CLASSIFICATION WITH CLASS-INDEPENDENT QUALITY INFORMATION FOR BIOMETRIC VERIFICATION

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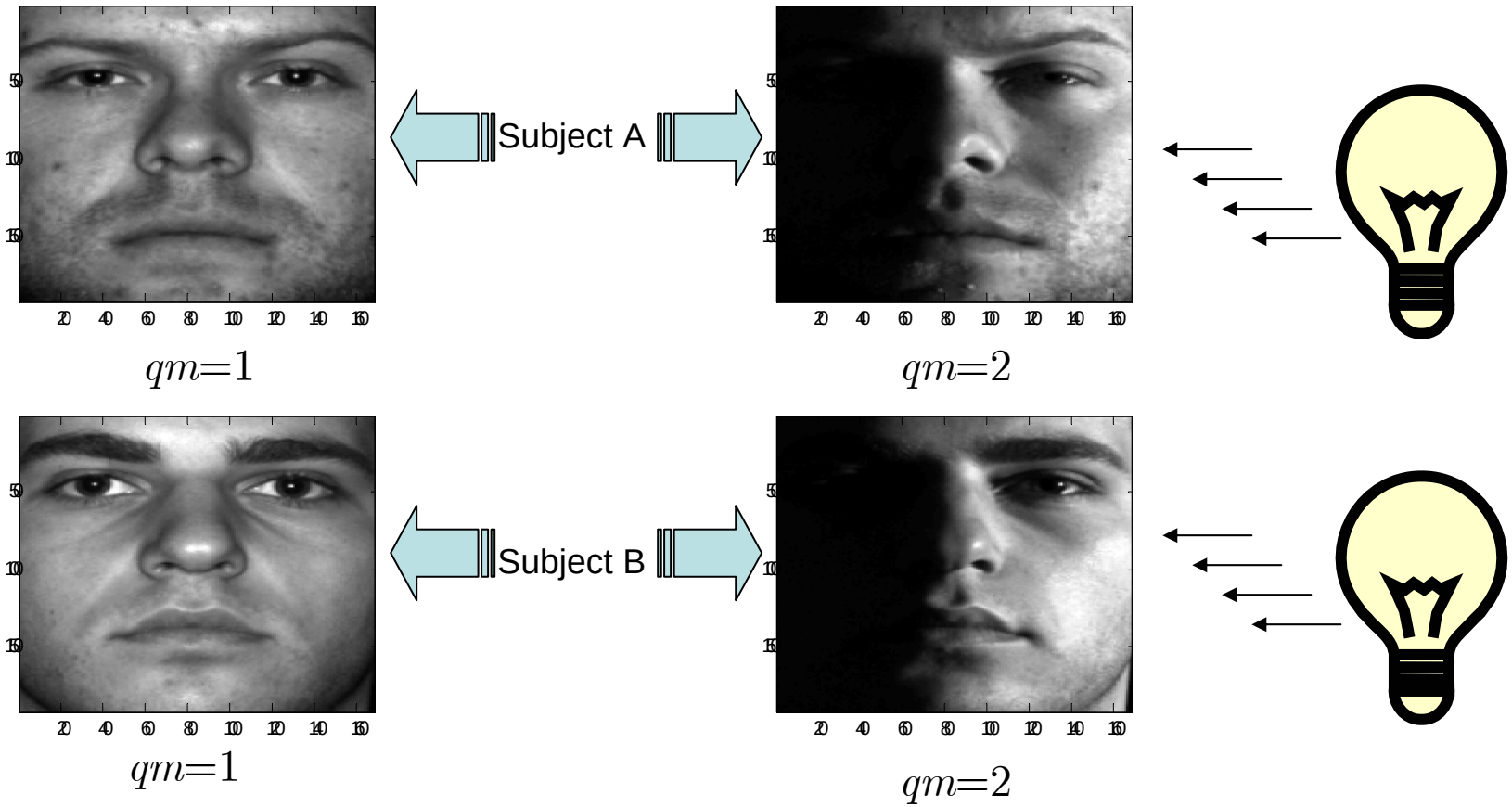
Presentation outline

- What is class-independent quality information in biometrics?
- How can class-independent information help in pattern classification?
- How to systematically improve biometric verification with quality information?
- Conclusions

Quality measures in biometrics

Images from the Extended Yale B corpus



Quality information is class-independent

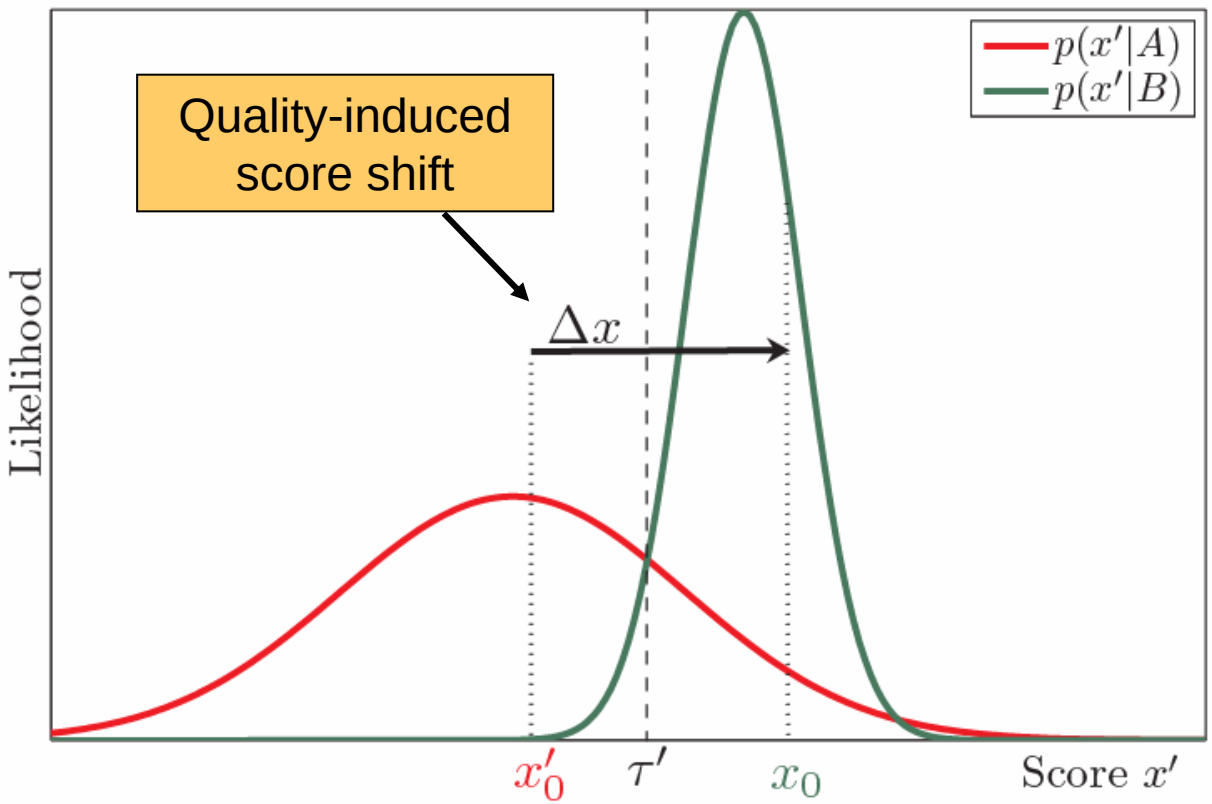
Motivation of this work

- Biometric data is **rarely** of constant, controlled quality
- Inconsistent data quality $\Rightarrow$ classification **ERRORS**
- Current understanding of the role of quality measures is **more intuitive than systematic**
- Existing approaches are mostly **heuristic and ad-hoc**

OBJECTIVE

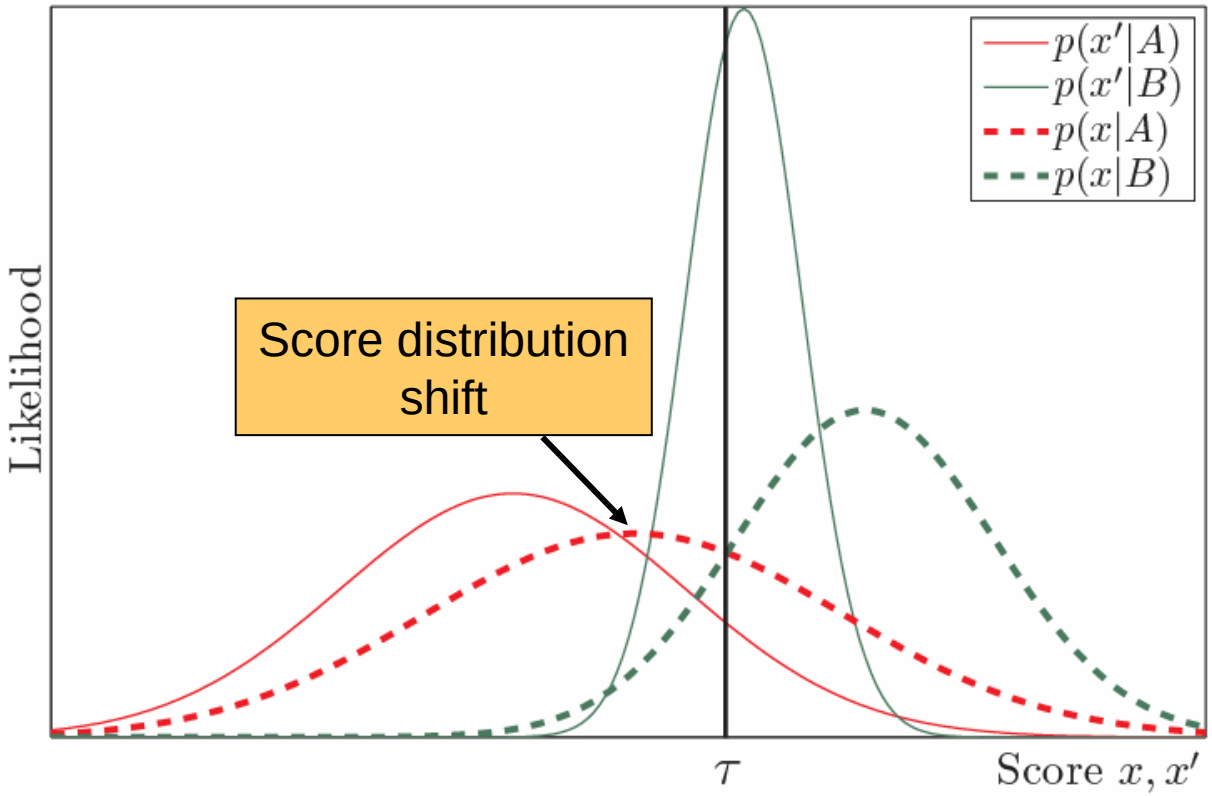
Create a **systematic method** of classification with **quality measures**, **generalizable** to single-, multi-classifier and multimodal systems.

Why errors occur?



$$x = x' + \Delta x = \Phi(n, x')$$

Why errors occur?



Distribution/model shift observed in face, fingerprint, speaker verification etc.

Why errors occur?

Shift in score distributions

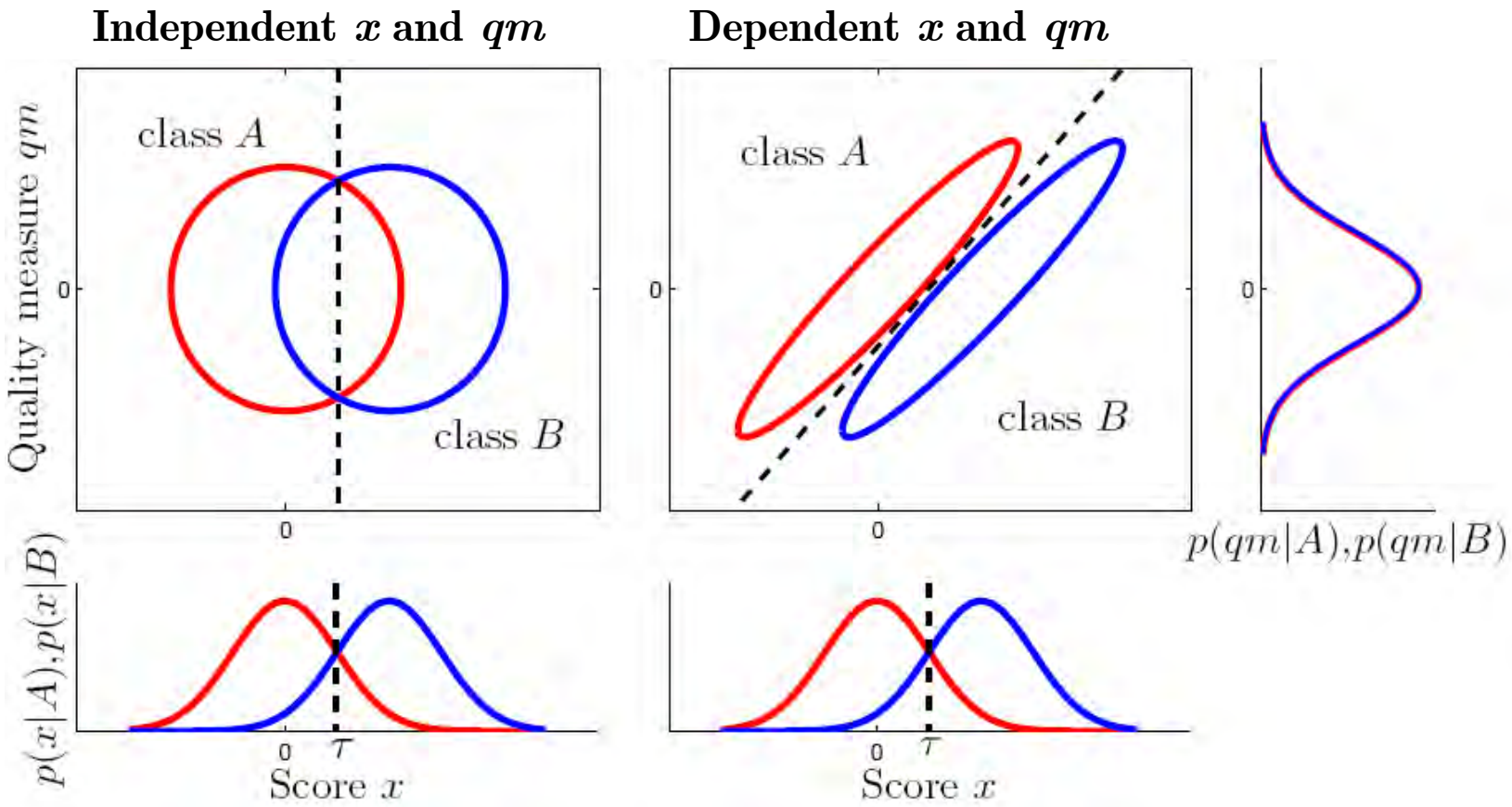
$\Downarrow$

Scores x and signal quality are **DEPENDENT**

$\Downarrow$

Scores x and **quality measures** qm are **DEPENDENT**

Improving classification with class-independent information



Evidence space $\mathbf{e}$=[scores x, quality measures qm]

In the context of x, **irrelevant** qm becomes **relevant**

Improving classification with quality measures

Properly collected quality measures are relevant, class-independent classification features.

Stronger dependence between quality measures and baseline classifier scores can lead to better class separation.

Class-independent quality features can help improve classification.

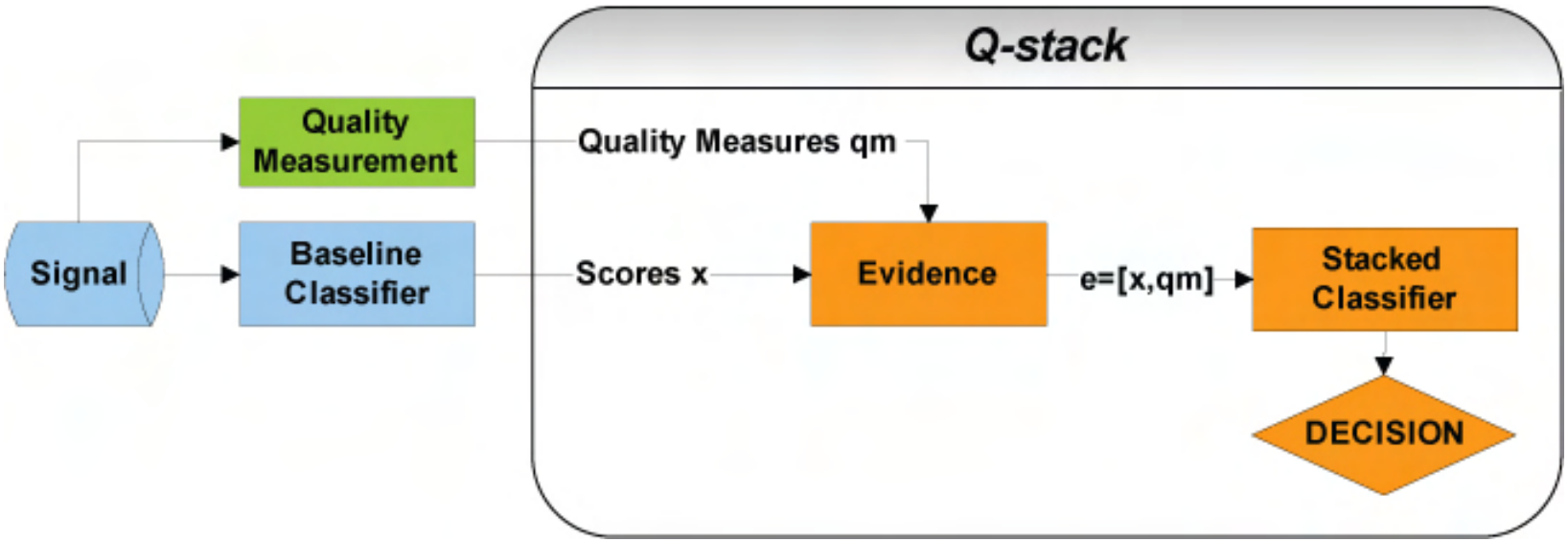
Q-stack: motivation

- Scores and quality measures can be considered as classification features
- Stronger dependence between quality measures and baseline classifier scores can lead to improved class separation
- Actual dependencies are hard to model analytically
- Data-driven approach: dependencies learned from data

Q-stack: a generalized stacking-based framework of classification using quality measures

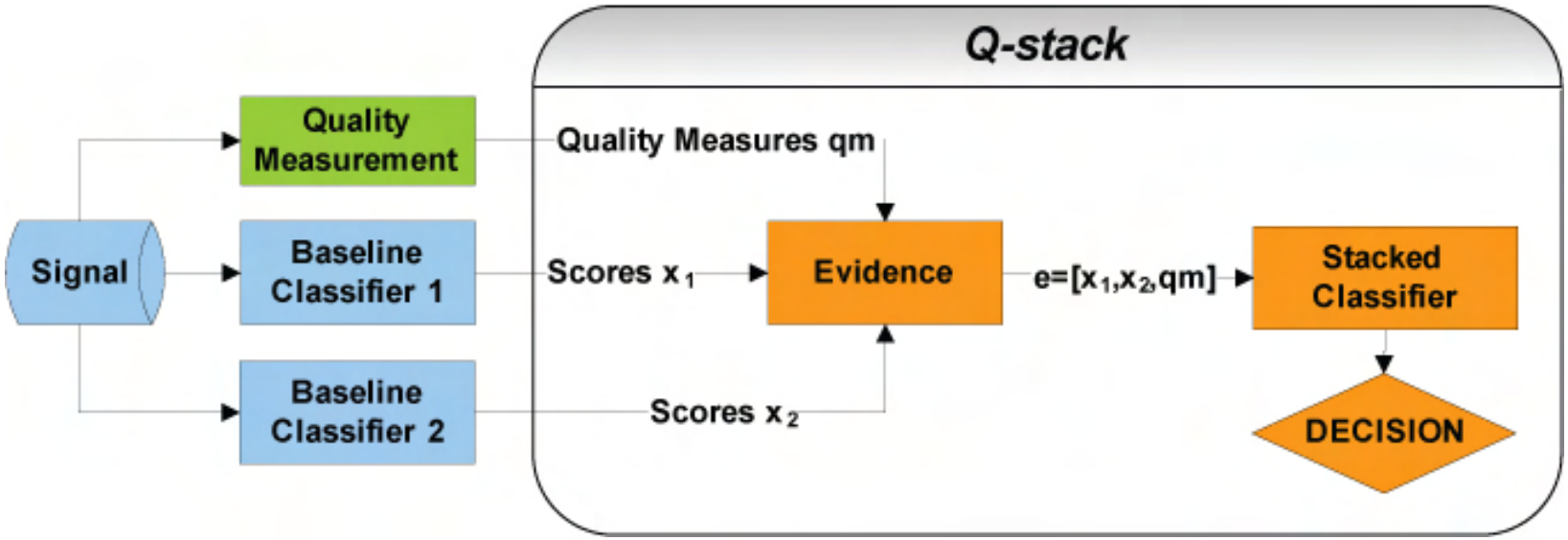
How to use quality measures?

- Introducing ***Q-stack***
- Based on the concept of ***classifier stacking***



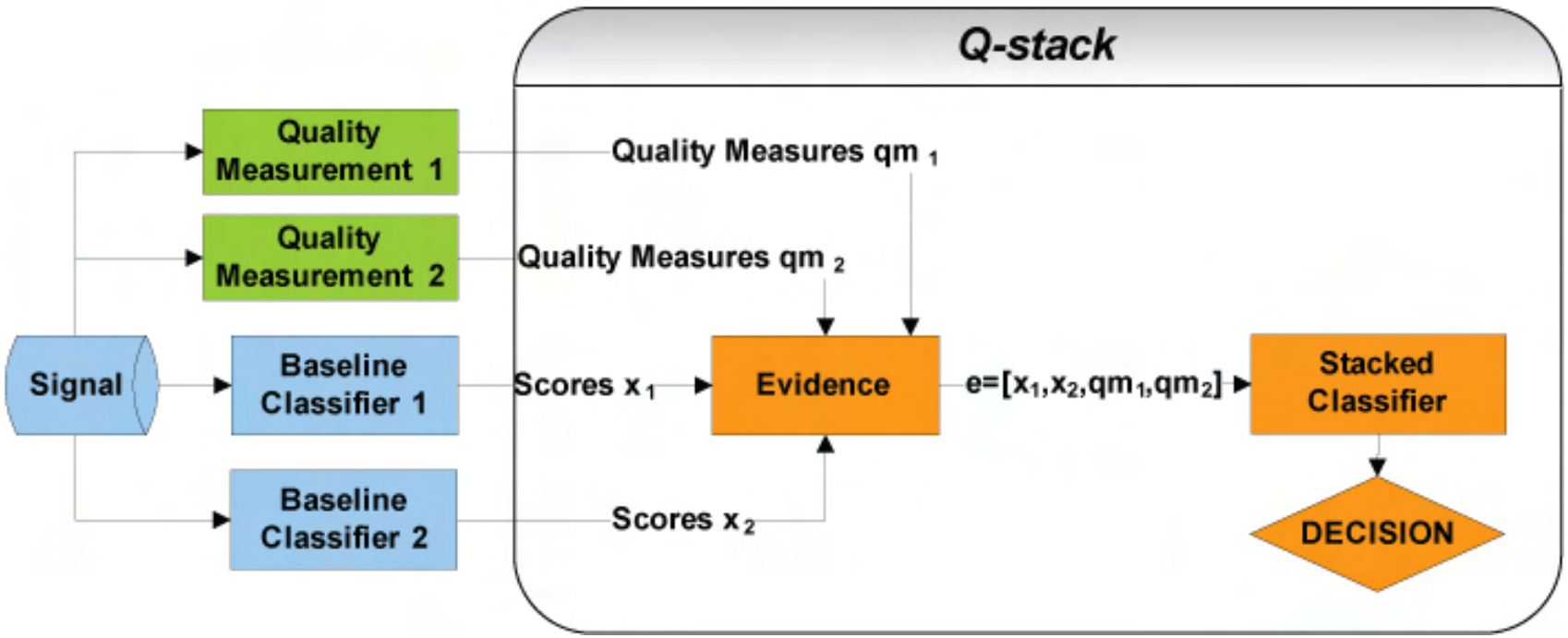
How to use quality measures?

Q-stack: multiple classifier application



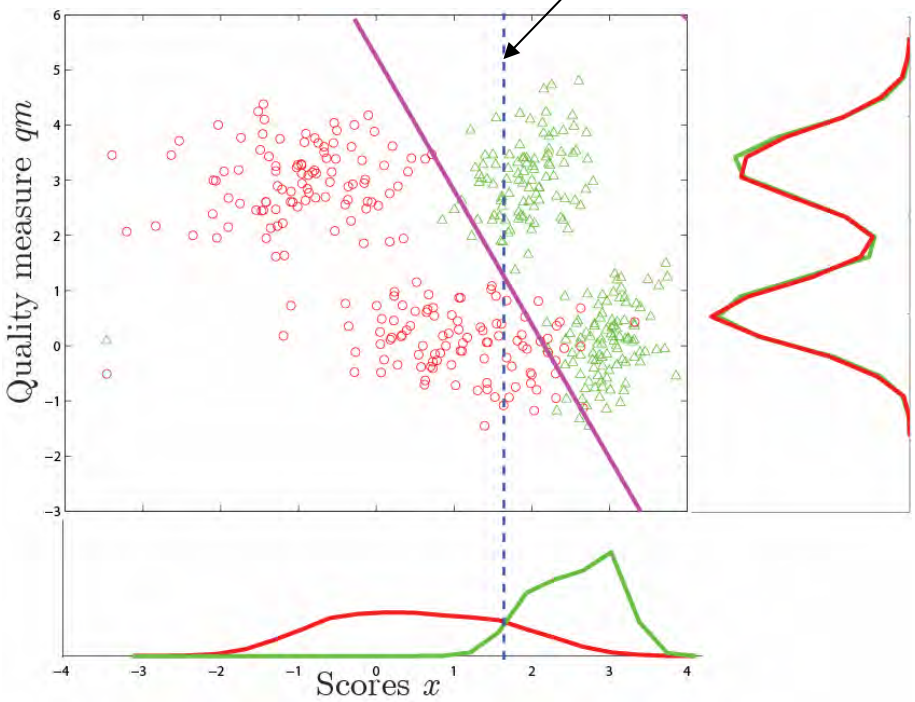
How to use quality measures?

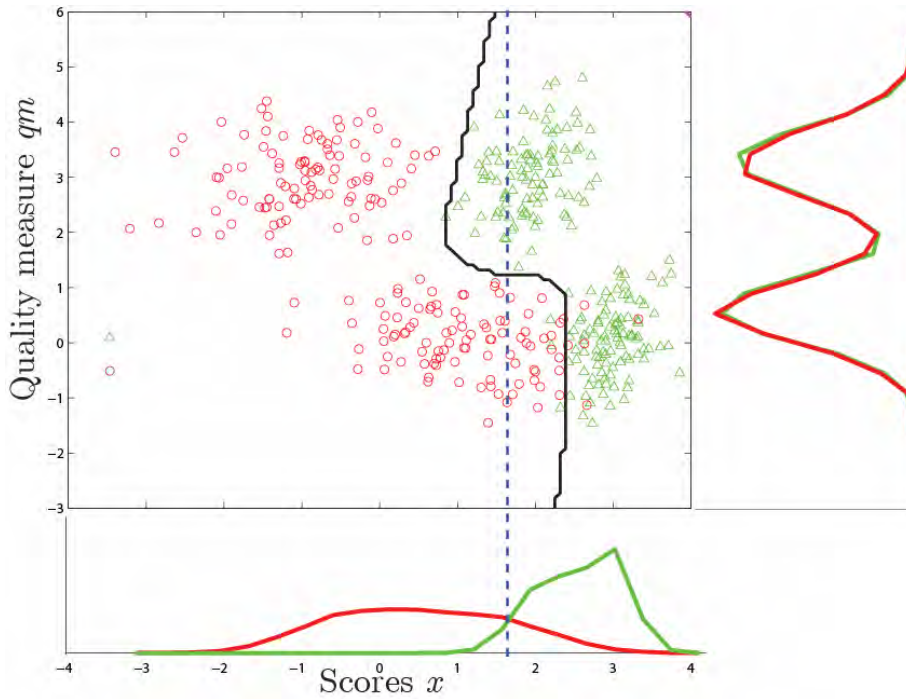
Q-stack: multiple quality measures



Q-stack: synthetic example

Score threshold, ER=0.13





Stacked classifier: LDA
ER=0.05

Stacked classifier: SVM
ER=0.03

Q-stack as a generalized framework

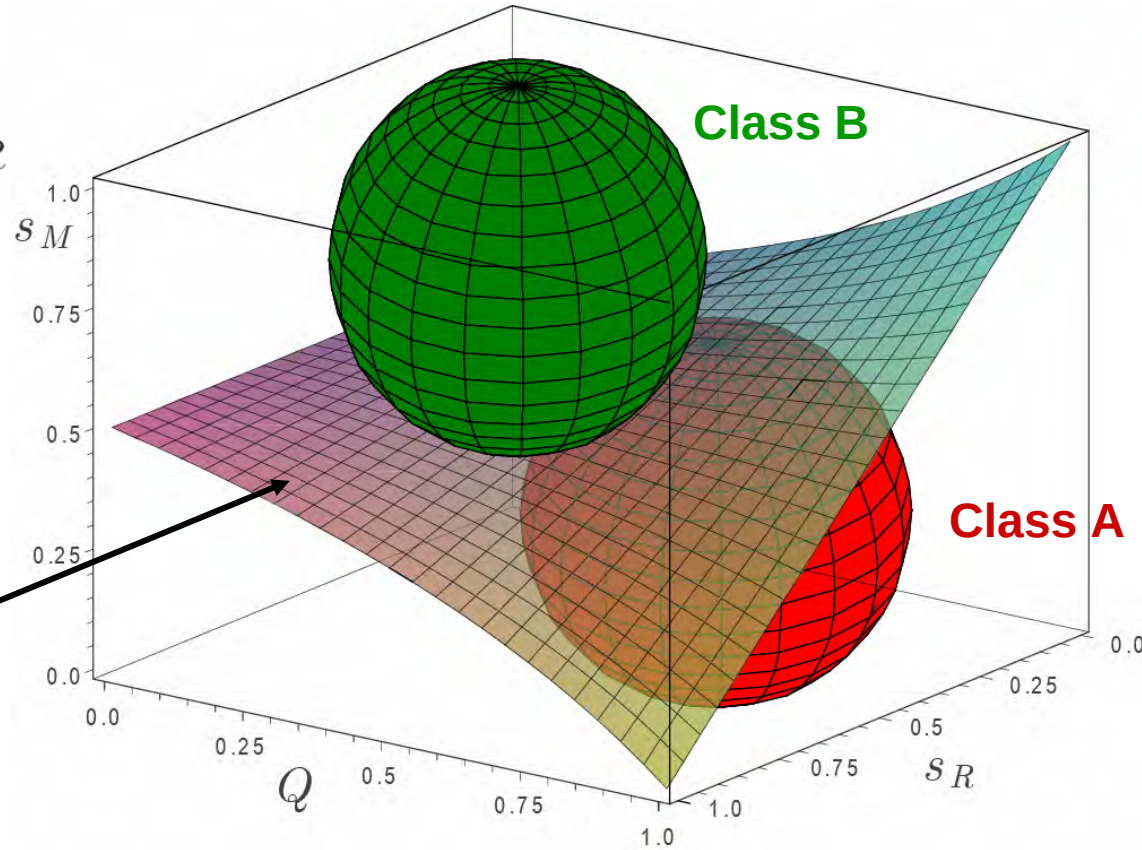
- Seeks an **optimal decision boundary** in the evidence space
- One **stacked classifier**
- **Modality-independent**
- Accepts **multiple quality measures**
- **Generalizable** to existing approaches

Generalization example – multiple classifier systems

Fusion function with quality parameter

Example of a multi-classifier fusion function

$$s_Q = \frac{Q}{2} s_M + (1 - \frac{Q}{2}) s_R$$



Heuristic approximation of optimal *Q-stack* decision boundary

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Experimental design

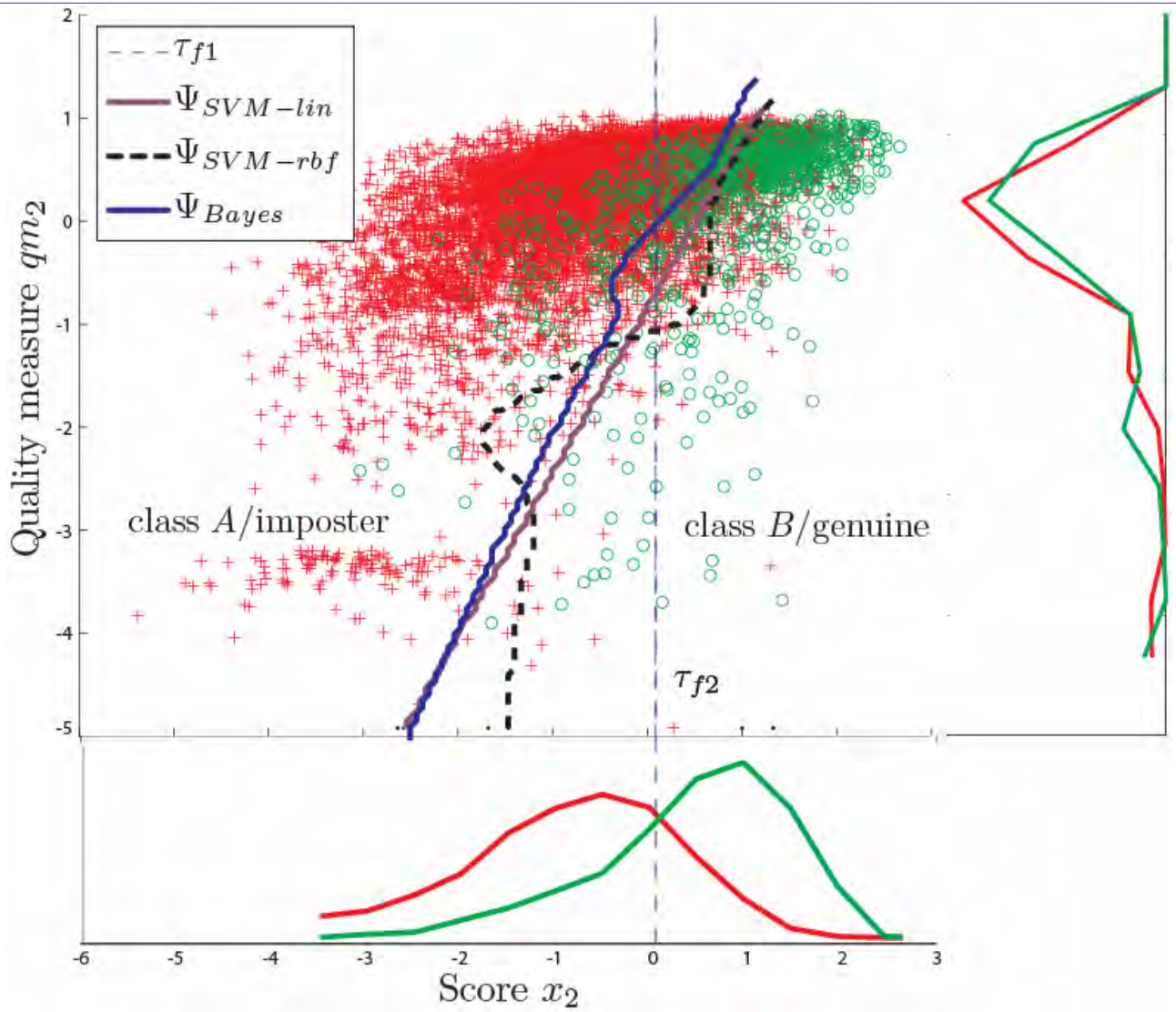
Goal of the experiment:
To demonstrate that quality measures bring a **systematic improvement** over baseline systems.

Used modalities: face, fingerprint

Used stacked classifiers in the Q-stack framework:

- SVM-rbf
- SVM-lin
- Bayes/GMM

Experimental evaluation: face verification



Baseline:
HTER=0.27

Q-stack SVM-lin:
HTER=**0.214**

Q-stack:SVM-rbf:
HTER=**0.217**

Q-stack Bayes:
HTER=**0.212**

Matcher:
PCA/Mahalanobis
Quality Measure:
Corr. coef. with
average face template

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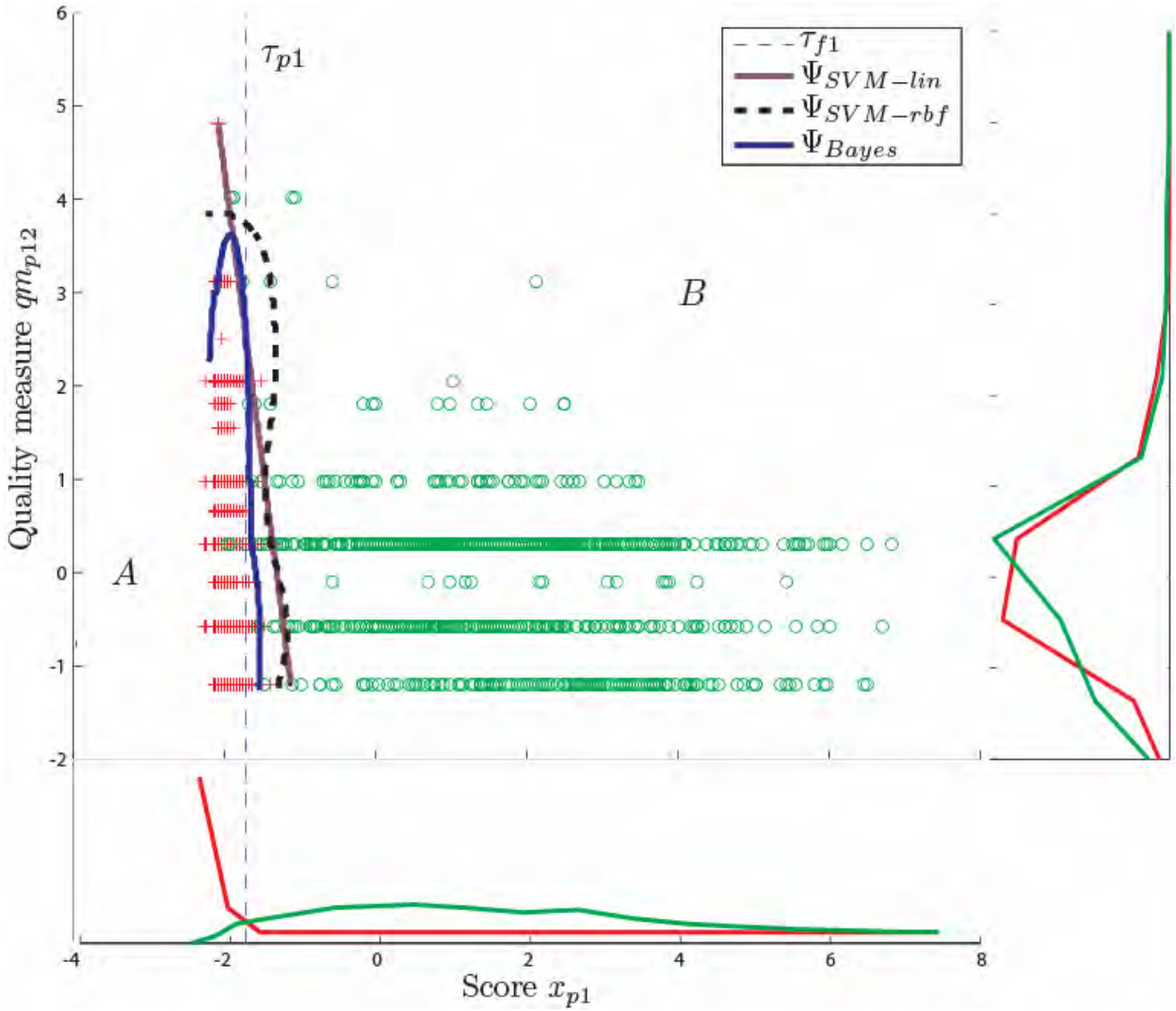
Experimental evaluation: fingerprint verification



Baseline:
HTER=0.0086

Q-stack SVM-lin:
HTER= **0.0047**

Q-stack SVM-rbf:
HTER= **0.0051**

Q-stack Bayes:
HTER= **0.0039**

Matcher:
NIST (NFIS2)
Quality Measure:
NIST (NFIQ)

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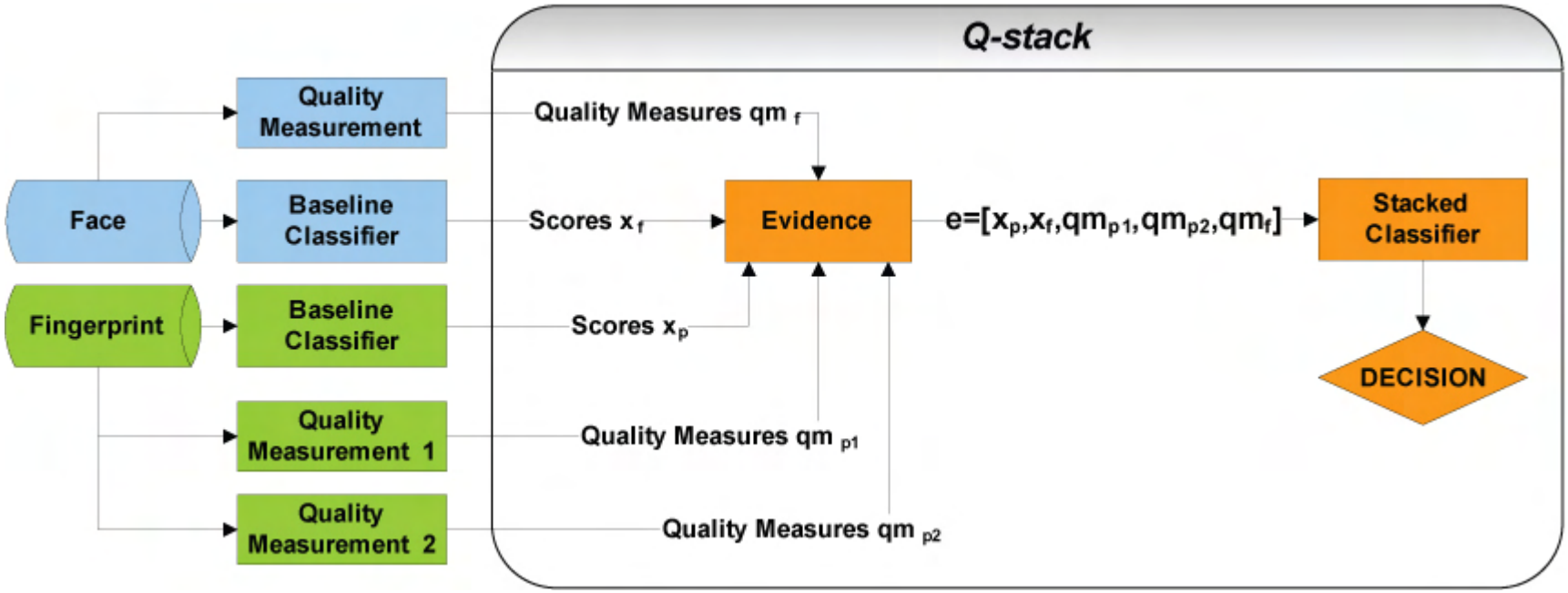
Experimental evaluation: multimodal fusion



Baseline fusion			
	HTER	ER_A	ER_B
SVM-lin	**0.0076**	0.0033	0.0118
Bayes	**0.0056**	0.001	0.0013

Q-stack			
	HTER	ER_A	ER_B
SVM-lin	**0.0026**	0.0029	0.0022
Bayes	**0.0027**	0.0038	0.0017

Conclusions

- Quality measures can be treated as **classification features**
- Class-independent quality measures can help separate between classes, given their **dependence** on the baseline classifier scores
- Proposed method *Q-stack* is a **general framework** of classification with quality measures in
  - **single classifier** systems
  - **multi-classifier/multimodal** systems
- Theoretical findings are supported by experiments with **real biometric data**

References

- Parts of presented results can be found in:

Quality measures in unimodal and multimodal biometric verification, J. Richiardi, K. Kryszczuk, A. Drygajlo, 15th European Conference on Signal Processing EUSIPCO 2007, Poznan, Poland.

Improving classification with class-independent quality measures: Q − stack in face verification, K. Kryszczuk, A. Drygajlo, 2nd International Conference in Biometrics ICB2007, Seoul Korea, August 2007

Q − stack: uni- and multimodal classifier stacking with quality measures, K. Kryszczuk, A. Drygajlo, 7th International Workshop on Multiple Classifier Systems 2007, Prague, Czech Republic