸ 0.0414	⁸⁸ 0.0565	⁸⁶ 0.0707	⁷⁹ 0.1031	⁸² 0.2050
23	CYBERLINK-001	⁸⁰ 0.0392	⁸² 0.0536	⁸¹ 0.0695	⁷⁶ 0.0973	⁷⁰ 0.1794
24	CYBERLINK-002	²² 0.0105	²⁵ 0.0148	²⁷ 0.0202	³⁸ 0.0399	³⁷ 0.1255
25	CYBERLINK-003	¹⁴ 0.0056	¹⁴ 0.0077	¹⁴ 0.0100	¹⁶ 0.0235	³⁴ 0.1237
26	DAHUA-001	¹⁰⁵ 0.0569	¹⁰⁴ 0.0727	⁸⁴ 0.0878	⁸⁹ 0.1148	⁷⁵ 0.1867
27	DAHUA-002	²⁶ 0.0108	²⁶ 0.0151	²³ 0.0191	²² 0.0291	³² 0.1153
28	DAHUA-003	²¹ 0.0100	²² 0.0139	²³ 0.0180	²³ 0.0296	²⁷ 0.1130
29	DEEPLINT-001	⁷ 0.0027	⁷ 0.0033	⁷ 0.0043	⁷ 0.0121	¹⁷ 0.0922
30	DEESEA-001	⁷² 0.0347	⁷⁴ 0.0462	⁶⁷ 0.0586	⁶⁵ 0.0802	⁶⁶ 0.1708
31	DERMLOG-005	¹¹⁹ 0.0700	¹¹³ 0.0880	¹⁰⁶ 0.1144	¹⁰⁷ 0.1578	¹⁰⁶ 0.2451
32	DERMLOG-006	⁸¹ 0.0395	⁷⁸ 0.0517	⁷² 0.0659	⁷⁵ 0.0973	⁶⁸ 0.1745
33	DERMLOG-007	¹¹⁶ 0.0691	¹¹³ 0.0863	¹⁰⁵ 0.1107	¹⁰³ 0.1504	¹⁰¹ 0.2299
34	DERMLOG-008	⁶⁹ 0.0338	⁷³ 0.0455	⁷⁰ 0.0626	⁸⁰ 0.1060	⁹⁹ 0.2276
35	F8-001	¹³⁷ 0.1140	¹³⁸ 0.1658	¹²¹ 0.1658	¹⁰⁹ 0.1658	⁶⁶ 0.1658
36	GORILLA-002	¹⁵² 0.1539	¹⁵² 0.1880	¹³⁸ 0.2184	¹²⁶ 0.2596	¹²⁴ 0.3398
37	GORILLA-004	¹¹⁸ 0.0699	¹¹⁸ 0.0892	¹⁰² 0.1048	⁹⁸ 0.1370	⁸⁴ 0.1969
38	GORILLA-005	⁹⁶ 0.0453	⁹² 0.0583	⁸⁵ 0.0704	⁷⁷ 0.0974	⁴⁹ 0.1474
39	HIK-003	¹²⁴ 0.0828	¹²³ 0.1028	¹⁰⁹ 0.1202	¹⁰⁶ 0.1525	¹⁰⁸ 0.2480
40	HIK-004	¹²² 0.0796	¹¹⁹ 0.0988	¹⁰⁷ 0.1147	¹⁰² 0.1474	¹⁰⁹ 0.2483
41	HIK-005	⁶² 0.0312	⁶² 0.0436	⁶⁶ 0.0560	⁶⁹ 0.0911	⁹² 0.2129
42	HR-000	⁴ 0.0019	³ 0.0020	³ 0.0023	⁴ 0.0072	¹⁰ 0.0701
43	IDEMIA-003	⁷⁰ 0.0346	⁷⁴ 0.0471	⁹⁵ 0.0892	¹²⁸ 0.2789	¹²⁸ 0.4311
44	IDEMIA-004	⁶¹ 0.0300	⁶⁴ 0.0373	⁵⁶ 0.0447	⁵⁴ 0.0617	⁶⁵ 0.1635
45	IDEMIA-005	⁷⁵ 0.0360	⁶⁷ 0.0440	⁶⁴ 0.0537	⁶⁴ 0.0764	⁷⁷ 0.1915
46	IDEMIA-006	⁷³ 0.0351	⁶⁴ 0.0433	⁶² 0.0525	⁶² 0.0734	⁹⁴ 0.2201
47	IDEMIA-007	³² 0.0136	³¹ 0.0181	²⁸ 0.0228	³¹ 0.0357	⁴⁷ 0.1402
48	IMAGUS-005	³³ 0.0137	³⁴ 0.0185	³³ 0.0237	³³ 0.0368	²⁴ 0.1067
49	IMPERIAL-000	⁴⁵ 0.0187	⁴⁶ 0.0259	⁵¹ 0.0358	⁶¹ 0.0733	⁷¹ 0.1794
50	INCODE-003	¹⁴⁵ 0.1324	¹⁴⁷ 0.1672	¹²⁸ 0.1961	¹²¹ 0.2345	¹²⁰ 0.3123
51	INCODE-004	⁸⁵ 0.0403	⁸⁶ 0.0538	⁷⁴ 0.0662	⁷⁰ 0.0917	⁶² 0.1619
52	INNOVATRICS-004	¹³⁴ 0.1082	¹³² 0.1317	¹¹⁵ 0.1394	¹⁰¹ 0.1394	⁴⁶ 0.1394
53	INNOVATRICS-005	⁵⁶ 0.0251	⁵⁶ 0.0340	⁵⁵ 0.0424	⁴³ 0.0482	⁵ 0.0482
54	INNOVATRICS-006	⁵⁰ 0.0194	⁴³ 0.0254	⁴² 0.0313	³² 0.0363	³ 0.0363
55	INTSYSMSU-000	²⁰¹ 0.9982	¹⁹³ 0.9984	¹⁴³ 0.9985	¹³⁸ 0.9987	¹³⁵ 0.9988
56	IREX-000	⁴⁹ 0.0190	⁵¹ 0.0280	⁵² 0.0391	⁵⁷ 0.0677	⁵² 0.1479
57	ISYSTEMS-002	¹⁰⁷ 0.0584	¹⁰⁷ 0.0783	⁹⁸ 0.0973	⁹⁹ 0.1373	¹⁰⁰ 0.2295
58	ISYSTEMS-003	⁹⁵ 0.0438	⁹³ 0.0590	⁹² 0.0807	⁹¹ 0.1259	¹⁰² 0.2357
59	KEDACOM-001	⁴² 0.0181	⁴¹ 0.0227	³⁶ 0.0265	⁴¹ 0.0422	⁴³ 0.1340
60	LOOKMAN-003	⁷¹ 0.0346	⁶⁶ 0.0437	⁶⁰ 0.0514	⁶⁰ 0.0724	⁶³ 0.1620
61	LOOKMAN-005	⁵⁵ 0.0240	⁵⁵ 0.0301	⁵⁰ 0.0356	⁴⁶ 0.0512	⁴² 0.1334
62	MEGVII-001	¹⁰³ 0.0562	¹⁰³ 0.0722	⁹³ 0.0872	⁹⁵ 0.1309	¹¹⁶ 0.2713
63	MICROFOCUS-005	¹⁹⁸ 0.9732	¹⁹³ 0.8354	¹⁴⁰ 0.8555	¹³⁶ 0.8755	¹³⁴ 0.8954
64	MICROSOFT-003	⁸¹ 0.0198	⁸⁰ 0.0278	⁴⁹ 0.0356	⁵⁰ 0.0538	⁵⁸ 0.1539
65	MICROSOFT-004	⁴⁴ 0.0185	⁴² 0.0259	⁴⁶ 0.0333	⁴⁷ 0.0517	⁵⁶ 0.1510
66	MICROSOFT-005	⁴³ 0.0181	⁴⁵ 0.0256	⁴⁵ 0.0320	⁴⁵ 0.0512	⁵⁴ 0.1491
67	MICROSOFT-006	¹⁹ 0.0091	¹⁸ 0.0120	²⁰ 0.0162	²⁴ 0.0301	⁵³ 0.1482
68	NEC-000	¹¹⁰ 0.0637	¹⁰⁸ 0.0789	⁹⁷ 0.0933	⁹⁰ 0.1163	⁷⁹ 0.1941
69	NEC-001	¹²⁵ 0.0863	¹²⁵ 0.1055	¹¹² 0.1249	¹⁰⁵ 0.1519	⁹⁷ 0.2253
70	NEC-002	⁵ 0.0020	⁶ 0.0026	⁶ 0.0033	⁹ 0.0135	⁸ 0.0653
71	NEC-003	⁶ 0.0021	⁵ 0.0024	⁴ 0.0028	³ 0.0059	⁷ 0.0540
72	NEUROTECHNOLOGY-003	¹⁸⁶ 0.5698	¹⁸⁶ 0.6362	¹³⁸ 0.7035	¹³⁴ 0.7602	¹³² 0.8224

Table 13: Identification-mode: Effect of N on FNIR at high threshold. Values are threshold-based miss rates i.e. FNIR at FPIR = 0.001 for five enrollment population sizes, N. The right six columns apply for enrollment of one image. Missing entries usually apply because another algorithm from the same developer was run instead. Some developers are missing because less accurate algorithms were not run on galleries with $N \geq 3\,000\,000$. Throughout blue superscripts indicate the rank of the algorithm for that column.

MISSES BELOW THRESHOLD, T		ENROL MOST RECENT				
FNIR(N, T > 0, R > L)		DATASET: FRVT 2018				
#	ALGORITHM	N=0.64M	N=1.6M	N=3.0M	N=6.0M	N=12.0M
73	NEUROTECHNOLOGY-004	⁵⁸ 0.0466	⁹⁷ 0.0629	⁸⁷ 0.0779	⁸⁷ 0.1135	⁸⁹ 0.2102
74	NEUROTECHNOLOGY-005	⁸² 0.0396	⁸⁶ 0.0538	⁷⁷ 0.0675	⁷⁴ 0.0950	⁸⁵ 0.1966
75	NEUROTECHNOLOGY-007	⁹⁴ 0.0436	⁹⁶ 0.0623	⁸⁹ 0.0802	⁹⁶ 0.1320	¹⁰⁴ 0.2393
76	NTECHLAB-003	⁹⁰ 0.0421	⁸⁴ 0.0537	⁷⁶ 0.0674	⁶⁸ 0.0907	⁶¹ 0.1582
77	NTECHLAB-004	⁶³ 0.0312	⁶² 0.0405	⁶⁹ 0.0519	⁵⁹ 0.0722	⁵⁵ 0.1503
78	NTECHLAB-005	⁶⁷ 0.0334	⁶³ 0.0424	⁶⁹ 0.0537	⁶³ 0.0760	⁵⁹ 0.1543
79	NTECHLAB-006	⁵⁹ 0.0288	⁵⁹ 0.0367	⁵⁹ 0.0471	⁵⁶ 0.0670	⁵⁷ 0.1523
80	NTECHLAB-007	⁴⁶ 0.0188	⁴⁴ 0.0256	⁴³ 0.0317	⁴⁴ 0.0495	⁴¹ 0.1306
81	NTECHLAB-008	²⁵ 0.0107	²⁵ 0.0145	²⁴ 0.0187	²⁰ 0.0286	¹⁸ 0.0995
82	NTECHLAB-009	¹² 0.0037	¹² 0.0049	¹² 0.0062	⁸ 0.0125	¹¹ 0.0735
83	PARAVISION-003	⁵⁷ 0.0260	⁵⁷ 0.0351	⁵⁷ 0.0447	⁵⁵ 0.0657	⁶⁴ 0.1630
84	PARAVISION-004	¹⁶ 0.0074	¹⁷ 0.0101	¹⁹ 0.0136	¹⁹ 0.0267	³⁸ 0.1256
85	PARAVISION-005	⁵ 0.0032	⁹ 0.0041	⁵ 0.0057	¹² 0.0174	²⁰ 0.1037
86	PARAVISION-007	⁸ 0.0030	⁸ 0.0040	⁷ 0.0055	¹³ 0.0211	²⁵ 0.1097
87	PIXELALL-002	¹²⁰ 0.0716	¹²⁴ 0.1052	¹¹⁹ 0.1475	¹²⁴ 0.2489	¹²⁷ 0.3904
88	PIXELALL-003	³⁸ 0.0158	³⁸ 0.0218	⁴¹ 0.0288	⁴² 0.0474	³⁰ 0.1138
89	PIXELALL-004	²⁸ 0.0129	³³ 0.0183	³⁵ 0.0245	³⁴ 0.0378	⁴⁴ 0.1375
90	PTAKURATSU-000	⁵⁸ 0.0275	⁵⁸ 0.0366	⁵⁹ 0.0458	⁴⁹ 0.0523	⁶ 0.0523
91	QUANTASOFT-001	¹⁸⁷ 0.6387	¹⁸⁷ 0.6387	¹³⁹ 0.6387		¹³⁰ 0.6387
92	RANKONE-002	¹³³ 0.0973	¹²⁸ 0.1175	¹¹⁴ 0.1359	¹¹⁰ 0.1718	¹¹³ 0.2613
93	RANKONE-003	¹³² 0.0973	¹²⁹ 0.1175	¹¹³ 0.1359	¹¹¹ 0.1718	¹¹⁴ 0.2613
94	RANKONE-005	⁹⁹ 0.0473	⁹⁴ 0.0592	⁸³ 0.0700	⁷² 0.0944	⁸⁵ 0.1998
95	RANKONE-007	⁴⁰ 0.0168	⁴⁰ 0.0222	³⁶ 0.0266	³⁶ 0.0381	²⁵ 0.1132
96	RANKONE-009	²⁹ 0.0132	³⁰ 0.0177	³⁸ 0.0230	²⁸ 0.0344	¹⁶ 0.0921
97	RANKONE-010	²³ 0.0106	²¹ 0.0136	²² 0.0174	¹⁸ 0.0265	¹² 0.0785
98	REALNETWORKS-002	¹⁵⁸ 0.1943	¹⁵⁷ 0.2314	¹³¹ 0.2656	¹³⁰ 0.3134	¹²² 0.3208
99	REALNETWORKS-003	¹⁴⁴ 0.1300	¹⁴³ 0.1594	¹²⁵ 0.1858	¹¹⁹ 0.2246	¹¹⁹ 0.3076
100	REALNETWORKS-004	¹⁴³ 0.1279	¹⁴² 0.1581	¹²⁴ 0.1857	¹²⁰ 0.2329	¹²¹ 0.3179
101	REMARKAI-000	⁸⁷ 0.0406	⁸⁷ 0.0552	⁷⁸ 0.0676	⁷⁸ 0.1028	⁸⁶ 0.2003
102	SCANOVATE-000	¹⁰⁰ 0.0498	¹⁰⁰ 0.0667	⁹⁶ 0.0804	⁸² 0.1097	²⁶ 0.1109
103	SCANOVATE-001	¹⁰⁹ 0.0630	¹⁰⁹ 0.0815	¹⁰⁰ 0.0993	⁹² 0.1292	⁸² 0.1960
104	SENSETIME-000	³⁷ 0.0158	³⁶ 0.0208	³⁸ 0.0270	³⁷ 0.0398	³³ 0.1232
105	SENSETIME-001	³⁹ 0.0161	³⁹ 0.0219	⁴⁰ 0.0277	⁴⁰ 0.0420	⁴⁰ 0.1304
106	SENSETIME-002	³⁵ 0.0146	²⁴ 0.0148	¹⁴ 0.0153	¹⁵ 0.0234	⁹ 0.0657
107	SENSETIME-003	² 0.0016	² 0.0018	² 0.0021	² 0.0054	³ 0.0451
108	SENSETIME-004	¹ 0.0015	¹ 0.0018	¹ 0.0021	¹ 0.0040	¹ 0.0354
109	SENSETIME-005	³ 0.0016	⁴ 0.0022	⁵ 0.0031	⁵ 0.0089	⁴ 0.0454
110	SHAMAN-007	¹⁴² 0.1212	¹³⁸ 0.1413	¹²⁵ 0.1587	¹¹⁴ 0.1879	¹⁰⁷ 0.2460
111	SIAT-001	³¹ 0.0136	²⁸ 0.0176	³¹ 0.0230	²⁷ 0.0344	¹⁹ 0.1035
112	SIAT-002	³⁶ 0.0154	³⁷ 0.0216	³⁹ 0.0273	³⁹ 0.0404	³⁹ 0.1283
113	SYNOPSIS-003	¹⁸⁴ 0.5341	¹⁸⁴ 0.5821	¹³⁶ 0.6113	¹³³ 0.6479	¹³¹ 0.6822
114	SYNOPSIS-003	¹⁰¹ 0.0499	⁹⁸ 0.0652	⁹¹ 0.0804	⁸¹ 0.1095	⁷⁸ 0.1916
115	SYNOPSIS-005	⁴¹ 0.0181	⁴² 0.0248	⁴⁴ 0.0319	⁴⁸ 0.0518	⁶⁰ 0.1580
116	TECH5-001	⁸⁹ 0.0420	⁸⁹ 0.0574	⁹⁶ 0.0911	¹¹⁷ 0.2106	¹²⁶ 0.3725
117	TEVIAN-005	¹¹⁷ 0.0692	¹¹⁴ 0.0873	¹⁰³ 0.1066	⁹⁴ 0.1301	⁷⁵ 0.1840
118	TIGER-002	¹¹² 0.0647	¹¹⁰ 0.0861	¹⁰¹ 0.1036	⁹⁷ 0.1332	⁹⁵ 0.2231
119	TOSHIBA-000	⁹⁷ 0.0460	⁹⁵ 0.0620	⁸⁸ 0.0780	⁸⁴ 0.1117	⁸⁸ 0.2082
120	TRUEFACE-000	³⁰ 0.0134	³² 0.0182	³⁴ 0.0238	³⁵ 0.0380	⁴⁵ 0.1385
121	VD-001	¹⁵⁴ 0.1642	¹⁵⁴ 0.2015	¹³⁴ 0.2351	¹²⁷ 0.2736	¹²³ 0.3293
122	VISIONLABS-004	⁹¹ 0.0427	⁹⁰ 0.0578	⁸⁴ 0.0703	⁷³ 0.0949	⁷⁴ 0.1853
123	VISIONLABS-005	⁷⁸ 0.0369	⁷⁷ 0.0502	⁶⁹ 0.0626	⁶⁶ 0.0847	⁷² 0.1815
124	VISIONLABS-006	⁴⁸ 0.0188	⁴⁹ 0.0267	⁴⁸ 0.0336	⁵² 0.0542	⁵⁰ 0.1478
125	VISIONLABS-007	⁴⁷ 0.0188	⁴⁸ 0.0266	⁴⁷ 0.0335	⁵¹ 0.0540	⁵¹ 0.1479
126	VISIONLABS-008	²⁰ 0.0096	²⁰ 0.0131	²¹ 0.0166	²¹ 0.0291	³⁵ 0.1247
127	VISIONLABS-009	¹⁰ 0.0034	¹⁰ 0.0046	¹⁰ 0.0060	¹⁰ 0.0140	¹⁴ 0.0881
128	VISIONLABS-010	¹³ 0.0038	¹³ 0.0051	¹³ 0.0070	¹¹ 0.0149	¹⁵ 0.0920
129	VOCORD-005	¹³⁹ 0.1179	¹⁴¹ 0.1577	¹²⁹ 0.2183	¹²⁹ 0.3122	¹²⁹ 0.4490
130	XFORWARDAI-000	²⁴ 0.0107	²⁷ 0.0151	²⁶ 0.0195	²⁶ 0.0324	²² 0.1057
131	XFORWARDAI-001	¹¹ 0.0037	¹¹ 0.0049	¹¹ 0.0060	⁶ 0.0120	¹³ 0.0800
132	YITU-002	²⁷ 0.0129	²⁹ 0.0177	²⁹ 0.0228	²⁹ 0.0345	²⁹ 0.1133
133	YITU-003	³⁴ 0.0138	³⁵ 0.0185	³² 0.0236	³⁰ 0.0353	³¹ 0.1148
134	YITU-004	¹⁵ 0.0067	¹⁵ 0.0096	¹⁵ 0.0129	¹⁴ 0.0232	²¹ 0.1046
135	YITU-005	¹⁷ 0.0074	¹⁶ 0.0101	¹⁶ 0.0135	¹⁷ 0.0255	²³ 0.1057

Table 14: **Identification-mode: Effect of N on FNIR at high threshold.** Values are threshold-based miss rates i.e. FNIR at FPIR = 0.001 for five enrollment population sizes, N. The right six columns apply for enrollment of one image. Missing entries usually apply because another algorithm from the same developer was run instead. Some developers are missing because less accurate algorithms were not run on galleries with $N \geq 3\,000\,000$. Throughout blue superscripts indicate the rank of the algorithm for that column.

MISSES AT GIVEN RANK		ENROL MOST RECENT											
FNIR(N, T=0, R)		RANK 1					RANK 50						
#	ALGORITHM	N=0.64M	N=1.6M	N=3.0M	N=6.0M	N=12.0M	aN^b	N=0.64M	N=1.6M	N=3.0M	N=6.0M	N=12.0M	aN^b
1	3DIVI-005	¹⁴³ 0.0137	¹⁴¹ 0.0176	¹²⁰ 0.0210	¹¹⁸ 0.0253	¹¹⁶ 0.0302	⁹⁴ 0.0004 N ^{0.271 99}	¹²⁸ 0.0040	¹²⁷ 0.0049	¹⁰⁹ 0.0057	¹⁰⁶ 0.0068	¹⁰⁷ 0.0081	⁴⁷ 0.0002 N ^{0.240 103}
2	ACER-000	¹¹⁵ 0.0081	¹²⁰ 0.0106	¹⁰⁸ 0.0128	¹¹⁰ 0.0157	¹⁰⁹ 0.0195	⁶⁷ 0.0001 N ^{0.289 122}	⁸⁴ 0.0020	⁹⁶ 0.0026	⁸⁸ 0.0031	⁹⁷ 0.0037	⁸⁹ 0.0045	¹⁷ 0.0000 N ^{0.284 116}
3	ALCHERA-003	¹¹² 0.0079	¹¹⁷ 0.0104	¹⁰⁶ 0.0123	¹⁰⁹ 0.0147	¹⁰⁶ 0.0180	⁶¹ 0.0002 N ^{0.278 110}	¹¹⁰ 0.0027	¹⁰⁸ 0.0032	⁹⁴ 0.0035	⁹⁶ 0.0042	⁸⁰ 0.0048	⁵⁰ 0.0002 N ^{0.199 93}
4	ALLGOVISION-000	¹²⁶ 0.0101	¹²³ 0.0114	¹⁰⁷ 0.0127	¹⁰⁸ 0.0145	¹⁰⁶ 0.0166	¹¹³ 0.0010 N ^{0.171 51}	¹⁴⁷ 0.0063	¹⁴¹ 0.0067	¹¹⁴ 0.0071	¹¹² 0.0075	¹⁰⁶ 0.0081	¹¹⁸ 0.0020 N ^{0.086 53}
5	ALLGOVISION-001	¹⁰⁵ 0.0069	¹⁰⁹ 0.0090	¹⁰⁰ 0.0107	¹⁰² 0.0128	¹⁰⁵ 0.0157	⁸⁷ 0.0002 N ^{0.277 108}	⁹⁹ 0.0023	⁹⁹ 0.0027	⁸⁹ 0.0031	⁸⁸ 0.0036	⁸⁶ 0.0043	⁴⁰ 0.0001 N ^{0.211 98}
6	ANKE-000	¹²⁹ 0.0102	¹³¹ 0.0132	¹¹⁶ 0.0155	¹¹⁹ 0.0188	¹¹² 0.0225	⁸¹ 0.0003 N ^{0.270 98}	¹¹⁹ 0.0032	¹²⁰ 0.0040	¹⁰⁵ 0.0046	¹⁰³ 0.0056	⁸⁶ 0.0066	³⁹ 0.0001 N ^{0.247 105}
7	ANKE-002	⁴⁹ 0.0024	⁴⁹ 0.0028	⁴⁹ 0.0032	⁴⁹ 0.0037	⁴⁶ 0.0043	⁴⁰ 0.0002 N ^{0.203 61}	⁶² 0.0016	⁶⁶ 0.0017	⁵⁷ 0.0017	⁴⁶ 0.0018	⁴⁰ 0.0019	⁸⁷ 0.0006 N ^{0.067 45}
8	AWARE-003	¹⁶⁰ 0.0238	¹⁵⁷ 0.0306	¹³¹ 0.0361	¹²⁹ 0.0431	¹²⁵ 0.0506	¹¹¹ 0.0008 N ^{0.158 93}	¹⁴¹ 0.0055	¹⁴⁶ 0.0075	¹²⁴ 0.0092	¹²⁴ 0.0113	¹²⁶ 0.0143	²⁸ 0.0001 N ^{0.323 126}
9	AWARE-005	¹⁶¹ 0.0245	¹⁵⁸ 0.0311	¹³² 0.0366	¹³⁰ 0.0434	¹²⁰ 0.0312	¹²⁷ 0.0056 N ^{0.118 30}	¹⁴⁵ 0.0062	¹⁵² 0.0082	¹²⁷ 0.0101	¹²⁷ 0.0128	¹⁰⁹ 0.0089	⁹⁵ 0.0007 N ^{0.169 87}
10	AYONIX-002	¹⁹³ 0.2935	¹⁹³ 0.3414	¹⁴² 0.3736	¹³⁸ 0.4101	¹³⁵ 0.4465	¹³³ 0.0440 N ^{0.143 39}	¹⁹² 0.0950	¹⁹⁴ 0.1274	¹⁴² 0.1524	¹³⁹ 0.1828	¹³⁴ 0.2150	¹²⁰ 0.0023 N ^{0.279 114}
11	CAMVI-004	¹³⁶ 0.0124	¹⁶⁷ 0.0468	¹³⁶ 0.0719	¹³⁷ 0.2363	¹³⁴ 0.2367	⁴ 0.0000 N ^{0.055 136}	¹⁶⁶ 0.0117	¹⁸⁰ 0.0464	¹³⁸ 0.0715	¹³⁸ 0.2361	¹³⁵ 0.2364	¹ 0.0000 N ^{0.171 136}
12	CIB-000	¹⁵ 0.0014	¹⁶ 0.0015	¹⁵ 0.0017	¹⁷ 0.0019	¹⁶ 0.0131	⁴ 0.0000 N ^{0.635 135}	²⁰ 0.0012	²⁰ 0.0012	¹⁹ 0.0012	¹⁹ 0.0012	¹²² 0.0122	² 0.0000 N ^{0.647 135}
13	COGENT-000	¹²⁷ 0.0101	¹¹⁹ 0.0105	¹⁰¹ 0.0109	⁹⁶ 0.0115	⁹³ 0.0125	¹²⁵ 0.0038 N ^{0.071 11}	⁹² 0.0021	⁹¹ 0.0024	⁸⁴ 0.0028	⁹⁰ 0.0036	¹¹² 0.0095	⁶ 0.0000 N ^{0.466 132}
14	COGENT-001	¹²⁸ 0.0101	¹¹⁸ 0.0105	¹⁰² 0.0109	⁹⁷ 0.0115	⁹⁴ 0.0125	¹²⁴ 0.0038 N ^{0.071 12}	⁹¹ 0.0021	⁹⁰ 0.0024	⁸³ 0.0028	⁹¹ 0.0036	¹¹³ 0.0095	⁷ 0.0000 N ^{0.466 131}
15	COGENT-002	³⁸ 0.0029	⁶¹ 0.0036	⁵⁹ 0.0041	⁶⁰ 0.0049	⁵⁷ 0.0059	³⁴ 0.0001 N ^{0.244 86}	⁵⁰ 0.0014	⁵³ 0.0015	⁴⁵ 0.0017	⁵⁰ 0.0019	⁵¹ 0.0021	⁵¹ 0.0002 N ^{0.144 81}
16	COGENT-003	⁶⁴ 0.0031	⁶³ 0.0038	⁶³ 0.0043	⁶³ 0.0051	⁶⁰ 0.0060	⁴⁰ 0.0001 N ^{0.230 77}	⁵⁶ 0.0015	⁶³ 0.0017	⁶³ 0.0018	⁶² 0.0020	⁵⁷ 0.0022	⁵⁴ 0.0002 N ^{0.143 80}
17	COGENT-004	³¹ 0.0018	³⁰ 0.0020	²⁹ 0.0022	²⁸ 0.0025	²⁴ 0.0028	⁴⁰ 0.0002 N ^{0.199 45}	⁴⁶ 0.0013	⁴⁴ 0.0014	³⁴ 0.0014	³⁴ 0.0015	²⁹ 0.0015	⁵⁰ 0.0007 N ^{0.050 34}
18	COGNITEC-000	¹⁵⁴ 0.0195	¹⁵³ 0.0252	¹²⁸ 0.0297	¹²⁷ 0.0352	¹²⁴ 0.0417	¹⁰⁵ 0.0006 N ^{0.259 94}	¹³⁷ 0.0050	¹⁴⁰ 0.0065	¹²¹ 0.0077	¹²² 0.0097	¹²¹ 0.0122	³⁵ 0.0001 N ^{0.305 120}
19	COGNITEC-001	¹²² 0.0090	¹²⁴ 0.0117	¹¹³ 0.0139	¹¹³ 0.0166	¹¹⁰ 0.0199	⁷⁴ 0.0002 N ^{0.271 101}	¹¹⁵ 0.0030	¹¹⁴ 0.0034	¹⁰² 0.0040	¹⁰² 0.0046	⁹⁴ 0.0054	⁴⁹ 0.0002 N ^{0.207 97}
20	COGNITEC-002	⁸⁸ 0.0048	⁸⁶ 0.0057	⁸⁰ 0.0067	⁷⁸ 0.0079	⁷⁹ 0.0094	⁸⁶ 0.0002 N ^{0.232 78}	¹⁰¹ 0.0024	⁹⁸ 0.0026	⁸⁶ 0.0028	⁸² 0.0030	⁷⁶ 0.0034	⁷⁶ 0.0005 N ^{0.117 70}
21	COGNITEC-003	⁹¹ 0.0053	⁹⁰ 0.0062	⁸³ 0.0072	⁸³ 0.0085	⁸² 0.0100	⁸⁰ 0.0003 N ^{0.222 70}	¹¹² 0.0028	¹⁰⁶ 0.0030	⁹³ 0.0032	⁸⁸ 0.0035	⁸⁰ 0.0037	⁹⁸ 0.0008 N ^{0.097 61}
22	CYBERLINK-000	⁶⁹ 0.0034	⁶⁵ 0.0040	⁶⁶ 0.0046	⁶⁵ 0.0054	⁶² 0.0063	³⁵ 0.0002 N ^{0.209 64}	⁸⁹ 0.0021	⁸⁵ 0.0022	⁷⁴ 0.0023	⁷⁵ 0.0025	⁶⁹ 0.0027	⁸⁴ 0.0006 N ^{0.092 58}
23	CYBERLINK-001	⁶¹ 0.0030	⁵⁹ 0.0035	⁶¹ 0.0042	⁶² 0.0050	⁵⁹ 0.0060	³⁵ 0.0001 N ^{0.243 85}	⁶⁷ 0.0016	⁵⁹ 0.0018	⁵⁰ 0.0018	⁵⁰ 0.0020	⁴⁴ 0.0022	⁶⁹ 0.0004 N ^{0.109 66}
24	CYBERLINK-002	⁵⁰ 0.0024	⁴⁶ 0.0026	⁴² 0.0028	⁴² 0.0031	³⁵ 0.0035	¹⁰³ 0.0005 N ^{0.121 31}	⁸⁵ 0.0020	⁸⁰ 0.0021	⁷³ 0.0021	⁶⁹ 0.0022	⁵⁶ 0.0022	¹¹¹ 0.012 N ^{0.036 23}
25	CYBERLINK-003	¹⁷ 0.0015	¹⁷ 0.0016	¹⁶ 0.0017	¹⁵ 0.0018	¹³ 0.0020	⁸⁸ 0.0003 N ^{0.110 24}	²⁰ 0.0011	¹⁹ 0.0012	¹⁶ 0.0012	¹⁷ 0.0012	¹⁵ 0.0013	⁸¹ 0.0006 N ^{0.047 32}
26	DAHUA-001	⁹² 0.0053	⁹⁴ 0.0067	⁸⁷ 0.0079	⁸⁸ 0.0093	⁸⁶ 0.0112	⁵⁷ 0.0002 N ^{0.256 92}	¹⁰⁹ 0.0027	¹⁰¹ 0.0029	⁹⁶ 0.0031	⁸⁷ 0.0034	⁸² 0.0038	⁷⁹ 0.0005 N ^{0.121 73}
27	DAHUA-002	²⁸ 0.0017	²⁶ 0.0018	²⁴ 0.0021	²¹ 0.0023	¹⁸ 0.0027	⁶² 0.0002 N ^{0.156 41}	⁴¹ 0.0013	³⁴ 0.0013	³¹ 0.0014	²⁸ 0.0014	²³ 0.0015	⁹² 0.0007 N ^{0.043 29}
28	DAHUA-003	⁵ 0.0010	⁷ 0.0012	⁵ 0.0014	⁶ 0.0016	¹¹ 0.0018	¹⁹ 0.0001 N ^{0.199 60}	¹¹ 0.0009	⁹ 0.0009	⁶ 0.0009	⁷ 0.0009	⁶ 0.0009	⁸² 0.0006 N ^{0.027 21}
29	DEEPLINT-001	¹⁴ 0.0014	¹² 0.0014	¹¹ 0.0015	¹¹ 0.0016	¹⁰ 0.0018	⁹⁸ 0.0004 N ^{0.089 19}	³⁹ 0.0013	²⁸ 0.0013	²⁵ 0.0013	²³ 0.0013	¹⁷ 0.0013	¹⁰⁸ 0.010 N ^{0.017 14}
30	DEEPLINT-002	⁶⁸ 0.0033	⁷⁰ 0.0043	⁷¹ 0.0052	⁷² 0.0065	⁷¹ 0.0081	¹⁵ 0.0001 N ^{0.311 125}	³⁴ 0.0012	³⁸ 0.0014	⁴² 0.0015	⁴² 0.0017	⁴¹ 0.0020	⁴³ 0.0001 N ^{0.157 83}
31	DERMALOG-005	¹³⁵ 0.0114	¹³⁵ 0.0149	¹¹⁸ 0.0201	¹²² 0.0289	¹²⁹ 0.0447	⁶ 0.0000 N ^{0.470 134}	¹⁶⁶ 0.0094	¹⁶¹ 0.0122	¹³¹ 0.0171	¹³¹ 0.0254	¹³⁰ 0.0406	⁶ 0.0000 N ^{0.508 133}
32	DERMALOG-006	¹⁰⁷ 0.0075	¹⁰⁴ 0.0081	⁹⁵ 0.0086	⁸⁹ 0.0093	⁸³ 0.0047	¹¹⁸ 0.0017 N ^{0.259 92}	¹⁴⁶ 0.0062	¹³⁹ 0.0063	¹¹⁷ 0.0064	¹⁰⁵ 0.0065	⁹⁹ 0.0068	¹²⁵ 0.0003 N ^{0.028 122}
33	DERMALOG-007	¹¹³ 0.0080	¹¹² 0.0092	⁹⁹ 0.0102	⁹⁹ 0.0118	⁹⁹ 0.0140	¹⁰⁴ 0.0006 N ^{0.190 57}	¹³⁹ 0.0051	¹³³ 0.0054	¹⁰⁸ 0.0056	¹⁰⁰ 0.0058	⁹⁷ 0.0063	¹¹⁹ 0.0020 N ^{0.068 46}
34	DERMALOG-008	⁴⁸ 0.0024	⁵⁰ 0.0029	⁵¹ 0.0034	⁵² 0.0040	⁵¹ 0.0048	³⁰ 0.0001 N ^{0.209 4}	⁵⁷ 0.0015	⁵⁰ 0.0015	⁴⁶ 0.0016	⁴³ 0.0017	³⁷ 0.0019	⁷² 0.0004 N ^{0.004 6}
35	F8-001	¹³³ 0.0113	¹²⁵ 0.0120	¹⁰⁵ 0.0120	¹⁰⁸ 0.0120	⁹¹ 0.0120	¹²⁹ 0.0090 N ^{0.019 4}	¹⁶¹ 0.0098	¹⁵⁴ 0.0099	¹²⁶ 0.0099	¹²² 0.0099	¹¹⁴ 0.0099	¹³⁷ 0.0009 N ^{0.004 6}
36	GORILLA-002	¹⁴⁵ 0.0147	¹⁴⁷ 0.0197	¹²⁴ 0.0238	¹²² 0.0288	¹²¹ 0.0351	⁸³ 0.0003 N ^{0.295 118}	¹¹⁸ 0.0032	¹²² 0.0041	¹⁰⁹ 0.0049	¹⁰⁶ 0.0062	¹⁰⁵ 0.0080	¹⁸ 0.0000 N ^{0.315 123}
37	GORILLA-004	⁸⁹ 0.0048	⁹¹ 0.0063	⁸⁵ 0.0075	⁸⁷ 0.0091	⁸⁶ 0.0114	³⁷ 0.0001 N ^{0.292 116}	⁶⁸ 0.0018	⁶⁵ 0.0018	⁷⁴ 0.0021	⁷⁴ 0.0025	⁷⁰ 0.0029	³⁰ 0.0001 N ^{0.222 100}
38	GORILLA-005	⁵² 0.0026	⁵⁴ 0.0032	⁵⁶ 0.0038	⁵⁷ 0.0046	⁵⁵ 0.0056	¹⁷ 0.0001 N ^{0.291 103}	³² 0.0012	²⁹ 0.0013	³³ 0.0014	³⁸ 0.0016	³⁵ 0.0018	⁵⁶ 0.0002 N ^{0.127 76}
39	HIK-003	¹²³ 0.0091	¹²⁵ 0.0117	¹¹⁴ 0.0140	¹¹⁴ 0.0169	¹¹¹ 0.0203	⁷⁰ 0.0002 N ^{0.274 106}	¹⁰⁰ 0.0024	¹⁰⁵ 0.0030	⁹⁶ 0.0036	⁹⁵ 0.0044	⁹³ 0.0053	²³ 0.0001 N ^{0.278 113}
40	HIK-004	¹⁰⁸	¹⁰⁸ 0.0112	¹⁰² 0.0113	¹¹¹ 0.0134	¹¹¹ 0.0163	⁷² 0.0002 N ^{0.271 104}	¹⁰⁰ 0.0024	¹⁰² 0.0030	⁹⁵ 0.0036	⁹⁷ 0.0042	⁹² 0.0052	²⁹ 0.0001 N ^{0.259 110}
41	HIK-005	⁷³ 0.0036	⁷⁴ 0.0046	⁷³ 0.0053	⁷¹ 0.0065	⁷⁰ 0.0081	²⁹ 0.0001 N ^{0.274 105}	³⁰ 0.0012	⁴⁷ 0.0015	⁴⁵ 0.0016	⁵¹ 0.0019	⁵³ 0.0022	³³ 0.0001 N ^{0.202 95}
42	HR-000	¹⁹ 0.0015	¹³ 0.0015	¹³ 0.0015	¹⁶ 0.0016	⁷ 0.0017	¹⁰⁷ 0.0007 N ^{0.054 9}	⁵³ 0.0014	⁴⁴ 0.0014	³⁴ 0.0014	³⁴ 0.0014	²² 0.0014	¹⁹ 0.0012 N ^{0.012 9}
43	IDEMIA-003	⁹⁴ 0.0054	⁹⁷ 0.0069	⁹² 0.0084	⁹⁴ 0.0101	⁹² 0.0122	⁵⁷ 0.0001 N ^{0.281 112}	⁹⁶ 0.0023	¹⁰⁰ 0.0027	⁸⁷ 0.0031	⁸⁹ 0.0036	⁸⁴ 0.0041	⁴⁴ 0.0002 N ^{0.201 94}
44	IDEMIA-004	⁹⁷ 0.0054	⁹³ 0.0066	⁸⁹ 0.0079	⁹⁷ 0.0097	⁹⁰ 0.0117	⁴¹ 0.0001 N ^{0.270 97}	⁷⁸ 0.0018	⁸¹ 0.0021</				

MISSES AT GIVEN RANK		ENROL MOST RECENT											
FNIR(N, T=0, R)		RANK 1					RANK 50						
#	ALGORITHM	N=0.64M	N=1.6M	N=3.0M	N=6.0M	N=12.0M	aN^b	N=0.64M	N=1.6M	N=3.0M	N=6.0M	N=12.0M	aN^b
73	NEUROTECHNOLOGY-003	¹⁵⁰ 0.0179	¹⁴⁹ 0.0225	¹²⁵ 0.0263	¹²⁴ 0.0306	¹²² 0.0361	¹¹⁰ 0.0007 N ^{0.239 84}	¹³¹ 0.0042	¹³⁴ 0.0057	¹¹⁷ 0.0072	¹²¹ 0.0090	¹²⁰ 0.0112	¹⁹ 0.0000 N ^{0.334 127}
74	NEUROTECHNOLOGY-004	⁸² 0.0046	⁸³ 0.0056	⁷⁹ 0.0064	⁷⁷ 0.0074	⁷⁴ 0.0088	⁷⁵ 0.0002 N ^{0.220 69}	⁹³ 0.0022	⁹² 0.0025	⁸⁵ 0.0028	⁸³ 0.0031	⁷⁶ 0.0034	⁶⁰ 0.0003 N ^{0.154 83}
75	NEUROTECHNOLOGY-005	⁷² 0.0035	⁶⁹ 0.0043	⁶⁸ 0.0049	⁶⁷ 0.0057	⁶⁵ 0.0068	⁵⁹ 0.0002 N ^{0.223 72}	⁹⁰ 0.0021	⁸⁸ 0.0023	⁷⁸ 0.0024	⁷⁷ 0.0025	⁷⁰ 0.0028	⁸⁵ 0.0006 N ^{0.092 59}
76	NEUROTECHNOLOGY-007	⁶⁶ 0.0032	⁶⁴ 0.0039	⁶⁵ 0.0044	⁶⁴ 0.0052	⁶¹ 0.0062	⁵⁰ 0.0002 N ^{0.222 71}	⁸⁶ 0.0020	⁸³ 0.0022	⁷⁶ 0.0023	⁷² 0.0024	⁶⁴ 0.0026	⁹⁴ 0.0007 N ^{0.076 49}
77	NTECHLAB-003	⁸⁶ 0.0046	⁸⁸ 0.0062	⁸⁶ 0.0076	⁹⁰ 0.0094	⁸⁷ 0.0114	²¹ 0.0001 N ^{0.310 124}	⁴² 0.0013	⁵⁵ 0.0016	⁶² 0.0018	⁶⁸ 0.0022	⁶⁵ 0.0026	²⁵ 0.0001 N ^{0.237 102}
78	NTECHLAB-004	⁷⁵ 0.0037	⁷⁸ 0.0048	⁷⁵ 0.0058	⁷⁴ 0.0071	⁷⁵ 0.0085	²³ 0.0001 N ^{0.291 115}	²² 0.0011	³⁵ 0.0013	⁴⁰ 0.0015	⁴¹ 0.0017	⁴⁹ 0.0021	³² 0.0001 N ^{0.198 92}
79	NTECHLAB-005	⁷⁰ 0.0035	⁷⁶ 0.0047	⁷⁶ 0.0058	⁷⁵ 0.0073	⁷⁷ 0.0092	¹³ 0.0000 N ^{0.334 130}	⁸ 0.0008	¹⁷ 0.0011	²¹ 0.0012	³⁶ 0.0015	³⁸ 0.0019	⁵ 0.0000 N ^{0.283 115}
80	NTECHLAB-006	⁶⁰ 0.0030	⁶⁸ 0.0041	⁶⁹ 0.0050	⁶⁹ 0.0062	⁶⁹ 0.0078	¹⁵ 0.0000 N ^{0.326 129}	⁶ 0.0008	¹⁰ 0.0009	¹⁶ 0.0011	²⁰ 0.0013	³¹ 0.0016	¹¹ 0.0000 N ^{0.253 106}
81	NTECHLAB-007	⁴³ 0.0022	⁴⁷ 0.0027	⁴⁷ 0.0031	⁴⁸ 0.0037	⁴⁸ 0.0044	²⁵ 0.0001 N ^{0.245 88}	²¹ 0.0011	²³ 0.0012	²⁵ 0.0013	²⁷ 0.0014	²⁷ 0.0015	⁵⁹ 0.0003 N ^{0.109 67}
82	NTECHLAB-008	¹⁶ 0.0014	²⁰ 0.0017	²⁰ 0.0020	²⁵ 0.0024	¹⁹ 0.0027	¹⁸ 0.0001 N ^{0.224 73}	¹⁶ 0.0010	¹⁶ 0.0010	¹⁵ 0.0011	¹⁵ 0.0011	¹⁵ 0.0012	⁷⁰ 0.0004 N ^{0.065 43}
83	NTECHLAB-009	⁹ 0.0012	⁸ 0.0013	⁷ 0.0014	⁷ 0.0015	⁹ 0.0018	⁵⁶ 0.0002 N ^{0.140 37}	¹³ 0.0009	¹² 0.0009	¹¹ 0.0010	¹¹ 0.0010	⁹ 0.0010	⁸⁰ 0.0005 N ^{0.041 27}
84	PARAVISION-003	⁵⁴ 0.0026	³³ 0.0031	³³ 0.0035	³³ 0.0042	³⁶ 0.0048	⁴⁵ 0.0002 N ^{0.210 65}	⁶⁶ 0.0016	⁶⁵ 0.0017	⁶¹ 0.0018	⁵⁸ 0.0020	⁵⁰ 0.0021	⁷⁵ 0.0005 N ^{0.089 55}
85	PARAVISION-004	² 0.0015	¹⁹ 0.0016	¹⁷ 0.0017	¹⁶ 0.0019	¹⁵ 0.0021	⁸⁹ 0.0003 N ^{0.111 25}	⁴⁰ 0.0013	³¹ 0.0013	²⁹ 0.0013	²⁴ 0.0013	²⁰ 0.0014	¹⁰⁷ 0.0010 N ^{0.020 19}
86	PARAVISION-005	¹⁸ 0.0015	¹⁵ 0.0015	¹⁴ 0.0016	¹⁴ 0.0018	¹⁶ 0.0019	⁹ 0.0004 N ^{0.094 21}	⁴⁴ 0.0013	³³ 0.0013	²⁸ 0.0013	²⁵ 0.0013	¹⁸ 0.0014	¹⁰⁹ 0.0011 N ^{0.015 13}
87	PARAVISION-007	⁷ 0.0011	⁶ 0.0012	⁶ 0.0012	⁵ 0.0013	⁷ 0.0015	⁵⁶ 0.0003 N ^{0.091 20}	¹⁷ 0.0010	¹⁴ 0.0010	¹² 0.0010	¹² 0.0010	¹¹ 0.0011	¹⁰⁰ 0.0008 N ^{0.018 16}
88	PIXELALL-002	⁷⁷ 0.0037	⁷³ 0.0045	⁷⁰ 0.0052	⁷⁰ 0.0062	⁶⁷ 0.0075	⁴³ 0.0002 N ^{0.238 82}	⁷¹ 0.0017	⁷⁶ 0.0019	⁷² 0.0021	⁷³ 0.0024	⁶² 0.0027	⁵³ 0.0002 N ^{0.154 84}
89	PIXELALL-003	³³ 0.0019	³⁴ 0.0021	³⁴ 0.0024	³³ 0.0028	³⁴ 0.0032	⁵⁸ 0.0002 N ^{0.182 56}	⁴⁹ 0.0014	⁴³ 0.0014	³⁷ 0.0014	³⁴ 0.0015	²⁸ 0.0016	⁹⁷ 0.0007 N ^{0.045 30}
90	PIXELALL-004	²⁹ 0.0017	³² 0.0020	³¹ 0.0023	³⁰ 0.0026	²⁹ 0.0030	³⁷ 0.0001 N ^{0.192 58}	⁴³ 0.0013	³⁶ 0.0013	³² 0.0014	³¹ 0.0014	²⁴ 0.0015	⁹¹ 0.0007 N ^{0.046 31}
91	PTAKURATSATU-000	⁵¹ 0.0025	³² 0.0030	³⁴ 0.0036	³¹ 0.0040	²⁸ 0.0040	²⁶ 0.0003 N ^{0.169 48}	³⁹ 0.0015	³⁷ 0.0016	³⁴ 0.0018	³⁷ 0.0020	²² 0.0020	⁷¹ 0.0004 N ^{0.096 60}
92	QUANTASOFT-001	¹⁹² 0.2177	¹⁸⁹ 0.2177	¹⁴¹ 0.2177	¹³⁰ 0.2177	¹³⁶ 0.2177	¹⁹⁵ 0.1116 N ^{0.000 1}	¹⁹⁵ 0.1116	¹⁹¹ 0.1116	¹⁴⁰ 0.1116	¹³² 0.1116	¹³⁶ 0.1116	¹³⁶ 0.1116 N ^{0.000 1}
93	RANKONE-002	¹⁴⁶ 0.0155	¹⁴⁵ 0.0194	¹²² 0.0224	¹²⁰ 0.0262	¹¹⁵ 0.0304	¹⁰⁸ 0.0007 N ^{0.230 76}	¹³⁶ 0.0048	¹³⁸ 0.0060	¹¹⁶ 0.0071	¹¹⁸ 0.0085	¹¹⁷ 0.0102	⁴⁵ 0.0002 N ^{0.254 108}
94	RANKONE-003	¹⁴⁷ 0.0155	¹⁴⁶ 0.0194	¹²¹ 0.0224	¹¹⁹ 0.0262	¹¹⁵ 0.0304	¹⁰⁹ 0.0007 N ^{0.230 75}	¹³⁵ 0.0048	¹³⁷ 0.0060	¹¹⁵ 0.0071	¹¹⁹ 0.0085	¹¹⁵ 0.0102	⁴⁶ 0.0002 N ^{0.254 109}
95	RANKONE-005	¹⁰⁸ 0.0075	¹¹⁴ 0.0094	¹⁰³ 0.0110	¹⁰⁴ 0.0132	¹⁰² 0.0156	⁷⁷ 0.0003 N ^{0.251 91}	¹⁰⁸ 0.0026	¹⁰⁹ 0.0032	⁹⁹ 0.0036	⁹⁷ 0.0043	⁹¹ 0.0050	⁴¹ 0.0001 N ^{0.221 99}
96	RANKONE-007	³⁷ 0.0028	³⁶ 0.0034	³⁵ 0.0038	³⁵ 0.0045	³⁵ 0.0053	⁵⁸ 0.0002 N ^{0.211 66}	⁵⁸ 0.0015	⁵⁹ 0.0017	⁵⁸ 0.0018	⁵³ 0.0019	²⁶ 0.0021	⁶² 0.0003 N ^{0.123 74}
97	RANKONE-009	³⁵ 0.0020	⁴⁰ 0.0024	⁴⁰ 0.0027	⁴³ 0.0032	⁴⁸ 0.0038	²⁸ 0.0001 N ^{0.219 68}	⁴⁷ 0.0013	⁴² 0.0014	³⁸ 0.0015	³⁵ 0.0015	³⁰ 0.0016	⁸³ 0.0006 N ^{0.059 39}
98	RANKONE-010	³⁷ 0.0020	³⁵ 0.0022	³⁵ 0.0025	³⁶ 0.0029	²⁹ 0.0032	⁶⁹ 0.0002 N ^{0.164 47}	⁵⁴ 0.0014	⁴⁵ 0.0015	⁴¹ 0.0015	³⁷ 0.0016	³⁴ 0.0017	⁸⁸ 0.0006 N ^{0.058 38}
99	REALNETWORKS-002	¹⁶⁴ 0.0299	¹⁶⁰ 0.0393	¹³⁴ 0.0470	¹³² 0.0562	¹³⁰ 0.0580	¹¹⁴ 0.0013 N ^{0.236 81}	¹⁴⁰ 0.0054	¹⁴⁷ 0.0076	¹²⁶ 0.0097	¹²⁶ 0.0126	¹²⁴ 0.0132	³¹ 0.0001 N ^{0.320 125}
100	REALNETWORKS-003	¹⁵² 0.0183	¹⁵² 0.0242	¹²⁷ 0.0291	¹²⁶ 0.0352	¹²⁵ 0.0423	⁹⁶ 0.0004 N ^{0.287 114}	¹³⁰ 0.0041	¹³⁰ 0.0054	¹¹² 0.0064	¹¹⁶ 0.0080	¹¹⁶ 0.0101	²⁹ 0.0001 N ^{0.307 121}
101	REALNETWORKS-004	¹⁴⁹ 0.0175	¹⁵⁰ 0.0236	¹²⁶ 0.0284	¹²⁵ 0.0347	¹²⁵ 0.0416	⁹⁰ 0.0003 N ^{0.295 117}	¹²⁷ 0.0040	¹²⁸ 0.0050	¹¹⁰ 0.0061	¹¹⁴ 0.0078	¹¹⁵ 0.0099	²⁹ 0.0001 N ^{0.315 122}
102	REMARKAI-000	⁵⁶ 0.0027	³⁸ 0.0034	³⁸ 0.0040	³⁹ 0.0048	³⁶ 0.0058	²⁷ 0.0001 N ^{0.260 96}	³⁵ 0.0014	³² 0.0015	⁴⁷ 0.0016	⁴⁵ 0.0018	⁴⁵ 0.0020	⁶⁴ 0.0003 N ^{0.108 64}
103	SCANOVATE-000	⁷⁰ 0.0038	⁷⁰ 0.0050	⁷⁷ 0.0059	⁷⁶ 0.0073	⁶⁷ 0.0073	⁵² 0.0002 N ^{0.235 80}	⁵² 0.0014	⁵⁴ 0.0015	⁵² 0.0017	⁶³ 0.0020	⁴⁸ 0.0020	³² 0.0002 N ^{0.142 79}
104	SCANOVATE-001	⁸⁰ 0.0041	⁸² 0.0053	⁷⁸ 0.0064	⁸⁰ 0.0079	⁸¹ 0.0098	²⁵ 0.0001 N ^{0.299 120}	⁴⁸ 0.0013	⁵¹ 0.0015	⁵¹ 0.0017	⁶⁴ 0.0021	⁶³ 0.0024	³⁴ 0.0001 N ^{0.207 96}
105	SENSETIME-000	⁴⁴ 0.0022	³⁸ 0.0023	³⁹ 0.0026	³⁵ 0.0028	³⁴ 0.0032	⁹² 0.0003 N ^{0.135 34}	⁶⁸ 0.0016	⁶⁴ 0.0017	⁵⁷ 0.0018	⁴⁸ 0.0018	⁴⁴ 0.0020	⁹⁶ 0.0007 N ^{0.060 40}
106	SENSETIME-001	⁴² 0.0022	³⁹ 0.0023	³⁸ 0.0025	³⁷ 0.0029	³⁸ 0.0037	⁶⁰ 0.0002 N ^{0.177 54}	⁶⁵ 0.0016	⁵⁸ 0.0016	⁵⁰ 0.0017	⁴⁷ 0.0018	⁶¹ 0.0024	⁶¹ 0.0003 N ^{0.125 75}
107	SENSETIME-002	¹⁴² 0.0136	¹³³ 0.0137	¹¹² 0.0137	¹⁰⁶ 0.0138	⁹⁰ 0.0139	¹³¹ 0.0124 N ^{0.007 2}	¹⁷⁰ 0.0136	¹⁶³ 0.0136	¹³⁰ 0.0136	¹²⁸ 0.0136	¹²⁵ 0.0136	¹³² 0.0135 N ^{0.001 3}
108	SENSETIME-003	⁴ 0.0010	³ 0.0010	³ 0.0010	³ 0.0011	³ 0.0012	⁸⁴ 0.0003 N ^{0.085 18}	¹² 0.0009	¹¹ 0.0009	¹⁰ 0.0009	¹⁰ 0.0010	⁸ 0.0010	⁹ 0.0008 N ^{0.013 11}
109	SENSETIME-004	³ 0.0010	³ 0.0010	³ 0.0010	³ 0.0011	³ 0.0012	⁸⁵ 0.0003 N ^{0.081 15}	⁹ 0.0008	⁷ 0.0009	⁷ 0.0009	⁶ 0.0009	⁵ 0.0009	⁸⁹ 0.0007 N ^{0.018 17}
110	SENSETIME-005	¹ 0.0008	¹ 0.0009	¹ 0.0009	¹ 0.0010	¹ 0.0011	⁷⁸ 0.0003 N ^{0.085 17}	⁷ 0.0008	⁶ 0.0008	⁶ 0.0008	³ 0.0008	¹ 0.0008	¹⁰¹ 0.0008 N ^{0.002 5}
111	SHAMAN-007	¹⁶⁸ 0.0371	¹⁶¹ 0.0396	¹³³ 0.0416									

MISSES OUTSIDE RANK R		RESOURCE USAGE		ENROL MOST RECENT, N = 1.6M						
FNIR(N, T=0, R)		TEMPLATE		FRVT 2018 MUGSHOTS						
#	ALGORITHM	BYTES	MSEC	R=1	R=5	R=10	R=20	R=50	WORK-10	
1	3DIVI-003	³⁵ 512	¹¹² 625	¹⁷⁸ 0.0833	¹⁷³ 0.0444	¹⁷³ 0.0349	¹⁷⁰ 0.0270	¹⁷⁰ 0.0191	¹⁷⁴ 1.447	
2	3DIVI-004	¹⁸⁶ 4096	¹¹⁵ 628	¹⁴⁰ 0.0175	¹³³ 0.0091	¹³¹ 0.0075	¹³⁰ 0.0061	¹²⁶ 0.0049	¹³⁷ 1.092	
3	3DIVI-005	¹⁹⁰ 4096	¹²⁰ 653	¹⁴¹ 0.0176	¹³⁴ 0.0091	¹²⁸ 0.0074	¹²⁹ 0.0061	¹²⁷ 0.0049	¹³⁸ 1.092	
4	3DIVI-006	⁴⁵ 528	¹²¹ 653	¹⁵¹ 0.0240	¹⁵⁸ 0.0171	¹⁶⁸ 0.0160	¹⁶¹ 0.0154	¹⁶⁶ 0.0148	¹⁵⁶ 1.162	
5	ACER-000	³⁶ 512	²⁸ 201	¹²⁰ 0.0106	¹⁰⁶ 0.0051	¹⁰³ 0.0041	¹⁰² 0.0034	⁹⁶ 0.0026	¹⁰⁷ 1.053	
6	ALCHERA-000	¹⁰³ 2048	⁴¹ 263	¹³⁶ 0.0161	¹⁴⁵ 0.0124	¹⁵⁰ 0.0117	¹⁵⁸ 0.0111	¹⁵⁶ 0.0105	¹⁴⁴ 1.116	
7	ALCHERA-001	¹⁰⁵ 2048	⁶ 66	²⁰⁵ 0.9869	²⁰³ 0.9782	²⁰⁵ 0.9735	²⁰³ 0.9679	²⁰² 0.9590	²⁰³ 9.811	
8	ALCHERA-002	¹²⁵ 2048	¹¹ 115	¹⁷⁸ 0.0949	¹⁷⁸ 0.0555	¹⁷⁶ 0.0443	¹⁷⁶ 0.0354	¹⁷² 0.0254	¹⁷⁸ 1.544	
9	ALCHERA-003	¹⁰⁶ 2048	¹⁰² 548	¹¹⁷ 0.0104	¹⁰⁸ 0.0054	¹⁰⁸ 0.0045	¹⁰⁸ 0.0038	¹⁰⁸ 0.0032	¹¹⁰ 1.055	
10	ALLGOVISION-000	¹²⁸ 2048	⁷⁸ 425	¹²⁵ 0.0114	¹²⁸ 0.0084	¹³⁴ 0.0078	¹³⁵ 0.0073	¹⁴¹ 0.0067	¹²⁸ 1.079	
11	ALLGOVISION-001	¹⁰⁰ 2048	¹⁶⁹ 792	¹⁰² 0.0090	¹⁰⁴ 0.0048	¹⁰² 0.0040	¹⁰¹ 0.0033	⁹⁹ 0.0027	¹⁰⁴ 1.048	
12	ANKE-000	¹⁶⁷ 2072	⁸⁰ 431	¹³¹ 0.0132	¹²⁰ 0.0073	¹²⁰ 0.0060	¹²⁰ 0.0050	¹²⁰ 0.0040	¹²⁴ 1.072	
13	ANKE-001	²⁰⁷²	⁴³³	¹²¹ 0.0132	¹²¹ 0.0073	¹²² 0.0061	¹²¹ 0.0050	¹²¹ 0.0040	¹²⁵ 1.073	
14	ANKE-002	¹⁶⁵ 2056	¹¹⁵ 641	⁴⁷ 0.0028	⁴⁹ 0.0020	⁴⁷ 0.0018	⁵⁶ 0.0018	⁶⁰ 0.0017	⁵⁶ 1.019	
15	AWARE-003	¹⁶⁸ 2076	¹⁵⁷ 716	¹⁵⁷ 0.0306	¹⁵⁵ 0.0162	¹⁵⁷ 0.0127	¹⁴⁸ 0.0100	¹⁴⁶ 0.0075	¹⁵⁷ 1.163	
16	AWARE-004	⁹²	¹⁴⁸ 712	¹⁷⁰ 0.0679	¹⁷⁰ 0.0348	¹⁶⁸ 0.0274	¹⁶⁸ 0.0208	¹⁶⁵ 0.0145	¹⁷⁰ 1.354	
17	AWARE-005	¹⁷⁸ 3100	¹⁷⁸ 827	¹⁵⁸ 0.0311	¹⁵⁶ 0.0167	¹⁵⁴ 0.0134	¹⁵¹ 0.0107	¹⁵² 0.0082	¹⁵⁸ 1.167	
18	AWARE-006	³ 124	¹⁷¹ 818	¹⁷⁵ 0.0697	¹⁷² 0.0369	¹⁶⁸ 0.0288	¹⁶⁹ 0.0223	¹⁶⁷ 0.0158	¹⁷² 1.371	
19	AYONIX-000	⁶⁹ 1036	¹ 10	¹⁹⁴ 0.4505	¹⁹⁹ 0.3540	¹⁹⁷ 0.3176	¹⁹⁹ 0.2834	¹⁹⁹ 0.2381	¹⁹⁹ 4.288	
20	AYONIX-001	⁶⁷ 1036	³ 12	¹⁹⁴ 0.3414	¹⁹³ 0.2338	¹⁹³ 0.1977	¹⁹⁴ 0.1652	¹⁹³ 0.1274	¹⁹³ 3.226	
21	AYONIX-002	⁶⁸ 1036	² 11	¹⁹⁴ 0.3414	¹⁹⁴ 0.2338	¹⁹⁵ 0.1977	¹⁹⁵ 0.1652	¹⁹⁴ 0.1274	¹⁹⁴ 3.226	
22	CAMVI-003	⁶⁰ 1024	¹⁴⁵ 707	¹⁶⁷ 0.0520	¹⁷⁷ 0.0517	¹⁸¹ 0.0517	¹⁸¹ 0.0517	¹⁸¹ 0.0517	¹⁷⁶ 1.466	
23	CAMVI-004	⁹⁹ 1024	¹⁵⁴ 718	¹⁶⁷ 0.0468	¹⁷⁵ 0.0465	¹⁷⁷ 0.0465	¹⁷⁸ 0.0464	¹⁸⁰ 0.0464	¹⁷³ 1.419	
24	CAMVI-005	⁸⁷ 1024	¹⁶³ 769	¹⁷⁴ 0.0652	¹⁷⁹ 0.0648	¹⁸³ 0.0648	¹⁸³ 0.0648	¹⁸⁵ 0.0647	¹⁷⁹ 1.584	
25	CIB-000	²⁰¹ 8196	¹²⁷ 674	¹⁸ 0.0015	¹⁸ 0.0013	¹⁷ 0.0012	¹⁹ 0.0012	²⁰ 0.0012	¹⁸ 1.012	
26	COGENT-000	⁴² 525	¹⁰⁵ 551	¹¹⁸ 0.0105	¹³⁹ 0.0096	¹⁴⁴ 0.0095	⁹⁷ 0.0032	⁹¹ 0.0024	¹³⁴ 1.088	
27	COGENT-001	⁴¹ 525	⁵⁵²	¹¹⁸ 0.0105	¹³⁸ 0.0096	¹⁴³ 0.0095	⁹⁶ 0.0032	⁹⁰ 0.0024	¹³⁵ 1.088	
28	COGENT-002	⁷¹ 1043	²⁰⁵ 987	⁶¹ 0.0036	⁵⁷ 0.0022	⁵⁶ 0.0020	⁵⁴ 0.0018	⁵³ 0.0015	⁵⁸ 1.021	
29	COGENT-003	⁷² 1043	²⁰⁵ 960	⁶¹ 0.0038	⁶⁷ 0.0024	⁶⁵ 0.0021	⁶⁷ 0.0019	⁶³ 0.0017	⁶⁴ 1.023	
30	COGENT-004	¹⁵⁷ 2053	²⁰¹ 952	³⁰ 0.0020	³⁰ 0.0016	³² 0.0015	³⁷ 0.0015	⁴⁰ 0.0014	³⁰ 1.015	
31	COGNITEC-000	¹⁴⁰ 2052	¹⁹ 176	¹⁵³ 0.0252	¹⁵¹ 0.0136	¹⁴⁹ 0.0107	¹⁴⁸ 0.0085	¹⁴⁰ 0.0065	¹⁵² 1.136	
32	COGNITEC-001	¹⁴⁰ 2052	²⁷ 202	¹²⁵ 0.0117	¹¹⁴ 0.0062	¹¹⁴ 0.0051	¹¹⁶ 0.0042	¹¹⁴ 0.0034	¹¹⁴ 1.062	
33	COGNITEC-002	¹⁴⁸ 2052	³² 227	⁸⁷ 0.0057	⁸⁷ 0.0037	⁸⁸ 0.0032	⁸⁹ 0.0029	⁹⁸ 0.0026	⁸⁷ 1.035	
34	COGNITEC-003	¹⁴⁷ 2052	⁵¹ 297	⁹⁰ 0.0062	⁹⁴ 0.0040	⁹⁶ 0.0036	¹⁰⁰ 0.0033	¹⁰⁶ 0.0030	⁹² 1.039	
35	CYBERLINK-000	¹⁵⁰ 2052	¹⁴⁰ 699	⁶⁶ 0.0040	⁷⁶ 0.0028	⁸⁰ 0.0026	⁸³ 0.0024	⁸⁵ 0.0022	⁷⁵ 1.027	
36	CYBERLINK-001	¹⁵⁰ 2052	⁸² 433	⁵⁹ 0.0035	⁶³ 0.0023	⁶² 0.0021	⁵⁸ 0.0018	⁶⁷ 0.0017	⁶⁰ 1.022	
37	CYBERLINK-002	²⁰⁰ 4140	¹⁶⁰ 738	⁴⁶ 0.0026	⁵⁹ 0.0023	⁷⁰ 0.0022	⁷⁶ 0.0021	⁸⁰ 0.0021	⁵⁶ 1.021	
38	CYBERLINK-003	²⁰² 4140	¹³⁸ 696	¹⁷ 0.0016	¹⁷ 0.0013	¹⁸ 0.0013	¹⁸ 0.0012	¹⁹ 0.0012	¹⁹ 1.012	
39	DAHUA-000	¹⁵⁸ 2048	⁶⁷ 378	¹¹⁷ 0.0093	¹¹⁷ 0.0066	¹²¹ 0.0061	¹²² 0.0057	¹³¹ 0.0054	¹¹⁵ 1.062	
40	DAHUA-001	¹²⁵ 2048	⁶³ 371	⁹⁸ 0.0067	⁹⁵ 0.0040	⁹⁵ 0.0036	⁹⁹ 0.0033	¹⁰¹ 0.0029	⁹⁵ 1.040	
41	DAHUA-002	¹¹⁵ 2048	¹³⁹ 699	²⁶ 0.0018	²⁸ 0.0015	³⁰ 0.0014	³³ 0.0014	³⁴ 0.0013	²⁸ 1.014	
42	DAHUA-003	¹⁰¹ 2048	¹⁵⁷ 725	⁷ 0.0012	⁶ 0.0010	⁸ 0.0009	⁹ 0.0009	⁹ 0.0009	⁸ 1.009	
43	DEEPLINT-001	¹⁸³ 4096	¹³¹ 687	¹¹ 0.0014	²⁰ 0.0014	²⁵ 0.0013	²⁵ 0.0013	²⁵ 0.0013	²⁰ 1.012	
44	DEESEA-001	¹⁴² 2048	¹⁶⁷ 780	⁷⁷ 0.0043	⁵⁸ 0.0022	⁷⁷ 0.0018	⁴⁴ 0.0016	³⁸ 0.0014	⁶¹ 1.022	
45	DERMALOG-003	⁴ 128	³² 211	¹⁸³ 0.1259	¹⁸² 0.0744	¹⁸¹ 0.0603	¹⁸⁰ 0.0480	¹⁷⁹ 0.0347	¹⁸² 1.731	
46	DERMALOG-004	⁶ 128	³⁰ 208	¹⁸² 0.1251	¹⁸¹ 0.0739	¹⁸⁰ 0.0598	¹⁷⁹ 0.0475	¹⁷⁸ 0.0343	¹⁸¹ 1.727	
47	DERMALOG-005	⁵ 128	⁵⁸ 532	¹³⁵ 0.0149	¹⁴⁸ 0.0129	¹⁵¹ 0.0125	¹⁵⁷ 0.0123	¹⁶¹ 0.0122	¹⁴⁵ 1.118	
48	DERMALOG-006	²⁰ 256	⁹⁸ 514	¹⁰⁴ 0.0081	¹¹⁹ 0.0069	¹²³ 0.0066	¹³¹ 0.0065	¹³⁹ 0.0063	¹¹⁷ 1.063	
49	DERMALOG-007	⁷ 128	⁷⁶ 413	¹¹² 0.0092	¹¹⁸ 0.0066	¹¹⁹ 0.0060	¹²⁶ 0.0057	¹³³ 0.0054	¹¹⁶ 1.062	
50	DERMALOG-008	⁴⁰ 512	⁶⁸ 370	⁵⁸ 0.0029	⁴⁵ 0.0020	⁴⁶ 0.0018	⁴⁶ 0.0017	⁵⁰ 0.0015	⁴⁵ 1.019	
51	EYDEA-003	⁷⁰ 1036	⁶⁸ 385	¹⁷⁷ 0.0800	¹⁷⁴ 0.0451	¹⁷⁴ 0.0362	¹⁷¹ 0.0289	¹⁷¹ 0.0211	¹⁷⁵ 1.448	
52	F8-001	¹²⁷ 2048	¹⁸⁴ 851	¹²⁸ 0.0120	¹⁴⁰ 0.0105	¹⁴⁷ 0.0102	¹⁵⁰ 0.0100	¹⁵⁴ 0.0099	¹⁴⁰ 1.096	
53	GLORY-000	²⁶ 418	¹⁵ 160	¹⁸⁹ 0.1781	¹⁸⁹ 0.1391	¹⁸⁸ 0.1266	¹⁸⁸ 0.1154	¹⁸⁹ 0.1007	¹⁸⁸ 2.298	
54	GLORY-001	⁹⁰ 1726	⁷¹ 405	¹⁸⁴ 0.1268	¹⁸⁴ 0.0967	¹⁸⁴ 0.0869	¹⁸⁵ 0.0778	¹⁸⁶ 0.0673	¹⁸⁴ 1.903	
55	GORILLA-001	¹⁰⁹ 2156	¹⁷ 169	¹⁶⁷ 0.0603	¹⁶⁵ 0.0304	¹⁶⁵ 0.0230	¹⁶⁸ 0.0174	¹⁵⁸ 0.0117	¹⁶⁸ 1.309	
56	GORILLA-002	⁷⁴ 1132	⁵⁹ 341	¹⁴⁷ 0.0197	¹³⁵ 0.0092	¹²⁶ 0.0070	¹²³ 0.0054	¹²² 0.0041	¹³⁹ 1.096	
57	GORILLA-003	¹⁷⁰ 2156	¹⁰⁸ 563	¹⁵⁹ 0.0361	¹⁵³ 0.0146	¹⁴⁵ 0.0106	¹⁴² 0.0078	¹³² 0.0054	¹⁵⁵ 1.158	
58	GORILLA-004	¹⁷¹ 2192	⁷⁰ 395	⁹¹ 0.0063	⁸⁴ 0.0032	⁸¹ 0.0026	⁷⁹ 0.0023	⁶⁸ 0.0018	⁸⁴ 1.033	
59	GORILLA-005	²⁰³ 6288	⁸⁹ 483	⁵⁴ 0.0032	⁴¹ 0.0019	⁴¹ 0.0017	³⁸ 0.0015	²⁹ 0.0013	⁴⁷ 1.018	
60	HIK-003	⁸⁰ 1408	¹¹⁴ 633	¹²⁵ 0.0117	¹¹³ 0.0060	¹¹² 0.0048	¹¹² 0.0039	¹⁰⁵ 0.0030	¹¹³ 1.061	
61	HIK-004	⁷⁵ 1152	⁹² 510	¹²² 0.0113	¹¹¹ 0.0059	¹¹¹ 0.0047	¹⁰⁶ 0.0037	¹⁰² 0.0030	¹¹² 1.060	
62	HIK-005	⁷⁹ 1408	¹¹¹ 619	⁷⁶ 0.0046	⁶⁹ 0.0025	⁵⁷ 0.0020	⁴⁹ 0.0017	⁴⁷ 0.0015	⁶⁹ 1.025	
63	HIK-006	⁷⁸ 1408	¹⁰⁸ 610	⁷⁶ 0.0046	⁶⁸ 0.0025	⁵⁸ 0.0020	⁵⁰ 0.0017	⁴⁶ 0.0015	⁷⁰ 1.025	
64	HR-000	¹³⁷ 2048	¹⁹⁴ 908	¹⁵ 0.0015	²⁶ 0.0014	²⁸ 0.0014	³⁴ 0.0014	⁴¹ 0.0014	²⁴ 1.013	
65	IDEMIA-003	⁴³ 528	¹³⁸ 689	⁹⁷ 0.0069	¹⁰⁰ 0.0045	¹⁰⁰ 0.0039	¹⁰³ 0.0034	¹⁰⁰ 0.0027	⁹⁸ 1.043	
66	IDEMIA-004	⁴⁴ 528	¹²⁵ 669	⁹³ 0.0066	⁹¹ 0.0038	⁸⁹ 0.0032	⁸⁸ 0.0027	⁸¹ 0.0021	⁸⁹ 1.038	
67	IDEMIA-005	²⁶ 352	⁶⁵ 374	¹⁰³ 0.0081	⁹⁸ 0.0044	⁹⁷ 0.0036	⁹⁸ 0.0032	¹⁰³ 0.0030	¹⁰⁰ 1.044	
68	IDEMIA-006	²⁷ 352	⁶⁴ 373	¹¹² 0.0096	¹⁰⁷ 0.0052	¹⁰⁵ 0.0042	¹¹¹ 0.0039	¹¹⁷ 0.0037	¹⁰⁸ 1.052	
69	IDEMIA-007	⁵⁴ 860	¹⁷⁸ 807	⁴⁷ 0.0026	³¹ 0.0016	²⁷ 0.0014	²² 0.0013	²² 0.0012	³³ 1.015	
70	IMAGUS-002	³² 512	⁷ 76	¹⁹⁰ 0.2203	¹⁸⁸ 0.1342	¹⁸⁷ 0.1090	¹⁸⁶ 0.0871	¹⁸⁴ 0.0632	¹⁸⁹ 2.308	
71	IMAGUS-003	³¹ 512	⁵ 57	¹⁹⁰ 0.3559</						

MISSES OUTSIDE RANK R		RESOURCE USAGE		ENROL MOST RECENT, N = 1.6M						
FNIR(N, T=0, R)		TEMPLATE		FRVT 2018 MUGSHOTS						
#	ALGORITHM	BYTES	MSEC	R=1	R=5	R=10	R=20	R=50	WORK-10	
73	IMPERIAL-000	¹¹¹ 2048	¹²⁵ 654	⁴² 0.0024	⁴³ 0.0019	⁴⁸ 0.0018	⁵⁵ 0.0018	⁶² 0.0017	⁴³ 1.018	
74	INCODE-000	⁶³ 1024	²⁴ 190	¹⁶⁸ 0.0489	¹⁶⁴ 0.0261	¹⁶⁴ 0.0204	¹⁶² 0.0160	¹⁵⁹ 0.0117	¹⁶⁴ 1.262	
75	INCODE-001	¹³¹ 2048	¹³⁴ 690	¹³⁸ 0.0166	¹²⁹ 0.0084	¹²⁵ 0.0067	¹²⁴ 0.0055	¹²⁴ 0.0043	¹³⁰ 1.086	
76	INCODE-002	⁹⁸ 2048	⁴² 291	¹⁴² 0.0178	¹³² 0.0090	¹²⁷ 0.0070	¹²⁵ 0.0056	¹²⁵ 0.0043	¹³⁶ 1.092	
77	INCODE-003	¹²⁴ 2048	¹⁴² 704	¹³⁹ 0.0129	¹¹⁶ 0.0064	¹¹⁵ 0.0051	¹¹⁰ 0.0040	¹⁰⁷ 0.0031	¹¹⁹ 1.066	
78	INCODE-004	¹³⁴ 2048	⁹¹ 508	⁶⁰ 0.0035	⁶⁴ 0.0024	⁶⁶ 0.0021	⁷⁰ 0.0020	⁷¹ 0.0019	⁶² 1.023	
79	INNOVATRIS-002	⁴⁷ 530	³⁵ 255	¹⁶⁸ 0.0451	¹⁶⁸ 0.0342	¹⁷⁶ 0.0322	¹⁷² 0.0308	¹⁹⁴ 0.0297	¹⁶⁹ 1.321	
80	INNOVATRIS-003	⁴⁶ 530	³⁹ 255	¹⁵⁴ 0.0263	¹⁴⁶ 0.0126	¹⁴² 0.0095	¹³⁷ 0.0074	¹²⁹ 0.0053	¹⁴⁹ 1.129	
81	INNOVATRIS-004	⁷³ 1076	⁷⁴ 406	¹²⁹ 0.0123	¹¹⁵ 0.0063	¹¹³ 0.0050	¹¹⁵ 0.0040	¹¹⁰ 0.0032	¹¹⁸ 1.064	
82	INNOVATRIS-005	⁴⁸ 538	¹⁸² 842	⁴³ 0.0024	³⁹ 0.0018	⁴⁰ 0.0017	⁴³ 0.0016	⁴⁴ 0.0014	³⁹ 1.017	
83	INNOVATRIS-006	⁵⁰ 538	¹⁷² 822	⁴⁴ 0.0025	⁴⁴ 0.0019	⁴⁴ 0.0018	⁴⁷ 0.0017	⁵⁶ 0.0016	⁴² 1.018	
84	INTSYSMSU-000	¹⁴¹ 2048	¹²⁸ 675	¹⁸⁵ 0.1457	¹⁸⁷ 0.1320	¹⁹⁸ 0.1272	¹⁹⁰ 0.1225	¹⁹² 0.1163	¹⁸⁷ 2.203	
85	IREX-000	¹⁷⁷ 3080	²⁰⁵ 2379	⁷¹ 0.0044	⁹⁶ 0.0043	¹⁰⁷ 0.0043	¹¹⁷ 0.0043	¹²⁵ 0.0043	⁹⁴ 1.039	
86	ISYSTEMS-002	¹⁰⁷ 2048	⁵⁶ 316	⁹² 0.0064	⁹⁷ 0.0043	¹⁰⁴ 0.0039	¹⁰⁵ 0.0037	¹¹⁵ 0.0034	⁹⁷ 1.041	
87	ISYSTEMS-003	¹¹² 2048	¹⁸¹ 856	⁸¹ 0.0052	⁹² 0.0039	⁹⁸ 0.0036	¹⁰⁴ 0.0034	¹¹¹ 0.0033	⁸⁸ 1.037	
88	KEDACOM-001	²⁴ 292	⁹⁸ 537	¹⁰⁰ 0.0077	¹²² 0.0074	¹²⁸ 0.0073	¹³⁴ 0.0072	¹⁴² 0.0072	¹²² 1.067	
89	KNERON-000	¹⁰⁹ 2048	⁹⁸ 530	⁸⁷ 0.0059	¹¹² 0.0059	¹¹⁸ 0.0059	¹²⁸ 0.0059	¹³⁵ 0.0059	¹⁰⁸ 1.053	
90	LOOKMAN-003	²⁷ 292	⁶⁸ 342	¹⁰⁸ 0.0088	¹²⁵ 0.0078	¹³² 0.0076	¹³⁹ 0.0075	¹⁴⁵ 0.0074	¹²² 1.071	
91	LOOKMAN-004	⁸² 548	³² 325	¹¹⁰ 0.0091	¹²⁶ 0.0079	¹³² 0.0076	¹³⁸ 0.0075	¹⁴⁴ 0.0073	¹²³ 1.072	
92	LOOKMAN-005	⁵¹ 548	⁹³ 514	¹⁰² 0.0080	¹²⁴ 0.0075	¹³⁰ 0.0074	¹³⁶ 0.0073	¹⁴³ 0.0072	¹²¹ 1.068	
93	MEGVII-001	¹⁸⁷ 4096	¹¹⁸ 652	¹²⁸ 0.0118	¹³⁶ 0.0093	¹³⁸ 0.0087	¹⁴⁶ 0.0084	¹⁵¹ 0.0080	¹³¹ 1.086	
94	MEGVII-002	¹⁹¹ 4096	¹²² 656	¹²⁷ 0.0118	¹³⁷ 0.0093	¹³⁸ 0.0088	¹⁴⁶ 0.0084	¹⁵⁰ 0.0080	¹³² 1.087	
95	MICROFOCUS-003	²¹ 256	⁴⁴ 269	²⁰¹ 0.5942	²⁰¹ 0.4692	²⁰¹ 0.4204	²⁰¹ 0.3724	²⁰¹ 0.3095	²⁰¹ 5.361	
96	MICROFOCUS-004	¹⁷ 256	⁴² 270	²⁰³ 0.5763	²⁰³ 0.4519	²⁰³ 0.4026	²⁰³ 0.3560	²⁰³ 0.2957	²⁰³ 5.199	
97	MICROFOCUS-005	¹⁷ 256	⁴² 266	¹⁹⁶ 0.4242	¹⁹⁶ 0.3028	¹⁹⁶ 0.2606	¹⁹⁶ 0.2209	¹⁹⁷ 0.1724	¹⁹⁶ 3.861	
98	MICROFOCUS-006	¹⁶ 256	⁴² 265	¹⁹⁷ 0.4268	¹⁹⁷ 0.3049	¹⁹⁷ 0.2623	¹⁹⁸ 0.2233	¹⁹⁸ 0.1746	¹⁹⁷ 3.880	
99	MICROSOFT-003	⁶¹ 1024	⁷⁴ 404	¹⁸ 0.0016	⁹ 0.0010	⁸ 0.0009	³ 0.0008	³ 0.0006	⁸ 1.009	
100	MICROSOFT-004	¹²⁶ 2048	¹⁶⁵ 773	¹⁴ 0.0015	⁵ 0.0009	⁵ 0.0008	¹ 0.0007	¹ 0.0006	⁷ 1.009	
101	MICROSOFT-005	⁵⁸ 1024	¹²⁸ 673	²⁷ 0.0019	⁷ 0.0010	⁷ 0.0008	² 0.0008	³ 0.0006	¹¹ 1.010	
102	MICROSOFT-006	⁶² 1024	¹³⁸ 695	²⁹ 0.0020	¹³ 0.0011	¹⁰ 0.0010	⁴ 0.0008	⁴ 0.0007	¹³ 1.011	
103	NEC-000	¹⁷⁶ 2592	⁸ 82	¹³⁹ 0.0170	¹³¹ 0.0086	¹²⁴ 0.0066	¹²² 0.0052	¹¹⁹ 0.0038	¹³³ 1.087	
104	NEC-001	¹⁷⁵ 2592	⁹ 88	¹⁴⁸ 0.0209	¹⁵² 0.0141	¹⁵³ 0.0128	¹⁵⁶ 0.0119	¹⁵⁷ 0.0113	¹⁵¹ 1.135	
105	NEC-002	⁸⁸ 1616	¹¹⁸ 653	⁴ 0.0010	² 0.0009	⁴ 0.0008	⁶ 0.0008	⁵ 0.0008	² 1.008	
106	NEC-003	⁸⁹ 1712	¹³³ 690	¹⁰ 0.0014	¹⁶ 0.0012	¹⁶ 0.0012	²⁰ 0.0012	²¹ 0.0012	¹⁴ 1.011	
107	NEUROTECHNOLOGY-003	¹¹⁷ 2048	¹⁰³ 547	¹⁴⁰ 0.0225	¹⁴⁷ 0.0126	¹⁴⁸ 0.0100	¹⁴³ 0.0078	¹³⁴ 0.0057	¹⁴⁸ 1.125	
108	NEUROTECHNOLOGY-004	¹²⁰ 2048	¹⁰⁵ 543	⁸³ 0.0056	⁸⁶ 0.0036	⁹² 0.0032	⁹³ 0.0029	⁹² 0.0025	⁸⁶ 1.035	
109	NEUROTECHNOLOGY-005	¹⁸ 256	⁷⁵ 412	⁶⁹ 0.0043	⁷⁸ 0.0029	⁸² 0.0027	⁸² 0.0024	⁸⁸ 0.0023	⁷⁸ 1.028	
110	NEUROTECHNOLOGY-006	¹⁴ 256	¹⁶¹ 746	¹⁴³ 0.0180	¹²⁷ 0.0079	¹¹⁷ 0.0059	¹¹⁸ 0.0046	¹¹² 0.0033	¹²⁹ 1.083	
111	NEUROTECHNOLOGY-007	¹⁷ 256	¹⁸ 169	⁶⁴ 0.0039	⁷³ 0.0027	⁷⁶ 0.0025	⁸⁰ 0.0023	⁸³ 0.0022	⁷¹ 1.026	
112	NEWLAND-002	¹¹⁸ 2048	¹⁸¹ 868	¹⁷⁶ 0.0786	¹⁷⁶ 0.0480	¹⁷⁸ 0.0397	¹⁷⁵ 0.0332	¹⁷³ 0.0263	¹⁷⁷ 1.468	
113	NOBLIS-001	¹¹⁹ 2048	³¹ 211	¹⁹² 0.2492	¹⁹² 0.1772	¹⁹² 0.1542	¹⁹² 0.1339	¹⁹⁰ 0.1112	¹⁹² 2.679	
114	NOBLIS-002	²⁰¹ 6144	⁹² 535	¹⁸² 0.1794	¹⁸⁵ 0.1108	¹⁸⁵ 0.0903	¹⁸⁴ 0.0722	¹⁸³ 0.0535	¹⁸⁵ 2.077	
115	NTECHLAB-003	¹⁸⁰ 3484	¹⁷⁷ 831	⁸⁸ 0.0062	⁸⁰ 0.0029	⁷⁶ 0.0023	⁶⁸ 0.0019	⁵⁵ 0.0016	⁸³ 1.030	
116	NTECHLAB-004	¹⁸¹ 3484	¹⁹⁹ 929	⁷⁸ 0.0048	⁶¹ 0.0023	⁵⁸ 0.0019	⁴⁵ 0.0016	³⁵ 0.0013	⁶⁷ 1.024	
117	NTECHLAB-005	⁹³ 1940	¹⁵³ 717	⁷⁶ 0.0047	⁵⁶ 0.0022	⁴³ 0.0017	²⁷ 0.0013	¹⁷ 0.0011	⁶³ 1.023	
118	NTECHLAB-006	⁹⁴ 1940	¹⁸¹ 841	⁶⁸ 0.0041	⁴² 0.0019	³⁴ 0.0015	¹⁷ 0.0012	¹⁰ 0.0009	⁵² 1.019	
119	NTECHLAB-007	¹⁷⁹ 3348	¹⁸¹ 834	⁴⁷ 0.0027	³⁵ 0.0017	²⁹ 0.0014	³⁰ 0.0013	²³ 0.0012	³⁶ 1.016	
120	NTECHLAB-008	⁷⁷ 1300	¹⁰⁵ 562	²⁹ 0.0017	¹⁴ 0.0012	¹⁵ 0.0012	¹⁵ 0.0011	¹⁶ 0.0010	¹⁵ 1.012	
121	NTECHLAB-009	⁷⁶ 1300	¹⁹² 900	⁸ 0.0013	¹¹ 0.0011	¹¹ 0.0010	¹¹ 0.0010	¹² 0.0009	¹² 1.010	
122	PARAVISION-000	¹⁰⁴ 2048	⁸¹ 438	¹⁴⁴ 0.0188	¹⁵⁷ 0.0171	¹⁶¹ 0.0167	¹⁶⁴ 0.0165	¹⁶⁹ 0.0164	¹⁵⁴ 1.156	
123	PARAVISION-001	¹⁴⁴ 2048	¹⁰⁷ 590	⁶² 0.0038	⁶⁶ 0.0024	⁶⁷ 0.0022	⁷³ 0.0020	⁷² 0.0019	⁶⁵ 1.023	
124	PARAVISION-002	¹²¹ 2048	⁶⁶ 377	⁶⁷ 0.0040	⁷⁰ 0.0025	⁷³ 0.0022	⁷⁵ 0.0021	⁷³ 0.0019	⁶⁸ 1.025	
125	PARAVISION-003	¹³⁰ 2048	¹⁵⁷ 735	⁵¹ 0.0031	⁵⁵ 0.0022	⁶¹ 0.0020	⁶⁴ 0.0019	⁶⁵ 0.0017	⁵⁵ 1.021	
126	PARAVISION-004	¹⁸⁴ 4096	¹⁵⁸ 720	¹⁹ 0.0016	²² 0.0014	²⁷ 0.0013	²⁸ 0.0013	³¹ 0.0013	²² 1.013	
127	PARAVISION-005	¹⁸⁹ 4096	¹⁸⁸ 858	¹⁵ 0.0015	²¹ 0.0014	²⁵ 0.0013	²⁹ 0.0013	³³ 0.0013	²¹ 1.013	
128	PARAVISION-007	¹⁸⁵ 4096	¹⁴³ 706	⁶ 0.0012	¹² 0.0011	¹³ 0.0010	¹³ 0.0010	¹⁴ 0.0010	¹⁰ 1.010	
129	PIXELALL-002	¹⁷² 2560	²⁸ 198	⁷³ 0.0045	⁷⁹ 0.0029	⁷⁵ 0.0025	⁷⁸ 0.0022	⁷⁶ 0.0019	⁷⁹ 1.028	
130	PIXELALL-003	¹⁷³ 2560	¹⁵⁸ 719	³⁴ 0.0021	³³ 0.0016	³⁶ 0.0015	³⁶ 0.0014	⁴³ 0.0014	³² 1.015	
131	PIXELALL-004	¹⁷⁴ 2560	⁸⁵ 453	³² 0.0020	²⁹ 0.0015	³¹ 0.0015	³⁵ 0.0014	³⁶ 0.0013	²⁹ 1.014	
132	PTAKURATSATU-000	⁴⁰ 538	¹⁹⁵ 910	⁵² 0.0030	⁵⁴ 0.0021	⁵⁶ 0.0019	⁵² 0.0018	⁵⁷ 0.0016	⁵³ 1.020	
133	QUANTASOF-001	¹²⁹ 2048	⁷¹ 396	¹⁸⁶ 0.2177	¹⁹¹ 0.1643	¹⁹¹ 0.1468	¹⁹¹ 0.1312	¹⁹¹ 0.1116	¹⁹¹ 2.539	
134	RANKONE-002	⁸ 133	¹² 113	¹⁴³ 0.0194	¹⁴² 0.0112	¹⁴¹ 0.0093	¹⁴¹ 0.0077	¹³⁸ 0.0060	¹⁴¹ 1.111	
135	RANKONE-003	⁸ 133	¹² 114	¹⁴⁶ 0.0194	¹⁴¹ 0.0112	¹⁴⁰ 0.0093	¹⁴⁰ 0.0077	¹³⁷ 0.0060	¹⁴² 1.111	
136	RANKONE-004	¹⁸⁵ 436	¹⁶³ 0.0415	¹⁶³ 0.0226	¹⁶² 0.0177	¹⁵⁹ 0.0141	¹⁵⁵ 0.0102	¹⁶³ 1.225		
137	RANKONE-005	¹⁰ 133	¹⁰ 94	¹¹⁴ 0.0094	¹⁰⁹ 0.0054	¹⁰⁸ 0.0046	¹¹² 0.0039	¹⁰⁹ 0.0032	¹⁰⁹ 1.054	
138	RANKONE-006	¹¹ 165	⁴⁰ 261	⁸⁰ 0.0050	⁸³ 0.0030	⁸³ 0.0027	⁸¹ 0.0024	⁷⁶ 0.0021	⁸² 1.030	
139	RANKONE-007	¹² 165	⁴⁰ 278	⁵⁶ 0.0034	⁶² 0.0023	⁶⁴ 0.0021	⁶¹ 0.0018	⁵⁹ 0.0017	⁵⁹ 1.022	
140	RANKONE-009	²² 260	²⁵ 191	⁴⁰ 0.0024	³⁴ 0.0016	³⁷ 0.0015	³⁹ 0.0015	⁴² 0.0014	³⁴ 1.015	
141	RANKONE-010	²² 261	²⁷ 200	³⁵ 0.0022	³⁷ 0.0018	³⁷ 0.0016	⁴² 0.0015	⁴⁵ 0.0015	³⁷ 1.016	
142	REALNETWORKS-000	¹⁹² 4100	³⁶ 244	¹⁶¹ 0.0402	¹⁶¹ 0.0195	¹⁵⁹ 0.0149	¹⁵³ 0.0111	¹⁴⁸ 0.0077	¹⁶² 1.201	
143	REALNETWORKS-001	¹⁹⁷ 4104								

MISSES OUTSIDE RANK R		RESOURCE USAGE		ENROL MOST RECENT, N = 1.6M						
FNIR(N, T=0, R)		TEMPLATE		FRVT 2018 MUGSHOTS						
#	ALGORITHM	BYTES	MSEC	R=1	R=5	R=10	R=20	R=50	WORK-10	
145	REALNETWORKS-003	⁹² 1848	²⁰ 178	¹⁵² 0.0242	¹⁴⁴ 0.0117	¹³⁹ 0.0090	¹³⁵ 0.0070	¹³⁰ 0.0054	¹⁴⁶ 1.120	
146	REALNETWORKS-004	⁹¹ 1848	²¹ 185	¹⁵⁰ 0.0236	¹⁴³ 0.0112	¹³⁷ 0.0087	¹³² 0.0068	¹²⁸ 0.0050	¹⁴³ 1.116	
147	REMARKAI-000	¹¹⁰ 2048	¹³⁵ 691	⁵⁸ 0.0034	⁵³ 0.0021	⁵⁰ 0.0019	⁴⁸ 0.0017	⁵² 0.0015	⁵⁴ 1.020	
148	REMARKAI-000	¹³² 2048	¹⁰⁹ 615	¹⁰⁷ 0.0086	⁹⁹ 0.0044	⁹⁴ 0.0036	⁹² 0.0031	⁹³ 0.0025	¹⁰¹ 1.045	
149	REMARKAI-002	¹³⁹ 2048	⁸³ 434	¹⁰⁸ 0.0081	⁹³ 0.0040	⁸⁷ 0.0031	⁸⁶ 0.0026	⁷⁹ 0.0021	⁹⁰ 1.041	
150	SCANOVATE-000	¹²² 2048	¹⁴⁹ 712	⁷⁹ 0.0050	⁷² 0.0026	⁶⁹ 0.0022	⁵⁹ 0.0018	⁵⁴ 0.0015	⁷⁴ 1.026	
151	SCANOVATE-001	⁹⁶ 2048	¹²⁸ 675	⁸² 0.0053	⁷⁴ 0.0027	⁷² 0.0022	⁶⁰ 0.0018	⁵¹ 0.0015	⁷² 1.028	
152	SENSETIME-000	¹⁹⁴ 4104	¹⁵¹ 715	³⁸ 0.0023	⁵⁰ 0.0020	⁵³ 0.0019	⁵⁷ 0.0018	⁶⁴ 0.0017	⁴⁵ 1.018	
153	SENSETIME-001	¹⁹³ 4104	¹²⁵ 656	³⁹ 0.0023	⁴⁷ 0.0020	⁵¹ 0.0019	⁵¹ 0.0017	³⁸ 0.0016	⁴⁴ 1.018	
154	SENSETIME-002	¹⁵⁹ 2056	¹¹⁷ 650	¹³³ 0.0137	¹⁵⁰ 0.0136	¹⁵⁵ 0.0136	¹⁵⁸ 0.0136	¹⁶³ 0.0136	¹⁴⁷ 1.122	
155	SENSETIME-003	¹⁵⁵ 2056	²⁰⁰ 940	² 0.0010	⁵ 0.0010	⁹ 0.0010	¹⁰ 0.0009	¹¹ 0.0009	⁴ 1.009	
156	SENSETIME-004	⁶⁵ 1032	¹⁴⁷ 710	² 0.0010	³ 0.0009	⁶ 0.0009	⁷ 0.0009	⁷ 0.0009	³ 1.008	
157	SENSETIME-005	⁶⁵ 1032	²⁰⁴ 1007	¹ 0.0009	¹ 0.0008	² 0.0008	³ 0.0008	⁶ 0.0008	¹ 1.008	
158	SHAMAN-003	¹¹⁴ 2048	¹⁴¹ 704	¹⁸⁰ 0.1243	¹⁸³ 0.0823	¹⁸³ 0.0708	¹⁸² 0.0616	¹⁸² 0.0518	¹⁸³ 1.789	
159	SHAMAN-004	¹³⁵ 2048	¹¹⁶ 642	¹⁹¹ 0.2221	¹⁹⁰ 0.1473	¹⁸⁸ 0.1241	¹⁸⁸ 0.1049	¹⁸⁷ 0.0825	¹⁹⁰ 2.411	
160	SHAMAN-006	¹¹⁴ 2048	¹⁴⁴ 706	¹⁶² 0.0398	¹⁶⁹ 0.0344	¹⁷² 0.0332	¹⁷⁴ 0.0323	¹⁷⁷ 0.0315	¹⁶⁸ 1.316	
161	SHAMAN-007	¹⁴⁰ 2048	¹⁴⁶ 709	¹⁶¹ 0.0396	¹⁶⁷ 0.0342	¹⁷¹ 0.0331	¹⁷³ 0.0322	¹⁷⁶ 0.0314	¹⁶⁶ 1.315	
162	SIAT-001	¹⁴⁵ 2052	¹⁸³ 842	²⁴ 0.0018	²⁴ 0.0014	¹⁹ 0.0013	¹⁶ 0.0012	¹⁸ 0.0011	²³ 1.013	
163	SIAT-002	¹⁵² 2052	¹⁹³ 906	²³ 0.0018	²³ 0.0014	²⁴ 0.0013	²⁴ 0.0013	²⁵ 0.0012	²³ 1.013	
164	SMILART-004	²⁹ 512	¹⁶ 167	²⁰² 0.9648	²⁰² 0.9641	²⁰² 0.9640	²⁰² 0.9639	²⁰³ 0.9638	²⁰² 9.678	
165	SMILART-005	⁹⁷ 2048	⁸⁶ 464						²⁰⁵ 10.000	
166	SYNOPSIS-003	¹⁸⁸ 4096	¹¹ 103	¹⁸⁶ 0.1700	¹⁸⁶ 0.1172	¹⁸⁶ 0.1047	¹⁸⁹ 0.0953	¹⁸⁸ 0.0869	¹⁸⁸ 2.120	
167	SYNOPSIS-003	¹³² 2048	³³ 215	¹²⁷ 0.0162	¹⁵⁴ 0.0160	¹⁵⁹ 0.0160	¹⁶⁰ 0.0160	¹⁶⁸ 0.0160	¹⁵³ 1.144	
168	SYNOPSIS-005	¹⁹⁰ 4104	¹⁶⁴ 772	¹⁰⁸ 0.0085	¹³⁰ 0.0085	¹³⁵ 0.0085	¹⁴⁷ 0.0085	¹⁵³ 0.0085	¹²⁷ 1.076	
169	TECH5-001	⁸¹ 1536	¹⁹¹ 898	⁶⁶ 0.0040	⁶⁹ 0.0024	⁶⁵ 0.0021	⁶² 0.0018	⁶¹ 0.0017	⁶² 1.024	
170	TEVIAN-003	¹³³ 2048	⁵³ 300	¹³⁴ 0.0147	¹²³ 0.0074	¹¹⁶ 0.0059	¹¹⁰ 0.0047	¹¹⁸ 0.0037	¹²⁵ 1.075	
171	TEVIAN-004	¹⁰² 2048	⁵² 299	¹²¹ 0.0113	¹¹⁰ 0.0057	¹¹⁰ 0.0047	¹⁰⁷ 0.0037	¹⁰³ 0.0030	¹¹¹ 1.058	
172	TEVIAN-005	⁹⁹ 2048	⁷⁷ 416	⁹⁹ 0.0073	⁹⁰ 0.0038	⁸⁶ 0.0031	⁸⁷ 0.0027	⁸² 0.0023	⁹² 1.038	
173	TIGER-000	¹⁵¹ 2052	⁷⁹ 428	¹⁷⁴ 0.0616	¹⁶⁶ 0.0310	¹⁶⁶ 0.0236	¹⁶⁸ 0.0178	¹⁶⁰ 0.0120	¹⁶⁷ 1.315	
174	TIGER-002	¹⁵⁰ 2052	⁸⁸ 464	⁸¹ 0.0056	⁸¹ 0.0029	⁷⁷ 0.0024	⁶⁸ 0.0019	⁴⁸ 0.0015	⁸⁰ 1.030	
175	TIGER-003	¹⁵¹ 2052	⁸⁷ 464	⁸⁵ 0.0056	⁸² 0.0029	⁷⁶ 0.0024	⁶⁸ 0.0019	⁴⁹ 0.0015	⁸¹ 1.030	
176	TONGYITRANS-000	¹⁶¹ 2070	²³ 190	⁹⁸ 0.0069	⁸⁸ 0.0038	⁹² 0.0032	⁹¹ 0.0029	⁹⁷ 0.0026	⁹⁰ 1.038	
177	TONGYITRANS-001	¹⁶² 2070	²² 189	⁹⁶ 0.0069	⁸⁹ 0.0038	⁹⁰ 0.0032	⁹² 0.0029	⁹⁵ 0.0026	⁹² 1.038	
178	TOSHIBA-000	⁸⁷ 1548	¹⁹⁸ 930	⁷² 0.0045	⁷¹ 0.0026	⁷¹ 0.0022	⁷⁰ 0.0020	⁷⁰ 0.0018	⁷² 1.026	
179	TOSHIBA-001	¹⁶¹ 2060	¹⁹⁹ 931	⁷⁷ 0.0048	⁷⁵ 0.0027	⁷⁴ 0.0023	⁷⁴ 0.0020	⁶⁹ 0.0018	⁷⁶ 1.027	
180	TRUEFACE-000	⁹⁵ 2000	⁶¹ 365	⁵² 0.0033	⁷⁷ 0.0028	⁸⁴ 0.0028	⁸⁸ 0.0026	⁹⁴ 0.0026	⁷⁵ 1.026	
181	VD-000	⁶⁴ 1028	⁵⁸ 337	¹⁹⁷ 0.4737	¹⁹⁸ 0.3204	¹⁹⁸ 0.2695	¹⁹⁶ 0.2215	¹⁹⁶ 0.1678	¹⁹⁸ 4.058	
182	VD-001	¹⁵⁰ 2052	¹³⁷ 695	¹⁵⁶ 0.0276	¹⁵⁹ 0.0181	¹⁶¹ 0.0162	¹⁶⁰ 0.0146	¹⁶² 0.0130	¹⁵⁹ 1.174	
183	VIGILANTSOLUTIONS-003	⁸³ 1544	¹⁷⁸ 832	¹⁵⁴ 0.0694	¹⁷¹ 0.0349	¹⁶⁷ 0.0262	¹⁶⁹ 0.0201	¹⁶⁴ 0.0140	¹⁷¹ 1.355	
184	VIGILANTSOLUTIONS-004	⁸⁴ 1544	¹⁷⁶ 830	¹⁸⁰ 0.1249	¹⁸⁰ 0.0706	¹⁷⁹ 0.0557	¹⁷⁶ 0.0434	¹⁷⁵ 0.0305	¹⁸⁰ 1.699	
185	VIGILANTSOLUTIONS-005	⁸⁶ 1544	¹⁶⁶ 778	¹¹¹ 0.0092	¹⁰¹ 0.0045	⁹⁵ 0.0036	⁹² 0.0029	⁸⁴ 0.0022	¹⁰² 1.046	
186	VIGILANTSOLUTIONS-006	⁸⁵ 1544	¹⁷⁹ 834	¹¹⁶ 0.0099	¹⁰³ 0.0048	⁹⁹ 0.0038	⁹⁴ 0.0030	⁸⁶ 0.0022	¹⁰⁵ 1.049	
187	VIGILANTSOLUTIONS-007	⁸⁵ 1544	¹⁸⁰ 818	⁵⁷ 0.0034	⁴⁶ 0.0020	⁴² 0.0017	⁴¹ 0.0015	³² 0.0013	⁵¹ 1.019	
188	VISIONLABS-004	¹³ 256	⁵⁵ 315	⁴⁸ 0.0027	³⁸ 0.0018	³⁸ 0.0016	⁴⁰ 0.0015	³⁹ 0.0014	⁴⁰ 1.017	
189	VISIONLABS-005	³⁴ 512	⁵⁴ 300	⁴¹ 0.0024	³⁶ 0.0017	³⁵ 0.0015	³¹ 0.0014	³⁰ 0.0013	³⁵ 1.016	
190	VISIONLABS-006	³⁸ 512	⁴⁹ 292	²⁴ 0.0018	²² 0.0015	²⁶ 0.0014	²⁶ 0.0013	²⁷ 0.0013	²⁹ 1.014	
191	VISIONLABS-007	³⁰ 512	⁵⁰ 293	²¹ 0.0018	²³ 0.0014	²¹ 0.0013	²¹ 0.0013	²⁴ 0.0012	²⁵ 1.013	
192	VISIONLABS-008	³⁷ 512	⁴⁶ 277	²¹ 0.0020	²⁰ 0.0018	⁴⁵ 0.0018	⁵⁸ 0.0018	⁶⁶ 0.0017	³⁸ 1.017	
193	VISIONLABS-009	³³ 512	⁹⁰ 494	⁷ 0.0011	¹⁰ 0.0011	¹² 0.0010	¹² 0.0010	¹³ 0.0010	⁹ 1.010	
194	VISIONLABS-010	³⁹ 512	¹⁵⁸ 732	¹¹ 0.0014	¹⁹ 0.0013	²⁰ 0.0013	²² 0.0013	²⁶ 0.0013	¹⁷ 1.012	
195	VOCORD-003	⁵⁵ 896	¹⁵⁰ 714	⁸⁰ 0.0062	⁸⁵ 0.0035	⁸⁵ 0.0030	⁸⁸ 0.0026	⁸⁹ 0.0023	⁸⁸ 1.035	
196	VOCORD-004	⁵⁶ 896	⁹⁹ 538	¹⁰¹ 0.0079	¹⁰⁵ 0.0049	¹⁰⁶ 0.0043	¹¹⁰ 0.0038	¹¹³ 0.0034	¹⁰³ 1.048	
197	VOCORD-005	⁵³ 768	¹⁷² 822	¹⁰² 0.0070	¹⁰² 0.0046	¹⁰⁴ 0.0041	¹⁰⁹ 0.0038	¹¹⁶ 0.0035	⁹⁰ 1.044	
198	VOCORD-006	²⁰⁵ 10240	¹⁷⁴ 825	²⁰⁴ 1.0000	²⁰⁵ 1.0000	²⁰⁵ 1.0000	²⁰⁴ 1.0000	²⁰⁴ 1.0000	²⁰⁴ 10.000	
199	XFORWARDAI-000	¹¹⁴ 2048	¹⁶² 768	³⁶ 0.0023	³¹ 0.0020	³⁷ 0.0020	⁶⁷ 0.0019	⁷⁵ 0.0019	⁴⁶ 1.018	
200	XFORWARDAI-001	¹⁰⁸ 2048	¹³⁰ 681	³⁵ 0.0020	⁴⁵ 0.0019	⁵⁴ 0.0019	⁶⁶ 0.0019	⁷⁴ 0.0019	⁴¹ 1.018	
201	YISHENG-001	¹⁸² 3704	⁶⁹ 387	¹⁵⁸ 0.0265	¹⁴⁹ 0.0130	¹⁴⁶ 0.0102	¹⁴⁴ 0.0080	¹³⁶ 0.0059	¹⁵⁰ 1.134	
202	YITU-002	¹⁹⁹ 4138	¹⁸⁹ 870	²⁵ 0.0018	¹⁵ 0.0012	¹⁴ 0.0011	¹⁴ 0.0011	¹⁵ 0.0010	¹⁶ 1.012	
203	YITU-003	¹⁹⁸ 4138	¹⁹⁰ 871	³¹ 0.0029	⁶⁰ 0.0023	⁶⁸ 0.0022	⁷⁷ 0.0021	⁸² 0.0021	⁵⁷ 1.021	
204	YITU-004	¹⁶² 2070	¹⁹⁶ 910	⁹ 0.0013	⁴ 0.0009	⁷ 0.0009	⁸ 0.0009	⁸ 0.0009	⁶ 1.009	
205	YITU-005	¹⁶² 2070	¹⁸⁸ 861	³⁷ 0.0023	³² 0.0021	⁶⁰ 0.0020	⁷¹ 0.0020	⁷⁷ 0.0020	⁴⁸ 1.019	

Table 19: Rank-based accuracy for the FRVT 2018 mugshot sets. In columns 3 and 4 are template size and template generation duration. Thereafter values are rank-based FNIR with $T = 0$ and $FPIR = 1$. This is appropriate to investigational uses but not those with higher volumes where candidates from all searches would need review. The next column is a workload statistic, a small value shows an algorithm front-loads mates into the first 10 candidates. Throughout, blue superscripts indicate the rank of the algorithm for that column, and the best value is highlighted in yellow.

MISSES BELOW THRESHOLD, T		ENROL RECENT MUGSHOT, N = 1.6M									ENROL APPLICATION PORTRAIT, N = 1.6M			
ENROL		DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: VISA		DATASET: VISA	
PROBE		DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: BORDER		DATASET: KIOSK	
#	ALGORITHM	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01
1	3DIVI-003	¹⁶⁴ 0.482	¹⁷⁵ 0.400	¹⁷⁸ 0.282	¹⁶⁴ 0.685	¹⁷³ 0.626	¹⁷⁶ 0.497				¹⁰³ 0.605	¹⁰³ 0.445	⁸⁸ 0.821	⁹⁰ 0.717
2	3DIVI-004	¹³⁸ 0.256	¹⁴⁹ 0.169	¹⁵² 0.093	¹³⁹ 0.400	¹⁵⁰ 0.343	¹⁵⁰ 0.237				⁸⁸ 0.277	⁹⁰ 0.172	⁶⁹ 0.607	⁷² 0.485
3	3DIVI-005	¹³⁷ 0.255	¹⁴⁶ 0.166	¹⁵¹ 0.093	¹³⁸ 0.395	¹⁵³ 0.339	¹⁵⁷ 0.234	⁸⁸ 0.998	⁸⁹ 0.996	⁹³ 0.990	¹⁰⁷ 0.864	¹⁰⁹ 0.846	⁶⁸ 0.597	⁷⁰ 0.484
4	3DIVI-006	¹³⁶ 0.253	¹⁴⁵ 0.168	¹⁵⁴ 0.096	¹⁴² 0.403	¹⁵⁴ 0.342	¹⁵⁹ 0.238				⁸⁹ 0.283	⁹¹ 0.174	⁷² 0.615	⁷⁰ 0.490
5	ACER-000	¹²⁶ 0.208	¹³⁷ 0.146	¹⁴¹ 0.074	¹²³ 0.300	¹³³ 0.246	¹³⁵ 0.157	⁵¹ 0.987	⁵⁶ 0.981	⁶¹ 0.955	⁸⁴ 0.201	⁸⁷ 0.114	⁵⁹ 0.490	⁶⁰ 0.363
6	ALCHERA-000	¹³¹ 0.231	¹³⁶ 0.138	¹³⁷ 0.070	¹¹⁶ 0.259	¹²¹ 0.216	¹²² 0.146	⁹⁶ 0.999	¹⁰³ 0.999	¹¹⁸ 0.996	⁸¹ 0.176	⁸⁵ 0.111	⁸⁴ 0.803	⁷⁹ 0.456
7	ALCHERA-001	²⁰¹ 1.000	²⁰¹ 0.999	²⁰² 0.999	¹⁹⁷ 1.000	¹⁹⁴ 1.000	²⁰³ 1.000				¹³⁷ 1.000	¹⁵¹ 1.000	¹²¹ 1.000	¹⁸⁸ 1.000
8	ALCHERA-002	¹⁸¹ 0.807	¹⁸² 0.486	¹⁸¹ 0.302	¹⁶⁷ 0.685	¹⁷¹ 0.591	¹⁷⁷ 0.442	¹²² 1.000	¹²¹ 1.000	¹³⁶ 0.999	¹⁰⁶ 0.827	¹⁰⁶ 0.770	⁸⁵ 0.811	⁹⁰ 0.705
9	ALCHERA-003	¹⁵⁹ 0.450	¹⁴⁰ 0.155	¹³⁸ 0.070	¹²⁸ 0.304	¹³⁰ 0.239	¹³² 0.152	¹¹⁶ 1.000	¹¹¹ 0.999	¹²⁵ 0.997	⁸⁰ 0.172	⁷⁹ 0.097	⁵⁶ 0.464	⁶⁸ 0.362
10	ALLGOVISION-000	⁹⁵ 0.138	¹¹⁶ 0.088	¹²¹ 0.045	¹⁰² 0.202	¹¹⁰ 0.166	¹¹⁶ 0.106	⁵⁹ 0.993	⁶⁸ 0.990	⁸⁴ 0.982	⁶⁷ 0.117	⁷¹ 0.066	⁶⁹ 0.526	⁷² 0.396
11	ALLGOVISION-001	¹⁰³ 0.155	¹²¹ 0.102	¹²⁵ 0.053	¹¹⁸ 0.275	¹²⁴ 0.221	¹²⁵ 0.141	⁶¹ 0.993	⁶² 0.986	⁸² 0.933	⁷⁵ 0.150	⁷⁵ 0.081	⁶⁰ 0.491	⁷² 0.389
12	ANKE-000	¹¹⁴ 0.184	¹²⁰ 0.117	¹³⁴ 0.063	¹¹³ 0.256	¹²³ 0.220	¹³⁰ 0.151	⁶⁶ 0.995	⁷⁰ 0.994	⁹¹ 0.990	¹⁸² 1.000	²⁰¹ 1.000	¹⁶⁵ 1.000	¹⁴² 1.000
13	ANKE-001	¹¹² 0.183	¹³⁰ 0.119	¹³⁵ 0.063	¹¹² 0.256	¹²² 0.220	¹³¹ 0.151	⁶⁹ 0.995	⁷⁰ 0.994	¹⁰¹ 0.992	¹¹⁸ 1.000	¹³⁴ 1.000	¹⁴² 1.000	¹⁶⁸ 1.000
14	ANKE-002	⁸³ 0.062	⁸⁴ 0.032	⁸³ 0.014	⁴¹ 0.103	⁴⁴ 0.079	⁴⁴ 0.050	³⁴ 0.975	³⁴ 0.948	³⁶ 0.795	³⁵ 0.034	³⁵ 0.018	²⁸ 0.245	³⁵ 0.190
15	AWARE-003	¹¹¹ 0.174	¹³⁴ 0.128	¹⁴⁴ 0.082	¹³² 0.351	¹⁴⁷ 0.298	¹⁵⁴ 0.204	⁴⁸ 0.987	⁶² 0.984	⁷⁹ 0.977	⁹⁶ 0.428	⁹⁷ 0.378	⁶⁵ 0.530	⁷⁰ 0.443
16	AWARE-004	¹⁵¹ 0.355	¹⁶² 0.269	¹⁶⁹ 0.175	¹⁵⁹ 0.619	¹⁶⁷ 0.509	¹⁶⁹ 0.375	¹²¹ 1.000	¹²⁴ 1.000	¹³⁷ 0.999	⁹⁴ 0.397	⁹⁴ 0.279	⁸⁶ 0.816	⁸⁸ 0.631
17	AWARE-005	¹⁷² 0.608	¹⁷³ 0.364	¹⁴⁶ 0.085	¹²⁹ 0.342	¹³⁴ 0.253	¹³⁵ 0.163	¹¹⁷ 1.000	¹²⁷ 1.000	¹³⁸ 0.999	⁸⁷ 0.255	⁸⁹ 0.122	⁹⁵ 0.916	⁹⁸ 0.714
18	AWARE-006	¹⁶³ 0.475	¹⁶³ 0.276	¹⁷⁰ 0.175	¹⁴⁹ 0.466	¹⁵⁸ 0.398	¹⁶² 0.283	¹⁰⁷ 1.000	¹¹⁹ 0.999	¹³³ 0.999	⁹² 0.368	⁹² 0.254	⁷⁹ 0.749	⁸⁴ 0.623
19	AYONIX-000	¹⁸⁴ 0.846	¹⁹⁰ 0.811	¹⁹⁴ 0.724	¹⁸⁸ 0.956	¹⁸⁸ 0.939	¹⁹⁰ 0.892	⁸⁹ 0.998	⁹¹ 0.998	¹¹⁶ 0.995	¹¹¹ 0.954	¹¹¹ 0.891	¹⁰³ 0.982	¹⁰⁶ 0.959
20	AYONIX-001	¹⁸⁵ 0.875	¹⁹² 0.824	¹⁹² 0.701	¹⁷⁹ 0.946	¹⁸³ 0.845	¹⁸⁶ 0.845	¹¹⁴ 1.000	¹¹⁷ 0.999	¹²⁰ 0.996	¹¹⁵ 0.999	¹¹⁵ 0.998	¹⁰⁰ 0.969	¹⁰² 0.926
21	AYONIX-002	¹⁸⁶ 0.876	¹⁹¹ 0.824	¹⁹³ 0.702	¹⁷⁶ 0.946	¹⁸⁴ 0.920	¹⁸⁷ 0.845	¹¹⁵ 1.000	¹¹⁵ 0.999	¹¹⁹ 0.996	¹⁰⁸ 0.915	¹⁰⁷ 0.821	¹⁰⁷ 0.969	¹⁰² 0.926
22	CAMVI-003	⁶⁹ 0.094	¹⁰¹ 0.071	¹³⁰ 0.058	⁷⁰ 0.152	⁸⁹ 0.132	¹¹¹ 0.108	³⁹ 0.979	⁴⁰ 0.970	⁵⁶ 0.940	⁶⁶ 0.114	⁸⁰ 0.100	⁵¹ 0.402	⁶⁸ 0.377
23	CAMVI-004	⁷⁸ 0.107	¹⁰² 0.072	¹²⁸ 0.054	¹⁰⁰ 0.240	⁹¹ 0.136	¹⁰⁶ 0.100	¹⁰⁸ 1.000	¹¹³ 0.999	¹²⁶ 0.998	⁶⁵ 0.100	⁷⁴ 0.081	⁸² 0.787	⁸⁸ 0.507
24	CAMVI-005	⁹⁶ 0.139	¹²⁰ 0.099	¹⁴³ 0.076	¹⁴⁸ 0.451	¹¹⁷ 0.179	¹²² 0.132	¹¹⁰ 1.000	¹²² 1.000	¹³² 0.998	⁷⁶ 0.156	⁸⁶ 0.112	¹¹⁰ 0.999	¹¹¹ 0.983
25	CIB-000	³⁶ 0.044	¹⁹ 0.012	¹⁷ 0.005	²⁹ 0.077	²⁰ 0.045	²⁰ 0.025	¹⁴¹ 1.000	¹³¹ 1.000	¹⁴² 1.000	¹⁸ 0.017	¹⁴ 0.008	⁹³ 0.894	⁸¹ 0.521
26	COGENT-000	¹⁰⁰ 0.143	⁸¹ 0.053	⁹⁵ 0.029	⁸¹ 0.175	⁹² 0.140	¹⁰⁸ 0.100	⁷² 0.996	⁸¹ 0.995	⁹⁸ 0.991				
27	COGENT-001	⁹⁹ 0.143	⁸⁰ 0.053	⁹⁶ 0.029	⁸⁰ 0.175	⁹³ 0.140	¹¹⁰ 0.100	⁷¹ 0.996	⁸¹ 0.995	⁹⁷ 0.991				
28	COGENT-002	¹⁰⁸ 0.159	⁶⁸ 0.044	⁶¹ 0.017	⁵⁷ 0.124	⁶² 0.098	⁶⁸ 0.063	⁹² 0.998	⁹³ 0.998	¹⁰⁶ 0.994				
29	COGENT-003	¹²⁴ 0.203	⁷² 0.046	⁵⁷ 0.016	⁵⁵ 0.121	⁵⁸ 0.095	⁶³ 0.061	⁹³ 0.999	⁹⁵ 0.998	¹¹⁴ 0.995				
30	COGENT-004	¹²⁷ 0.209	⁵⁸ 0.033	²¹ 0.006	²² 0.067	²⁴ 0.051	²⁴ 0.031	⁸⁷ 0.998	⁹¹ 0.997	¹¹⁵ 0.995	²¹ 0.022	²² 0.012	⁵⁵ 0.456	³¹ 0.178
31	COGNITEC-000	¹³⁰ 0.226	¹⁴⁴ 0.161	¹⁵³ 0.095	¹⁴⁶ 0.439	¹⁴⁸ 0.303	¹⁴⁹ 0.200	⁷⁰ 0.996	⁷⁰ 0.992	⁶⁹ 0.971				
32	COGNITEC-001	¹²² 0.192	¹²² 0.102	¹²⁶ 0.053	¹⁹⁰ 0.997	¹²⁸ 0.230	¹²⁴ 0.135	¹⁵⁹ 1.000	¹⁸⁰ 1.000	⁶⁵ 0.965				
33	COGNITEC-002	⁸⁵ 0.122	⁸² 0.053	⁸⁶ 0.025	¹⁸⁹ 0.990	¹¹⁶ 0.178	¹¹³ 0.101	¹⁶⁸ 1.000	¹³² 1.000	⁶² 0.956				
34	COGNITEC-003	⁷³ 0.099	⁷⁰ 0.053	⁸⁸ 0.025	¹⁰⁸ 0.222	¹⁰⁸ 0.162	¹⁰⁰ 0.100	¹⁶⁰ 1.000	¹³⁵ 1.000	⁵⁷ 0.946				
35	CYBERLINK-000	⁹⁴ 0.137	⁸⁸ 0.056	⁷⁹ 0.023	⁸¹ 0.162	⁷⁴ 0.116	⁷⁹ 0.070	⁸³ 0.997	⁸⁵ 0.995	⁸³ 0.981	³⁵ 0.063	⁵³ 0.032	⁴⁹ 0.339	⁴⁶ 0.232
36	CYBERLINK-001	⁷⁰ 0.096	⁸⁰ 0.054	⁷⁷ 0.022	⁶⁸ 0.138	⁷¹ 0.109	⁷⁶ 0.067	⁸² 0.997	⁸¹ 0.995	⁸⁵ 0.984	⁵² 0.062	⁴⁹ 0.031	⁷³ 0.652	⁴⁸ 0.239
37	CYBERLINK-002	³² 0.038	²⁵ 0.015	²⁴ 0.006	²⁴ 0.068	²⁷ 0.053	²⁷ 0.032	⁶³ 0.994	⁶⁵ 0.988	⁶³ 0.957	²² 0.024	²³ 0.013	³⁴ 0.288	²⁵ 0.157
38	CYBERLINK-003	³⁹ 0.045	¹⁴ 0.008	¹⁴ 0.004	¹⁴ 0.045	¹⁶ 0.035	¹⁴ 0.021	⁶⁴ 0.995	⁴⁴ 0.972	⁴² 0.845	¹³ 0.012	¹³ 0.007	⁴⁷ 0.368	¹³ 0.120
39	DAHUA-000	⁸⁰ 0.128	¹¹² 0.086	¹¹⁸ 0.045	⁸⁰ 0.179	⁹⁰ 0.135	⁹³ 0.083							
40	DAHUA-001	⁷⁷ 0.106	¹⁰⁴ 0.073	¹⁰⁶ 0.037	⁷⁵ 0.151	⁸² 0.122	⁸⁴ 0.075	⁵⁰ 0.987	⁵⁴ 0.980	⁵³ 0.933				
41	DAHUA-002	²⁰ 0.026	²⁶ 0.015	²³ 0.006	¹⁹ 0.060	²² 0.046	²² 0.029	⁹ 0.681	¹² 0.638	¹⁹ 0.522	¹⁷ 0.017	¹⁸ 0.008	¹³ 0.159	¹⁴ 0.125
42	DAHUA-003	¹⁹ 0.025	²² 0.014	¹⁹ 0.005	¹⁷ 0.054	¹⁹ 0.041	¹⁸ 0.024	⁸ 0.647	¹⁰ 0.579	¹⁴ 0.447	¹⁴ 0.013	¹² 0.006	⁹ 0.134	⁸ 0.109
43	DEEPLINT-001	⁶ 0.010	⁷ 0.003	⁸ 0.002	⁴ 0.018	⁴ 0.014	³ 0.010	¹²⁴ 1.000	¹²⁰ 1.000	¹⁶ 0.503	³ 0.006	⁵ 0.004	¹² 0.159	⁵ 0.097
44	DEEPSEA-001	⁶¹ 0.073	⁷¹ 0.046	⁷⁵ 0.022	⁶¹ 0.129	⁶⁴ 0.101	⁵⁹ 0.059	⁵⁴ 0.988	⁶¹ 0.985	⁷⁴ 0.973	⁵⁹ 0.077	⁶⁰ 0.041	⁴³ 0.326	⁴⁶ 0.251
45	DERMALOG-003	¹⁶⁹ 0.550	¹⁸¹ 0.482	¹⁸⁴ 0.360	¹⁶⁷ 0.715	¹⁷⁵ 0.655	¹⁸⁸ 0.526				¹⁰⁸ 0.677	¹⁰⁸ 0.554	⁹¹ 0.870	⁹⁰ 0.791
46	DERMALOG-004	¹⁷¹ 0.554	¹⁸⁰ 0.480	¹⁸³ 0.358	¹⁶⁶ 0.711	¹⁷⁶ 0.657	¹⁷⁸ 0.526	⁷⁶ 0.997	⁸⁶ 0.995	¹⁰⁰ 0.991	¹⁰² 0.603	¹⁰⁴ 0.458	⁹⁰ 0.856	⁹⁶ 0.751

Table 20: **Threshold-based accuracy.** Values are $FNIR(N, T, L)$ with $N = 1.6$ million with thresholds set to produce $FPIR = 0.0003, 0.001$, and 0.01 in non-mate searches. Throughout blue superscripts indicate the rank of the algorithm for that column. Caution: The Power-low models are mostly intended to draw attention to the kind of behavior, not as a model to be used for prediction.

MISSES BELOW THRESHOLD, T		ENROL RECENT MUGSHOT, N = 1.6M									ENROL APPLICATION PORTRAIT, N = 1.6M			
ENROL		DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: VISA		DATASET: VISA	
PROBE		DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: BORDER		DATASET: KIOSK	
#	ALGORITHM	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01
47	DERMLOG-005	¹²¹ 0.189	¹¹⁵ 0.088	¹¹⁴ 0.043	⁹⁸ 0.201	¹⁰¹ 0.154	¹⁰⁵ 0.096	⁷³ 0.996	⁶⁷ 0.990	⁶⁰ 0.950	⁸⁰ 0.300	⁹³ 0.267	⁷¹ 0.614	⁷⁶ 0.459
48	DERMLOG-006	⁷² 0.098	⁷⁸ 0.052	⁹⁰ 0.026	⁶⁷ 0.137	⁶⁶ 0.105	⁶⁹ 0.067	⁵⁵ 0.989	⁵⁸ 0.981	⁵⁴ 0.933	⁵⁰ 0.059	⁵¹ 0.031	⁴² 0.318	⁴⁴ 0.230
49	DERMLOG-007	¹¹⁹ 0.188	¹¹³ 0.086	¹¹² 0.040	⁹⁷ 0.200	⁹⁹ 0.152	¹⁰⁸ 0.093	⁷⁴ 0.996	⁶⁸ 0.990	⁵⁹ 0.950	⁶⁴ 0.099	⁶⁶ 0.052	⁶⁷ 0.557	⁶¹ 0.299
50	DERMLOG-008	¹⁴¹ 0.268	⁷⁰ 0.045	⁶⁰ 0.017	¹⁰⁷ 0.231	⁵⁵ 0.094	³⁵ 0.054	¹⁴³ 1.000	¹⁴¹ 1.000	¹⁴³ 1.000	⁴⁷ 0.057	⁴⁴ 0.025	⁹⁹ 0.940	⁸⁹ 0.678
51	EYDEA-003	¹⁶⁷ 0.509	¹⁷³ 0.388	¹⁷⁶ 0.265	¹⁵⁹ 0.625	¹⁶⁹ 0.543	¹⁷⁰ 0.404	⁷⁷ 0.997	⁷⁸ 0.994	⁹⁰ 0.990	¹⁰⁰ 0.570	⁹⁹ 0.392	⁸³ 0.792	⁸⁶ 0.658
52	F8-001	¹⁶¹ 0.458	¹⁴⁵ 0.166	¹⁰⁴ 0.036				⁹⁸ 0.999	¹⁰⁸ 0.998	¹¹⁷ 0.995				
53	GLORY-000	¹³⁸ 0.441	¹⁷¹ 0.367	¹⁸⁰ 0.295	¹⁵⁸ 0.586	¹⁷⁰ 0.547	¹⁷⁴ 0.470	⁶⁵ 0.995	⁸¹ 0.995	¹⁰⁴ 0.993	⁹⁸ 0.453	⁹⁸ 0.381	⁸⁹ 0.839	¹⁰⁰ 0.795
54	GLORY-001	¹⁵⁰ 0.355	¹⁶⁴ 0.305	¹⁷³ 0.236	¹⁵⁵ 0.582	¹⁶⁸ 0.537	¹⁷² 0.448	⁶² 0.994	⁷¹ 0.993	⁹⁵ 0.991	⁹⁵ 0.408	⁹⁵ 0.336	⁸⁷ 0.819	⁹⁶ 0.753
55	GORILLA-001	¹⁸⁰ 0.747	¹⁷⁶ 0.406	¹⁷⁴ 0.246	¹⁵⁹ 0.590	¹⁶³ 0.453	¹⁶⁴ 0.314	¹²⁹ 1.000	¹⁴⁷ 1.000	¹⁵³ 1.000				
56	GORILLA-002	¹⁴⁰ 0.266	¹⁵⁷ 0.188	¹⁵⁸ 0.106	¹³¹ 0.342	¹⁴¹ 0.268	¹⁴¹ 0.170	¹³⁵ 1.000	¹³⁵ 1.000	¹⁰⁵ 0.993				
57	GORILLA-003	¹⁷⁸ 0.694	¹⁶⁸ 0.318	¹⁶⁸ 0.157	¹⁶² 0.684	¹⁶² 0.434	¹⁶⁶ 0.247	²⁰⁰ 1.000	¹⁷¹ 1.000	¹⁴⁷ 1.000				
58	GORILLA-004	⁹³ 0.135	¹¹⁸ 0.089	¹¹⁵ 0.043	⁹⁰ 0.202	¹⁰⁷ 0.160	¹¹¹ 0.101	³² 0.972	⁵⁶ 0.959	⁴⁶ 0.903	⁷² 0.135	⁷³ 0.072	⁵⁴ 0.438	⁶³ 0.309
59	GORILLA-005	⁶⁷ 0.086	⁹² 0.058	⁹¹ 0.026	⁸⁸ 0.179	⁹⁵ 0.142	⁹⁵ 0.088	¹³ 0.770	³⁰ 0.700	²⁰ 0.553	⁶³ 0.088	⁵⁹ 0.040	⁴¹ 0.315	⁴¹ 0.223
60	HIK-003	¹⁰⁹ 0.159	¹²¹ 0.103	¹²⁹ 0.057	⁹⁰ 0.190	¹⁰³ 0.158	¹¹⁵ 0.105	⁴¹ 0.980	⁴⁰ 0.969	⁵⁰ 0.925				
61	HIK-004	¹⁰⁵ 0.156	¹¹⁹ 0.099	¹²⁷ 0.054	⁹⁹ 0.182	¹⁰⁰ 0.153	¹¹² 0.101	⁴⁵ 0.983	⁴⁶ 0.976	⁵⁸ 0.947				
62	HIK-005	⁷⁵ 0.102	⁶⁵ 0.044	⁶⁵ 0.019	³⁹ 0.098	⁴³ 0.077	⁴³ 0.048	¹¹² 1.000	¹¹⁸ 0.999	¹²⁸ 0.998				
63	HIK-006	⁹⁸ 0.142	⁷¹ 0.047	⁶⁷ 0.020	⁴⁸ 0.111	⁴⁷ 0.086	⁴⁷ 0.052	¹²⁵ 1.000	¹⁴⁵ 1.000	¹³⁹ 0.999				
64	HR-000	³ 0.004	⁷ 0.002	⁵ 0.002	⁷ 0.015	⁵ 0.013	⁵ 0.012	¹ 0.188	¹ 0.133	¹ 0.095	¹ 0.005	¹ 0.003	¹ 0.099	¹ 0.075
65	IDEMIA-003	¹⁷⁰ 0.552	⁷⁴ 0.047	⁷¹ 0.021	¹⁹⁴ 1.000	¹⁰⁹ 0.165	⁸⁸ 0.079			¹⁸³ 1.000	⁶⁹ 0.123	⁶⁸ 0.061	⁸⁰ 0.766	⁸⁶ 0.630
66	IDEMIA-004	⁴⁵ 0.055	⁶¹ 0.037	⁷⁰ 0.021	⁷¹ 0.144	⁷⁸ 0.118	⁸⁷ 0.079	³⁶ 0.976	⁴⁸ 0.973	⁶⁶ 0.968	⁶⁸ 0.123	⁶⁷ 0.061	⁸¹ 0.766	⁸⁶ 0.630
67	IDEMIA-005	⁵⁹ 0.066	⁶⁷ 0.044	⁸⁹ 0.026	⁹⁷ 0.181	⁹⁸ 0.150	¹¹⁴ 0.102	⁴⁰ 0.979	⁴⁷ 0.978	⁷² 0.973	⁷⁰ 0.130	⁷² 0.070	⁹² 0.879	⁹⁸ 0.743
68	IDEMIA-006	⁵⁷ 0.065	⁶⁴ 0.043	⁸⁷ 0.025	¹¹⁷ 0.266	¹²⁶ 0.226	¹³⁴ 0.161	⁴⁷ 0.984	⁵⁷ 0.982	⁸² 0.980	⁷⁴ 0.144	⁷⁷ 0.090	⁷⁷ 0.733	⁸⁷ 0.531
69	IDEMIA-007	²⁸ 0.035	³¹ 0.018	³³ 0.008	²⁶ 0.073	²⁹ 0.055	²⁶ 0.033	¹⁷⁶ 1.000	¹⁶⁹ 1.000	¹⁶² 1.000	⁴³ 0.052	⁴³ 0.022	¹⁸² 1.000	¹¹⁰ 0.982
70	IMAGUS-002	¹⁸⁹ 0.908	¹⁸⁸ 0.749	¹⁹⁰ 0.564	¹⁷⁹ 0.944	¹⁸⁰ 0.816	¹⁸⁵ 0.645	¹³⁶ 1.000	¹⁴⁸ 1.000	¹⁴⁶ 1.000				
71	IMAGUS-003	¹⁸⁸ 0.898	¹⁸⁷ 0.807	¹⁹¹ 0.669	¹⁷⁷ 0.954	¹⁸² 0.909	¹⁸³ 0.809	¹³² 1.000	¹³¹ 1.000	¹⁴⁴ 1.000				
72	IMAGUS-005	²⁷ 0.034	³⁴ 0.018	³⁴ 0.008	³⁰ 0.088	³⁵ 0.066	³⁴ 0.040	²⁴ 0.926	²⁴ 0.838	²⁴ 0.647	²⁴ 0.029	³¹ 0.016	²⁵ 0.231	³⁴ 0.189
73	IMPERIAL-000	¹⁰² 0.154	⁴⁶ 0.026	⁴⁰ 0.009	³⁷ 0.089	³⁷ 0.068	³¹ 0.041	¹²⁷ 1.000	¹⁸⁶ 0.999	¹¹⁰ 0.995	³⁸ 0.042	⁴⁰ 0.020	²³ 0.245	²⁴ 0.168
74	INCODE-000	¹⁵⁷ 0.423	¹⁶⁷ 0.310	¹⁷¹ 0.199	¹⁵⁷ 0.486	¹⁶⁰ 0.420	¹⁶⁴ 0.304	¹¹³ 1.000	⁹⁷ 0.998	¹⁰⁷ 0.994				
75	INCODE-001	¹⁴⁸ 0.319	¹⁵⁷ 0.212	¹⁵⁹ 0.112	¹³³ 0.348	¹⁴⁴ 0.296	¹⁴⁷ 0.198	¹³⁷ 1.000	¹³⁸ 1.000	¹⁴¹ 1.000				
76	INCODE-002	¹⁴⁵ 0.285	¹⁵¹ 0.184	¹⁵⁷ 0.100	¹²⁸ 0.333	¹⁴² 0.269	¹⁴³ 0.176	⁸⁶ 0.998	⁷² 0.993	⁷⁸ 0.976				
77	INCODE-003	¹⁴⁶ 0.286	¹⁴⁷ 0.167	¹⁴⁵ 0.084	¹³⁷ 0.372	¹³⁸ 0.264	¹³⁷ 0.164	¹¹⁹ 1.000	¹¹⁶ 0.999	¹²¹ 0.996				
78	INCODE-004	⁷⁴ 0.099	⁸⁵ 0.054	⁸¹ 0.023	⁸⁸ 0.167	⁸¹ 0.120	⁷⁶ 0.070	⁸⁴ 0.997	⁷⁹ 0.995	⁵¹ 0.929	⁵⁴ 0.063	⁵⁰ 0.031	³⁹ 0.313	⁴² 0.226
79	INNOVATRICS-002	¹⁵⁵ 0.379	¹⁶⁰ 0.234	¹⁶⁷ 0.139	¹⁴¹ 0.403	¹⁴⁹ 0.310	¹⁵³ 0.209	¹⁴² 1.000	¹⁴² 1.000	¹⁴⁰ 0.999				
80	INNOVATRICS-003	¹⁴⁷ 0.297	¹⁵⁶ 0.221	¹⁶³ 0.132	¹³⁵ 0.351	¹⁴⁵ 0.297	¹⁵⁰ 0.203	¹²⁰ 1.000	¹²⁵ 1.000	¹³¹ 0.998				
81	INNOVATRICS-004	¹¹⁷ 0.184	¹³⁵ 0.132	¹⁴² 0.074	¹¹⁵ 0.262	¹²⁵ 0.222	¹²⁸ 0.149	⁴⁶ 0.984	⁵² 0.980	⁷¹ 0.973				
82	INNOVATRICS-005	⁵⁰ 0.057	⁵⁶ 0.034	⁵⁴ 0.014	⁴⁷ 0.114	⁵⁰ 0.089	⁴⁸ 0.052	²⁰ 0.890	²⁵ 0.846	²⁸ 0.723	⁴¹ 0.047	⁴² 0.022	³⁰ 0.251	³¹ 0.182
83	INNOVATRICS-006	³⁵ 0.044	⁴³ 0.025	⁵⁰ 0.012	⁶⁰ 0.140	⁷⁰ 0.107	⁵⁶ 0.058	²³ 0.925	³⁰ 0.899	⁴⁰ 0.811	²⁵ 0.029	²⁸ 0.015	²¹ 0.198	²⁴ 0.154
84	INTSYSMSU-000	¹⁹⁷ 0.999	¹⁹⁹ 0.998	²⁰⁰ 0.990	¹⁹¹ 1.000	¹⁹³ 1.000	¹⁹⁴ 0.998	¹¹⁸ 1.000	¹²⁶ 1.000	¹²⁷ 0.998	¹¹⁴ 0.999	¹¹⁴ 0.989	¹¹¹ 0.999	¹¹² 0.988
85	IREX-000	⁶⁰ 0.068	⁵¹ 0.028	³² 0.008	⁴⁰ 0.099	³¹ 0.060	²⁵ 0.032	⁵³ 0.988	³⁸ 0.957	²⁷ 0.680	³⁹ 0.044	²¹ 0.011	¹⁵ 0.170	¹⁸ 0.135
86	ISYSTEMS-002	¹⁰⁴ 0.155	¹⁰⁷ 0.078	¹⁰³ 0.032	⁷⁰ 0.161	⁸⁵ 0.126	⁹⁰ 0.080	⁹¹ 0.998	⁹² 0.998	¹⁰³ 0.993				
87	ISYSTEMS-003	¹²⁵ 0.204	⁹² 0.059	⁸⁴ 0.024	⁶⁶ 0.135	⁶⁹ 0.107	⁷⁵ 0.068	¹²³ 1.000	¹²⁵ 1.000	¹²⁵ 0.997				
88	KEDACOM-001	³⁴ 0.041	⁴¹ 0.023	⁵² 0.013	³⁷ 0.096	⁴⁰ 0.072	⁵¹ 0.054	⁵⁶ 0.989	⁶⁴ 0.986	⁷⁵ 0.973	⁴⁶ 0.055	⁶¹ 0.043	³⁷ 0.305	⁵² 0.264
89	KNERON-000			¹⁰³ 0.033			¹⁰⁸ 0.099							
90	LOOKMAN-003	⁵⁸ 0.066	⁶⁶ 0.044	⁸⁵ 0.025	⁶⁴ 0.131	⁷³ 0.112	⁹¹ 0.082				⁶² 0.084	⁶⁹ 0.061	⁴⁶ 0.355	⁶² 0.304
91	LOOKMAN-004	⁶² 0.074	⁶⁷ 0.045	⁸² 0.024	⁵⁶ 0.123	⁶⁸ 0.105	⁸² 0.075	³⁸ 0.979	⁴⁷ 0.977	⁷⁶ 0.974				
92	LOOKMAN-005	⁴⁷ 0.050	⁵³ 0.030	⁵⁸ 0.017	⁴¹ 0.102	⁴⁶ 0.086	⁶⁶ 0.063	⁴² 0.980	⁵⁰ 0.978	⁷³ 0.973	⁵³ 0.062	⁶³ 0.047	³⁸ 0.308	⁵⁴ 0.273

Table 21: **Threshold-based accuracy.** Values are $FNIR(N, T, L)$ with $N = 1.6$ million with thresholds set to produce $FPIR = 0.0003, 0.001$, and 0.01 in non-mate searches. Throughout blue superscripts indicate the rank of the algorithm for that column. Caution: The Power-low models are mostly intended to draw attention to the kind of behavior, not as a model to be used for prediction.

2021/03/04
11:49:04
FNIR(N, T) =
FPIR(N, T) =
False neg. identification rate
False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

MISSES BELOW THRESHOLD, T		ENROL RECENT MUGSHOT, N = 1.6M									ENROL APPLICATION PORTRAIT, N = 1.6M			
ENROL PROBE		DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: VISA		DATASET: VISA	
		DATASET: MUGSHOT			DATASET: WEBCAM			DATASET: PROFILE			DATASET: BORDER		DATASET: KIOSK	
#	ALGORITHM	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01
93	MEGVII-001	¹²⁸ 0.210	¹⁰³ 0.072	¹⁰⁵ 0.037	⁵² 0.119	⁶¹ 0.097	⁶¹ 0.061							
94	MEGVII-002	¹³⁹ 0.258	¹⁰⁶ 0.077	¹⁰⁷ 0.037	⁵³ 0.120	⁶⁰ 0.096	⁵⁸ 0.059	⁹⁷ 0.999	¹⁰¹ 0.998	⁴⁵ 0.872				
95	MICROFOCUS-003	¹⁹² 0.958	¹⁹⁵ 0.931	¹⁹⁷ 0.866	¹⁸⁶ 0.988	¹⁹² 0.979	¹⁹² 0.948				¹¹³ 0.982	¹¹³ 0.945	¹⁰⁷ 0.991	¹⁰⁹ 0.977
96	MICROFOCUS-004	¹⁹⁹ 0.999	²⁰⁰ 0.999	²⁰³ 0.999	¹⁸⁵ 0.984	¹⁹⁰ 0.975	¹⁹¹ 0.940				¹¹² 0.974	¹¹² 0.935	¹⁰⁵ 0.989	¹⁰⁸ 0.976
97	MICROFOCUS-005	¹⁸⁷ 0.883	¹⁹⁰ 0.835	¹⁹⁵ 0.736	¹⁷⁸ 0.951	¹⁸⁶ 0.928	¹⁸⁸ 0.865				¹¹⁰ 0.935	¹¹⁰ 0.848	¹⁰⁴ 0.985	¹⁰⁵ 0.965
98	MICROFOCUS-006	¹⁹⁵ 0.983	¹⁹⁷ 0.978	¹⁹⁸ 0.963	¹⁷⁷ 0.950	¹⁸⁵ 0.923	¹⁸⁷ 0.858				¹⁰⁹ 0.923	¹⁰⁸ 0.843	¹⁰² 0.971	¹⁰⁴ 0.939
99	MICROSOFT-003	⁴⁵ 0.049	⁵⁰ 0.028	⁴⁹ 0.012	⁴⁸ 0.117	⁵³ 0.091	⁵⁵ 0.056				³⁶ 0.036	³⁸ 0.019	²⁷ 0.233	³⁰ 0.176
100	MICROSOFT-004	⁴¹ 0.046	⁴⁷ 0.026	⁴⁵ 0.011	⁴⁵ 0.111	⁴⁸ 0.087	⁵⁰ 0.053				³³ 0.033	³⁶ 0.018	²³ 0.222	²⁸ 0.170
101	MICROSOFT-005	⁴² 0.047	⁴⁸ 0.026	⁴⁴ 0.010	³⁸ 0.090	³⁸ 0.070	³⁸ 0.041	¹⁰⁴ 0.999	¹¹ 0.587	¹² 0.354	²³ 0.027	²⁴ 0.013	¹⁷ 0.180	¹⁶ 0.134
102	MICROSOFT-006	¹⁸ 0.025	¹⁸ 0.012	²² 0.006	¹⁵ 0.048	¹⁷ 0.037	¹⁹ 0.024	⁴ 0.452	⁴ 0.386	⁹ 0.281	³⁰ 0.032	²⁷ 0.015	¹⁶ 0.178	¹⁸ 0.138
103	NEC-000	⁸¹ 0.113	¹⁰⁸ 0.079	¹²² 0.047	⁸⁴ 0.171	⁹⁴ 0.140	⁹⁴ 0.093	⁴⁴ 0.983	⁵¹ 0.979	⁶⁸ 0.969			⁵⁸ 0.474	⁷⁰ 0.377
104	NEC-001	¹⁰¹ 0.148	¹²⁵ 0.106	¹³³ 0.060	¹⁰⁸ 0.238	¹¹⁹ 0.197	¹²³ 0.133	⁵⁷ 0.991	⁶³ 0.986	⁷⁰ 0.972	⁷¹ 0.133	⁷⁶ 0.082	⁵⁷ 0.468	⁷¹ 0.378
105	NEC-002	¹² 0.018	⁶ 0.003	⁴ 0.002	⁷ 0.029	⁷ 0.020	⁷ 0.013	¹⁰⁹ 1.000	¹¹⁴ 0.999	¹¹² 0.995	⁶ 0.008	⁹ 0.005	⁷⁵ 0.676	⁵⁵ 0.292
106	NEC-003	⁴ 0.005	⁵ 0.002	⁶ 0.002	⁶ 0.021	⁶ 0.017	⁶ 0.013	²¹ 0.902	²¹ 0.824	²¹ 0.628	⁹ 0.008	¹⁰ 0.006	⁷⁴ 0.668	⁵¹ 0.261
107	NEUROTECHNOLOGY-003	¹⁹⁸ 0.999	¹⁸⁶ 0.636	¹⁵⁶ 0.099	¹⁶⁷ 0.773	¹⁴⁰ 0.266	¹³⁶ 0.164	¹⁷⁰ 1.000	¹⁹⁷ 1.000	²⁰³ 1.000				
108	NEUROTECHNOLOGY-004	⁸³ 0.120	⁹⁷ 0.063	⁹³ 0.028	⁷² 0.146	⁷⁵ 0.117	⁷⁵ 0.073	⁷⁵ 0.996	⁷⁵ 0.994	⁹² 0.990				
109	NEUROTECHNOLOGY-005	⁸² 0.117	⁸⁶ 0.054	⁷⁶ 0.022	¹¹¹ 0.252	⁸⁷ 0.130	⁸¹ 0.074	⁹⁵ 0.999	⁹⁶ 0.998	⁹⁹ 0.989				
110	NEUROTECHNOLOGY-006	¹⁹⁶ 0.987	¹⁶¹ 0.249	¹⁶¹ 0.121	¹⁹⁸ 1.000	¹⁵⁹ 0.418	¹⁵² 0.206							
111	NEUROTECHNOLOGY-007	¹³⁵ 0.252	⁵⁶ 0.062	⁷⁴ 0.021	¹⁸⁹ 0.996	¹¹³ 0.173	⁷¹ 0.068	¹³⁴ 1.000	¹³⁰ 1.000	¹²⁴ 0.997	⁹¹ 0.339	⁵⁶ 0.036	¹⁸¹ 1.000	¹¹⁵ 0.989
112	NEWLAND-002	¹⁶⁸ 0.523	¹⁷⁸ 0.438	¹⁷⁹ 0.294	¹⁵² 0.535	¹⁶⁴ 0.466	¹⁶⁶ 0.335	¹⁰¹ 0.999	¹⁰⁸ 0.999	¹³⁰ 0.998				
113	NOBLIS-001	²⁰² 1.000	²⁰² 1.000	²⁰¹ 0.991	¹⁹³ 1.000	¹⁹⁷ 1.000	²⁰² 1.000	¹³¹ 1.000	¹⁴⁶ 1.000	¹⁵² 1.000				
114	NOBLIS-002	²⁰¹ 1.000	¹⁹⁸ 0.997	¹⁸⁸ 0.488	²⁰³ 1.000	²⁰² 1.000	¹⁹⁷ 1.000	¹³⁹ 1.000	¹³⁷ 1.000	¹⁴⁹ 1.000				
115	NTECHLAB-003	⁶⁴ 0.080	⁸¹ 0.054	⁵⁸ 0.028	⁷³ 0.148	⁷⁶ 0.118	⁸³ 0.075	¹⁹ 0.873	²³ 0.837	³⁴ 0.752				
116	NTECHLAB-004	⁵⁵ 0.063	⁶² 0.041	⁷² 0.021	⁶³ 0.131	⁶⁷ 0.105	⁶⁸ 0.065	¹⁸ 0.868	²² 0.833	³² 0.746	⁴⁵ 0.053	⁴⁸ 0.030	³³ 0.263	⁴⁰ 0.214
117	NTECHLAB-005	⁵⁴ 0.062	⁶³ 0.042	⁷³ 0.021	⁶⁴ 0.130	⁶⁵ 0.102	⁶⁷ 0.063	¹⁶ 0.816	¹⁸ 0.771	²⁶ 0.661	⁵⁷ 0.073	⁵⁸ 0.039	³⁵ 0.294	⁴³ 0.227
118	NTECHLAB-006	⁴⁹ 0.056	⁵⁸ 0.037	⁶³ 0.018	⁵⁴ 0.121	⁵⁶ 0.094	⁵⁷ 0.059	¹⁵ 0.802	¹⁷ 0.754	²² 0.635	⁴⁸ 0.057	⁵² 0.032	³² 0.260	³⁸ 0.207
119	NTECHLAB-007	³³ 0.040	⁴¹ 0.026	³¹ 0.012	³² 0.085	³⁶ 0.067	³⁶ 0.041	¹⁴ 0.796	¹⁶ 0.750	²³ 0.642	³¹ 0.032	³⁴ 0.017	²⁴ 0.223	²⁹ 0.176
120	NTECHLAB-008	¹⁶ 0.024	²³ 0.014	²⁶ 0.007	¹⁸ 0.057	²¹ 0.045	²³ 0.029	⁶ 0.601	⁹ 0.529	¹³ 0.391	³⁴ 0.033	³⁷ 0.018	¹⁸ 0.183	¹⁹ 0.140
121	NTECHLAB-009	⁵ 0.010	¹² 0.005	¹² 0.003							¹⁵ 0.015	¹⁶ 0.008	¹⁰ 0.142	⁹ 0.114
122	PARAVISION-000	¹⁴⁴ 0.278	¹¹⁹ 0.089	¹²⁰ 0.045	¹⁴⁷ 0.447	¹¹¹ 0.170	¹⁰⁵ 0.100	¹²⁶ 1.000	¹¹⁰ 0.999	¹²² 0.997	⁹⁹ 0.470	¹⁰² 0.443	⁹⁸ 0.926	⁹⁸ 0.779
123	PARAVISION-001	⁹⁷ 0.140	⁷⁵ 0.049	⁶⁹ 0.020	¹⁰³ 0.207	⁸⁶ 0.128	⁸⁰ 0.074	¹⁴⁴ 1.000	¹⁰⁵ 0.999	¹⁰⁸ 0.994	⁹⁷ 0.444	¹⁰¹ 0.428	⁷⁸ 0.739	⁸³ 0.573
124	PARAVISION-002	⁶⁶ 0.085	⁷⁶ 0.050	⁷⁸ 0.022	⁷⁷ 0.152	⁷⁹ 0.119	⁸⁵ 0.076	⁵⁸ 0.992	⁵⁸ 0.983	³³ 0.748	⁶⁰ 0.080	⁶² 0.043	⁶¹ 0.497	⁵⁹ 0.268
125	PARAVISION-003	⁵⁶ 0.063	⁵⁹ 0.035	⁵⁶ 0.016	⁵⁹ 0.124	⁵⁹ 0.096	⁶⁰ 0.060	⁸¹ 0.997	⁷⁶ 0.994	⁸⁷ 0.733	⁴⁹ 0.058	⁵⁵ 0.034	³⁶ 0.296	⁴⁵ 0.232
126	PARAVISION-004	¹⁷ 0.025	¹⁷ 0.010	¹⁶ 0.004	¹⁶ 0.049	¹⁸ 0.038	¹⁷ 0.024	¹²⁸ 1.000	¹⁴⁰ 1.000	³⁸ 0.797	¹⁹ 0.018	²⁰ 0.011	⁹⁴ 0.908	³⁹ 0.211
127	PARAVISION-005	¹¹ 0.014	⁹ 0.004	¹⁰ 0.002	⁸ 0.031	⁸ 0.024	⁹ 0.016	⁷⁹ 0.997	⁵³ 0.980	⁶ 0.181	¹² 0.011	¹⁷ 0.008	⁷ 0.132	¹² 0.120
128	PARAVISION-007	⁴³ 0.048	⁸ 0.004	⁷ 0.002	¹⁵³ 0.560	⁹ 0.025	⁸ 0.015	¹³⁰ 1.000	¹⁴⁸ 1.000	¹⁵⁴ 1.000	¹¹ 0.009	¹¹ 0.006	¹⁴⁵ 1.000	¹⁷¹ 1.000
129	PIXELALL-002	¹⁷⁵ 0.664	¹²⁴ 0.105	⁹⁷ 0.030	¹⁸² 0.974	¹⁵⁷ 0.388	⁹² 0.083		¹⁴⁴ 1.000	¹⁴⁸ 1.000	¹⁰¹ 0.602	⁶⁵ 0.047	¹²⁷ 1.000	¹¹⁴ 1.000
130	PIXELALL-003	⁴⁴ 0.049	³⁸ 0.022	³⁸ 0.009	⁴² 0.102	⁴¹ 0.073	⁴⁰ 0.043		¹²³ 1.000	¹²⁹ 0.998	³⁷ 0.037	³⁹ 0.020	⁶⁶ 0.554	⁵⁰ 0.255
131	PIXELALL-004	⁸⁴ 0.120	³³ 0.018	²⁸ 0.007	¹⁷⁰ 0.783	⁴⁵ 0.079	³² 0.037		¹³⁴ 1.000	¹³⁵ 0.999	⁴² 0.051	²⁹ 0.015	¹⁰⁸ 0.994	¹⁰⁸ 0.942
132	PTAKURATSATU-000	⁵¹ 0.057	⁵⁸ 0.037	⁵⁷ 0.017	⁸² 0.165	⁸⁴ 0.124	⁷⁷ 0.071	³⁰ 0.947	³² 0.924	⁴⁴ 0.868	⁴⁰ 0.046	⁴¹ 0.022	²⁶ 0.232	³⁵ 0.179
133	QUANTASOFT-001	¹⁷⁹ 0.713	¹⁸⁷ 0.639	¹⁸⁸ 0.493										
134	RANKONE-002	¹¹⁵ 0.184	¹²⁸ 0.118	¹⁴⁰ 0.071	¹²⁸ 0.308	¹³⁶ 0.261	¹⁴⁶ 0.190							
135	RANKONE-003	¹¹⁶ 0.184	¹²⁹ 0.118	¹³⁹ 0.071	¹²⁵ 0.300	¹³⁵ 0.255	¹⁴⁴ 0.187							
136	RANKONE-004	¹³⁴ 0.250	¹⁵³ 0.193	¹⁶² 0.124	¹⁵⁰ 0.482	¹⁶¹ 0.426	¹⁶⁵ 0.324							
137	RANKONE-005	⁷¹ 0.096	⁹¹ 0.059	¹⁰² 0.033	¹⁰⁴ 0.212	¹¹⁴ 0.173	¹¹⁹ 0.119	¹⁰³ 0.999	⁹⁷ 0.998	¹⁰⁹ 0.994				
138	RANKONE-006	⁵² 0.061	⁶⁰ 0.037	⁶⁶ 0.020				⁴⁹ 0.987	⁴⁸ 0.977	⁵⁵ 0.937				

Table 22: **Threshold-based accuracy.** Values are $FNIR(N, T, L)$ with $N = 1.6$ million with thresholds set to produce $FPIR = 0.0003, 0.001$, and 0.01 in non-mate searches. Throughout blue superscripts indicate the rank of the algorithm for that column. Caution: The Power-low models are mostly intended to draw attention to the kind of behavior, not as a model to be used for prediction.

2021/03/04
11:49:04FNIR(N, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

MISSES BELOW THRESHOLD, T		ENROL RECENT MUGSHOT, N = 1.6M										ENROL APPLICATION PORTRAIT, N = 1.6M			
ENROL PROBE		DATASET: MUGSHOT DATASET: MUGSHOT			DATASET: MUGSHOT DATASET: WEBCAM			DATASET: MUGSHOT DATASET: PROFILE			DATASET: VISA DATASET: BORDER		DATASET: VISA DATASET: KIOSK		
#	ALGORITHM	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	
139	RANKONE-007	²⁶ 0.034	⁴⁰ 0.022	⁴⁶ 0.011	⁵¹ 0.118	⁵⁷ 0.095	⁶² 0.061	³⁵ 0.975	³⁹ 0.967	⁴⁹ 0.924					
140	RANKONE-009	²³ 0.031	³⁰ 0.018	³⁶ 0.008	³⁸ 0.098	⁴² 0.076	⁴² 0.045	⁴³ 0.983	⁴¹ 0.969	⁴³ 0.859	⁵¹ 0.062	⁴⁹ 0.029	⁴⁴ 0.328	³⁷ 0.206	
141	RANKONE-010	¹⁵ 0.023	²¹ 0.014	²⁹ 0.007	²⁸ 0.077	³⁰ 0.058	³¹ 0.036	²² 0.905	²⁰ 0.802	²⁵ 0.652	⁴⁴ 0.052	⁴³ 0.027	³¹ 0.259	³⁶ 0.194	
142	REALNETWORKS-000	¹³³ 0.374	¹³⁸ 0.234	¹⁶⁶ 0.138	¹⁴² 0.433	¹⁵² 0.319	¹⁵⁵ 0.209								
143	REALNETWORKS-001	¹⁵⁴ 0.374	¹⁵⁹ 0.234	¹⁶⁵ 0.138	¹⁴⁵ 0.433	¹⁵¹ 0.319	¹⁵⁴ 0.209								
144	REALNETWORKS-002	¹⁵² 0.370	¹⁵⁷ 0.231	¹⁶⁴ 0.137	¹⁴³ 0.416	¹⁵⁰ 0.315	¹⁵⁶ 0.209								
145	REALNETWORKS-003	¹⁴² 0.273	¹⁴³ 0.159	¹⁴⁸ 0.090	¹³⁷ 0.342	¹³⁹ 0.266	¹⁴² 0.172	¹⁰⁰ 0.999	¹⁰⁰ 0.998	⁸⁶ 0.987	⁷⁸ 0.164	⁸¹ 0.103	⁶² 0.500	⁶⁷ 0.364	
146	REALNETWORKS-004	¹³³ 0.242	¹⁴² 0.158	¹⁴⁷ 0.090	¹³⁶ 0.353	¹³⁷ 0.263	¹³⁹ 0.169	¹¹¹ 1.000	¹¹² 0.999	¹⁰² 0.992	⁷⁹ 0.170	⁸² 0.103	⁷⁶ 0.613	⁶⁸ 0.370	
147	REMARKAI-000	⁸⁸ 0.125	⁸⁷ 0.055	⁸⁰ 0.023	⁸⁵ 0.173	⁸⁰ 0.120	⁷⁴ 0.070	¹⁰⁵ 0.999	¹⁰⁹ 0.999	¹¹¹ 0.995	⁵⁶ 0.069	⁵⁴ 0.033	⁷⁶ 0.717	⁶⁴ 0.315	
148	REMARKAI-000	¹²³ 0.197	¹³³ 0.128	¹³² 0.059	¹¹⁶ 0.263	¹²⁰ 0.203	¹²¹ 0.123								
149	REMARKAI-002	¹²⁰ 0.188	¹³² 0.124	¹³¹ 0.059	¹¹⁰ 0.248	¹¹⁸ 0.196	¹²⁰ 0.122	⁶⁰ 0.993	⁶⁹ 0.991	⁸¹ 0.980					
150	SCANOVATE-000	⁷⁶ 0.103	¹⁰⁰ 0.067	⁹⁸ 0.030	¹²⁴ 0.296	¹³² 0.240	¹²⁹ 0.150	²⁶ 0.931	²⁹ 0.893	³⁹ 0.803	⁸⁵ 0.215	⁸⁸ 0.118	⁵⁰ 0.400	⁶⁰ 0.299	
151	SCANOVATE-001	⁸⁰ 0.128	¹⁰⁹ 0.081	¹⁰⁸ 0.037	¹²¹ 0.281	¹²⁷ 0.227	¹²⁵ 0.140	²⁷ 0.935	³¹ 0.911	⁴¹ 0.834	⁸² 0.192	⁸³ 0.103	⁵³ 0.404	⁵⁷ 0.290	
152	SENSETIME-000	²⁹ 0.036	³⁶ 0.021	³⁹ 0.009	²⁹ 0.078	³³ 0.063	³³ 0.040	¹⁶² 1.000	²⁰² 1.000	⁸⁷ 0.988					
153	SENSETIME-001	³⁰ 0.036	³⁹ 0.022	⁴¹ 0.010	³¹ 0.080	³⁴ 0.064	³⁹ 0.041								
154	SENSETIME-002	³¹ 0.037	²⁴ 0.015	³⁵ 0.014	⁵⁸ 0.124	¹³ 0.028	¹⁶ 0.023	⁷⁸ 0.997	⁷⁴ 0.994	⁸⁰ 0.979	²⁹ 0.032	³³ 0.017	⁶³ 0.523	²⁵ 0.160	
155	SENSETIME-003	² 0.004	² 0.002	³ 0.001	¹ 0.014	¹ 0.012	¹ 0.009	⁷ 0.607	⁷ 0.477	¹⁰ 0.311	⁷ 0.008	⁸ 0.005	⁸ 0.133	¹⁰ 0.115	
156	SENSETIME-004	¹ 0.003	¹ 0.002	² 0.001	² 0.015	² 0.013	⁴ 0.010	³ 0.301	³ 0.229	⁴ 0.149	² 0.006	² 0.004	⁵ 0.113	⁶ 0.100	
157	SENSETIME-005	⁸ 0.011	⁴ 0.002	¹ 0.001	⁵ 0.018	⁵ 0.014	² 0.010	² 0.259	² 0.173	² 0.103	⁴ 0.007	³ 0.004	² 0.104	³ 0.093	
158	SHAMAN-003	¹⁶⁶ 0.506	¹⁷⁹ 0.451	¹⁸² 0.347	¹⁶¹ 0.650	¹⁷² 0.597	¹⁷³ 0.472								
159	SHAMAN-004	¹⁷⁶ 0.679	¹⁸⁵ 0.615	¹⁸⁷ 0.488	¹⁷¹ 0.812	¹⁷⁸ 0.754	¹⁸¹ 0.639								
160	SHAMAN-006	¹¹⁸ 0.185	¹³⁷ 0.141	¹⁵⁰ 0.092	¹¹⁹ 0.278	¹²⁹ 0.237	¹³⁸ 0.168	³⁷ 0.978	⁴³ 0.972	⁶⁴ 0.960					
161	SHAMAN-007	¹¹³ 0.183	¹³⁸ 0.141	¹⁴⁹ 0.092	¹²⁰ 0.280	¹³¹ 0.240	¹⁴⁰ 0.169								
162	SIAT-001	⁹² 0.132	²⁸ 0.018	²⁷ 0.007	¹⁶⁸ 0.641	¹⁵⁶ 0.365	¹⁶³ 0.348				²⁷ 0.031	²⁵ 0.014			
163	SIAT-002	¹⁵⁶ 0.417	³⁷ 0.022	³⁰ 0.007	¹⁷³ 0.942	¹⁶⁵ 0.478	¹⁷³ 0.460				⁹³ 0.372	⁹⁶ 0.356	⁹⁷ 0.923	²⁷ 0.169	
164	SMILART-004	¹⁹⁴ 0.970	¹⁹⁶ 0.968	¹⁹⁹ 0.965	¹⁸³ 0.977	¹⁹¹ 0.976	¹⁹³ 0.973								
165	SMILART-005														
166	SYNOPSIS-003	¹⁷⁴ 0.648	¹⁸¹ 0.582	¹⁸⁶ 0.443	¹⁶⁵ 0.708	¹⁷⁴ 0.646	¹⁷⁷ 0.524								
167	SYNOPSIS-003	⁸⁰ 0.111	⁹⁸ 0.065	⁹⁹ 0.032	⁷⁸ 0.155	⁸³ 0.123	⁸⁶ 0.078	³³ 0.973	³⁷ 0.960	⁴⁷ 0.911	⁵⁸ 0.075	⁵⁷ 0.039	⁴⁰ 0.314	⁴⁷ 0.235	
168	SYNOPSIS-005	⁴⁶ 0.050	⁴² 0.025	⁴⁸ 0.011	³⁴ 0.088	³⁹ 0.072	⁴¹ 0.043	⁶⁷ 0.995	⁵⁹ 0.984	³⁵ 0.795	³² 0.032	³⁰ 0.016	²² 0.214	²⁴ 0.158	
169	TECH5-001	¹⁸² 0.807	⁸⁹ 0.057	⁸² 0.018	¹⁸⁸ 0.994	¹⁸⁷ 0.935	⁵⁴ 0.055	¹⁵⁸ 1.000	¹⁵⁰ 1.000	¹⁴⁵ 1.000	⁸⁶ 0.244	⁴⁶ 0.028	¹⁰⁹ 0.994	¹⁰⁷ 0.817	
170	TEVIAN-003	¹³² 0.239	¹⁵⁰ 0.177	¹⁵⁵ 0.096	¹³² 0.346	¹⁴⁶ 0.298	¹⁴⁸ 0.198								
171	TEVIAN-004	¹¹⁰ 0.170	¹²⁷ 0.117	¹³⁶ 0.063	¹⁰⁸ 0.216	¹¹⁵ 0.176	¹¹⁸ 0.115								
172	TEVIAN-005	⁹¹ 0.129	¹¹⁴ 0.087	¹¹⁹ 0.045	⁹⁰ 0.180	⁹⁶ 0.144	⁹⁶ 0.089	⁵² 0.988	³⁸ 0.962	³⁷ 0.796					
173	TIGER-000	¹⁶² 0.462	¹⁷⁴ 0.390	¹⁷⁵ 0.261	¹⁵⁴ 0.565	¹⁶⁶ 0.500	¹⁶⁸ 0.366								
174	TIGER-002	¹⁰⁶ 0.158	¹¹⁰ 0.086	¹¹¹ 0.039	¹⁰⁰ 0.202	¹⁰⁵ 0.158	¹⁰² 0.095	¹⁰⁶ 0.999	¹⁰⁰ 0.999	⁷⁷ 0.975					
175	TIGER-003	¹⁰⁷ 0.158	¹¹¹ 0.086	¹¹⁰ 0.039	¹⁰¹ 0.202	¹⁰⁴ 0.158	¹⁰¹ 0.095								
176	TONGYITRANS-000	⁷⁹ 0.107	¹⁰⁸ 0.074	¹⁰⁹ 0.038	⁷⁶ 0.141	⁷² 0.112	⁷³ 0.069								
177	TONGYITRANS-001	⁸⁷ 0.124	⁹⁹ 0.066	¹⁰⁰ 0.032	⁶⁰ 0.128	⁶³ 0.101	⁶⁴ 0.062								
178	TOSHIBA-000	⁸⁶ 0.123	⁹⁵ 0.062	⁹² 0.027	⁷⁴ 0.150	⁷⁷ 0.118	⁷⁹ 0.074	⁸⁰ 0.997	⁸⁴ 0.995	⁸⁸ 0.988					
179	TOSHIBA-001	¹²⁹ 0.225	⁹¹ 0.058	⁶⁴ 0.019	⁶⁵ 0.133	⁵⁴ 0.092	⁵³ 0.054								
180	TRUEFACE-000	⁴⁰ 0.046	³² 0.018	³⁵ 0.008	³⁰ 0.079	³² 0.062	³³ 0.039	⁶⁸ 0.995	²⁶ 0.882	¹⁵ 0.499	²⁶ 0.030	³² 0.016	²⁰ 0.188	²⁰ 0.145	
181	VD-000	¹⁹¹ 0.950	¹⁹⁴ 0.917	¹⁹⁶ 0.827	¹⁸¹ 0.968	¹⁸⁹ 0.946	¹⁸⁹ 0.871								
182	VD-001	¹⁴³ 0.278	¹⁵⁴ 0.201	¹⁶⁰ 0.116	¹²⁷ 0.331	¹⁴³ 0.281	¹⁴⁵ 0.188								
183	VIGILANTSOLUTIONS-003	¹⁶⁵ 0.482	¹⁷⁷ 0.408	¹⁷⁷ 0.282	¹⁶⁸ 0.730	¹⁷⁷ 0.660	¹⁷⁸ 0.526	¹⁰² 0.999	¹⁰⁴ 0.999	¹¹³ 0.995					
184	VIGILANTSOLUTIONS-004	¹⁷³ 0.624	¹⁸³ 0.549	¹⁸⁵ 0.422	¹⁷² 0.858	¹⁸¹ 0.817	¹⁸³ 0.709	⁹⁰ 0.998	⁸⁸ 0.996	⁹⁶ 0.991					

Table 23: **Threshold-based accuracy.** Values are FNIR(N, T, L) with N = 1.6 million with thresholds set to produce FPIR = 0.0003, 0.001, and 0.01 in non-mate searches. Throughout blue superscripts indicate the rank of the algorithm for that column. Caution: The Power-low models are mostly intended to draw attention to the kind of behavior, not as a model to be used for prediction.

2021/03/04
11:49:04FNIR(N, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

MISSES BELOW THRESHOLD, T		ENROL RECENT MUGSHOT, N = 1.6M									ENROL APPLICATION PORTRAIT, N = 1.6M			
ENROL		DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: VISA		DATASET: VISA	
PROBE		DATASET: MUGSHOT			DATASET: WEBCAM			DATASET: PROFILE			DATASET: BORDER		DATASET: KIOSK	
#	ALGORITHM	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.0003	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01
185	VIGILANTSOLUTIONS-005	¹⁹⁰ 0.936	¹⁷³ 0.388	¹¹³ 0.043				¹⁴⁰ 1.000	¹⁴³ 1.000	¹⁵¹ 1.000				
186	VIGILANTSOLUTIONS-006	¹⁹³ 0.959	¹⁶⁸ 0.353	¹¹⁶ 0.043				¹³⁸ 1.000	¹³⁶ 1.000	¹⁵⁰ 1.000				
187	VIGILANTSOLUTIONS-007	⁶³ 0.076	⁵² 0.028	⁴⁷ 0.011	⁴⁶ 0.113	⁴⁹ 0.088	⁴⁹ 0.053	⁸⁵ 0.997	⁸⁷ 0.996	⁹⁹ 0.991	⁶¹ 0.081	⁶⁴ 0.047	⁴⁹ 0.391	⁵⁶ 0.295
188	VISIONLABS-004	⁶⁸ 0.091	⁹⁰ 0.058	⁸³ 0.024	⁹⁶ 0.199	¹⁰⁶ 0.159	¹⁰⁴ 0.097	²⁸ 0.944	²⁹ 0.890	³¹ 0.742				
189	VISIONLABS-005	⁶⁵ 0.080	⁷⁷ 0.050	⁶⁸ 0.020	⁹³ 0.183	⁹⁷ 0.147	⁹⁴ 0.087	²⁹ 0.945	²⁷ 0.888	³⁰ 0.736				
190	VISIONLABS-006	³⁸ 0.044	⁴⁹ 0.027	⁴³ 0.010	⁵⁶ 0.117	⁵² 0.090	⁴⁶ 0.051	¹² 0.764	¹³ 0.672	¹⁸ 0.511				
191	VISIONLABS-007	³⁷ 0.044	⁴⁸ 0.027	⁴² 0.010	⁴⁹ 0.117	⁵¹ 0.090	⁴⁵ 0.051	¹¹ 0.764	¹⁴ 0.672	¹⁷ 0.511	²⁶ 0.031	²⁶ 0.014	¹⁹ 0.185	²¹ 0.145
192	VISIONLABS-008	²¹ 0.028	²⁰ 0.013	²⁰ 0.006	²³ 0.068	²⁵ 0.051	²⁶ 0.032	⁵ 0.574	⁸ 0.481	¹¹ 0.317	¹⁶ 0.017	¹⁵ 0.008	¹¹ 0.151	¹¹ 0.119
193	VISIONLABS-009	⁸ 0.012	¹⁰ 0.005	⁹ 0.002	⁹ 0.032	¹⁰ 0.025	¹⁰ 0.017	²⁵ 0.930	¹⁹ 0.799	⁷ 0.196	¹⁰ 0.008	⁶ 0.004	⁴ 0.113	⁴ 0.093
194	VISIONLABS-010	¹⁰ 0.014	¹³ 0.005	¹¹ 0.002	¹⁰ 0.034	¹² 0.027	¹² 0.019			⁵ 0.169	⁵ 0.008	⁴ 0.004	³ 0.109	² 0.089
195	VOCORD-003	¹⁴⁹ 0.354	¹³¹ 0.122	¹²³ 0.048	⁹⁵ 0.195	¹⁰² 0.155	⁹⁹ 0.093	⁹⁴ 0.999	⁹⁶ 0.998	⁹⁴ 0.991	⁷⁷ 0.157	⁸⁴ 0.105	⁵² 0.404	⁵⁶ 0.289
196	VOCORD-004	¹⁸³ 0.826	¹⁶⁹ 0.355	¹²⁴ 0.051	¹⁴⁰ 0.401	¹¹² 0.173	⁹⁷ 0.093	¹³³ 1.000	¹²⁹ 1.000	¹³⁴ 0.999	⁸³ 0.193	⁷⁰ 0.065	¹⁰⁶ 0.991	⁹⁷ 0.776
197	VOCORD-005	¹⁷⁷ 0.689	¹⁴¹ 0.158	¹¹⁷ 0.044	⁸⁶ 0.161	⁸⁶ 0.130	⁸⁹ 0.080	⁹⁹ 0.999	⁹⁶ 0.997	⁹⁷ 0.968	⁷³ 0.138	⁷⁵ 0.090	⁴⁵ 0.381	⁵⁷ 0.287
198	VOCORD-006	²⁰³ 1.000	²⁰³ 1.000	²⁰⁵ 1.000	²⁰⁵ 1.000	²⁰⁰ 1.000	¹⁹⁹ 1.000	¹⁸⁴ 1.000	¹⁵⁴ 1.000	¹⁷⁰ 1.000	¹⁷⁹ 1.000	¹⁹⁸ 1.000	¹⁶² 1.000	¹³⁹ 1.000
199	XFORWARDAI-000	²² 0.029	²⁷ 0.015	²⁵ 0.006	²⁵ 0.070	²⁸ 0.053	³⁰ 0.034	¹⁰ 0.698	⁹ 0.440	⁸ 0.250	²⁰ 0.021	¹⁹ 0.011	¹⁴ 0.169	¹⁵ 0.134
200	XFORWARDAI-001	⁷ 0.010	¹¹ 0.005	¹³ 0.003	¹² 0.036	¹⁴ 0.028	¹³ 0.020	¹⁷ 0.838	⁶ 0.448	³ 0.143	⁸ 0.008	⁷ 0.005	⁶ 0.123	⁷ 0.102
201	YISHENG-001	¹⁶⁰ 0.452	¹⁶⁷ 0.346	¹⁷² 0.206	¹⁸⁴ 0.983	¹⁷⁹ 0.808	¹⁶¹ 0.269				¹⁰⁴ 0.666	¹⁰⁰ 0.396	⁹⁶ 0.919	⁹⁶ 0.695
202	YITU-002	²⁴ 0.031	²⁷ 0.018	³¹ 0.008	²⁶ 0.063	²³ 0.049	²¹ 0.028							
203	YITU-003	²⁵ 0.032	³⁵ 0.019	³⁷ 0.009	²¹ 0.067	²⁶ 0.052	²⁹ 0.033							
204	YITU-004	¹³ 0.019	¹⁵ 0.010	¹⁵ 0.004	¹¹ 0.035	¹¹ 0.027	¹¹ 0.017	³¹ 0.948	³³ 0.936	⁴⁸ 0.913				
205	YITU-005	¹⁴ 0.022	¹⁶ 0.010	¹⁸ 0.005	¹³ 0.039	¹⁵ 0.032	¹⁵ 0.023							

Table 24: **Threshold-based accuracy.** Values are $FNIR(N, T, L)$ with $N = 1.6$ million with thresholds set to produce $FPIR = 0.0003, 0.001$, and 0.01 in non-mate searches. Throughout blue superscripts indicate the rank of the algorithm for that column. Caution: The Power-low models are mostly intended to draw attention to the kind of behavior, not as a model to be used for prediction.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

Appendices

Appendix A Accuracy on large-population FRVT 2018 mugshots

This publication is available free of charge from: <https://doi.org/10.6028/NIST.IR.8271>

2021/03/04 11:49:04	FNIR(N, R, T) = FPIR(N, T) =	False neg. identification rate False pos. identification rate	N = Num. enrolled subjects R = Num. candidates examined	T = Threshold	T = 0 → Investigation T > 0 → Identification
------------------------	---------------------------------	--	--	---------------	---

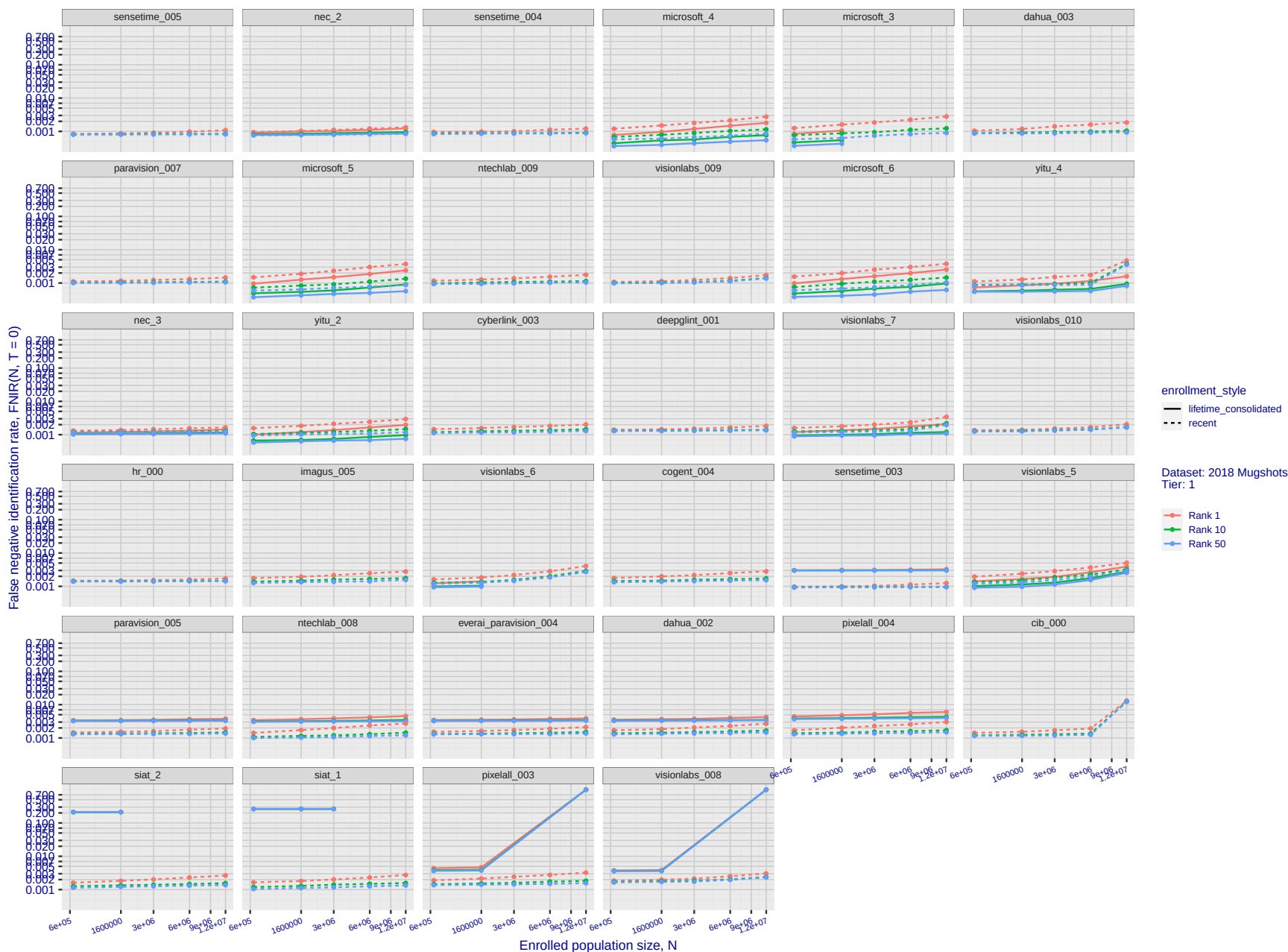


Figure 20: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects. The figure shows false negative identification rates, $FNIR(N, R)$, across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means $FPIR = 1$, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

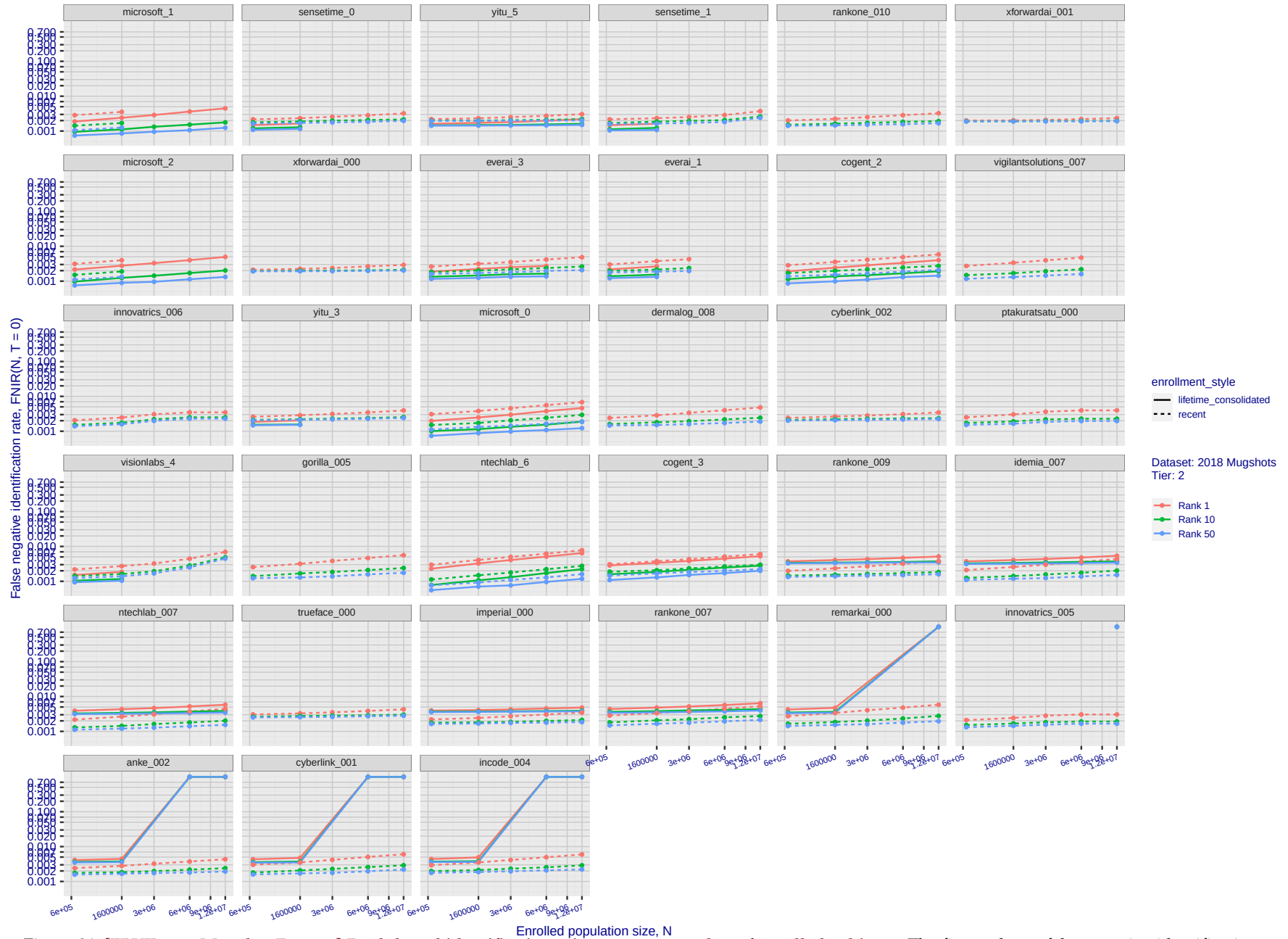
T = 0 → Investigation
T > 0 → Identification

Figure 21: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects. The figure shows false negative identification rates, $FNIR(N, R)$, across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means $FPIR = 1$, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.

2021/03/04
11:49:04
FNIR(N, R, T) =
FPIR(N, T) =
False neg. identification rate
False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

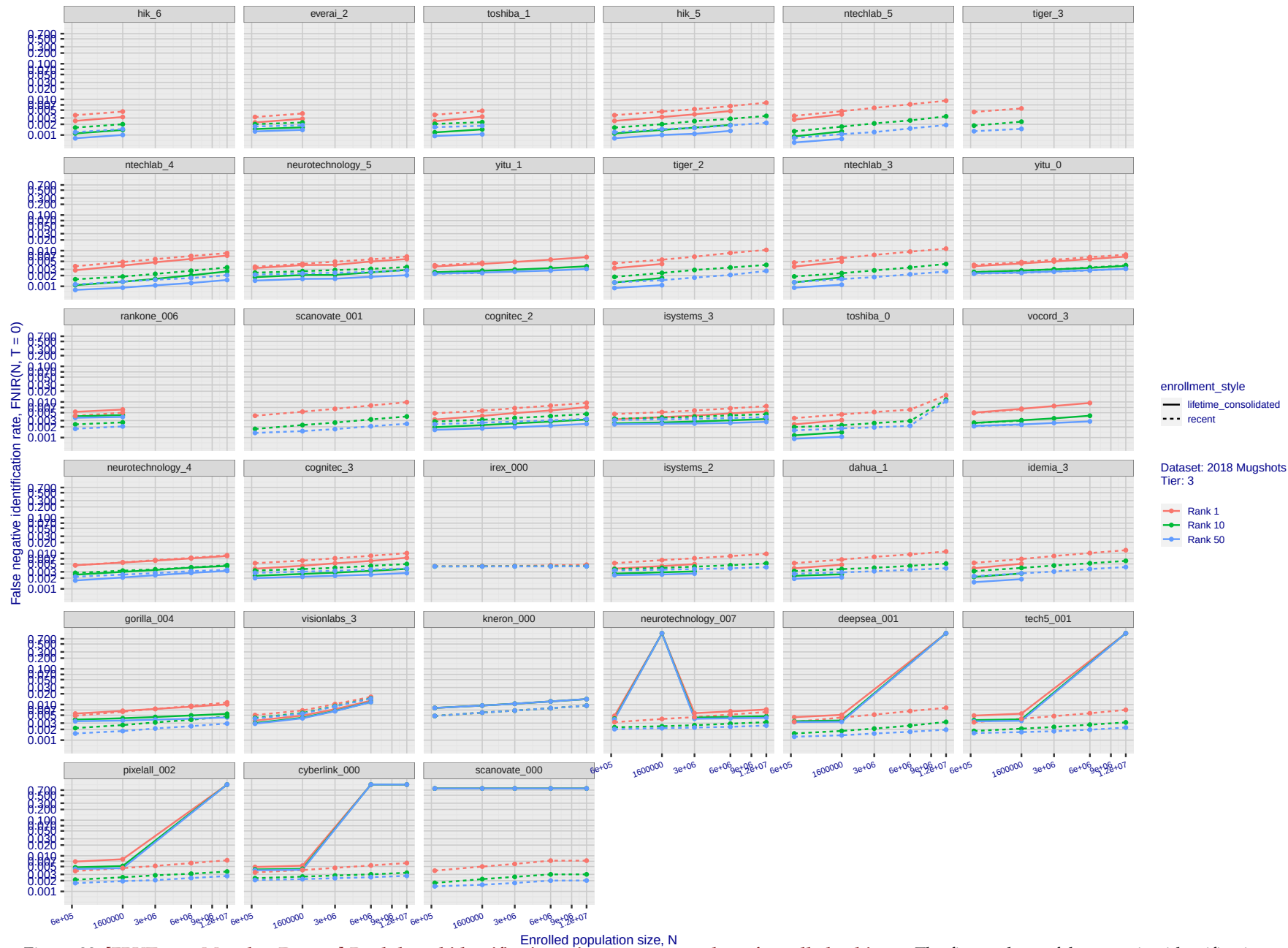


Figure 22: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects. The figure shows false negative identification rates, $FNIR(N, R)$, across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means $FPIR = 1$, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

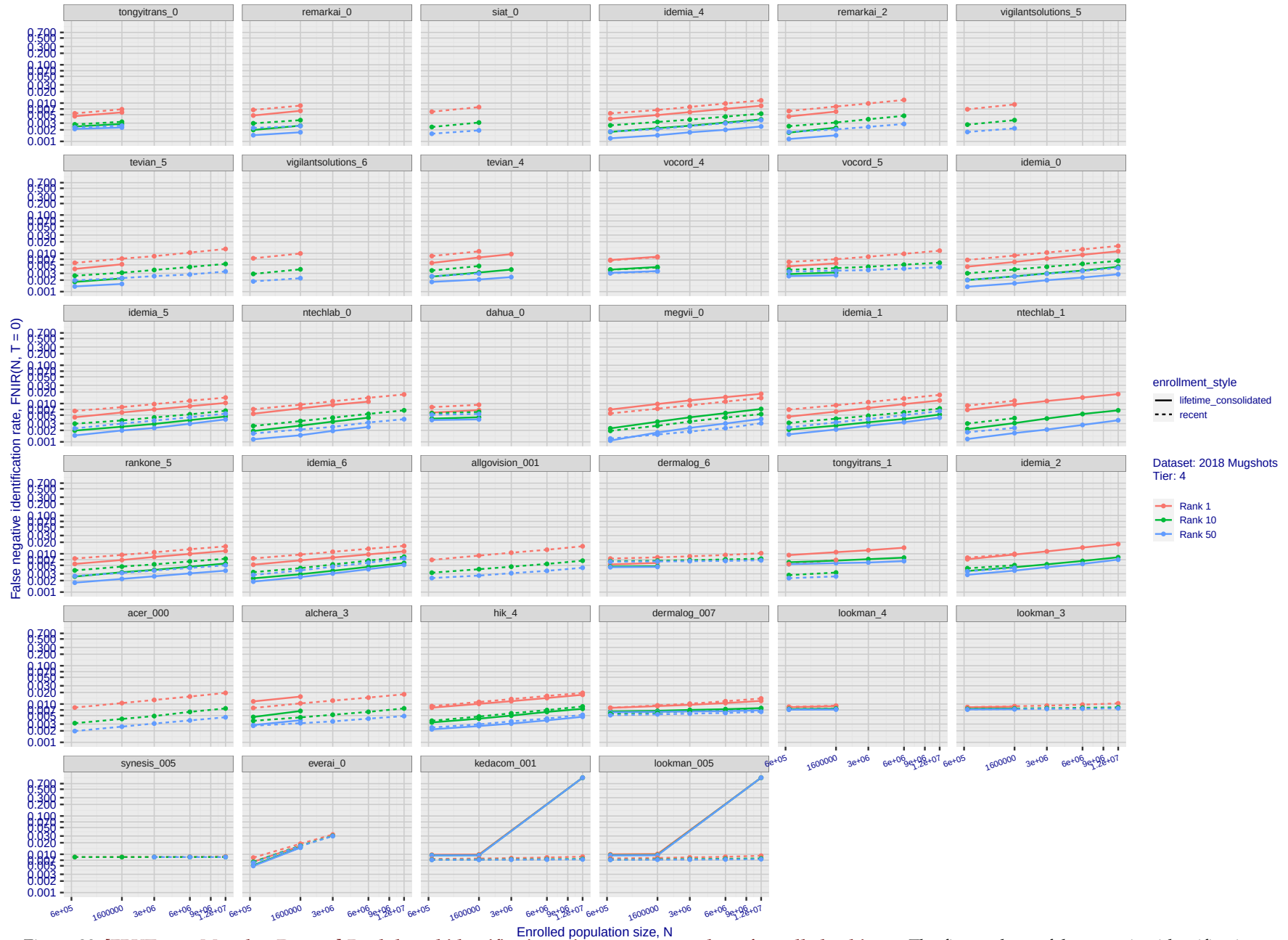
T = 0 → Investigation
T > 0 → Identification

Figure 23: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects. The figure shows false negative identification rates, $FNIR(N, R)$, across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means $FPIR = 1$, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

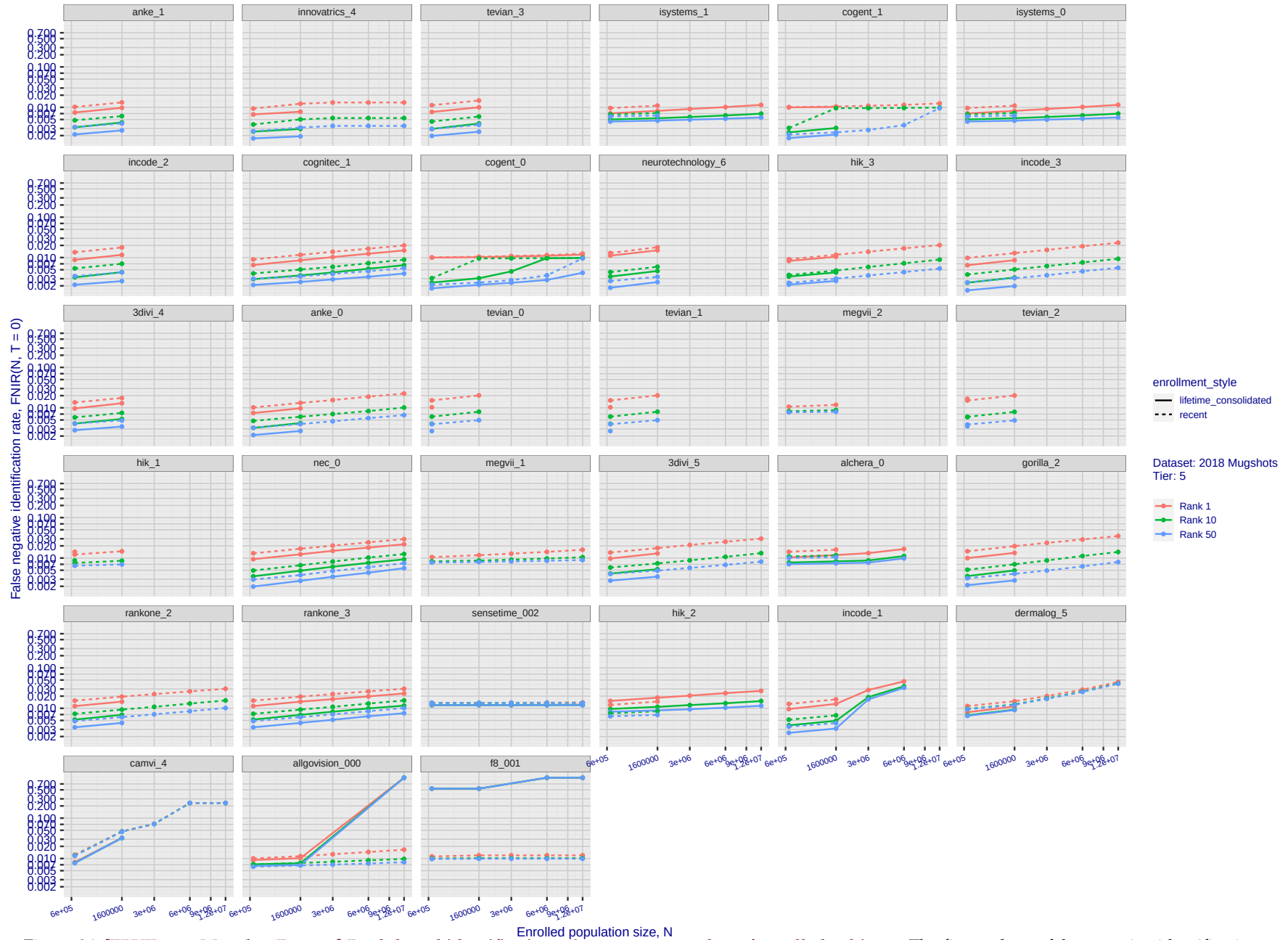
T = 0 → Investigation
T > 0 → Identification

Figure 24: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects. The figure shows false negative identification rates, $FNIR(N, R)$, across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means $FPIR = 1$, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.

2021/03/04
11:49:04FNIR(N, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

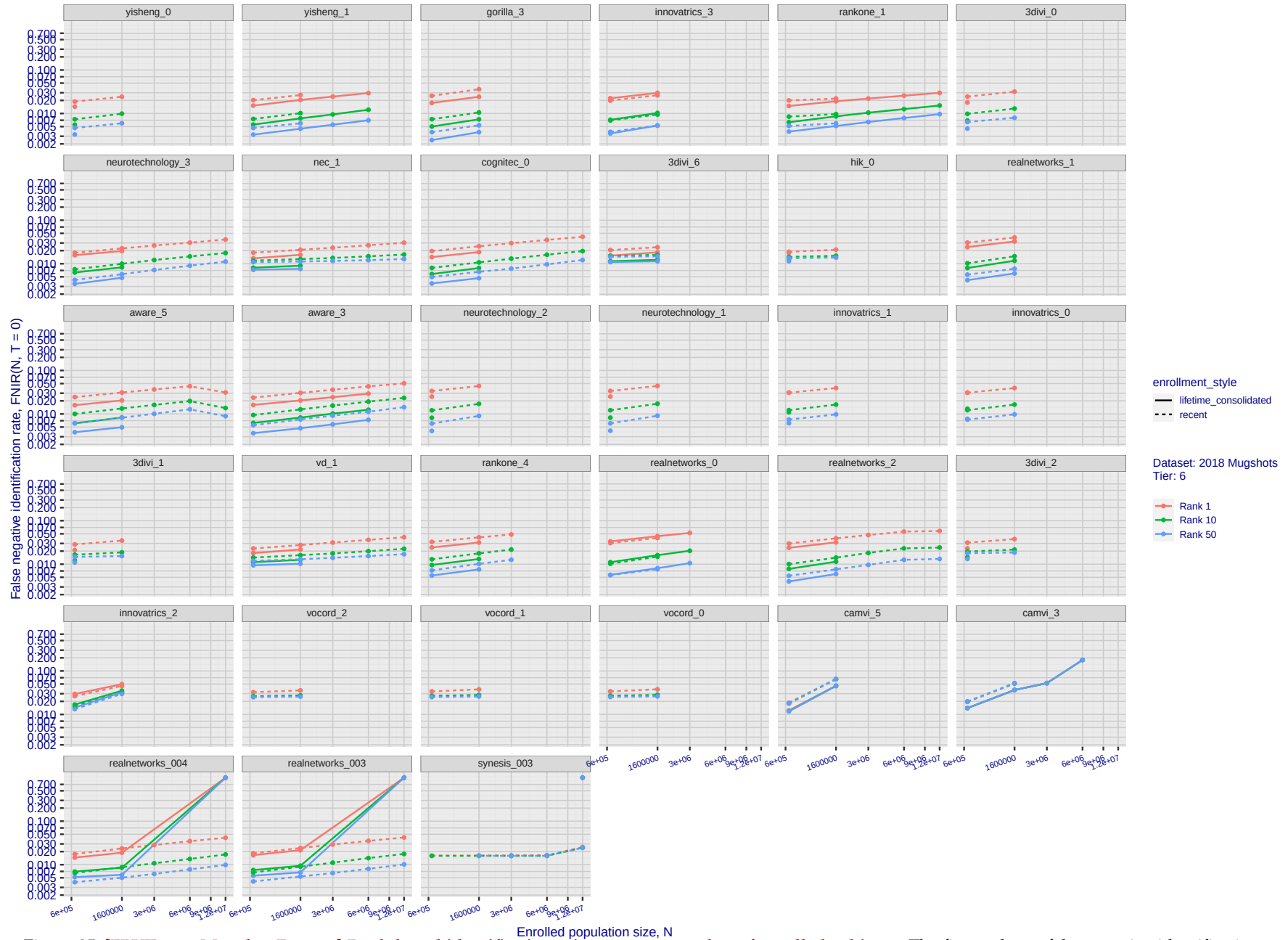
T = 0 → Investigation
T > 0 → Identification

Figure 25: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects. The figure shows false negative identification rates, $FNIR(N, R)$, across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means $FPIR = 1$, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

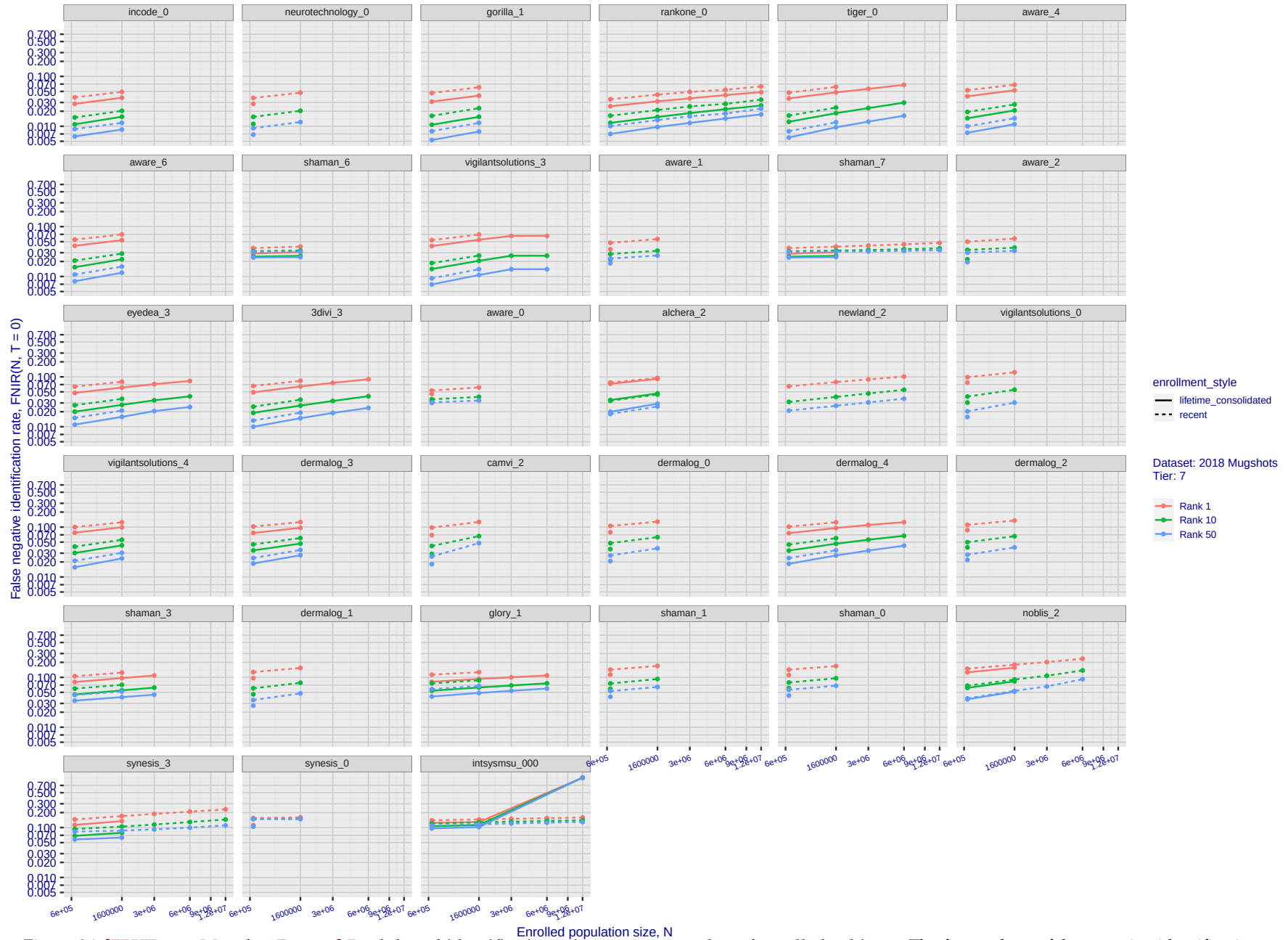
T = 0 → Investigation
T > 0 → Identification

Figure 26: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects. The figure shows false negative identification rates, $FNIR(N, R)$, across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means $FPIR = 1$, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.

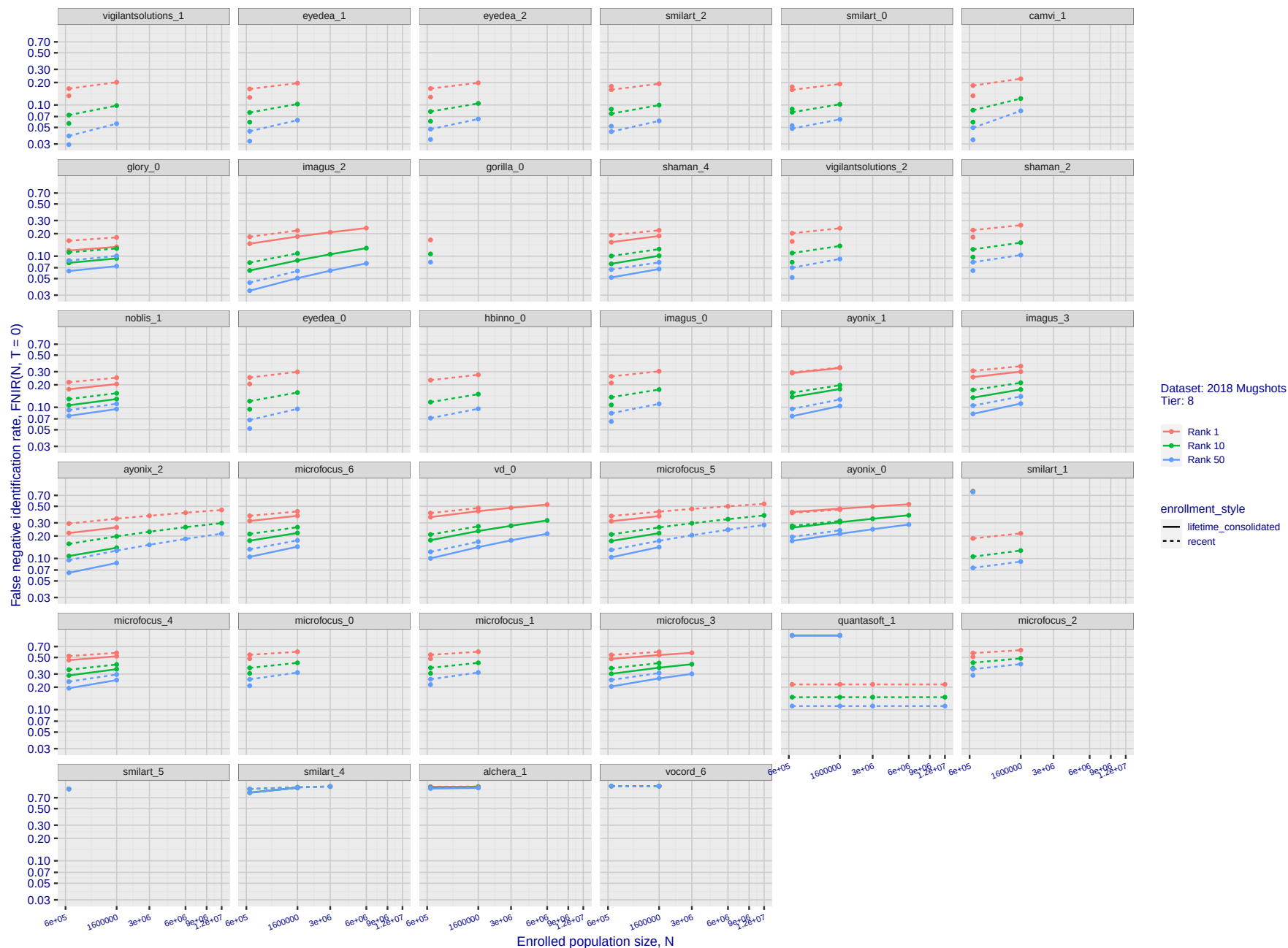


Figure 27: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects. The figure shows false negative identification rates, $FNIR(N, R)$, across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means $FPIR = 1$, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.

2021/03/04 11:49:04	FNIR(N, R, T) = FPIR(N, T) =	False neg. identification rate False pos. identification rate	N = Num. enrolled subjects R = Num. candidates examined	T = Threshold	T = 0 → Investigation T > 0 → Identification
------------------------	---------------------------------	--	--	---------------	---

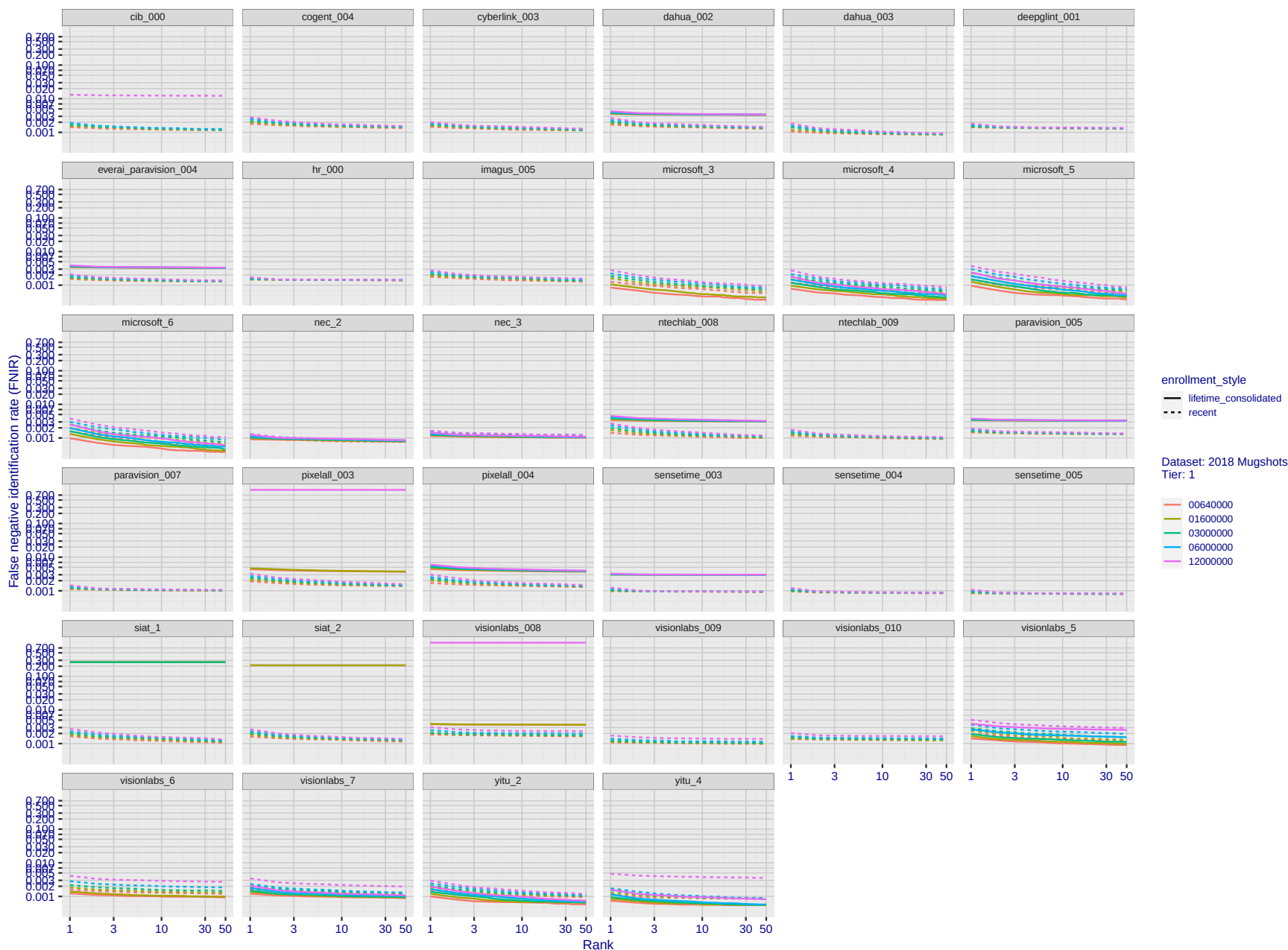


Figure 28: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. rank. The figure shows false negative identification rates (FNIR) for ranks up to 50. This metric is appropriate to investigational applications where human reviewers will adjudicate sorted candidate lists. Note that with threshold set to zero, FPIR = 1, i.e. any search without an enrolled mate will return non-mated candidates. Results are sorted and reported into tiers for clarity, with the tiering criteria being rank 1 hit rate on a gallery size of $N = 640\,000$ subjects.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

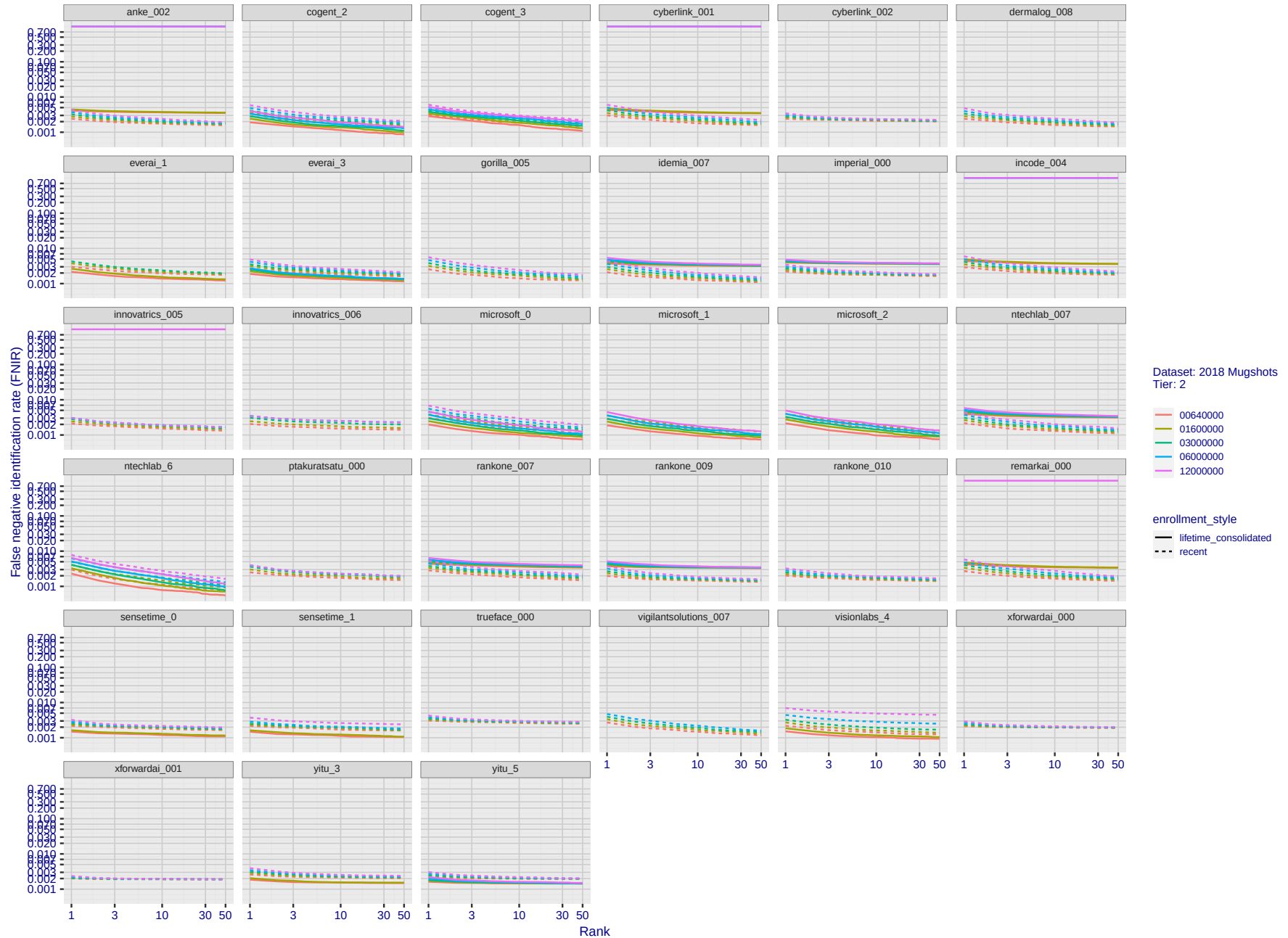
T = 0 → Investigation
T > 0 → Identification

Figure 29: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. rank. The figure shows false negative identification rates (FNIR) for ranks up to 50. This metric is appropriate to investigational applications where human reviewers will adjudicate sorted candidate lists. Note that with threshold set to zero, FPIR = 1, i.e. any search without an enrolled mate will return non-mated candidates. Results are sorted and reported into tiers for clarity, with the tiering criteria being rank 1 hit rate on a gallery size of $N = 640\,000$ subjects.

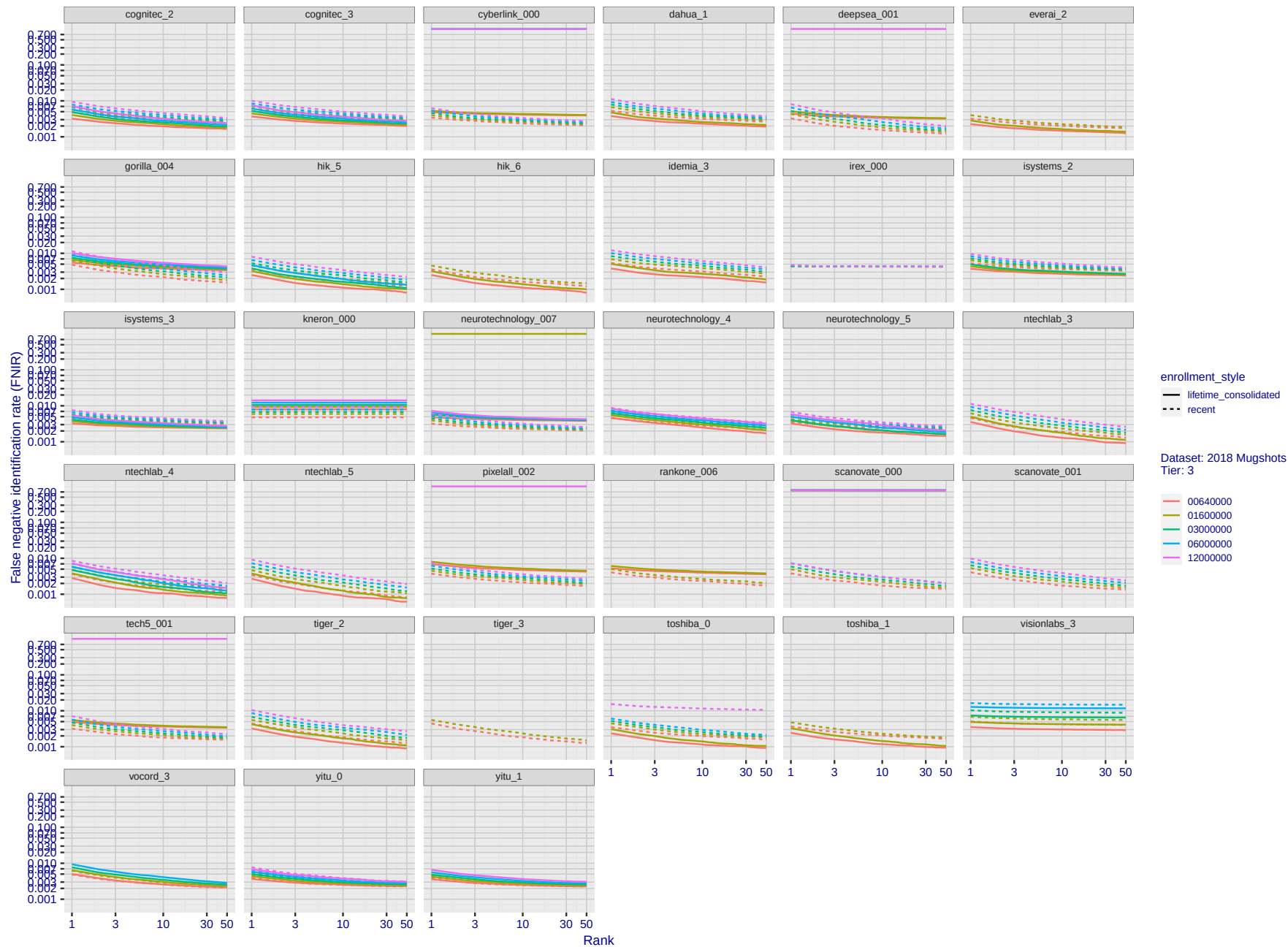


Figure 30: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. rank. The figure shows false negative identification rates (FNIR) for ranks up to 50. This metric is appropriate to investigational applications where human reviewers will adjudicate sorted candidate lists. Note that with threshold set to zero, FPIR = 1, i.e. any search without an enrolled mate will return non-mated candidates. Results are sorted and reported into tiers for clarity, with the tiering criteria being rank 1 hit rate on a gallery size of $N = 640\,000$ subjects.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

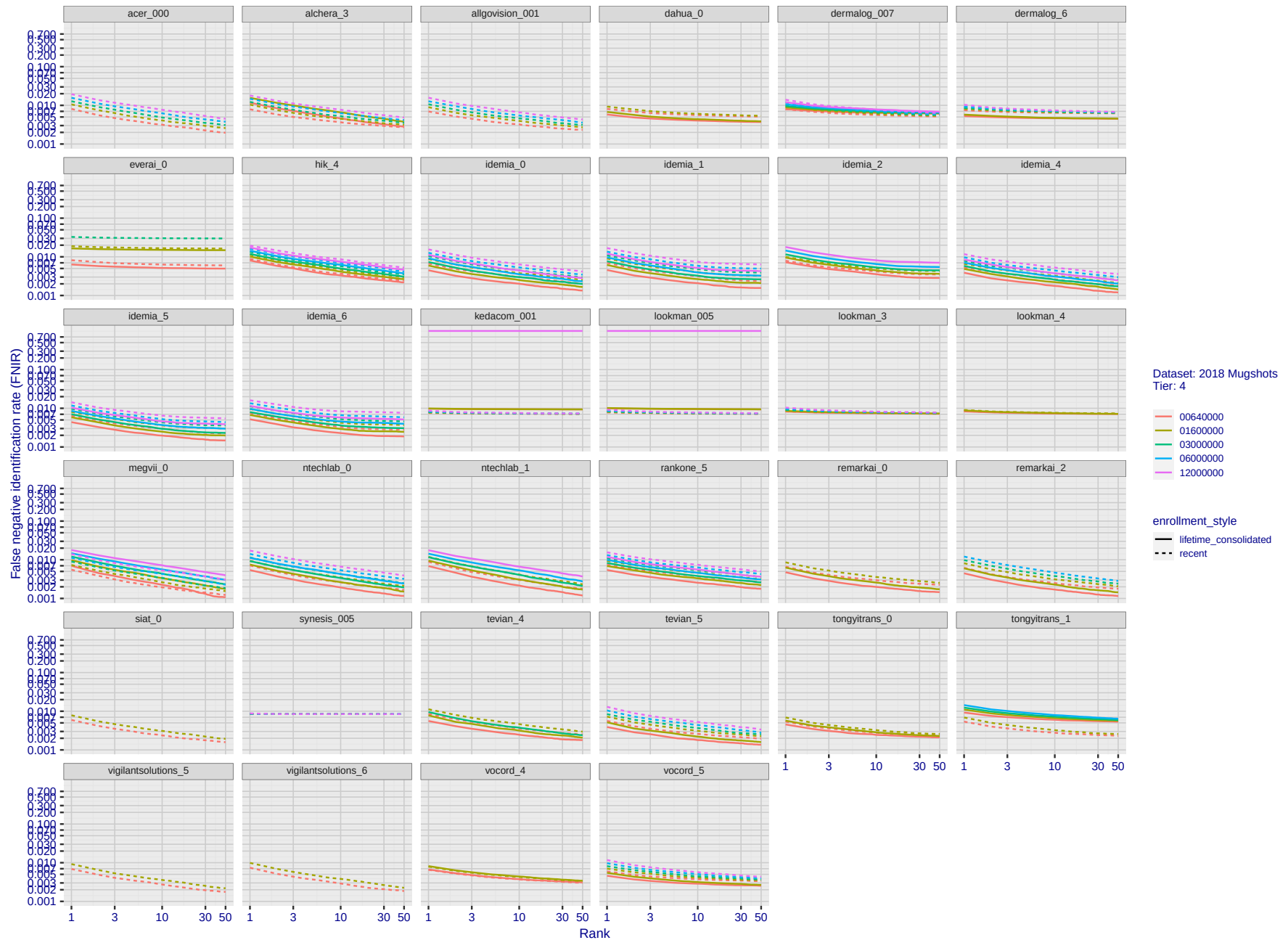
T = 0 → Investigation
T > 0 → Identification

Figure 31: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. rank. The figure shows false negative identification rates (FNIR) for ranks up to 50. This metric is appropriate to investigational applications where human reviewers will adjudicate sorted candidate lists. Note that with threshold set to zero, FPIR = 1, i.e. any search without an enrolled mate will return non-mated candidates. Results are sorted and reported into tiers for clarity, with the tiering criteria being rank 1 hit rate on a gallery size of $N = 640\,000$ subjects.

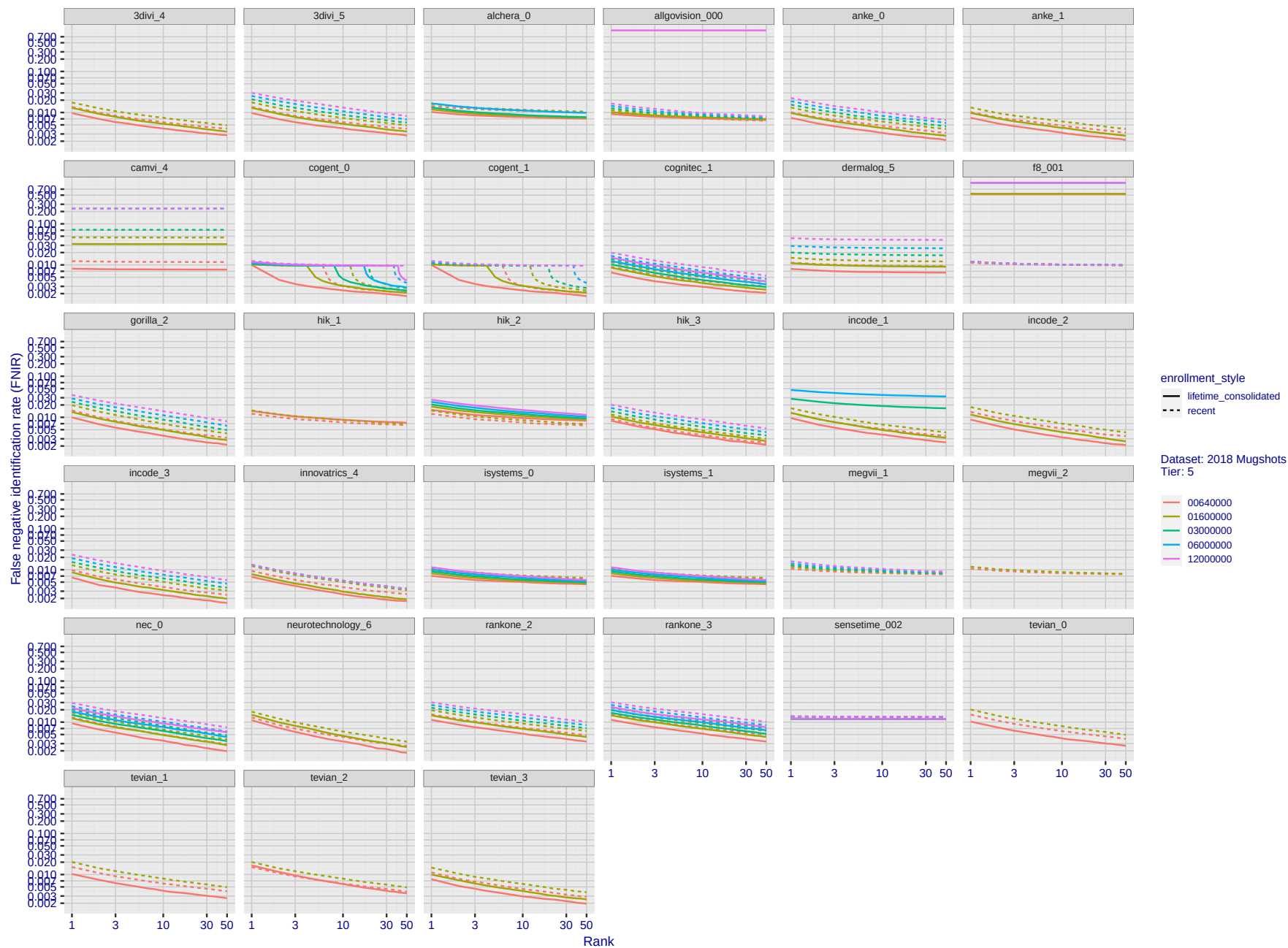


Figure 32: **[FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. rank.** The figure shows false negative identification rates (FNIR) for ranks up to 50. This metric is appropriate to investigational applications where human reviewers will adjudicate sorted candidate lists. Note that with threshold set to zero, FPIR = 1, i.e. any search without an enrolled mate will return non-mated candidates. Results are sorted and reported into tiers for clarity, with the tiering criteria being rank 1 hit rate on a gallery size of $N = 640\,000$ subjects.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

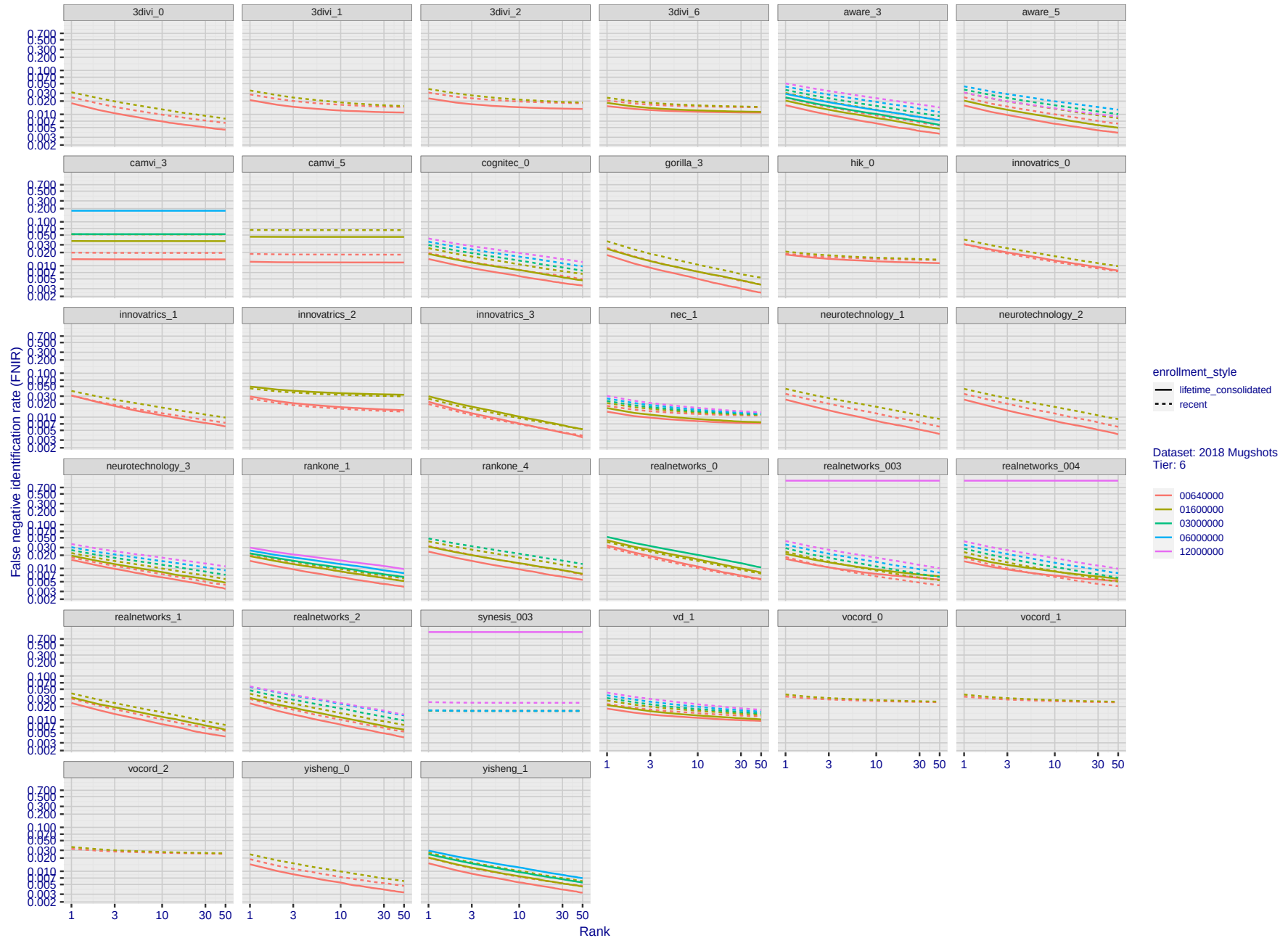
T = 0 → Investigation
T > 0 → Identification

Figure 33: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. rank. The figure shows false negative identification rates (FNIR) for ranks up to 50. This metric is appropriate to investigational applications where human reviewers will adjudicate sorted candidate lists. Note that with threshold set to zero, FPIR = 1, i.e. any search without an enrolled mate will return non-mated candidates. Results are sorted and reported into tiers for clarity, with the tiering criteria being rank 1 hit rate on a gallery size of $N = 640\,000$ subjects.

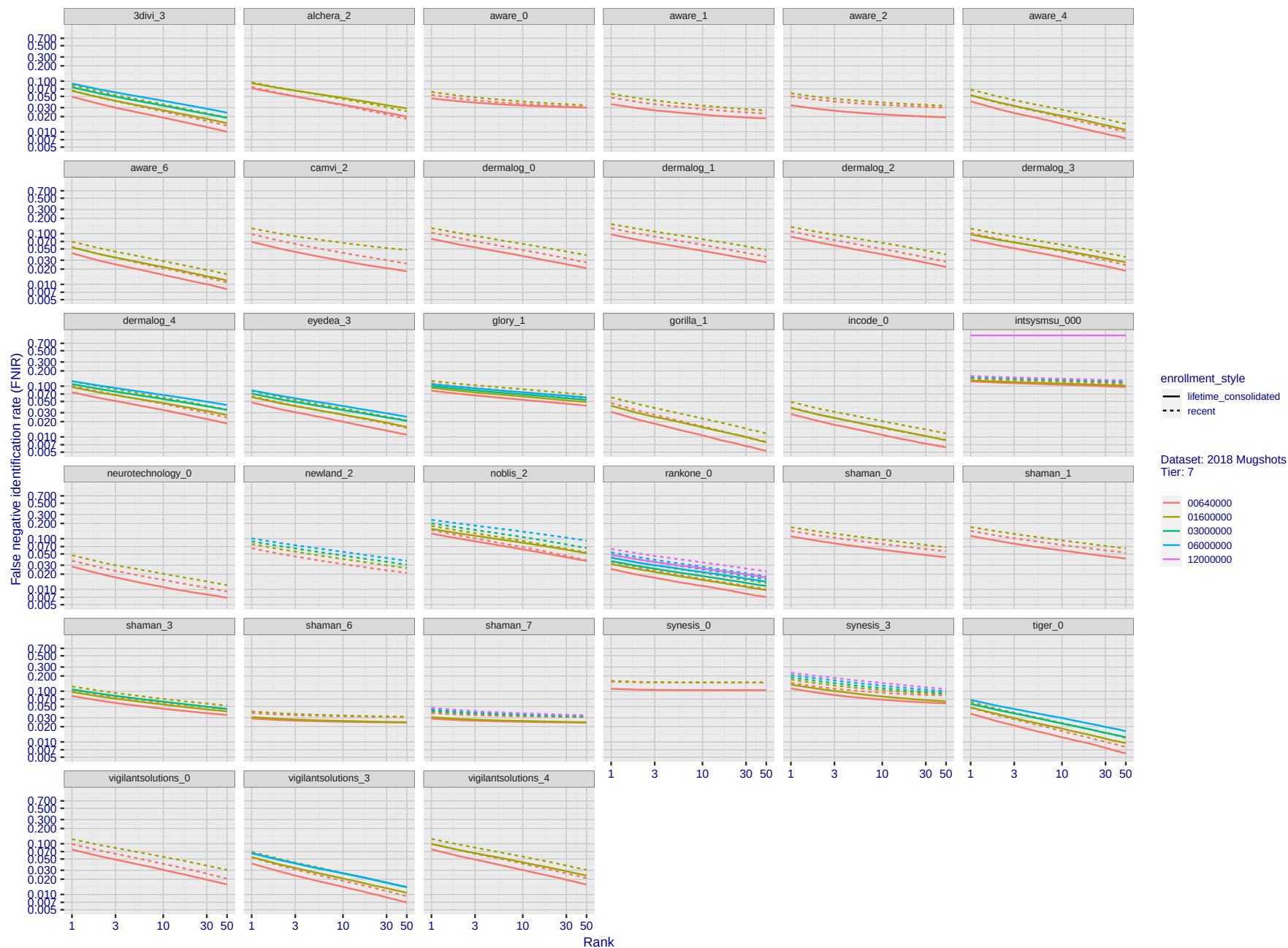


Figure 34: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. rank. The figure shows false negative identification rates (FNIR) for ranks up to 50. This metric is appropriate to investigational applications where human reviewers will adjudicate sorted candidate lists. Note that with threshold set to zero, FPIR = 1, i.e. any search without an enrolled mate will return non-mated candidates. Results are sorted and reported into tiers for clarity, with the tiering criteria being rank 1 hit rate on a gallery size of $N = 640\,000$ subjects.

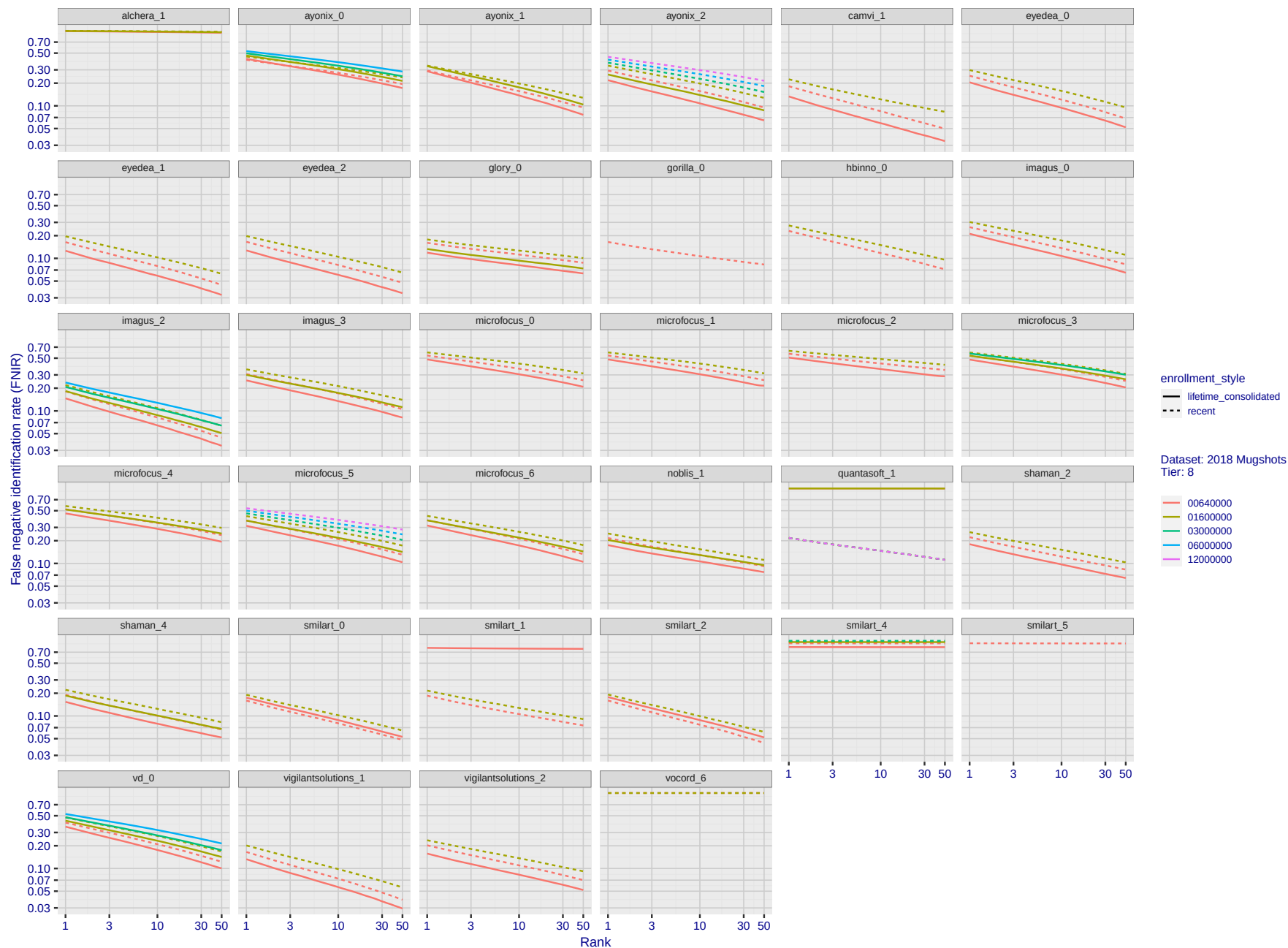


Figure 35: [FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. rank. The figure shows false negative identification rates (FNIR) for ranks up to 50. This metric is appropriate to investigational applications where human reviewers will adjudicate sorted candidate lists. Note that with threshold set to zero, FPIR = 1, i.e. any search without an enrolled mate will return non-mated candidates. Results are sorted and reported into tiers for clarity, with the tiering criteria being rank 1 hit rate on a gallery size of $N = 640\,000$ subjects.

2021/03/04 11:49:04	FNIR(N, R, T) = FPIR(N, T) =	False neg. identification rate False pos. identification rate	N = Num. enrolled subjects R = Num. candidates examined	T = Threshold	T = 0 → Investigation T > 0 → Identification
------------------------	---------------------------------	--	--	---------------	---

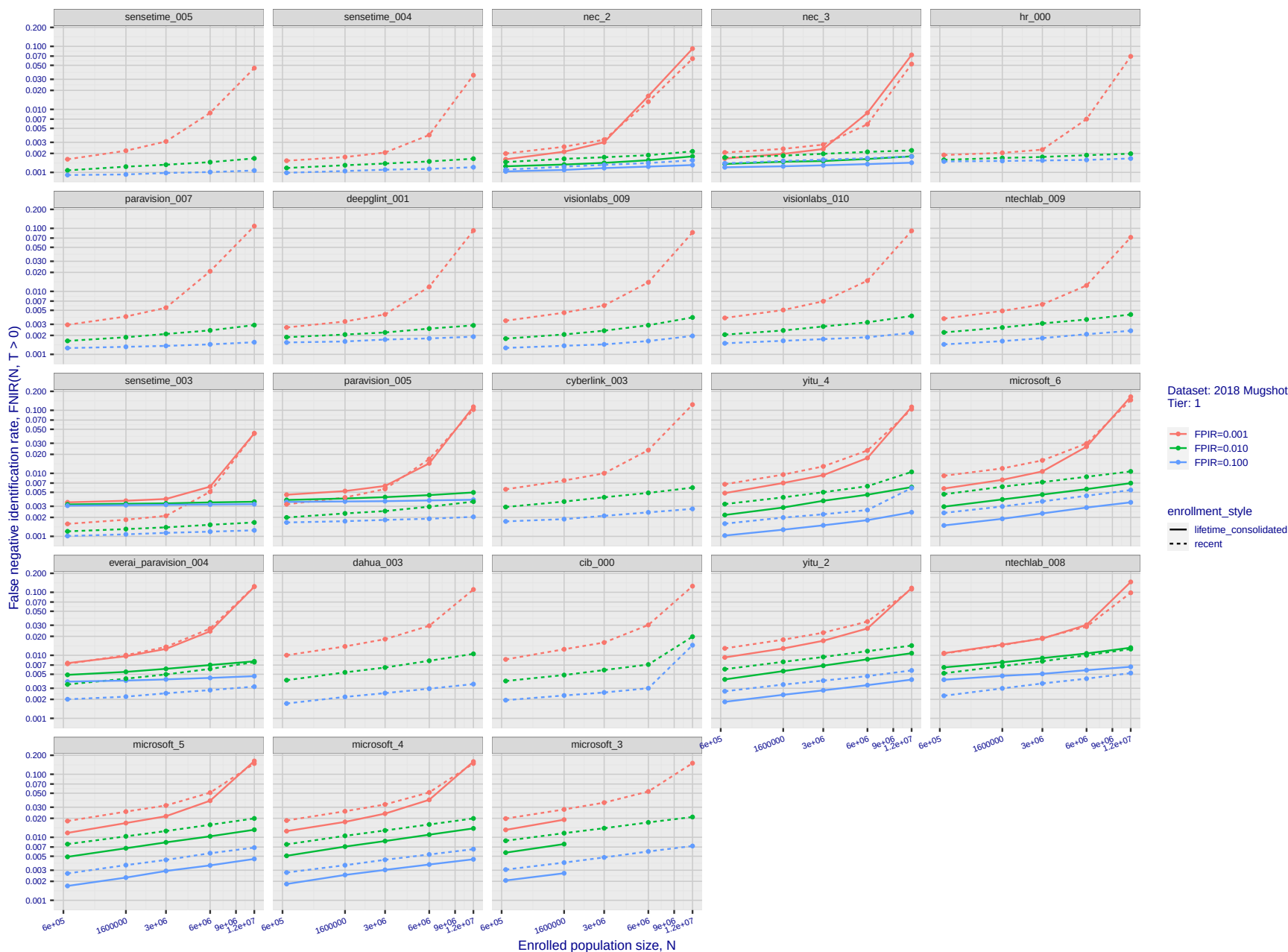


Figure 36: [FRVT-2018 Mugshot Dataset] Threshold-based identification miss rates vs. number of enrolled subjects. The figure shows FNIR(N, T) across various gallery sizes when the threshold is set to achieve the given FPIRs. The rank criterion is irrelevant at high thresholds as mates are always at rank 1. The results are computed from the trials listed in rows 1-10 of Table 1. Less accurate algorithms were not run on large N, so results are missing. For clarity, results are sorted and reported into tiers spanning multiple pages. The tiering criteria is complicated: First paging by FNIR(N_b, 1, 0), then sorting by median FNIR(N_b, T), N_b = 640 000.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

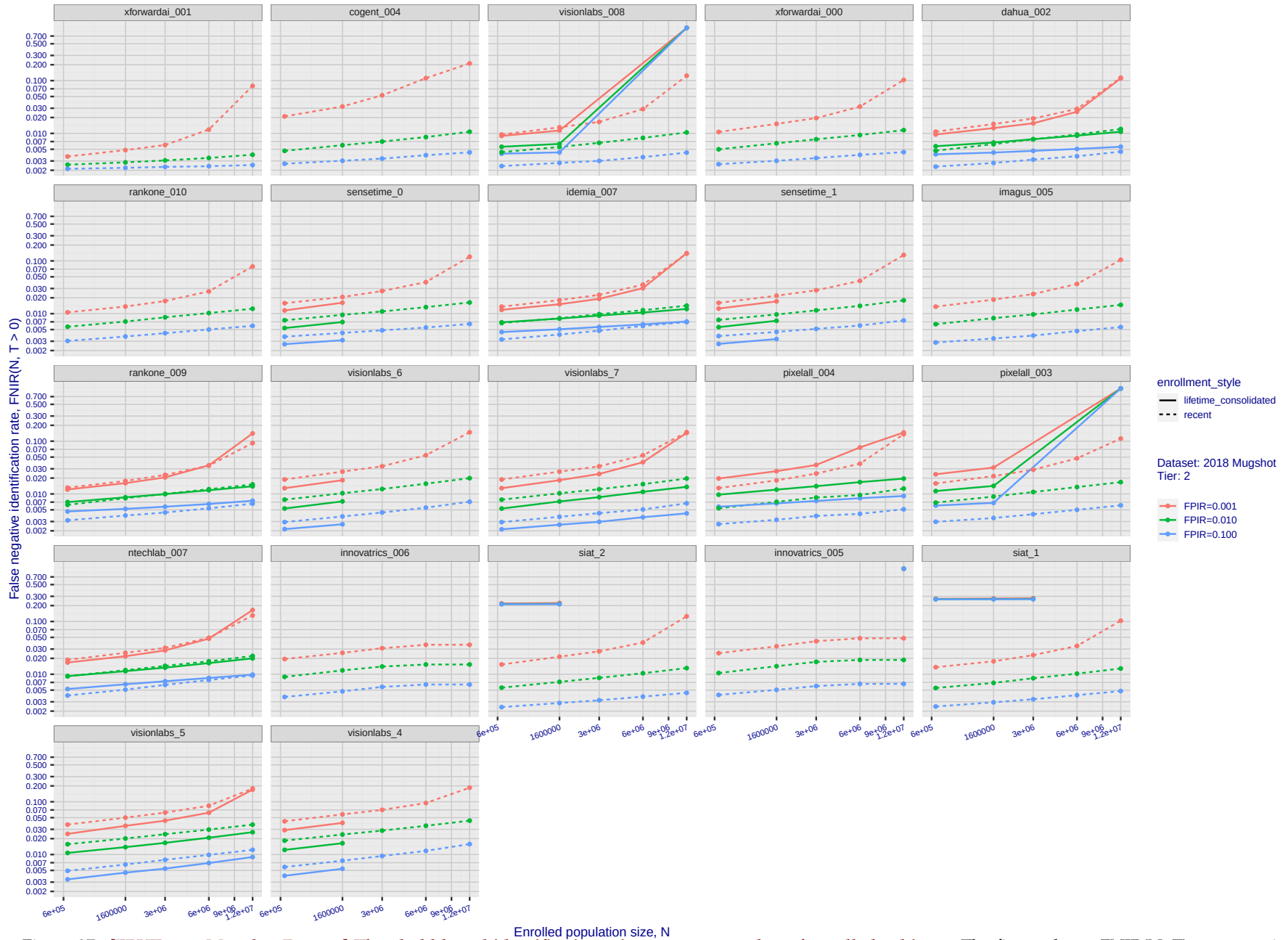
T = 0 → Investigation
T > 0 → Identification

Figure 37: [FRVT-2018 Mugshot Dataset] Threshold-based identification miss rates vs. number of enrolled subjects. The figure shows $FNIR(N, T)$ across various gallery sizes when the threshold is set to achieve the given FPIRs. The rank criterion is irrelevant at high thresholds as mates are always at rank 1. The results are computed from the trials listed in rows 1-10 of Table 1. Less accurate algorithms were not run on large N , so results are missing. For clarity, results are sorted and reported into tiers spanning multiple pages. The tiering criteria is complicated: First paging by $FNIR(N_b, 1, 0)$, then sorting by median $FNIR(N_b, T)$, $N_b = 640\,000$.

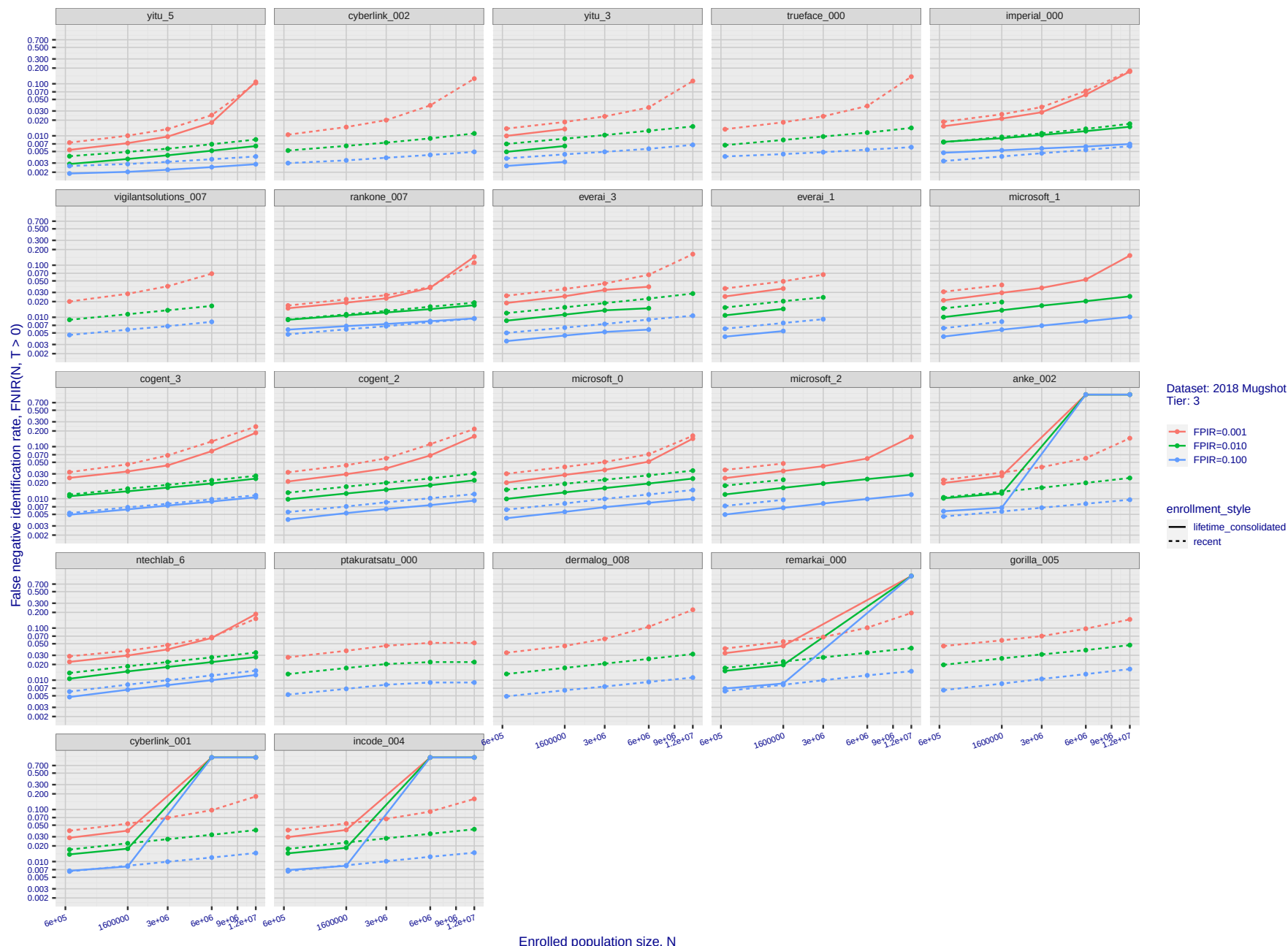


Figure 38: [FRVT-2018 Mugshot Dataset] Threshold-based identification miss rates vs. number of enrolled subjects. The figure shows $FNIR(N, T)$ across various gallery sizes when the threshold is set to achieve the given FPIRs. The rank criterion is irrelevant at high thresholds as mates are always at rank 1. The results are computed from the trials listed in rows 1-10 of Table 1. Less accurate algorithms were not run on large N , so results are missing. For clarity, results are sorted and reported into tiers spanning multiple pages. The tiering criteria is complicated: First paging by $FNIR(N_b, 1, 0)$, then sorting by median $FNIR(N_b, T)$, $N_b = 640\,000$.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

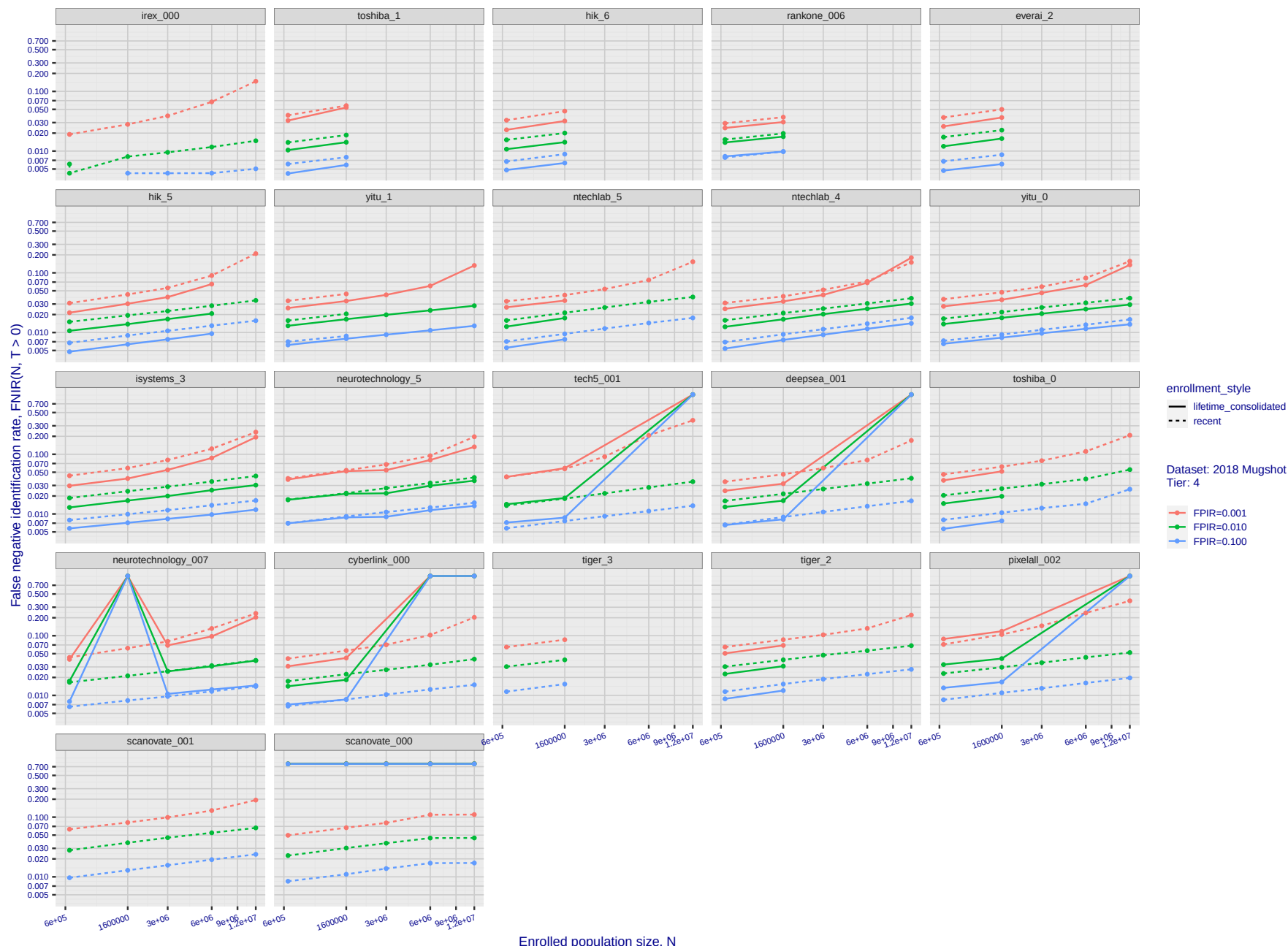


Figure 39: [FRVT-2018 Mugshot Dataset] Threshold-based identification miss rates vs. number of enrolled subjects. The figure shows $FNIR(N, T)$ across various gallery sizes when the threshold is set to achieve the given FPIRs. The rank criterion is irrelevant at high thresholds as mates are always at rank 1. The results are computed from the trials listed in rows 1-10 of Table 1. Less accurate algorithms were not run on large N , so results are missing. For clarity, results are sorted and reported into tiers spanning multiple pages. The tiering criteria is complicated: First paging by $FNIR(N_b, 1, 0)$, then sorting by median $FNIR(N_b, T)$, $N_b = 640,000$.

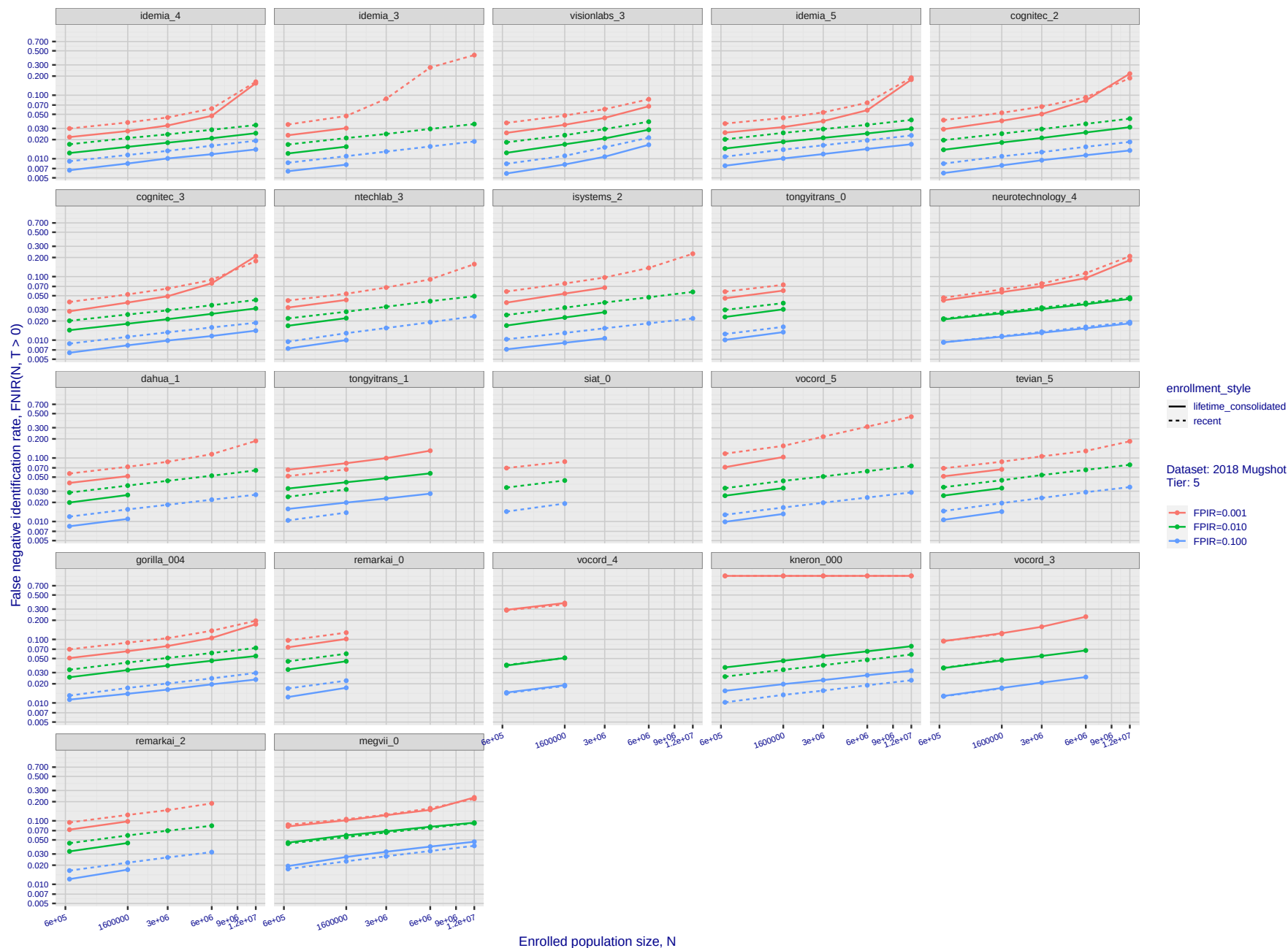


Figure 40: [FRVT-2018 Mugshot Dataset] Threshold-based identification miss rates vs. number of enrolled subjects. The figure shows $FNIR(N, T)$ across various gallery sizes when the threshold is set to achieve the given FPIRs. The rank criterion is irrelevant at high thresholds as mates are always at rank 1. The results are computed from the trials listed in rows 1-10 of Table 1. Less accurate algorithms were not run on large N , so results are missing. For clarity, results are sorted and reported into tiers spanning multiple pages. The tiering criteria is complicated: First paging by $FNIR(N_b, 1, 0)$, then sorting by median $FNIR(N_b, T)$, $N_b = 640\,000$.

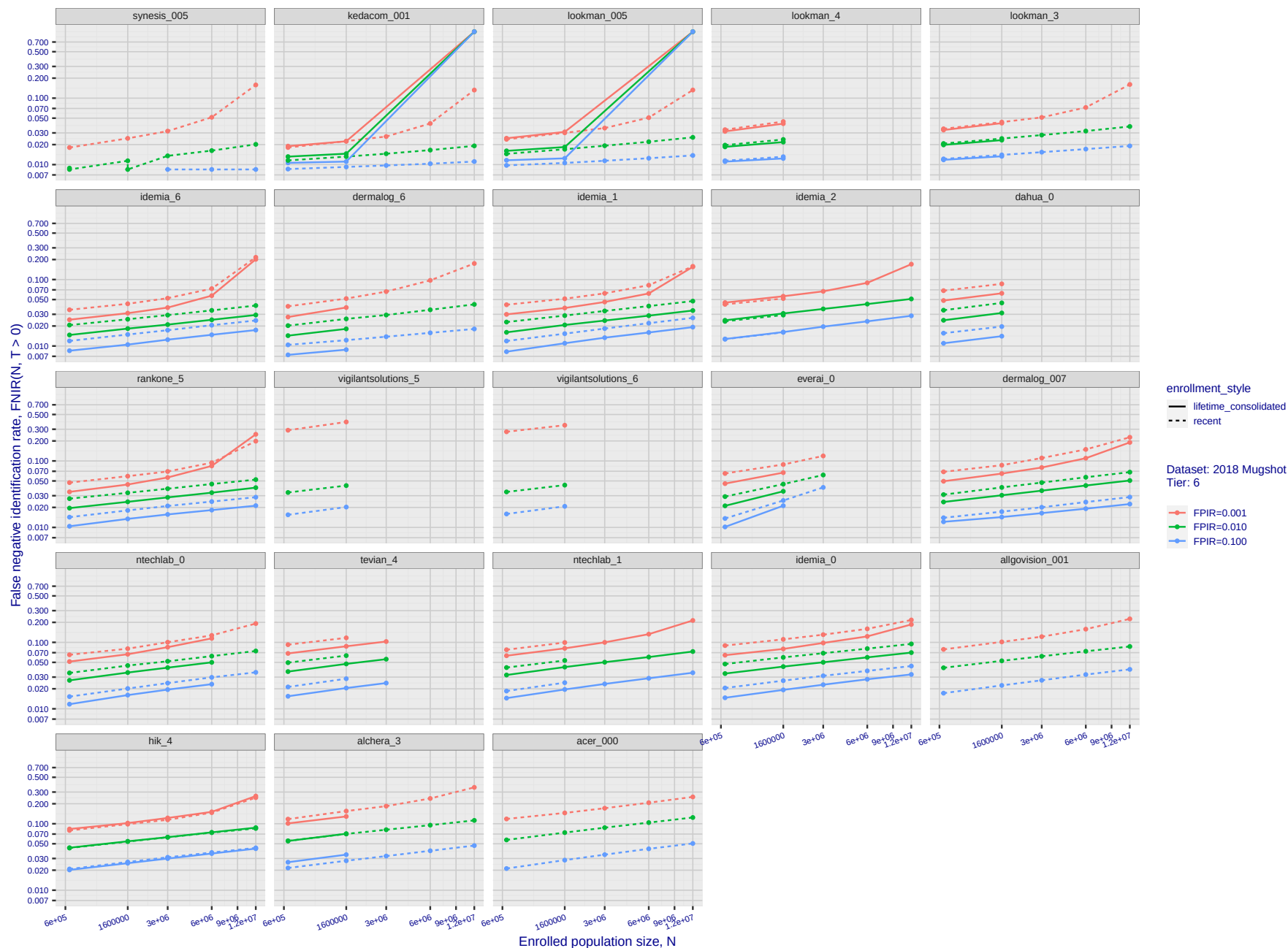


Figure 41: [FRVT-2018 Mugshot Dataset] Threshold-based identification miss rates vs. number of enrolled subjects. The figure shows $FNIR(N, T)$ across various gallery sizes when the threshold is set to achieve the given FPIRs. The rank criterion is irrelevant at high thresholds as mates are always at rank 1. The results are computed from the trials listed in rows 1-10 of Table 1. Less accurate algorithms were not run on large N , so results are missing. For clarity, results are sorted and reported into tiers spanning multiple pages. The tiering criteria is complicated: First paging by $FNIR(N_b, 1, 0)$, then sorting by median $FNIR(N_b, T)$, $N_b = 640,000$.

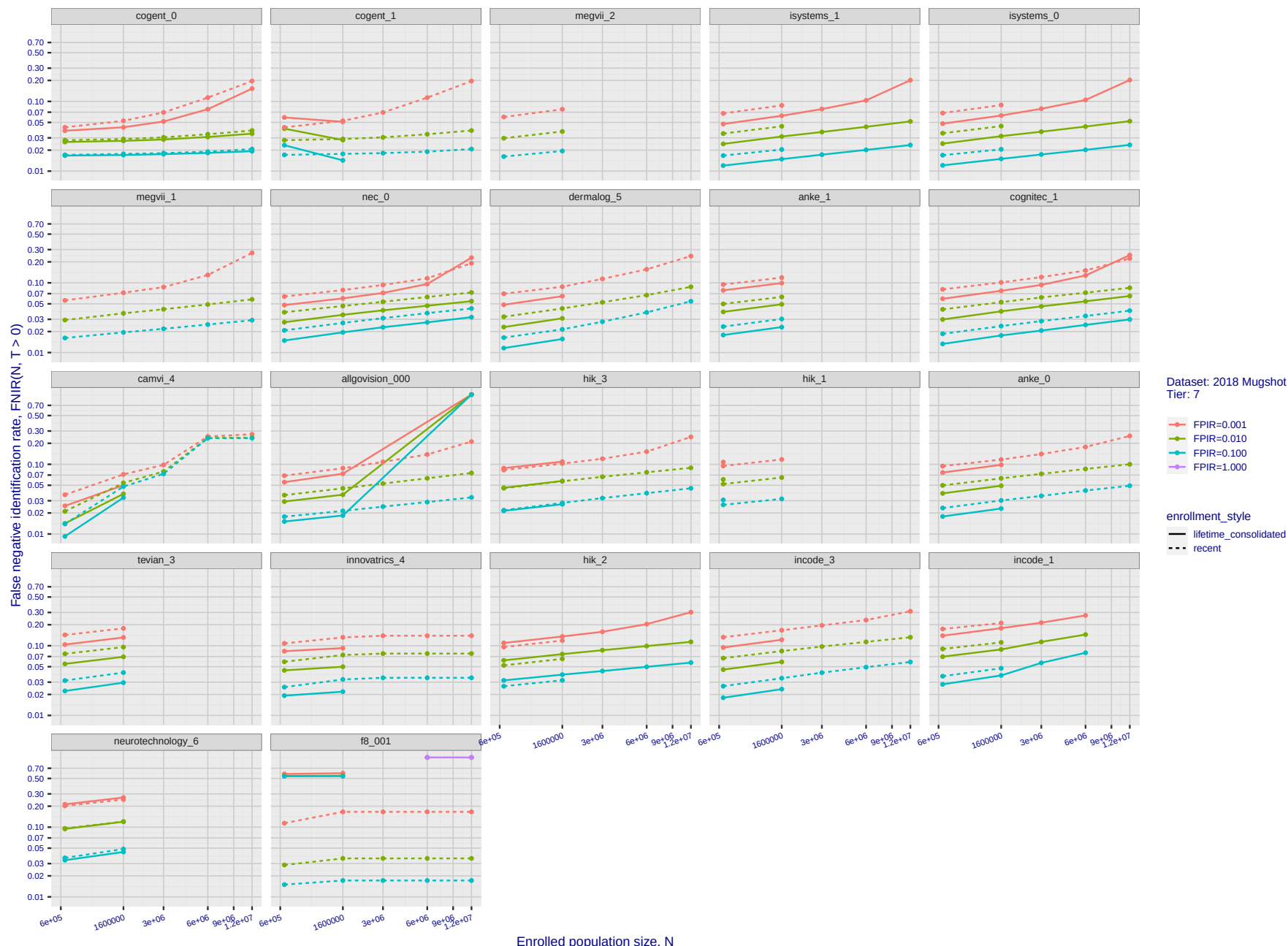


Figure 42: [FRVT-2018 Mugshot Dataset] Threshold-based identification miss rates vs. number of enrolled subjects. The figure shows $FNIR(N, T)$ across various gallery sizes when the threshold is set to achieve the given FPIRs. The rank criterion is irrelevant at high thresholds as mates are always at rank 1. The results are computed from the trials listed in rows 1-10 of Table 1. Less accurate algorithms were not run on large N , so results are missing. For clarity, results are sorted and reported into tiers spanning multiple pages. The tiering criteria is complicated: First paging by $FNIR(N_b, 1, 0)$, then sorting by median $FNIR(N_b, T)$, $N_b = 640\,000$.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rate N = Num. enrolled subjects
 R = Num. candidates examined T = Threshold $T = 0 \rightarrow$ Investigation
 $T > 0 \rightarrow$ Identification

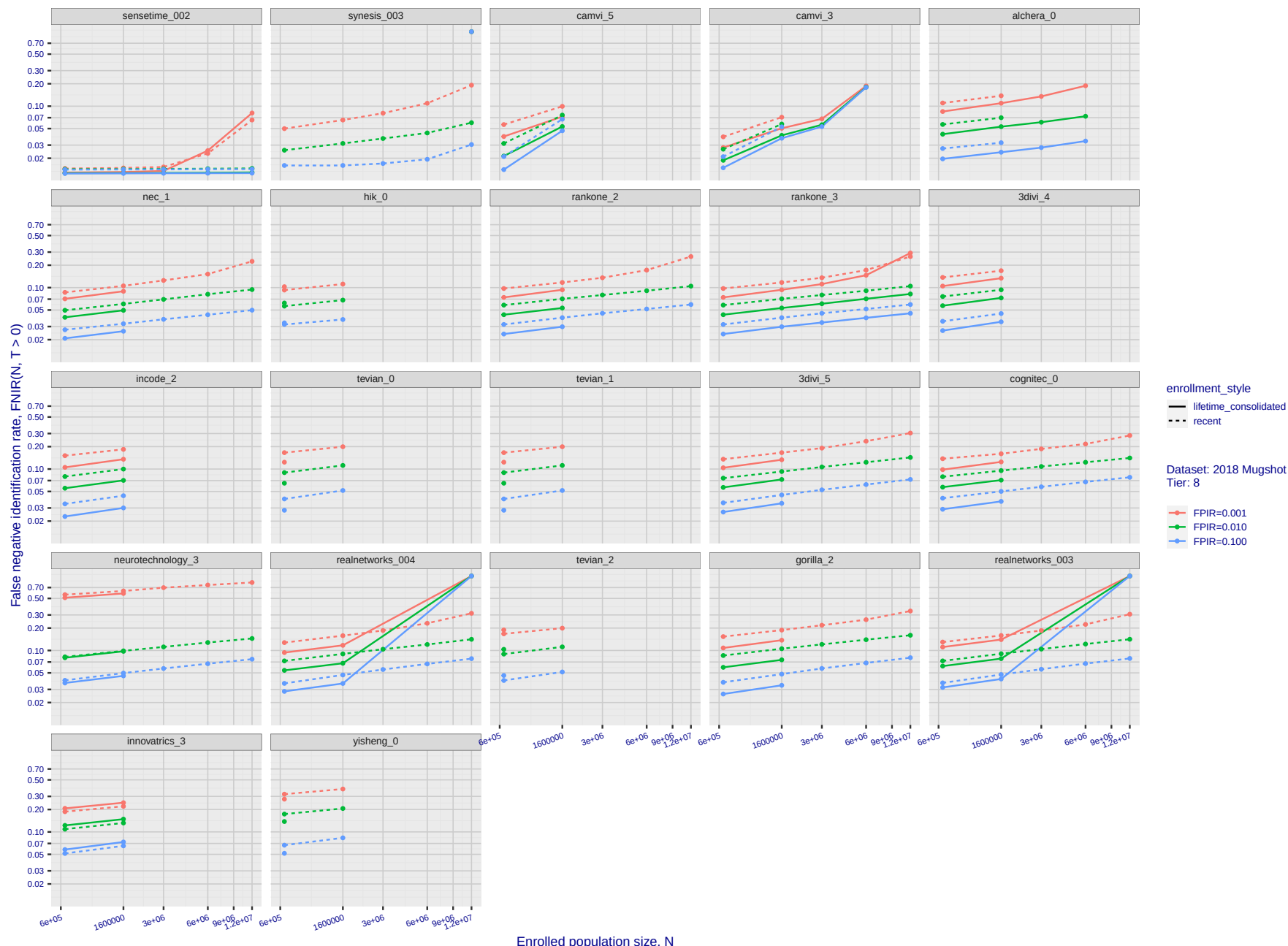


Figure 43: **[FRVT-2018 Mugshot Dataset] Threshold-based identification miss rates vs. number of enrolled subjects.** The figure shows $FNIR(N, T)$ across various gallery sizes when the threshold is set to achieve the given FPIRs. The rank criterion is irrelevant at high thresholds as mates are always at rank 1. The results are computed from the trials listed in rows 1-10 of Table 1. Less accurate algorithms were not run on large N , so results are missing. For clarity, results are sorted and reported into tiers spanning multiple pages. The tiering criteria is complicated: First paging by $FNIR(N_b, 1, 0)$, then sorting by median $FNIR(N_b, T)$, $N_b = 640\,000$.

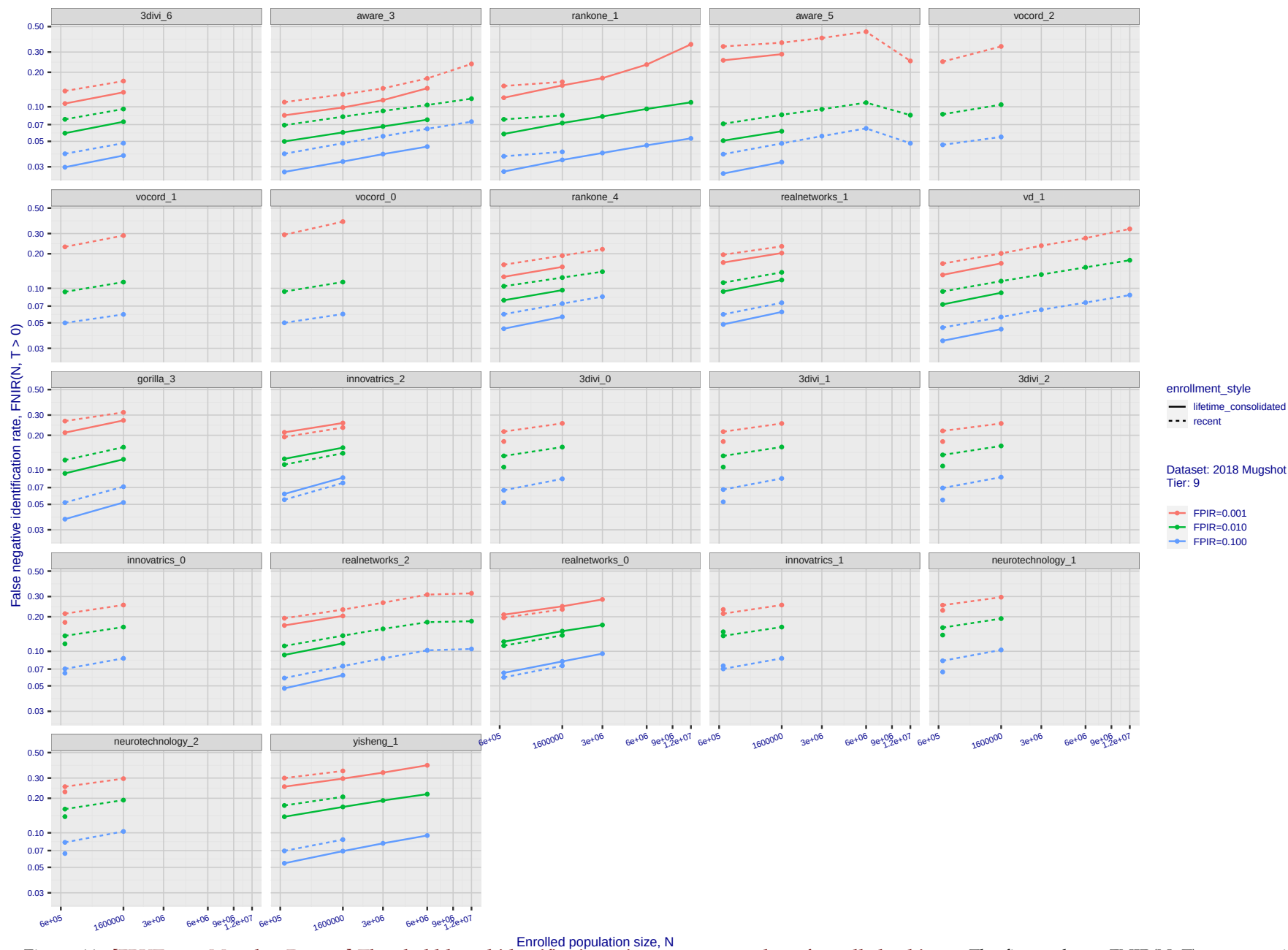


Figure 44: [FRVT-2018 Mugshot Dataset] Threshold-based identification miss rates vs. number of enrolled subjects. The figure shows $FNIR(N, T)$ across various gallery sizes when the threshold is set to achieve the given FPIRs. The rank criterion is irrelevant at high thresholds as mates are always at rank 1. The results are computed from the trials listed in rows 1-10 of Table 1. Less accurate algorithms were not run on large N , so results are missing. For clarity, results are sorted and reported into tiers spanning multiple pages. The tiering criteria is complicated: First paging by $FNIR(N_b, 1, 0)$, then sorting by median $FNIR(N_b, T)$, $N_b = 640\,000$.

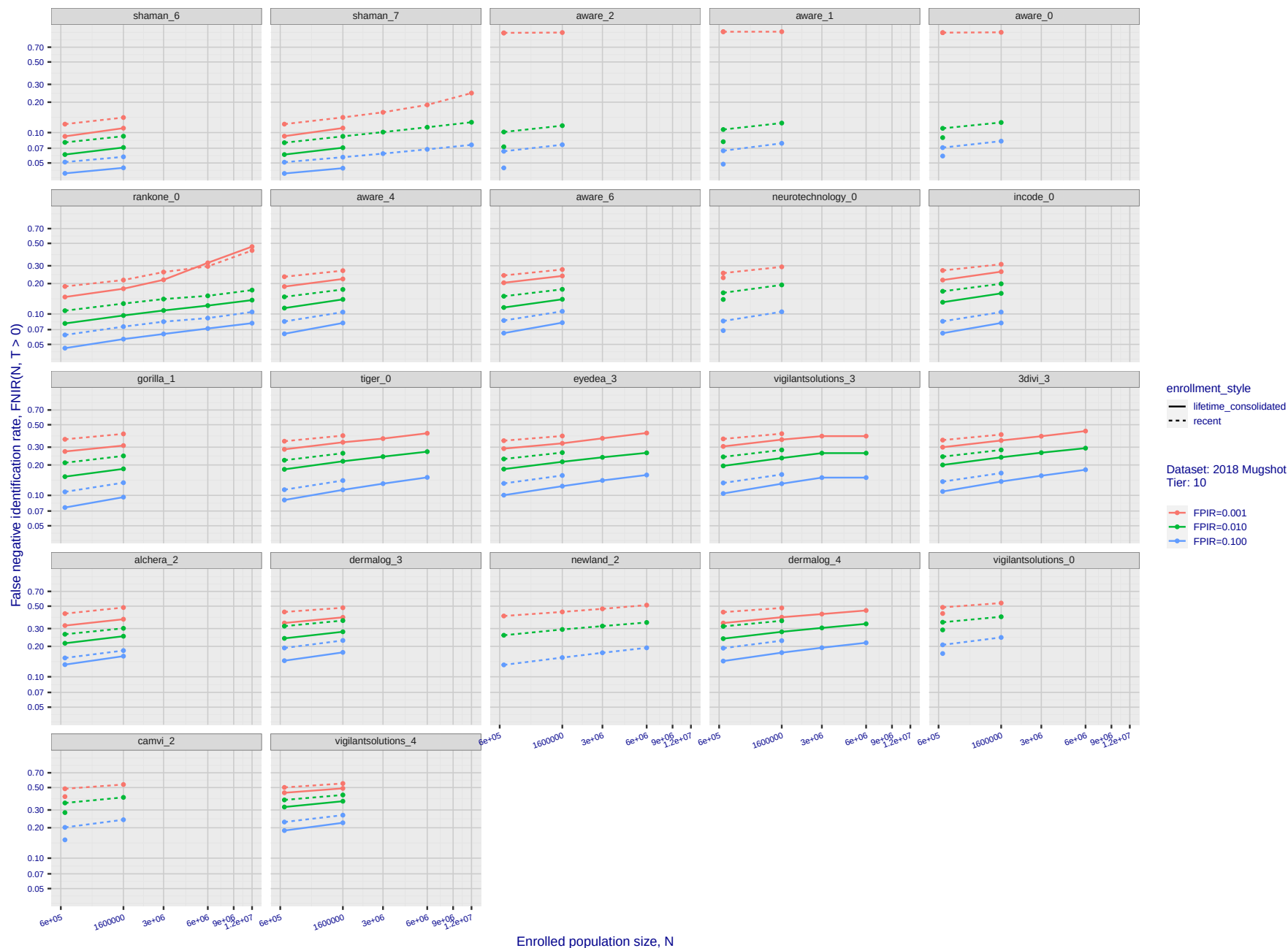


Figure 45: [FRVT-2018 Mugshot Dataset] Threshold-based identification miss rates vs. number of enrolled subjects. The figure shows $FNIR(N, T)$ across various gallery sizes when the threshold is set to achieve the given FPIRs. The rank criterion is irrelevant at high thresholds as mates are always at rank 1. The results are computed from the trials listed in rows 1-10 of Table 1. Less accurate algorithms were not run on large N , so results are missing. For clarity, results are sorted and reported into tiers spanning multiple pages. The tiering criteria is complicated: First paging by $FNIR(N_b, 1, 0)$, then sorting by median $FNIR(N_b, T)$, $N_b = 640\,000$.

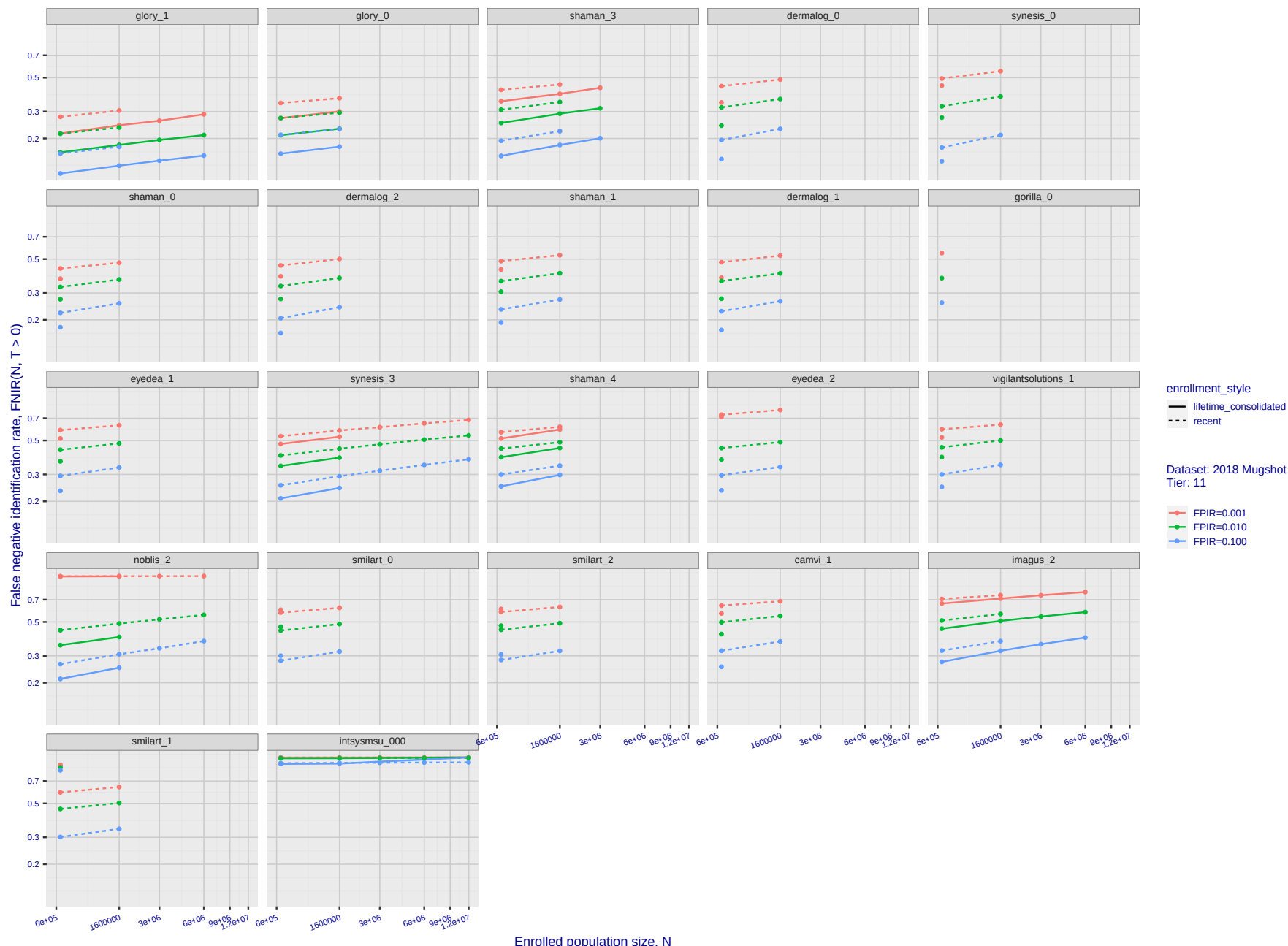


Figure 46: [FRVT-2018 Mugshot Dataset] Threshold-based identification miss rates vs. number of enrolled subjects. The figure shows $FNIR(N, T)$ across various gallery sizes when the threshold is set to achieve the given FPIRs. The rank criterion is irrelevant at high thresholds as mates are always at rank 1. The results are computed from the trials listed in rows 1-10 of Table 1. Less accurate algorithms were not run on large N , so results are missing. For clarity, results are sorted and reported into tiers spanning multiple pages. The tiering criteria is complicated: First paging by $FNIR(N_b, 1, 0)$, then sorting by median $FNIR(N_b, T)$, $N_b = 640\,000$.

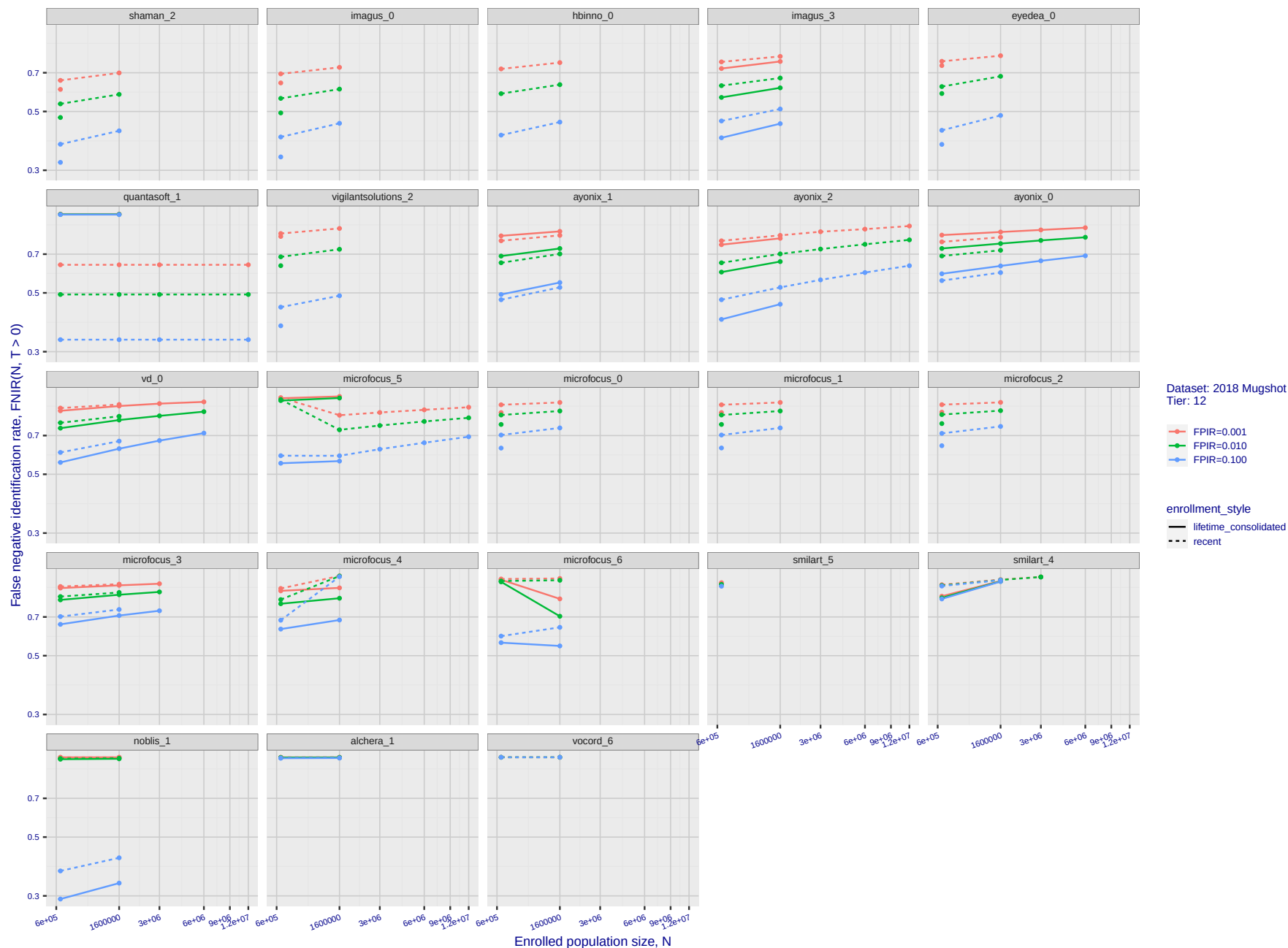


Figure 47: [FRVT-2018 Mugshot Dataset] Threshold-based identification miss rates vs. number of enrolled subjects. The figure shows $FNIR(N, T)$ across various gallery sizes when the threshold is set to achieve the given FPIRs. The rank criterion is irrelevant at high thresholds as mates are always at rank 1. The results are computed from the trials listed in rows 1-10 of Table 1. Less accurate algorithms were not run on large N , so results are missing. For clarity, results are sorted and reported into tiers spanning multiple pages. The tiering criteria is complicated: First paging by $FNIR(N_b, 1, 0)$, then sorting by median $FNIR(N_b, T)$, $N_b = 640\,000$.

2021/03/04 11:49:04	FNIR(N, R, T) = FPIR(N, T) =	False neg. identification rate False pos. identification rate	N = Num. enrolled subjects R = Num. candidates examined	T = Threshold	T = 0 → Investigation T > 0 → Identification
------------------------	---------------------------------	--	--	---------------	---

2021/03/04
11:49:04

FNIR(N, R, T) = False neg. identification rate
FPIR(N, T) = False pos. identification rate

N = Num. enrolled subjects
R = Num. candidates examined

T = Threshold
T = 0 → Investigation
T > 0 → Identification

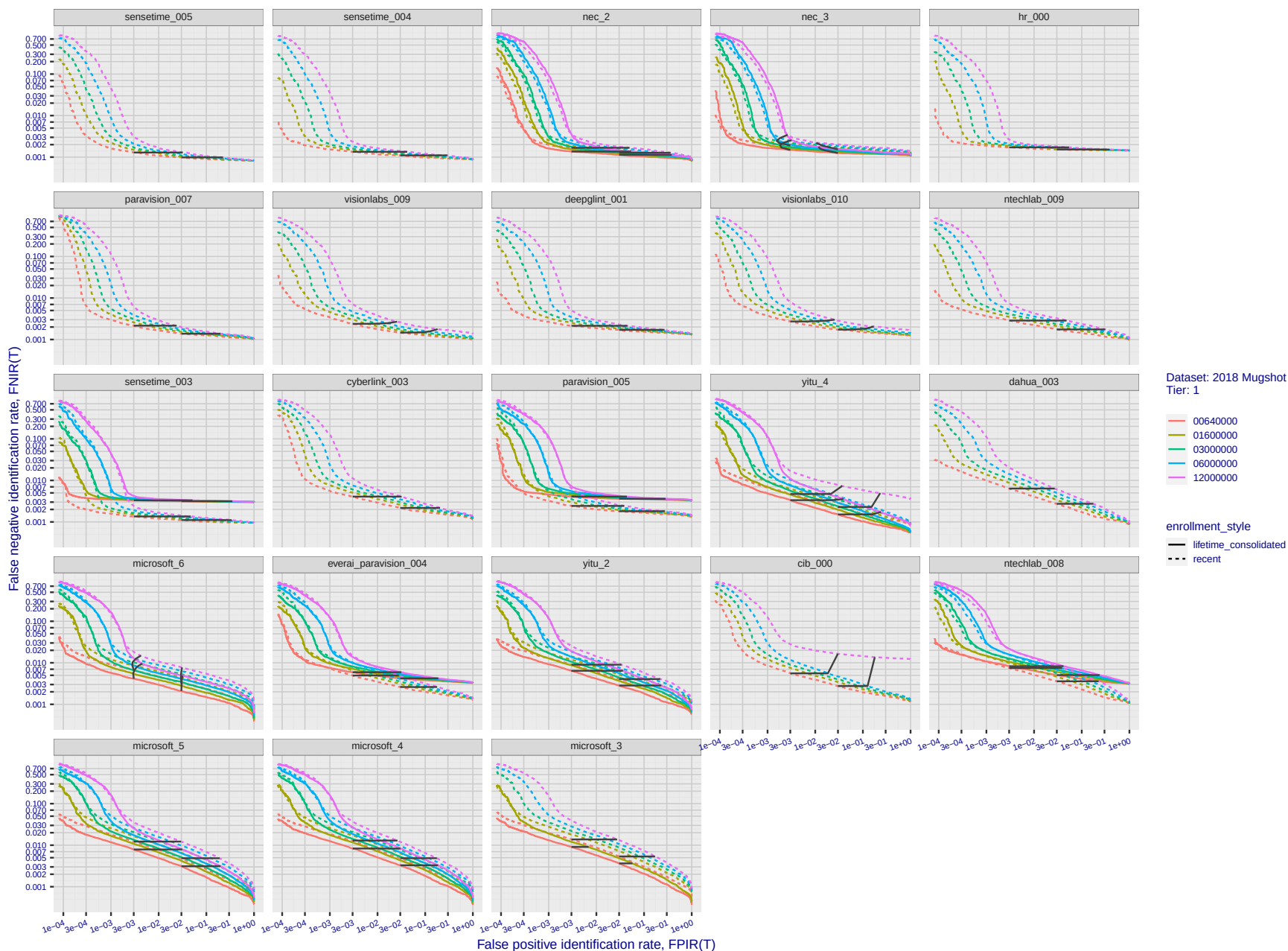


Figure 48: [FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates. The figure shows miss rates $FNIR(N, L, T)$ as a function of $FPIR(N, T)$, with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, $FPIR(T)$ rises with N , and mate scores are independent of N . Other algorithms adjust scores in an attempt to make $FPIR(T)$ independent of N .

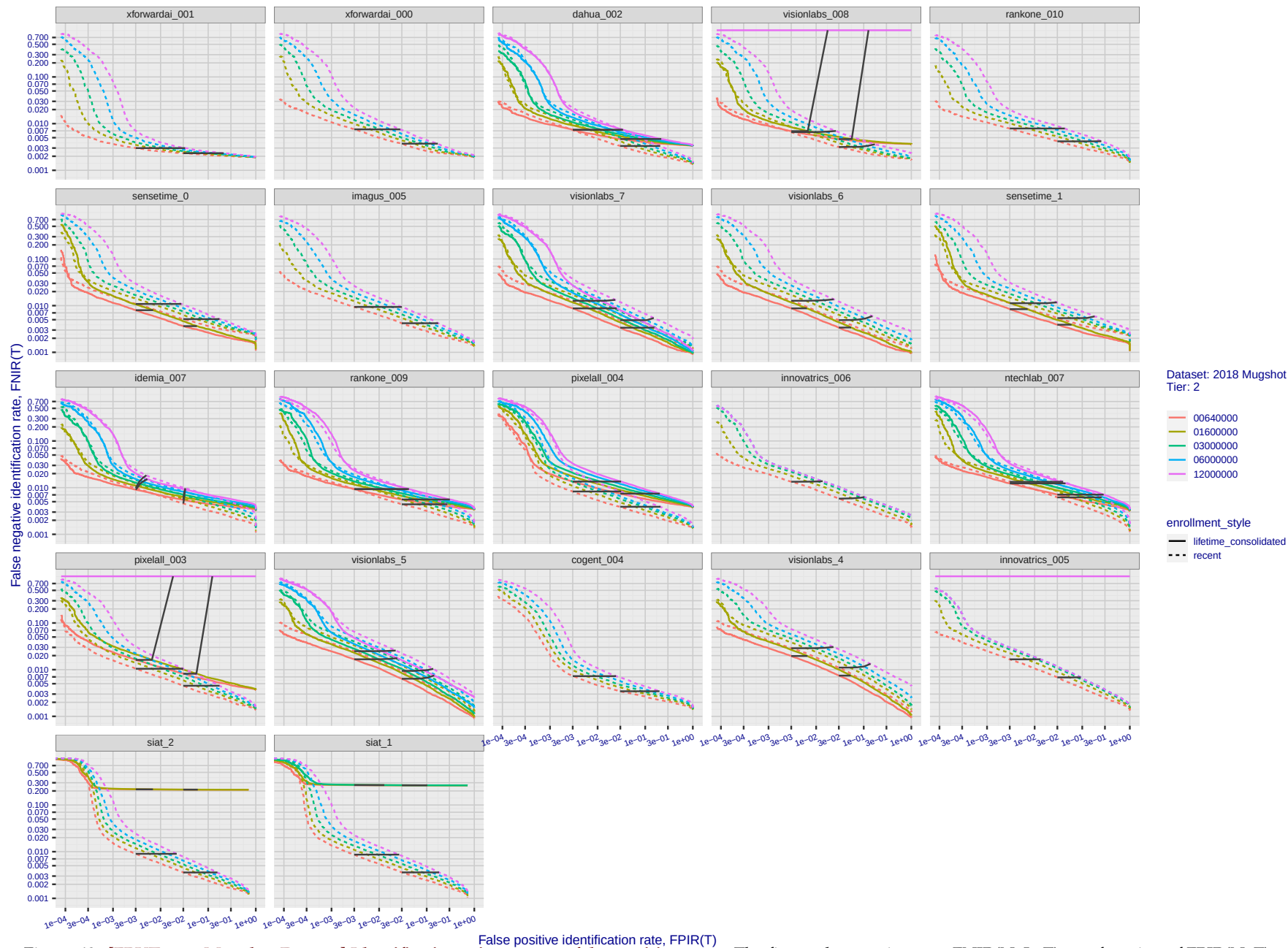


Figure 49: [FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates. The figure shows miss rates $FNIR(N, L, T)$ as a function of $FPIR(N, T)$, with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, $FPIR(T)$ rises with N , and mate scores are independent of N . Other algorithms adjust scores in an attempt to make $FPIR$ independent of N .

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

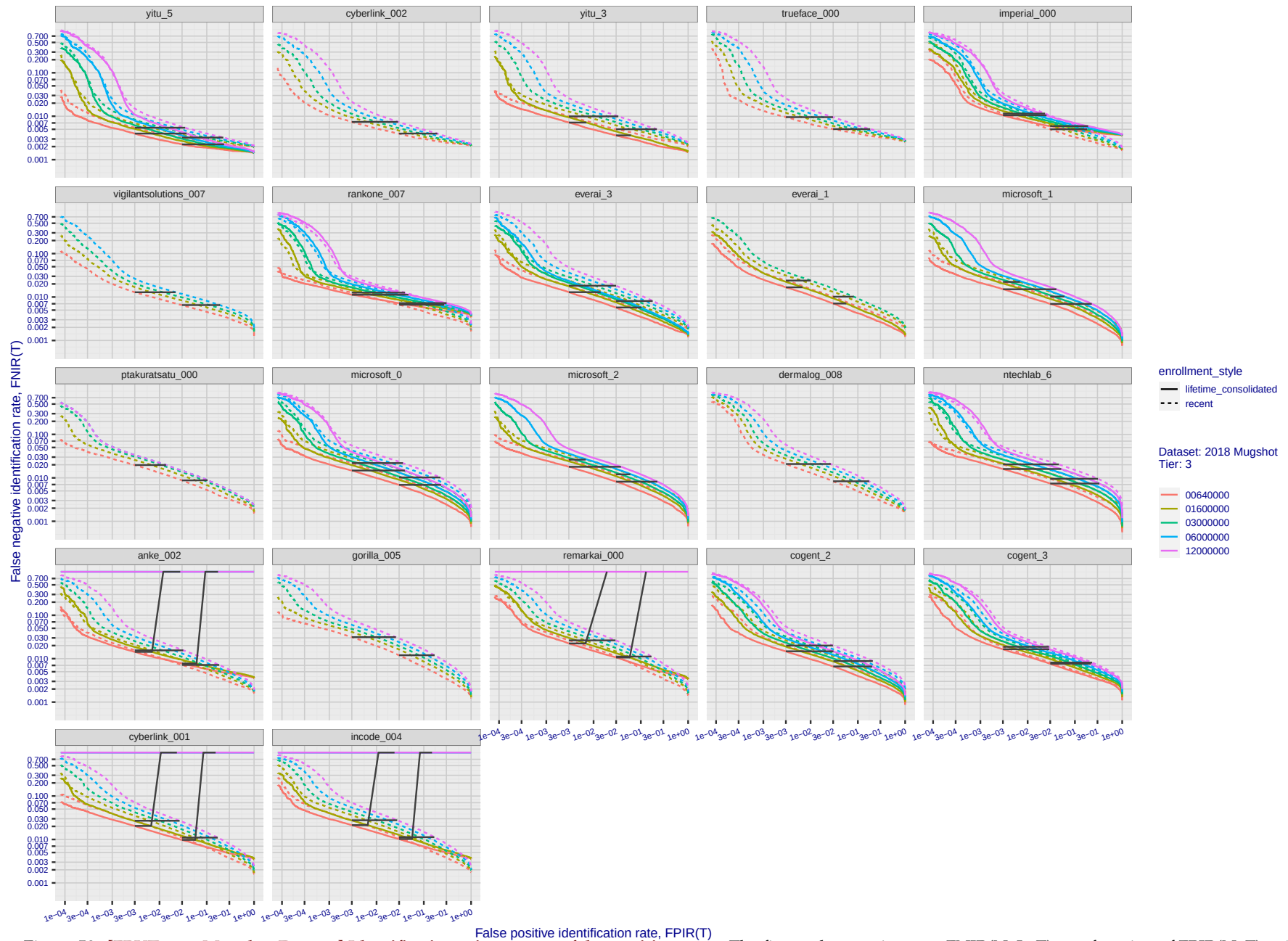
T = 0 → Investigation
T > 0 → Identification

Figure 50: **[FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates.** The figure shows miss rates $FNIR(N, L, T)$ as a function of $FPIR(N, T)$, with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, $FPIR(T)$ rises with N , and mate scores are independent of N . Other algorithms adjust scores in an attempt to make $FPIR$ independent of N .

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

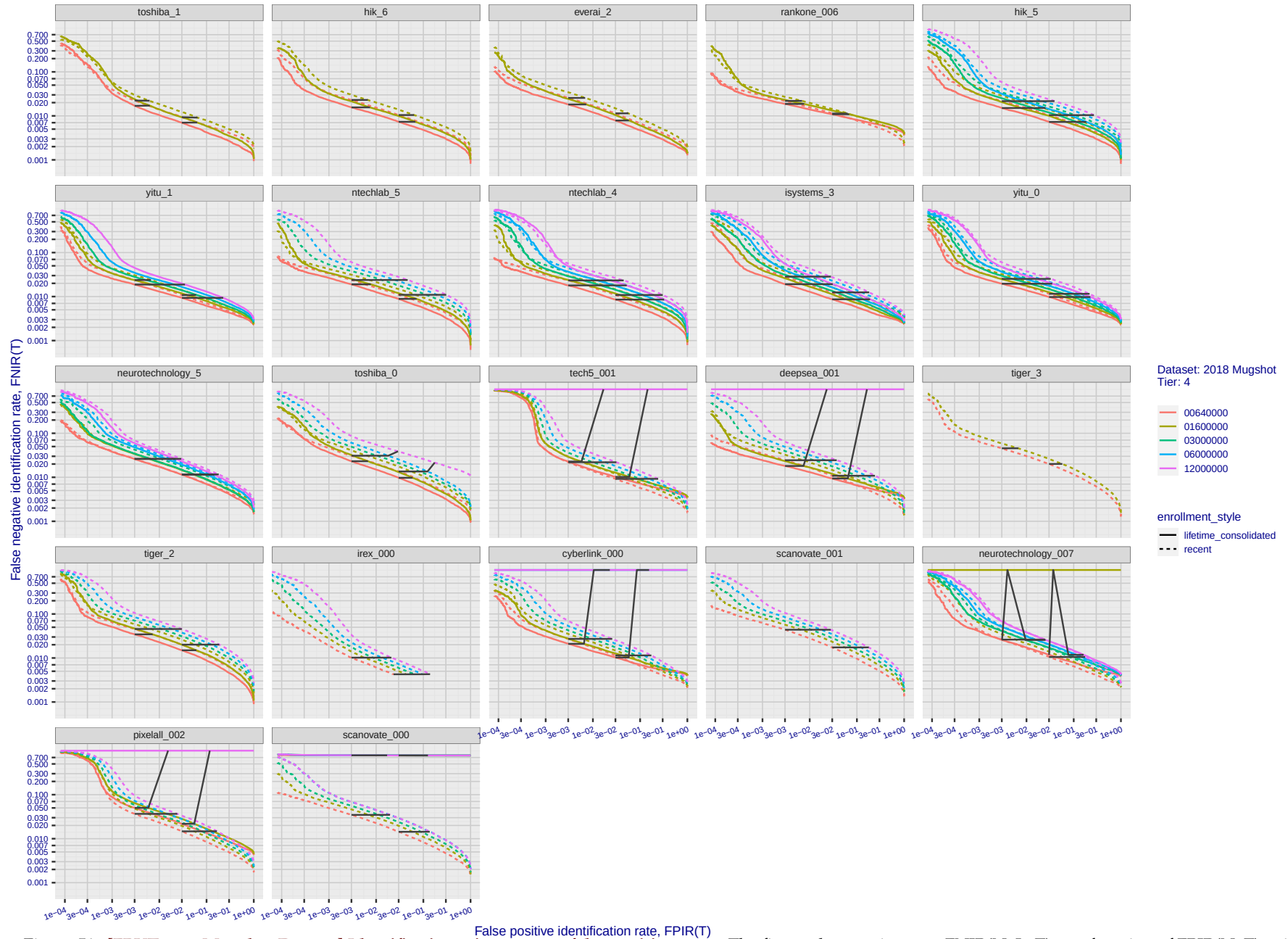
T = 0 → Investigation
T > 0 → Identification

Figure 51: **[FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates.** The figure shows miss rates $FNIR(N, L, T)$ as a function of $FPIR(N, T)$, with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, $FPIR(T)$ rises with N , and mate scores are independent of N . Other algorithms adjust scores in an attempt to make $FPIR$ independent of N .

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

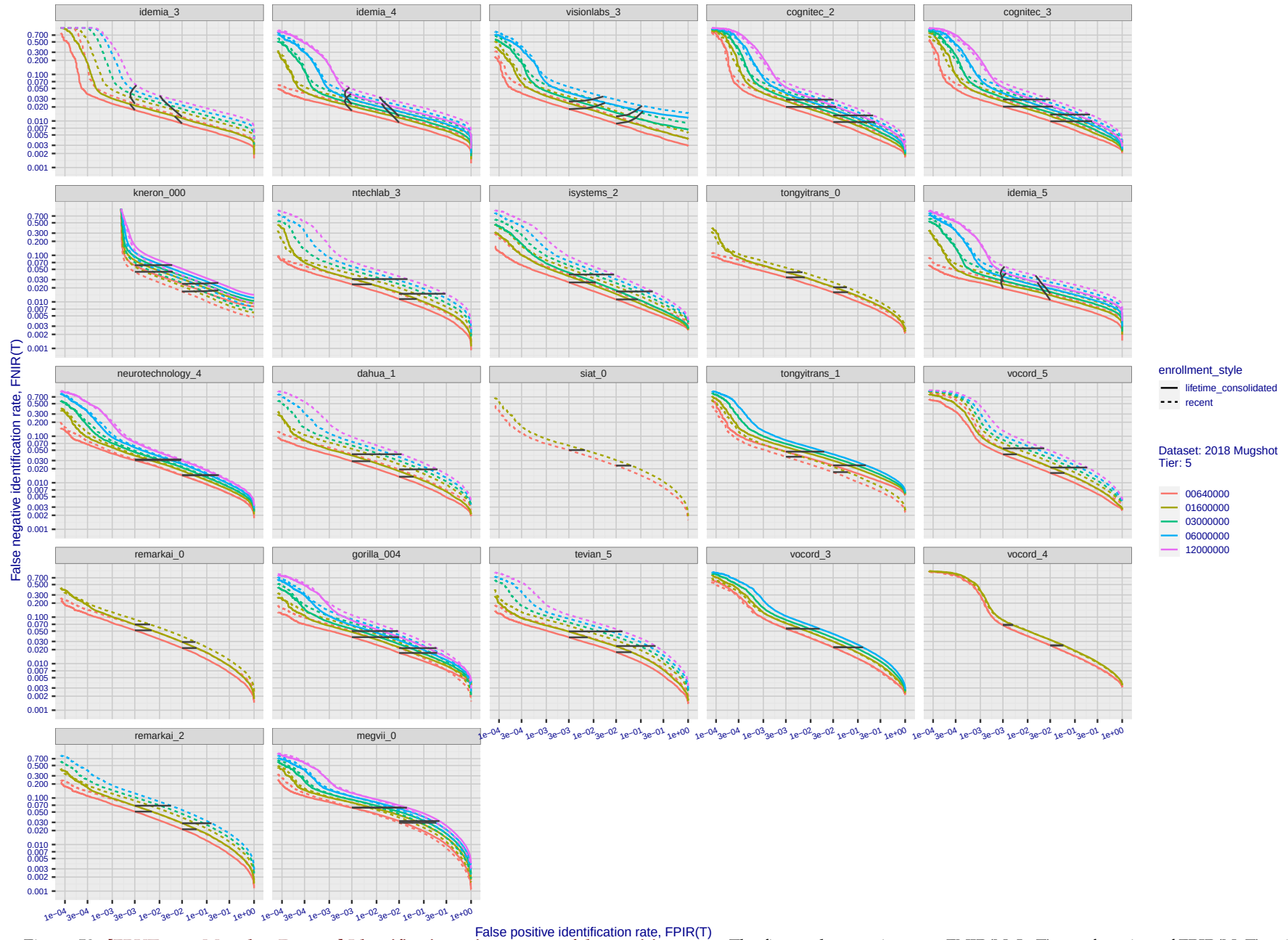
T = 0 → Investigation
T > 0 → Identification

Figure 52: [FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates. The figure shows miss rates $FNIR(N, L, T)$ as a function of $FPIR(N, T)$, with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, $FPIR(T)$ rises with N , and mate scores are independent of N . Other algorithms adjust scores in an attempt to make $FPIR$ independent of N .

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

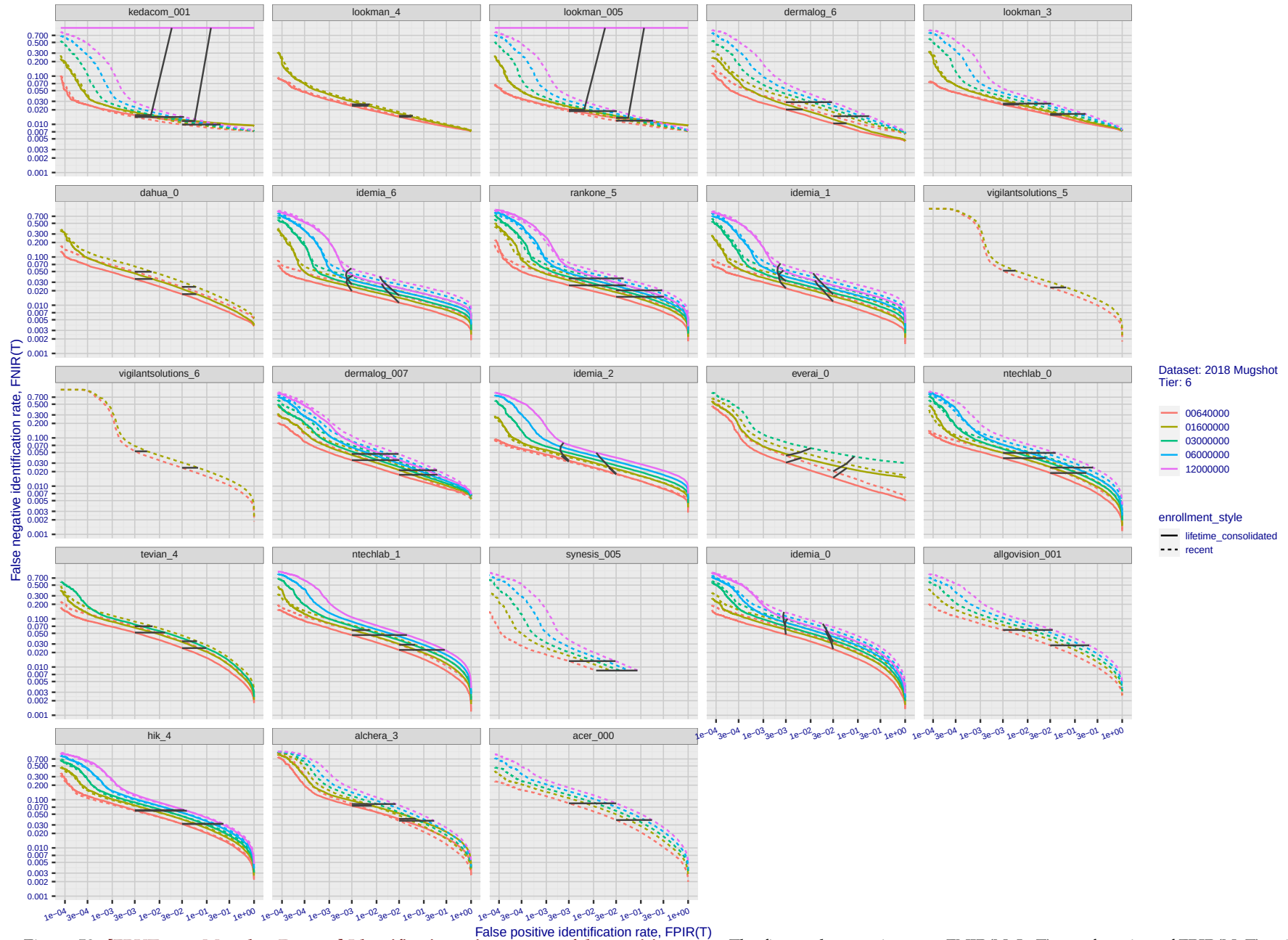
T = 0 → Investigation
T > 0 → Identification

Figure 53: **[FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates.** The figure shows miss rates $FNIR(N, L, T)$ as a function of $FPIR(N, T)$, with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, $FPIR(T)$ rises with N , and mate scores are independent of N . Other algorithms adjust scores in an attempt to make $FPIR$ independent of N .

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

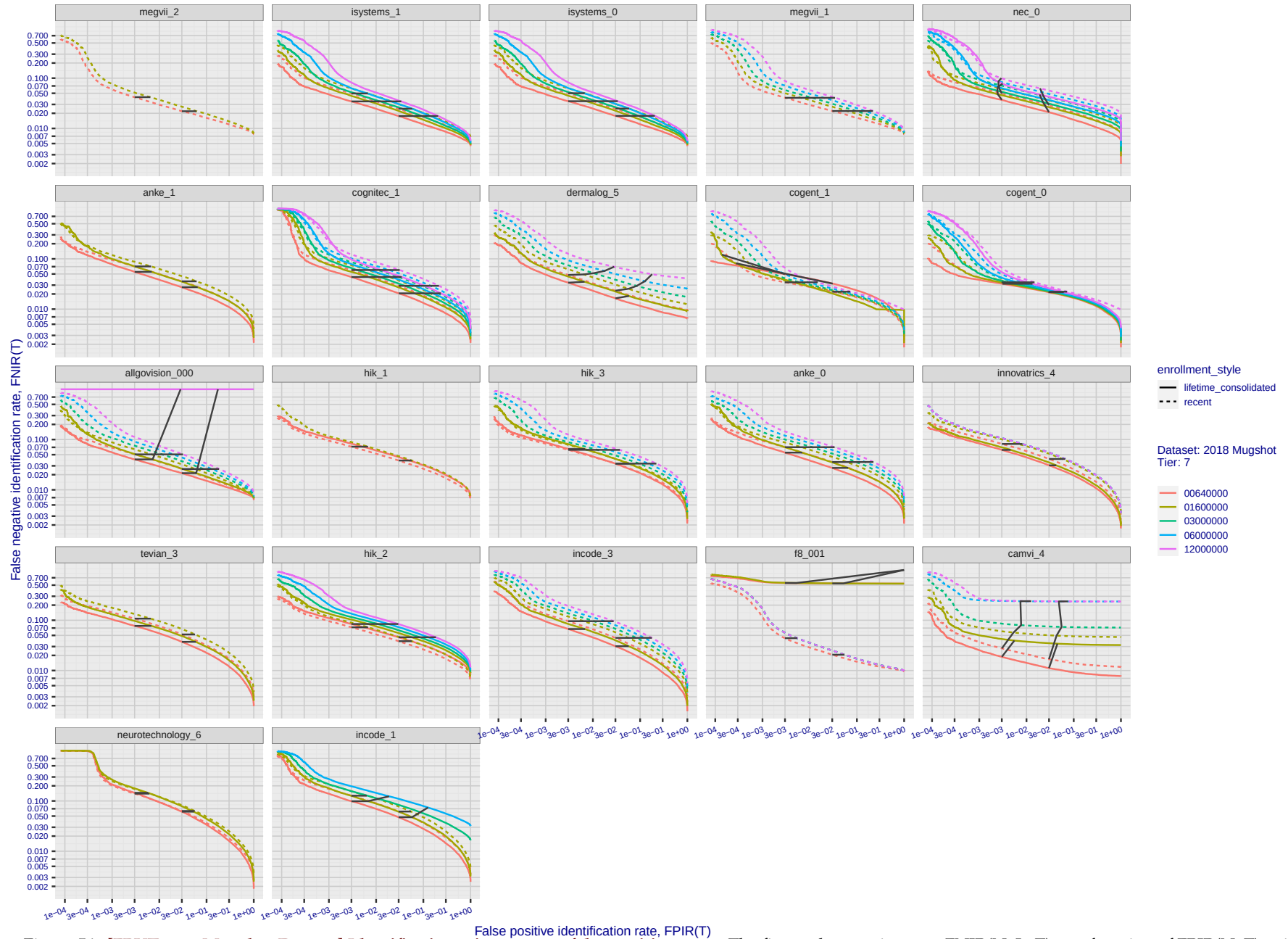
T = 0 → Investigation
T > 0 → Identification

Figure 54: [FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates. The figure shows miss rates $FNIR(N, L, T)$ as a function of $FPIR(N, T)$, with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, $FPIR(T)$ rises with N , and mate scores are independent of N . Other algorithms adjust scores in an attempt to make $FPIR$ independent of N .

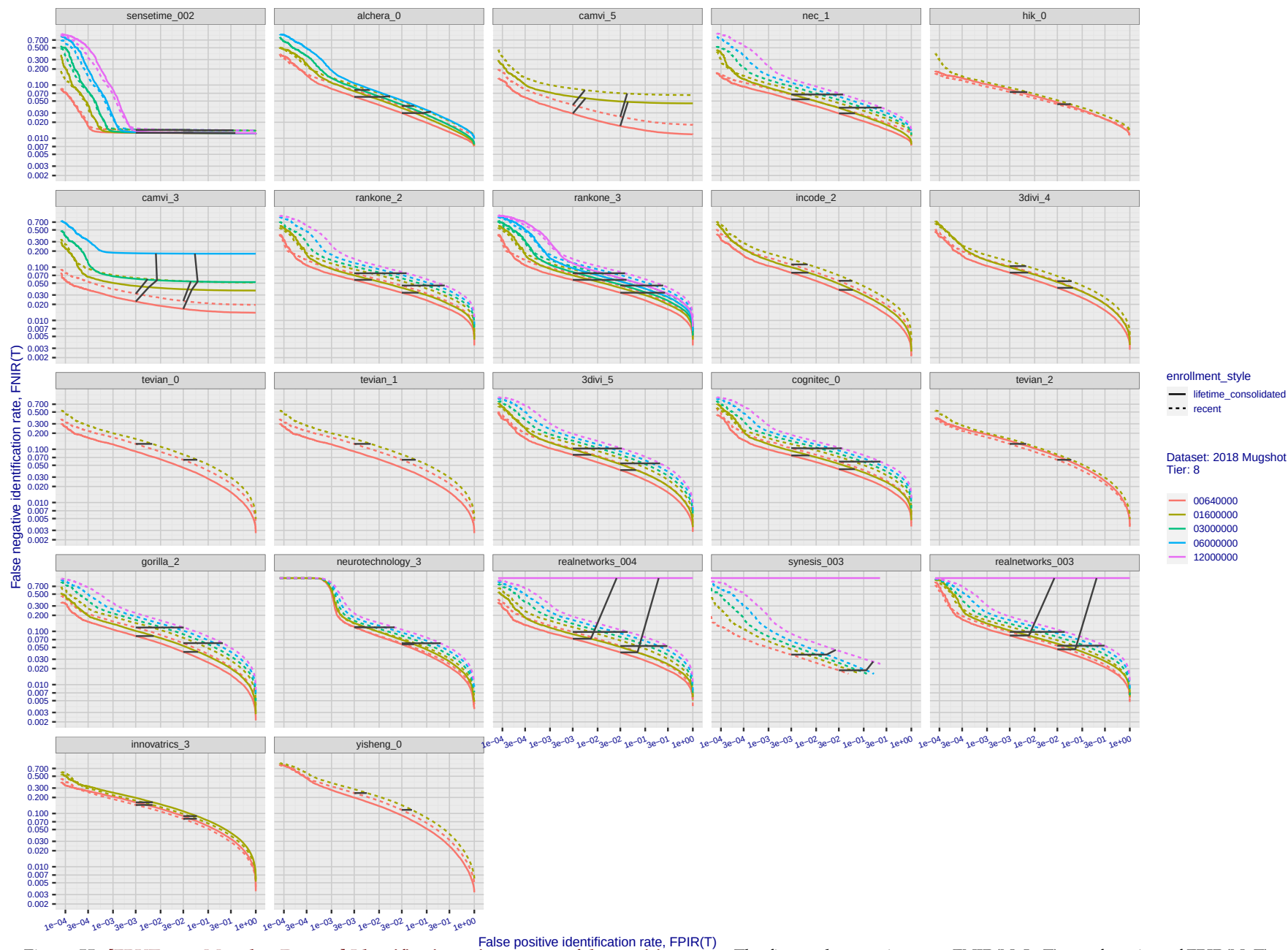


Figure 55: [FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates. The figure shows miss rates $FNIR(N, L, T)$ as a function of $FPIR(N, T)$, with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, $FPIR(T)$ rises with N , and mate scores are independent of N . Other algorithms adjust scores in an attempt to make $FPIR(T)$ independent of N .

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

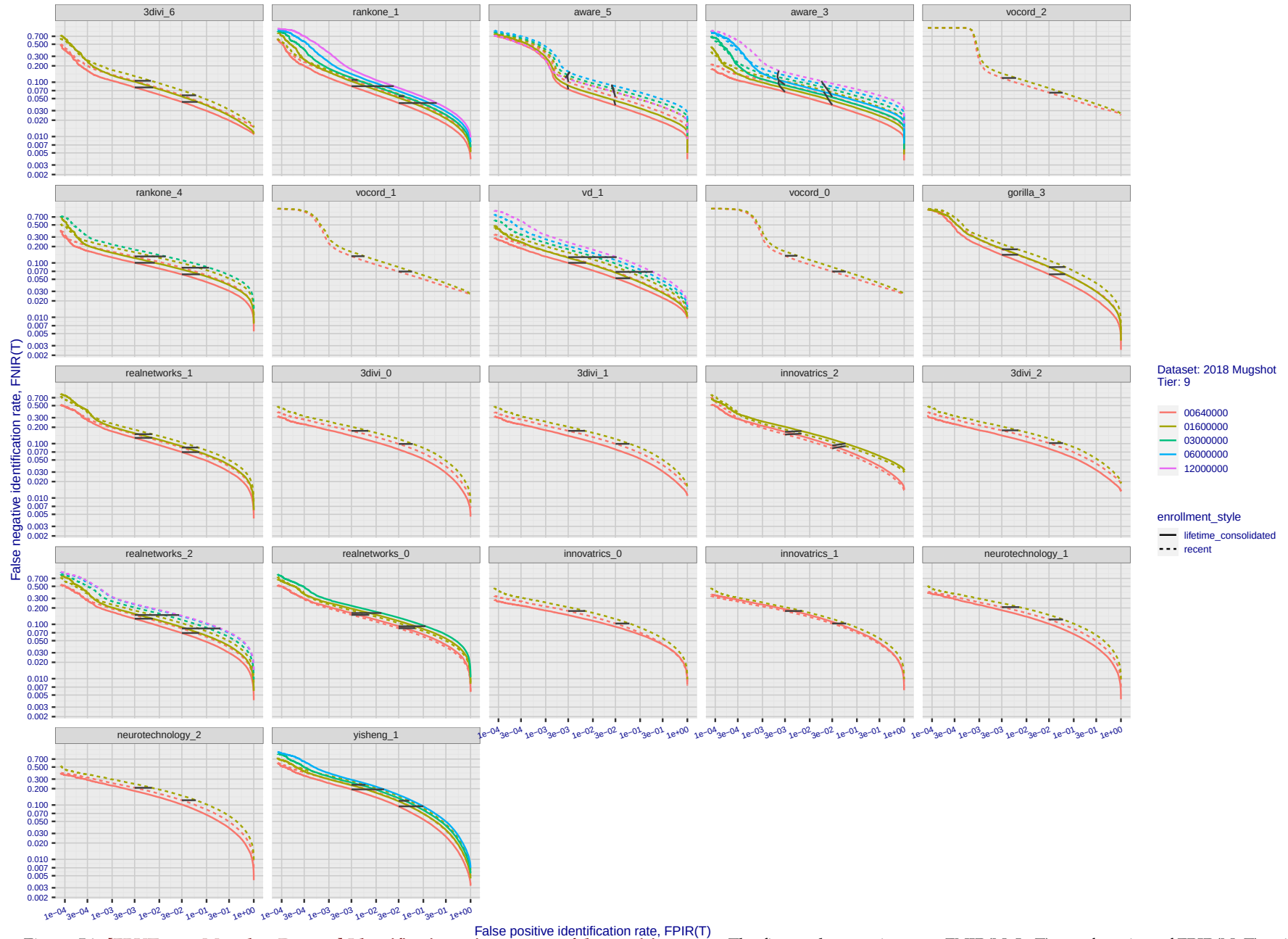
T = 0 → Investigation
T > 0 → Identification

Figure 56: [FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates. The figure shows miss rates $FNIR(N, L, T)$ as a function of $FPIR(N, T)$, with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, $FPIR(T)$ rises with N , and mate scores are independent of N . Other algorithms adjust scores in an attempt to make $FPIR$ independent of N .

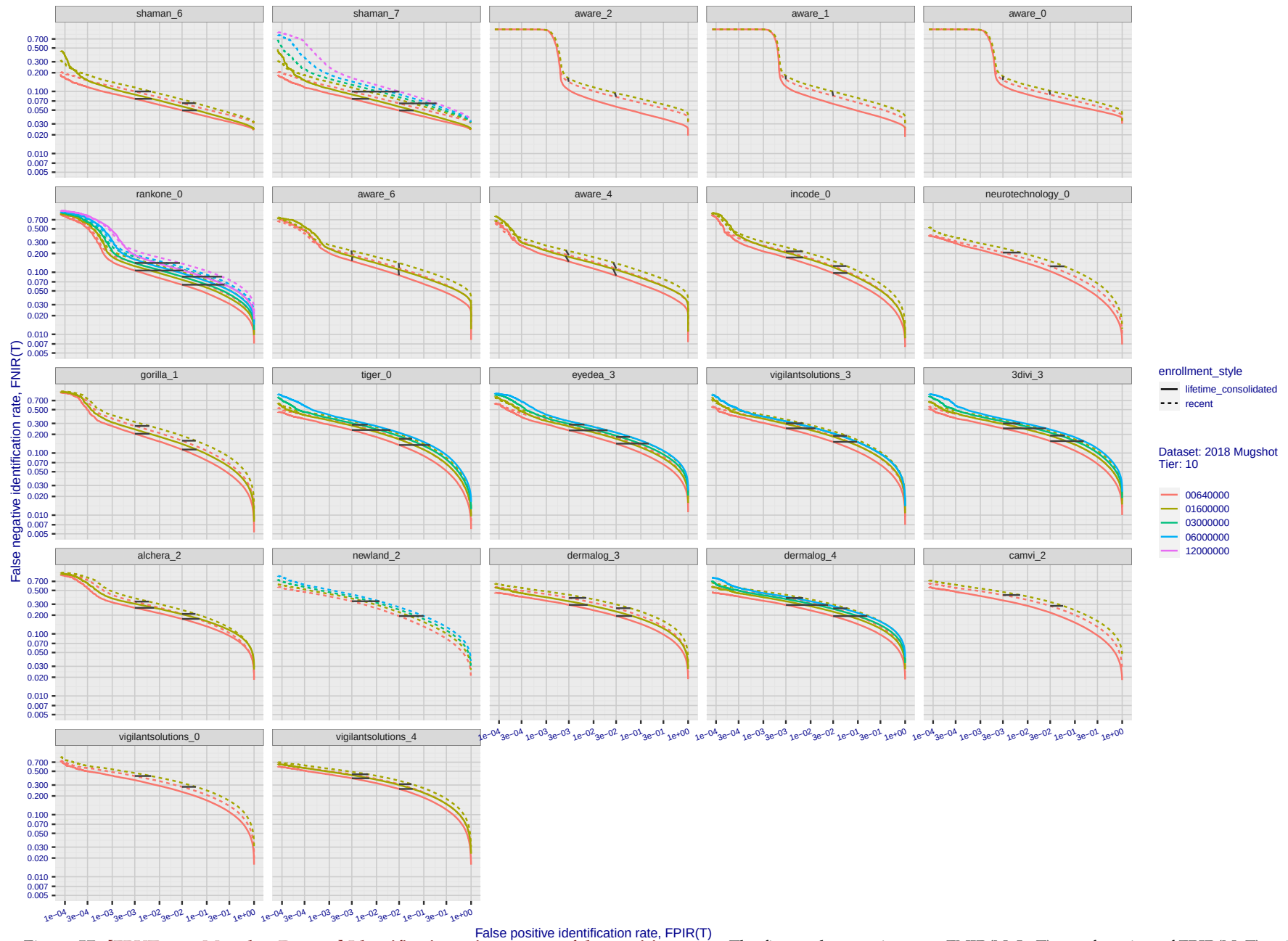


Figure 57: [FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates. The figure shows miss rates $FNIR(N, L, T)$ as a function of $FPIR(N, T)$, with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, $FPIR(T)$ rises with N , and mate scores are independent of N . Other algorithms adjust scores in an attempt to make $FPIR$ independent of N .

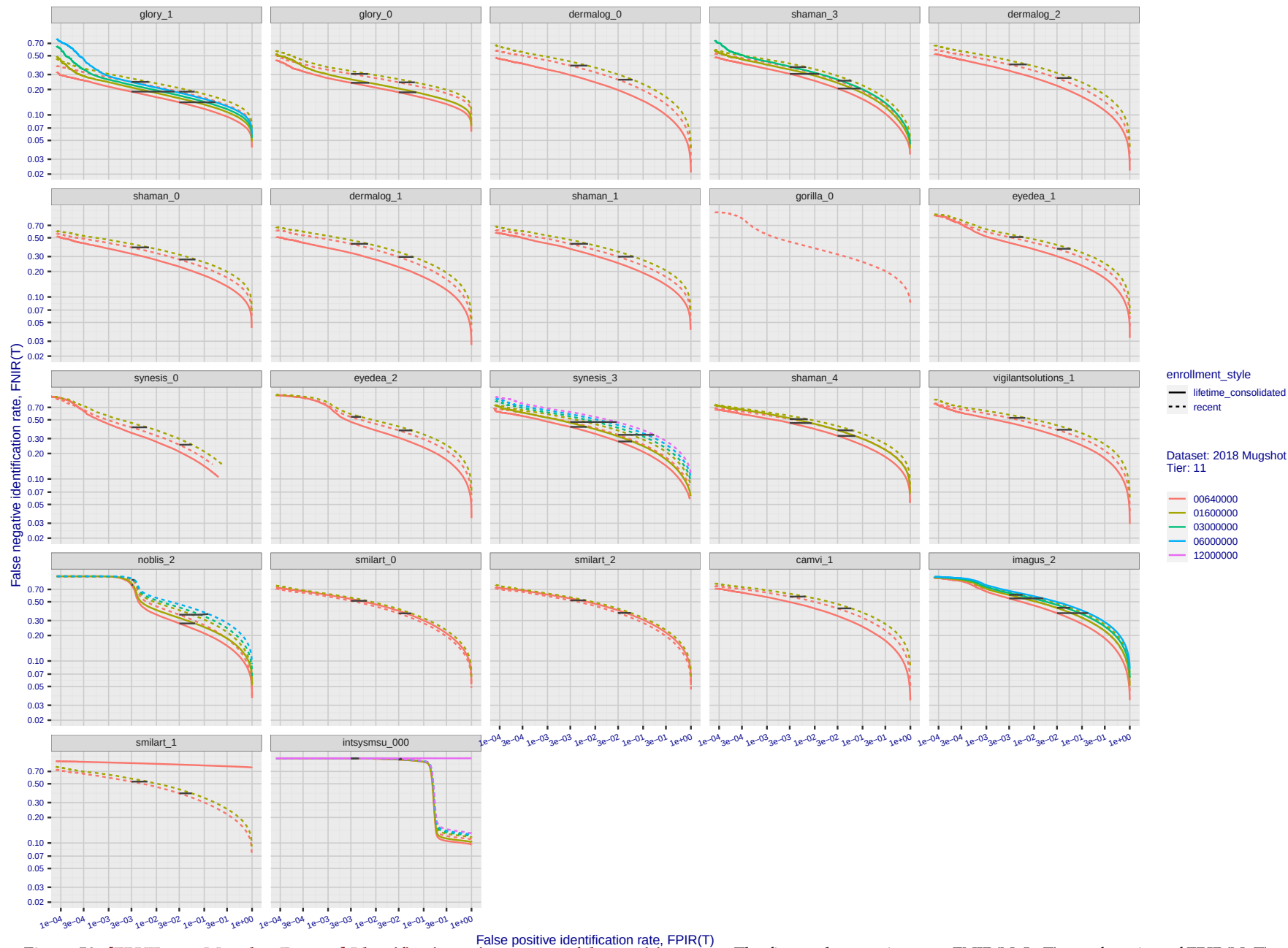


Figure 58: [FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates. The figure shows miss rates $FNIR(N, L, T)$ as a function of $FPIR(N, T)$, with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, $FPIR(T)$ rises with N , and mate scores are independent of N . Other algorithms adjust scores in an attempt to make $FPIR$ independent of N .

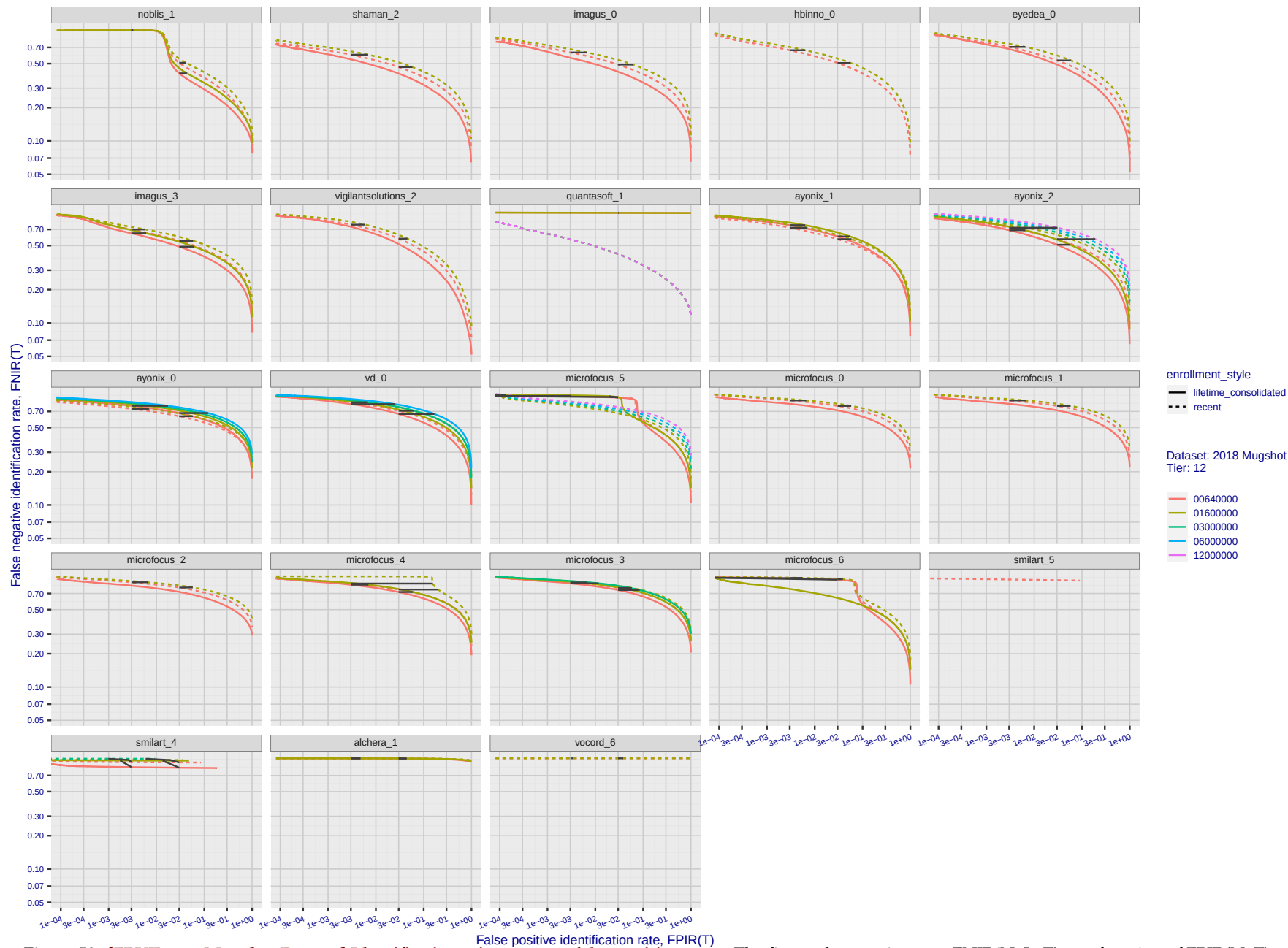


Figure 59: [FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates. The figure shows miss rates $FNIR(N, L, T)$ as a function of $FPIR(N, T)$, with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, $FPIR(T)$ rises with N , and mate scores are independent of N . Other algorithms adjust scores in an attempt to make $FPIR$ independent of N .

Appendix B Effect of time-lapse: Accuracy after face ageing

This publication is available free of charge from: <https://doi.org/10.6028/NIST.IR.8271>

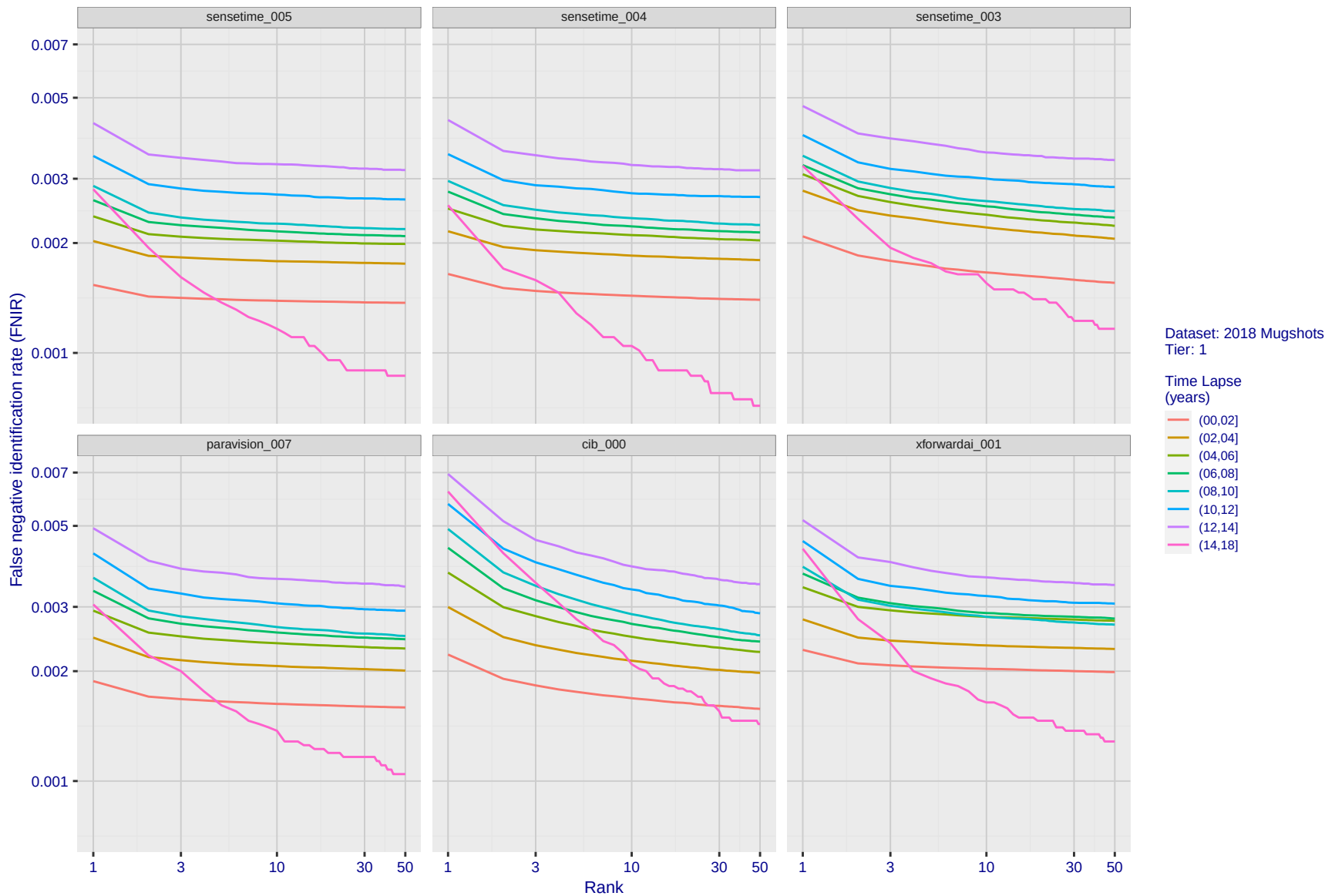


Figure 60: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

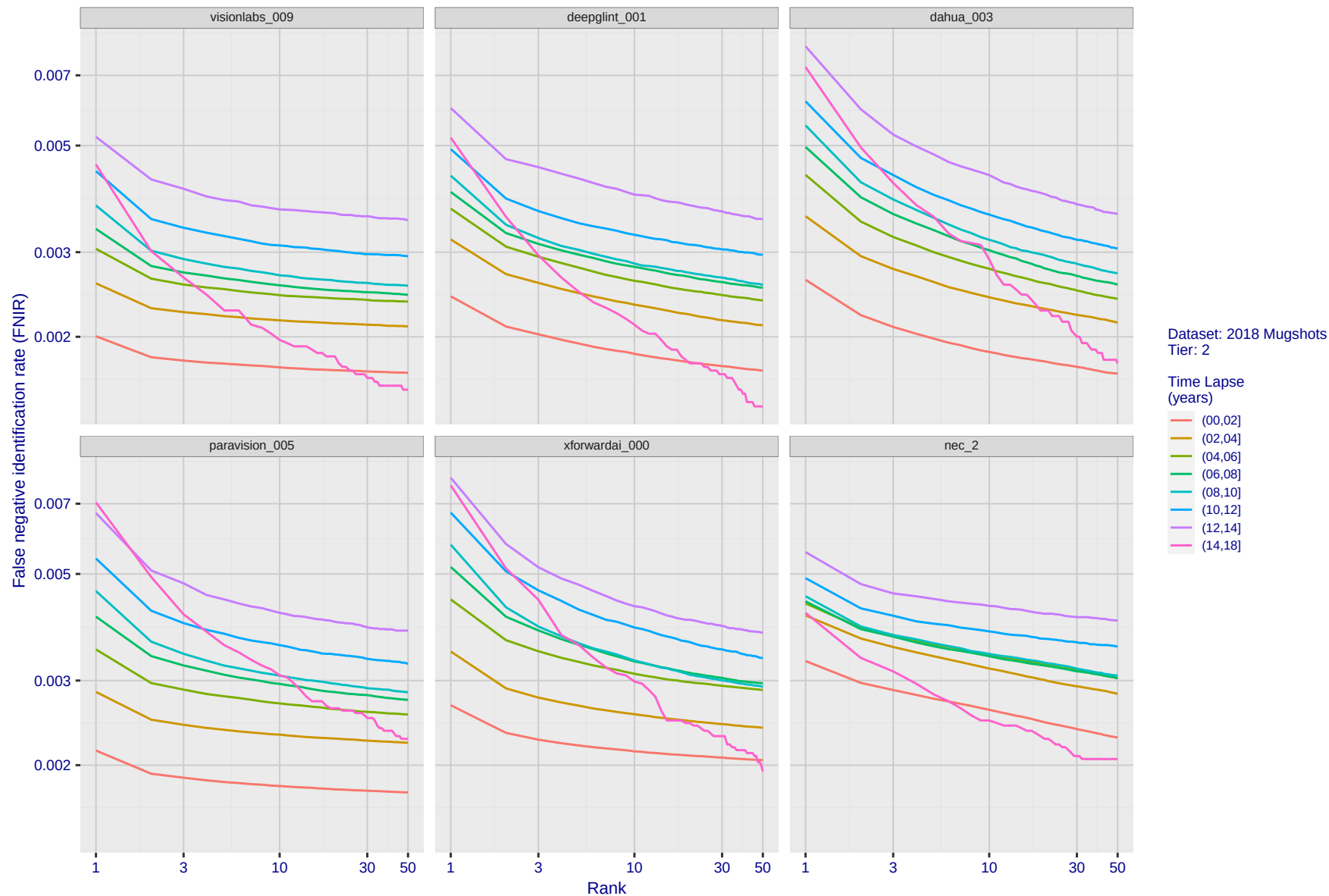


Figure 61: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsd. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

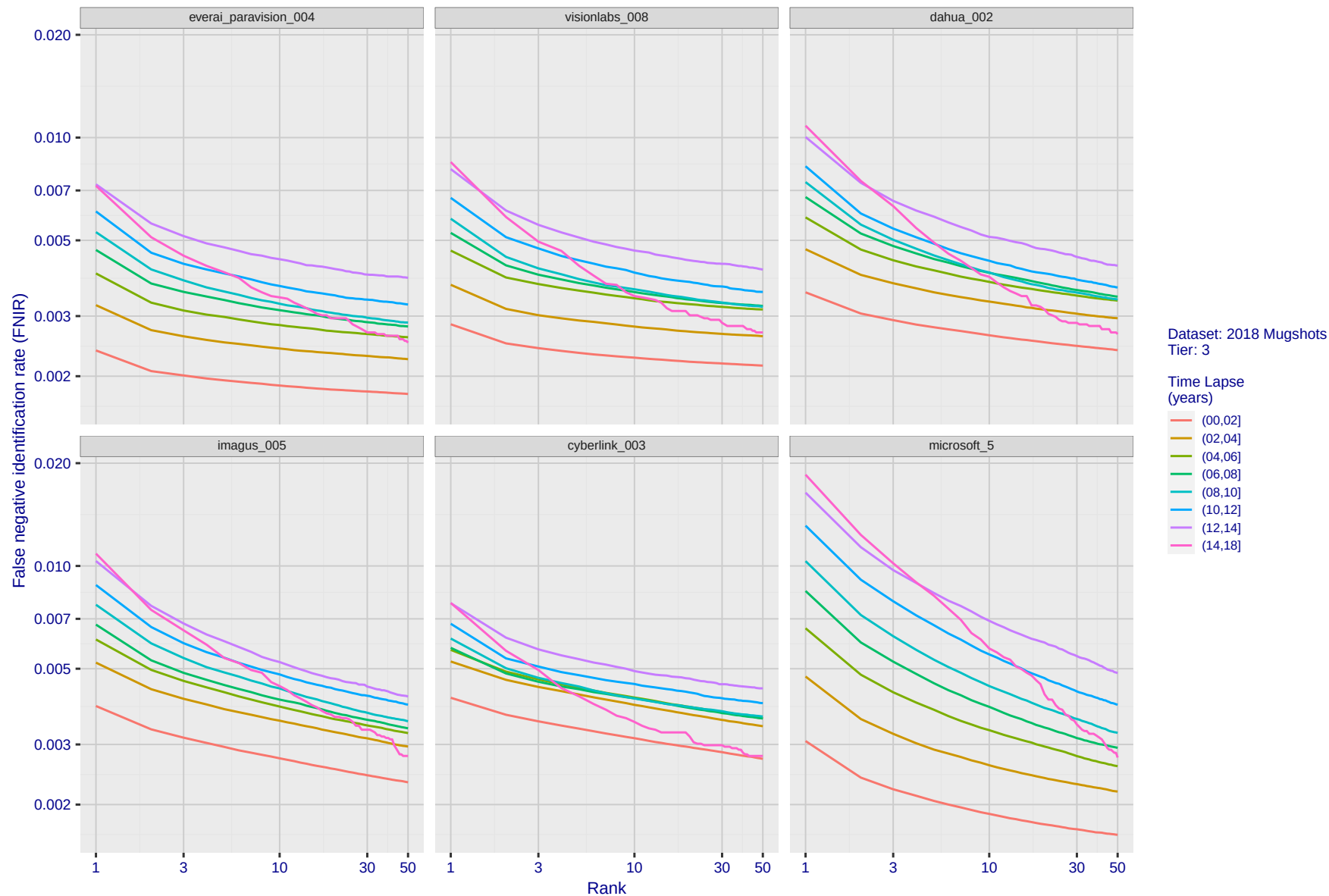


Figure 62: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsing. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

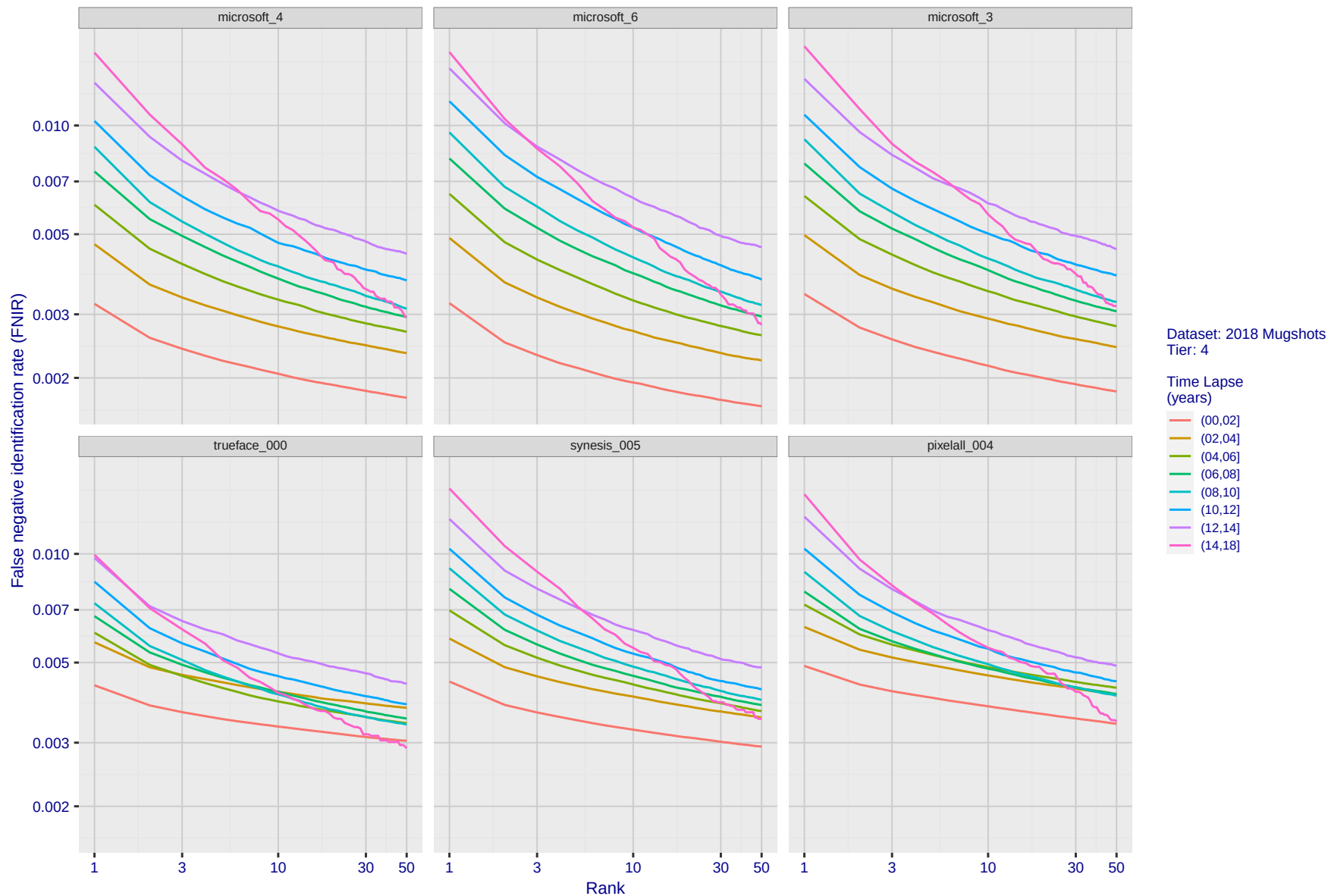


Figure 63: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

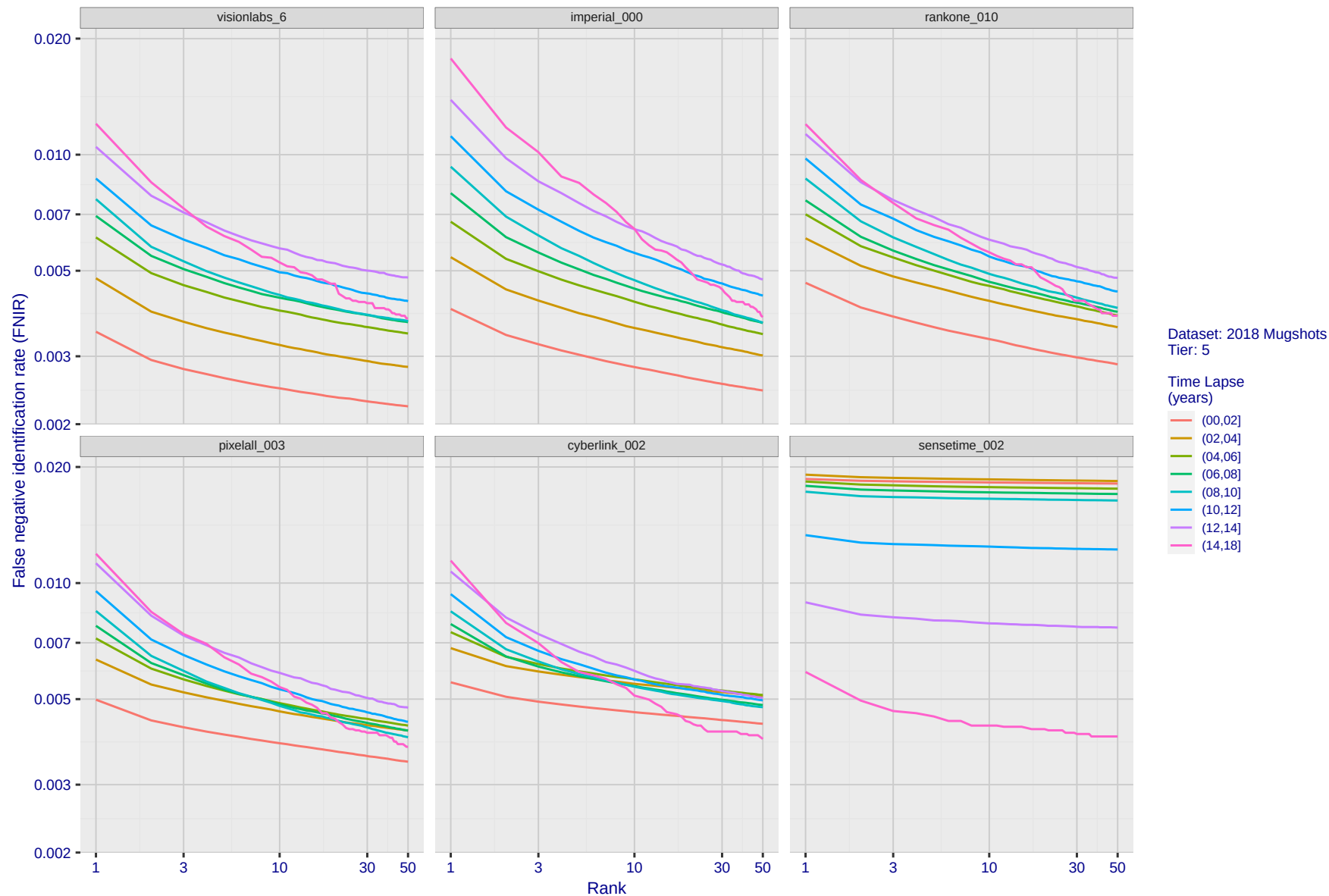


Figure 64: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

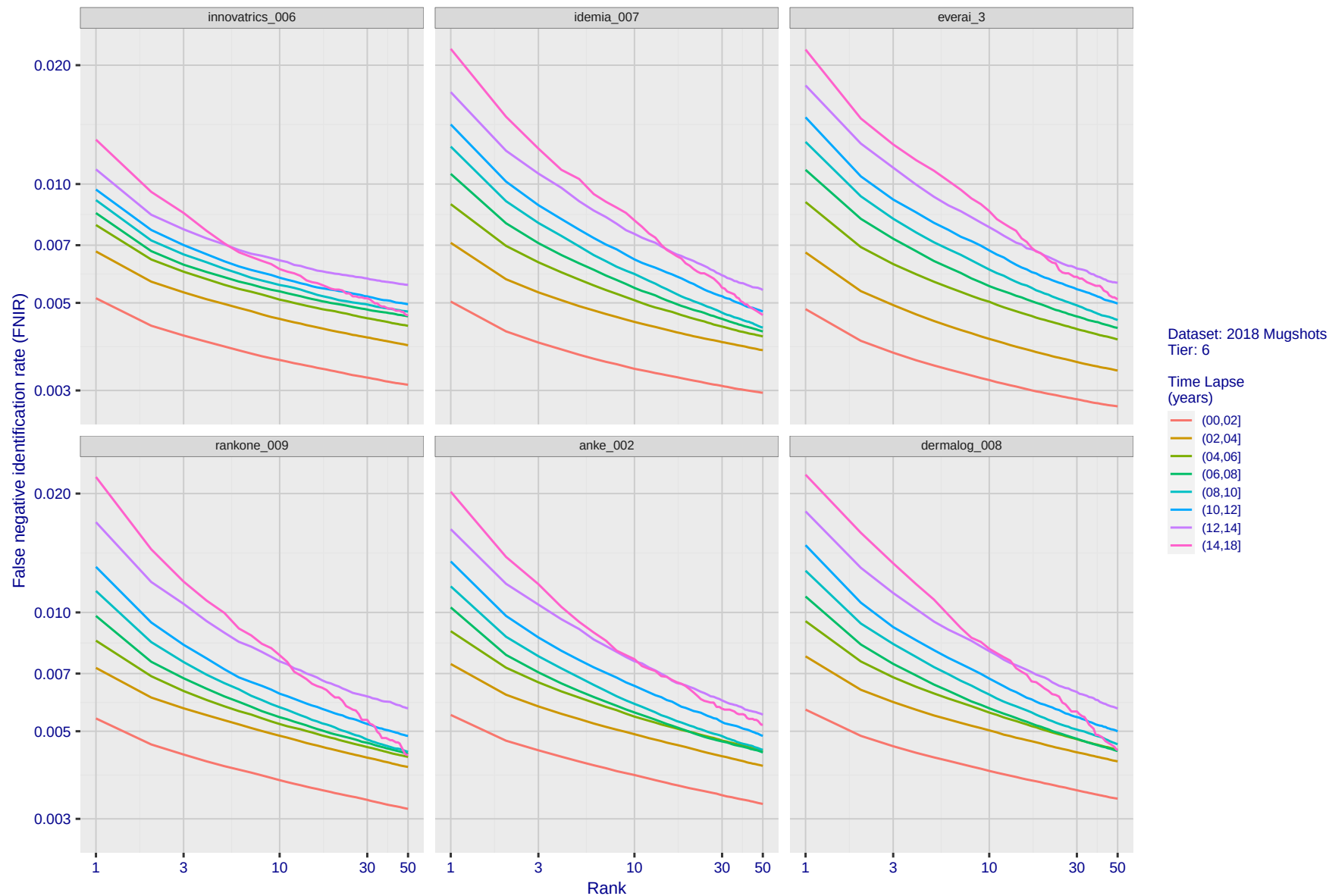


Figure 65: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

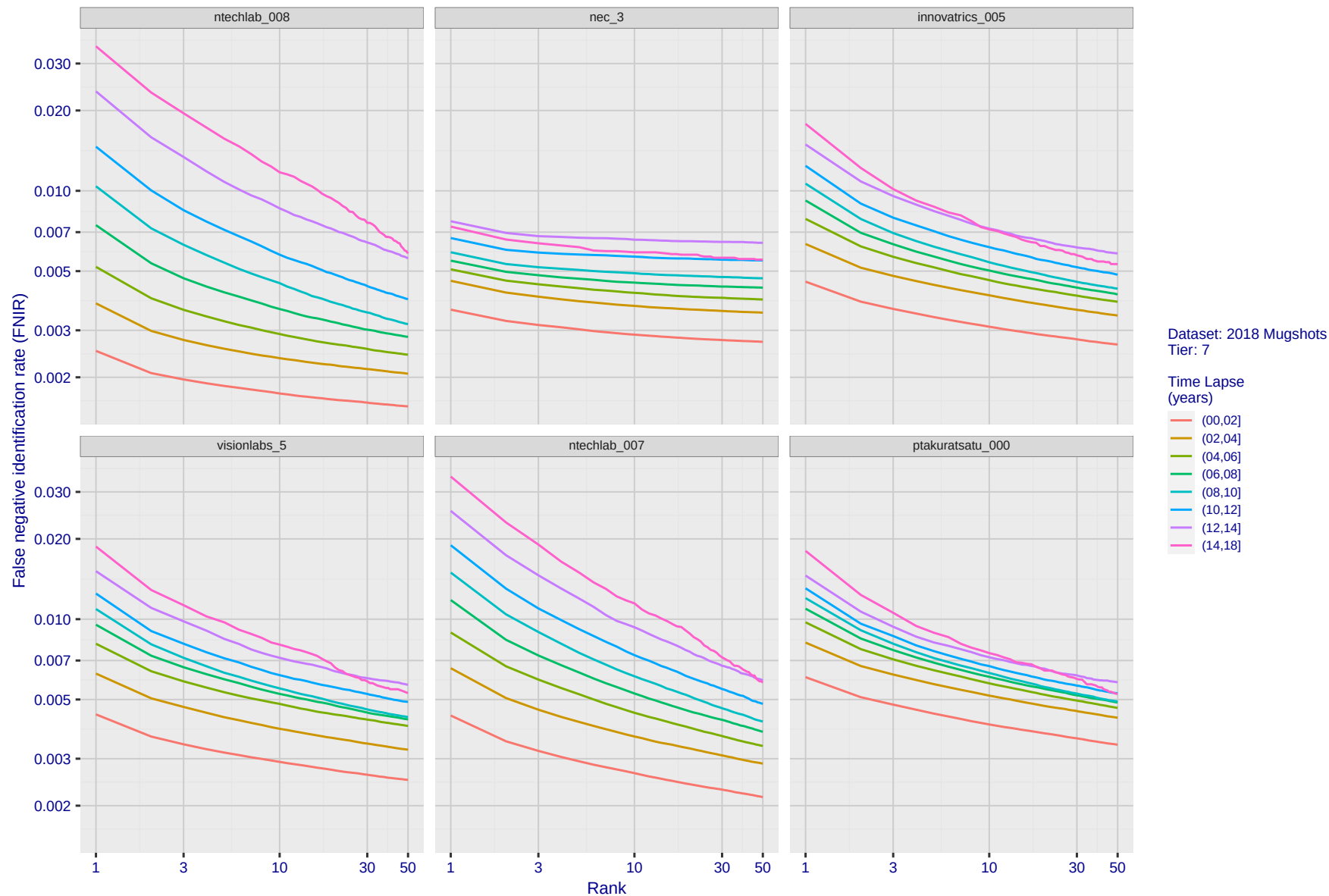


Figure 66: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

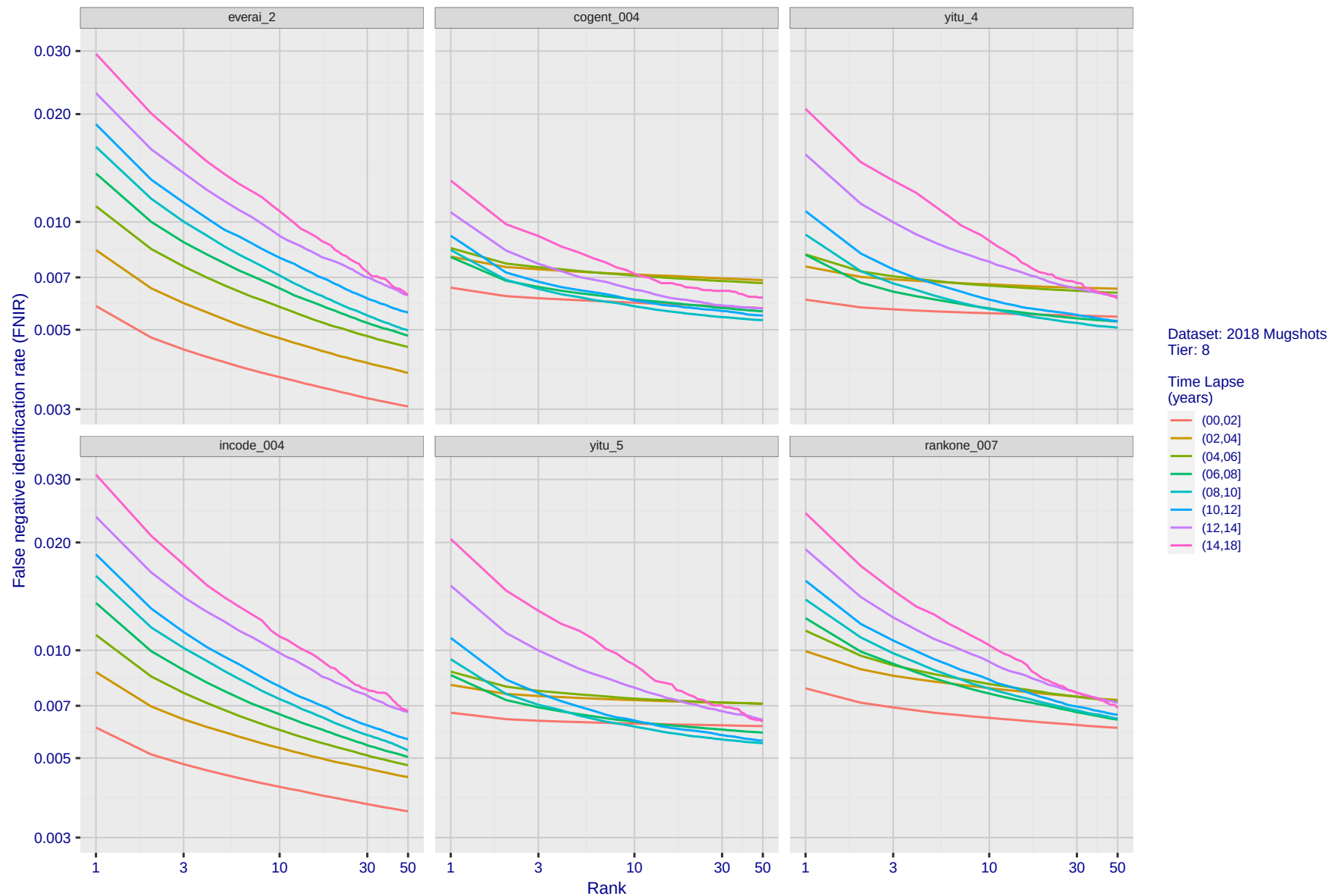


Figure 67: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

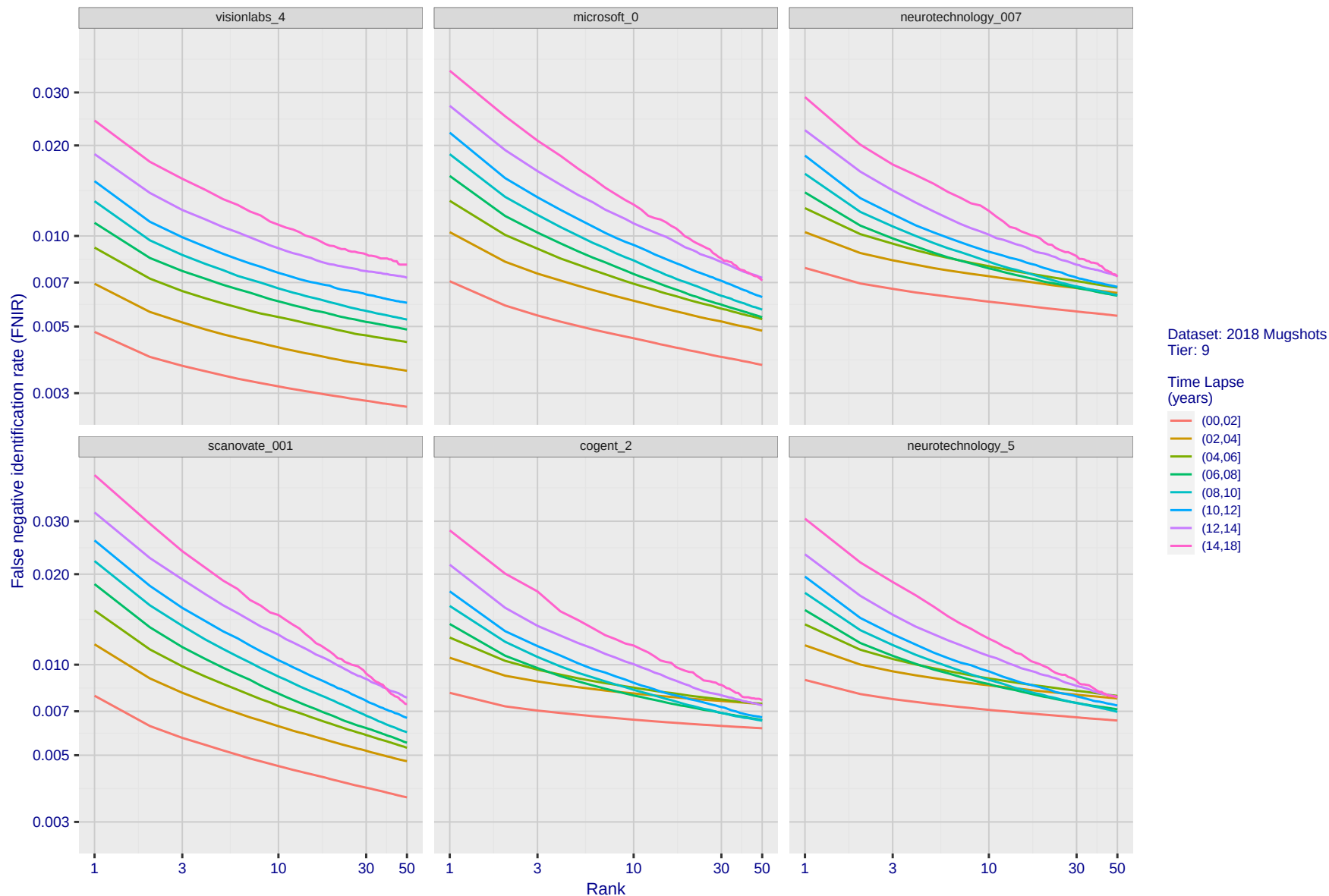


Figure 68: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

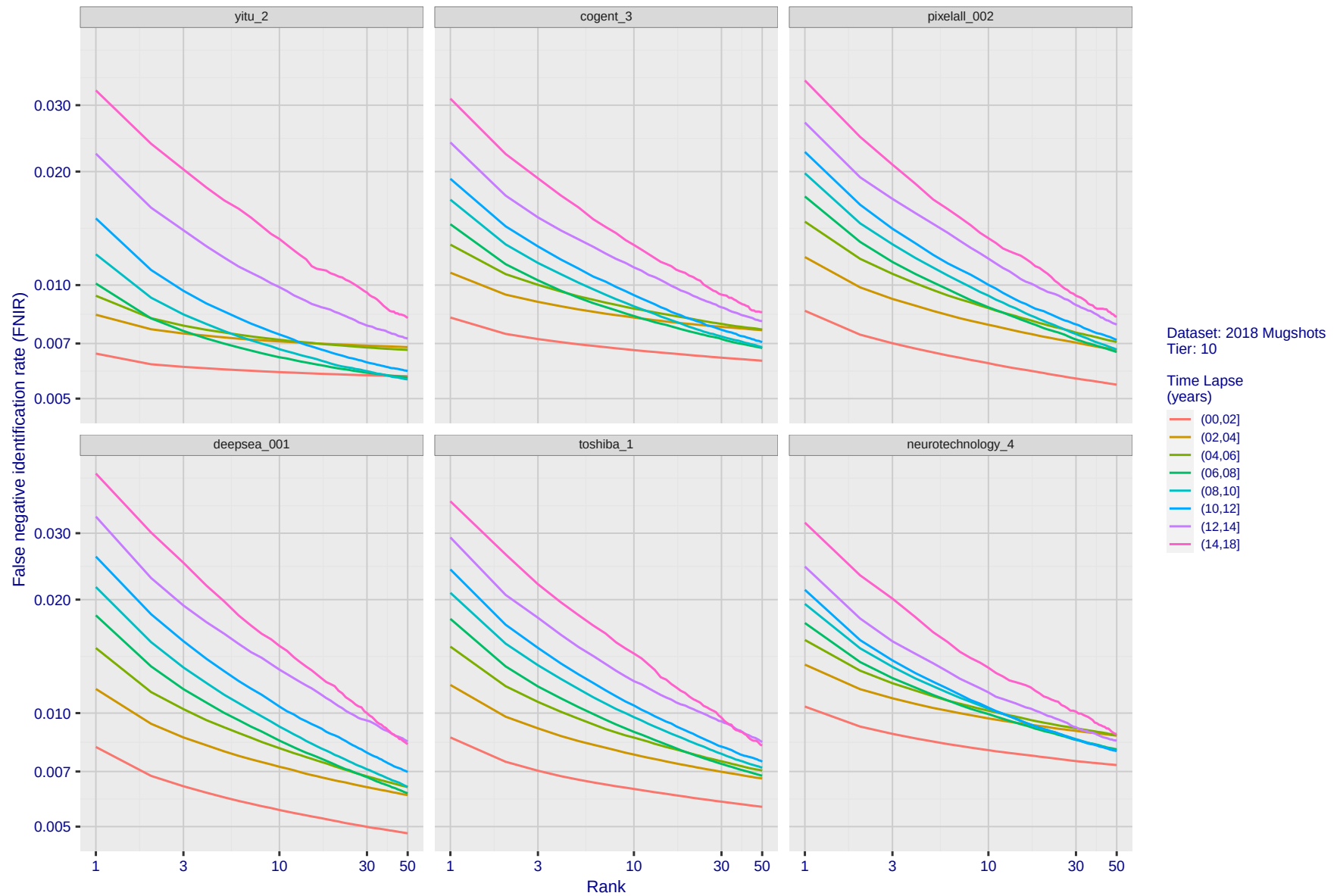


Figure 69: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsd. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

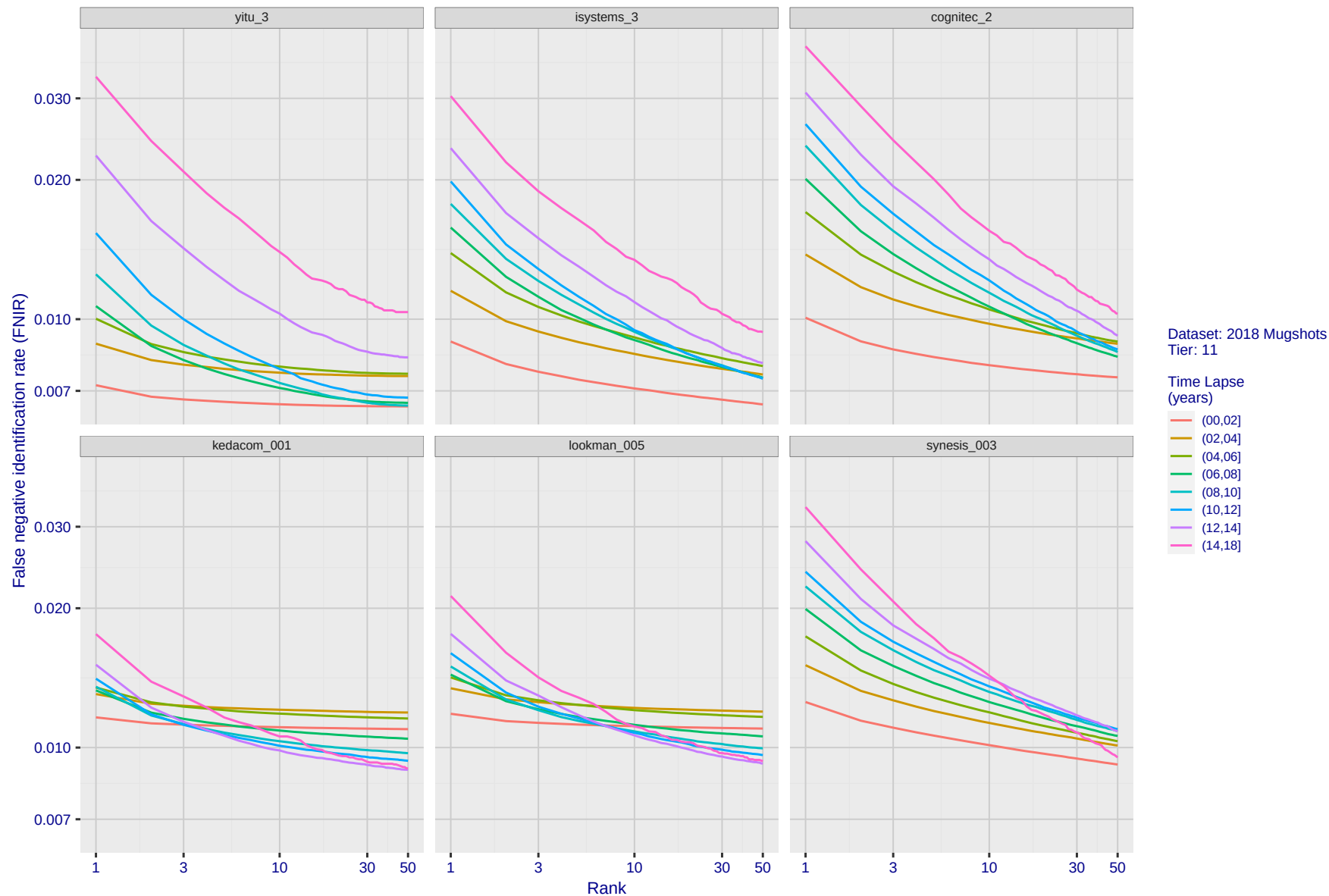


Figure 70: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsd. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

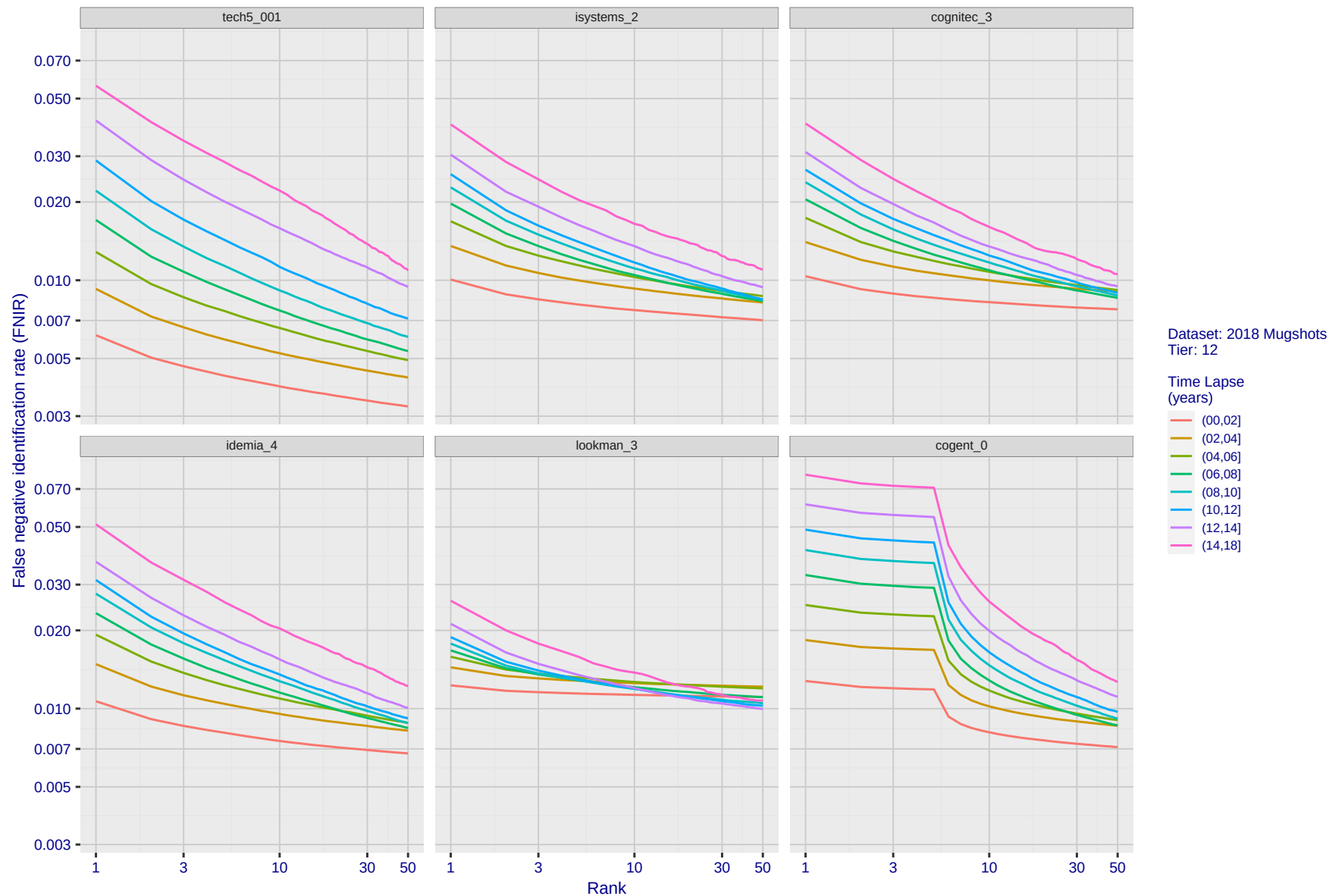


Figure 71: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsd. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

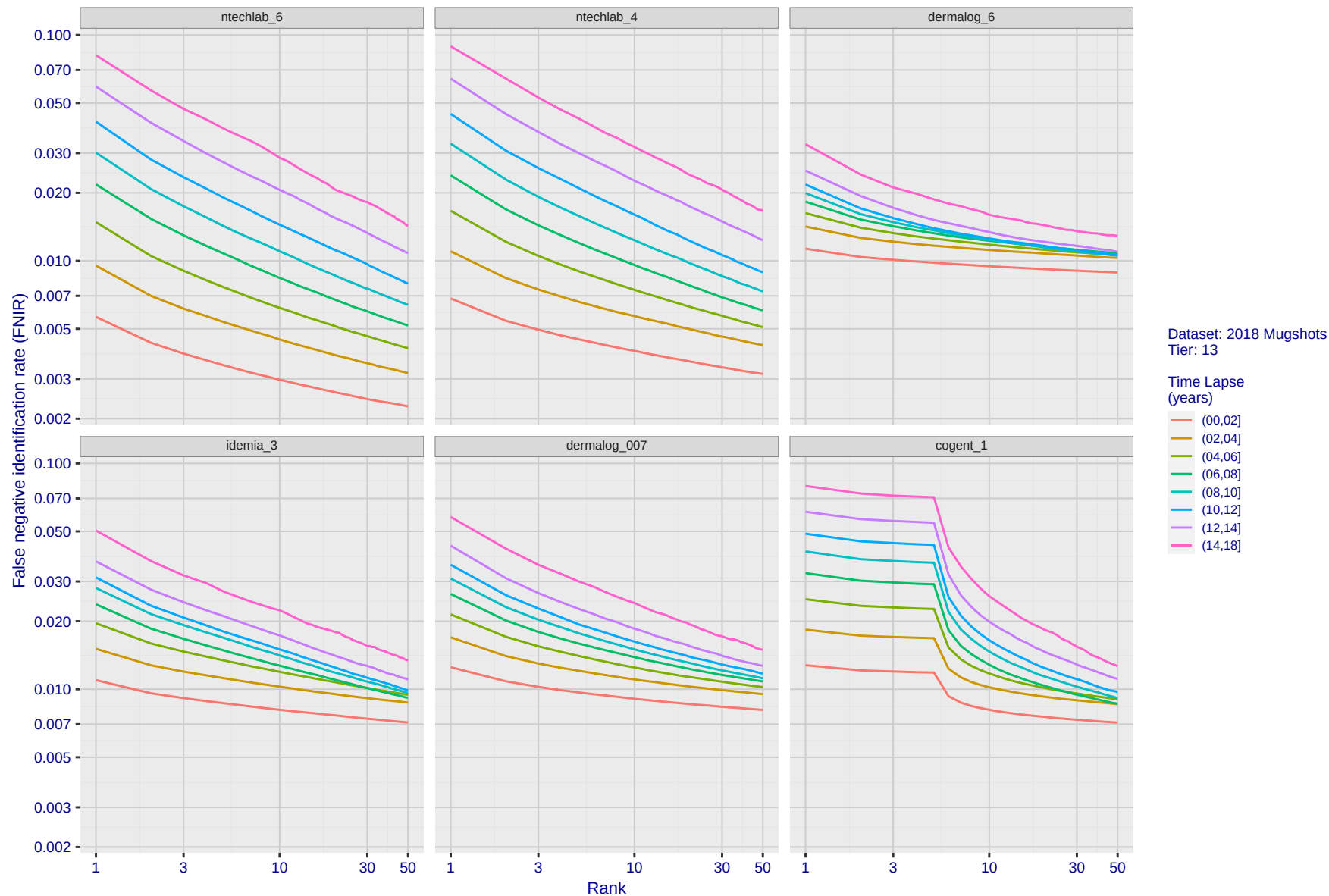


Figure 72: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

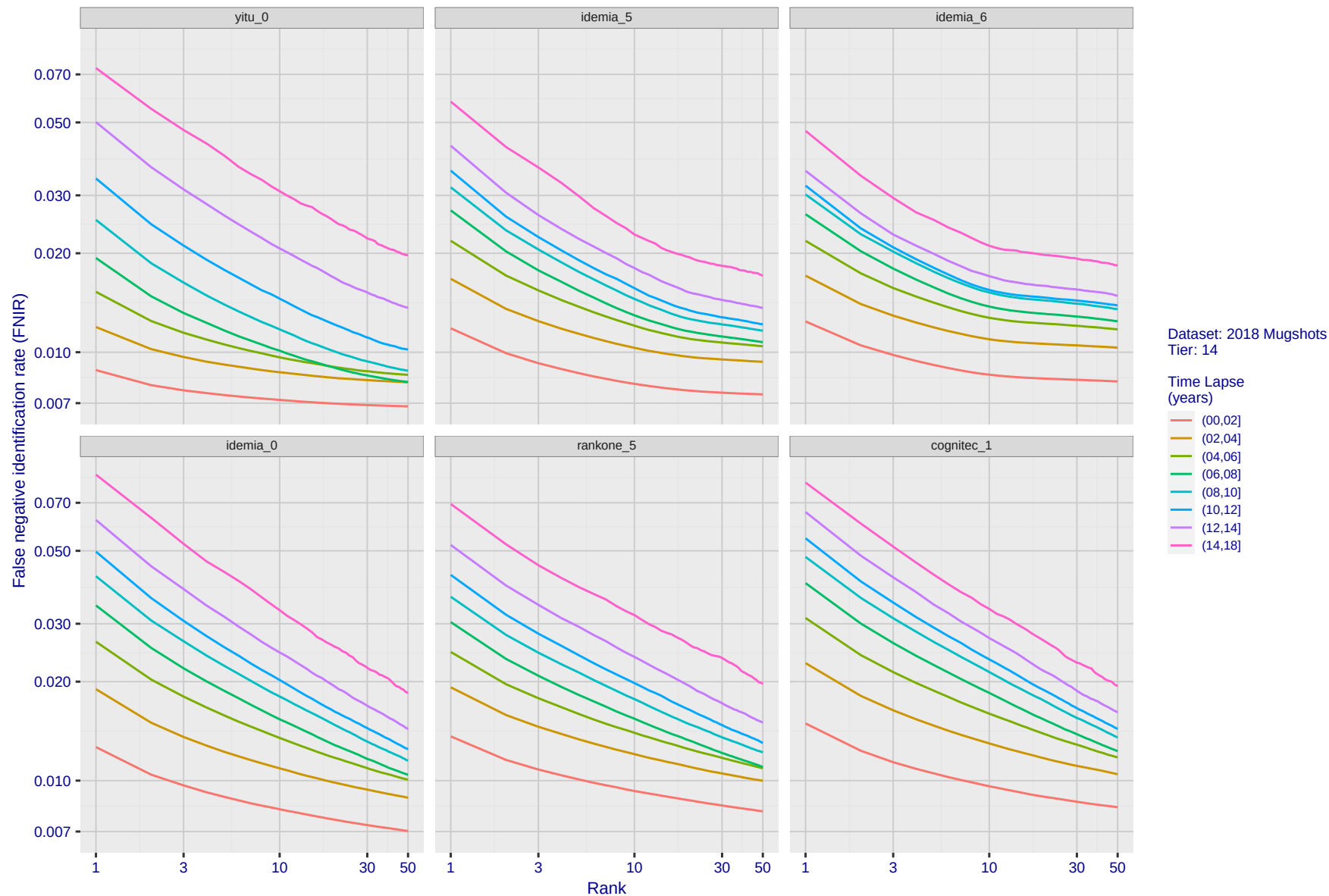


Figure 73: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

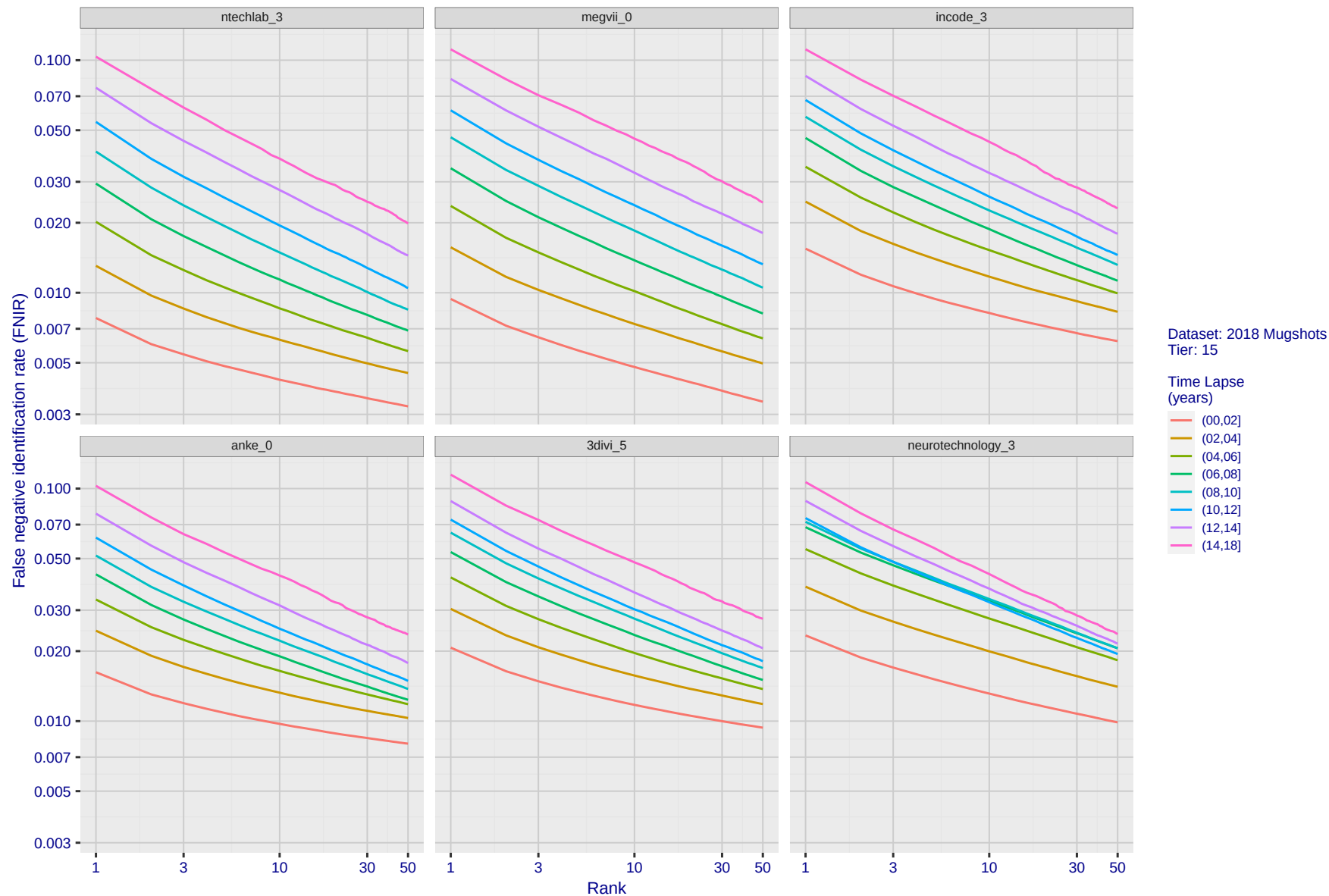


Figure 74: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

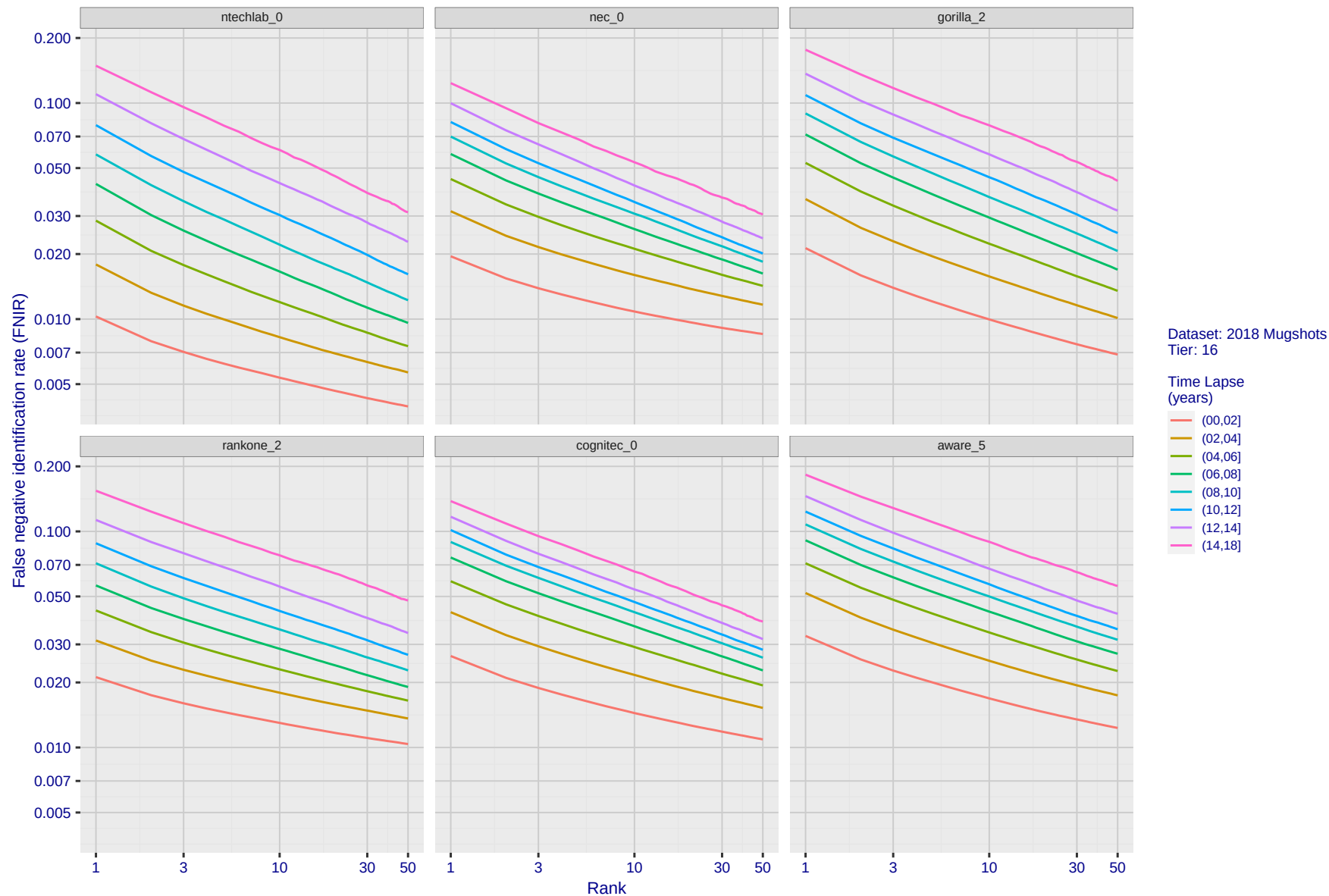


Figure 75: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

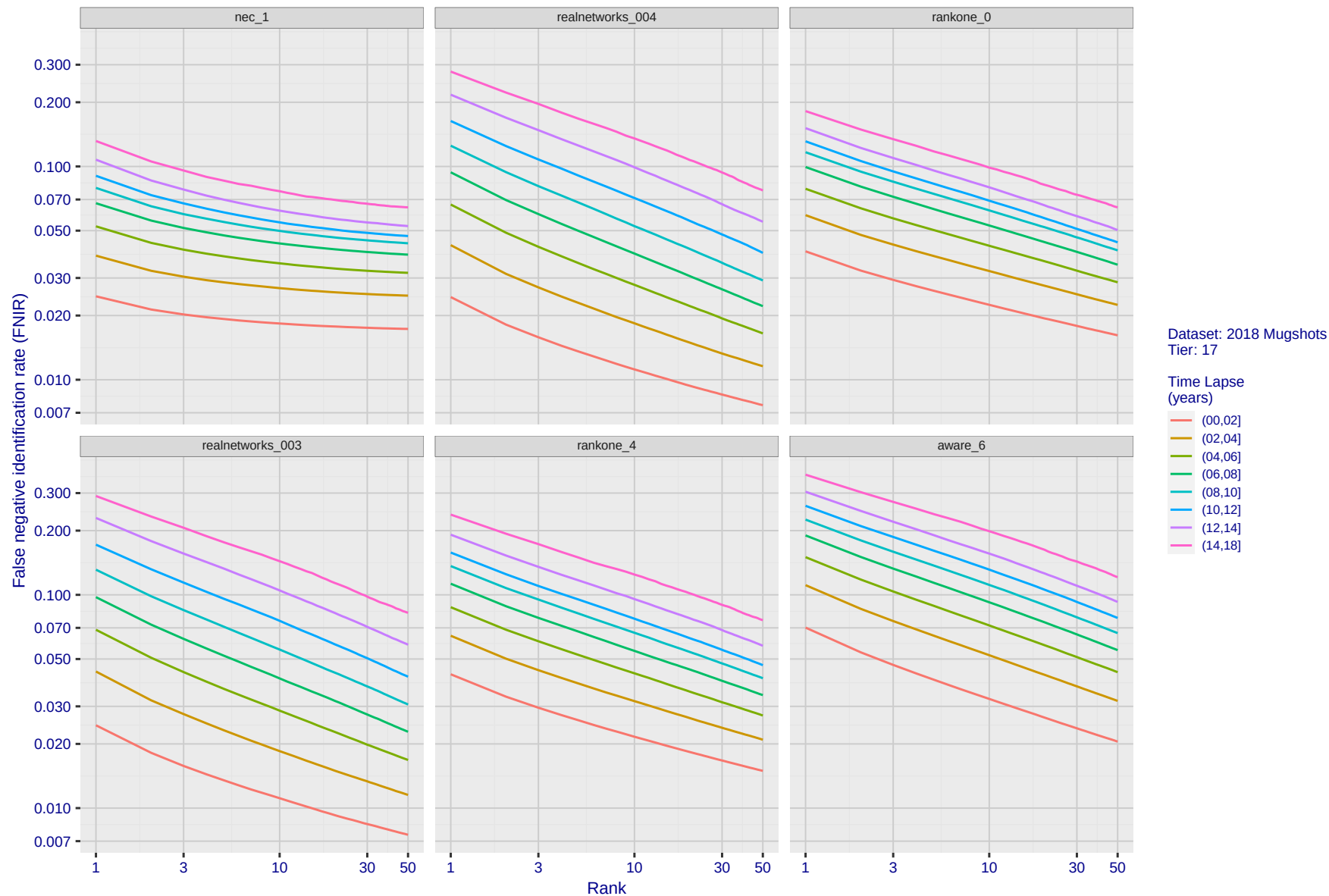


Figure 76: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsd. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

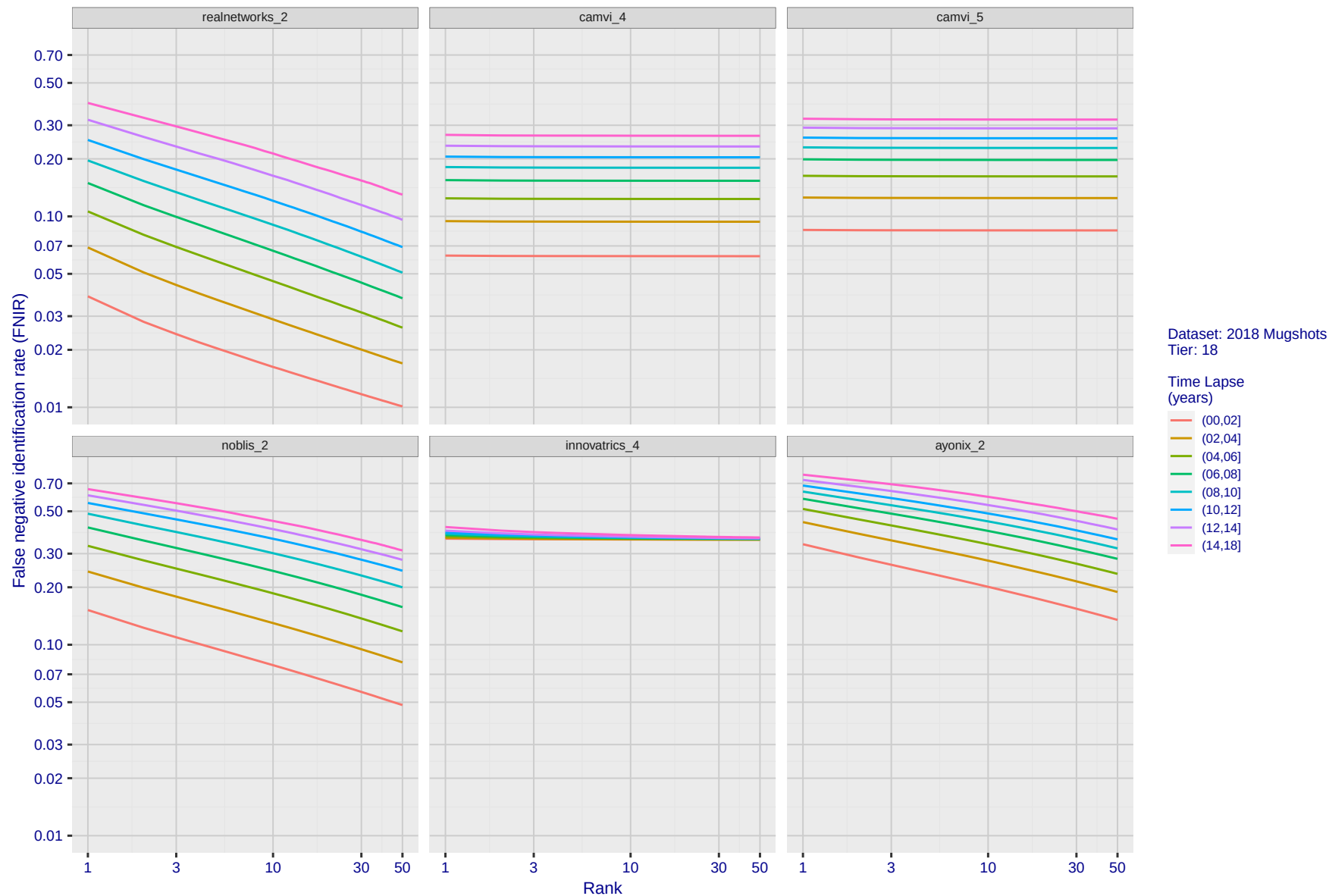


Figure 77: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

2021/03/04 11:49:04 FNIR(N, R, T) = False neg. identification rate N = Num. enrolled subjects T = Threshold
FPR(N, T) = False pos. identification rate R = Num. candidates examined T > 0 → Investigation
T > 0 → Identification

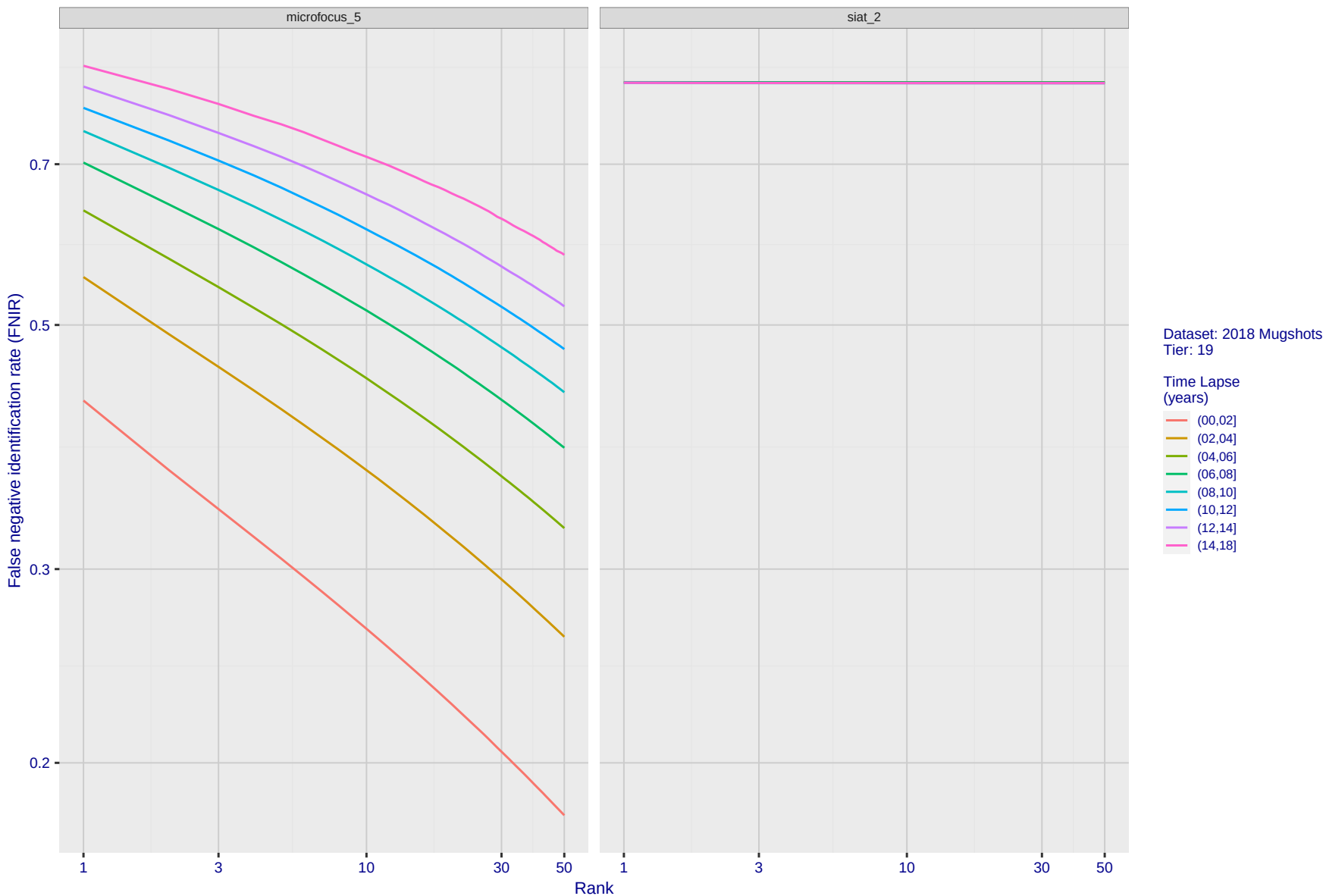


Figure 78: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsd. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.

2021/03/04 11:49:04	FNIR(N, R, T) = FPIR(N, T) =	False neg. identification rate False pos. identification rate	N = Num. enrolled subjects R = Num. candidates examined	T = Threshold	T = 0 → Investigation T > 0 → Identification
------------------------	---------------------------------	--	--	---------------	---

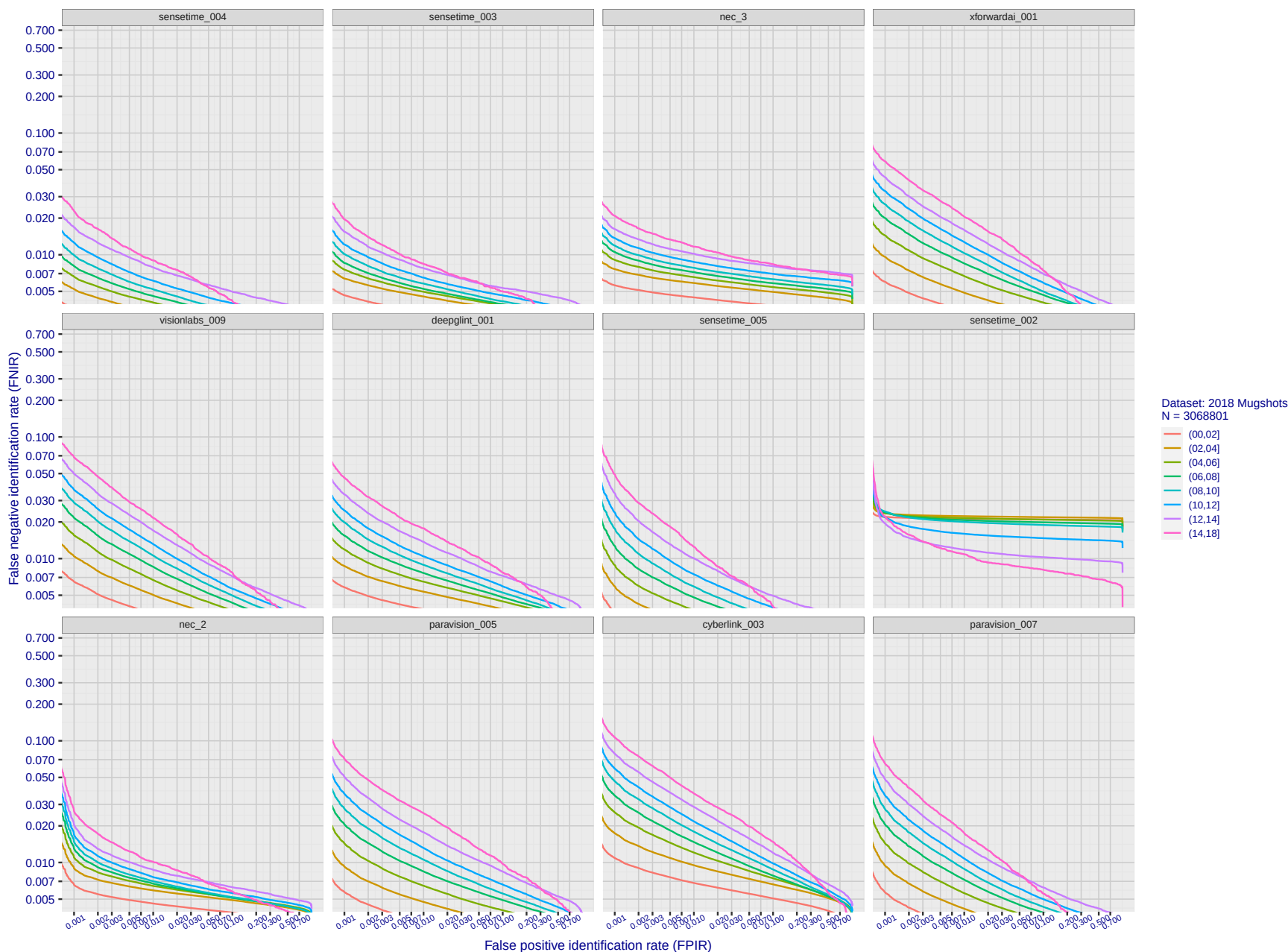


Figure 79: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsd. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with $N = 3\,000\,000$.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

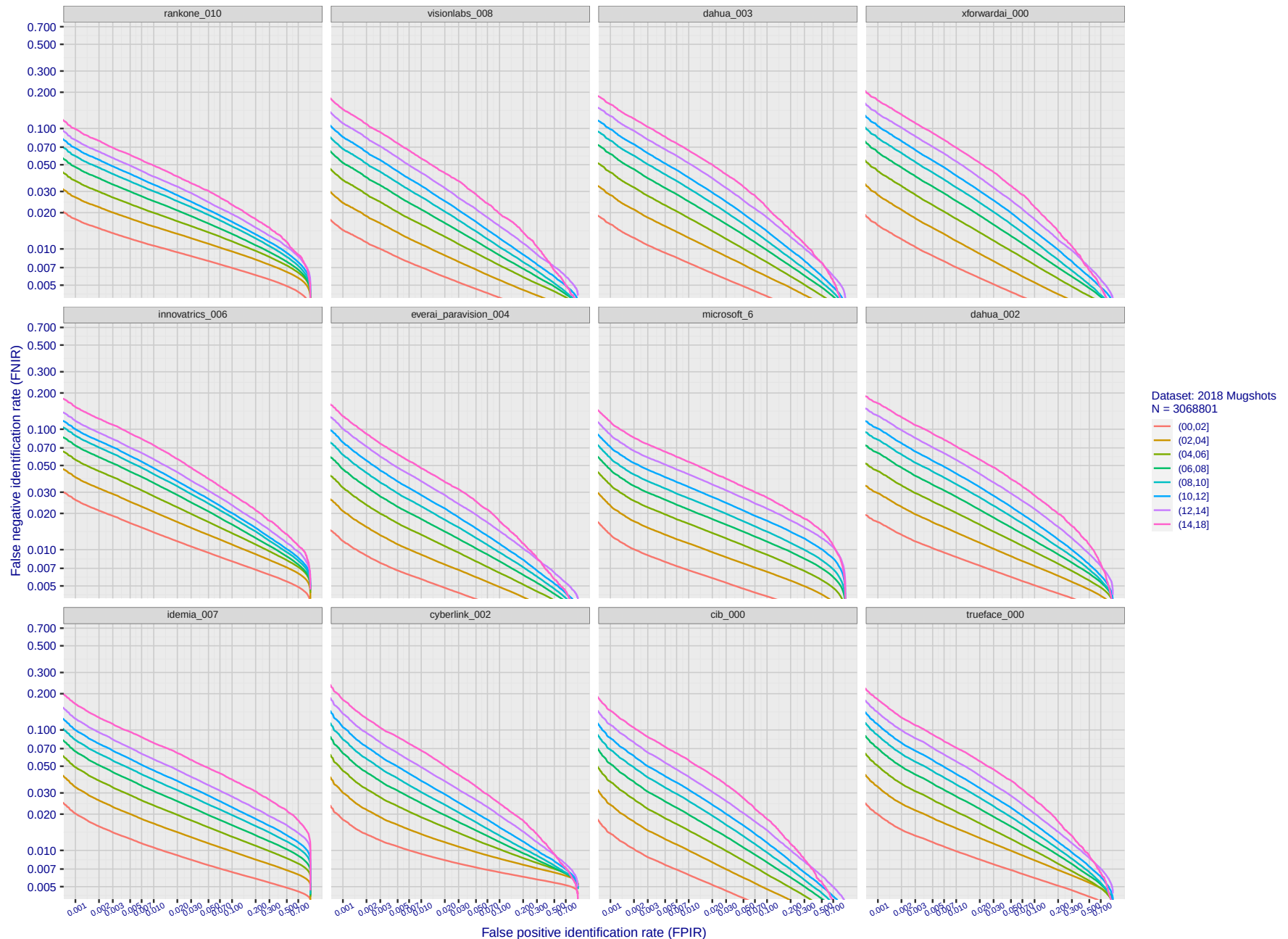
T = 0 → Investigation
T > 0 → Identification

Figure 80: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsd. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with $N = 3\,000\,000$.

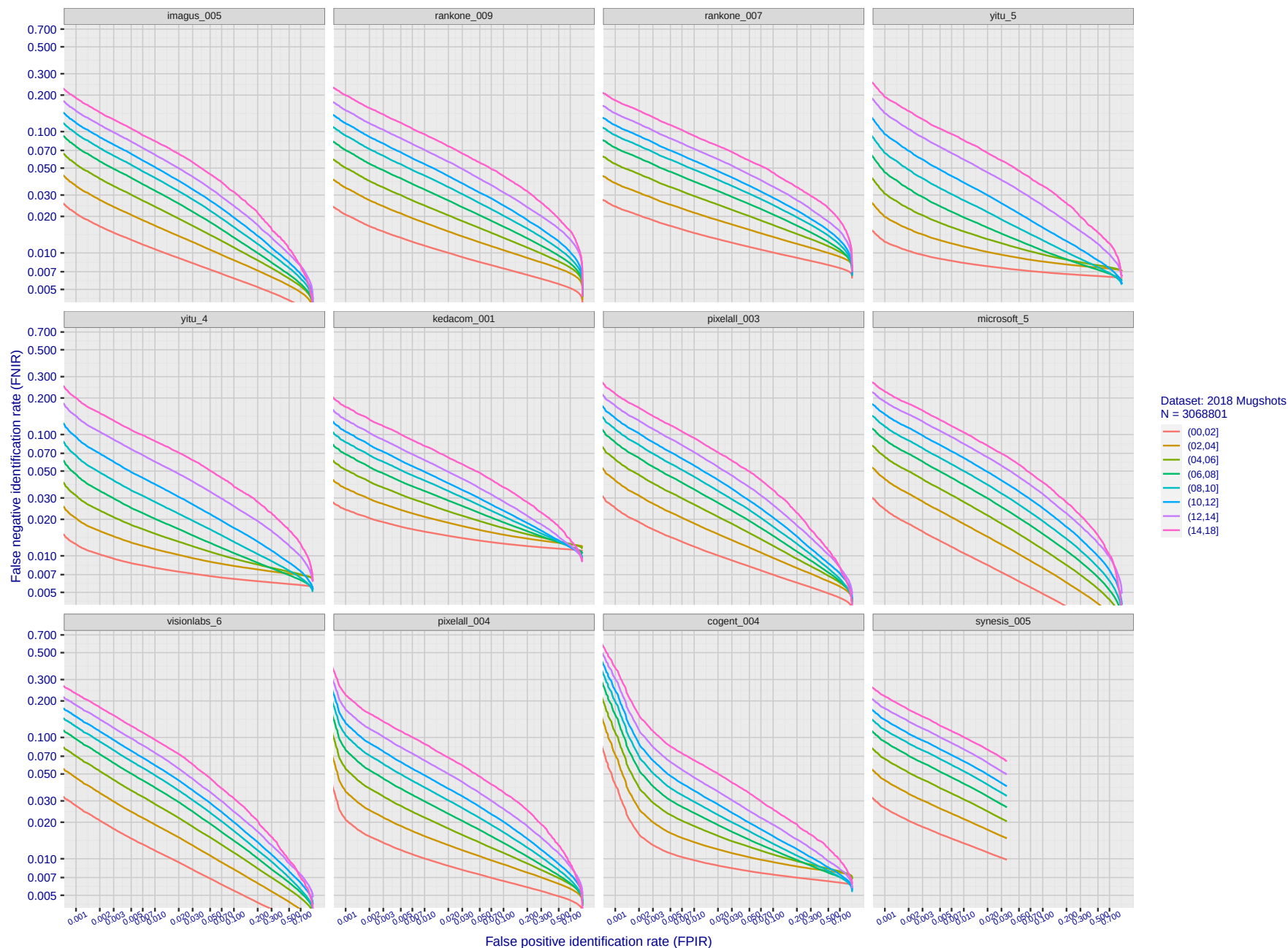


Figure 81: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with $N = 3\,000\,000$.

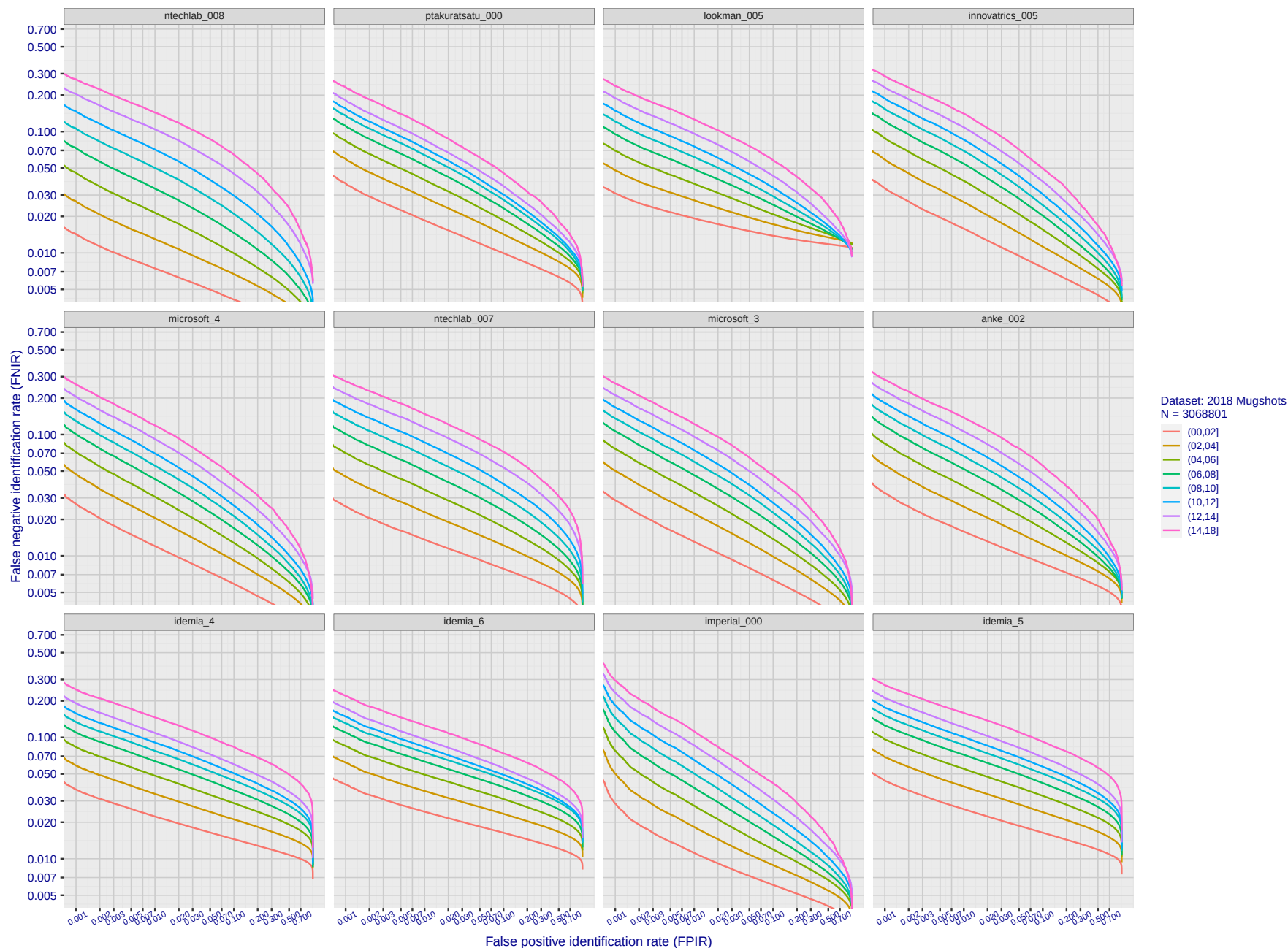


Figure 82: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with $N = 3\,000\,000$.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

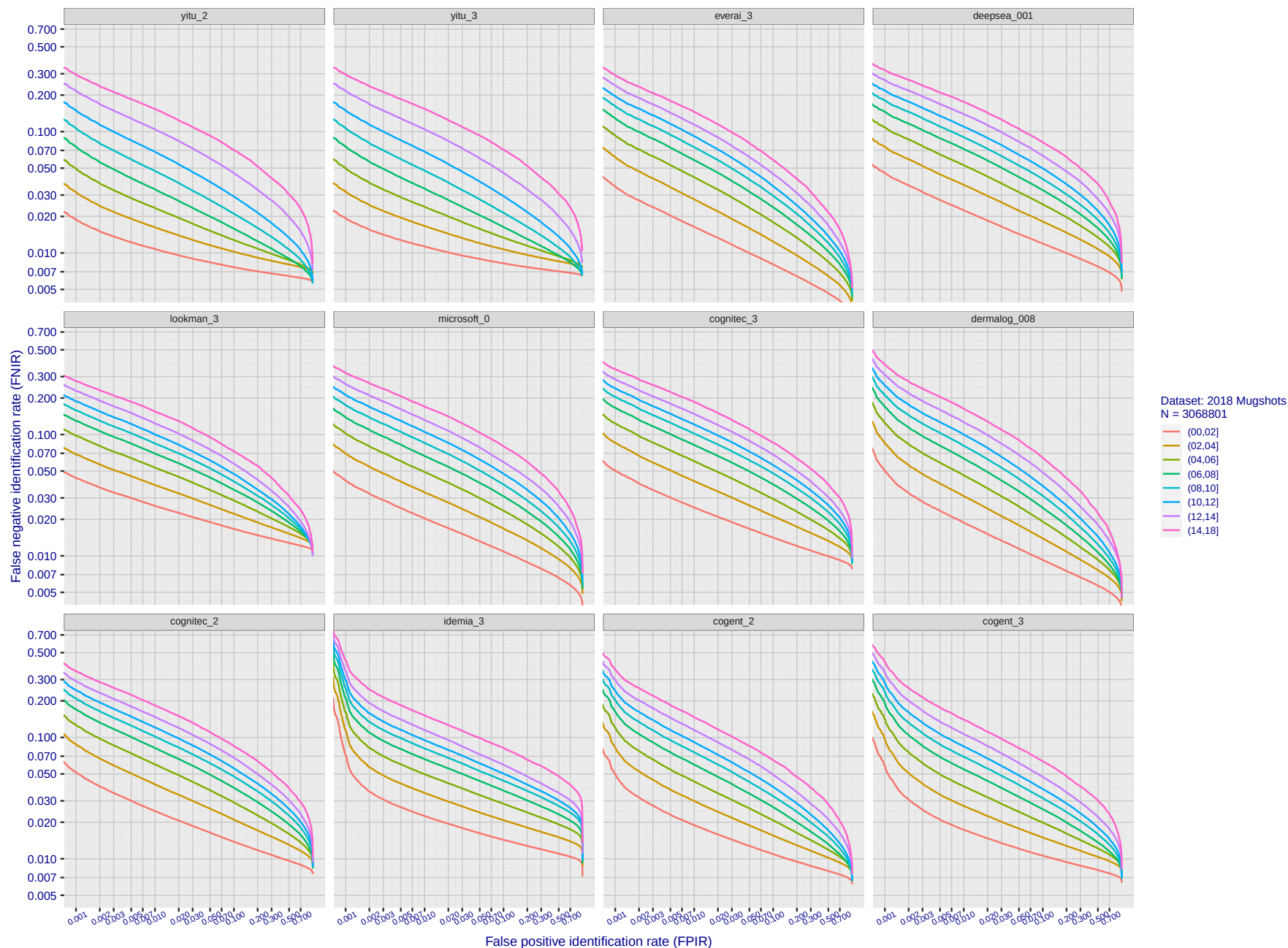


Figure 83: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with $N = 3\,000\,000$.

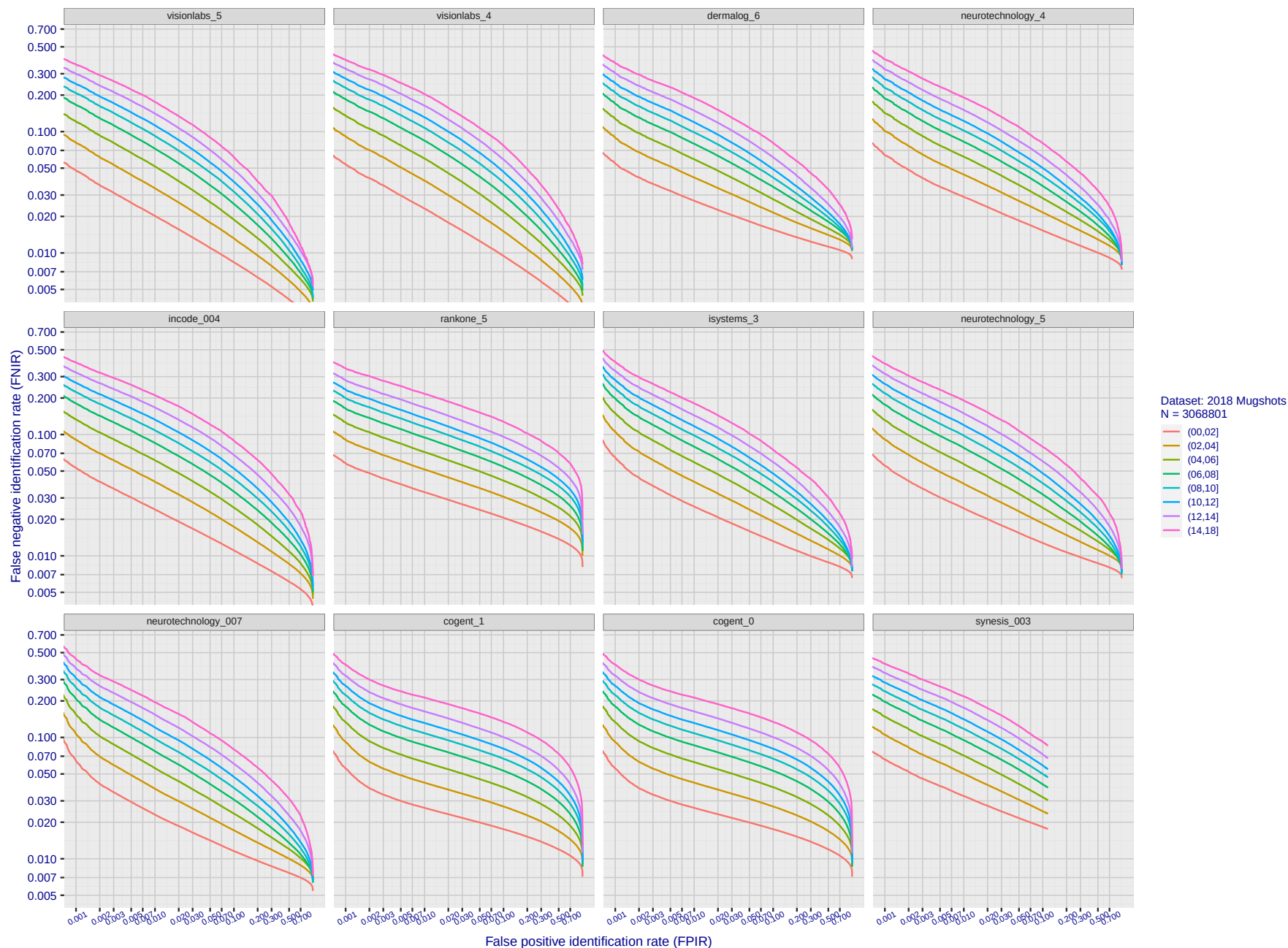


Figure 84: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsd. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with $N = 3\,000\,000$.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

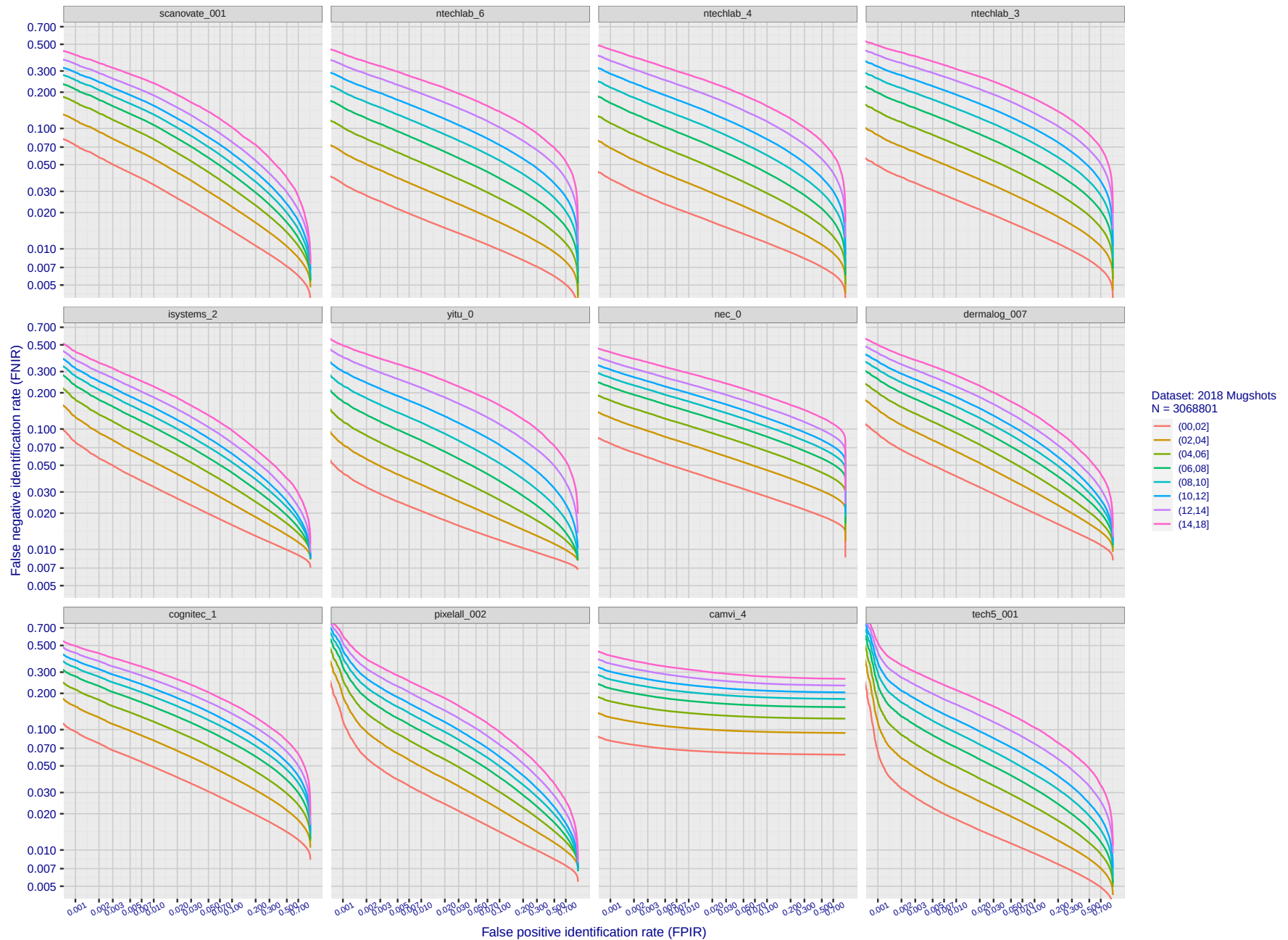
T = 0 → Investigation
T > 0 → Identification

Figure 85: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with $N = 3\,000\,000$.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

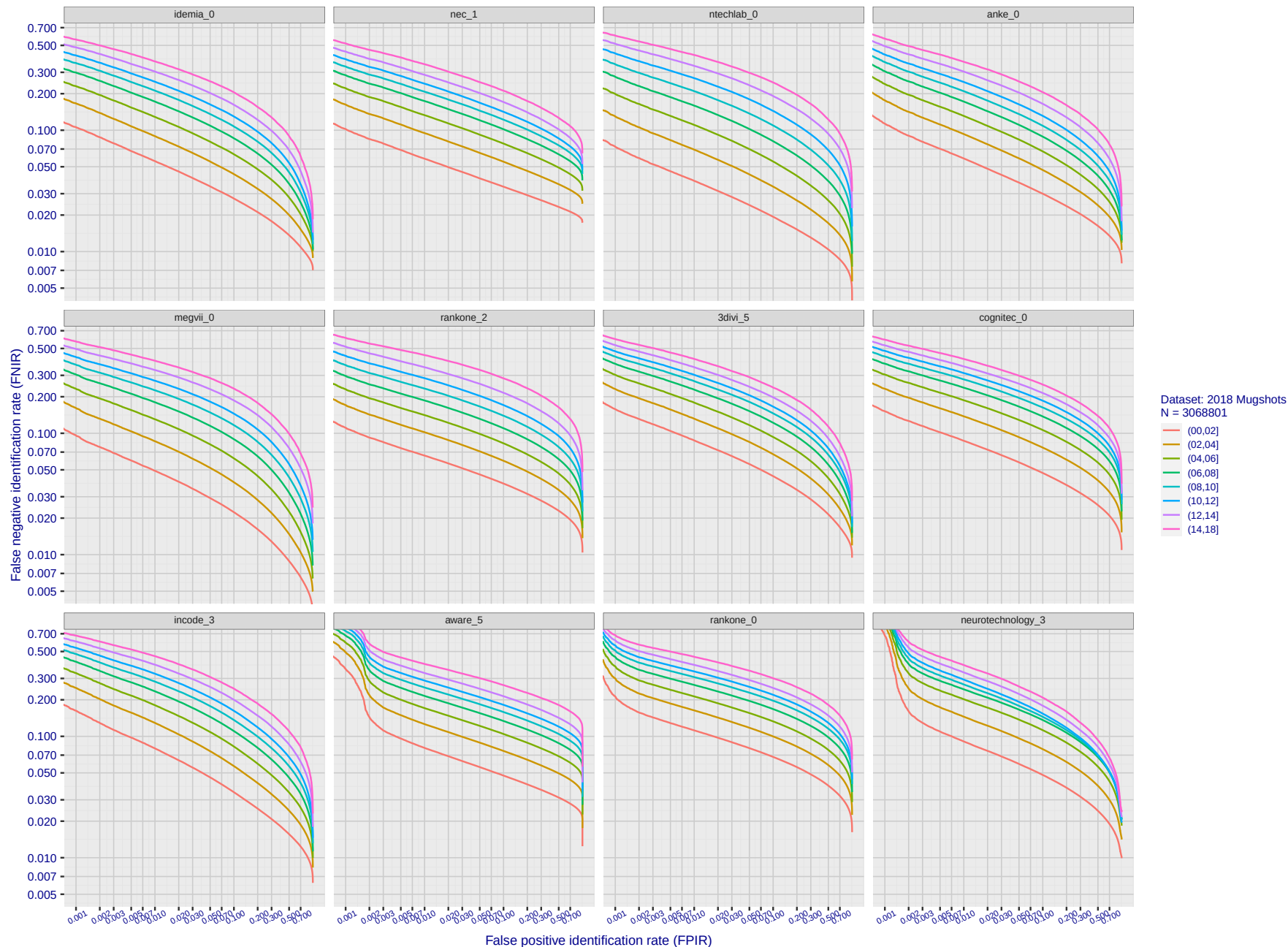
T = 0 → Investigation
T > 0 → Identification

Figure 86: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsd. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with $N = 3\,000\,000$.

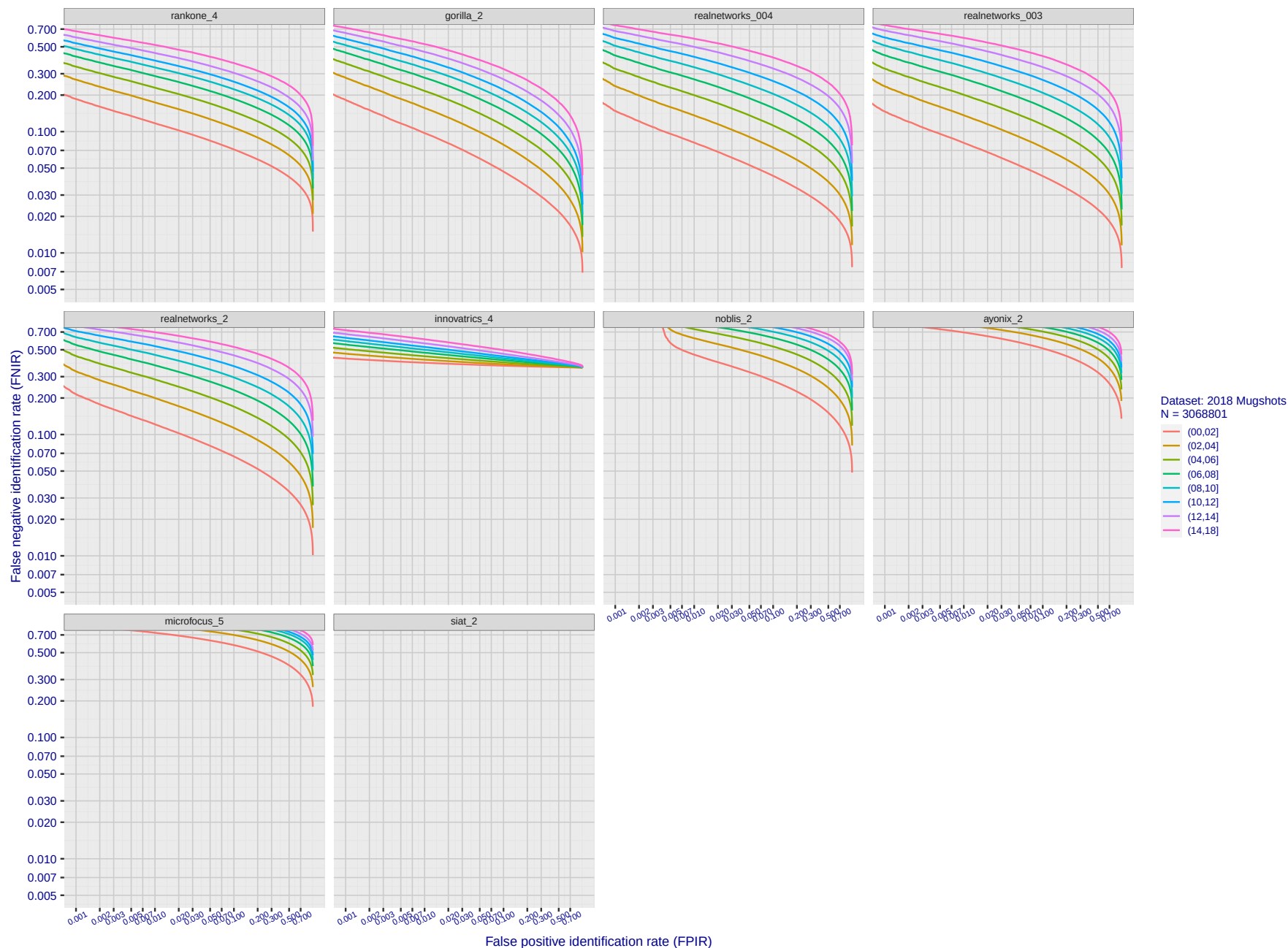


Figure 87: [FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with $N = 3\,000\,000$.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

2021/03/04 11:49:04	FNIR(N, R, T) = FPIR(N, T) =	False neg. identification rate False pos. identification rate	N = Num. enrolled subjects R = Num. candidates examined	T = Threshold	T = 0 → Investigation T > 0 → Identification
------------------------	---------------------------------	--	--	---------------	---

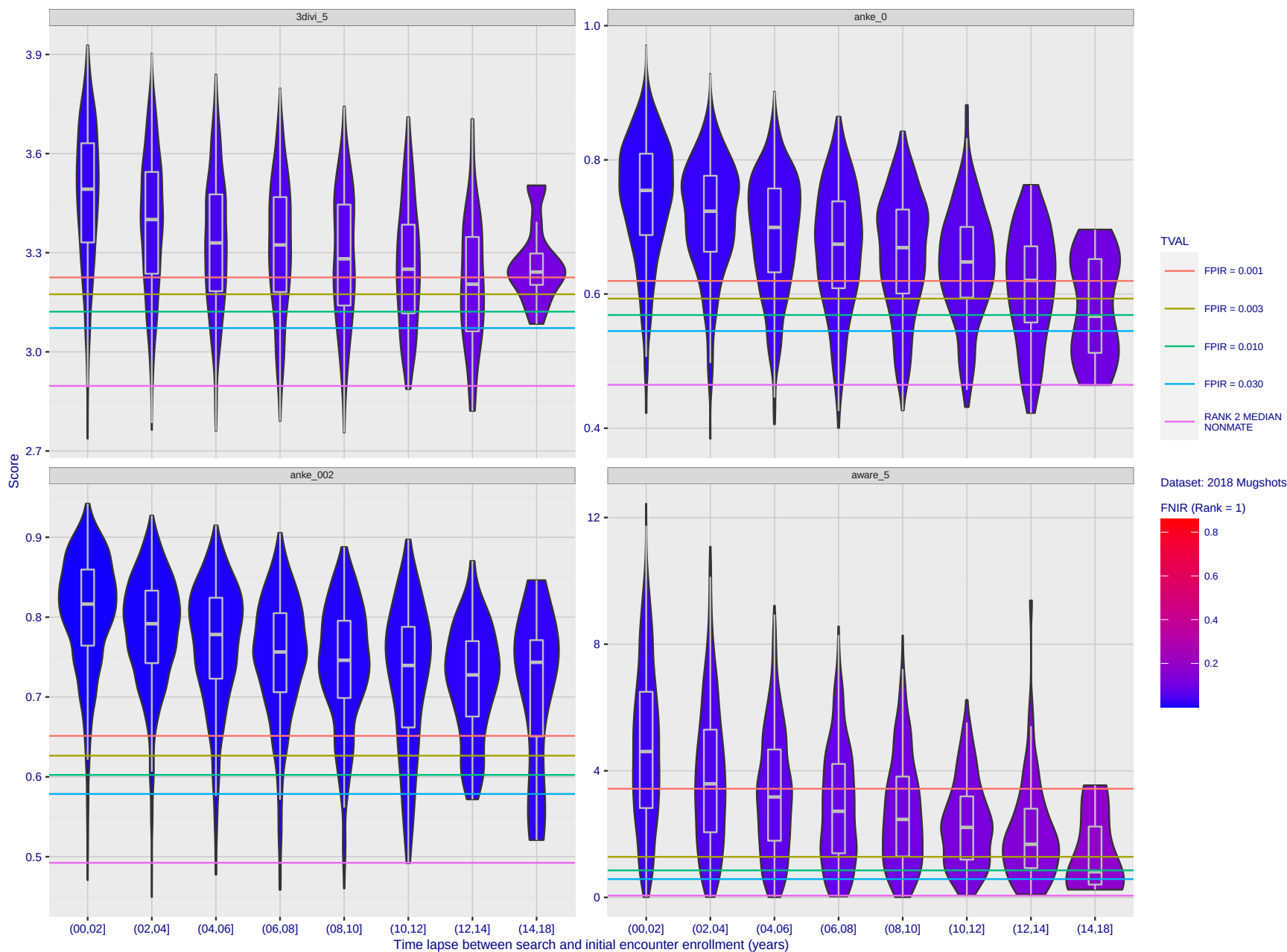


Figure 88: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

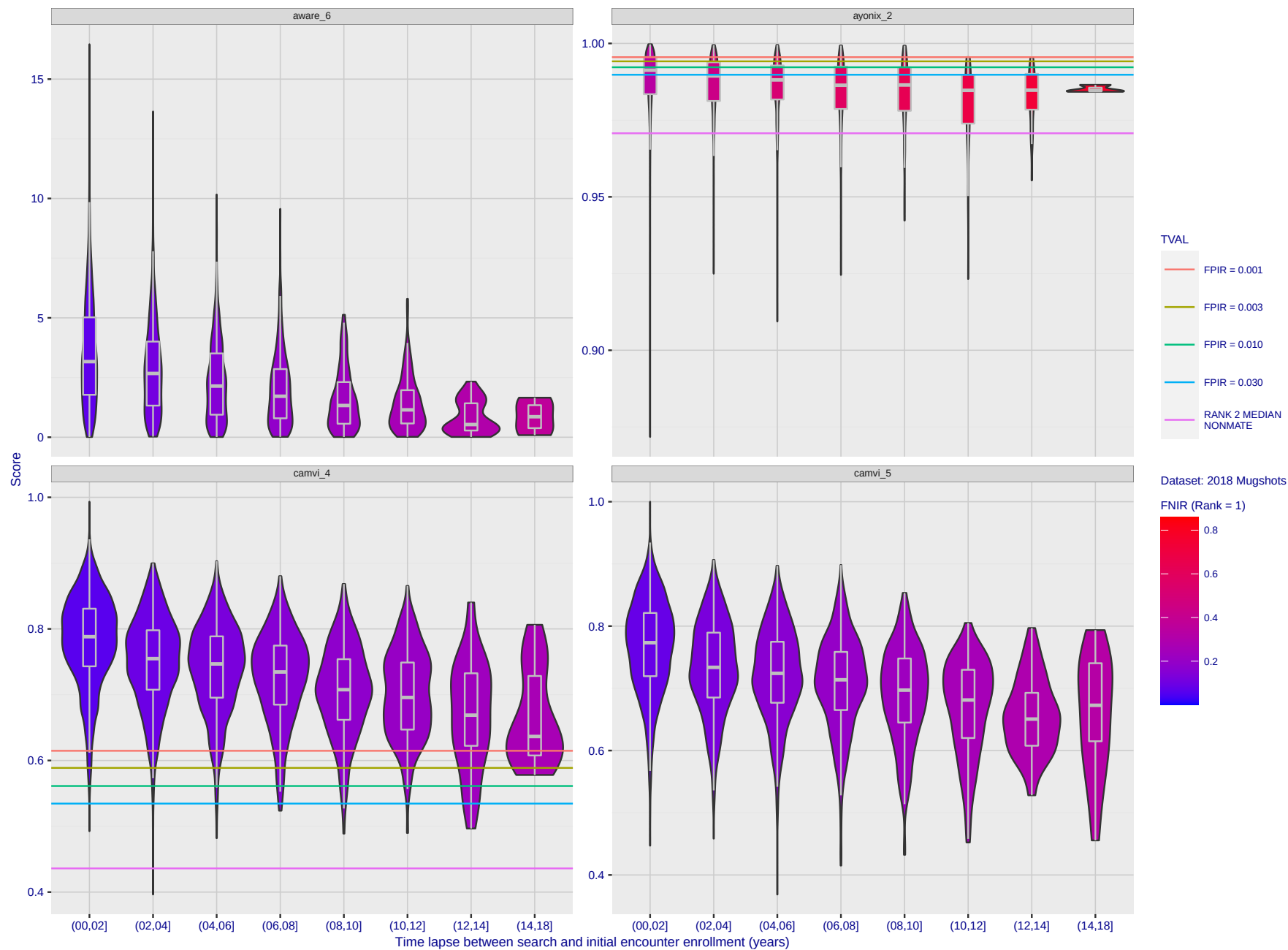


Figure 89: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

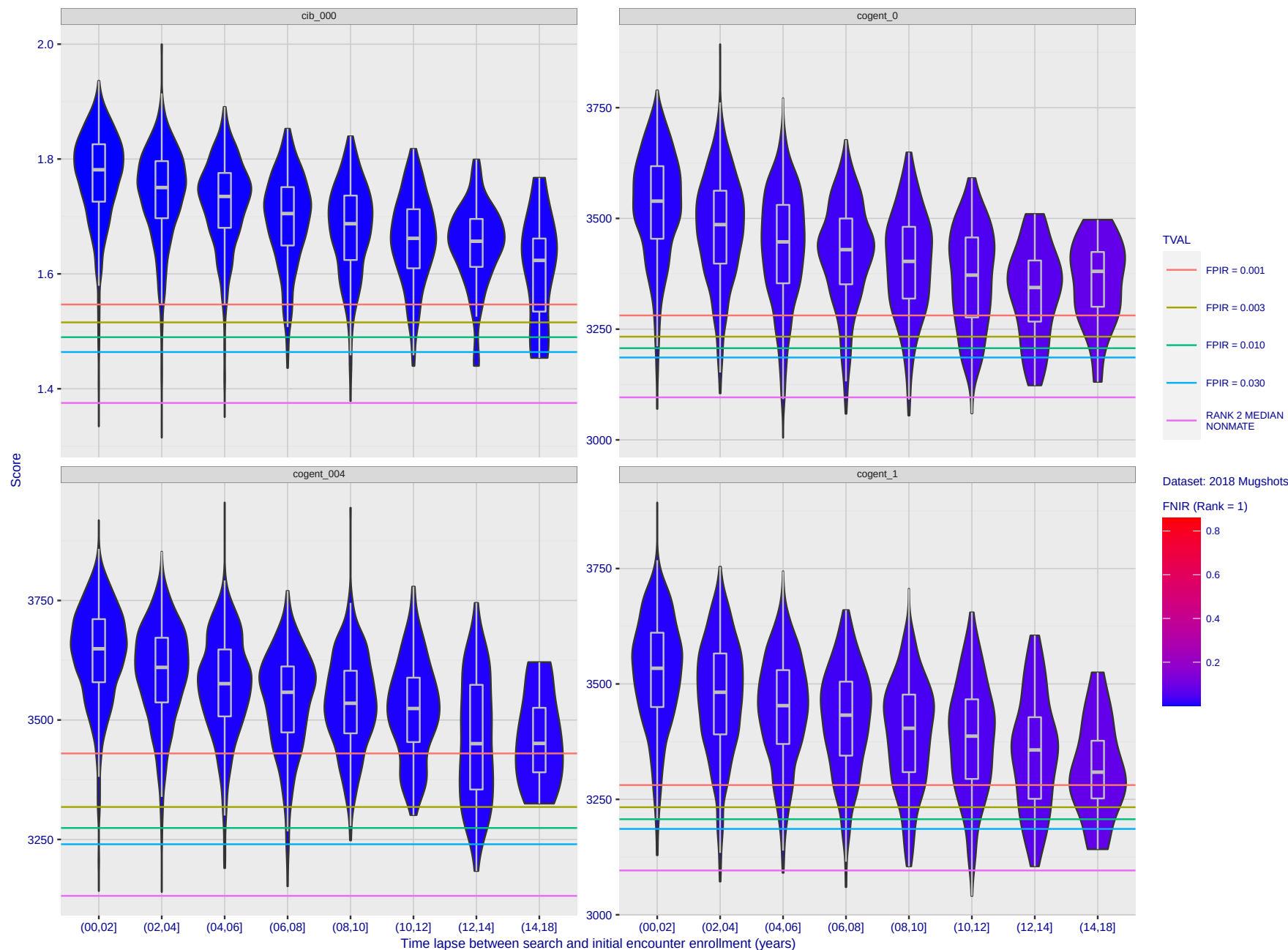


Figure 90: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04
FNIR(N, R, T) =
FPIR(N, T) =
False neg. identification rate
False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

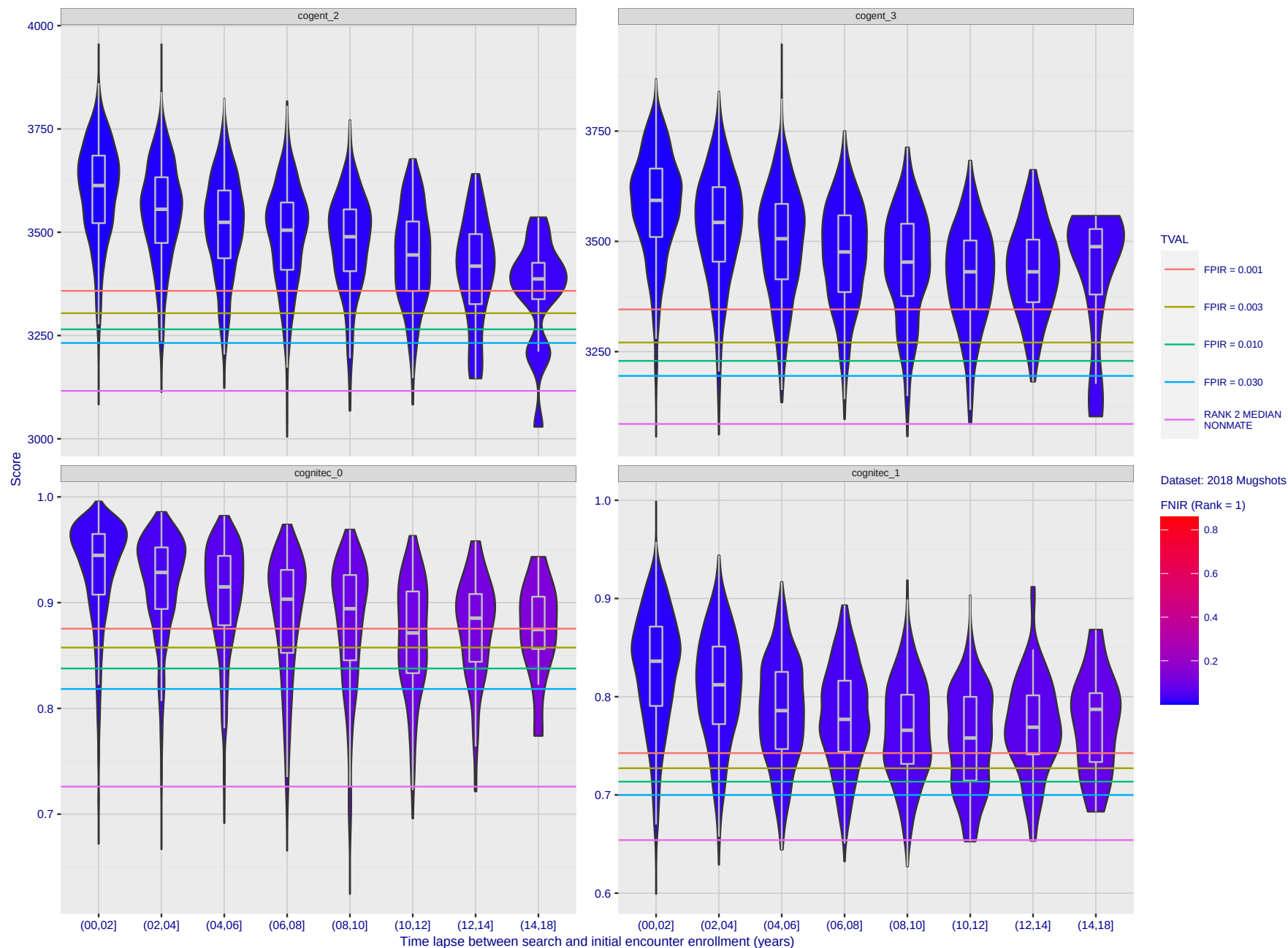


Figure 91: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

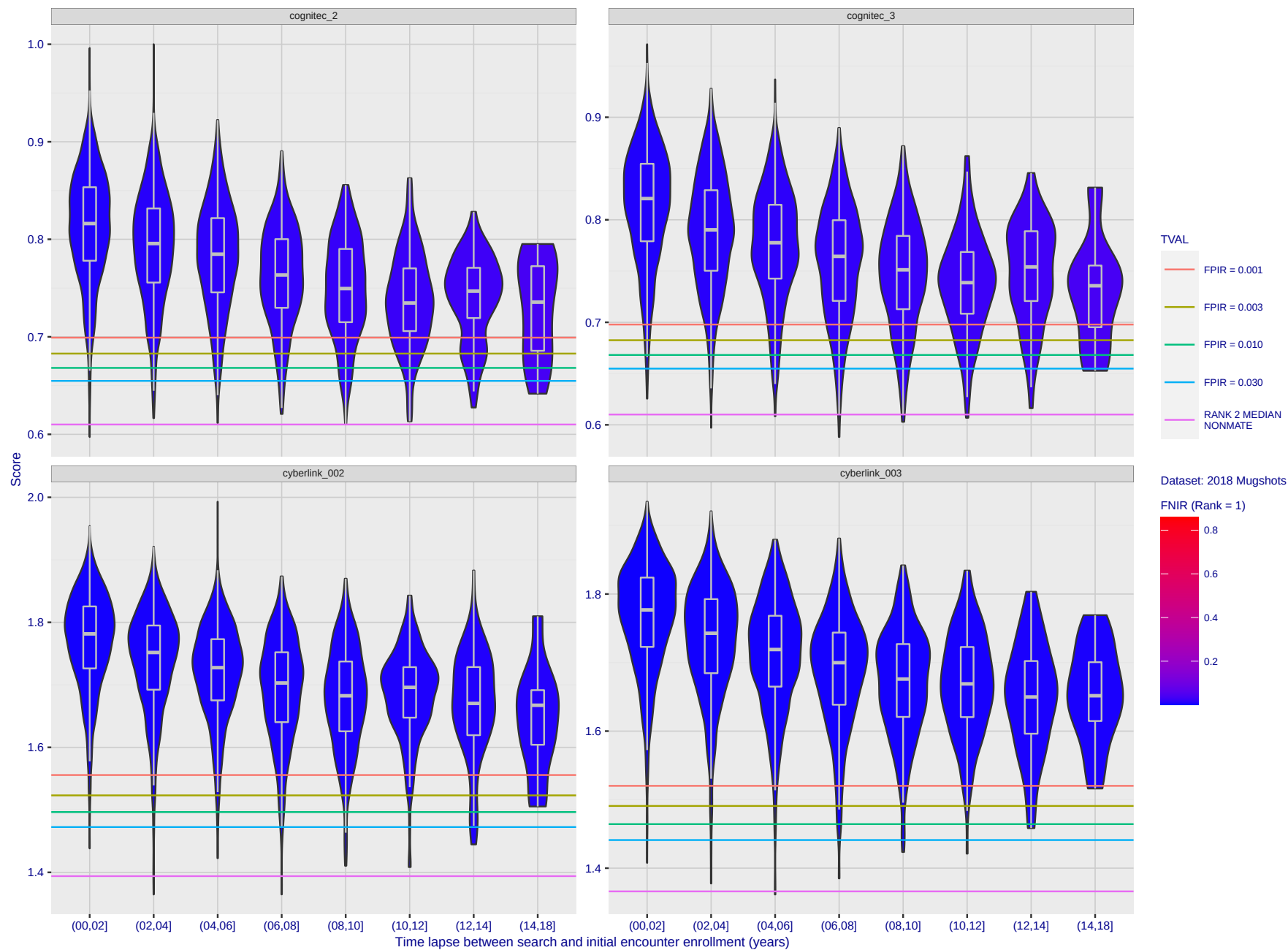


Figure 92: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

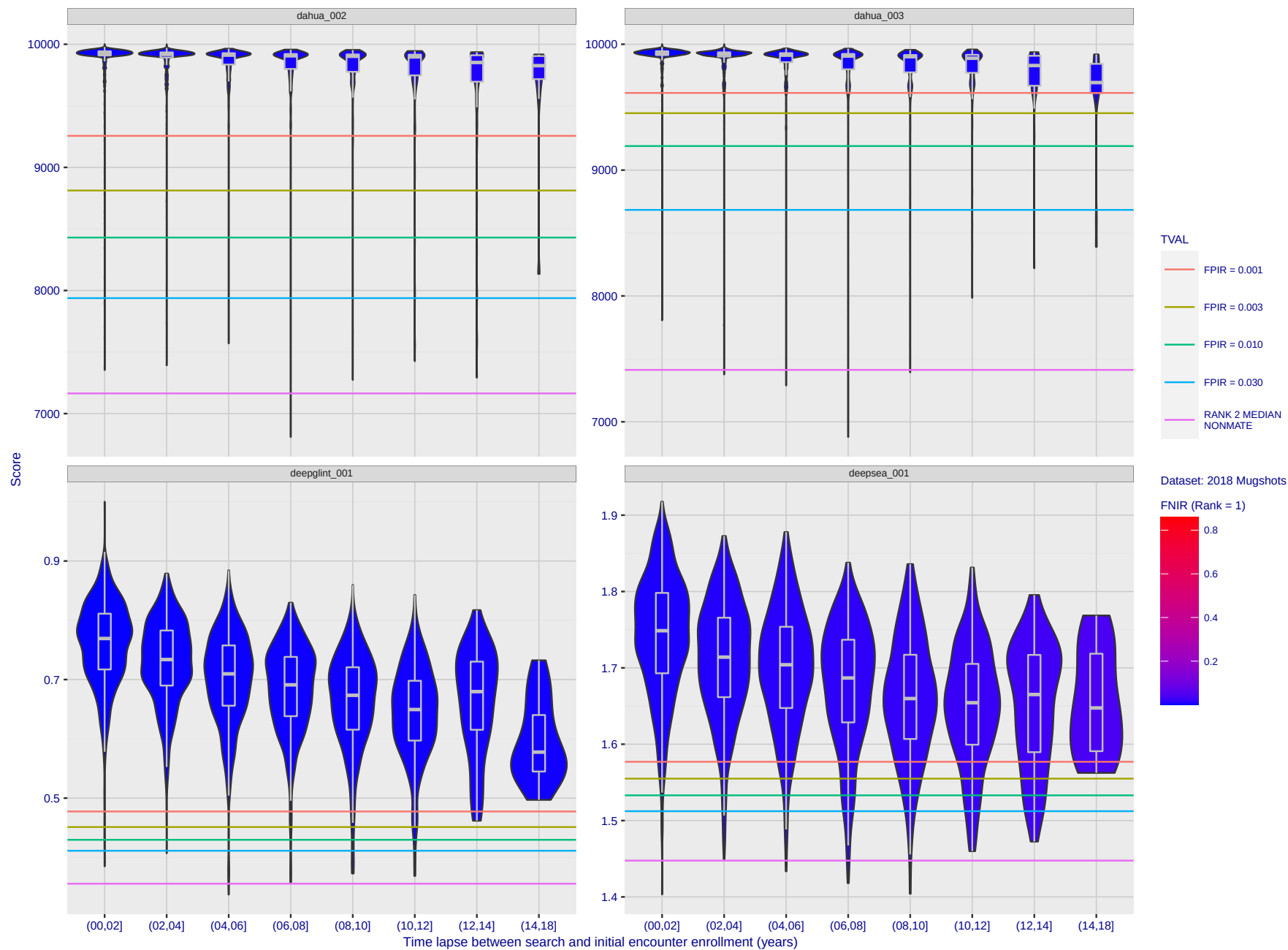


Figure 93: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

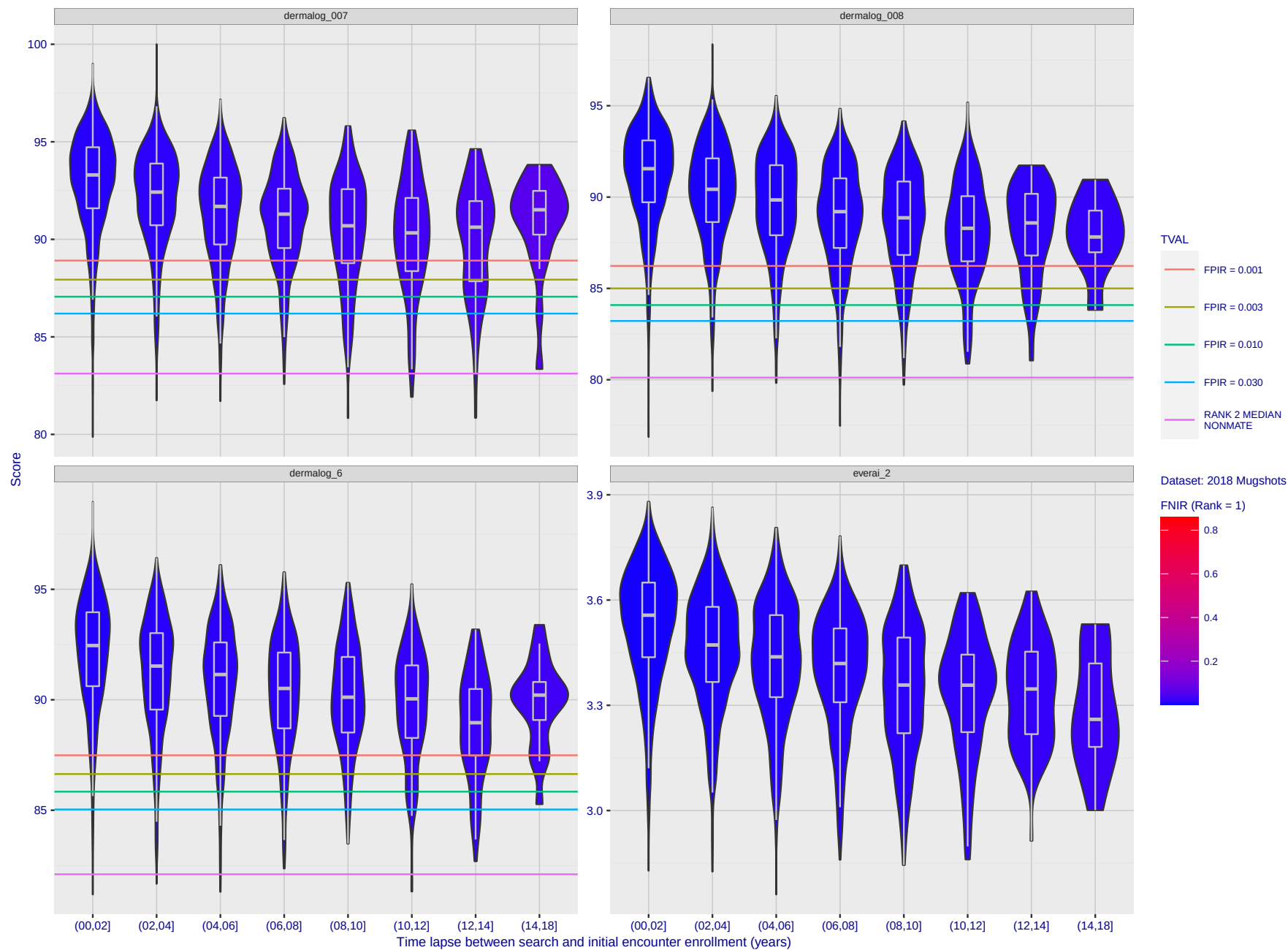


Figure 94: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

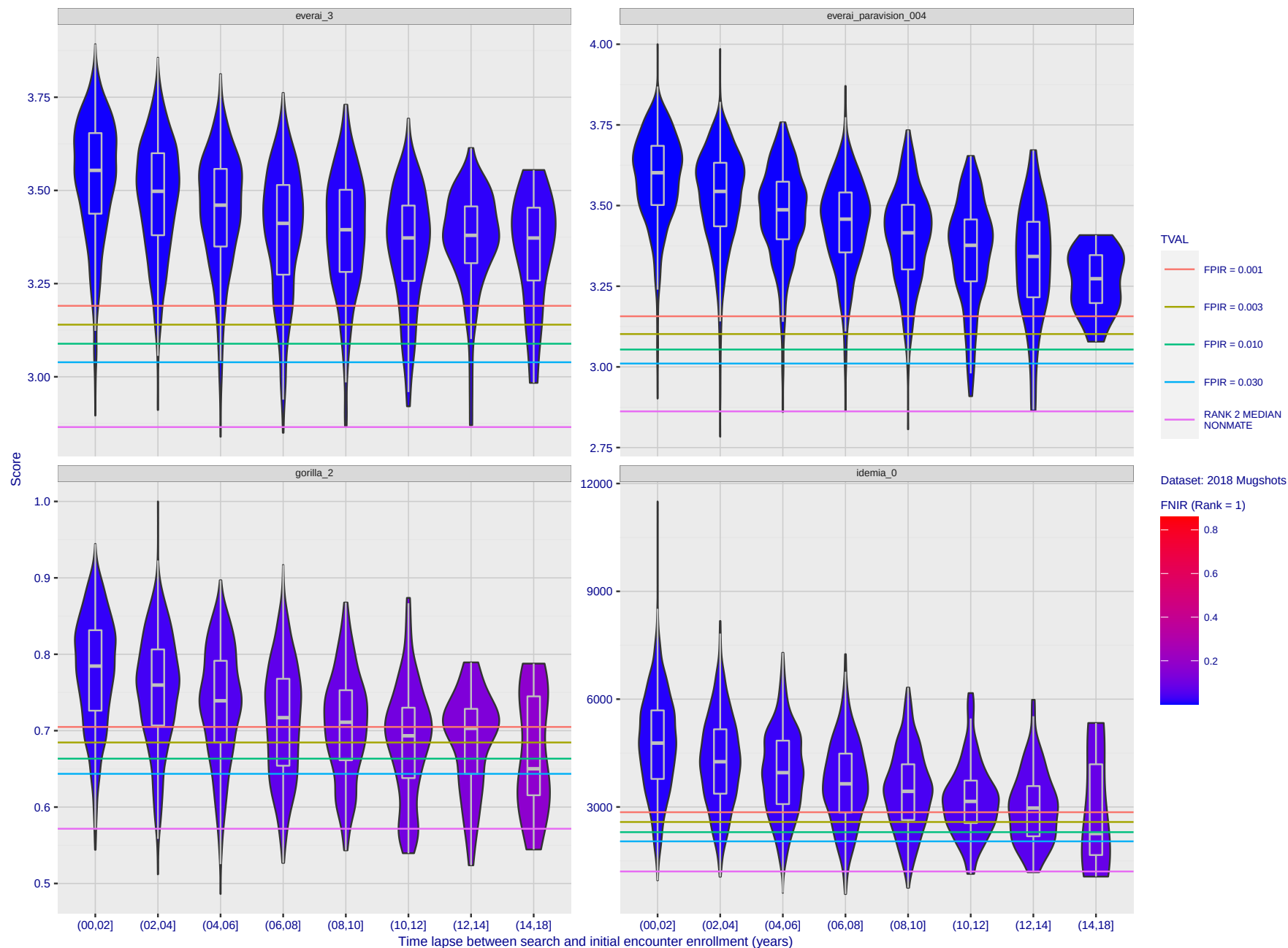


Figure 95: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

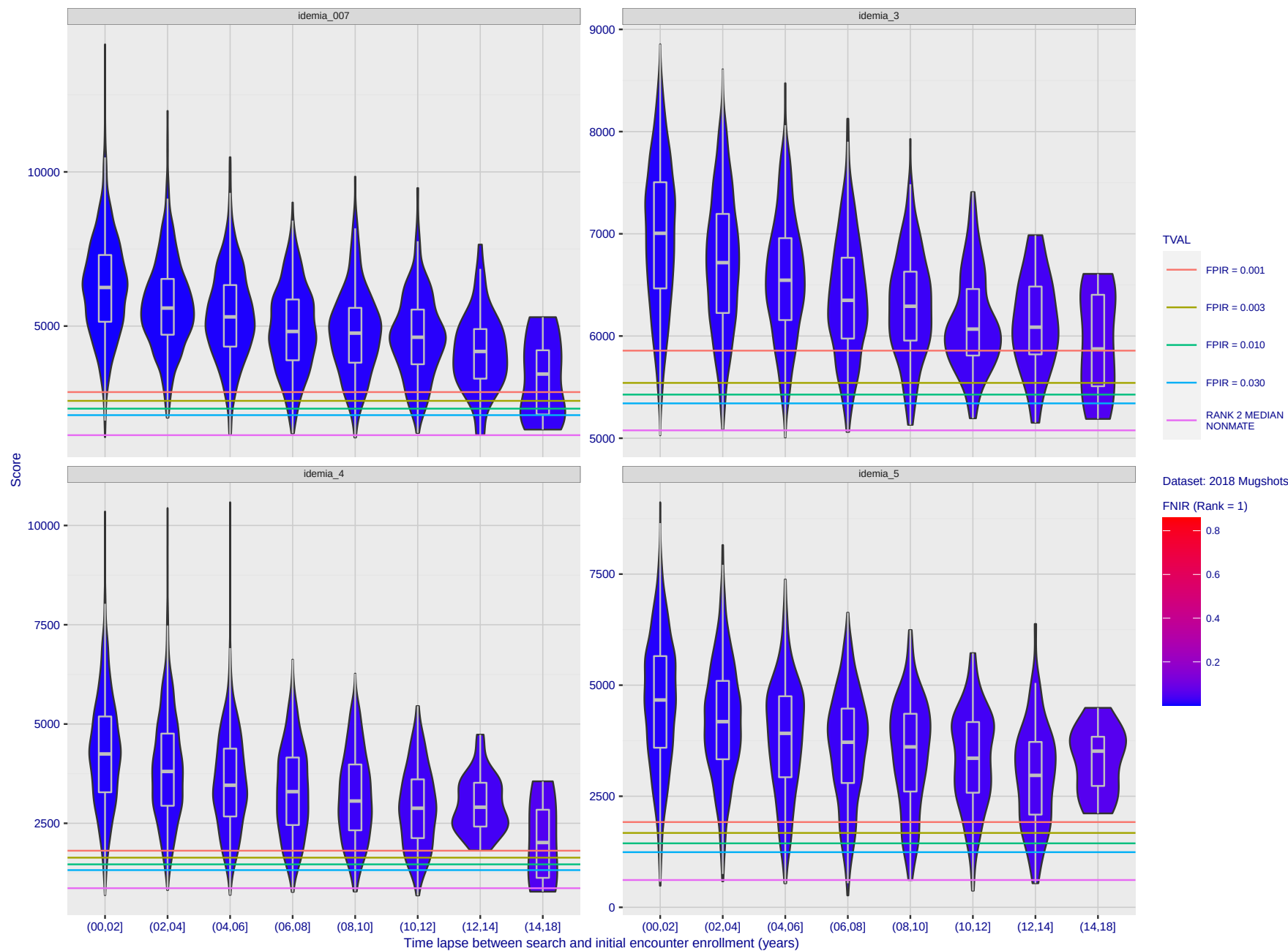


Figure 96: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

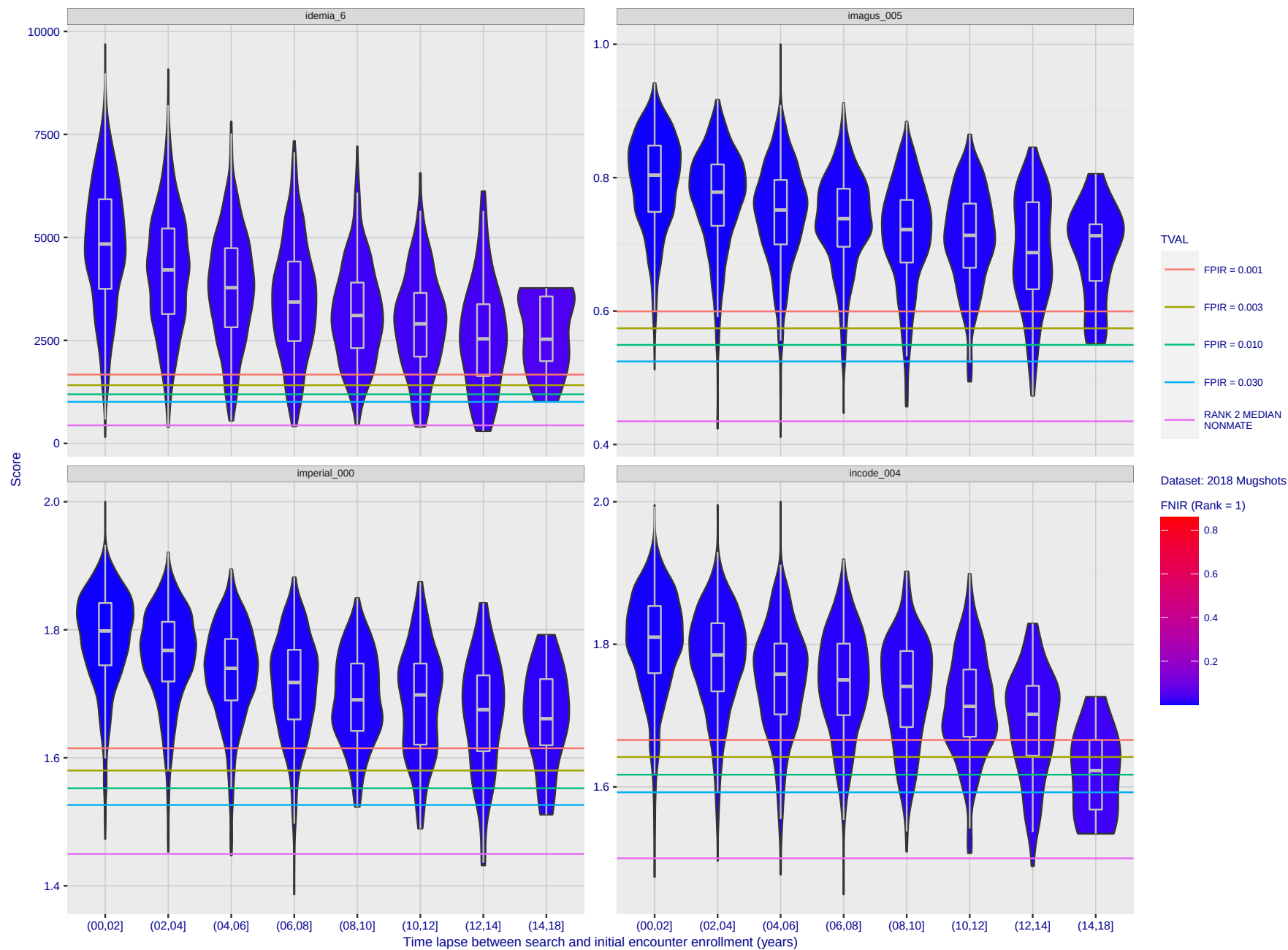


Figure 97: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04
FNIR(N, R, T) =
FPIR(N, T) =
False neg. identification rate
False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

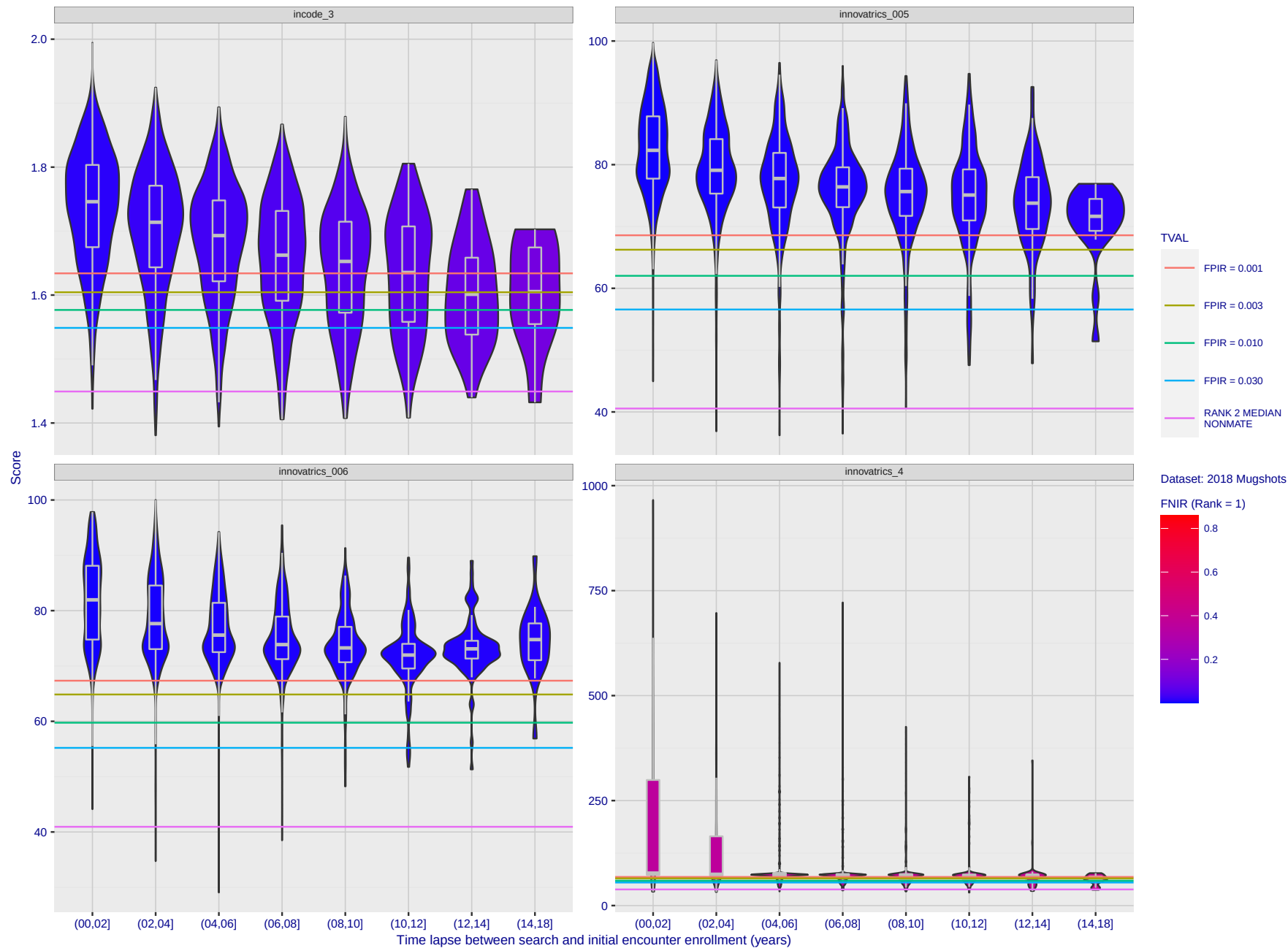


Figure 98: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

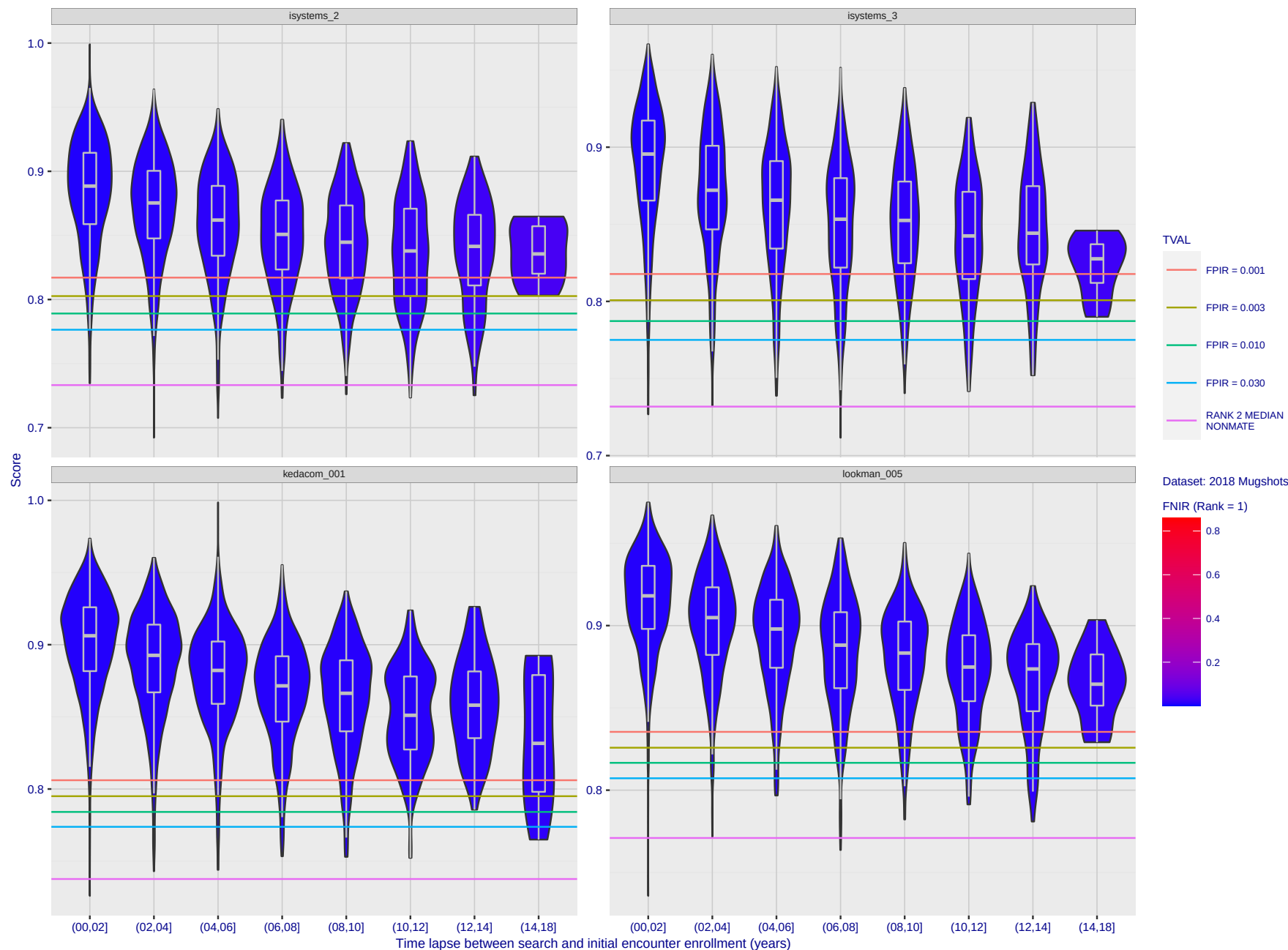


Figure 99: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

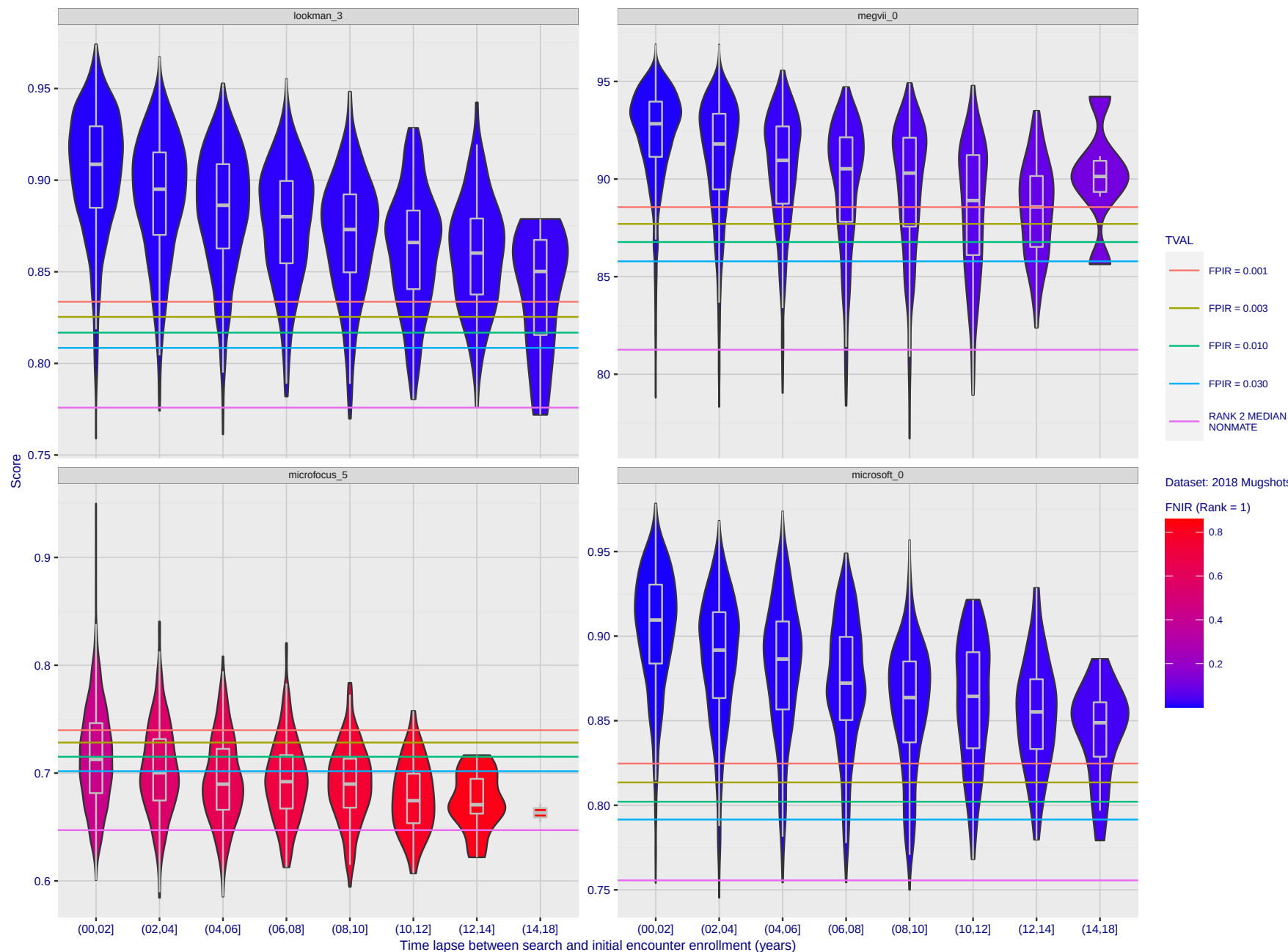


Figure 100: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04 11:49:04 FNIR(N, R, T) = False neg. identification rate N = Num. enrolled subjects T = Threshold T = 0 → Investigation
FPIR(N, T) = False pos. identification rate R = Num. candidates examined R > 0 → Identification

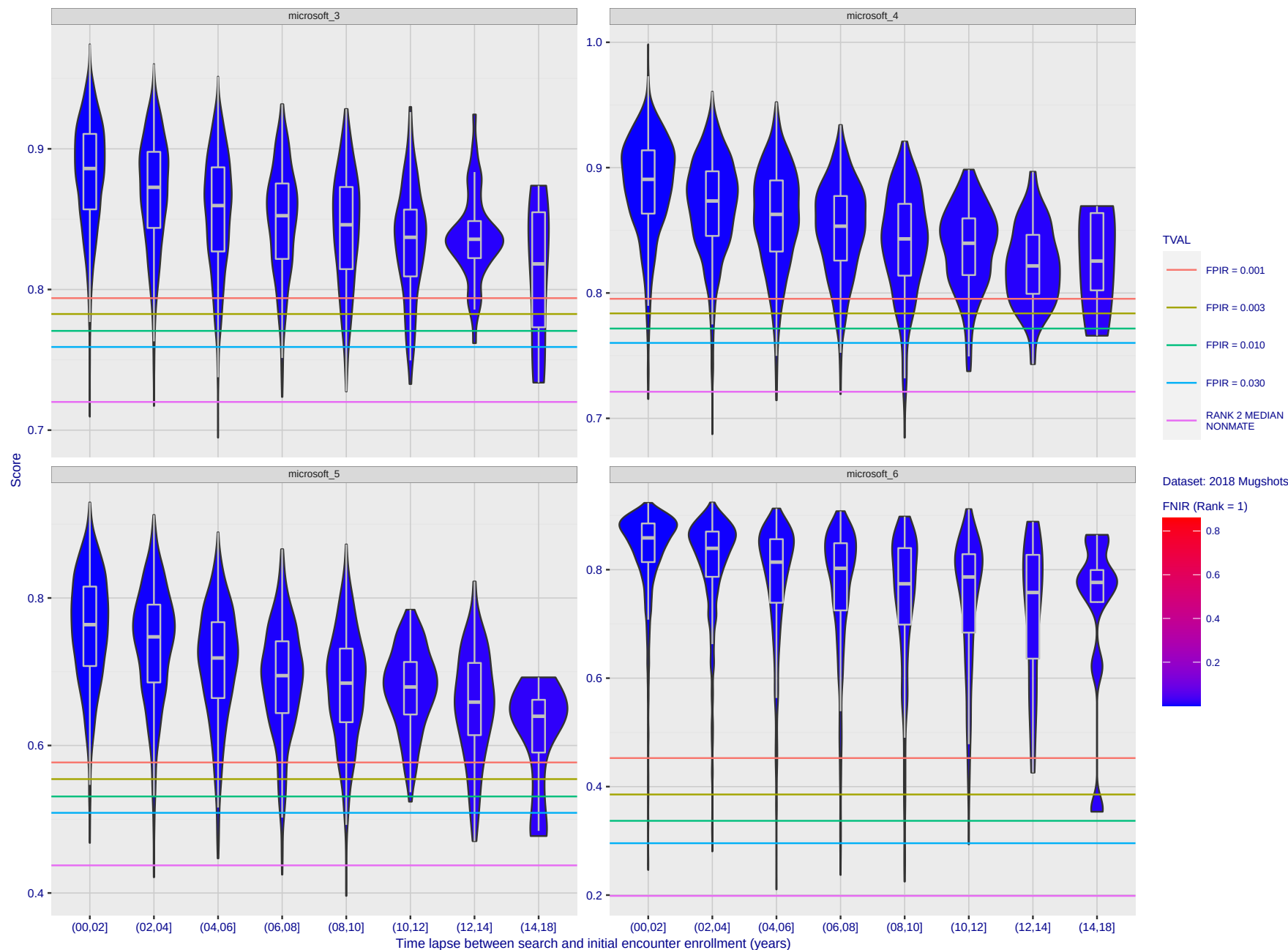


Figure 101: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed.** The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04

FNIR(N, R, T) =
FPIR(N, T) =

False neg. identification rate
False pos. identification rate

N = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

2021/03/04 11:49:04
 FNIR(N, R, T) = False neg. identification rate
 FPIR(N, T) = False pos. identification rate
 N = Num. enrolled subjects
 R = Num. candidates examined
 T = Threshold
 T = 0 → Investigation
 T > 0 → Identification

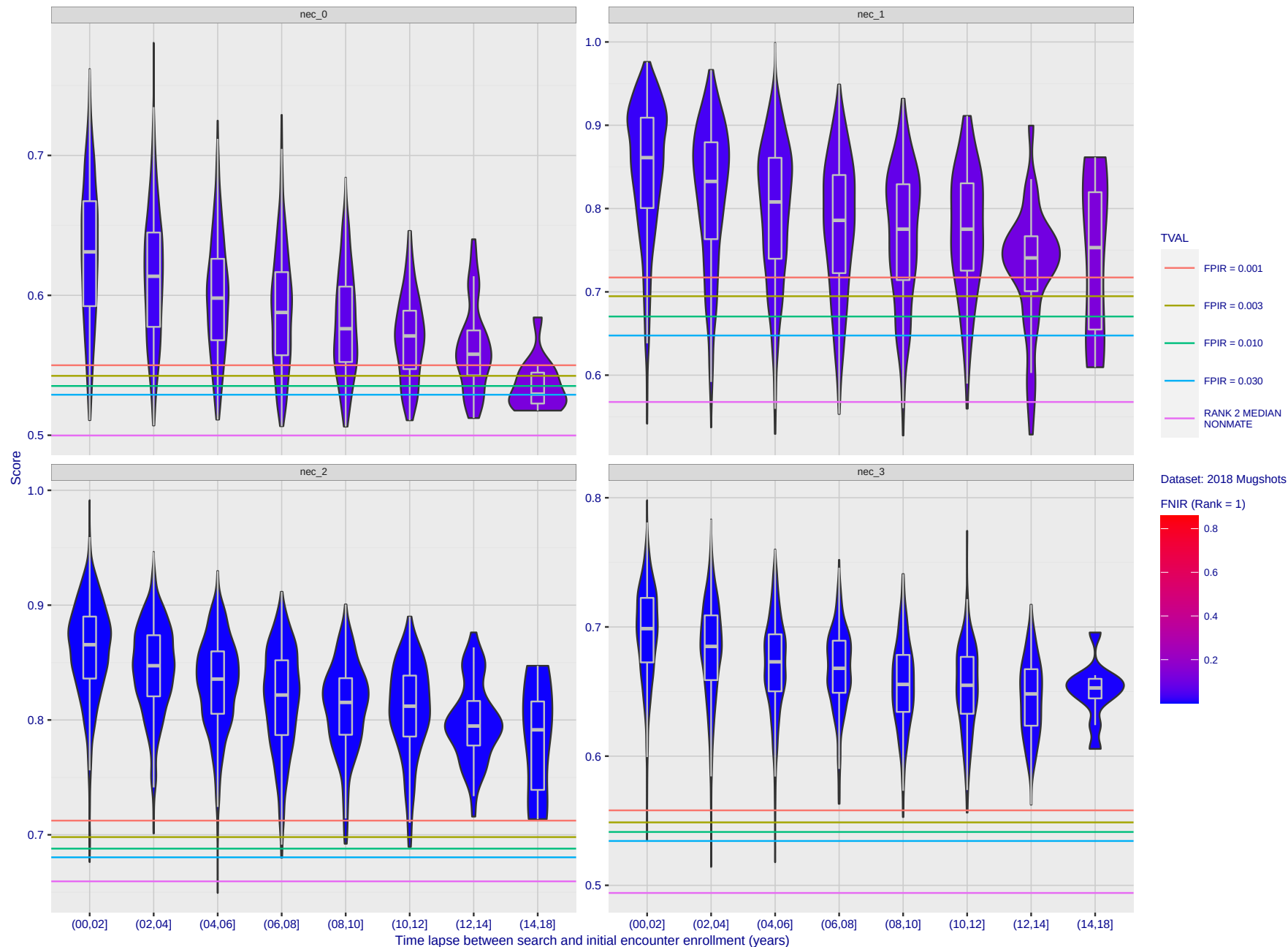


Figure 102: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

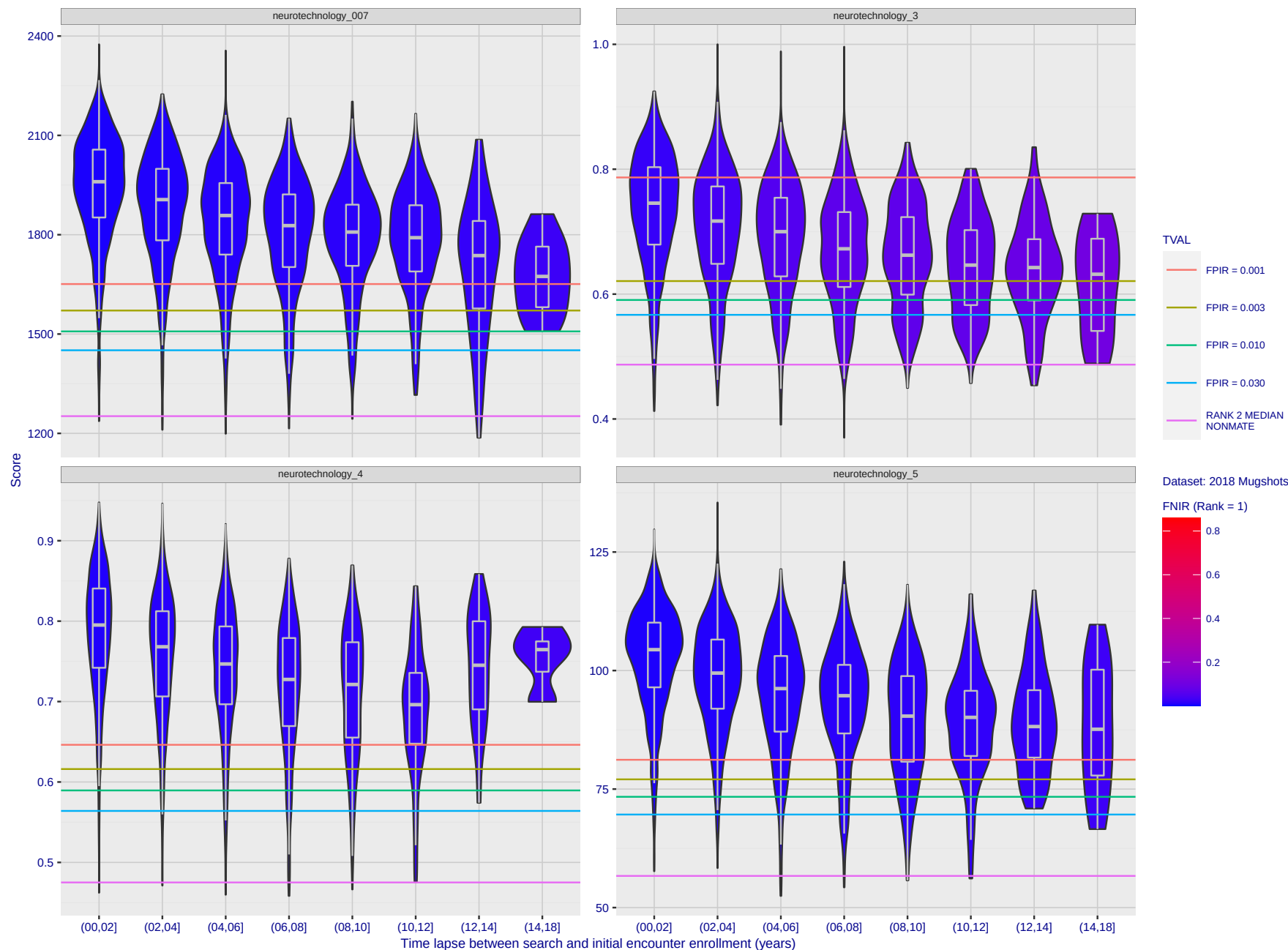


Figure 103: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04 11:49:04 FNIR(N, R, T) = False neg. identification rate N = Num. enrolled subjects T = Threshold T = 0 → Investigation
FPIR(N, T) = False pos. identification rate R = Num. candidates examined T > 0 → Identification

2021/03/04 11:49:04
FNIR(N, R, T) = False neg. identification rate
FPIR(N, T) = False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

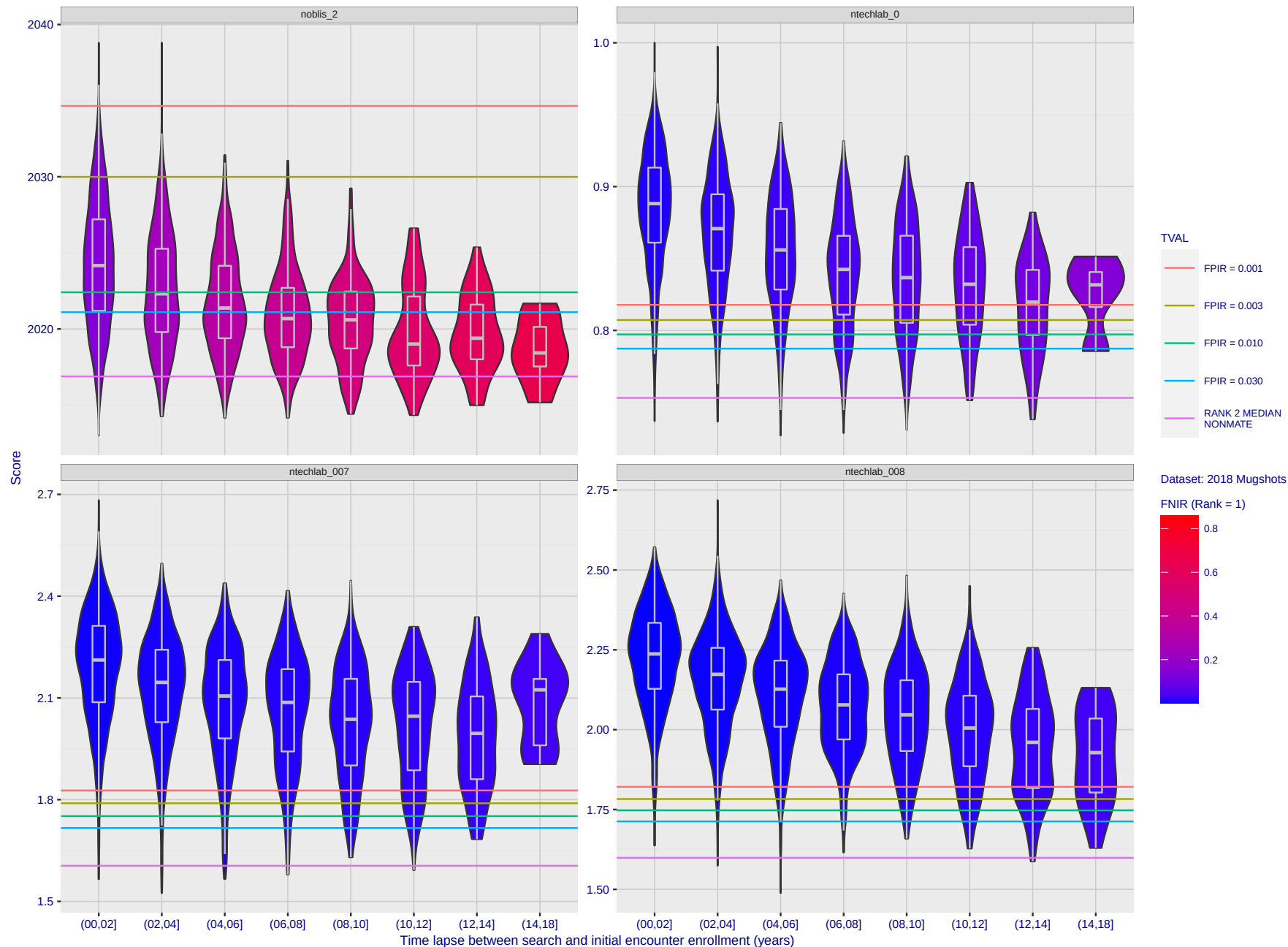


Figure 104: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04
FNIR(N, R, T) =
FPIR(N, T) =
False neg. identification rate
False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

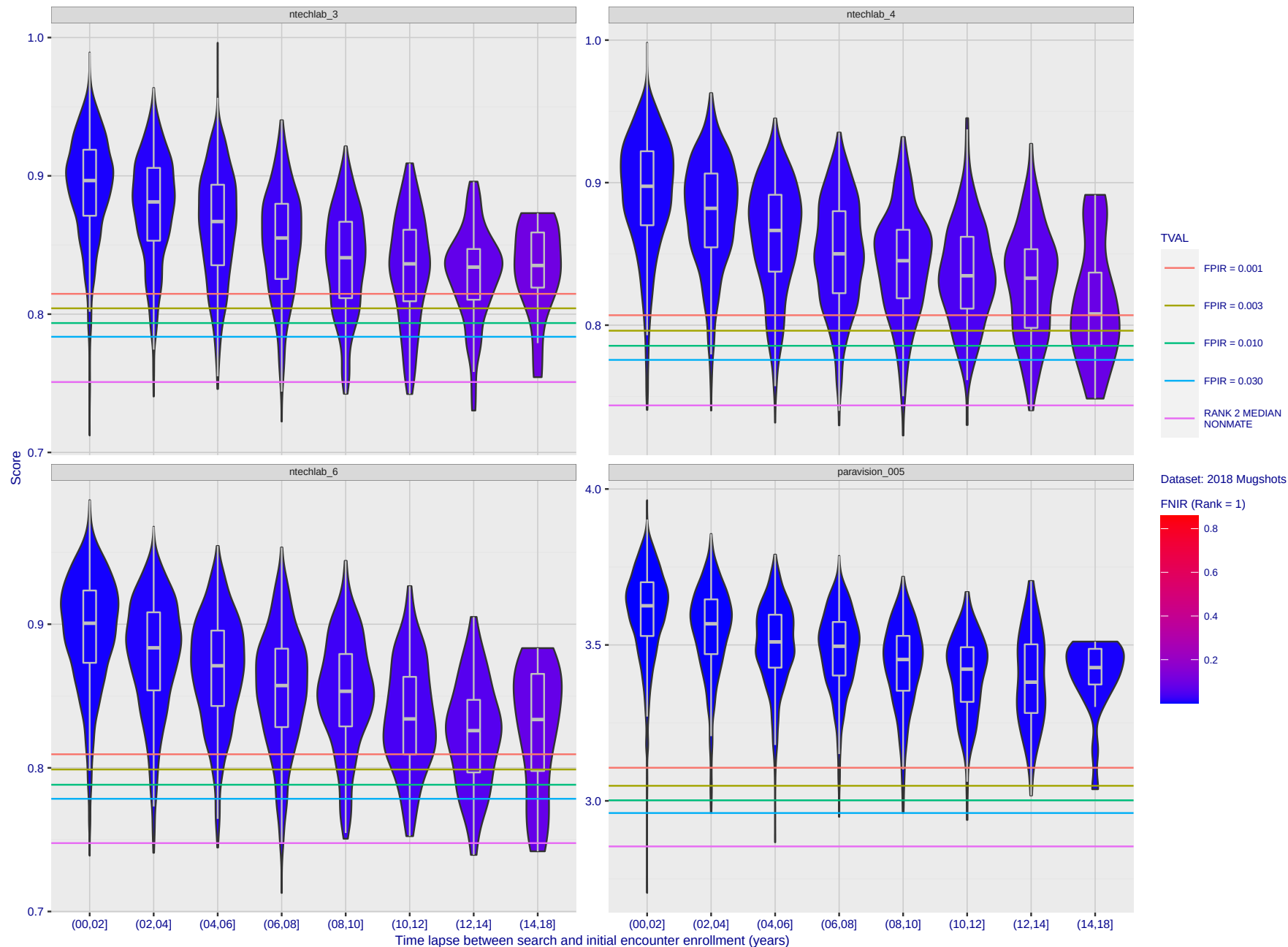
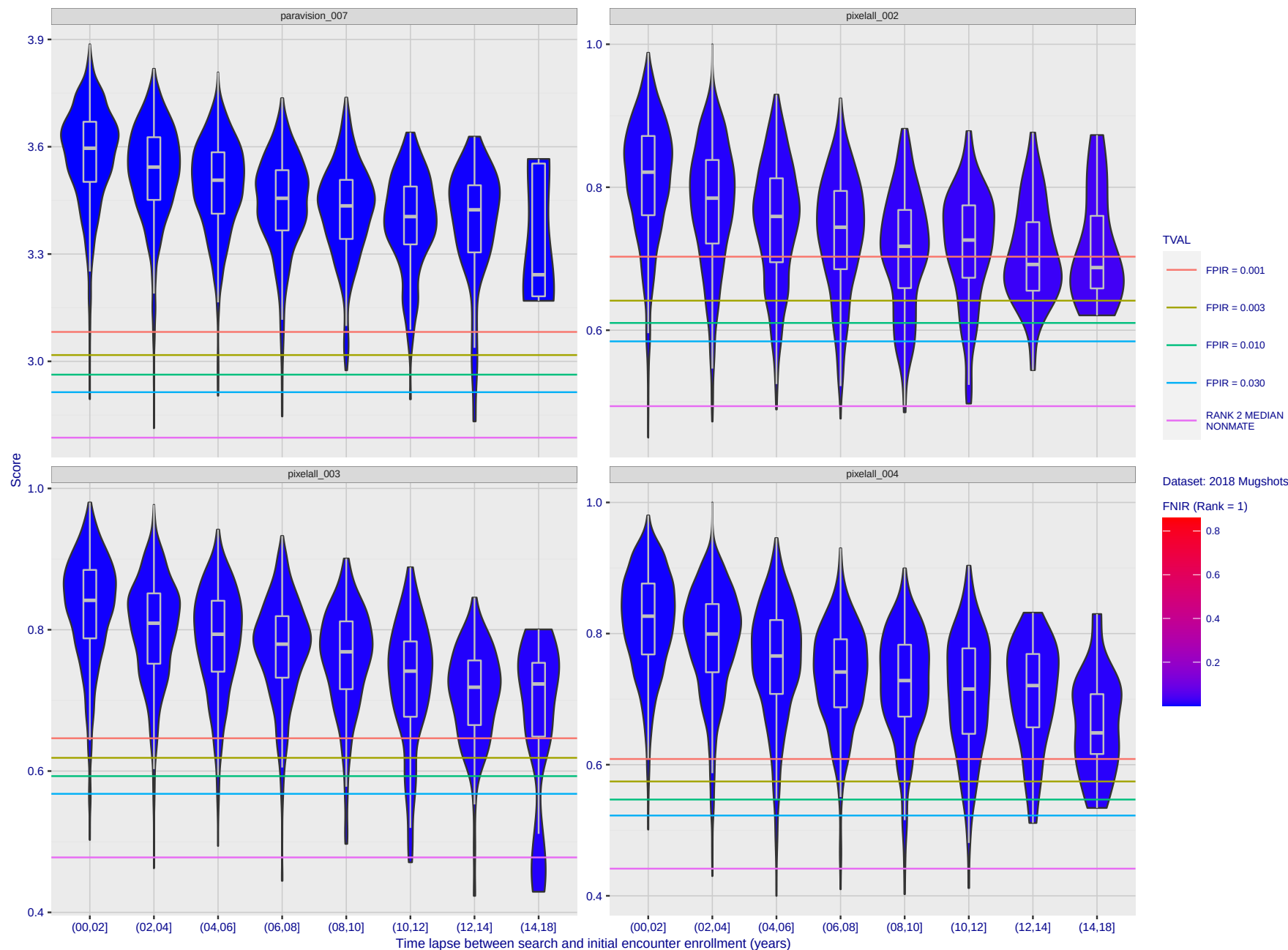


Figure 105: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.



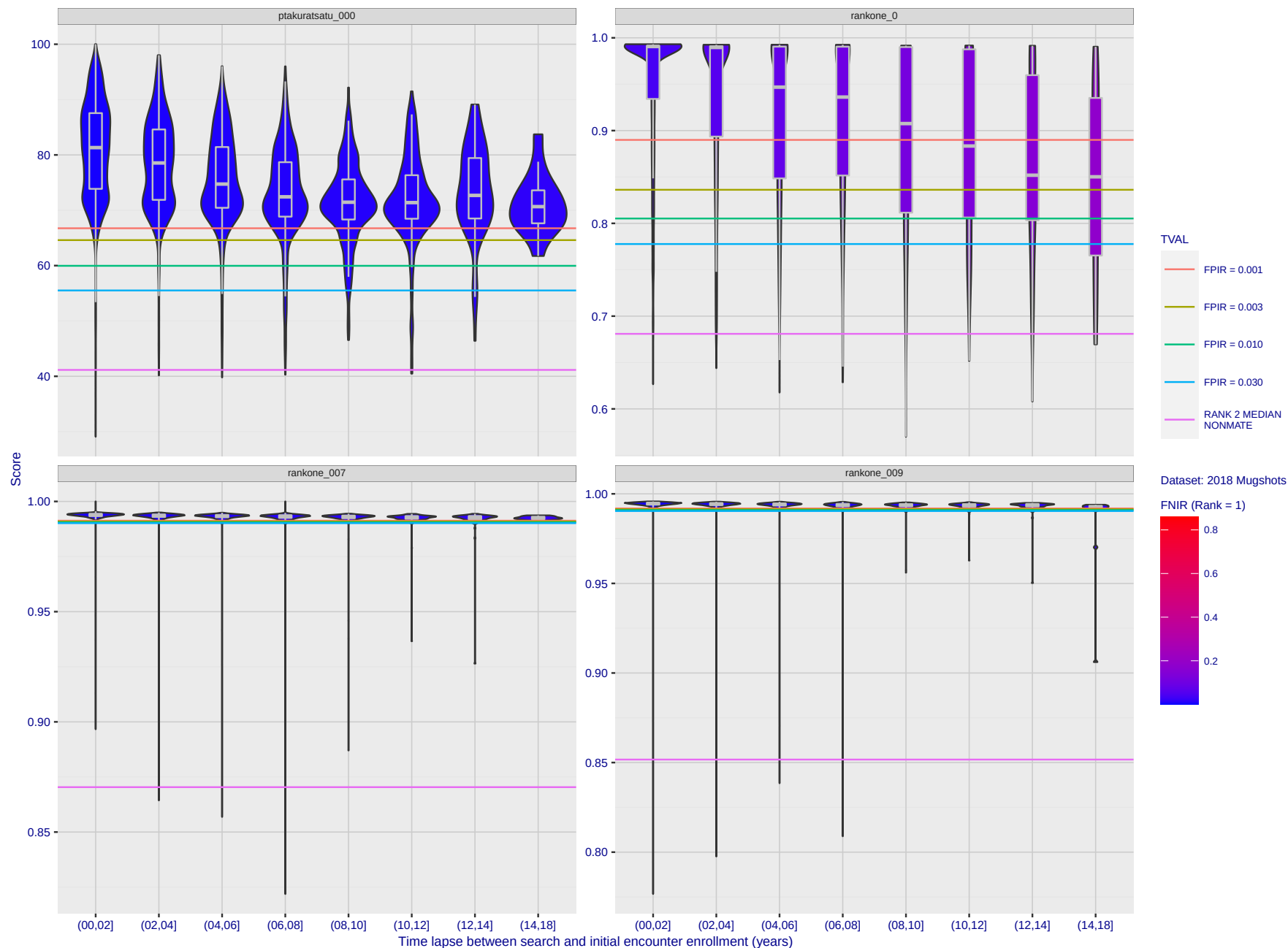


Figure 107: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed.** The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04 11:49:04 FNIR(N, R, T) = False neg. identification rate N = Num. enrolled subjects T = Threshold
FPIR(N, T) = False pos. identification rate R = Num. candidates examined T > 0 → Investigation
T > 0 → Identification

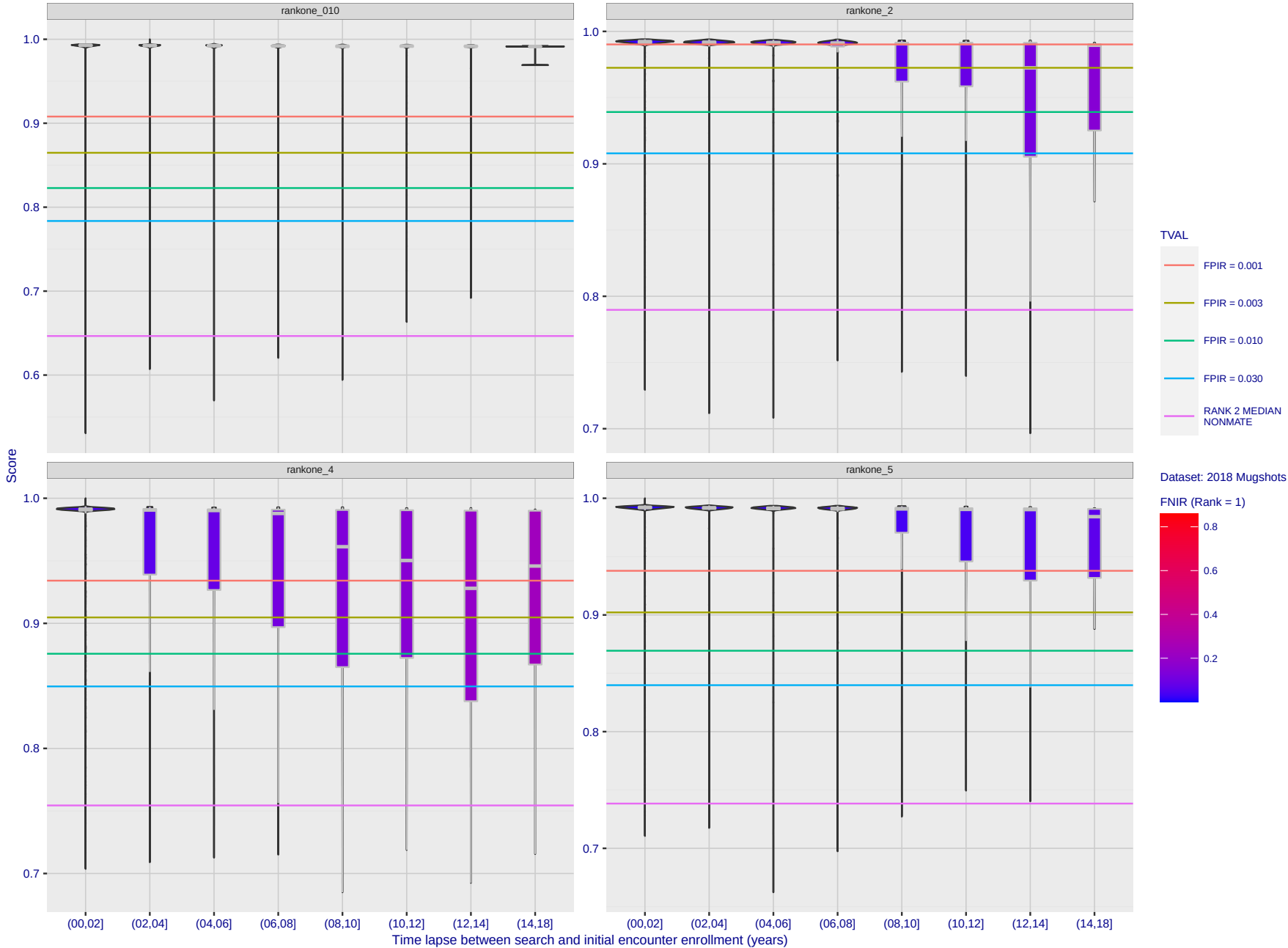


Figure 108: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

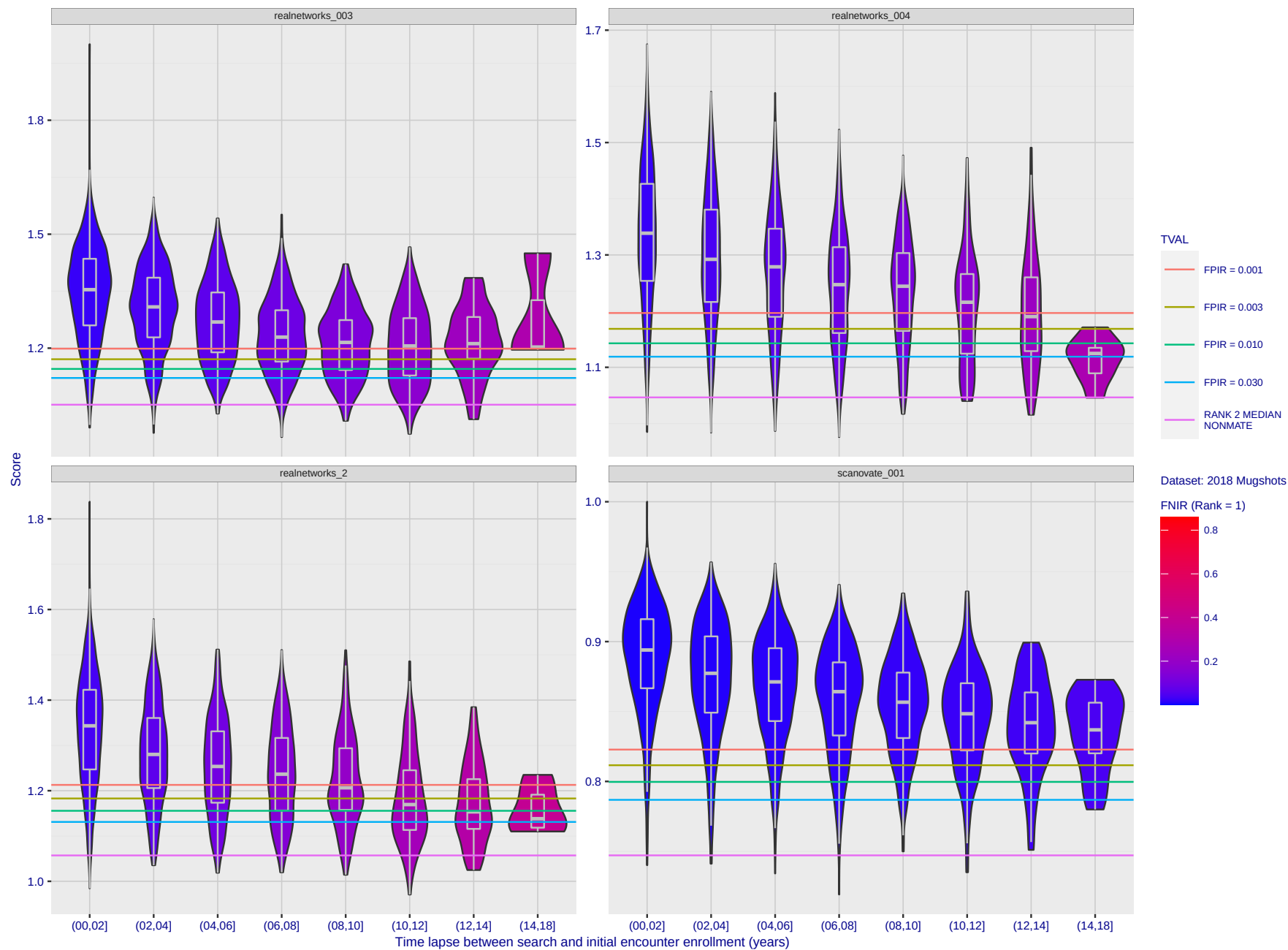


Figure 109: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

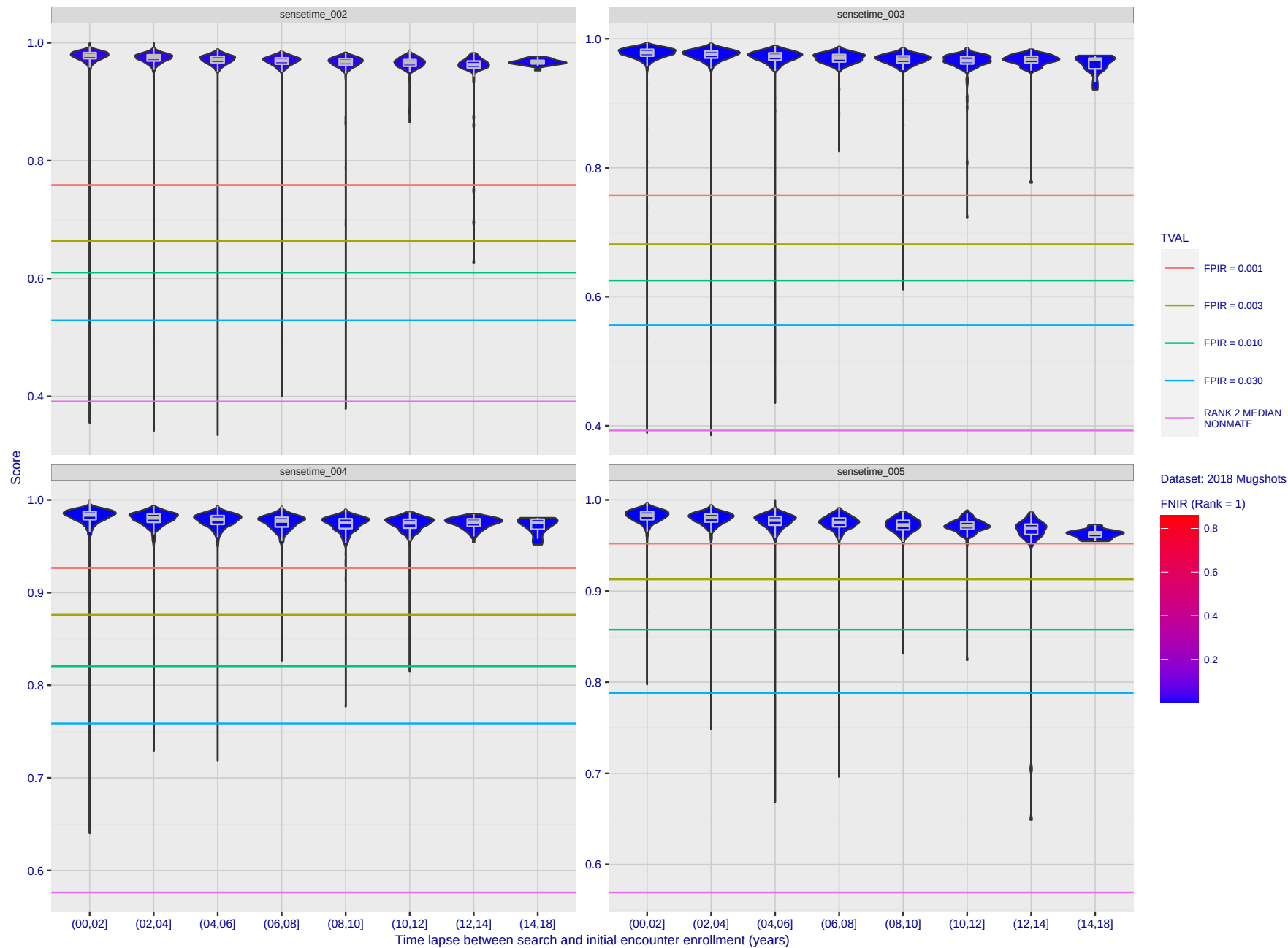


Figure 110: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed.** The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04

FNIR(N, R, T) =
FPIR(N, T) =

False neg. identification rate
False pos. identification rate

N = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

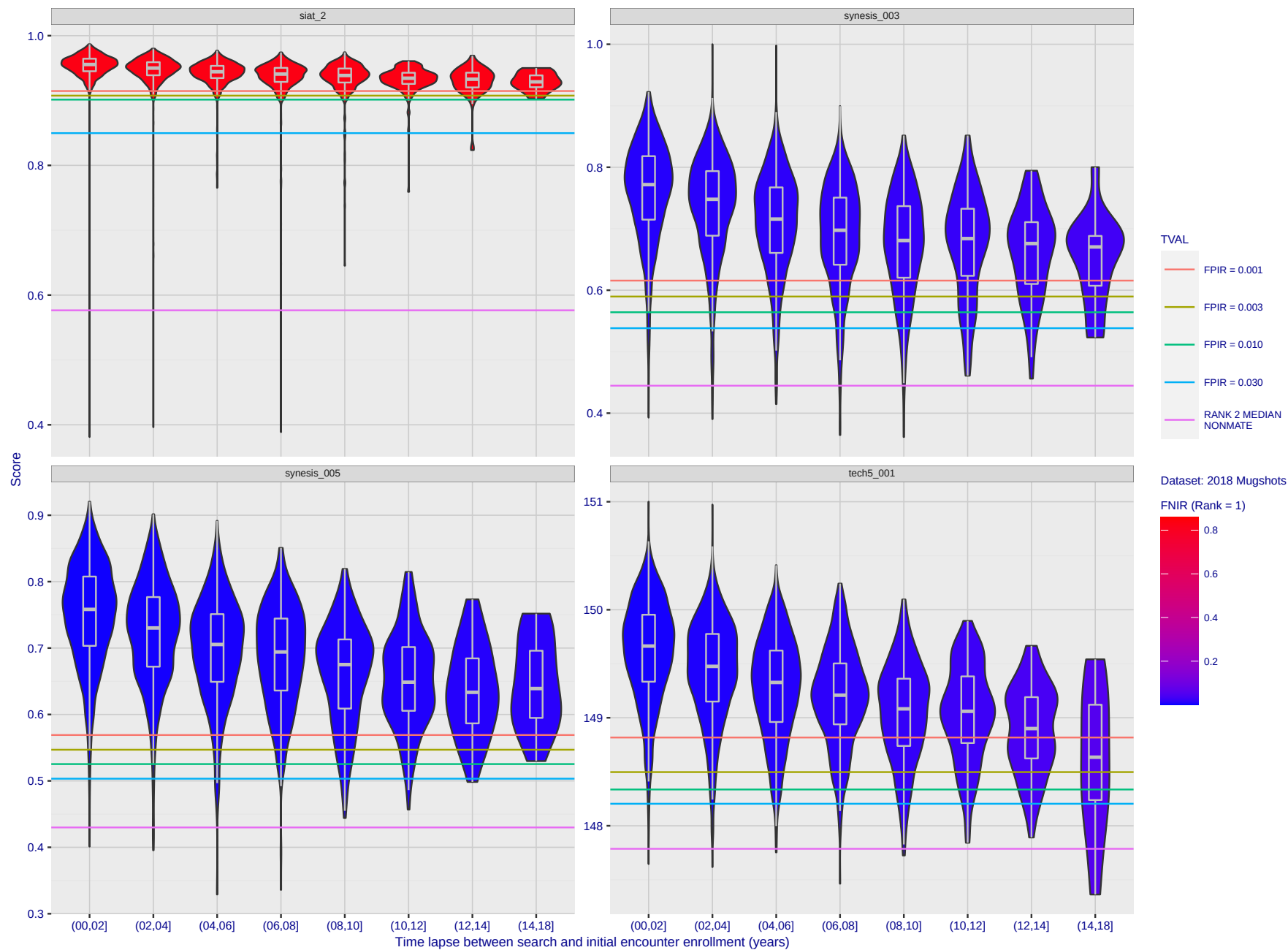


Figure 111: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04

FNIR(N, R, T) =
FPIR(N, T) =
False neg. identification rate
False pos. identification rate

N = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

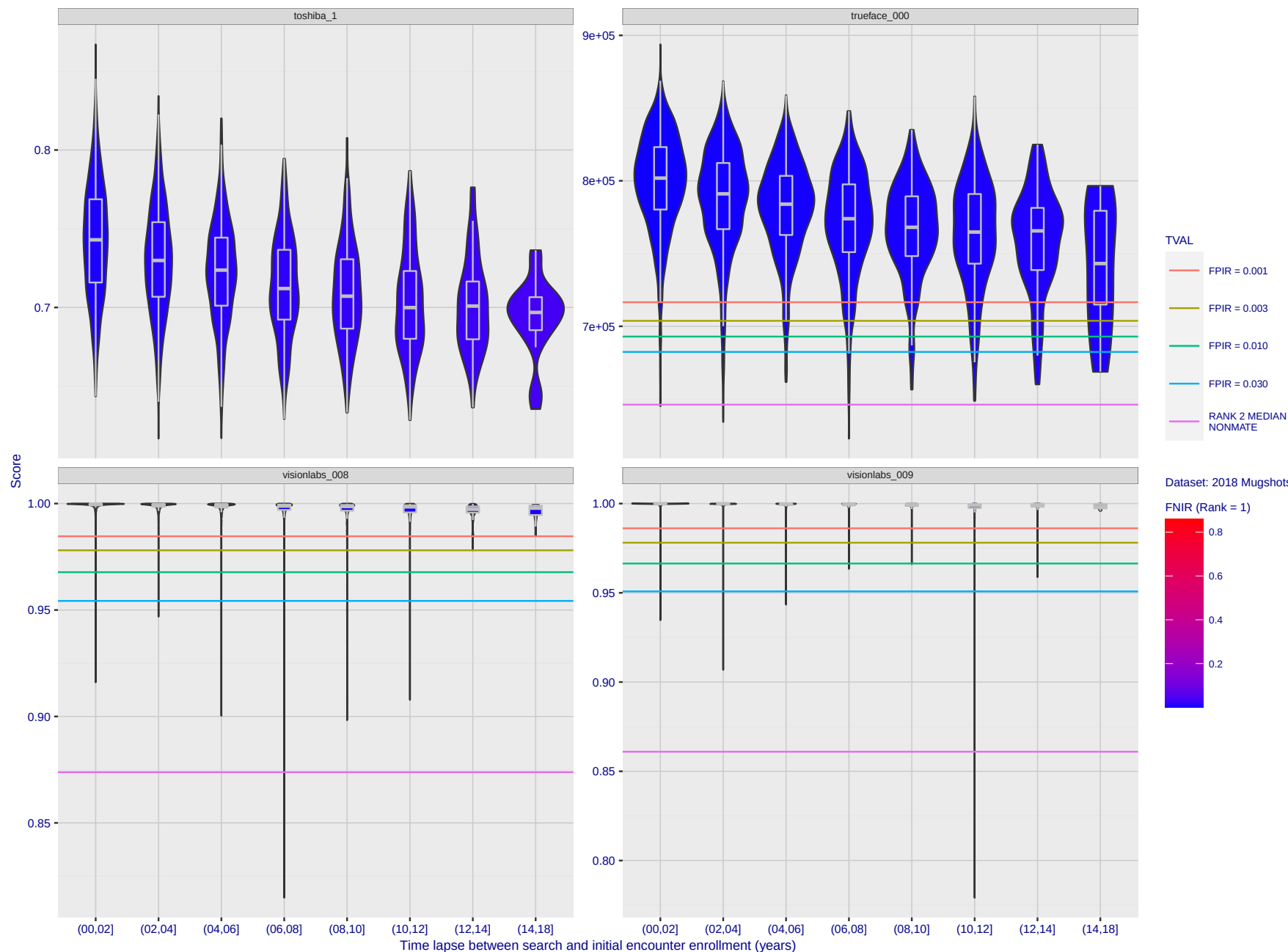


Figure 112: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

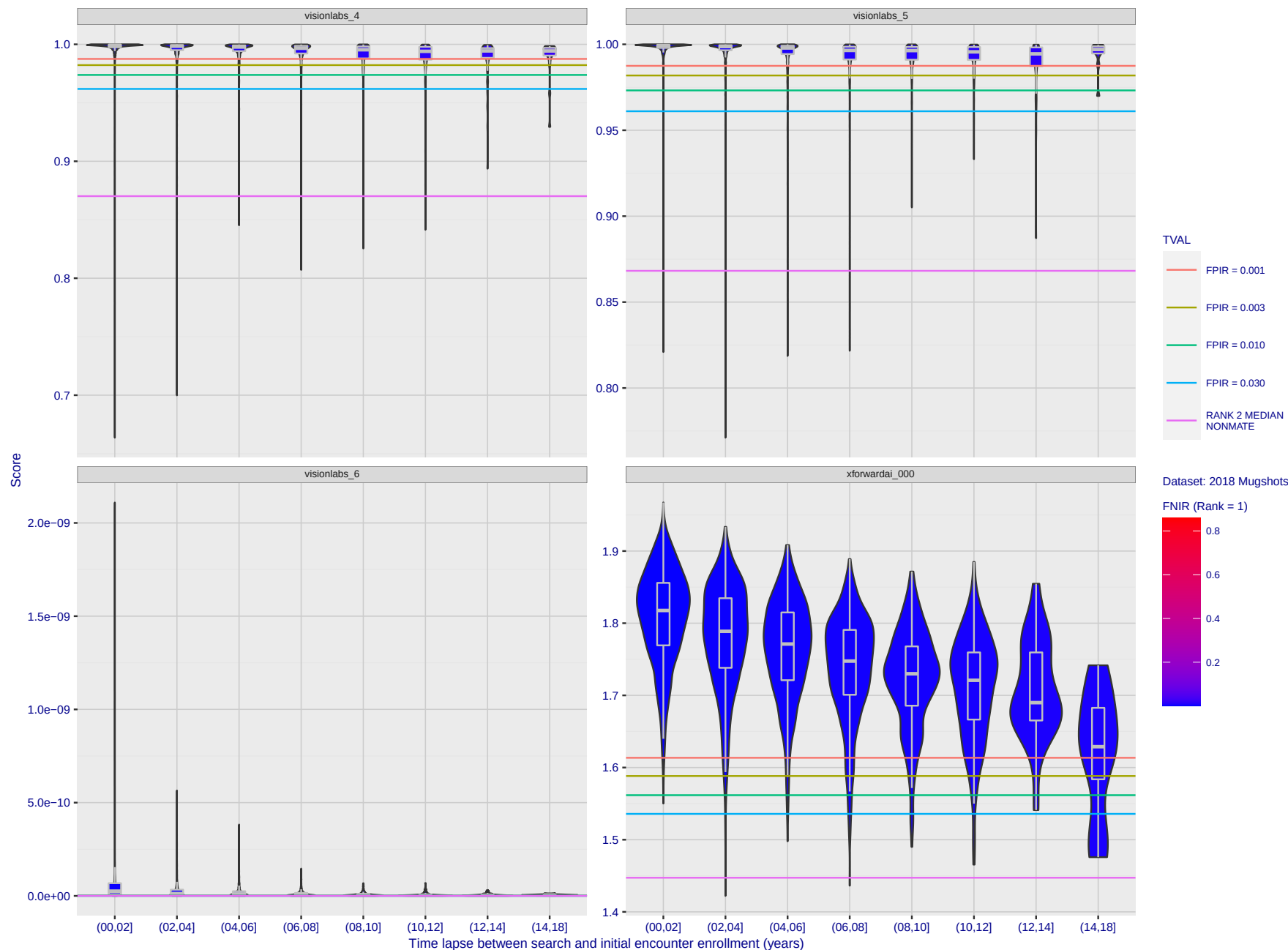


Figure 113: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

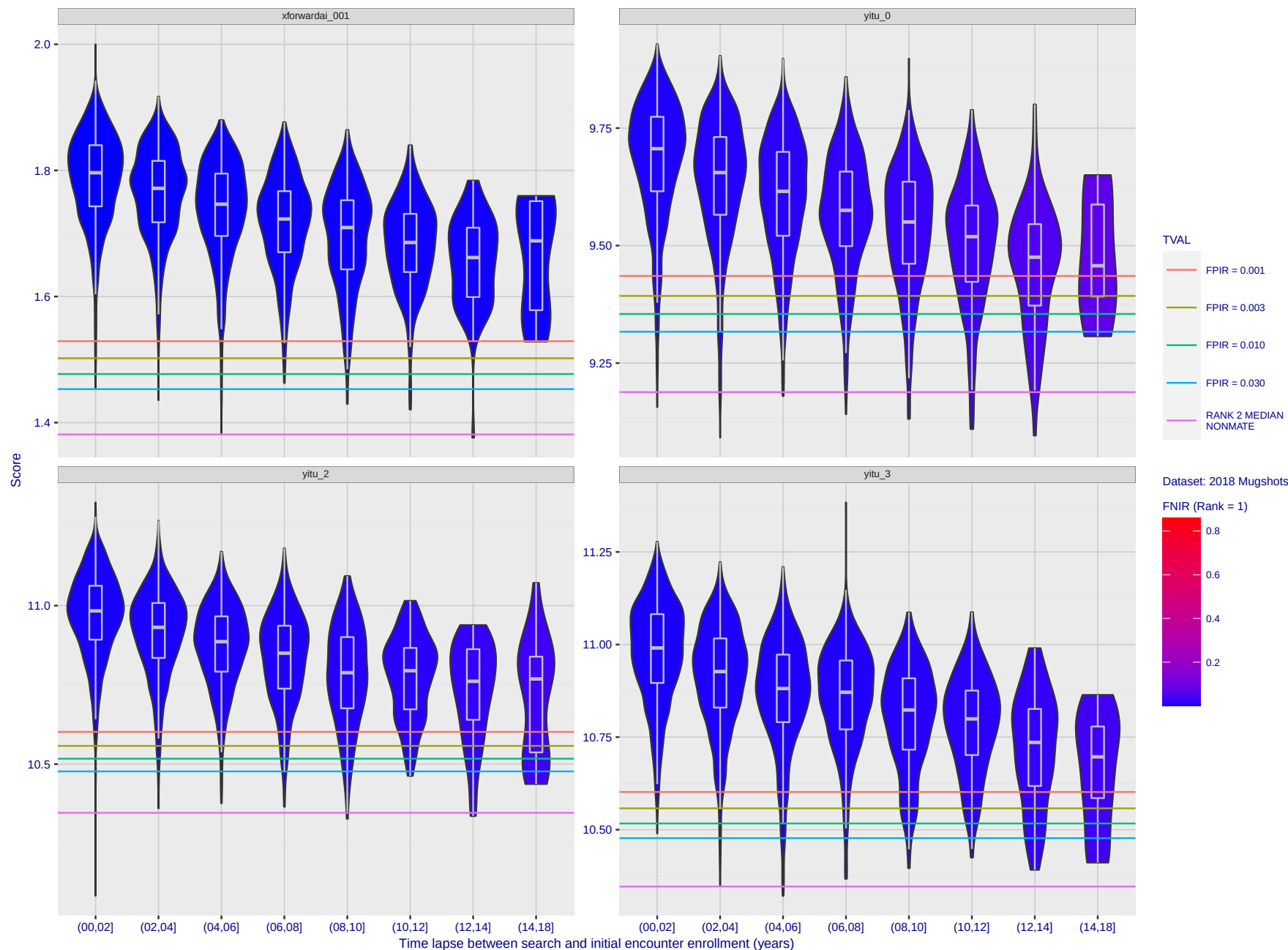


Figure 114: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04 11:49:04
 FNIR(N, R, T) =
 FPIR(N, T) =
 False neg. identification rate
 False pos. identification rate
 N = Num. enrolled subjects
 R = Num. candidates examined
 T = Threshold
 T = 0 → Investigation
 T > 0 → Identification

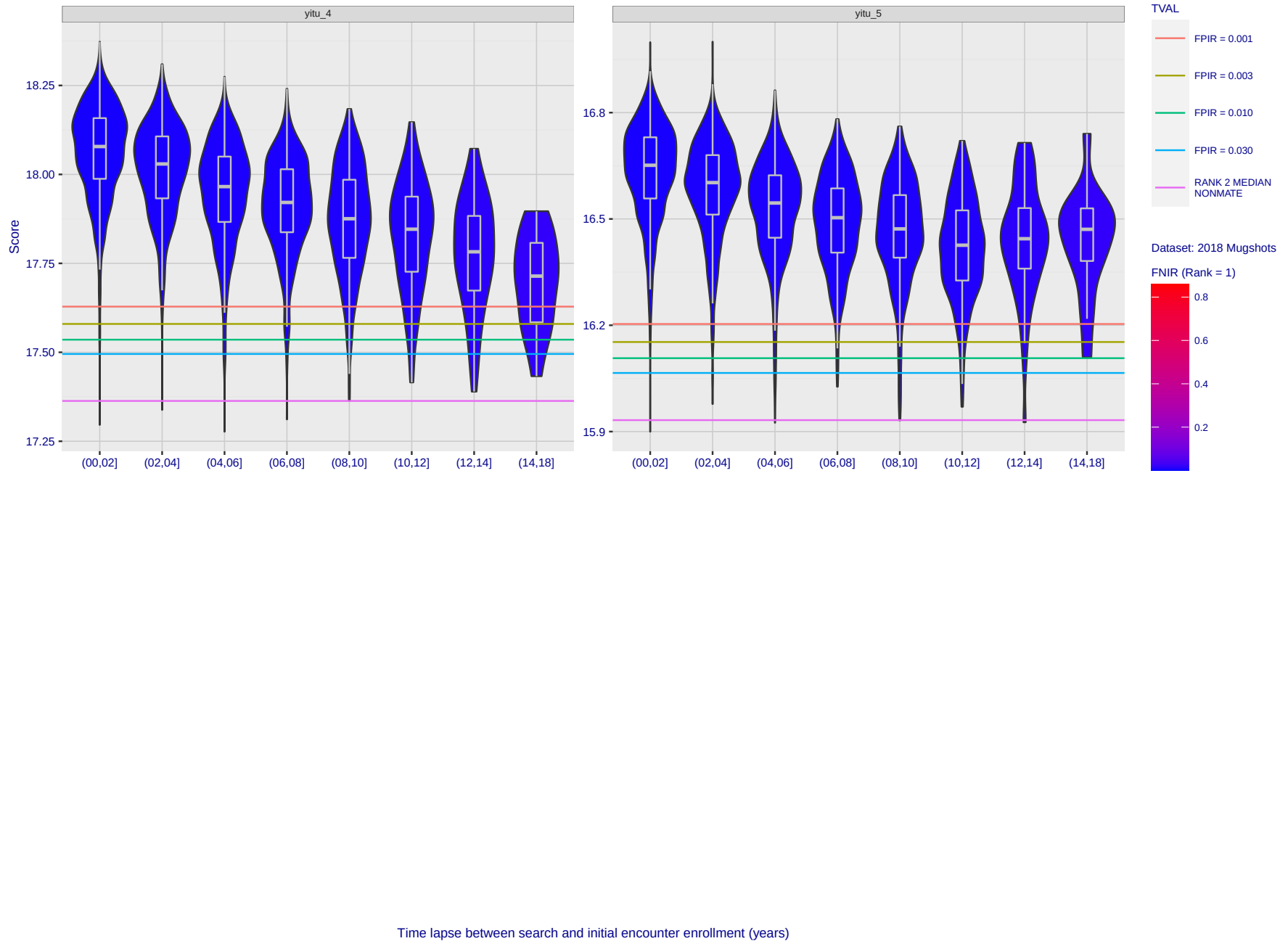


Figure 115: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

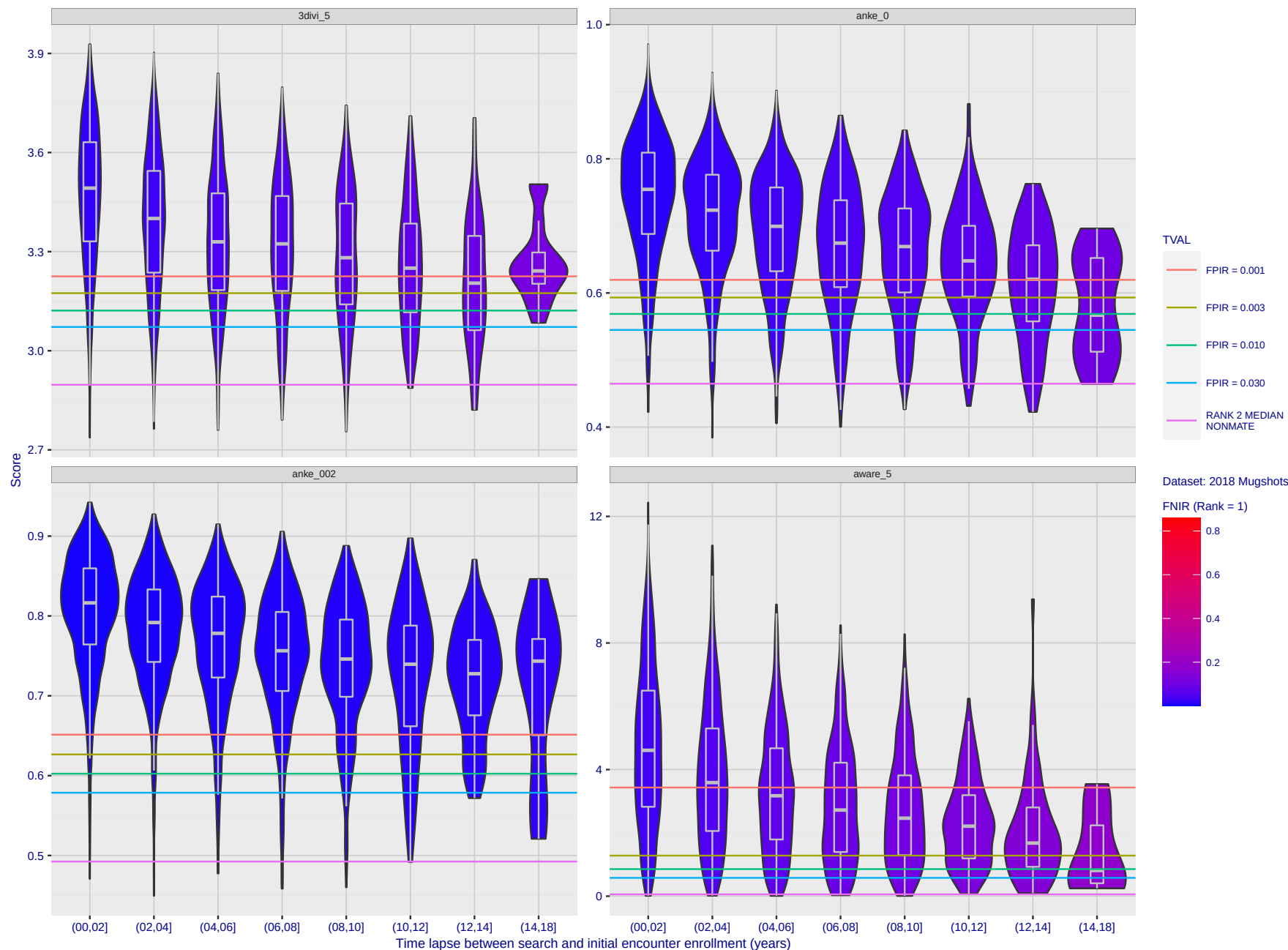


Figure 116: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

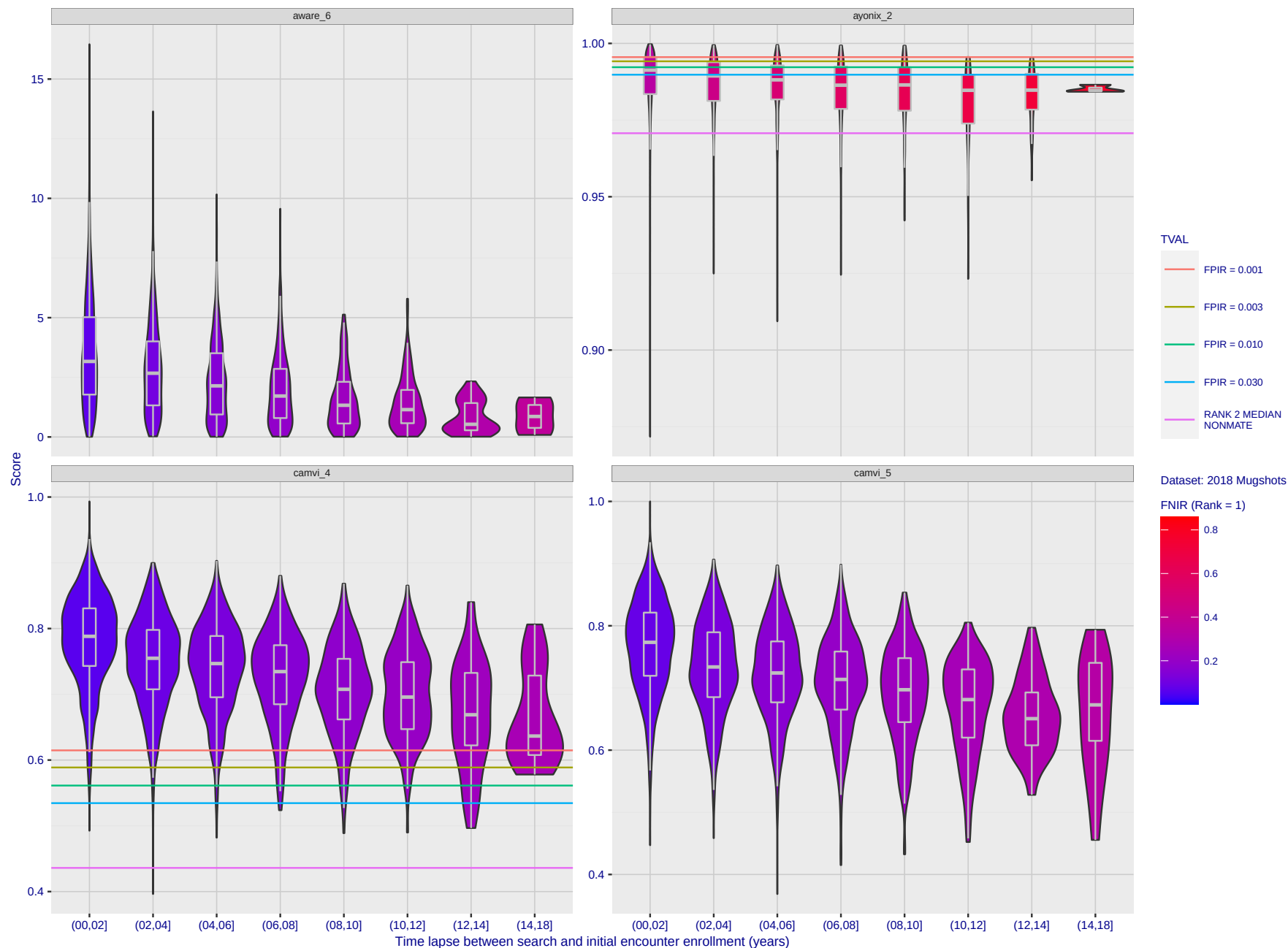


Figure 117: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

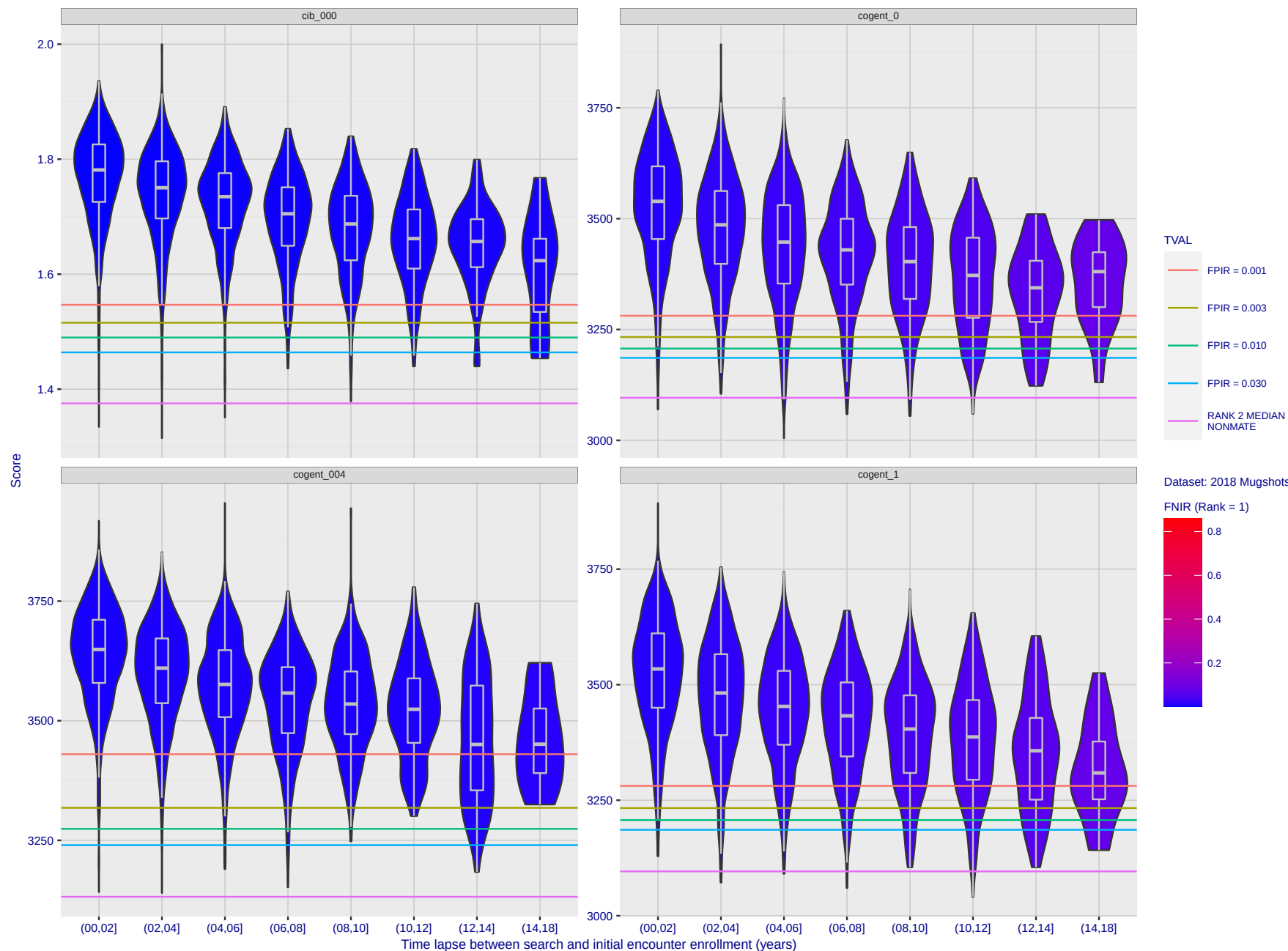


Figure 118: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

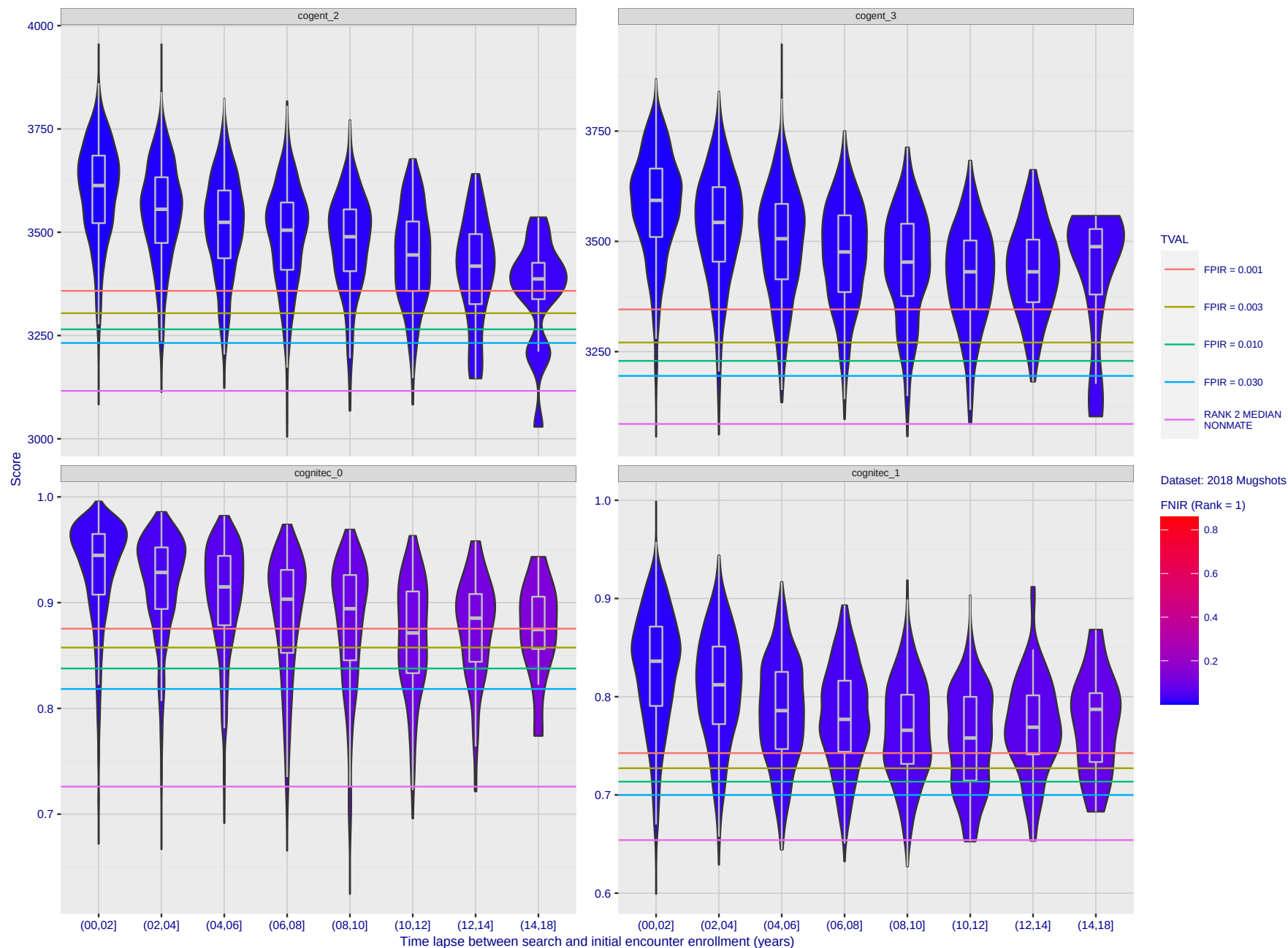


Figure 119: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04
FNIR(N, R, T) =
FPIR(N, T) =
False neg. identification rate
False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

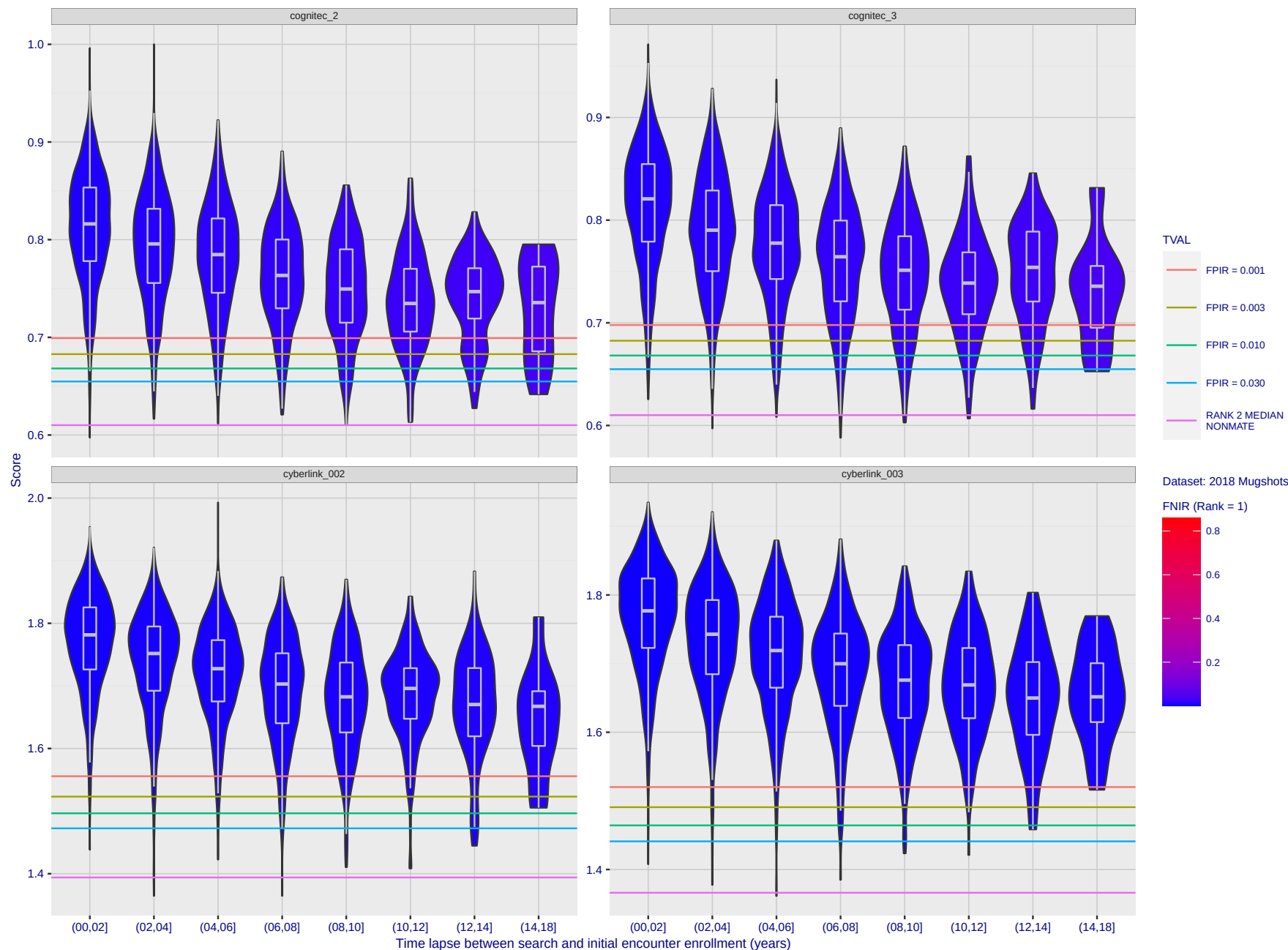


Figure 120: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04 11:49:04

FNIR(N, R, T) = False neg. identification rate

FPIR(N, T) = False pos. identification rate

N = Num. enrolled subjects

R = Num. candidates examined

T = Threshold

T = 0 → Investigation

T > 0 → Identification

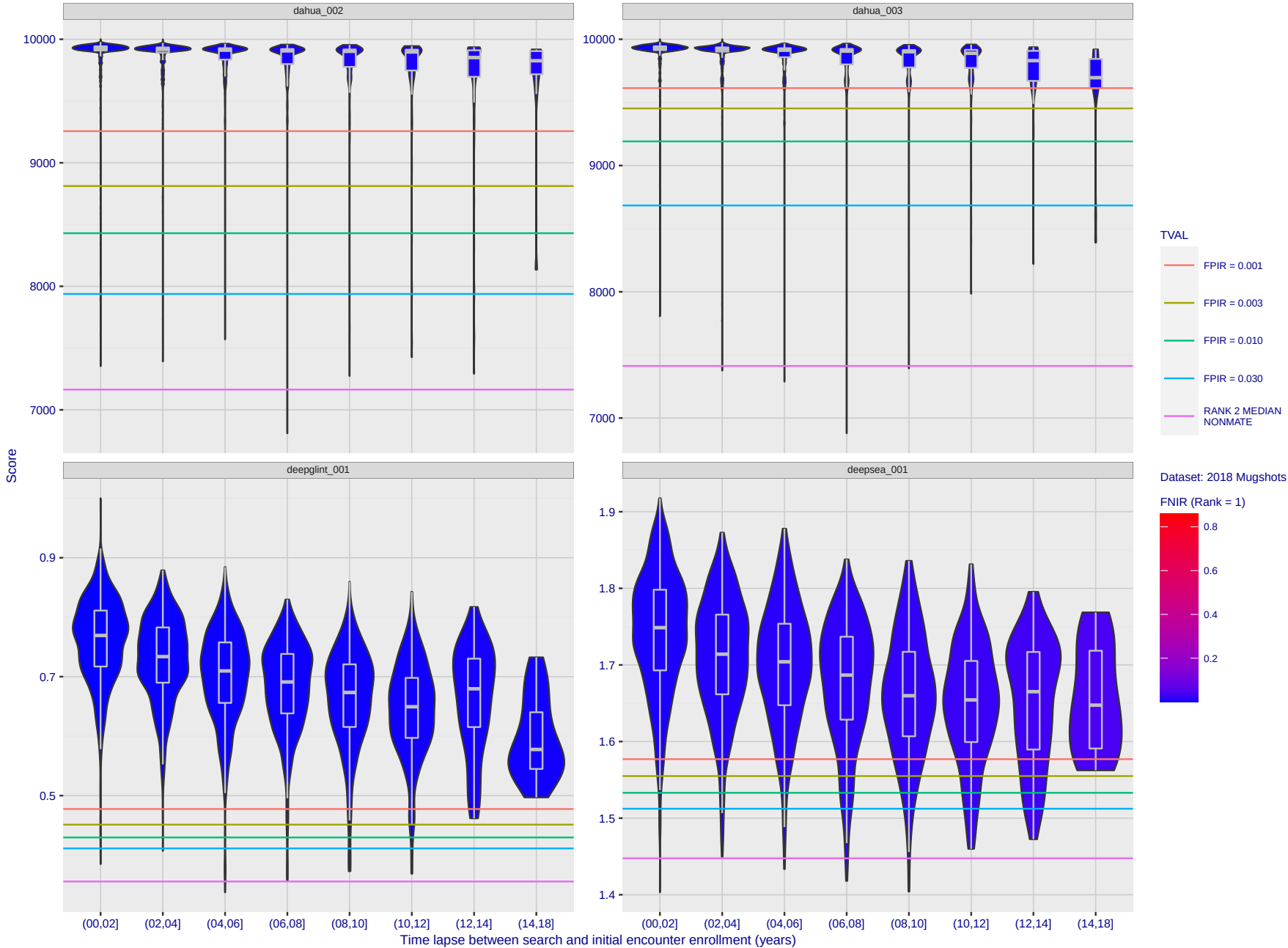


Figure 121: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

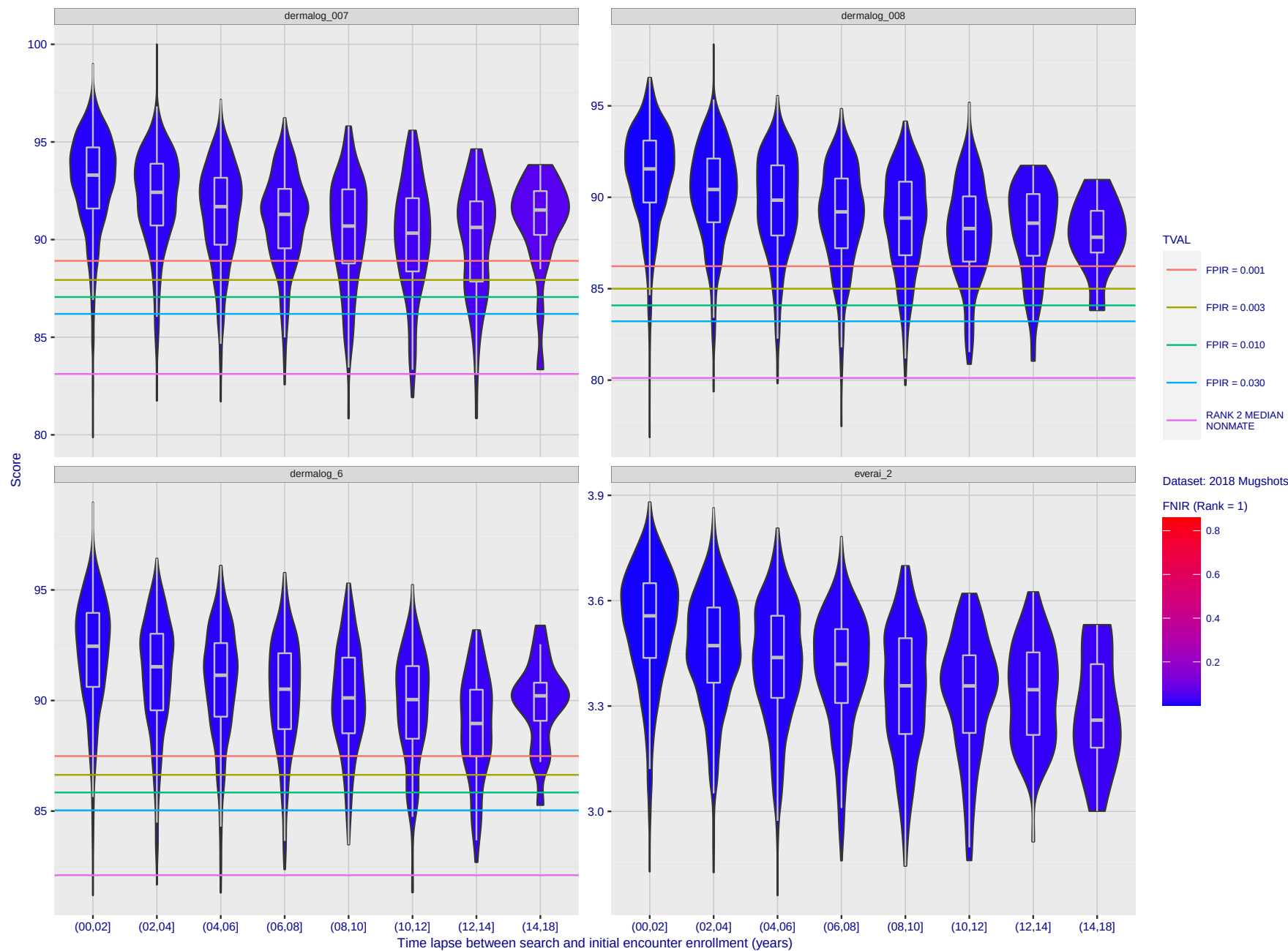


Figure 122: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

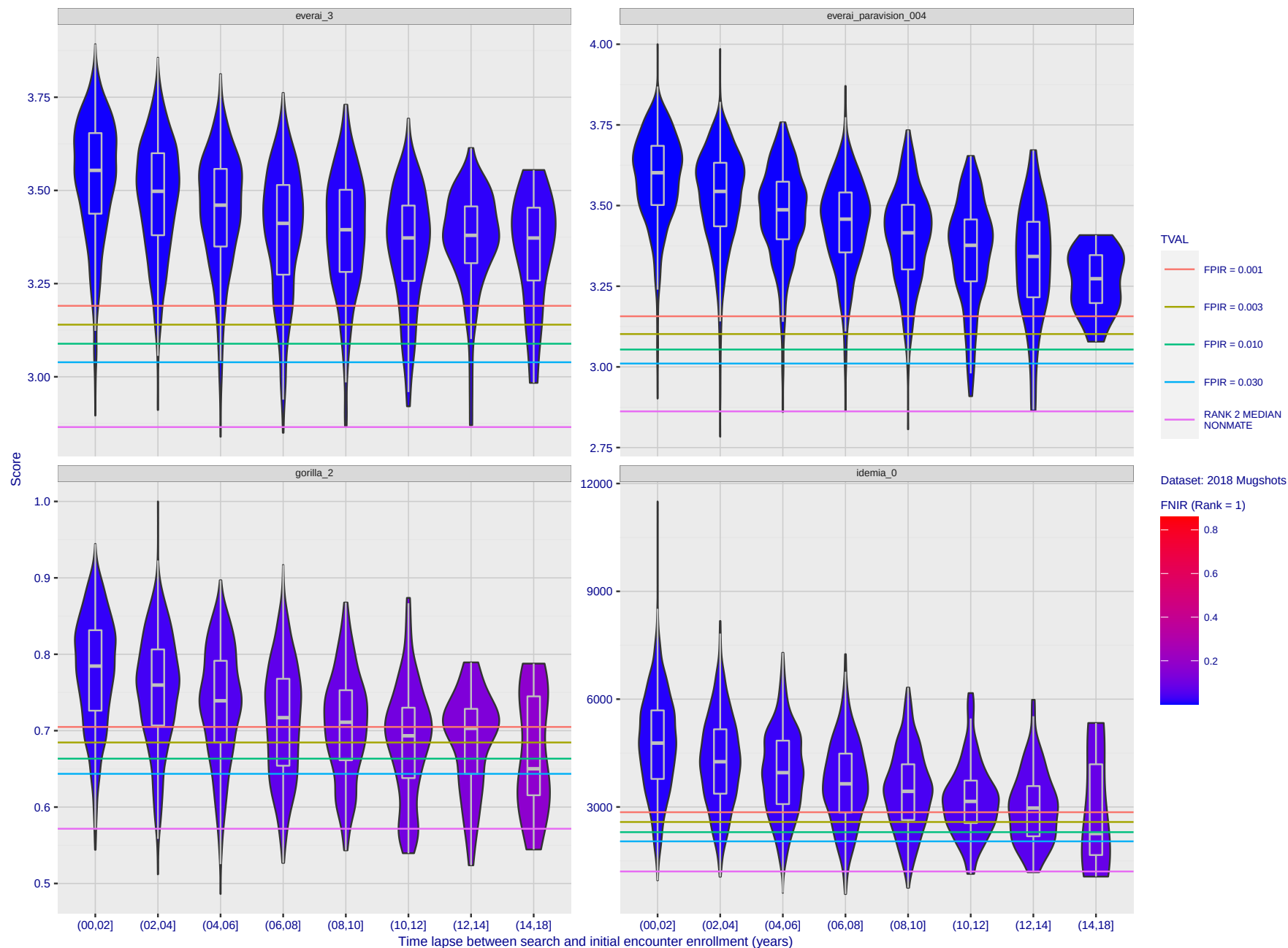


Figure 123: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04 11:49:04
FNIR(N, R, T) = False neg. identification rate
FPIR(N, T) = False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

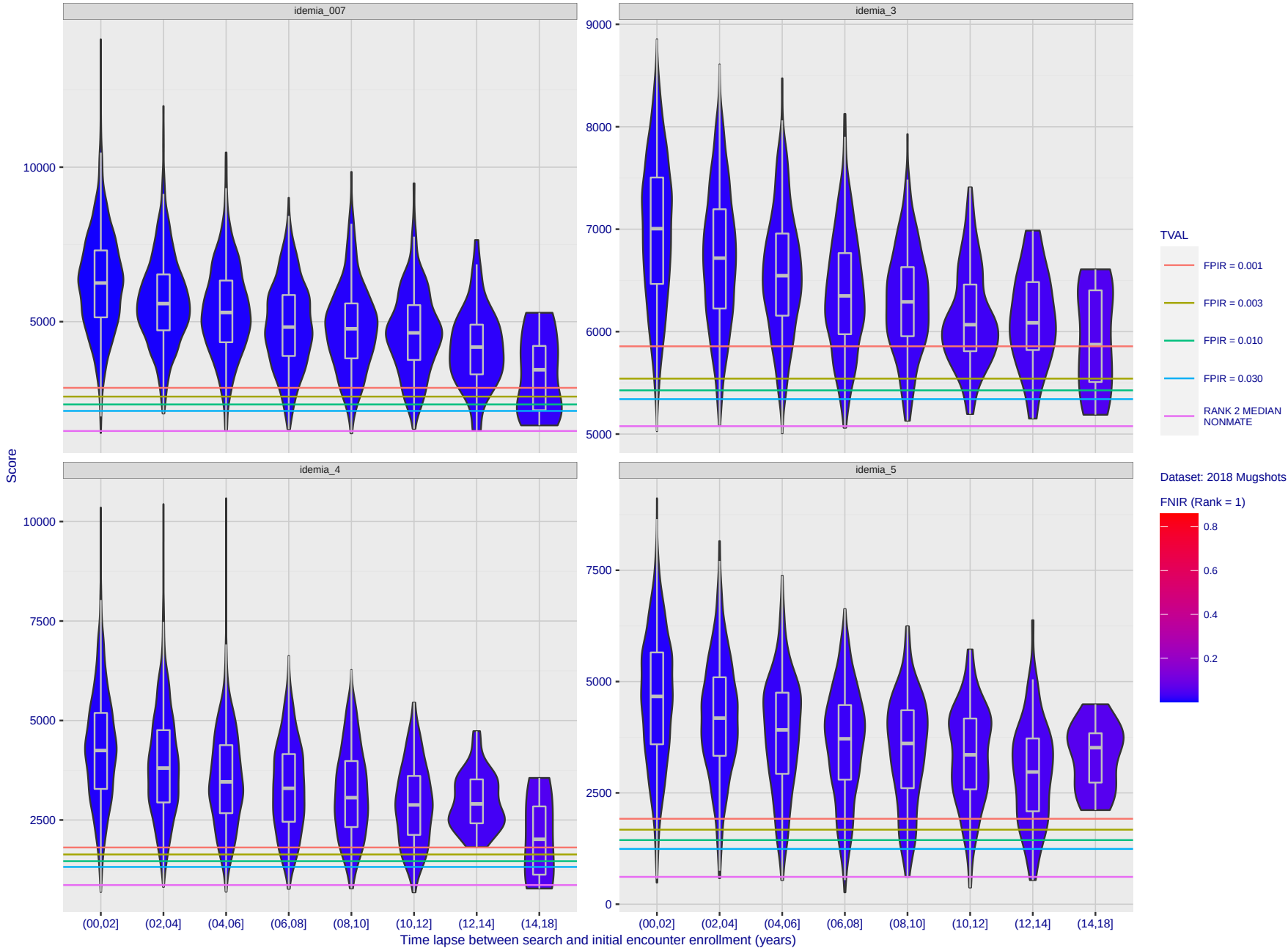


Figure 124: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

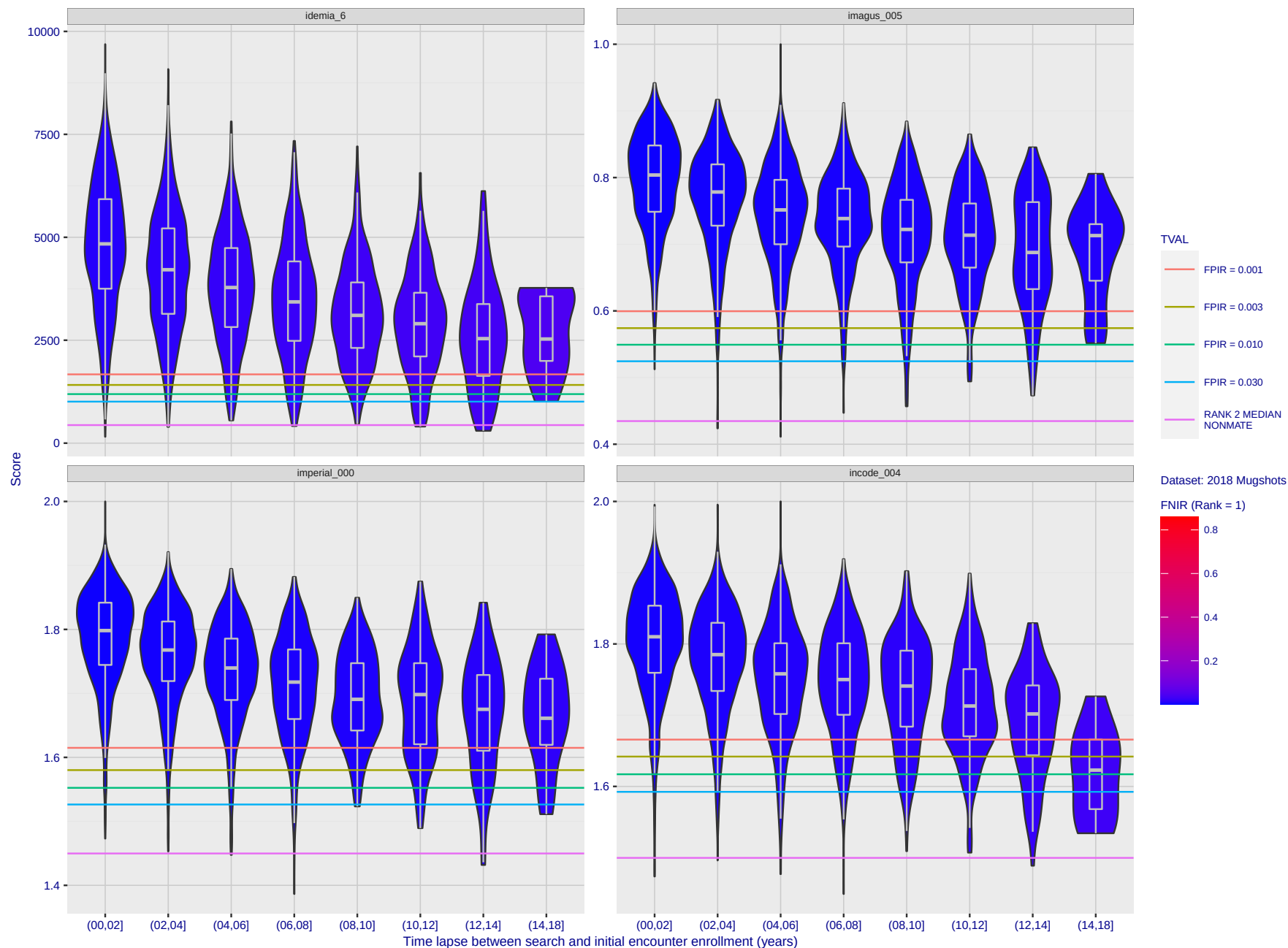


Figure 125: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

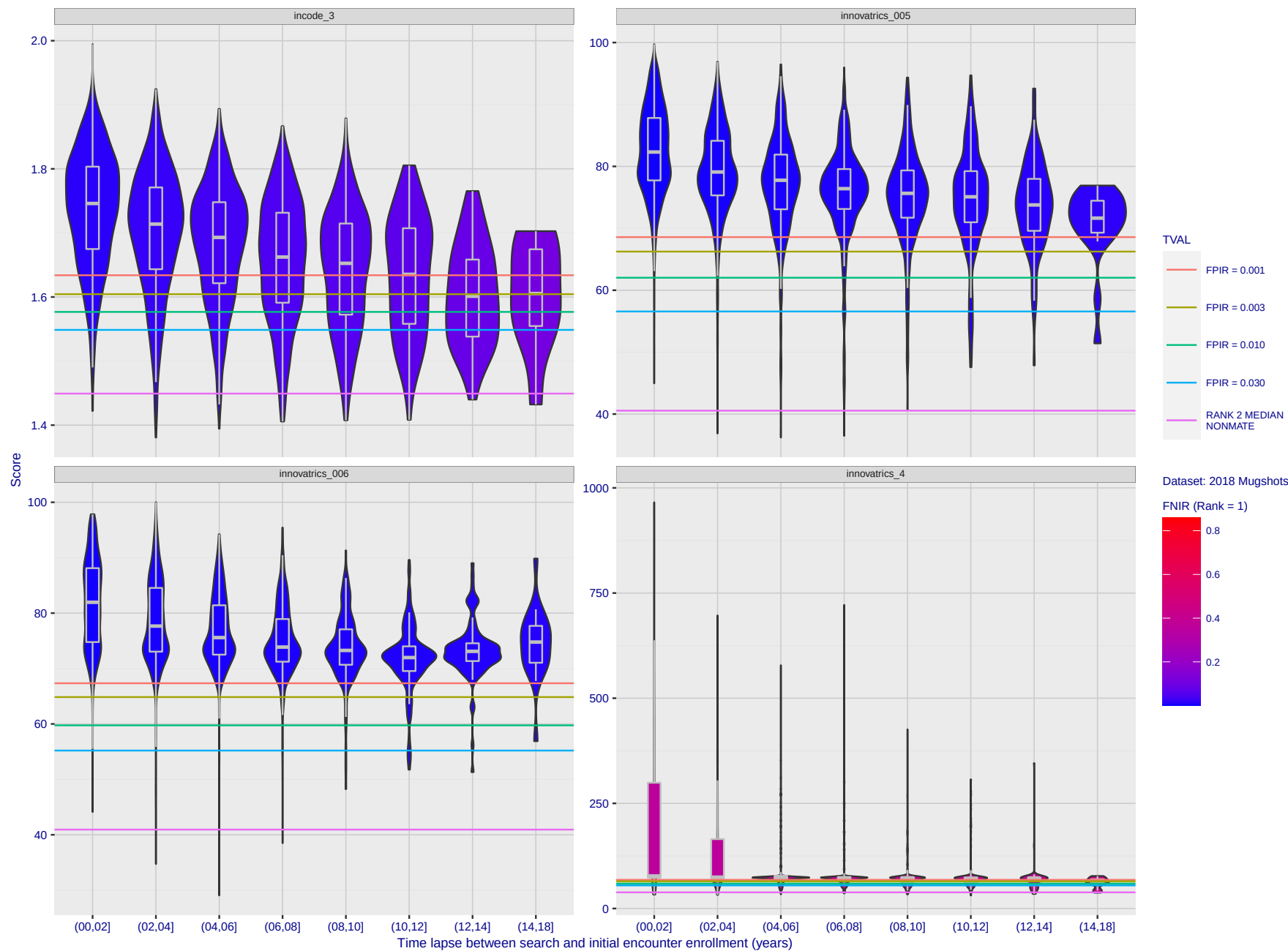


Figure 126: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

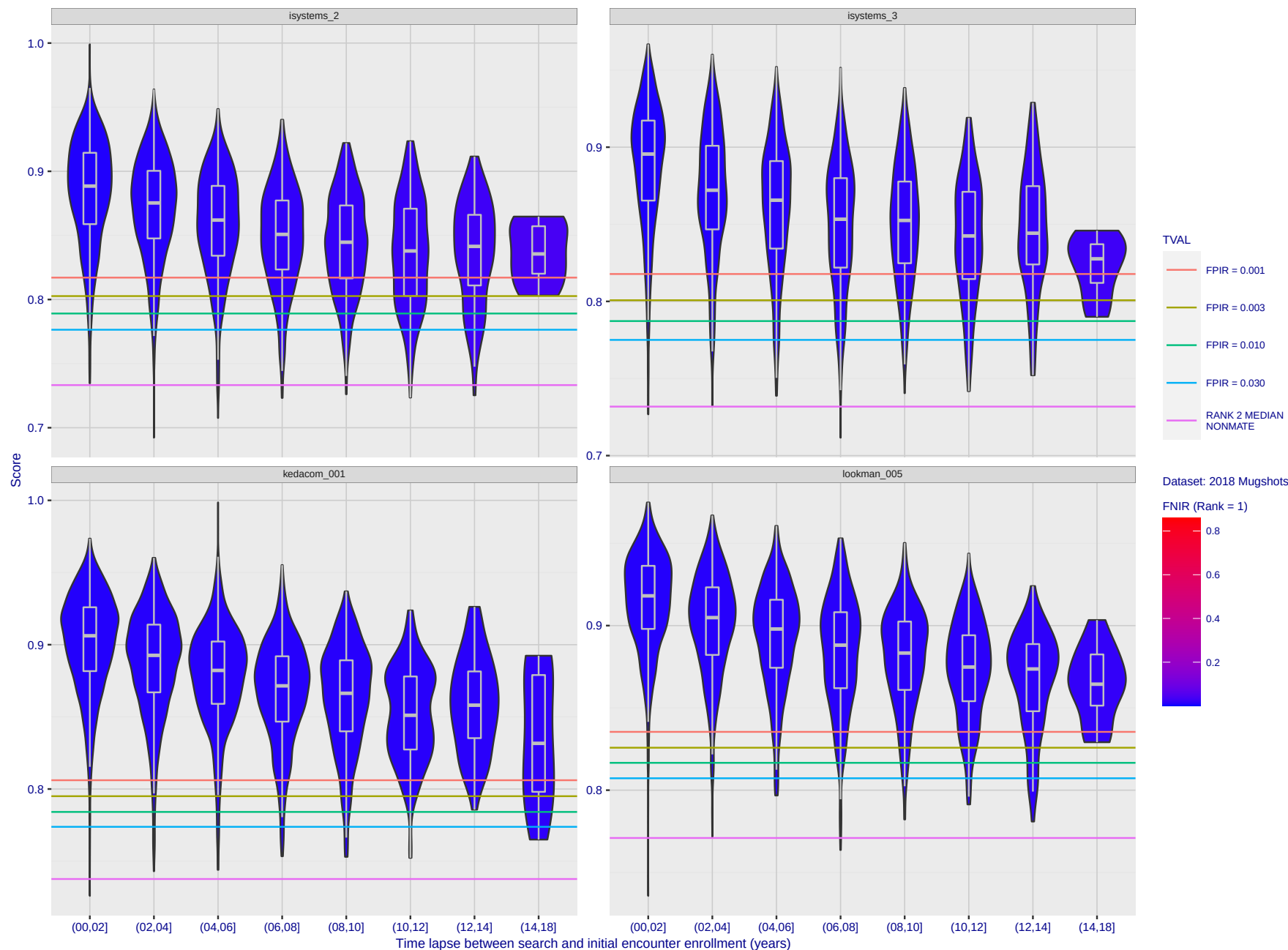


Figure 127: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

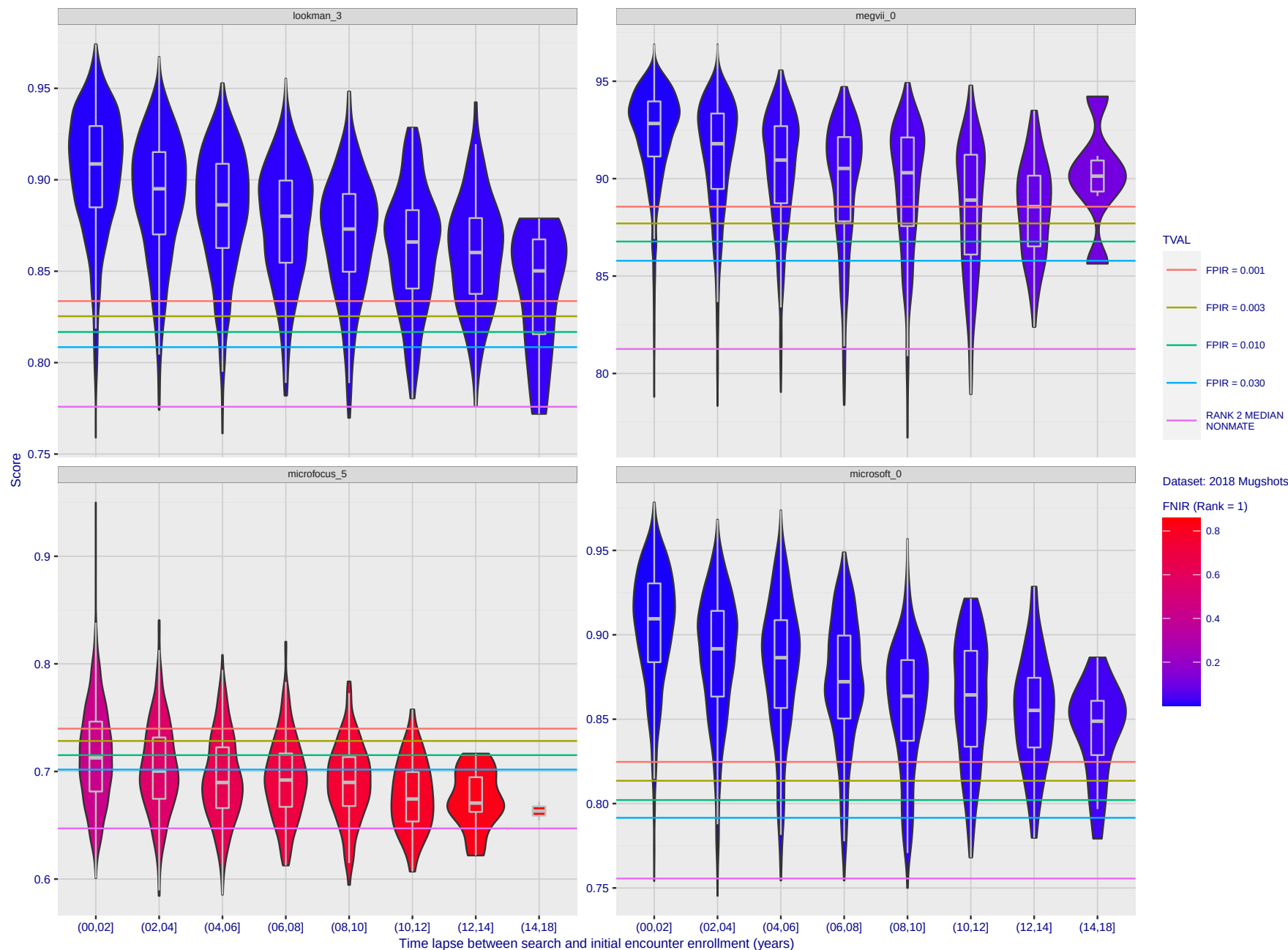


Figure 128: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

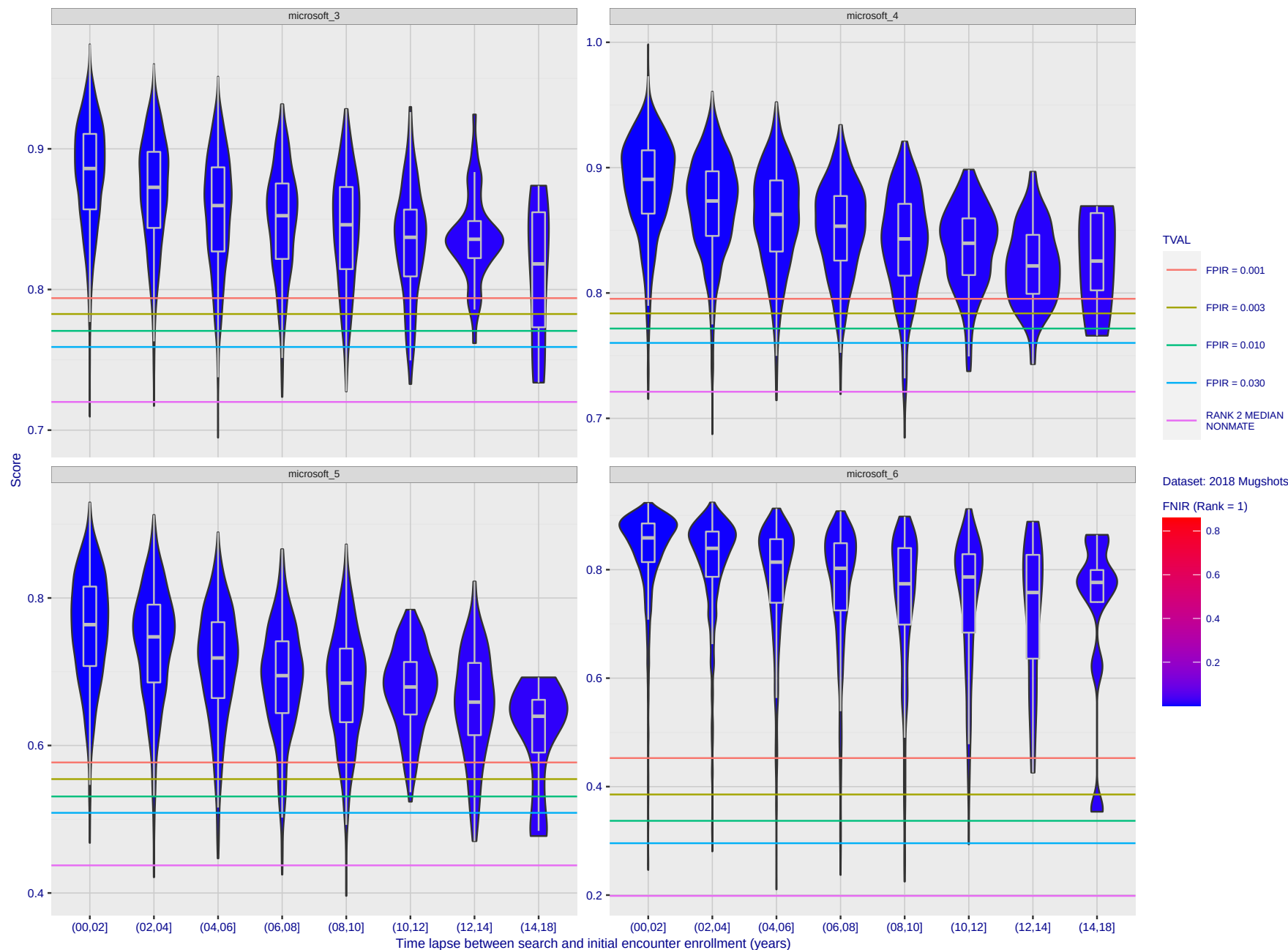


Figure 129: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

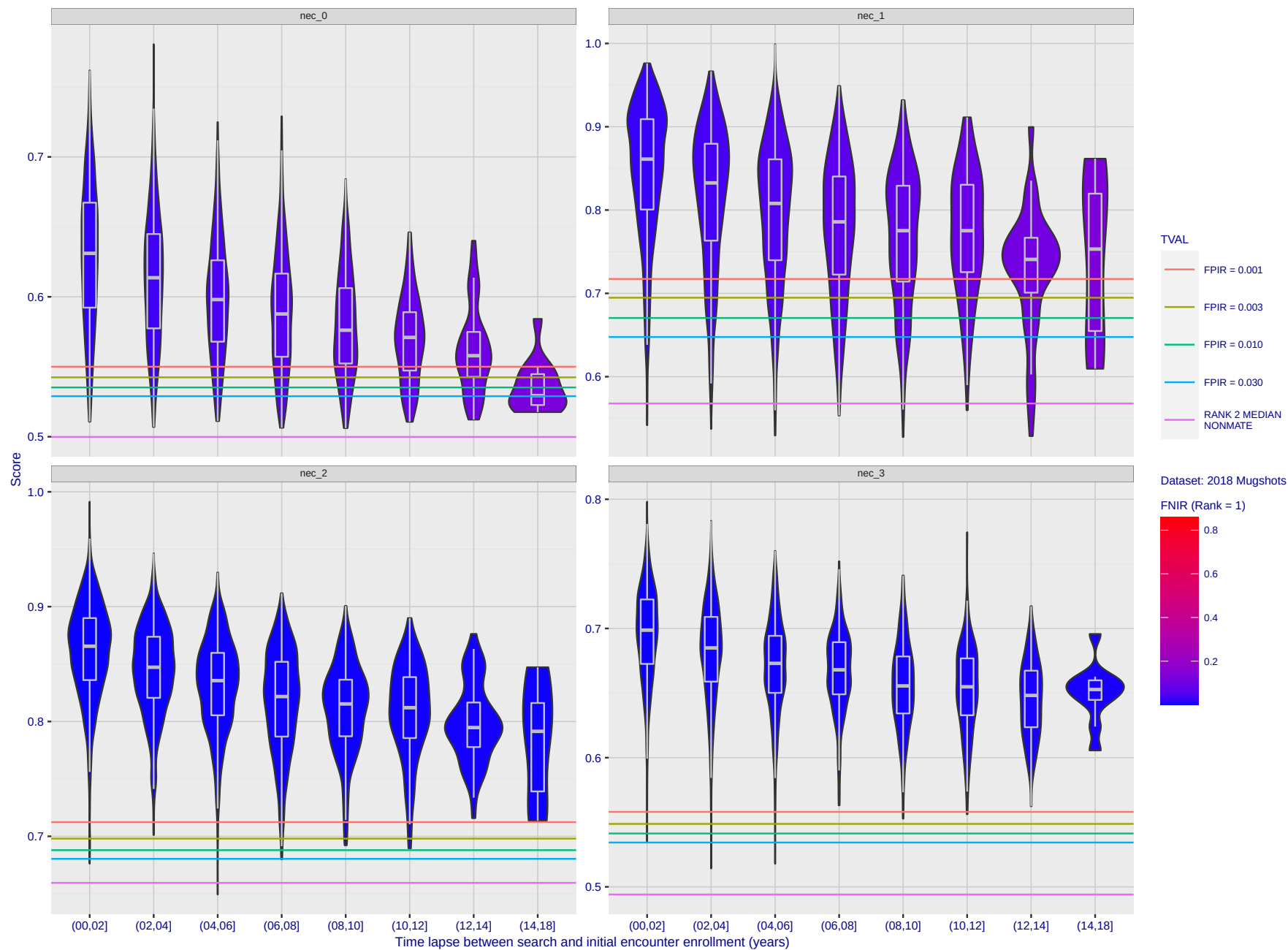


Figure 130: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04

FNIR(N, R, T) =
FPIR(N, T) =

False neg. identification rate
False pos. identification rate

N = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

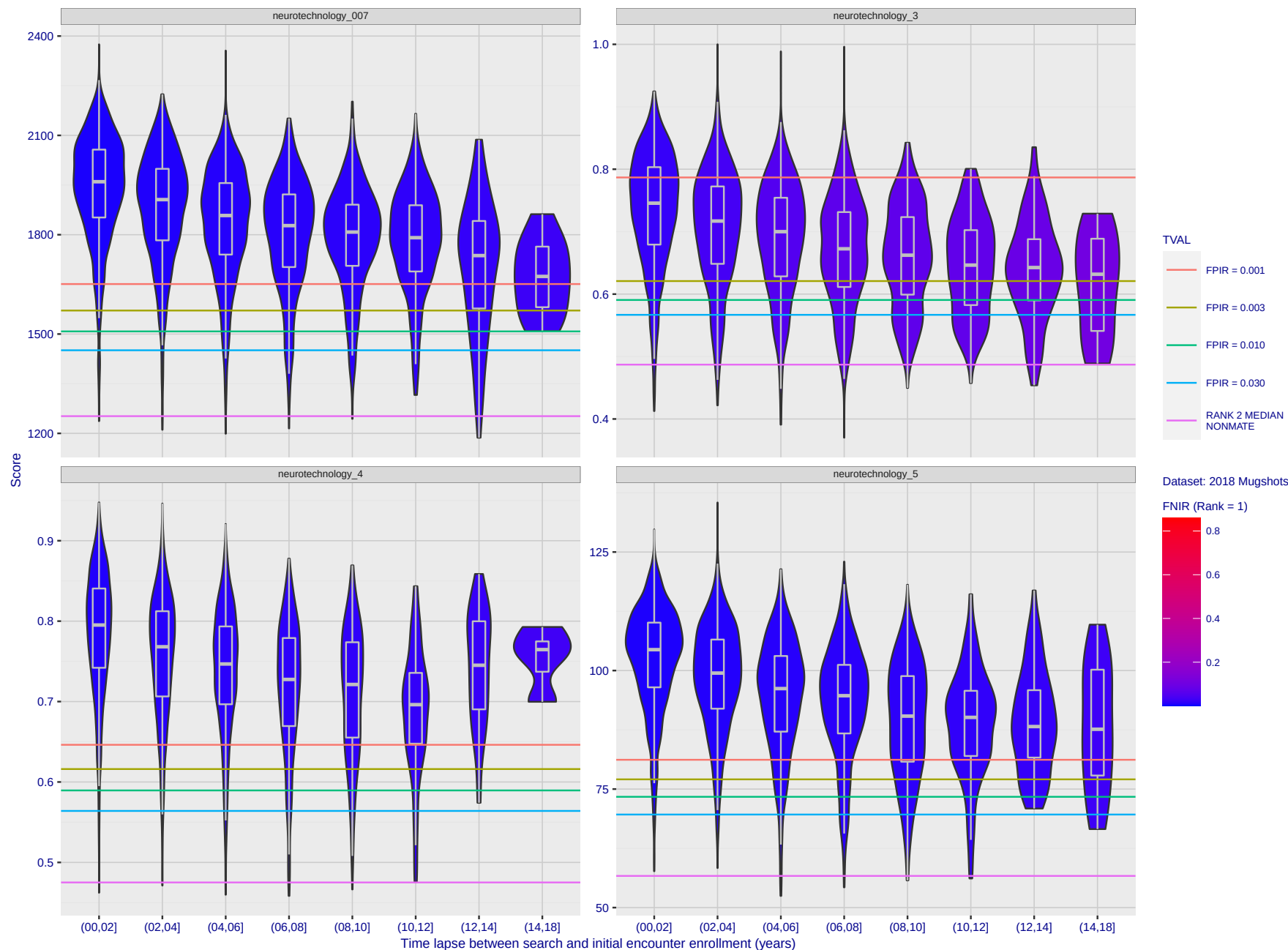


Figure 131: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04 11:49:04 FNIR(N, R, T) = False neg. identification rate N = Num. enrolled subjects T = Threshold T = 0 → Investigation
FPIR(N, T) = False pos. identification rate R = Num. candidates examined R > 0 → Identification

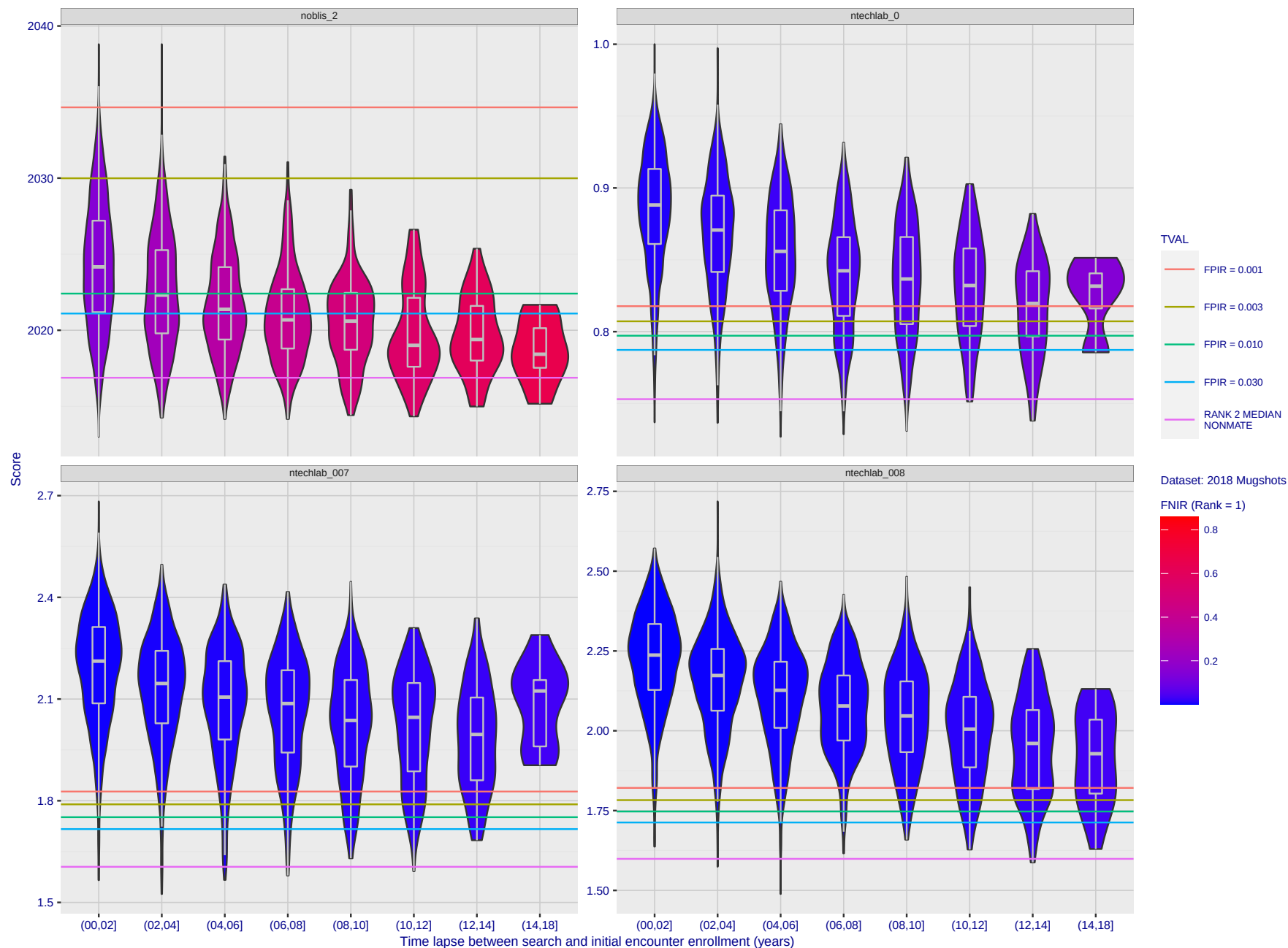


Figure 132: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04

FNIR(N, R, T) =
FPIR(N, T) =

False neg. identification rate
False pos. identification rate

N = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

2021/03/04
11:49:04
FNIR(N, R, T) =
FPIR(N, T) =
False neg. identification rate
False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

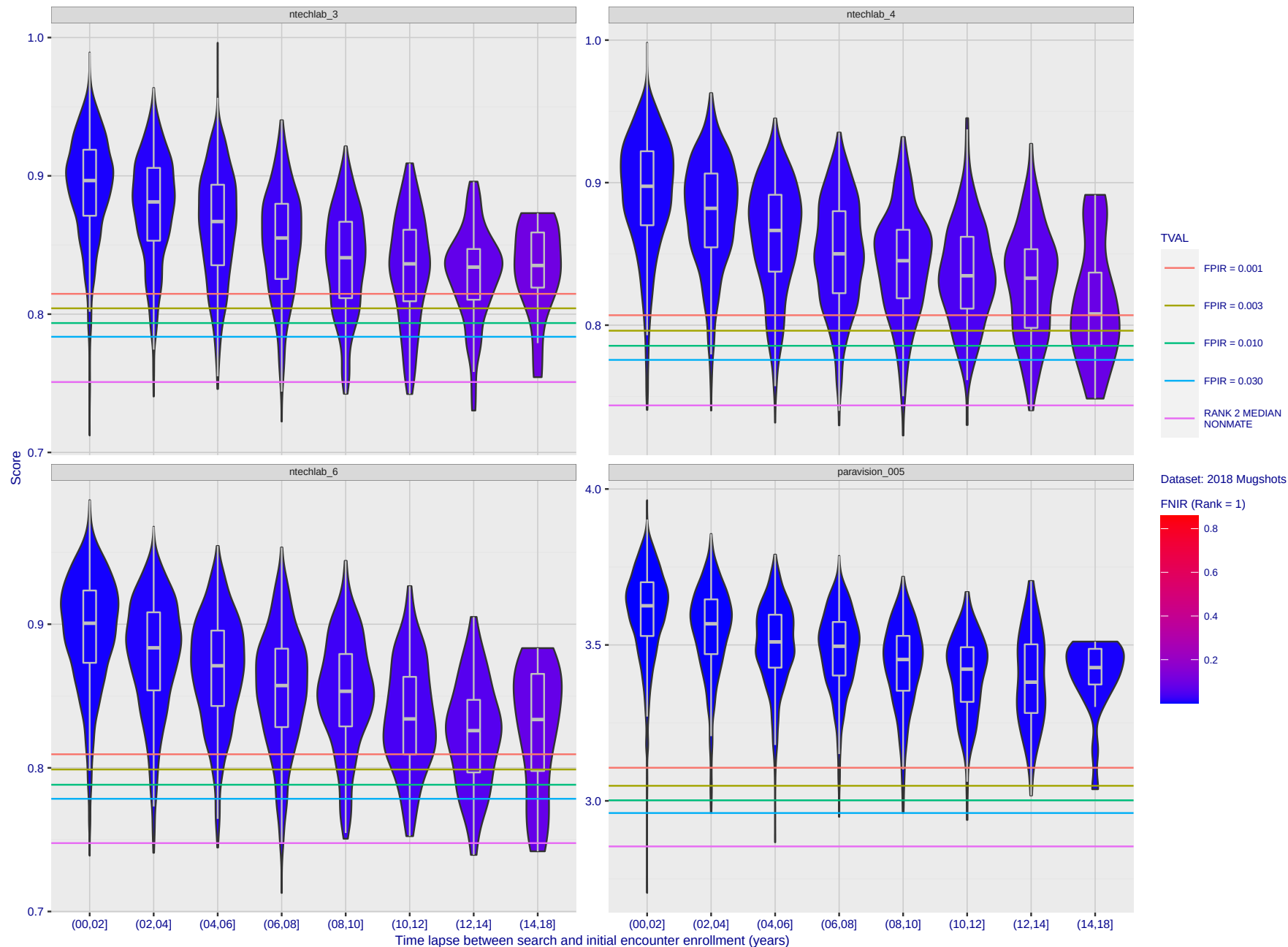


Figure 133: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

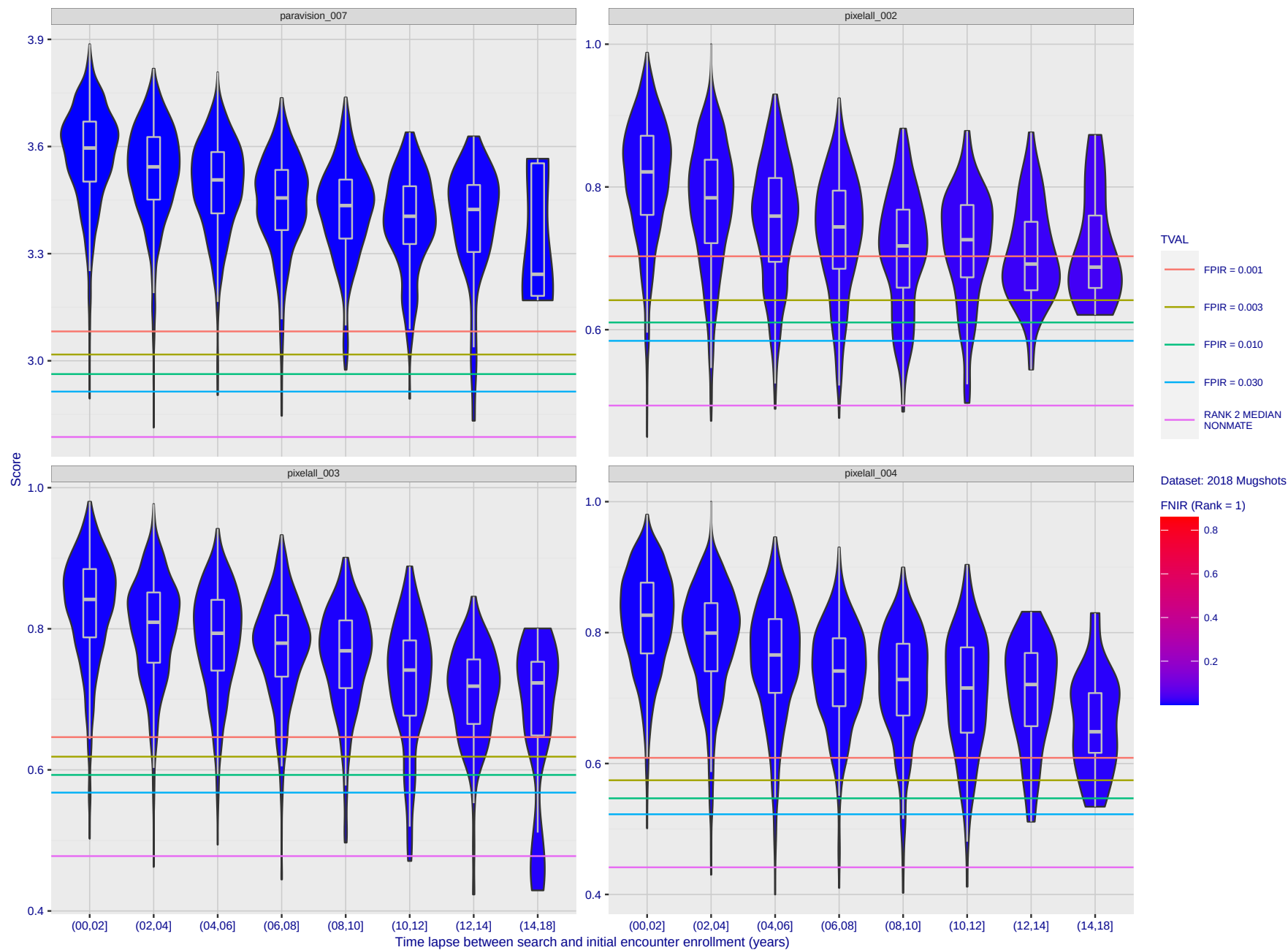


Figure 134: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04

FNIR(N, R, T) =
FPIR(N, T) =

False neg. identification rate
False pos. identification rate

N = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

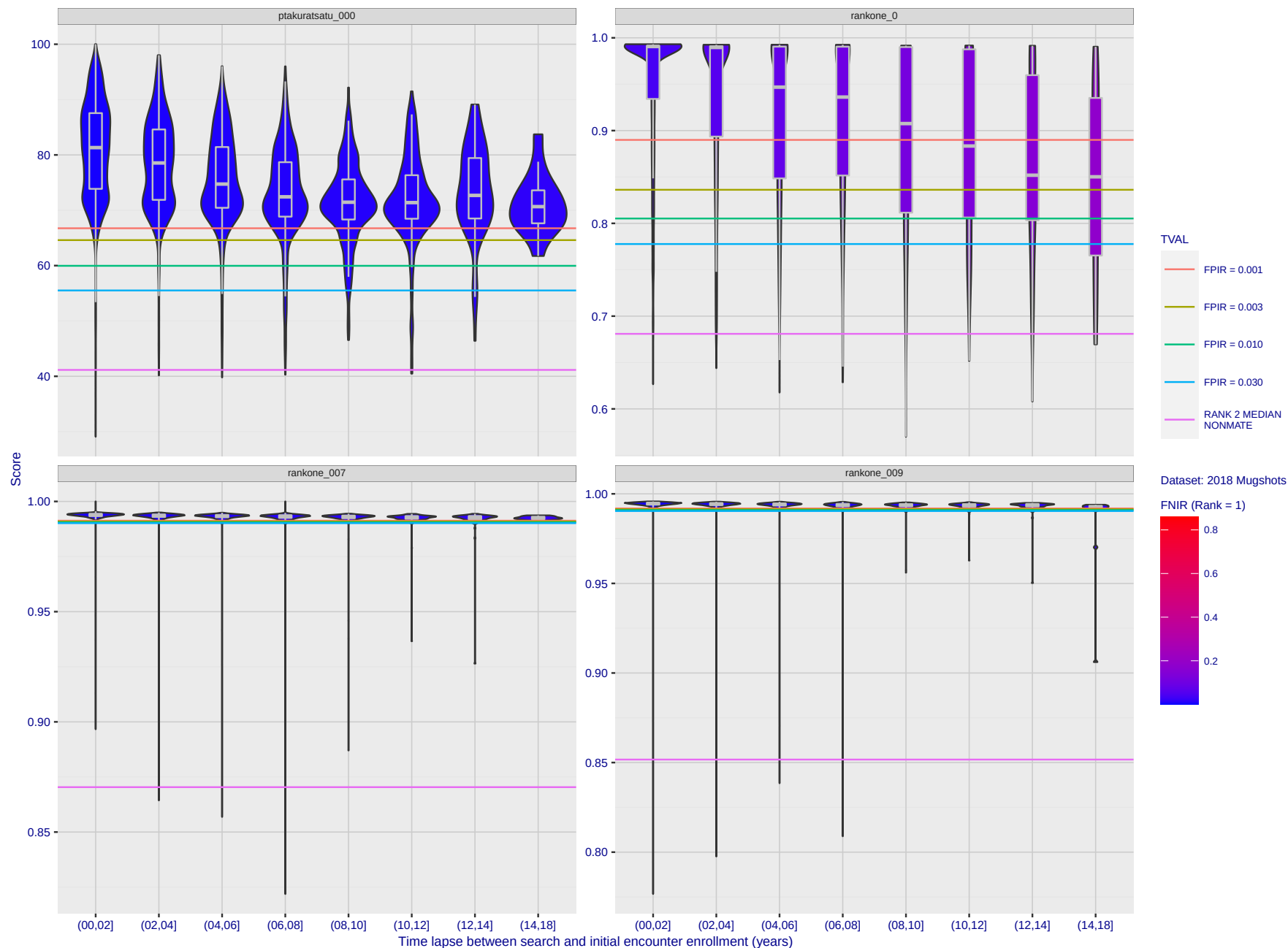


Figure 135: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

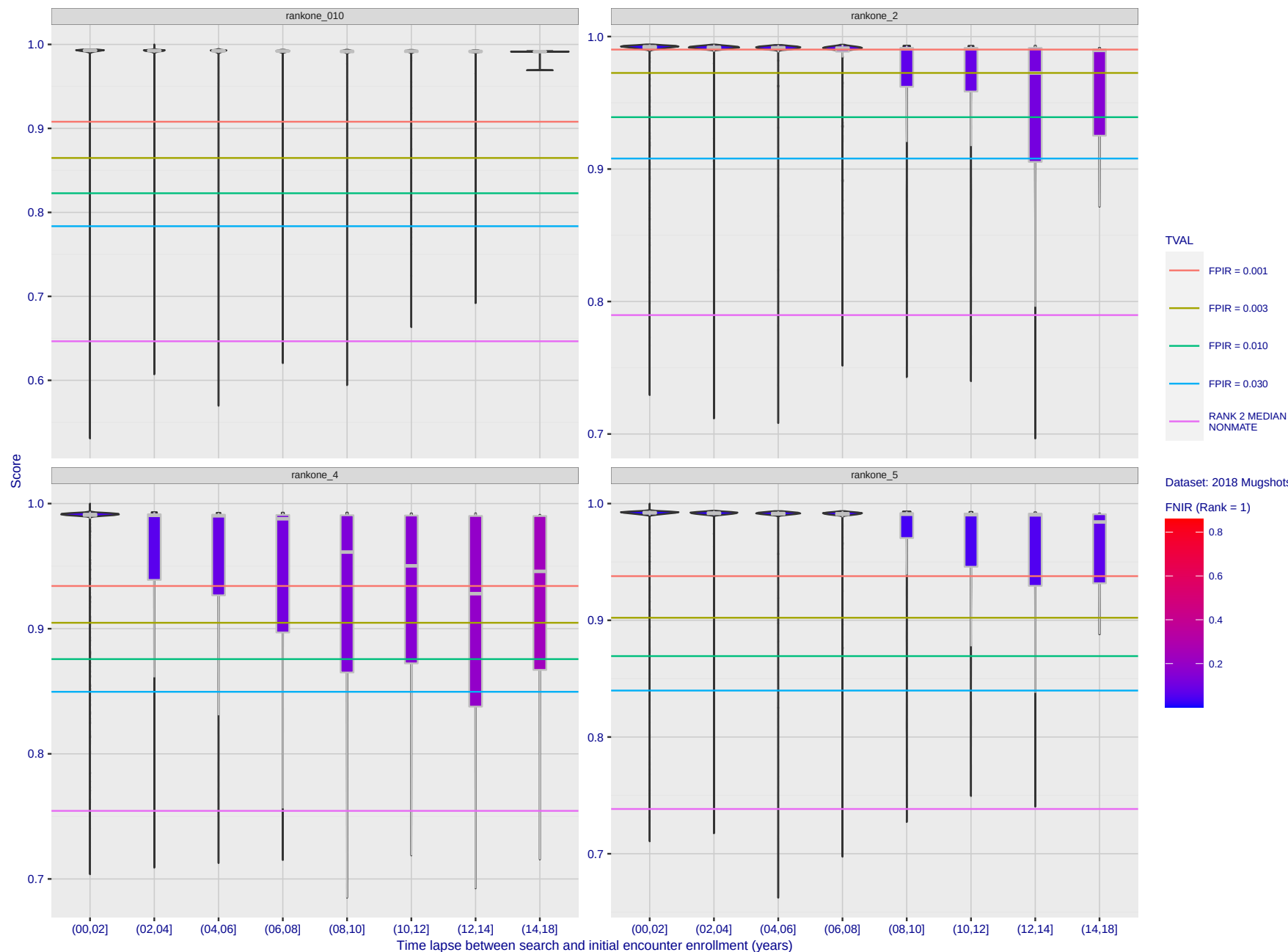


Figure 136: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04
FNIR(N, R, T) =
FPIR(N, T) =
False neg. identification rate
False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

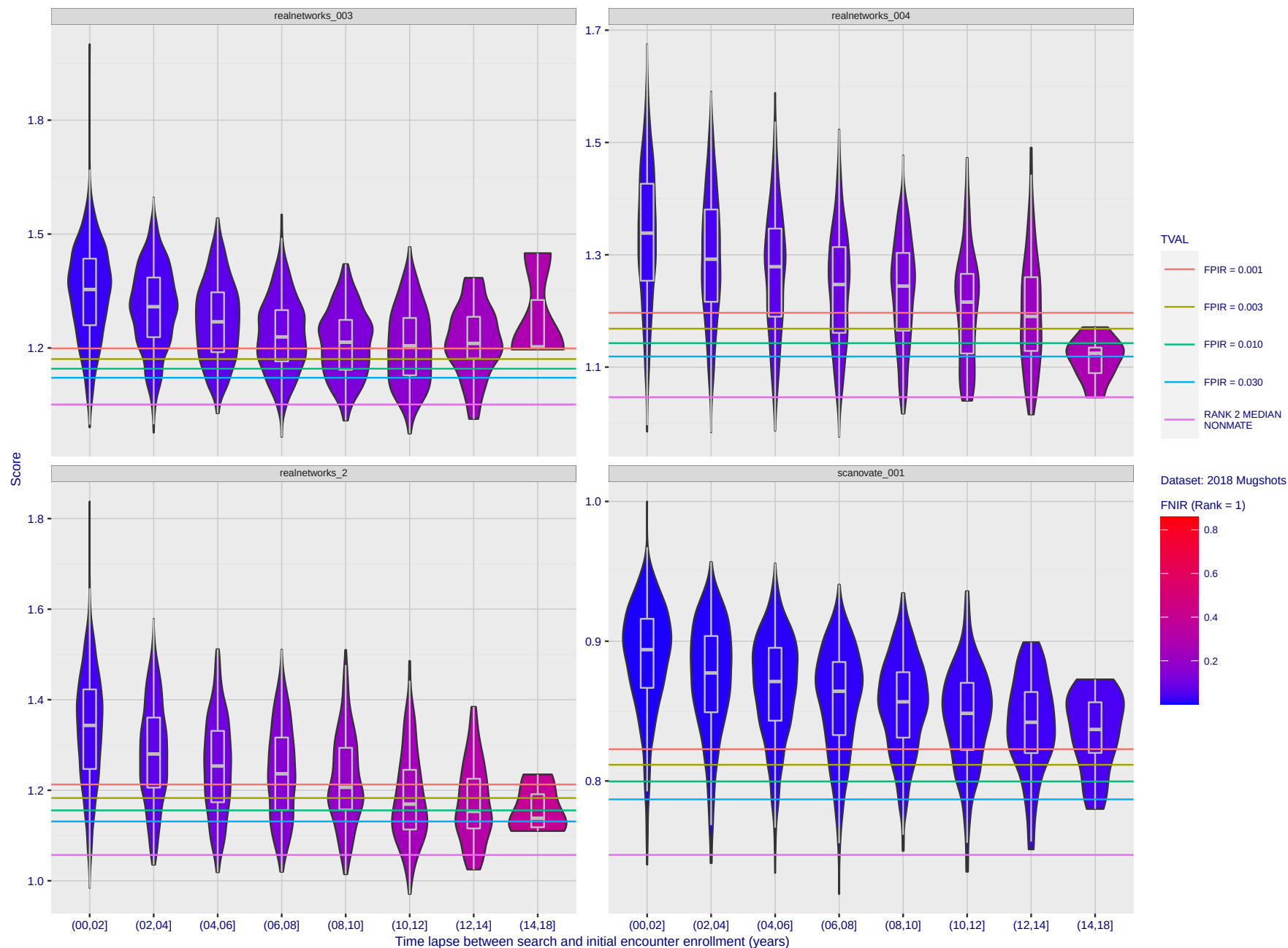


Figure 137: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

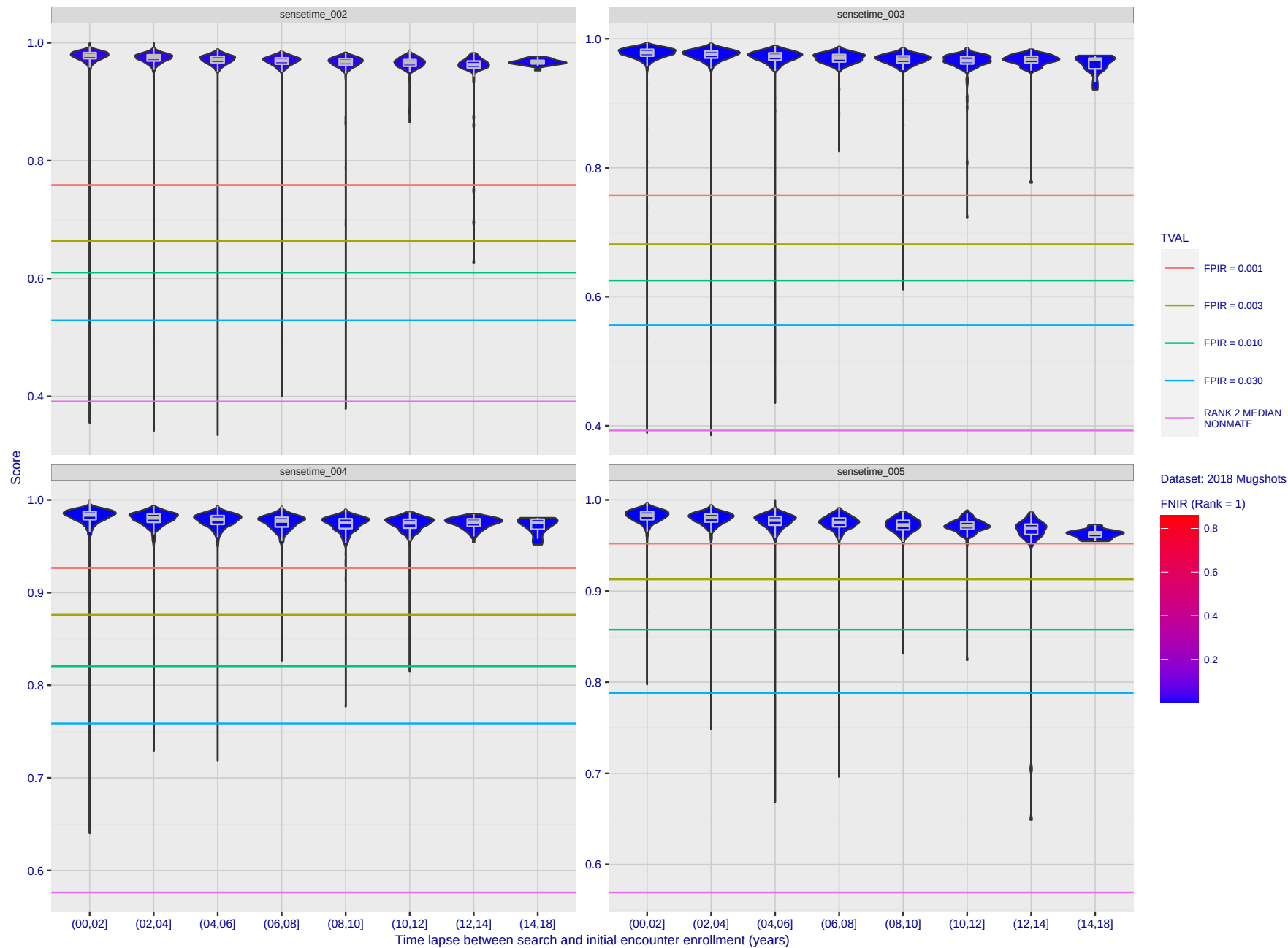


Figure 138: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed.** The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04
11:49:04

FNIR(N, R, T) =
FPIR(N, T) =

False neg. identification rate
False pos. identification rate

N = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

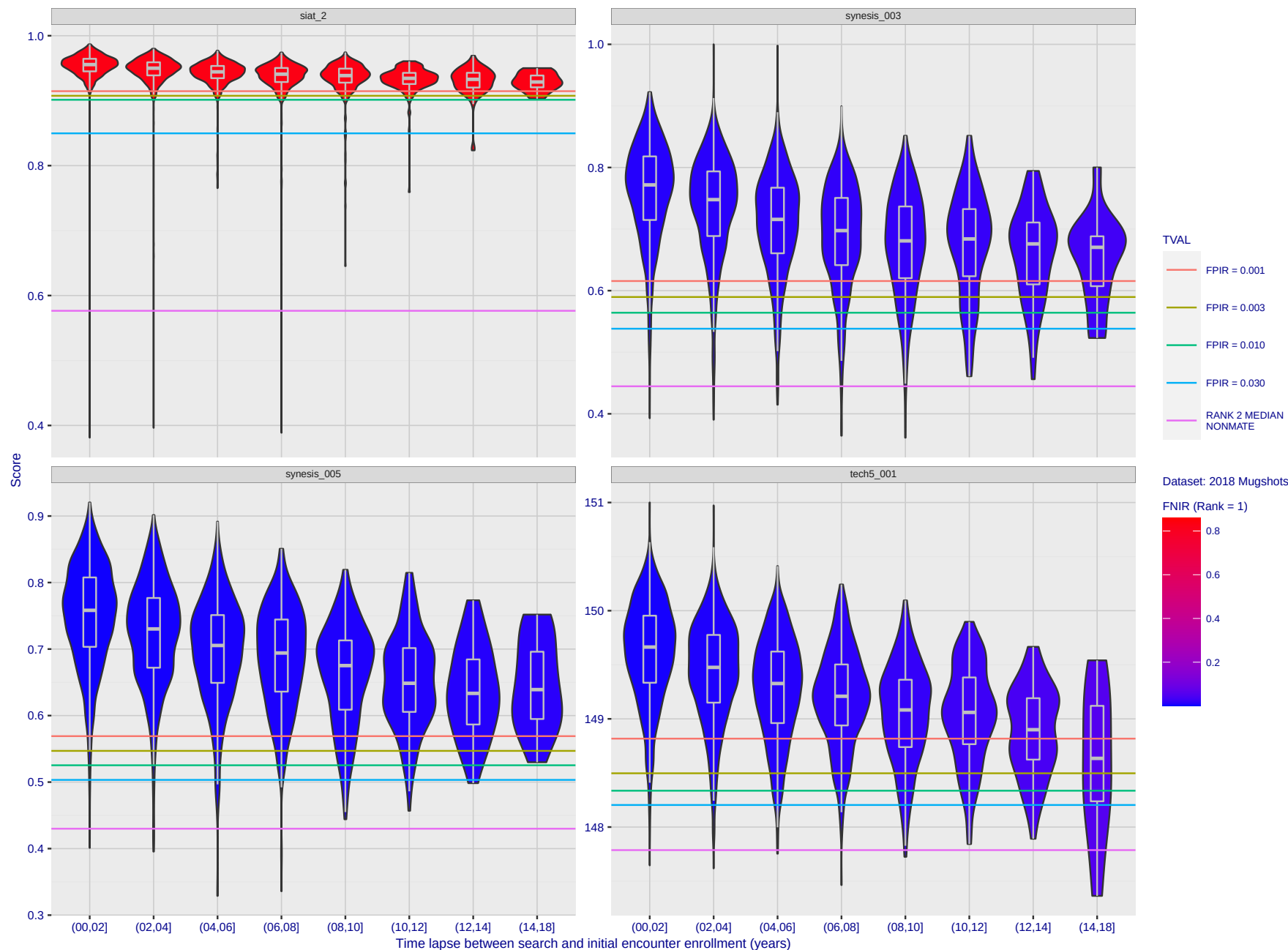


Figure 139: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

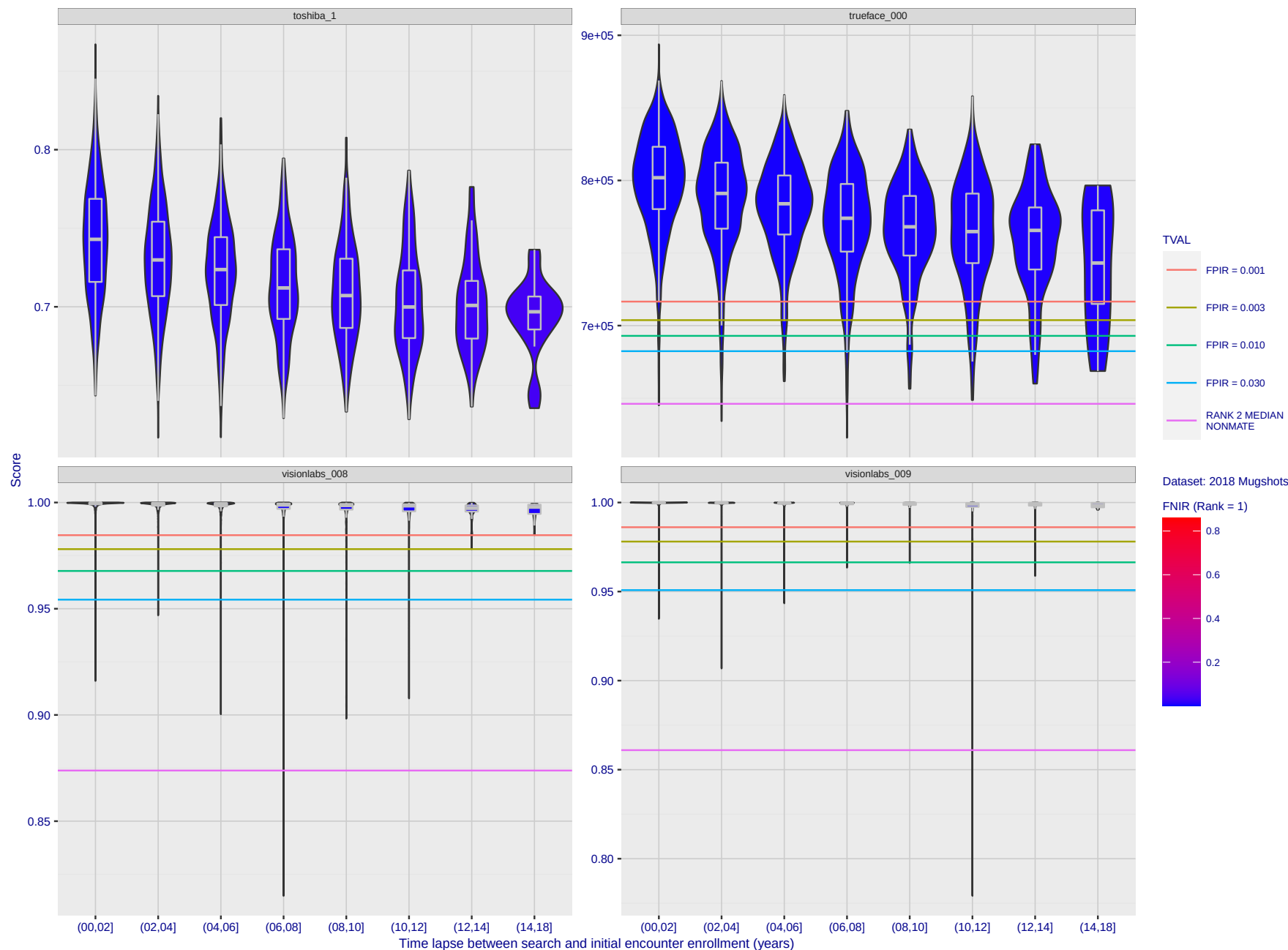


Figure 140: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04 11:49:04 FNIR(N, R, T) = False neg. identification rate N = Num. enrolled subjects T = Threshold T = 0 → Investigation FPIR(N, T) = False pos. identification rate R = Num. candidates examined T > 0 → Identification

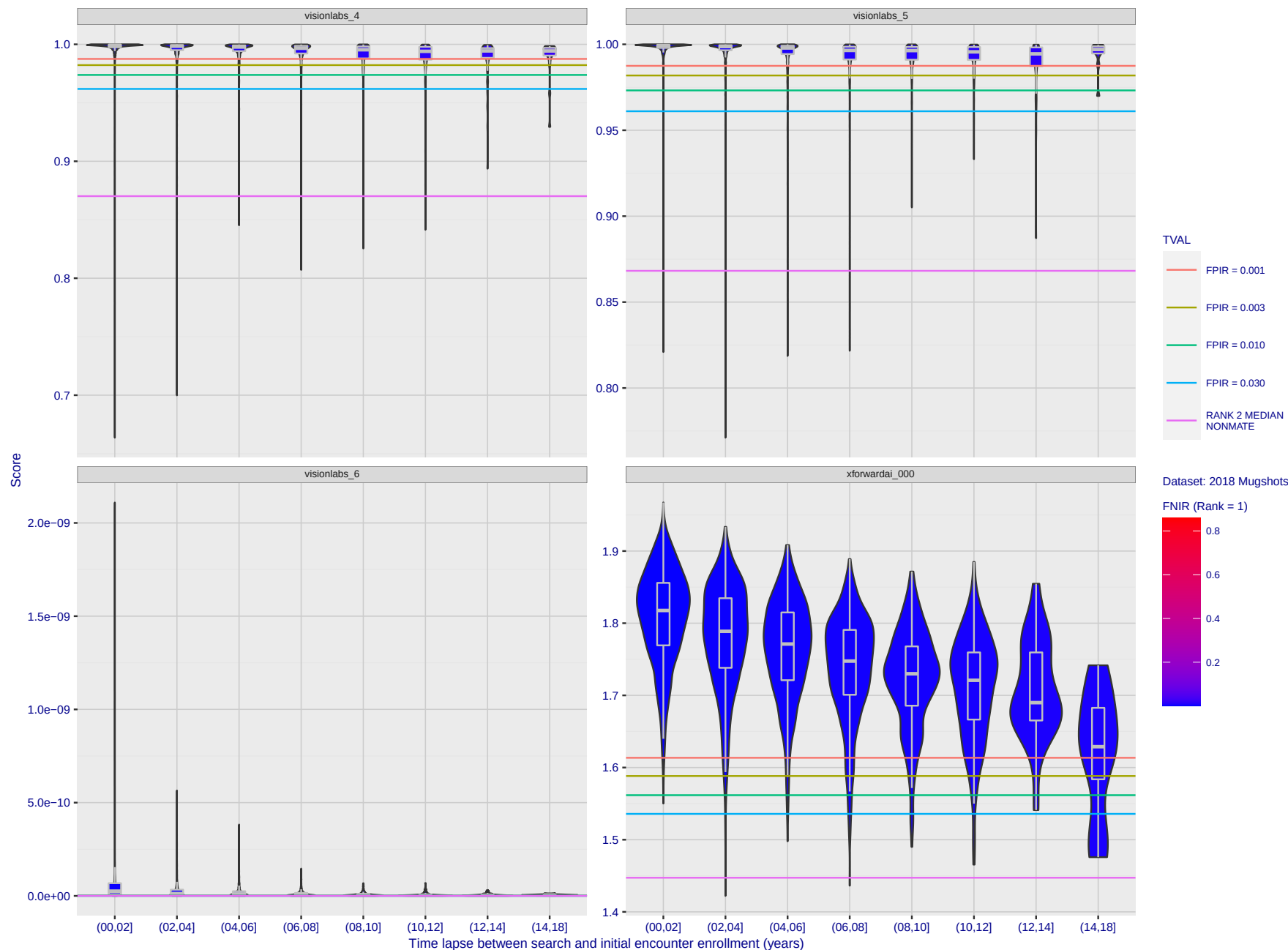


Figure 141: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

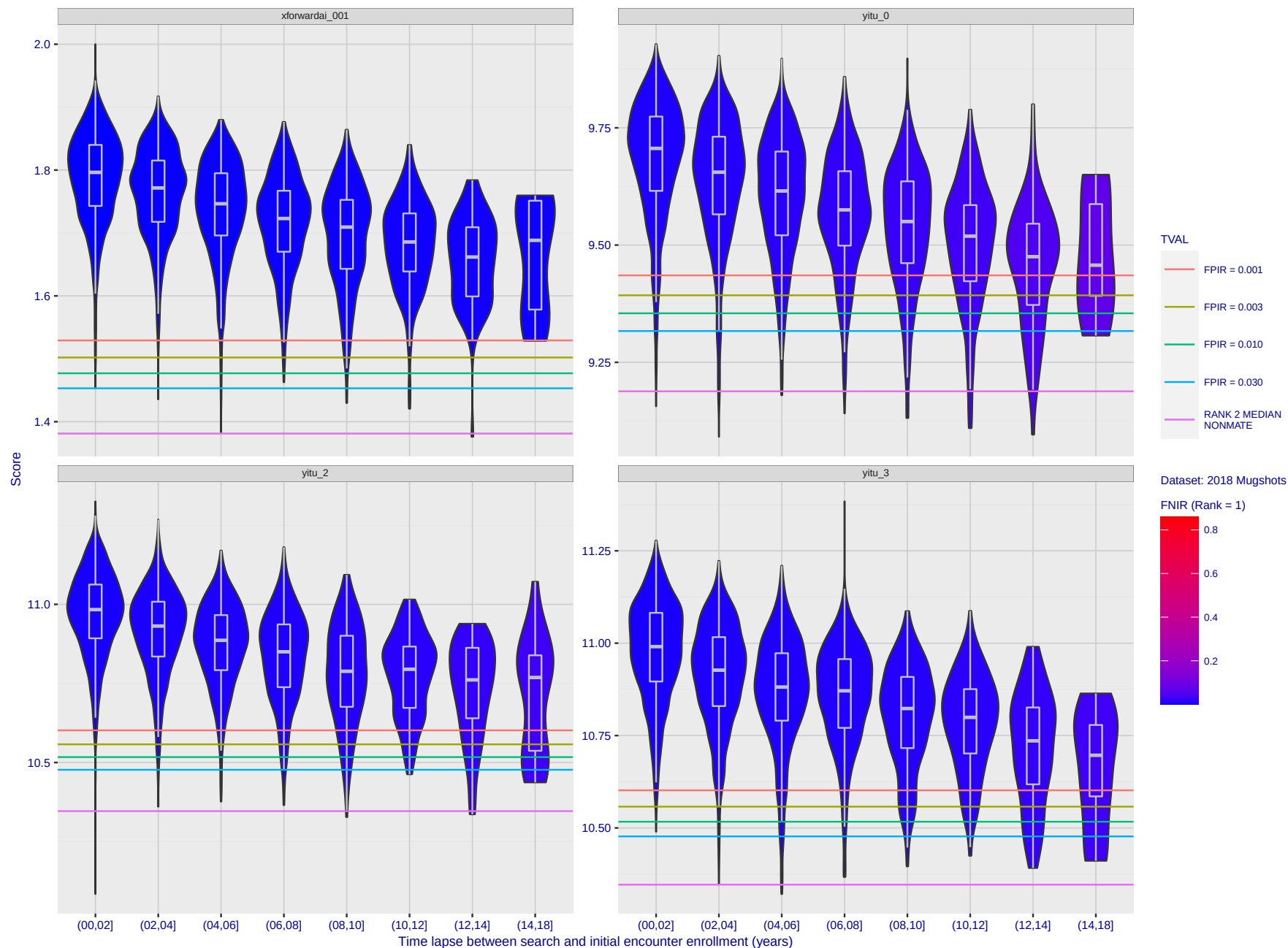


Figure 142: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

2021/03/04 11:49:04
 FNIR(N, R, T) =
 FPIR(N, T) =
 False neg. identification rate
 False pos. identification rate
 N = Num. enrolled subjects
 R = Num. candidates examined
 T = Threshold
 T = 0 → Investigation
 T > 0 → Identification

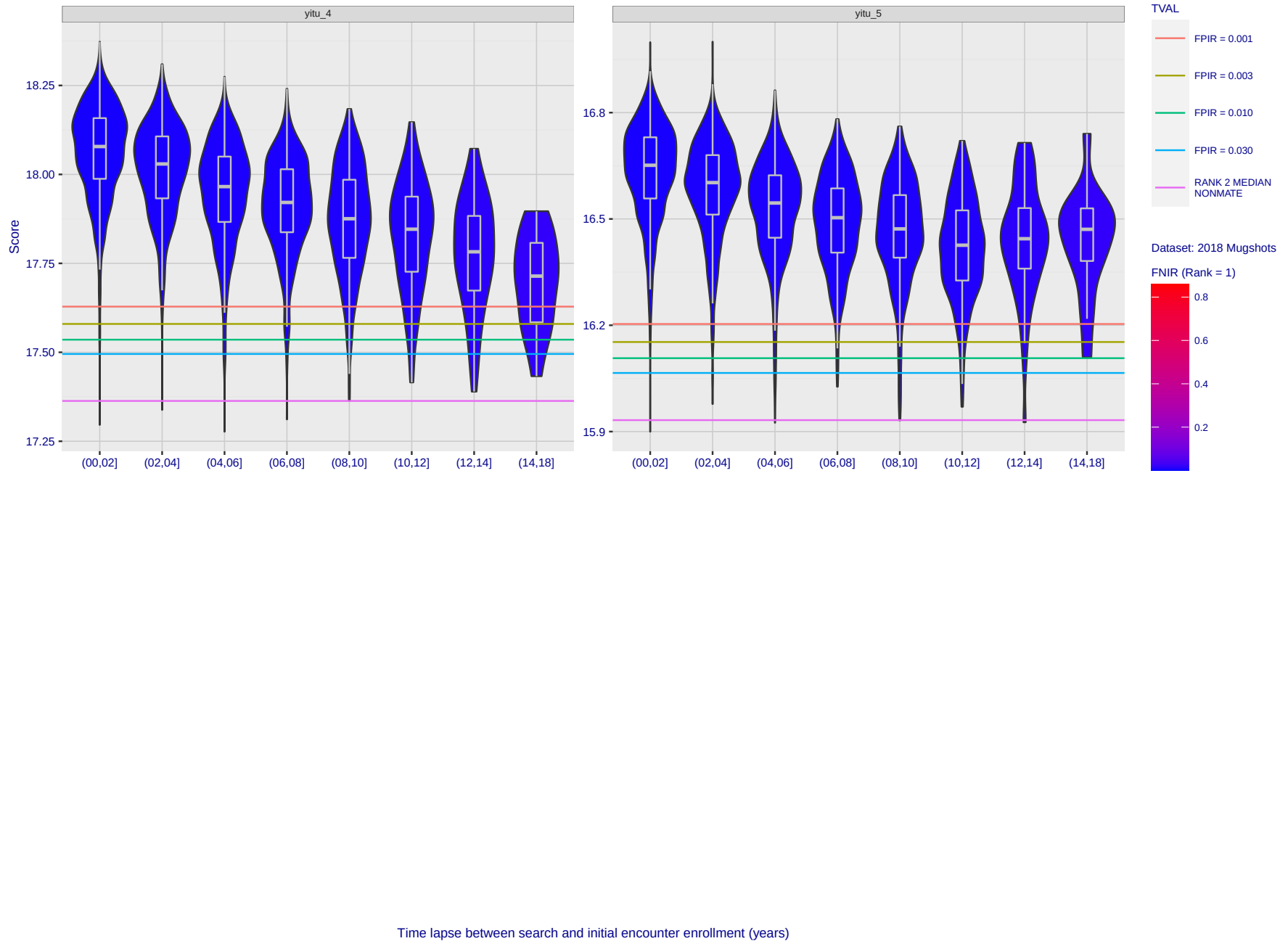


Figure 143: [FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed. The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.

Appendix C Effect of enrolling multiple images

This publication is available free of charge from: <https://doi.org/10.6028/NIST.IR.8271>

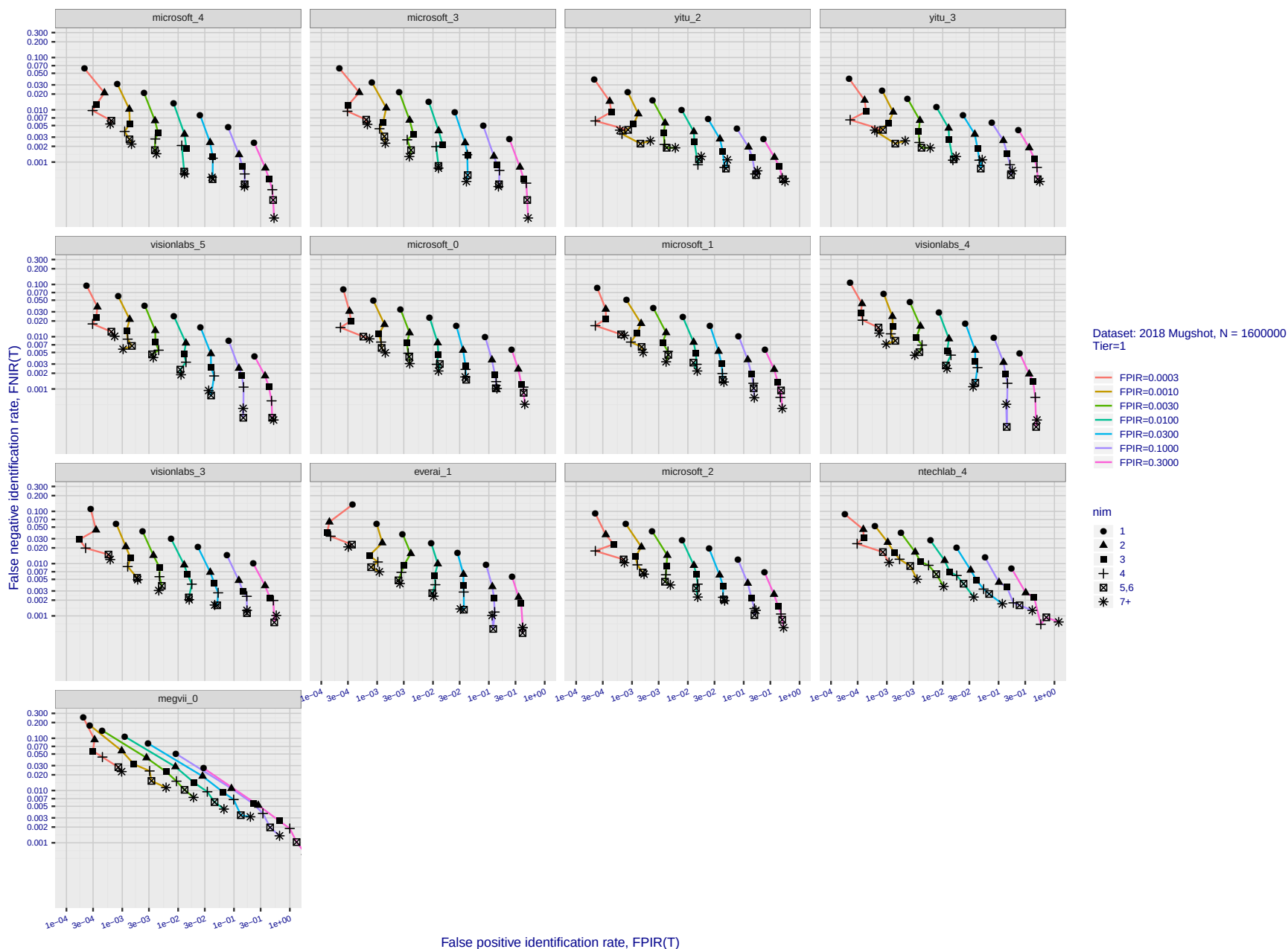


Figure 144: [FRVT-2018 Mugshot Dataset] Effect of enrolling multiple images for each identity. The plot shows an identification miss rates vs. false positive rates, at seven operating thresholds. The enrolled population size is fixed. The images are enrolled with lifetime-consolidation - see section 2.3.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 → Investigation
T > 0 → Identification

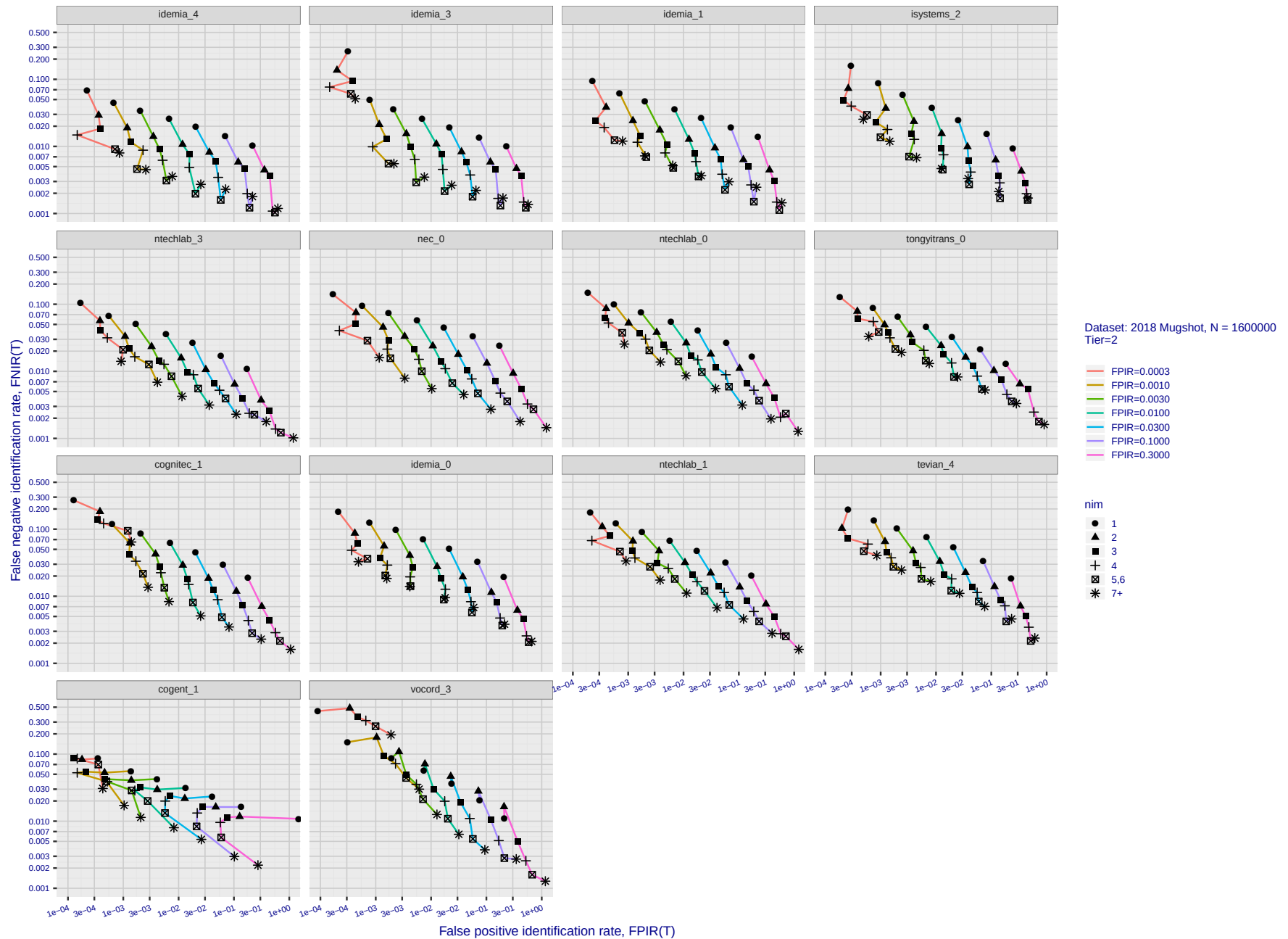


Figure 145: [FRVT-2018 Mugshot Dataset] Effect of enrolling multiple images for each identity. The plot shows an identification miss rates vs. false positive rates, at seven operating thresholds. The enrolled population size is fixed. The images are enrolled with lifetime-consolidation - see section 2.3.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

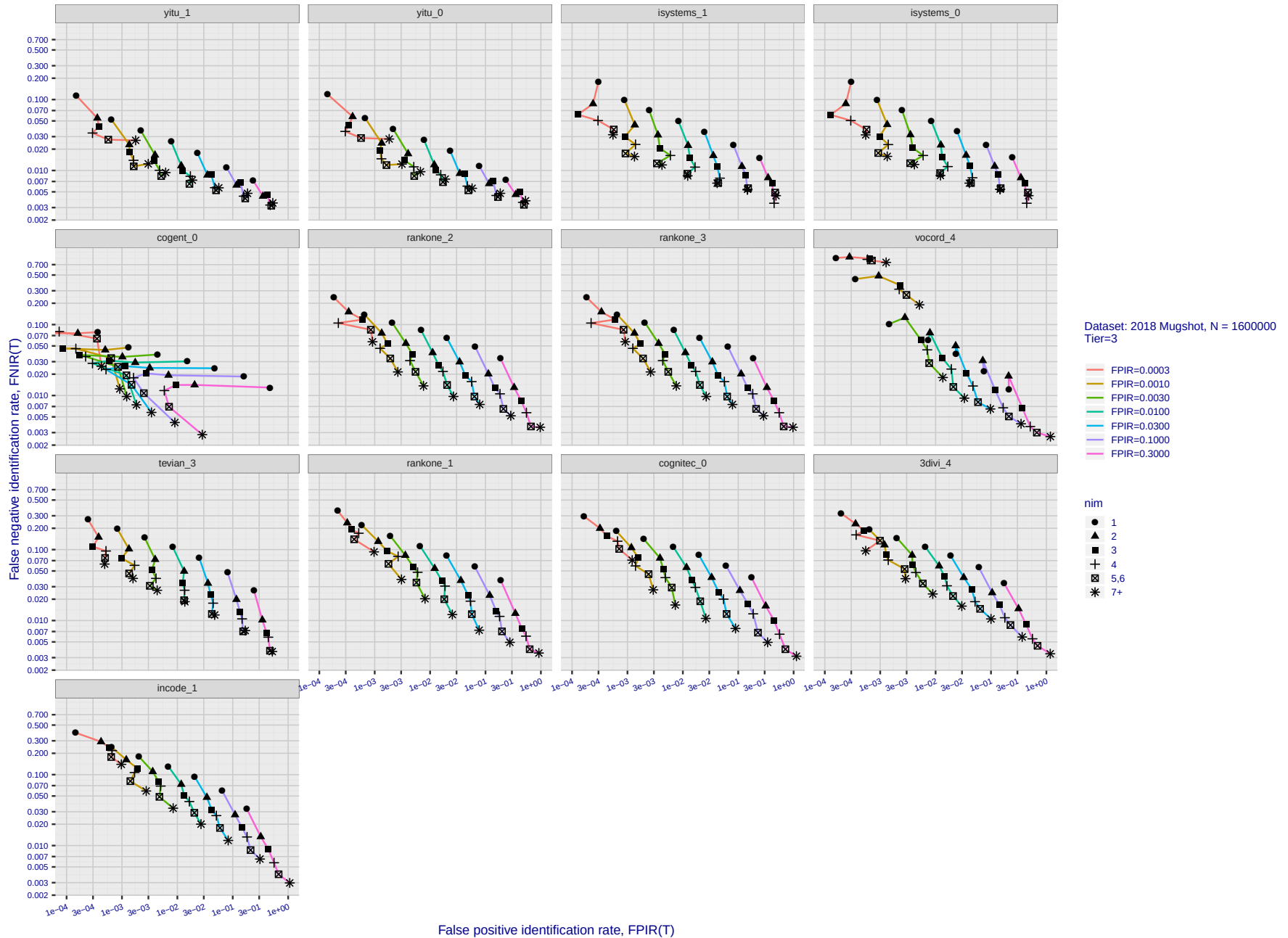
T = 0 → Investigation
T > 0 → Identification

Figure 146: [FRVT-2018 Mugshot Dataset] Effect of enrolling multiple images for each identity. The plot shows an identification miss rates vs. false positive rates, at seven operating thresholds. The enrolled population size is fixed. The images are enrolled with lifetime-consolidation - see section 2.3.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

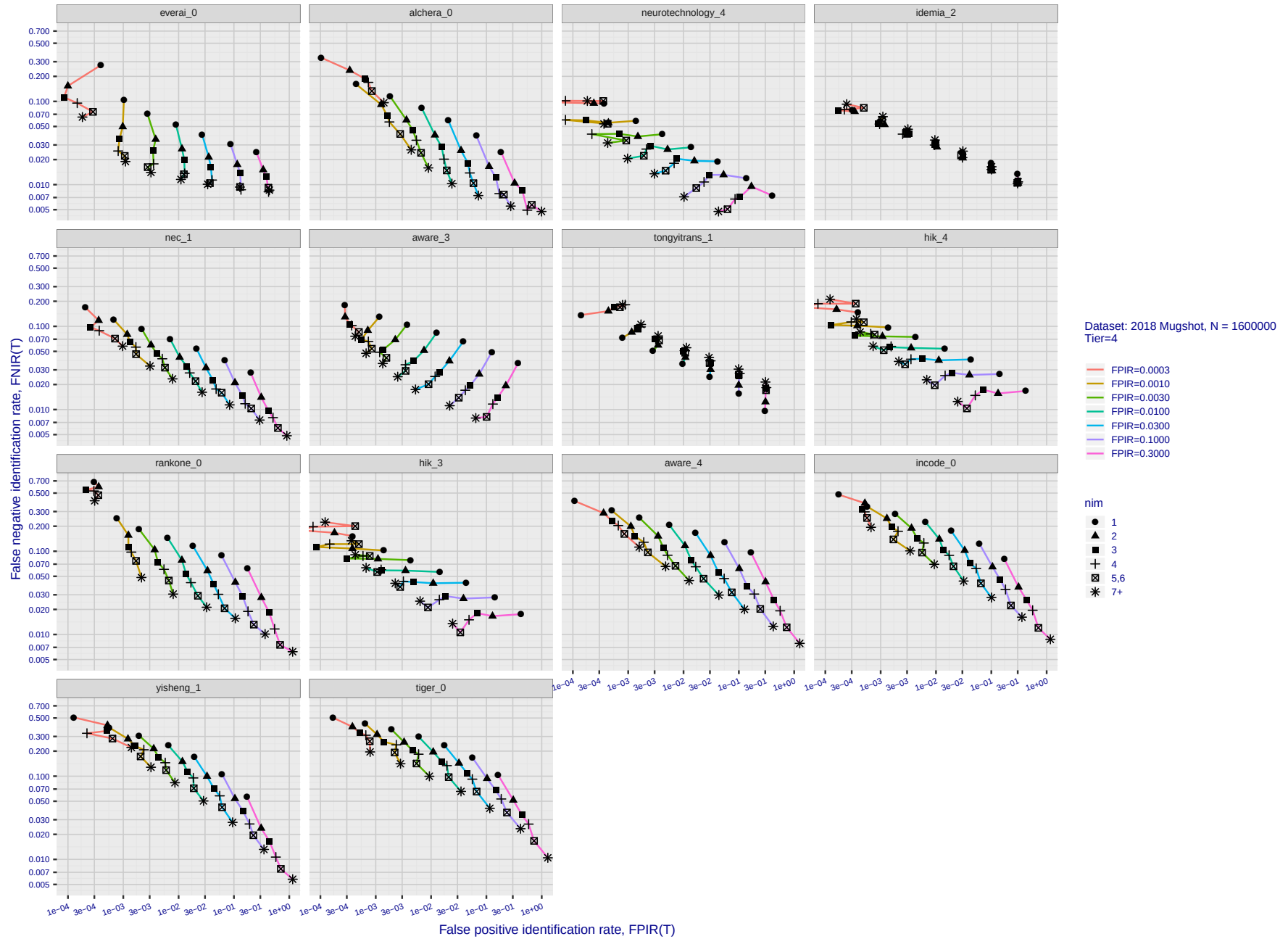
T = 0 → Investigation
T > 0 → Identification

Figure 147: [FRVT-2018 Mugshot Dataset] Effect of enrolling multiple images for each identity. The plot shows an identification miss rates vs. false positive rates, at seven operating thresholds. The enrolled population size is fixed. The images are enrolled with lifetime-consolidation - see section 2.3.

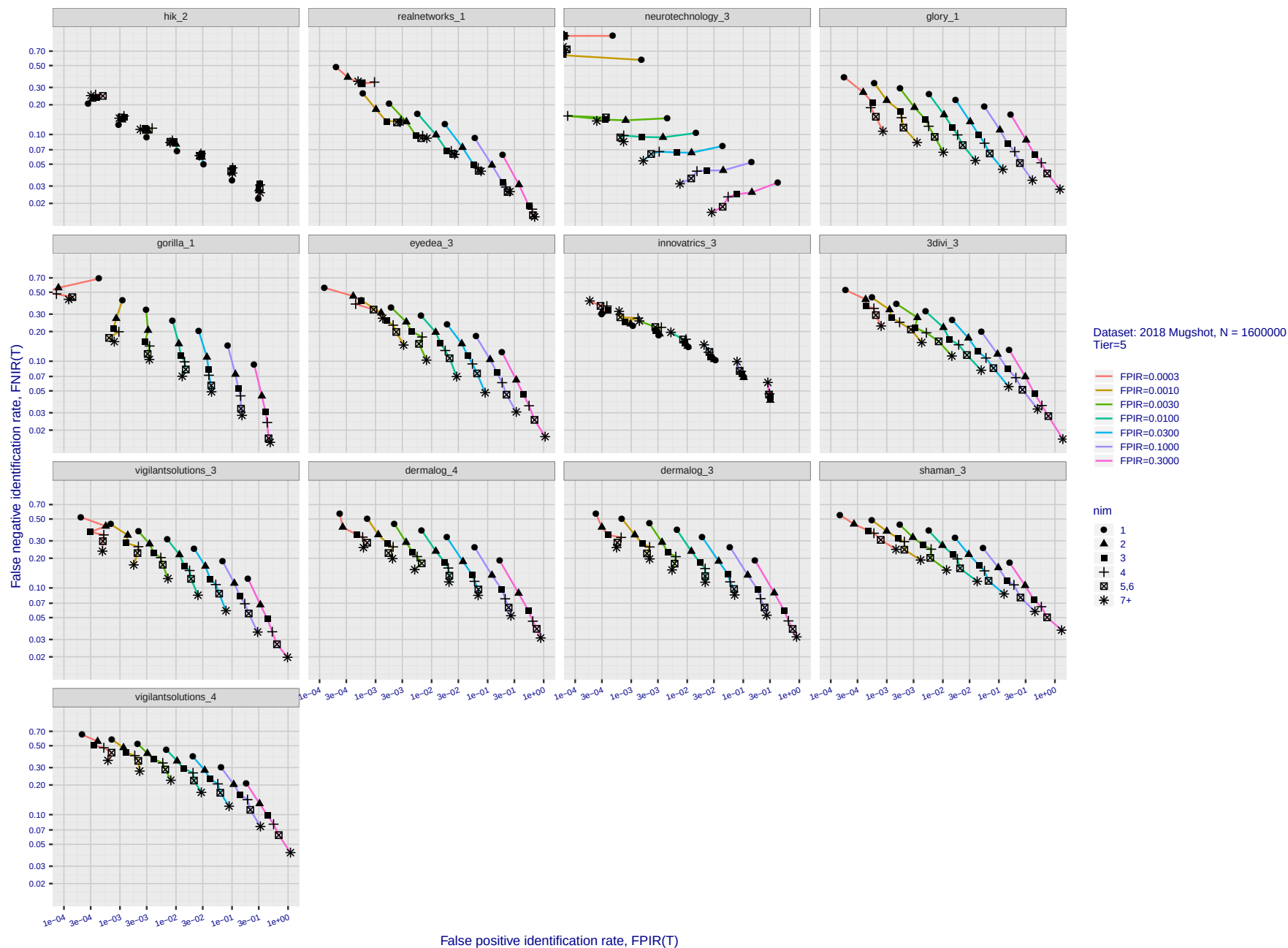


Figure 148: [FRVT-2018 Mugshot Dataset] Effect of enrolling multiple images for each identity. The plot shows an identification miss rates vs. false positive rates, at seven operating thresholds. The enrolled population size is fixed. The images are enrolled with lifetime-consolidation - see section 2.3.

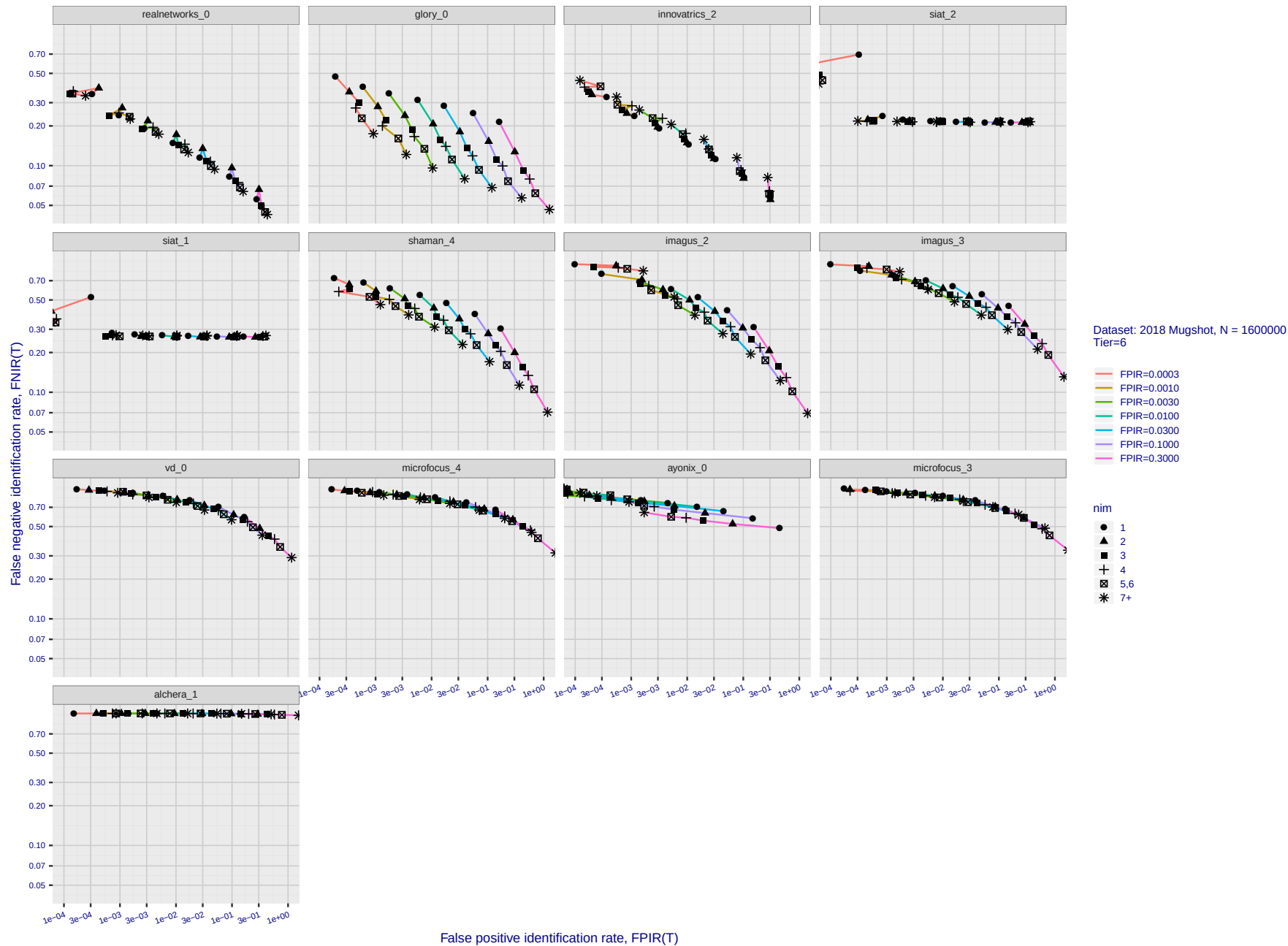


Figure 149: [FRVT-2018 Mugshot Dataset] Effect of enrolling multiple images for each identity. The plot shows an identification miss rates vs. false positive rates, at seven operating thresholds. The enrolled population size is fixed. The images are enrolled with lifetime-consolidation - see section 2.3.

Appendix D Accuracy with poor quality webcam images

This publication is available free of charge from: <https://doi.org/10.6028/NIST.IR.8271>

2021/03/04 11:49:04	FNIR(N, R, T) = FPIR(N, T) =	False neg. identification rate False pos. identification rate	N = Num. enrolled subjects R = Num. candidates examined	T = Threshold	T = 0 → Investigation T > 0 → Identification
------------------------	---------------------------------	--	--	---------------	---

2021/03/04
11:49:04FNIR(N, R, T) =
FPR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

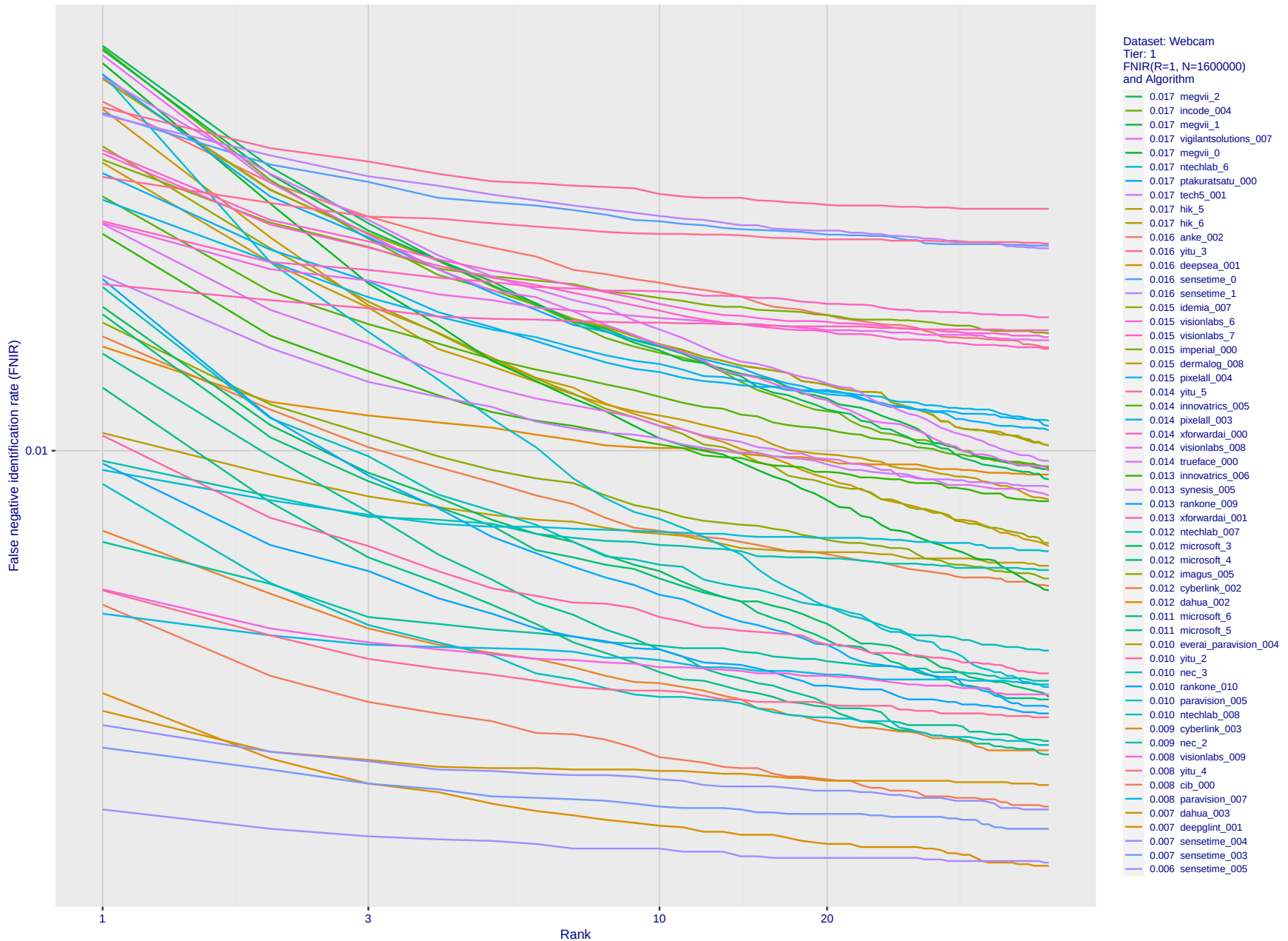
T = 0 → Investigation
T > 0 → Identification

Figure 150: [Webcam Dataset] Identification miss rates vs. rank. The results apply to cross-domain recognition in which webcams are searched against enrolled mugshots. The FNIR values are higher than those for mugshot-mugshot identification due to low image resolution, lighting and less constrained subject pose in webcam images - see Figure 6.

2021/03/04
11:49:04FNIR(N, R, T) =
FPR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

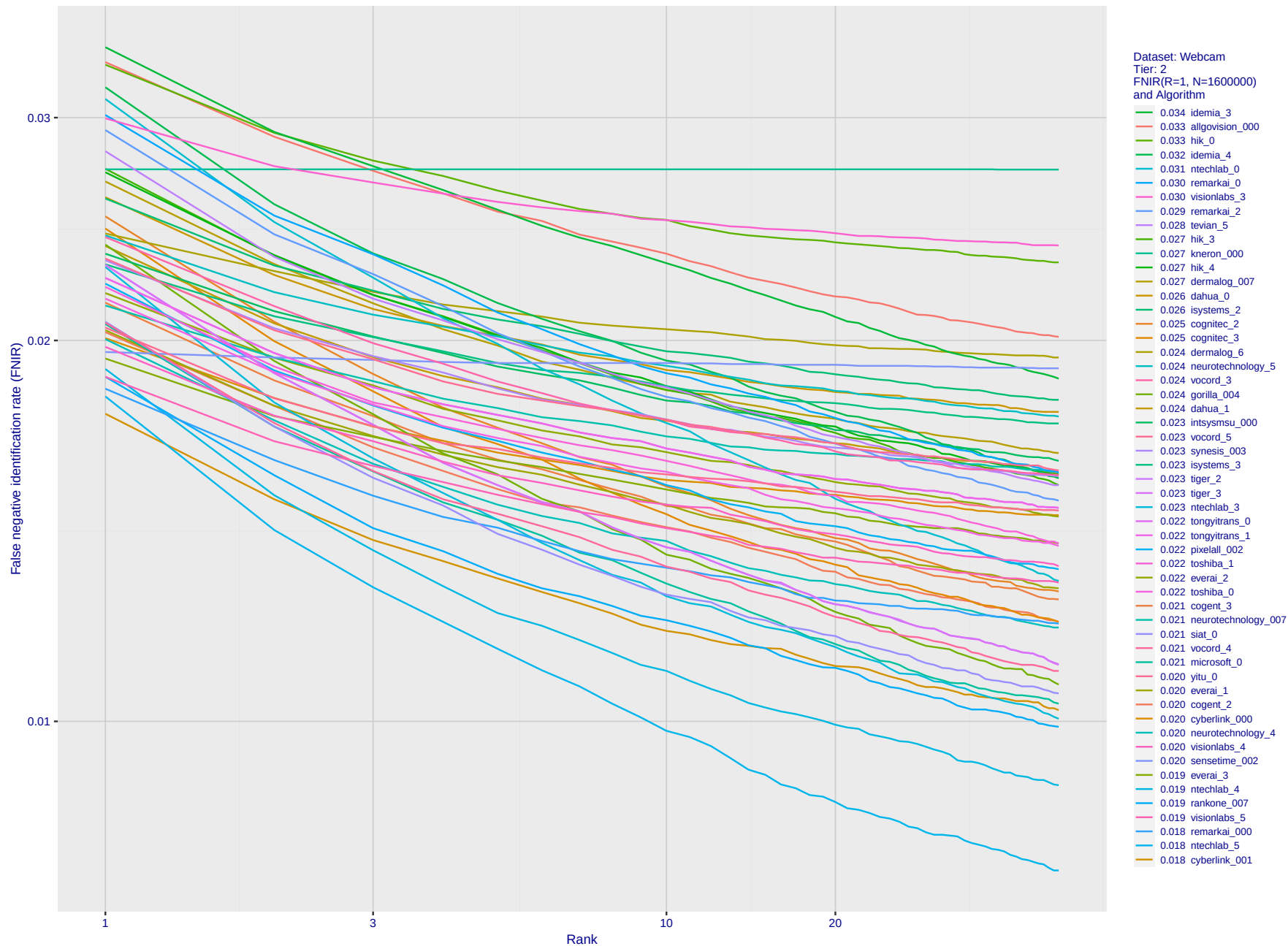
T = 0 → Investigation
T > 0 → Identification

Figure 151: [Webcam Dataset] Identification miss rates vs. rank. The results apply to cross-domain recognition in which webcams are searched against enrolled mugshots. The FNIR values are higher than those for mugshot-mugshot identification due to low image resolution, lighting and less constrained subject pose in webcam images - see Figure 6.

2021/03/04
11:49:04FNIR(N, R, T) =
FPR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

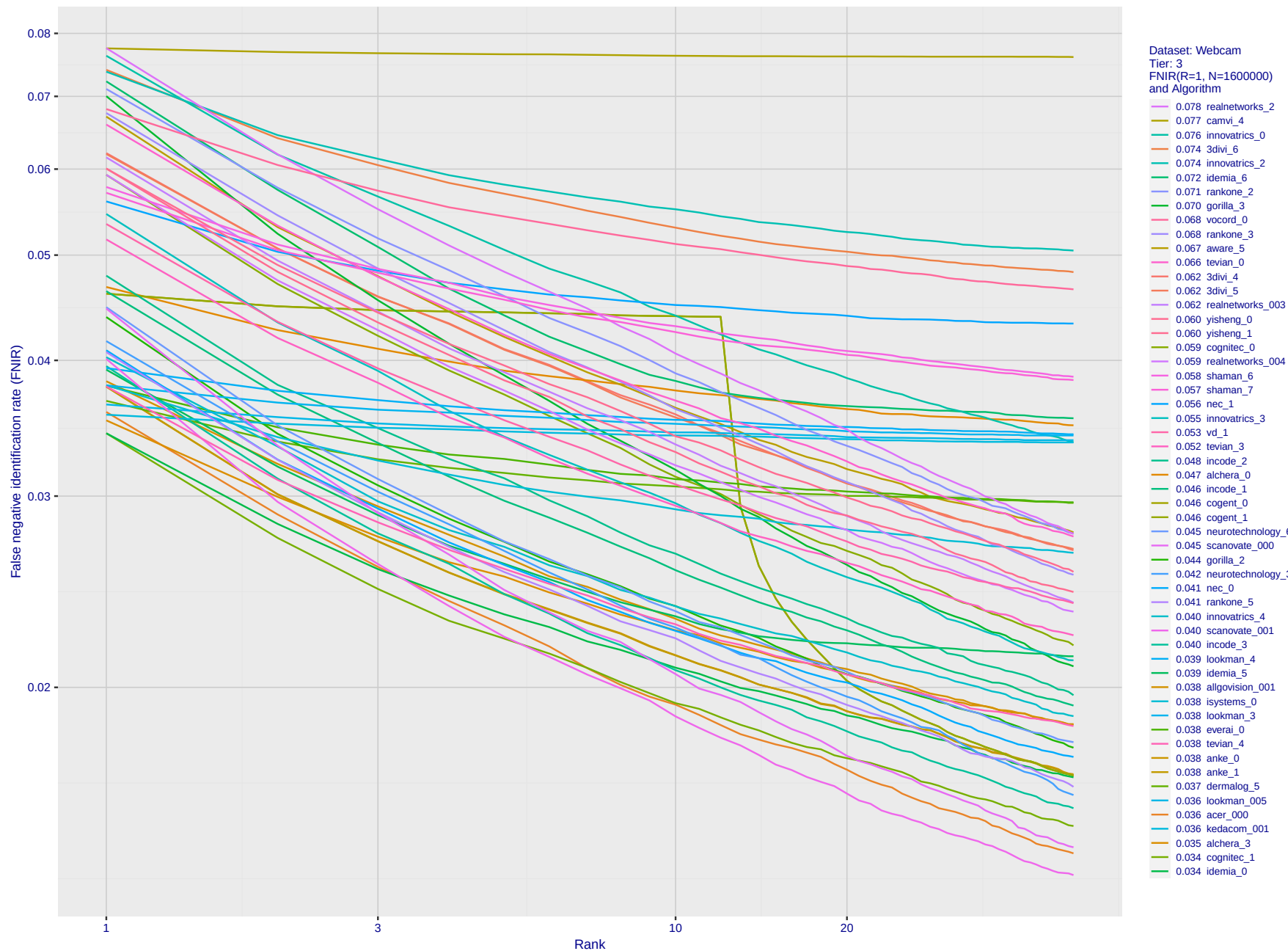
T = 0 → Investigation
T > 0 → Identification

Figure 152: [Webcam Dataset] Identification miss rates vs. rank. The results apply to cross-domain recognition in which webcams are searched against enrolled mugshots. The FNIR values are higher than those for mugshot-mugshot identification due to low image resolution, lighting and less constrained subject pose in webcam images - see Figure 6.

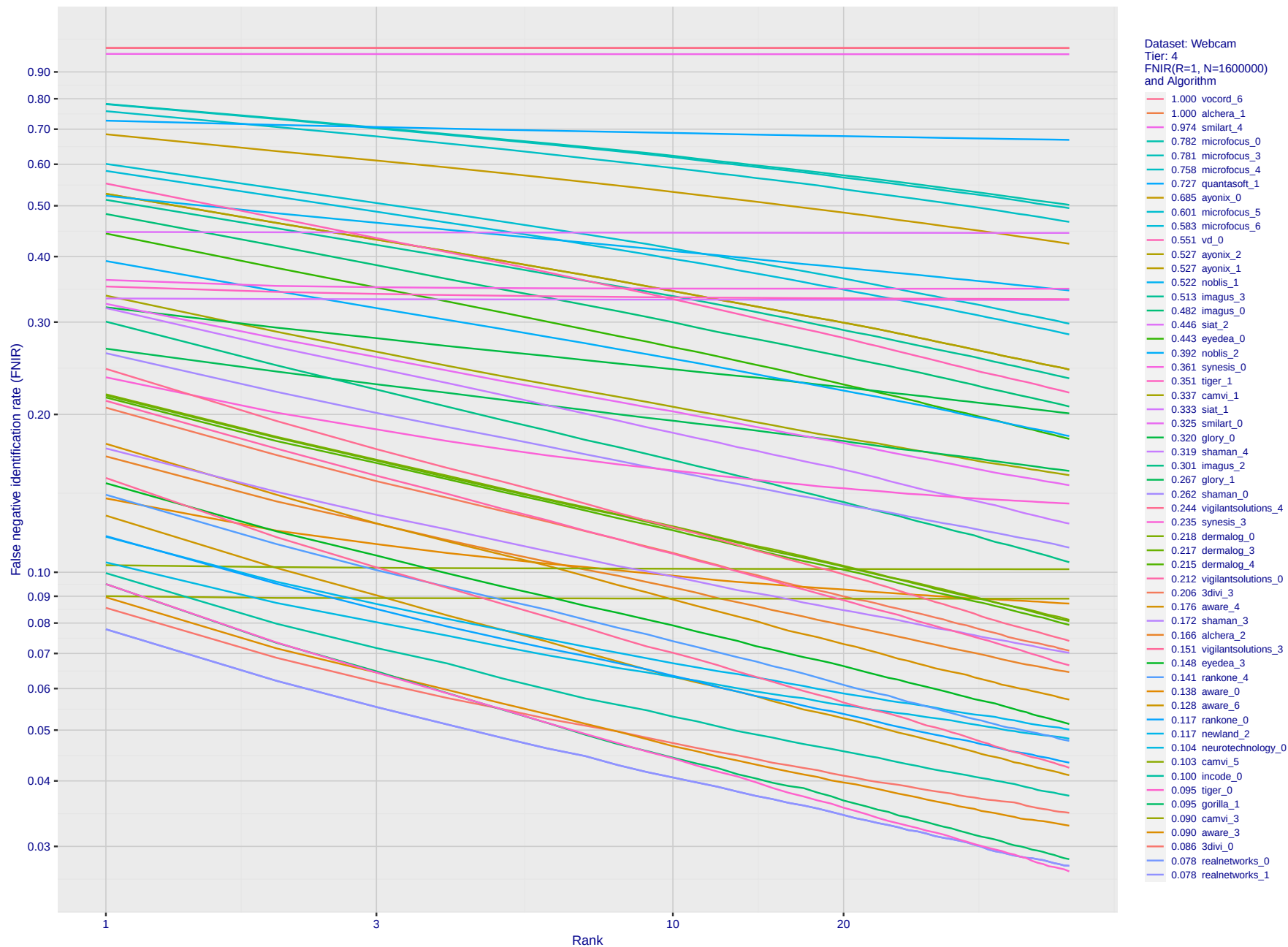


Figure 153: [Webcam Dataset] Identification miss rates vs. rank. The results apply to cross-domain recognition in which webcams are searched against enrolled mugshots. The FNIR values are higher than those for mugshot-mugshot identification due to low image resolution, lighting and less constrained subject pose in webcam images - see Figure 6.

2021/03/04 11:49:04	FNIR(N, R, T) = FPIR(N, T) =	False neg. identification rate False pos. identification rate	N = Num. enrolled subjects R = Num. candidates examined	T = Threshold	T = 0 → Investigation T > 0 → Identification
------------------------	---------------------------------	--	--	---------------	---

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

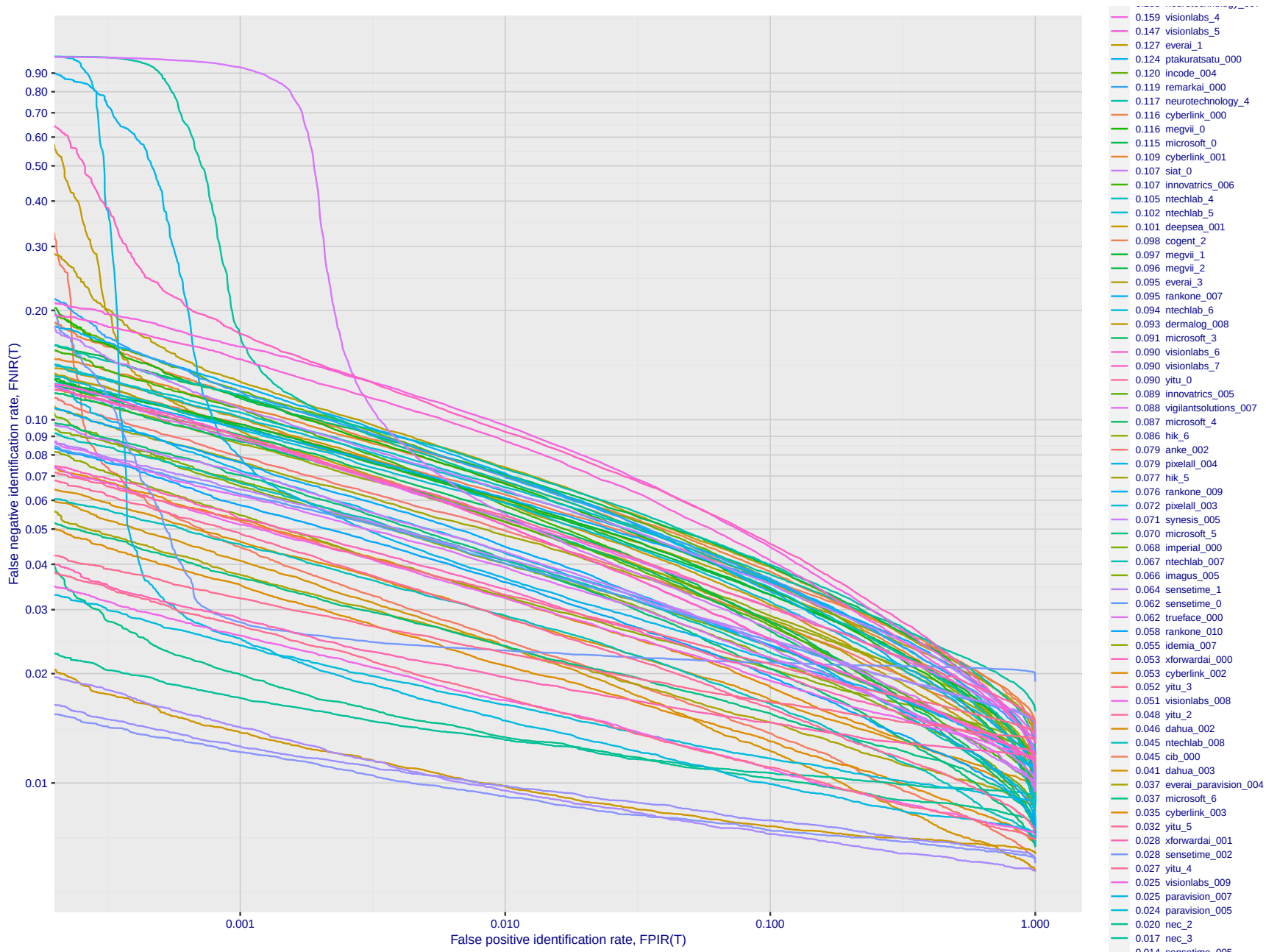
T = 0 → Investigation
T > 0 → Identification

Figure 154: [Webcam Dataset] Identification miss rates vs. false positive rates. The results apply to cross-domain recognition in which webcams are searched against enrolled mugshots. The FNIR values are higher than those for mugshot-mugshot identification due to low image resolution, lighting and less constrained subject pose in webcam images - see Figure 6.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

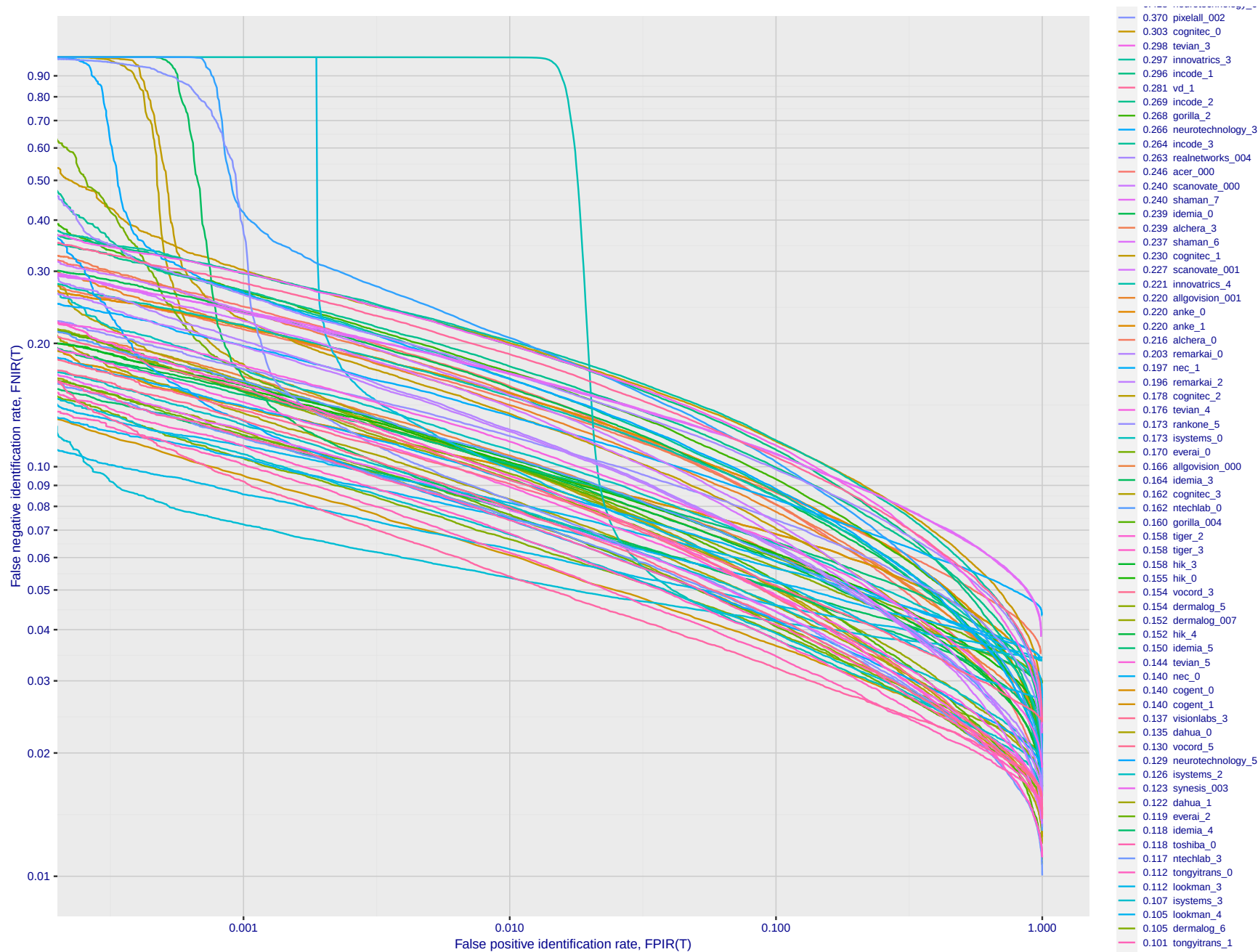
T = 0 → Investigation
T > 0 → Identification

Figure 155: **[Webcam Dataset] Identification miss rates vs. false positive rates.** The results apply to cross-domain recognition in which webcams are searched against enrolled mugshots. The FNIR values are higher than those for mugshot-mugshot identification due to low image resolution, lighting and less constrained subject pose in webcam images - see Figure 6.

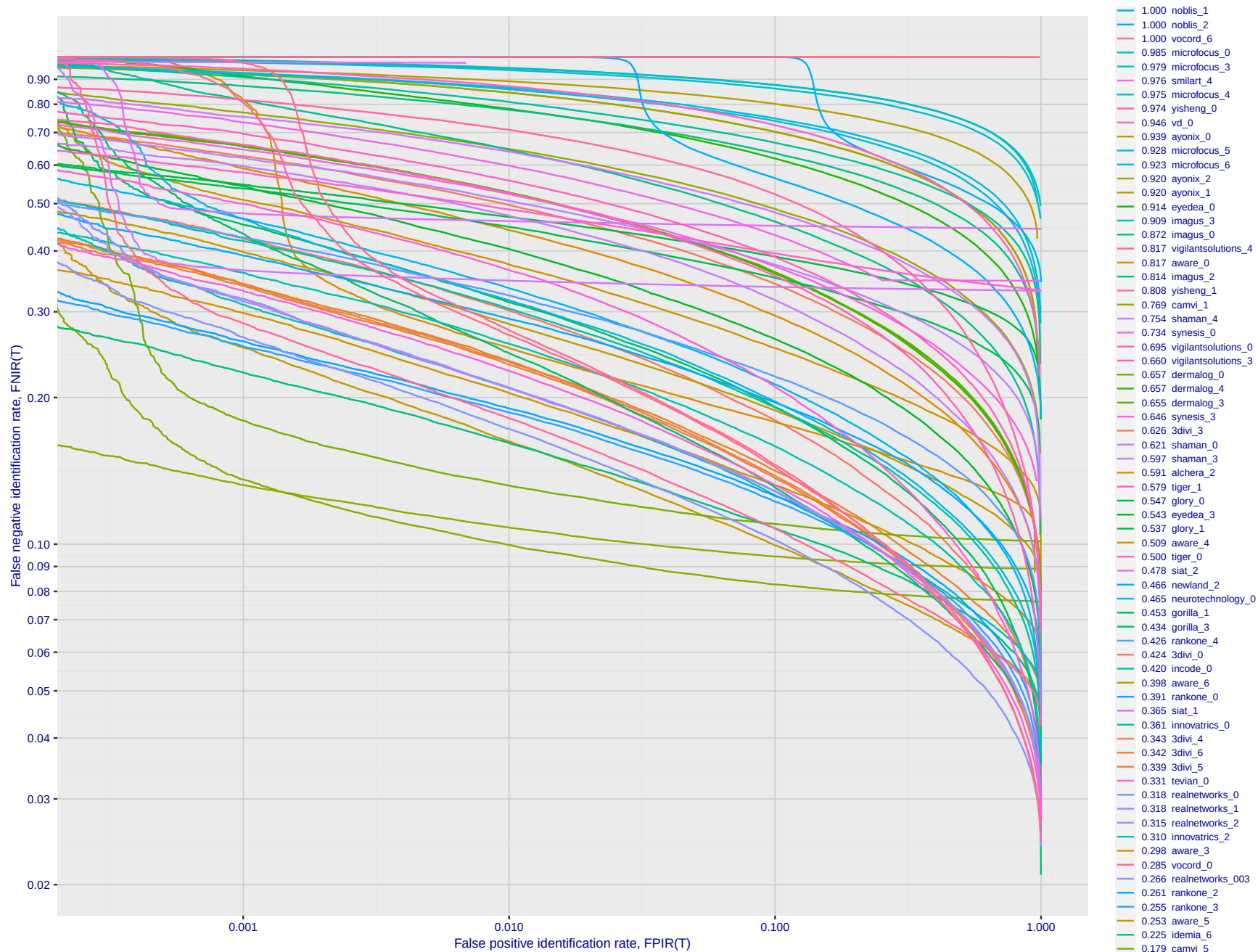


Figure 156: **[Webcam Dataset] Identification miss rates vs. false positive rates.** The results apply to cross-domain recognition in which webcams are searched against enrolled mugshots. The FNIR values are higher than those for mugshot-mugshot identification due to low image resolution, lighting and less constrained subject pose in webcam images - see Figure 6.

Appendix E Accuracy for profile-view to frontal recognition

Figures 157 - 159 gives accuracy results for searching 100 000 mated and 100 000 non-mated profile-view images against the same FRVT 2018 frontal enrollment dataset, N = 1 600 000, used in the main mugshot trials. This experiment corresponds to row-13 of Table 1. An example of profile-view image is given in Figure 7.

This publication is available free of charge from: <https://doi.org/10.6028/NIST.IR.8271>

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

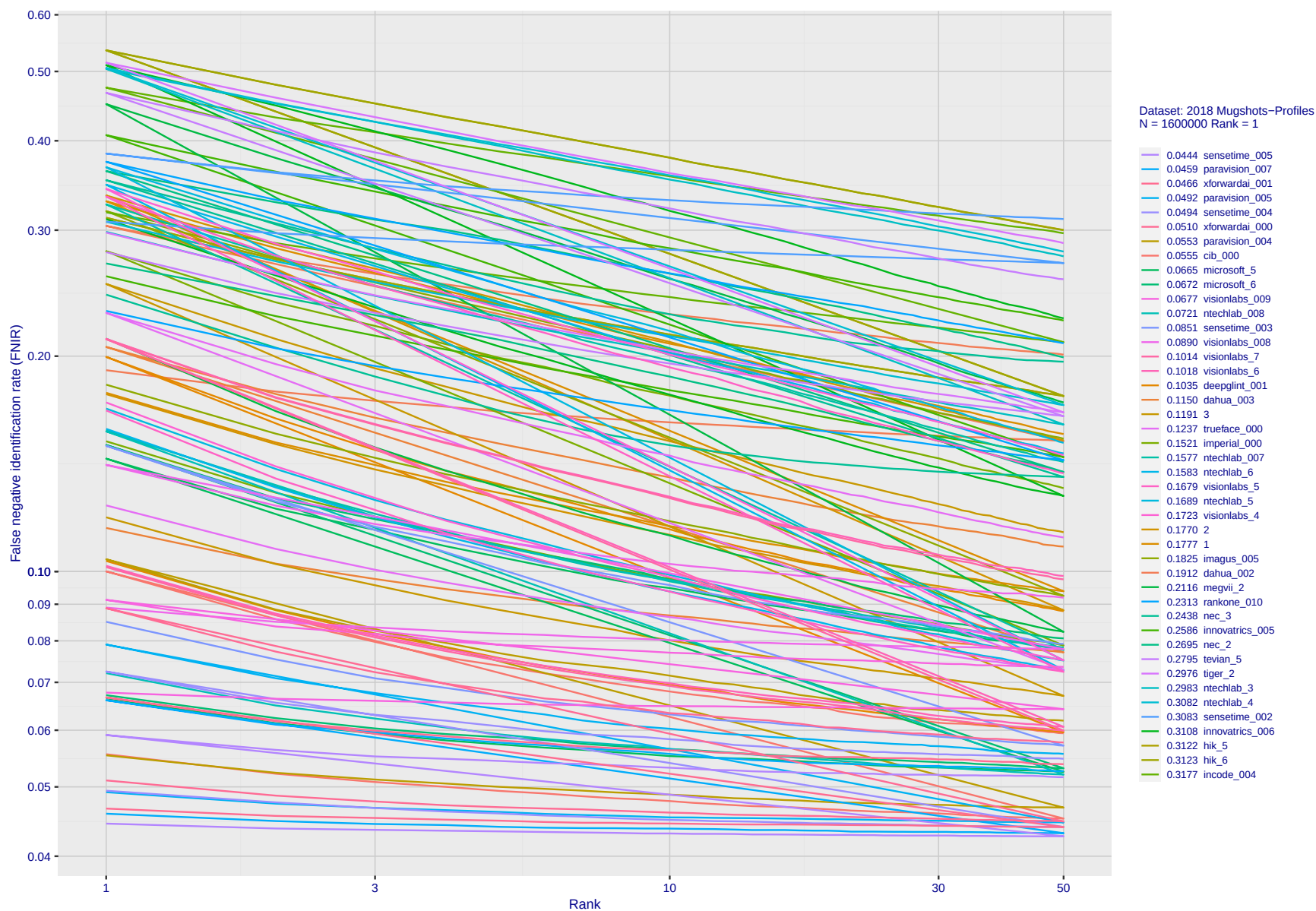
T = 0 → Investigation
T > 0 → Identification

Figure 157: [Mugshot and profile-view dataset] Rank-based accuracy. For some of the more accurate Phase 3 algorithms the figure plots error tradeoff characteristics for frontal and profile-view searches into an enrolled set of $N = 1\,600\,000$ frontal images. Note that some algorithms fail on profile-view images with $FNIR \rightarrow 1$ - this evaluation did not ask developers to provide profile-view capability. Some algorithms, on the other hand, give $FNIR$ approaching that for frontal-view searches using c. 2010 algorithms. The best result is that 91% of profile-view searches yield the correct mate at rank 1, and better than 94% in the top-50 candidates.

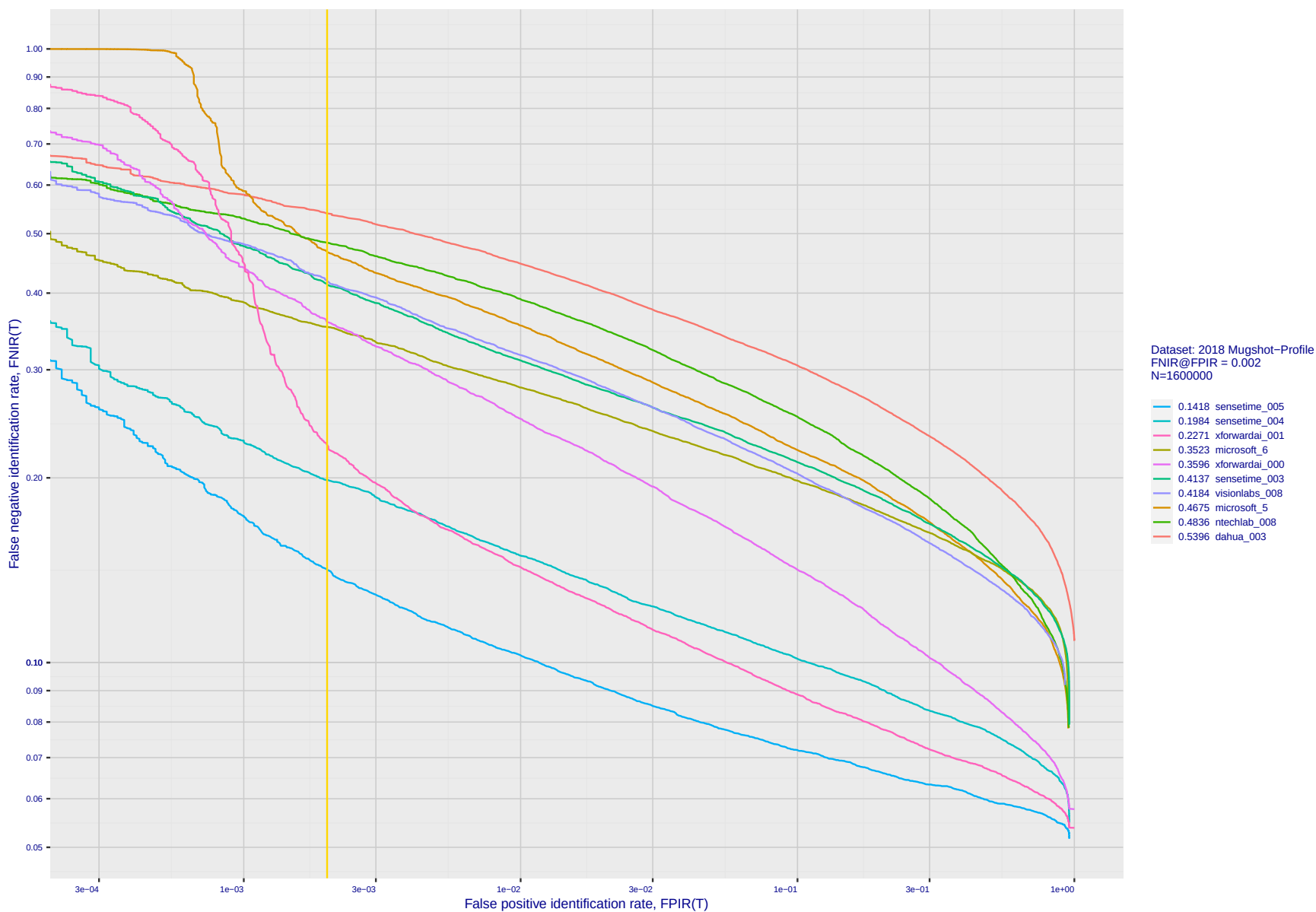


Figure 158: [Mugshot and profile-view dataset] Threshold-based accuracy. For some of the more accurate Phase 3 algorithms the figure plots error tradeoff characteristics for frontal and profile-view searches into an enrolled set of $N = 1\,600\,000$ frontal images. Note that some algorithms fail on profile-view images with $\text{FNIR} \rightarrow 1$ - this evaluation did not ask developers to provide profile-view capability. Some algorithms, on the other hand, give FNIR approaching that for frontal-view searches using c. 2010 algorithms.

2021/03/04
11:49:04FNIR(N, R, T) =
FPIR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

T = 0 $\rightarrow$ Investigation
T > 0 $\rightarrow$ Identification

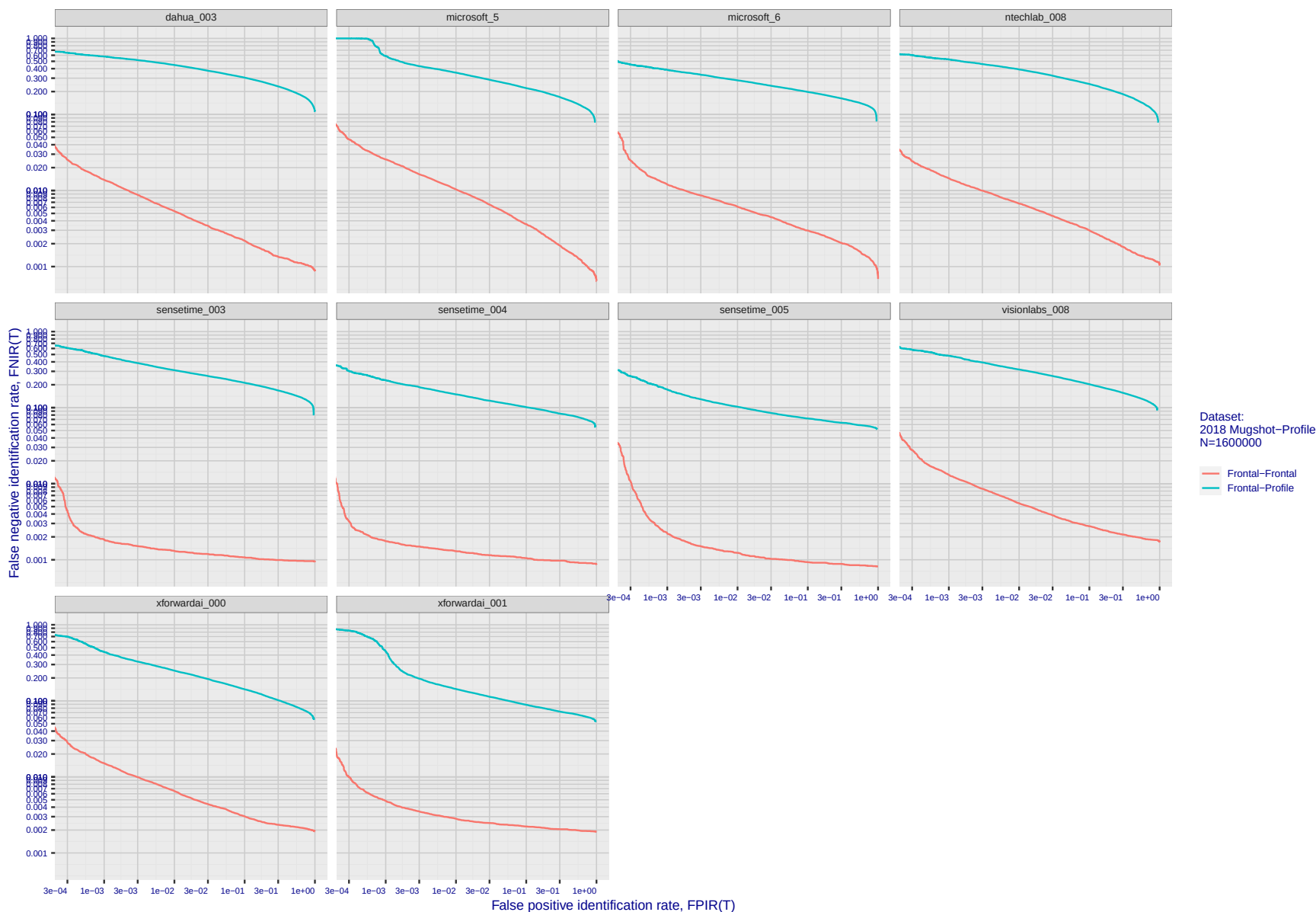


Figure 159: [Mugshot and profile-view dataset] Speed-accuracy tradeoff. For some of the more accurate Phase 3 algorithms the figure plots error tradeoff characteristics for frontal and profile-view searches into an enrolled set of $N = 1\,600\,000$ frontal images. Some algorithms fail on profile-view images with $FNIR \rightarrow 1$ - this evaluation did not ask developers to provide profile-view capability. Some algorithms, on the other hand, give $FNIR$ approaching that for frontal-view searches using c. 2010 algorithms. Blue lines connect points of equal threshold from which it is evident that some algorithms would give markedly higher false positive outcomes if profile-view images were searched in a system configured for frontal searches. This would be a vulnerability in an access control system.

Appendix F Search duration

As in and prior tests, this section documents search speeds spanning three orders of magnitude. In applications where search volumes are high enough, this will have implications for hardware requirements especially for large N or when search duration is appreciably larger than the time it takes to prepare a template from the search image(s). Further, given very large (and growing) operational databases, the scalability of algorithms is important. It has been reported previously [8] that search duration can scale sublinearly with enrolled population size N . Further there has been considerable recent research on indexing, exact [13] and approximate nearest neighbor search [1, 13] and fast-search [14, 16].

Figure 160 charts the search duration measurements presented earlier in Tables 2 - 4.

- ▷ Most algorithms scale linearly. For those in that category, there is a wide range in speed with search durations ranging from 82 milliseconds for a 12 million gallery (for NEC-3) to more than 40 seconds (for Yitu-3, Toshiba-2) and even higher for less accurate algorithms.
- ▷ Some developers (Camvi, Dermalog, EverAI, Innvoviatrics, and Visionlabs) provide algorithms whose template search durations grow approximately logarithmically i.e. $T(N) \sim a \log N$ with the constant a varying between implementations. In the figure this model is fit using the point $T(1) = 0$, and $T(640\,000)$. This very sublinear behaviour affords extremely fast search times in very large galleries. One caveat for the sublinear algorithms is that their fast-search data structures can require considerable computation time - on the order of hours - for N in the millions, and this scales mildly super-linearly, i.e. $O(N^b)$, $b > 1$. There are exceptions: the Camvi algorithms take minutes; and Innvoviatrics' scale sublinearly.

2021/03/04 11:49:04	FNIR(N, R, T) = FPIR(N, T) =	False neg. identification rate False pos. identification rate	N = Num. enrolled subjects R = Num. candidates examined	T = Threshold	T = 0 → Investigation T > 0 → Identification
------------------------	---------------------------------	--	--	---------------	---

2021/03/04
11:49:04FNIR(N, R, T) =
FPR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

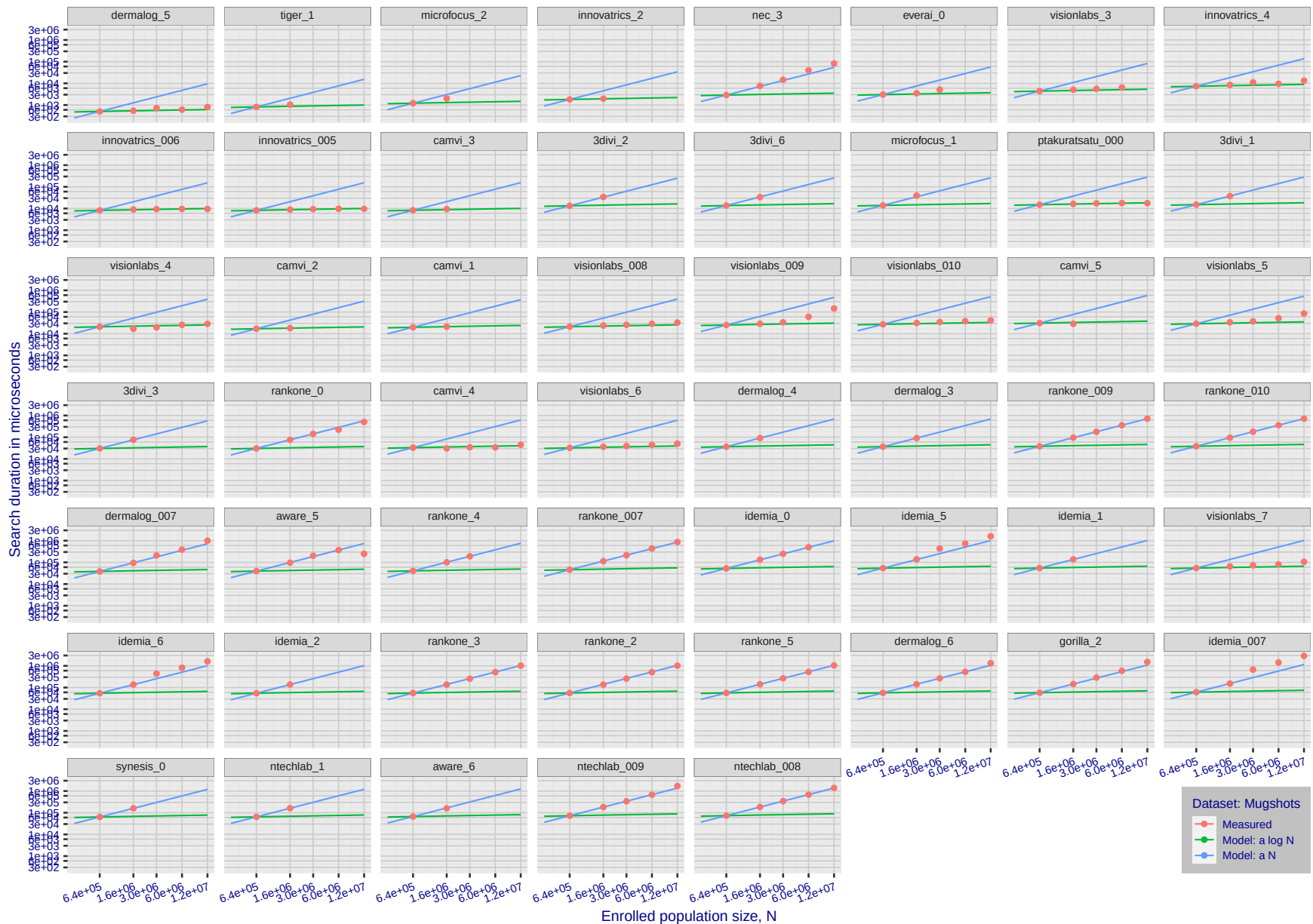
T = 0 → Investigation
T > 0 → Identification

Figure 160: [Mugshot Dataset] Search duration vs. enrolled population size. In red are the actual point durations measured on a single c. 2016 core. The blue shows linear growth from $N = 640\,000$. The green line shows logarithmic growth from that point to $N = 1\,600\,000$. Note the sublinear growth from algorithms from Camvi, Dermalog, EverAI, Innovatrics, and Visionlabs. The tiger_1 algorithm is also sublinear, but inaccurate and inoperable at $N \geq 3\,000\,000$. This capability sometimes comes at the additional expense of converting a linear gallery data structure into whatever fast-search data structure is used. Note that search times are sometimes dominated by the template generation times shown in Table 17.

2021/03/04
11:49:04FNIR(N, R, T) =
FPR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

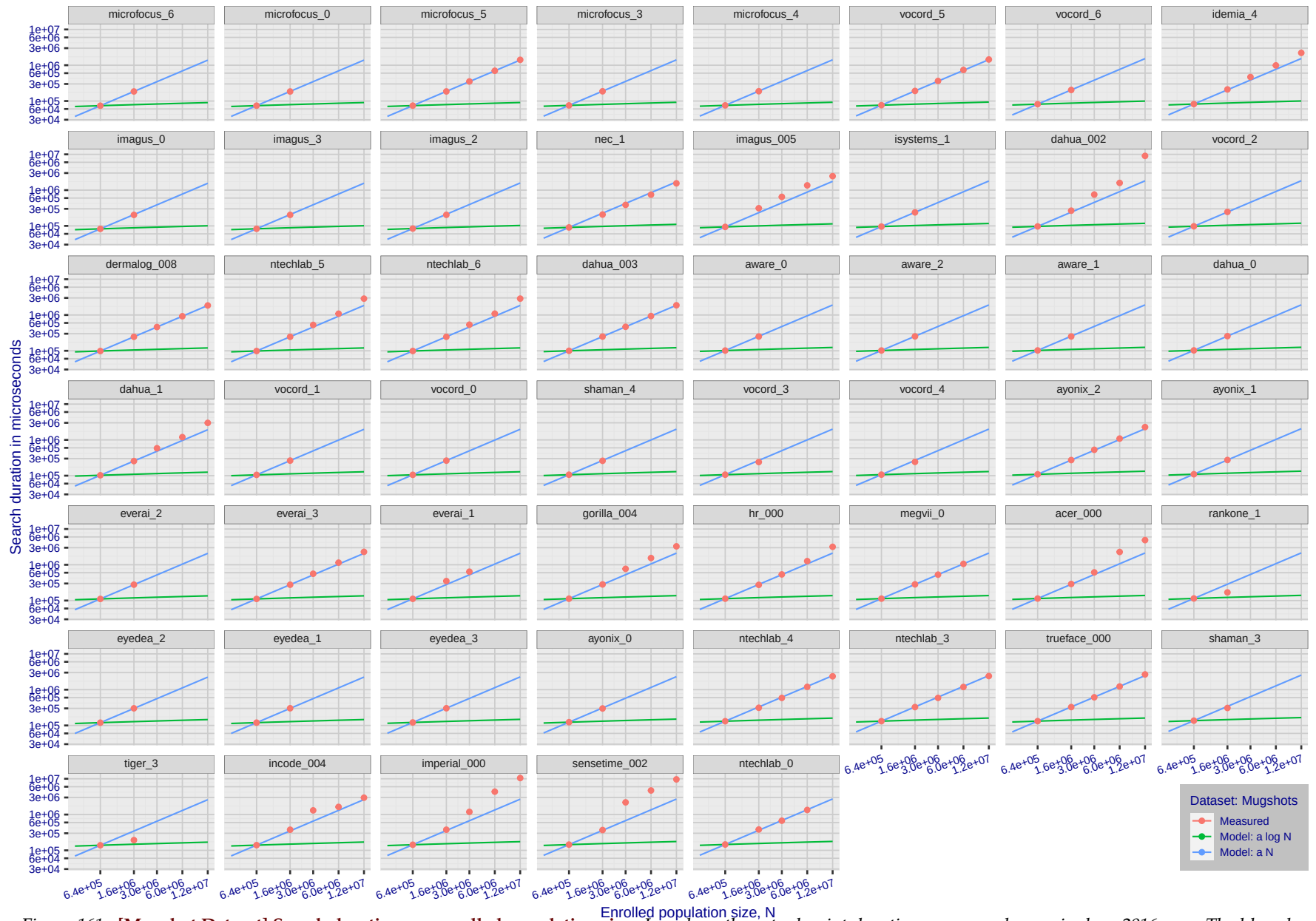
T = 0 → Investigation
T > 0 → Identification

Figure 161: **[Mugshot Dataset] Search duration vs. enrolled population size.** In red are the actual point durations measured on a single c. 2016 core. The blue shows linear growth from $N = 640\,000$. The green line shows logarithmic growth from that point to $N = 1\,600\,000$. Note the sublinear growth from algorithms from Camvi, Dermalog, EverAI, Innovatrics, and Visionlabs. The tiger.1 algorithm is also sublinear, but inaccurate and inoperable at $N \geq 3\,000\,000$. This capability sometimes comes at the additional expense of converting a linear gallery data structure into whatever fast-search data structure is used. Note that search times are sometimes dominated by the template generation times shown in Table 17.

2021/03/04
11:49:04FNIR(N, R, T) =
FPR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

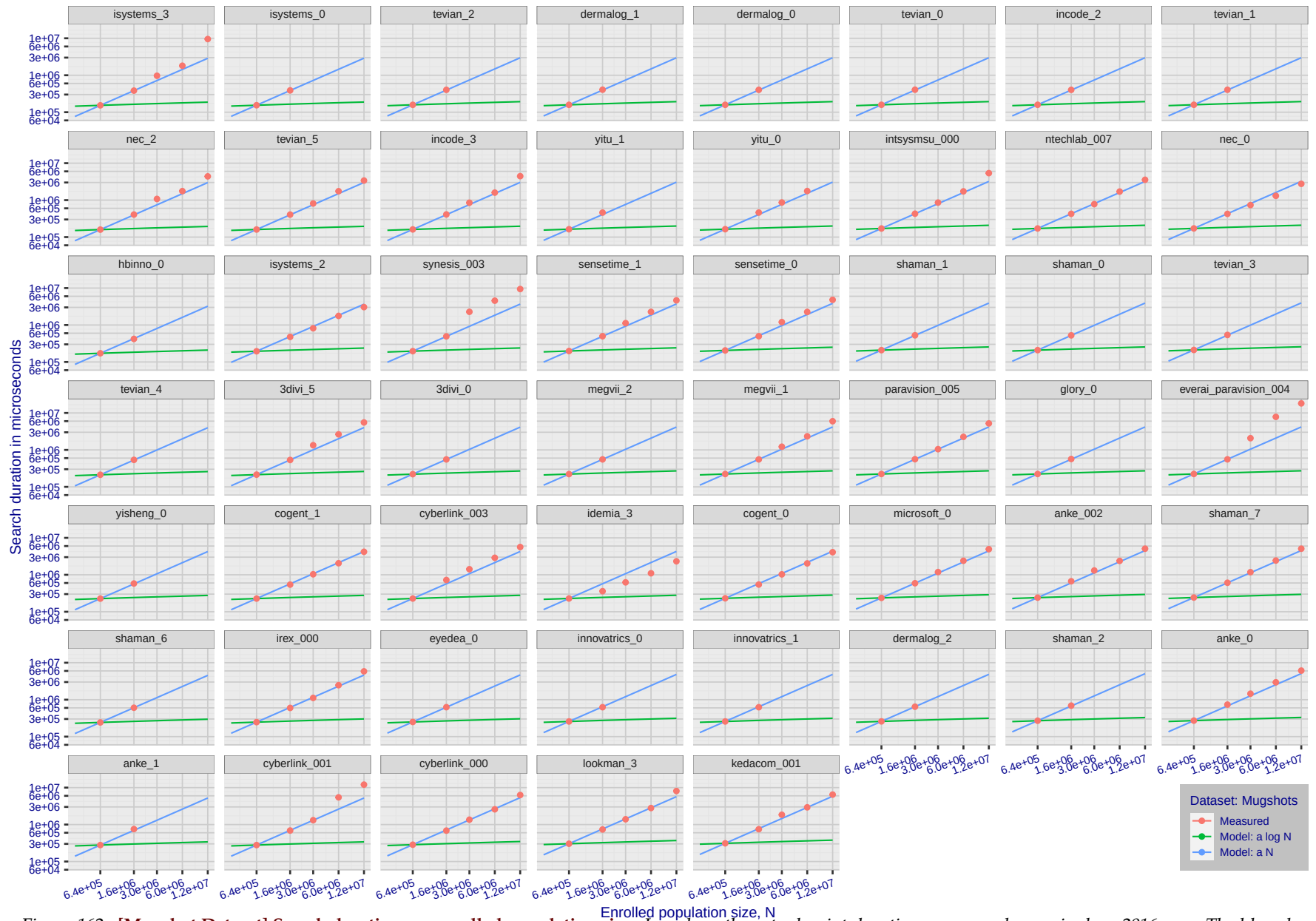
T = 0 → Investigation
T > 0 → Identification

Figure 162: **[Mugshot Dataset] Search duration vs. enrolled population size.** In red are the actual point durations measured on a single c. 2016 core. The blue shows linear growth from $N = 640\,000$. The green line shows logarithmic growth from that point to $N = 1\,600\,000$. Note the sublinear growth from algorithms from Camvi, Dermalog, EverAI, Innovatrics, and Visionlabs. The tiger.1 algorithm is also sublinear, but inaccurate and inoperable at $N \geq 3\,000\,000$. This capability sometimes comes at the additional expense of converting a linear gallery data structure into whatever fast-search data structure is used. Note that search times are sometimes dominated by the template generation times shown in Table 17.

2021/03/04
11:49:04FNIR(N, R, T) =
FPR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

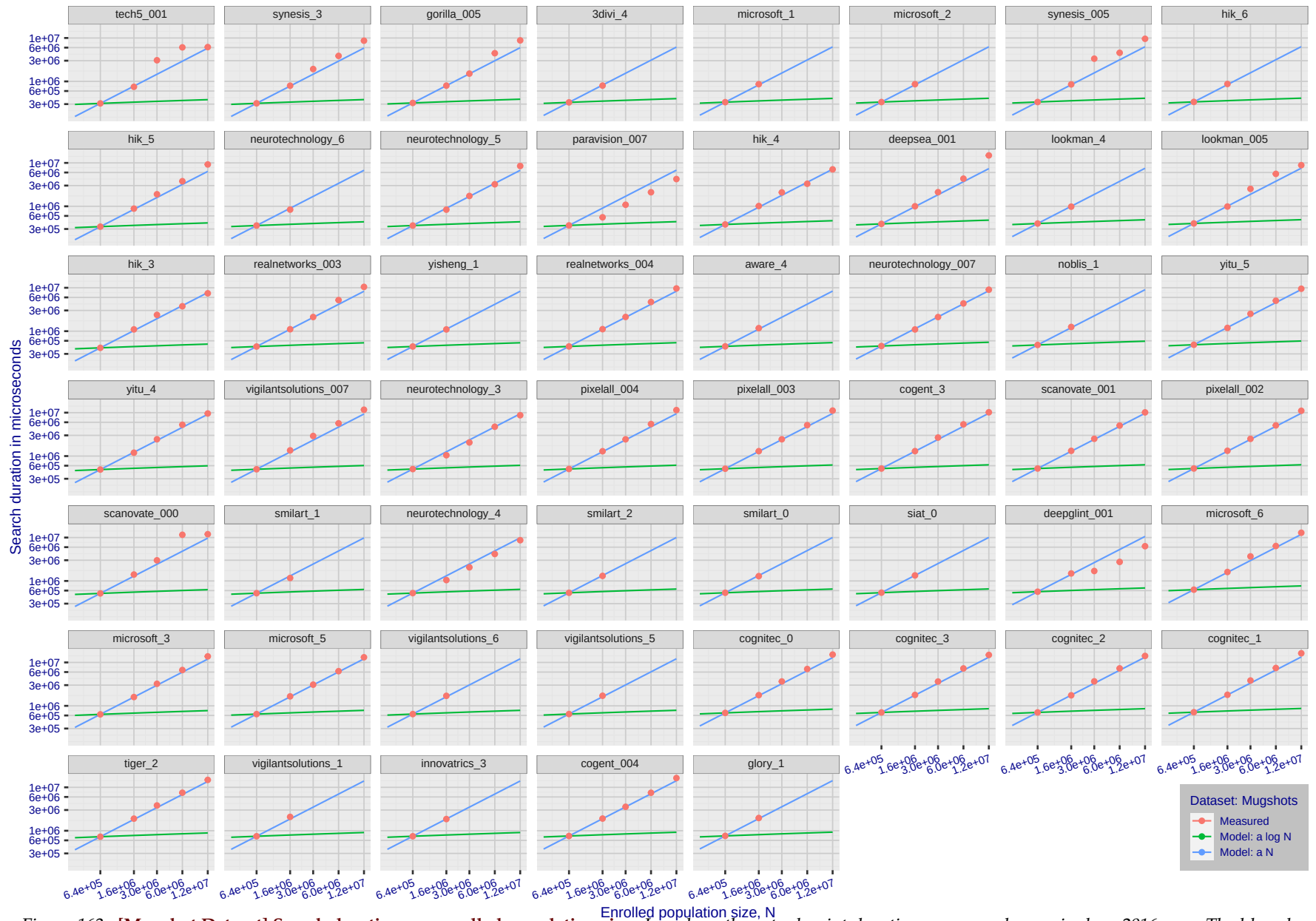
T = 0 → Investigation
T > 0 → Identification

Figure 163: **[Mugshot Dataset] Search duration vs. enrolled population size.** In red are the actual point durations measured on a single c. 2016 core. The blue shows linear growth from $N = 640\,000$. The green line shows logarithmic growth from that point to $N = 1\,600\,000$. Note the sublinear growth from algorithms from Camvi, Dermalog, EverAI, Innovatrics, and Visionlabs. The tiger.1 algorithm is also sublinear, but inaccurate and inoperable at $N \geq 3\,000\,000$. This capability sometimes comes at the additional expense of converting a linear gallery data structure into whatever fast-search data structure is used. Note that search times are sometimes dominated by the template generation times shown in Table 17.

2021/03/04
11:49:04FN(R,N,T) =
FP(R,N,T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

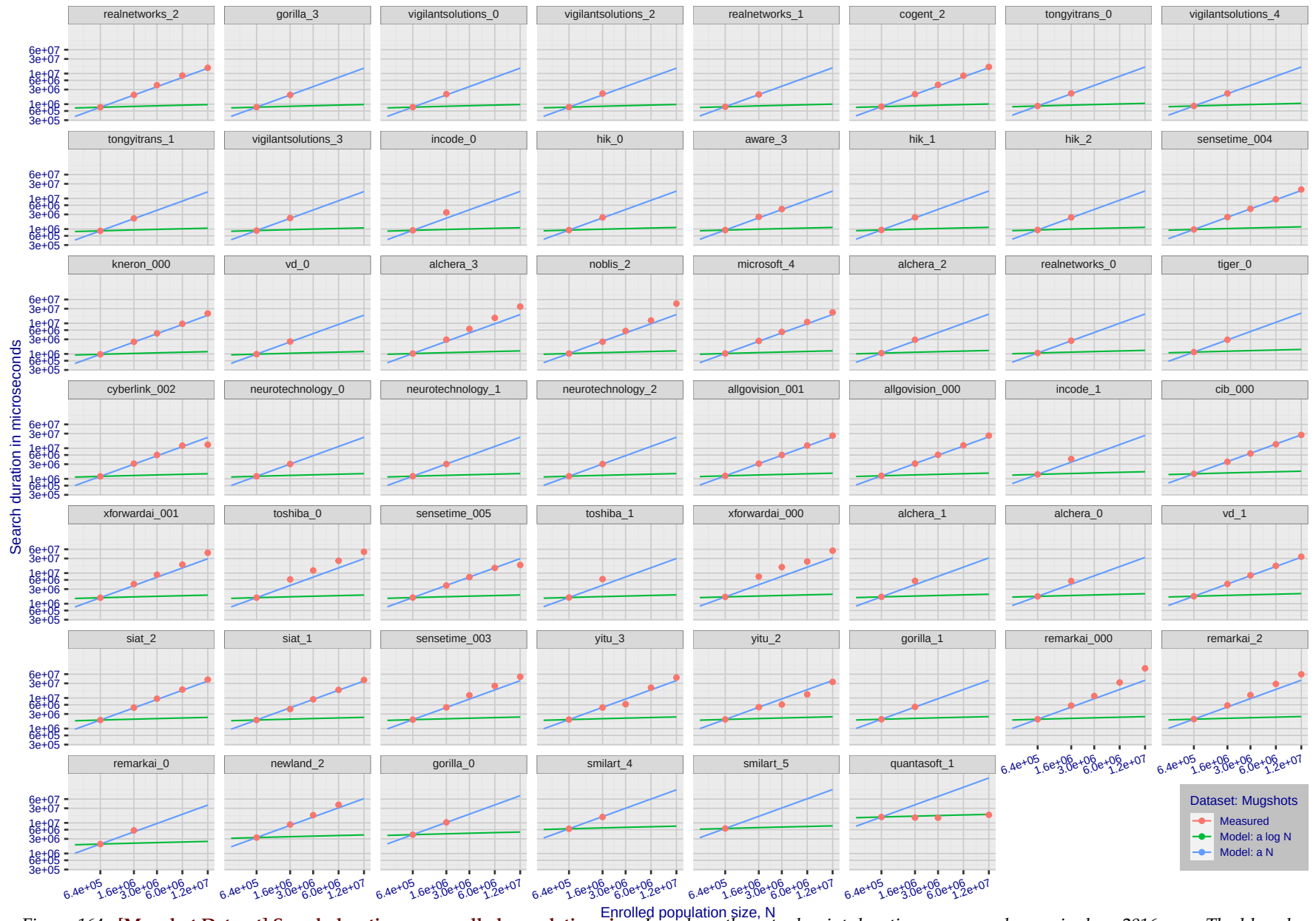
T = 0 → Investigation
T > 0 → Identification

Figure 164: **[Mugshot Dataset] Search duration vs. enrolled population size.** In red are the actual point durations measured on a single c. 2016 core. The blue shows linear growth from $N = 640\,000$. The green line shows logarithmic growth from that point to $N = 1\,600\,000$. Note the sublinear growth from algorithms from Camvi, Dermalog, EverAI, Innovatrics, and Visionlabs. The tiger.1 algorithm is also sublinear, but inaccurate and inoperable at $N \geq 3\,000\,000$. This capability sometimes comes at the additional expense of converting a linear gallery data structure into whatever fast-search data structure is used. Note that search times are sometimes dominated by the template generation times shown in Table 17.

Appendix G Gallery Insertion Timing

This publication is available free of charge from: <https://doi.org/10.6028/NIST.IR.8271>

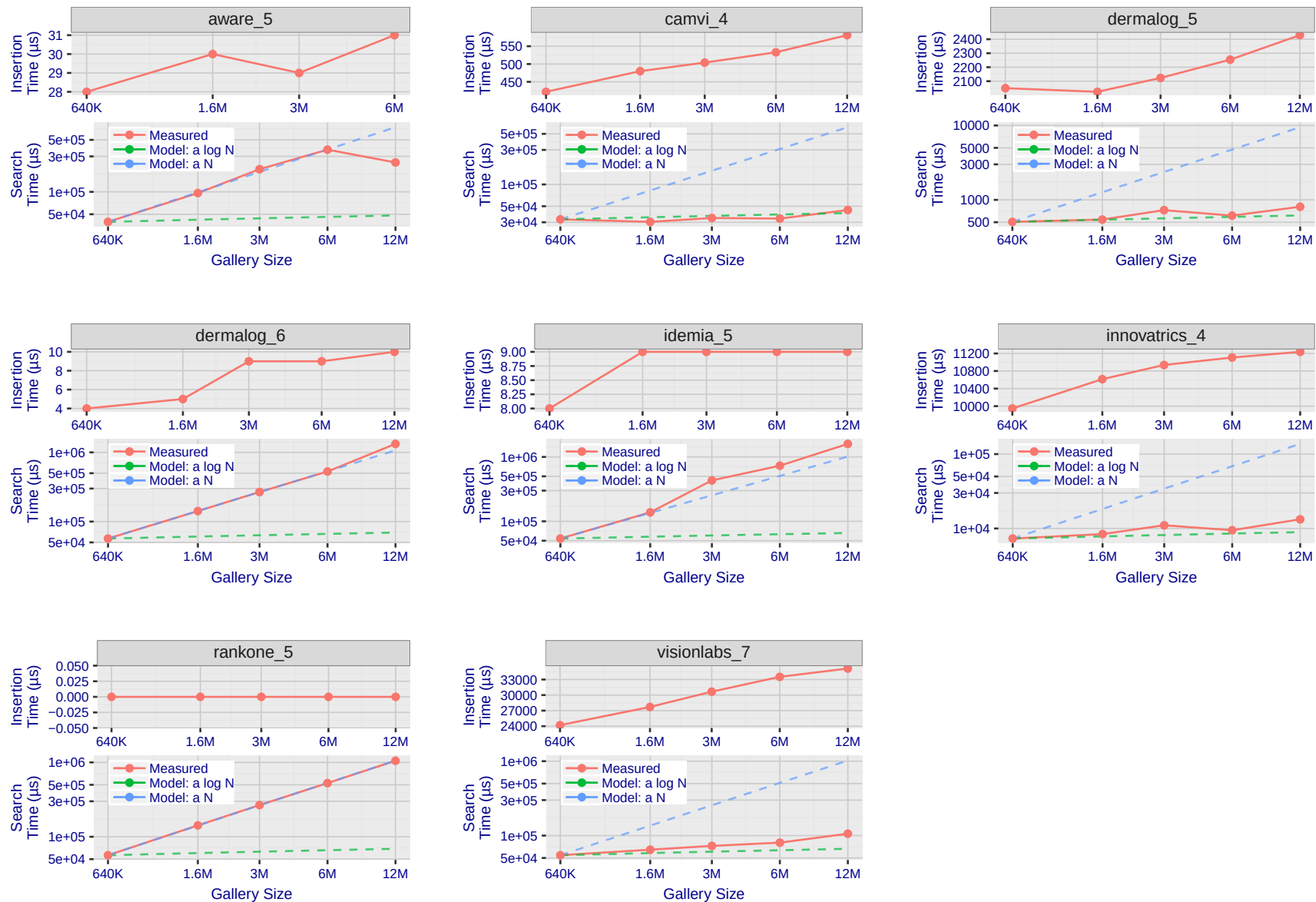


Figure 165: [Mugshot Dataset] Gallery insertion duration vs. enrolled population size. This chart plots the time it takes to insert a single template into a finalized gallery, illustrated over increasing gallery sizes. For reference, search times on finalized galleries of corresponding sizes are plotted right underneath. Gallery insertion time plots were generated on algorithms that 1) successfully implemented gallery insertion with no errors and 2) that were run on galleries with N up to 12 000 000. Generally, only the more accurate algorithms were run on galleries with N up to 12 000 000.

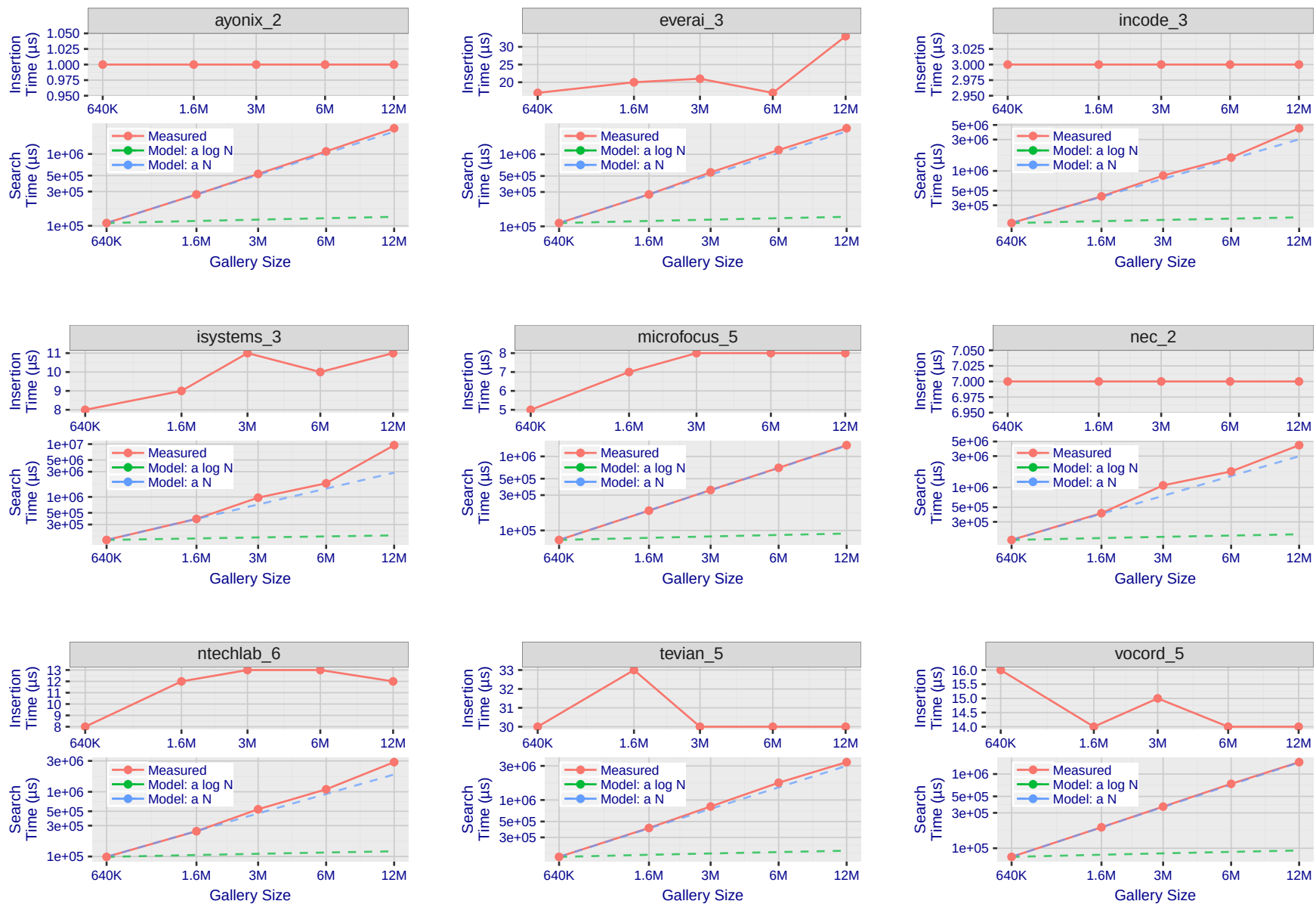


Figure 166: **[Mugshot Dataset] Gallery insertion duration vs. enrolled population size.** This chart plots the time it takes to insert a single template into a finalized gallery, illustrated over increasing gallery sizes. For reference, search times on finalized galleries of corresponding sizes are plotted right underneath. Gallery insertion time plots were generated on algorithms that 1) successfully implemented gallery insertion with no errors and 2) that were run on galleries with N up to 12 000 000. Generally, only the more accurate algorithms were run on galleries with N up to 12 000 000.

2021/03/04
11:49:04FNIR(N, R, T) =
FPR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

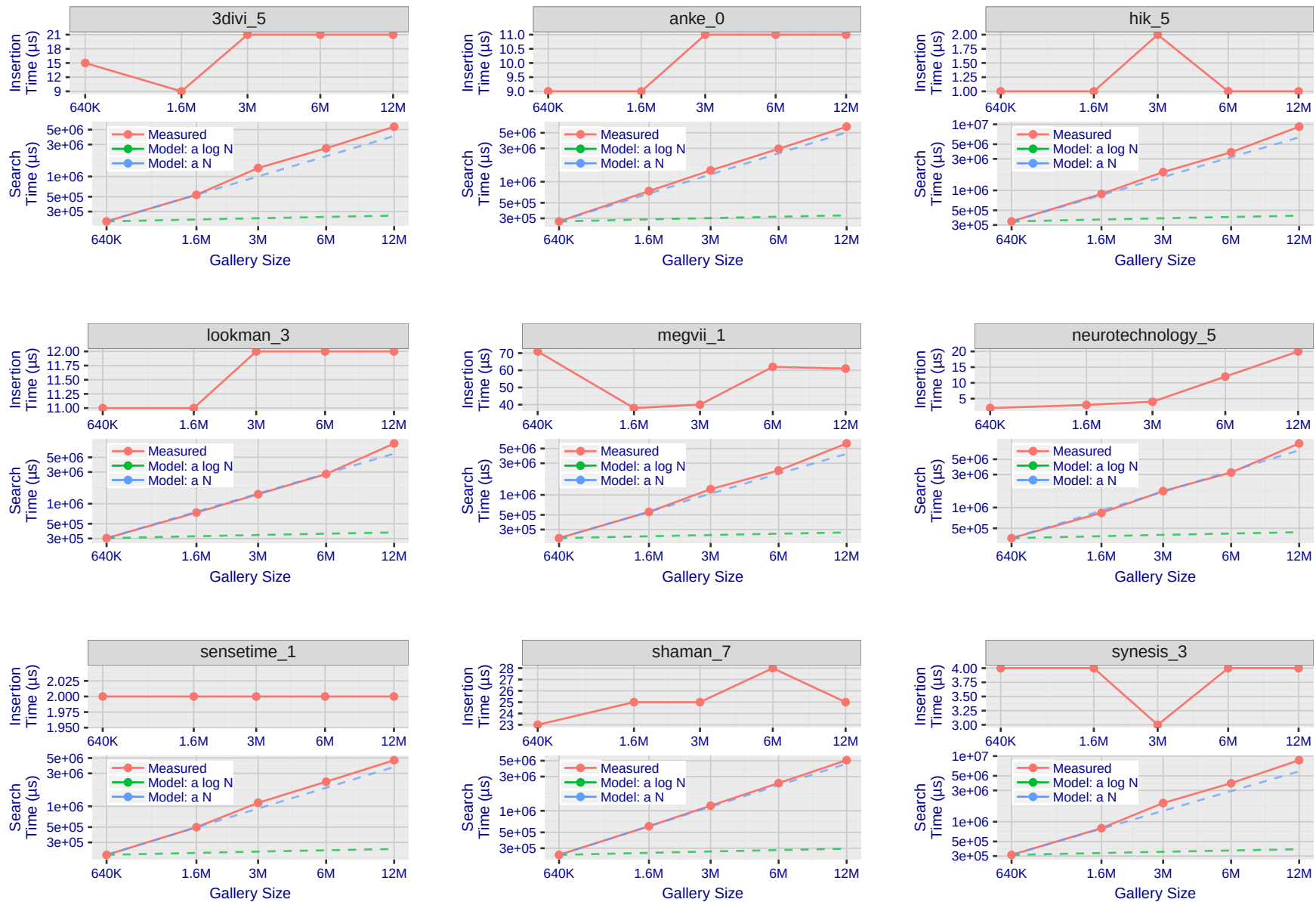
T = 0 → Investigation
T > 0 → Identification

Figure 167: **[Mugshot Dataset] Gallery insertion duration vs. enrolled population size.** This chart plots the time it takes to insert a single template into a finalized gallery, illustrated over increasing gallery sizes. For reference, search times on finalized galleries of corresponding sizes are plotted right underneath. Gallery insertion time plots were generated on algorithms that 1) successfully implemented gallery insertion with no errors and 2) that were run on galleries with N up to 12 000 000. Generally, only the more accurate algorithms were run on galleries with N up to 12 000 000.

2021/03/04
11:49:04FNIR(N, R, T) =
FPR(N, T) =False neg. identification rate
False pos. identification rateN = Num. enrolled subjects
R = Num. candidates examined

T = Threshold

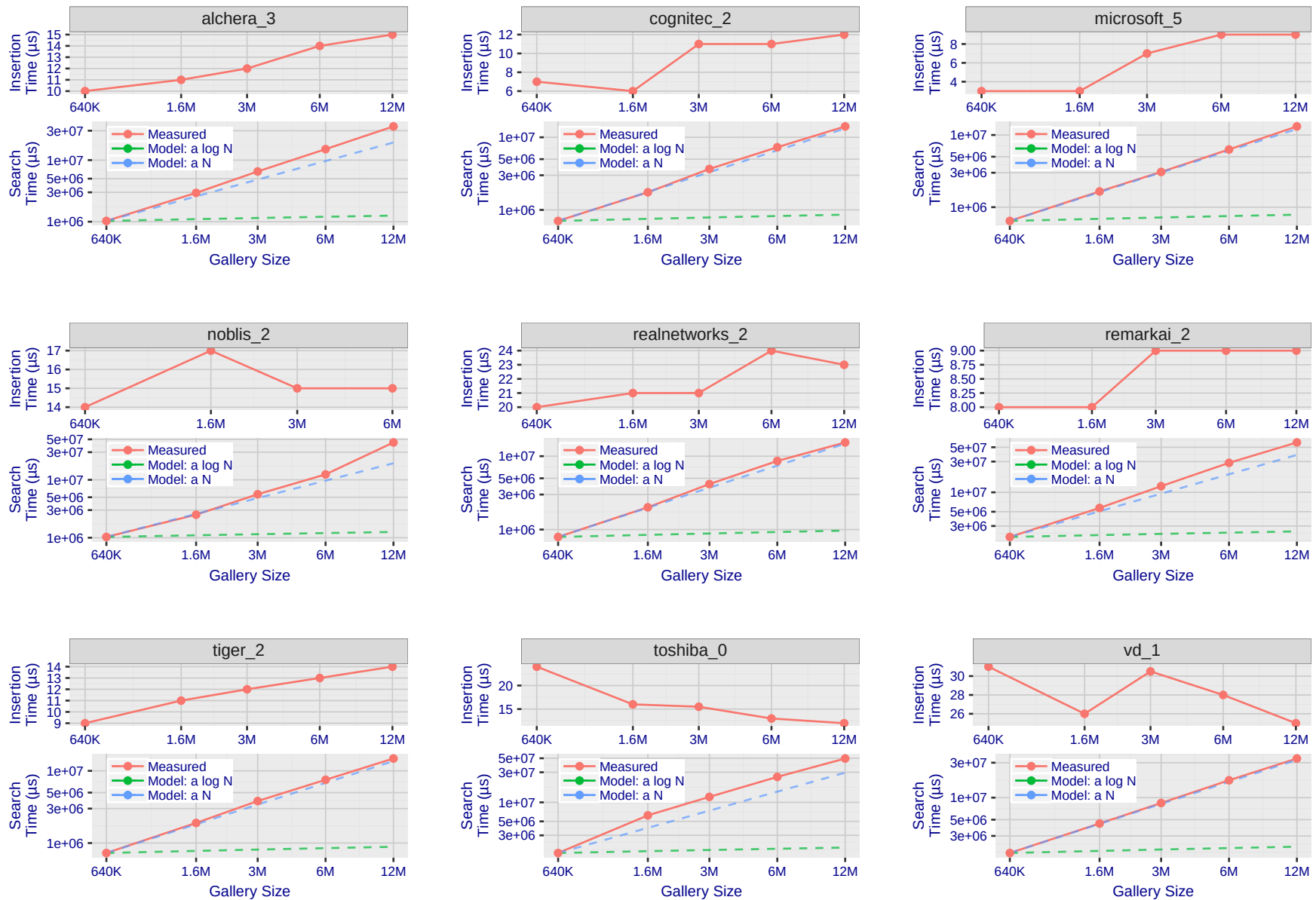
T = 0 → Investigation
T > 0 → Identification

Figure 168: **[Mugshot Dataset] Gallery insertion duration vs. enrolled population size.** This chart plots the time it takes to insert a single template into a finalized gallery, illustrated over increasing gallery sizes. For reference, search times on finalized galleries of corresponding sizes are plotted right underneath. Gallery insertion time plots were generated on algorithms that 1) successfully implemented gallery insertion with no errors and 2) that were run on galleries with N up to 12 000 000. Generally, only the more accurate algorithms were run on galleries with N up to 12 000 000.

References

- [1] Artem Babenko and Victor Lempitsky. Efficient indexing of billion-scale datasets of deep descriptors. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2016.
- [2] L. Best-Rowden and A. K. Jain. Longitudinal study of automatic face recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 40(1):148–162, Jan 2018.
- [3] Blumstein, Cohen, Roth, and Visser, editors. *Random parameter stochastic models of criminal careers*. National Academy of Sciences Press, 1986.
- [4] Thomas P. Bonczar and Lauren E. Glaze. Probation and parole in the united statesm 2007, statistical tables. Technical report, Bureau of Justice Statistics, December 2008.
- [5] White D., Kemp R. I., Jenkins R., Matheson M, and Burton A. M. Passport officers’ errors in face matching. *PLoS ONE*, 9(8), 2014. e103510. doi:10.1371/journal.pone.0103510.
- [6] P. Grother, G. W. Quinn, and P. J. Phillips. Evaluation of 2d still-image face recognition algorithms. NIST Interagency Report 7709, National Institute of Standards and Technology, 8 2010. <http://face.nist.gov/mbeas/MBE2010FRVT2010>.
- [7] P. J. Grother, R. J. Micheals, and P. J. Phillips. Performance metrics for the frvt 2002 evaluation. In *Proceedings of Audio and Video Based Person Authentication Conference (AVBPA)*, June 2003.
- [8] Patrick Grother and Mei Ngan. Interagency report 8009, performance of face identification algorithms. *Face Recognition Vendor Test (FRVT)*, May 2014.
- [9] Patrick Grother, George Quinn, and Mei Ngan. Face in video evaluation (five) face recognition of non-cooperative subjects. Interagency Report 8173, National Institute of Standards and Technology, March 2017. <https://doi.org/10.6028/NIST.IR.8173>.
- [10] Patrick Grother, George W. Quinn, and Mei Ngan. Face recognition vendor test - still face image and video concept, evaluation plan and api. Technical report, National Institute of Standards and Technology, 7 2013. http://biometrics.nist.gov/cs_links/face/frvt/frvt2012/NIST_FRVT2012_api_Aug15.pdf.
- [11] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, June 2016.
- [12] Gary B. Huang, Manu Ramesh, Tamara Berg, and Erik Learned-Miller. Labeled faces in the wild: A database for studying face recognition in unconstrained environments. Technical Report 07-49, University of Massachusetts, Amherst, October 2007.
- [13] Masato Ishii, Hitoshi Imaoka, and Atsushi Sato. Fast k-nearest neighbor search for face identification using bounds of residual score. In *2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017)*, pages 194–199, Los Alamitos, CA, USA, May 2017. IEEE Computer Society.
- [14] Jeff Johnson, Matthijs Douze, and Hervé Jégou. Billion-scale similarity search with gpus. *CoRR*, abs/1702.08734, 2017.

- [15] Ira Kemelmacher-Shlizerman, Steven M. Seitz, Daniel Miller, and Evan Brossard. The megaface benchmark: 1 million faces for recognition at scale. *CoRR*, abs/1512.00596, 2015.
- [16] Yury A. Malkov and D. A. Yashunin. Efficient and robust approximate nearest neighbor search using hierarchical navigable small world graphs. *CoRR*, abs/1603.09320, 2016.
- [17] Joyce A. Martin, Brady E. Hamilton, Michelle J.K. Osterman, Anne K. Driscoll, , and Patrick Drake. National vital statistics reports. Technical Report 8, Centers for Disease Control and Prevention, National Center for Health Statistics, National Vital Statistics System, Division of Vital Statistics, November 2018.
- [18] O. M. Parkhi, A. Vedaldi, and A. Zisserman. Deep face recognition. In *British Machine Vision Conference*, 2015.
- [19] P. Jonathon Phillips, Amy N. Yates, Ying Hu, Carina A. Hahn, Eilidh Noyes, Kelsey Jackson, Jacqueline G. Cava-zos, Géraldine Jeckeln, Rajeev Ranjan, Swami Sankaranarayanan, Jun-Cheng Chen, Carlos D. Castillo, Rama Chel-lappa, David White, and Alice J. O'Toole. Face recognition accuracy of forensic examiners, superrecognizers, and face recognition algorithms. *Proceedings of the National Academy of Sciences*, 115(24):6171–6176, 2018.
- [20] Florian Schroff, Dmitry Kalenichenko, and James Philbin. Facenet: A unified embedding for face recognition and clustering. *CoRR*, abs/1503.03832, 2015.
- [21] Jeroen Smits and Christiaan Monden. Twinning across the developing world. *PLOS ONE*, 6(9):1–5, 09 2011.
- [22] Yaniv Taigman, Ming Yang, Marc' Aurelio Ranzato, and Lior Wolf. Deepface: Closing the gap to human-level performance in face verification. In *Proceedings of the 2014 IEEE Conference on Computer Vision and Pattern Recognition*, CVPR '14, pages 1701–1708, Washington, DC, USA, 2014. IEEE Computer Society.
- [23] A. Towler, R. I. Kemp, and D White. *Unfamiliar face matching systems in applied settings*. Nova Science, 2017.
- [24] Working Group 3. Ed. M. Werner. *ISO/IEC 19794-5 Information Technology - Biometric Data Interchange Formats - Part 5: Face image data*. JTC1 :: SC37, 2 edition, 2011. <http://webstore.ansi.org>.
- [25] David White, James D. Dunn, Alexandra C. Schmid, and Richard I. Kemp. Error rates in users of automatic face recognition software. *PLoS ONE*, 10:1–14, October 2015.
- [26] Bradford Wing and R. Michael McCabe. Special publication 500-271: American national standard for information systems data format for the interchange of fingerprint, facial, and other biometric information part 1. Technical report, NIST, September 2015. ANSI/NIST ITL 1-2015.
- [27] Andreas Wolf. Portrait quality - (reference facial images for mrtd). Technical report, ICAO, April 2018.
- [28] D. Yadav, N. Kohli, P. Pandey, R. Singh, M. Vatsa, and A. Noore. Effect of illicit drug abuse on face recognition. In *2016 IEEE Winter Conference on Applications of Computer Vision (WACV)*, pages 1–7, Los Alamitos, CA, USA, mar 2016. IEEE Computer Society.