

# Stating Comparison Score Uncertainty and Verification Decision Confidence Towards Transparent Face Recognition

Marco Huber<sup>1,2</sup>, Philipp Terhörst<sup>1,3,4</sup>, Florian Kirchbuchner<sup>1</sup>, Naser Damer<sup>1,2</sup>, Arjan Kuijper<sup>1,2</sup>

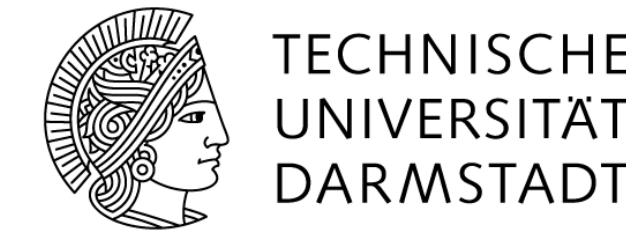
marco.huber@igd.fraunhofer.de

<sup>1</sup> Fraunhofer Institute for Computer Graphics Research IGD, Darmstadt, Germany

<sup>2</sup> Technical University of Darmstadt, Darmstadt, Germany

<sup>3</sup> Norwegian University of Science and Technology, Gjøvik, Norway

<sup>4</sup> Paderborn University, Paderborn, Germany



## Abstract

Face Recognition (FR) is increasingly used in critical verification decisions and thus, there is a need for **assessing the trustworthiness** of such decisions. The confidence of a decision is often based on the overall performance of the model or on the image quality. We propose to **propagate model uncertainties to scores and decisions in an effort to increase the transparency of verification decisions**. This work presents two contributions. First, we propose an approach to **estimate the uncertainty of face comparison scores**. Second, we introduce a **confidence measure of the system's decision** to provide insights into the verification decision. The suitability of the comparison scores uncertainties and the verification decision confidences have been experimentally proven on three face recognition models on two datasets.

## Introduction

- Human operators can intuitively state how sure they are about their decisions and may even conclude that they cannot make a meaningful, justifiable decision
- Current state-of-the-art face recognition models do not offer this confidence or uncertainty estimates

## Definitions [1]

**Uncertainty:** the belief about the variability of possible outcomes

**Confidence:** the belief that a given prediction is correct

## Score Uncertainty Estimation

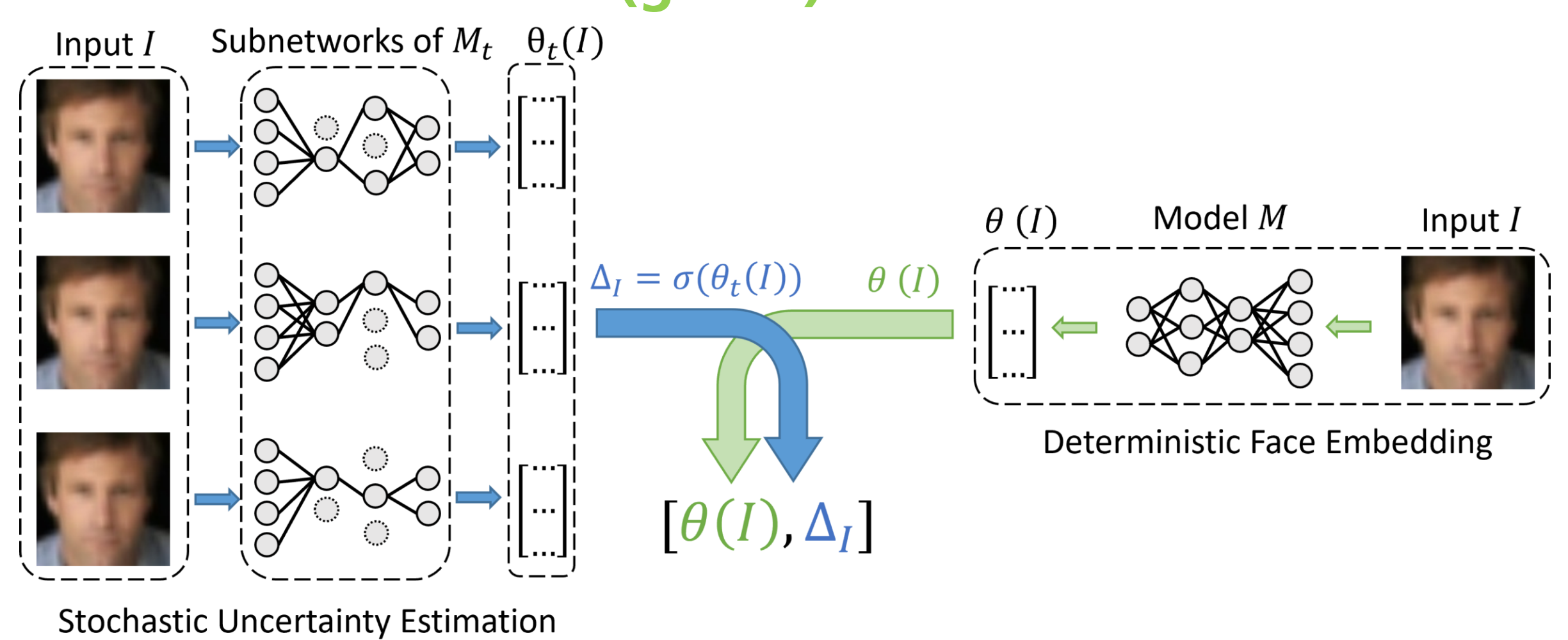
- To estimate the model uncertainty, we apply multiple stochastic forward passes with different dropout patterns being applied as proven by [2] and calculate the embedding uncertainty as the standard deviation of this set of stochastic embeddings
- To decide whether two embeddings represent the same identity or not, we use the cosine similarity (a). We then apply the formula of the propagation of uncertainty (c) [2] to obtain the score uncertainty based on the embedding uncertainties.

## Decision Confidence Estimation

- The score uncertainty only indicates how certain the system is about the score, not how reliable the decision is
- To obtain a decision confidence (g), we also apply the formula of the propagation of uncertainty (c) on a modified sigmoid function (e) that approximate the decision function and takes the decision threshold  $d$  into account



**Transparent Face Verification:** In addition to the usual information, such as the score and the decisions made, we propose the following to increase the transparency of the FR system: **the score uncertainty (orange)** and the **decision confidence (green)**.



**Uncertainty Estimation of the Embedding:** A deterministic and a set of stochastic embeddings are created using different dropout patterns. The uncertainty is calculated as the standard deviation of the stochastic embeddings.

$$S_c(X, Y) = \frac{X \cdot Y}{\|X\| \|Y\|} \quad (a) \quad S_c(X, Y) = \sum_{n=1}^N x_n \cdot y_n \quad (b)$$

$$\Delta_E = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 \cdot \Delta^2} \quad (c) \quad \Delta_{S_c} = \sqrt{\sum_{i=1}^n y^2 \cdot \Delta_{x_i}^2 + \sum_{i=1}^n x^2 \cdot \Delta_{y_i}^2} \quad (d)$$

**Uncertainty Estimation of the Comparison Score:** the cosine similarity (a) simplifies to (b) when normalized. The formula of propagation of uncertainty [2] (c) applied to (b) leads to (d), which allows the calculation of the comparison score uncertainty.

$$(e) \quad \delta(S_c) = \frac{1}{1 + e^{-\alpha(S_c - d)}} \quad (f) \quad \Lambda_{Int}(s) = |s - d_{th}|$$

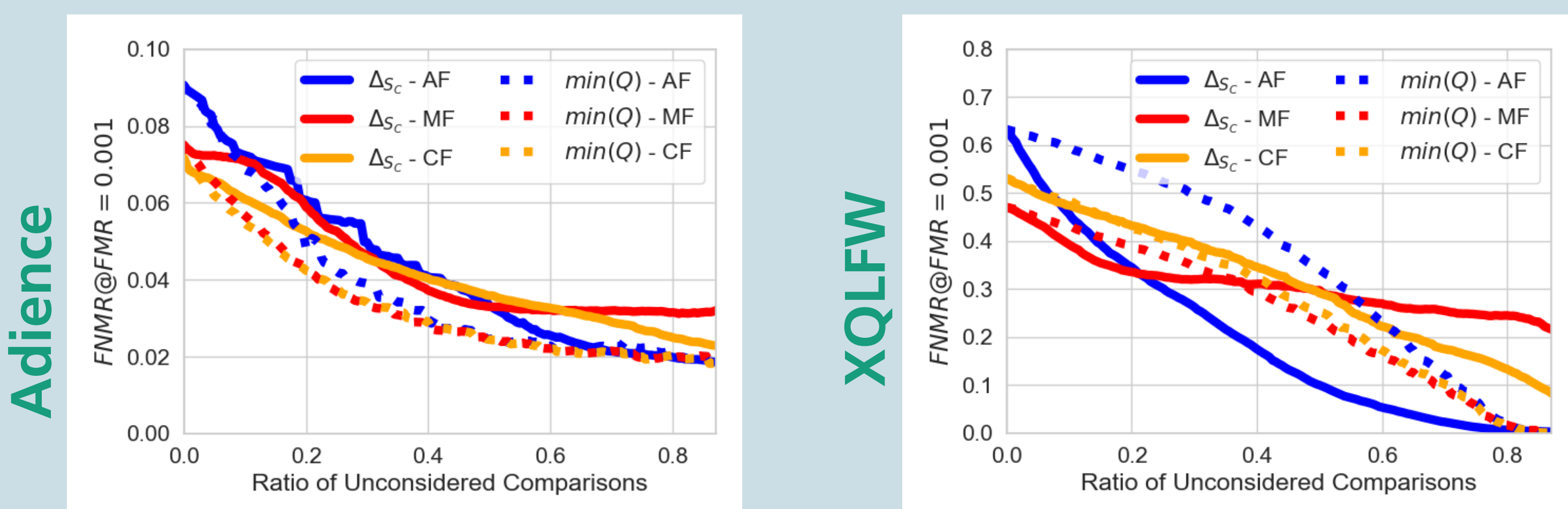
$$(g) \quad \Lambda_d(S_c) = 1 - \left[ \frac{\sum^N \delta(S_c) \cdot (1 - \delta(S_c)) \cdot \alpha x_n \cdot \Delta_{y_n}^2}{\sum^N \delta(S_c) \cdot (1 - \delta(S_c)) \cdot \alpha y_n \cdot \Delta_{x_n}^2} \right]^{\frac{1}{2}}$$

**Confidence Estimation of the Decision:** the decision step function is approximated with a modified sigmoid (e) to gain a derivable decision function. Then (c) is applied which leads to (g), that allows the calculation of a confidence estimate. (f) shows the "intuitive confidence", where the confidence increases as the actual scores moves further away from the decision threshold.

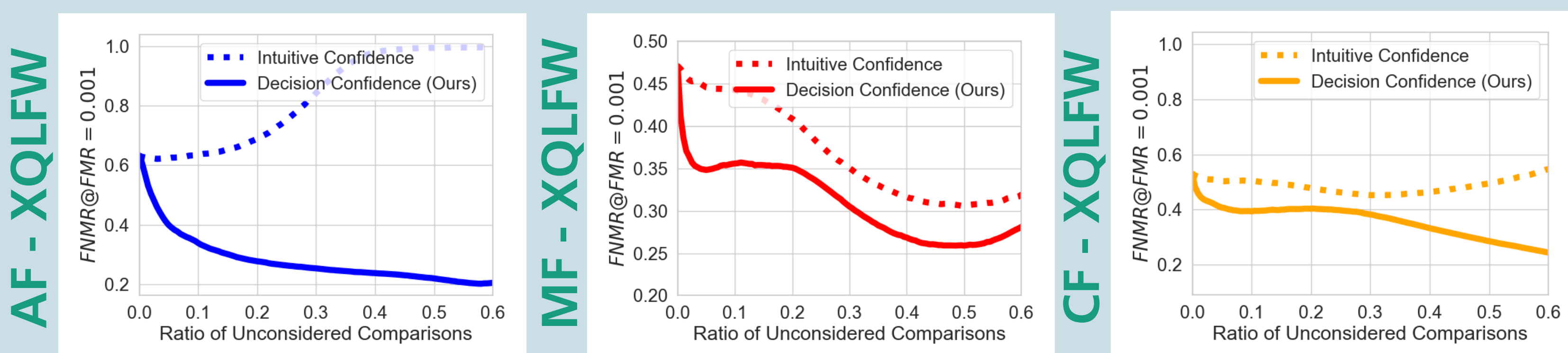
[1] Dane K Peterson and Gordon F Pitz. Confidence, uncertainty and use of information. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 14(1): 85, 1988.

[2] H.H. Ku. Notes on the use of propagation of error formulas. *Journal of Research of the National Bureau of Standards. Section C: Engineering and Instrumentation*, 70C, 1966

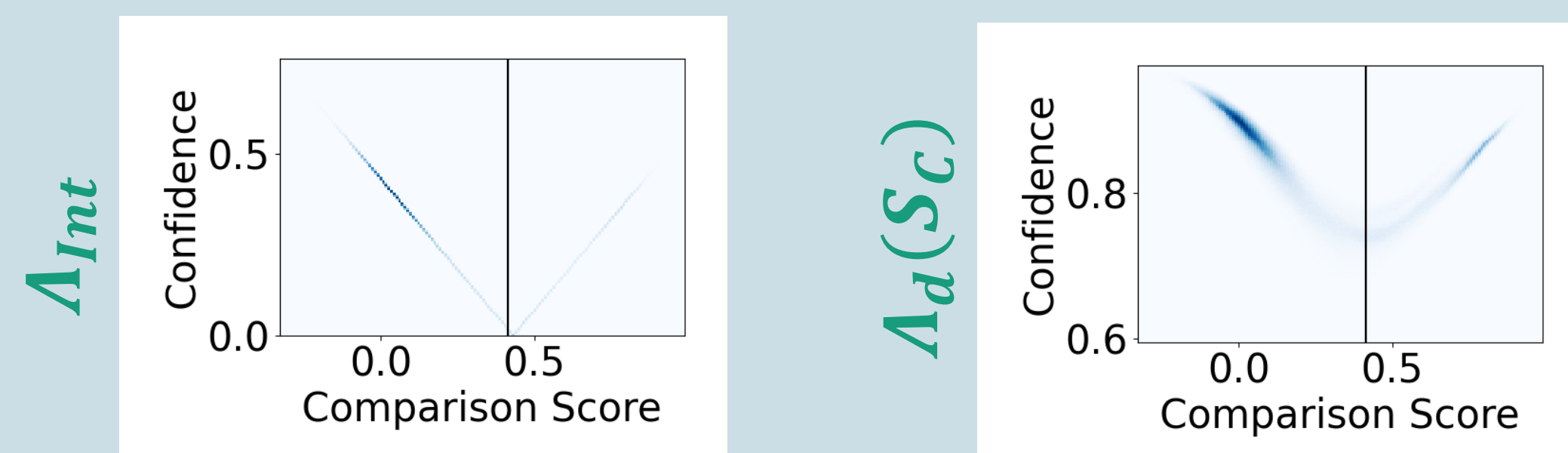
## Results



**Score Uncertainty Evaluation based on ERC curves:** With a higher score uncertainty ( $\Delta_{S_c}$ ), more wrong decisions are made. Evaluated on three FR models, ArcFace (AF), MagFace (MF) and CurricularFace (CF).



**Decision Confidence Evaluation based on ERC curves:** The proposed confidence outperforms the intuitive confidence in terms of reliability.



**Comparison of the Confidence Measures:** The proposed confidence provides a more natural understanding of confidence than the intuitive confidence.