# Face Recognition III

COMP 388-002/488-002 Biometrics

**Daniel Moreira**

Fall 2025

LOYOLA UNIVERSITY CHICAGO

# Today we will…

*Get to know*
Face description and matching.



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# Today's Attendance

**Please fill out the form**

forms.gle/WvKhQG6ShaPcae3Y8



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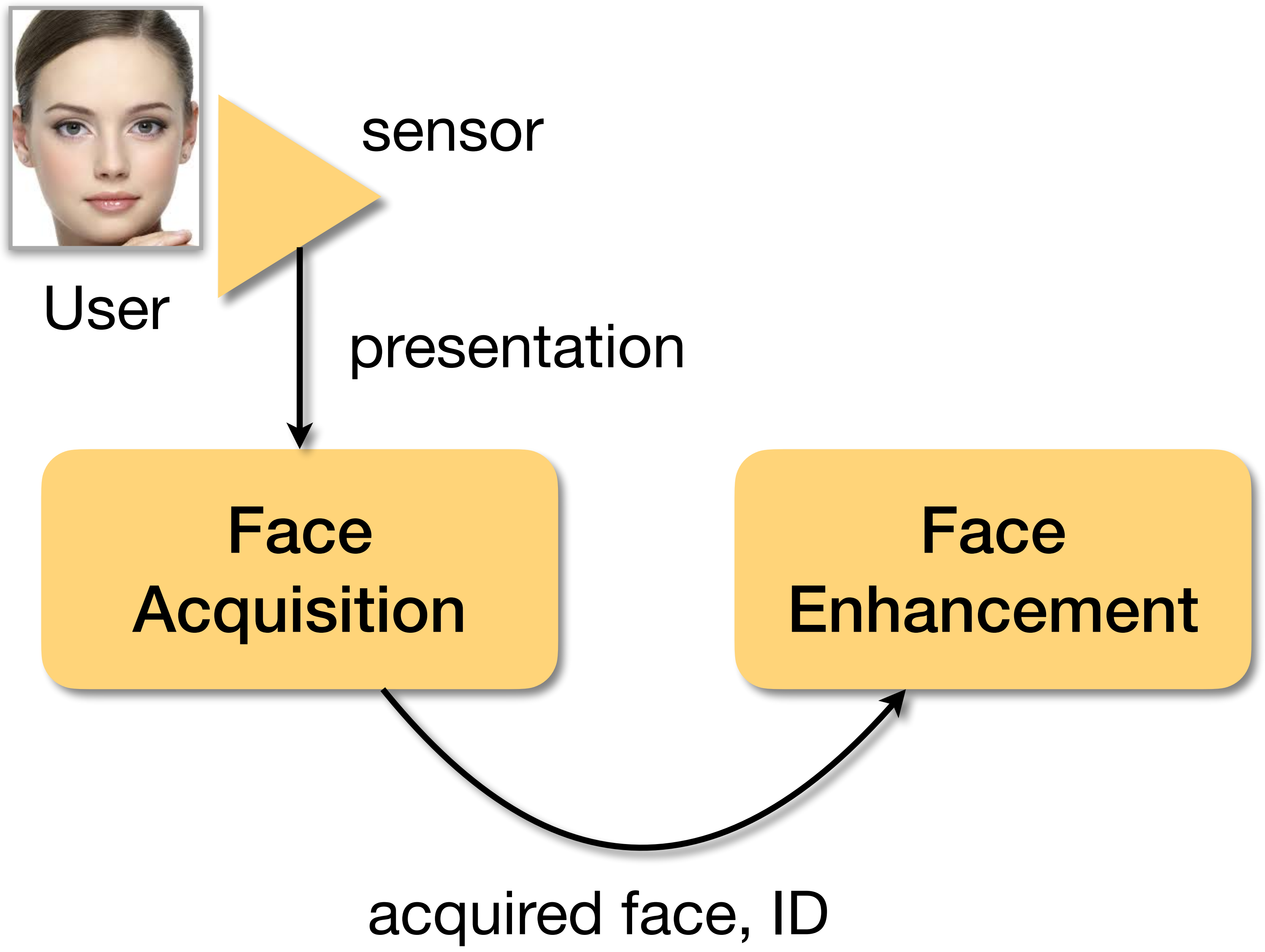
# Face Recognition



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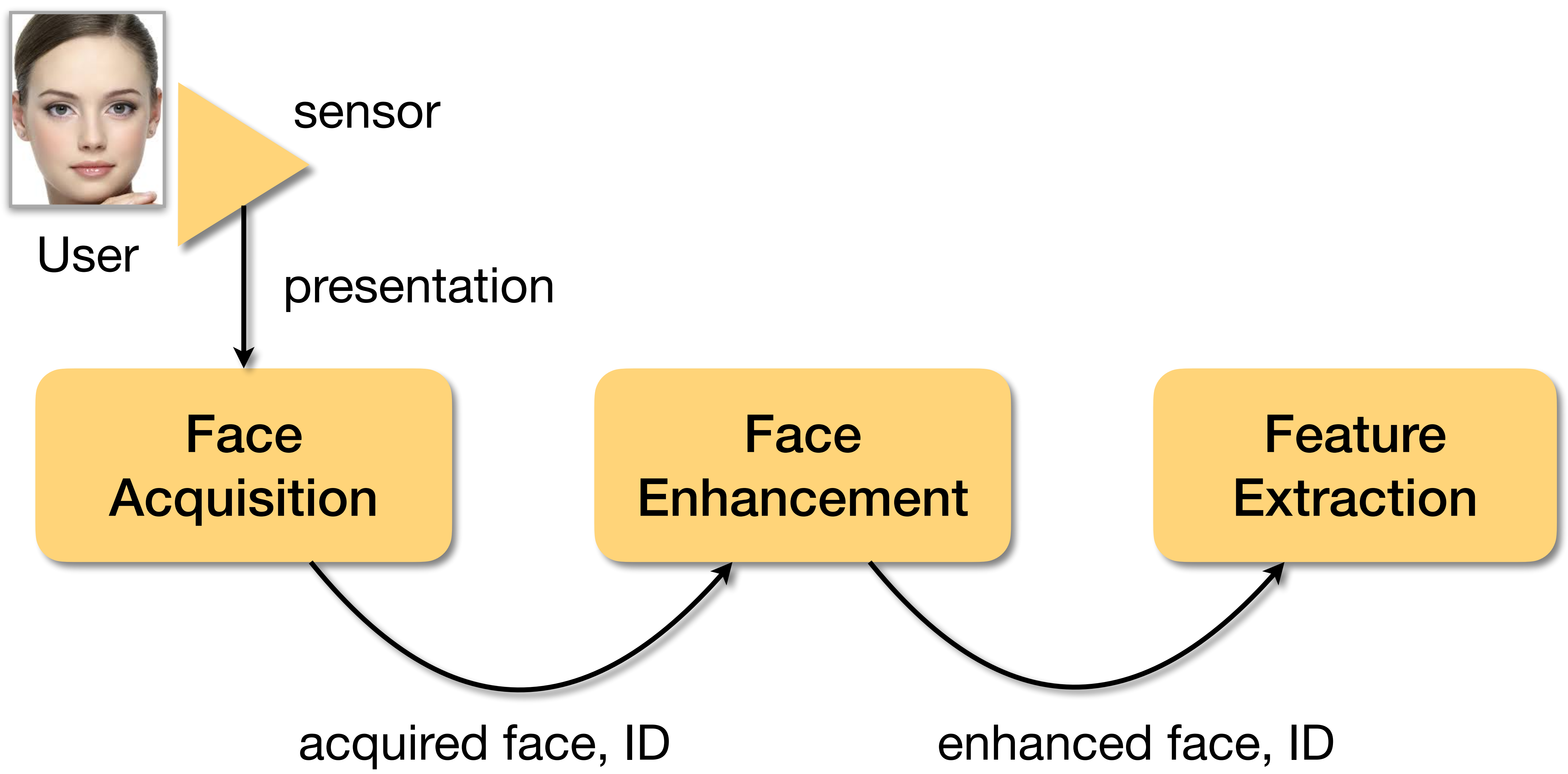
# Face Recognition



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# Feature Extraction

**Focus**
2D-appearance-based methods.

**Types**
Handcrafted features from Computer Vision.

Data-driven learned features from Machine Learning.



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# Feature Extraction

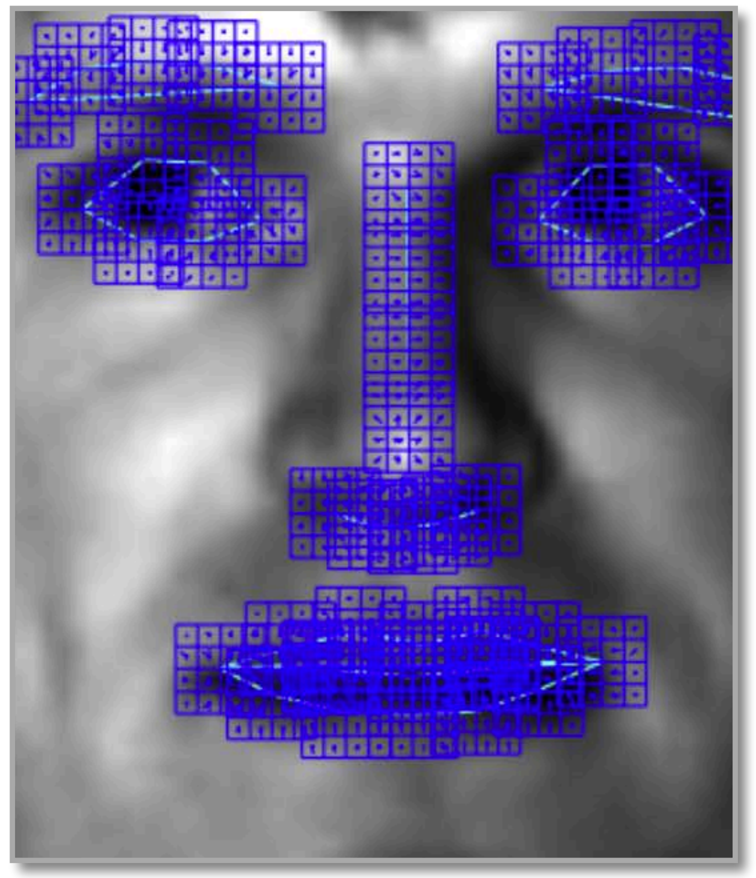
**Focus**
2D-appearance-based methods.

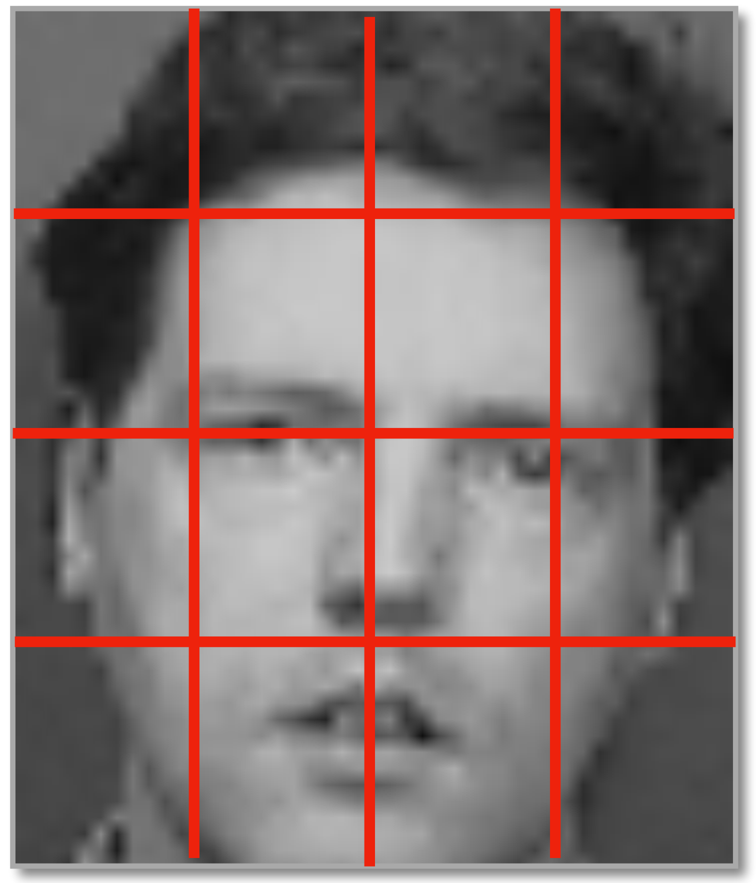
**Types**
**Handcrafted features from Computer Vision.**

Data-driven learned features from Machine Learning.

Source: Domingo Mery

Déniz et al. *Face recognition using histograms of oriented gradients.* Pattern recognition letters, 2011.





**Handcrafted**
An expert designs what and how facial regions should be used.



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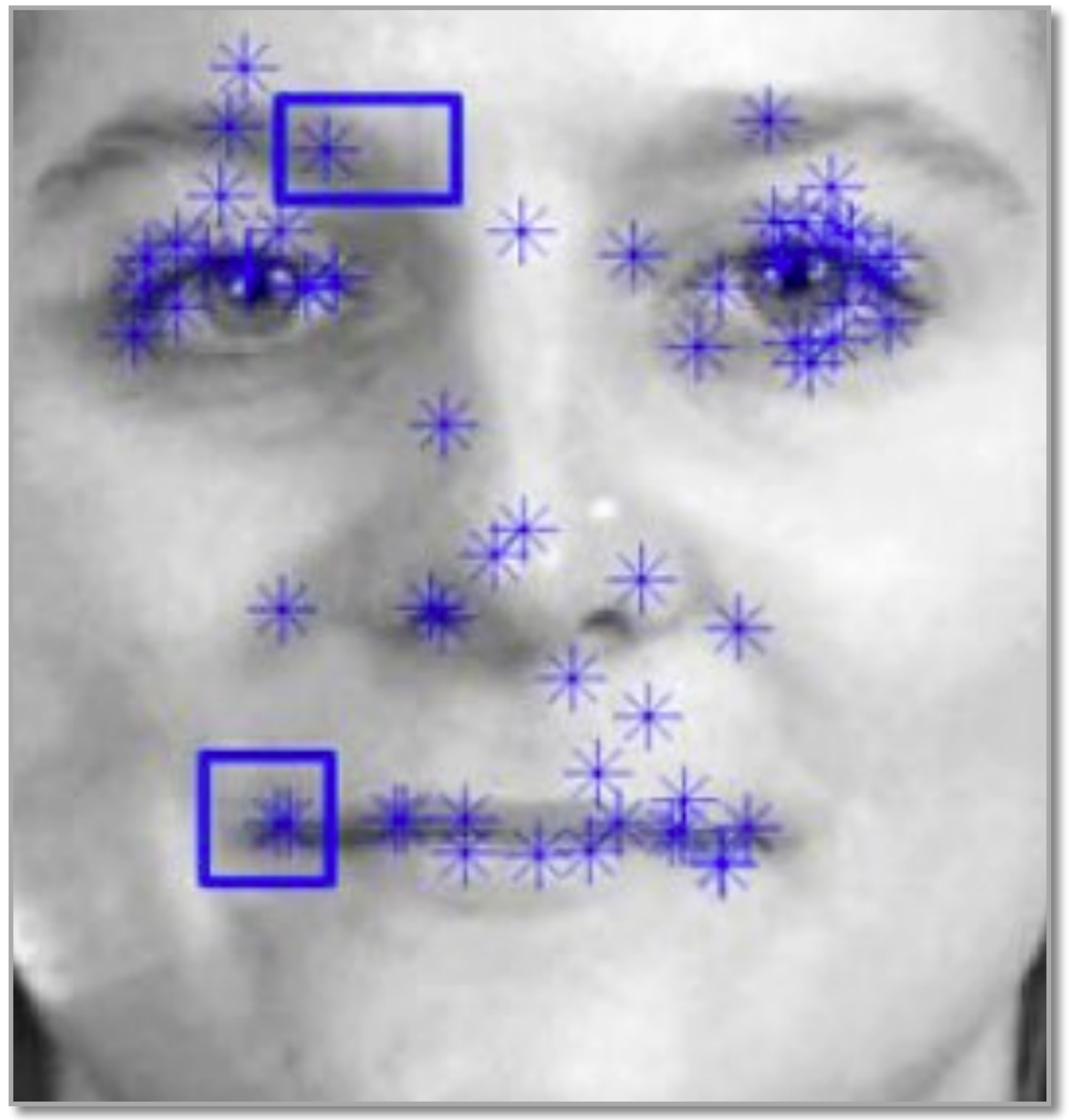
# Feature Extraction

**Handcrafted Features**

**Examples**

Based on Gabor filters, interest points (e.g., SIFT[1], SURF[2], HOG[3]), or texture descriptors (e.g., LBP[4]).

1 - Lowe. *Distinctive image features from scale-invariant keypoints*. IJCV, 2004.
2 - Bay et al. *SURF: Speeded up robust features*. ECCV, 2006.
3 - Dalal and Triggs. Histograms of oriented gradients for human detection. CVPR 2005.
4 - Ojala et al. *Performance evaluation of texture measures(…).* ICPR, 1994.



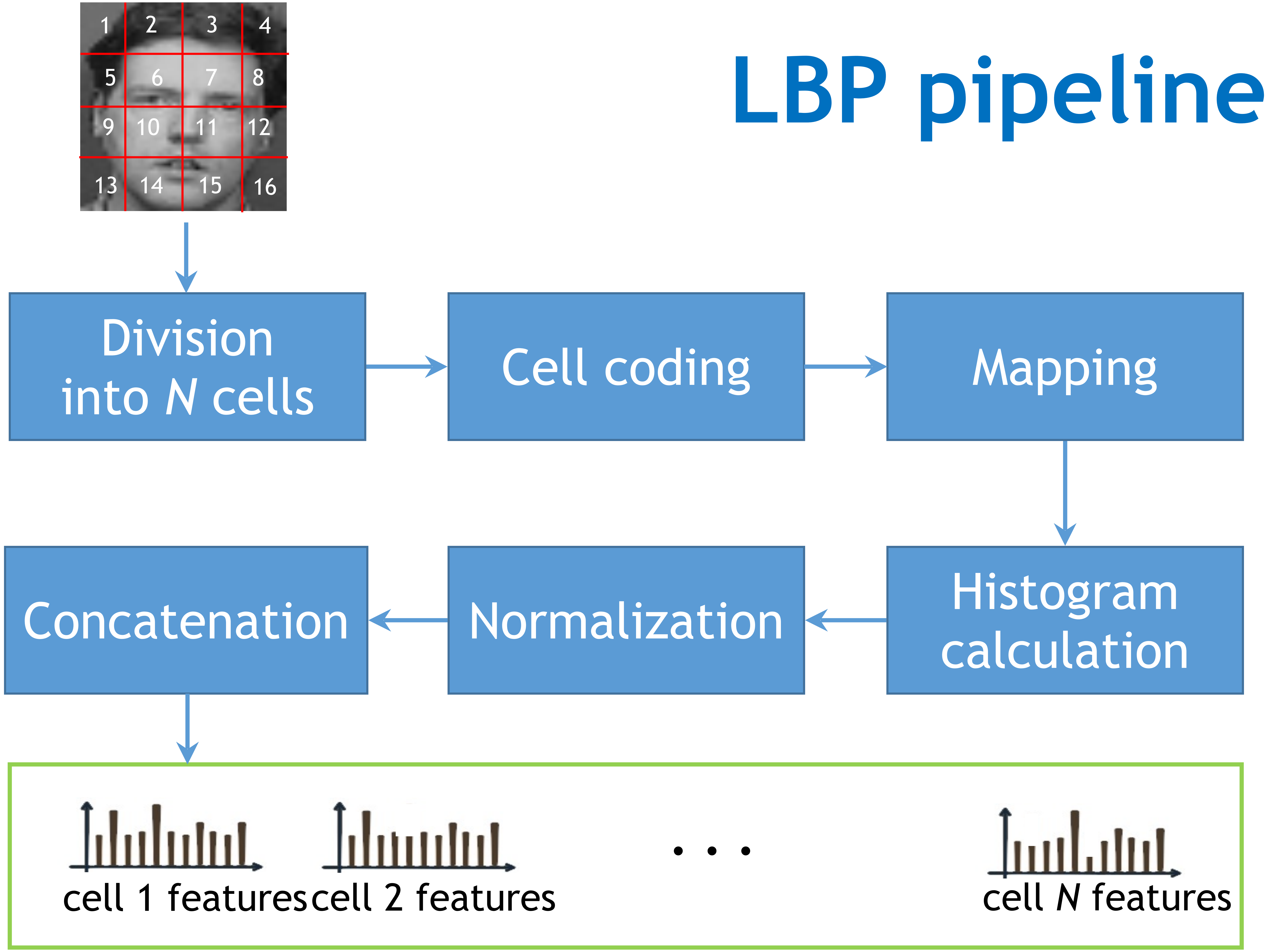
Geng and Jiang.
*SIFT features for face recognition*.
ICCSIT, 2009.

# Local Binary Patterns

**Selected Solution**
Local Binary Patterns to describe
face texture.

Next slides provided by Dr. Domingo Mery.
(http://domingomery.ing.puc.cl)

# LBP pipeline



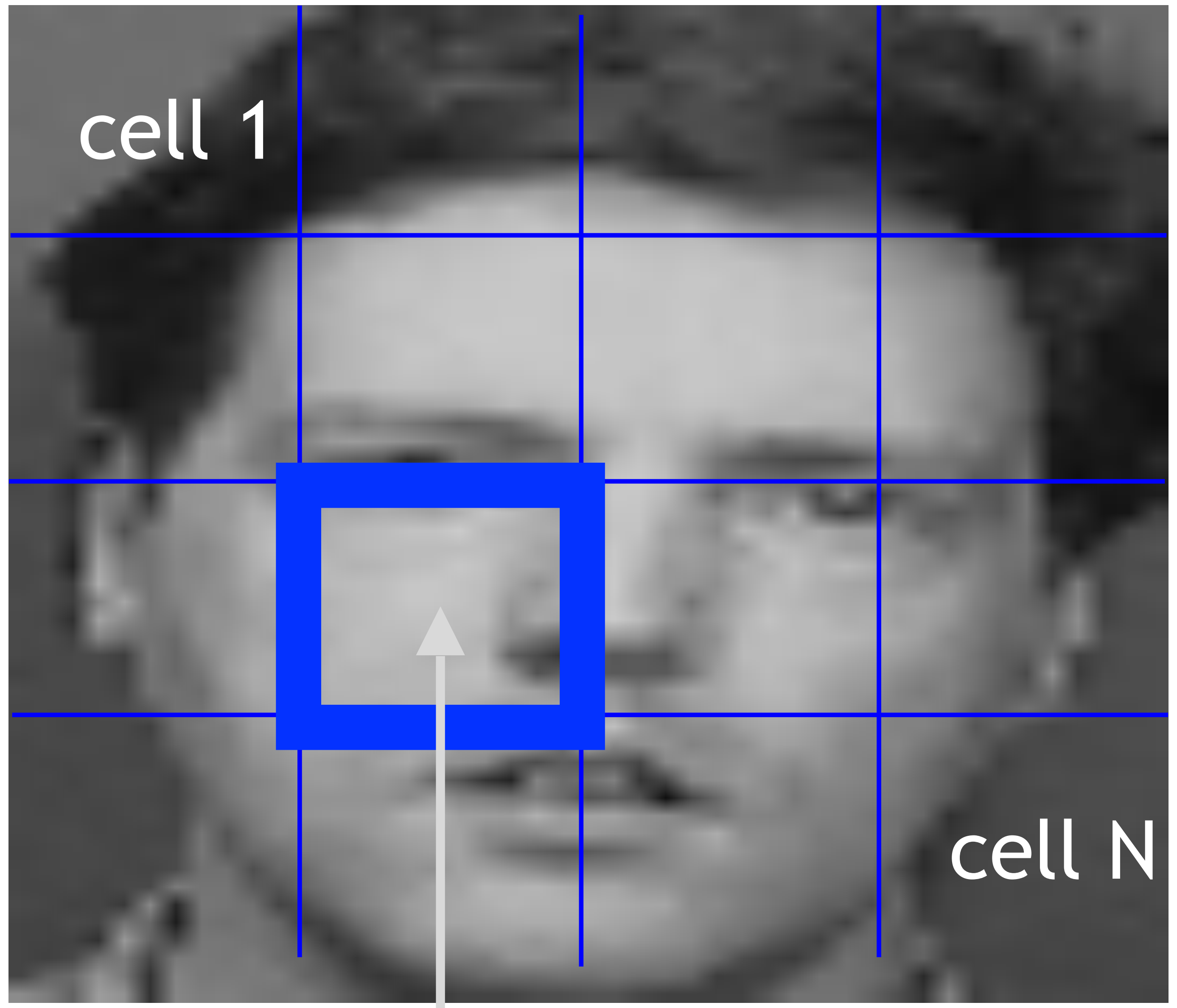



Source: Domingo Mery

| Division into $N$ cells | Cell coding | Mapping | Histogram calculation | Normalization | Concatenation |
|---|---|---|---|---|---|

- LBP descriptors are calculated in image sub-regions (cells)

- Number and size of cells cannot be arbitrary (note space-scale considerations)

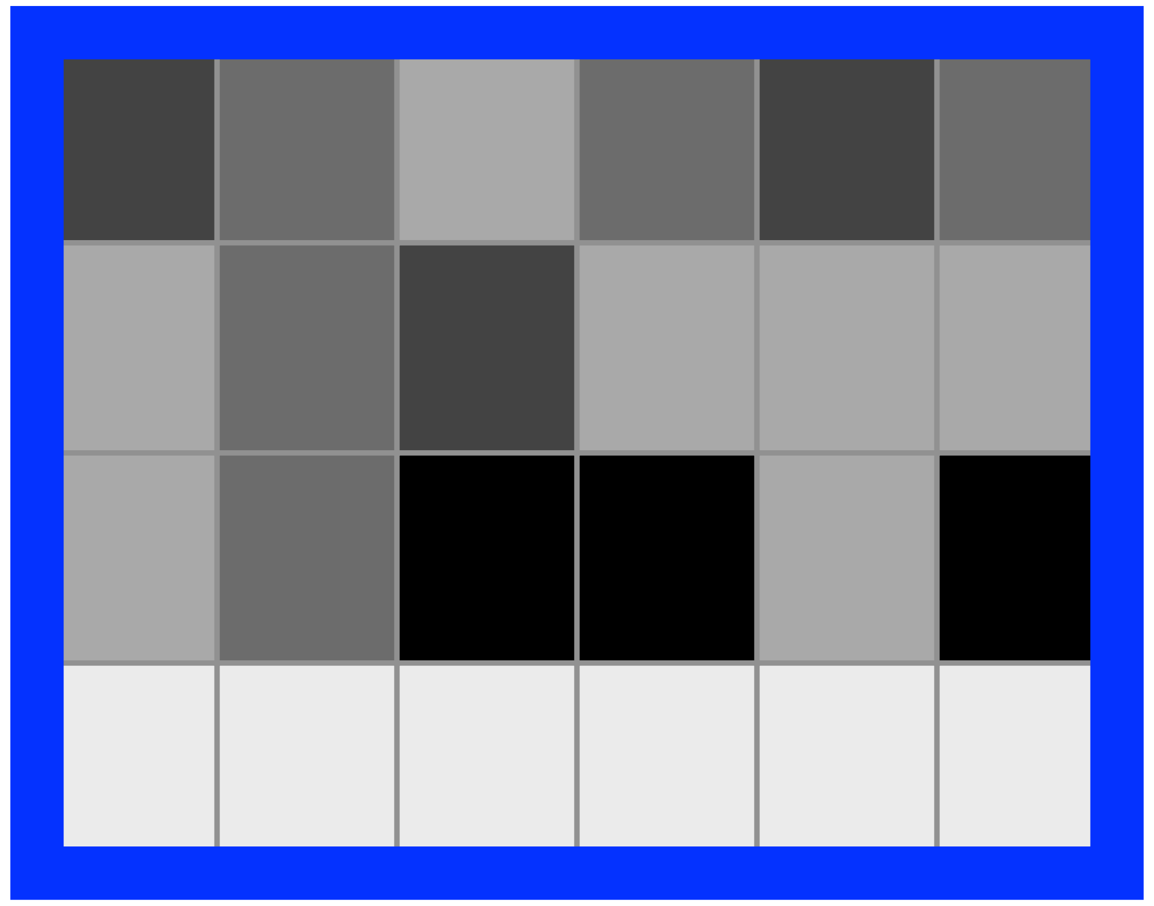



example cell



Source: Domingo Mery

Division into $N$ cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation



Source: Domingo Mery

Division into *N* cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |



Source: Domingo Mery

| Division into *N* cells | Cell coding | Mapping | Histogram calculation | Normalization | Concatenation |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
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Division into *N* cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |



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Division into $N$ cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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| 4 | 6 | 9 |
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Source: Domingo Mery

| Division into *N* cells | Cell coding | Mapping | Histogram calculation | Normalization | Concatenation |
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|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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| 4 | 6 | 9 |
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| 9 | 6 | 2 |

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Source: Domingo Mery

Division into *N* cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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| 4 | 6 | 9 |
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| 9 | 6 | 2 |

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Source: Domingo Mery

Division into *N* cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation

| | | | | | |
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| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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| 4 | 6 | 9 |
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| 9 | 6 | 2 |

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Source: Domingo Mery

| | | | | | |
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| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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| 4 | 6 | 9 |
| 9 | 6 | 4 |
| 9 | 6 | 2 |

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Source: Domingo Mery

| | | | | | |
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| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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|---|---|---|
| 4 | 6 | 9 |
| 9 | 6 | 4 |
| 9 | 6 | 2 |

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| 0 | 1 | 1 |
| | | 0 |
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Source: Domingo Mery

Division into *N* cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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| 4 | 6 | 9 |
| 9 | 6 | 4 |
| 9 | 6 | 2 |

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| 0 | 1 | 1 |
| | | 0 |
| | | 0 |

Source: Domingo Mery

| Division into $N$ cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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|---|---|---|
| 4 | 6 | 9 |
| 9 | 6 | 4 |
| 9 | 6 | 2 |

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1: ≥

| | | |
|---|---|---|
| 0 | 1 | 1 |
| | | 0 |
| | 1 | 0 |

Source: Domingo Mery

Division into *N* cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

| | | |
|---|---|---|
| 4 | 6 | 9 |
| 9 | 6 | 4 |
| 9 | 6 | 2 |

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| 0 | 1 | 1 |
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| 1 | 1 | 0 |



Source: Domingo Mery

| | | | | | |
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| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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|---|---|---|
| 4 | 6 | 9 |
| 9 | 6 | 4 |
| 9 | 6 | 2 |

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| 0 | 1 | 1 |
| 1 | | 0 |
| 1 | 1 | 0 |

Source: Domingo Mery

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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|---|---|---|
| 4 | 6 | 9 |
| 9 | 6 | 4 |
| 9 | 6 | 2 |

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|---|---|---|
| 0 | 1 | 1 |
| 1 | | 0 |
| 1 | 1 | 0 |

x

| | | |
|---|---|---|
| 1 | 2 | 4 |
| 128 | + | 8 |
| 64 | 32 | 16 |

$$= 0 + 2 + 4 + 0 + 0 + 32 + 64 + 128 = 230$$

Source: Domingo Mery

Division into $N$ cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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| 4 | 6 | 9 |
| 9 | 6 | 4 |
| 9 | 6 | 2 |

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| 0 | 1 | 1 |
| 1 | | 0 |
| 1 | 1 | 0 |

x

| | | |
|---|---|---|
| 1 | 2 | 4 |
| 128 | + | 8 |
| 64 | 32 | 16 |

$= 0 + 2 + 4 + 0 + 0 + 32 + 64 + 128 = 230$

Source: Domingo Mery

| Division into *N* cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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| | | | | | |
| | 230 | | | | |
| | | | | | |
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|---|---|---|
| 4 | 6 | 9 |
| 9 | 6 | 4 |
| 9 | 6 | 2 |

0: <
1: ≥

| | | |
|---|---|---|
| 0 | 1 | 1 |
| 1 | | 0 |
| 1 | 1 | 0 |

x

| | | |
|---|---|---|
| 1 | 2 | 4 |
| 128 | + | 8 |
| 64 | 32 | 16 |

$= 0 + 2 + 4 + 0 + 0 + 32 + 64 + 128 = 230$

Source: Domingo Mery

- Division into *N* cells
- **Cell coding**
- Mapping
- Histogram calculation
- Normalization
- Concatenation

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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| 6 | 9 | 6 |
| 6 | 4 | 9 |
| 6 | 2 | 2 |

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x

| | | |
|---|---|---|
| 1 | 2 | 4 |
| 128 | + | 8 |
| 64 | 32 | 16 |

Source: Domingo Mery

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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| | | | | | |
| | 230 | 207 | | | |
| | | | | | |
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|---|---|---|
| 6 | 9 | 6 |
| 6 | 4 | 9 |
| 6 | 2 | 2 |

0: <
1: ≥

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 1 | | 1 |
| 1 | 0 | 0 |

x

| | | |
|---|---|---|
| 1 | 2 | 4 |
| 128 | + | 8 |
| 64 | 32 | 16 |

= 1 + 2 + 4 + 8 + 64 + 128 = 207

Source: Domingo Mery

Division into *N* cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

| | | | | | |
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| | 230 | 207 | ? | | |
| | | | | | |
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Source: Domingo Mery

| Division into *N* cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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| | | | | | |
| | 230 | 207 | 25 | | |
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|---|---|---|
| 9 | 6 | 4 |
| 4 | 9 | 9 |
| 2 | 2 | 9 |

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1: ≥

| | | |
|---|---|---|
| 1 | 0 | 0 |
| 0 | | 1 |
| 0 | 0 | 1 |

x

| | | |
|---|---|---|
| 1 | 2 | 4 |
| 128 | + | 8 |
| 64 | 32 | 16 |

$= 1 + 8 + 16 = 25$

Source: Domingo Mery

Division into *N* cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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| | 230 | 207 | 25 | 168 | |
| | | | | | |
| | | | | | |



Source: Domingo Mery

Division into $N$ cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | |
| | 230 | 207 | 25 | 168 | |
| | 243 | | | | |
| | | | | | |



Source: Domingo Mery

Division into *N* cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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| | | | | | |
| | 230 | 207 | 25 | 168 | |
| | 243 | 255 | | | |
| | | | | | |

Source: Domingo Mery

Division into $N$ cells | **Cell coding** | Mapping | Histogram calculation | Normalization | Concatenation

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | |
| | 230 | 207 | 25 | 168 | |
| | 243 | 255 | 255 | | |
| | | | | | |

Source: Domingo Mery

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

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|---|---|---|---|---|---|
| | | | | | |
| | 230 | 207 | 25 | 168 | |
| | 243 | 255 | 255 | 119 | |
| | | | | | |



Source: Domingo Mery

# Note on neighborhood definition

- Original algorithm uses 3x3 pixel neighborhood
- Further extensions (Ojala, 2002) introduced arbitrary neighborhood with interpolation

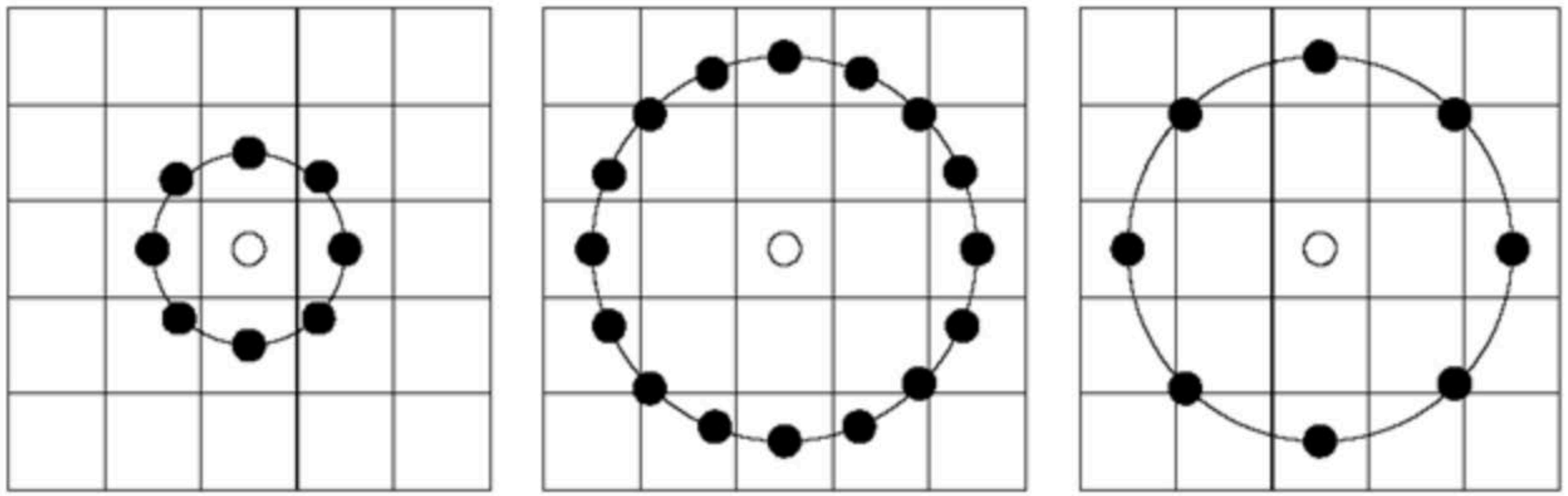
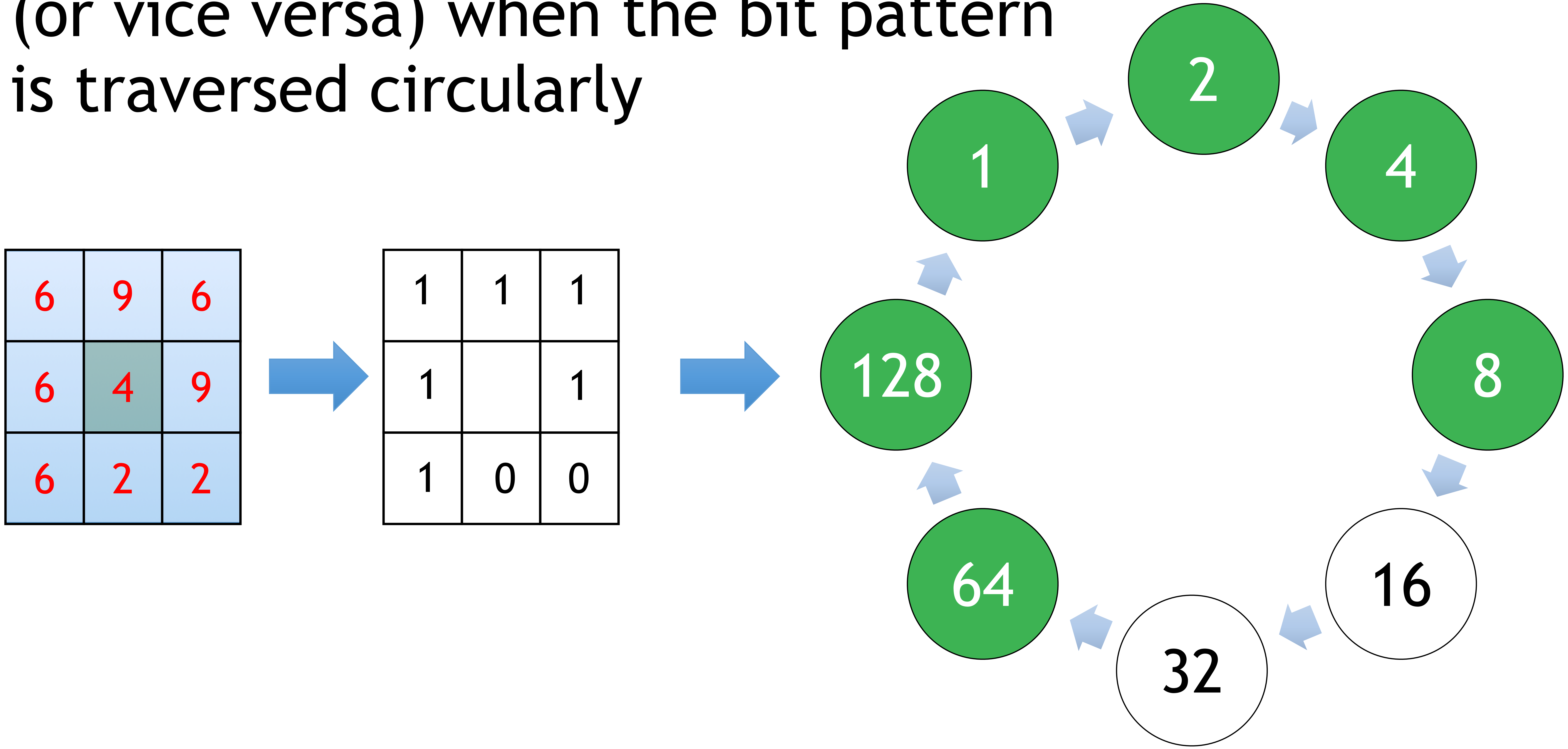


Image source: http://what-when-how.com/face-recognition/local-representation-of-facial-features-face-image-modeling-and-representation-face-recognition-part-1/



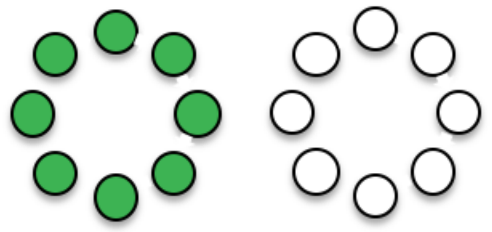
Source: Domingo Mery

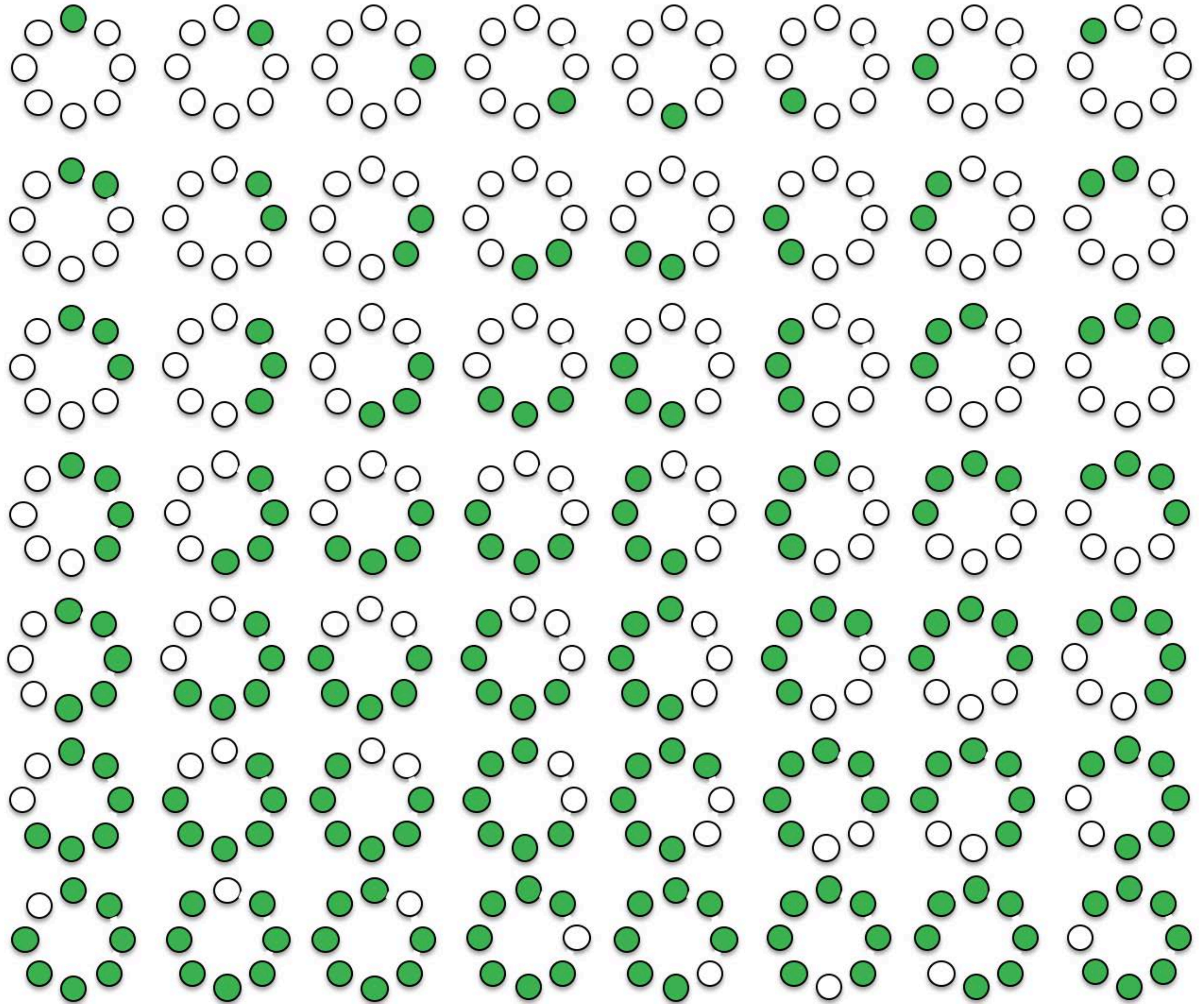
**Uniform pattern:** contains **at most two bitwise transitions (U) from 0 to 1** (or vice versa) when the bit pattern is traversed circularly




Source: Domingo Mery

# Uniform patterns

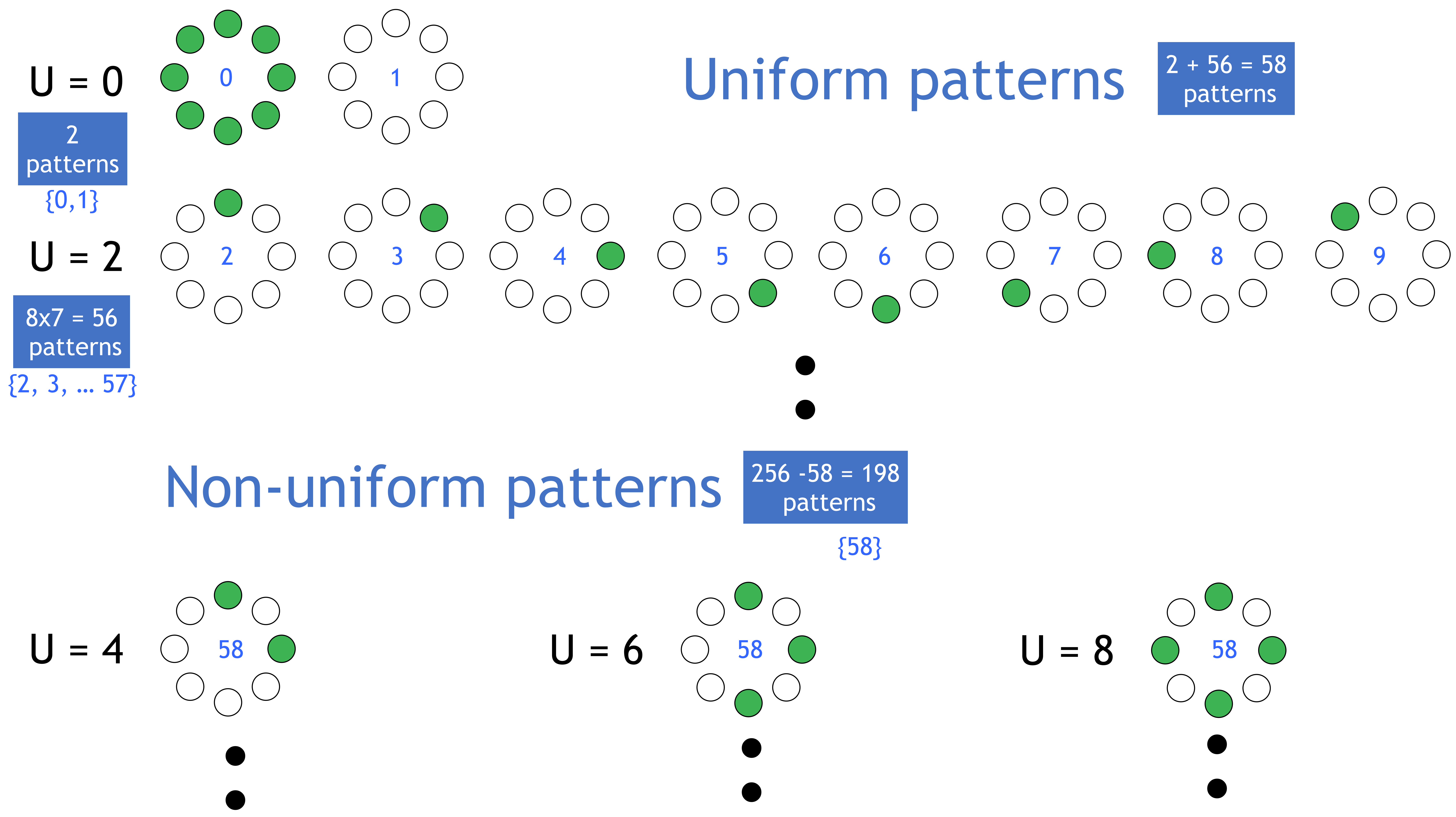
U = 0 

U = 2 

Uniform patterns account for almost 90% of all patterns.

Source: Domingo Mery

Division into *N* cells | Cell coding | **Mapping** | Histogram calculation | Normalization | Concatenation




Source: Domingo Mery

# Result of cell code mapping

| | | | | | |
|---|---|---|---|---|---|
| 4 | 6 | 9 | 6 | 4 | 6 |
| 9 | 6 | 4 | 9 | 9 | 9 |
| 9 | 6 | 2 | 2 | 9 | 2 |
| 10 | 10 | 10 | 10 | 10 | 10 |

Cell

| | | | | | |
|---|---|---|---|---|---|
| | | | | | |
| | 230 | 207 | 25 | 168 | |
| | 243 | 255 | 255 | 119 | |
| | | | | | |

Coded cell

| | | | | | |
|---|---|---|---|---|---|
| | | | | | |
| | 58 | 46 | 58 | 58 | |
| | 23 | 0 | 0 | 58 | |
| | | | | | |

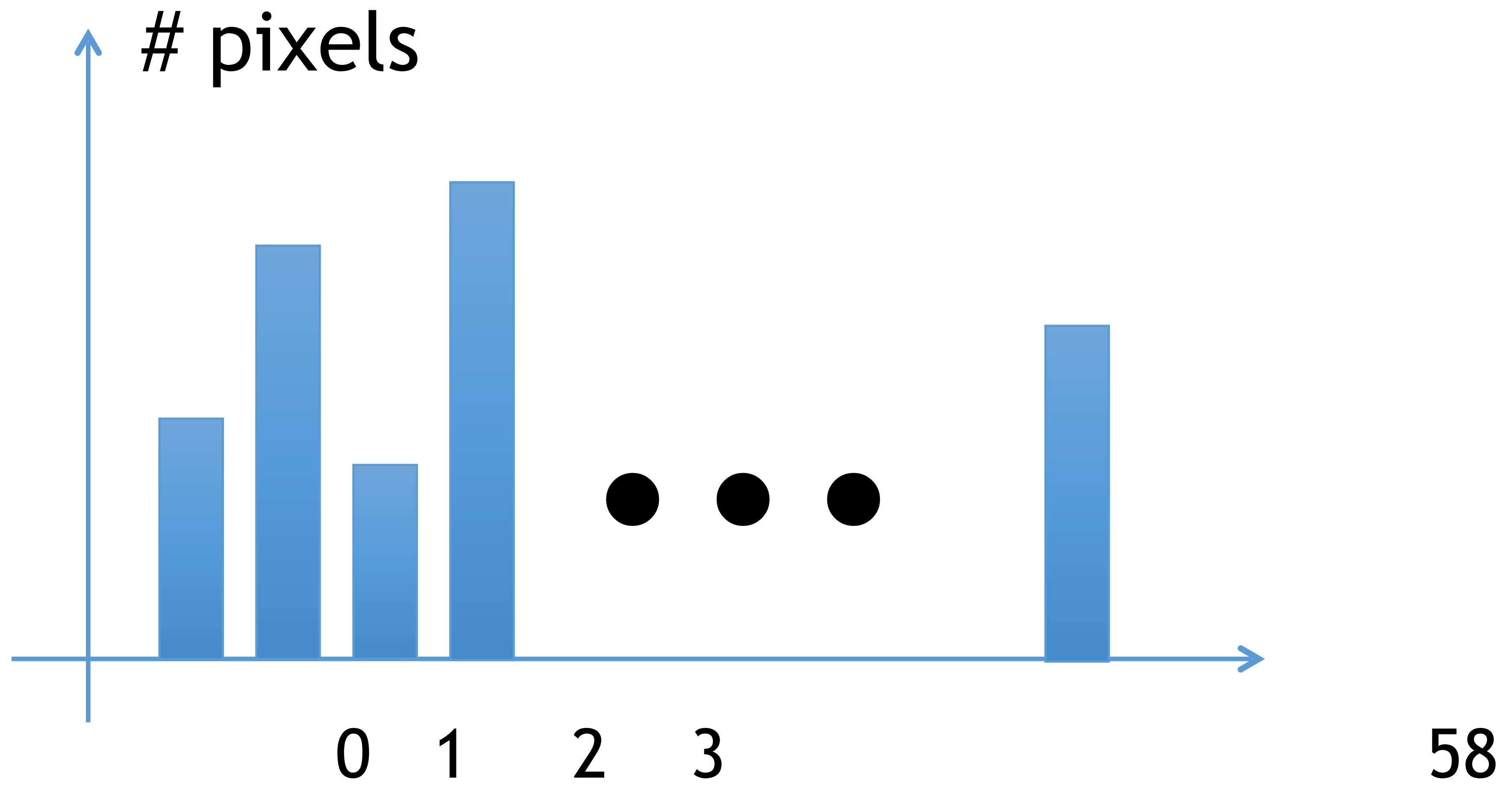
Mapped cell

Source: Domingo Mery

Division into *N* cells | Cell coding | Mapping | **Histogram calculation** | Normalization | Concatenation

**Mapped cell**

| | | | | | |
|---|---|---|---|---|---|
| | | | | | |
| | 58 | 46 | 58 | 58 | |
| | 23 | 0 | 0 | 58 | |
| | | | | | |



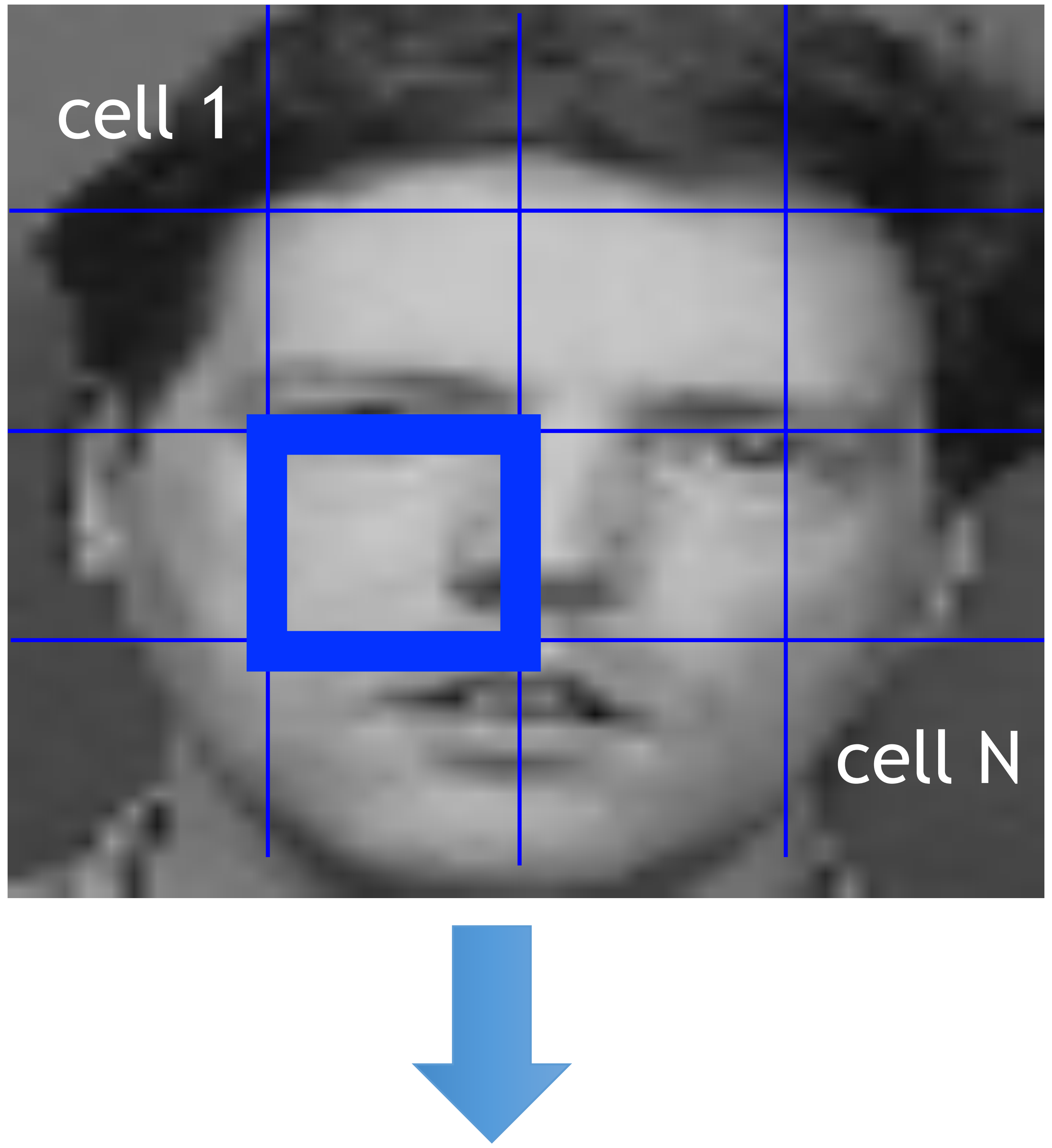

- Each cell is represented as 59-digit LBP descriptor
- Similar textures have similar histograms.



Source: Domingo Mery

Division into $N$ cells | Cell coding | Mapping | Histogram calculation | **Normalization** | **Concatenation**

- Normalization of histograms makes LBP descriptors size-invariant
- Concatenation of all cell histograms provides the image LPB descriptor

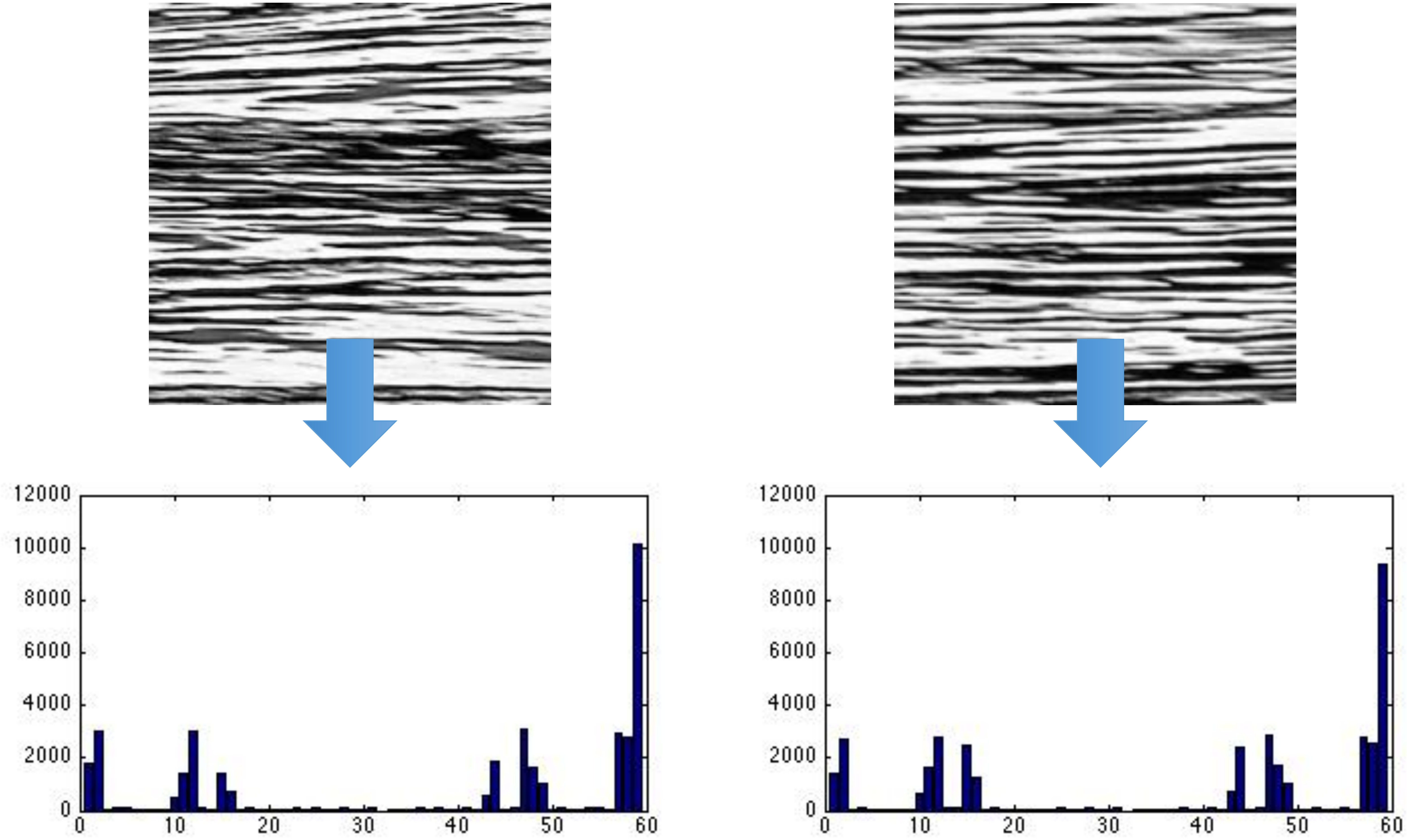




Source: Domingo Mery

# Local Binary Patterns

## Similar textures have similar histograms

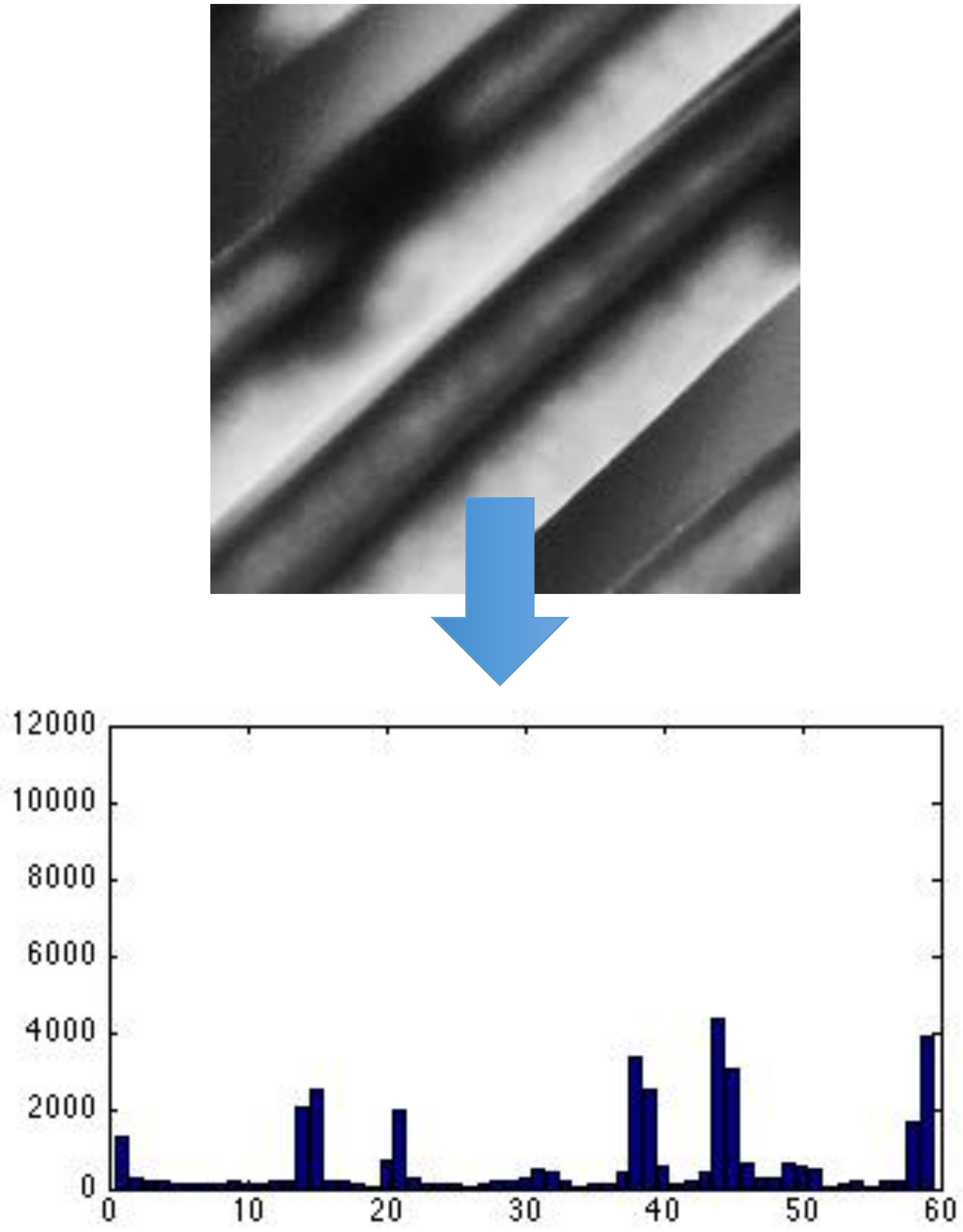


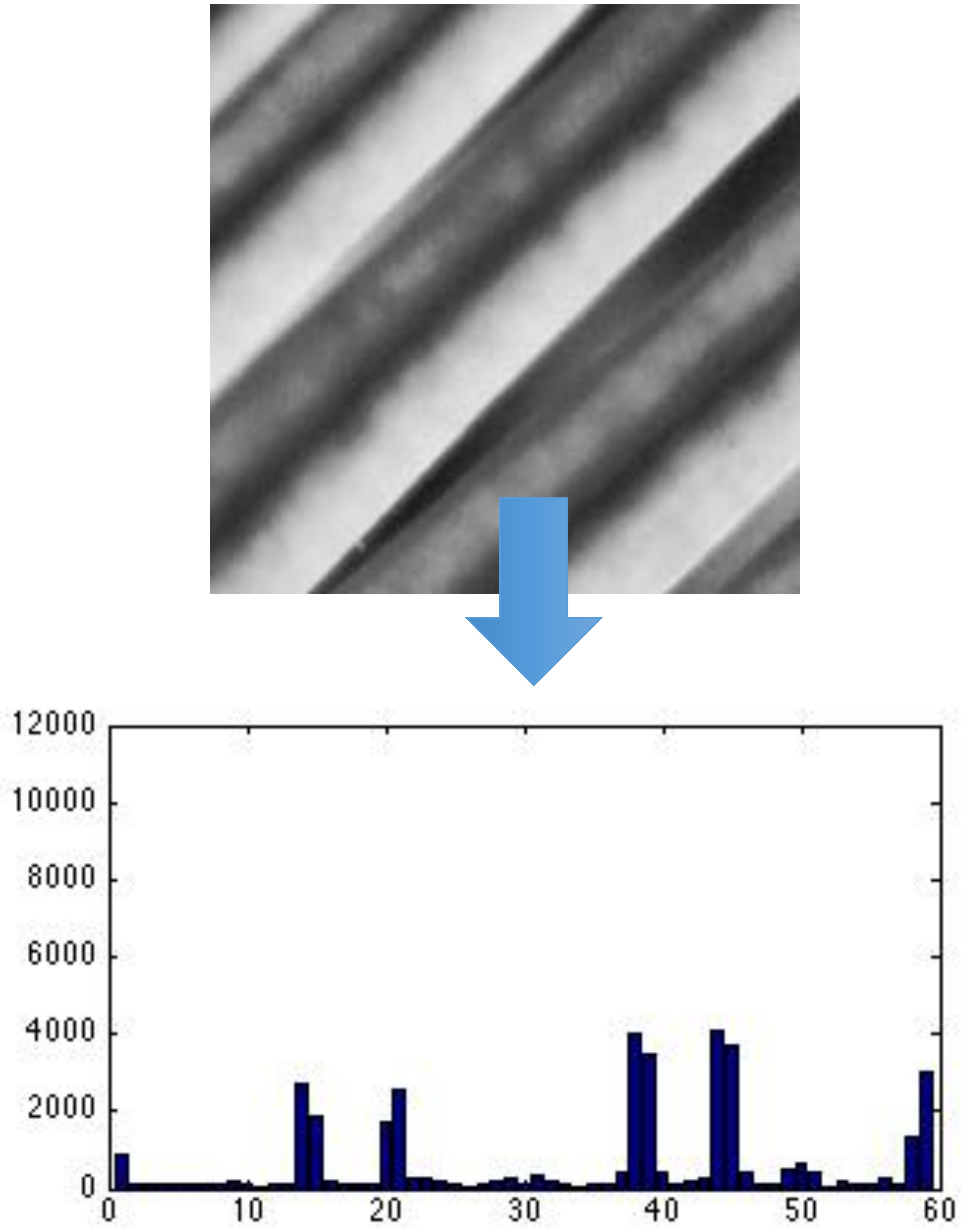



Source: Domingo Mery

# Local Binary Patterns

Similar textures have similar histograms



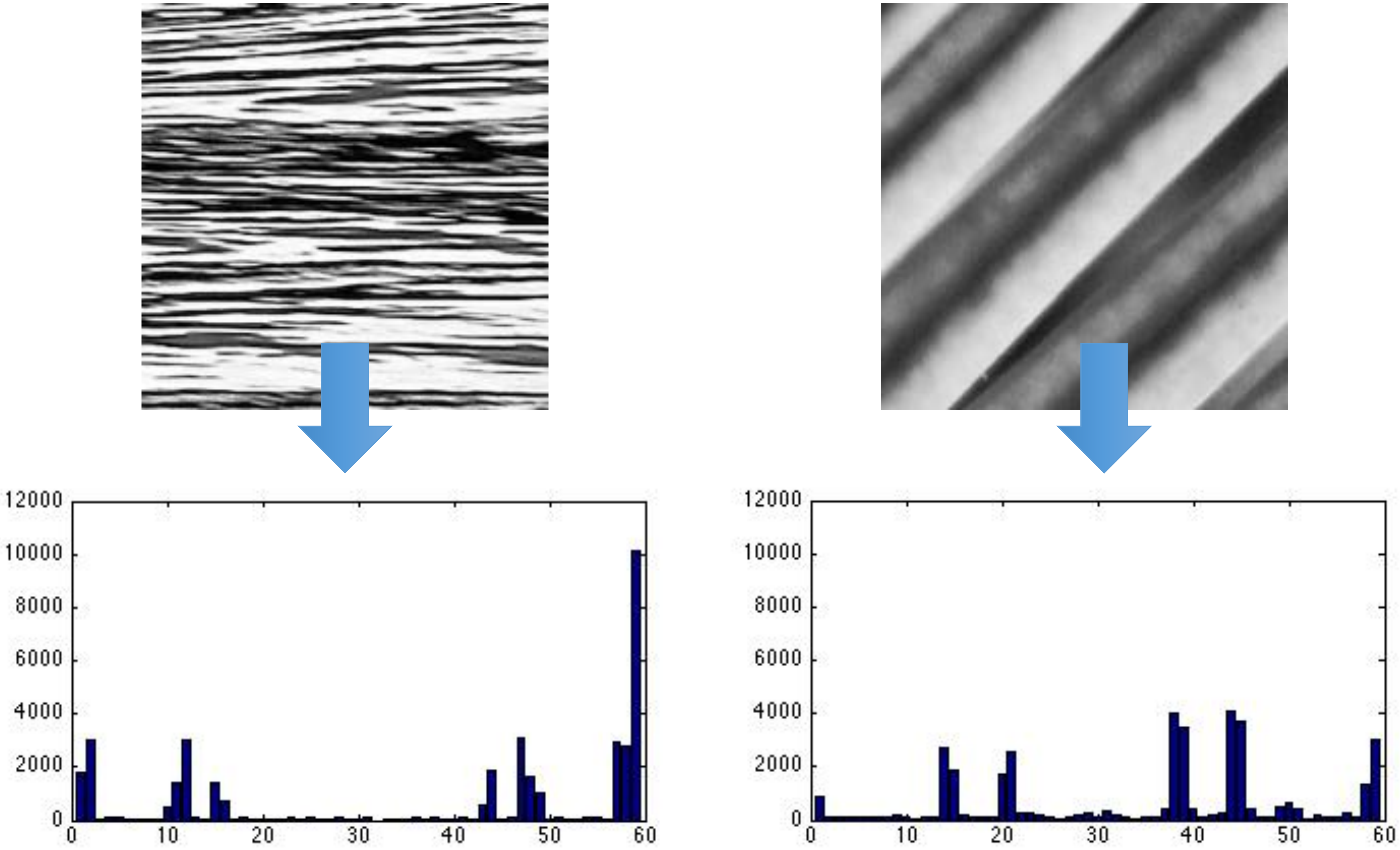






Source: Domingo Mery

# Local Binary Patterns

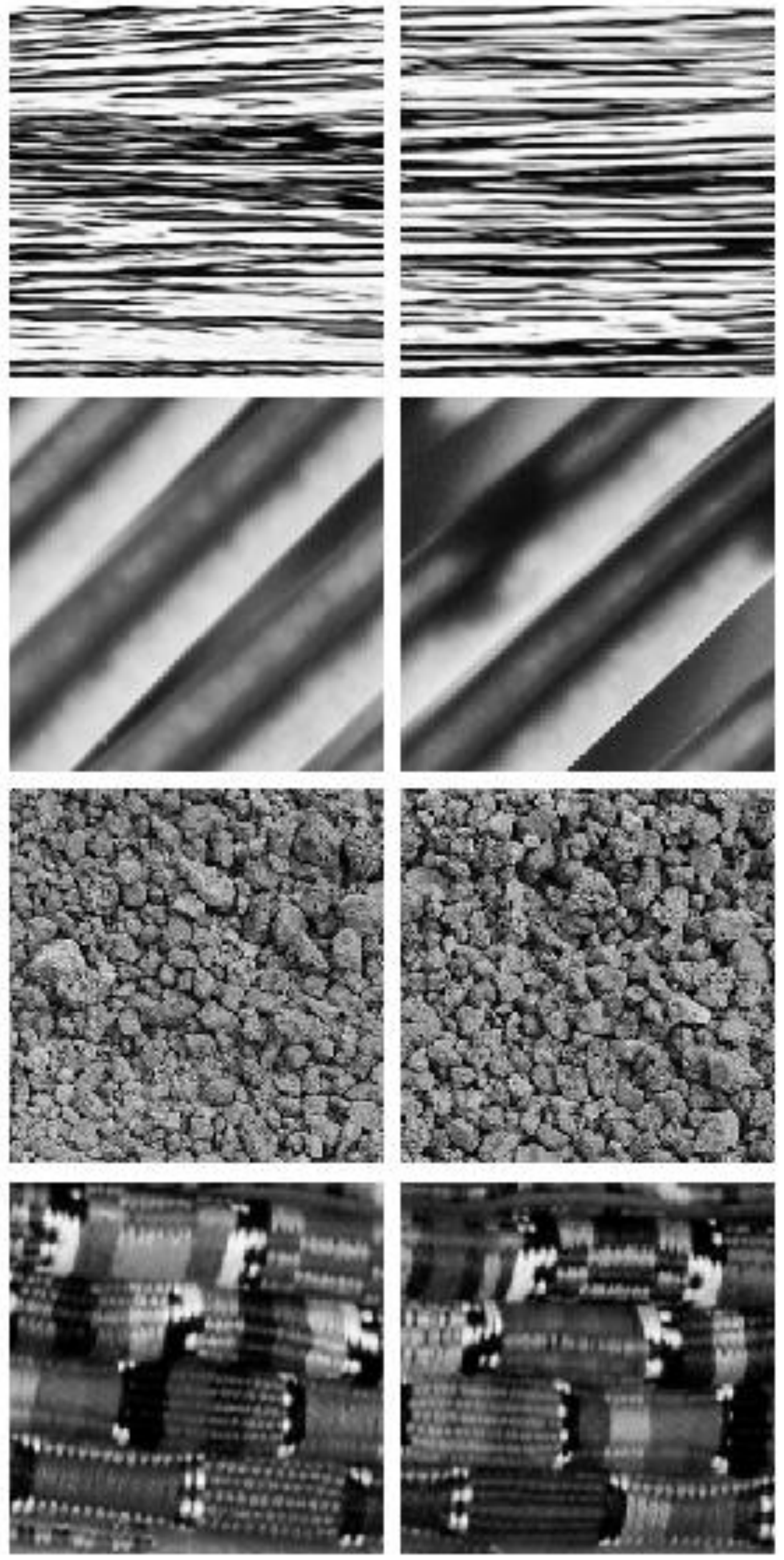
Similar textures have similar histograms

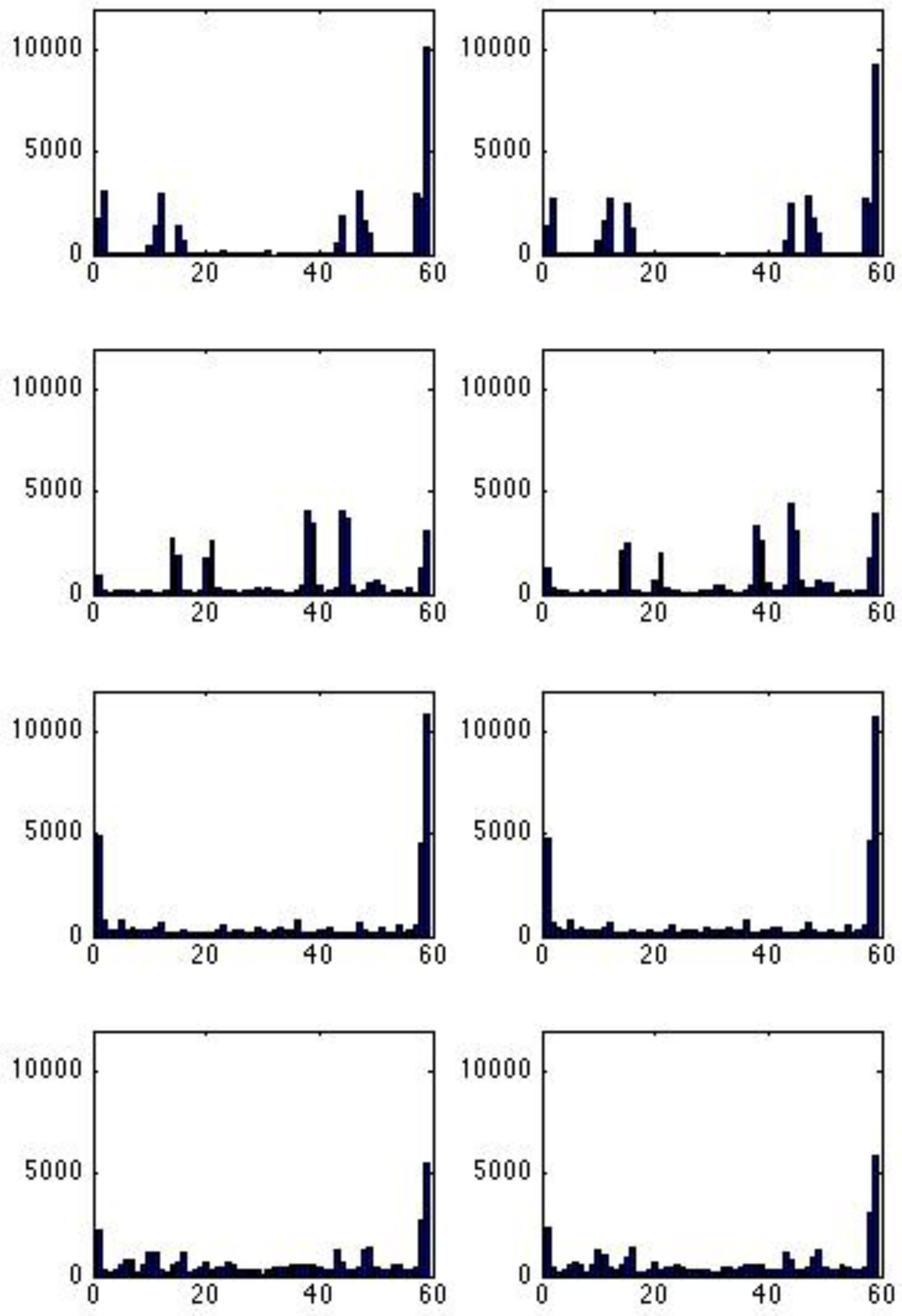



Source: Domingo Mery

# Local Binary Patterns

## Similar textures have similar histograms






Source: Domingo Mery

# LBP for face recognition

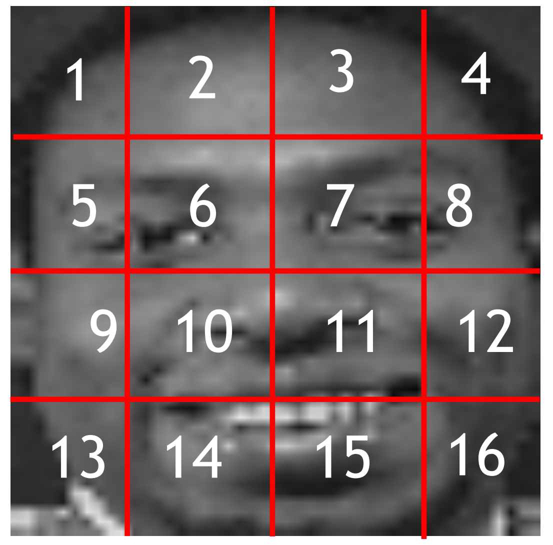
In the training set there are *k* classes.

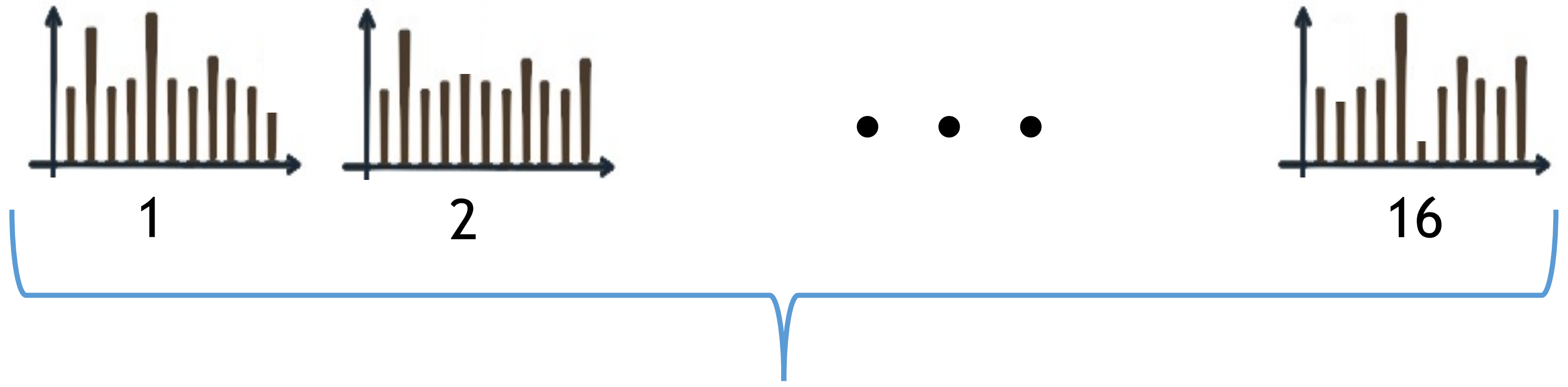
For each class we have *n* training images.

In this example there are 40 classes with 9 images in each class.

Each image in partitioned into 16 cells.

In each cell we extract LBP features.




A face is described using a feature of 16 x 59 = 944 elements



Source: Domingo Mery

# LBP for face recognition


**Training Data**

Table with:

9x40 = 360 rows

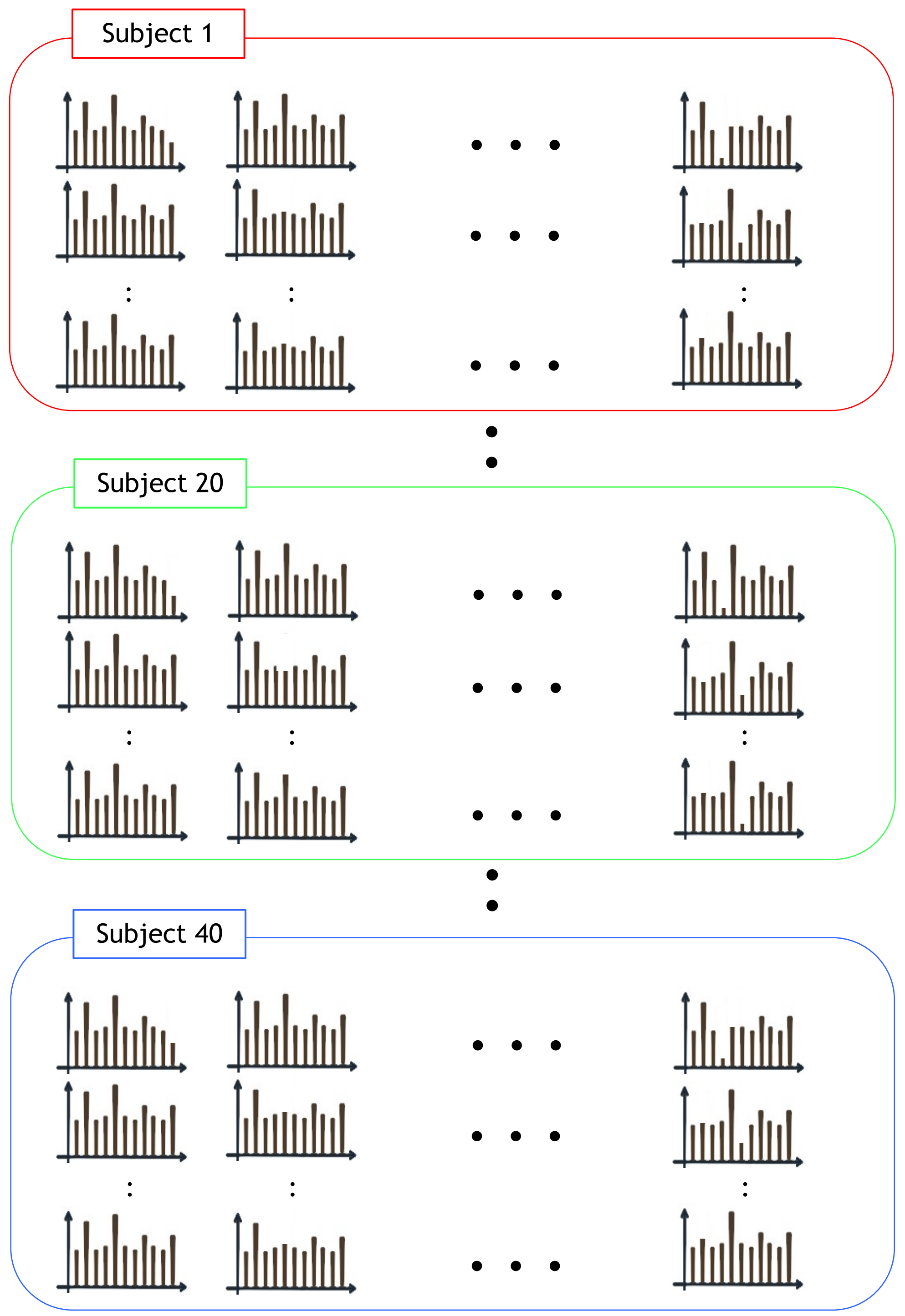
and

16 x 59 = 944 columns



Source: Domingo Mery

# LBP for face recognition





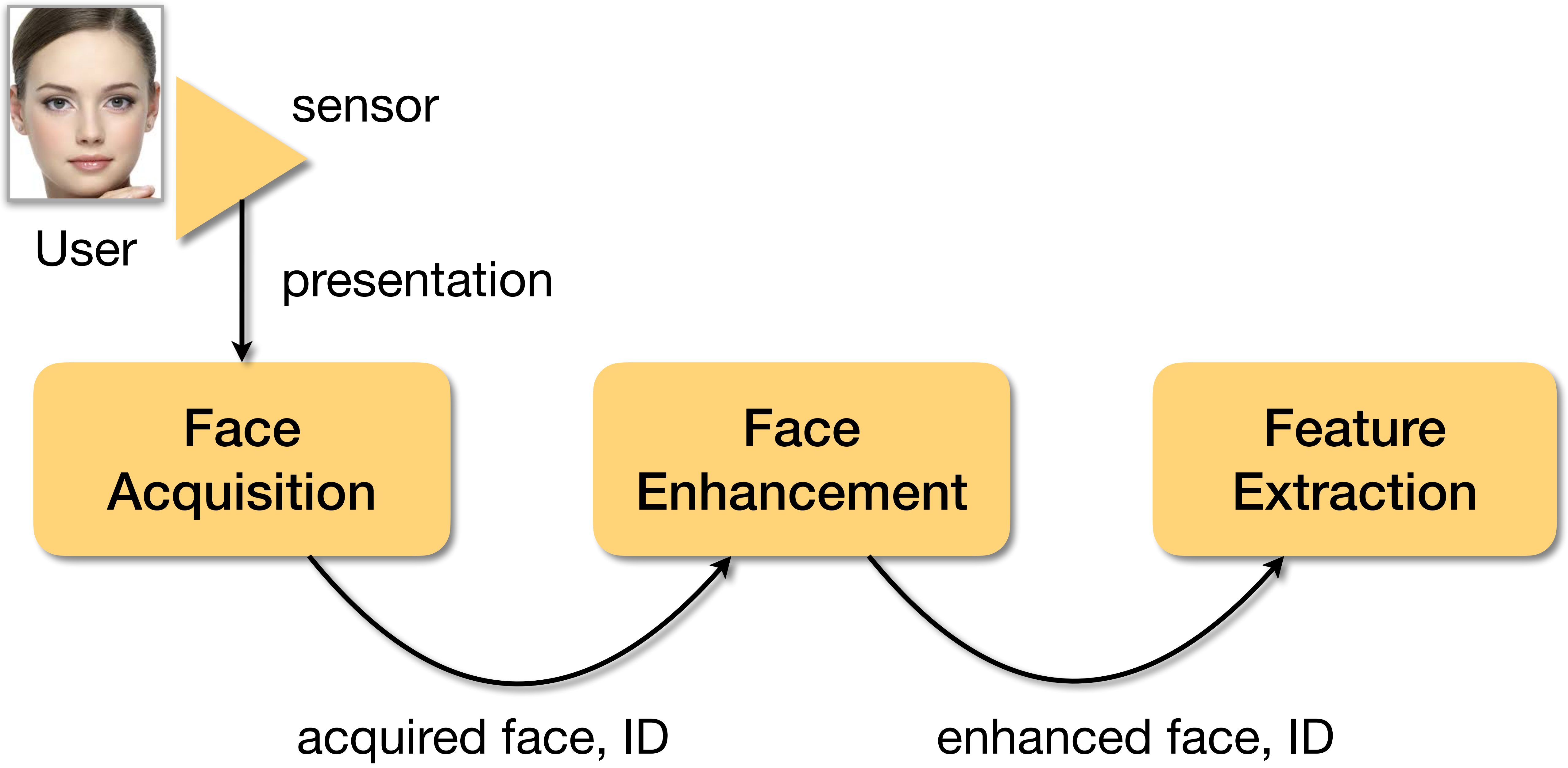

Source: Domingo Mery

# LBP for face recognition

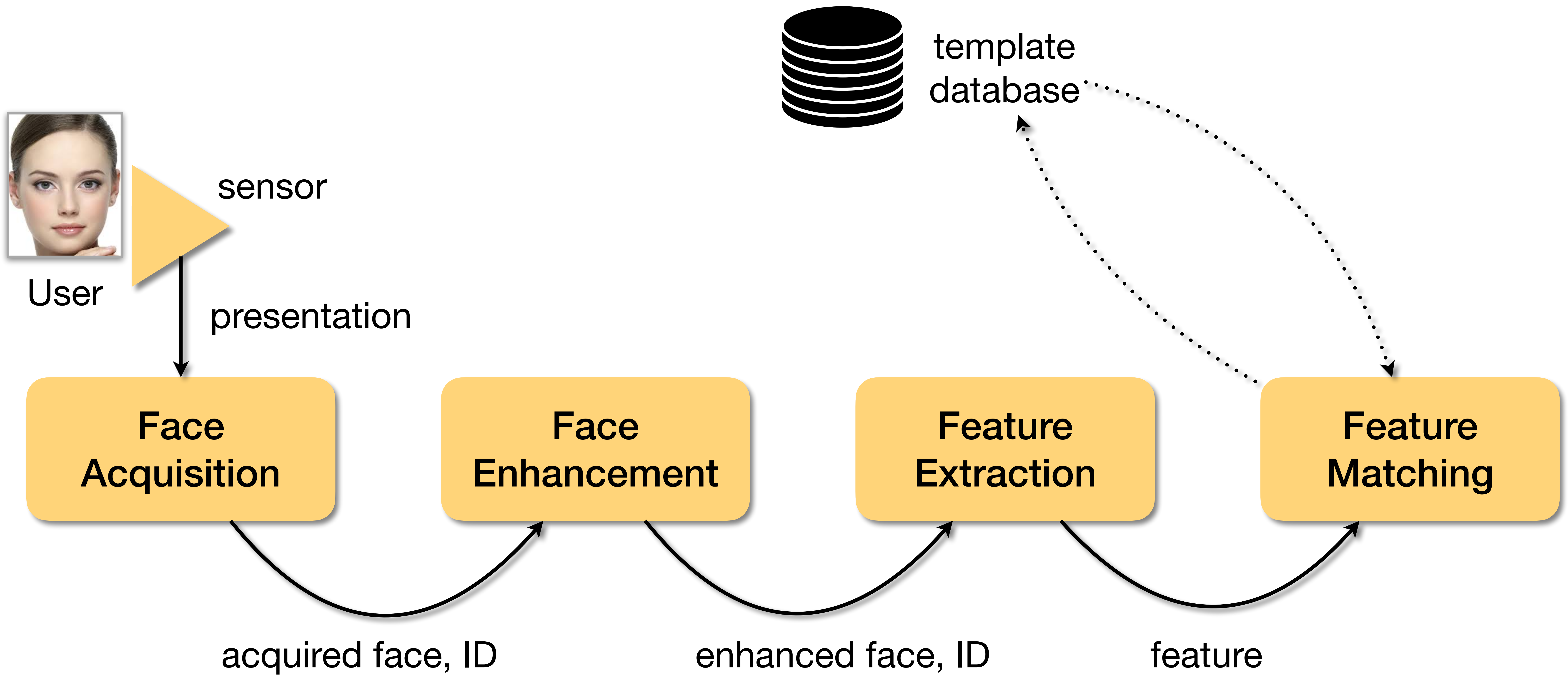



Source: Domingo Mery

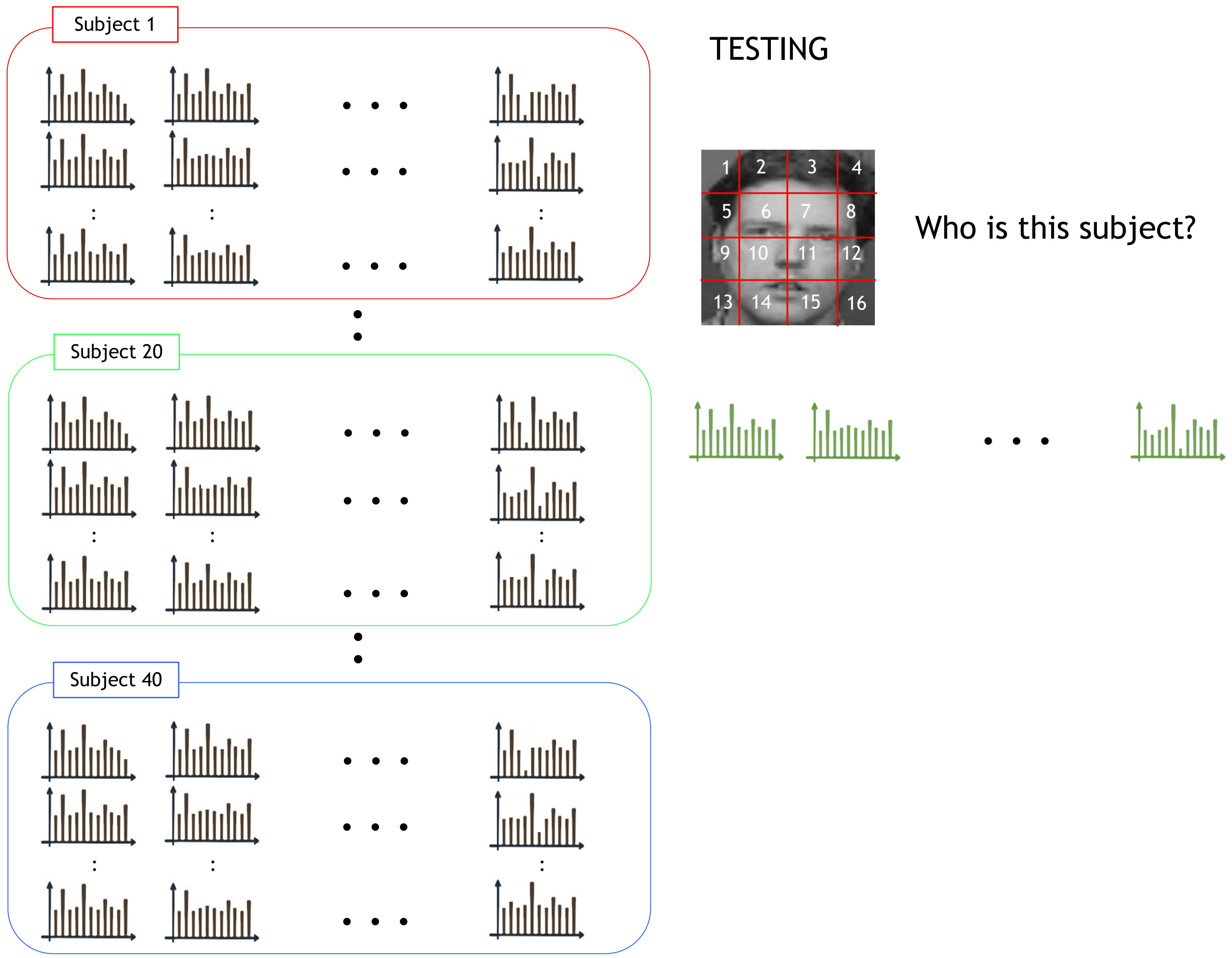
# Face Recognition



# Face Recognition



# LBP for face recognition (Feature Matching)





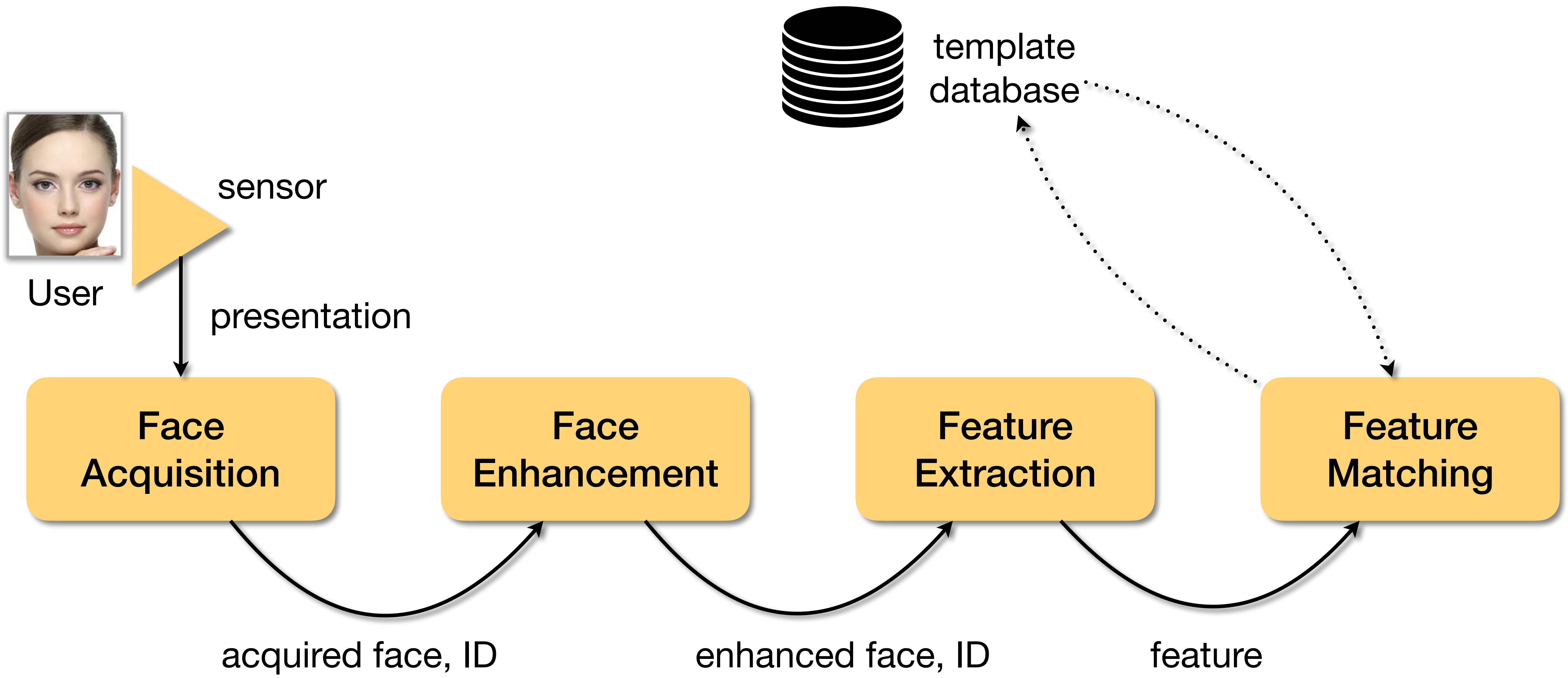

Source: Domingo Mery

# LBP for face recognition (Feature Matching)

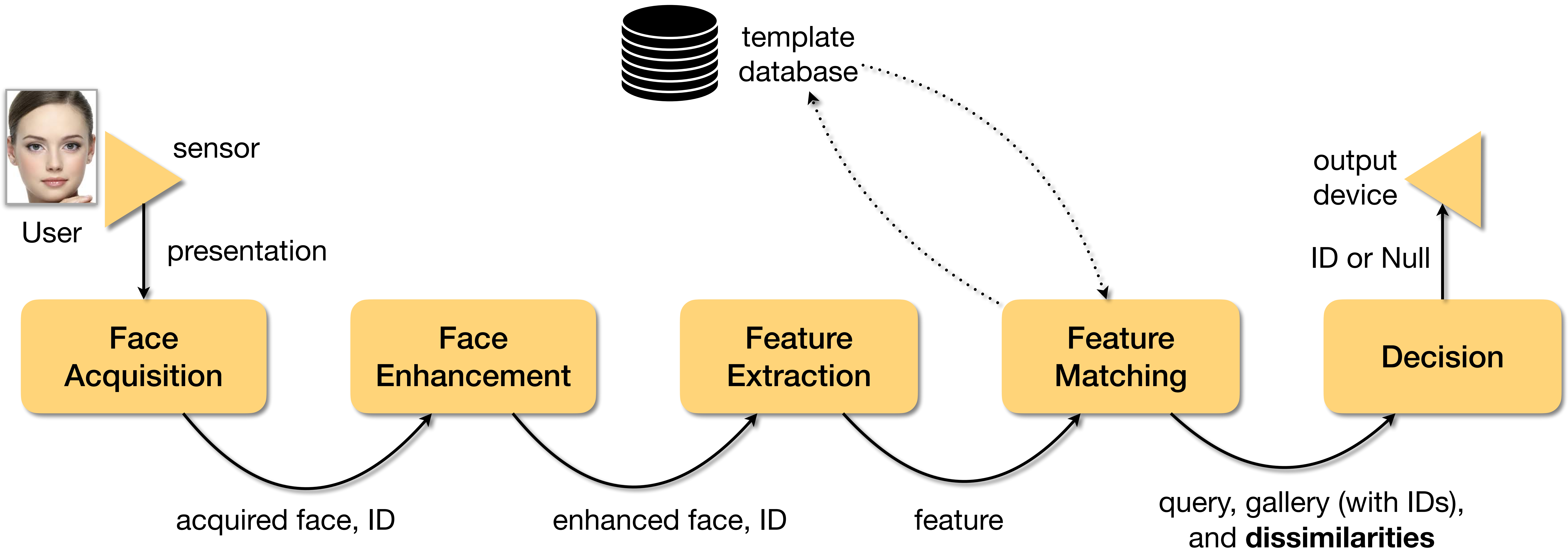



Source: Domingo Mery

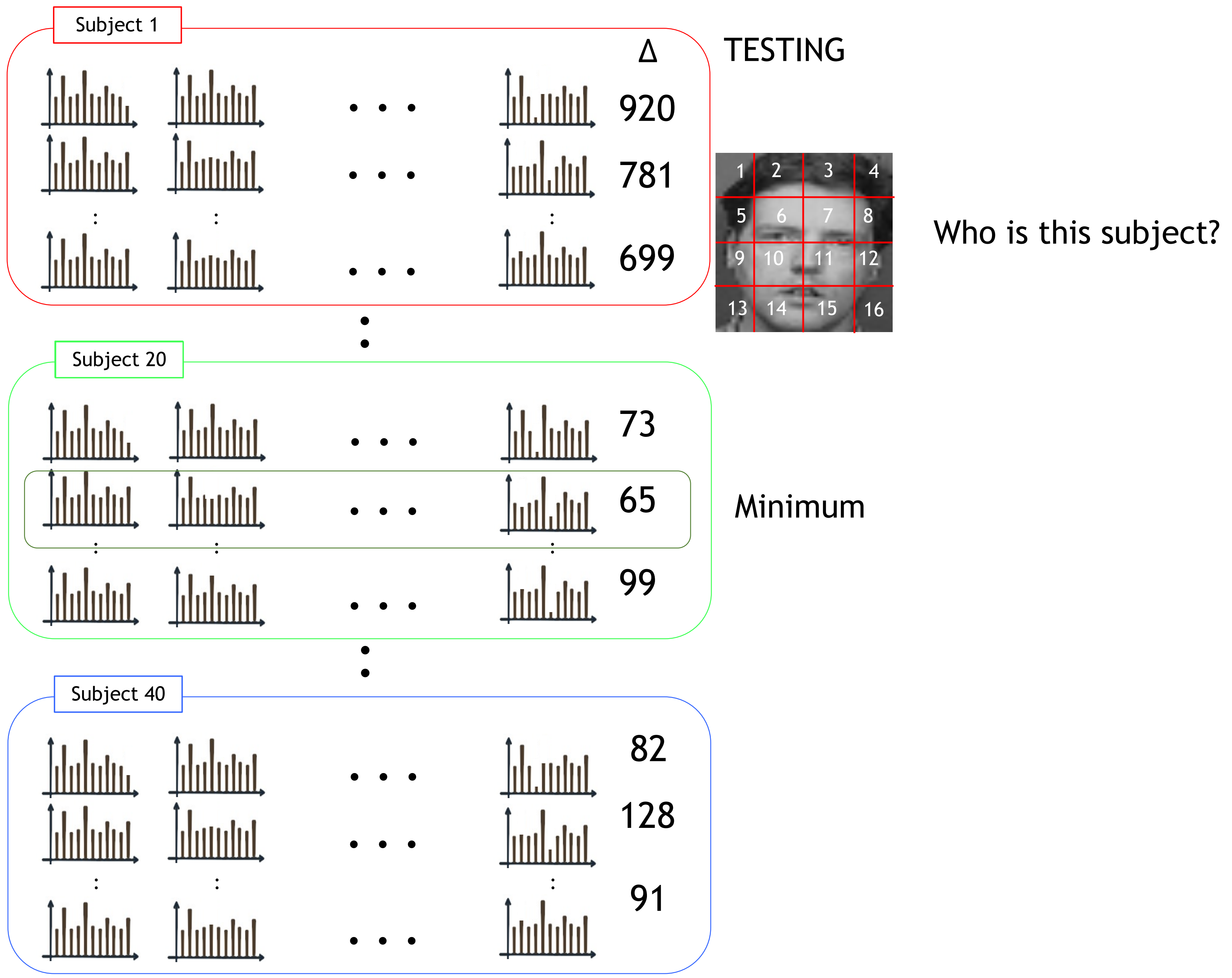
# Face Recognition



# Face Recognition



# LBP for face recognition (Decision)






Source: Domingo Mery

# Feature Extraction

**Focus**
2D-appearance-based methods.

**Types**
Handcrafted features from Computer Vision.

Data-driven learned features from Machine Learning.

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**Focus**
2D-appearance-based methods.

**Types**
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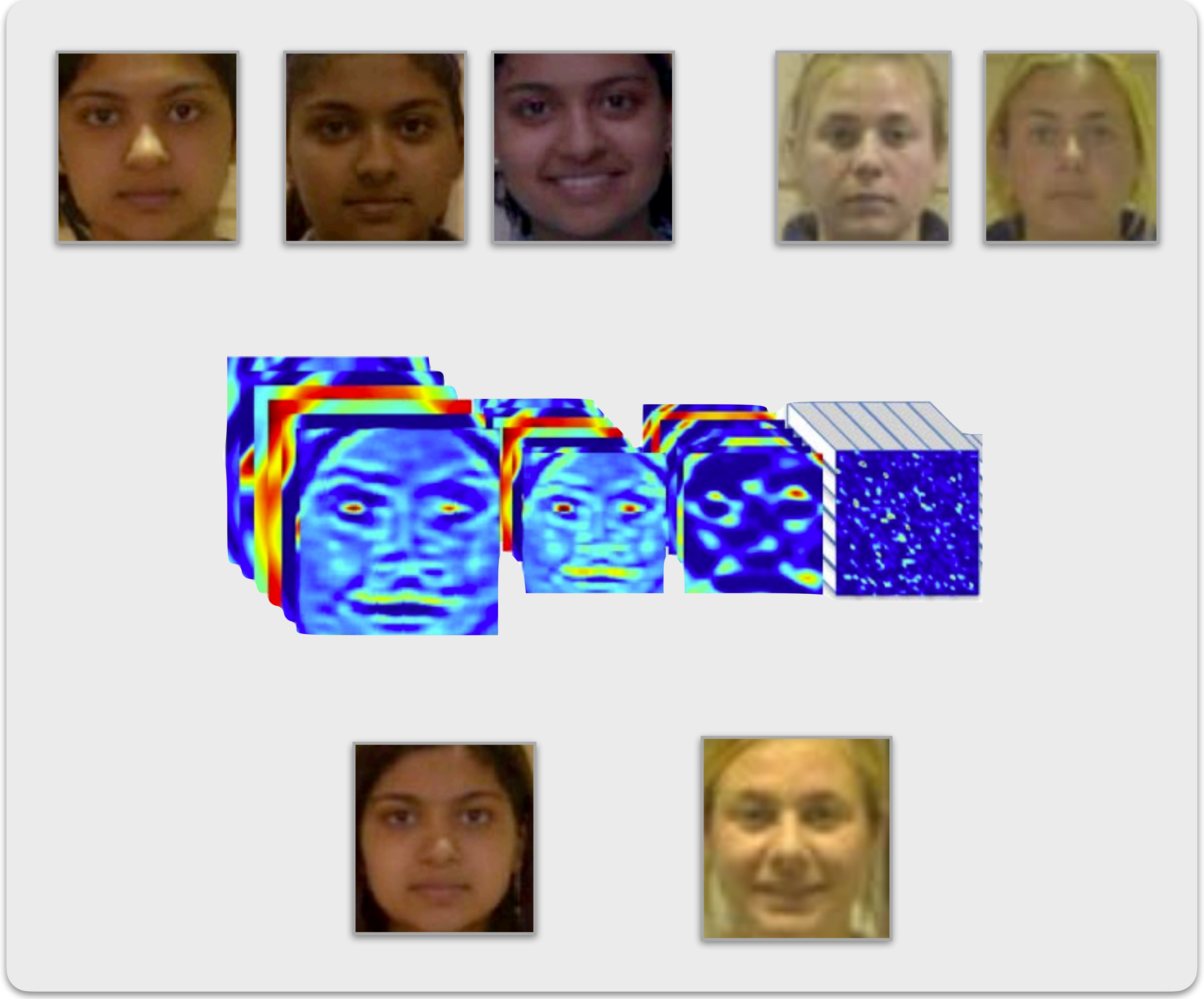
**Data-driven learned features from Machine Learning.**



# Feature Extraction

**Deep Convolutional Neural Networks**

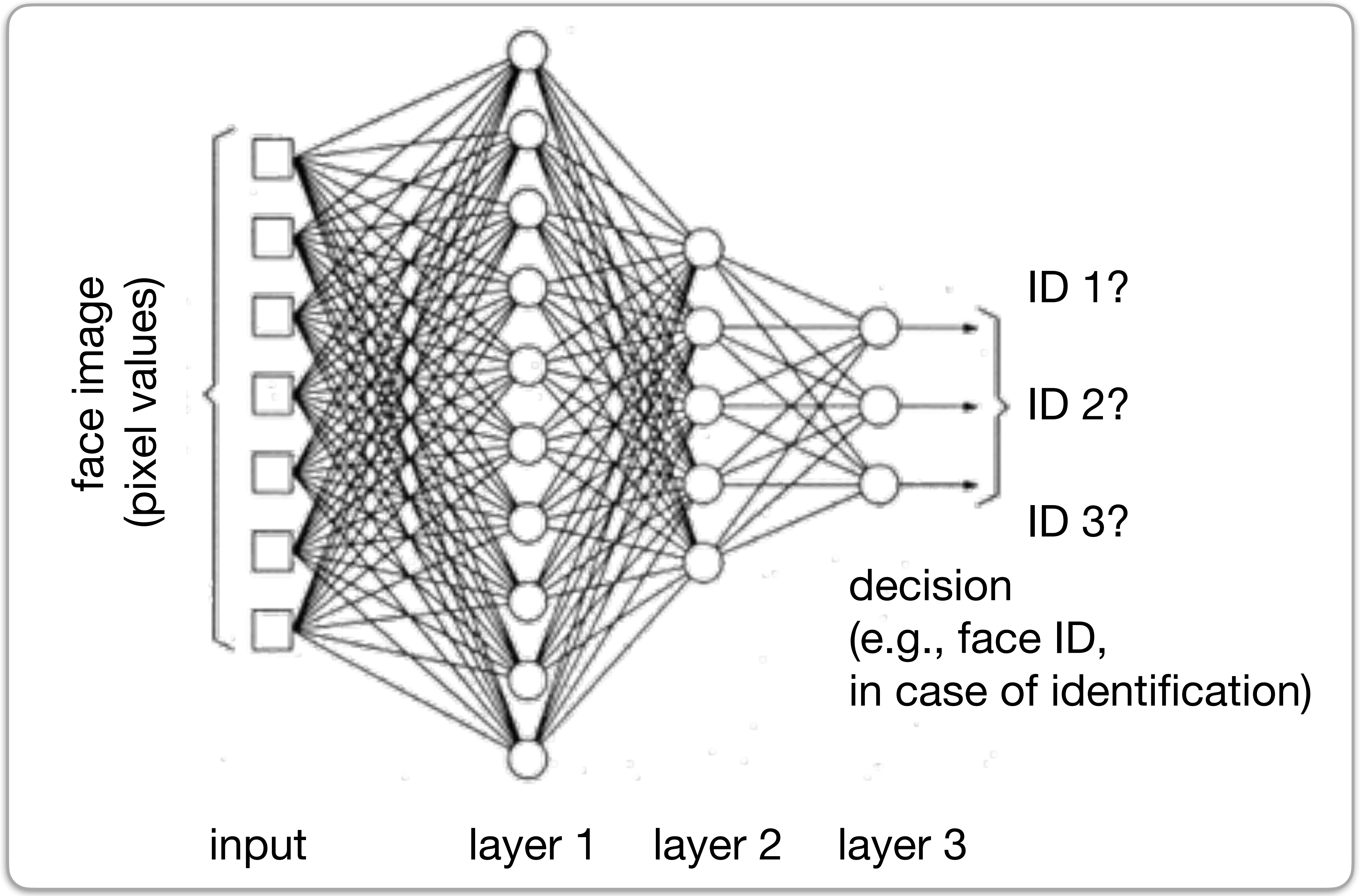
# Feature Extraction

**Deep Convolutional Neural Networks**

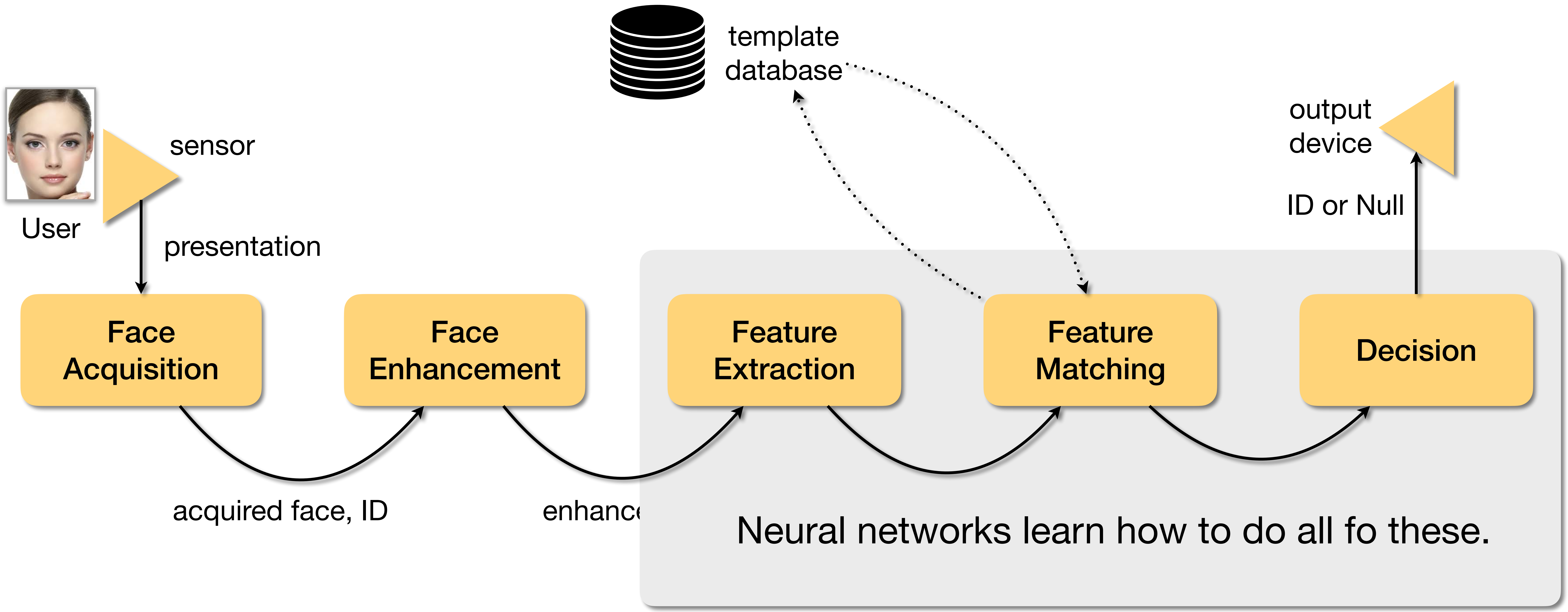
From pixels to classification decision.

Hierarchy of feature extractors.

Each layer extracts features from previous layer.



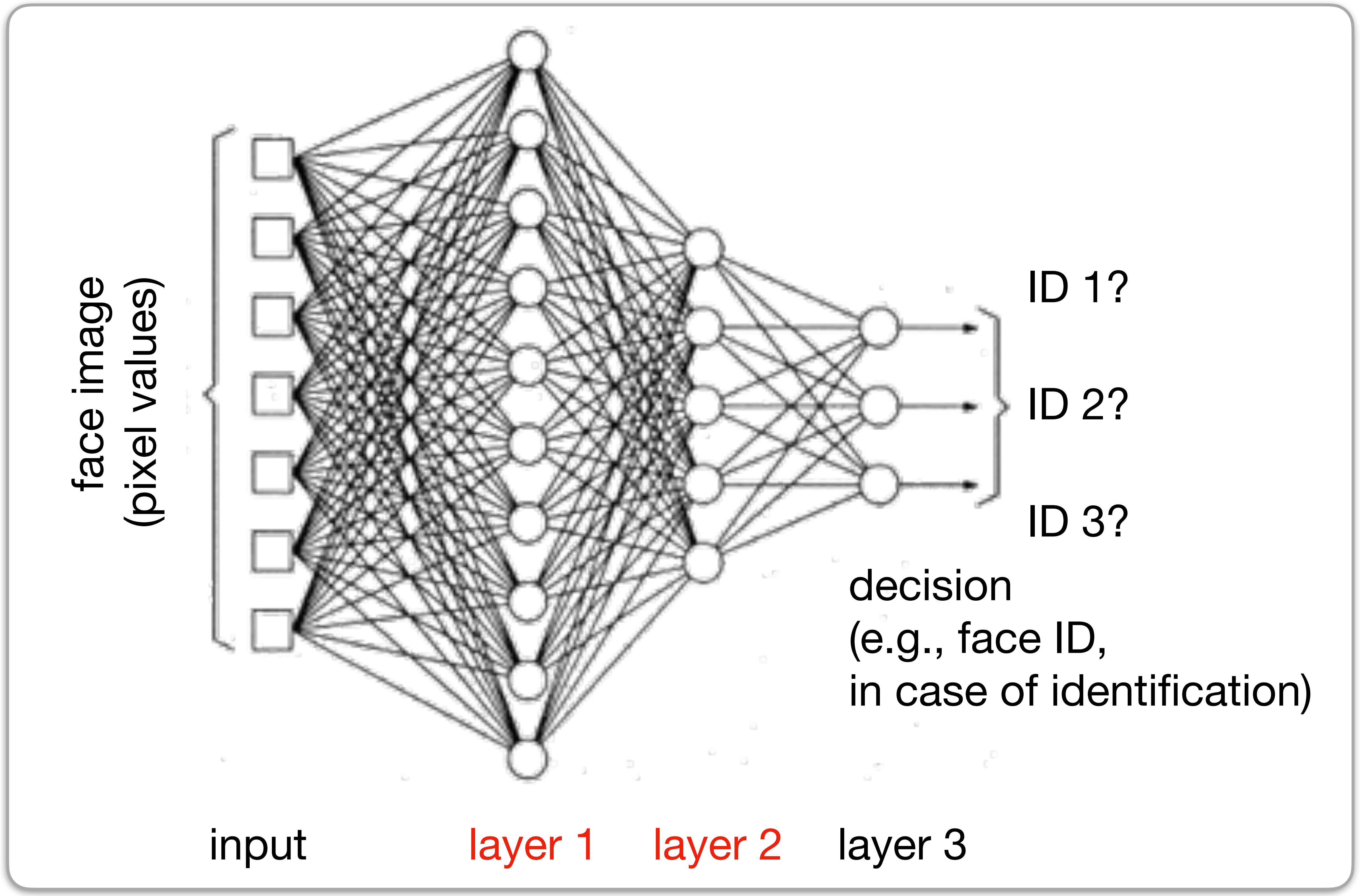
# Face Recognition



# Data-driven Face Recognition

**Deep Convolutional Neural Networks**

**Convolutional Layers**
E.g., layers 1 and 2.
Feature extractors are convolutional operations which are performed on the output of the previous layer.



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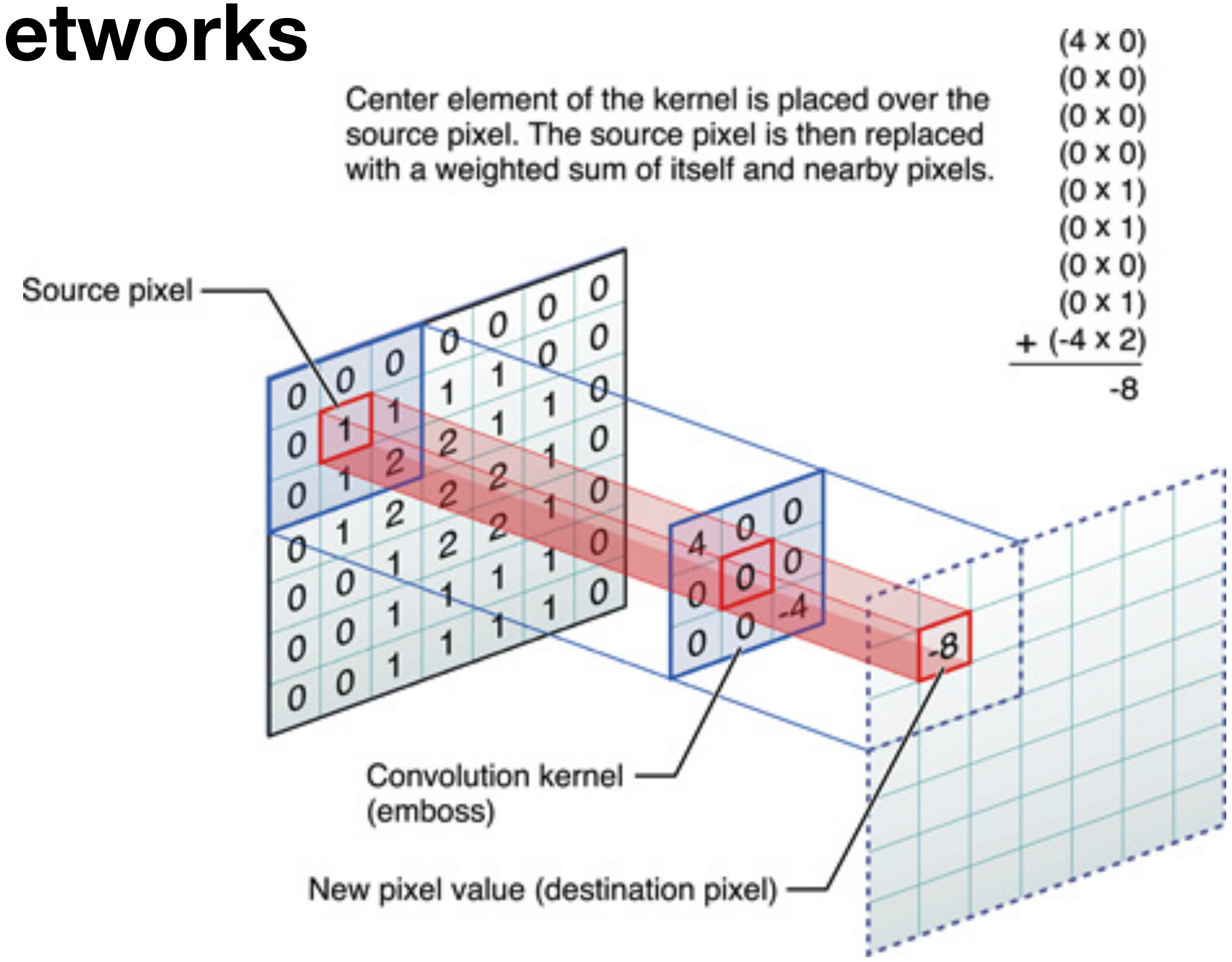
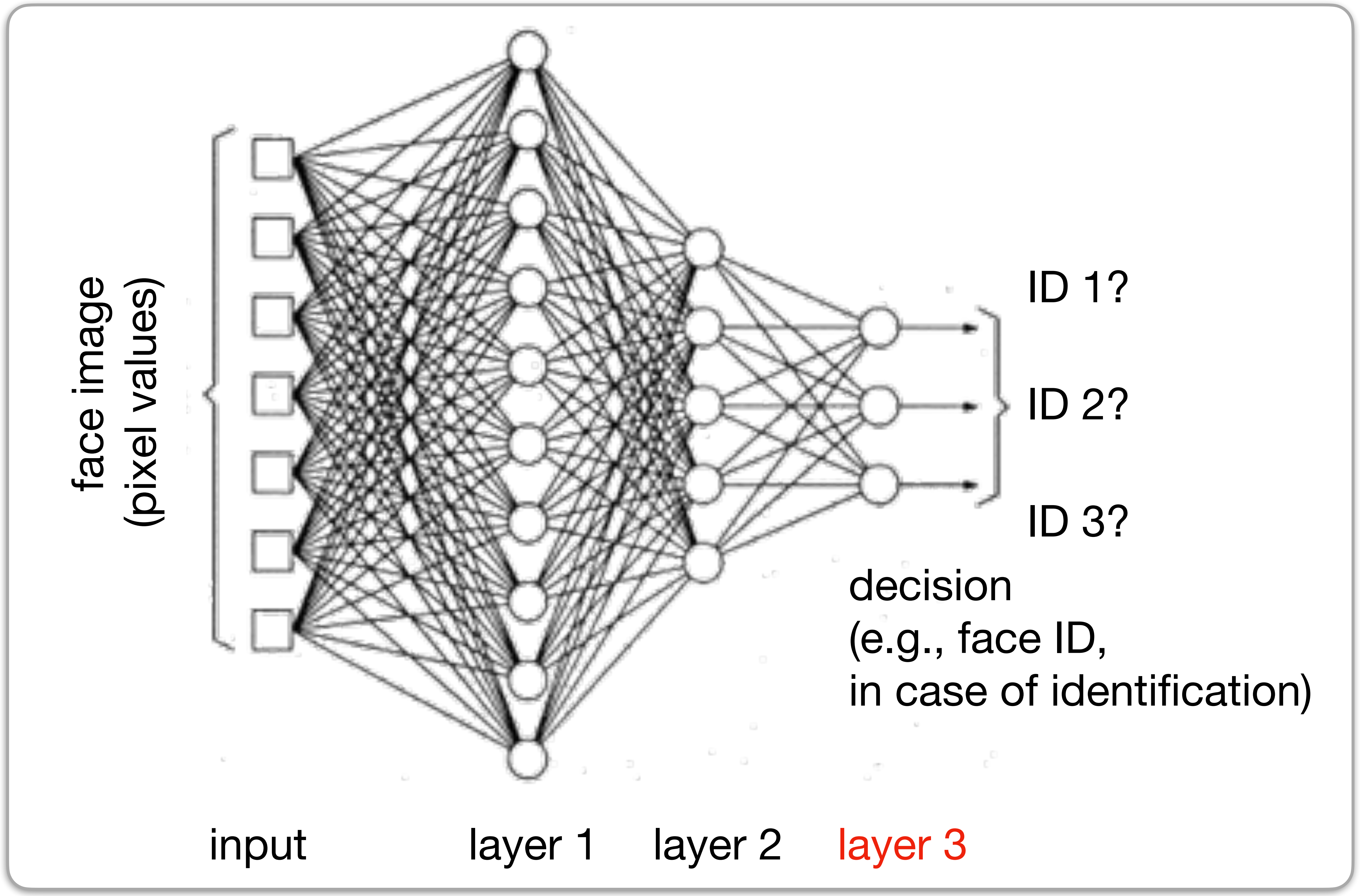



Source:https://developer.apple.com/library/archive/documentation/Performance/Conceptual/vImage/ConvolutionOperations/ConvolutionOperations.html

# Data-driven Face Recognition

**Deep Convolutional Neural Networks**

**Fully Connected Layer**
E.g., layer 3.
It performs the classification, presenting one score output for each class (identity, in the case of Biometrics).



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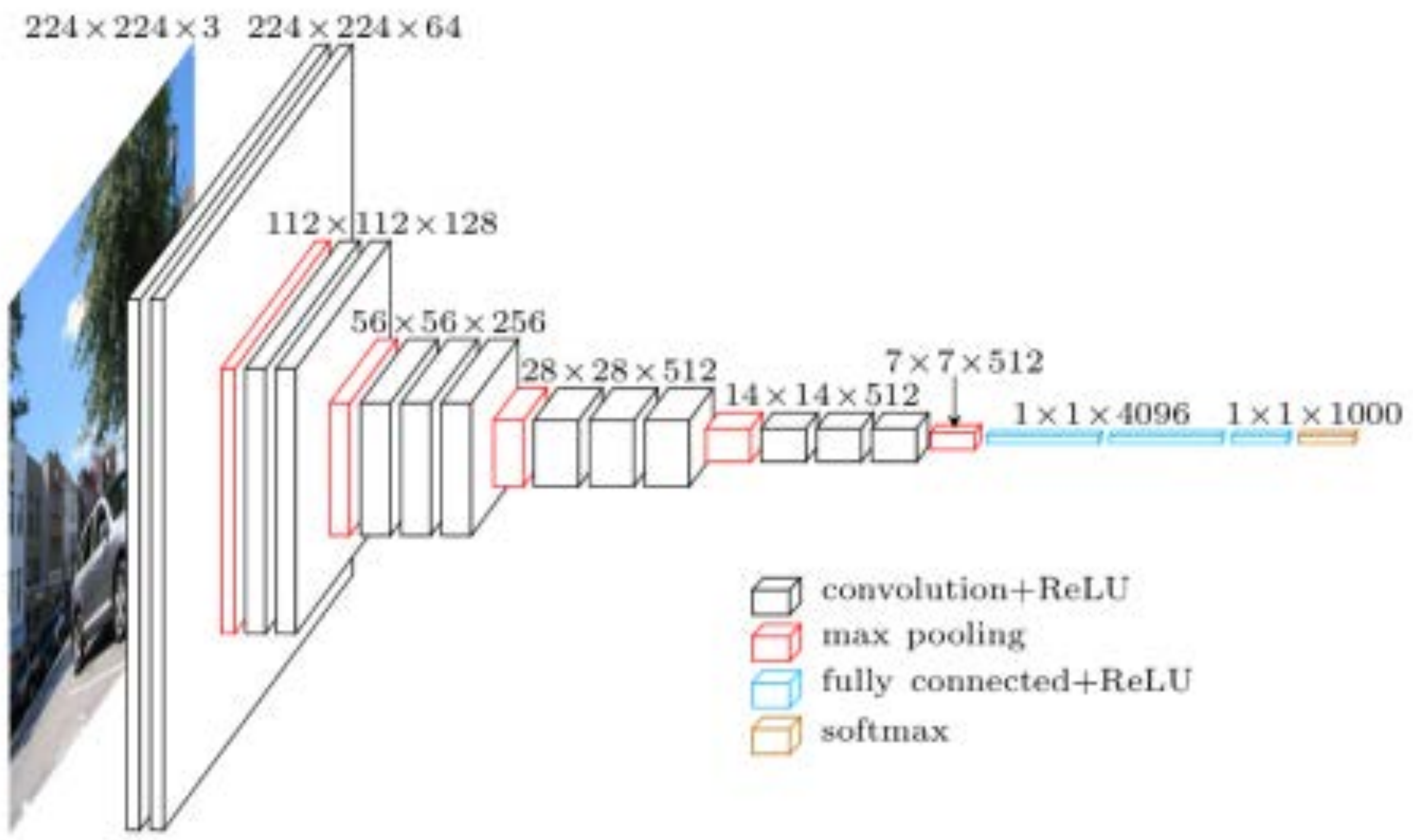
# Data-driven Face Recognition

## Deep Convolutional Neural Networks

**How deep can they be?**
"Deep" refers to the number of layers.

E.g., VGG16
Simonyan and Zisserman
*Very Deep Convolutional Networks for Large-Scale Image Recognition*




16 to 19 convolutional layers



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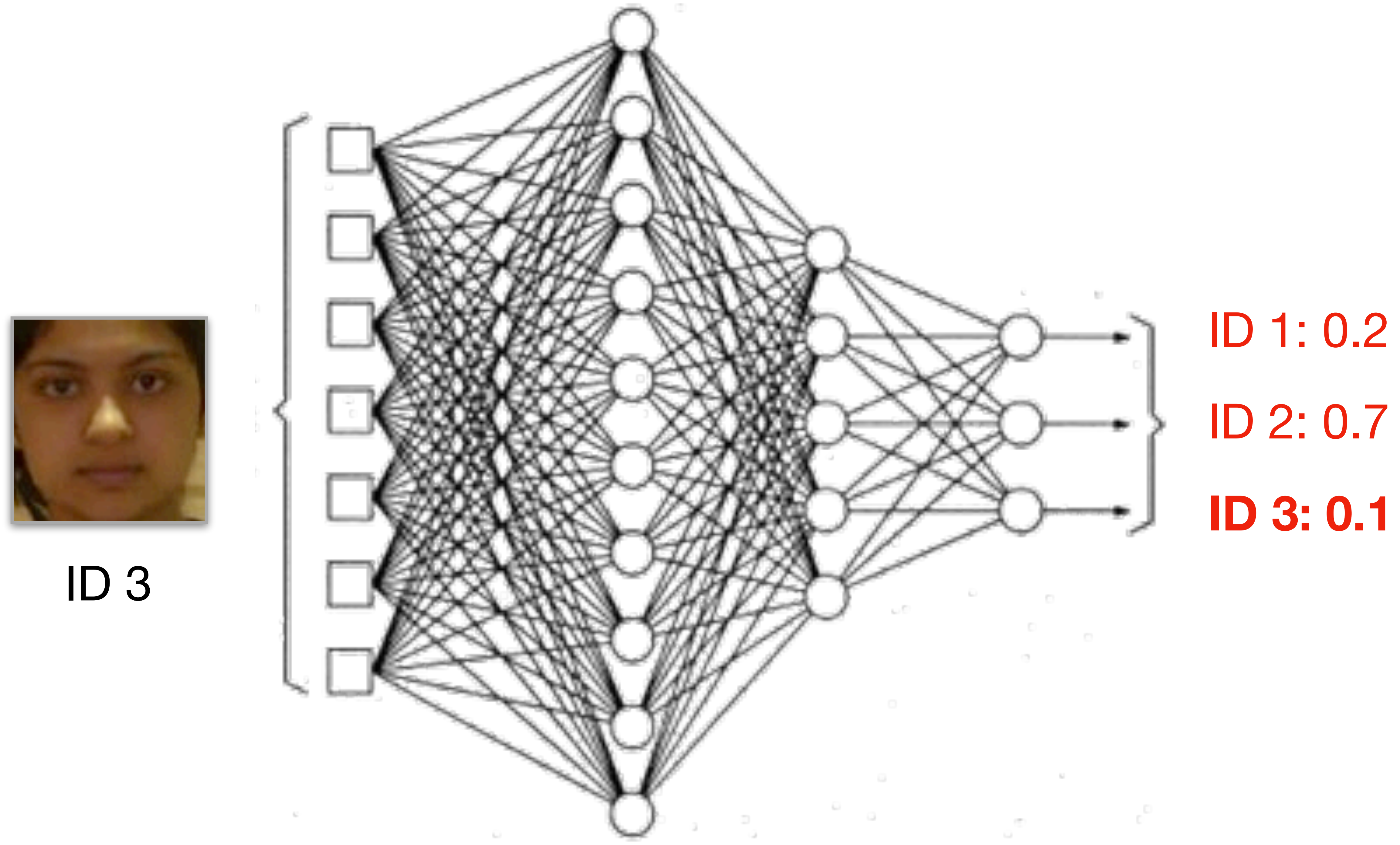
# Data-driven Face Recognition

**Deep Learning**

**Training**
Labeled examples
(e.g., faces and expected IDs)
are used to teach the network
to classify them correctly.




Random weights in the beginning.



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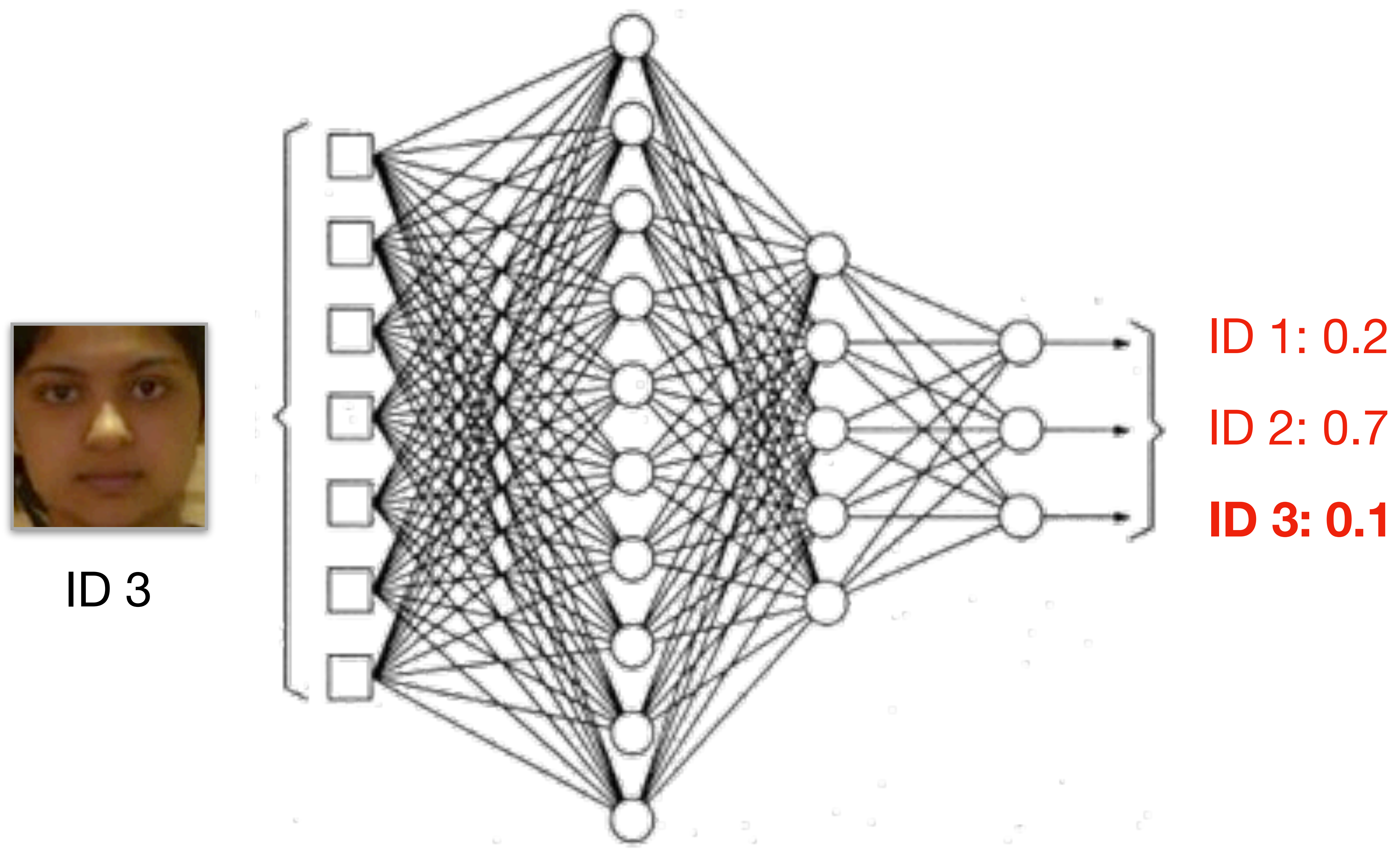
# Data-driven Face Recognition

**Deep Learning**

**Training**
Back-propagation is used to fix the weights of the convolutions within the network.

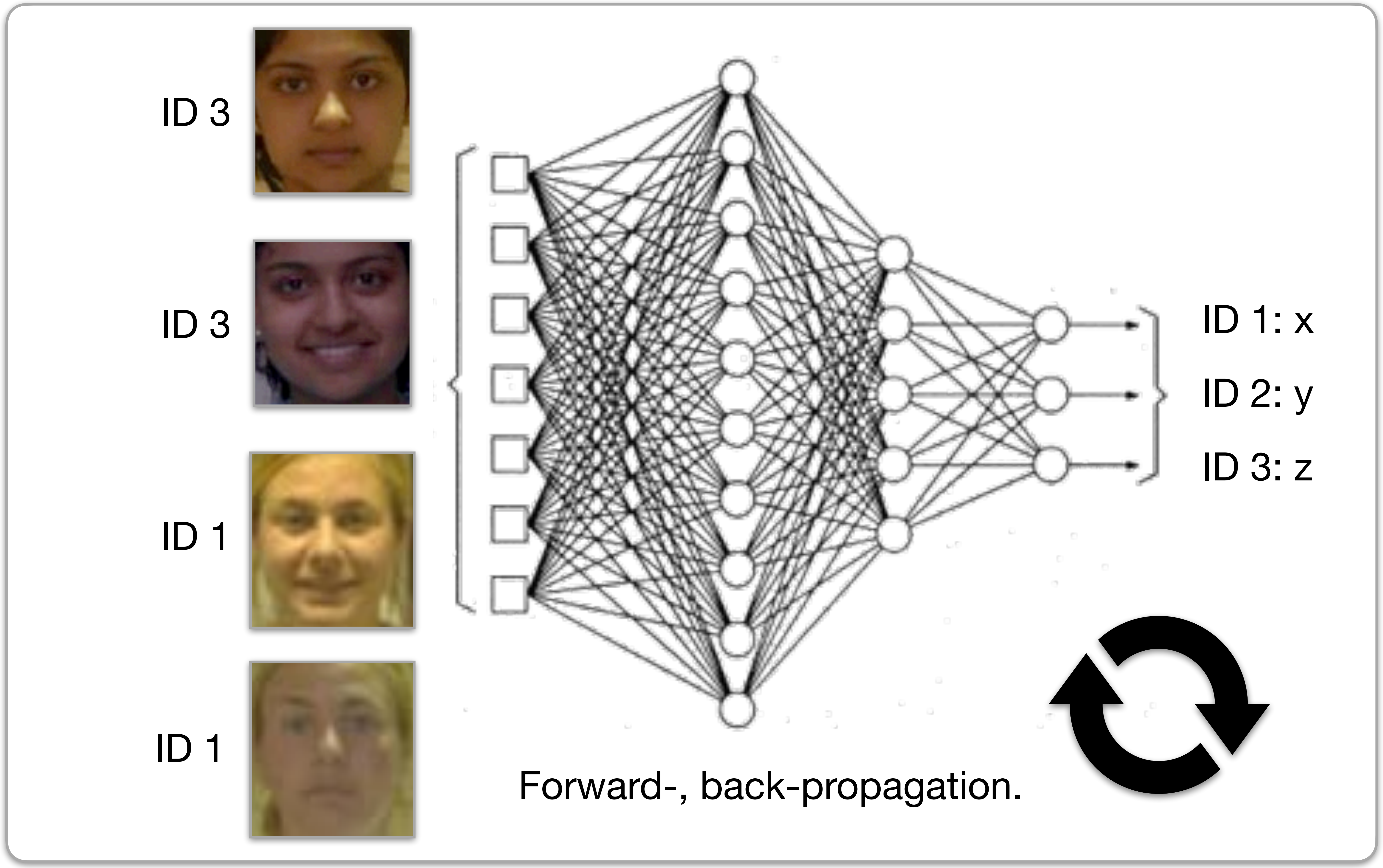



Weights are fixed with back-propagation.

# Data-driven Face Recognition

**Deep Learning**

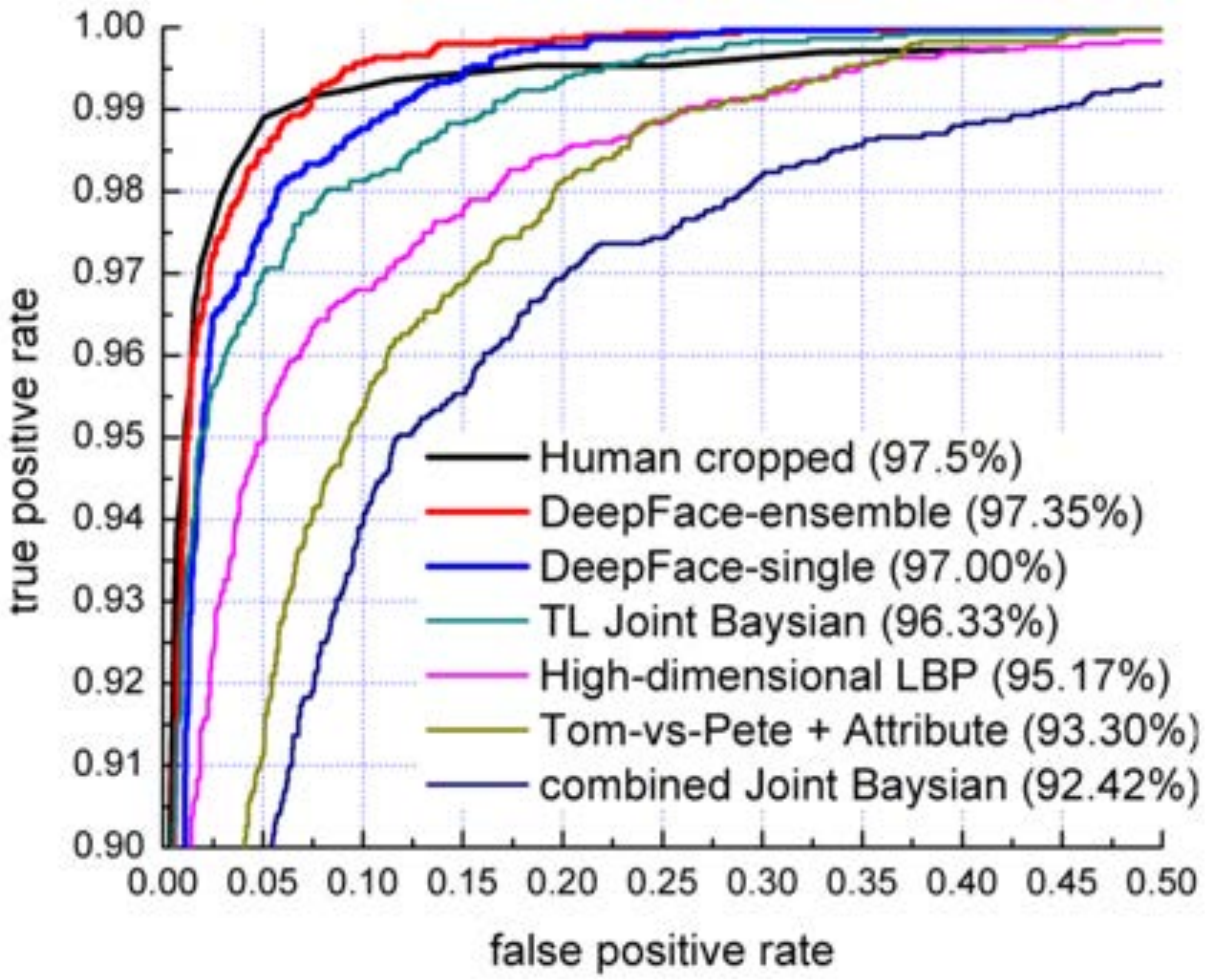
Present various examples of each class and perform forward-, back-propagation.



# Data-driven Face Recognition

**How good can it be?**

**E.g., DeepFace (Facebook)**
Taigman *et al.*
*DeepFace: Closing the Gap to Human-Level Performance in Face Verification*
CVPR, 2014

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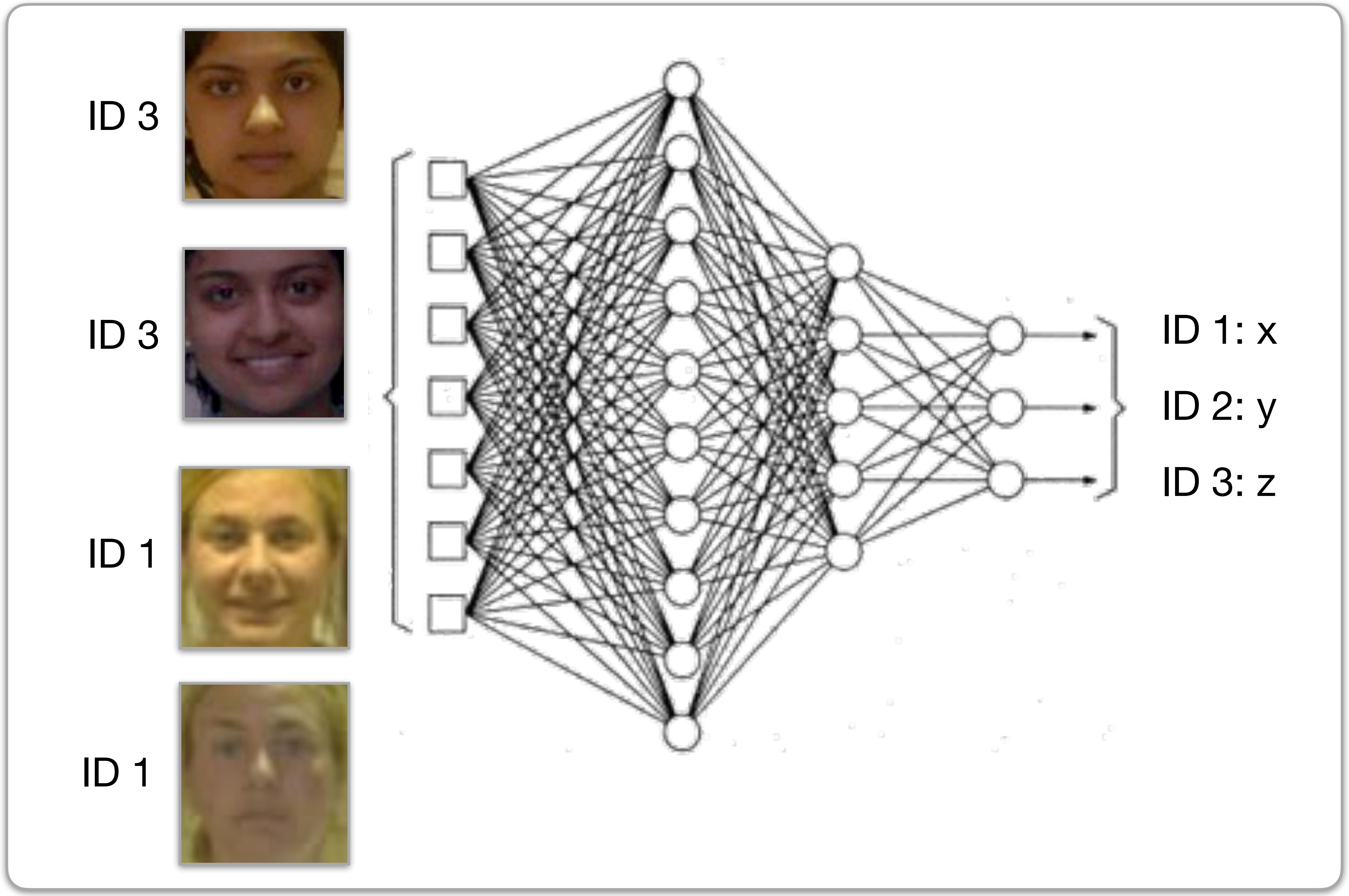
# Data-driven Face Recognition

**Deep Learning**

**What are the cons here?**
How to enroll a new person?

Fixed number of classes (i.e., persons).

Need for large training dataset (thousands of sample per class).

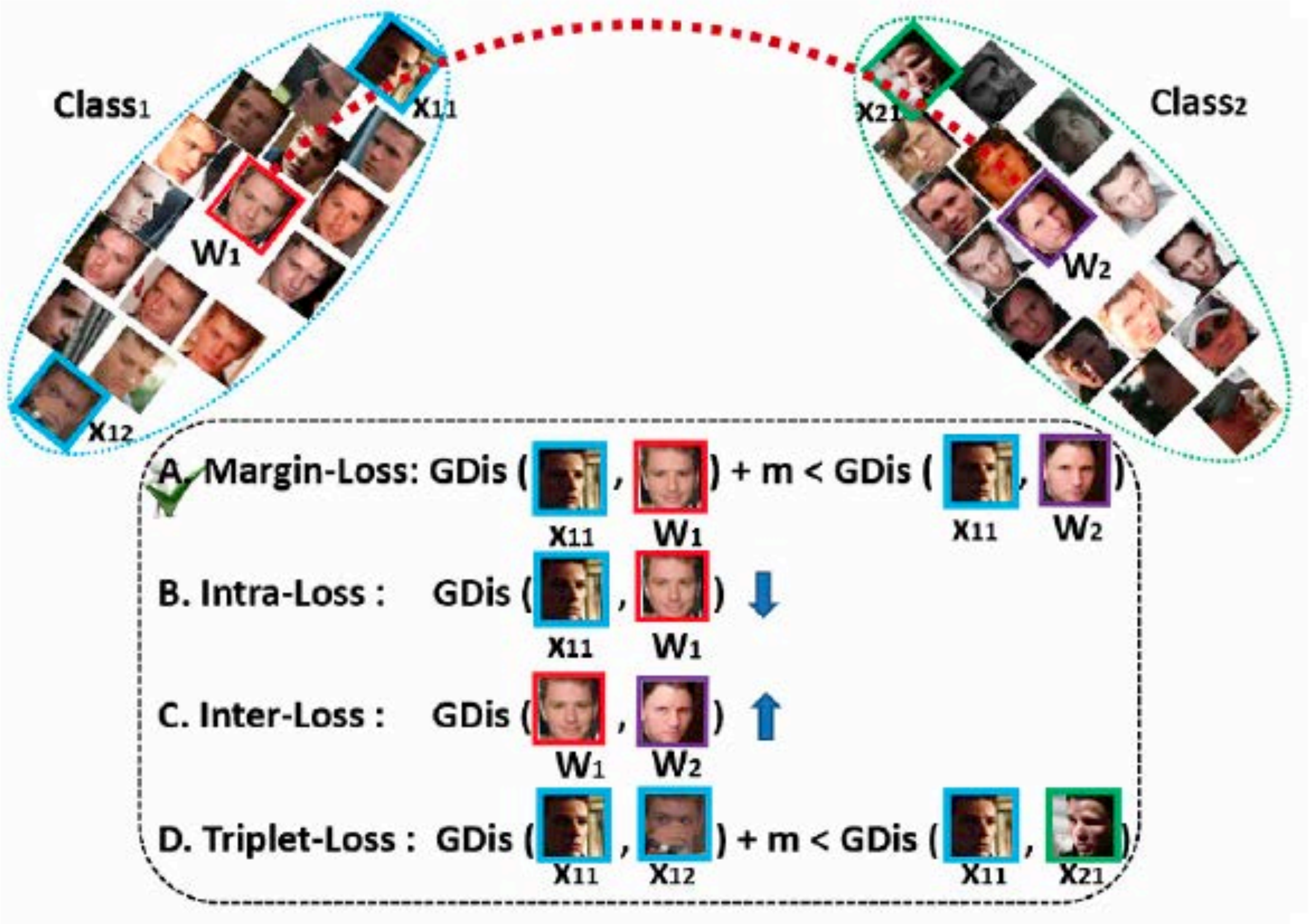


# What’s Next?

**Improving Deep Learning**

**ArcFace**
*Additive Angular Margin Loss for Deep Face Recognition*
Deng et al., CVPR 2019.
https://bit.ly/3qsQmch

**Fill out your *Today-I-missed* Statement**
Please visit
sakai.luc.edu/x/BCJs8K.



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