Fusion of Multimodal Biometrics

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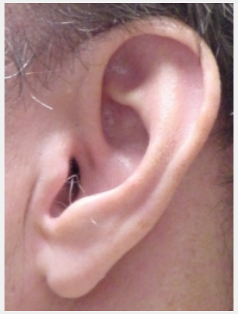
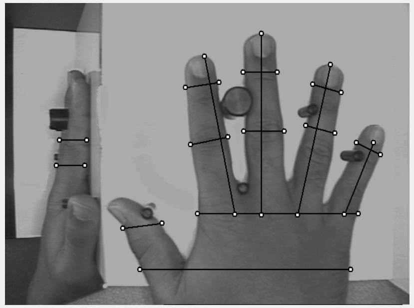
Multimodal biometrics

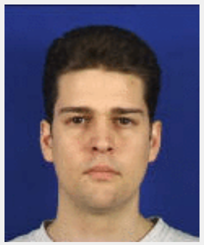
- Different biometric modalities developed
  - –finger print
  - –iris
  - –face (2D, 3D)
  - –voice
  - –hand
  - –lips dynamics
  - –gait





Different traits- different properties

- •usability
- •acceptability
- •performance
- •robustness in changing environment
- •reliability
- •applicability (different scenarios)



Benefits of multimodality

- Motivation for multiple biometrics
  - To enhance performance
  - To increase population coverage by reducing the failure to enrol rate
  - To improve resilience to spoofing
  - To permit choice of biometric modality for authentication
  - To extend the range of environmental conditions under which authentication can be performed

OUTLINE

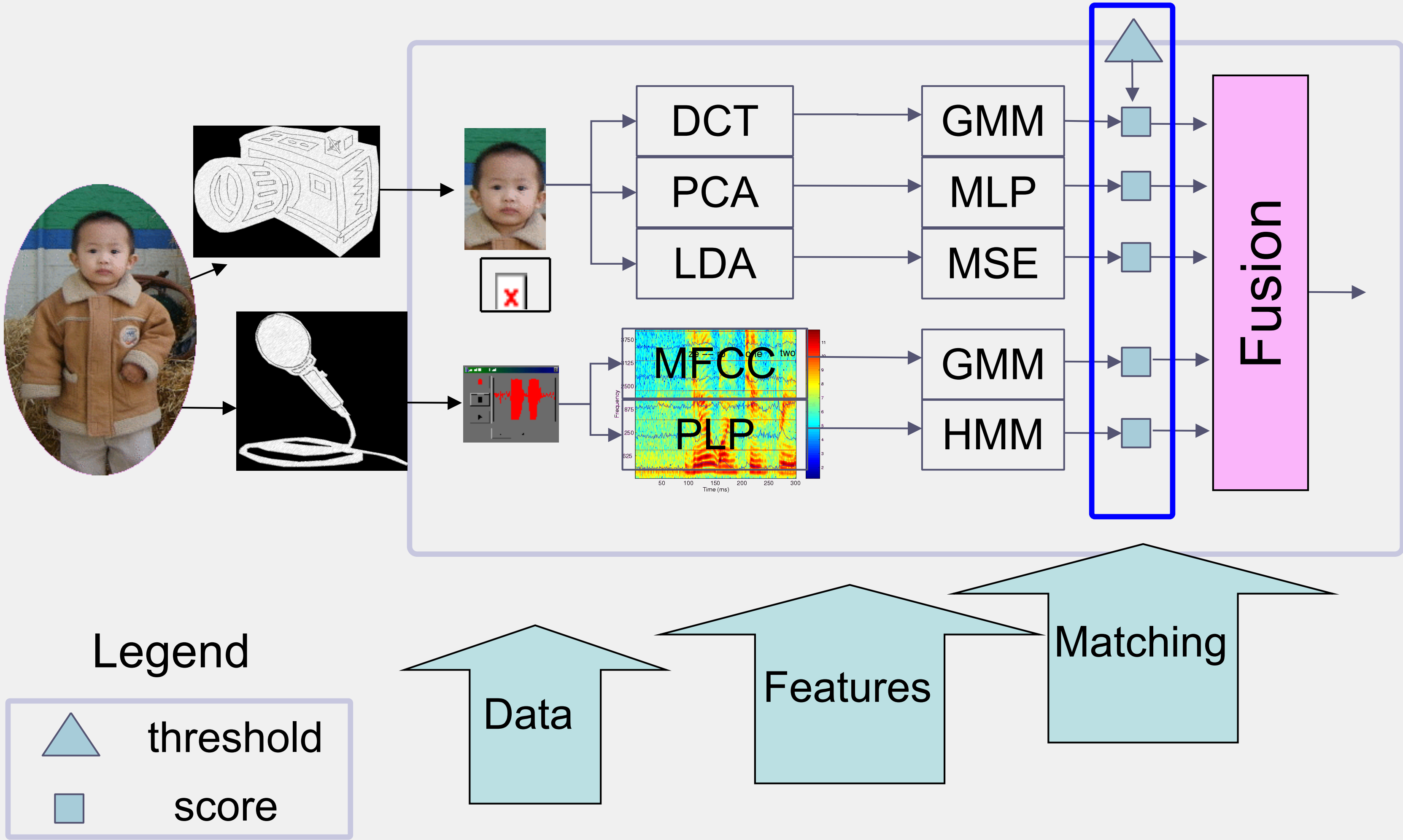
- Fusion architectures
- Problem formulation
- Estimation error
- Case study: Multimodal and cross-modal person re-identification
- Conclusions

The aim: *To discuss the purpose of multimodal biometrics fusion, and to introduce basic fusion architectures and underlying mathematical models*

Fusion architectures

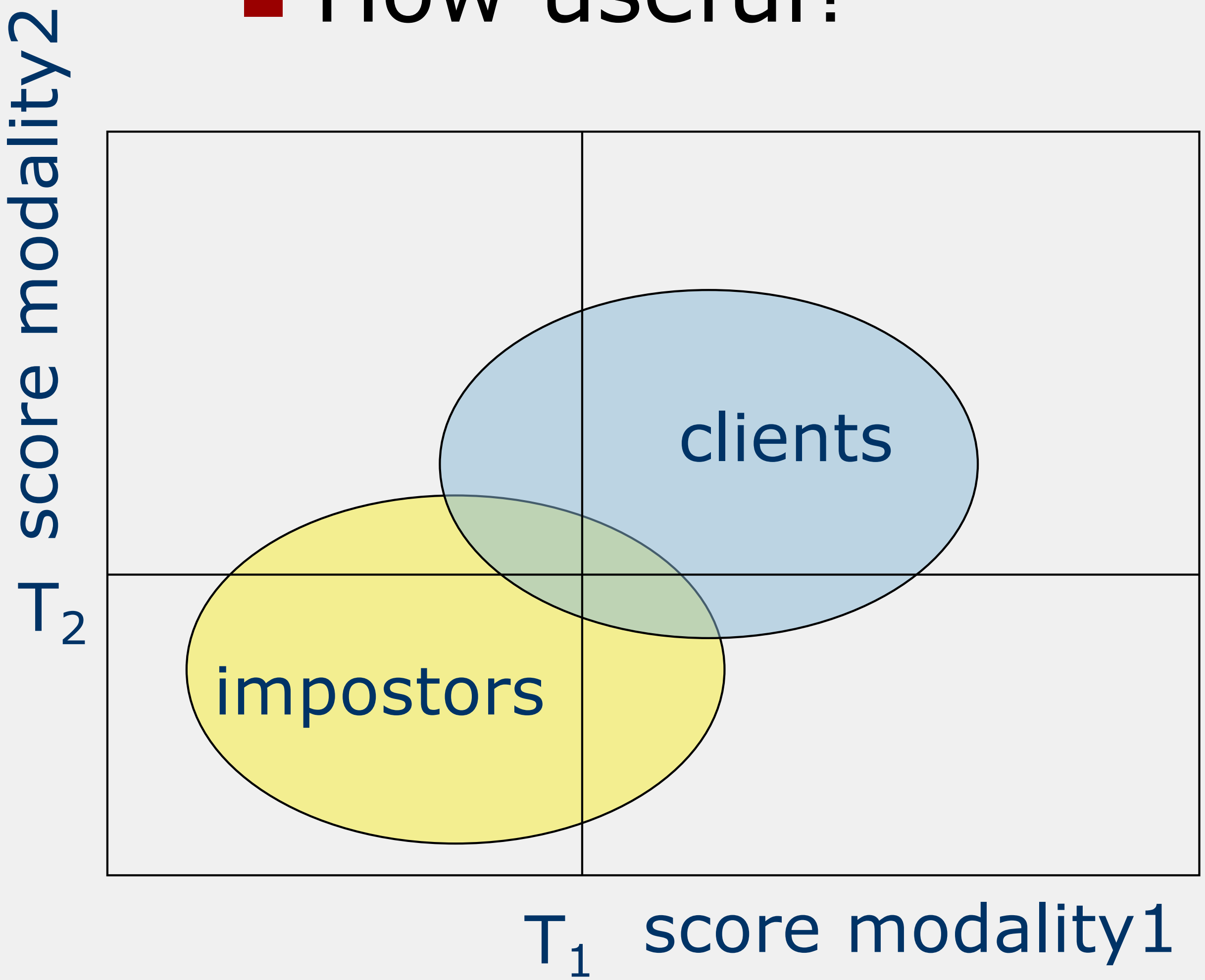
- Integration of multiple biometric modalities
- Sensor (data) level fusion
  - Linear/nonlinear combination of registered variables
  - Representation space augmentation
- Feature level fusion
- Soft decision level fusion
- Decision level fusion

Decision level fusion



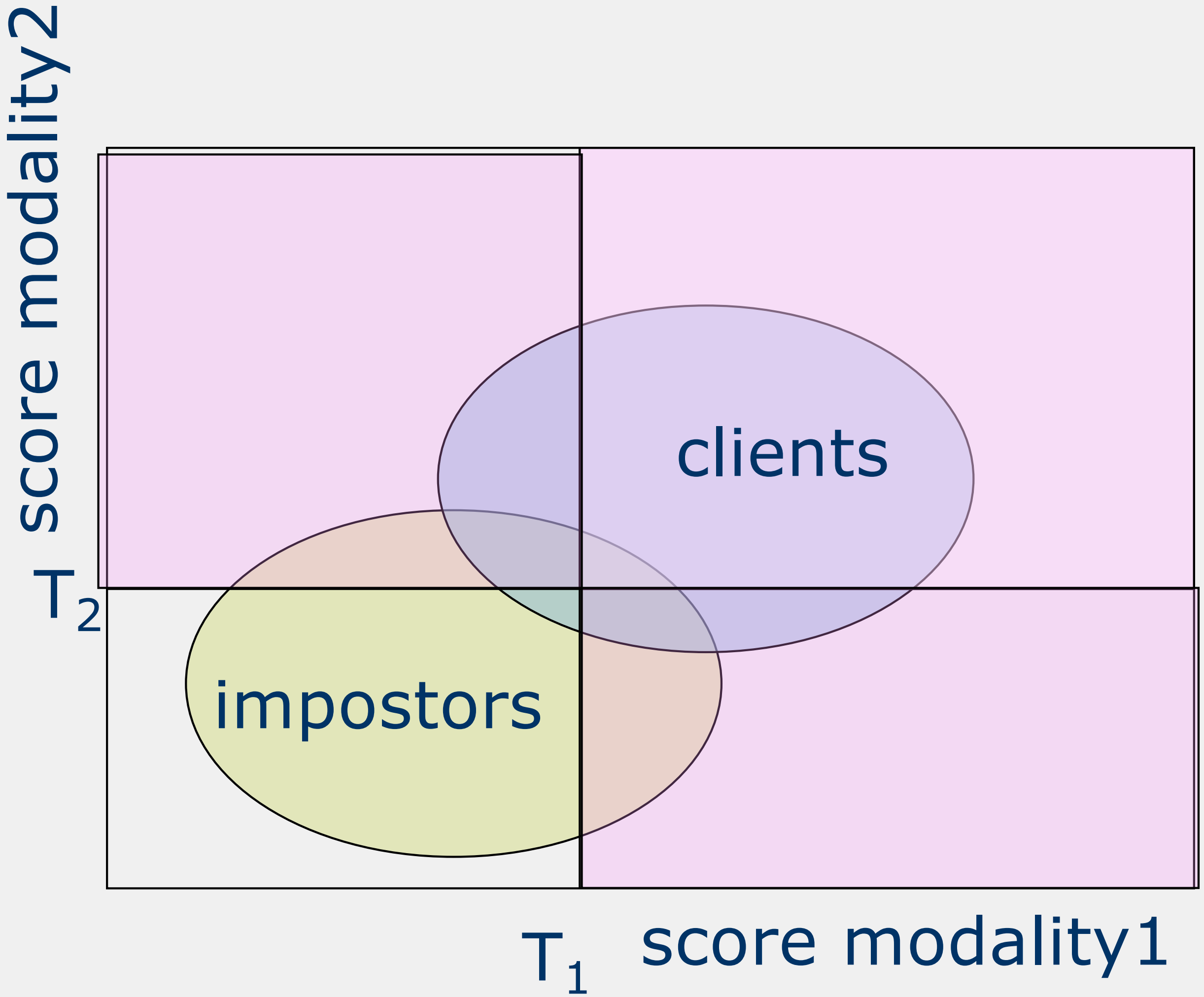
Decision-level fusion

- How useful?



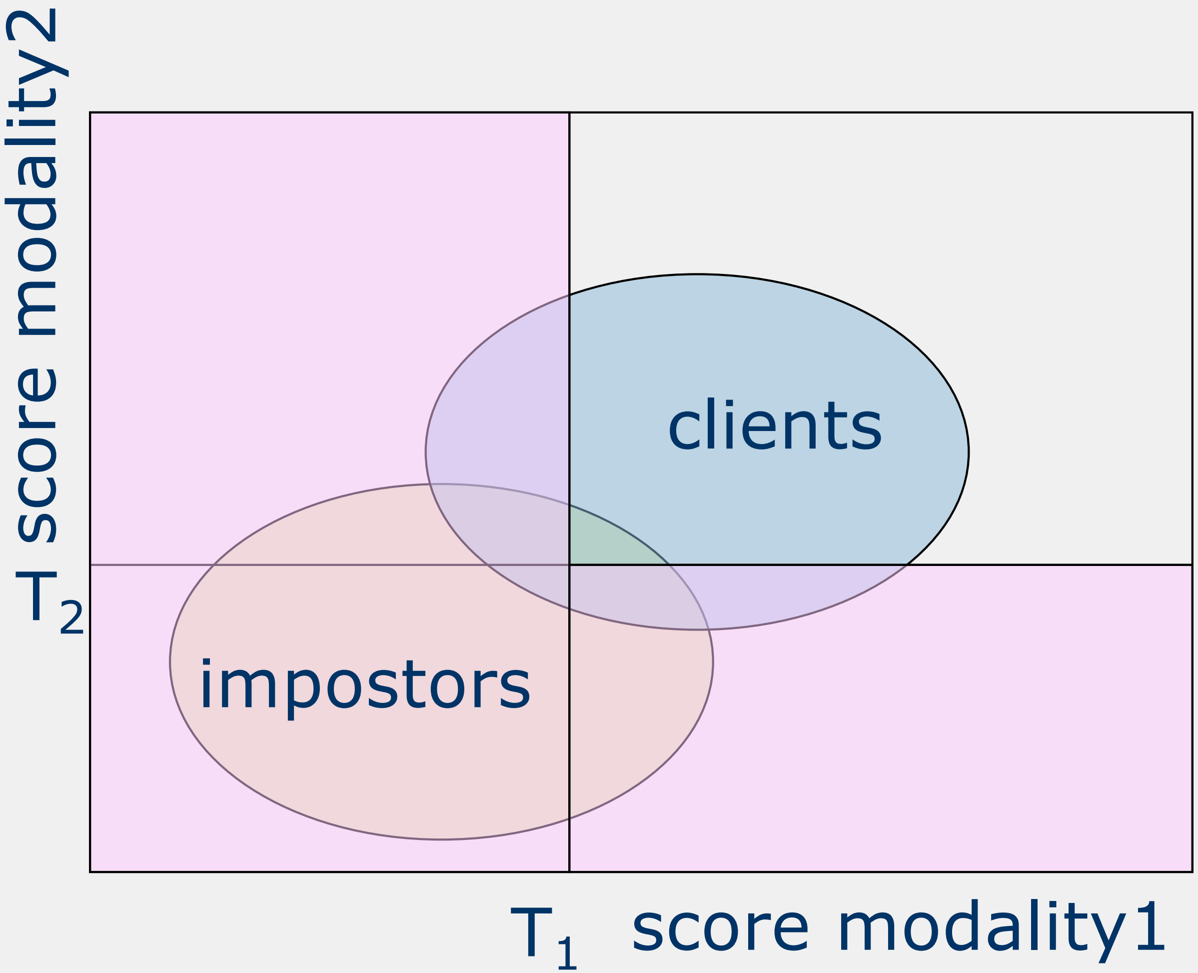
Decision-level fusion

- Accepted by either modality



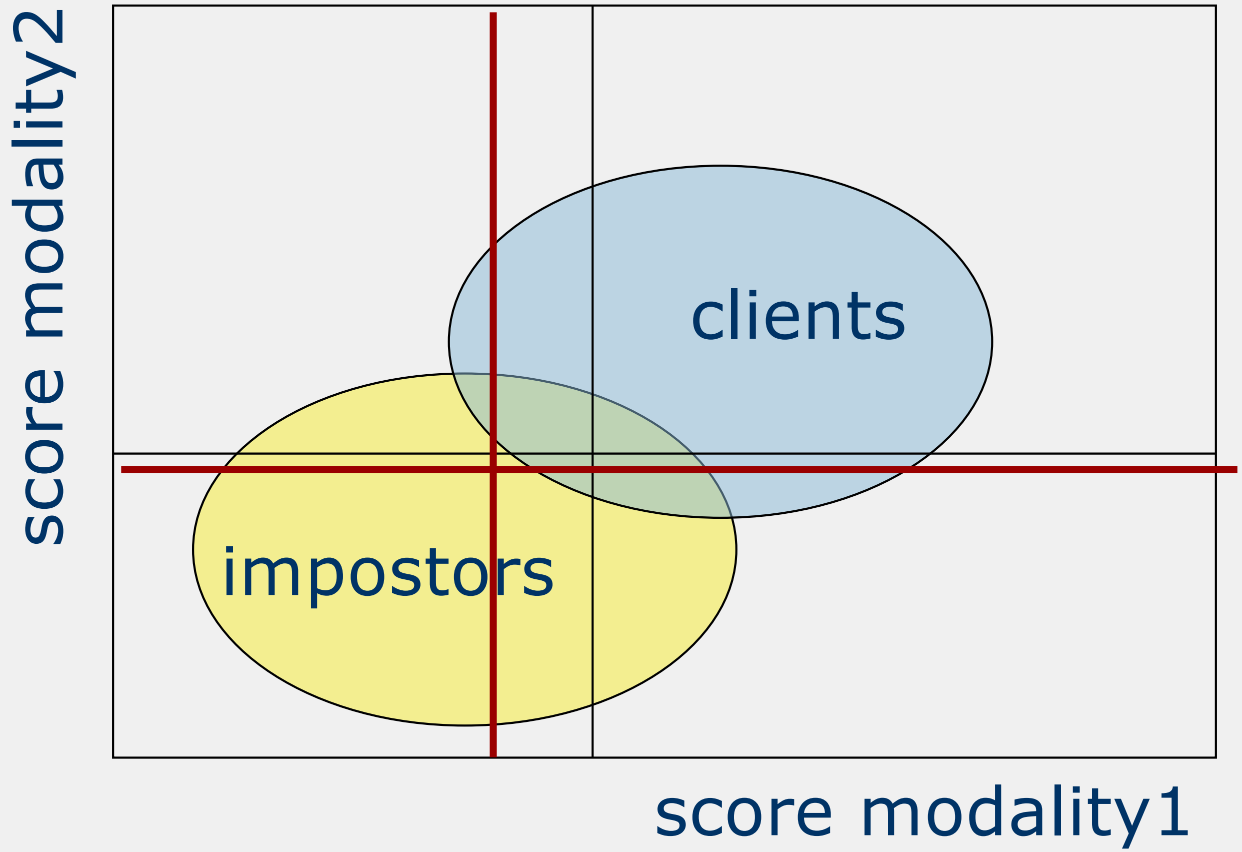
Decision-level fusion

- Accepted by both



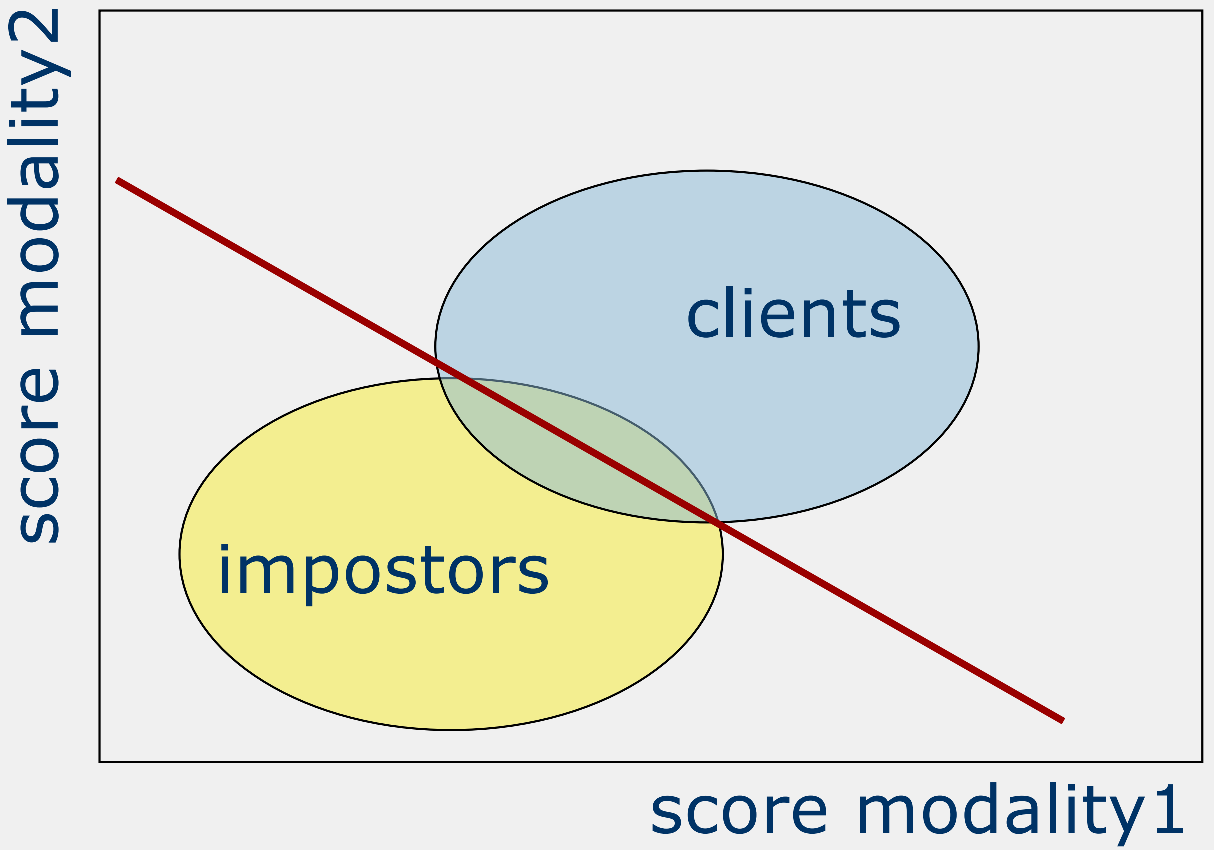
Decision-level fusion

Better performance by adapting the thresholds

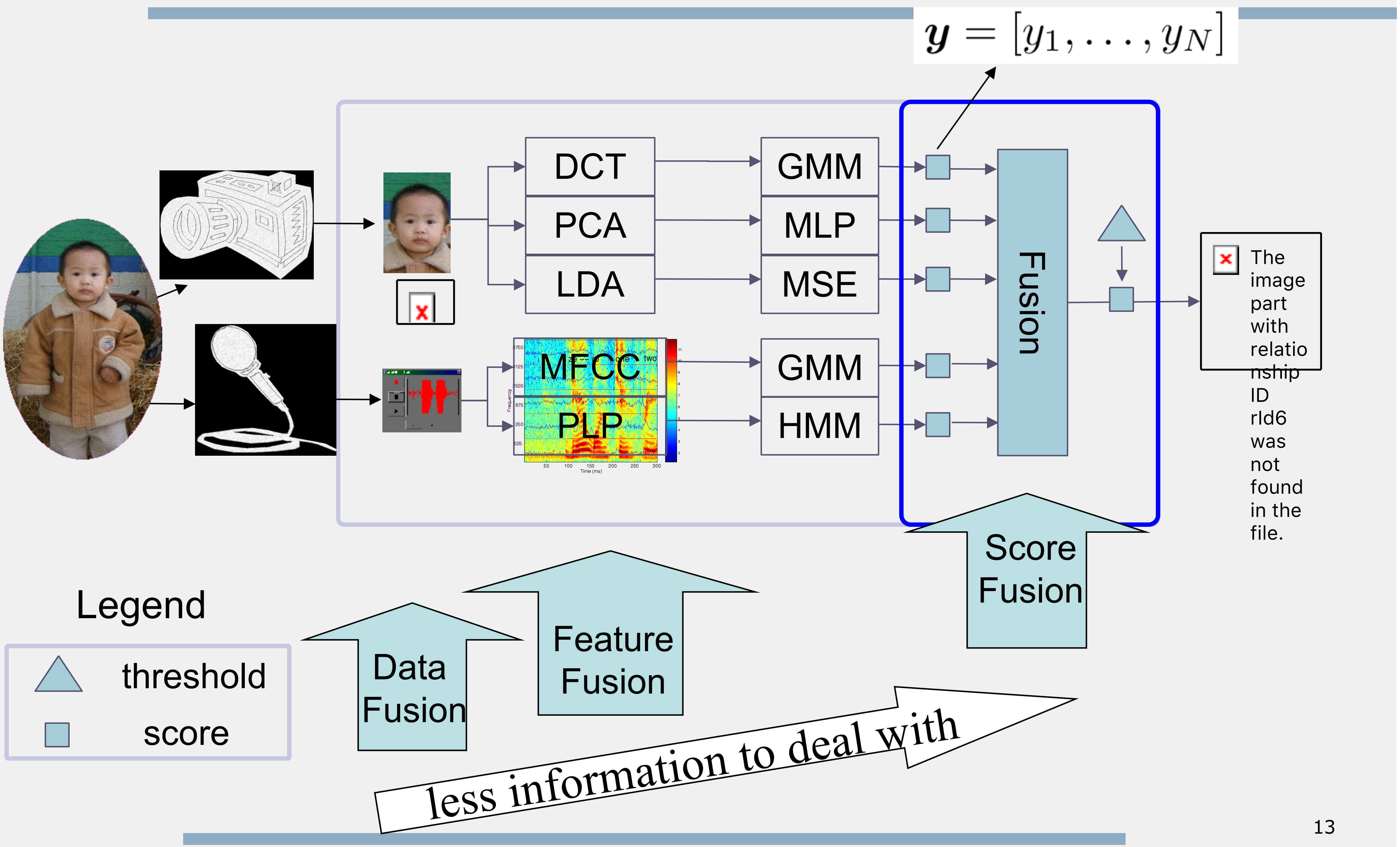


Score-level fusion

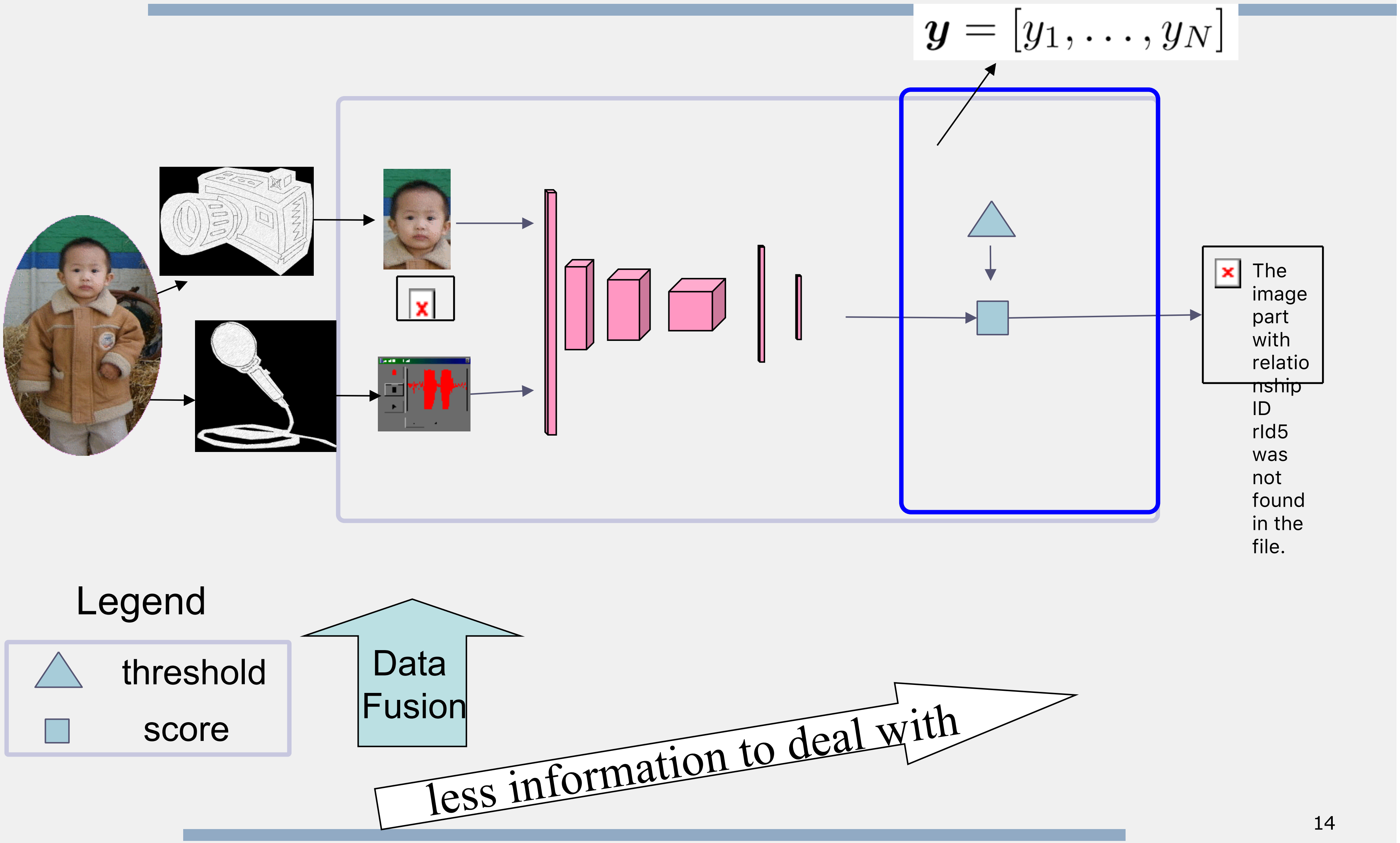
- Should improve performance



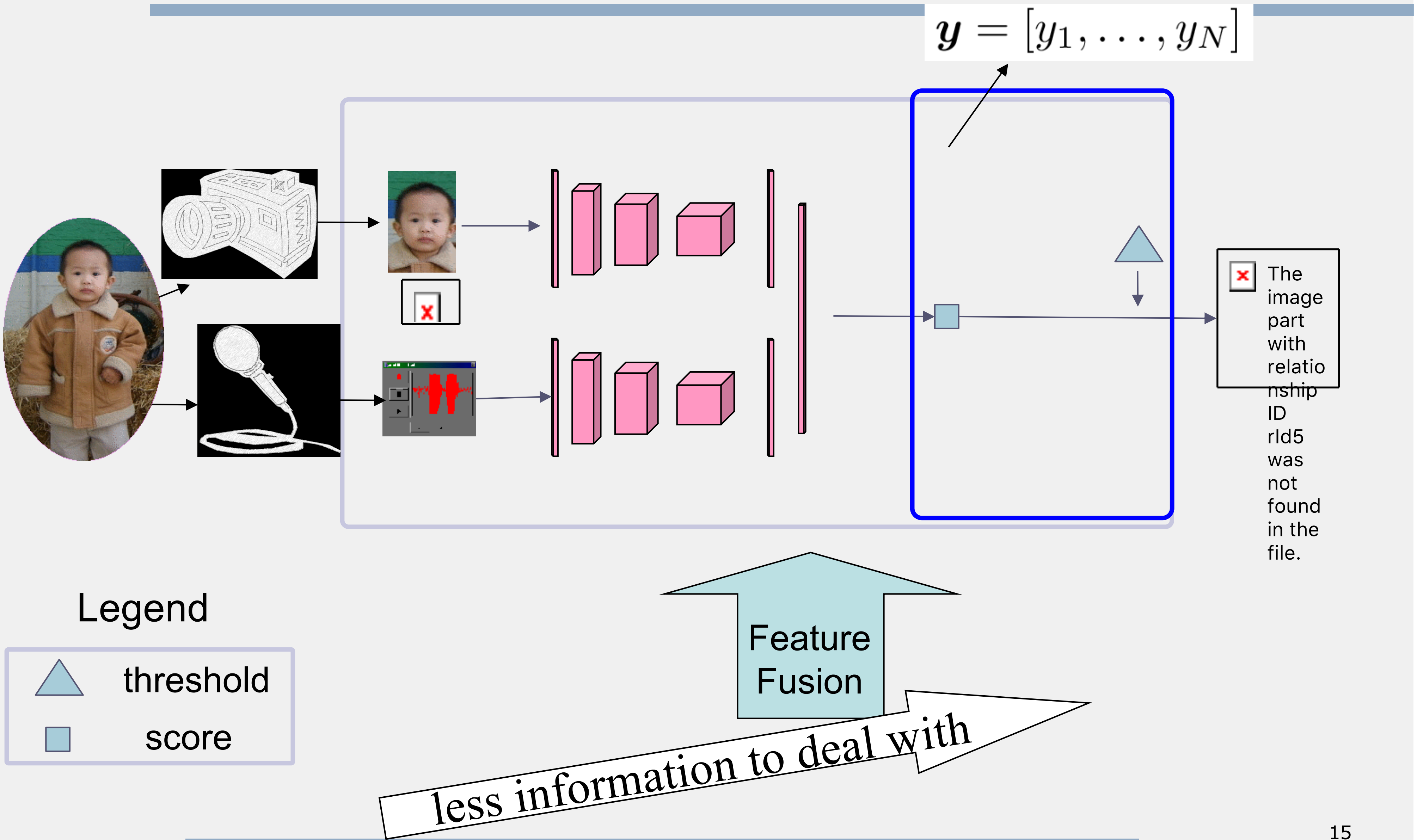
Levels of Fusion



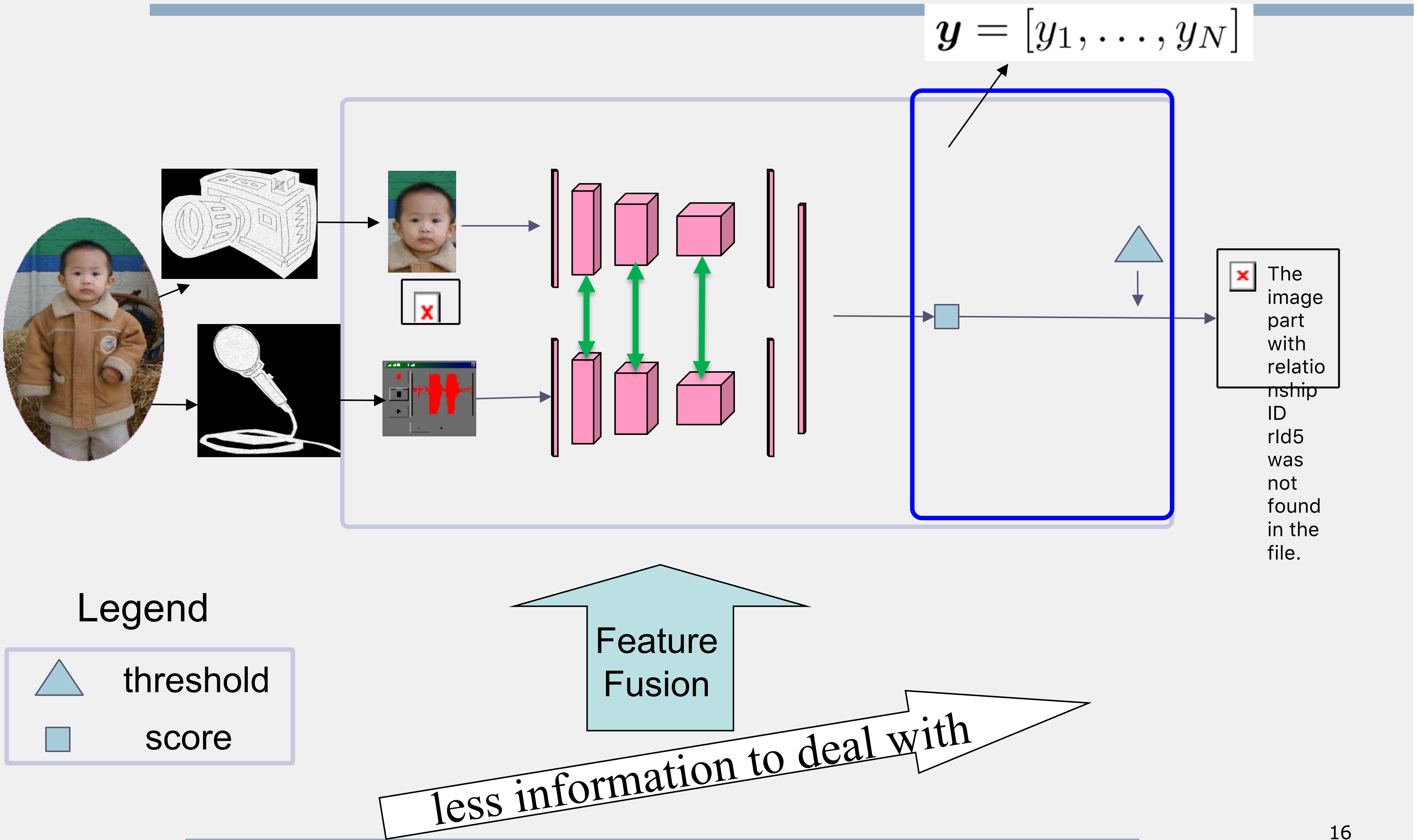
Data level fusion



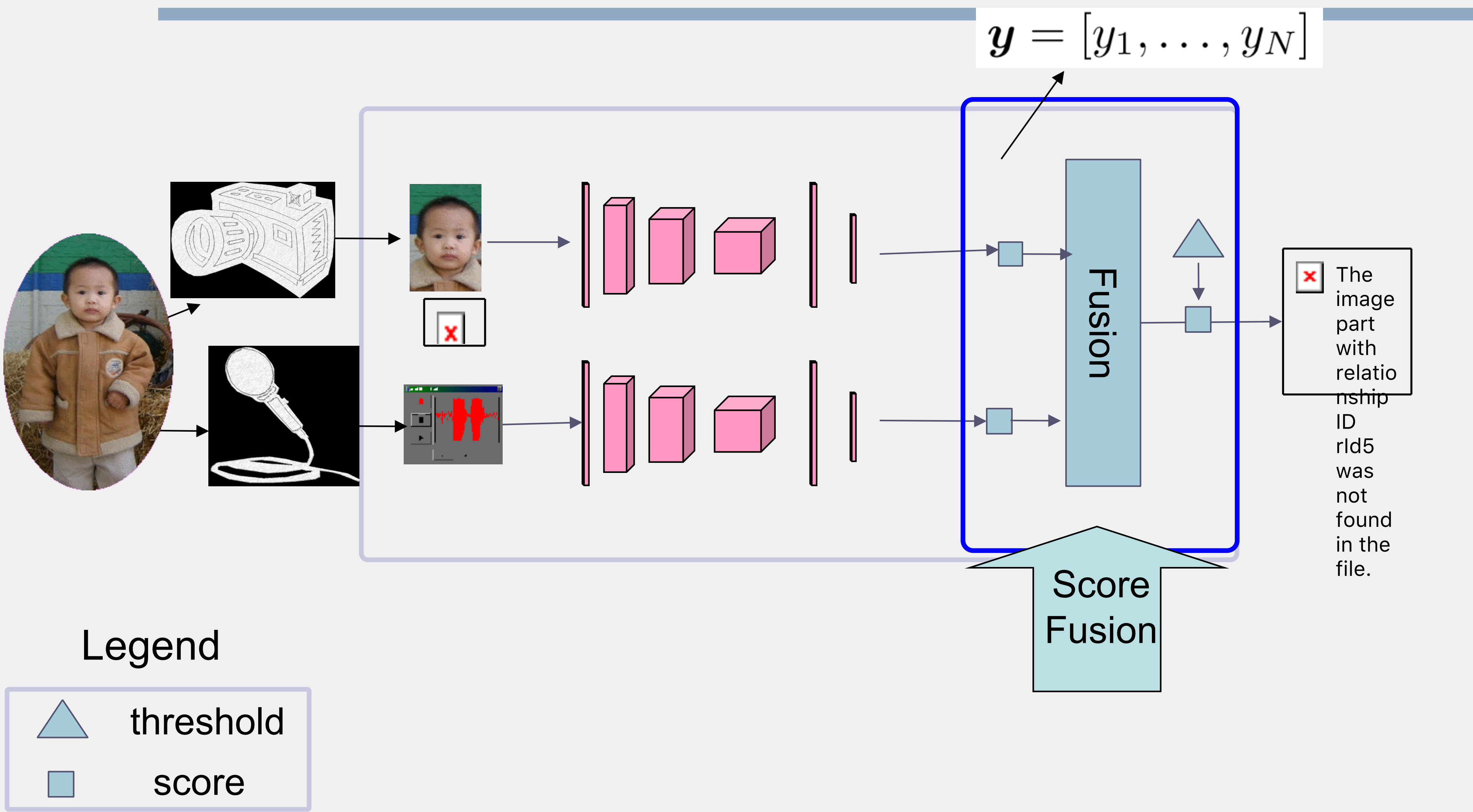
Feature level fusion



Feature level fusion

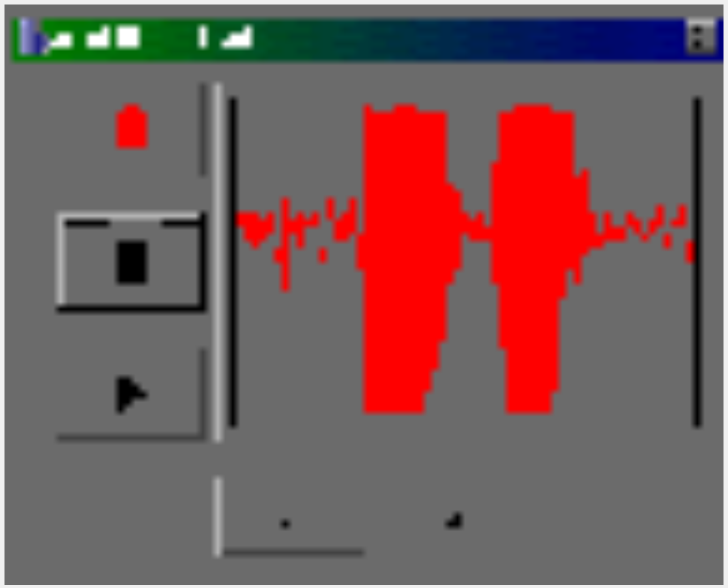


Score level fusion



Biometric system

Pattern representation



Pattern recognition problem

- N – number of classes
- b - biometric trait
- x - feature vector

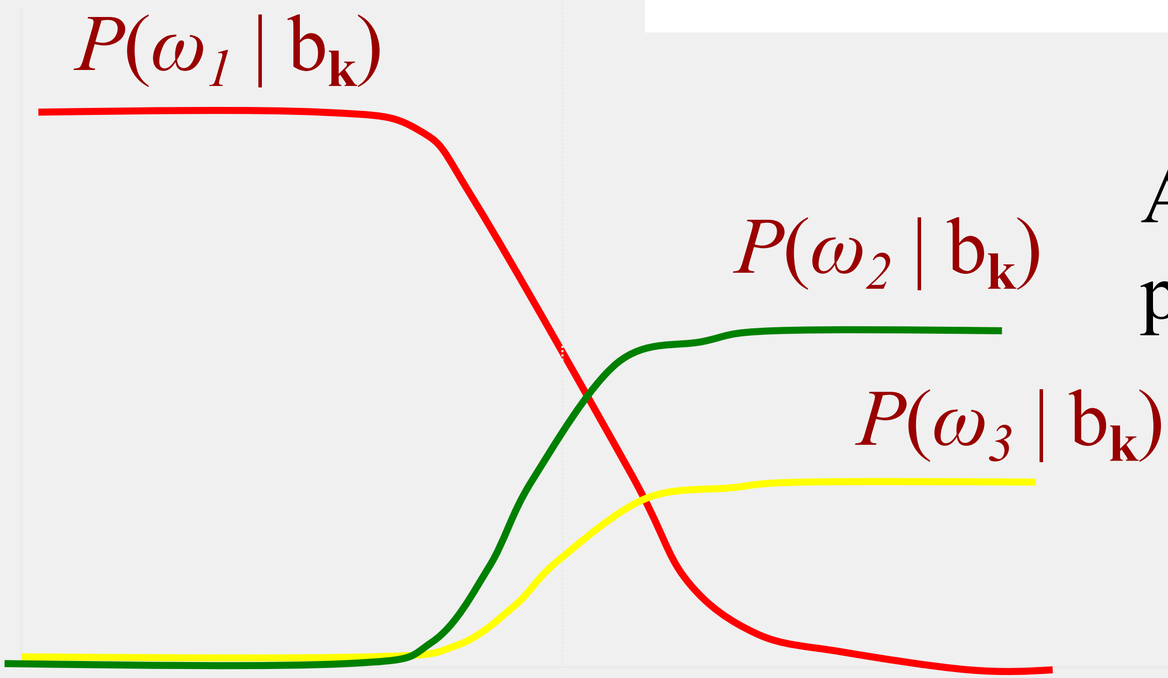
$P(\theta)$ -priori probability of class θ

$p(x_k|\theta)$
$p(b_k|\theta)$ -measurement distributions of patterns in class θ

Bayesian decision making

Bayes minimum Error rule

$$b_k \rightarrow \omega \ if$$
$$P(\omega|b_k) = max_{\theta} P(\theta|b_k)$$



Aposteriori class probabilities

Problem formulation

- Given

biometric traits:	$[b_1, ...b_K]$
biometric features:	$[x_1, ...x_K]$
identities:	$[\theta_1, ..., \theta_R]$

- Bayes decision rule
  - *Assign* subject *to class* θ *if*

$$P(\omega | b_1,\dots, b_K) = \max P(\theta | b_1,\dots, b_K)$$

- Note

$$P(\omega|b_1, ..., b_K) \propto \frac{p(b_1, ..., b_K|\omega)P(\omega)}{normalisation\ \ factor}$$

Fusion options

- **Signal level fusion**

$$\begin{aligned} p(b_1, ..., b_K|\omega) &\propto \int_{\hat{x}} p(\hat{x}, b_1, ..., b_K|\omega) \\ &\propto \int_{\hat{x}} \hat{P}(\omega|\hat{x}) p(\hat{x}|b_1, ..., b_K) \\ &\propto P(\omega|x) \end{aligned}$$

- The integration over $\hat{x}$ is marginalisation over the distribution $p(\hat{x}|b_1, ..., b_K)$
  - x is a feature vector determined by all traits
  - Implicitly a multiple classifier fusion
    - Bagging, boosting, drop out, hard sample mining
  - Marginalised estimate of class posterior $P(\omega|x)$

Fusion options

- Feature level fusion

$$
\begin{aligned}
p(b_1,.,b_K|\omega) &\propto \int_{\hat{x}_1,.,\hat{x}_K} p(\hat{x}_1,.,\hat{x}_K,b_1,....,b_K|\omega) \\
&\propto \int_{\hat{x}_1,.,\hat{x}_K} \hat{P}(\omega|\hat{x}_1,.,\hat{x}_K)\prod_i p(\hat{x}_i|b_i) \\
&\propto P(\omega|x_1,..,x_K)
\end{aligned}
$$

- Each modality has its own set of features x_i
- Score is a function of all x_i jointly
- Fusion process marginalisation is over the joint distribution of all modalities
- In addition, there could be modality specific marginalisation at the feature extraction level

Fusion options

- Score level fusion

$$
\begin{aligned}
p(b_1, ..., b_K|\omega) &\propto \prod_i \int_{\hat{x}_i} p(\hat{x}_i, b_i|\omega) \\
&\propto \prod_i \int_{\hat{x}_i} \hat{P}(\omega|\hat{x}_i)p(\hat{x}_i|b_i) \\
&\propto \prod_i P(\omega|x_i)
\end{aligned}
$$

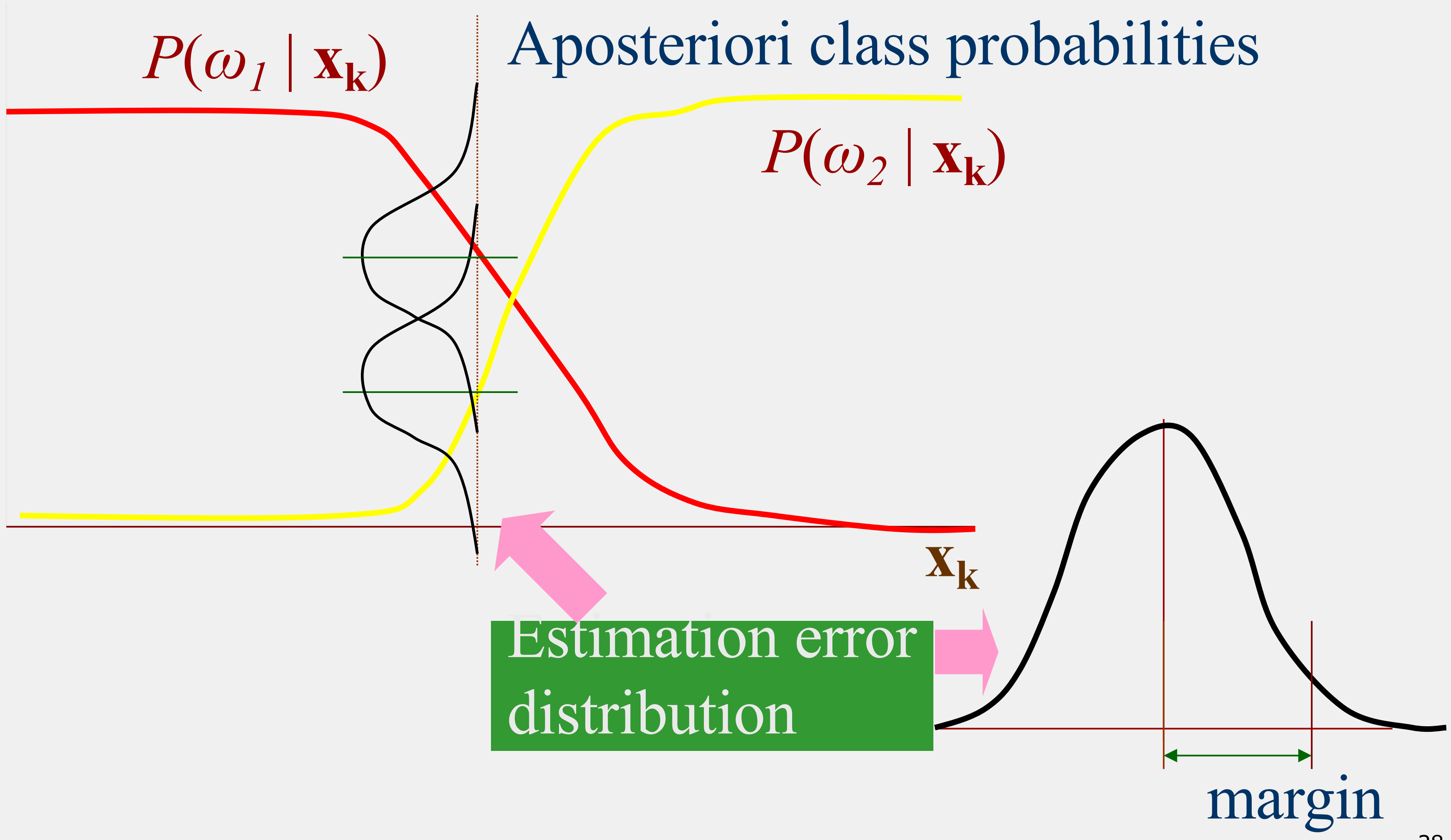
- Each modality has its own set of features x_i
- The fused score is a product of individual modality specific scores
- Fusion process marginalisation is over modality specific distributions

Problem formulation: comments

- basic score level fusion is by product
- product can be approximated by a sum if $\hat{P}(\theta|x_k)$ does not deviate much from $P(\theta)$
  i.e. $\hat{P}(\theta|x_k) = P(\theta) + \Delta_k$
- the resulting decision rule becomes

$$\begin{aligned} p(b_1, ..., b_K|\omega) &\propto \prod_i P(\omega|x_i) \\ &\propto \sum_i P(\omega|x_i) \end{aligned}$$

Effect of estimation errors



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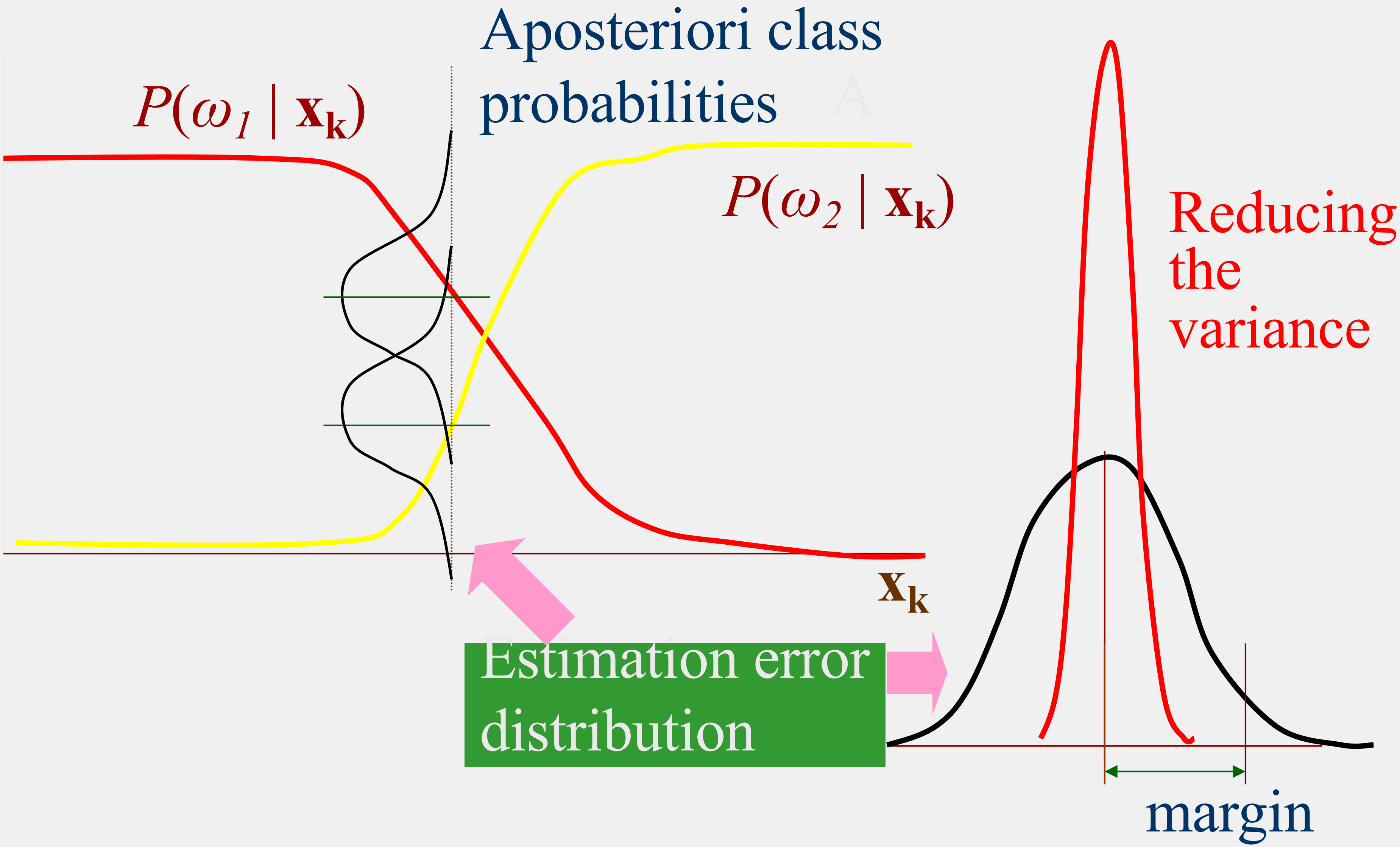
Sources of estimation errors

$$\tilde{P}(\omega|\mathbf{x}_i) = \int\int P(\omega|\mathbf{x}_i, X_i, M, \gamma_i)p(M)p(\gamma_i)dMd\gamma_i$$

$\mathbf{x}_i$	Feature vector output by sensor i
X_i	Training set for the i-th expert
M	Classifier model
$p(M)$	Distribution of models
γ_i	Parameters for expert i
$p(\gamma_i)$	Distribution of expert i parameter

Coping with estimation errors



Case study in multimodal soft biometric fusion

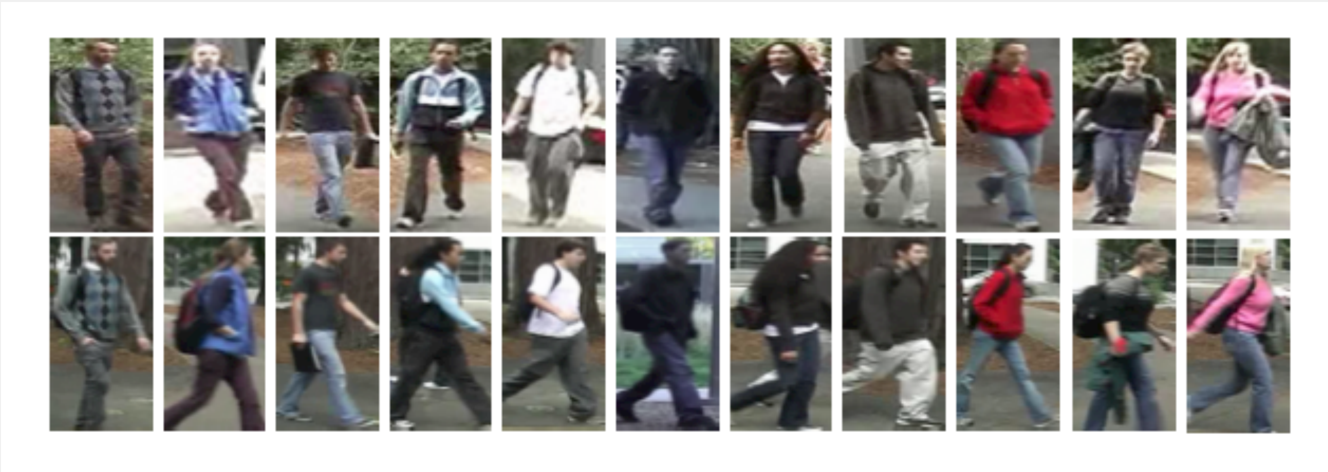
- Multimodal biometric traits
- Multimodal sensing of the same biometric trait
  - Different spectral bands
  - Voice/image sensed lips dynamics
  - Visual/language modalities for person re-identification

Background and motivation

- Video surveillance very important tool for crime prevention and detection
  - Watch list
  - Forensic video analysis
- Hard biometrics (face) not always available
- Other video analytics tools are useful alternatives
  - Soft biometrics (clothing, gait)
  - Tracking

Soft biometrics and re-identification

- Person Re-Identification
  - Recognising a person from non-overlapping cameras
- Formulated as a ranking problem



Re-ID with V&L

- The majority of existing methods are vision only
  - Images or videos
- Joint vision and language modelling
  - Image and video captioning, Visual question answering, Image synthesis from language, …
- Can language help vision in Re-ID?

Language annotation

- Augmenting existing datasets
  - CUHK03: ~2700 descriptions
  - VIPeR: ~1300 descriptions
- Crowd-sourced, 8 annotators
- Annotation
  - Free style sentences, not attributes
  - Encouraged to cover details
  - On average 45 words per description
  - Per image rather than per identity

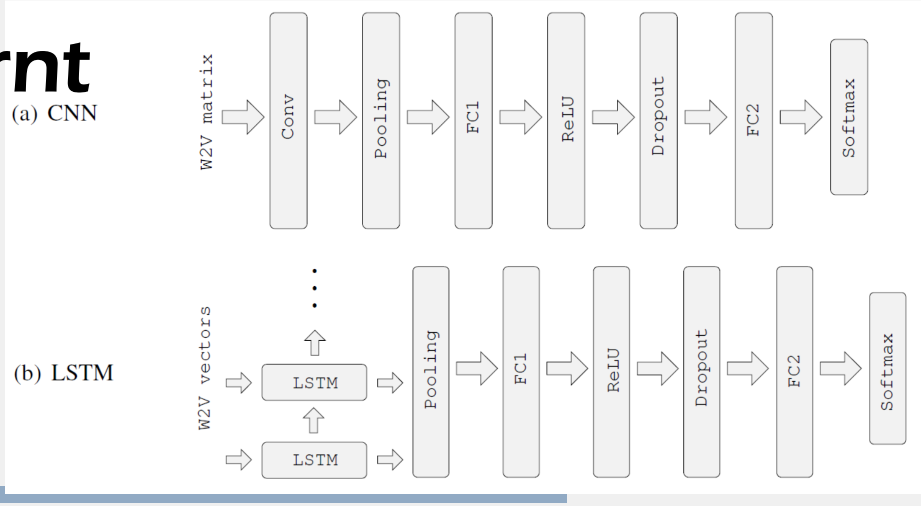
Language annotation

A front profile of a young, slim and average height, black female with long brown hair. She wears sunglasses and possibly earrings and necklace. She wears a brown t-shirt with a golden coloured print on its chest, blue jeans and white sports shoes.

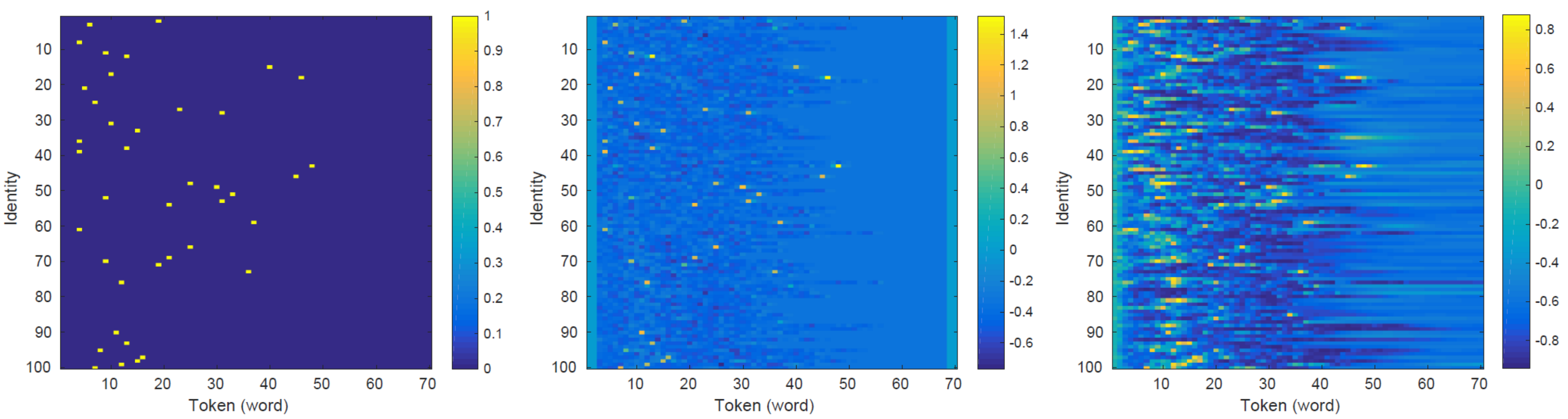
A short and slim young woman carrying a tortilla coloured rectangular shoulder bag with caramel straps, on her right side. She has a light complexion and long, straight auburn hair worn loose. She wears a dark brown short sleeved top along with bell bottomed ice blue jeans and her shoes can't be seen but she might be wearing light colored flat shoes.

Re-ID with language

- ResNet-50 for visual information
- Word2Vec embedding
- Neural networks: CNN and LSTM
- Multi-class setting, 2 examples per class (identity)
- Data augmentation
- Metric learning with learnt representations (XQDA)
- Canonical Correlation



Re-ID with language



- Detecting the concept of "spectacles"
  - "bespectacled", "glasses", "eye-glasses", ...
  - GT, CNN, LSTM
  - One channel becomes "spectacles" detector during training
  - Good representation learnt from unstructured data

Canonical correlation analysis

- Consider features x and y extracted from two biometric modalities
- Basic principle – find direction in the respective feature spaces that yield maximum correlation
  - Gauging linear relationship between two multidimensional random variables (feature vectors of two biometric modalities)
  - Finding two sets of basis vectors such that the projection of the feature vectors onto these bases is maximised
  - Determine correlation coefficients

CAA problem formulation

- Training set of pairs of vectors $(x_i, y_i),\ \ i = 1, n$
- Maximisation of the correlation of the projections

$$\max_{w_x, w_y} E\{w_x^T x y^T w_y\} = \max_{w_x, w_y} w_x^T C_{xy} w_y \ \ s.t.$$
$$E\{w_x^T x x^T w_x\} = w_x^T C_{xx} w_x = 1$$
$$E\{w_y^T y y^T w_y\} = w_y^T C_{yy} w_y = 1$$

- Leads to an eigenvalue problem

$$\begin{bmatrix} 0 & C_{xy} \\ C_{yx} & 0 \end{bmatrix} \begin{bmatrix} w_x \\ w_y \end{bmatrix} =$$
$$= \lambda \begin{bmatrix} (1-\kappa)C_{xx} + \kappa I & 0 \\ 0 & (1-\kappa)C_{yy} + \kappa I \end{bmatrix} \begin{bmatrix} w_x \\ w_y \end{bmatrix}$$

- With cov matrices regularised by κI

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Re-ID with V&L

- Three sets:
  - Training, query, gallery
  - Training: image and language pairs
- Various settings, query x gallery:
  - V x V, L x L, V x L, V x VL, VL x VL
- Asymmetric settings:
  - Transfer language info. With CCA
- XQDA as metric learning

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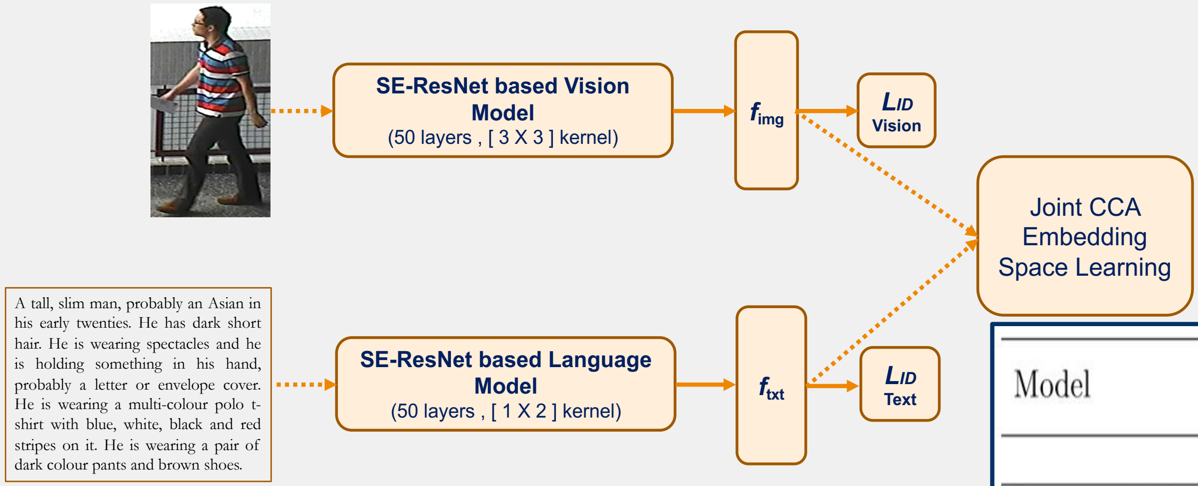
Re-ID with V&L

	Gated CNN	68.1	88.1	94.6
Ours	V x V	70.3	93.2	96.6
	L x L	41.1	69.8	82.5
	V x L	17.7	48.5	66.0
	V x VL	73.5	94.5	97.7
	VL x VL	**81.8**	**98.1**	**99.3**

- Results on CUHK03, R1, R5, R10
- LxL worse than VxV: more information in vision
- VxVL 3.2 points higher than VxV
- VLxVL 12.7 points higher than VxV, better than state-of-the-art
- Language helps

Person Re-ID

- Crossmodal & multimodal matching facilitated by CAA



- Performance gain due to
  - Joint training
  - Fusion of modalities

Model	Rank@1 (%)	Rank@5 (%)	Rank@10 (%)	mAP (%)	medR
		V × V			
Separately Train	59.91	80.5	85.7	64.45	1
Jointly Train + CCA	82.05	94.3	96.8	84.75	1
		L × V			
Separately Train	13.6	32.99	43.04	18.5	15
Jointly Train + CCA	27.9	50.6	60.7	33.4	5
		VL × V			
Separately Train	65.87	84.19	88.9	64.8	1
Jointly Train + CCA	84.7	95.0	97.1	84.1	1
		VL × VL			
Separately Train	68.0	84.7	89.58	71.8	1
Jointly Train + CCA	80.86	94.16	96.6	83.85	1

Take home message

- Role of multimodal biometrics
- Fusion levels
- Math formulation of different alternatives
- The concept of marginalisation/multiple classifier systems
- Notion of quality based, user specific and cohort based extensions of fusion
- Multimodal sensing and fusion of a single biometric
- Example: fusion of vision/language modalities for soft biometrics

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