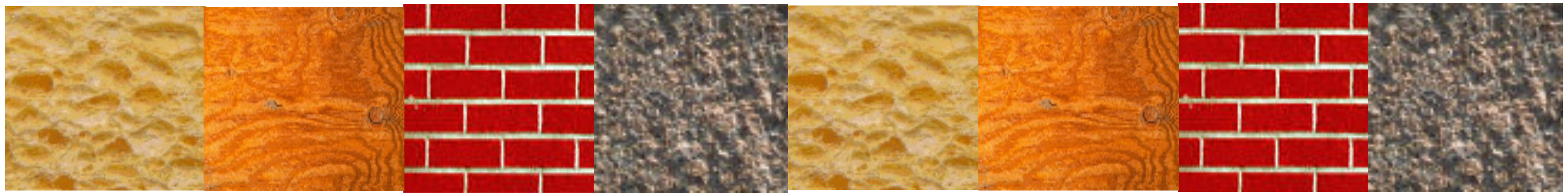
THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision



Lecture 16: Texture (cont)

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

Menu for Today (**October 16, 2020**)

Topics:

— Texture Synthesis

— Texture Analysis

Redings:

— **Today's** Lecture: Forsyth & Ponce (2nd ed.) 3.1-3.3

— **Next** Lecture:

Reminders:

— **Assignment 3**: Texture Synthesis is due **October 23rd**

— **Quiz 3** is out and available until end of the day **tomorrow** (due to my error)

— **Midterm** (prep answers today, review session **Monday** and **Tuesday**)

Today's "**fun**" Example: Texture Camouflage

https://en.wikipedia.org/wiki/File:Camouflage.jpg

Today’s “**fun**” Example: Texture Camouflage

Cuttlefish on gravel seabed

Seconds later…

http://www.marinet.org.uk/campaign-article/an-illustrated-guide-to-uk-marine-animals

Re-cap

Summary of what we have seen so far:

Representation	Results in	Approach	Technique
intensity	dense	template matching	(normalized) correlation
edge	relatively sparse	derivatives	Sobel, LoG, Canny
corner	sparse	locally distinct features	Harris (and variants)
blob	sparse	locally distinct features	LoG

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Texture

What is **texture**?

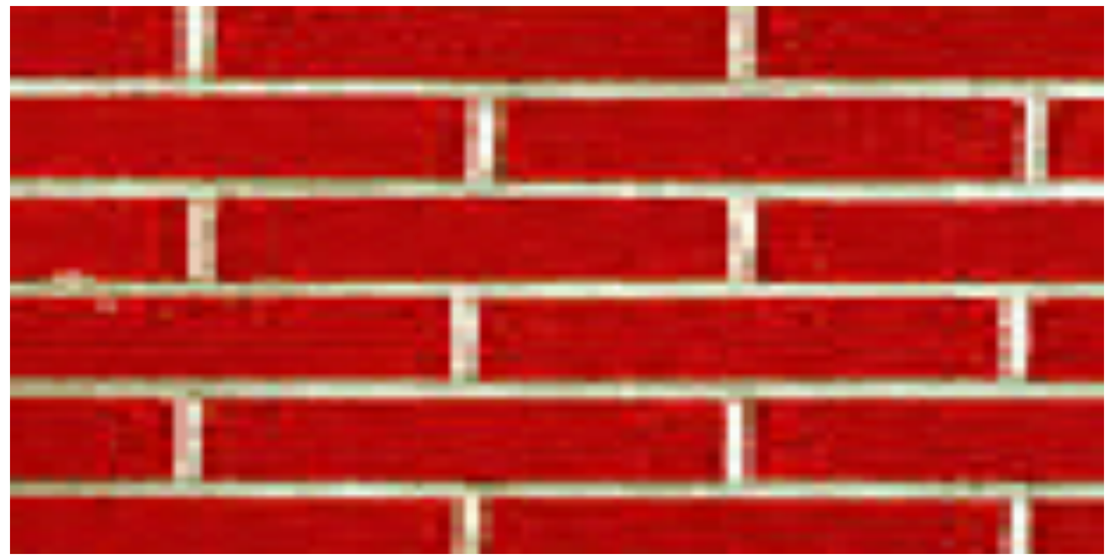 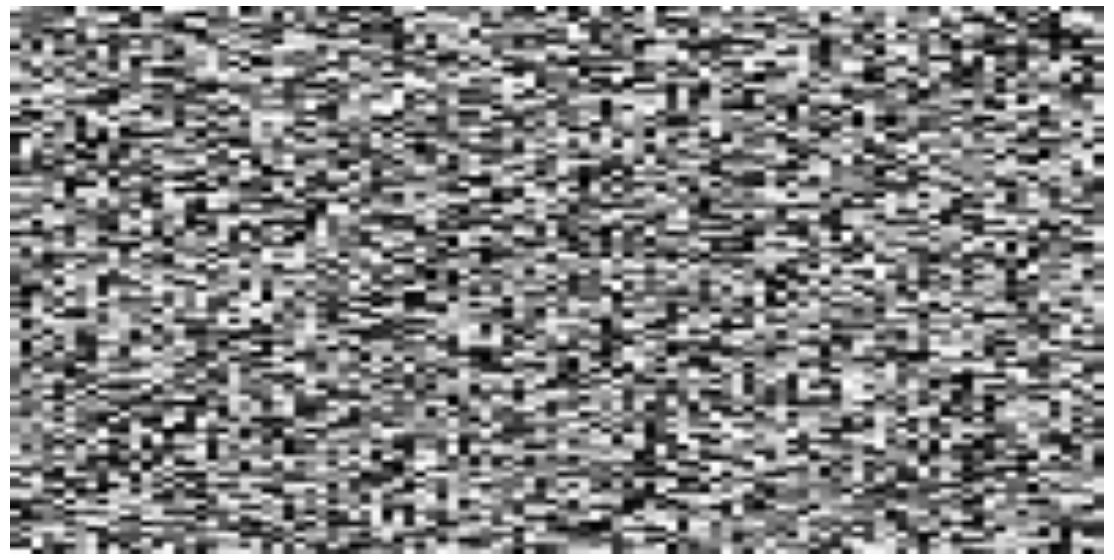 

Figure Credit: Alexei Efros and Thomas Leung

Texture is widespread, easy to recognize, but hard to define

Views of large numbers of small objects are often considered textures
— e.g. grass, foliage, pebbles, hair

Patterned surface markings are considered textures
— e.g. patterns on wood

Definition of **Texture**

(Functional) **Definition**:

Texture is detail in an image that is at a scale too small to be resolved into its constituent elements and at a scale large enough to be apparent in the spatial distribution of image measurements

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(Functional) **Definition**:

Texture is detail in an image that is at a scale too small to be resolved into its constituent elements and at a scale large enough to be apparent in the spatial distribution of image measurements

Sometimes, textures are thought of as patterns composed of repeated instances of one (or more) identifiable elements, called **textons**.

— e.g. bricks in a wall, spots on a cheetah

Uses of **Texture**

Texture can be a strong cue to **object identity** if the object has distinctive material properties

Texture can be a strong cue to an **object's shape** based on the deformation of the texture from point to point.

— Estimating surface orientation or shape from texture is known as "**shape from texture**"

Texture

We will look at two main questions:

1. How do we represent texture?
   → Texture **analysis**

2. How do we generate new examples of a texture?
   → Texture **synthesis**

We begin with texture synthesis to set up **Assignment 3**

Texture **Synthesis**

Why might we want to synthesize texture?

1. To fill holes in images (**inpainting**)

— Art directors might want to remove telephone wires. Restorers might want to remove scratches or marks.

— We need to find something to put in place of the pixels that were removed

— We synthesize regions of texture that fit in and look convincing

Texture **Synthesis**

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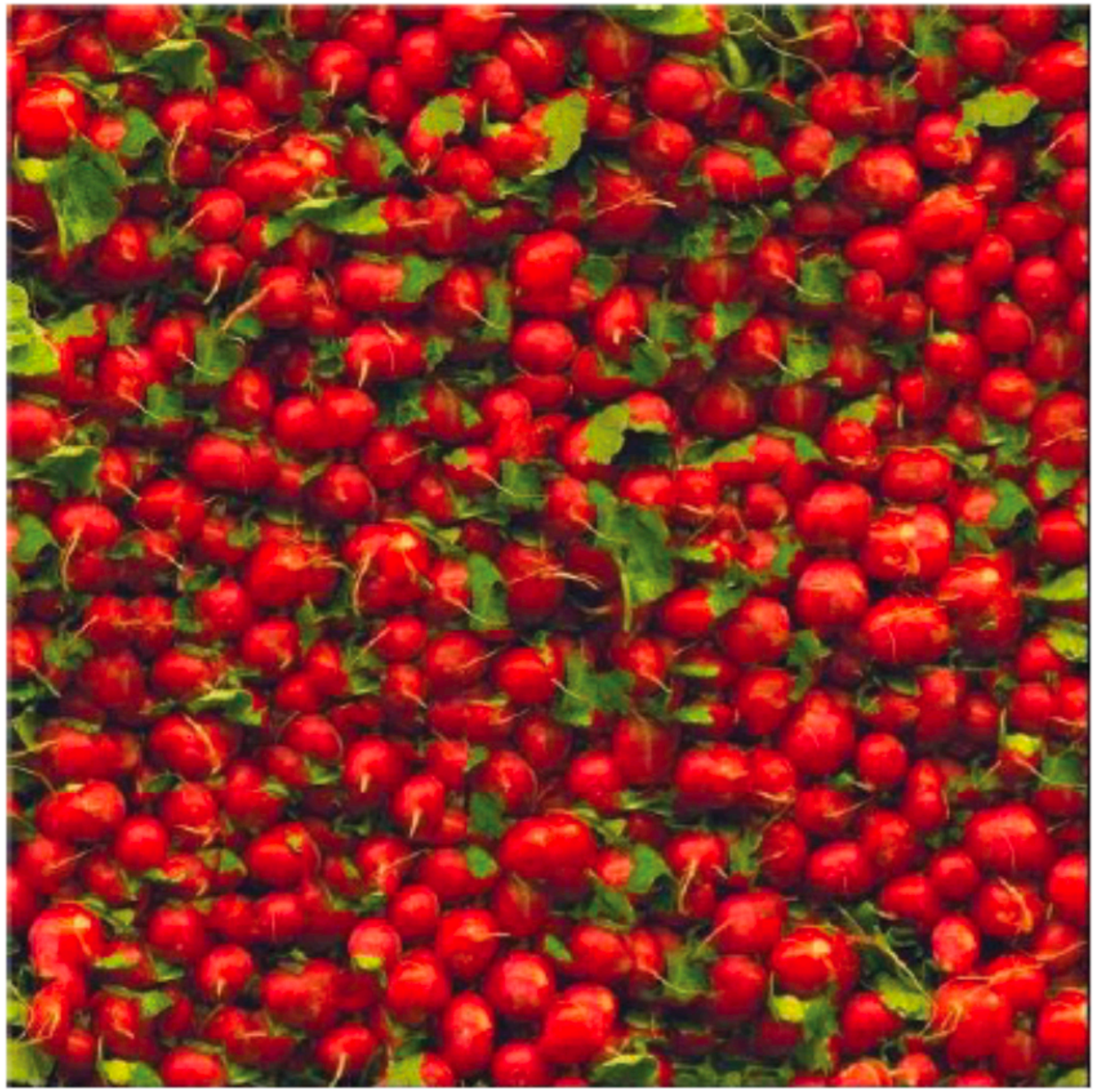
— We synthesize regions of texture that fit in and look convincing

2. To produce large quantities of texture for computer graphics

— Good textures make object models look more realistic

Texture **Synthesis**

radishes



lots more radishes

Szeliski, Fig. 10.49

Texture **Synthesis**

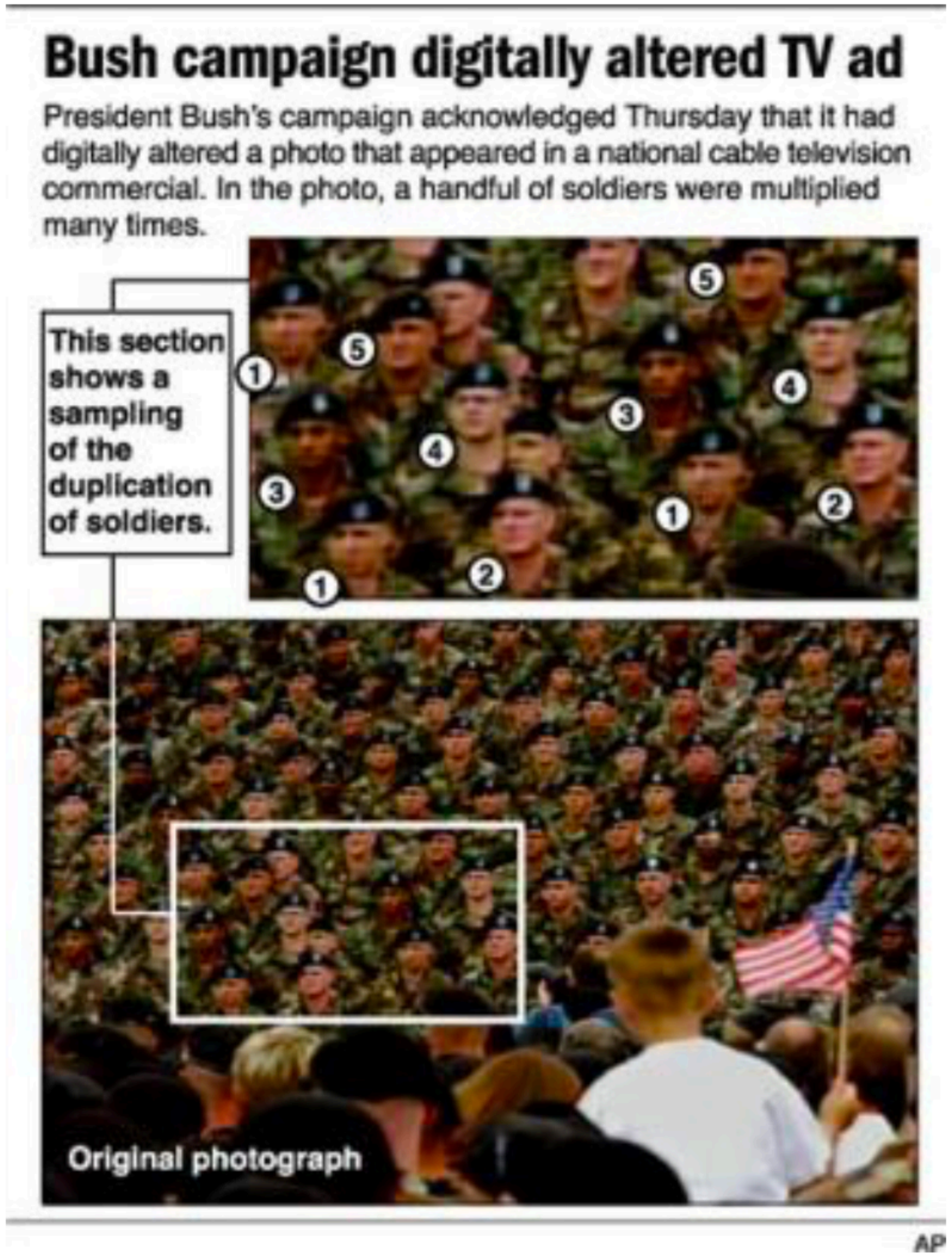


Photo Credit: Associated Pres

Texture **Synthesis**

Cover of “The Economist,” June 19, 2010

Photo Credit (right): Reuters/Larry Downing

Assignment 3 Preview: Texture Synthesis

Task: Make donkey vanish

Assignment 3 Preview: Texture Synthesis

Task: Make donkey vanish

Method: Fill-in regions using texture from the white box

Assignment 3 Preview: Texture Synthesis

Task: Make donkey vanish

Method: Fill-in regions using texture from the white box

Texture Synthesis

Objective: Generate new examples of a texture. We take a “data-driven" approach

Idea: Use an image of the texture as the source of a probability model

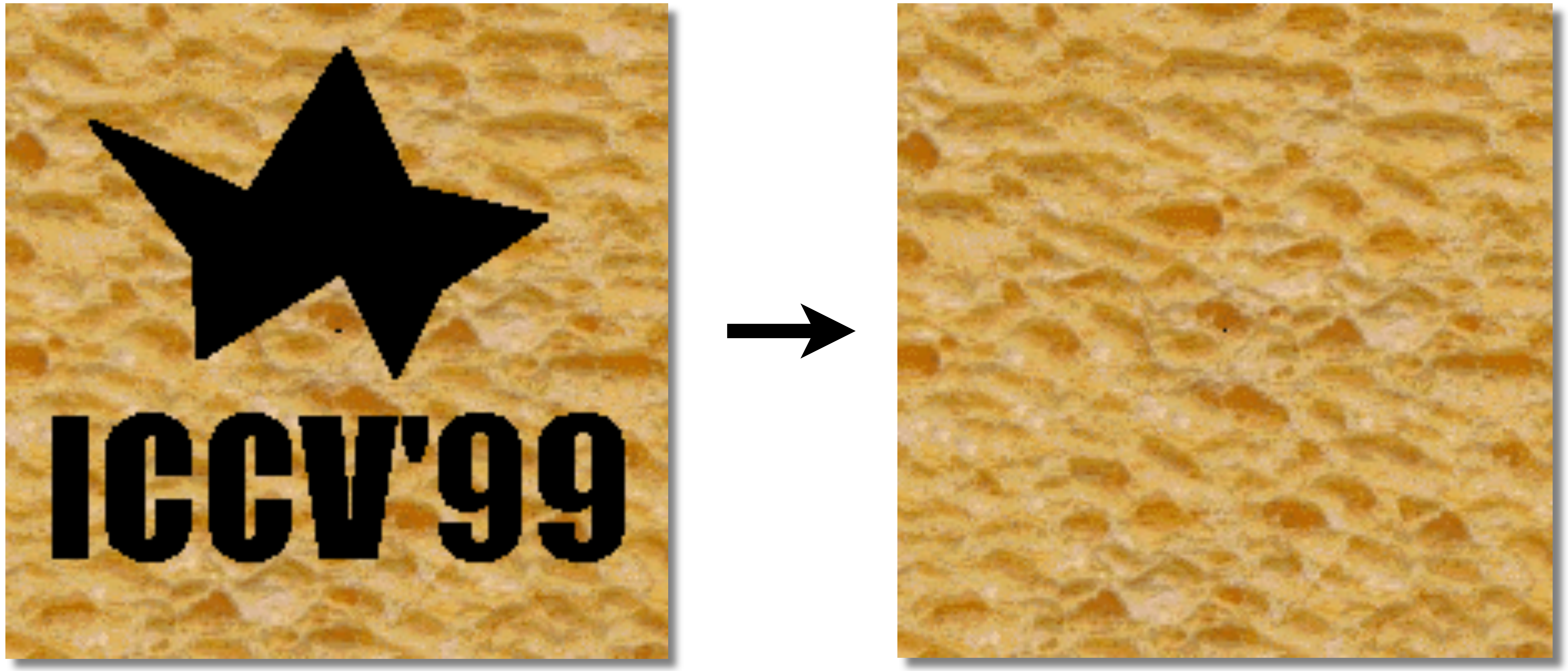
— Draw samples directly from the actual texture

— Can account for more types of structure

— Very simple to implement

— Success depends on choosing a correct “distance”

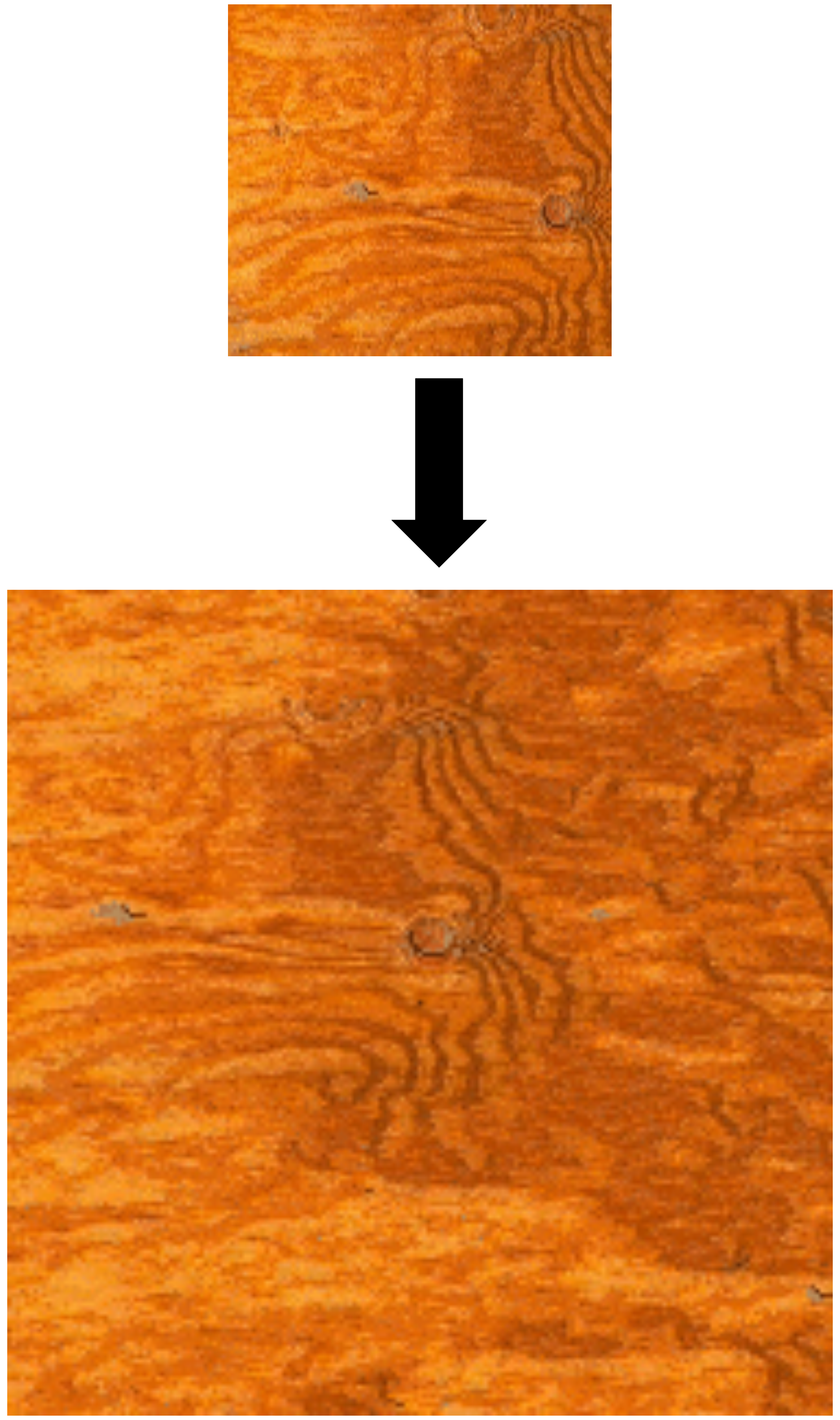
Texture Synthesis by Non-parametric Sampling



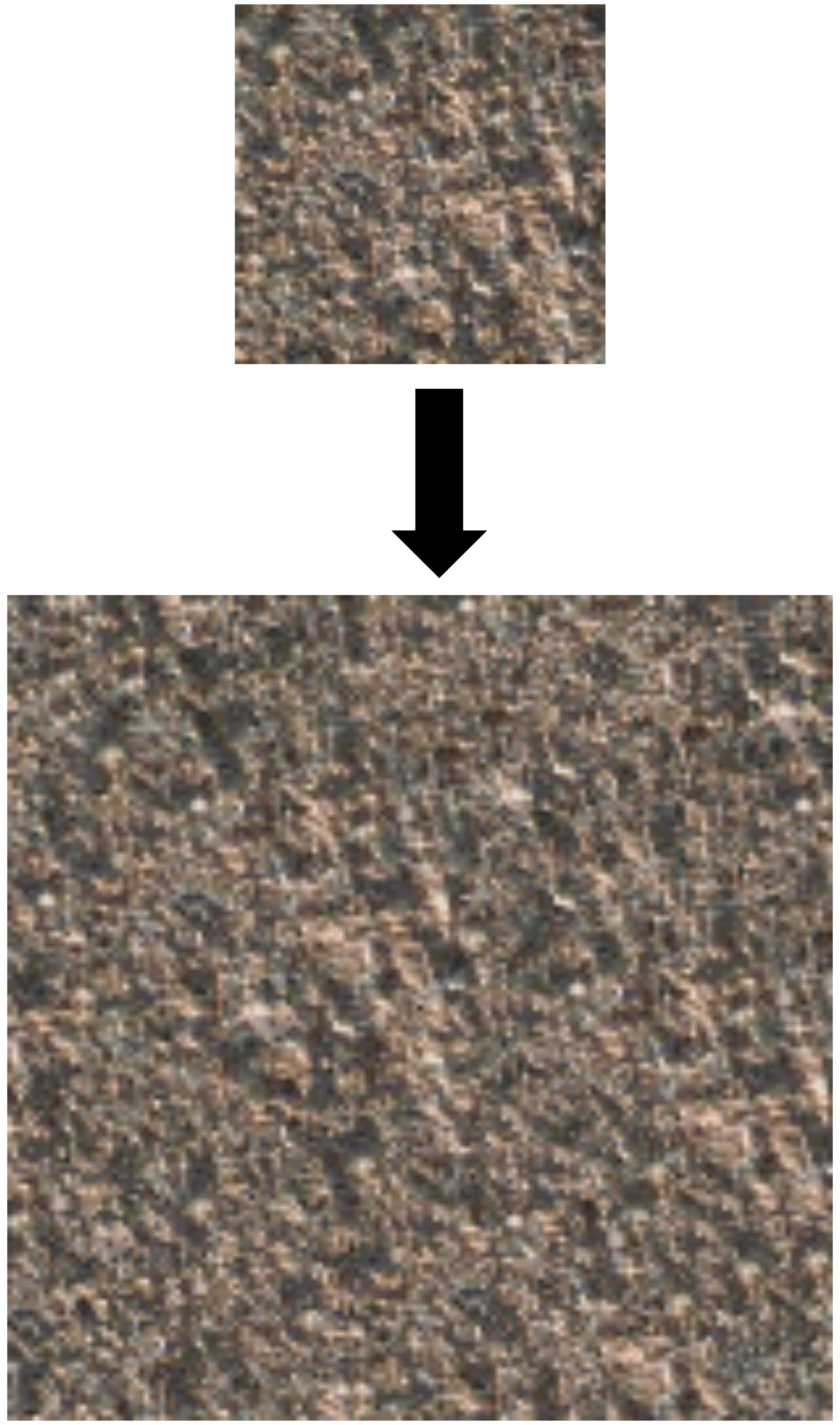
Alexei Efros and Thomas Leung
UC Berkeley

Slide Credit: http://graphics.cs.cmu.edu/people/efros/research/NPS/efros-iccv99.ppt

Efros and Leung

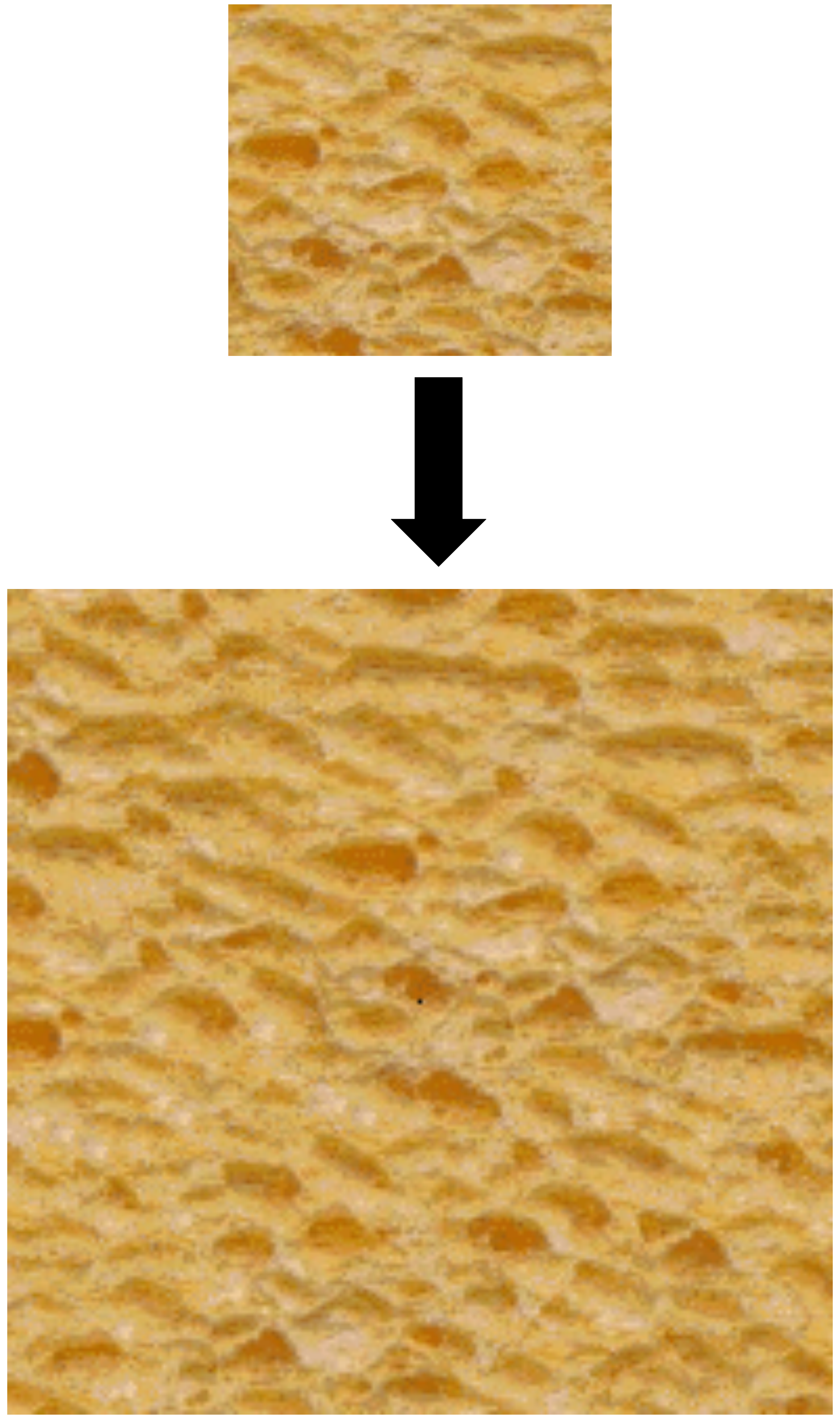


wood

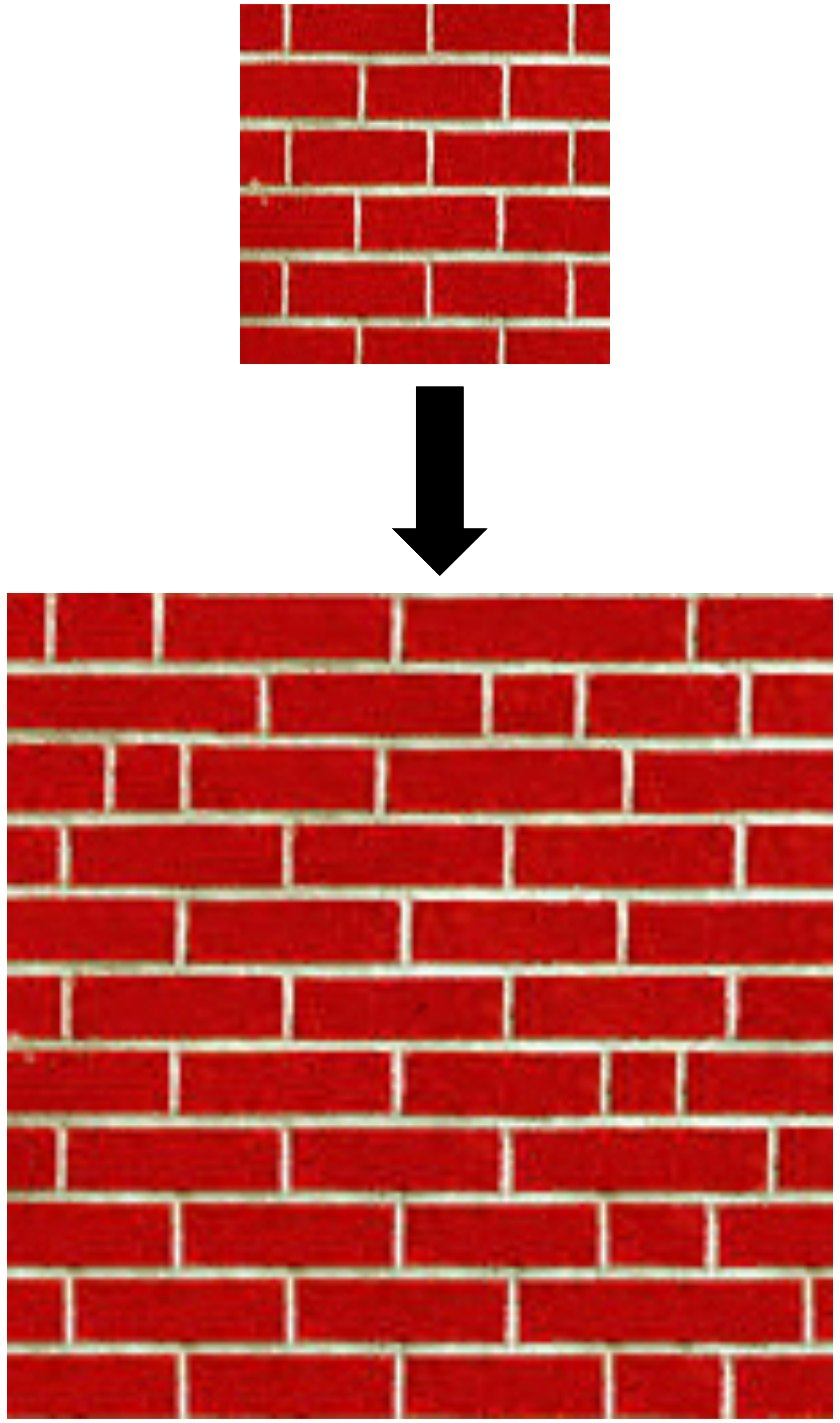


granite

Efros and Leung

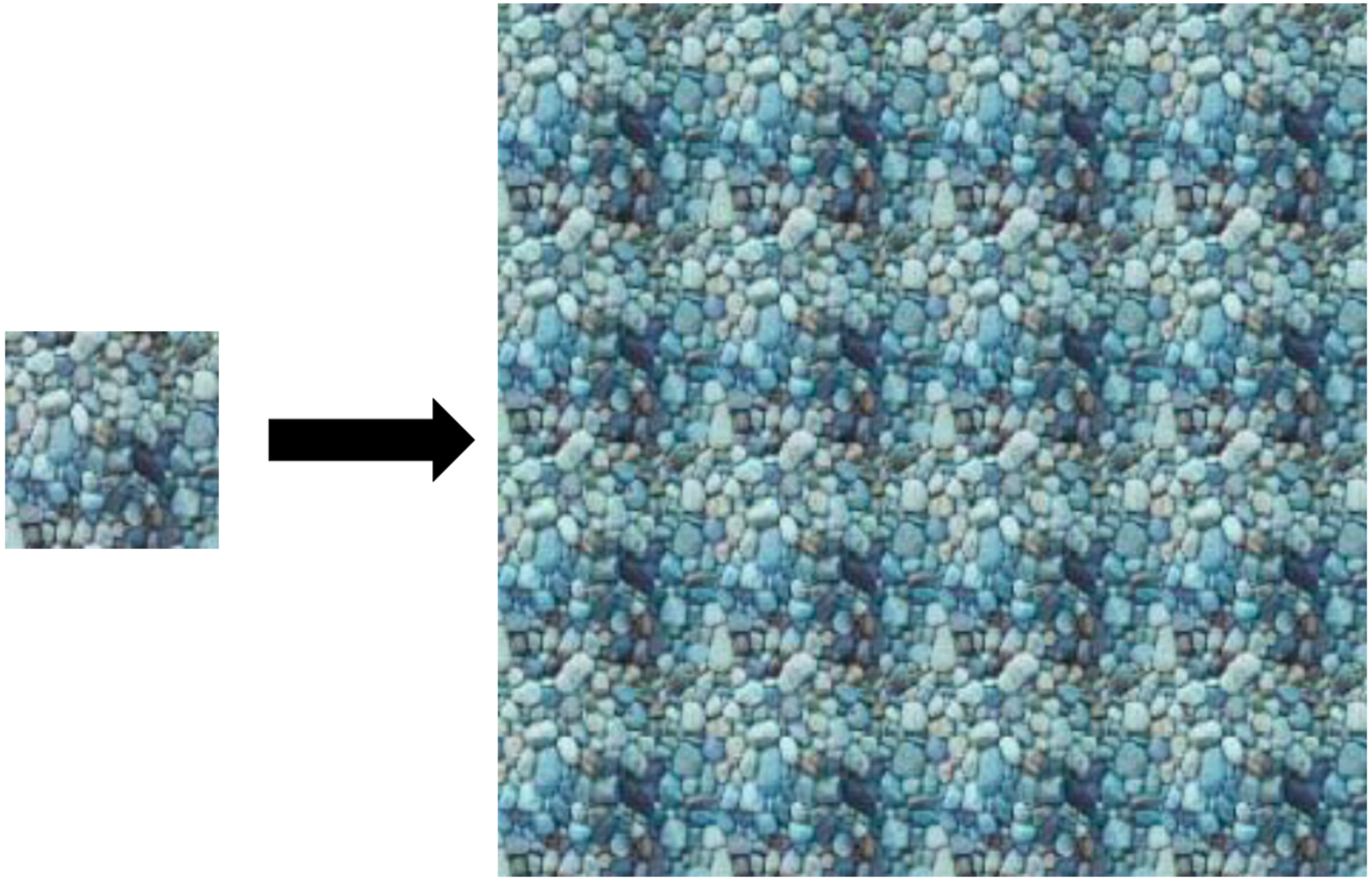


white bread

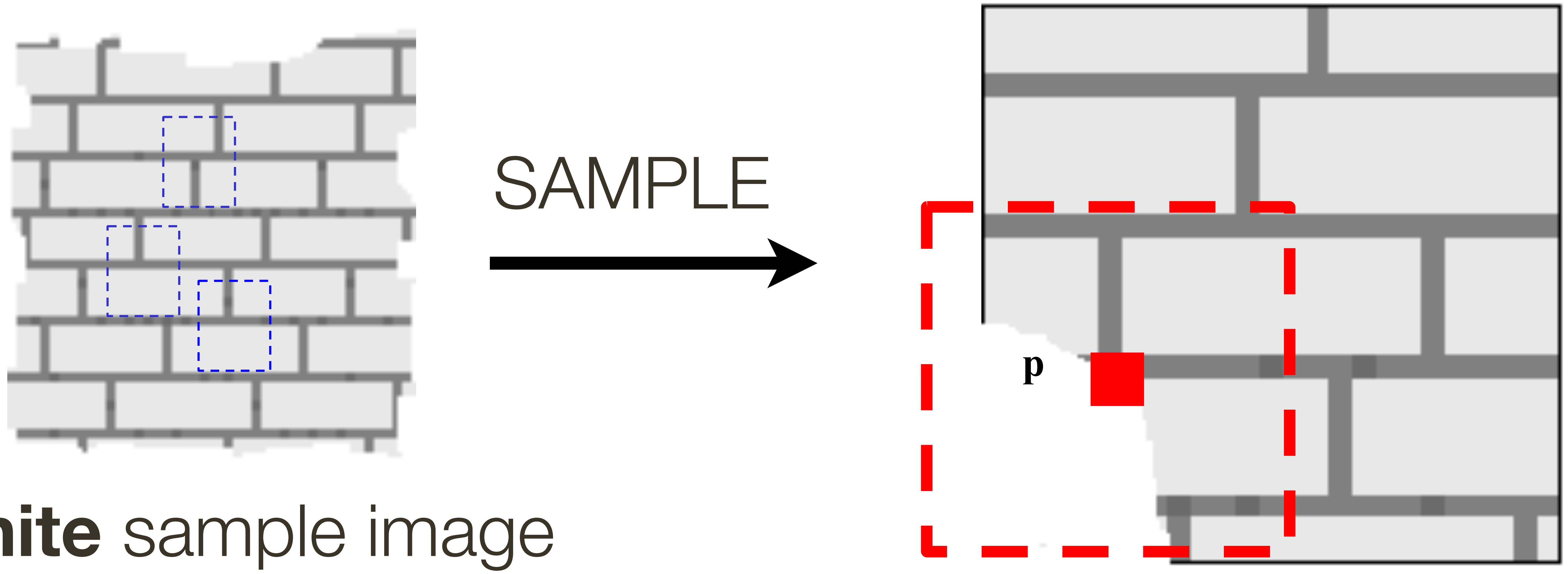


brick wall

Like **Copying**, But not Just Repetition



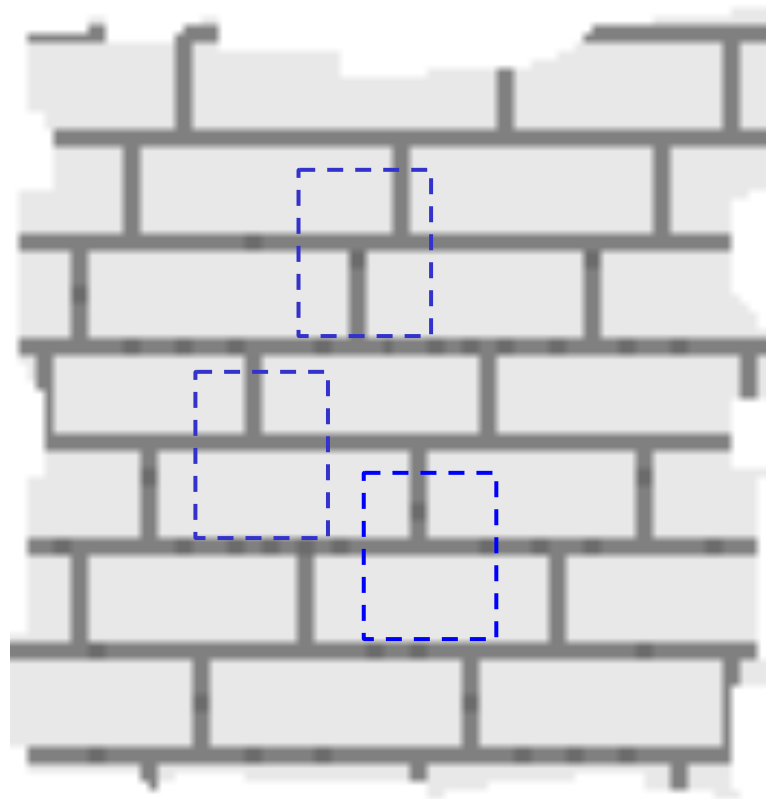
Efros and Leung: Synthesizing One Pixel



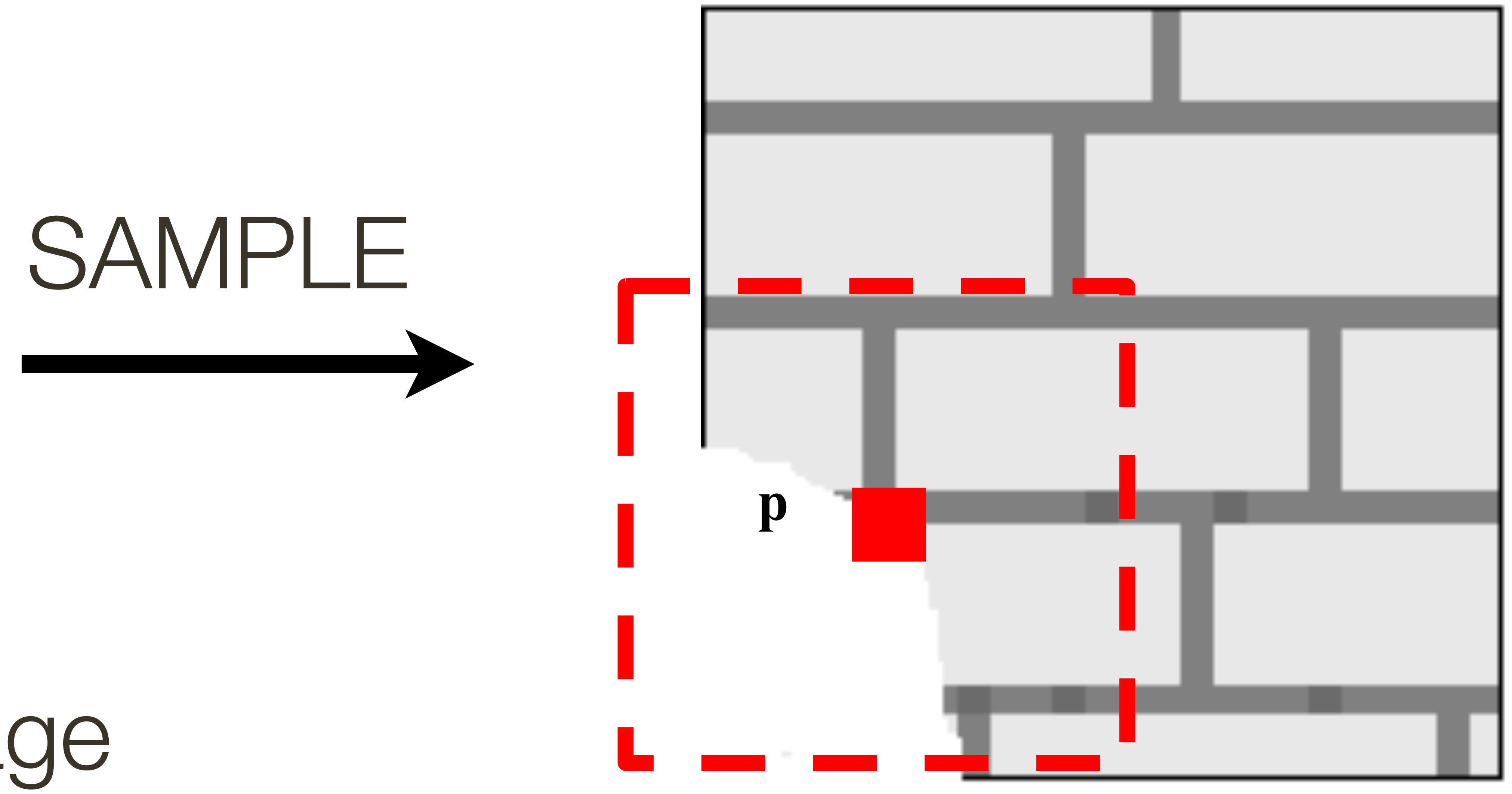
Infinite sample image

— What is **conditional** probability distribution of *p*, given the neighbourhood window?

Efros and Leung: Synthesizing One Pixel



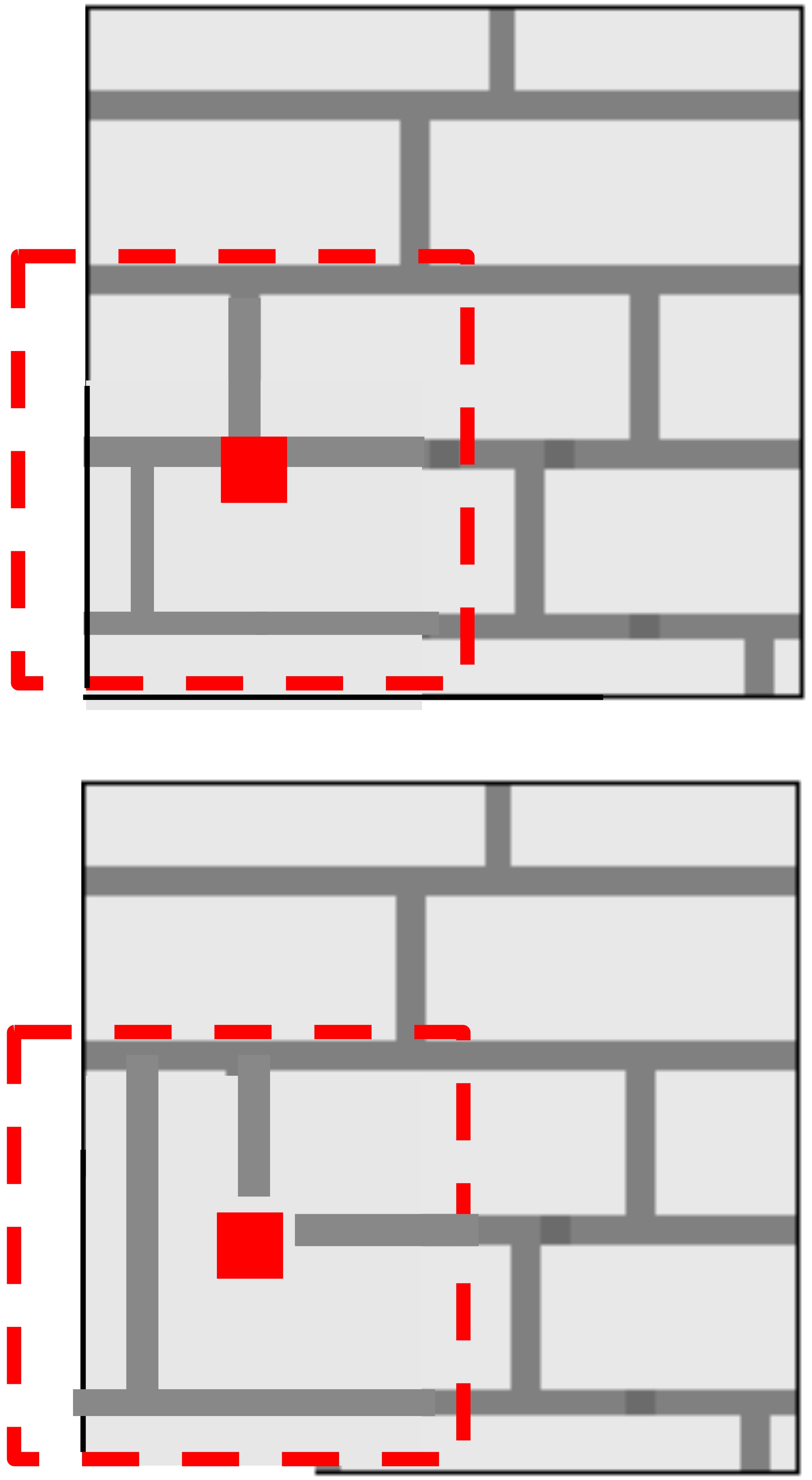
Infinite sample image

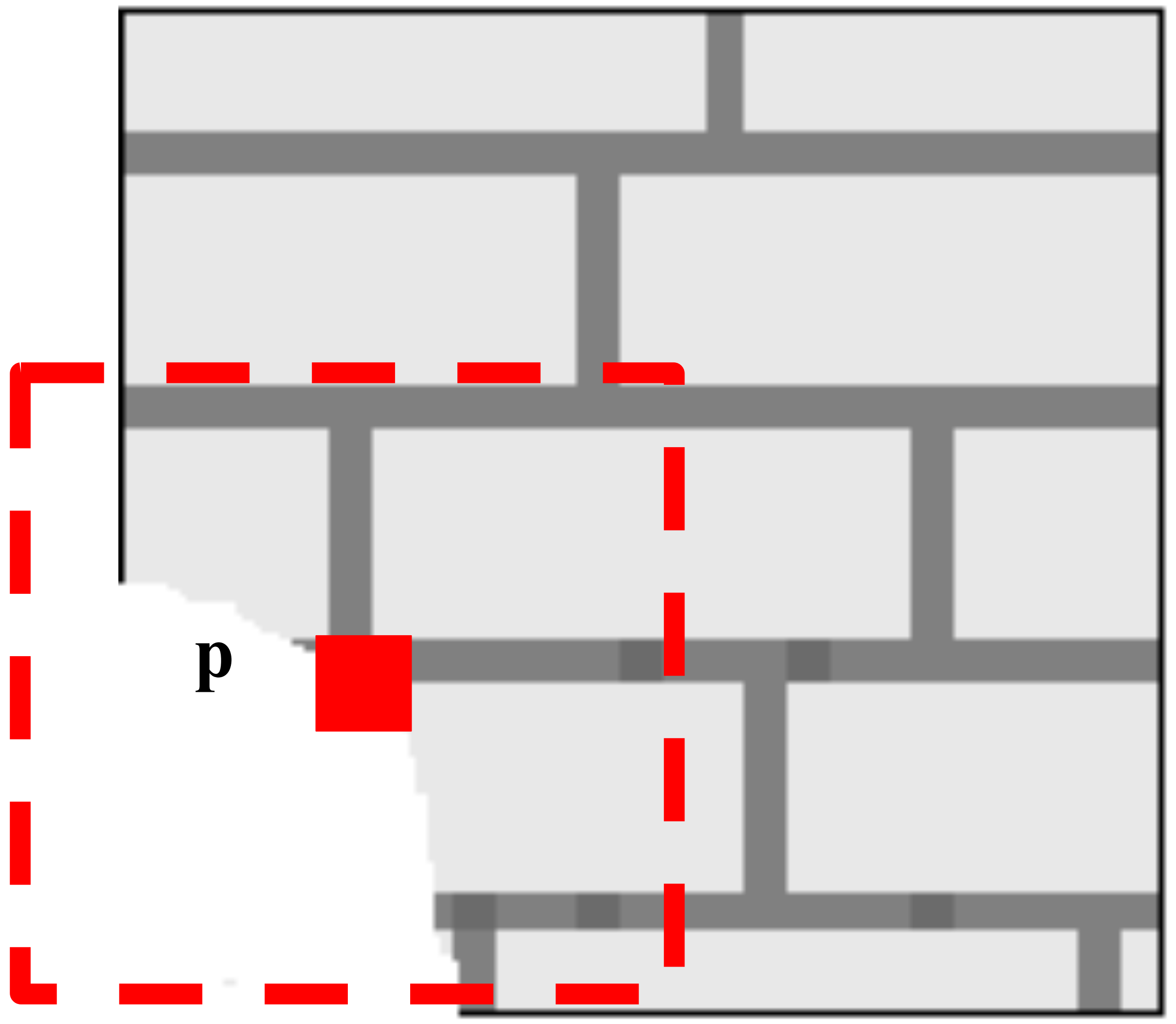


— What is **conditional** probability distribution of *p*, given the neighbourhood window?

— Directly search the input image for all such neighbourhoods to produce a **histogram** for *p*

Efros and Leung: Synthesizing One Pixel





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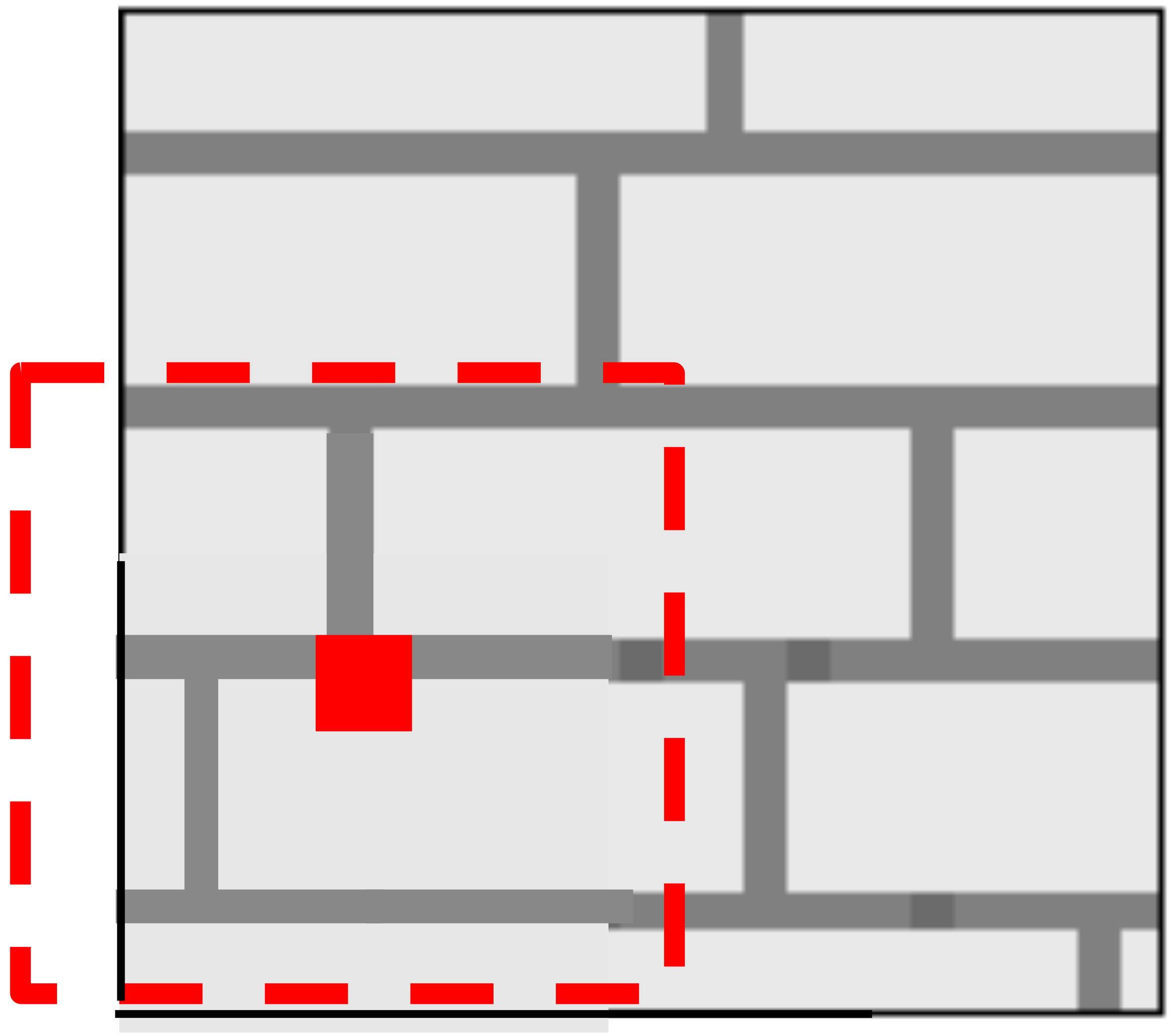
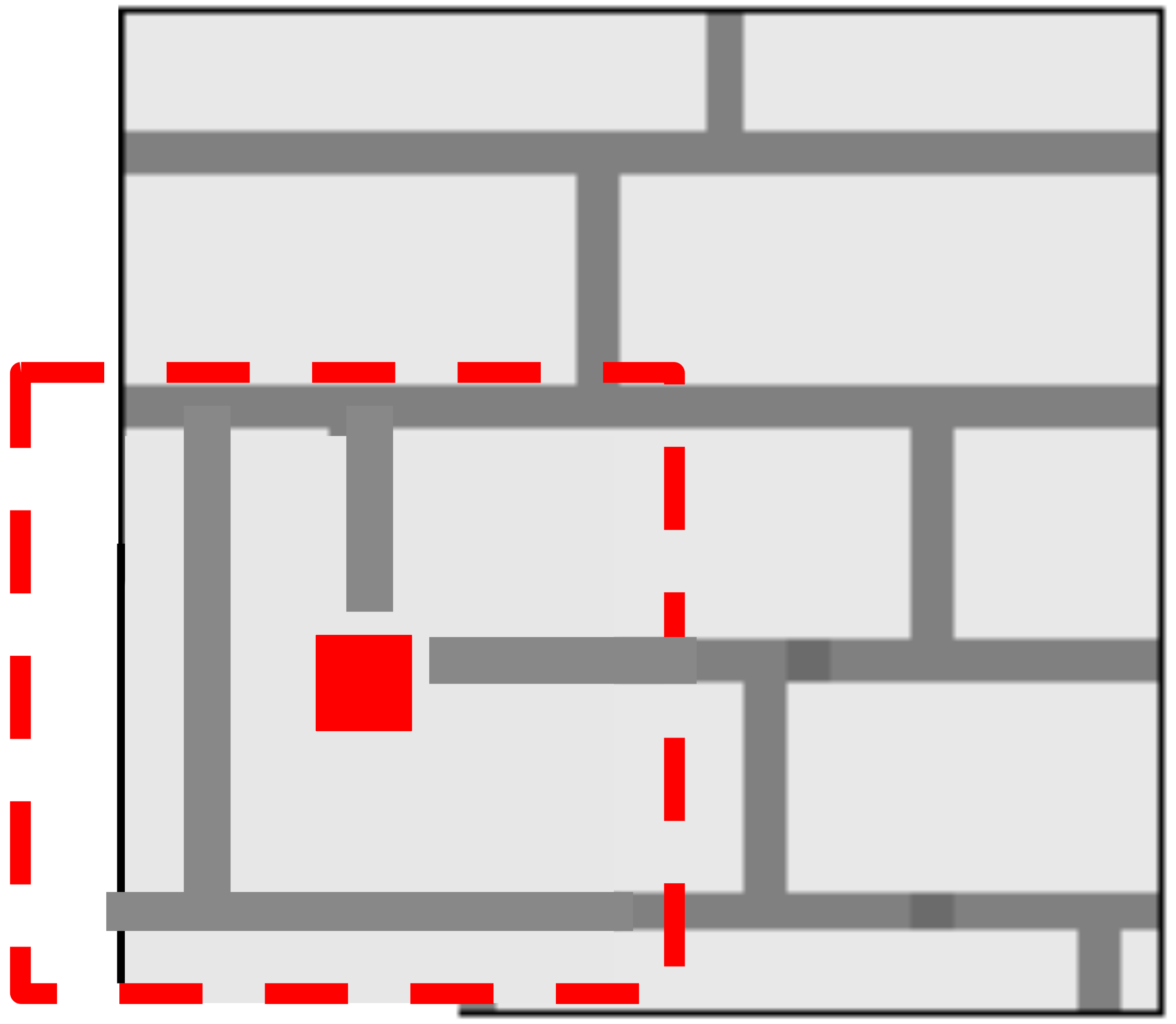
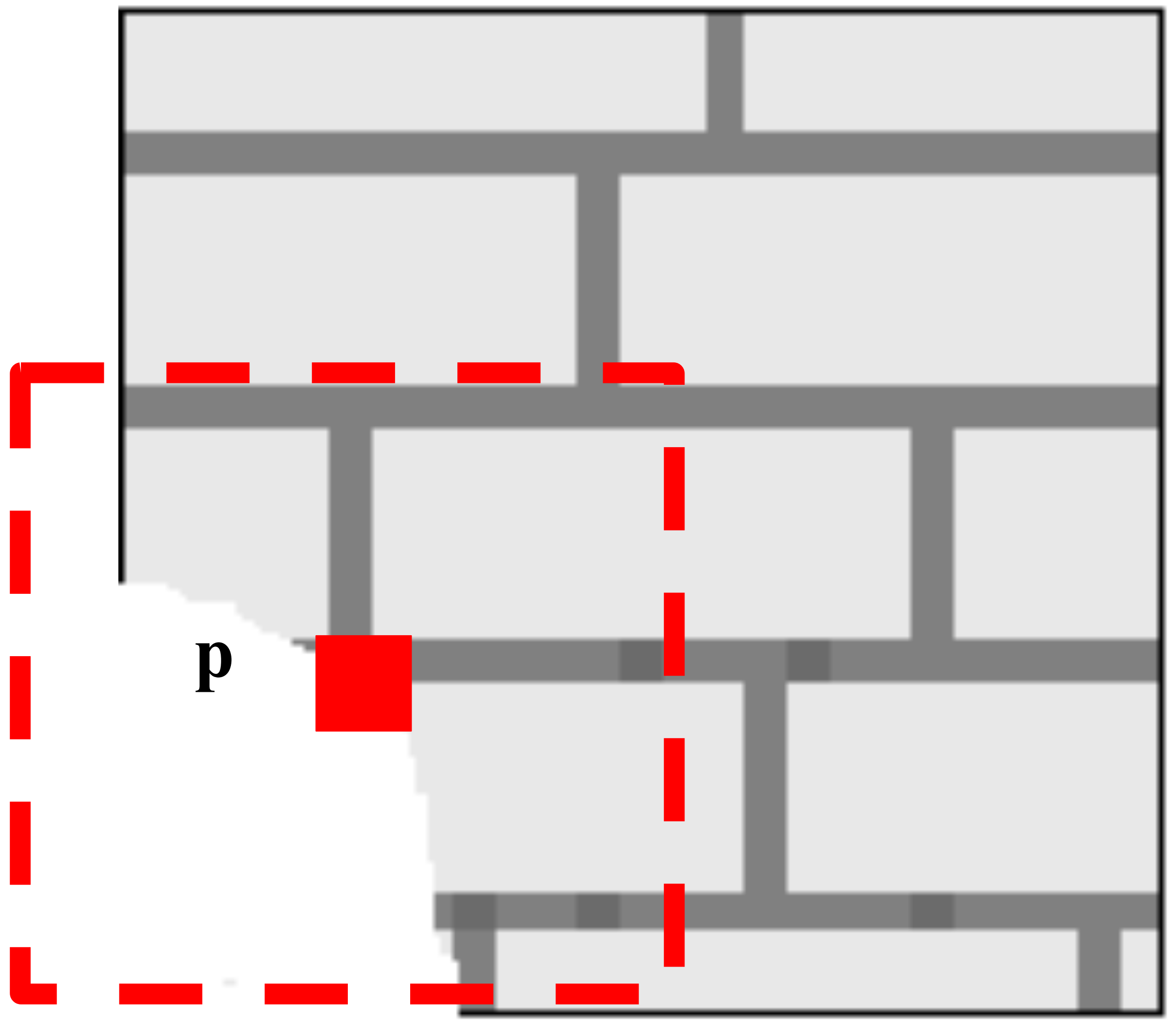


p(dark gray) = 0.5



p(light gray) = 0.5



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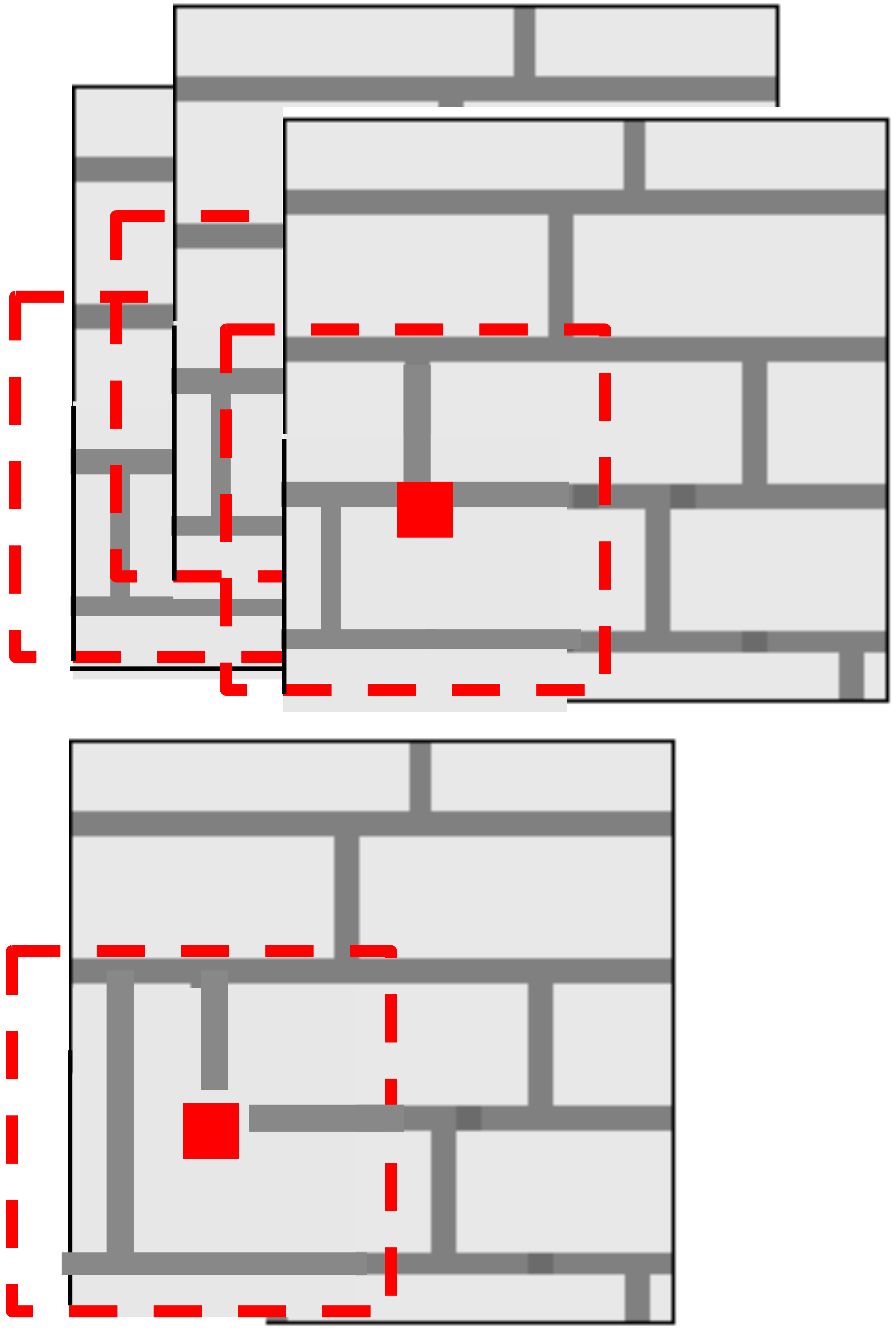

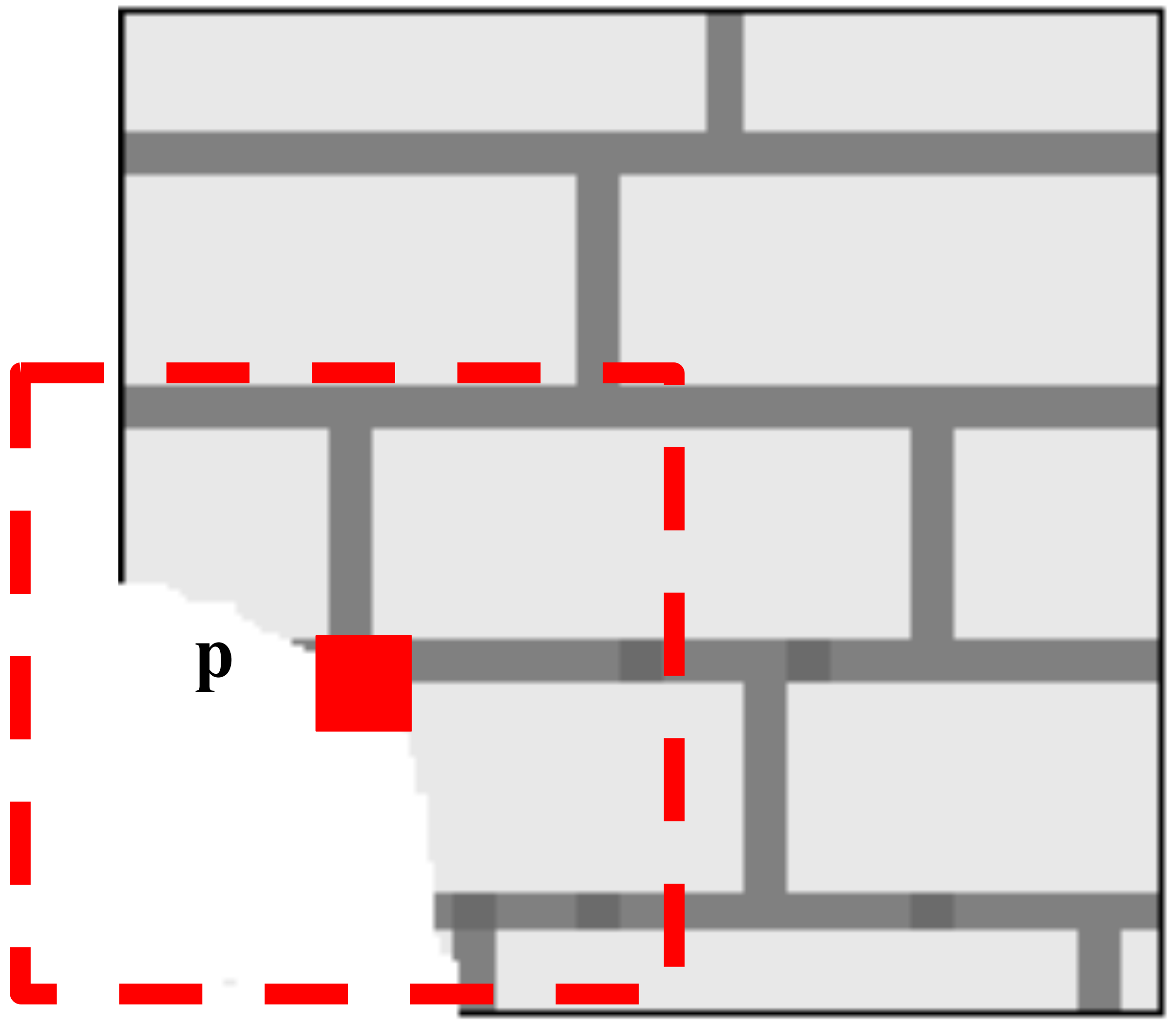

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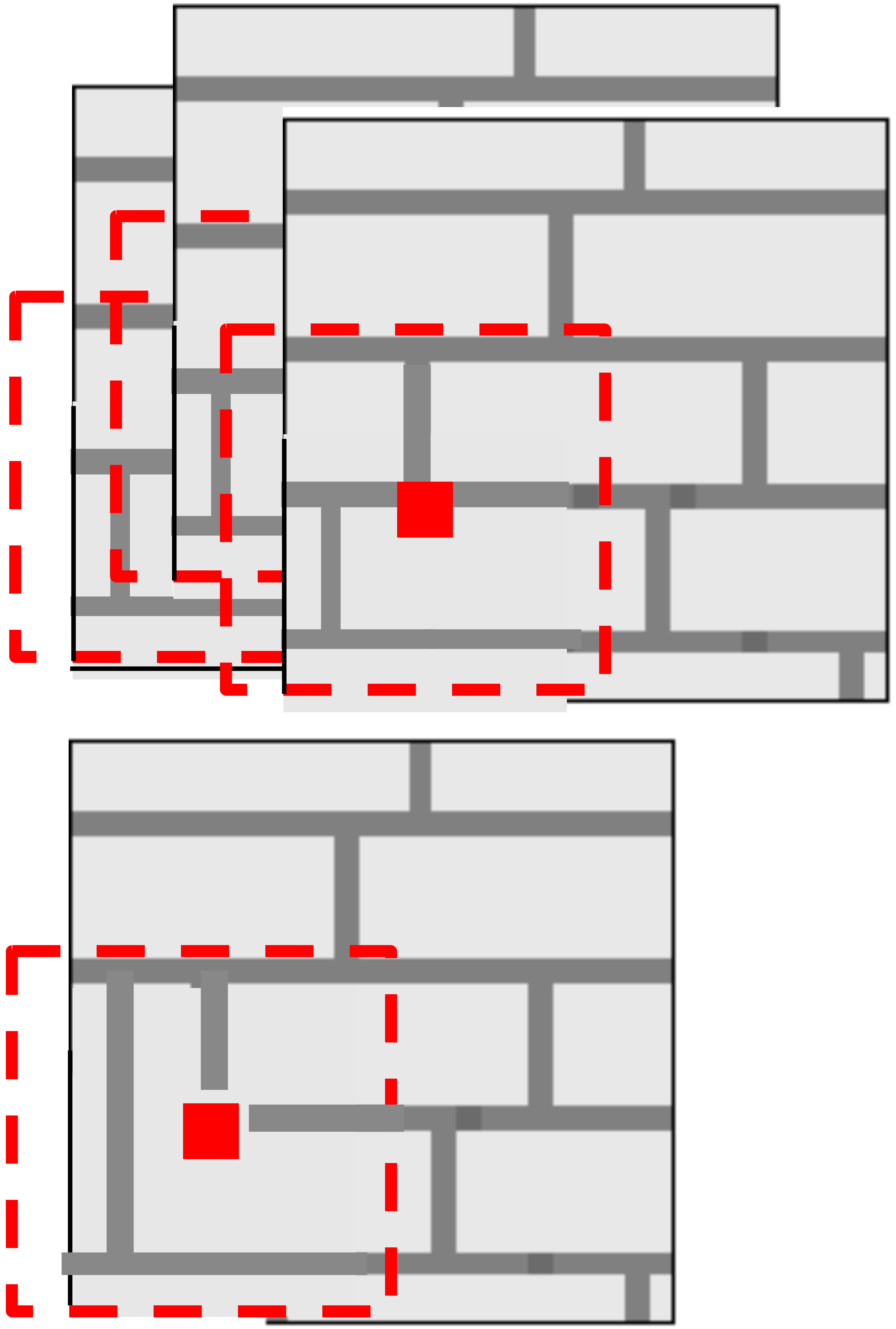
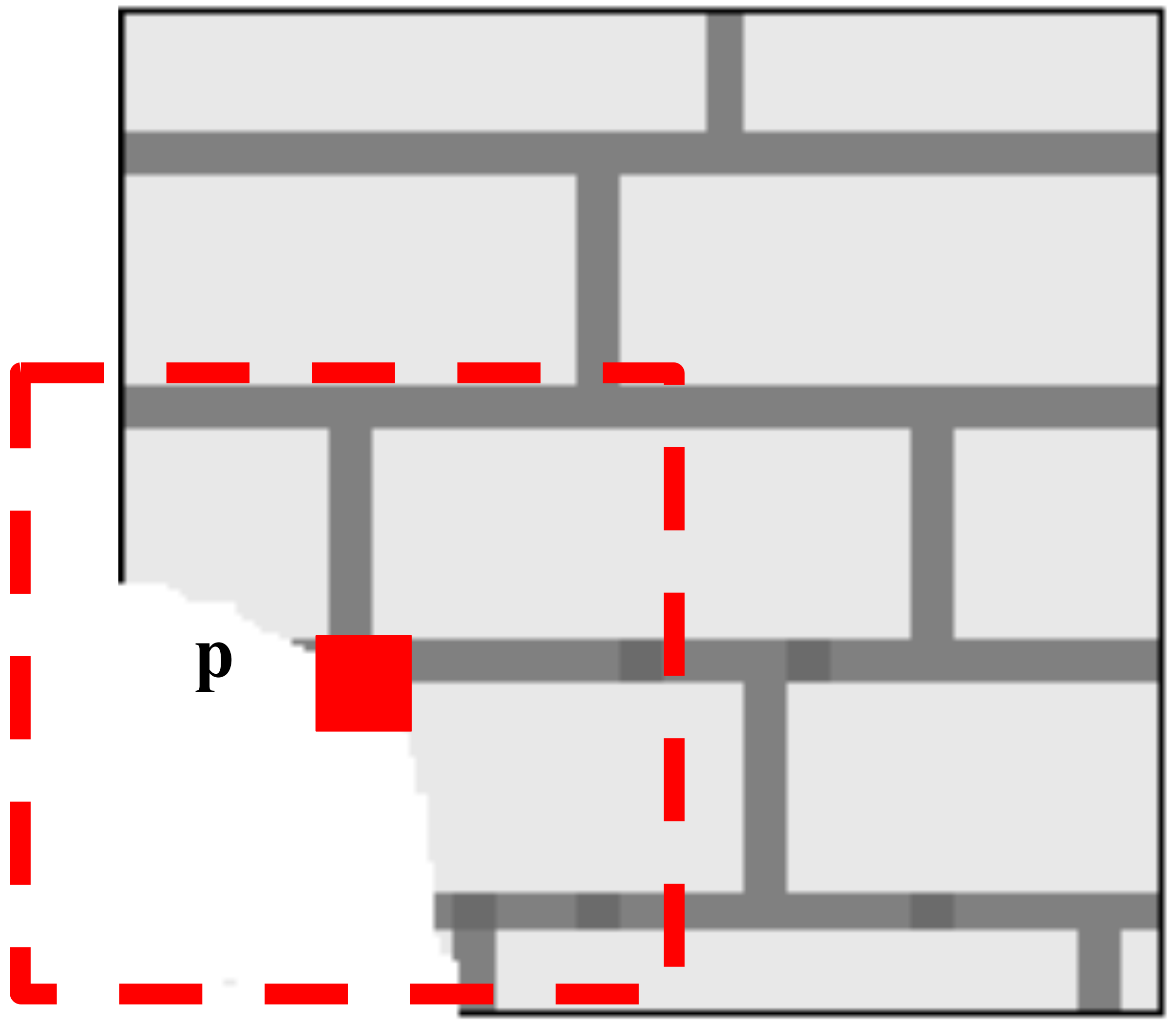
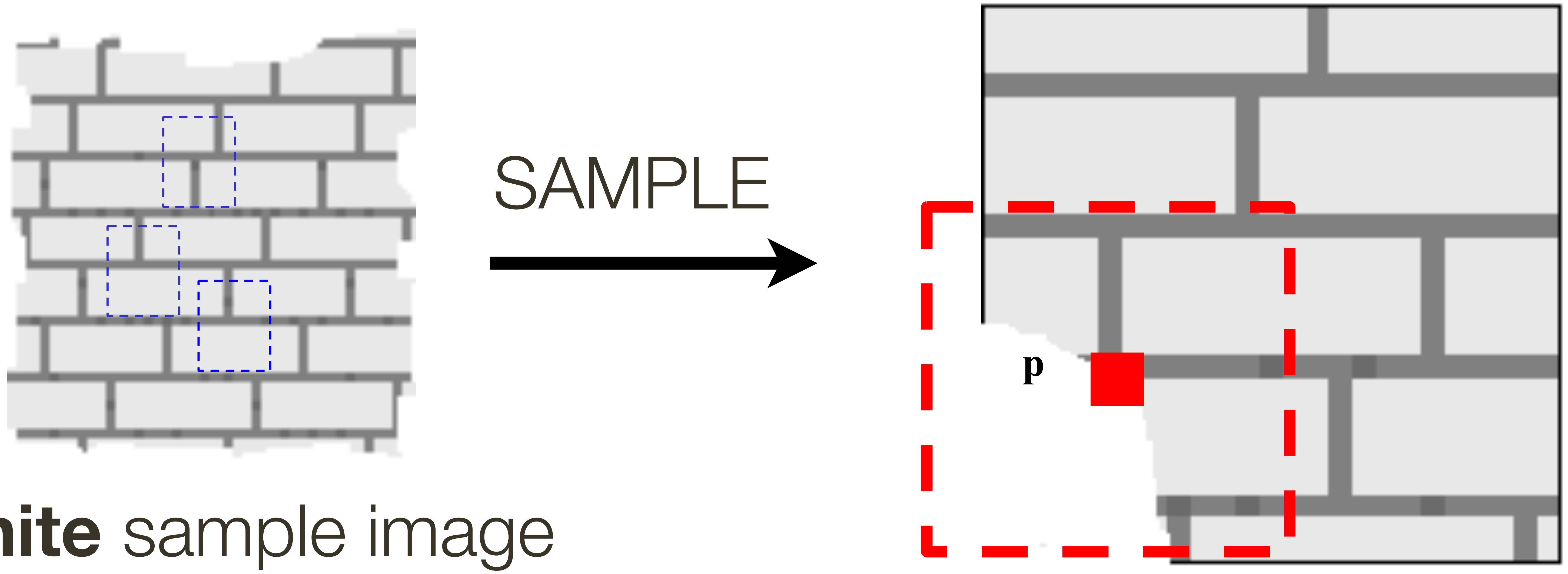


p(dark gray) = 0.75

p(light gray) = 0.25



Efros and Leung: Synthesizing One Pixel



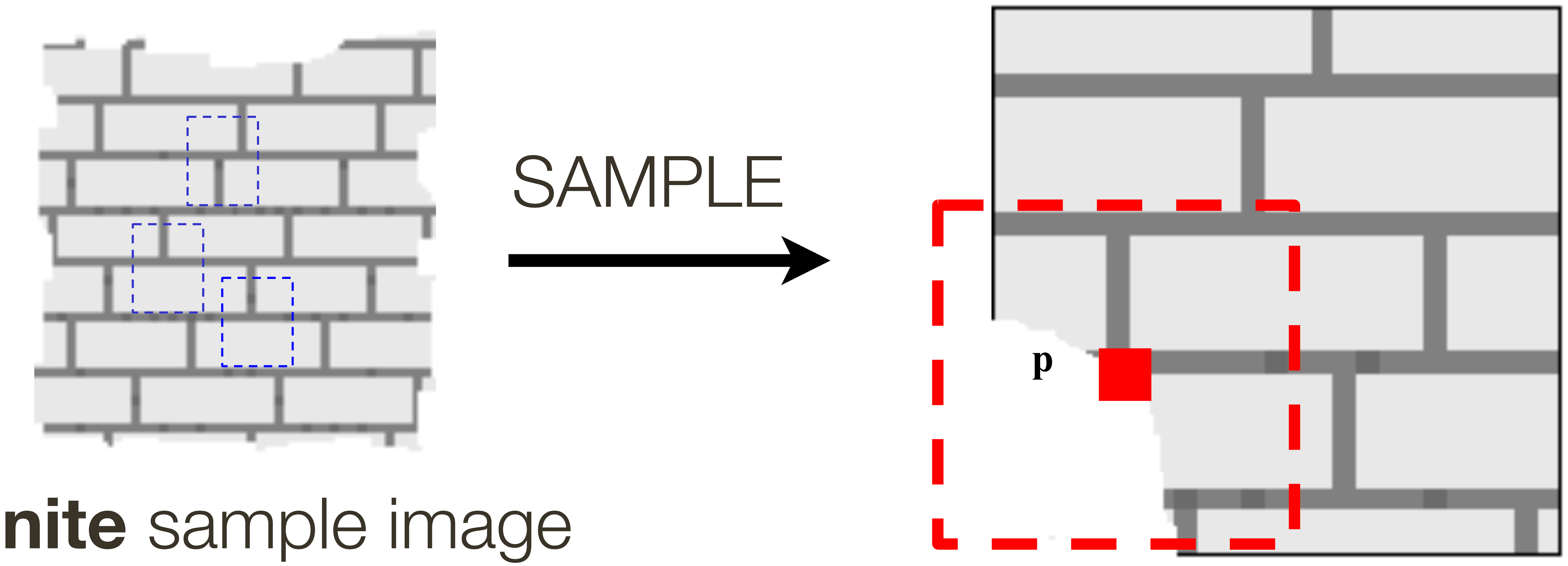
Infinite sample image

— What is **conditional** probability distribution of *p*, given the neighbourhood window?

— Directly search the input image for all such neighbourhoods to produce a **histogram** for *p*

— To **synthesize** *p*, pick one match at random

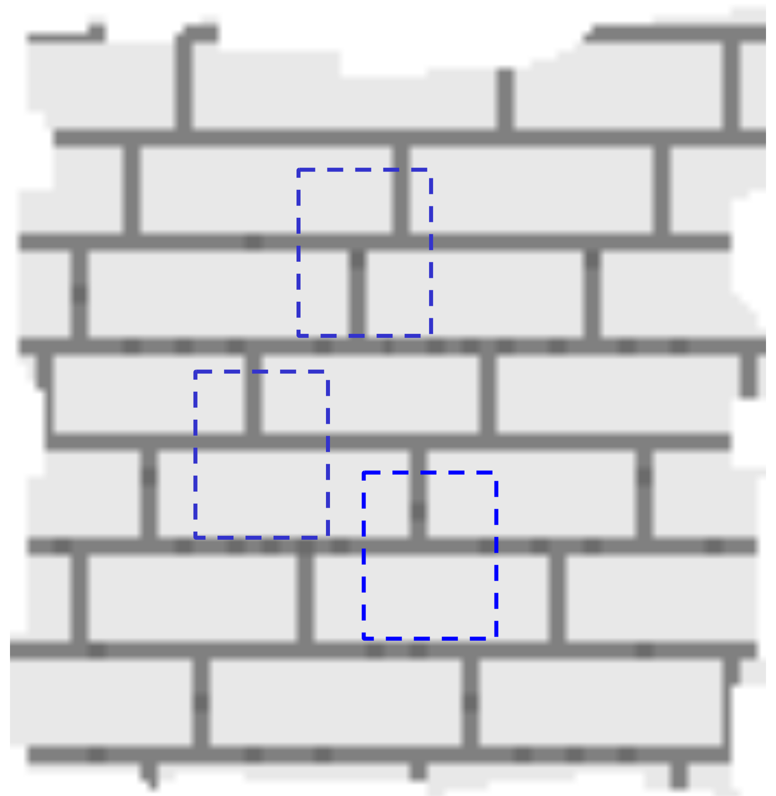
Efros and Leung: Synthesizing One Pixel



Infinite sample image

— Since the sample image is finite, an exact neighbourhood match might not be present

Efros and Leung: Synthesizing One Pixel



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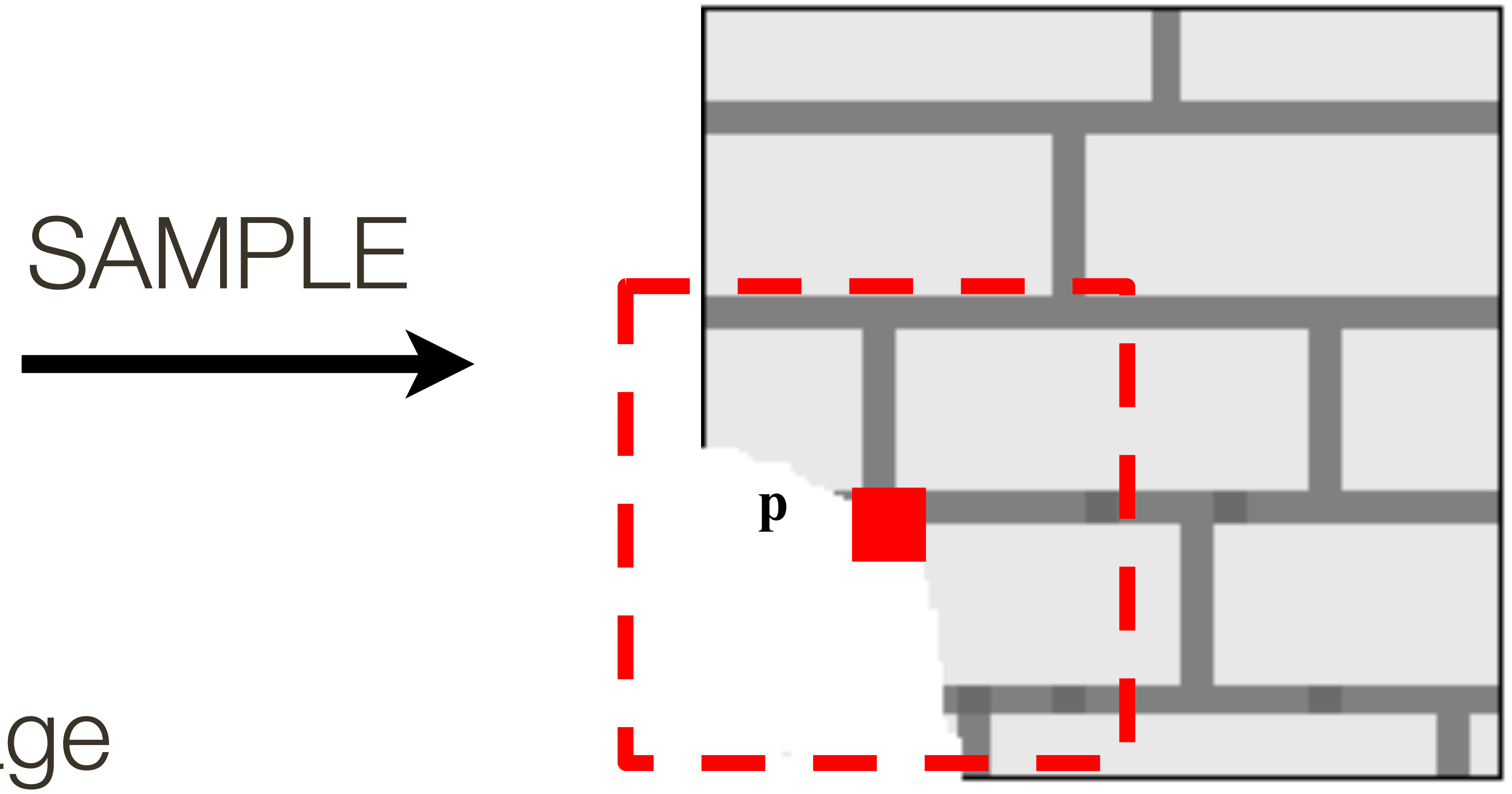


— Since the sample image is finite, an exact neighbourhood match might not be present

— Find the **best match** using SSD error, weighted by Gaussian to emphasize local structure, and take all samples within some distance from that match

Efros and Leung: Synthesizing Many Pixels

For multiple pixels, "grow" the texture in layers

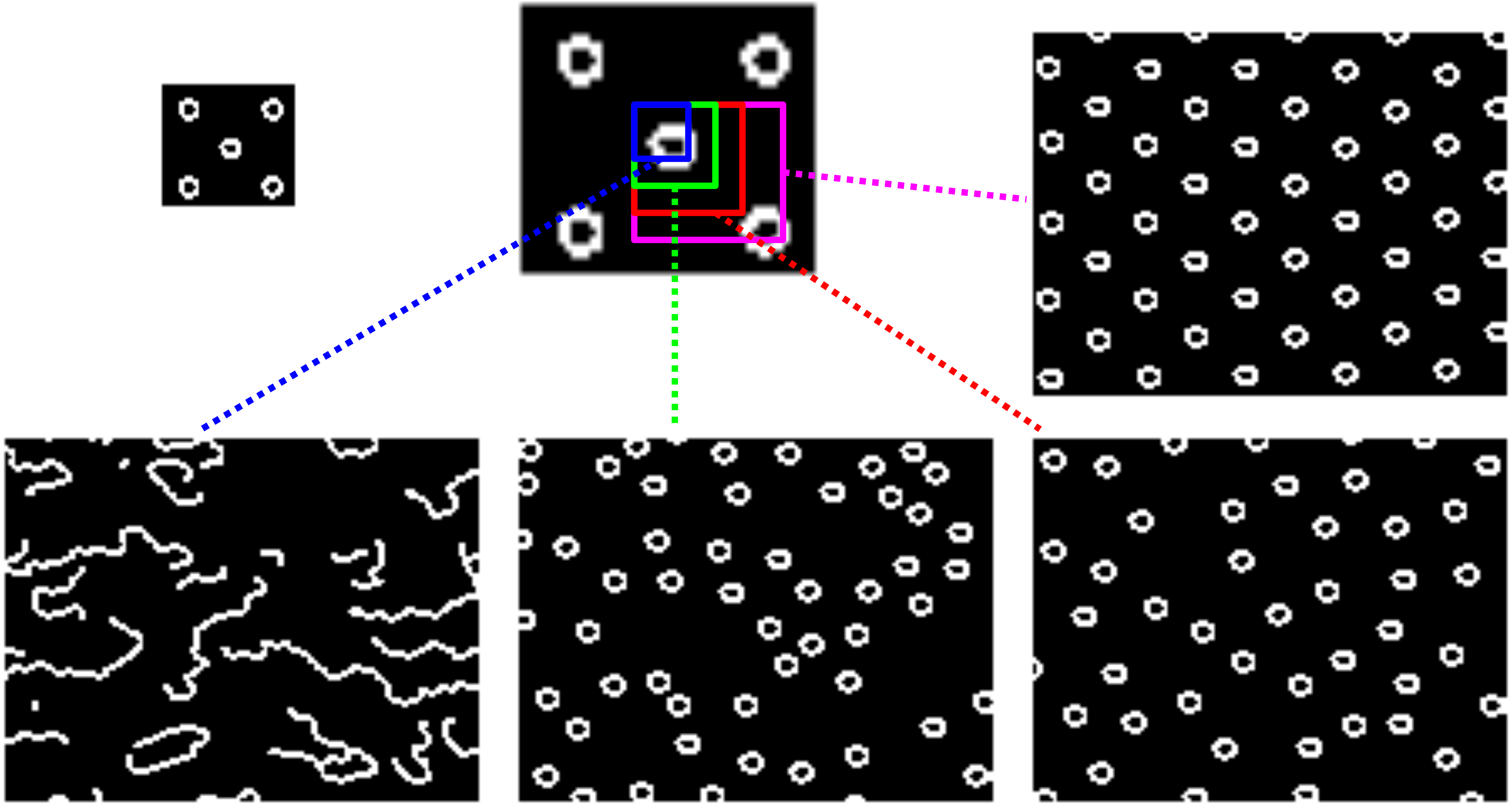
— In the case of hole-filling, start from the edges of the hole

For an interactive demo, see

https://una-dinosauria.github.io/efros-and-leung-js/

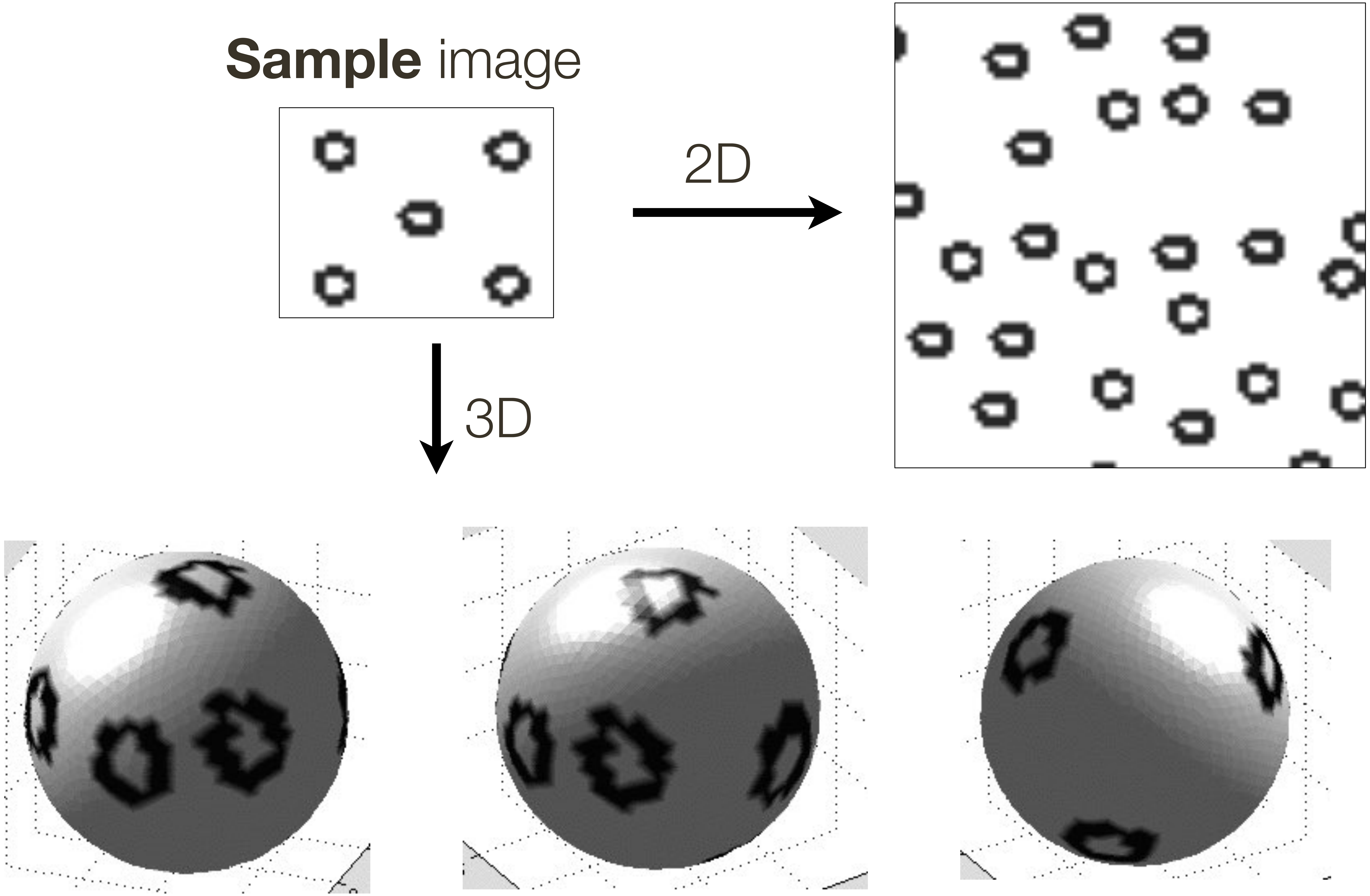
(written by Julieta Martinez, a previous CPSC 425 TA)

Randomness Parameter



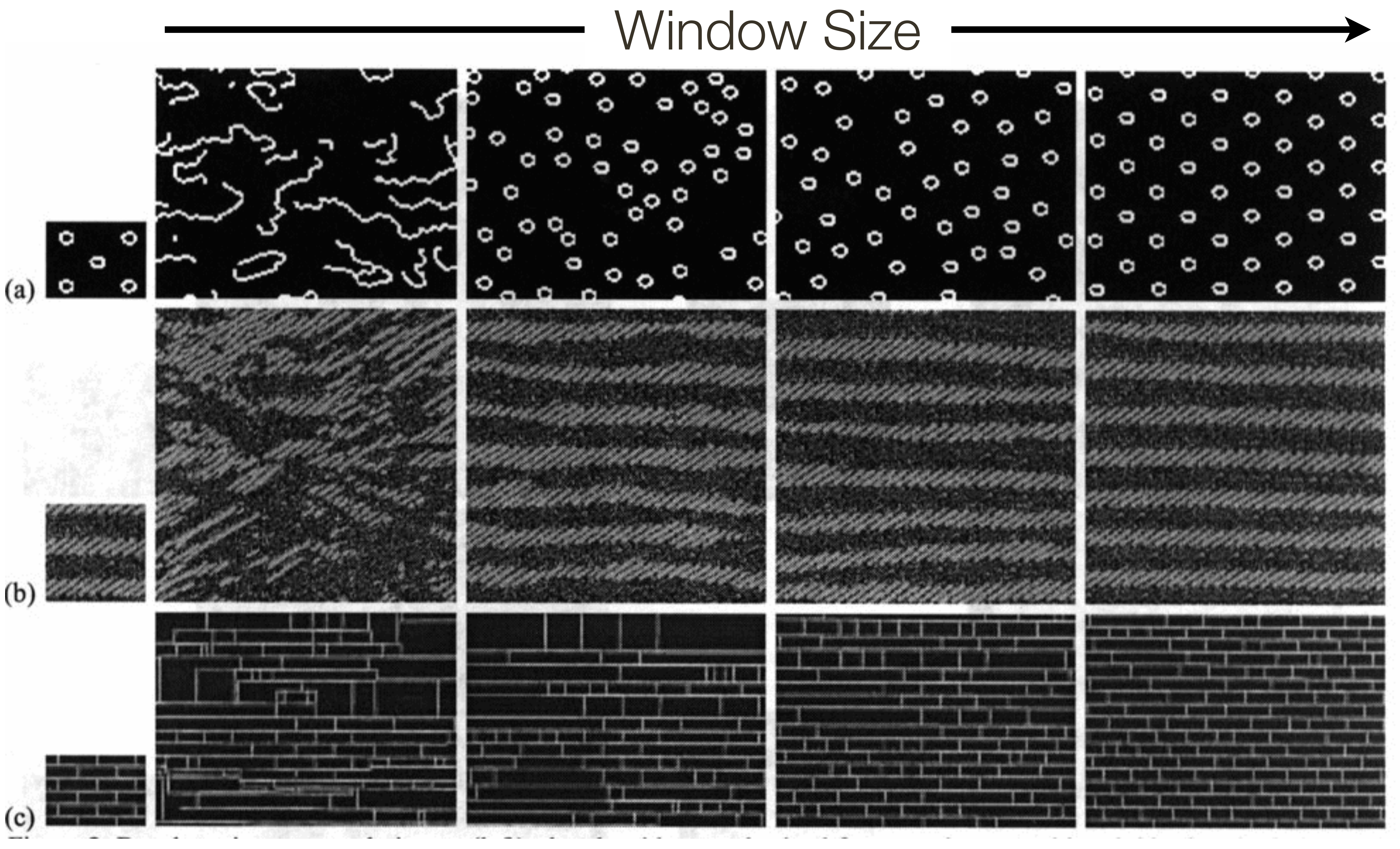
Slide Credit: http://graphics.cs.cmu.edu/people/efros/research/NPS/efros-iccv99.ppt

Texturing a Sphere



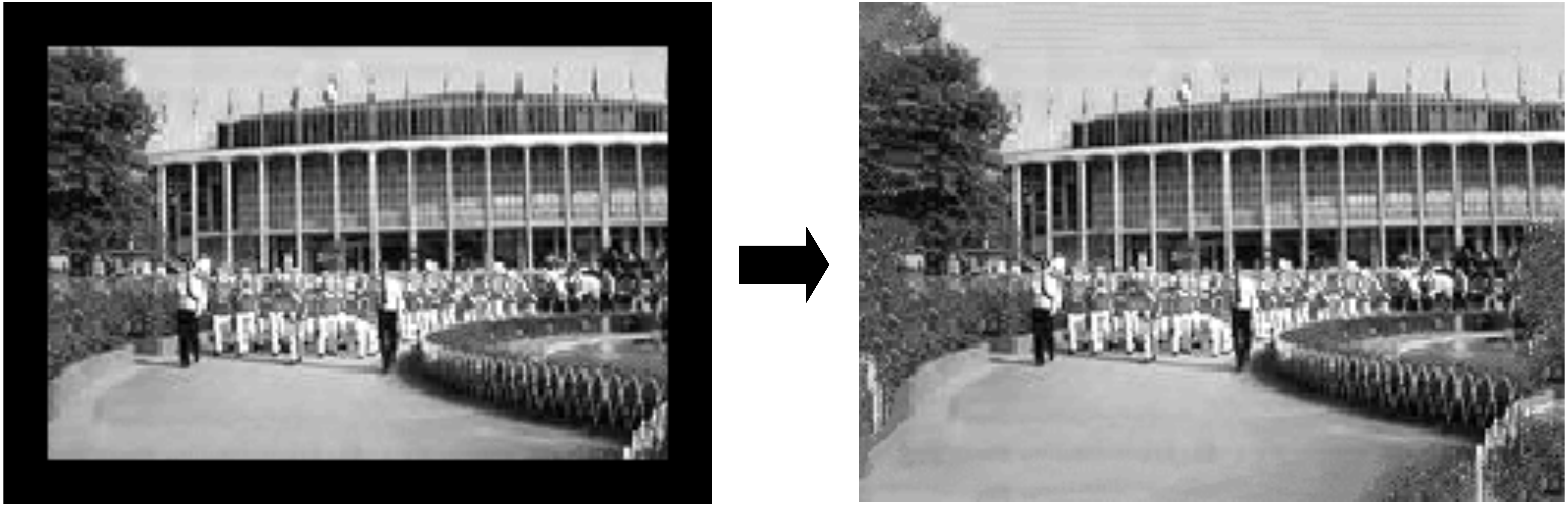
Slide Credit: http://graphics.cs.cmu.edu/people/efros/research/NPS/efros-iccv99.ppt

Efros and Leung: More Synthesis Results



Forsyth & Ponce (2nd ed.) Figure 6.12

Efros and Leung: Image Extrapolation



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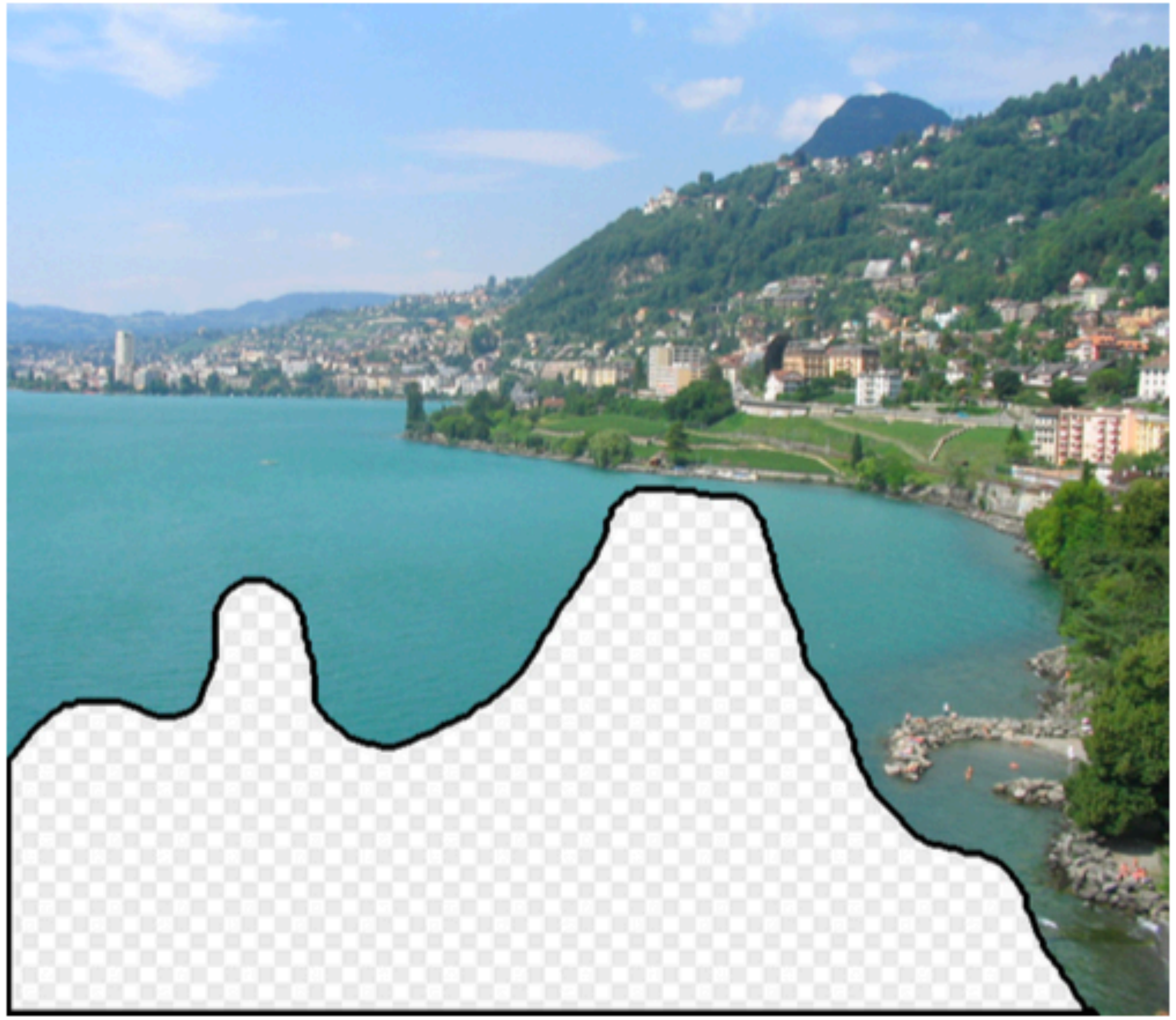
“**Big** Data” Meets Inpainting

“**Big** Data" enables surprisingly simple non-parametric, matching-based techniques to solve complex problems in computer graphics and vision.

Suppose instead of a single image, you had a massive database of a million images. What could you do?

"**Big** Data" Meets Inpainting

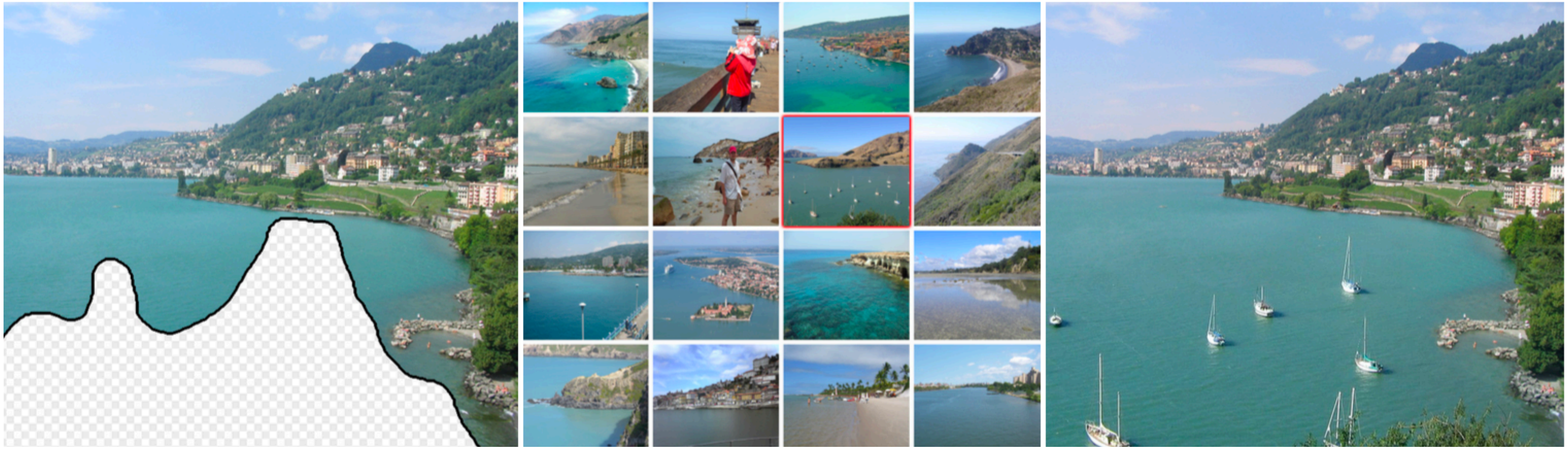
Original Image



Input

Figure Credit: Hays and Efros 2007

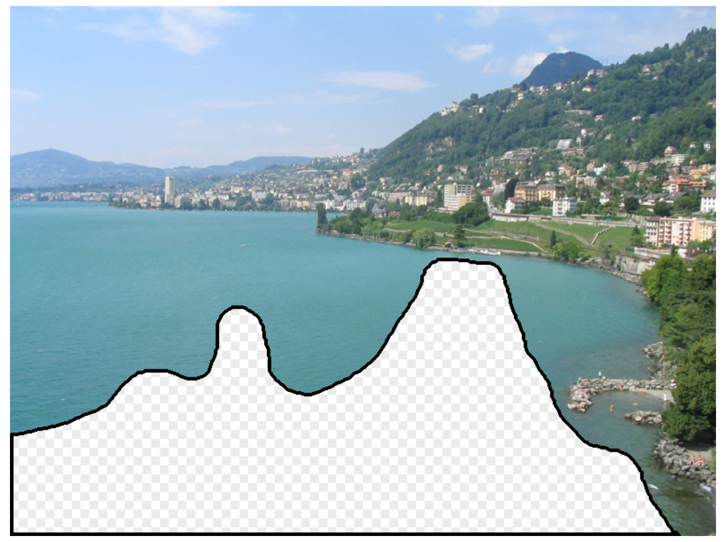
“**Big** Data” Meets Inpainting



Input   Scene Matches   Output

Figure Credit: Hays and Efros 2007

Effectiveness of "Big Data"



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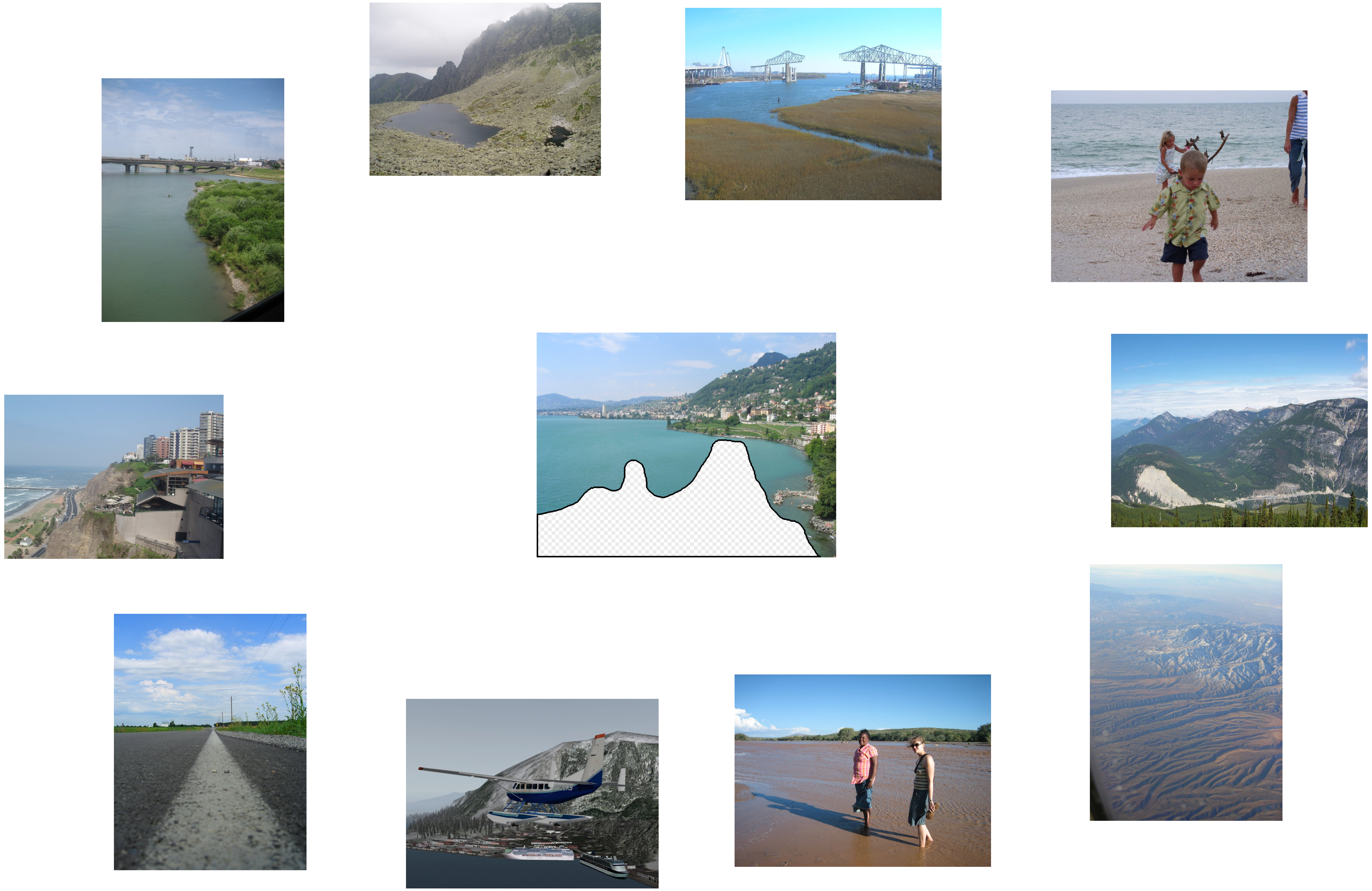
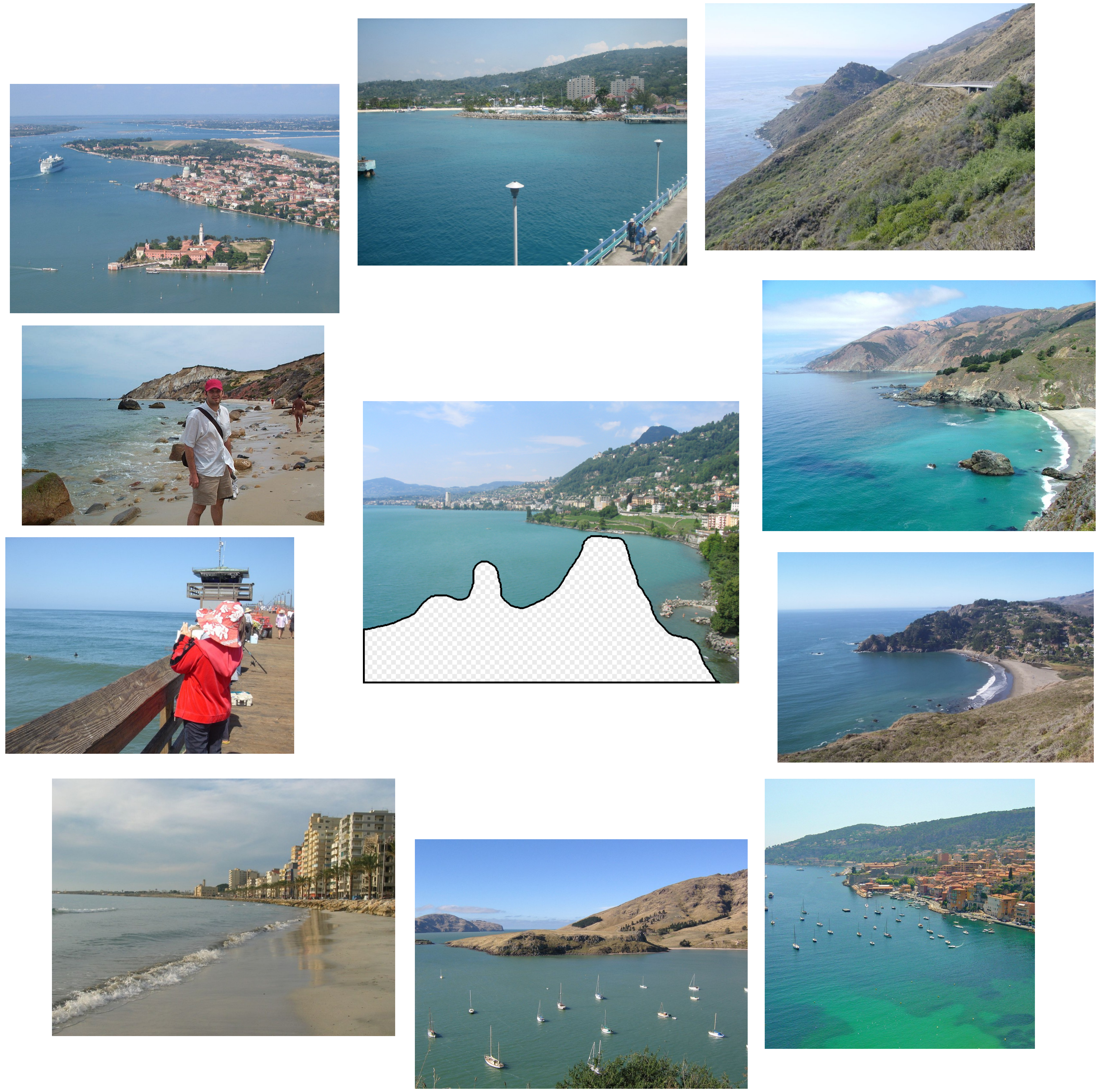


10 nearest neighbors from a collection of 20,000 images

Figure Credit: Hays and Efros 2007

Effectiveness of "Big Data"



10 nearest neighbors from a collection of 2 million images

Figure Credit: Hays and Efros 2007

“**Big** Data” Meets Inpainting

Figure Credit: Hays and Efros 2007

“**Big** Data” Meets Inpainting

Algorithm sketch (Hays and Efros 2007):

1. Create a short list of a few hundred “best matching" images based on global image statistics

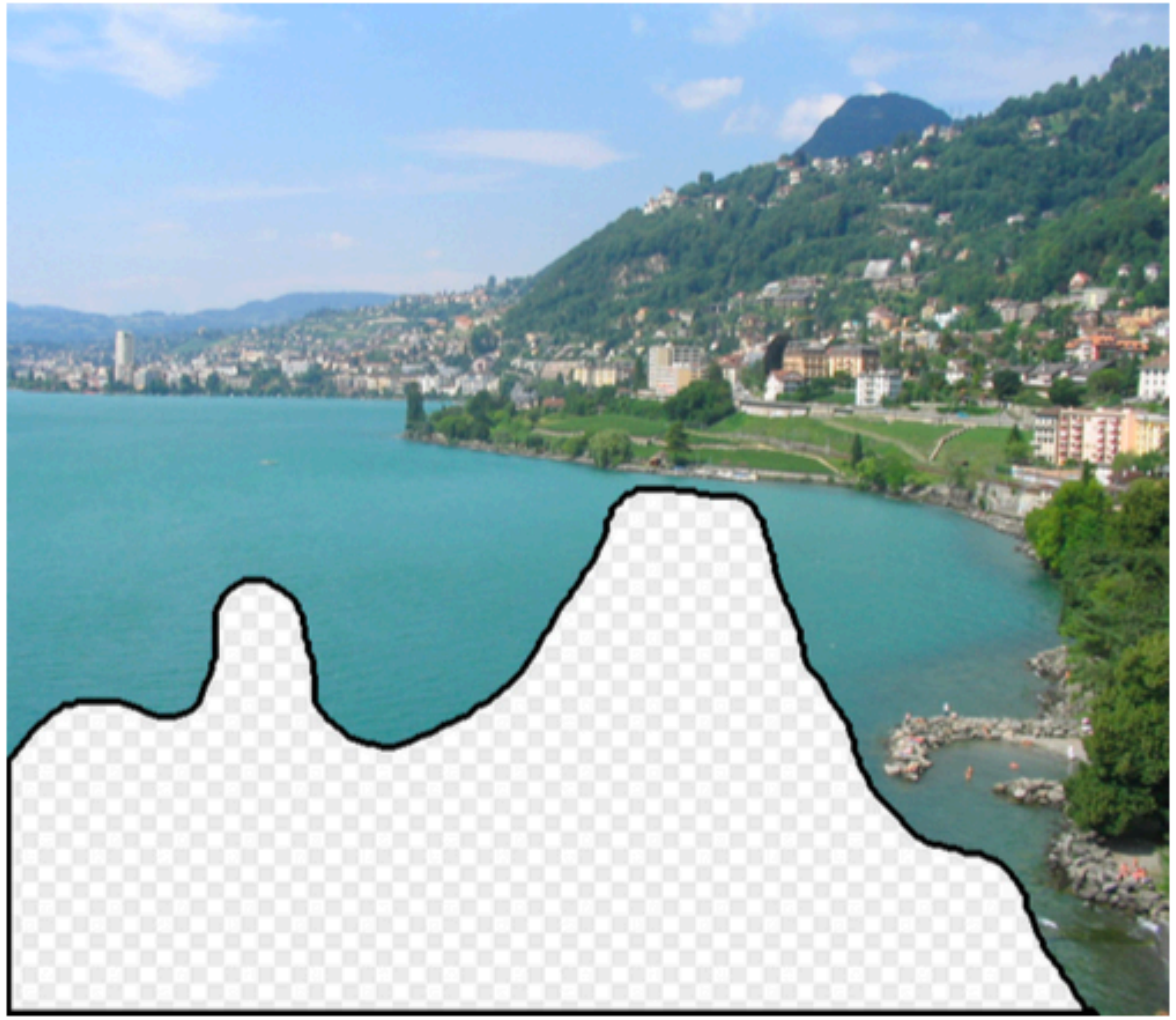
2. Find patches in the short list that match the context surrounding the image region we want to fill

3. Blend the match into the original image

Purely **data-driven**, requires no manual labeling of images

“**Big** Data” Meets Inpainting

Original Image



Input

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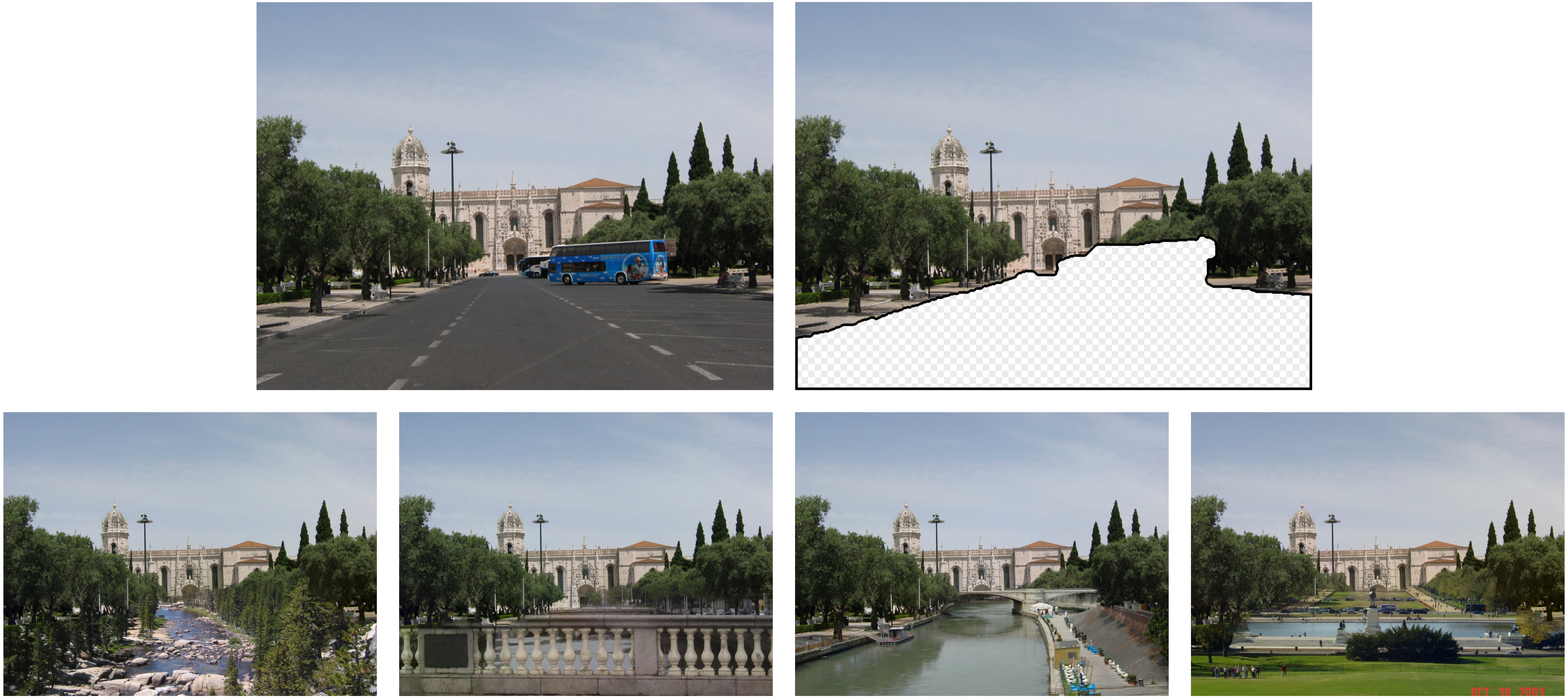

Figure Credit: Hays and Efros 2007

Texture

We will look at two main questions:

1. How do we represent texture?
   → Texture **analysis**

2. How do we generate new examples of a texture?
   → Texture **synthesis**

Texture **Segmentation**

Question: Is texture a property of a point or a property of a region?

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There is a “chicken–and–egg” problem. Texture segmentation can be done by detecting boundaries between regions of the same (or similar) texture. Texture boundaries can be detected using standard edge detection techniques applied to the texture measures determined at each point

Recall: Boundary Detection

Features:

- Raw Intensity
- Orientation Energy
- Brightness Gradient
- Color Gradient
- Texture gradient

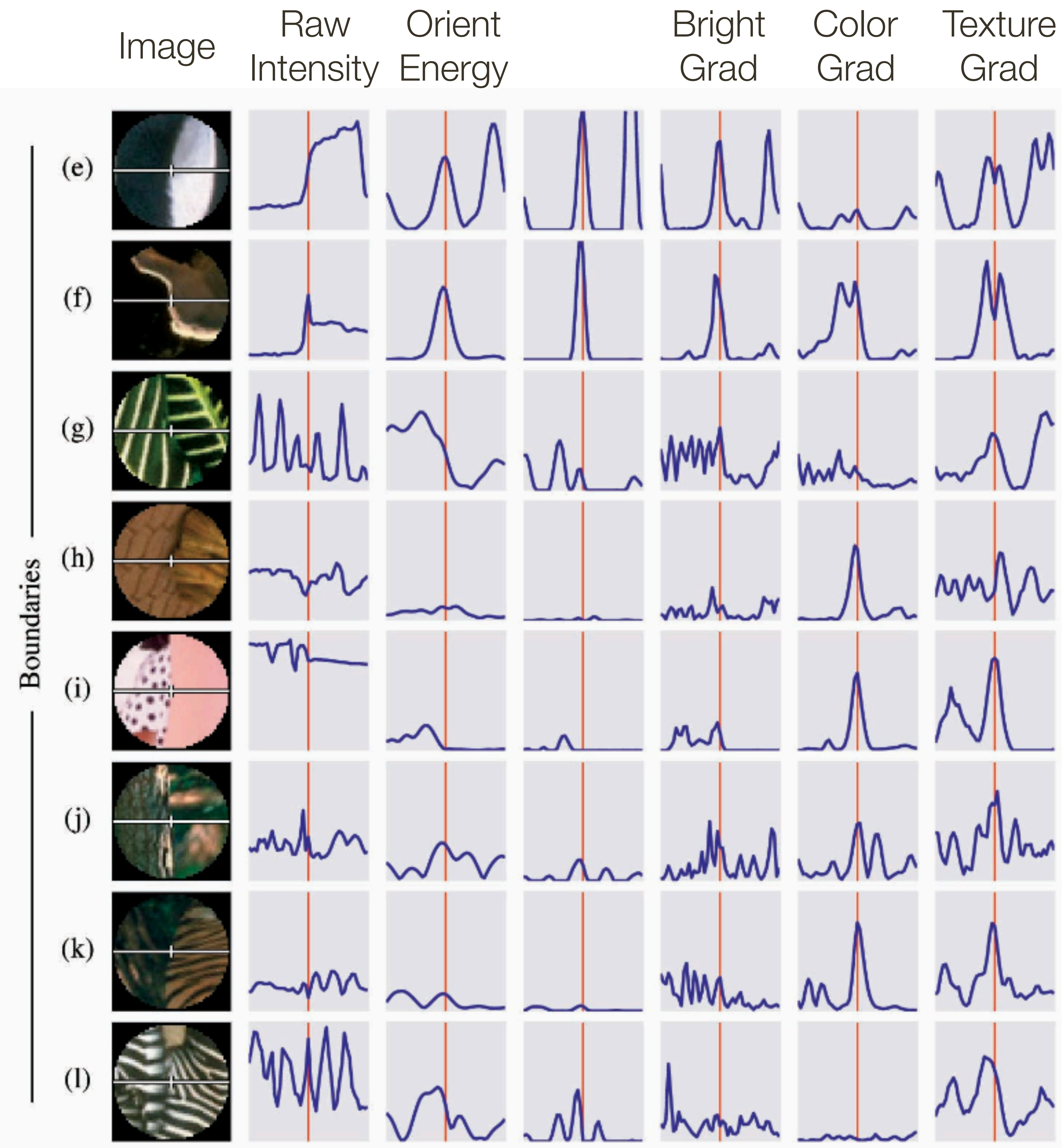


Figure Credit: Martin et al. 2004

Texture **Segmentation**

Question: Is texture a property of a point or a property of a region?

Answer: We need a region to have a texture.

There is a “chicken–and–egg” problem. Texture segmentation can be done by detecting boundaries between regions of the same (or similar) texture. Texture boundaries can be detected using standard edge detection techniques applied to the texture measures determined at each point

We compromise! Typically one uses a local window to estimate texture properties and assigns those texture properties as point properties of the window’s center row and column

Texture **Representation**

Question: How many degrees of freedom are there to texture?

Texture **Representation**

Question: How many degrees of freedom are there to texture?

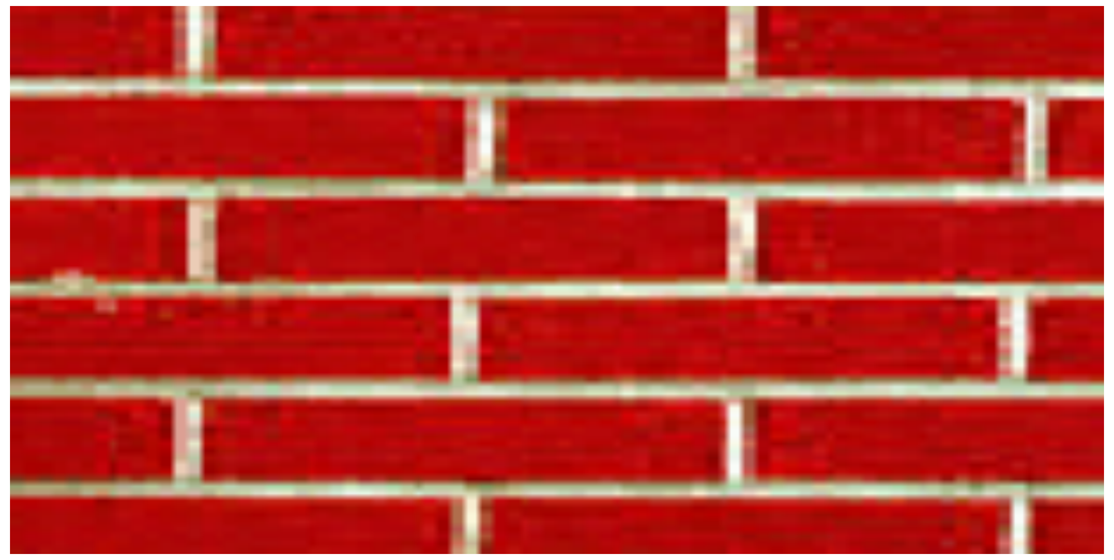
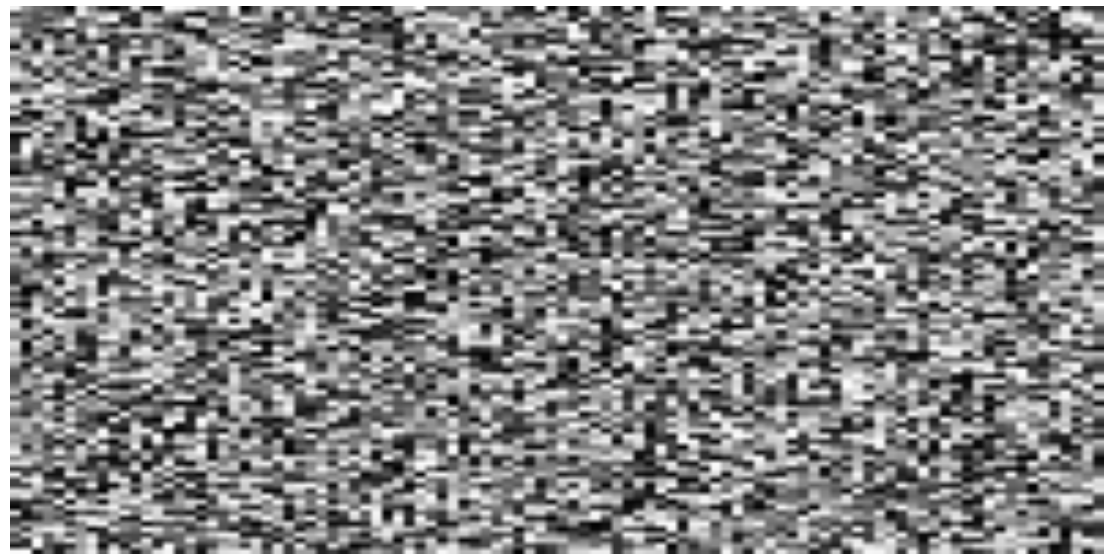
(**Mathematical**) Answer: Infinitely many

(**Perceptual Psychology**) Answer: There are perceptual constraints. But, there is no clear notion of a “texture channel” like, for example, there is for an RGB colour channel

Texture **Representation**

Observation: Textures are made up of generic sub-elements, repeated over a region with similar statistical properties

Idea: Find the sub-elements with filters, then represent each point in the image with a summary of the pattern of sub-elements in the local region

Texture **Representation**

Observation: Textures are made up of generic sub-elements, repeated over a region with similar statistical properties

Idea: Find the sub-elements with filters, then represent each point in the image with a summary of the pattern of sub-elements in the local region

Question: What filters should we use?

Answer: Human vision suggests spots and oriented edge filters at a variety of different orientations and scales

Texture **Representation**

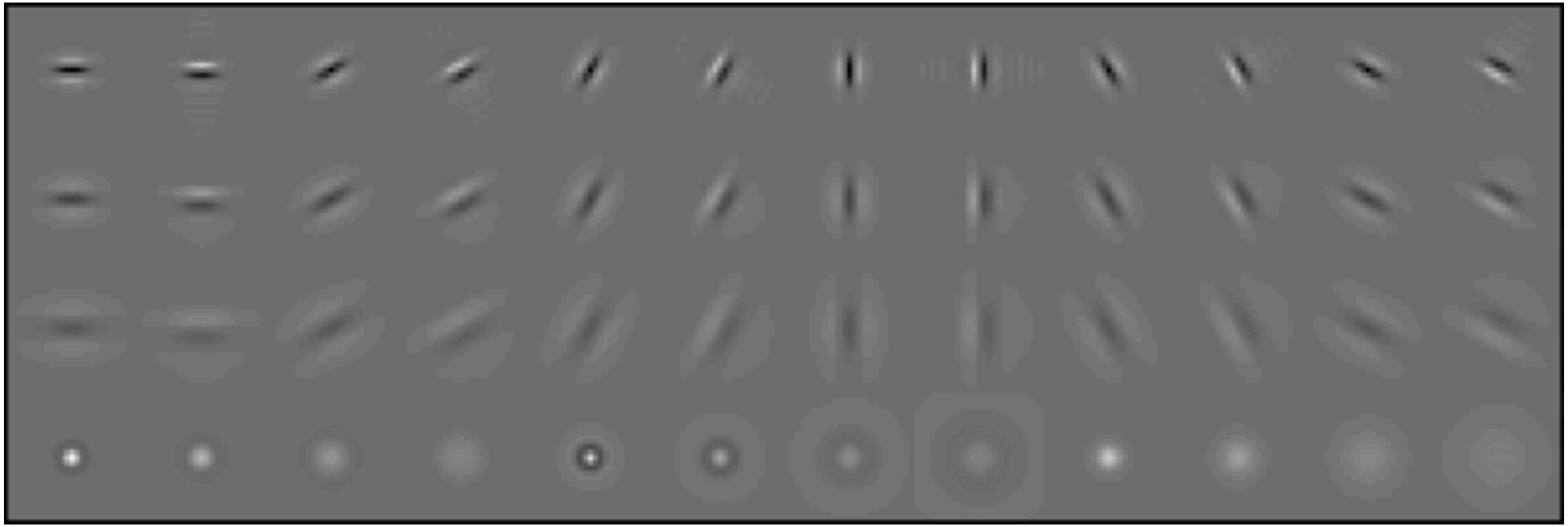


Figure Credit: Leung and Malik, 2001

Texture **Representation**

First derivative of Gaussian at 6 orientations and 3 scales

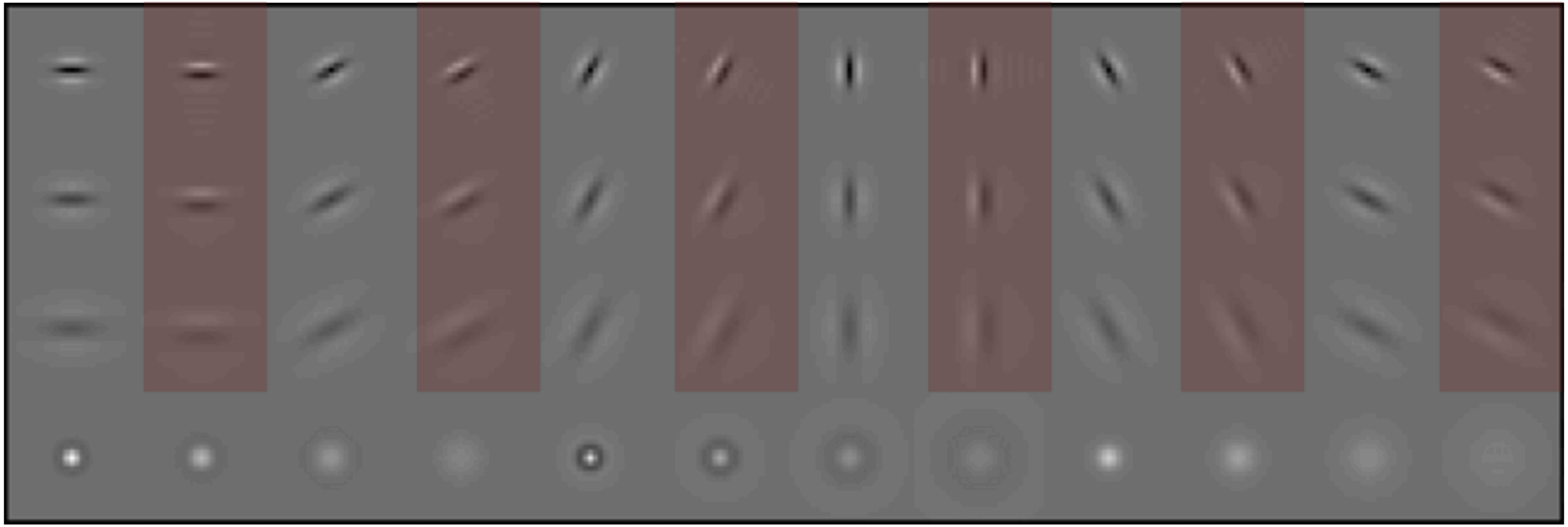


Figure Credit: Leung and Malik, 2001

Texture **Representation**

Second derivative of Gaussian at 6 orientations 3 scales

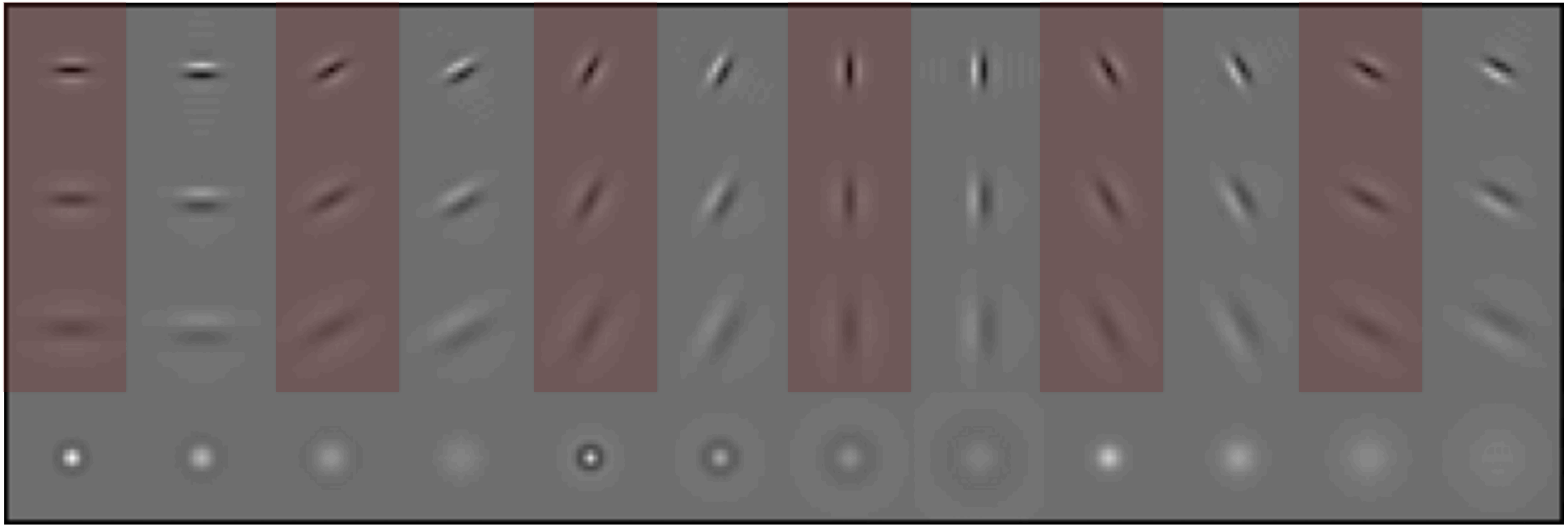


Figure Credit: Leung and Malik, 2001

Texture **Representation**

Laplacian of the Gaussian filters at different scales

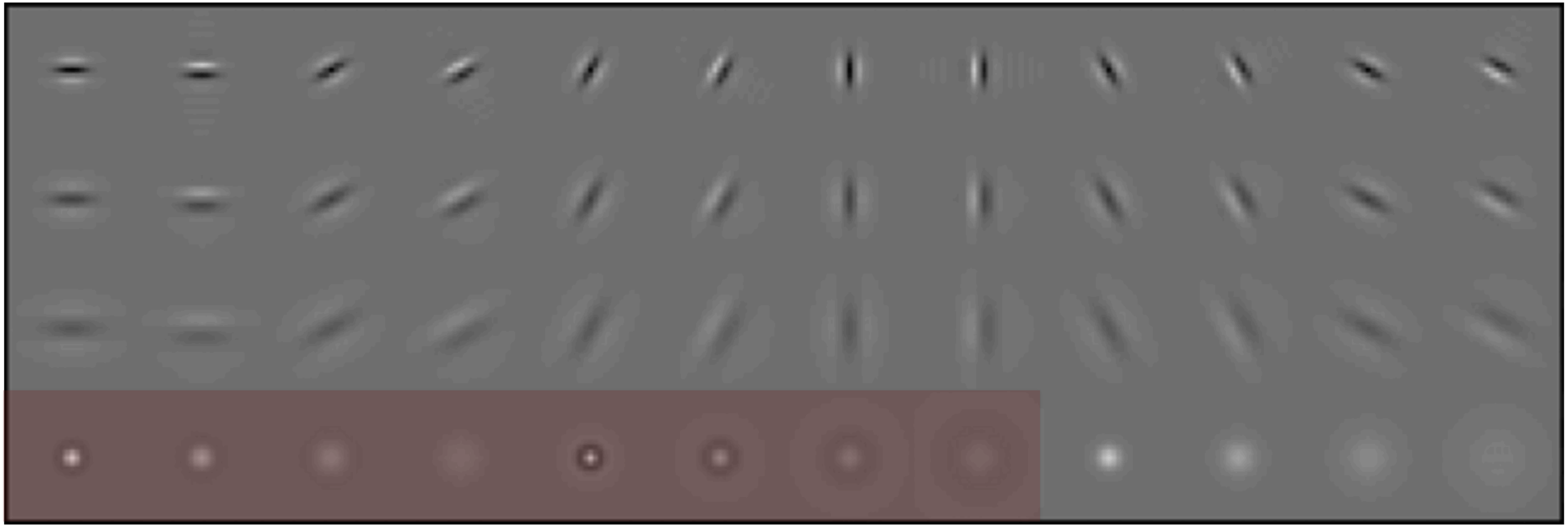


Figure Credit: Leung and Malik, 2001

Texture **Representation**

Gaussian filters at different scales

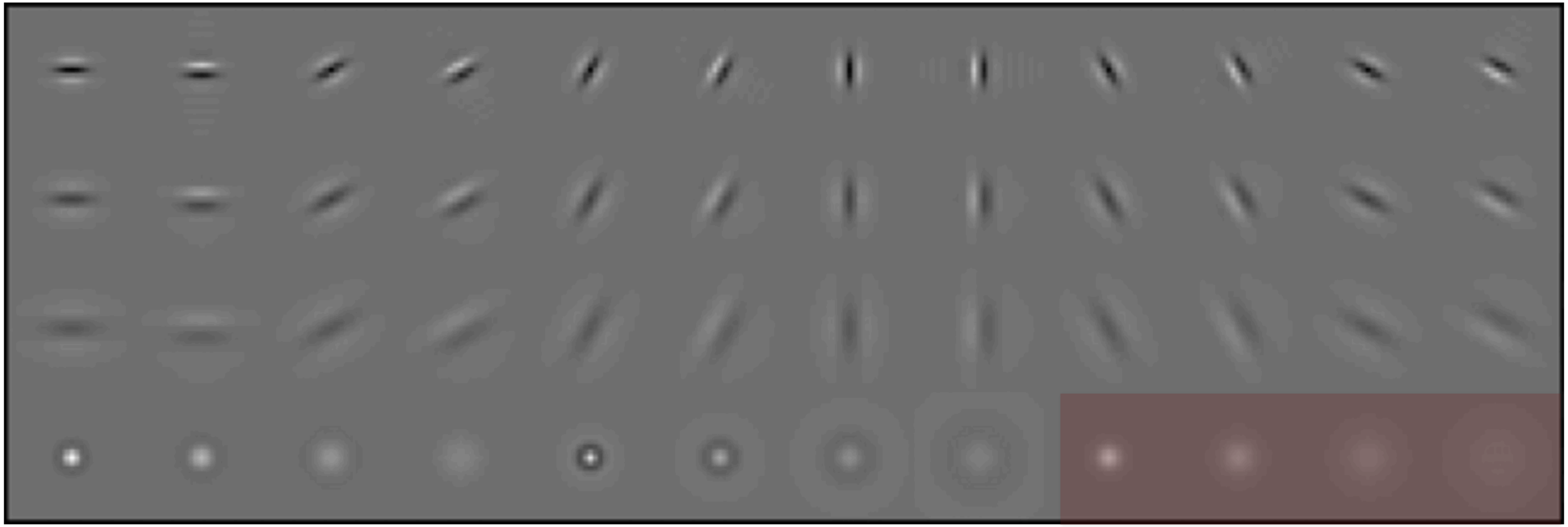
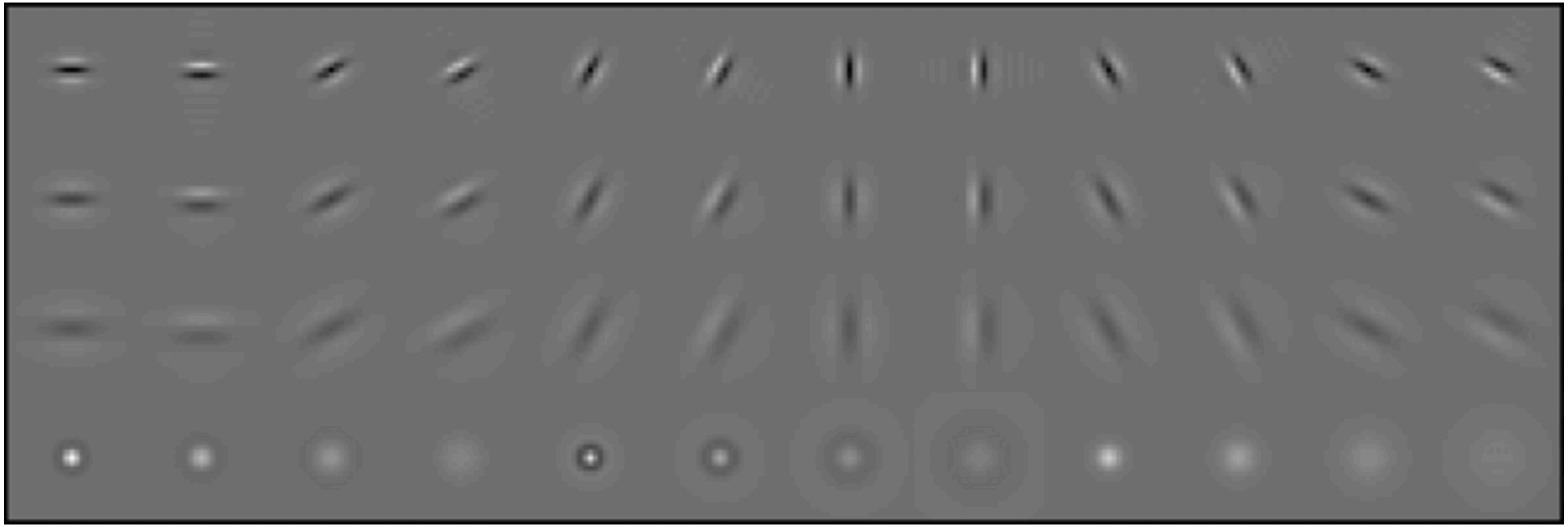


Figure Credit: Leung and Malik, 2001

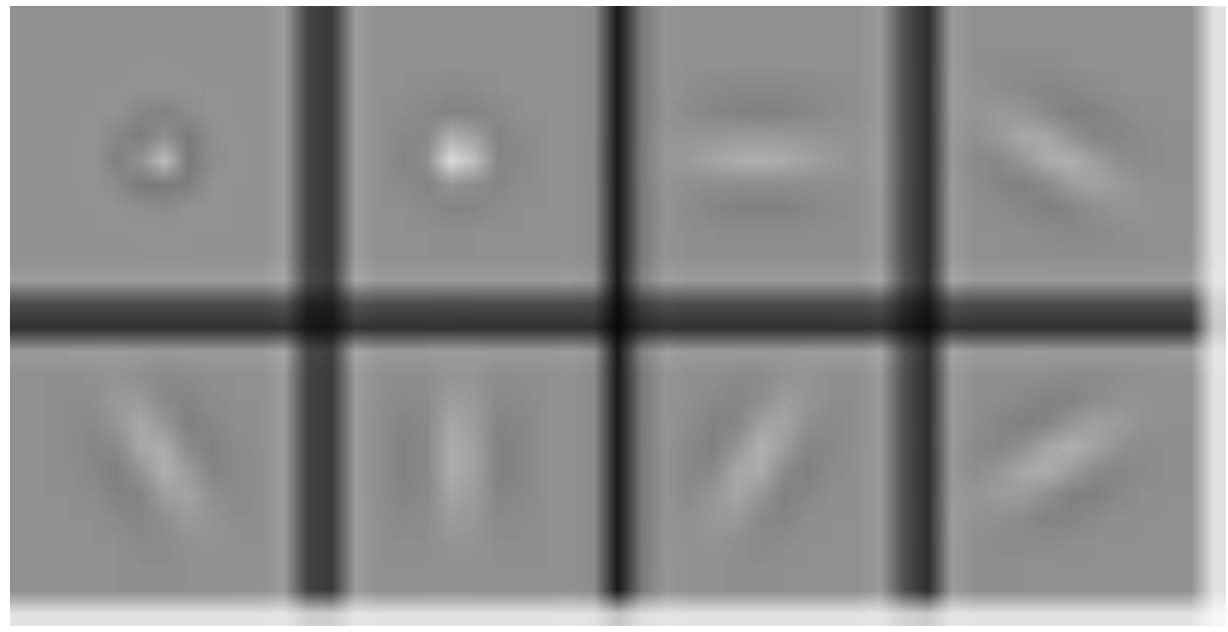
Texture **Representation**

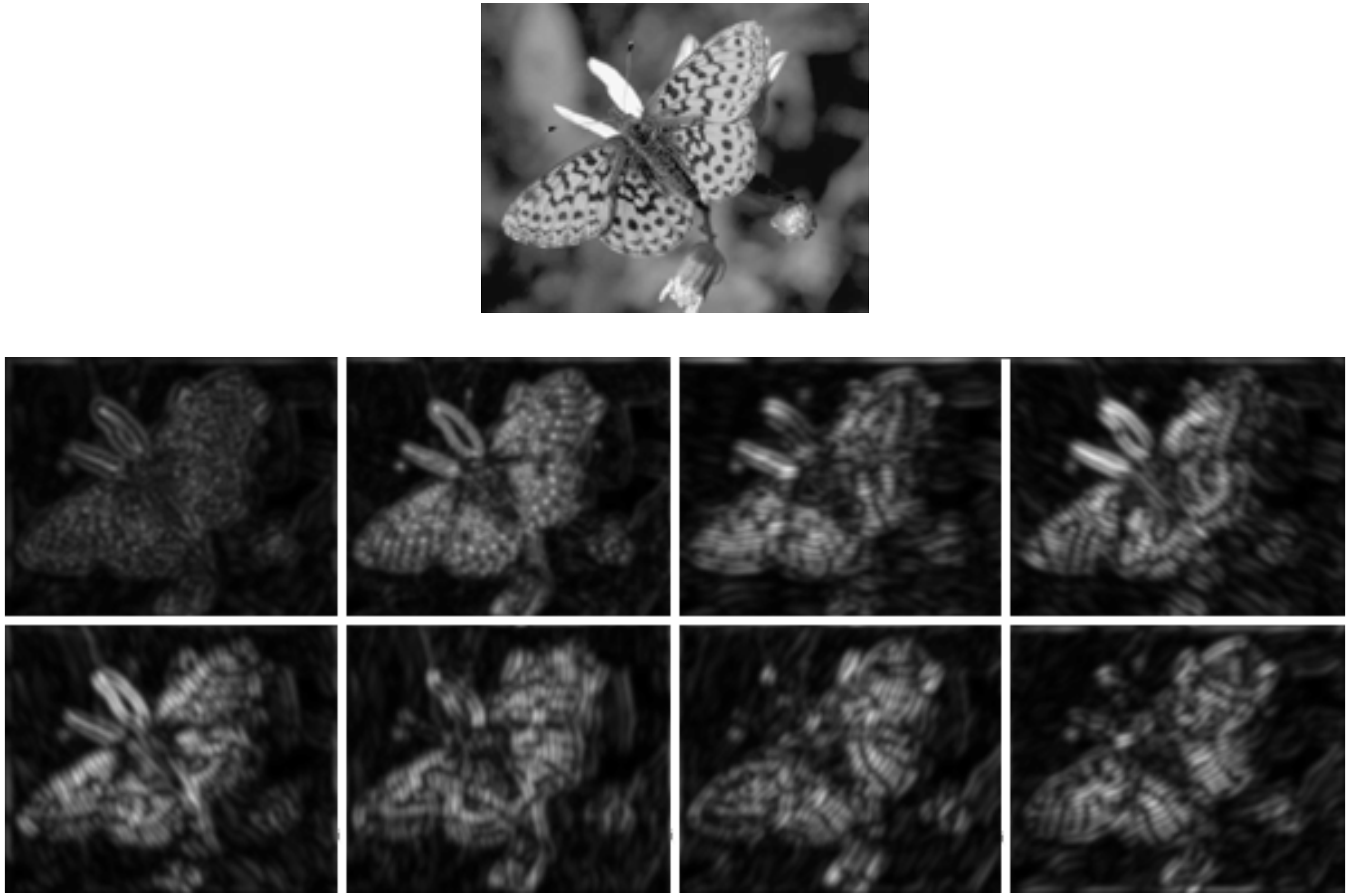


Result: 48-channel “image”

Figure Credit: Leung and Malik, 2001

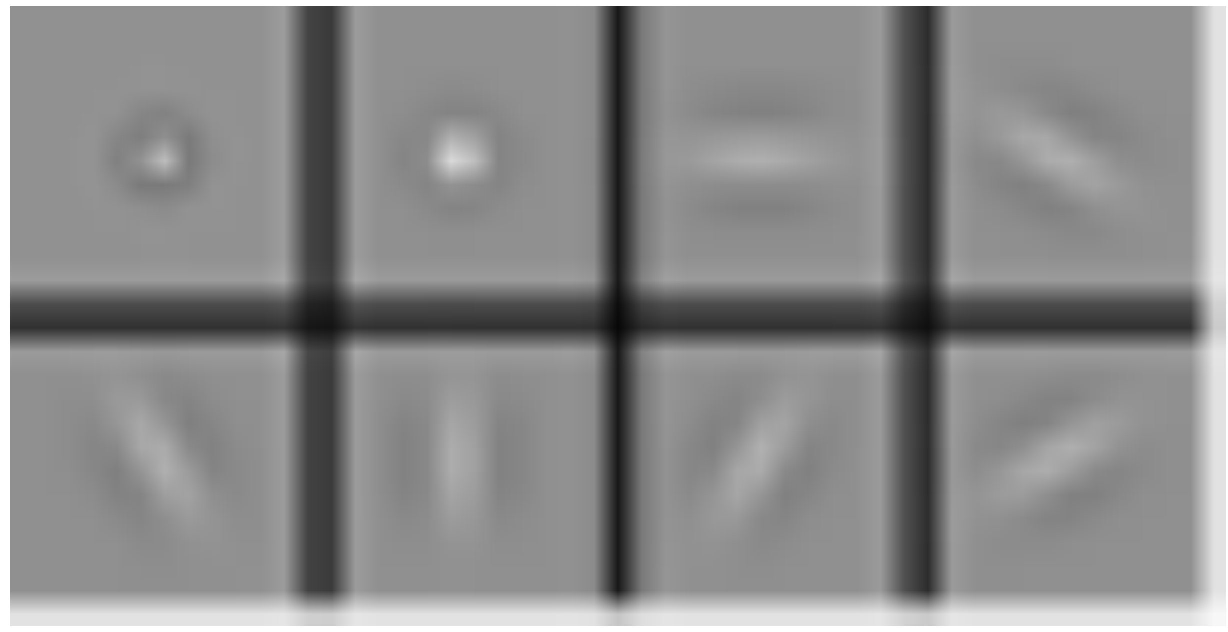
Spots and Bars (Fine Scale)

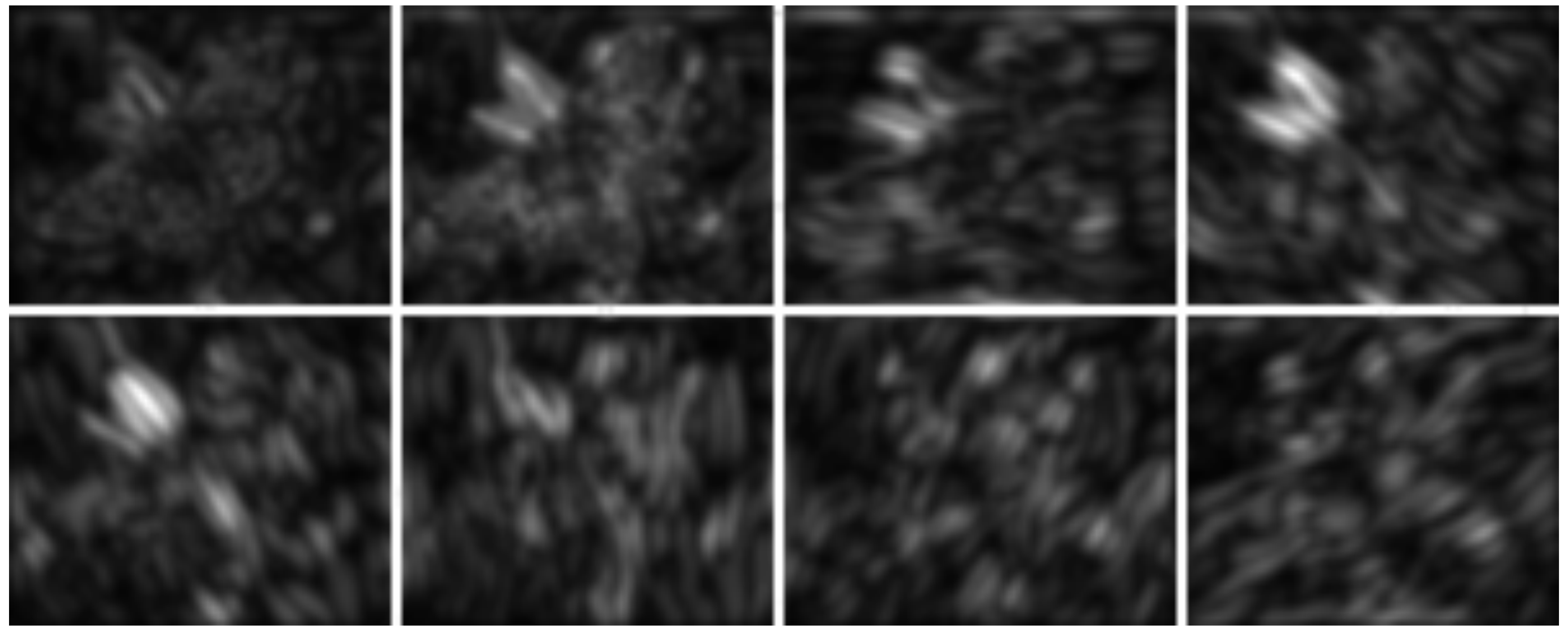




Forsyth & Ponce (1st ed.) Figures 9.3–9.4

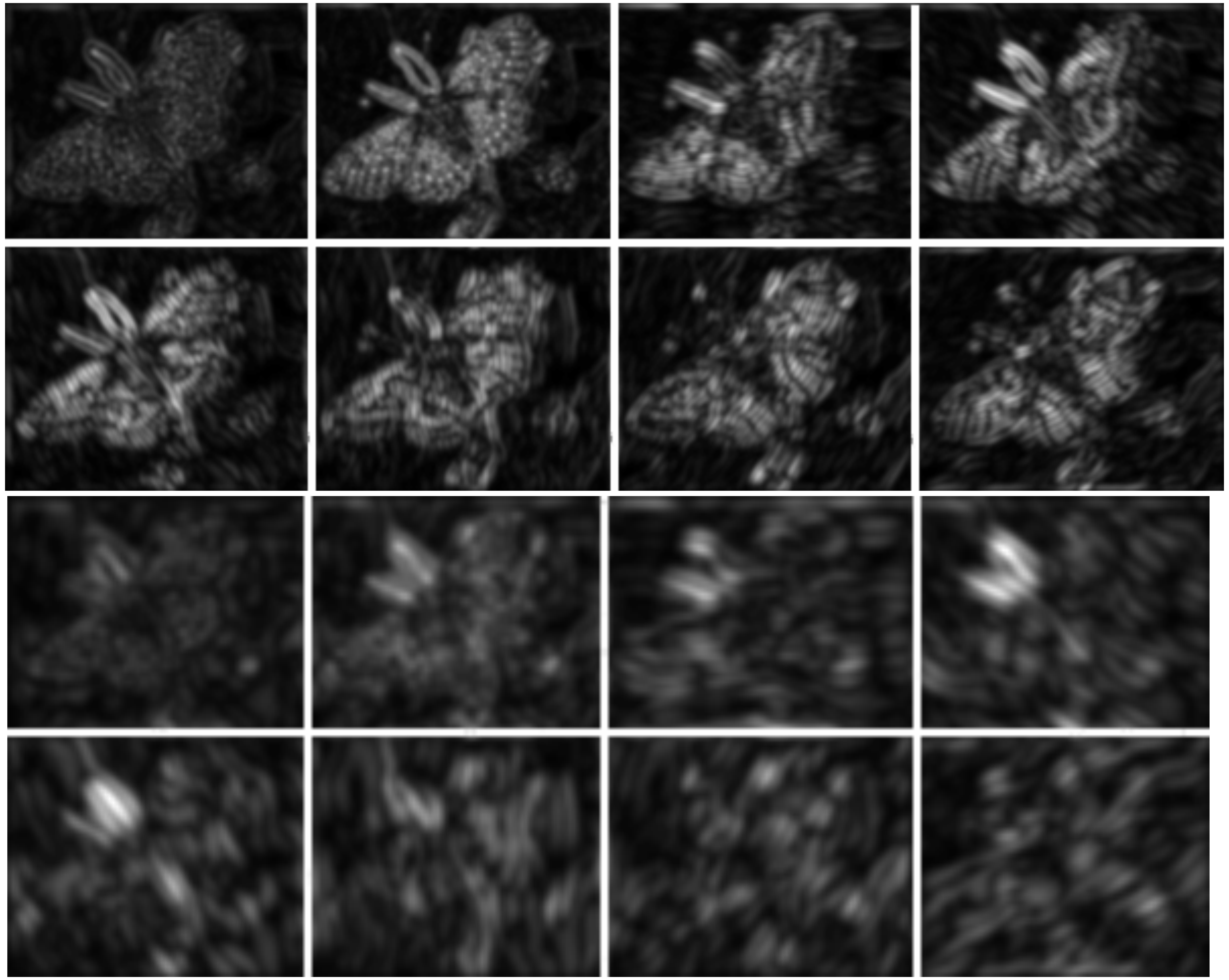
Spots and Bars (Coarse Scale)





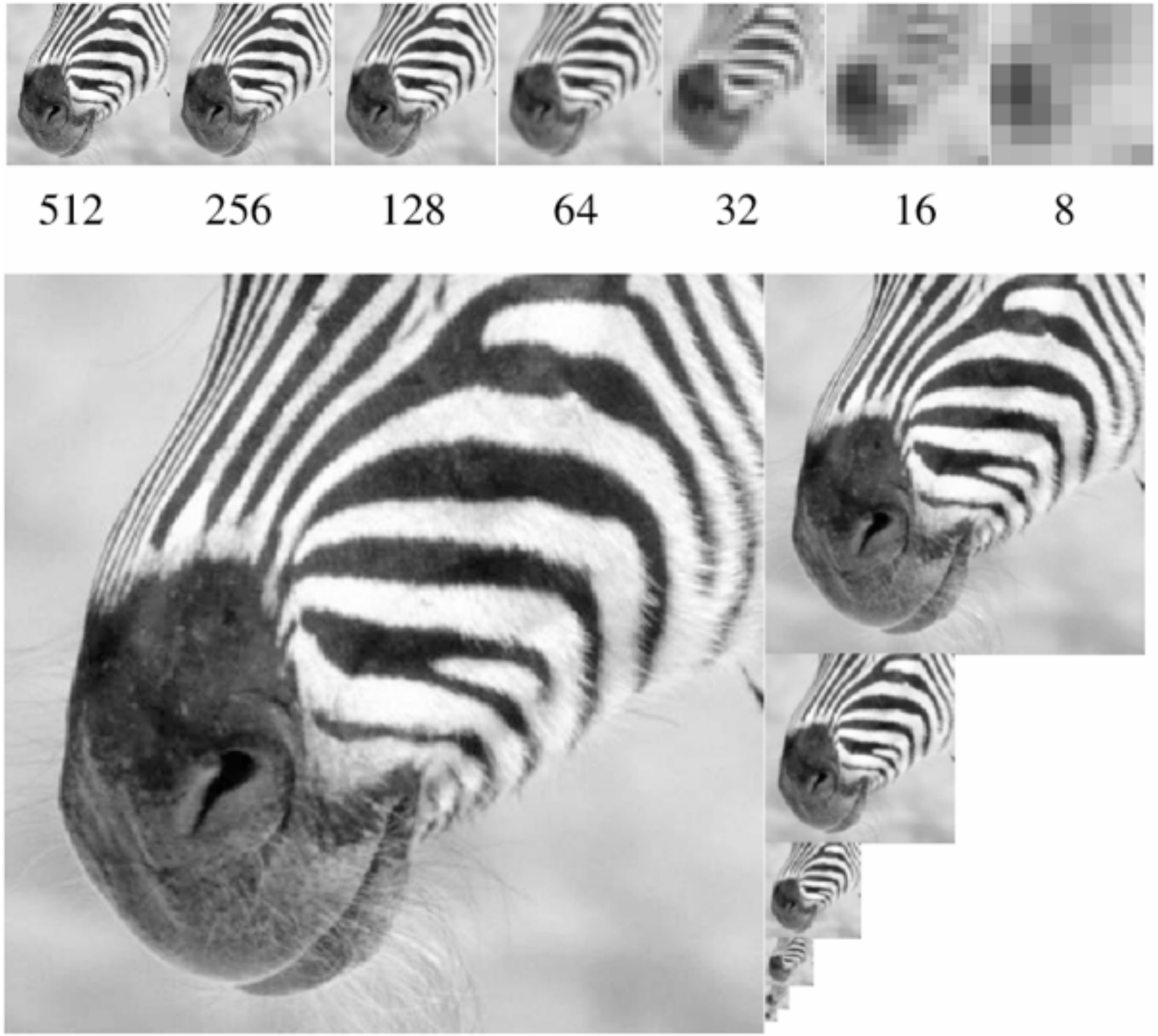
Forsyth & Ponce (1st ed.) Figures 9.3 and 9.5

Comparison of Results



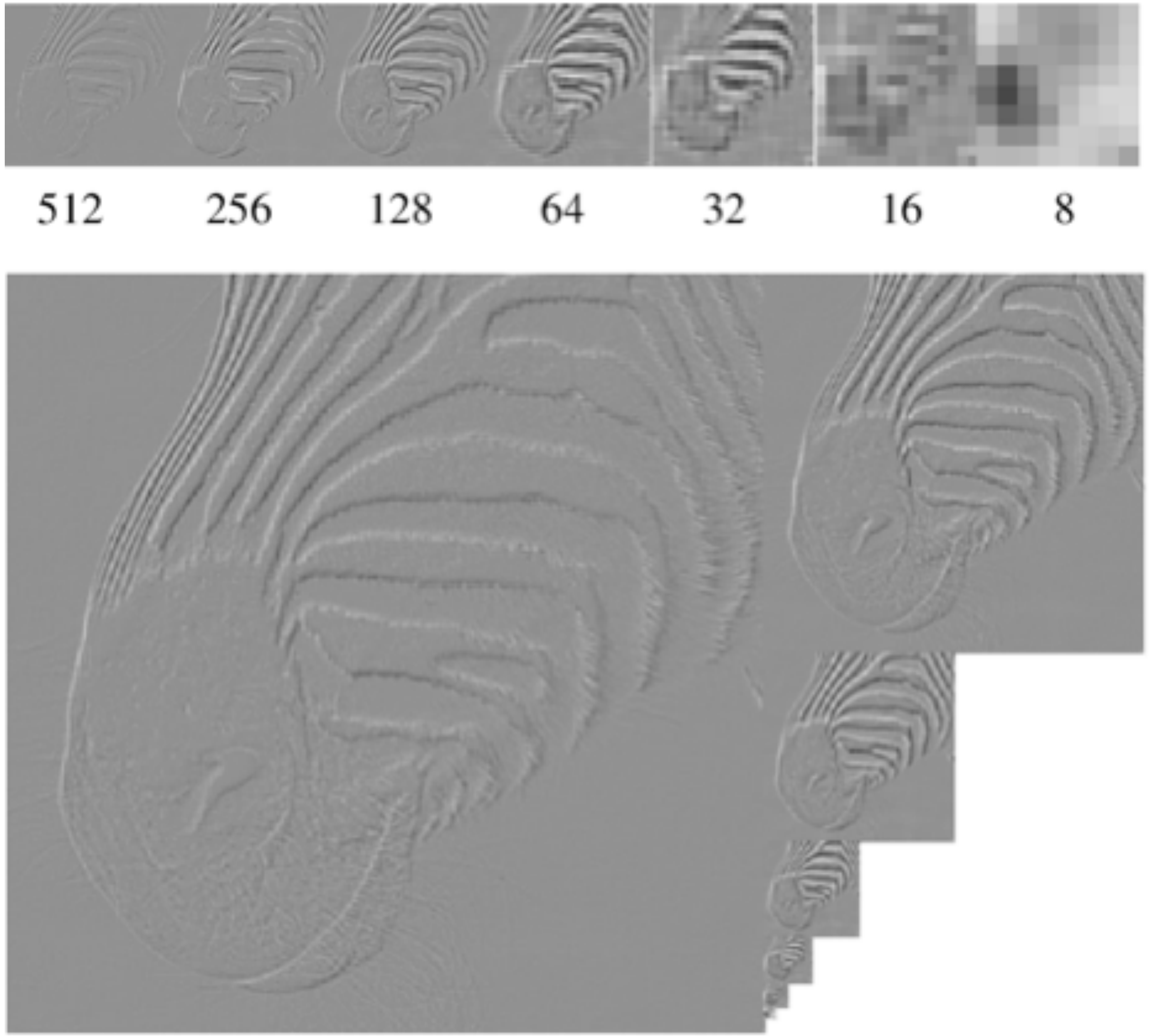
Forsyth & Ponce (1st ed.) Figures 9.4–9.5

Gaussian Pyramid



Forsyth & Ponce (2nd ed.) Figure 4.17

Laplacian Pyramid



Oriented Pyramids

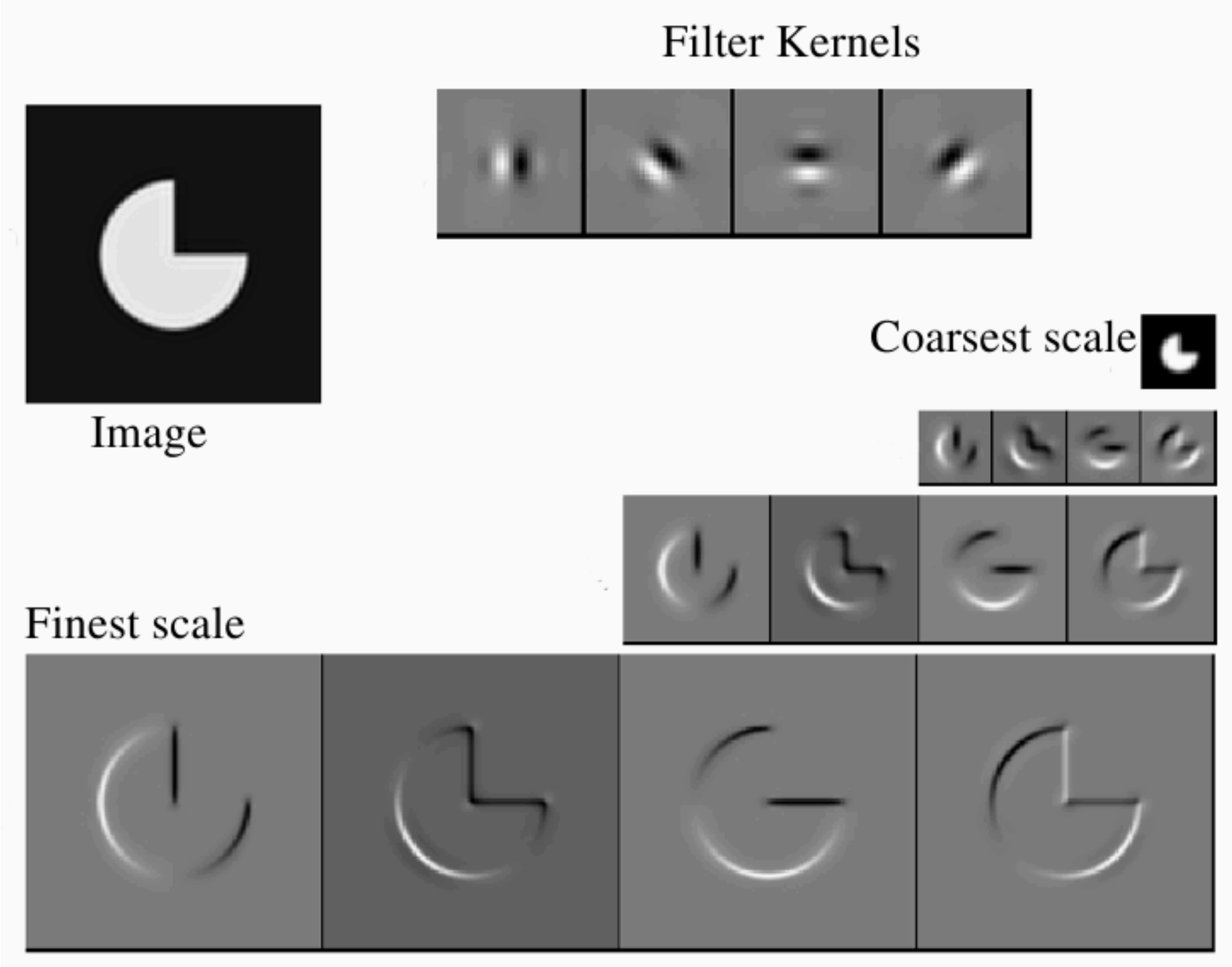
Laplacian pyramid is orientation independent

Idea: Apply an oriented filter at each layer

— represent image at a particular scale and orientation

— Aside: We do not study details in this course

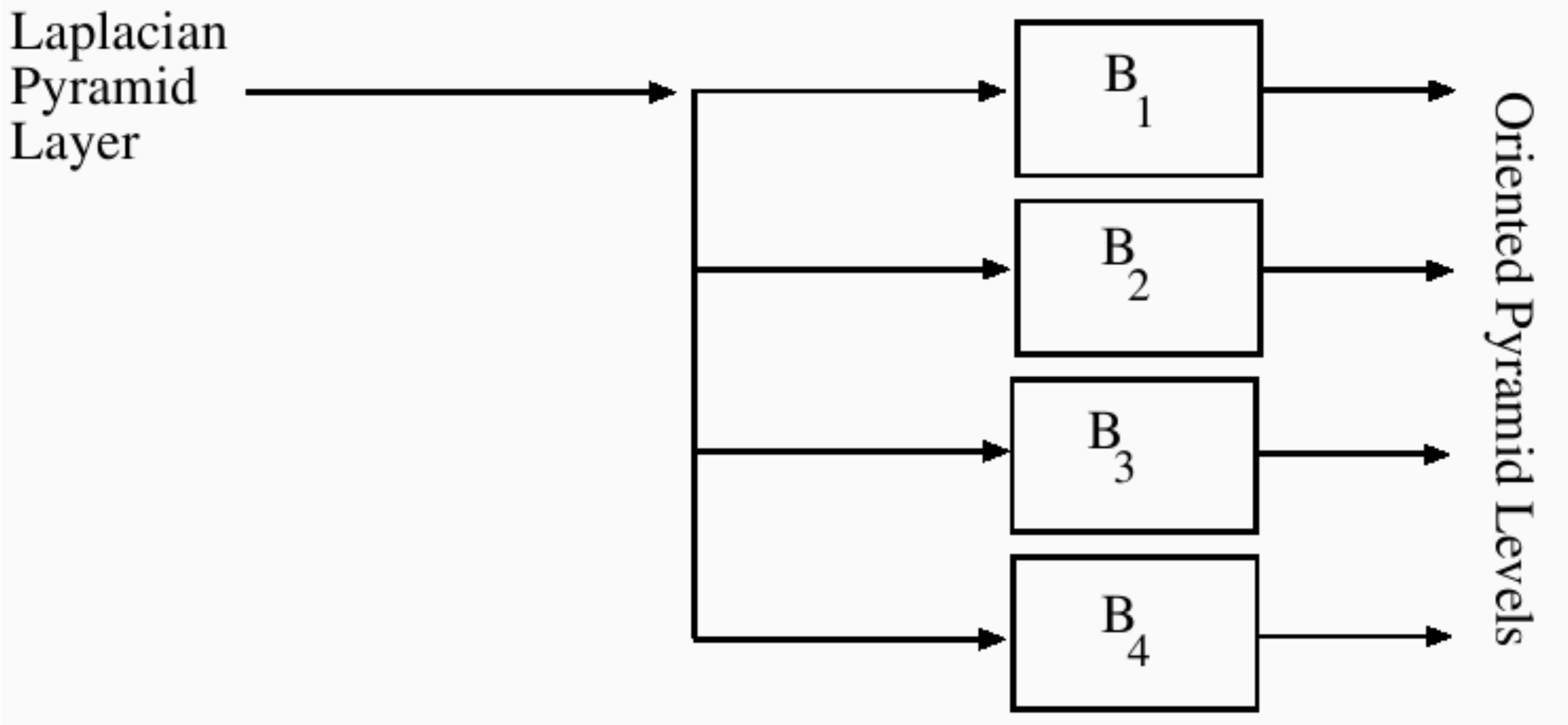
Oriented Pyramids



Forsyth & Ponce (1st ed.) Figure 9.13

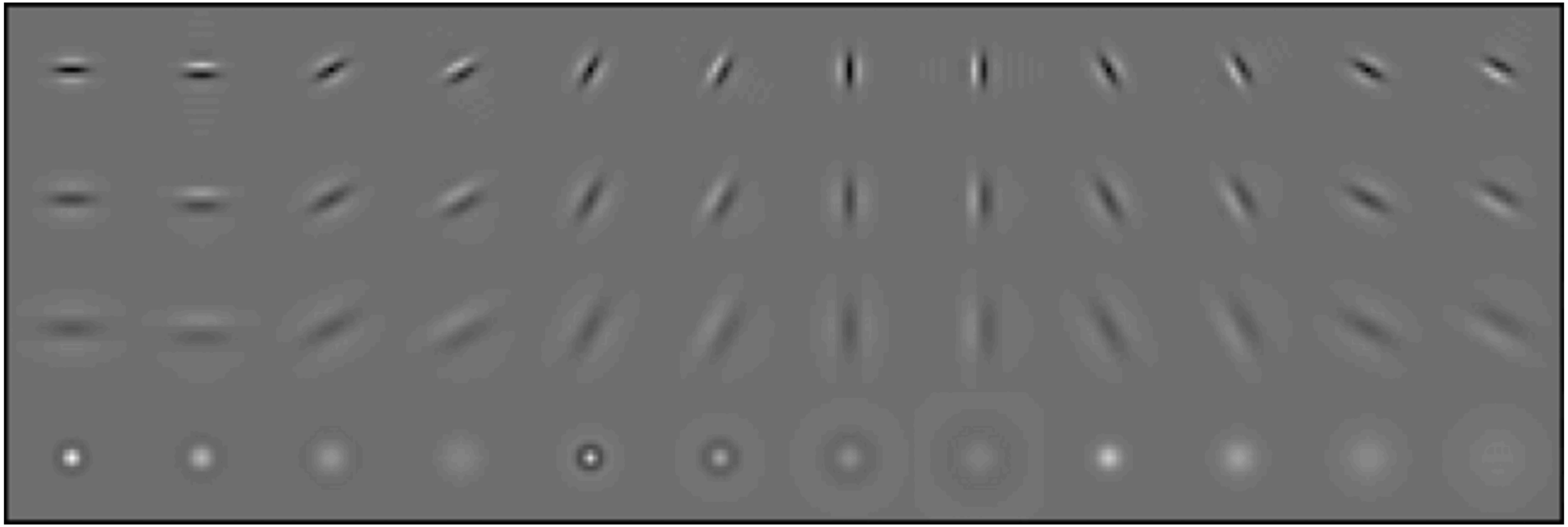
Oriented Pyramids

Oriental Filters



Forsyth & Ponce (1st ed.) Figure 9.14

Texture **Representation**



Result: 48-channel "image"

Figure Credit: Leung and Malik, 2001

Texture **Representation**

Observation: Textures are made up of generic sub-elements, repeated over a region with similar statistical properties

Idea: Find the sub-elements with filters, then represent each point in the image with a summary of the pattern of sub-elements in the local region

Question: What filters should we use?

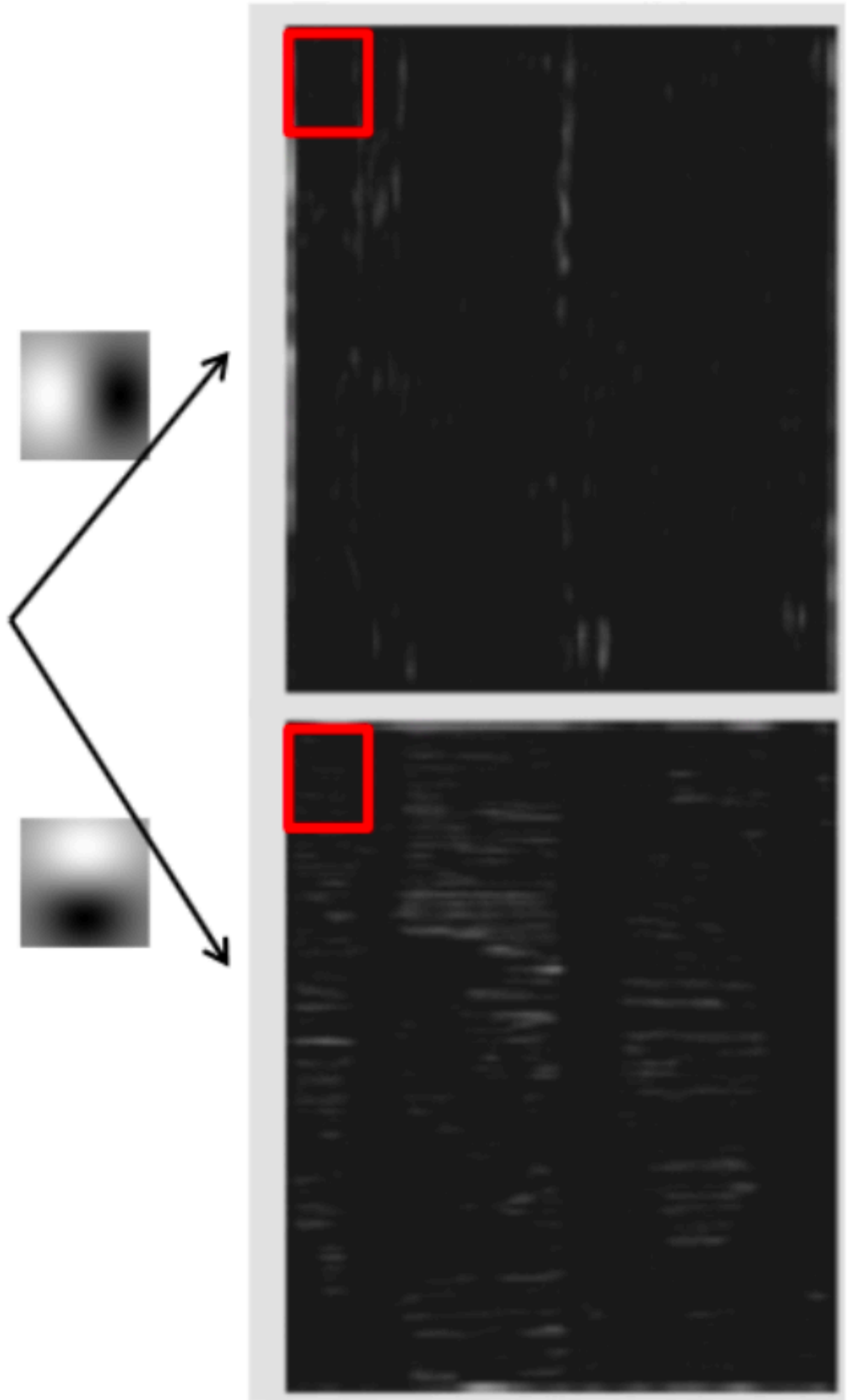
Answer: Human vision suggests spots and oriented edge filters at a variety of different orientations and scales

Question: How do we “summarize”?

Answer: Compute the mean or maximum of each filter response over the region
— Other statistics can also be useful

Texture **Representation**

original image



derivative filter responses, squared

	mean d/dx value	mean d/dy value
Win. #1	4	10

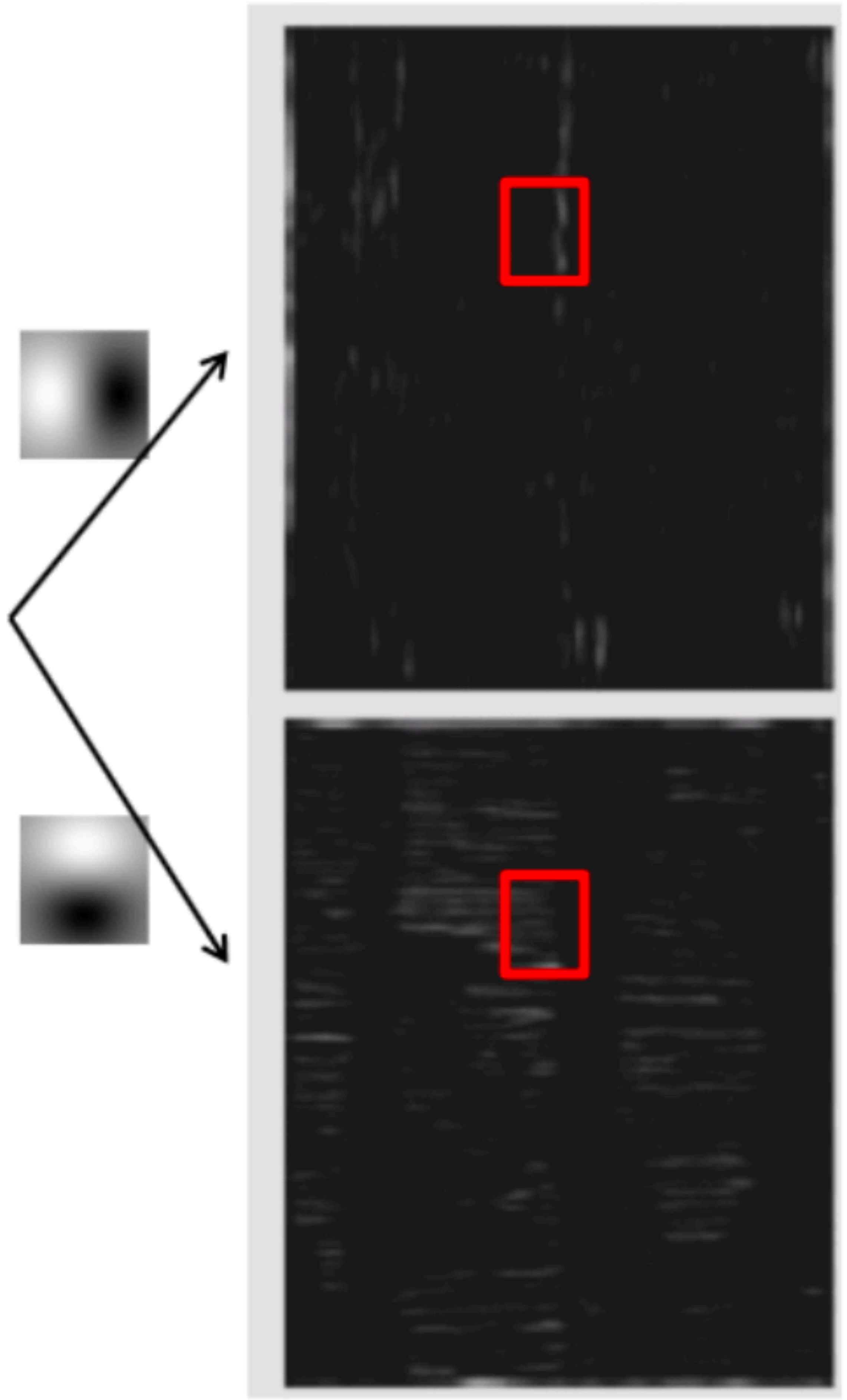
⋮

statistics to summarize patterns in small windows

Slide Credit: Trevor Darrell

Texture **Representation**

original image



derivative filter responses, squared

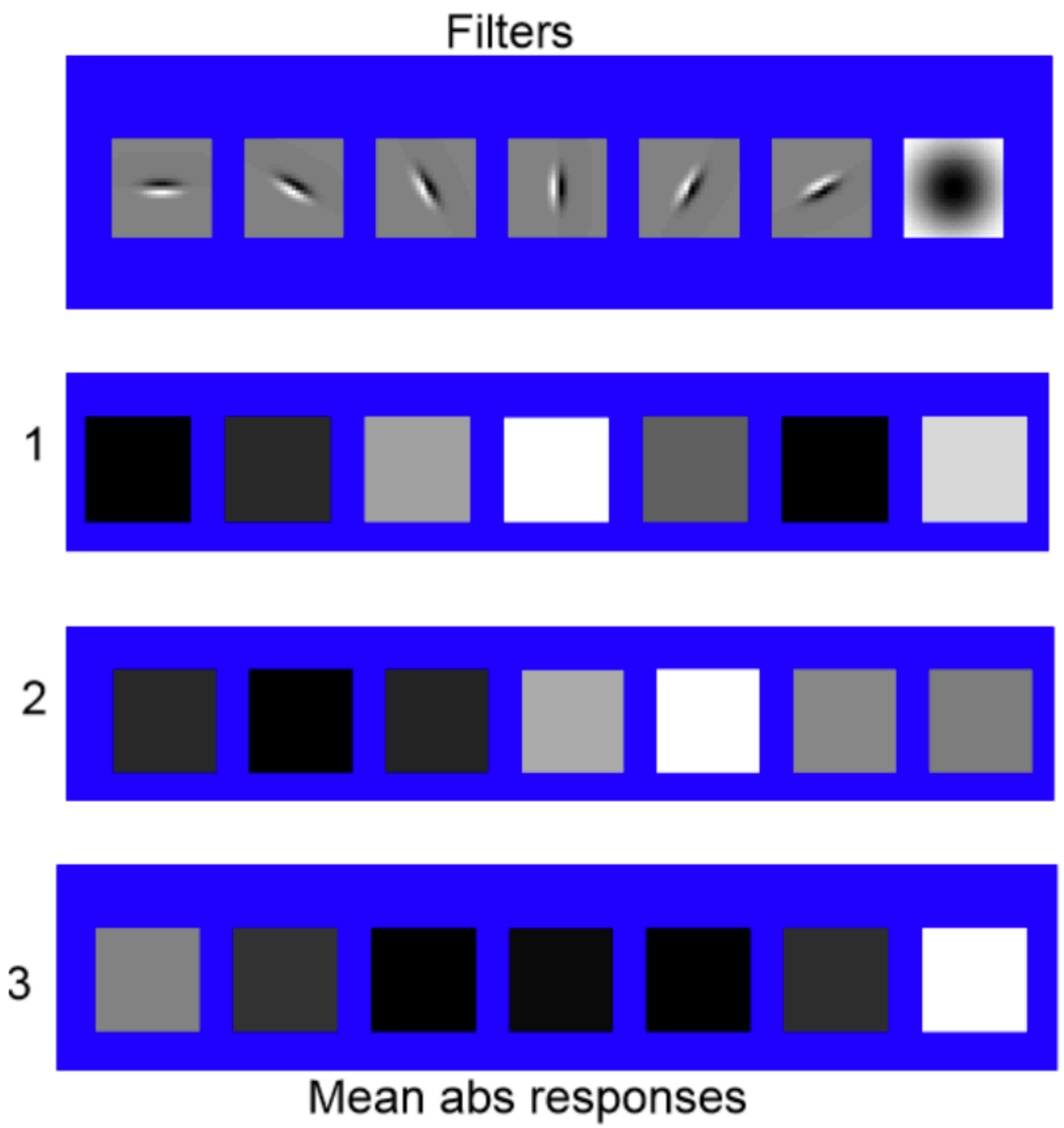
	mean d/dx value	mean d/dy value
Win. #1	4	10
Win.#2 ⋮	18	7
Win.#9	20	20

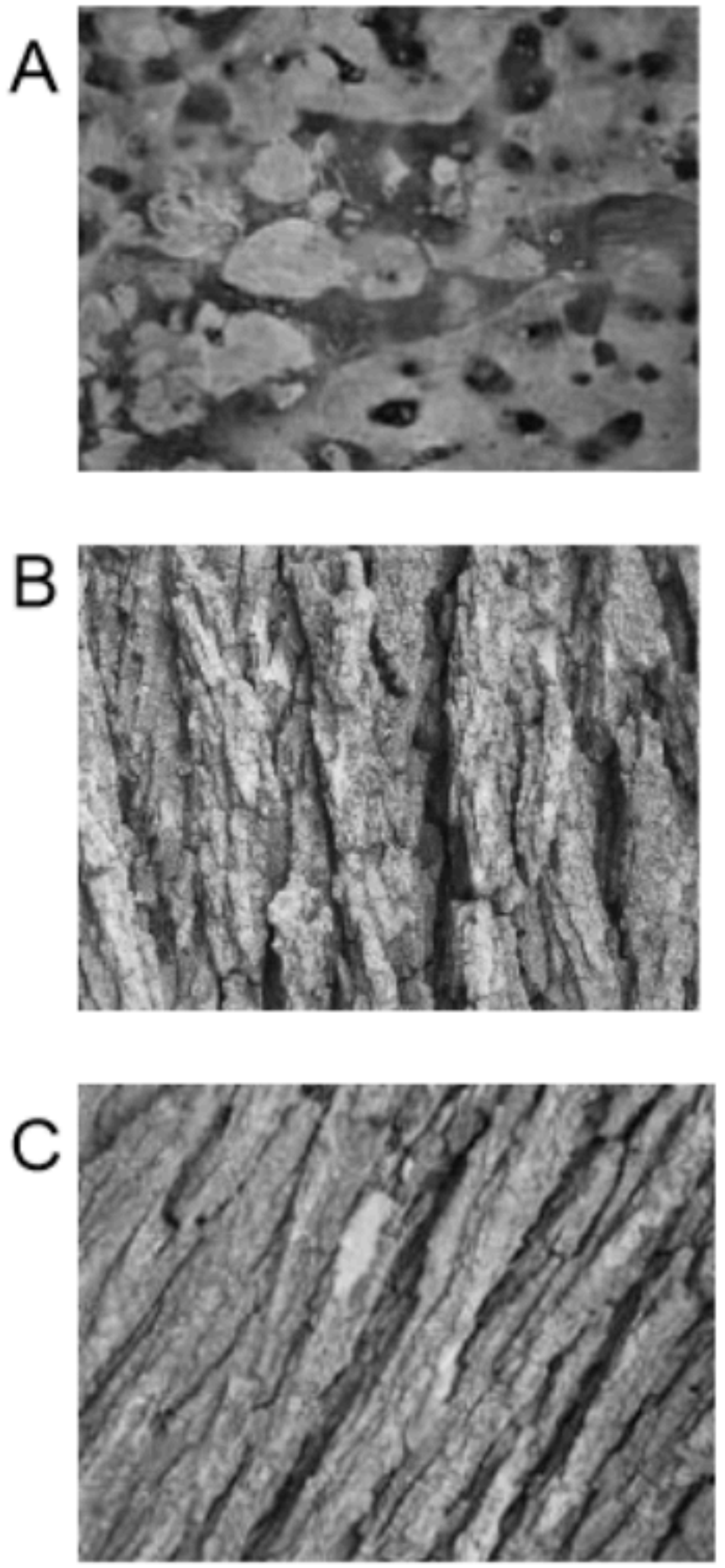
⋮

statistics to summarize patterns in small windows

Slide Credit: Trevor Darrell

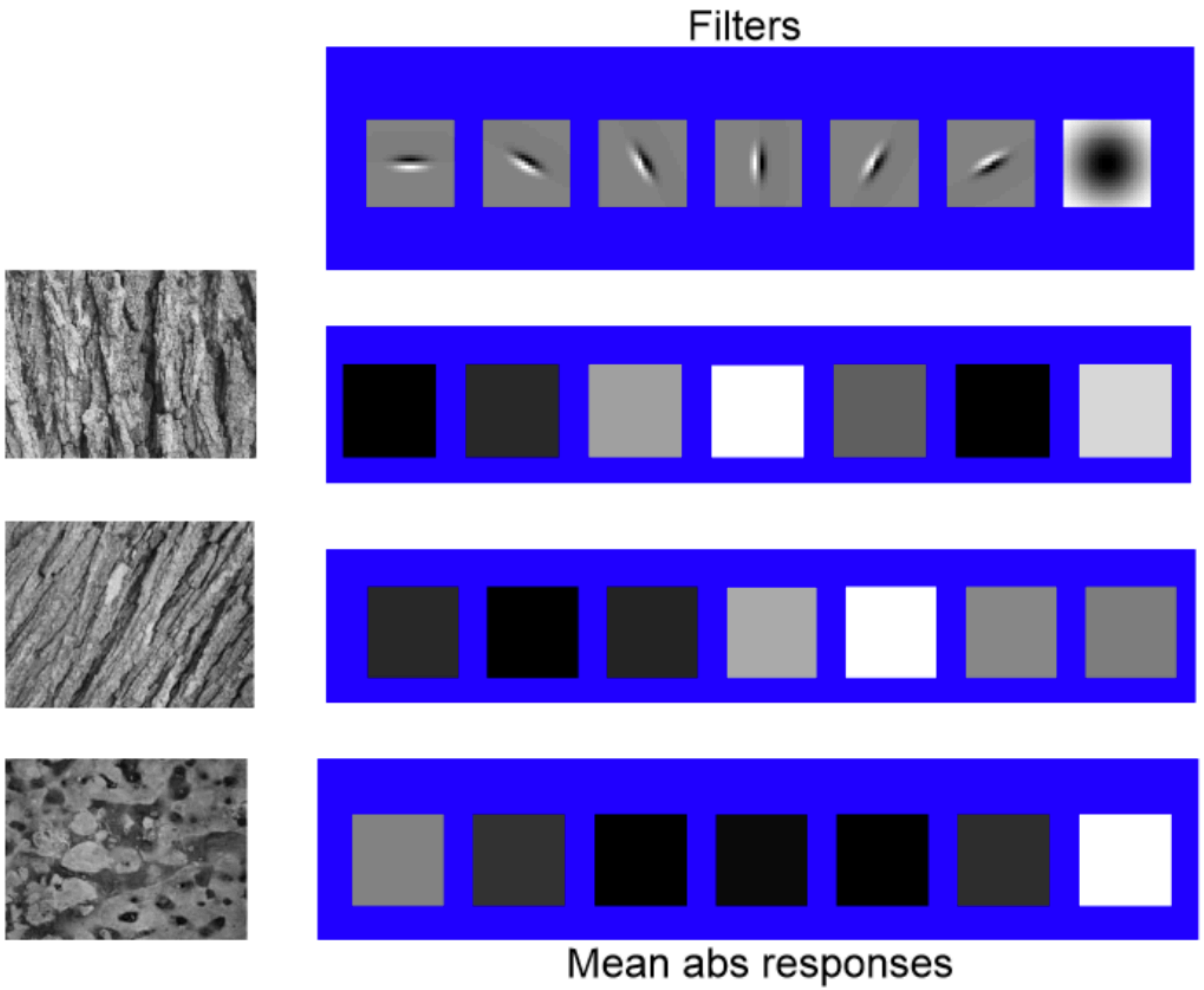
A Short **Exercise**: Match the texture to the response





Slide Credit: James Hays

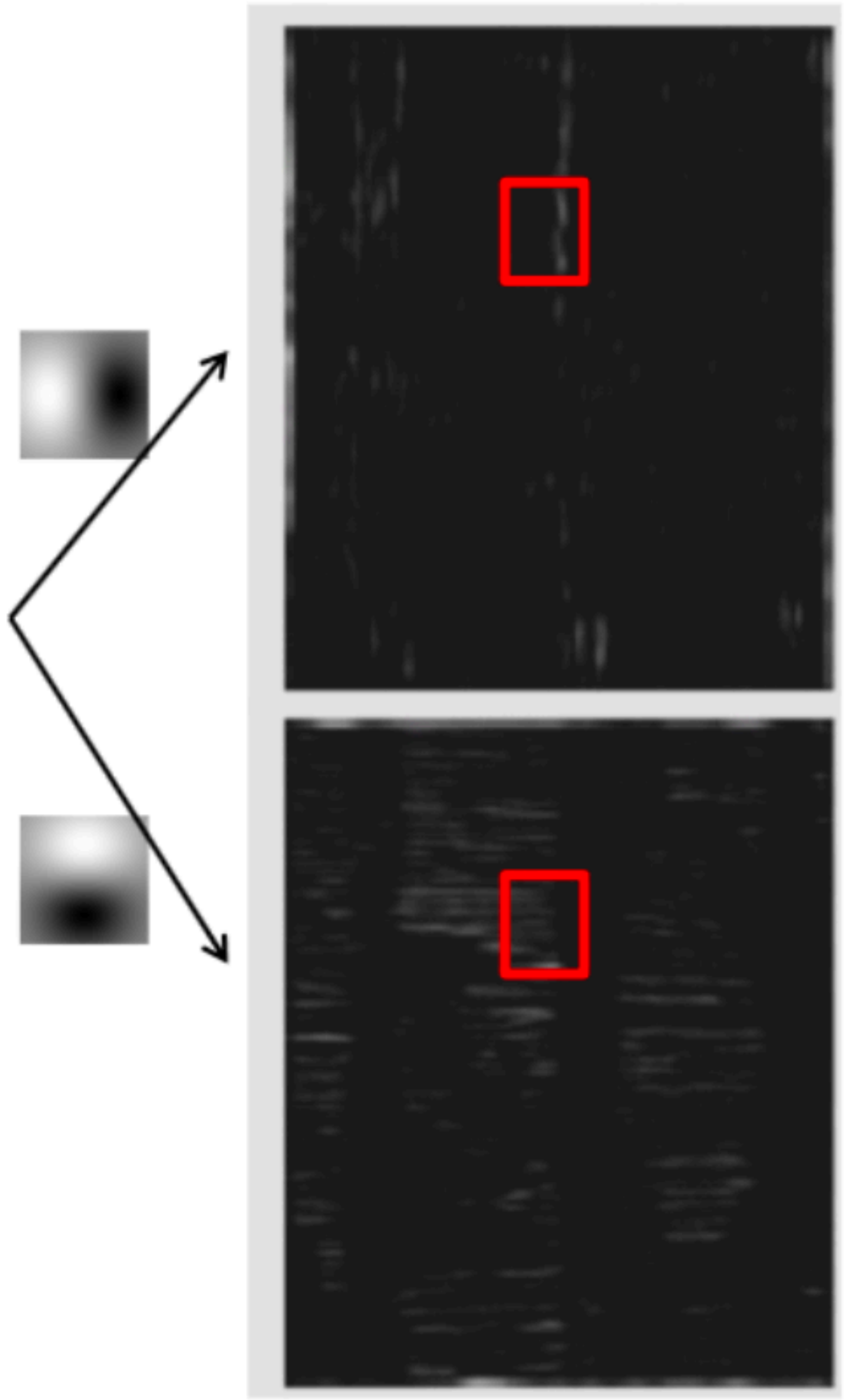
A Short **Exercise**: Match the texture to the response



Slide Credit: James Hays

Texture **Representation**

original image



derivative filter responses, squared

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⋮		
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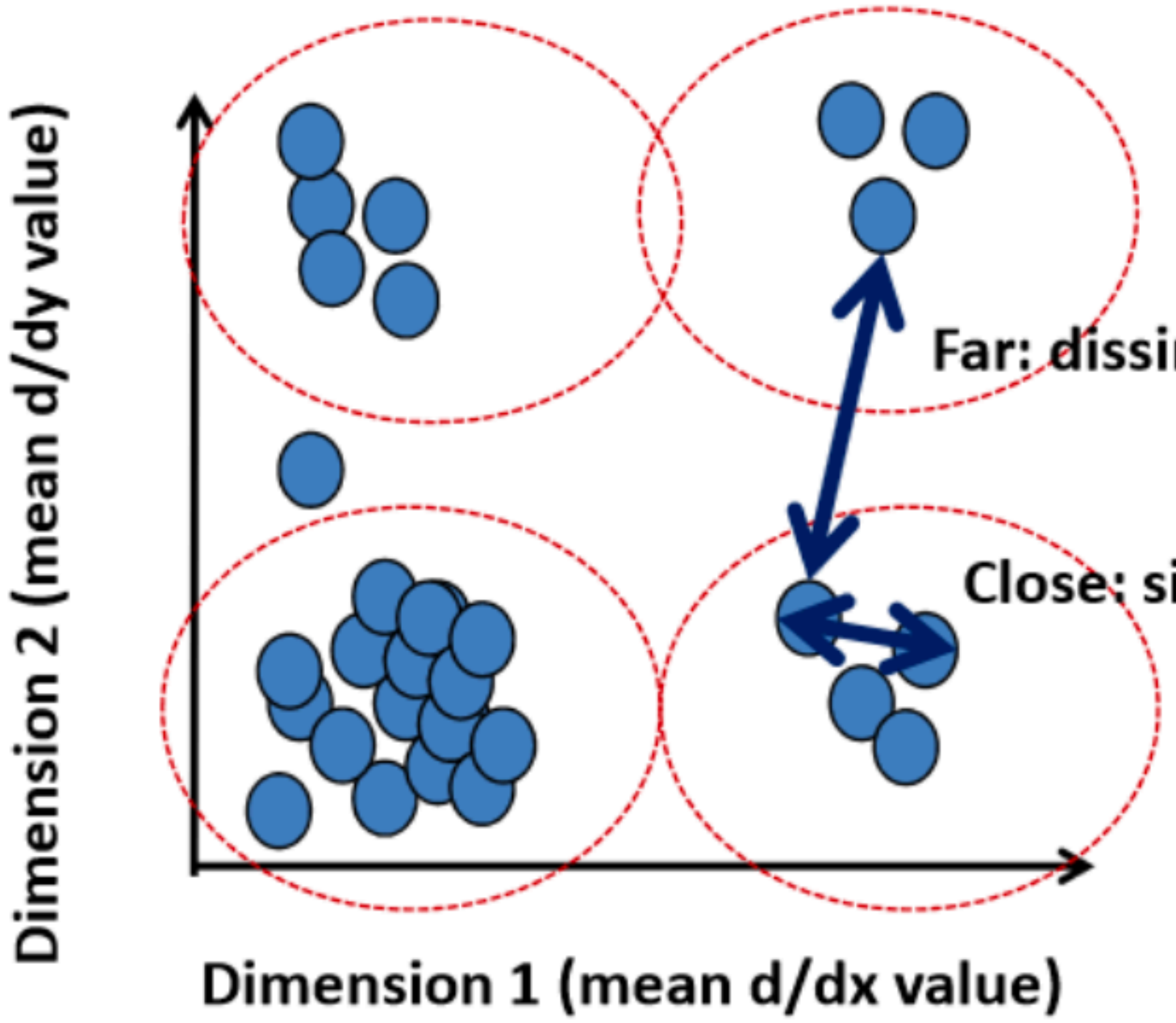
statistics to summarize patterns in small windows

Slide Credit: Trevor Darrell

Texture **Representation**



	mean d/dx value	mean d/dy value
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Win.#2	18	7
⋮		
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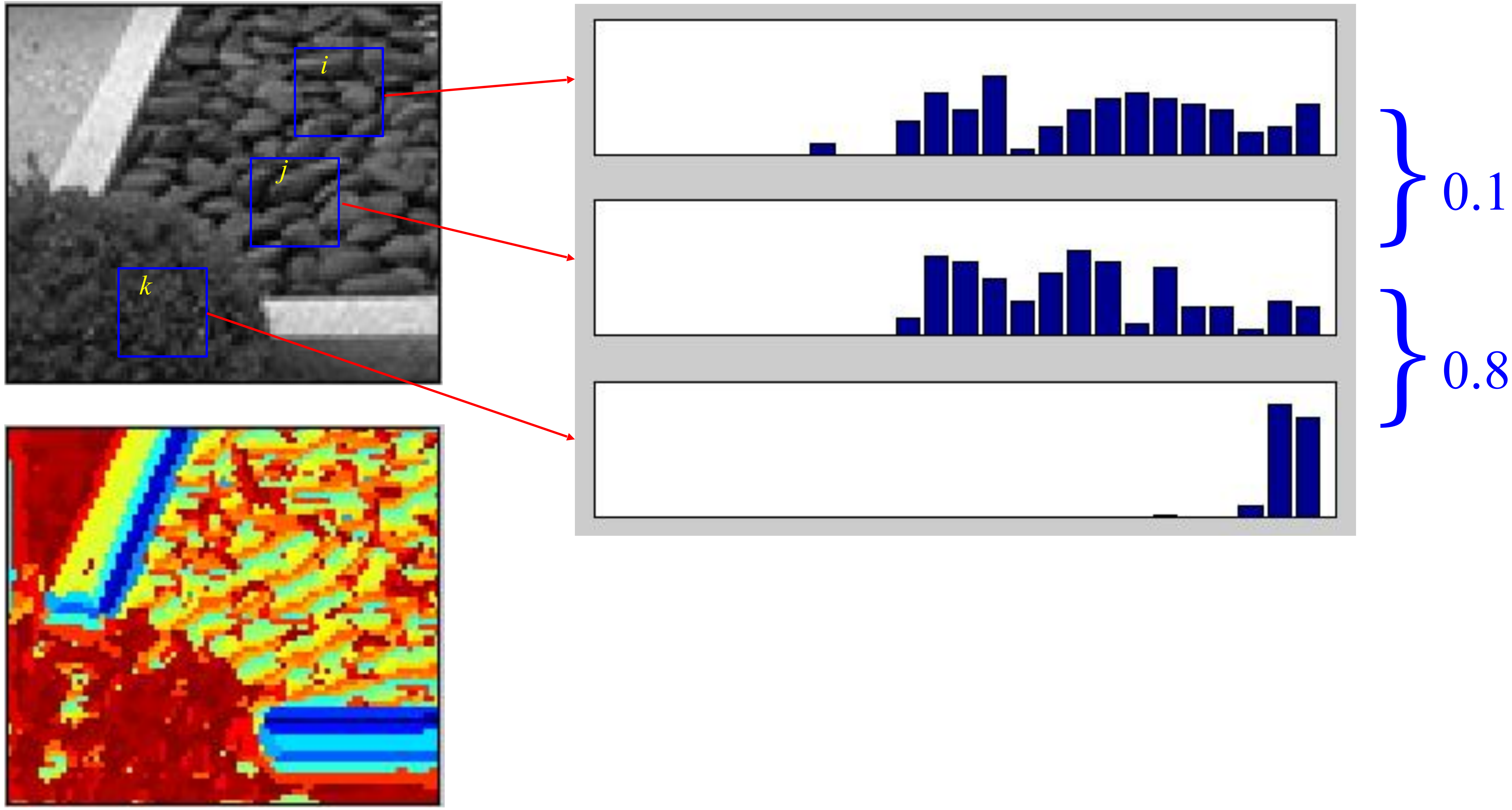
⋮

statistics to summarize patterns in small windows

Slide Credit: Trevor Darrell

Texture **Representation**



Chi-square

Bag-of-Words Representation

Take a large **corpus of text**:

Bag-of-Words Representation

Take a large **corpus of text**:

— Represent every **letter** by a 26 dimensional (unit) vector

$$a = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \cdot \\ \cdot \\ \cdot \\ 0 \\ 0 \end{bmatrix} \qquad b = \begin{bmatrix} 0 \\ 1 \\ 0 \\ \cdot \\ \cdot \\ \cdot \\ 0 \\ 0 \end{bmatrix}$$

Bag-of-Words Representation

Take a large **corpus of text**:

— Represent every **letter** by a 26 dimensional (unit) vector

— Represent each **word** by an average of letter representations in it

$$ab = \begin{bmatrix} \frac{1}{2} \\ \frac{1}{2} \\ 0 \\ . \\ . \\ . \\ 0 \\ 0 \end{bmatrix}$$

Bag-of-Words Representation

Take a large **corpus of text**:

— Represent every **letter** by a 26 dimensional (unit) vector

— Represent each **word** by an average of letter representations in it

— Cluster the words, to get a "**dictionary**". Words that have very similar representations would get clustered together (e.g., smile and smiled)

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— Now represent every document by **histogram** of "dictionary" atoms by associating every word to an atom that is closest in terms of distance in 26D

Bag-of-Words Representation

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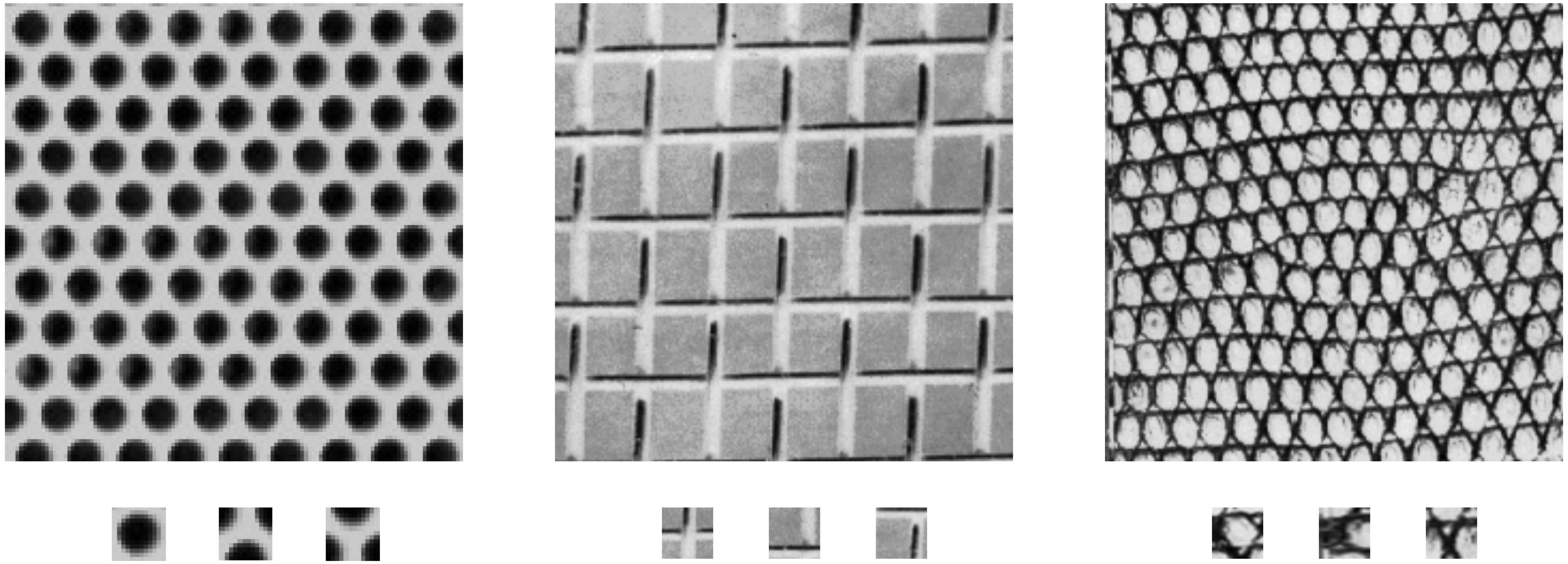
— Now represent every document by **histogram** of "dictionary" atoms by associating every word to an atom that is closest in terms of distance in 26D

corpus of text = collection of images
letter = pixel location
word = patch with pixel in the center
dictionary = textons

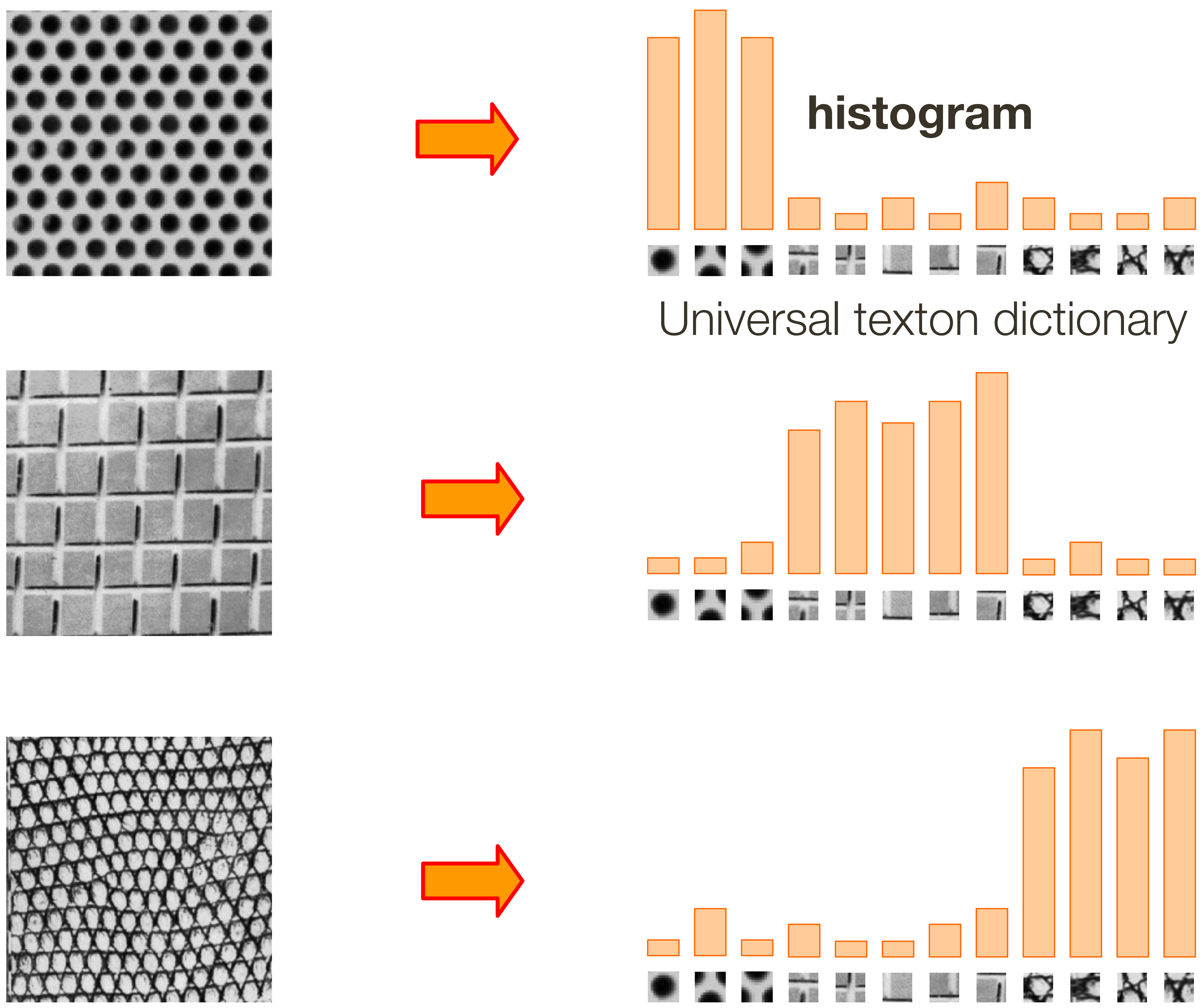
Texture representation and recognition

- Texture is characterized by the repetition of basic elements or **textons**
- For stochastic textures, it is the **identity of the textons**, not their spatial arrangement, that matters

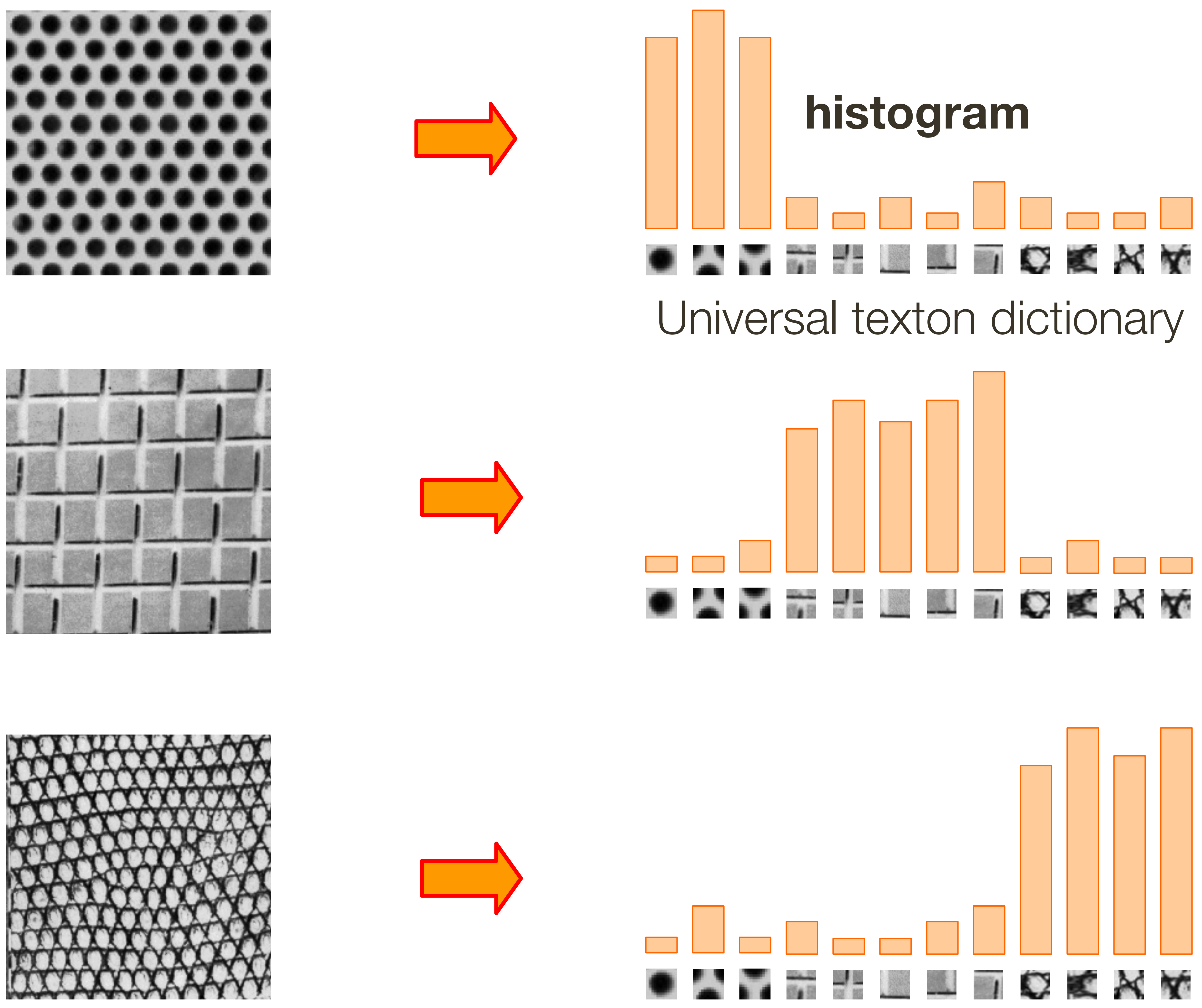


Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001; Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

Texture representation and recognition



Texture representation and recognition



Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001; Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

Summary

Texture representation is hard
— difficult to define, to analyze
— texture synthesis appears more tractable

Objective of texture **synthesis** is to generate new examples of a texture
— Efros and Leung: Draw samples directly from the texture to generate one pixel at a time. A “data-driven" approach.

Approaches to texture embed assumptions related to human perception