Computer Vision

Image Segmentation

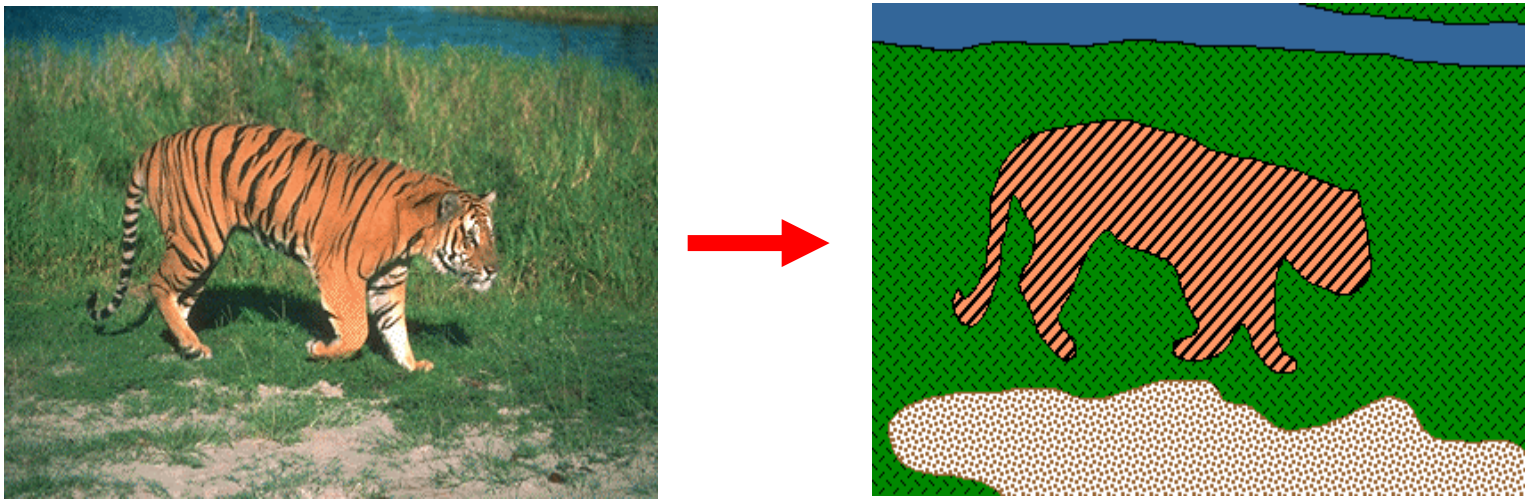
Dr. Mrinmoy Ghorai

Indian Institute of Information Technology
Sri City, Chittoor

Today's class

Image Segmentation

Group pixels into meaningful or perceptually similar regions



Today's class

- Segmentation and grouping
  - Clustering (k-means, mean-shift)
  - Graph (graph cuts)
- Semantic Segmentation
  - Sliding Window
  - FCN
  - DeconNet
- Instance Segmentation
  - Mask-RCNN

Segmentation using clustering

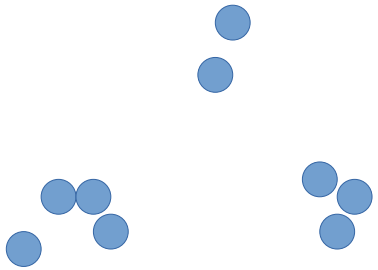
- Kmeans
- Mean-shift

K-means algorithm

$$\underset{S,\mu_i,i=1..K}{\operatorname{argmin}} \sum_{i=1}^{K} \sum_{x \in S_i} ||x - \mu_i||^2$$

Partition the data into K sets S = {S_1, S_2, … S_K} with corresponding centers μ_i

Partition such that variance in each partition is as low as possible



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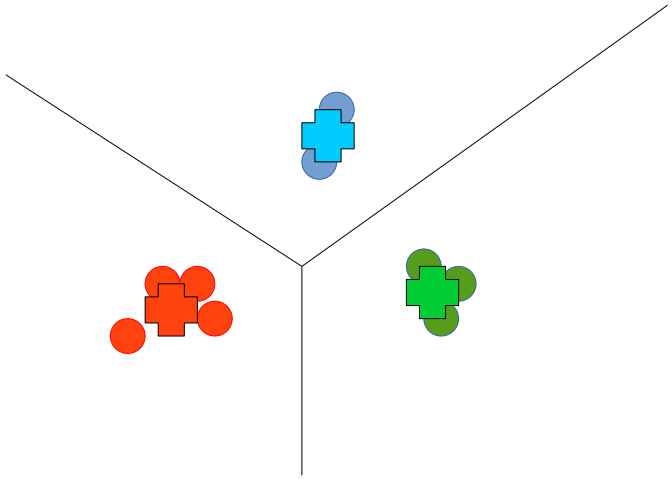

K-means algorithm

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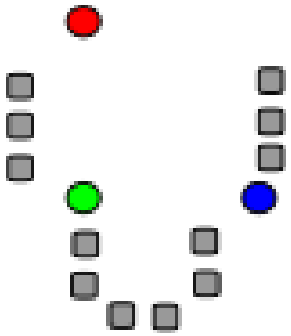
3. Update cluster centers as the mean of its members

4. Repeat 2-3 until convergence (t = t+1)

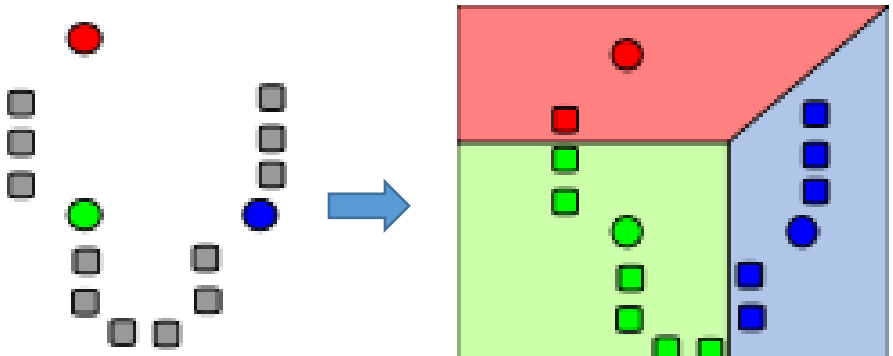
K-means clustering



1. Initialize Cluster Centers

Illustration Source: wikipedia

K-means clustering

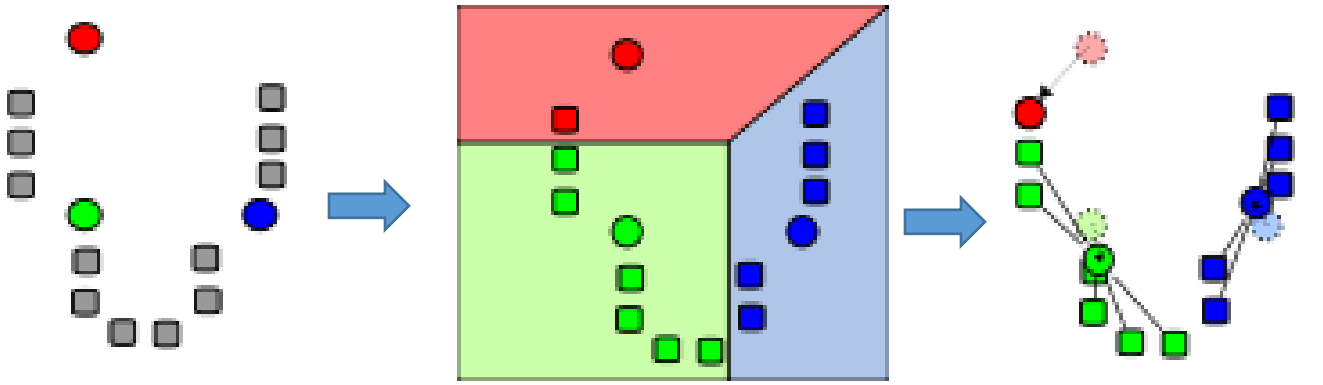


1. Initialize Cluster Centers

2. Assign Points to Clusters

Illustration Source: wikipedia

K-means clustering



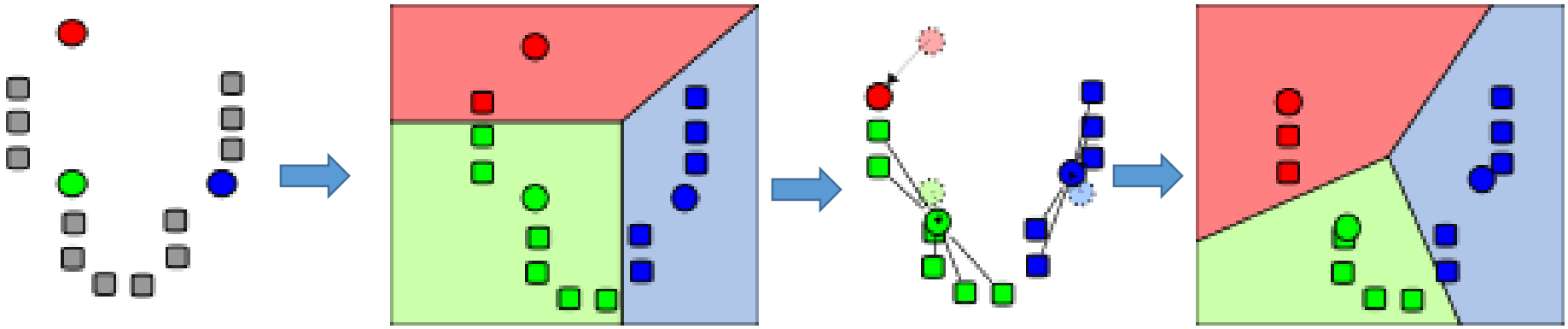
1. Initialize Cluster Centers

2. Assign Points to Clusters

3. Re-compute Means

Illustration Source: wikipedia

K-means clustering



1. Initialize Cluster Centers

2. Assign Points to Clusters

3. Re-compute Means

Repeat (2) and (3)

Illustration Source: wikipedia

Image Segmentation by K-Means

- Select a value of K
- Select a feature vector for every pixel (color, texture, position, or combination of these etc.)
- Define a similarity measure between feature vectors (Usually Euclidean Distance).
- Apply K-Means Algorithm.
- Merge any components of size less than some threshold to an adjacent component that is most similar to it.

* From Marc Pollefeys COMP 256 2003

K-means clustering using intensity alone and color alone

Image

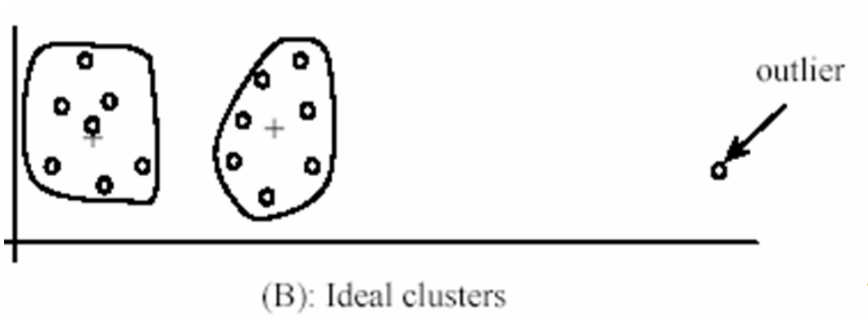
Clusters on intensity

Clusters on color

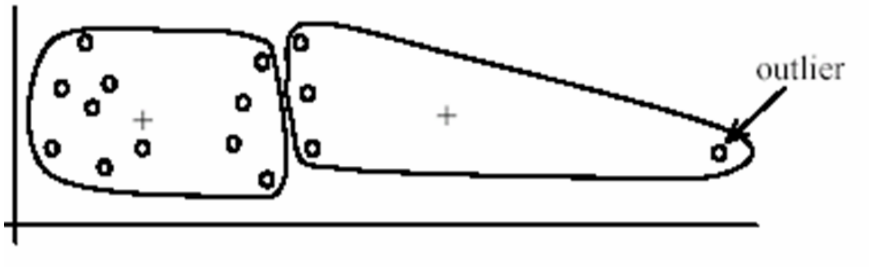
There is no requirement that clusters be spatially localized and they're not

K-Means pros and cons

- Pros
  - –Simple and fast
  - –Easy to implement
- Cons
  - –Need to choose K
  - –Sensitive to outliers
- Usage
  - –Unsupervised clustering
  - –Rarely used for pixel segmentation

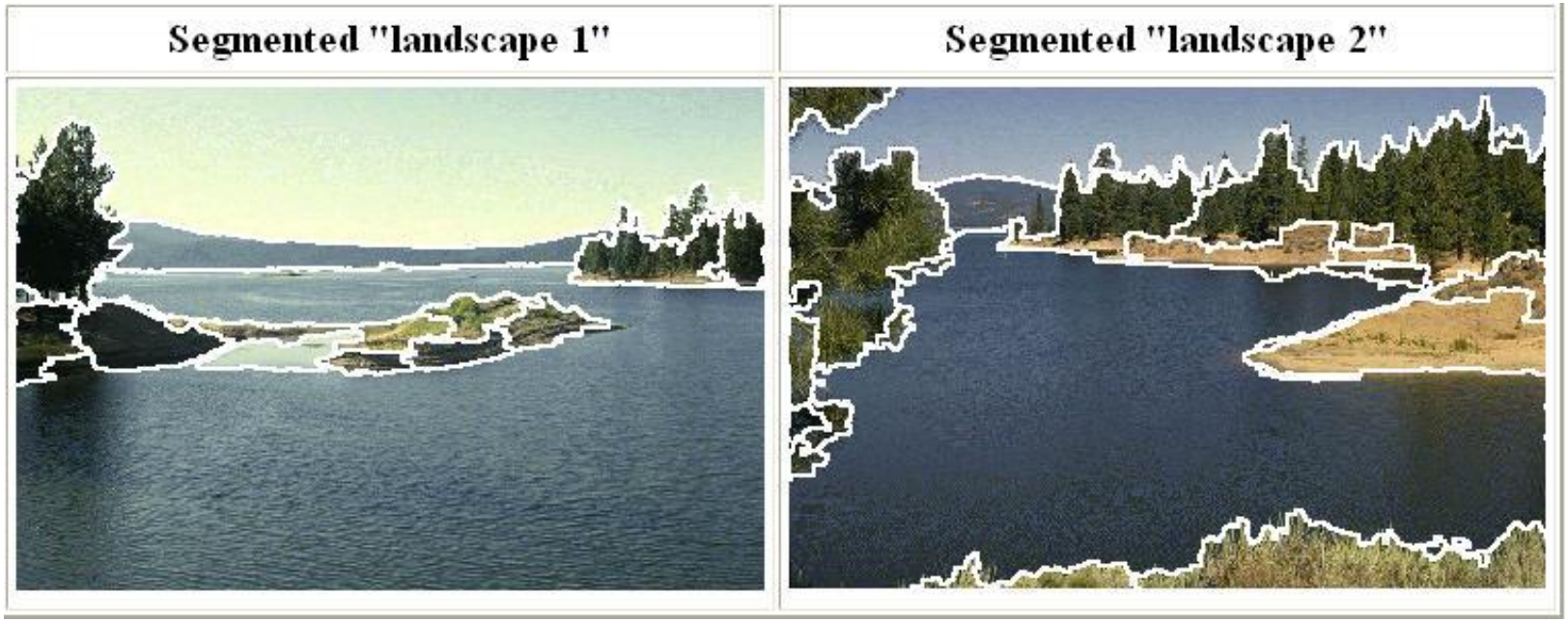


(B): Ideal clusters



Mean shift segmentation

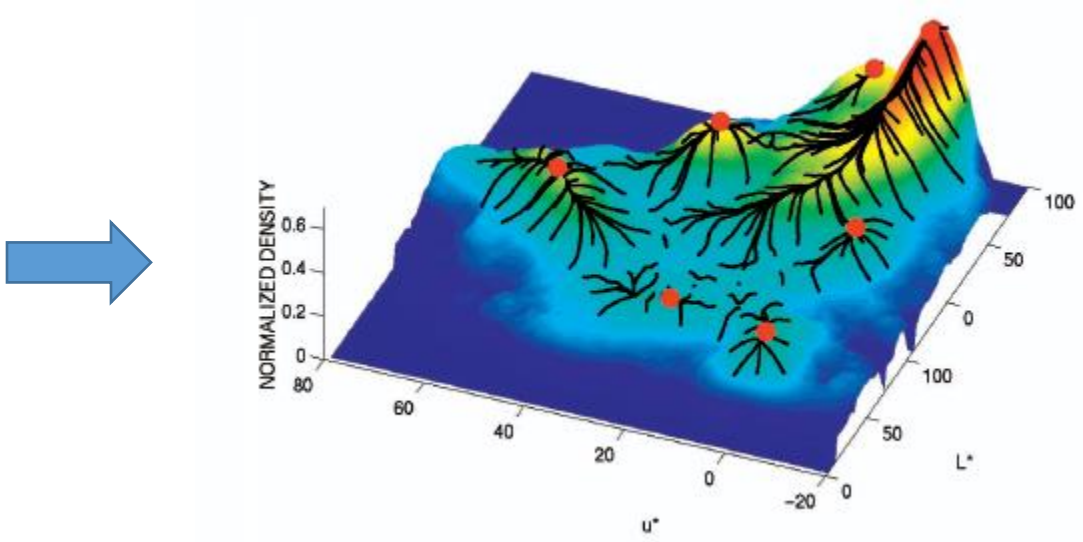
- Versatile technique for clustering-based segmentation



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

Mean shift algorithm

- Find *modes* of the non-parametric density
- Locate the maxima of a density function

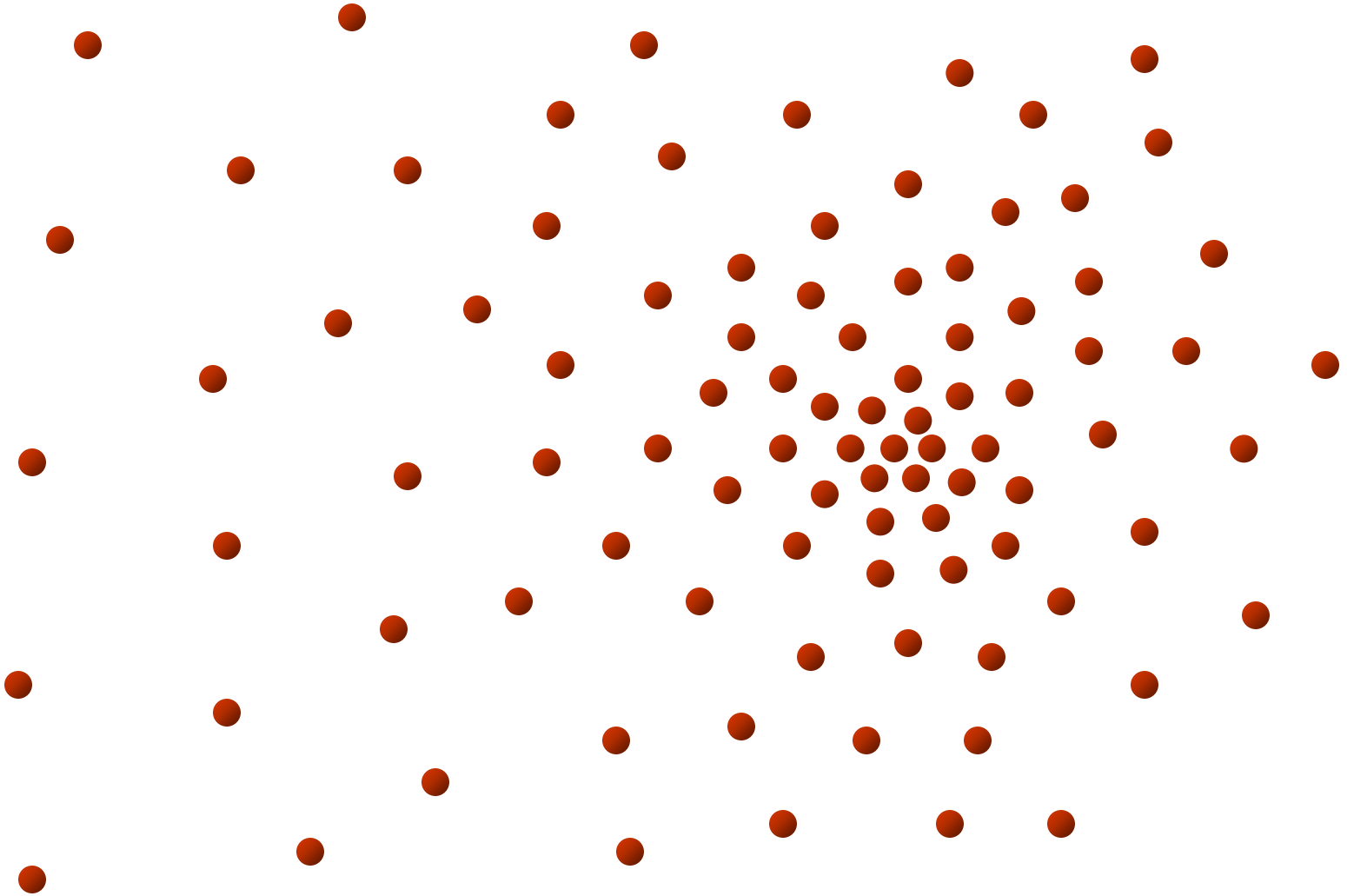


Mean-Shift Algorithm

- Iterative Mode Search
  1. Initialize random seed, and window W
  2. Calculate center of mass (the “mean”) of W: $\sum_{x \in W} xH(x)$
  3. Shift the search window to the mean
  4. Repeat Step 2 until convergence

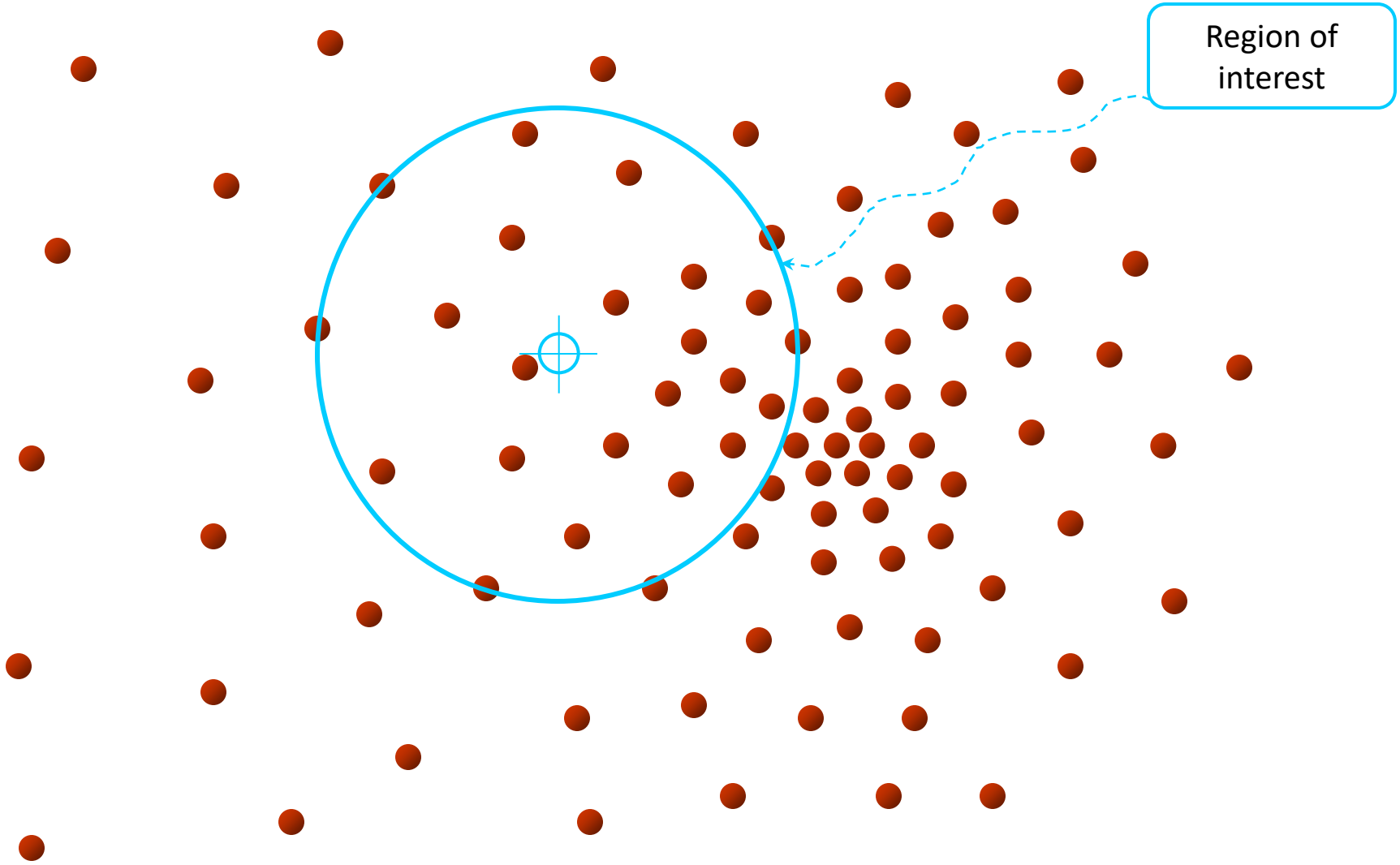
Slide credit: Steve Seitz

Mean shift



Slide by Y. Ukrainitz & B. Sarel

Mean shift



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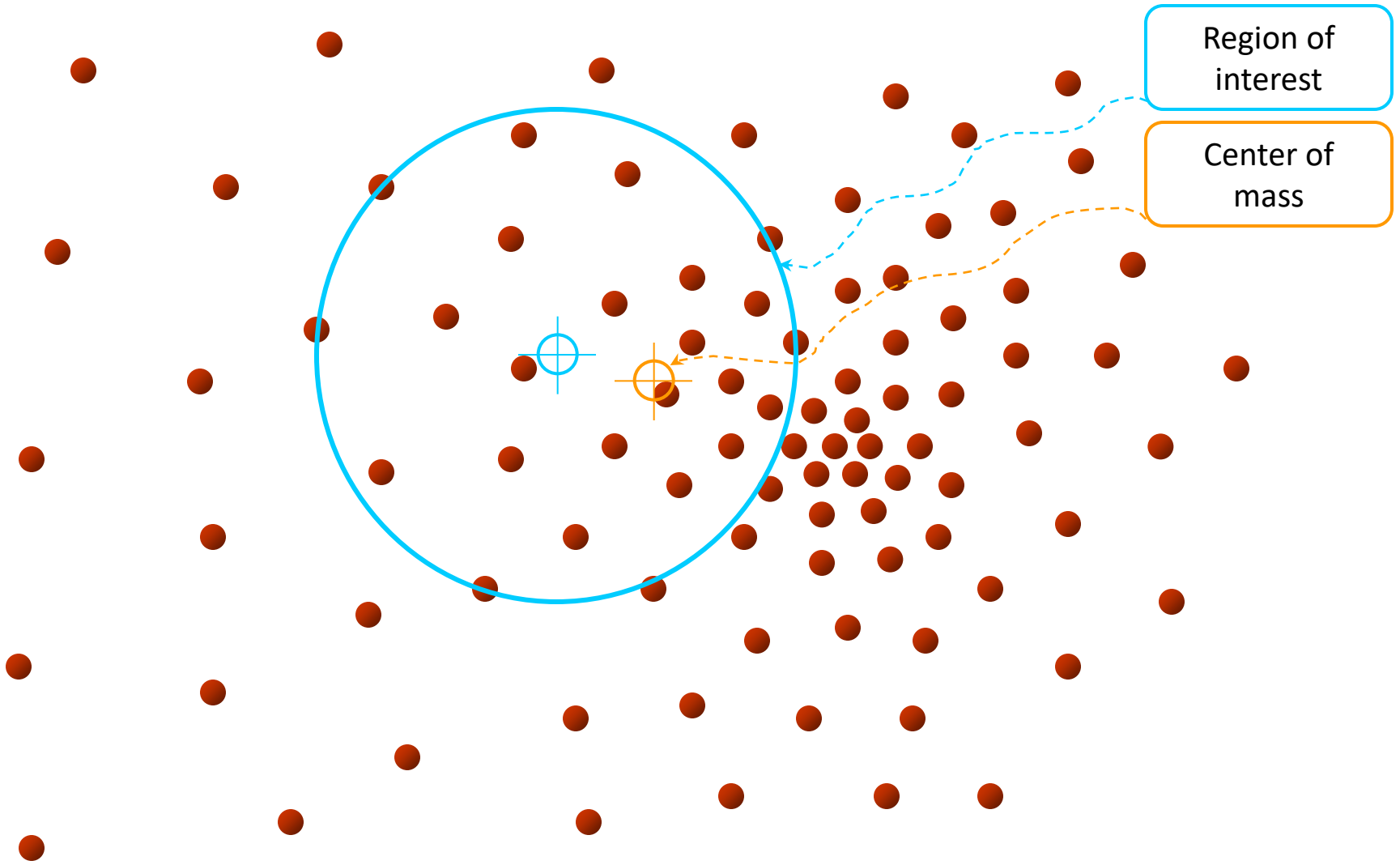

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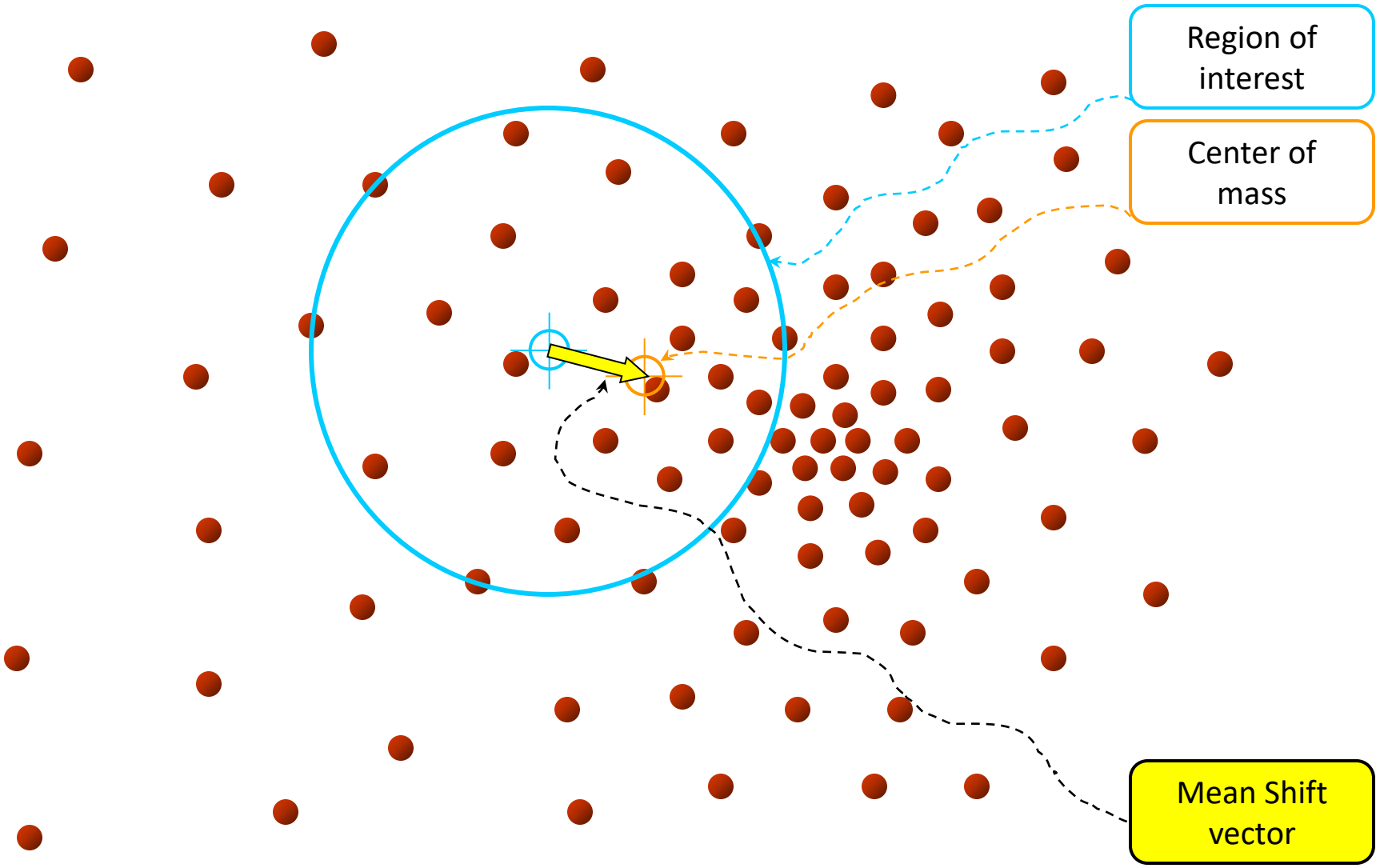

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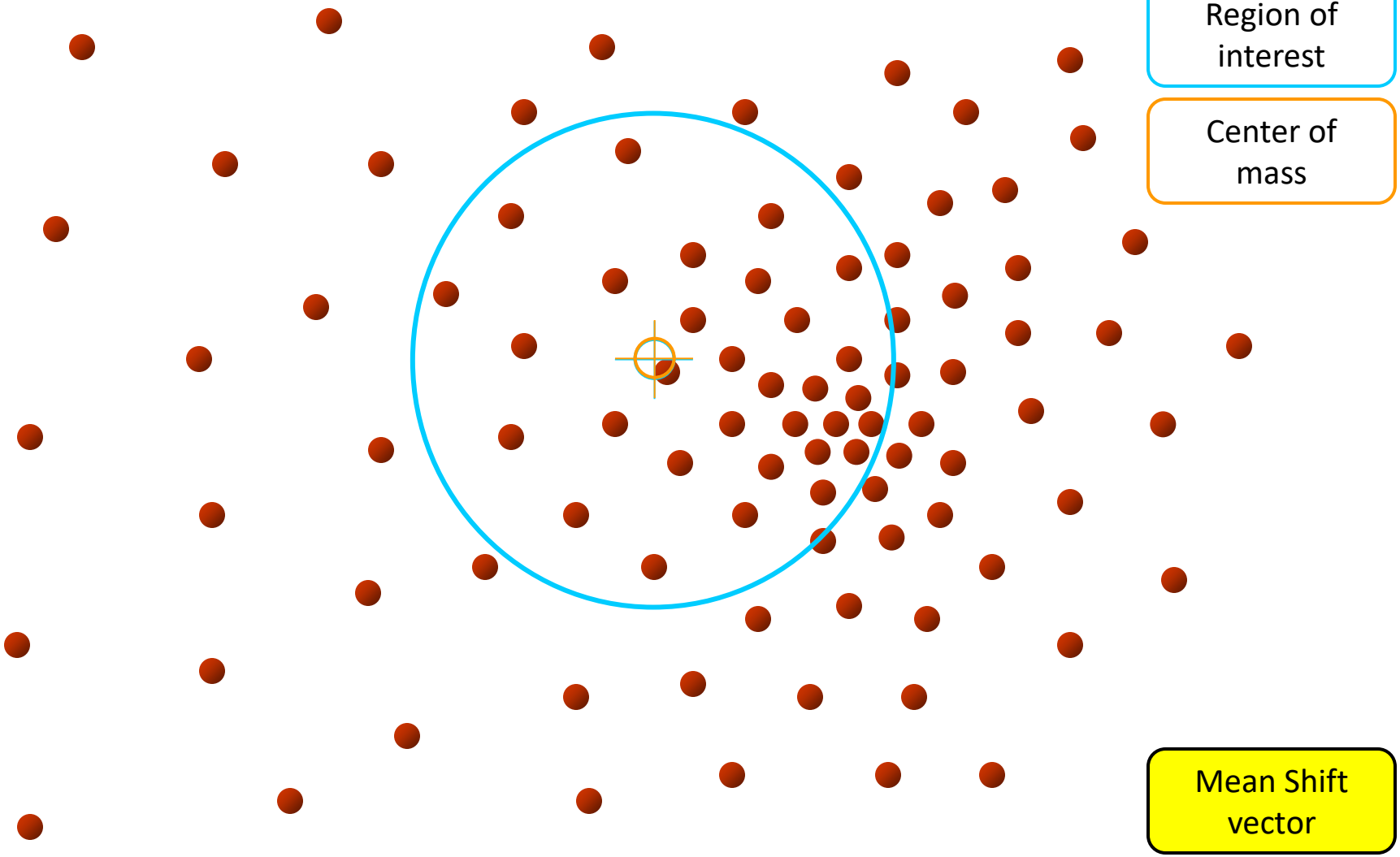

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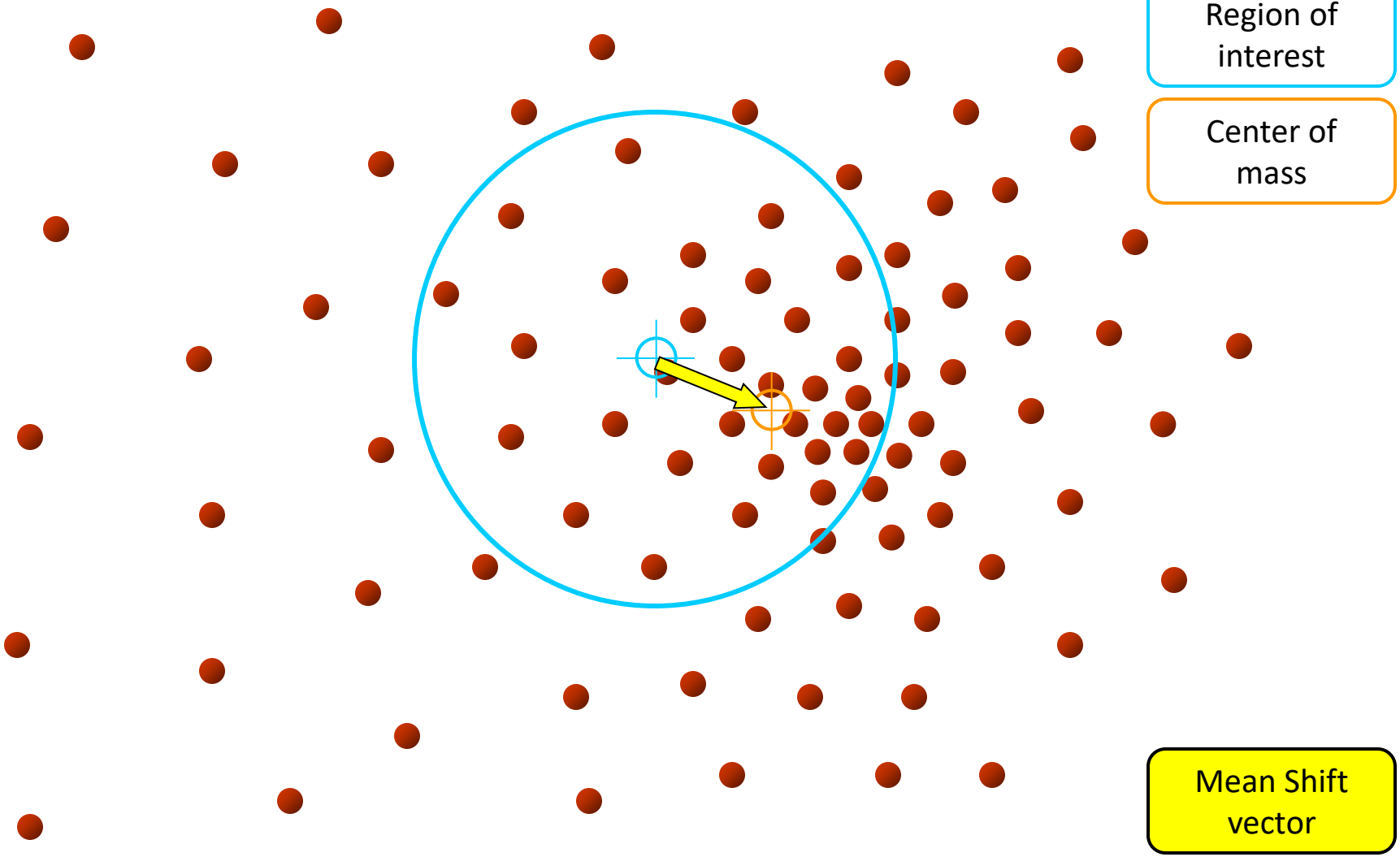

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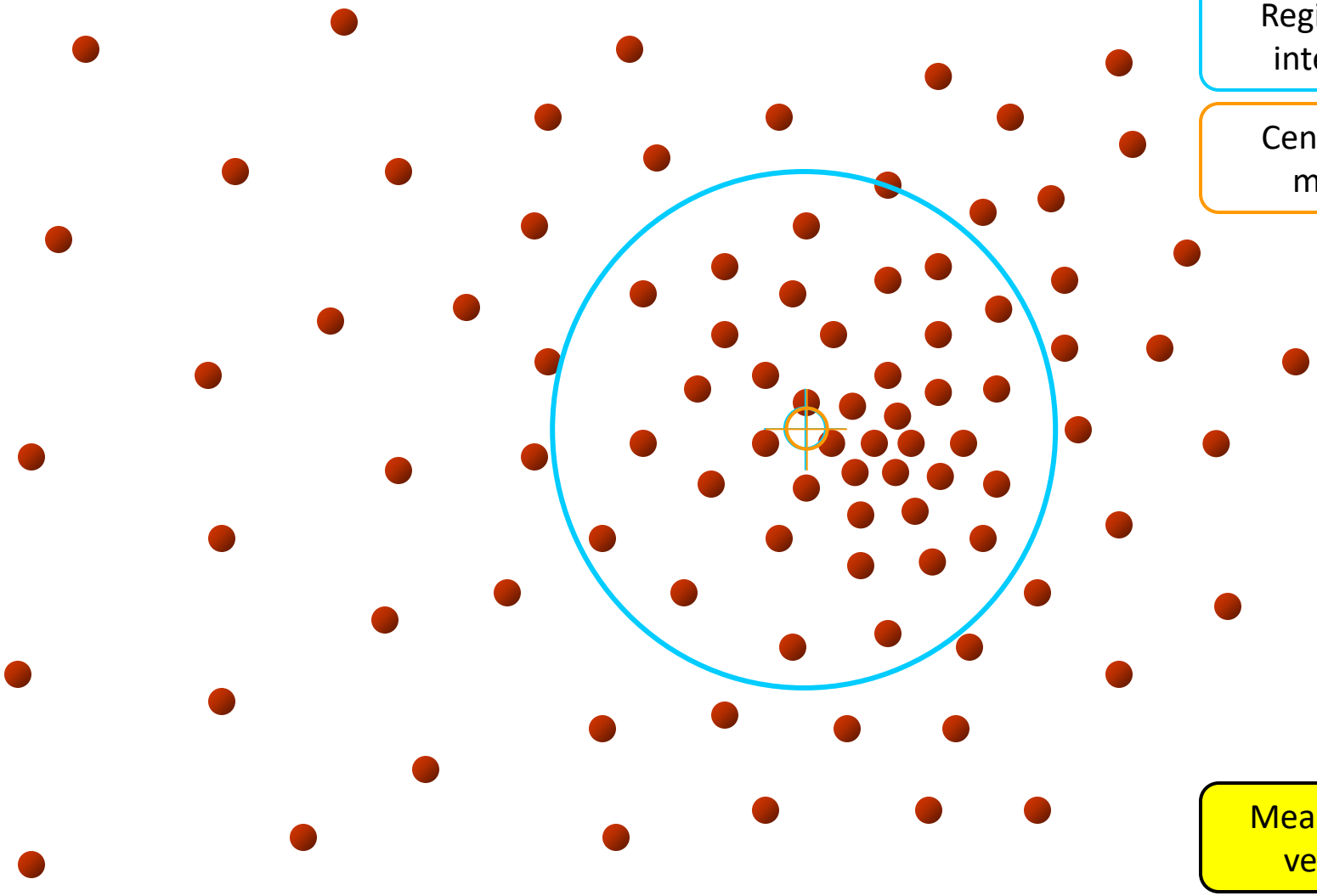

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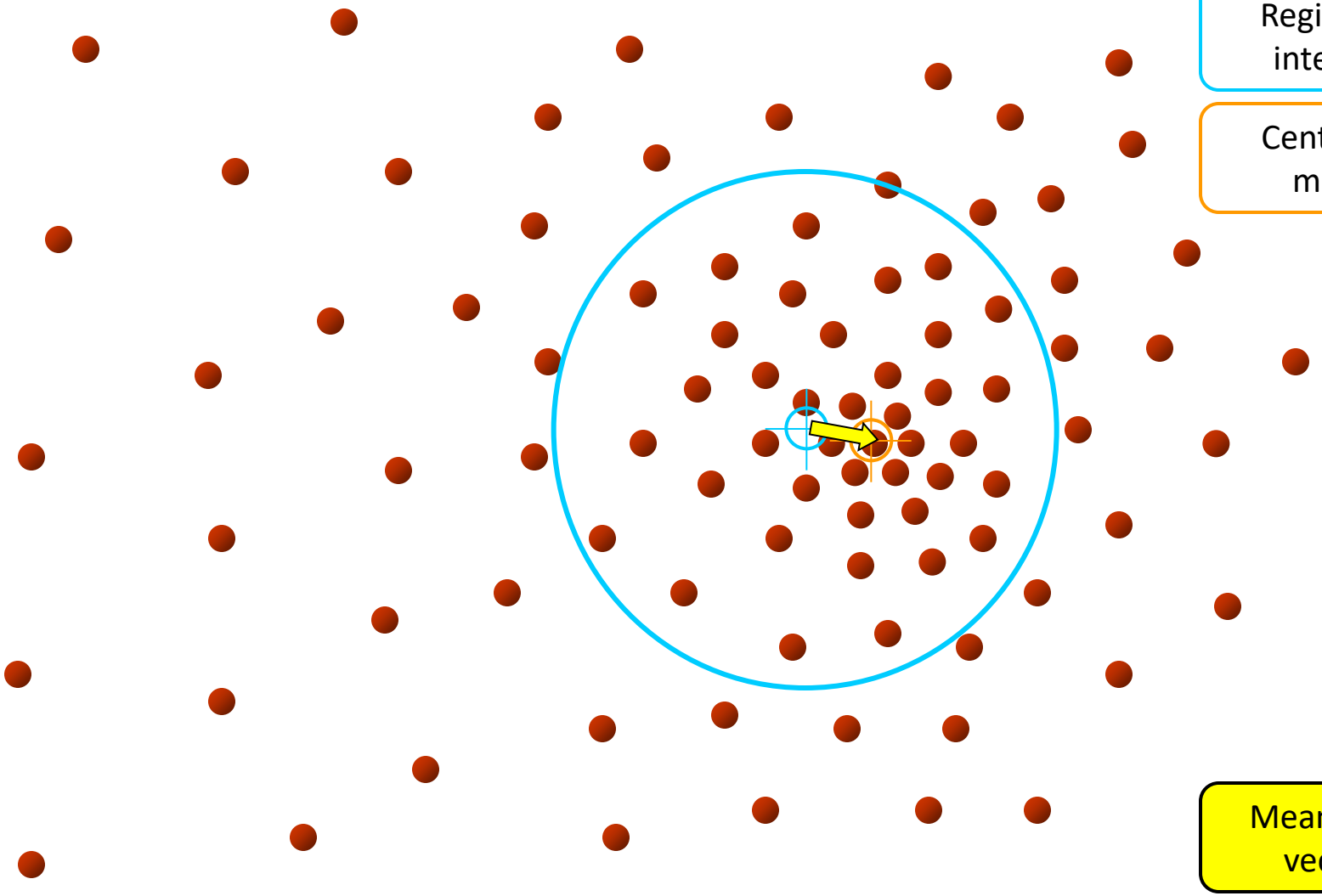

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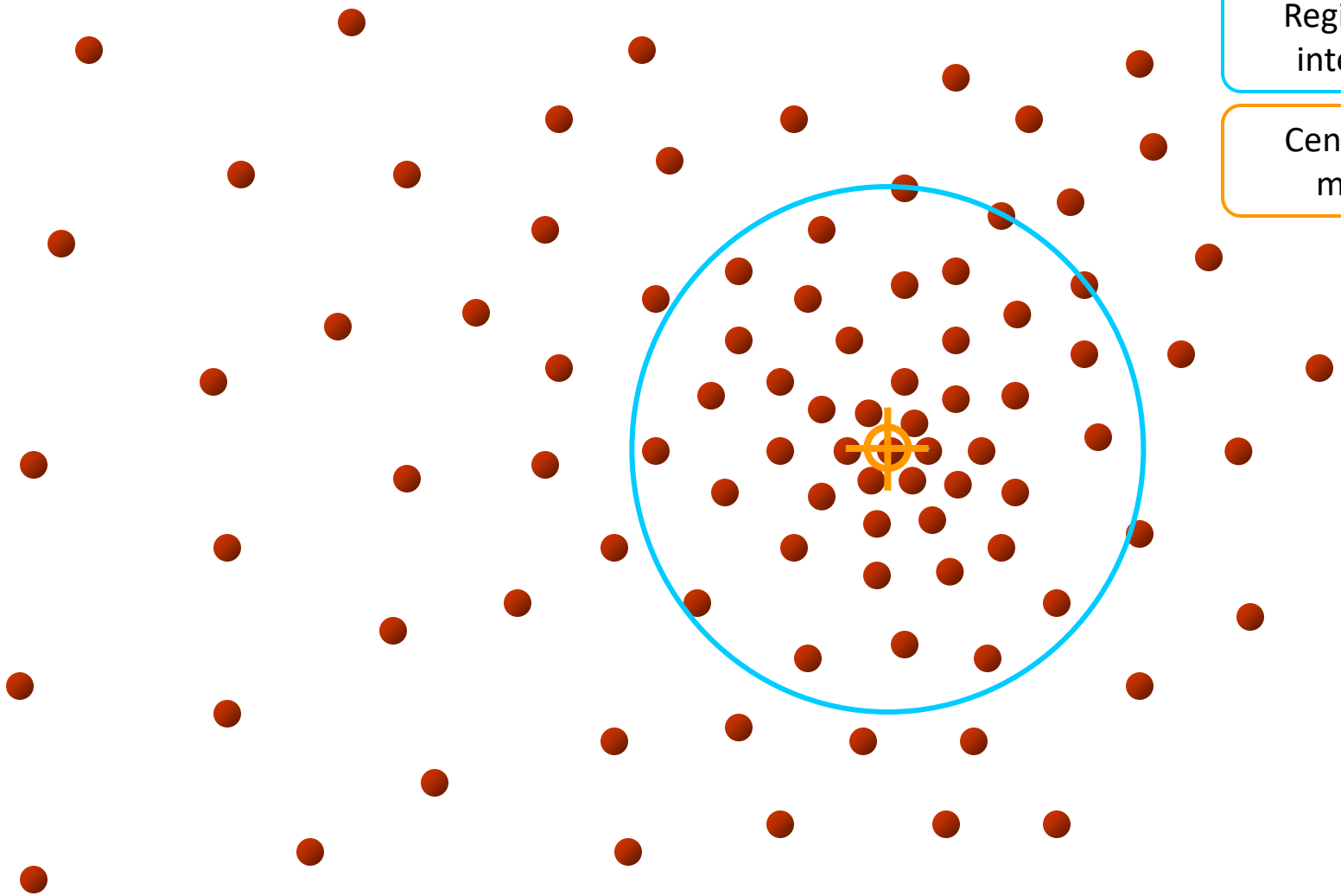
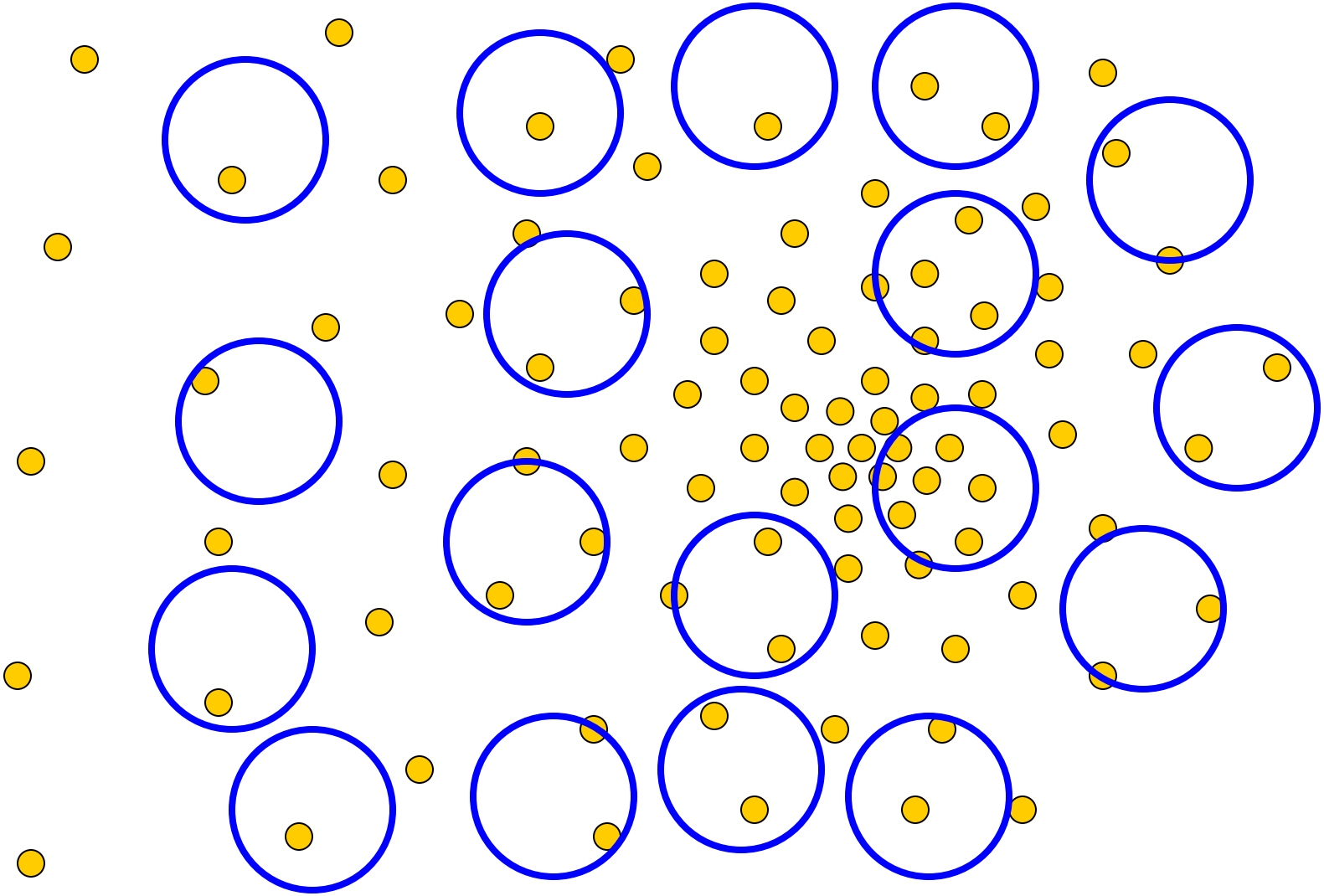


Slide by Y. Ukrainitz & B. Sarel

Real Modality Analysis

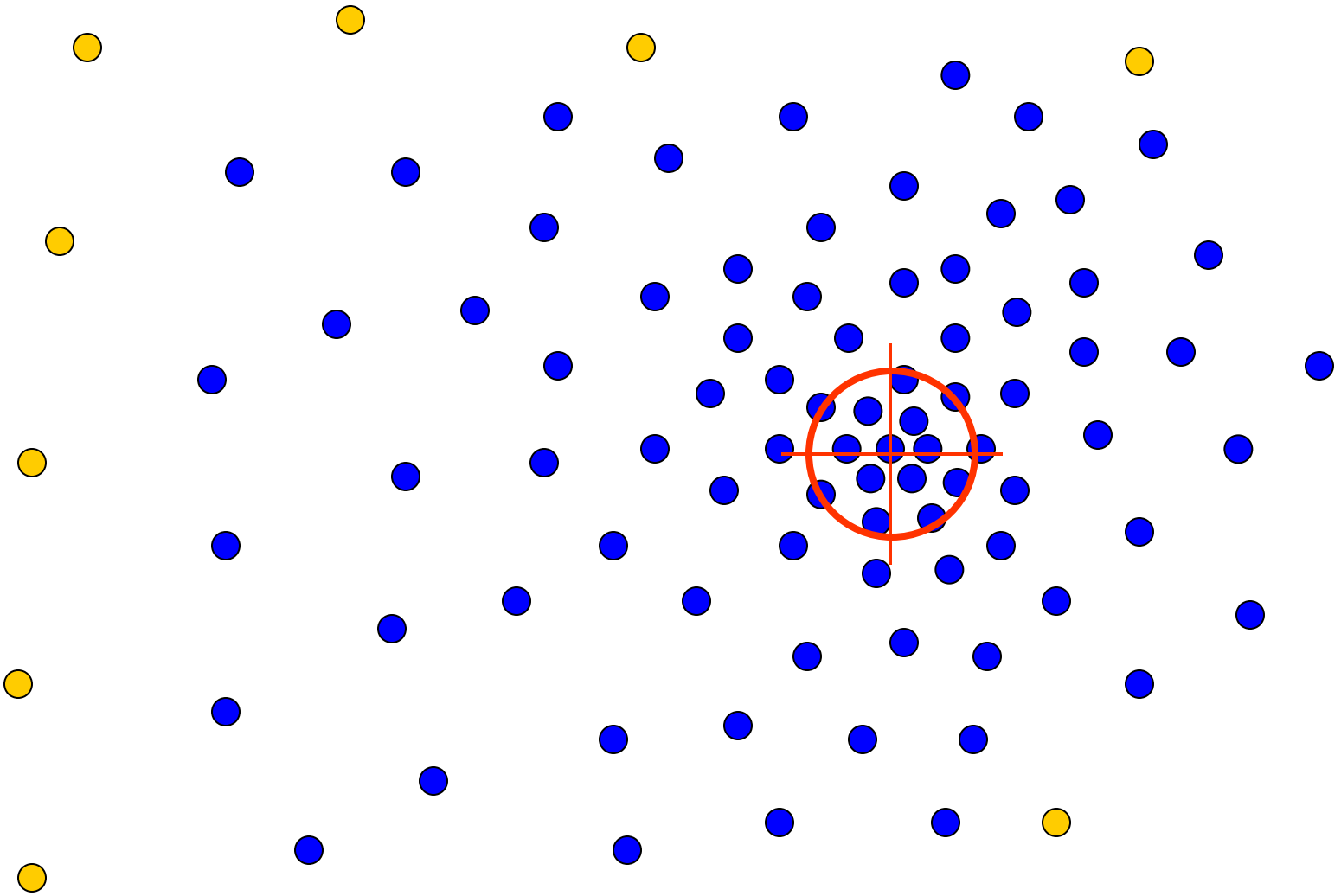


Tessellate the space with windows

Run the procedure in parallel

Slide by Y. Ukrainitz & B. Sarel

Real Modality Analysis

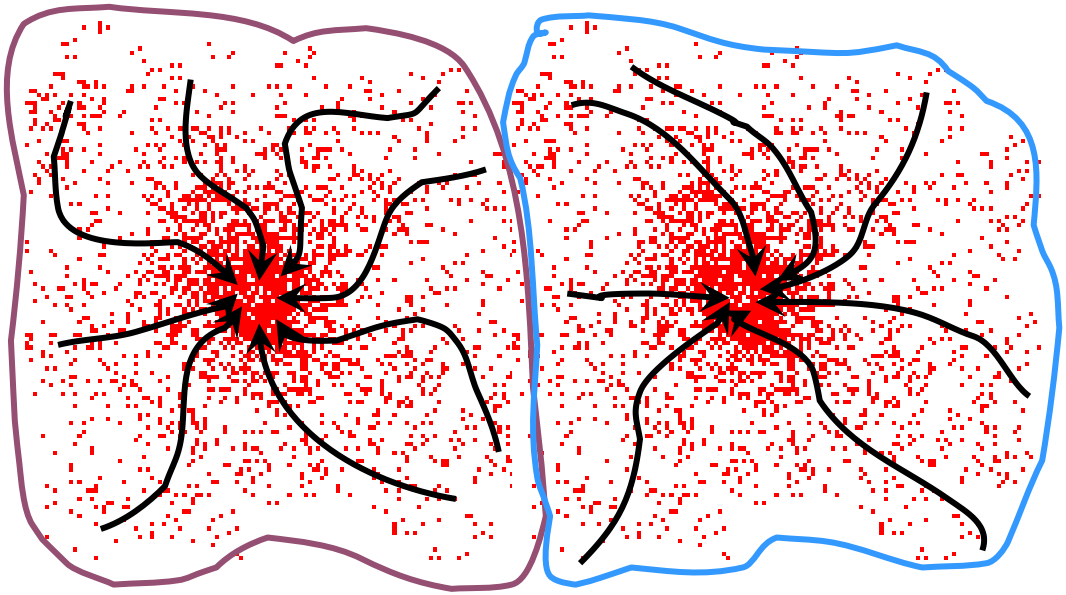


The blue data points were traversed by the windows towards the mode.

Slide by Y. Ukrainitz & B. Sarel

Attraction basin

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

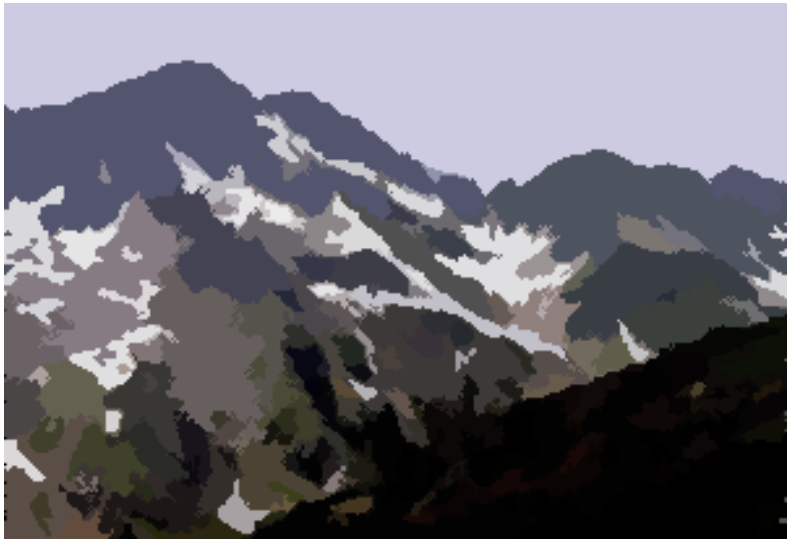


Slide by Y. Ukrainitz & B. Sarel

Segmentation by Mean Shift

- Find features (color, gradients, texture, etc)
- Initialize windows at individual pixel locations
- Perform mean shift for each window until convergence
- Merge windows that end up near the same “peak” or mode

Mean shift segmentation results



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

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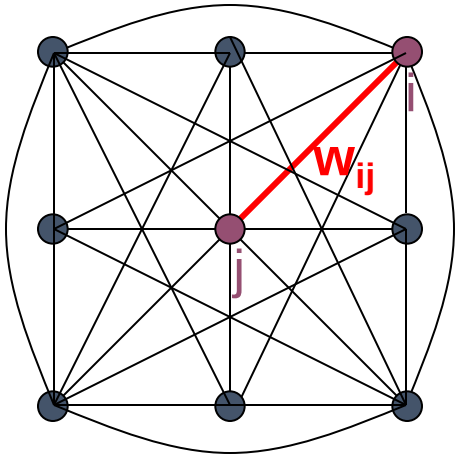
Mean shift pros and cons

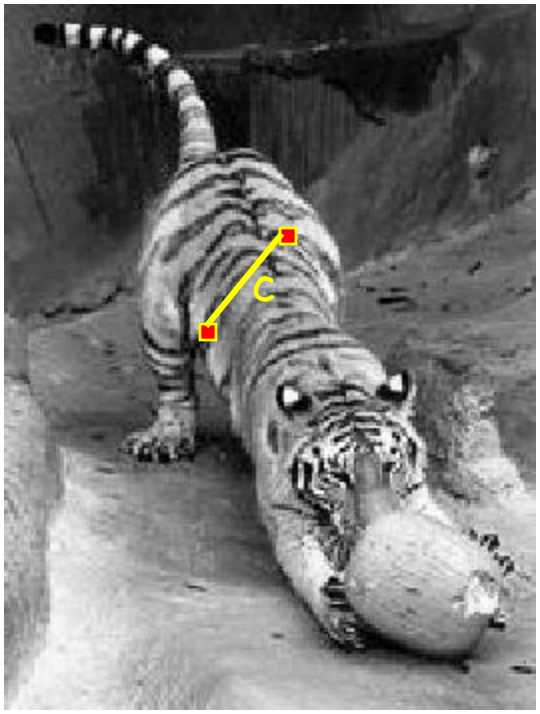
- Pros
  - Good general-purpose segmentation
  - Flexible in number and shape of regions
  - Robust to outliers
- Cons
  - Have to choose kernel size in advance
  - Not suitable for high-dimensional features
- When to use it
  - Multiple segmentations
  - Tracking, clustering, filtering applications
    - Comaniciu et al., *Real-Time Tracking of Non-Rigid Objects using Mean Shift*, CVPR 2000. *Best Paper Award*

Graph-based Segmentation

- Min-cut
- Normalized-cut

Images as graphs

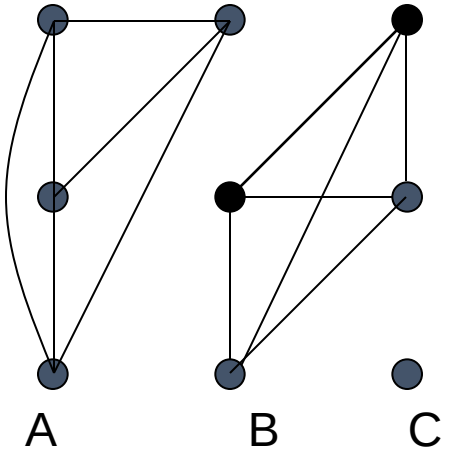




- *Fully-connected* graph
  - node for every pixel
  - link between *every* pair of pixels, **p**,**q**
  - similarity $\mathbf{w_{ij}}$ for each link

Source: Seitz

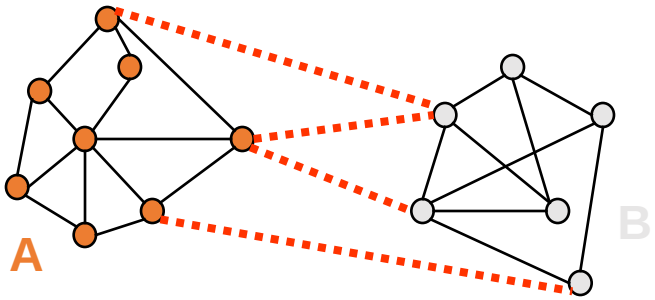
Segmentation by Graph Cuts



- Break Graph into Segments
  - –Delete links that cross between segments
  - –Easiest to break links that have low cost (low similarity)
    - similar pixels should be in the same segments
    - dissimilar pixels should be in different segments

Source: Seitz

Cuts in a graph

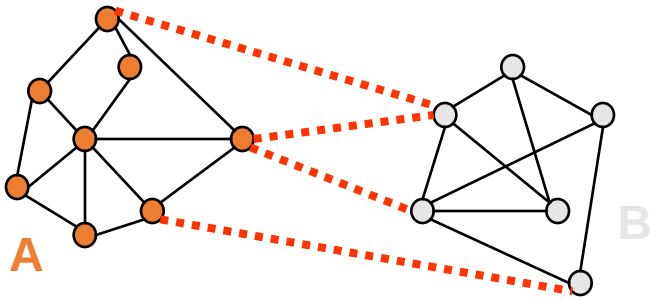


- Link Cut
  - –set of links whose removal makes a graph disconnected
  - –cost of a cut:

$$cut(A, B) = \sum_{p \in A, q \in B} c_{p,q}$$

Source: Seitz

Cuts in a graph



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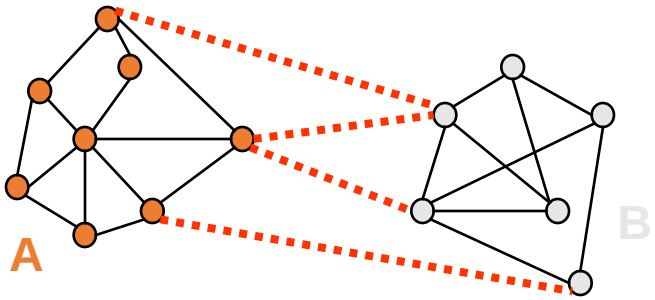
How to find the set of links to remove?

Source: Seitz

Cuts in a graph



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How to find the set of links to remove?

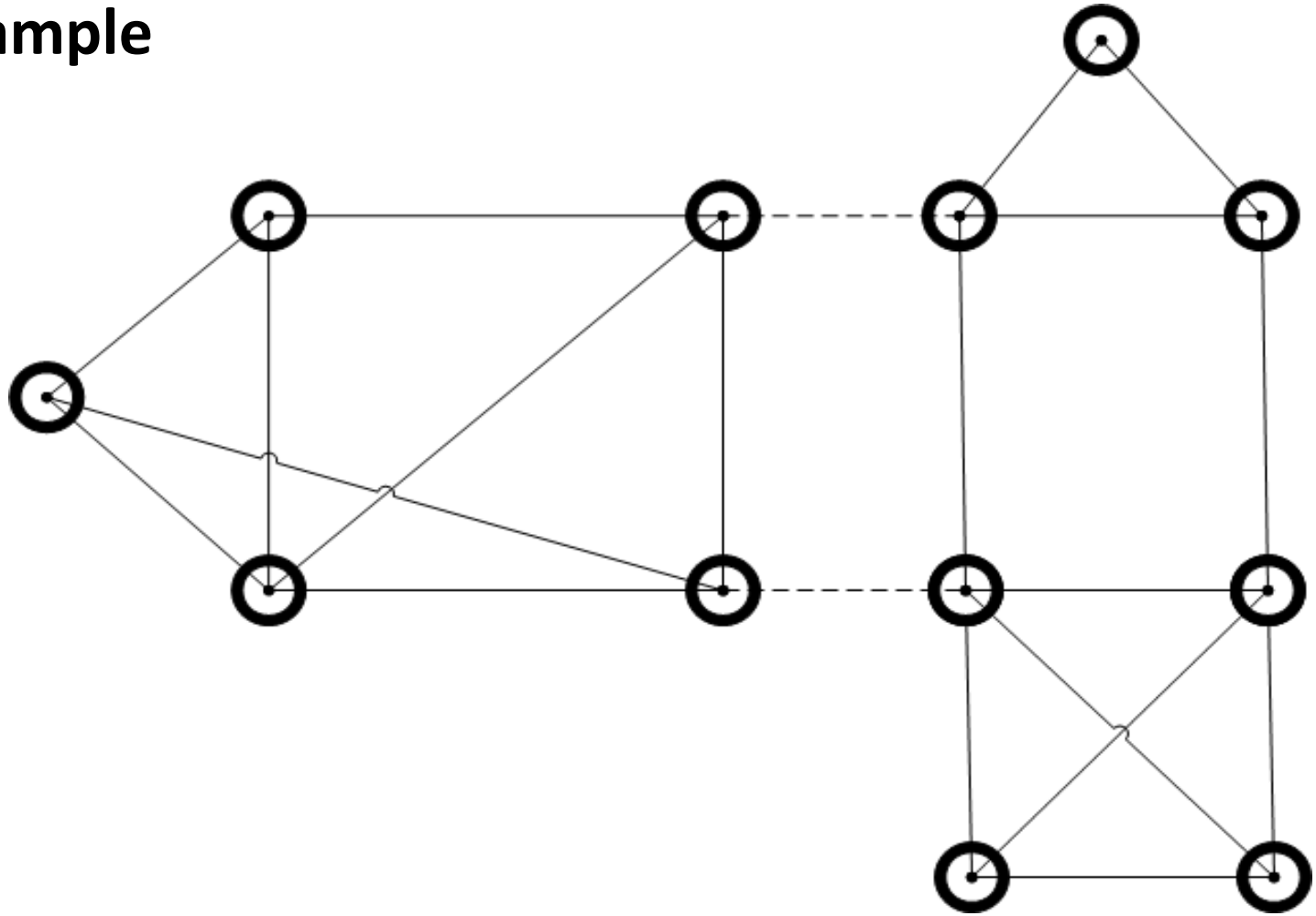
One idea: Find minimum cut

- gives you a segmentation
- fast algorithms exist for doing this

Source: Seitz

Min Cut method

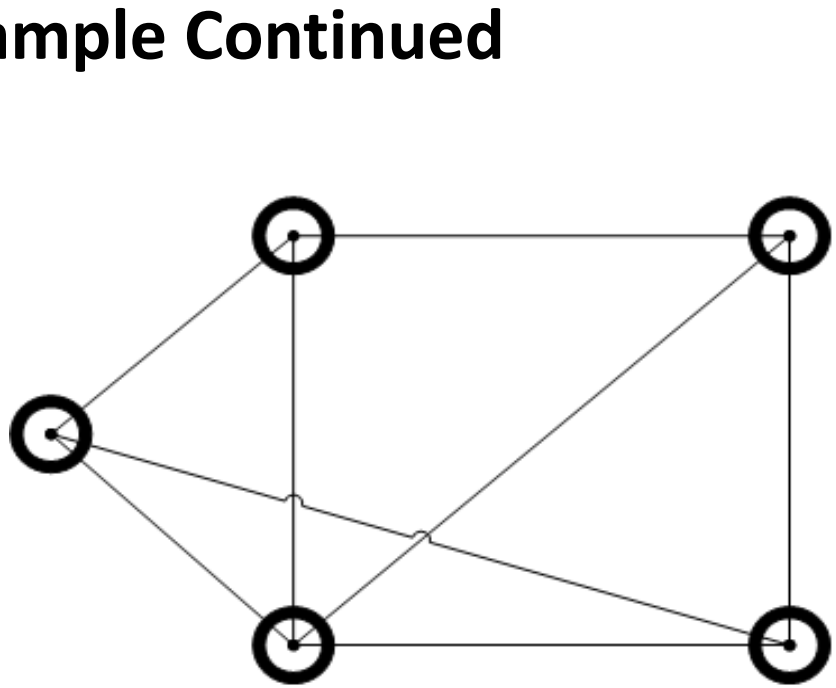
Example

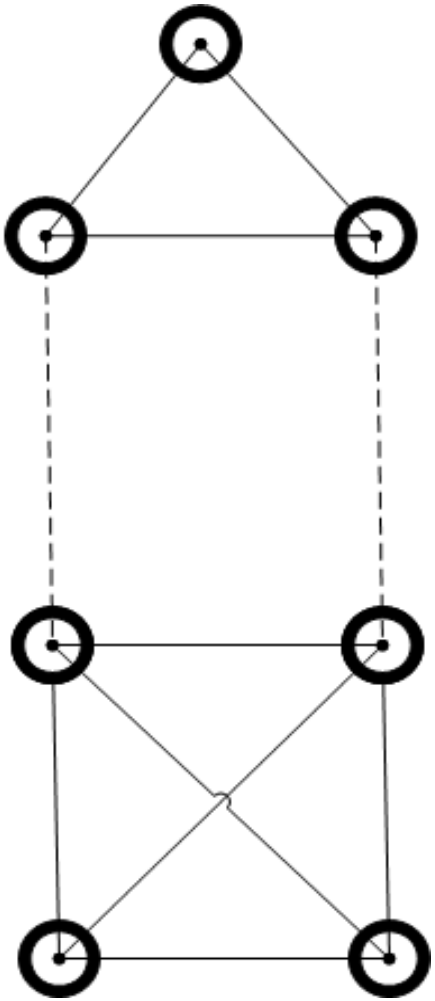


Slide credit: Balakrishna Thiagarajan

Min Cut method

Example Continued

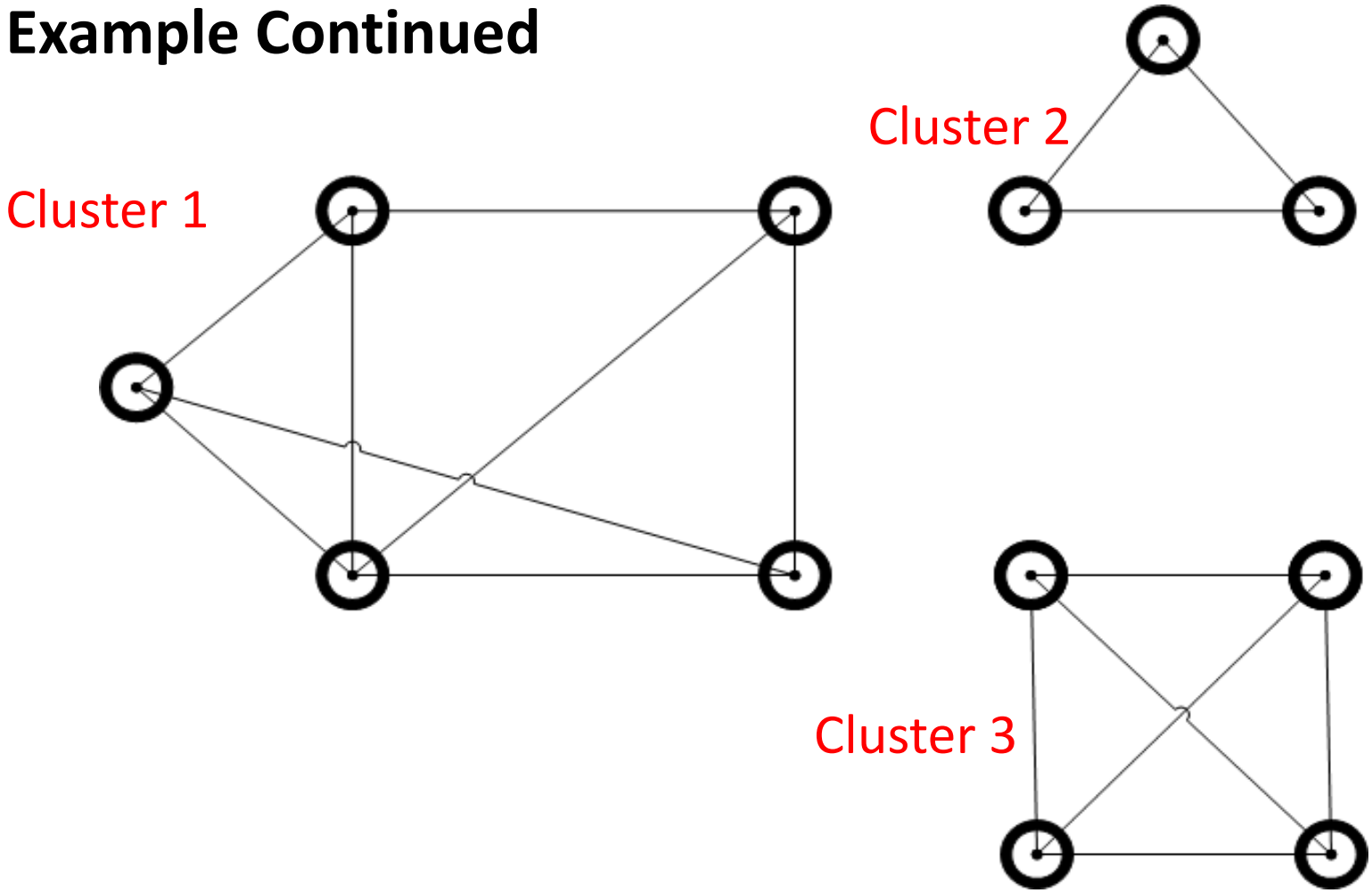




Slide credit: Balakrishna Thiagarajan

Min Cut method

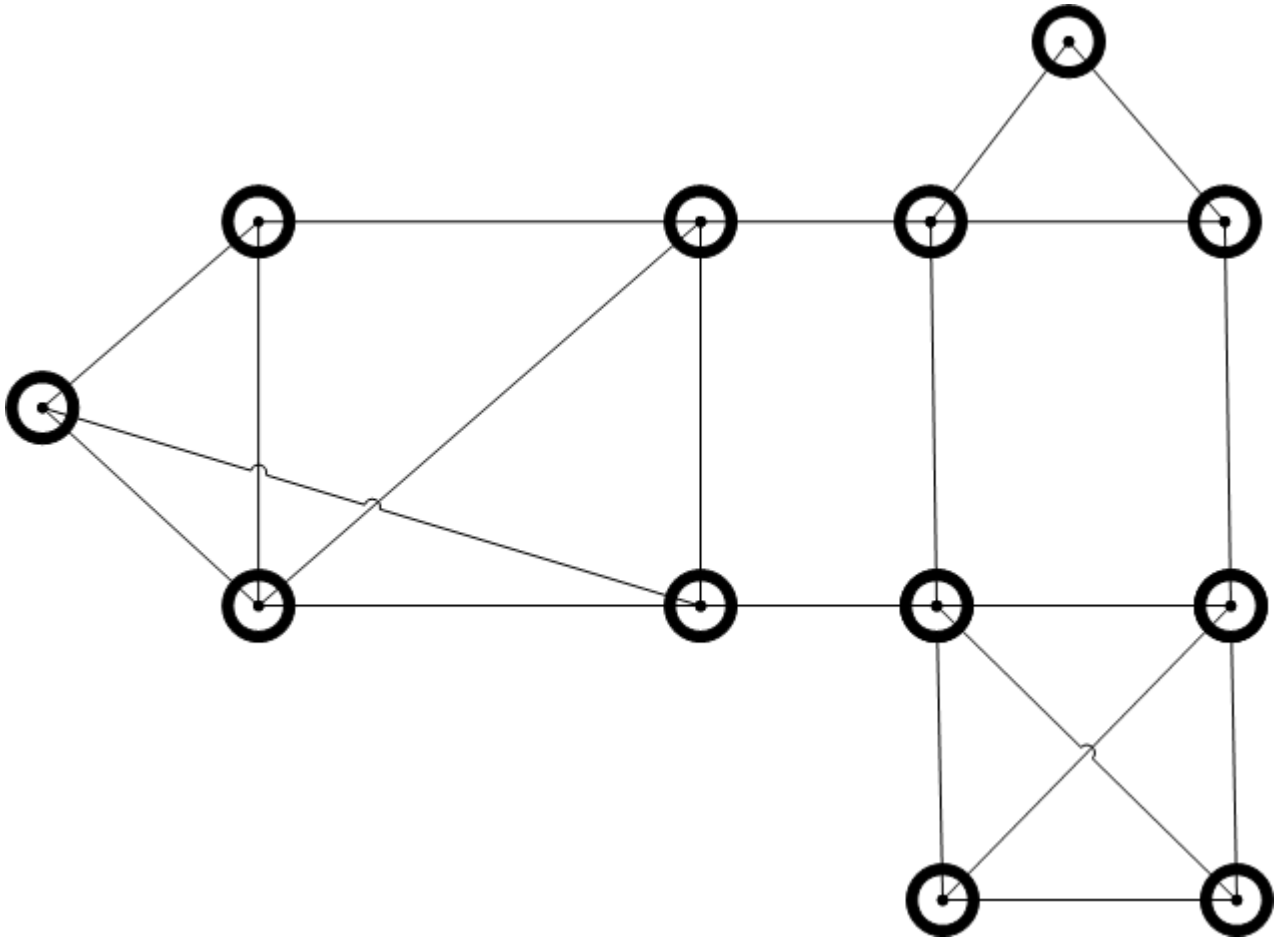
Example Continued



Slide credit: Balakrishna Thiagarajan

Min Cut method – main problem

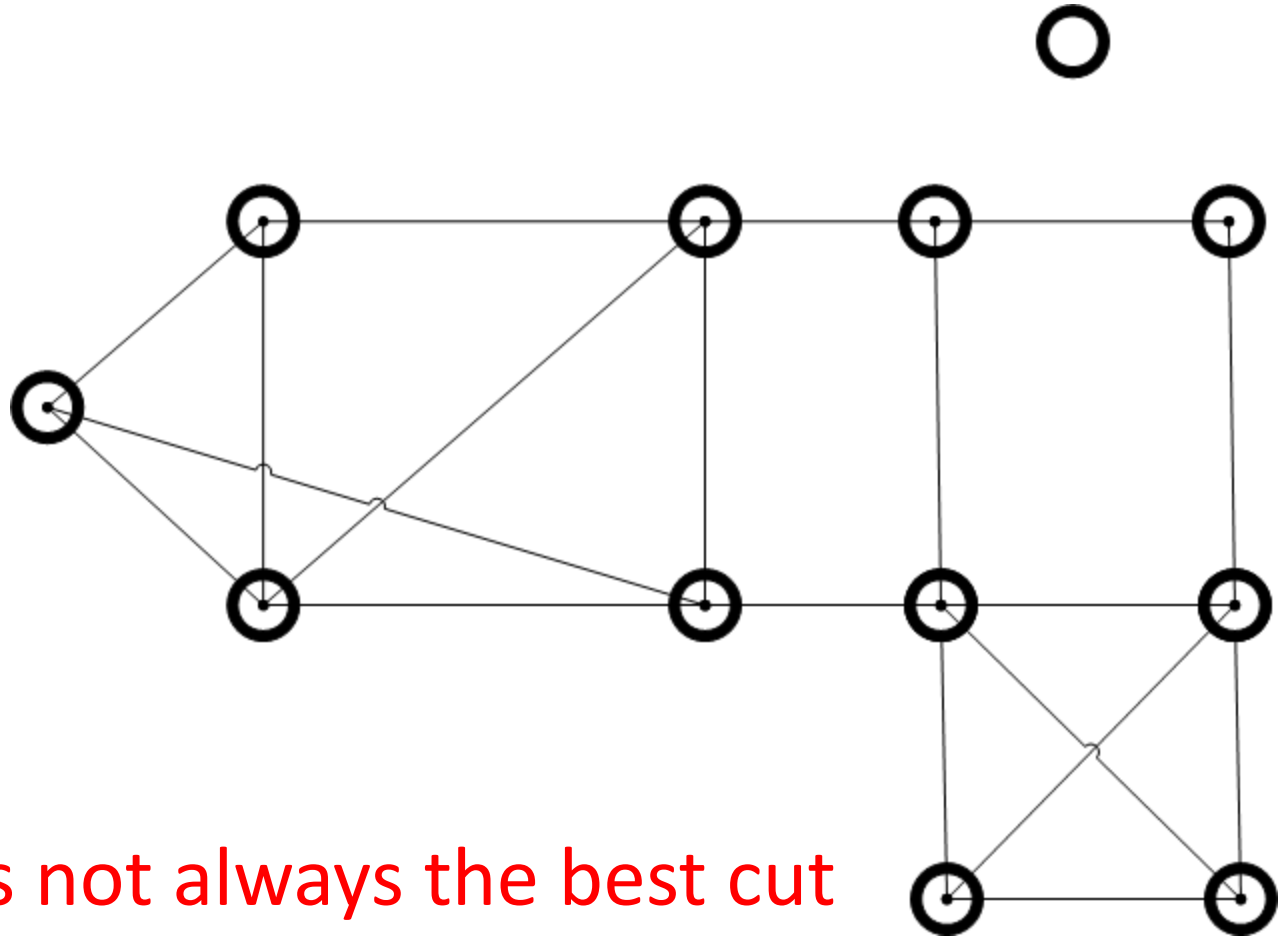
Example



Slide credit: Balakrishna Thiagarajan

Min Cut method – main problem

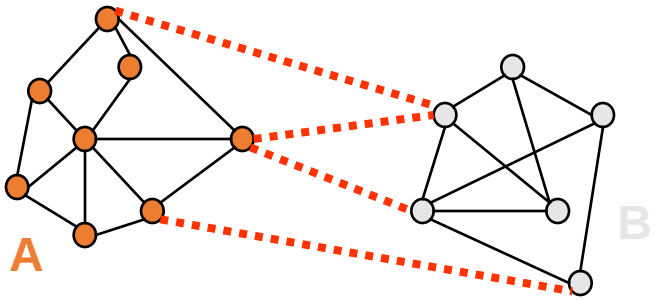
Example – Another possible cut



Min cut is not always the best cut

Slide credit: Balakrishna Thiagarajan

Cuts in a graph



Normalized Cut

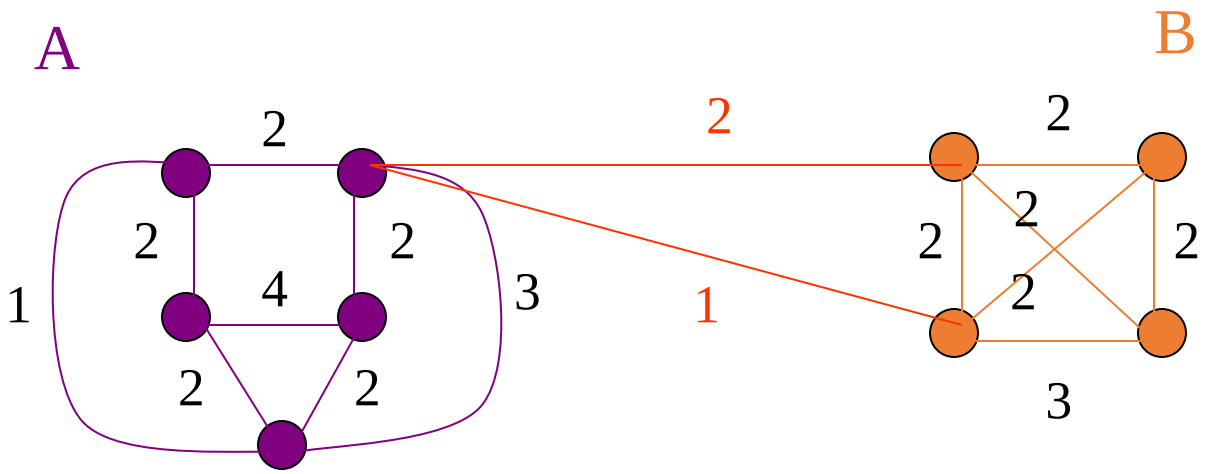
- a cut penalizes small segments
- fix by normalizing for size of segments

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

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

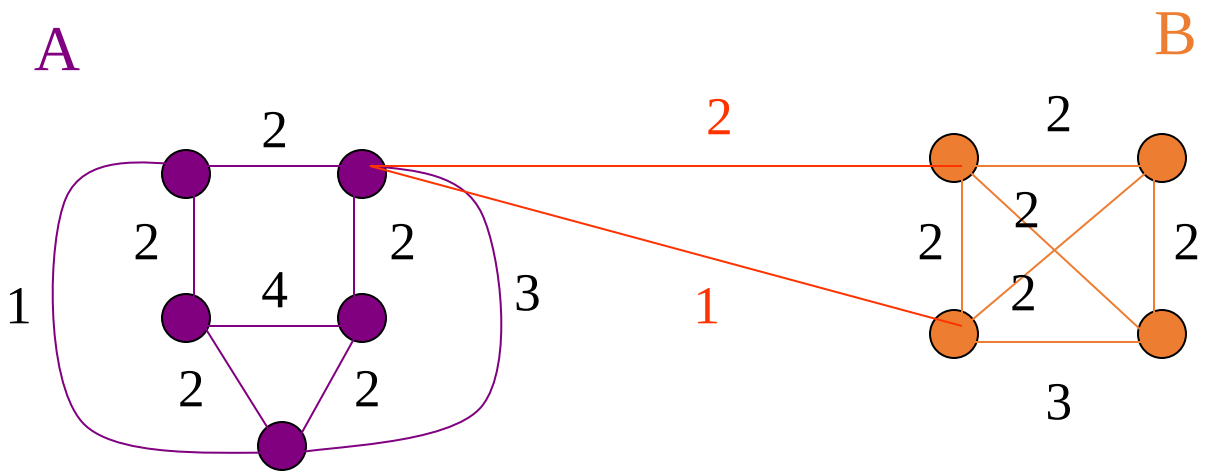
Source: Seitz

Example Normalized Cut



Slide credit: L. Shapiro

Example Normalized Cut



$$Ncut(A,B) = \frac{3}{21} + \frac{3}{16}$$

Slide credit: L. Shapiro

Normalized cuts results

Normalized cuts: Pro and con

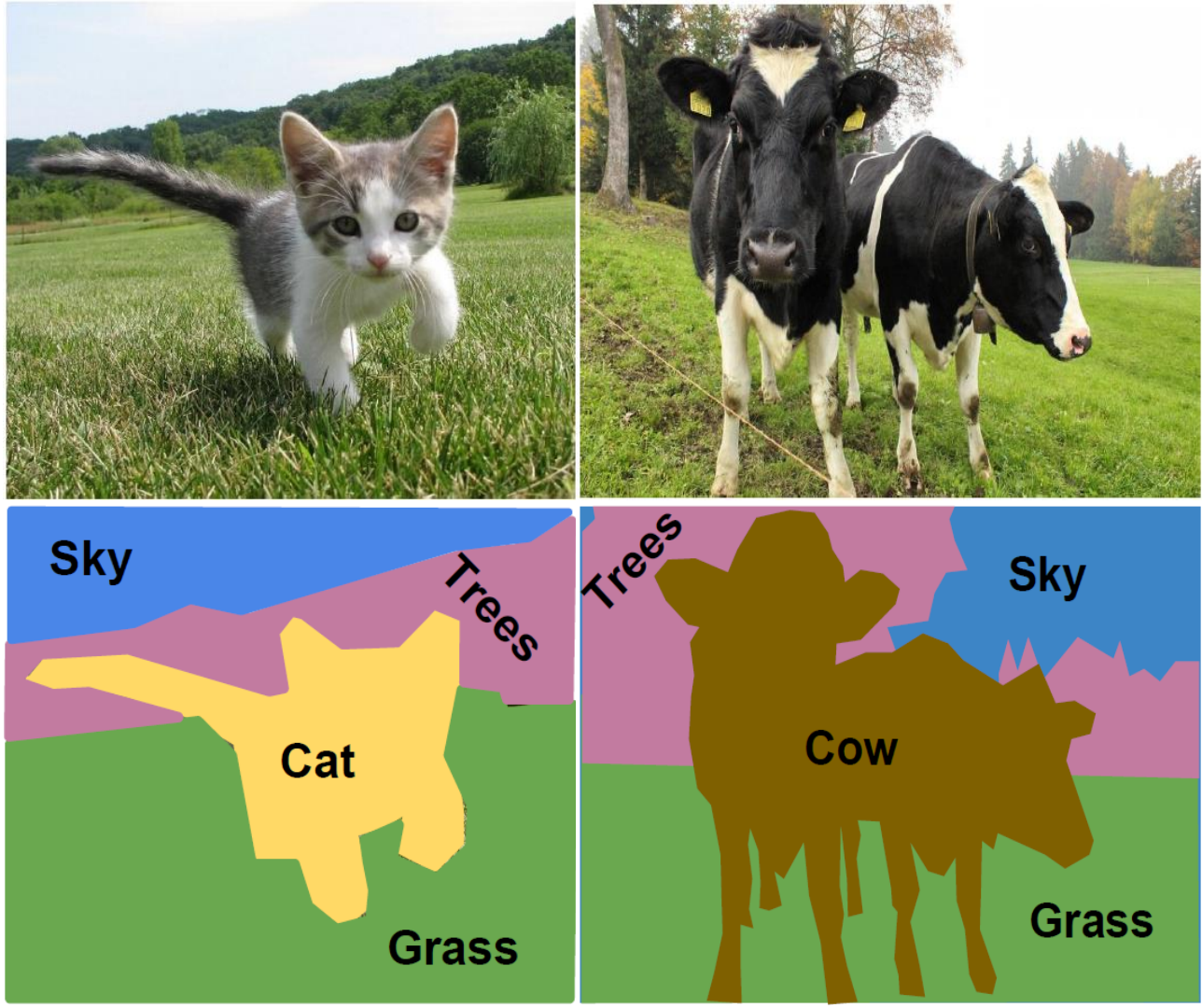
- Pros
  - Generic framework, can be used with many different features and affinity formulations
  - Provides regular segments
- Cons
  - Need to chose number of segments
  - High storage requirement and time complexity

Semantic Segmentation

These images are CC0 public domain source1 source2

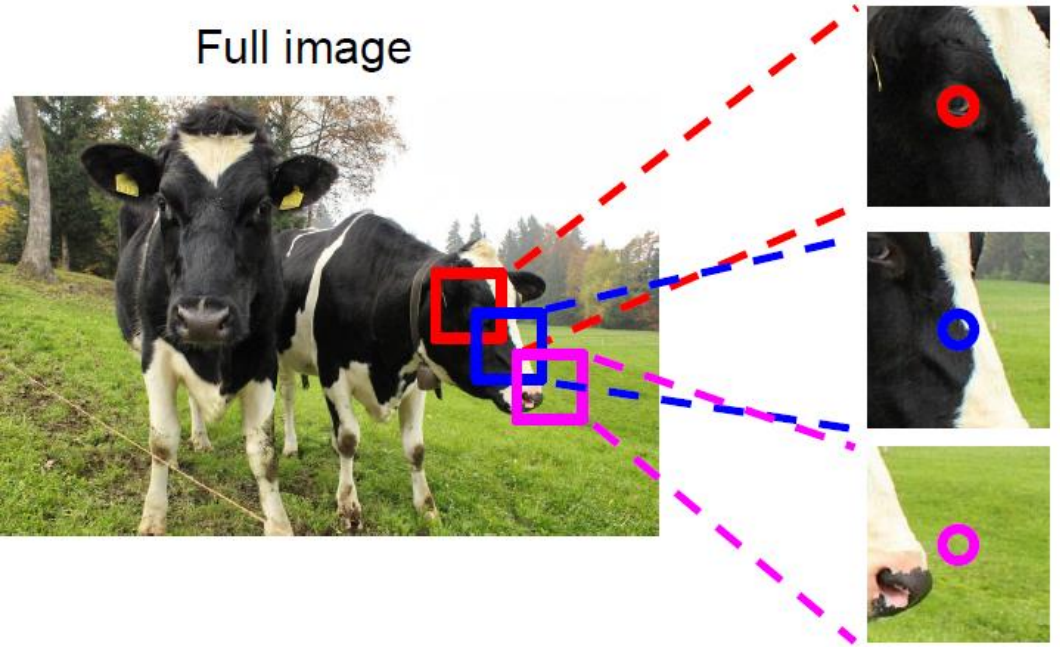
Label each pixel in the image with a category label

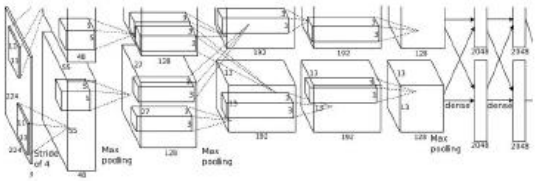
Don’t differentiate instances, only care about pixels



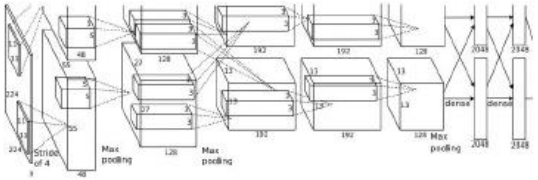
Slide credit: cs231n

Semantic Segmentation: Sliding Window

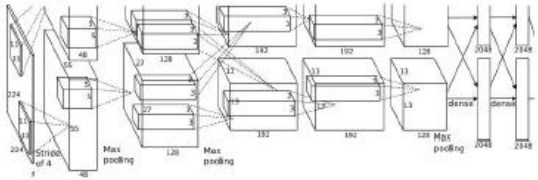




Cow



Cow

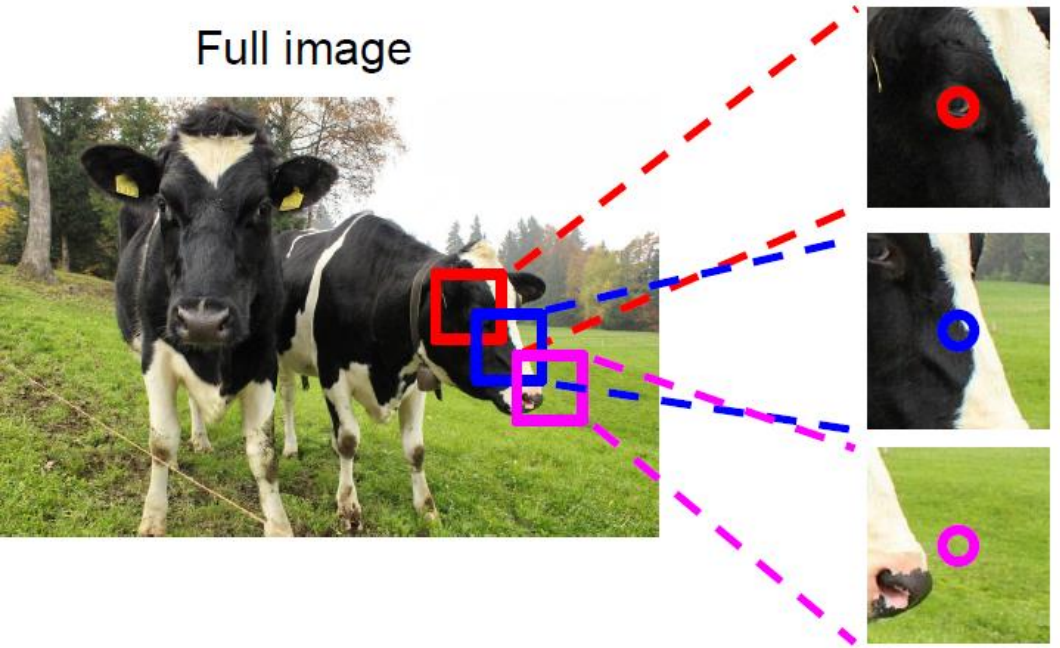


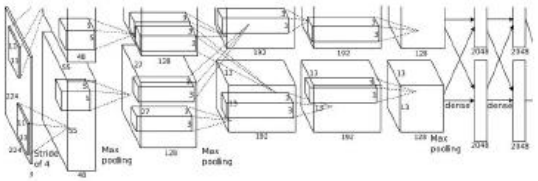
Grass

Farabet et al, “Learning Hierarchical Features for Scene Labeling,” TPAMI 2013
Pinheiro and Collobert, “Recurrent Convolutional Neural Networks for Scene Labeling”, ICML 2014

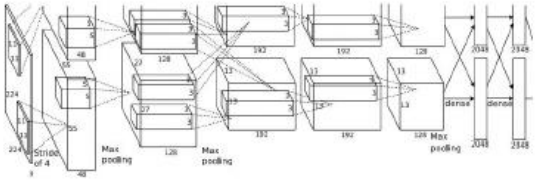
Slide credit: cs231n

Semantic Segmentation: Sliding Window

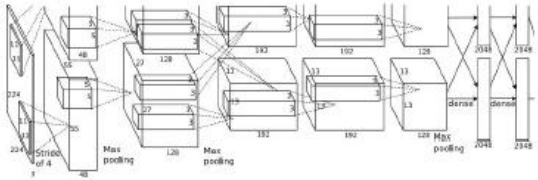




Cow



Cow



Grass

Problem:

Very inefficient!

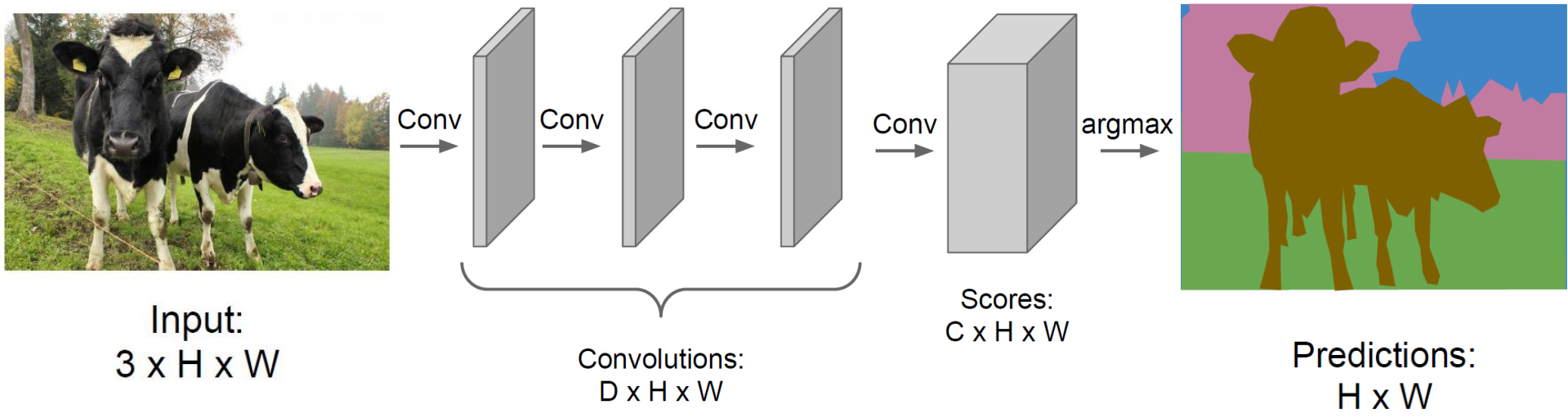
Not reusing shared features between overlapping patches

Farabet et al, “Learning Hierarchical Features for Scene Labeling,” TPAMI 2013
Pinheiro and Collobert, “Recurrent Convolutional Neural Networks for Scene Labeling”, ICML 2014

Slide credit: cs231n

Semantic Segmentation: Fully Convolutional

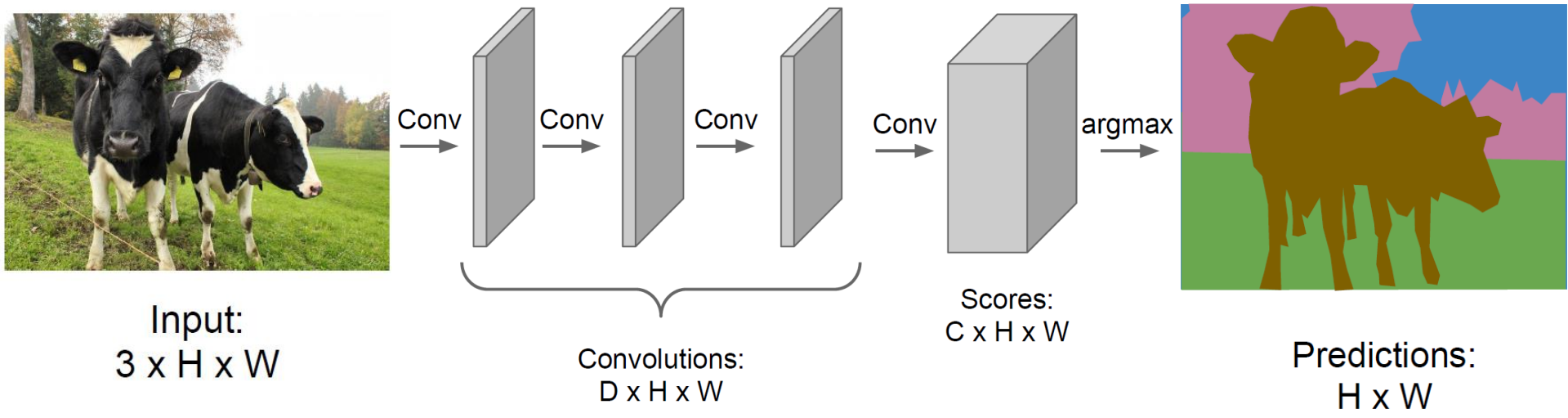
Design a network as a bunch of convolutional layers to make predictions for pixels all at once!



Slide credit: cs231n

Semantic Segmentation: Fully Convolutional

Design a network as a bunch of convolutional layers to make predictions for pixels all at once!



Problem:

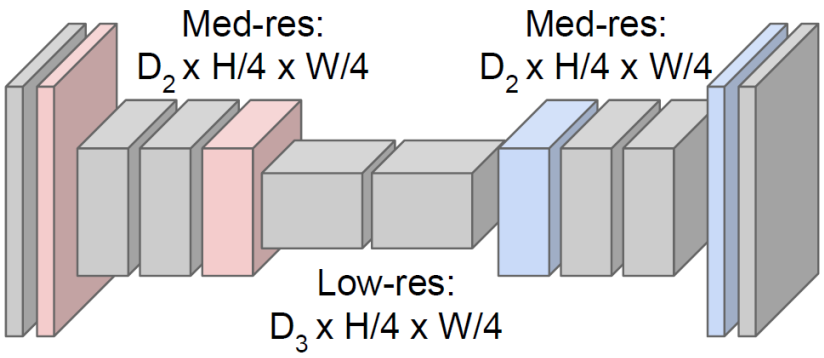
Convolutions at original image resolution will be very expensive ...

Slide credit: cs231n

Semantic Segmentation: Fully Convolutional

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Input:
3 x H x W



Predictions:
H x W

Long et al. Fully Convolutional Networks for Semantic Segmentation, CVPR 2015
Noh et al. Learning Deconvolution Network for Semantic Segmentation, ICCV 2015

Slide credit: cs231n

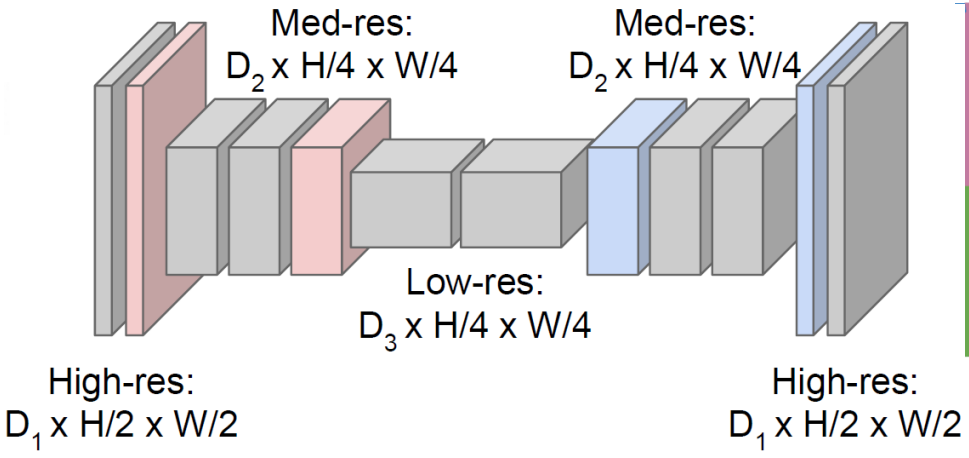
Semantic Segmentation: Fully Convolutional

Downsampling: Pooling, strided convolution

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Upsampling: ??

Input:
3 x H x W



Predictions:
H x W

Long et al. Fully Convolutional Networks for Semantic Segmentation, CVPR 2015
Noh et al. Learning Deconvolution Network for Semantic Segmentation, ICCV 2015

Slide credit: cs231n

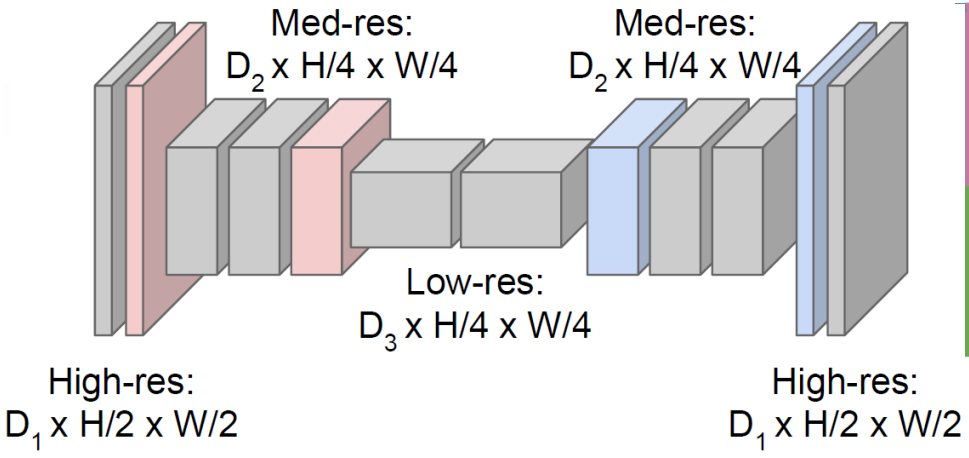
Semantic Segmentation: Fully Convolutional

Downsampling: Pooling, strided convolution

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Upsampling: Unpooling or strided transpose convolution

Input:
3 x H x W



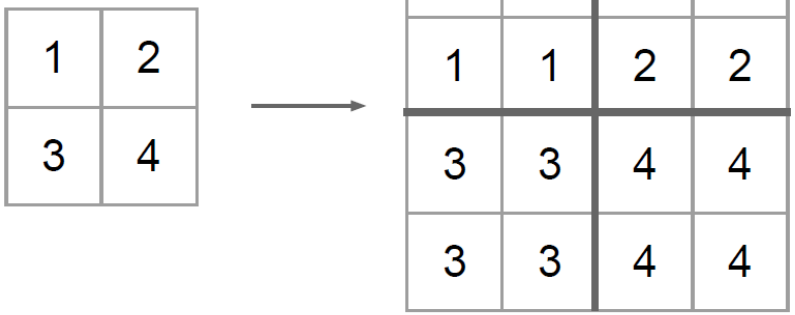
Predictions:
H x W

Long et al. Fully Convolutional Networks for Semantic Segmentation, CVPR 2015
Noh et al. Learning Deconvolution Network for Semantic Segmentation, ICCV 2015

Slide credit: cs231n

Upsampling: Unpooling

Nearest Neighbor



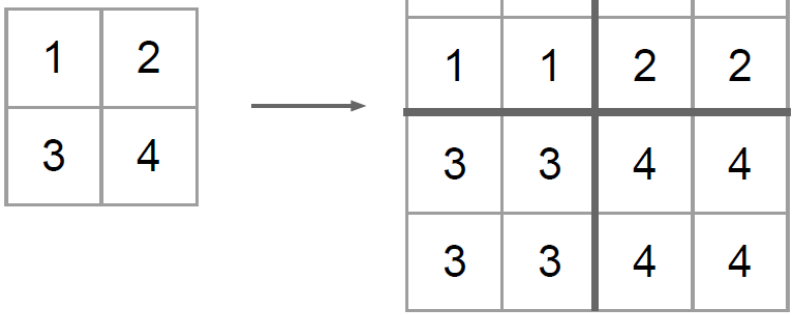
Input: 2 x 2

Output: 4 x 4

Slide credit: cs231n

Upsampling: Unpooling

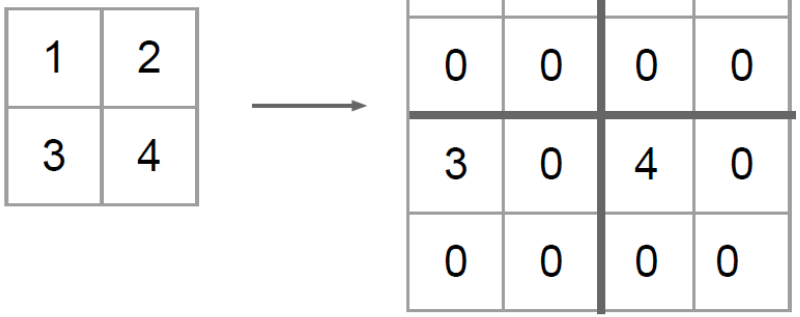
Nearest Neighbor



Input: 2 x 2

Output: 4 x 4

“Bed of Nails”



Input: 2 x 2

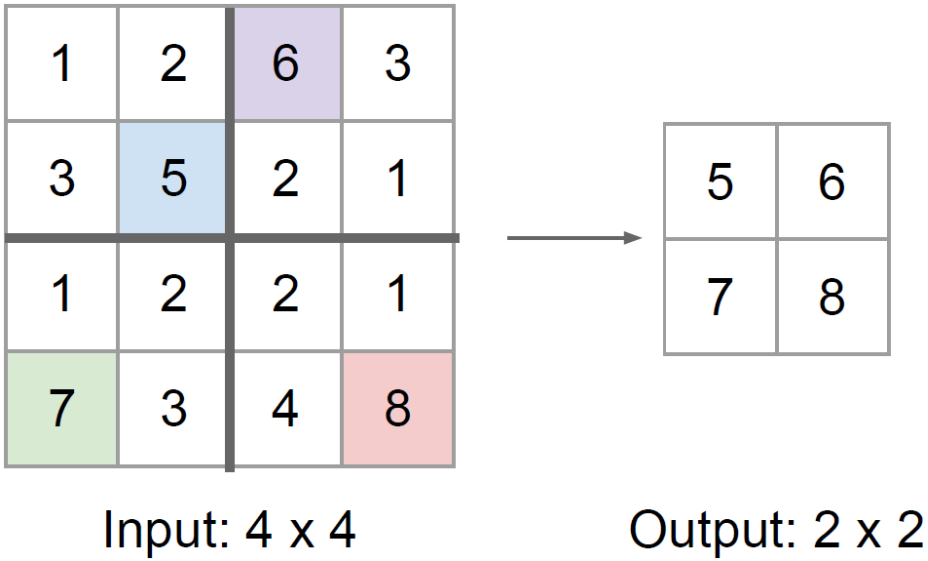
Output: 4 x 4

Slide credit: cs231n

Upsampling: Max Unpooling

Max Pooling

Remember which element was max!

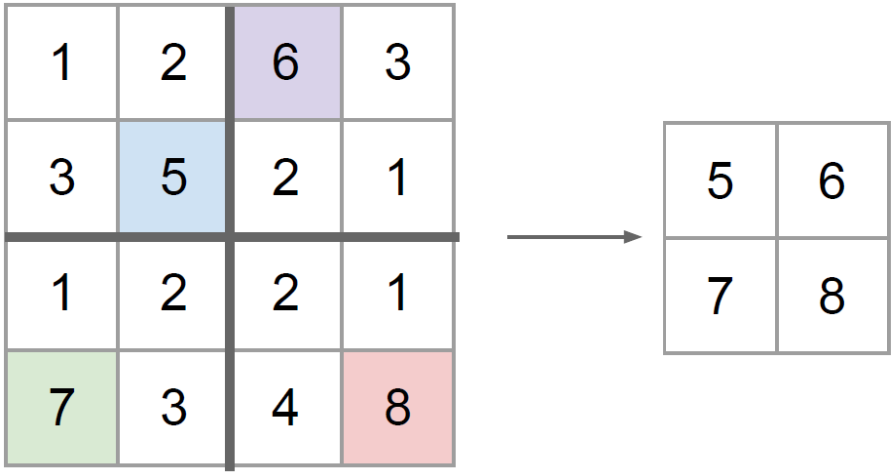


Slide credit: cs231n

Upsampling: Max Unpooling

Max Pooling

Remember which element was max!

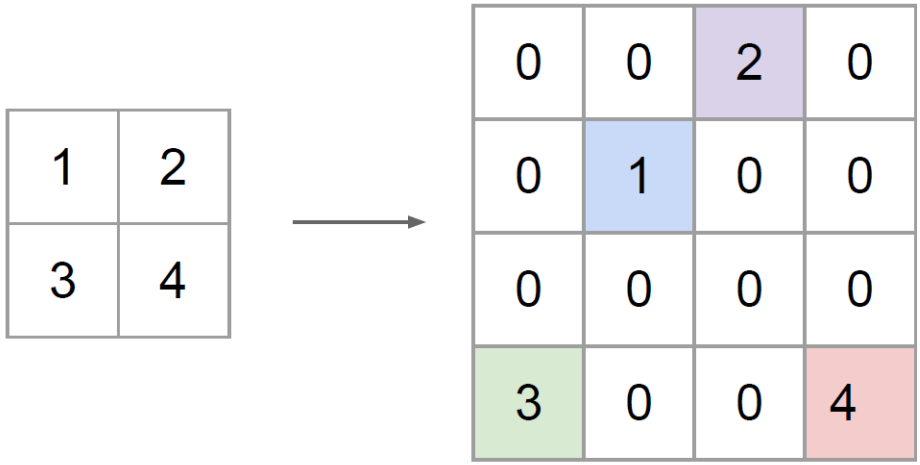


Input: 4 x 4

Output: 2 x 2

Max Unpooling

Use positions from pooling layer



Input: 2 x 2

Output: 4 x 4

Slide credit: cs231n

Upsampling: Max Unpooling

Max Pooling

Remember which element was max!

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

Input: 4 x 4

→

5	6
7	8

Output: 2 x 2

Max Unpooling

Use positions from pooling layer

1	2
3	4

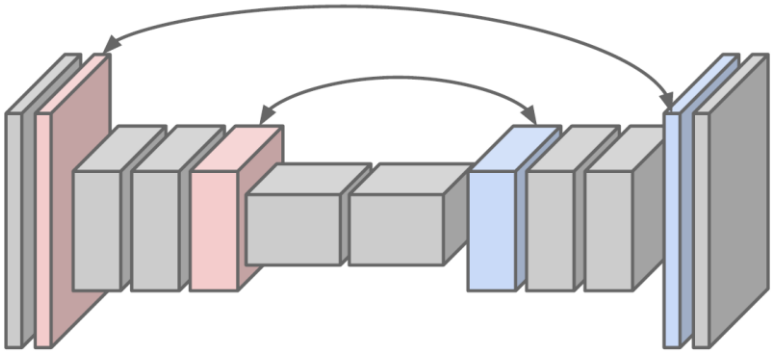
Input: 2 x 2

→

0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

Output: 4 x 4

Corresponding pairs of downsampling and upsampling layers

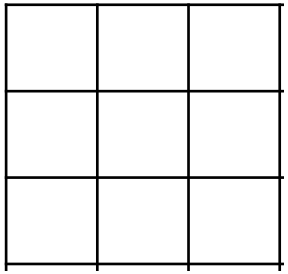


Slide credit: cs231n

Upsampling: Transpose Convolution

3 x 3 **transpose** convolution, stride 2 pad 1

Input: 2 x 2

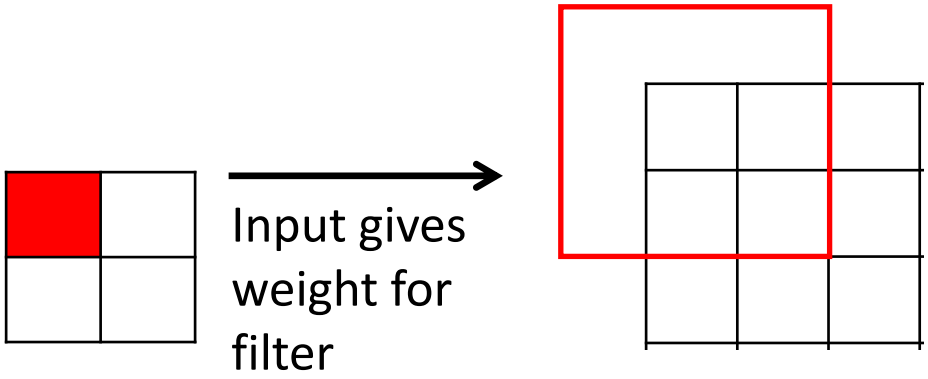


Output: 3 x 3

Slide credit: cs231n

Upsampling: Transpose Convolution

3 x 3 **transpose** convolution, stride 2 pad 1



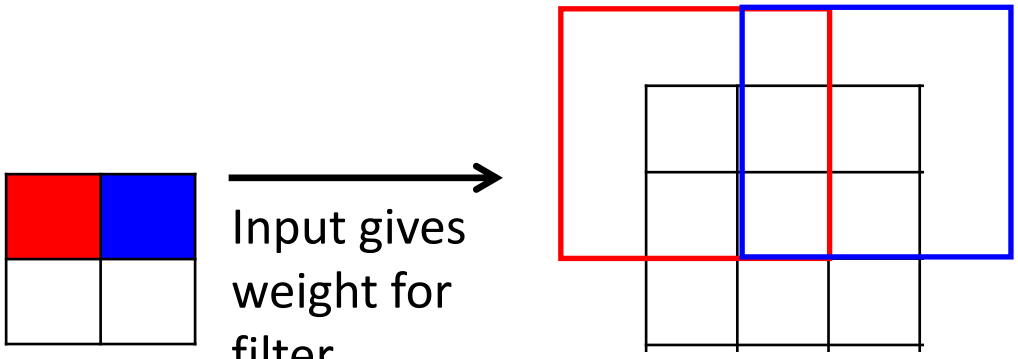
Input: 2 x 2

Output: 3 x 3

Slide credit: cs231n

Upsampling: Transpose Convolution

3 x 3 **transpose** convolution, stride 2 pad 1



Input: 2 x 2

Output: 3 x 3

Filter moves 2 pixels in the output for every one pixel in the input

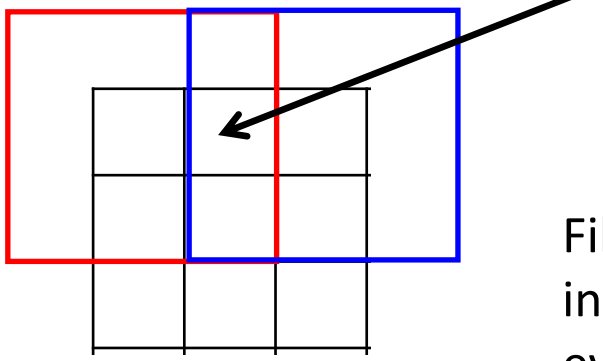
Stride gives ratio between movement in output and input

Slide credit: cs231n

Upsampling: Transpose Convolution

3 x 3 **transpose** convolution, stride 2 pad 1

Input gives weight for filter



Input: 2 x 2

Output: 3 x 3

Filter moves 2 pixels in the output for every one pixel in the input

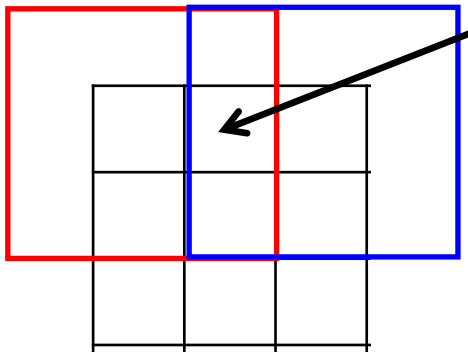
Stride gives ratio between movement in output and input

Slide credit: cs231n

Upsampling: Transpose Convolution

3 x 3 **transpose** convolution, stride 2 pad 1

Input gives weight for filter



Sum where output overlaps

Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

Input: 2 x 2

Output: 3 x 3

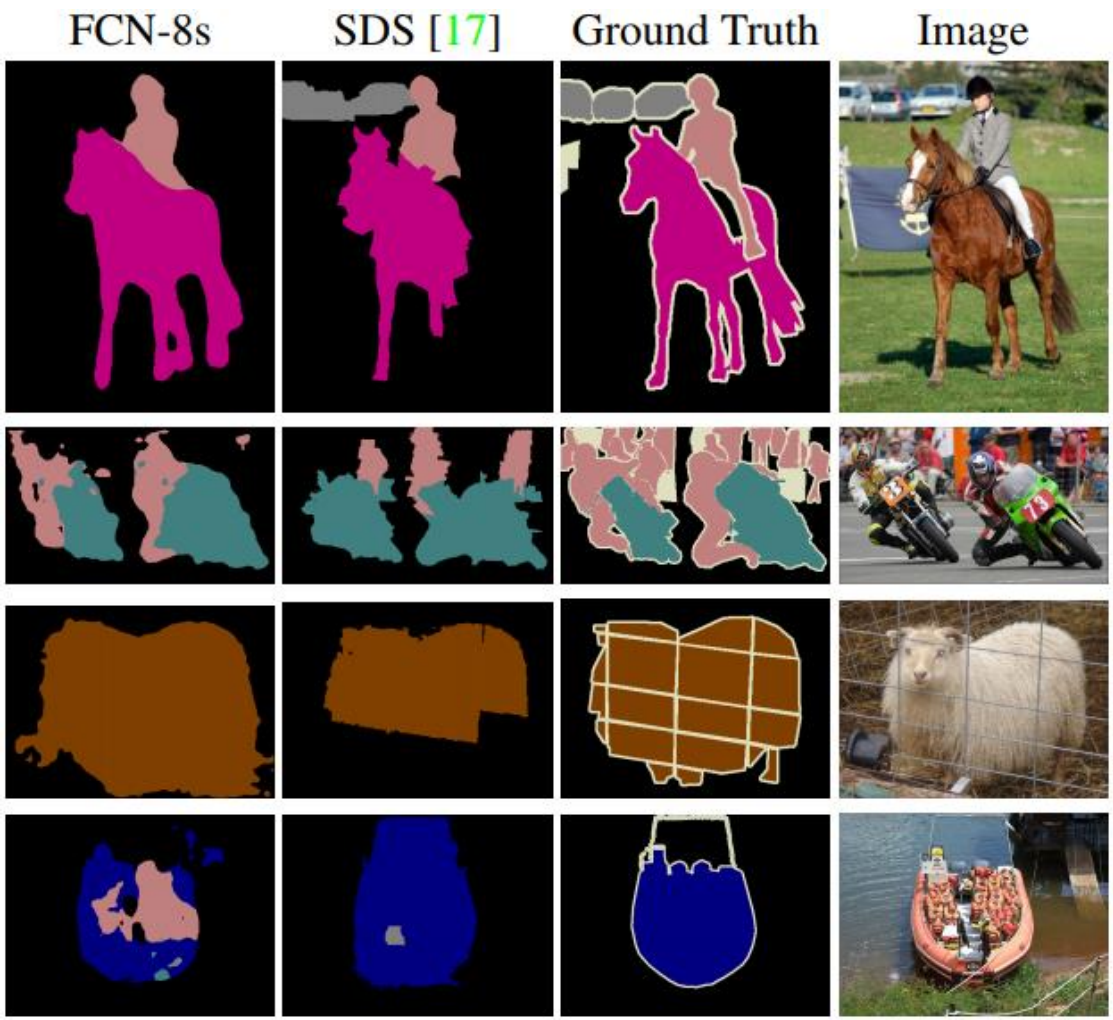
Actual output: 5*5

Need to crop 3*3 centrally

Slide credit: cs231n

“Fully convolutional (FCN)” results

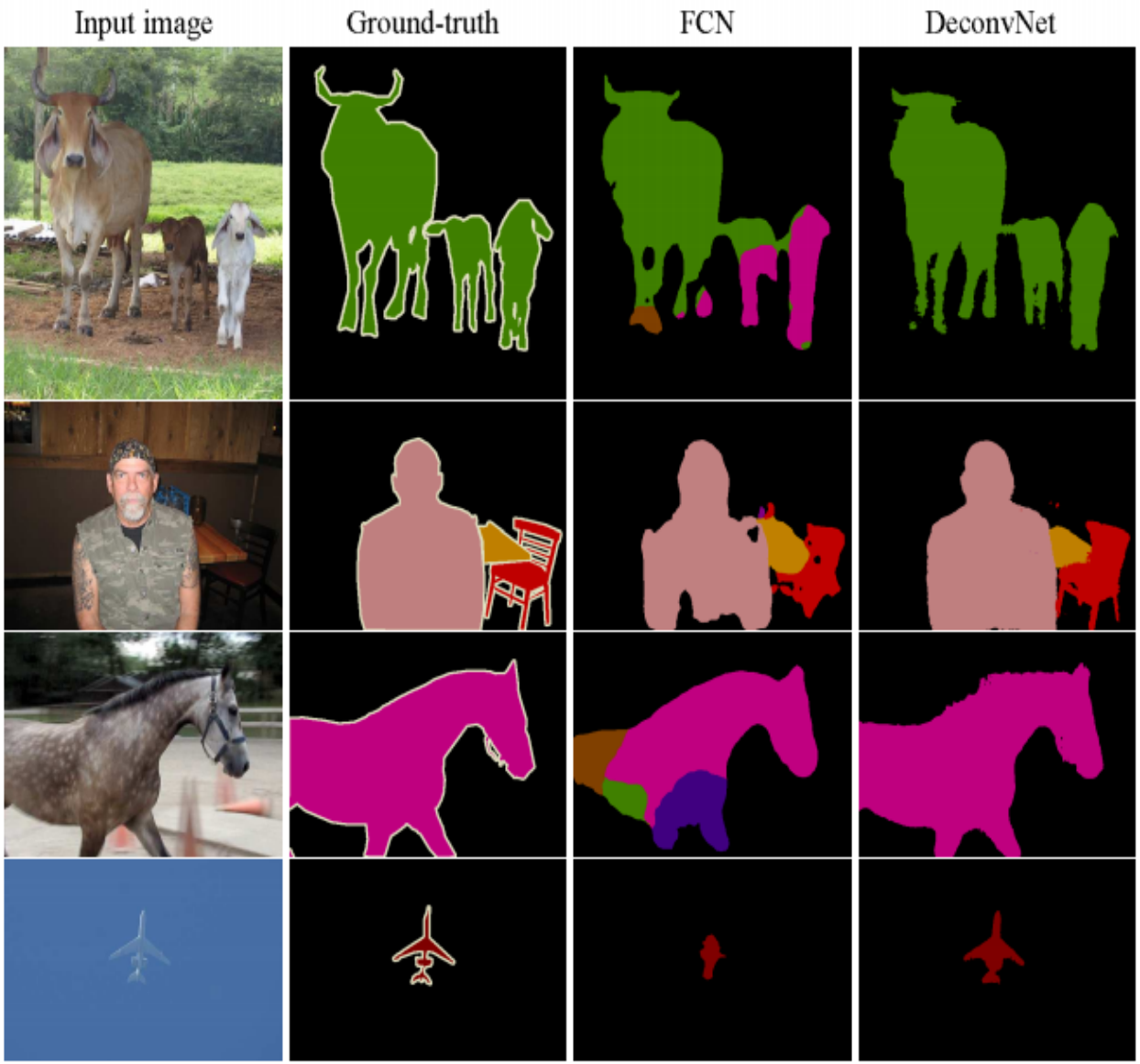
- Takes advantage of pre-training from classification
- Applied to objects and scenes (NYUd v2)
- But feature pooling reduces spatial sensitivity and resolution



Long et al. Fully Convolutional Networks for Semantic Segmentation, CVPR 2015

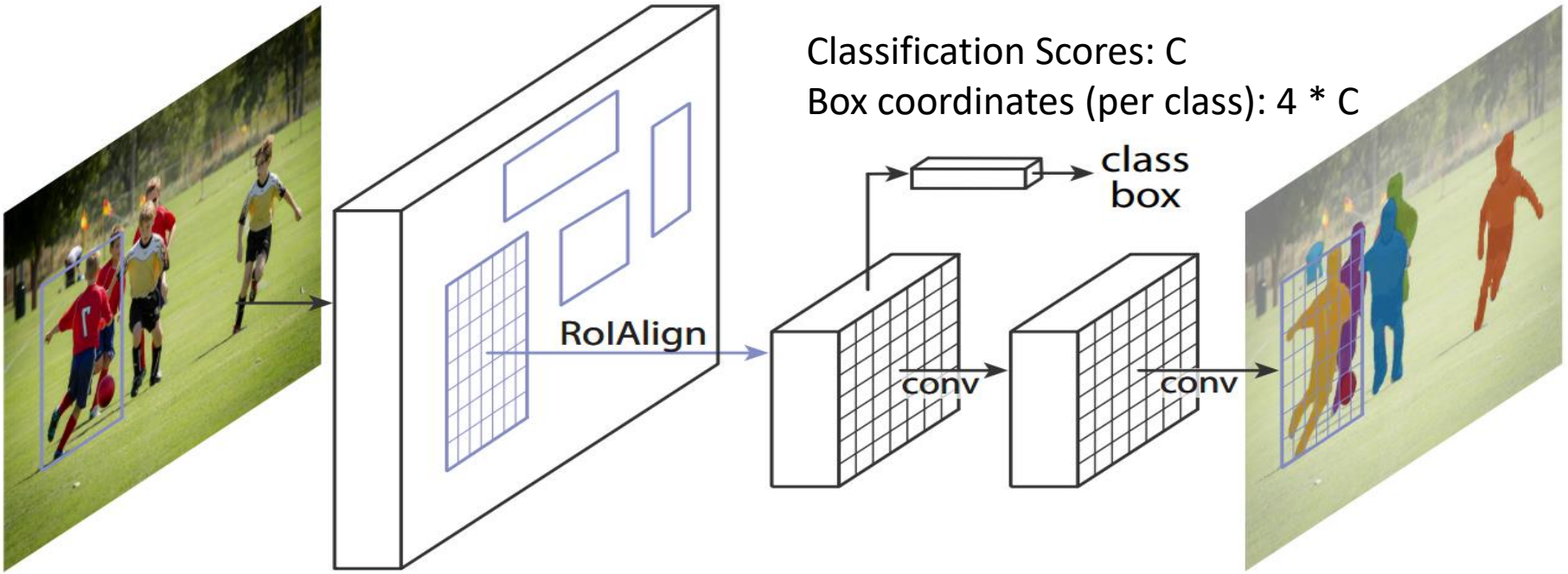
“DeconNet” results

- A deep deconvolution network
- Pixel-wise prediction



Noh et al. Learning Deconvolution Network for Semantic Segmentation, ICCV 2015

Instance Segmentation: Mask R-CNN (He et al. ICCV 2017)

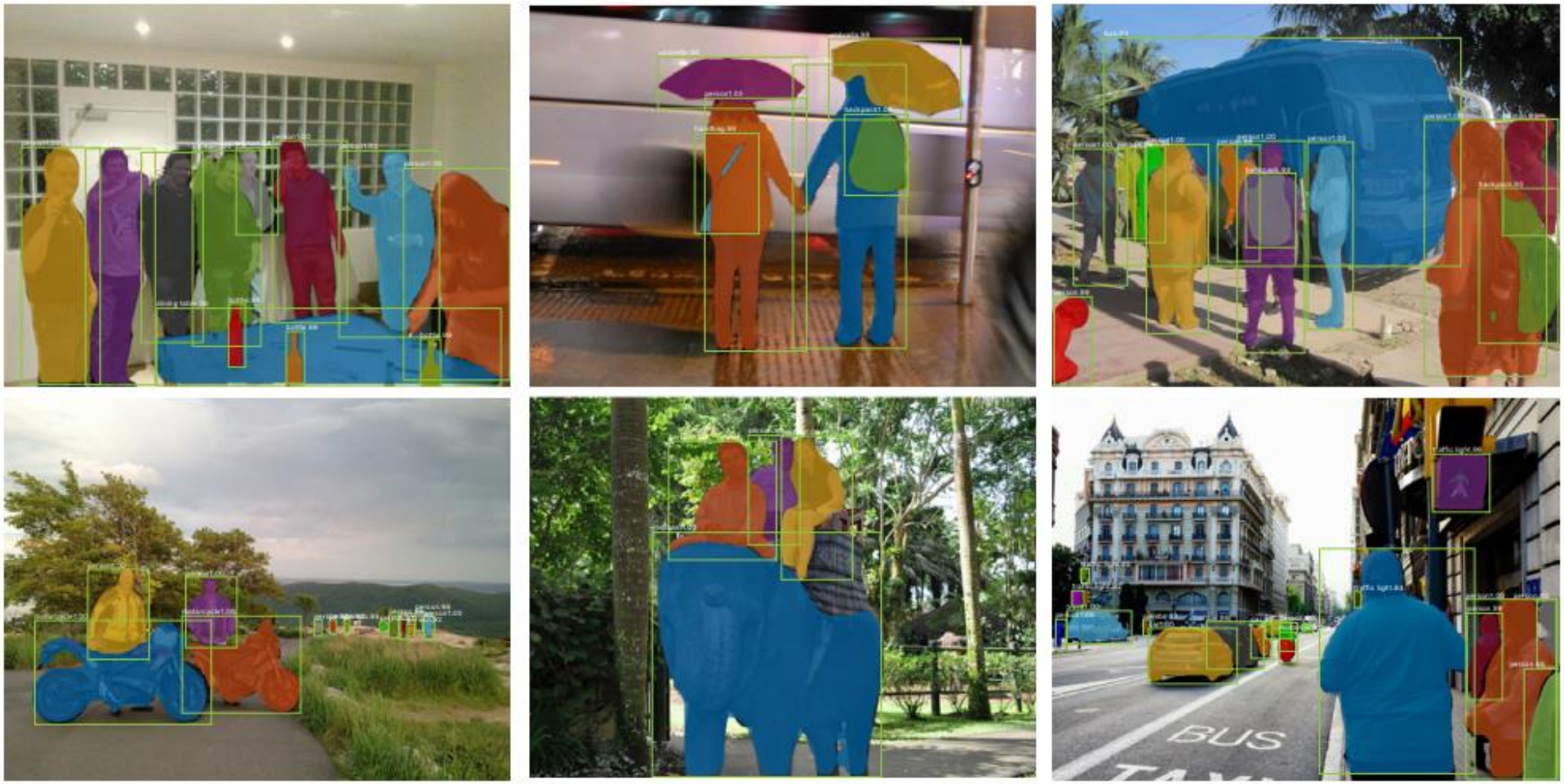


Mask R-CNN - extends Faster R-CNN by adding a branch for predicting an object mask in parallel with the existing branch for bounding box recognition.

Mask R-CNN is simple to train and adds only a small overhead to Faster R-CNN, running at 5 fps.

He et al. Mask R-CNN, ICCV 2017. https://arxiv.org/pdf/1703.06870.pdf

Instance Segmentation: Mask R-CNN (He et al. ICCV 2017)

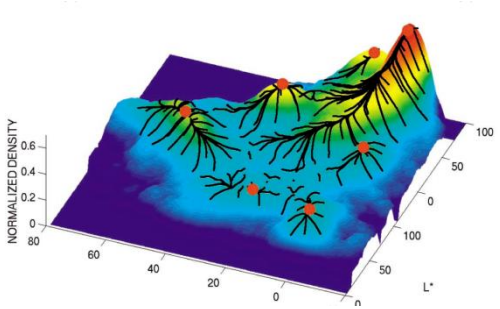


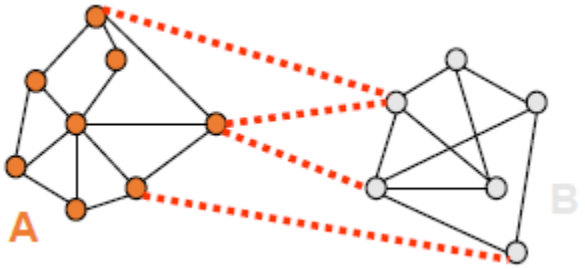
Mask R-CNN results on the COCO test set. These results are based on ResNet-101, achieving a mask AP of 35.7 and running at 5 fps. Masks are shown in color, and bounding box, category, and confidences are also shown.

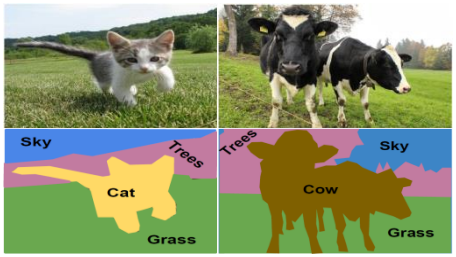
He et al. Mask R-CNN, ICCV 2017. https://arxiv.org/pdf/1703.06870.pdf

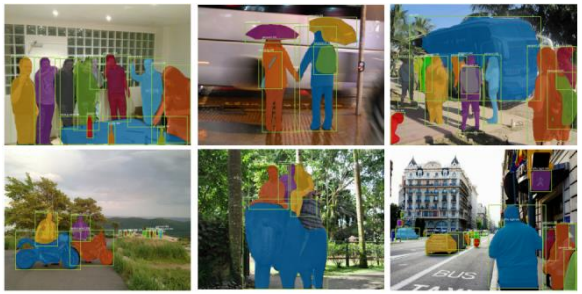
Things to remember

- Mean-shift segmentation
  - Good general-purpose segmentation method
  - Generally useful clustering, tracking technique
- Graph Cut Segmentation
  - Normalized graph cut is better
  - High storage requirement and time complexity
- Semantic Segmentation
  - Sliding window inefficient
  - Fully Convolutional: Convolutions at original image resolution is very expensive
  - Fully Convolutional: Down sampling and Up sampling
  - Unsampling usning Unpooling and Transpose Convolution
  - DeconvNet: deeper network
- Instance Segmentation
  - Mak-RCNN: Extension of faster RCNN









Acknowledgements

- Thanks to the following researchers for making their teaching/research material online
  - Forsyth
  - Steve Seitz
  - Noah Snavely
  - J.B. Huang
  - Derek Hoiem
  - J. Hays
  - J. Johnson
  - R. Girshick
  - S. Lazebnik
  - K. Grauman
  - Antonio Torralba
  - Rob Fergus
  - Leibe
  - And many more …….

Next class

- Projective Geometry and Camera Models