

Face Recognition III

CSE 40537/60537 Biometrics

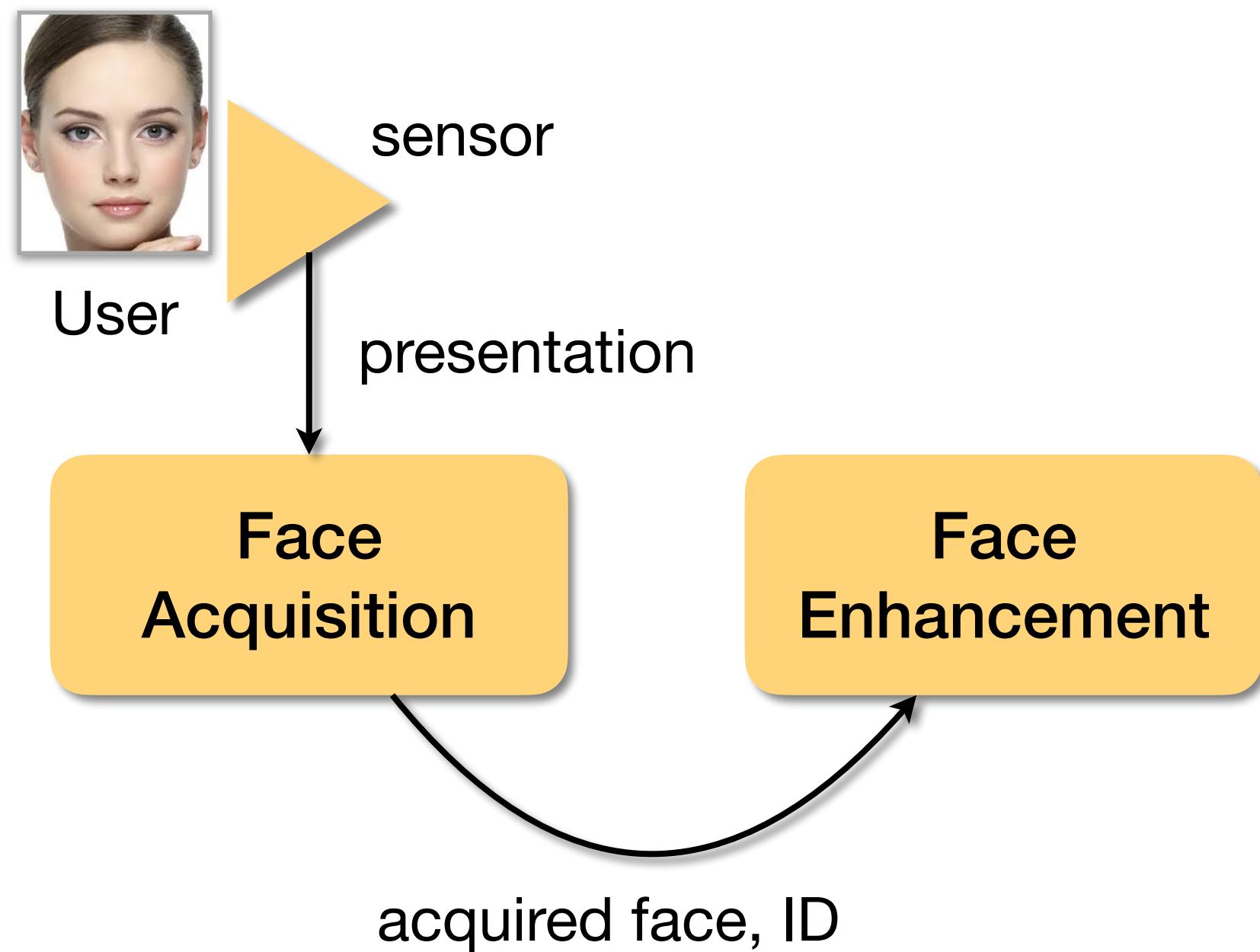
Daniel Moreira
Spring 2022



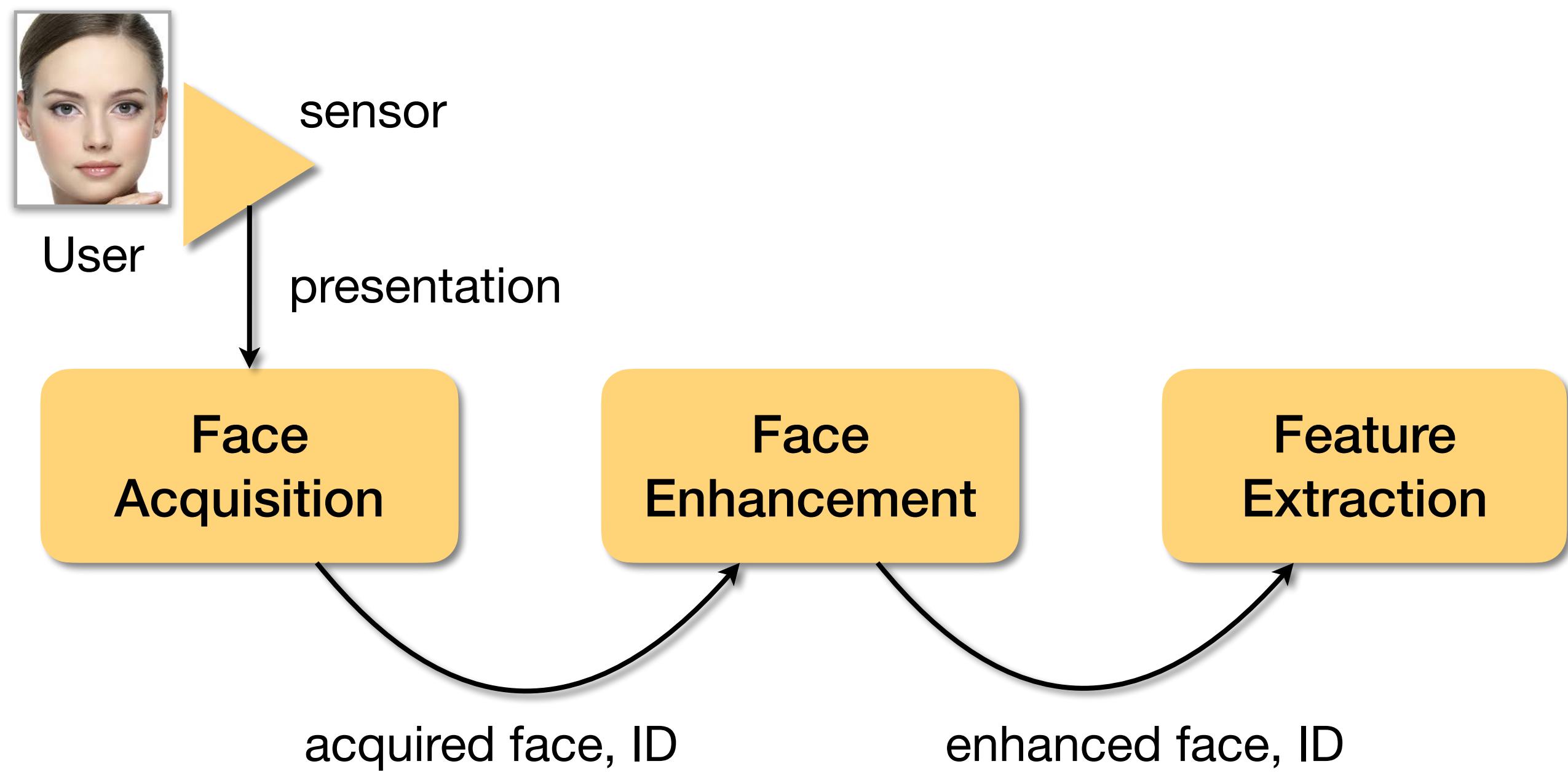
Today you will...

Get to know
Face description and matching.

Face Recognition



Face Recognition



Feature Extraction

Focus

2D-appearance-based methods.



Types

Handcrafted features from Computer Vision.

Data-driven learned features from Machine Learning.

Feature Extraction

Focus

2D-appearance-based methods.

Types

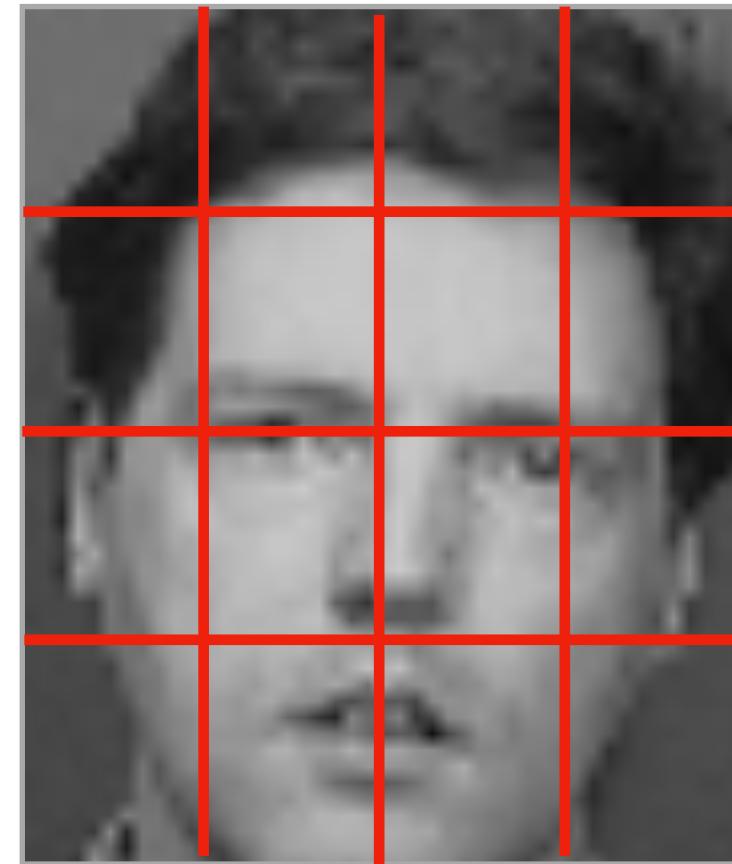
Handcrafted features from Computer Vision.

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

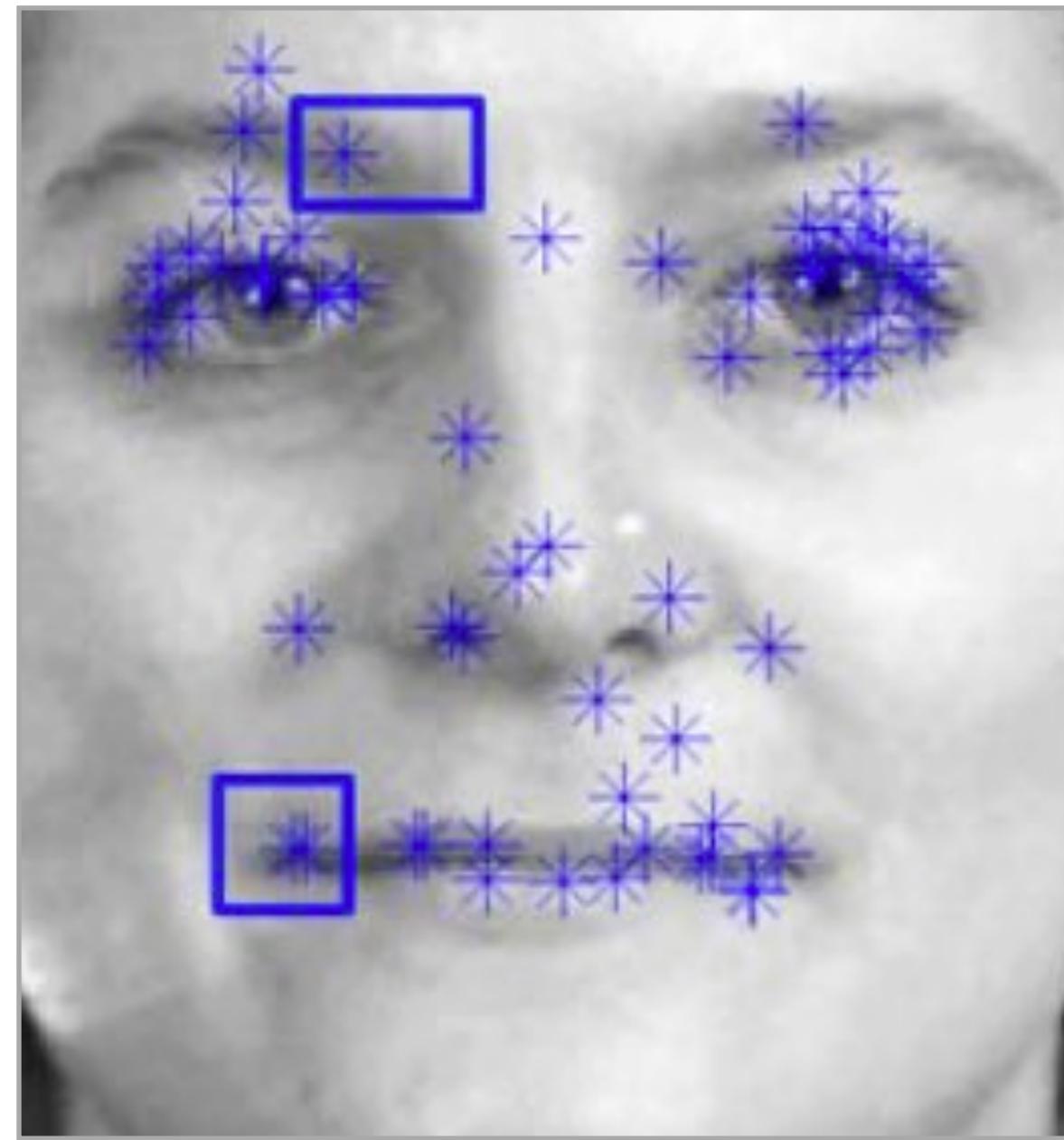
An expert designs what and how facial regions should be used.

Feature Extraction

Handcrafted Features

Examples

Based on Gabor filters, interest points (e.g., SIFT¹, SURF², HOG³), or texture descriptors (e.g., LBP⁴).



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.

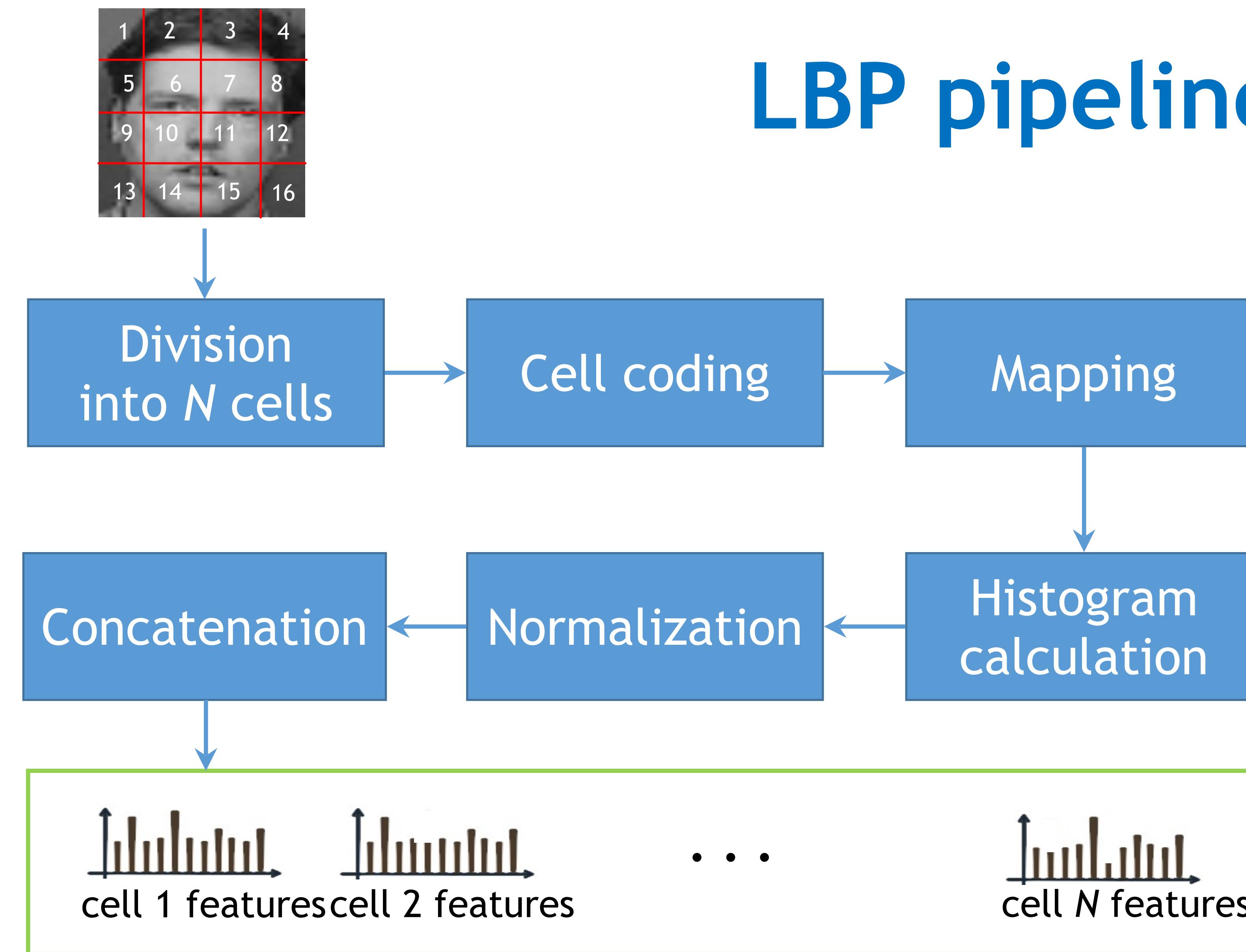
Local Binary Patterns

Selected Solution

Local Binary Patterns to describe
face texture.

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

LBP pipeline



Division
into N cells

Cell coding

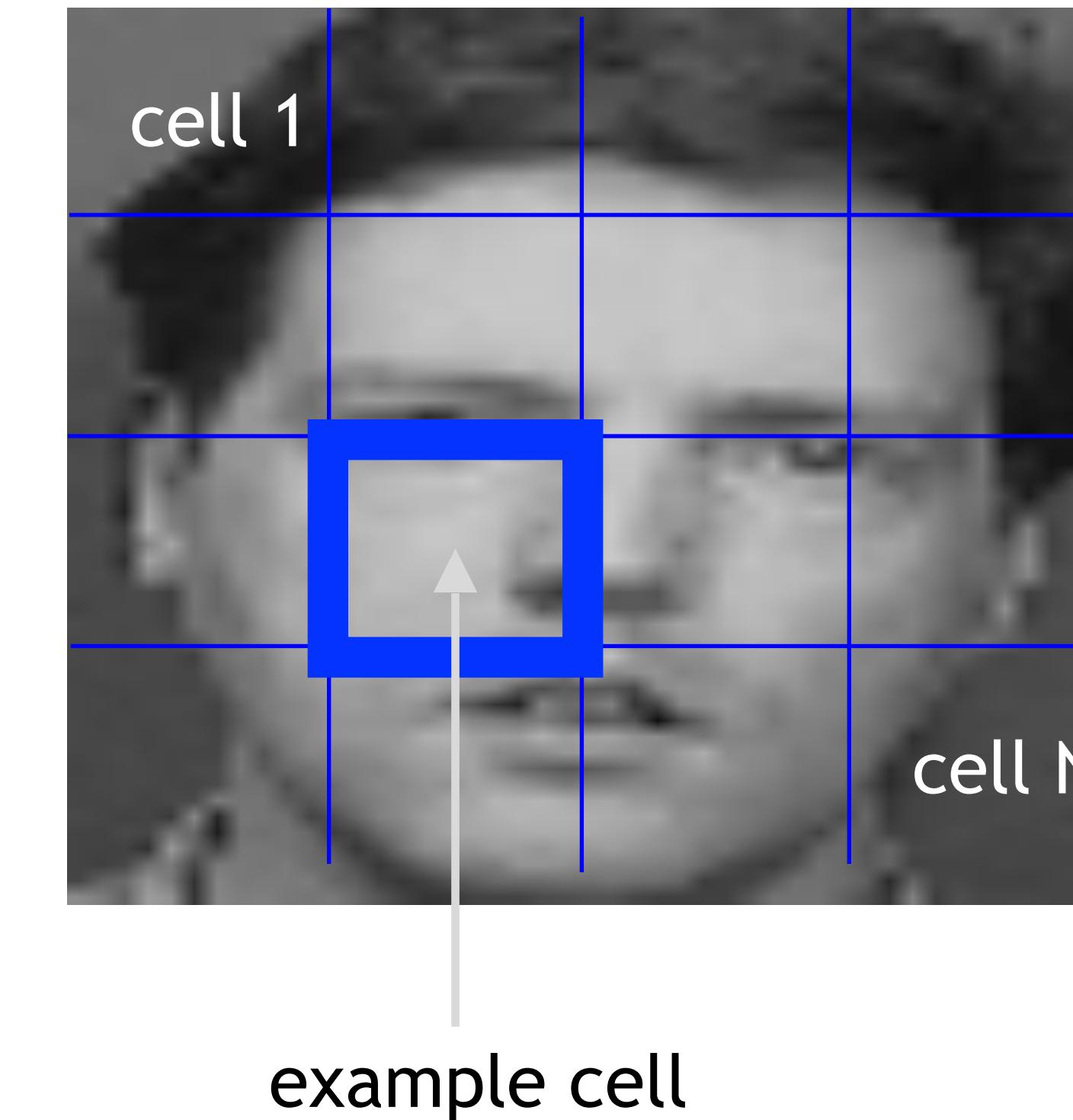
Mapping

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)



Division
into N cells

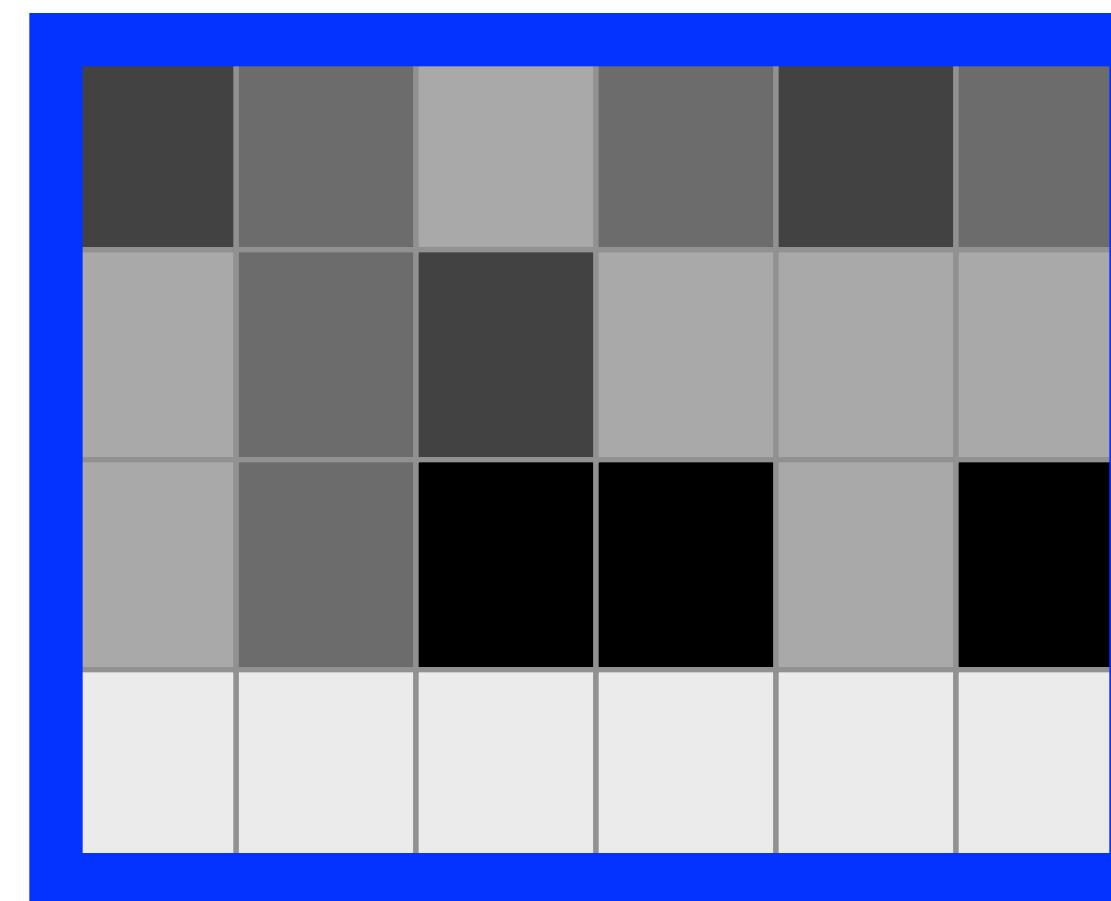
Cell coding

Mapping

Histogram
calculation

Normalization

Concatenation



Division
into N cells

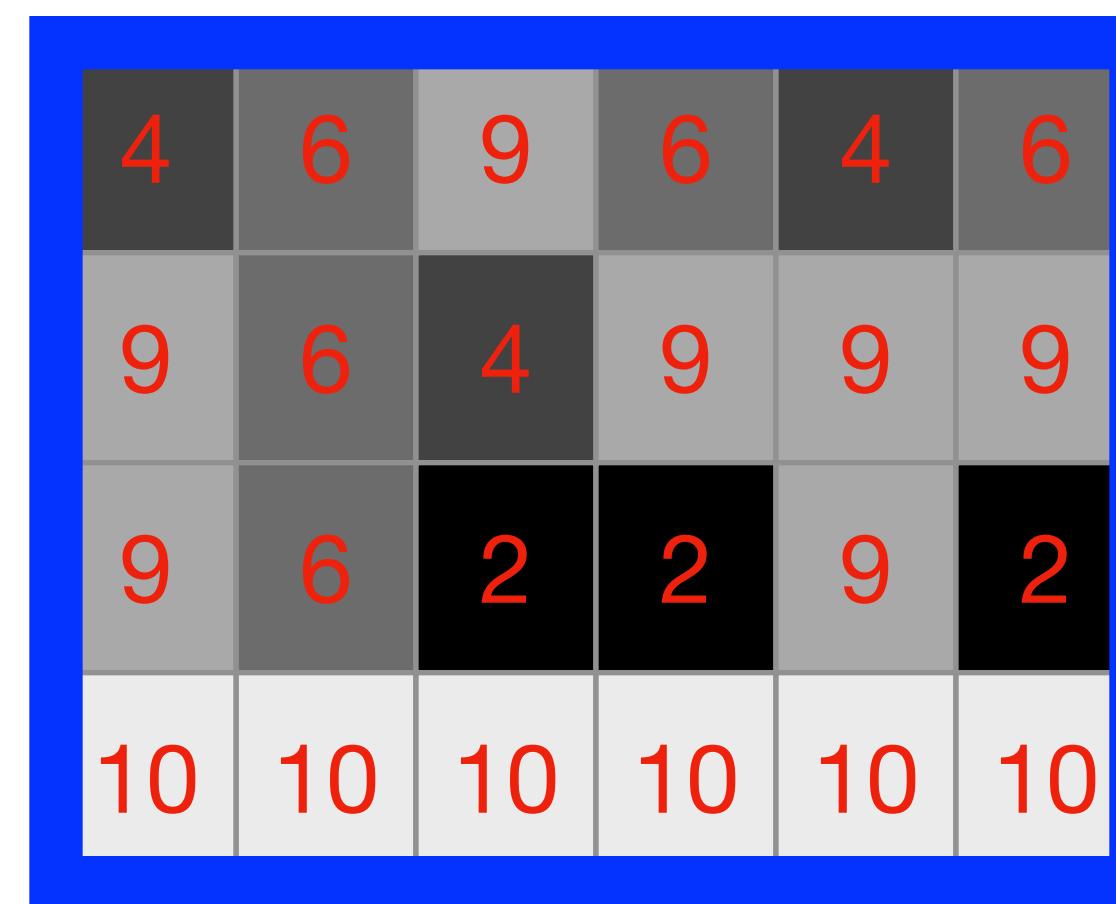
Cell coding

Mapping

Histogram
calculation

Normalization

Concatenation



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

Division
into N cells

Cell coding

Mapping

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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

Division
into N cells

Cell coding

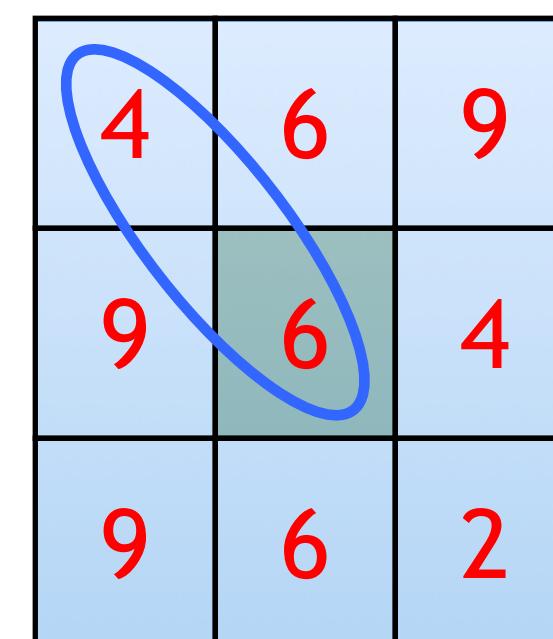
Mapping

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			

<		

Division
into N cells

Cell coding

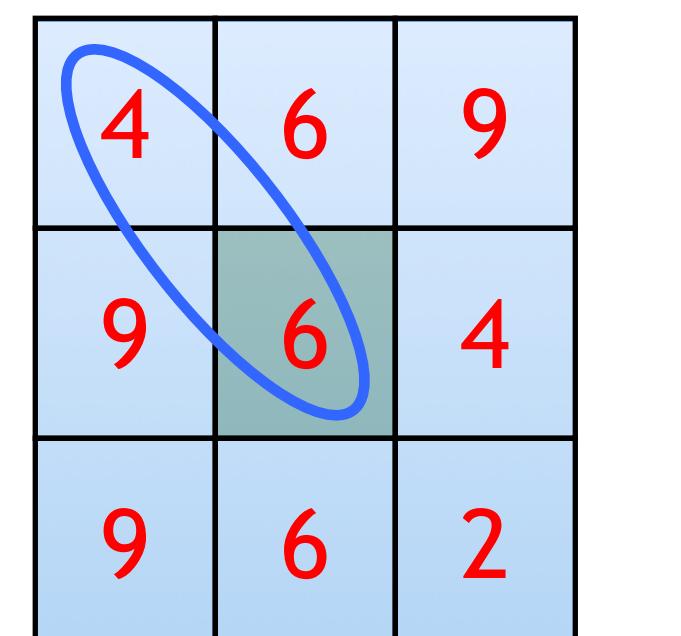
Mapping

Histogram
calculation

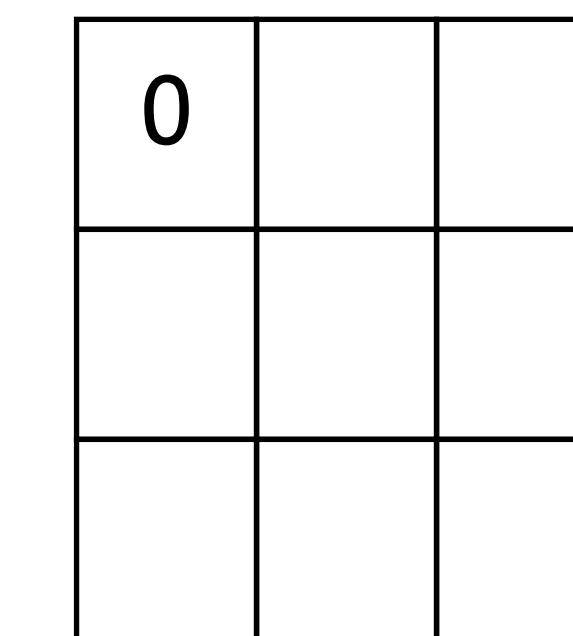
Normalization

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



0: <
1: \geq



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			

0: <
1: \geq

0	\geq	

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

0: <
1: \geq

0	1	

Division
into N cells

Cell coding

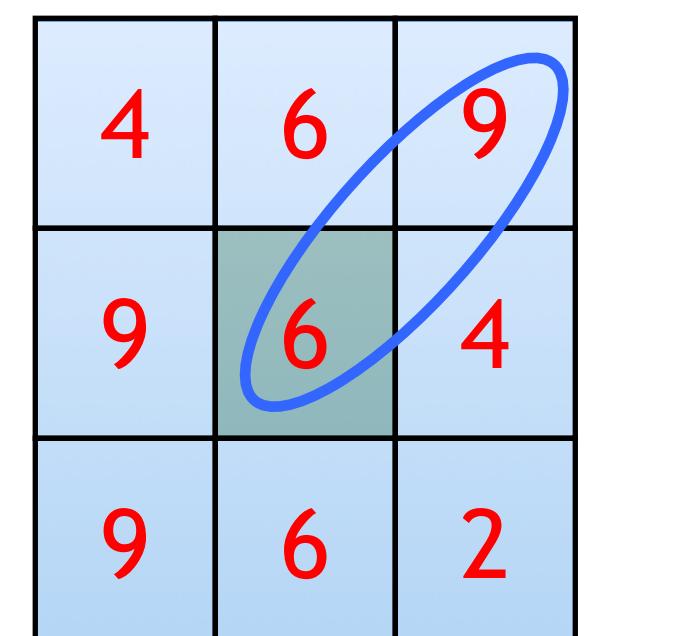
Mapping

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



0: <
1: \geq

0	1	1

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

0: <
1: \geq

0	1	1
		0

Division
into N cells

Cell coding

Mapping

Histogram
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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

0: <
1: \geq

0	1	1
		0
		0

Division
into N cells

Cell coding

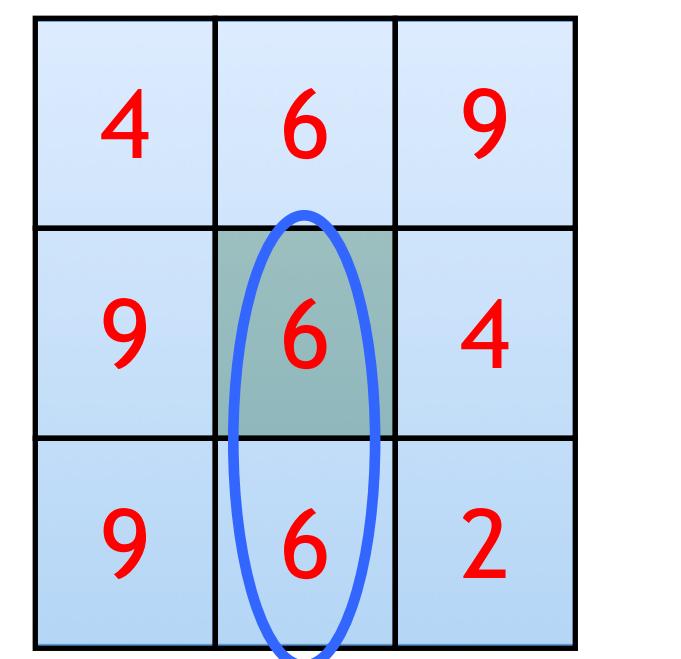
Mapping

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



0: <
1: \geq

0	1	1
		0
	1	0

Division
into N cells

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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

0: <
1: \geq

0	1	1
		0
1	1	0

Division
into N cells

Cell coding

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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

0: <
1: \geq

0	1	1
1		0
1	1	0

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

$0: <$
 $1: \geq$

0	1	1
1		0
1	1	0

1	2	4
128	+ 32	8
64	32	16

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

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

$0: <$
 $1: \geq$

0	1	1
1		0
1	1	0

1	2	4
128	+ ↗	8
64	32	16

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

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					

4	6	9
9	6	4
9	6	2

0: <
1: \geq

0	1	1
1		0
1	1	0

1	2	4
128	+ 32	8
64	32	16

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

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	?				

6	9	6
6	4	9
6	2	2

0: <
1: \geq

\times

1	2	4
128	+ 128	8
64	32	16

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				

6	9	6
6	4	9
6	2	2

0: <
1: \geq

1	1	1
1		1
1	0	0

1	2	4
128	+ 8	8
64	32	16

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

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	?			

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			

9	6	4
4	9	9
2	2	9

0: <
1: \geq

1	0	0
0		1
0	0	1

1	2	4
128	+ 16	8
64	32	16

$$= 1 + 8 + 16 = 25$$

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		

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					

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				

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			

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	119		

Division
into N cells

Cell coding

Mapping

Histogram
calculation

Normalization

Concatenation

Note on neighborhood definition

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

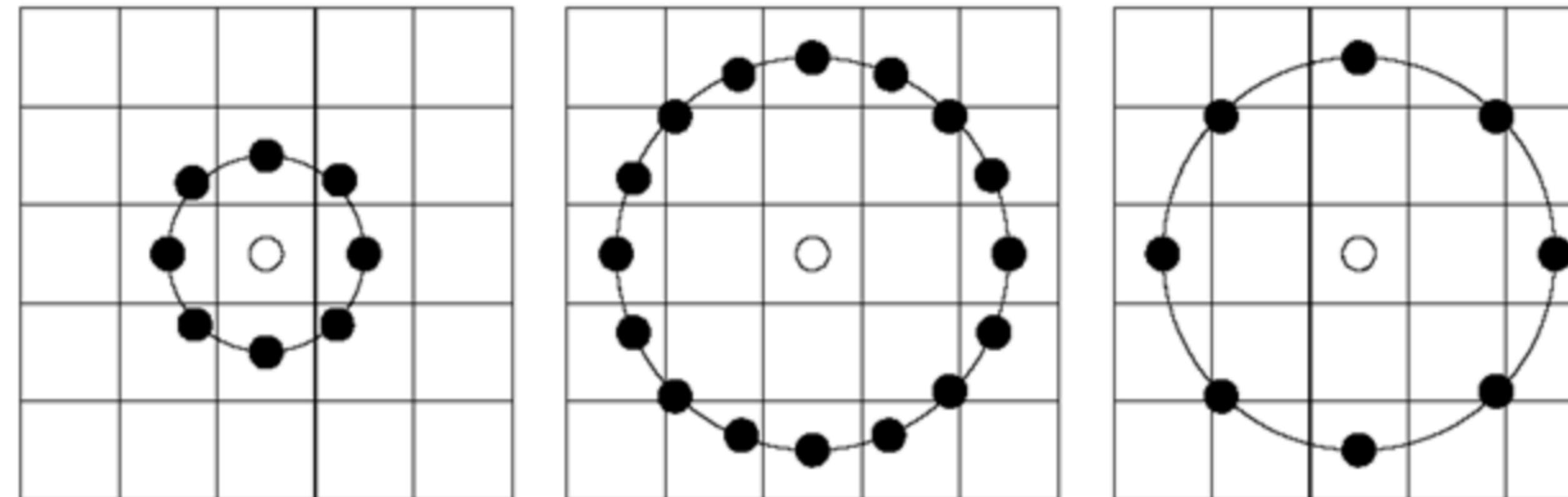


Image source: <http://what-when-how.com/face-recognition/local-representation-of-facial-features-face-image-modeling-and-representation-face-recognition-part-1/>

Division
into N cells

Cell coding

Mapping

Histogram
calculation

Normalization

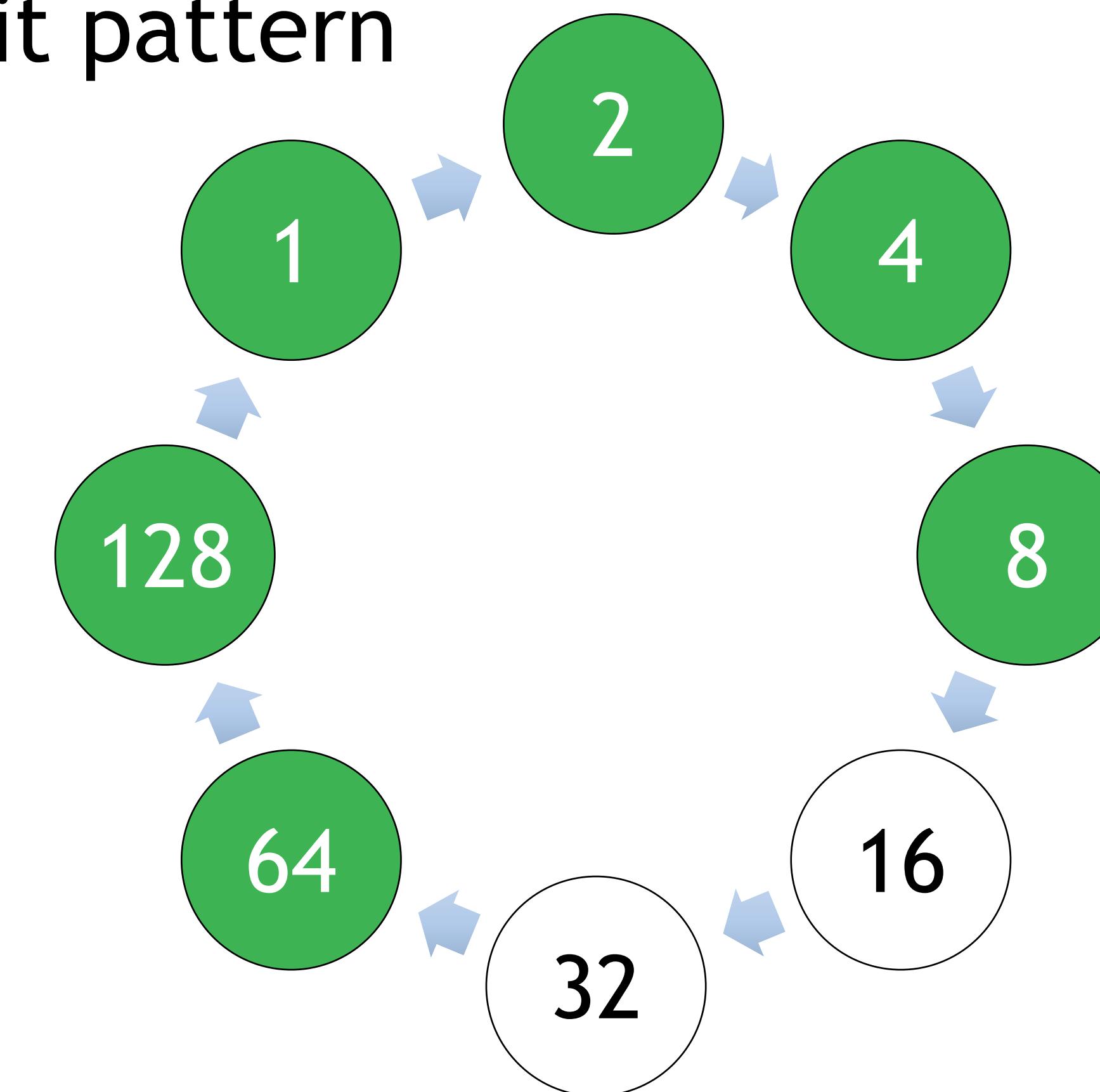
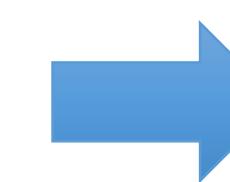
Concatenation

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

6	9	6
6	4	9
6	2	2



1	1	1
1		1
1	0	0



Division
into N cells

Cell coding

Mapping

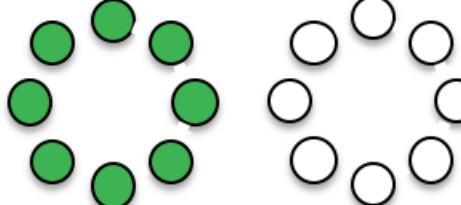
Histogram
calculation

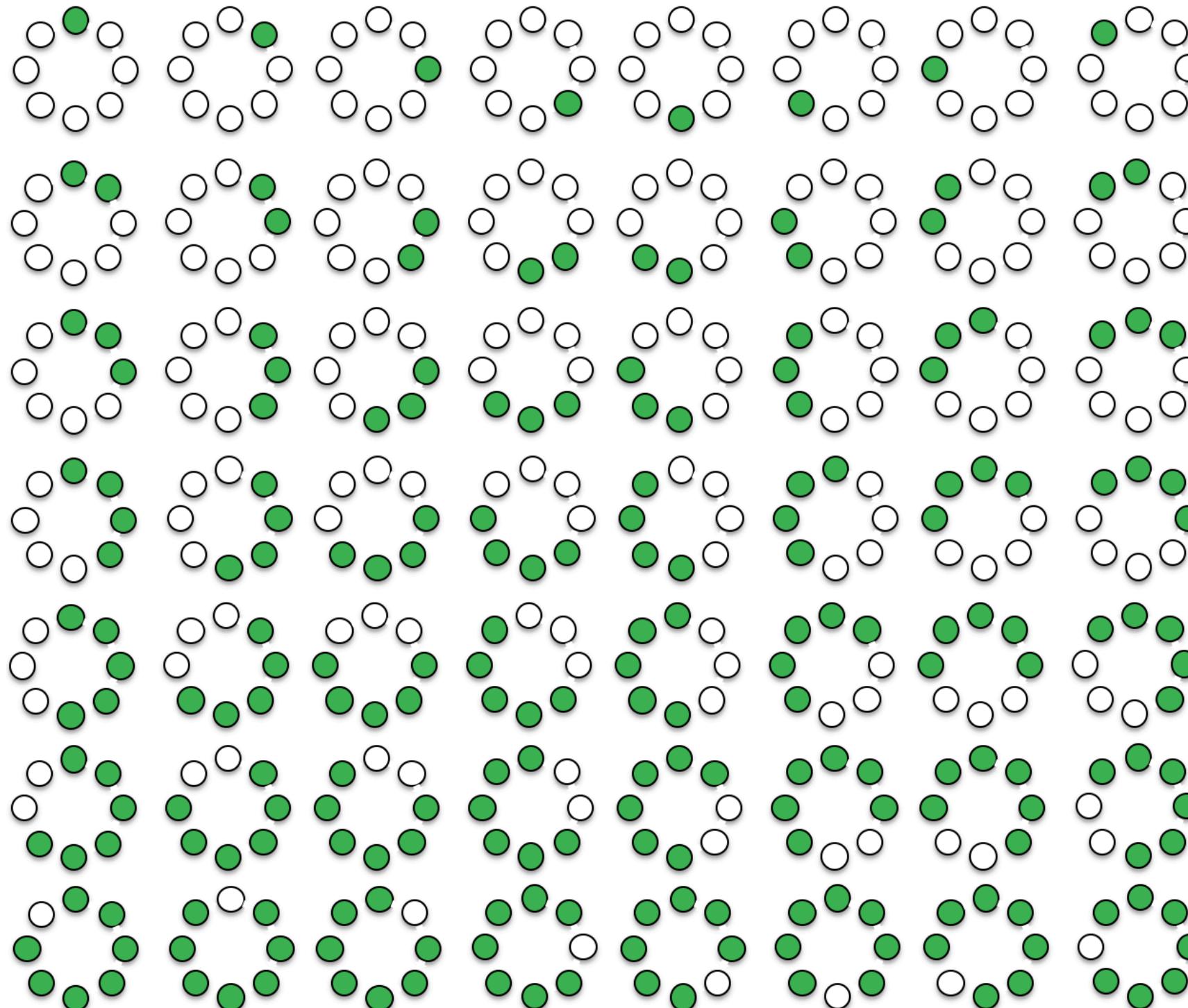
Normalization

Concatenation

Uniform patterns

Uniform patterns
account for almost
90% of all patterns.

$U = 0$ 

$U = 2$ 

Division
into N cells

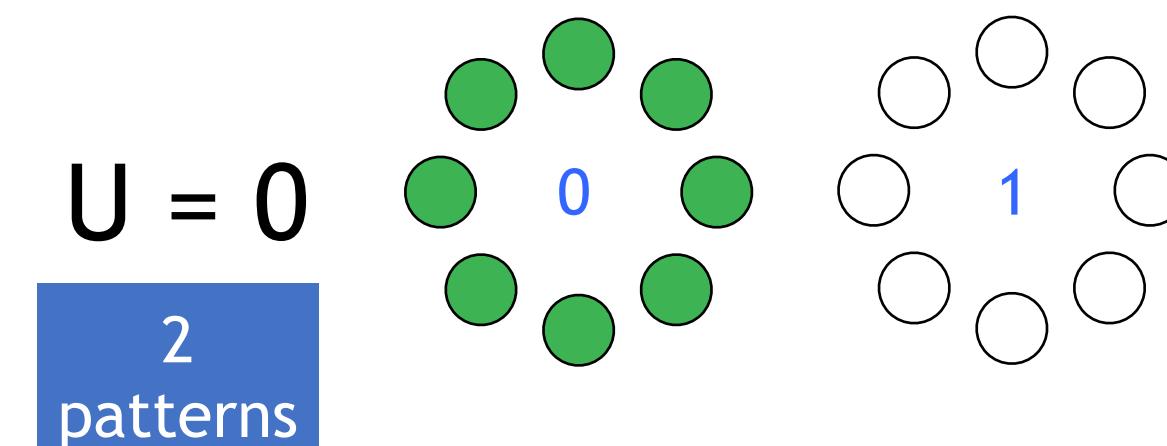
Cell coding

Mapping

Histogram
calculation

Normalization

Concatenation



$U = 2$

$8 \times 7 = 56$ patterns

$\{2, 3, \dots 57\}$

Uniform patterns

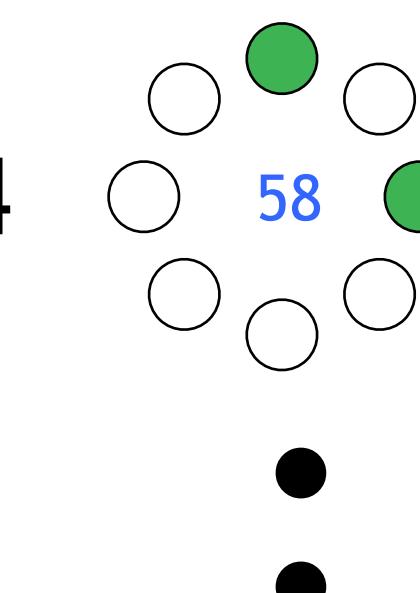
$2 + 56 = 58$
patterns

Non-uniform patterns

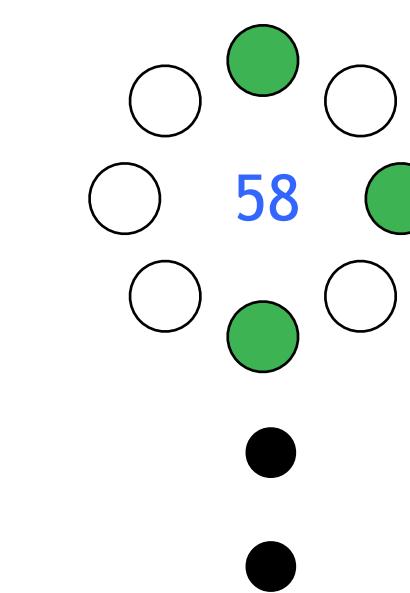
$256 - 58 = 198$
patterns

{58}

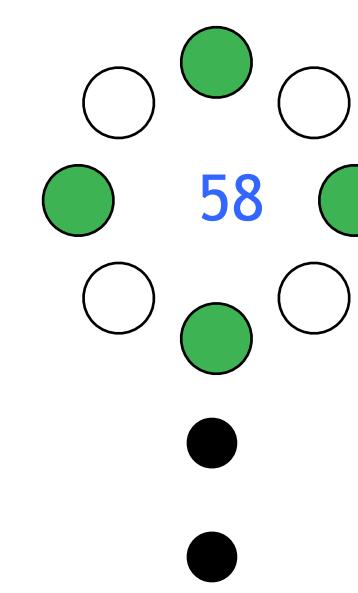
$U = 4$



$U = 6$



$U = 8$



Division
into N cells

Cell coding

Mapping

Histogram
calculation

Normalization

Concatenation

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		

Coded cell

58	46	58	58		
23	0	0	58		

Mapped cell

Division
into N cells

Cell coding

Mapping

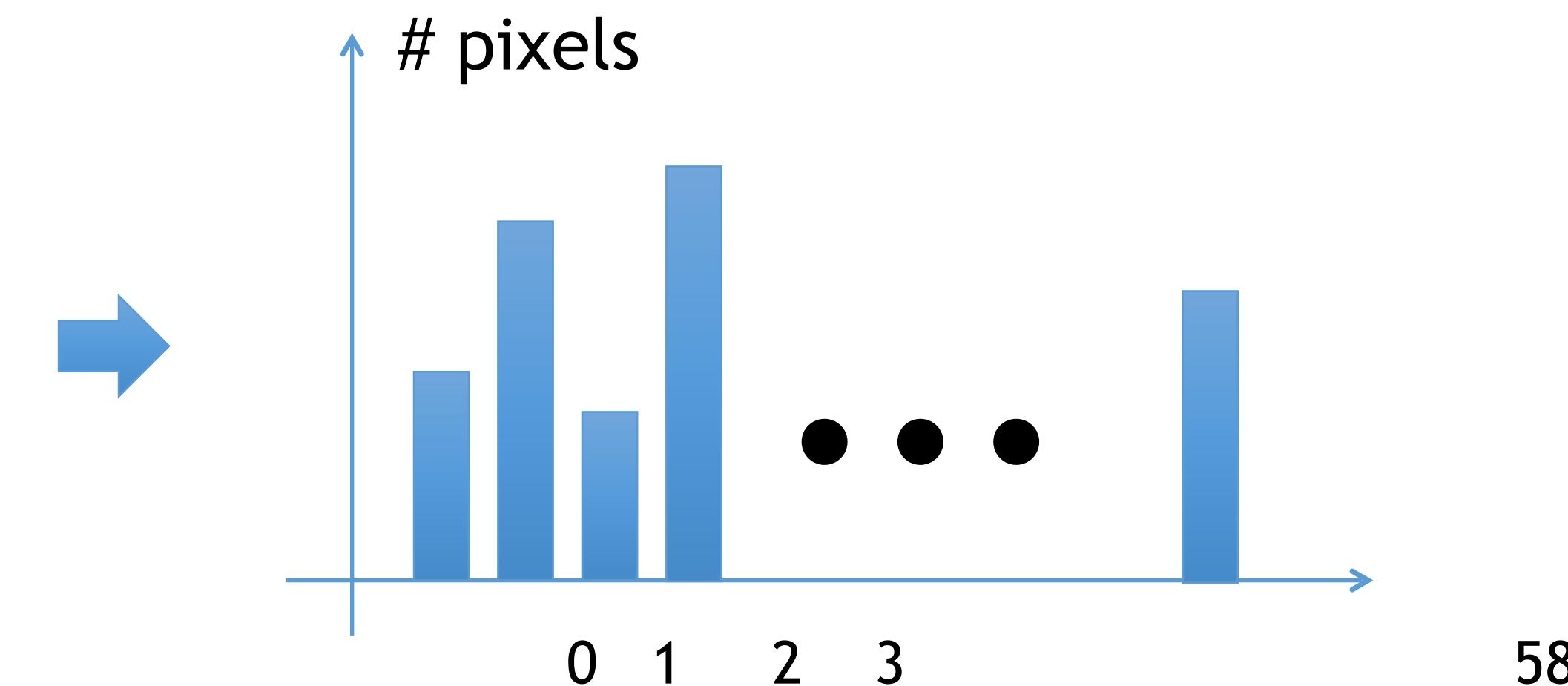
Histogram
calculation

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.

Division
into N cells

Cell coding

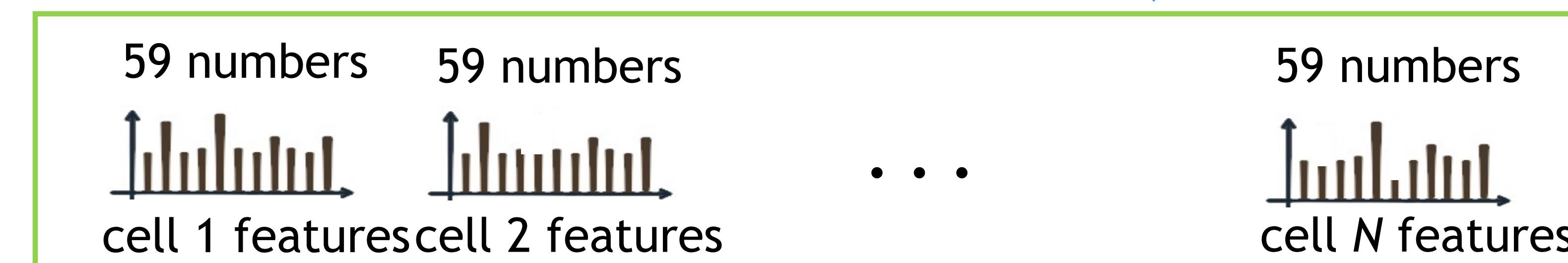
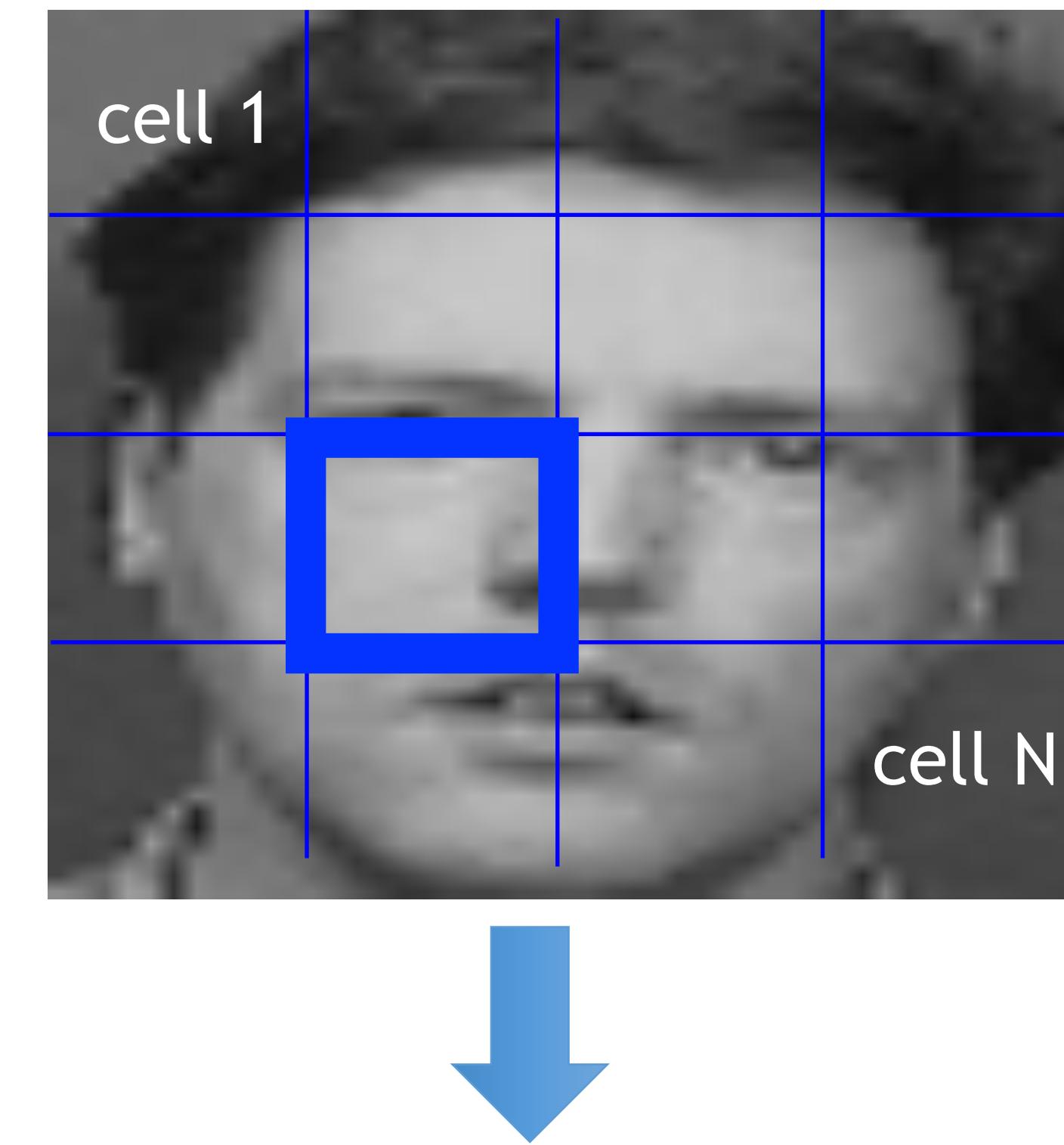
Mapping

Histogram
calculation

Normalization

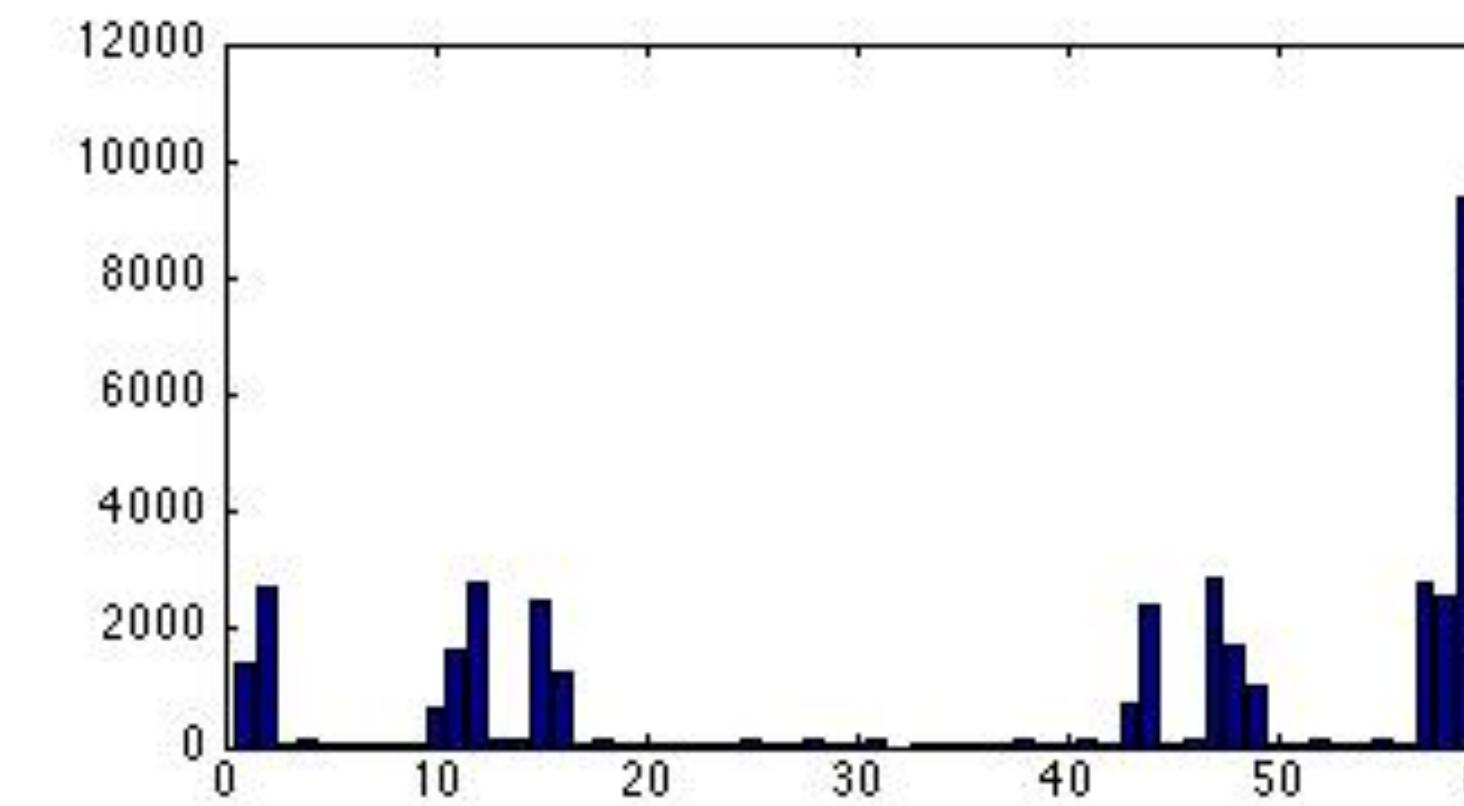
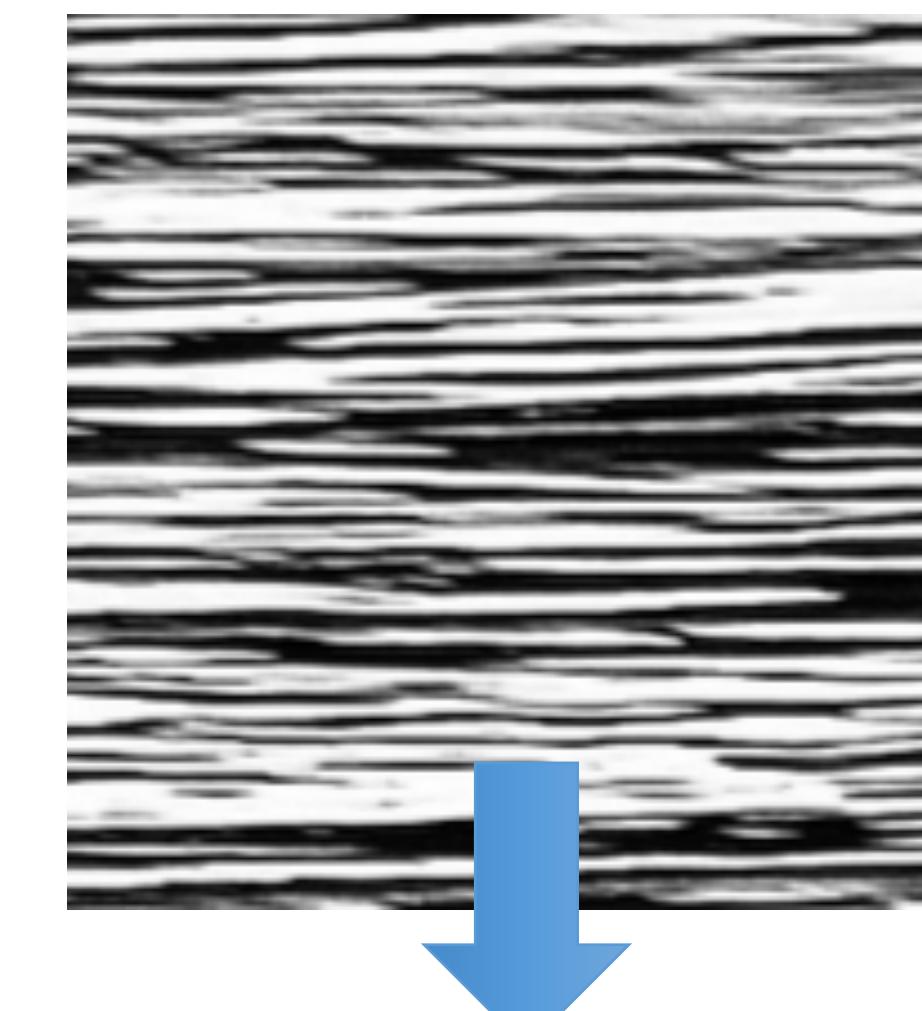
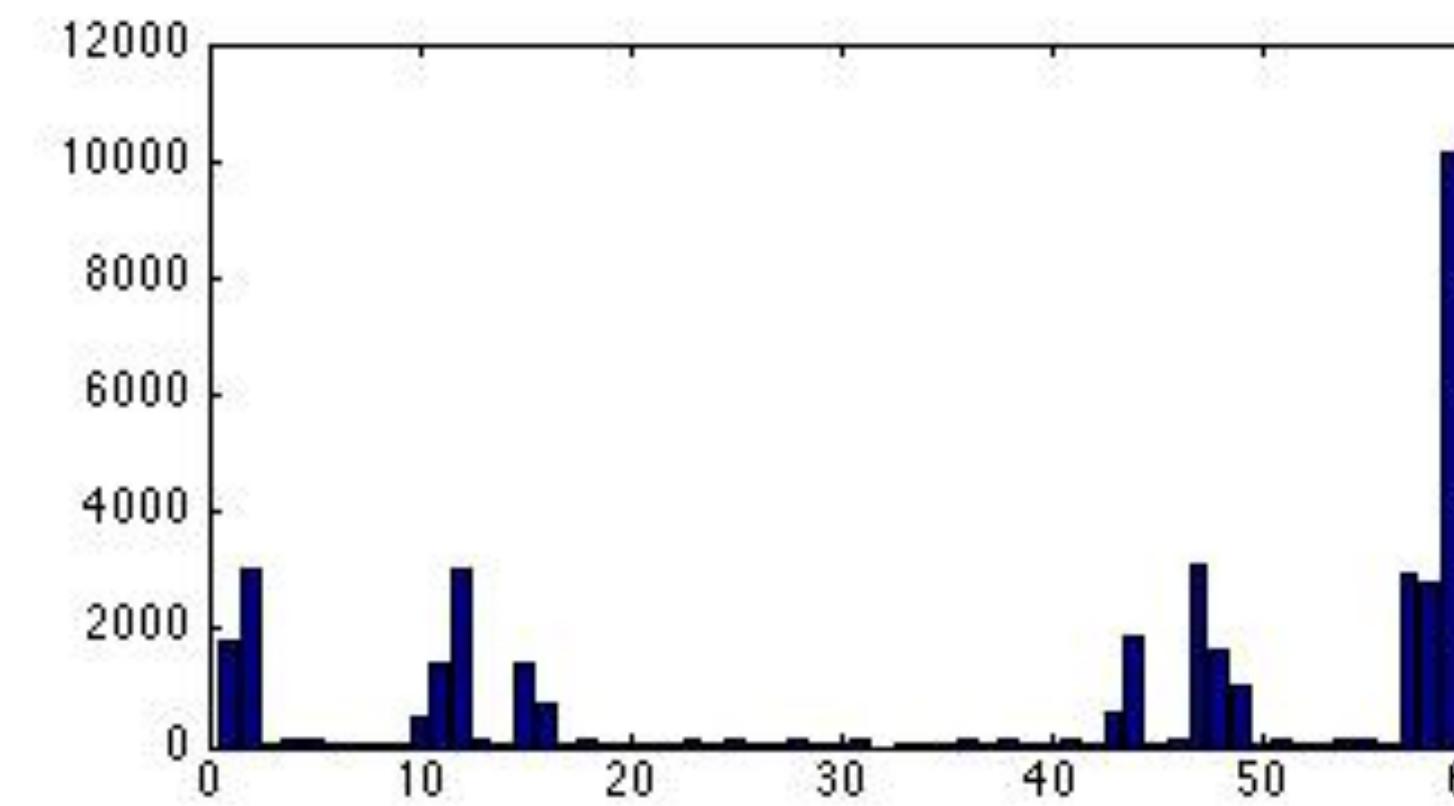
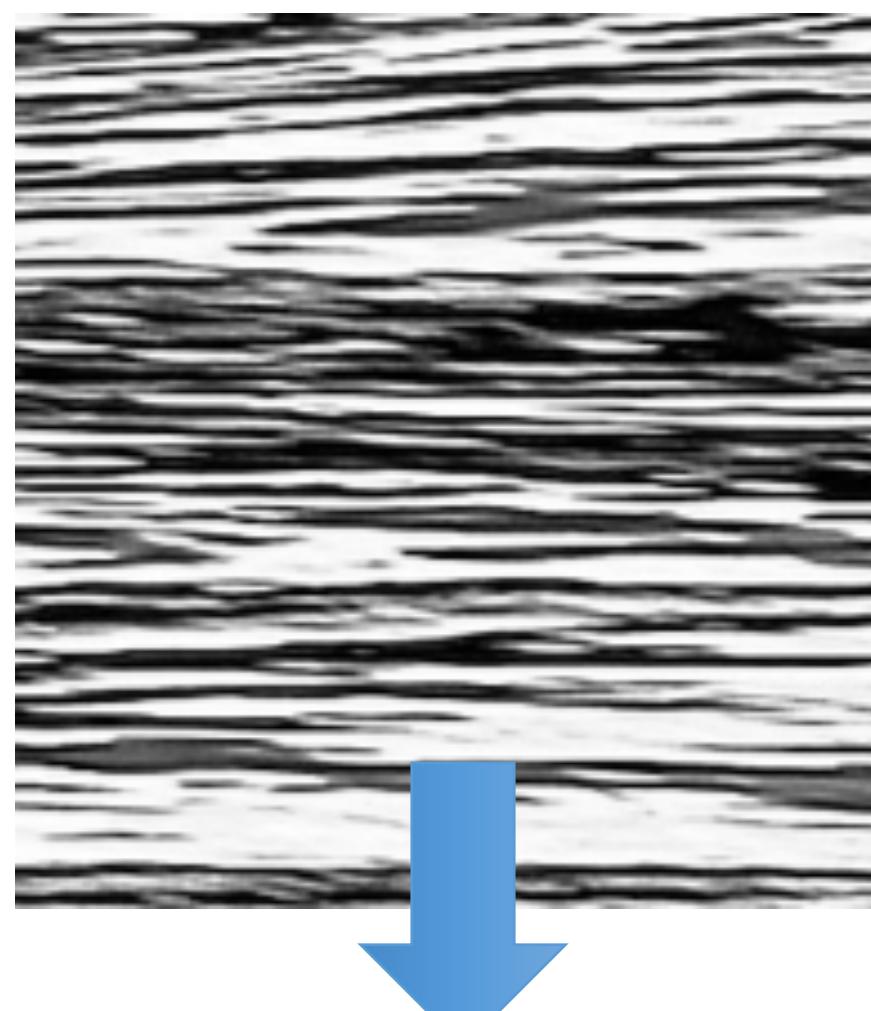
Concatenation

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



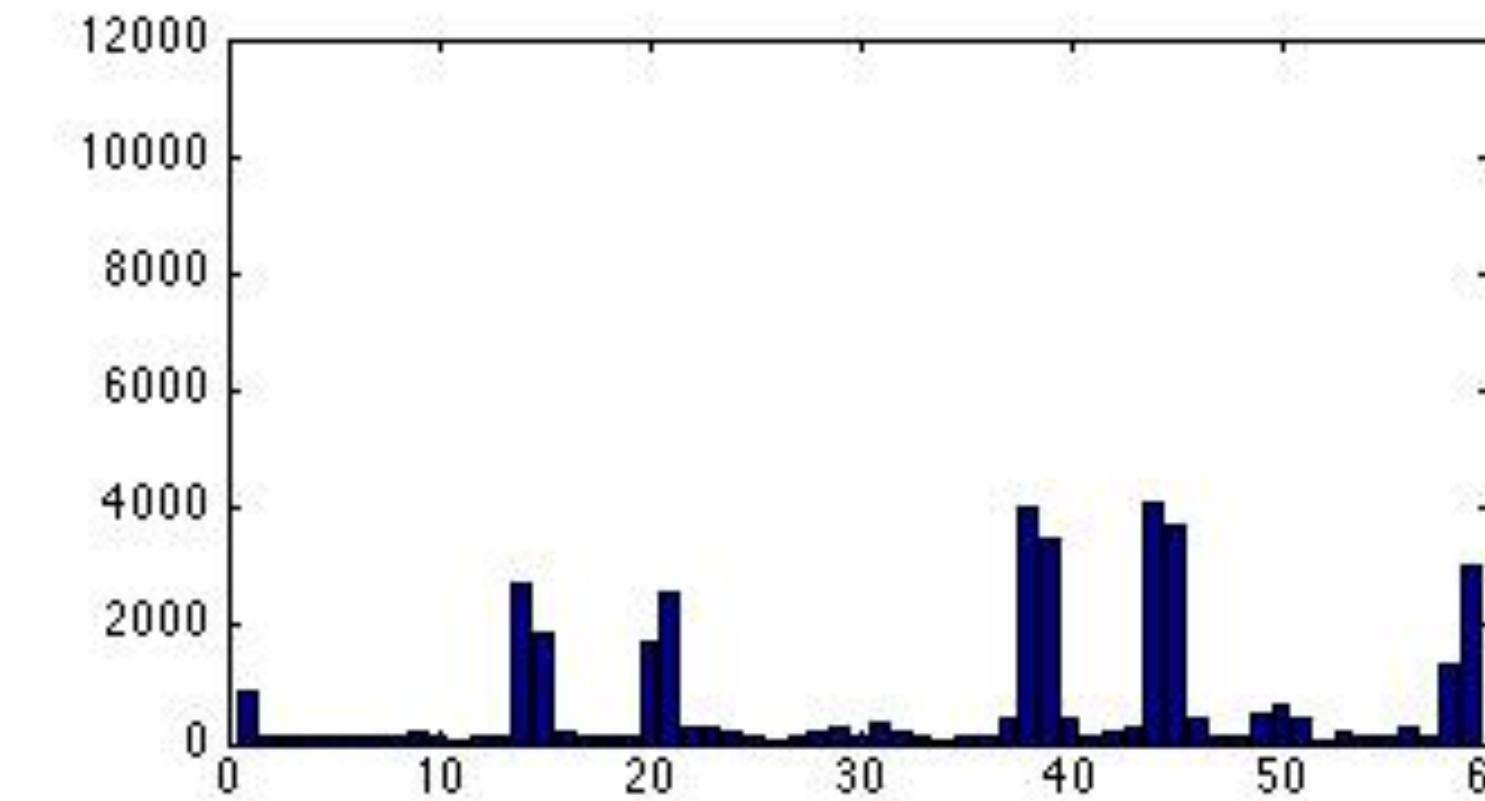
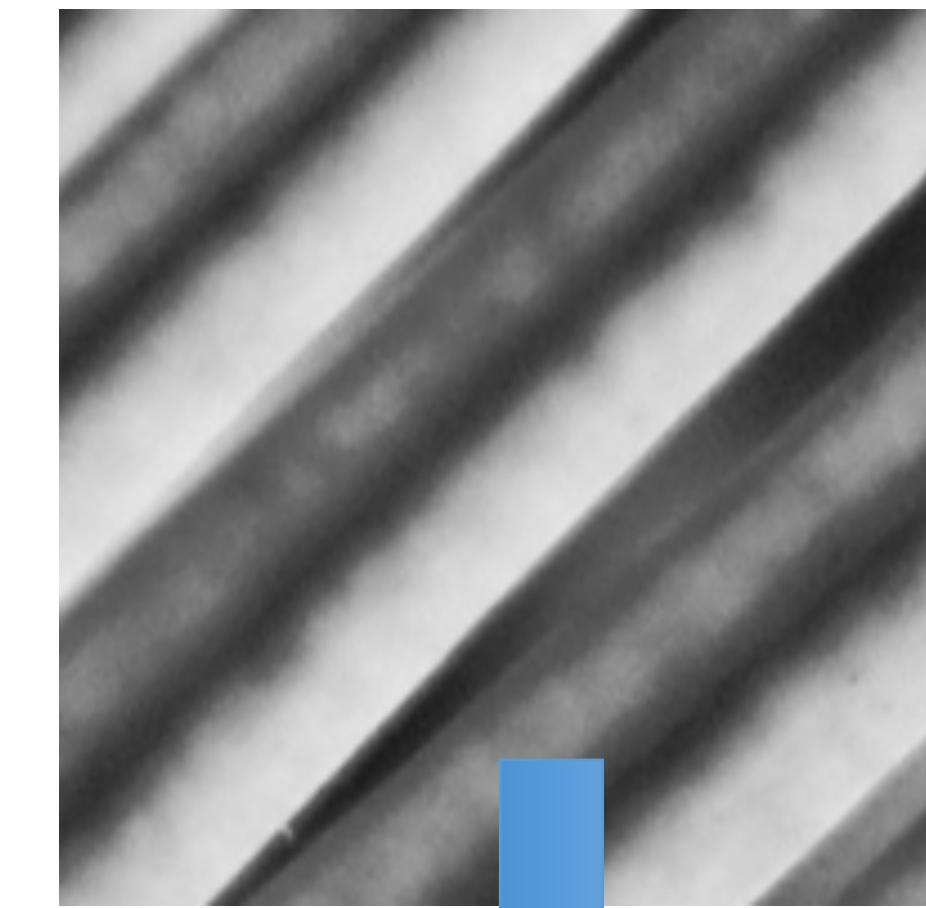
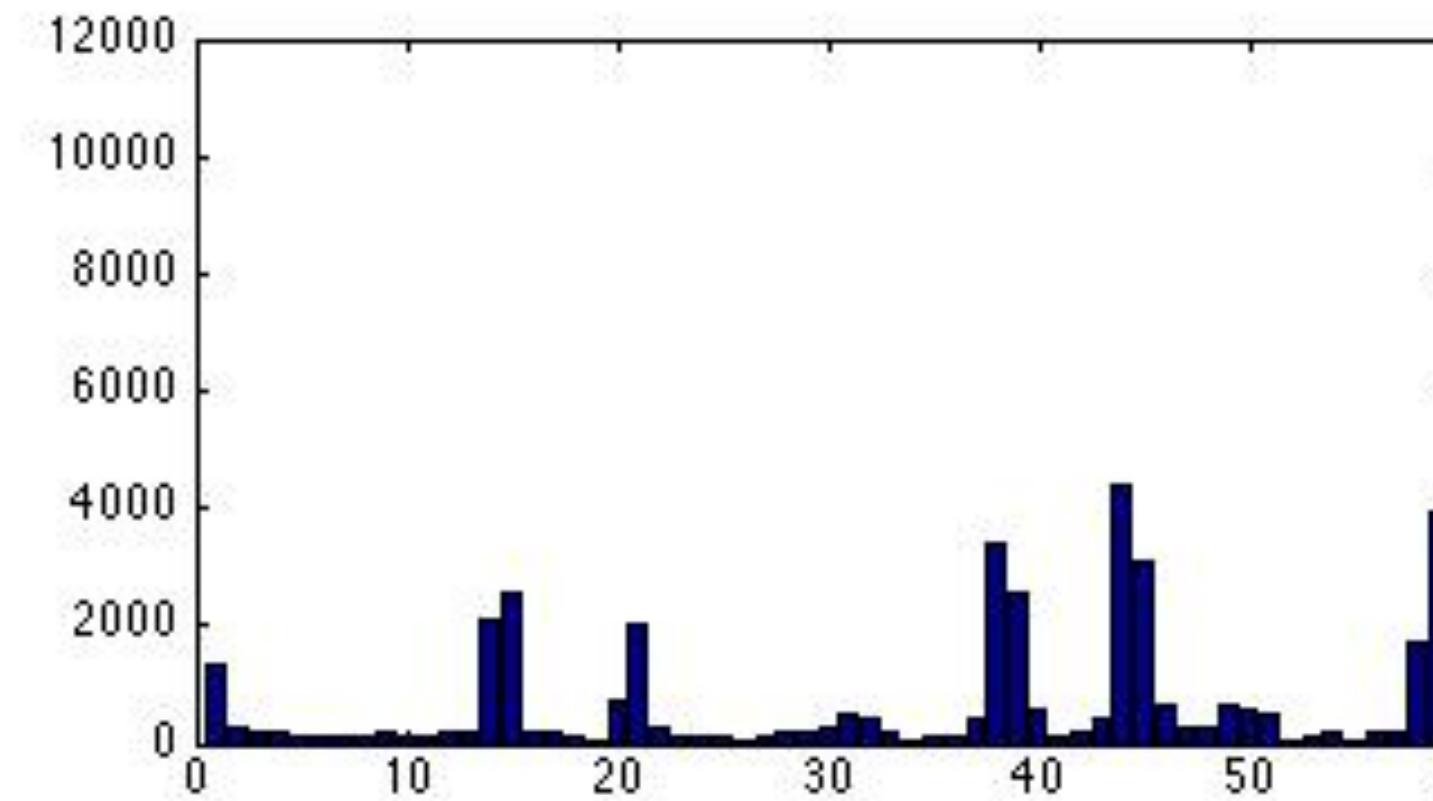
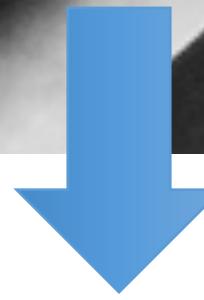
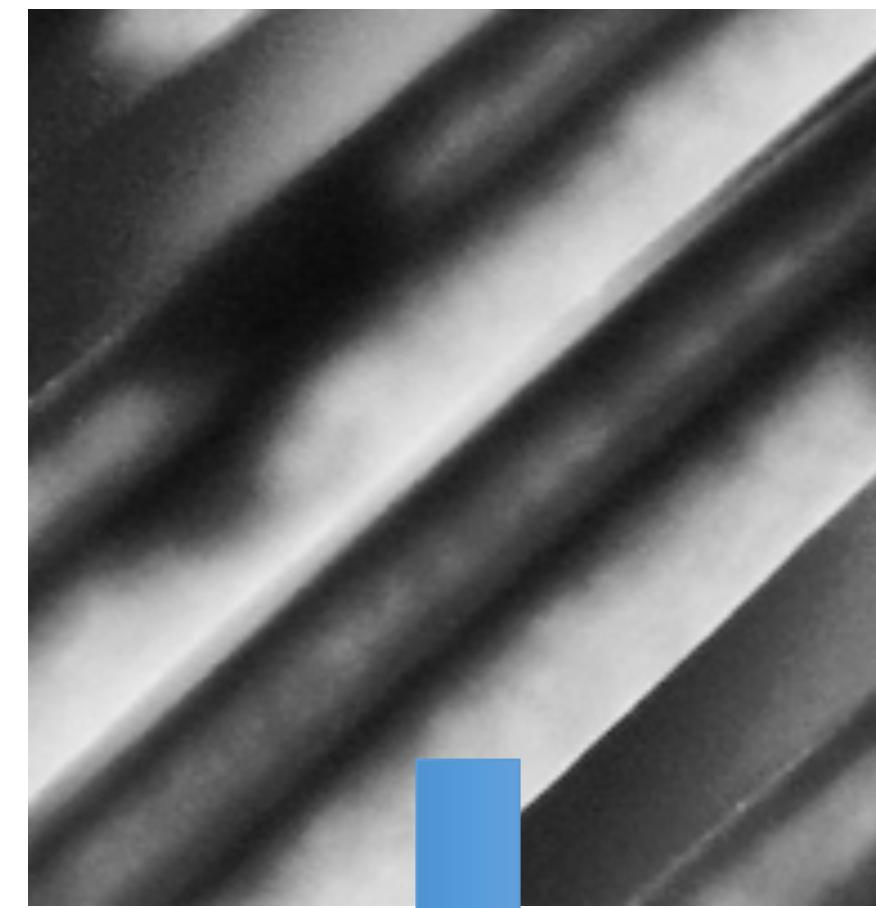
Local Binary Patterns

Similar textures have similar histograms



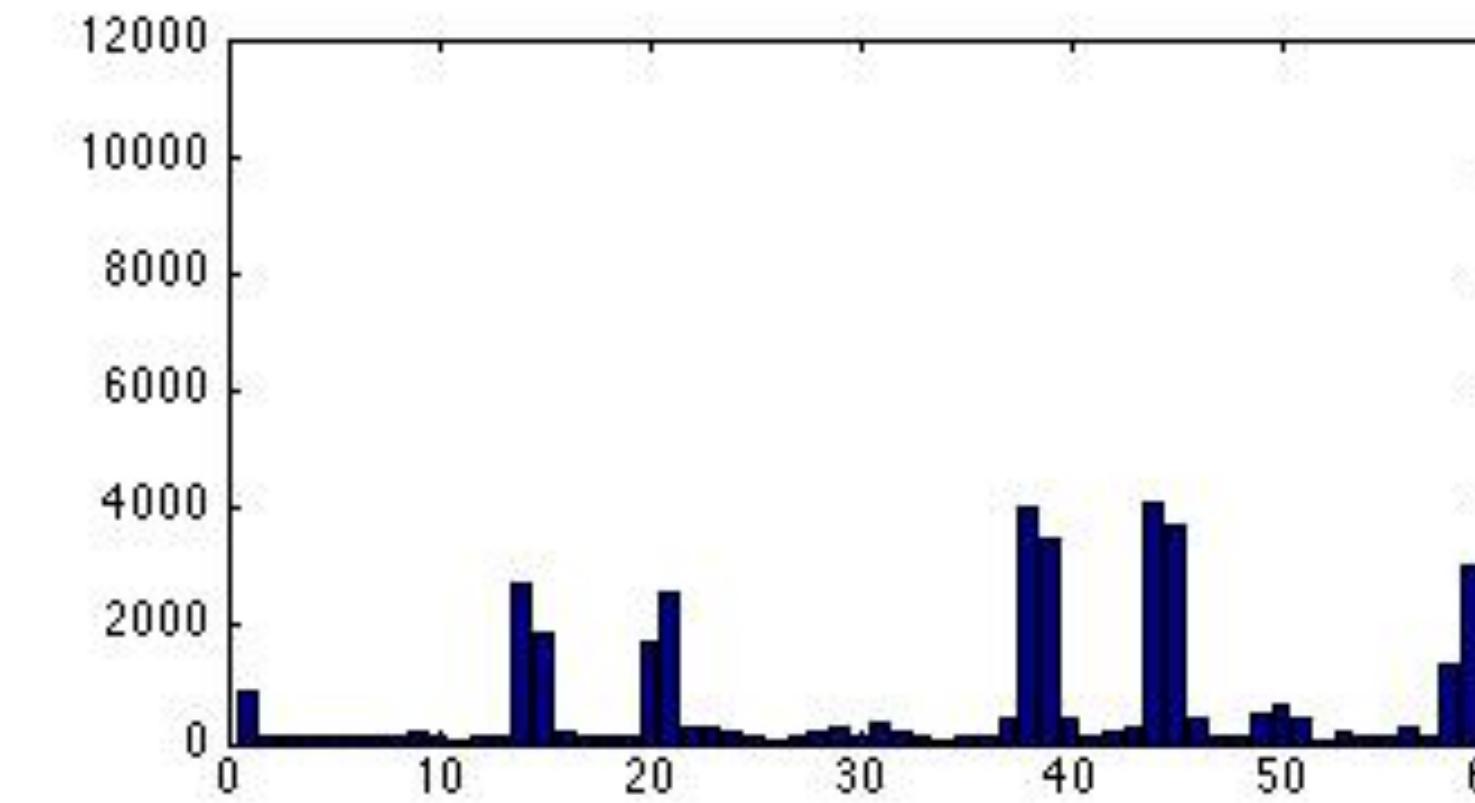
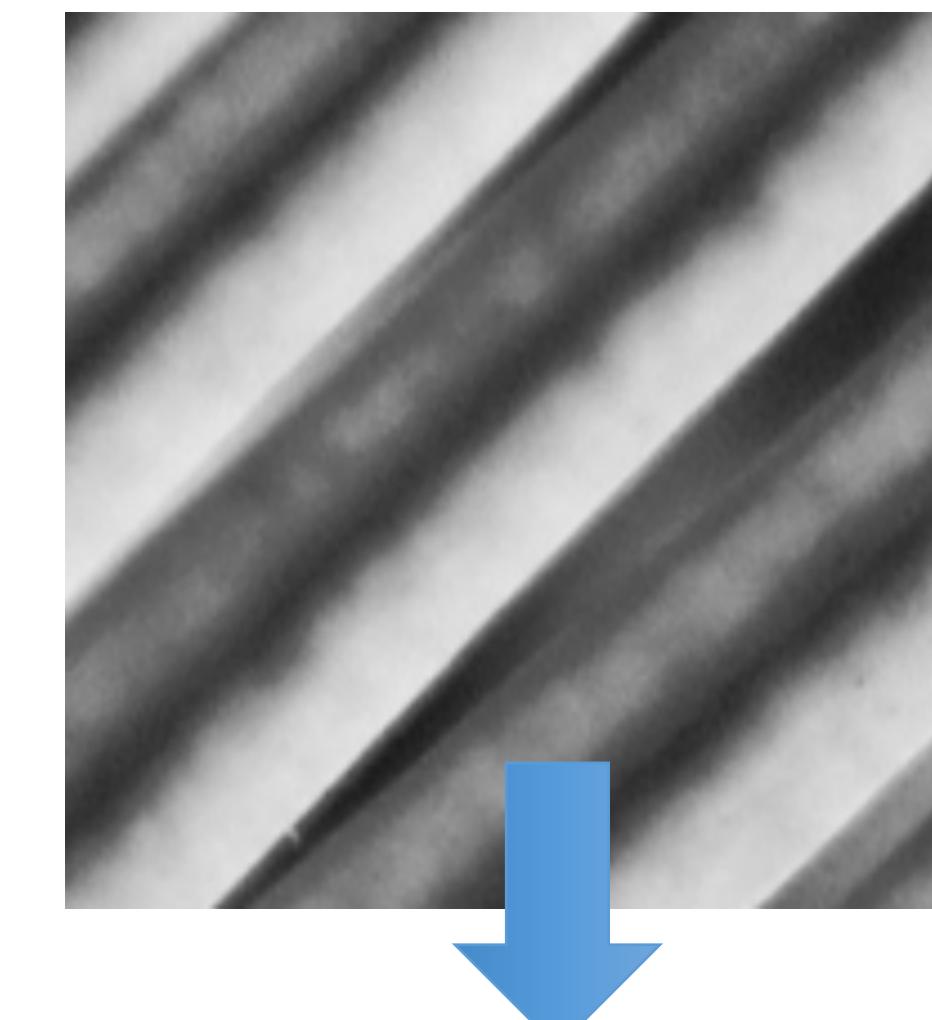
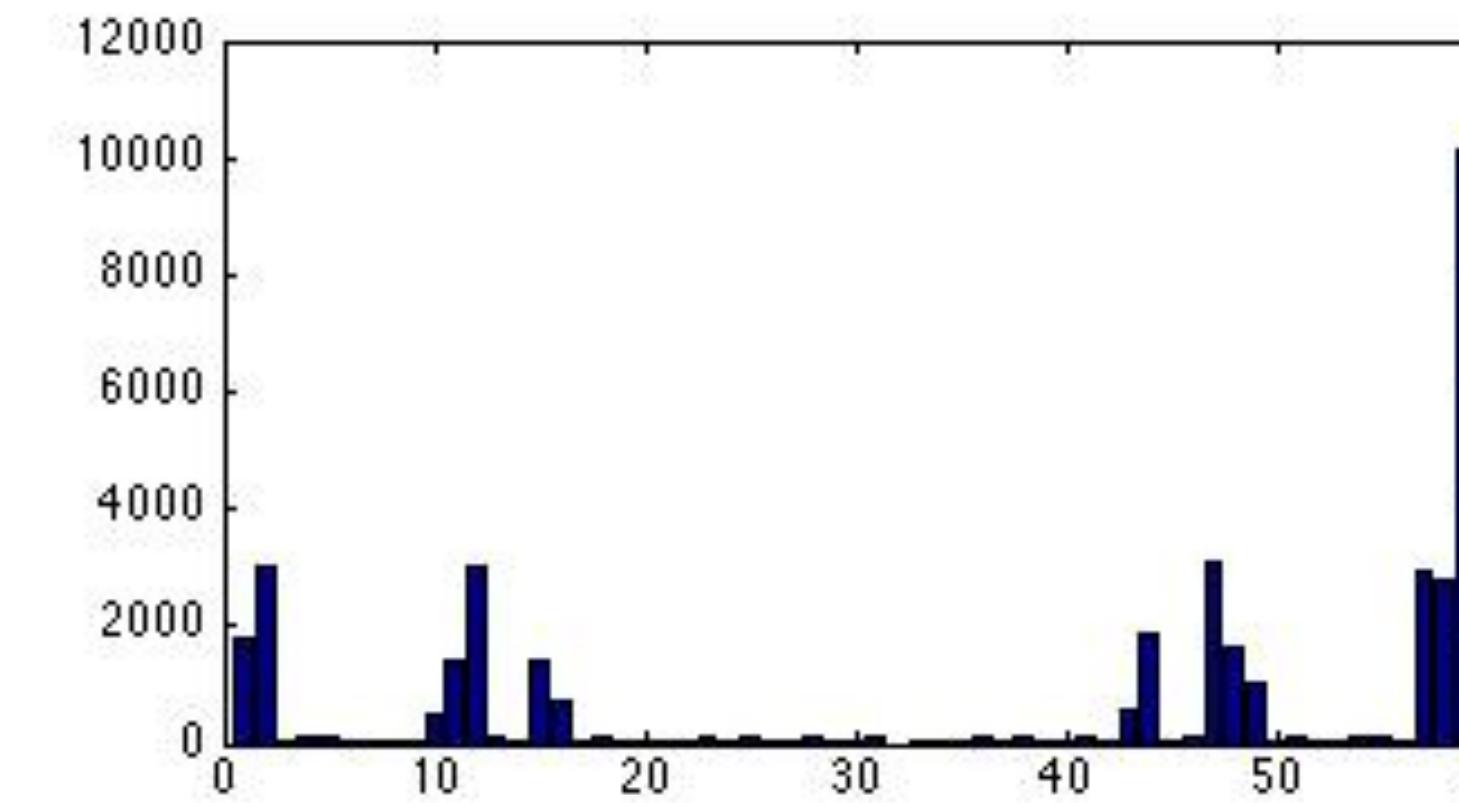
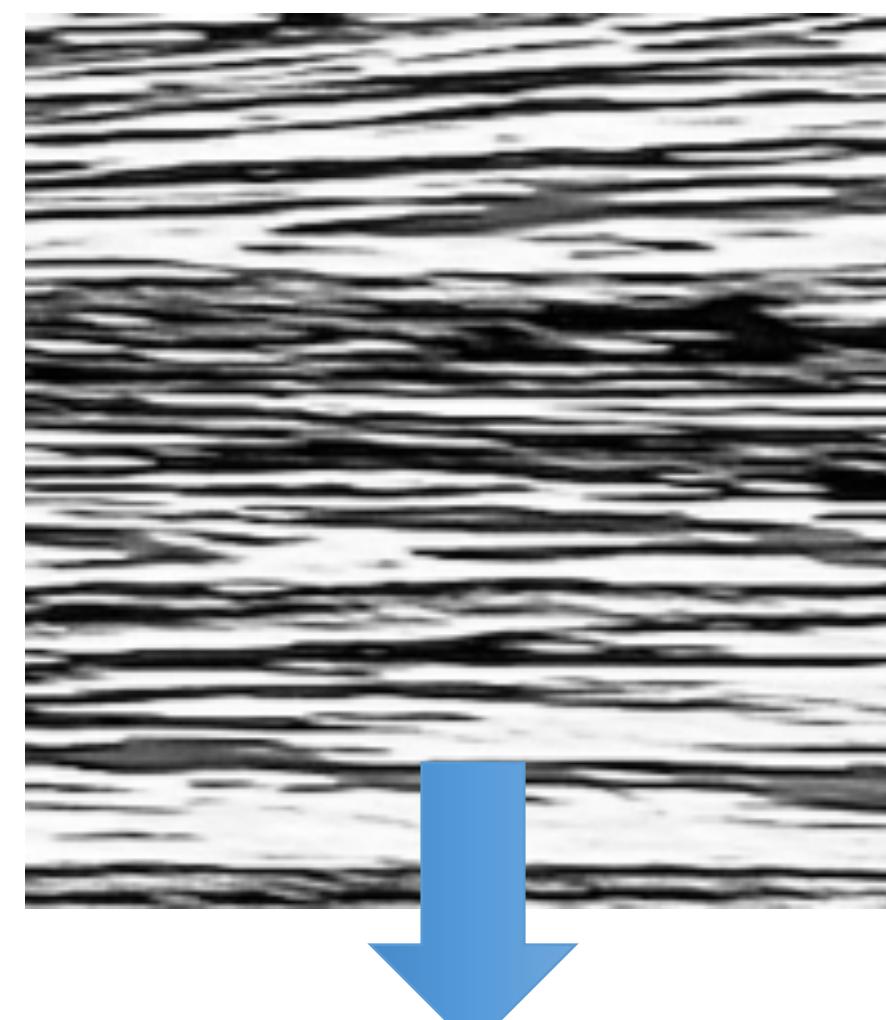
Local Binary Patterns

Similar textures have similar histograms



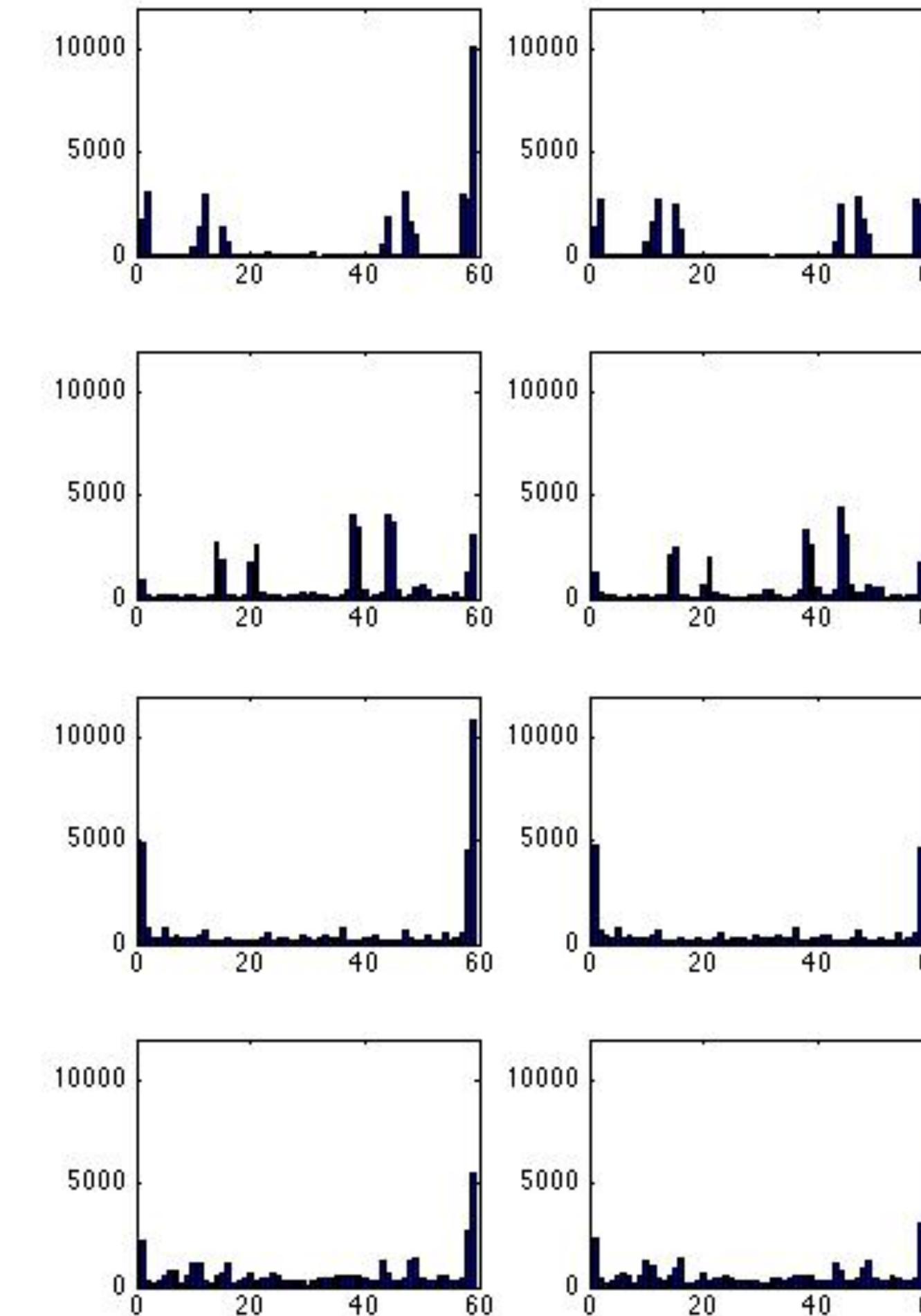
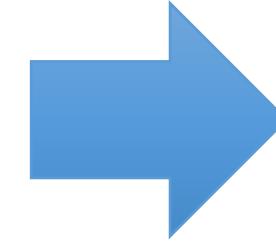
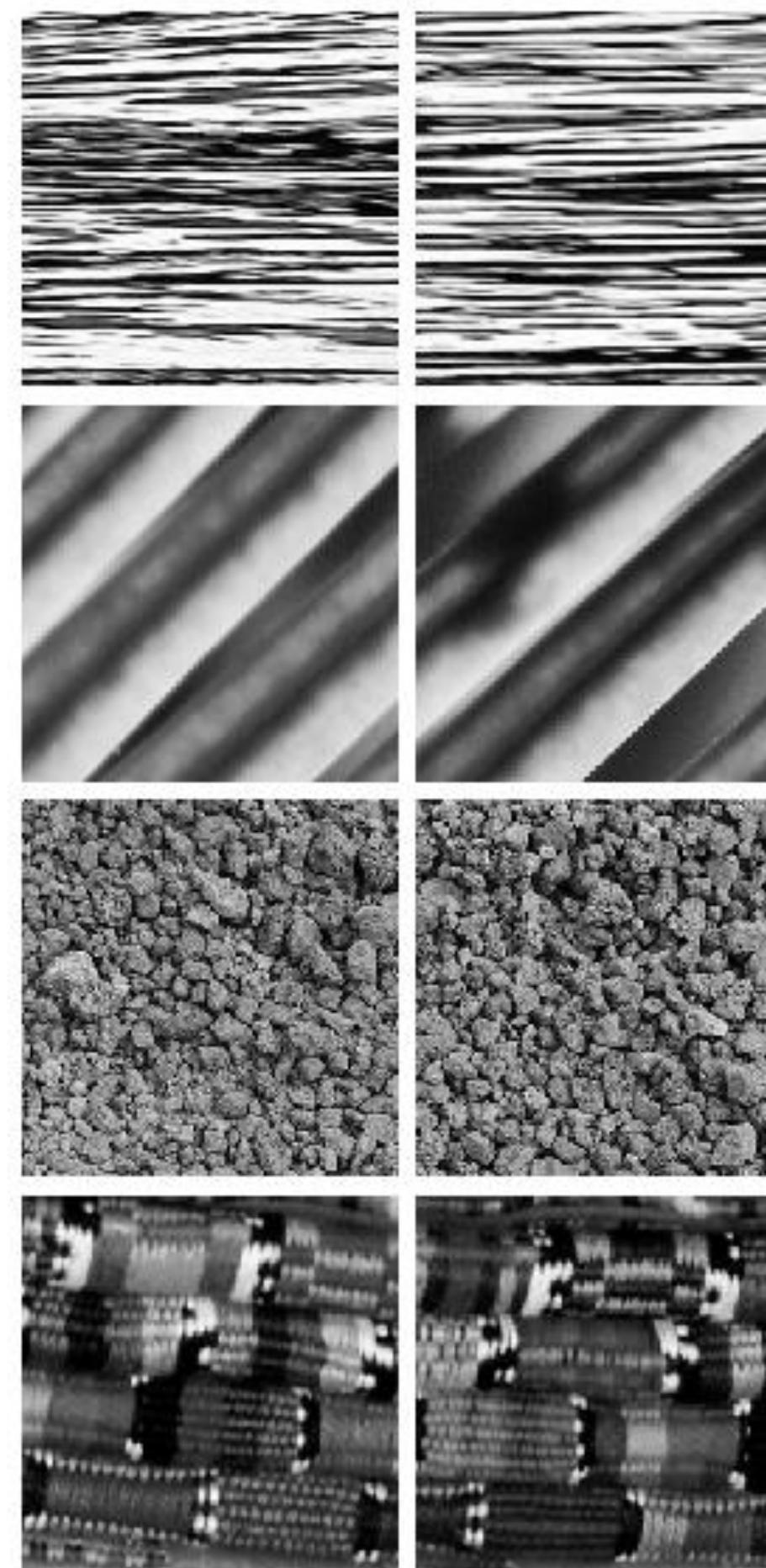
Local Binary Patterns

Similar textures have similar histograms



Local Binary Patterns

Similar textures have similar histograms



LBP for face recognition



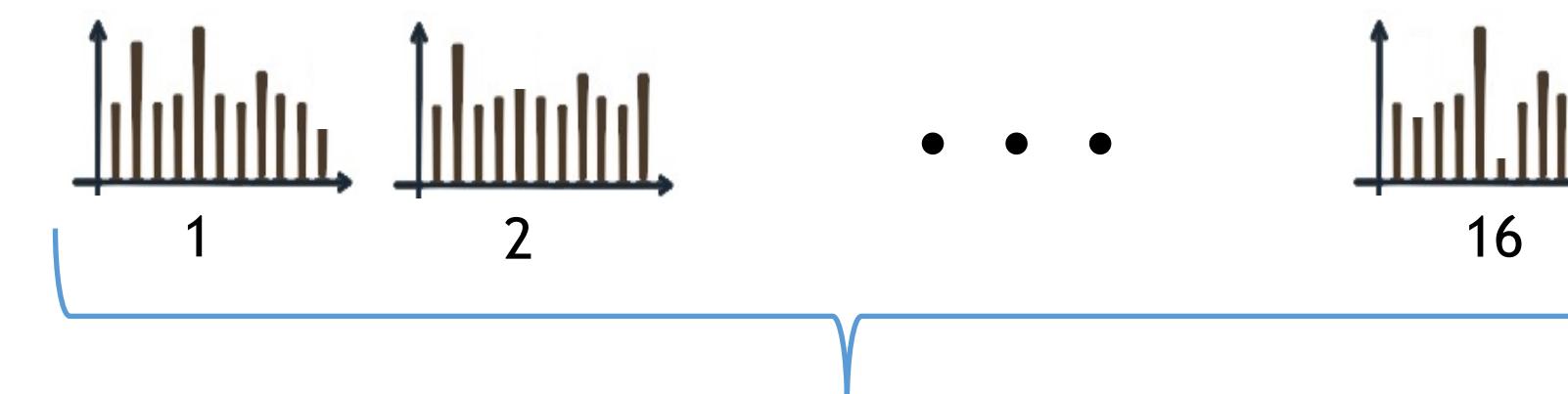
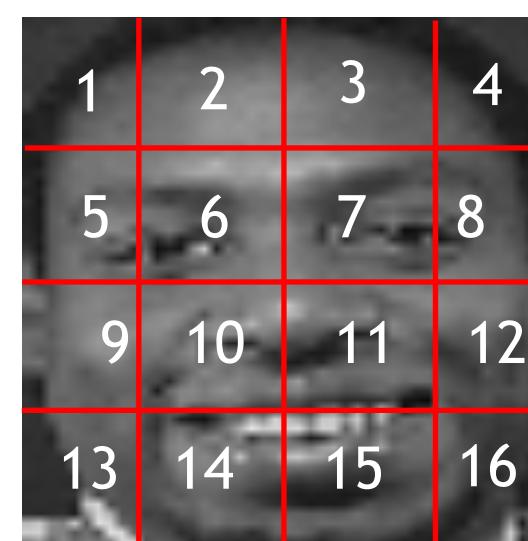
In the training set there are k classes.

For each class we have n training images.

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

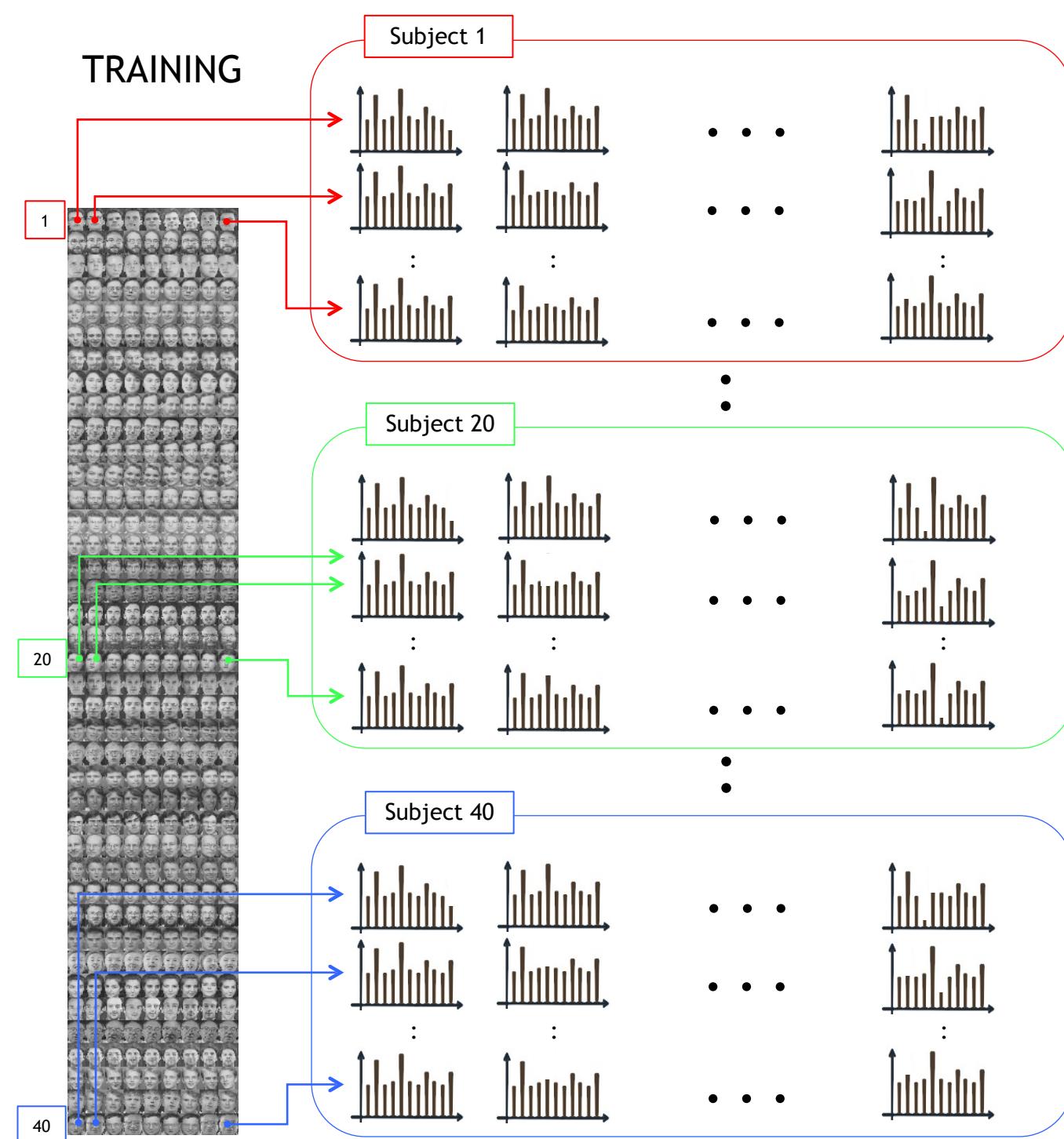
Each image is partitioned into 16 cells.

In each cell we extract LBP features.



A face is described using a feature of $16 \times 59 = 944$ elements

LBP for face recognition



Training Data

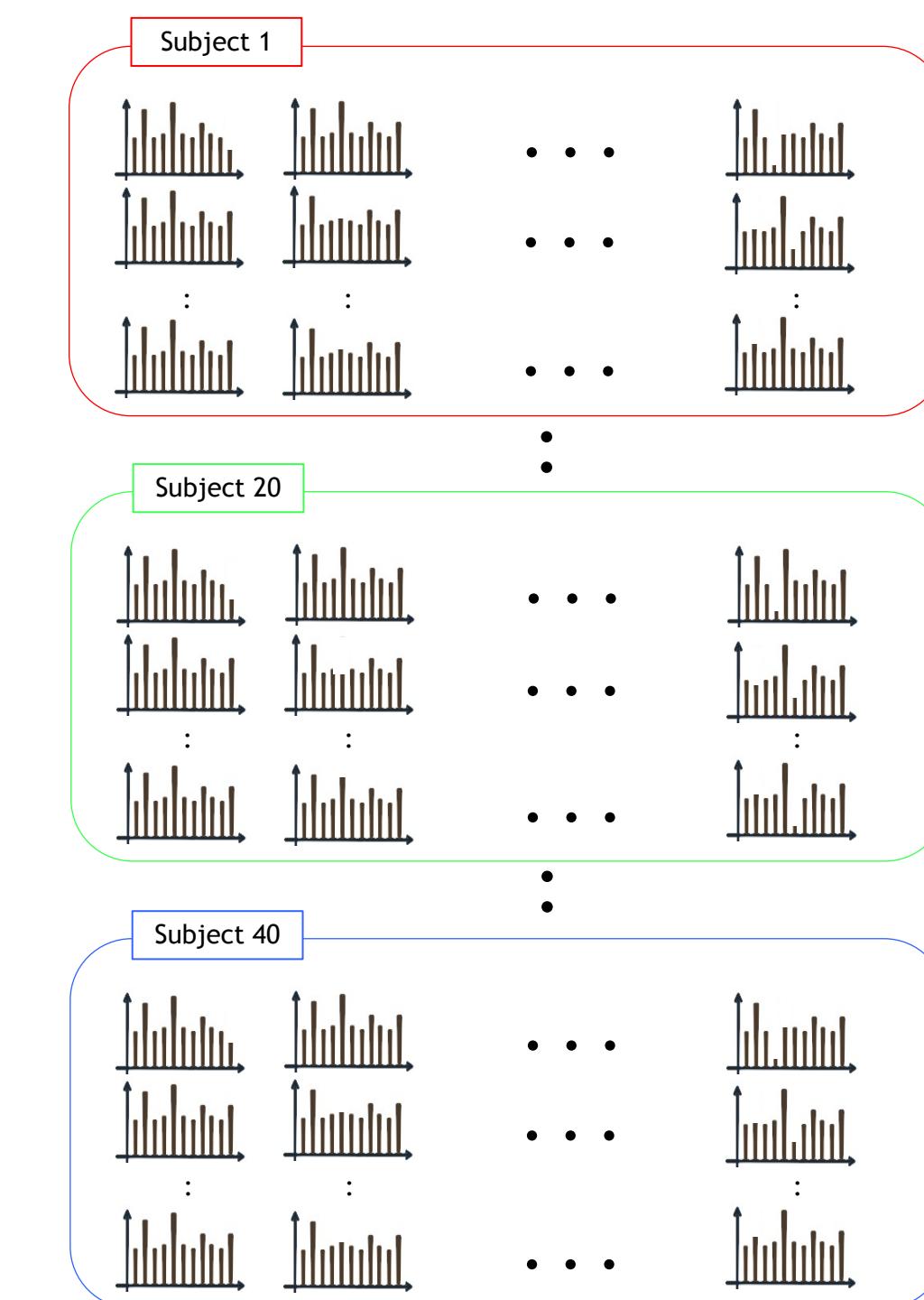
Table with:

$$9 \times 40 = 360 \text{ rows}$$

and

$$16 \times 59 = 944 \text{ columns}$$

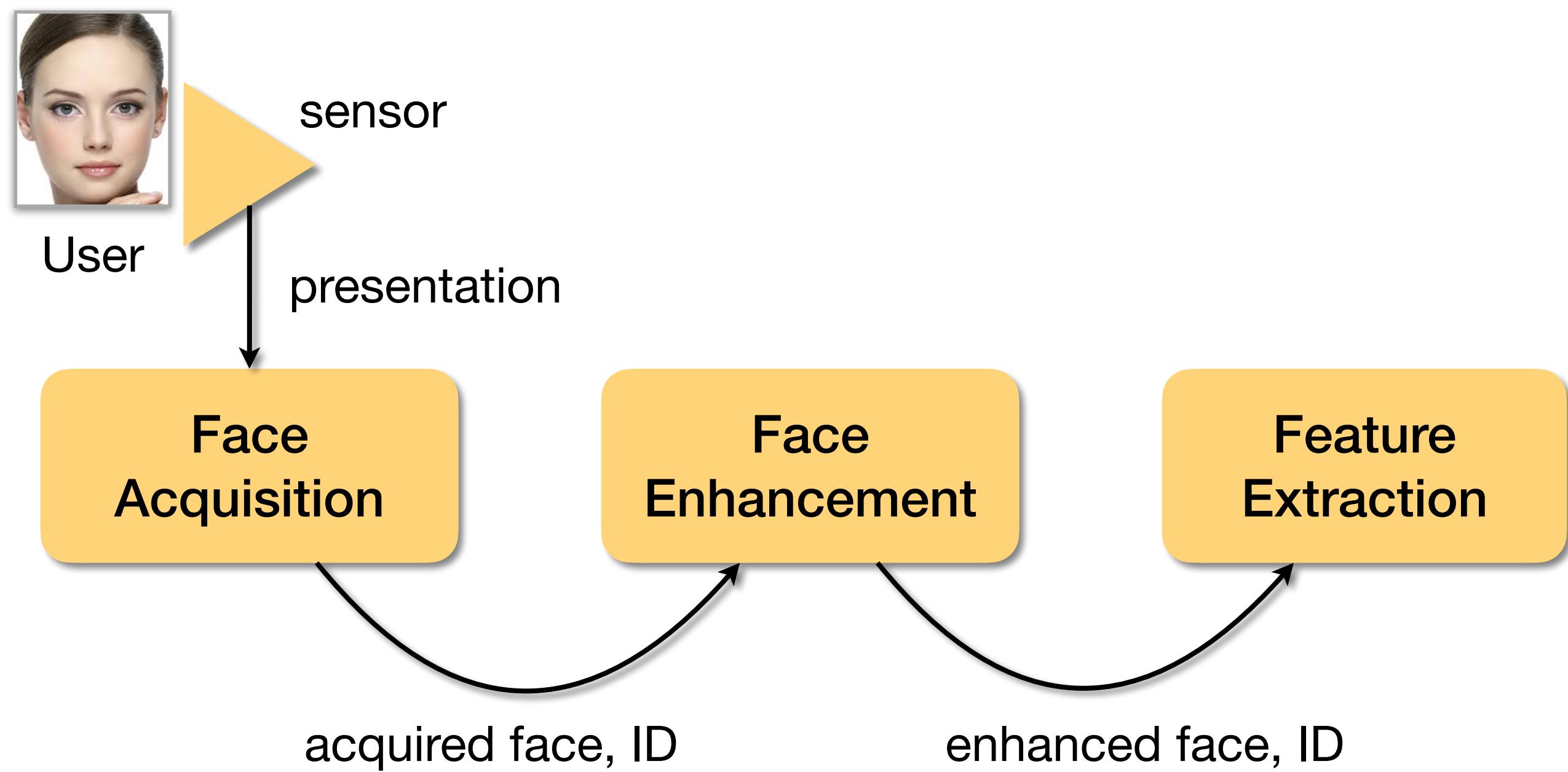
LBP for face recognition



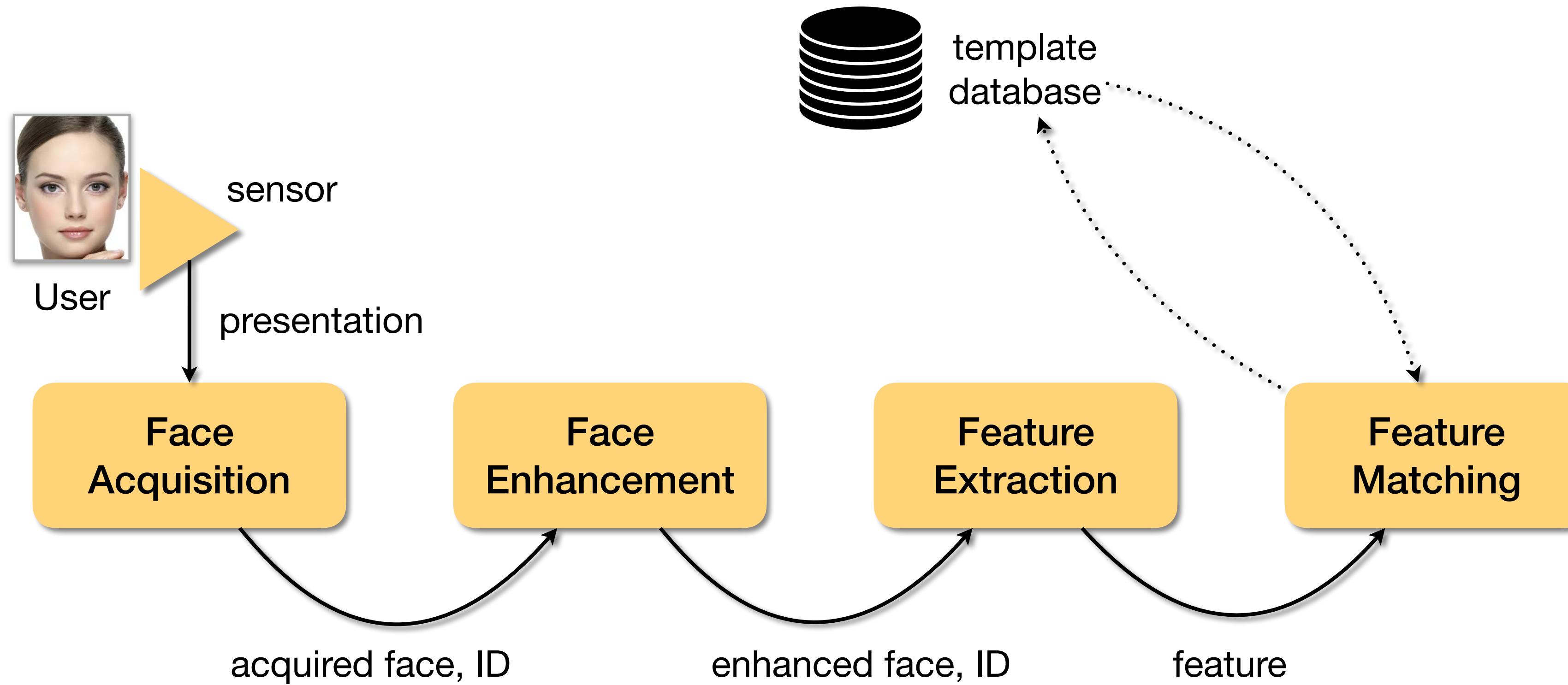
LBP for face recognition



Face Recognition



Face Recognition



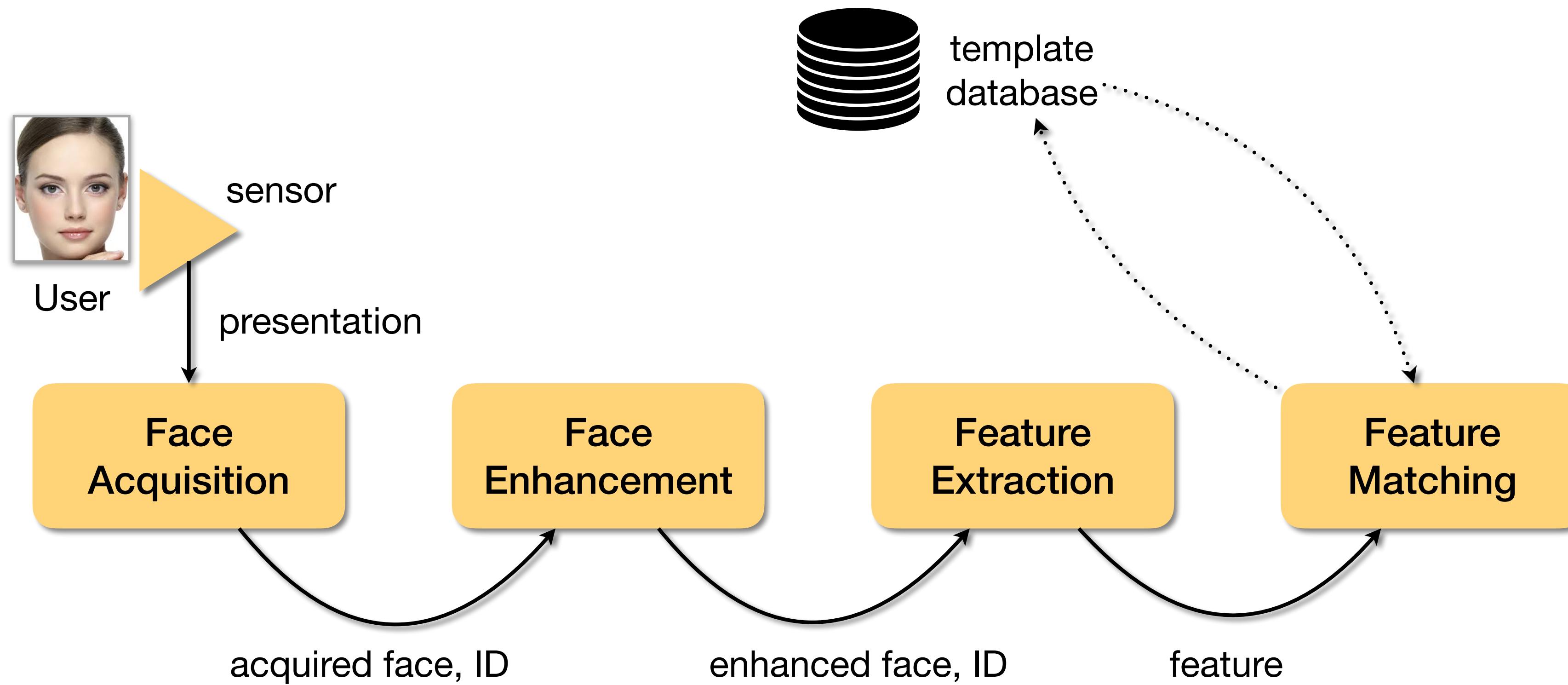
LBP for face recognition (Feature Matching)



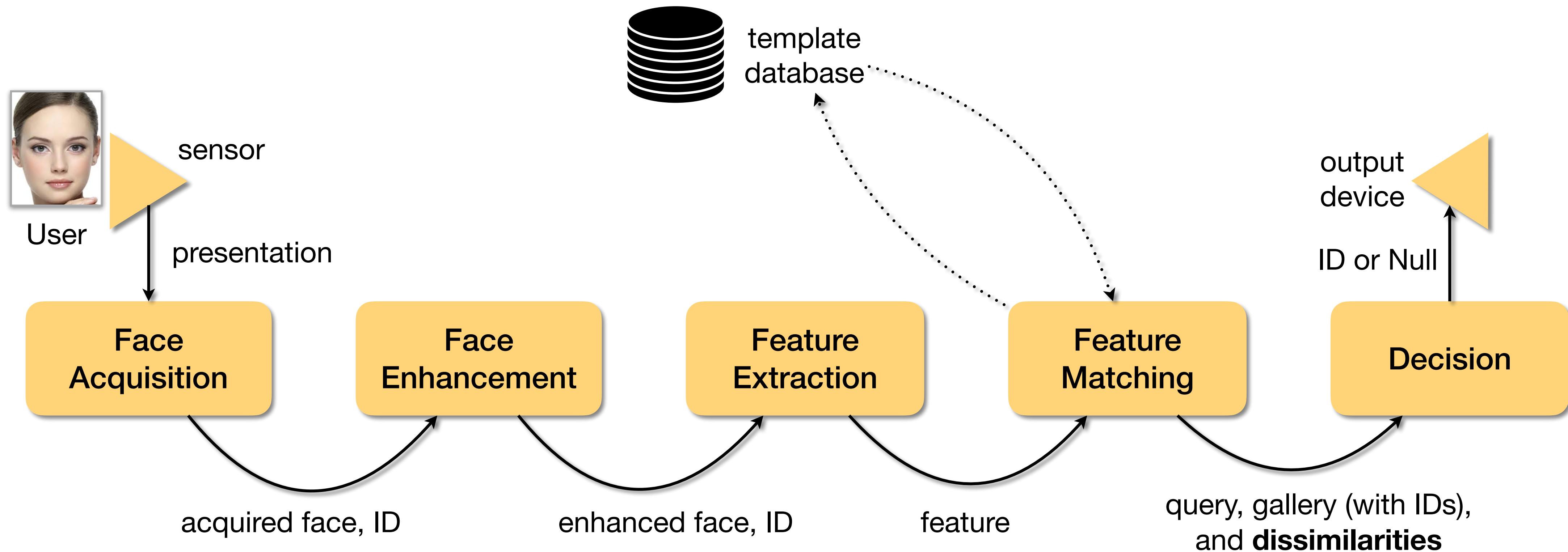
LBP for face recognition (Feature Matching)



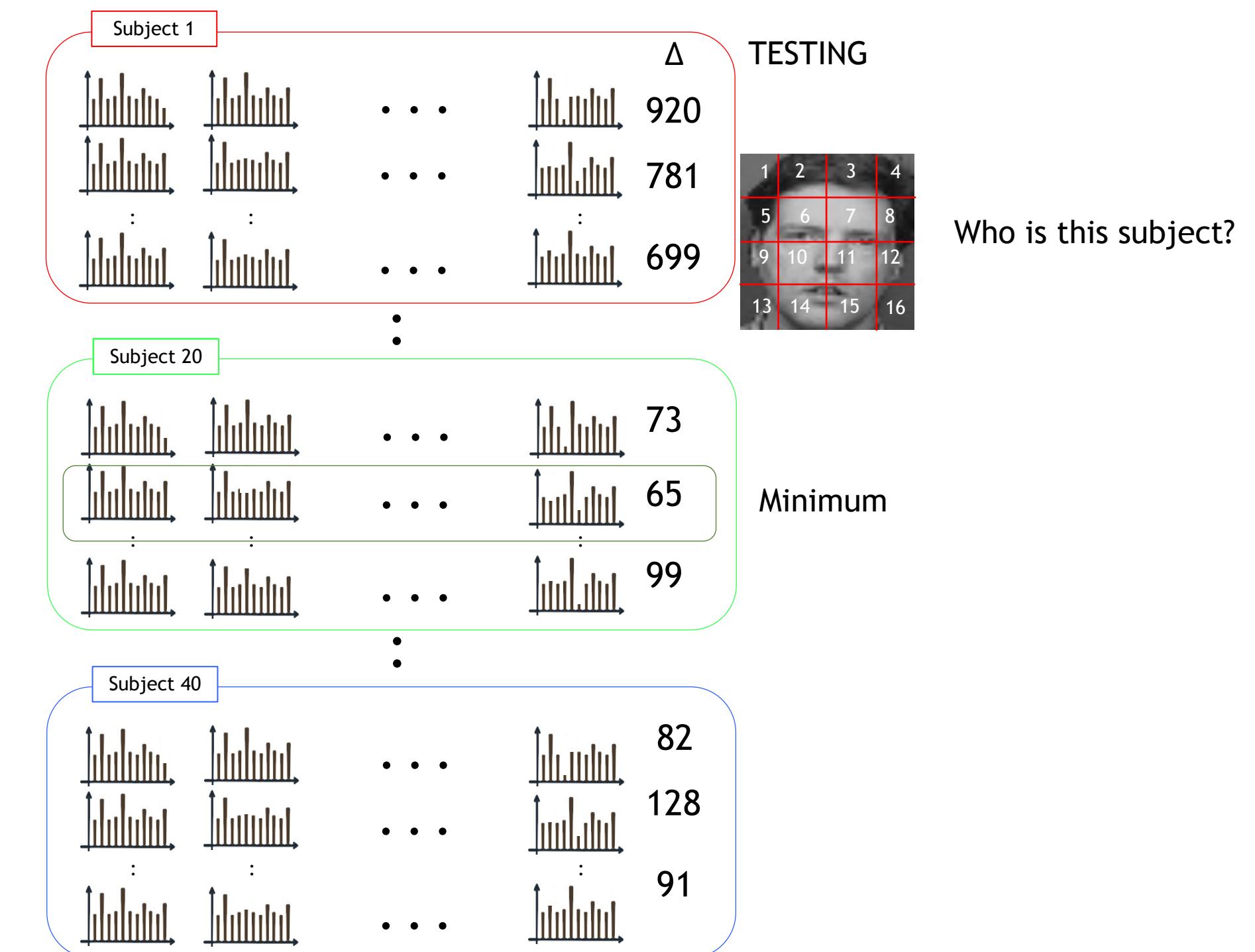
Face Recognition



Face Recognition



LBP for face recognition (Decision)



Feature Extraction

Focus

2D-appearance-based methods.



Types

Handcrafted features from Computer Vision.

Data-driven learned features from Machine Learning.

Feature Extraction

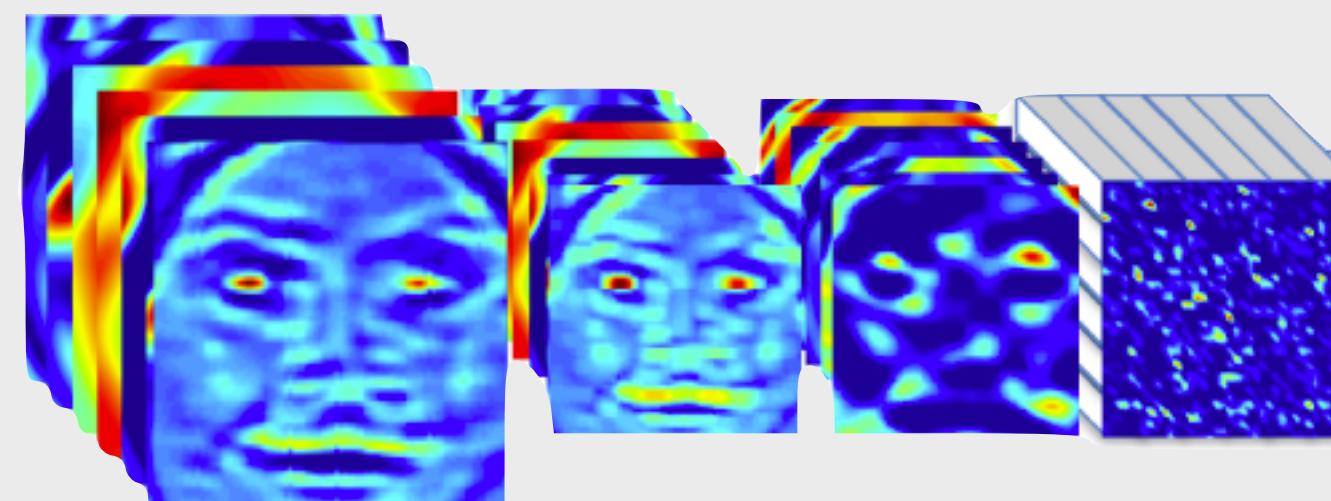
Focus

2D-appearance-based methods.

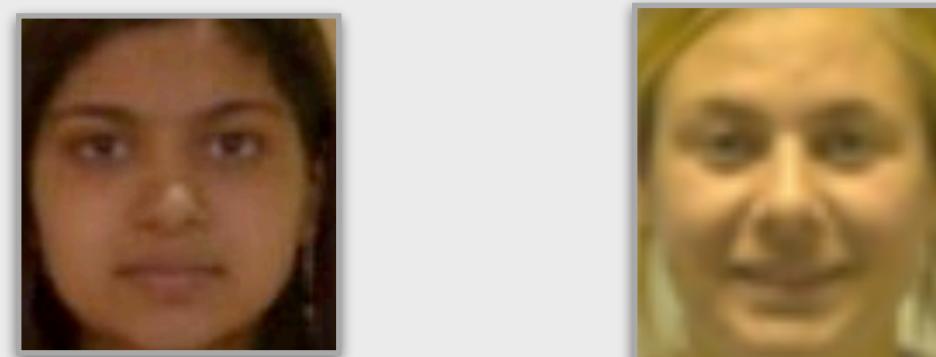


Types

Handcrafted features from Computer Vision.



Data-driven learned features from Machine Learning.



Feature Extraction

Deep Convolutional Neural Networks

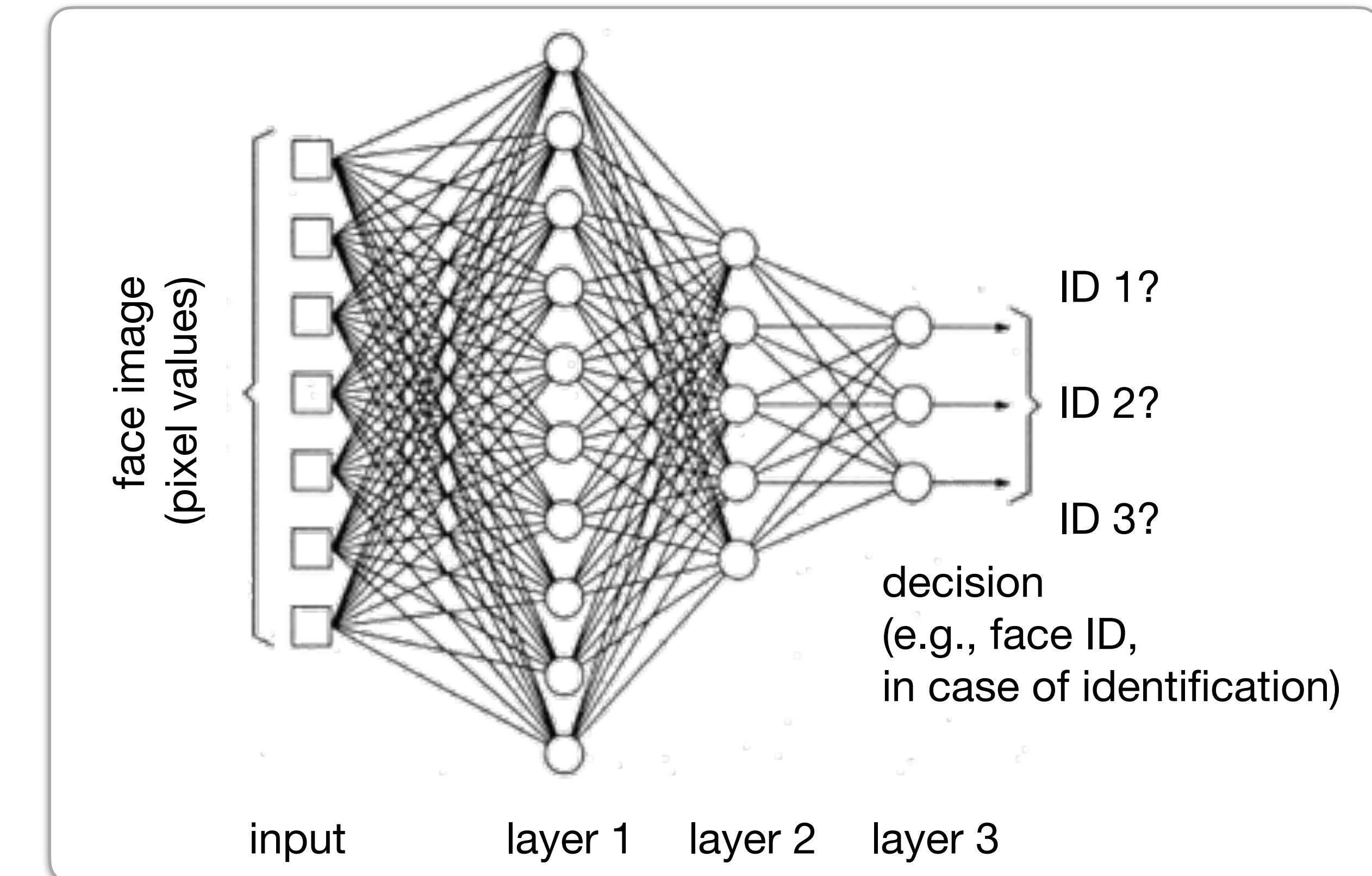
Feature Extraction

Deep Convolutional Neural Networks

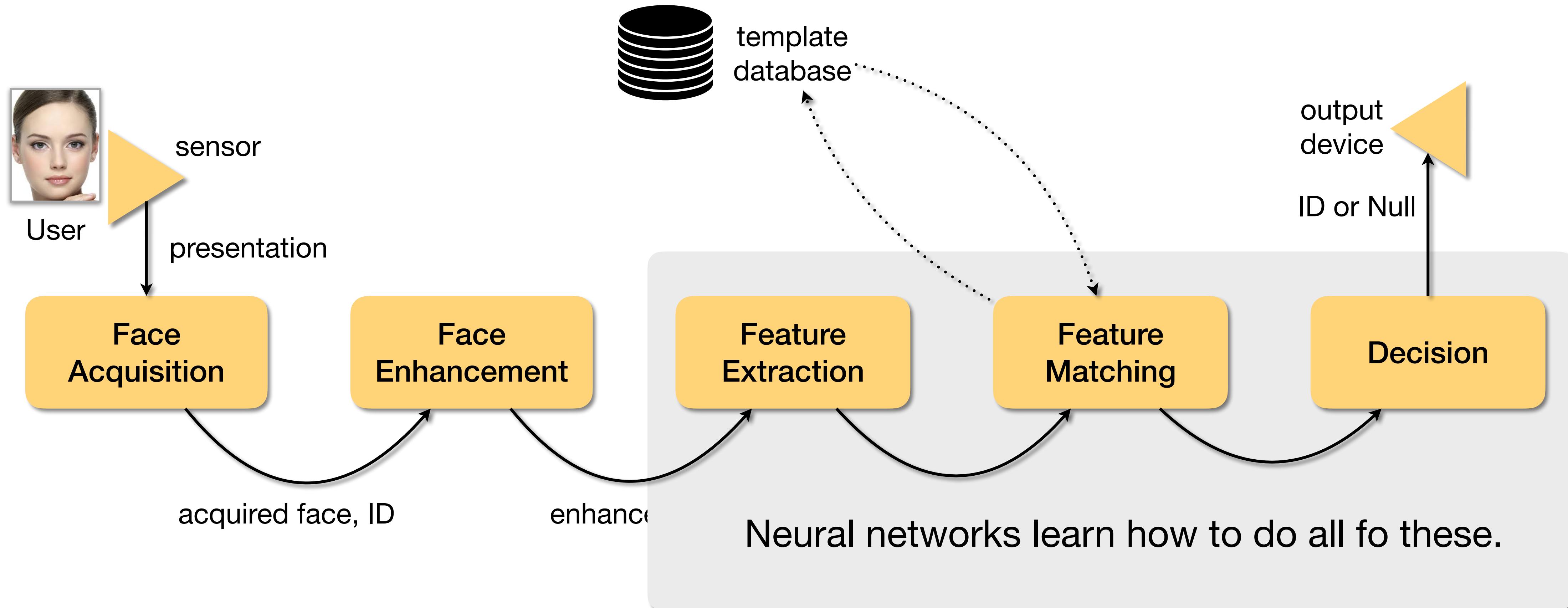
From pixels to classification decision.

Hierarchy of feature extractors.

Each layer extracts features from previous layer.



Face Recognition



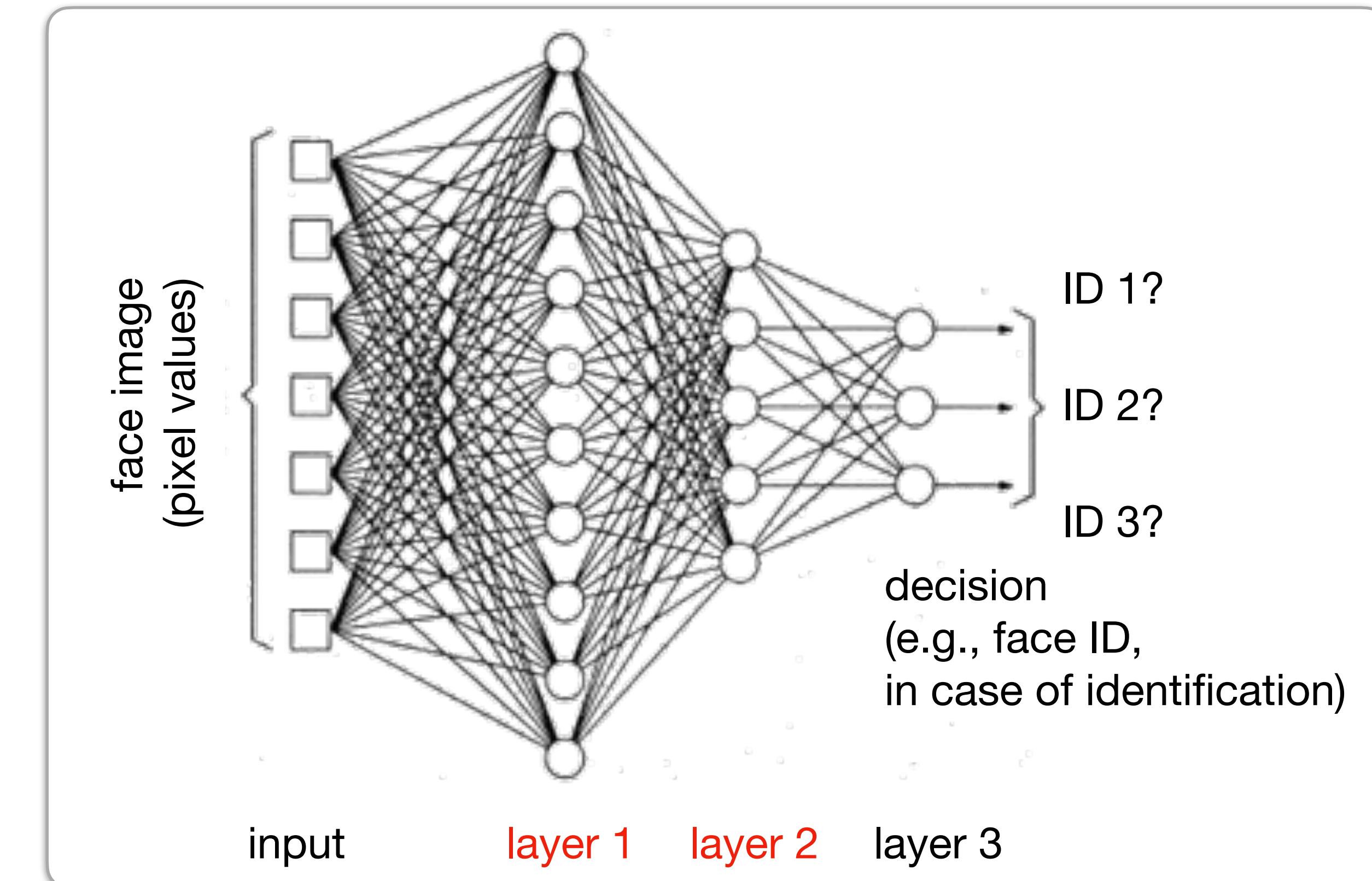
Data-Driven Face Recognition

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.



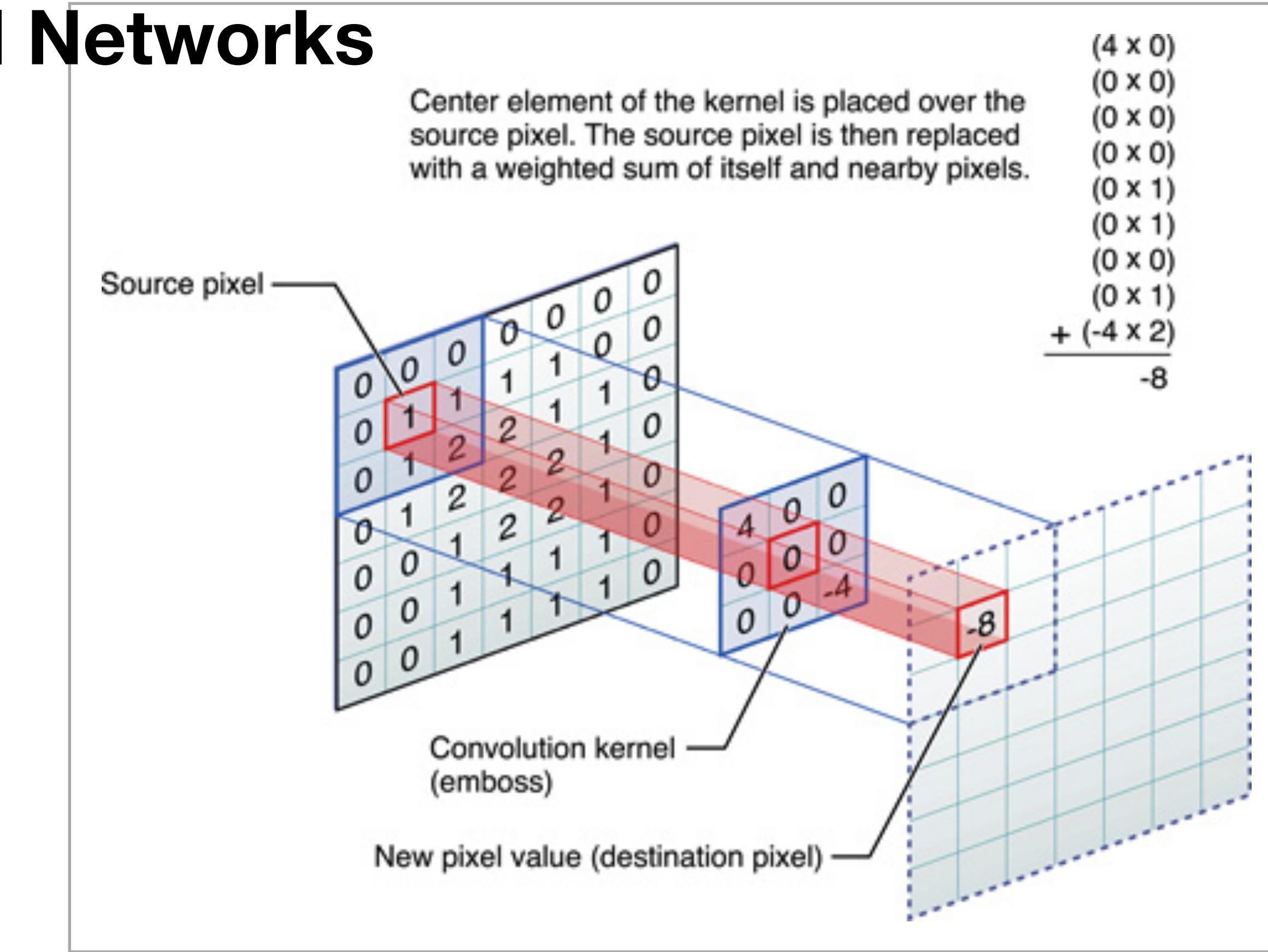
Data-Driven Face Recognition

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/library/archive/documentation/Performance/Conceptual/vImage/ConvolutionOperations/ConvolutionOperations.html>

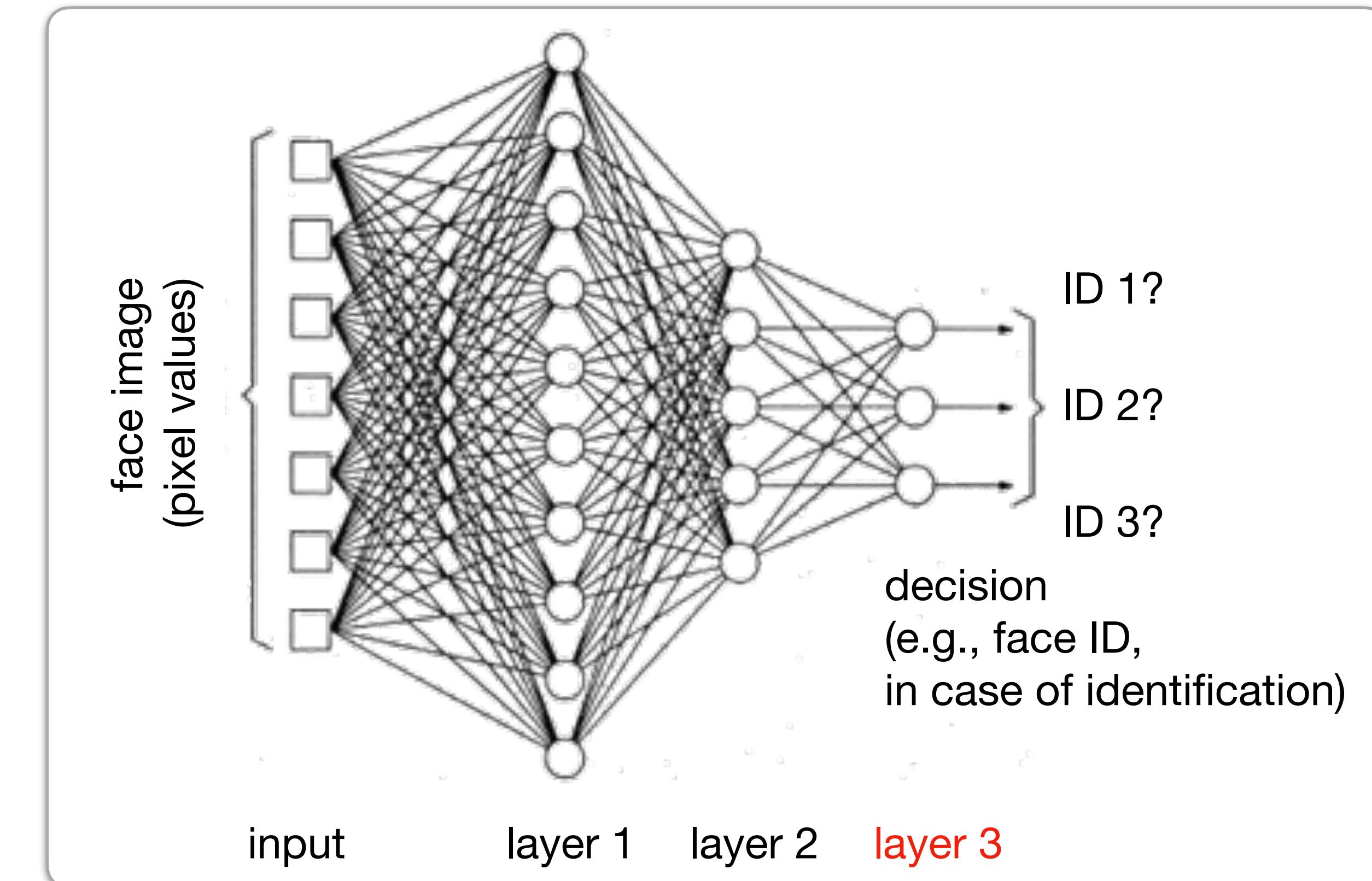
Data-Driven Face Recognition

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).



Data-Driven Face Recognition

Deep Convolutional Neural Networks

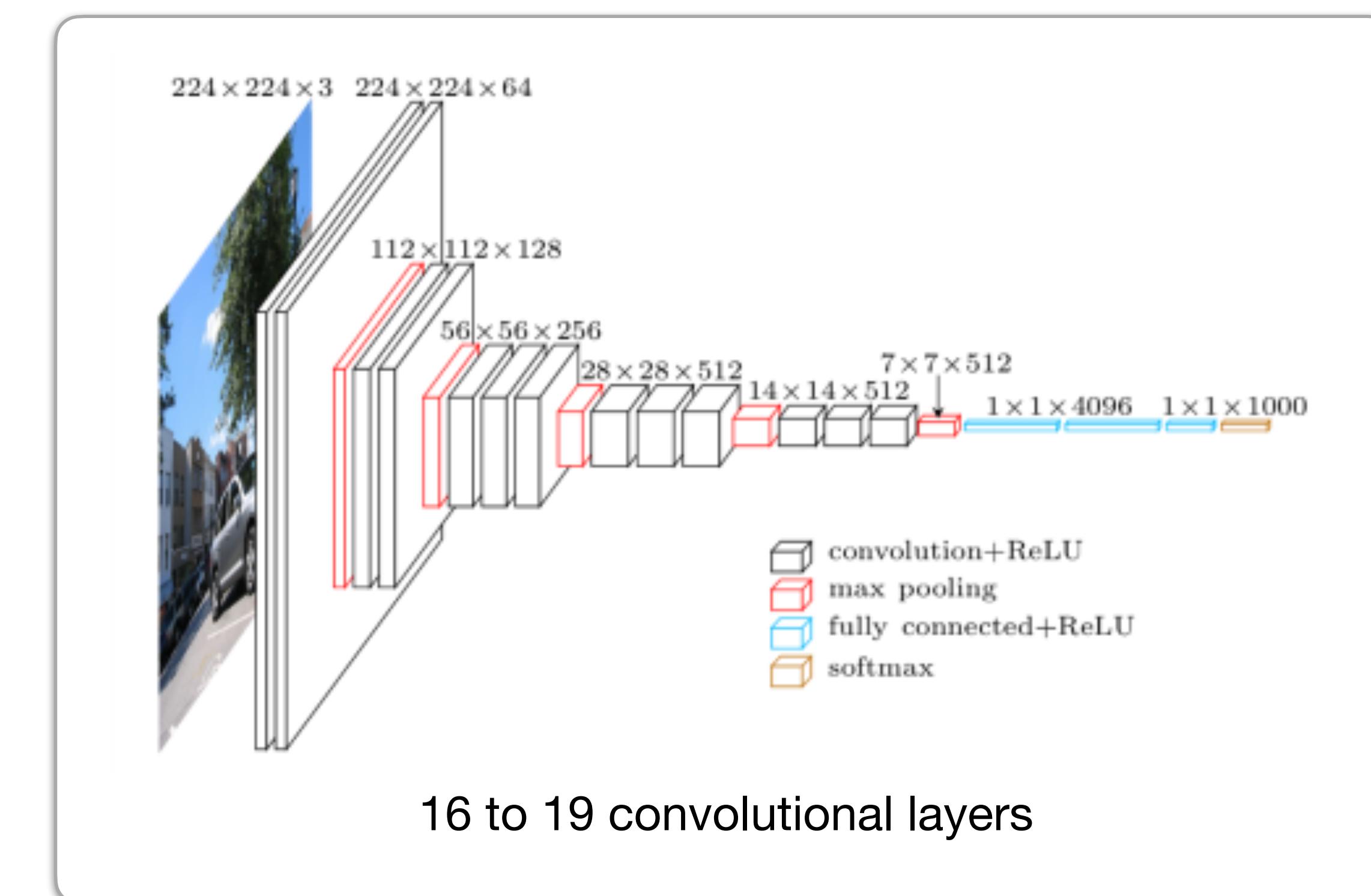
How deep can they be?

“Deep” refers to the number of layers.

E.g., VGG16

Simonyan and Zisserman

*Very Deep Convolutional Networks
for Large-Scale Image Recognition*

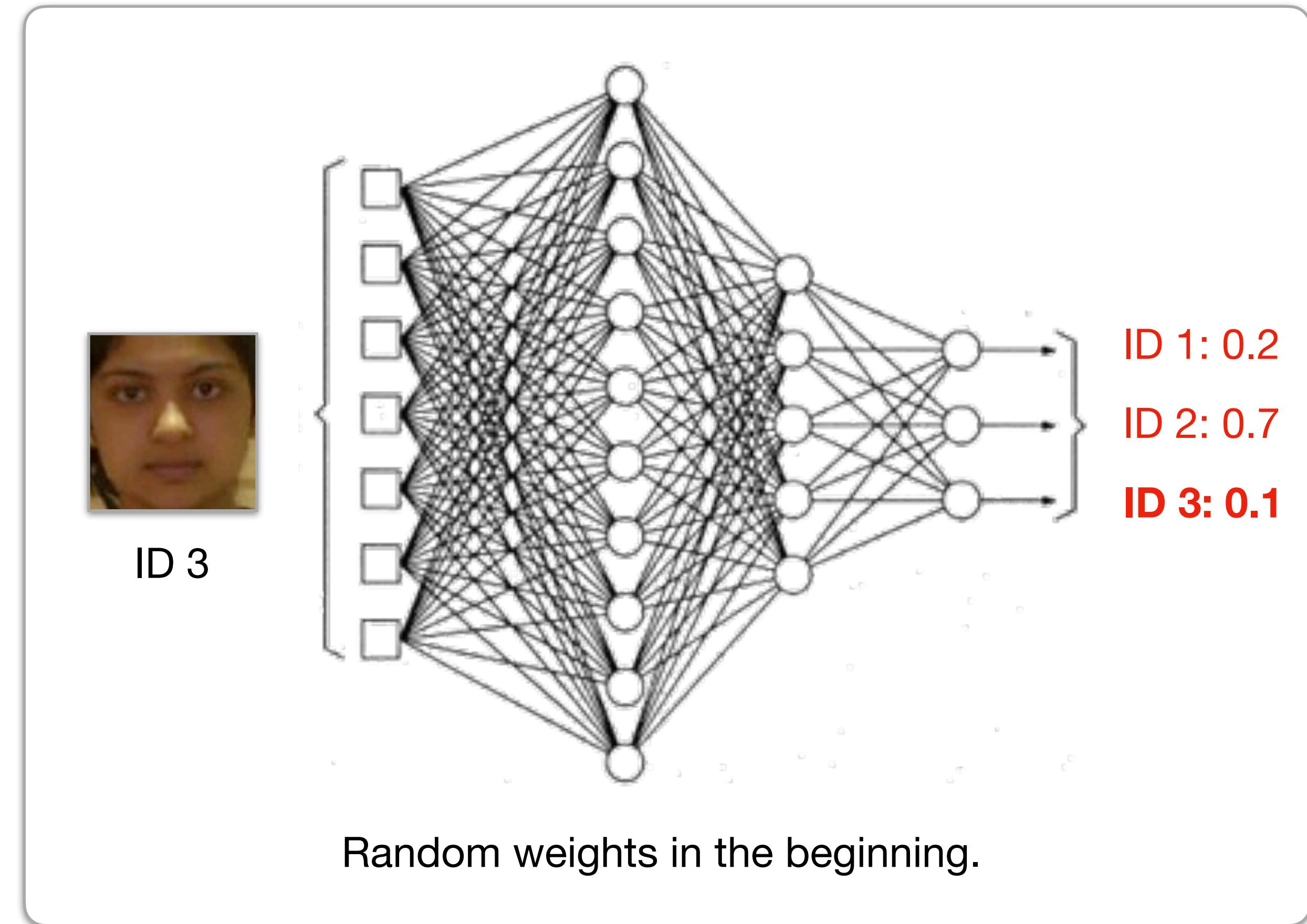


Data-Driven Face Recognition

Deep Learning

Training

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

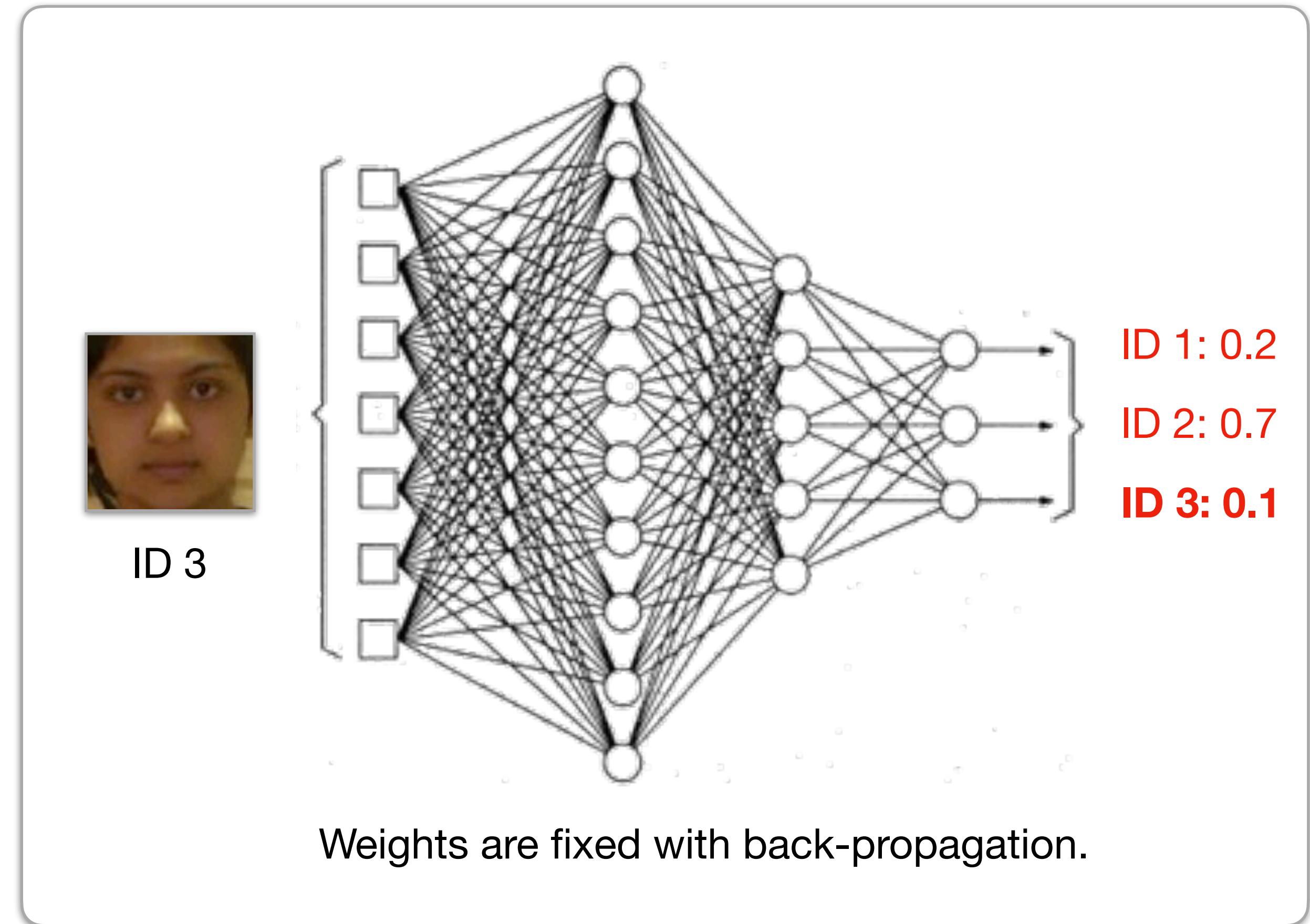


Data-Driven Face Recognition

Deep Learning

Training

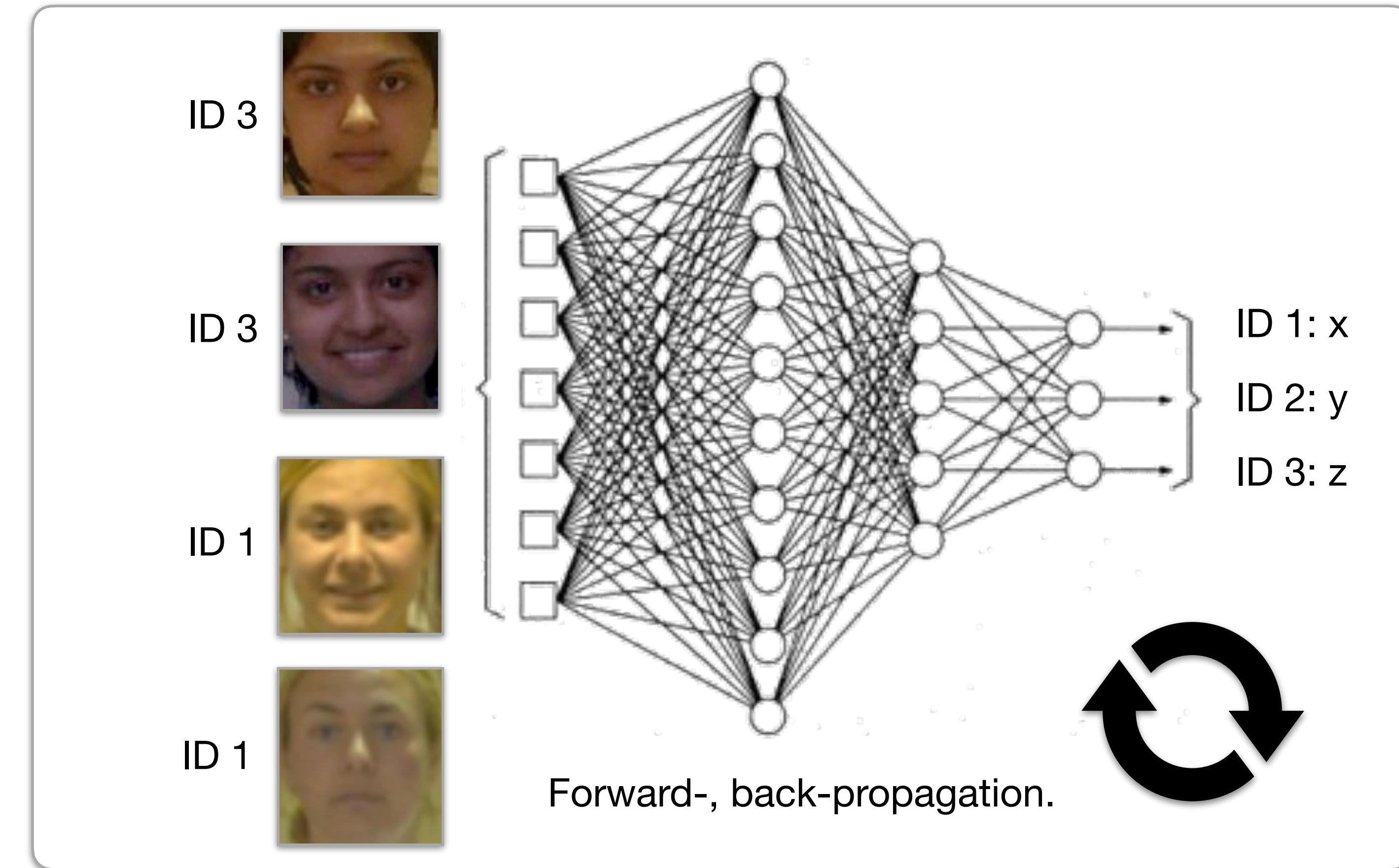
Back-propagation is used to fix the weights of the convolutions within the network.



Data-Driven Face Recognition

Deep Learning

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



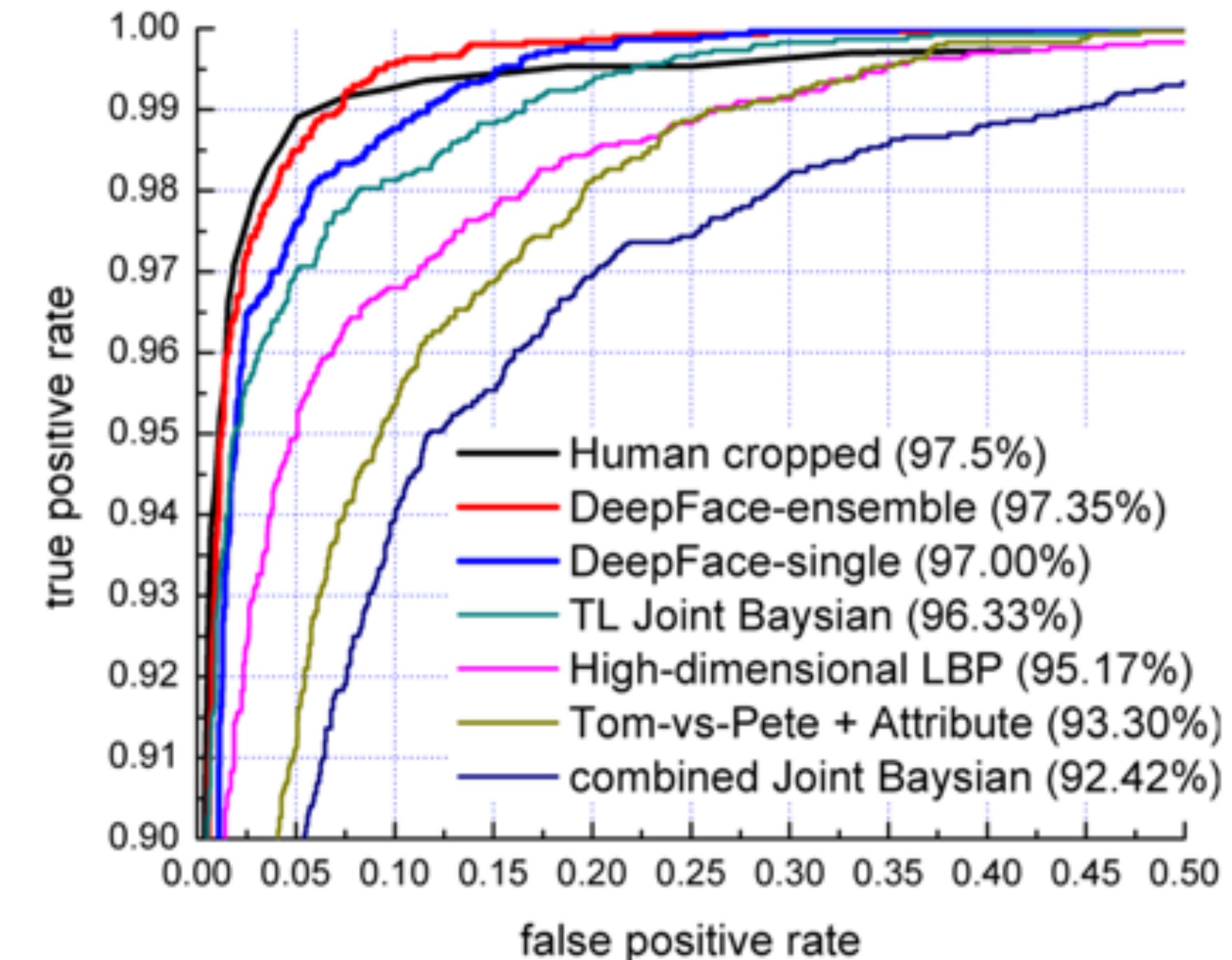
Data-Driven Face Recognition

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



Data-Driven Face Recognition

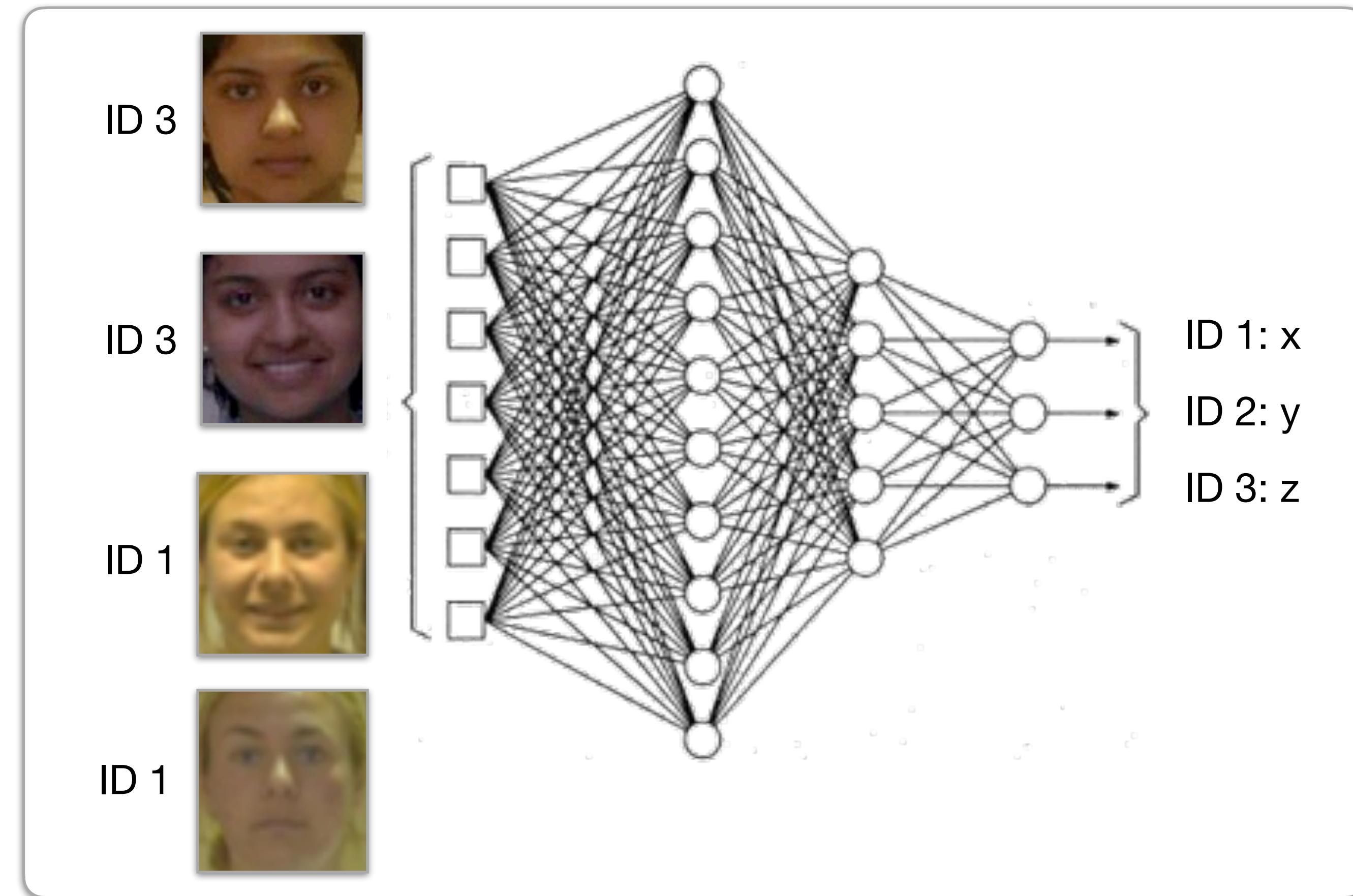
Deep Learning

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).



S'up Next?

Improving Deep Learning

ArcFace

Additive Angular Margin Loss for Deep Face Recognition

Deng et al., CVPR 2019.

<https://bit.ly/3qsQmch>

