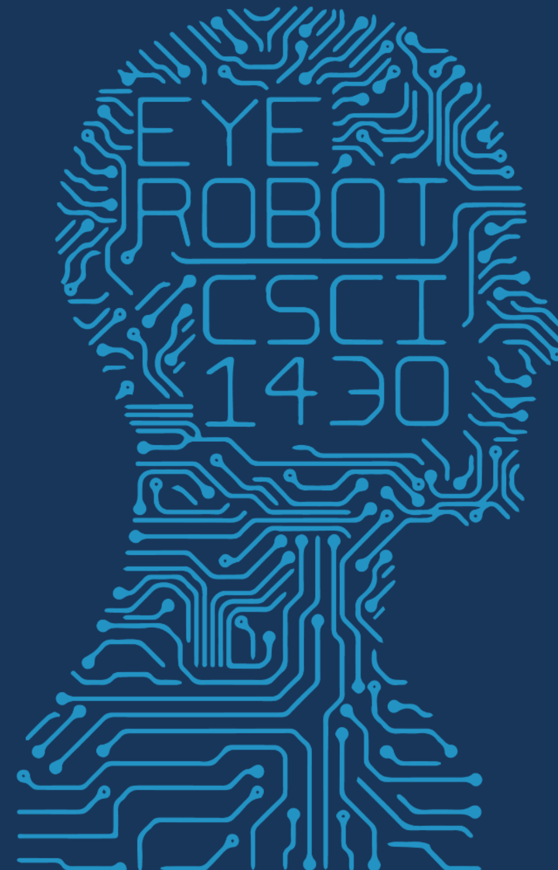
1950

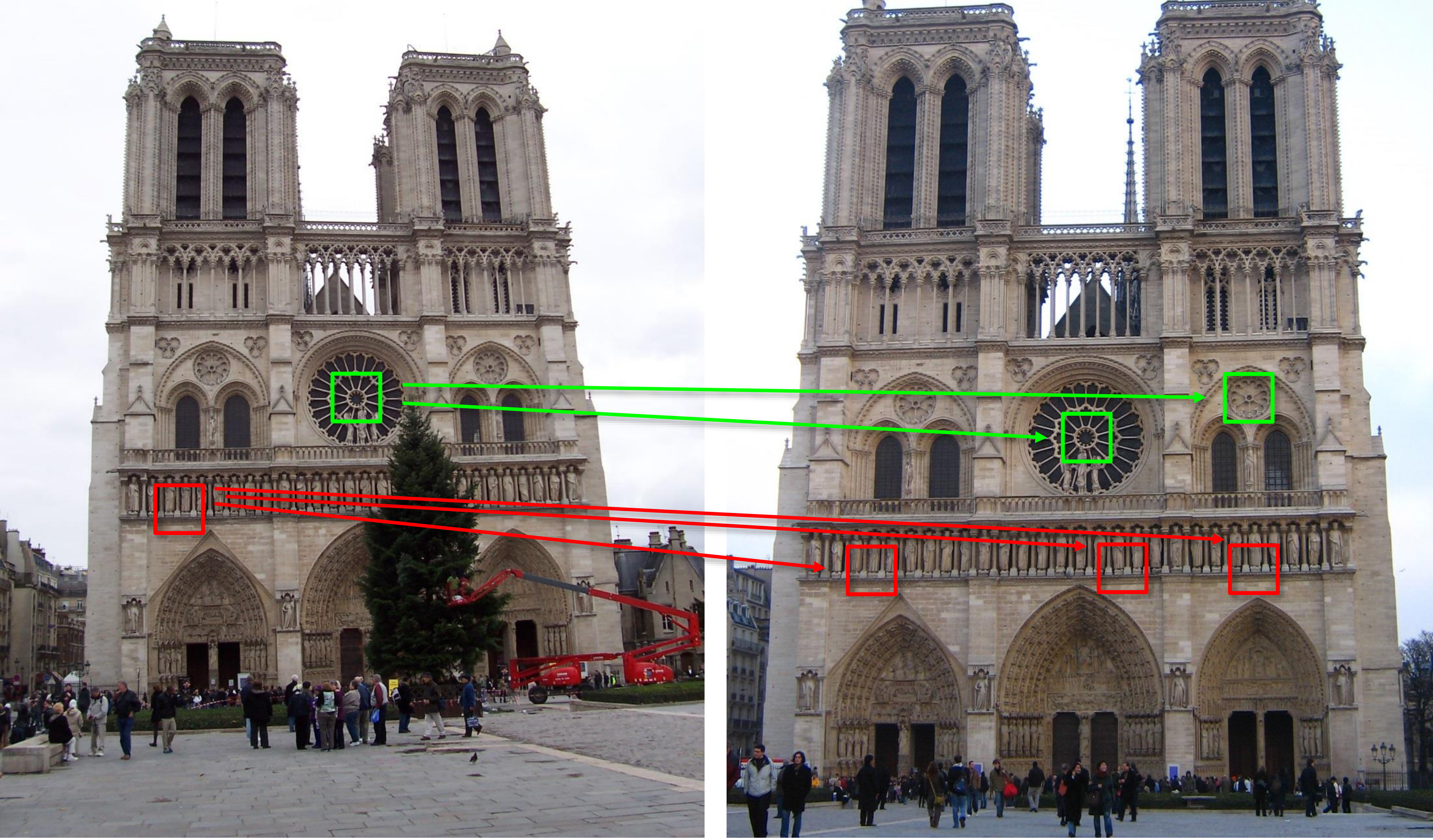
Future Vision



2017 MWF 1pm

Computer Vision

How do we decide which features match?



Distance: 0.34, 0.30, 0.40

Distance: 0.61, 1.22

Euclidean distance vs. Cosine Similarity

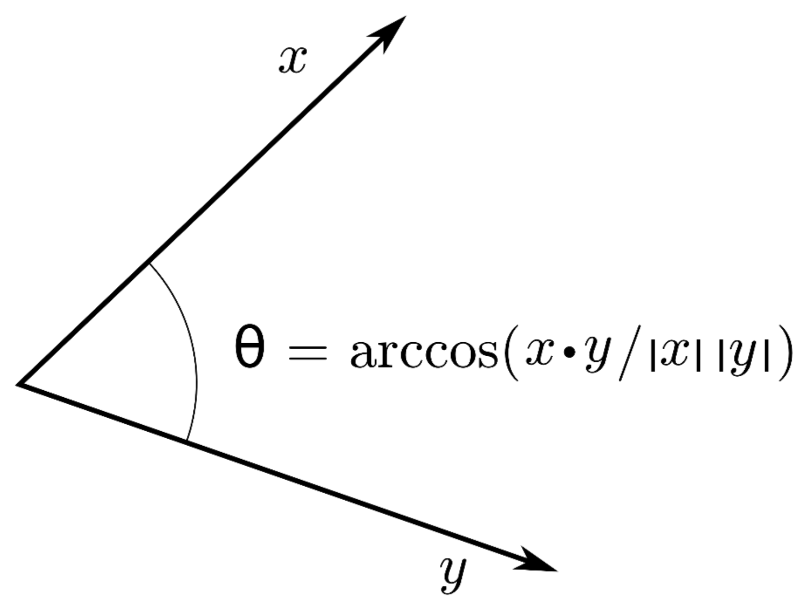
- E $\mathrm{d}(\mathbf{p},\mathbf{q}) = \mathrm{d}(\mathbf{q},\mathbf{p}) = \sqrt{(q_1-p_1)^2 + (q_2-p_2)^2 + \cdots + (q_n-p_n)^2}$

$$= \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}.$$

$$\|\mathbf{q}-\mathbf{p}\| = \sqrt{(\mathbf{q}-\mathbf{p})\cdot(\mathbf{q}-\mathbf{p})}.$$

- C $\mathbf{a}\cdot\mathbf{b} = \|\mathbf{a}\|_2 \|\mathbf{b}\|_2 \cos\theta$ y:

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A}\cdot\mathbf{B}}{\|\mathbf{A}\|_2 \|\mathbf{B}\|_2}$$



Wikipedia

Nearest Neighbor Distance Ratio

Compare distance of closest (NN1) and second-closest (NN2) feature vector neighbor.

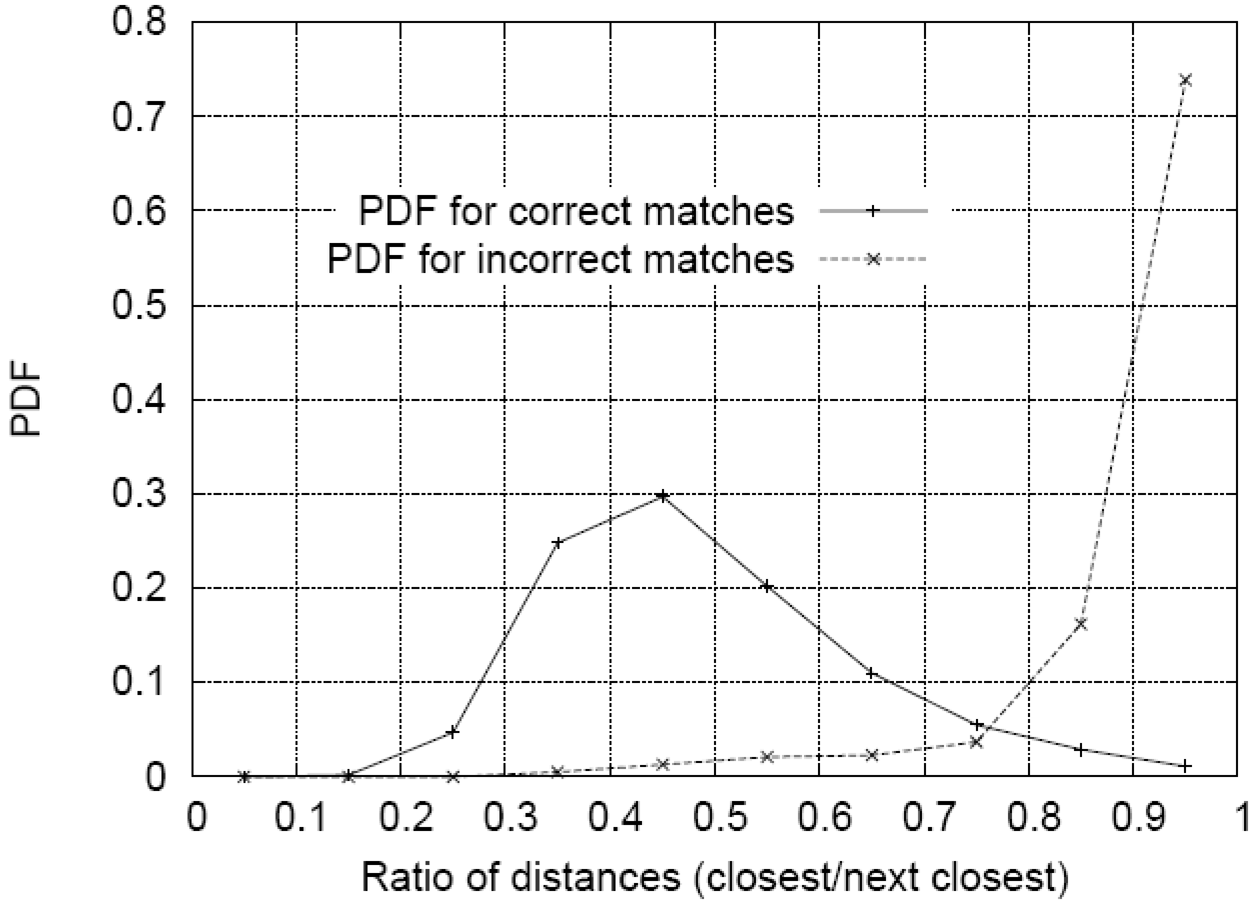
- If NN1 ≈ NN2, ratio $\frac{NN1}{NN2}$ will be ≈ 1 -> matches too close.
- As NN1 << NN2, ratio $\frac{NN1}{NN2}$ tends to 0.

Sorting by this ratio puts matches in order of confidence.

Threshold ratio – but how to choose?

Nearest Neighbor Distance Ratio

- Lowe computed a probability distribution functions of ratios
- 40,000 keypoints with hand-labeled ground truth



Ratio threshold depends on your application's view on the trade-off between the number of false positives and true positives!

Lowe IJCV 20

Where to go from our basic building block?

Feature Points

Recognition

Scenes, places, objects,

~ 5 weeks (inc. CNNs)

Reconstruction

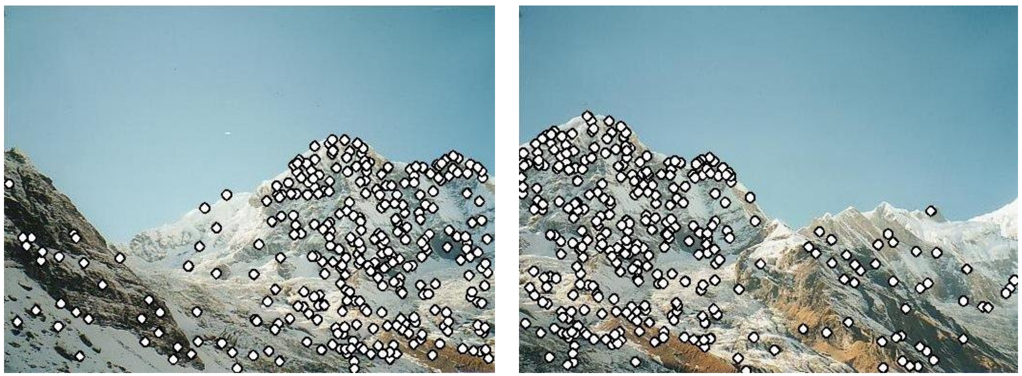
Geometric understanding

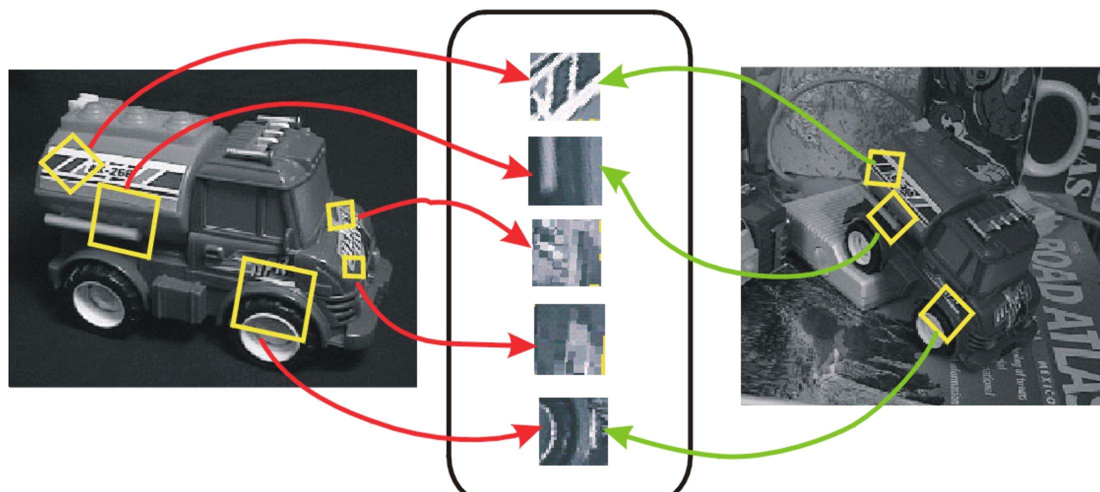
~10th November

Panorama stitching / instance recognition

Often needs geometric understanding…

…but we'll see it later on.

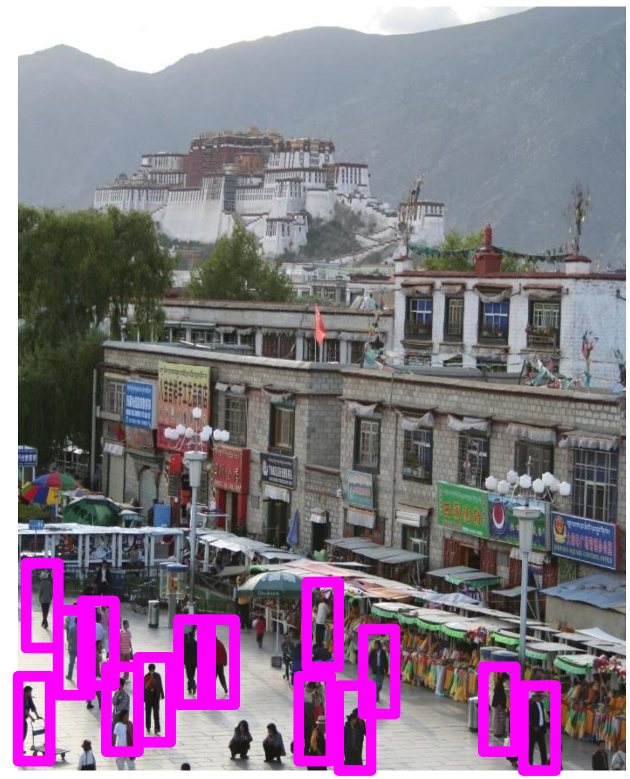




Recognition

Often needs machine learning
for compact descriptions of the visual world.

Scene recognition
- City/forest/factory/…



Find pedestrians

ML CRASH COURSE

Photo: CMU Machine Learning Department Protests G20

Slides: James Hays, Isabelle Guyon, Erik Sudderth, Mark Johnson, Derek Hoiem

Photo: CMU Machine Learning Department Protests G20

Slides: James Hays, Isabelle Guyon, Erik Sudderth, Mark Johnson, Derek Hoiem

Our approach

- We will look at ML as a tool. We will not detail the underpinnings of each learning method.

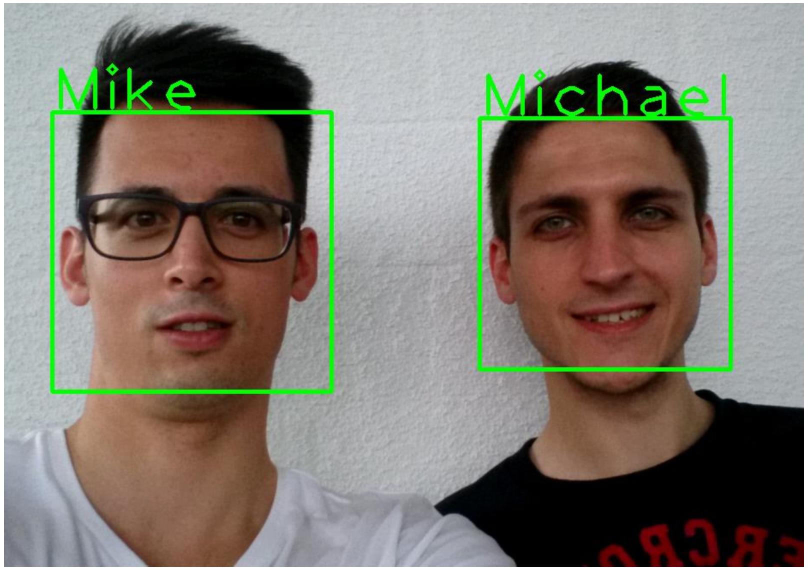
- Please take a machine learning course if you want to know more!

Machine Learning

- Learn from and make predictions on data.
- Arguably the greatest export from computing to other scientific fields.
- Statisticians might disagree with CompScis on the true origins…

ML for Computer Vision

- Face Recognition
- Object Classification
- Scene Segmentation



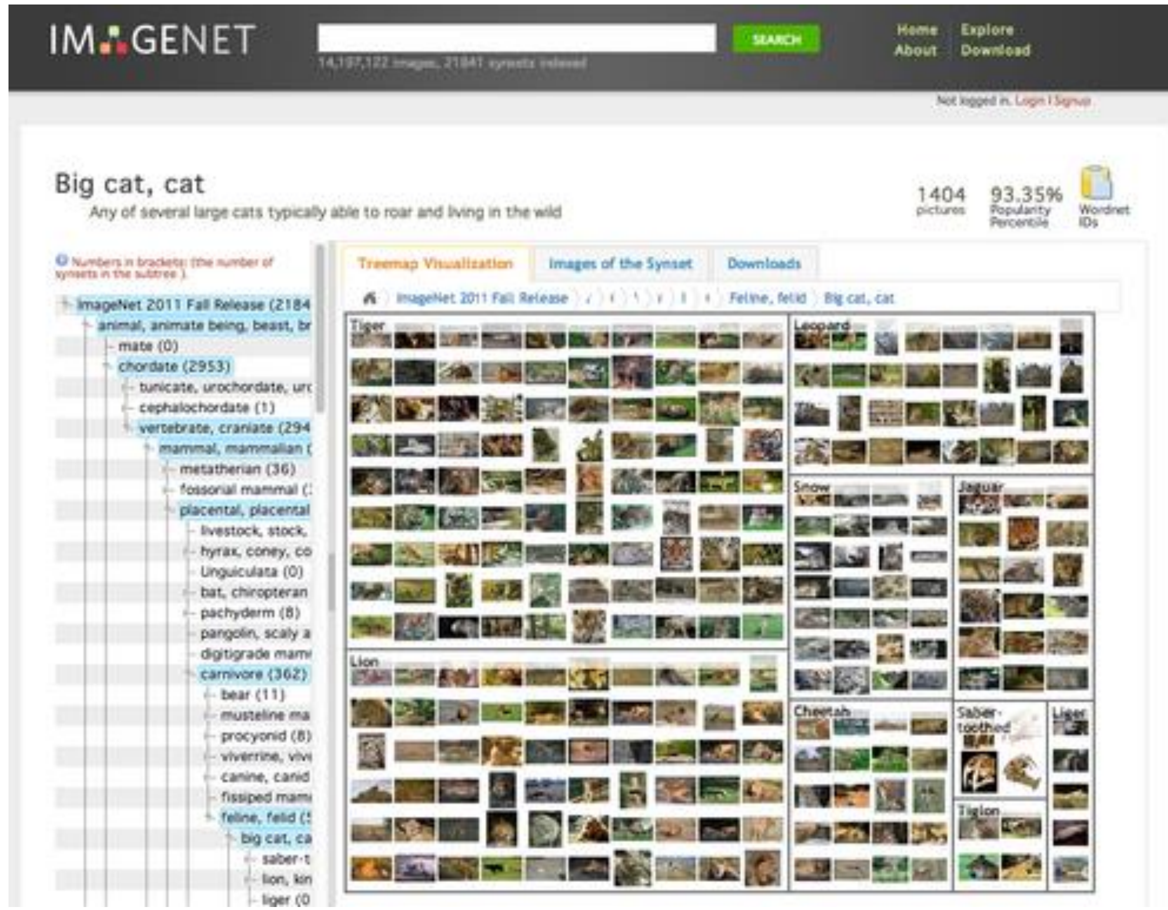
Data, data, data!

- Norvig – “The Unreasonable Effectiveness of Data” (IEEE Intelligent Systems, 2009)
  - “... invariably, simple models and a lot of data trump more elaborate models based on less data”

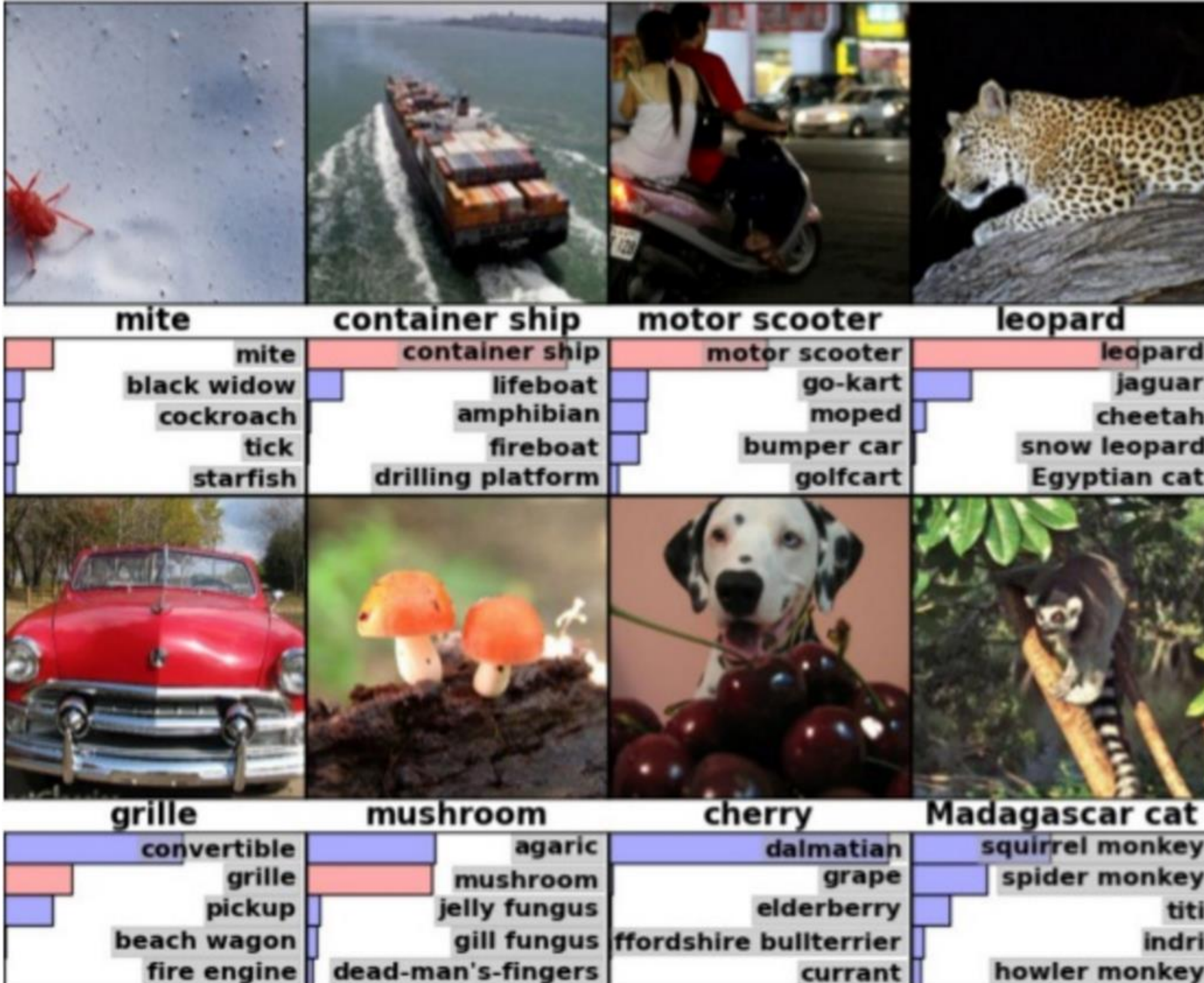
ImageNet

- Images for each category of WordNet
- 1000 classes
- 1.2mil images
- 100k test

- Top 5 error

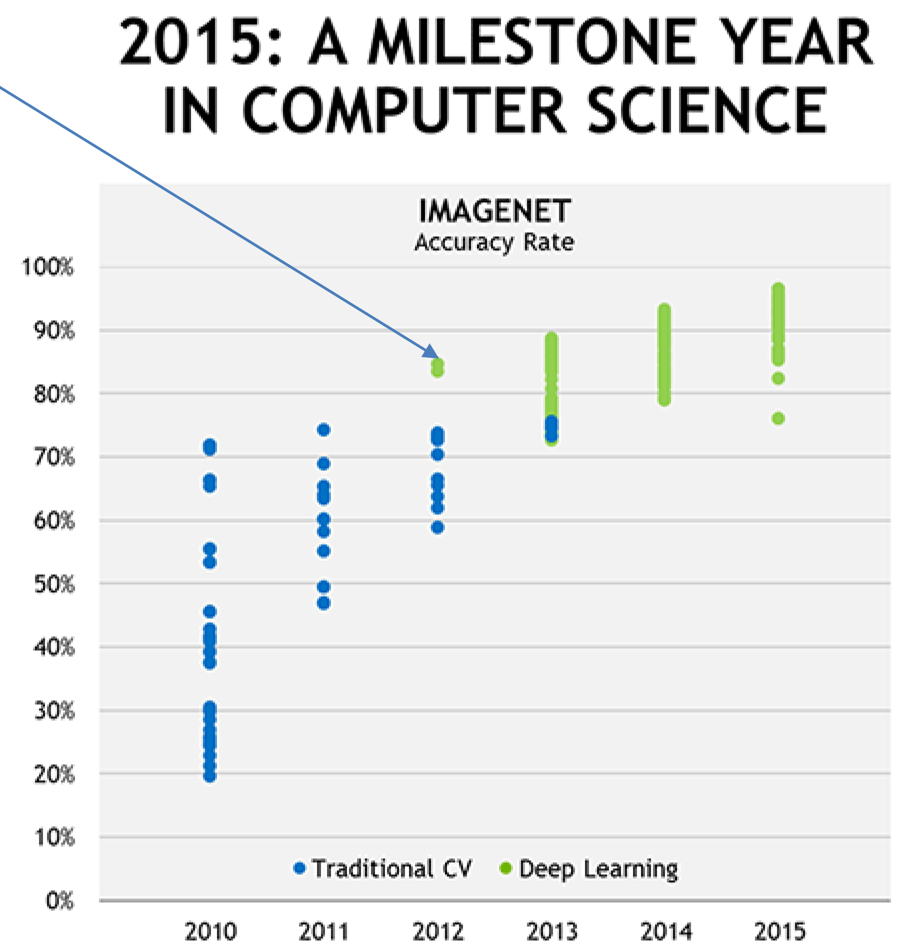


IMAGENET


mite
mite
black widow
cockroach
tick
starfish
container ship
container ship
lifeboat
amphibian
fireboat
drilling platform
motor scooter
motor scooter
go-kart
moped
bumper car
golfcart
leopard
leopard
jaguar
cheetah
snow leopard
Egyptian cat
grille
convertible
grille
pickup
beach wagon
fire engine
mushroom
agaric
mushroom
jelly fungus
gill fungus
dead-man's-fingers
cherry
dalmatian
grape
elderberry
ffordshire bullterrier
currant
Madagascar cat
squirrel monkey
spider monkey
titi
indri
howler monkey

ImageNet Competition

- Krizhevsky, 2012
- Google, Microsoft 2015
  - Beat the best human score in the ImageNet challenge.



Machine Learning Problems

	Supervised Learning	Unsupervised Learning
Discrete	classification or categorization	clustering
Continuous	regression	dimensionality reduction

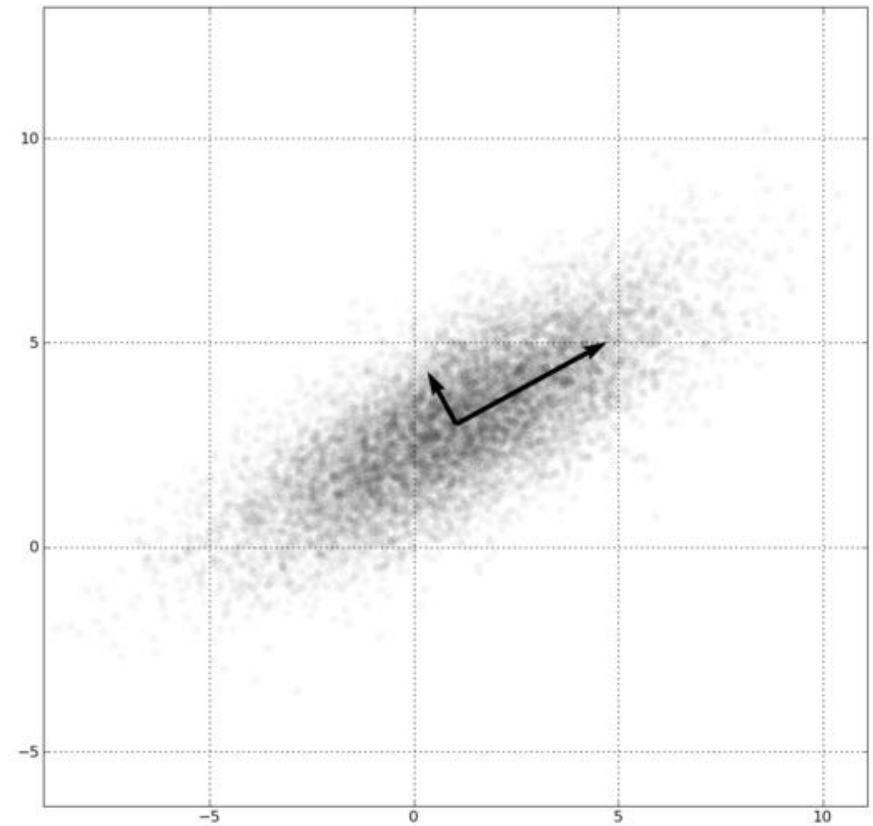
Machine Learning Problems

	Supervised Learning	***Unsupervised Learning***
Discrete	classification or categorization	clustering
Continuous	regression	dimensionality reduction

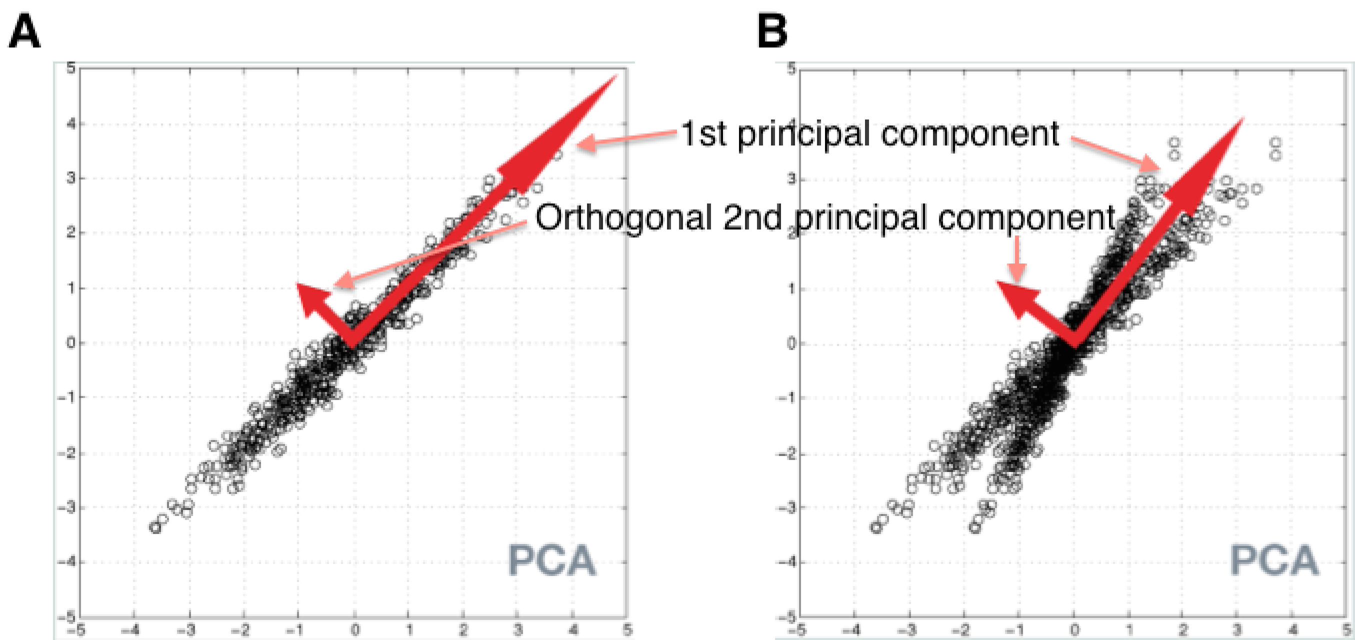
Dimensionality Reduction

- **PCA**, ICA, LLE, Isomap

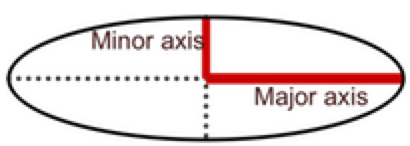
- Principal component analysis
  - Creates a basis where the axes represent the dimensions of variance, from high to low.
  - Finds correlations in data dimensions to produce *best possible* lower-dimensional representation based on linear projections.



PCA

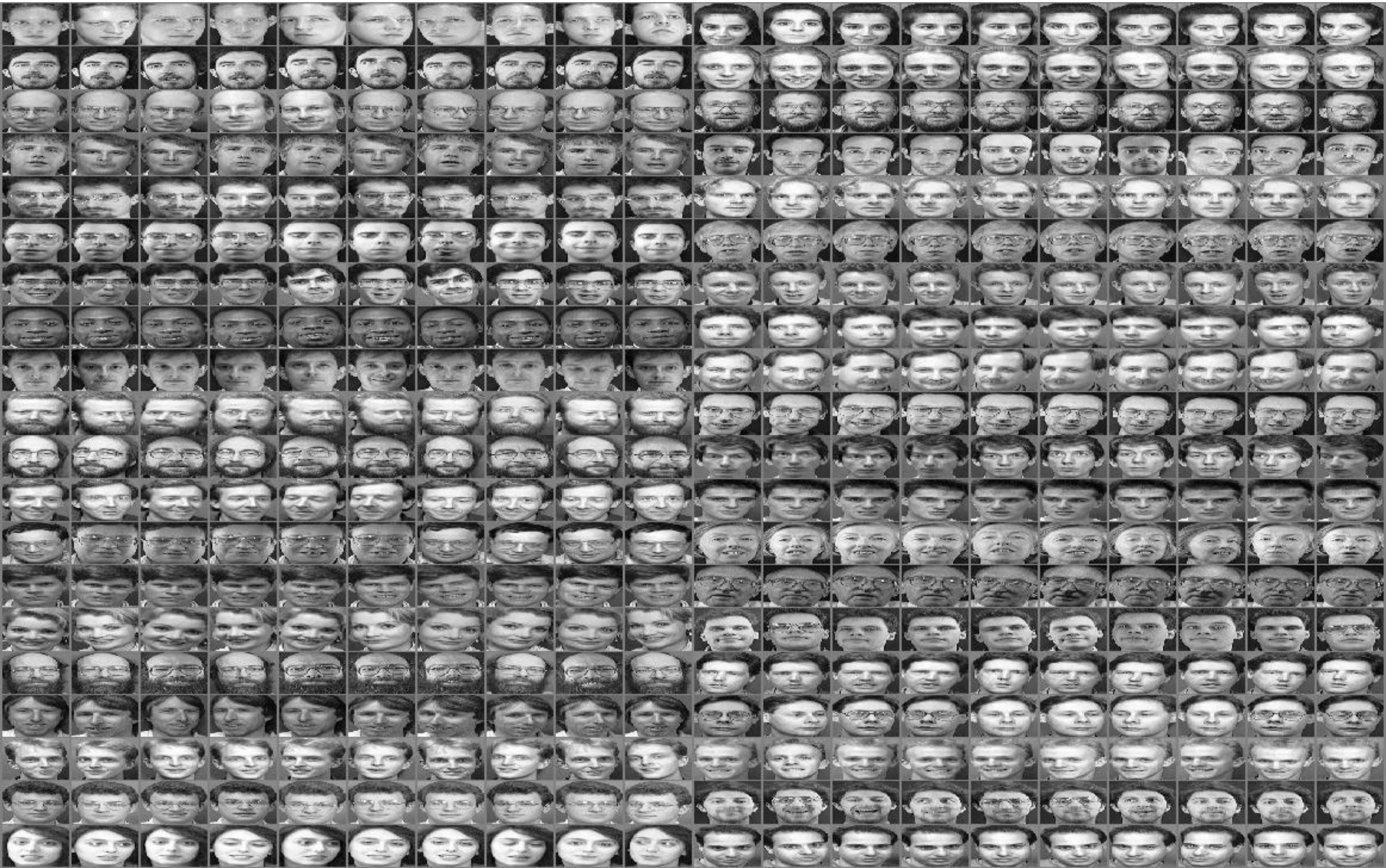


(Figure adapted from C. Beckmann, Oxford FMRIB)



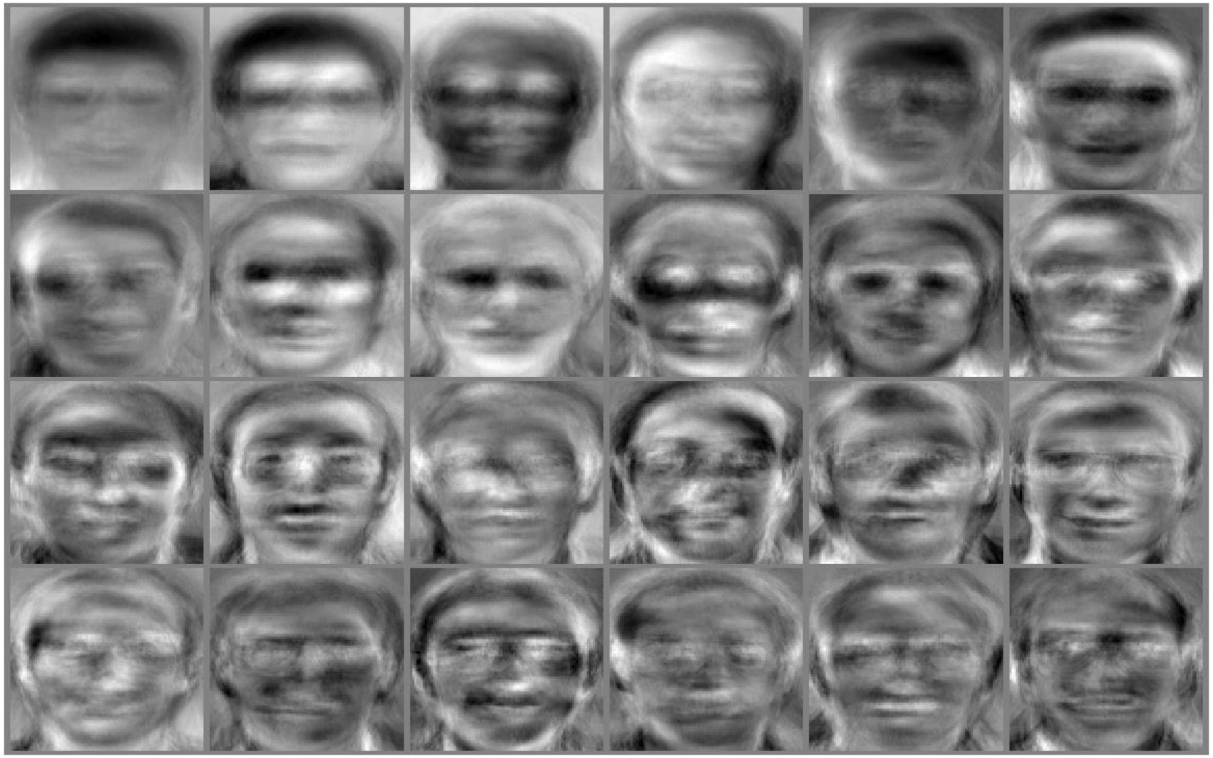
Eigenfaces

The ATT face database (formerly the ORL database), 10 pictures of 40 subjects each



Eigenfaces

Mean face



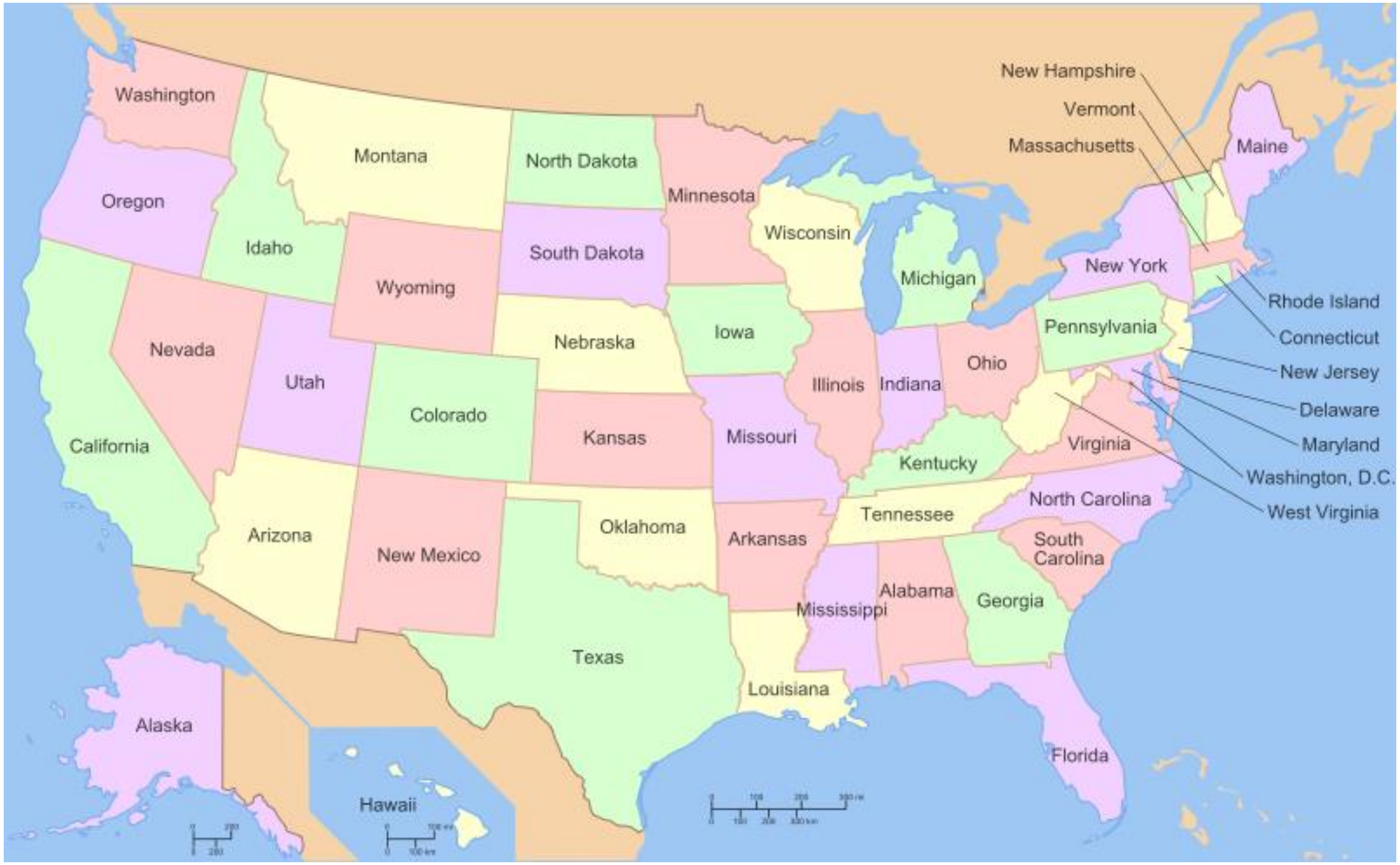
Basis of variance (eigenvectors)

M. Turk; A. Pentland (1991). ["Face recognition using eigenfaces"](#) (PDF). Proc. IEEE Conference on Computer Vision and Pattern Recognition. pp. 586–591.

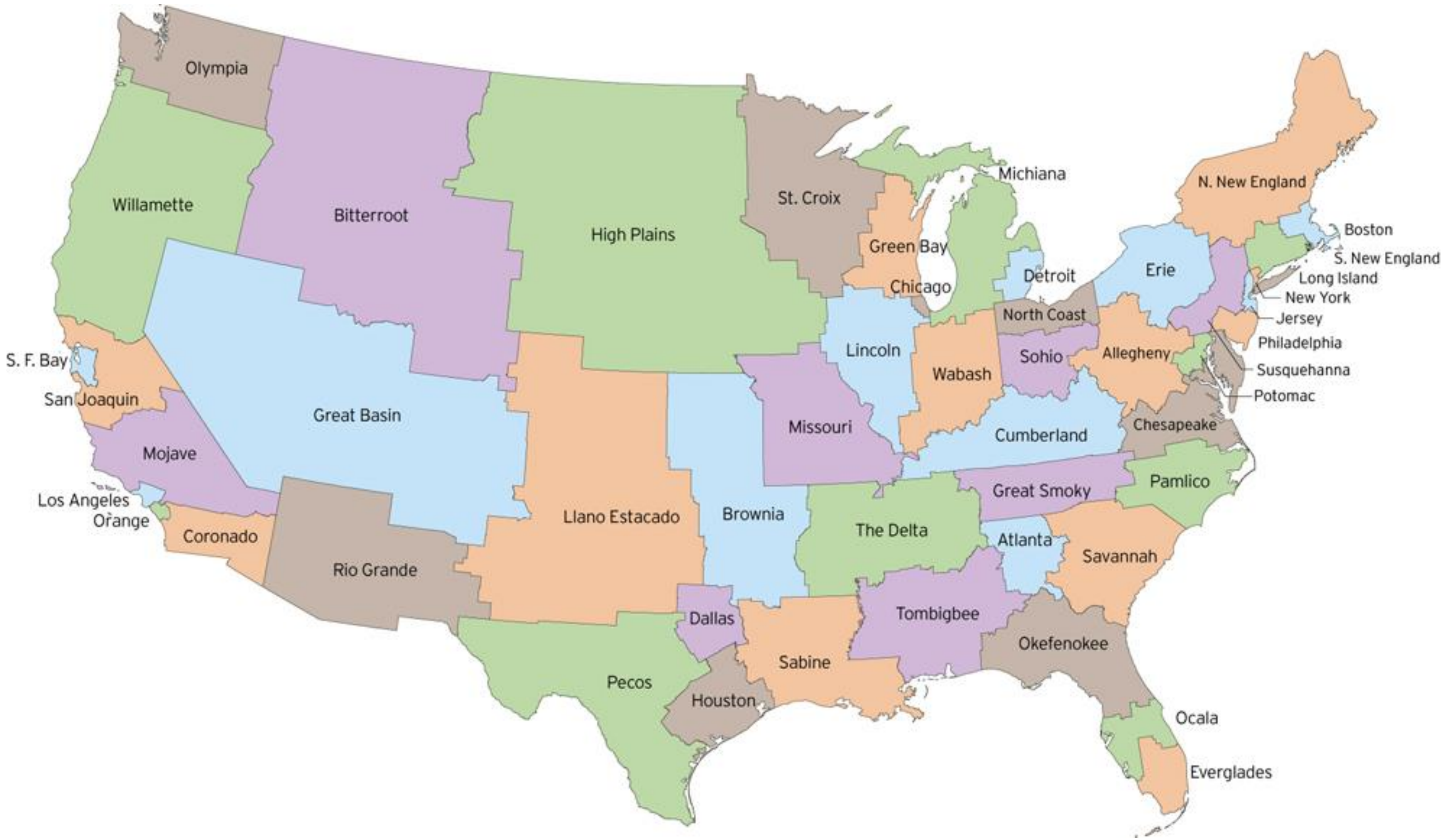
[R.P.W. Duin](#)

Machine Learning Problems

	Supervised Learning	***Unsupervised Learning***
Discrete	classification or categorization	clustering
Continuous	regression	dimensionality reduction



Washington
Oregon
California
Idaho
Montana
Nevada
Utah
Wyoming
Arizona
Colorado
New Mexico
North Dakota
South Dakota
Nebraska
Kansas
Oklahoma
Texas
Minnesota
Iowa
Missouri
Arkansas
Louisiana
Wisconsin
Illinois
Mississippi
Michigan
Indiana
Kentucky
Tennessee
Alabama
Ohio
Georgia
Florida
South Carolina
North Carolina
Virginia
Pennsylvania
New York
Maine
New Hampshire
Vermont
Massachusetts
Rhode Island
Connecticut
New Jersey
Delaware
Maryland
Washington, D.C.
West Virginia
Alaska
Hawaii



http://fakeisthenewreal.org/reform/

The United States *redrawn as* Fifty States *with* Equal Population

Clustering example: image segmentation

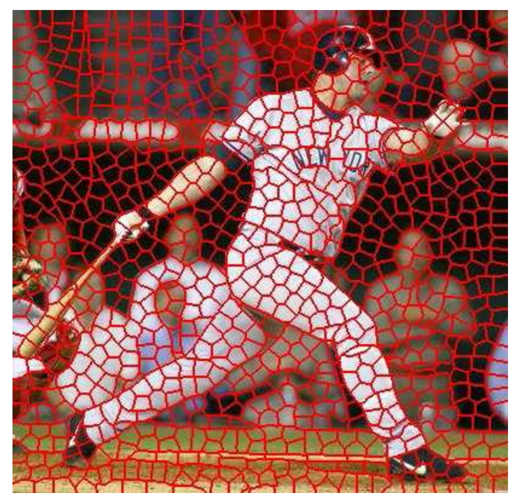
Goal: Break up the image into meaningful or perceptually similar regions

Segmentation for feature support or efficiency

50x50 Patch

50x50 Patch

[Felzenszwalb and Huttenlocher 2004]



Superpixels!

[Shi and Malik 2001]

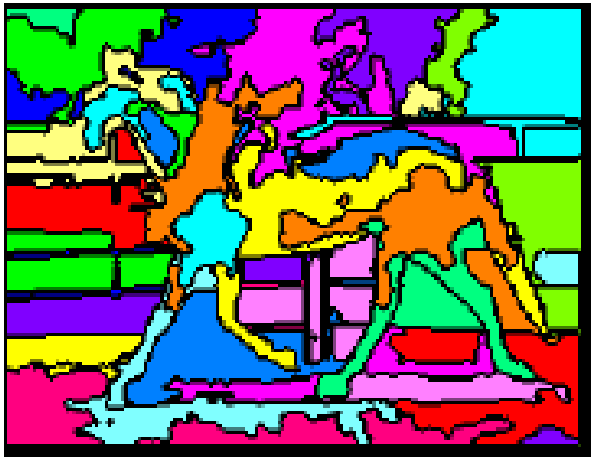
[Hoiem et al. 2005, Mori 2005]

Derek Hoiem

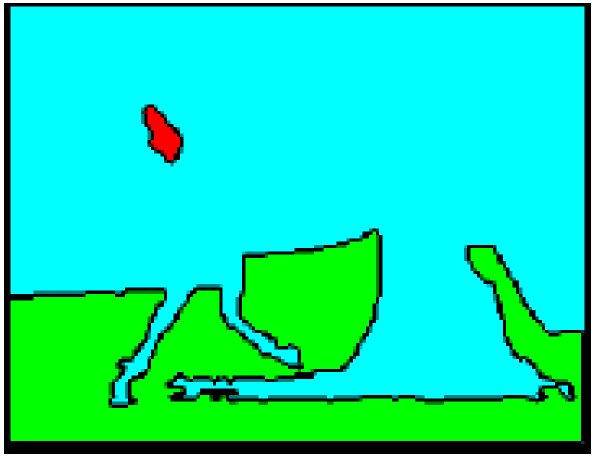
Segmentation as a result

GrabCut, Rother et al. 2004

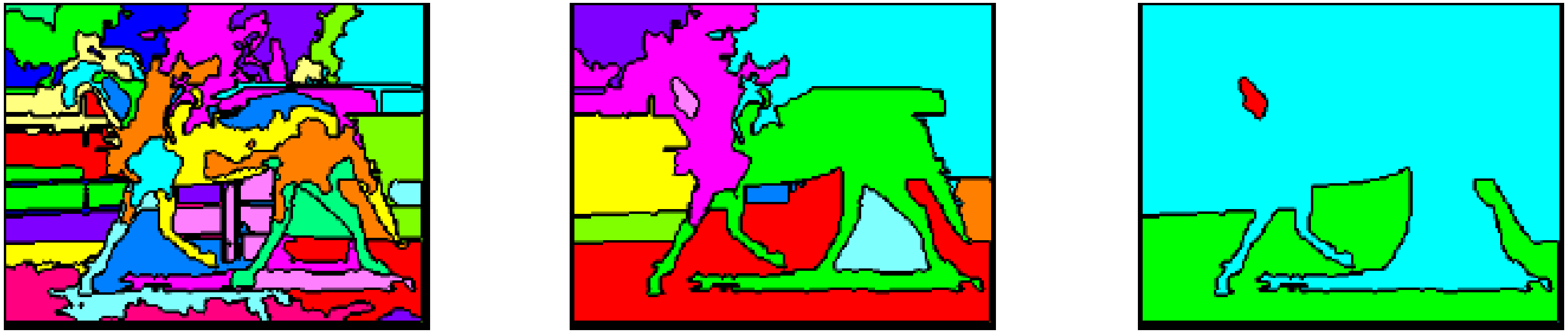
Types of segmentations



Oversegmentation



Undersegmentation



Hierarchical Segmentations

Clustering

Group together similar ‘points’ and represent them with a single token.

Key Challenges:

1) What makes two points/images/patches similar?

2) How do we compute an overall grouping from pairwise similarities?

Derek Hoiem

Why do we cluster?

- **Summarizing data**
  – Look at large amounts of data
  – Patch-based compression or denoising
  – Represent a large continuous vector with the cluster number
- **Counting**
  – Histograms of texture, color, SIFT vectors
- **Segmentation**
  – Separate the image into different regions
- **Prediction**
  – Images in the same cluster may have the same labels

Derek Hoiem

How do we cluster?

- K-means
  - Iteratively re-assign points to the nearest cluster center
- Agglomerative clustering
  - Start with each point as its own cluster and iteratively merge the closest clusters
- Mean-shift clustering
  - Estimate modes of pdf
- Spectral clustering
  - Split the nodes in a graph based on assigned links with similarity weights

K-means algorithm

1. Randomly select K centers

2. Assign each point to nearest center

3. Compute new center (mean) for each cluster

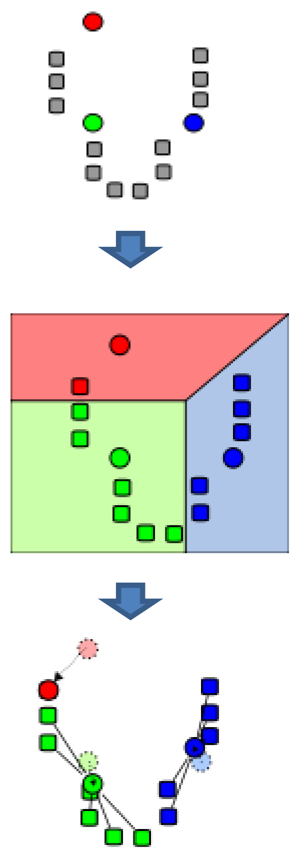
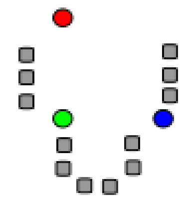


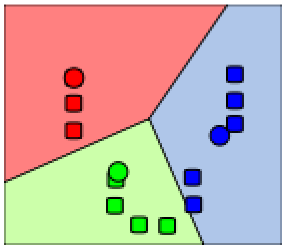
Illustration: http://en.wikipedia.org/wiki/K-means_clustering

K-means algorithm

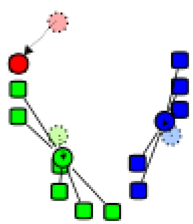
1. Randomly select K centers



2. Assign each point to nearest center



3. Compute new center (mean) for each cluster



Back to 2

Illustration: http://en.wikipedia.org/wiki/K-means_clustering

K-means

1. Initialize cluster centers: $\mathbf{c}^0$; t=0

2. Assign each point to the closest center

$$\boldsymbol{\delta}^t = \underset{\boldsymbol{\delta}}{\operatorname{argmin}} \tfrac{1}{N} \sum_j^N \sum_i^K \delta_{ij} \left(\mathbf{c}_i^{t-1} - \mathbf{x}_j \right)^2$$

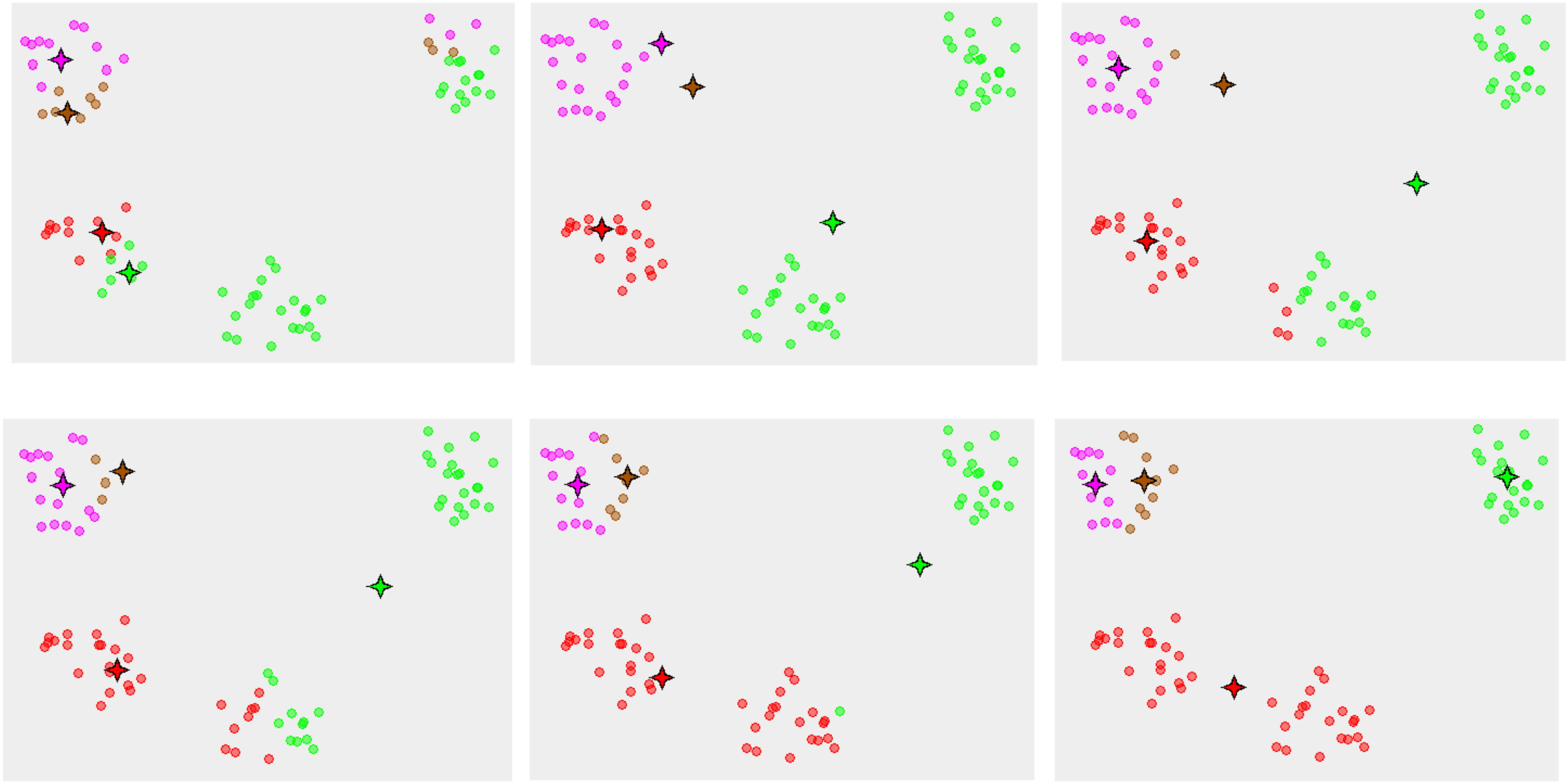
3. Update cluster centers as the mean of the points

$$\mathbf{c}^t = \underset{\mathbf{c}}{\operatorname{argmin}} \tfrac{1}{N} \sum_j^N \sum_i^K \delta_{ij}^t \left(\mathbf{c}_i - \mathbf{x}_j \right)^2$$

4. Repeat 2-3 until no points are re-assigned (t=t+1)

Slide: Derek Hoiem

K-means convergence



Think-Pair-Share

- What is good about k-means?
- What is bad about k-means?
- Where could you apply k-means?

K-means: design choices

- Initialization
  - Randomly select K points as initial cluster center
  - Or greedily choose K points to minimize residual
- Distance measures
  - Traditionally Euclidean, could be others
- Optimization
  - Will converge to a *local minimum*
  - May want to perform multiple restarts

K-means clustering using intensity or color

Image

Clusters on intensity

Clusters on color

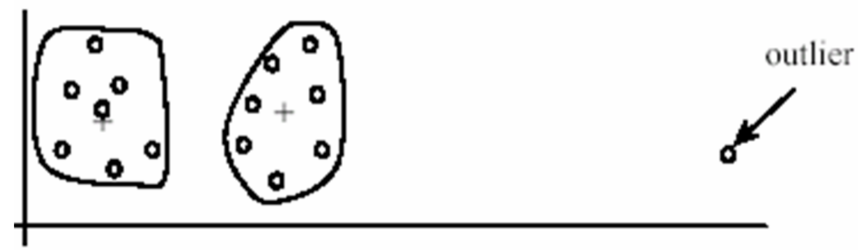
How to choose the number of clusters?

- Validation set
  - Try different numbers of clusters and look at performance
    - When building dictionaries (discussed later), more clusters typically work better.

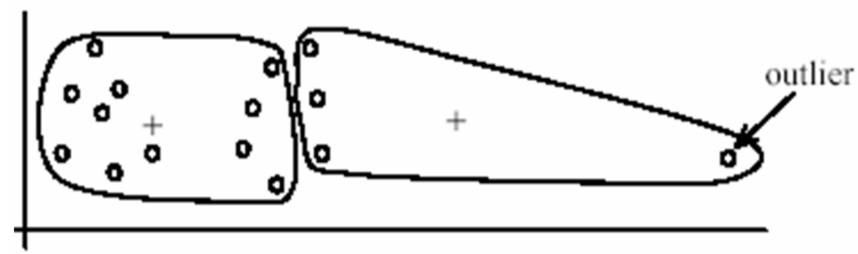
Slide: Derek Hoiem

K-Means pros and cons

- Pros
  - Finds cluster centers that minimize conditional variance (good representation of data)
  - Simple and fast*
  - Easy to implement
- Cons
  - Need to choose K
  - Sensitive to outliers
  - Prone to local minima
  - All clusters have the same parameters (e.g., distance measure is non-adaptive)
  - *Can be slow: each iteration is O(KNd) for N d-dimensional points
- Usage
  - Cluster features to build visual dictionaries



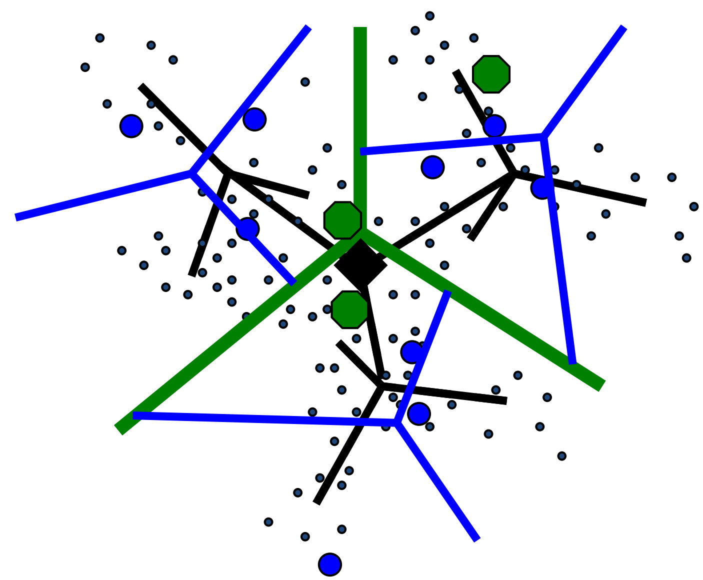
(B): Ideal clusters



Building Visual Dictionaries

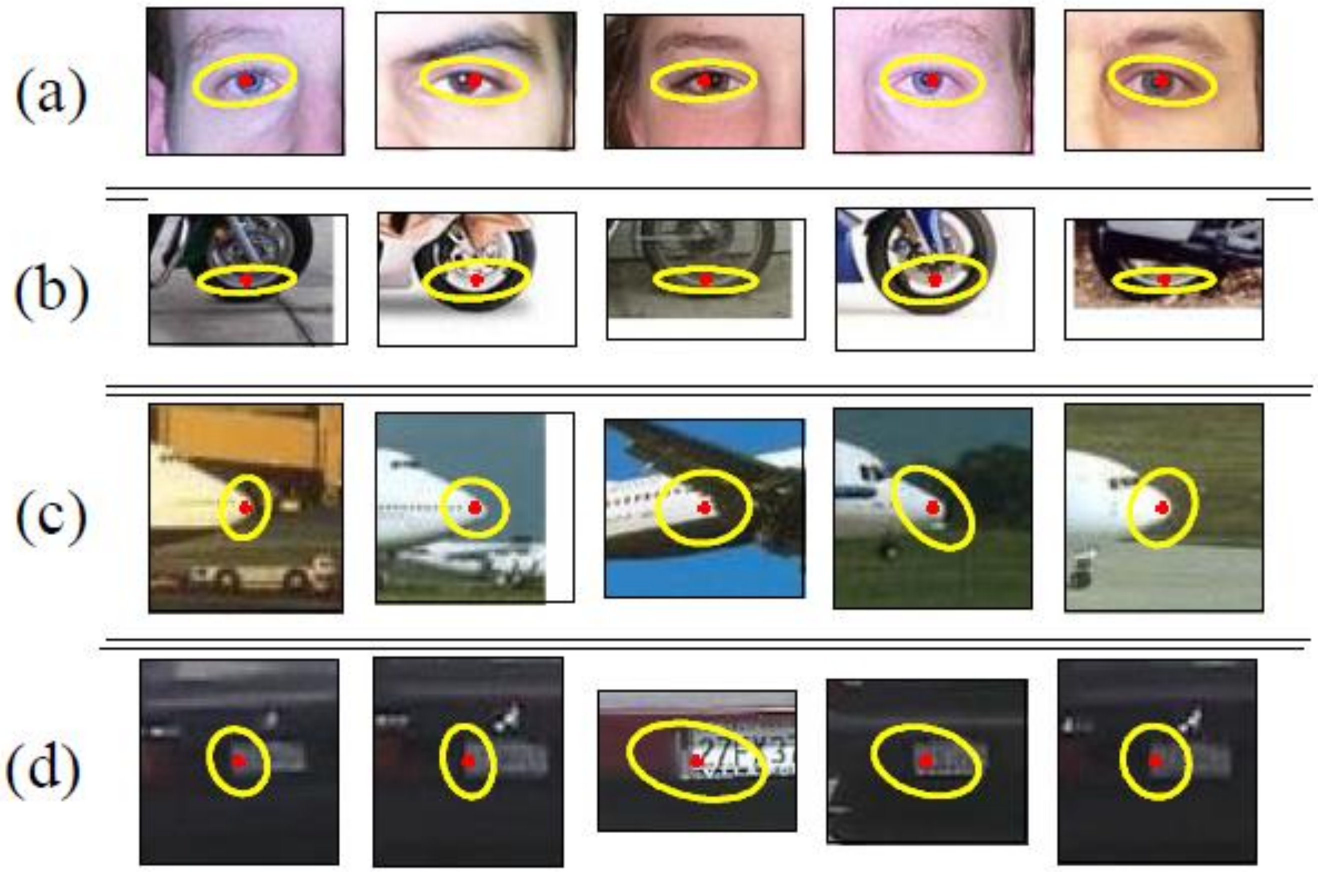
1. Sample features from a database
   – E.g., 128 dimensional SIFT vectors

2. Cluster to build dictionary
   – Cluster centers are the dictionary words



3. To match new features, assign to the nearest cluster to save rebuilding dictionary

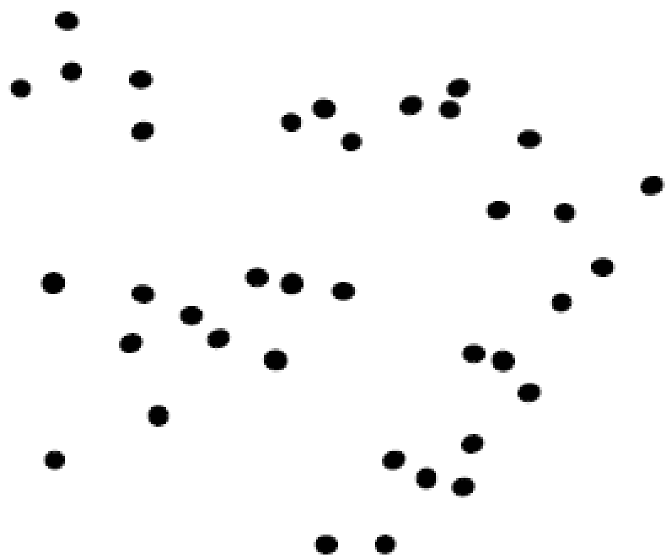
Examples of learned codewords



Most likely codewords for 4 learned "topics"
EM with multinomial (problem 3) to get topics

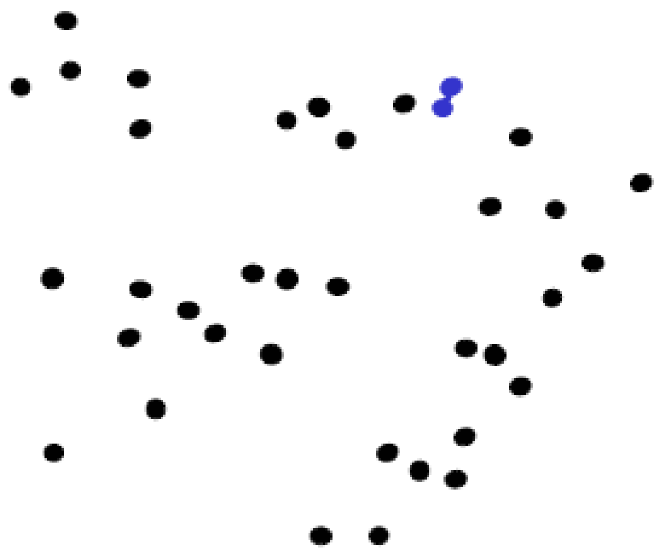
http://www.robots.ox.ac.uk/~vgg/publications/papers/sivic05b.pdf Sivic et al. ICCV 2005

Agglomerative clustering

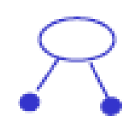


1. Say "Every point is its own cluster"

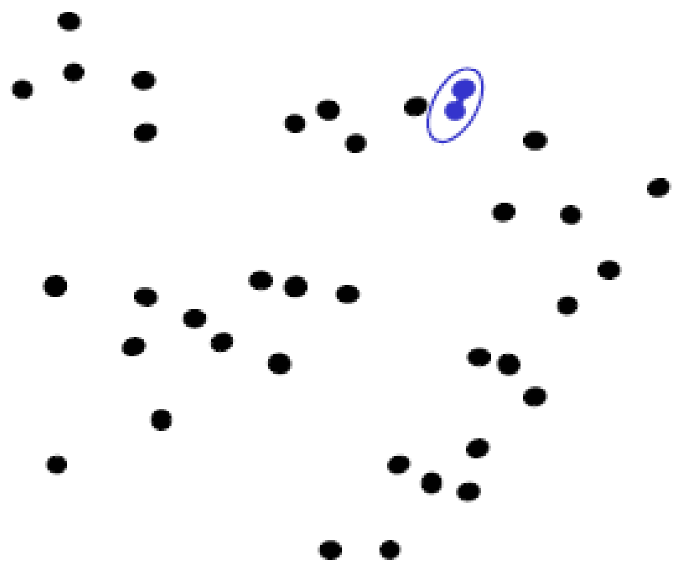
Agglomerative clustering



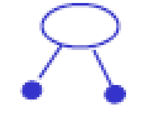
1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters



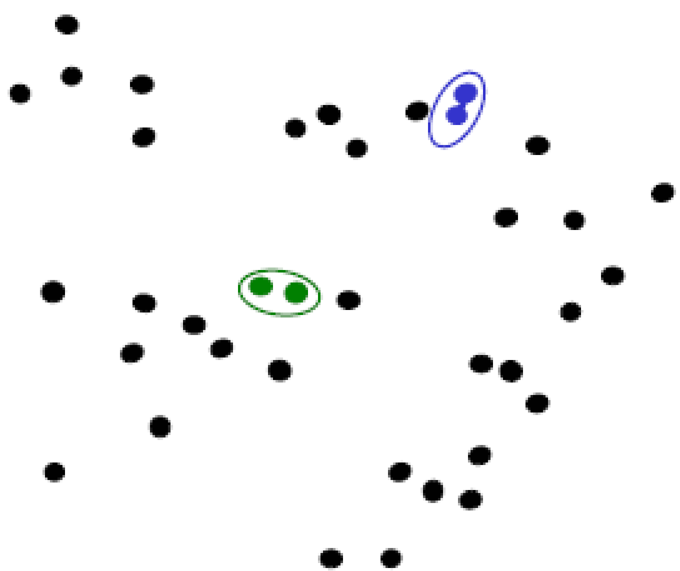
Agglomerative clustering



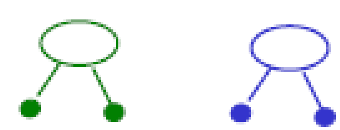
1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters
3. Merge it into a parent cluster



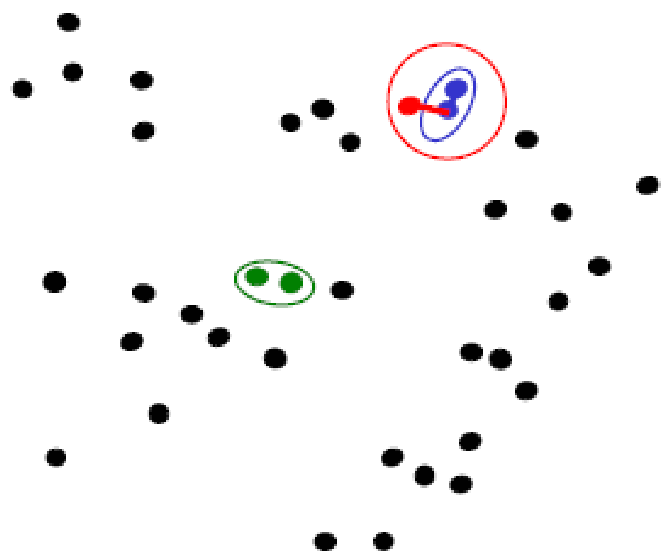
Agglomerative clustering



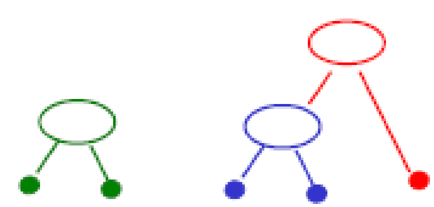
1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters
3. Merge it into a parent cluster
4. Repeat



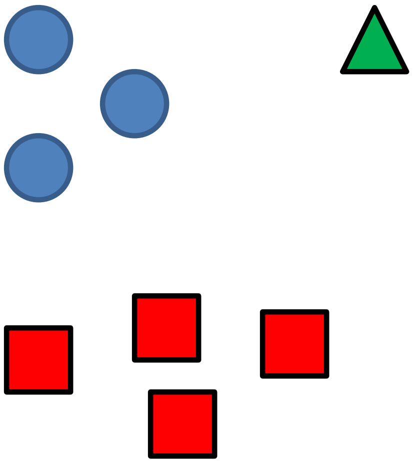
Agglomerative clustering



1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters
3. Merge it into a parent cluster
4. Repeat



Agglomerative clustering

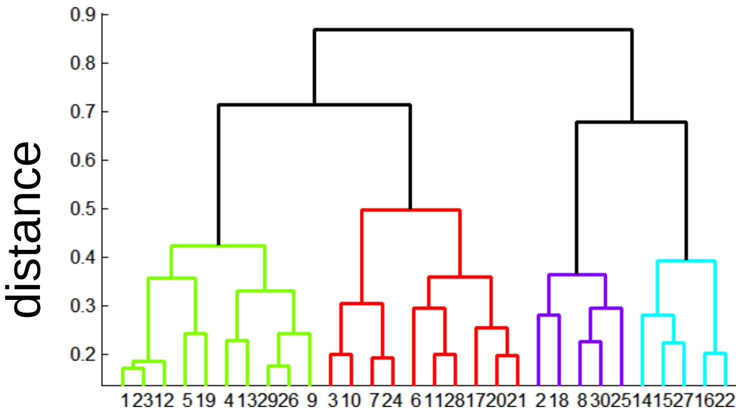


How to define cluster similarity?

- Average distance between points, maximum distance, minimum distance
- Distance between means or medoids

How many clusters?

- Clustering creates a dendrogram (a tree)
- Threshold based on max number of clusters or based on distance between merges



Conclusions: Agglomerative Clustering

Good

- Simple to implement, widespread application
- Clusters have adaptive shapes
- Provides a hierarchy of clusters

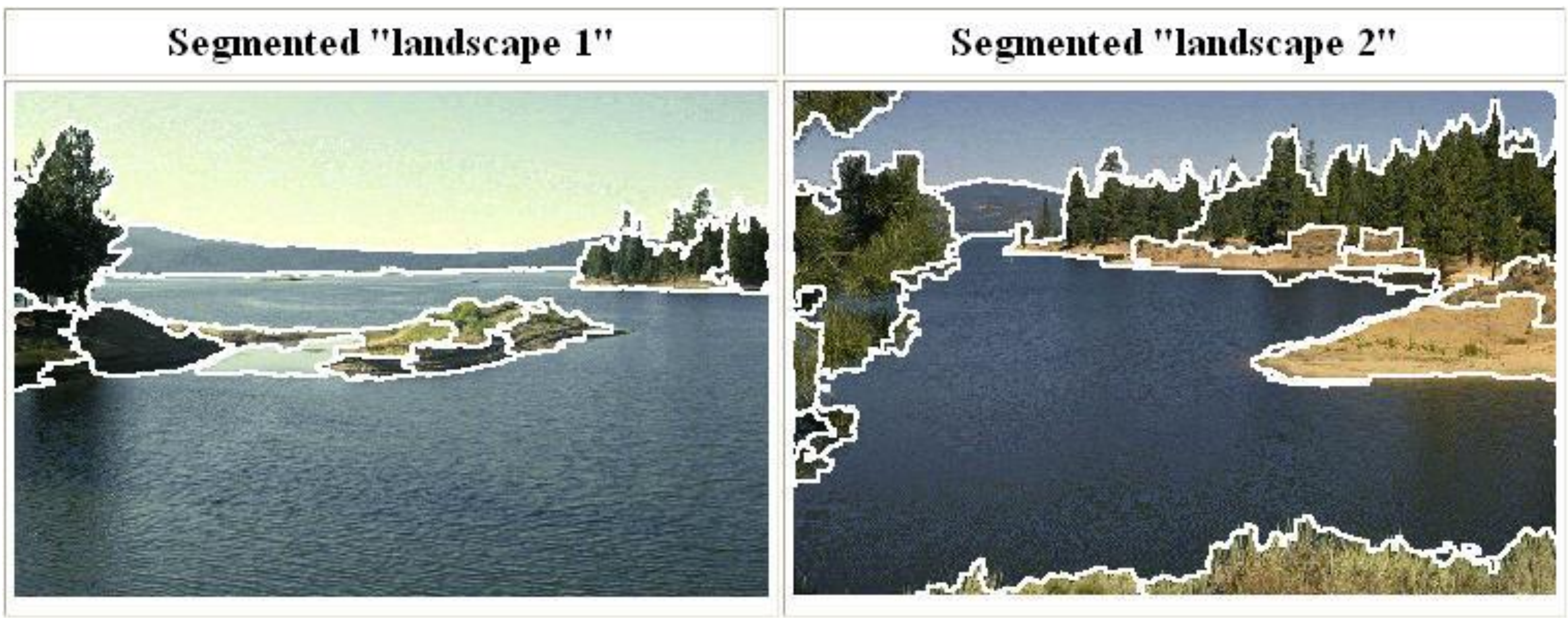
Bad

- May have imbalanced clusters
- Still have to choose number of clusters or threshold
- Need to use an “ultrametric” to get a meaningful hierarchy

Mean shift segmentation

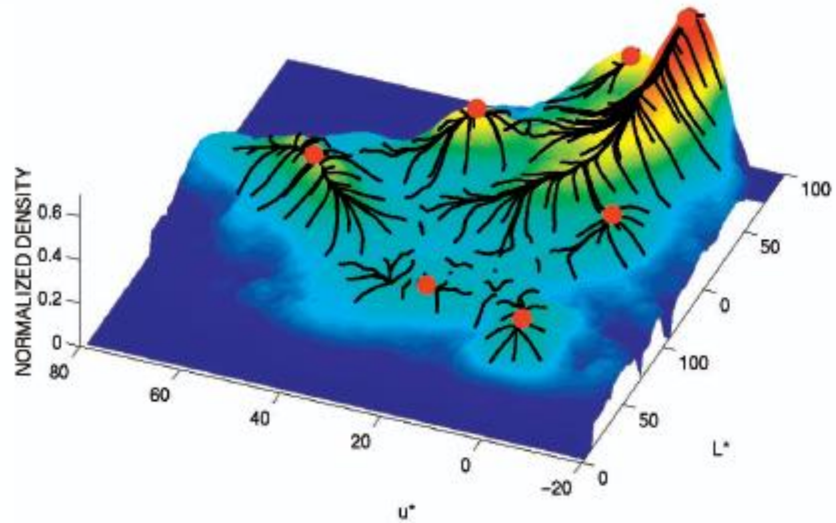
D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

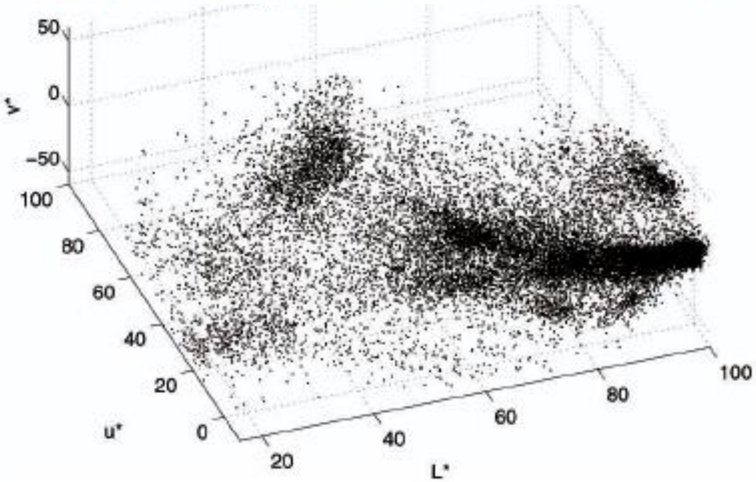
- Versatile technique for clustering-based segmentation



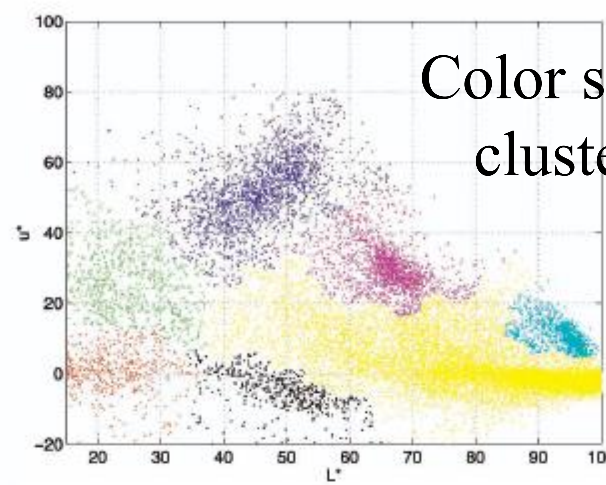
Mean shift algorithm

Try to find *modes* of a non-parametric density.





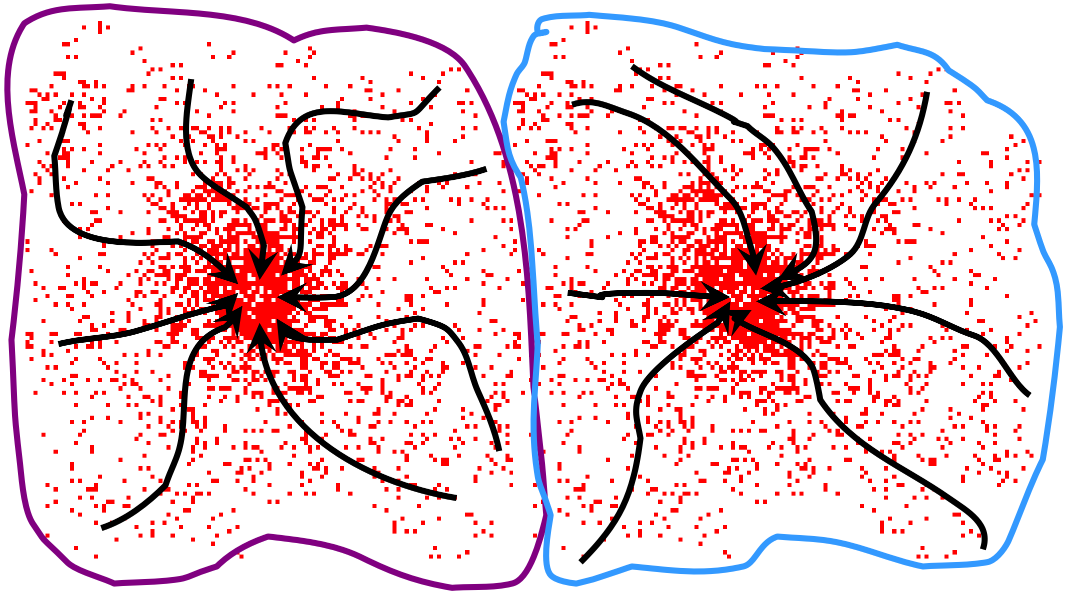
Color space



Color space clusters

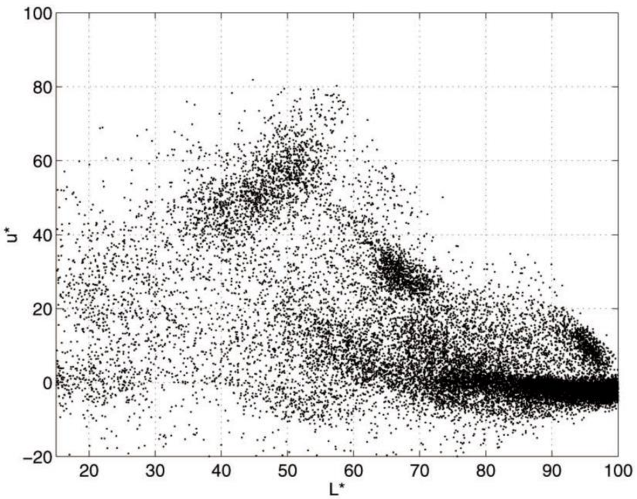
Attraction basin

- Attraction basin: the region for which all trajectories lead to the same mode
- Cluster: all data points in the attraction basin of a mode

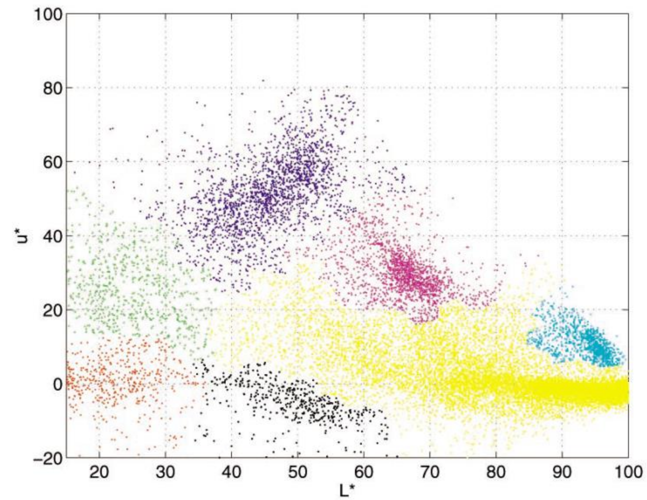


Slide by Y. Ukrainitz & B. Sarel

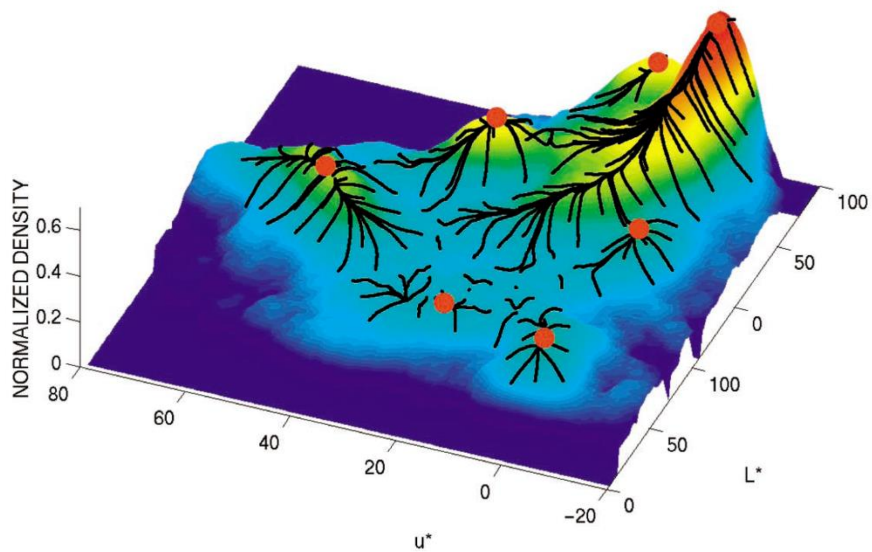
Attraction basin



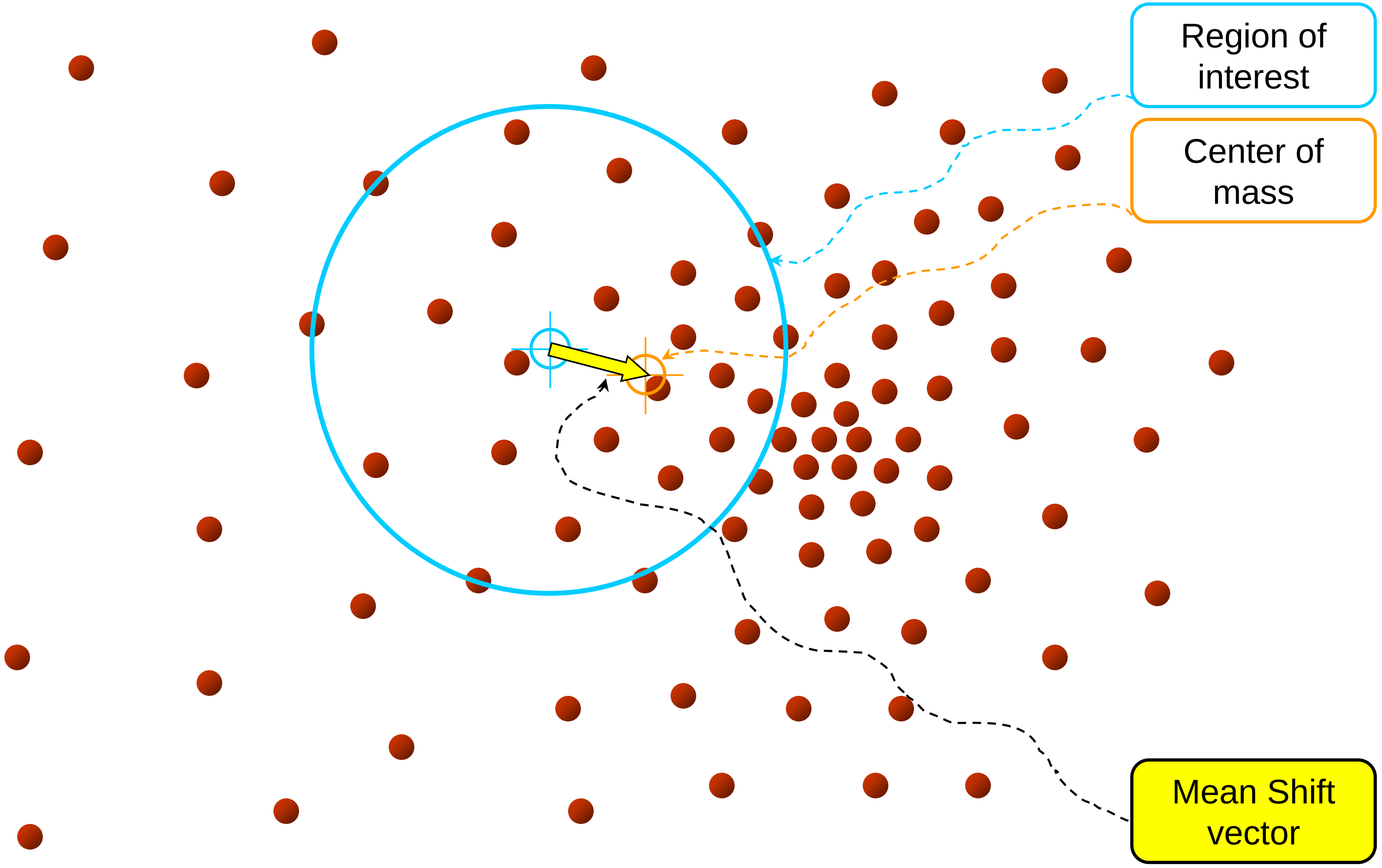
(a)



(b)



Mean shift



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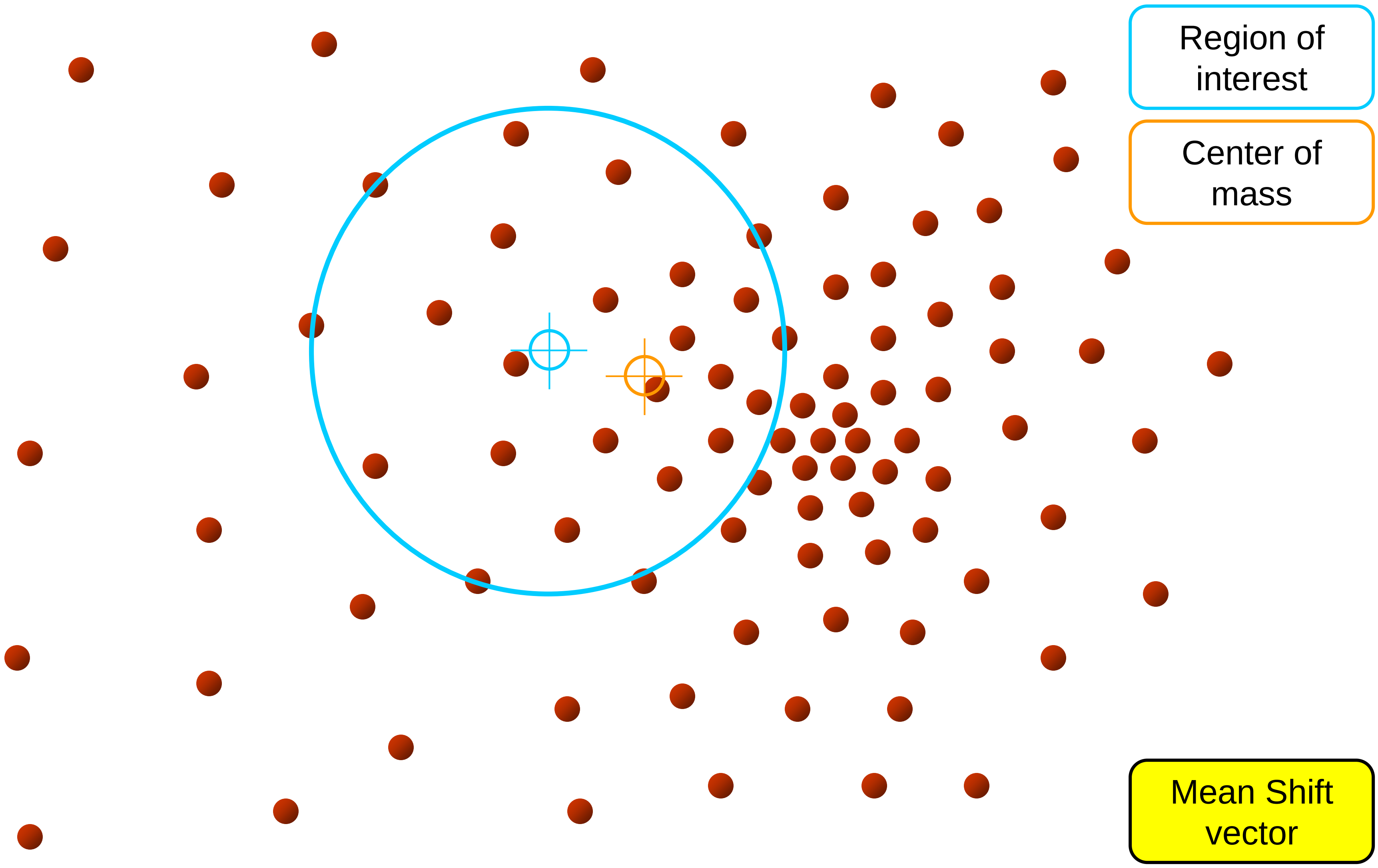
Mean shift



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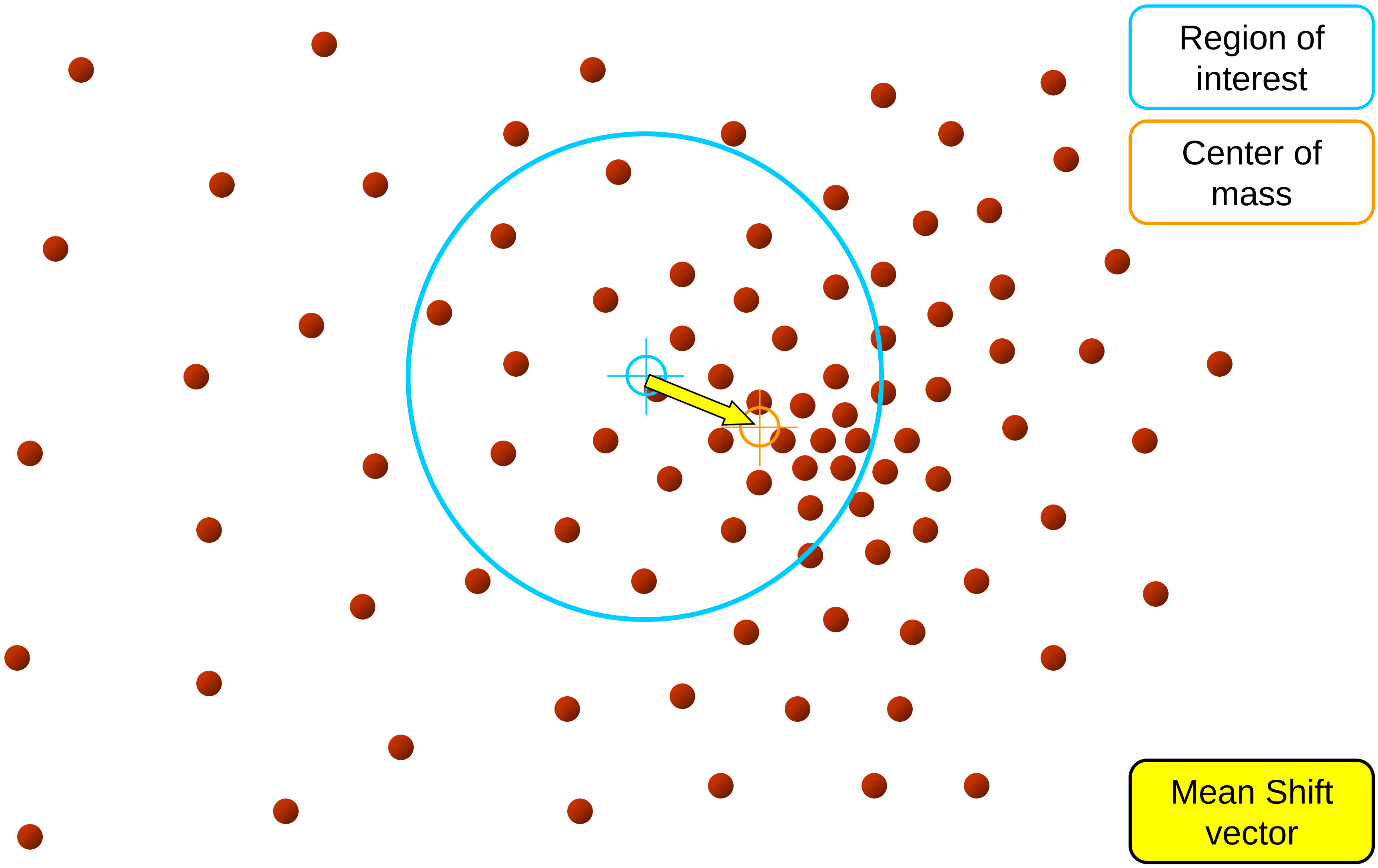
Mean shift



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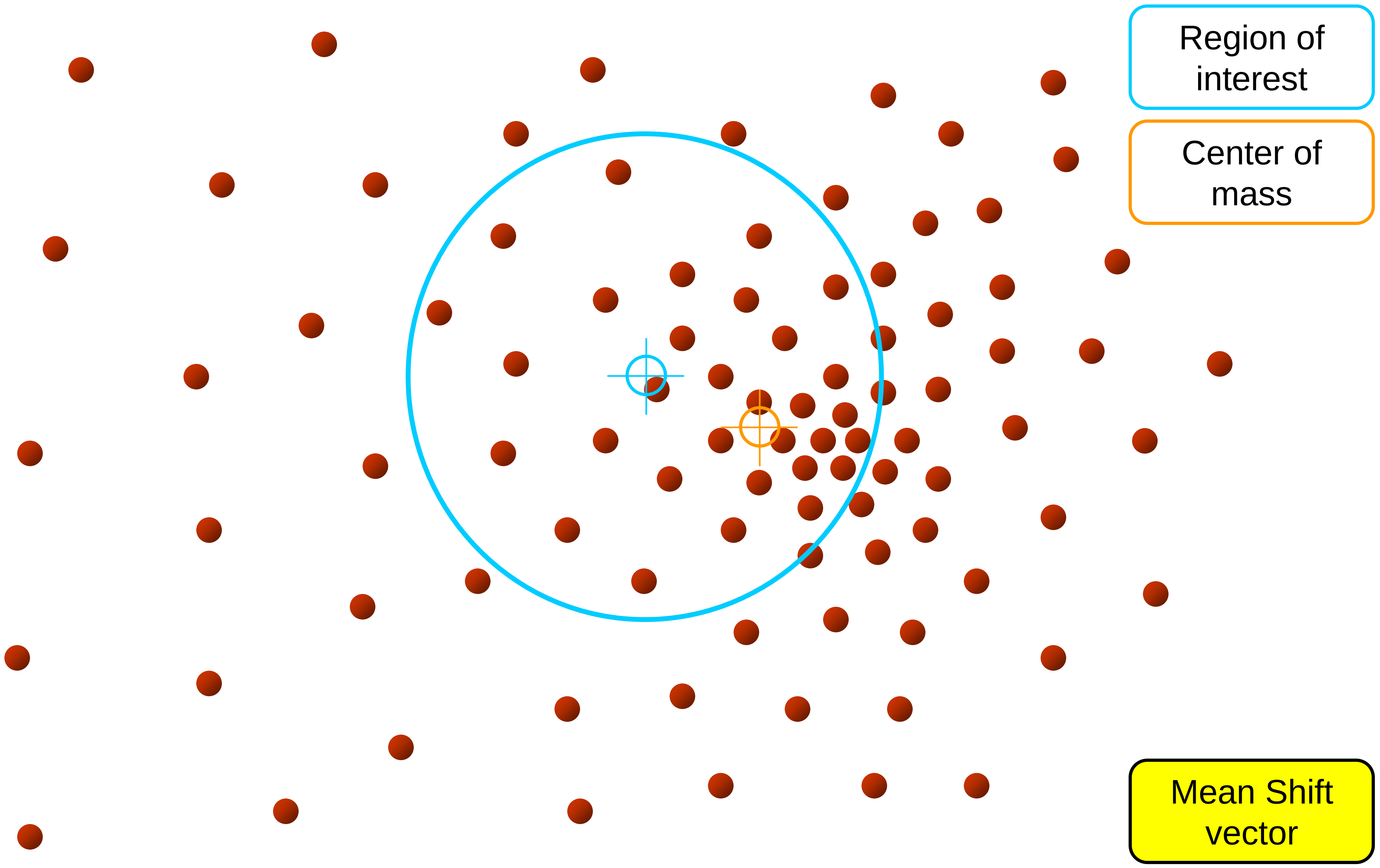
Mean shift



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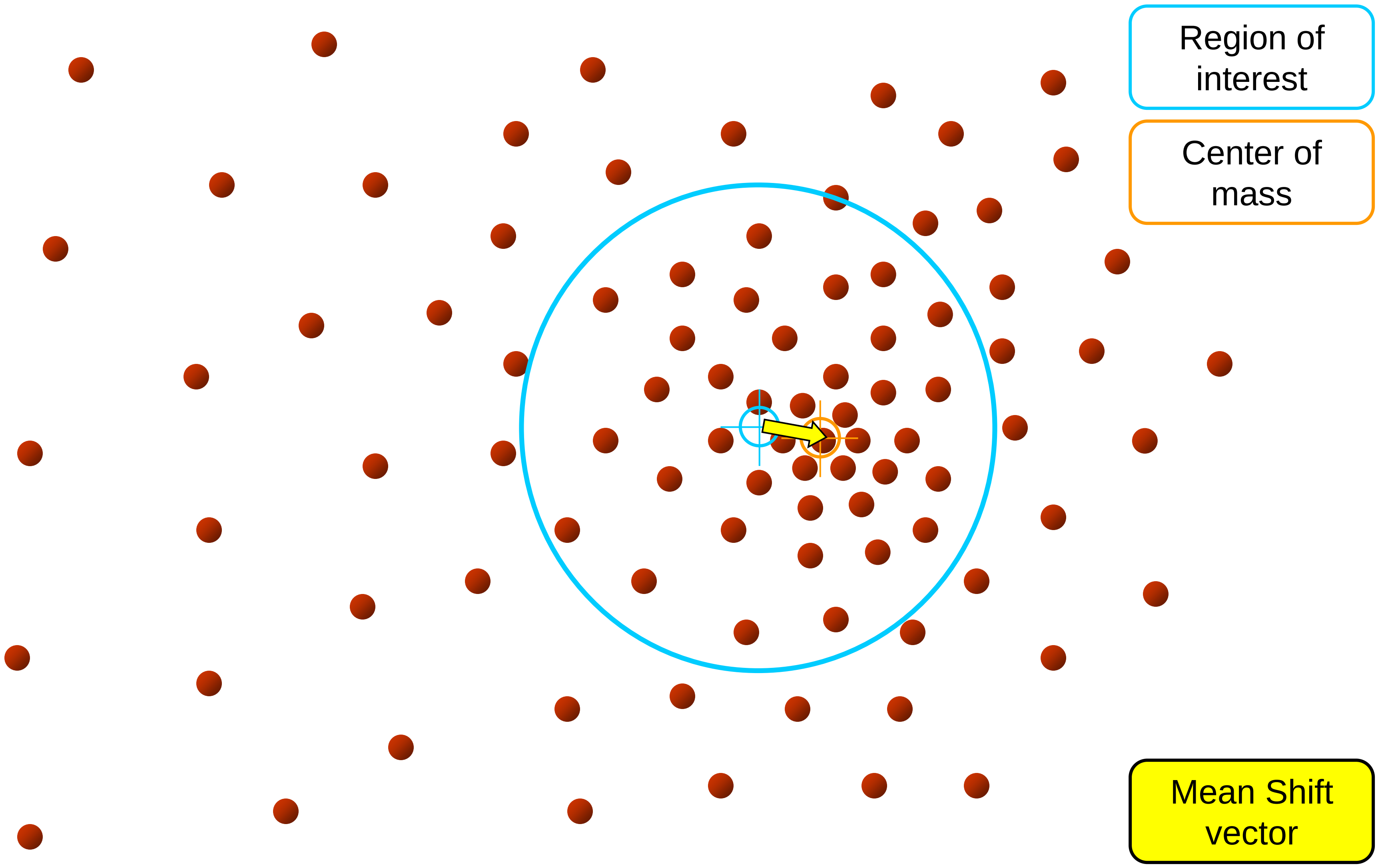
Mean shift



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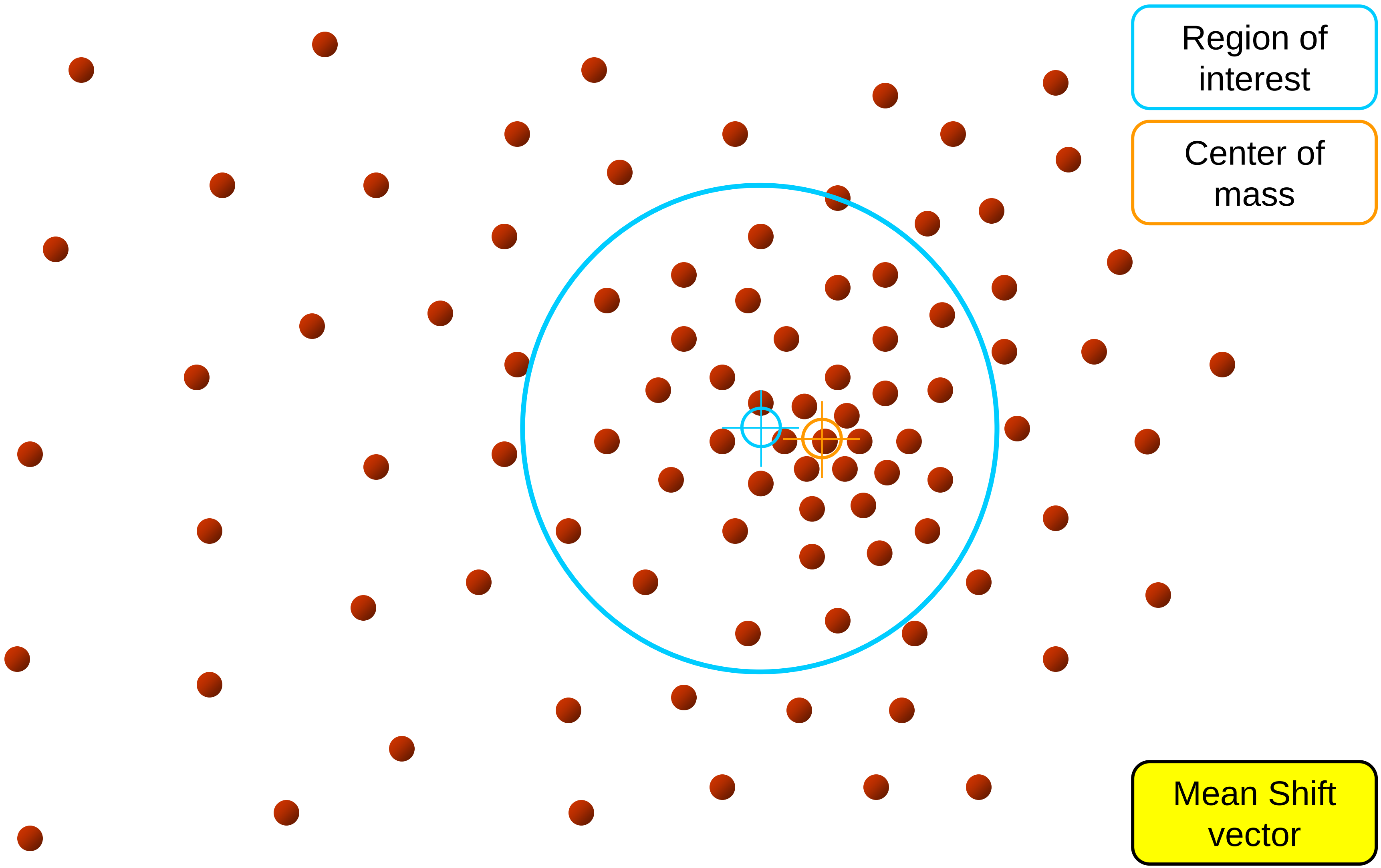
Mean shift



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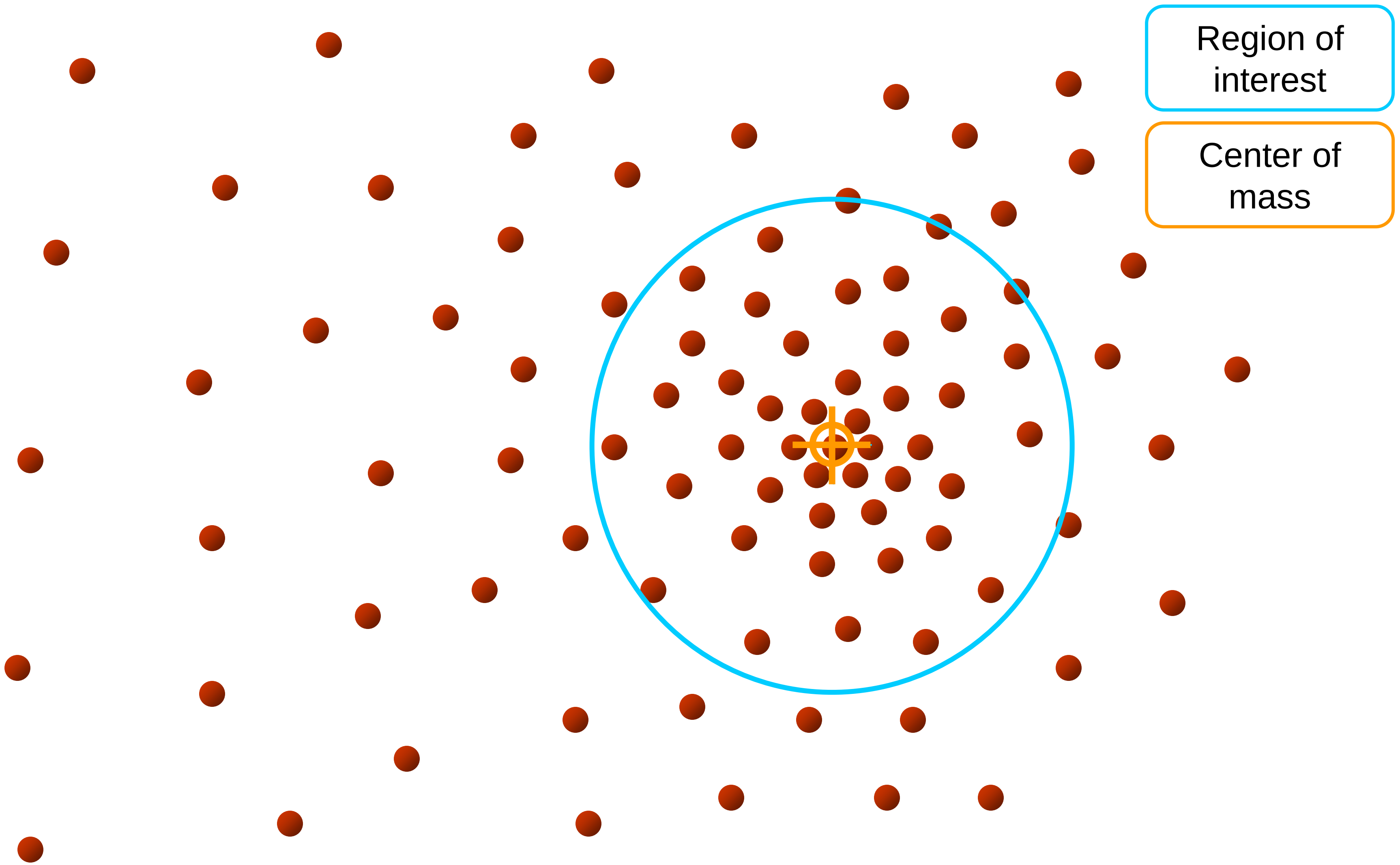
Mean shift



Slide by Y. Ukrainitz & B. Sarel

Kernel density estimation

Kernel density estimation function

$$\widehat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$$

Gaussian kernel

$$K\left(\frac{x - x_i}{h}\right) = \frac{1}{\sqrt{2\pi}}\, e^{-\frac{(x-x_i)^2}{2h^2}}.$$

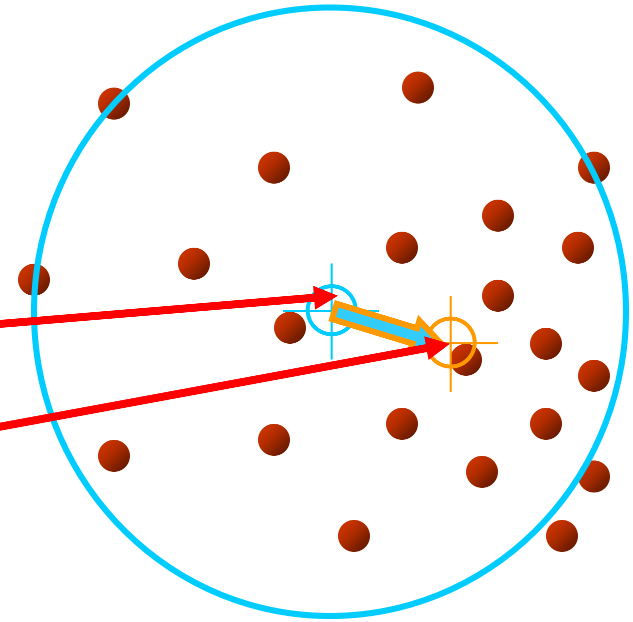
Computing the Mean Shift

<u>Simple Mean Shift procedure</u>:

• Compute mean shift vector **m(x)**

• Iteratively translate the kernel window by **m(x)** until convergence.

$$\mathbf{m}(\mathbf{x}) = \left[\boxed{\frac{\sum_{i=1}^{n} \mathbf{x}_i g\left(\frac{\left\| \mathbf{x} - \mathbf{x}_i \right\|^2}{h} \right)}{\sum_{i=1}^{n} g\left(\frac{\left\| \mathbf{x} - \mathbf{x}_i \right\|^2}{h} \right)}} - \boxed{\mathbf{x}} \right]$$



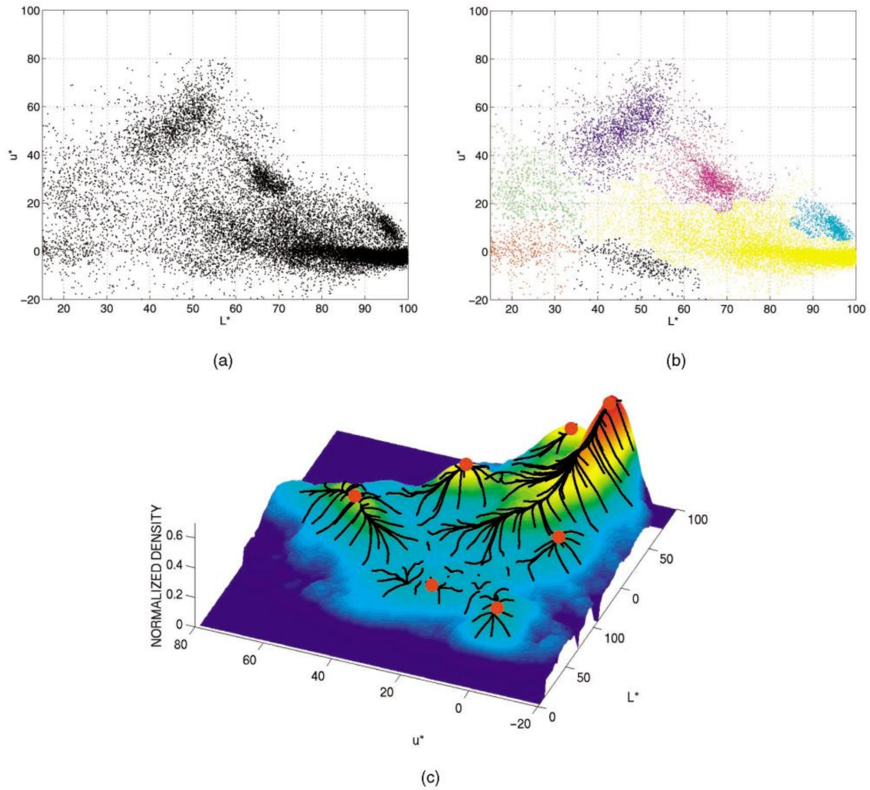
$$g(\mathbf{x}) = -k'(\mathbf{x})$$

Mean shift clustering

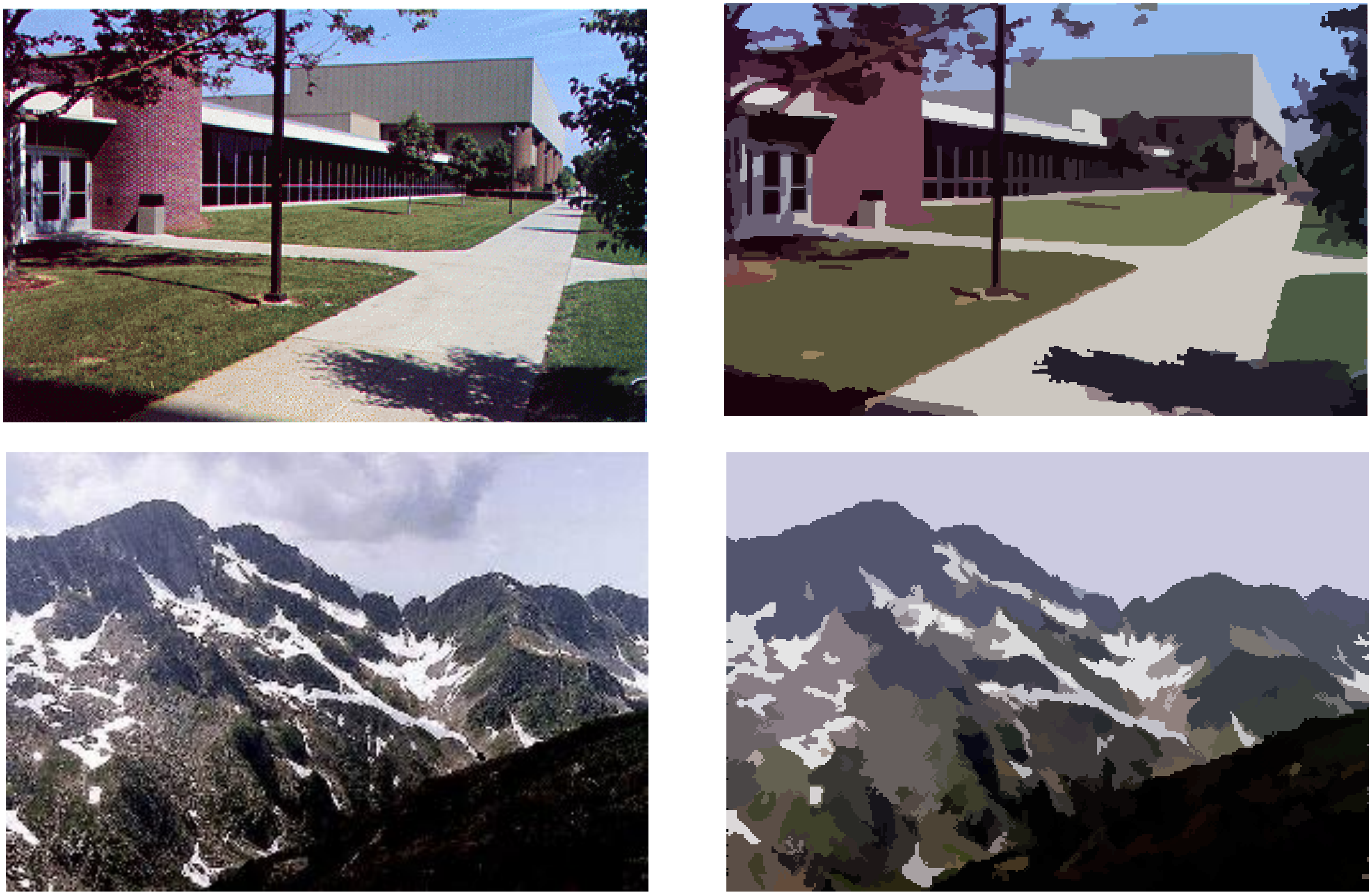
- The mean shift algorithm seeks *modes* of the given set of points
  1. Choose kernel and bandwidth
  2. For each point:
     a) Center a window on that point
     b) Compute the mean of the data in the search window
     c) Center the search window at the new mean location
     d) Repeat (b,c) until convergence
  3. Assign points that lead to nearby modes to the same cluster

Segmentation by Mean Shift

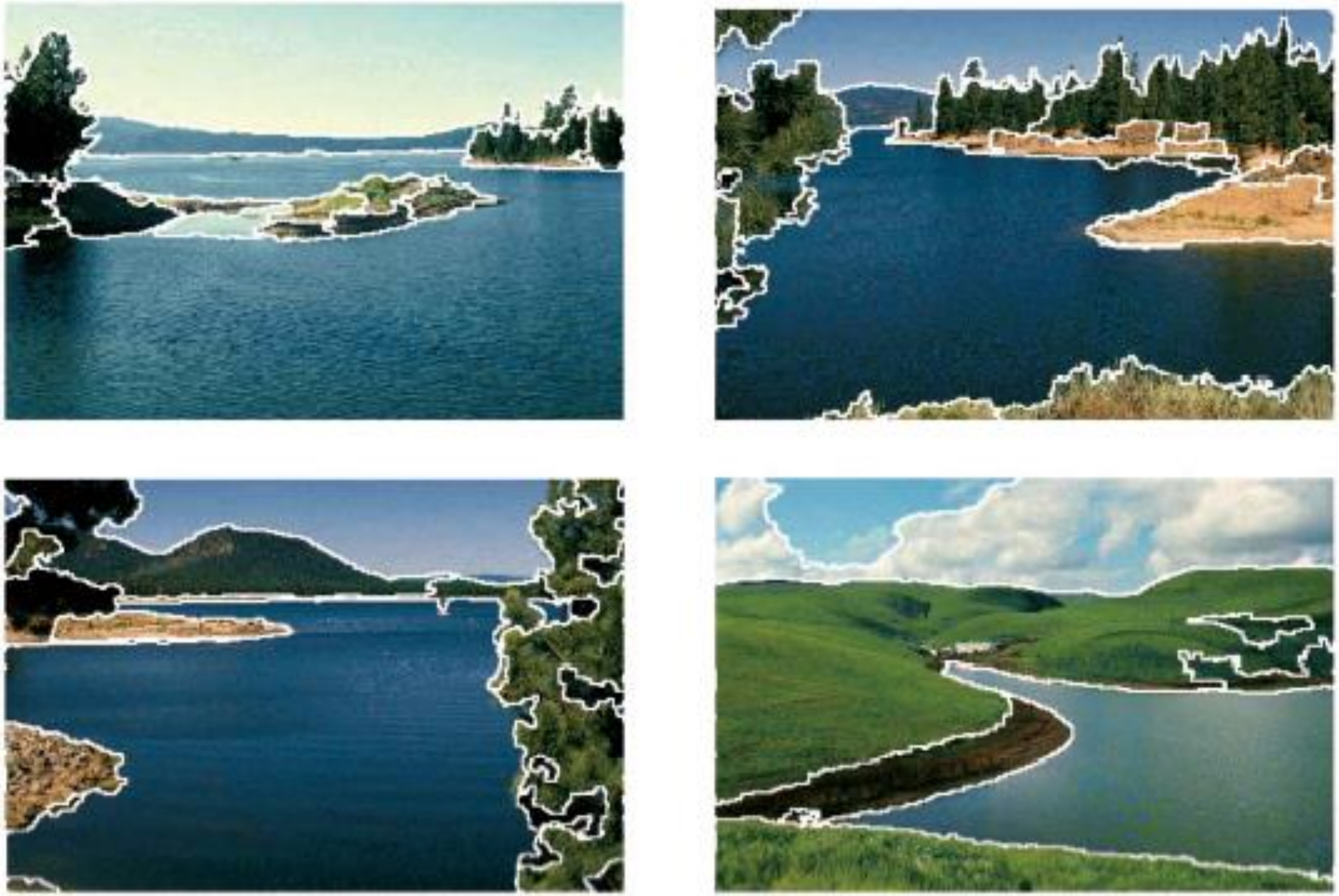
- Compute features for each pixel (color, gradients, texture, etc.).
- Set kernel size for features K_f and position K_s.
- Initialize windows at individual pixel locations.
- Perform mean shift for each window until convergence.
- Merge windows that are within width of K_f and K_s.



Mean shift segmentation results



Comaniciu and Meer 2002



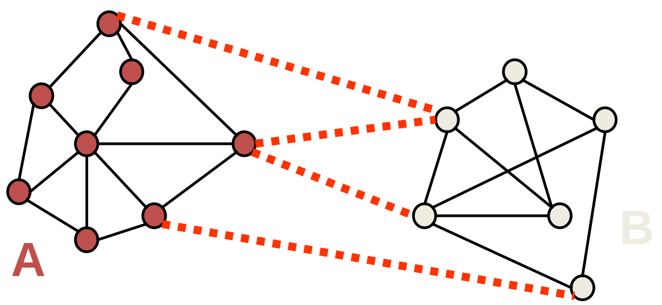
Comaniciu and Meer 2002

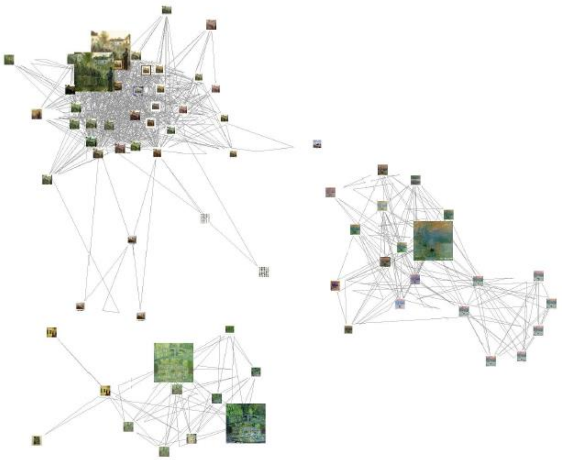
Mean shift pros and cons

- Pros
  - Good general-practice segmentation
  - Flexible in number and shape of regions
  - Robust to outliers
- Cons
  - Have to choose kernel size in advance
  - Not suitable for high-dimensional features
- When to use it
  - Oversegmentation
  - Multiple segmentations
  - Tracking, clustering, filtering applications

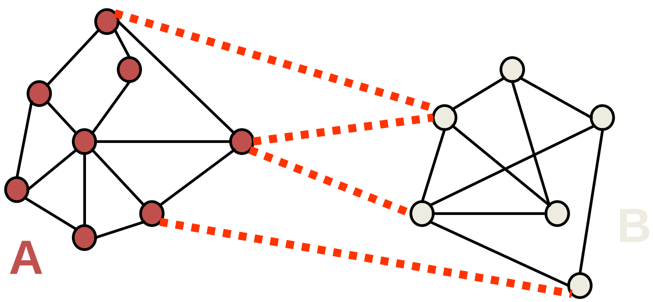
Spectral clustering

Group points based on links in a graph





Cuts in a graph



Normalized Cut

- a cut penalizes large segments
- fix by normalizing for size of segments

$$Ncut(A, B) = \frac{cut(A, B)}{volume(A)} + \frac{cut(A, B)}{volume(B)}$$

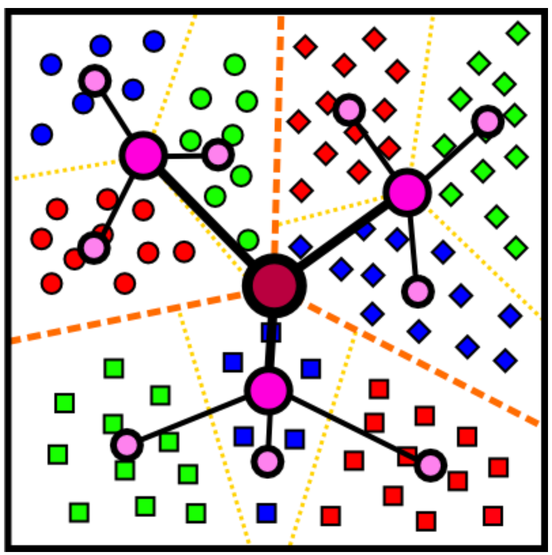
- volume(A) = sum of costs of all edges that touch A

Source: Seitz

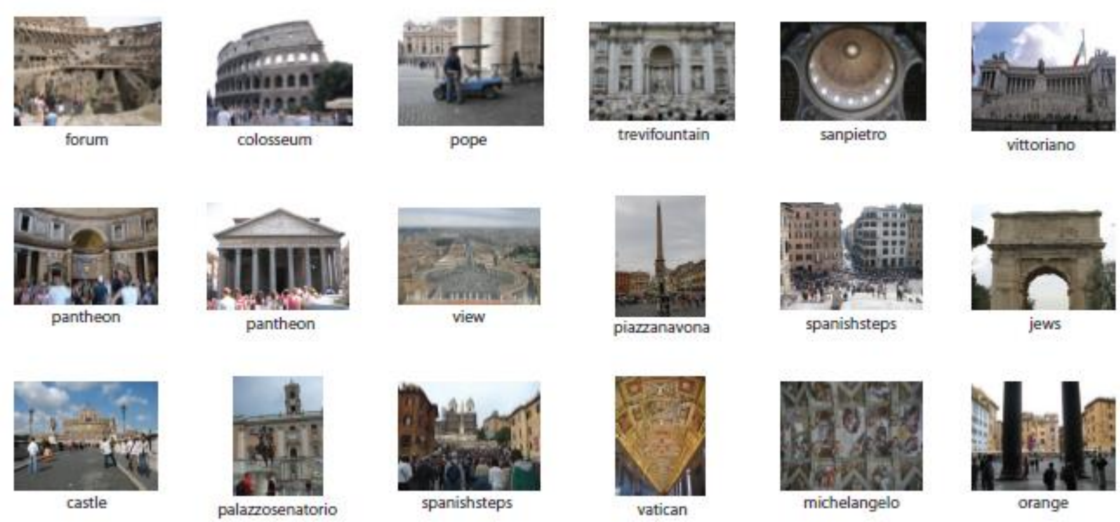
Normalized cuts for segmentation

Which algorithm to use?

- Quantization/Summarization: K-means
  - Aims to preserve variance of original data
  - Can easily assign new point to a cluster



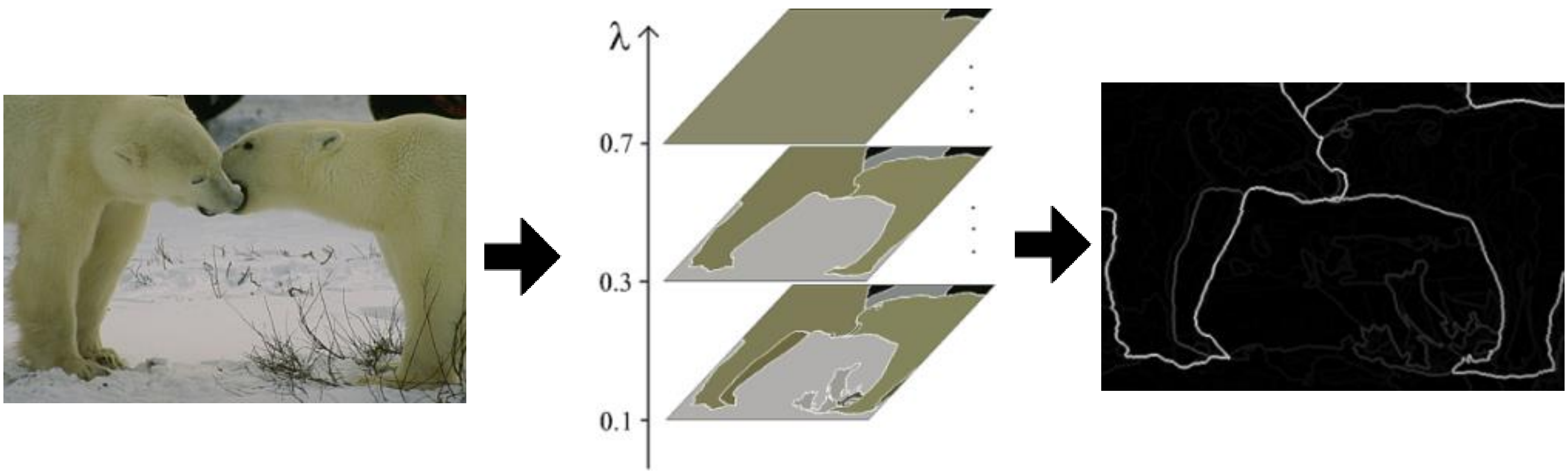
Quantization for computing histograms



Summary of 20,000 photos of Rome using "greedy k-means"
http://grail.cs.washington.edu/projects/canonview/

Which algorithm to use?

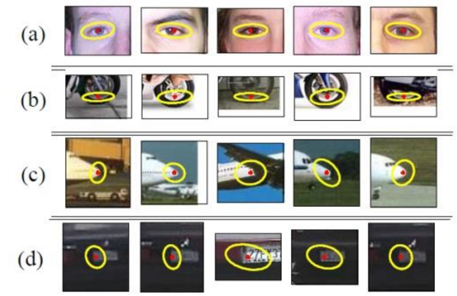
- Image segmentation: agglomerative clustering
  - More flexible with distance measures (e.g., can be based on boundary prediction)
  - Adapts better to specific data
  - Hierarchy can be useful



http://www.cs.berkeley.edu/~arbelaez/UCM.html

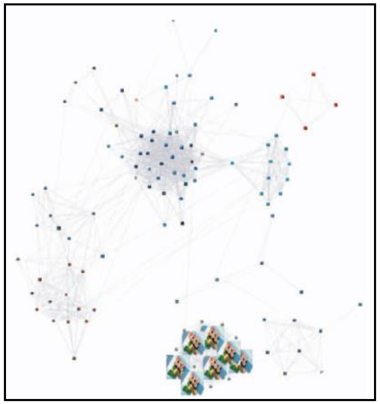
Things to remember

- K-means useful for summarization, building dictionaries of patches, general clustering



- Agglomerative clustering useful for segmentation, general clustering

- Spectral clustering useful for determining relevance, summarization, segmentation



Machine Learning Problems

	Supervised Learning	Unsupervised Learning
Discrete	classification or categorization	clustering
Continuous	regression	dimensionality reduction