

Face Recognition II

COMP 388-002/488-002 Biometrics

Daniel Moreira
Fall 2026



LOYOLA
UNIVERSITY CHICAGO

Today we will...

Get to know

Face acquisition and enhancement.

Today's Attendance

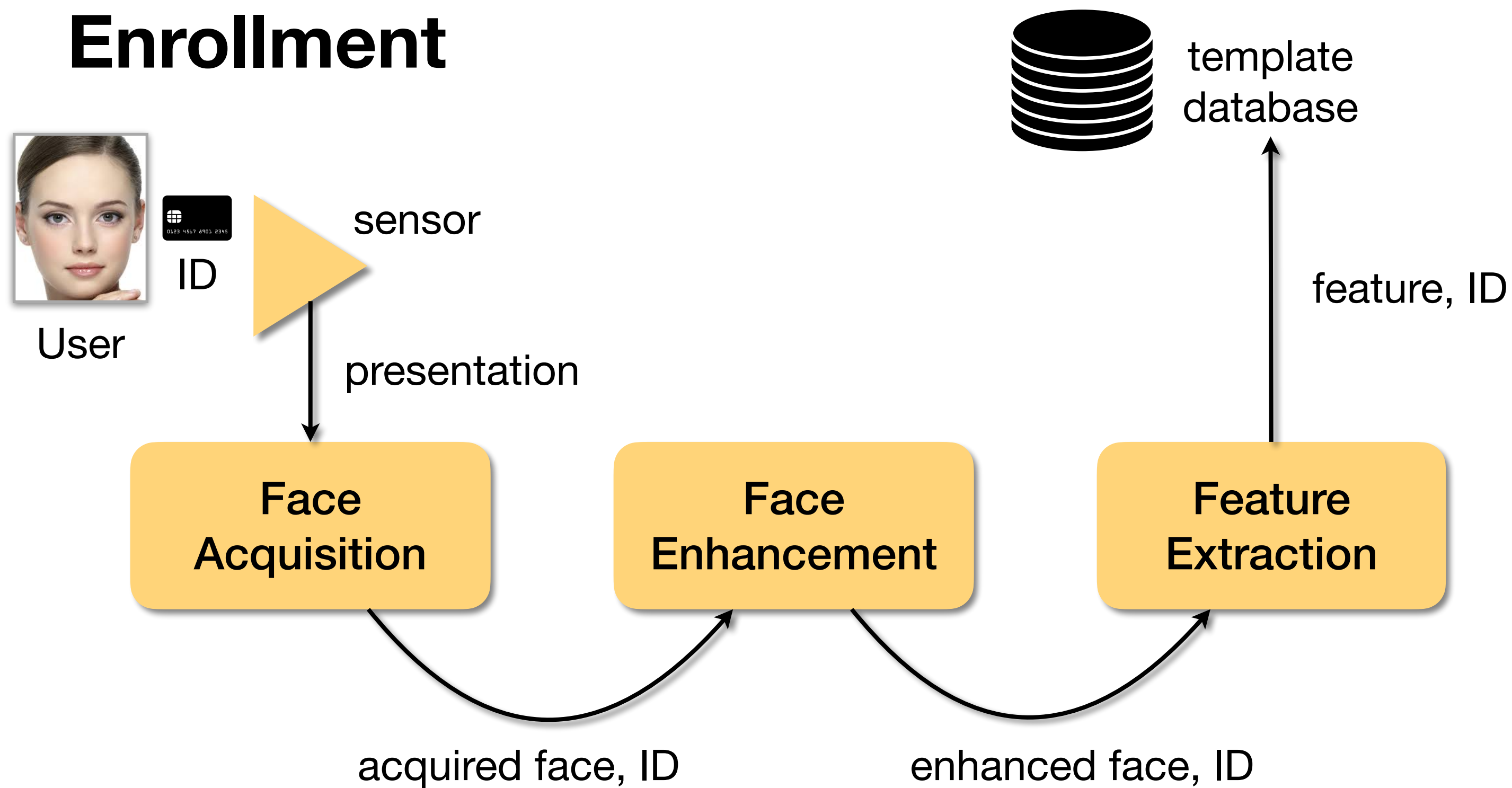
Please fill out the form

forms.gle/wNQkVZXm1AQLsdNE9



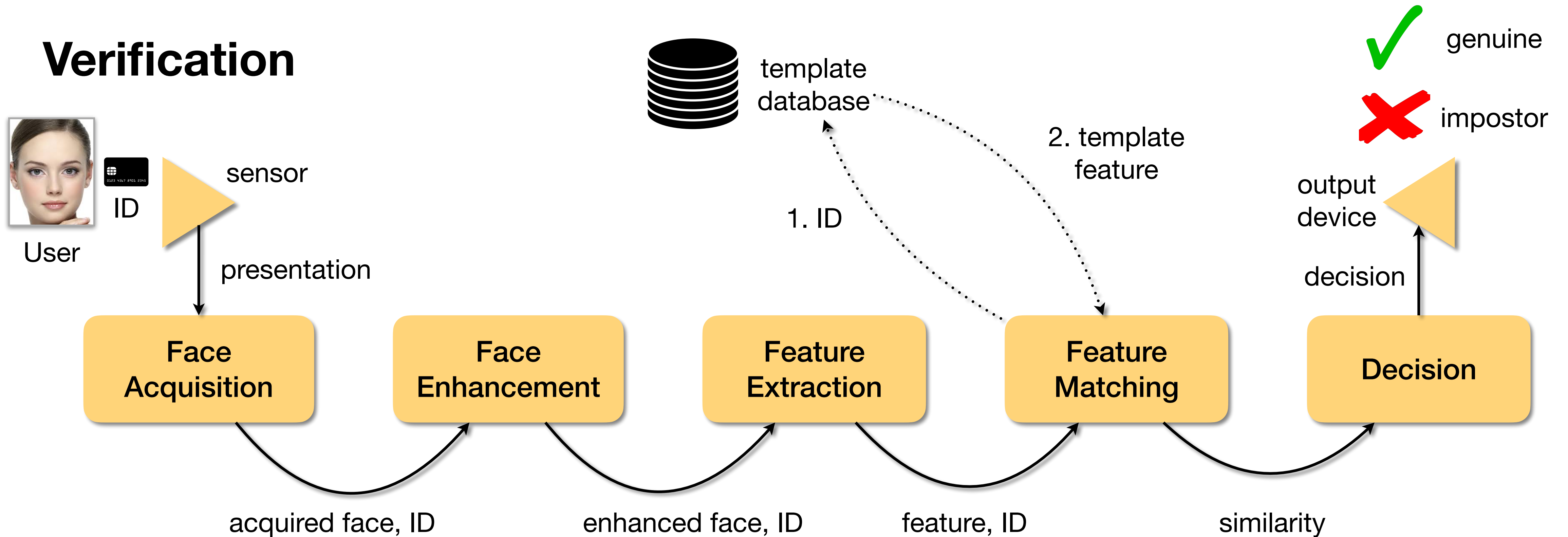
Face Recognition

Enrollment



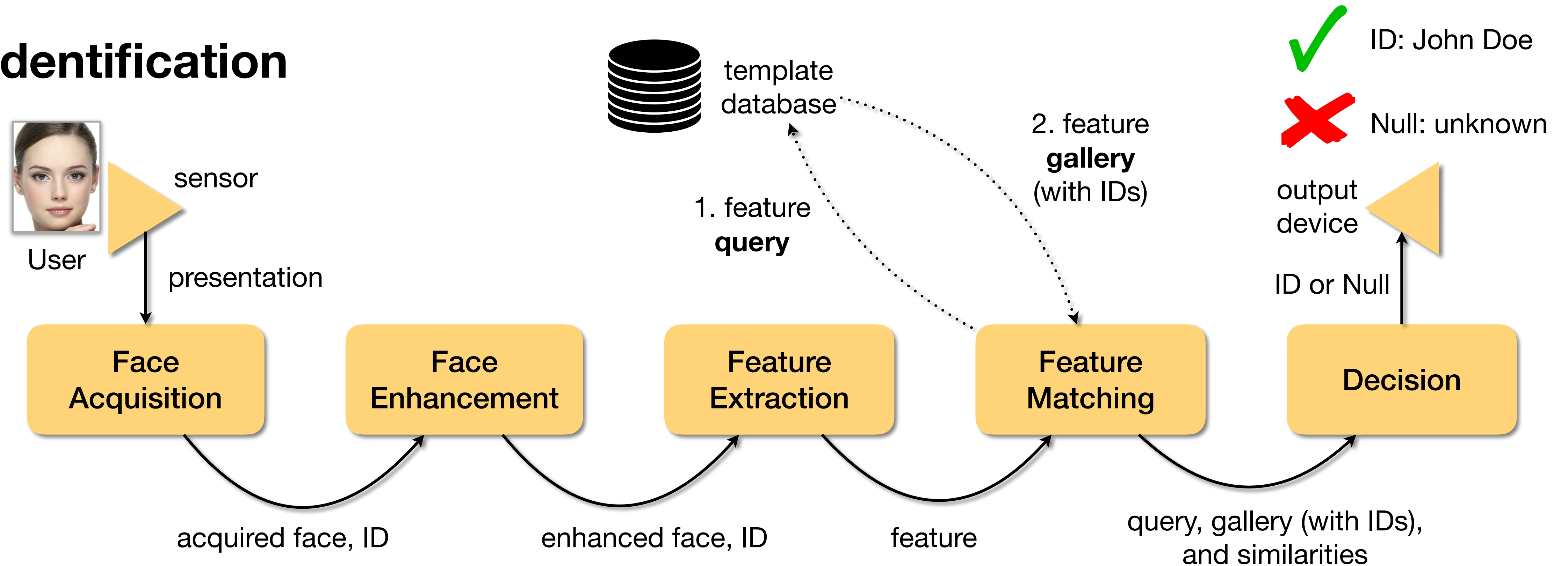
Face Recognition

Verification

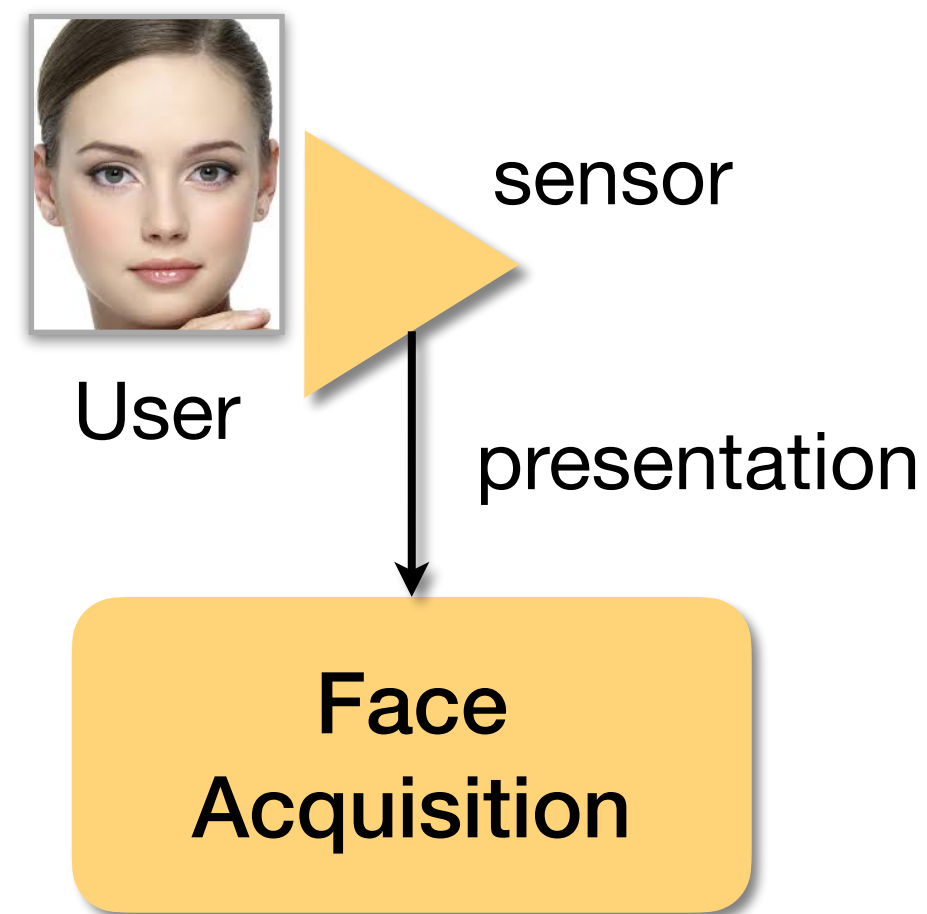


Face Recognition

Identification



Face Recognition



Acquisition

On-line versus Off-line



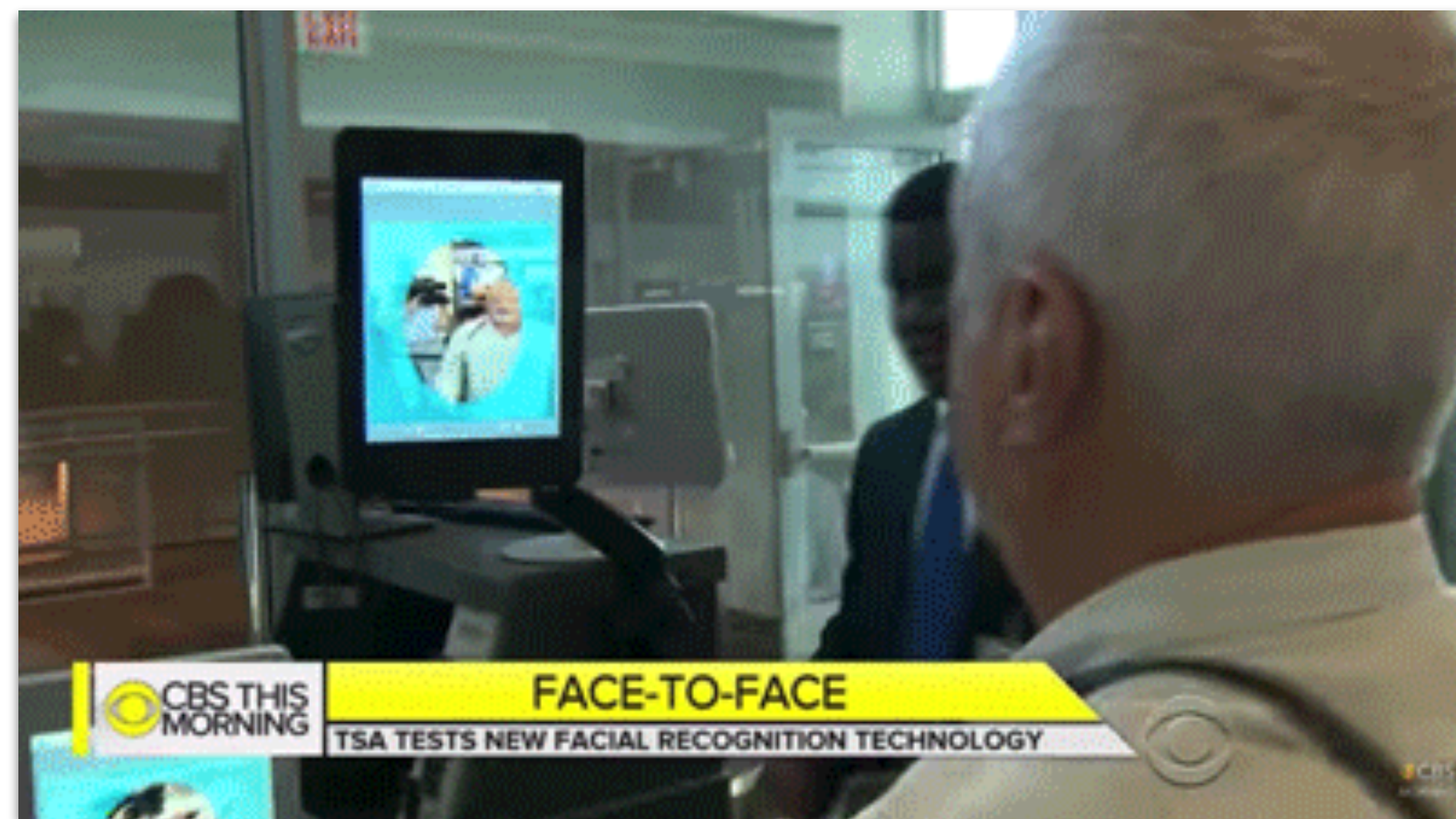
https://www.youtube.com/watch?v=BYN4oF_bi4c



Acquisition

Controlled Acquisition

Right pose, distance and illumination.



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



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

Acquisition

Controlled Acquisition

Different light wavelengths.



Captures at visible and near-infrared spectra.

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



Sony infrared camera.

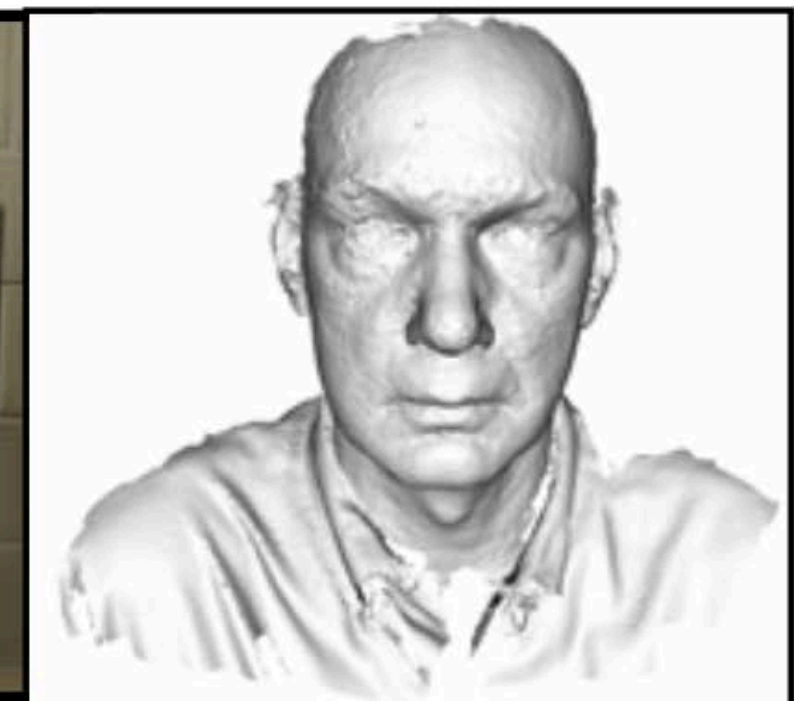
Acquisition

Controlled Acquisition 3D Information

Source:
Dr. Walter Scheirer



Minolta Vivid 900/910



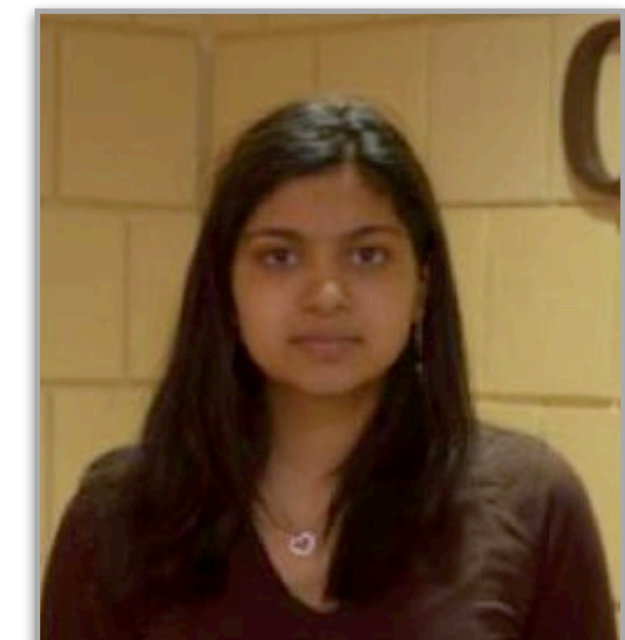
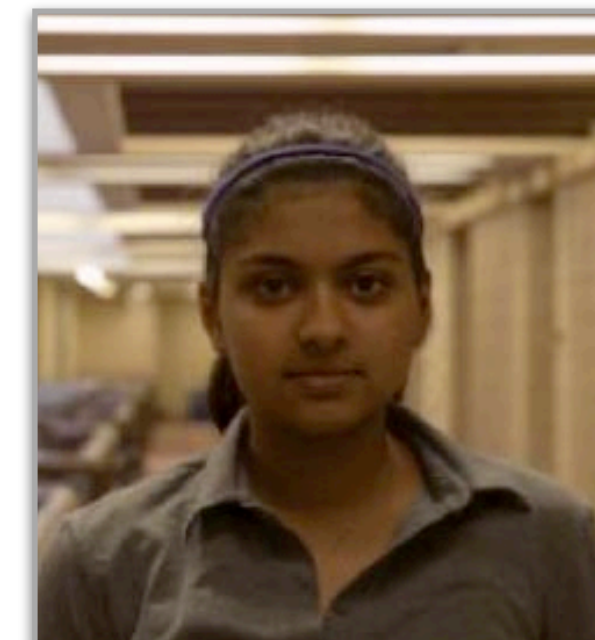
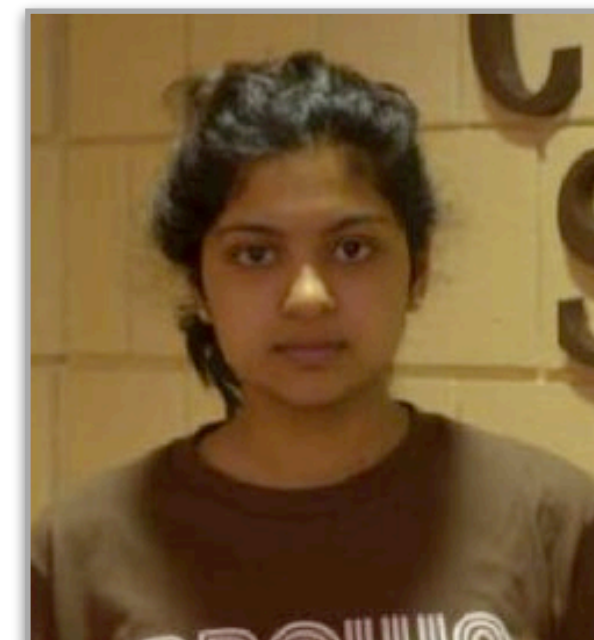
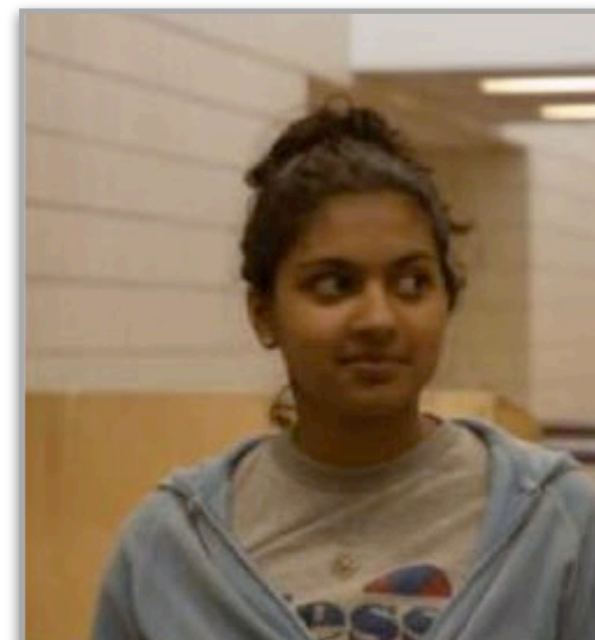
3DMD "Qlonerator"

Acquisition

Unconstrained Acquisition

No illumination control.

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



Acquisition

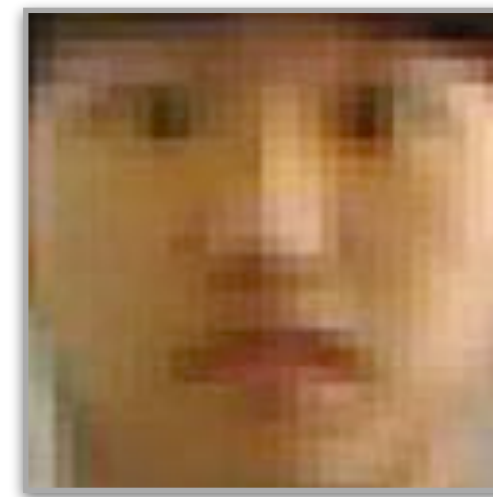
Unconstrained Acquisition

No distance control.

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



1m



3m



5m

Acquisition

Unconstrained Acquisition

No pose control.



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

Acquisition

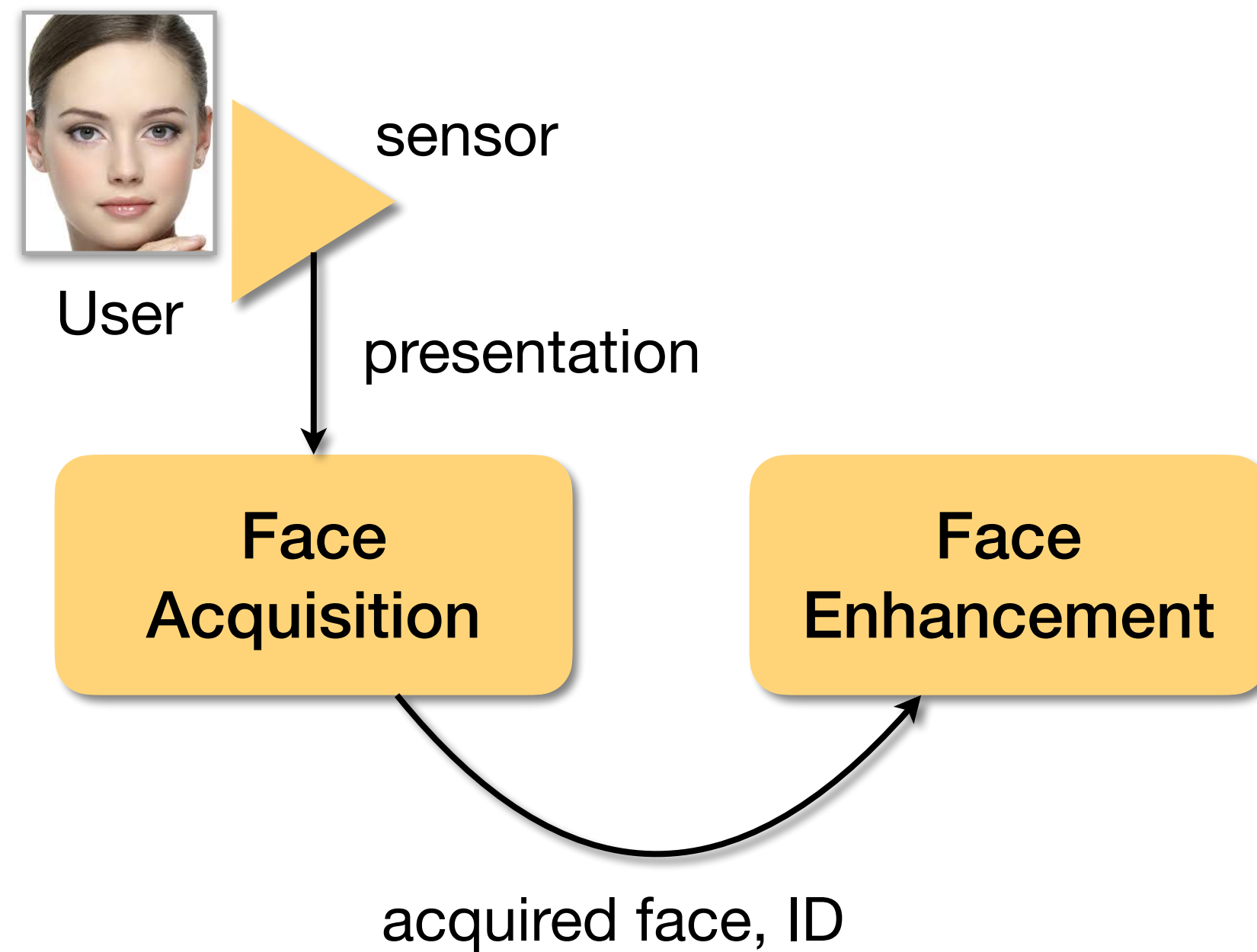
Problems

Presentation Attack



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

Face Recognition

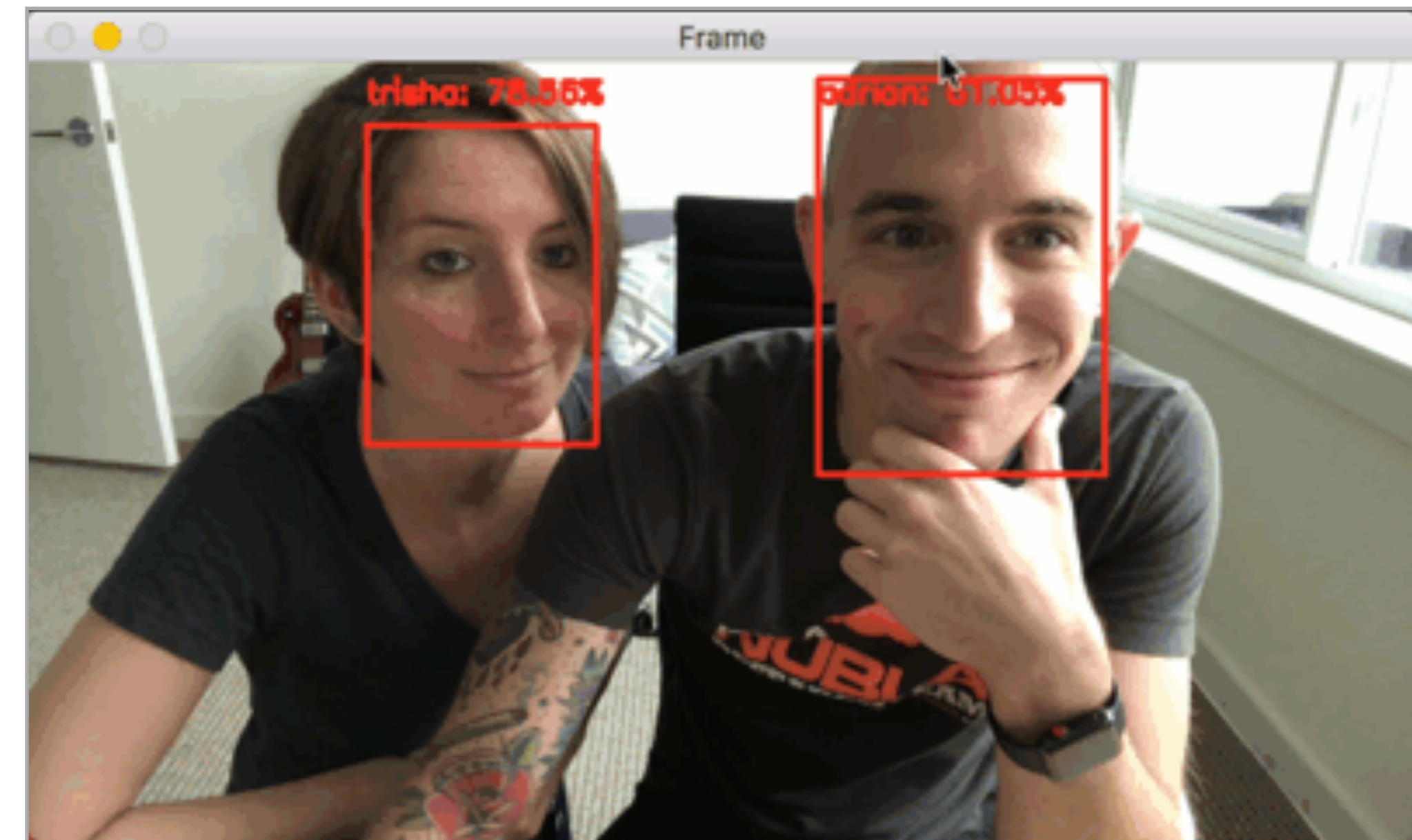


Enhancement

Face Detection

Goal

Localize faces for segmentation and further recognition.



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

Enhancement

Face Detection

2016 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>)

Enhancement

Face Detection

2021 Progress

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>)



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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.

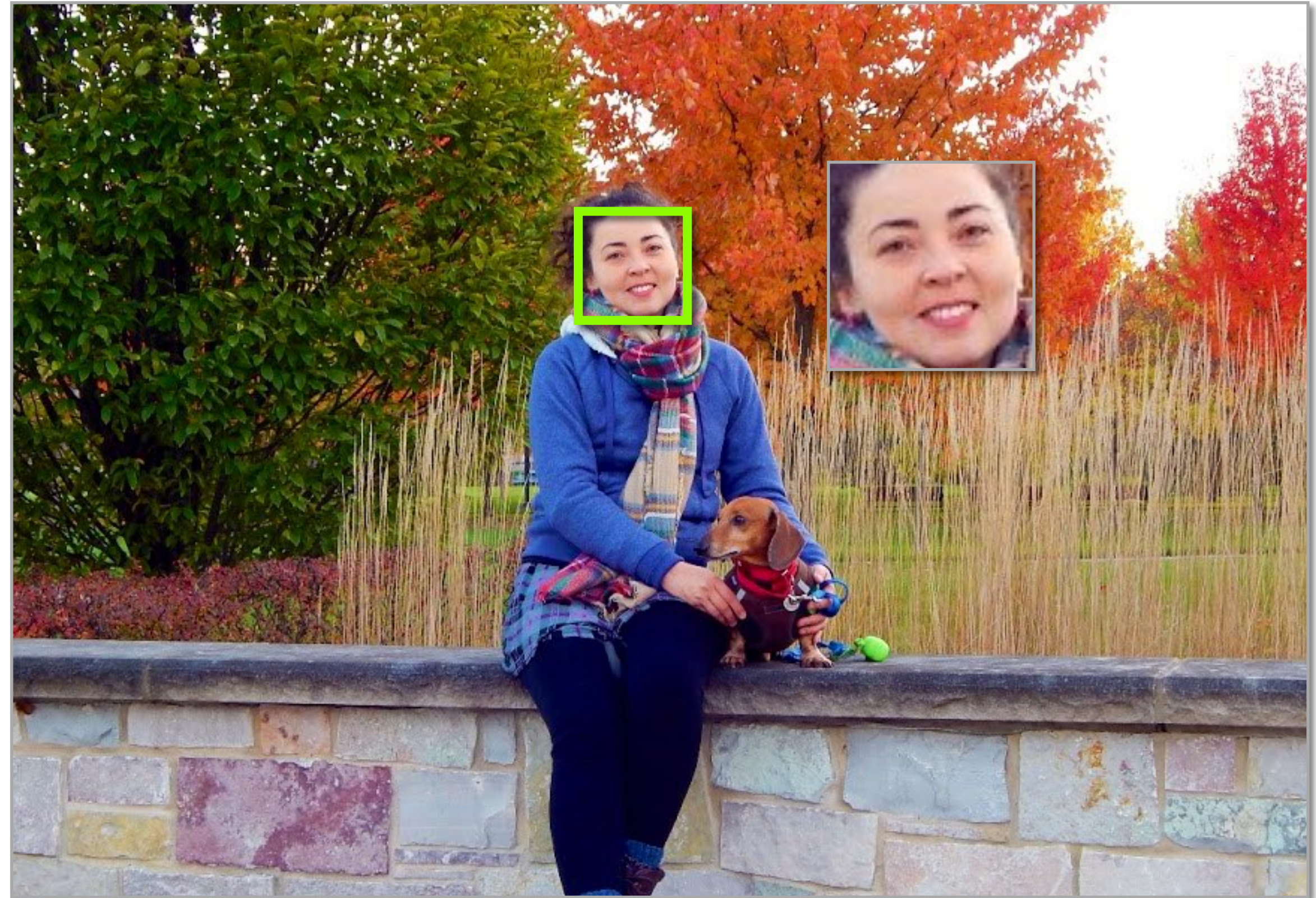


Enhancement

Face Detection

Sliding Windows

Scans of the image with windows of different scales.



Enhancement

Face Detection

Regions of Interest

Techniques from Computer Vision or Machine Learning to segment regions.

E.g., Maximally Stable Extremal Regions (MSER¹) or Deep Local Features (DELF²).



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.

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.



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.

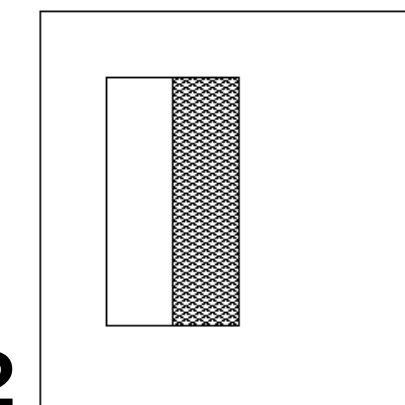
$$value = \sum pixels\ in\ white\ area - \sum pixels\ in\ black\ area$$

Filter types

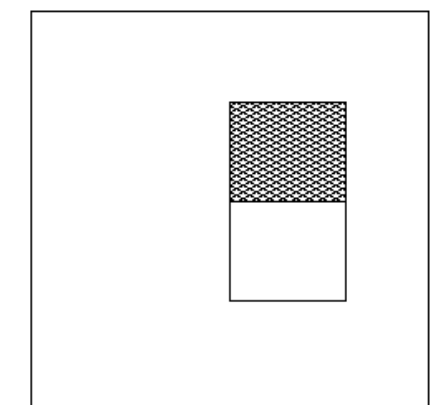
2, 3, and 4 rectangles.



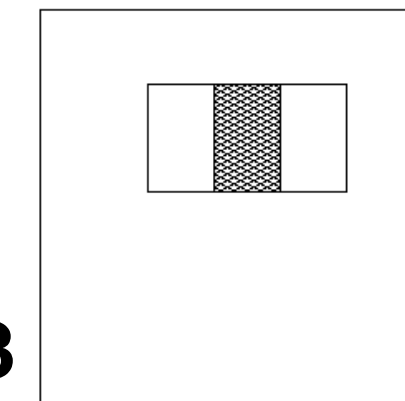
2



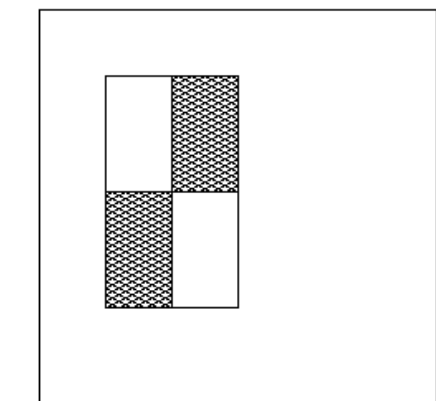
2



3



4



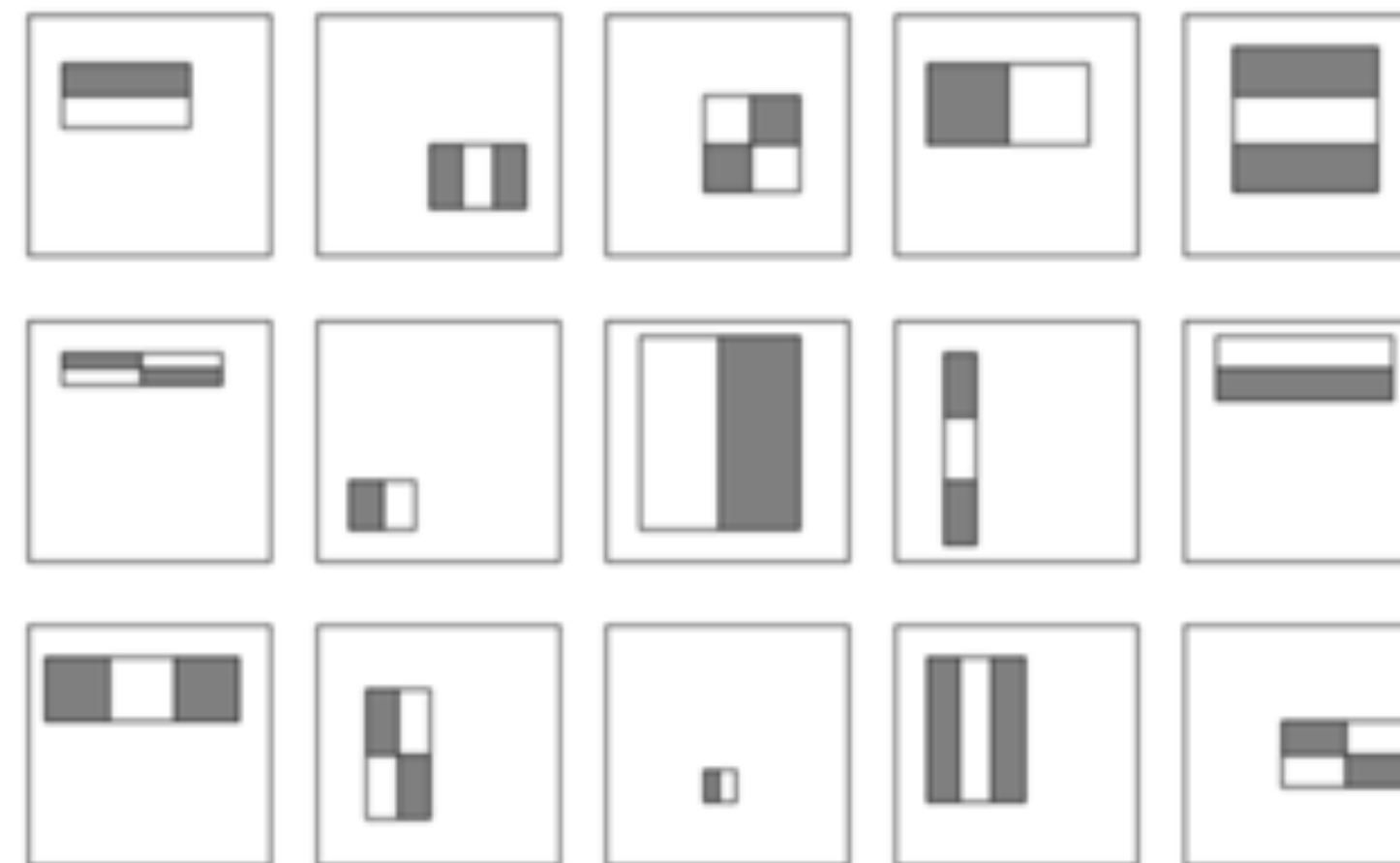
Enhancement

Viola-Jones Detector

Haar-like Features (1/4)

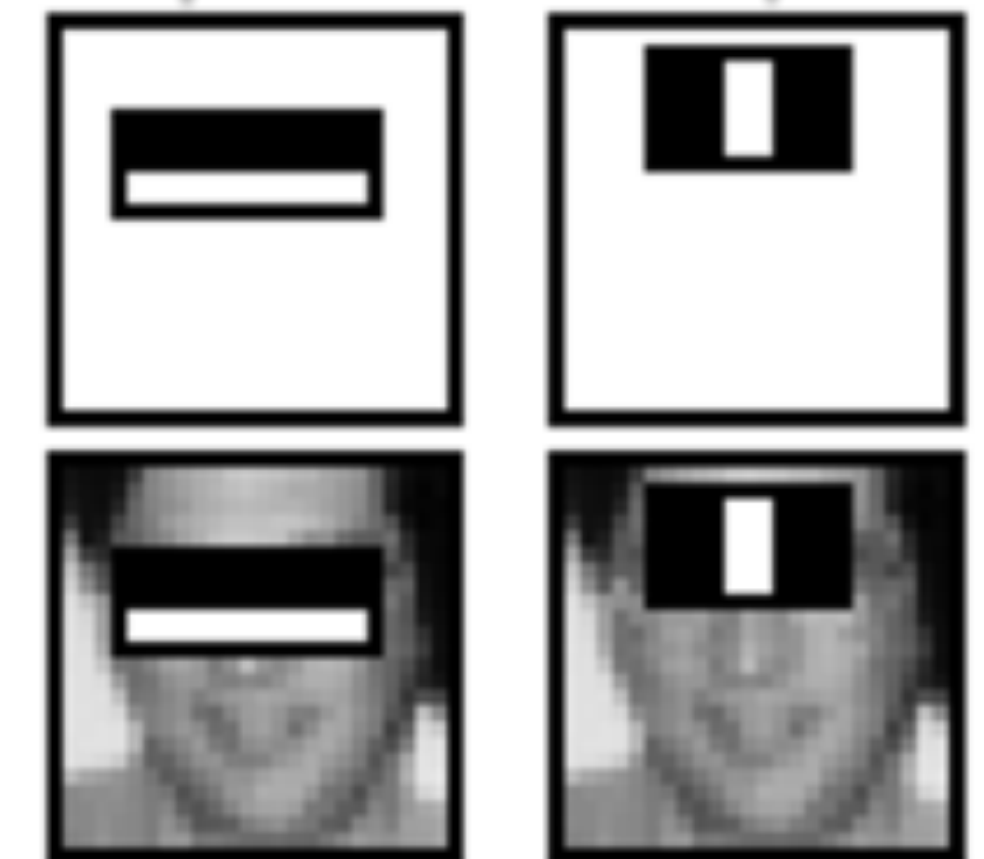
Take a 24-by-24-pixel window.

The number of possible features is nearly 160,000.



Good to detect eyes.

Good to detect nose bridges.



How to apply and how to select features fast?

Enhancement

Face Detection

Viola-Jones Detector

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Based on sliding windows.

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Haar-like features.

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Attentional Cascade to reject non-faces.



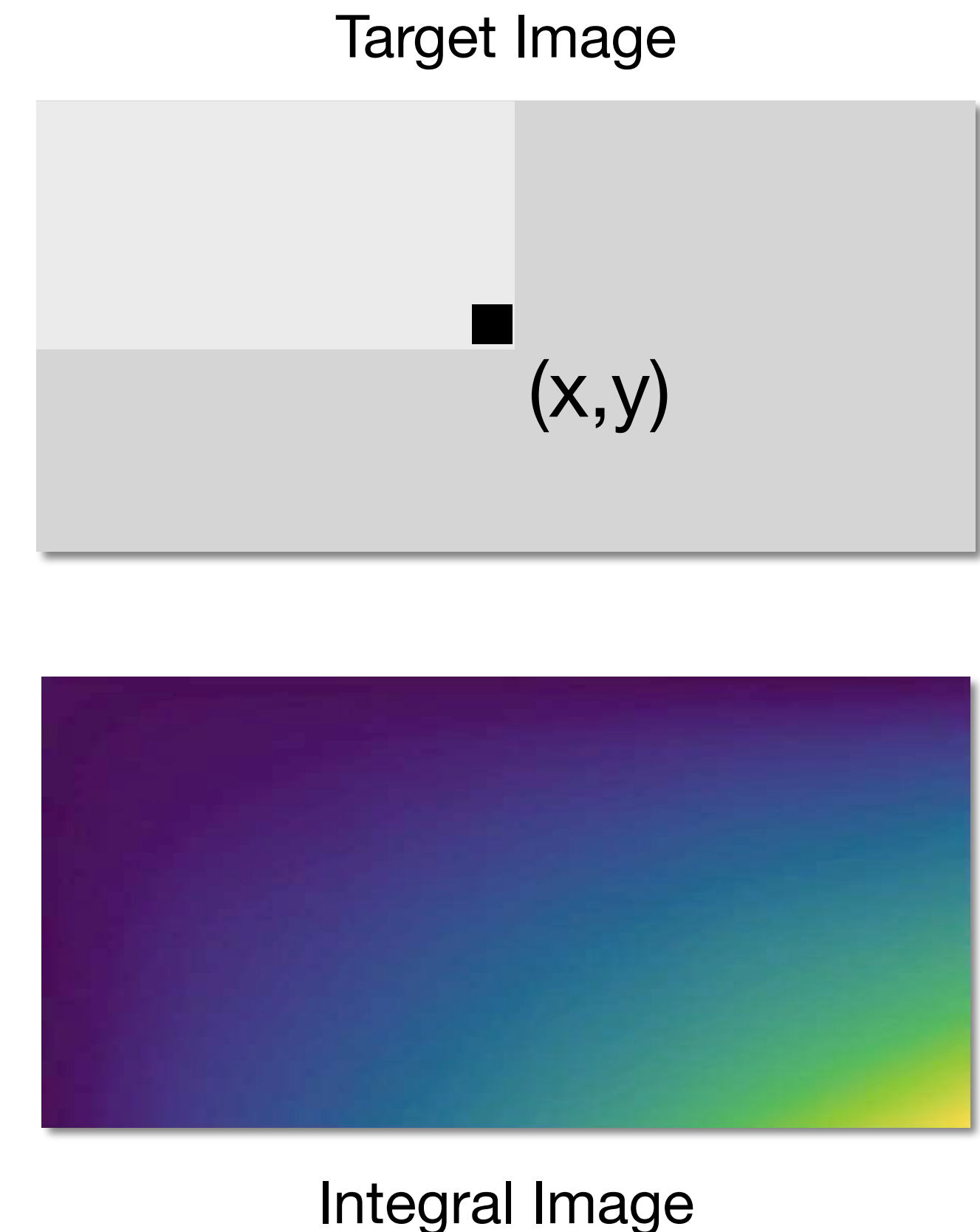
Enhancement

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.



Enhancement

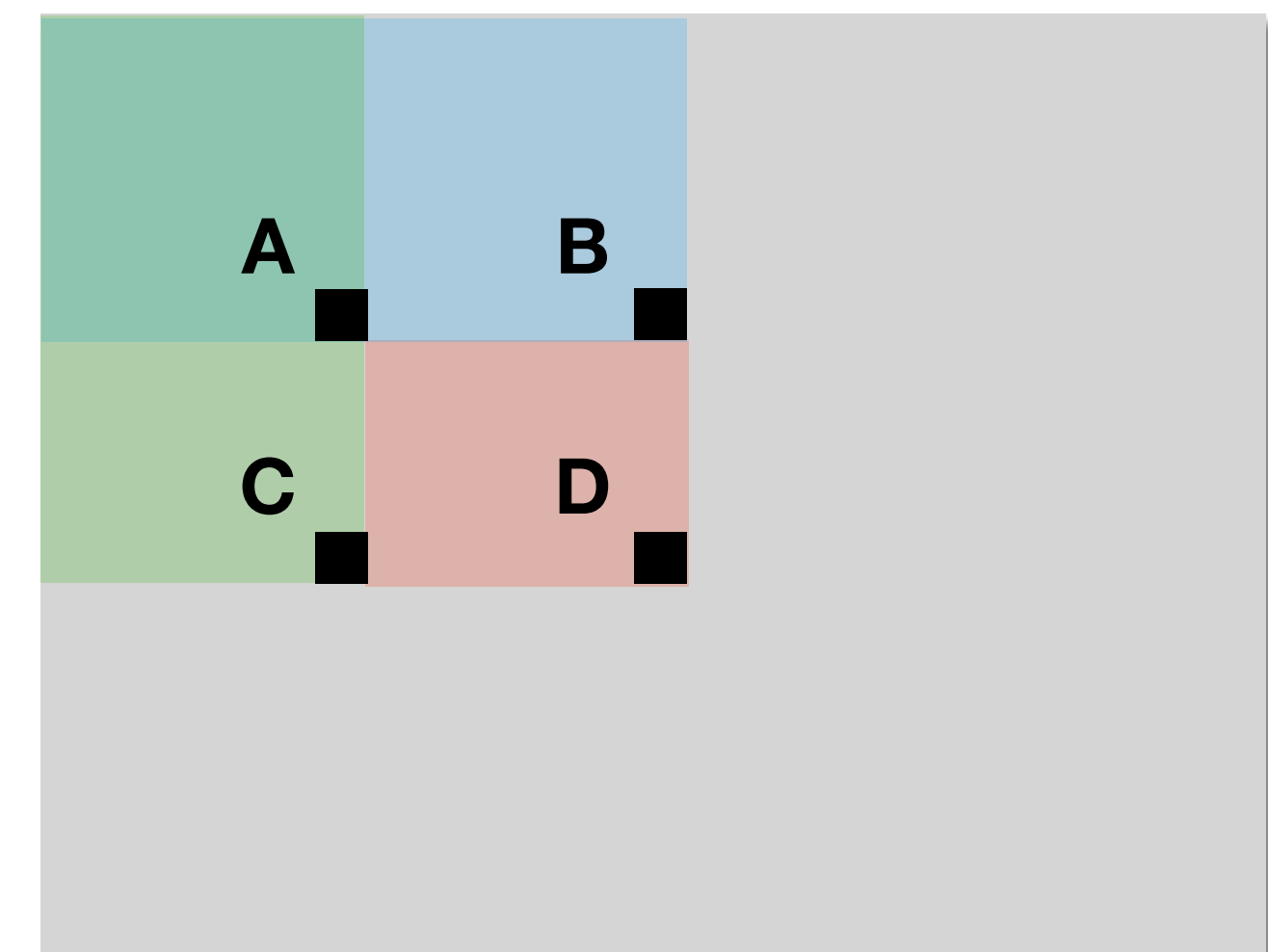
Viola-Jones Detector

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.

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.

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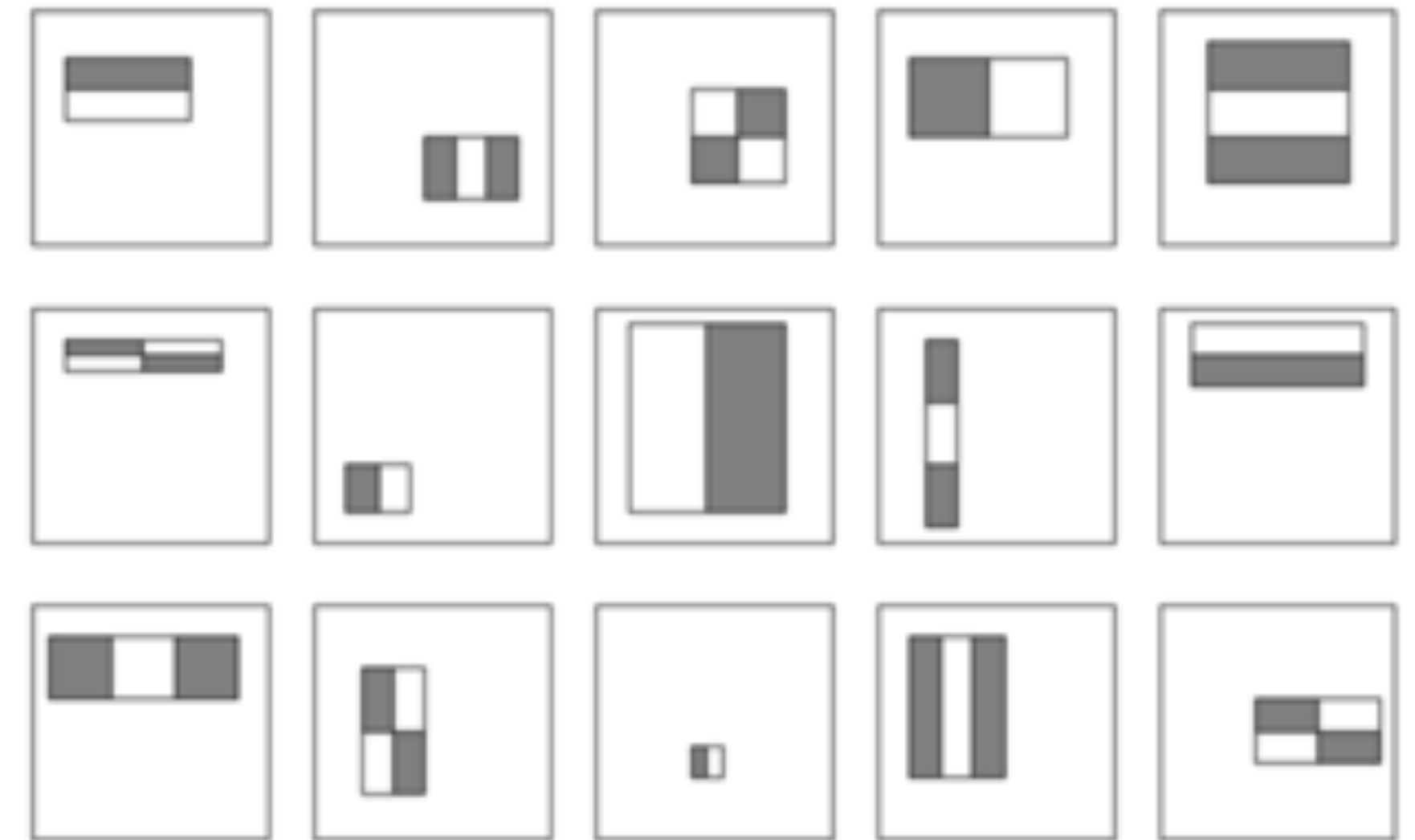


Enhancement

Viola-Jones Detector

Boosting for Feature Selection (3/4)

Goal: select combinations of
Haar-like features that are useful
for face detection.

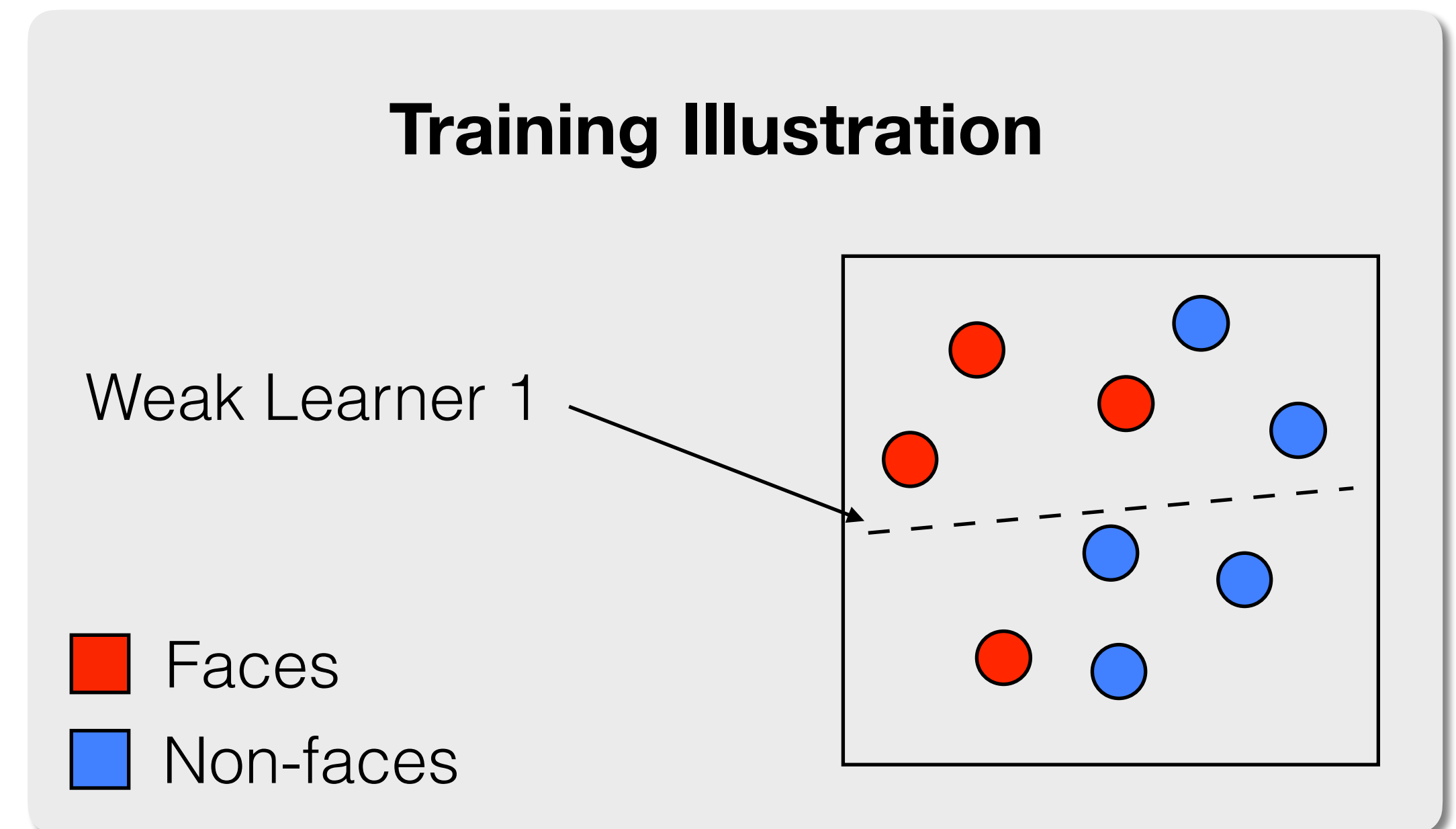


Enhancement

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.



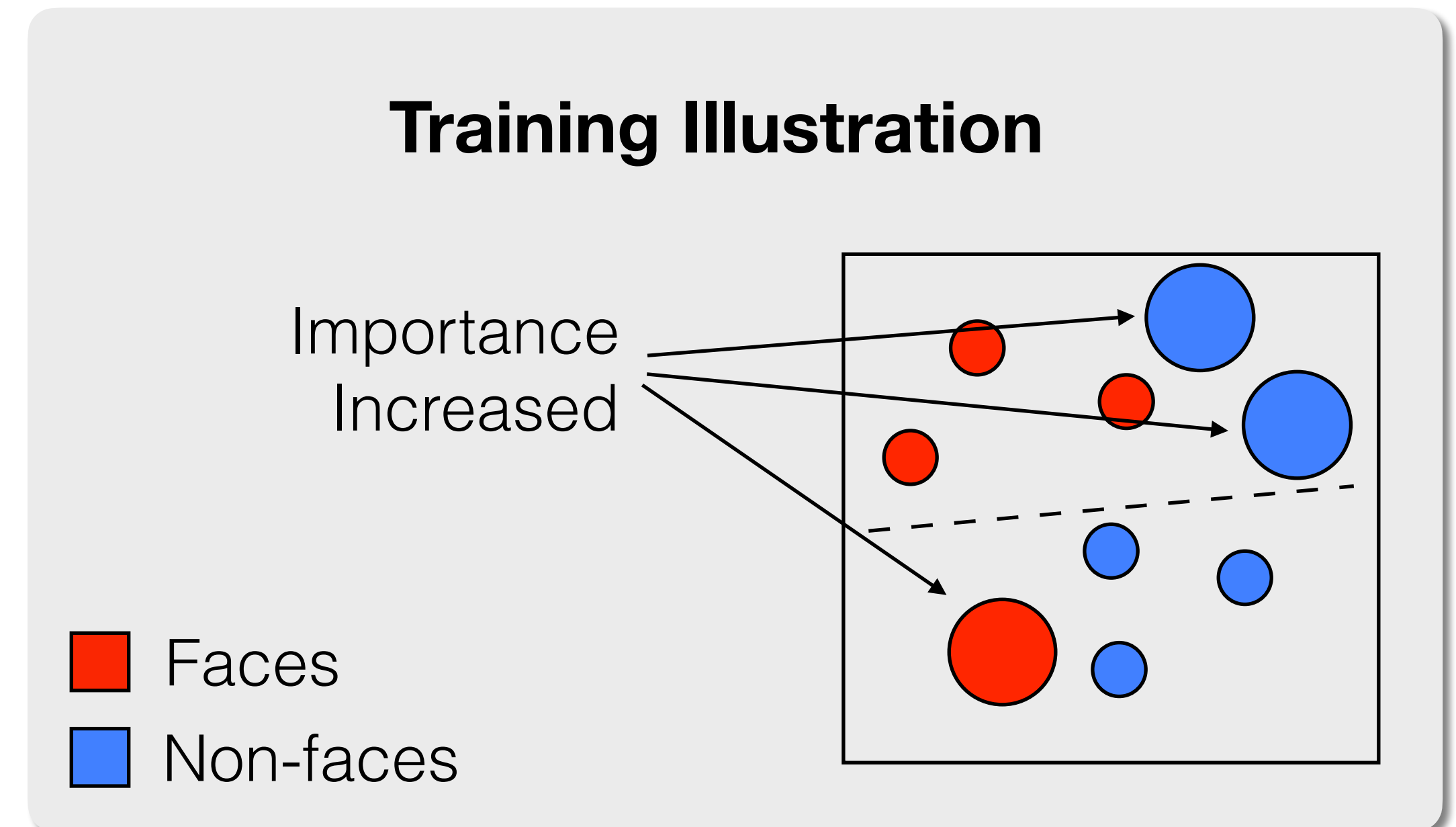
Source: Dr. Walter Scheirer

Enhancement

Viola-Jones Detector

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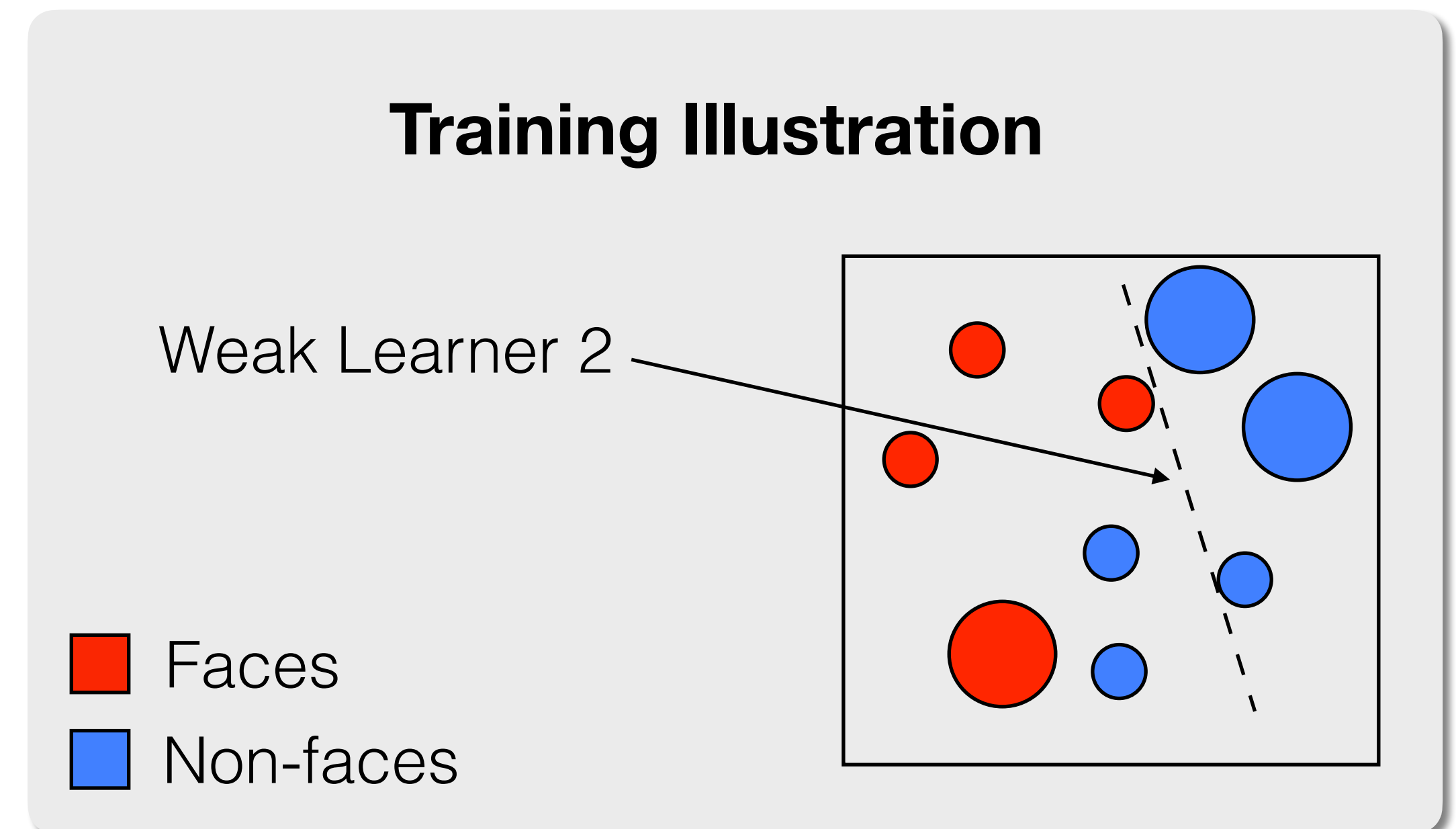
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Enhancement

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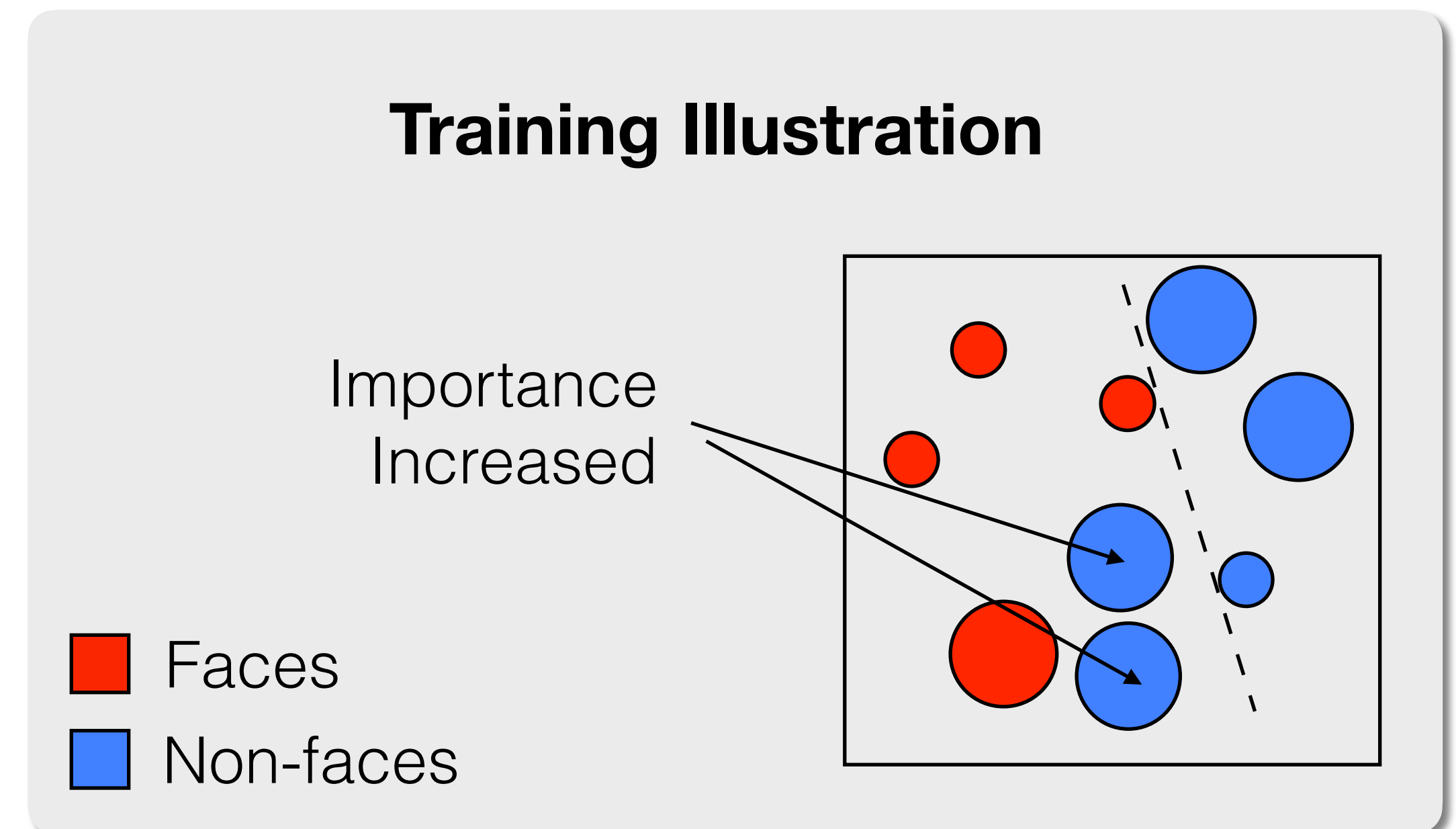
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Enhancement

Viola-Jones Detector

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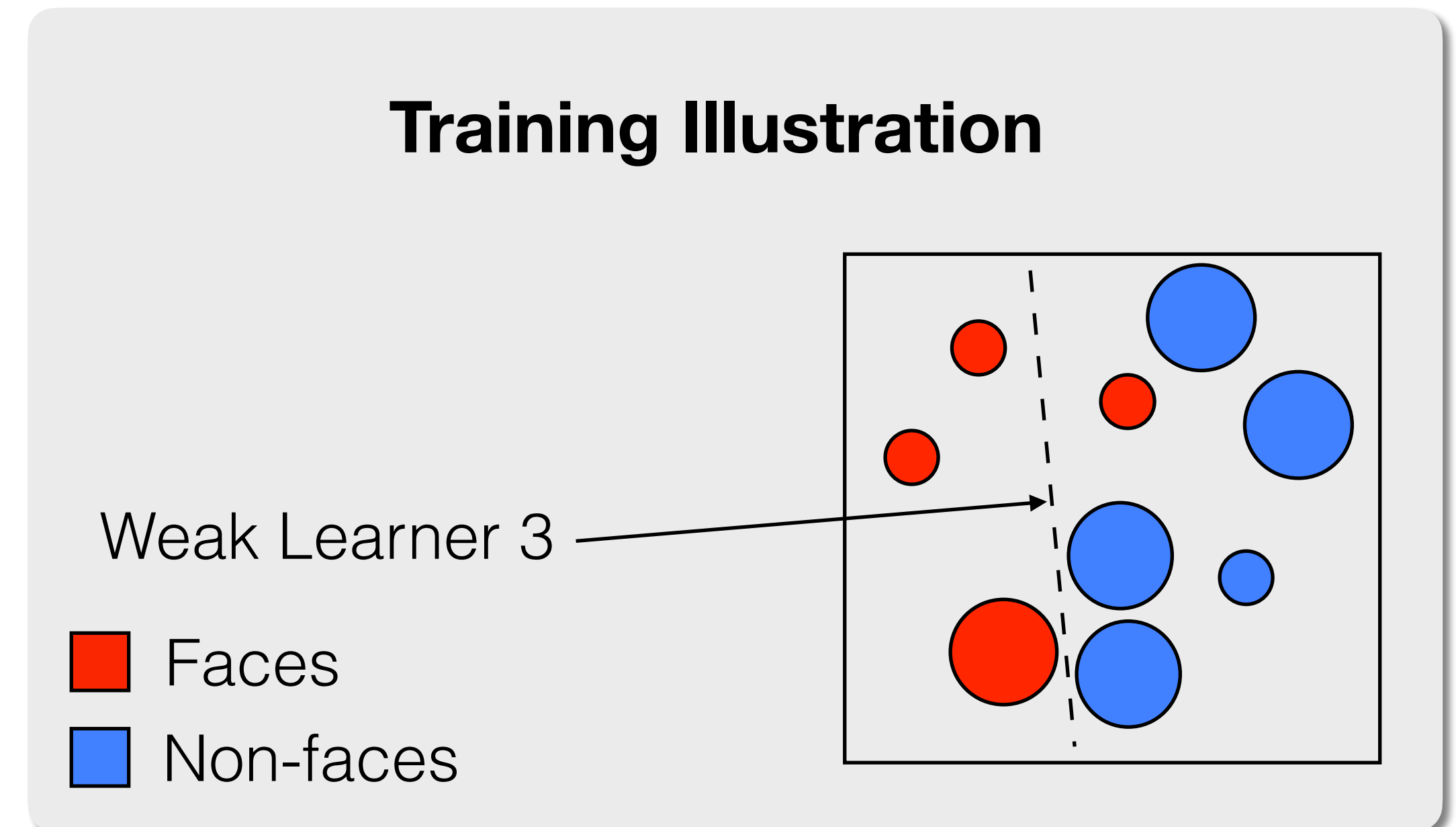
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Enhancement

Viola-Jones Detector

Boosting for Feature Selection (3/4)

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Enhancement

Viola-Jones Detector

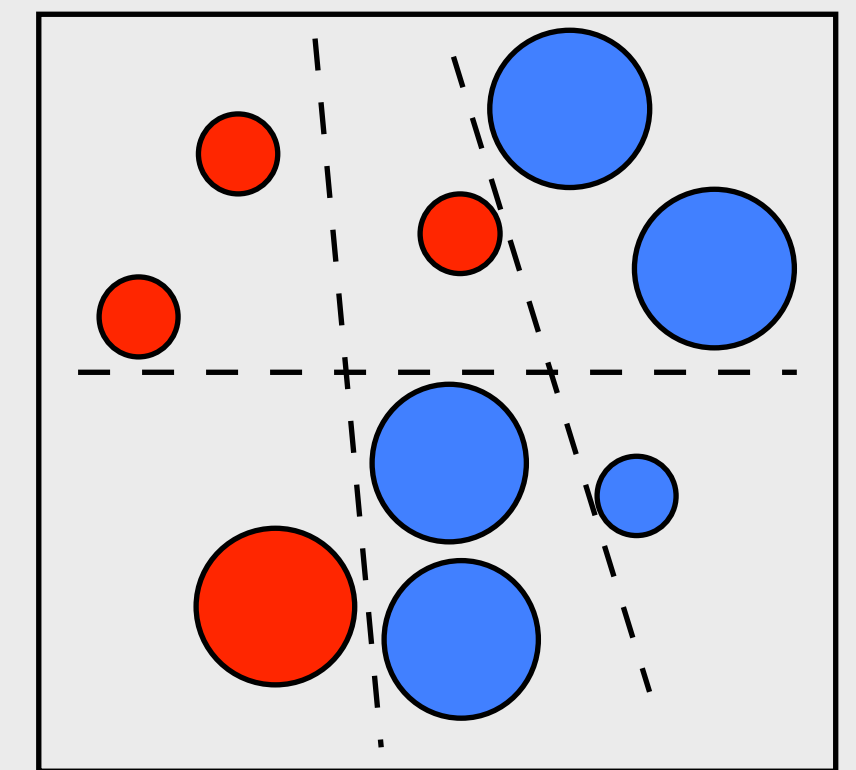
Boosting for Feature Selection (3/4)

Solution: *boosting*, a combination of weak classifiers that when learned in sequence and applied together, lead to better final classification.

Training Illustration

Final classifier is a combination of 3 weaker classifiers.

■ Faces
■ Non-faces



Source: Dr. Walter Scheirer

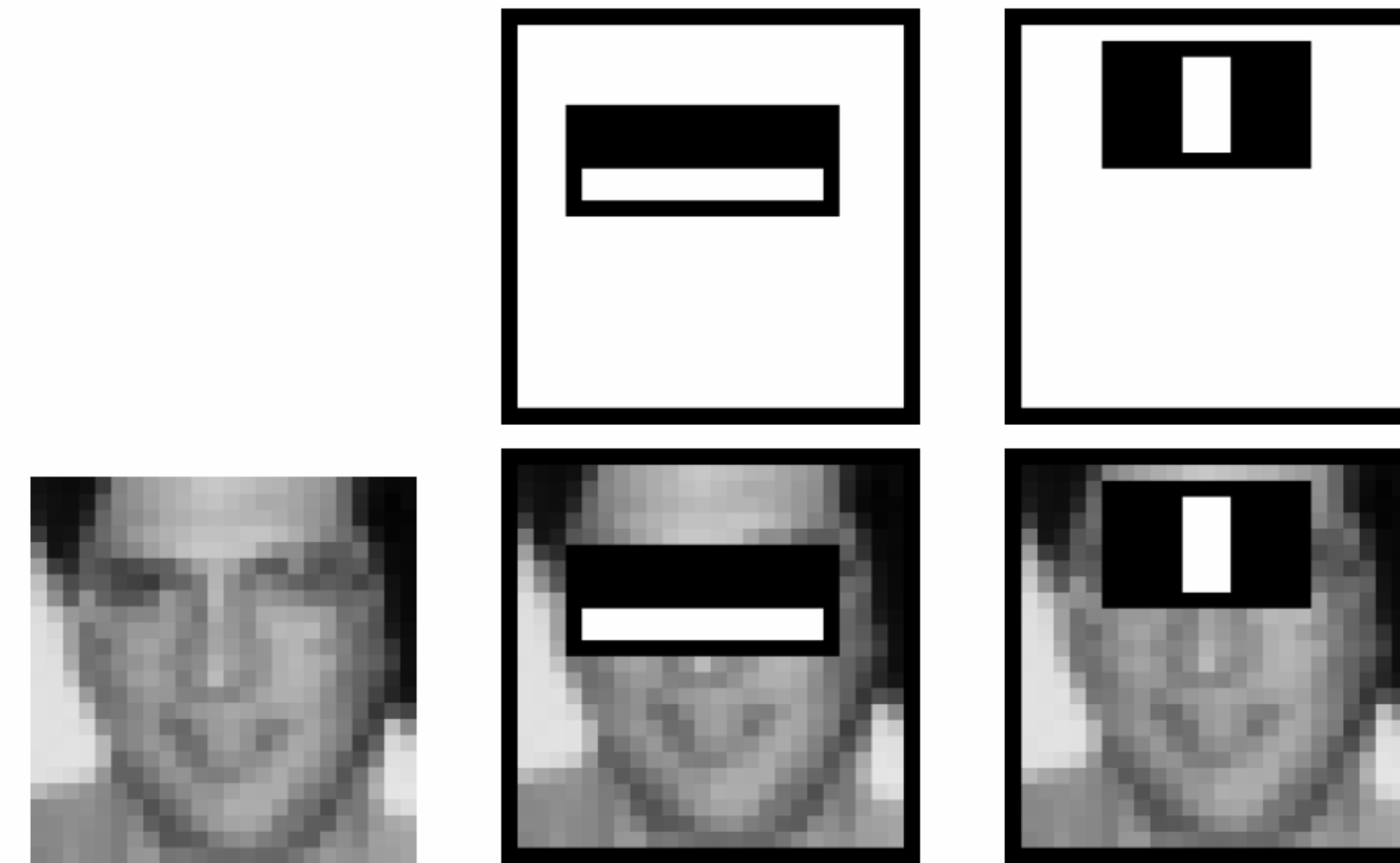
Enhancement

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

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.



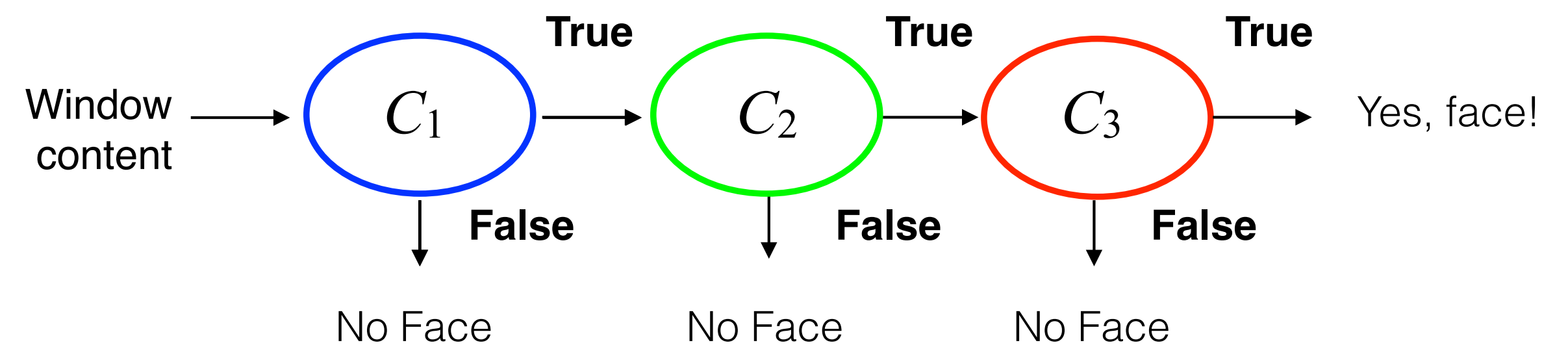
Enhancement

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.



Enhancement

Viola-Jones Detector

Results

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



clean background



cluttered background



tilted head

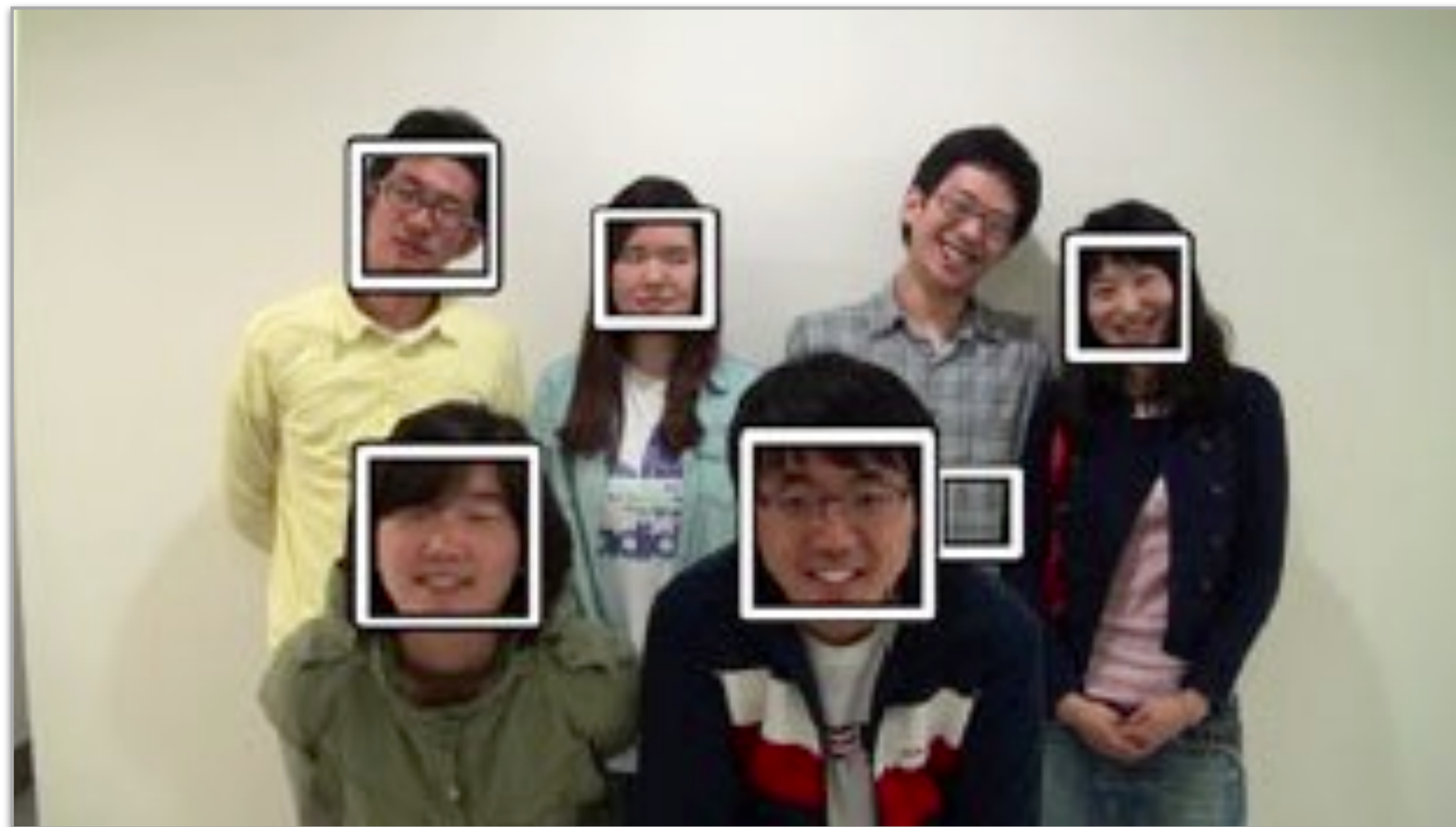


upside down

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>



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.
© Springer International Publishing Switzerland 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.

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Main task: detect face region and five landmarks
Auxiliary tasks: smiling?; gender?; glasses?; etc.

Enhancement

Face Detection



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

Key Ideas (3)

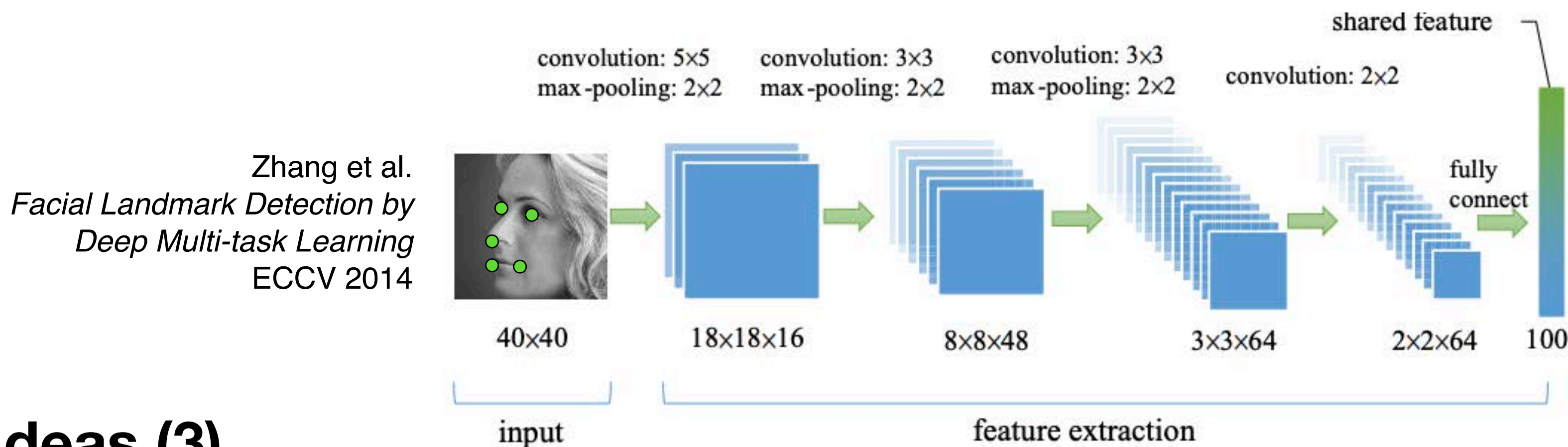
Data-driven machine-learning approach.

Main task: detect face region and five landmarks

Auxiliary tasks: smiling?; gender?; glasses?; etc.

Enhancement

Face Detection



Key Ideas (3)

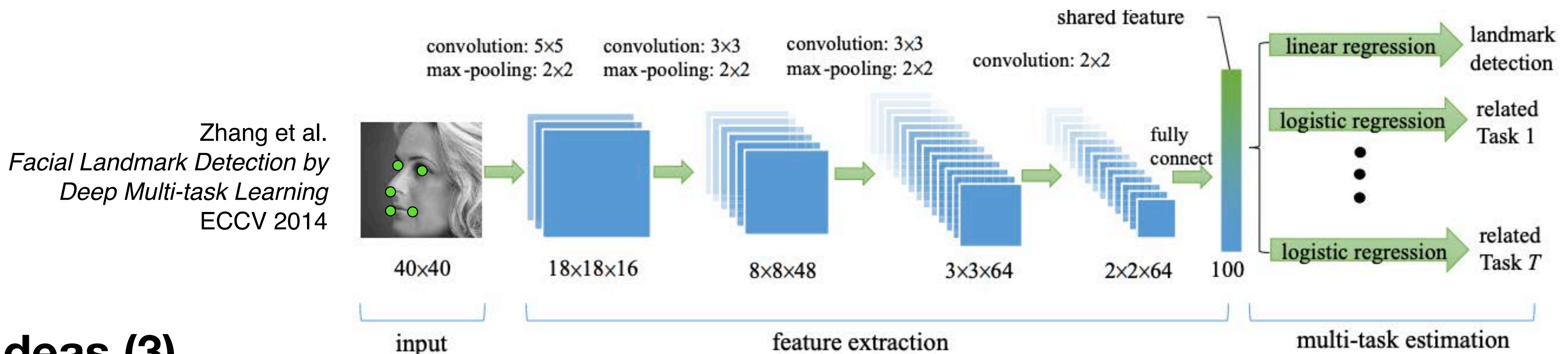
Data-driven machine-learning approach.

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Enhancement

Face Detection



Key Ideas (3)

Data-driven machine-learning approach.

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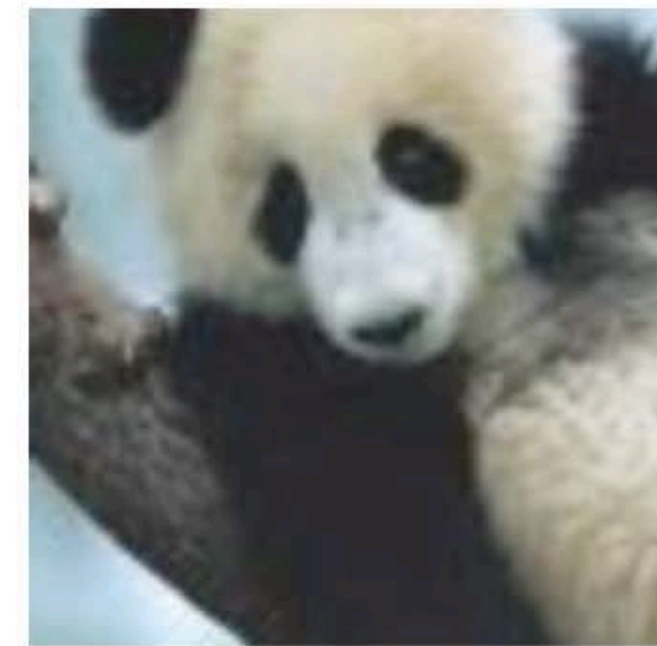
Enhancement

Face Detection

Attack

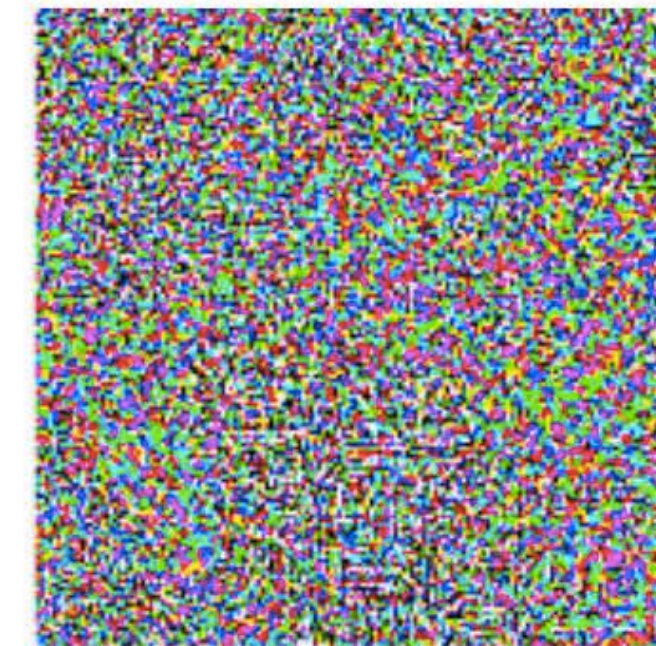
Adversarial machine learning.

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



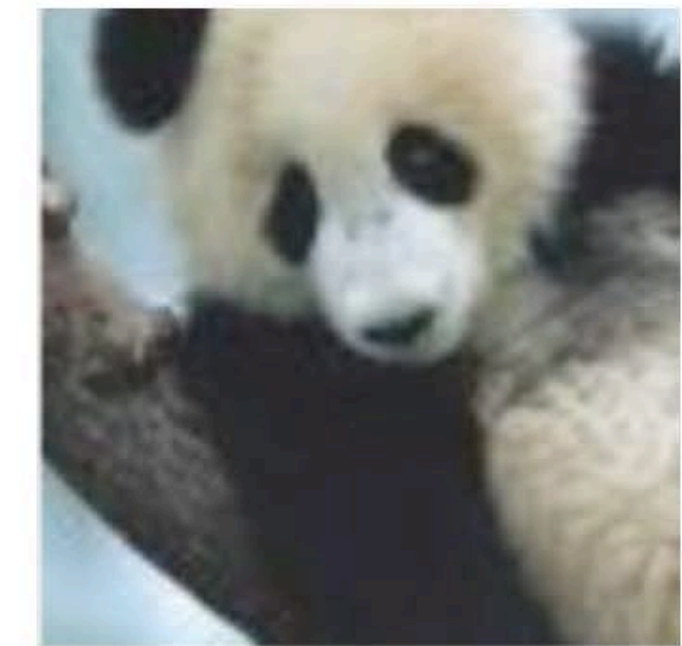
"panda"
57.7% confidence

+ .007 ×



noise

=



"gibbon"
99.3% confidence

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

Enhancement

Face Detection

Attack

Adversarial machine learning.

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

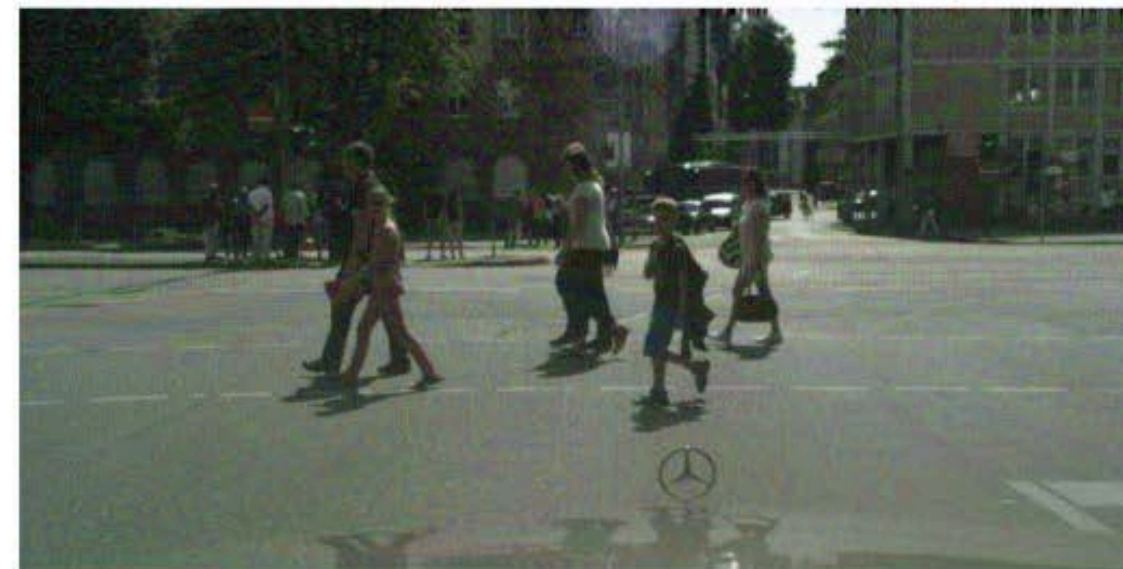
(a) Image



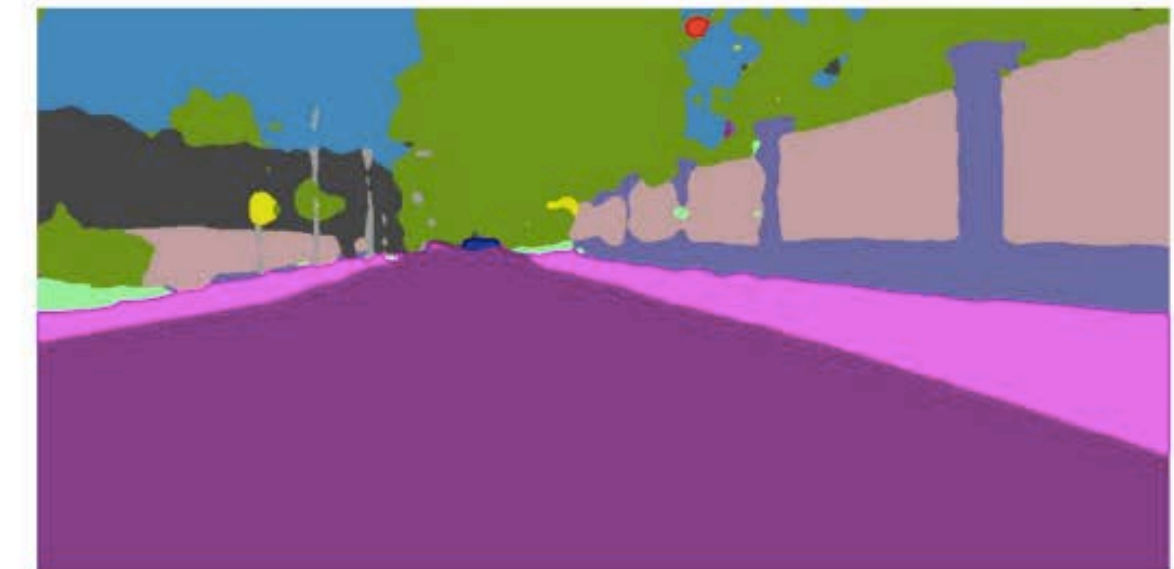
(b) Prediction



(c) Adversarial Example



(d) Prediction



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

Enhancement

Face Detection

Attack

Adversarial machine learning.

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

Daily Mail

Tesla cars tricked into autonomously accelerating up to 85 MPH in a 35 MPH zone while in cruise control using just a two-inch strip of electrical tape



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

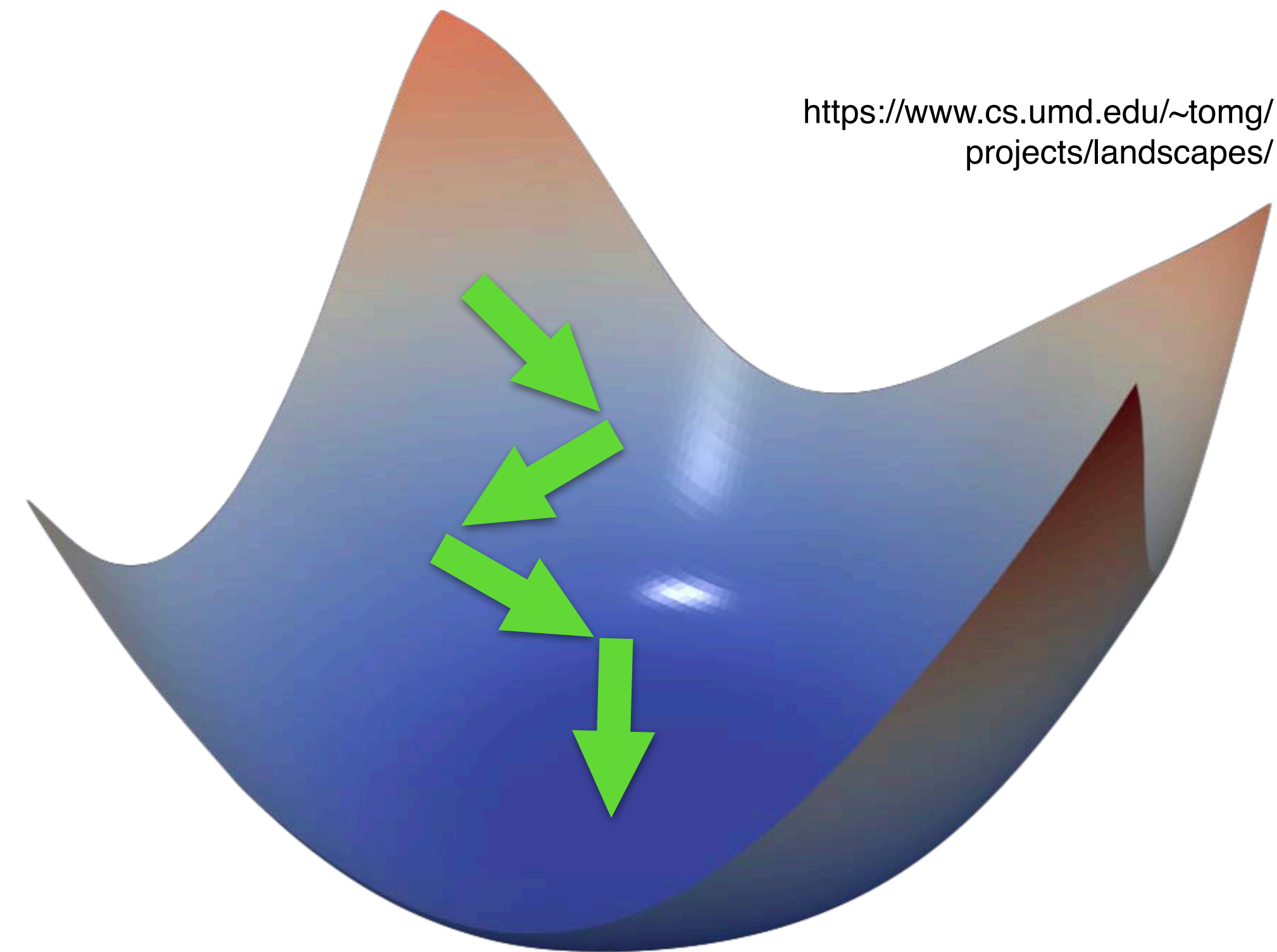
Enhancement

Face Detection

Attack

Adversarial machine learning.

Example:
Fast Gradient Sign Method (FGSM).



CNN Error Surface

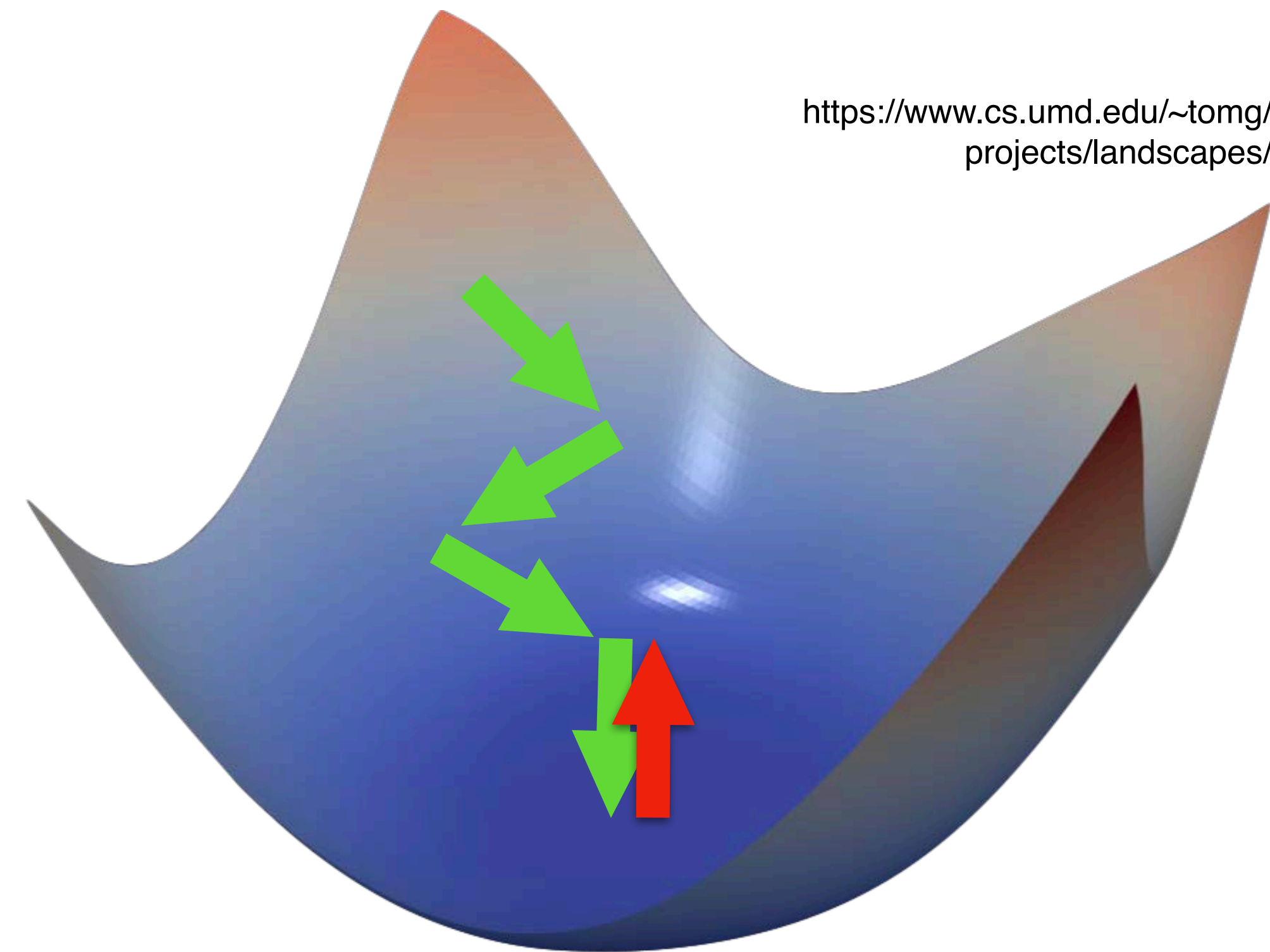
Enhancement

Face Detection

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CNN Error Surface

Enhancement

Face Detection

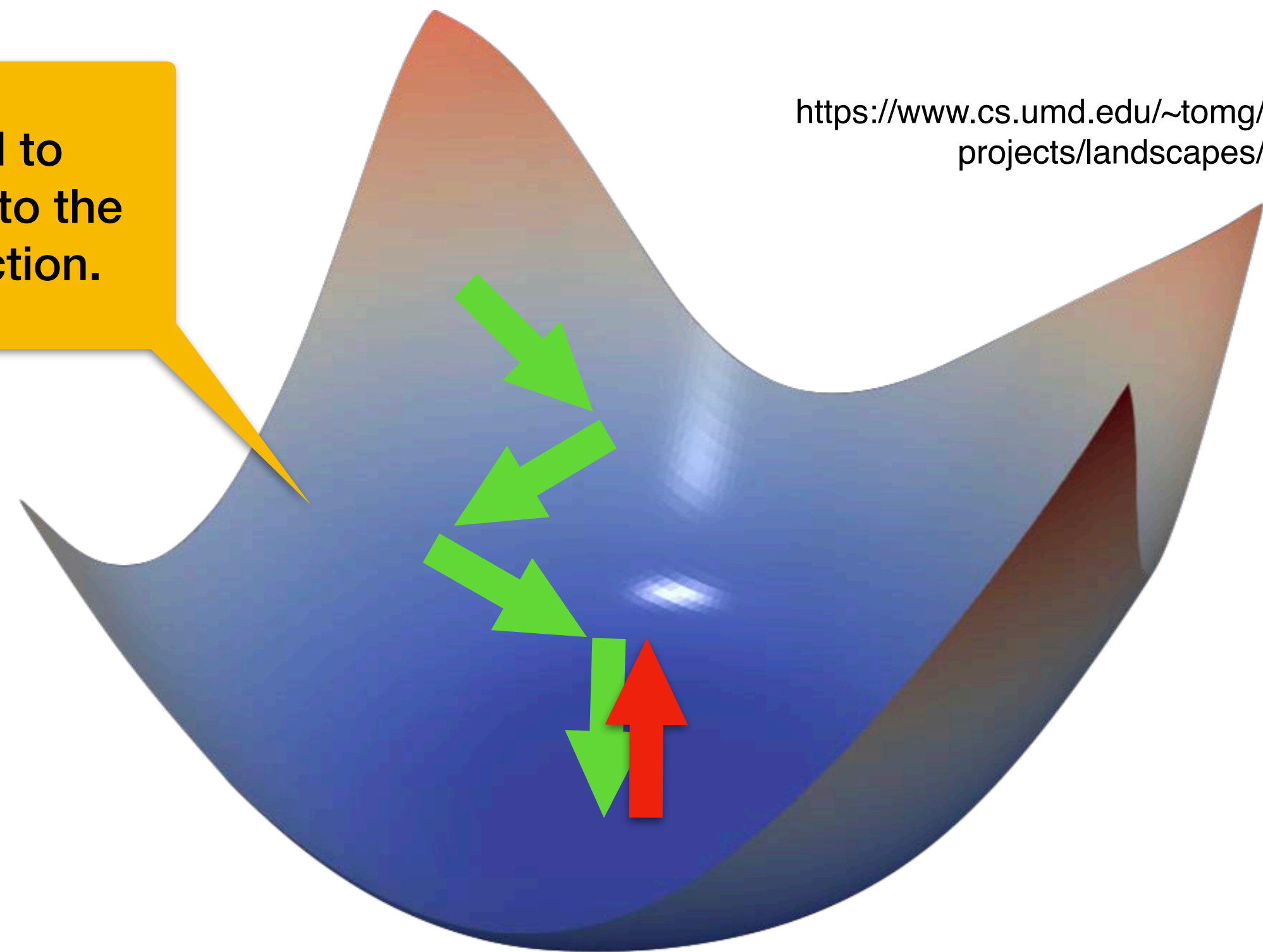
Attack

Adversarial machine learning.

Example:
Fast Gradient Sign Method (FGSM).

This can be used to modify faces up to the point of no detection.

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



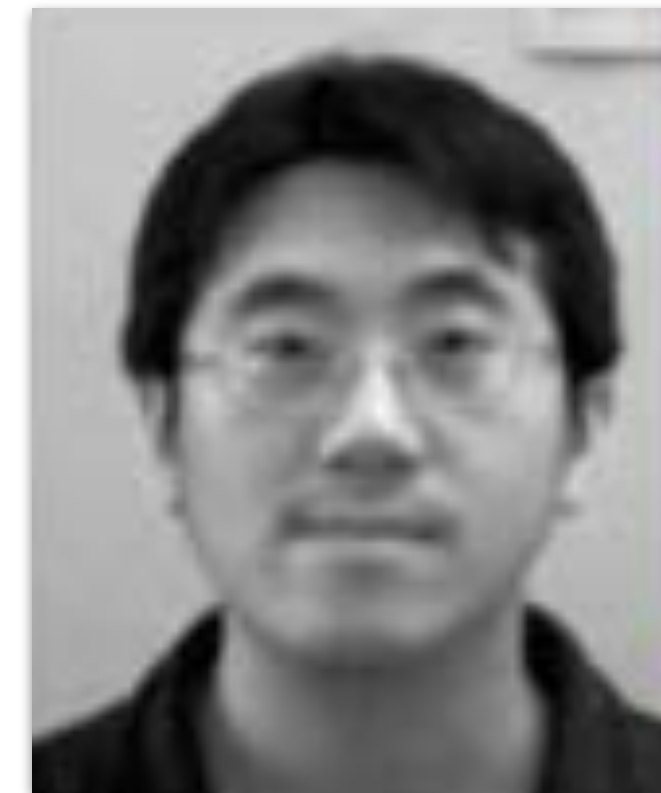
CNN Error Surface

Enhancement

Face Alignment

Goal

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



template



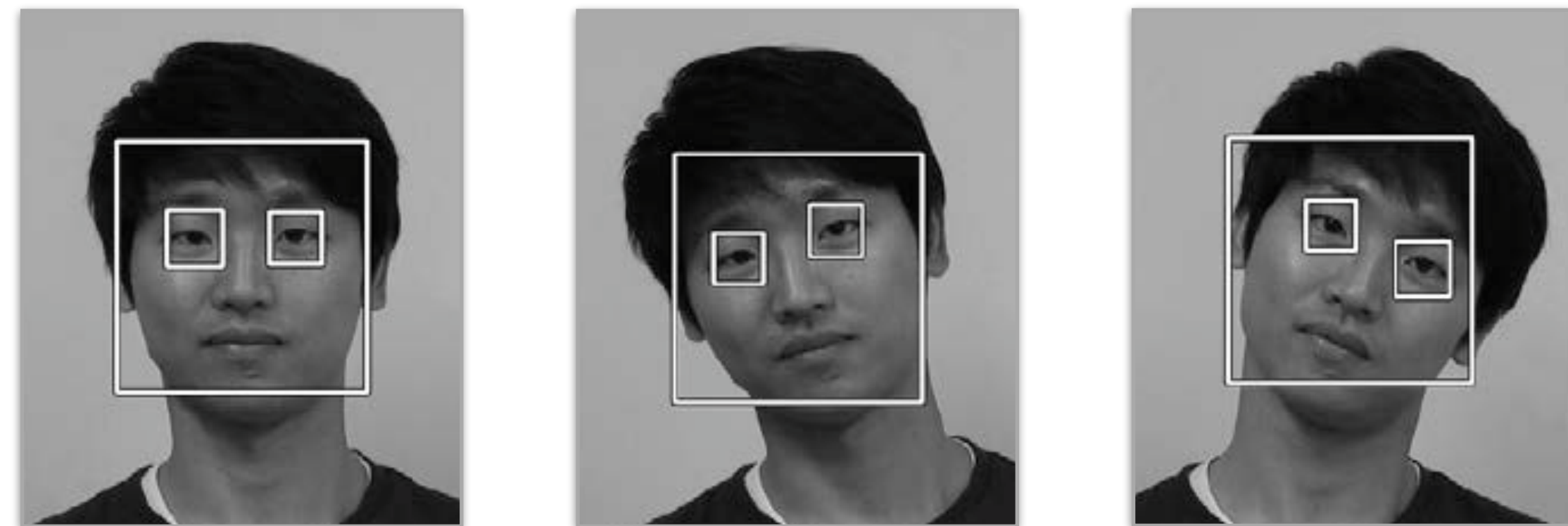
sample

Enhancement

Face Alignment

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

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



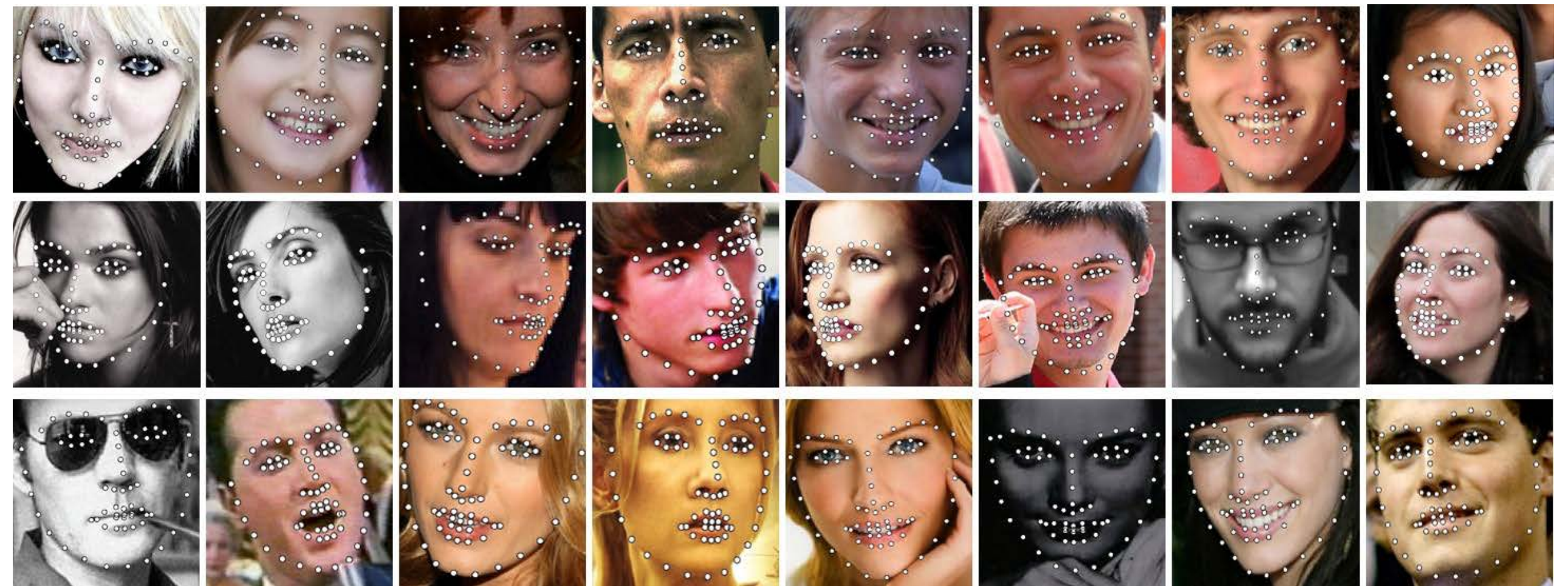
Possible solution: eye detection using Viola-Jones approach.

Enhancement

Face Alignment

Detection of Face Landmarks

There are better solutions in the literature, using deep neural networks, for instance.



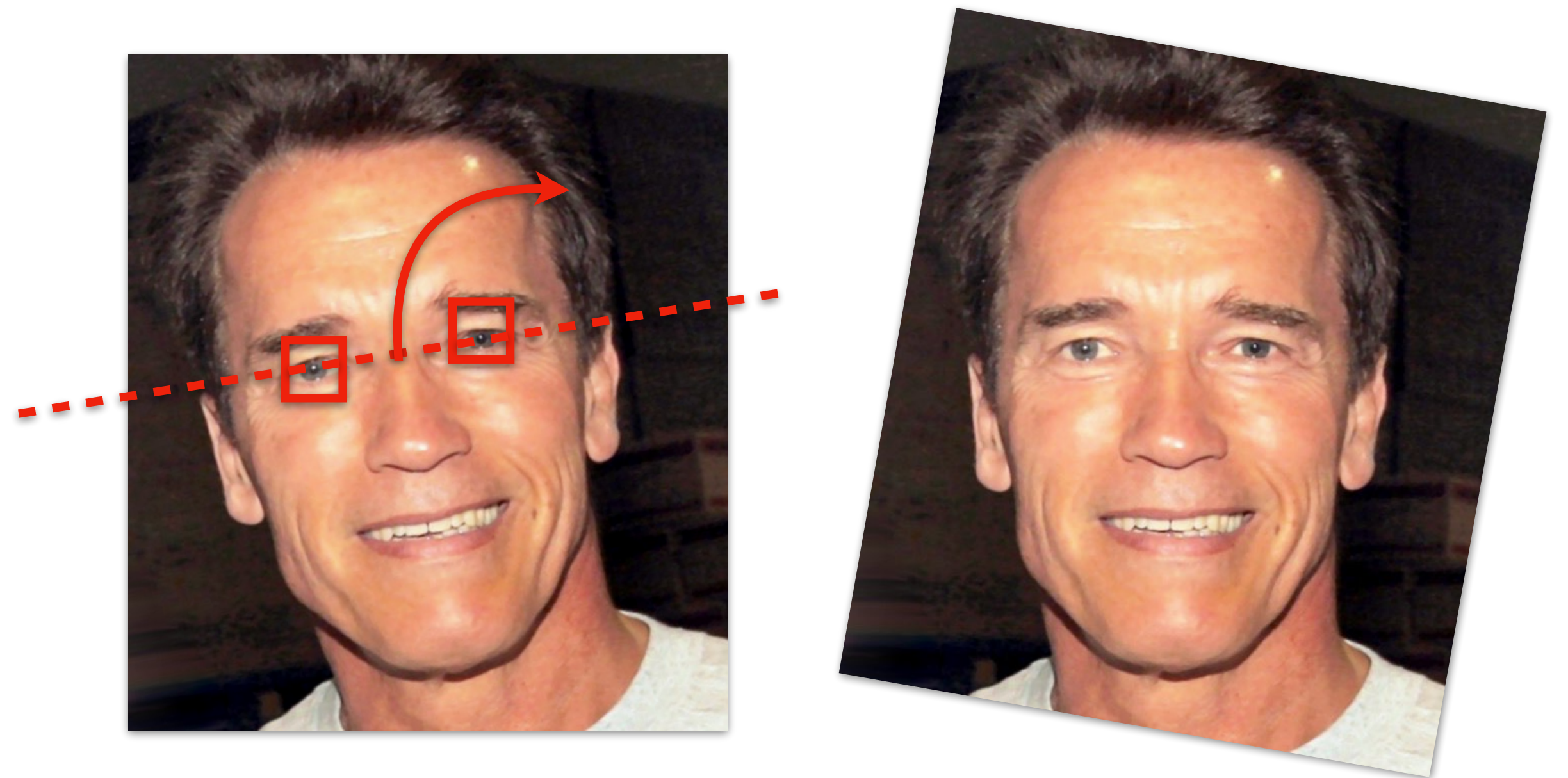
Zhang et al.
Facial Landmark Detection by Deep Multi-task Learning
ECCV 2014

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/

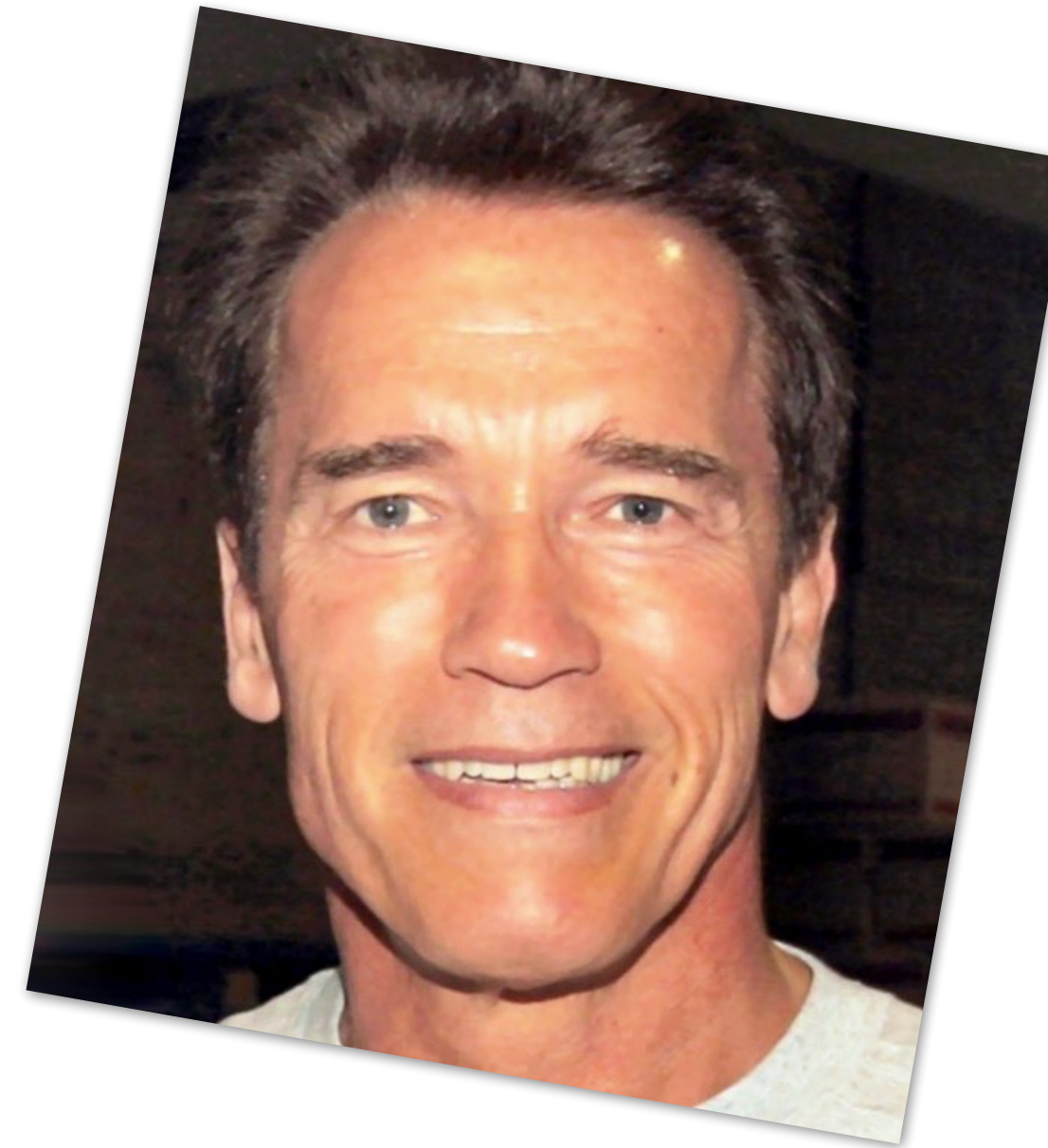
Enhancement

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.



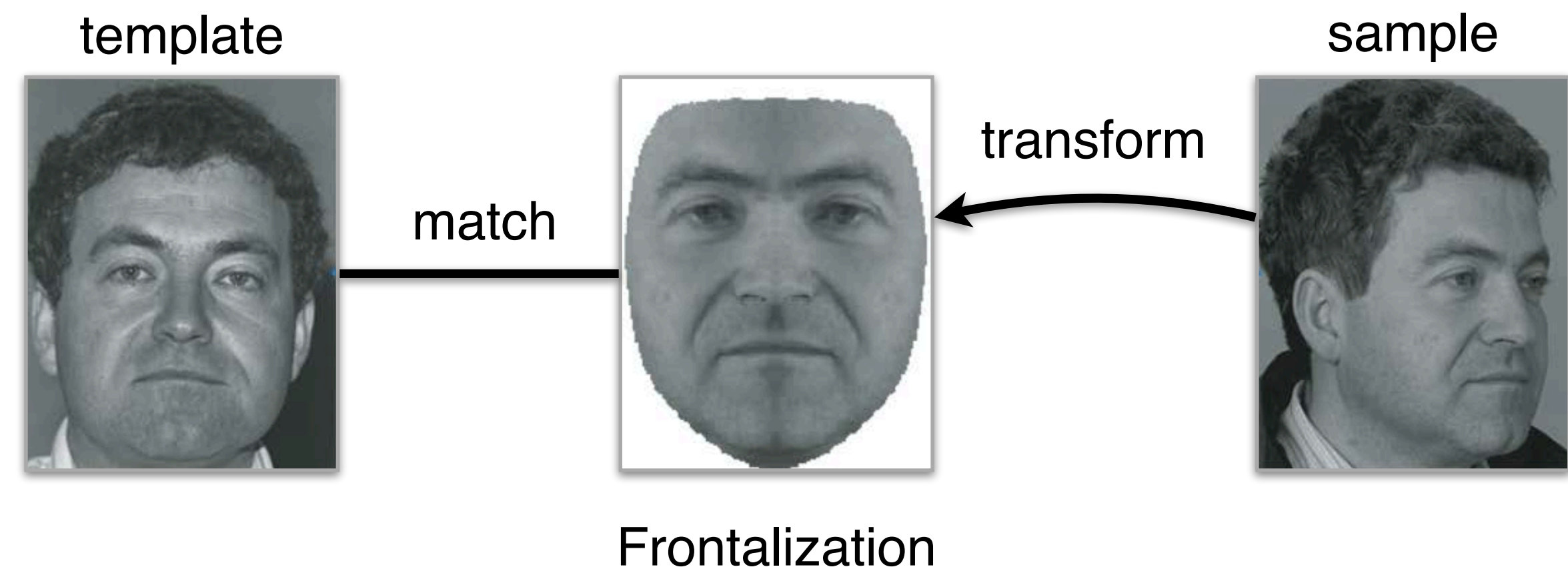
Enhancement

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

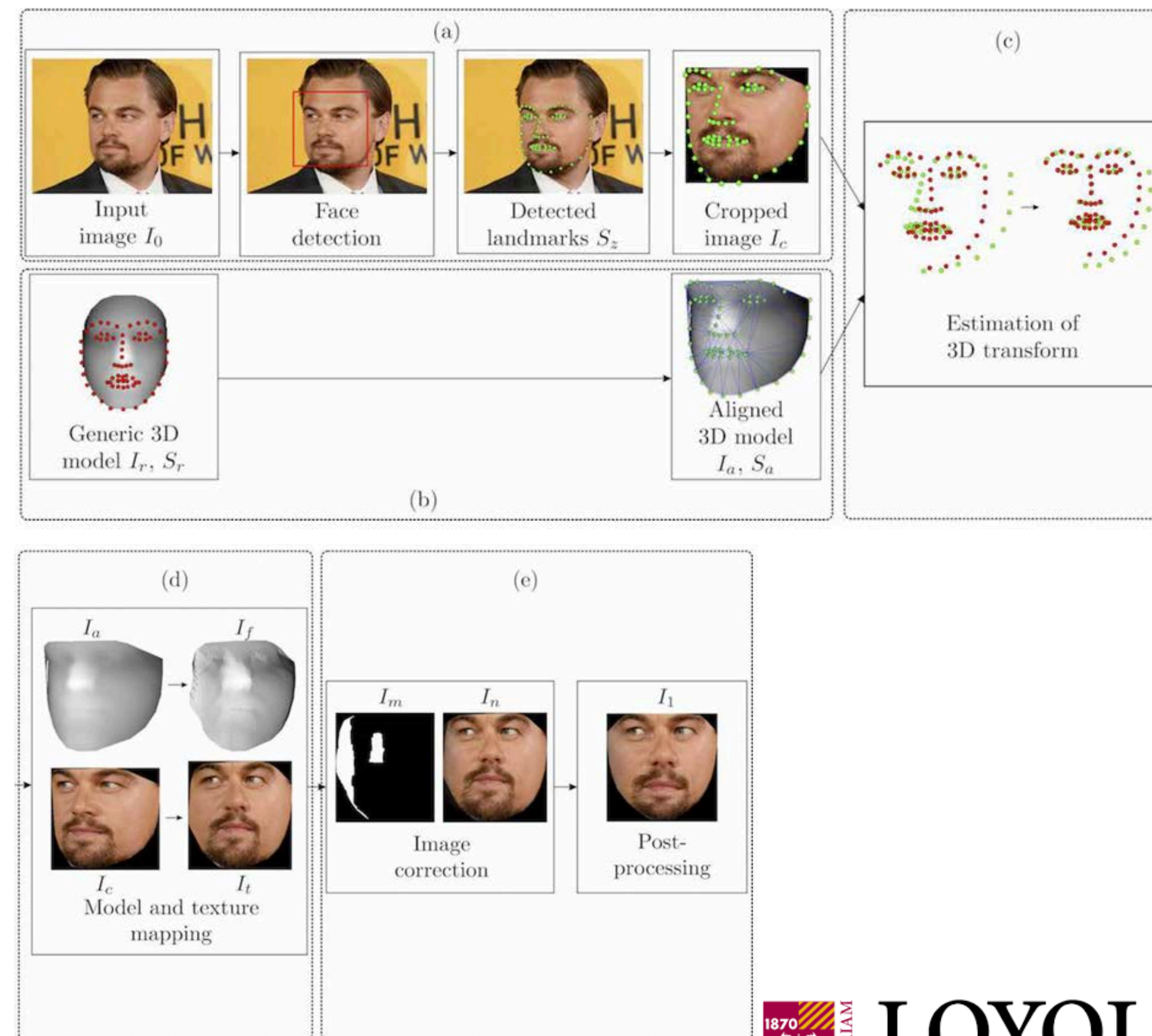


Enhancement

Face Alignment

More Severe Pose Variations

Alternative approaches.
3D information will help
to do frontalization.



Banerjee et al.

*To frontalize or not to frontalize: Do we really need elaborate
pre-processing to improve face recognition?*

WACV 2018

Enhancement

Illumination Correction

Simplest Solution

Color histogram equalization.

Alternatives

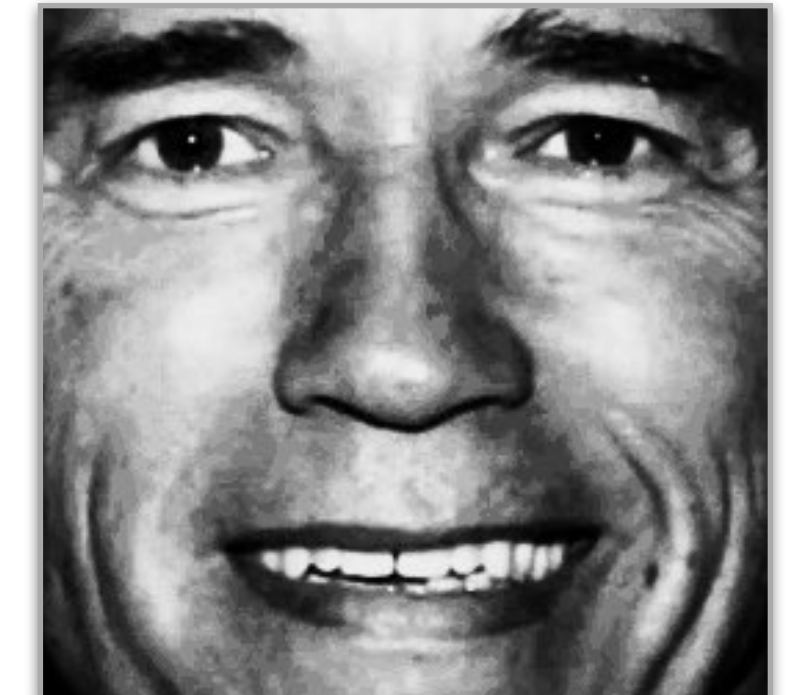
Photometric normalization, illumination modeling, etc.



Original



Grayscale



Equalized

What's Next?

Face Description and Matching

**Fill out your
Today-I-missed Statement**
Please visit
sakai.luc.edu/x/Dv5DsU.

