Face Recognition III

COMP 388-002/488-002 Biometrics

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Fall 2026



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Today we will…

Get to know
Face description and matching.

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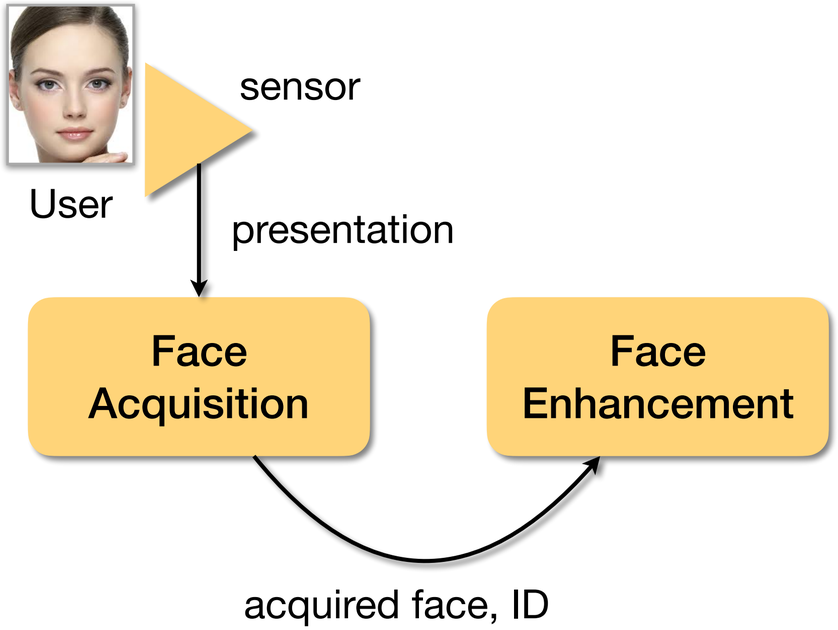
Today's Attendance

Please fill out the form

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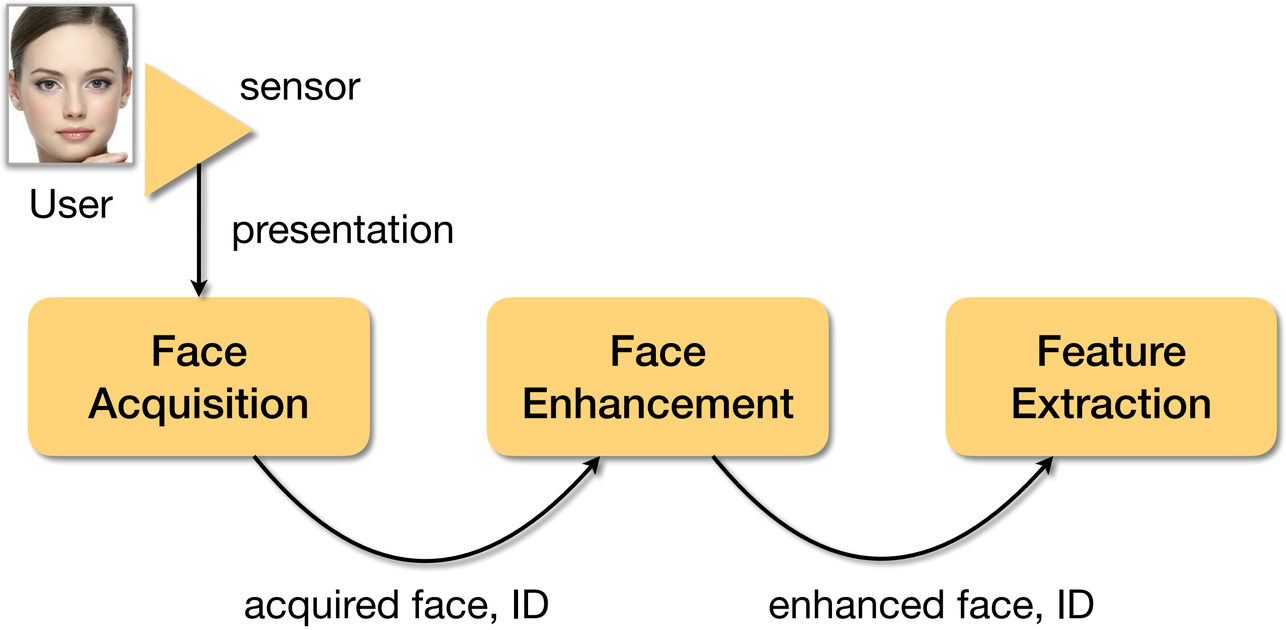
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Face Recognition



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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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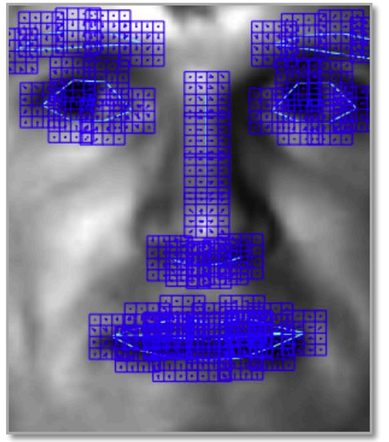
Feature Extraction

Focus
2D-appearance-based methods.

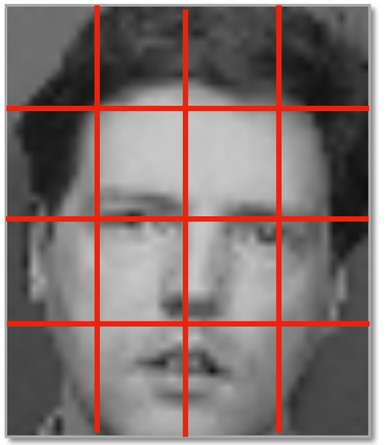
Types
Handcrafted features from Computer Vision.

Data-driven learned features from Machine Learning.

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



Source: Domingo Mery



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

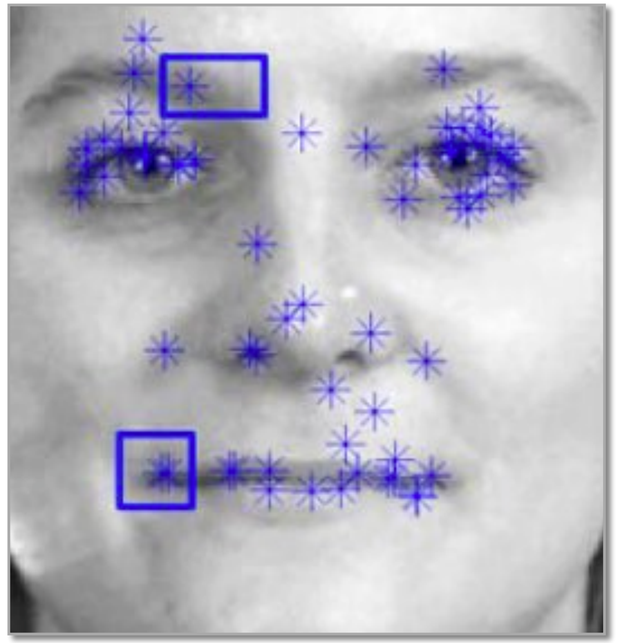
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Feature Extraction

Handcrafted Features

Examples

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



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

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.

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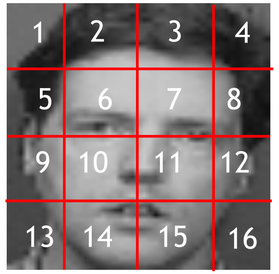
Local Binary Patterns

Selected Solution
Local Binary Patterns to describe
face texture.

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

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LBP pipeline



Division into *N* cells

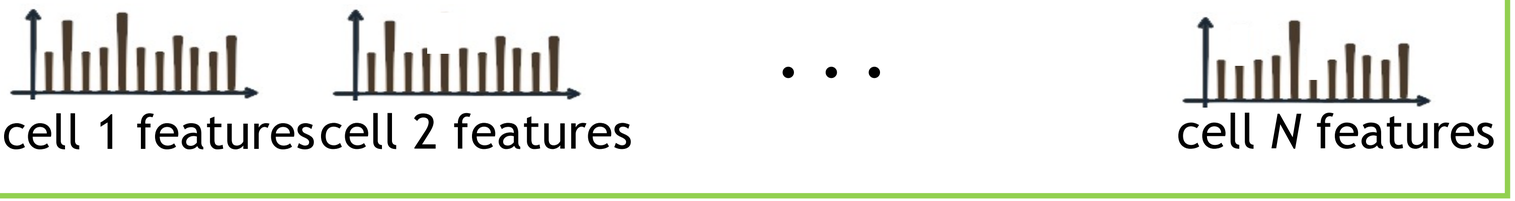
Cell coding

Mapping

Histogram calculation

Normalization

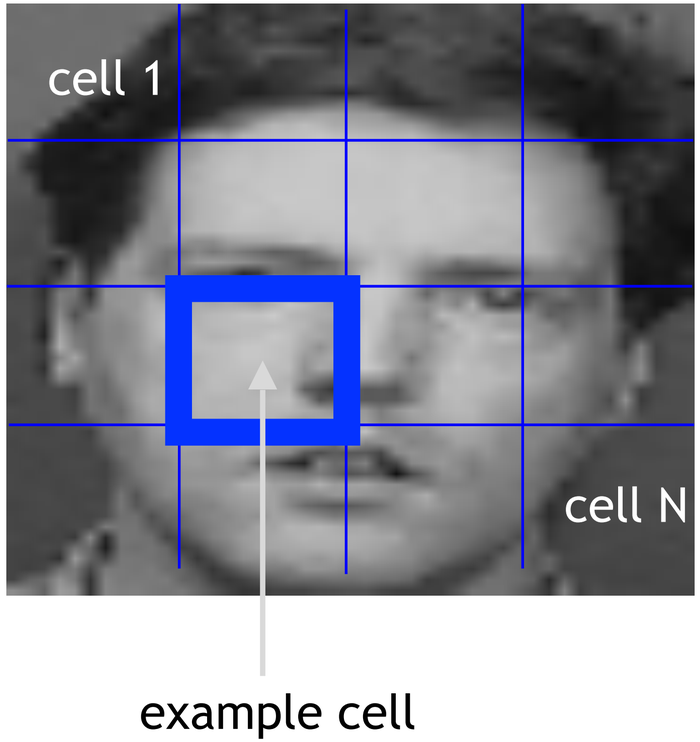
Concatenation



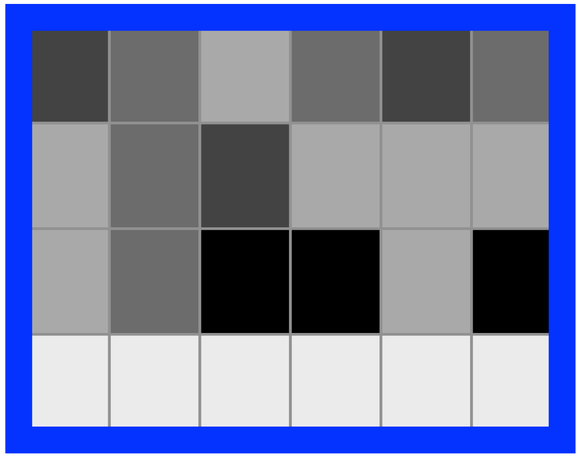
Source: Domingo Mery

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

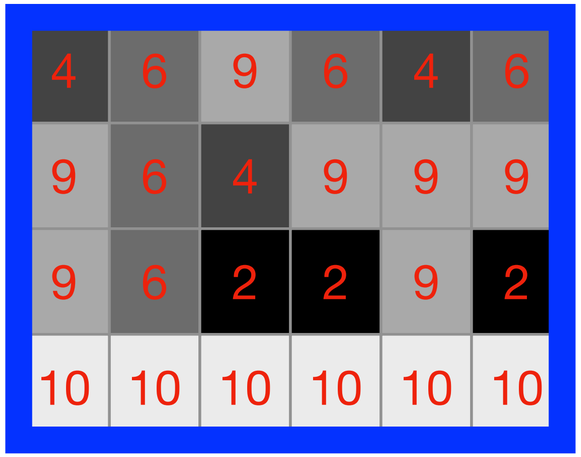
- Number and size of cells cannot be arbitrary (note space-scale considerations)



Source: Domingo Mery



Source: Domingo Mery



Source: Domingo Mery

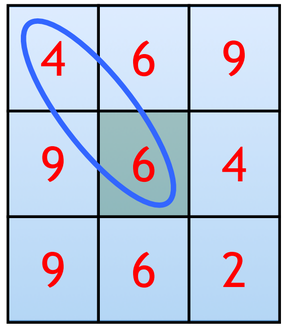
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9	6	4	9	9	9
9	6	2	2	9	2
10	10	10	10	10	10

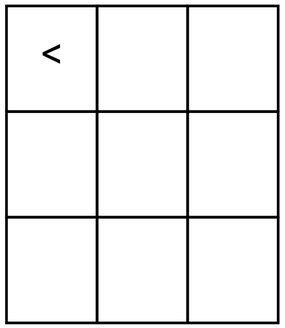
Source: Domingo Mery

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

Source: Domingo Mery

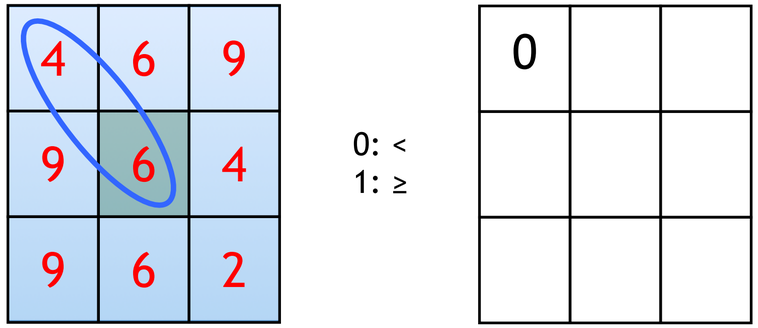
4	6	9	6	4	6
9	6	4	9	9	9
9	6	2	2	9	2
10	10	10	10	10	10





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



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

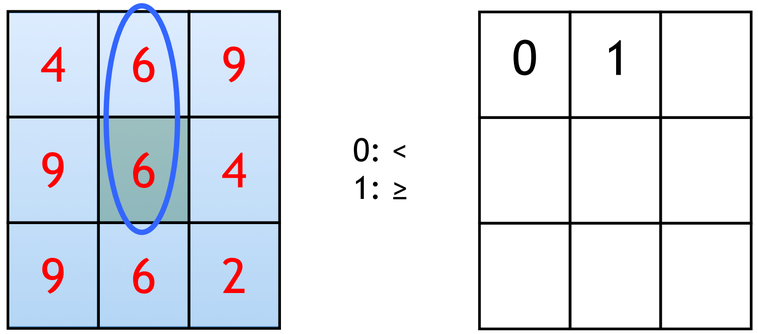
4	6	9
9	6	4
9	6	2

0: <
1: ≥

0	≥	

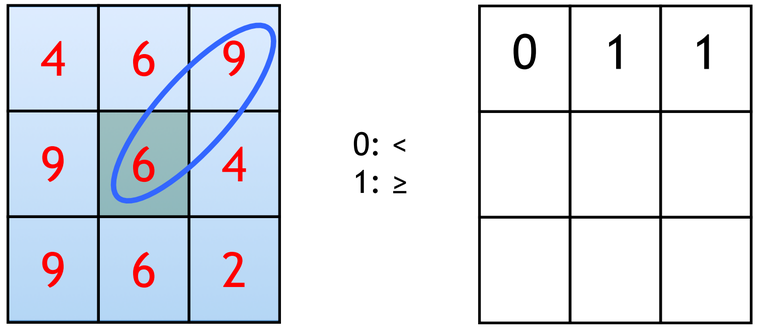
Source: Domingo Mery

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



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



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

4	6	9
9	6	4
9	6	2

0: <
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

4	6	9
9	6	4
9	6	2

0: <
1: ≥

0	1	1
		0
		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

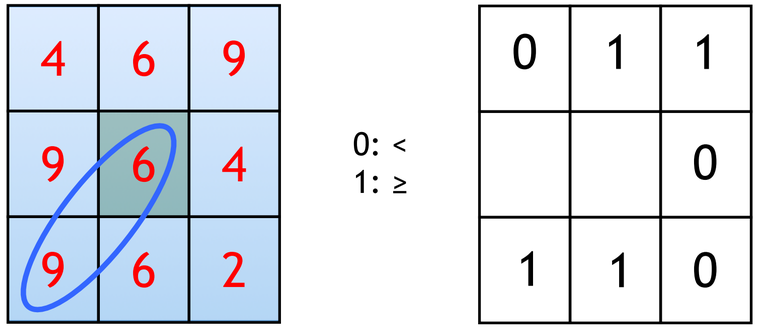
4	6	9
9	6	4
9	6	2

0: <
1: ≥

0	1	1
		0
	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



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

4	6	9
9	6	4
9	6	2

0: <
1: ≥

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

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

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

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

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				

4	6	9
9	6	4
9	6	2

0: <
1: ≥

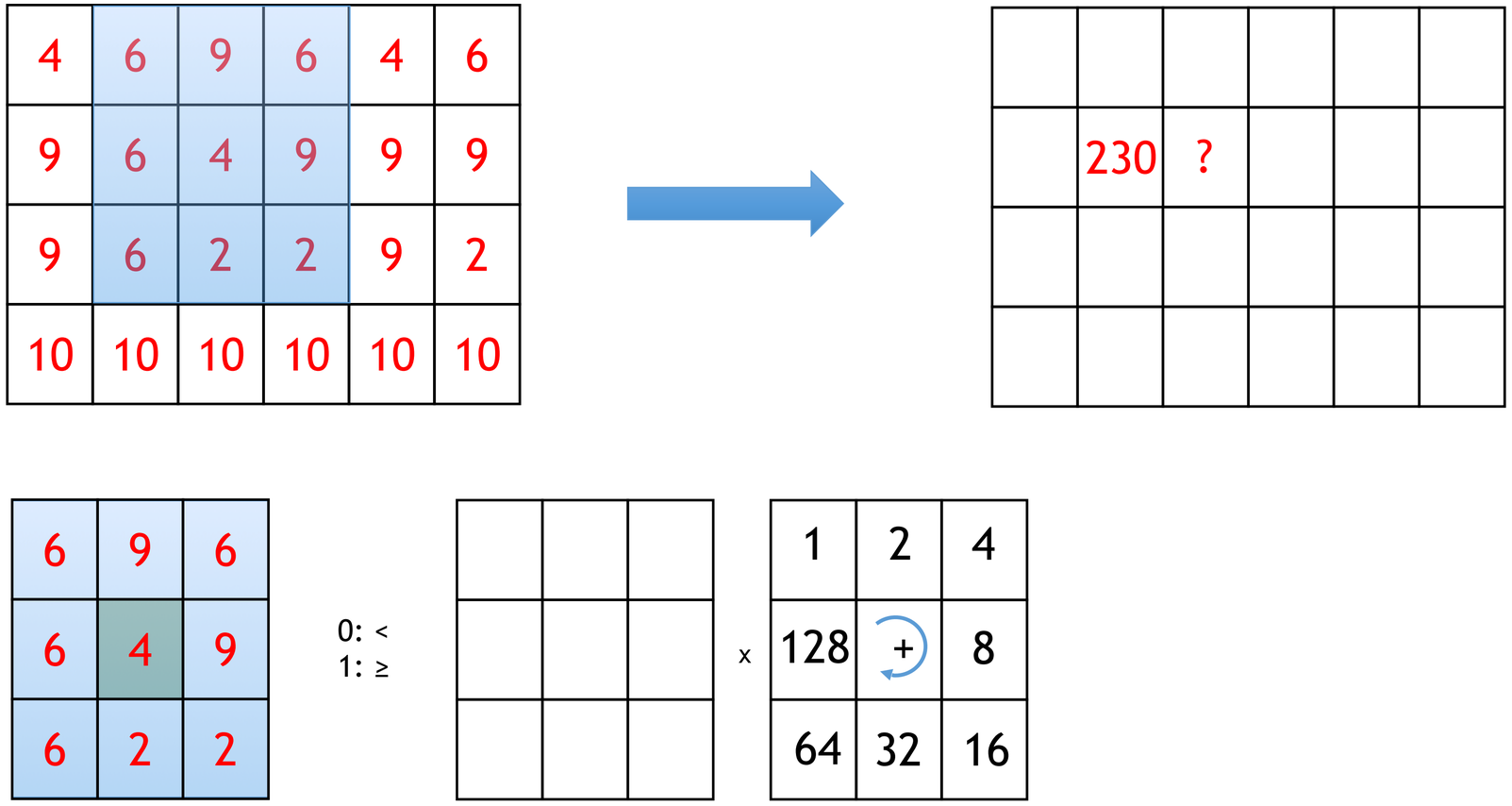
0	1	1
1		0
1	1	0

x

1	2	4
128	+	8
64	32	16

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

Source: Domingo Mery



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



	230	207			

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

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	?		

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



	230	207	25		

9	6	4
4	9	9
2	2	9

0: <
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

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	

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



	230	207	25	168	
	243				

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



	230	207	25	168	
	243	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



	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



	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

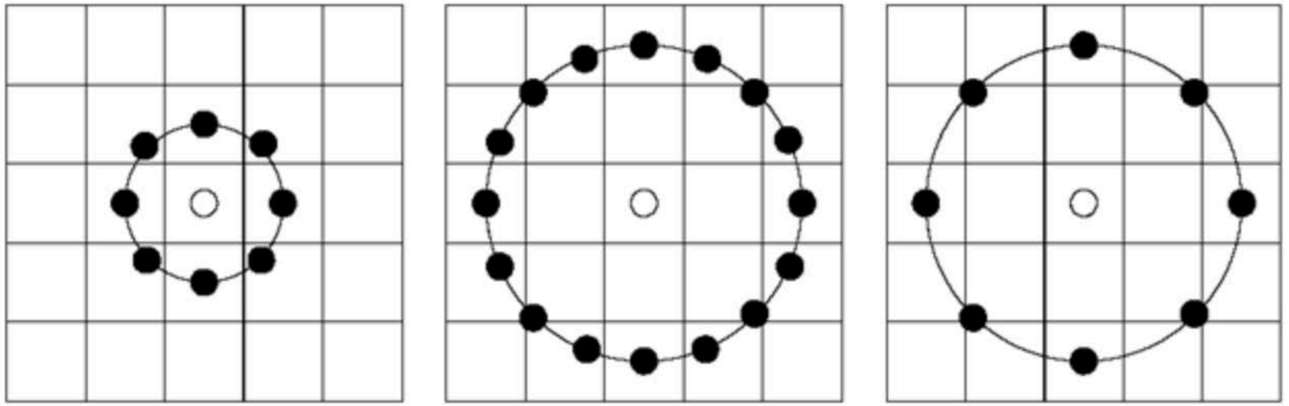
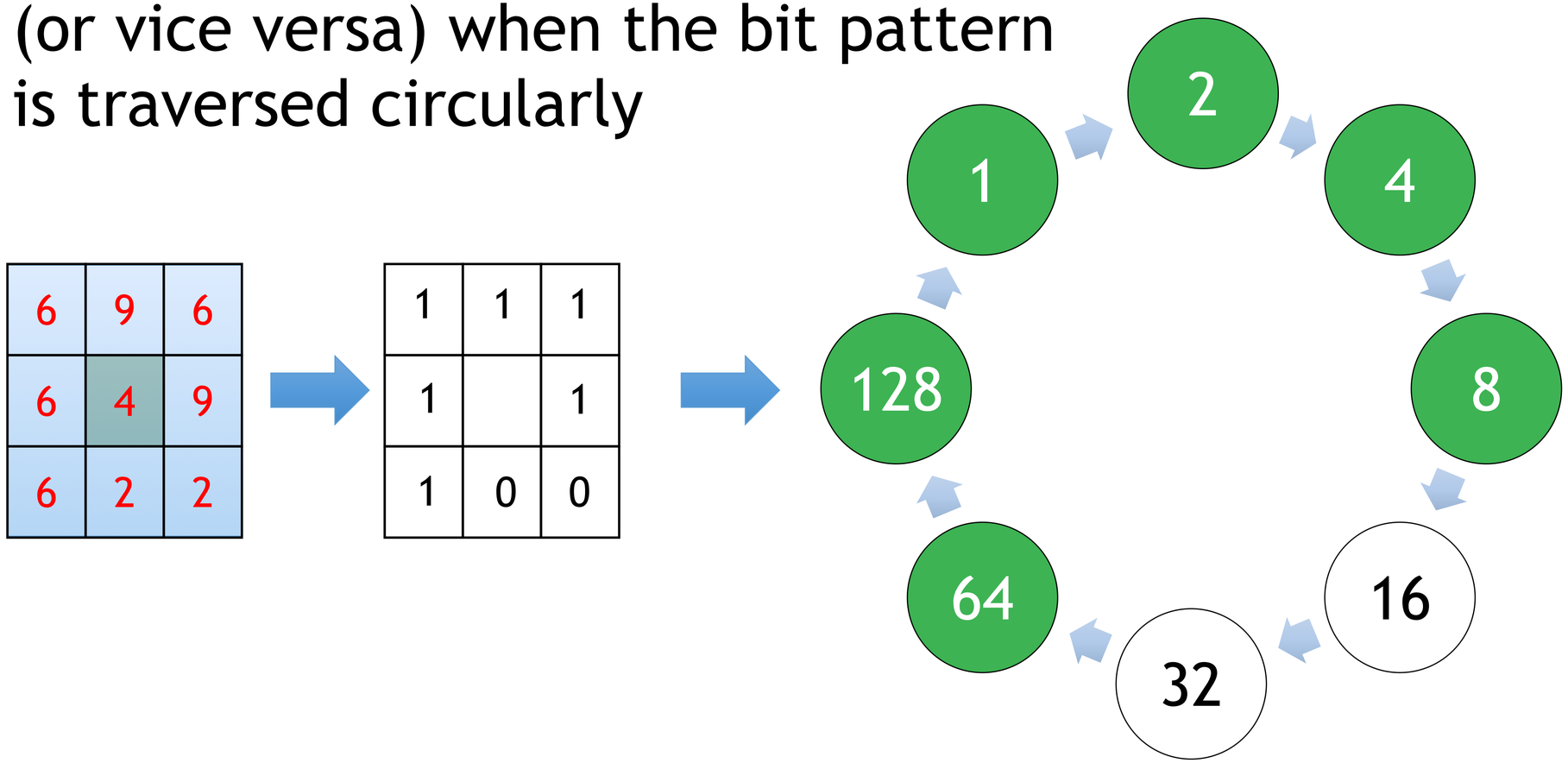


Image source: http://what-when-how.com/face-recognition/local-representation-of-facial-features-face-image-modeling-and-representation-face-recognition-part-1/

Source: Domingo Mery

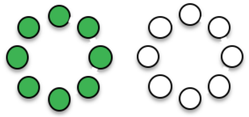
Uniform pattern: contains at most two bitwise transitions (U) from 0 to 1 (or vice versa) when the bit pattern is traversed circularly



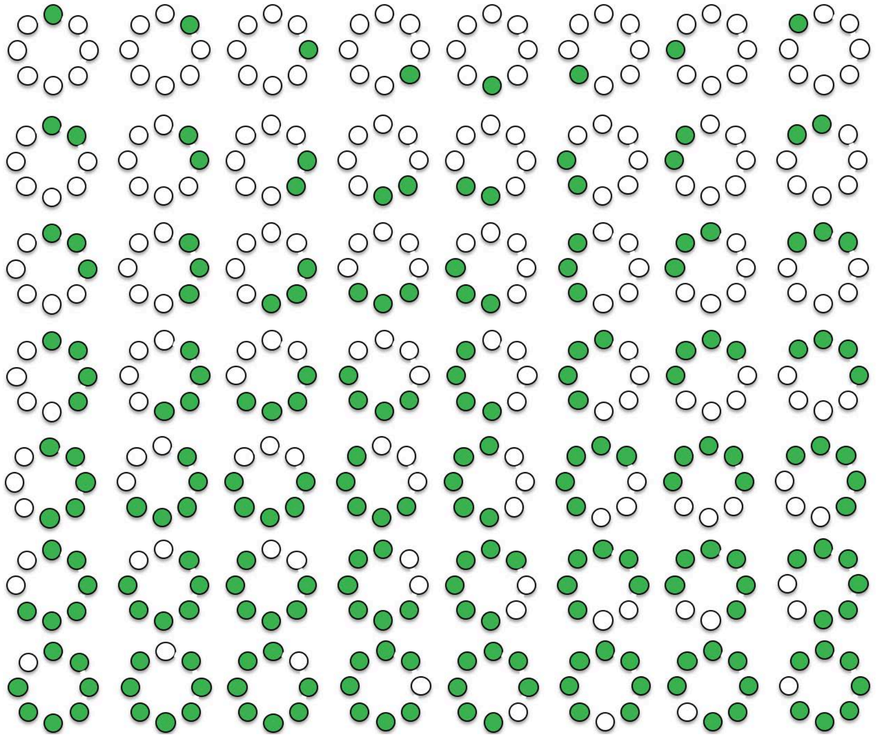
Source: Domingo Mery

Uniform patterns

U = 0



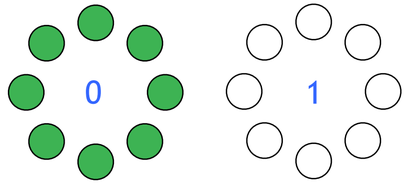
U = 2



Uniform patterns account for almost 90% of all patterns.

Source: Domingo Mery

U = 0



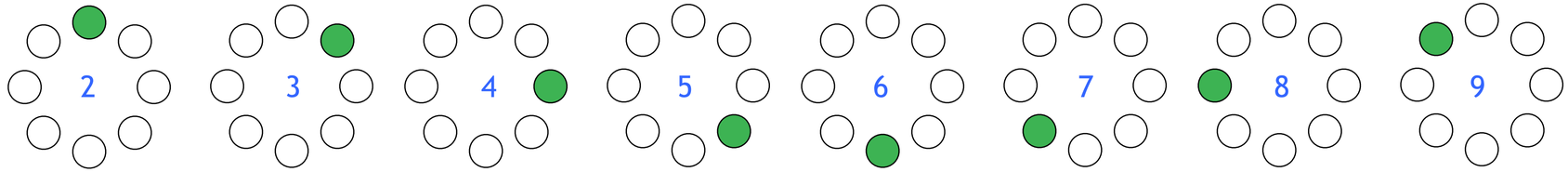
2 patterns

{0,1}

Uniform patterns

2 + 56 = 58 patterns

U = 2



8x7 = 56 patterns

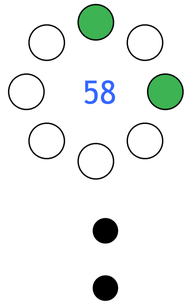
{2, 3, … 57}

Non-uniform patterns

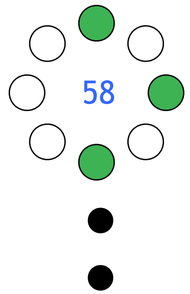
256 -58 = 198 patterns

{58}

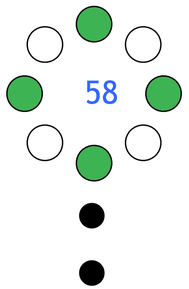
U = 4



U = 6

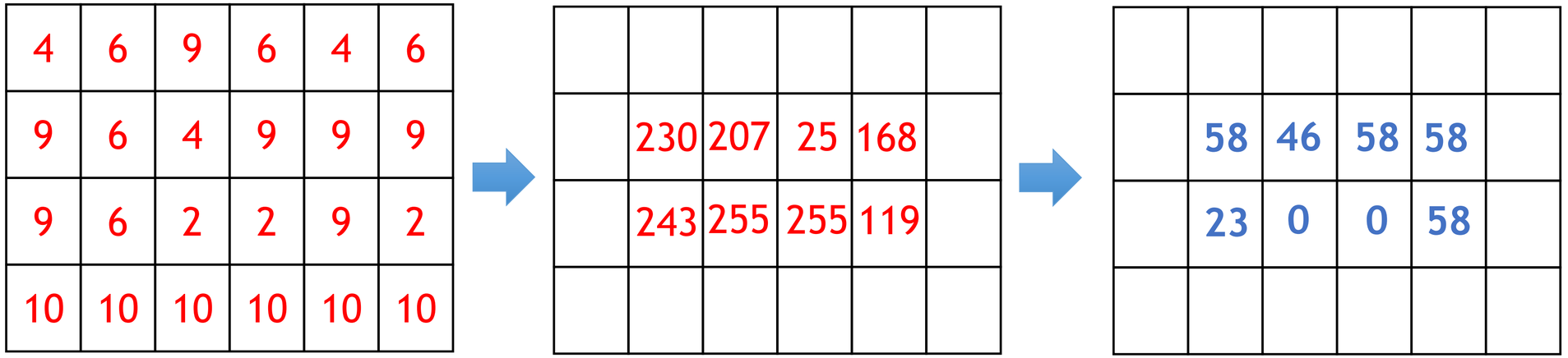


U = 8



Source: Domingo Mery

Result of cell code mapping

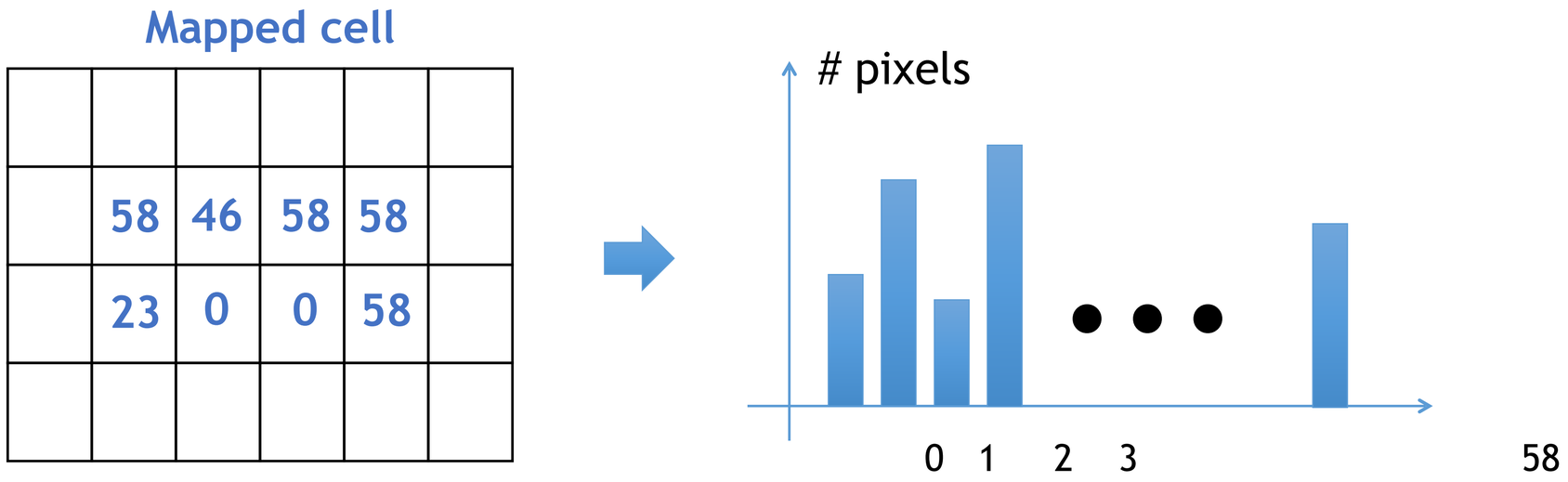


Cell

Coded cell

Mapped cell

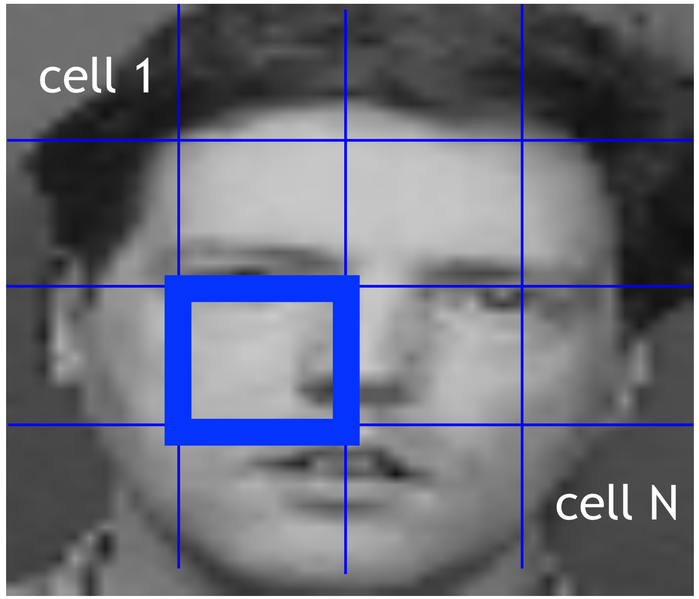
Source: Domingo Mery



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

Source: Domingo Mery

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

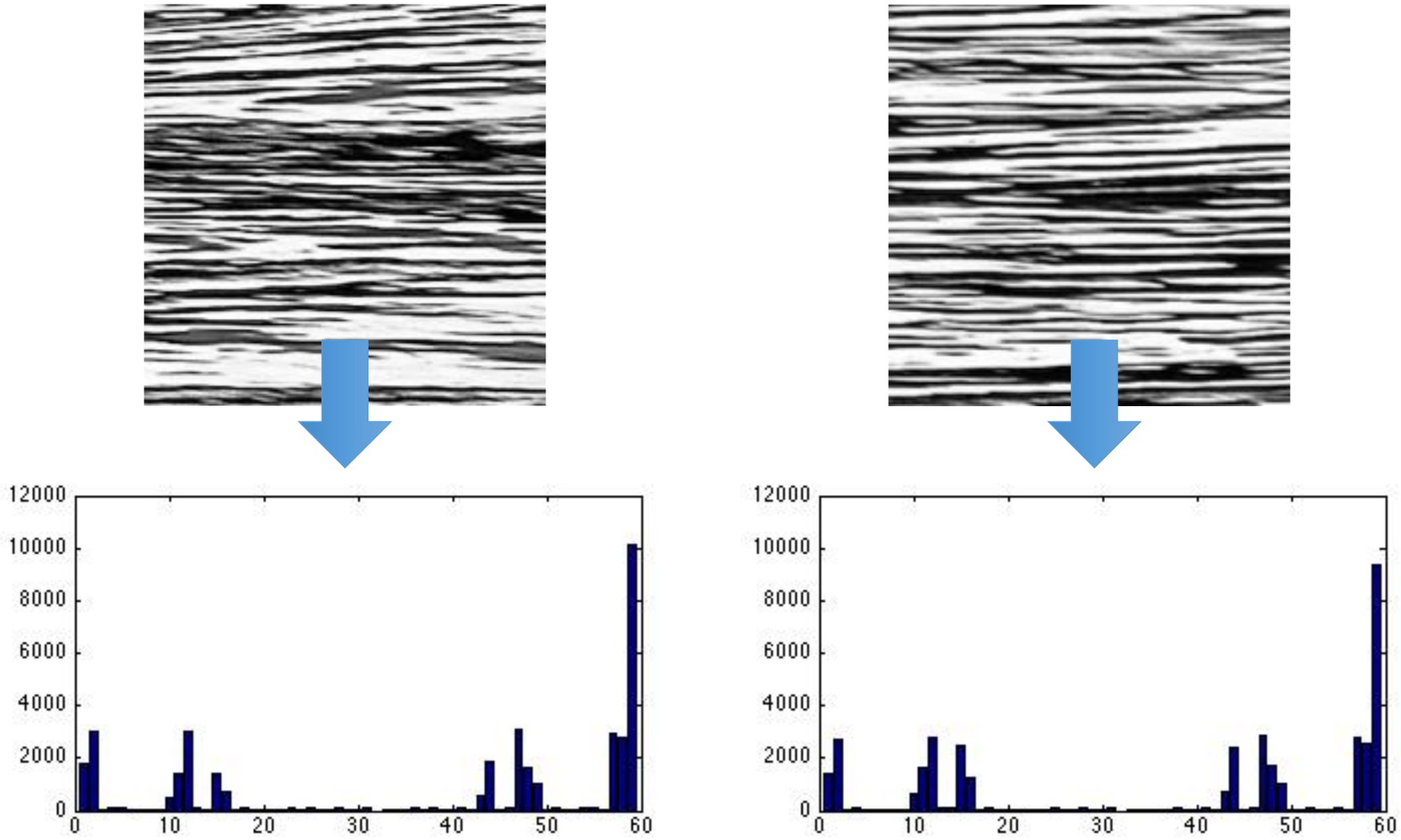




Source: Domingo Mery

Local Binary Patterns

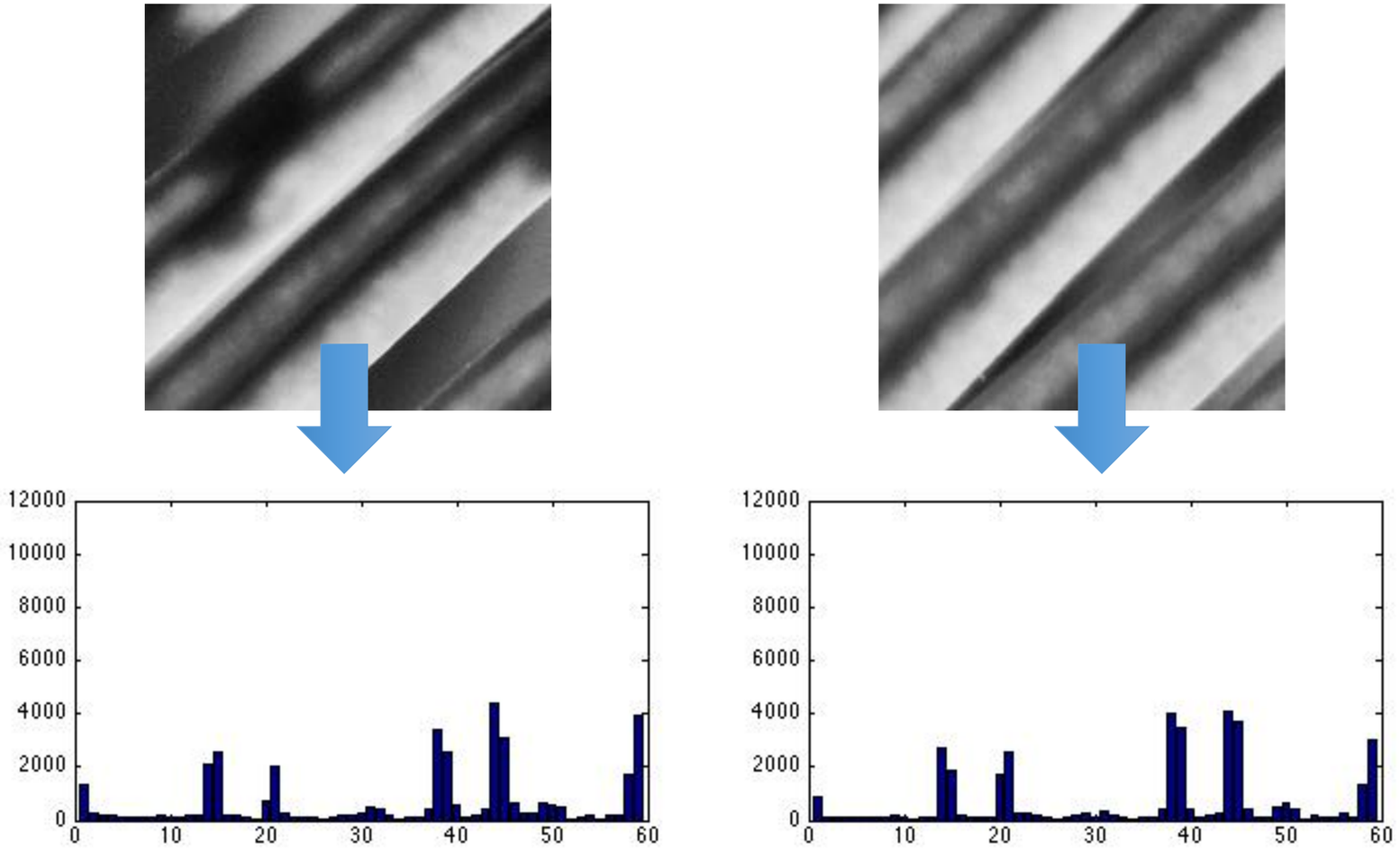
Similar textures have similar histograms



Source: Domingo Mery

Local Binary Patterns

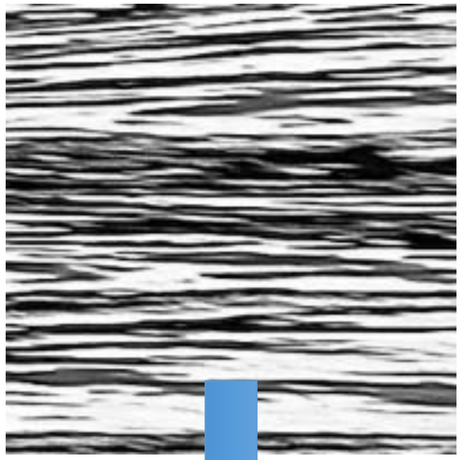
Similar textures have similar histograms

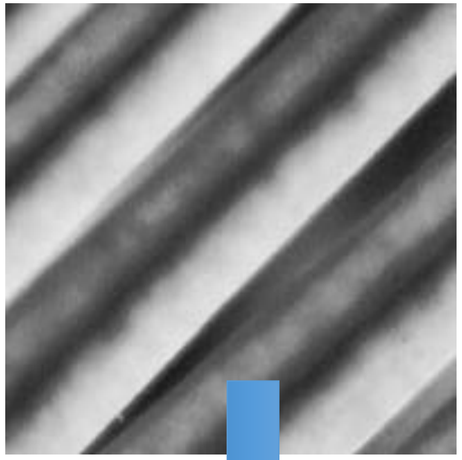


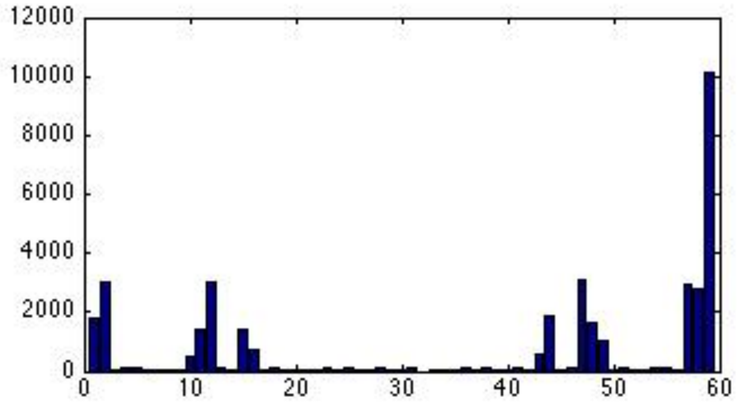
Source: Domingo Mery

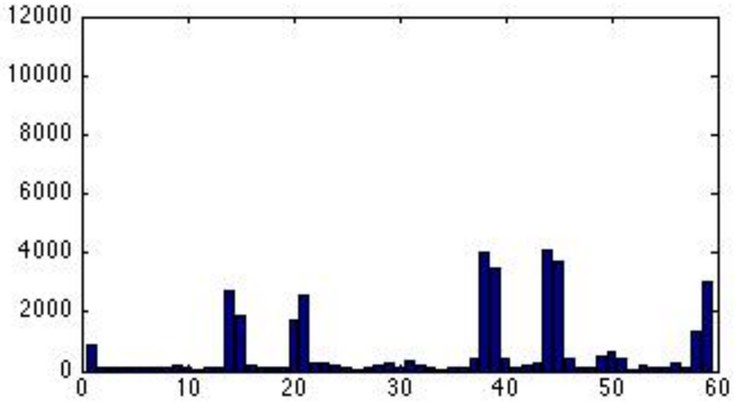
Local Binary Patterns

Similar textures have similar histograms





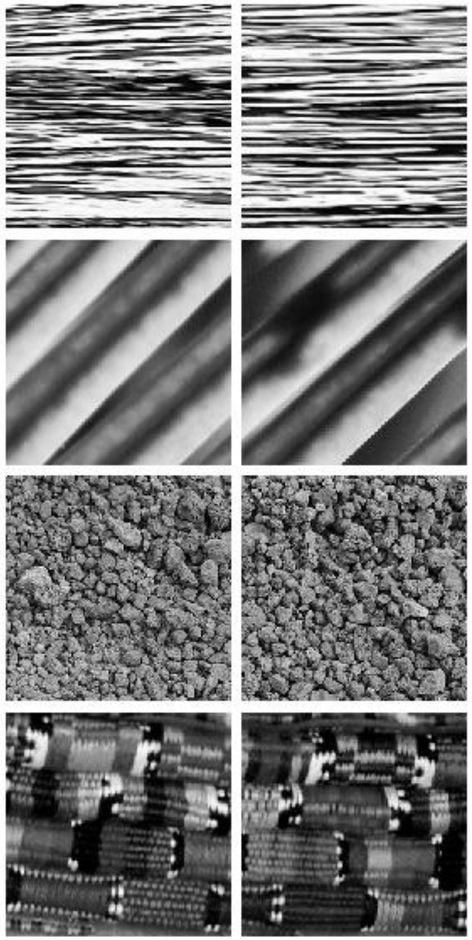


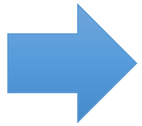


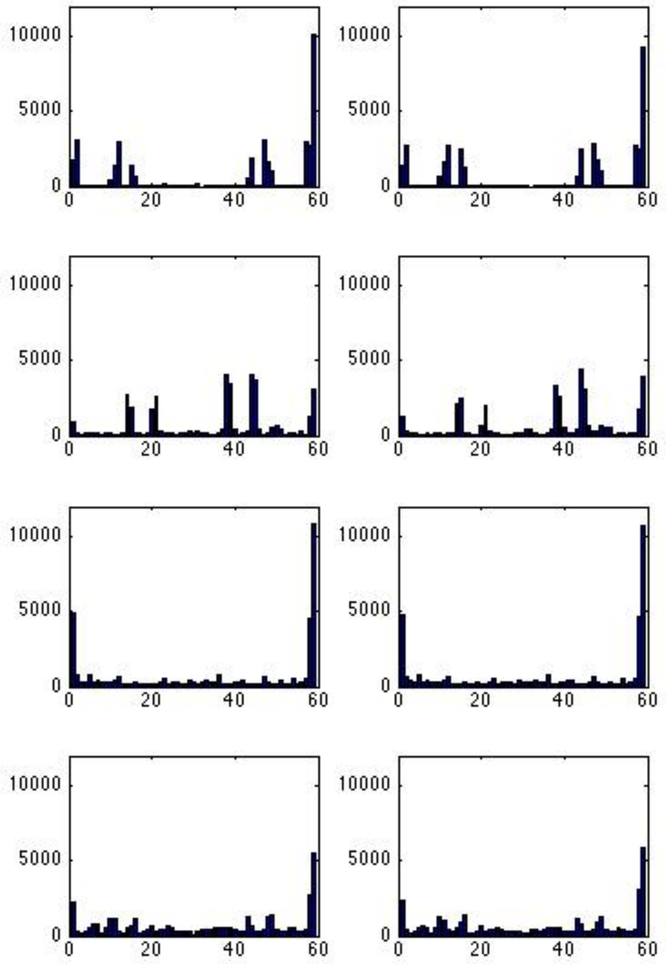
Source: Domingo Mery

Local Binary Patterns

Similar textures have similar histograms







Source: Domingo Mery

LBP for face recognition



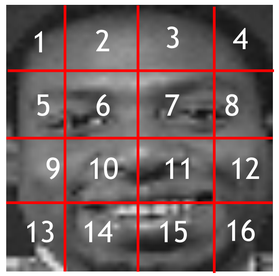
In the training set there are *k* classes.

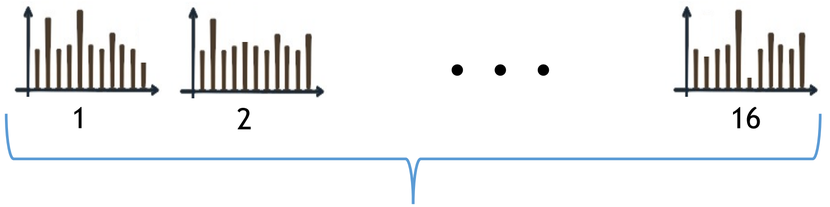
For each class we have *n* training images.

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:

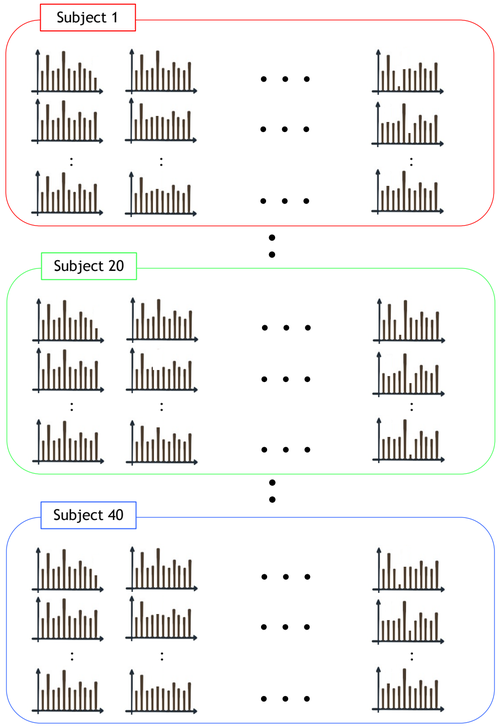
9x40 = 360 rows

and

16 x 59 = 944 columns

Source: Domingo Mery

LBP for face recognition



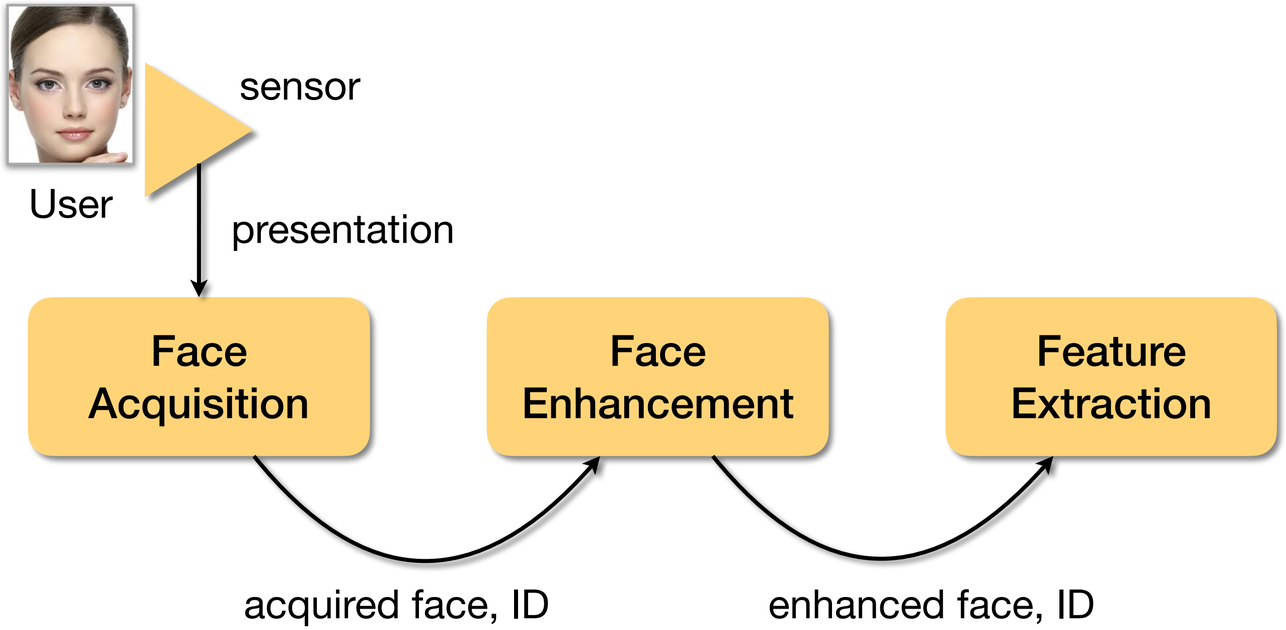
Source: Domingo Mery

LBP for face recognition



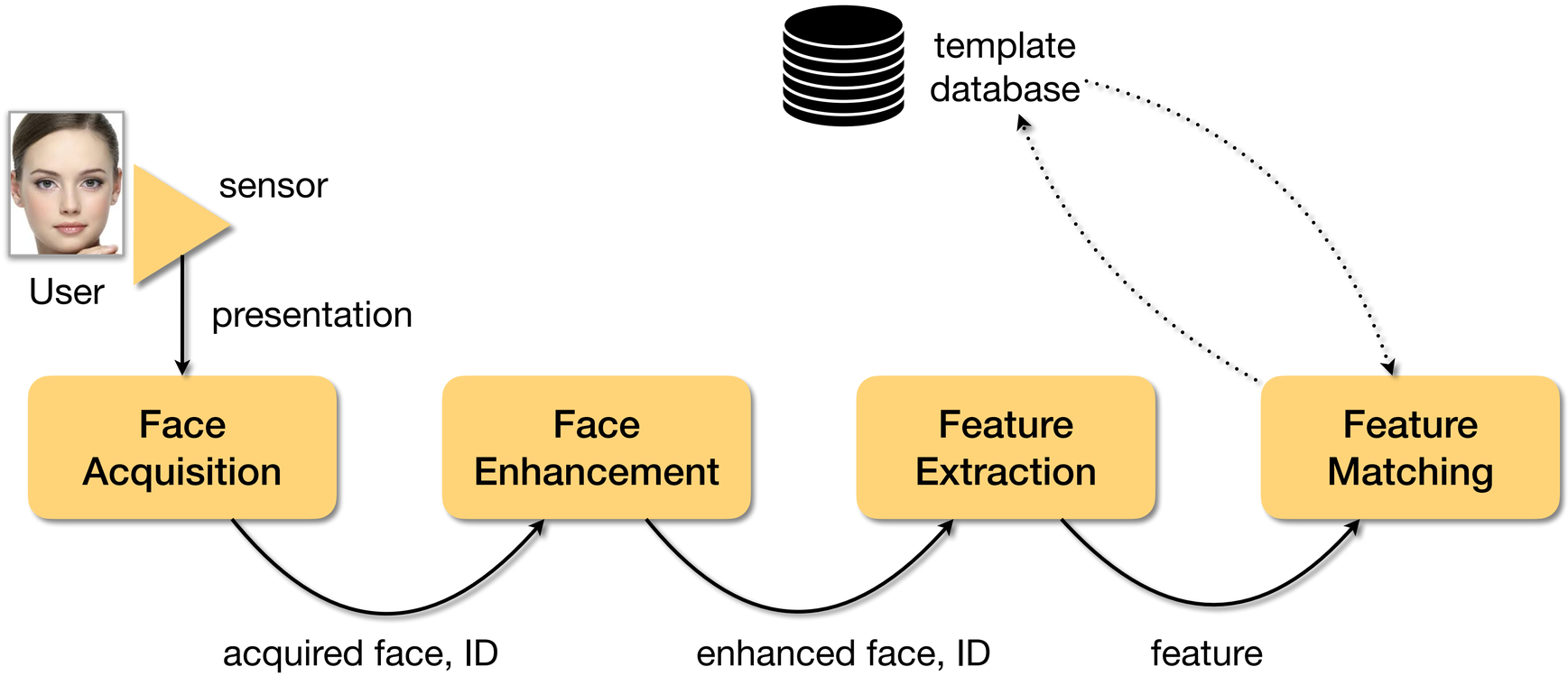
Source: Domingo Mery

Face Recognition



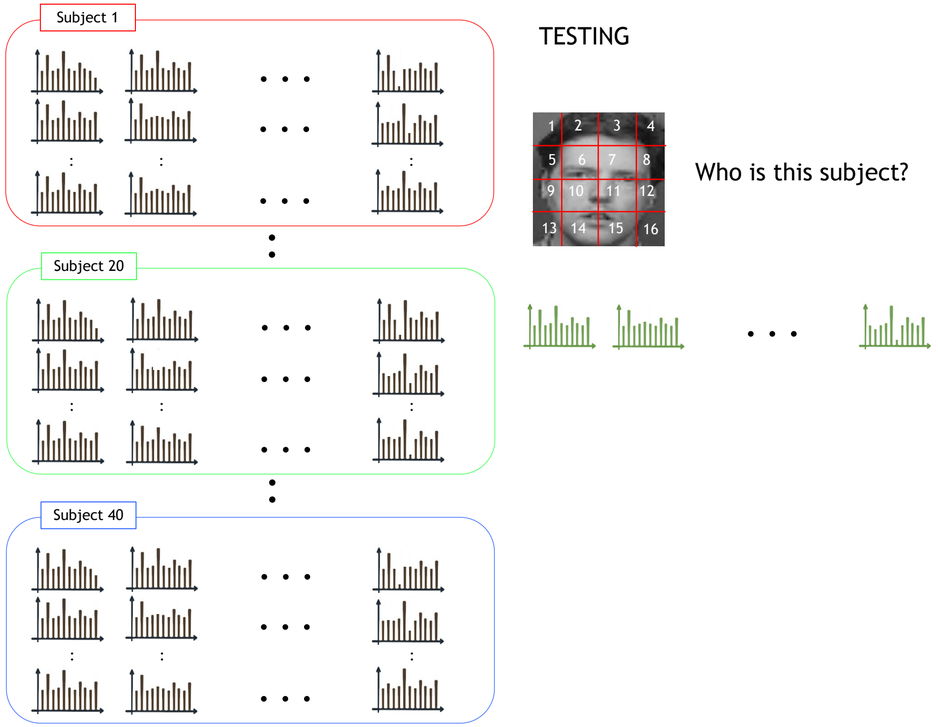
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Face Recognition



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LBP for face recognition (Feature Matching)



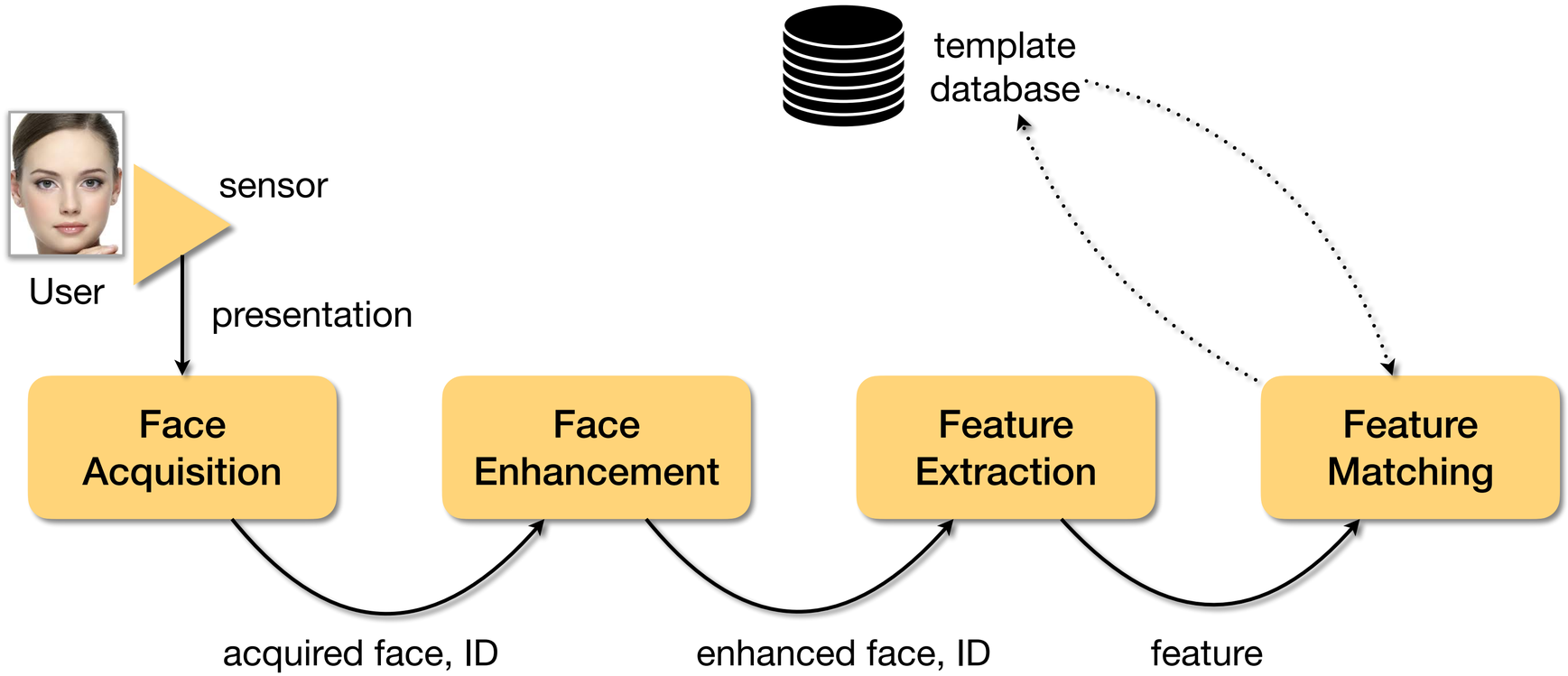
Source: Domingo Mery

LBP for face recognition (Feature Matching)



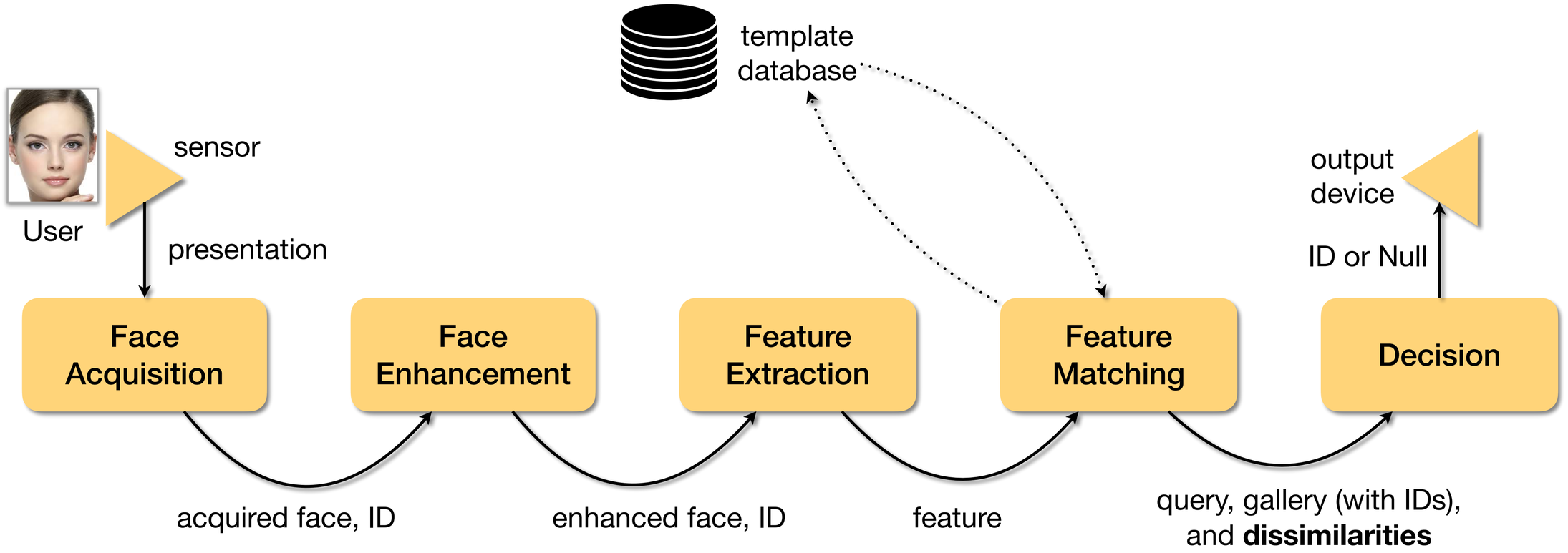
Source: Domingo Mery

Face Recognition



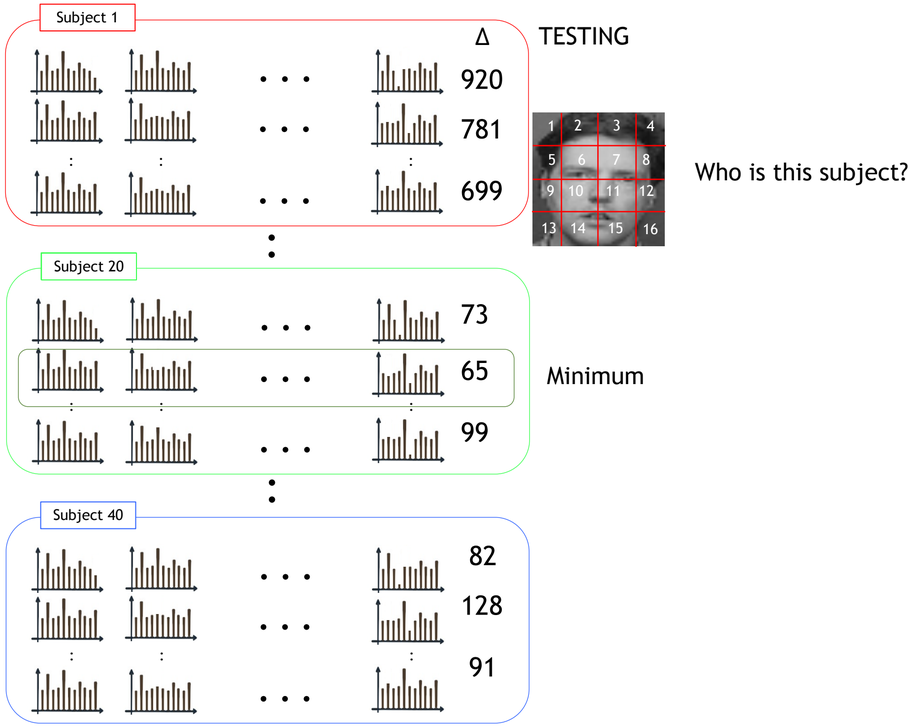
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Face Recognition



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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.



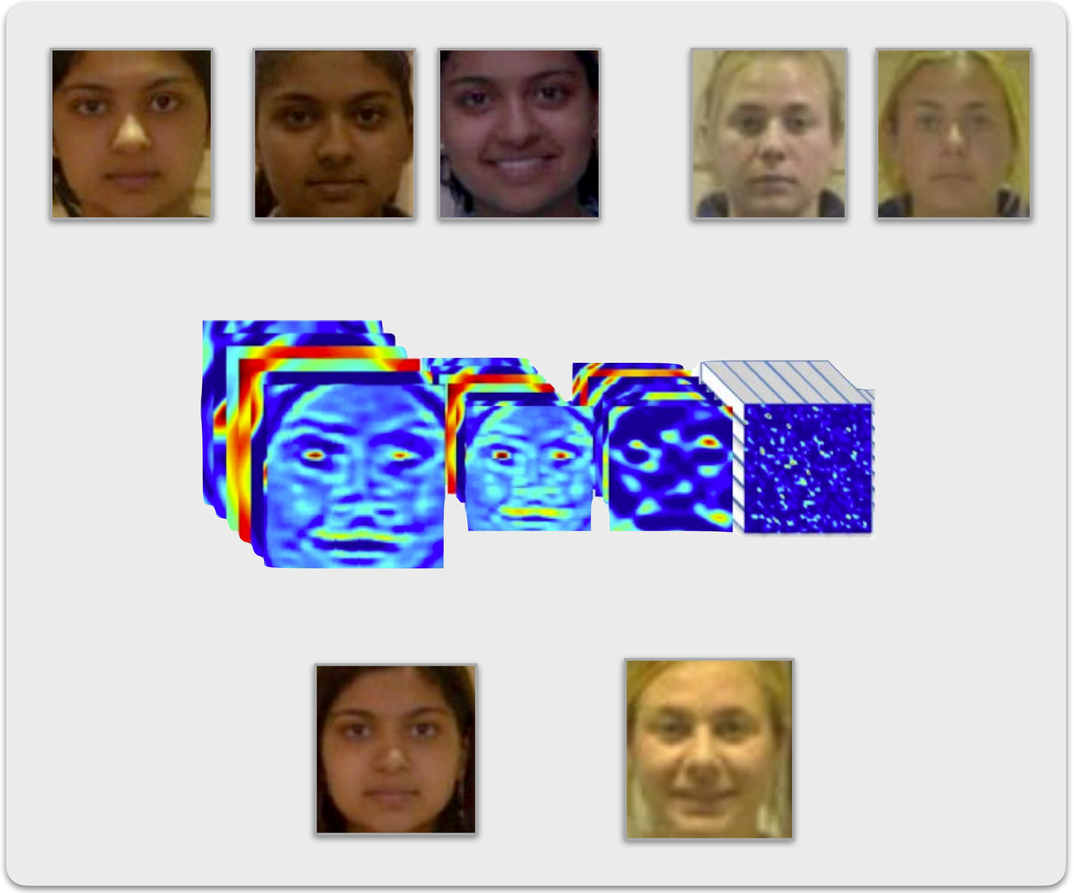
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Feature Extraction

Focus
2D-appearance-based methods.

Types
Handcrafted features from Computer Vision.

Data-driven learned features from Machine Learning.



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Feature Extraction

Deep Convolutional Neural Networks

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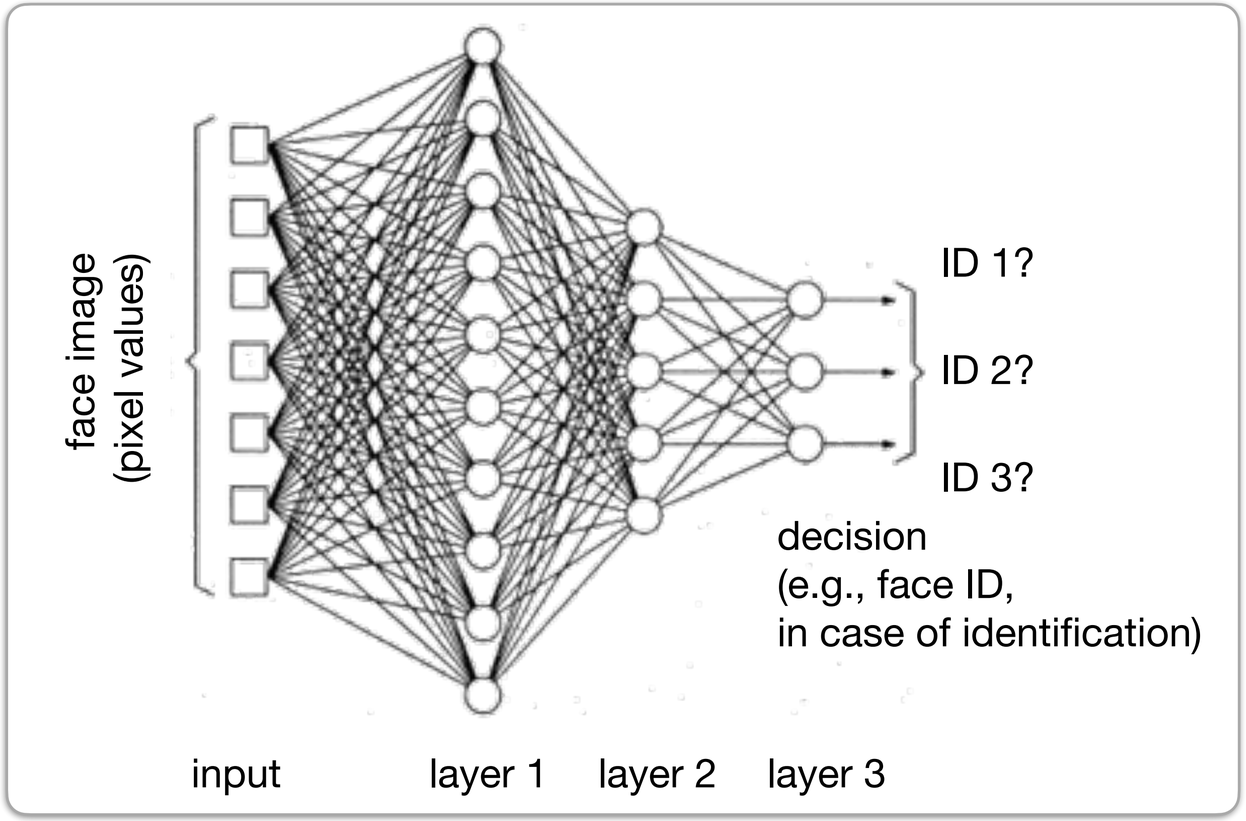
Feature Extraction

Deep Convolutional Neural Networks

From pixels to classification decision.

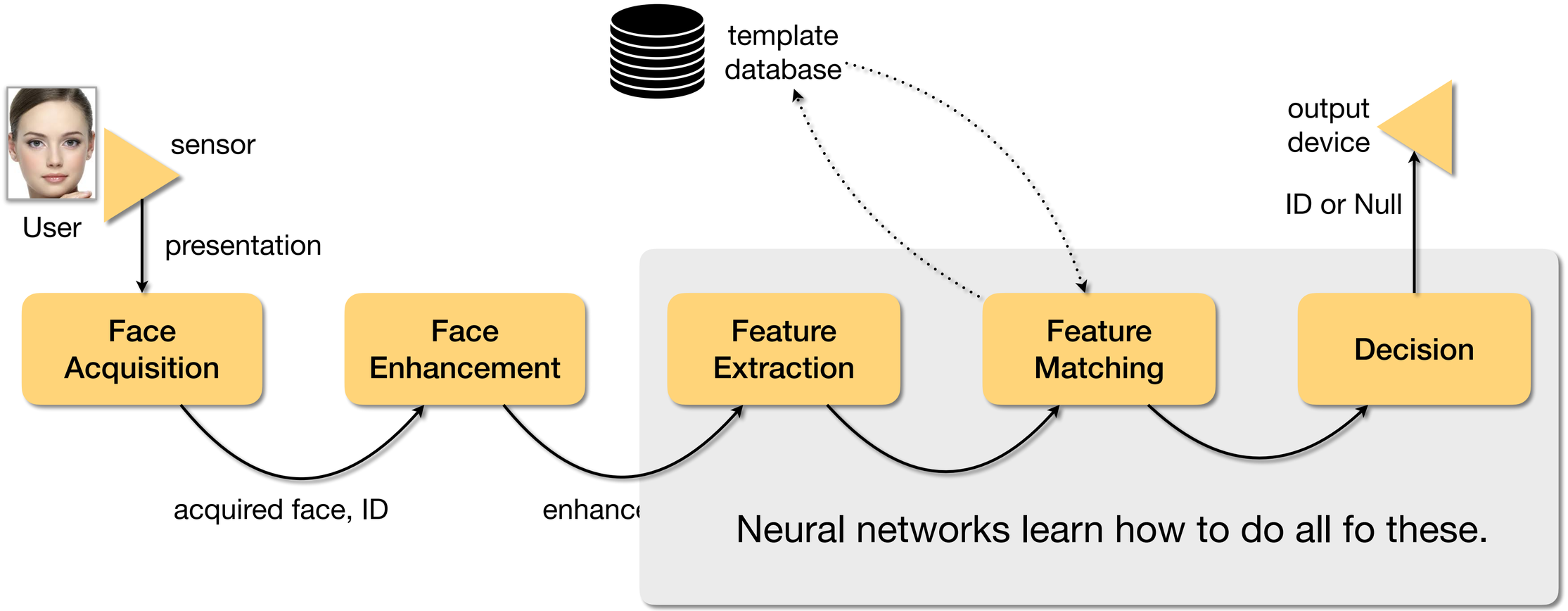
Hierarchy of feature extractors.

Each layer extracts features from previous layer.



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Face Recognition

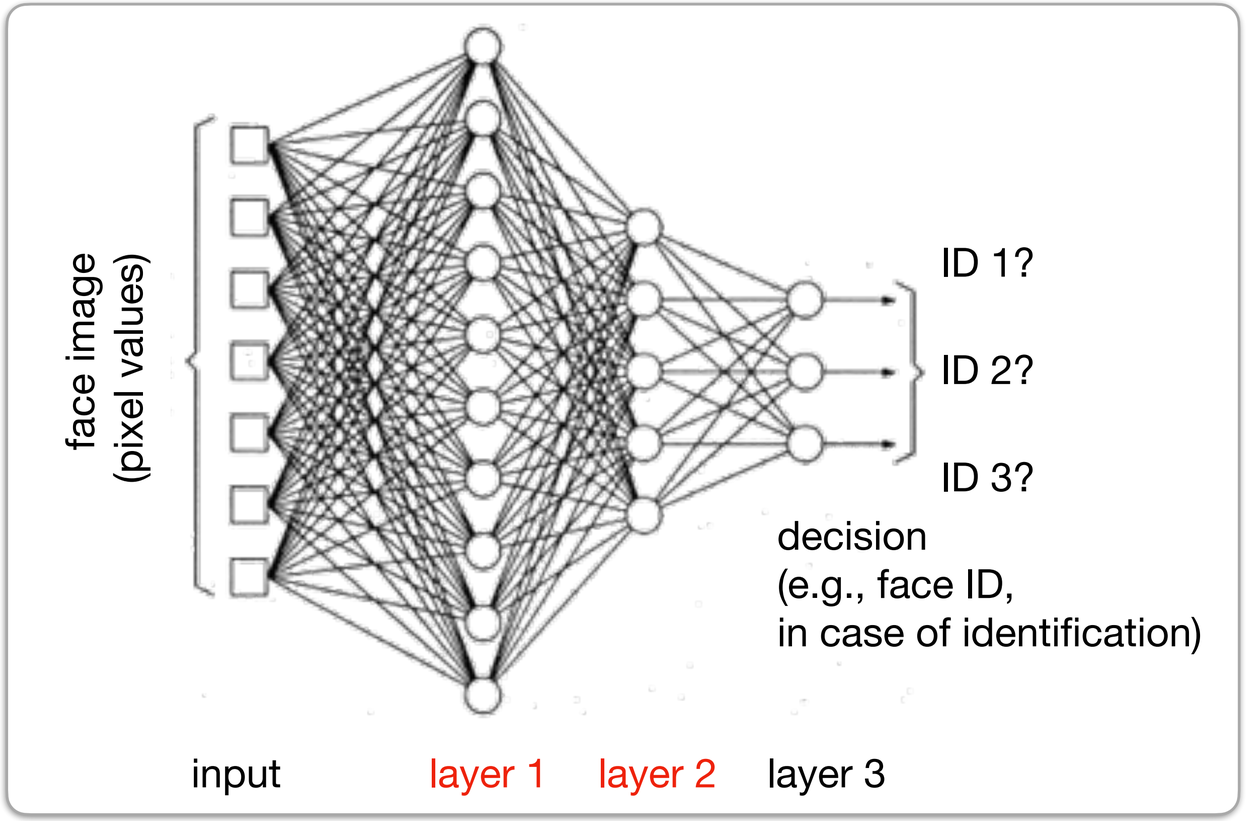


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Data-driven Face Recognition

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.

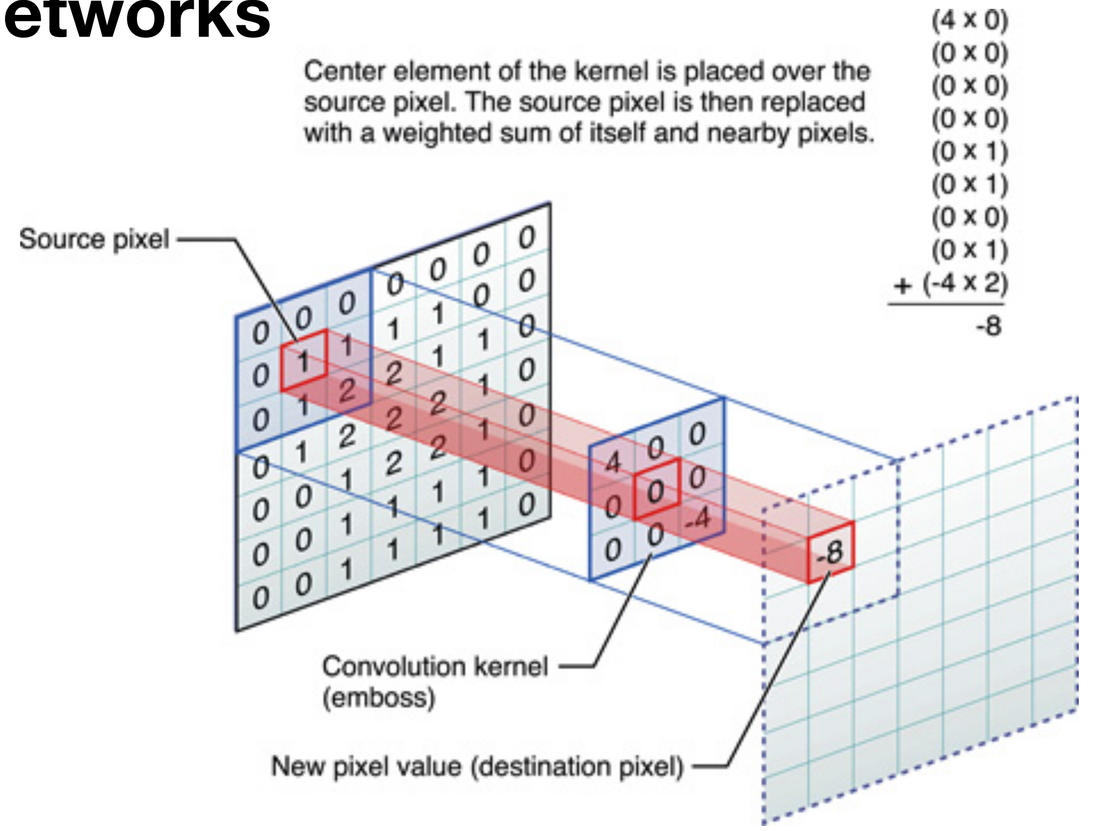


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Data-driven Face Recognition

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.



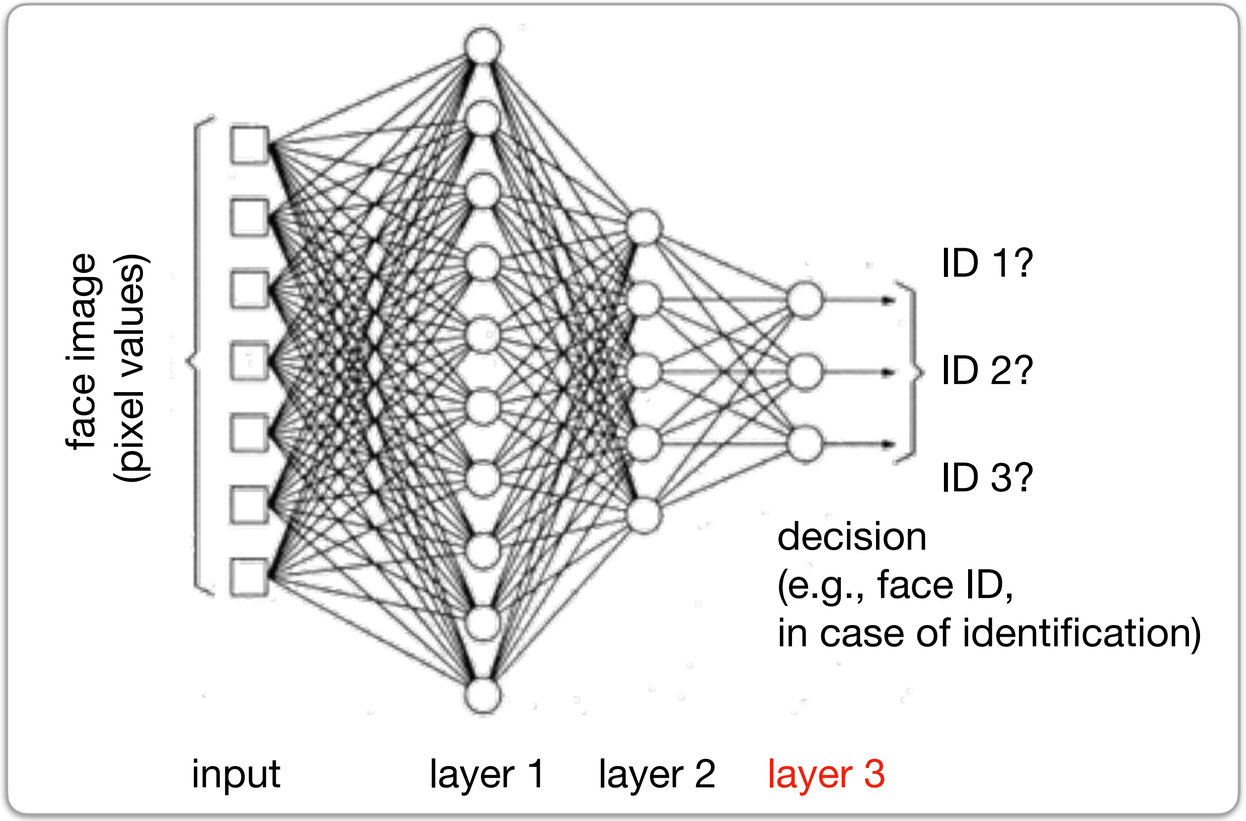
Source:https://developer.apple.com/library/archive/documentation/Performance/Conceptual/vImage/ConvolutionOperations/ConvolutionOperations.html

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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).



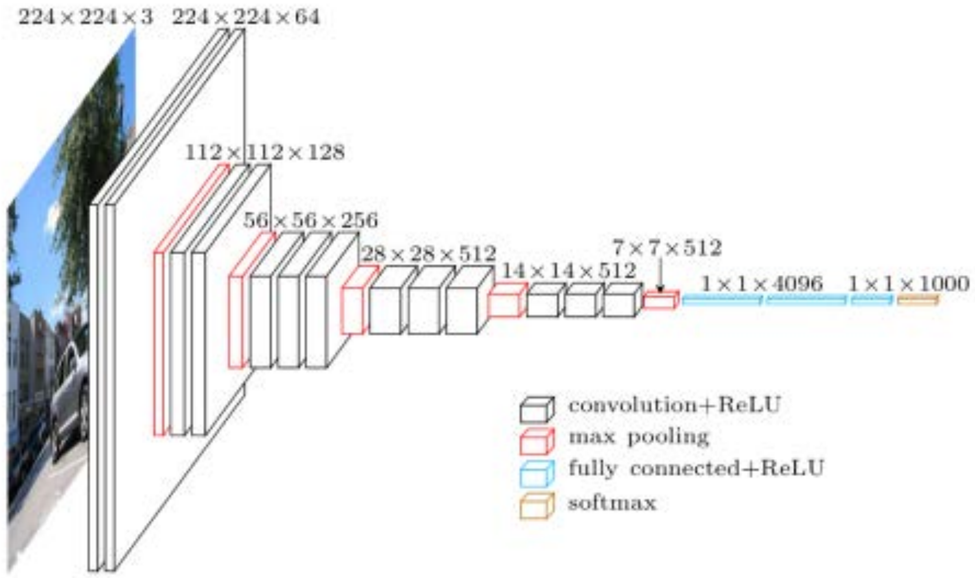
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Data-driven Face Recognition

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



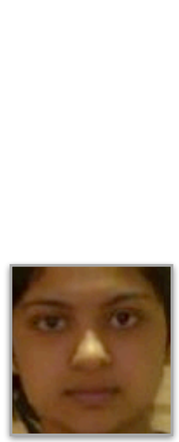
16 to 19 convolutional layers

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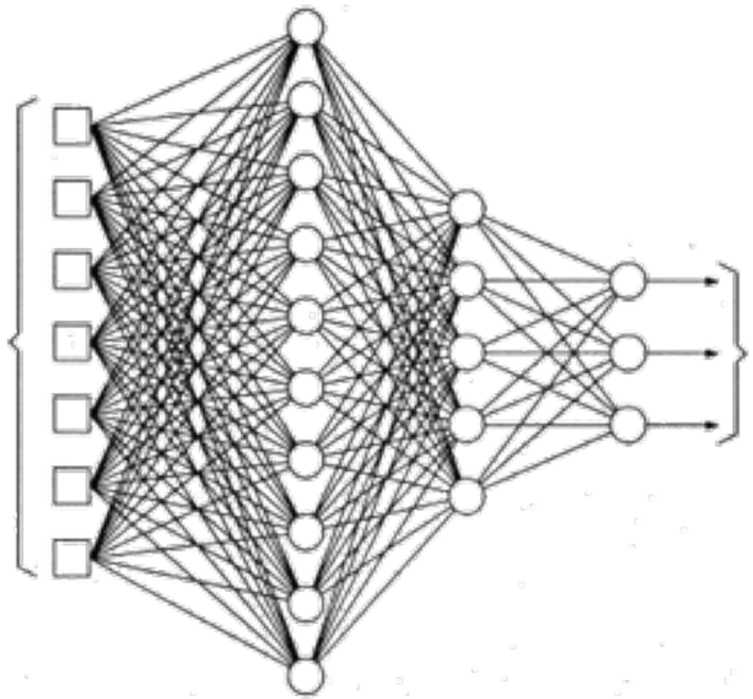
Data-driven Face Recognition

Deep Learning

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



ID 3



ID 1: 0.2

ID 2: 0.7

ID 3: 0.1

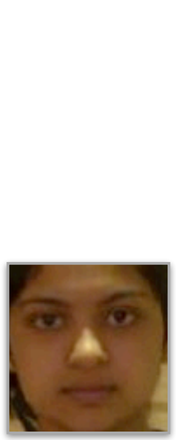
Random weights in the beginning.

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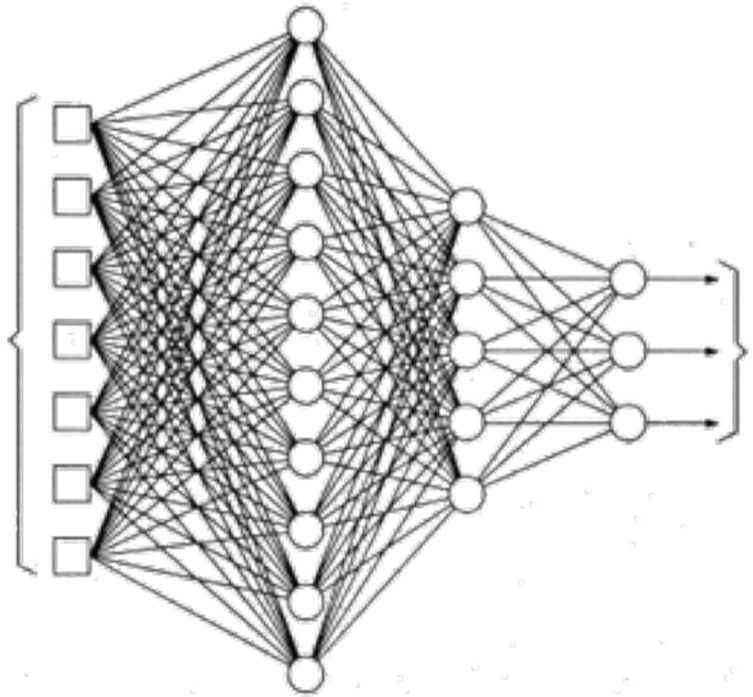
Data-driven Face Recognition

Deep Learning

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



ID 3



ID 1: 0.2

ID 2: 0.7

ID 3: 0.1

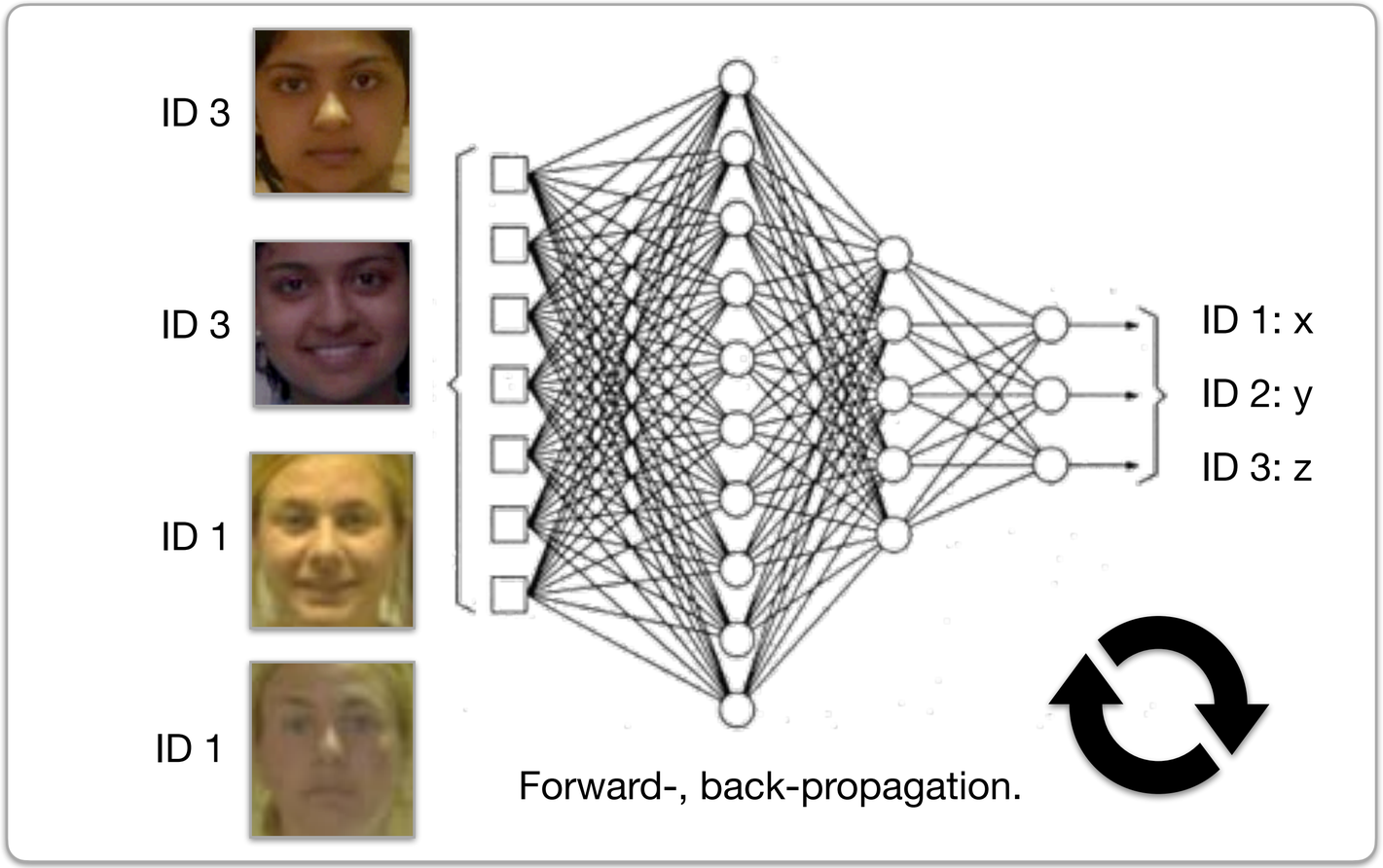
Weights are fixed with back-propagation.

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Data-driven Face Recognition

Deep Learning

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

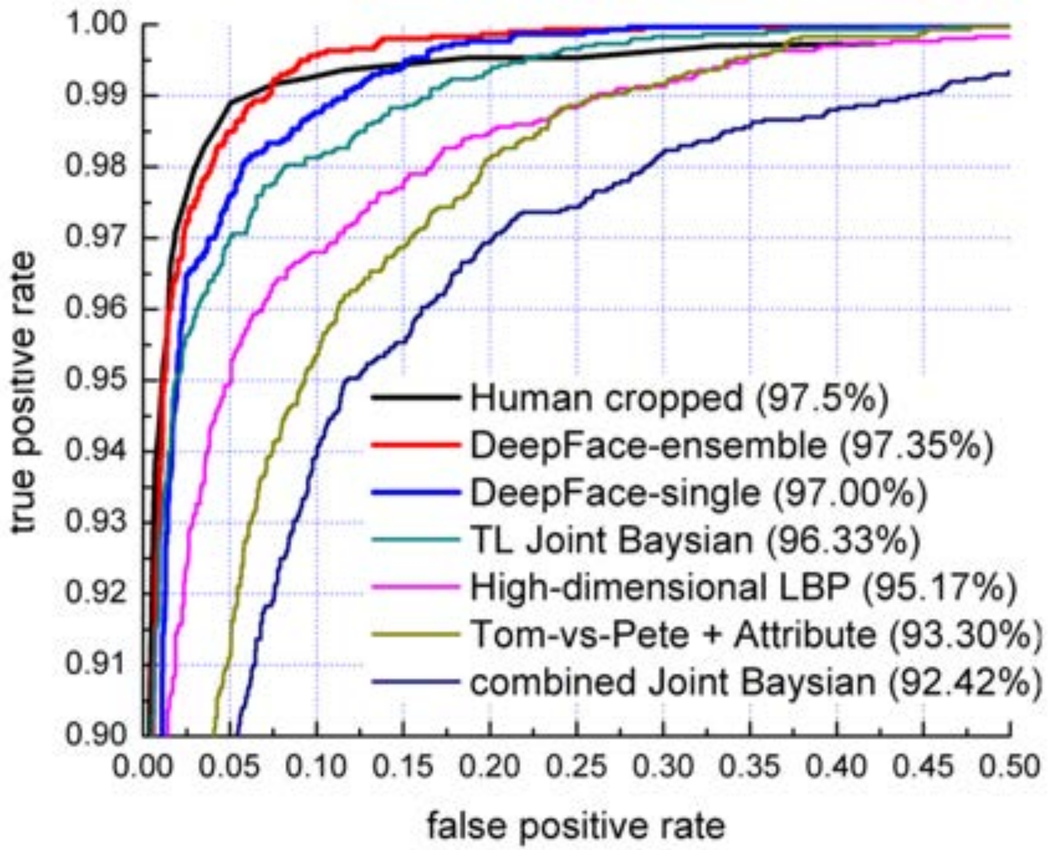


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Data-driven Face Recognition

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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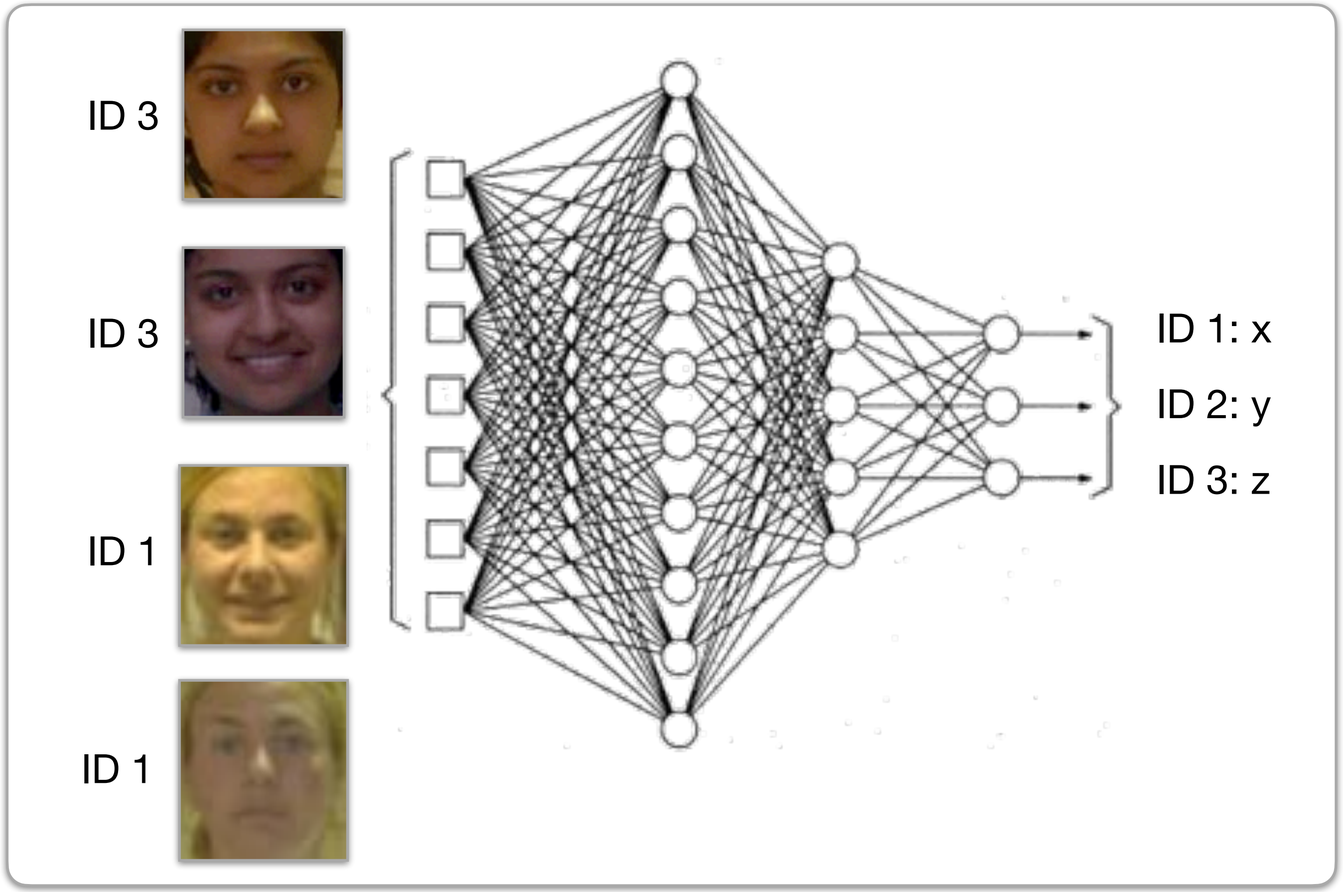
Data-driven Face Recognition

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).



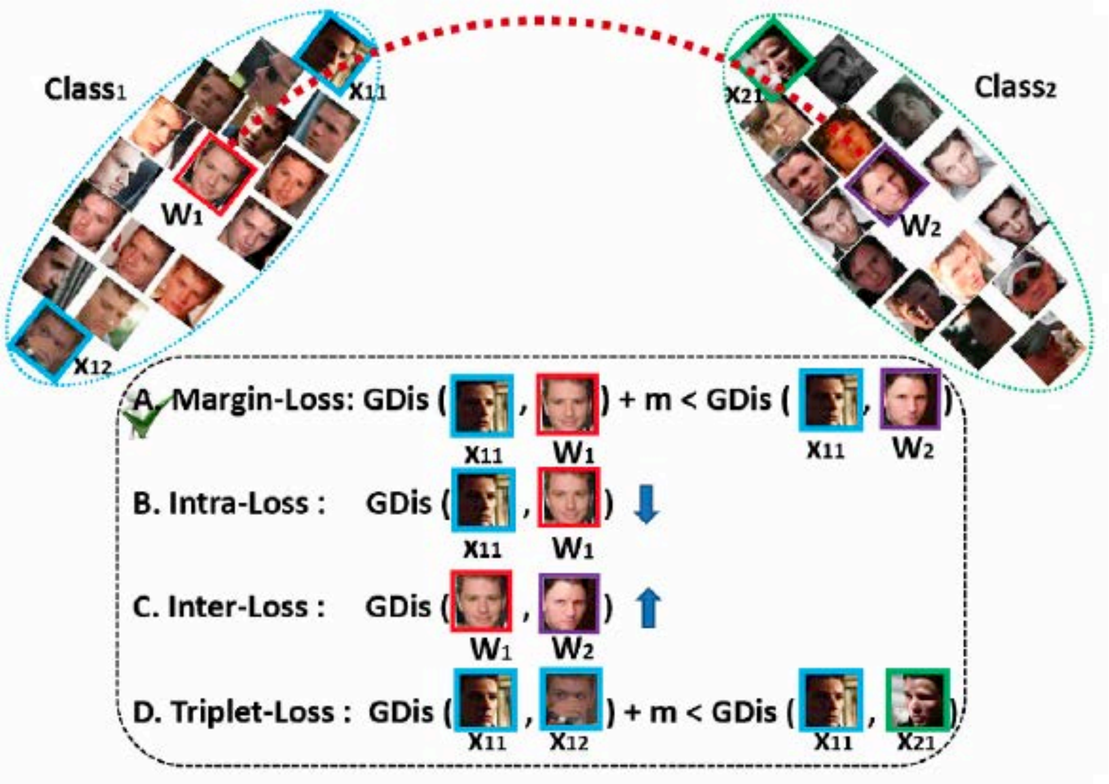
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What's Next?

Improving Deep Learning

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

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***Today-I-missed* Statement**
Please visit
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