The University of Texas at Austin
Electrical and Computer Engineering
Cockrell School of Engineering

Spring 2024

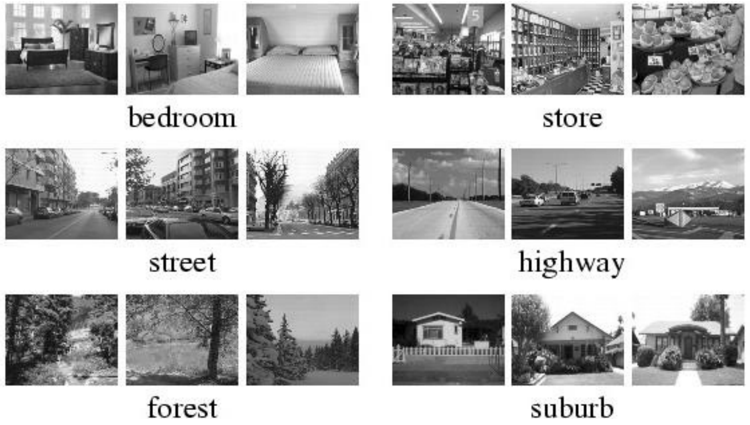
INTRODUCTION TO COMPUTER VISION

Atlas Wang
Associate Professor, The University of Texas at Austin

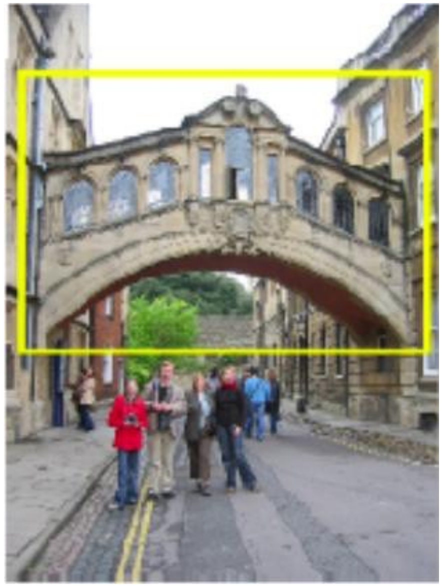
Visual Informatics Group@UT Austin
https://vita-group.github.io/

Recognition so far

Category:
- Is this a bedroom?
- What class of scene is this?
- Holistic features/quantization



Instance:
- Find this specific famous building.
- Find this person.
- Local features/precise correspondence
- Often within a database of images



"Image classification is not real computer vision… so don't be too obsessed with that"

Recognition so far

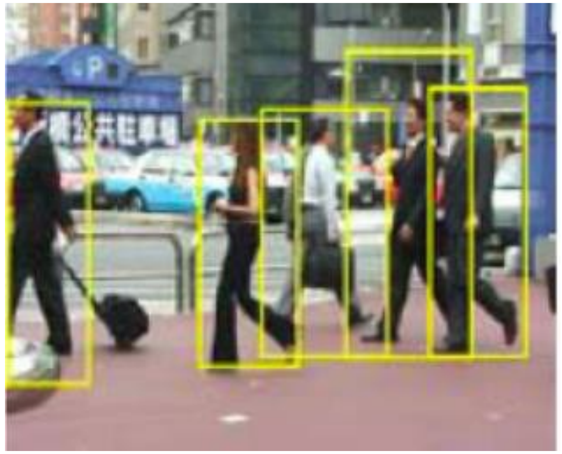
Object (category) detection:

– Find all the people

– Find all the faces

– Often within a single image

– Often ‘sliding window’



Scenes have “stuff” – distribution of materials and surfaces with arbitrary shape.

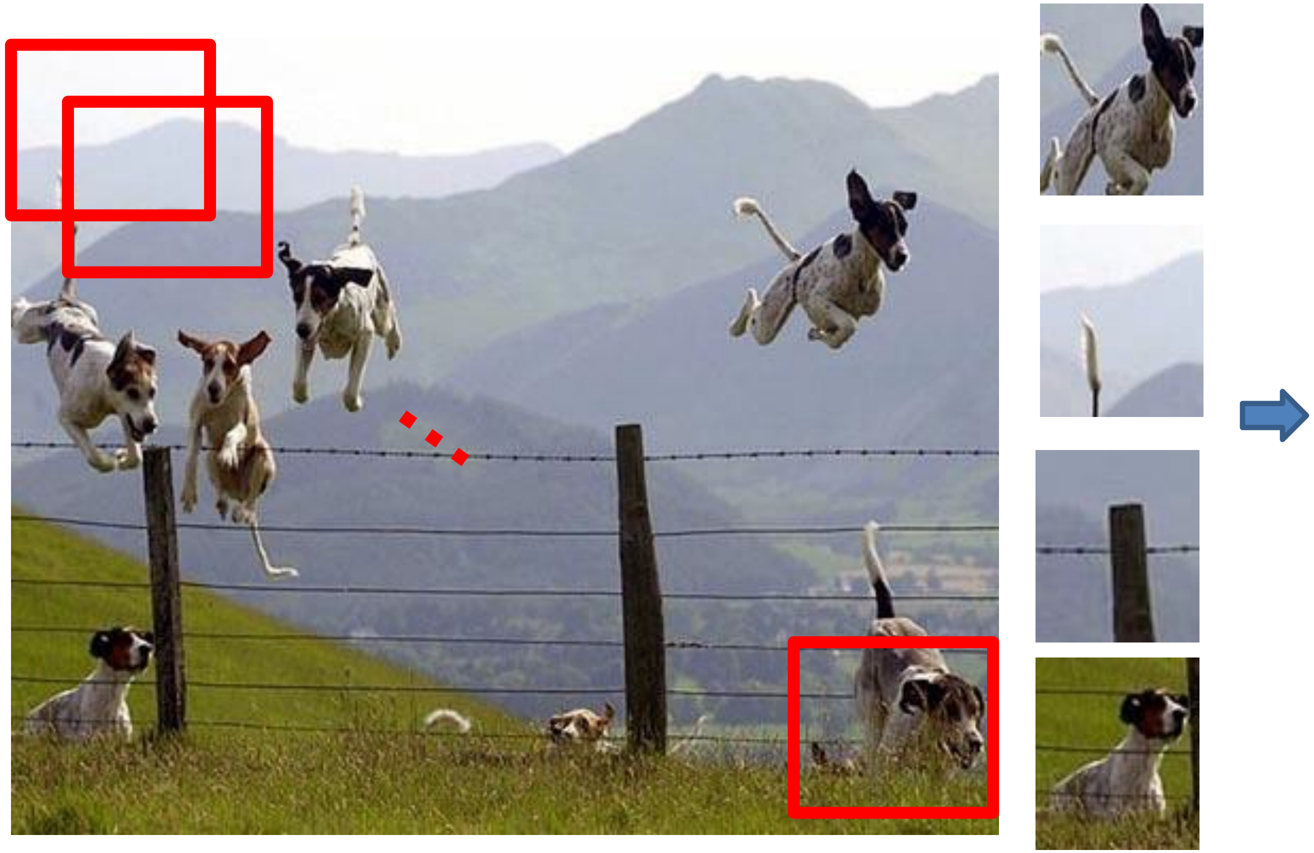
- Bag of Words ok!

Objects are “things” with shape, boundaries.

- **Bag of Words less ok as spatial layout is lost!**

Object Category Detection

- Focus on object search: “Where is it?”
- Build templates that quickly differentiate object patch from background patch



Object or **Non-Object?**

James Hays

Object Detection Design challenges

- How to efficiently search for likely objects
  - Even simple models require searching hundreds of thousands of positions and scales.
- Feature design and scoring
  - How should appearance be modeled?
  - What features correspond to the object?
- How to deal with different viewpoints?
  - Often train different models for a few different viewpoints

General Process of Object Detection

Specify Object Model

Generate Hypotheses

Score Hypotheses

Resolve Detections

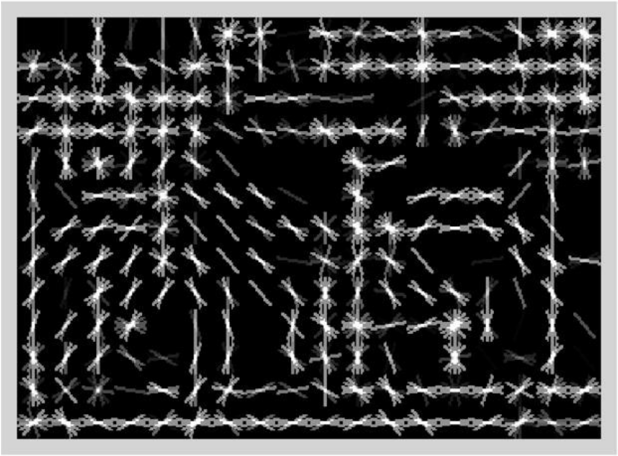
What are the object parameters?

James Hays

Specifying an object model

1. Statistical Template in Bounding Box
   - Object is some (x,y,w,h) in image
   - Features defined wrt bounding box coordinates

Image

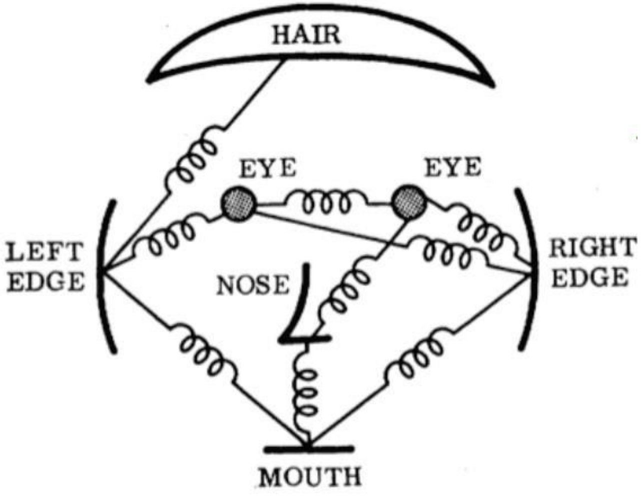


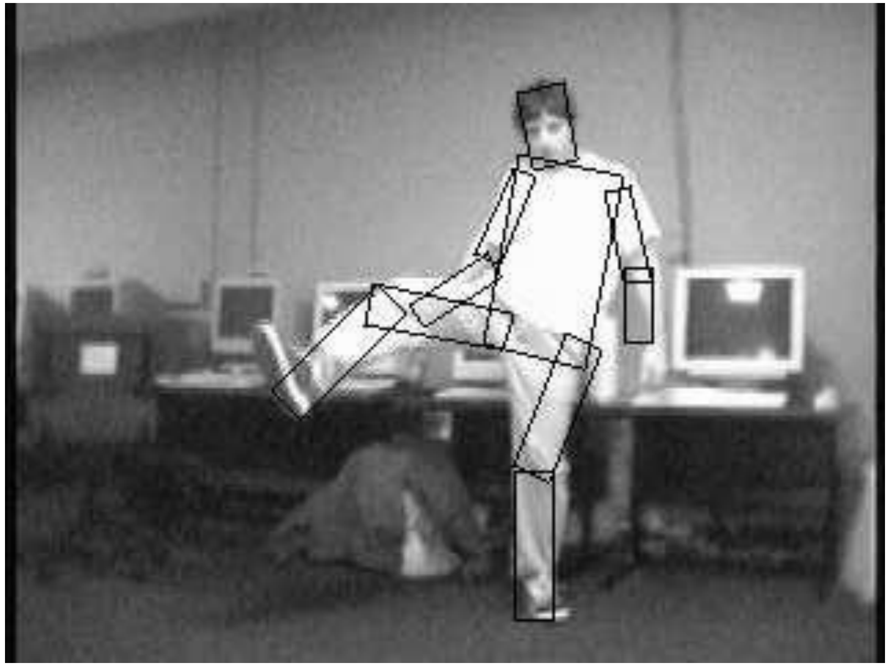
Template Visualization

Images from Felzenszwalb

Specifying an object model

2. Articulated parts model
   – Object is configuration of parts
   – Each part is detectable





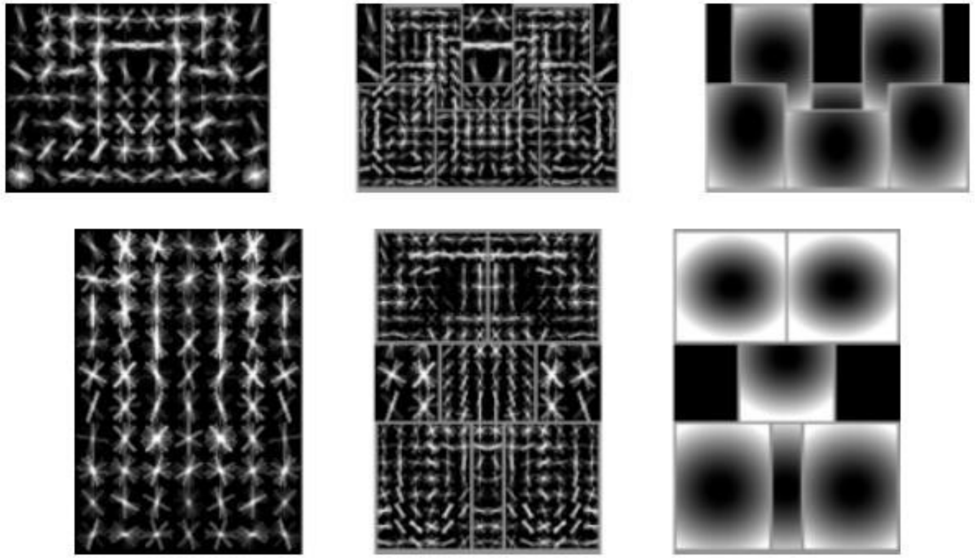
Images from Felzenszwalb

Specifying an object model

3. Hybrid template/parts model

Detections

Template Visualization



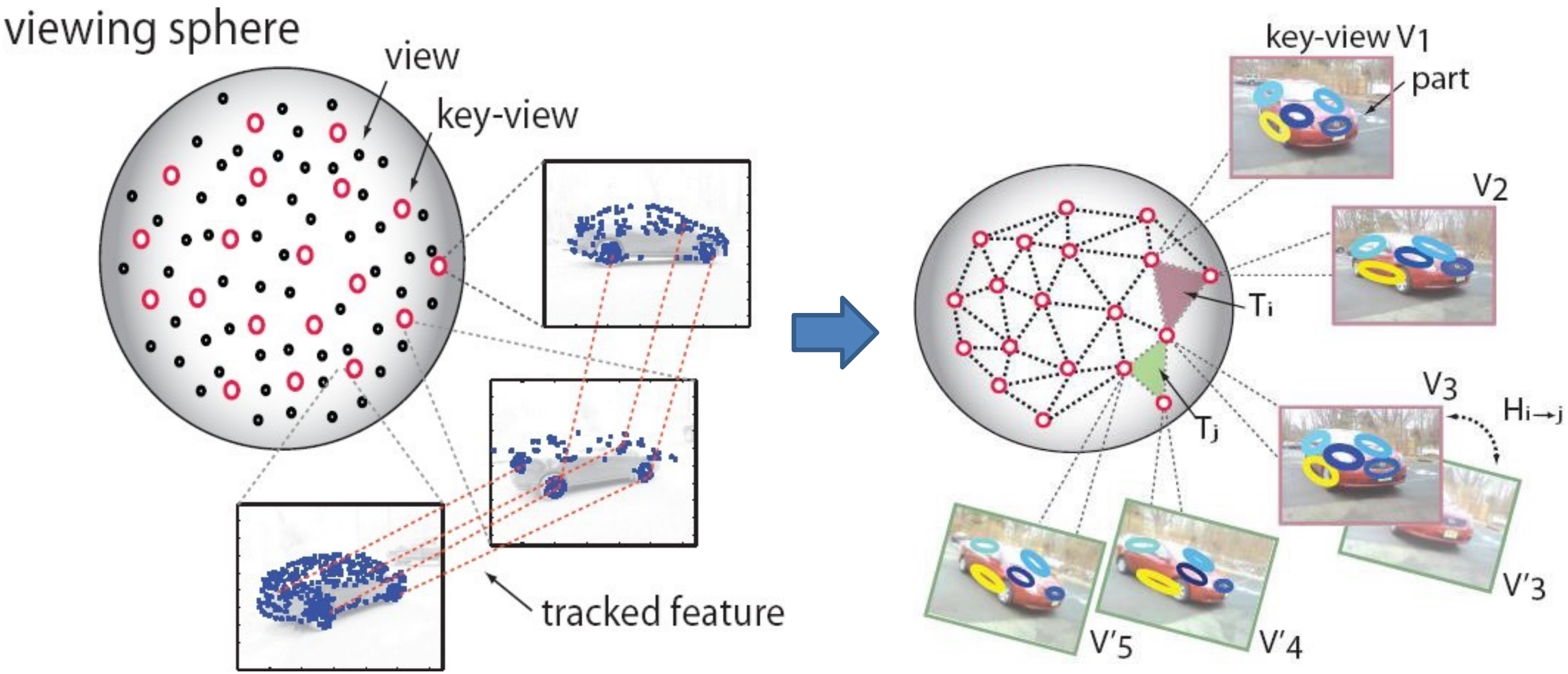
root filters coarse resolution | part filters finer resolution | deformation models

Felzenszwalb et al. 2008

Specifying an object model

4. 3D-ish model

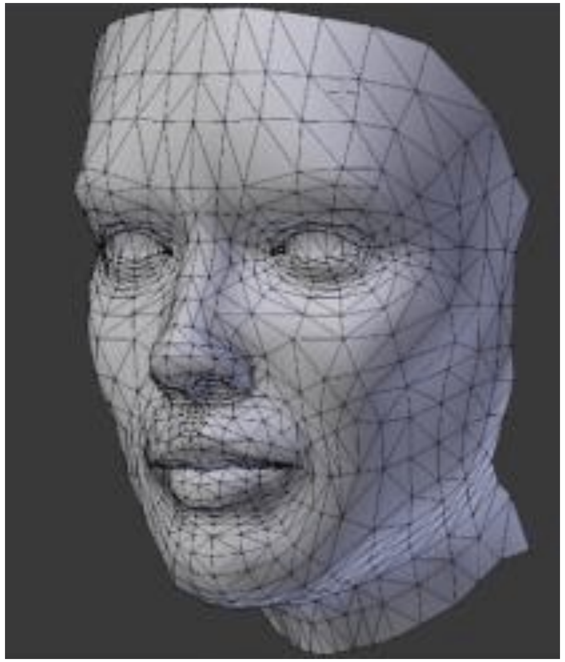
- Object is collection of 3D planar patches under affine transformation



Specifying an object model

5. Deformable 3D model

- Object is a parameterized space of shape/pose/deformation of class of 3D object



Why not just pick the most complex model?

- Inference is harder
  - More parameters
  - Harder to 'fit' (infer / optimize fit)
  - Longer computation
  - Need more in-domain prior knowledge

- "**Bounding Box**" is still practically the most popular

General Process of Object Detection

Specify Object Model

↓

Generate Hypotheses — Propose an alignment of the model to the image

↓

Score Hypotheses

↓

Resolve Detections

Generating hypotheses

1. 2D template model / sliding window

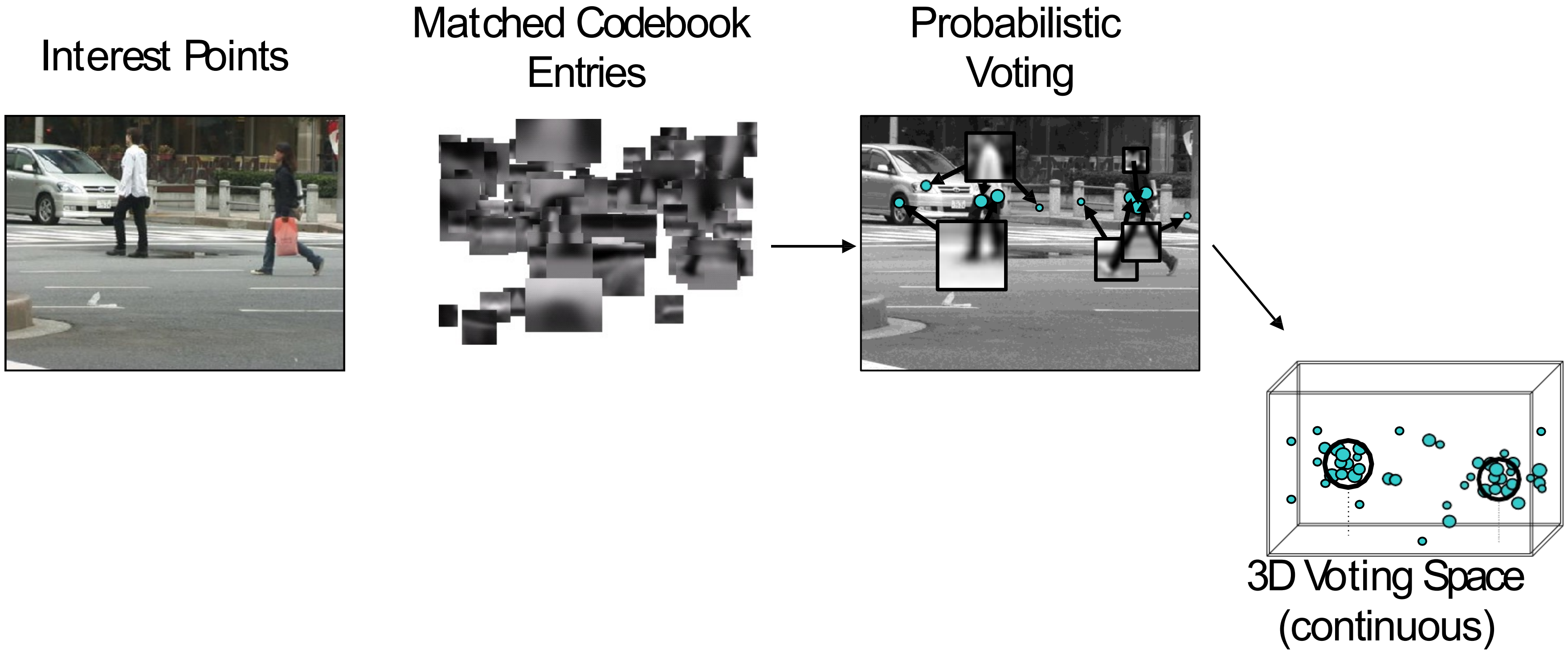
– Test patch at each location and scale

Note – Template did not change size

Each window is separately classified

Generating hypotheses

2. Voting from patches/keypoints



Implicit Shape Model by Leibe et al.

General Process of Object Detection

Specify Object Model

↓

Generate Hypotheses

↓

Score Hypotheses

↓

Resolve Detections

Mainly gradient-based features, usually based on summary representation, many classifiers.

General Process of Object Detection

Specify Object Model

↓

Generate Hypotheses

↓

Score Hypotheses

↓

Resolve Detections

“Globally ”rescore each proposed object based on whole set, to resolve conflicts (non-max suppression, context-reasoning…)

Influential Works in Object Detection

- Sung-Poggio (1994, 1998) : ~2000 citations
  - Basic idea of statistical template detection, bootstrapping to get “face-like” negative examples, multiple whole-face prototypes (in 1994)
- Rowley-Baluja-Kanade (1996-1998) : ~3600
  - “Parts” at fixed position, non-maxima suppression, simple cascade, rotation, pretty good accuracy, fast
- Schneiderman-Kanade (1998-2000,2004) : ~1700
  - Careful feature engineering, excellent results, cascade
- Viola-Jones (2001, 2004) : ~13,000
  - Haar-like features, Adaboost as feature selection, hyper-cascade, very fast
- Dalal-Triggs (2005) : ~16,000 citations
  - Careful feature engineering, excellent results, HOG feature, online code
- Felzenszwalb-McAllester-Ramanan (2008): ~4,600 citations
  - Template/parts-based blend
- Girshick et al. (2013): ~2000 citations
  - R-CNN / Fast R-CNN / Faster R-CNN. Deep learned models on object proposals.

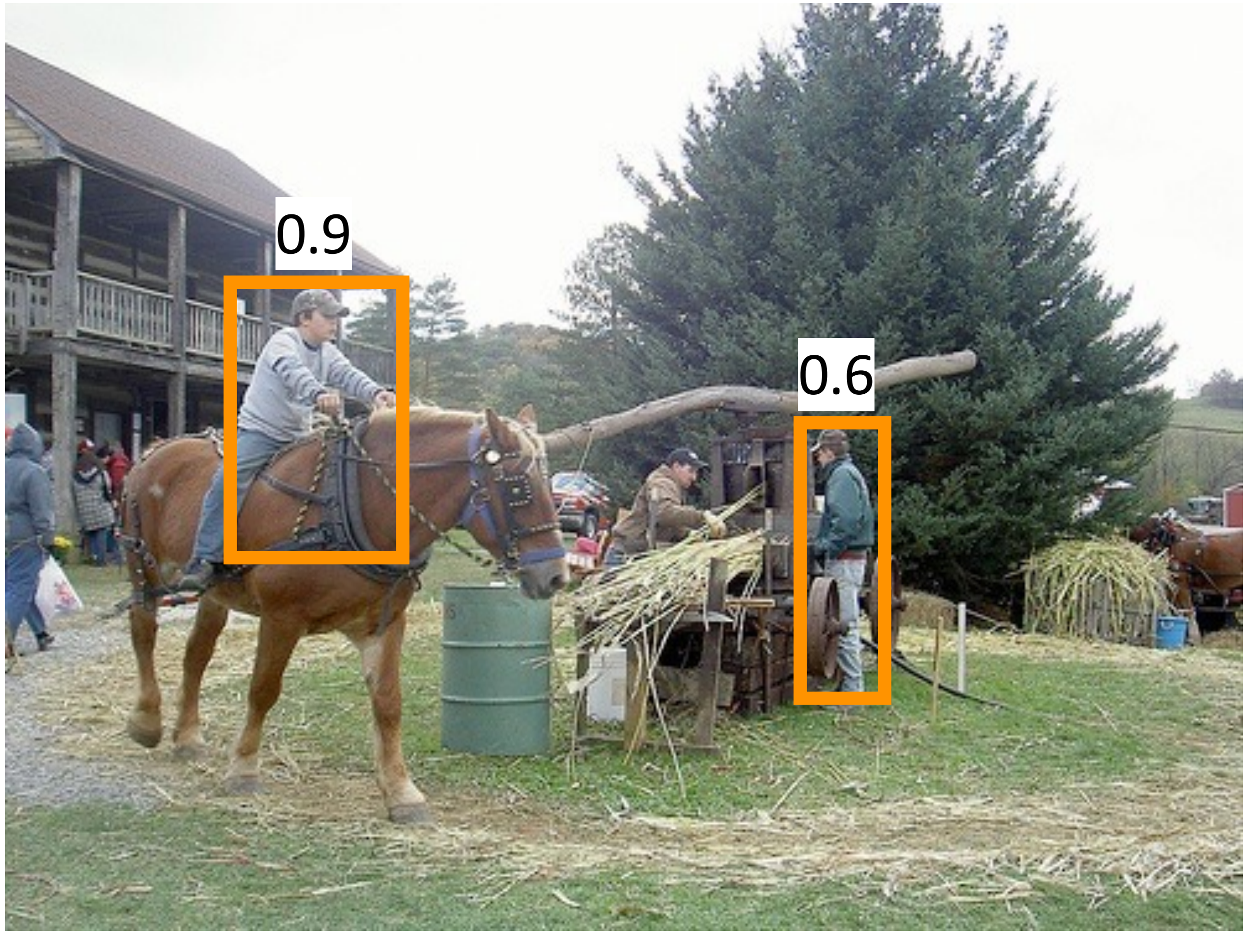
Evaluating a detector

Test image (previously unseen)

First detection ...

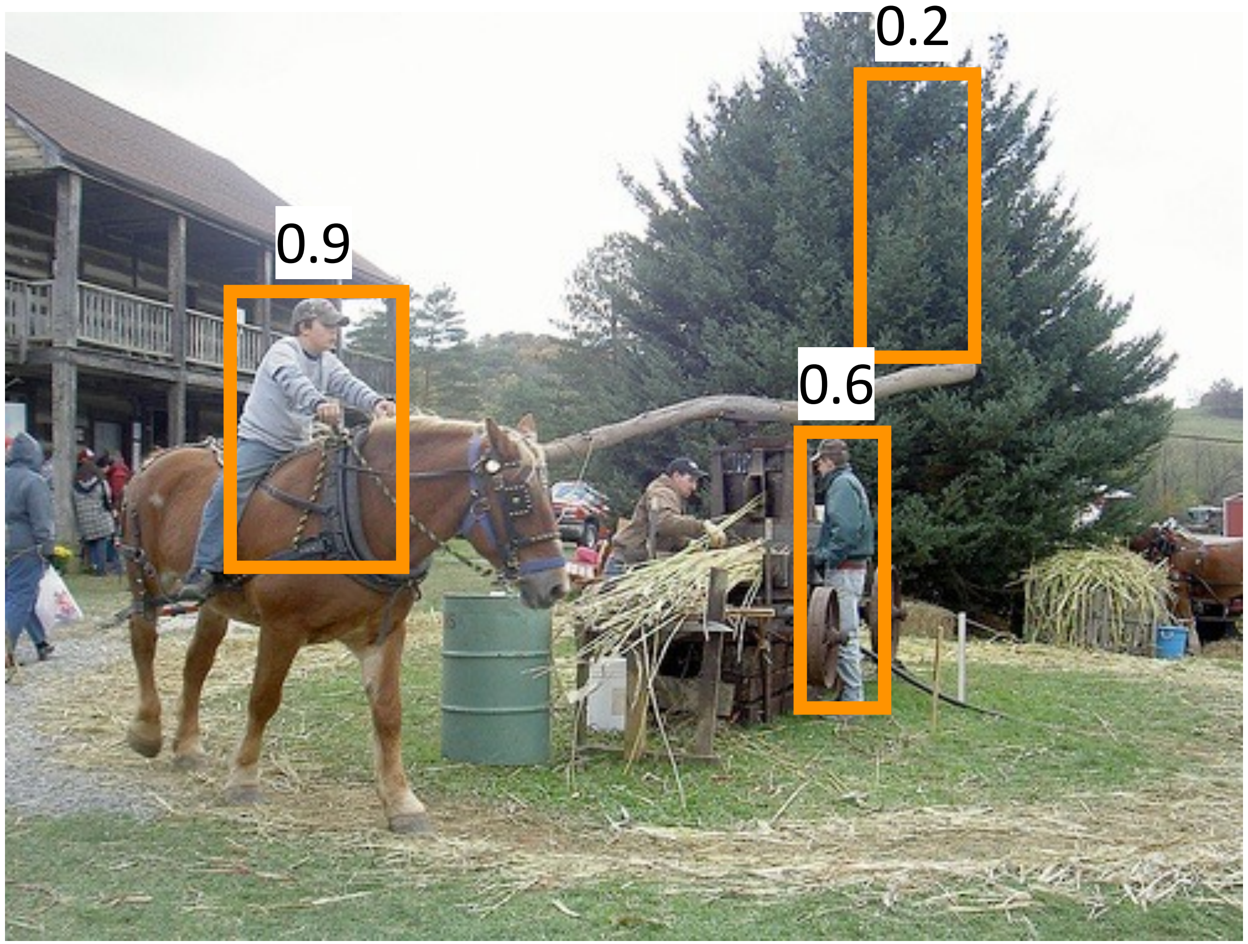
'person' detector predictions

Second detection ...



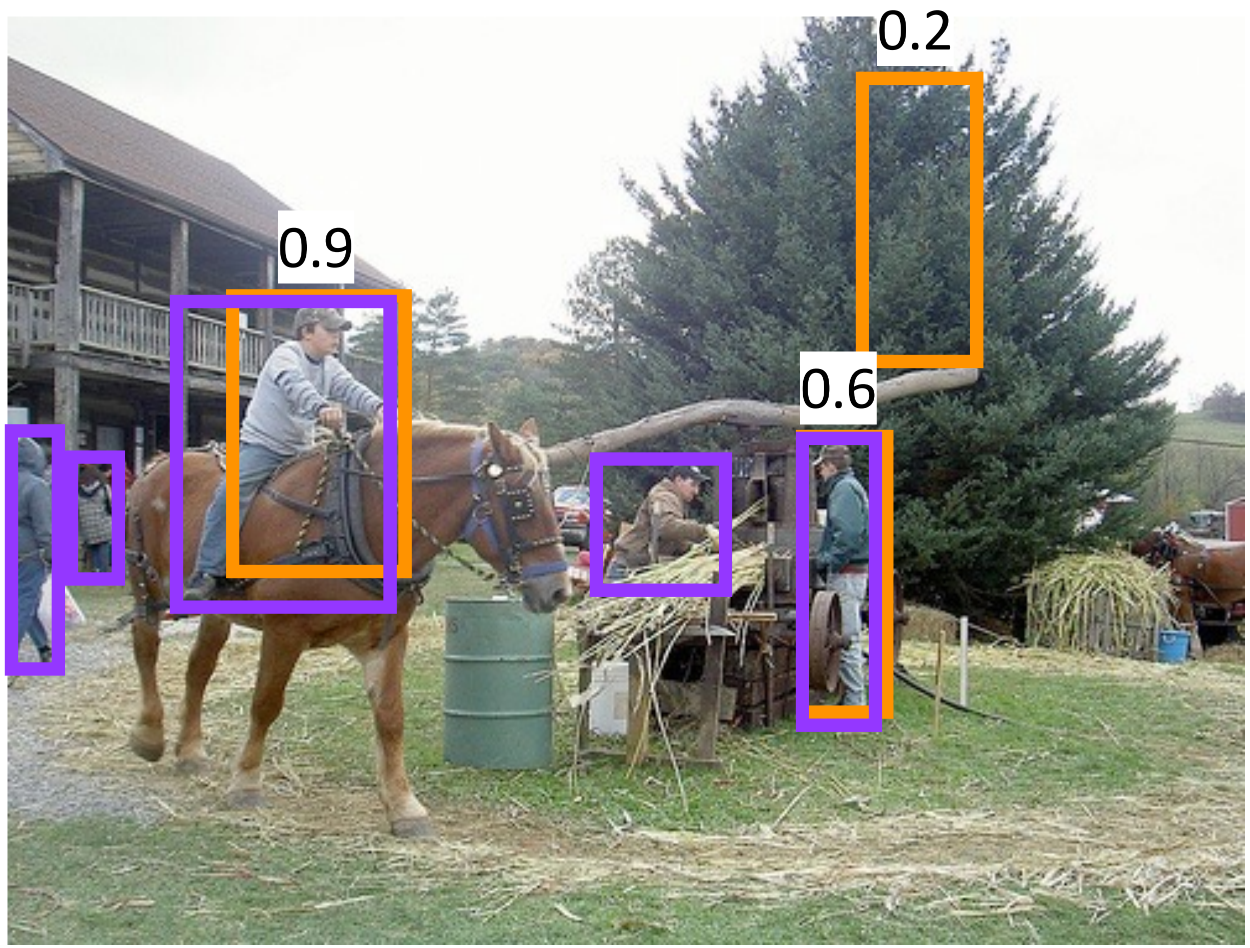
'person' detector predictions

Third detection ...



'person' detector predictions

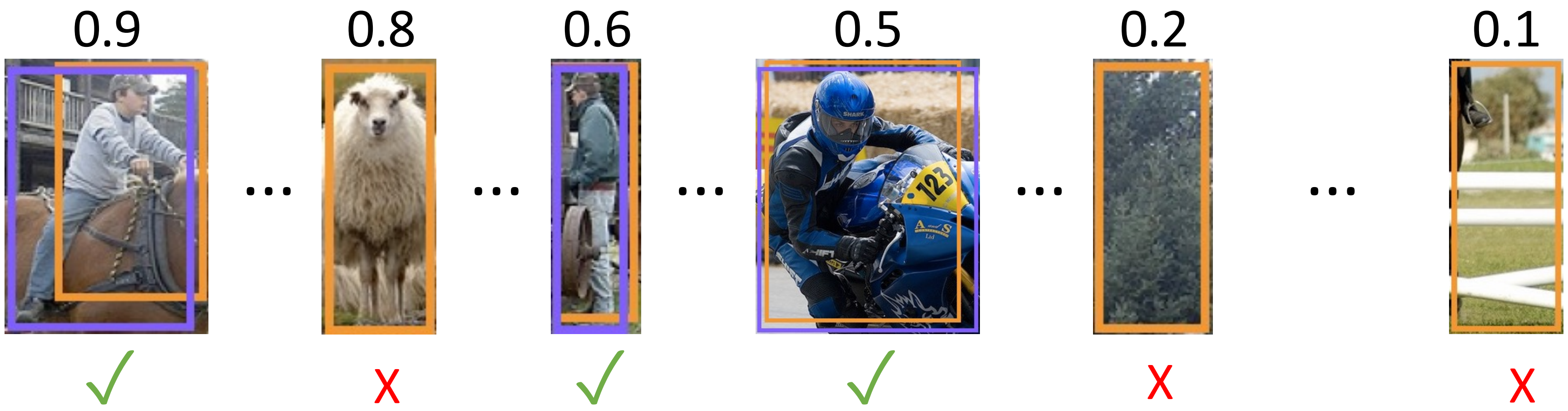
Compare to ground truth



'person' detector predictions

ground truth 'person' boxes

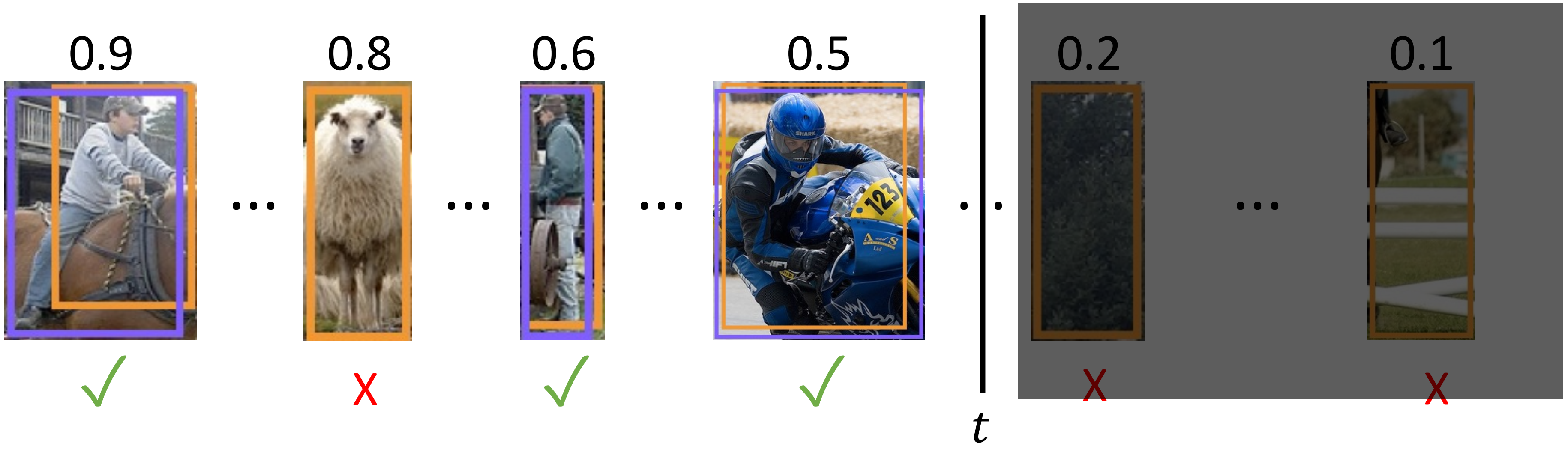
Sort by confidence



true positive
(high overlap)

false positive
(no overlap, low overlap, or duplicate)

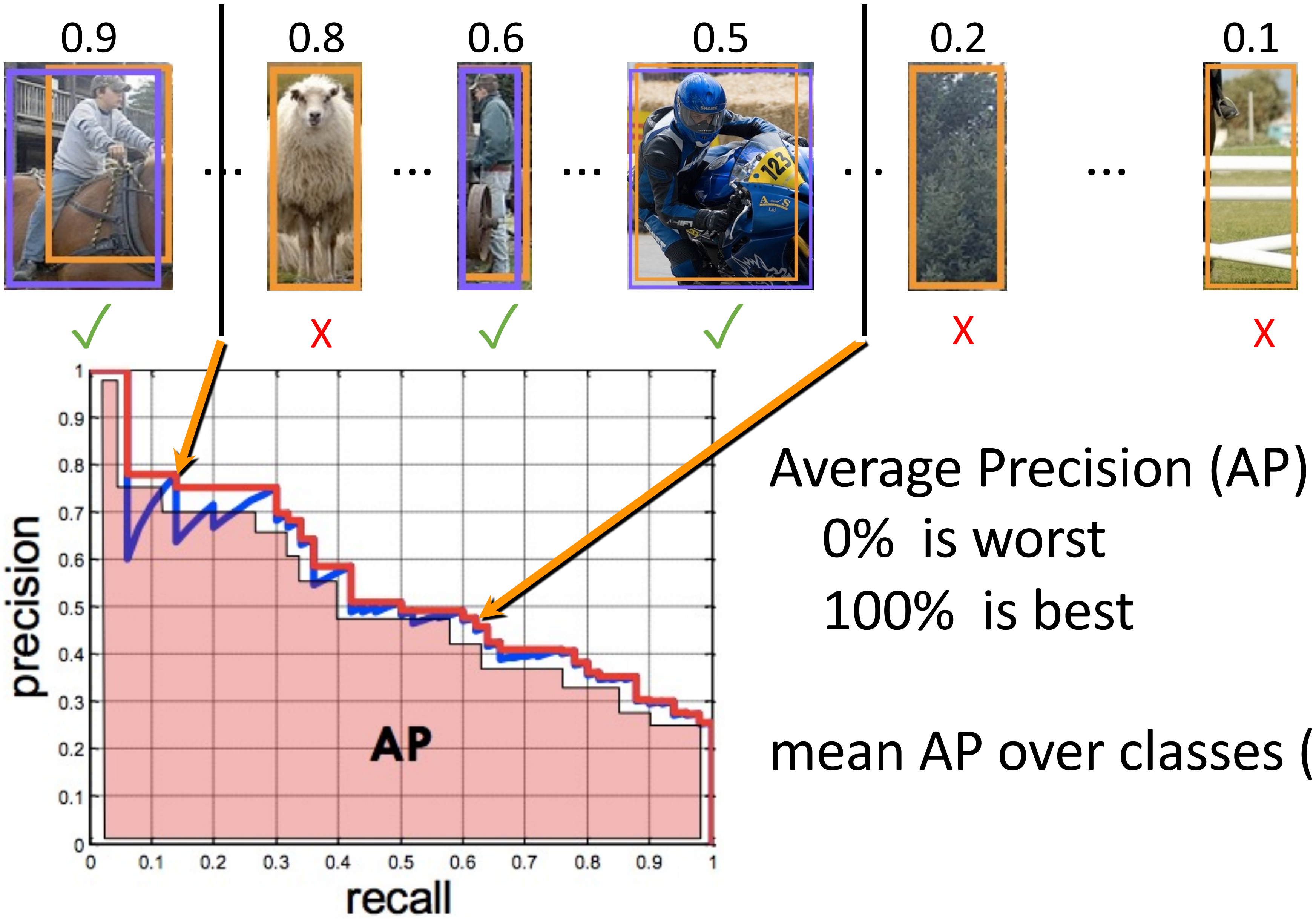
Evaluation metric



$$precision@t = \frac{\#true\ positives@t}{\#true\ positives@t + \#false\ positives@t} \qquad \frac{\checkmark}{\checkmark + X}$$

$$recall@t = \frac{\#true\ positives@t}{\#ground\ truth\ objects}$$

Evaluation metric



Average Precision (AP)

0% is worst

100% is best

mean AP over classes (mAP)

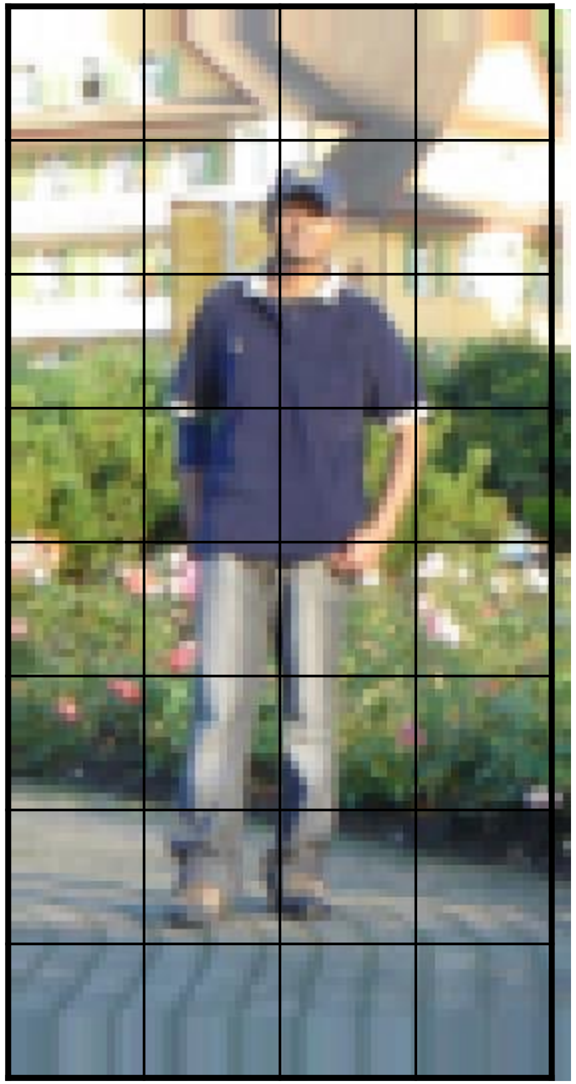
Dalal-Triggs Object Detector

- Histograms of Oriented Gradients for Human Detection, Navneet Dalal, Bill Triggs, International Conference on Computer Vision & Pattern Recognition - June 2005
- http://lear.inrialpes.fr/pubs/2005/DT05/

Example: Dalal-Triggs pedestrian detection

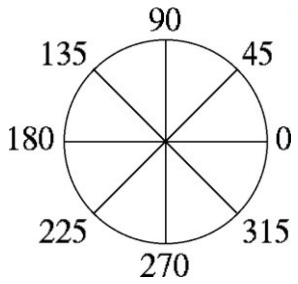
1. Extract fixed-sized (64x128 pixel) **window** at each position and scale
2. Compute **HOG** (histogram of oriented gradient) features within each window
3. Score the window with **a linear SVM classifier**
4. Perform **non-maxima suppression** to remove overlapping or conflicting detections with lower scores

Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05

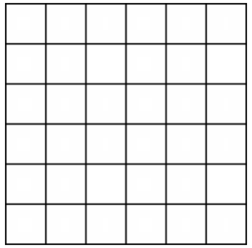


Histogram of Oriented Gradients

Orientation by bins



Histograms over
k x k pixel cells



– Votes weighted by magnitude

Slides by Pete Barnum

Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05

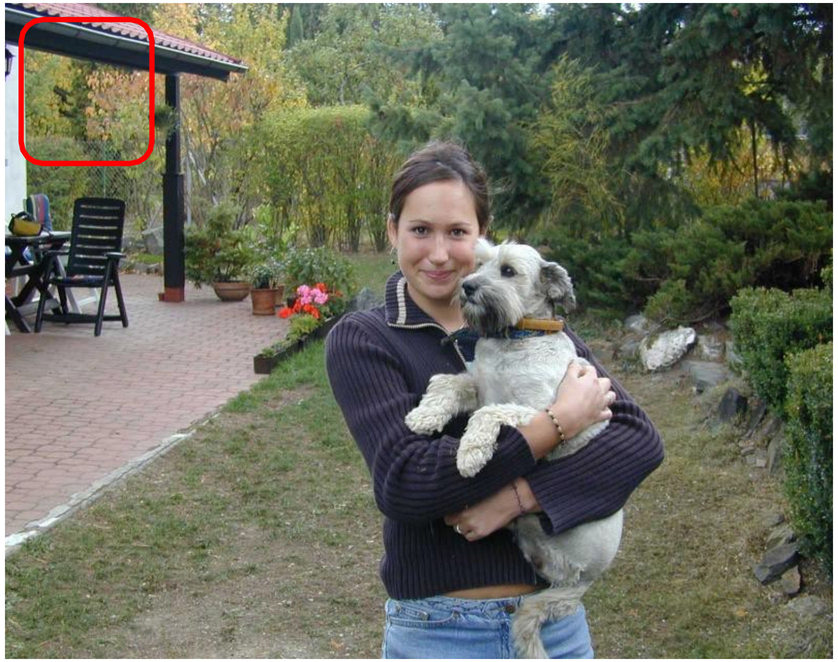
Dalal-Triggs uses a template with a **rigid form**

- Human bodies are boxed shaped
- That's why Dalal-Triggs is best known for pedestrian detection

But…is there a way to learn the spatial layout more **fluidly**?

- Might help us capture more appearance variation…
- What about faster, too? Since many positions might be "filtered"

Face detection and recognition



Detection

Recognition

"Sally"

Challenges of Face Detection

Sliding window = tens of thousands of location/scale evaluations, especially since faces are small

- One megapixel image has ~10^6 pixels
- …and a comparable number of candidate face locations

Faces are also rare: 0–10 per image

- For computational efficiency, spend as little time as possible on non-face windows.
- For 1M pix, to avoid having a false positive in every image, our false positive rate must be less than 10^{-6}

James Hays

The Viola/Jones Face Detector

A seminal approach to real-time object detection

Training is slow, but detection is very fast

Key ideas:

1. *Integral images* for fast feature evaluation
2. *Boosting* for feature selection
3. *Attentional cascade* for fast non-face window rejection

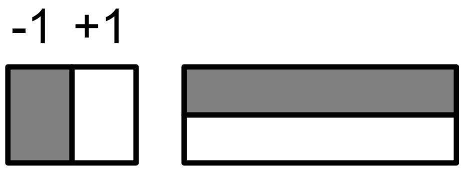
P. Viola and M. Jones. *Rapid object detection using a boosted cascade of simple features.* CVPR 2001.
P. Viola and M. Jones. *Robust real-time face detection.* IJCV 57(2), 2004.

“Haar-like features”

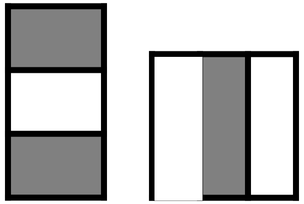
– Binary-valued filters, computing differences of sums of intensity between two regions

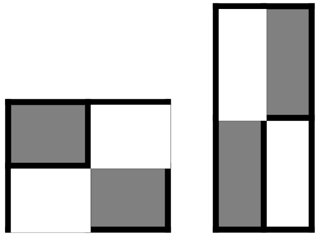
– Computed at different positions and scales within sliding window

– Very fast to compute (thanks to a clever implementation trick called “integral image”)

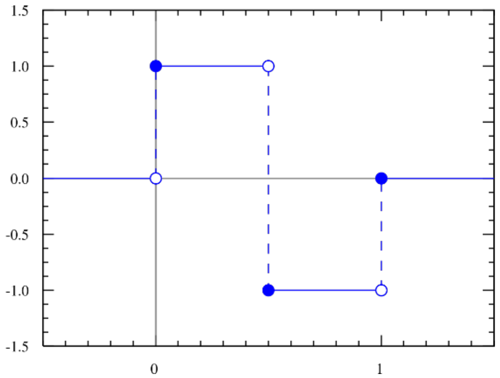


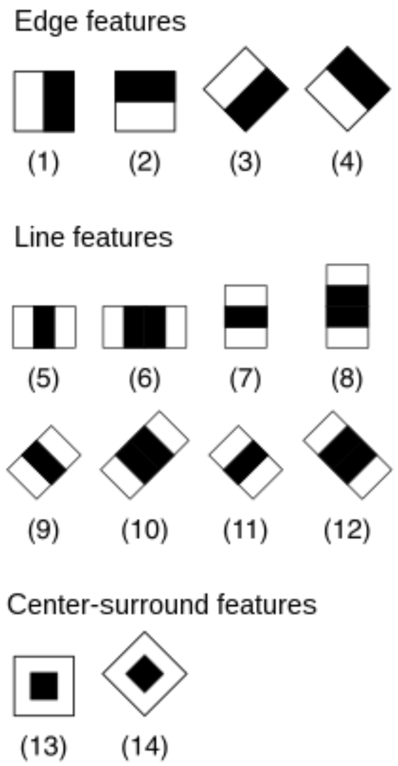
Two-rectangle features


Three-rectangle features

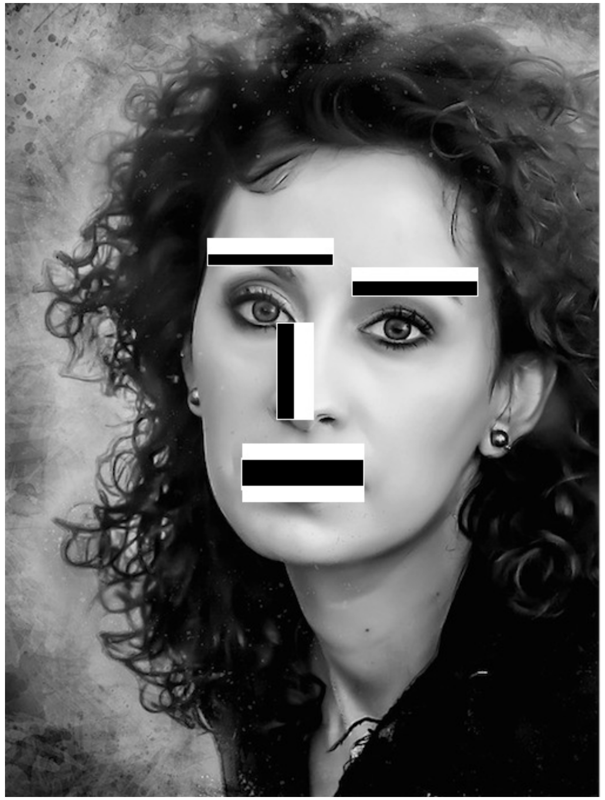

Etc.

Haar wavelet

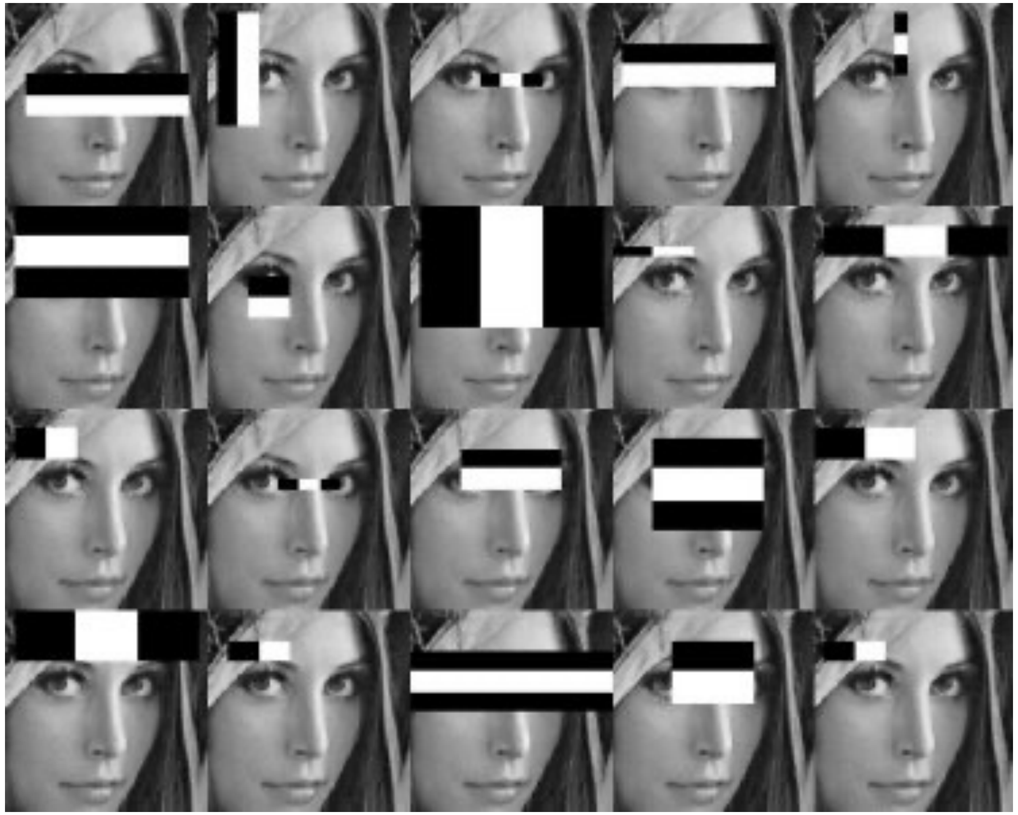




Why "Haar-like features"?



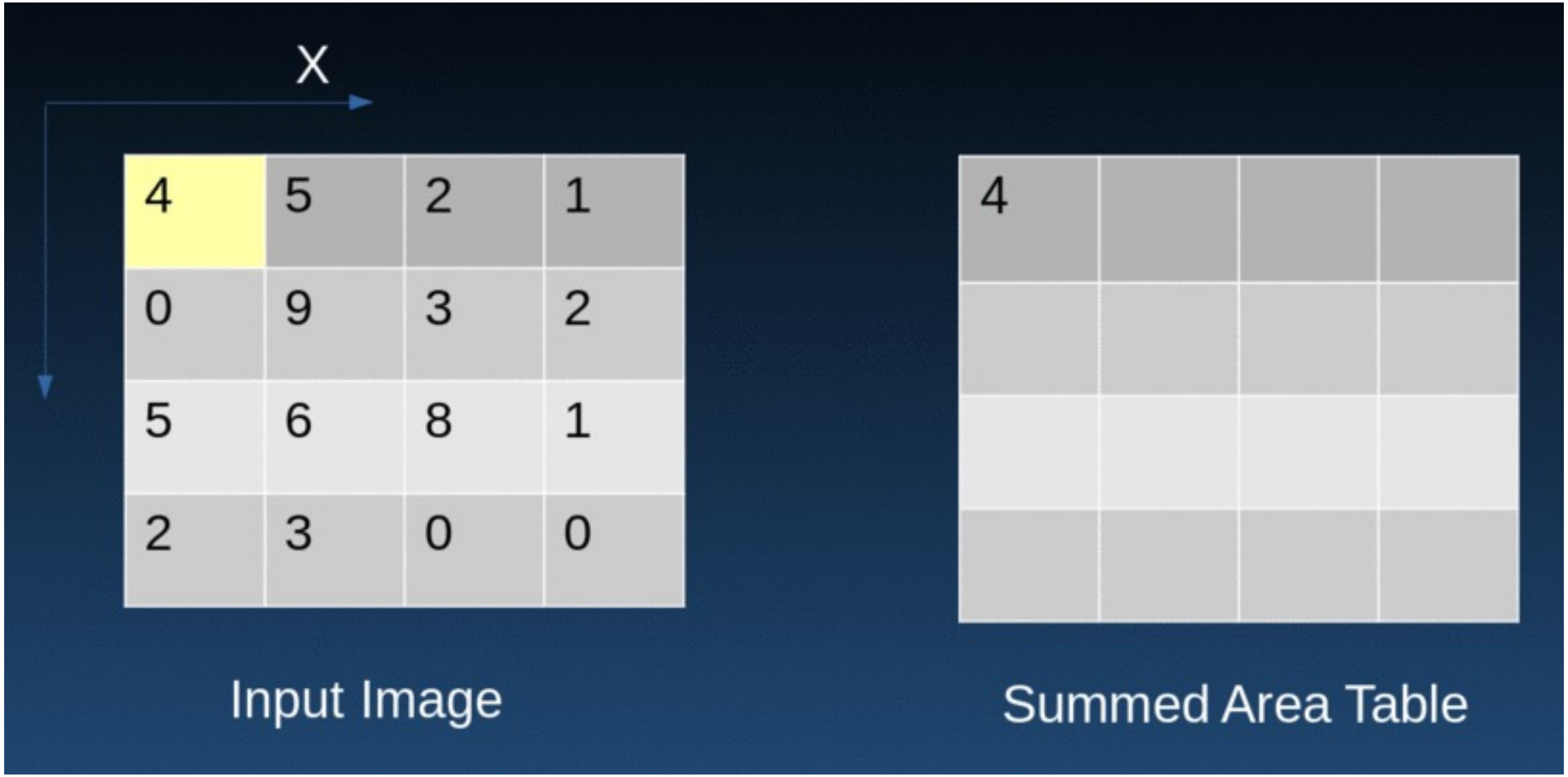
Example: Two "eyebrow" filters, one "nose" filter, and one "mouth" filter



Harr features are **NOT ROBUST**, but CHEAP to compute

- For example, with a human face, it is a common observation that among all **faces the region of the eyes is darker than the region of the cheeks.**
- Therefore, a common Haar feature for face detection is **a set of two adjacent rectangles that lie above the eye and the cheek region**. The position of these rectangles is defined relative to a face bounding box

How to Speedup “Haar-like features”? **Integral Image**



O(N) complexity to build the integral image, N = pixel number

How to Speedup "Haar-like features"? **Integral Image**

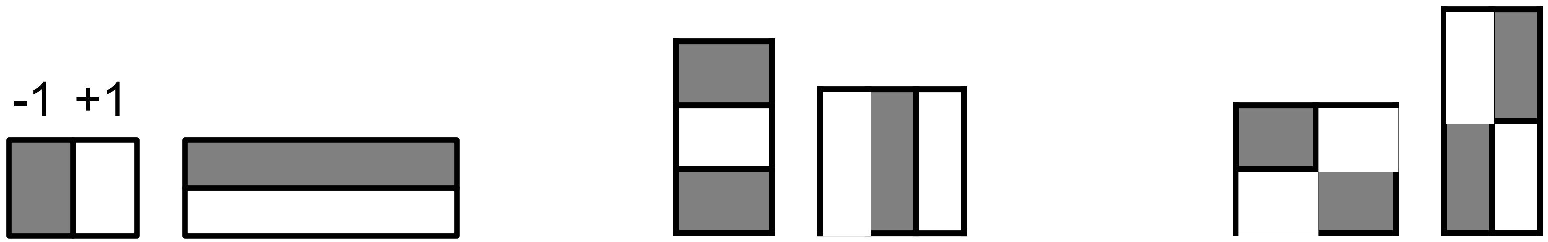
O(1) complexity to compute the partial region sum, **regardless of region size**!

But these features are rubbish…!

Yes, individually they are ‘weak classifiers’

Jargon: ‘feature’ and ‘classifier’ are used interchangeably here.
Also with ‘learner’, ‘filter’.

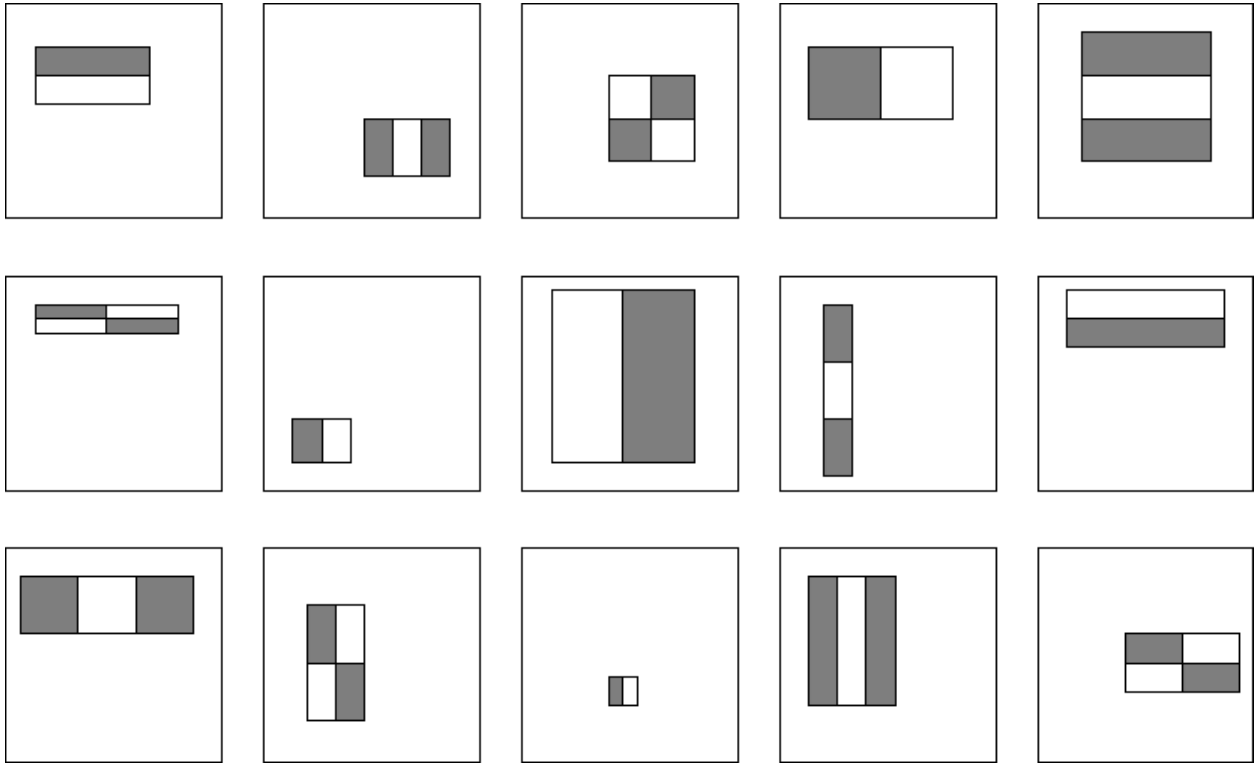
But, what if we combine *thousands* of them…



Two-rectangle features Three-rectangle features Etc.

How many features are there?

For a 24x24 detection region, the number of possible rectangle features is ~160,000!



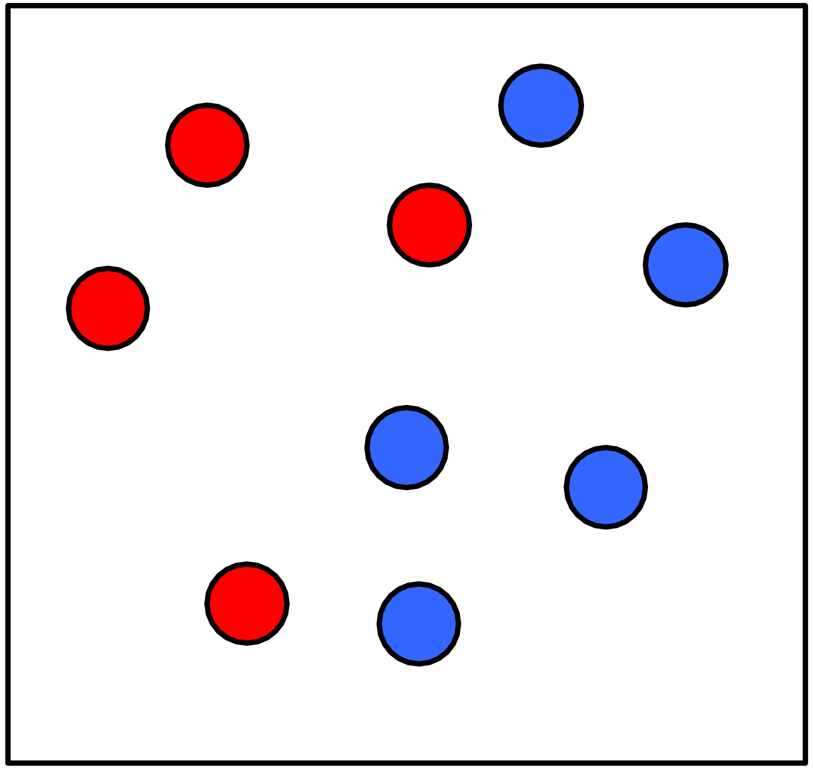
How many features are there?

- For a 24x24 detection region, the number of possible rectangle features is ~160,000!
- At test time, it is impractical to evaluate the entire feature set.
- Can we learn a ‘strong classifier’ using just a small subset of all possible features?

Boosting for feature selection

Initially, weight each training example equally.

Weight = size of point



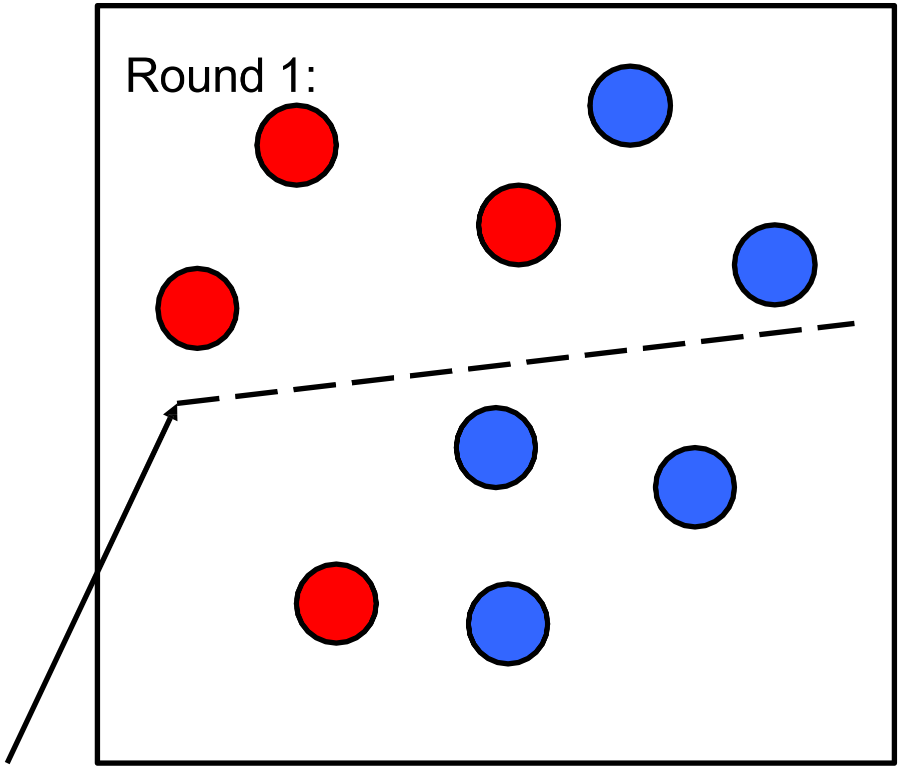
Slide credit: Paul Viola

Boosting for feature selection

In each boosting round:

Find the weak classifier that achieves the lowest *weighted* training error.

Raise the weights of training examples misclassified by current weak classifier.



Weak Classifier 1

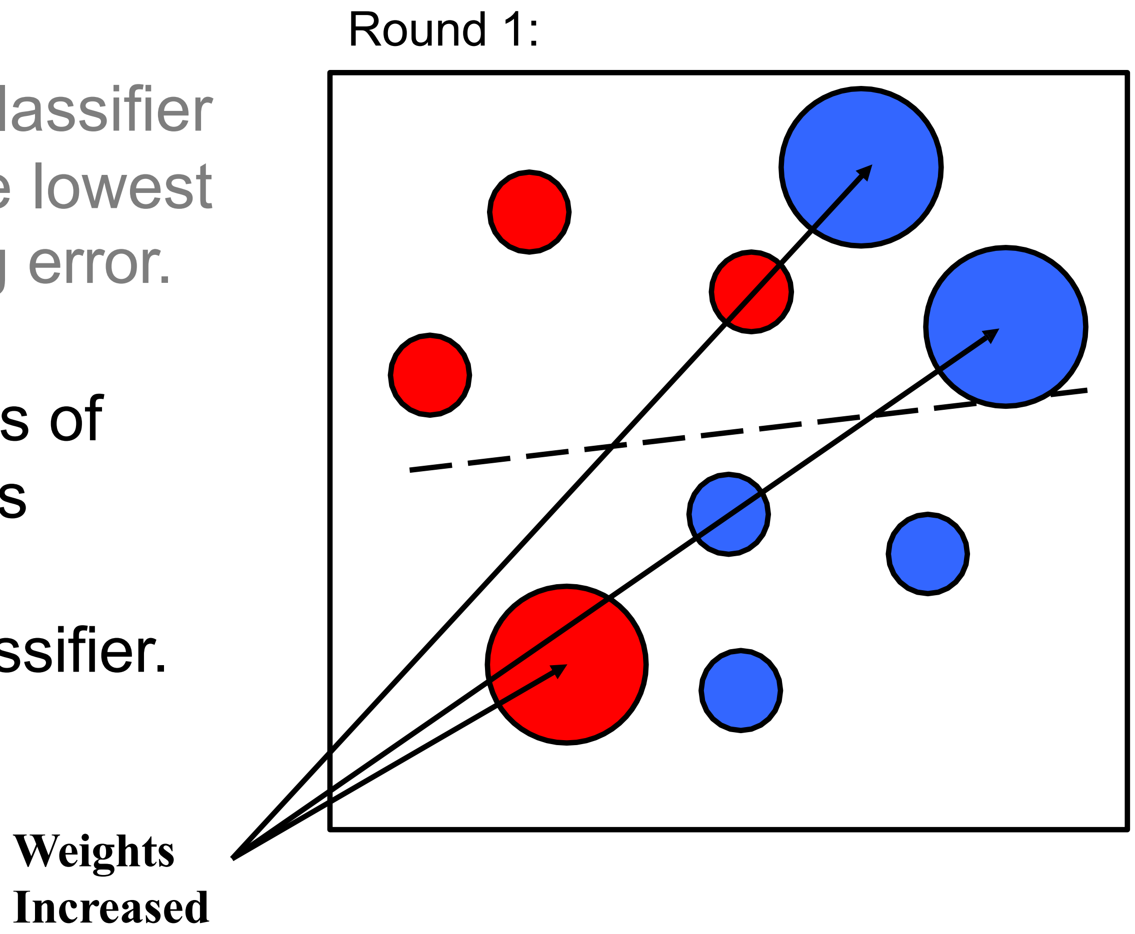
Slide credit: Paul Viola

Boosting illustration

In each boosting round:

Find the weak classifier that achieves the lowest *weighted* training error.

Raise the weights of training examples misclassified by current weak classifier.

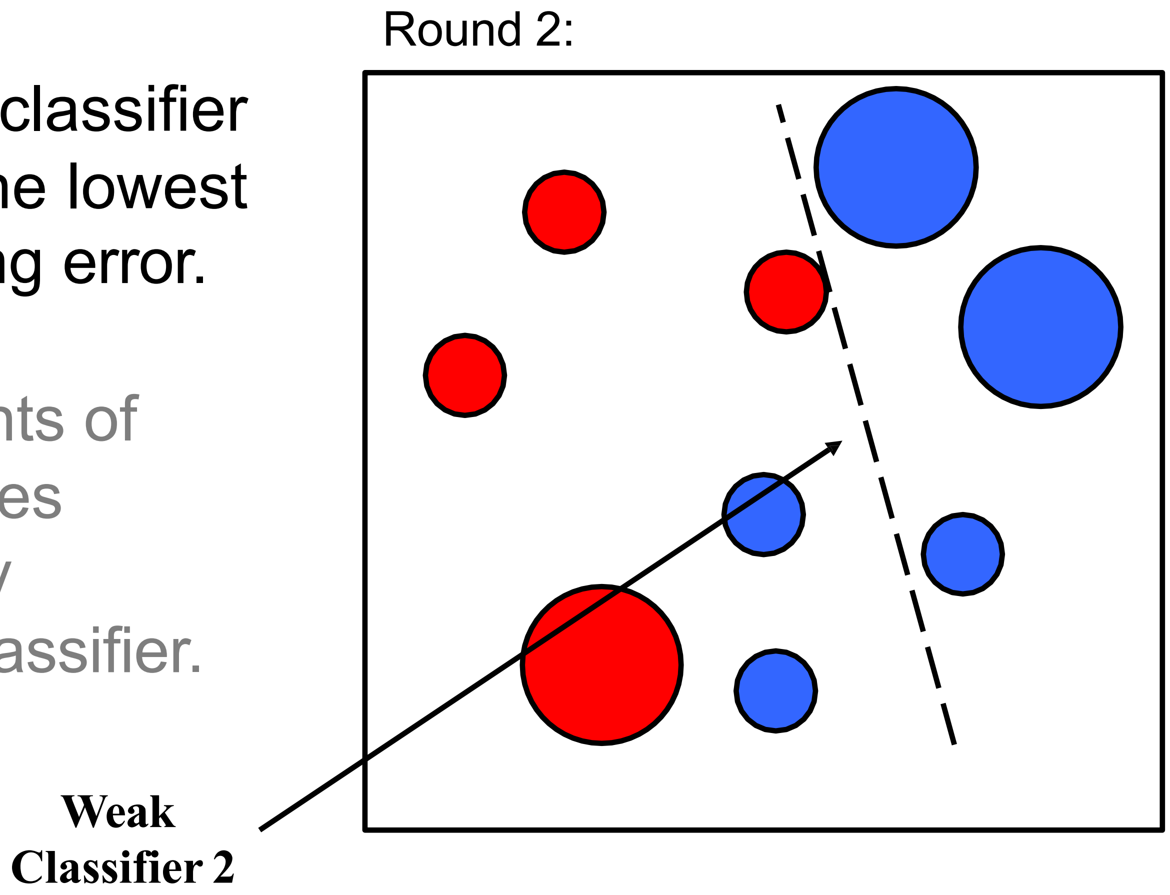


Boosting illustration

In each boosting round:

Find the weak classifier that achieves the lowest *weighted* training error.

Raise the weights of training examples misclassified by current weak classifier.

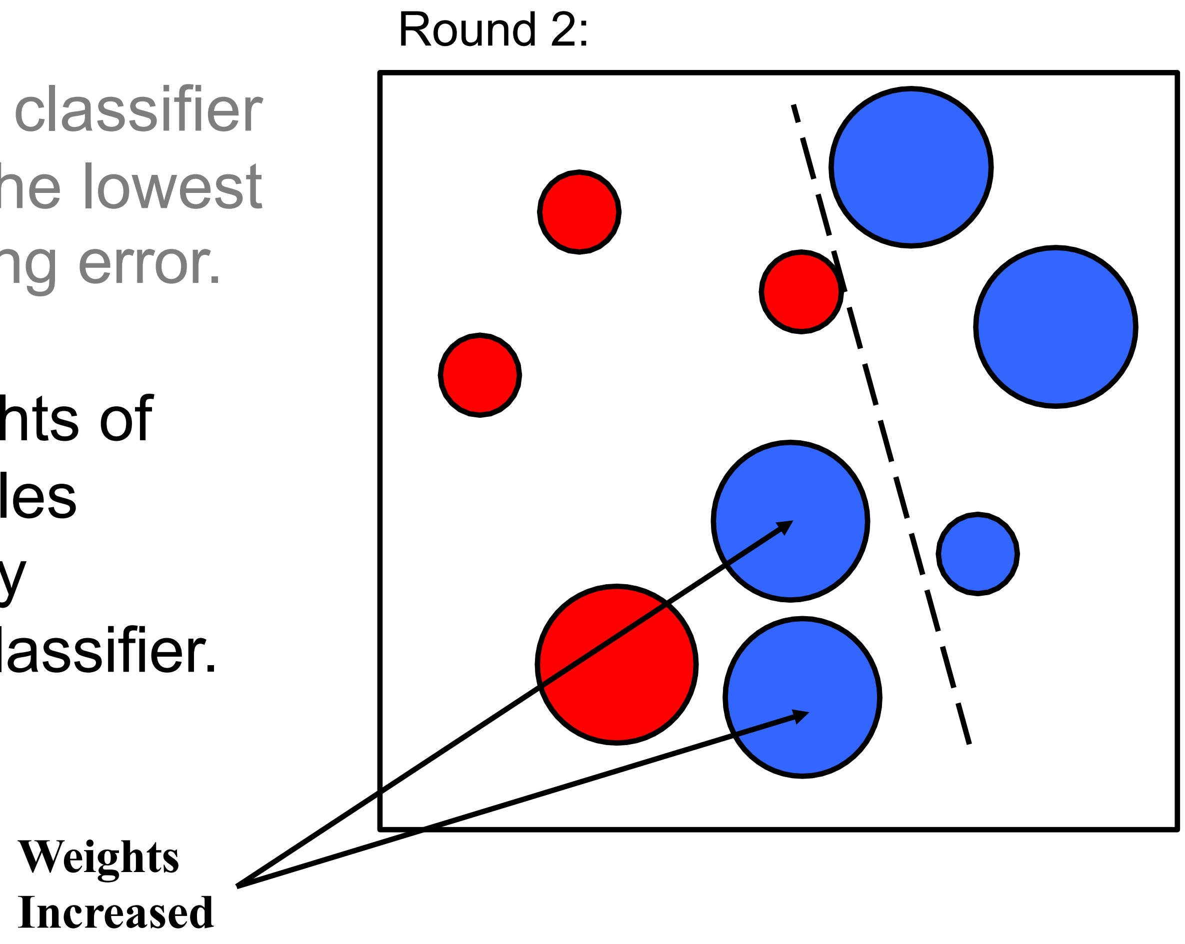


Boosting illustration

In each boosting round:

Find the weak classifier that achieves the lowest *weighted* training error.

Raise the weights of training examples misclassified by current weak classifier.

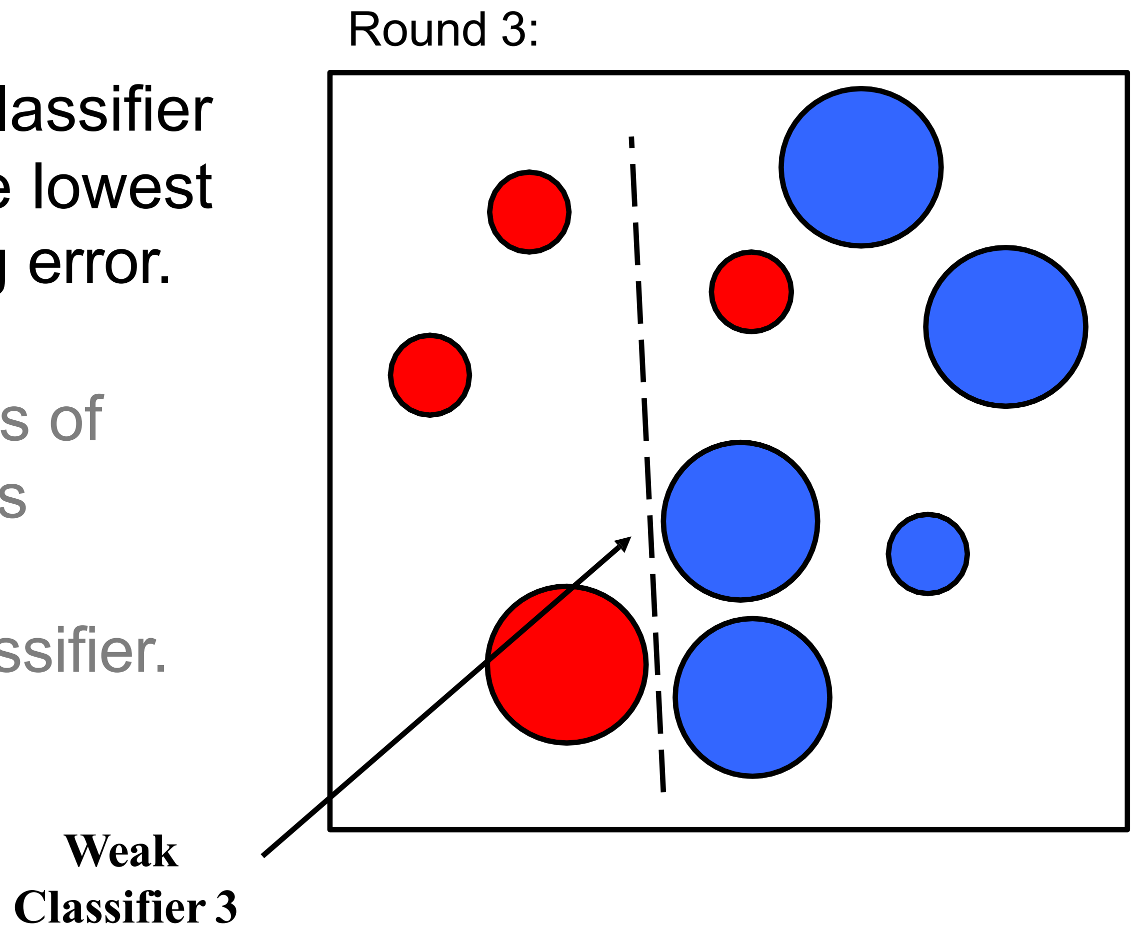


Boosting illustration

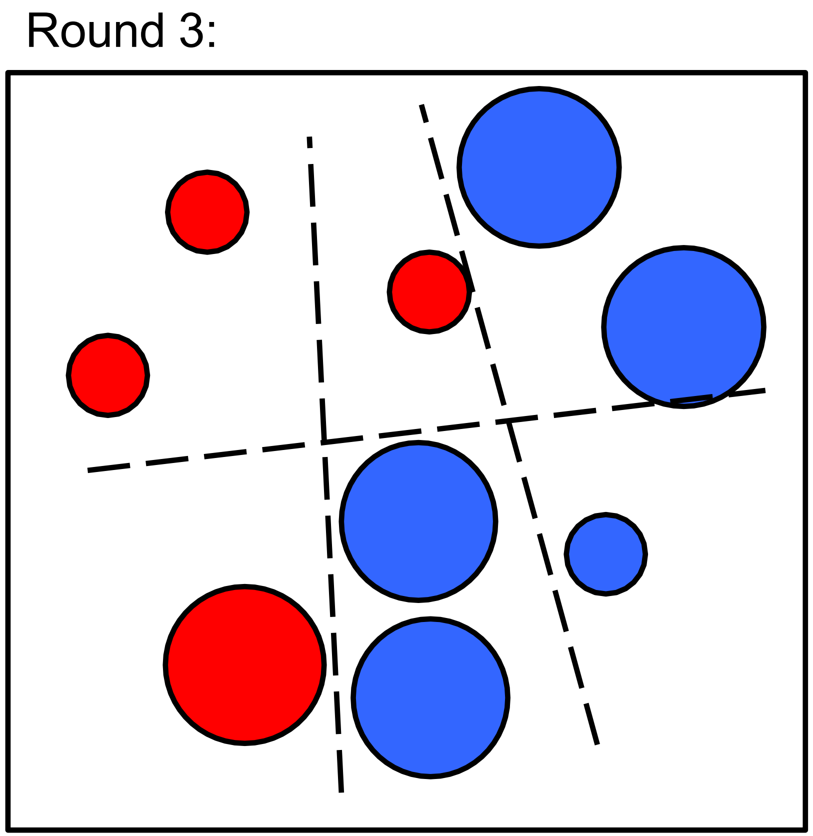
In each boosting round:

Find the weak classifier that achieves the lowest *weighted* training error.

Raise the weights of training examples misclassified by current weak classifier.



Boosting illustration



Compute final classifier as linear combination of all weak classifier.

Weight of each classifier is directly proportional to its accuracy.

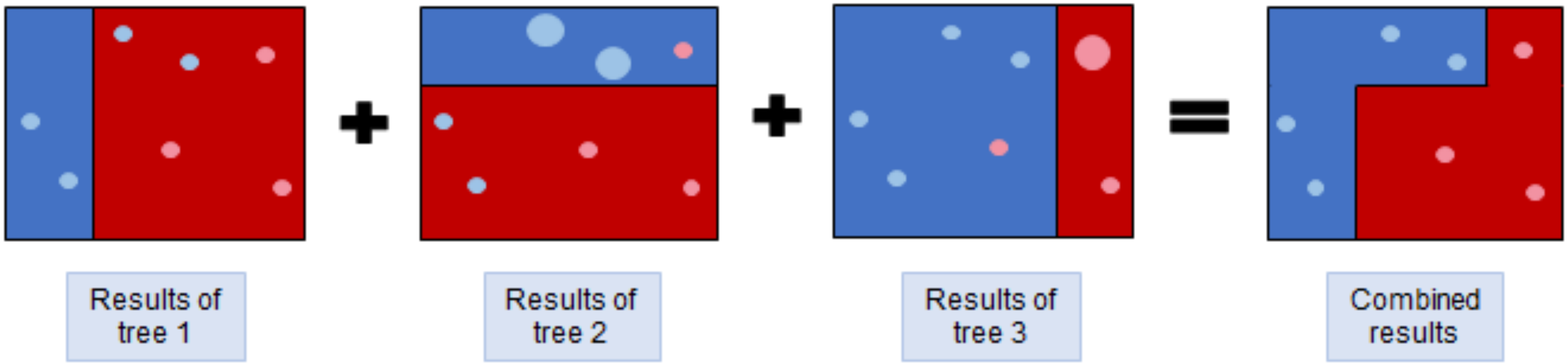
Exact formulas for re-weighting and combining weak learners depend on the boosting scheme (e.g., AdaBoost).

Y. Freund and R. Schapire, A short introduction to boosting,
Journal of Japanese Society for Artificial Intelligence, 14(5):771-780, September, 1999.

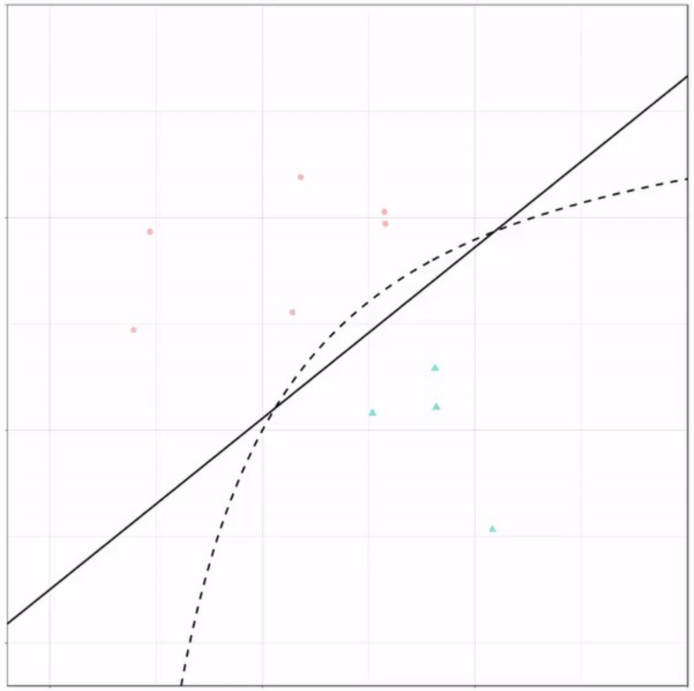
Boosting illustration: Overall Workflow

AdaBoost:

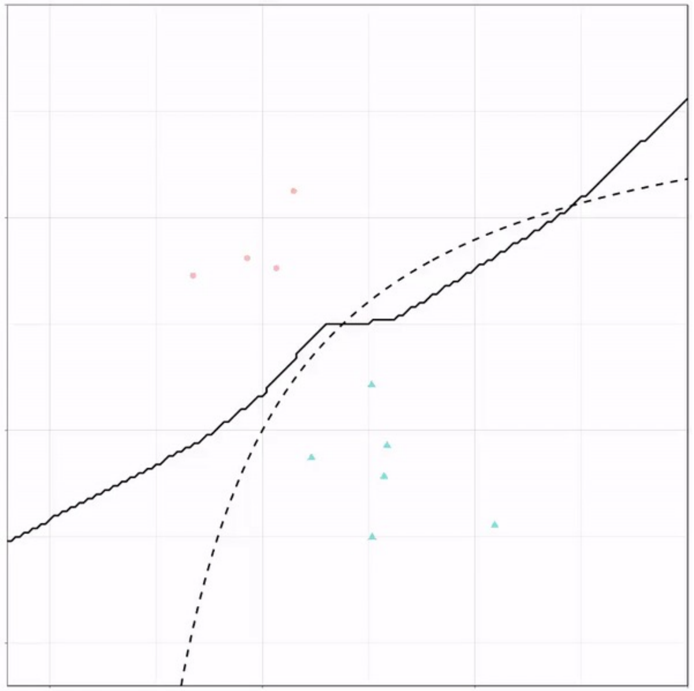
- Combining **weak learners** (decision trees)
- Assigning **weights to incorrect values**
- **Sequential tree growing** considering past mistakes



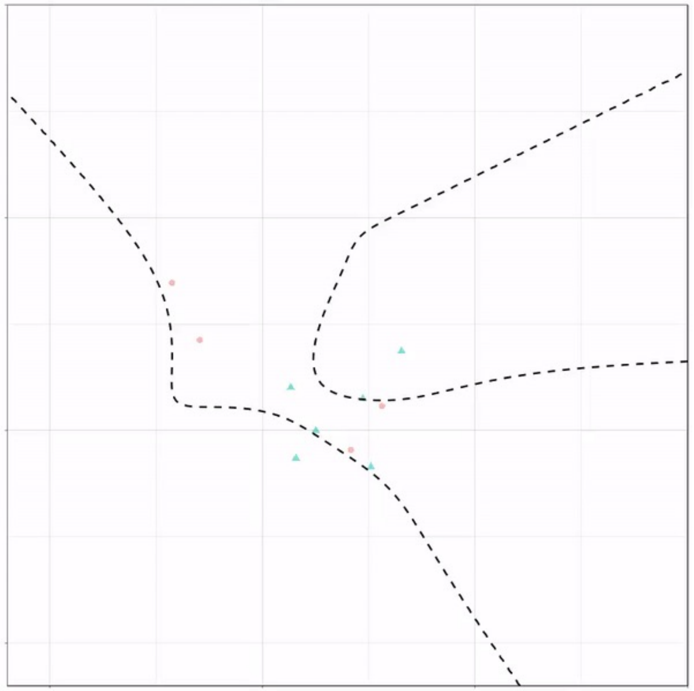
Boosting illustration: Decision Boundary Visualization



Logistic Classifier



K-NN Classifier



Boosting
(here we used gradient boosting)

Harr feature selection with boosting

- Create a large pool of features (160K)
- Select discriminative features that work well together

Final strong learner

Weak learner

$$h(\mathbf{x}) = \operatorname{sign}\left(\sum_{j=1}^{M} \alpha_j h_j(\mathbf{x})\right)$$

window

Learner weight

  – "Weak learner" = feature + threshold + 'polarity'

value of rectangle feature

$$h_j(\mathbf{x}) = \begin{cases} -s_j & \text{if } f_j < \theta_j \\ s_j & \text{otherwise} \end{cases}$$

threshold

'polarity' = black or white region flip $\longrightarrow$ $s_j \in \pm 1$

  – Train & choose weak learner that minimizes error on the weighted training set, then reweight



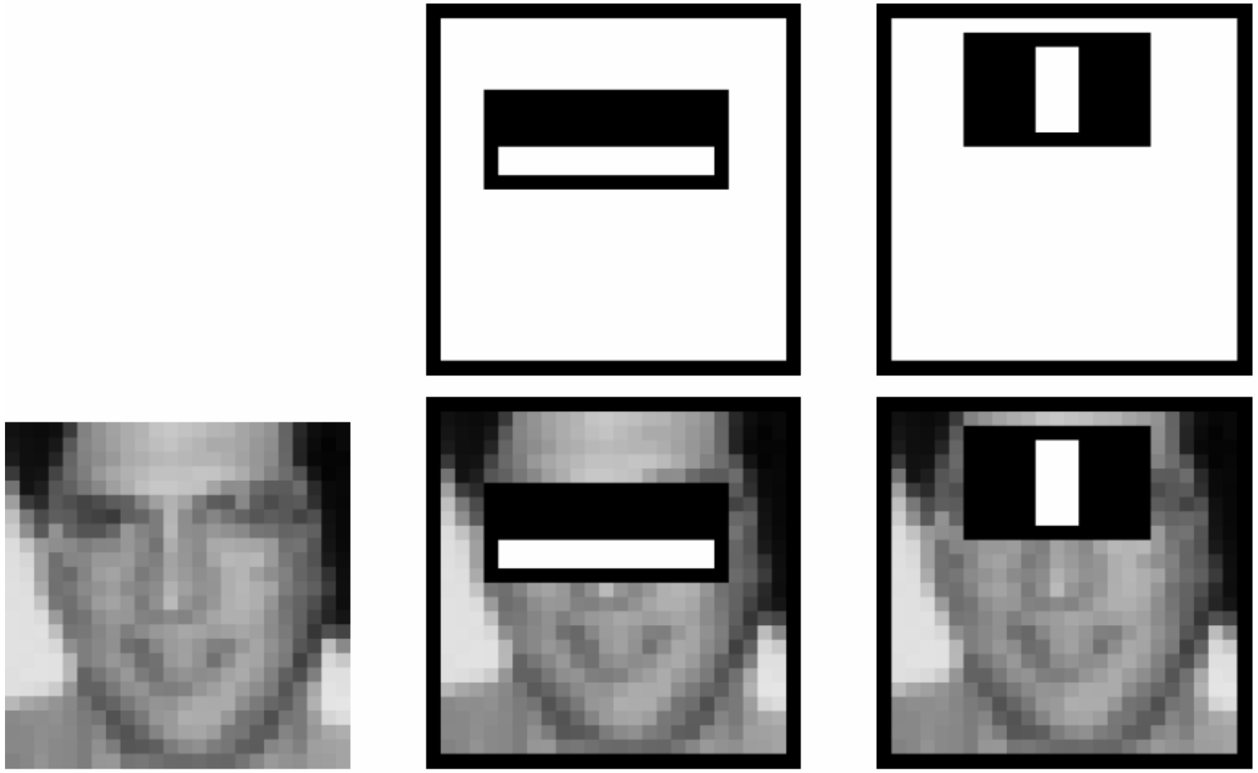




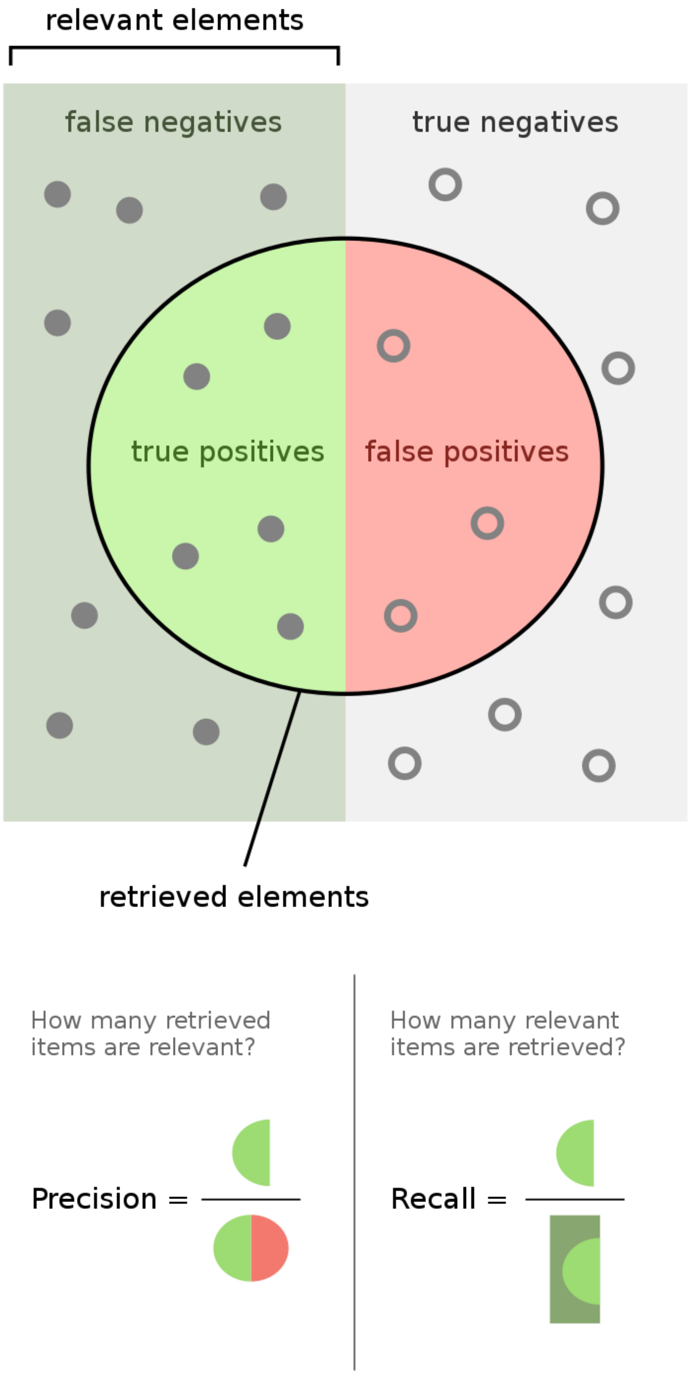


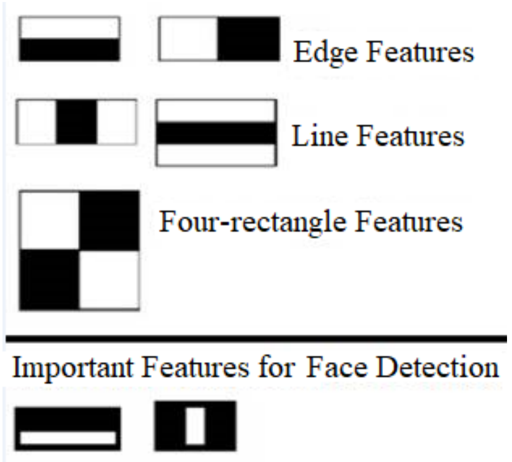

Boosting for face detection

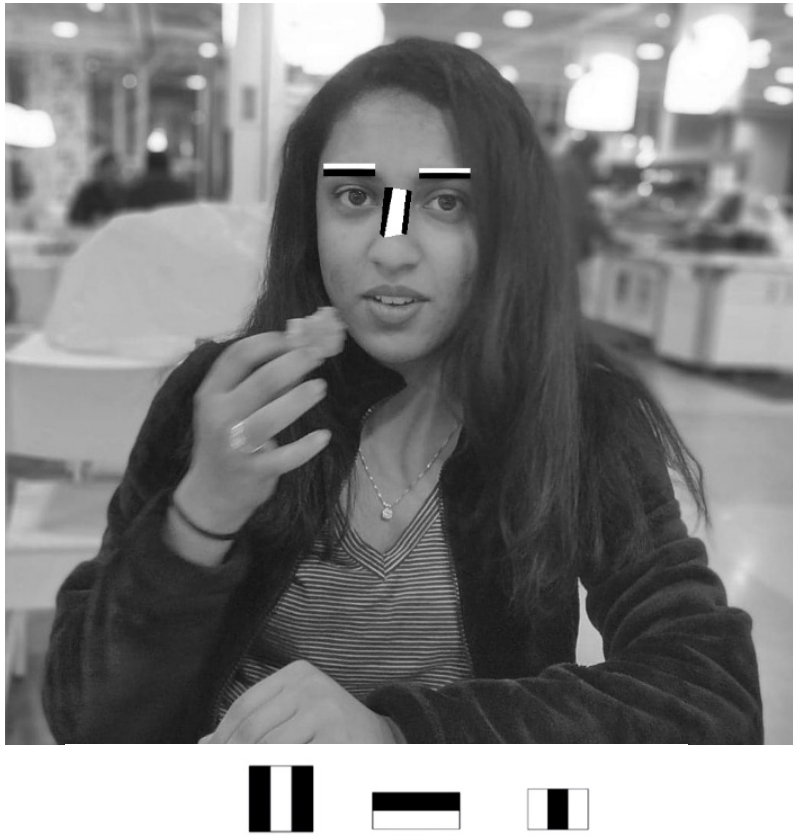
- First two features selected by boosting:



This feature combination can already yield 100% recall and 50% false positive rate!





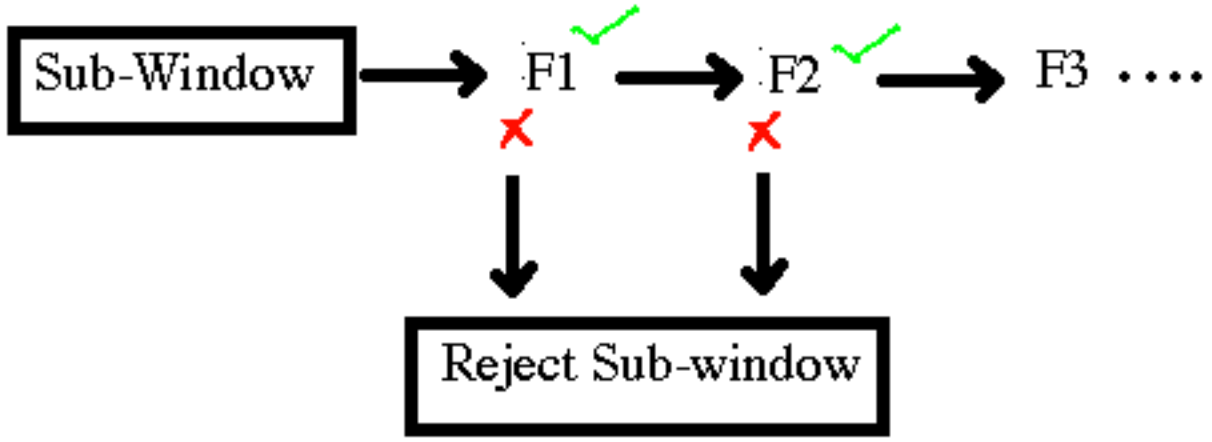


$$F(x) = \alpha_1 f_1(x) + \alpha_2 f_2(x) + \alpha_3 f_3(x) + \ldots$$

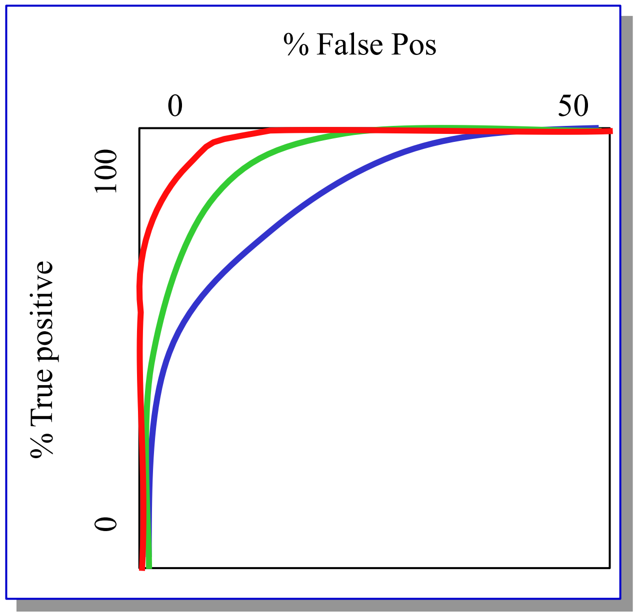
3. Attentional cascade

- Chain classifiers that are progressively more complex
- Minimize *false positive rates* at each stage, not absolute error

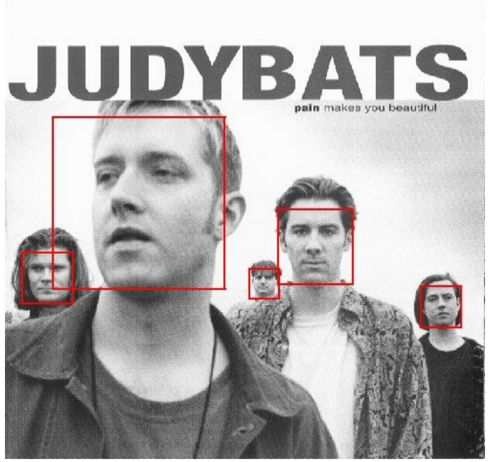
$$F(x) = a1f1(x) + a2f2(x) + a3f3(x) \ldots\ldots$$

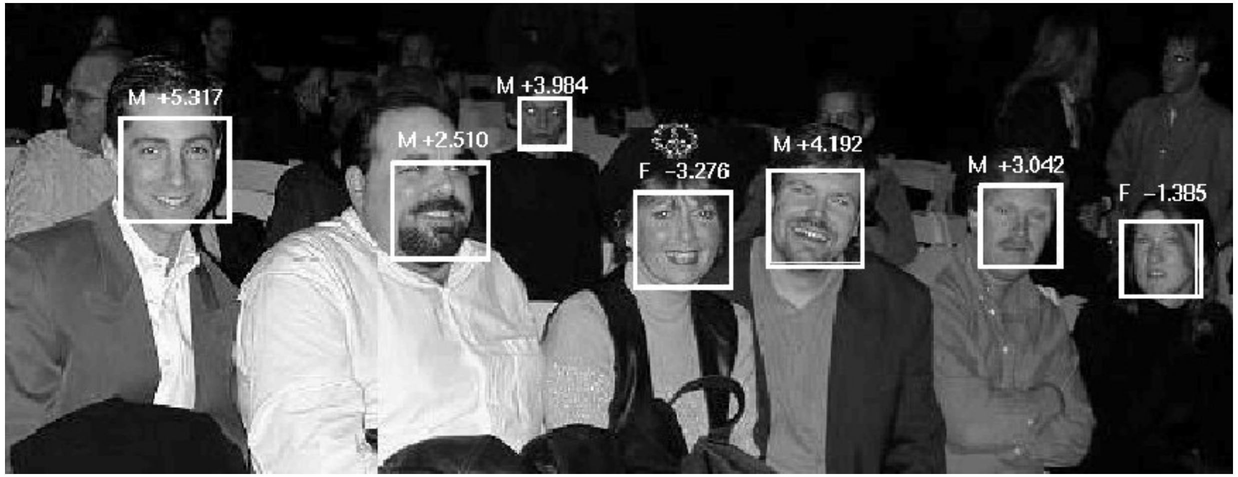


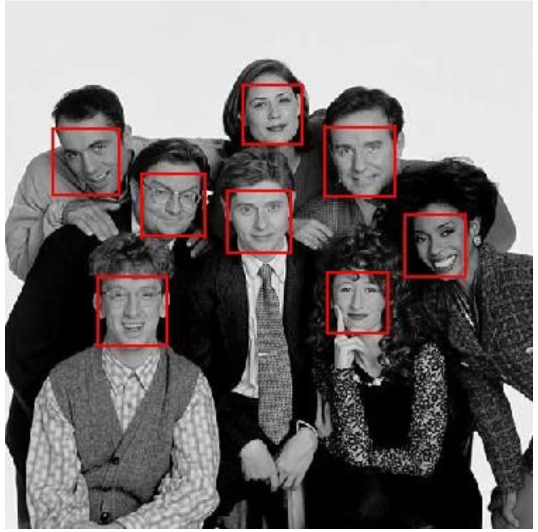
Receiver operating characteristic

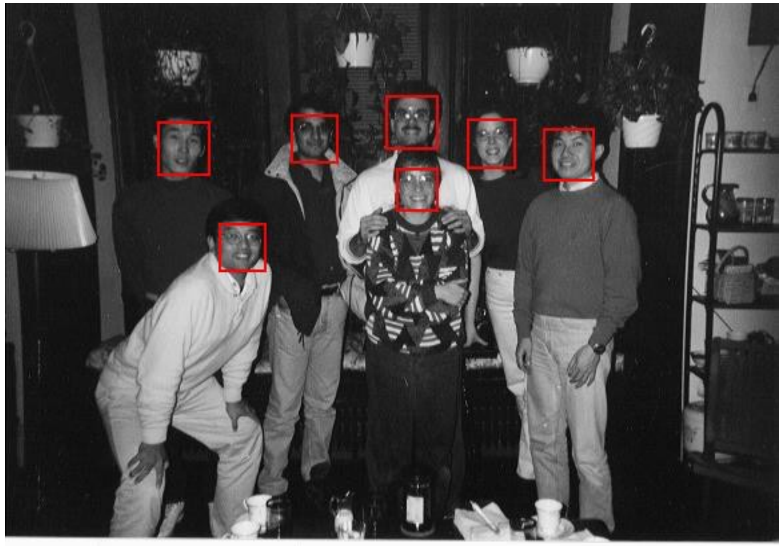


Viola/Jones detector is very powerful

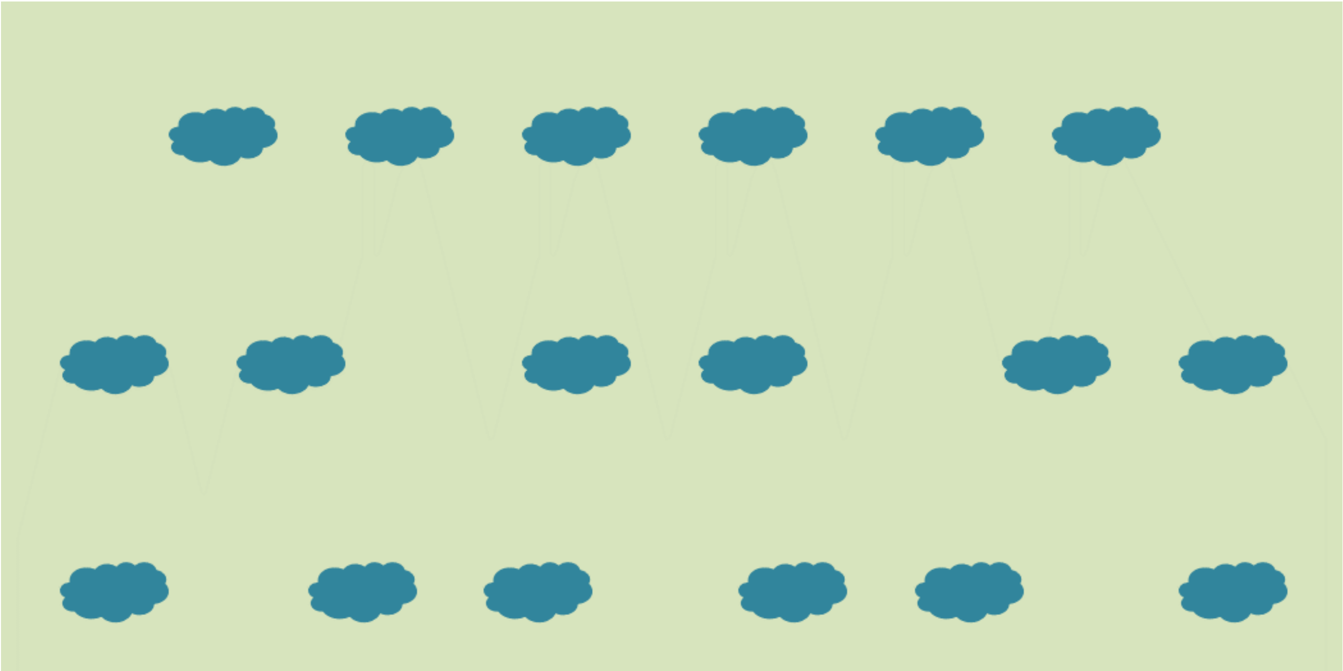






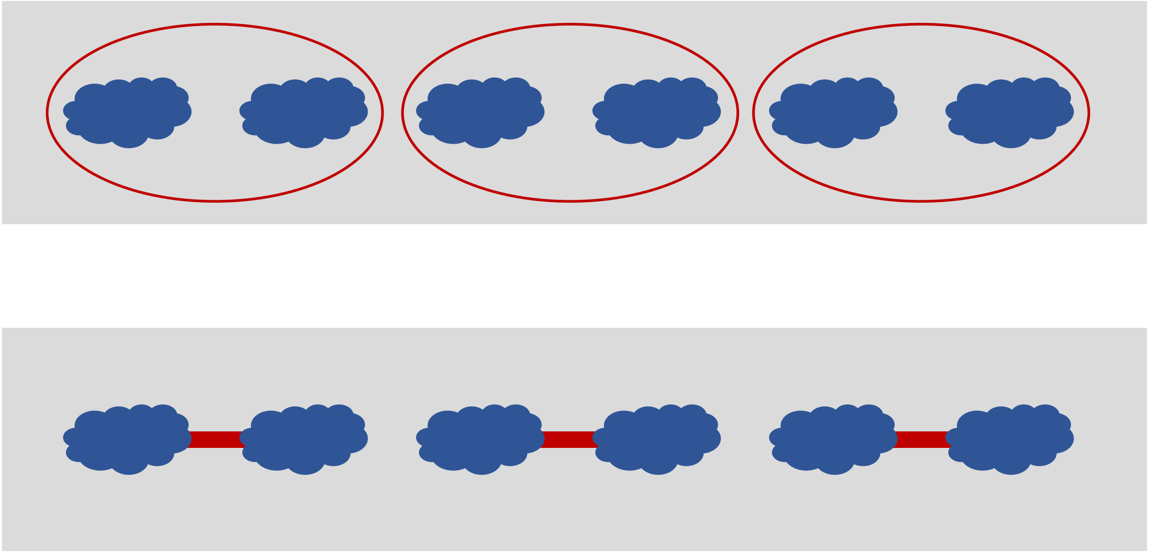


Question: what makes an object "segmentable"?



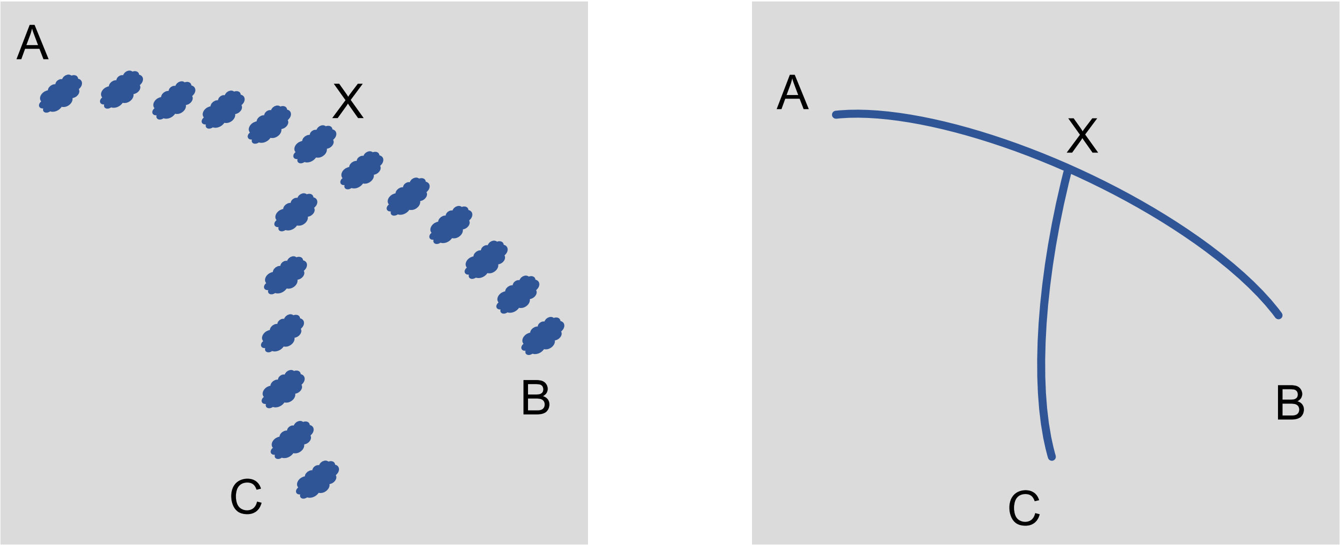
Objects with similar motion or change in appearance are grouped together

Common Region/Connectivity



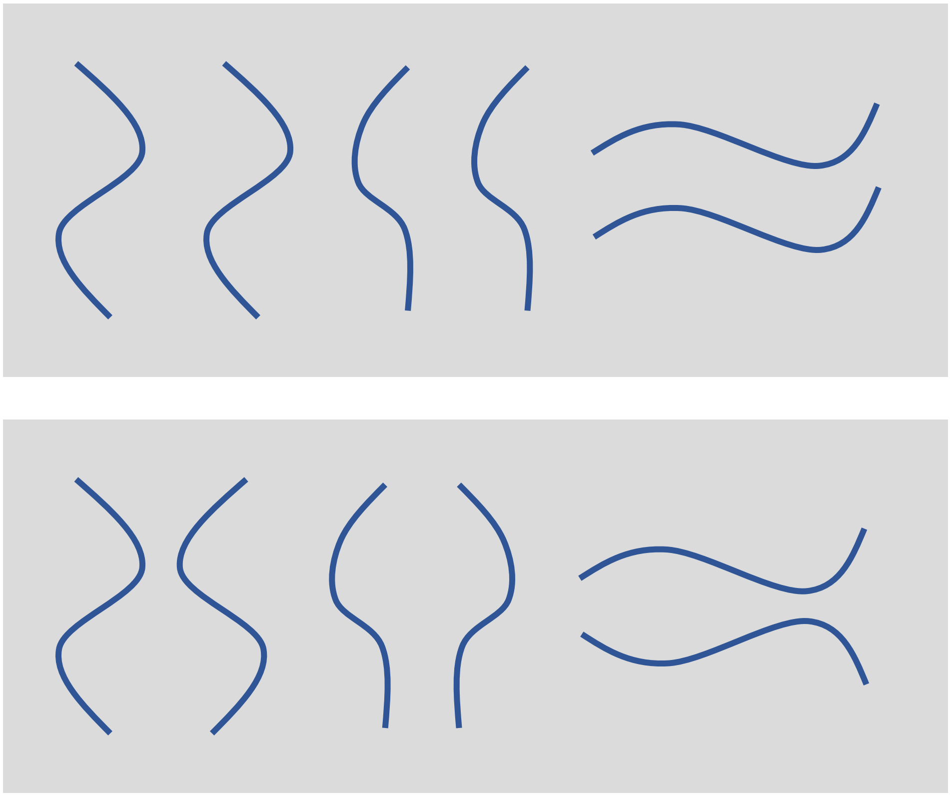
Connected objects are grouped together

Continuity Principle

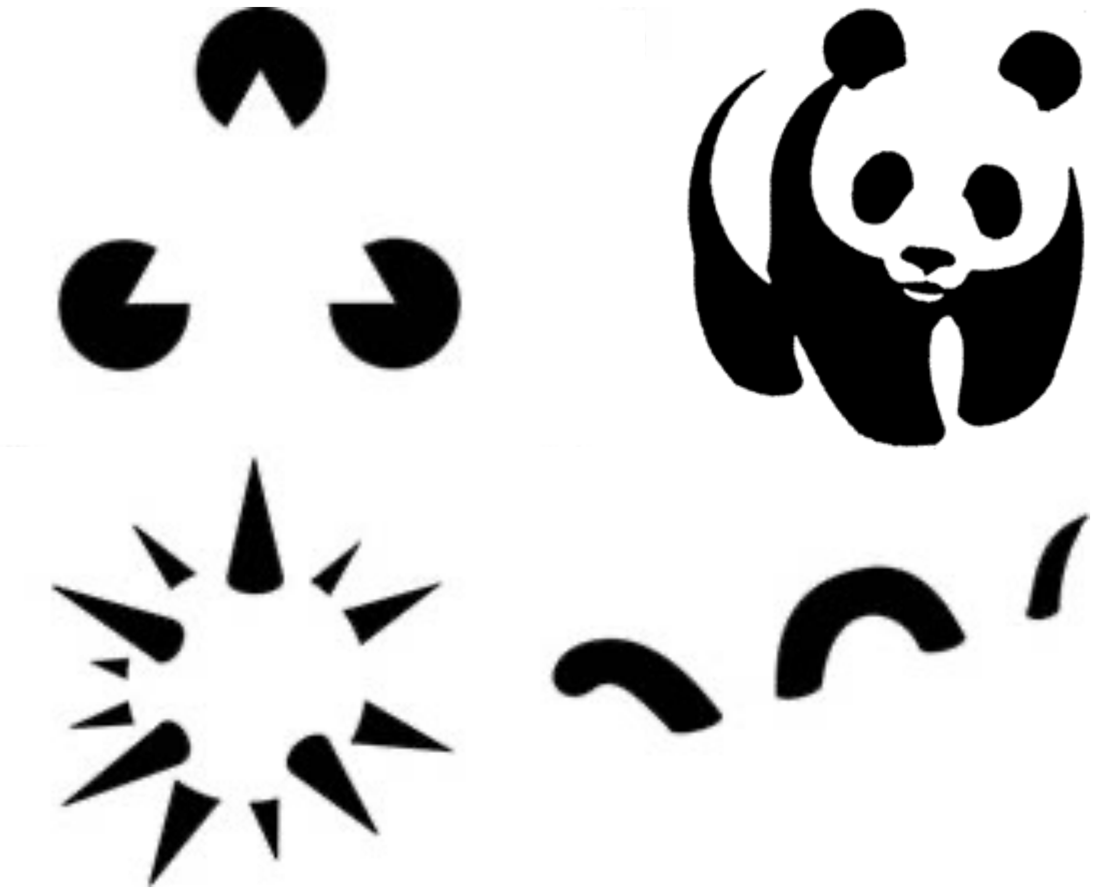


Features on a continuous curve are grouped together

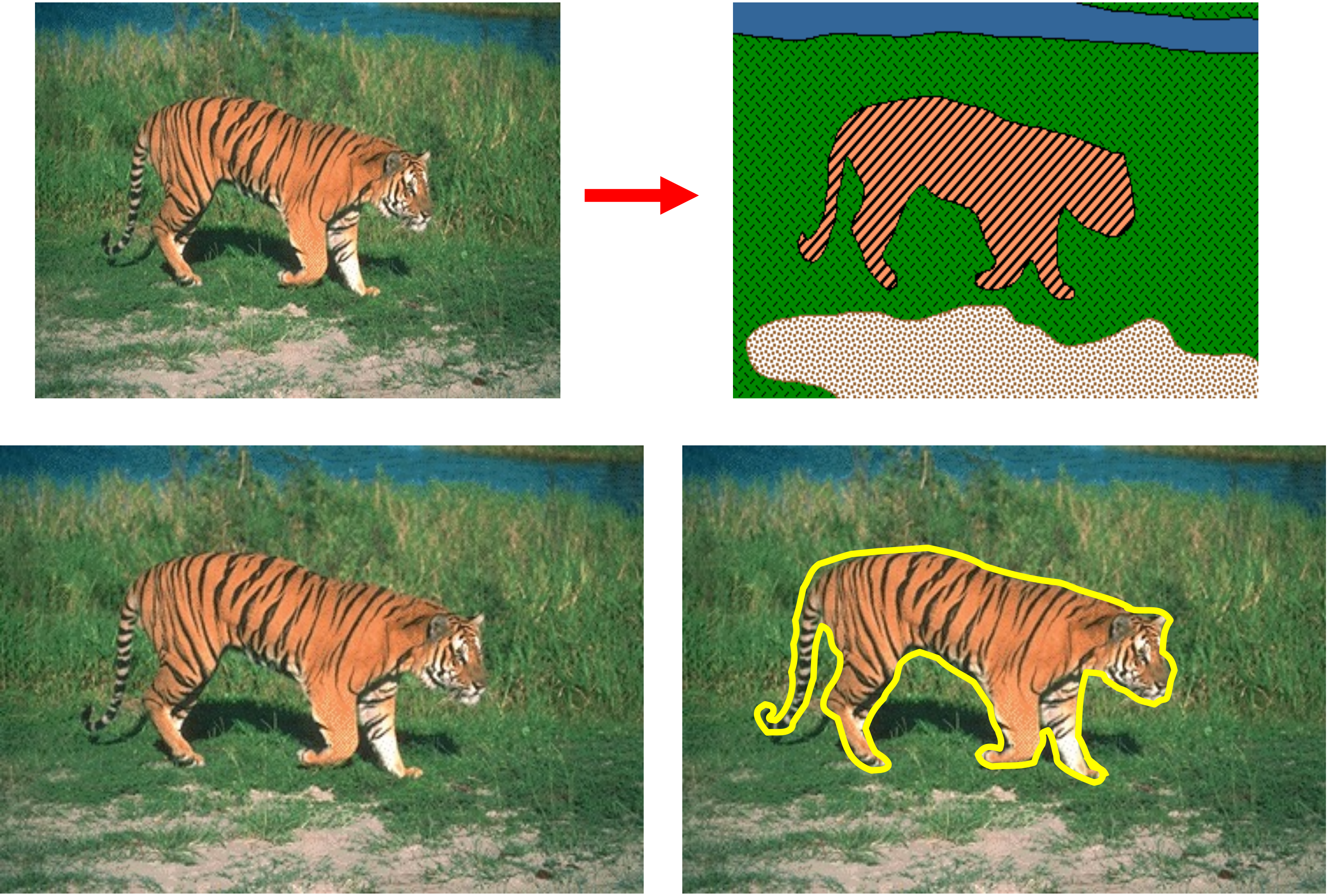
Symmetry Principle



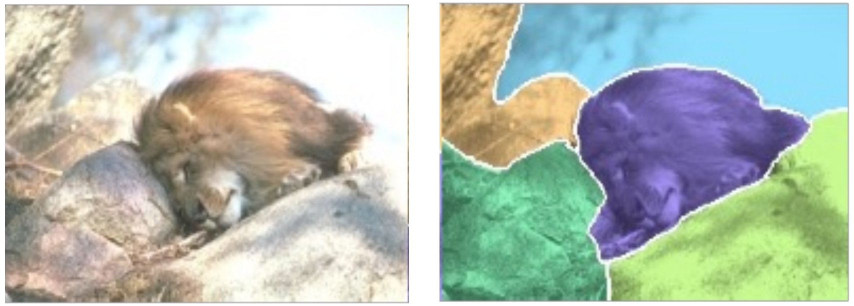
Completion



Illusory or subjective contours are perceived



$k = 4$ $nc = .0017$



$k = 5$ $nc = .0060$

$k = 11$

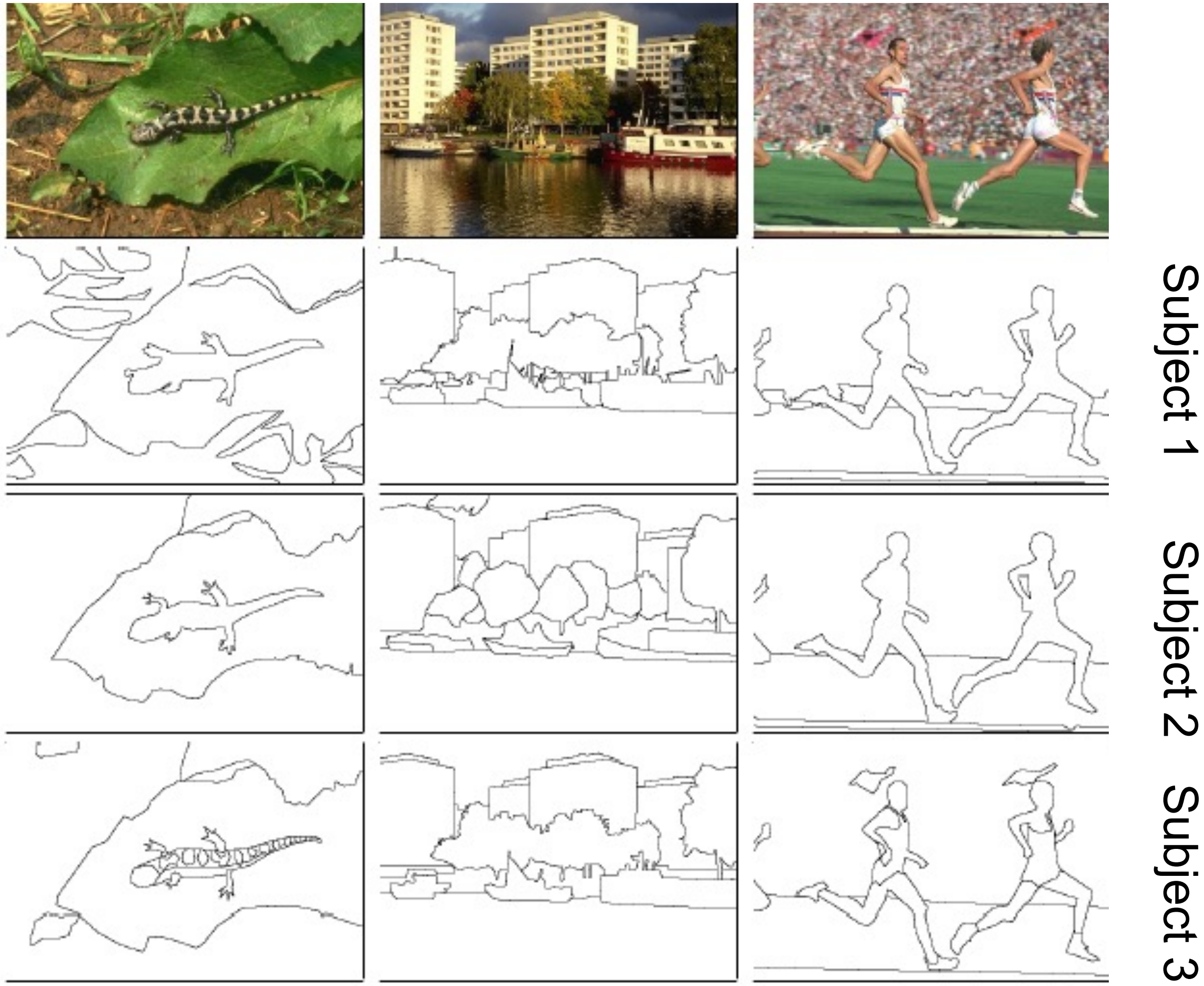
Segmentation may never have “ground truth”…

Segmentation may never have "ground truth"…

What is a “good” segmentation??

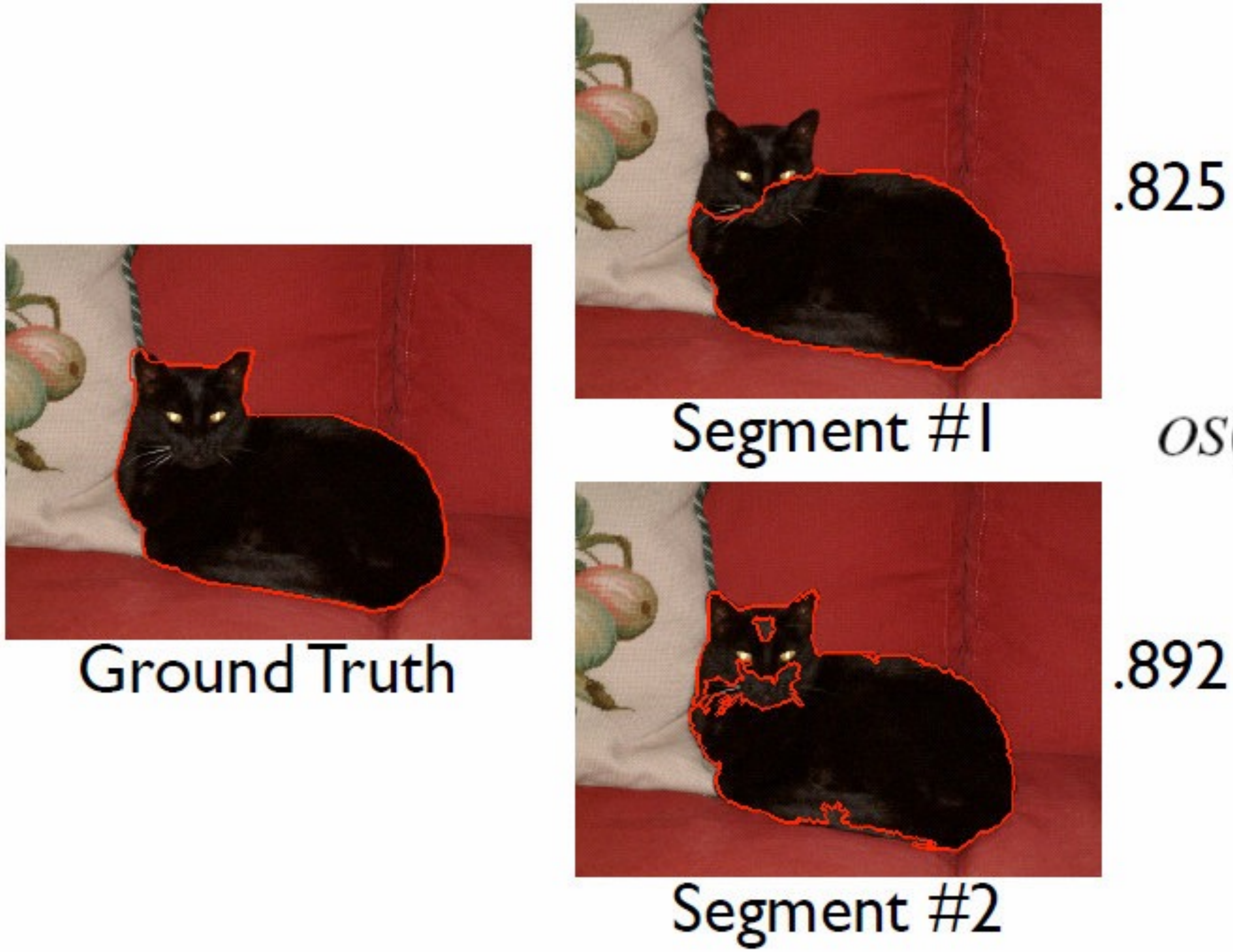
- No objective definition of segmentation!

- Compare to human “ground truth”



- http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/resources.html

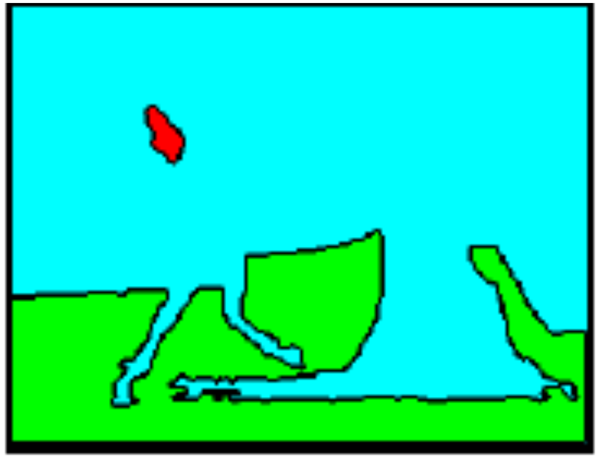
Evaluation: Intersection-over-Union (**IoU**) with ground truth

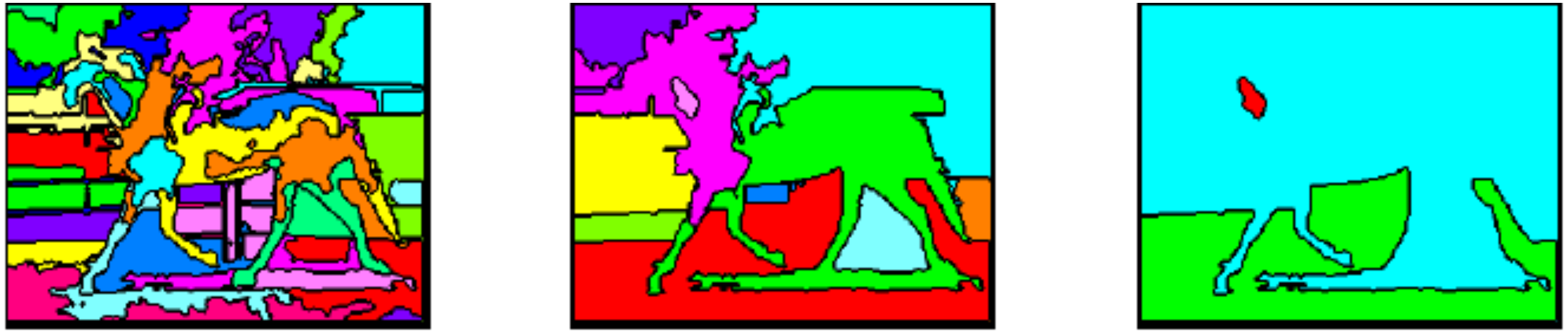


$$OS(S,G) = \frac{|S \cap G|}{|S \cup G|}$$

Types of segmentations

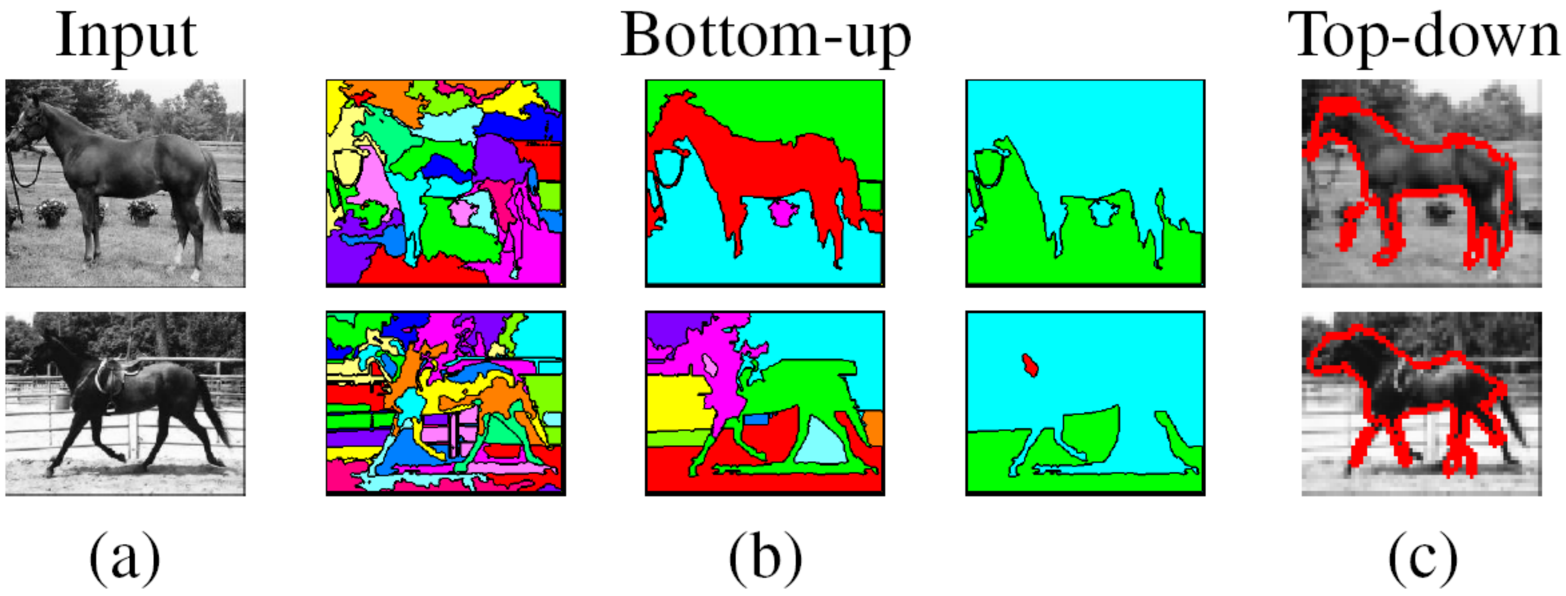

Oversegmentation


Undersegmentation


Multiple Segmentations

Major ideas for segmentation

- Bottom-up: group tokens with similar features
- Top-down: group tokens that likely belong to the same object

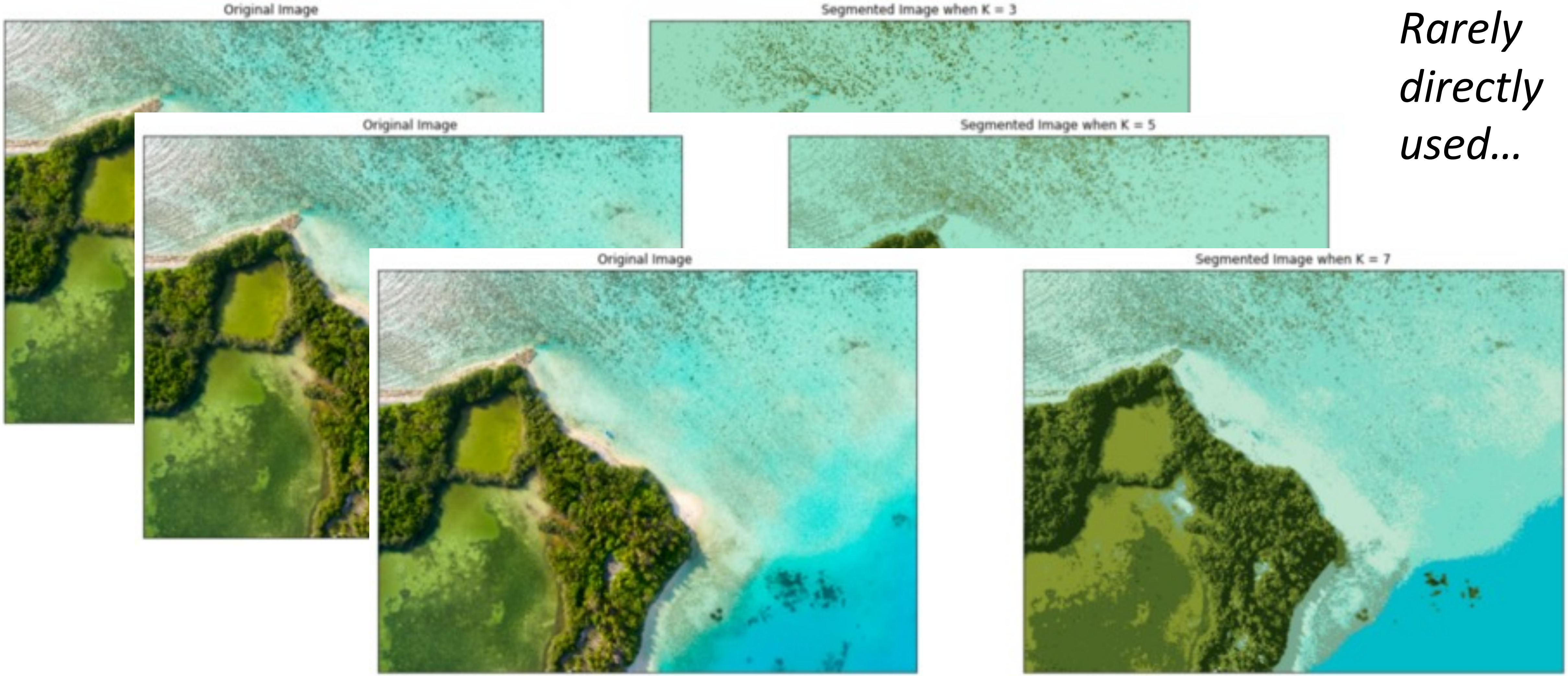


[Levin and Weiss 2006]

Main approaches

- Spectral techniques
- Segmentation as boundary detection
- **Clustering and mean shift**
- **Graph-based techniques**
- Deep learning techniques

K-means can be “okay” image segmentation

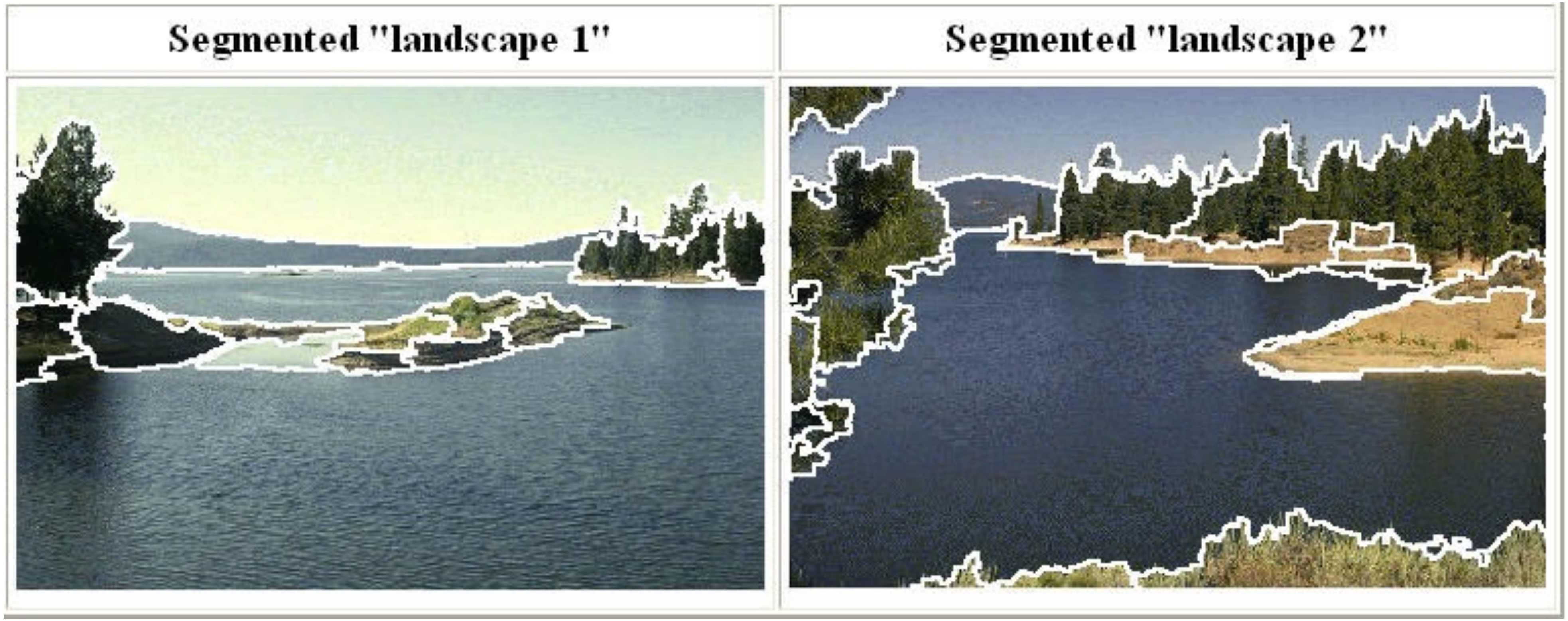


Rarely directly used…

Mean shift segmentation

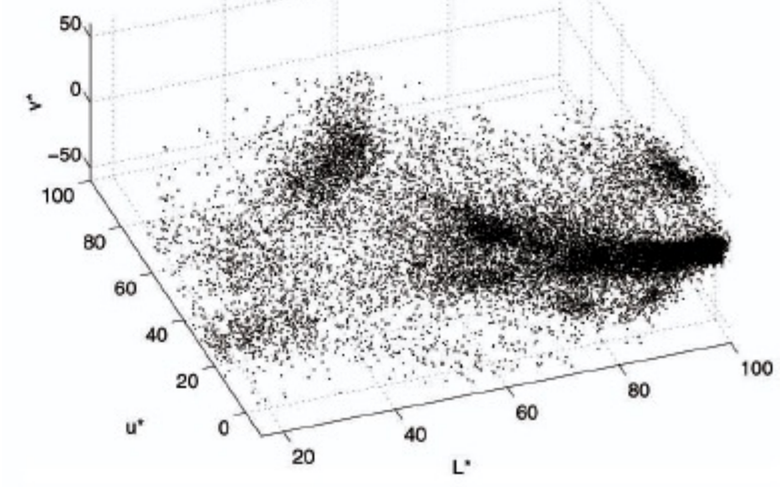
D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

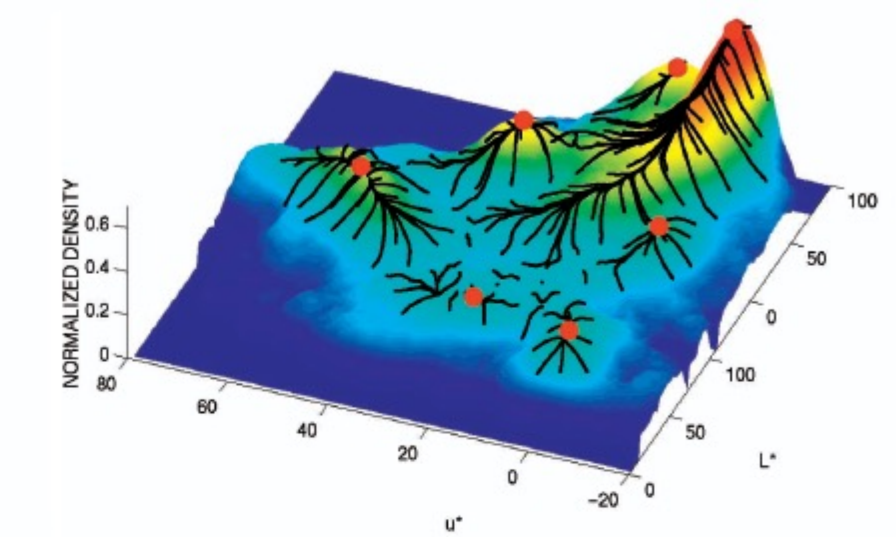
- Versatile technique for clustering-based segmentation!
- non- parametric algorithm that clusters data iteratively by finding the densest regions (clusters) in a feature space

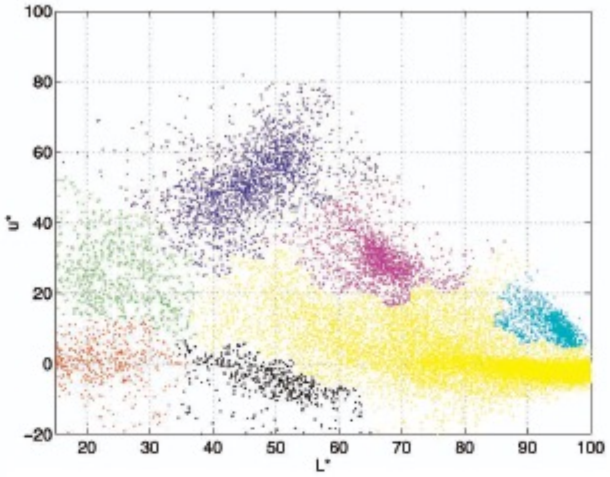


Mean shift algorithm

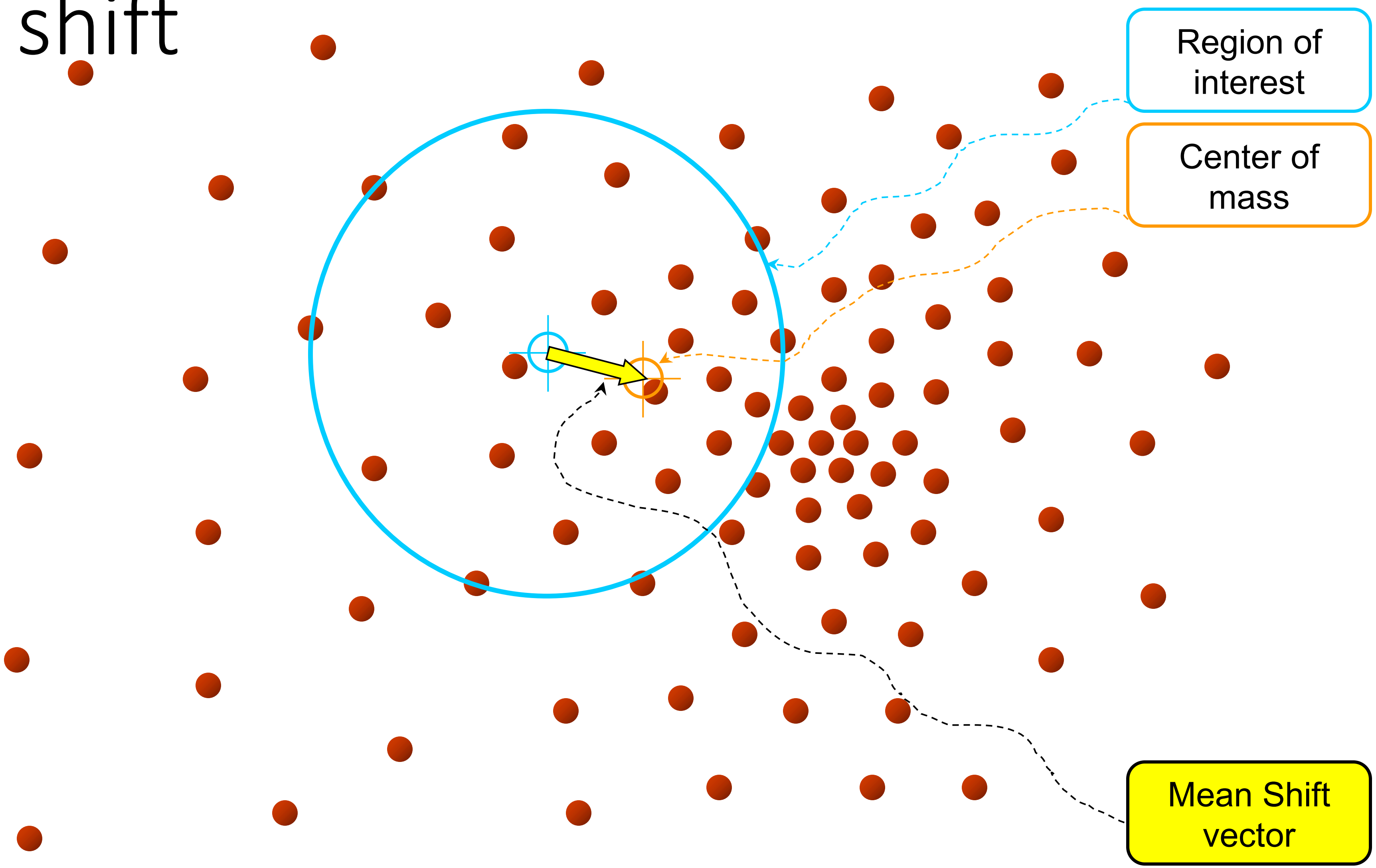
- Try to find *modes* of this non-parametric density





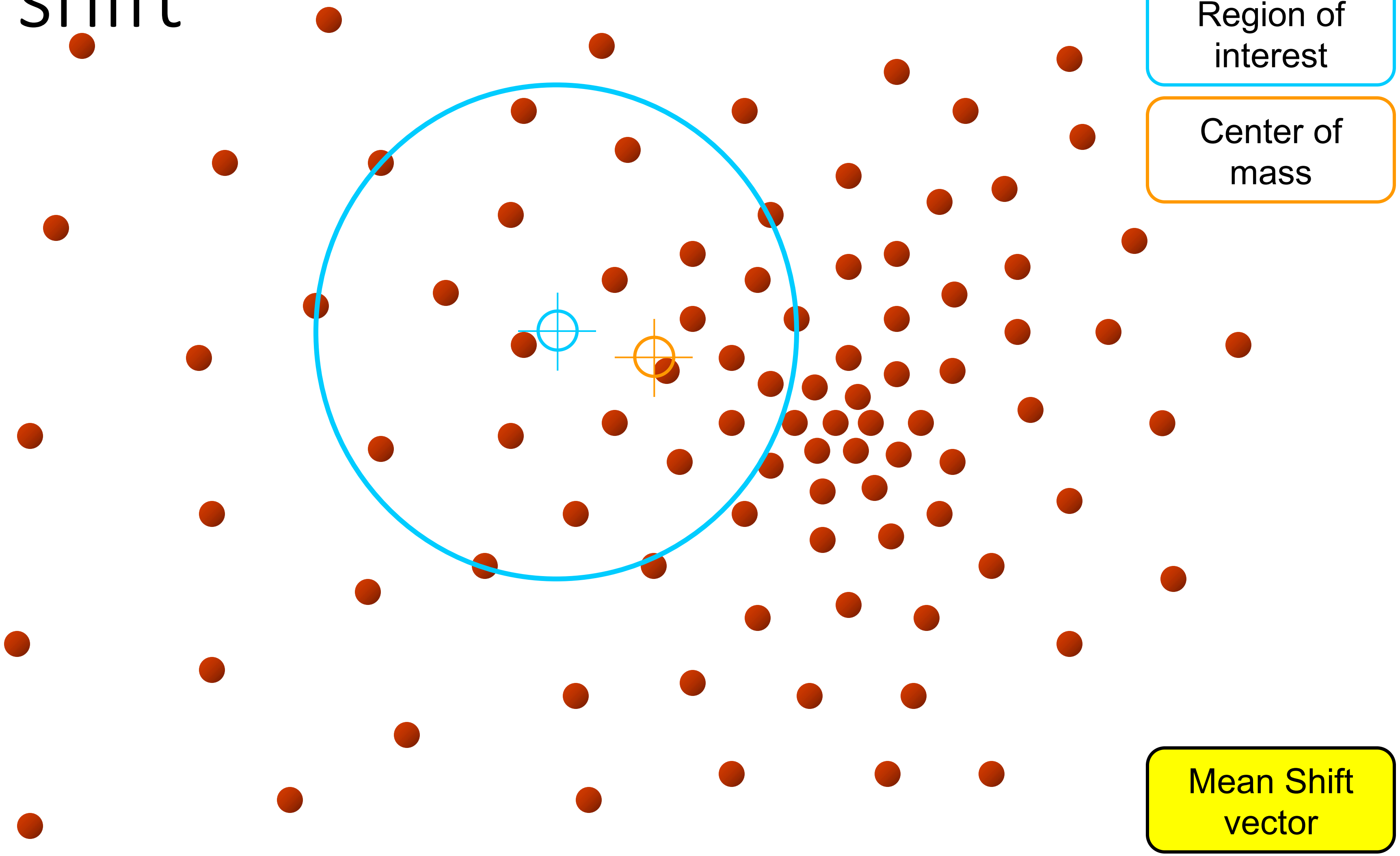


Mean shift



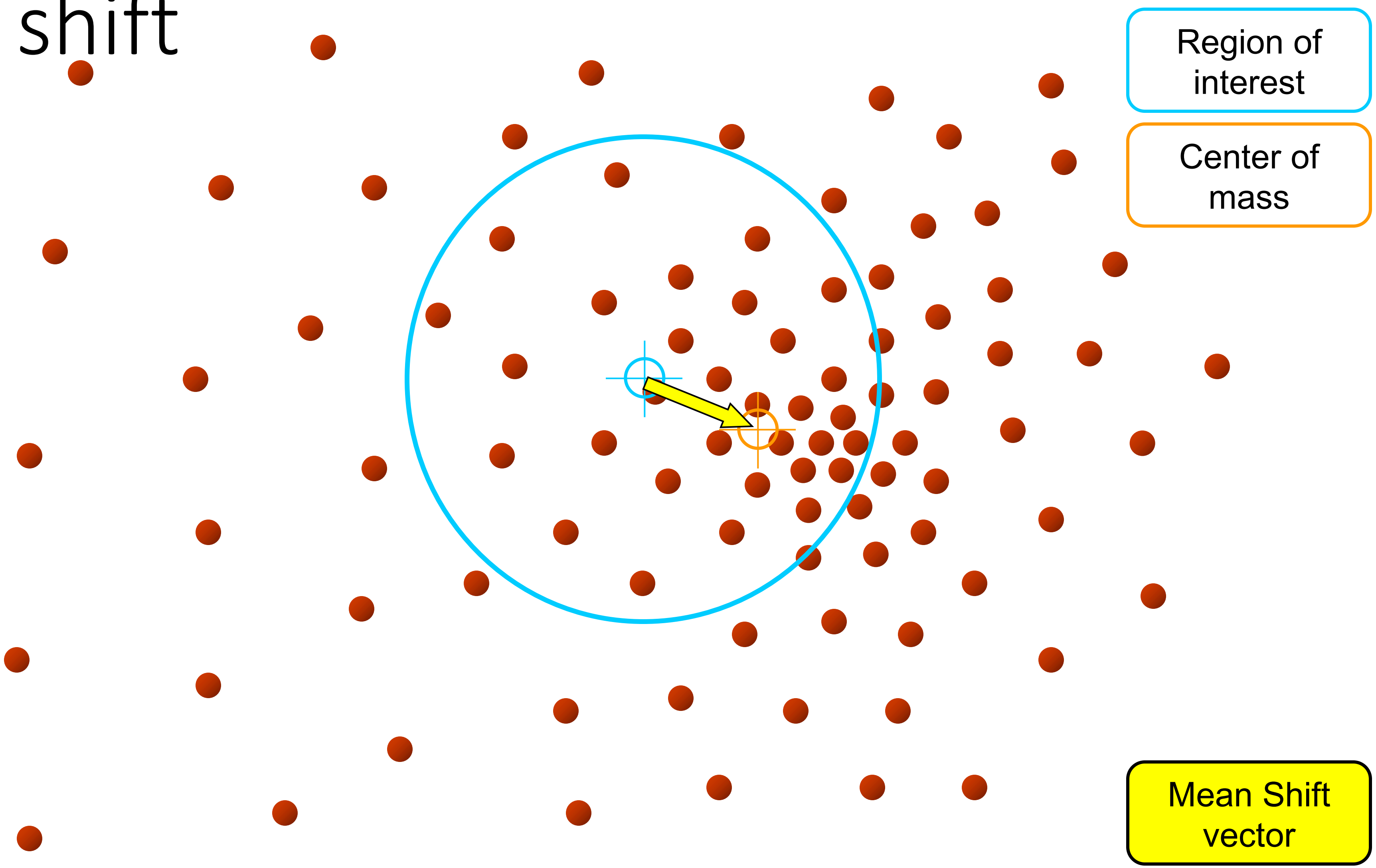
Slide by Y. Ukrainitz & B. Sarel

Mean shift



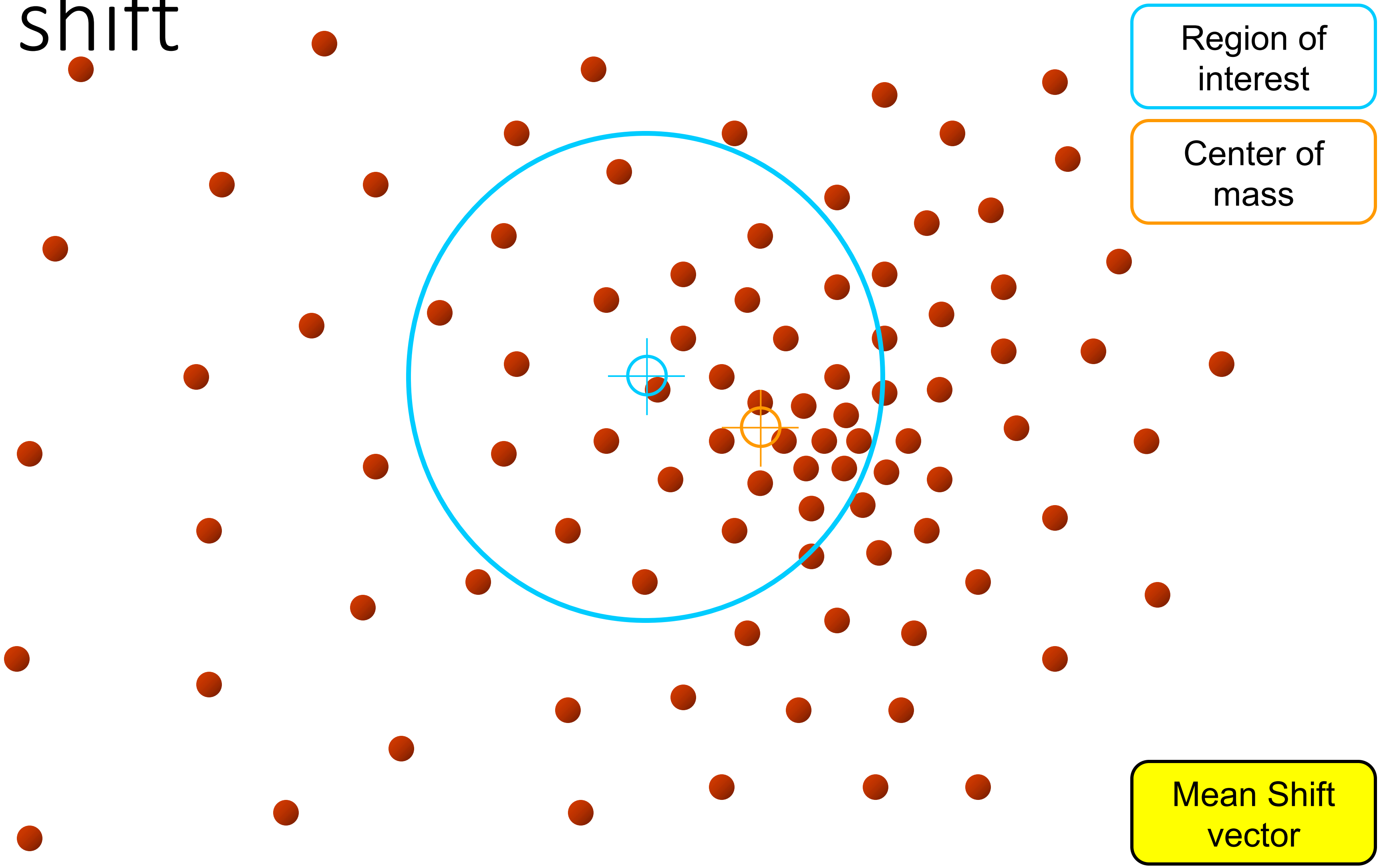
Slide by Y. Ukrainitz & B. Sarel

Mean shift



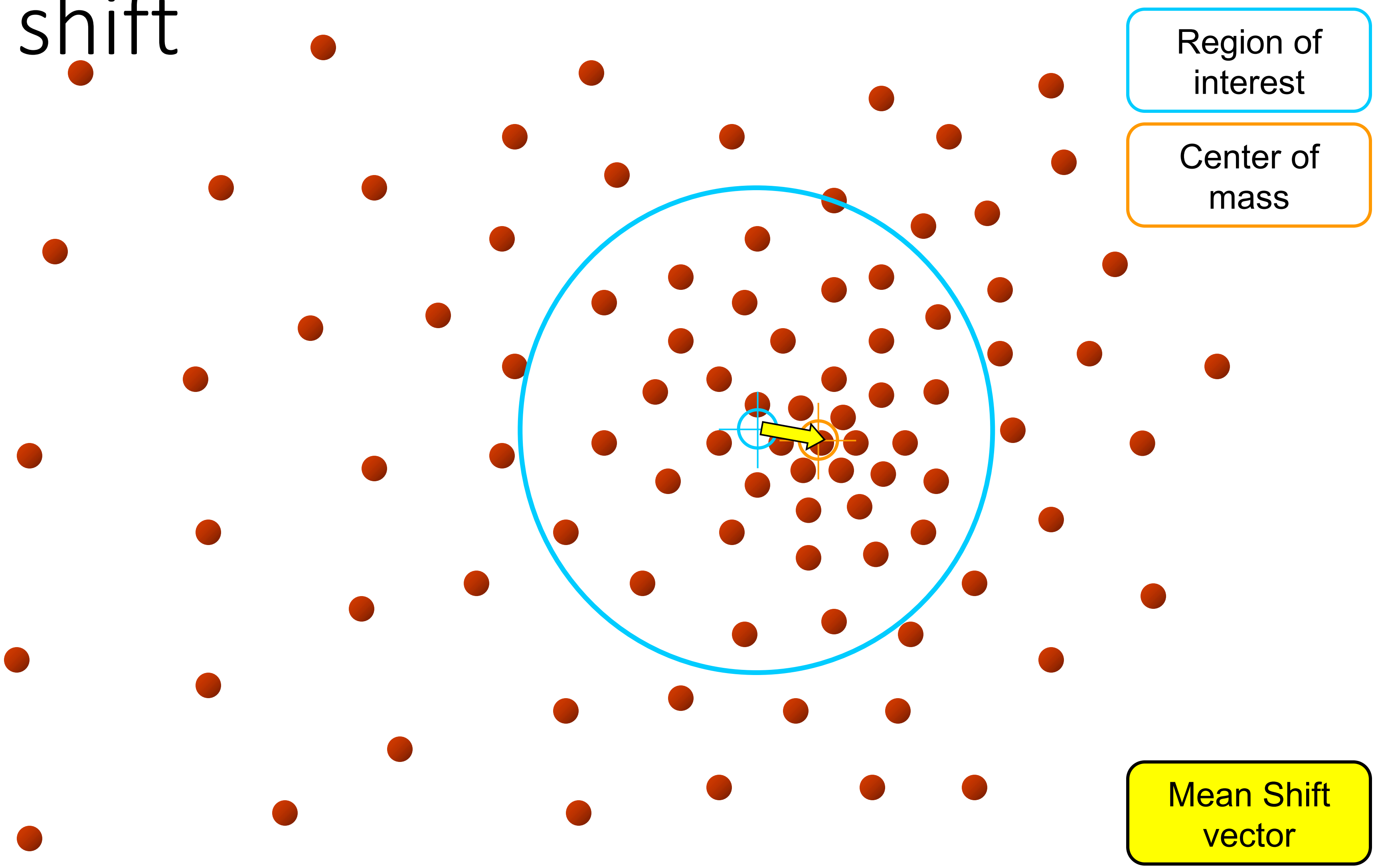
Slide by Y. Ukrainitz & B. Sarel

Mean shift



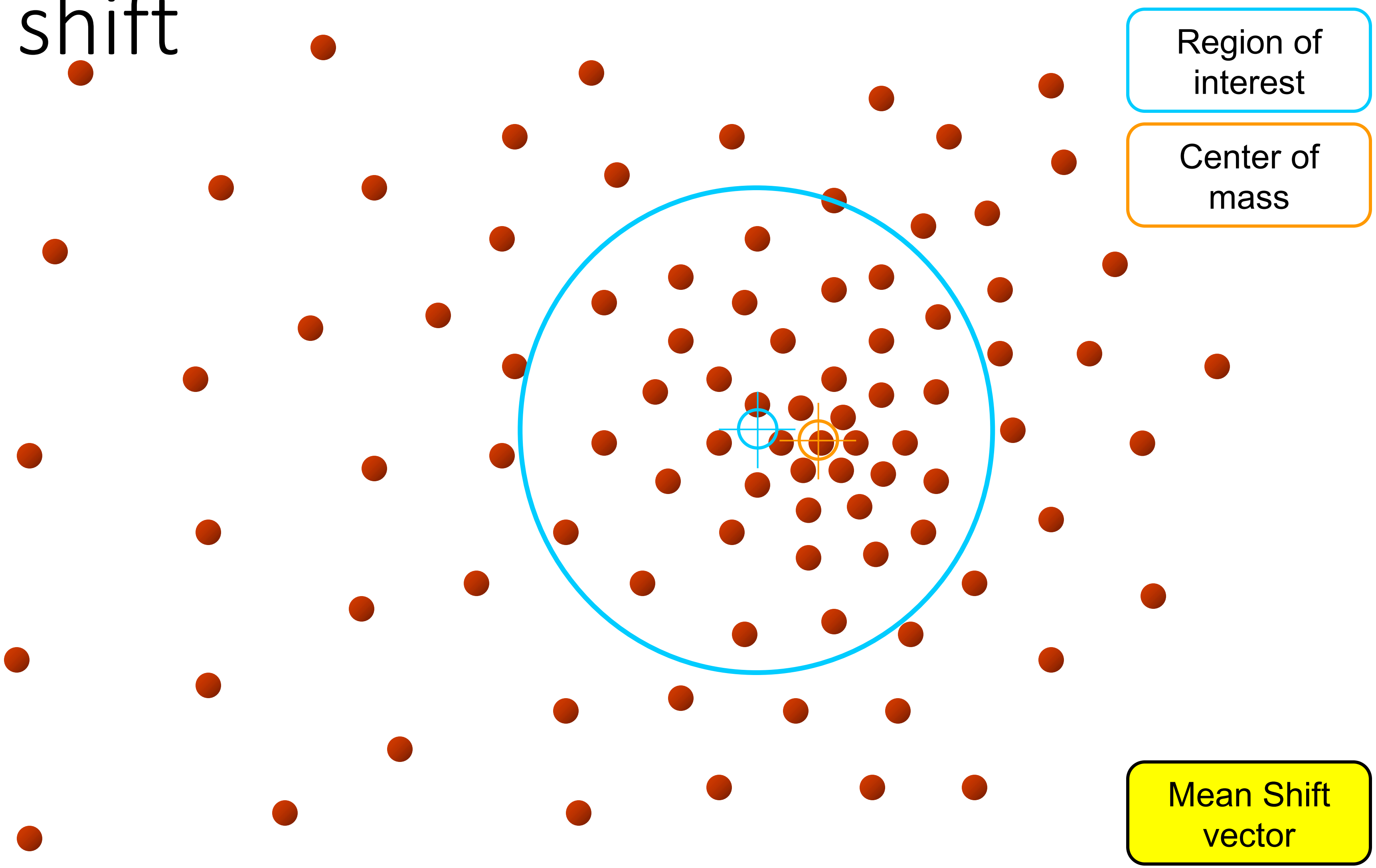
Slide by Y. Ukrainitz & B. Sarel

Mean shift



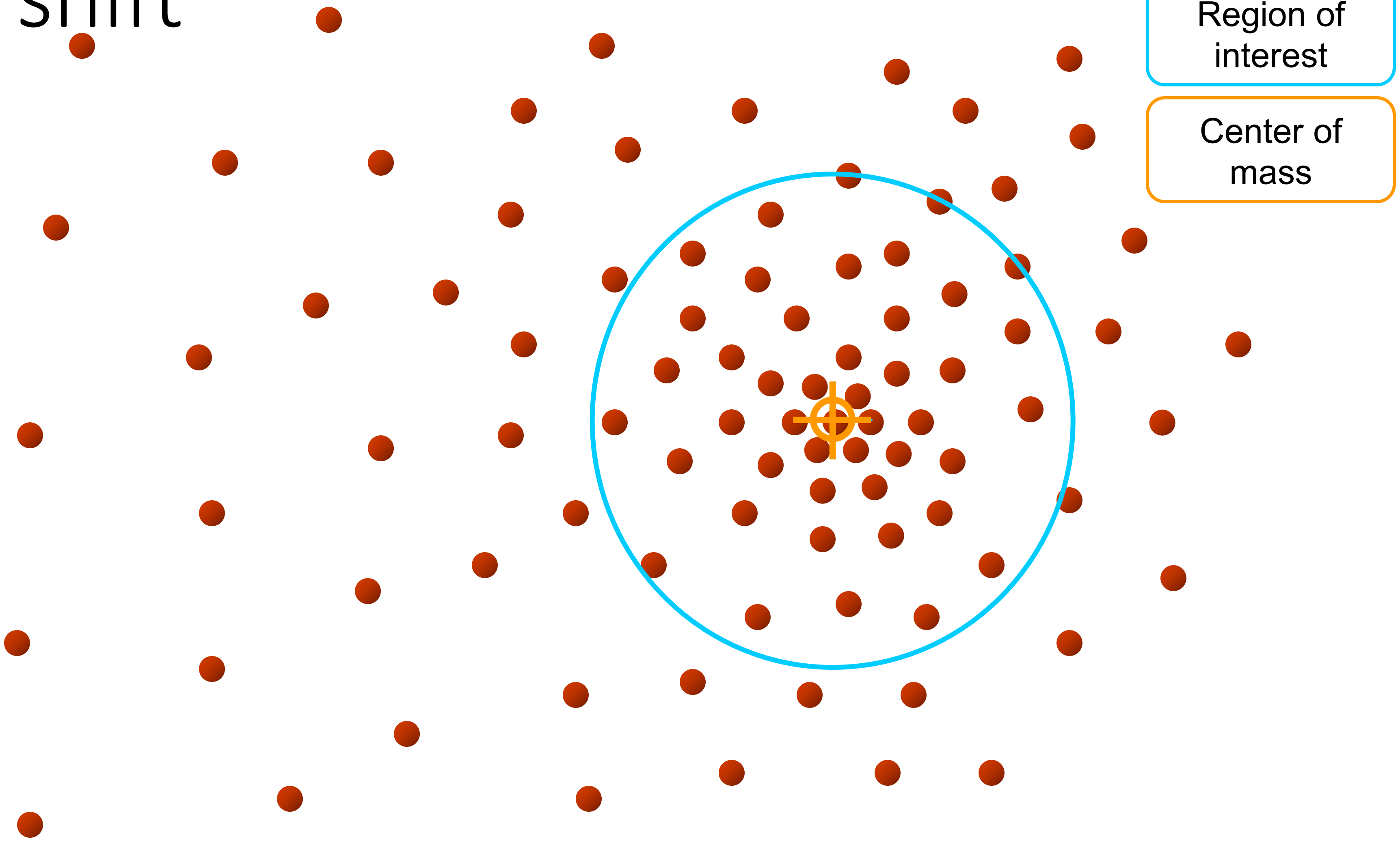
Slide by Y. Ukrainitz & B. Sarel

Mean shift



Slide by Y. Ukrainitz & B. Sarel

Mean shift



Slide by Y. Ukrainitz & B. Sarel

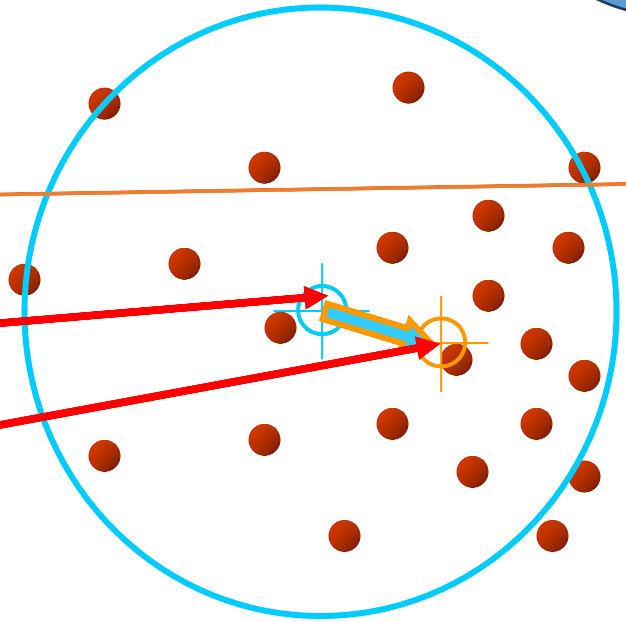
Computing the Mean Shift

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

- Compute mean shift vector
- Translate the Kernel window by **m(x)**
- **g is called a "kernel function"**

Key Difference with K-means: the "mean" is not simple averaging, but a "weighted average" counting in the **point distribution** (a special case of Kernel Density Estimation)

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



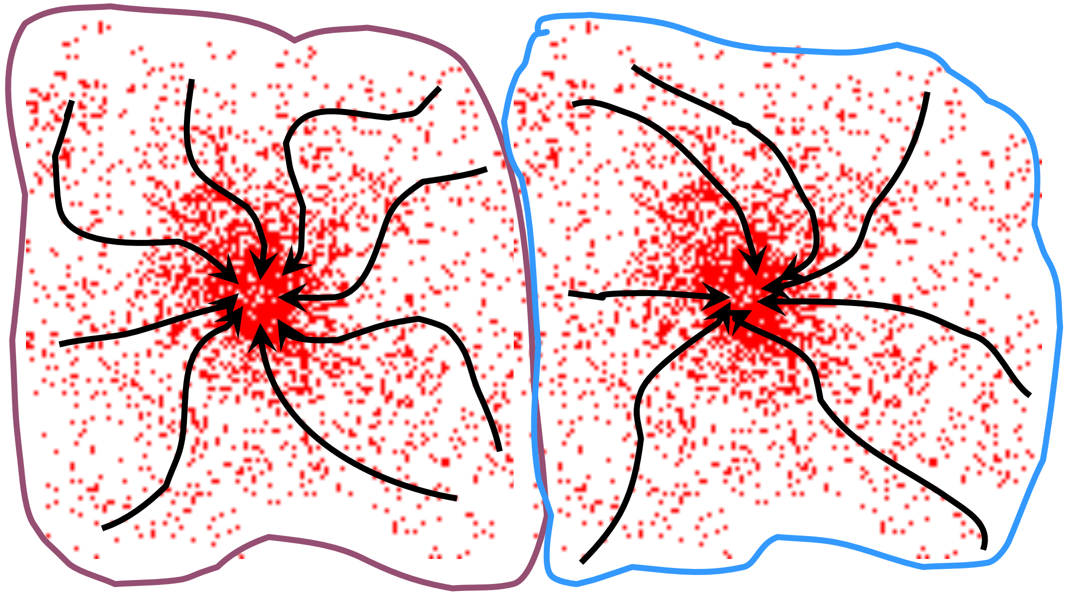
$$K\left(\frac{x - x_i}{h}\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-x_i)^2}{2h^2}}$$

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

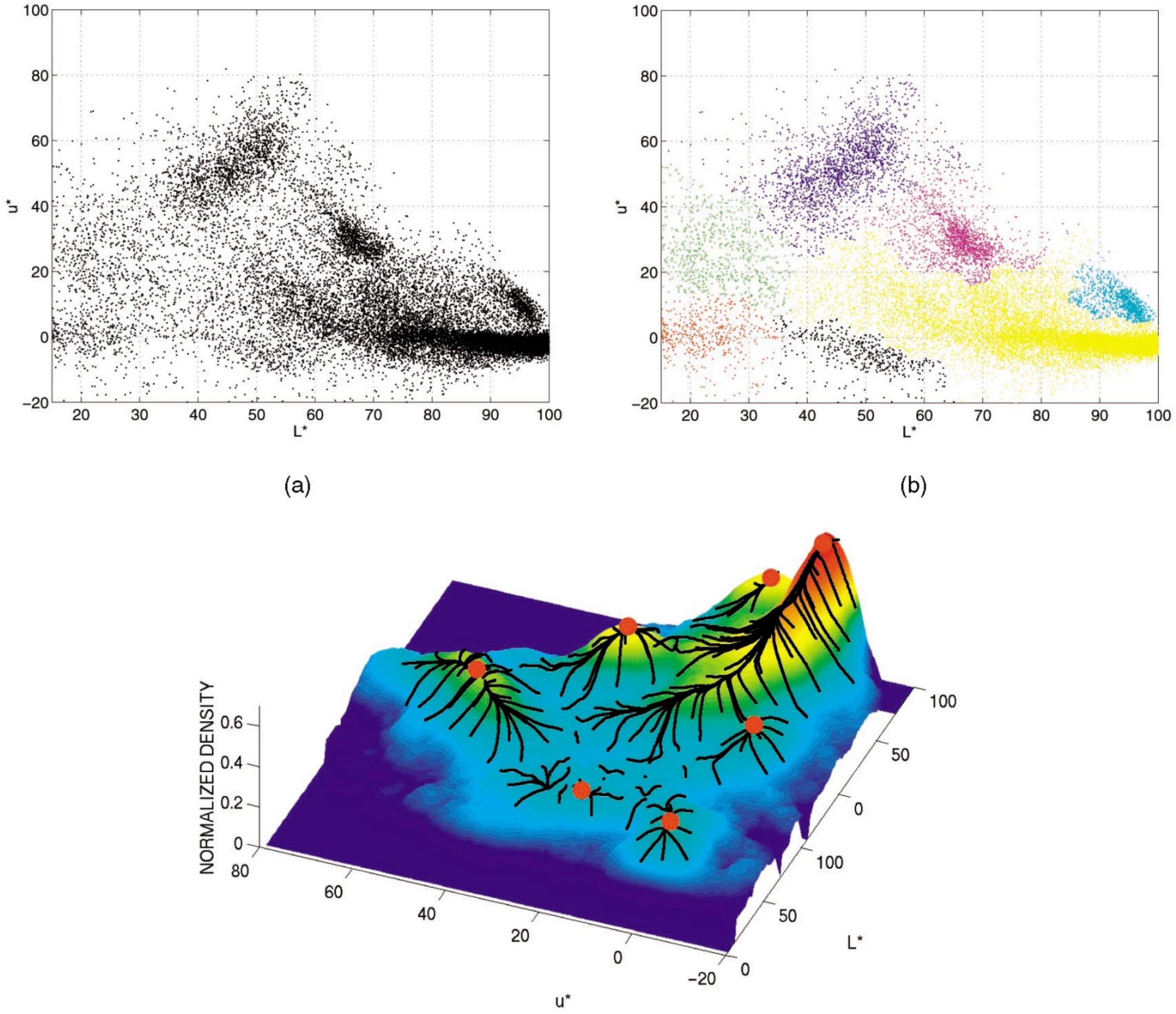
Slide by Y. Ukrainitz & B. Sarel

Solution Stability: 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



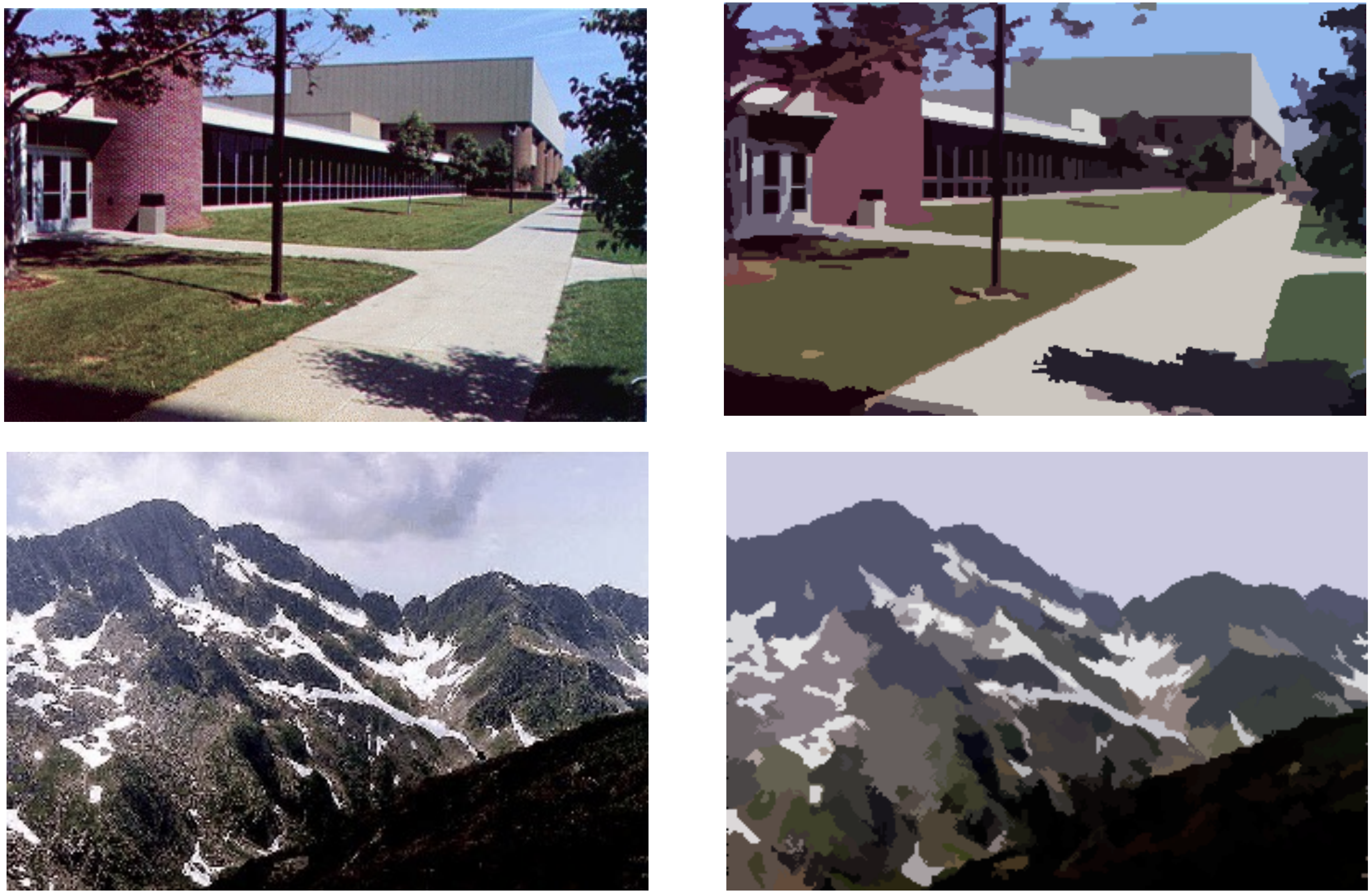
Summary of Mean Shift

- The mean shift algorithm seeks *density modes* of the given set of points
- **We don't have to specify cluster number *K***
- … but instead, have to pick the *"kernel function" and its hyperparameter*

Using MeanShift for image segmentation:

- 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



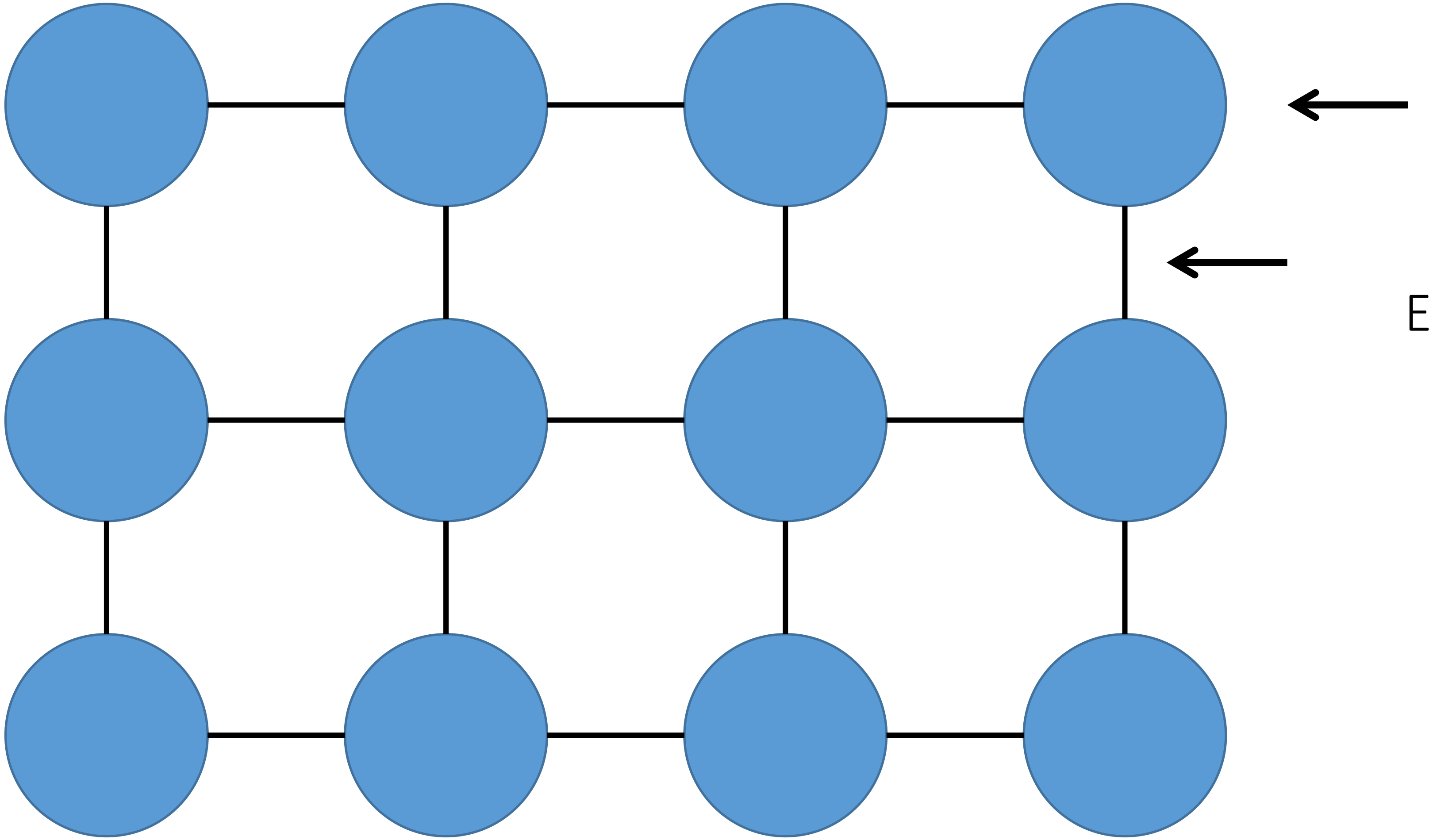
http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

Mean shift pros and cons

- Pros
  - Good general-practice segmentation
  - Flexible in number and shape of regions, no need to pre-choose region number K
  - Robust to outliers
- Cons
  - Have to choose kernel size in advance
  - Not suitable for high-dimensional features
  - Much slower than k-means (due to computing kernels)
- When to use it
  - Oversegmentatoin
  - Multiple segmentations
  - Tracking, clustering, filtering applications

New Idea: Images can be viewed as graphs

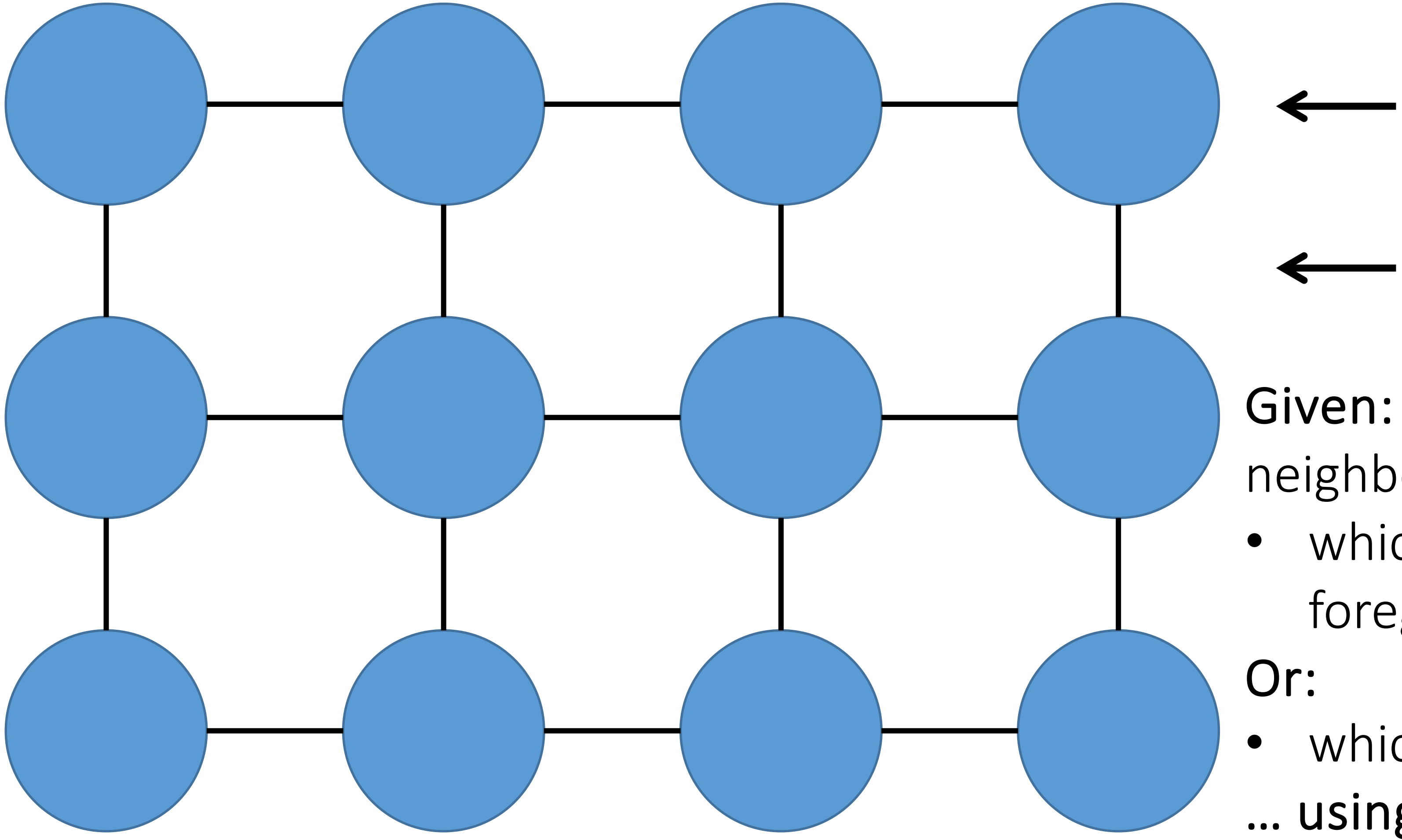


Nodes: pixels

Edges: Constraints between neighboring pixels

Graph-view of segmentation problem

Segmentation is node-labeling



Nodes: pixels

Edges: Constraints between neighboring pixels

Given: pixel values and neighborhoods, **Decide:**

- which nodes to label as foreground/background

Or:

- which nodes to label as seams

… using graph algorithms

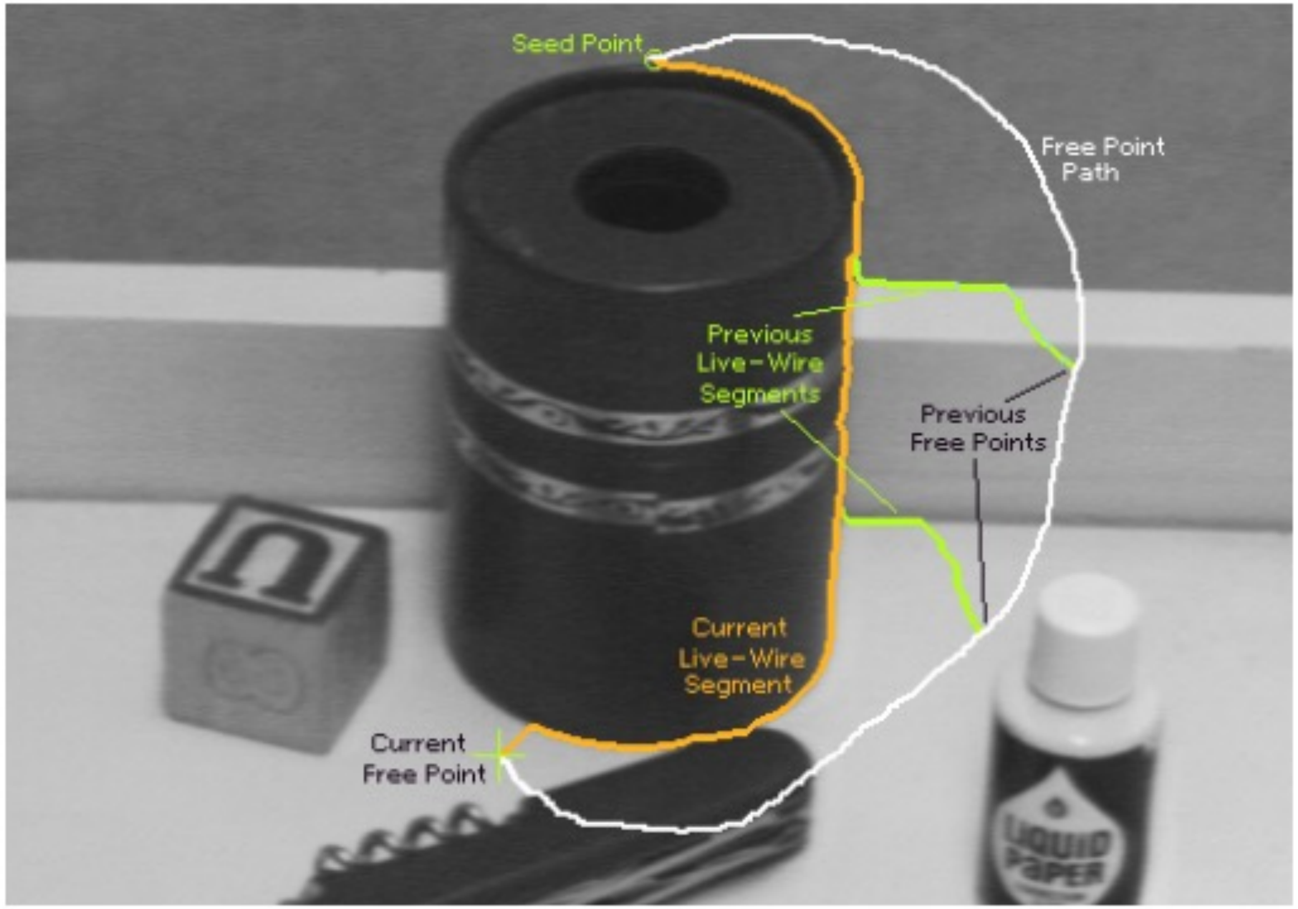
Intelligent scissors

Problem statement:

Given <u>two seed points</u>, find a good boundary connecting them

Challenges:

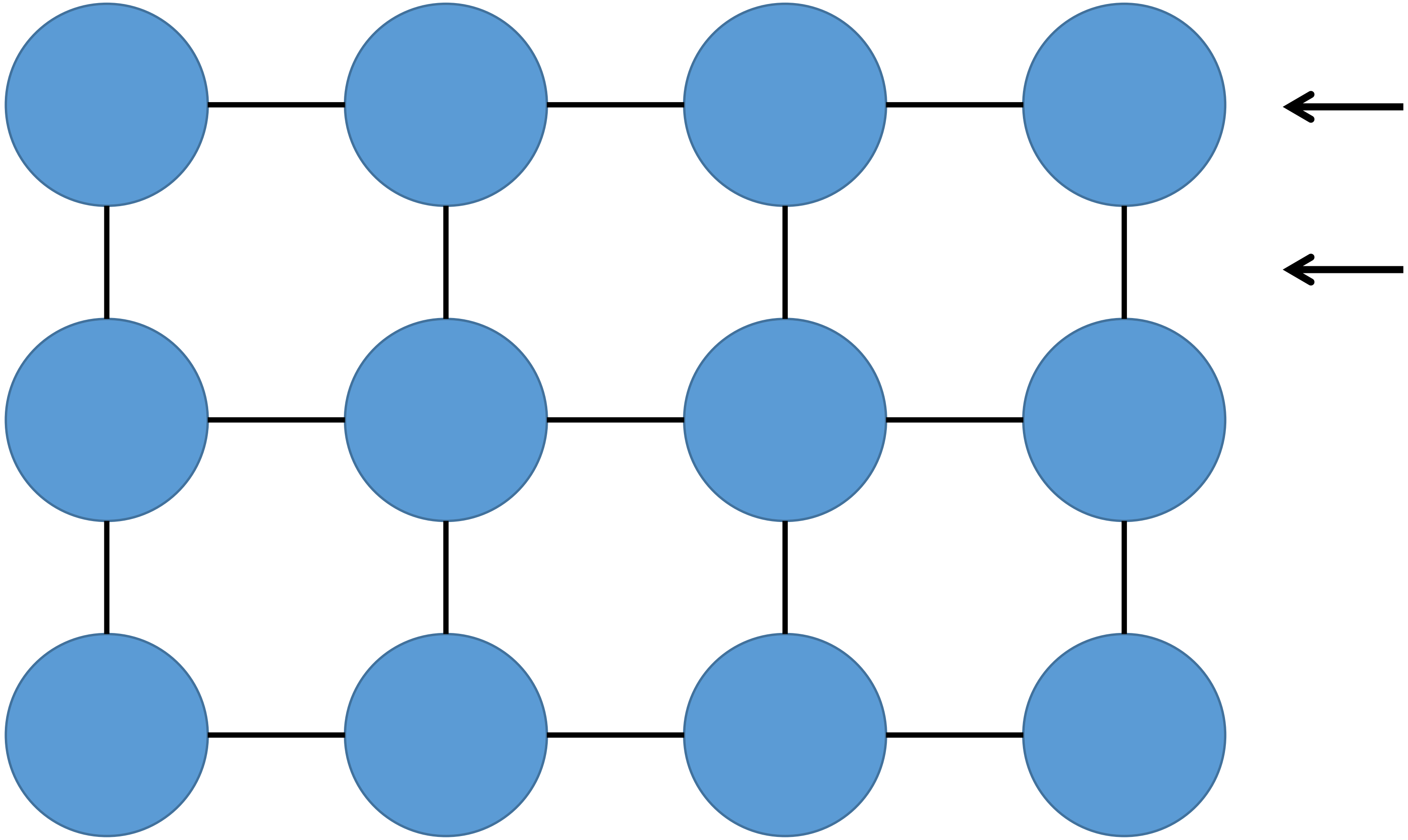
- Make this real-time for interaction
- Define what makes a good boundary



Mortenson and Barrett (SIGGRAPH 1995)
(you can tell it's old from the paper's low quality teaser figure)

Graph-view of this problem

Images can be viewed as graphs

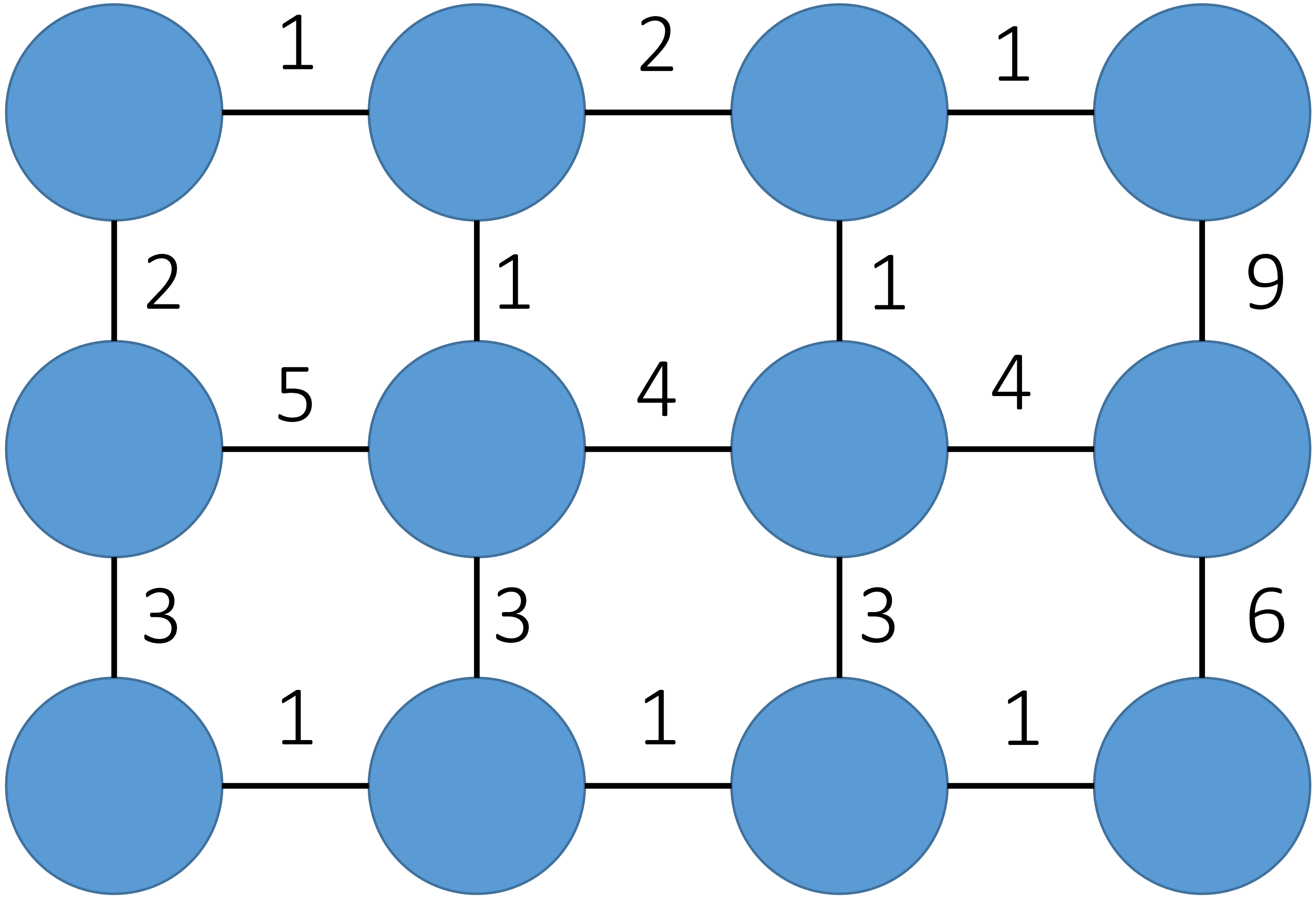


Nodes: pixels

Edges: Constraints between neighboring pixels

Graph-view of this problem

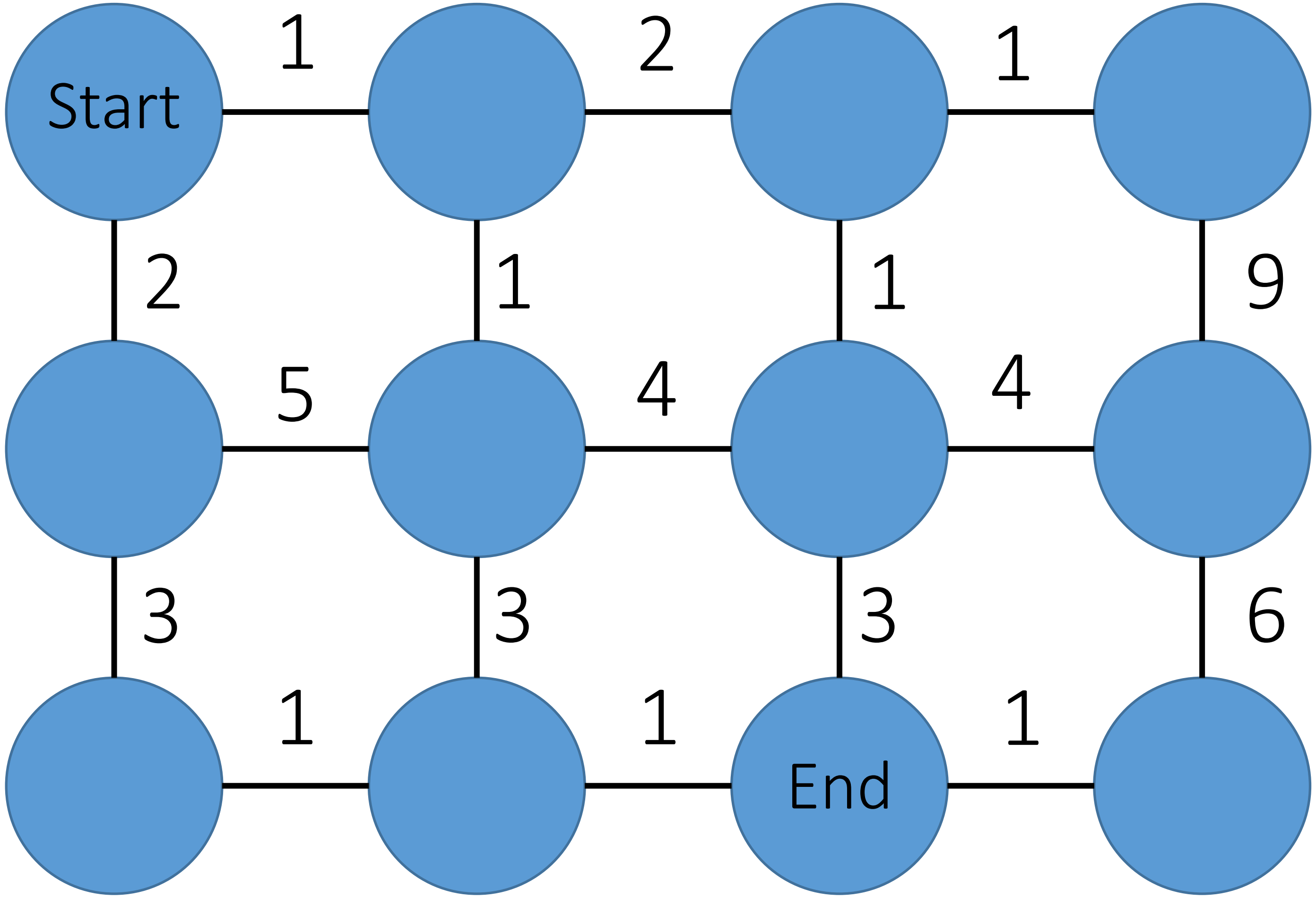
Graph-view of intelligent scissors:



1. Assign weights (costs) to edges

Graph-view of this problem

Graph-view of intelligent scissors:

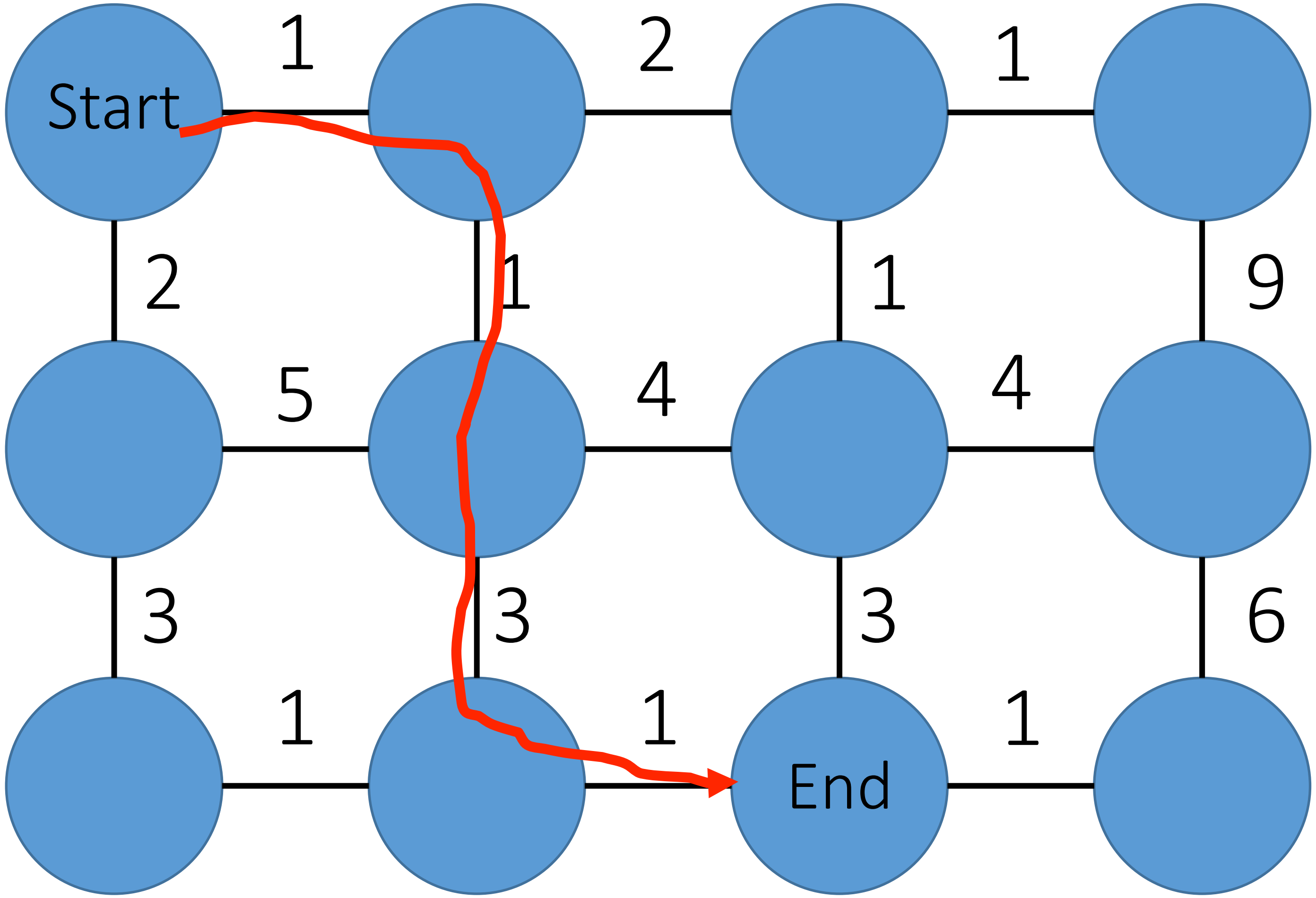


1. Assign weights (costs) to edges

2. Select the seed nodes

Graph-view of this problem

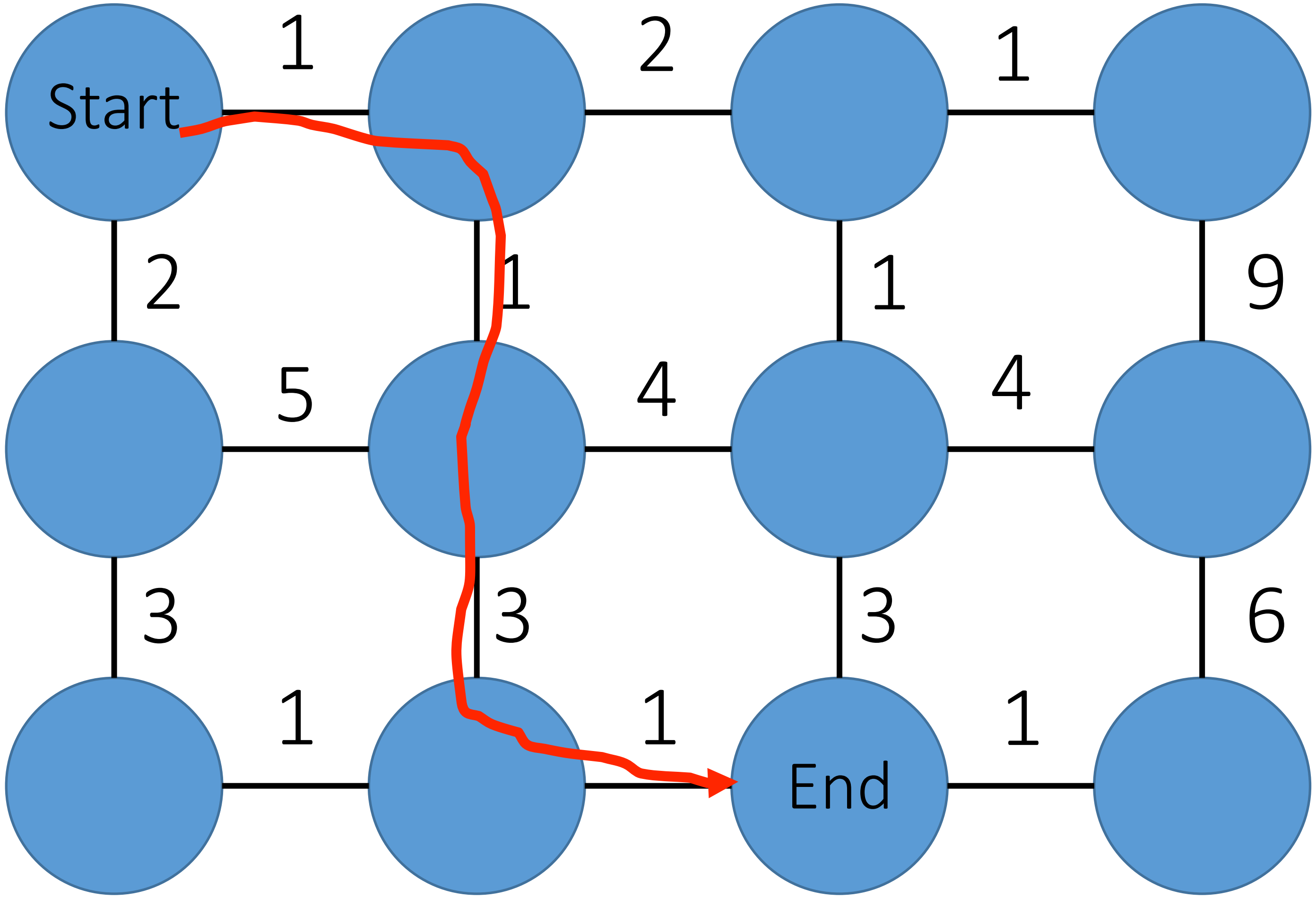
Graph-view of intelligent scissors:



1. Assign weights (costs) to edges
2. Select the seed nodes
3. Find shortest path between them

Graph-view of this problem

Graph-view of intelligent scissors:

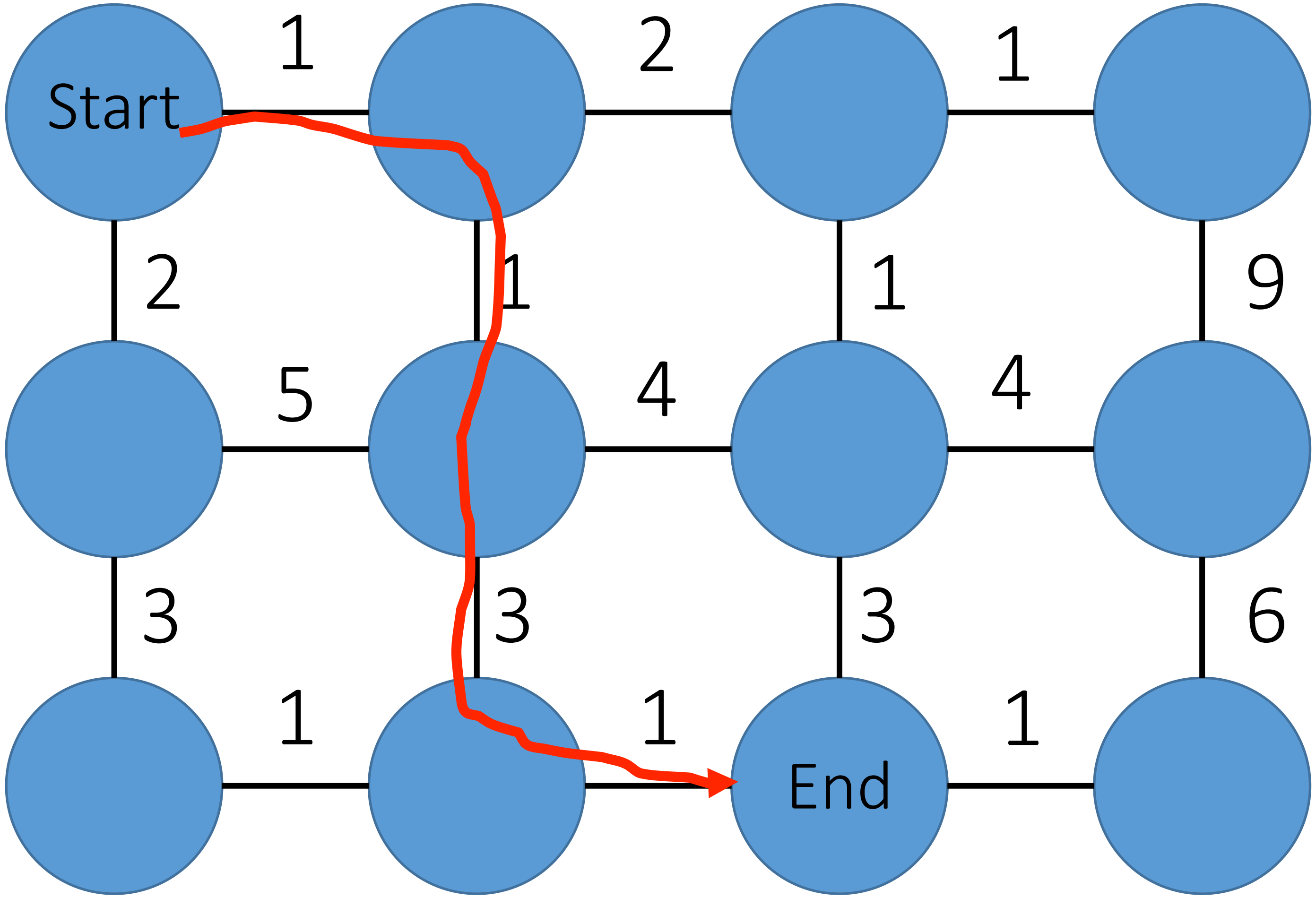


1. Assign weights (costs) to edges
2. Select the seed nodes
3. Find shortest path between them

What algorithm can we use to find the shortest path?

Graph-view of this problem

Graph-view of intelligent scissors:



1. Assign weights (costs) to edges
2. Select the seed nodes
3. Find shortest path between them

What algorithm can we use to find the shortest path?

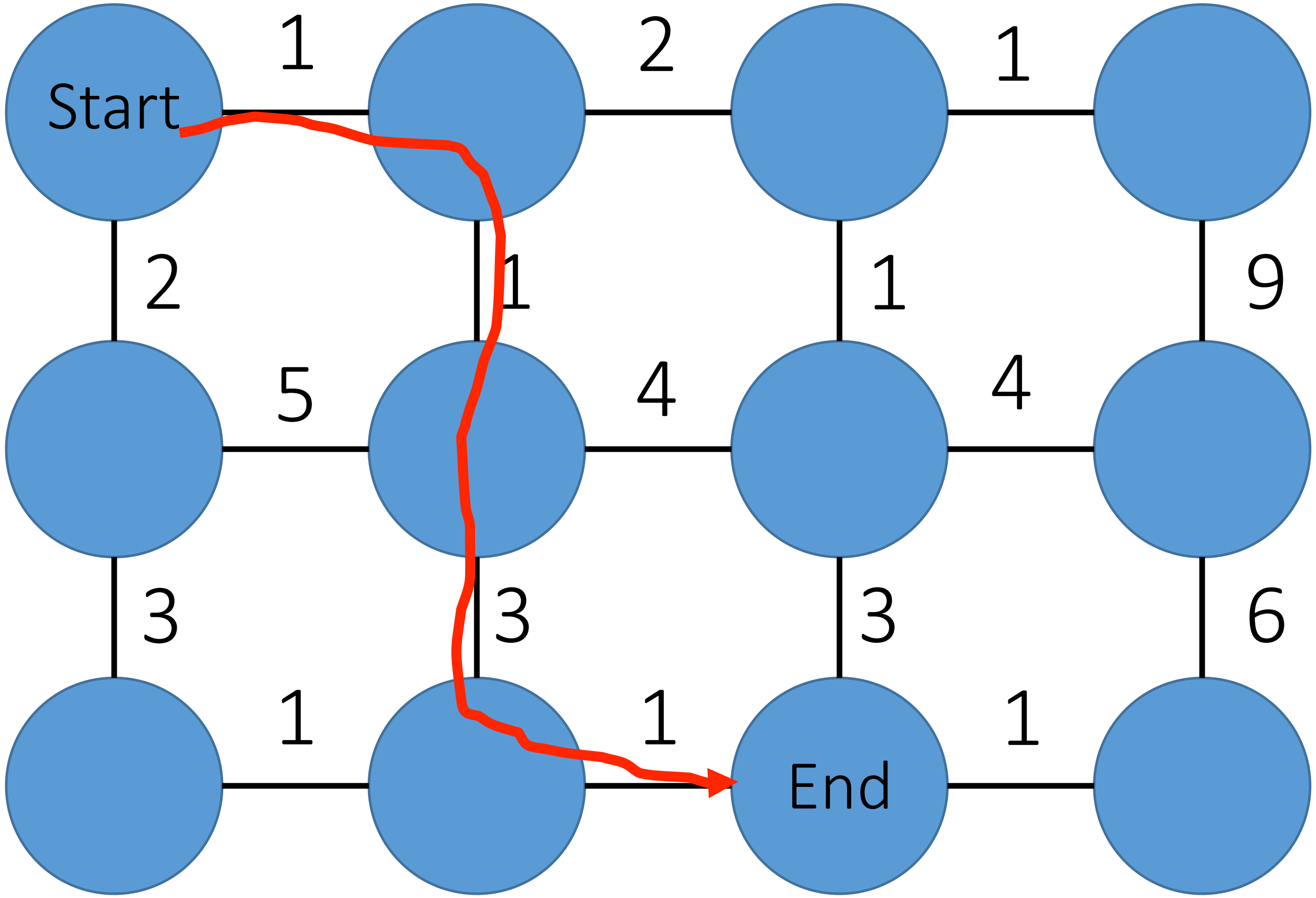
- Dijkstra's algorithm (dynamic programming)

Dijkstra's shortest path algorithm

```
Initialize, given seed s (pixel ID):
 • cost(s) = 0           % total cost from seed to this point
 • cost(!s) = big
 • A = {all pixels}      % set to be expanded
 • prev(s)=undefined     % pointer to pixel that leads to q=s

Precompute cost2(q, r)  % cost between q to neighboring pixel r

Loop while A is not empty

1.q = pixel in A with lowest cost

2.Remove q from A

3.For each pixel r in neighborhood of q that is in A

  a)cost_tmp = cost(q) + cost2(q,r) %this updates the costs

  b)if (cost_tmp < cost(r))
     i.cost(r) = cost_tmp
     ii. prev(r) = q
```

Graph-view of this problem

Graph-view of intelligent scissors:



1. Assign weights (costs) to edges
2. Select the seed nodes
3. Find shortest path between them

What algorithm can we use to find the shortest path?

- Dijkstra's algorithm (dynamic programming)

How should we select the edge weights to get good boundaries?

Selecting edge weights

Define boundary cost between neighboring pixels:

1. Lower if an image edge is present (e.g., as found by Sobel filtering).

2. Lower if the gradient magnitude at that point is strong.

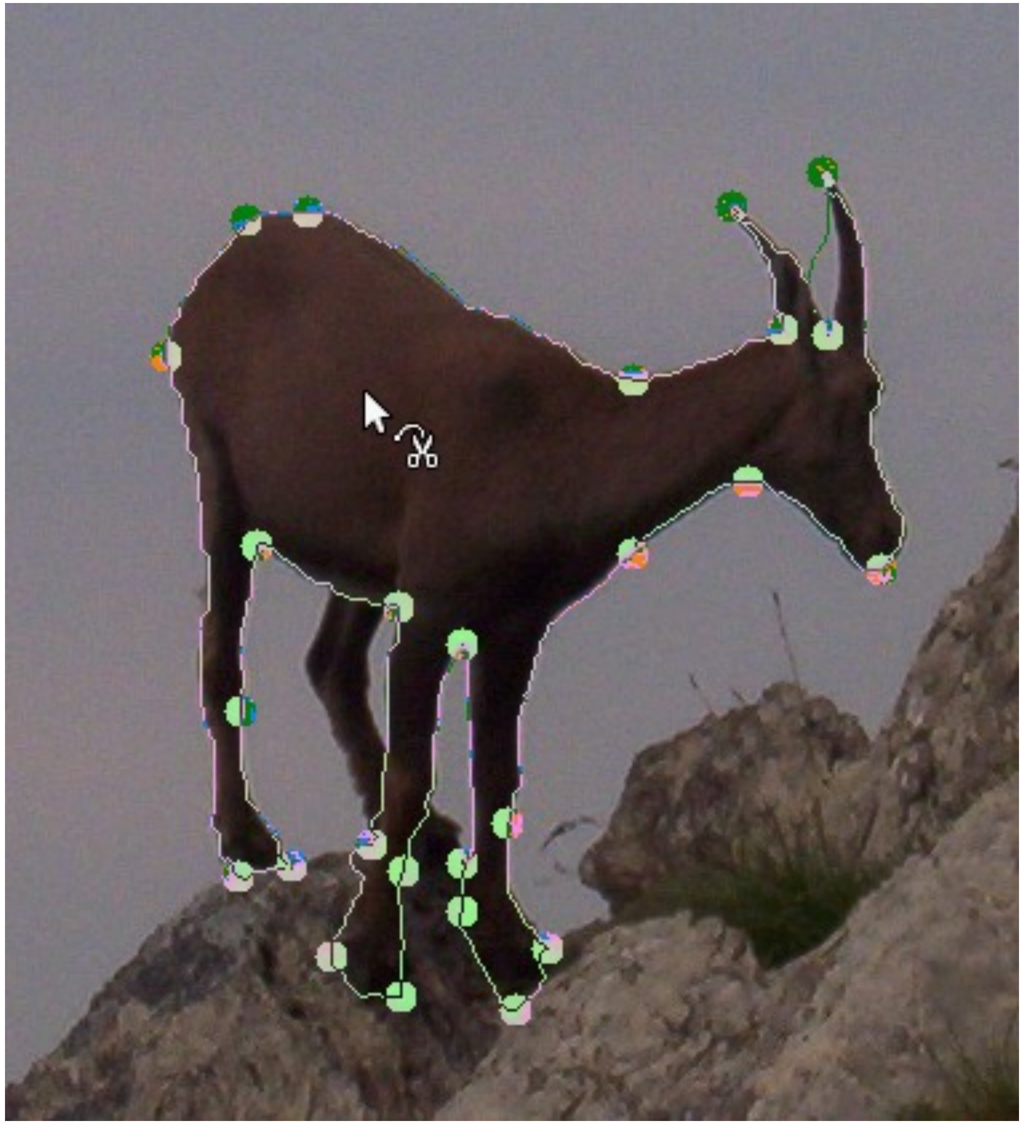
3. Lower if gradient is similar in boundary direction.

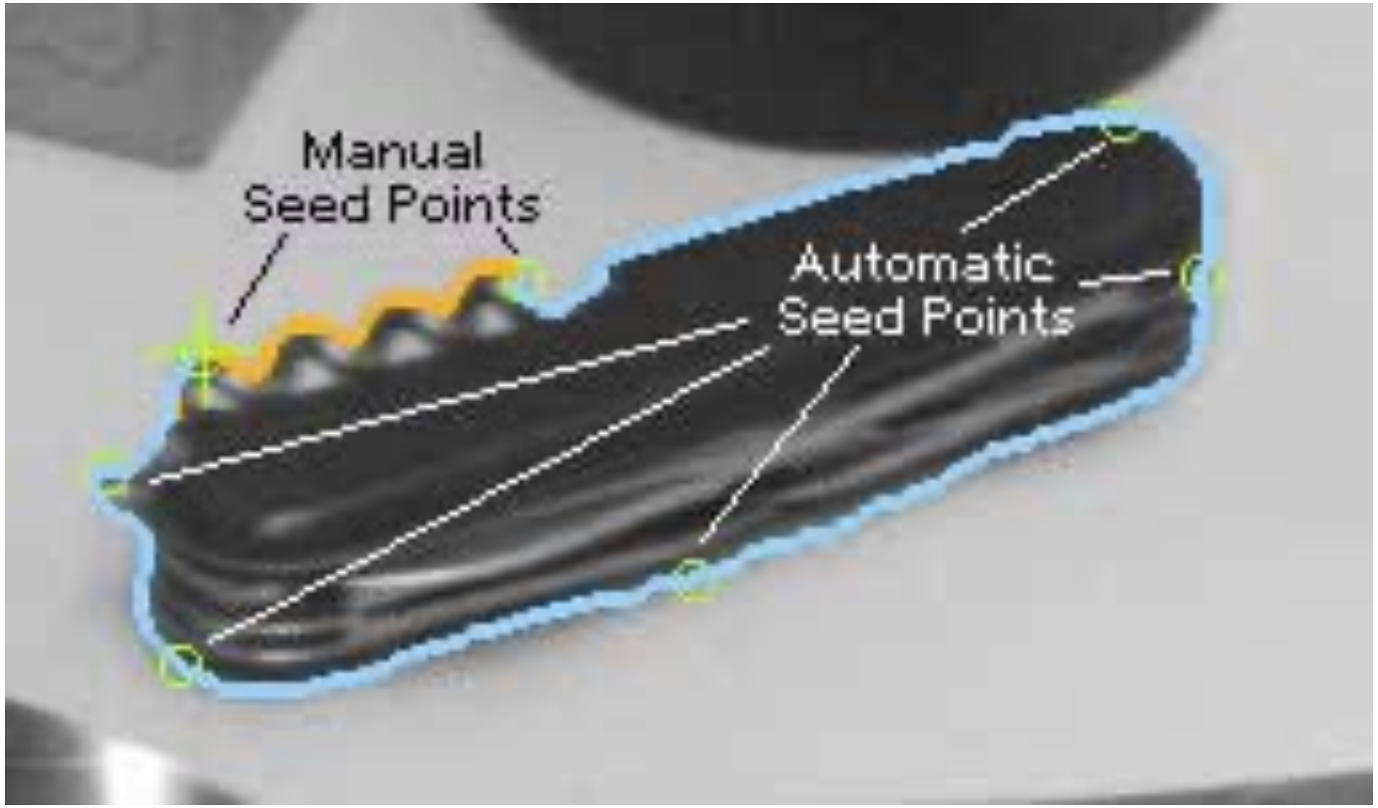
Selecting edge weights

Gradient magnitude

Edge image

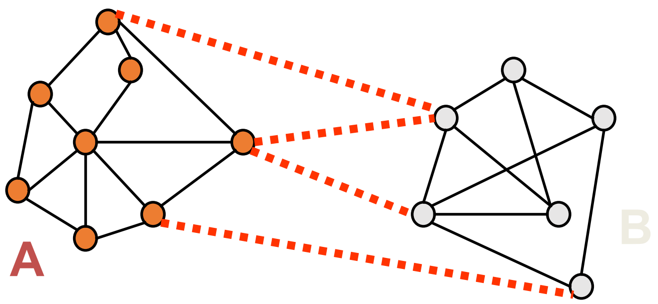
Pixel-wise cost




Manual
Seed Points
Automatic
Seed Points

More Advanced Graph-based Segmentations…

Normalized Cut (CVPR 1997, TPAMI 2000)



- 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

The University of Texas at Austin
Electrical and Computer Engineering
Cockrell School of Engineering