From points to regions

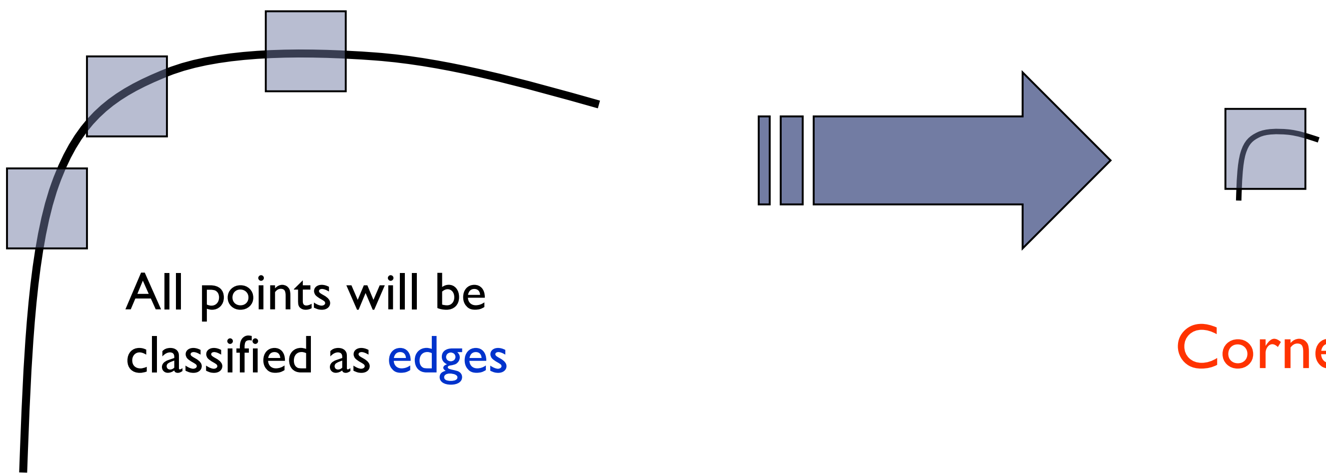
Lihi Zelnik-Manor, Computer Vision

Today

- Local invariant features
  - Motivation
  - Requirements, invariances
- Keypoint localization
  - Harris corner detector
  - Hessian detector
- Scale invariant region selection
  - Automatic scale selection
  - Laplacian-of-Gaussian detector
  - Difference-of-Gaussian detector

Harris Detector: Properties

- Is it invariant to image scale?



All points will be classified as edges

Corner !

No: Not invariant to image scale!

From points to regions

- The Harris and Hessian operators define interest points
  - Precise localization
  - High repeatability

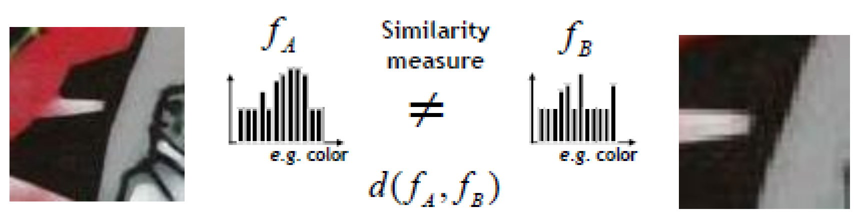
מעוניינים בגלאי סקאלה, שיגיד לנו מה הסקלה שכדאי להסתכל עליה

- In order to compare (and match) those points, we need to compute a descriptor over their local region
  - How can we define such a region in a scale invariant manner?
  - How can we detect scale invariant interest region?

Naïve approach: Exhaustive search

- Multi-scale procedure
  - Compare descriptors while varying patch size

הריבועים באותו גודל אך התמונה לא באותו זום



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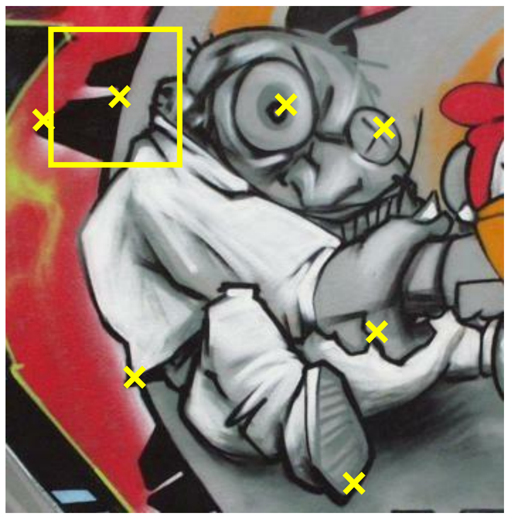
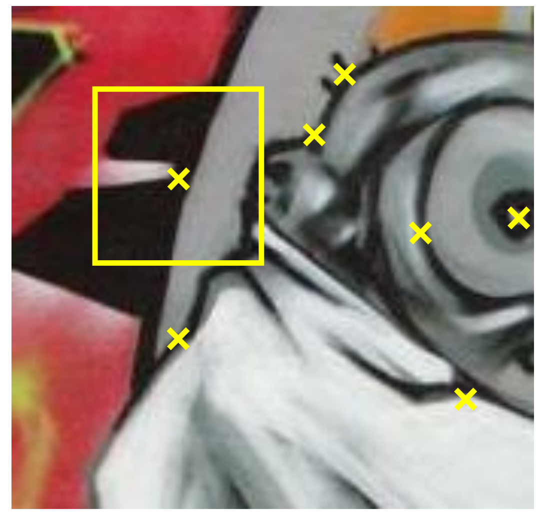
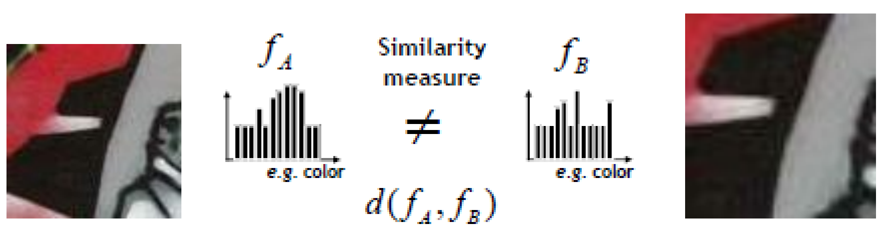




לכן נתחיל להגדיל את הריבוע בצד
ימין ובאיזשהו שלב יהיה לנו שוויון



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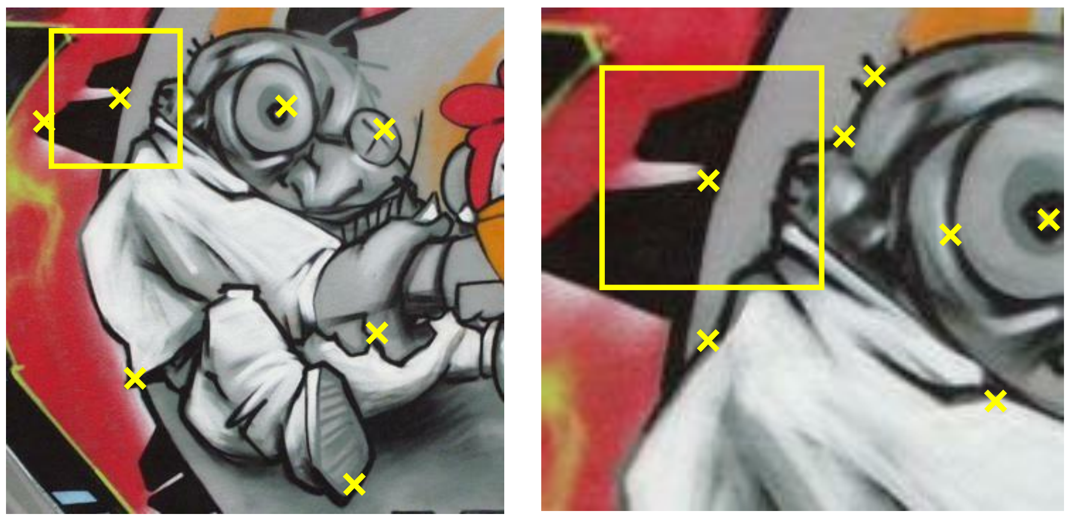

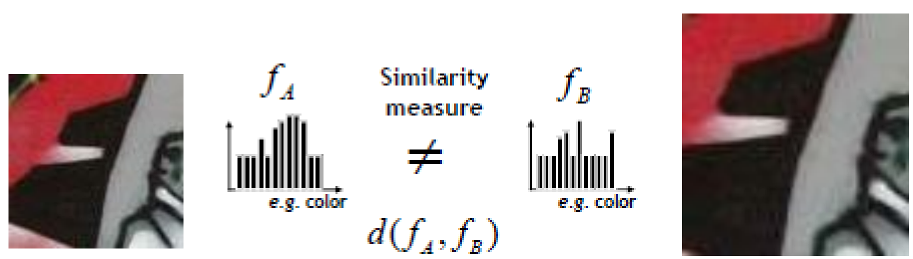

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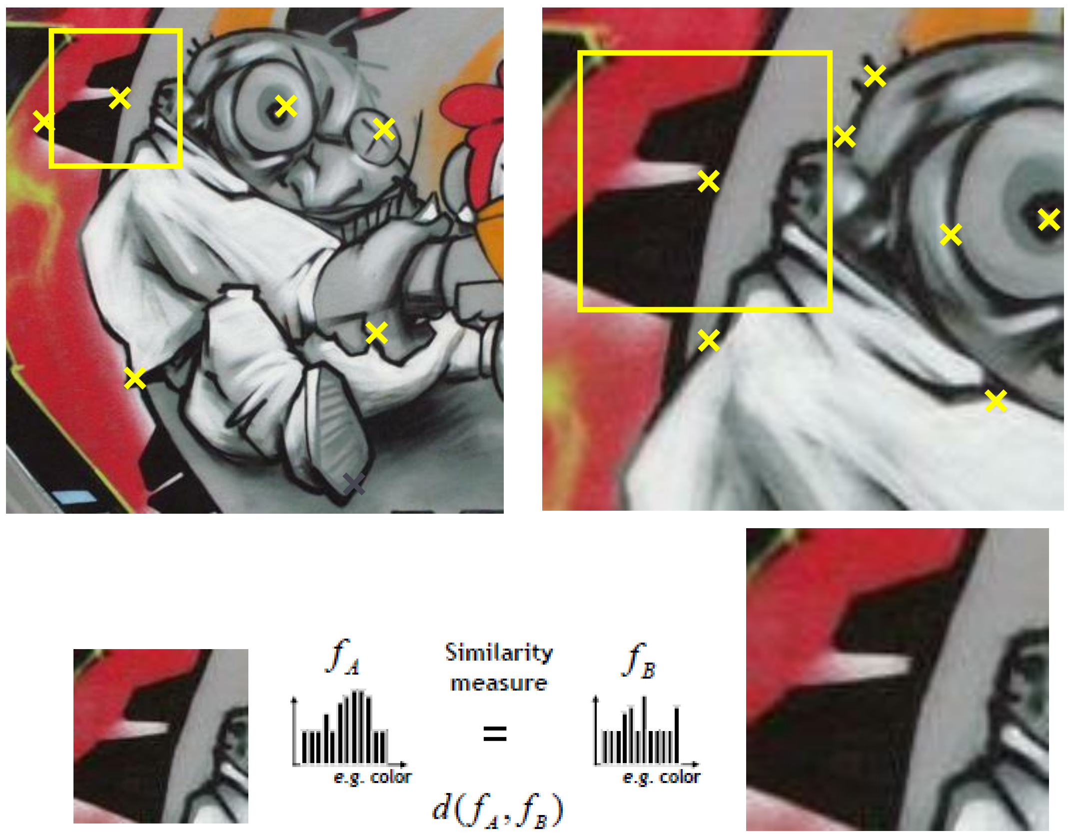
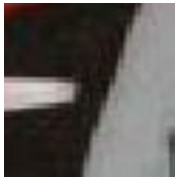


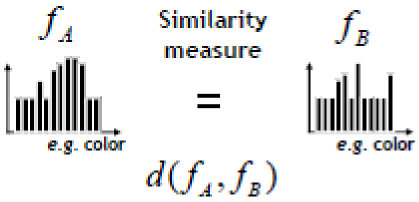
זו השיטה הנאיבית
לוקחים אוסף של סקאלות
ורצים עליהם ,

Naïve approach: Exhaustive search

- Compare descriptors while varying patch size
  - Computationally inefficient
  - Prohibitive for retrieval in large databases
  - Prohibitive for recognition



בשיטה הנאיבית נוכל להתאים דברים שלא בהכרח מתאימים



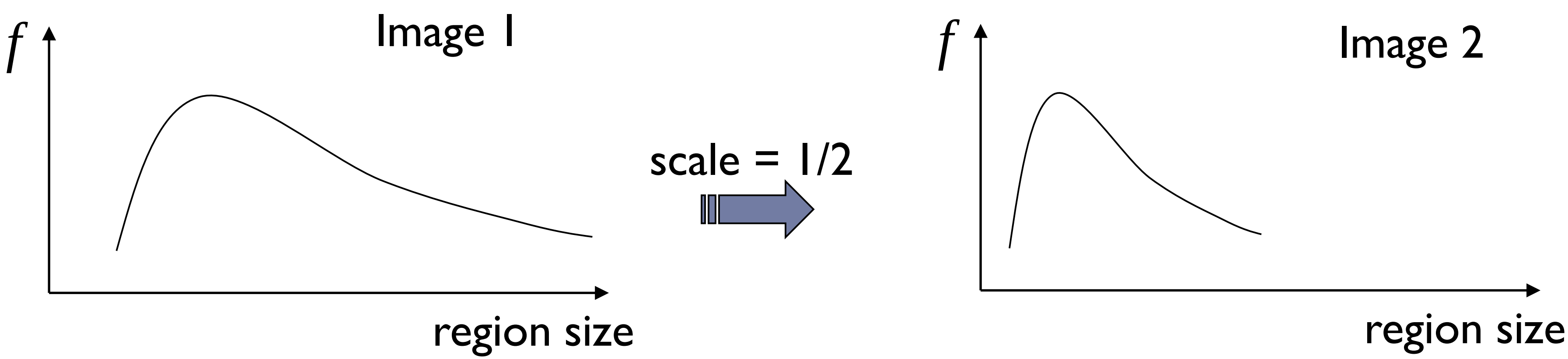
Automatic scale selection

- Solution:
  - Design a function on the region, which is "scale invariant" (*the same for corresponding regions, even if they are at different scales*)

<u>Example</u>: average intensity. For corresponding regions (even of different sizes) it will be the same.

  - For a point in one image, we can consider it as a function of region size (patch width)

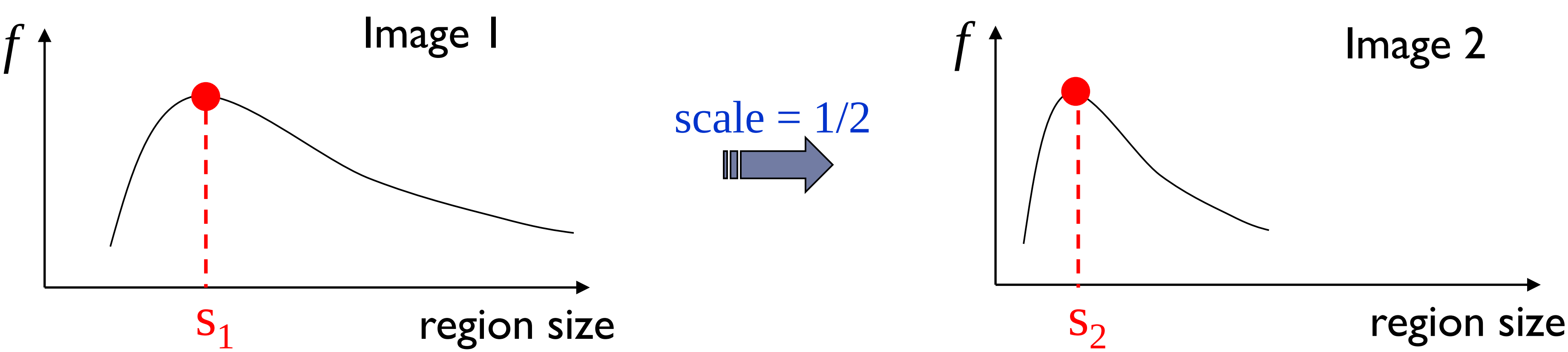
לפונקציה הזאת יש אותה צורה מתוחה
אבל עם אותה מקסימום



Automatic scale selection

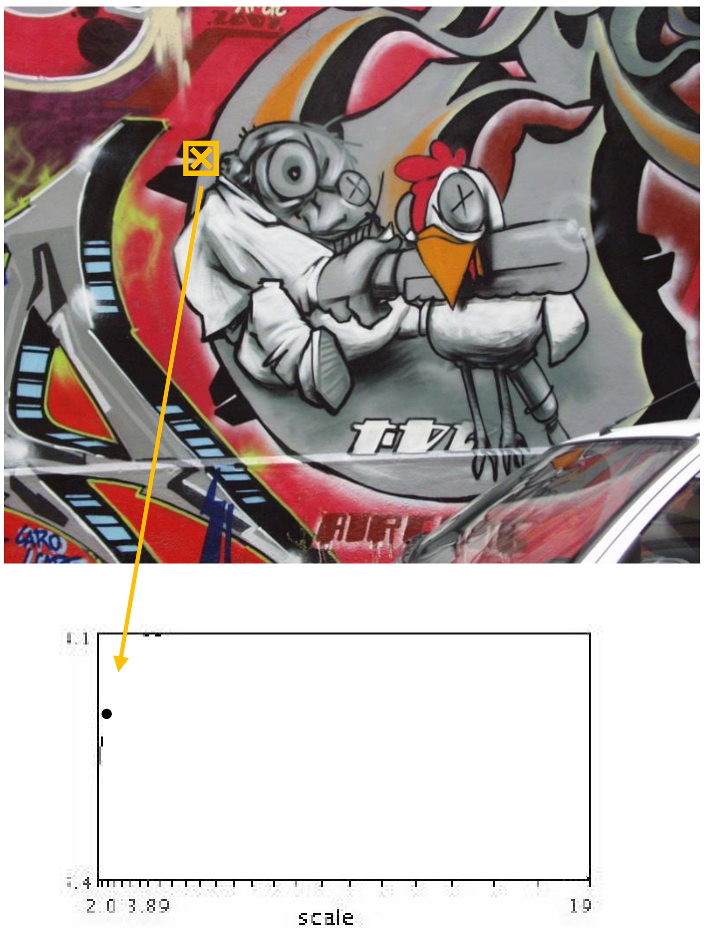
- Common approach:
  - Take a local maximum of this function
  - <u>Observation</u>: region size, for which the maximum is achieved, should be *invariant* to image scale.

Important: this scale invariant region size is found in each image independently!

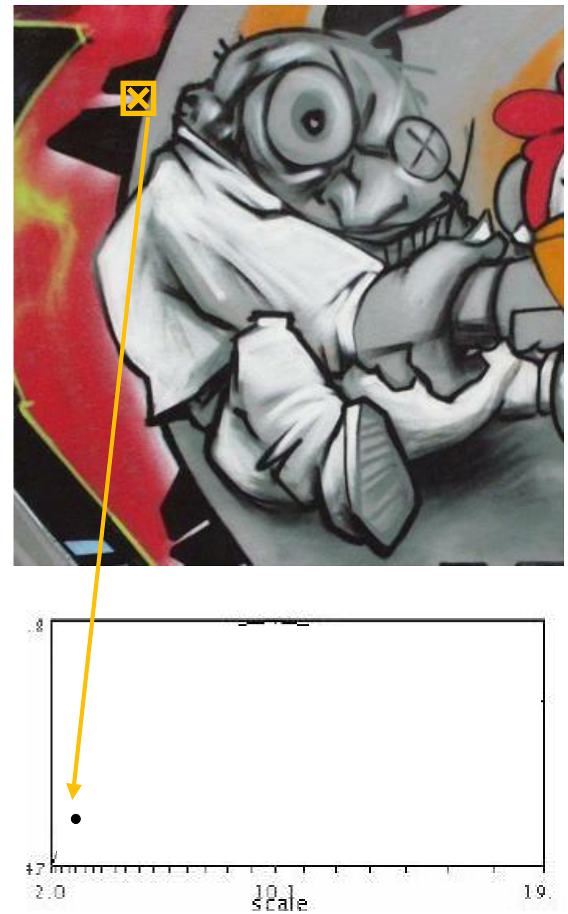


Automatic Scale Selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \ldots i_m}(x, \sigma))$



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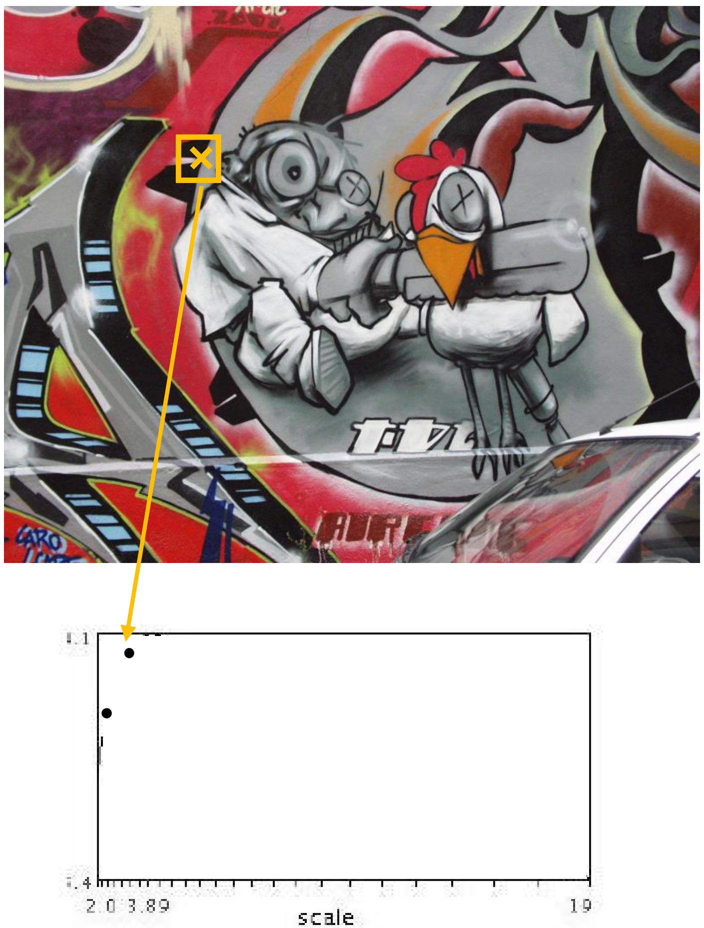

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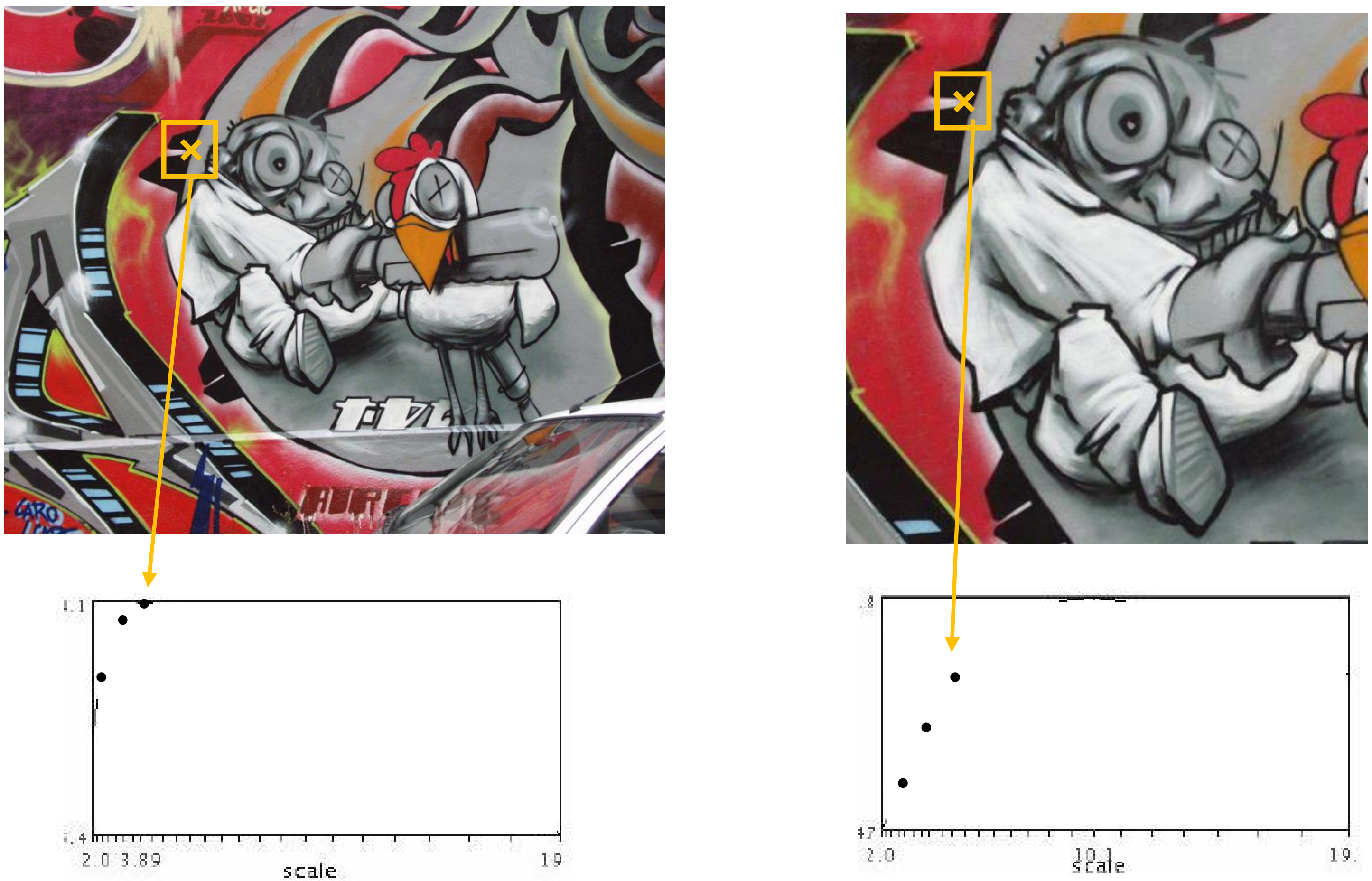

$f(I_{i_1 \ldots i_m}(x, \sigma))$ $f(I_{i_1 \ldots i_m}(x', \sigma))$

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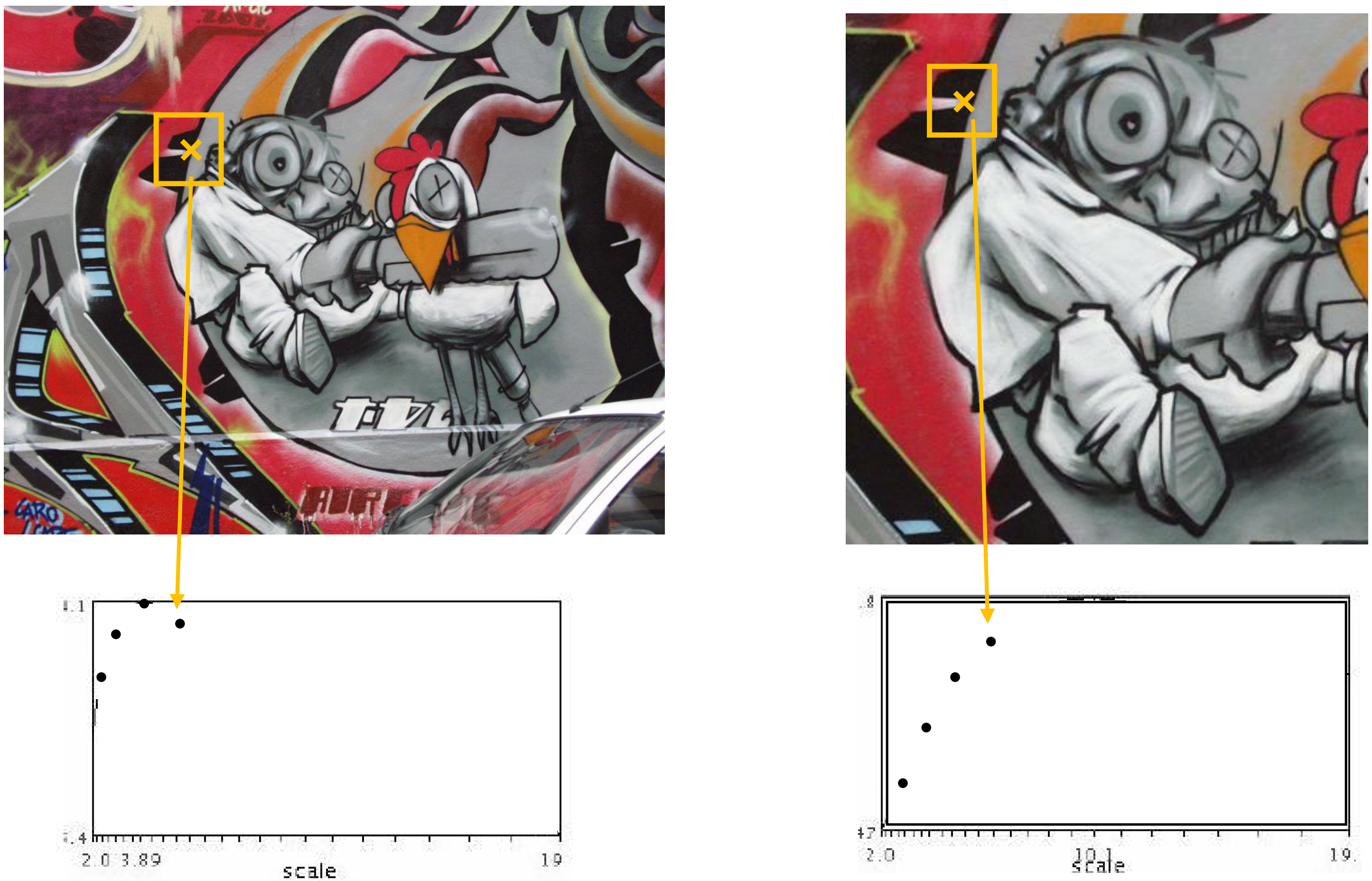

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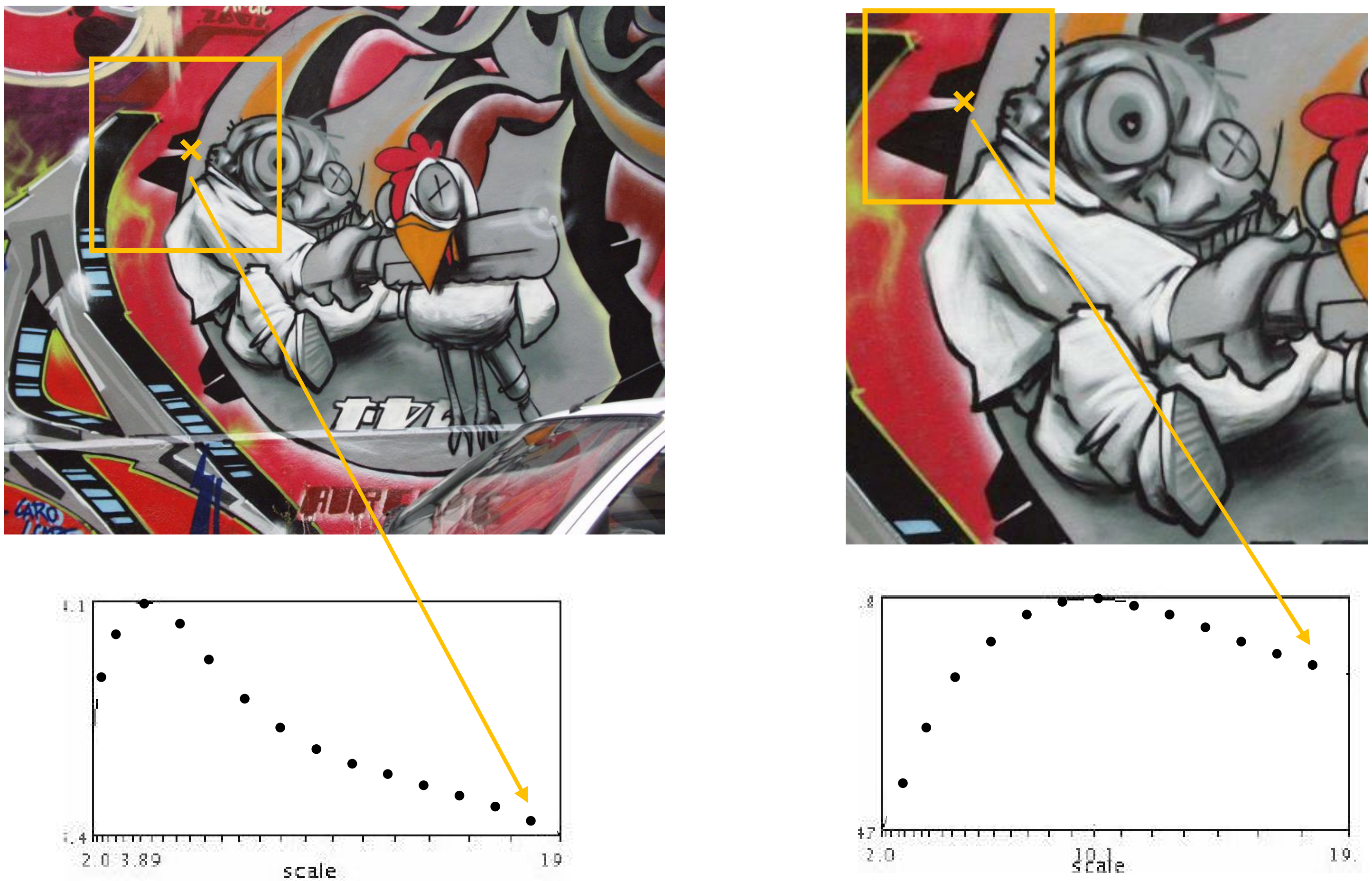

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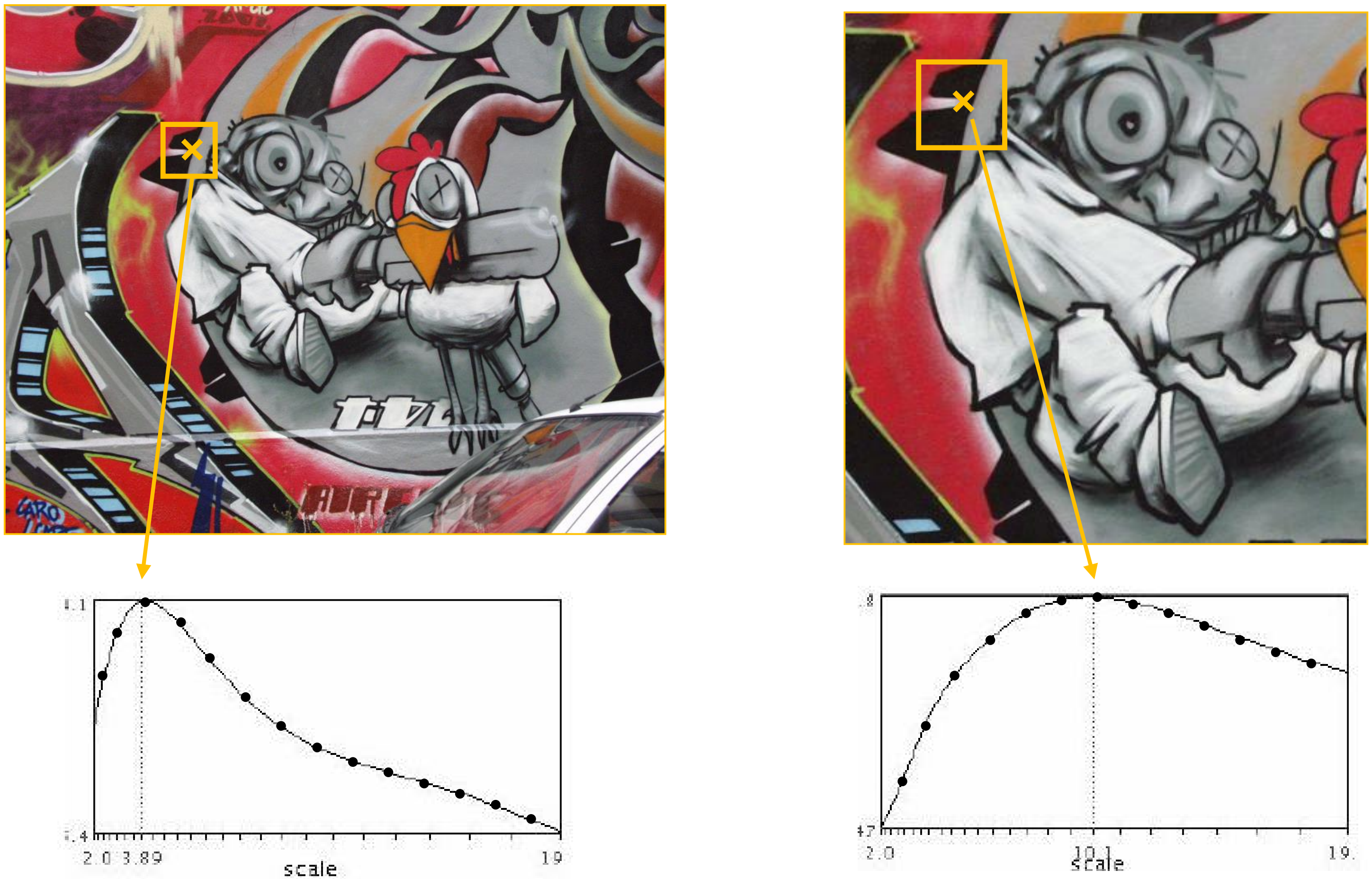
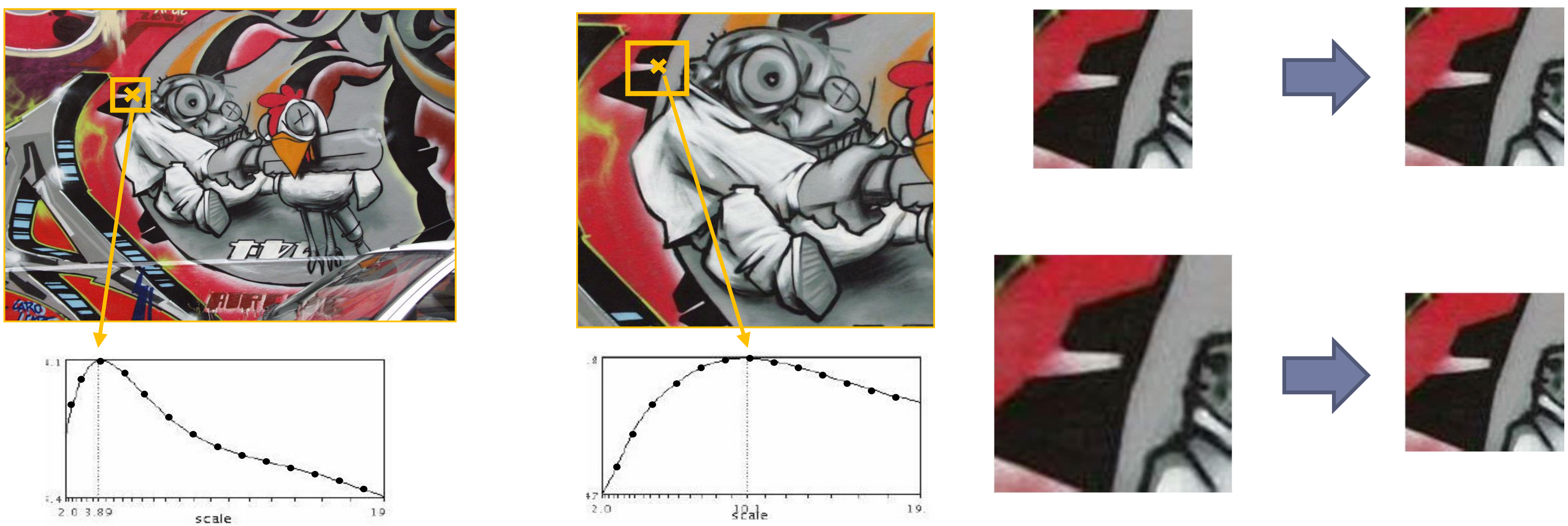


$f(I_{i_1 \ldots i_m}(x,\sigma))$ $\quad$ $f(I_{i_1 \ldots i_m}(x',\sigma'))$

Automatic Scale Selection

- Normalize: rescale selected regions to a fixed size

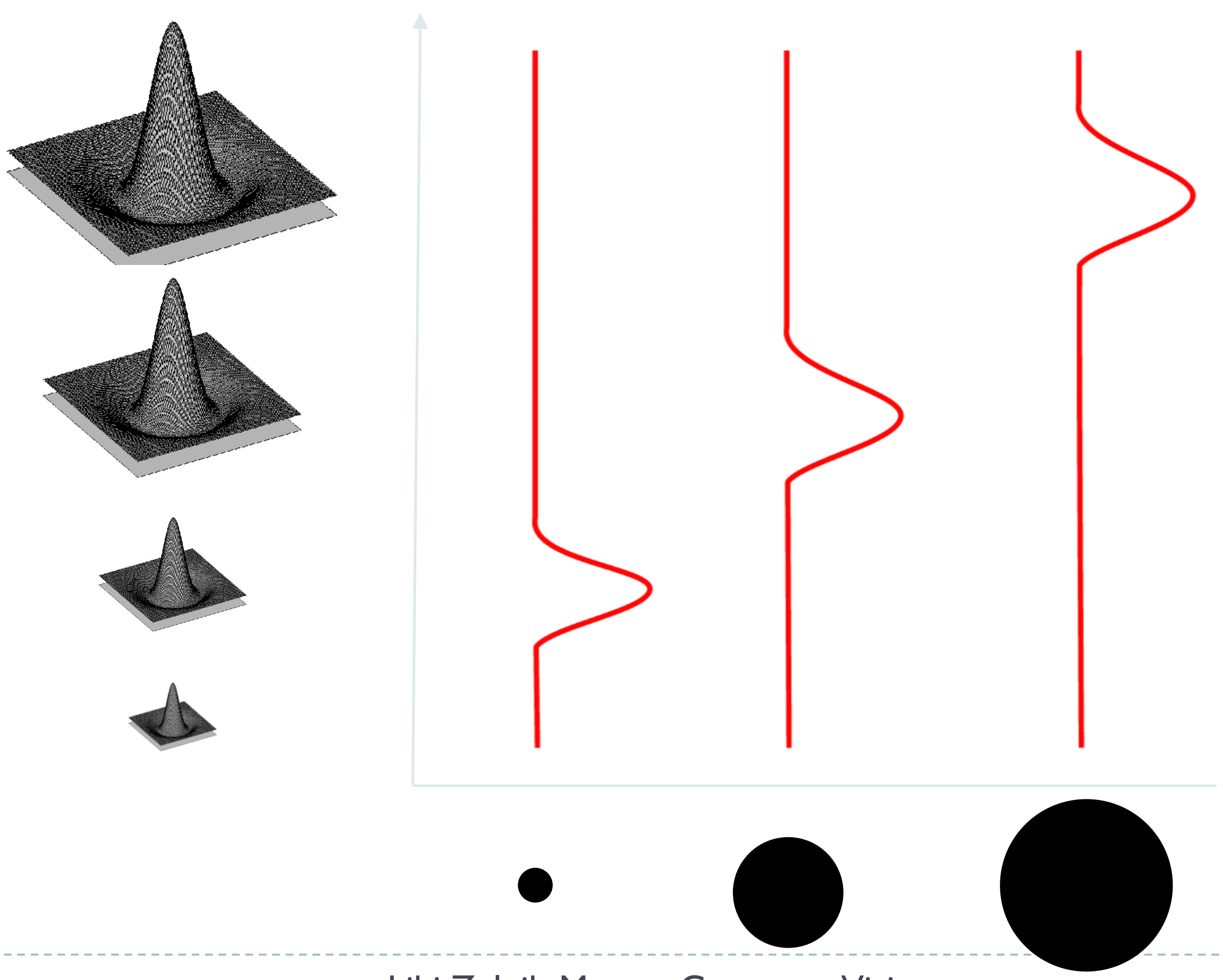


$f(I_{i_1 \ldots i_m}(x,\sigma))$ $f(I_{i_1 \ldots i_m}(x',\sigma'))$

התוצאה היא הסקלוט השונות לריבועית שאני רוצה להשוות אותם

A useful scale “signature” function

- Laplacian-of-Gaussian = “blob” detector



Harris – Laplace [Mikolajczyk’01]

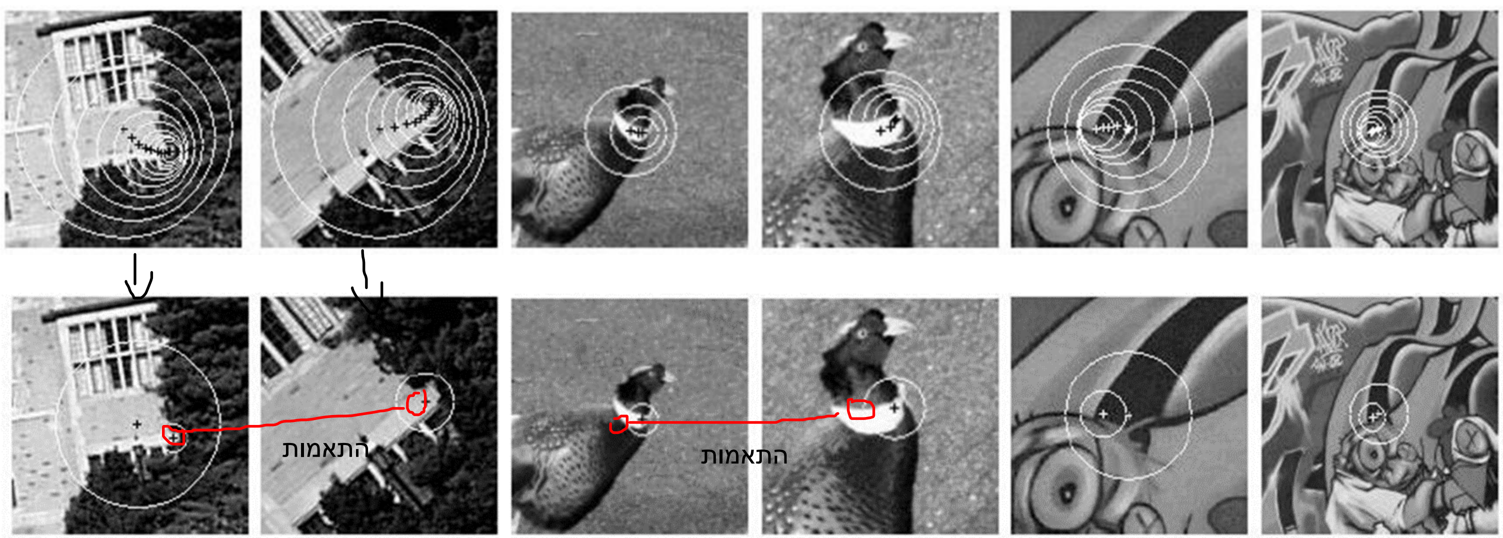
1. Keypoint detection:
   - Multi-scale Harris corner detection
2. Scale selection
   - Scale selection based on Laplacian signature

מסתכל על התמונה שלי בסביבות בגודל שונה
ובכל סביבה אני מוצא נקודת הריס

Harris points

אקסים שונים
שהתקבלו מהאריס
העגולים מיצגים את הסקלות
השונות בתמונה

Harris-Laplace points



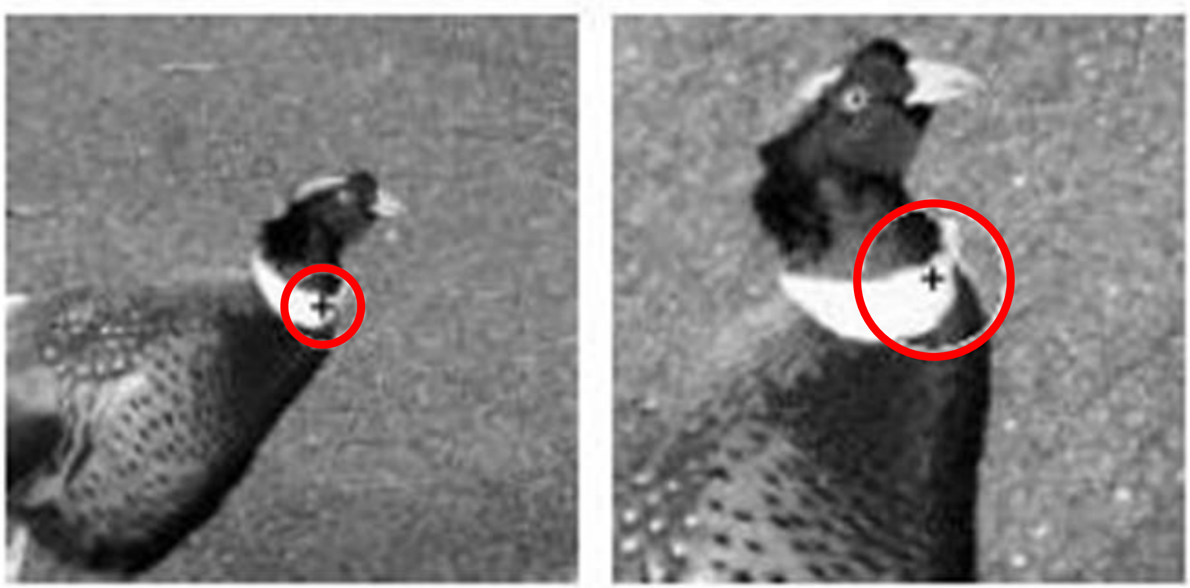
אחרי הוספת של הלפלסיאן אני
נשאר עם שתי נקודות של הריס

הנקודות שנשארו זה
מה שאני מקבל לאחר הפעלת הלפלסיאן הספציפי

התרומה של הלפלסיאן זה בעצם להגיד לי מה הסקלות הנכונות
להסתכל על הסביבה שבחרת

Harris – Laplace [Mikolajczyk'01]

1. **Keypoint detection:**
   - Multi-scale Harris corner detection
2. **Scale selection**
   - Scale selection based on Laplacian signature



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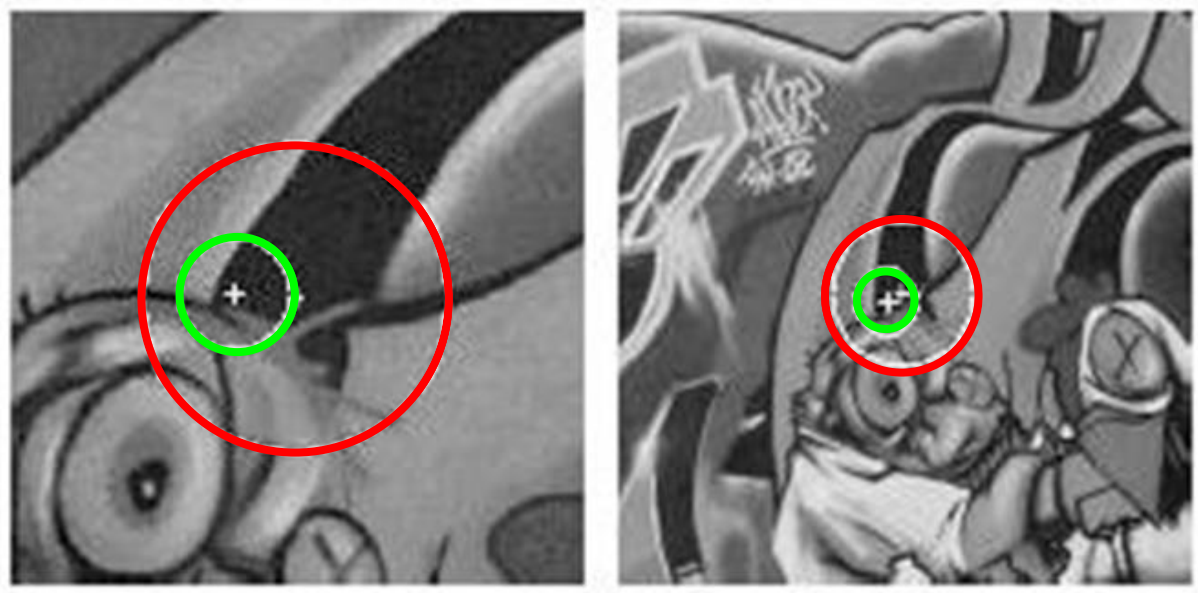

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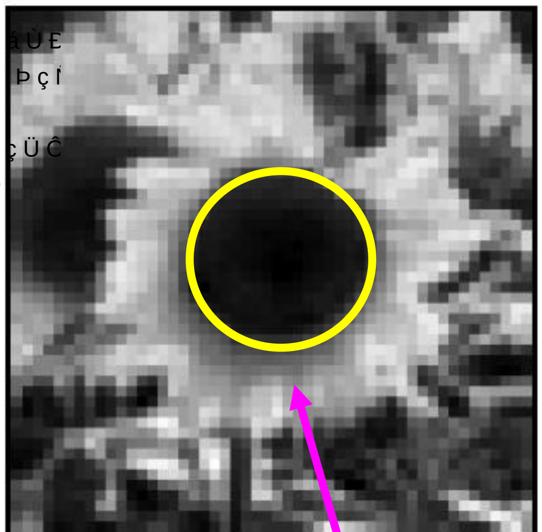
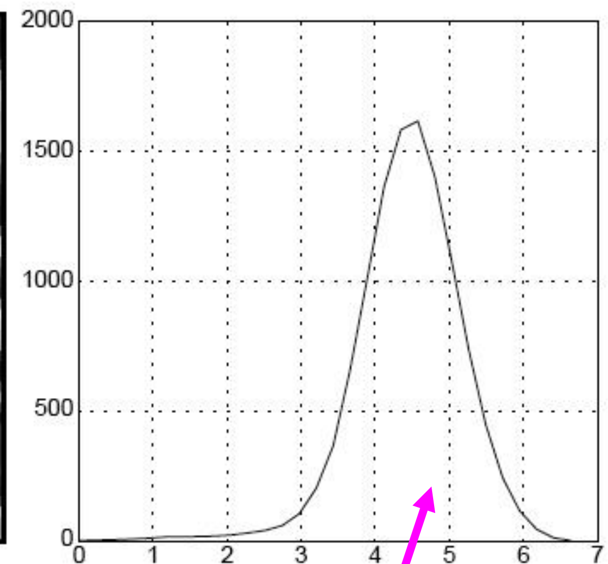
blob deduction
גודל של הבלוב בתמונה
יגדיר לי את הסקייל שבו אני רוצה להסתכל על האיזור הספציפי

Characteristic scale

- We define the *characteristic scale* as the scale that produces peak of Laplacian response

ÐàÙ âÕÑè âÝ ÛÞÔ ÜäÜ
ÕÐàÙ èÕÐÔ ÐÙäÔ ÐàÙ
ÔÒÓÕÜÔ ÑÙÕêè
ÕéÞÔ ÐàÙ çÕÑâ Ðê Ôá
éÑÔ ÐàÙ èÕæÔ ÜâÑÕÓ





characteristic scale

T. Lindeberg (1998). "Feature detection with automatic scale selection." *International Journal of Computer Vision* **30** (2): pp 77--116.

Laplacian-of-Gaussian (LoG)

- Interest points:

  Local maxima in scale space of Laplacian-of-Gaussian

$$L_{xx}(\sigma) + L_{yy}(\sigma) \rightarrow$$

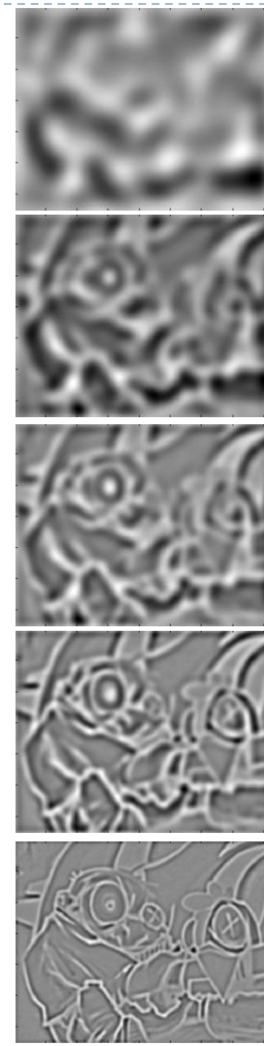
σ^5

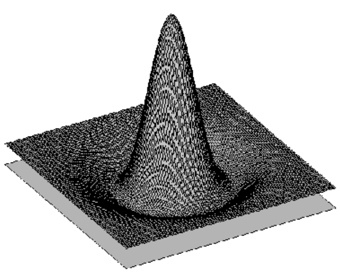
σ^4

σ^3

σ^2

σ





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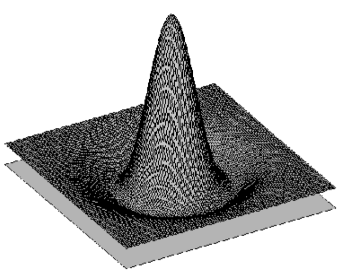
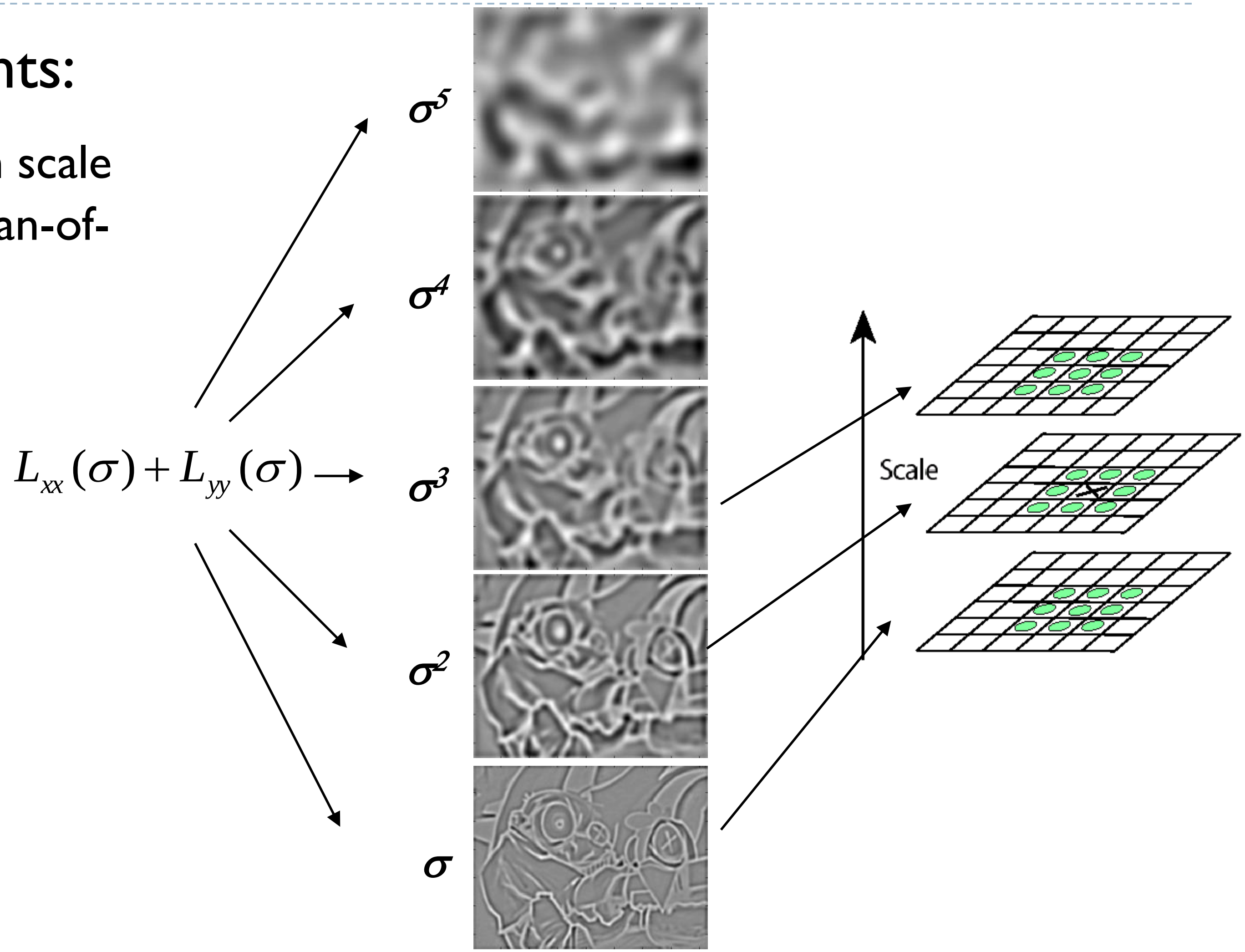


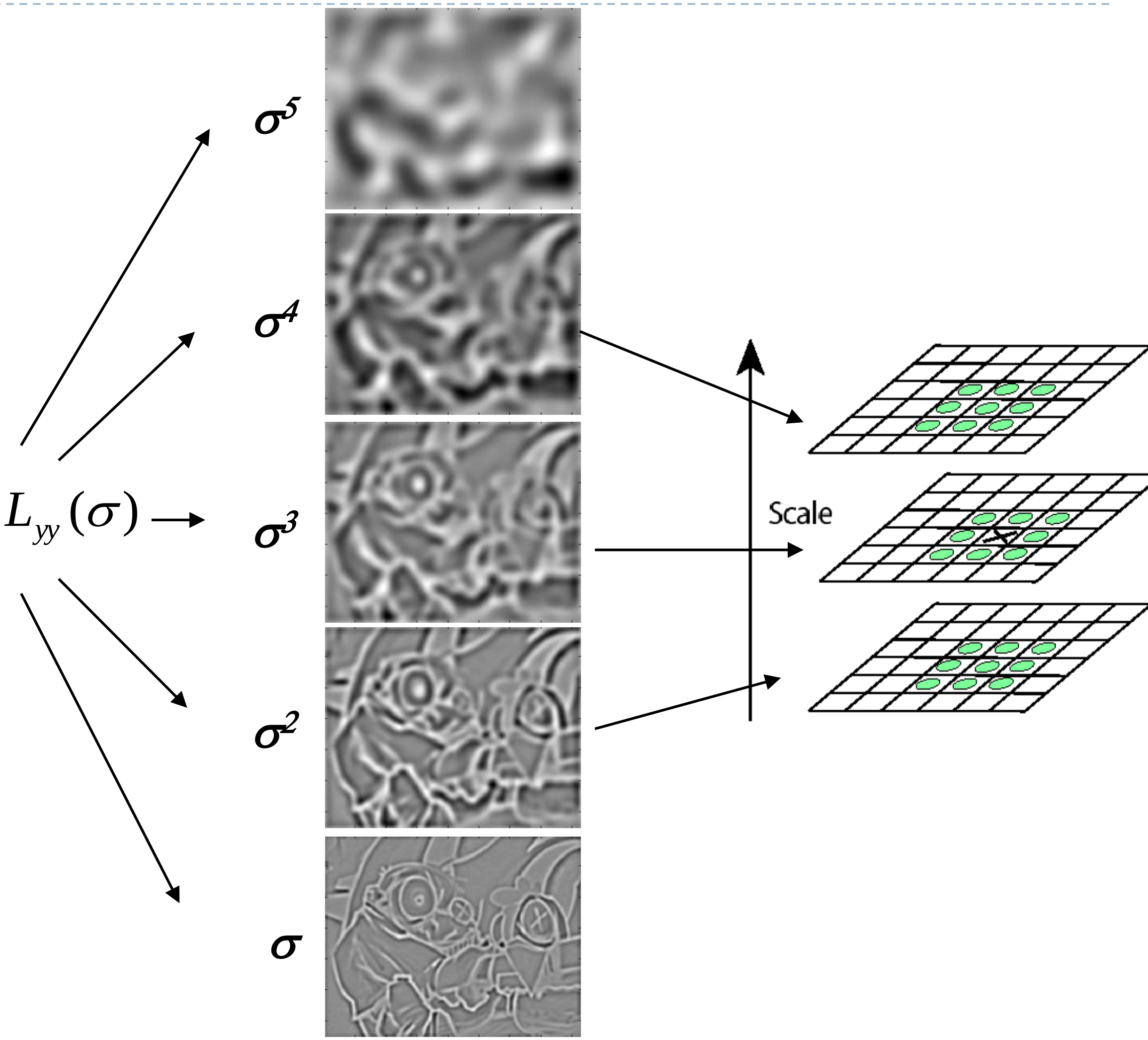


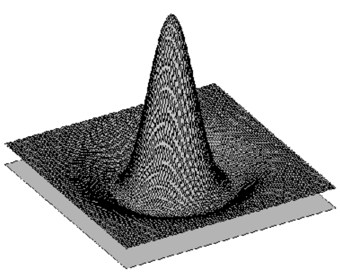
Laplacian-of-Gaussian (LoG)

- Interest points:

  Local maxima in scale space of Laplacian-of-Gaussian

$$L_{xx}(\sigma) + L_{yy}(\sigma) \longrightarrow$$





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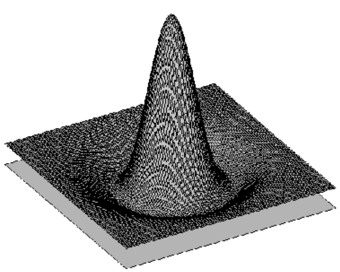
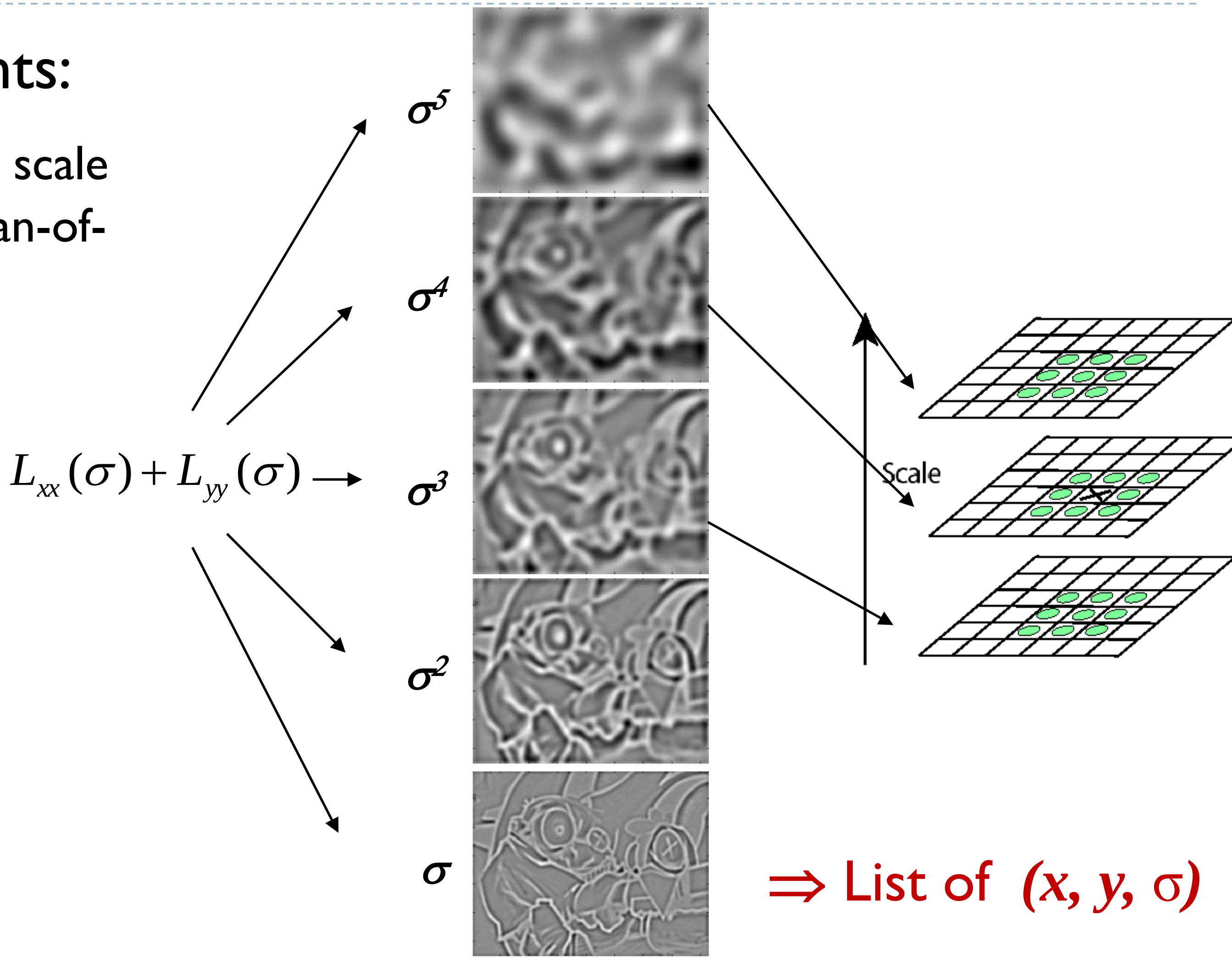




$\Rightarrow$ List of (x, y, σ)

רשימה בכל נקודה מה הסיגמה שהביאה לתגובה החזקה ביותר

LoG detector: workflow

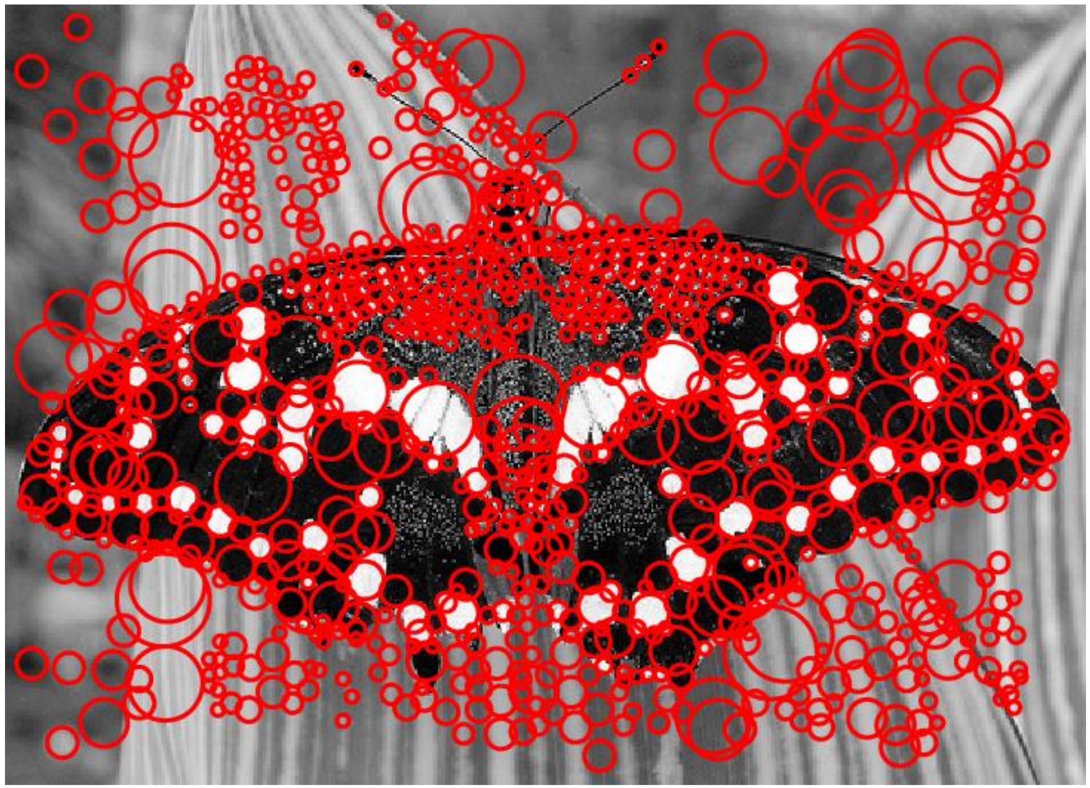
אני לוקח הרבה מאות סיגמות

לוקחים לוג דיטיקטור עם הרבה סיגמות שונות

LoG detector: workflow

sigma = 11.9912

LoG detector: example result



כאשר אני מסתכל על
כל הבלובים בתמונה אחת
הבלובים מתקבלים בהתאם לסיגמות

בלוב קטן סיגמט קטנה
בלוב גדול סיגמא גדולה

LoG technical details

- We can efficiently approximate the Laplacian with a difference of Gaussians:
  - Laplacian:

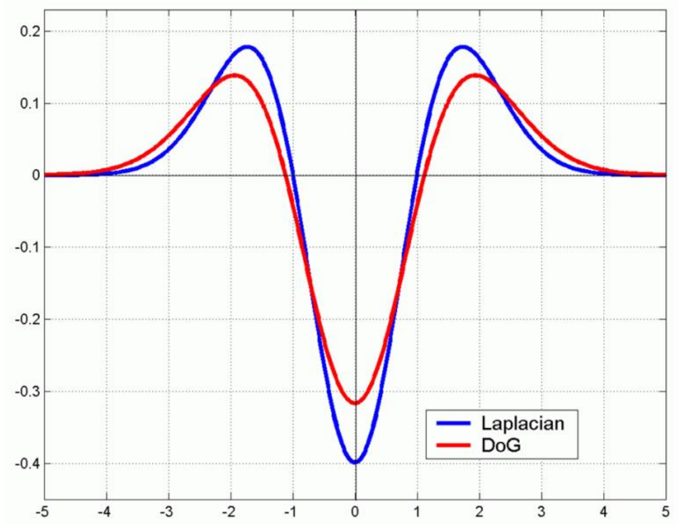
$$L = \sigma^2 \left(G_{xx}(x, y, \sigma) + G_{yy}(x, y, \sigma) \right)$$

  - DoG = Difference of Gaussians:

עניין של חישוב זריז
דימוי של לבלסיאן

$$DoG = G(x, y, k\sigma) - G(x, y, \sigma) \approx L$$

גוסיאן גדול   גוסיאן קטן



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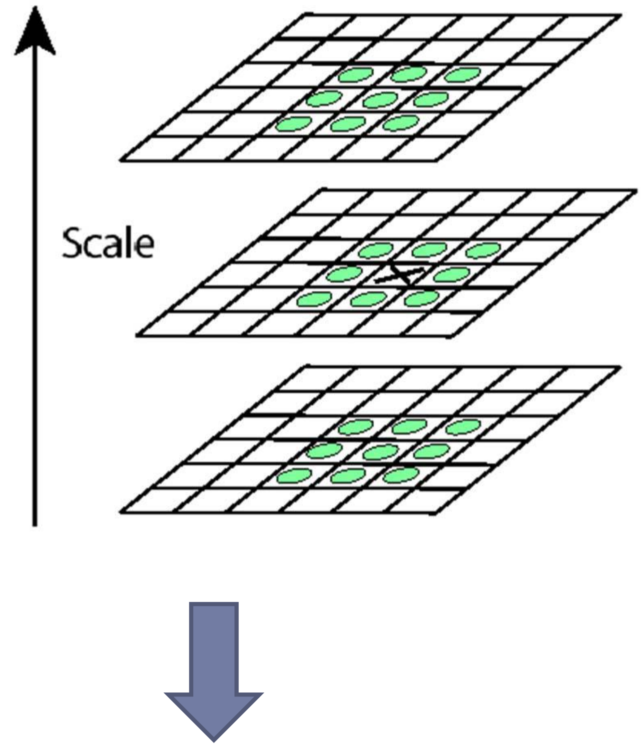
Key point localization with DoG

- Detect maxima of difference-of-Gaussian (DoG) in scale space
- Then reject points with low contrast (threshold)
- Eliminate edge responses



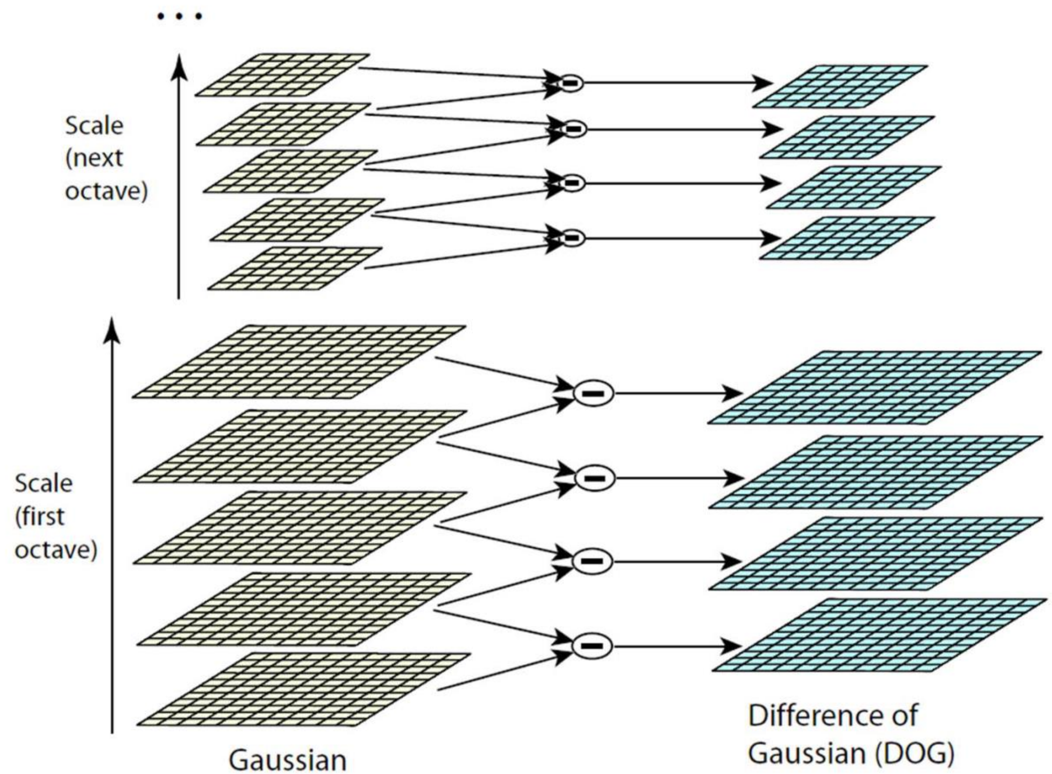
Candidate keypoints: list of (x,y,σ)

DoG – efficient computation

- Computation in Gaussian scale pyramid

Sampling with step $\sigma^4 = 2$

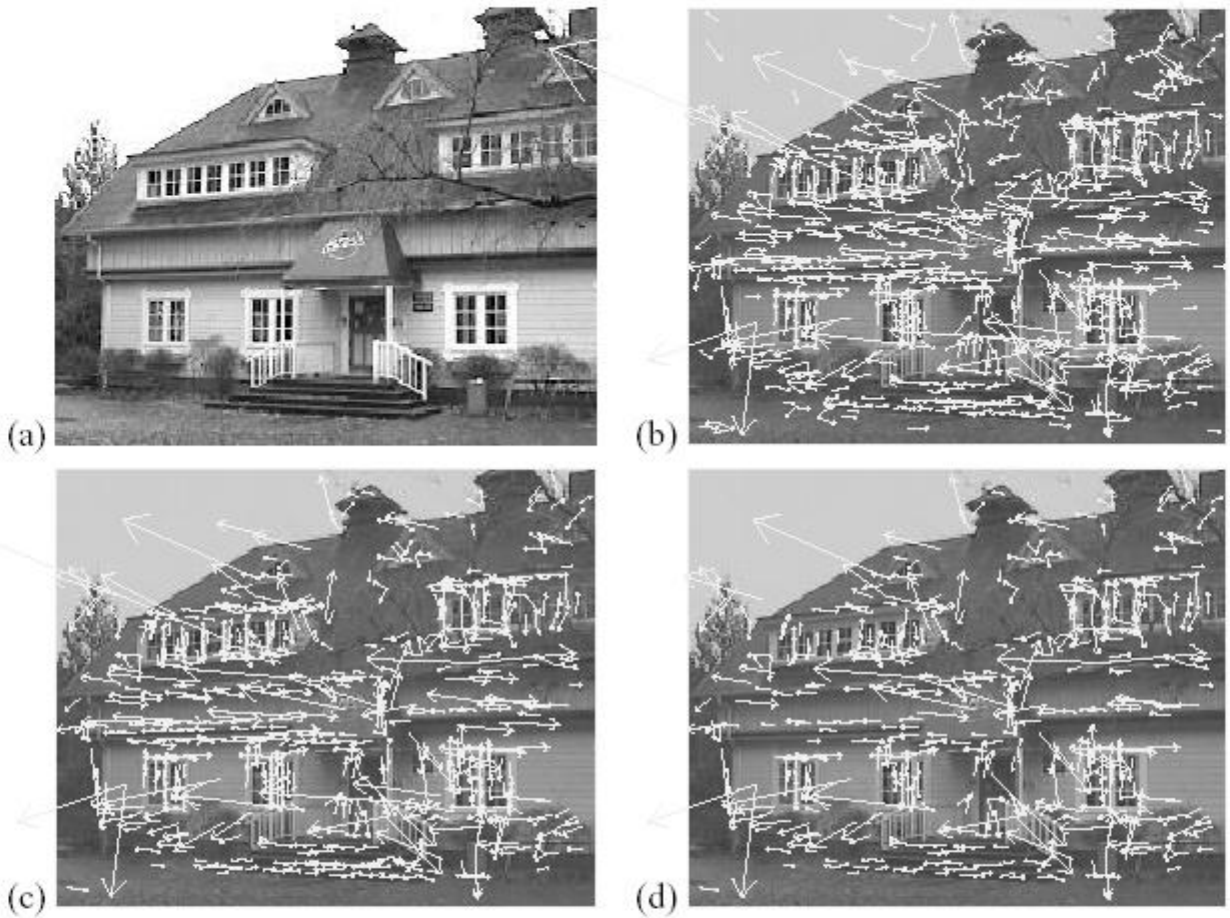
Original image



[Lowe 2004]

DoG – example result

DoG – example result



(a) 233x189 image

(b) 832 DOG extrema

(c) 729 left after peak value threshold

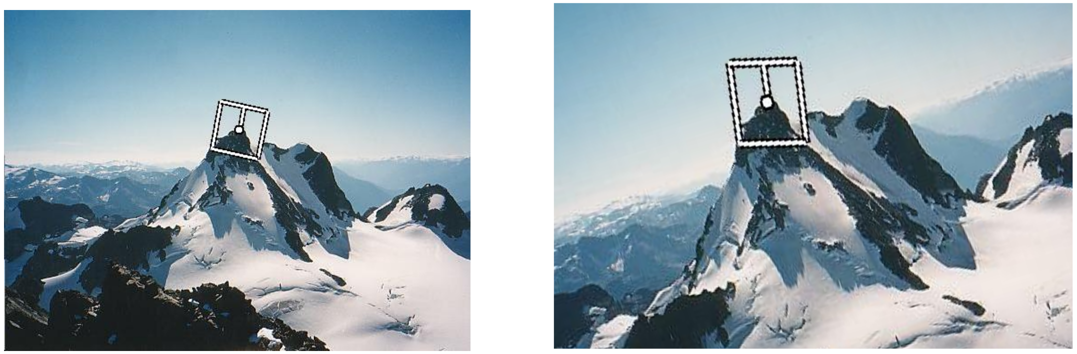
(d) 536 left after testing ratio of principle curvatures (removing edge responses)

Scale Invariant Detection: Summary

- Given: two images of the same scene with a large *scale difference* between them
- Goal: find *the same* interest points *independently* in each image
- Solution: search for *maxima* of suitable functions in *scale* and in *space* (over the image)
  1. Laplacian of Gaussian (LoG)
  2. Difference of Gaussians (DoG) – fast approximation of LoG
  3. Harris + Laplace
  4. Hessian + Laplace

Invariant regions

- So far our regions are:
  - Translation invariant (since they are centered at keypoints)
  - Scale-invariant
- What about:
  - Orientation?



Rotation invariant regions

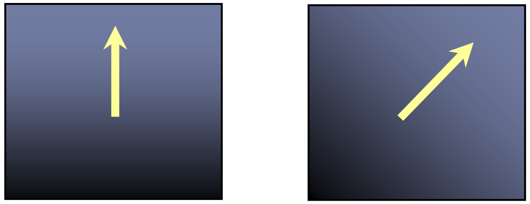
- Find local orientation
  - Compute a weighted histogram of gradient directions

נבנה הוסטרגמת כווני הגרדינטים
על ה
patch

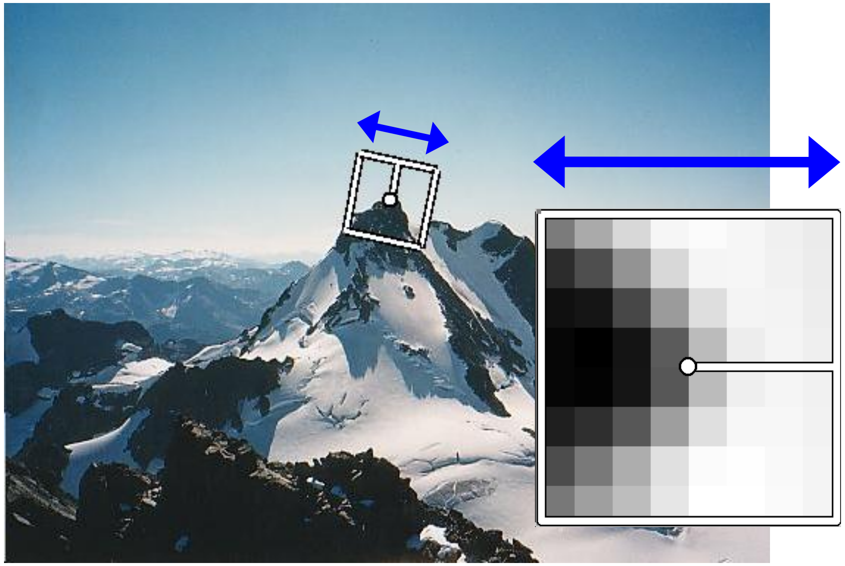
  - Find the dominant direction

רזולציית הזוויות, אני קובע אותה לפי הפינים של ההסטוגרמה
אפשר לא להכליל גרדינטים שהם לא חזקים
כלומר לא עוברים ערך סף

- Normalize orientation
  - Rotate patch according to this angle
  - This puts the patches into a canonical orientation.



רוצים למצוא את הכוון של הגרדיאנט



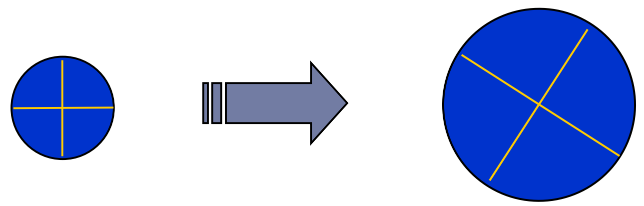
Invariant regions

- So far our regions are:
  - Translation invariant (since they are centered at keypoints)
  - Scale-invariant
  - Rotation-invariant
- What about:
  - Other transformations?

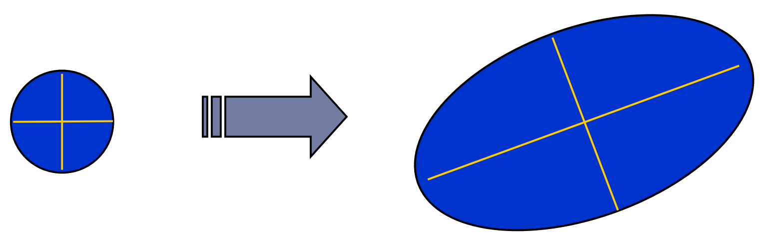
יש כאן טרנספורמציה שיר,שזה טרנספורמציה אפינית אחרת

Affine invariant regions

- Above we considered:
  Similarity transform (rotation + uniform scale)



- Now we go on to:
  Affine transform (rotation + non-uniform scale)



Affine adaption

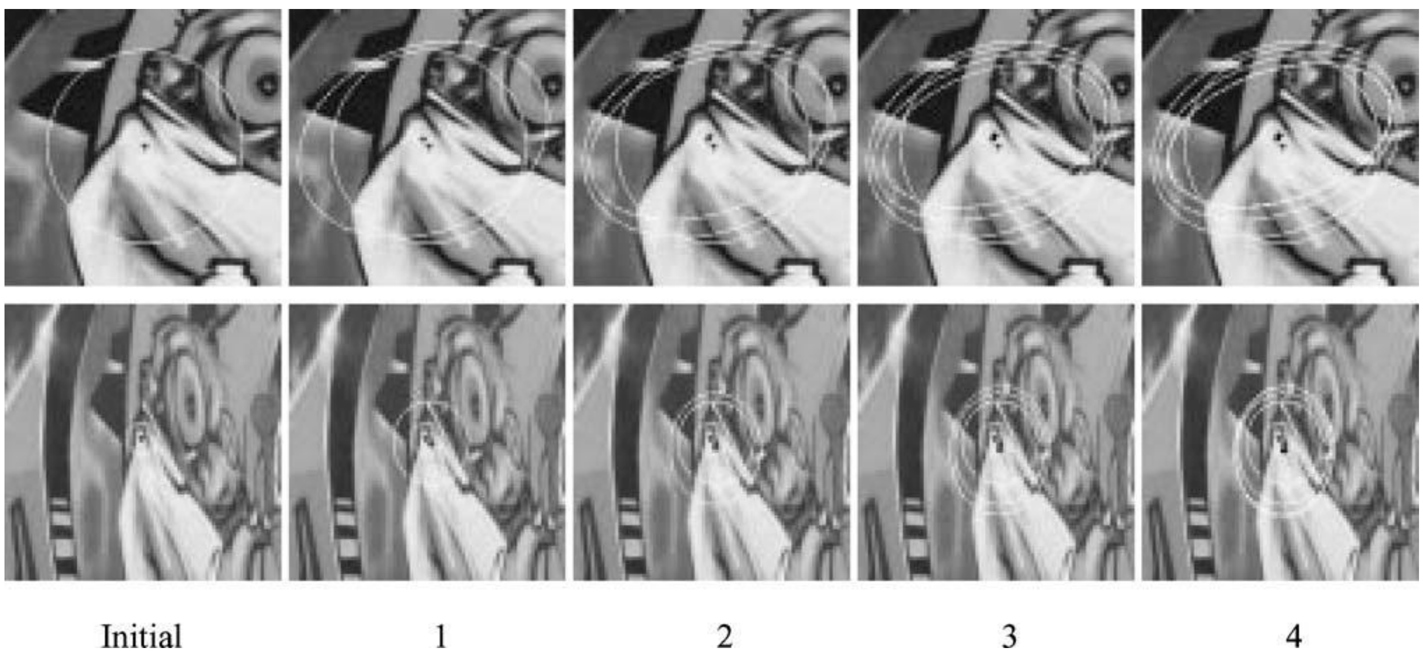
- Problem
  - Determine the characteristic shape of the region
- Assumption
  - Shape can be described by a "local affine frame"
- Solution
  - Use a circular window to compute the second-moment matrix
  - Compute eigenvectors to adapt the circle to an ellipse
  - Re-compute second-moment matrix using the new window
  - Iterate…

צורה שקל לשנות לה את הצורה
עוטפת את
האובייקט בצטרה מדוייקת יחסית

ככל שמתווצות יותר טרנספורמציות
התאמה אכותית תרד

Iterative affine adaptation

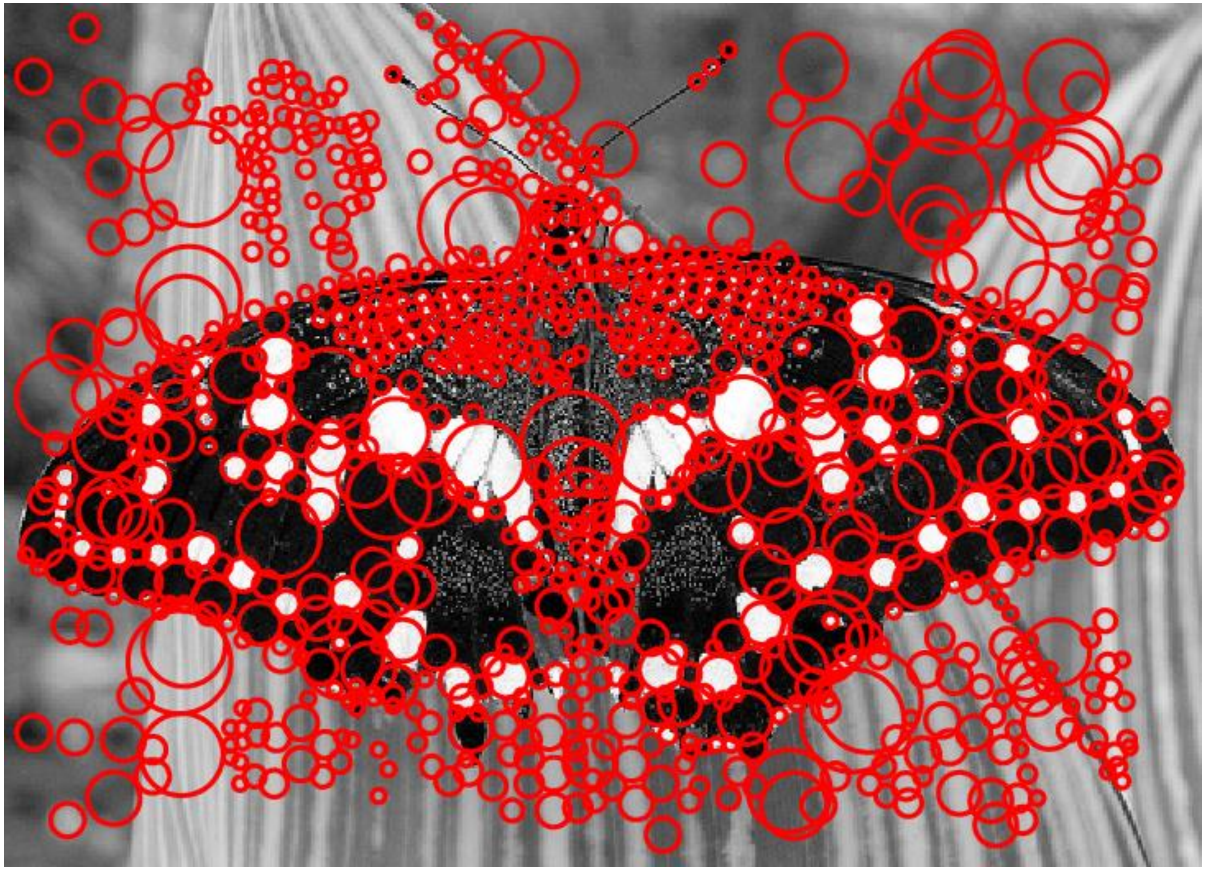
1. Detect keypoint (e.g., multi-scale Harris)
2. Automatically select the scales (e.g., Laplace signature)
3. Adapt affine shape based on second order moment matrix
4. Refine point location



Affine normalization (deskewing)

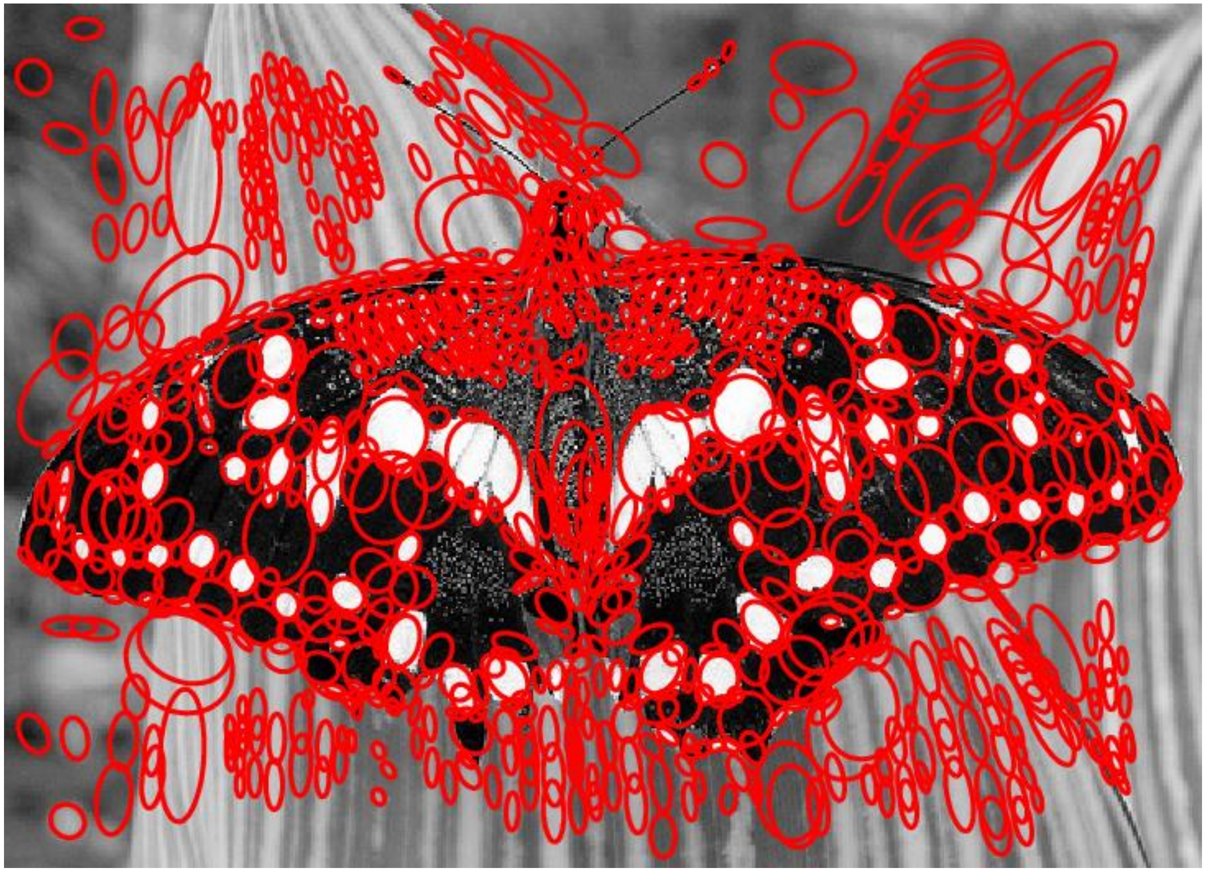
- Steps:
  - Rotate the ellipse's main axis to horizontal
  - Scale the x axis, such that it forms a circle

Affine adaptation example



Scale-invariant regions

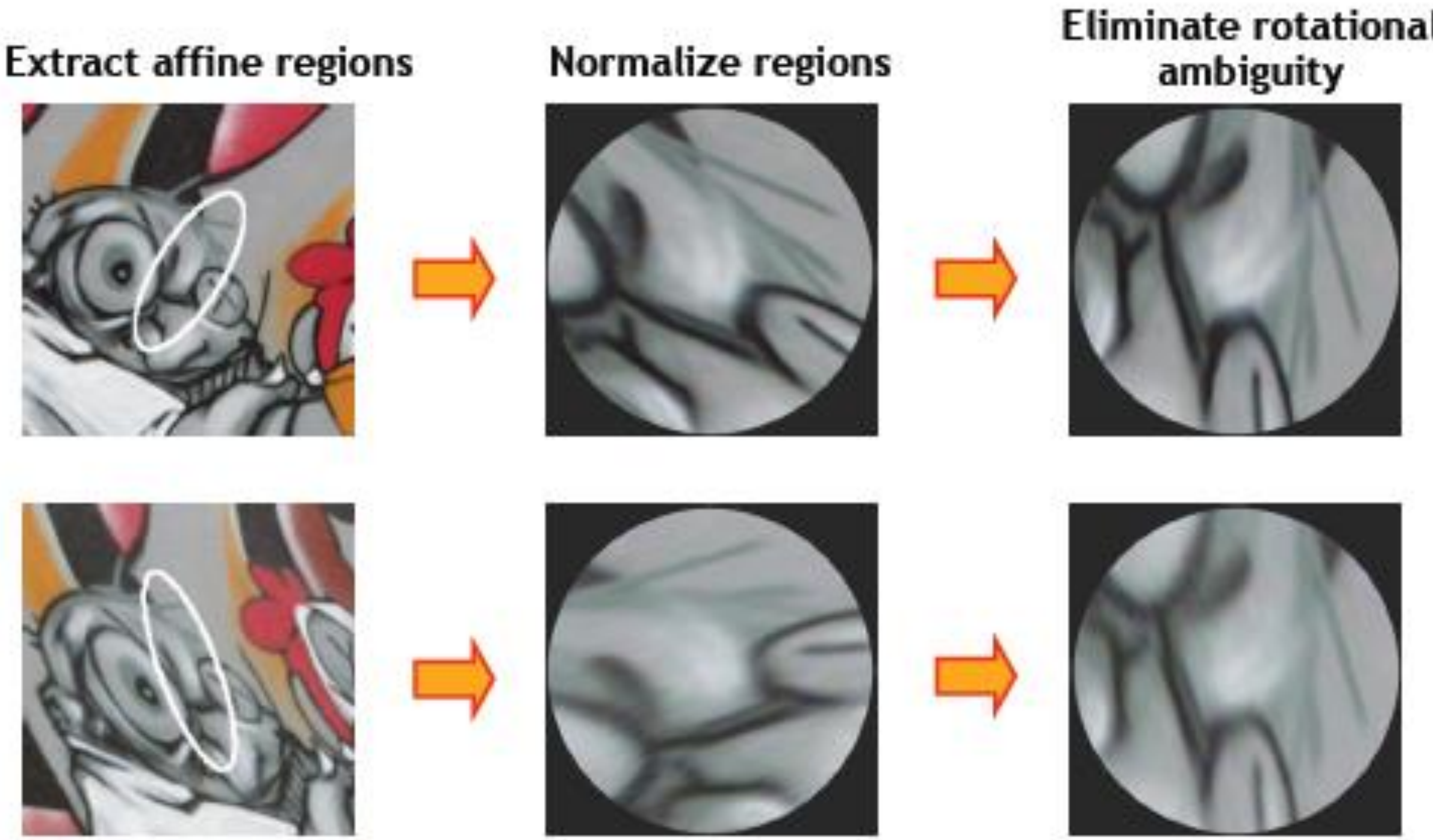
Affine adaptation example



Affine-adapted regions

Affine invariant regions example

Affine invariant regions - summary



End – From points to regions

Now you know how it works