Face Recognition II

COMP 388-002/488-002 Biometrics

Daniel Moreira

Fall 2025

LOYOLA UNIVERSITY CHICAGO

Today we will…

Get to know
Face acquisition and enhancement.

Today's Attendance

Please fill out the form

forms.gle/YcL7kqRcZQZMHmWY6

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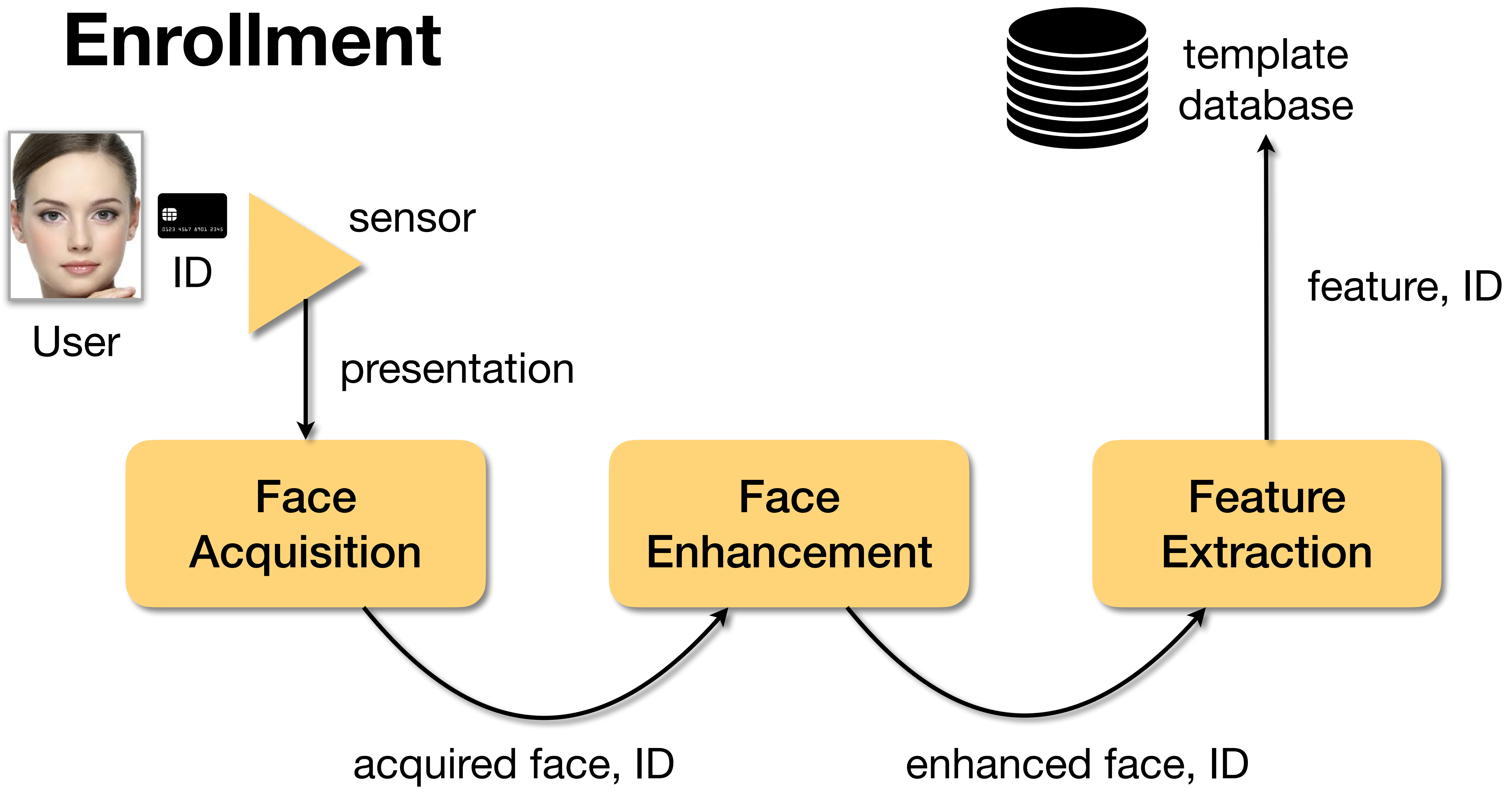
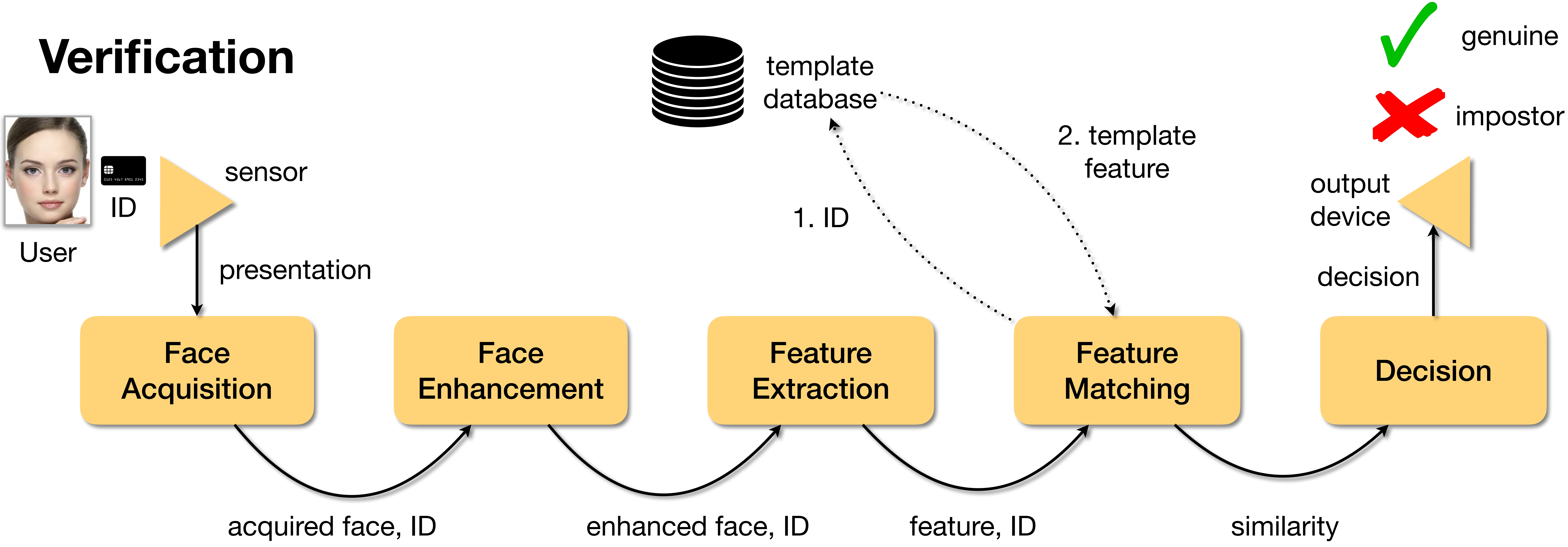
Face Recognition

Enrollment



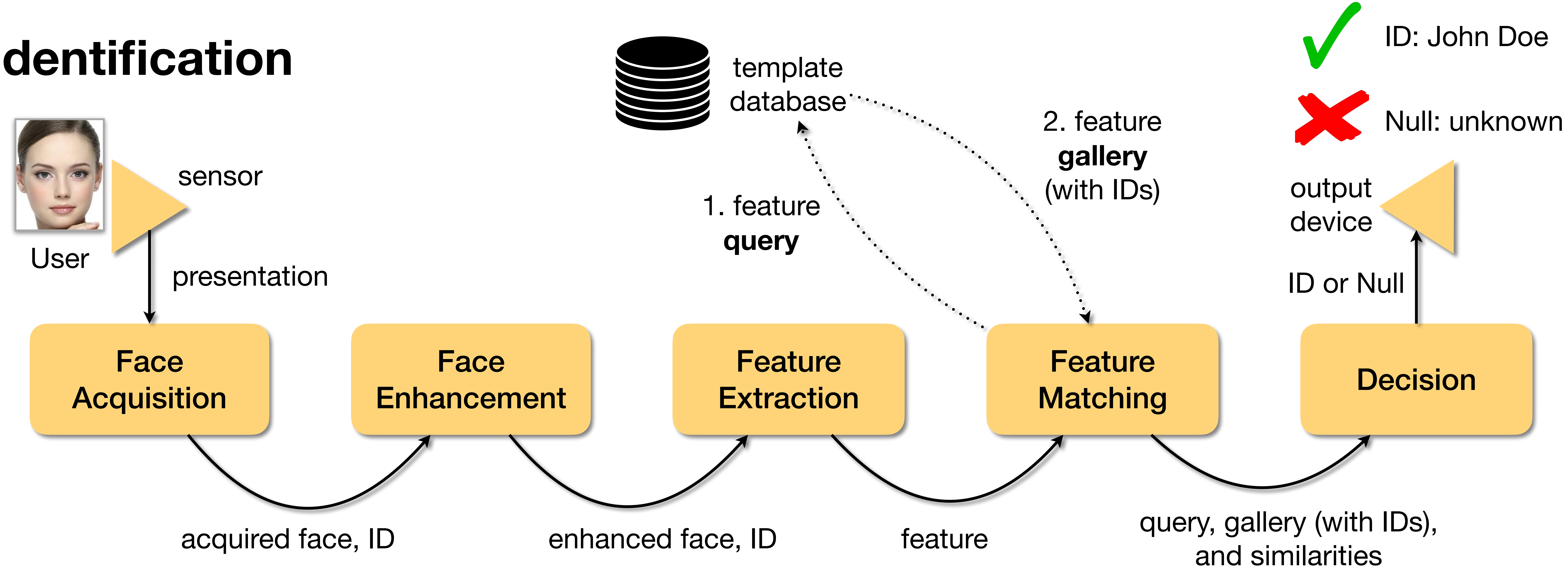
Face Recognition

Verification

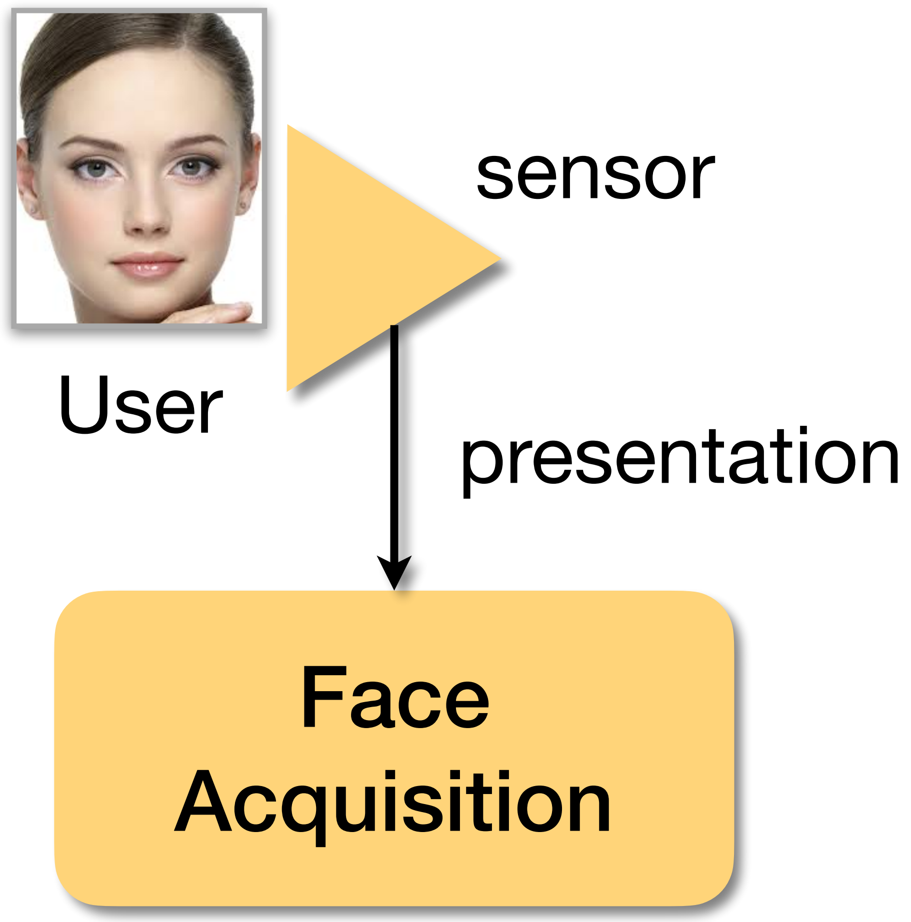


Face Recognition

Identification



Face Recognition



Acquisition

On-line versus Off-line

https://www.youtube.com/watch?v=BYN4oF_bi4c

Acquisition

Controlled Acquisition
Right pose, distance and illumination.

https://www.youtube.com/watch?v=BYN4oF_bi4c

https://www.youtube.com/watch?v=-cjoJR3oWcQ

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Acquisition

Controlled Acquisition
Different light wavelengths.

Jain, Ross, and Nadakumar
Introduction to Biometrics
Springer Books, 2011

Captures at visible and near-infrared spectra.

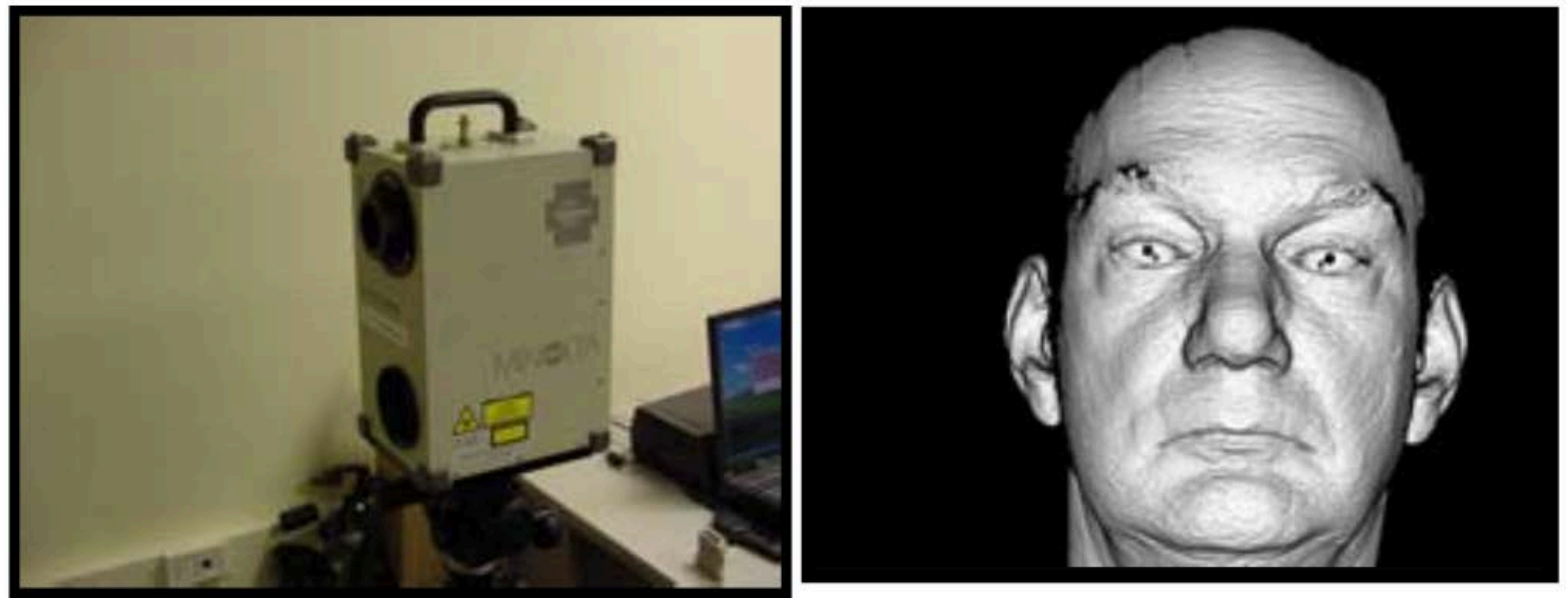
Sony infrared camera.

Acquisition

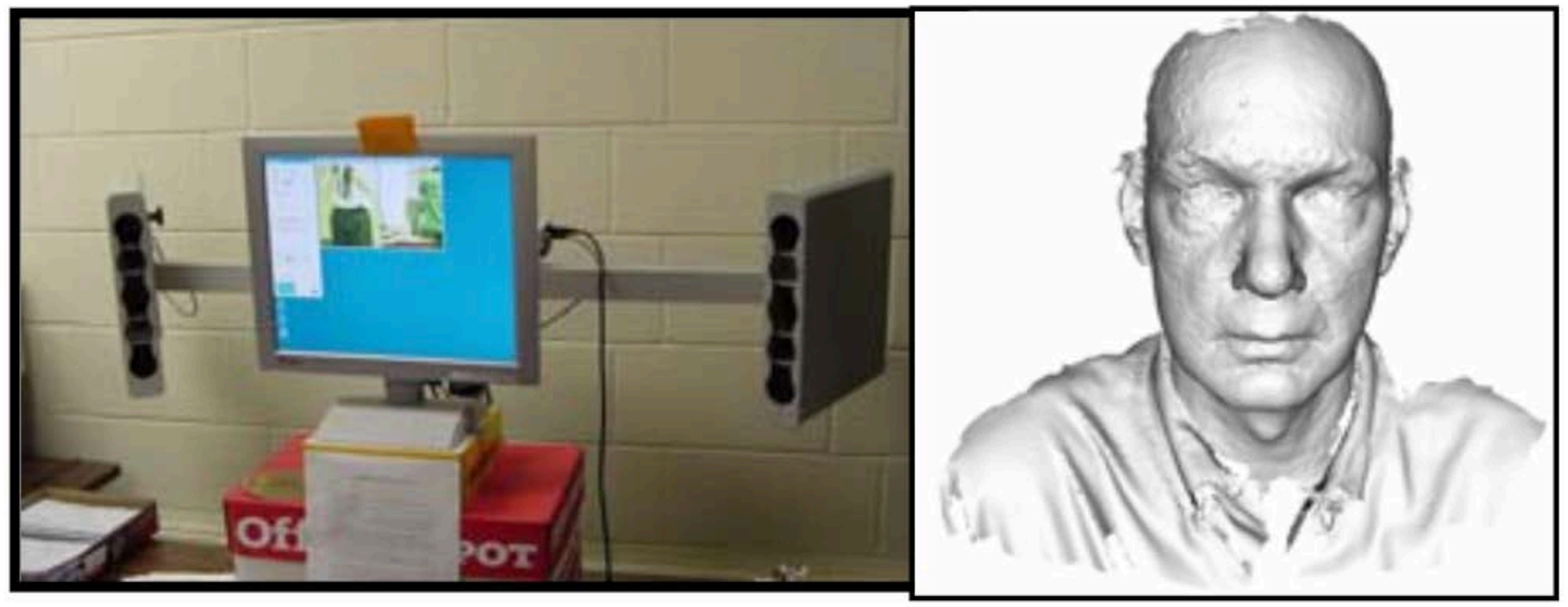
Controlled Acquisition

3D Information

Source:
Dr. Walter Scheirer



Minolta Vivid 900/910



3DMD “Qlonerator”

Acquisition

Unconstrained Acquisition

No illumination control.

https://www.nist.gov/system/files/documents/itl/iad/ig/05771424.pdf

Acquisition

Unconstrained Acquisition

No distance control.

Jain, Ross, and Nadakumar
Introduction to Biometrics
Springer Books, 2011

1m

3m

5m

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Acquisition

Unconstrained Acquisition

No pose control.

Hsu
Face detection and modeling for recognition
PhD Thesis, MSU, 2002.

Acquisition

Problems

Presentation Attack

https://www.youtube.com/watch?v=BGgQ9woZQOg

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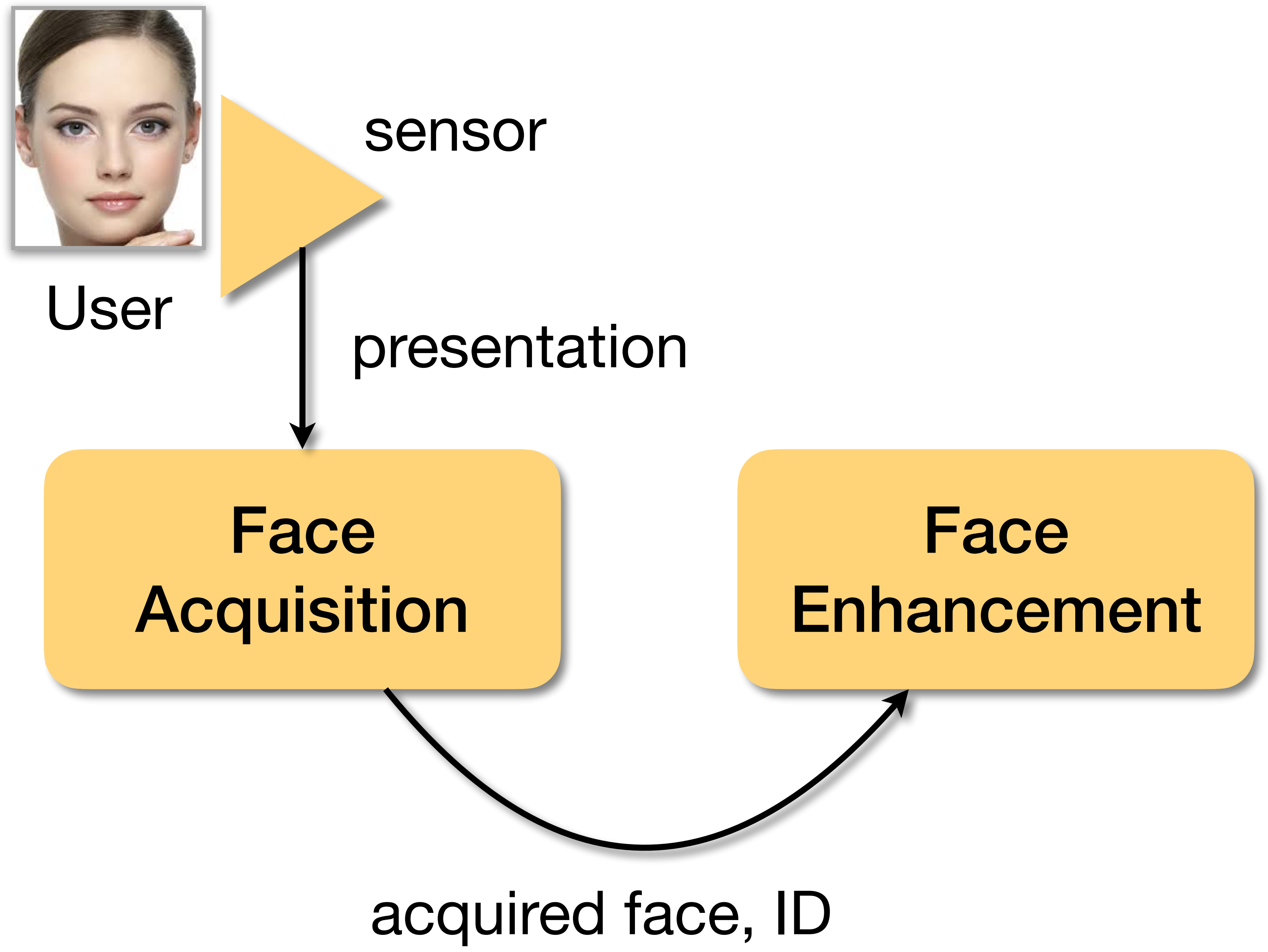
Face Recognition



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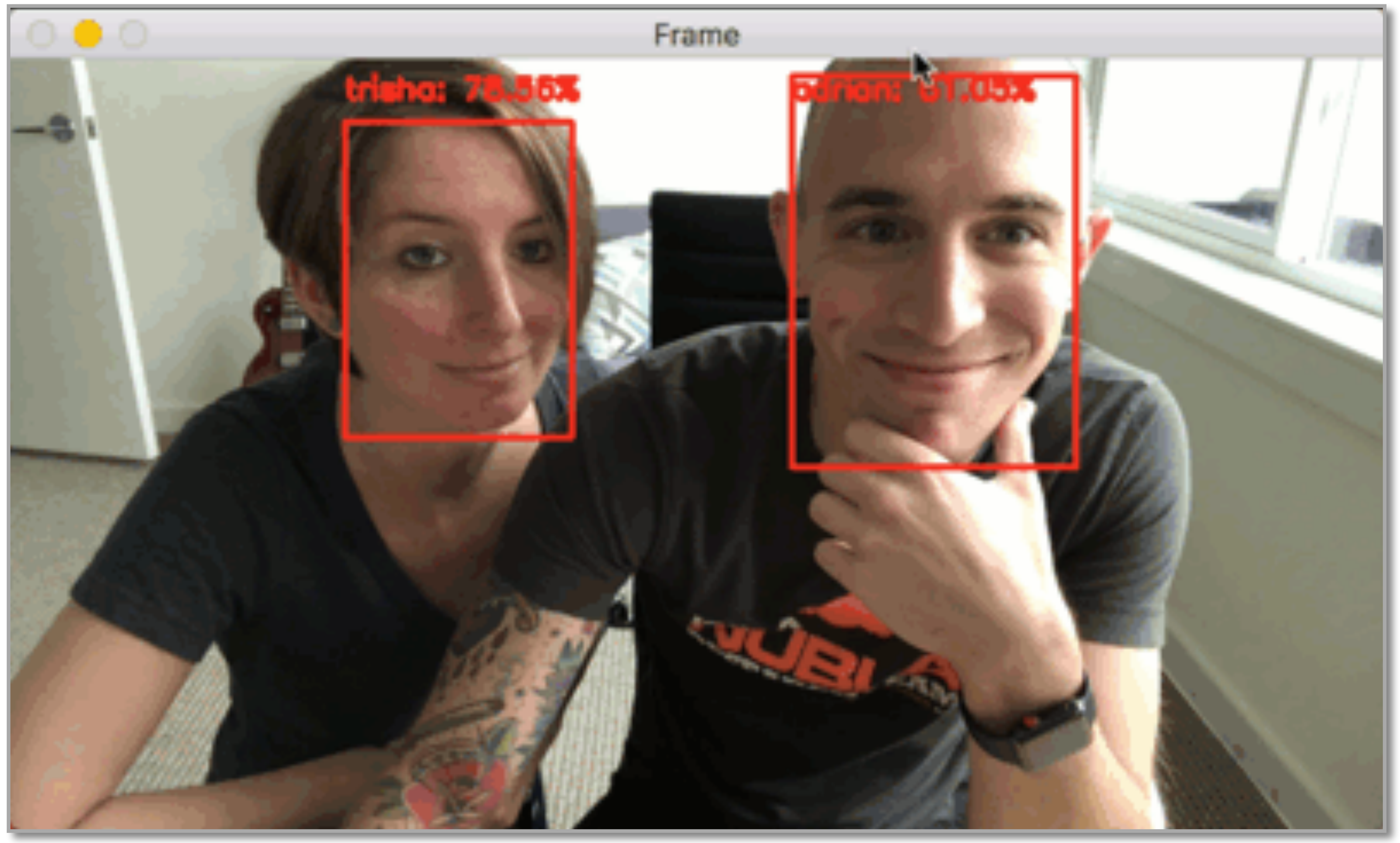
Enhancement

Face Detection

Goal
Localize faces for segmentation and further recognition.



https://www.pyimagesearch.com/2018/09/24/opencv-face-recognition/

Enhancement

Face Detection

Challenges
Megapixel image
Nearly millions of possible locations and scales combined.

False positives should be below 1 in 1 million.

Source: Hu et al., *Finding Tiny Faces*, 2016 (https://arxiv.org/abs/1612.04402)

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Enhancement

Face Detection

2021 State of the Art
Megapixel image
Nearly millions of possible locations, scales,
and poses combined.
Detection and pose estimation.

Available at
https://github.com/vitoralbiero/img2pose

Source: Albiero et al.
img2pose: Face Alignment and Detection via 6DoF, Face Pose Estimation
2021 (https://arxiv.org/abs/2012.07791)

Enhancement

Face Detection

Methods
Either based on *sliding windows* or on *regions of interest*.

Enhancement

Face Detection

Sliding Windows
Scans of the image with windows of different scales.

Enhancement

Face Detection

Sliding Windows
Scans of the image with windows of different scales.

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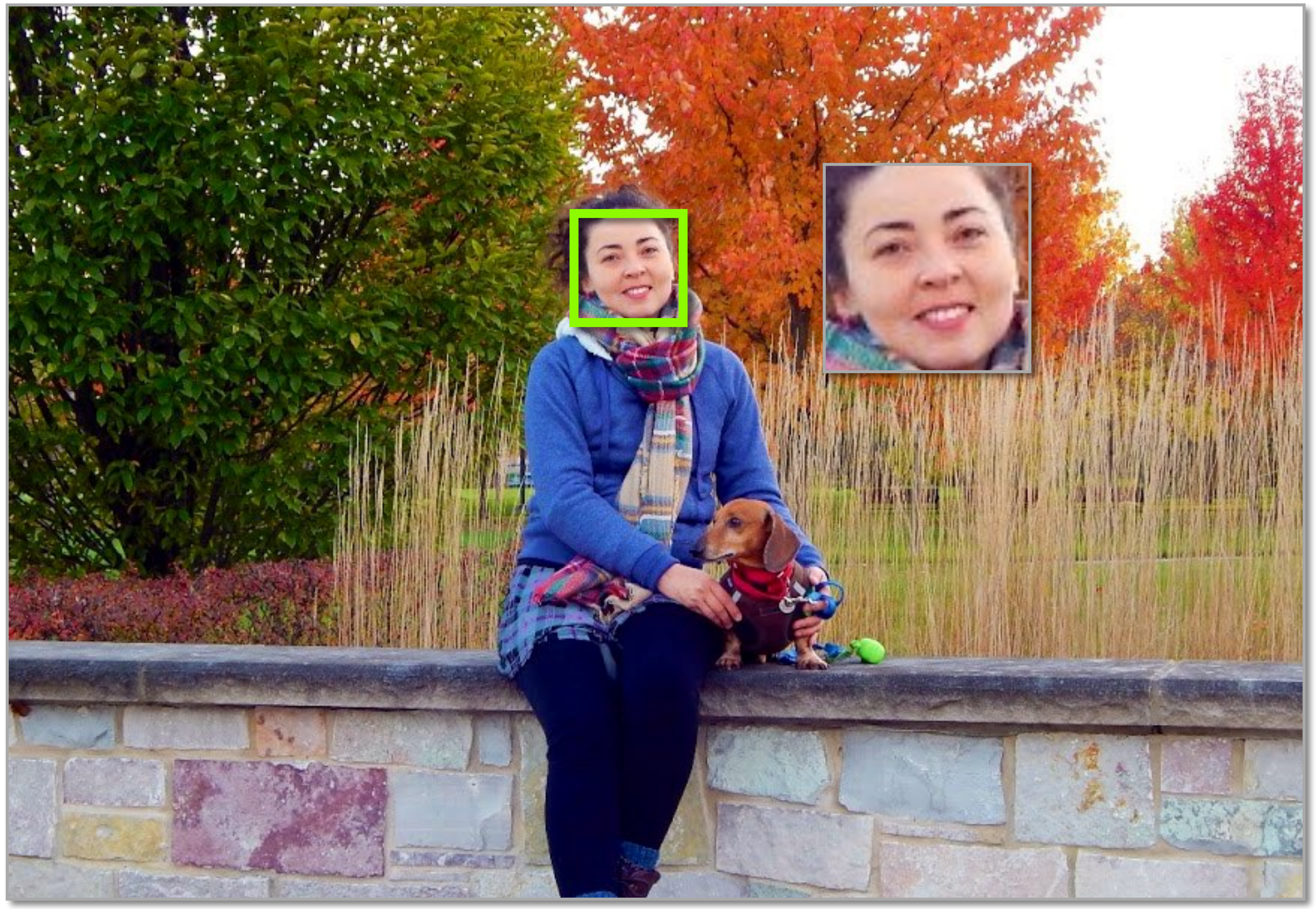
Enhancement

Face Detection

Sliding Windows
Scans of the image with windows of different scales.



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Enhancement

Face Detection

Regions of Interest
Techniques from Computer Vision or Machine Learning to segment regions.

E.g., Maximally Stable Extremal Regions (MSER[1]) or Deep Local Features (DELF[2]).

1. Matas et al. *Robust Wide Baseline Stereo from Maximally Stable Extremal Regions*. BMVC 2002.
2. Noh et al. *Large-Scale Image Retrieval with Attentive Deep Local Features*. ICCV 2017.

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Enhancement

Face Detection

Regions of Interest
Techniques from Machine Learning to classify each region as *face or non-face.*

E.g., Support Vector Machines (SVM).

Enhancement

Face Detection

Viola-Jones Detector
First real-time face detector.
Based on sliding windows.

Key Ideas (4)
Haar-like features.
Integral image.
Boosting for feature selection.
Attentional Cascade to reject non-faces.

SECOND INTERNATIONAL WORKSHOP ON STATISTICAL AND COMPUTATIONAL THEORIES OF VISION – MODELING, LEARNING, COMPUTING, AND SAMPLING

VANCOUVER, CANADA, JULY 13, 2001.

Robust Real-time Object Detection

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201 Broadway, 8th FL
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Michael Jones
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Compaq CRL
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Enhancement

Face Detection

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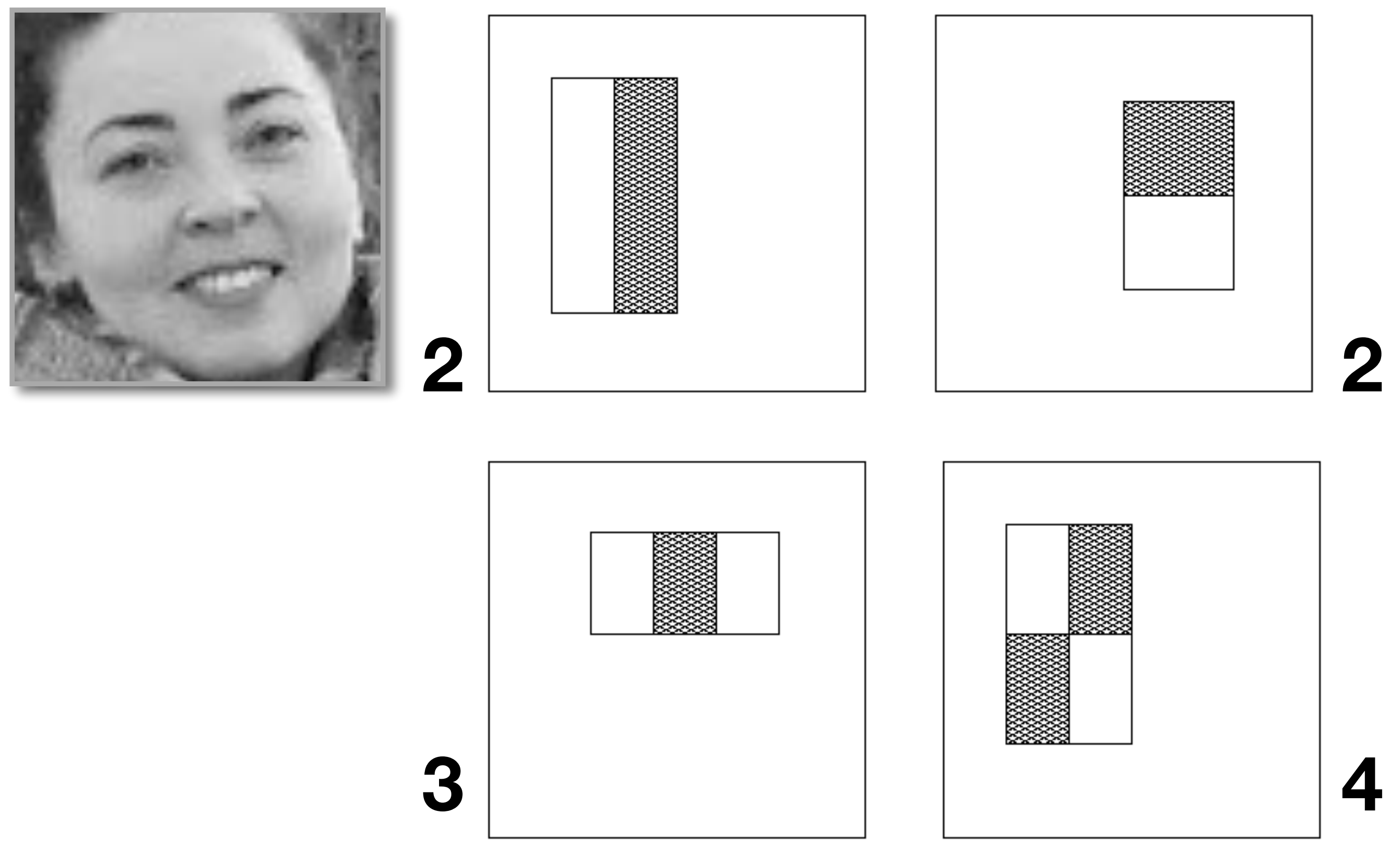
Enhancement

Viola-Jones Detector

Haar-like Features (1/4)
Binary rectangle filters
used to extract features
from the sliding window.

$$value = \sum pixels\ in\ white\ area - \sum pixels\ in\ black\ area$$

Filter types
2, 3, and 4 rectangles.



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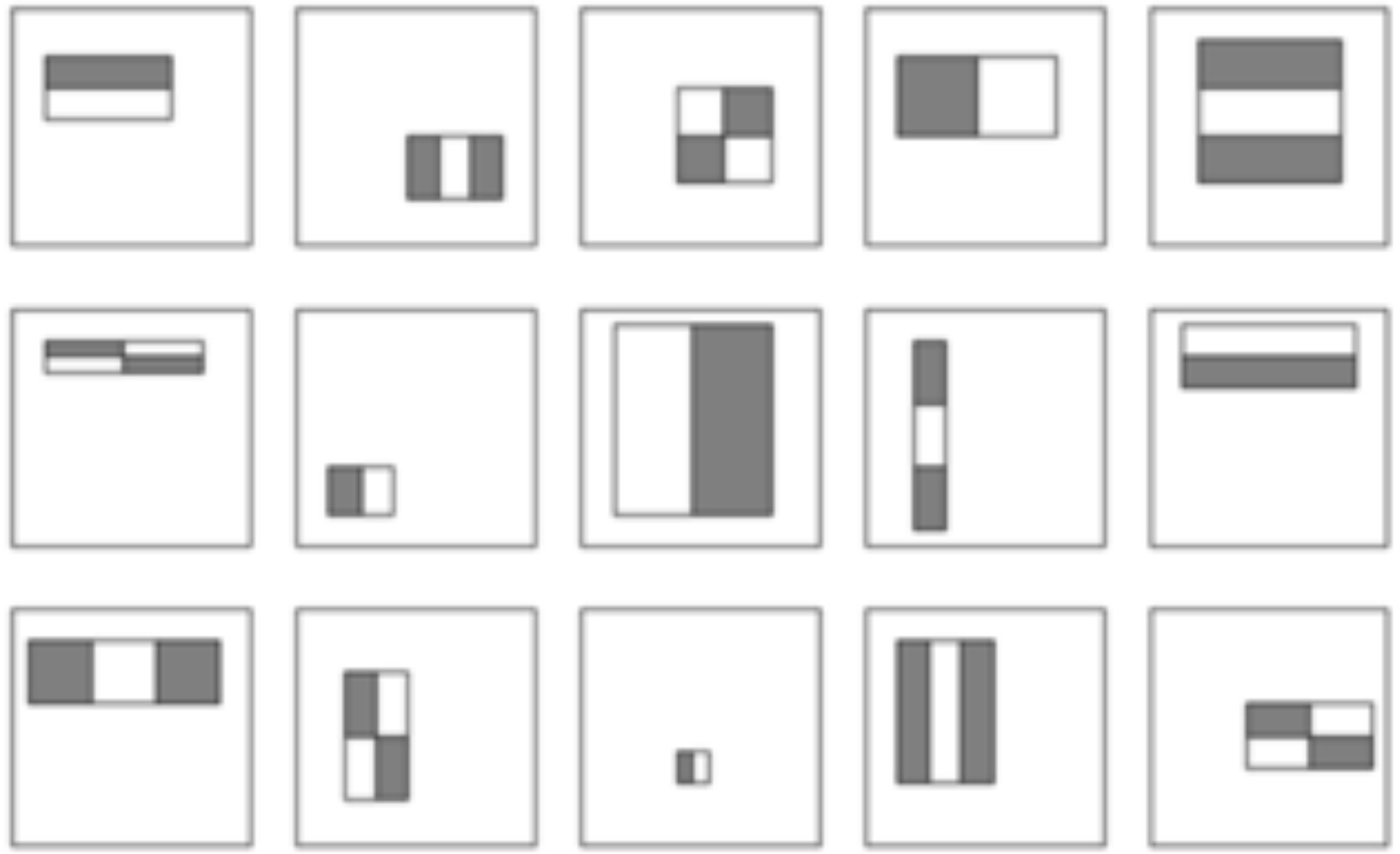
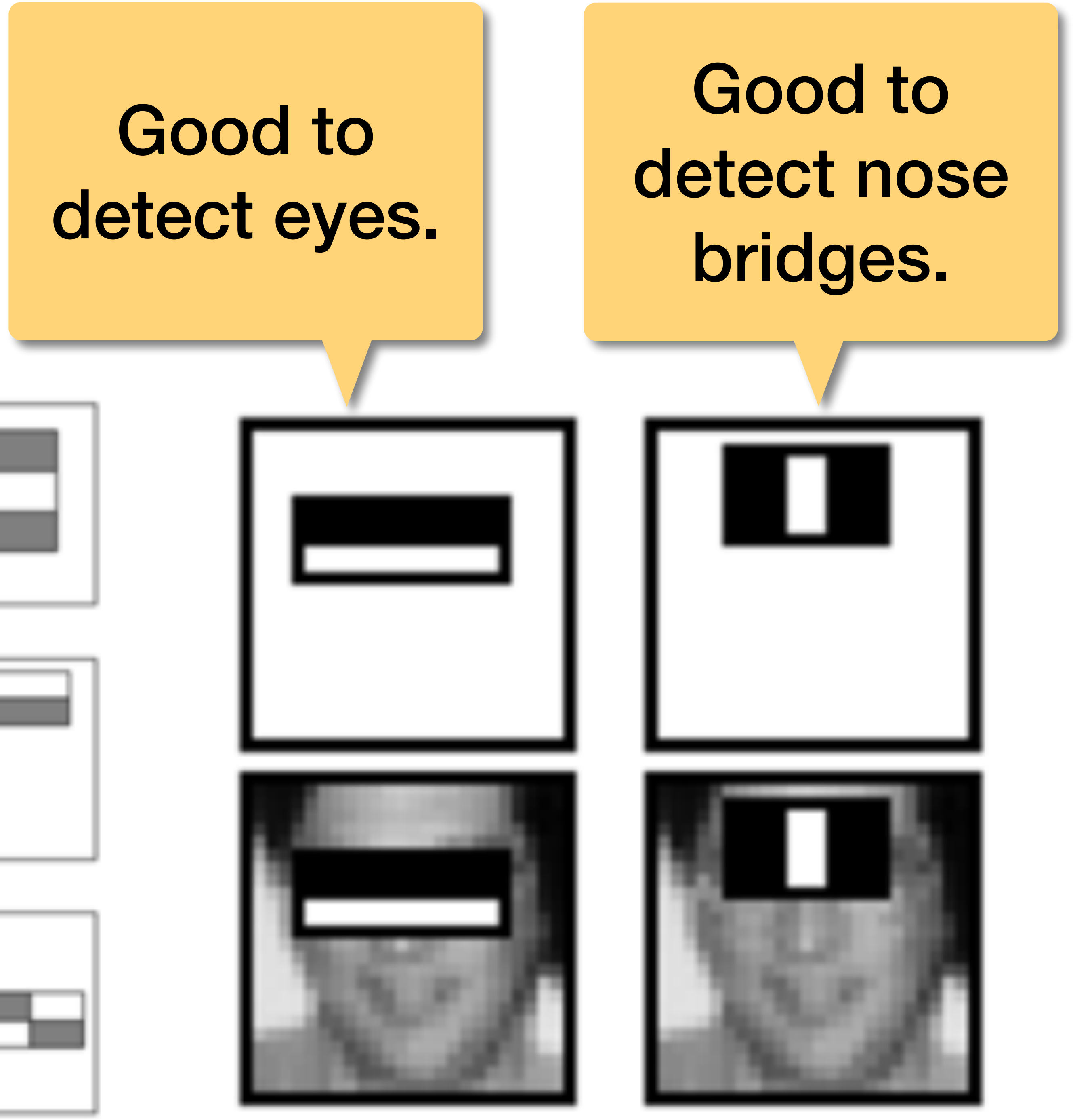
Enhancement

Viola-Jones Detector

Haar-like Features (1/4)
Take a 24-by-24-pixel window.
The number of possible features is nearly 160,000.





How to apply and how to select features fast?

Enhancement

Face Detection

Viola-Jones Detector
First real-time face detector.
Based on sliding windows.

Key Ideas (4)
Haar-like features.
Integral image.
Boosting for feature selection.
Attentional Cascade to reject non-faces.

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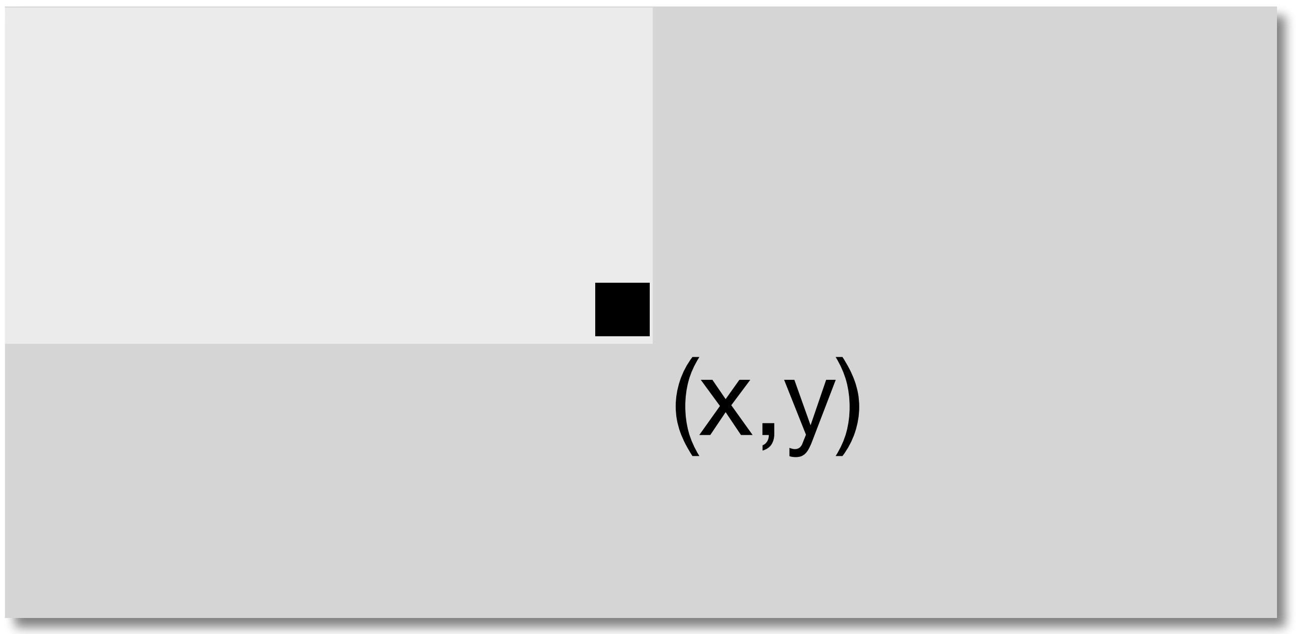
Enhancement

Viola-Jones Detector

Integral Image (2/4)
Solution to apply Haar-like features fast.

Precomputed data structure with the same dimensions of the target image.

Target Image



Integral Image

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Enhancement

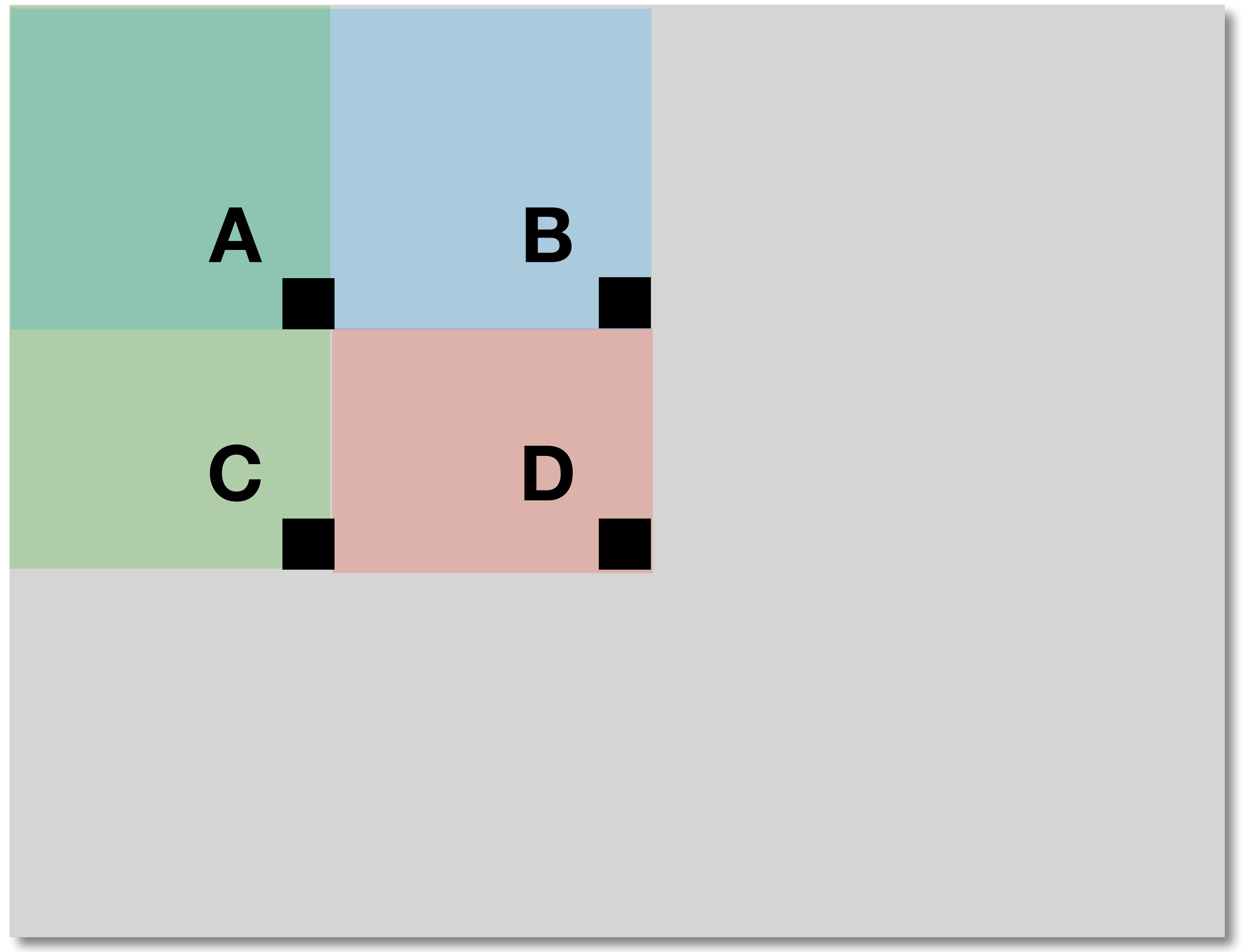
Viola-Jones Detector

Integral Image (2/4)

Remember Haar feature *value*:

$$value = \sum pixels\ in\ white\ area - \sum pixels\ in\ black\ area$$

Integral images allow the computation of the sum of pixel values in any target area in constant time, regardless of the size of the area.



Sum of pixels in red area

$$content = D - B - C + A$$

Only and always 4 accesses.

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Enhancement

Face Detection

Viola-Jones Detector
First real-time face detector.
Based on sliding windows.

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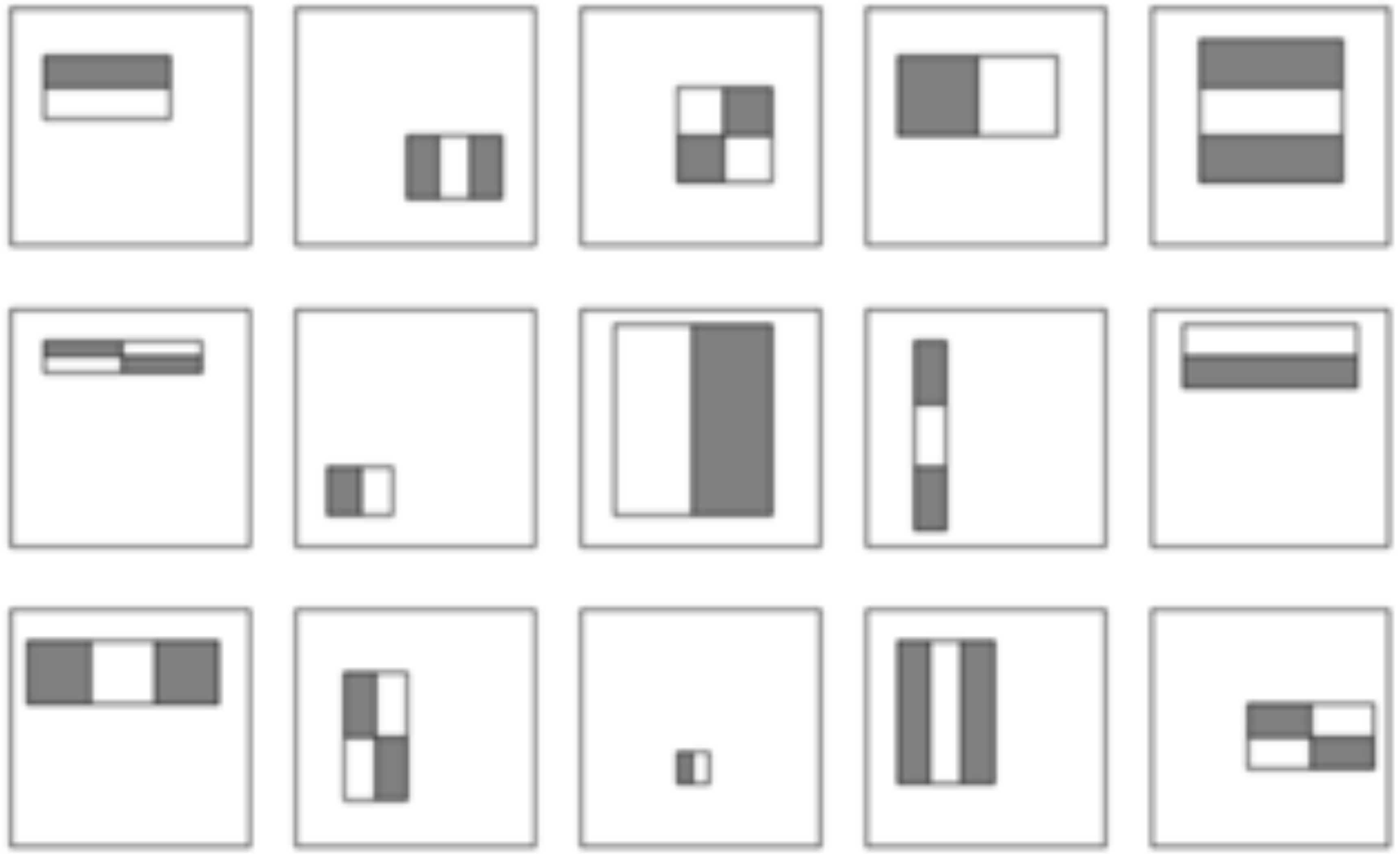
Enhancement

Viola-Jones Detector

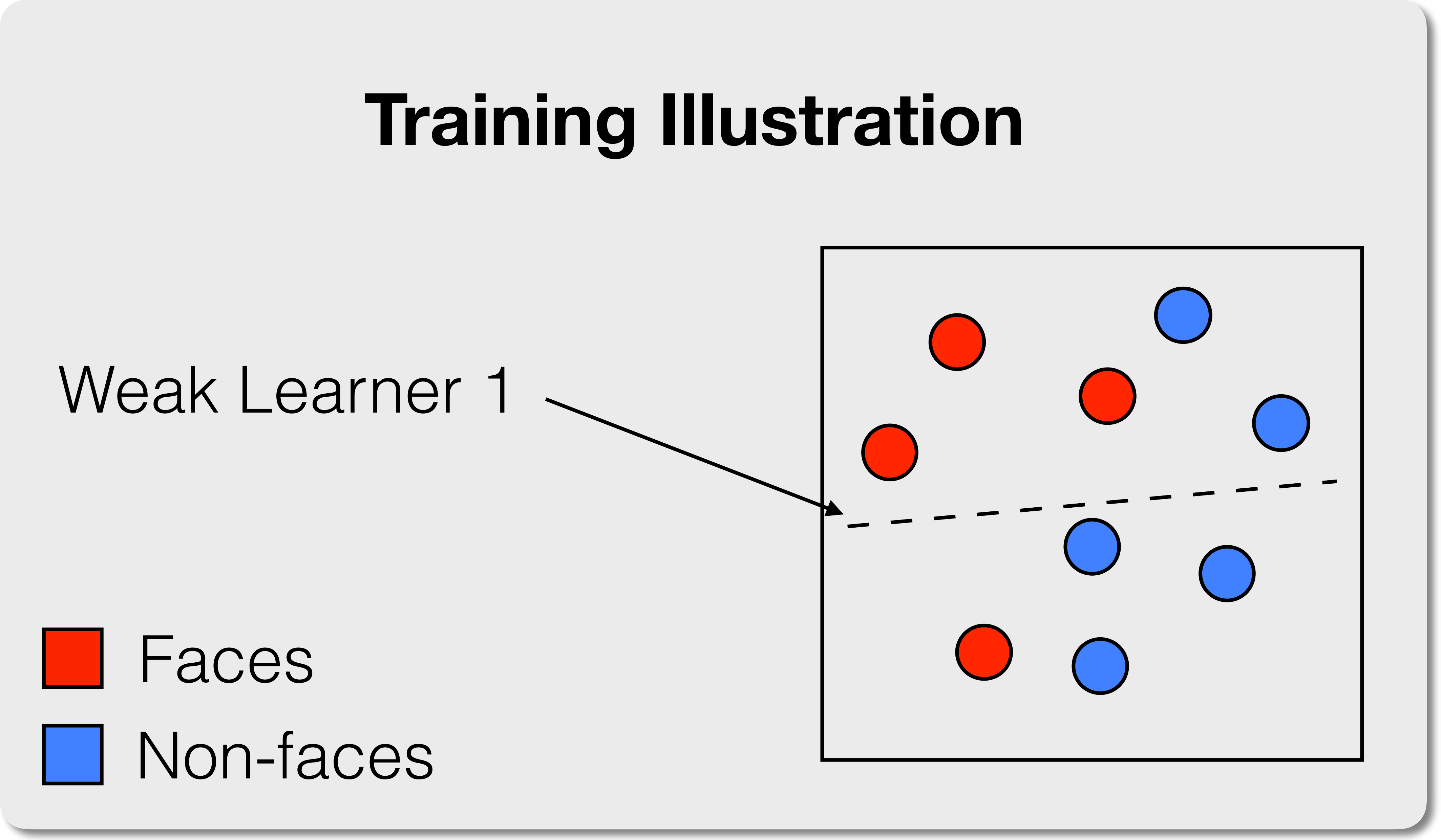
Boosting for
Feature Selection (3/4)
Goal: select combinations of Haar-like features that are useful for face detection.



Enhancement

Viola-Jones Detector

Boosting for
Feature Selection (3/4)
Solution: *boosting*, a combination of weak classifiers that when learned in sequence and applied together, lead to better final classification.



Source: Dr. Walter Scheirer

Enhancement

Viola-Jones Detector

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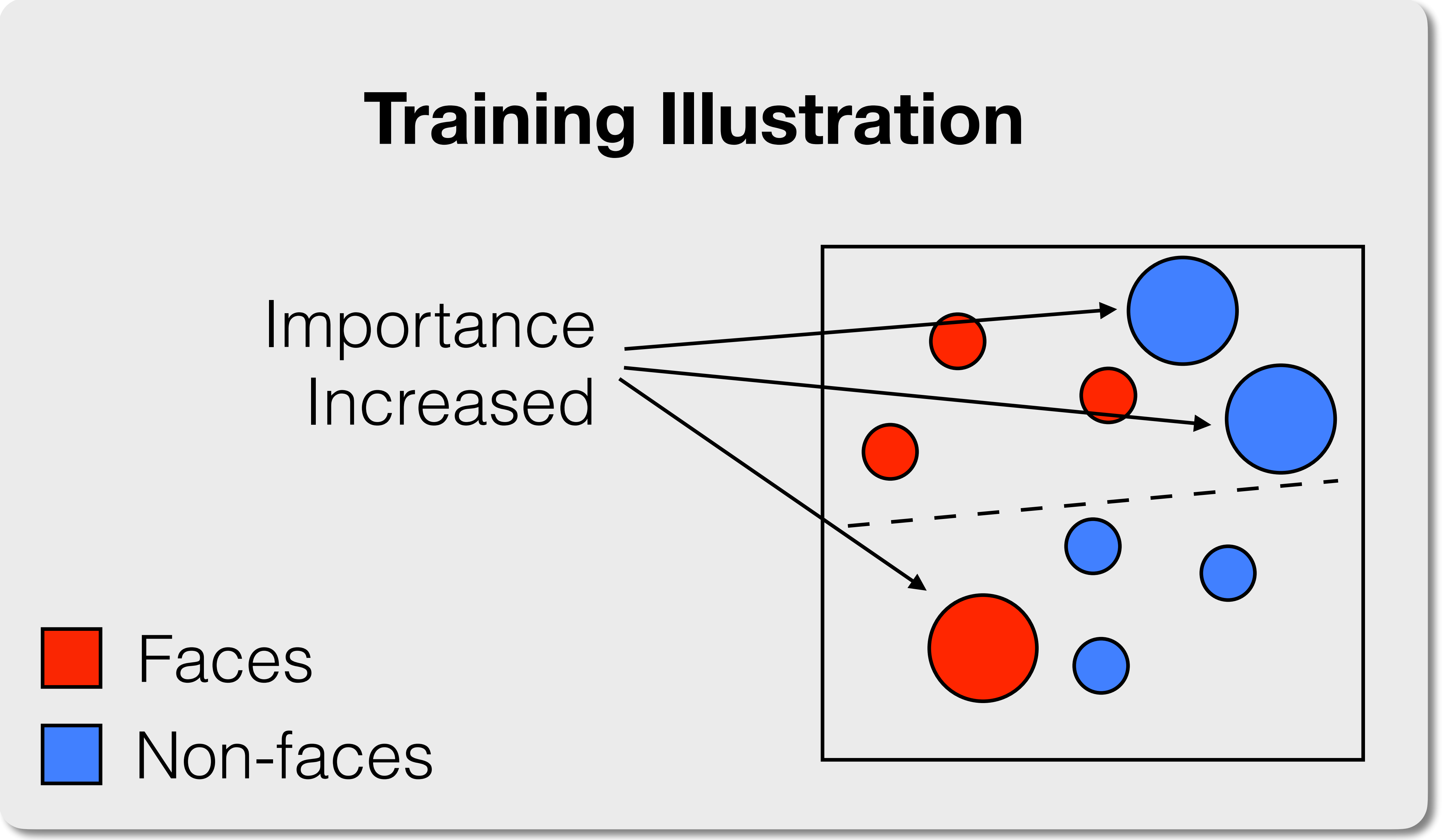

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Enhancement

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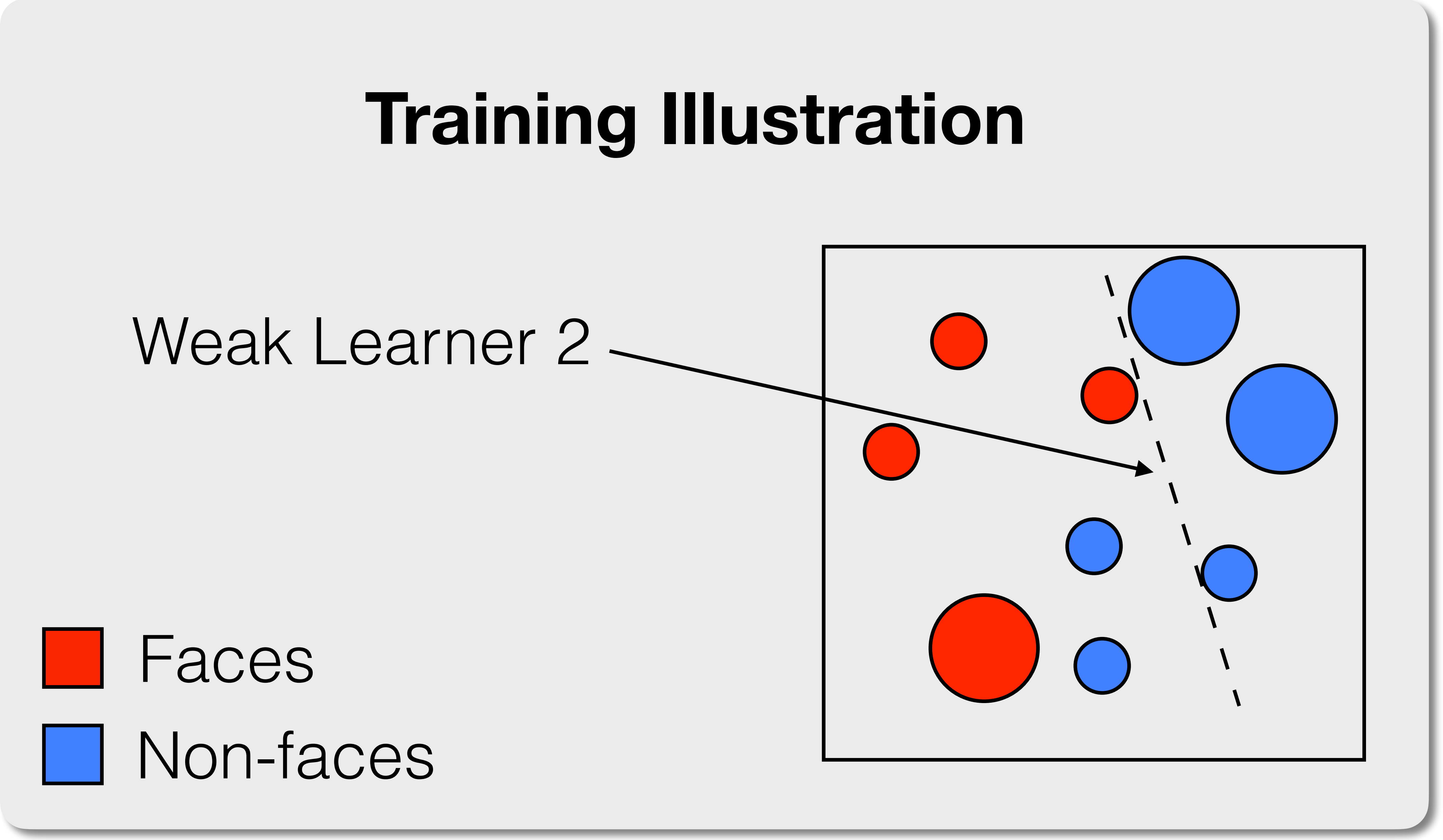

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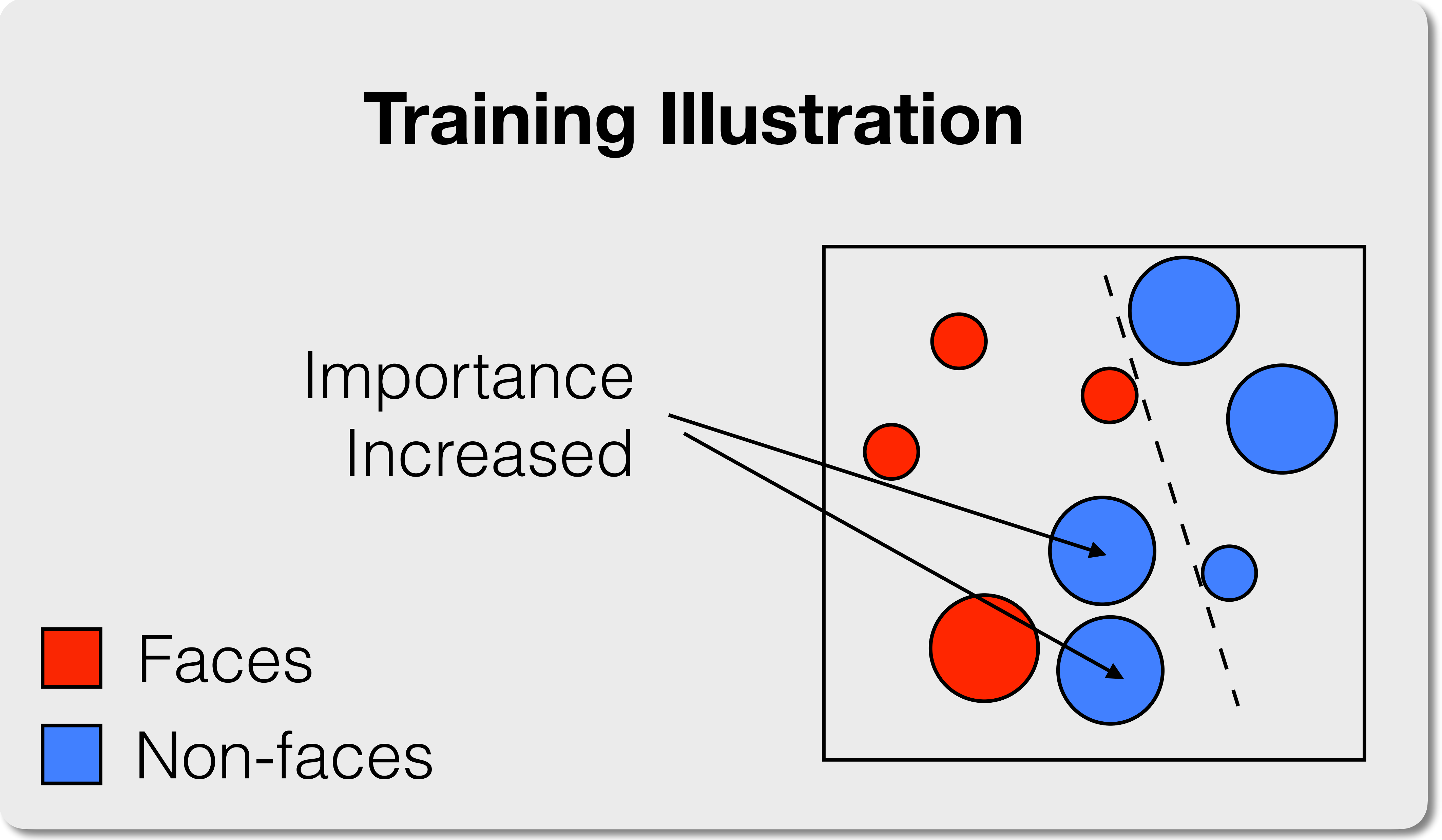

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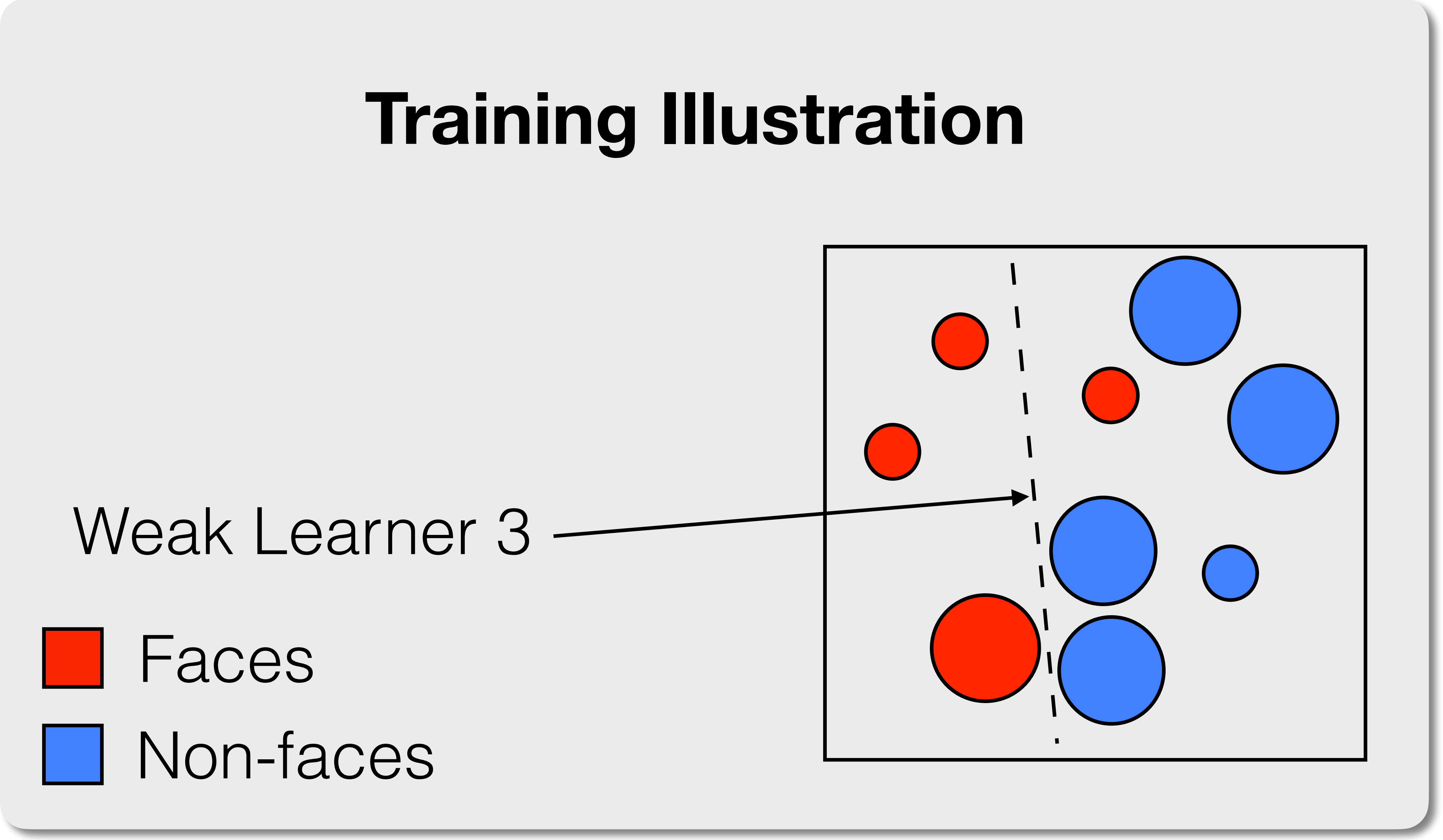

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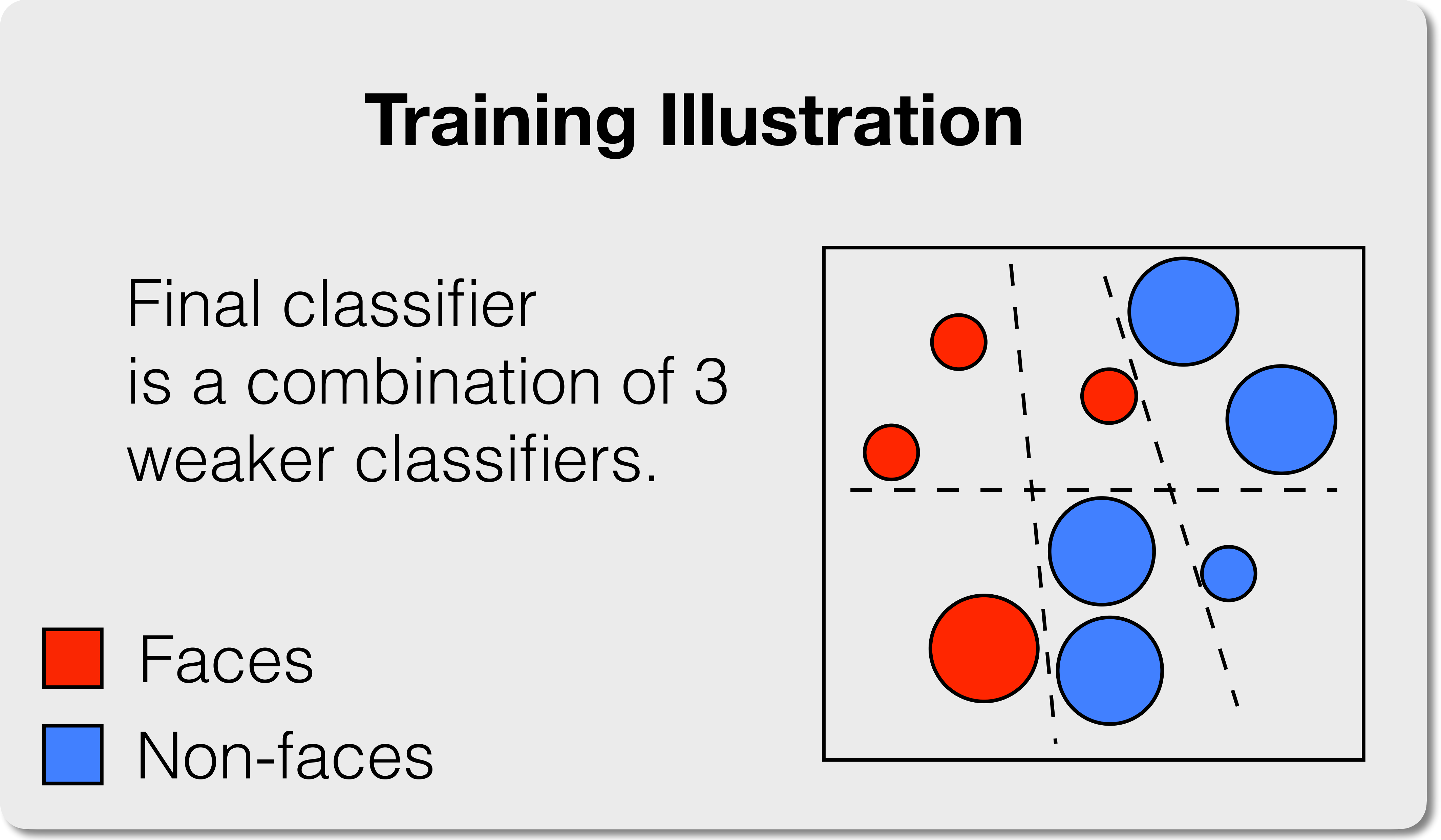

Source: Dr. Walter Scheirer

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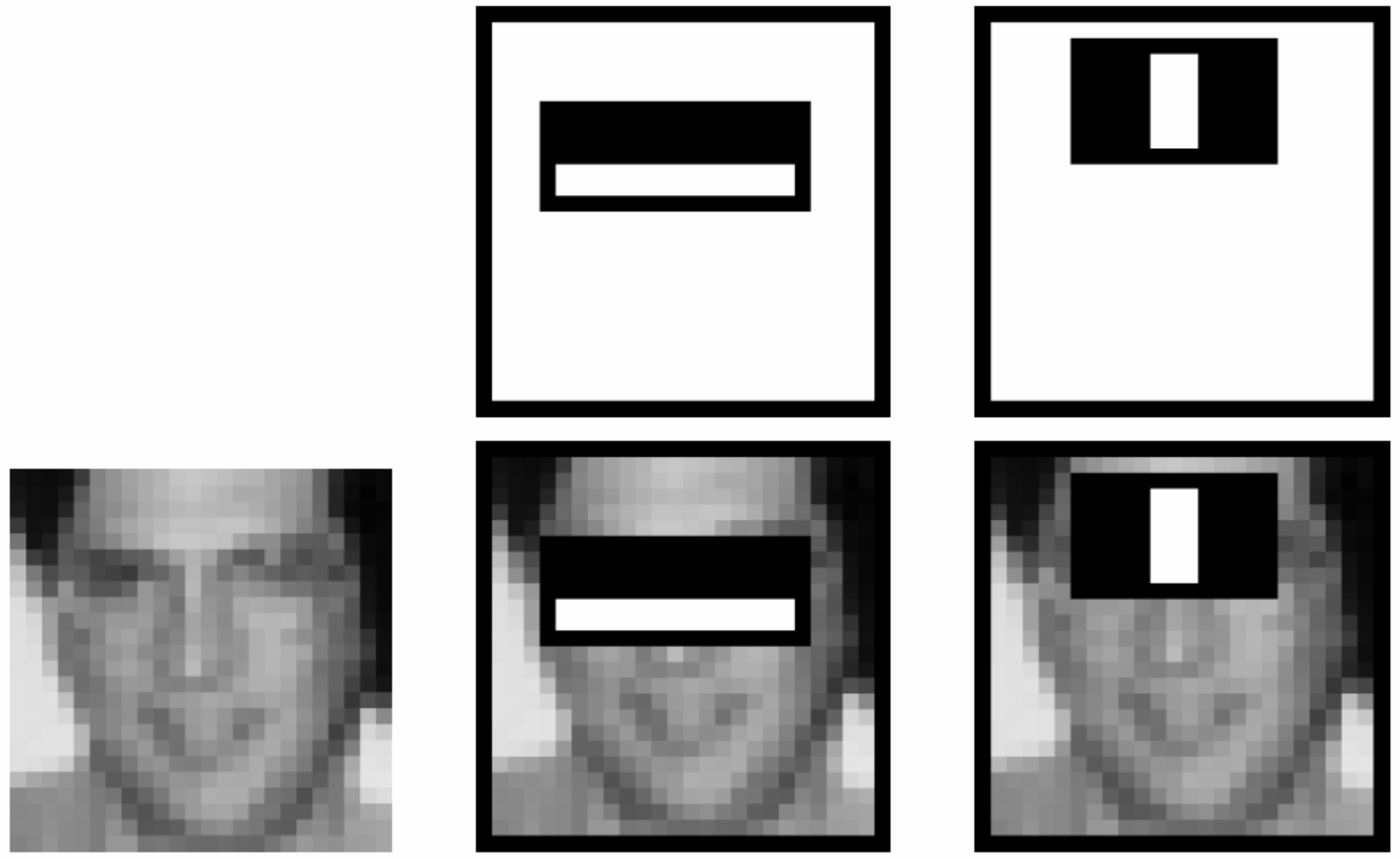
Enhancement

Viola-Jones Detector

Boosting for
Feature Selection (3/4)
Possible outcome.

This combination is enough
to lead to perfect True Positive Rate,
but poor False Positive Rate.

All faces are detected as positive, but many
non-faces are detected as positive too.



First two selected features.

Whenever this classifier says an object is not a face (rejection), it is probably right.

Enhancement

Face Detection

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First real-time face detector.
Based on sliding windows.

Key Ideas (4)
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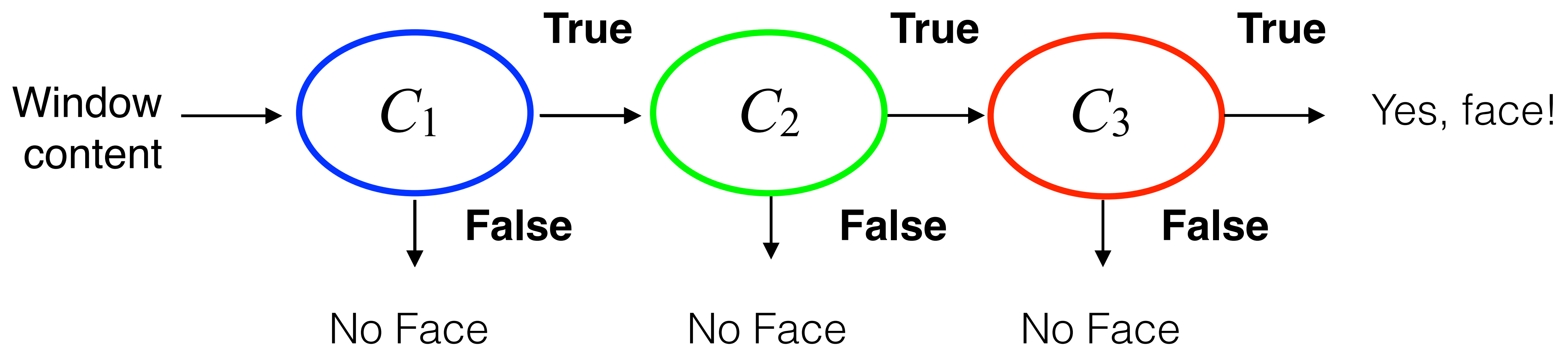
Enhancement

Viola-Jones Detector

Attentional Cascade (4/4)
Make a cascade of different classifiers that are good at rejecting faces.

Start with simpler and faster classifiers.



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Enhancement

Viola-Jones Detector

Results

Jain, Ross, and Nadakumar
Introduction to Biometrics
Springer Books, 2011

clean background

cluttered background

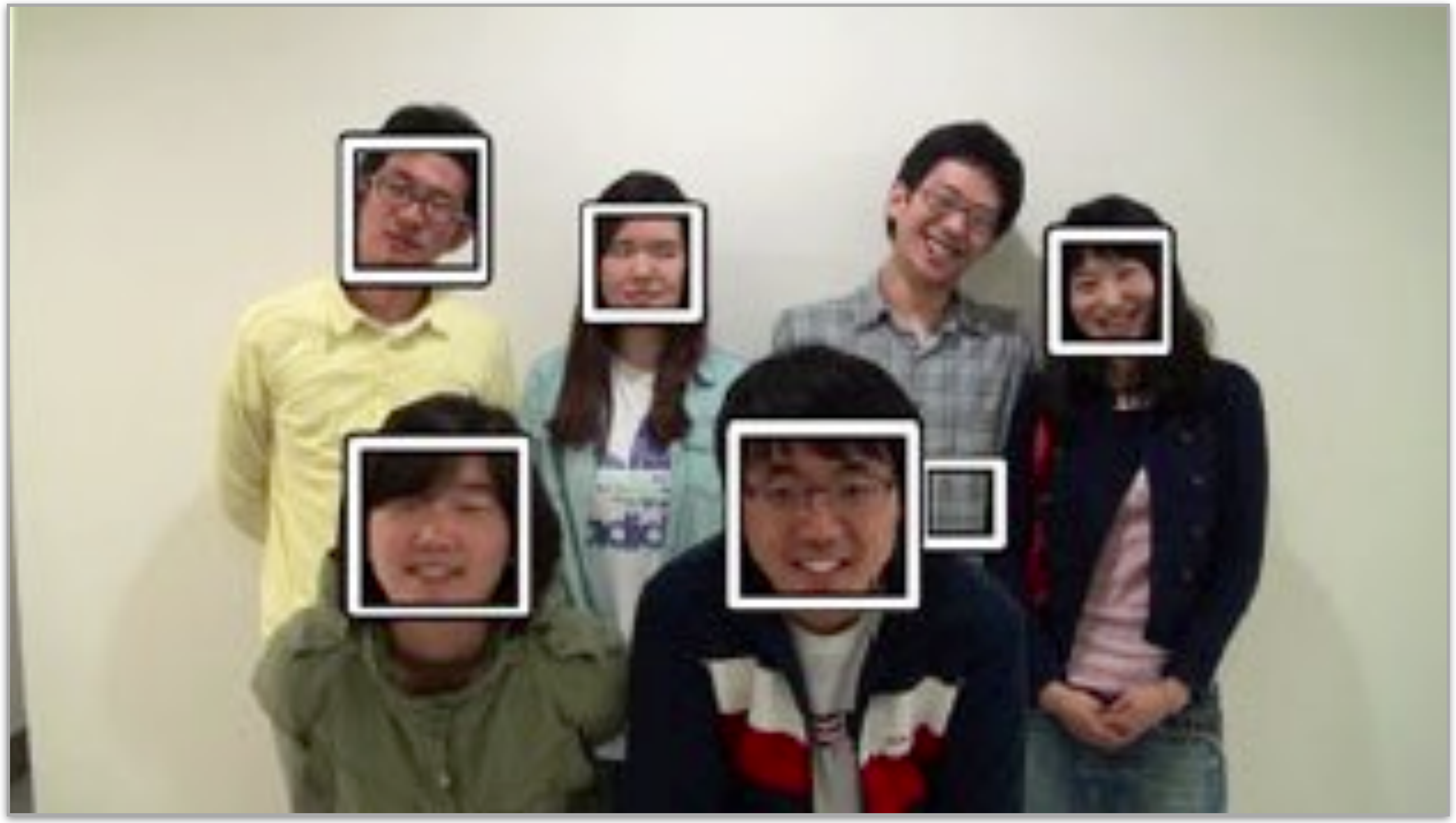
tilted head

upside down

Enhancement

Viola-Jones Detector

Results



Jain, Ross, and Nadakumar
Introduction to Biometrics
Springer Books, 2011

Enhancement

Face Detection

Attack
Non-live faces and some special patterns may be used to trigger the face detector on purpose.

If it happens too often, it will flood the system.

https://www.theguardian.com/world/2019/aug/13/the-fashion-line-designed-to-trick-surveillance-cameras

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Enhancement

Face Detection

Attack
Make-up can be used to hinder detection.

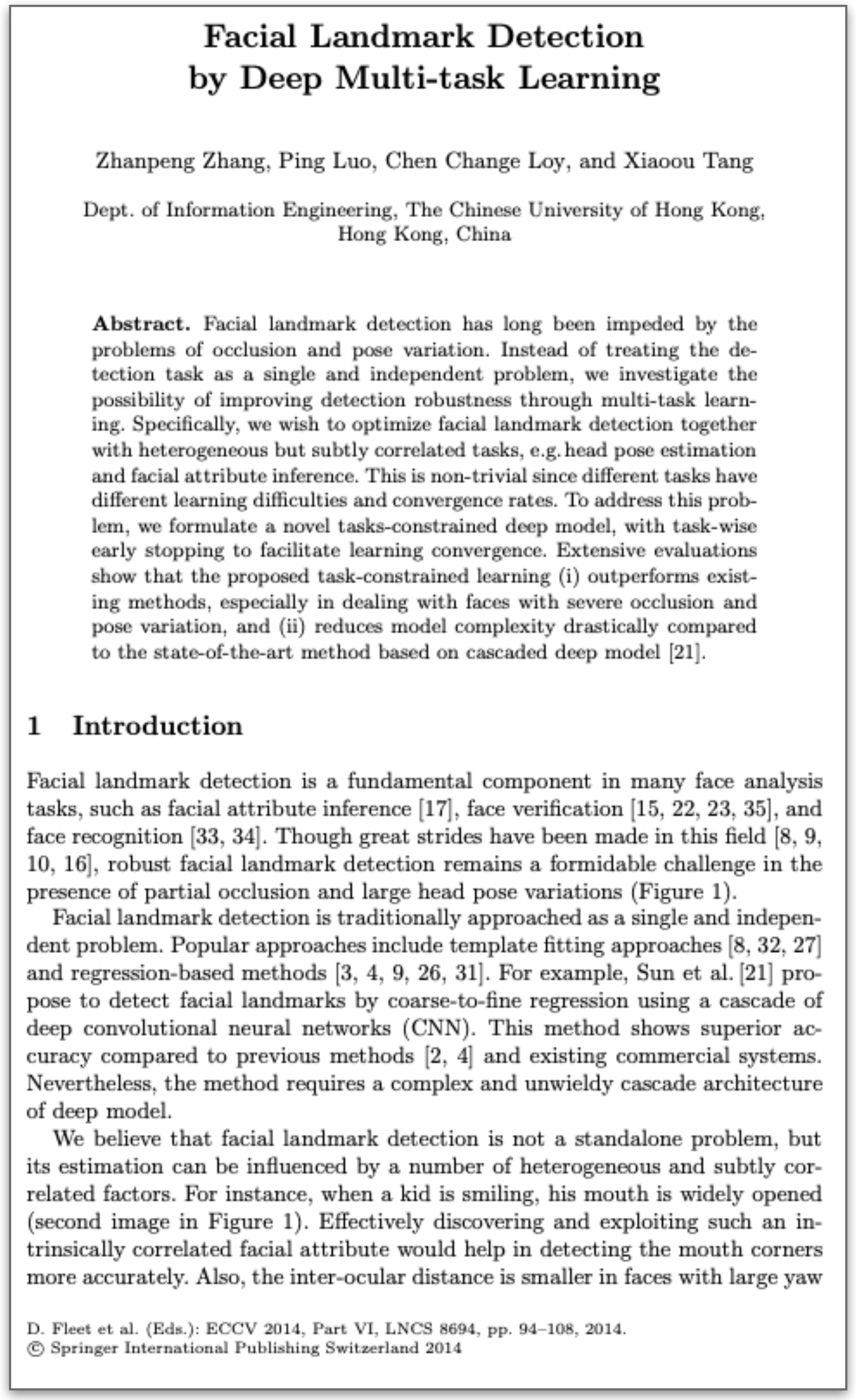
https://twitter.com/glichfield/status/925425702194810882

Enhancement

Face Detection

Convolutional neural network (CNN)-based Detector
Real-time in contemporary hardware.
Based on regions of interest.

Key Ideas (3)
Data-driven machine-learning approach.
Main task: detect face region and five landmarks
Auxiliary tasks: smiling?; gender?; glasses?; etc.



Facial Landmark Detection by Deep Multi-task Learning

Zhanpeng Zhang, Ping Luo, Chen Change Loy, and Xiaoou Tang

Dept. of Information Engineering, The Chinese University of Hong Kong, Hong Kong, China

Abstract. Facial landmark detection has long been impeded by the problems of occlusion and pose variation. Instead of treating the detection task as a single and independent problem, we investigate the possibility of improving detection robustness through multi-task learning. Specifically, we wish to optimize facial landmark detection together with heterogeneous but subtly correlated tasks, e.g. head pose estimation and facial attribute inference. This is non-trivial since different tasks have different learning difficulties and convergence rates. To address this problem, we formulate a novel tasks-constrained deep model, with task-wise early stopping to facilitate learning convergence. Extensive evaluations show that the proposed task-constrained learning (i) outperforms existing methods, especially in dealing with faces with severe occlusion and pose variation, and (ii) reduces model complexity drastically compared to the state-of-the-art method based on cascaded deep model [21].

1 Introduction

Facial landmark detection is a fundamental component in many face analysis tasks, such as facial attribute inference [17], face verification [15, 22, 23, 35], and face recognition [33, 34]. Though great strides have been made in this field [8, 9, 10, 16], robust facial landmark detection remains a formidable challenge in the presence of partial occlusion and large head pose variations (Figure 1).

Facial landmark detection is traditionally approached as a single and independent problem. Popular approaches include template fitting approaches [8, 32, 27] and regression-based methods [3, 4, 9, 26, 31]. For example, Sun et al. [21] propose to detect facial landmarks by coarse-to-fine regression using a cascade of deep convolutional neural networks (CNN). This method shows superior accuracy compared to previous methods [2, 4] and existing commercial systems. Nevertheless, the method requires a complex and unwieldy cascade architecture of deep model.

We believe that facial landmark detection is not a standalone problem, but its estimation can be influenced by a number of heterogeneous and subtly correlated factors. For instance, when a kid is smiling, his mouth is widely opened (second image in Figure 1). Effectively discovering and exploiting such an intrinsically correlated facial attribute would help in detecting the mouth corners more accurately. Also, the inter-ocular distance is smaller in faces with large yaw

D. Fleet et al. (Eds.): ECCV 2014, Part VI, LNCS 8694, pp. 94–108, 2014.

Zhang et al.
Facial Landmark Detection by Deep Multi-task Learning
ECCV 2014

Enhancement

Face Detection

Convolutional neural network (CNN)-based Detector
Real-time in contemporary hardware.
Based on regions of interest.

Key Ideas (3)
Data-driven machine-learning approach.
Main task: detect face region and five landmarks
Auxiliary tasks: smiling?; gender?; glasses?; etc.

Enhancement

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Enhancement

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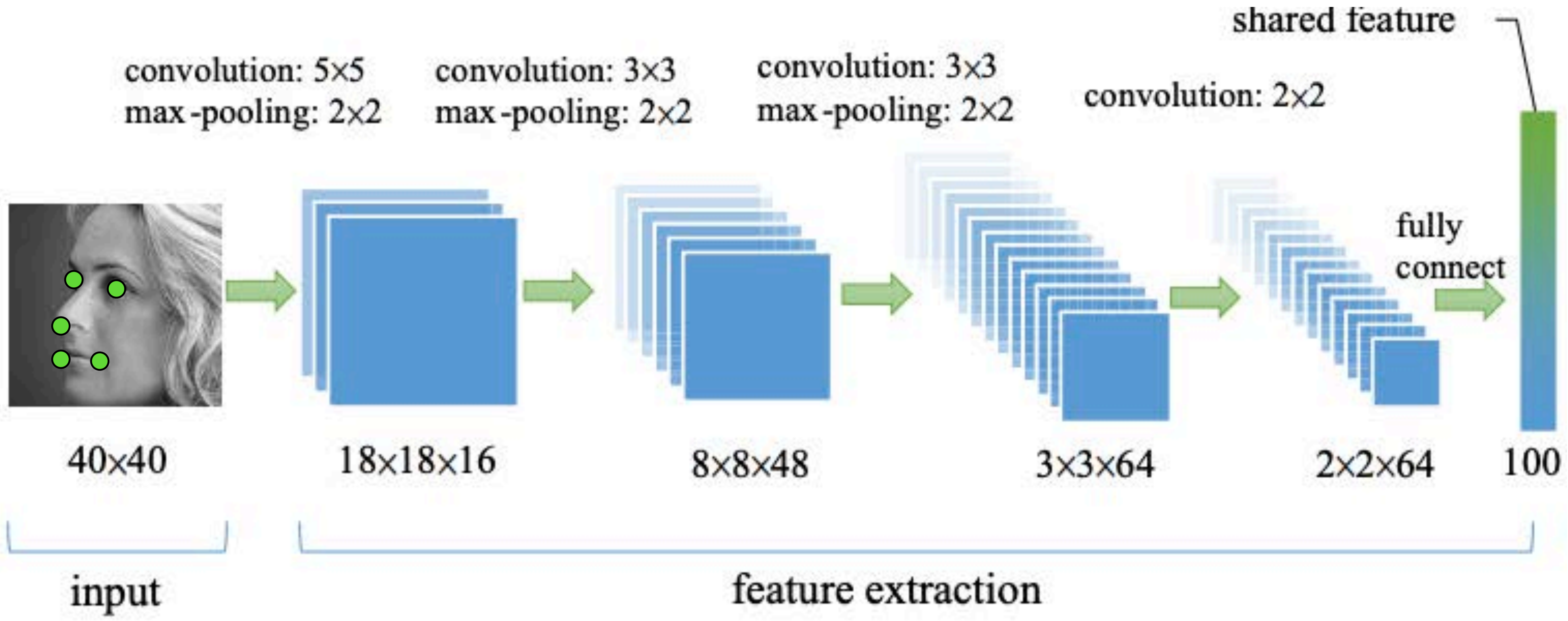

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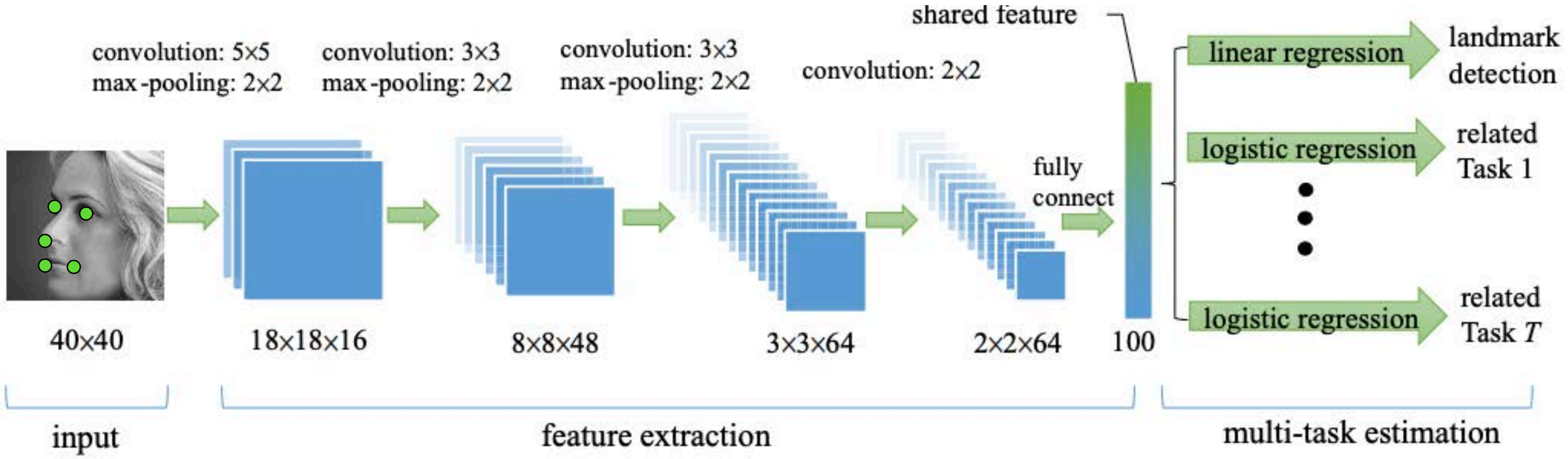

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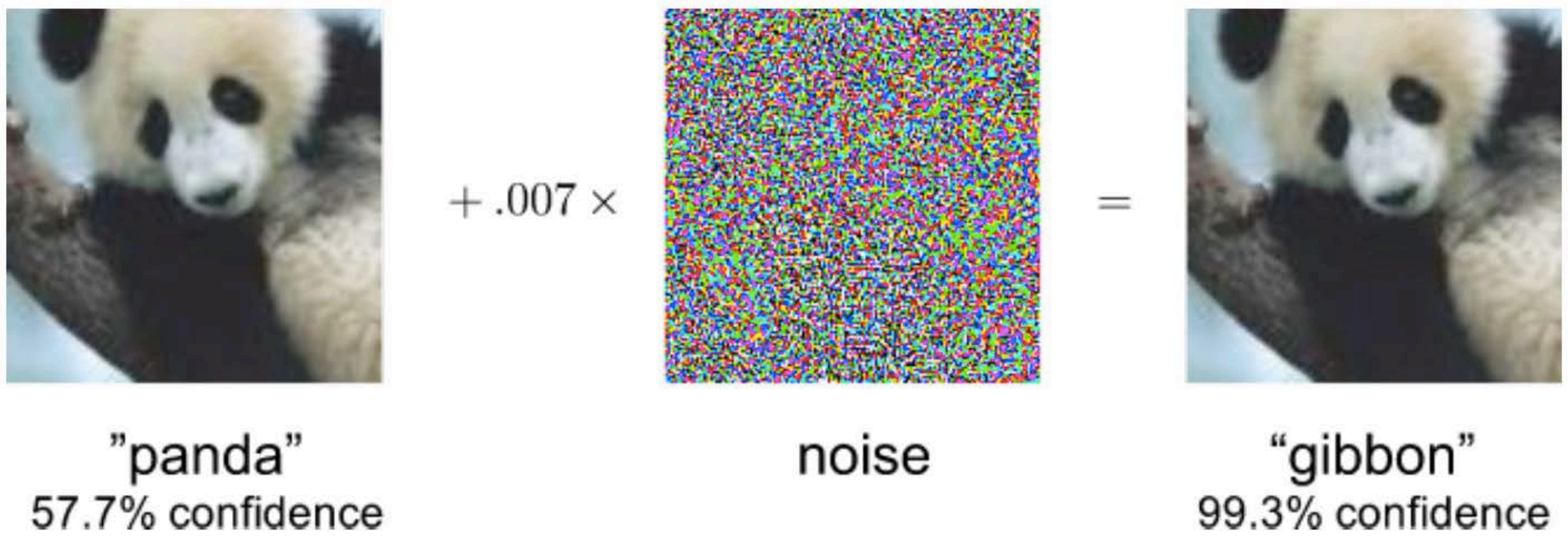
Enhancement

Face Detection

Attack
Adversarial
machine learning.

The attacker avoids data detection by feeding the system with adversarial data.



Goodfellow, Shlens, and Szegedy
Explaining and Harnessing Adversarial Examples
ICLR 2015

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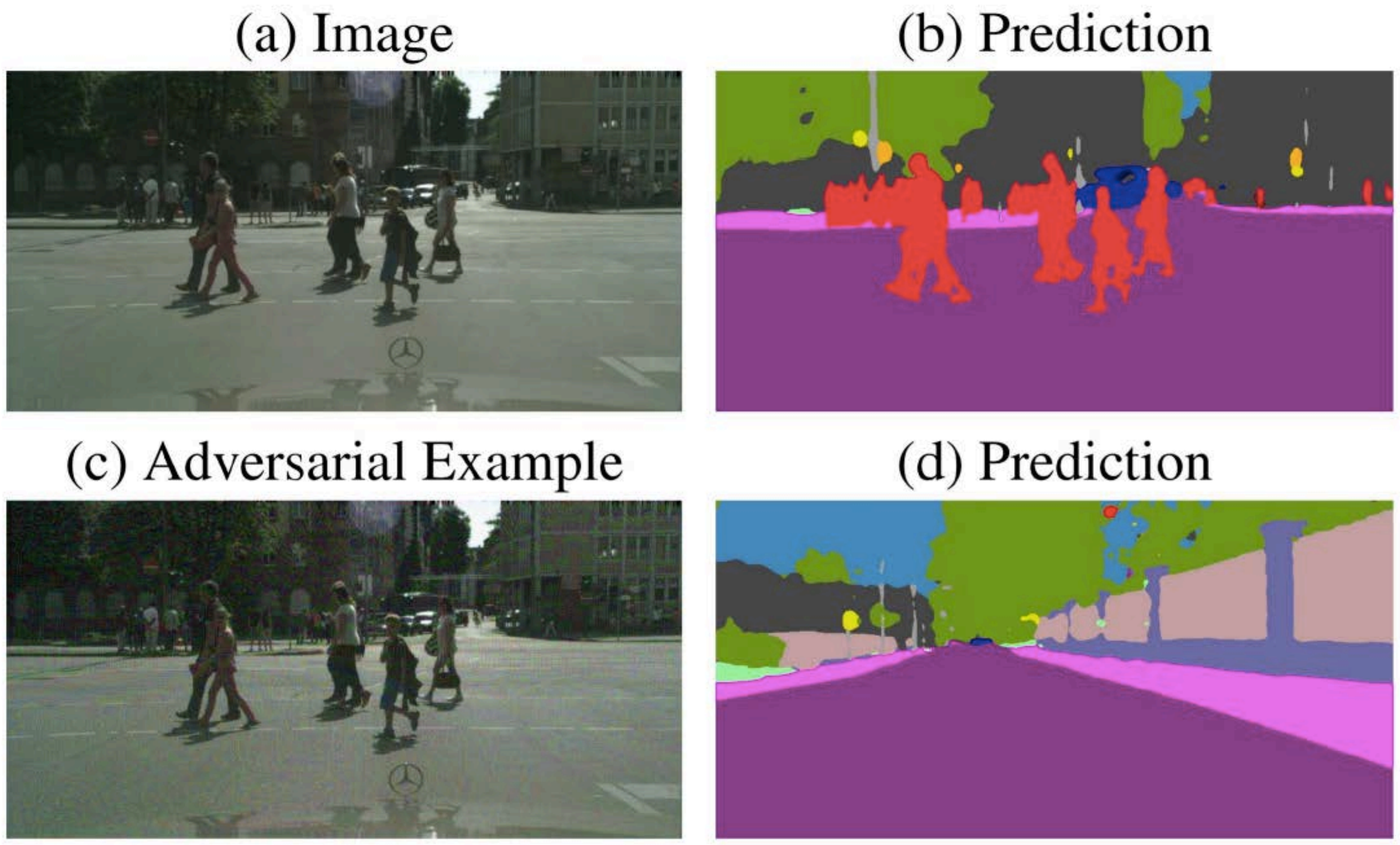

Metzen et al.
Universal Adversarial Perturbations Against Semantic Image Segmentation
ICCV 2017

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https://www.youtube.com/watch?v=4uGV_fRj0UA

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Enhancement

Face Detection

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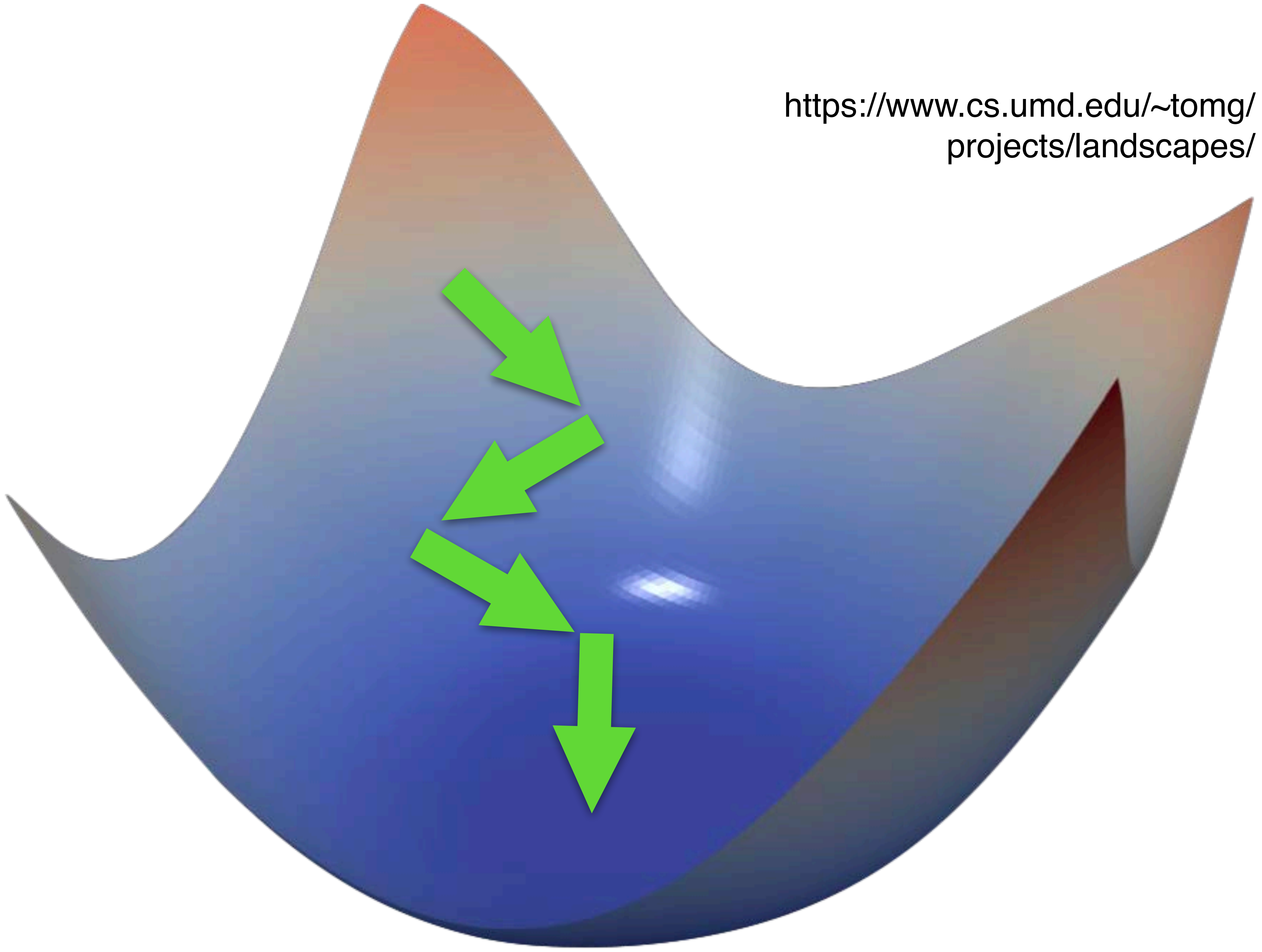
machine learning.

Example:
Fast Gradient Sign Method
(FGSM).



https://www.cs.umd.edu/~tomg/projects/landscapes/

CNN Error Surface

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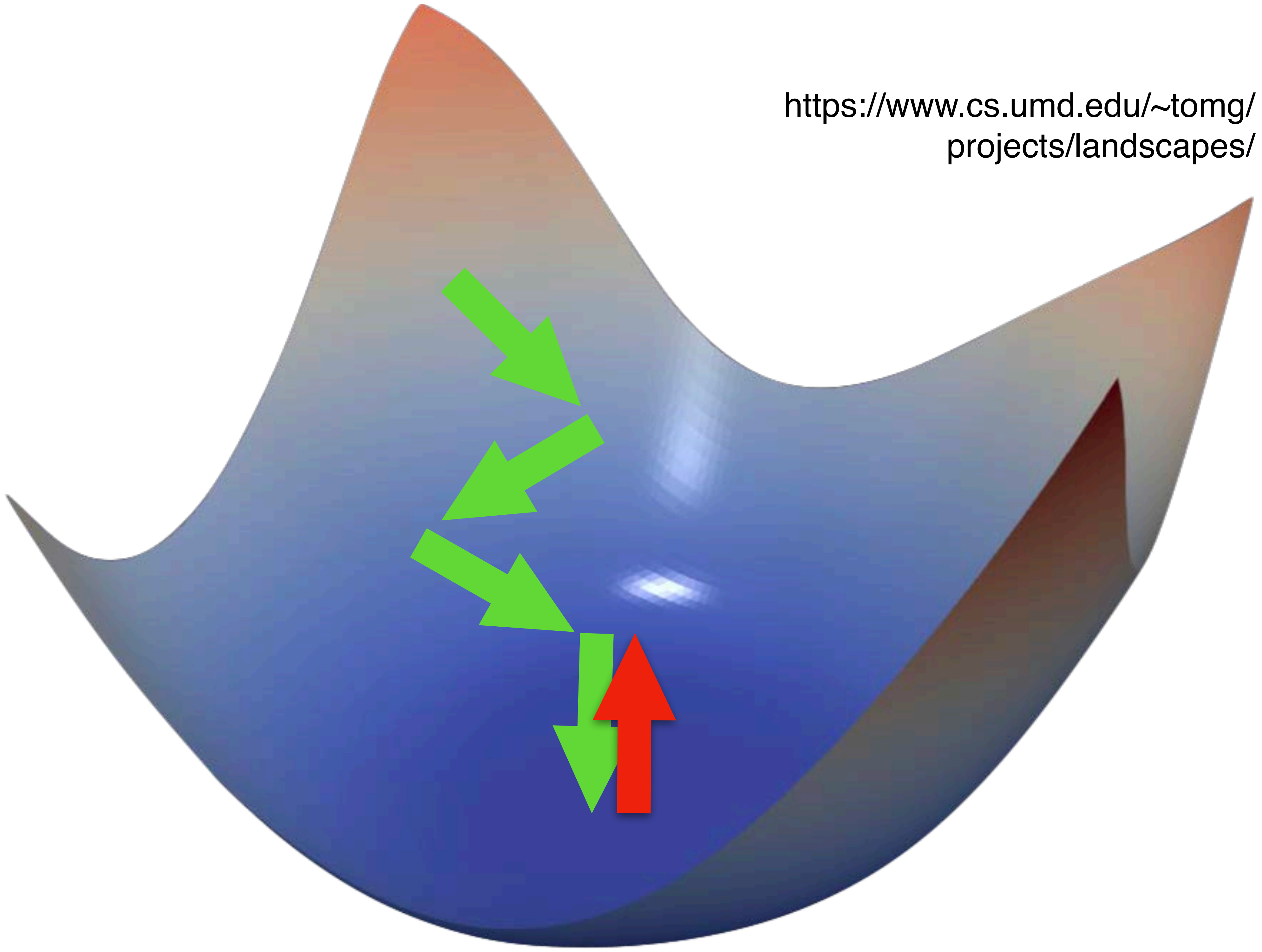

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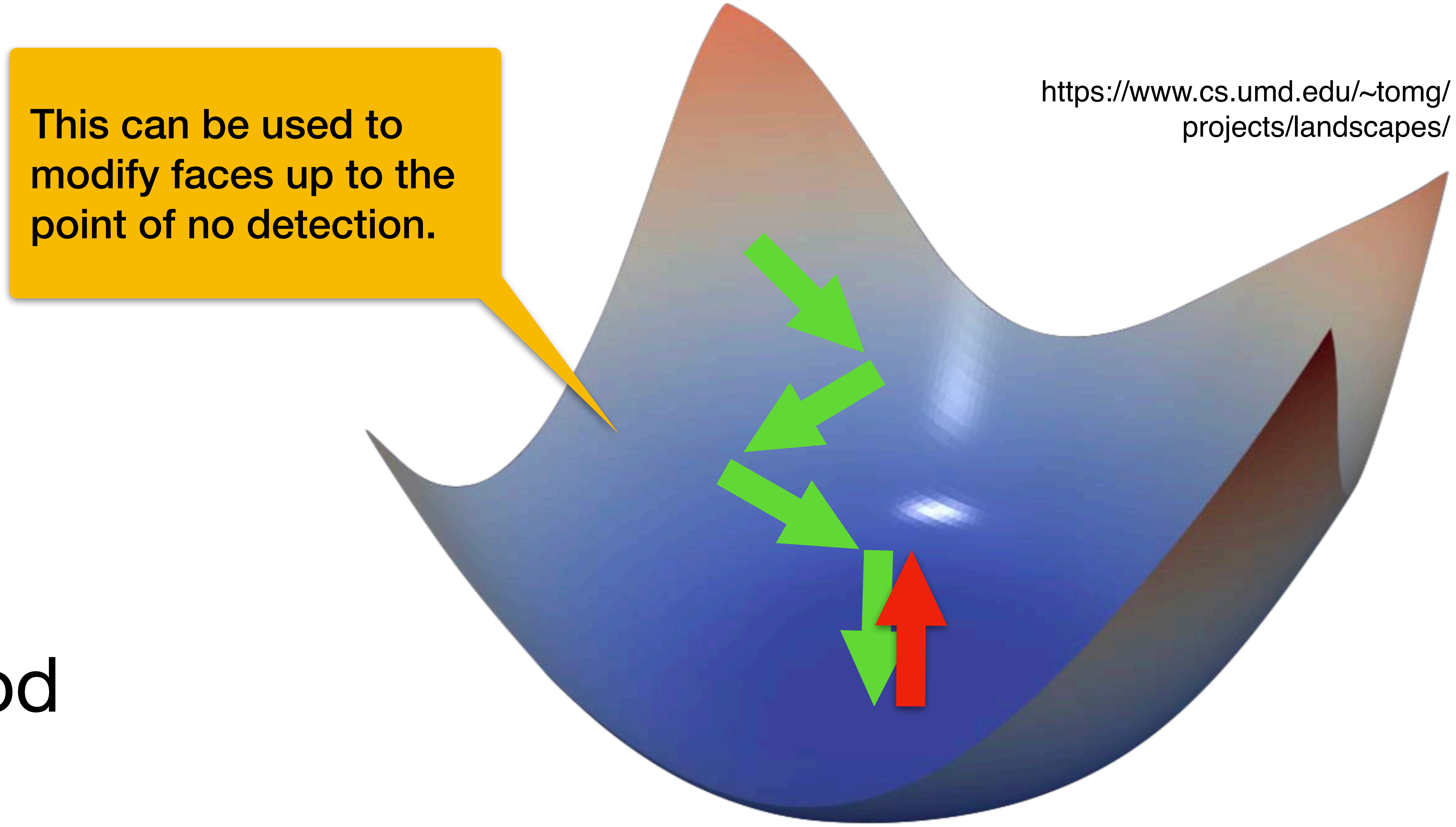

CNN Error Surface

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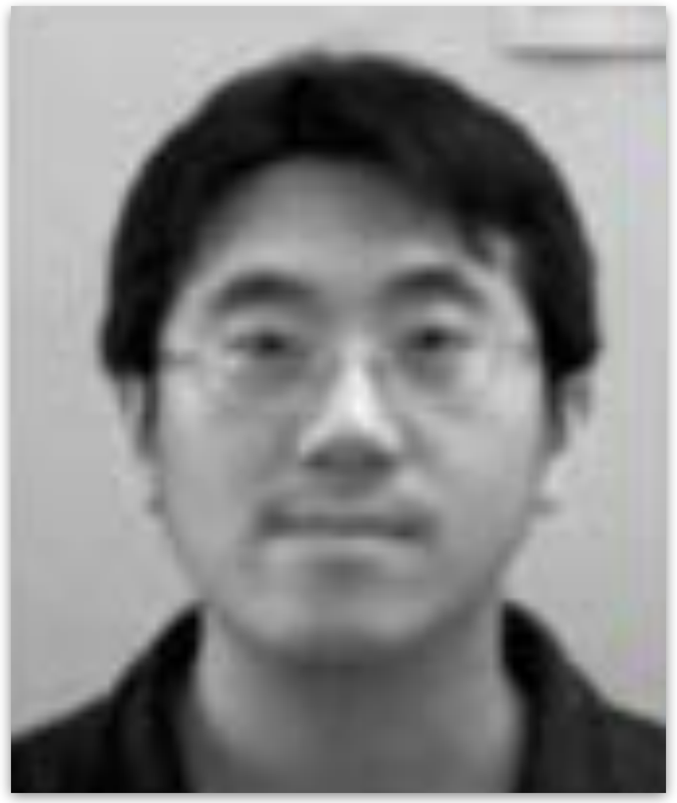
Enhancement

Face Alignment

Goal
Make template and sample faces be in similar poses, to make further description and matching easier.



template

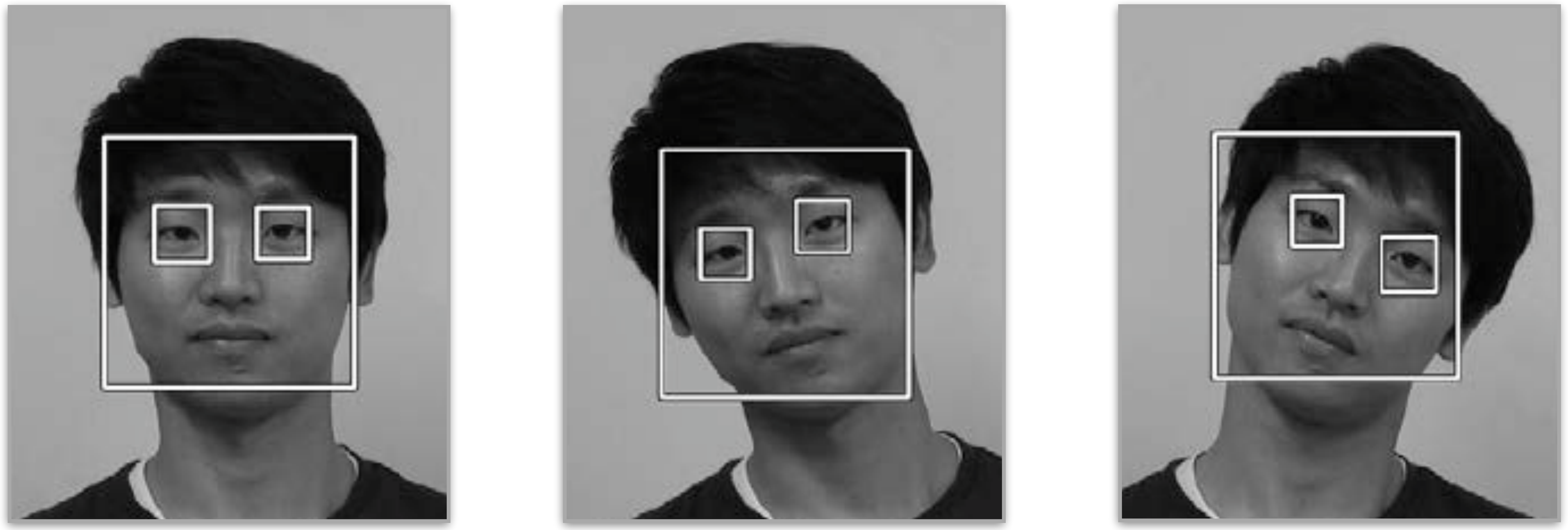
sample

Enhancement

Face Alignment

Detection of
Face Landmarks
E.g., position of eyes.

Jain, Ross, and Nadakumar
Introduction to Biometrics
Springer Books, 2011

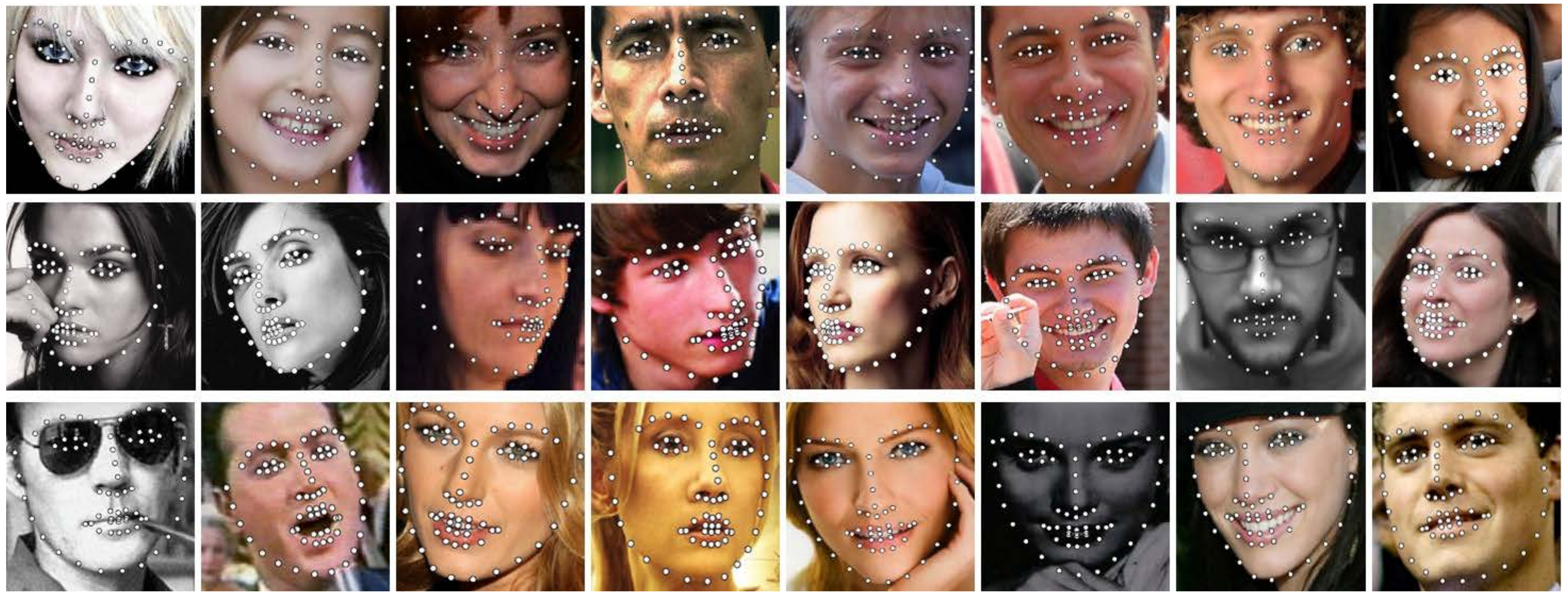


Possible solution: eye detection using Viola-Jones approach.

Enhancement

Face Alignment

Detection of
Face Landmarks
There are better solutions in the literature, using deep neural networks, for instance.



Zhang et al.
Facial Landmark Detection by Deep Multi-task Learning
ECCV 2014

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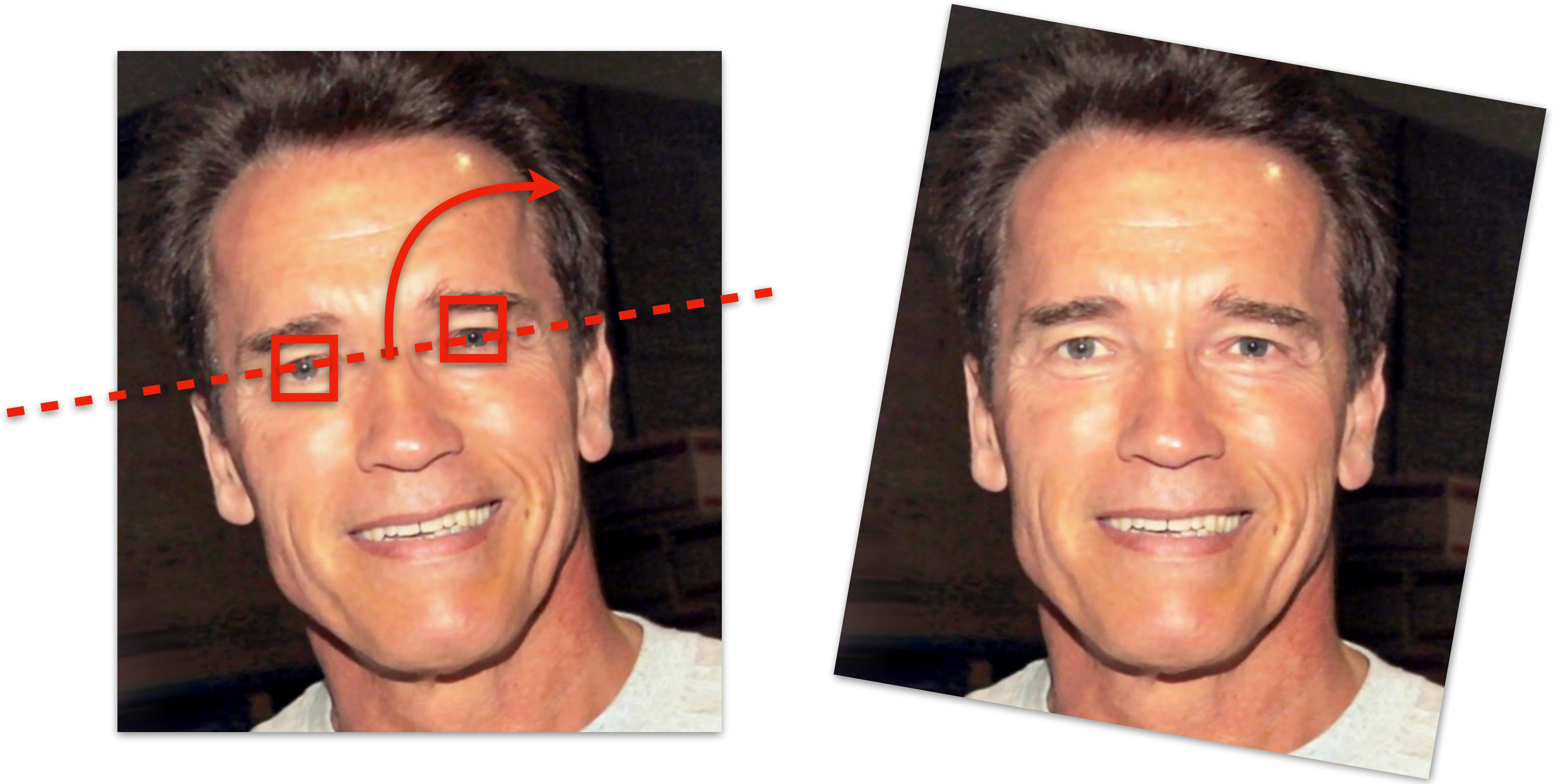
Enhancement

Face Alignment

Landmark Alignment
E.g., make the positions of the eyes horizontally aligned, by rotating the face image.



http://www.bytefish.de/blog/aligning_face_images/

Enhancement

Face Alignment

Cropping
Make a tight crop of the face, to remove background.

Keep eyes, nose, and mouth.

http://www.bytefish.de/blog/aligning_face_images/

Enhancement

Face Alignment

More Severe
Pose Variations
Naïve approach will not work.

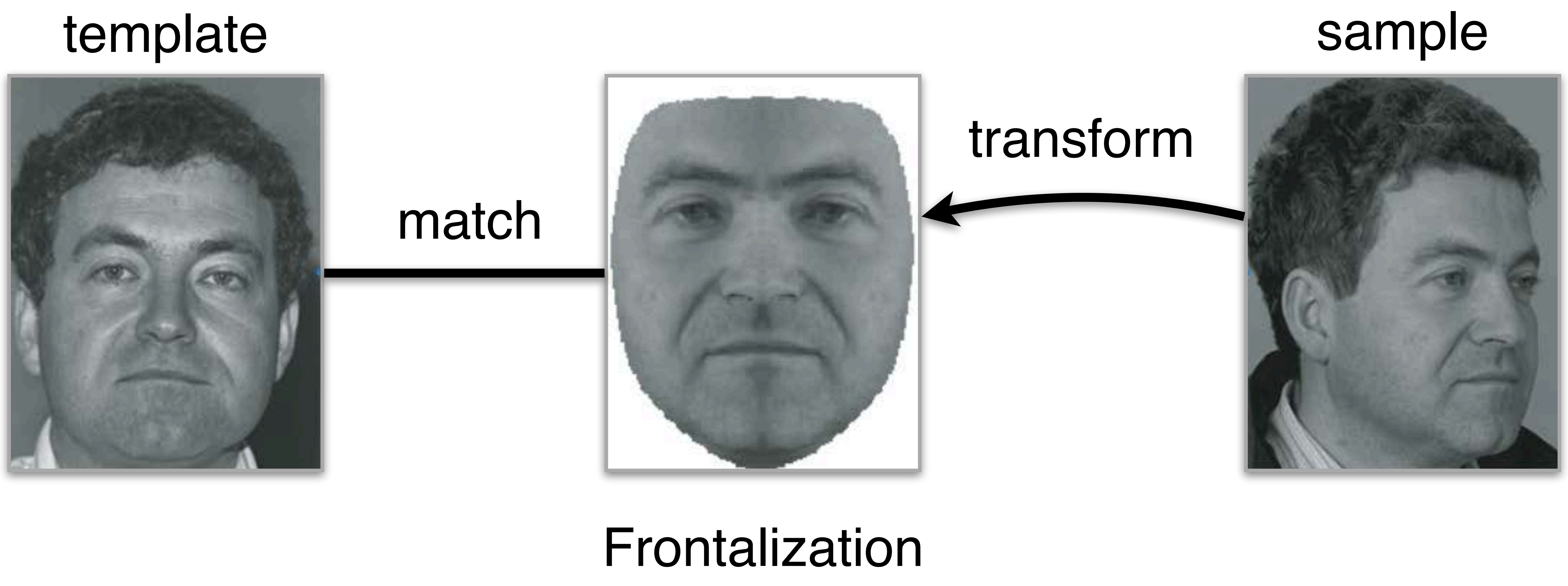


Enhancement

Face Alignment

More Severe
Pose Variations
Alternative approaches.
3D information will help
to do frontalization.

Yi et al.
Towards Pose Robust Face Recognition
CVPR 2013



Enhancement

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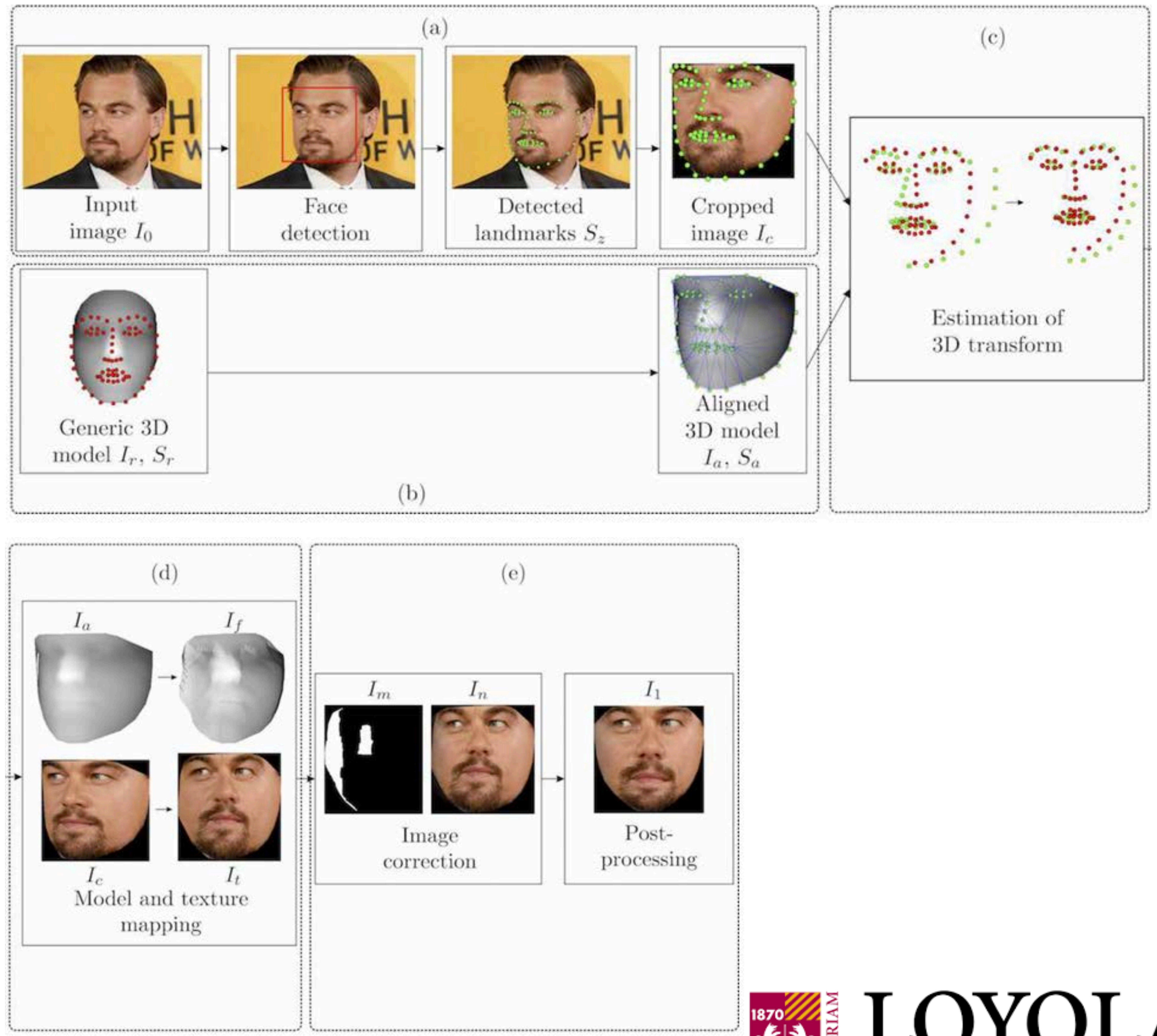

Banerjee et al.
To frontalize or not to frontalize: Do we really need elaborate pre-processing to improve face recognition?
WACV 2018

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Enhancement

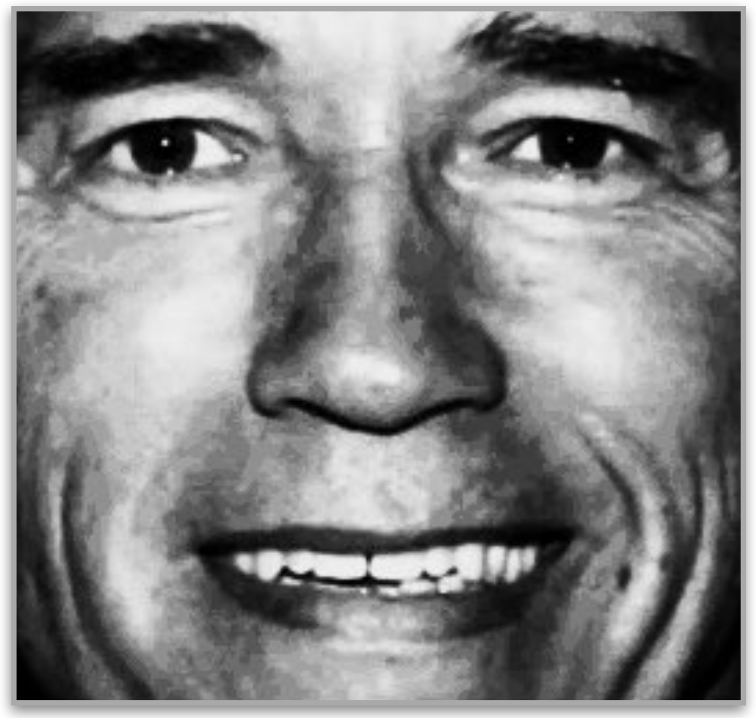
Illumination Correction

Simplest Solution
Color histogram equalization.

Alternatives
Photometric normalization, illumination modeling, etc.

Original

Grayscale



Equalized

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What's Next?

Face Description and Matching

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

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