(in camera) **White** balance

R: 200
G: 255
B: 190

→

R-correction: + 55
G-correction: + 0
B-correction: + 65

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

White Balance

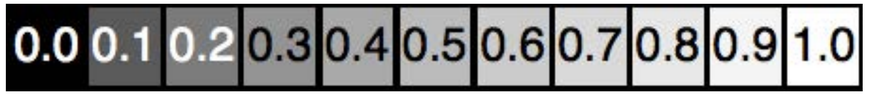
- Humans are good at adapting to global illumination conditions: you would still describe a white object as white whether under blue sky or candle light.
- However, when the picture is viewed later, the viewer is no longer correcting for the environment and the illuminant colour typically appears too strong.
- **White balancing** is the process of correcting for the illuminant

- A simple white balance algorithm is to assume the scene is grey on average "greyworld", state of the art methods use learning, e.g., Barron ICCV 2015

Gamma Correction

- Equal steps in luminance ≠ equal in perceived brightness

linear luminance (raw)



equal brightness steps

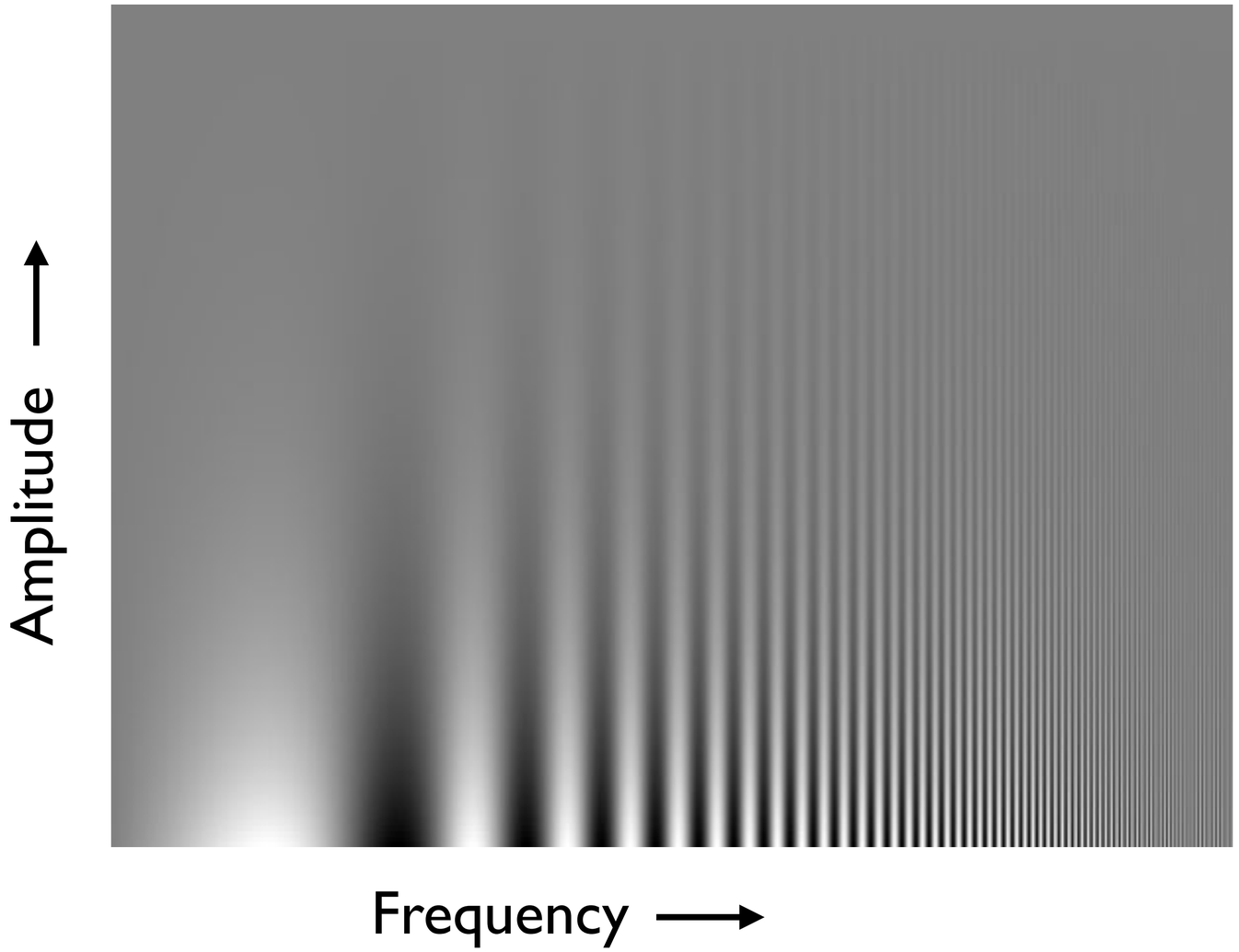
- Equal steps in human perceived brightness are achieved by increasingly large steps in luminance (sensor counts)
- So we encode pixel values V using a power law:

$$L = V^{\gamma}$$

- Using raw sensor counts wastes bits as we can't differentiate the large values → use **gamma corrected encoding (V)** that allocates more bits to smaller

Contrast Sensitivity

Human visual system is most sensitive to mid-frequencies



THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision

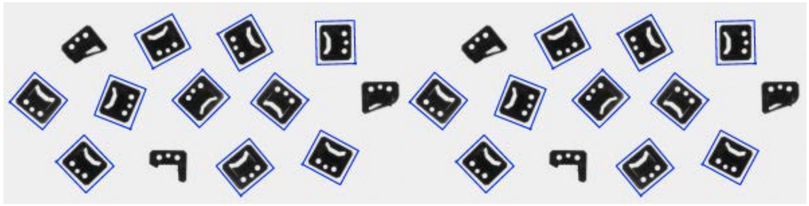


Image Credit: https://docs.adaptive-vision.com/4.7/studio/machine_vision_guide/TemplateMatching.html

Lecture 7: Digital Imaging Pipeline, Template Matching

(unless otherwise stated slides are taken or adopted from **Bob Woodham, Jim Little** and **Fred Tung**)

Menu for Today

Topics:

- **Digital Imaging** Pipeline
- **Scaled** Representations
- Template **Matching**
- Normalised **Correlation**

Readings:

- **Today's** Lecture: Szeliski 2.3, 3.5, Forsyth & Ponce (2nd ed.) 4.5 - 4.7

Reminders:

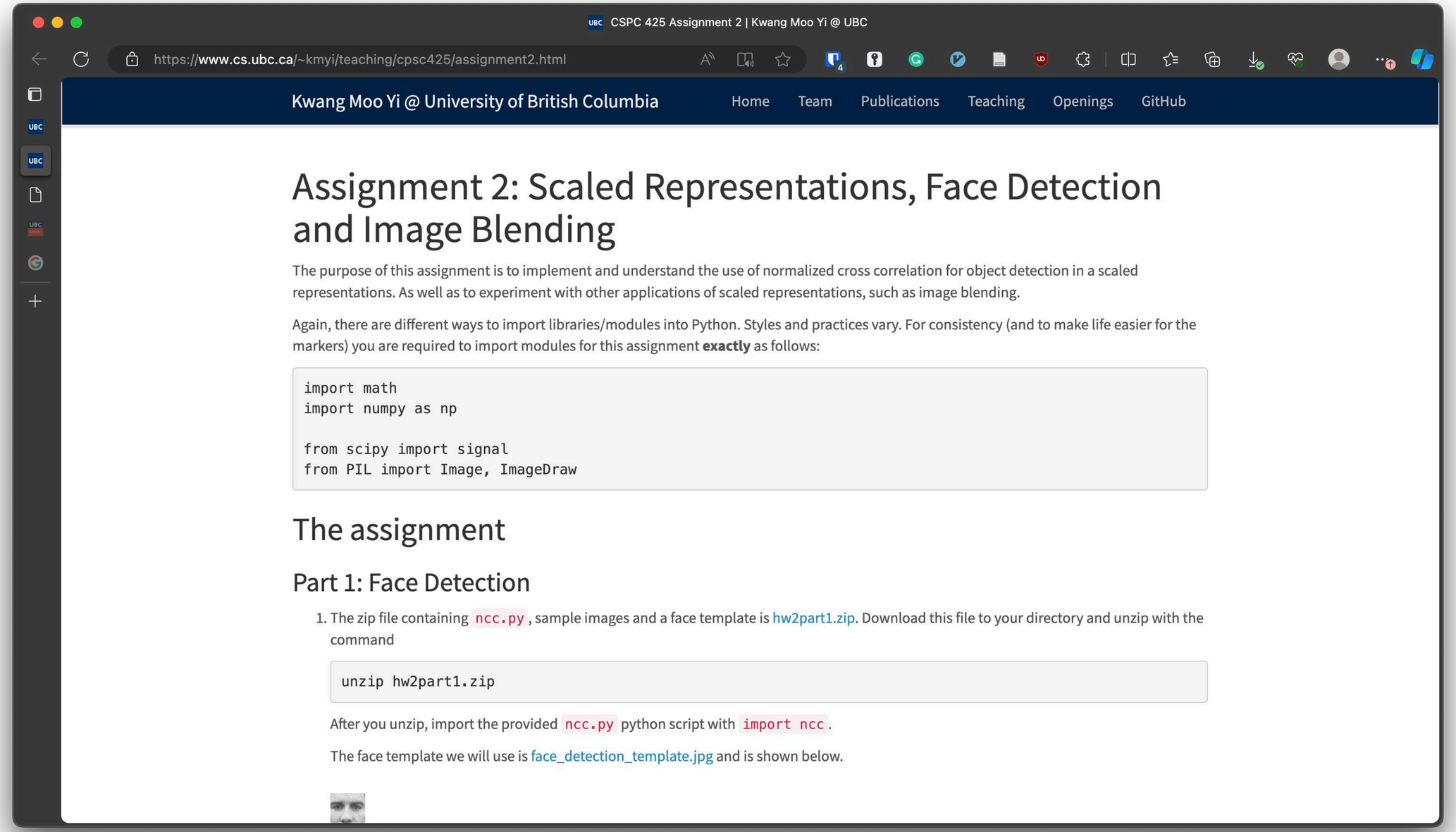
- **Assignment 1**: due **Today**
- **Assignment 2**: Scaled Representations, Face Detection and Image Blending available now

Goal

1. See how image filtering can be used in practice

2. Understand the concept behind template matching

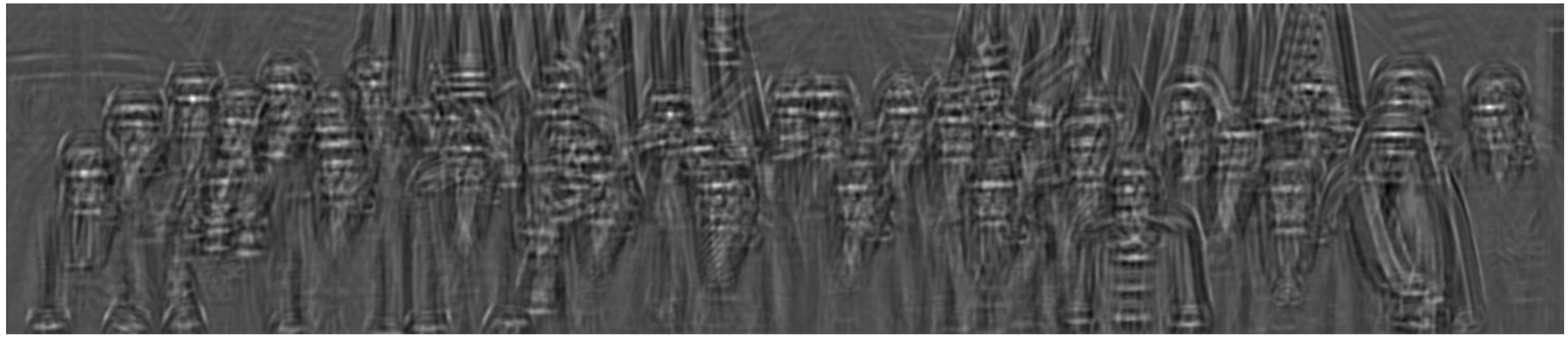
Assignment 2 available now



Template Matching

Convolve image with template, find local maxima

$*$  $\rightarrow$ Non-max suppress $\rightarrow$



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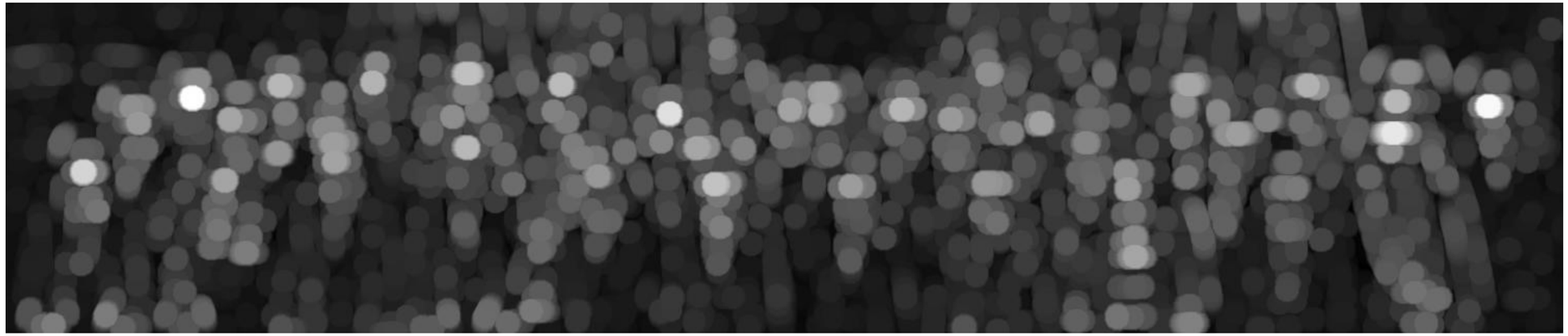
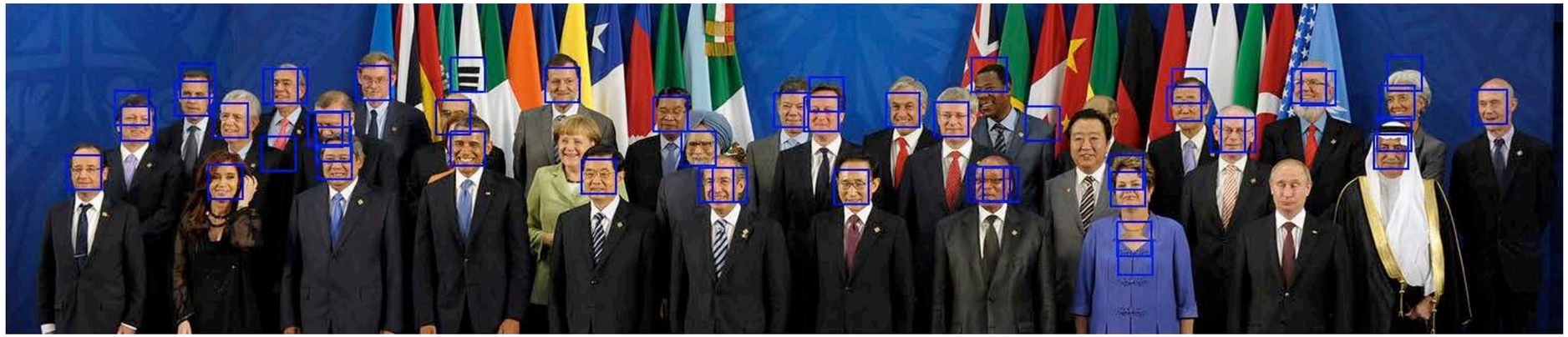


Template Matching

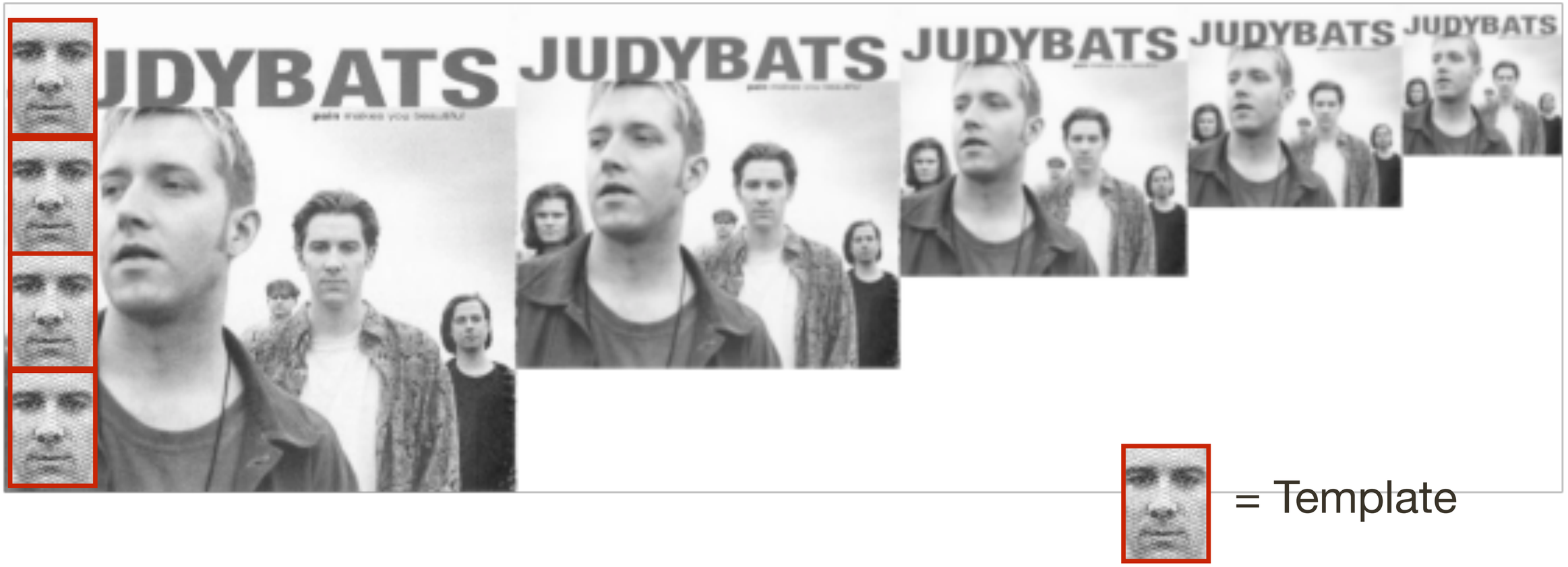
Convolve image with template, find local maxima

$*$  $\rightarrow$ Non-max suppress $\rightarrow$
+ threshold



Multi-Scale Template Matching

Correlation with a **fixed-sized template** only detects faces at **specific scales**



[Assignment 2]

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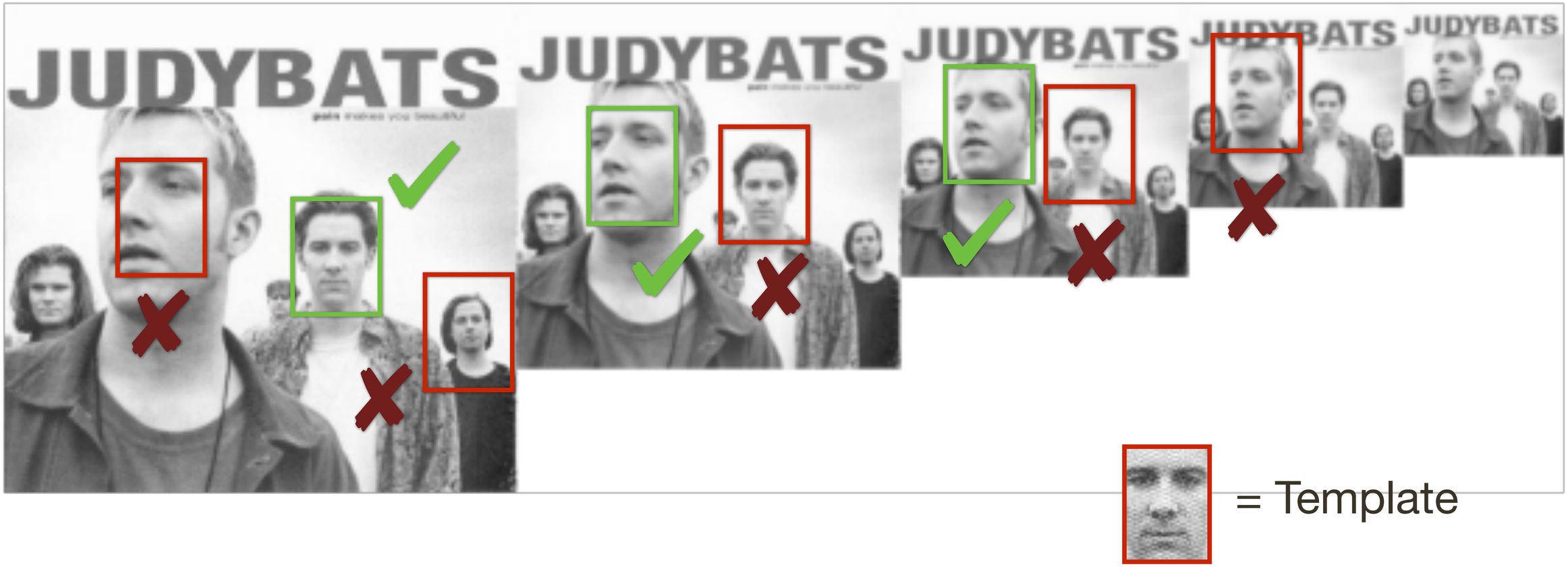
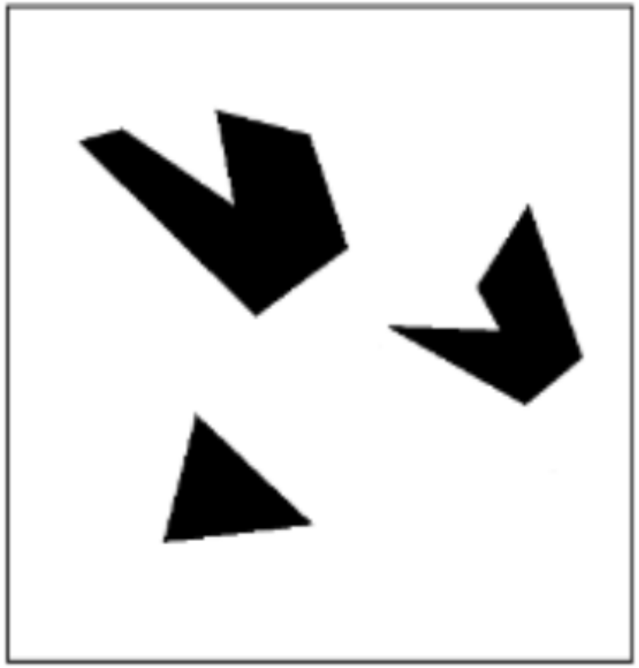


[Assignment 2]

Template Matching



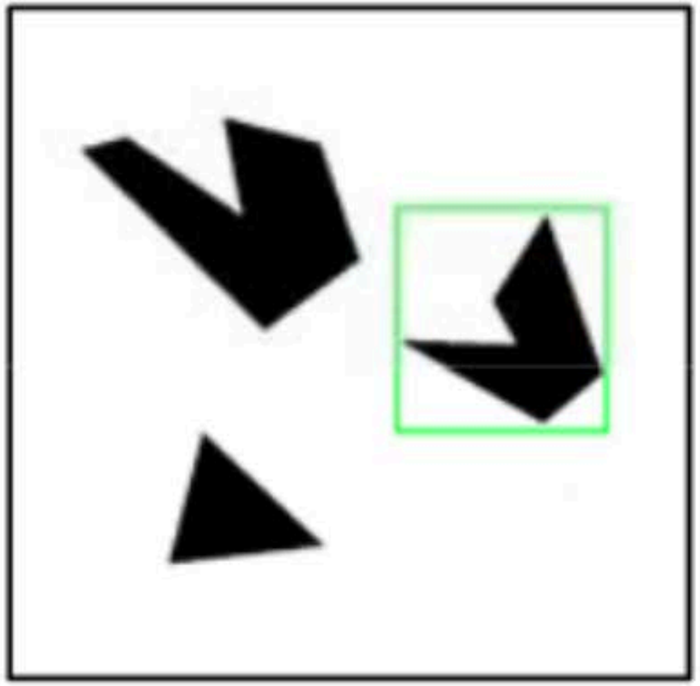
Scene

Template (mask)

A toy example

Slide Credit: Kristen Grauman

Template Matching



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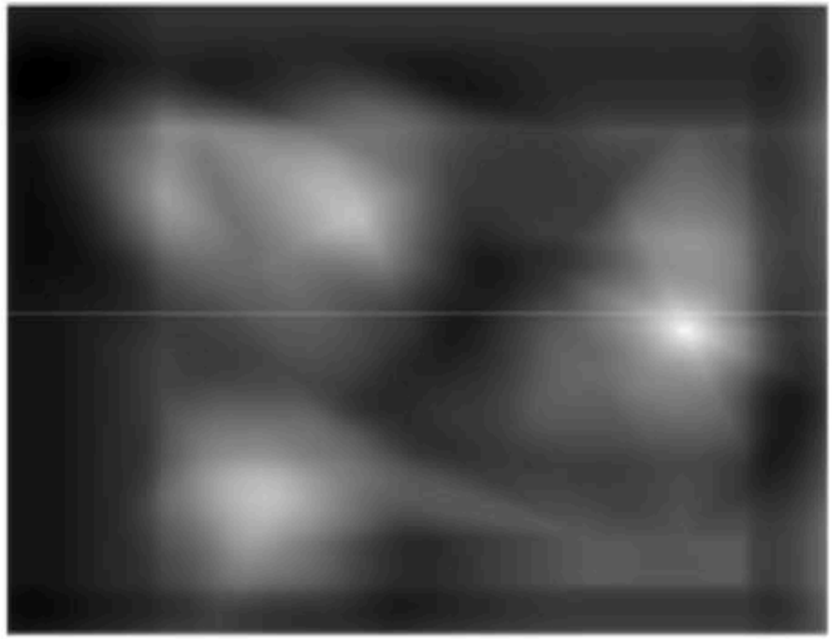
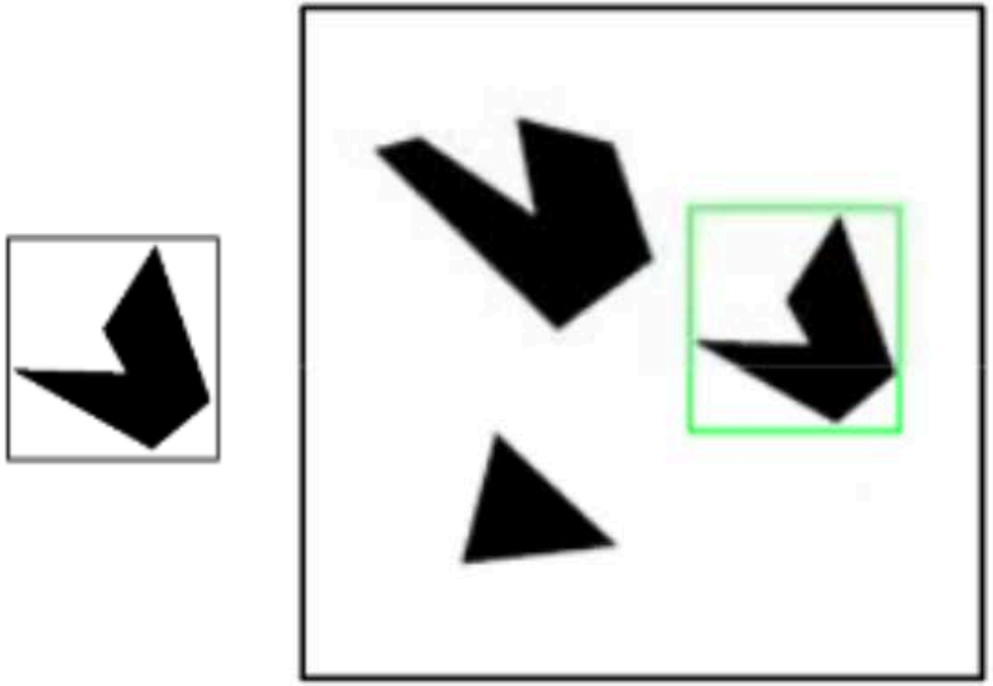


Correlation map

Slide Credit: Kristen Grauman

Template Matching

Assuming template is all positive, what does this tell us about correlation map?



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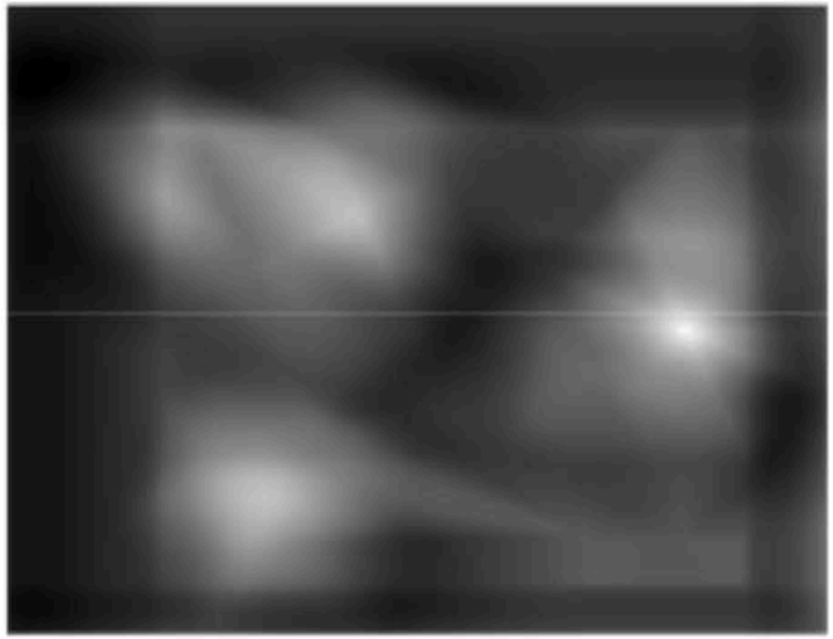

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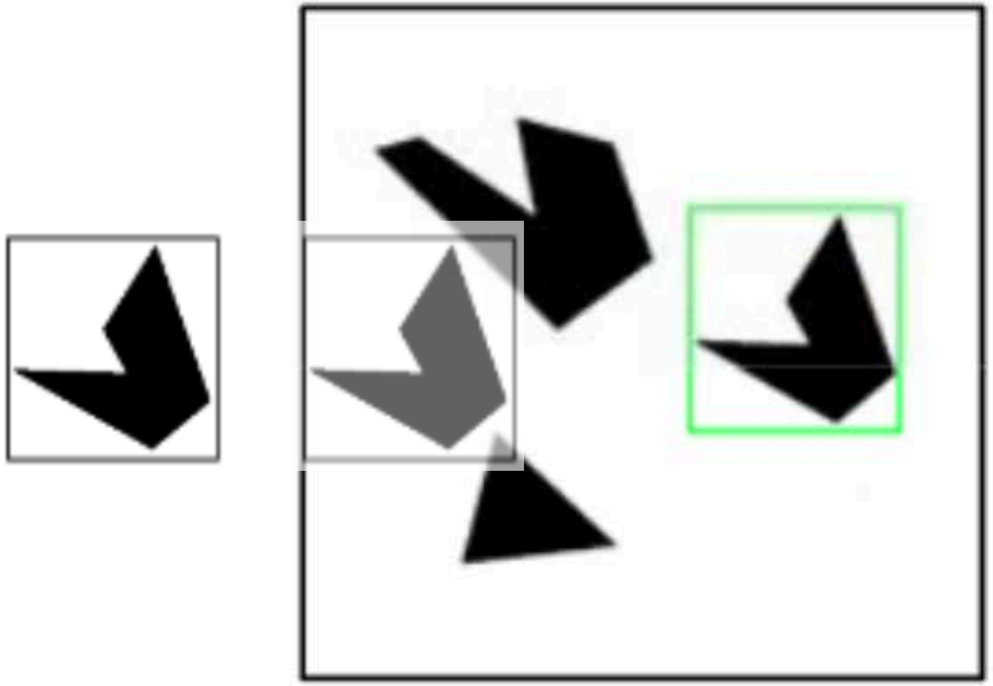

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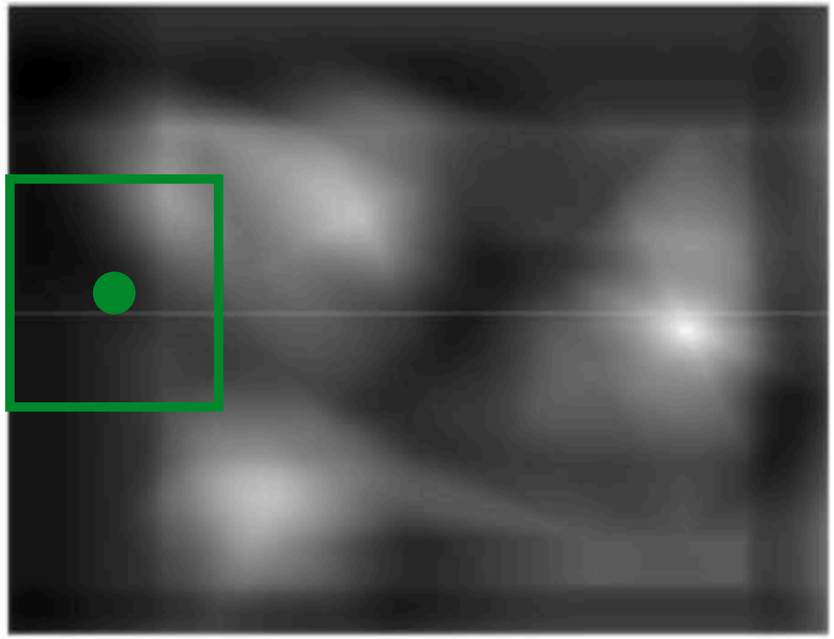

Correlation map

$$\frac{a}{|a|}\frac{b}{|b|} = ?$$

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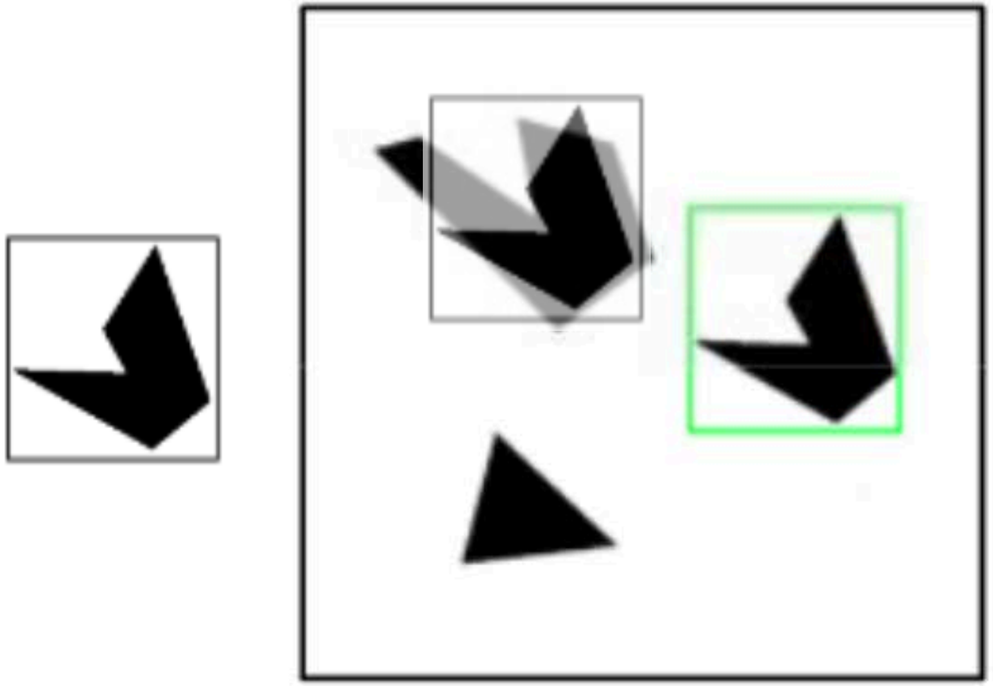

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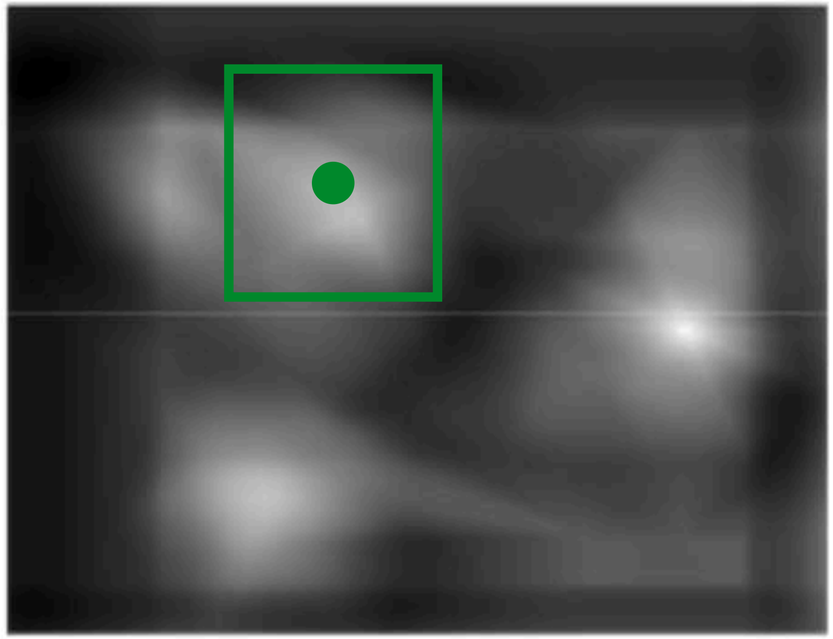

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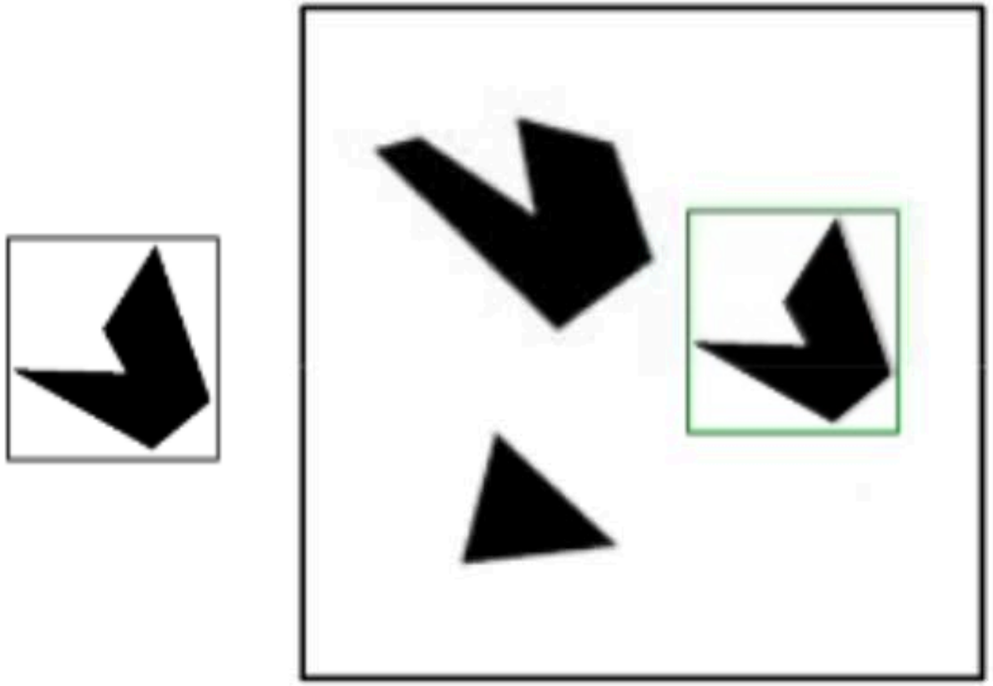

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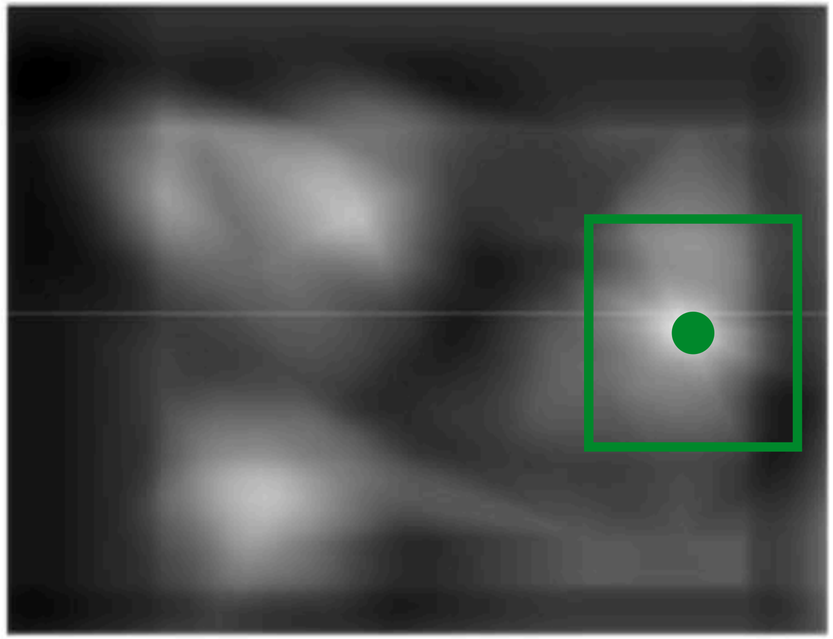

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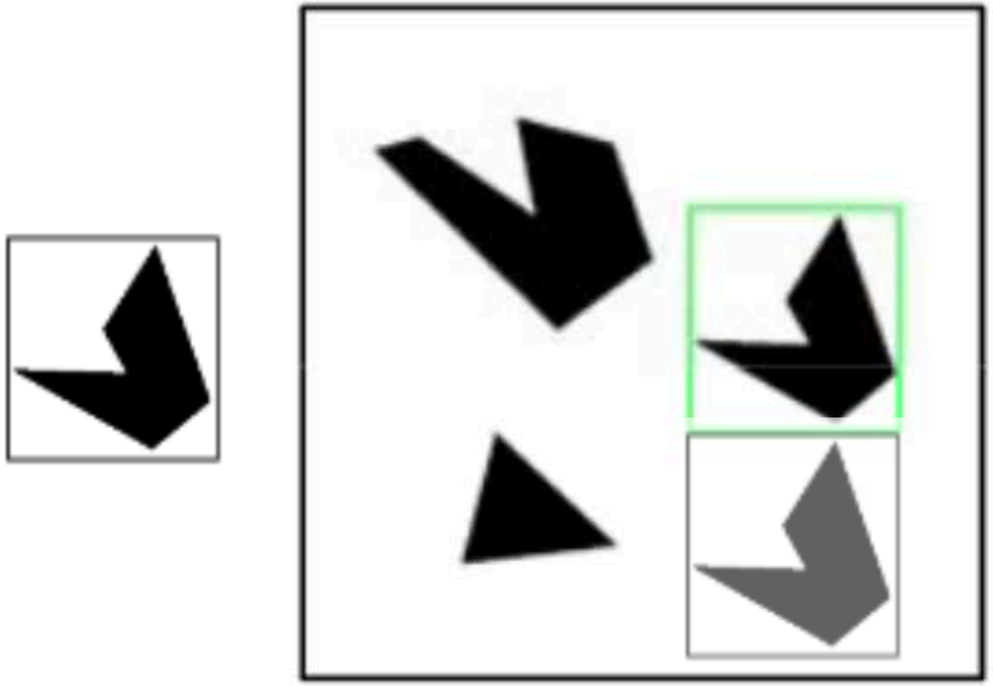

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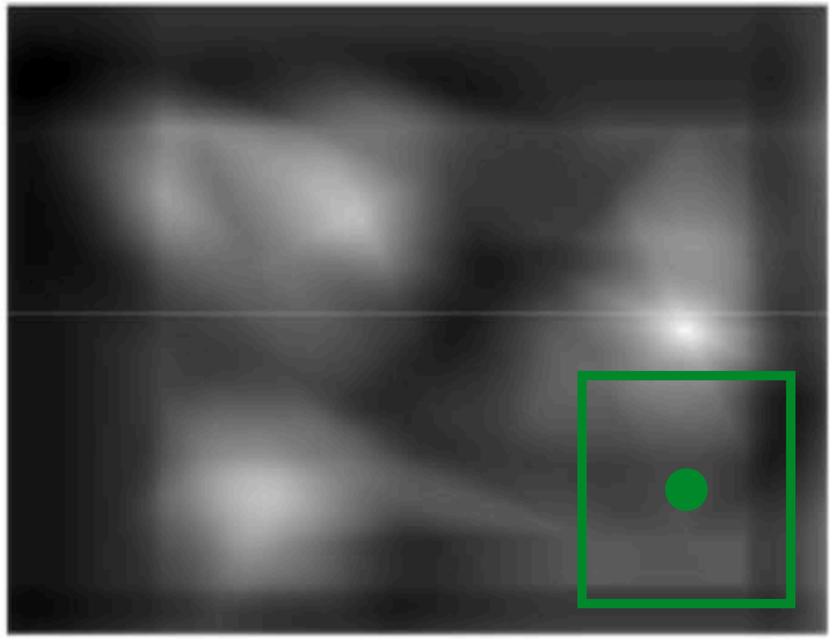

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Template Matching

We can think of convolution/**correlation** as comparing a template (the filter) with each local image patch.

— Consider the filter and image patch as vectors.

— Applying a filter at an image location can be interpreted as computing the dot product between the filter and the local image patch.

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Template

0	0	0
0	1	0
0	1	1

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Image Patch 1

0	0	0
0	1	0
0	1	1

Image Patch 2

1	0	1
0	1	0
0	0	0

Template

0	0	0
0	1	0
0	1	1

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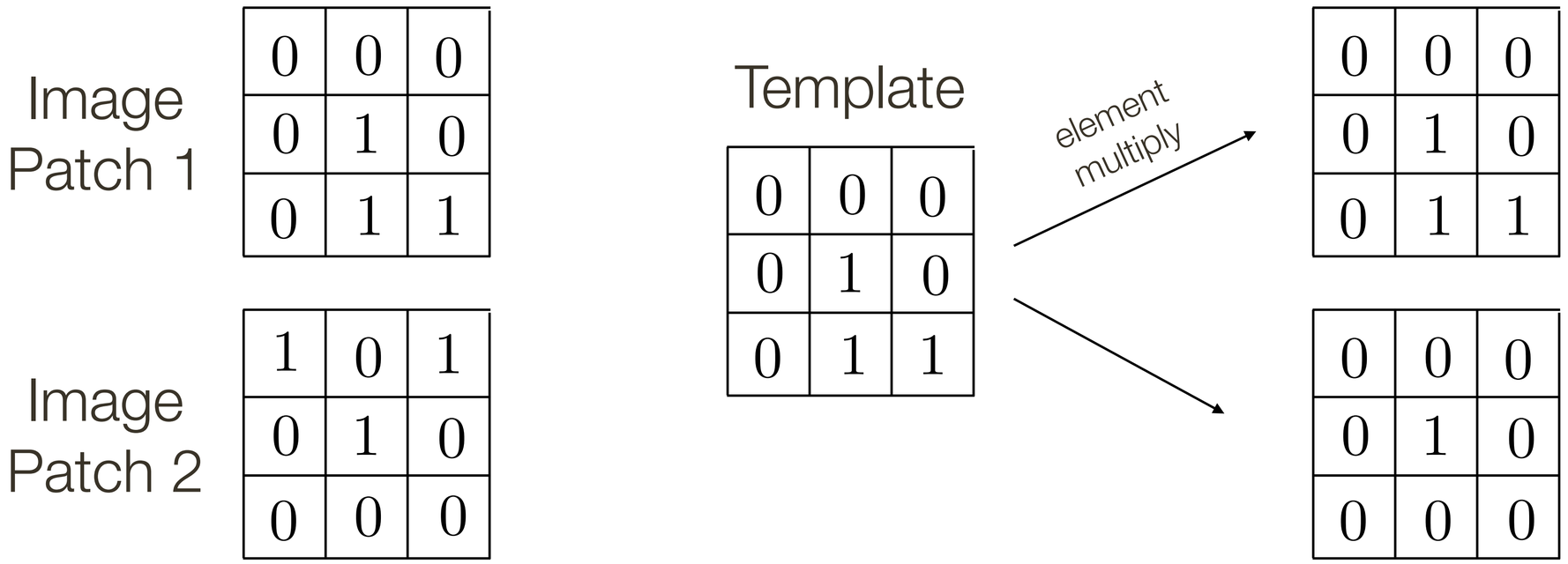

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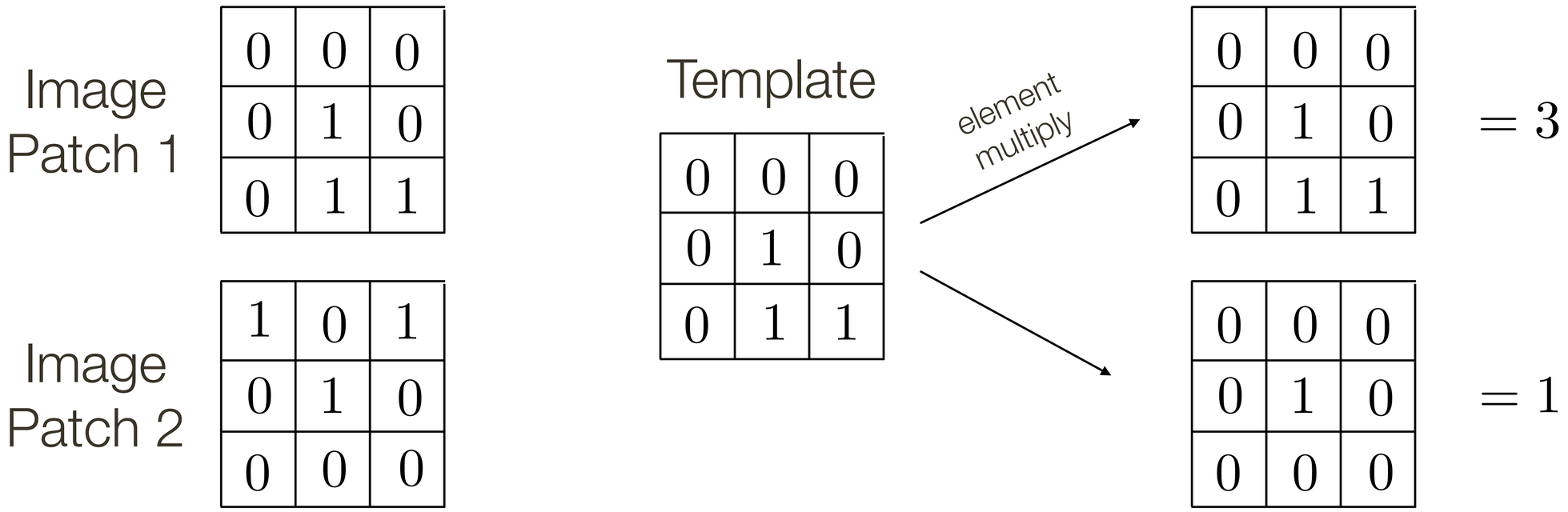

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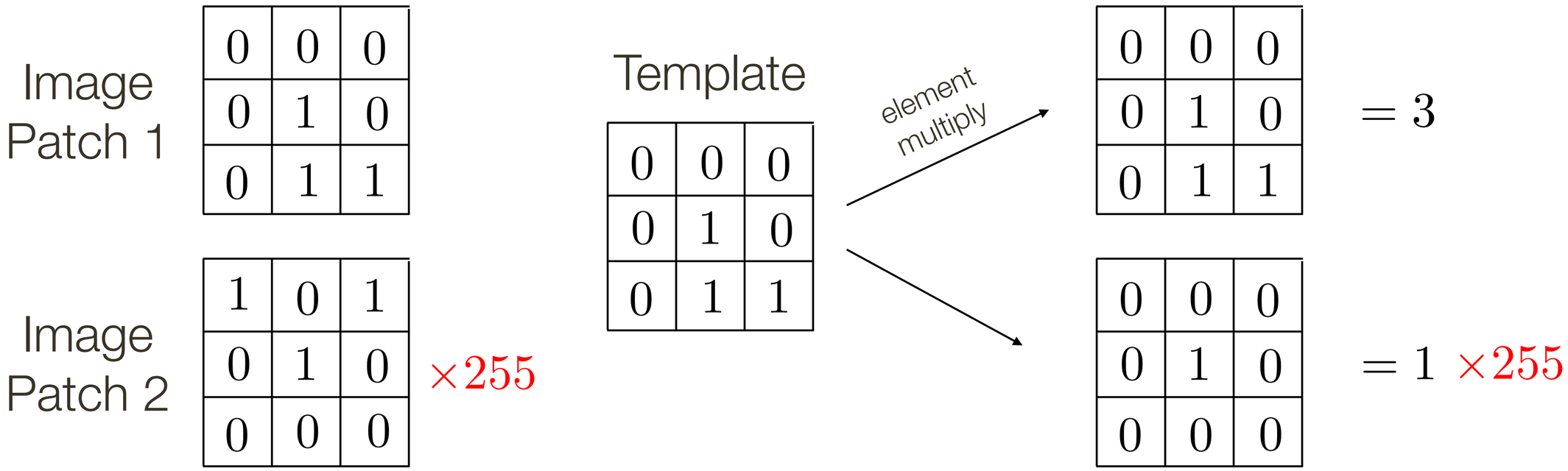

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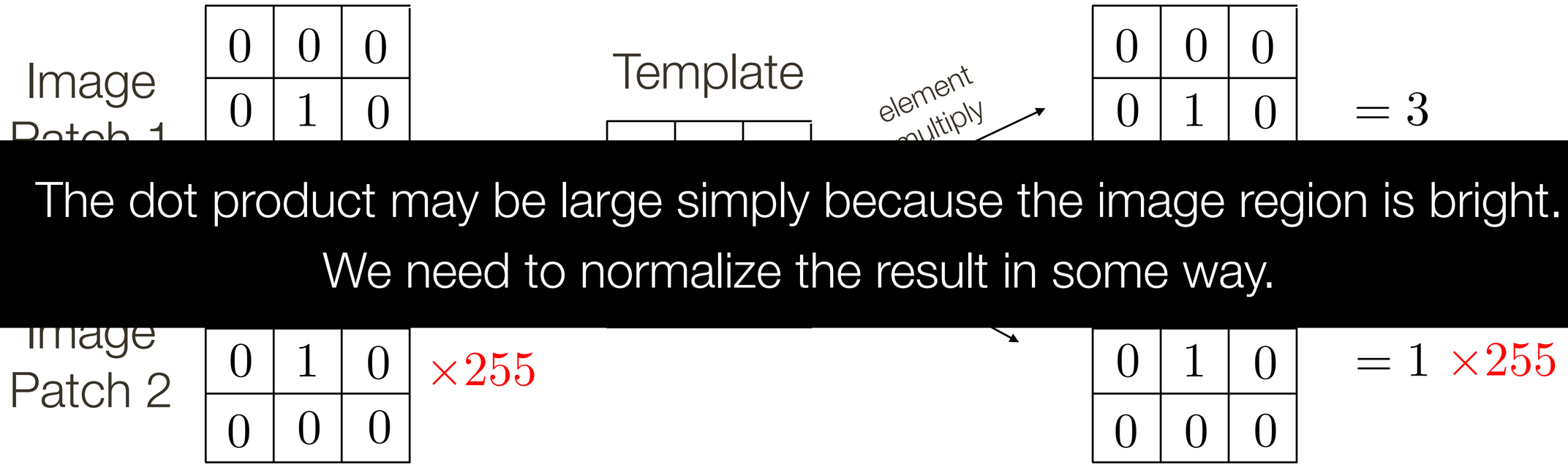


Template Matching

Correlation, Normalised Correlation, SSD

Template Matching

Similarity measures between a filter $\mathbf{J}$ local image region $\mathbf{I}$

Correlation, CORR = $\mathbf{I} \cdot \mathbf{J} = \mathbf{I}^T \mathbf{J}$

Normalised Correlation, NCORR = $\dfrac{\mathbf{I}^T \mathbf{J}}{|\mathbf{I}||\mathbf{J}|} = \cos\theta$

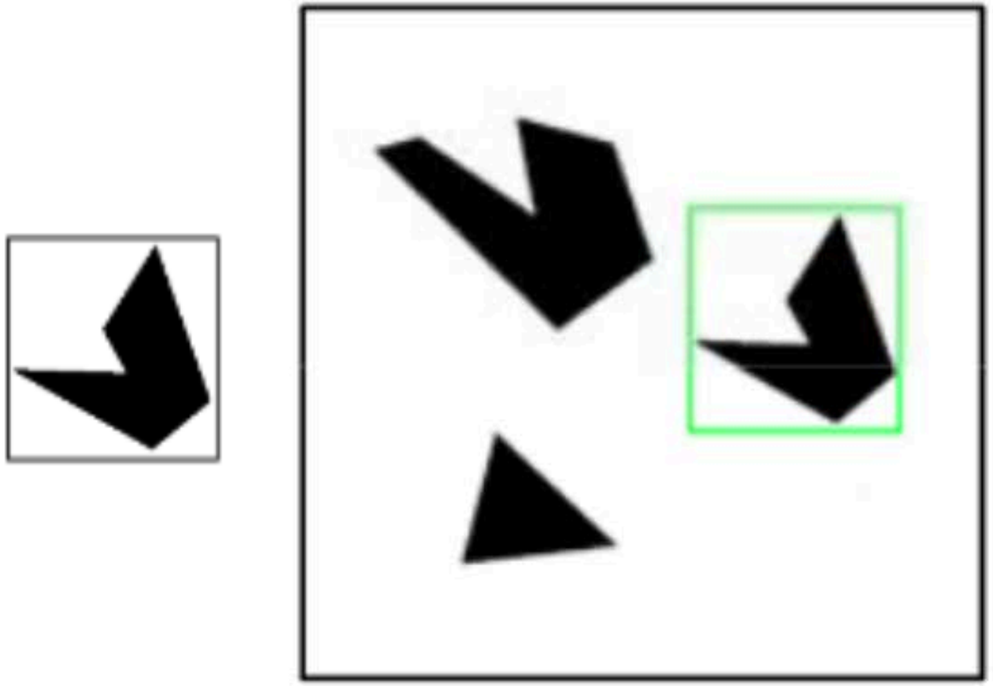
Sum Squared Difference, SSD = $|\mathbf{I} - \mathbf{J}|^2$

Normalized correlation varies between –1 and 1, attains the value 1 when the filter and image region are identical (up to a scale factor)

Minimising SSD and maximizing Normalized Correlation
are equivalent if $|\mathbf{I}| = |\mathbf{J}| = 1$

Template Matching

Assuming template is all positive, what does this tell us about correlation map?



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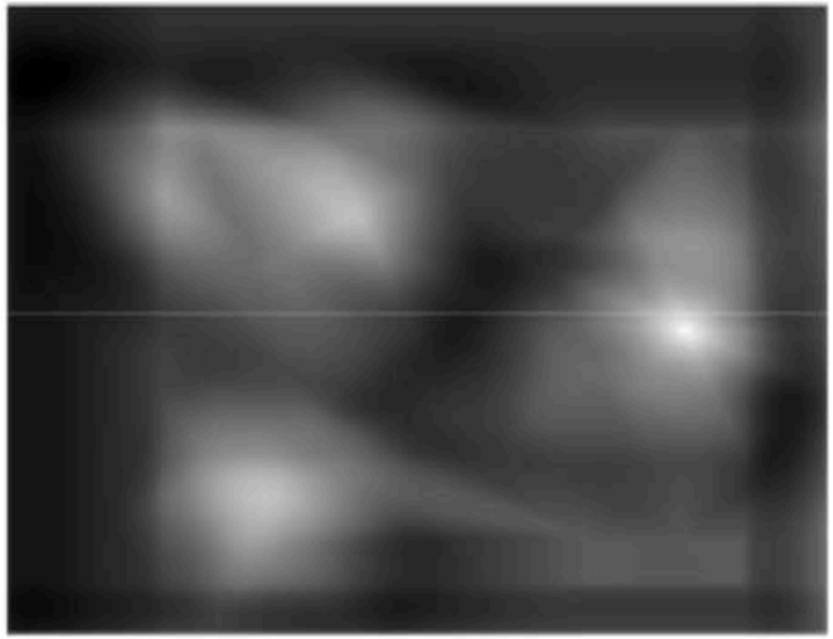

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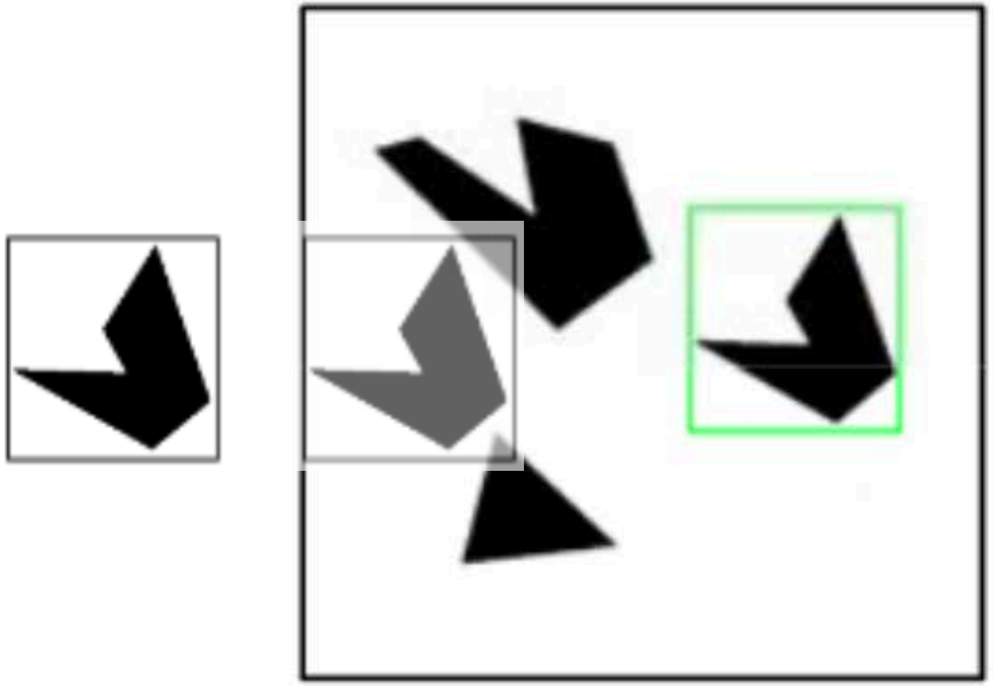

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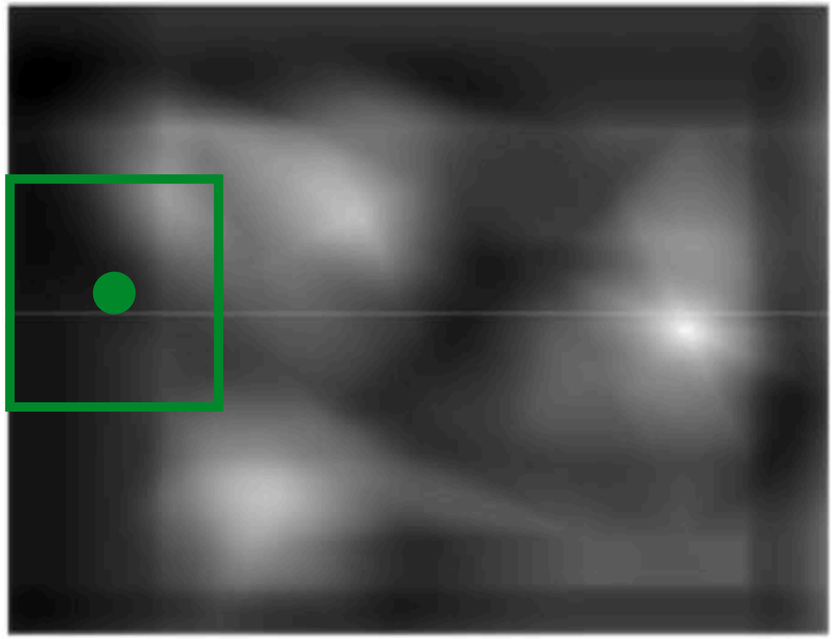

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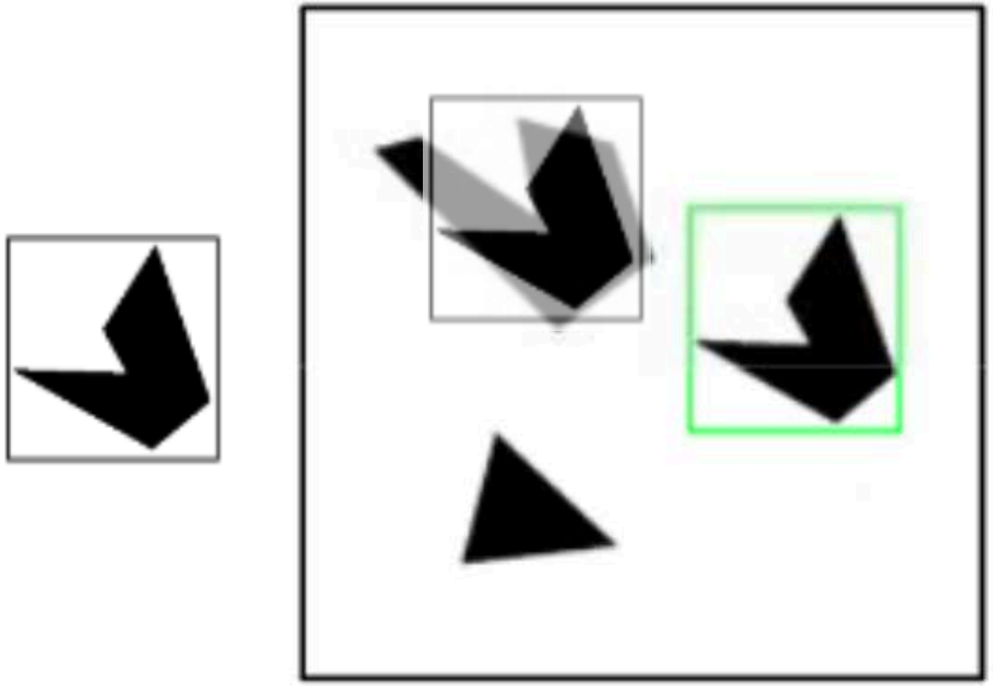

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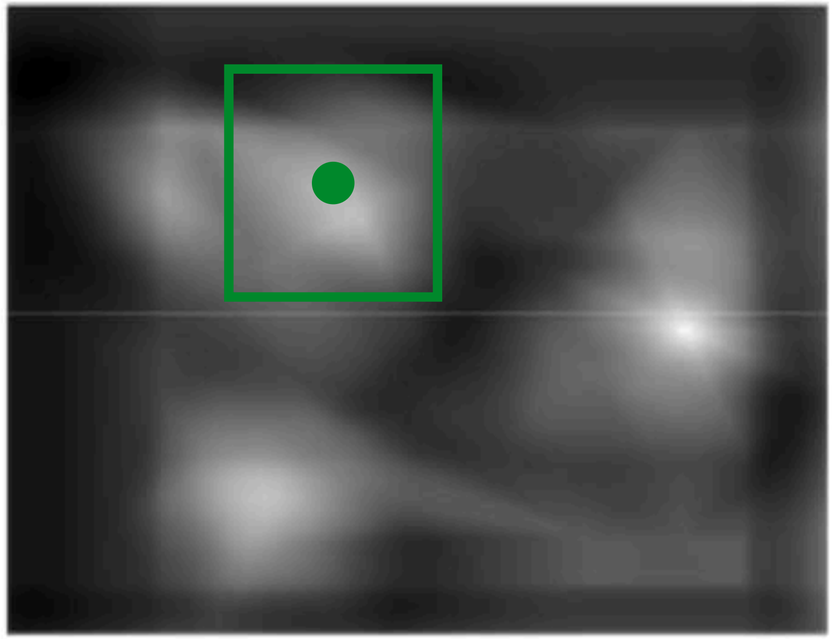

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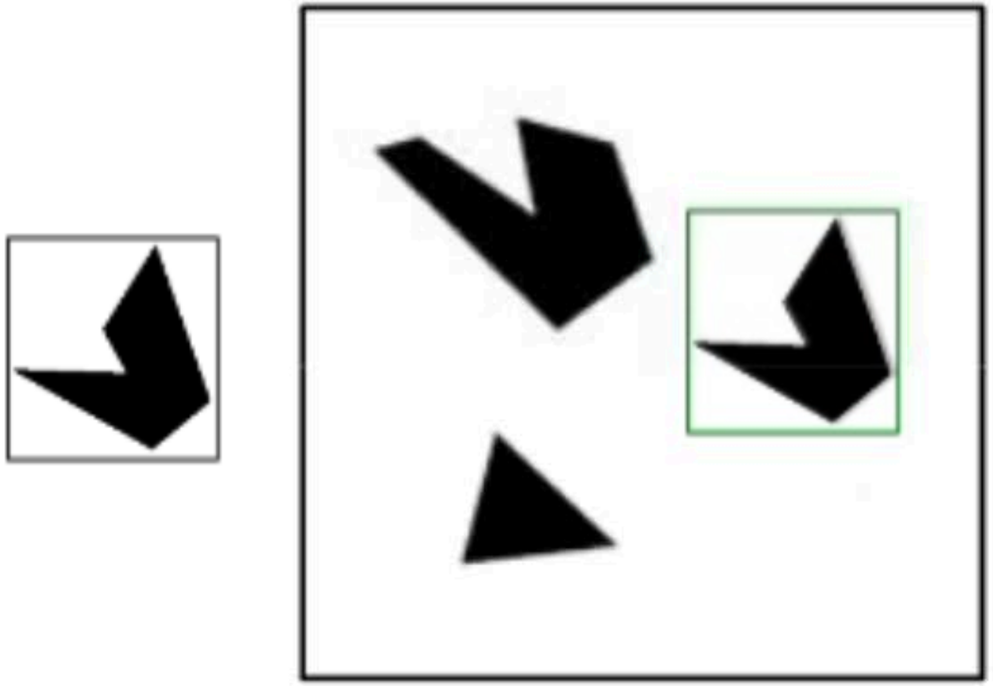

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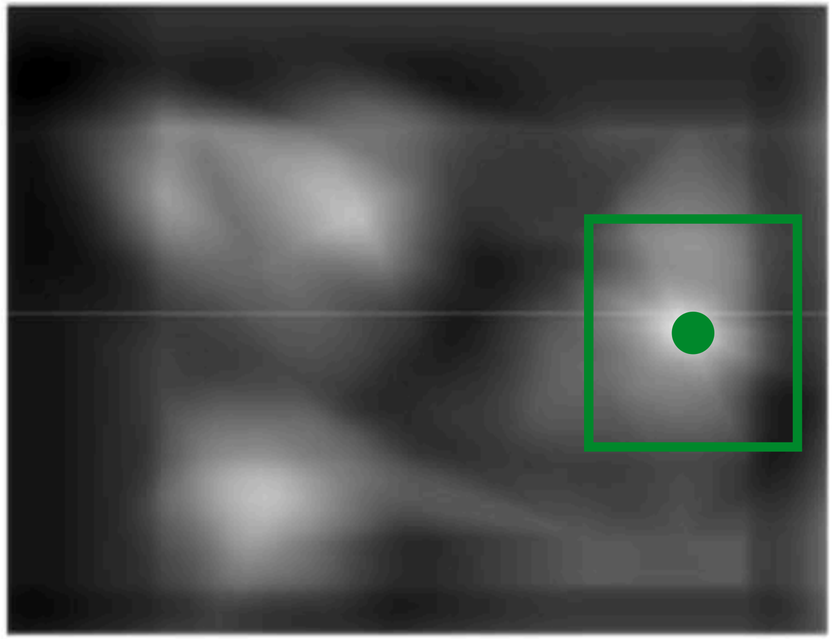

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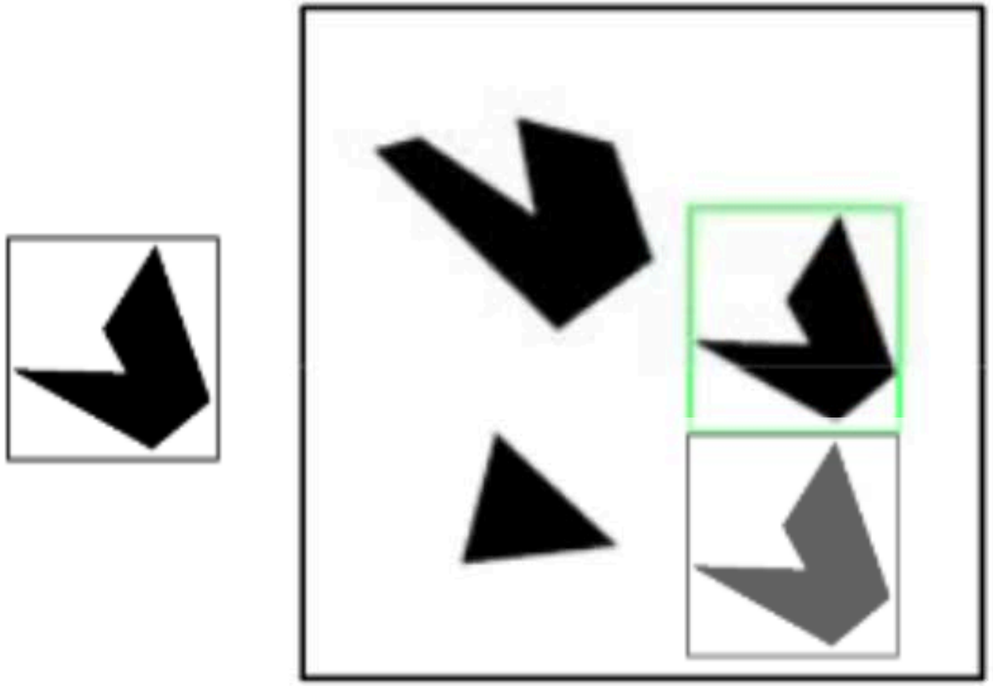

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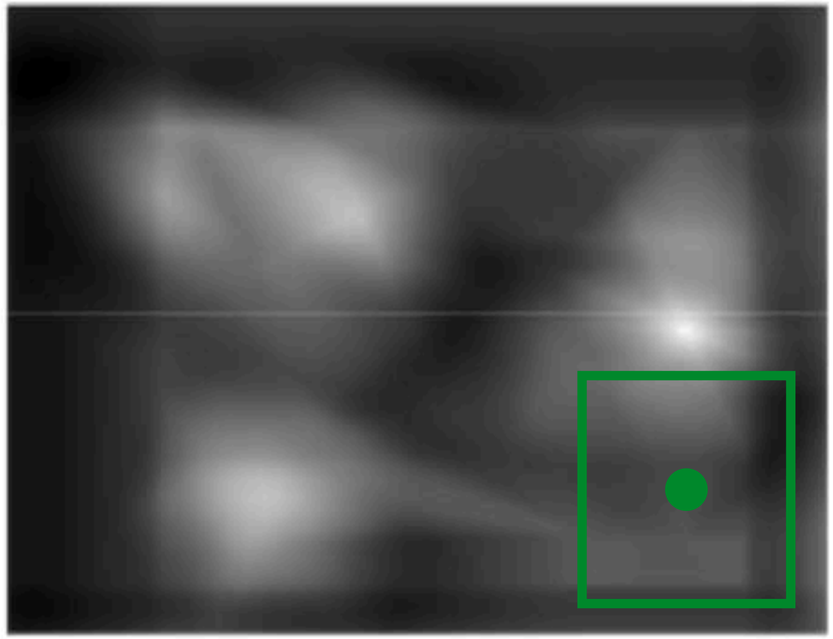

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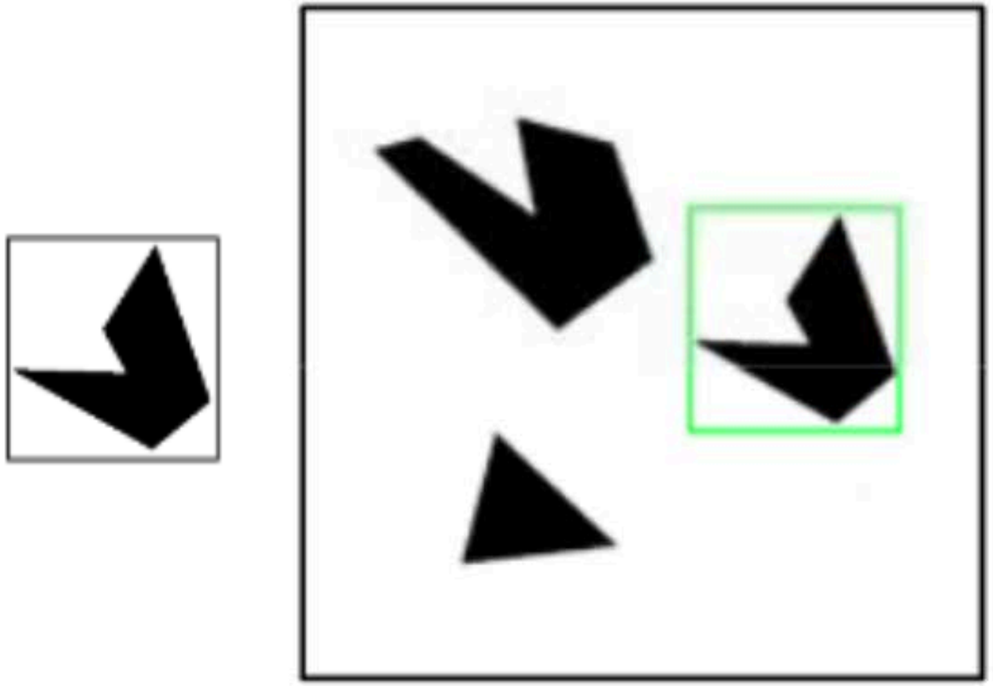
Template Matching

Detection can be done by comparing correlation map score to a threshold



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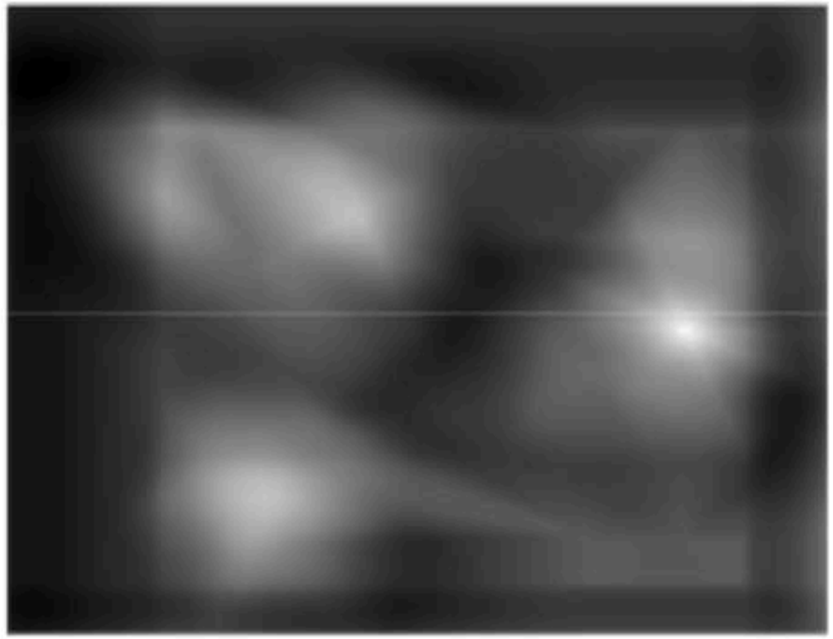

Correlation map

What happens if the threshold is relatively low?

Slide Credit: Kristen Grauman

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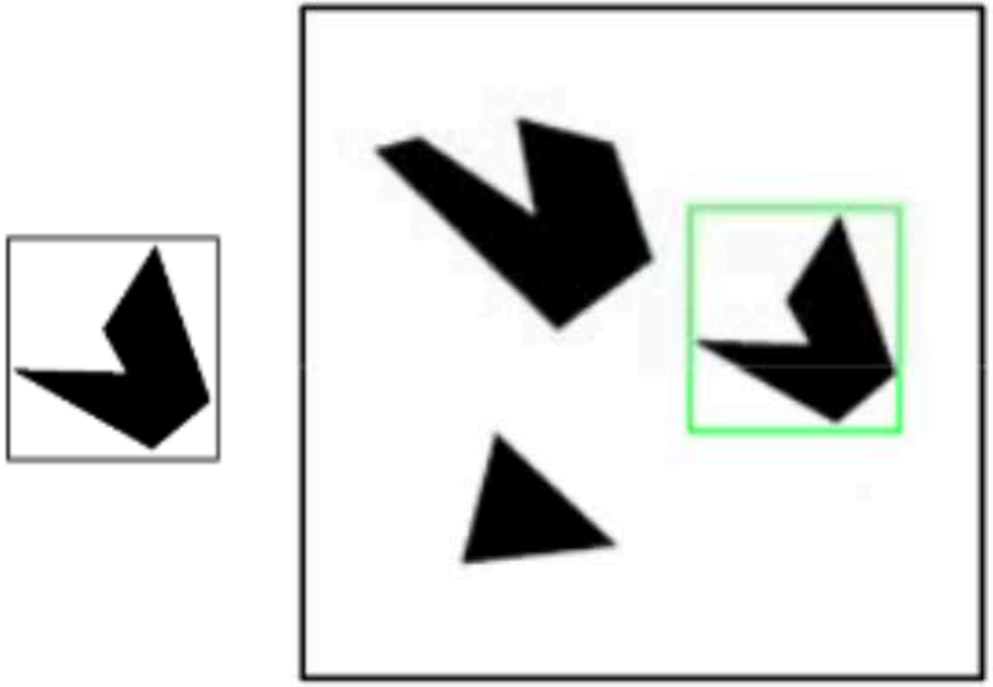

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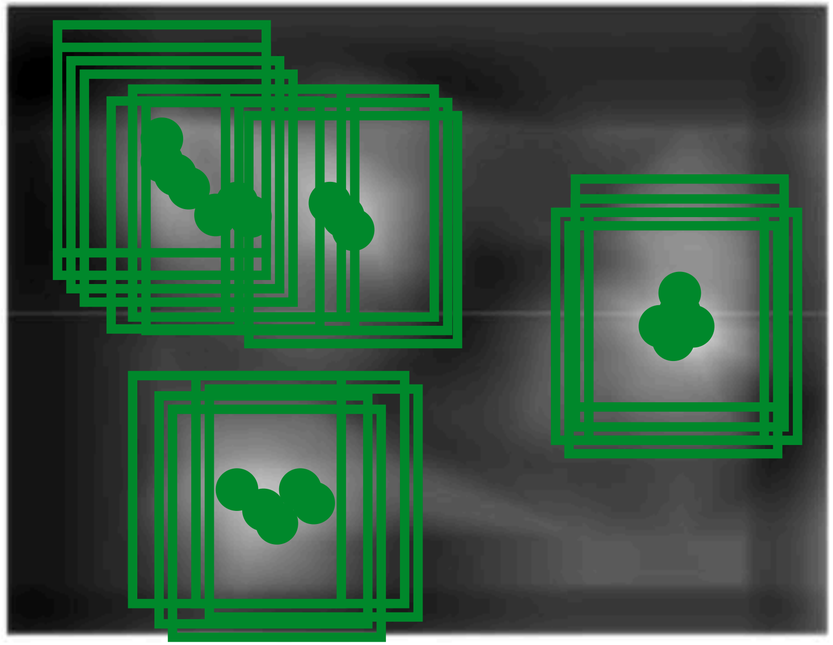

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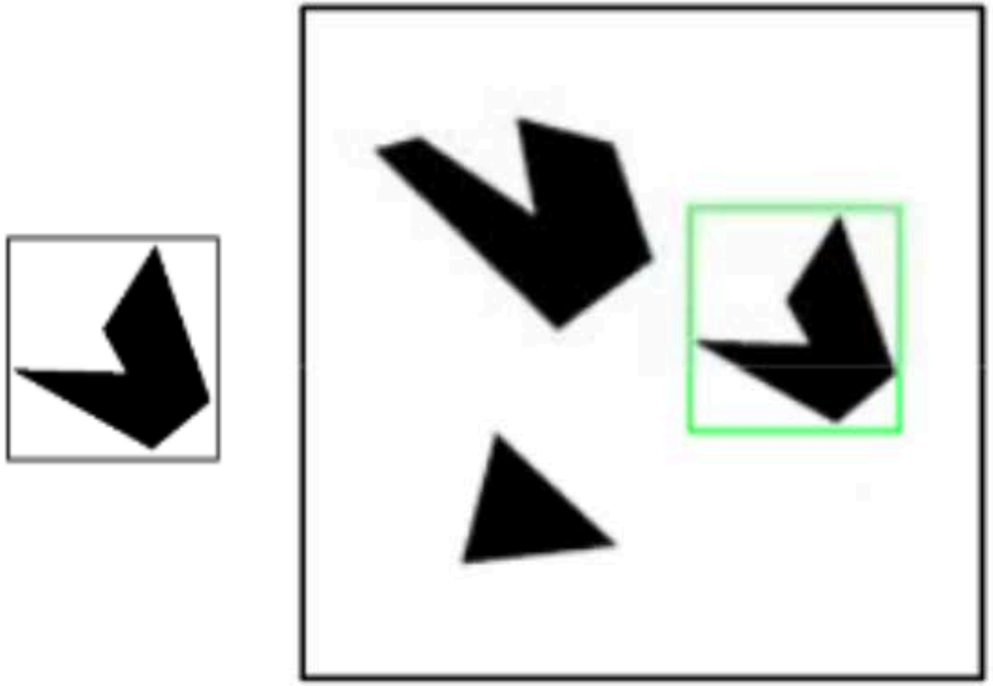

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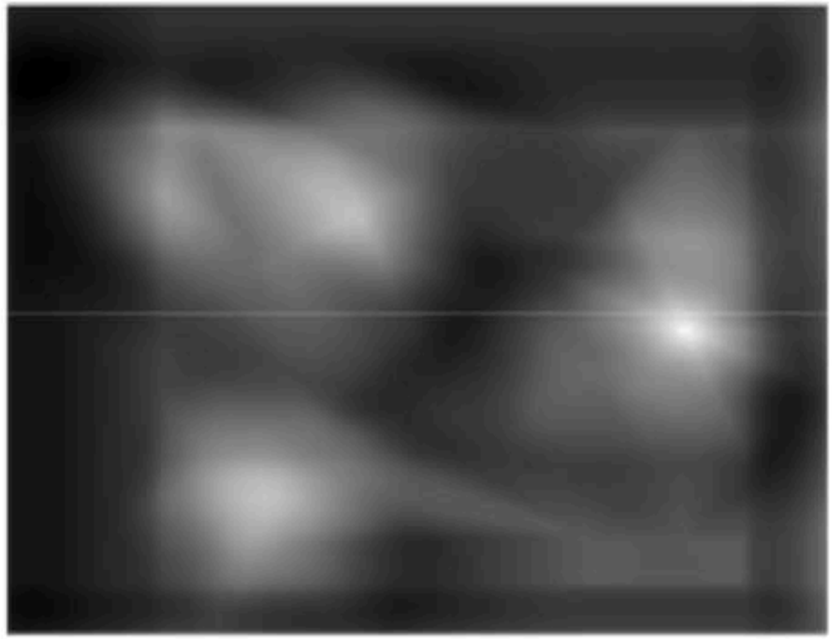

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What happens if the threshold is very high (e.g., 0.99)?

Slide Credit: Kristen Grauman

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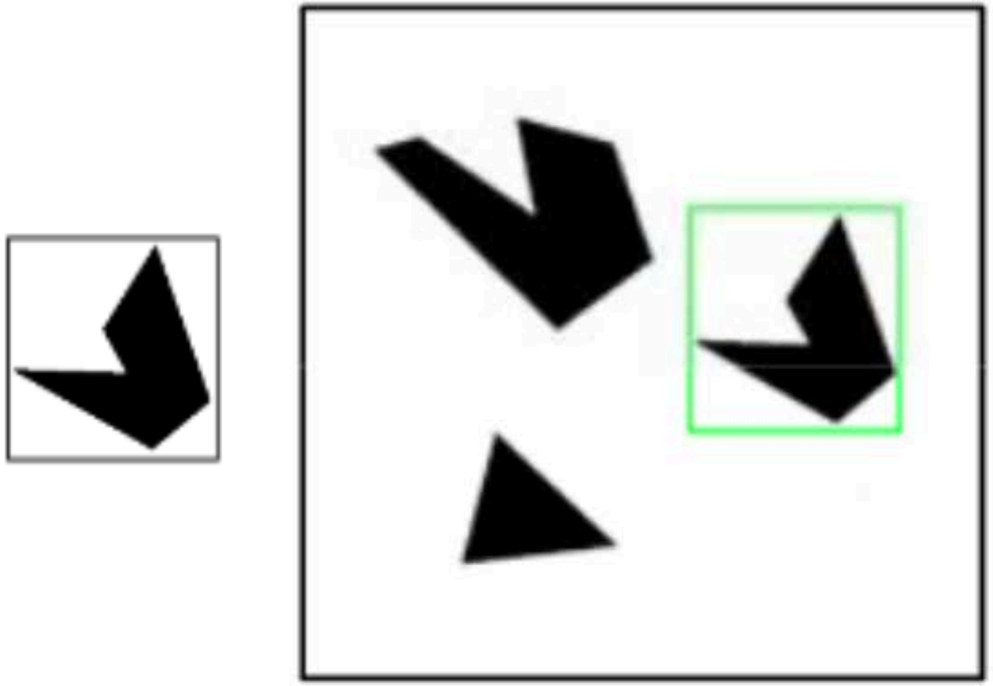

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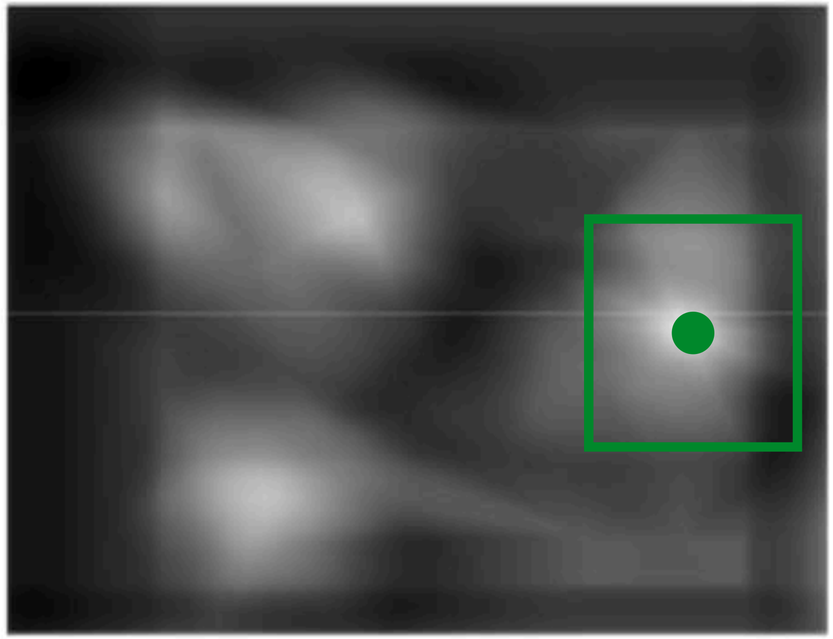

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Template Matching

Let a and b be vectors. Let θ be the angle between them. We know

$$\cos\theta = \frac{a \cdot b}{|a||b|} = \frac{a \cdot b}{\sqrt{(a \cdot a)(b \cdot b)}} = \frac{a}{|a|}\frac{b}{|b|}$$

where $\cdot$ is dot product and $|\ |$ is vector magnitude

Template Matching

Let a and b be vectors. Let θ be the angle between them. We know

$$\cos\theta = \frac{a \cdot b}{|a||b|} = \frac{a \cdot b}{\sqrt{(a \cdot a)(b \cdot b)}} = \frac{a}{|a|}\frac{b}{|b|}$$

where $\cdot$ is dot product and $|\,|$ is vector magnitude

1. Normalize the template / filter (b) in the beginning

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2. Compute norm of $|a|$ by convolving squared image with a filter of all 1's of equal size to the the template and square-rooting the response
3. We can compute the dot product by correlation of image (a) with normalized filter (b)
4. We can finally compute the normalized correlation by dividing element-wise result in Step 3 by result in Step 2

Template Matching

Linear filtering the entire image computes the entire set of dot products, one for each possible alignment of filter and image

Important **Insight**:

— filters look like the pattern they are intended to find

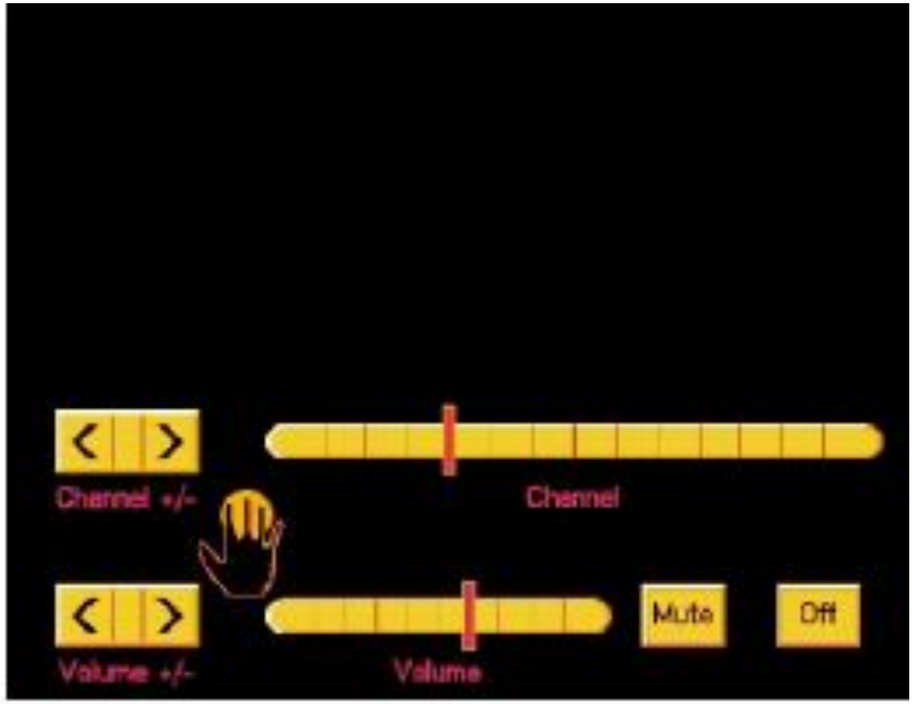
— filters find patterns they look like

Linear filtering is sometimes referred to as **template matching**

Example 1:

Credit: W. Freeman et al., “Computer Vision for Interactive Computer Graphics,” IEEE Computer Graphics and Applications, 1998

Example 1:



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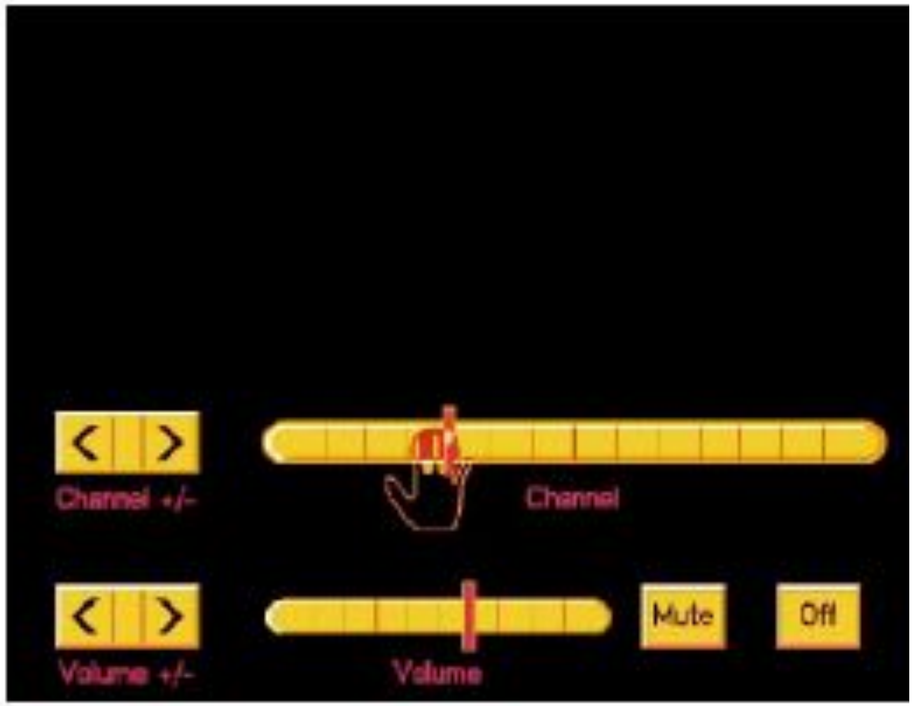

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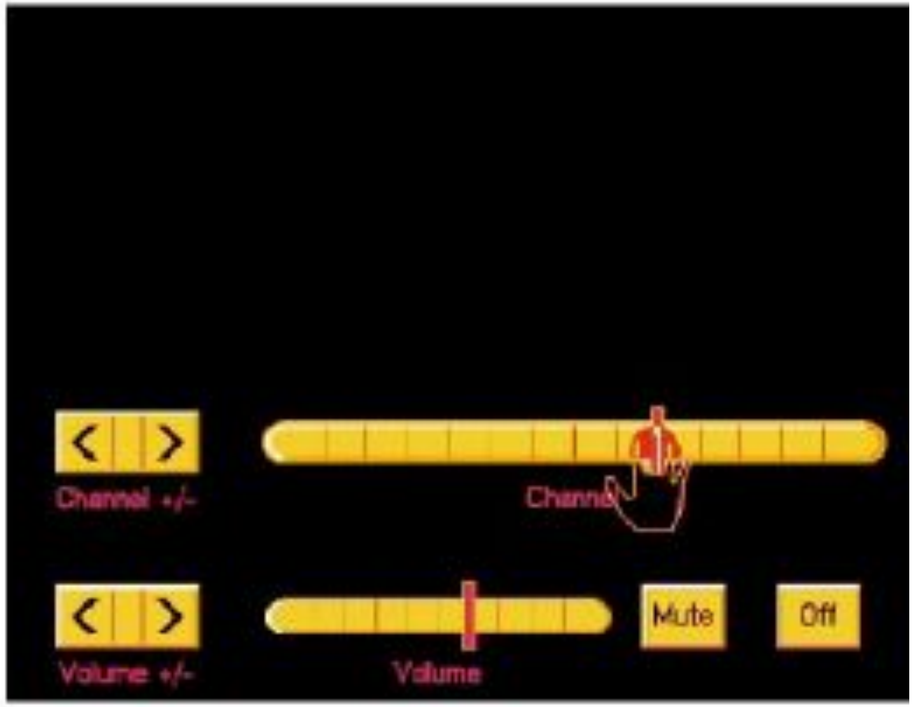

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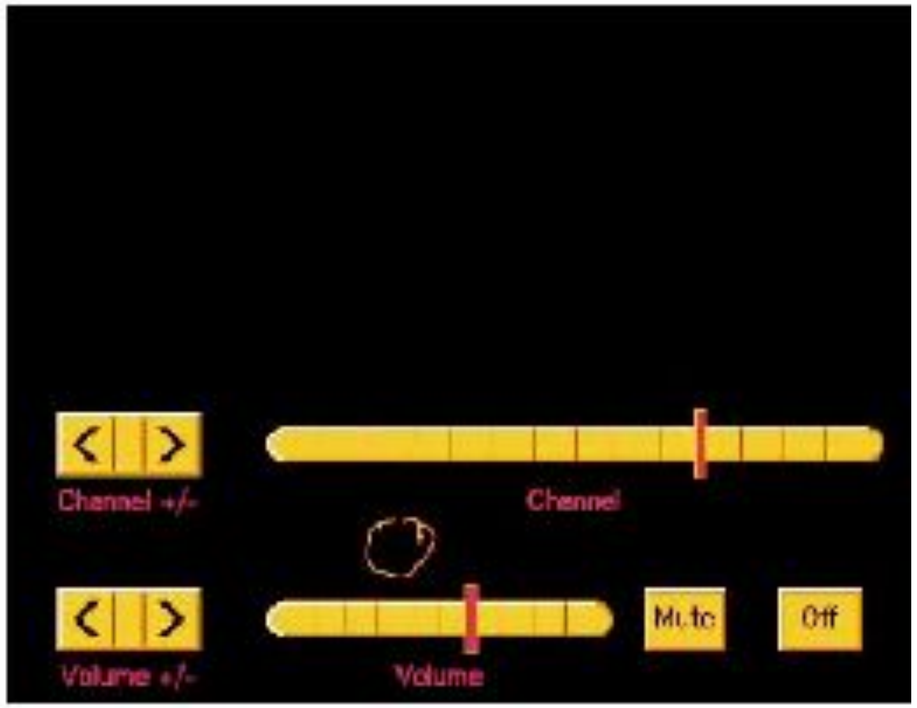

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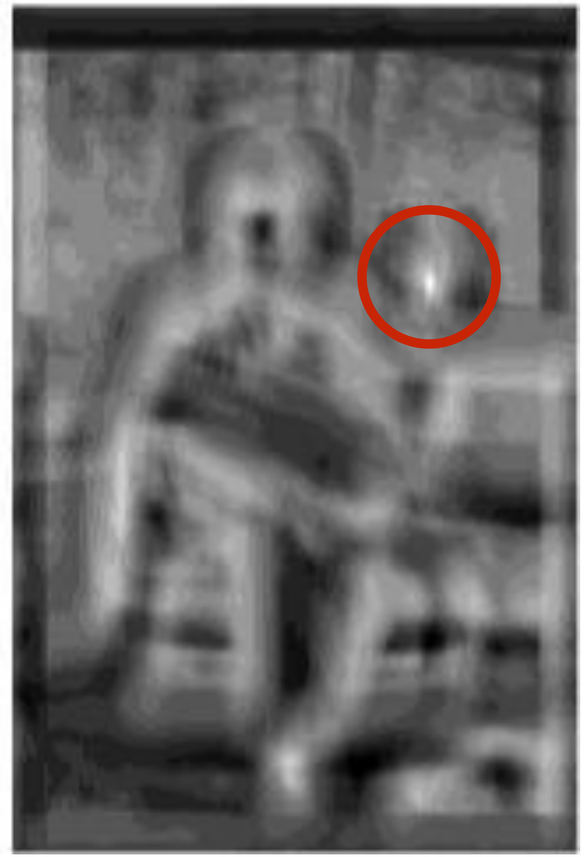
Example 1:

Template (left), image (middle), normalized correlation (right)

Note peak value at the true position of the hand



Credit: W. Freeman et al., “Computer Vision for Interactive Computer Graphics,” IEEE Computer Graphics and Applications, 1998

Template Matching

When might **template matching fail** to recognise objects?

Template Matching

When might **template matching fail**?

— Different scales  

Template Matching

When might **template matching fail**?

— Different scales 

— Different orientation 

Template Matching

When might **template matching fail**?

— Different scales 

— Different orientation 

— Lighting conditions 

Template Matching

When might **template matching fail**?

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— Left vs. Right hand 

Template Matching

When might **template matching fail**?

— Different scales 

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— Partial Occlusions 

Template Matching

When might **template matching fail**?

— Different scales 

— Different orientation 

— Lighting conditions 

— Left vs. Right hand 

— Partial Occlusions 

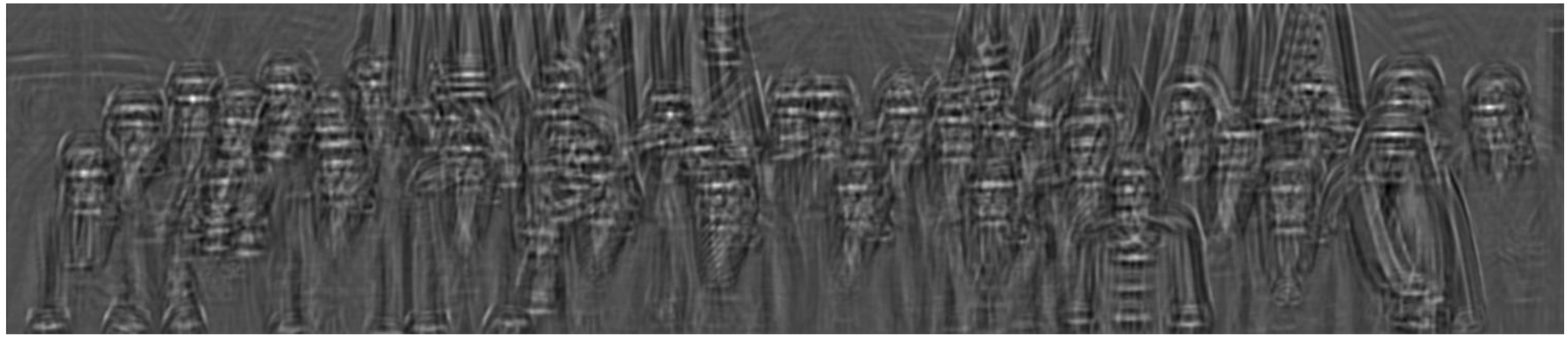
— Different Perspective

— Motion / blur

Template Matching

Convolve image with template, find local maxima

$*$  $\rightarrow$ Non-max suppress $\rightarrow$



Template Matching

Convolve image with template, find local maxima

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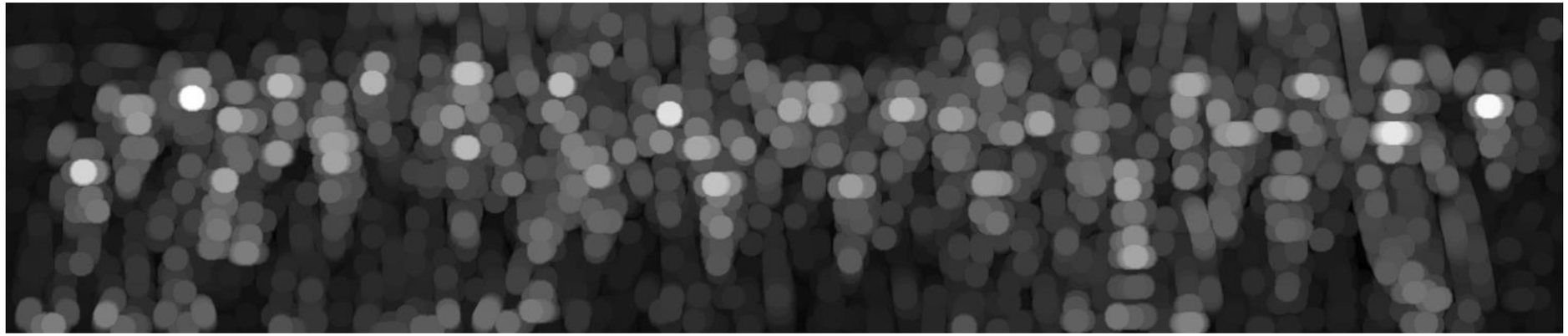
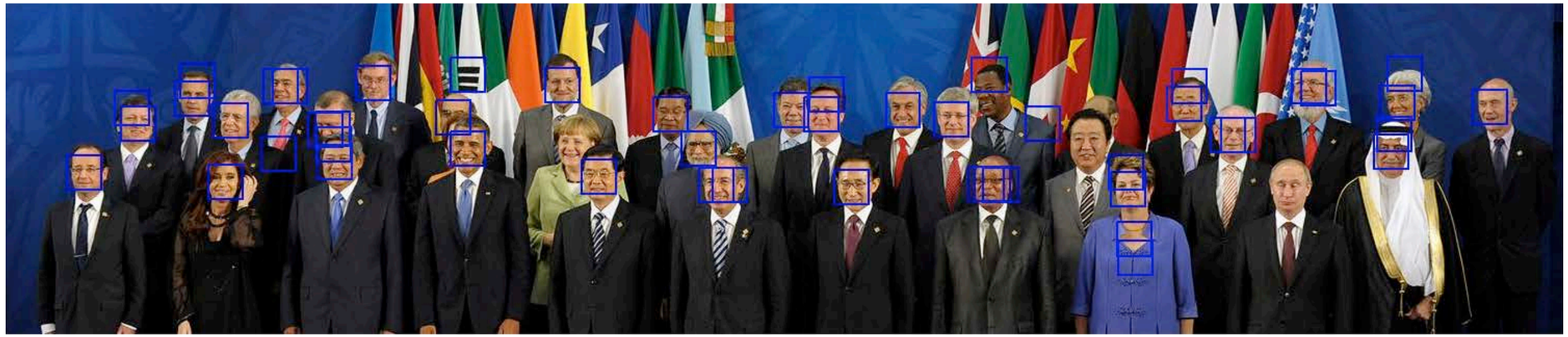


Template Matching

Convolve image with template, find local maxima

$*$  $\rightarrow$ Non-max suppress $\rightarrow$
+ threshold



Detection Performance

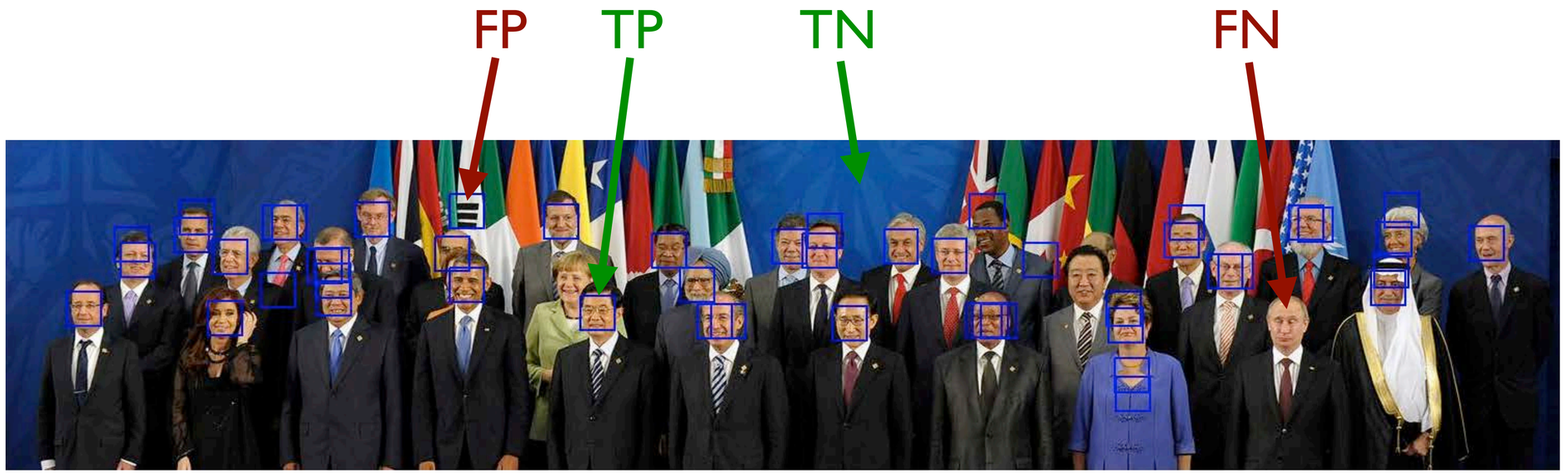
Types of error in detection:

TP = True positive (true face and detected)

FP = False positive (not face and detected)

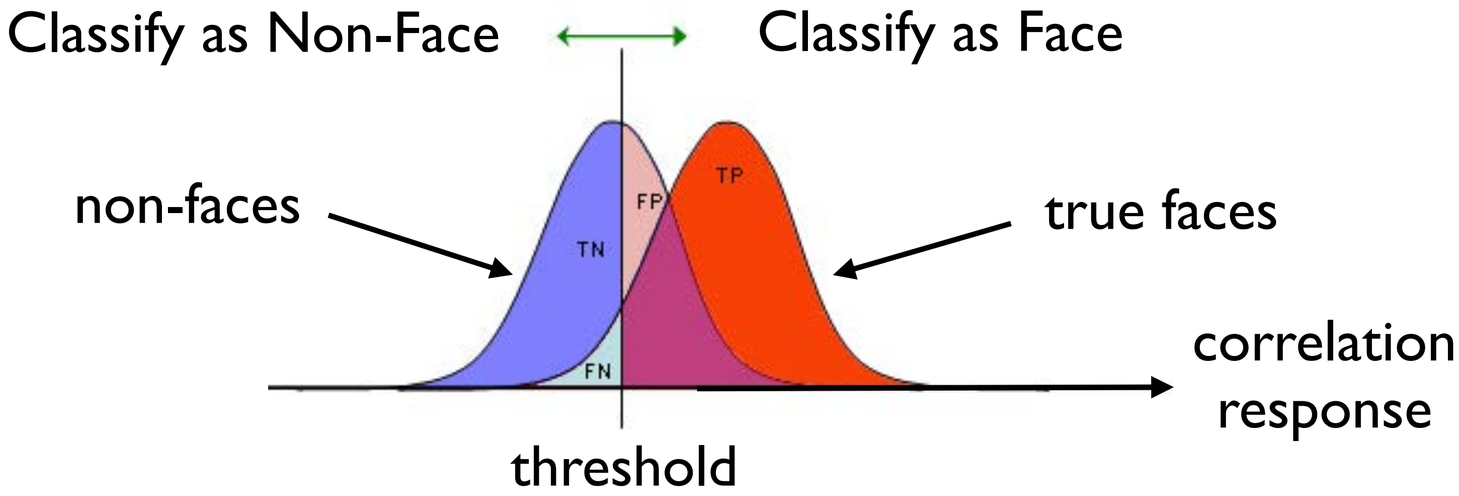
TN = True negative (not face and no detection)

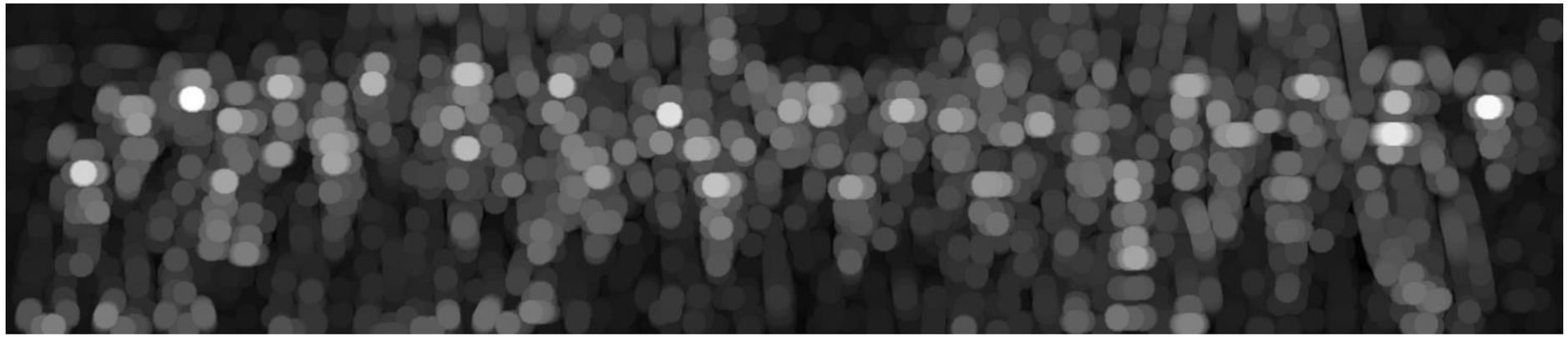
FN = False negative (true face and not detected)



Detection Performance

Depending on where we set the threshold, we can tradeoff between true positives and false positives





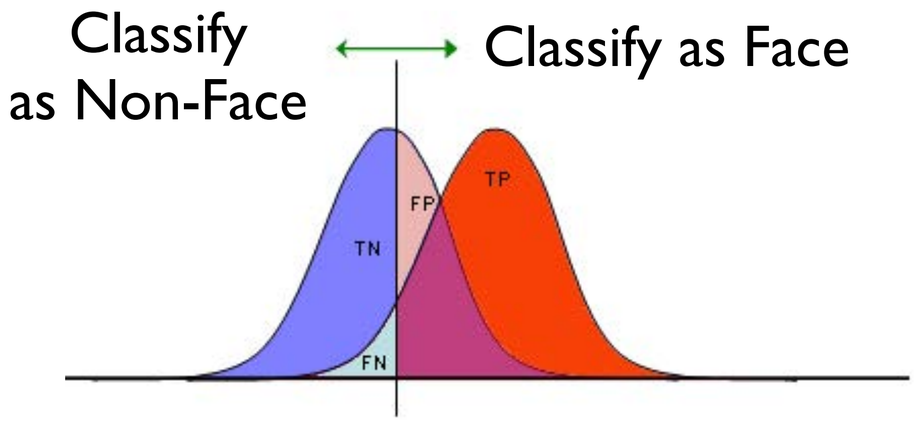
ROC Curves

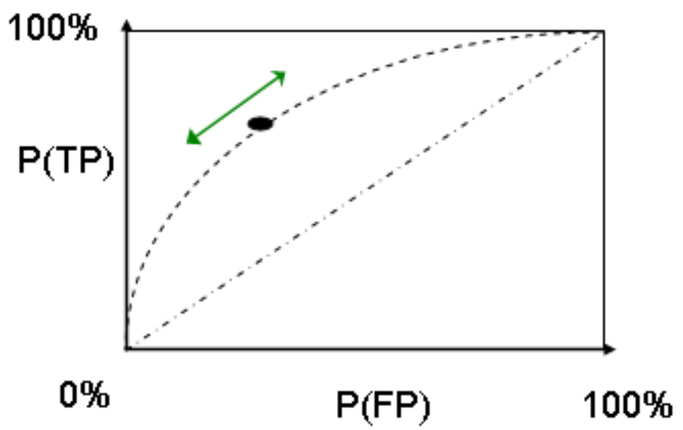
Note that we can easily get 100% true positives (if we are prepared to get 100% false positives as well!)

It is a tradeoff between **true positive rate (TP)** and **false positive rate (FP)**

We can plot a curve of all TP rates vs FP rates by varying the classifier threshold

This is a **Receiver Operating Characteristic (ROC)** curve





red = actual faces, blue = actual non-faces

Template Matching Summary

Good News:

- works well in presence of noise
- relatively easy to compute

Bad News:

- sensitive to (spatial) scale change
- sensitive to 2D rotation

More Bad News:

When imaging 3D worlds:

- sensitive to viewing direction and pose
- sensitive to conditions of illumination