

# Modelling the odds of false acceptance and false rejection of a privacy-preserved multimodal system involving face modality



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# Talk abstract

In this talk, I propose a likelihood ratio framework that can model the odds of false acceptance and false rejection of the performance of a multimodal biometric system involving face and two palms. The methodology is generic and can be applied to any unimodal or multimodal systems.

To cope with limited training data, the quality conditions (which are manually annotated) are assumed to be independent of each other. Moreover, it is also assumed that there is no distinction between a probe sample and a gallery template.

This model was applied to a field study taking place in Africa. The software used Trust Stamp's privacy-preserved biometric representation known as Irreversibly Transformed Identity Token, or IT2.

Despite using the simplified assumptions above and that the model can only observe the fused score (without access to the underlying matching scores of the individual modalities), the model is found to be powerful enough to explain capture conditions that favour the face and palm biometric modalities *individually*.

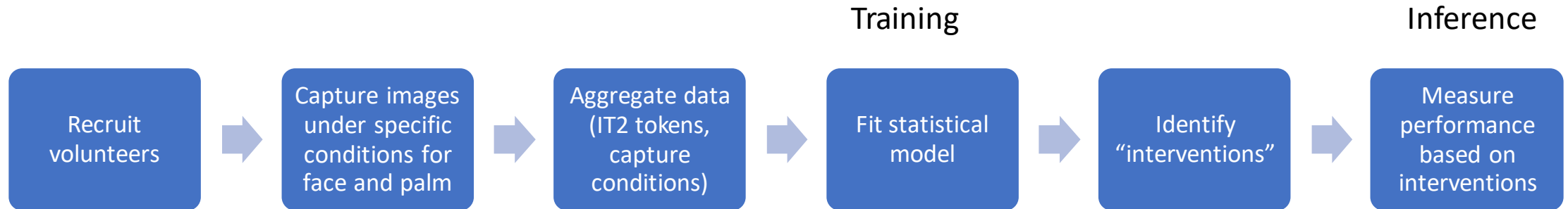
For instance, the model found that, for the face modality, dark lighting increases the odds of false rejection and false acceptance at the same time; whereas indoor/well-lit conditions improve the odds of true acceptance and true rejection at the same time. Outdoor direct sunlight, on the other hand, increases false acceptance whereas outdoor shade improves the true rejection. This forms lighting-based intervention that can be used to build a gallery. In addition to the lighting-based intervention, a full intervention consist of taking off glasses and hats for the face modality and cleaning palms for the contactless palmprint modality.

Identification experiments were simulated with varying proportions of templates fulfilling the above interventions in the gallery without subjecting the probe samples to the same interventions. If the same interventions were applied to the probe samples, the identification error rates can improve even further, thus demonstrating the effectiveness of the proposed LLR model in relating biometric performance to the capture conditions.



- Project requirements:
  - Contactless biometrics – left and right palms and face
  - Biometric data never leaves the device
  - All biometric templates are represented using [Trust Stamp's Irreversibly Transformed Identity Token, or IT2](#) (privacy-preserved biometrics) which was delivered in the form of an Android SDK
  - Must support 1:1 and 1:N at scale on device
  - Must operate offline most of the time. The biometric gallery is synched to server when it has access to the Internet
  - Affordable Android devices

# Goal: Understand the factors that influence the multimodal smartphone-based capture solution in *the privacy-preserved domain (IT2)*



Binary covariates  $q$

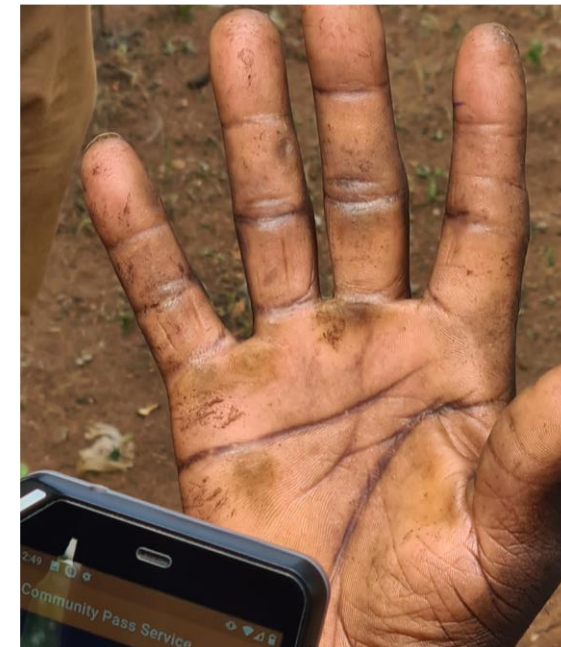
## Face

covar	value
F.Facial Hair	No
F.Flashlight	Off
F.Lighting	On
	Dark Light
	Indoor-Well Lit
	Outdoor/direct sun/overhead
	Outdoor/shade
	Semi dim condition
F.Position	Full frontal
F.Surface	Altered/dirty
	Unaltered
F.wear_glasses	FALSE
	TRUE
F.wear_hat	FALSE
	TRUE

## Palm

covar	value
P.Flashlight	On
P.Lighting	Indoor/Dark-Lit
	Indoor/Dim-Lit
	Indoor/Well-Lit
	Outdoor/direct sun
	Outdoor/shade
P.Surface	Dirty
	Unaltered

$q \in \{present, absent\}$





# How to improve the “odds” of a correct outcome?

- Definition of a correct outcome

	System accepts claim	System rejects claim
Mated comparison, $\omega_1$	Correct Acceptance	False Rejection
Nonmated comparison, $\omega_0$	False Acceptance	Correct Rejection

$$P(\text{correct}|\mathbf{q}, y) = \sum_{\omega \in \{\omega_0, \omega_1\}} P(\text{correct}|\mathbf{q}, \omega) P(\omega|y)$$

CR                      CA

If we can pick a subset of  $\mathbf{q} = [q_0, q_1, \dots]$  as interventions, we can improve the odds of success

Map a comparison score to probability

# Naïve Bayes assumption

$$P(\text{correct}|\mathbf{q}, y) = \sum_{\omega \in \{\omega_0, \omega_1\}} P(\text{correct}|\mathbf{q}, \omega)P(\omega|y)$$



Naïve Bayes

$$P(\text{correct}|\mathbf{q}, y, NB) = \sum_{\omega \in \{\omega_0, \omega_1\}} \prod_{i \in \{1 \dots Q\}} P(\text{correct}|q_i, \omega)P(\omega|y)$$

Don't care if it is a template or a probe

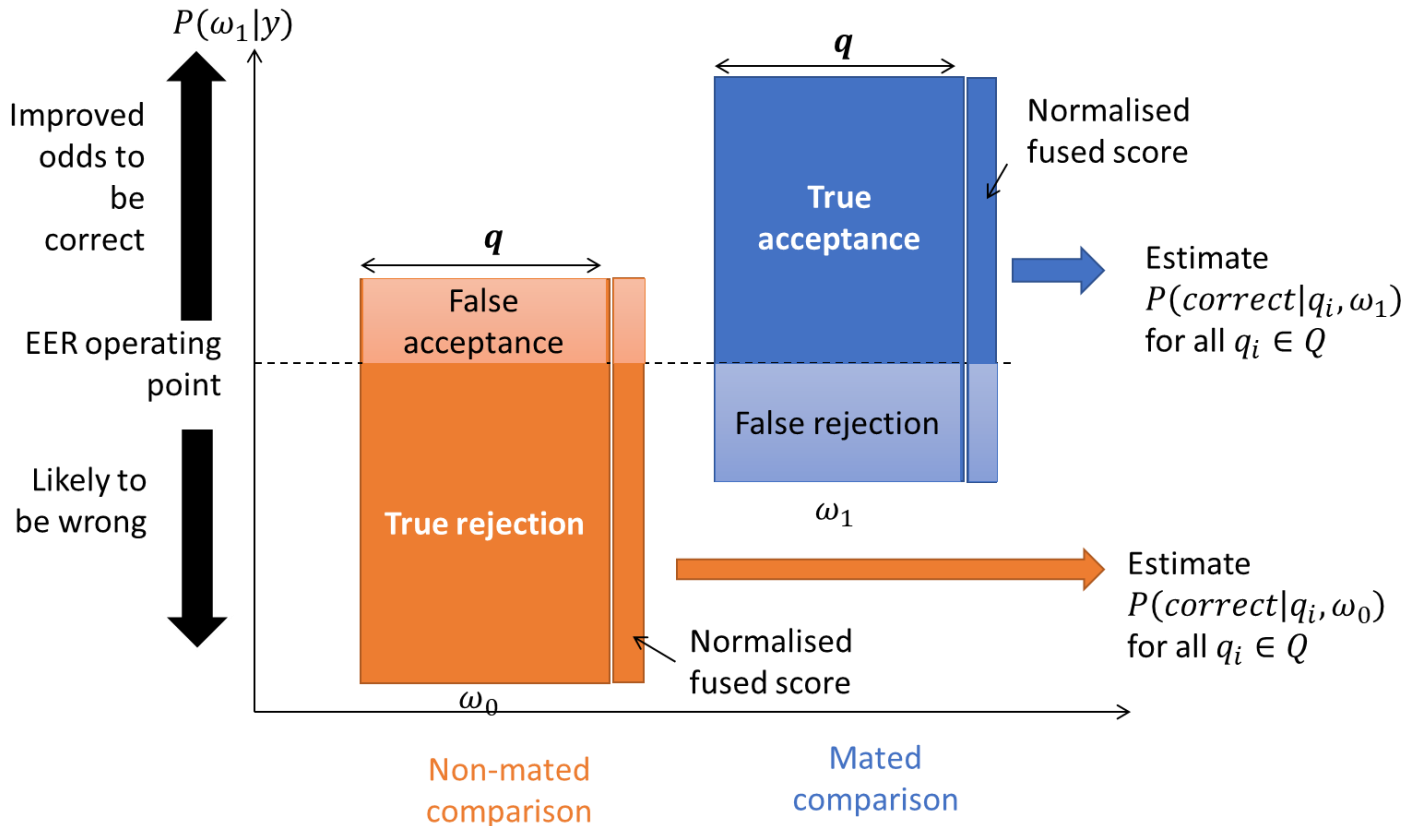


Var	Domain	meaning
$o$	$o \in \{\text{correct}, \text{wrong}\}$	Outcome of the comparison: correct means true acceptance and true rejection
$\mathbf{q}$	$q = [q_1, \dots, q_Q]$	Quality conditions assigned during data collection. They contain the quality conditions of template and probe.
$\omega$	$\omega \in \{\omega_0, \omega_1\}$	Non-mated and mated comparison, respectively
$P(\omega y)$	Probability (normalised score)	Calibrated probability, mapping from distance $y$ to probability score

Terms	Meaning
$P(\text{correct} q_i, \omega_0)$	Probability of true rejection for quality condition $q_i$
$P(\text{correct} q_i, \omega_1)$	Probability of true acceptance for quality condition $q_i$

Bottom line: By estimating the probability of a correct decision, we can determine which covariates (quality conditions) are important.

# Work in the log-likelihood ratio domain



$$LLR(q|\omega_1) = \log \frac{P(\text{correct}|q, \omega_1)}{P(\text{wrong}|q, \omega_1)} - CR$$

What is the merit of quality condition  $q$  to improve the odds of True Acceptance over False Rejection?

$$LLR(q|\omega_0) = \log \frac{P(\text{correct}|q, \omega_0)}{P(\text{wrong}|q, \omega_0)} - CR$$

What is the merit of quality condition  $q$  to improve the odds of True Rejection over False Acceptance?

LLR Estimator

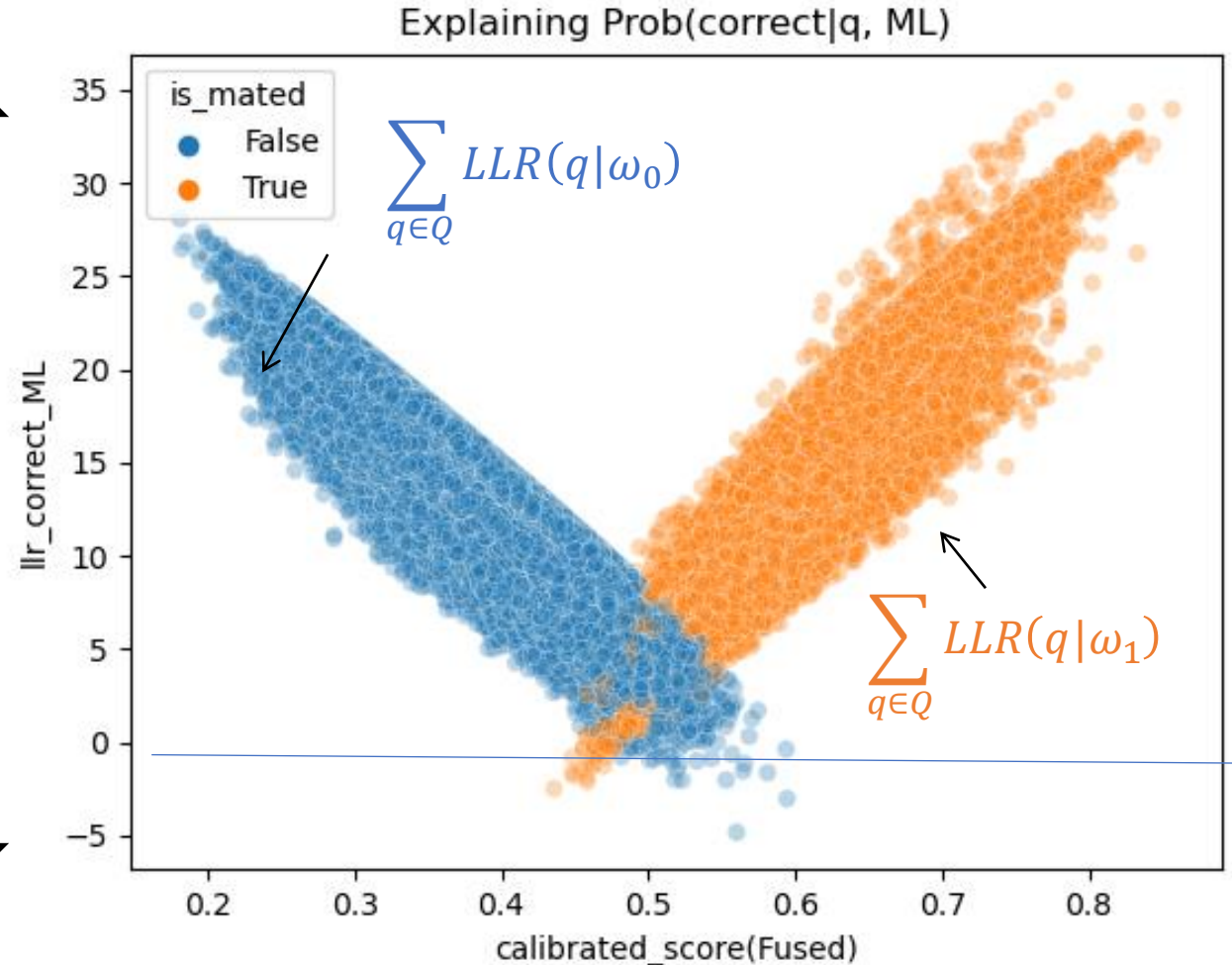
$$LLR(q|\omega) = \log \frac{\# \text{ correct } \omega|q + 1}{\# \text{ wrong } \omega|q + 1}$$

$$CR = \log \frac{P(\text{correct})}{P(\text{wrong})}$$

How well does the model fit the data?

Improved odds to be correct

Likely to be wrong



Bottom line: The model fits the data very well, capable of explaining True acceptance and True rejection. So, in the subsequent slides, we are going to interpret the LLR for each individual quality condition (the covariate).<sup>9</sup>



# Face covariates

- Flashlight off, indoor well-lit, outdoor shade
- Take off glasses and hat
- Although no facial hair is better, it requires people to shave – this may not be culturally acceptable

Improved odds to be correct

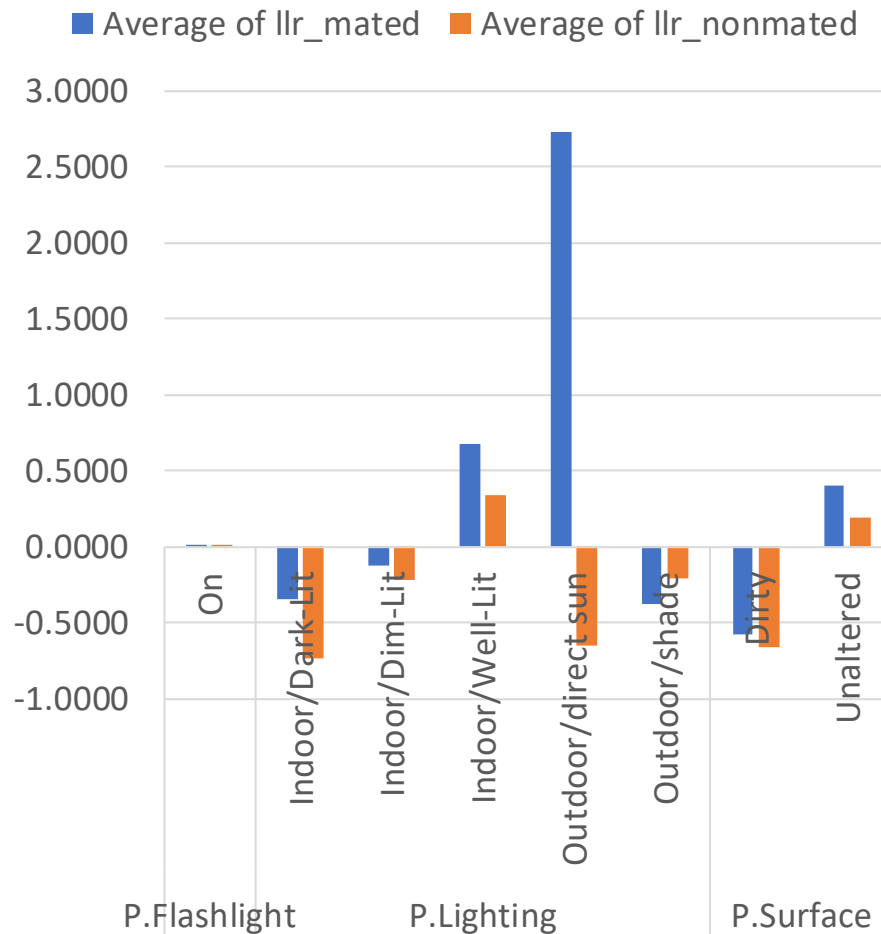
Likely to be wrong



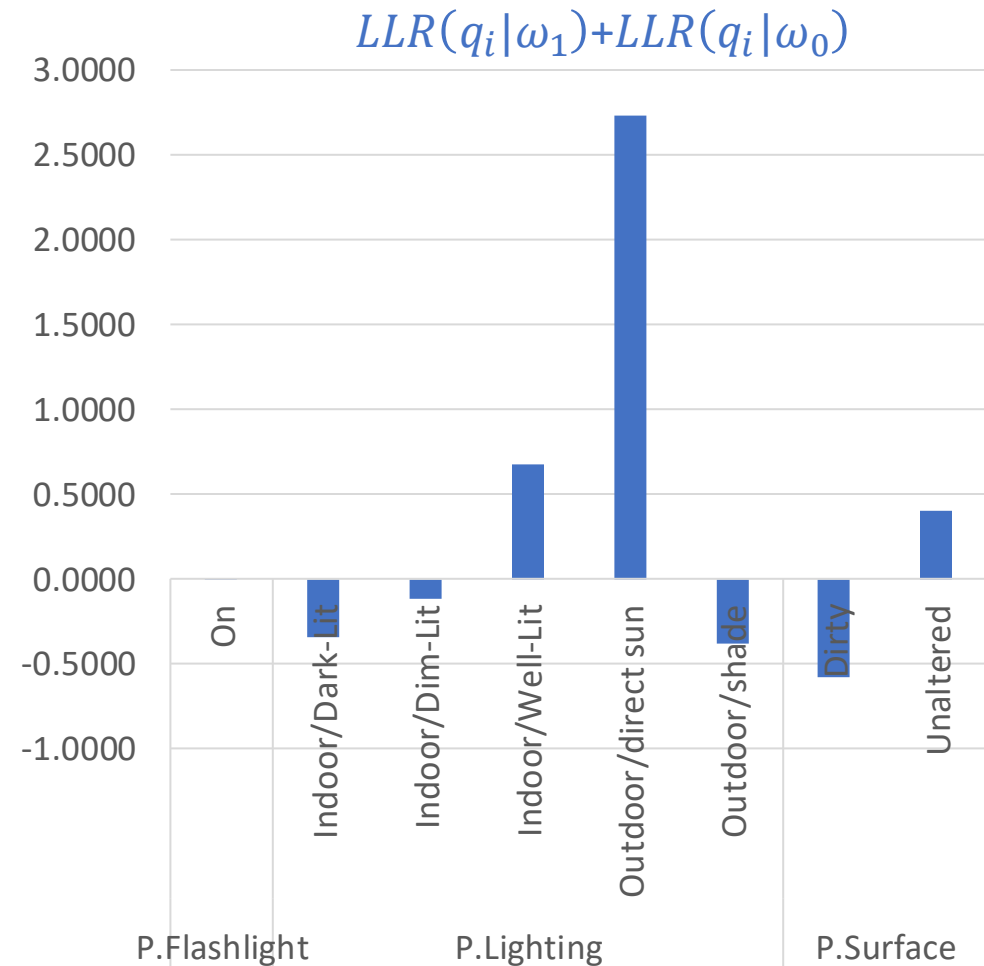
	No	Yes	Off	On	Dark Light	Indoor-Well Lit	Outdoor/direct sun/over head	Outdoor/shade	Semi dim condition	Full frontal	Altered/dirty	Unaltered	FALSE	TRUE	FALSE	TRUE			
	F.Facial Hair		F.Flashlight		F.Lighting							F.Position		F.Surface		F.wear_glasses		F.wear_hat	
■ Average of llr_mated	1.1249	-0.2633	0.2733	-0.1640	-0.6000	0.7587	0.5733	2.0499	-0.0261	0.0001	-0.3617	0.1210	0.1689	-0.1837	0.0502	-0.0662			
■ Average of llr_nonmated	0.1404	-0.3419	0.2118	-0.2705	-0.7633	0.3816	-1.6244	0.0089	-0.3328	0.0000	-0.9099	0.1895	0.0823	-0.1771	0.2414	-0.4614			

# Palmprint covariates

- Outdoor/direct-sun improves true acceptance but worsens false acceptance
- Indoor well-lit and “unaltered” improve both true acceptance and true rejection



Consolidate LLR



# Full vs lighting-based intervention

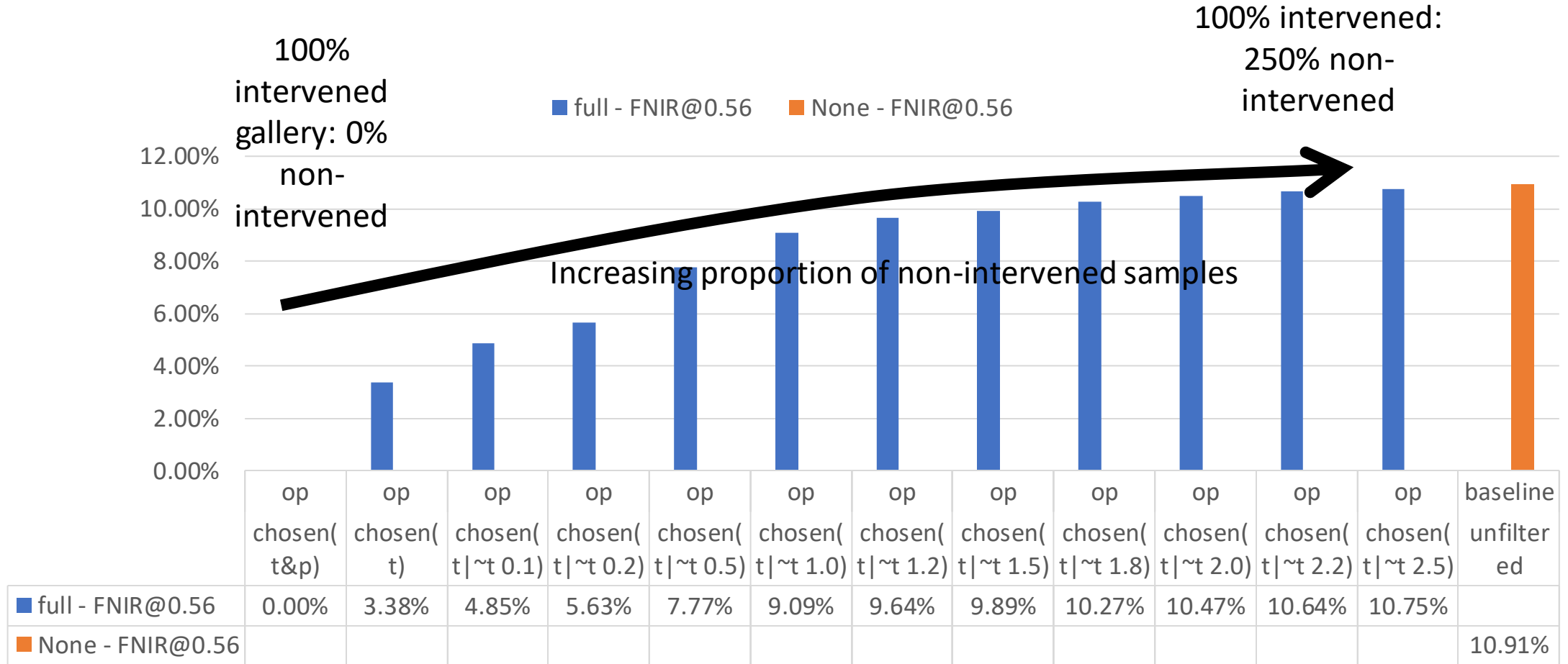
- chosen(t) = apply intervention to the gallery
- chosen(p) = apply intervention to the probe samples
- chosen(t&p) – apply intervention to the gallery and the probes

		full	lighting
		Average of	Average of
covar	covar_conditions	percentage	percentage
		Sum of count	Sum of count
Conjunction	chosen(p)	17.39%	32.86%
	chosen(t&p)	4.60%	14.27%
	chosen(t)	26.54%	43.50%
Individual selected criterion	p.F.Flashlight on/off	71.78%	71.78%
	p.F.Lighting	78.91%	78.91%
	p.F.wear_glasses	72.83%	
	p.F.wear_hat	76.85%	
	p.L.Lighting	65.19%	65.19%
	p.L.Surface	89.55%	
	p.R.Lighting	65.19%	65.19%
	p.R.Surface	89.55%	
	t.F.Flashlight on/off	58.01%	58.01%
	t.F.Lighting	64.95%	64.95%
	t.F.wear_glasses	67.59%	
	t.F.wear_hat	68.86%	
	t.L.Lighting	55.61%	55.61%
	t.L.Surface	78.45%	
	t.R.Lighting	55.61%	55.61%
t.R.Surface	80.99%		

“Either or”

# Full intervention

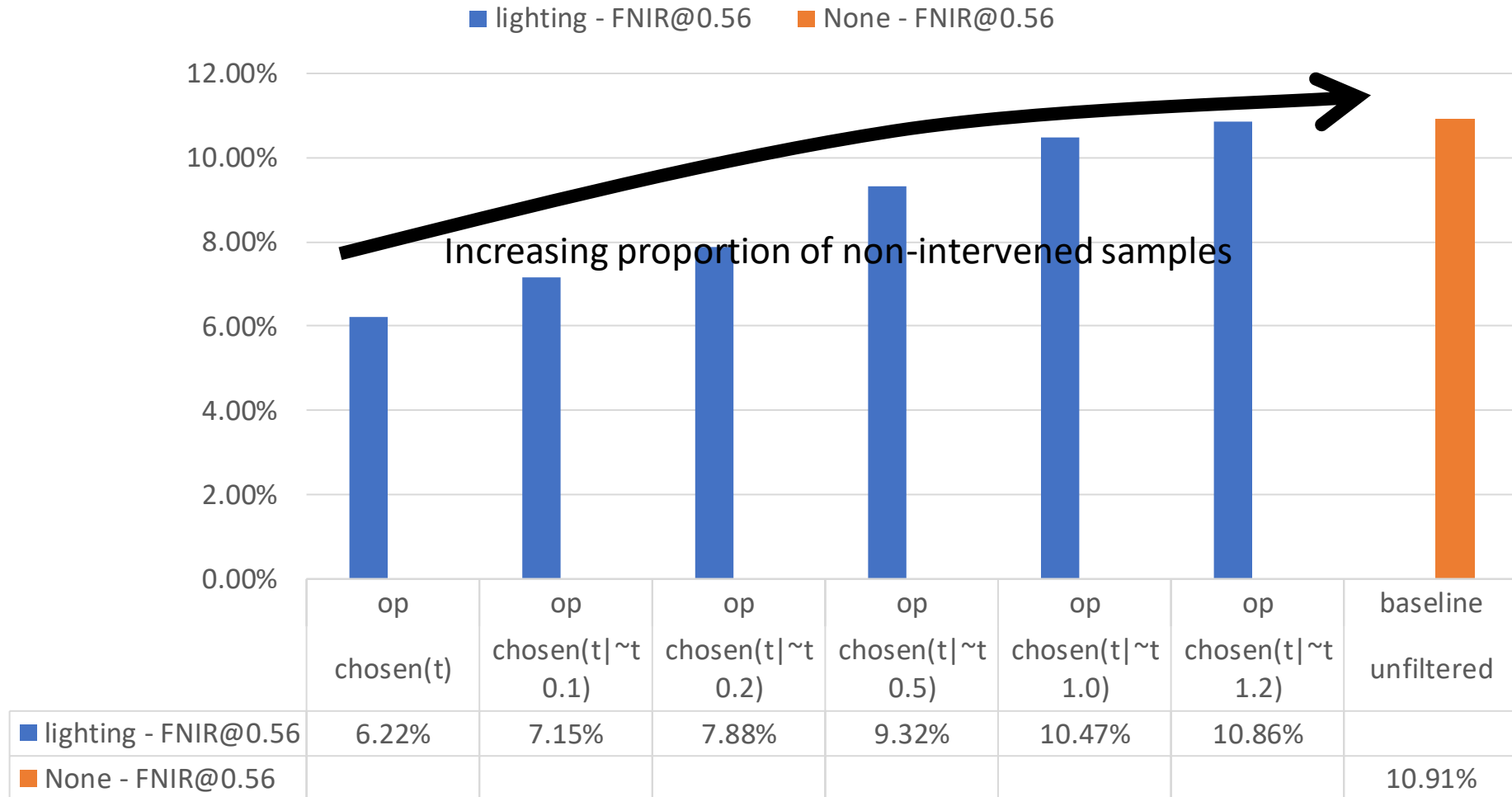
Face – flashlight off, indoor well-lit, outdoor shade, take off glasses and hat  
 Palmprint – indoor well-lit, unaltered, outdoor direct sun



Note: FPIR has near zero error values at the identification threshold of 0.56 of the fused score

# Lighting-based intervention

Face – flashlight off, indoor well-lit, outdoor shade  
 Palmprint – indoor well-lit, outdoor direct sun





# Summary

- We have developed a statistical method to identify capture conditions that are favourable during registration.
- The method only observes the fused score of a multimodal biometric system in the privacy preserved domain (IT2)
- The covariates found form the basis of a lighting-based or a full intervention
- The interventions were validated in the identification setting
- Future work:
  - Apply the same methodology to biometric sample quality (quality measures)
  - Apply it to analyse performance differentials

