BEUTH HOCHSCHULE FÜR TECHNIK BERLIN
University of Applied Sciences

Learning from Images

Image Descriptors and Marker detection

Master DataScience
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Course outline

- **Image descriptors**
- Image matching


What do you see?

One step back:
How do we describe an image?
How do we compare images?

Image descriptors

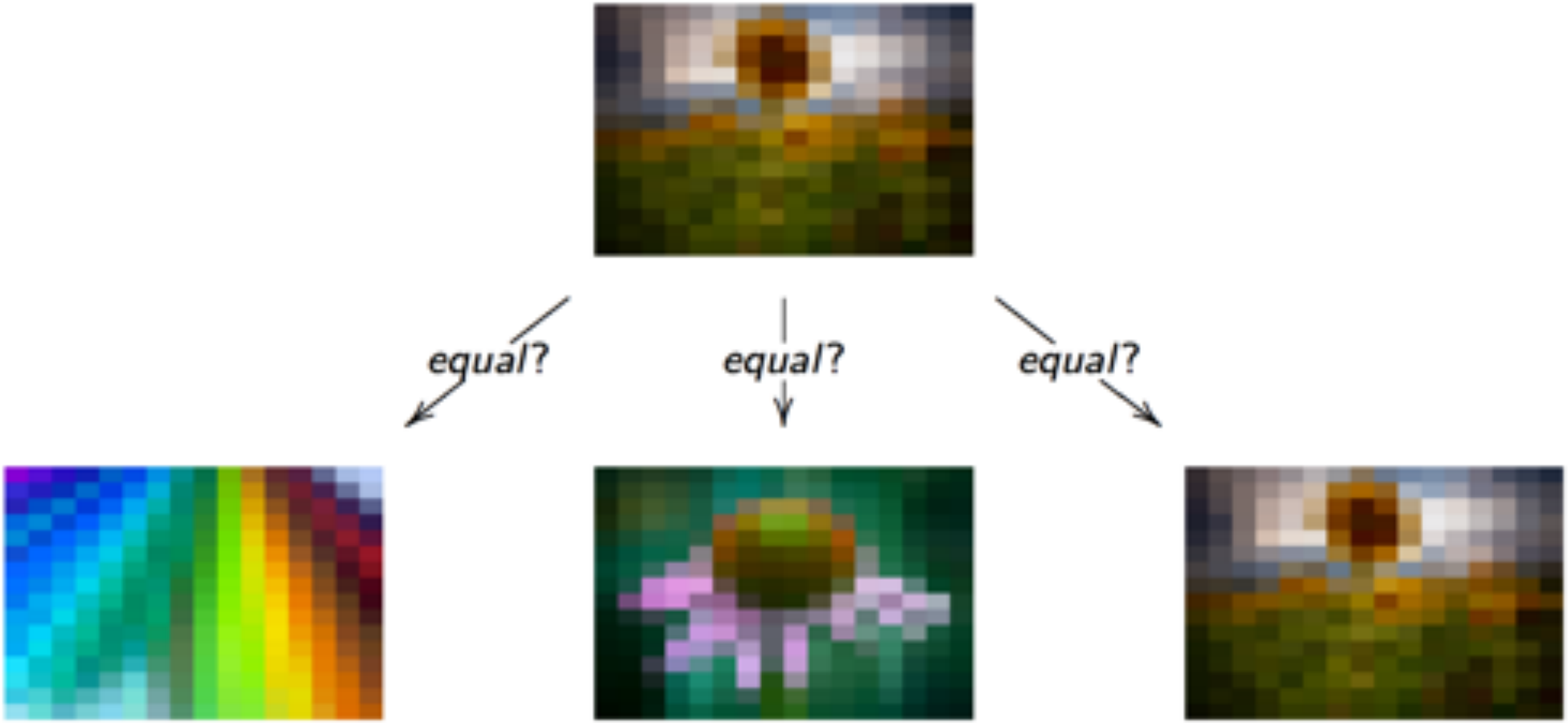
- Descriptor - a piece of stored information that is used to identify an item in an information storage and retrieval system.
  - Descriptors save pertinent information, saving the processing time in future queries
  - Descriptors can save image features that are essential for search and comparison

Global image descriptors

https://groups.csail.mit.edu/vision/TinyImages/

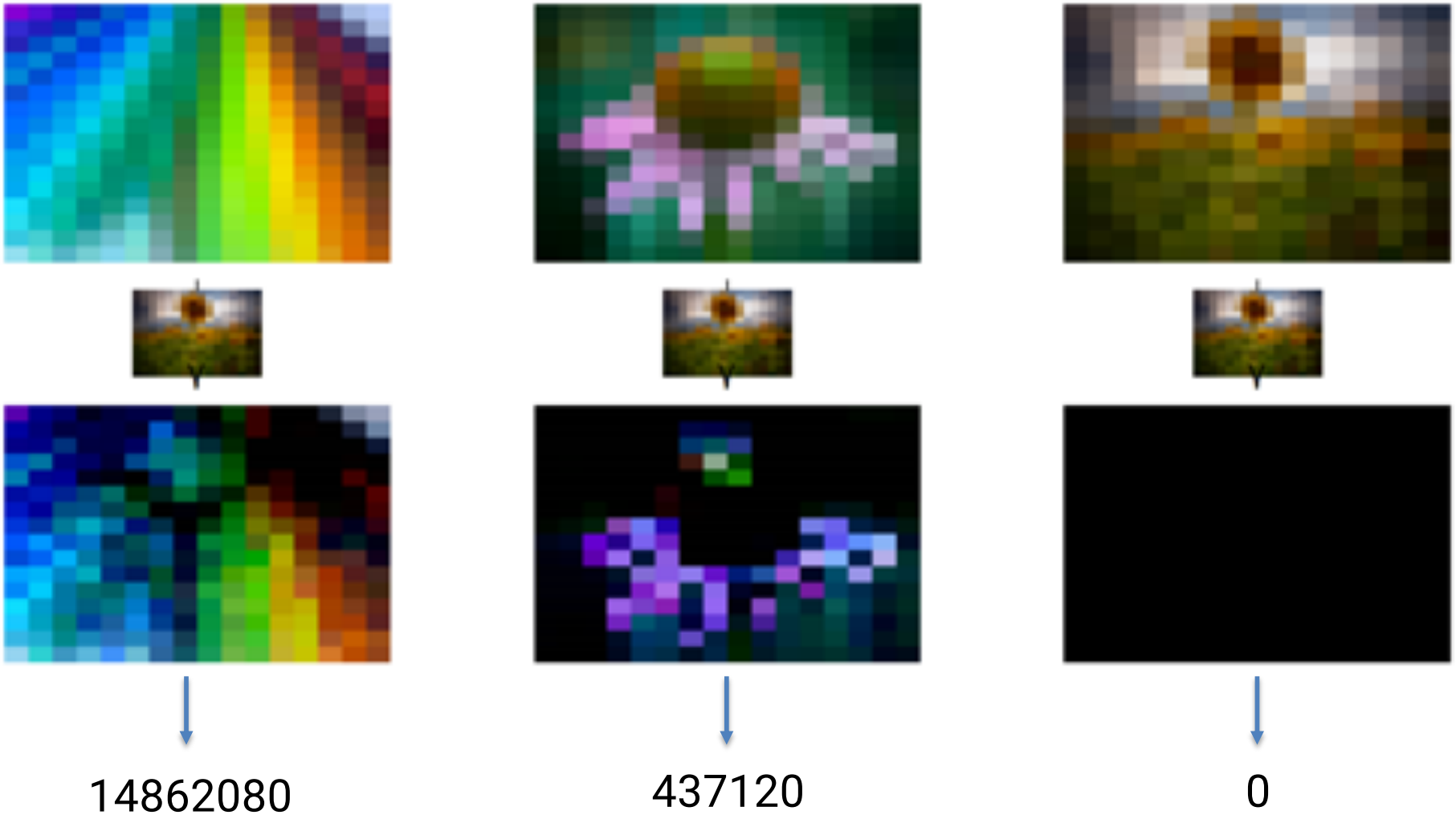
http://www.flickr.com/photos/alphageek/2759567956/

Global image descriptors



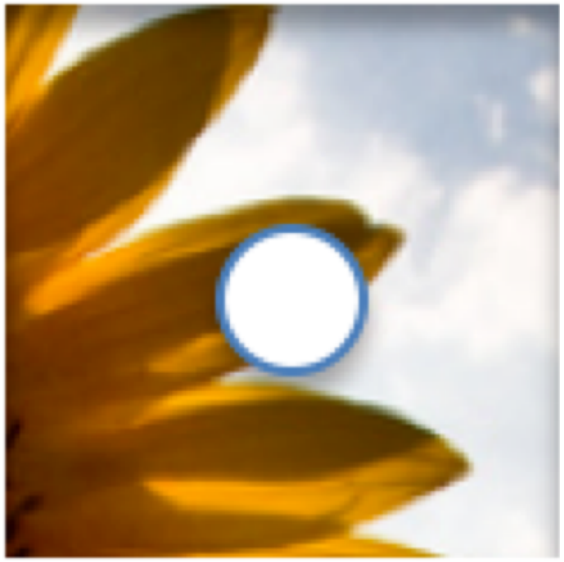
http://www.flickr.com/photos/40513596@N00/71762740
http://www.flickr.com/photos/alphageek/2993813155/

Comparison example

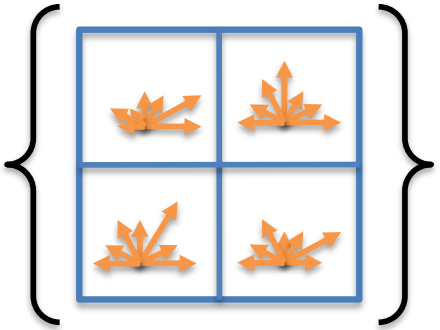


Global vs Local Features

Image as a vector



Feature description



Histogram:
http://tinlizzie.org/histograms/

0.5
0.25
0.3
0.01
0.9
0.56
0.67
…

Why local features?

- Locality
  - features are local, so robust to occlusion and clutter
- Distinctiveness:
  - can differentiate a large database of objects
- Quantity
  - hundreds or thousands in a single image
- Efficiency
  - real-time performance achievable
- Generality
  - exploit different types of features in different situations

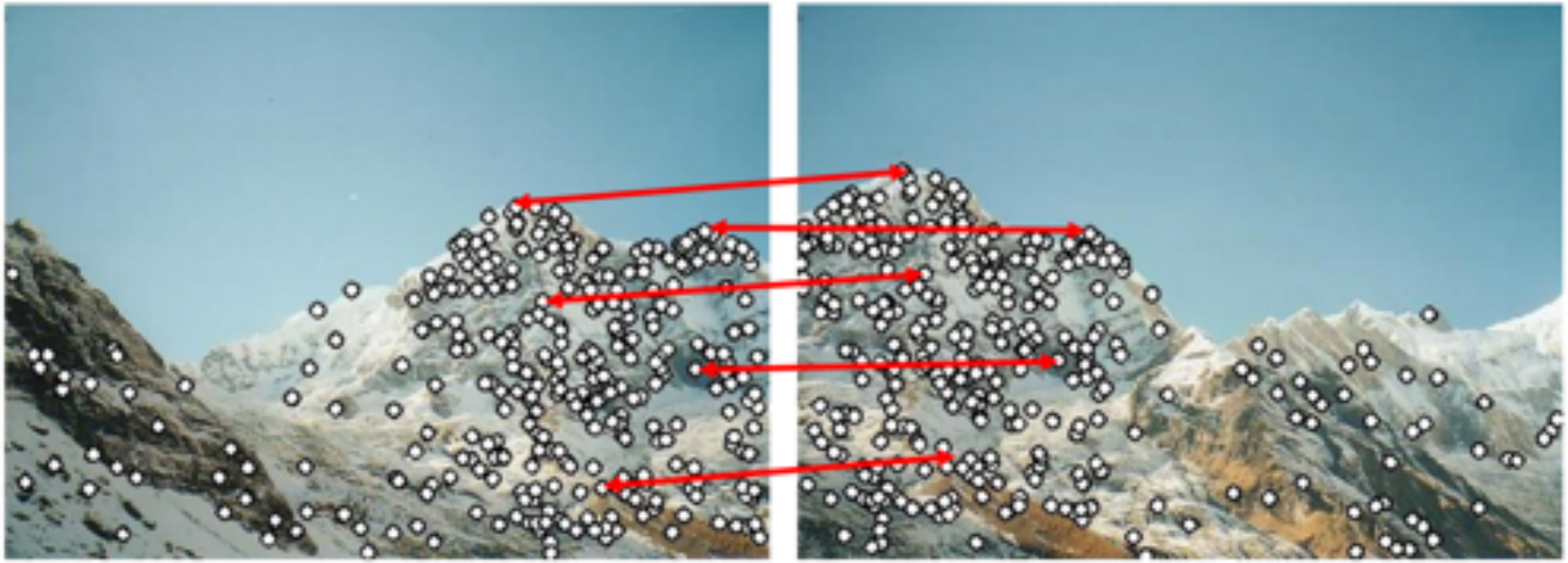
Applications

- Features are used for:
  - Image alignment (e.g., panoramic mosaics)
  - Object recognition
  - 3D reconstruction (e.g., stereo)
  - Motion tracking
  - Indexing and content-based retrieval
  - Robot navigation
  - …

What is a keypoint?

What is a good feature?

- need to detect that feature in the next frame again



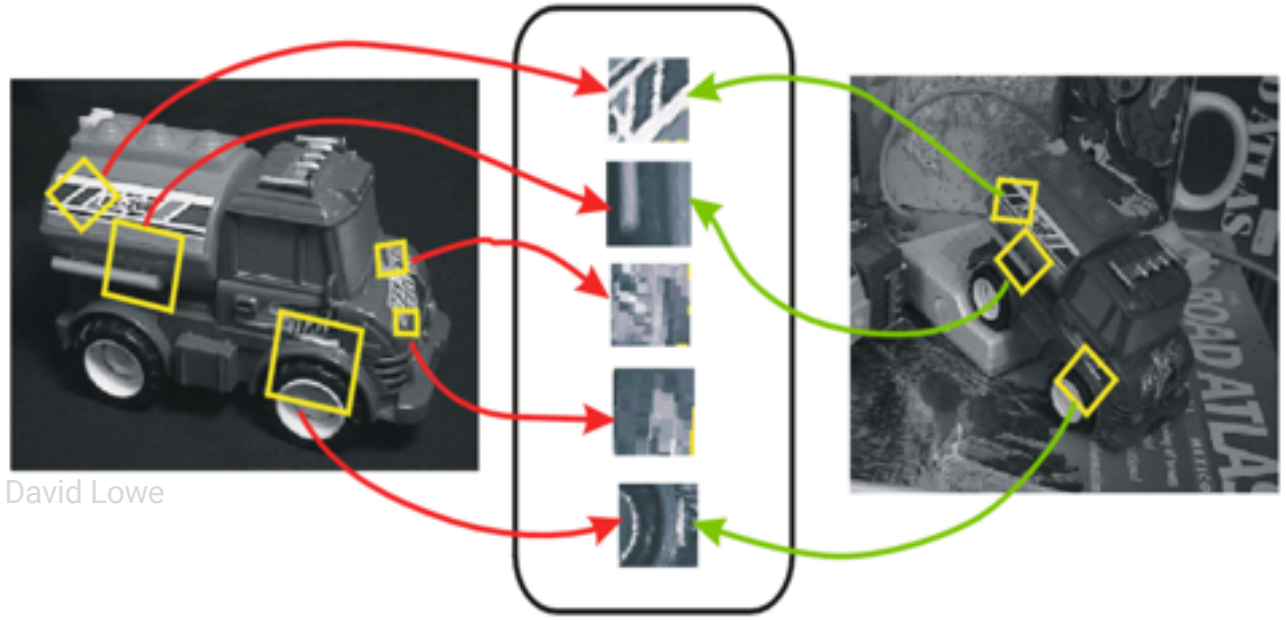
David Lowe

What makes a good feature?

- Want uniqueness
  - Leads to unambiguous matches in other images
- Look for “interest points”
- Stable under lighting and viewpoint changes
- Keypoints that are similarity- and affine-invariant, or at least stable
- Enable accurate matching of keypoints between images
  - Object recognition / Marker detection / image registration

Transformation invariance

- Want features that are invariant to transformations (affine-invariant)
  - geometric invariance: translation, rotation, scale
  - photometric invariance: brightness, exposure, …



David Lowe

Features descriptors

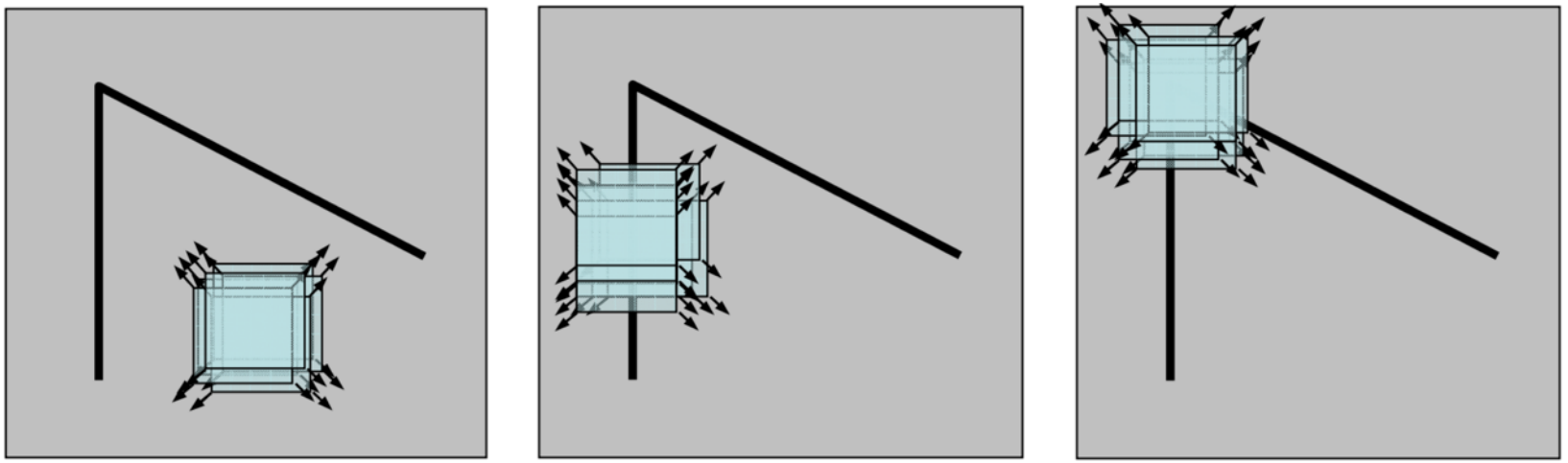
Feature Detection / Location

- What could be a possible detector?
  - random?
  - uniform?
  - edges?
  - **corners?**
- corners – intersection of edges
  - point where direction of intersections change
  - gradient of the image (in both directions) has high variation
    - this can be detected = we look for variation

Harris corner detector – The basic idea

- C.Harris, M.Stephens. “A Combined Corner and Edge Detector”. 1988
- We should easily recognize the point by looking through a small window
- Shifting a window in any direction should give a large change in intensity

https://courses.cs.washington.edu/



“flat” region:
no change in all directions

“edge”: no change
along the edge direction

“corner”: significant
change in all directions

Harris corner detector
Demo

Harris corner detector – The math

- detect change of intensity for a window shift

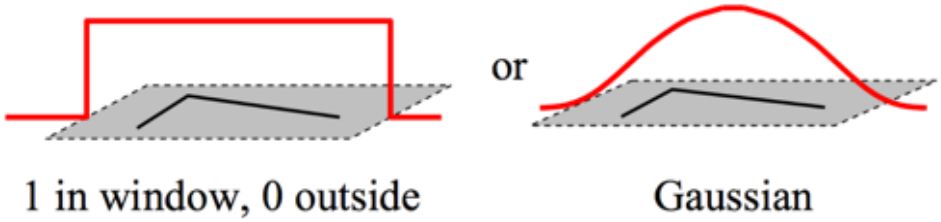
$$E(u,v) = \sum_{x,y} \quad w \quad [I(x+u, y+v) - I(x,y)]^2$$

w: Window function

$I(x+u, y+v)$: Shifted intensity

$I(x,y)$: Intensity

- Window function w(x,y):



https://courses.cs.washington.edu/

- Maximize variation within window

Harris Corner Detector – the Math

First order approximation from Taylor Series

$$f(x+u, y+v) \approx f(x,y) + u f_x(x,y) + v f_y(x,y)$$

$$\begin{aligned}
E(u,v) &= \sum_{x,y} w(x,y)[I(x+u,y+v) - I(x,y)]^2 \\
&\approx \sum_{x,y} w(x,y)[I(x,y) + uI_x(x,y) + vI_y(x,y) - I(x,y)]^2 \\
&= \sum_{x,y} w(x,y)u^2 I_x^2 + 2uvI_xI_y + v^2 I_y^2 \\
&= \sum_{x,y} \begin{pmatrix} u & v \end{pmatrix} \begin{pmatrix} I_x^2 & I_xI_y \\ I_xI_y & I_y^2 \end{pmatrix} \begin{pmatrix} u \\ v \end{pmatrix}
\end{aligned}$$

rewrite as matrix equation

just the product of components of the gradient I_x, I_y also known as structure tensor

Harris corner detector – The math

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

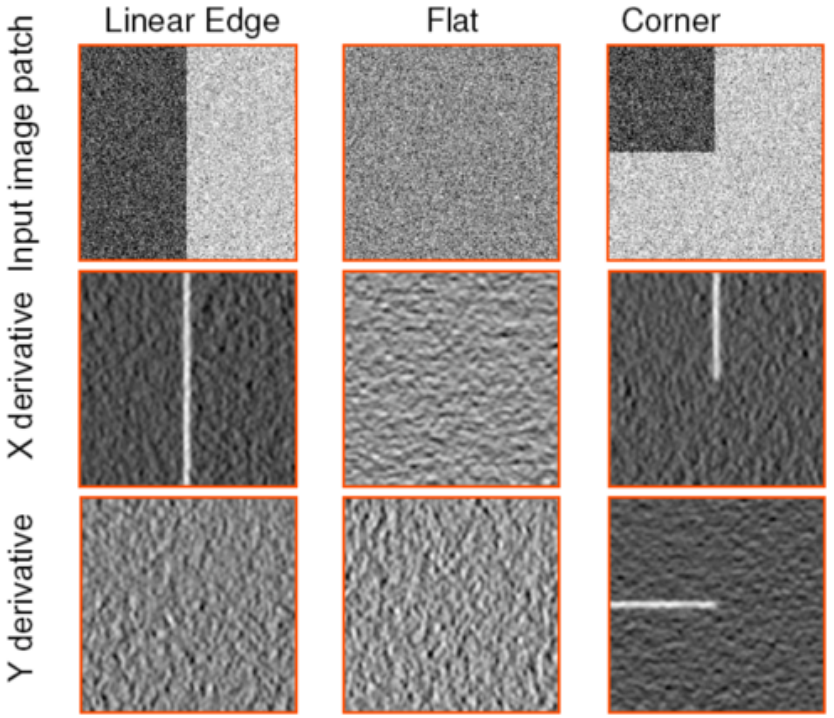
$$E(u,v) = \begin{pmatrix} u & v \end{pmatrix} M \begin{pmatrix} u \\ v \end{pmatrix}$$

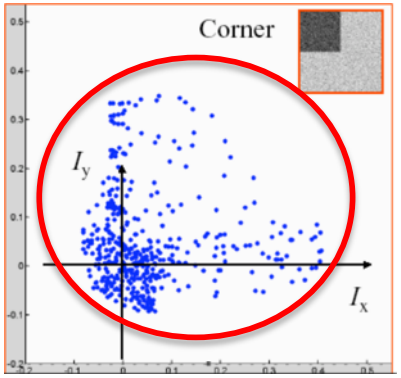
- where M is a 2×2 matrix computed from image derivatives:

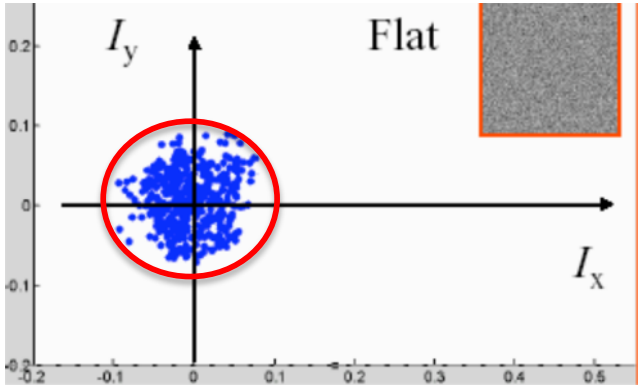
$$M = \sum_{x,y} w(x,y) \begin{pmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{pmatrix}$$

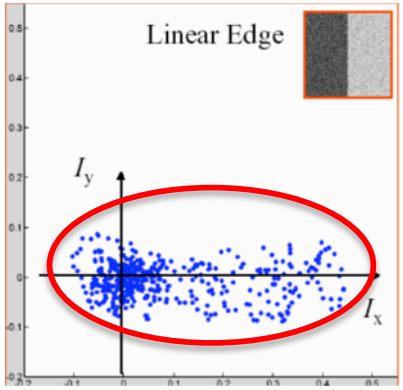
Harris corner detector – The intuitive way

- Treat gradient vectors as a set of *(dx,dy)* points with a center of mass defined as being at (0,0)
- Fit an ellipse to that set of points via scatter matrix
- Analyze ellipse parameters for varying cases



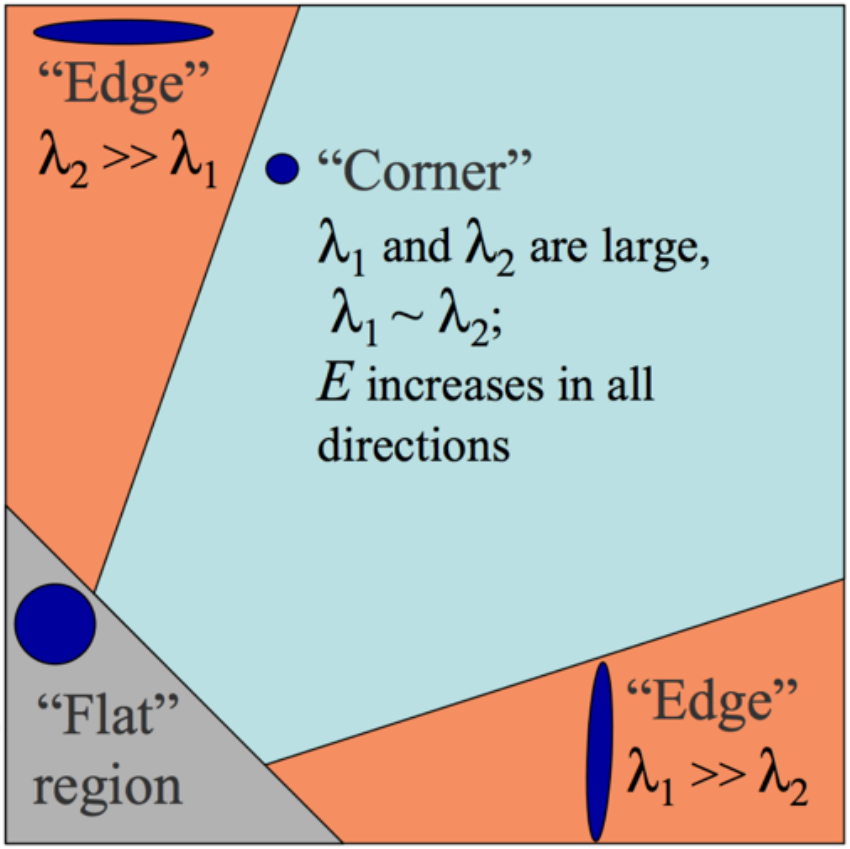






Harris corner detector

- Classification of image points using **eigenvalues of M ???**



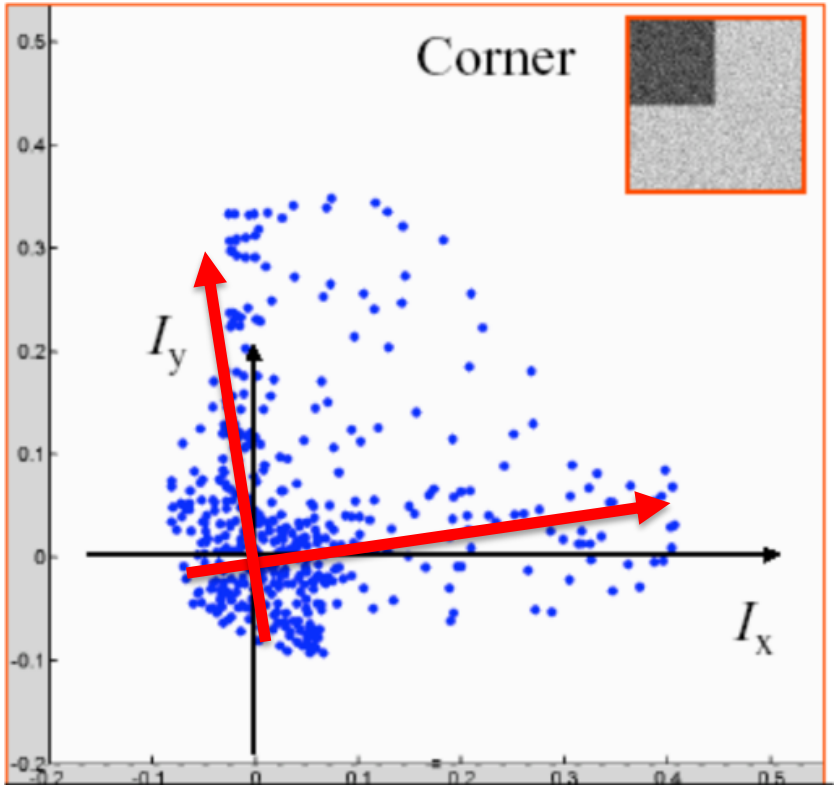
https://courses.cs.washington.edu/

EigenWhat?

Eigenvectors / Eigenvalues

Eigenvectors - Definition

$$A\mathbf{v} = \lambda\mathbf{v}$$

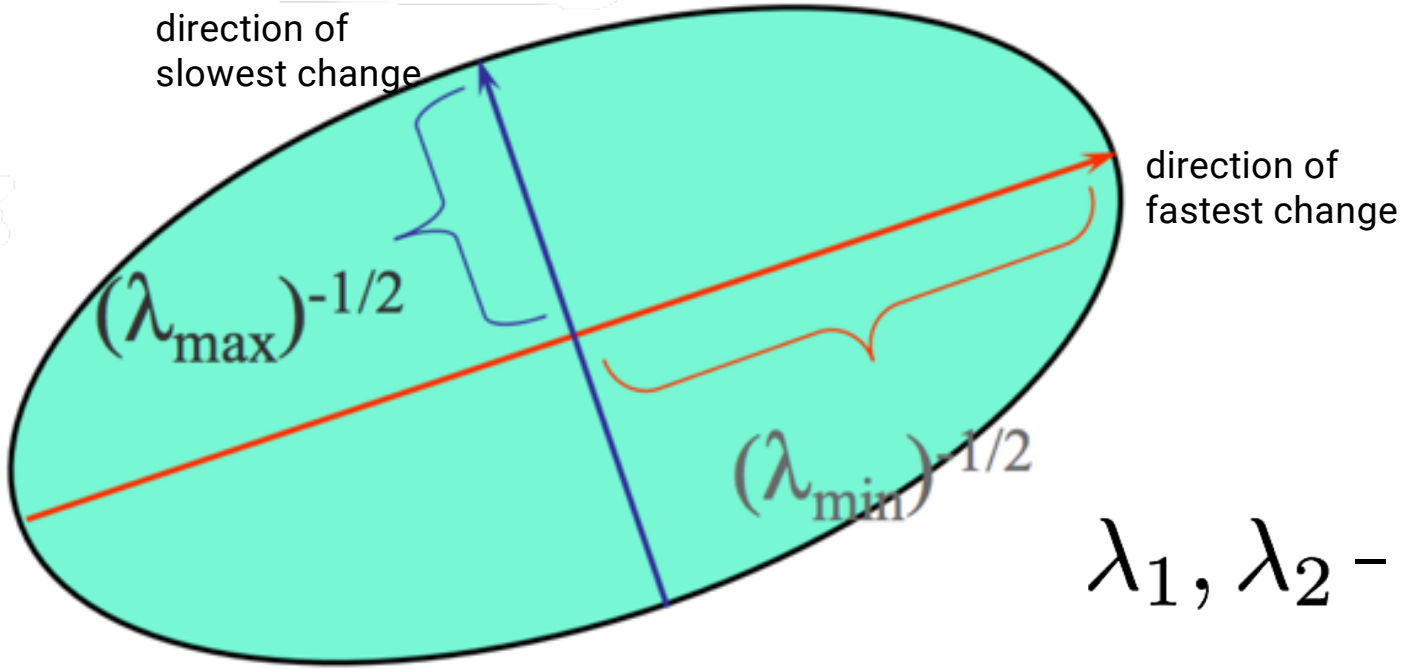


Harris corner detector – The math

- Intensity change in shifting window: eigenvalue analysis:

$$E(x,y) \simeq \begin{pmatrix} u & v \end{pmatrix} M \begin{pmatrix} u \\ v \end{pmatrix}$$

- Ellipse E(u,v) = const

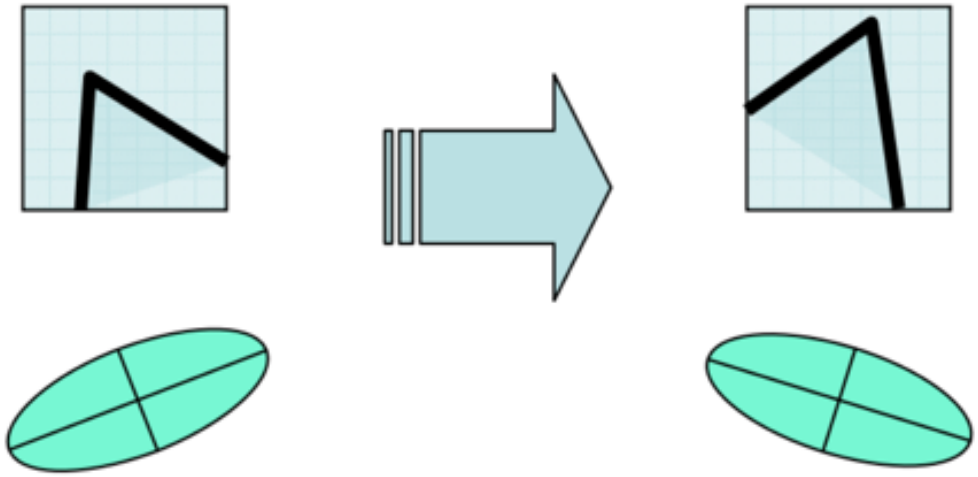


λ_1, λ_2 – eigenvalues of M

https://courses.cs.washington.edu/

Harris corner detector – Rotation invariance

- Ellipse rotates but its shape (i.e. eigenvalues) remains the same



https://courses.cs.washington.edu/

Harris corner detector – Efficient implementation

- One way to compute the eigenvalues efficiently

$$\lambda_{min} \approx \frac{\lambda_1 \lambda_2}{\lambda_1 + \lambda_2} = \frac{det(M)}{trace(M)}$$

- To avoid computing the eigenvalues which is computationally expensive one uses an approximation to determine if point is corner:

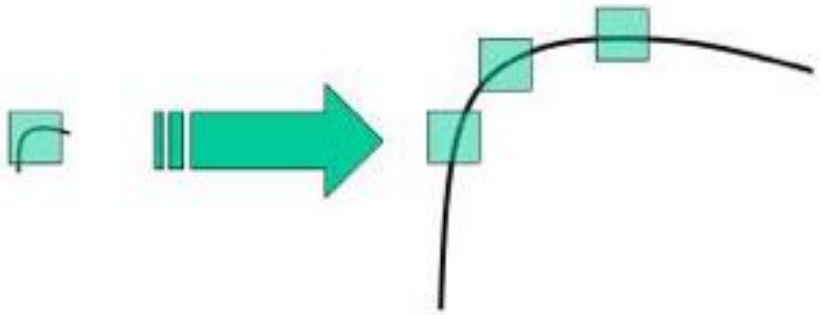
$$R = det(M) - k(trace(M))^2$$

Implementation is done as homework

Scale invariant feature transform (SIFT)

Scale invariant feature transform (SIFT)

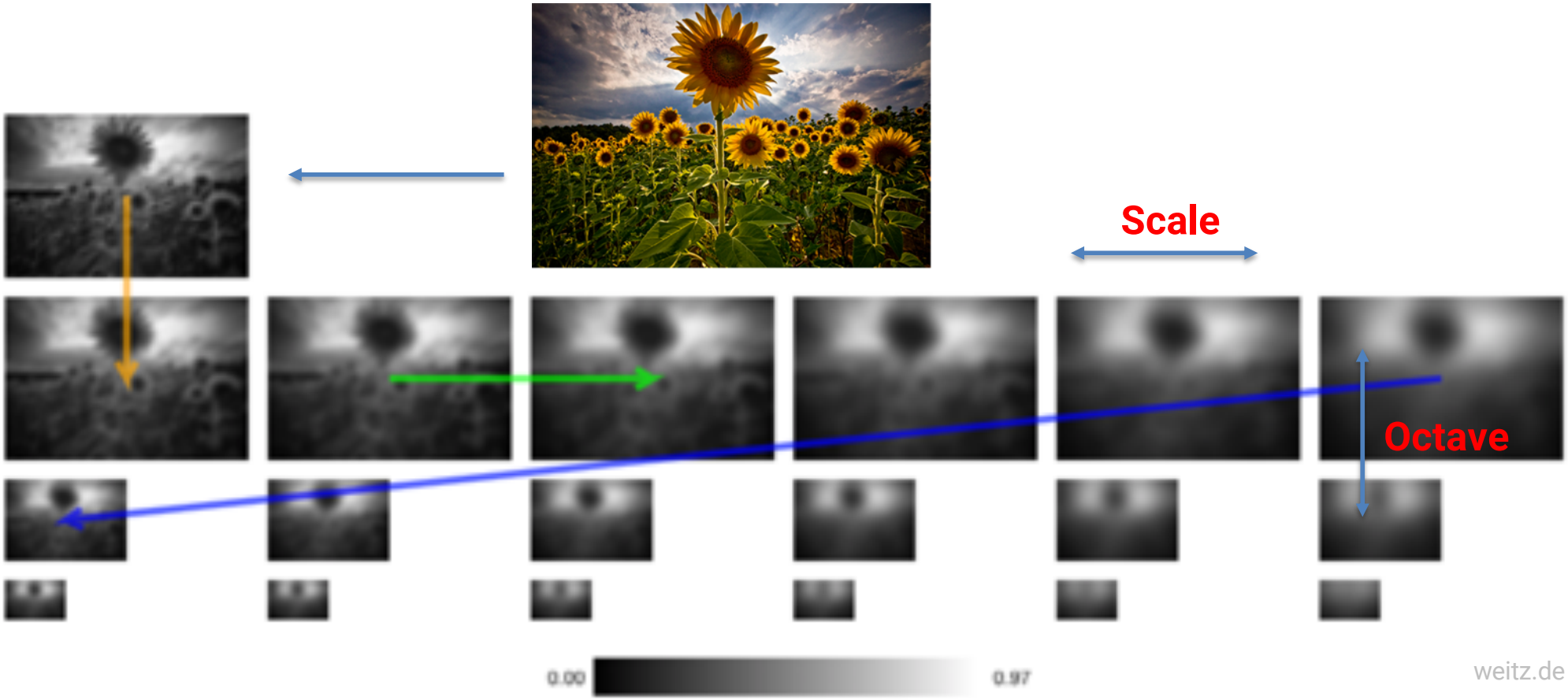
- Distinctive Image Features from Scale-Invariant Keypoints, David Lowe, 2004
- corner detectors are rotation-invariant
  - even if the image is rotated, one can find the same corners
  - corners remain corners in rotated image
- this is not true for scaling



opencv.org

- Harris detector is not scale-invariant

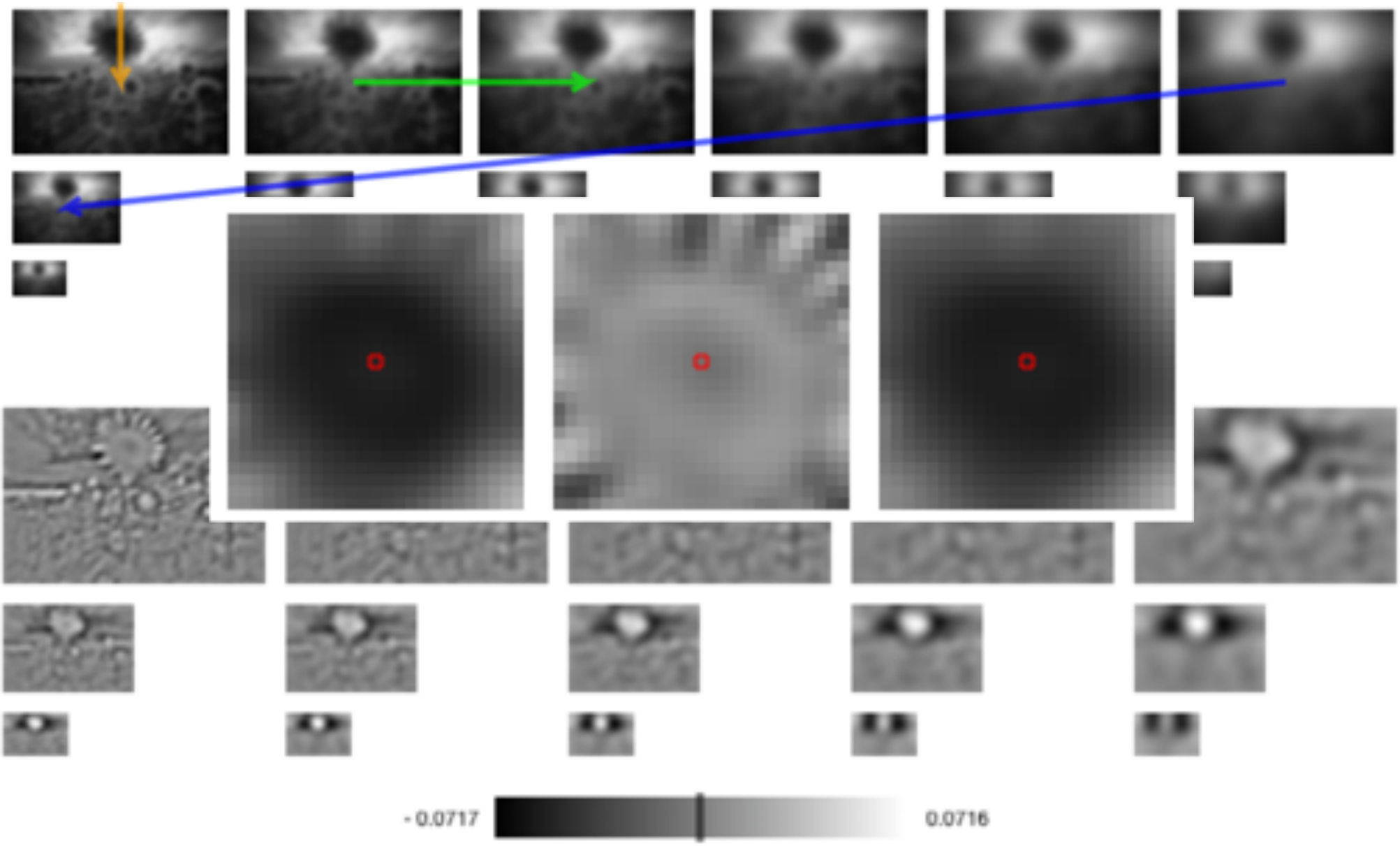
SIFT - Scale-space Extrema Detection



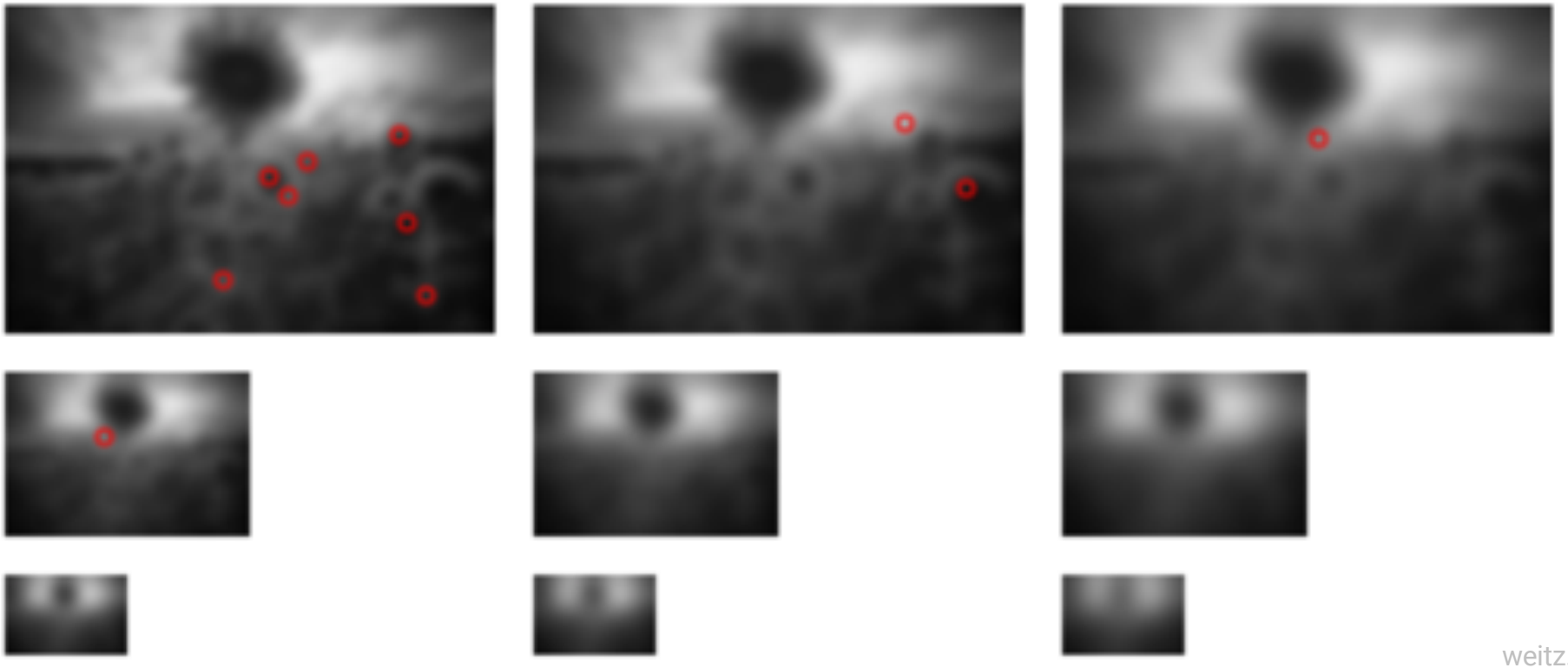
Scale-space using bilinear interpolation and gaussian convolution

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$$

SIFT - Difference of Gaussians



SIFT - Keypoints localization



- one pixel in an image is compared with its 8 neighbours as well as 9 pixels in next scale and 9 pixels in previous scales
- If it is a local extrema, it is a potential keypoint
- It basically means that keypoint is best represented in that scale

Feature

Description of the image window around the keypoint

SIFT - Keypoint Descriptor

- 16x16 neighbourhood around the keypoint
- devided into 16 sub-blocks of 4x4 size
- each sub-block, 8 bin orientation histogram is created
  - total of 128 bin values are available
- represented as a vector to form keypoint descriptor

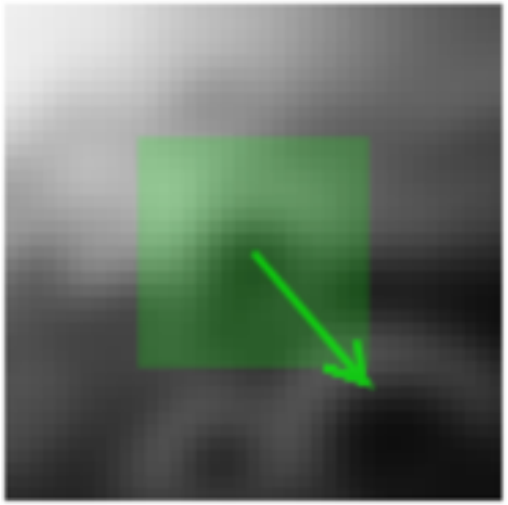
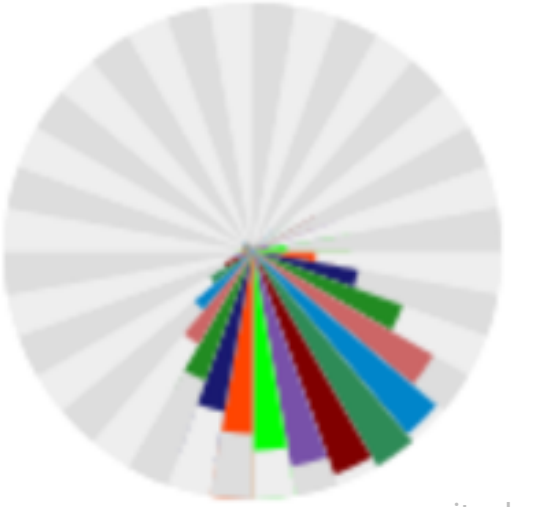


Image Gradients



Keypoint descriptor

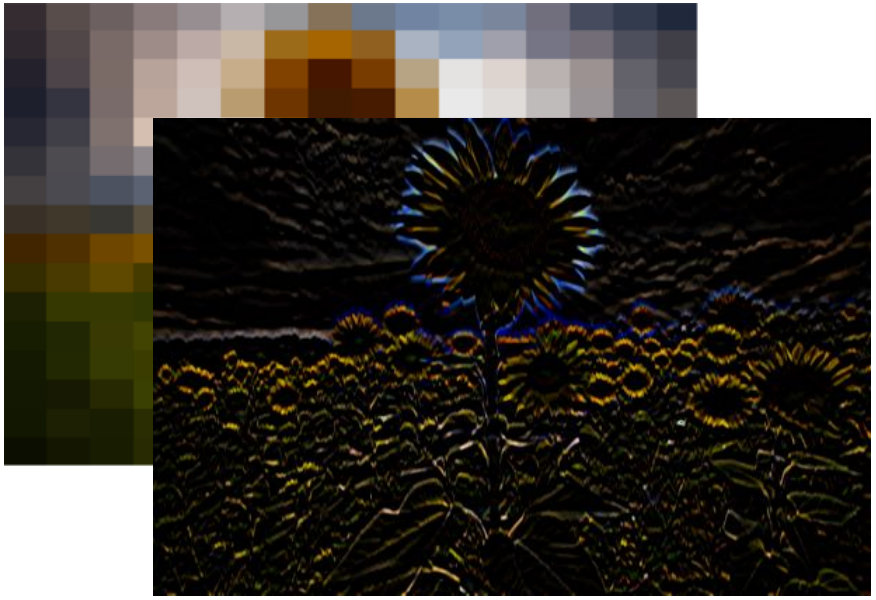
SIFT keypoint detector
Demo

Intermediate take away

Image feature example applications

Image features

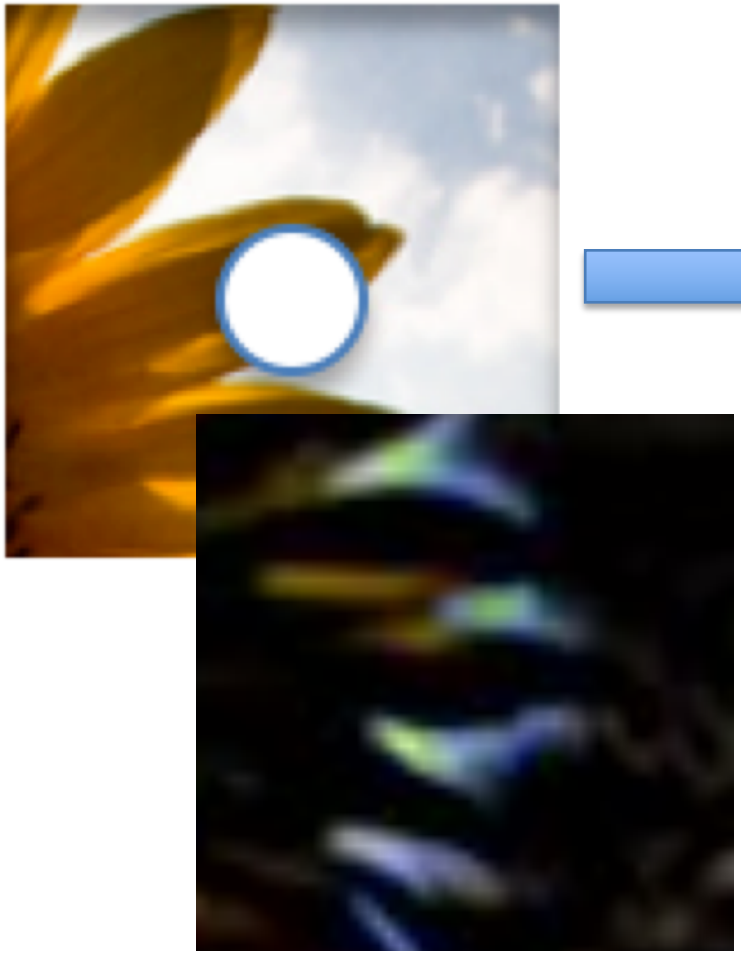
Global Descriptor



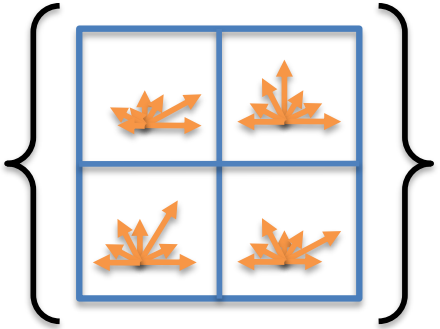
Local Descriptor

Image as a vector

What is the advantage of local feature information?



Feature description



0.5
0.25
0.3
0.01
0.9
0.56
0.67
...

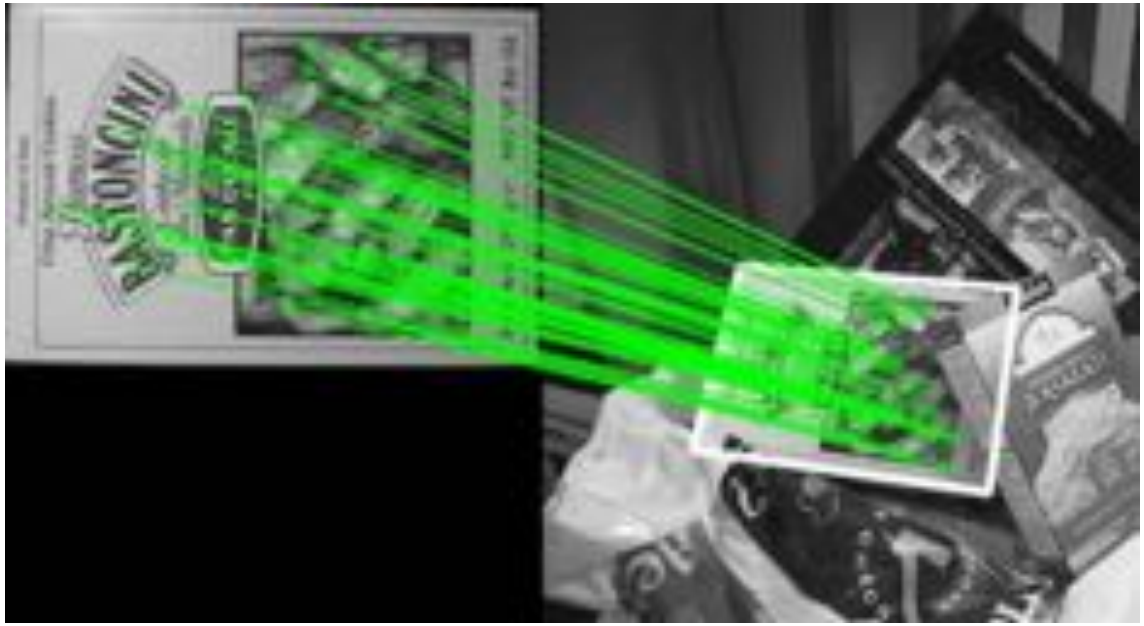
Real-valued

2
0
1
3
1
3
0
...

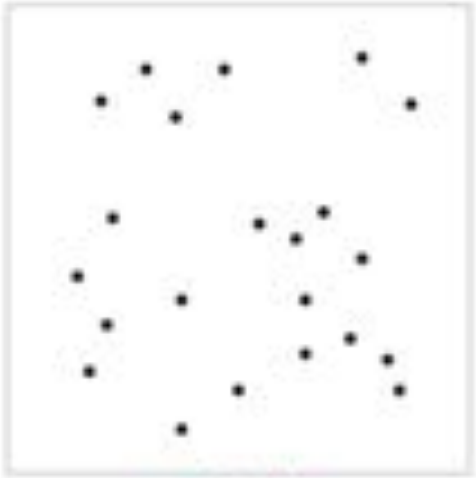
Histogram

Feature Matching

Feature Matching



http://www.ubc.ca



set of points

4 nearest neighbors

https://www.cs.princeton.edu

Feature Matching

- **searching** for the **most similar matches to high-dimensional vectors**

  ← **nearest neighbor matching**

- **no known exact algorithms** for solving these high-dimensional problems that are faster than linear search

  ← **Curse of dimensionality**

- **efficient algorithm** for fast nearest neighbor (NN) matching in large data **sets can bring speed improvements of several orders of magnitude**

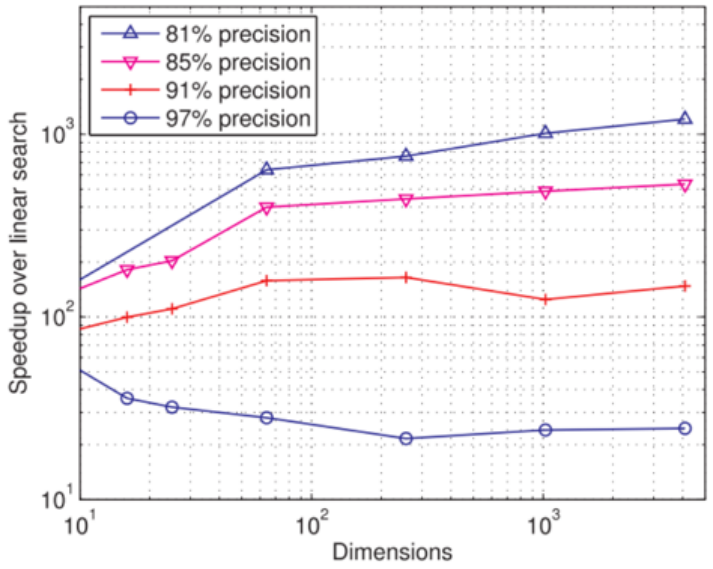
- **FLANN – Fast Library for Approximate Nearest Neighbor**
  - library for performing fast approximate nearest neighbor searches in high dimensional spaces

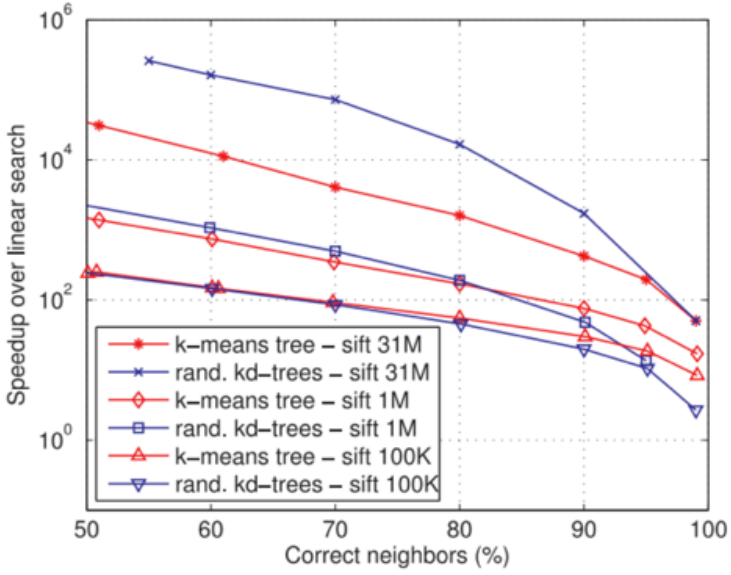
Feature Matching

- Obtain **speed improvement by allowing an approximate search**
  - not all the neighbors returned are exact
  - some are approximate but still close to the exact neighbors

- **Approximate nearest neighbor** search algorithms provide **~95% correct neighbors**
  - **BUT**: are **two or more orders of magnitude faster** than linear search

http://www.ubc.ca





Feature Matching Applications

- Nearest neighbor search problem is also of major importance for many **applications**:
  - machine learning
  - image- / document-retrieval
  - data compression
  - bio-informatics
  - data analysis
  - computer vision

Demo – Image stitching

Feature Matching

- Given a set of points in metric space *M* and a query point *q*

$$P = \{p_1, p_2, p_3, \ldots, p_n\} \quad q \in M$$

- Find elements that is closest to q with respect to a metric distance *d*

$$NN(q, P) = argmin_{x \in P}\, d(q, x)$$

Feature Matching

- **How to compare feature vectors in high-dimensional space?**
  - Distance Metric

- How to compare feature vectors in high-dimensional space **efficiently**?
  - Spatial Datastructure
  - Approximate Nearest Neighbor

Distance Metrics

Distance metric

- **Euclidean distance**
  - ‘straight-line’ distance between points (L^2-norm)

$$d_{l2}(p,q) = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2}$$

- **Manhatthan distance**
  - L1-norm

$$d_{l1}(p,q) = \sum_{i=1}^{n}|p_i - q_i|$$

- **Maximum norm**
  - L^{∞}

$$d_{l\infty}(p,q) = \max_i(|p_i - q_i|)$$

Distance metric

- **Hamming distance**
  - distance between binary code
    - ”foobar" and ”f00bat" is 3.
    - 1011101 and 1001001 is 2.
    - 2173896 and 2233796 is 3.

- **Cosine similarity (no proper distance metric)**
  - similarity between two vectors (inner product, cos(angle) between vectors)
  - distance between histograms

$$a \cdot b = \|a\| \|b\| \cos\theta$$

Fast Approximate Nearest Neighbor

Fast Approximate Nearest Neighbor (FLANN)

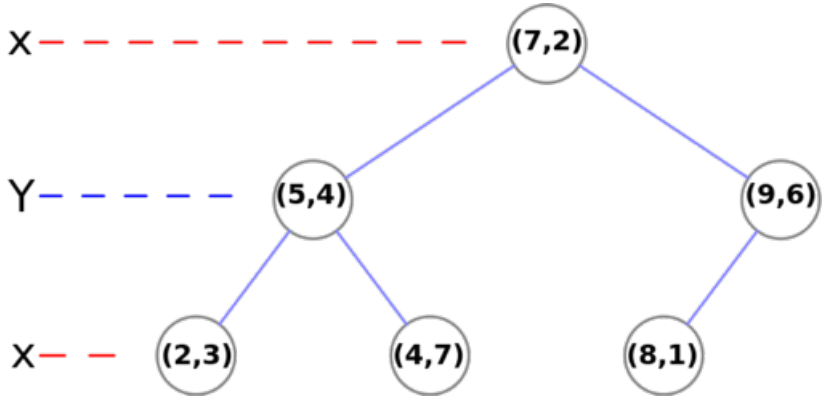
- Library for performing fast **approximate nearest neighbor** searches in **high dimensional spaces**
  - http://www.cs.ubc.ca/research/flann/
  - collection of standard algorithms that work best in practice
  - written in c++ with binding for Matlab and Python

- Algorithm evaluation showed two best performing algorithms:
  - **Multiple randomized k-d trees**
  - **Priority search k-means tree**

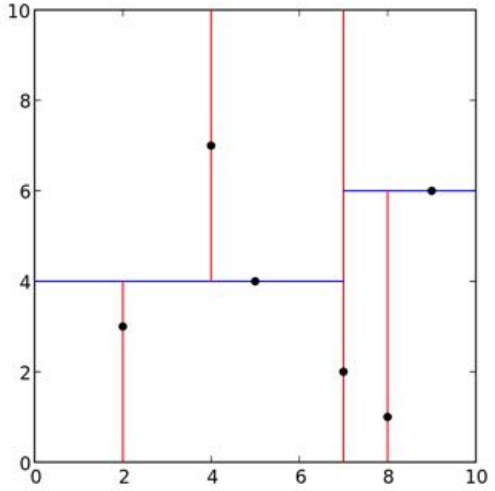
Multiple Randomzied kd-Trees

kd-tree (Recap)

- **spatial data structure** for organizing points in **high dimensionality spaces**
- **binary tree** where each node is a k-d point
- every **node** can be seen **as a plane dividing space in two parts**
- splitting along changing dimensions / axis
- **results in balanced k-d tree**

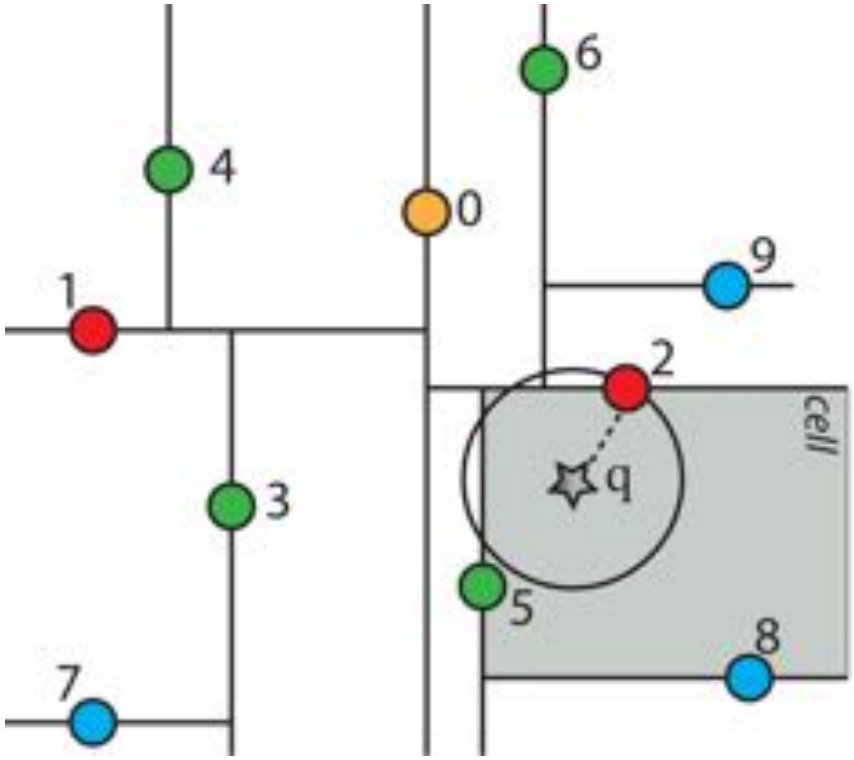


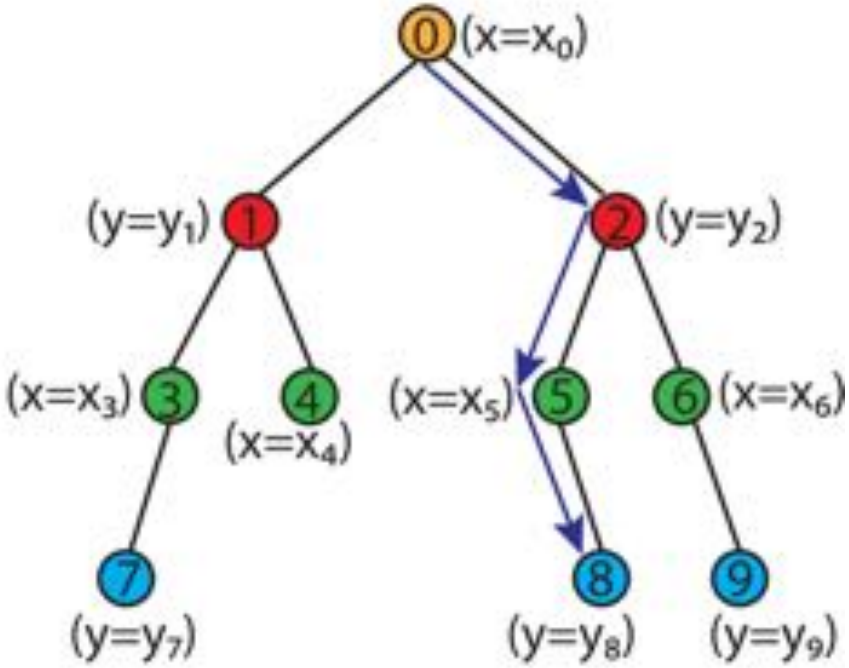
white board example



http://wikipedia.org

Query in kd-trees





http://www.mdpi.com/

kd-tree

- Very **effective in low dimensional** spaces
- Performance **decreases for high dimensional data**
  - requires searching a large number of nodes

- Speedup by approximating queries:
  - **‘error bound’** approximate search
  - **‘time bound’** approximate search

Randomized kd-Trees

- **Idea:** multiple randomized k-d trees which are searched in parallel
  - build scheme similar to classic kd-tree

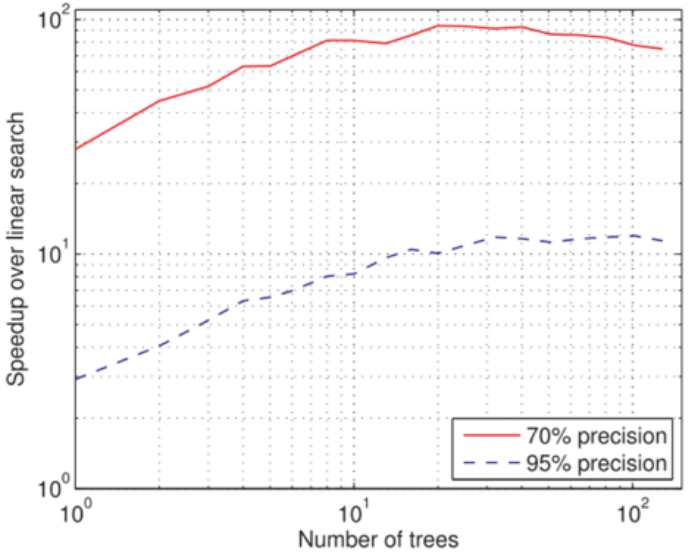
- **Difference to classic kd-tree:**
  - classic – split dimensions are chosen by highest variance
  - randomized – split dimensions are chosen randomly from the **top 5 dimensions highest variance**

- In practice often **20 trees** used

Searching randomized k-d forest

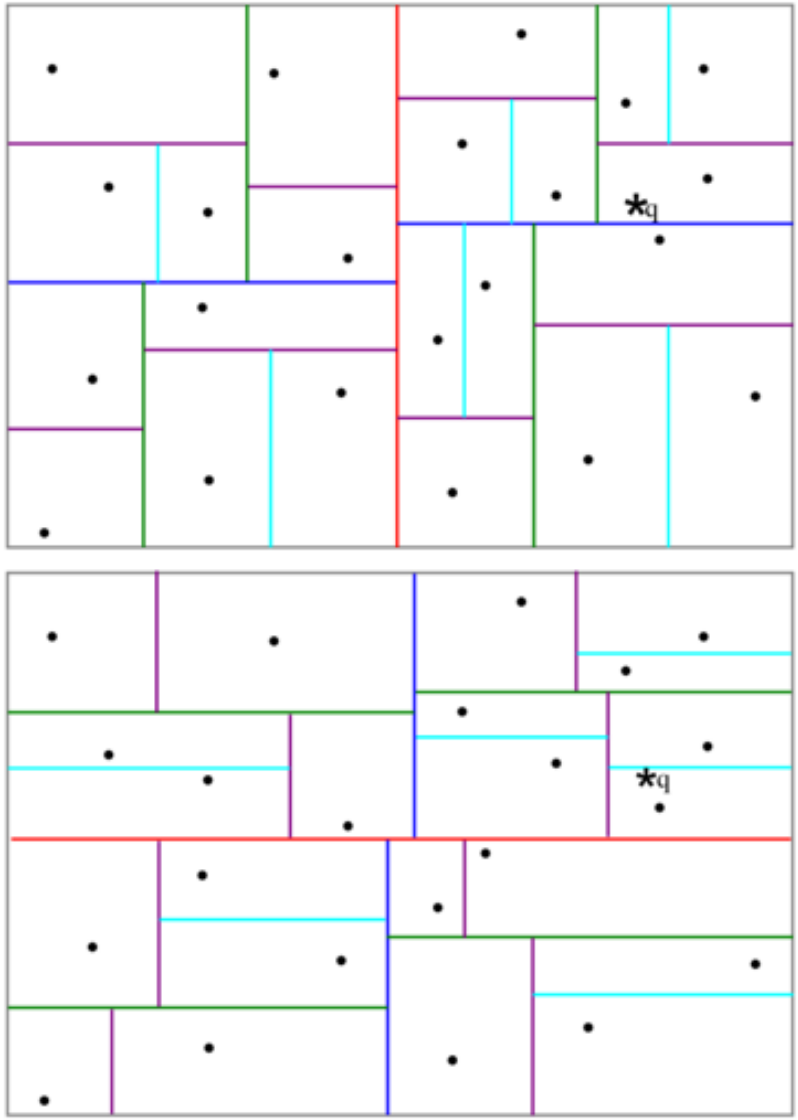
- Maintain **single priority queue across forest**
- PQ is ordered by increasing distance
  - the search will explore first the closest leaves from all the trees
- examined **points are marked as visited across all trees** (not visited in another tree again)
- approximation is determined by **maximum number of visited leaf nodes**

http://www.ubc.ca



100k SIFT feature data set

Randomized kd-Trees



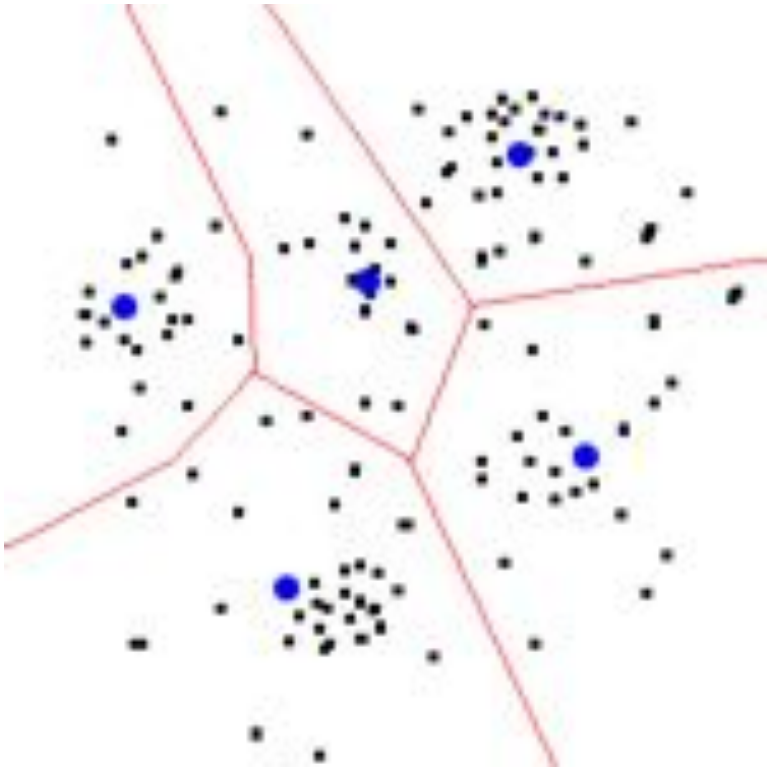
Priority Search
k–means Tree

k-means

- important **clustering method** in CS
- partitions ***N* data points** in ***k* clusters** $S = \{S_1, S_2, \ldots S_k\}$
- each **data point belongs to cluster with nearest mean**
  - mean of the cluster is cluster center/ representative

$$\arg\min_{s} \sum_{i=1}^{k} \sum_{x \in s_i} \|x - \mu_i\|^2$$

- **results in partitioning of data space (voronoi cells)**
- also known as **Lloyd's Algorithm**



http://mnemstudio.org/

k-means Trees

- **Contruction:**
  - Tree is constructed by **partitioning the data points** at each **level into *K* distinct regions** using k-means clustering
    - Apply recursively to the points in each region
  - Recursion is stopped when the number of points in a region is smaller than *K*
- **Search:**
  - initially traversing the tree from the root to the closest leaf (following closest cluster centre)
  - add unvisited branches to priority queue
  - use branch that has the closest center to the query point
  - restart the tree traversal from that branch
  - stop after number of visited leaf nodes

k-means Trees