Georgia Institute of Technology

Computational Photography

Dr. Irfan Essa
Professor
School of Interactive Computing

Study the basics of computation and its impact on the entire workflow of photography, from capturing, manipulating and collaborating on, and sharing photographs.

Feature Detection and Matching

Dr. Irfan Essa
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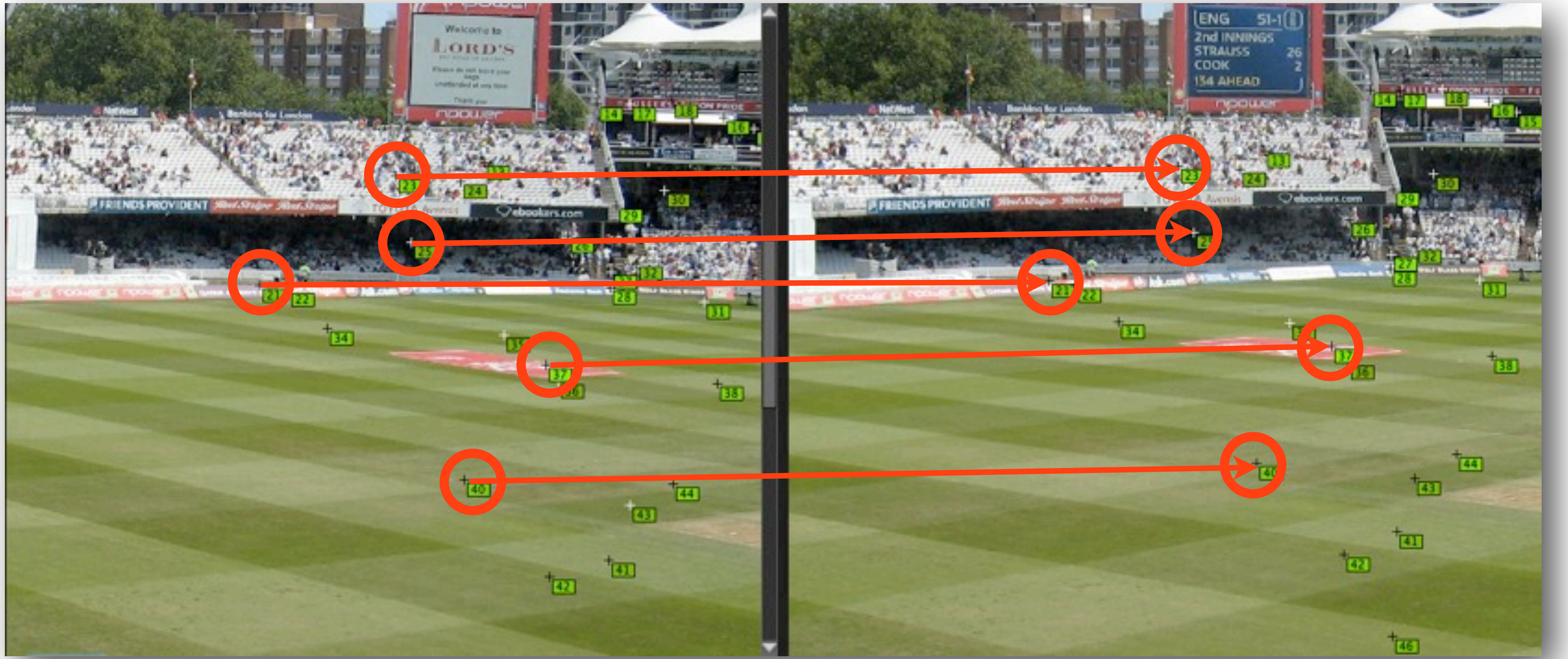
Methods for Detecting Features in Images that can be Matched for Registration and Alignment.

Lesson Objectives

- ★ Describe in your own words two (2) benefits of Feature Detection and Matching in images
- ★ Describe in your own words the four (4) Characteristics of Good Features.
- ★ Explain in your own words why corners are Good Features.
- ★ Outline the five (5) steps of Harris Corner Detector Algorithm
- ★ Outline the four (4) stages of a SIFT detector



REVIEW: Detection and Matching

Image Matching

Image Matching

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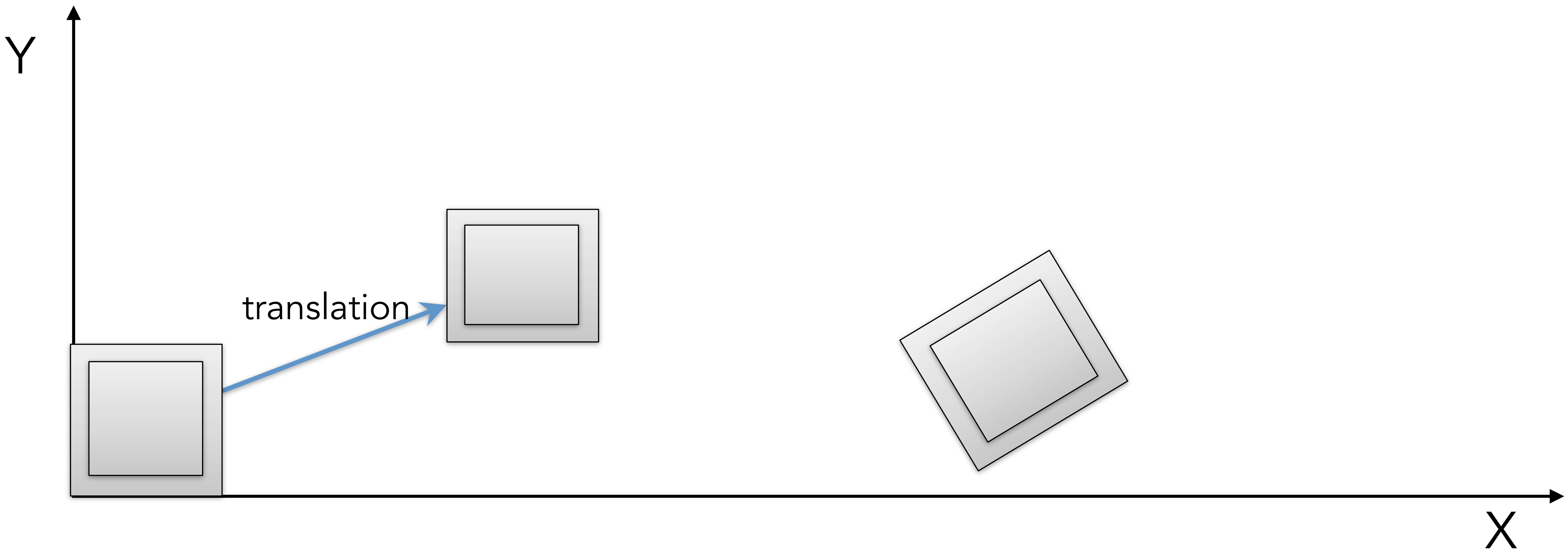
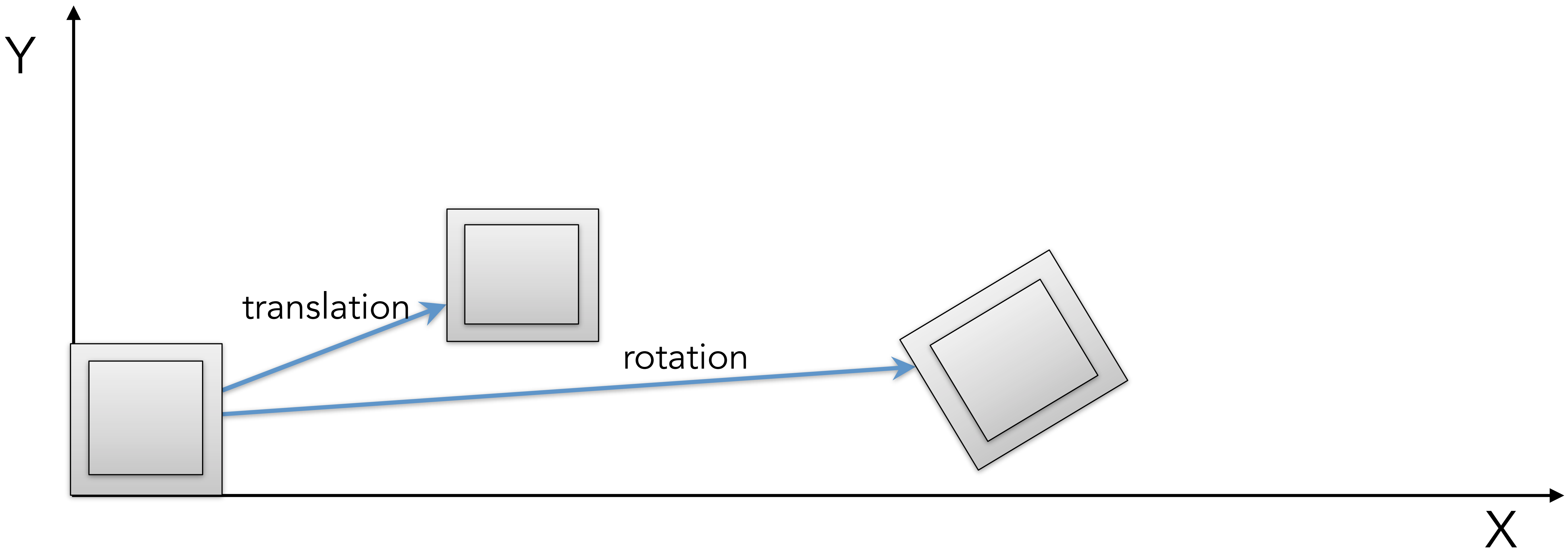


Image Matching



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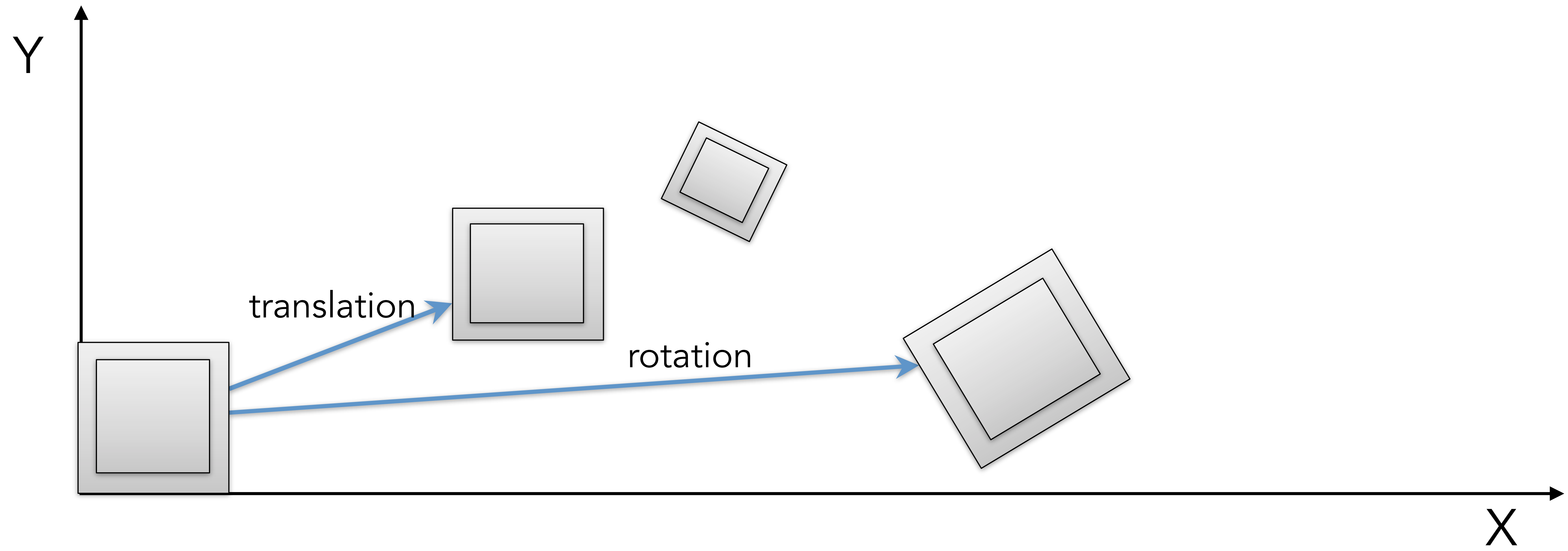

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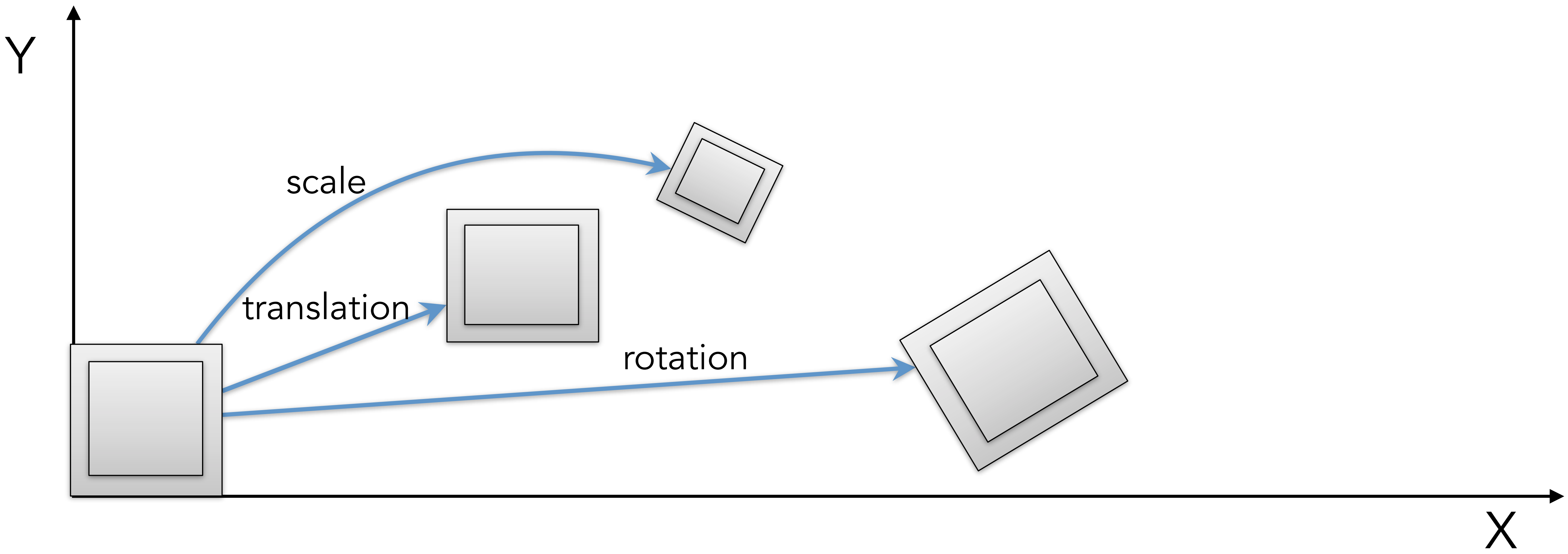

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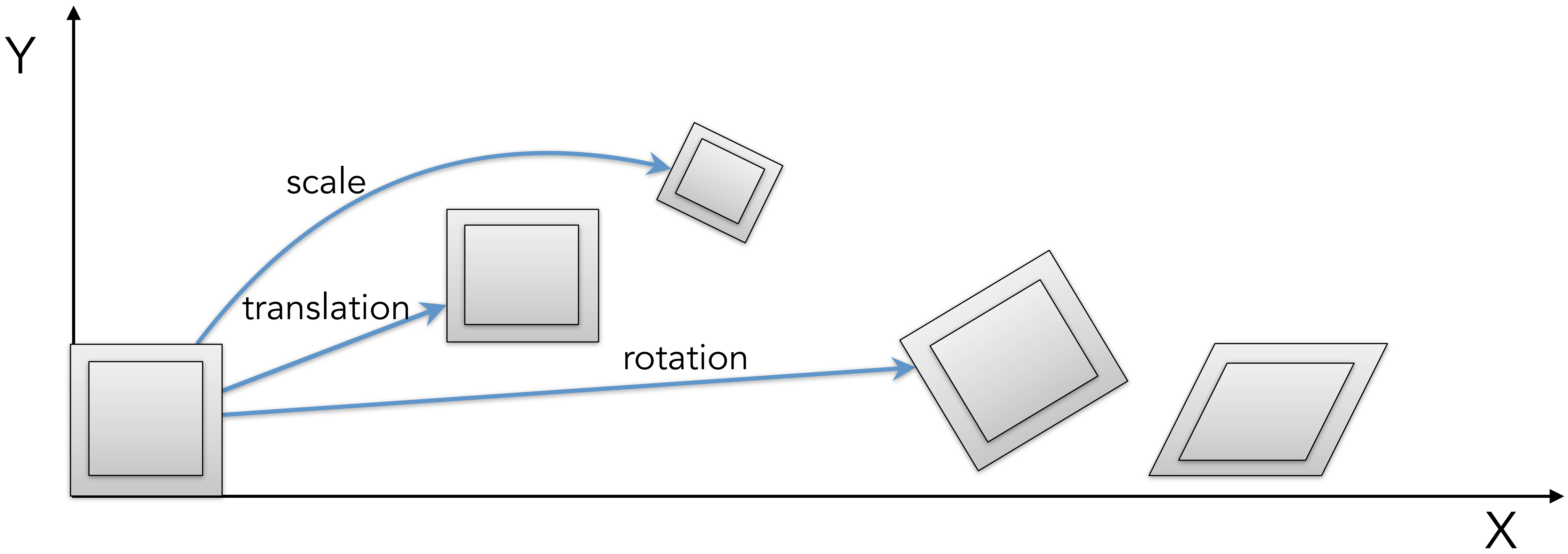

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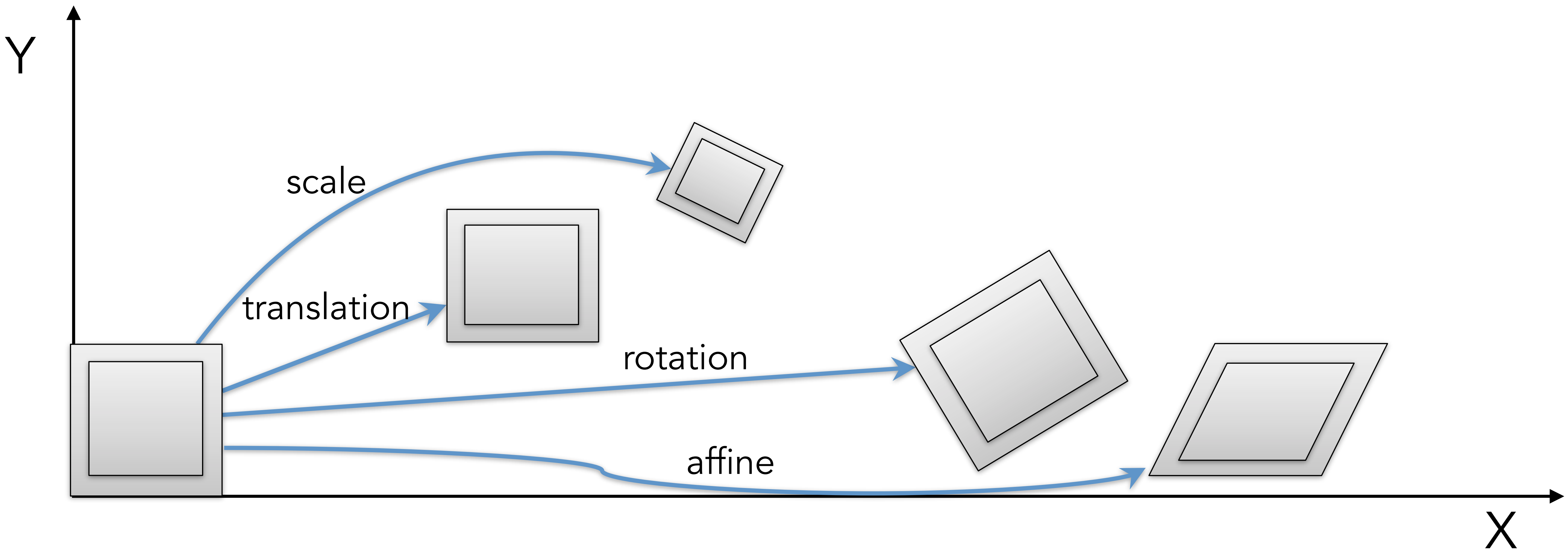

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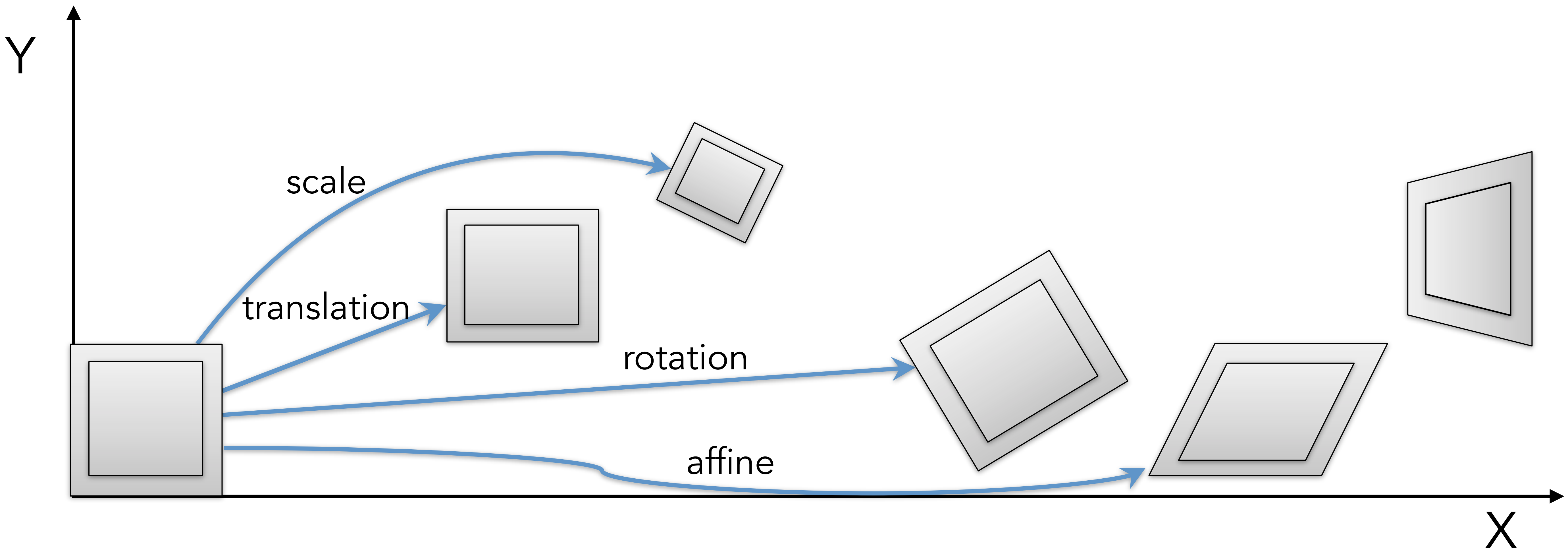

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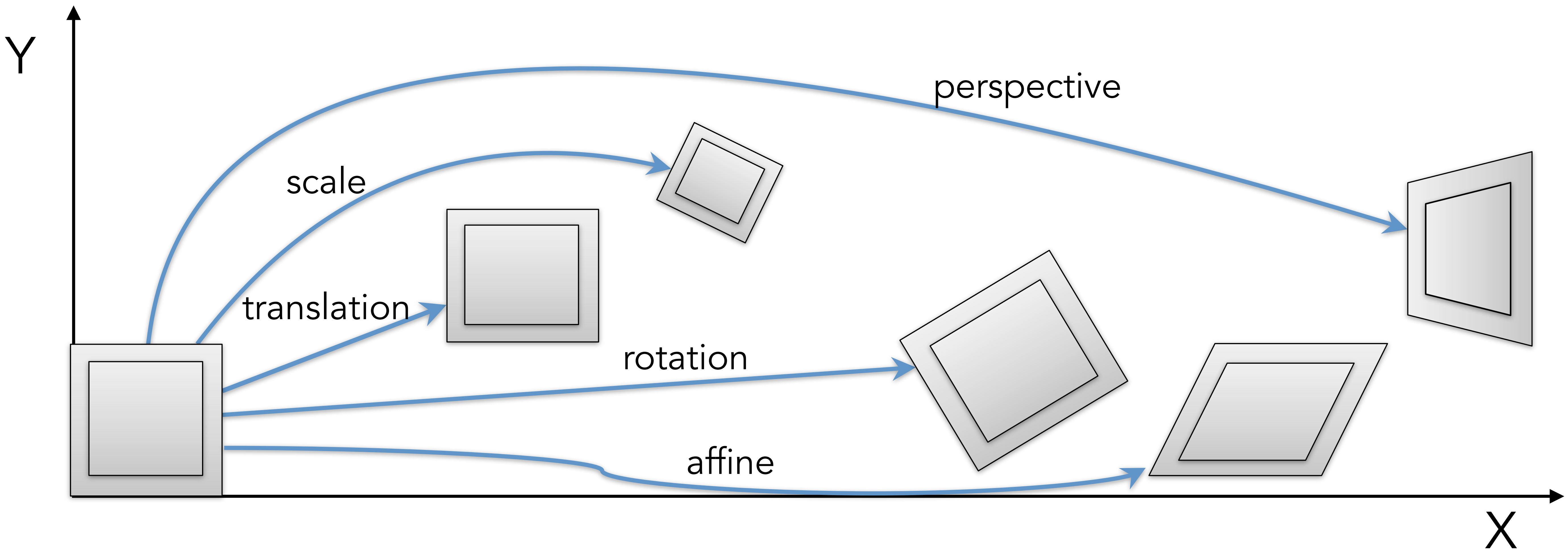
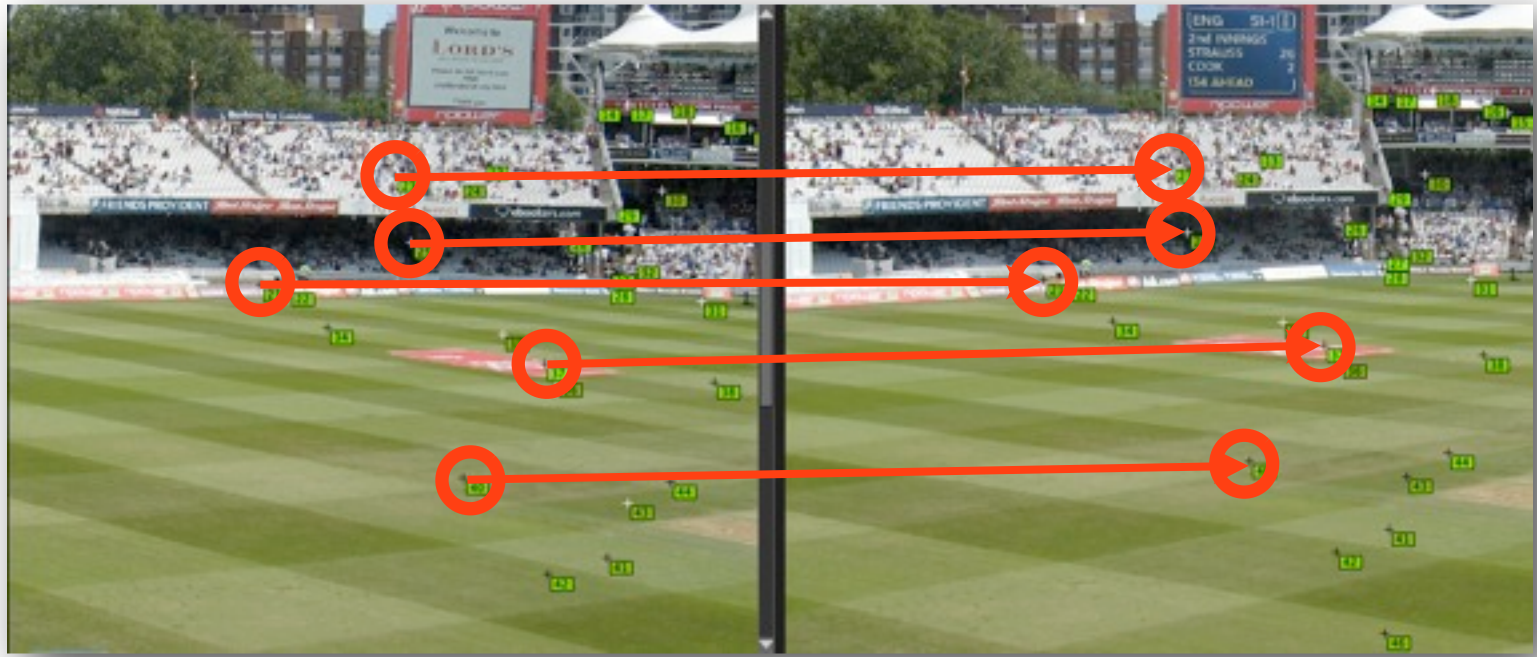


Image Matching

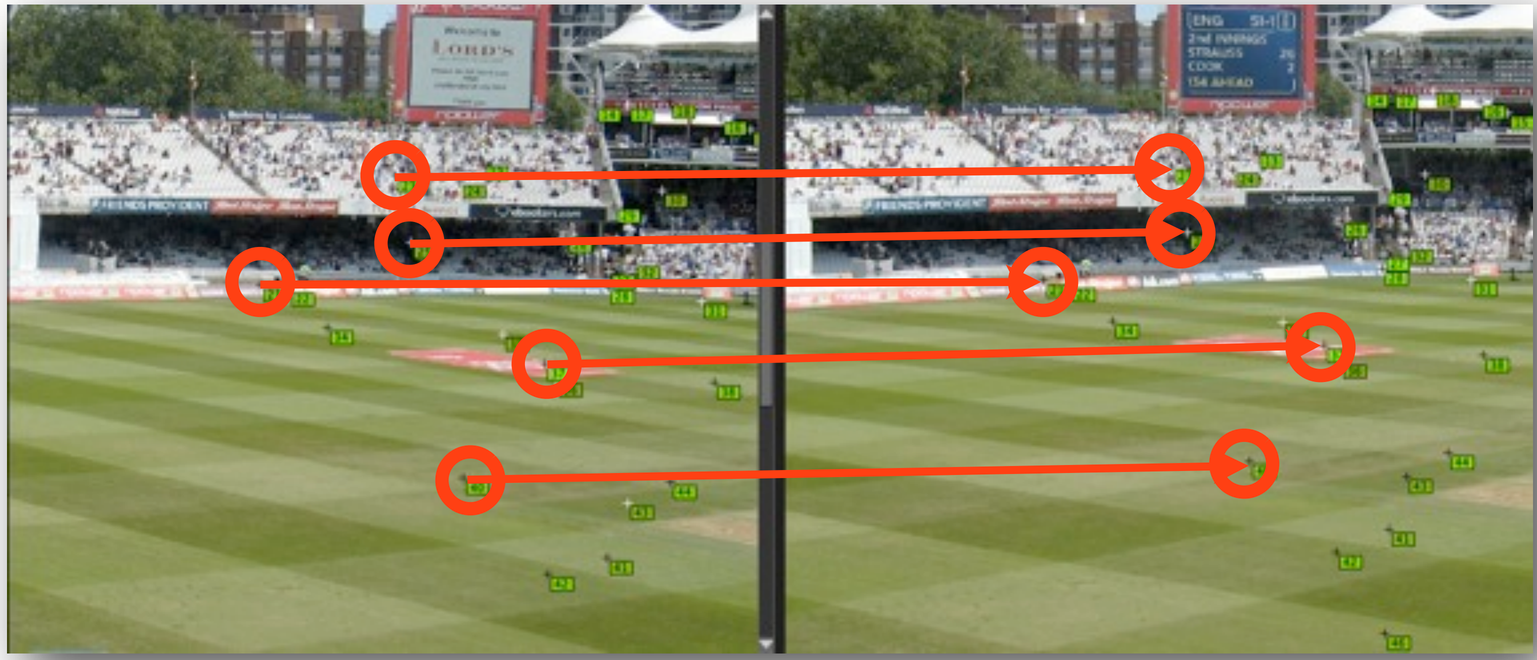
Finding Features



Finding Features

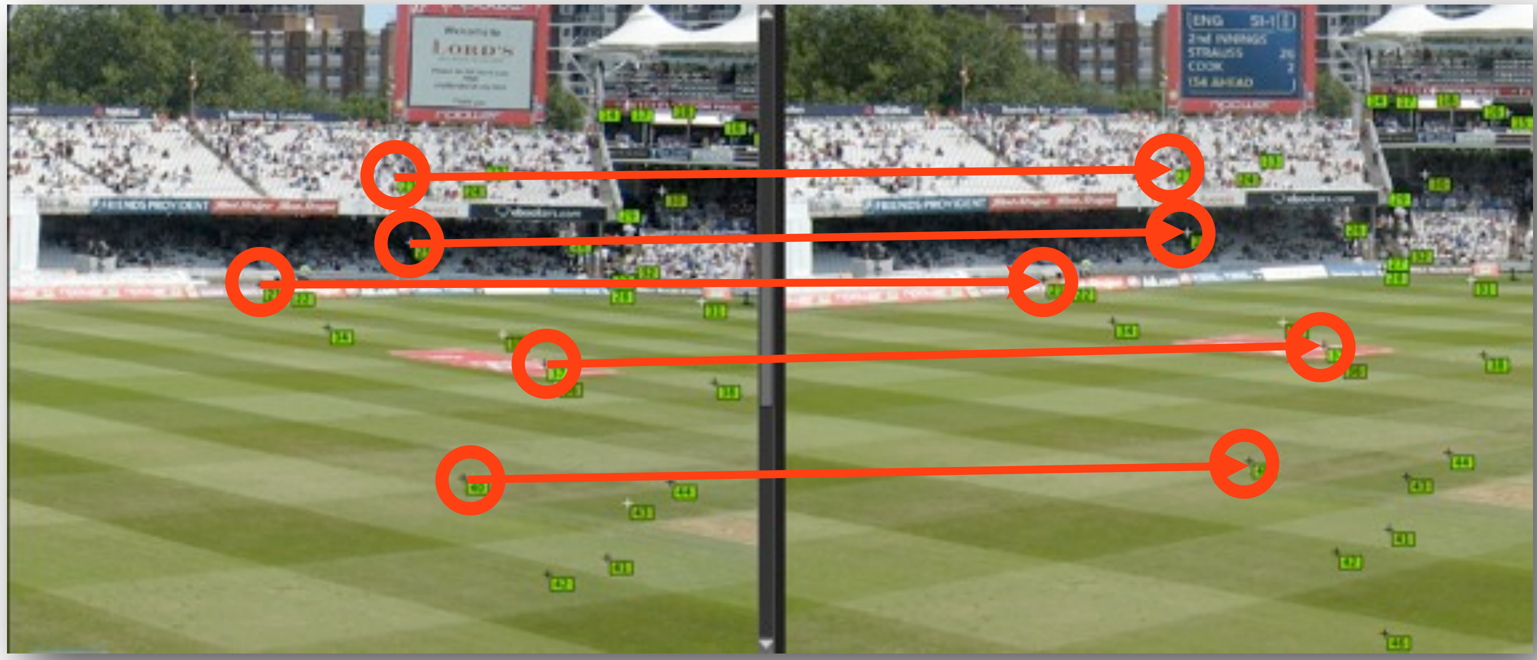
★ Goal: Find points in an image that can be:

- Found in other images
- Found precisely – well localized
- Found reliably – well matched



Finding Features

- Goal: Find points in an image that can be:
  - Found in other images
  - Found precisely – well localized
  - Found reliably – well matched
- Why?
  - Align Images
  - Build a Panorama,
  - Etc.



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Characteristics of Good Features

Slide motivated by Aaron Bobick

Characteristics of Good Features

★ Repeatability/Precision

- The same feature can be found in several images despite geometric and photometric transformations

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  - Each feature has a distinctive description

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- ★ Compactness and efficiency
  - Many fewer features than image pixels

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Characteristics of Good Features

- Repeatability/Precision
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- Saliency/Matchability
  - Each feature has a distinctive description
- Compactness and efficiency
  - Many fewer features than image pixels
- Locality
  - A feature occupies a relatively small area of the image; robust to clutter and occlusion

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Find Corners

Find Corners

★ Key property: in the region around a corner, image gradient has two or more dominant directions

Find Corners

- ★ Key property: in the region around a corner, image gradient has two or more dominant directions
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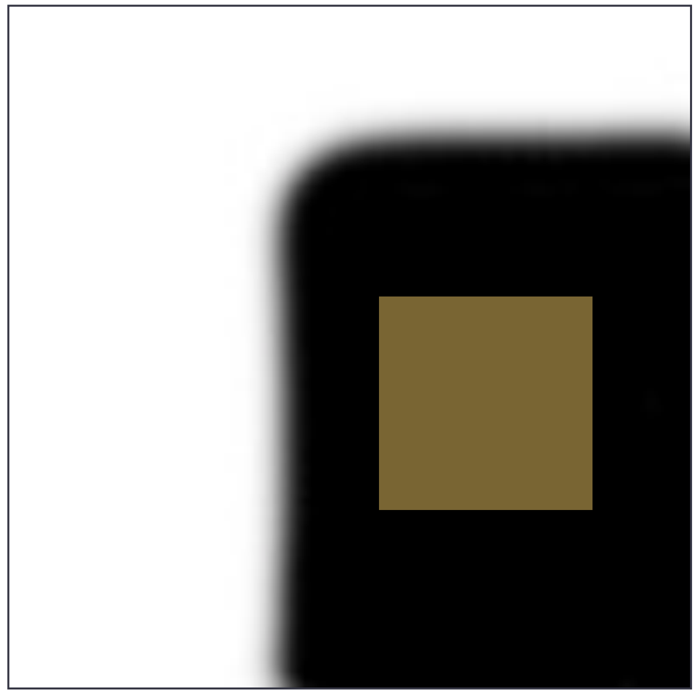
Find Corners

- ★ Key property: in the region around a corner, image gradient has two or more dominant directions
- ★ Corners are repeatable and distinctive
- ★ Harris and Stephens (1988)

8

Corner Detection: The Basics

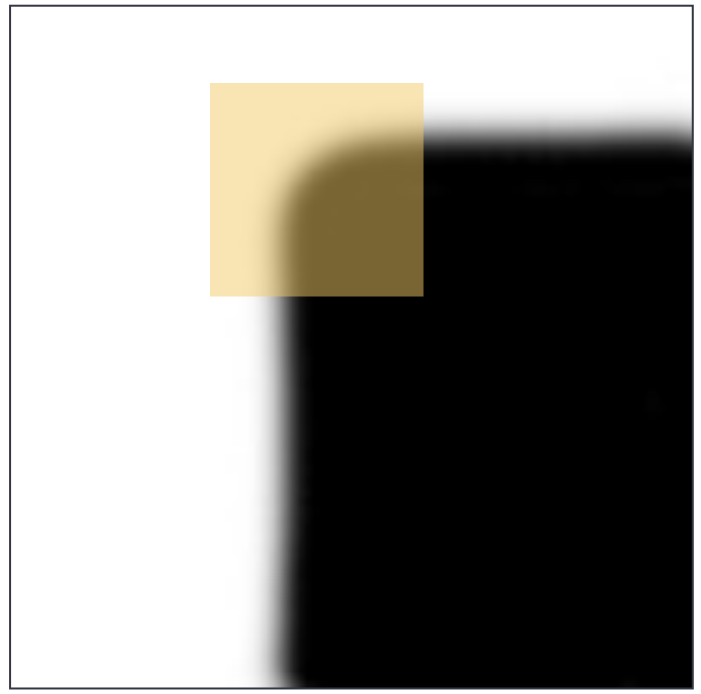


"flat"

No change in any directions

"edge"

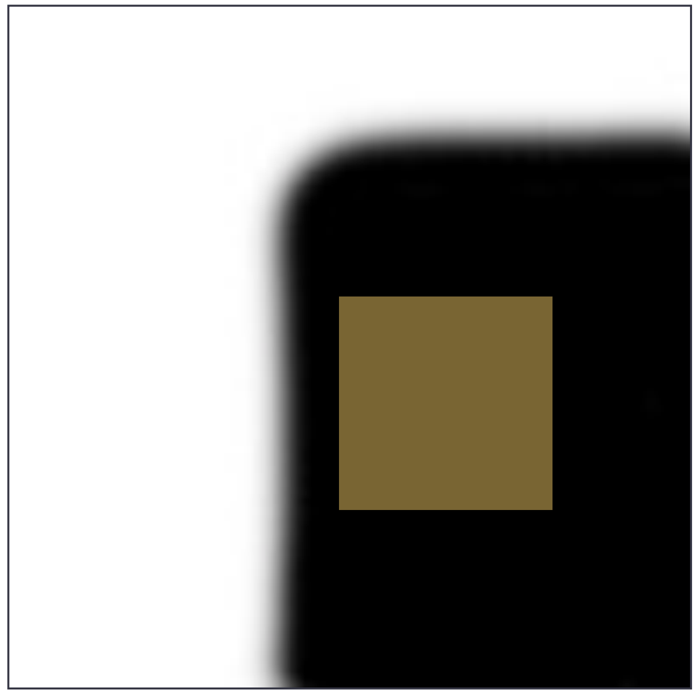
no change along the edge direction

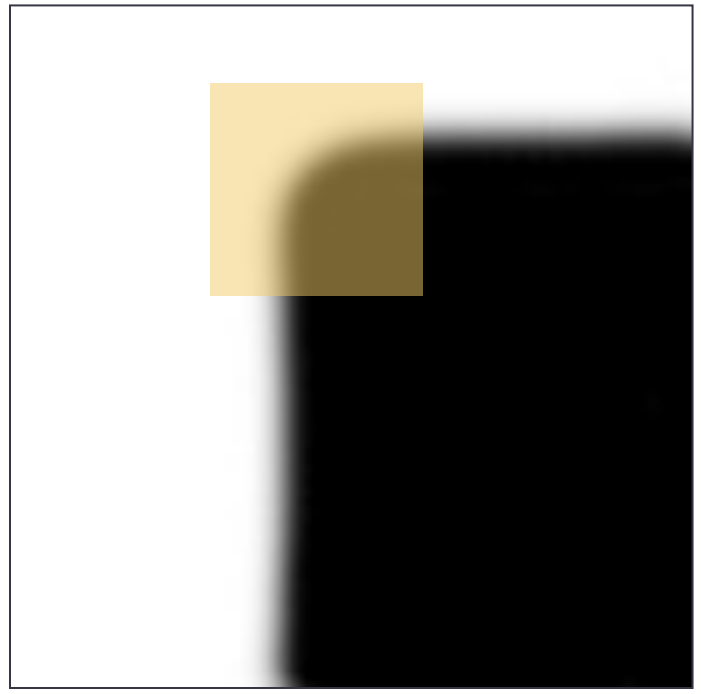


"corner"

change in all directions

Slide motivated by Alyosha Efros





Corner Detection: The Basics

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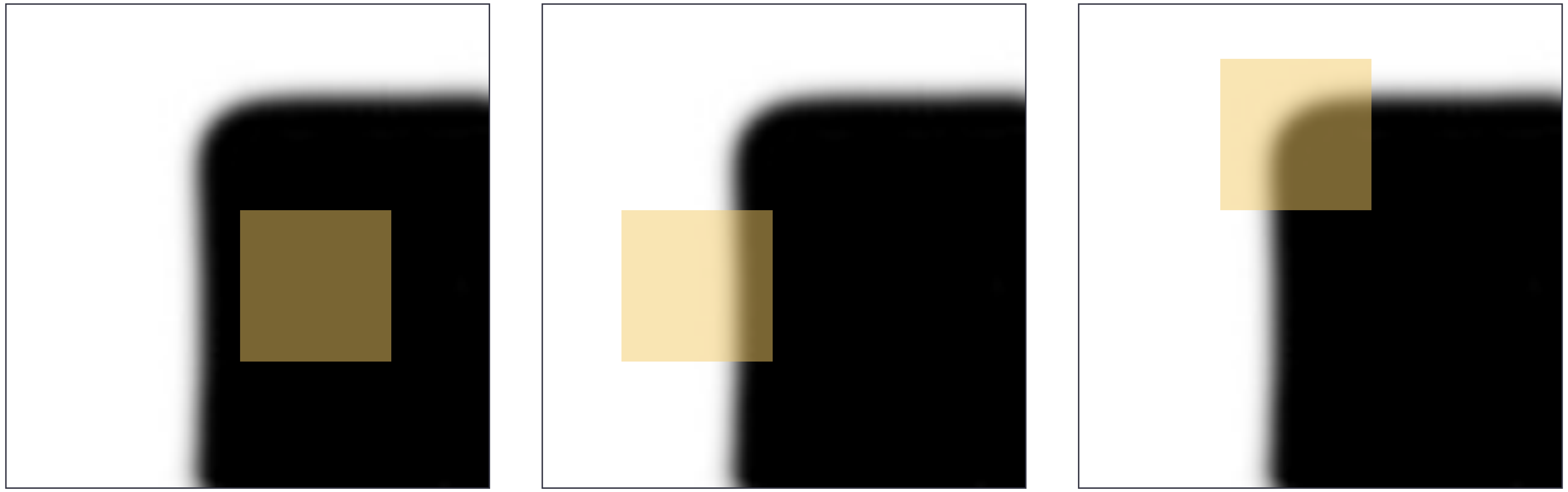

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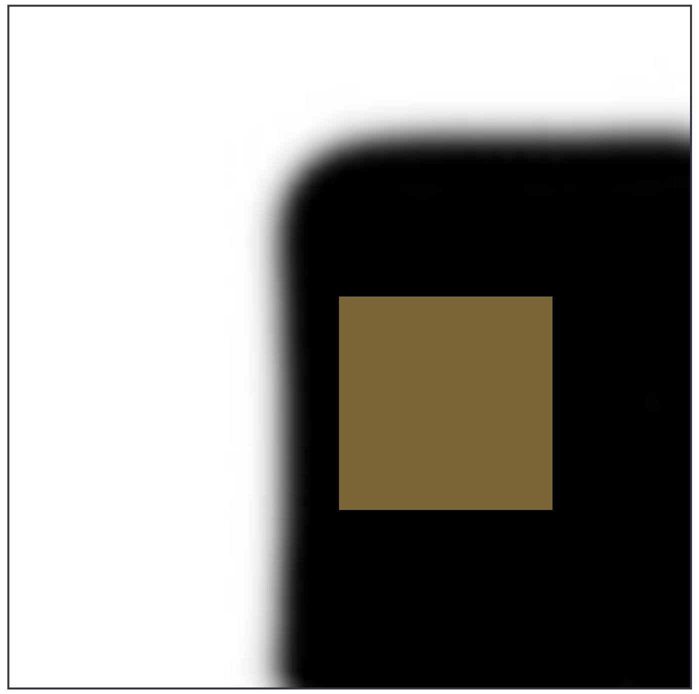

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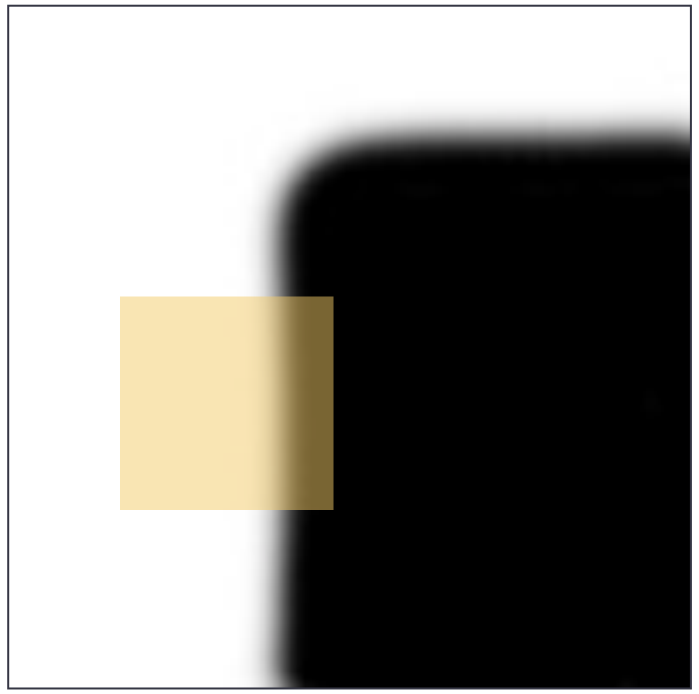

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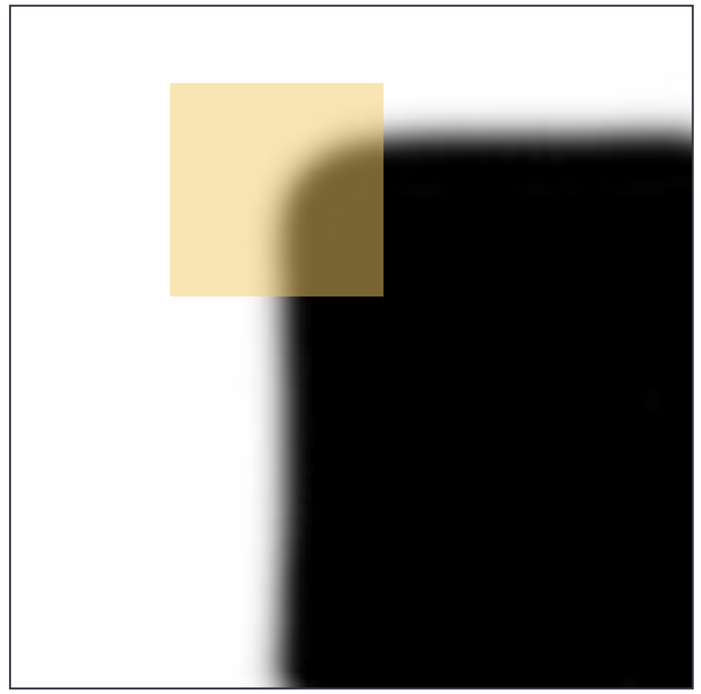

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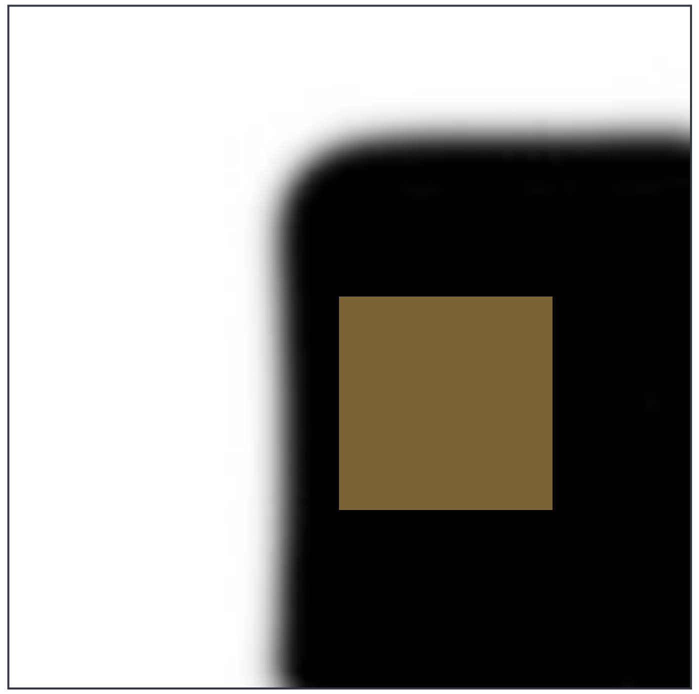

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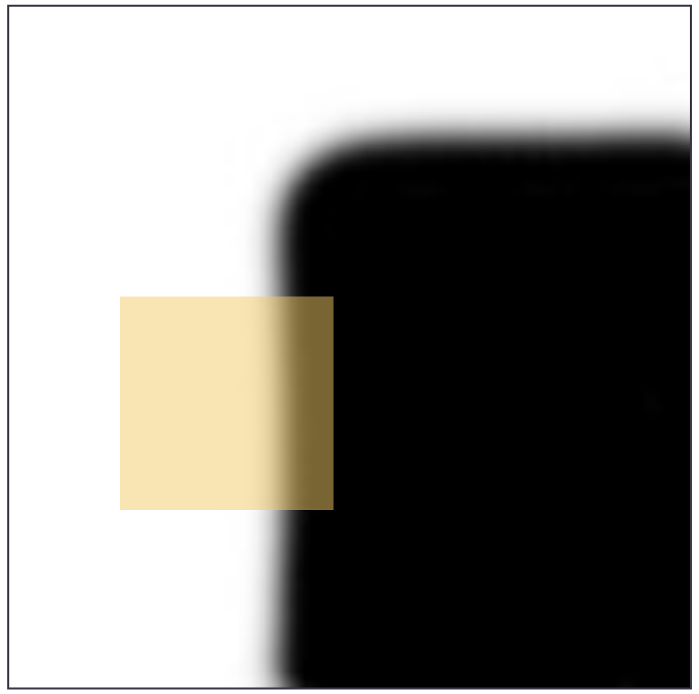

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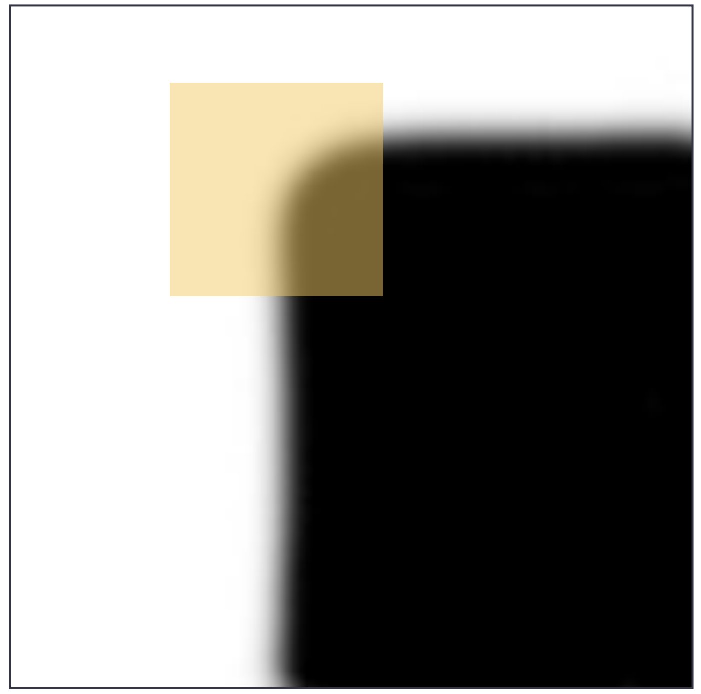

"corner"
change in all directions

- ★ Possible to recognize a point by looking through a small window
- ★ Shifting a window in any direction gives a large change in intensity

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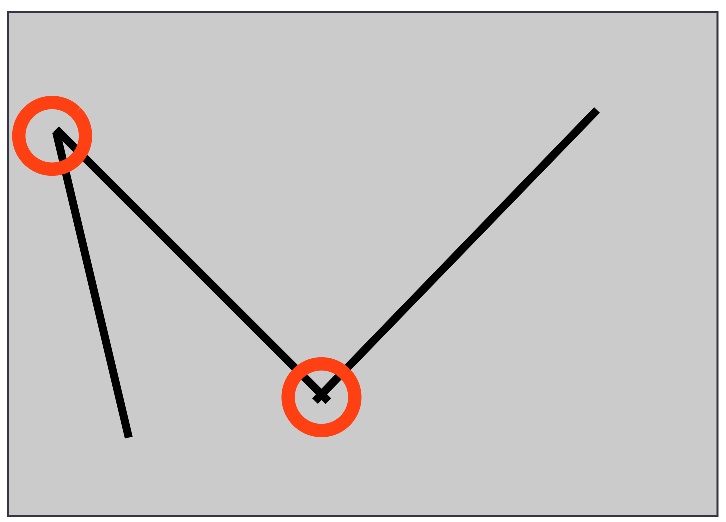
Corner Detection: The Basics



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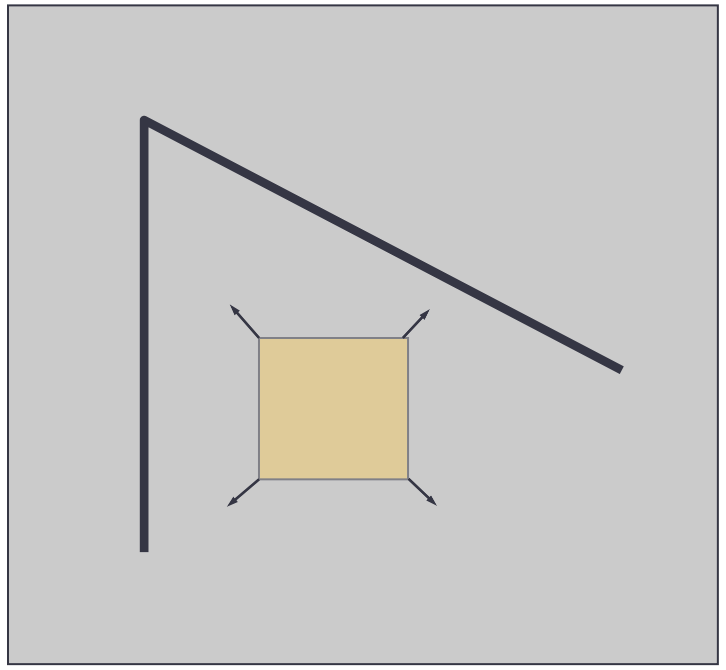

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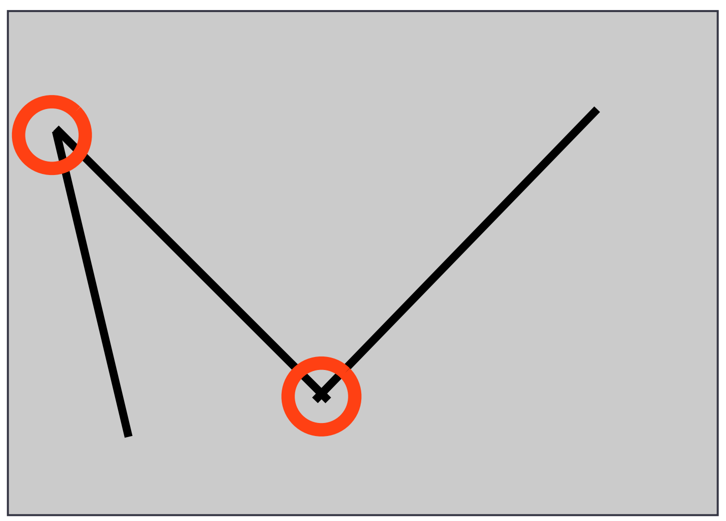

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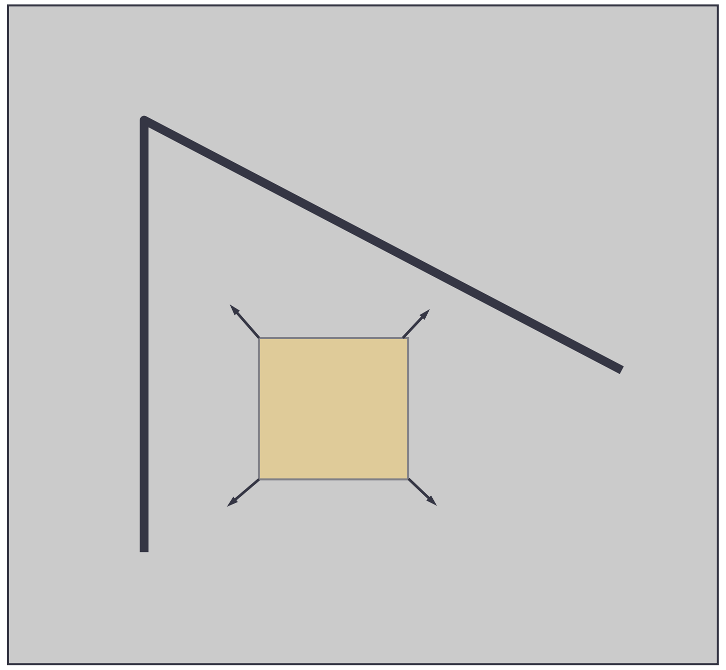

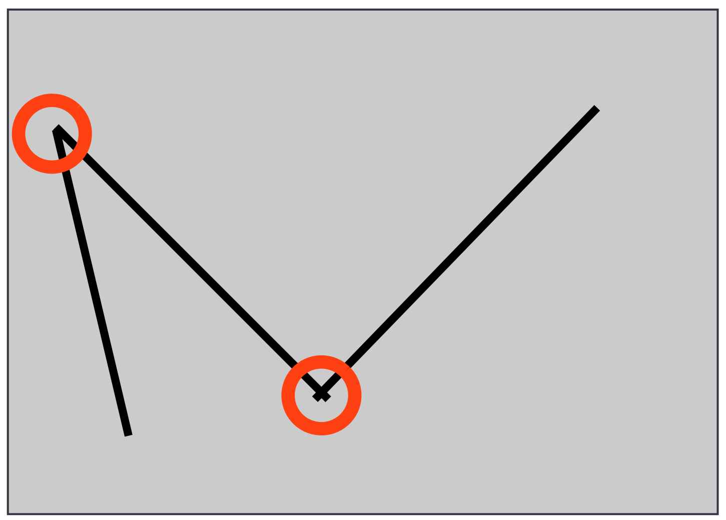

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10

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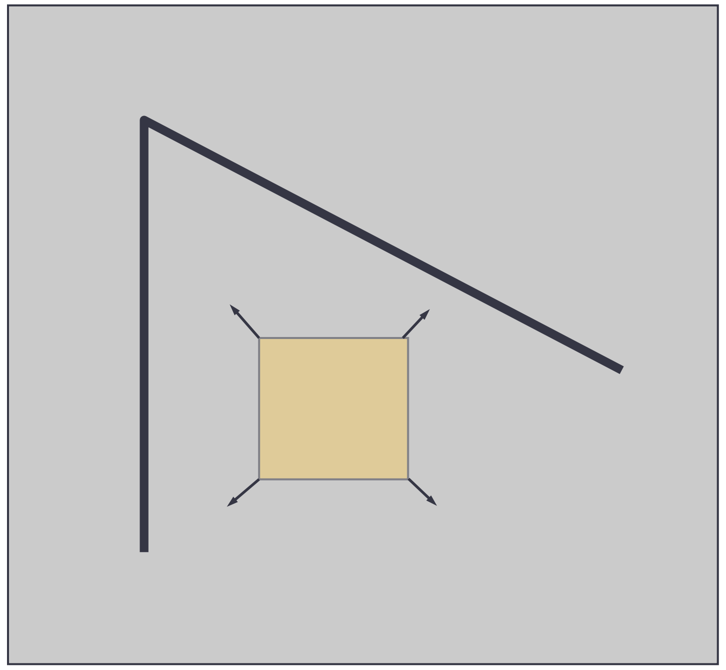

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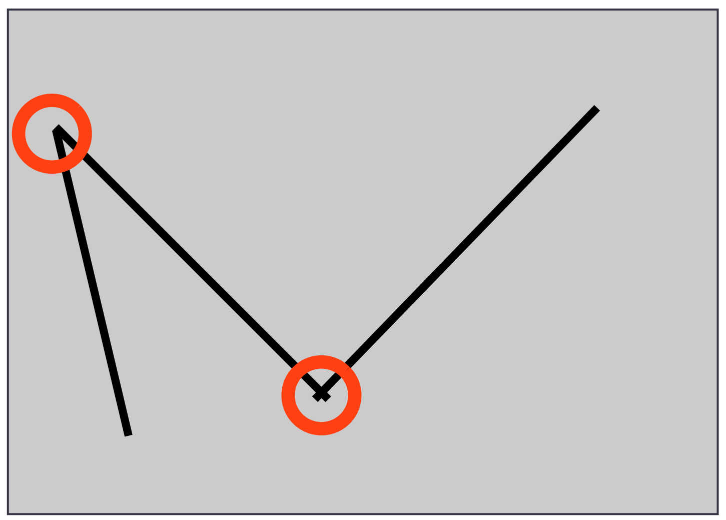

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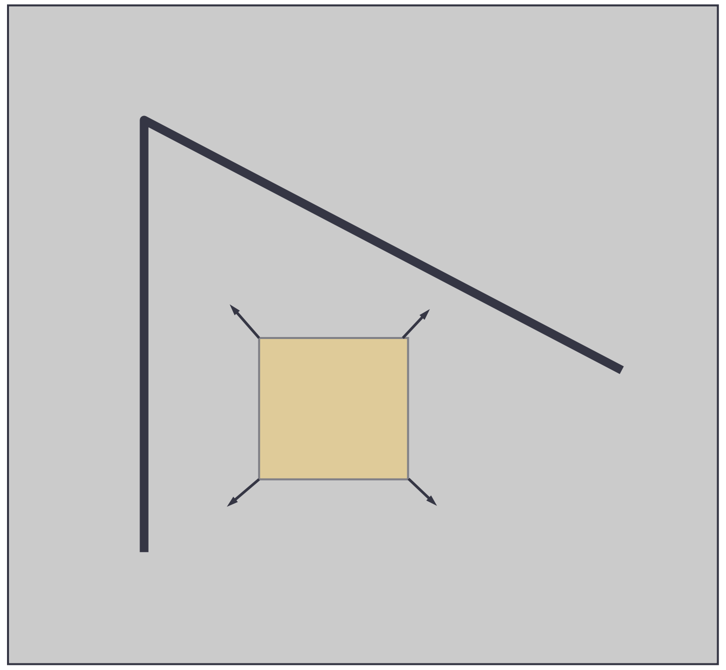

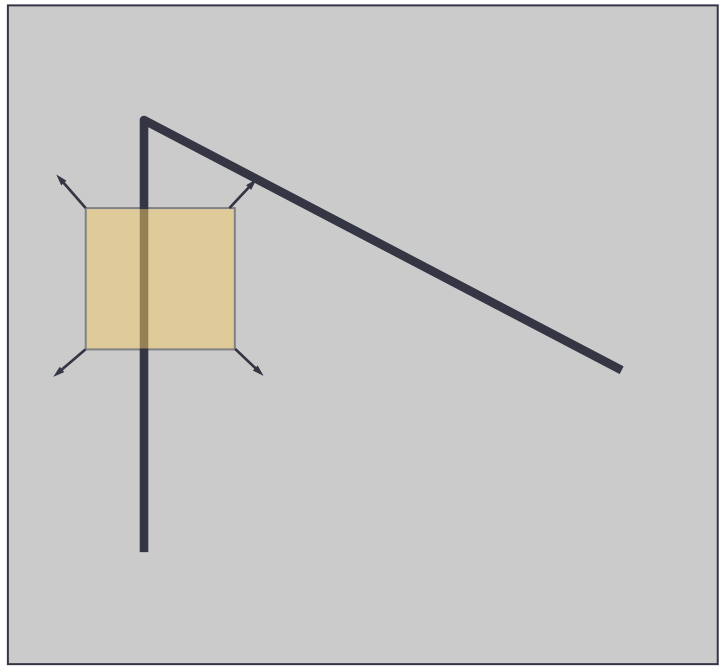

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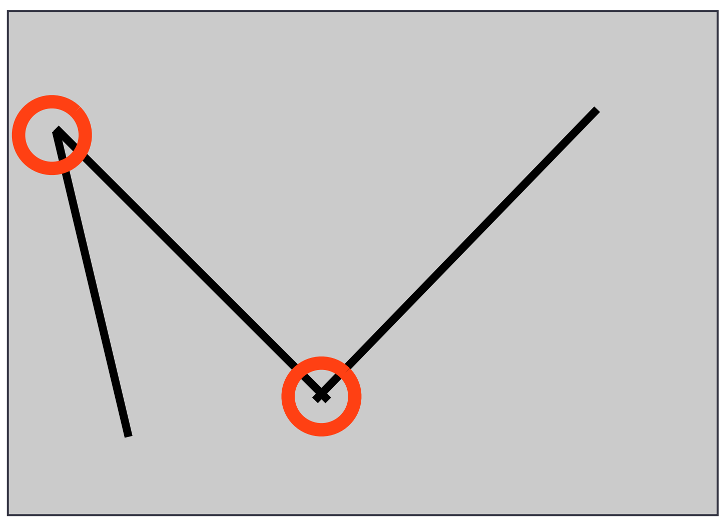

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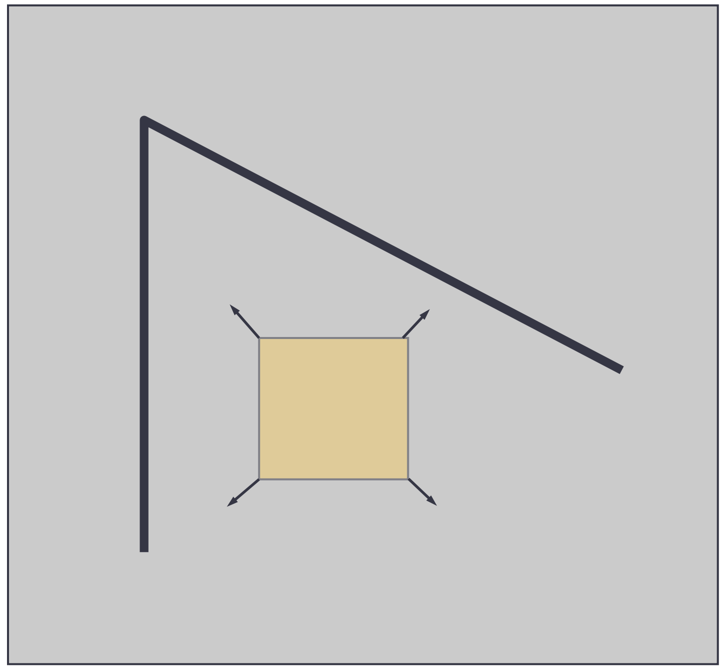

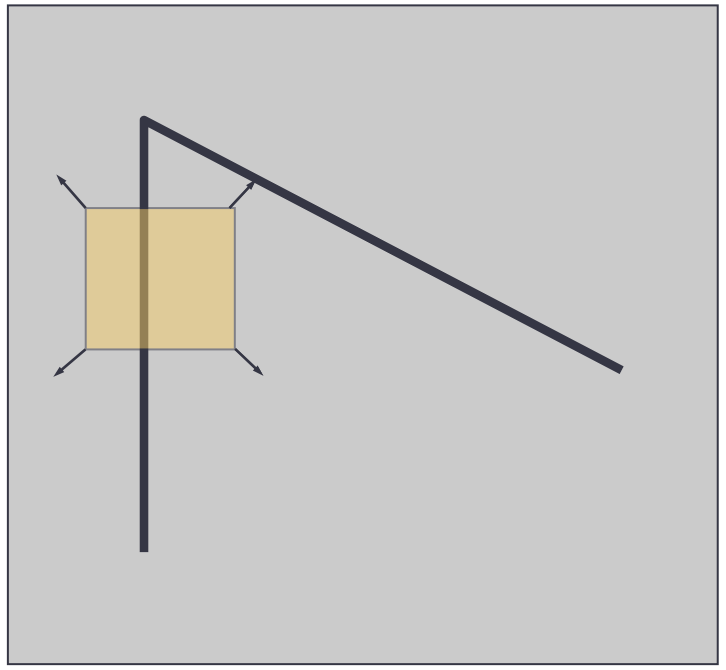

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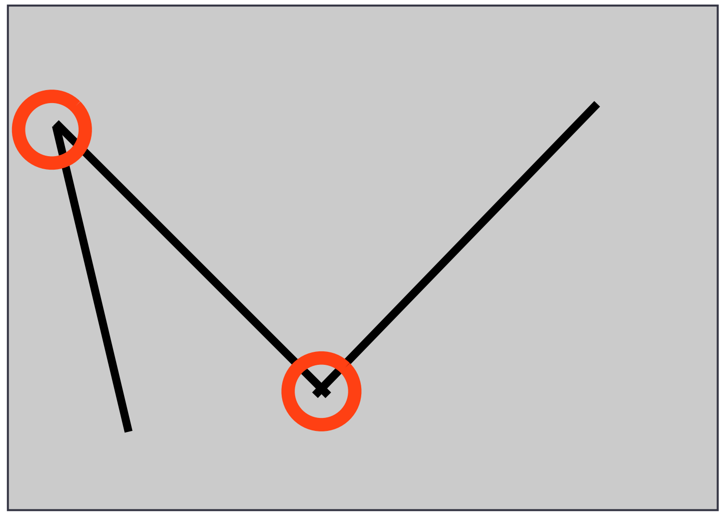

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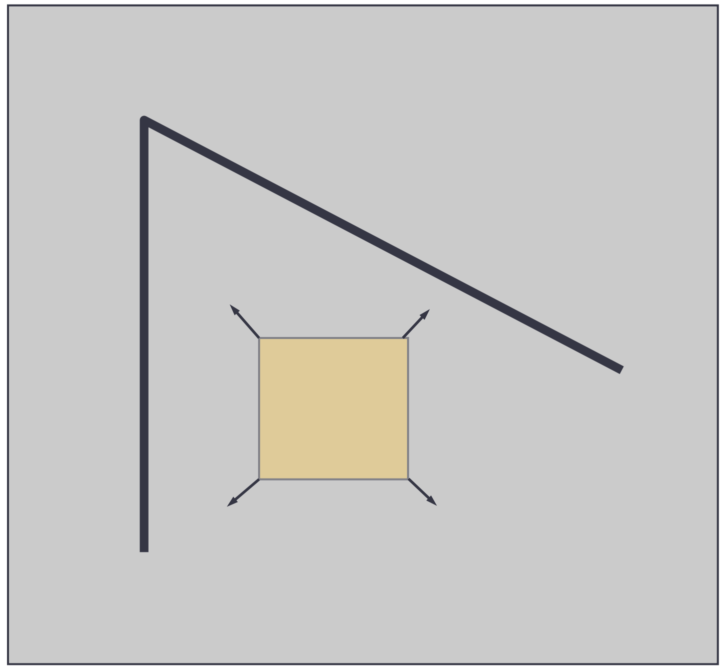
10

Corner Detection: The Basics



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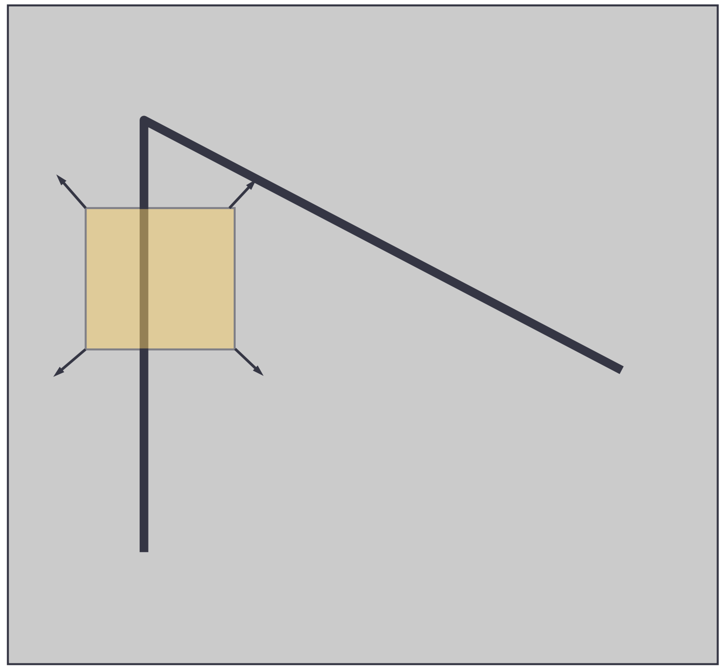

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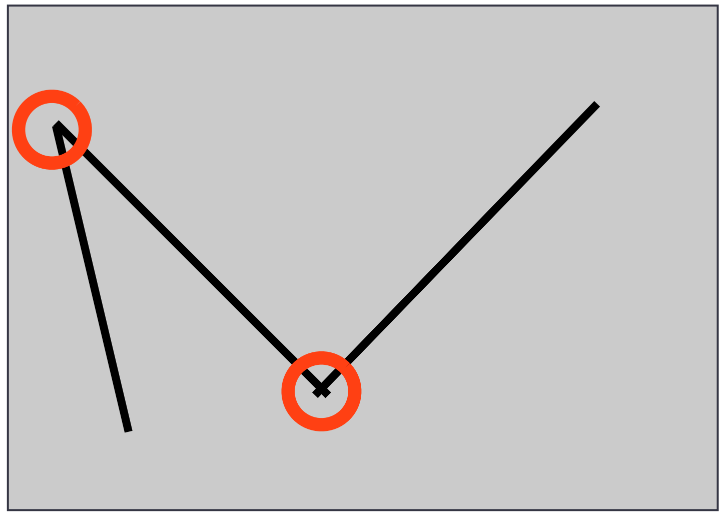

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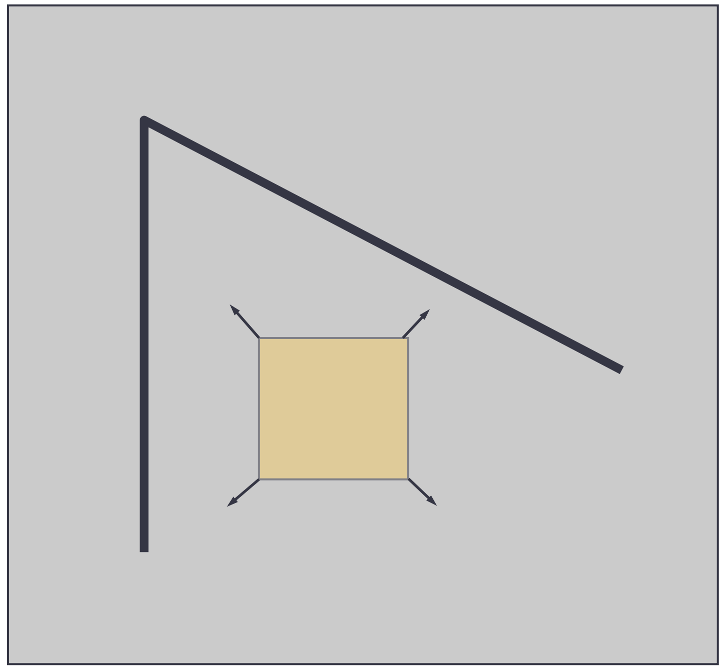

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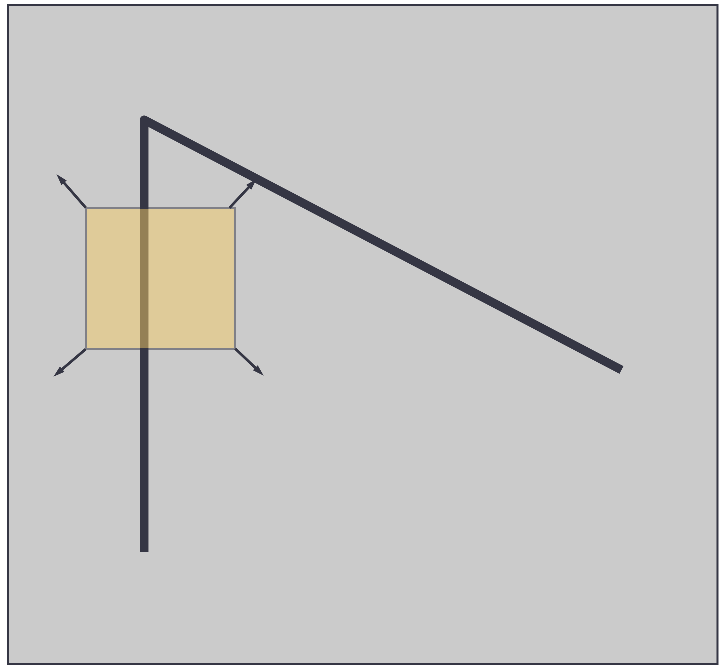

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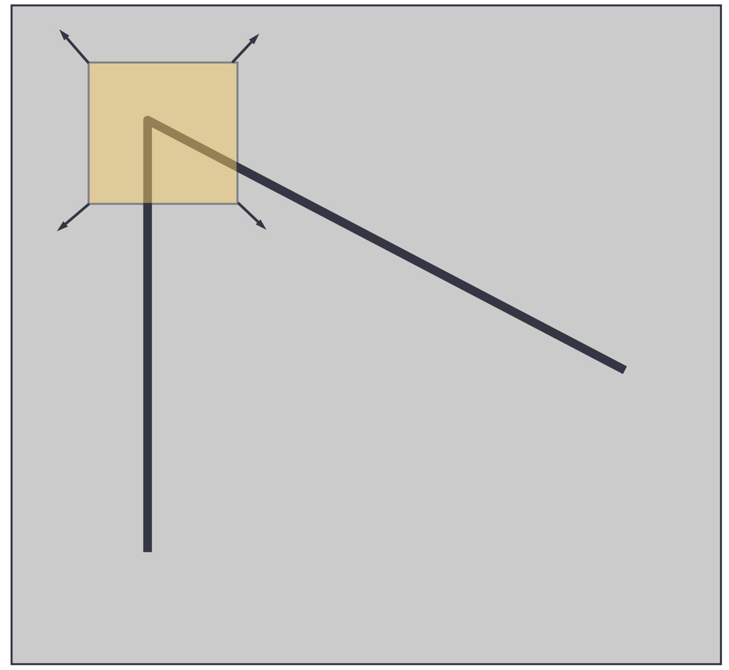

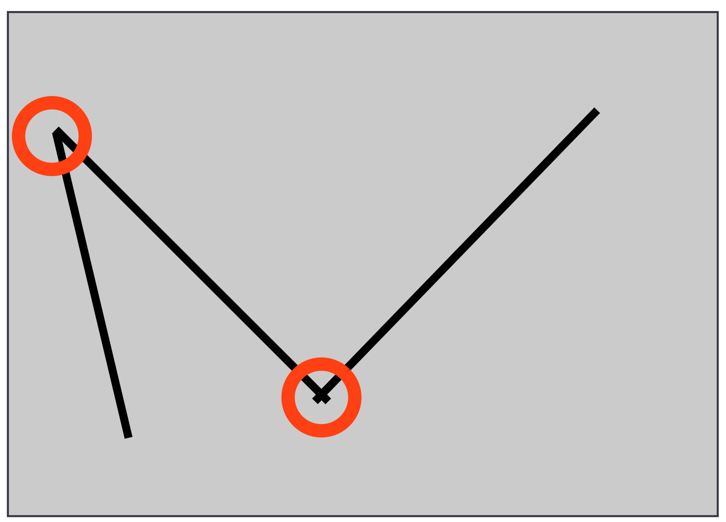

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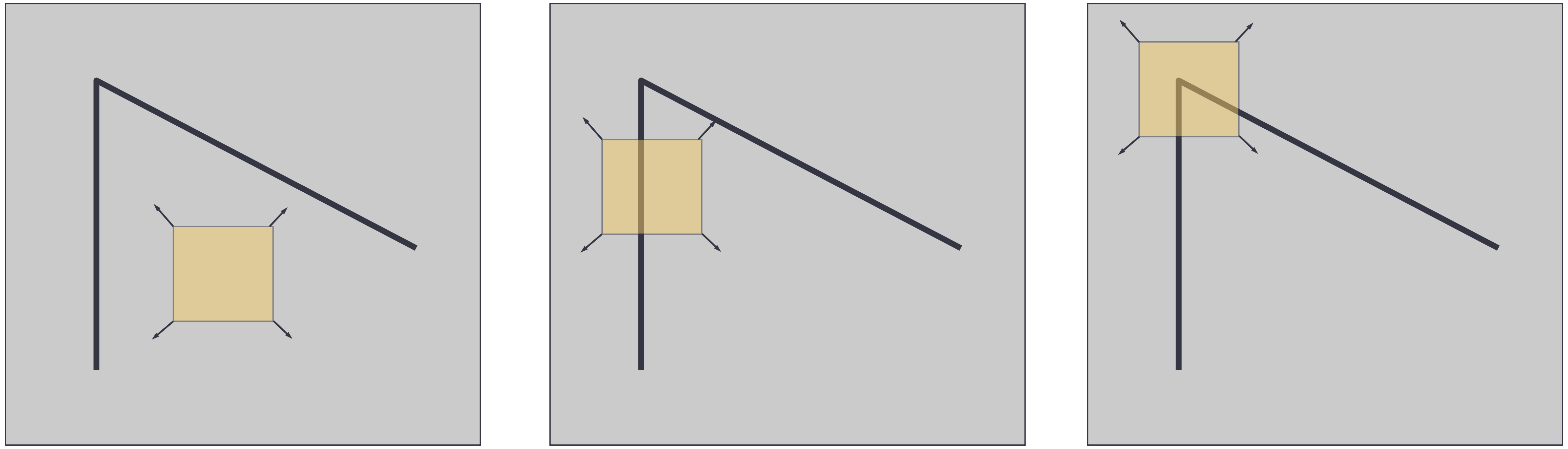

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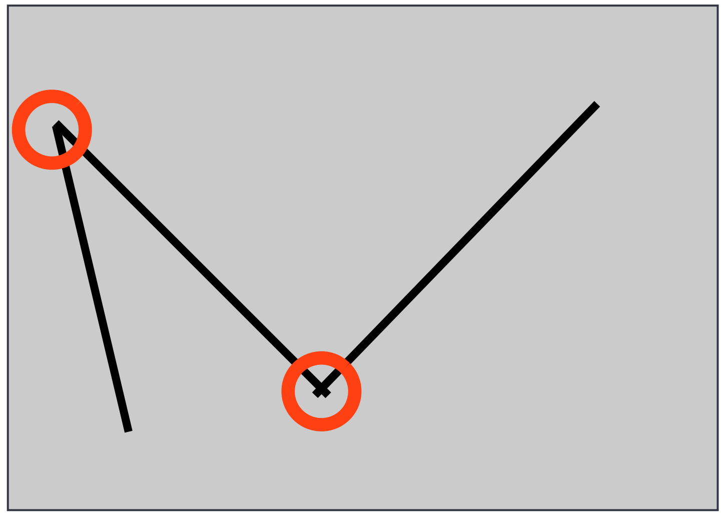

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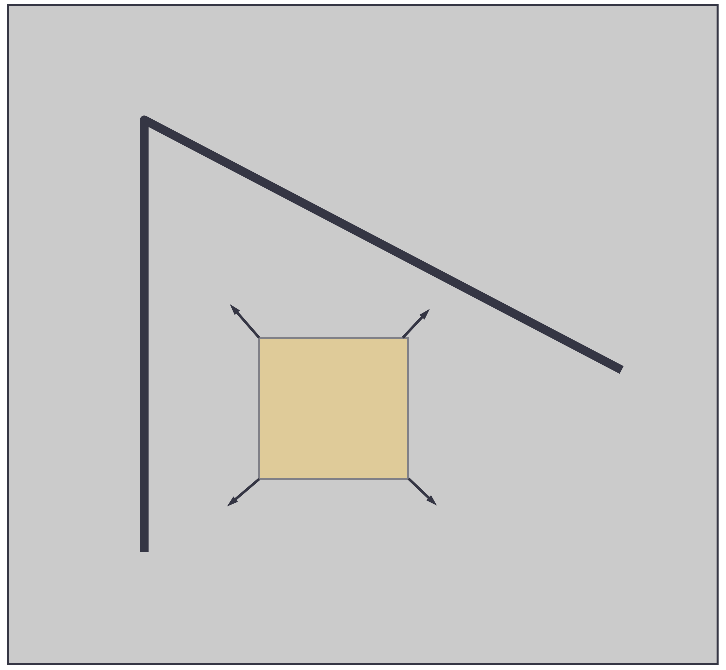

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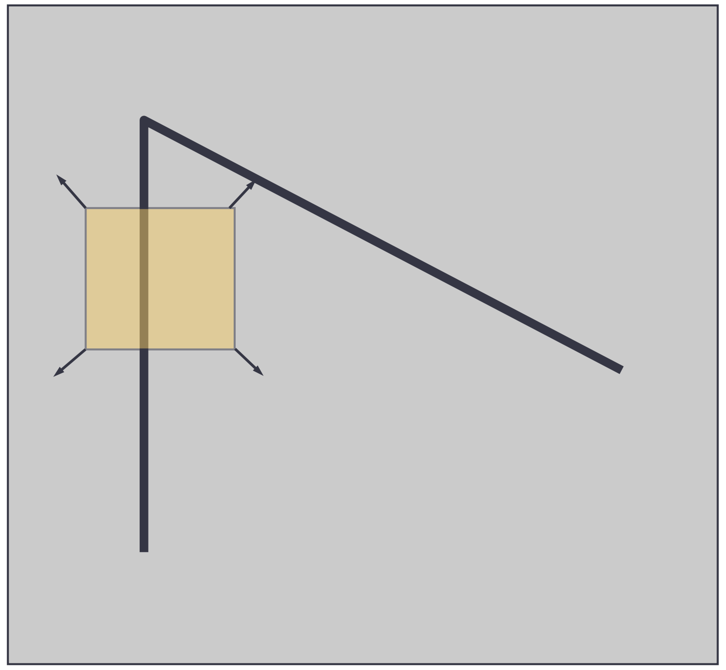

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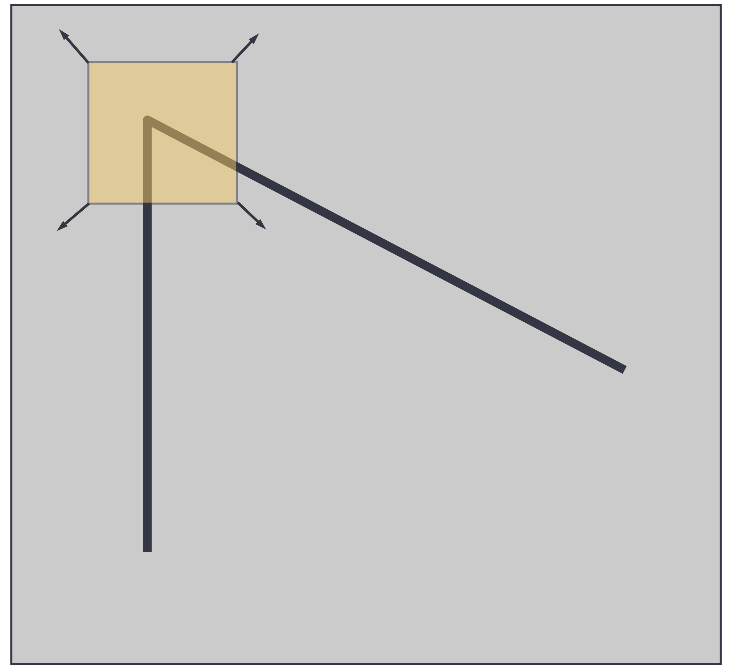

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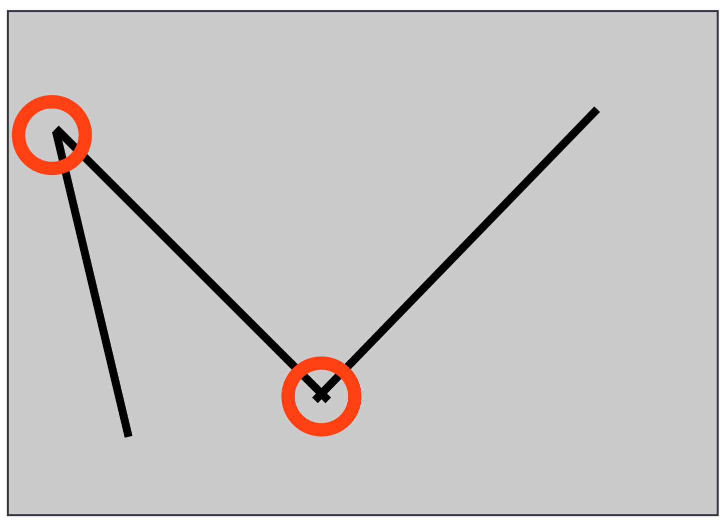

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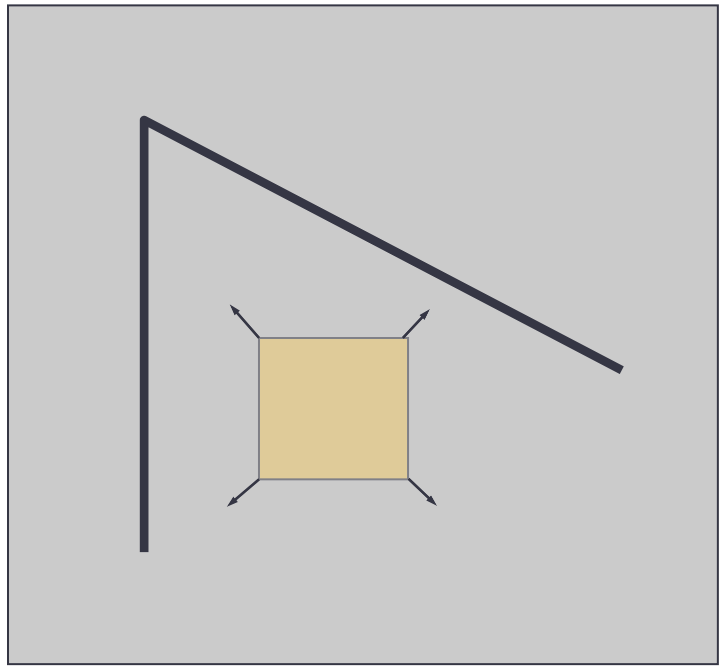
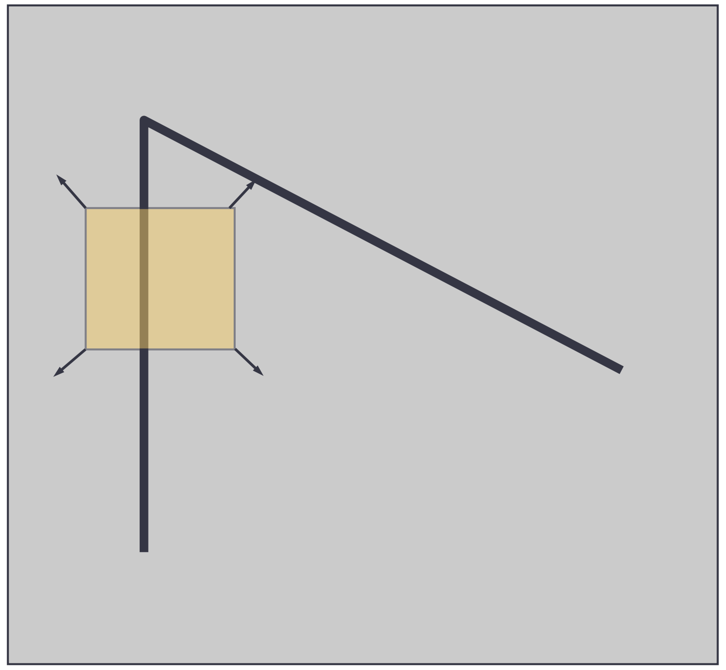
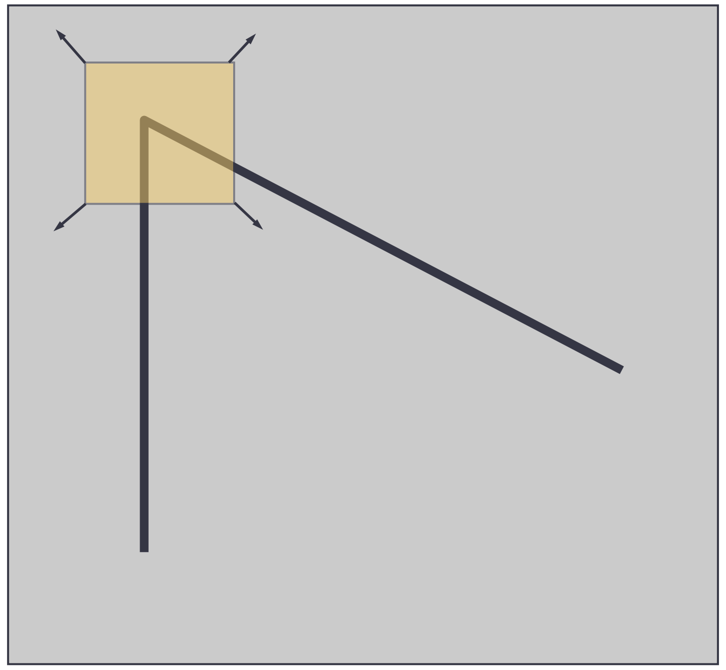

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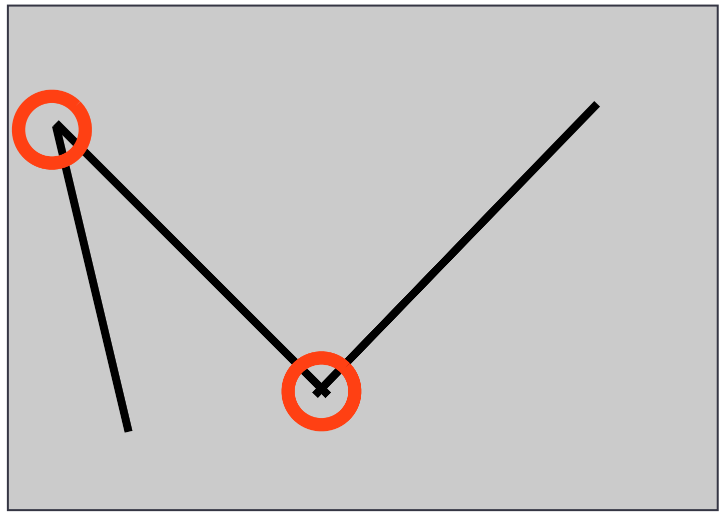
- ★ Harris Corners (Harris and Stephens,1988)



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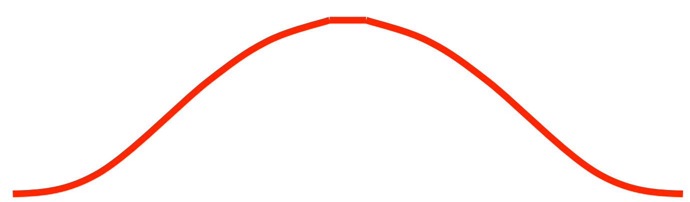
Corner Detection: Mathematics

Computation of the change in appearance by shifting the window by *u*,*v*:

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

$$w(x,y) \begin{cases} \text{box function} \\ \\ \text{a Gaussian} \end{cases}$$



1 inside, 0 outside

Corner Detection: Mathematics

Computation of the change in appearance by shifting the window by *u*,*v*:

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

intensity

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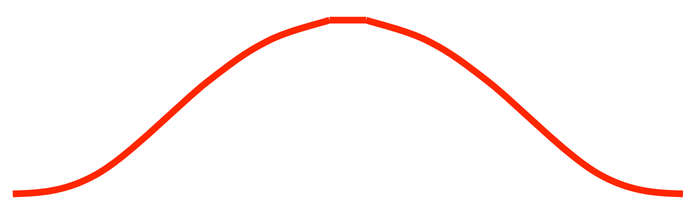

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Corner Detection: Mathematics

Computation of the change in appearance by shifting the window by *u*,*v*:

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

shifted intensity

intensity

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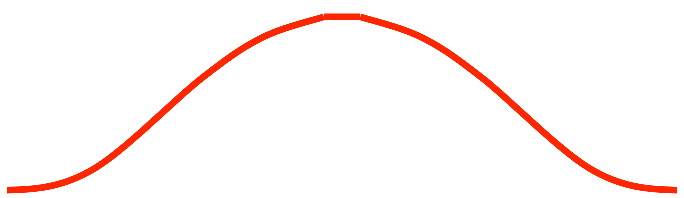

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Corner Detection: Mathematics

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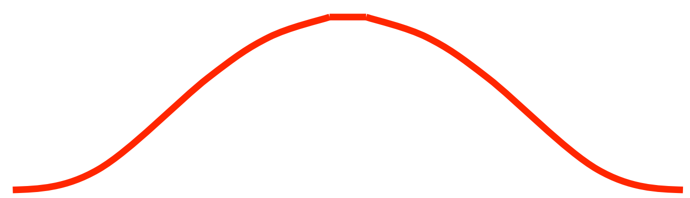
$$E(u,v) = \sum_{x,y} \underbrace{w(x,y)}_{\text{window function}} \, [\underbrace{I(x+u,y+v)}_{\text{shifted intensity}} - \underbrace{I(x,y)}_{\text{intensity}}]^2$$

$w(x,y)$ $\begin{cases} \text{box function} \\ \text{a Gaussian} \end{cases}$

box function

a Gaussian



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Corner Detection: Mathematics

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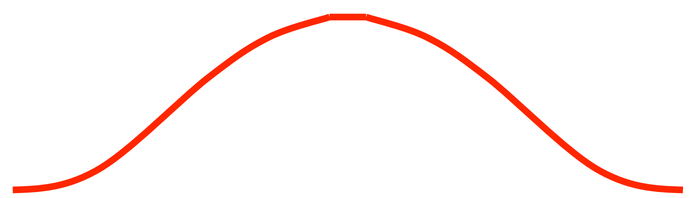
change in appearance — window function — shifted intensity — intensity

$$w(x,y) \begin{cases} \text{box function} \\ \text{a Gaussian} \end{cases}$$



1 inside, 0 outside

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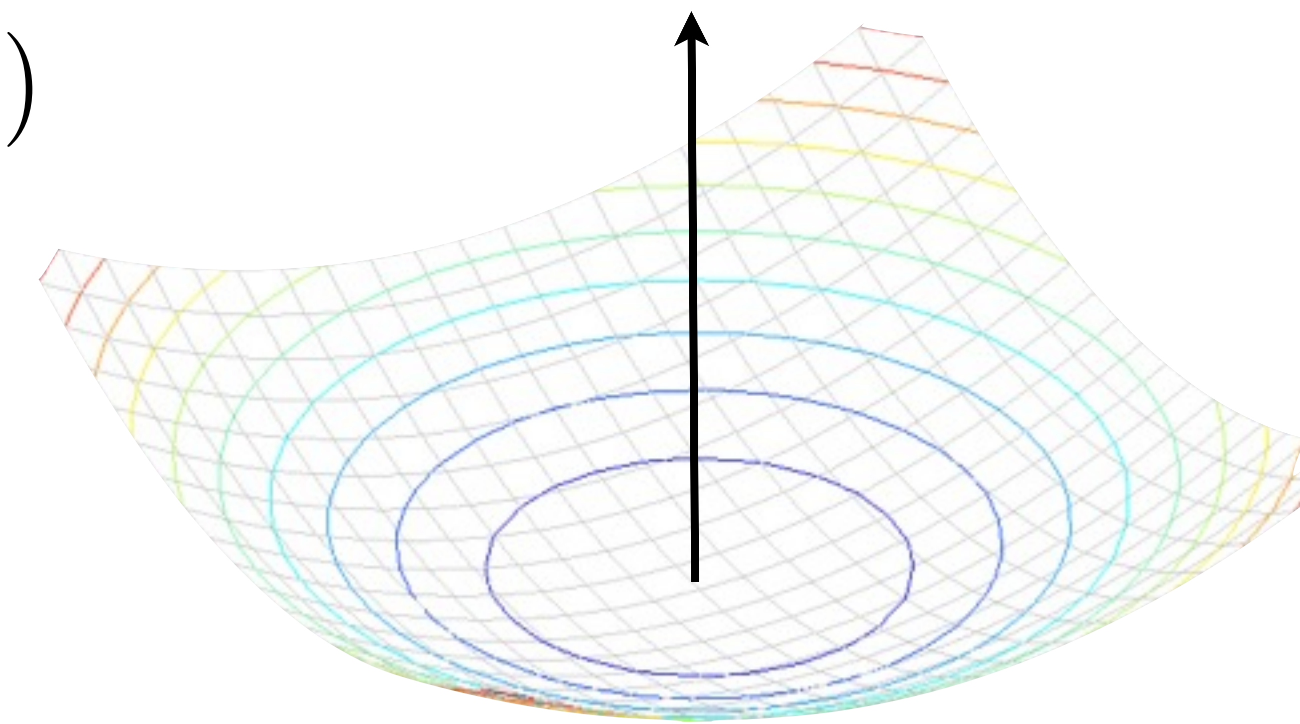

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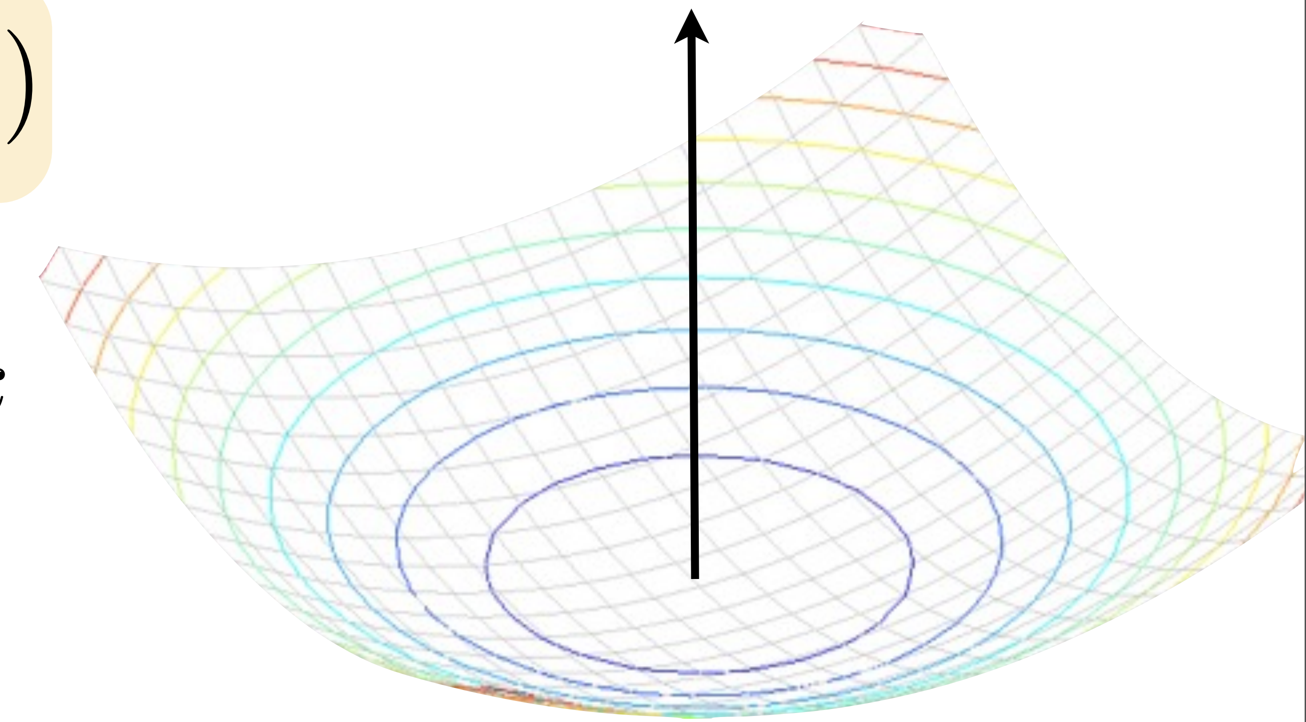

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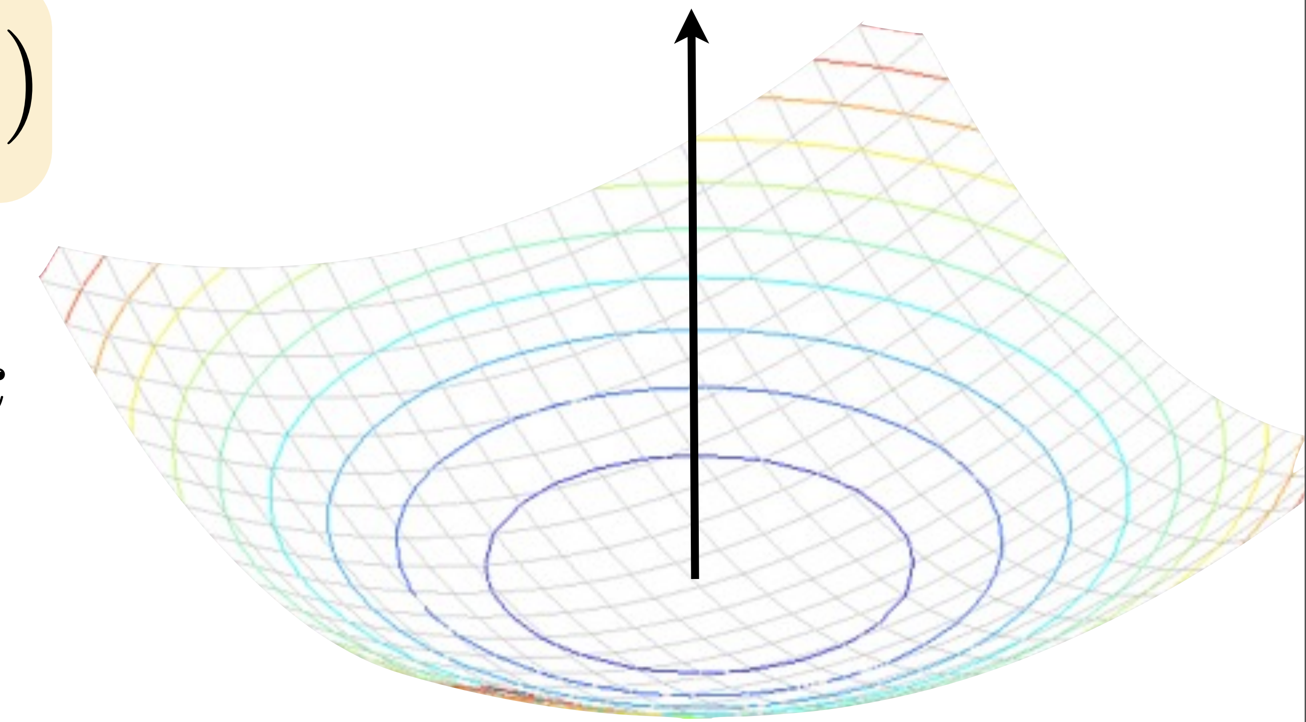

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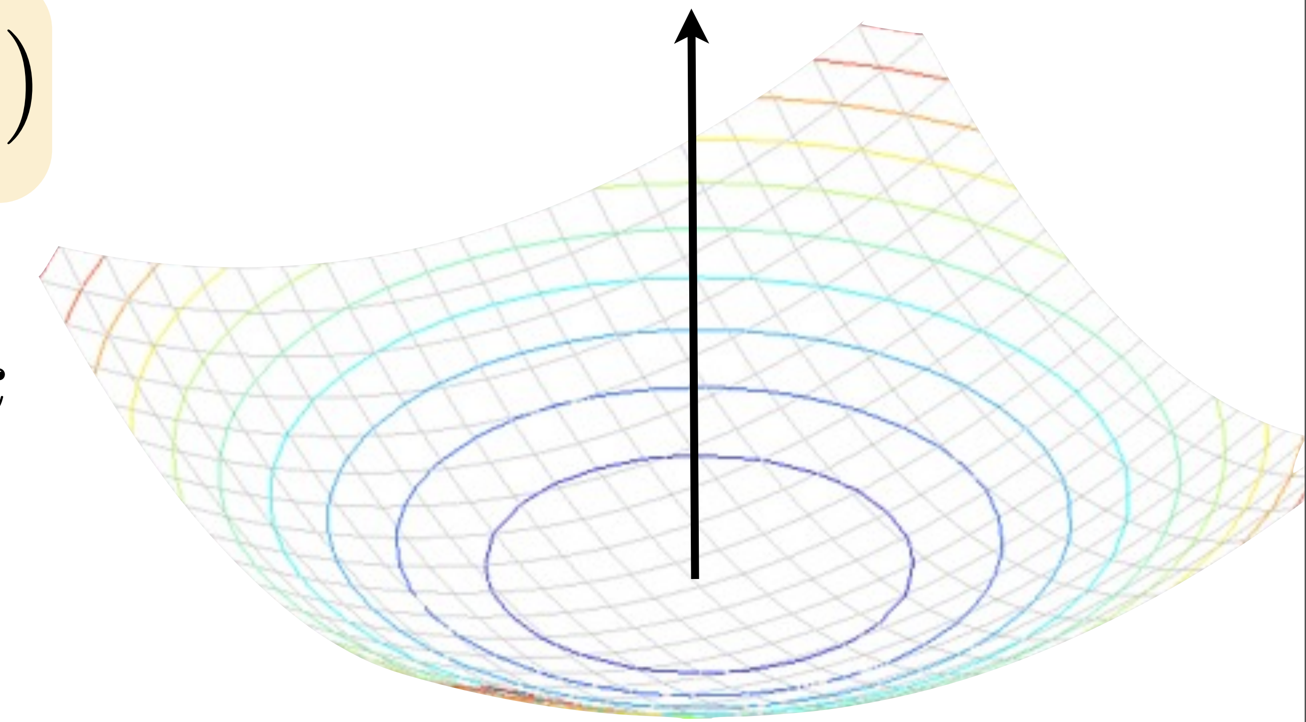

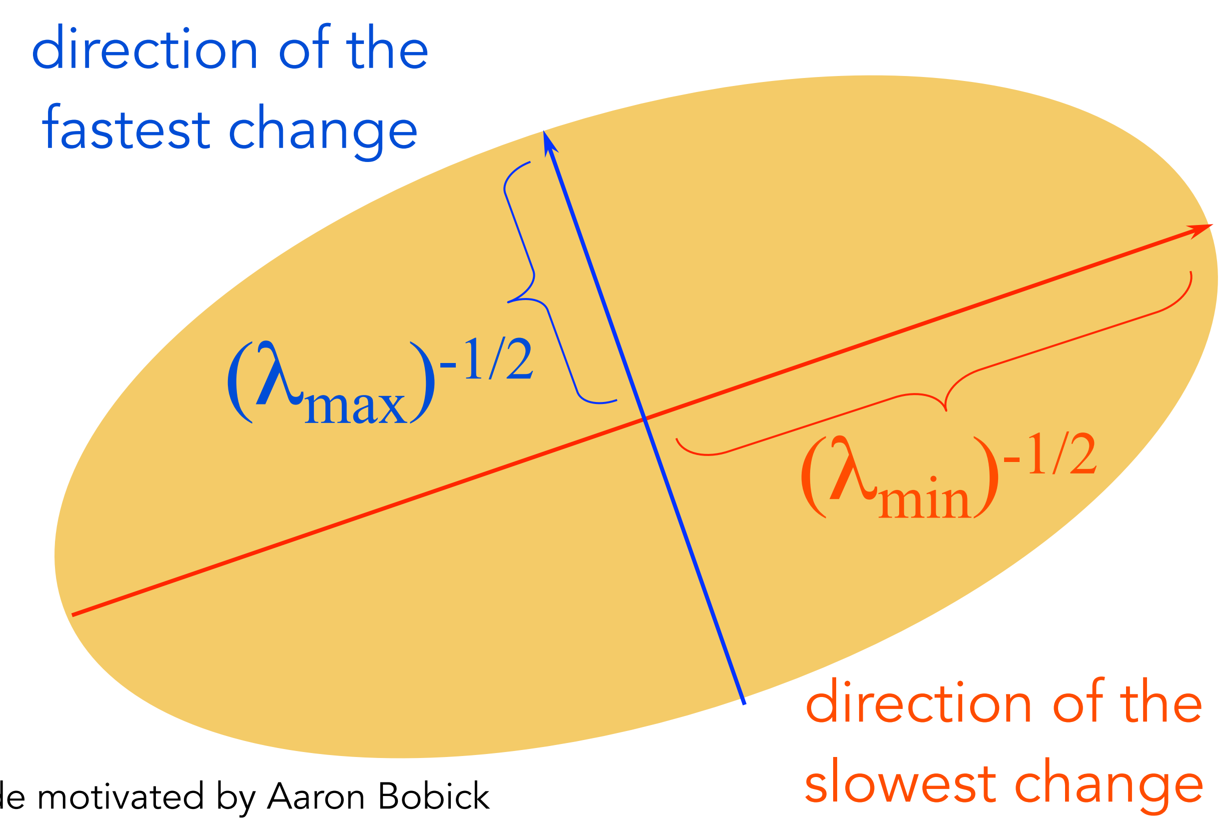

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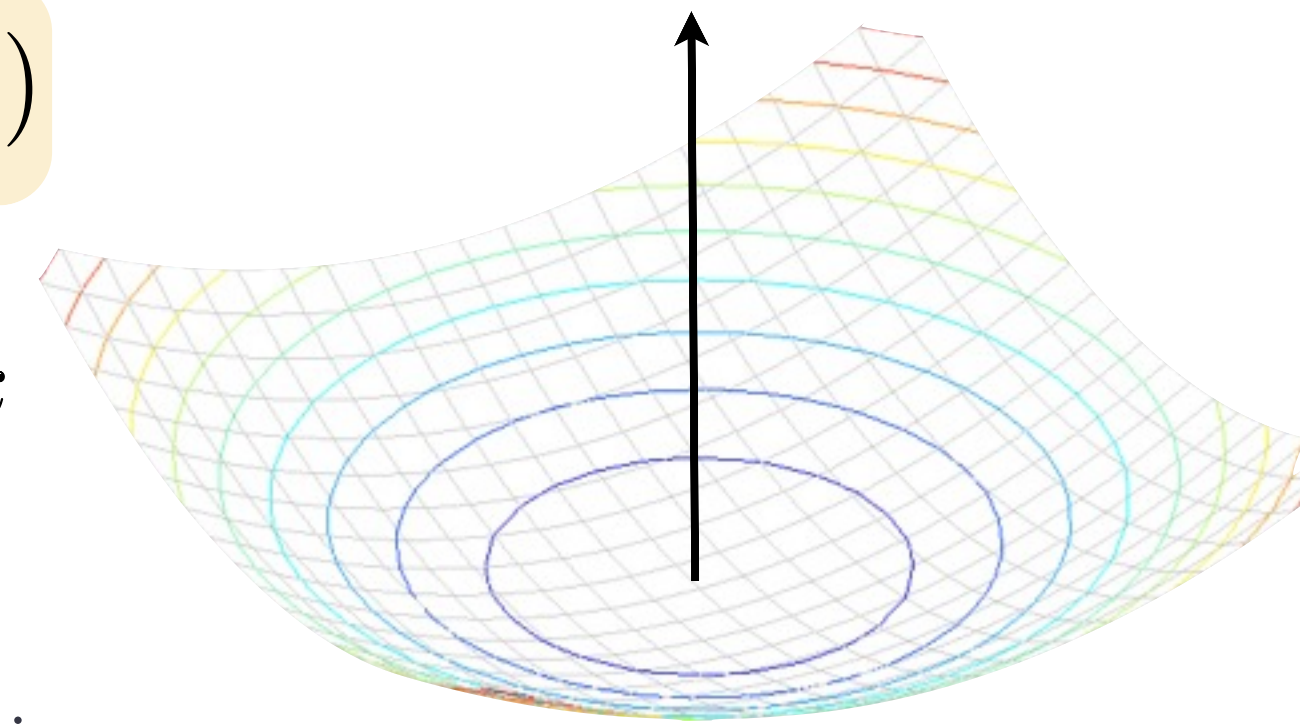

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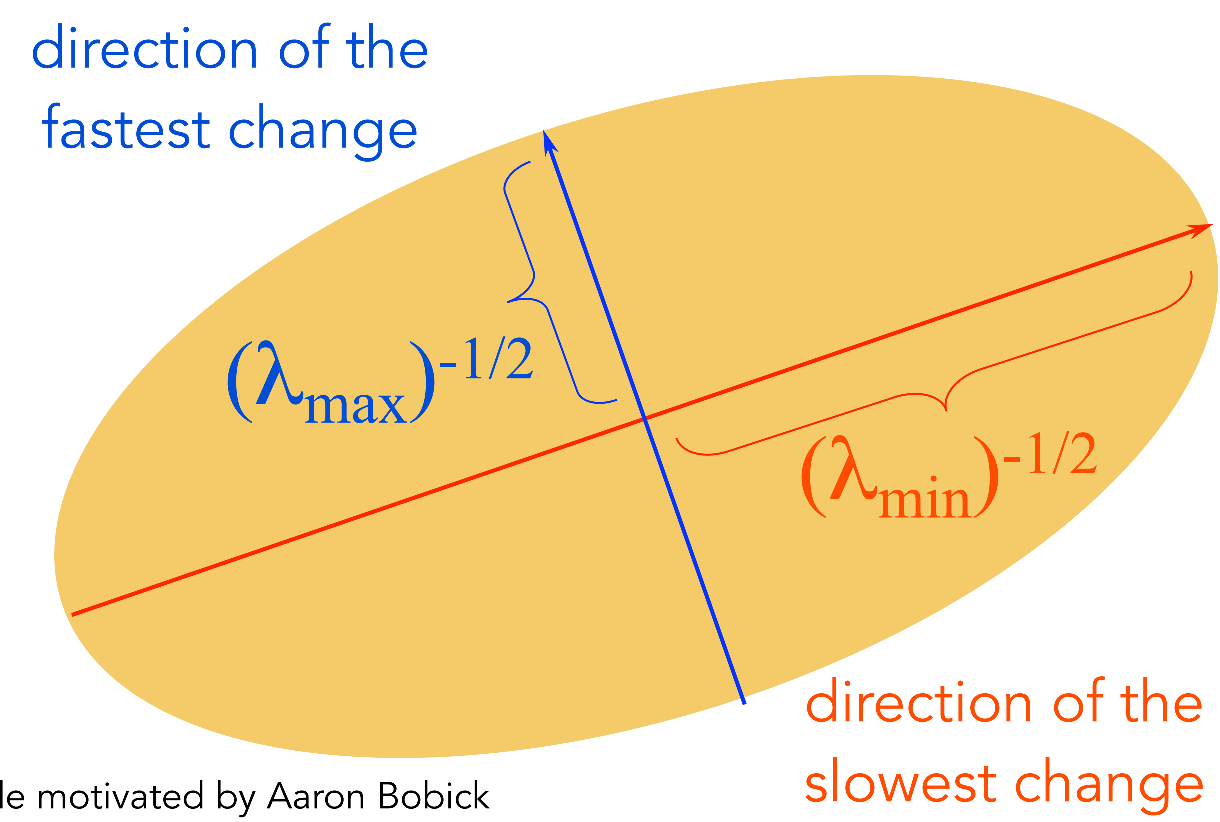

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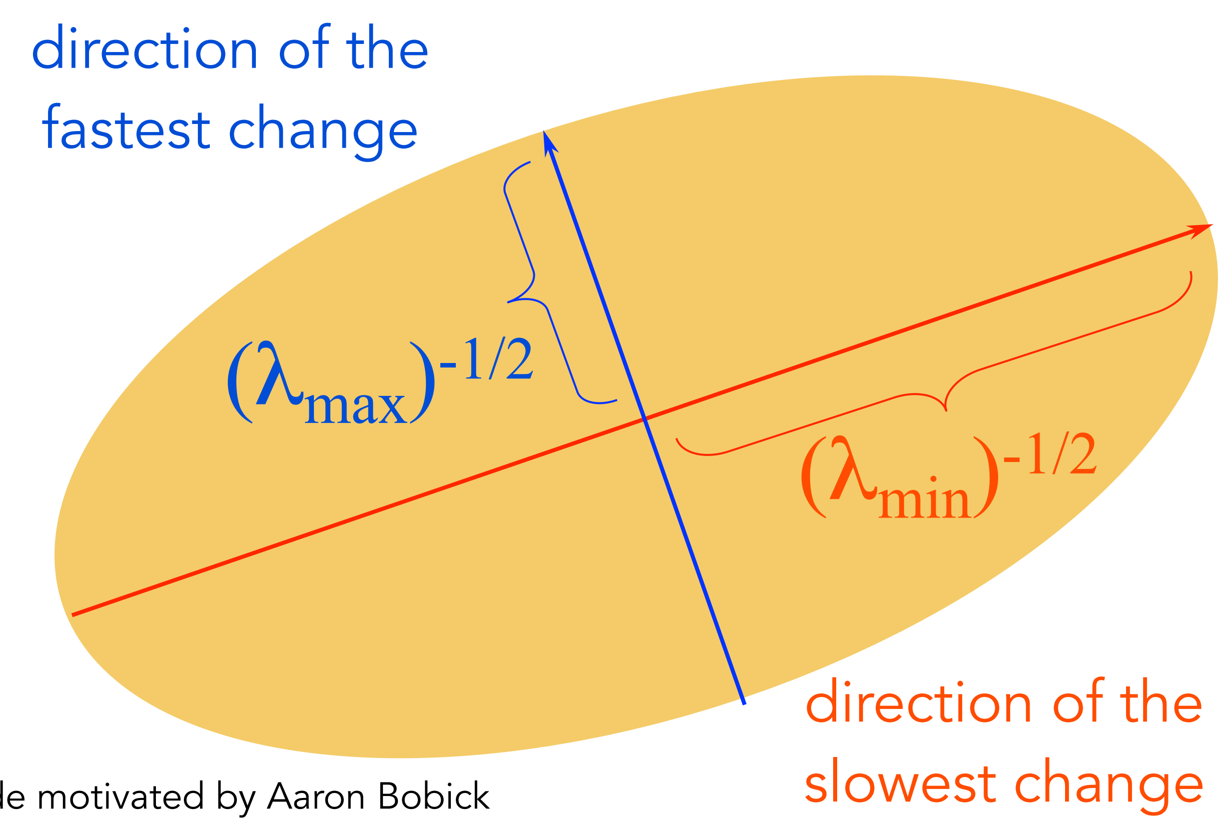

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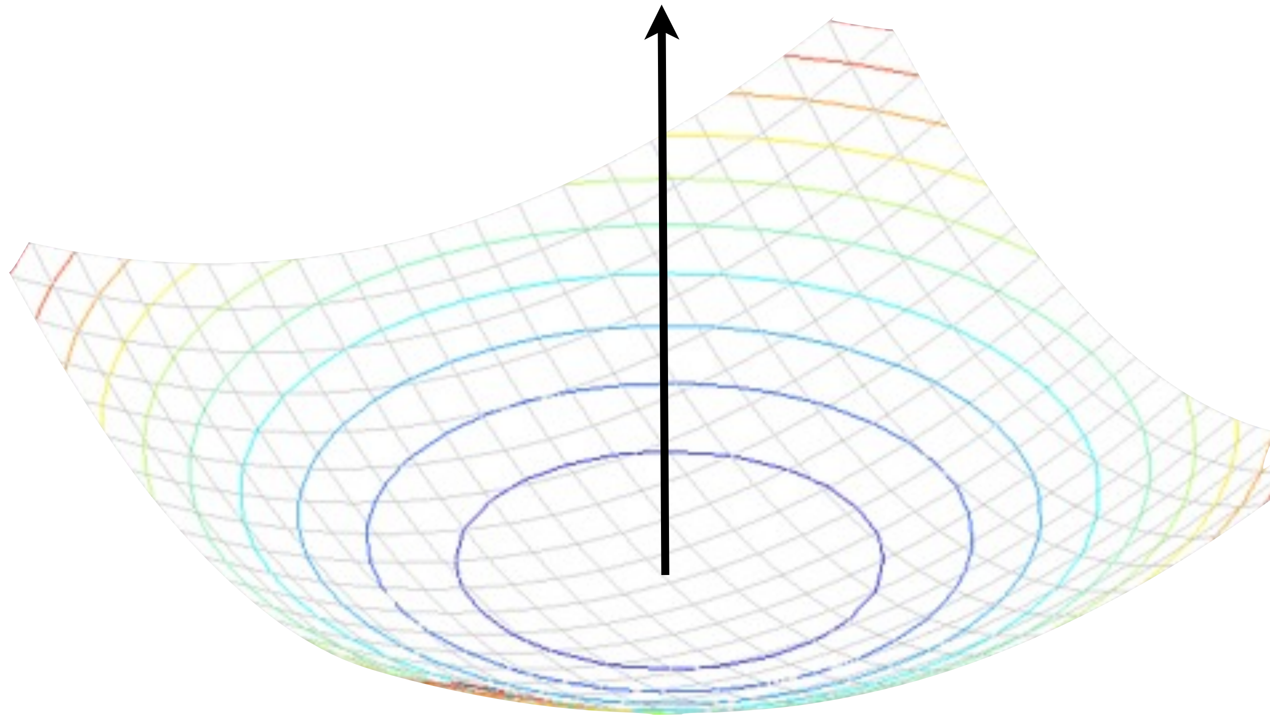

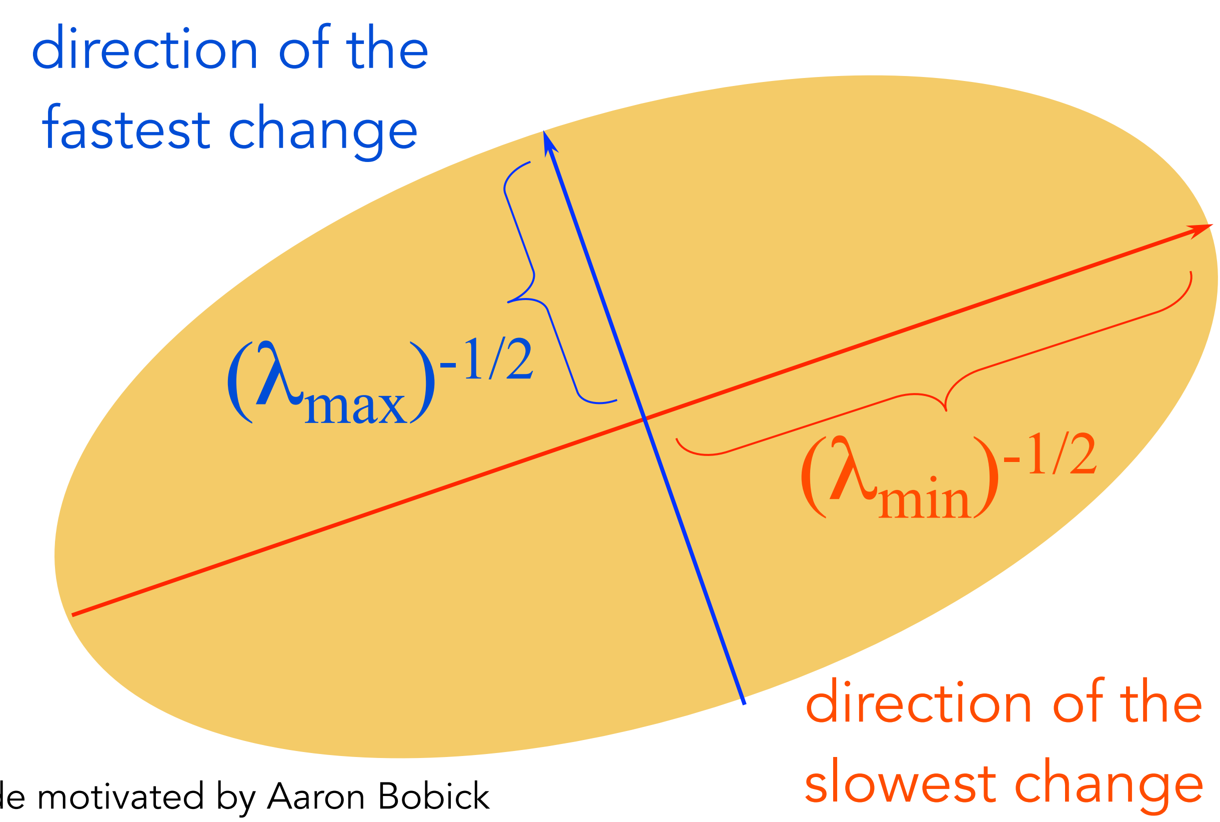

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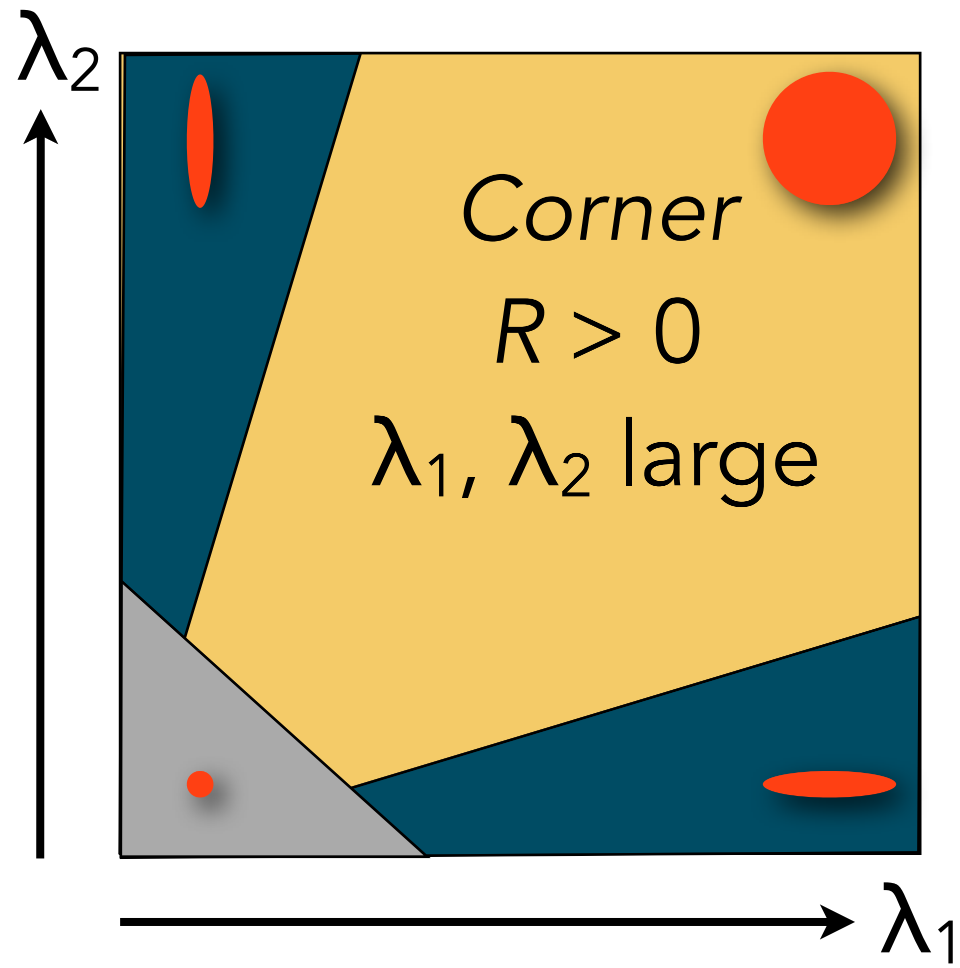
$$R = \det(M) - \alpha \operatorname{trace}(M)^2 = \lambda_1\lambda_2 - \alpha(\lambda_1 + \lambda_2)^2$$

α: constant (0.04 to 0.06)



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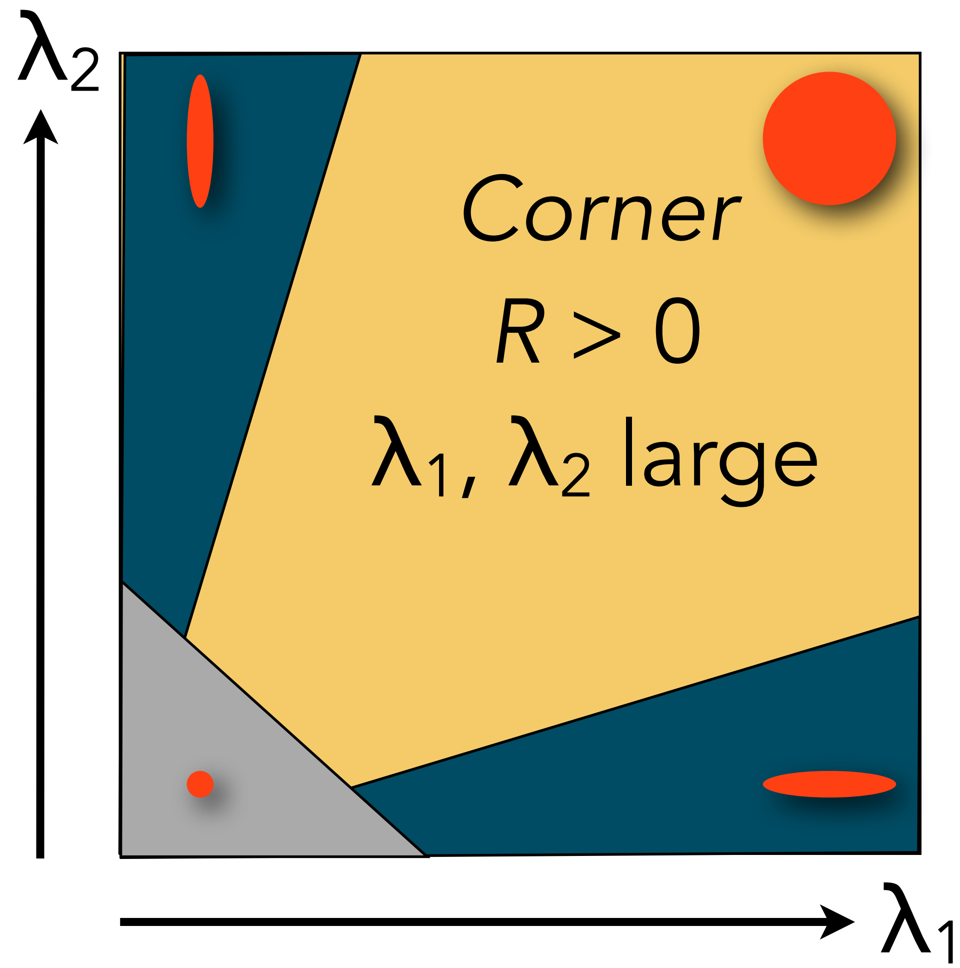

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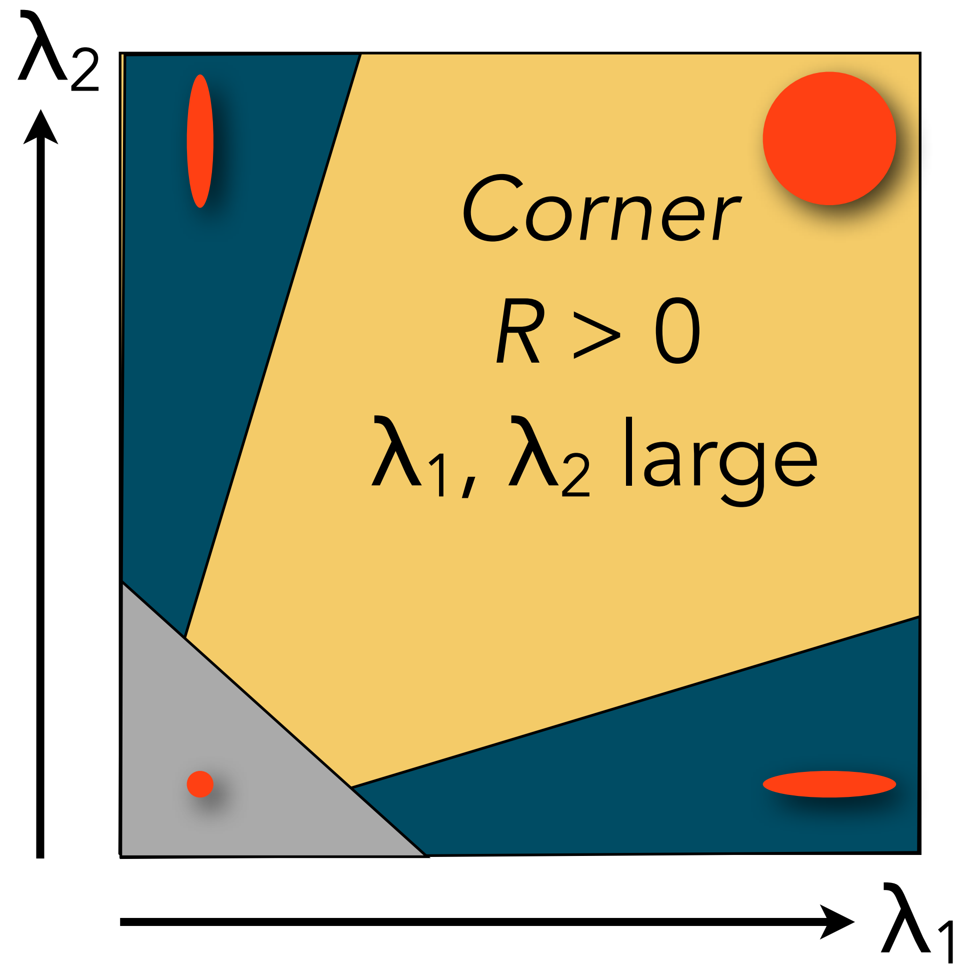

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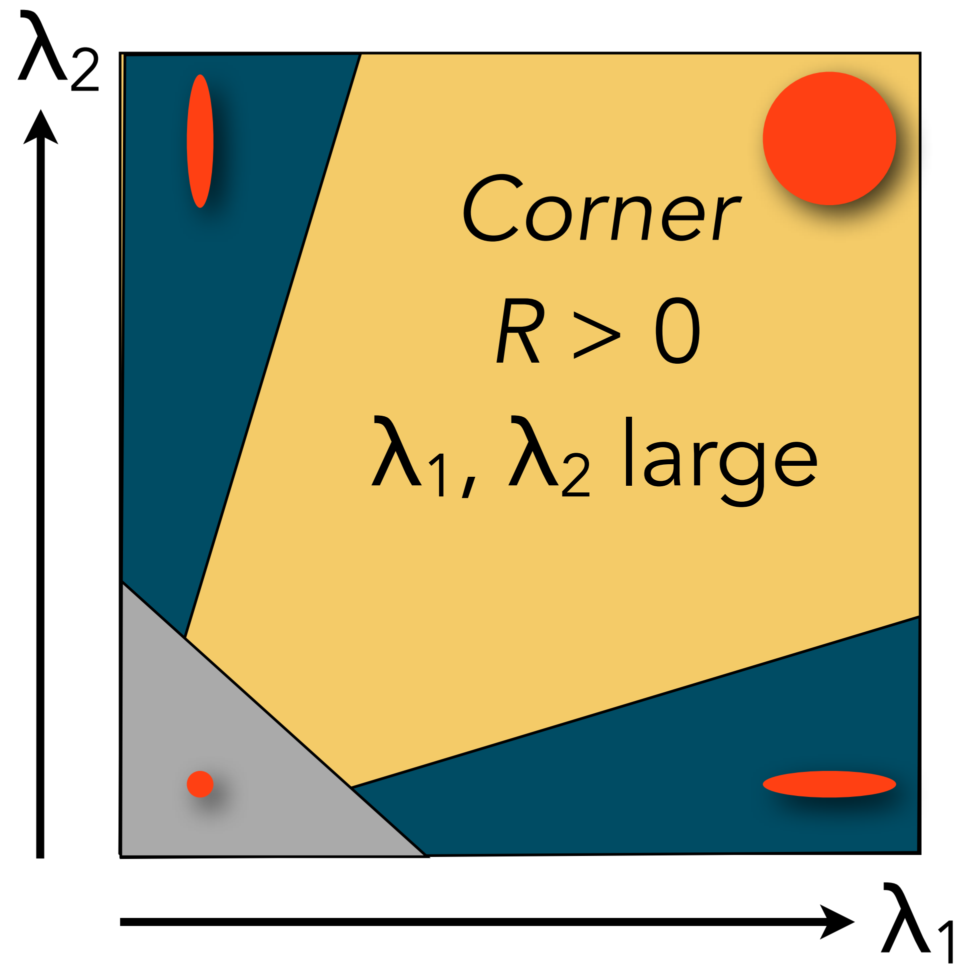

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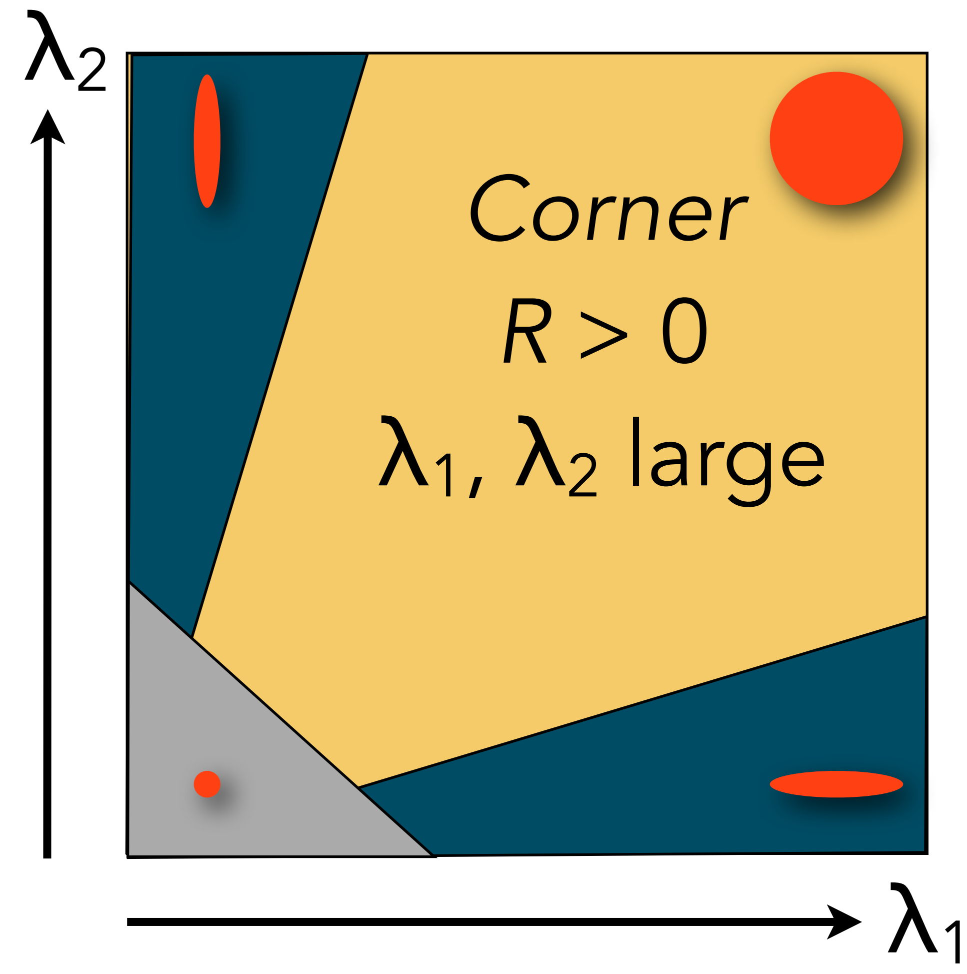

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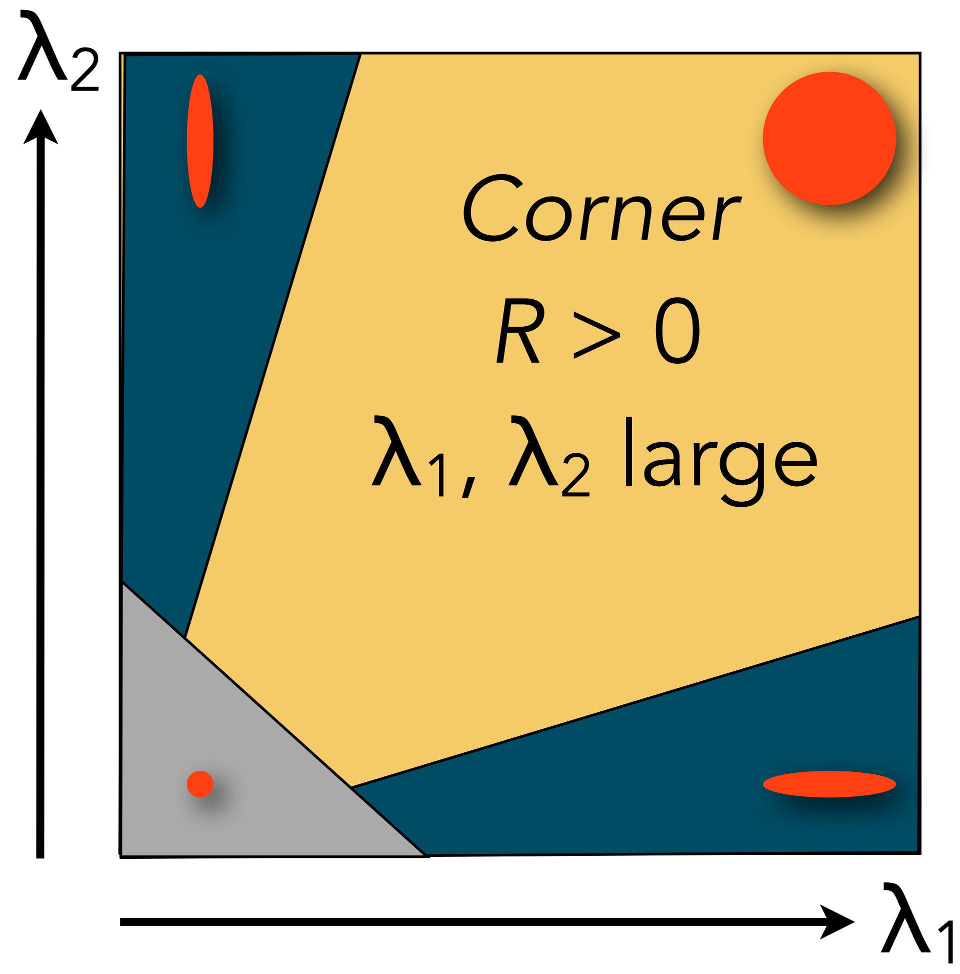

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5. Find local maxima of response function (non-maximum suppression)

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- Scale Invariant
  - NO! Dependent on Window Size!
  - USE Pyramids (or Frequency Domain!)

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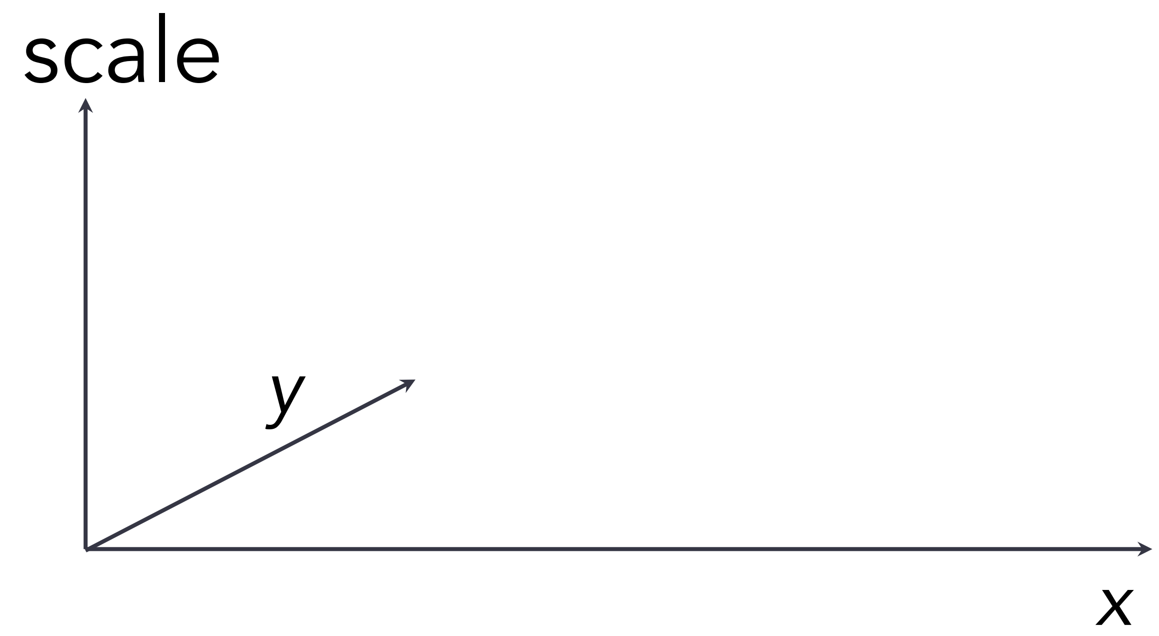

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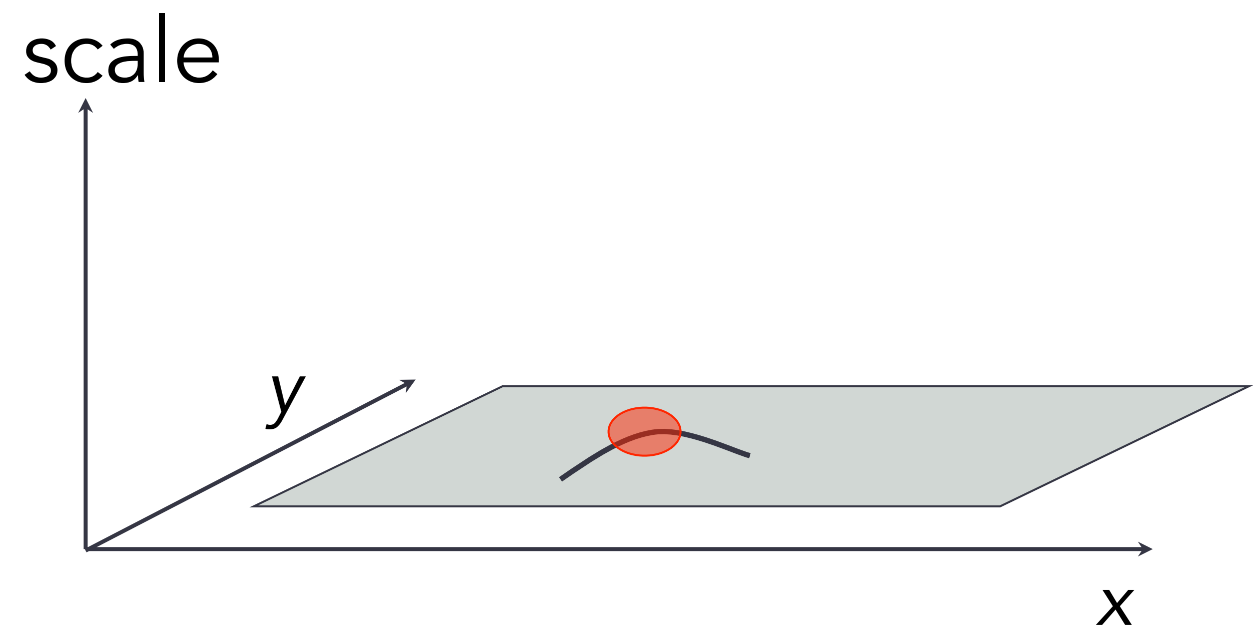

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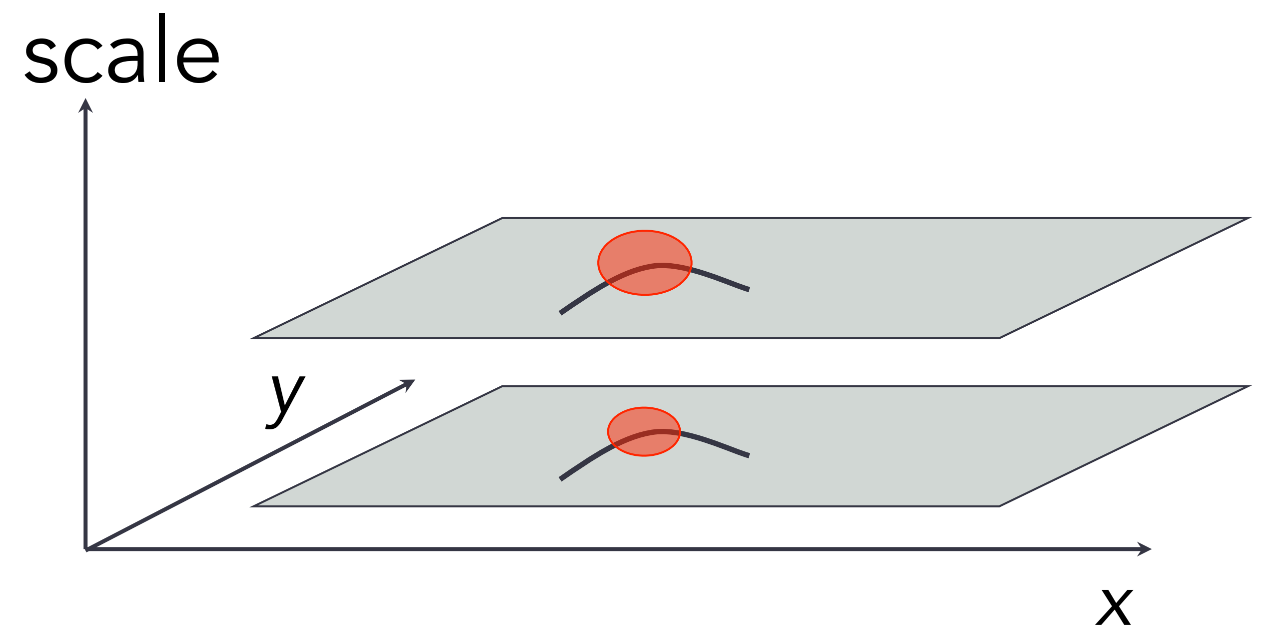

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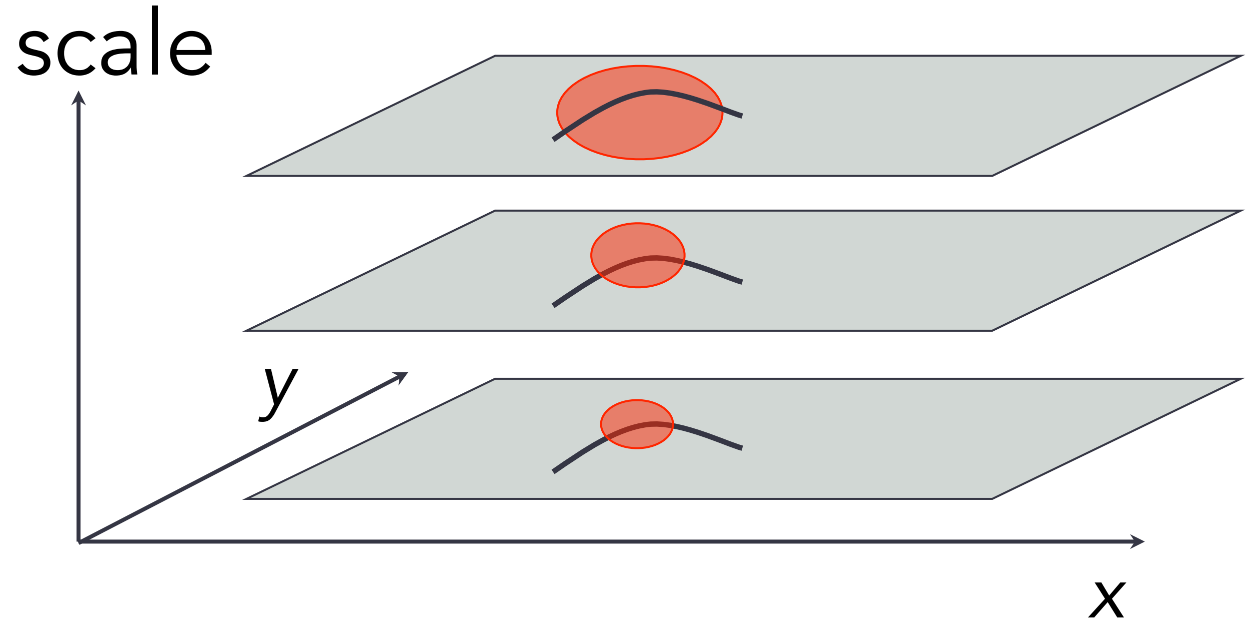

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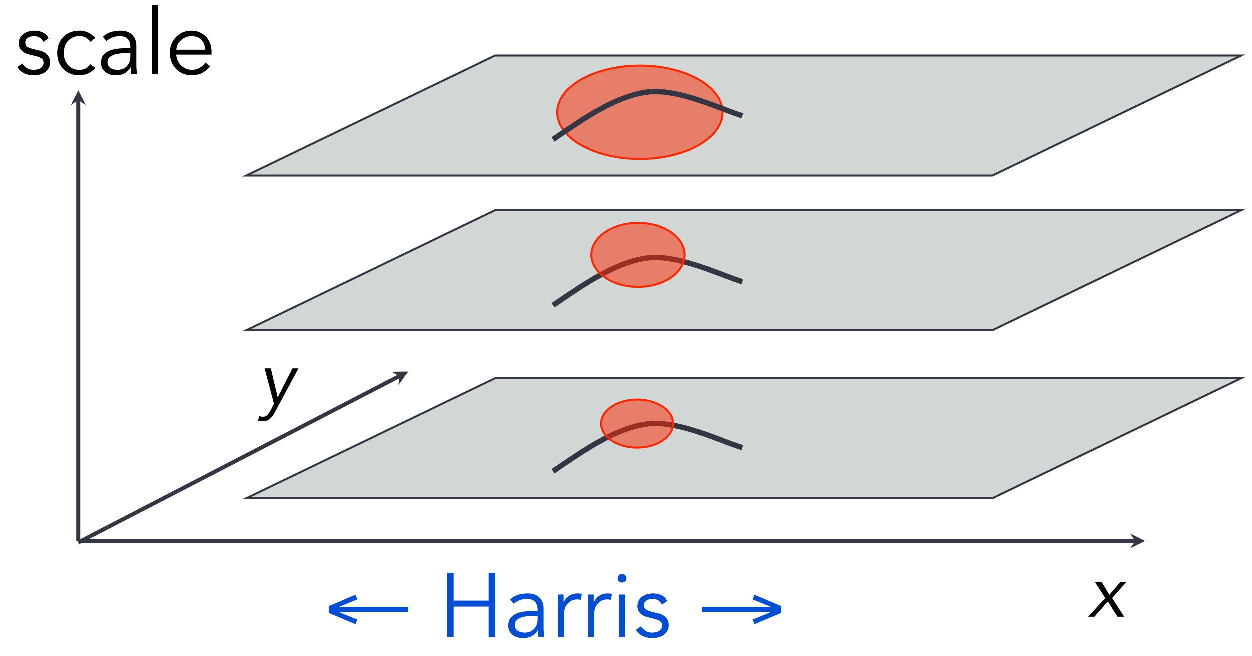

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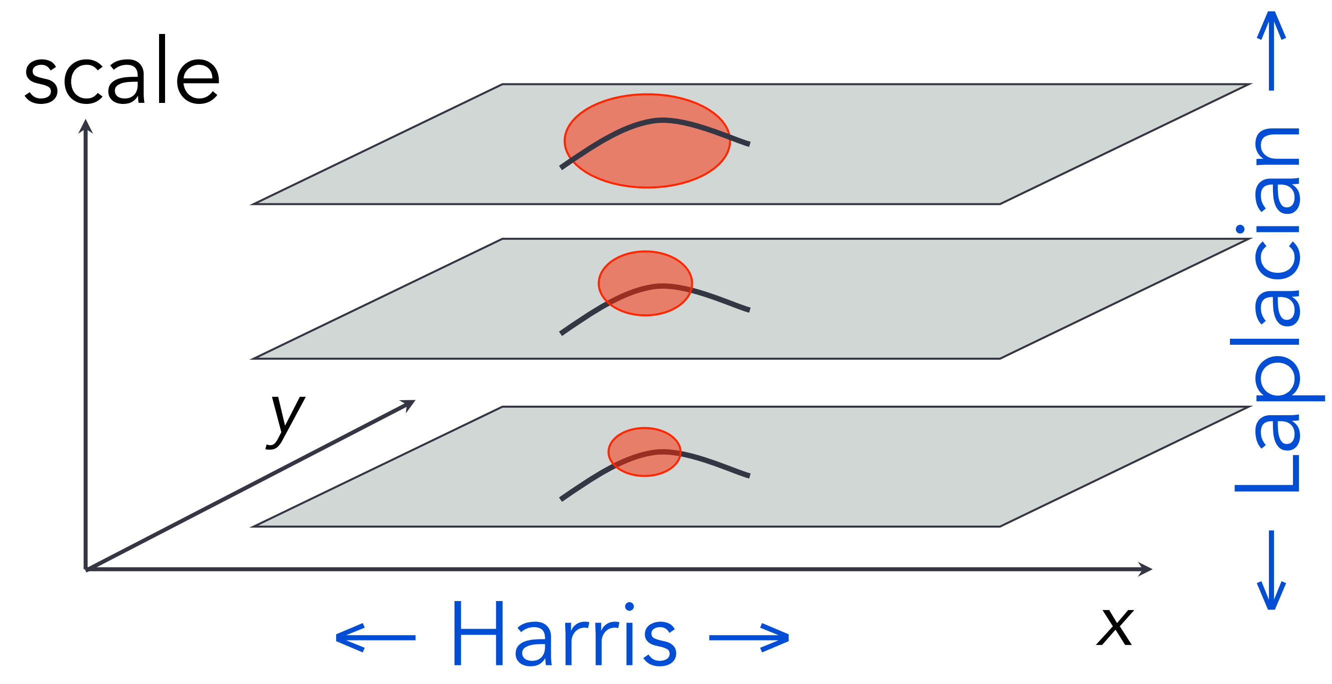

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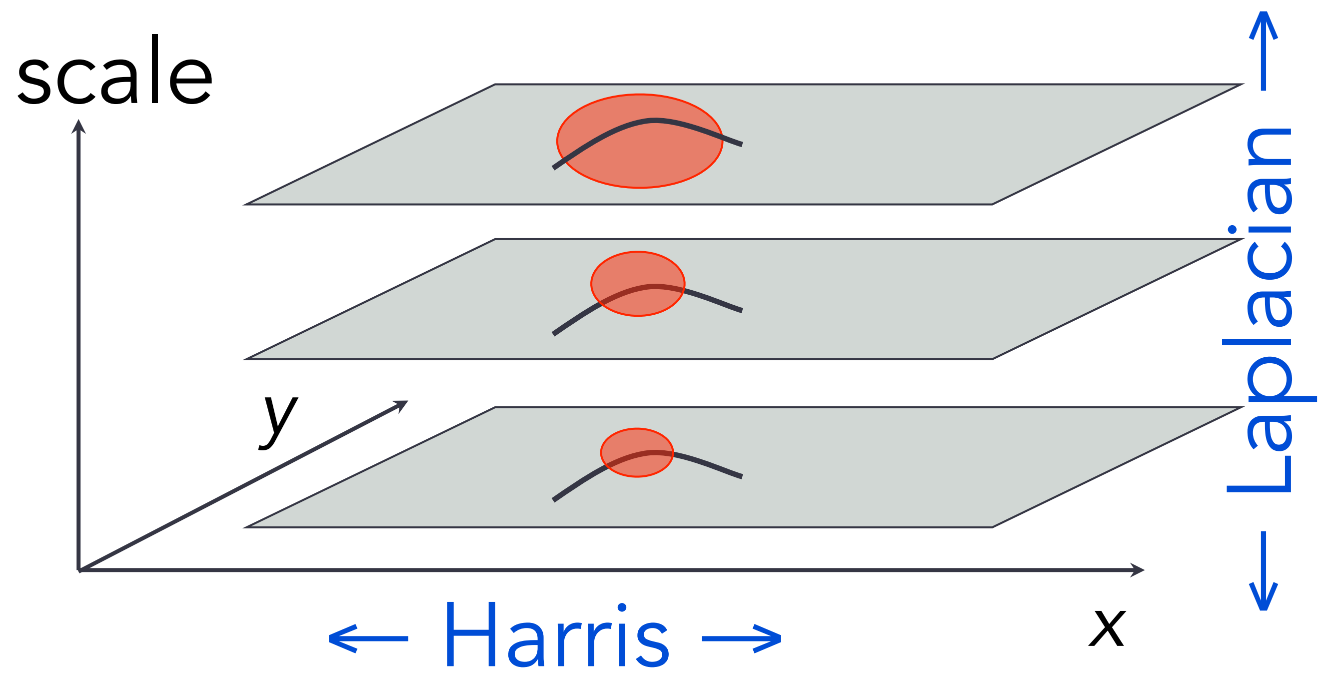

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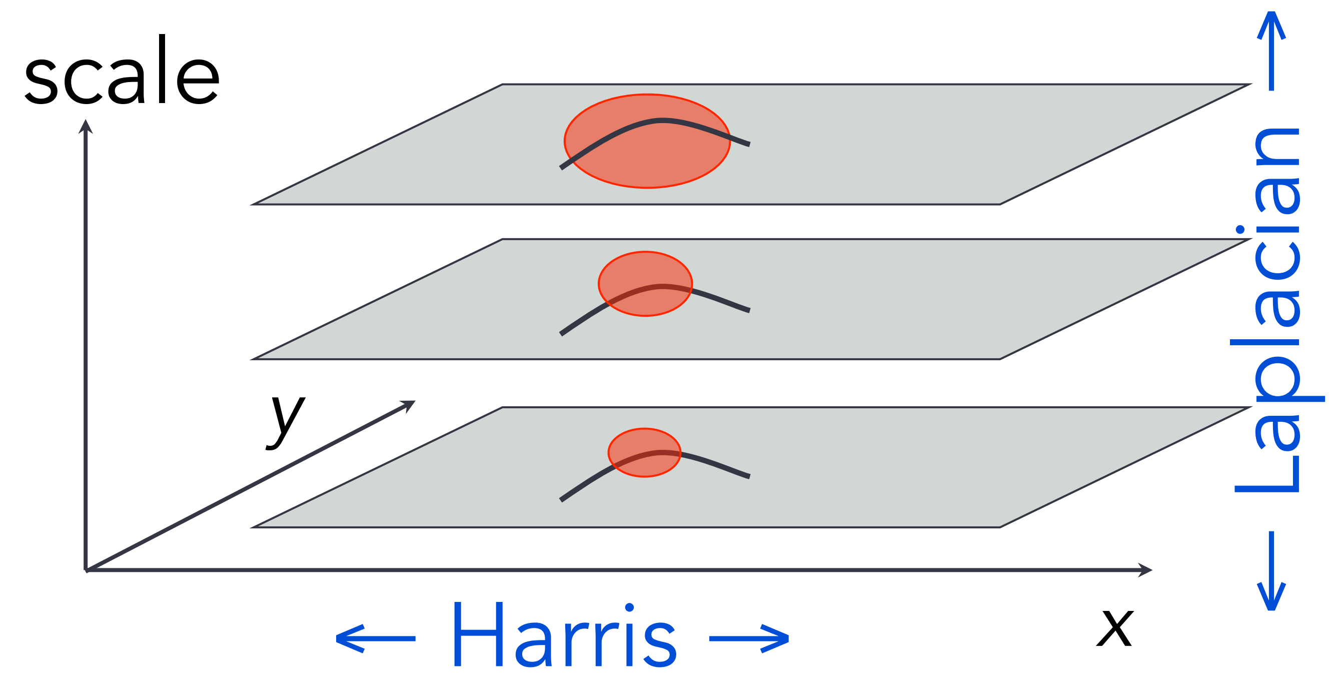

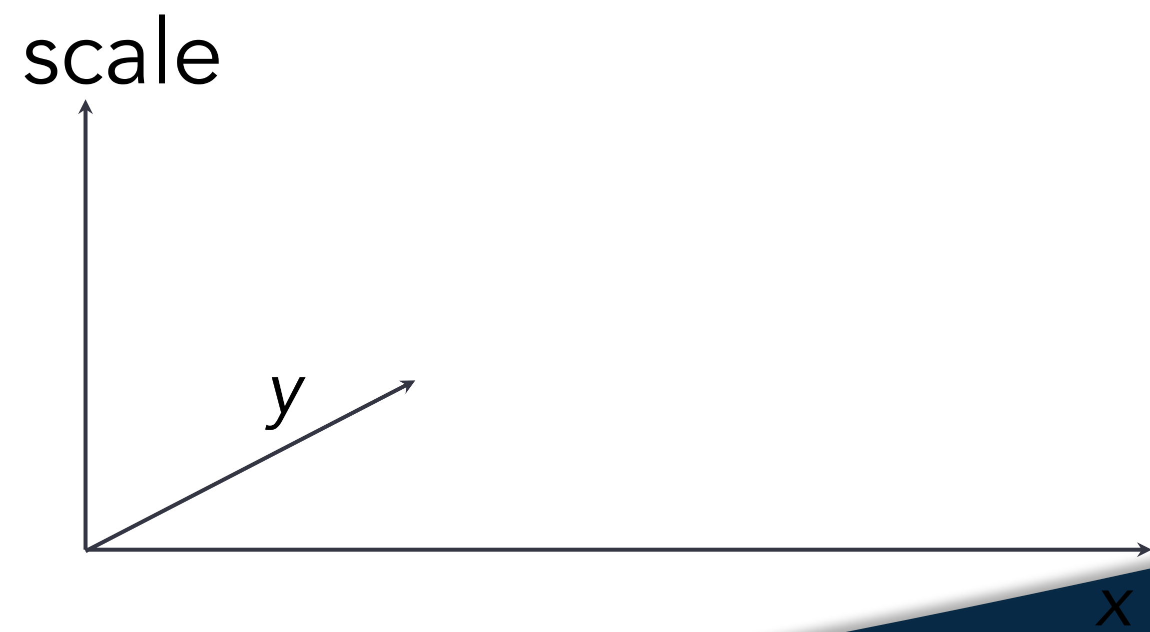

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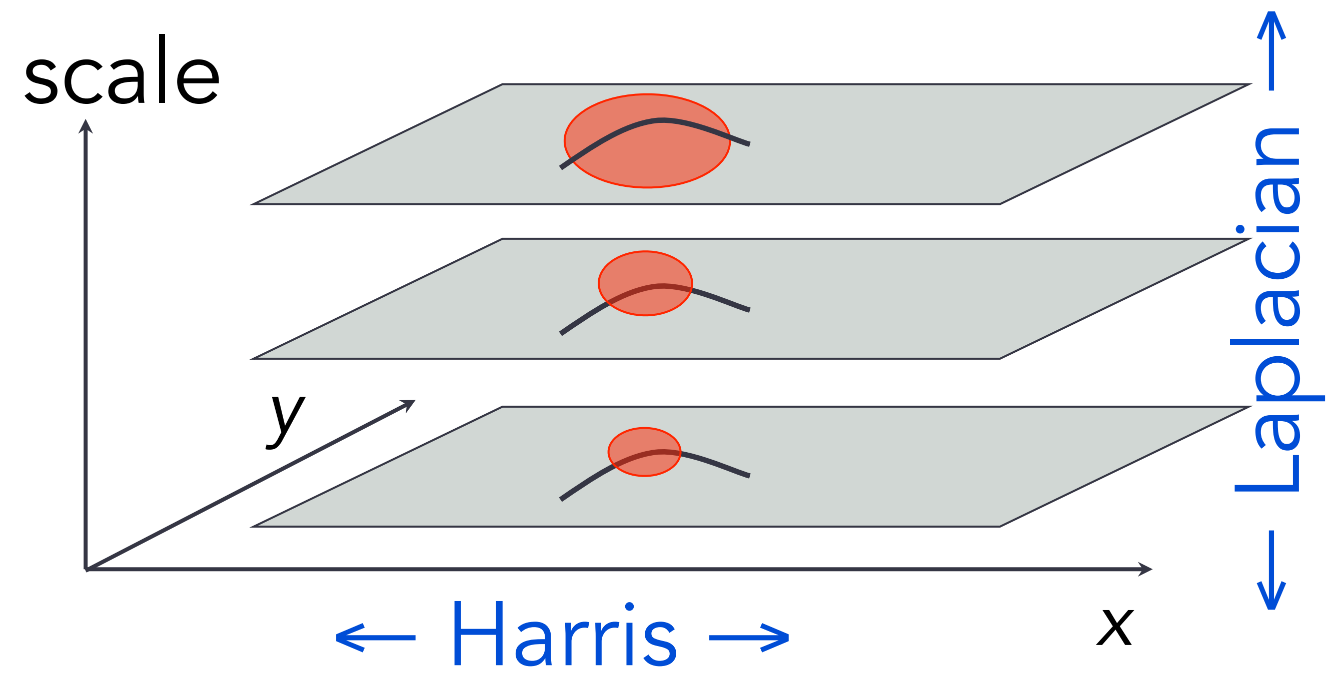

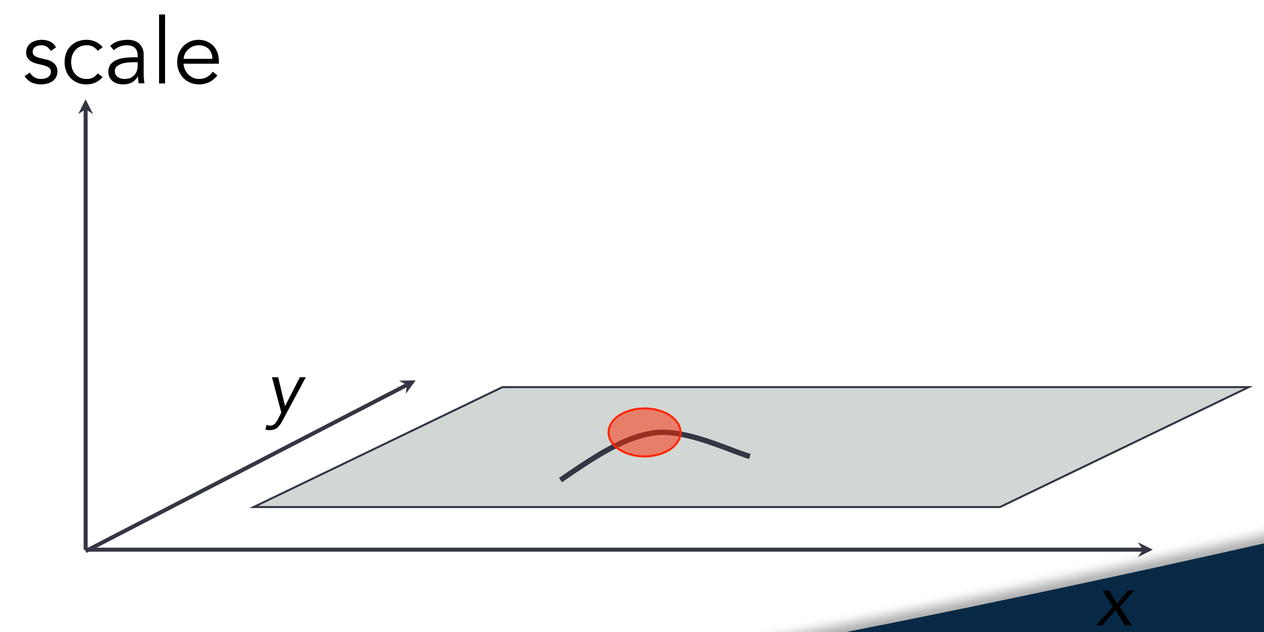

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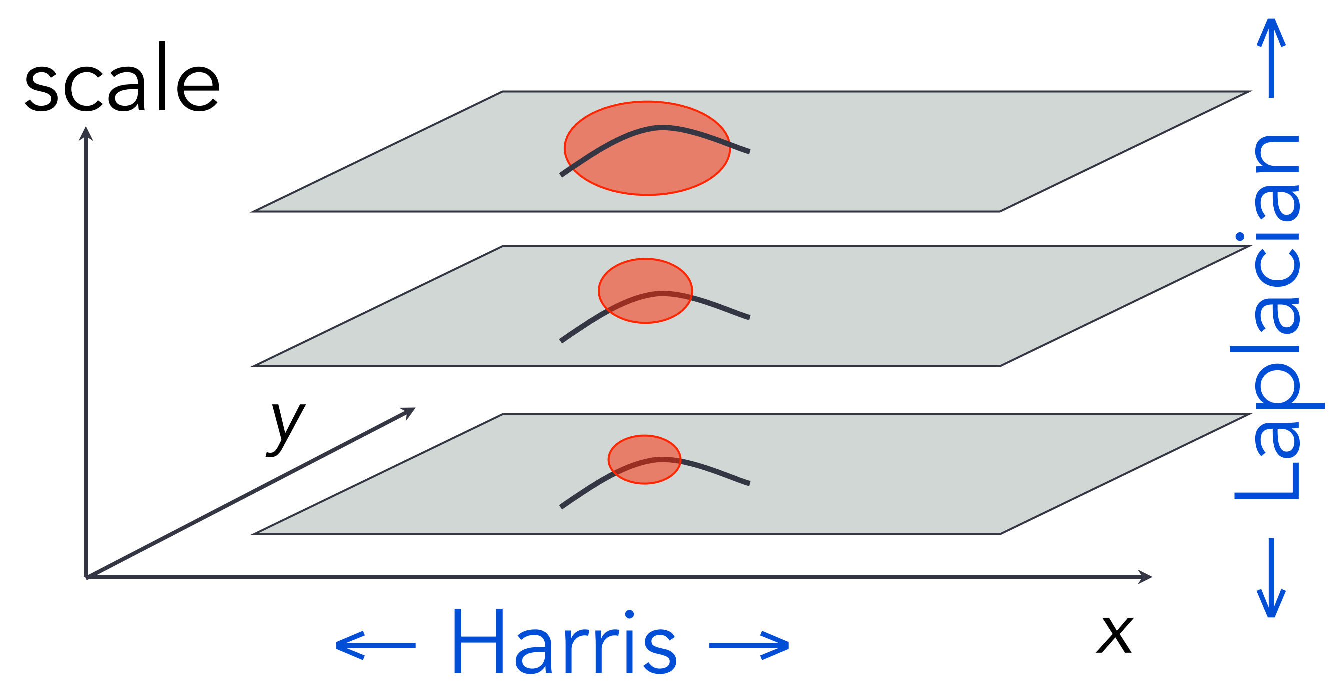

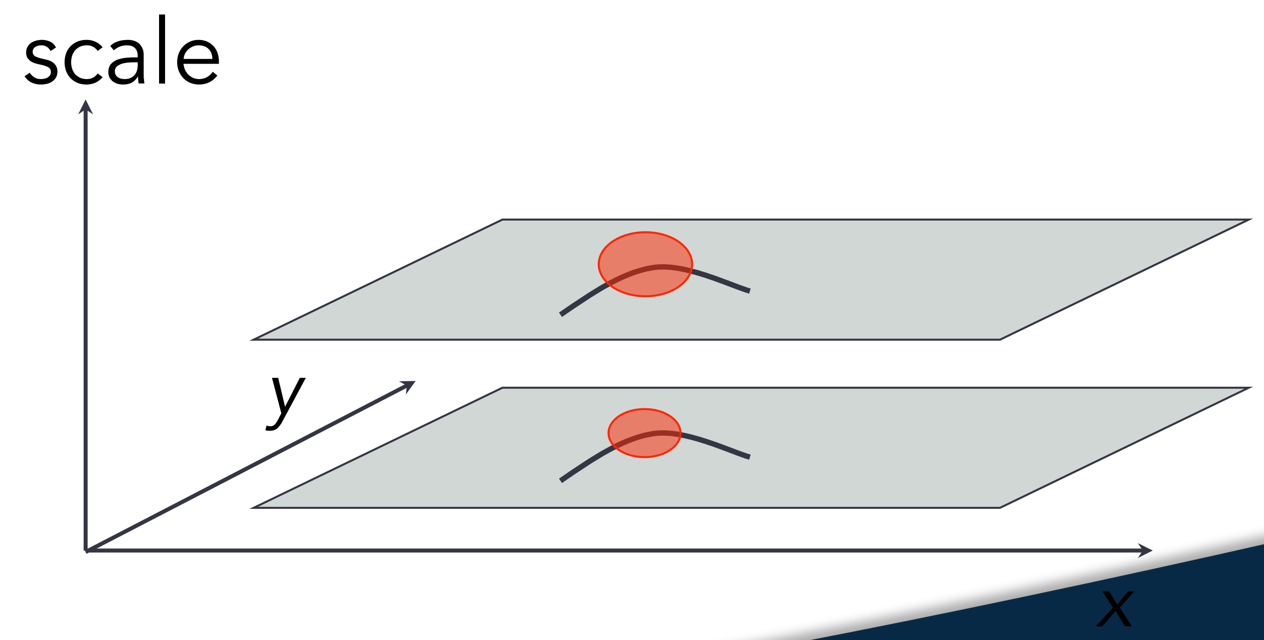

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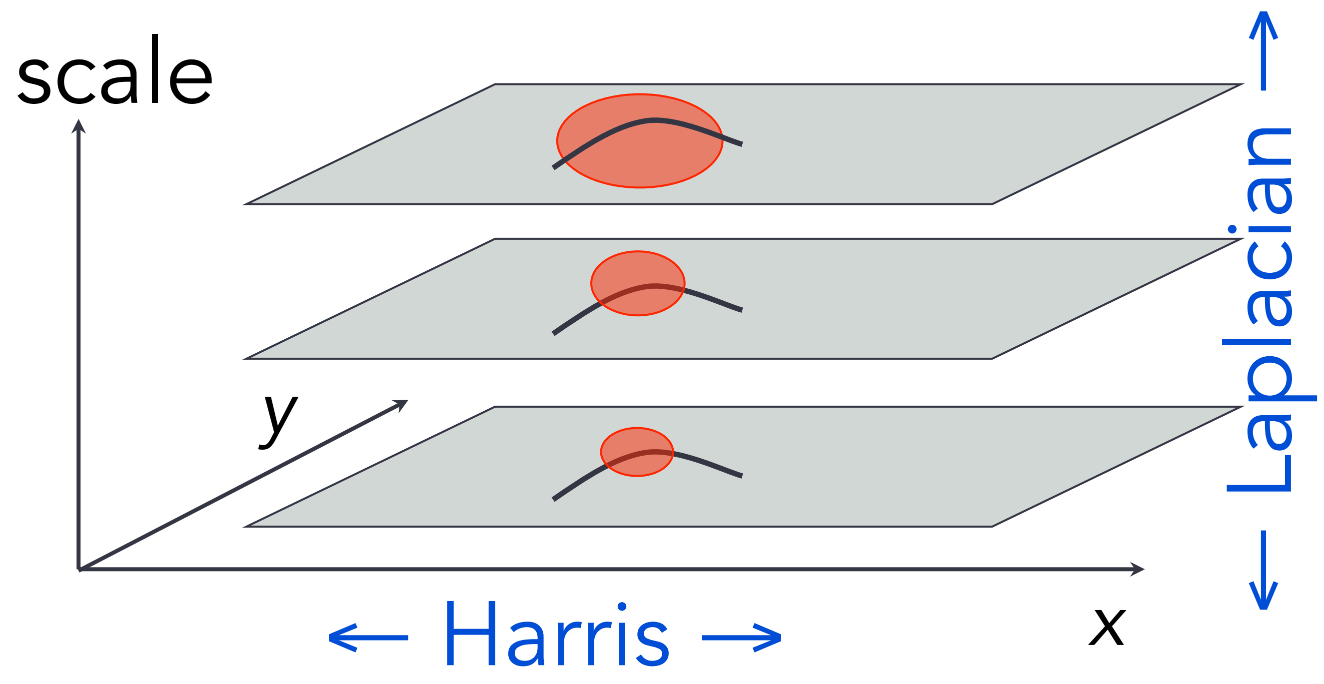

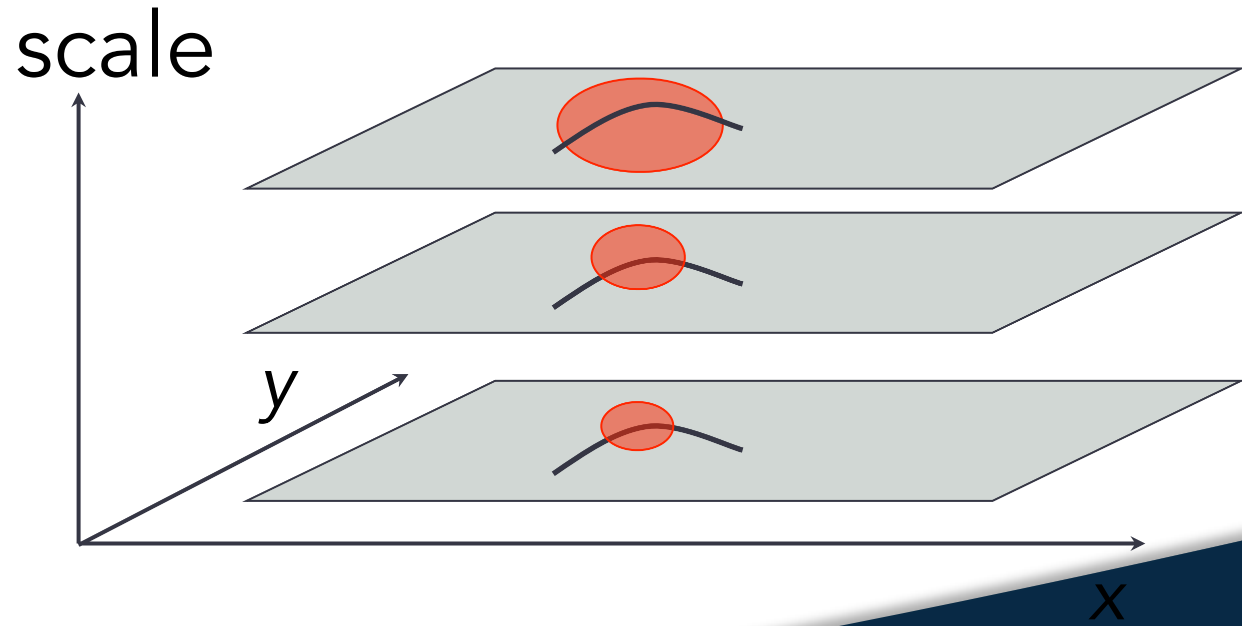

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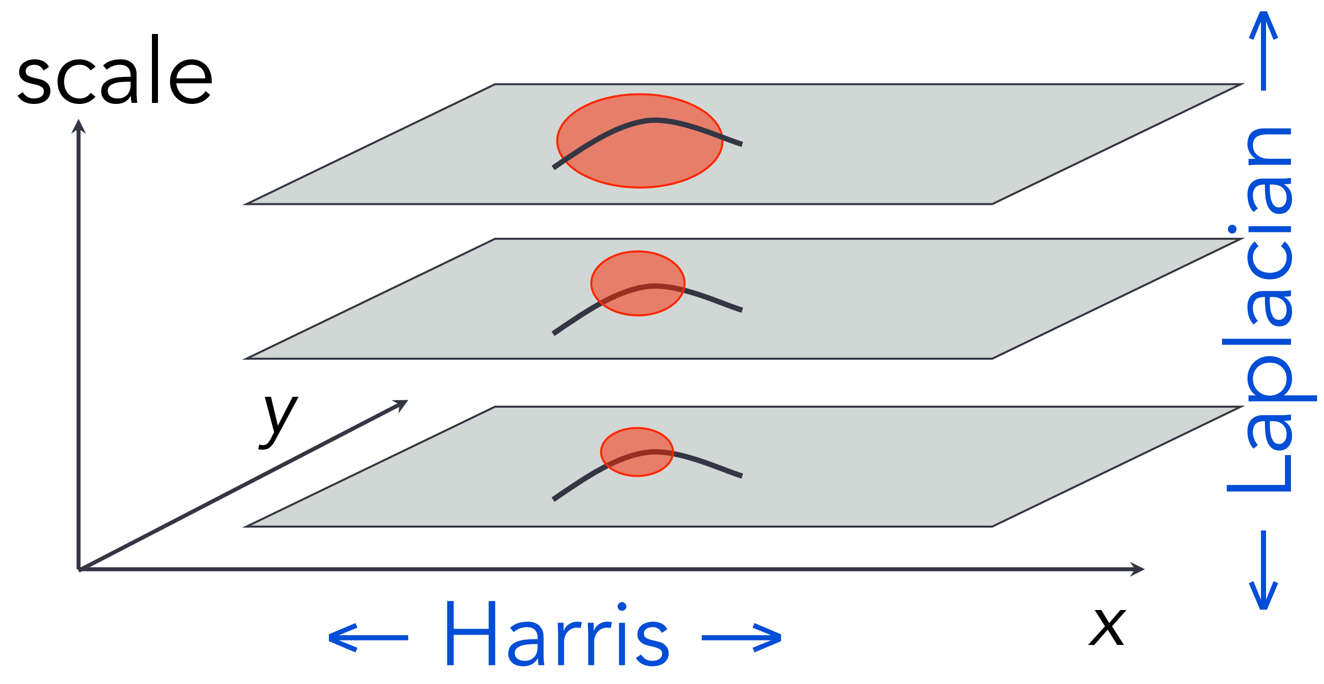

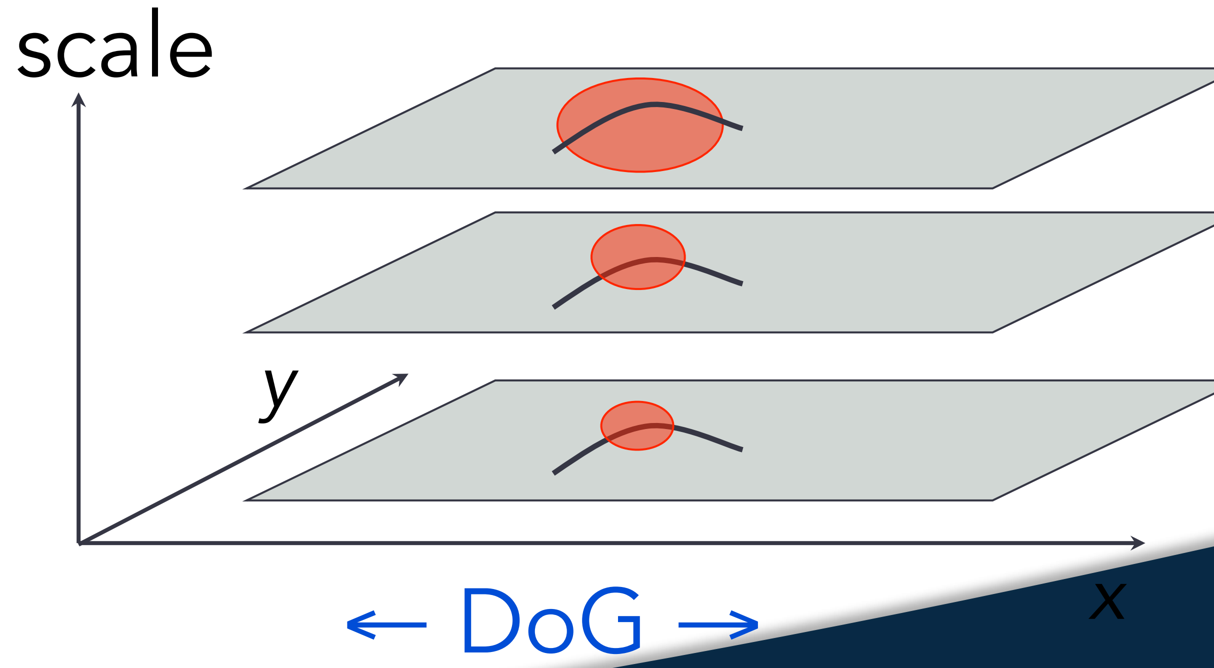

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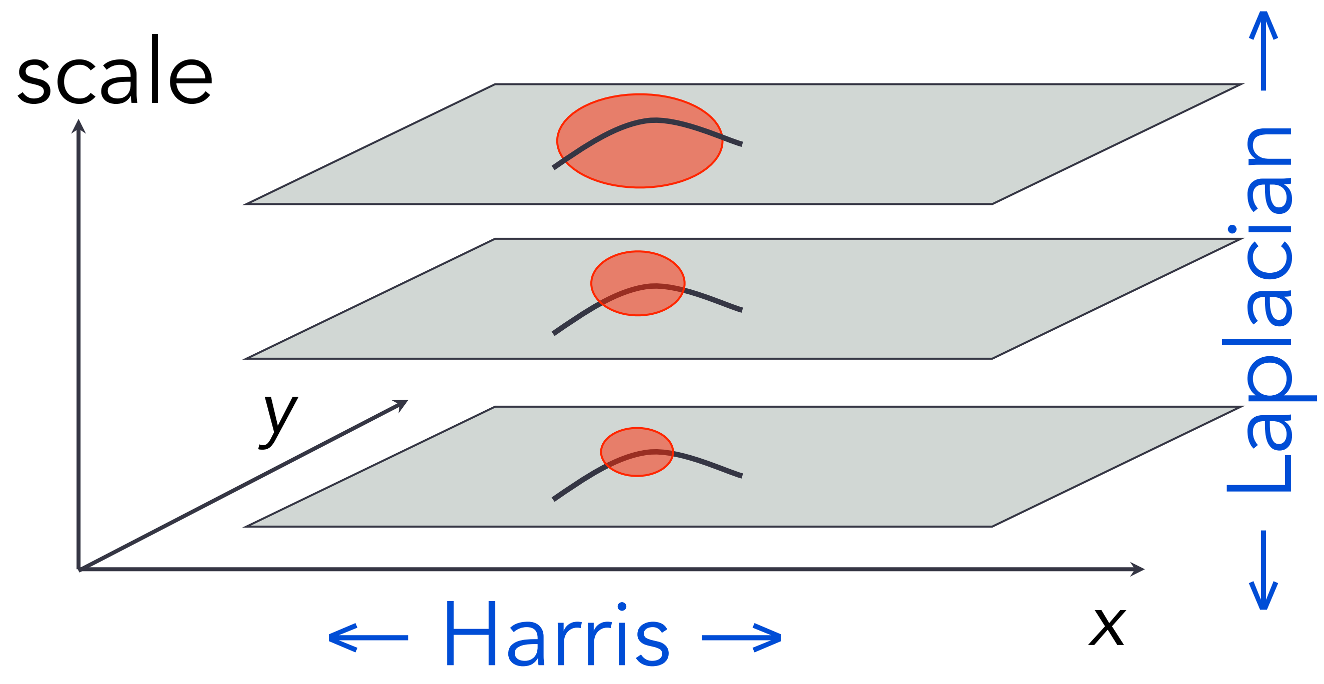
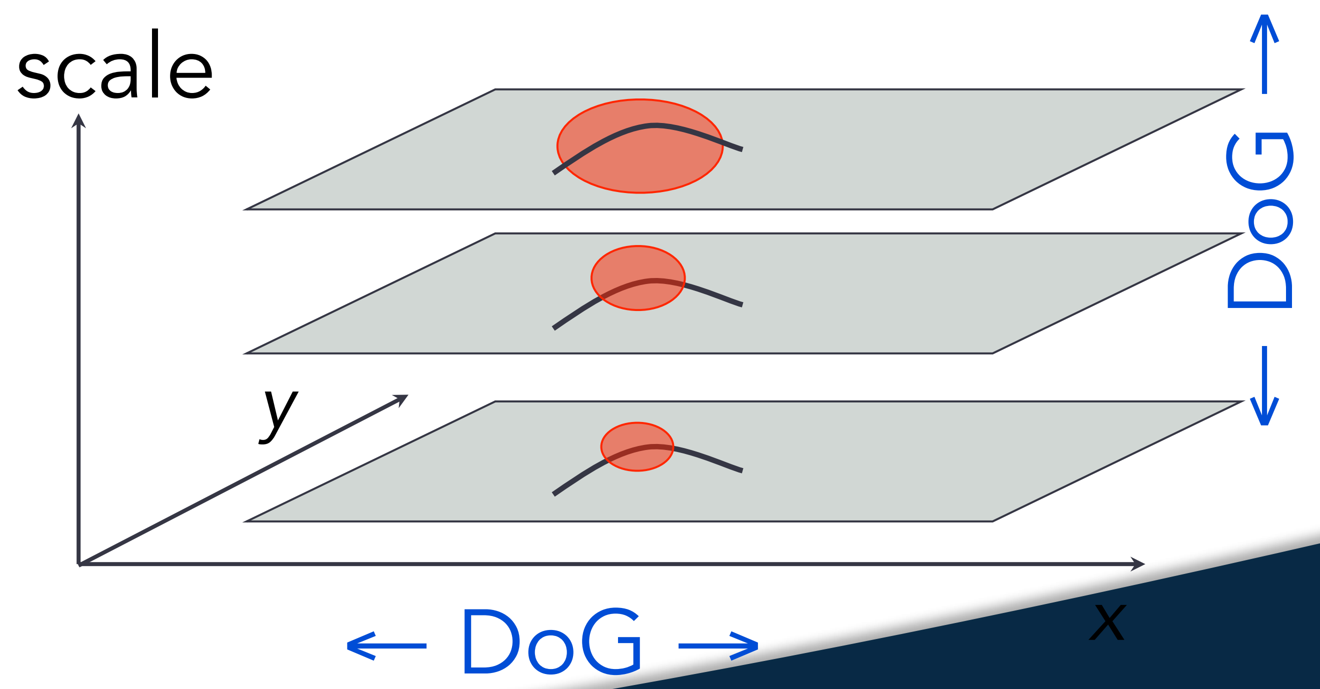
  - Difference of Gaussians (DoG) in space and scale
  - Where DoG is simply a pyramid of the difference of Gaussians within each octave





SIFT (Scale-Invariant Feature Transform)

http://en.wikipedia.org/wiki/File:Sift_keypoints_filtering.jpg

19

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- ★ Scale-space extrema detection
  - Search over multiple scales and image locations

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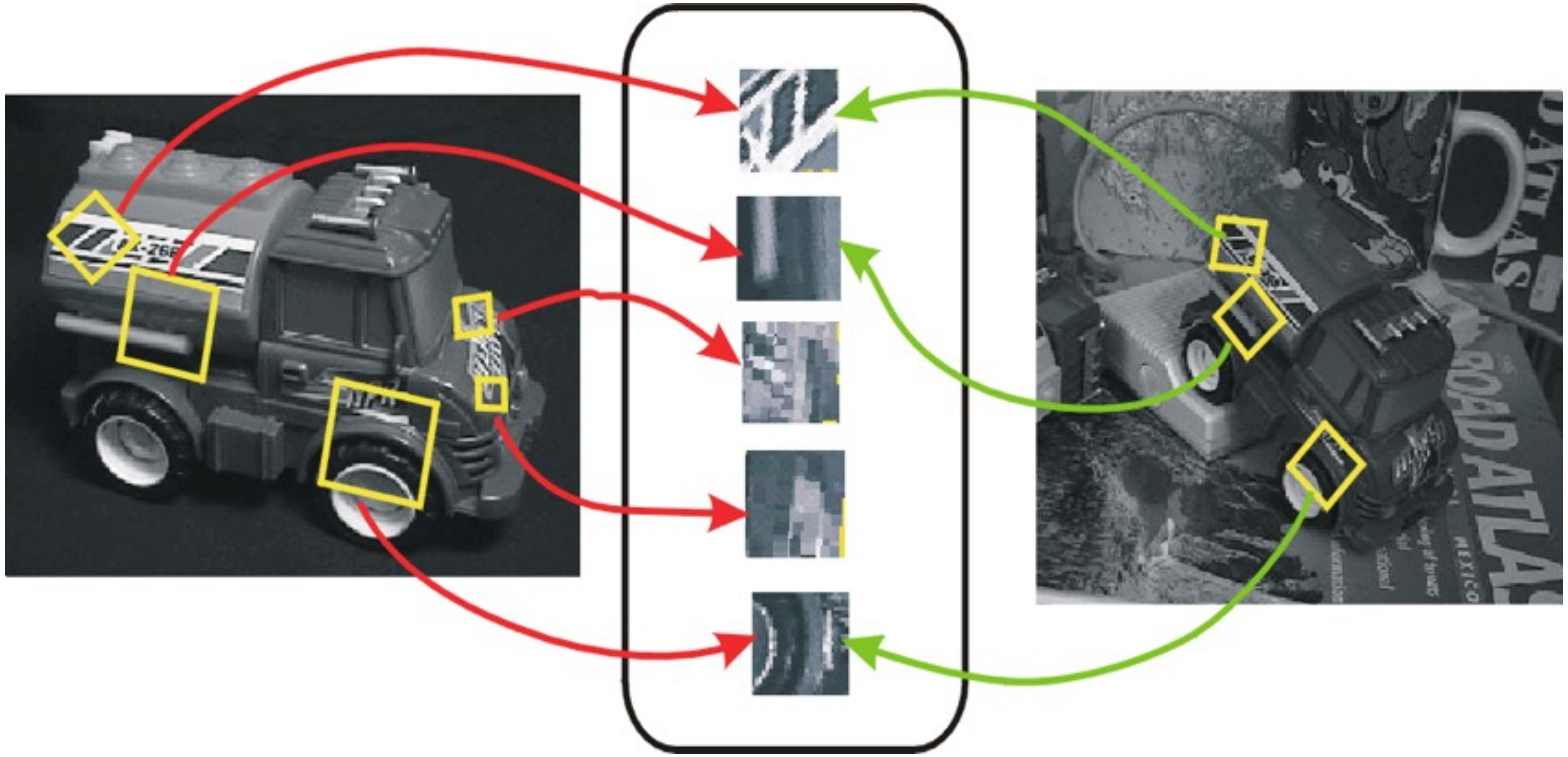
  - Define a model to determine location and scale. Select keypoints based on a measure of stability.
- ★ Orientation assignment
  - Compute best orientation(s) for each keypoint region.
- ★ Keypoint description
  - Use local image gradients at selected scale and rotation to describe each keypoint region.

http://en.wikipedia.org/wiki/File:Sift_keypoints_filtering.jpg

19



Invariant Local Features

- ★ Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters
- ★ (Lowe, 2004)

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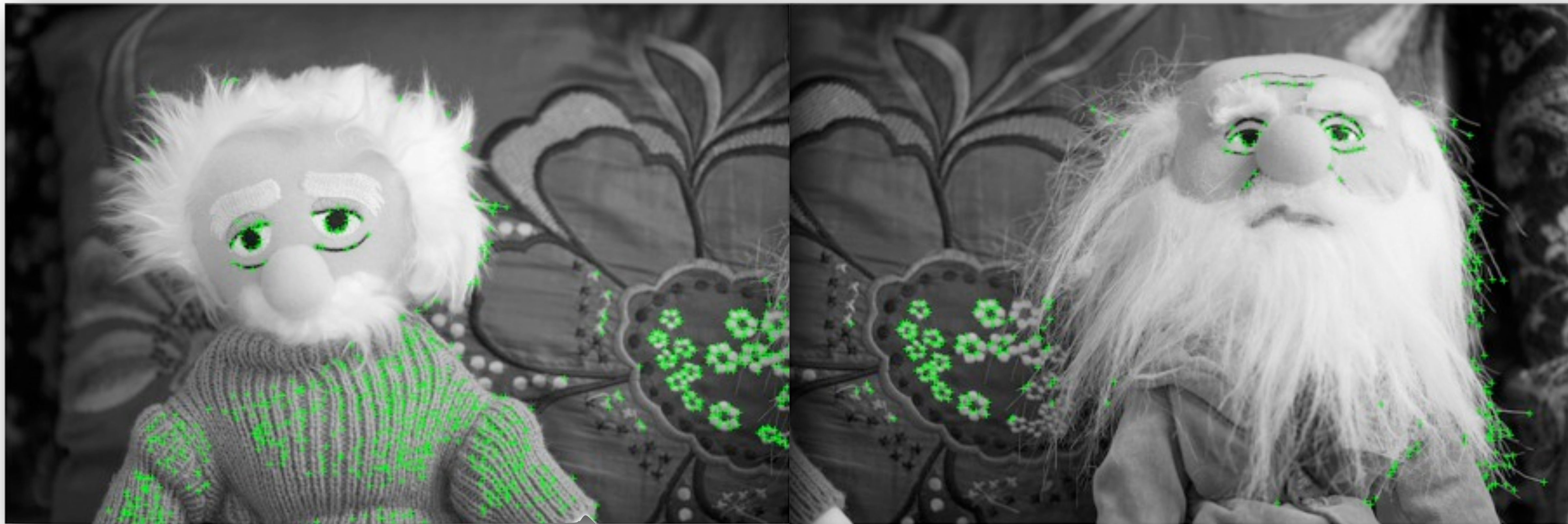
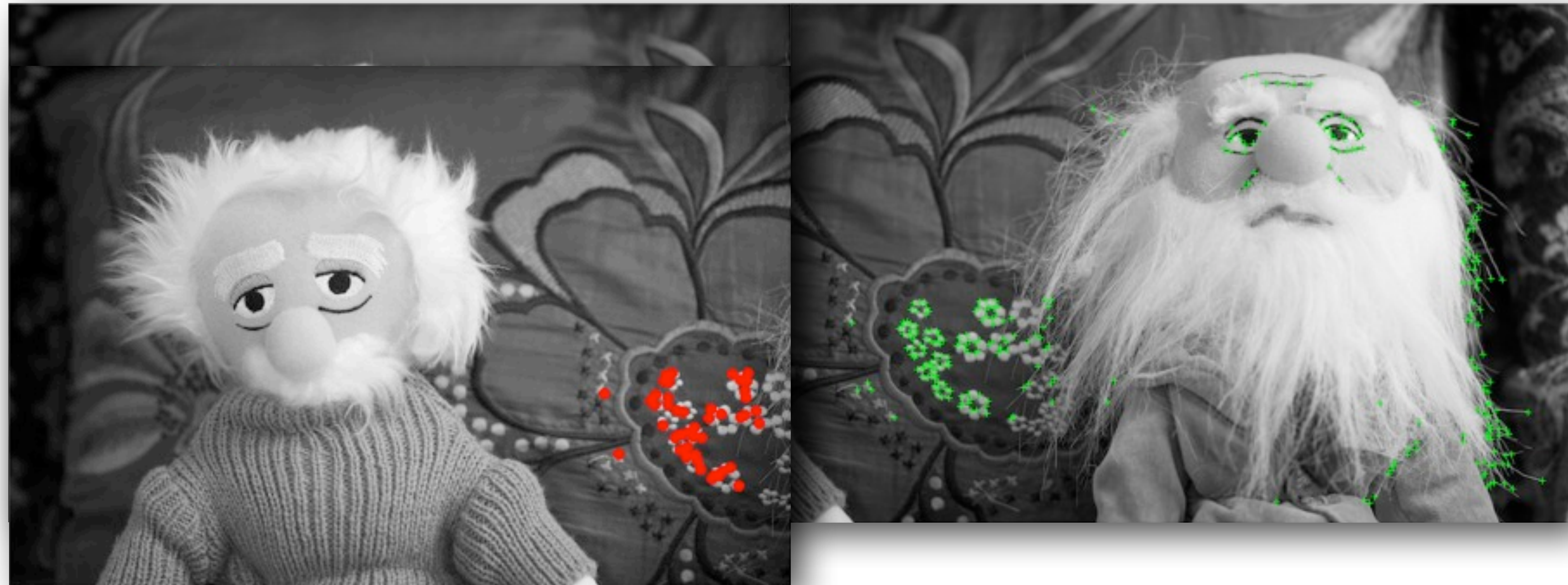
Results

Detect



[Results](#)

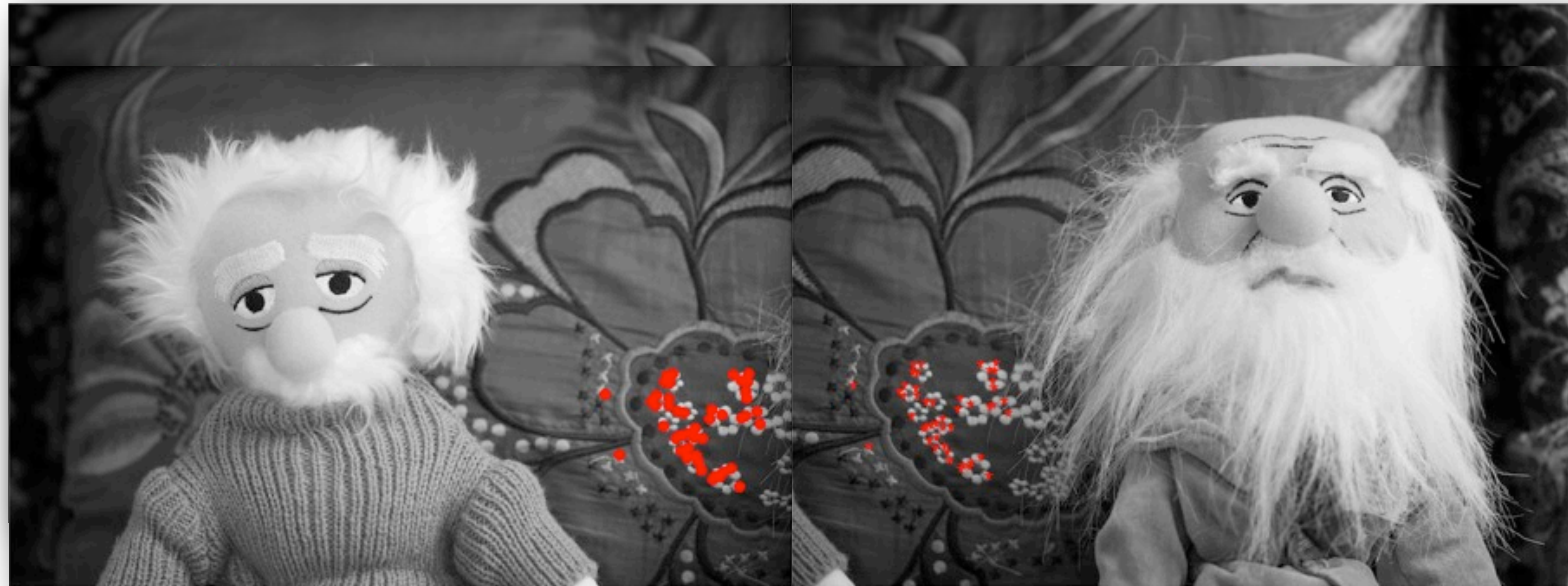
Detect



Results

Detect

Match

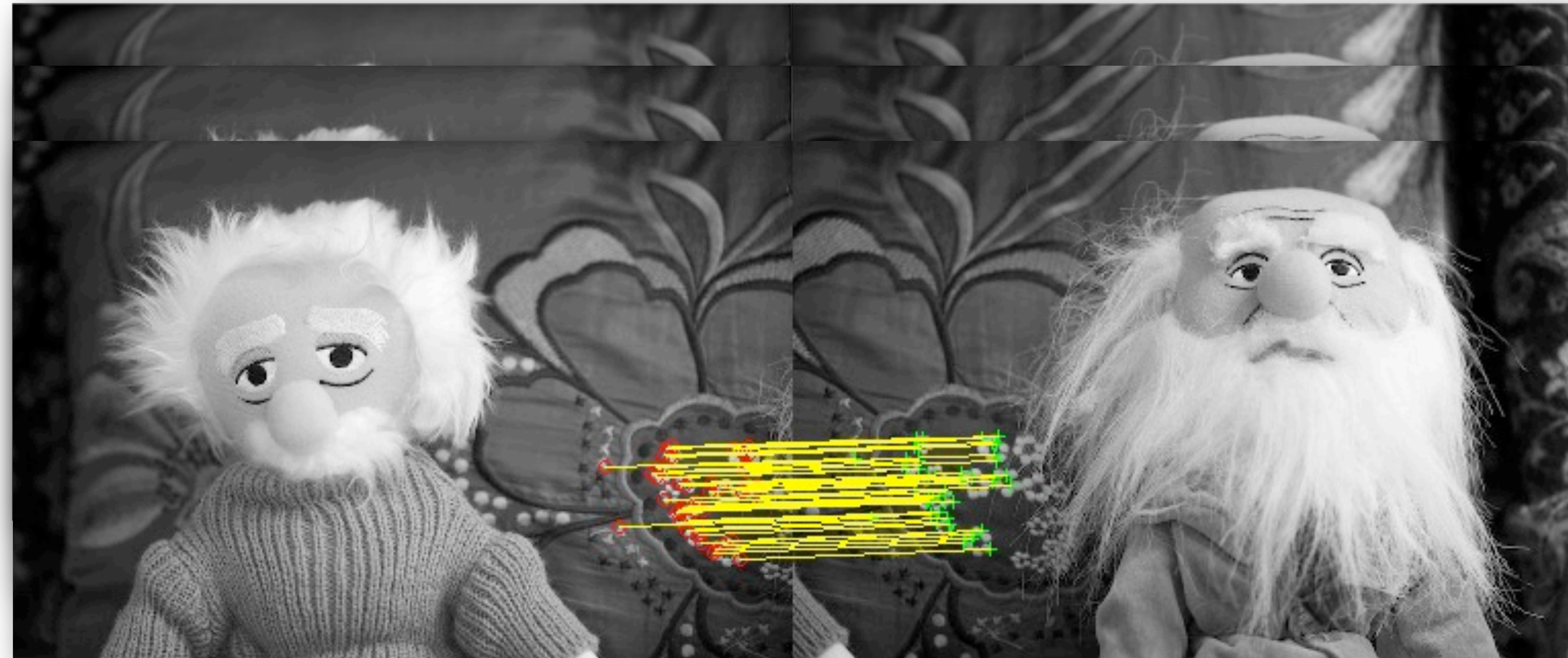


Results

Detect

Match

Show



Results

Summary

- ★ Introduced Feature Detection and Matching for images
- ★ Discussed the four (4) Characteristics of Good Features.
- ★ Introduced the Harris Corner Detector Framework
- ★ Introduced the SIFT detector

Further Reading

- ★ Harris and Stephens (1988) "A Combined Corner and Edge Detector." Proceedings of the 4th Alvey Vision Conference, 1988, [PDF][DOI]
- ★ Mikolajczyk and Schmid (2001). "Indexing Based on Scale Invariant Interest Points". ICCV 2001
- ★ Lowe (2004) "Distinctive Image Features from Scale-Invariant Keypoints". IJCV 2004
- ★ Search for "Features" on OpenCV site

commons.wikimedia.org/

Next Class

★ How to do Alignment for Panoramas

Credits

★ For more information, see

- Richard Szeliski (2010) Computer Vision: Algorithms and Applications, Springer.

★ Some concepts in slides motivated by similar slides by A. Efros and J. Hays.

★ Some images retrieved from

- http://commons.wikimedia.org/.
- List will be available on website.

www.flickr.com/photos/neneonline/231886965/

Computational Photography

Dr. Irfan Essa
Professor
School of Interactive Computing

Study the basics of computation and its impact on the entire workflow of photography, from capturing, manipulating and collaborating on, and sharing photographs.