THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision

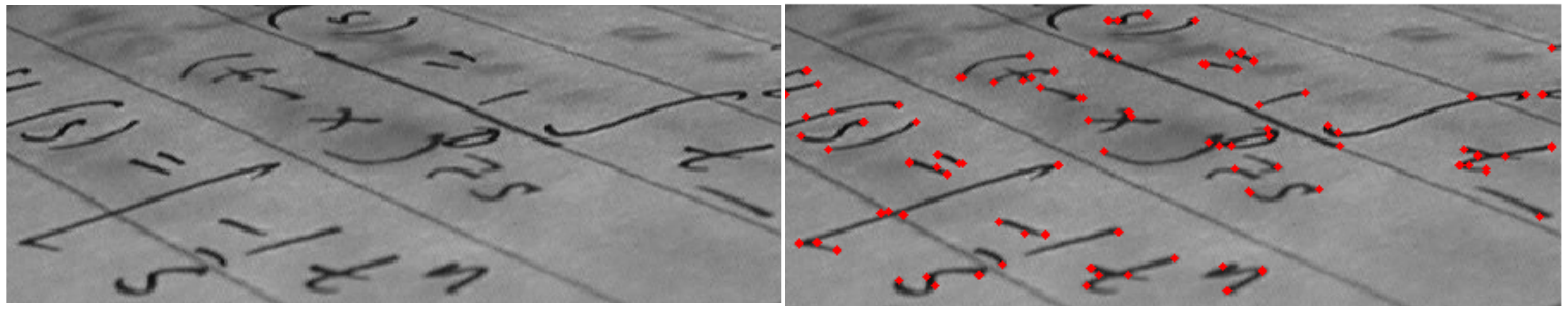


Image Credit: https://en.wikipedia.org/wiki/Corner_detection

Lecture 10: Corner Detection (cont)

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

Menu for Today (**February 6, 2020**)

Topics:

- Harris **Corner** Detector (review)
- **Blob** Detection
- Searching over **Scale**

Redings:

- **Today's** Lecture: Forsyth & Ponce (2nd ed.) 5.3, 6.1, 6.3
- **Next** Lecture: Forsyth & Ponce (2nd ed.) 3.1-3.3

Reminders:

- **Assignment 2**: Face Detection in a Scaled Representation is **February 11th**

Today's "**fun**" Example: Colour Constancy

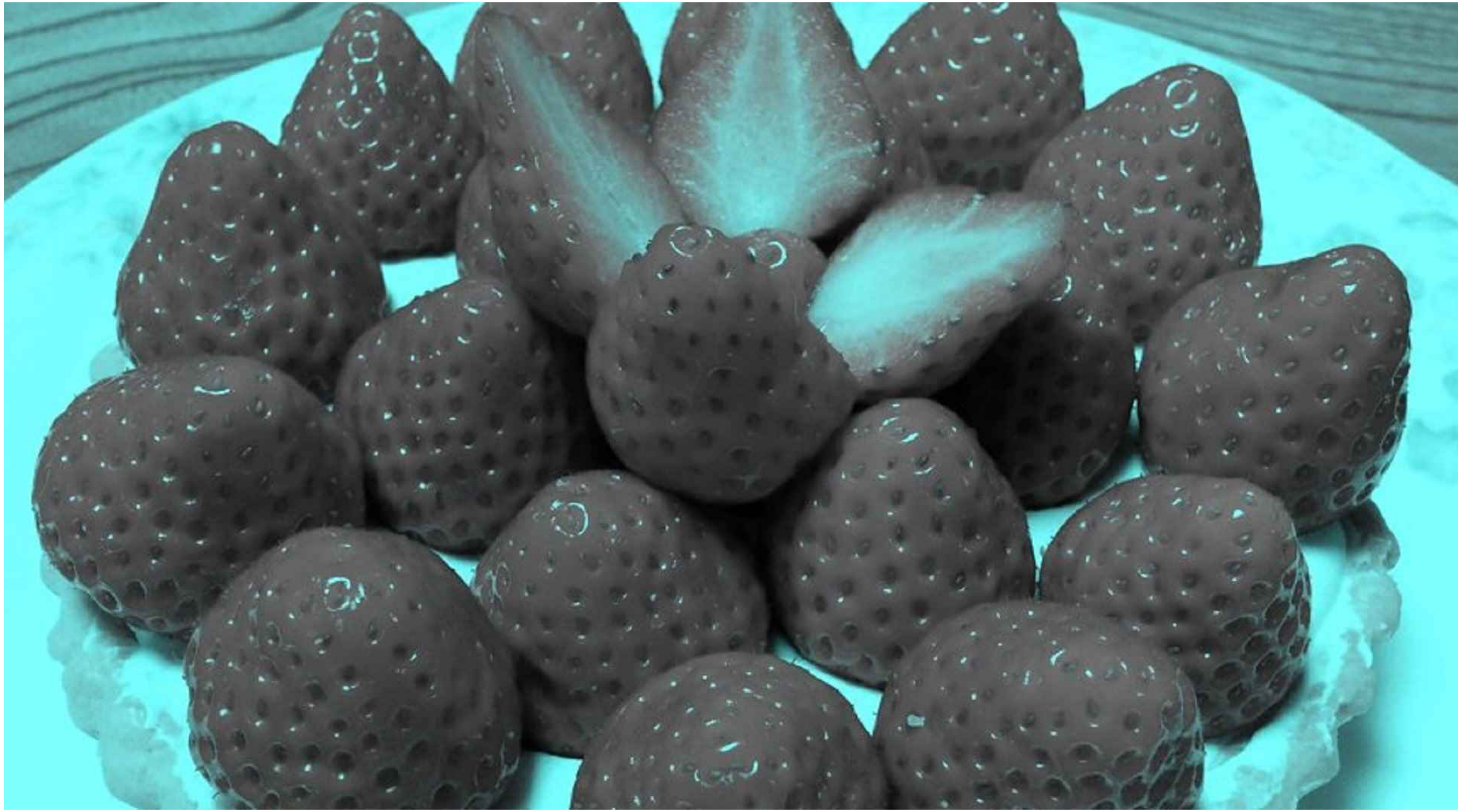


Image Credit: Akiyosha Kitoaka

Today's "**fun**" Example: Colour Constancy

— Some people see a white and gold dress.

— Some people see a blue and black dress.

— Some people see one interpretation and then switch to the other

https://www.nytimes.com/interactive/2015/02/28/science/white-or-blue-dress.html

Today’s “**fun**” Example: Colour Constancy

— Some people see a white and gold dress.

— Some people see a blue and black dress.

— Some people see one interpretation and then switch to the other

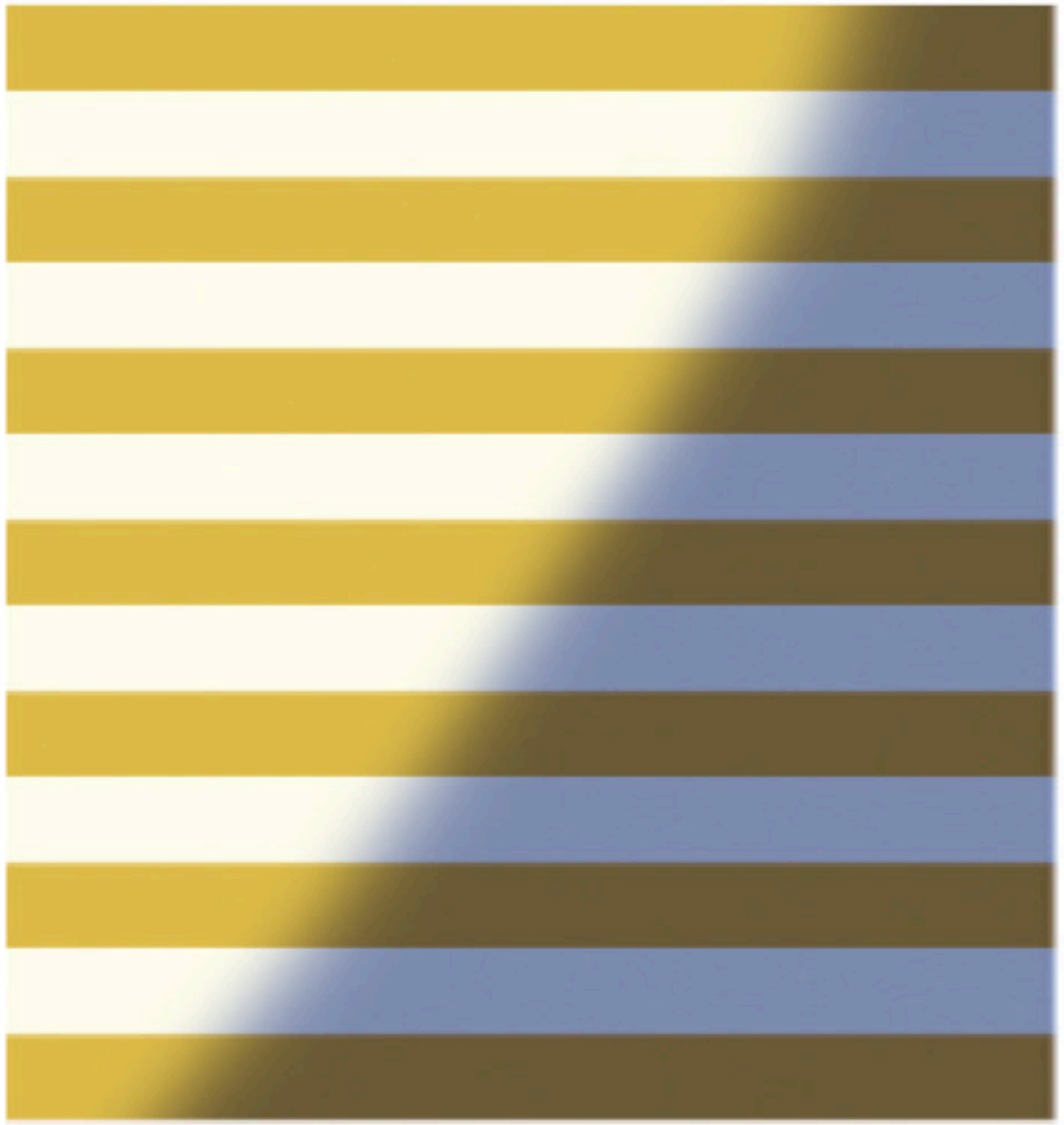
Two pieces of the dress | Average colors | The basic pattern of the dress

https://www.nytimes.com/interactive/2015/02/28/science/white-or-blue-dress.html

Today's "**fun**" Example: Colour Constancy

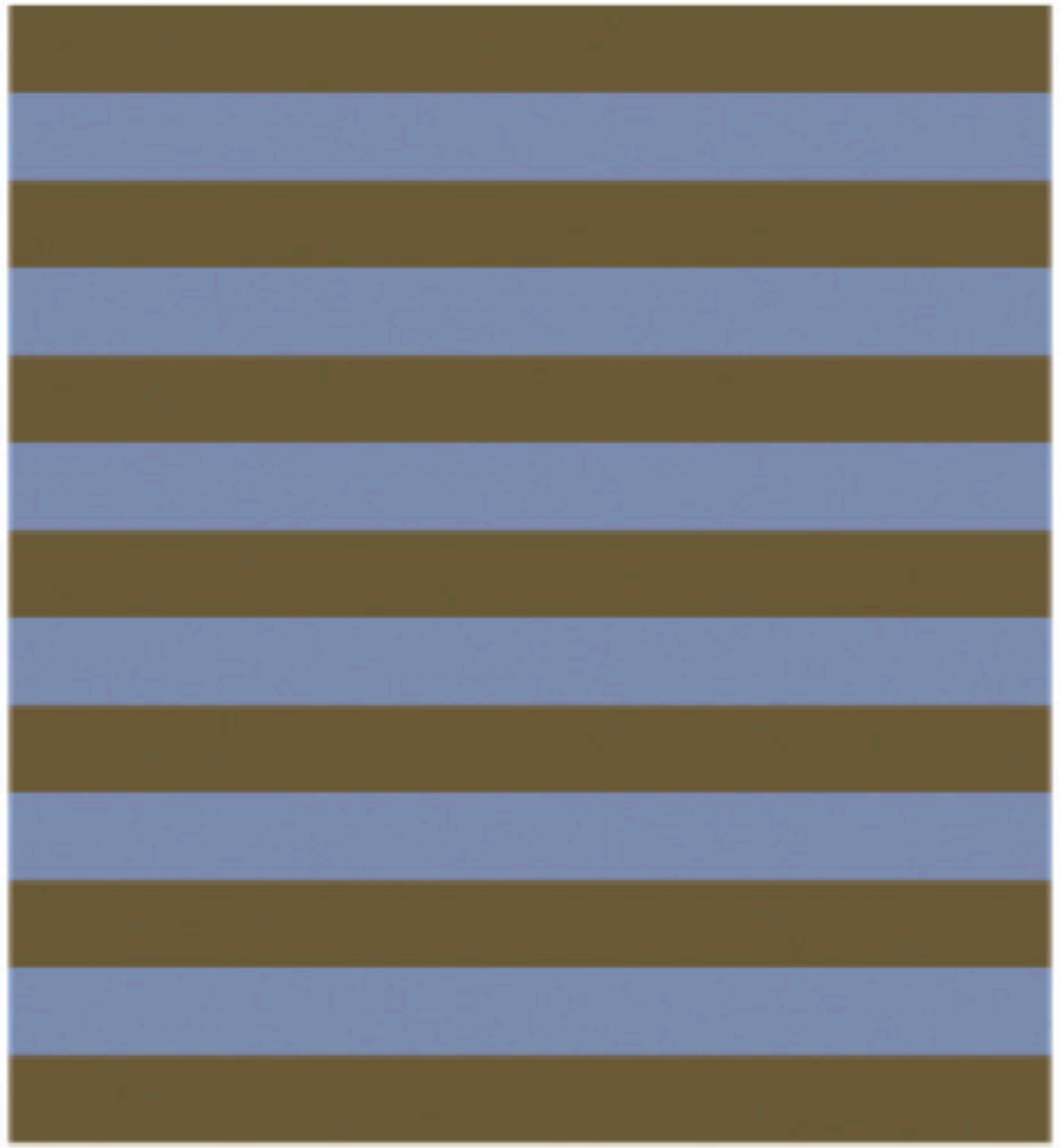
IS THE DRESS IN SHADOW?

If you think the dress is in shadow, your brain may remove the blue cast and perceive the dress as being white and gold.



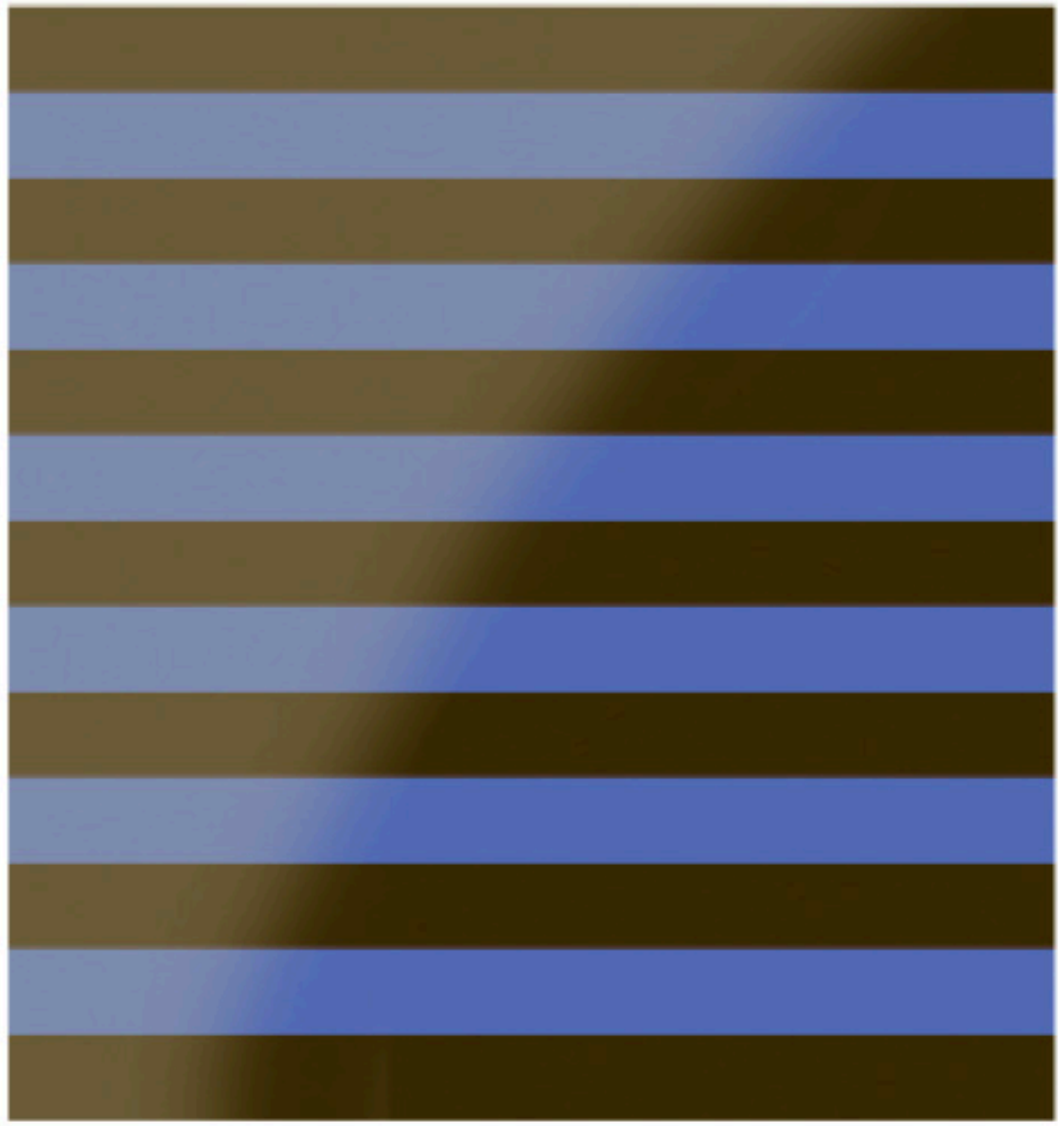
THE DRESS IN THE PHOTO

If the photograph showed more of the room, or if skin tones were visible, there might have been more clues about the ambient light.



IS THE DRESS IN BRIGHT LIGHT?

If you think the dress is being washed out by bright light, your brain may perceive the dress as a darker blue and black.



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Today’s “**fun**” Example: Colour Constancy

https://www.nytimes.com/interactive/2015/02/28/science/white-or-blue-dress.html

Lecture 9: Re-cap (Harris Corner Detection)

```
1.Compute image gradients over
 small region

2.Compute the covariance matrix

3.Compute eigenvectors and
 eigenvalues

4.Use threshold on eigenvalues to
 detect corners
```

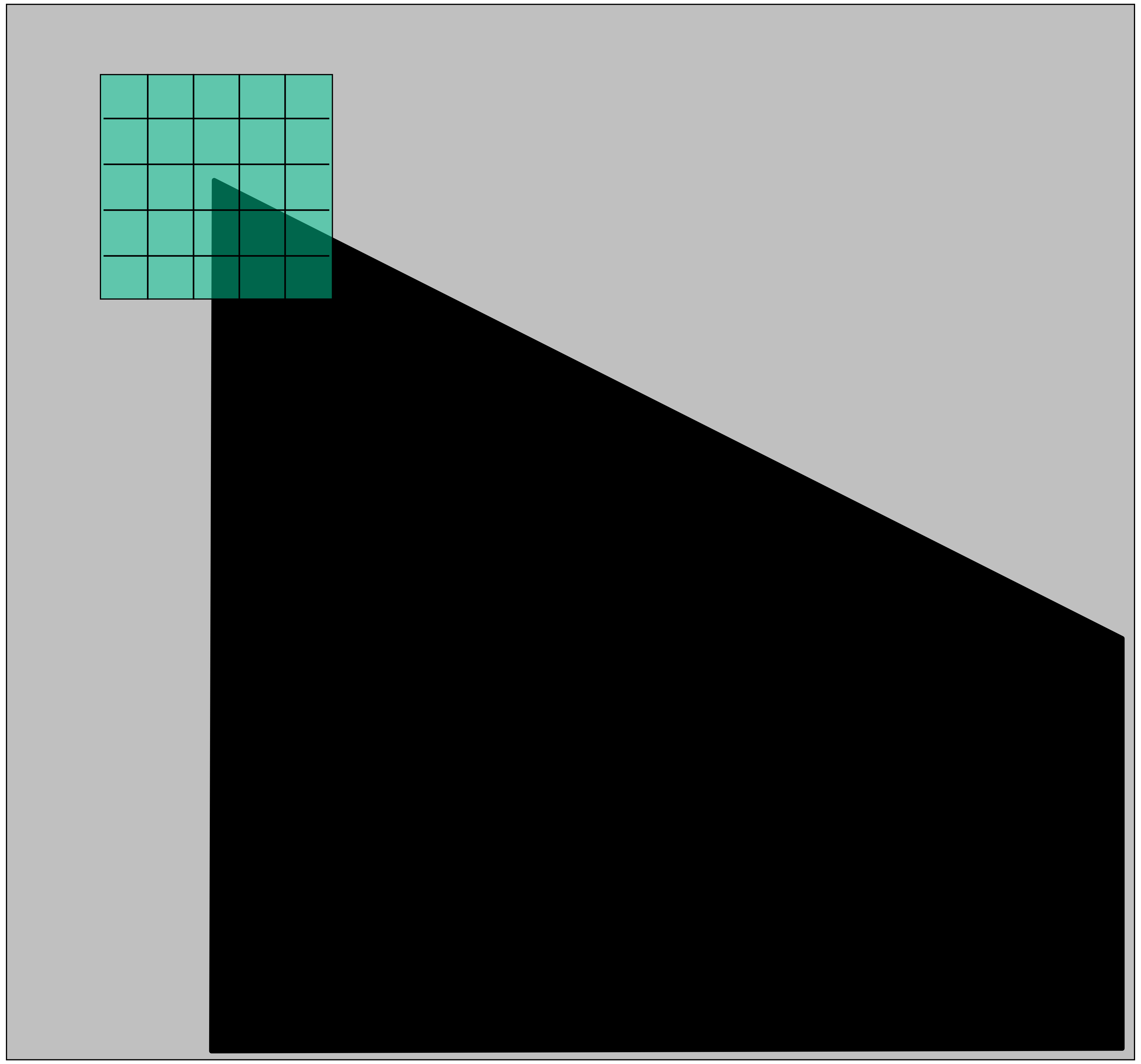
$$I_x = \frac{\partial I}{\partial x} \qquad I_y = \frac{\partial I}{\partial y}$$

$$\begin{bmatrix} \sum\limits_{p \in P} I_x I_x & \sum\limits_{p \in P} I_x I_y \\ \sum\limits_{p \in P} I_y I_x & \sum\limits_{p \in P} I_y I_y \end{bmatrix}$$

Slide Adopted: Ioannis (Yannis) Gkioulekas (CMU)

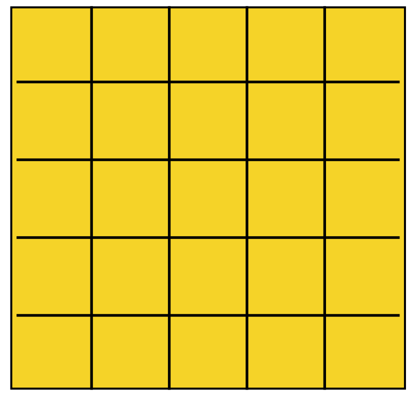
Lecture 9: Re-cap (compute image gradients at patch)

(not just a single pixel)



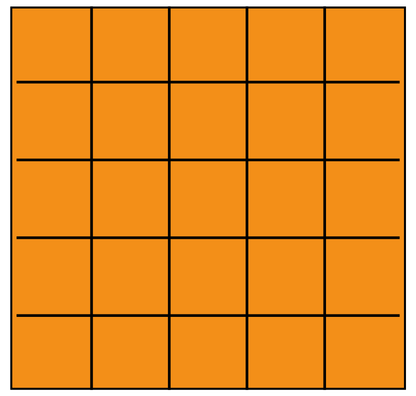
array of x gradients

$$I_x = \frac{\partial I}{\partial x}$$



array of y gradients

$$I_y = \frac{\partial I}{\partial y}$$



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Lecture 9: Re-cap (compute the covariance matrix)

Sum over small region around the corner

Gradient with respect to x, times gradient with respect to y

$$C = \begin{bmatrix} \sum_{p \in P} I_x I_x & \sum_{p \in P} I_x I_y \\ \sum_{p \in P} I_y I_x & \sum_{p \in P} I_y I_y \end{bmatrix}$$

Matrix is **symmetric**

Lecture 9: Re-cap

It can be shown that since every C is symmetric:

$$C = \begin{bmatrix} \sum\limits_{p \in P} I_x I_x & \sum\limits_{p \in P} I_x I_y \\ \sum\limits_{p \in P} I_y I_x & \sum\limits_{p \in P} I_y I_y \end{bmatrix} = R^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$

Lecture 9: Re-cap (computing eigenvalues and eigenvectors)

eigenvalue

$$Ce = \lambda e$$

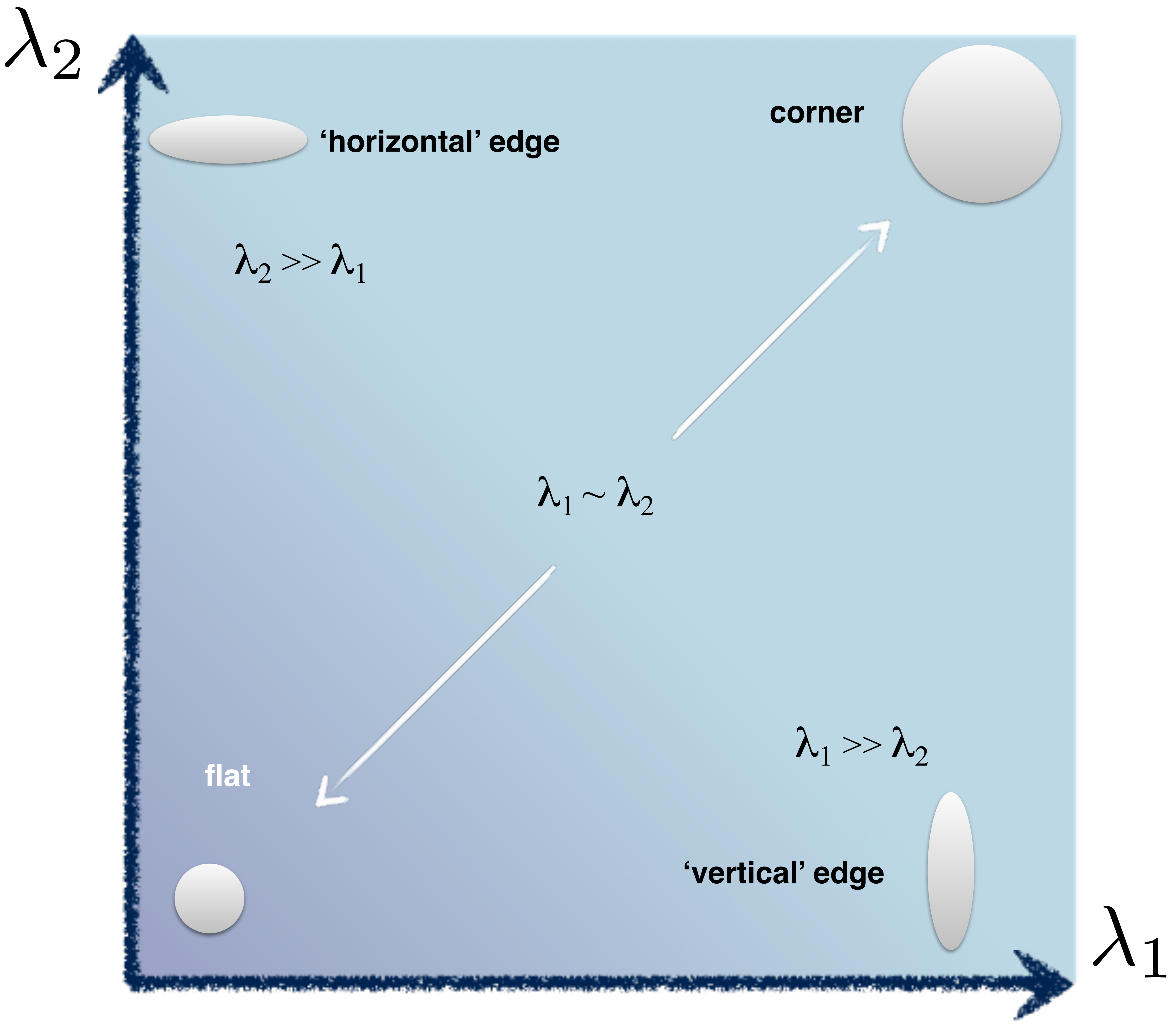
eigenvector

$$(C - \lambda I)e = 0$$

1. Compute the determinant of (returns a polynomial)	$C - \lambda I$
2. Find the roots of polynomial (returns eigenvalues)	$\det(C - \lambda I) = 0$
3. For each eigenvalue, solve (returns eigenvectors)	$(C - \lambda I)e = 0$

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Lecture 9: Re-cap (interpreting eigenvalues)



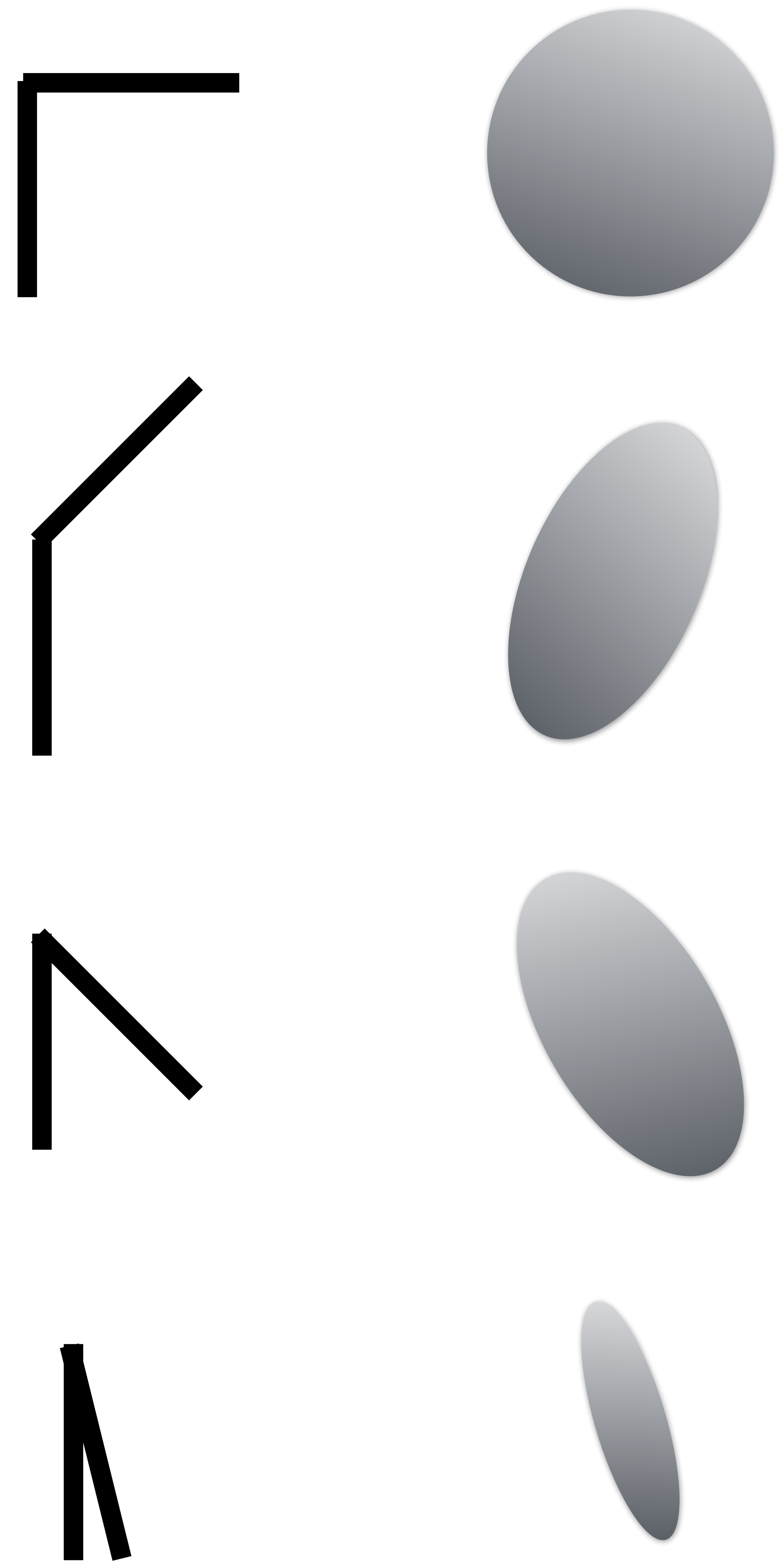


Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

Lecture 9: Re-cap (**Threshold** on Eigenvalues to **Detect Corners)**

Harris & Stephens (1988)

$$\det(C) - \kappa \operatorname{trace}^2(C)$$

Kanade & Tomasi (1994)

$$\min(\lambda_1, \lambda_2)$$

Nobel (1998)

$$\frac{\det(C)}{\operatorname{trace}(C) + \epsilon}$$

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Harris Corner Detection Review

— Filter image with **Gaussian**

— Compute magnitude of the x and y **gradients** at each pixel

— Construct C in a window around each pixel

— Harris uses a **Gaussian window**

Harris & Stephens (1988)

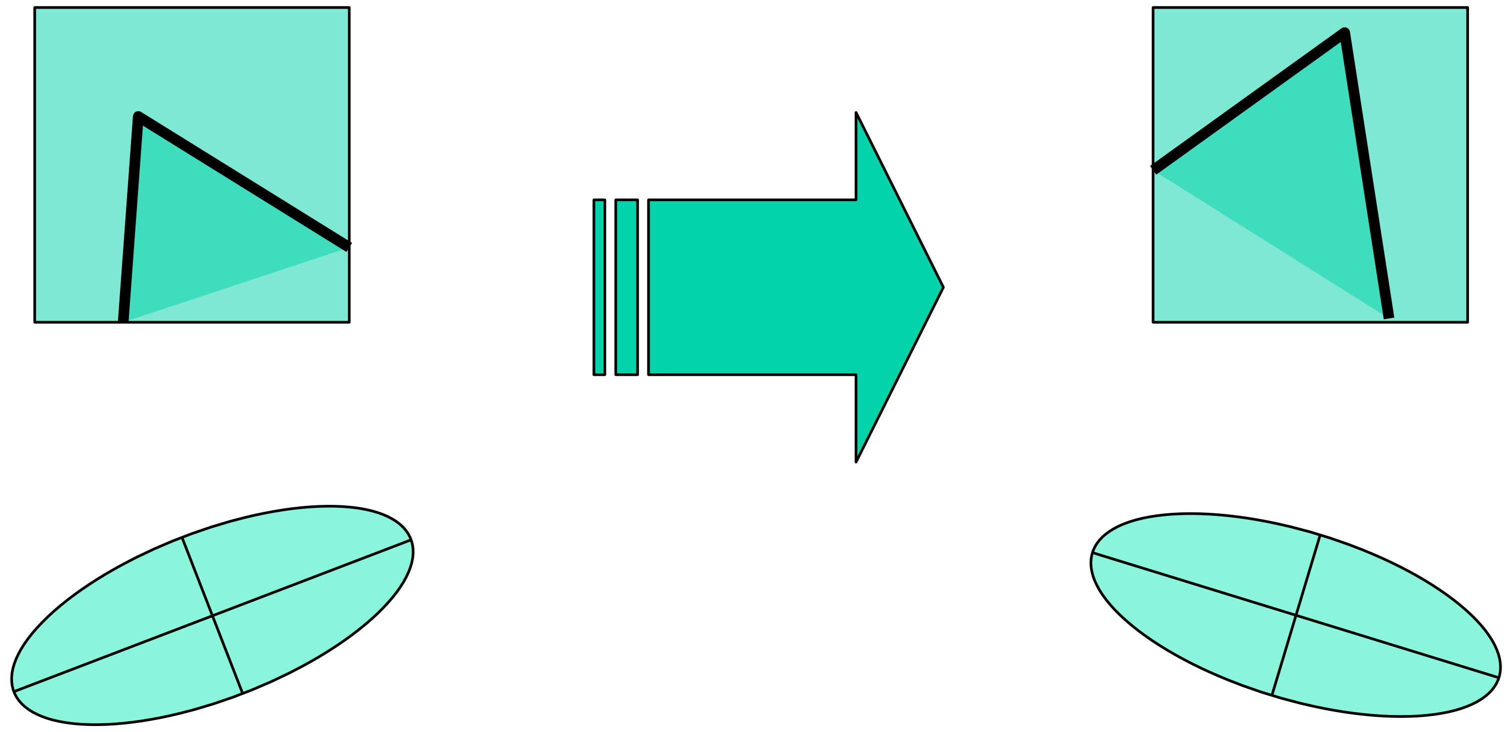
$$\det(C) - \kappa \operatorname{trace}^2(C)$$

— Solve for product of the λ's

— If λ's both are big (product reaches local maximum above threshold) then we have a corner

— Harris also checks that ratio of λs is not too high

Properties: Rotational Invariance



Ellipse rotates but its shape
(**eigenvalues**) remains the same

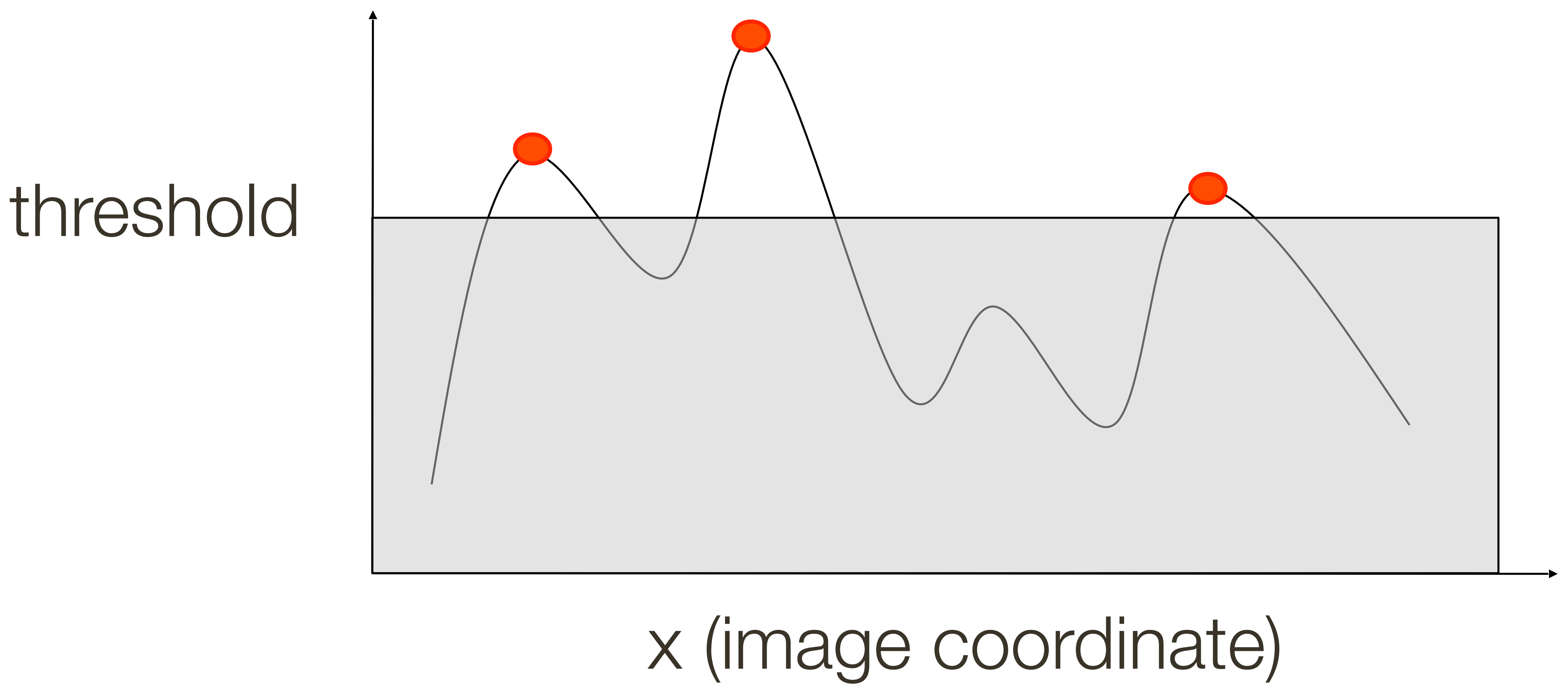
Corner response is **invariant** to image rotation

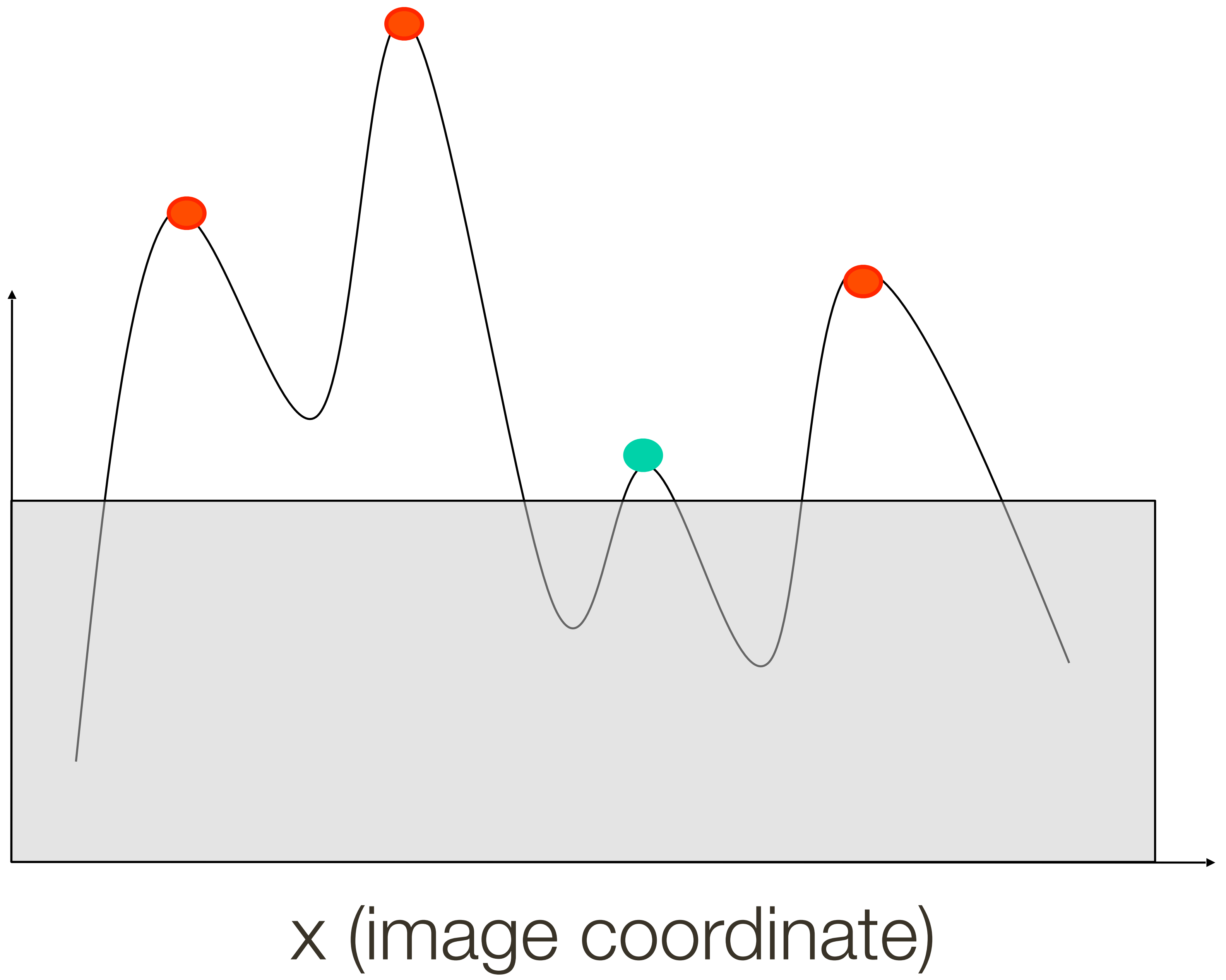
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Properties: (partial) Invariance to Intensity Shifts and Scaling

Only derivatives are used -> Invariance to intensity shifts

Intensity scale could effect performance





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Properties: NOT Invariant to Scale Changes

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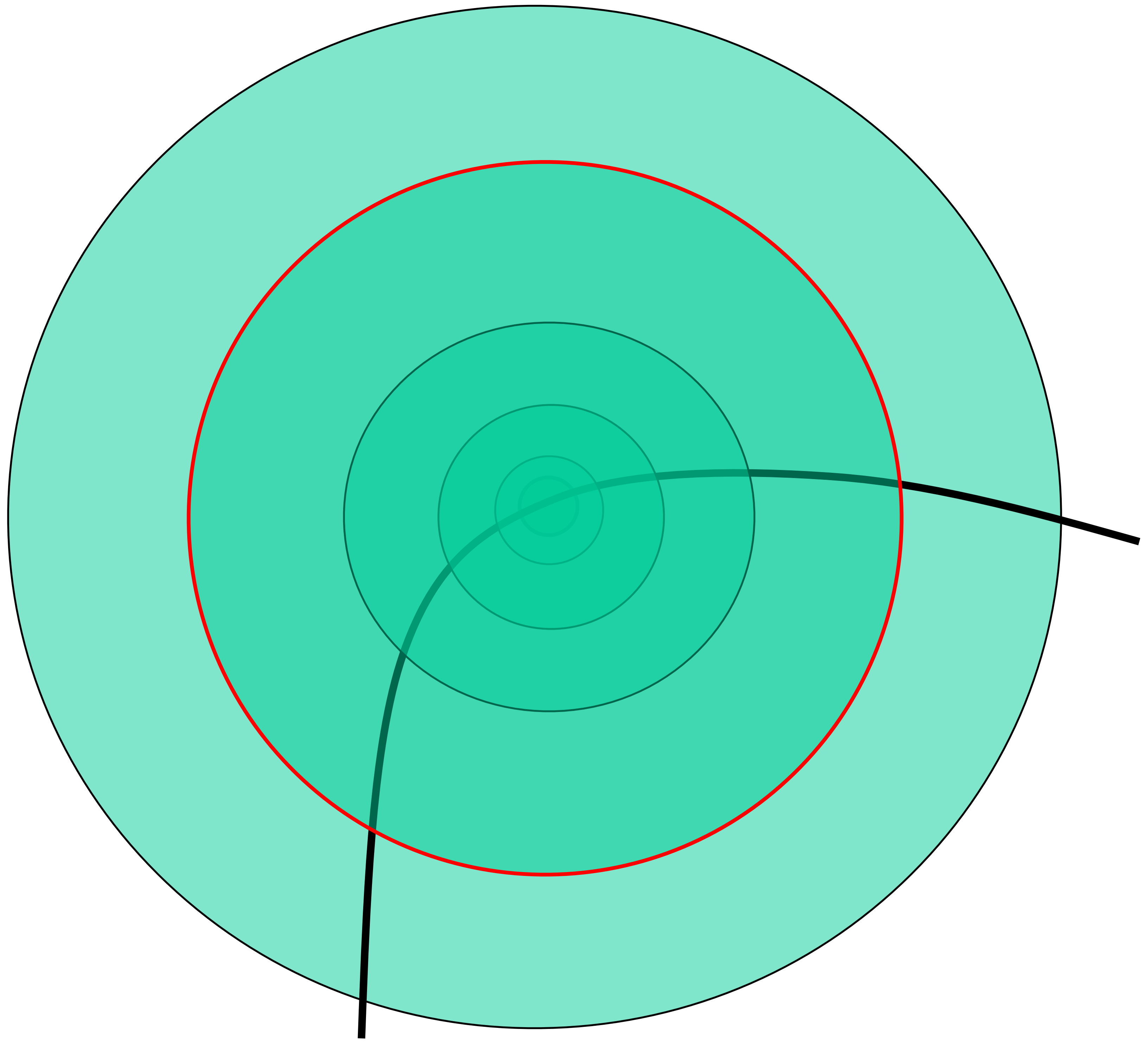
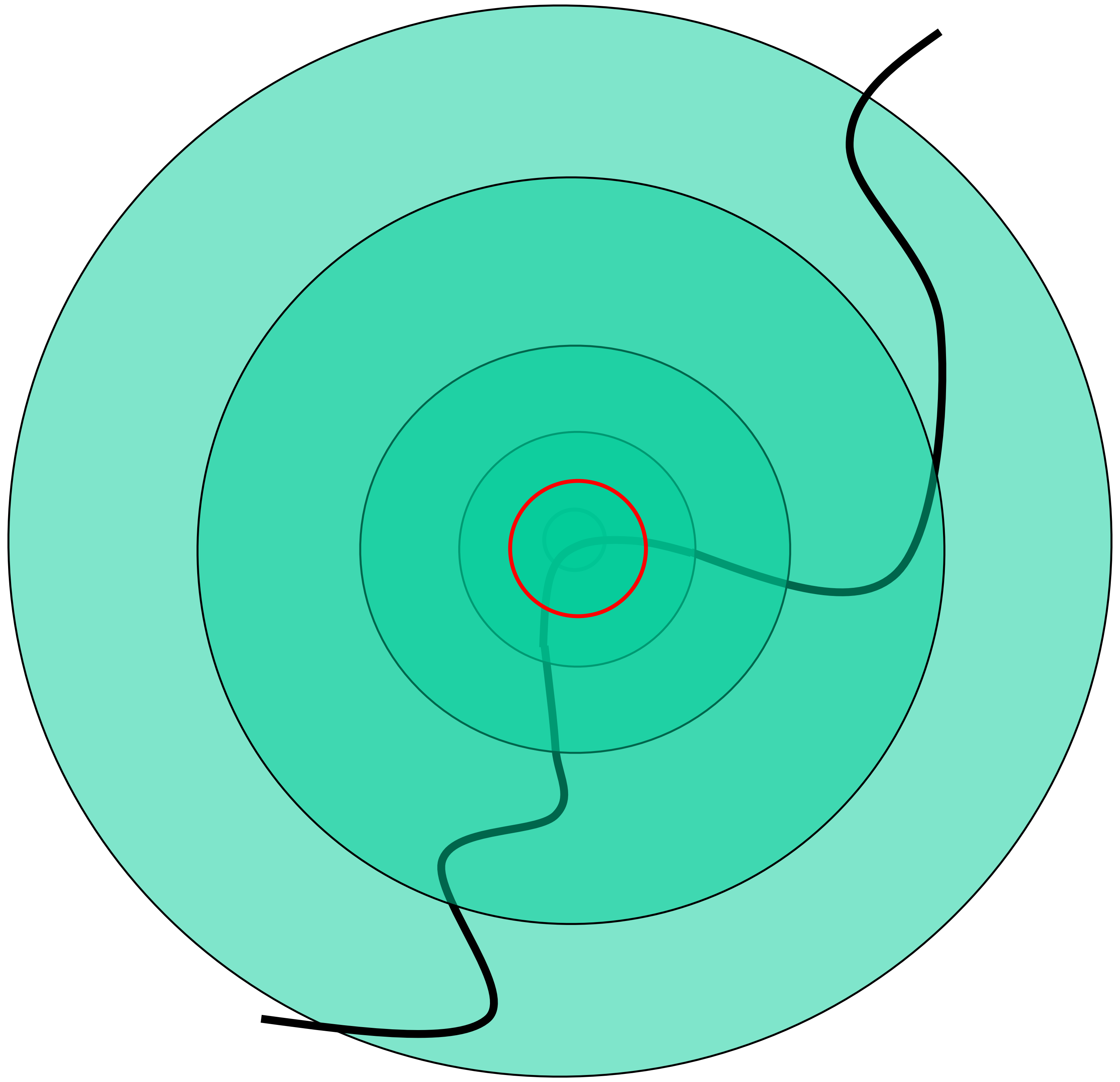
Intuitively …





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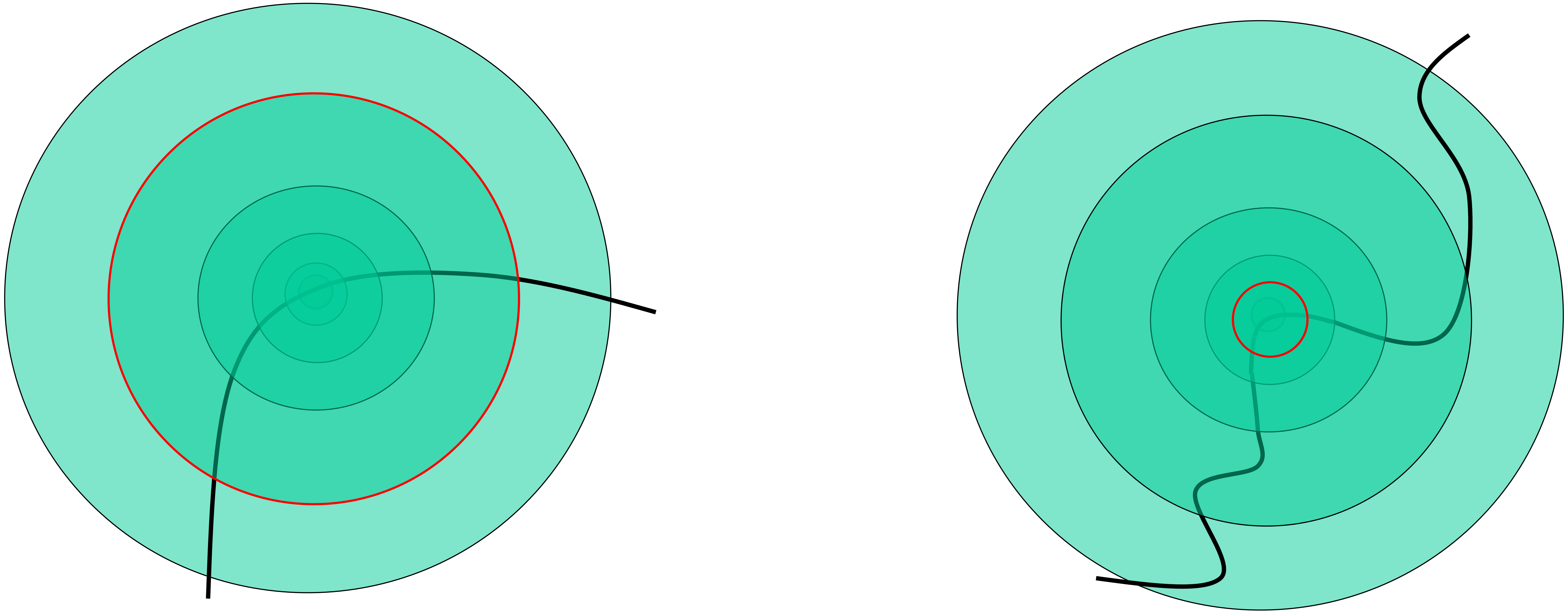
Intuitively …

Find local maxima in both **position** and **scale**



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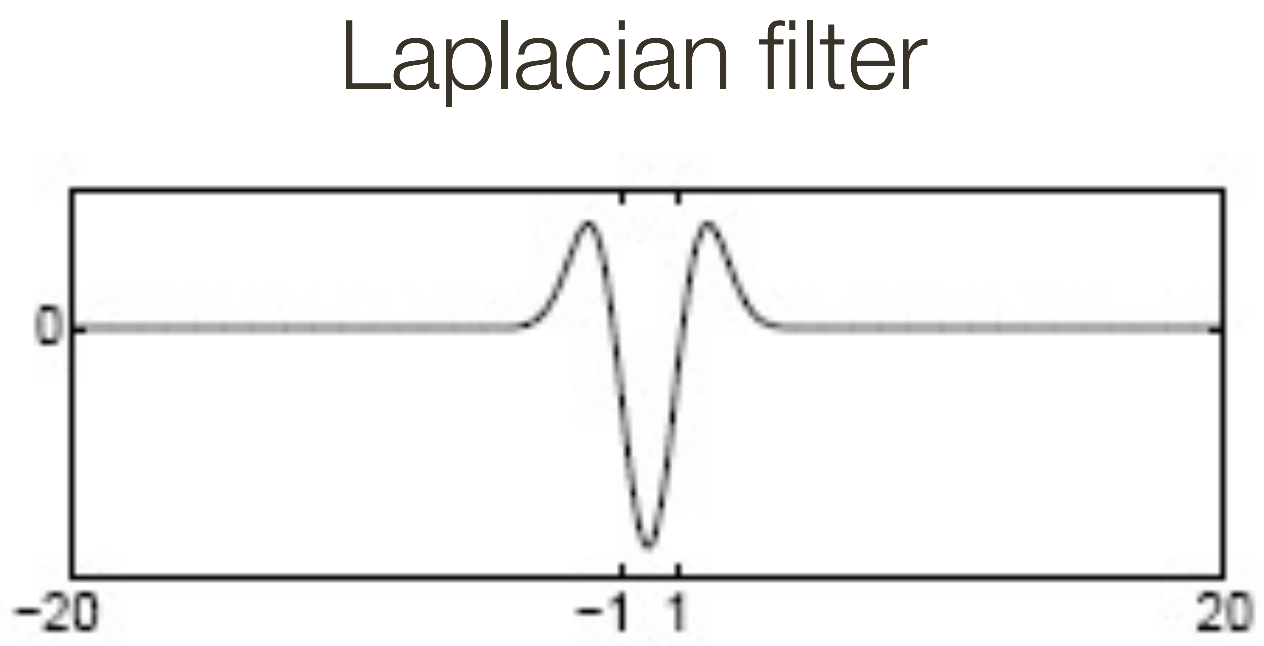
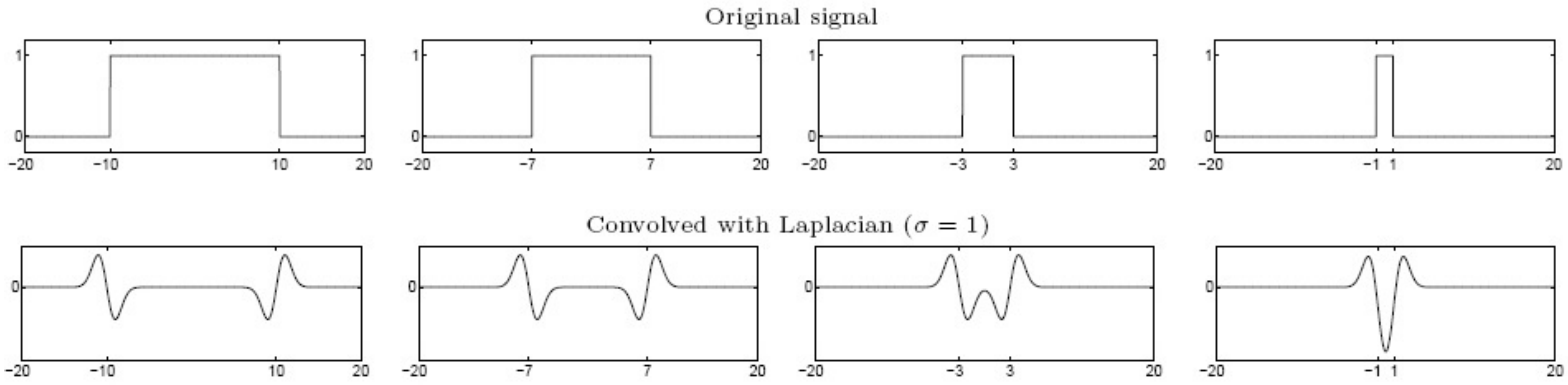
Formally …





Highest response when the signal has the same **characteristic scale** as the filter

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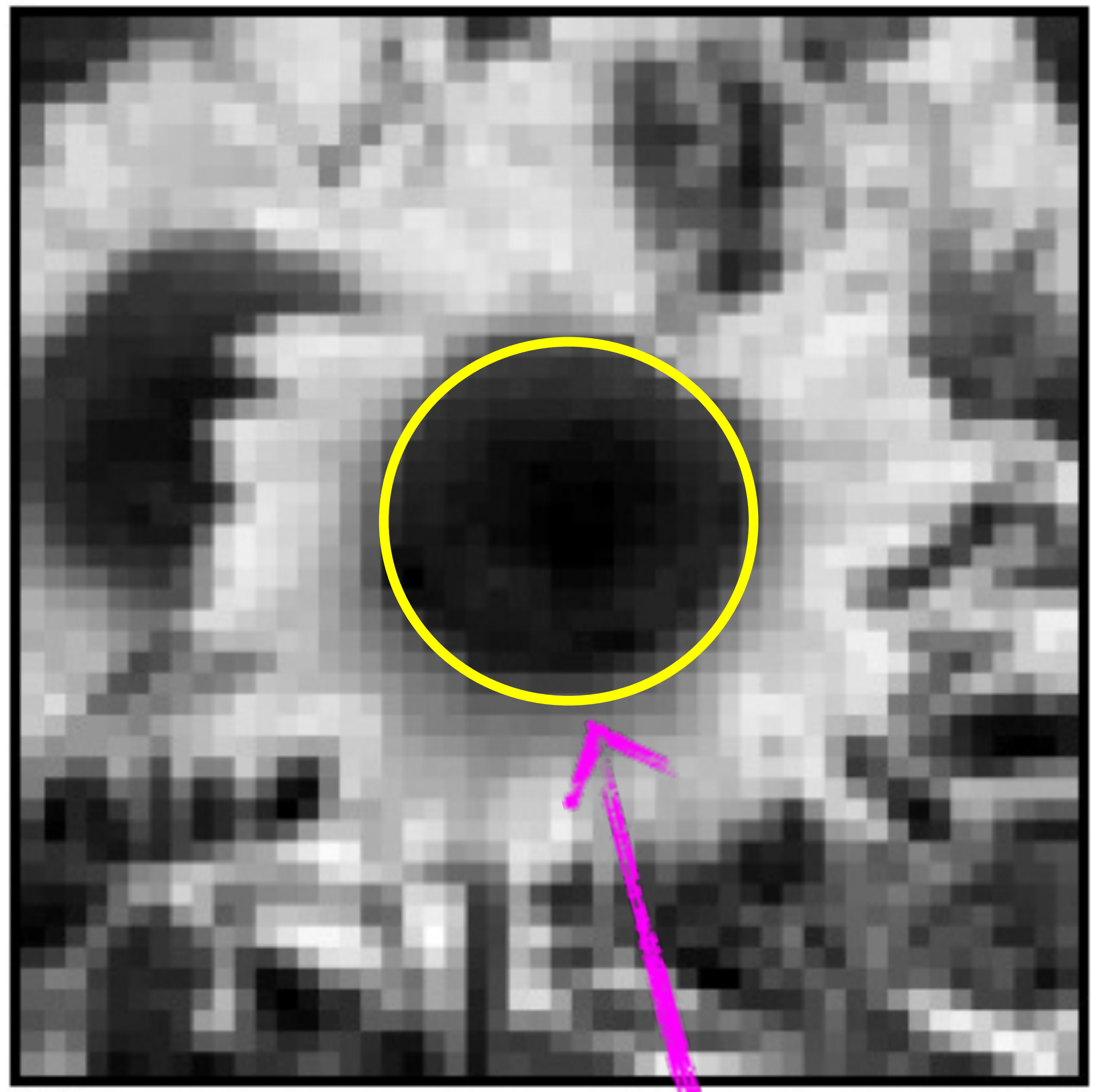
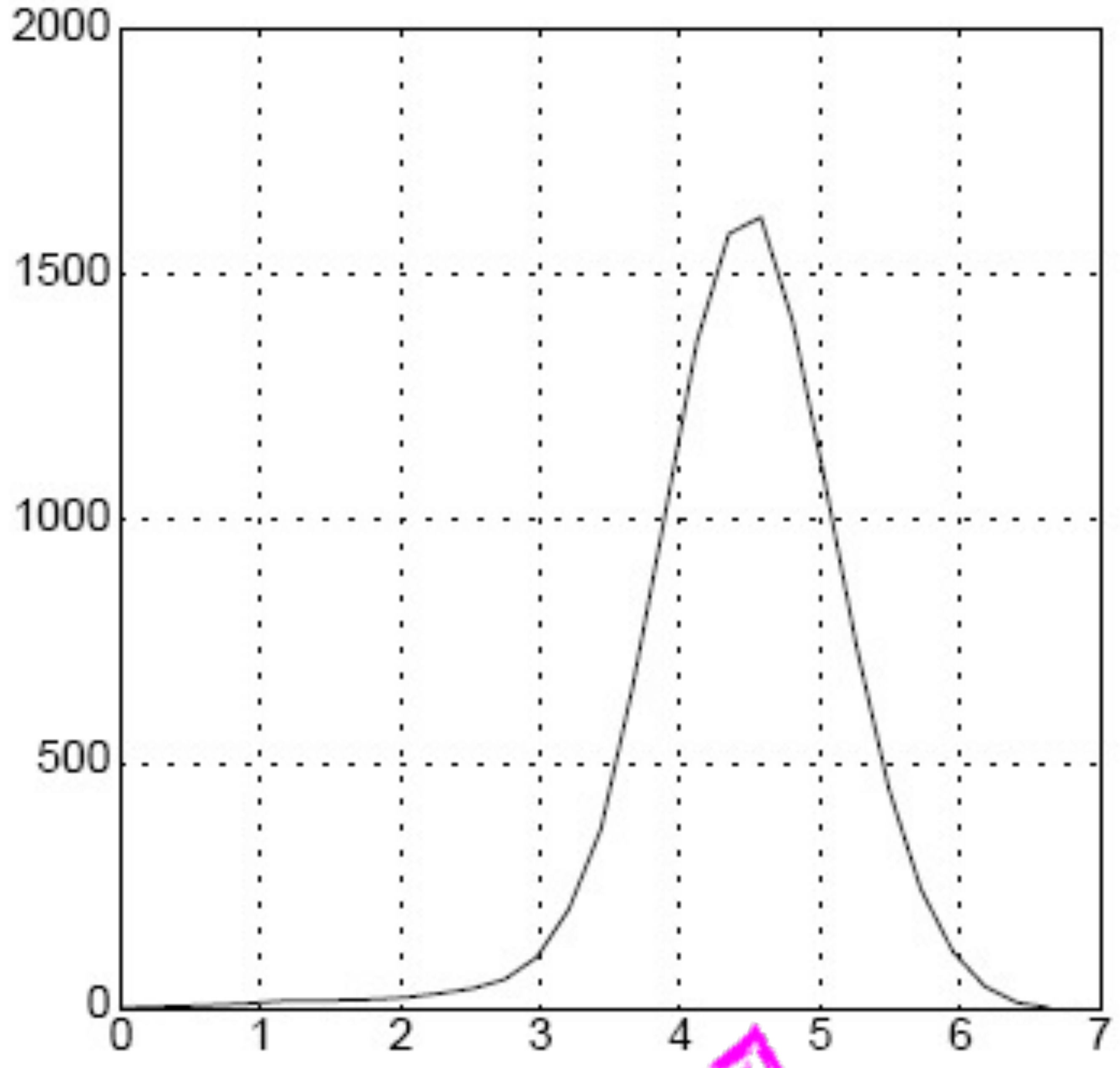
Characteristic Scale

characteristic scale - the scale that produces peak filter response





characteristic scale

we need to search over characteristic scales

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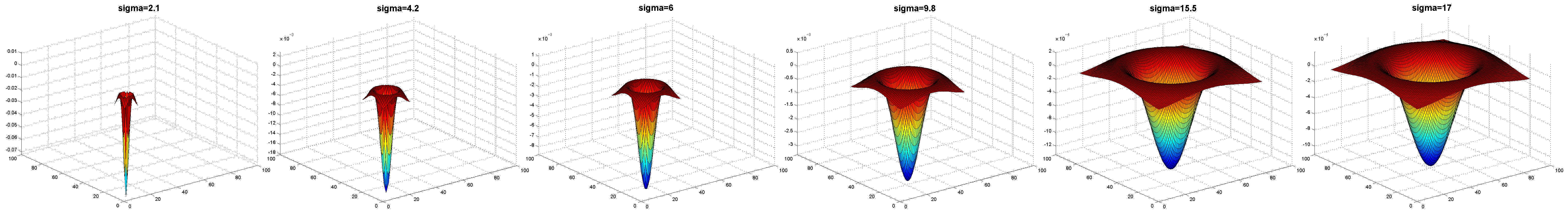
Applying **Laplacian** Filter at Different **Scales**



Full size

3/4 size

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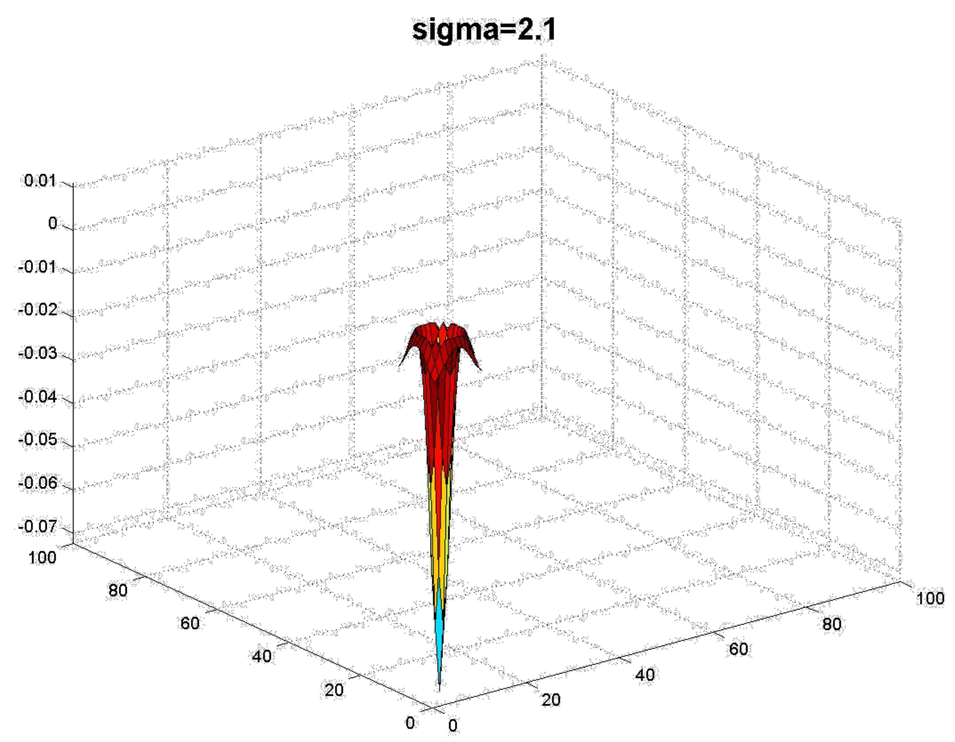

jet color scale
blue: low, red: high

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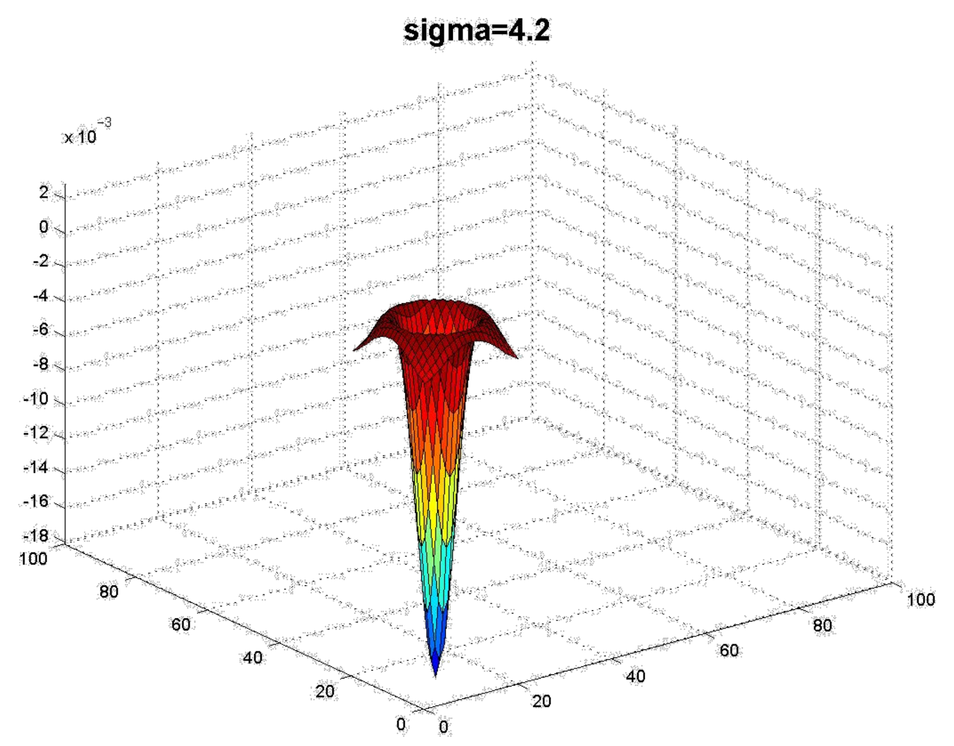

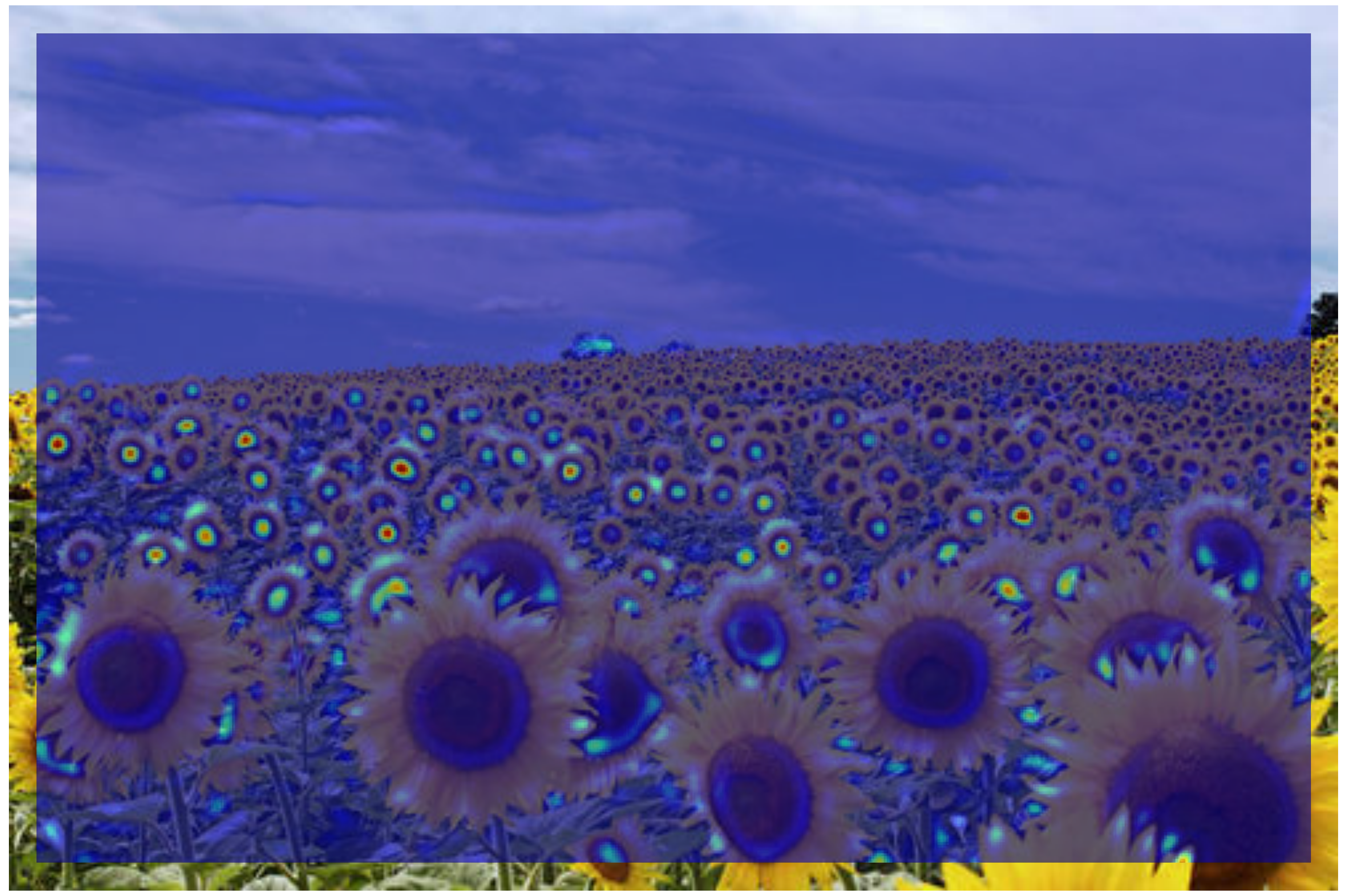

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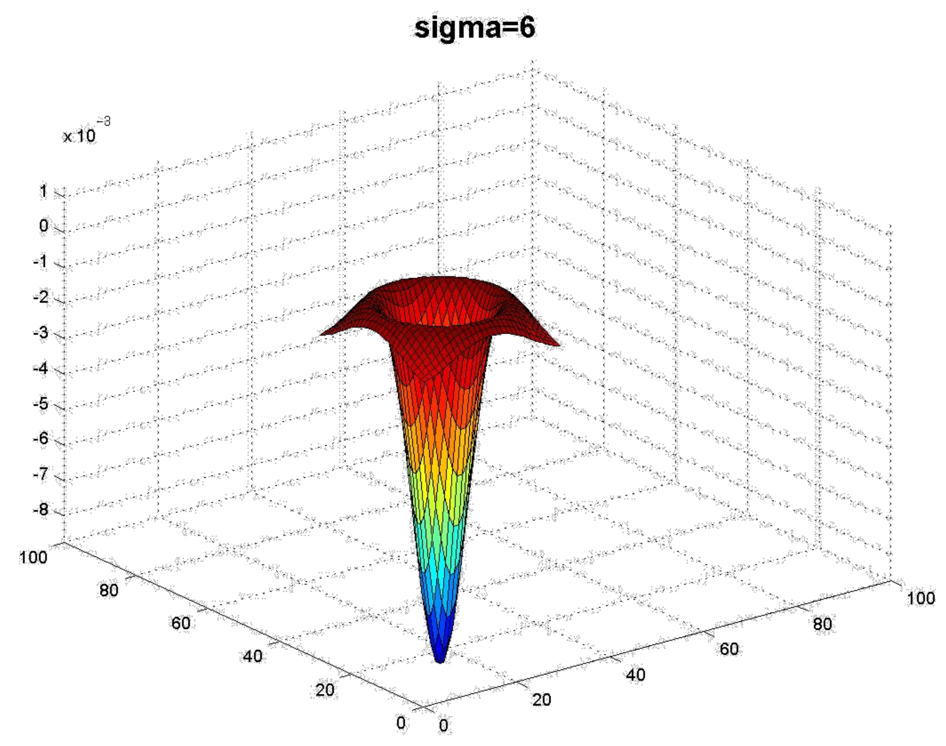

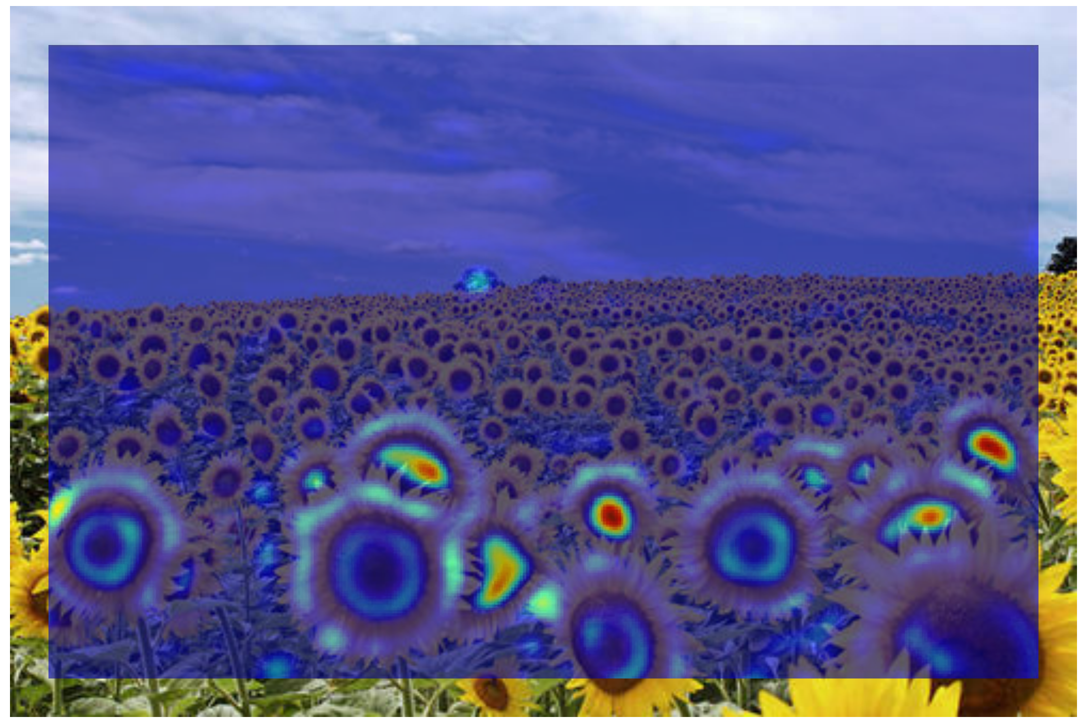

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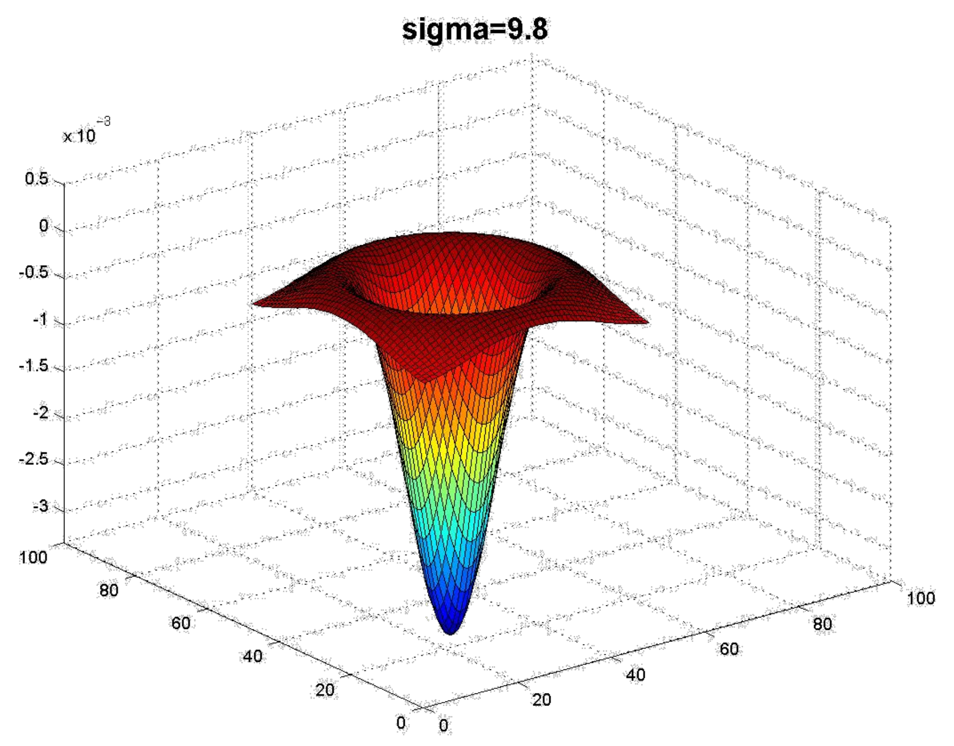

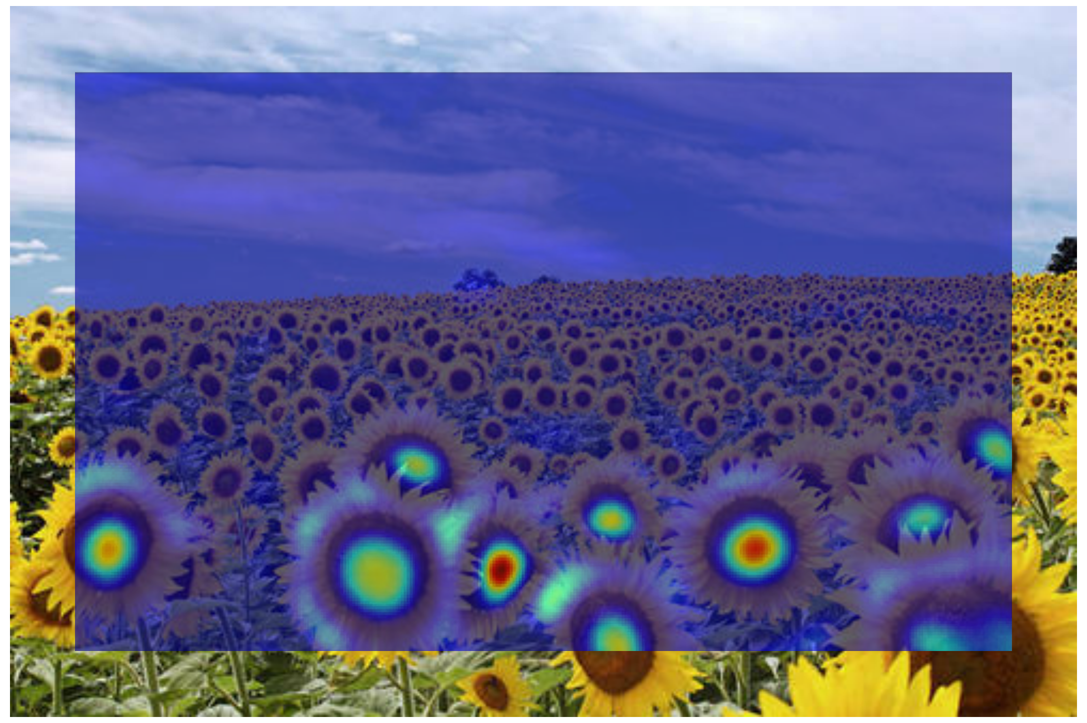

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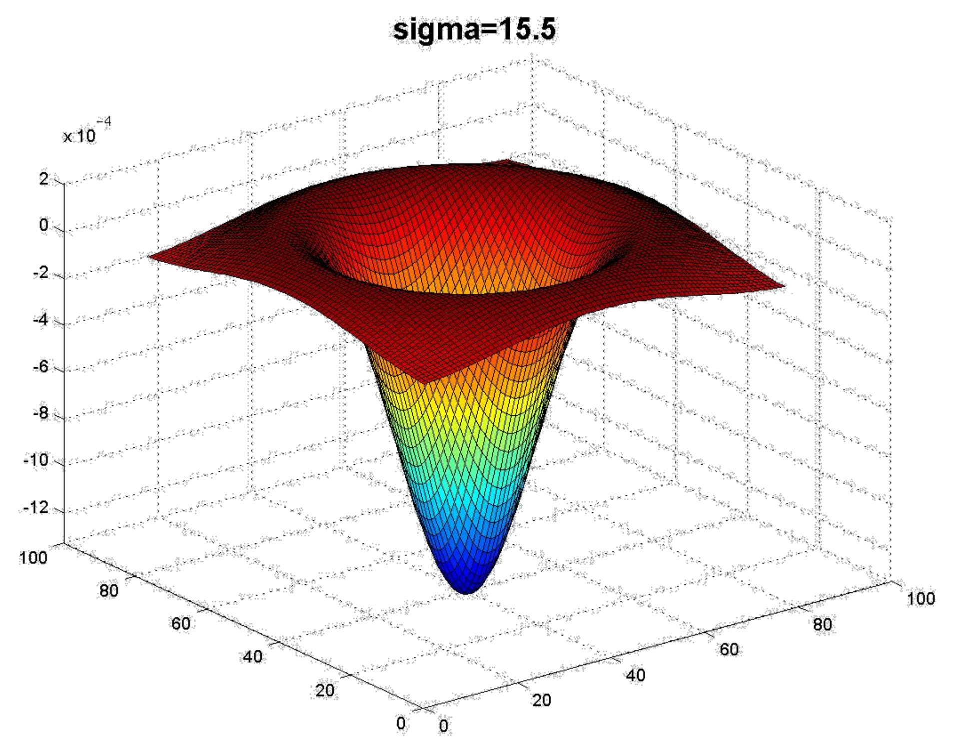

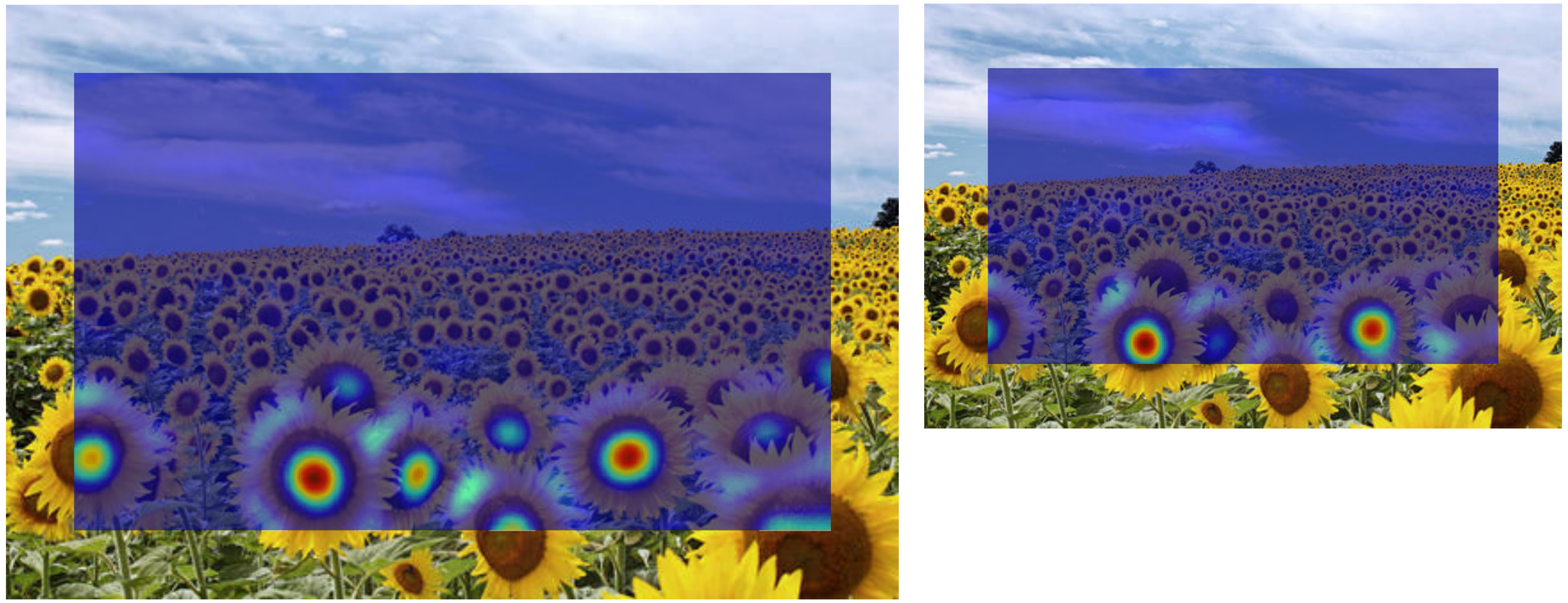

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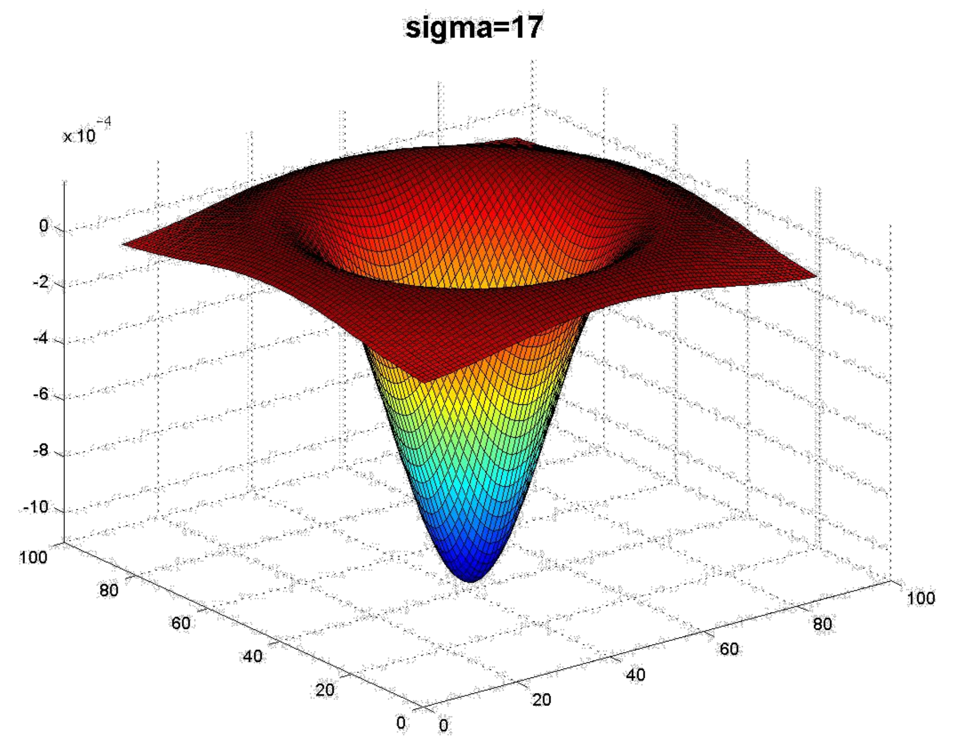

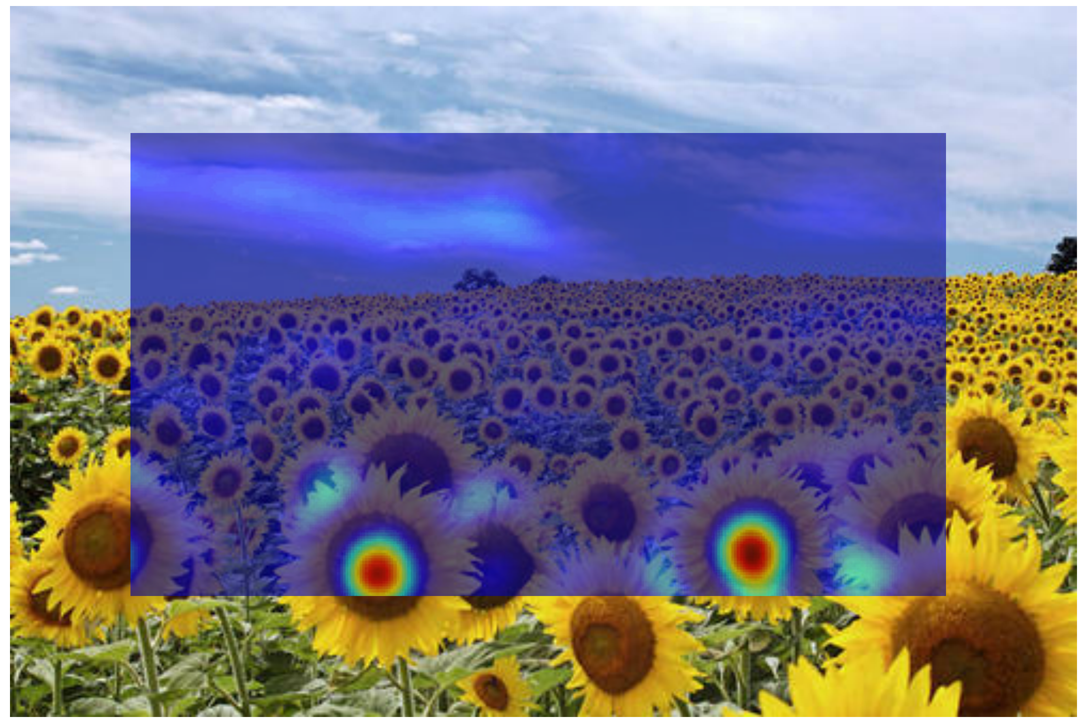

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Applying **Laplacian** Filter at Different **Scales**

Full size

3/4 size

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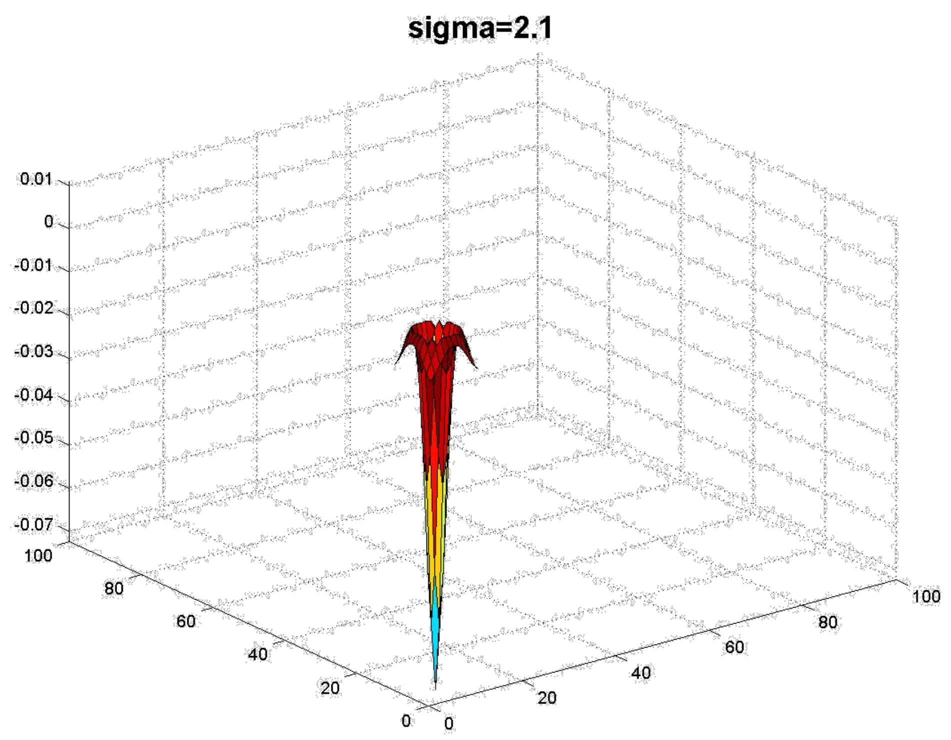

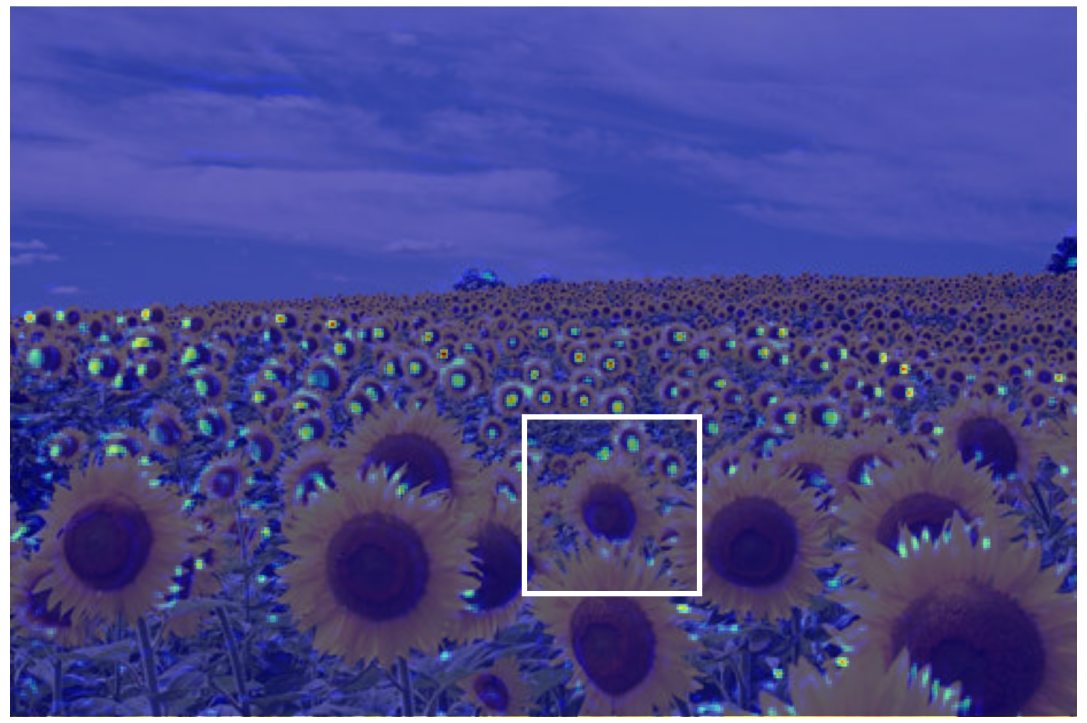

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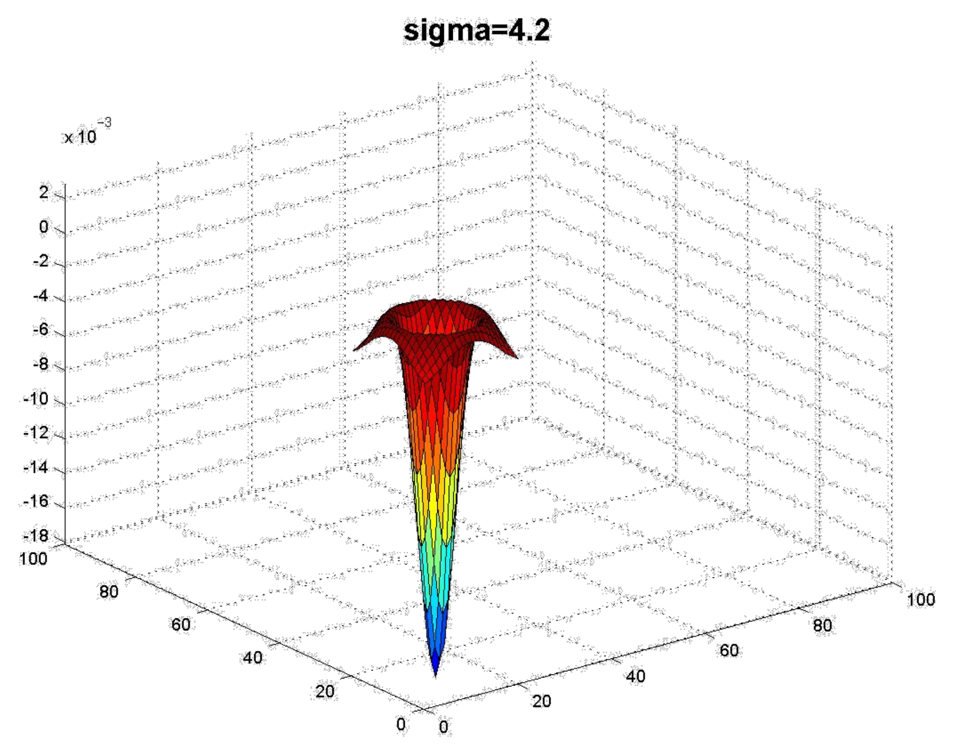

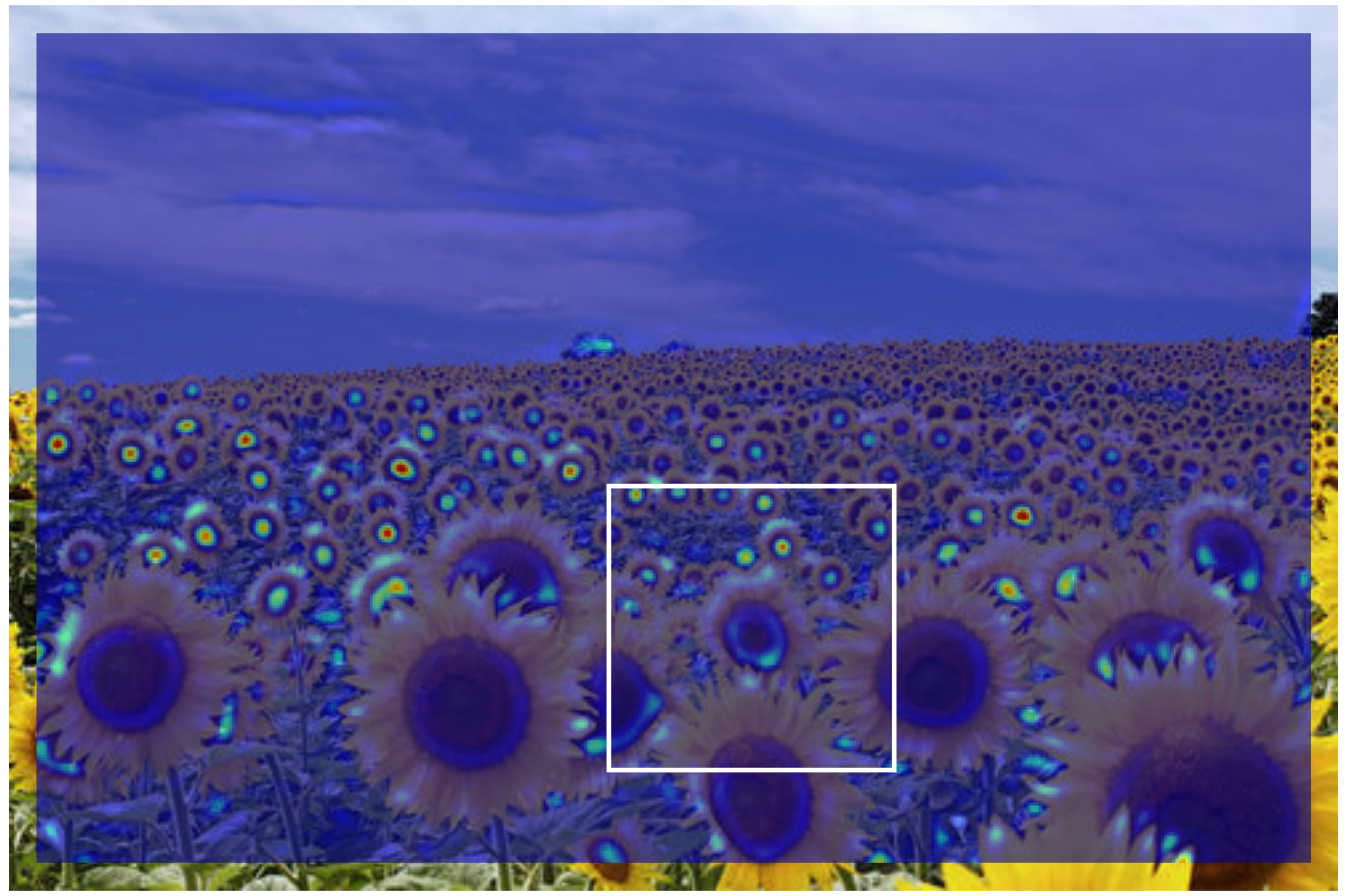

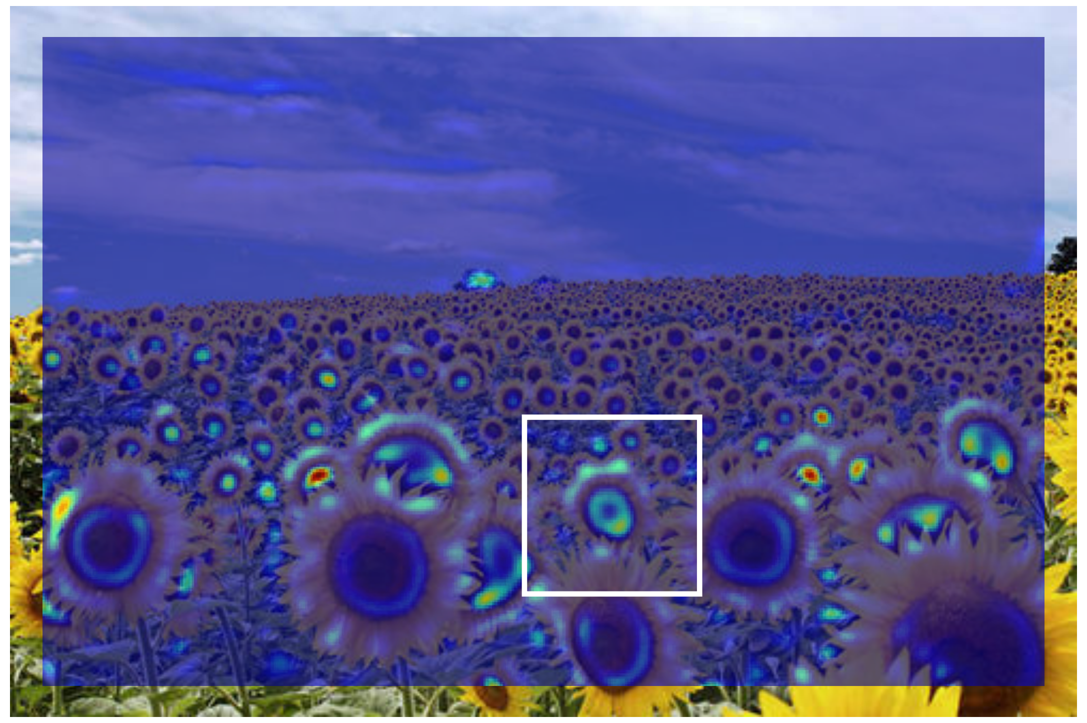

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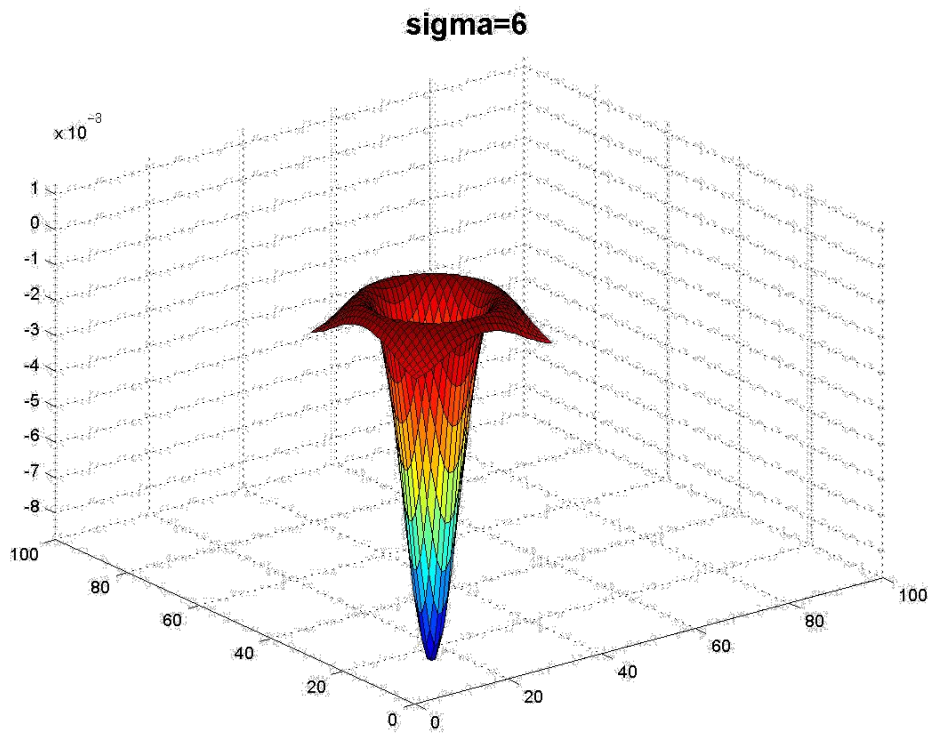

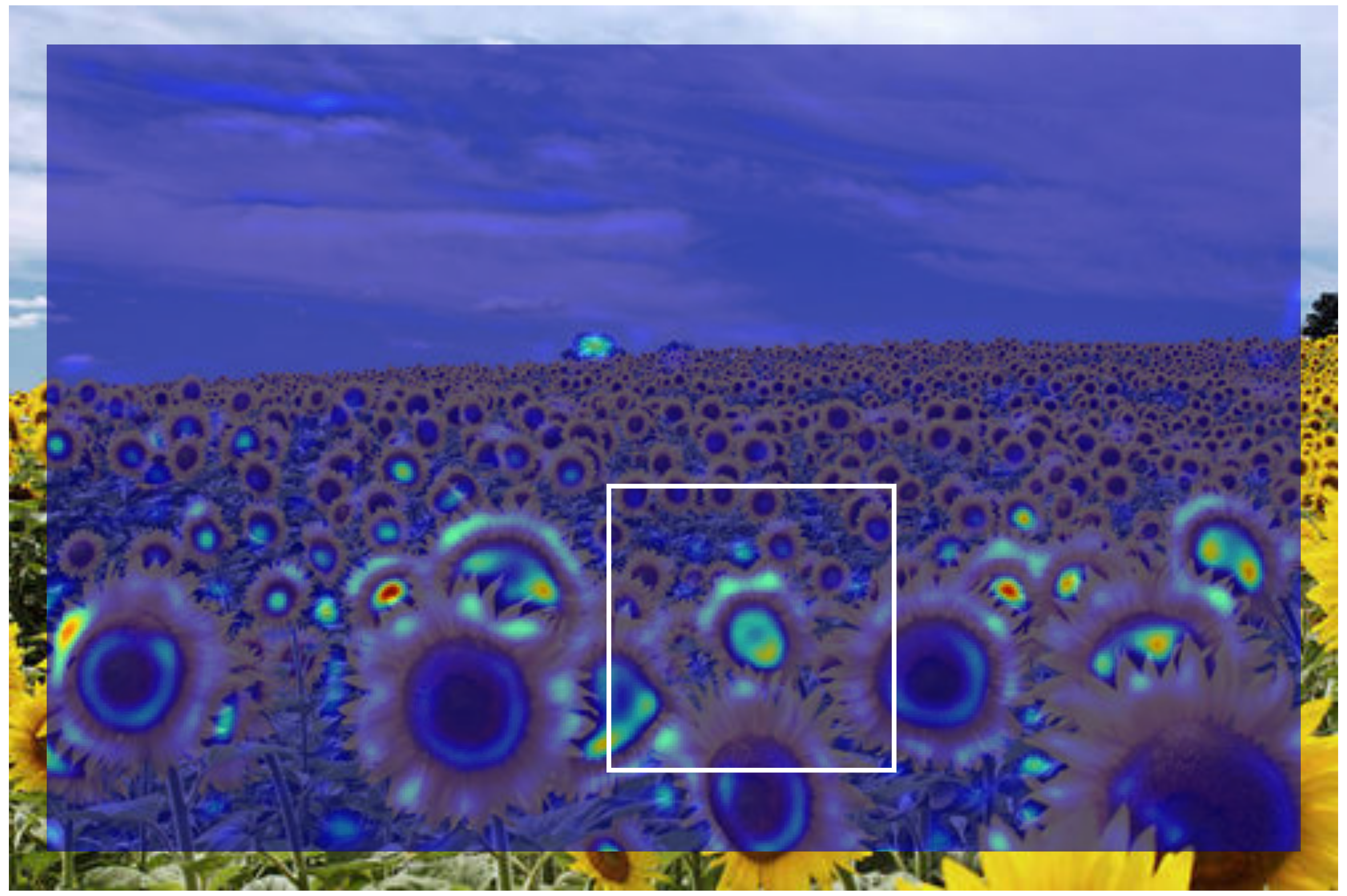

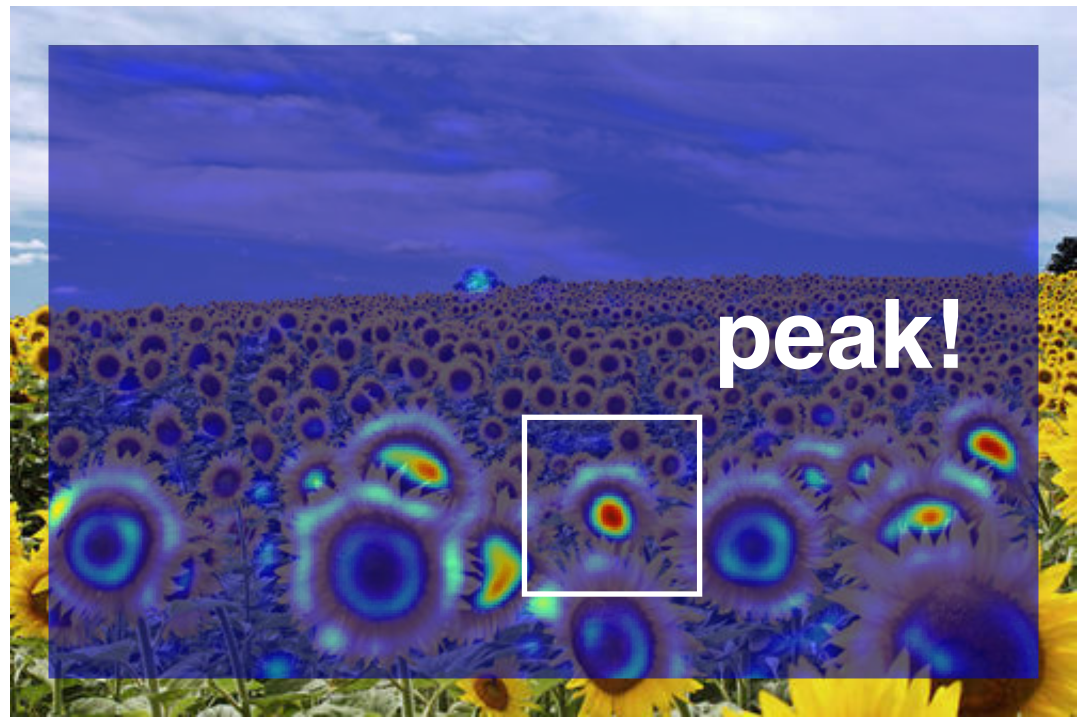

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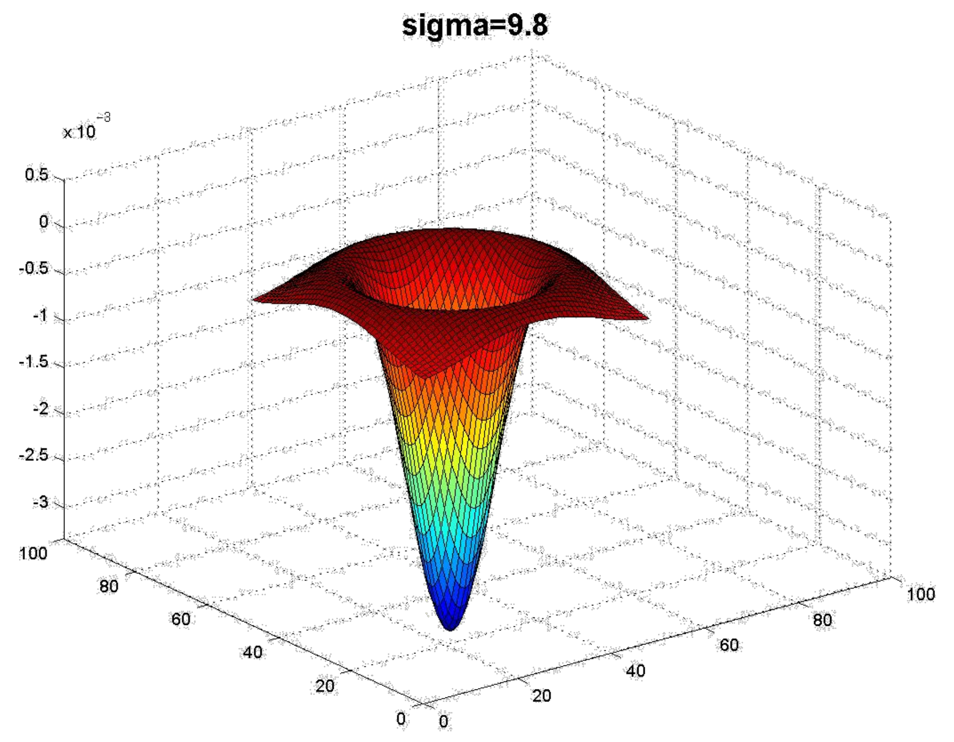

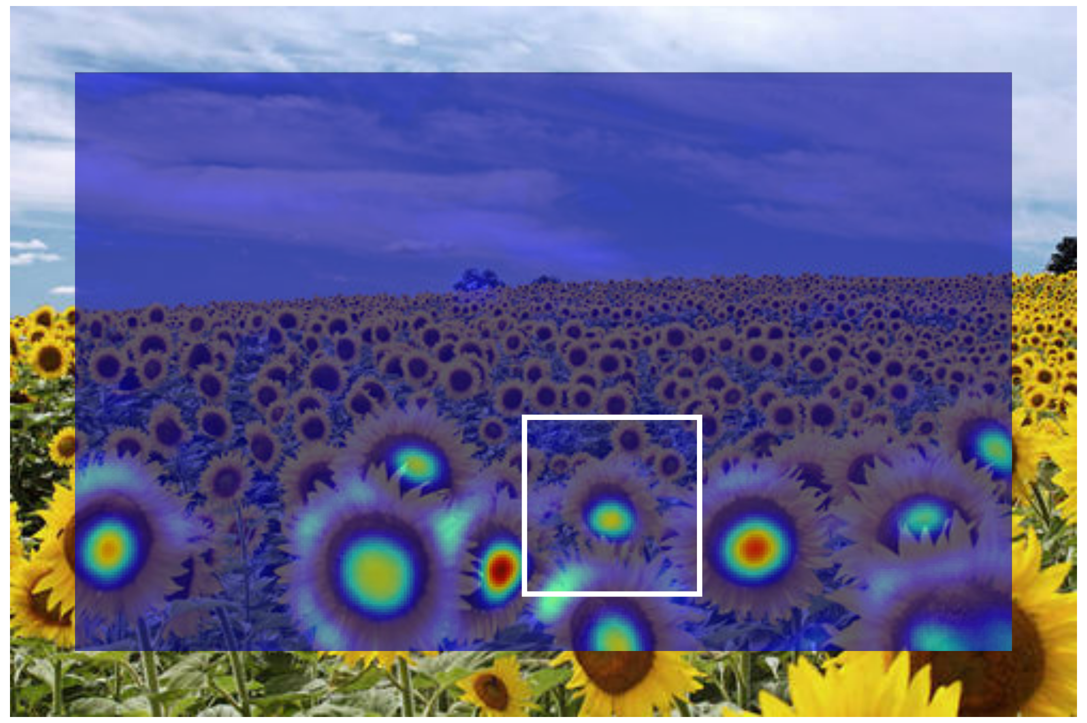

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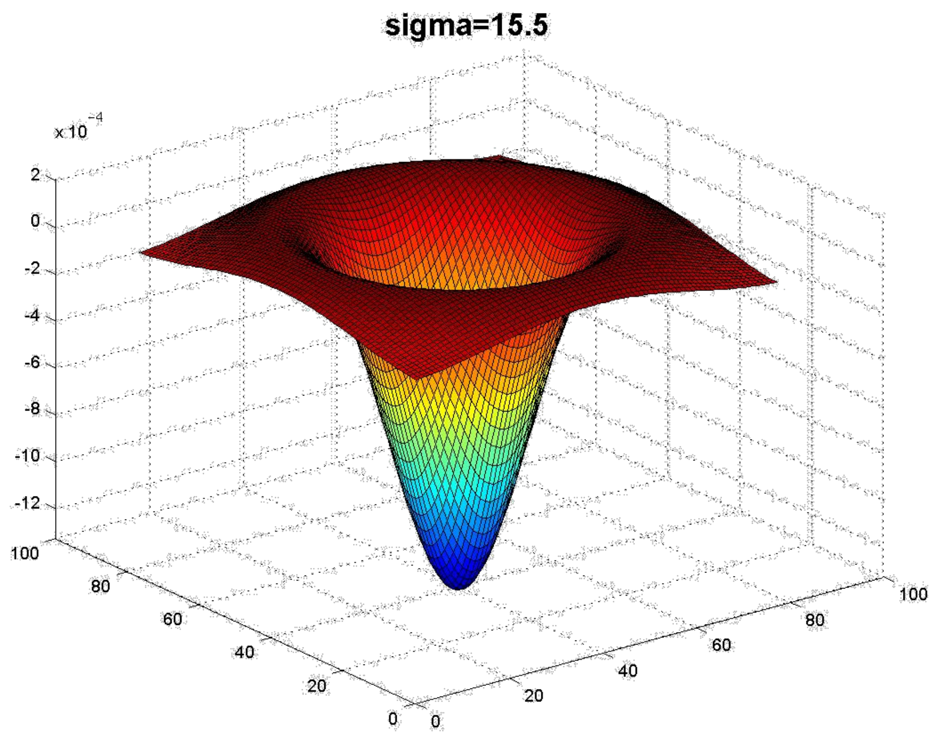

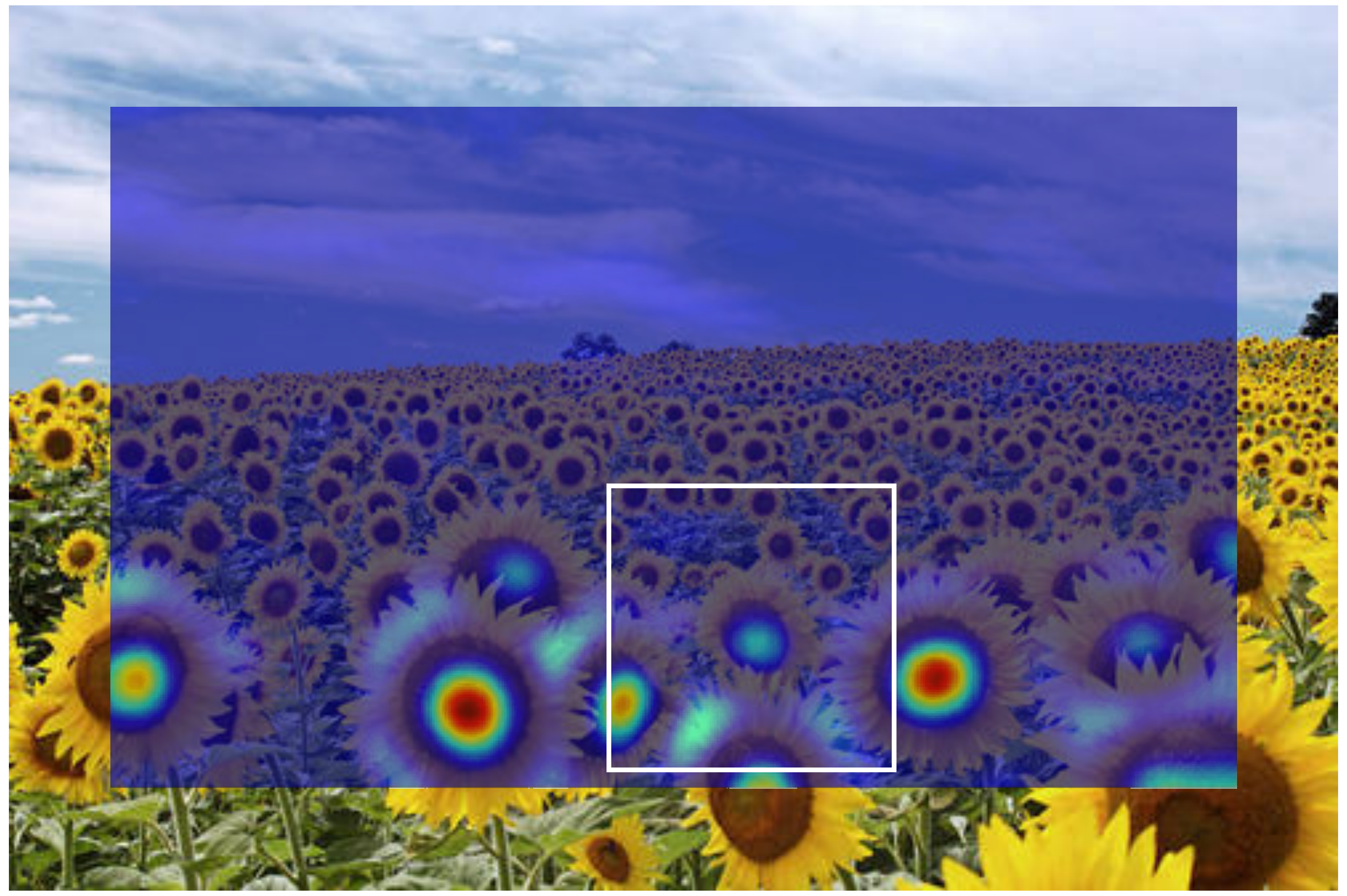

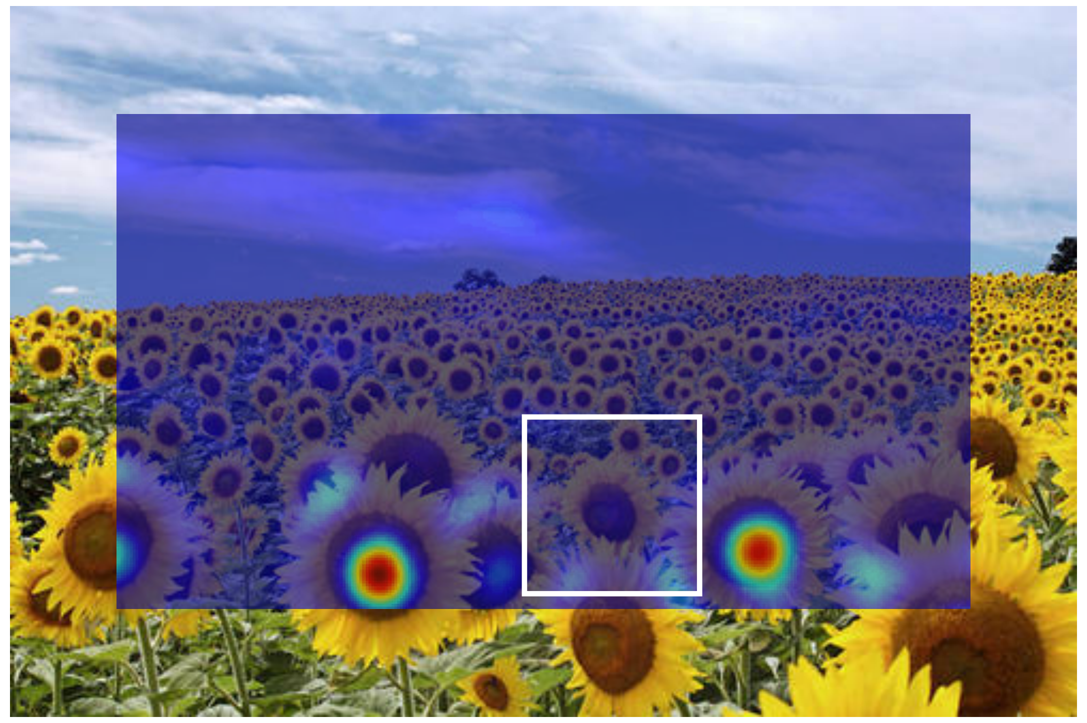

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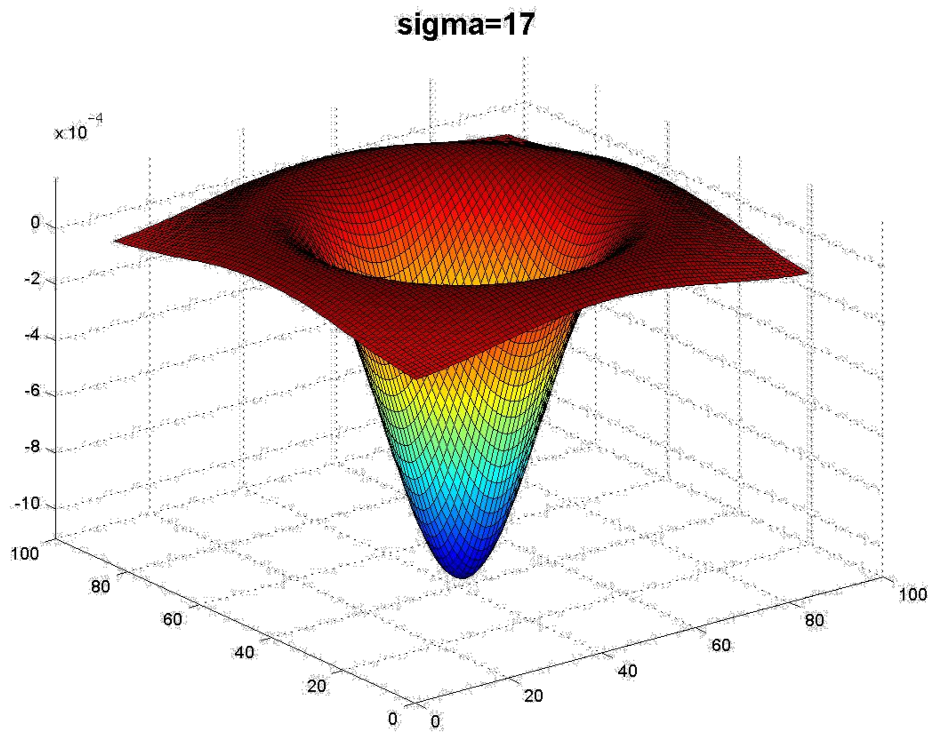

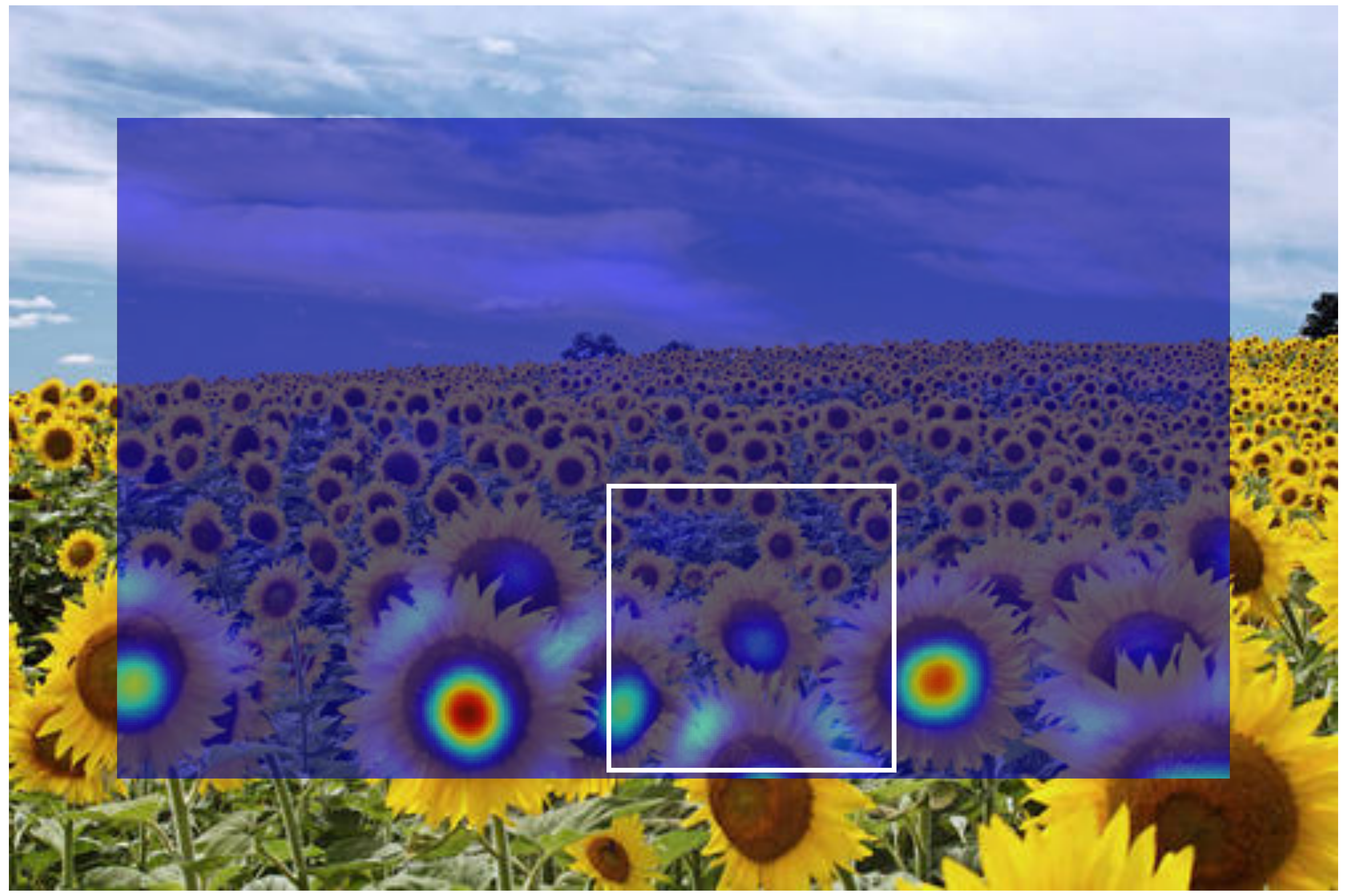

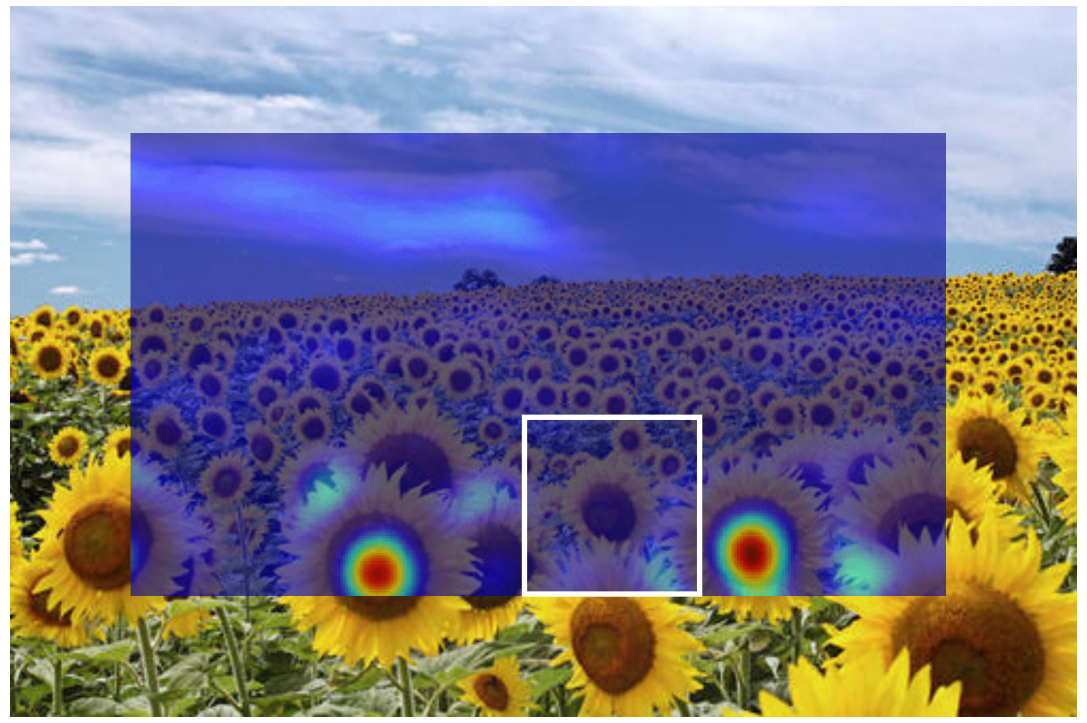

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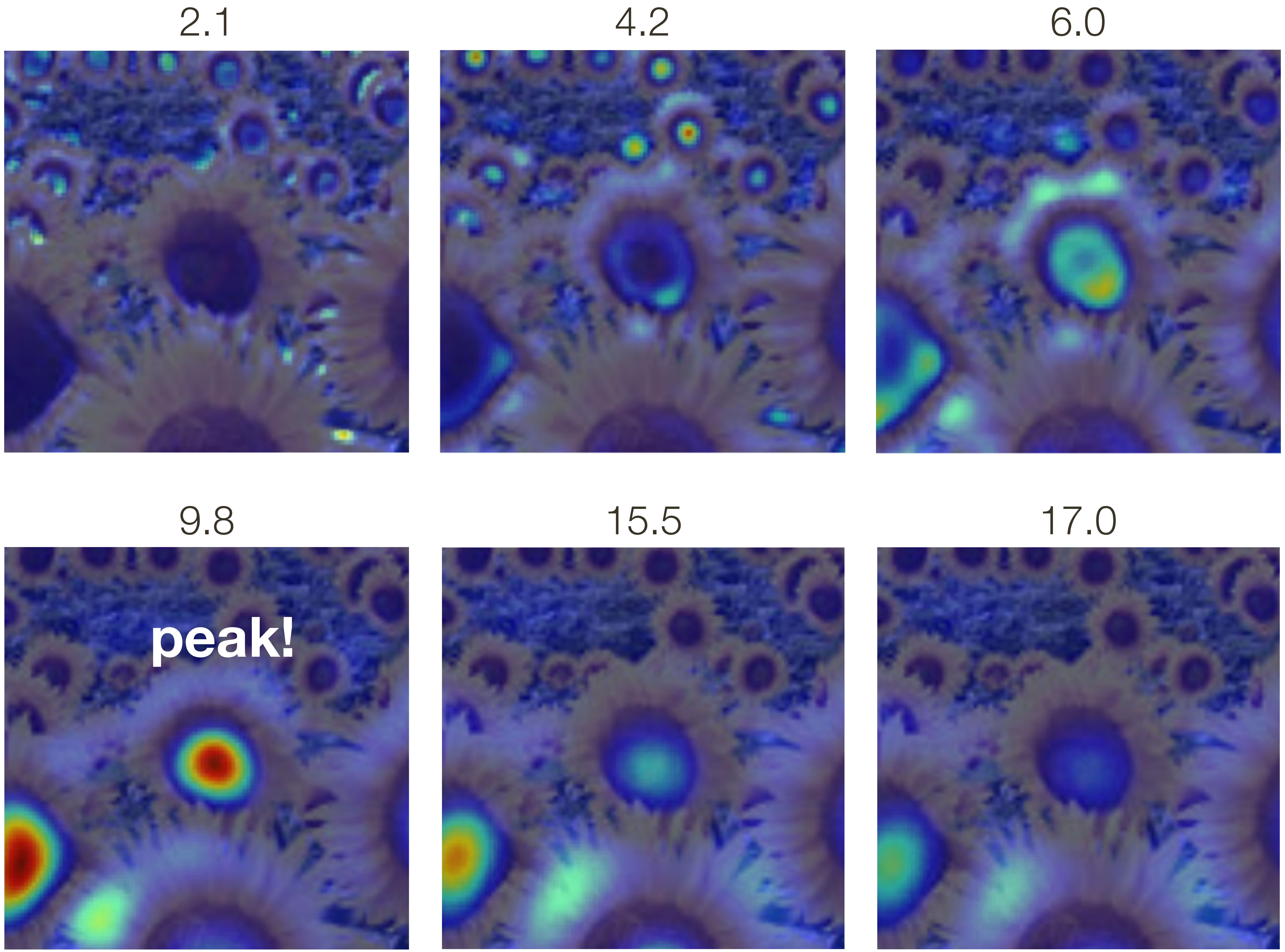
Applying **Laplacian** Filter at Different **Scales**

Full size

3/4 size

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Applying **Laplacian** Filter at Different **Scales**



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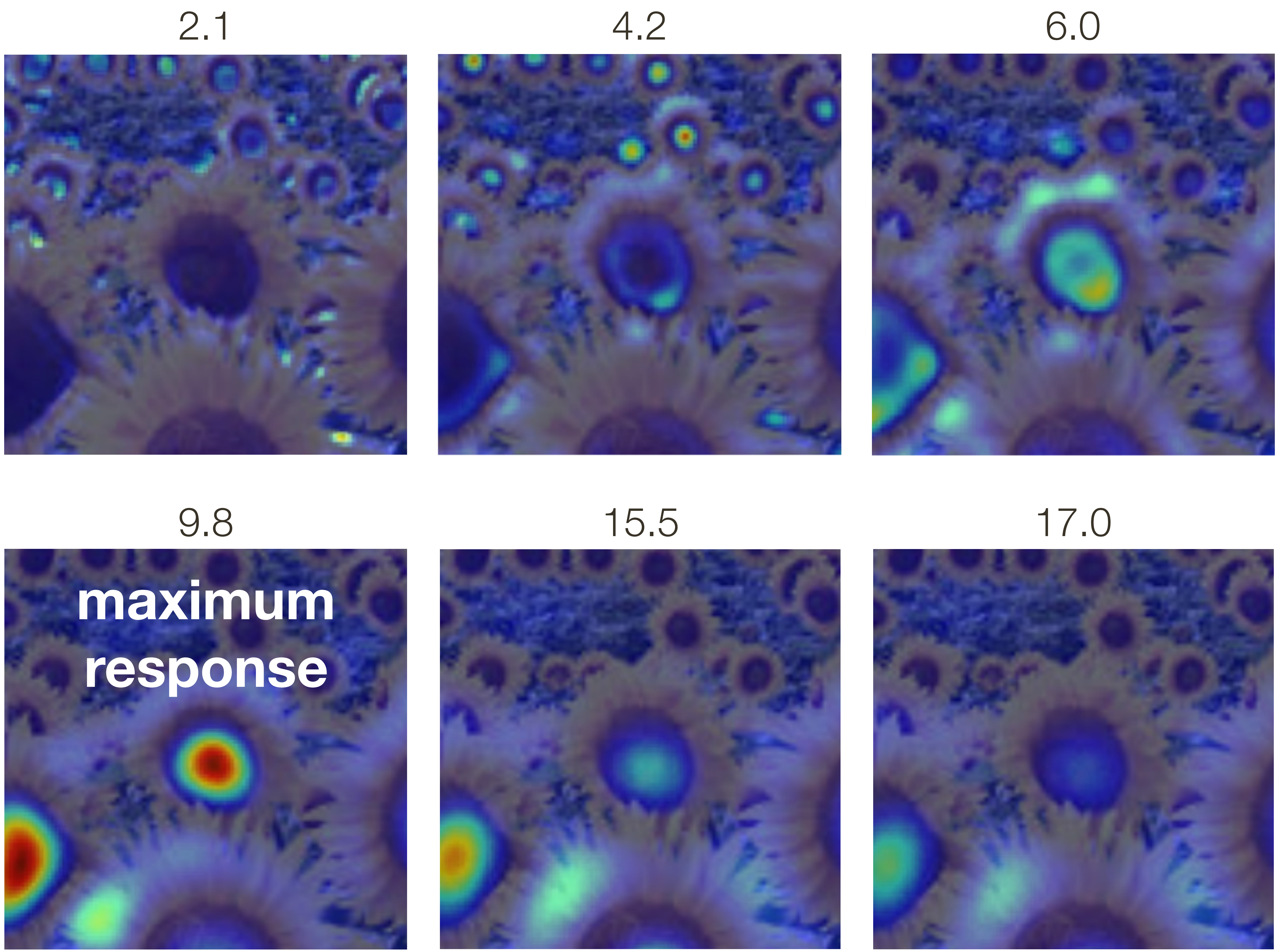
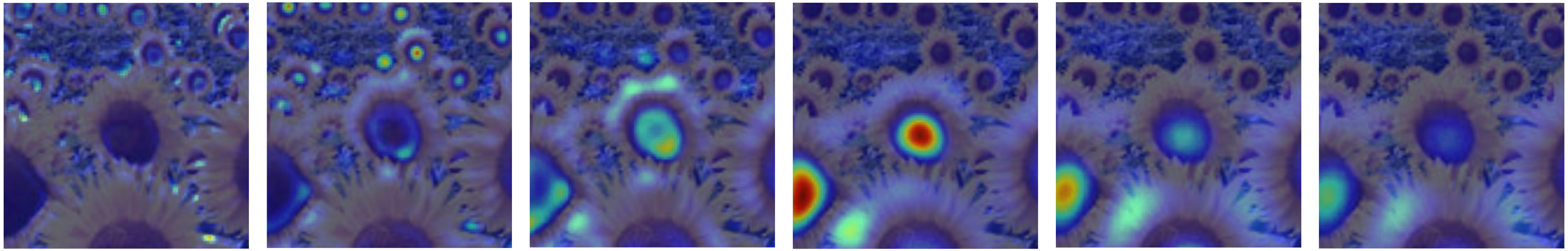


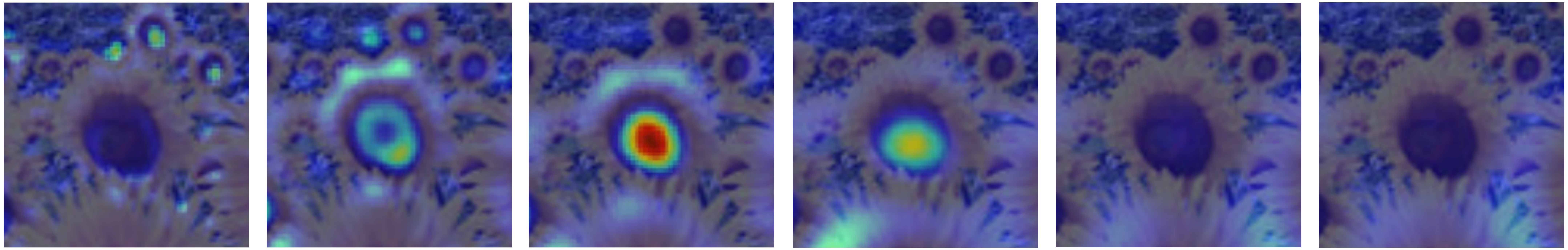
Optimal **Scale**

2.1 4.2 6.0 9.8 15.5 17.0



Full size image

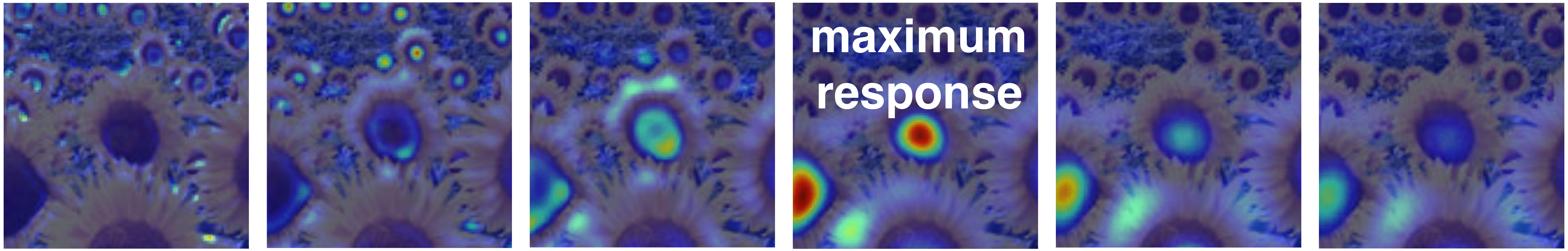
2.1 4.2 6.0 9.8 15.5 17.0



3/4 size image

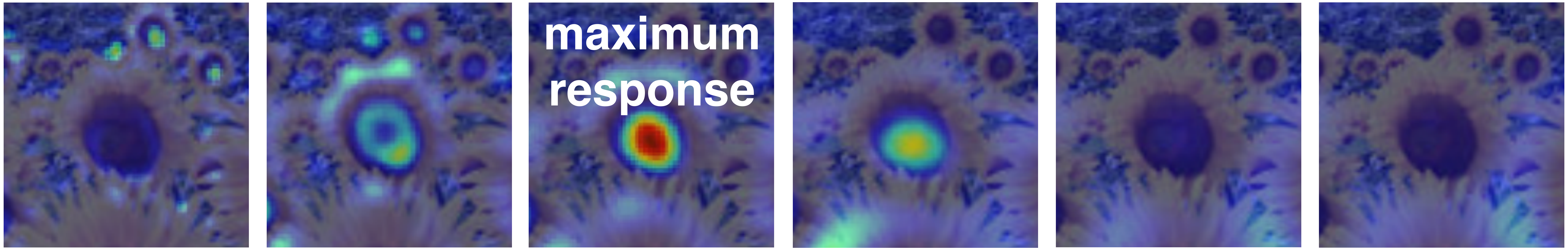
Optimal **Scale**

2.1 4.2 6.0 9.8 15.5 17.0



Full size image

2.1 4.2 6.0 9.8 15.5 17.0



3/4 size image

Implementation

```
For each level of the Gaussian pyramid
compute feature response (e.g. Harris, Laplacian)

For each level of the Gaussian pyramid
    if local maximum and cross-scale
    save scale and location of feature
```
(x, y, s)

Summary

A **corner** is a distinct 2D feature that can be localized reliably

Edge detectors perform poorly at corners
→ consider corner detection directly

Harris corner detection
— corners are places where intensity gradient direction takes on multiple distinct values
— interpret in terms of autocorrelation of local window
— translation and rotation invariant, but not scale invariant