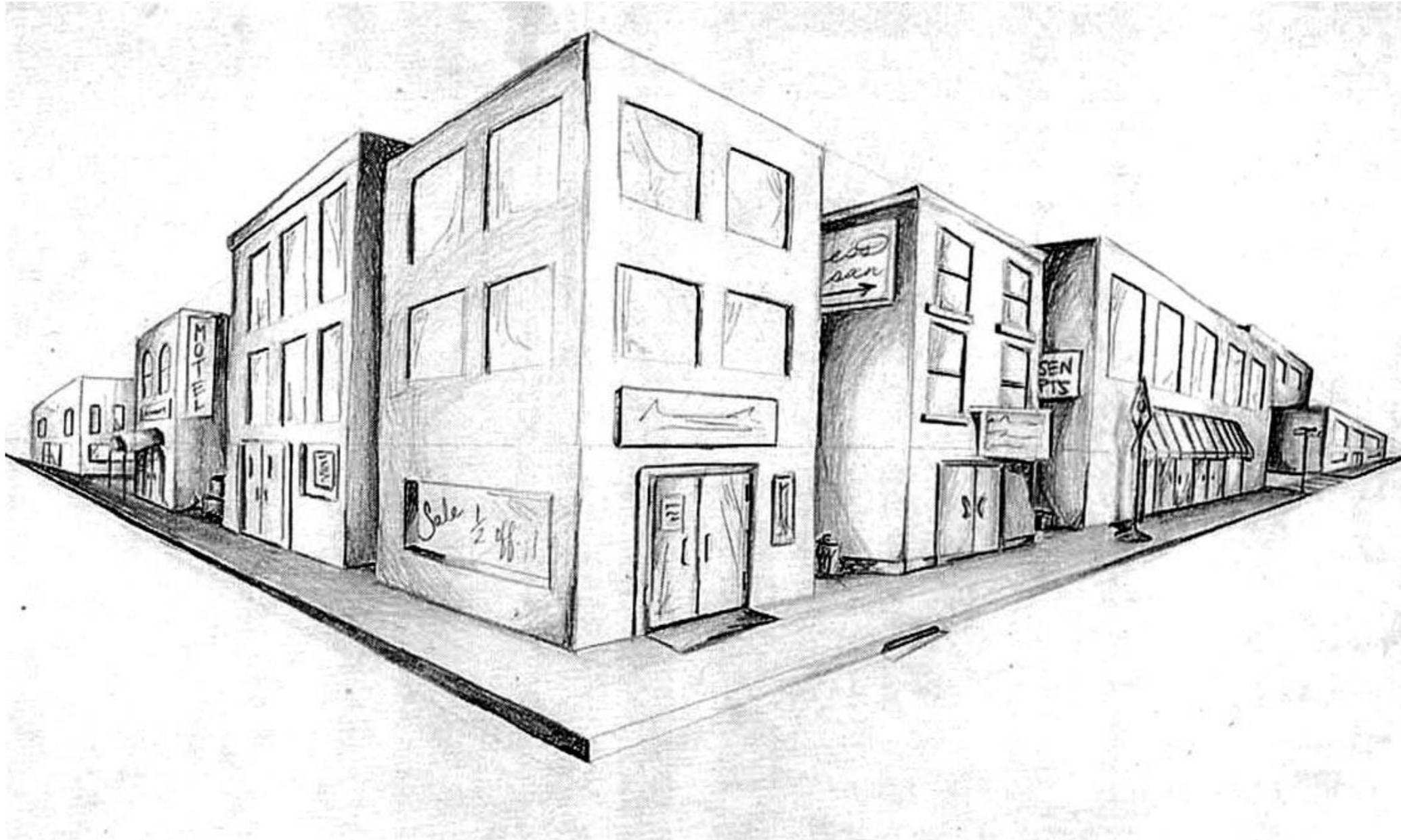


Detecting corners



Course announcements

- Homework 0 and homework 1 are available on course website.
 - Homework 1 is due on February 7th.
 - Any questions about the homeworks?
 - How many of you have looked at/started/finished homework 0?
 - How many of you have looked at/started/finished homework 1?
- There was a small correction to homework 1.
 - Posted on Piazza.
 - Make sure to download the latest version.

Overview of today's lecture

Leftover from Lecture 4:

- Hough circles.

New in lecture 5:

- Why detect corners?
- Visualizing quadratics.
- Harris corner detector.
- Multi-scale detection.
- Multi-scale blob detection.

Slide credits

Most of these slides were adapted from:

- Kris Kitani (15-463, Fall 2016).

Some slides were inspired or taken from:

- Fredo Durand (MIT).
- James Hays (Georgia Tech).

Why detect corners?

Why detect corners?

Image alignment (homography, fundamental matrix)

3D reconstruction

Motion tracking

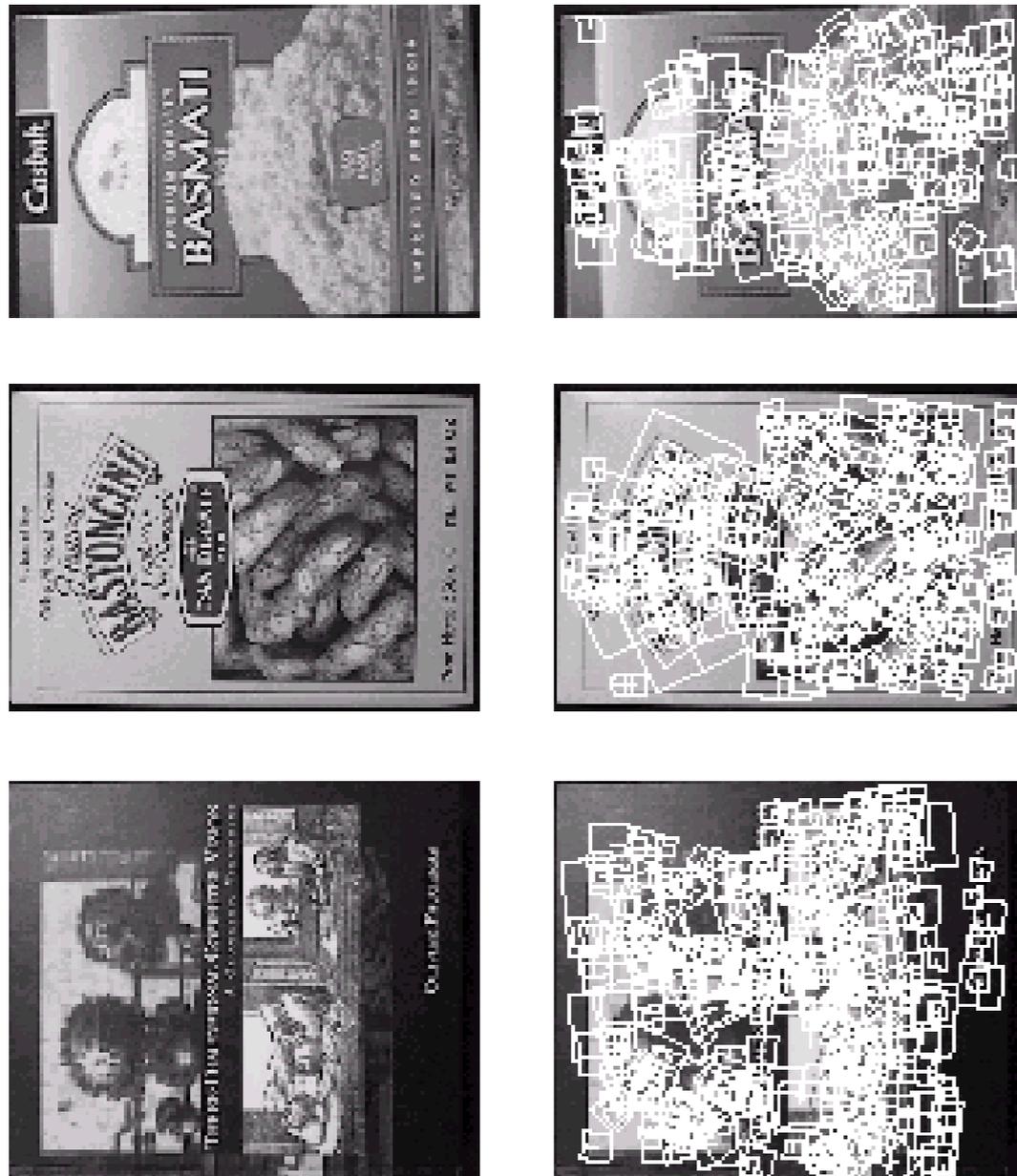
Object recognition

Indexing and database retrieval

Robot navigation

Planar object instance recognition

Database of planar objects



Instance recognition



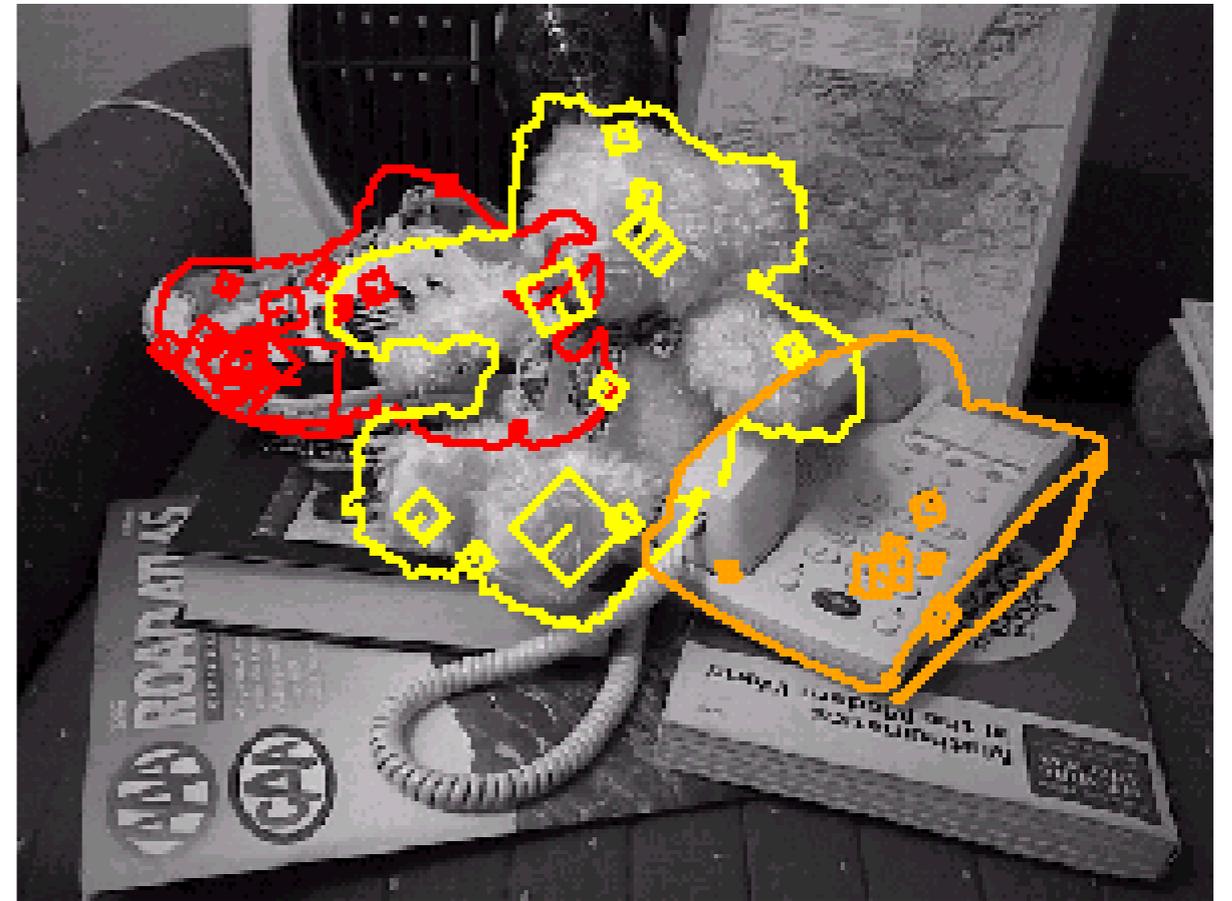
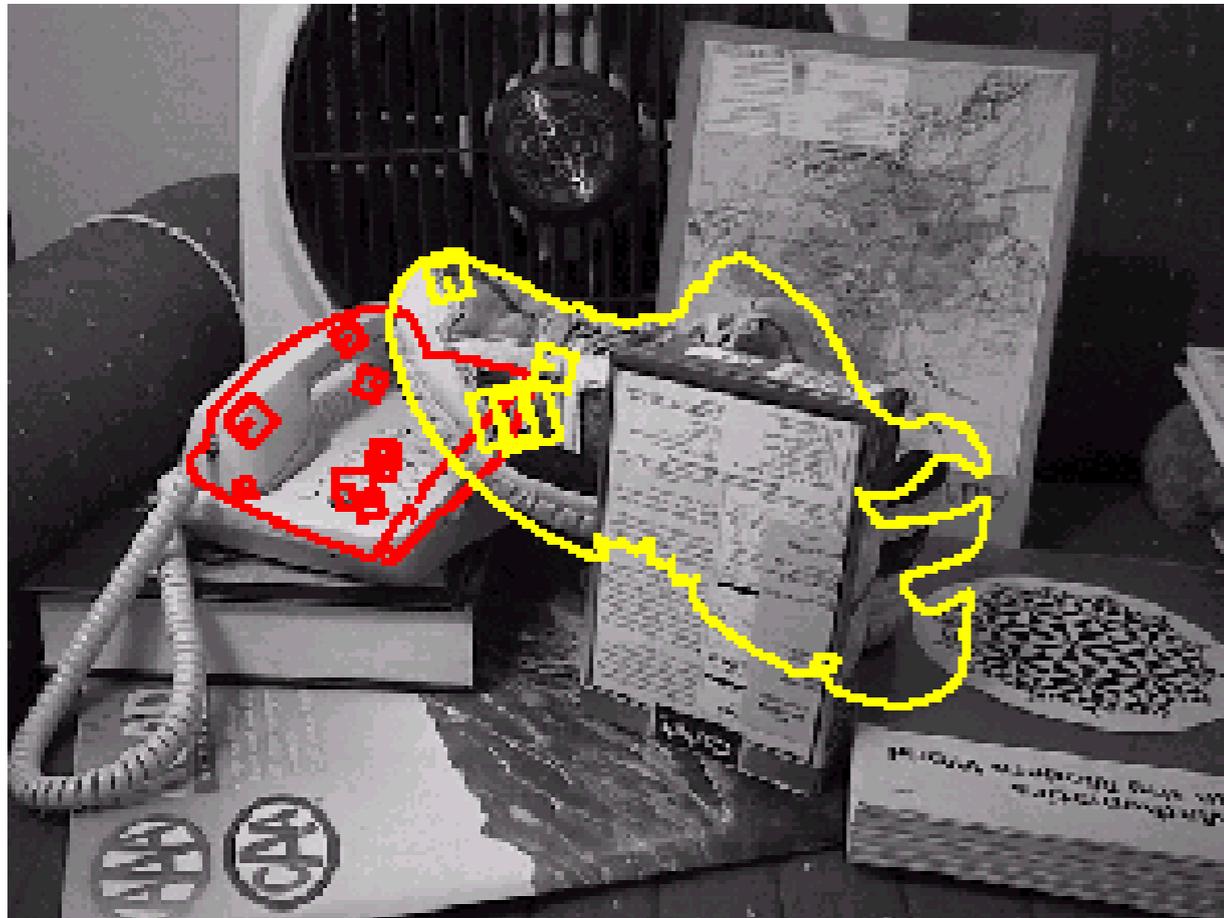
3D object recognition

Database of 3D objects



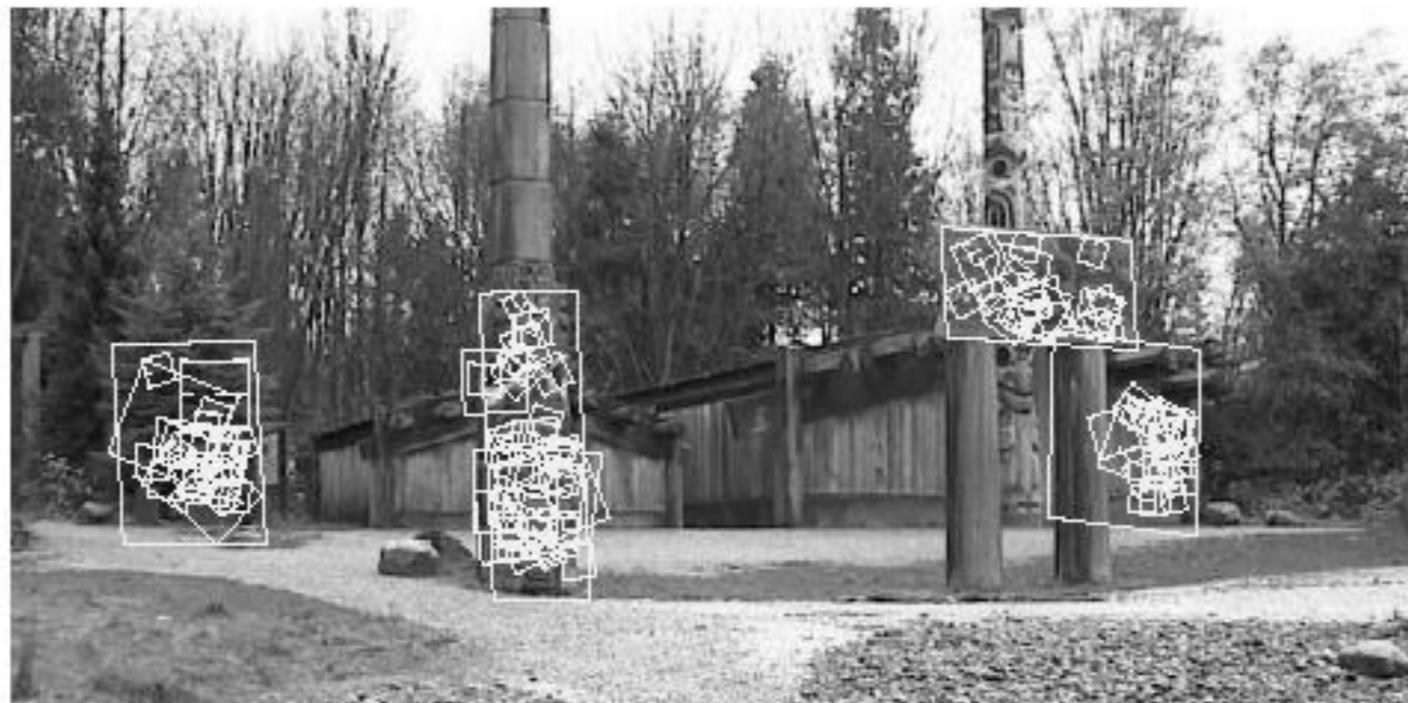
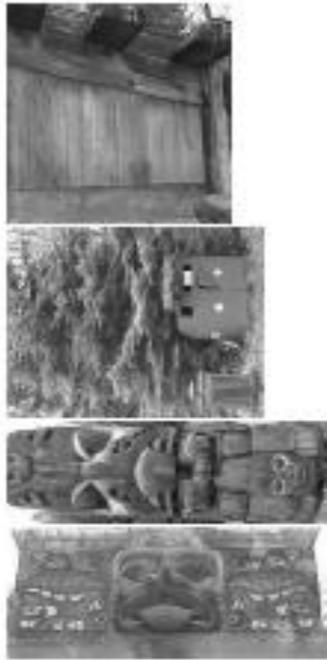
3D objects recognition





Recognition under occlusion

Location Recognition



Robot Localization

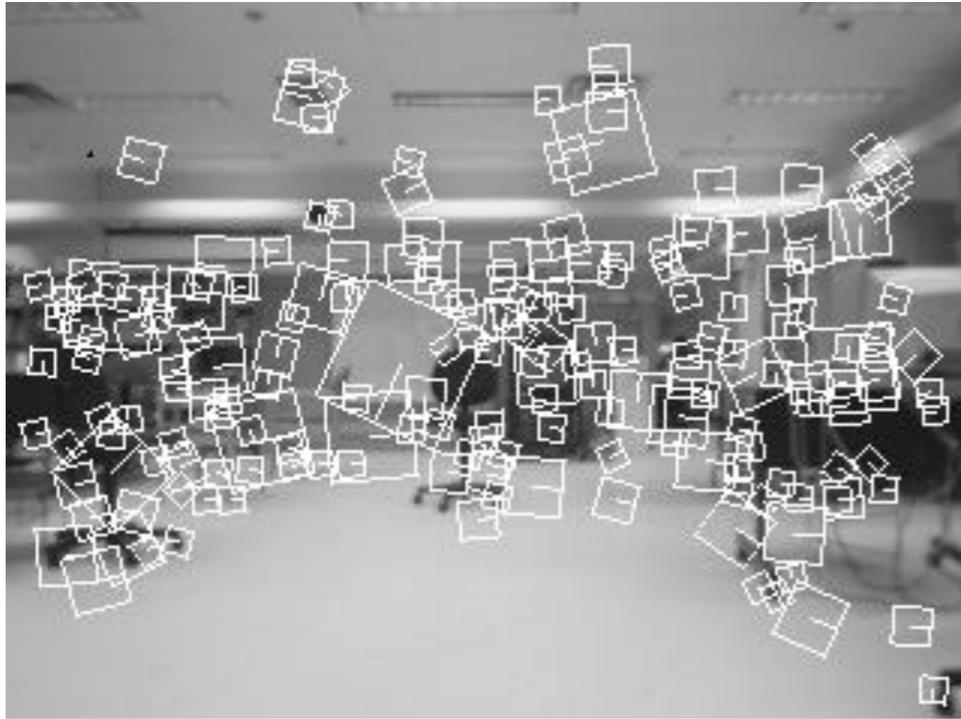
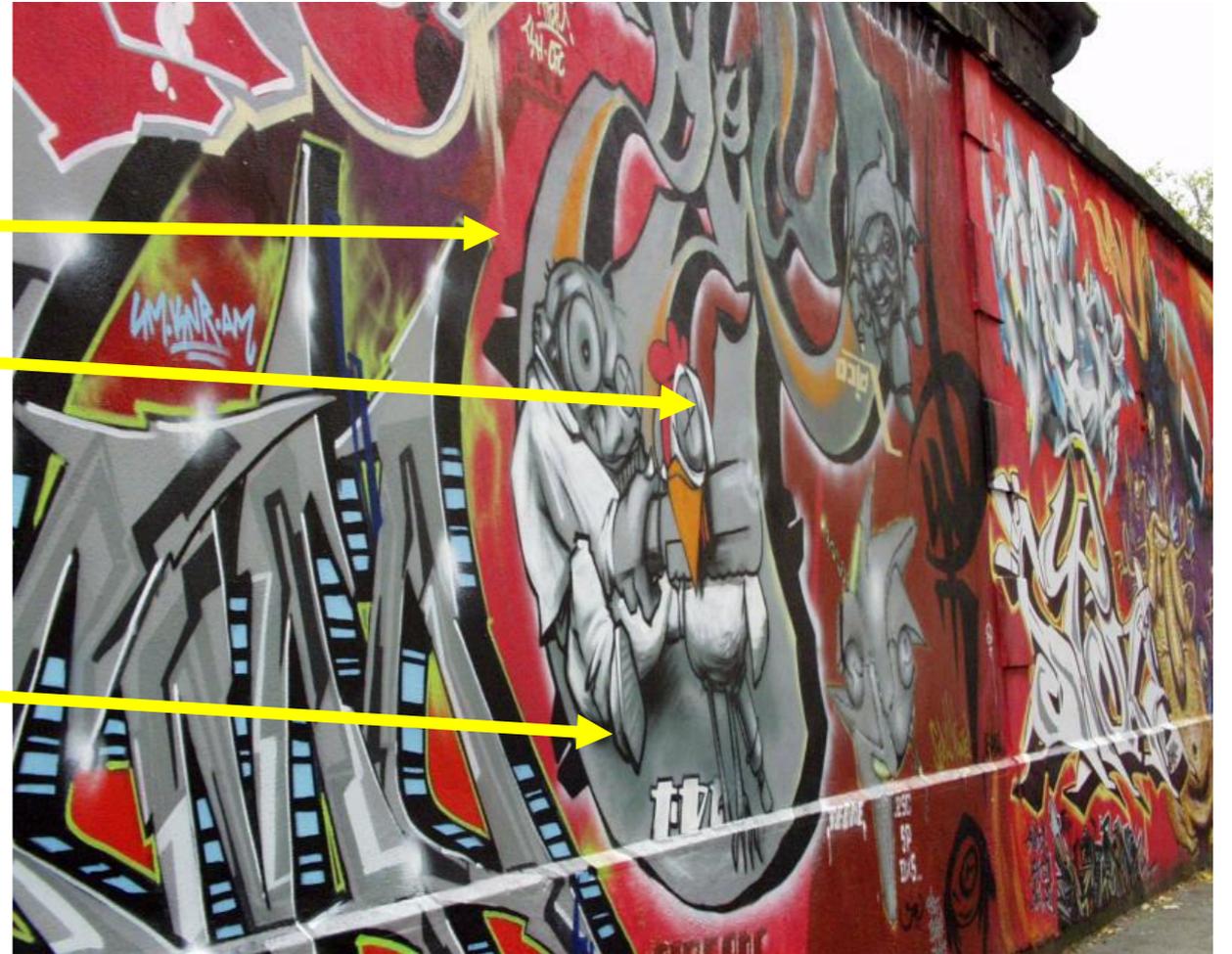
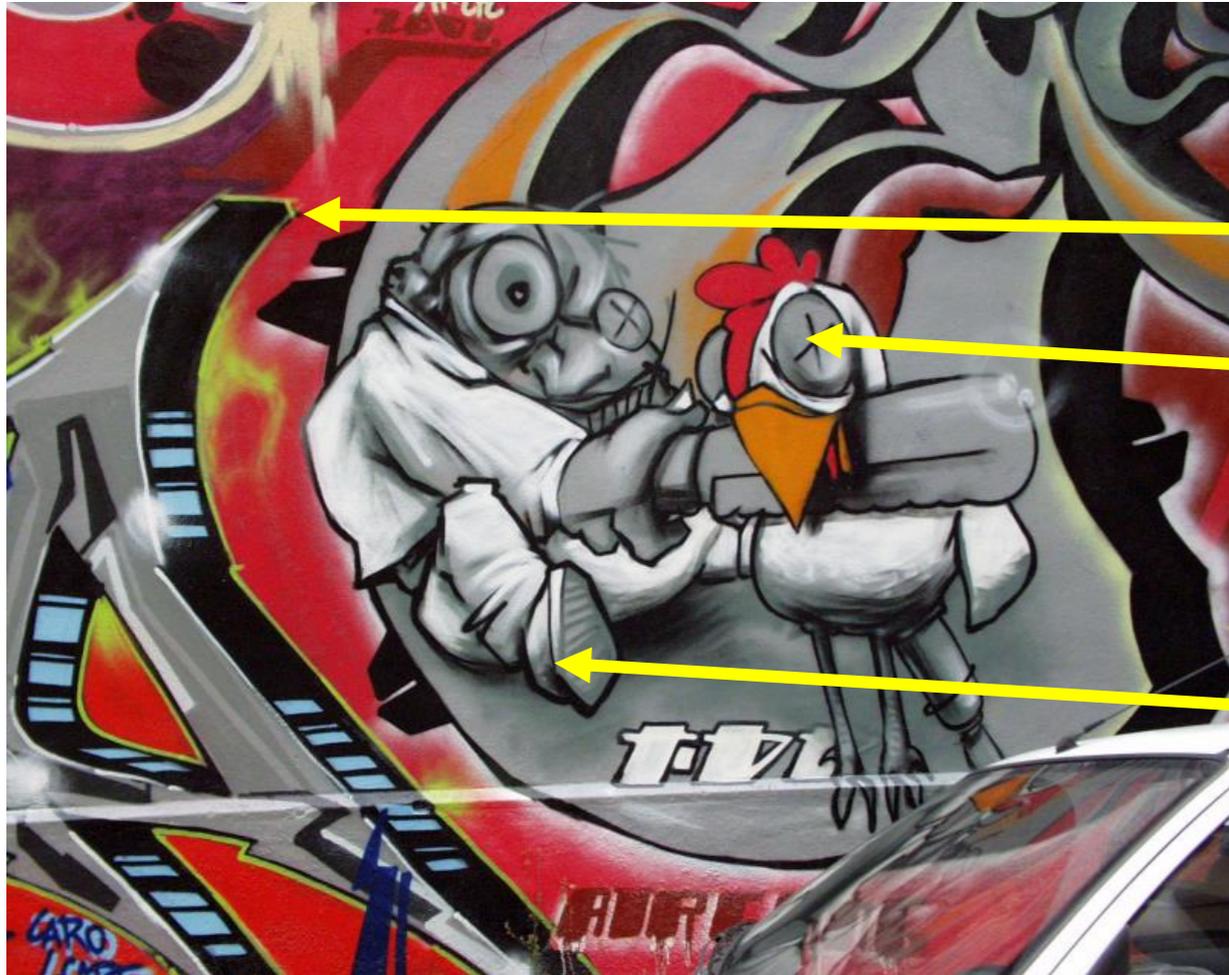
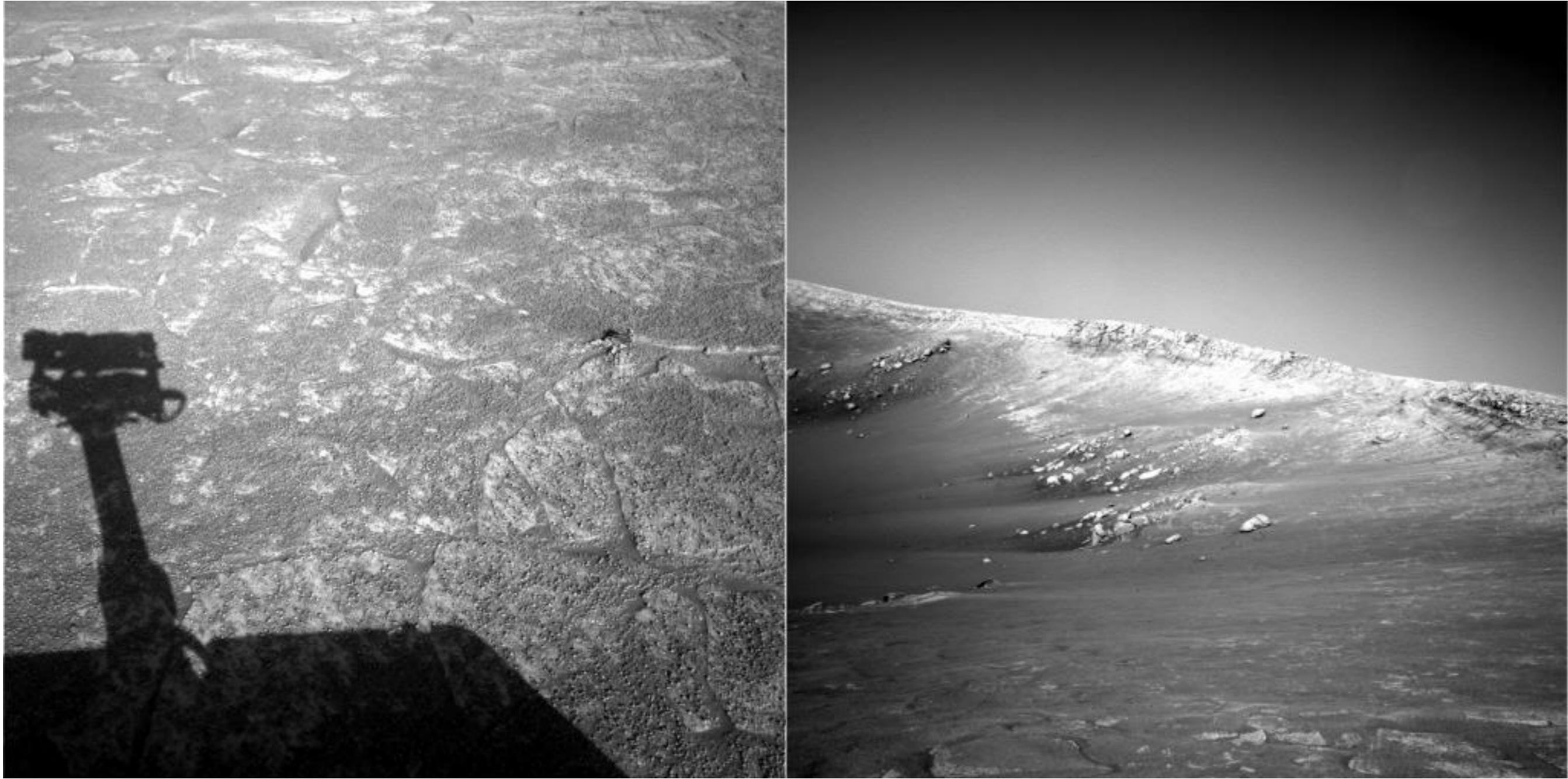


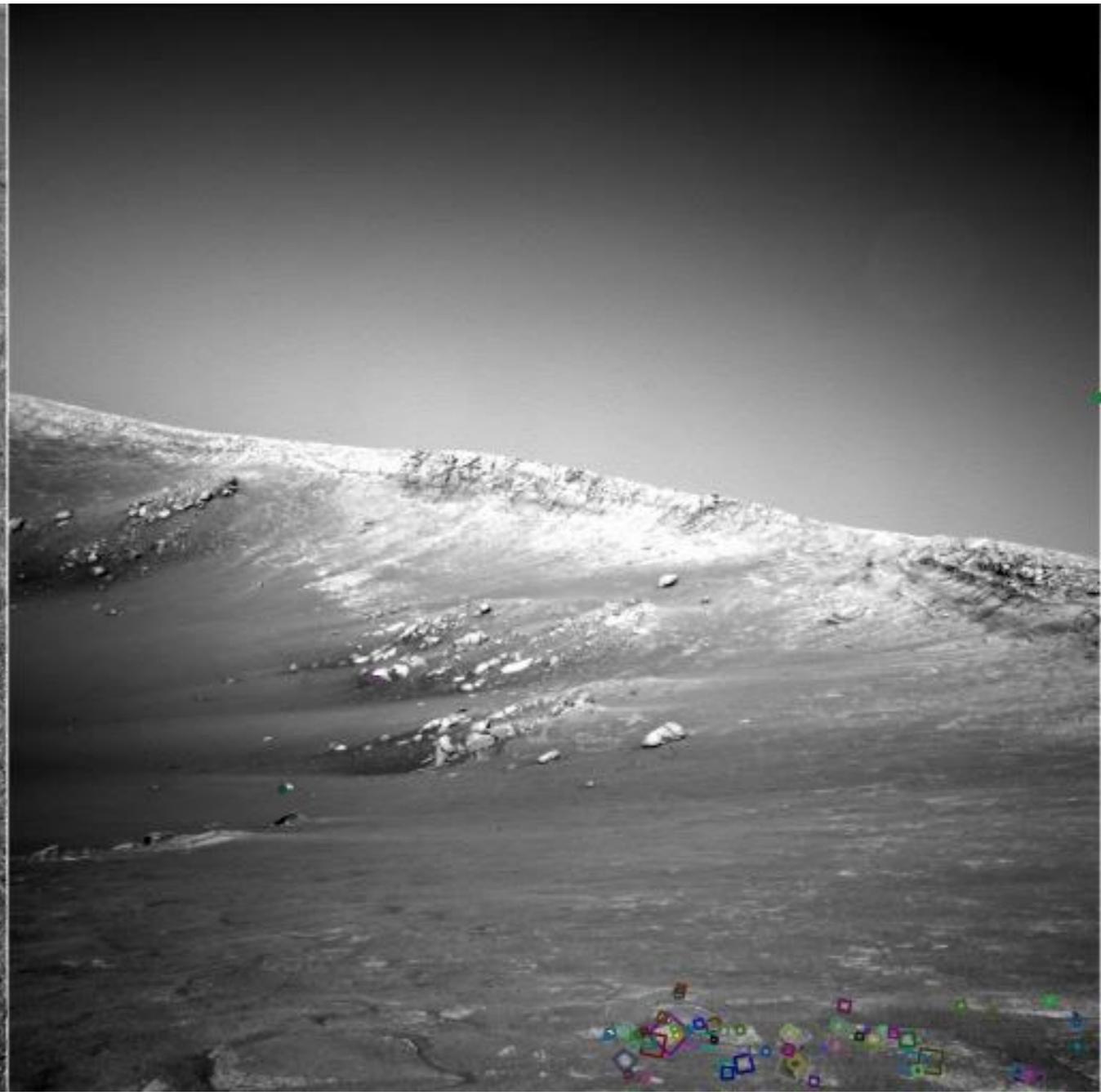
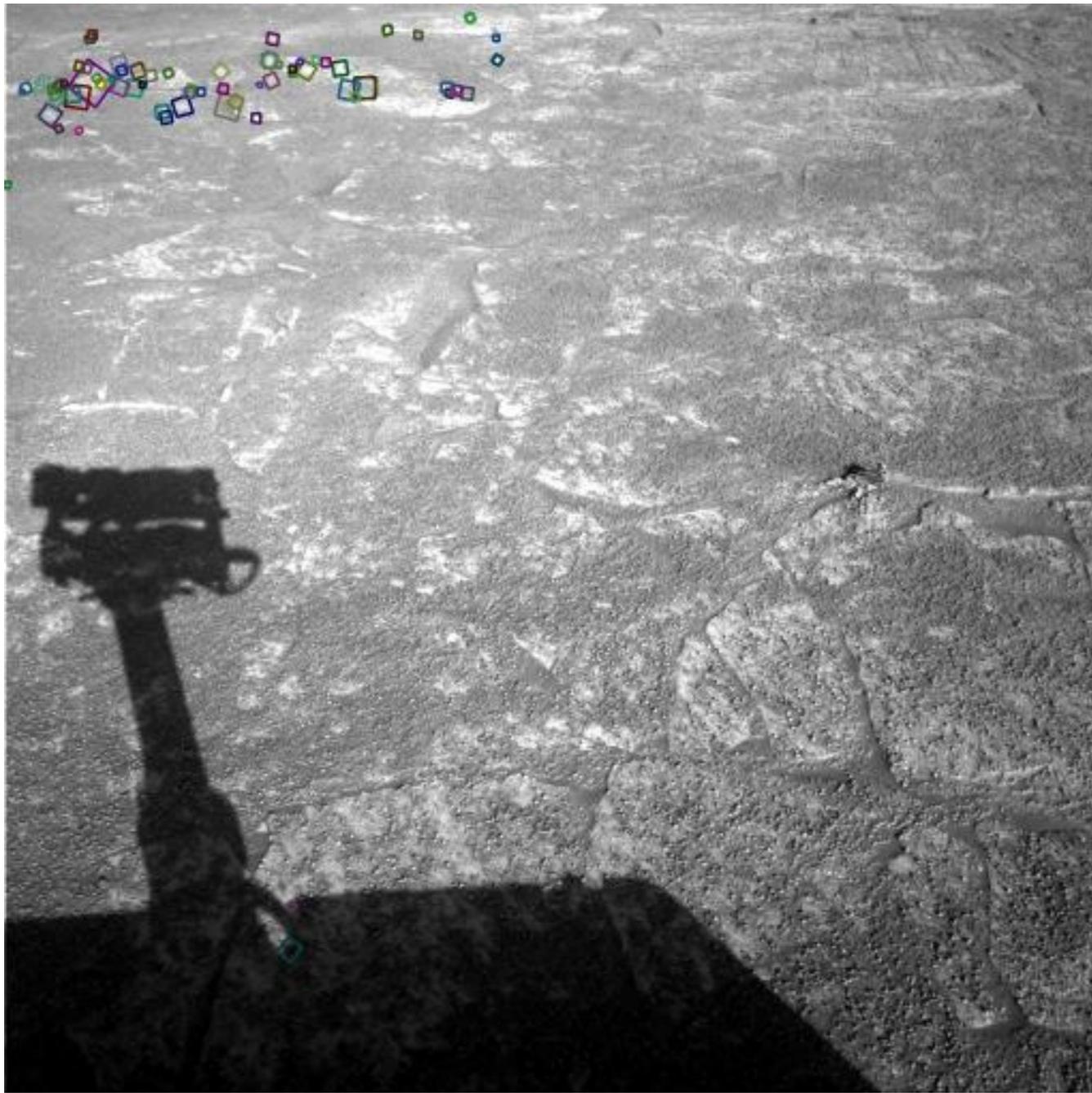
Image matching

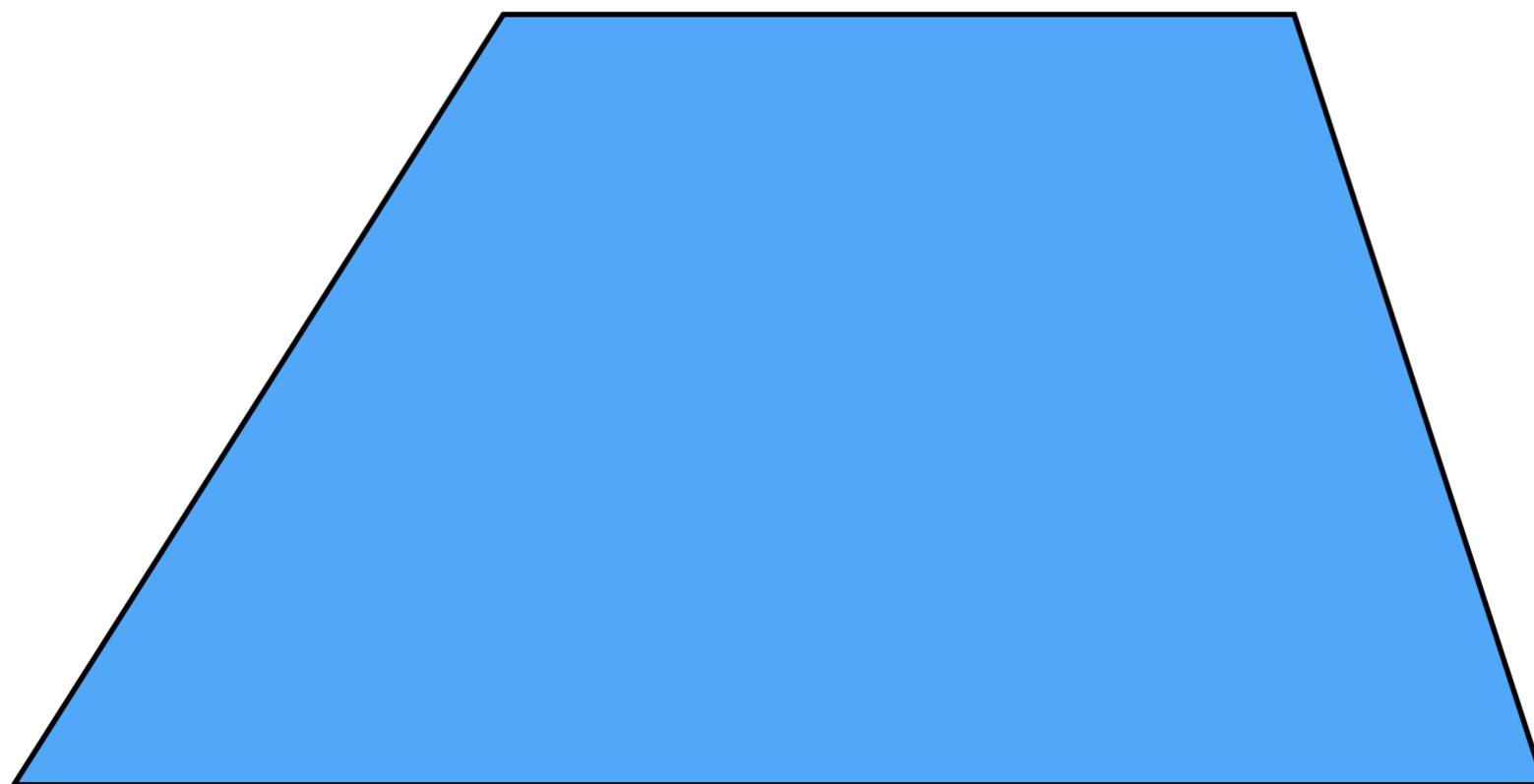




NASA Mars Rover images

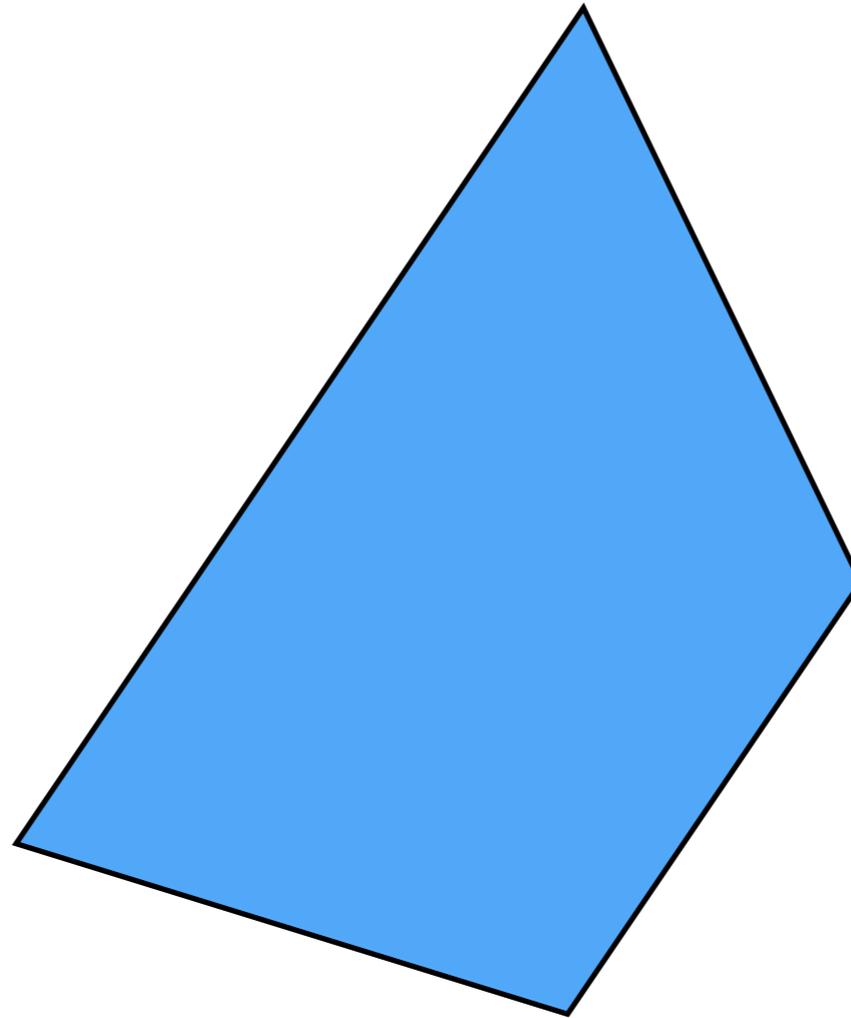
Where are the corresponding points?





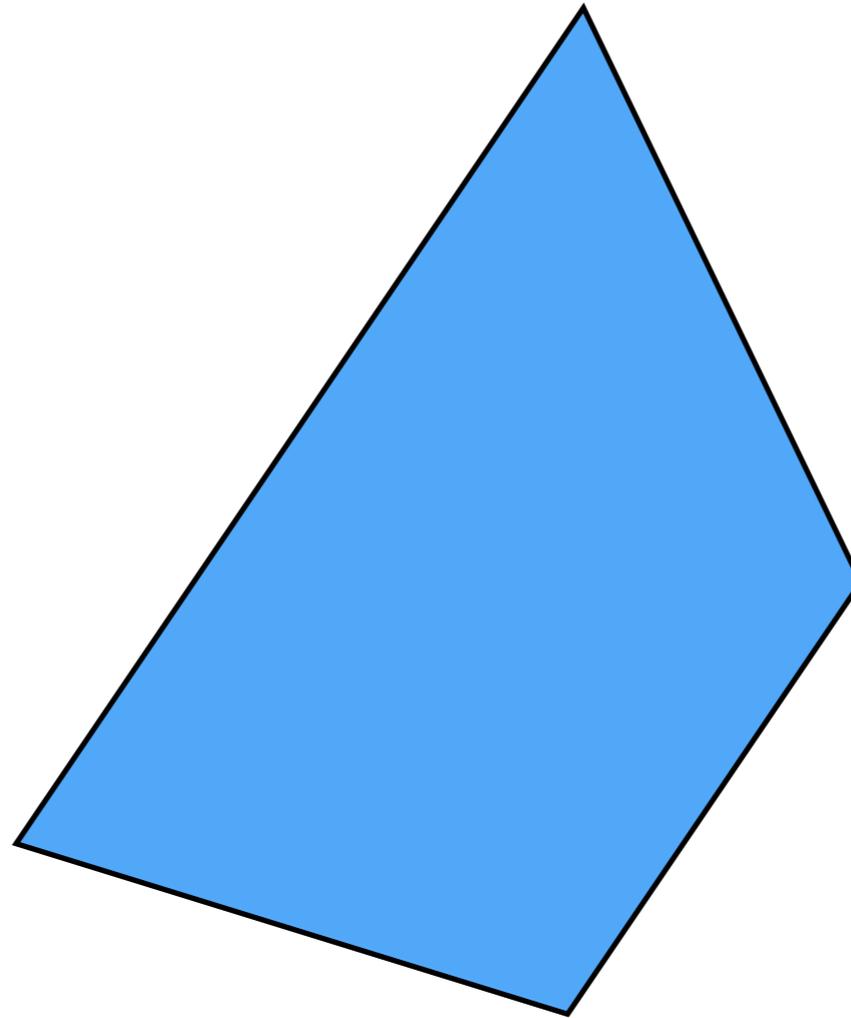
Pick a point in the image.
Find it again in the next image.

What type of feature would you select?



Pick a point in the image.
Find it again in the next image.

What type of feature would you select?

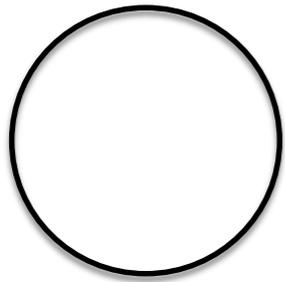


Pick a point in the image.
Find it again in the next image.

What type of feature would you select?

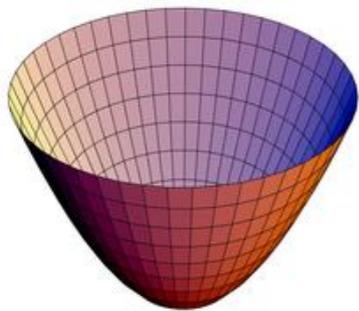
a corner

Visualizing quadratics



Equation of a circle

$$1 = x^2 + y^2$$



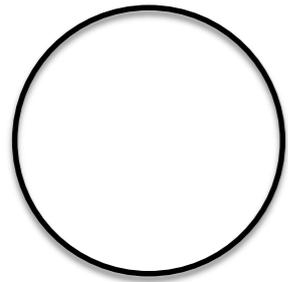
Equation of a 'bowl' (paraboloid)

$$f(x, y) = x^2 + y^2$$

If you slice the bowl at

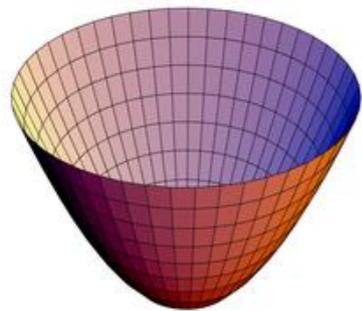
$$f(x, y) = 1$$

what do you get?



Equation of a circle

$$1 = x^2 + y^2$$



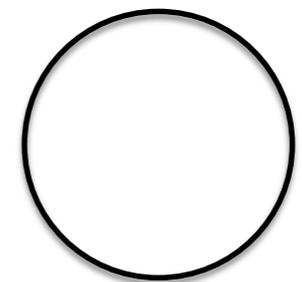
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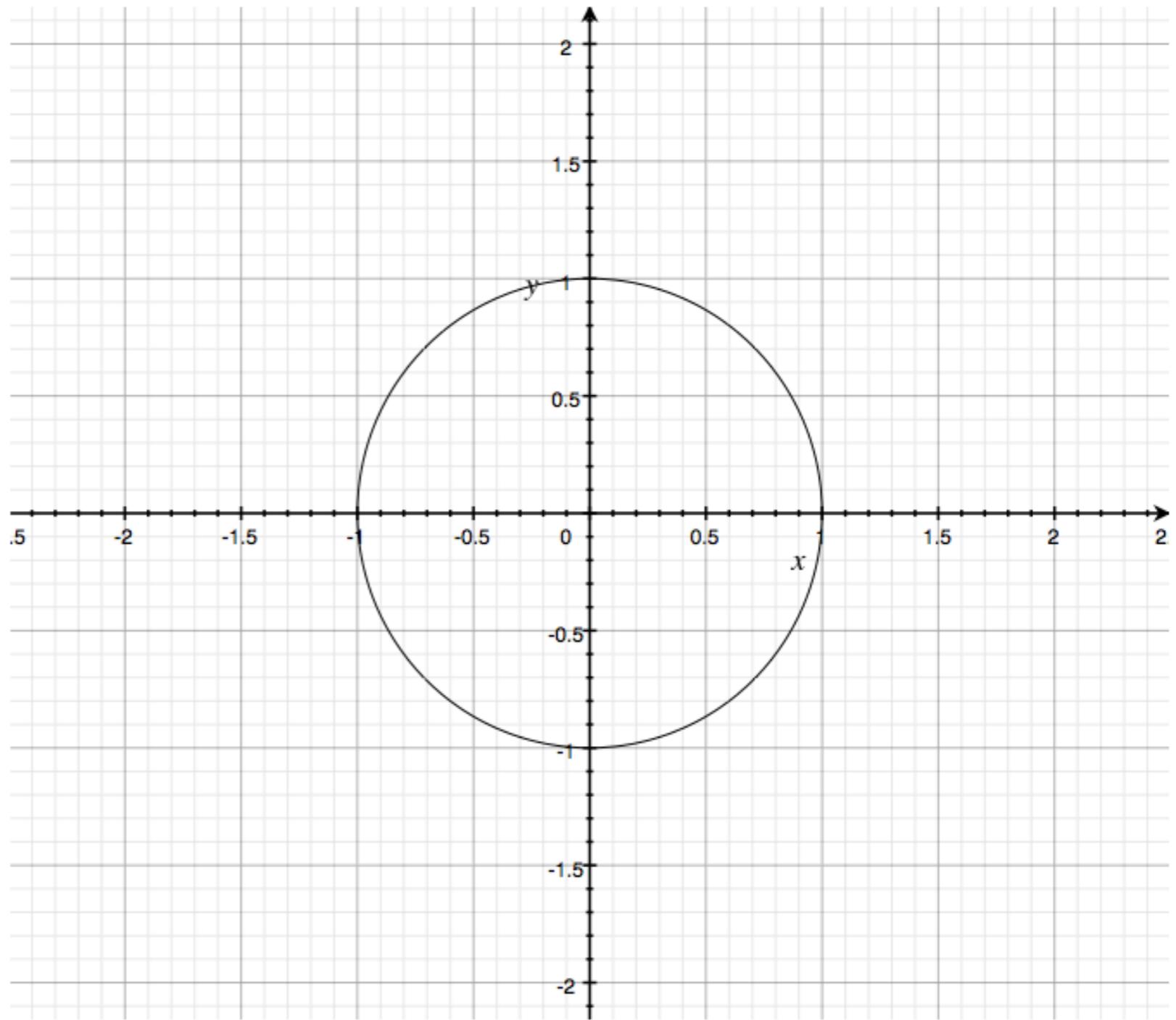
$$f(x, y) = x^2 + y^2$$

can be written in matrix form like this...

$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

'sliced at 1'



What happens if you *increase*
coefficient on x ?

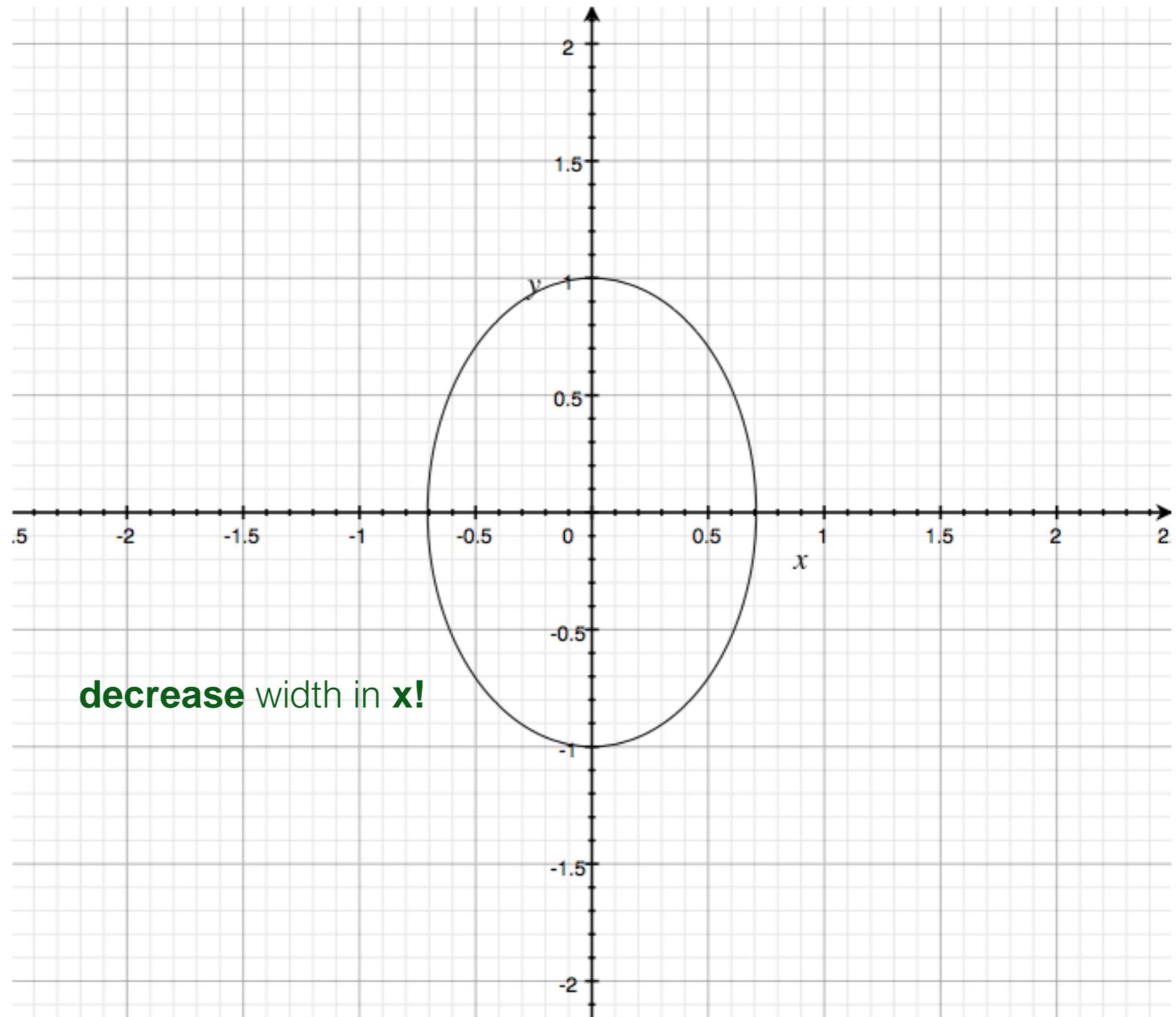
$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

and slice at 1

What happens if you *increase* coefficient on x ?

$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

and slice at 1



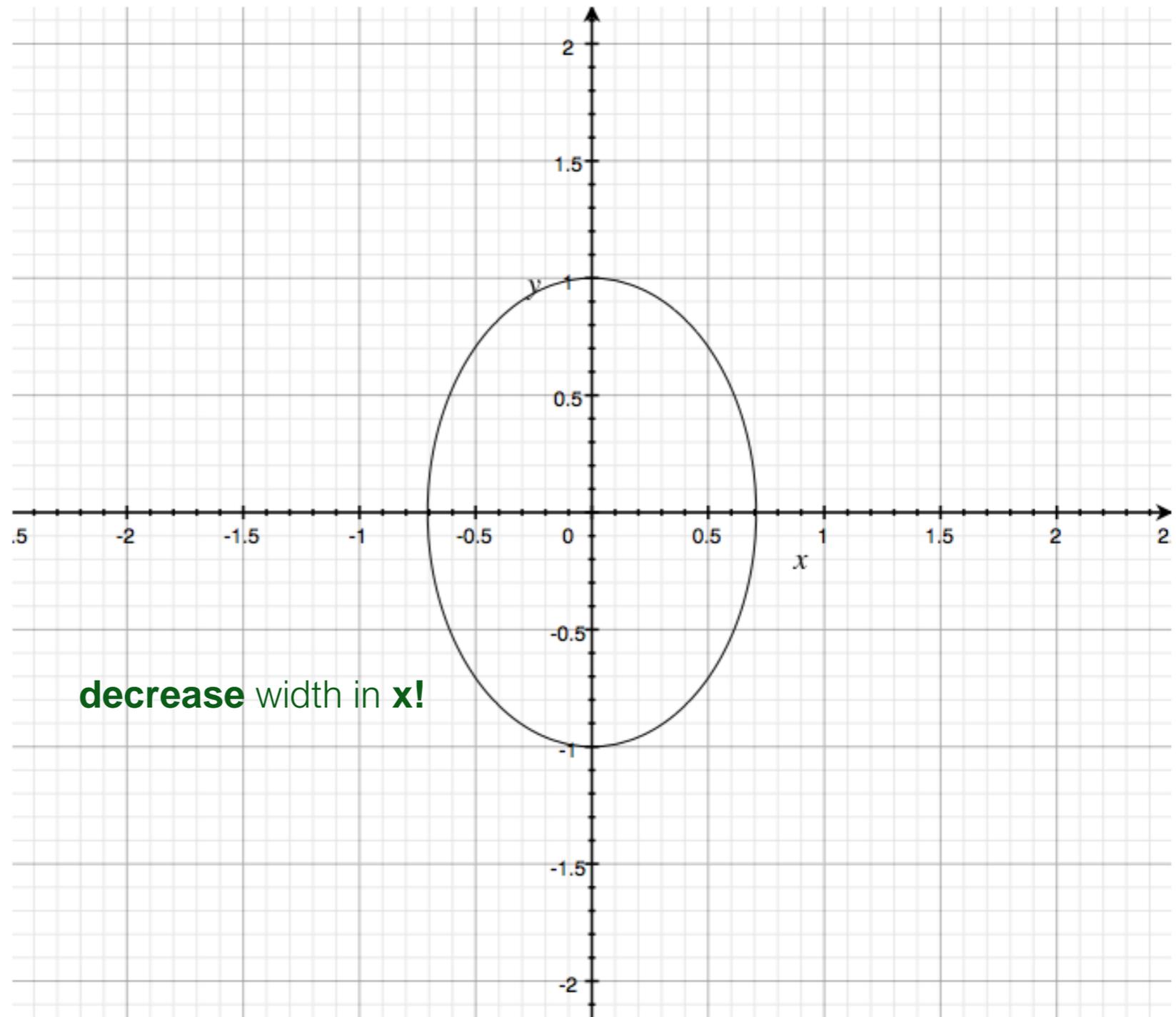
What happens if you *increase* coefficient on x ?

$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

and slice at 1

What happens to the gradient in x ?

increases gradient in x
'thins the bowl in x '



What happens if you **increase**
coefficient on ***y***?

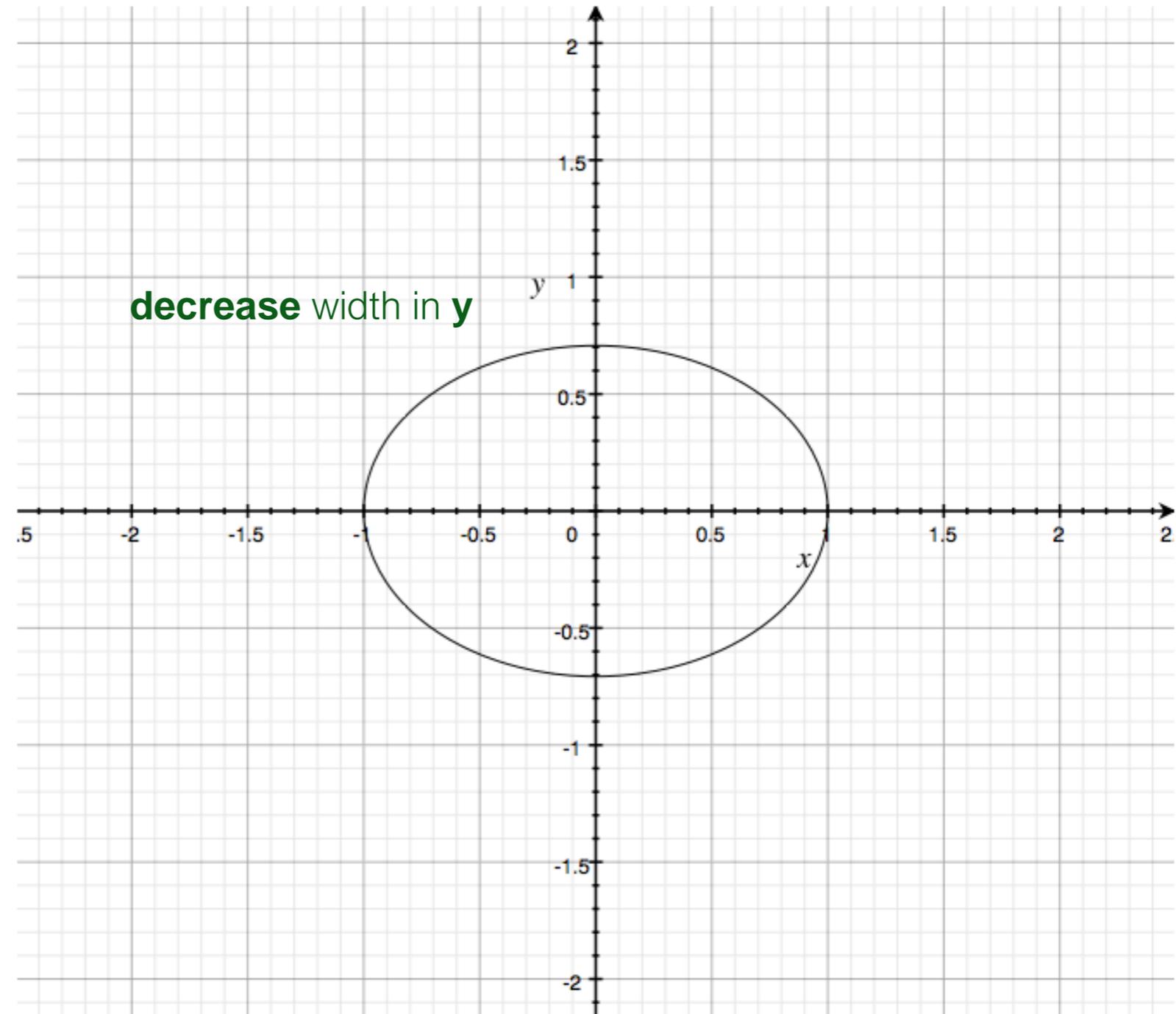
$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

and slice at 1

What happens if you *increase* coefficient on y ?

$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

and slice at 1

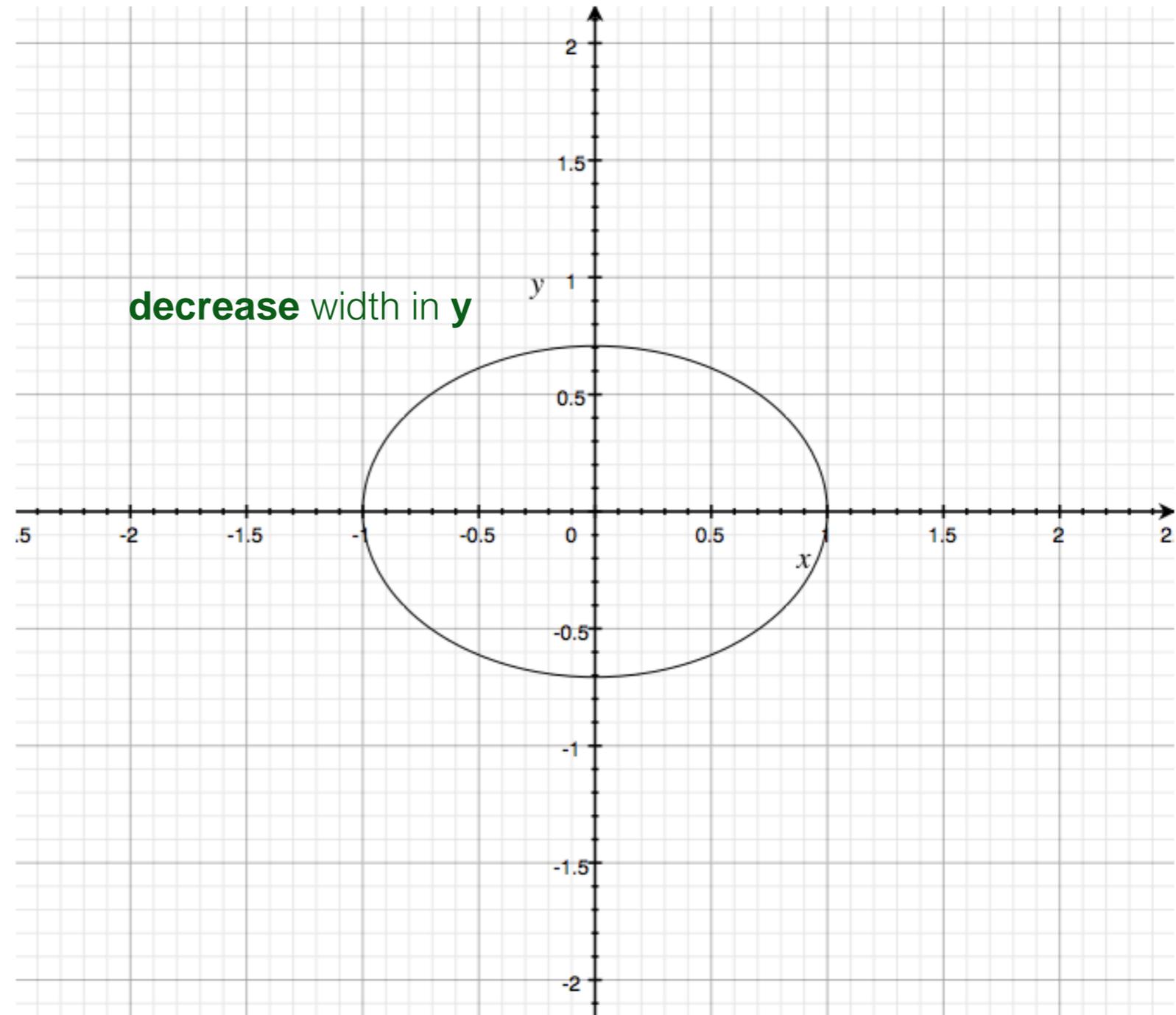


What happens if you *increase* coefficient on y ?

$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

and slice at 1

What happens to the gradient in y ?



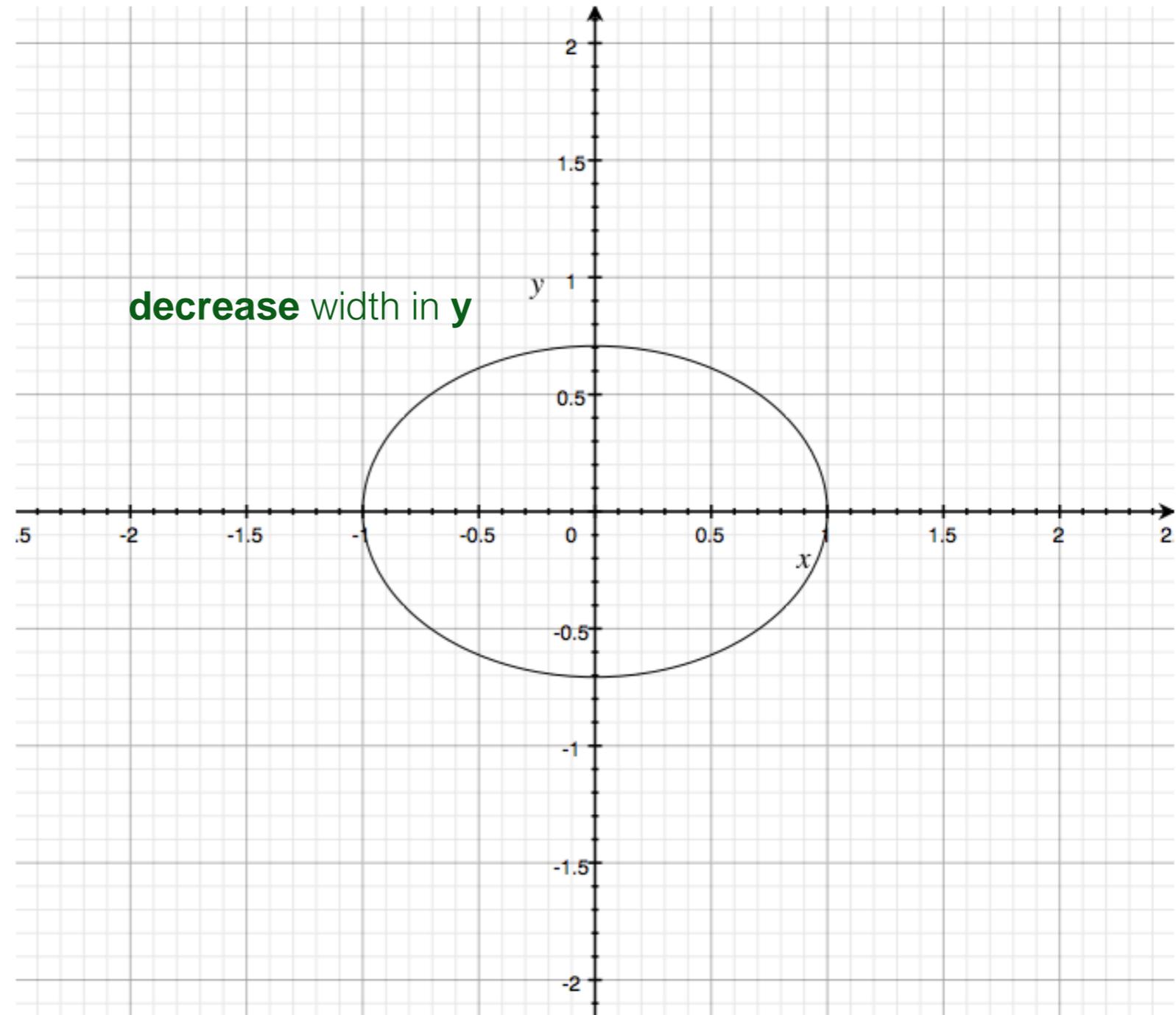
What happens if you *increase* coefficient on *y*?

$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

and slice at 1

What happens to the gradient in *y*?

increases gradient in *y*
'thins the bowl in *y*'



$$f(x, y) = x^2 + y^2$$

can be written in matrix form like this...

$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

What's the shape?

What are the eigenvectors?

What are the eigenvalues?

$$f(x, y) = x^2 + y^2$$

can be written in matrix form like this...

$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Result of Singular Value Decomposition (SVD)

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} \boxed{1} & \boxed{0} \\ \boxed{0} & \boxed{1} \end{bmatrix} \begin{bmatrix} \boxed{1} & 0 \\ 0 & \boxed{1} \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}^T$$

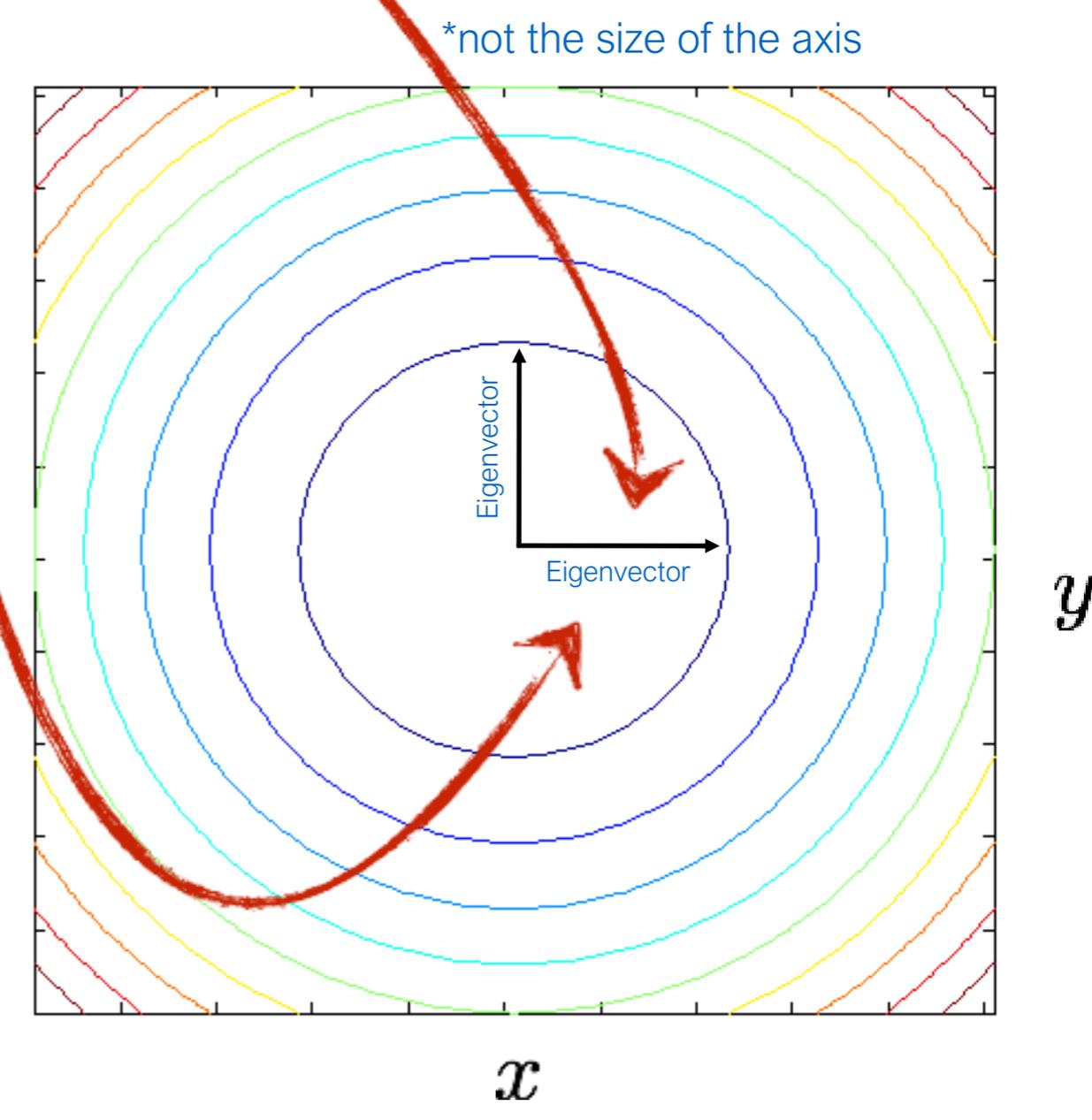
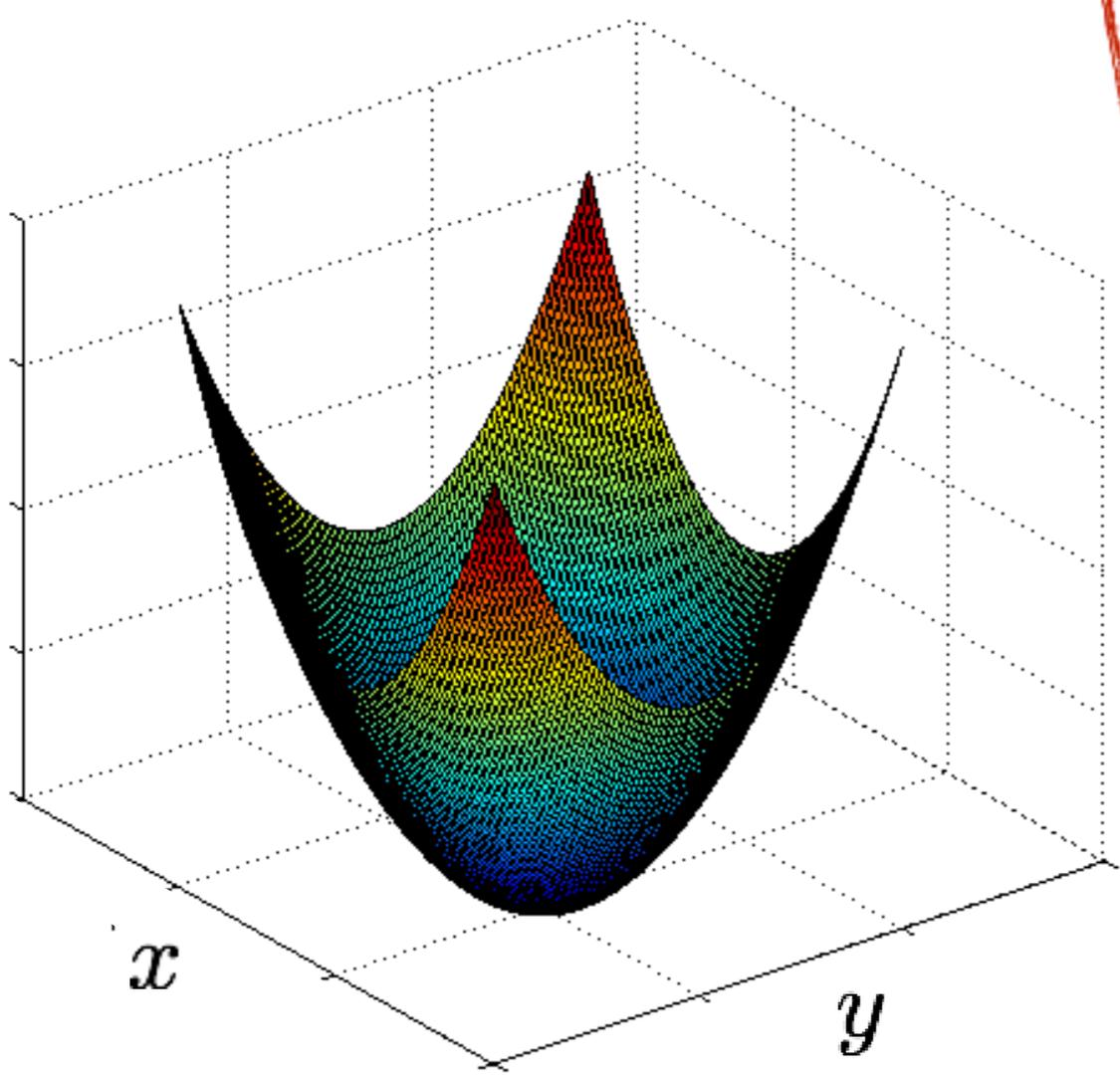
eigenvectors
eigenvalues
along diagonal

axis of the 'ellipse
slice'
gradient of the
quadratic along
the axis

$$\mathbf{A} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}^T$$

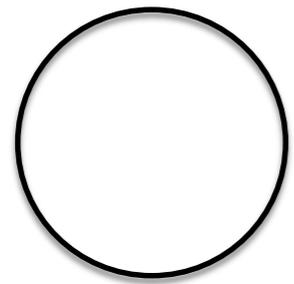
Eigenvectors Eigenvalues

Eigenvectors



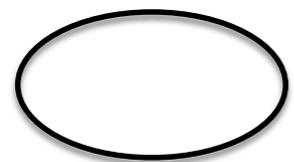
*not the size of the axis

Recall:



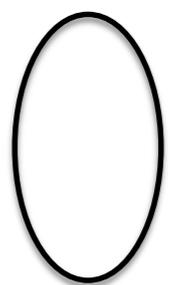
$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

you can smash this bowl in the **y** direction



$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 4 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

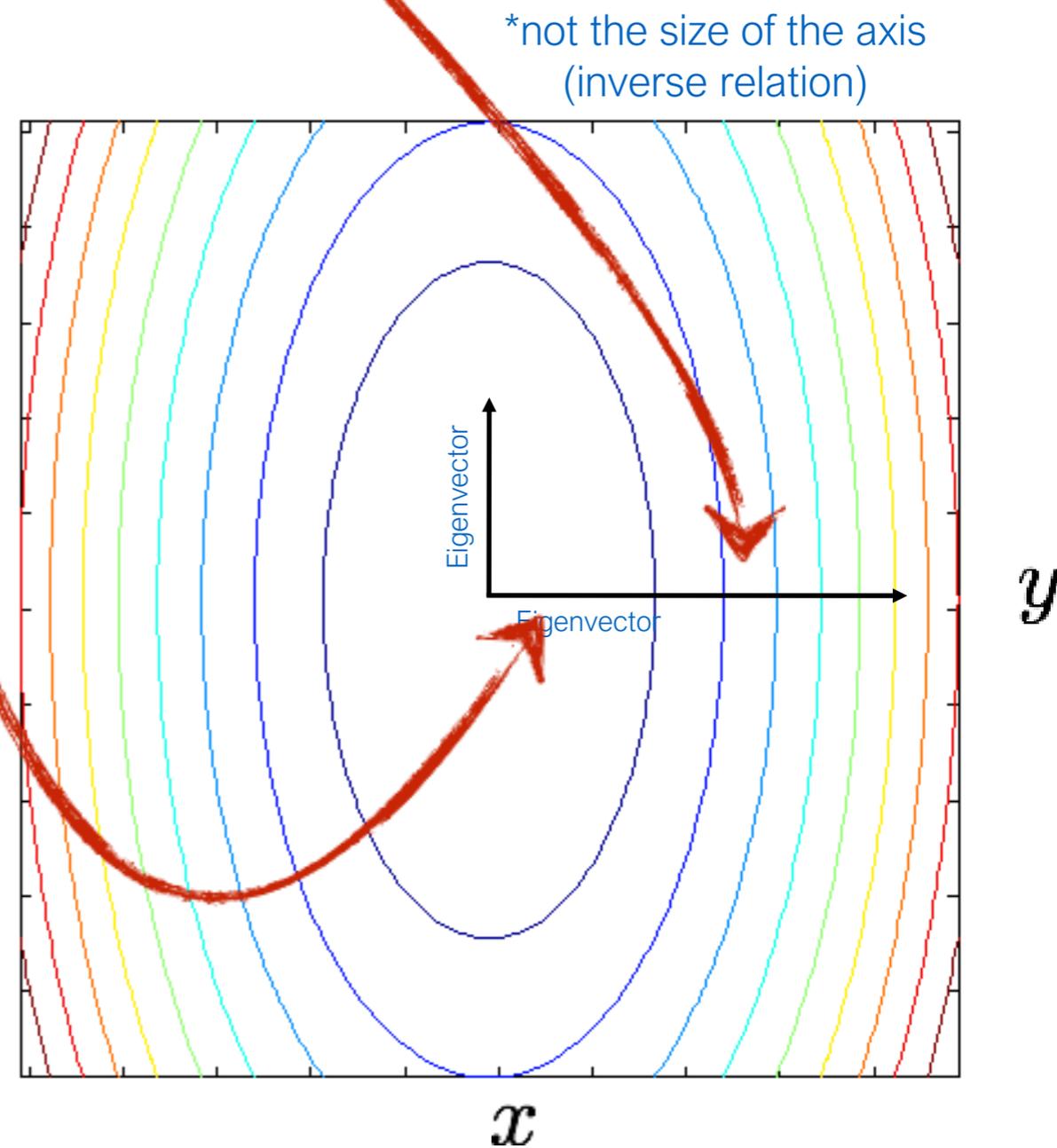
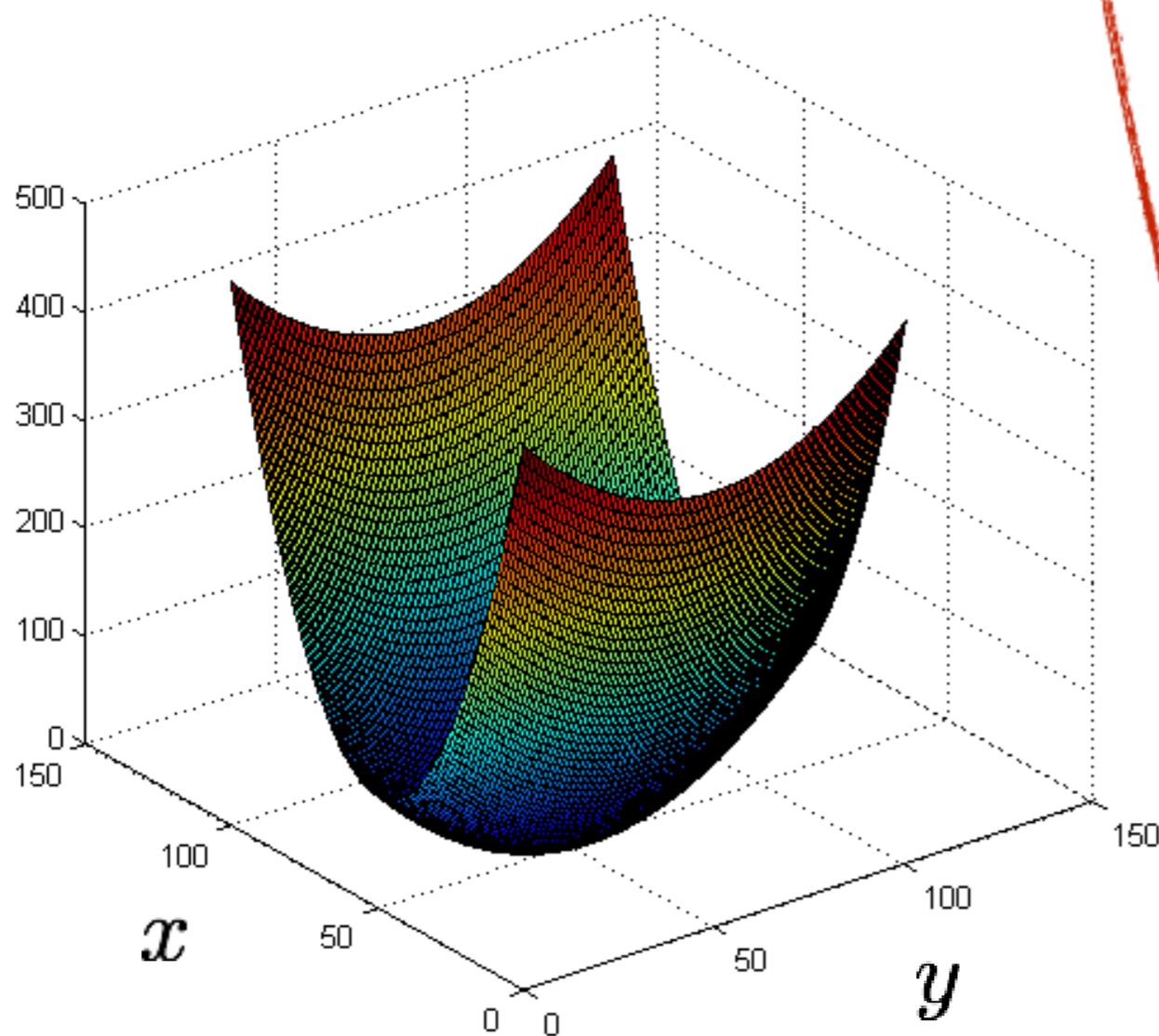
you can smash this bowl in the **x** direction



$$f(x, y) = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

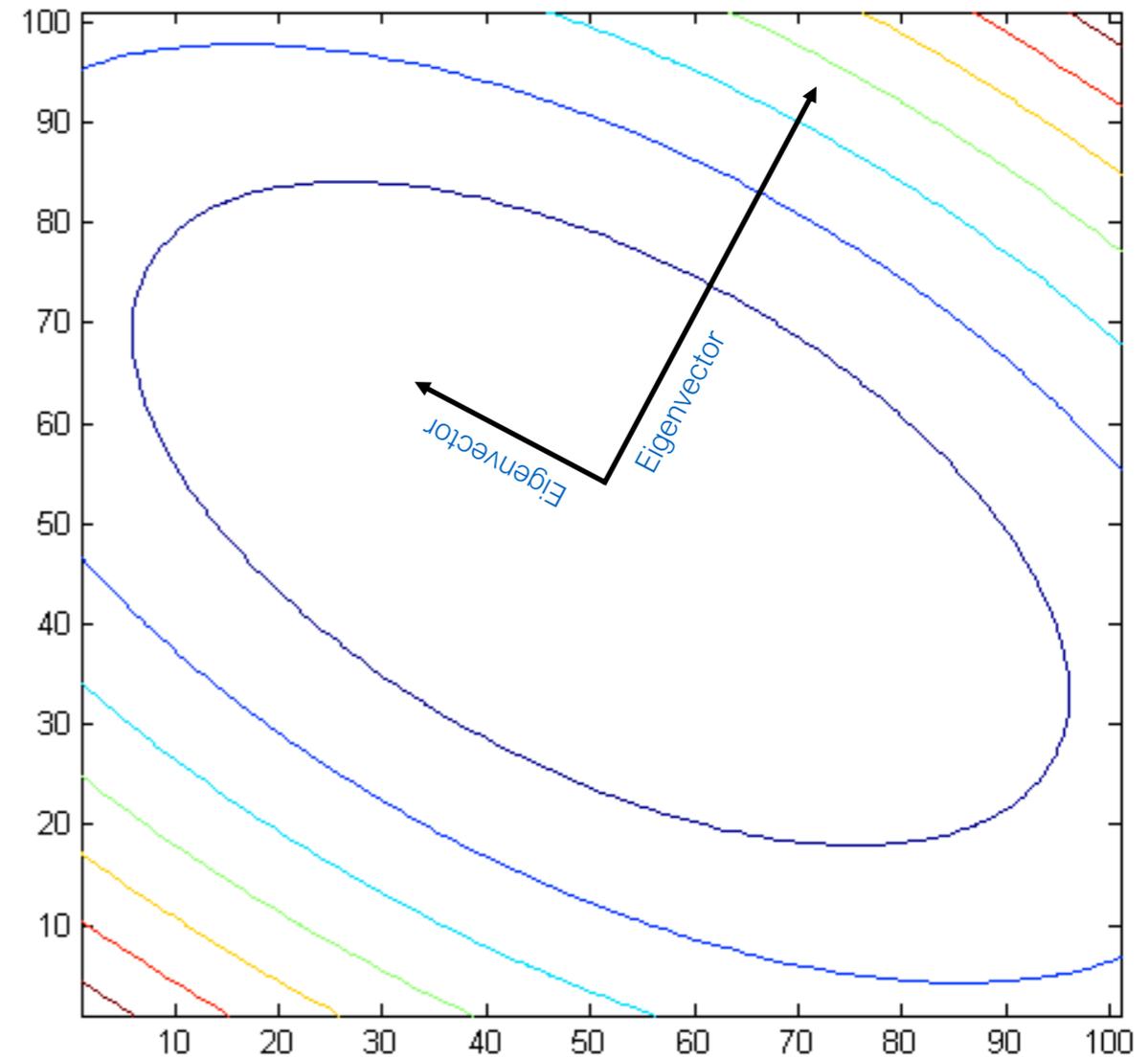
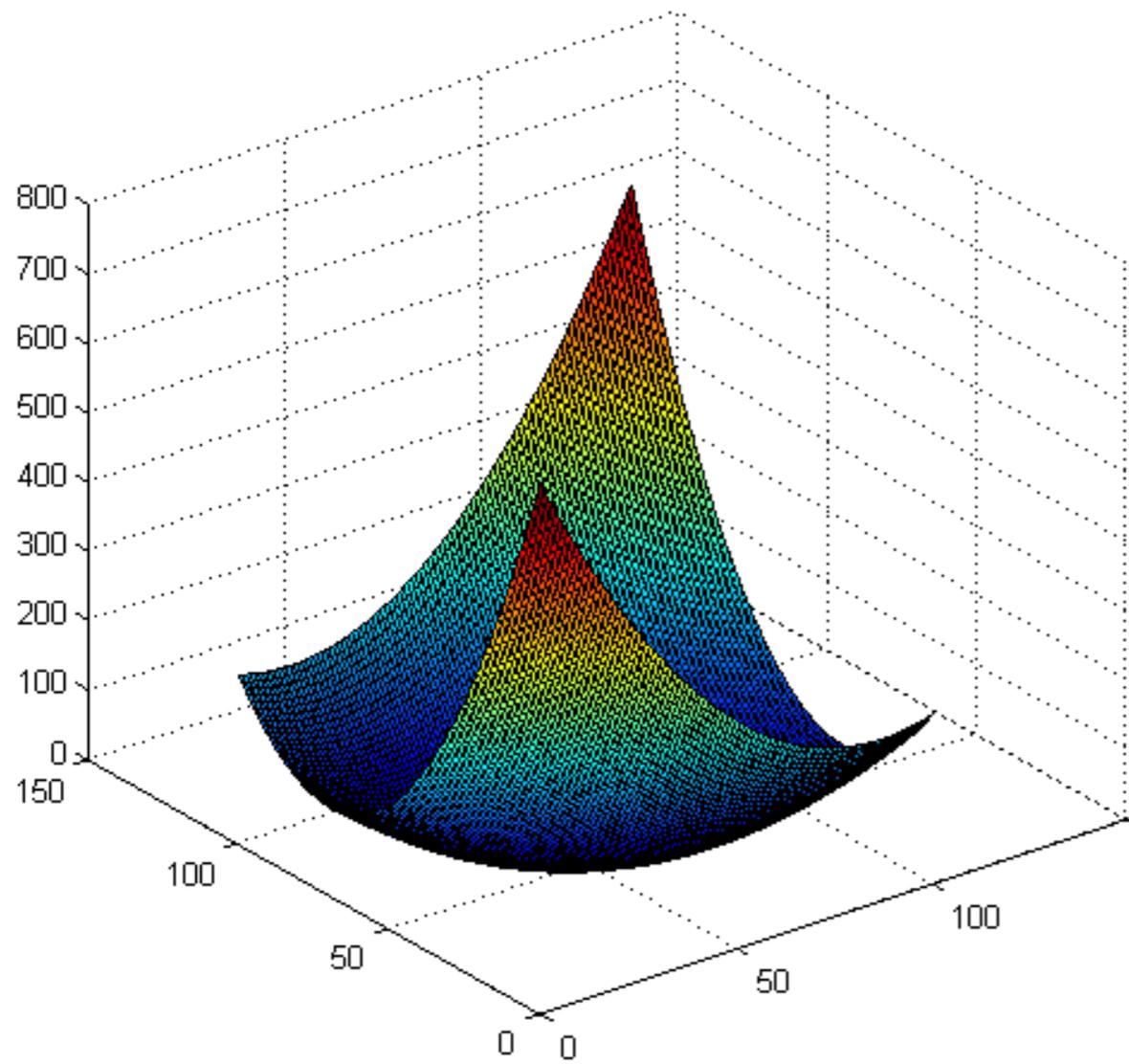
$$\mathbf{A} = \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}^T$$

Eigenvectors
Eigenvalues
Eigenvectors



$$\mathbf{A} = \begin{bmatrix} 3.25 & 1.30 \\ 1.30 & 1.75 \end{bmatrix} = \begin{bmatrix} 0.50 & -0.87 \\ -0.87 & -0.50 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 4 \end{bmatrix} \begin{bmatrix} 0.50 & -0.87 \\ -0.87 & -0.50 \end{bmatrix}^T$$

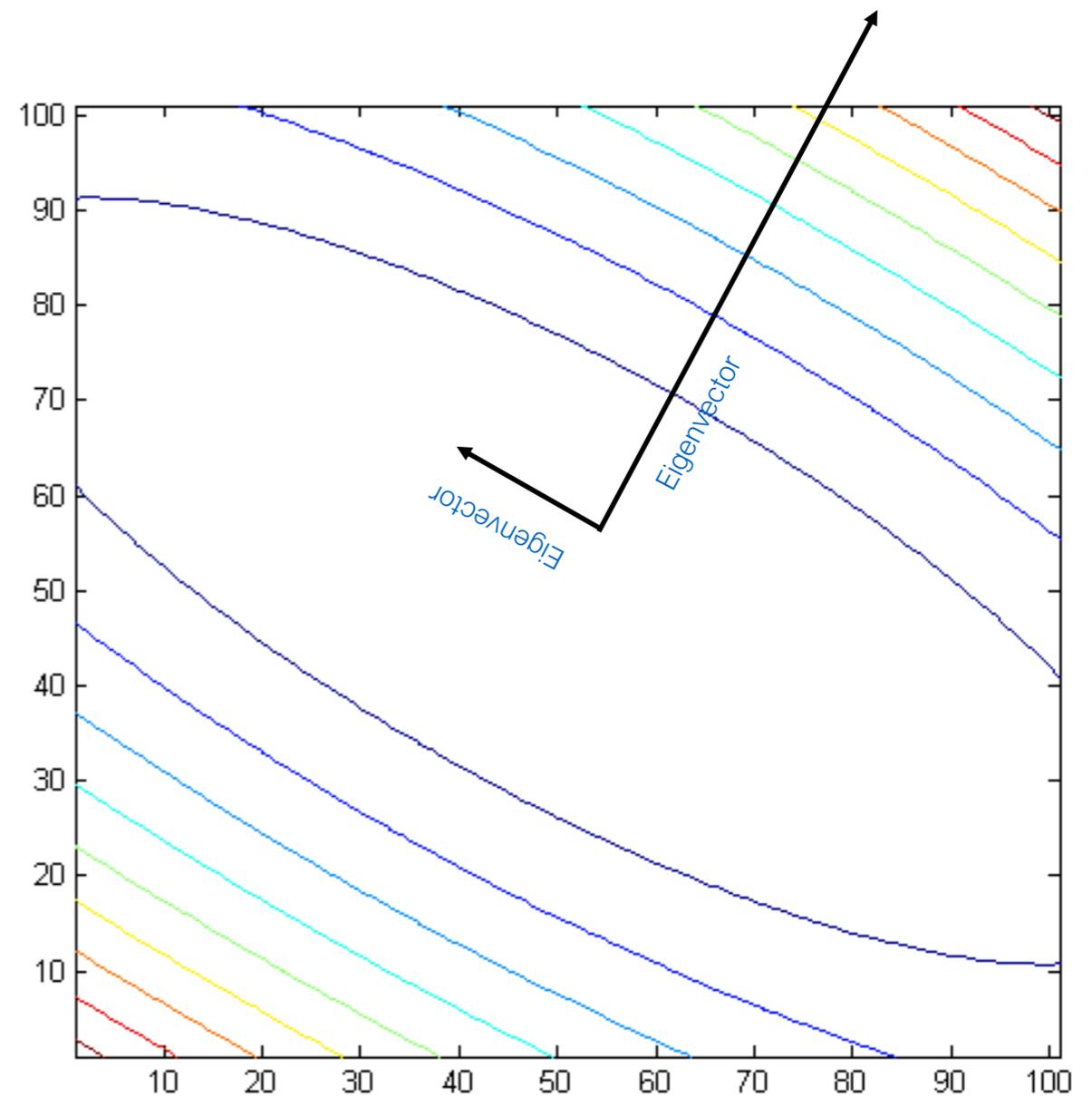
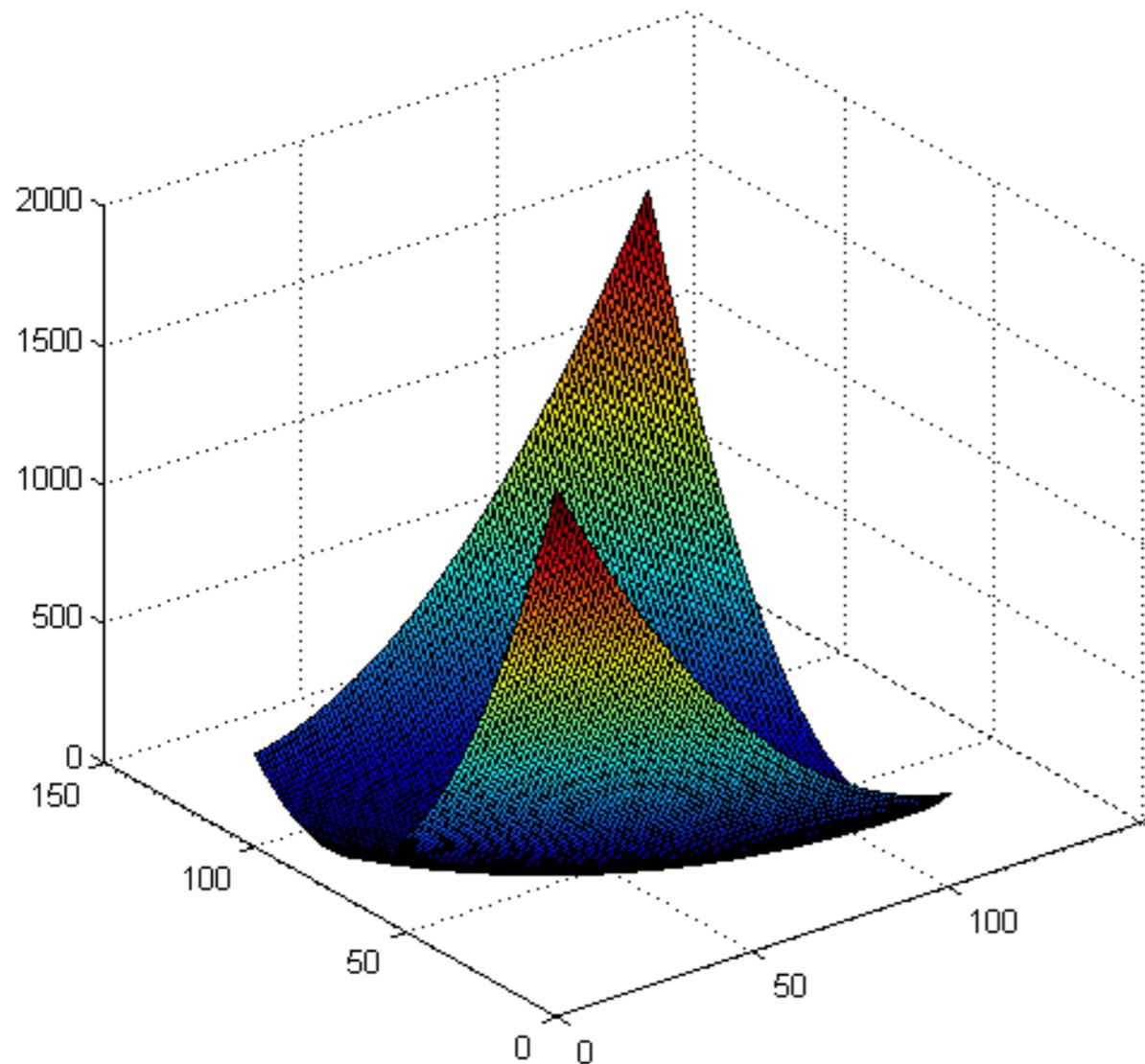
Eigenvectors
Eigenvalues
Eigenvectors



$$\mathbf{A} = \begin{bmatrix} 7.75 & 3.90 \\ 3.90 & 3.25 \end{bmatrix} = \begin{bmatrix} 0.50 & -0.87 \\ -0.87 & -0.50 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 10 \end{bmatrix} \begin{bmatrix} 0.50 & -0.87 \\ -0.87 & -0.50 \end{bmatrix}^T$$

Eigenvalues
Eigenvalues

Eigenvectors
Eigenvectors



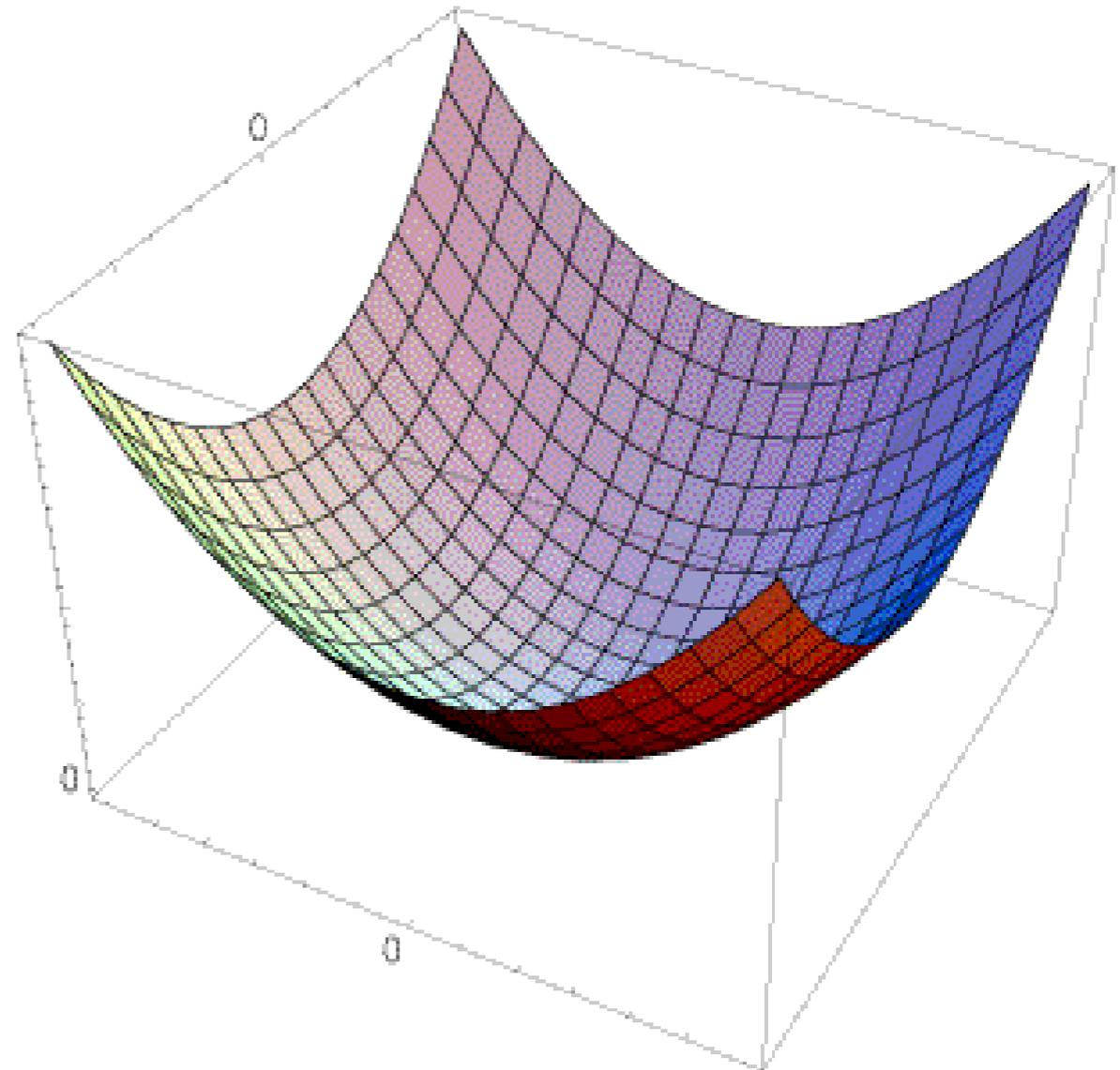
We will need this to understand the...

Error function for Harris Corners

The surface $E(u, v)$ is locally approximated by a quadratic form

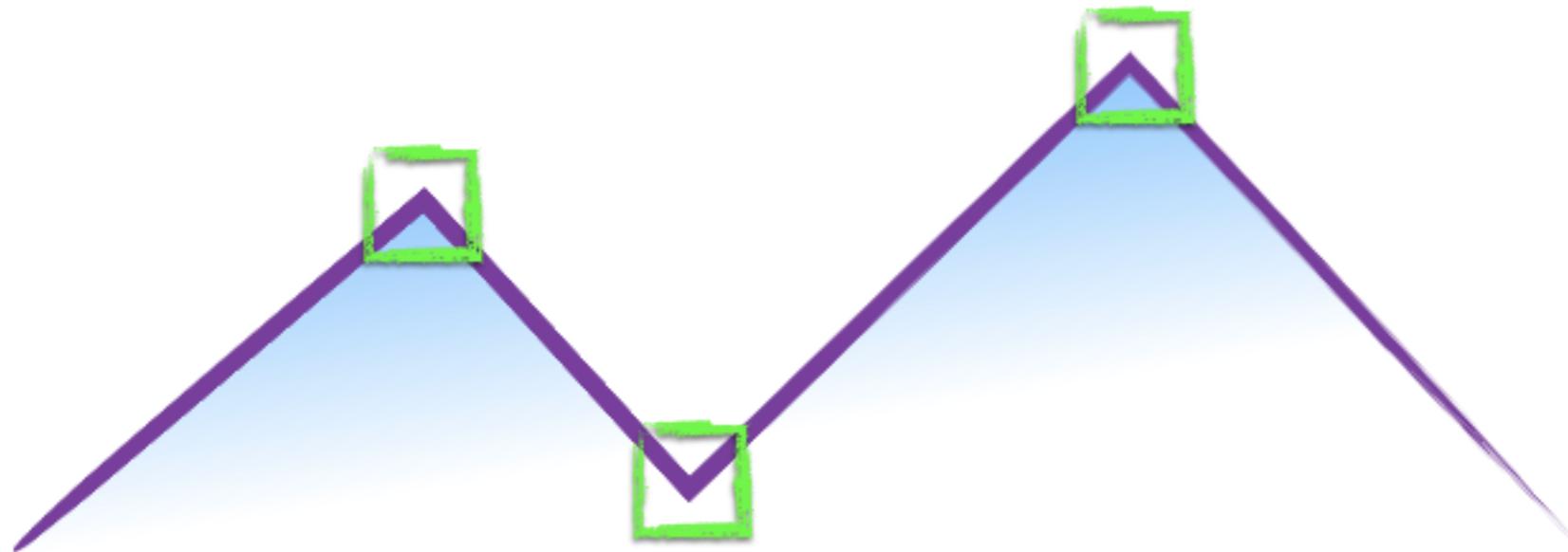
$$E(u, v) \approx [u \ v] M \begin{bmatrix} u \\ v \end{bmatrix}$$

$$M = \sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$



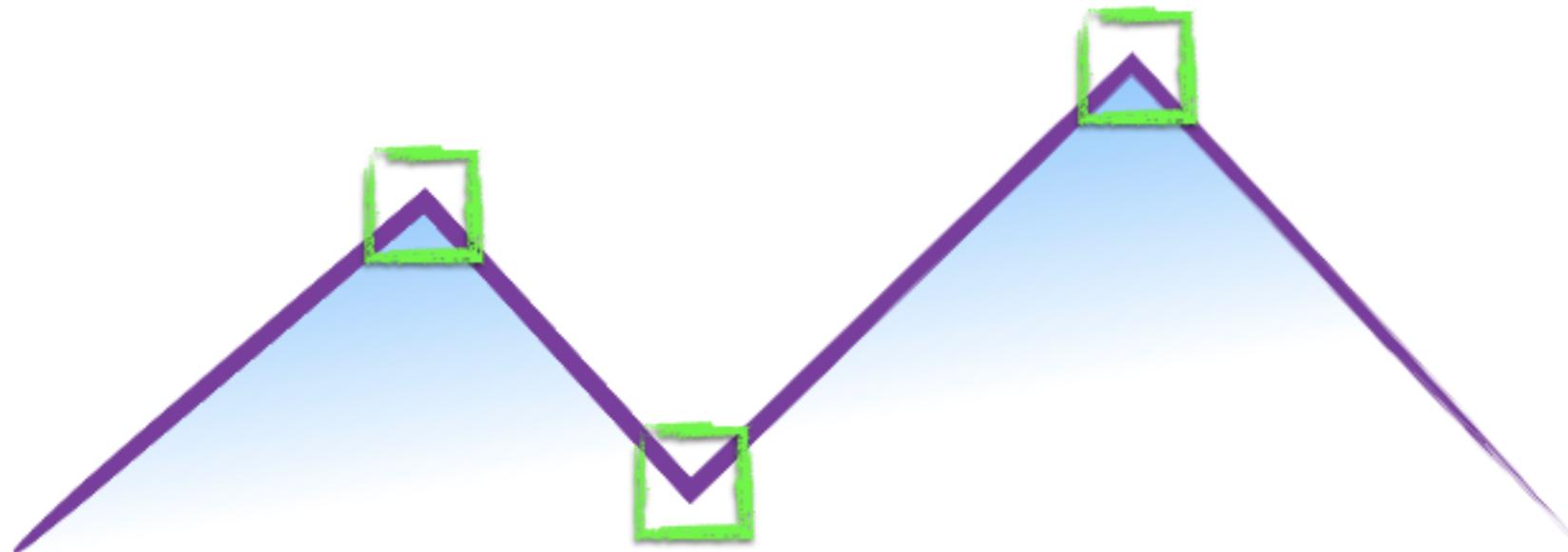
Harris corner detector

How do you find a corner?



How do you find a corner?

[Moravec 1980]

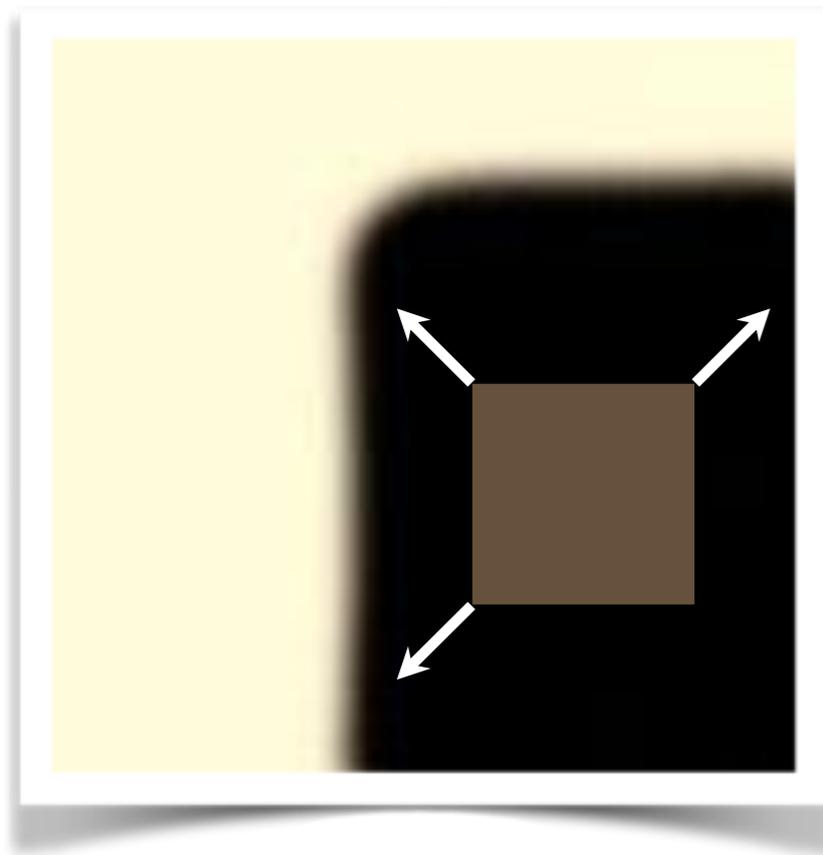


Easily recognized by looking through a small window

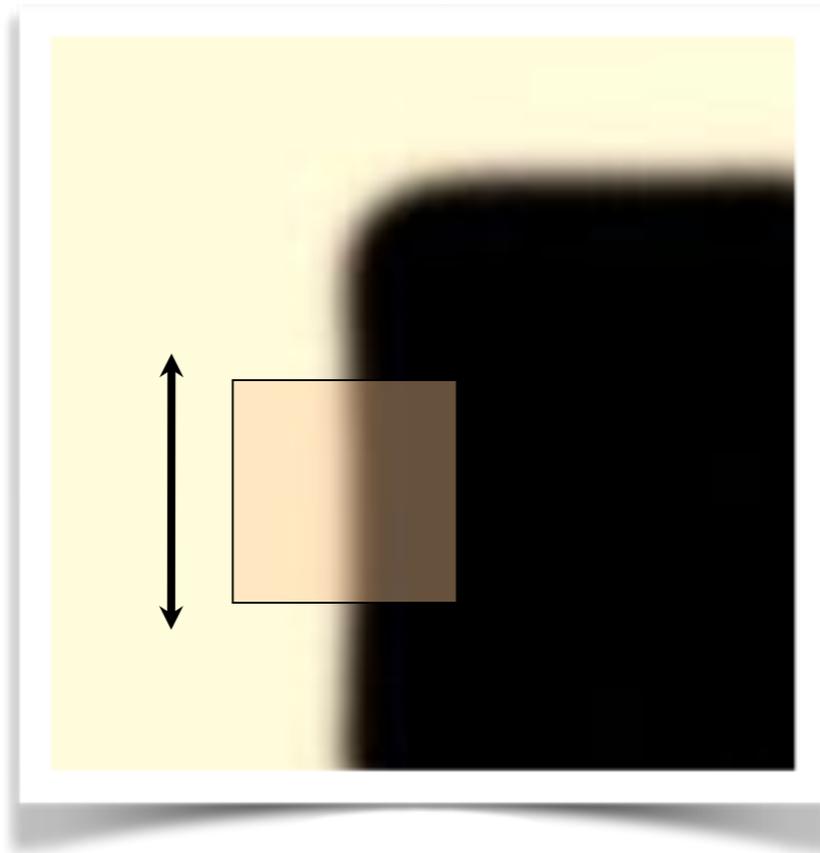
Shifting the window should give large change in intensity

Easily recognized by looking through a small window

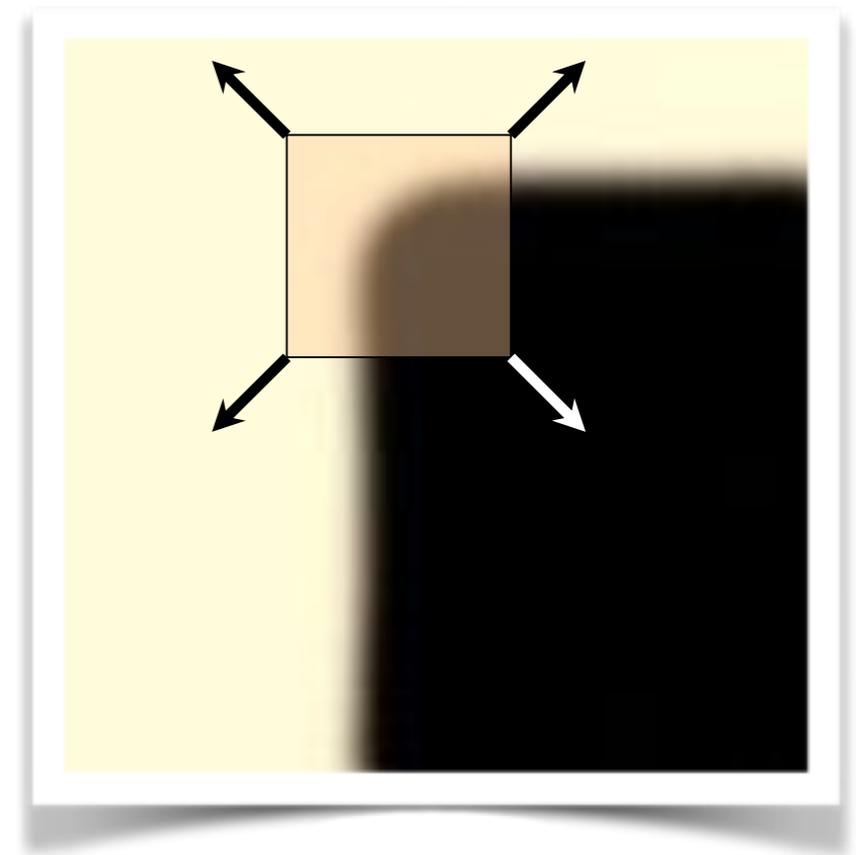
Shifting the window should give large change in intensity



“flat” region:
no change in all
directions



“edge”:
no change along the edge
direction



“corner”:
significant change in all
directions

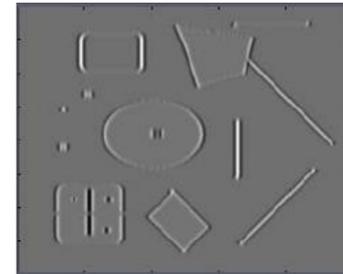
Design a program to detect corners
(hint: use image gradients)

Finding corners

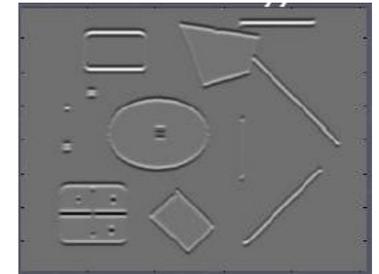
(a.k.a. PCA)

1. Compute image gradients over small region
2. Subtract mean from each image gradient
3. Compute the covariance matrix
4. Compute eigenvectors and eigenvalues
5. Use threshold on eigenvalues to detect corners

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



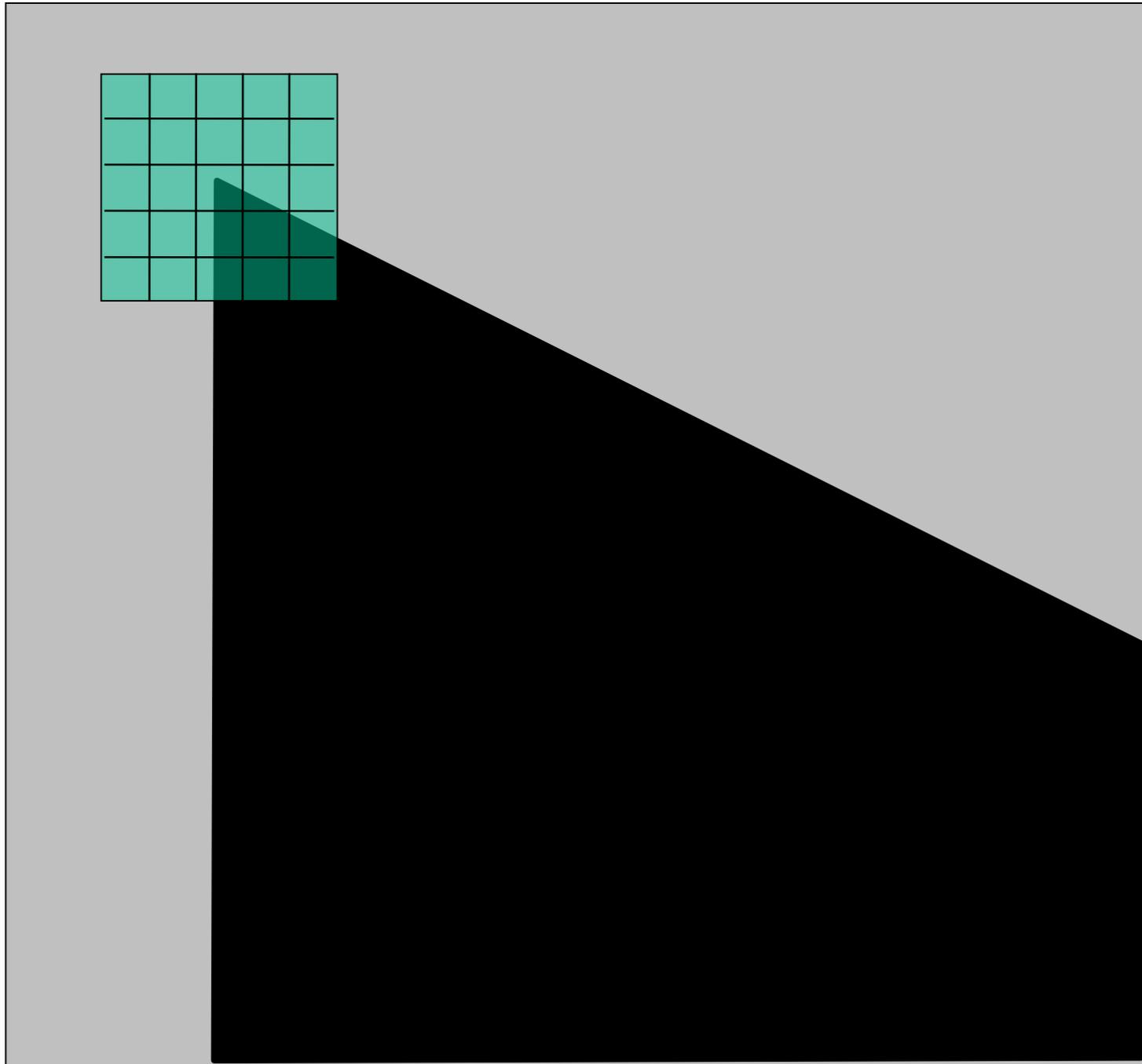
$$I_y = \frac{\partial I}{\partial y}$$



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

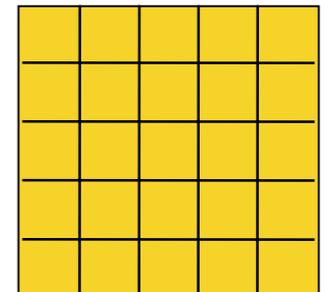
1. Compute image gradients over a small region
(not just a single pixel)

1. Compute image gradients over a small region (not just a single pixel)



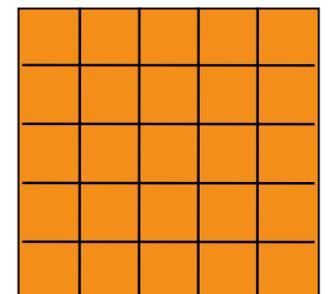
array of x gradients

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



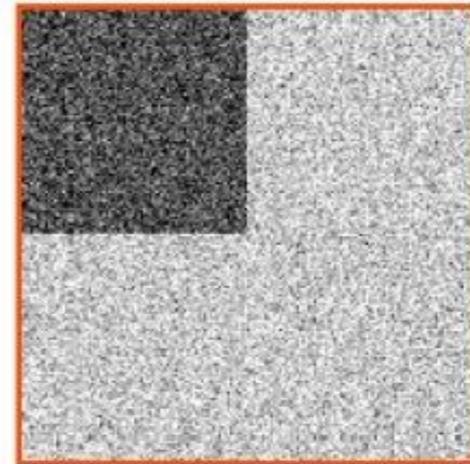
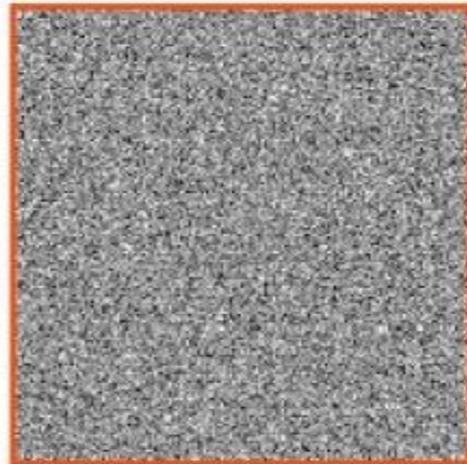
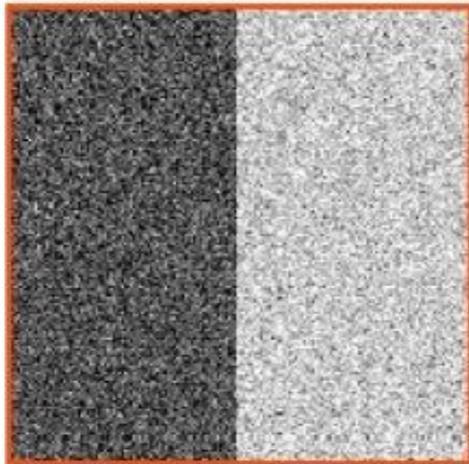
array of y gradients

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

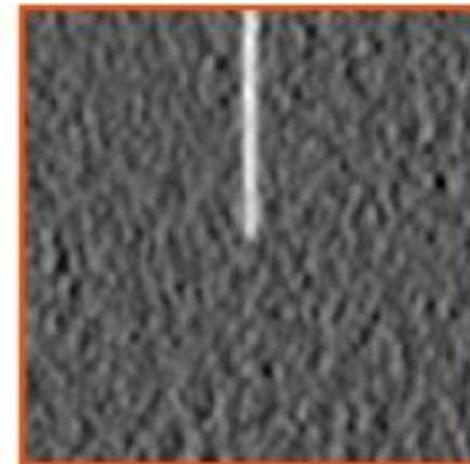
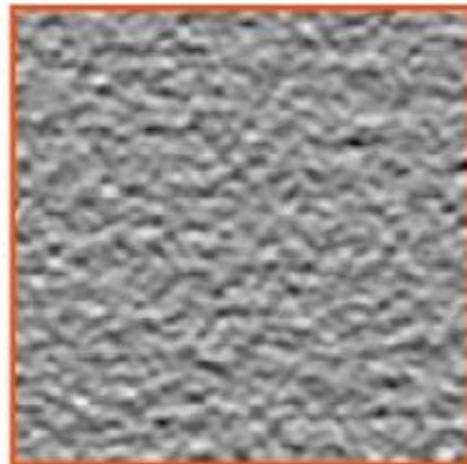
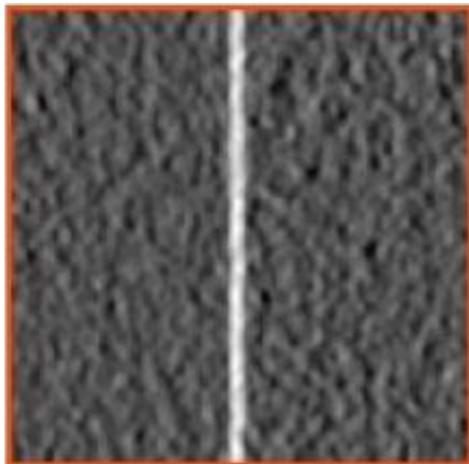


visualization of gradients

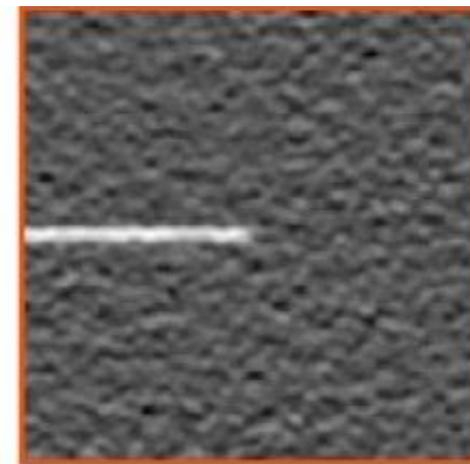
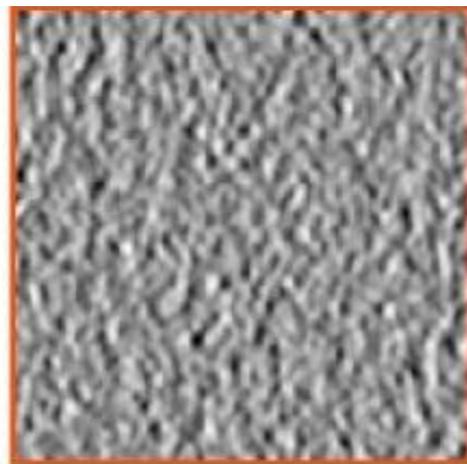
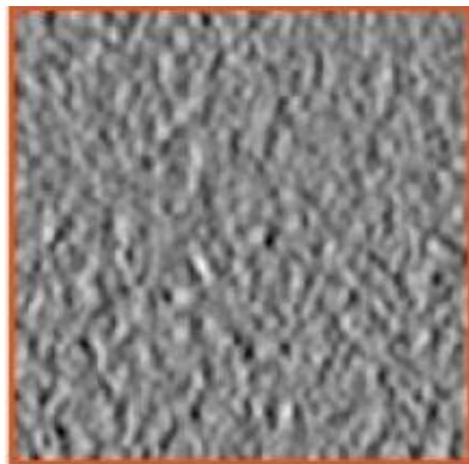
image

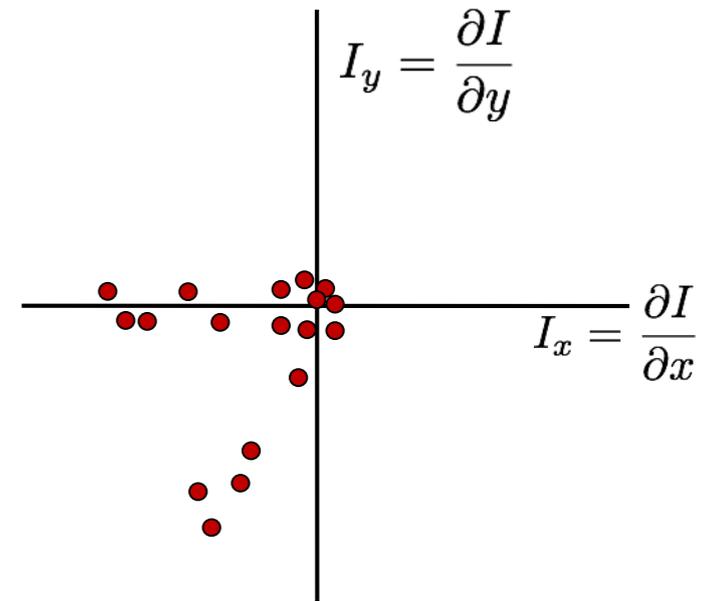
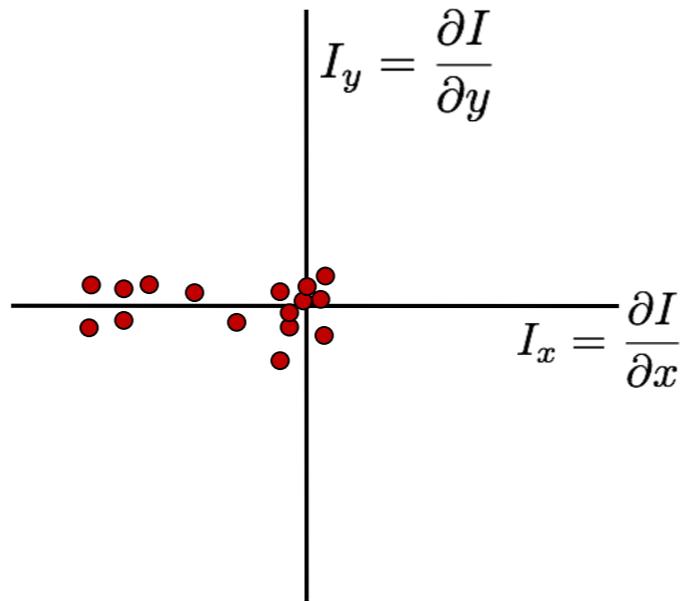
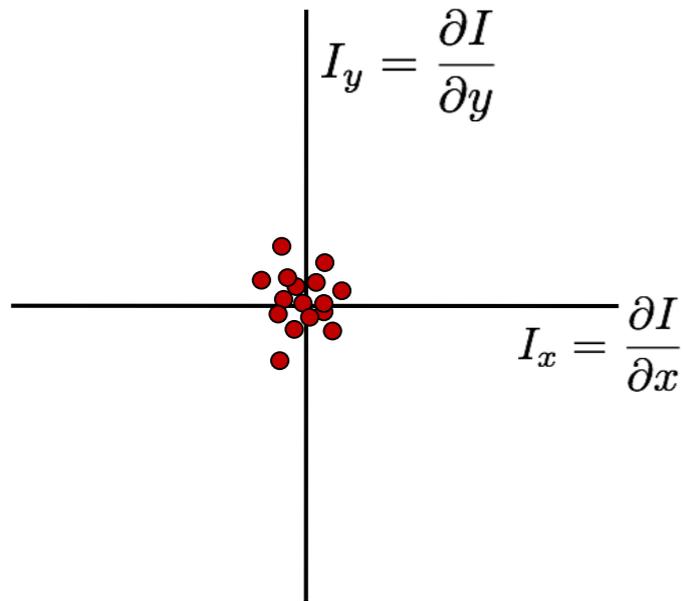
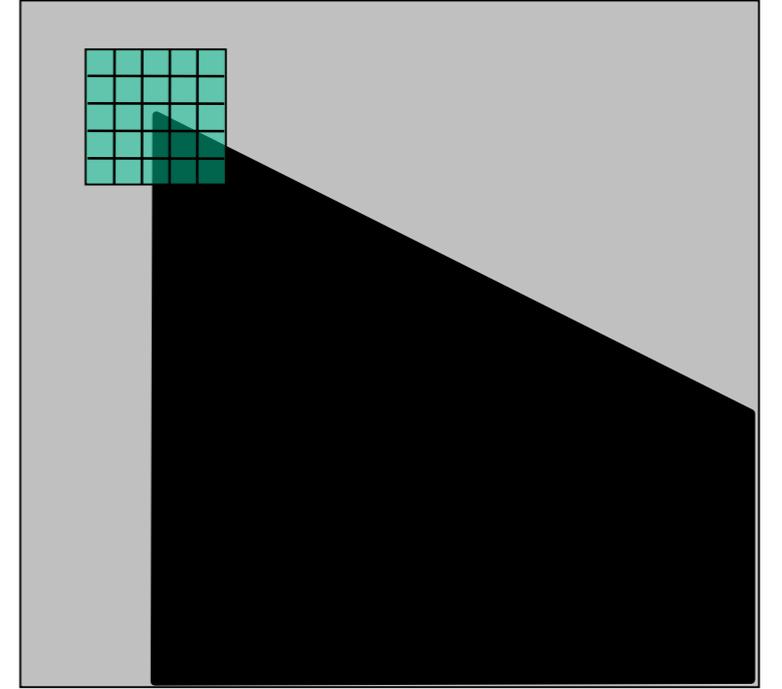
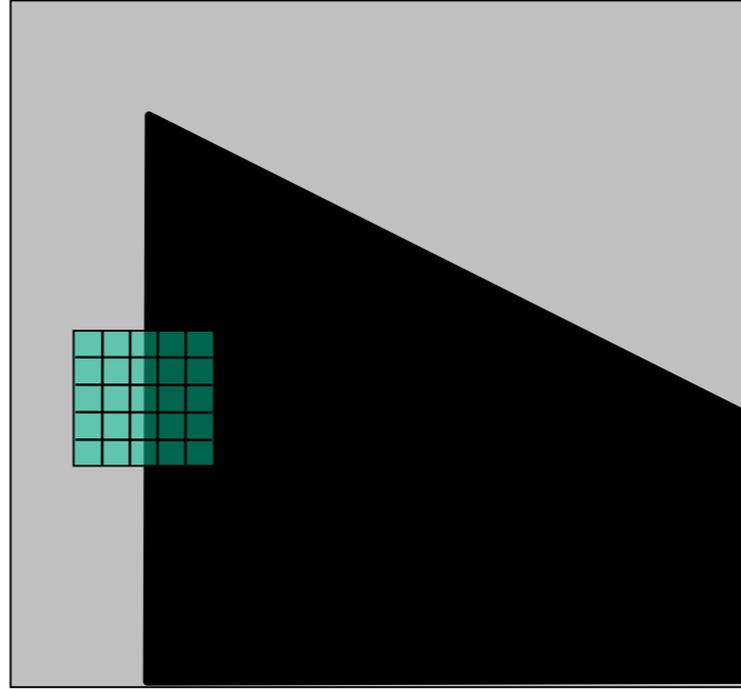
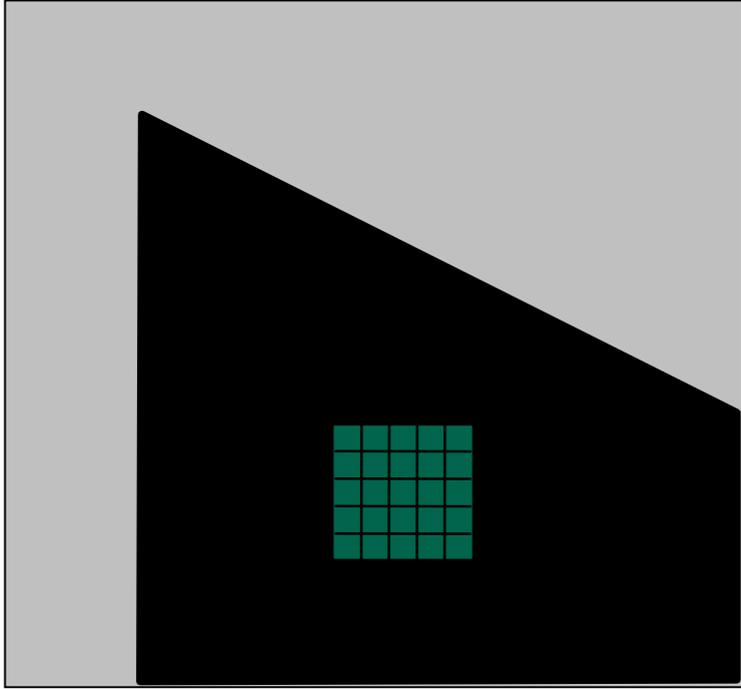


X derivative

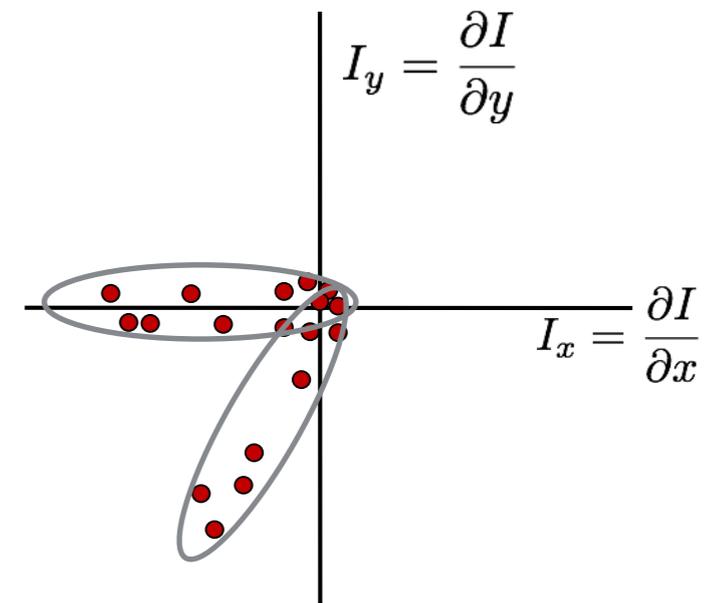
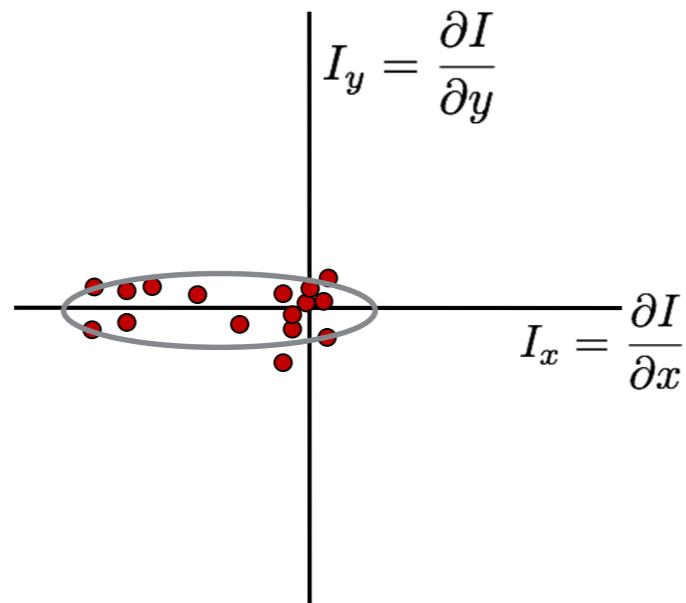
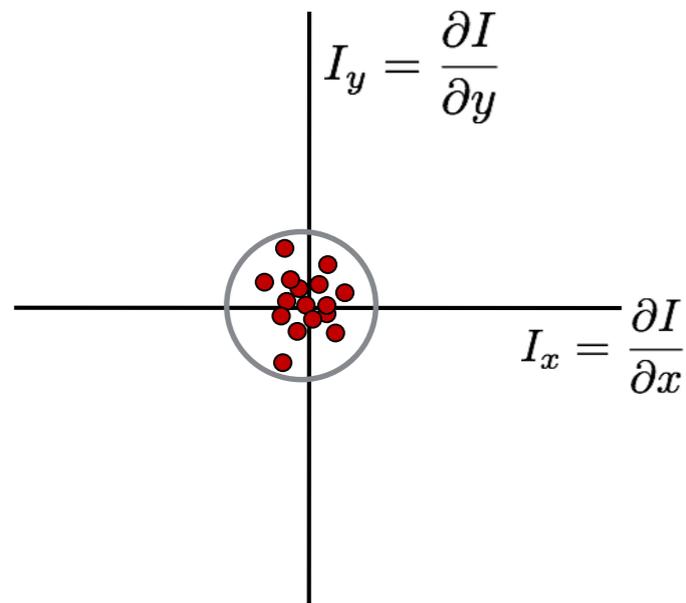
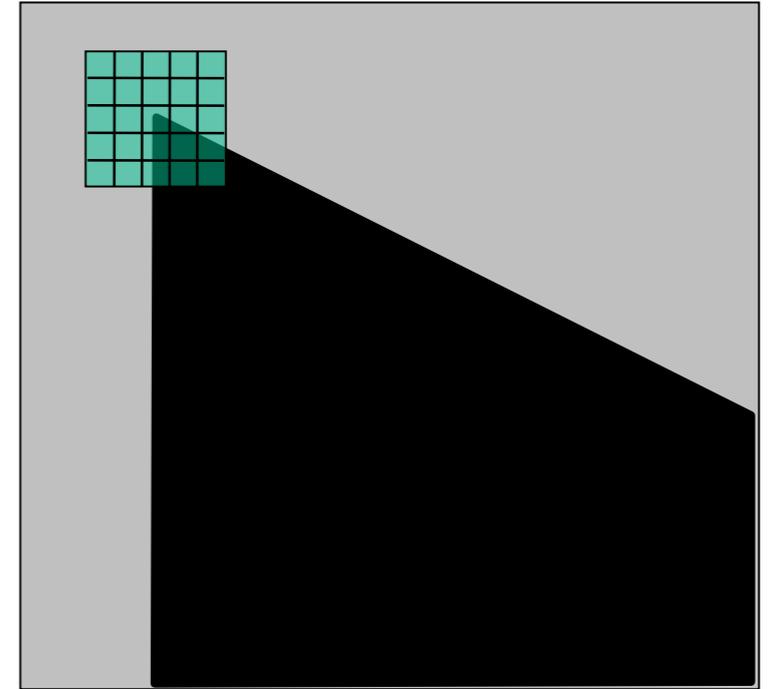
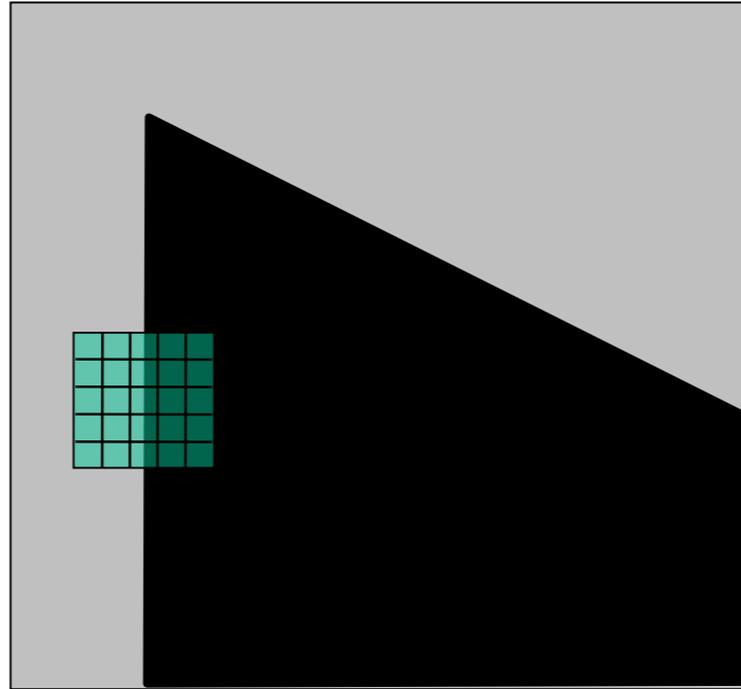
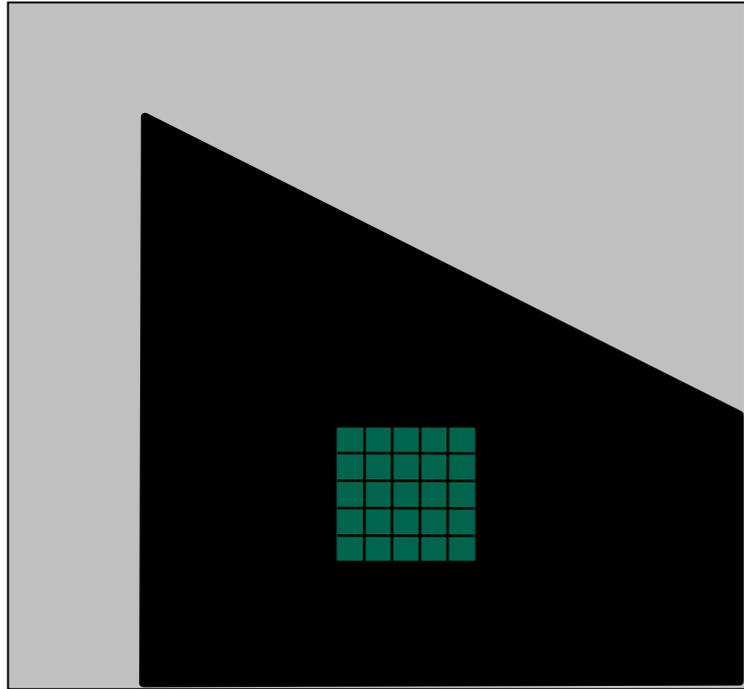


Y derivative

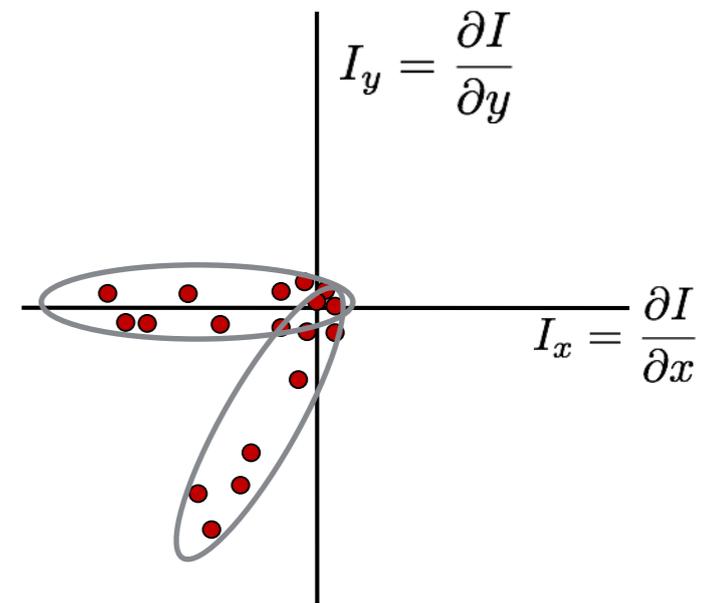
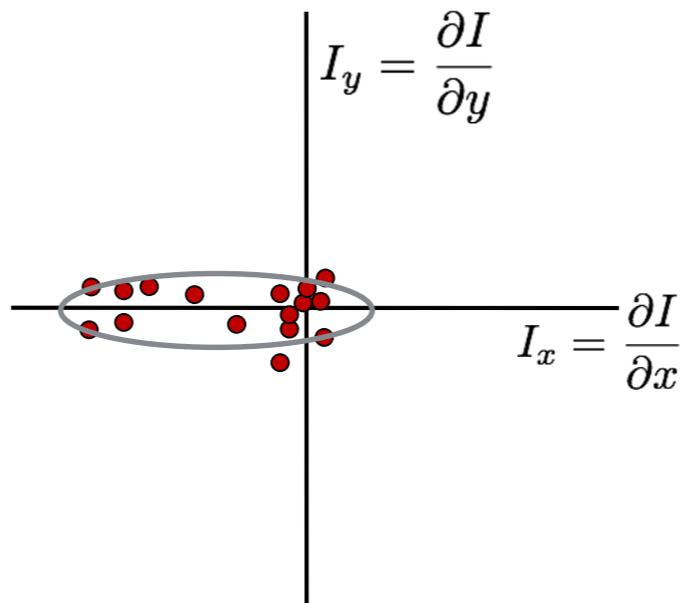
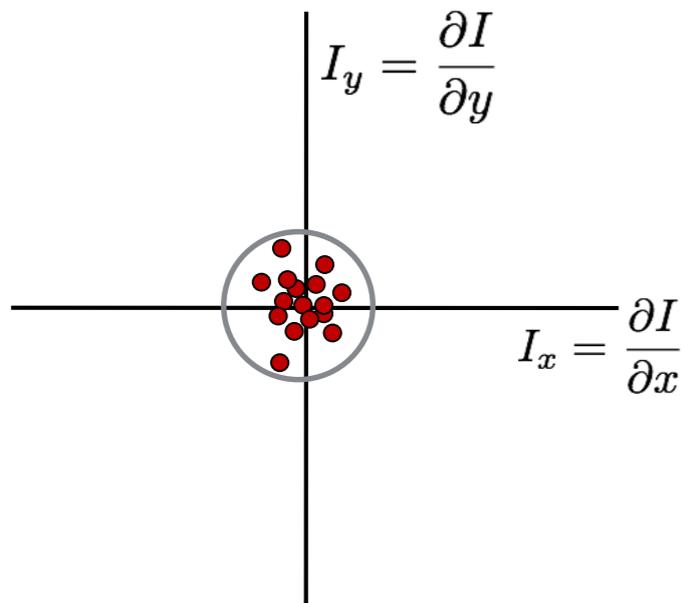
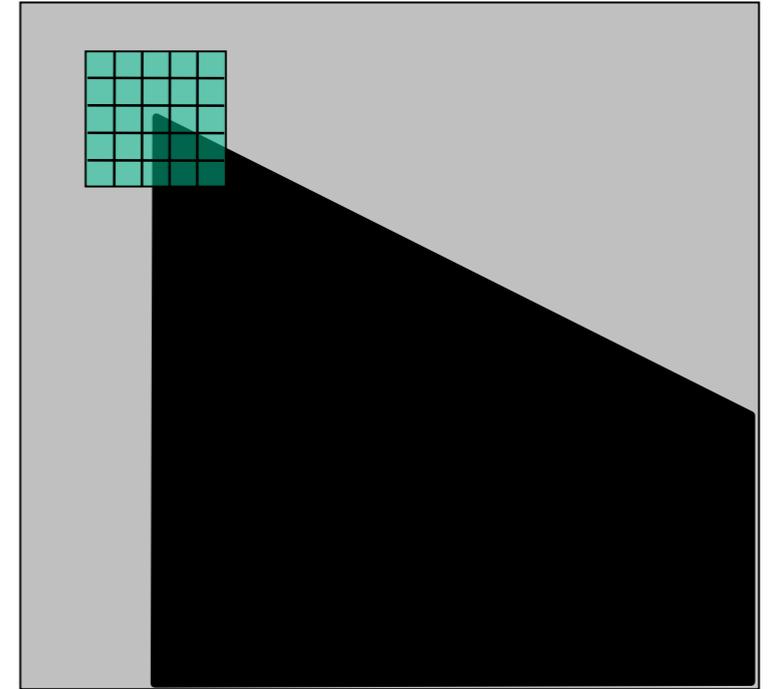
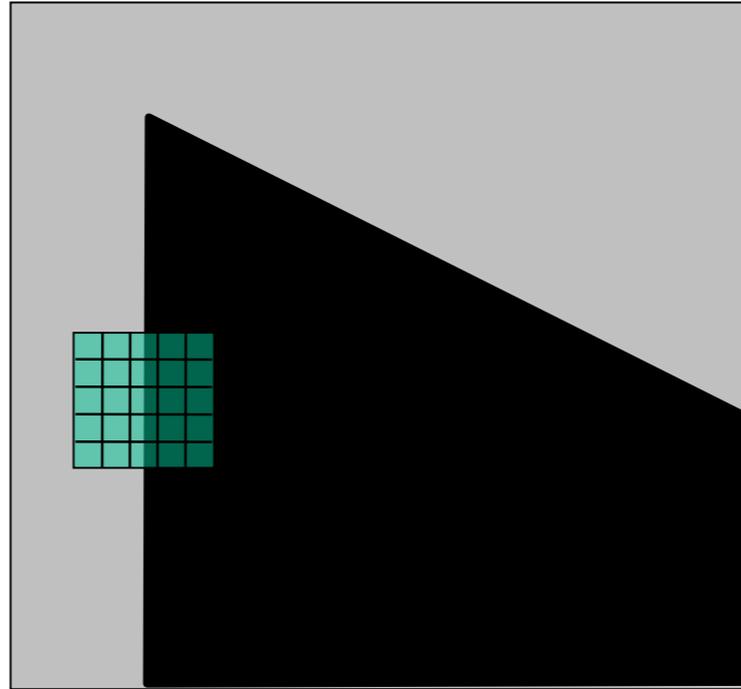
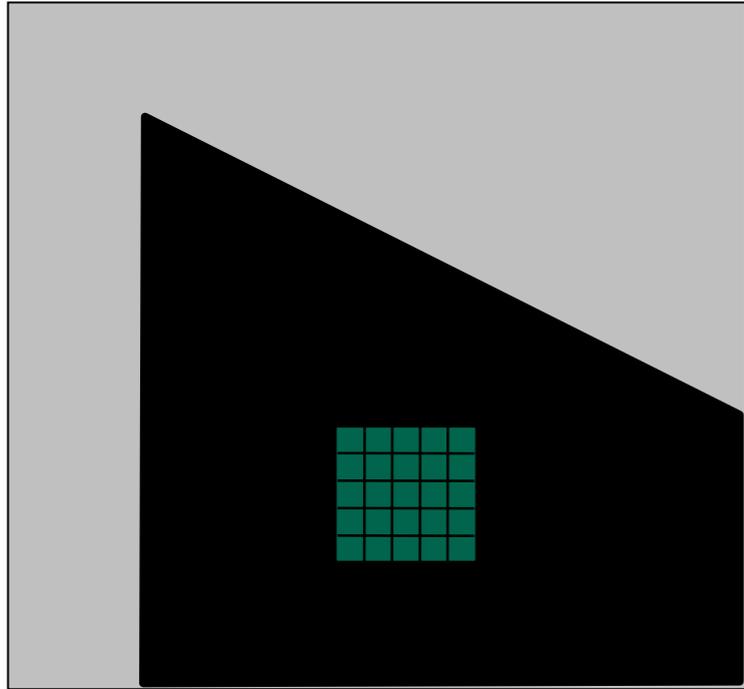




What does the distribution tell you about the region?



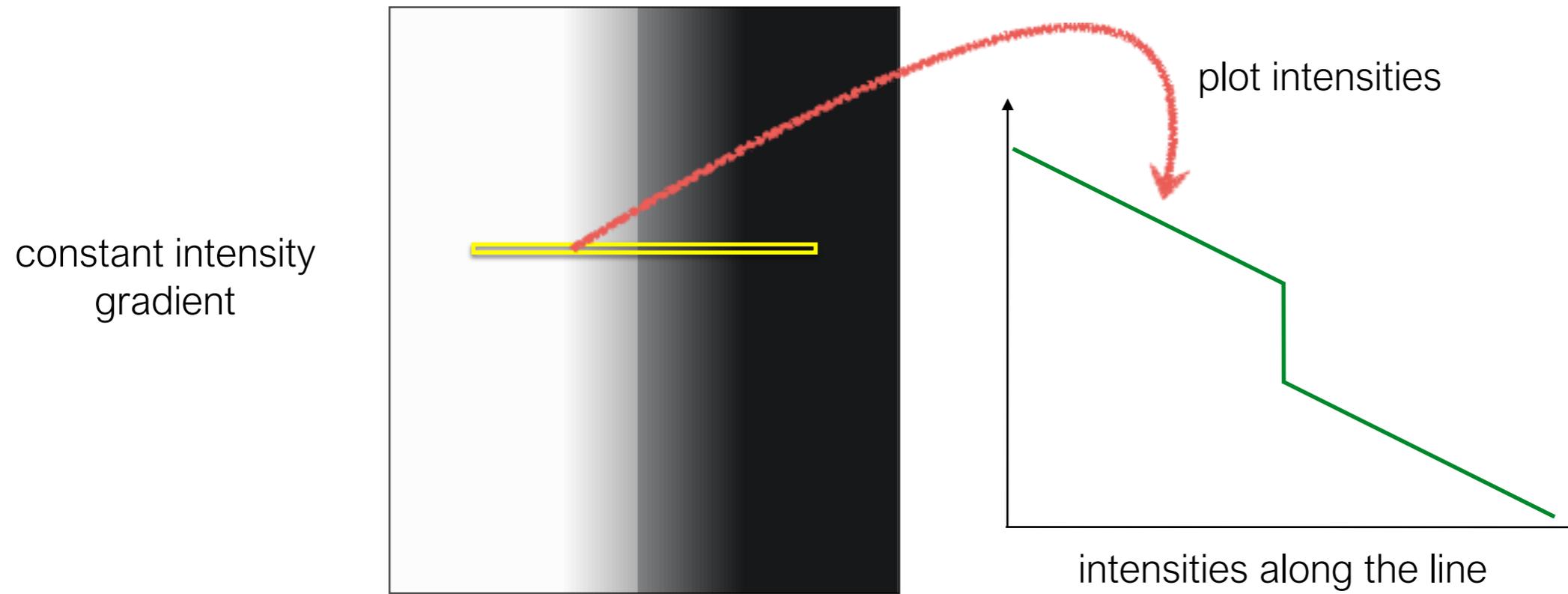
distribution reveals edge orientation and magnitude



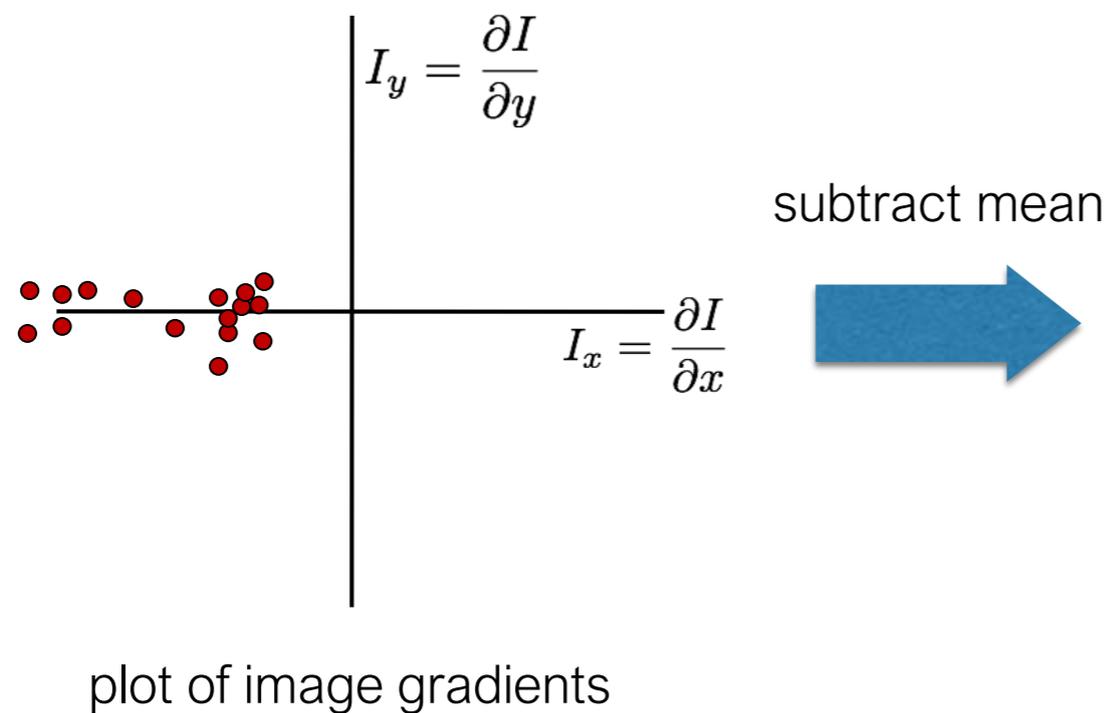
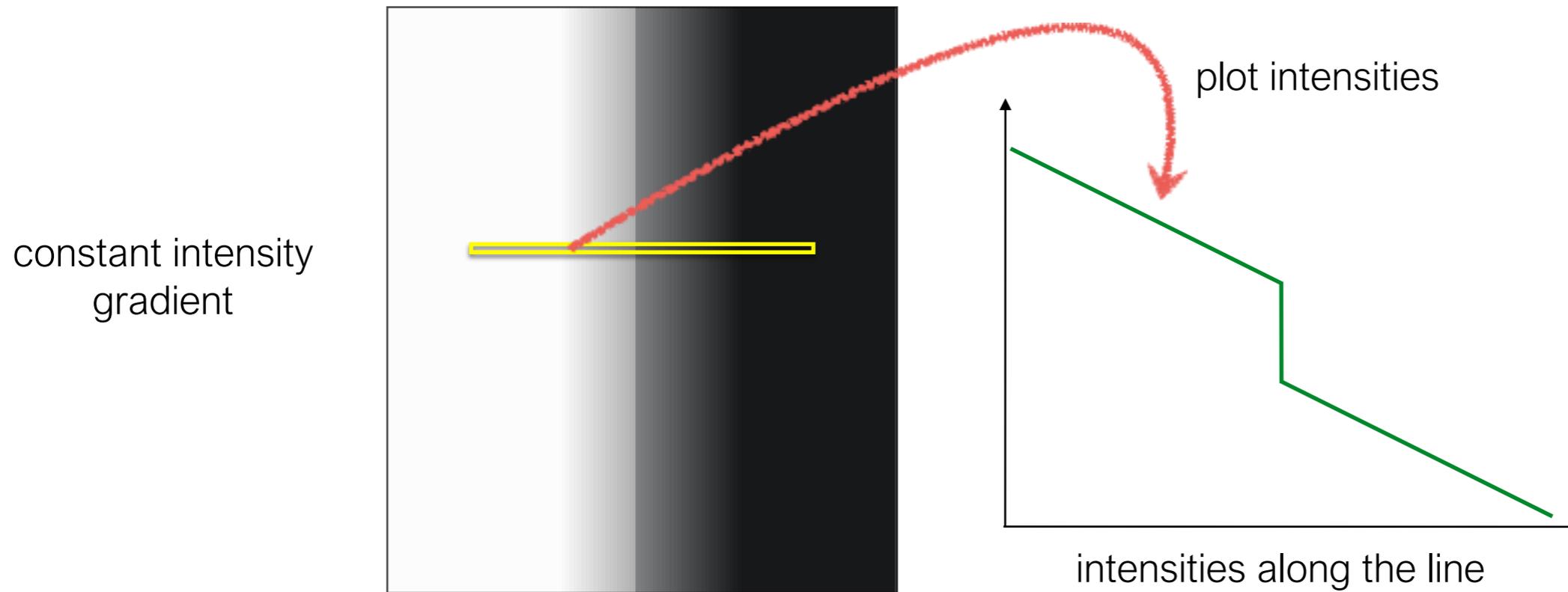
How do you quantify orientation and magnitude?

2. Subtract the mean from each image gradient

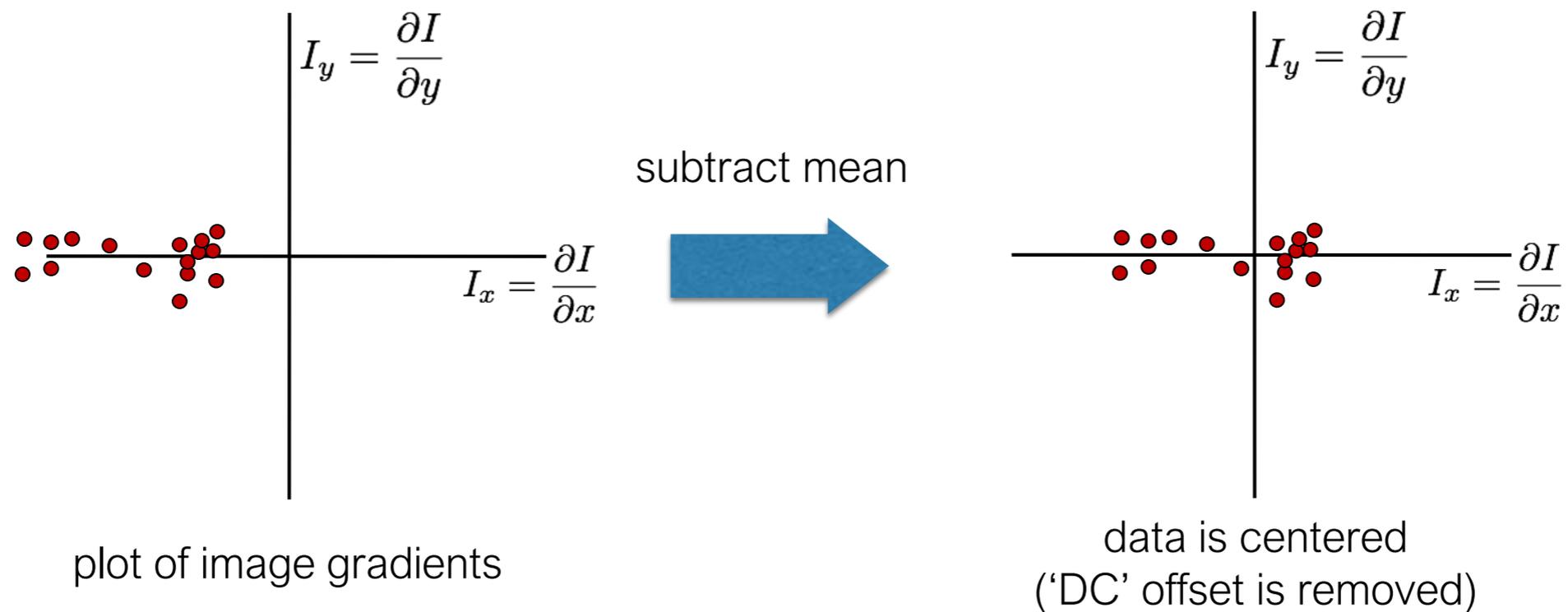
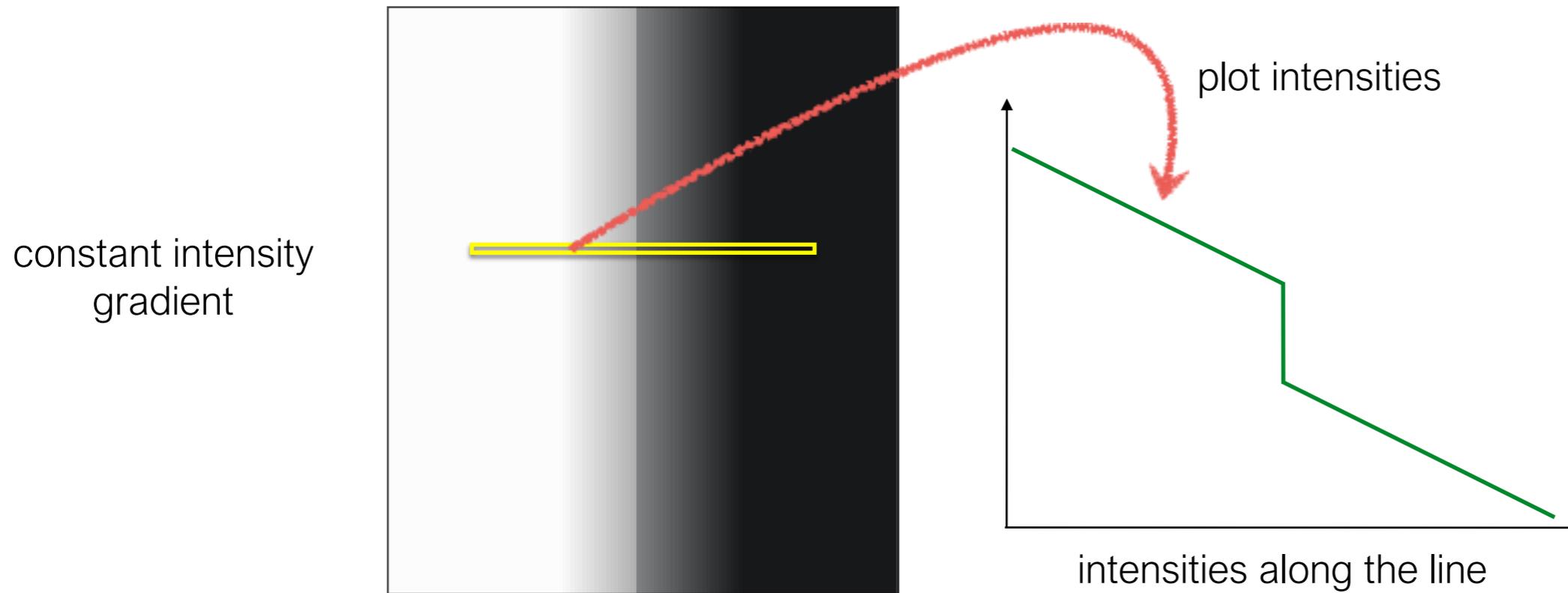
2. Subtract the mean from each image gradient



2. Subtract the mean from each image gradient



2. Subtract the mean from each image gradient



3. Compute the covariance matrix

3. Compute the covariance matrix

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

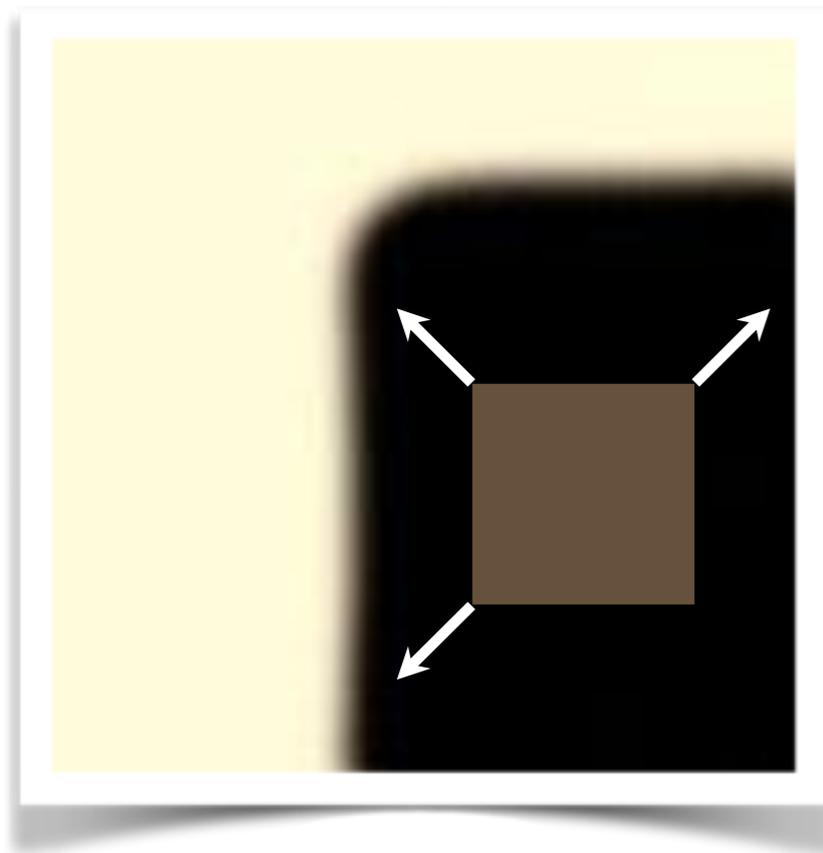
$$\sum_{p \in P} I_x I_y = \text{sum} \left(\begin{array}{c} I_x = \frac{\partial I}{\partial x} \\ \begin{array}{|c|c|c|c|c|} \hline & & & & \\ \hline \end{array} * \begin{array}{c} I_y = \frac{\partial I}{\partial y} \\ \begin{array}{|c|c|c|c|c|} \hline & & & & \\ \hline \end{array} \right)$$

array of x gradients array of y gradients

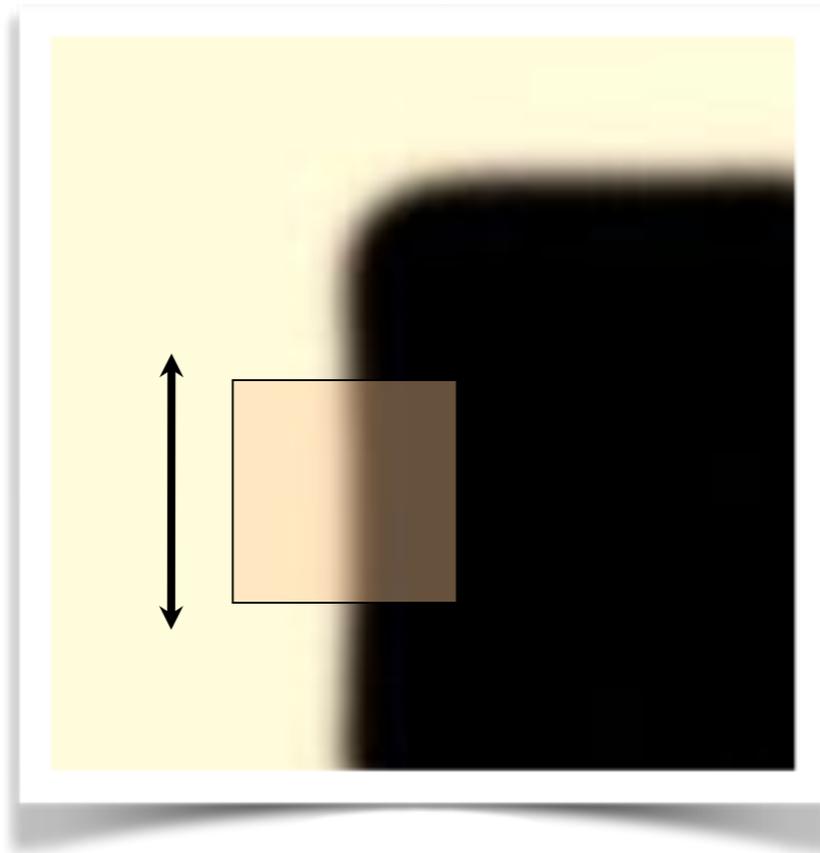
Where does this covariance matrix come from?

Easily recognized by looking through a small window

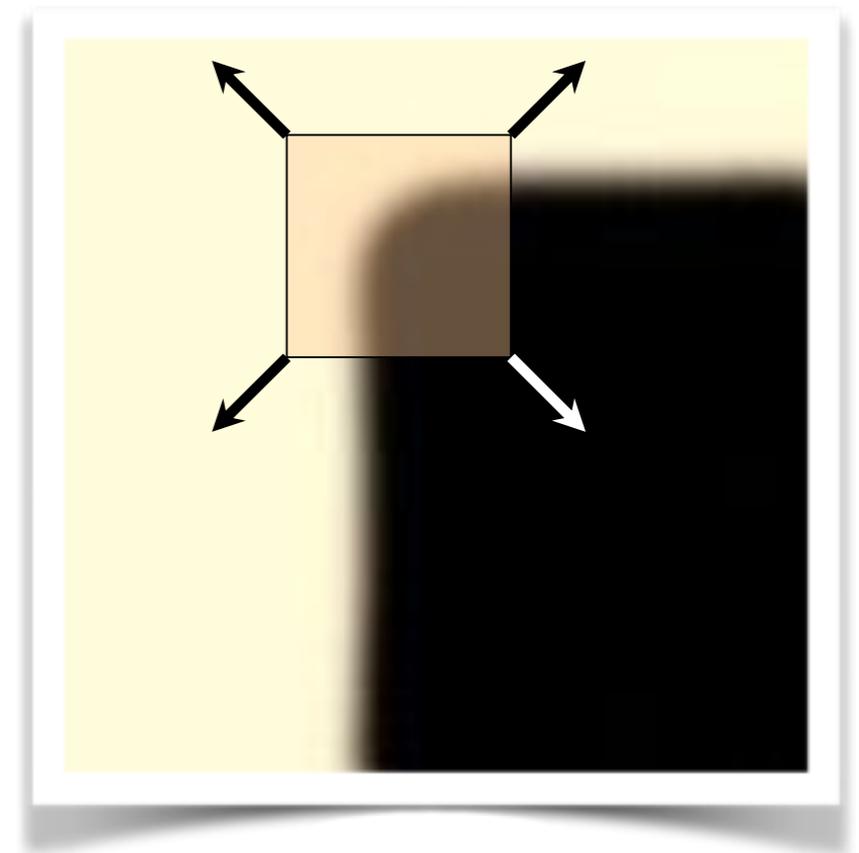
Shifting the window should give large change in intensity



“flat” region:
no change in all
directions



“edge”:
no change along the edge
direction



“corner”:
significant change in all
directions

Some mathematical background...

Error function

Change of intensity for the shift $[u, v]$:

$$E(u, v) = \sum_{x, y} w(x, y) [I(x + u, y + v) - I(x, y)]^2$$

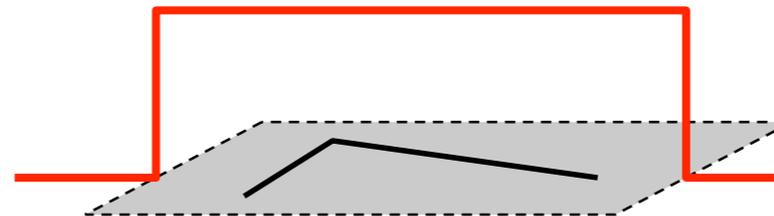
Error
function

Window
function

Shifted
intensity

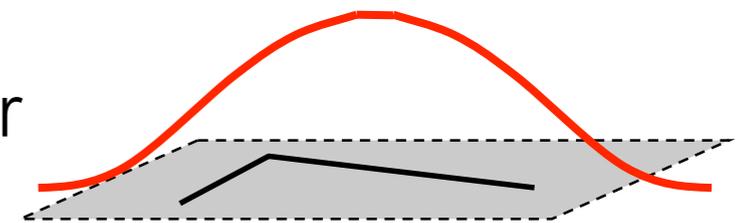
Intensity

Window function $w(x, y) =$



1 in window, 0 outside

or



Gaussian

Error function approximation

Change of intensity for the shift $[u, v]$:

$$E(u, v) = \sum_{x, y} w(x, y) [I(x + u, y + v) - I(x, y)]^2$$

First-order Taylor expansion of $I(x, y)$ about $(0, 0)$
(bilinear approximation for small shifts)

Bilinear approximation

For small shifts $[u, v]$ we have a 'bilinear approximation':

Change in
appearance for a
shift $[u, v]$

$$E(u, v) \cong [u, v] M \begin{bmatrix} u \\ v \end{bmatrix}$$

where M is a 2×2 matrix computed from image derivatives:

'second moment' matrix
'structure tensor'

$$M = \sum_{x, y} w(x, y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

By computing the gradient covariance matrix...

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

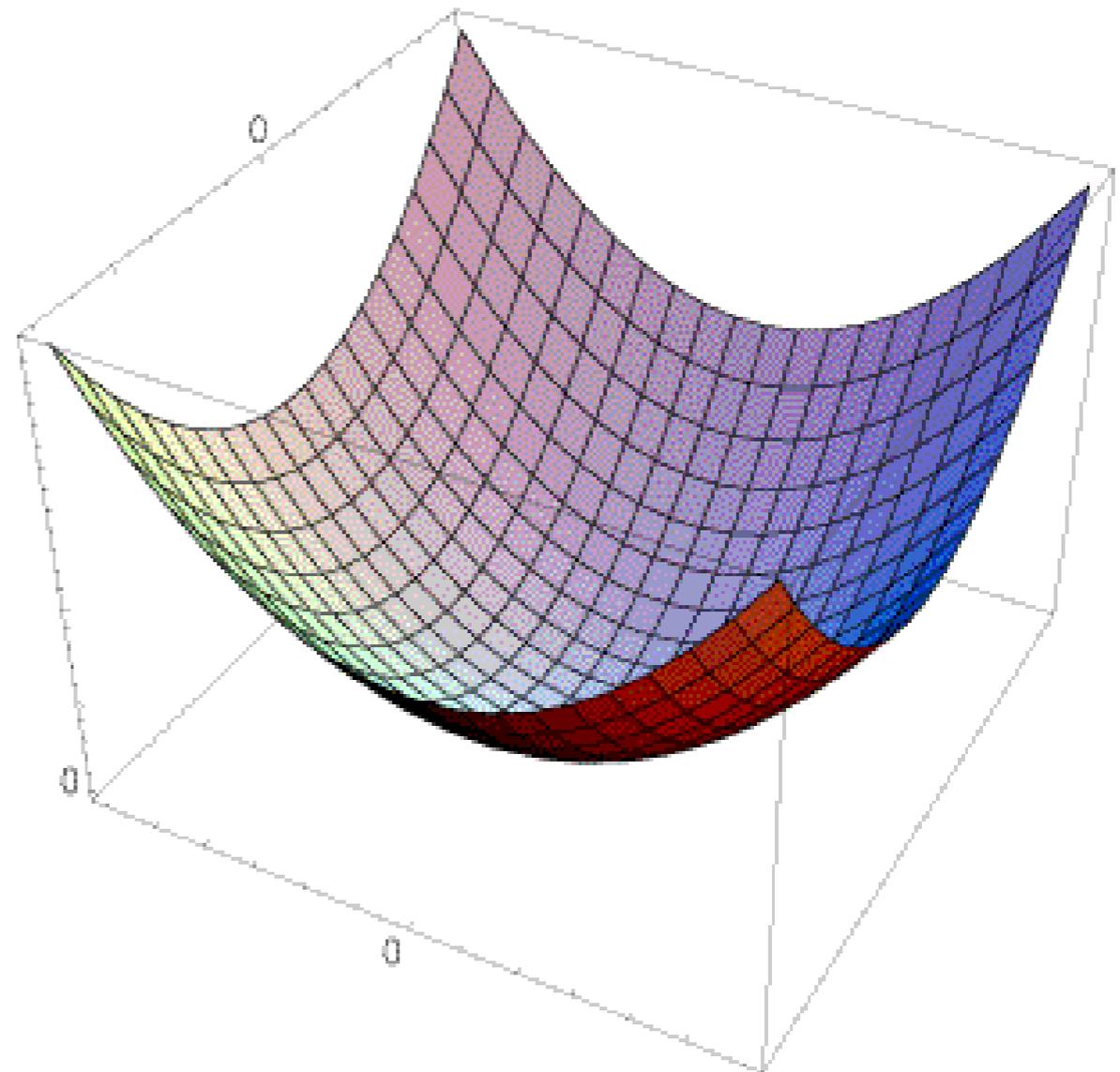
we are fitting a quadratic to the gradients over a small image region

Visualization of a quadratic

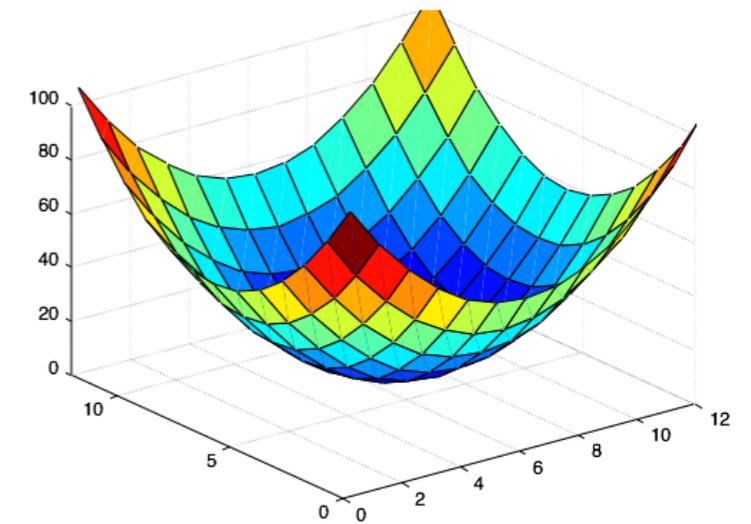
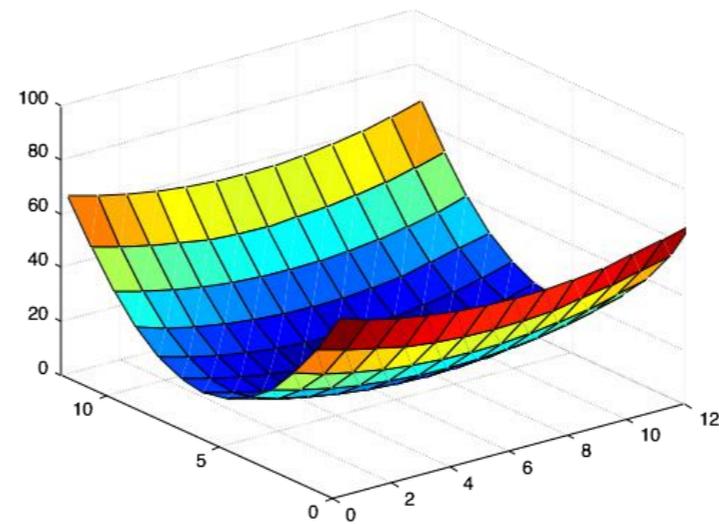
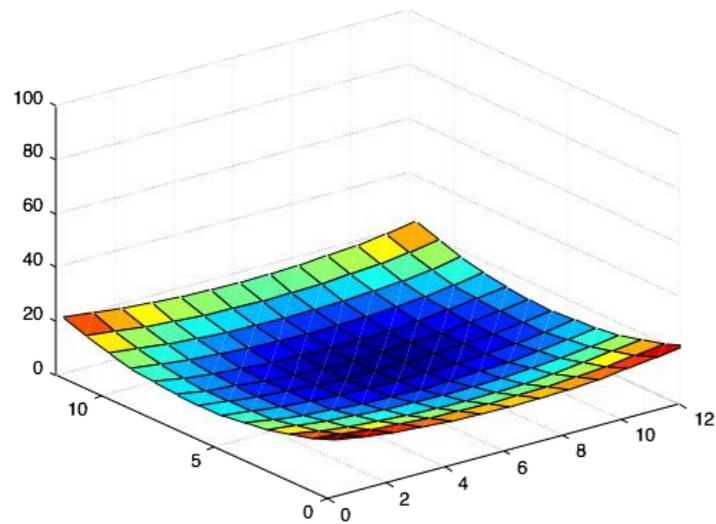
The surface $E(u, v)$ is locally approximated by a quadratic form

$$E(u, v) \approx [u \ v] M \begin{bmatrix} u \\ v \end{bmatrix}$$

$$M = \sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

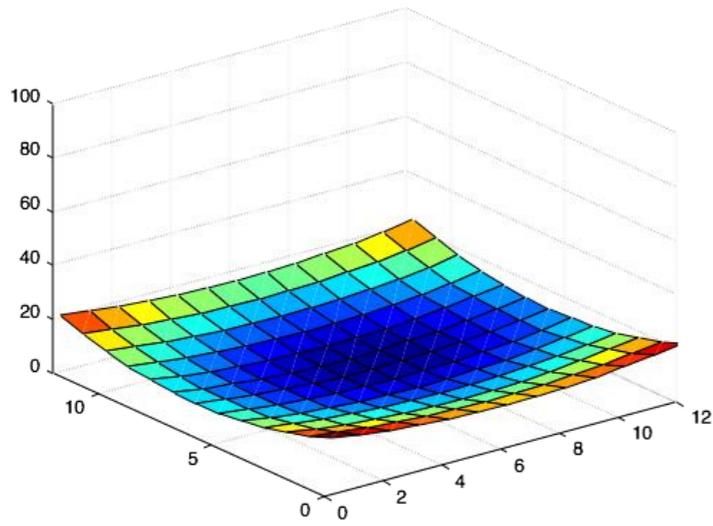


Which error surface indicates a good image feature?

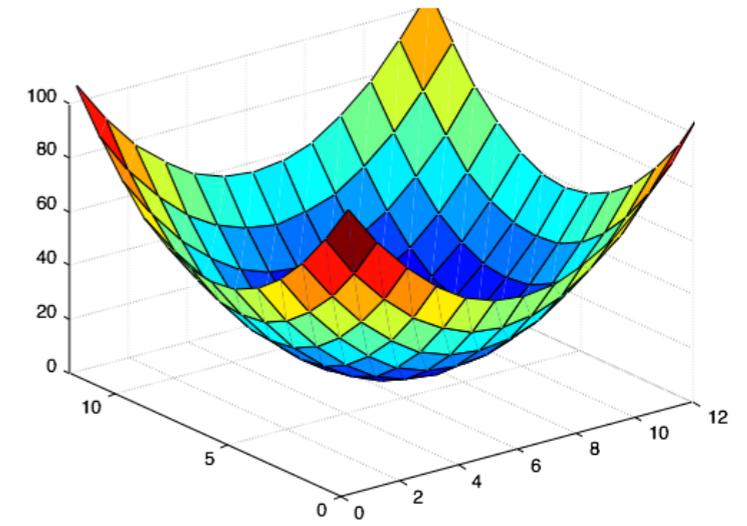
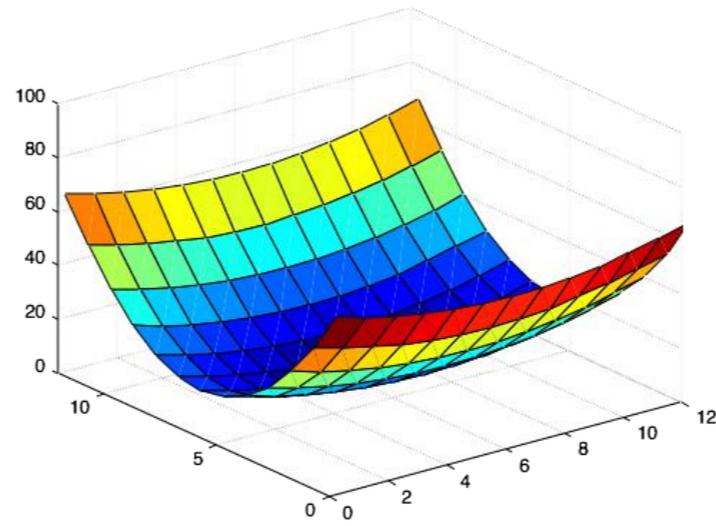


What kind of image patch do these surfaces represent?

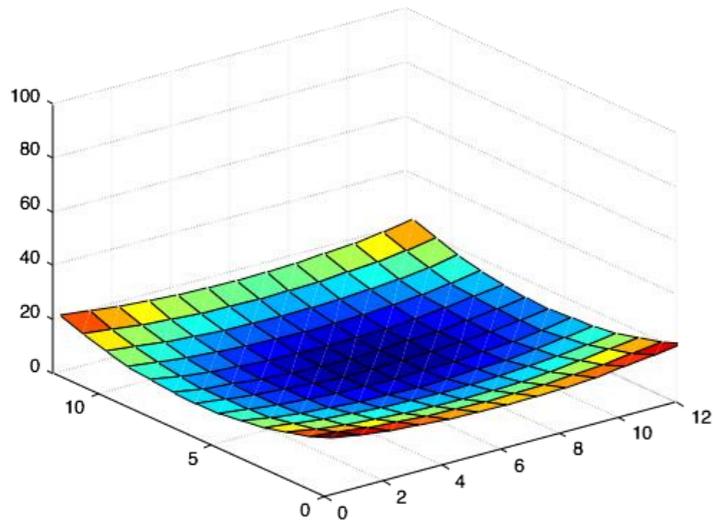
Which error surface indicates a good image feature?



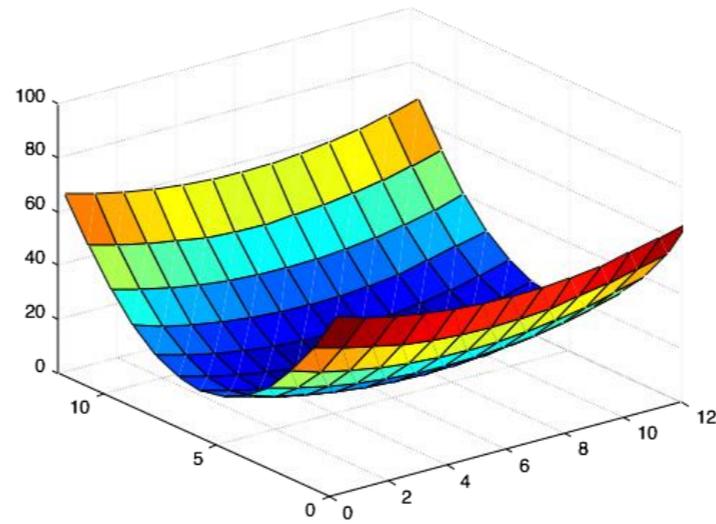
flat



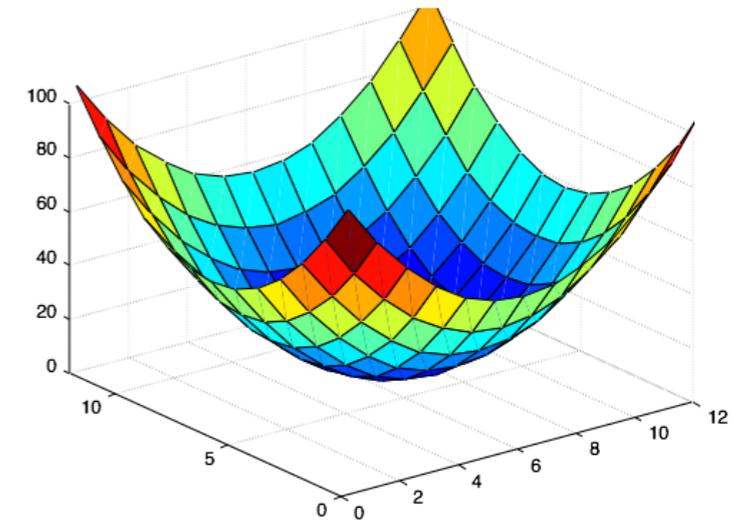
Which error surface indicates a good image feature?



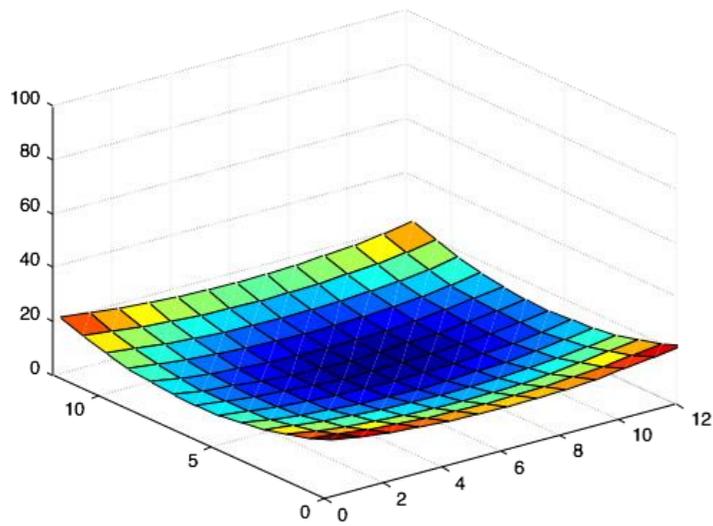
flat



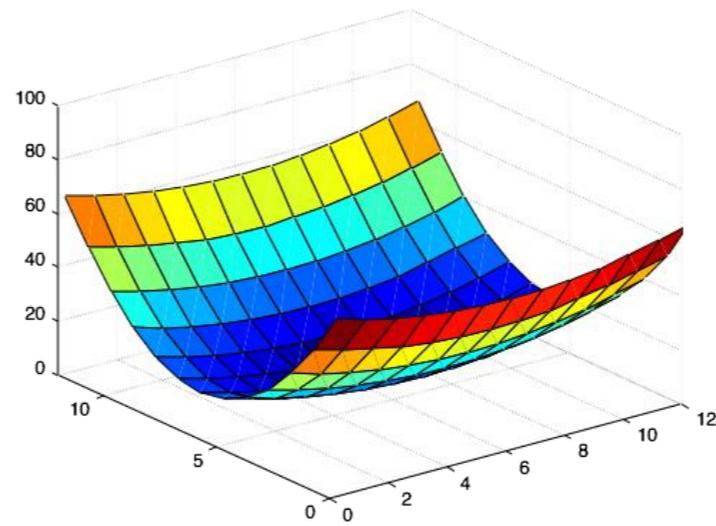
edge
'line'



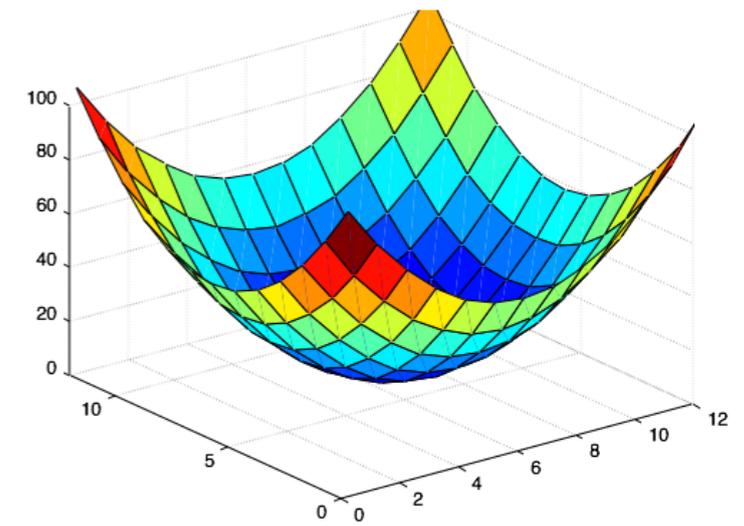
Which error surface indicates a good image feature?



flat



edge
'line'

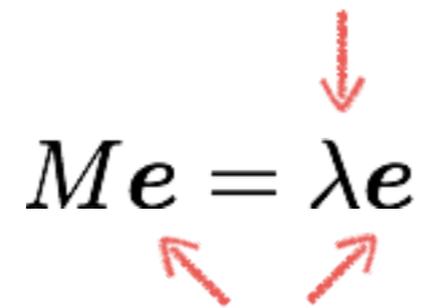


corner
'dot'

4. Compute eigenvalues and eigenvectors

4. Compute eigenvalues and eigenvectors

eigenvalue

$$M\mathbf{e} = \lambda\mathbf{e}$$


eigenvector

$$(M - \lambda I)\mathbf{e} = \mathbf{0}$$

4. Compute eigenvalues and eigenvectors

eigenvalue

$$M\mathbf{e} = \lambda\mathbf{e}$$

eigenvector

$$(M - \lambda I)\mathbf{e} = 0$$

1. Compute the determinant of
(returns a polynomial)

$$M - \lambda I$$

4. Compute eigenvalues and eigenvectors

eigenvalue

$$M\mathbf{e} = \lambda\mathbf{e}$$

eigenvector

$$(M - \lambda I)\mathbf{e} = 0$$

1. Compute the determinant of
(returns a polynomial)

$$M - \lambda I$$

2. Find the roots of polynomial
(returns eigenvalues)

$$\det(M - \lambda I) = 0$$

4. Compute eigenvalues and eigenvectors

eigenvalue

$$M\mathbf{e} = \lambda\mathbf{e}$$

eigenvector

$$(M - \lambda I)\mathbf{e} = 0$$

1. Compute the determinant of
(returns a polynomial)

$$M - \lambda I$$

2. Find the roots of polynomial
(returns eigenvalues)

$$\det(M - \lambda I) = 0$$

3. For each eigenvalue, solve
(returns eigenvectors)

$$(M - \lambda I)\mathbf{e} = 0$$

$\text{eig}(M)$

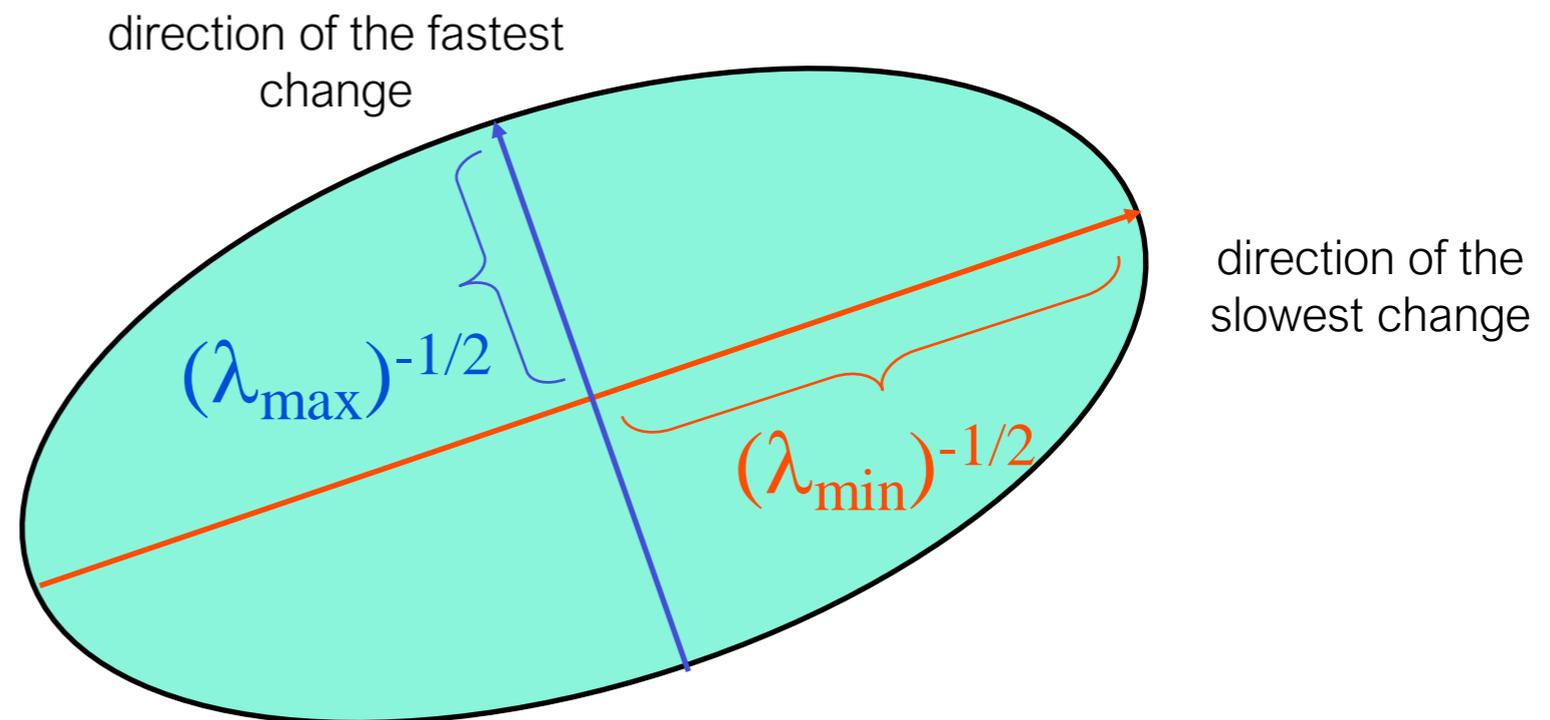
Visualization as an ellipse

Since M is symmetric, we have
$$M = R^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$

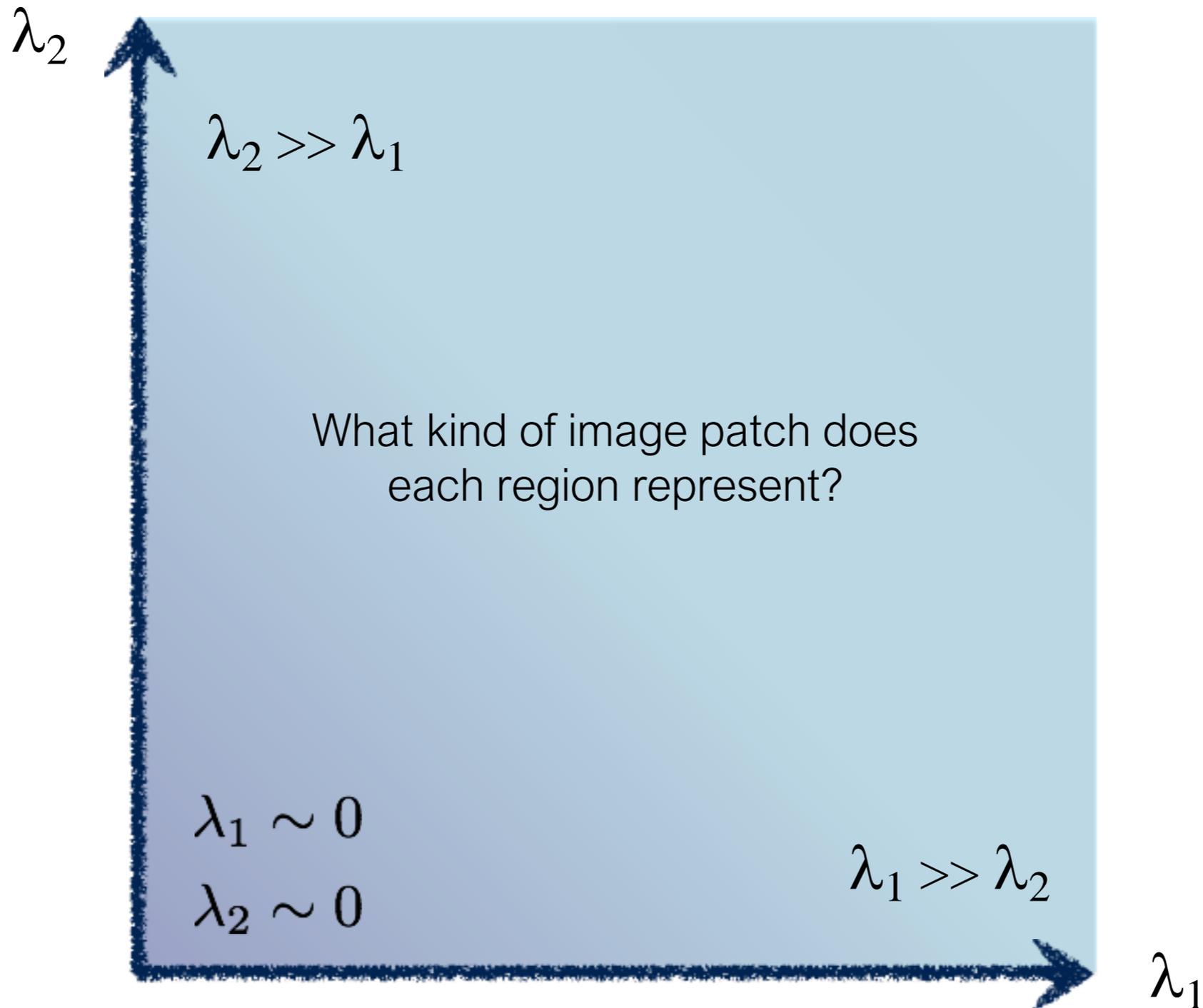
We can visualize M as an ellipse with axis lengths determined by the eigenvalues and orientation determined by R

Ellipse equation:

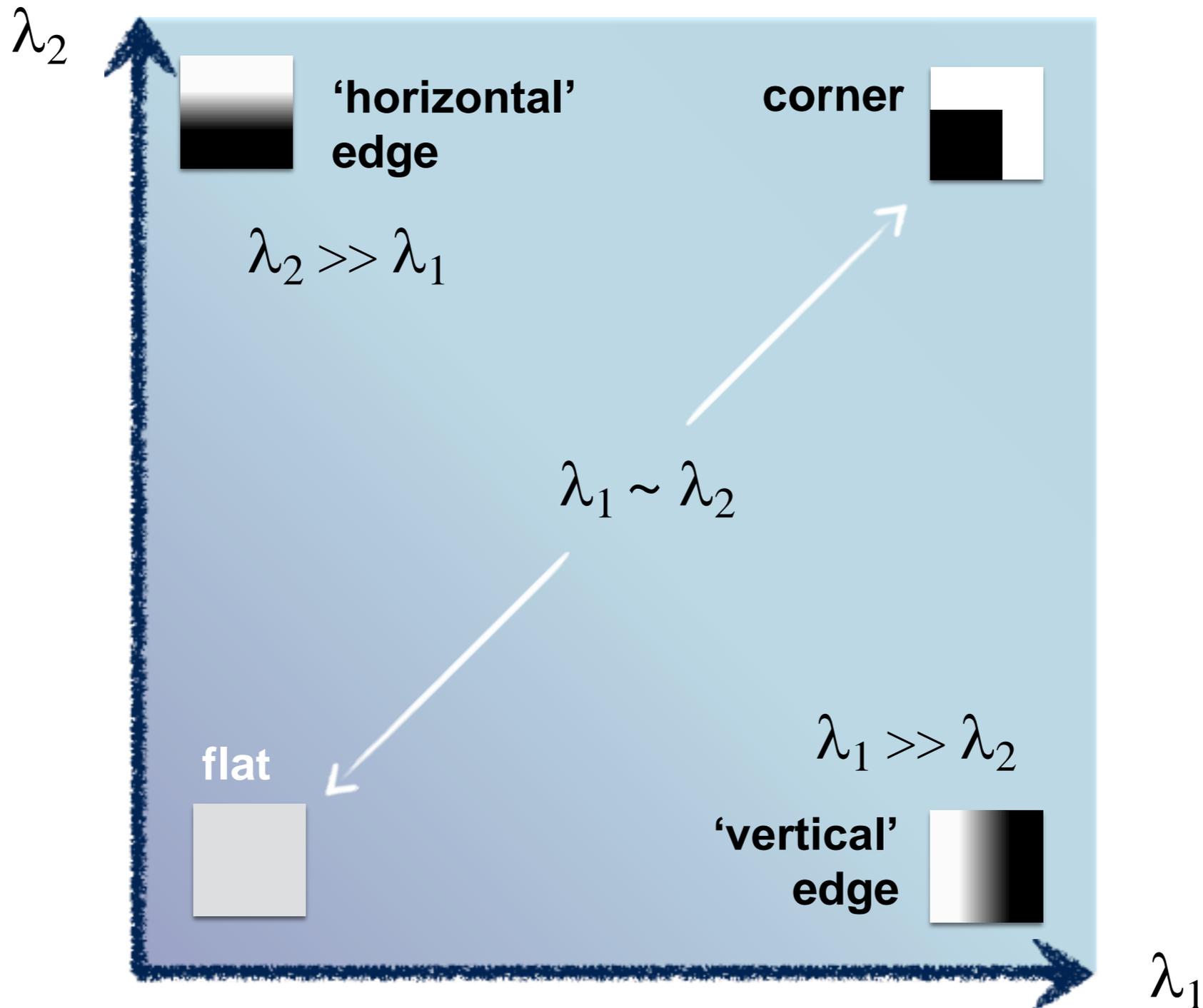
$$[u \ v] M \begin{bmatrix} u \\ v \end{bmatrix} = \text{const}$$



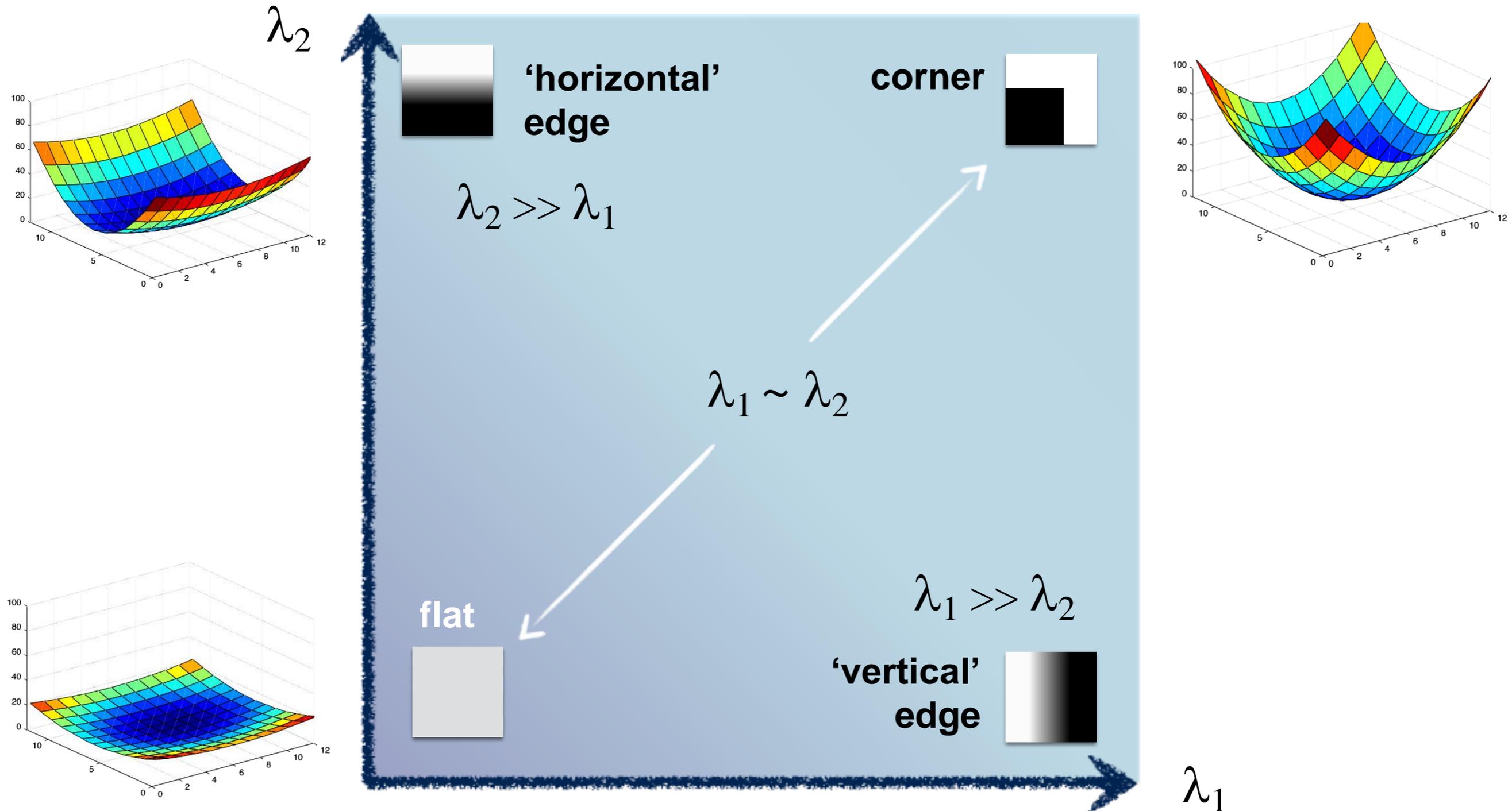
interpreting eigenvalues



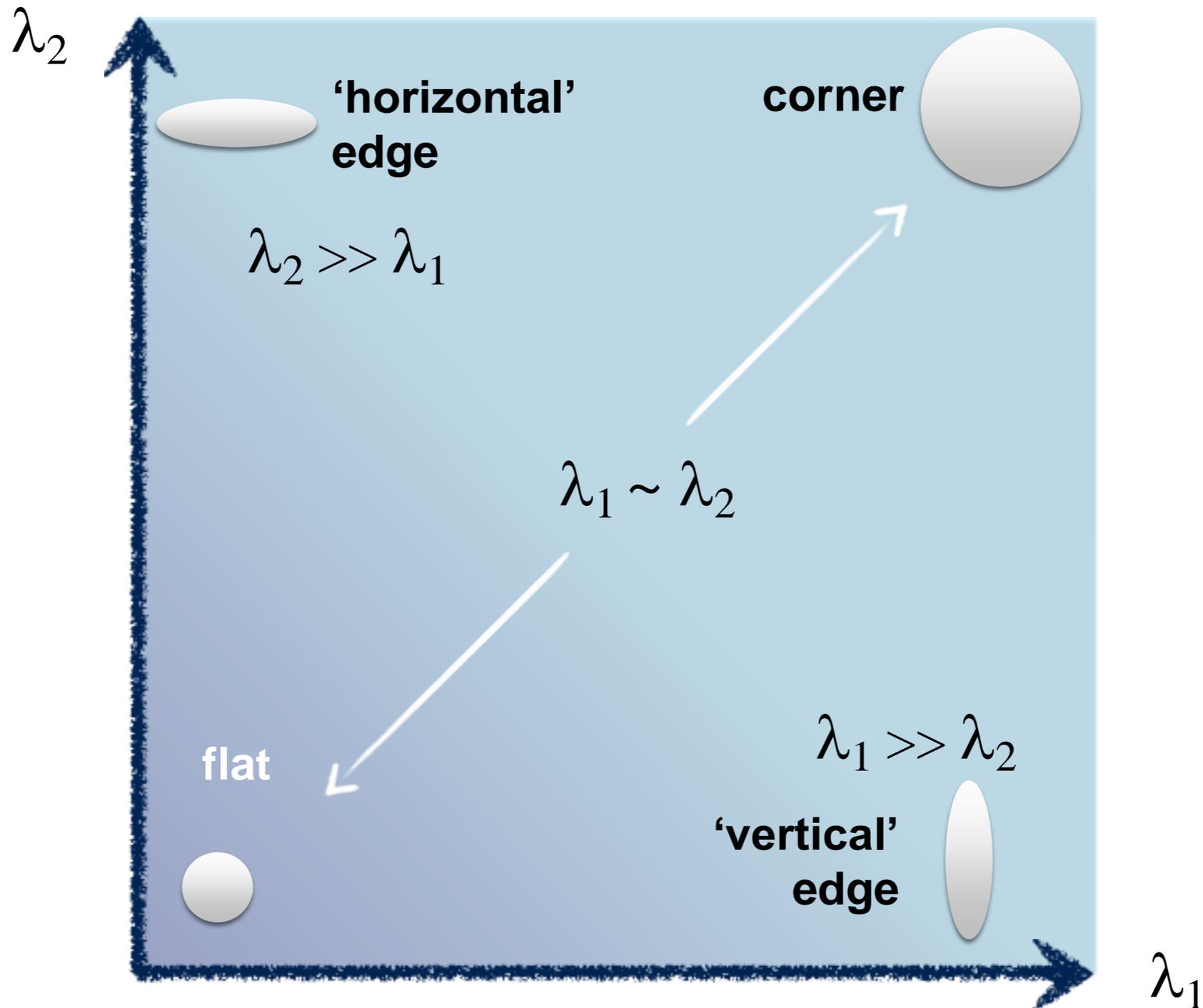
interpreting eigenvalues



interpreting eigenvalues

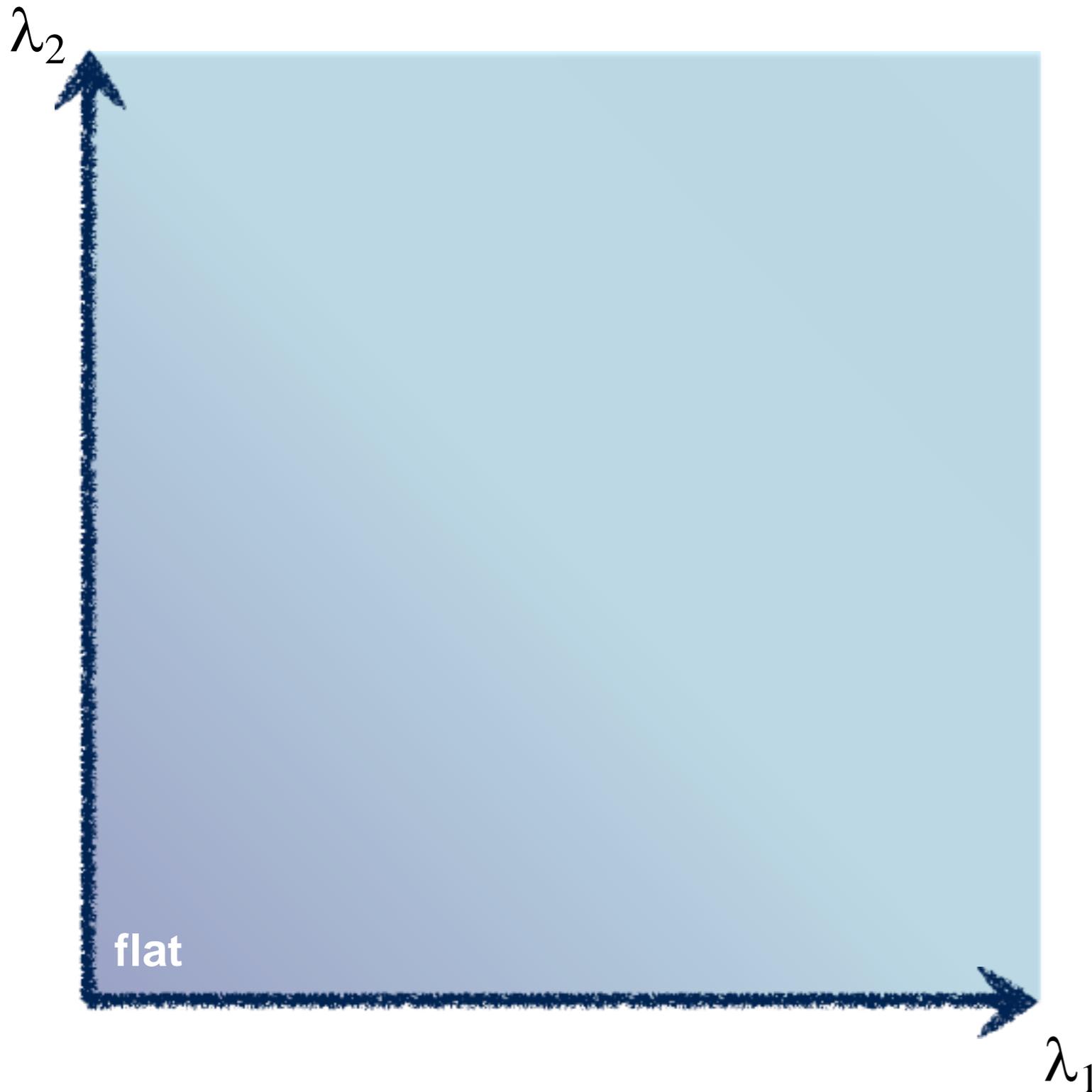


interpreting eigenvalues



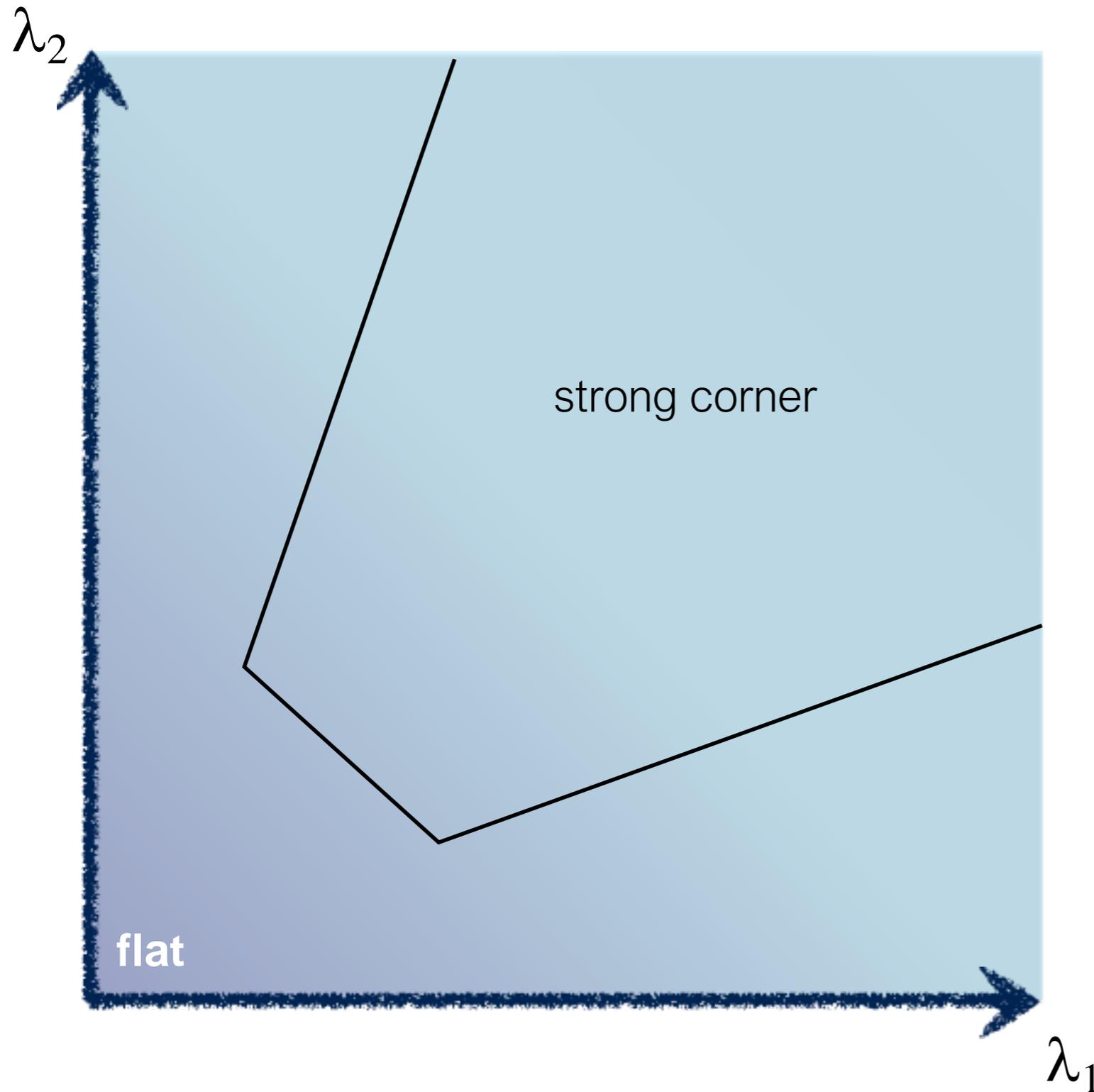
5. Use threshold on eigenvalues to detect corners

5. Use threshold on eigenvalues to detect corners



Think of a function to score 'corneriness'

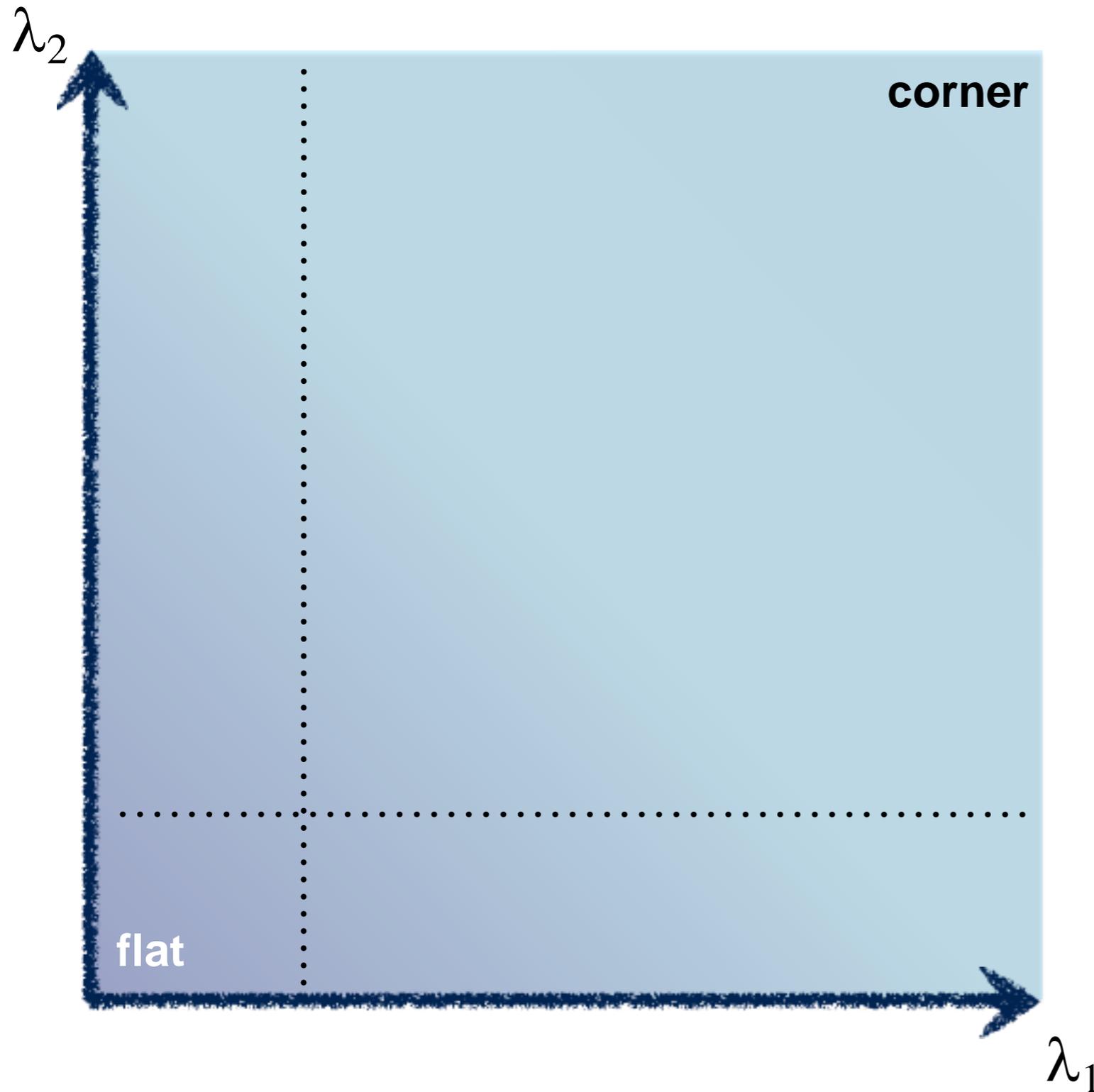
5. Use threshold on eigenvalues to detect corners



Think of a function to score 'corneriness'

5. Use threshold on eigenvalues to detect corners

$\hat{\lambda}$
(a function of)

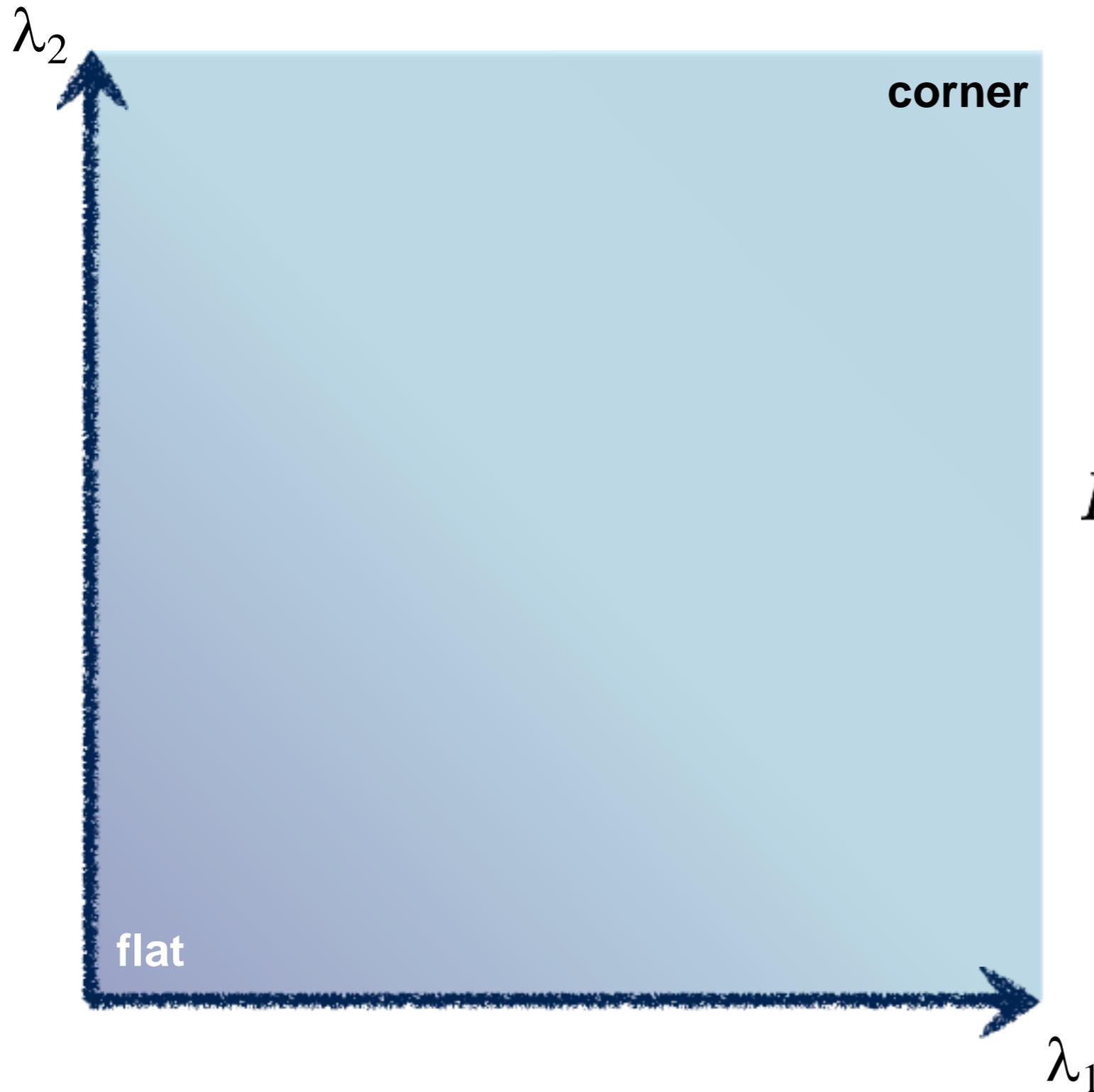


Use the smallest eigenvalue as
the response function

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

5. Use threshold on eigenvalues to detect corners

$\hat{\kappa}$
(a function of)



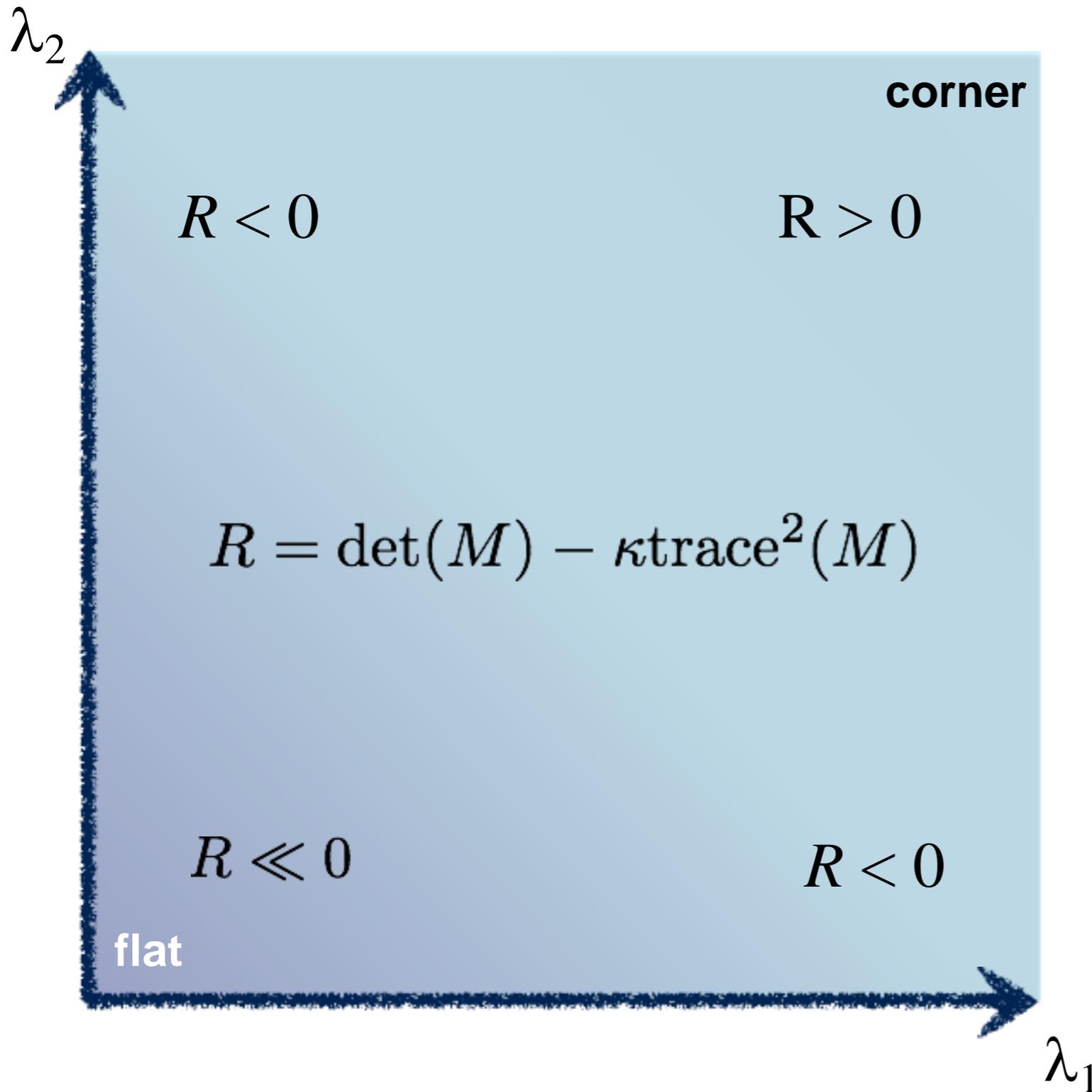
Eigenvalues need to be bigger than one.

$$R = \lambda_1 \lambda_2 - \kappa (\lambda_1 + \lambda_2)^2$$

Can compute this more efficiently...

5. Use threshold on eigenvalues to detect corners

$\hat{\kappa}$
(a function of)



$$\det M = \lambda_1 \lambda_2$$

$$\text{trace } M = \lambda_1 + \lambda_2$$

$$\det \begin{pmatrix} a & b \\ c & d \end{pmatrix} = ad - bc$$

$$\text{trace} \begin{pmatrix} a & b \\ c & d \end{pmatrix} = a + d$$

Harris & Stephens (1988)

$$R = \det(M) - \kappa \text{trace}^2(M)$$

Kanade & Tomasi (1994)

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

Nobel (1998)

$$R = \frac{\det(M)}{\text{trace}(M) + \epsilon}$$

Harris Detector

C.Harris and M.Stephens. "A Combined Corner and Edge Detector." 1988.

1. Compute x and y derivatives of image

$$I_x = G_\sigma^x * I \quad I_y = G_\sigma^y * I$$

2. Compute products of derivatives at every pixel

$$I_{x^2} = I_x \cdot I_x \quad I_{y^2} = I_y \cdot I_y \quad I_{xy} = I_x \cdot I_y$$

3. Compute the sums of the products of derivatives at each pixel

$$S_{x^2} = G_{\sigma'} * I_{x^2} \quad S_{y^2} = G_{\sigma'} * I_{y^2} \quad S_{xy} = G_{\sigma'} * I_{xy}$$

Harris Detector

C.Harris and M.Stephens. "A Combined Corner and Edge Detector." 1988.

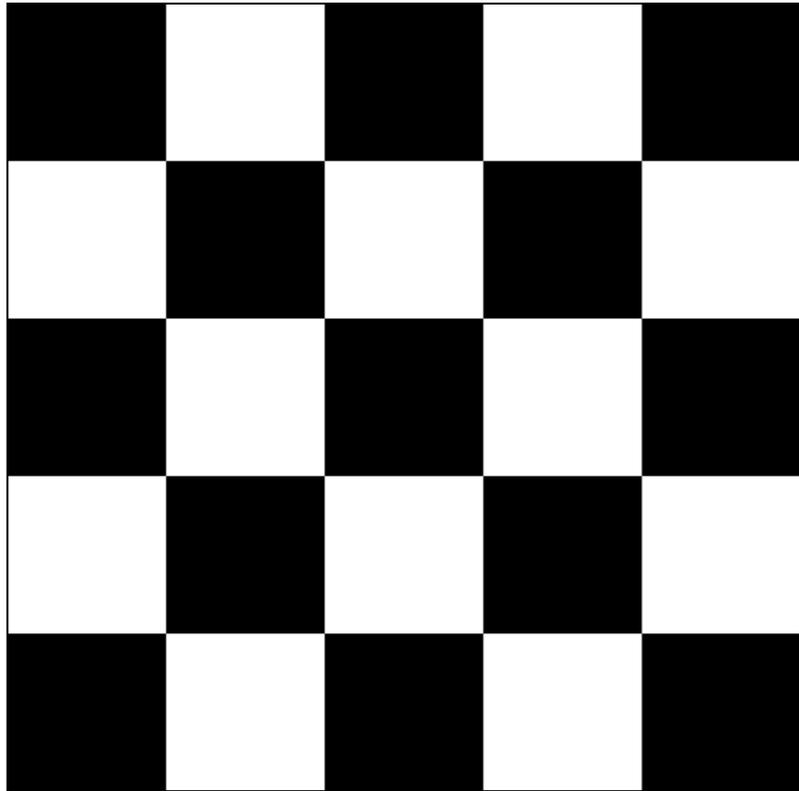
4. Define the matrix at each pixel

$$M(x, y) = \begin{bmatrix} S_{x^2}(x, y) & S_{xy}(x, y) \\ S_{xy}(x, y) & S_{y^2}(x, y) \end{bmatrix}$$

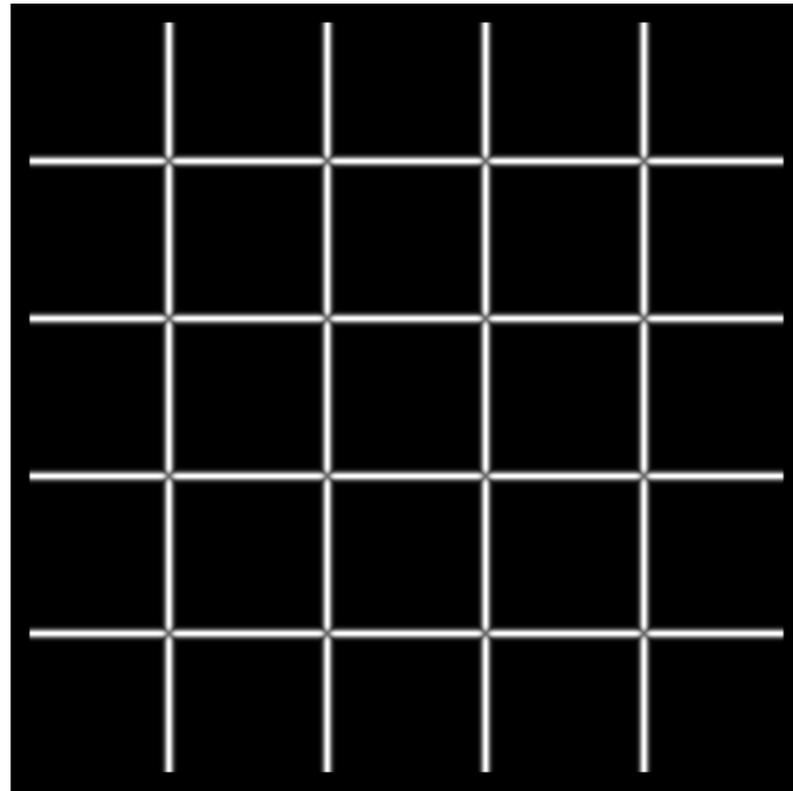
5. Compute the response of the detector at each pixel

$$R = \det M - k(\text{trace}M)^2$$

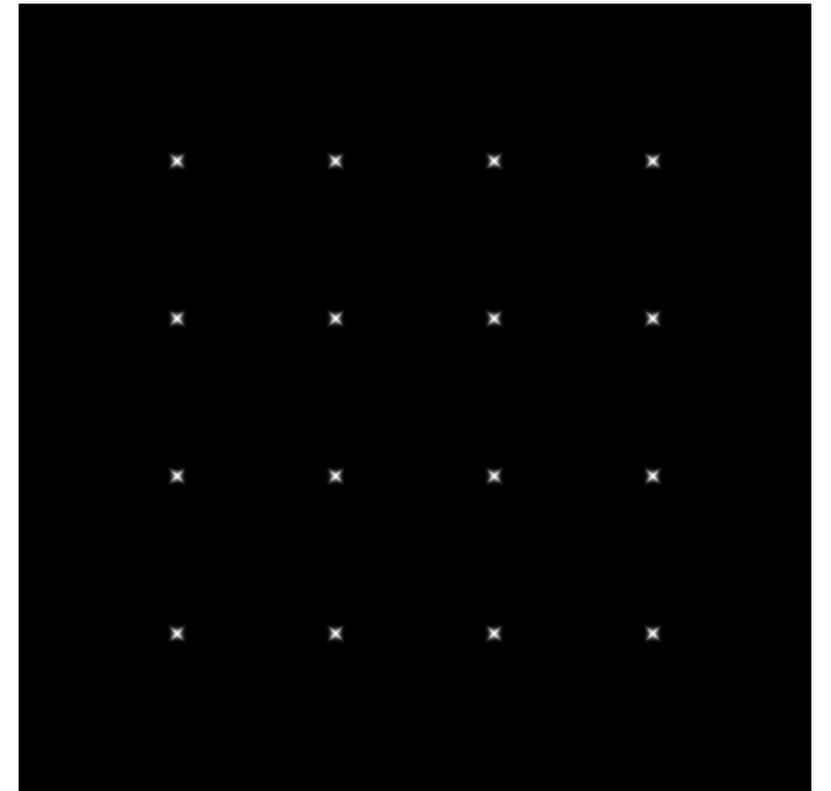
6. Threshold on value of R; compute non-max suppression.



I



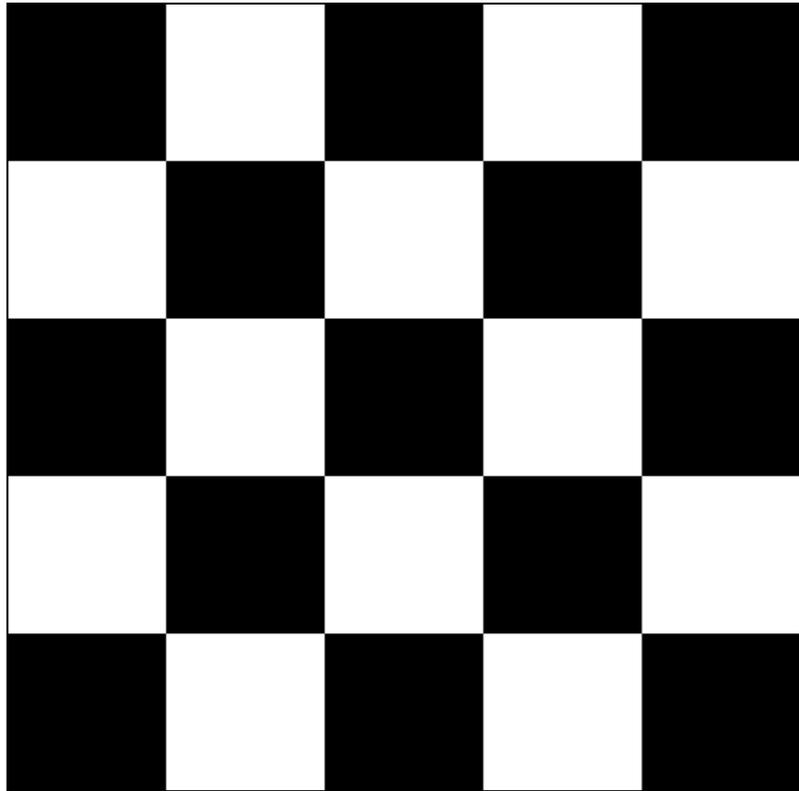
λ_{\max}



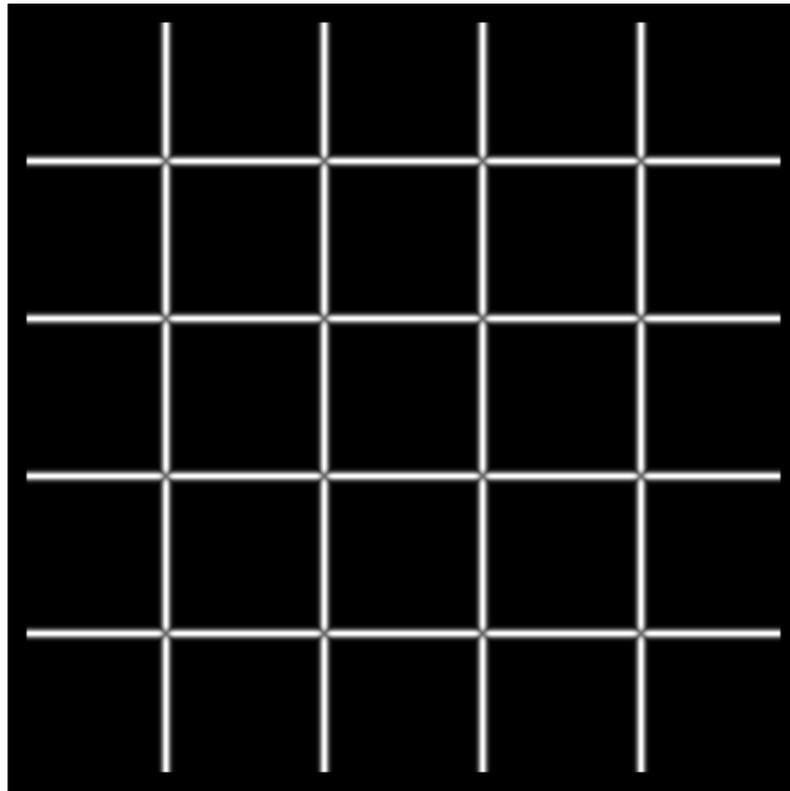
λ_{\min}

Yet another option: $f = \frac{\lambda_1 \lambda_2}{\lambda_1 + \lambda_2}$

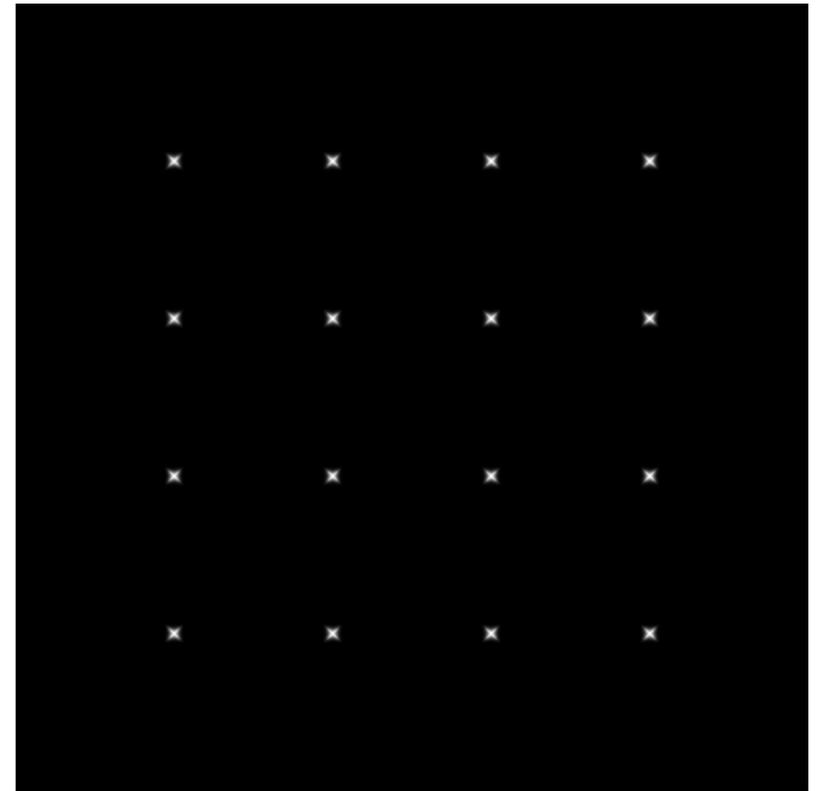
How do you write this equivalently using determinant and trace?



I



λ_{\max}

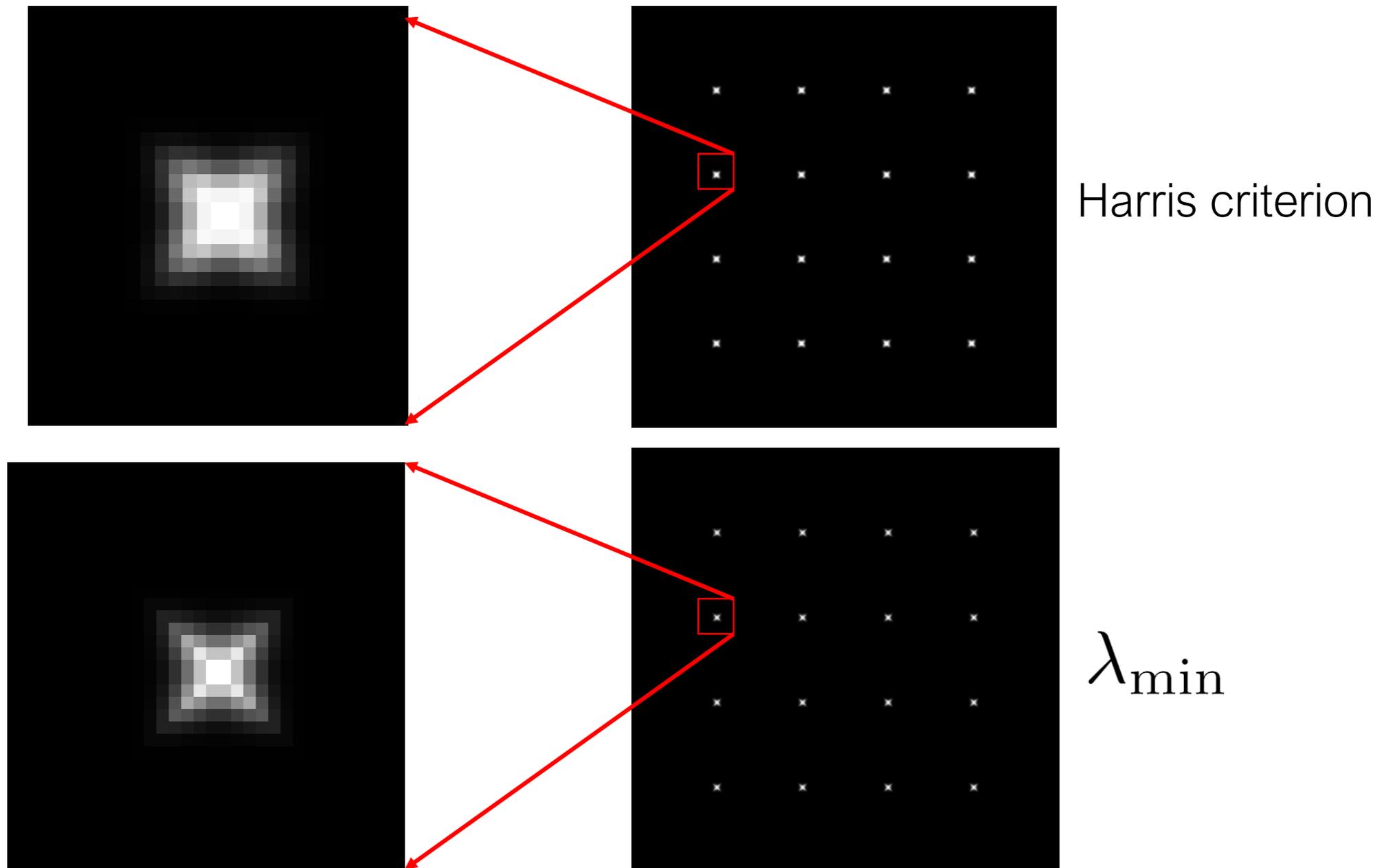


λ_{\min}

Yet another option:

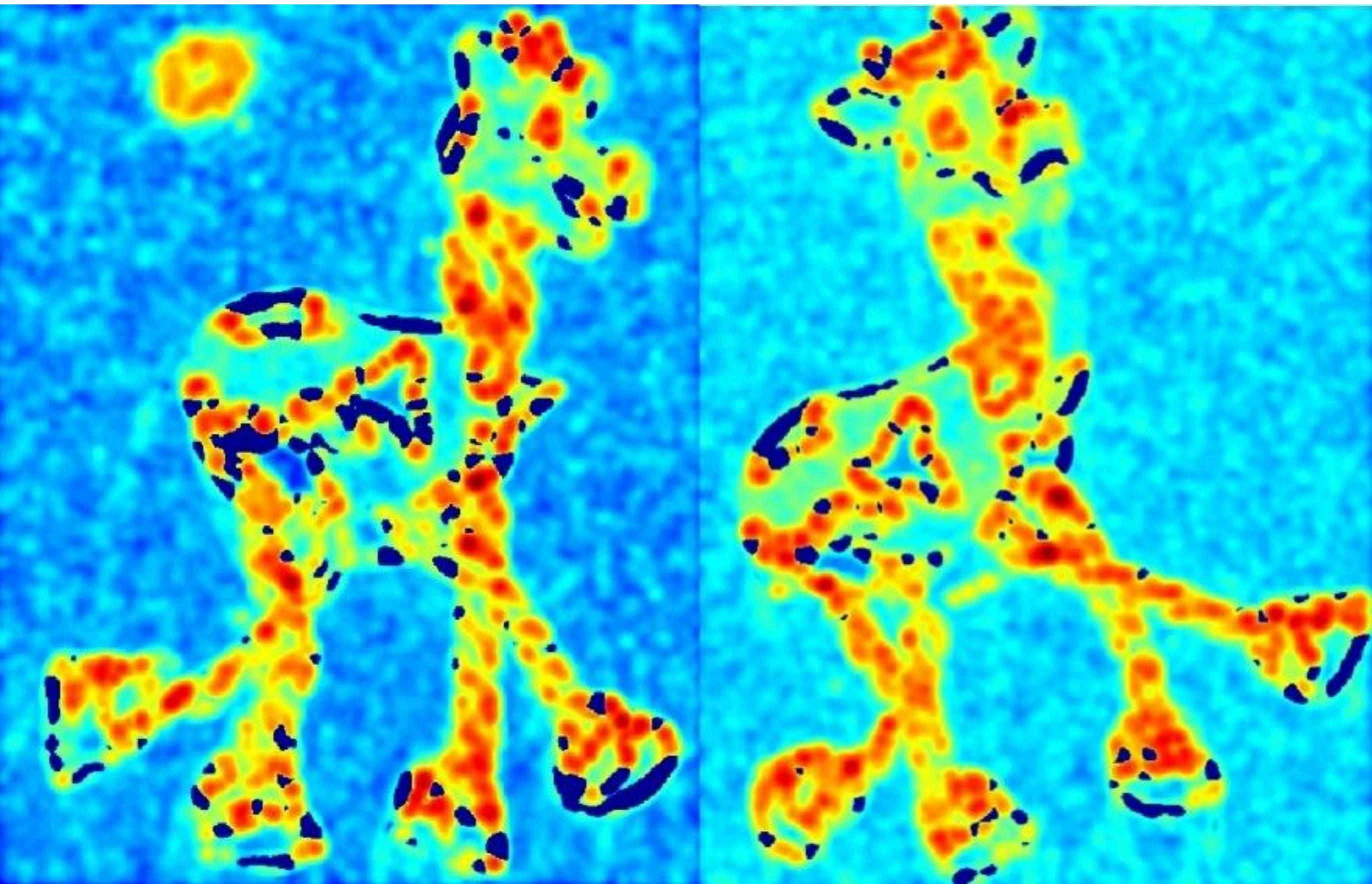
$$f = \frac{\lambda_1 \lambda_2}{\lambda_1 + \lambda_2} = \frac{\text{determinant}(H)}{\text{trace}(H)}$$

Different criteria



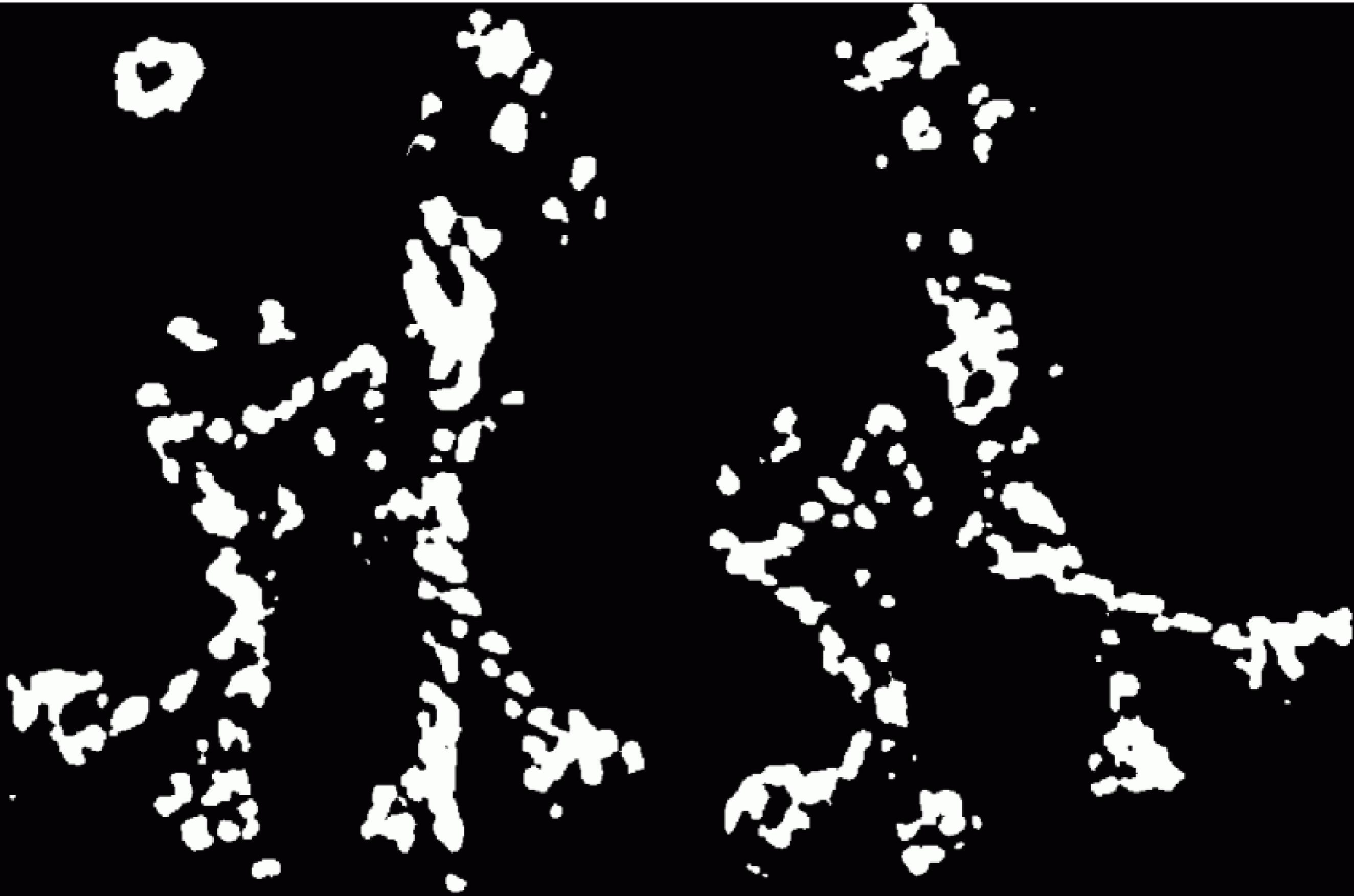


Corner response





Thresholded corner response

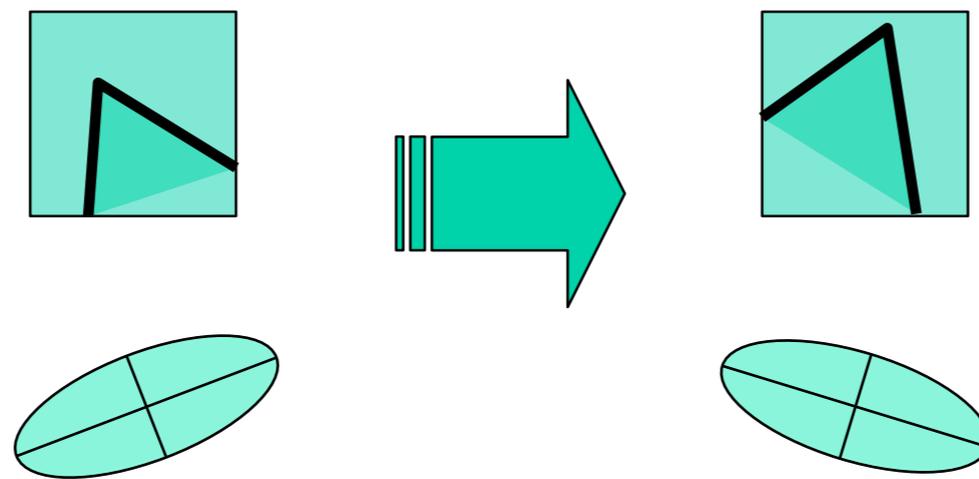


Non-maximal suppression





Harris corner response is invariant to rotation



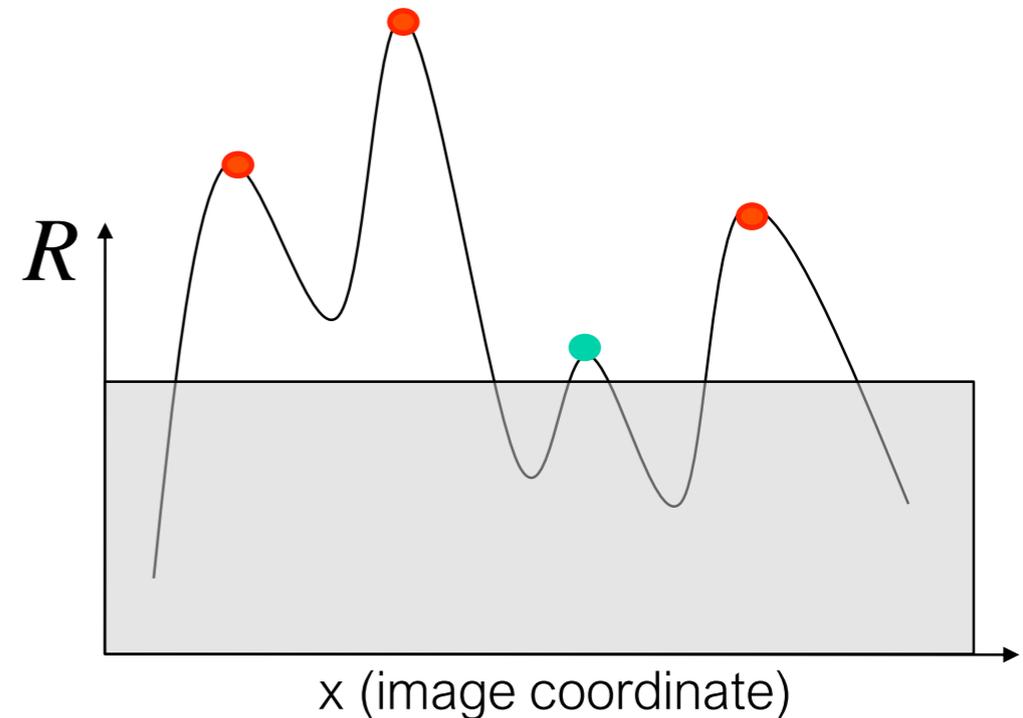
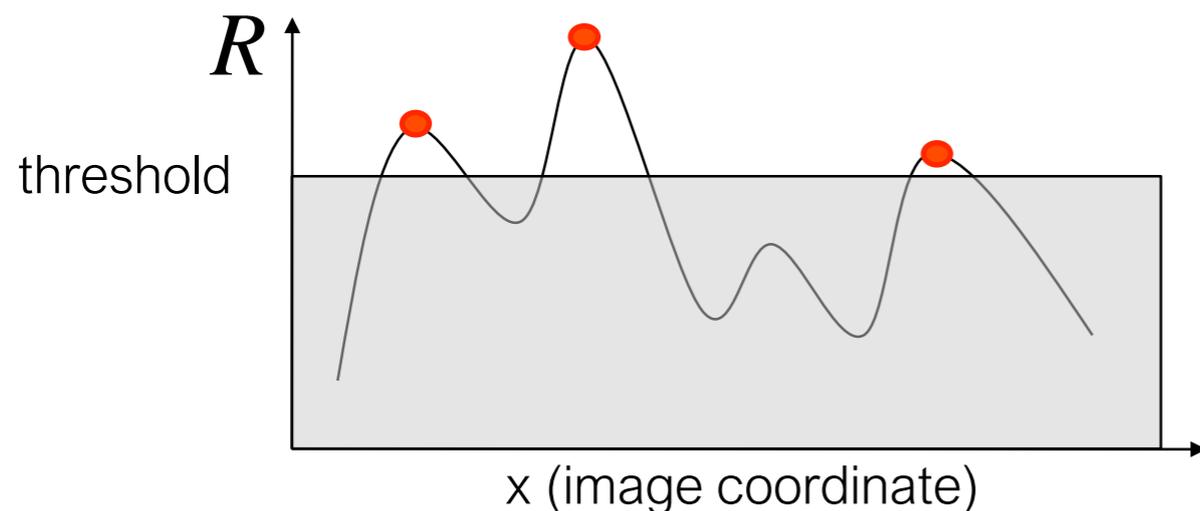
Ellipse rotates but its shape
(**eigenvalues**) remains the same

Corner response R is invariant to image rotation

Harris corner response is invariant to intensity changes

Partial invariance to *affine intensity* change

- Only derivatives are used => invariance to intensity shift $I \rightarrow I + b$
- Intensity scale: $I \rightarrow a I$



The Harris detector is not invariant to changes in ...

The Harris corner detector is not
invariant to scale

edge!



corner!



Multi-scale detection

How can we make a feature detector scale-invariant?

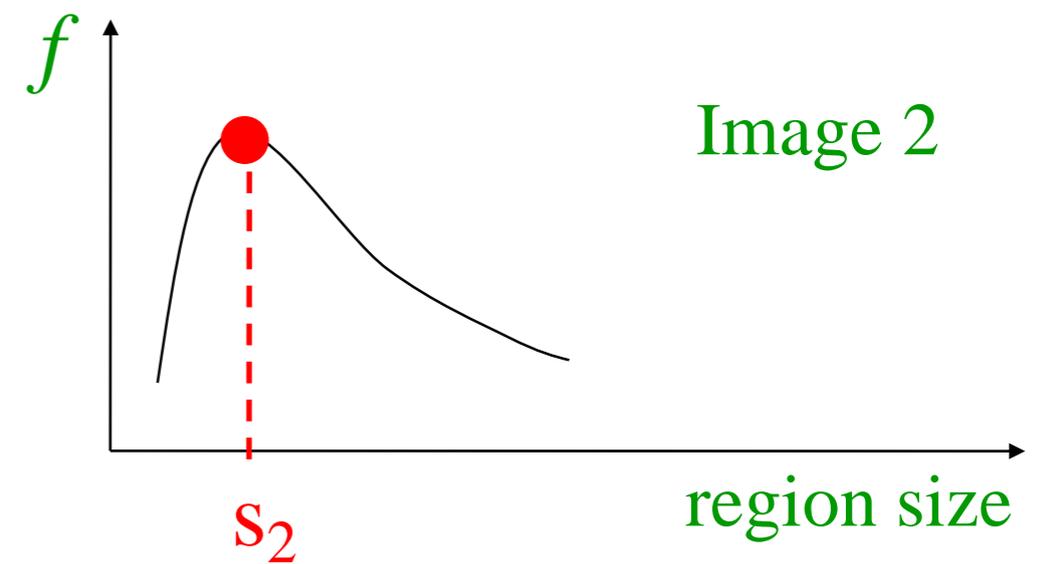
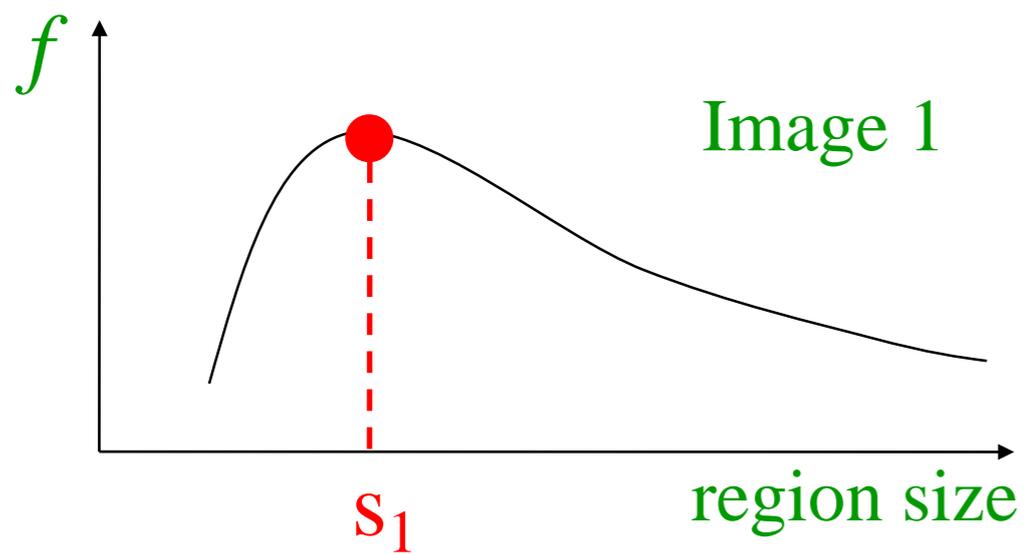
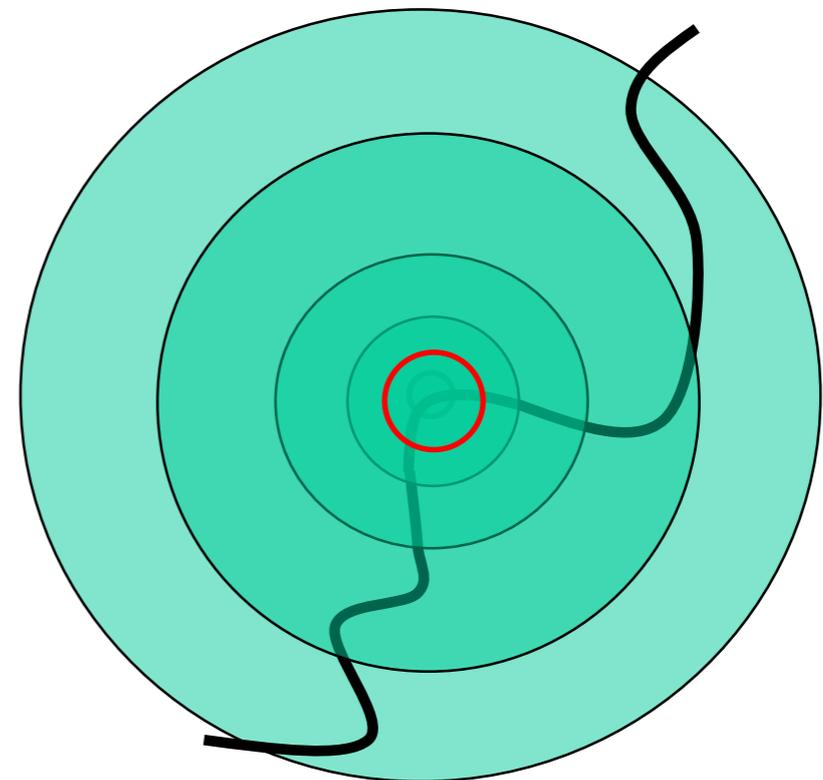
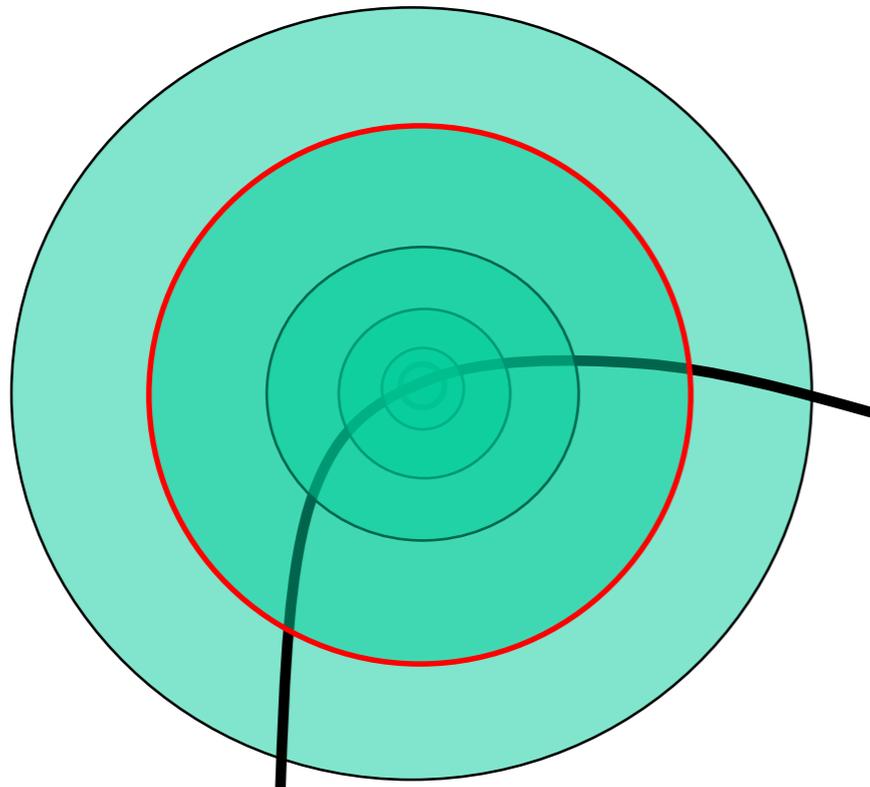
How can we automatically select the scale?

Multi-scale blob detection



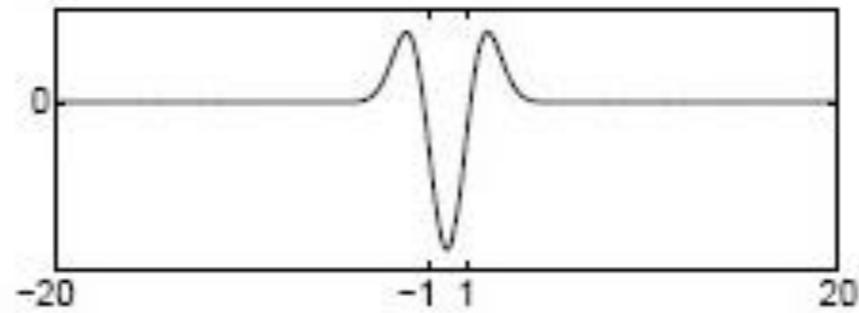
Intuitively...

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

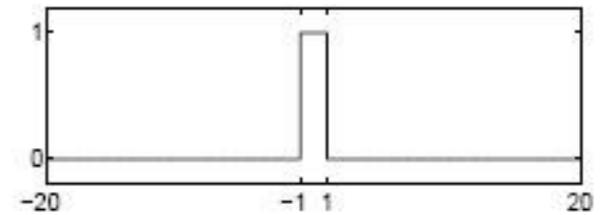
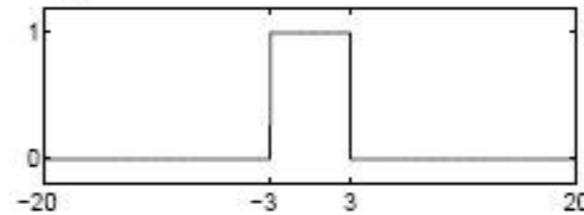
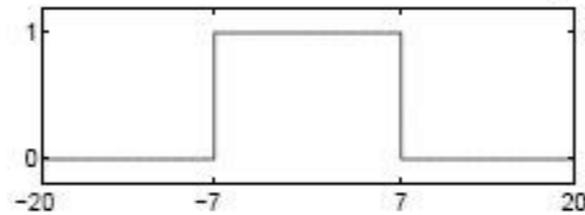
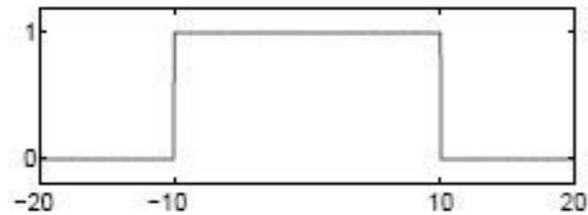


Formally...

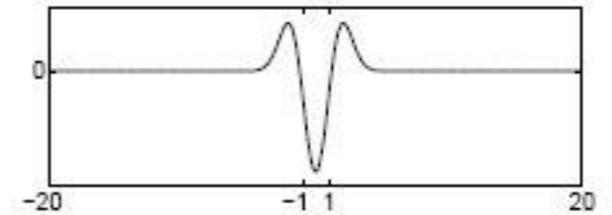
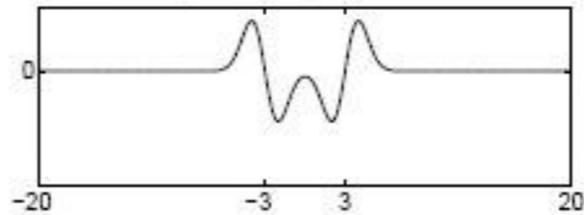
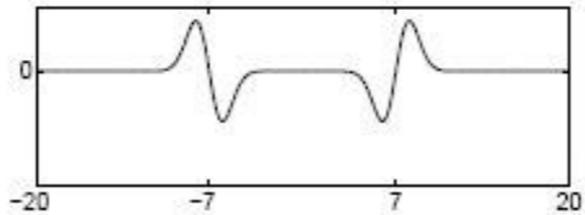
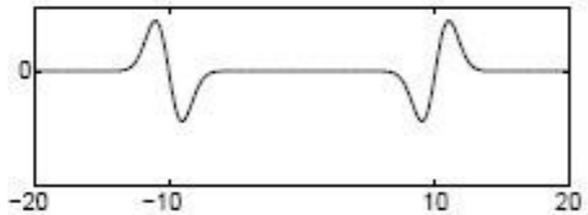
Laplacian filter



Original signal

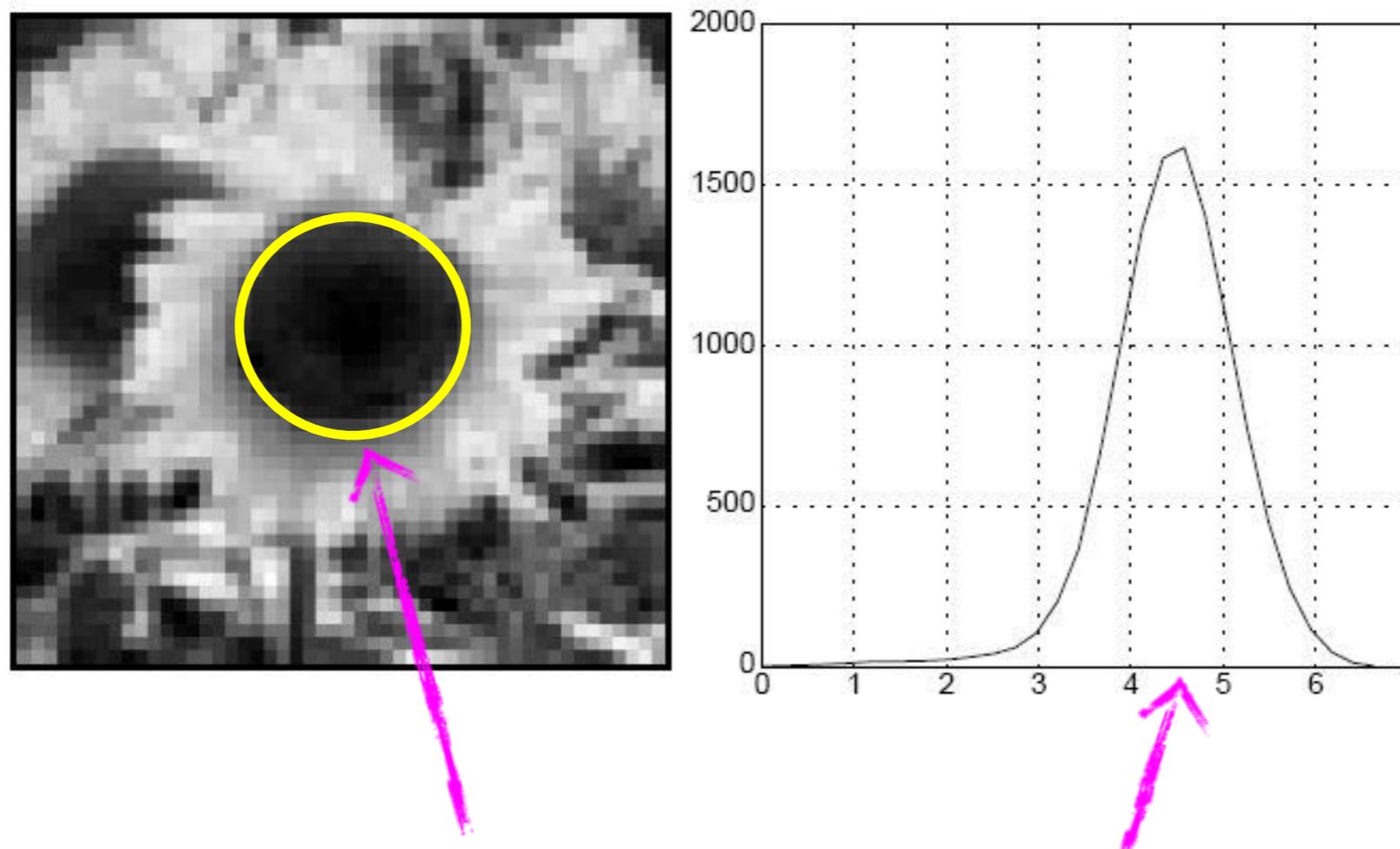


Convolved with Laplacian ($\sigma = 1$)



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

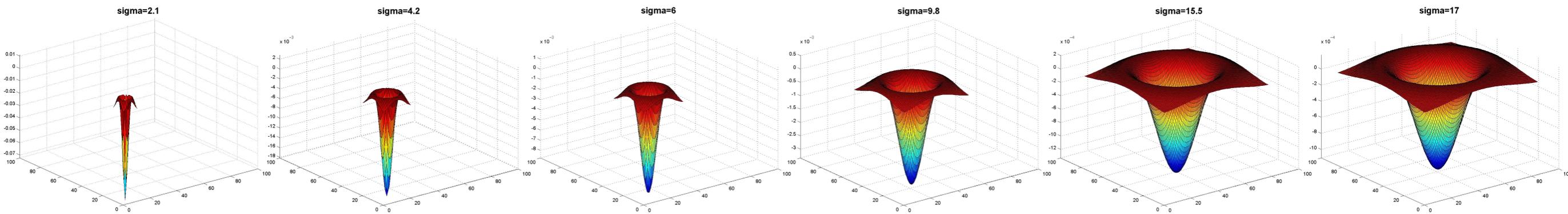
characteristic scale - the scale that produces peak filter response



characteristic scale

we need to search over characteristic scales

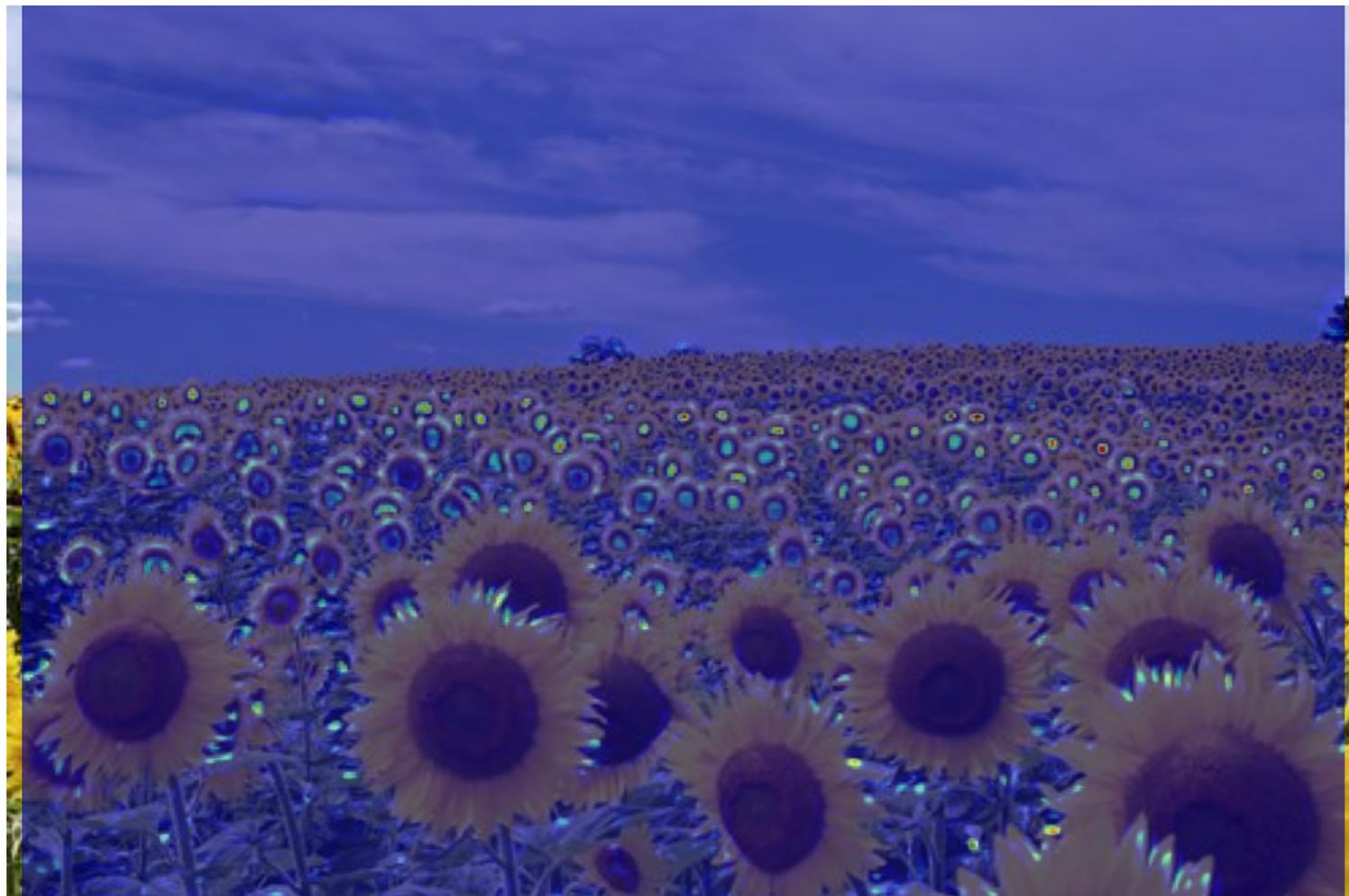
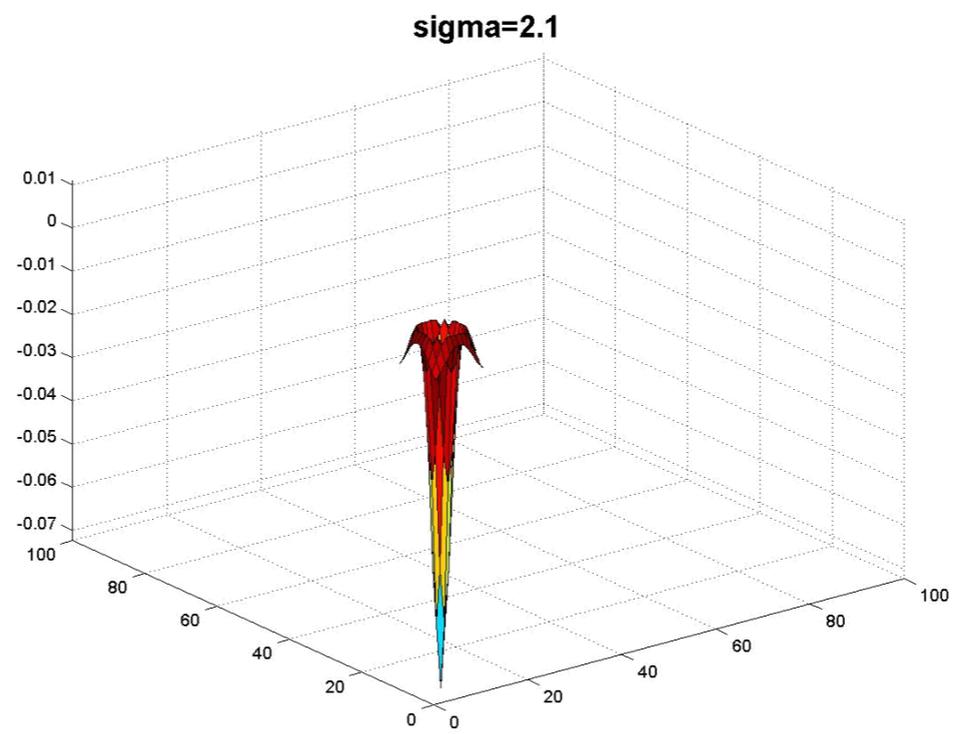
What happens if you apply different Laplacian filters?



Full size

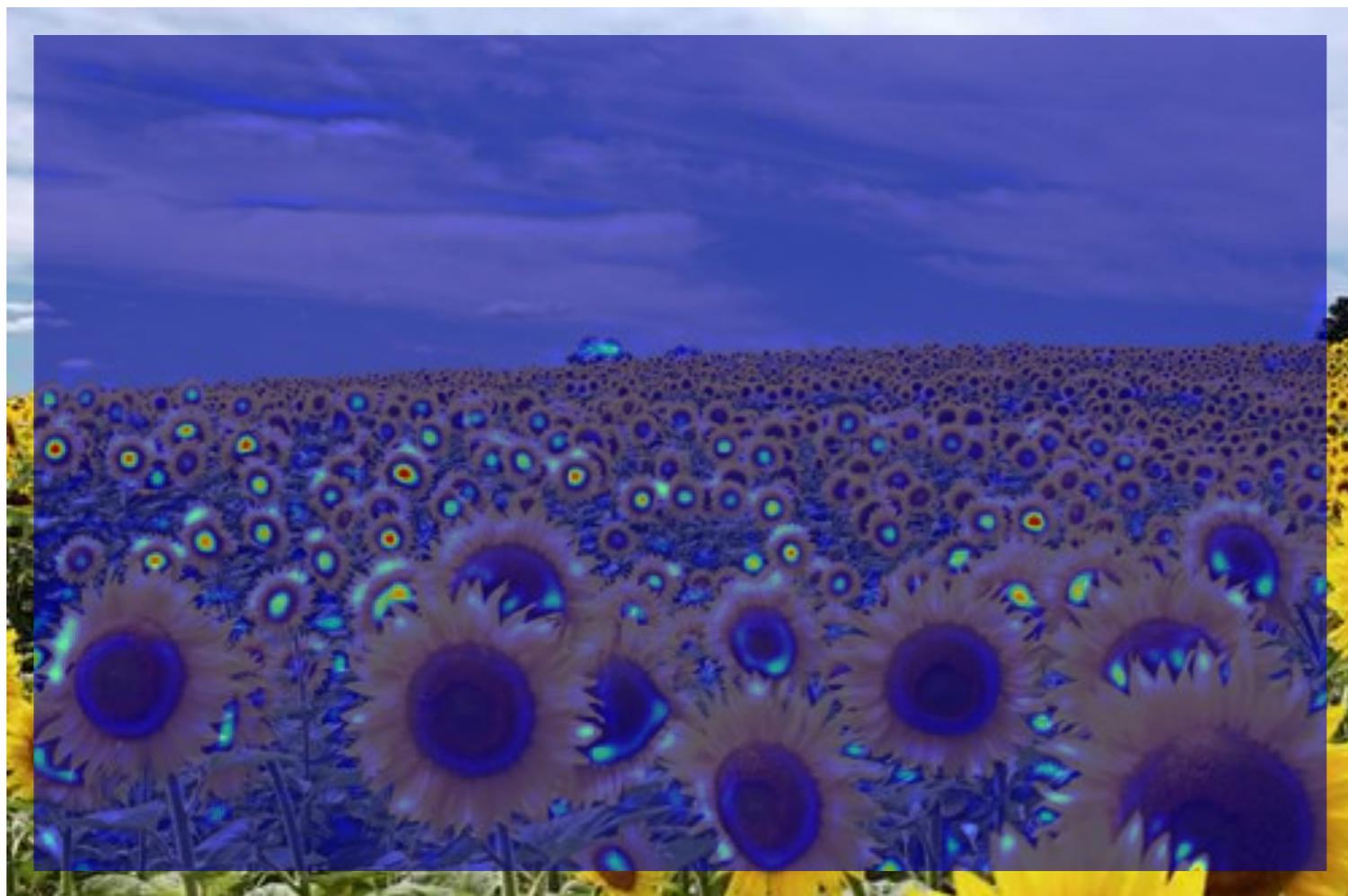
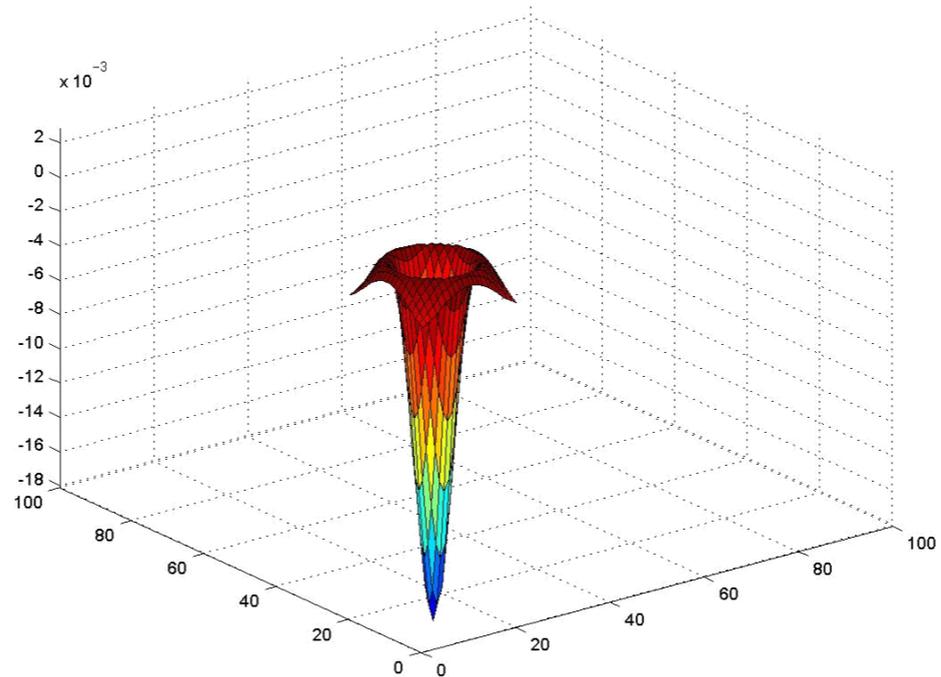
3/4 size



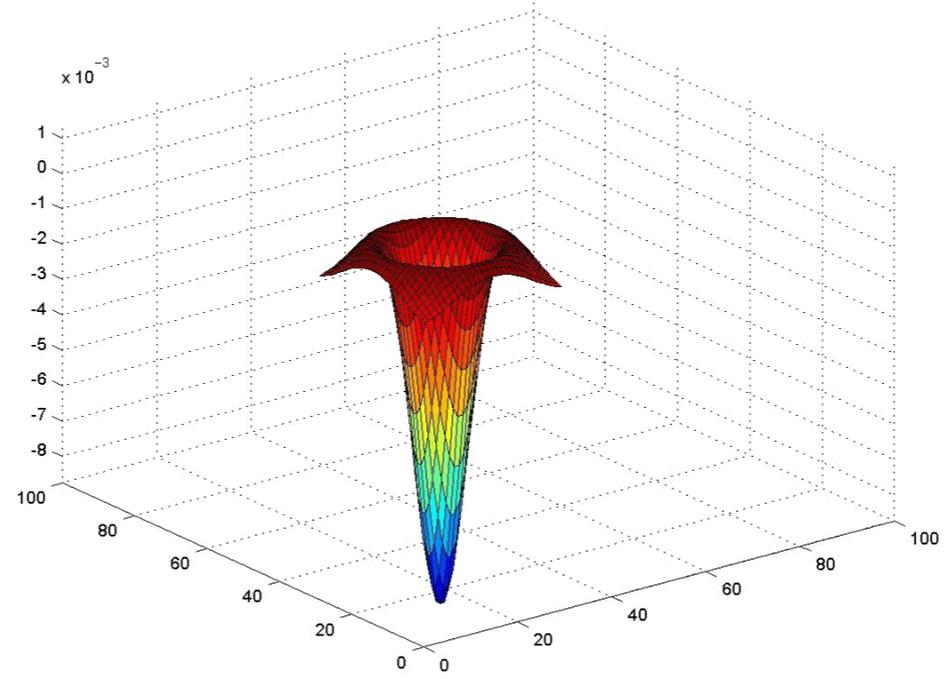


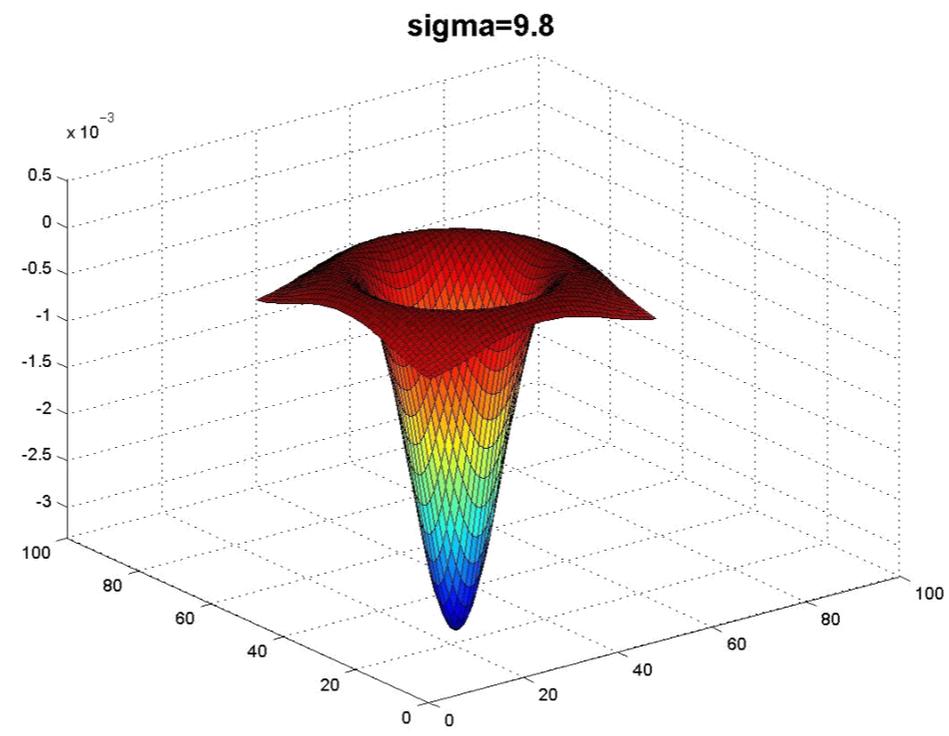
jet color scale
blue: low, red: high

sigma=4.2

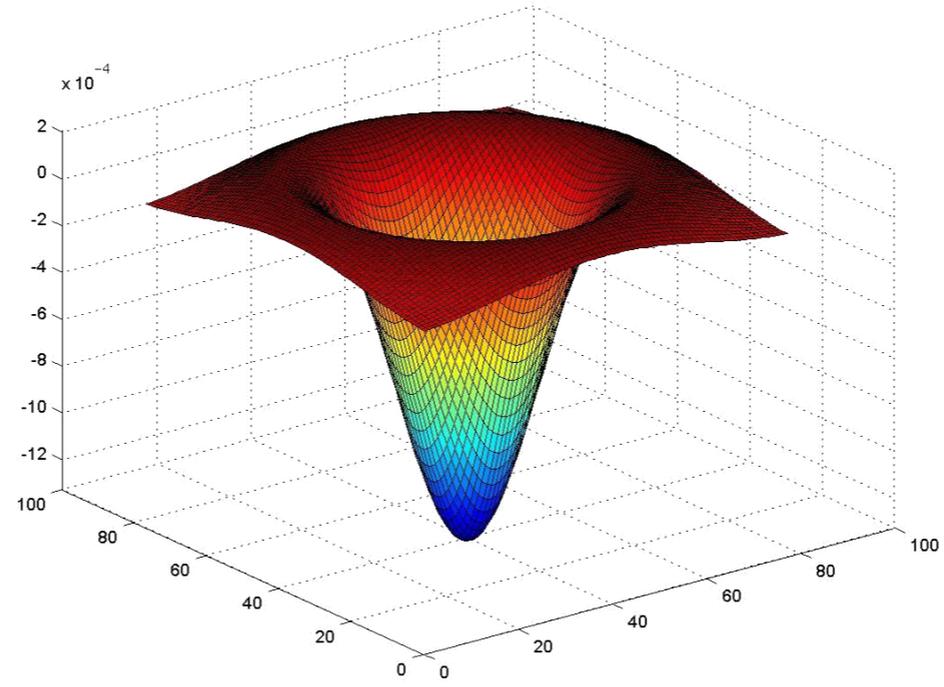


sigma=6

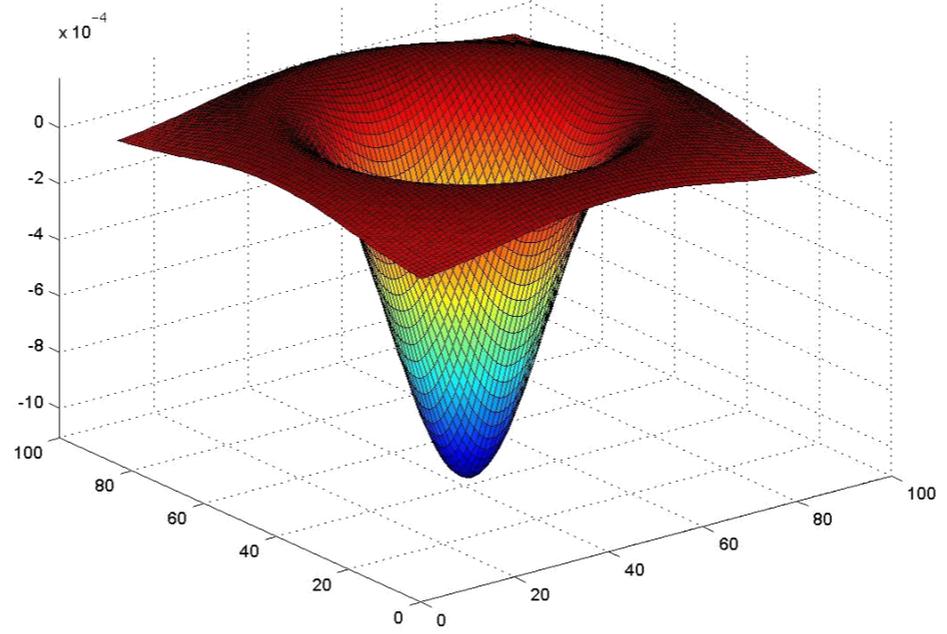




sigma=15.5



sigma=17



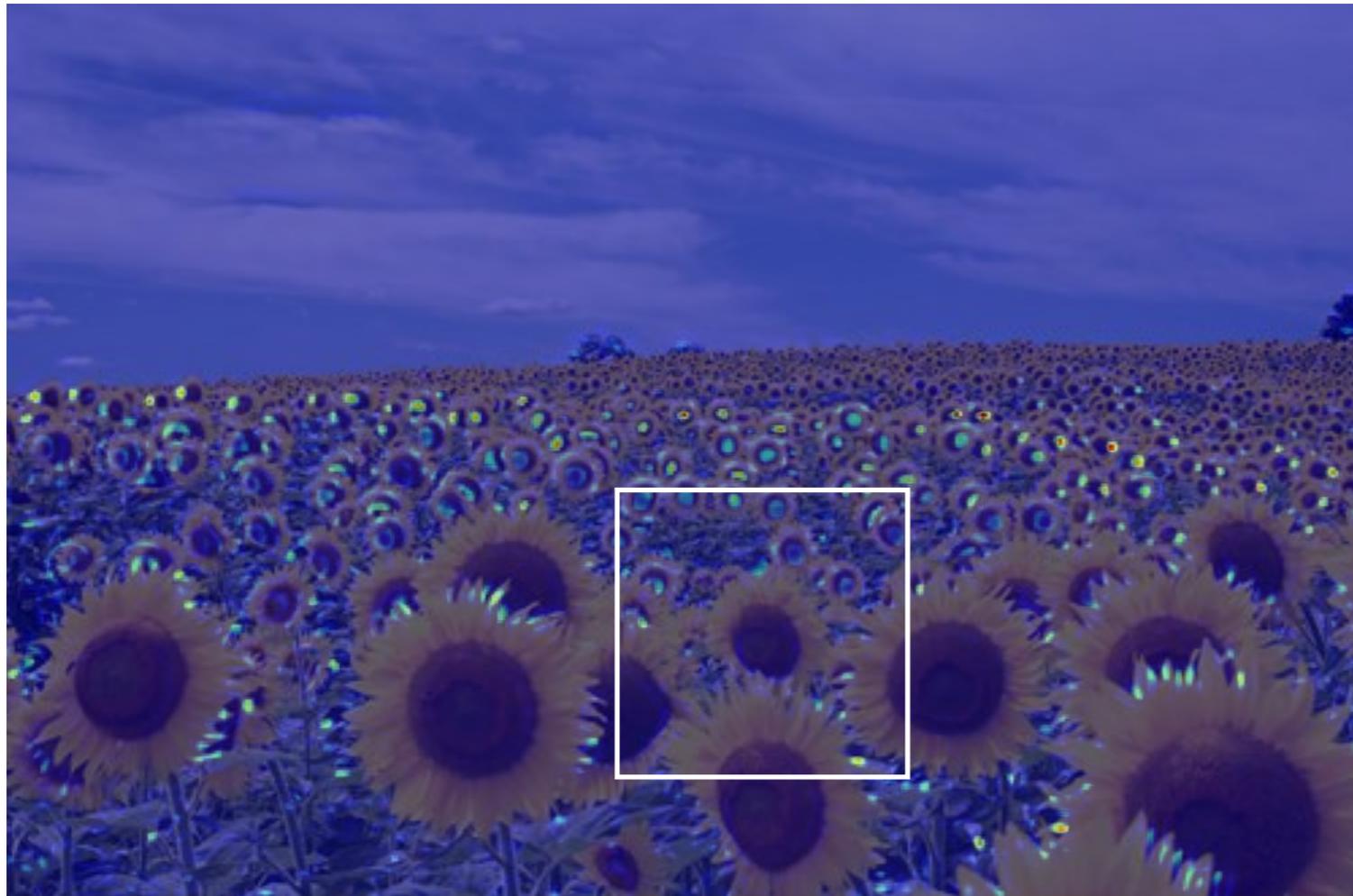
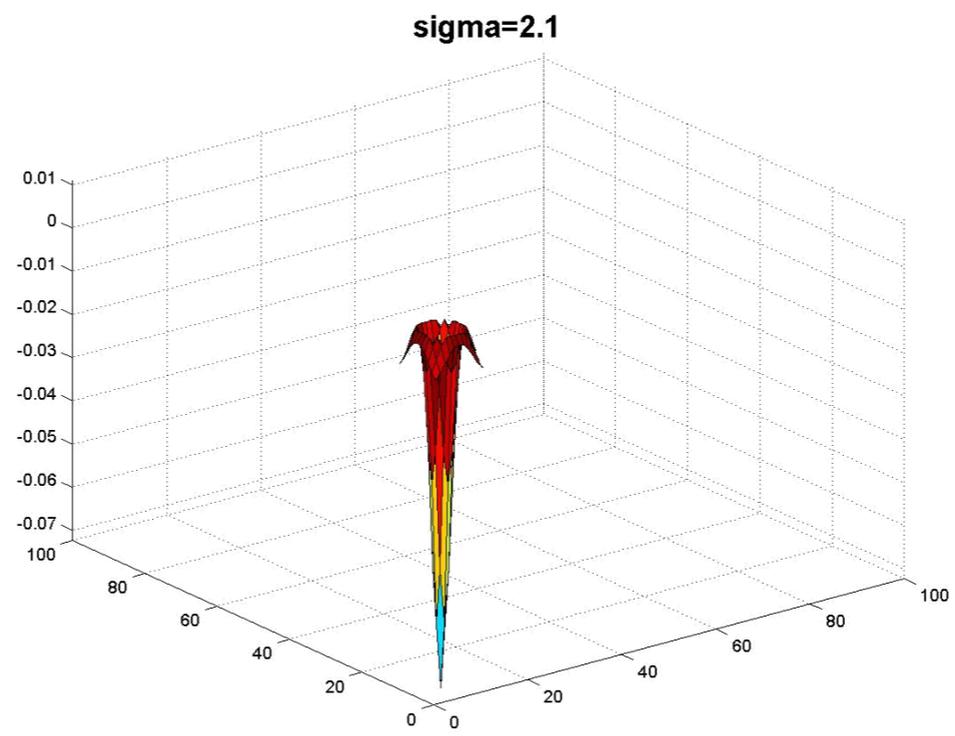
What happened when you applied different Laplacian filters?

Full size

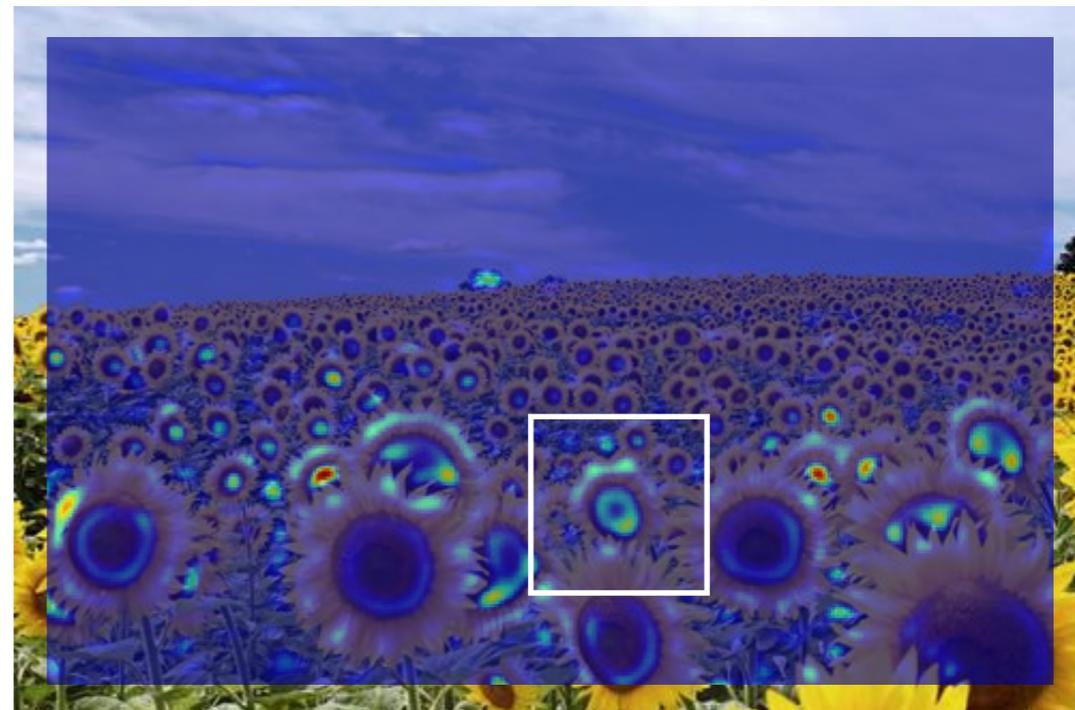
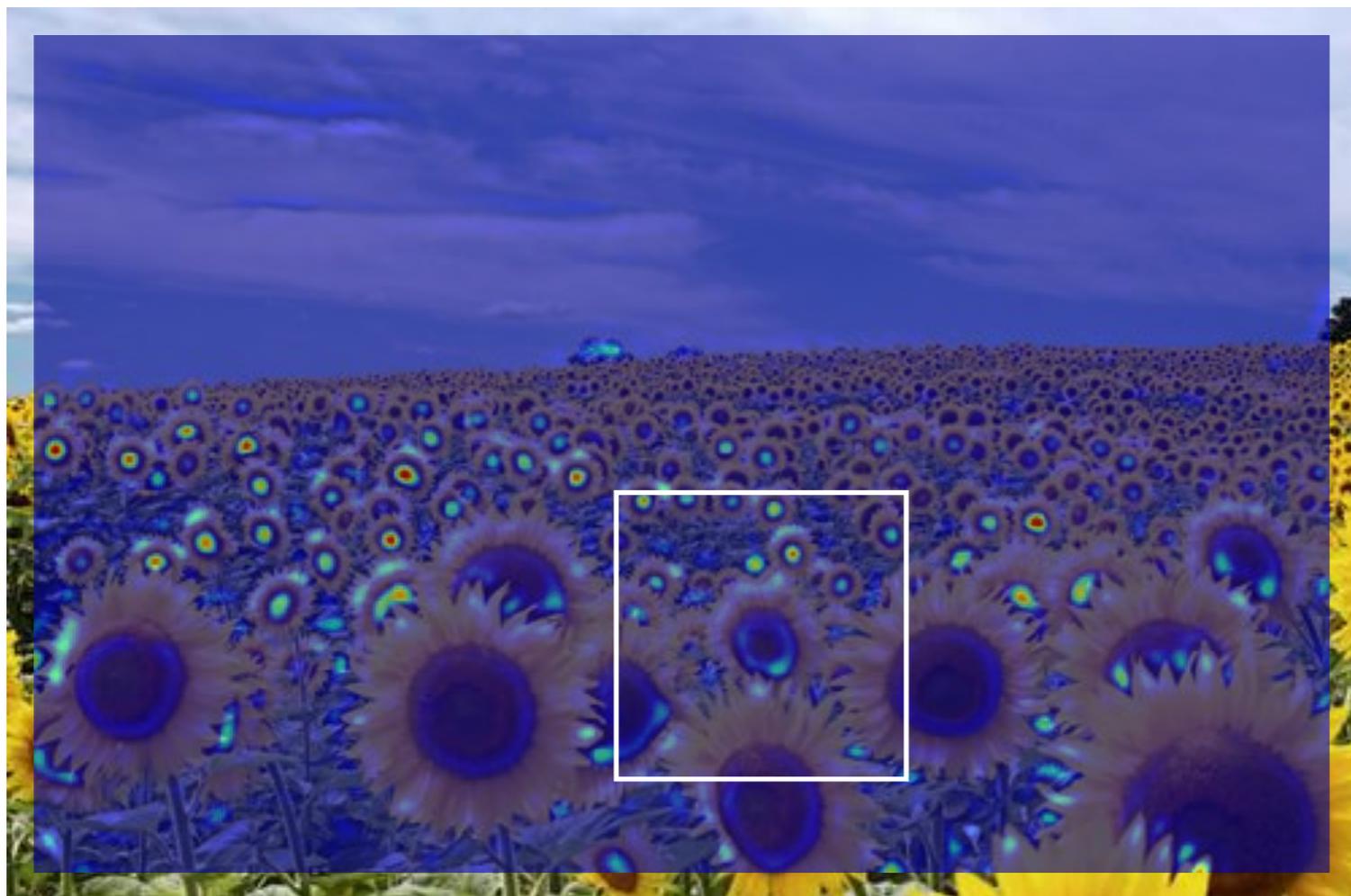
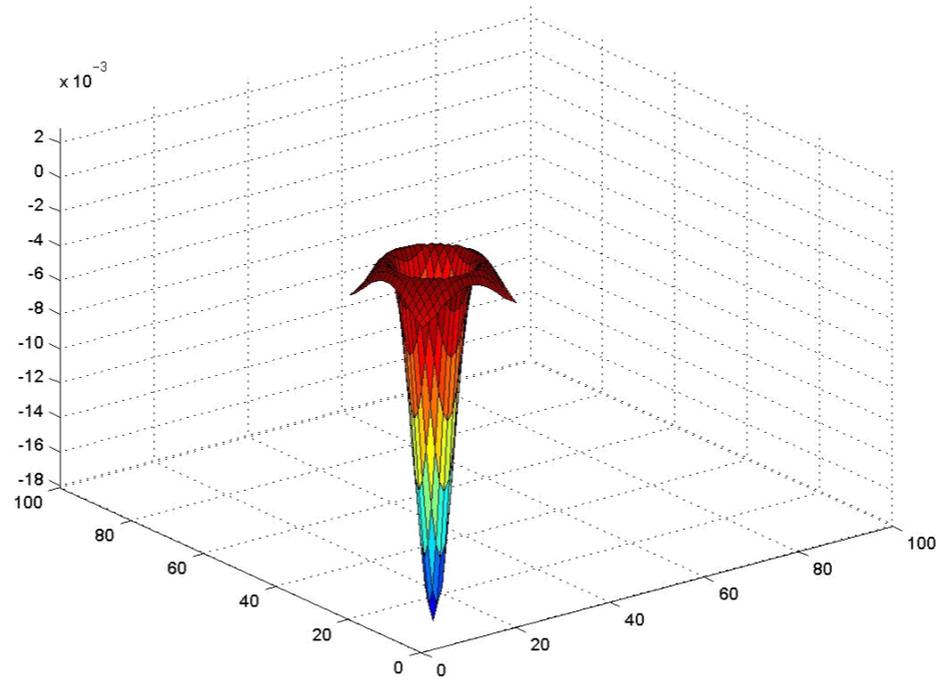


3/4 size

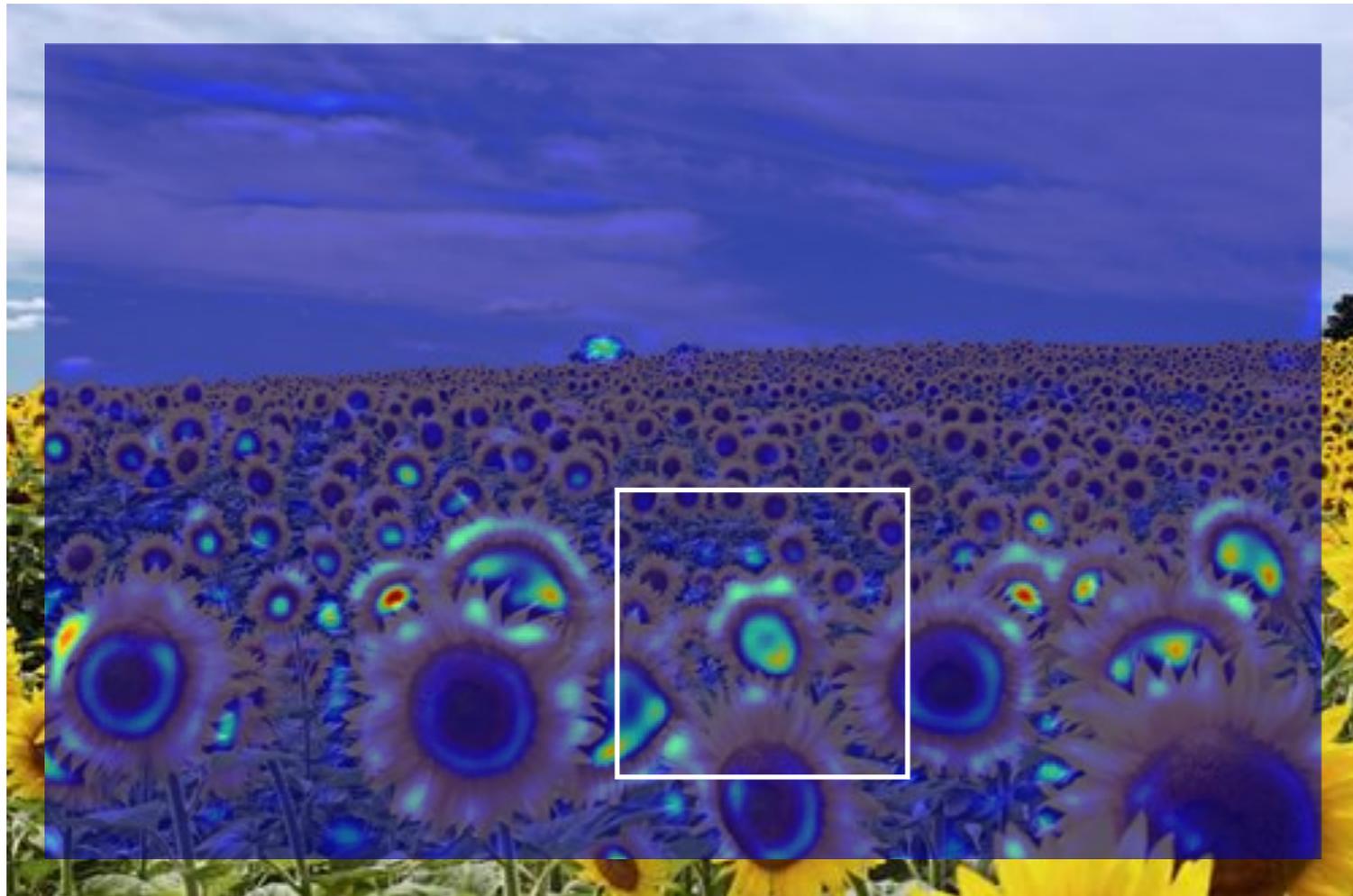
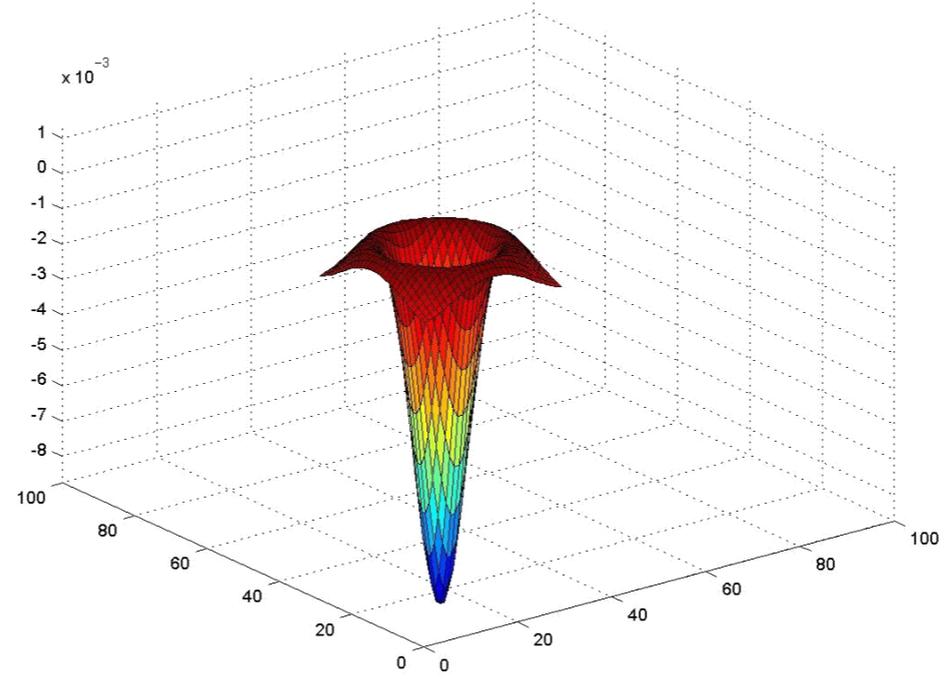


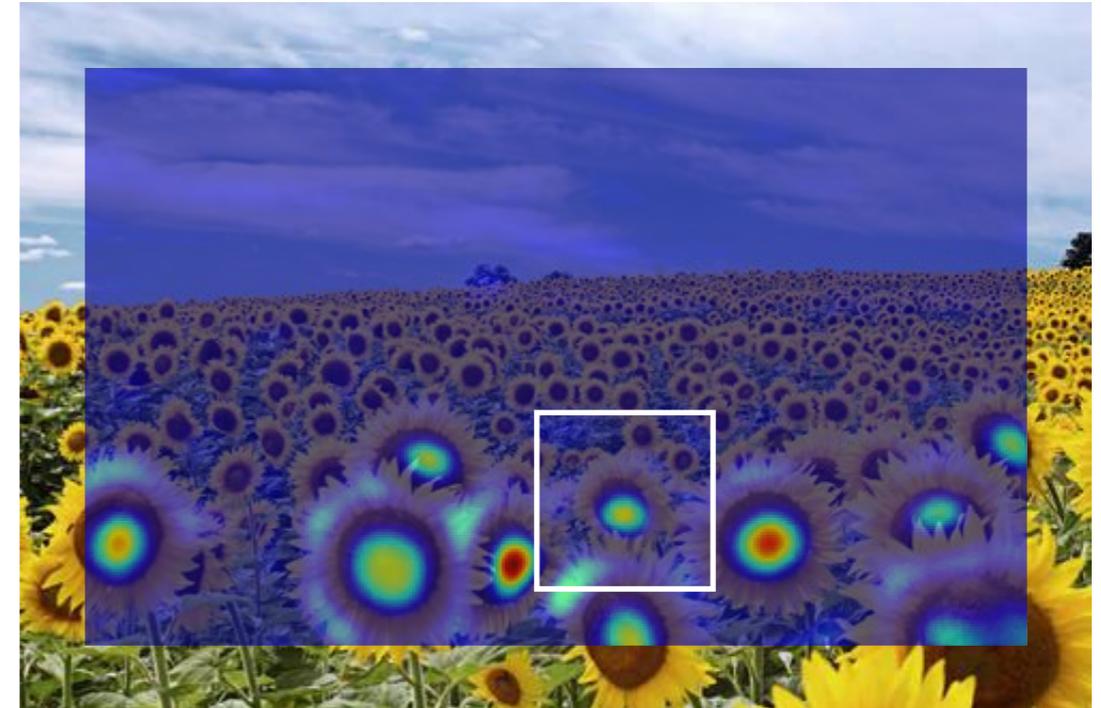
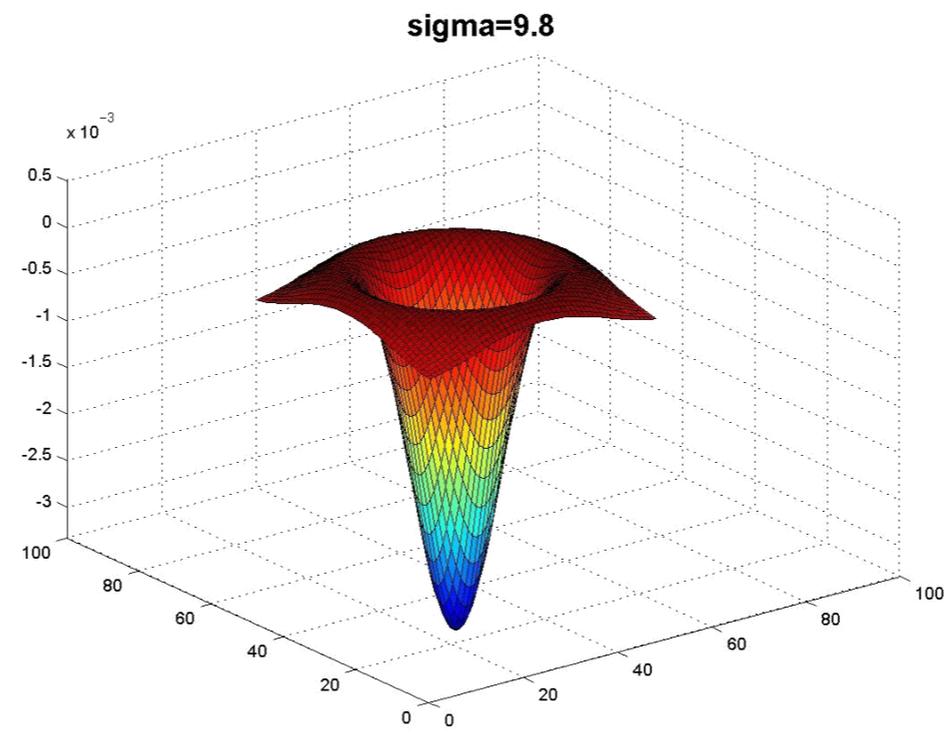


sigma=4.2

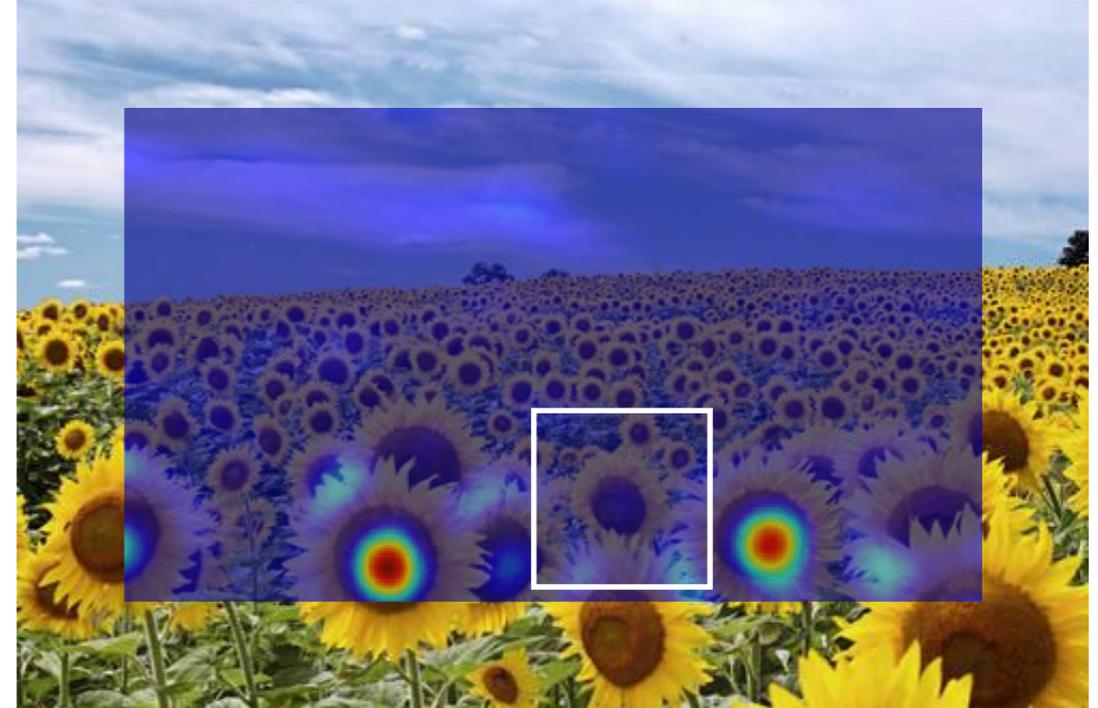
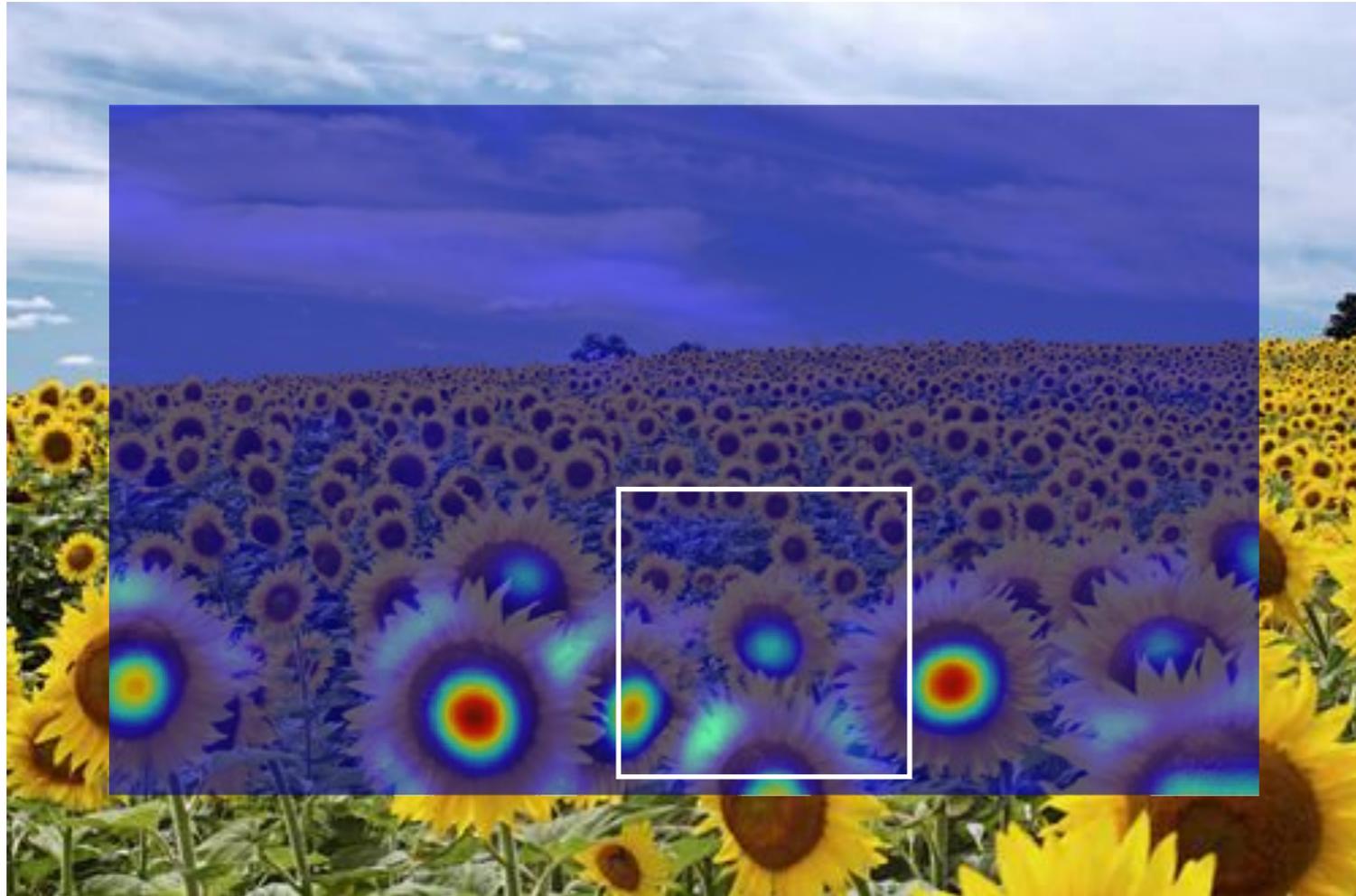
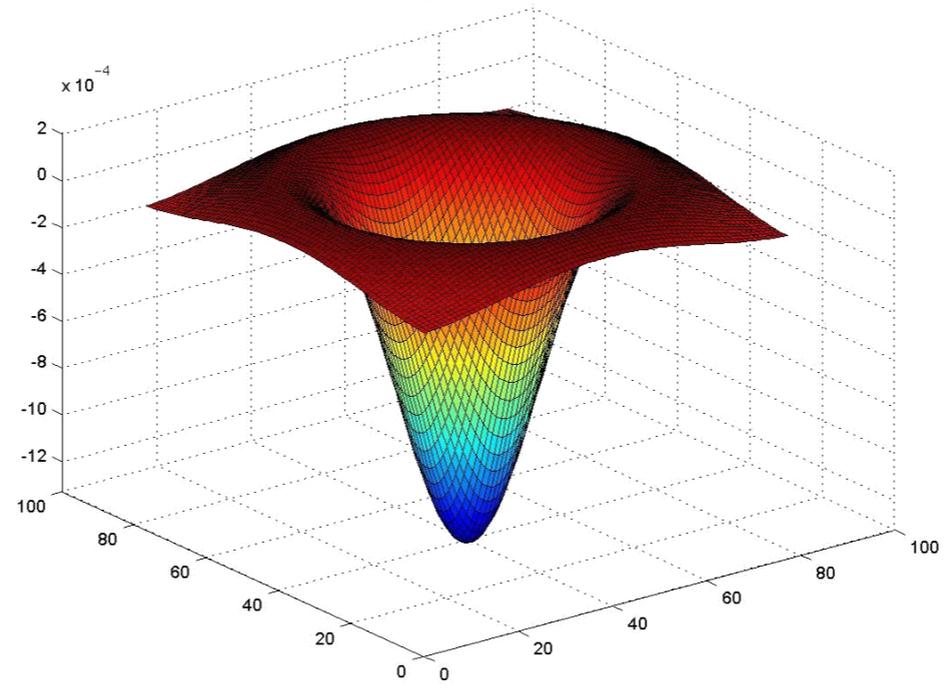


sigma=6

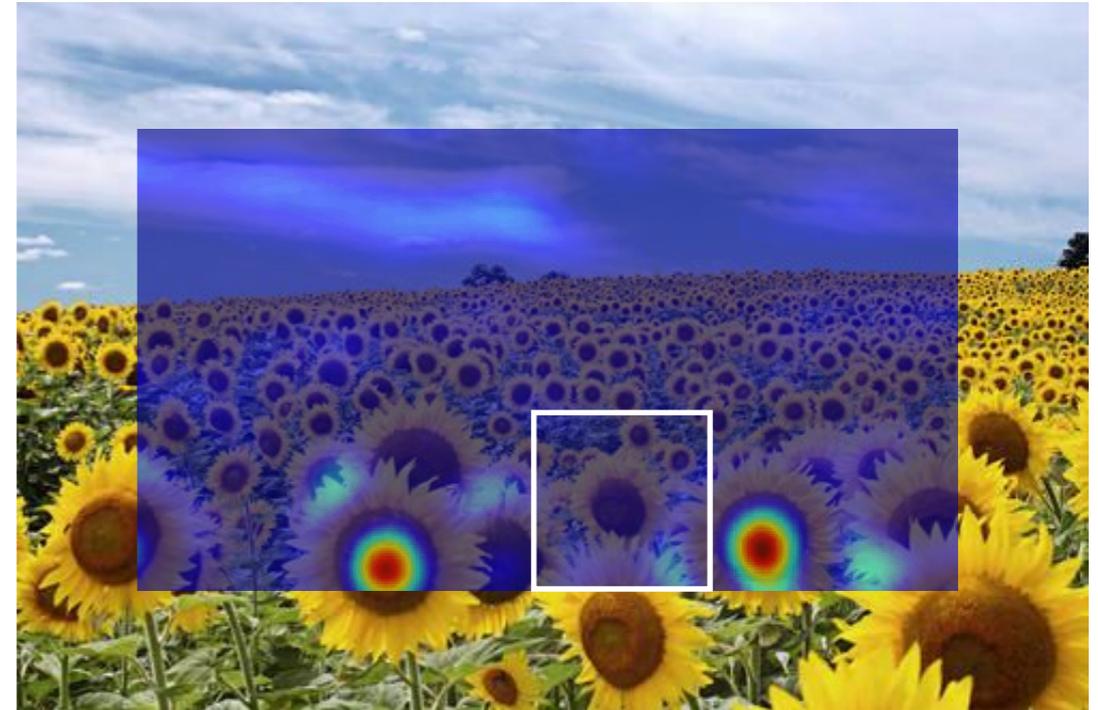
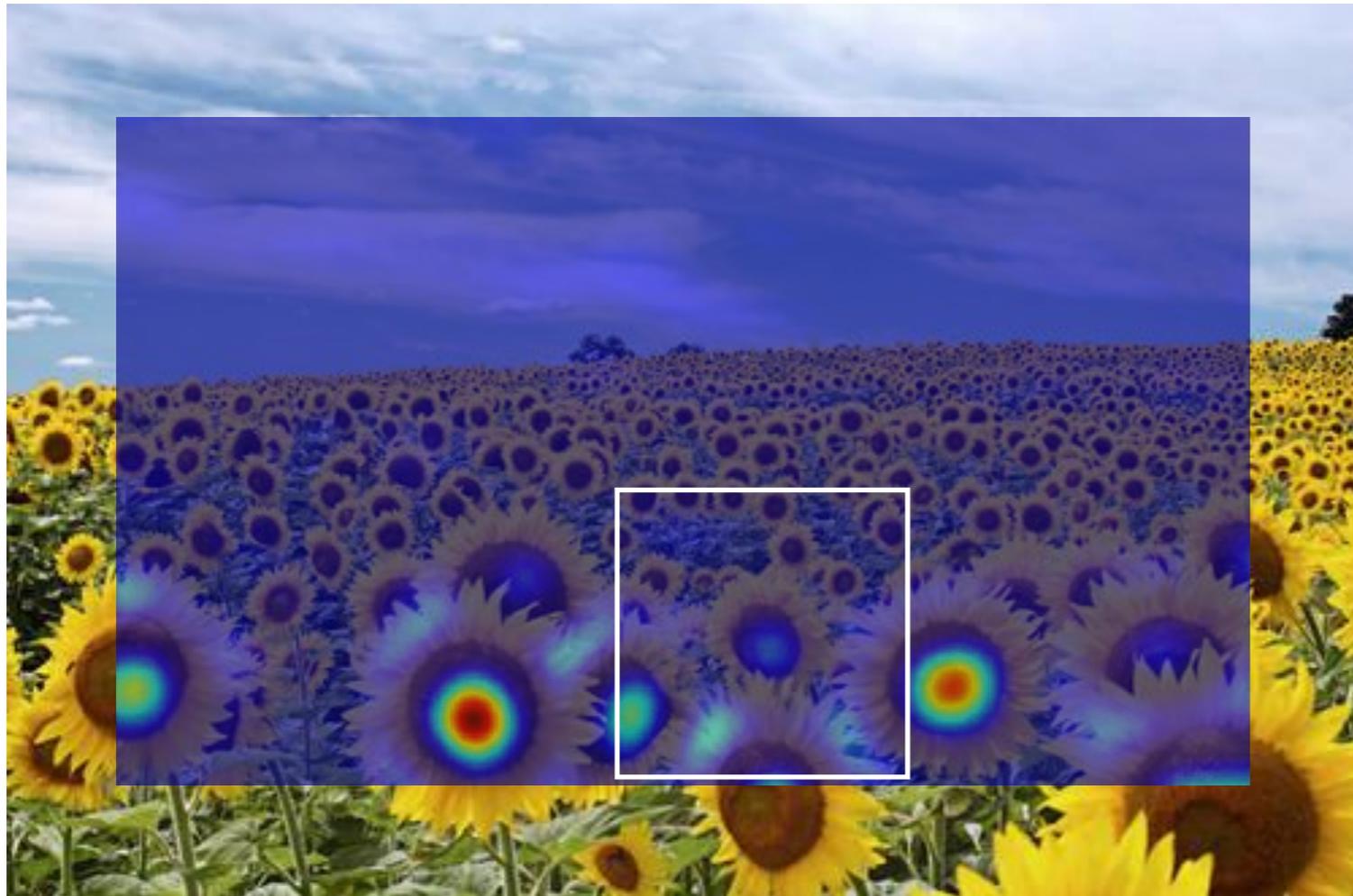
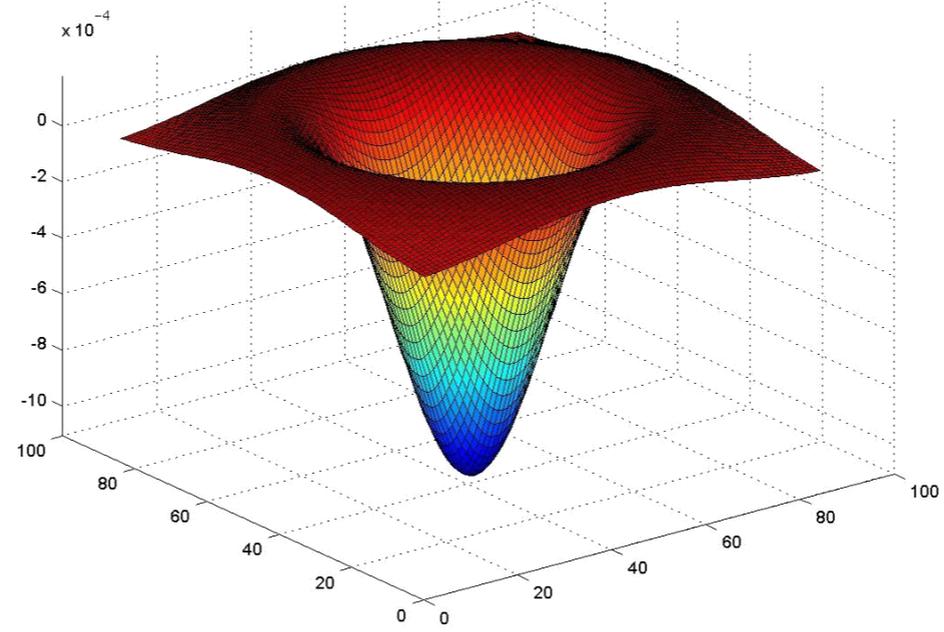




sigma=15.5



sigma=17



What happened when you applied different Laplacian filters?

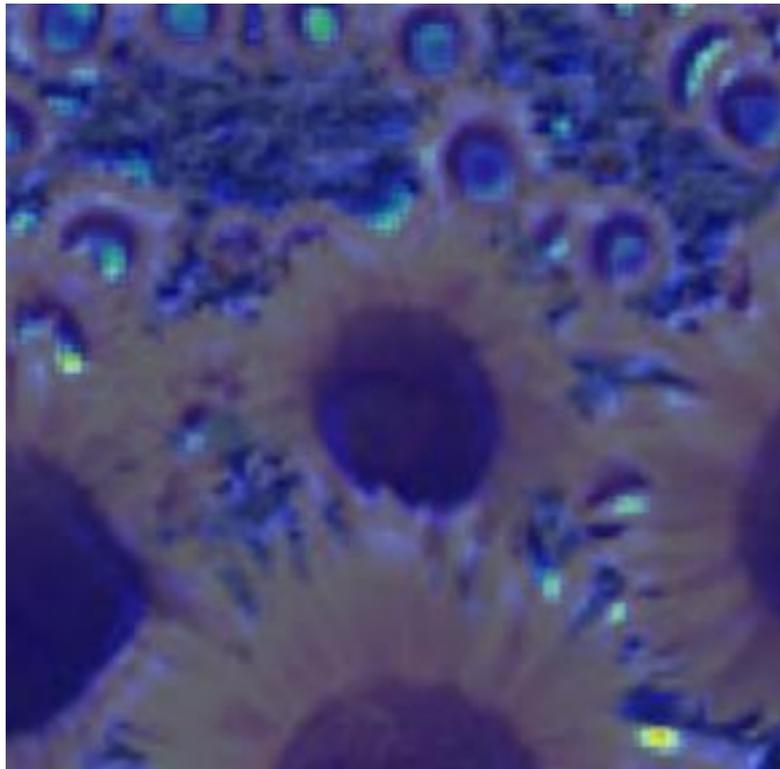
Full size



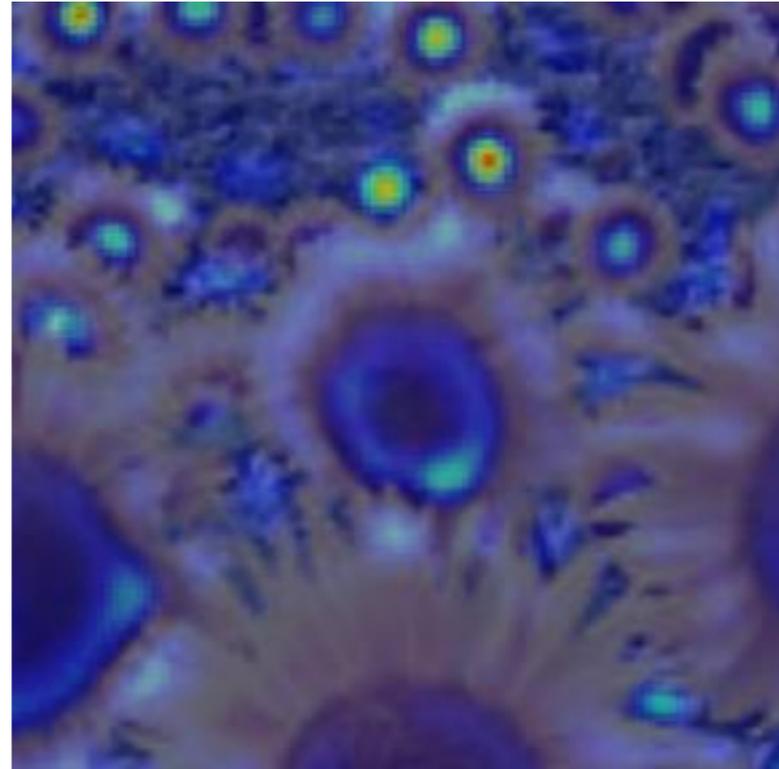
3/4 size



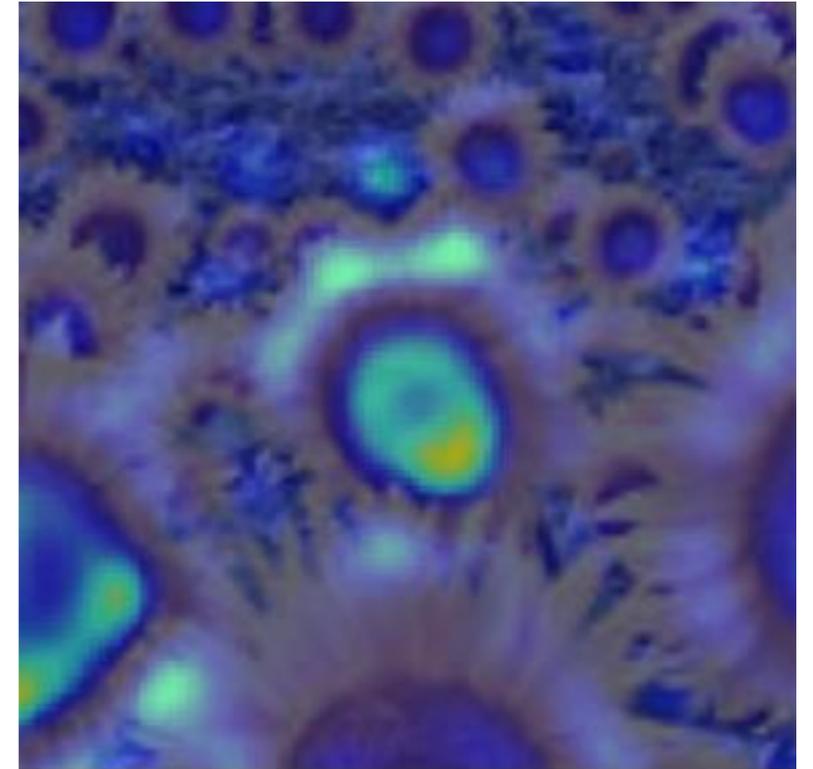
2.1



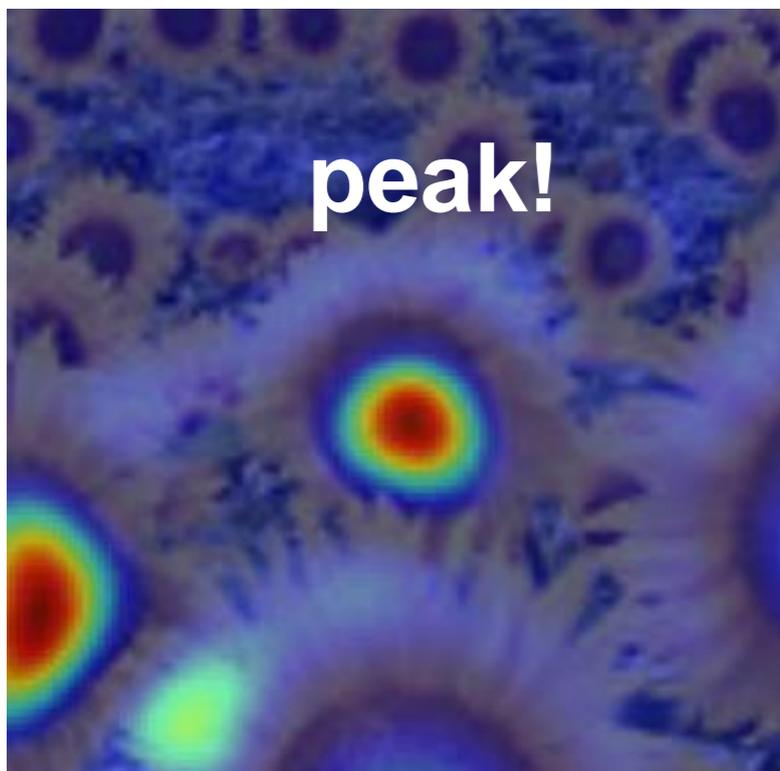
4.2



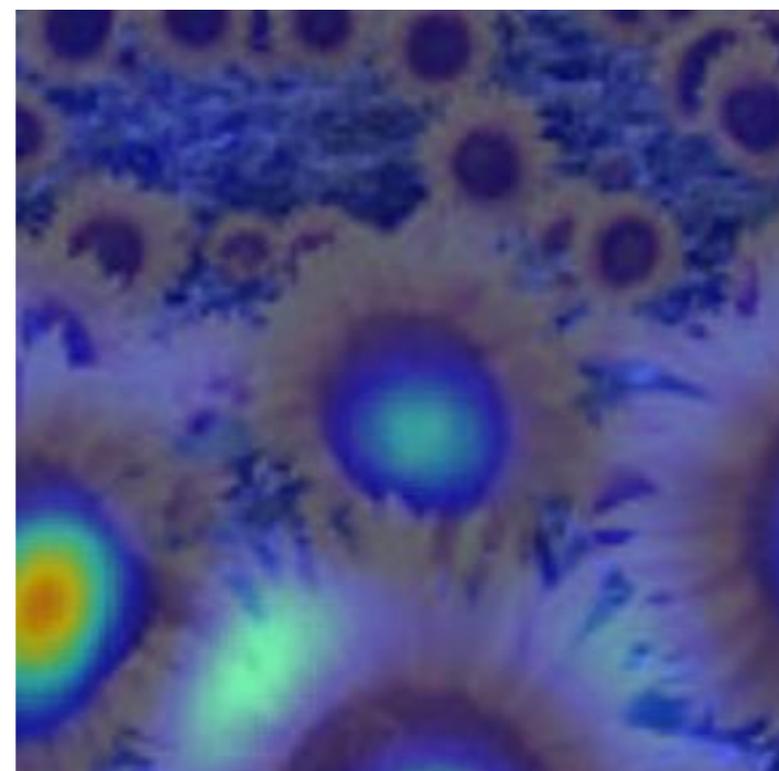
6.0



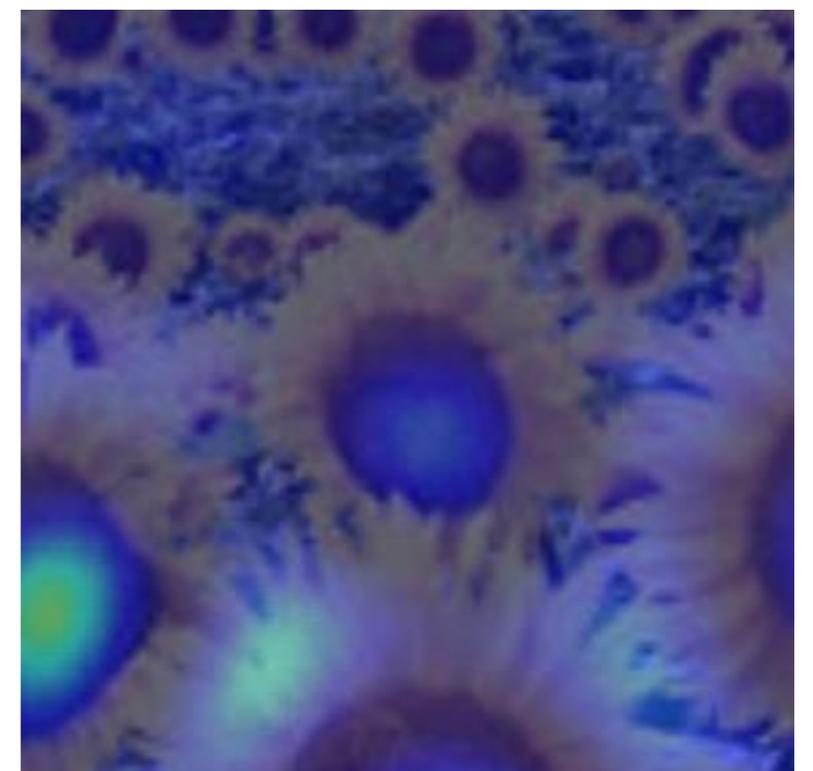
9.8



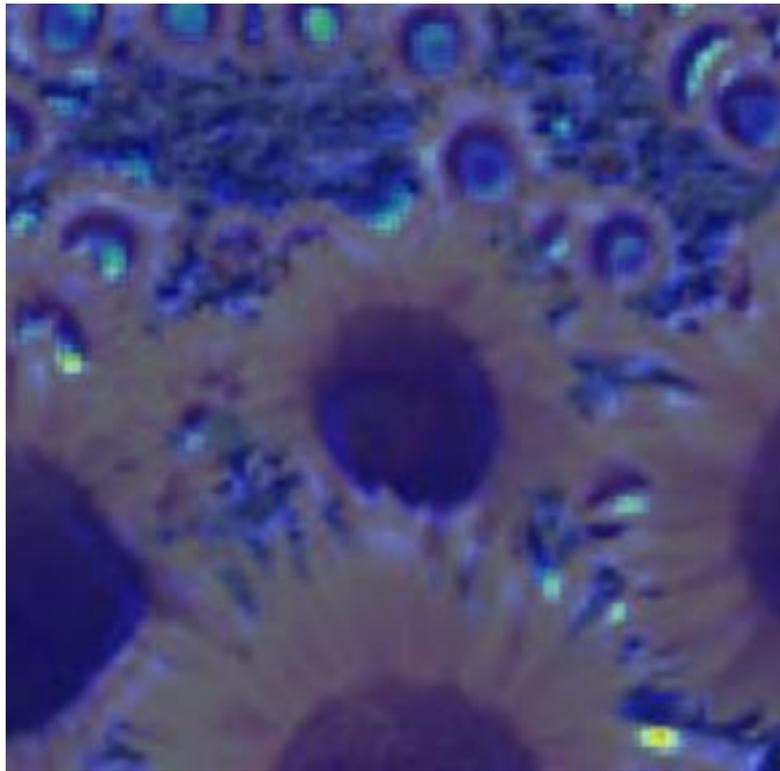
15.5



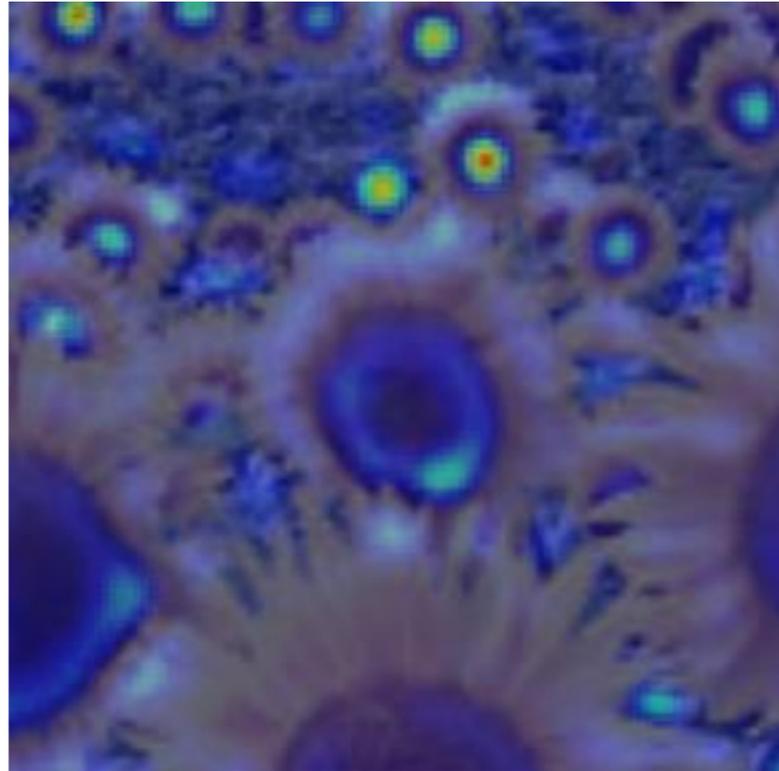
17.0



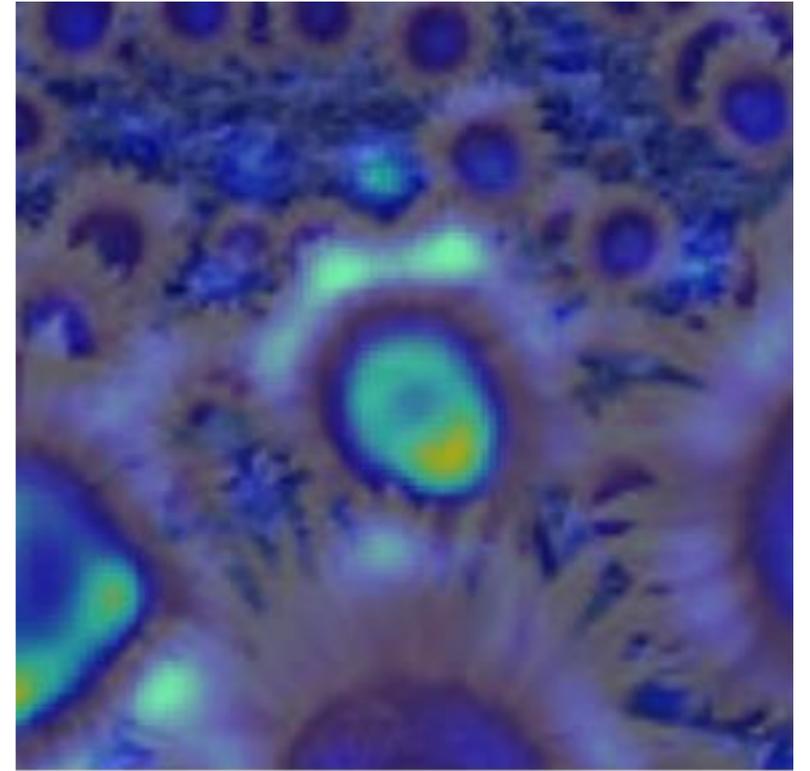
2.1



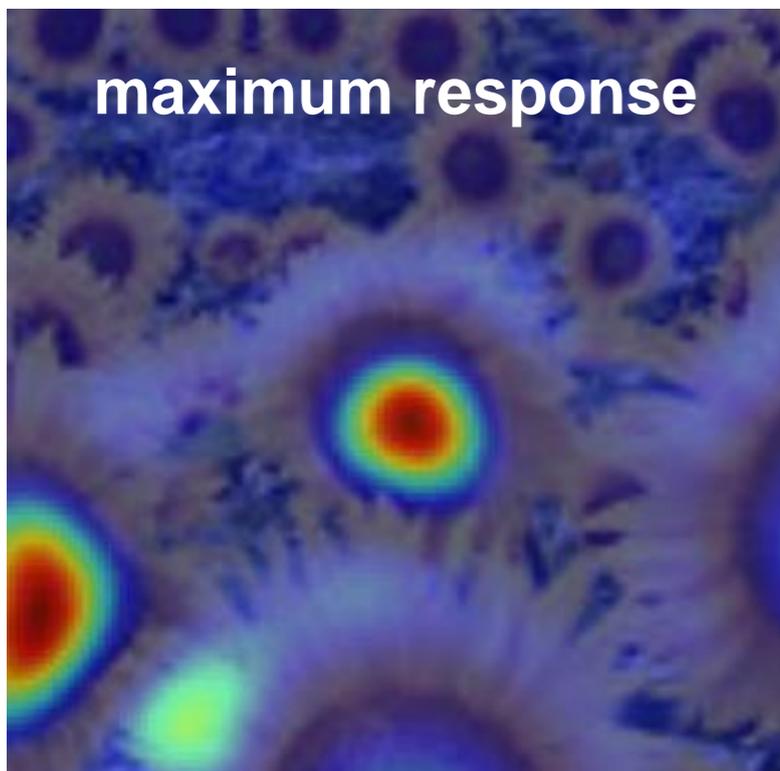
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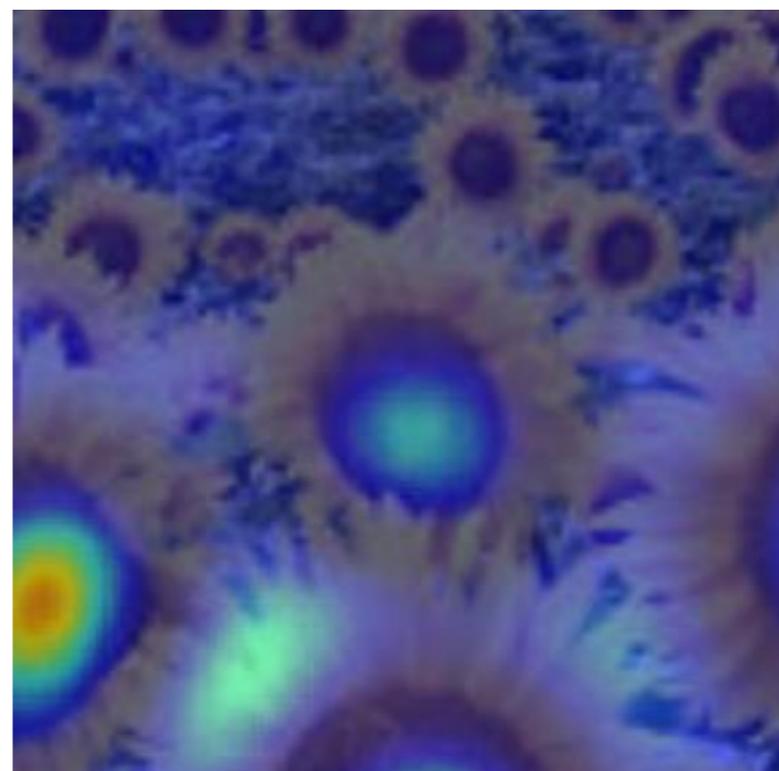
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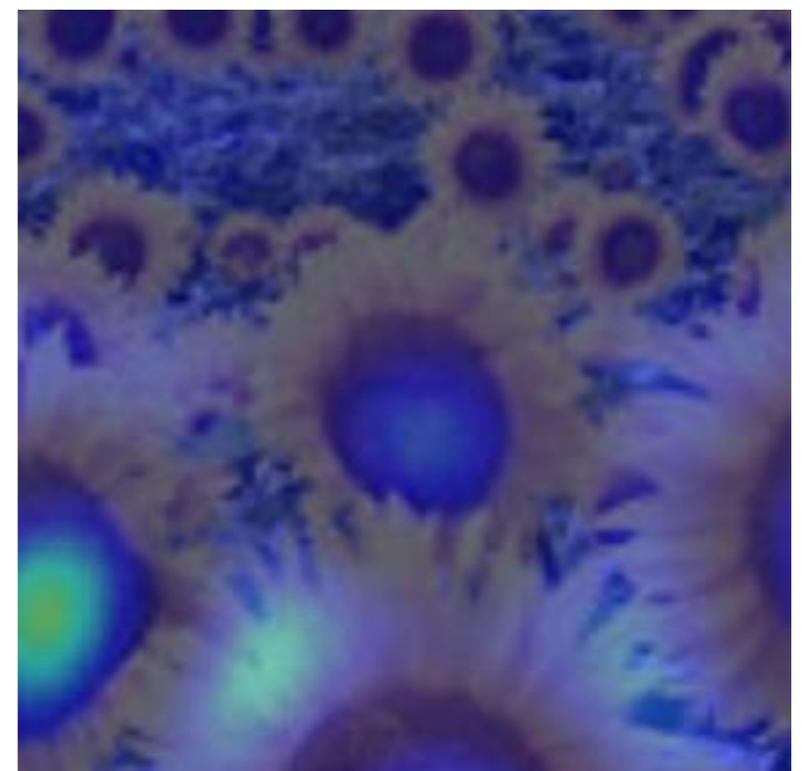
9.8



15.5

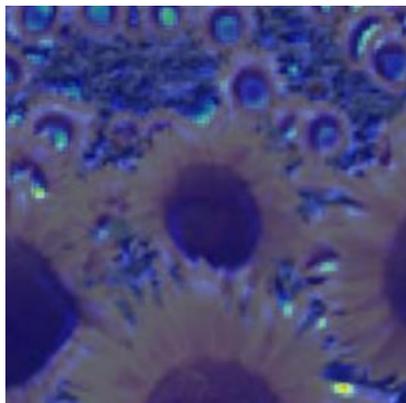


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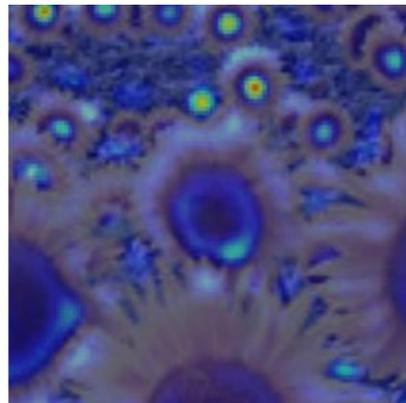


optimal scale

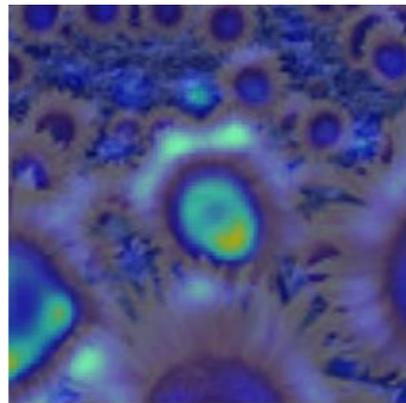
2.1



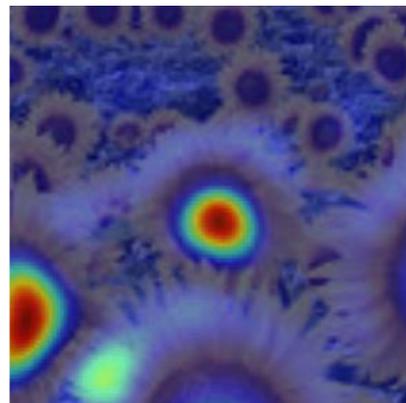
4.2



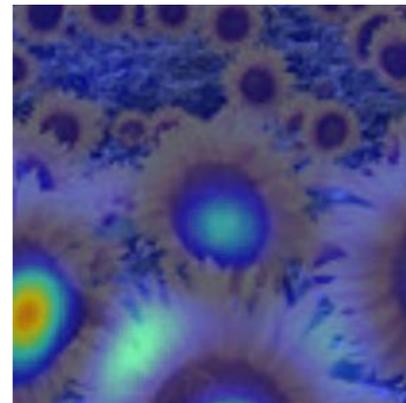
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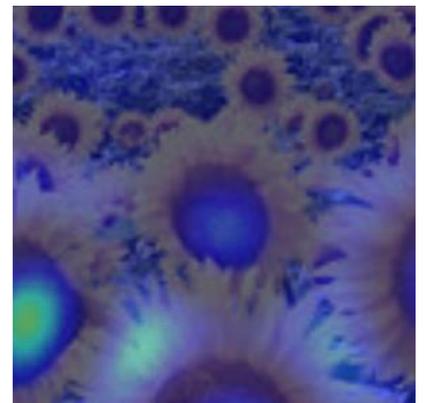
9.8



15.5

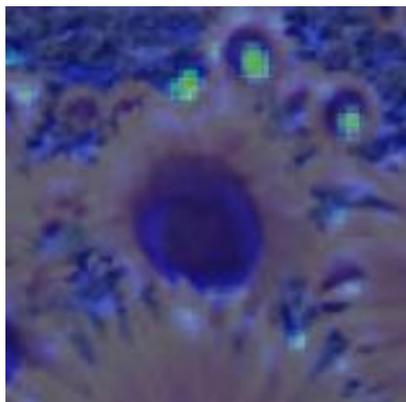


17.0

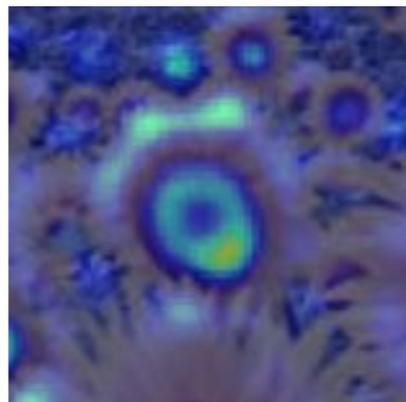


Full size image

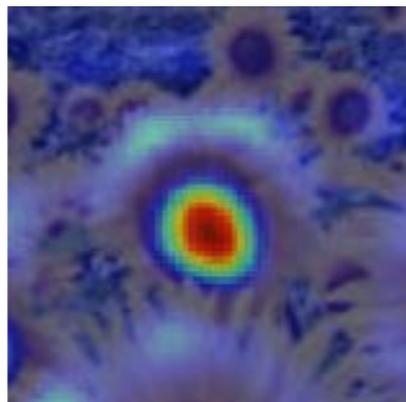
2.1



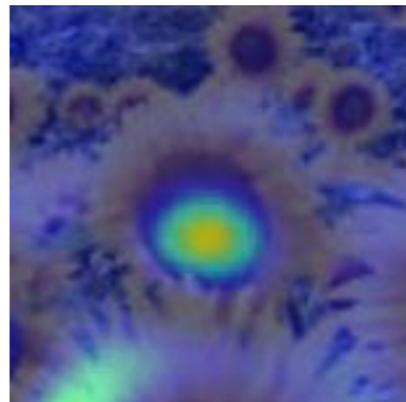
4.2



6.0



9.8



15.5



17.0



3/4 size image

optimal scale

2.1

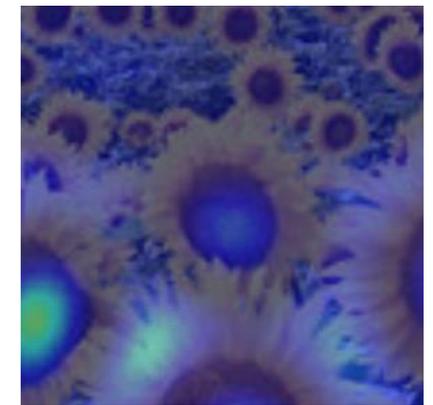
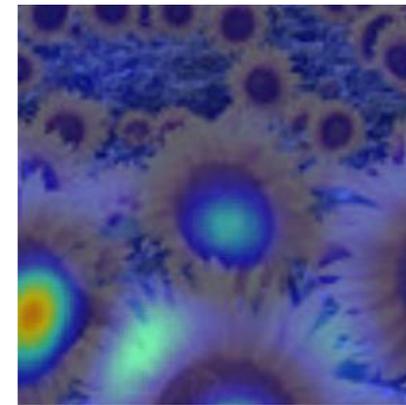
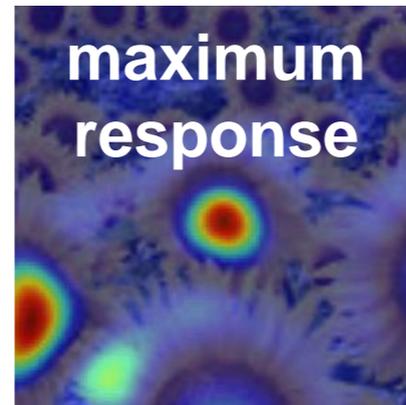
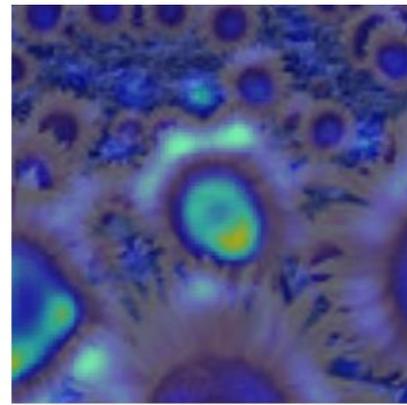
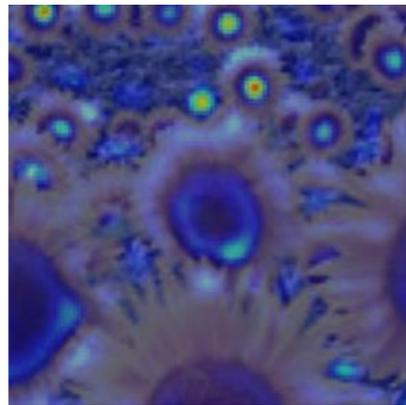
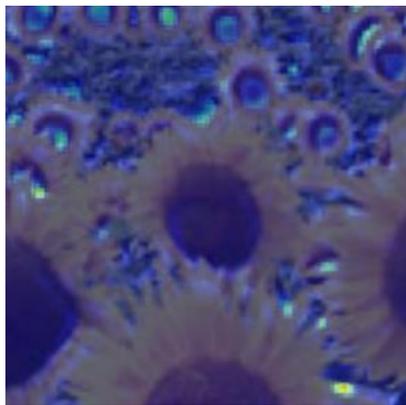
4.2

6.0

9.8

15.5

17.0



Full size image

2.1

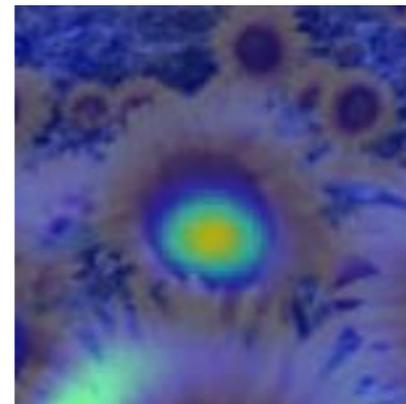
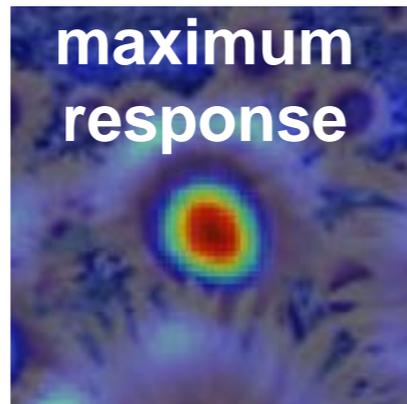
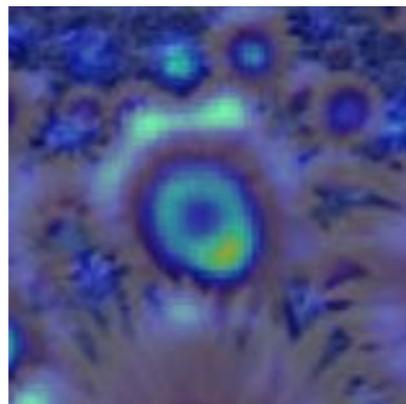
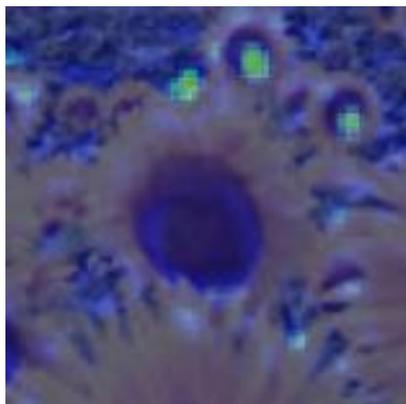
4.2

6.0

9.8

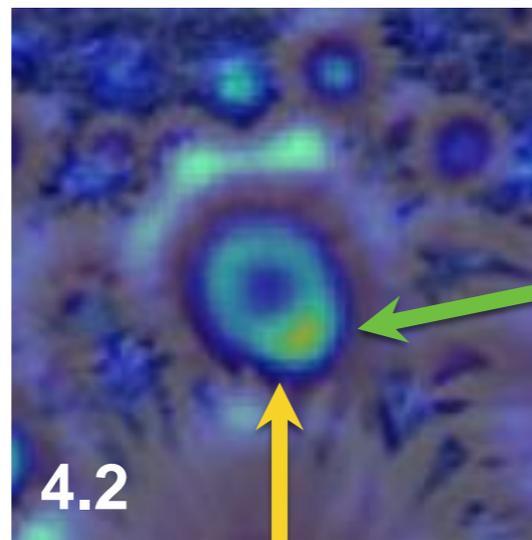
15.5

17.0

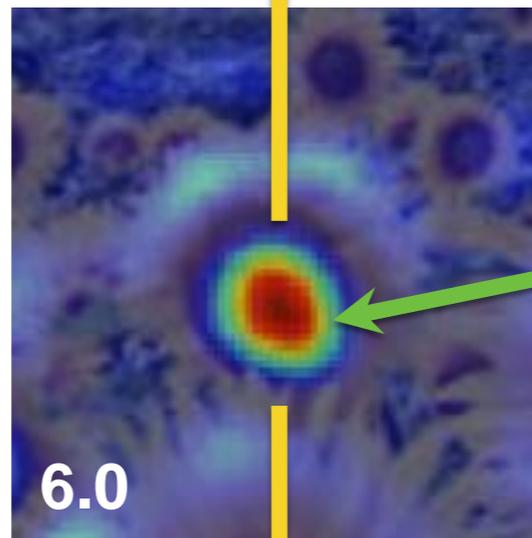


3/4 size image

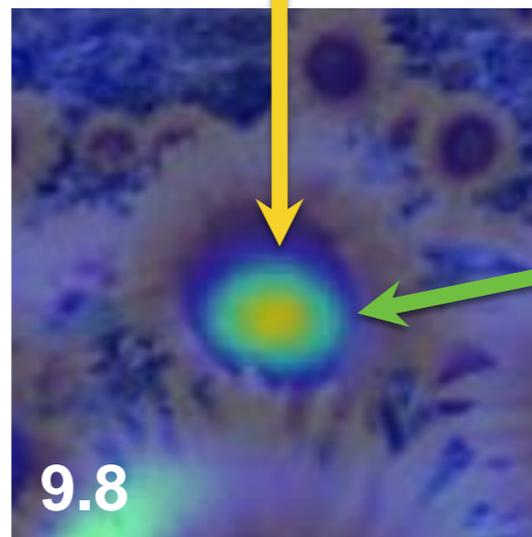
cross-scale maximum



local maximum



local maximum



local maximum

How would you implement
scale selection?

implementation

For each level of the Gaussian pyramid

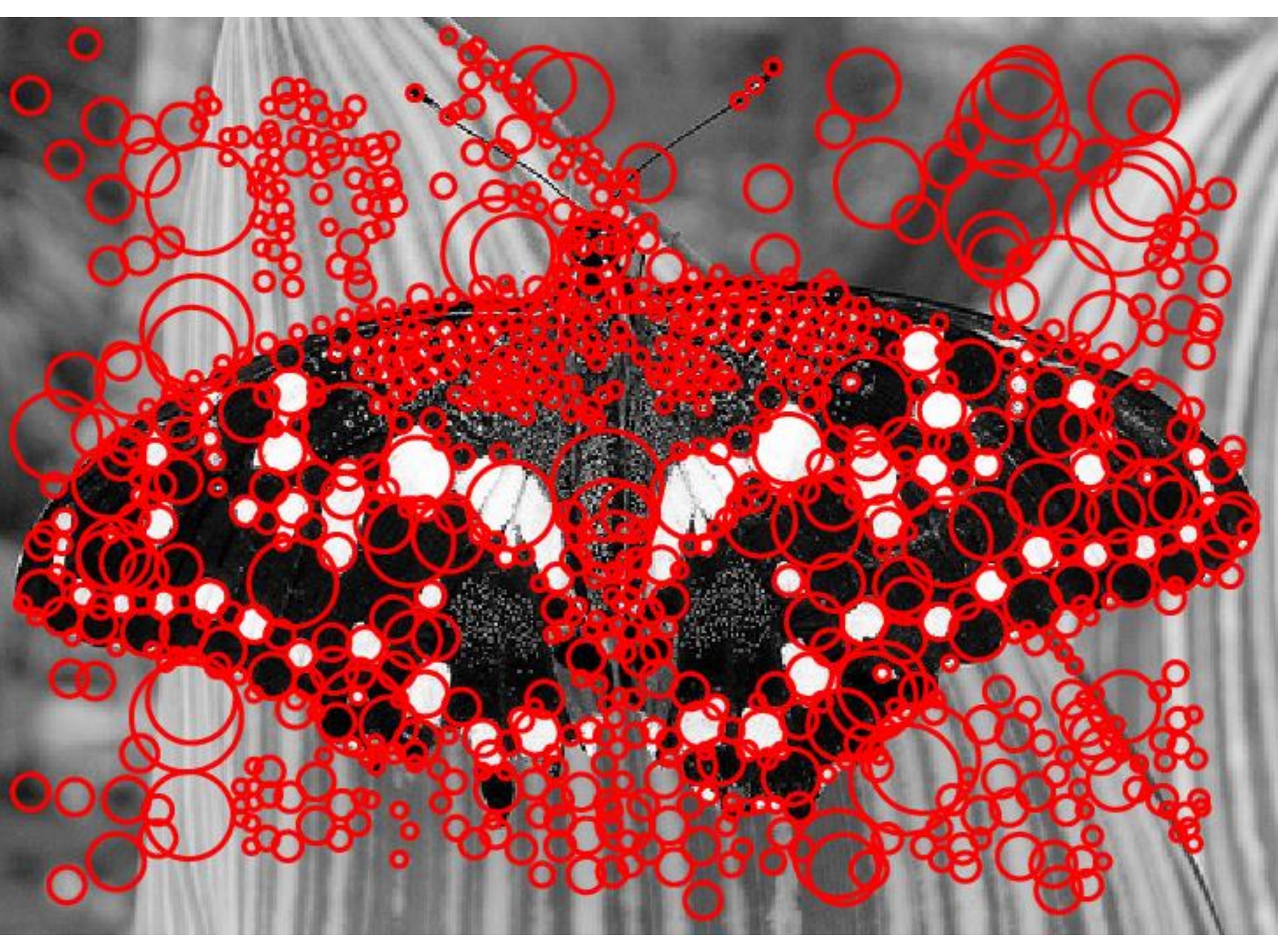
compute feature response (e.g. Harris, Laplacian)

For each level of the Gaussian pyramid

if local maximum and cross-scale

save scale and location of feature (x, y, s)





References

Basic reading:

- Szeliski textbook, Sections 4.1.