

# Image Segmentation

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# Image Segmentation

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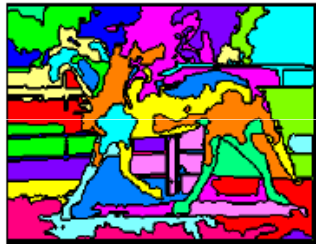
- Goal: Group pixels into meaningful or perceptually similar regions



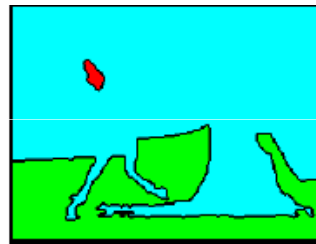
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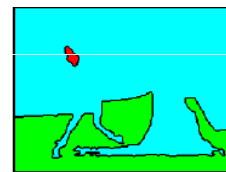
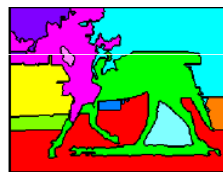
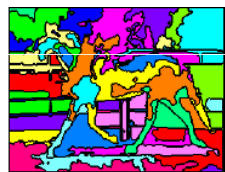
## Types of Segmentations<sup>3</sup>



Oversegmentation



Undersegmentation



Multiple Segmentations

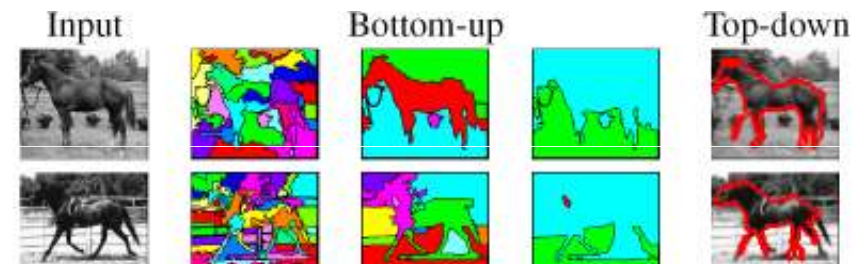
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## Segmentation Methods<sup>4</sup>

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- **Bottom-up:** Group pixels with similar features, relying mainly on continuity principles.
- **Top-down:** Use prior knowledge about an object such as its possible shape, color, or texture, to guide the segmentation



[Levin and Weiss 2006]

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# Segmentation Methods <sup>5</sup>

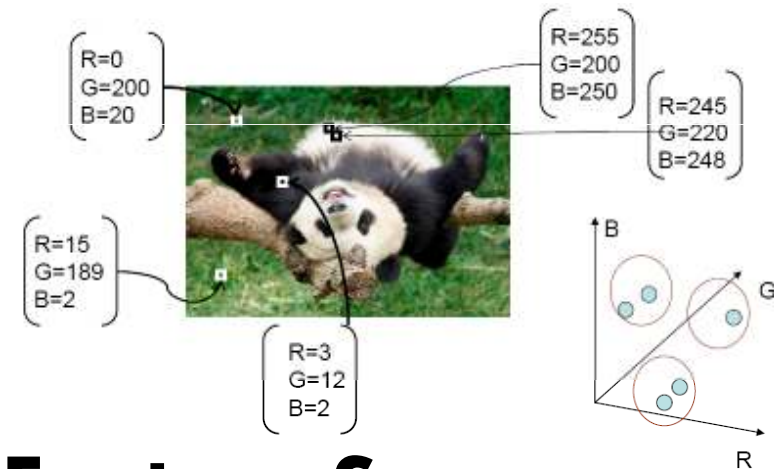
- Bottom-up Approaches
  - Clustering
    - K-means
    - Mean-shift
  - Boundary
    - Watershed
  - Graph-Based
    - Felzenszwalb and Huttenlocher
- Top-down Approaches
  - Deformable Templates
  - Active Shape Models
  - Active Contours (Snake)

<http://www.cs.brown.edu/~pff/segment/>

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# Segmentation by Clustering <sup>6</sup>



## Feature Space

Source: K. Grauman

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# K-means Clustering <sup>7</sup>

1. Choose the number of cluster  $K$
2. Initialize the centers of every cluster
3. Assign each sample to nearest center  $\rightarrow$  They will belong to the same cluster
4. Find mean of the samples that belong to the same cluster  $\rightarrow$  Use mean as new centers for that cluster
5. Repeat 3 and 4 until the centers are converged

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# K-means Clustering Using Intensity or Color alone <sup>8</sup>

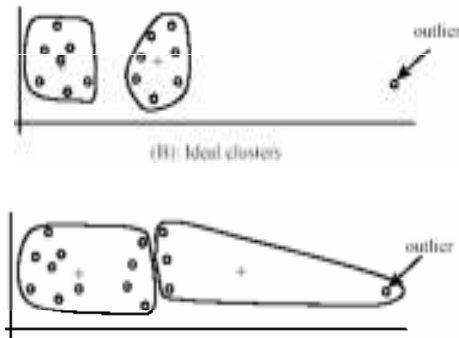


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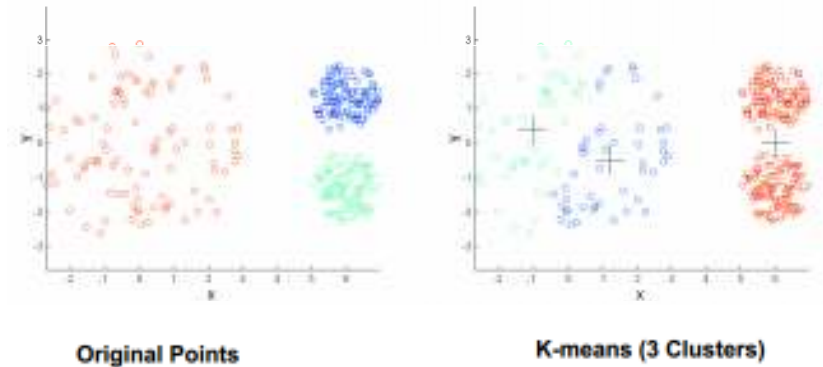
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# K-means Pros and Cons<sup>9</sup>

- Pros
  - Simple and fast
  - Easy to implement
- Cons
  - Need to choose K
  - Sensitive to outliers
  - Sensitive to initial condition



# K-means Pros and Cons<sup>10</sup>

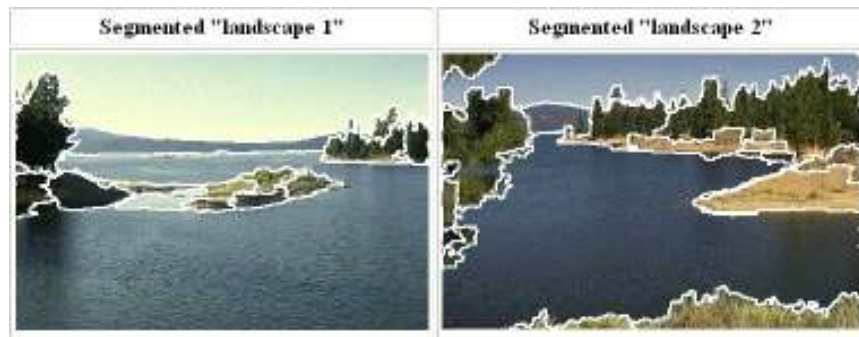


<http://www.cs.uvm.edu/~xwu/kdd/Slides/Kmeans-ICDM06.pdf>

# Mean shift Segmentation<sup>11</sup>

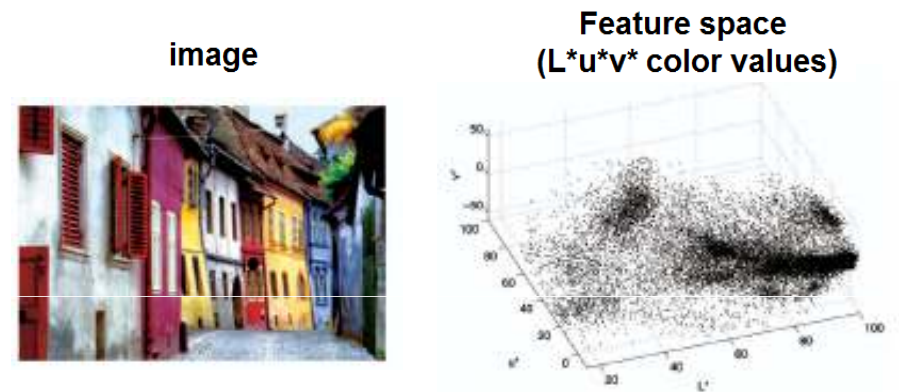
D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

- Versatile technique for clustering-based segmentation



# Mean-shift Algorithm<sup>12</sup>

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

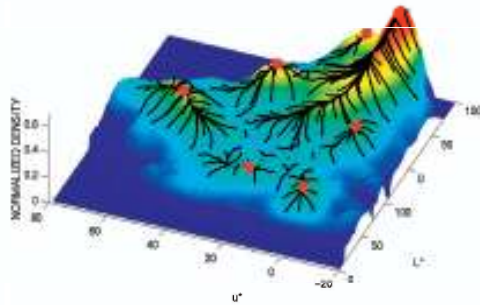


[http://img.my.csdn.net/uploads/201210/05/1349427627\\_8823.png](http://img.my.csdn.net/uploads/201210/05/1349427627_8823.png)

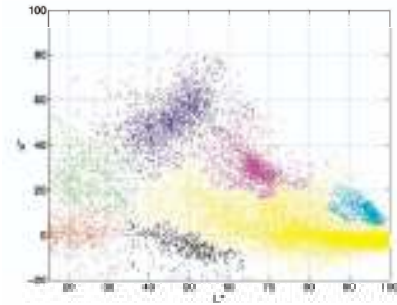
# Mean-shift Algorithm

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

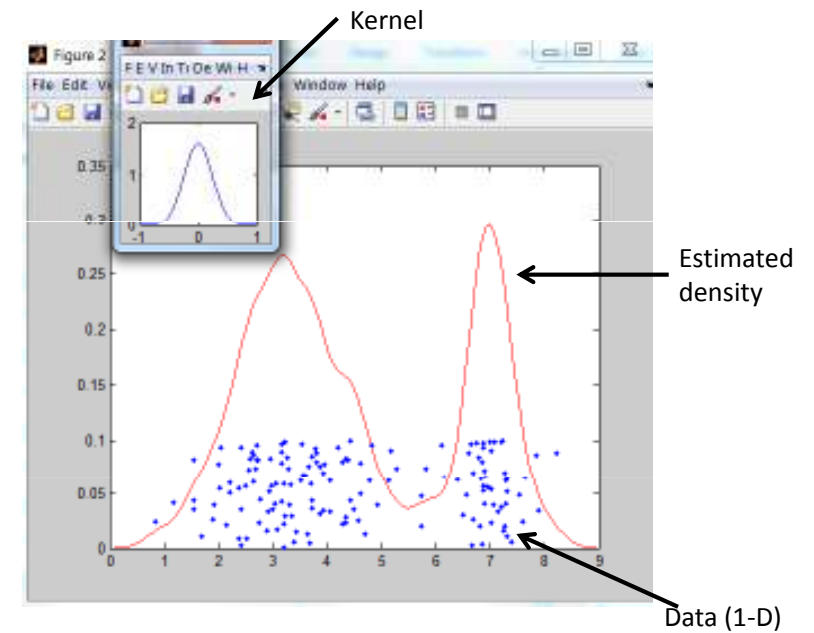


Density

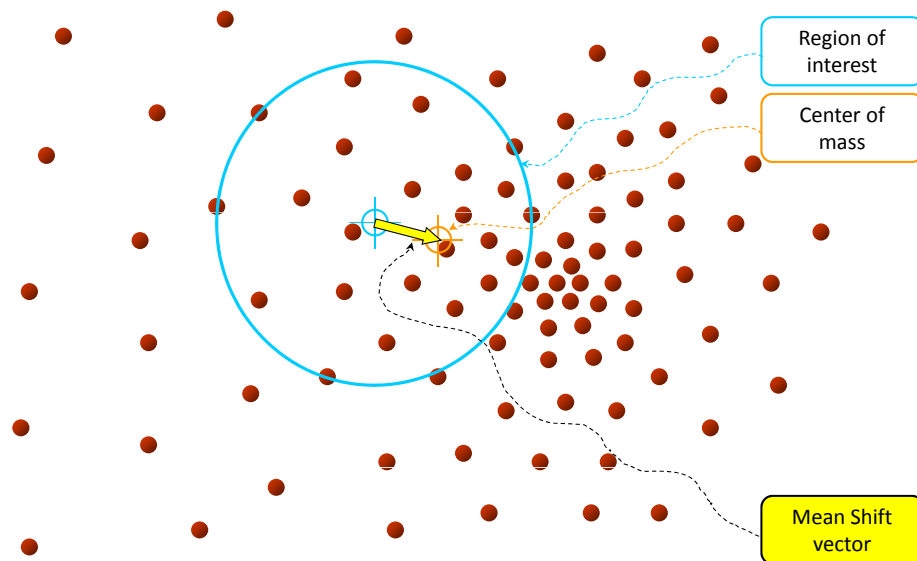


Cluster

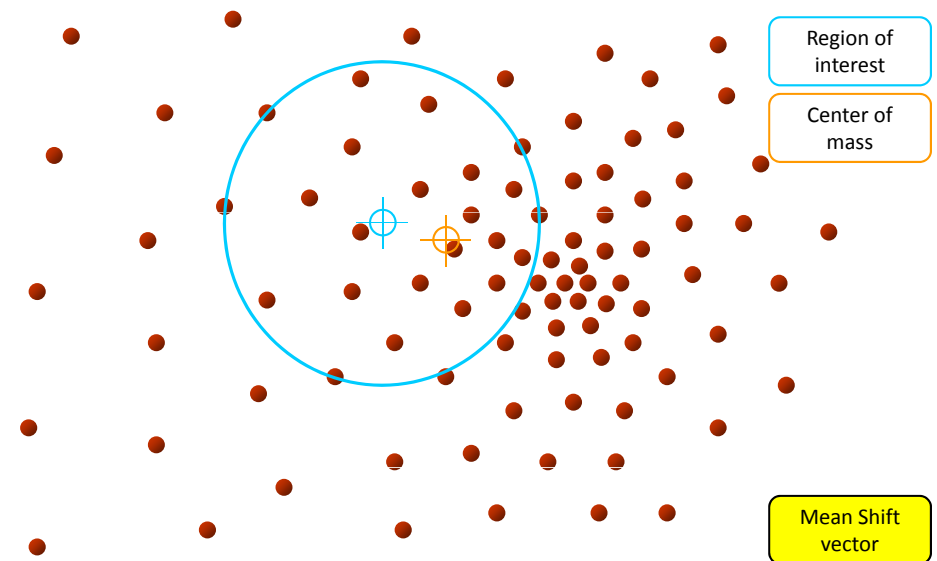
14



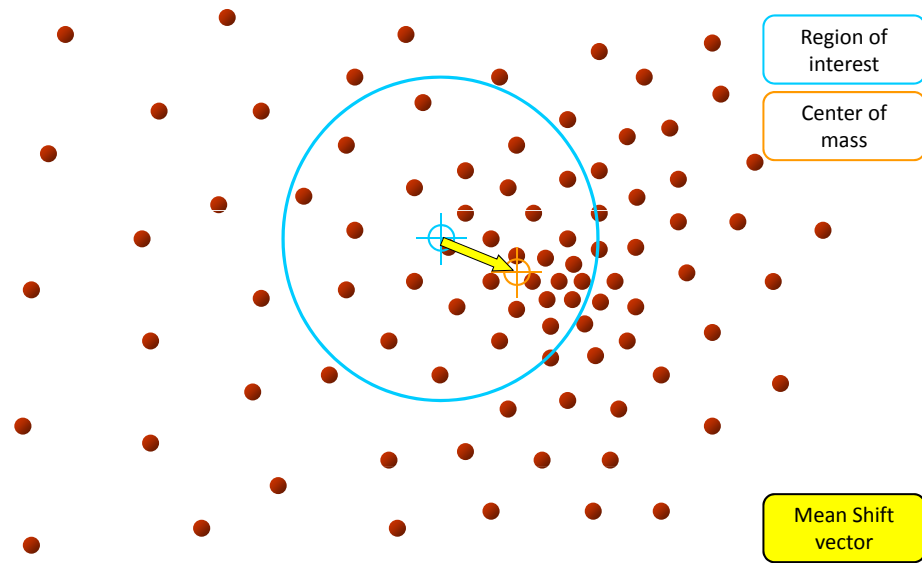
15



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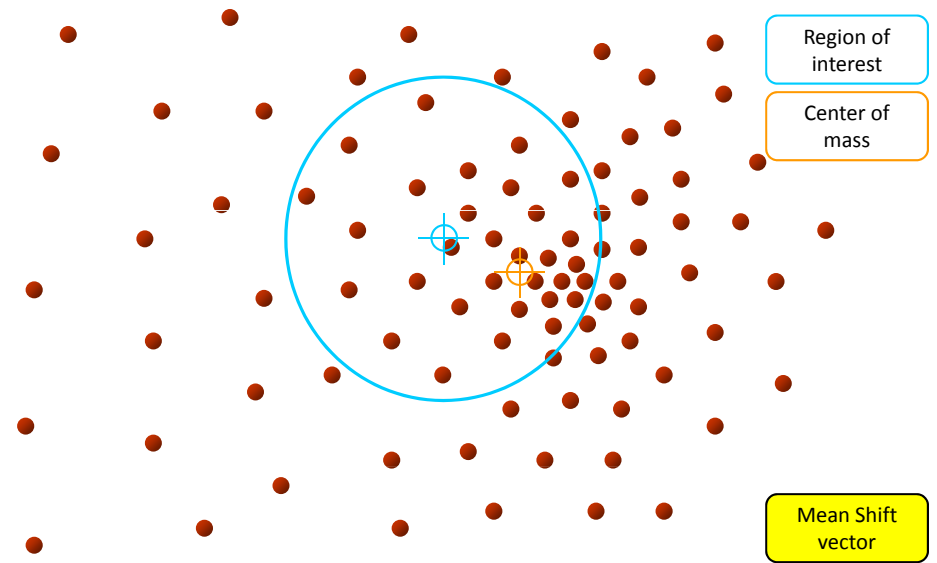


Slide by Y. Ukrainitz &amp; B. Sarel

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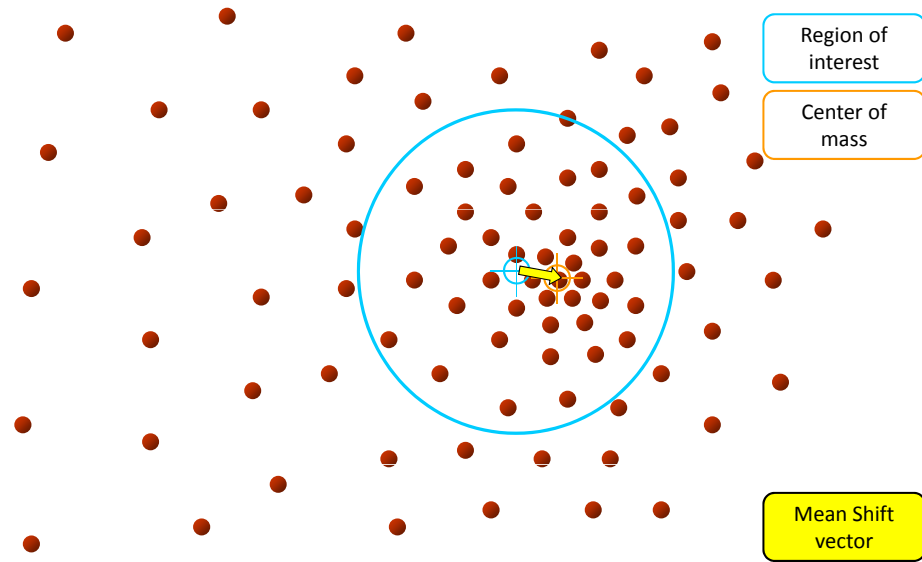


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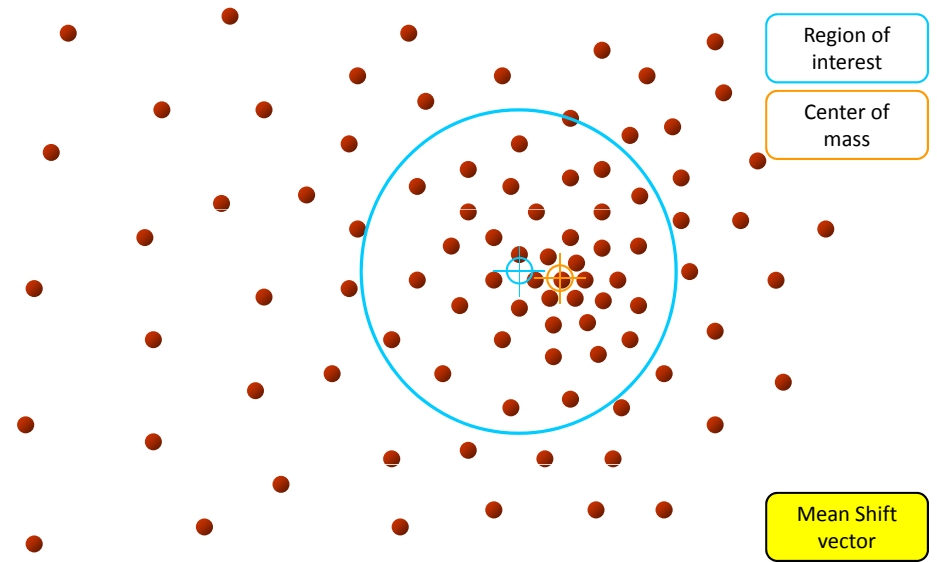


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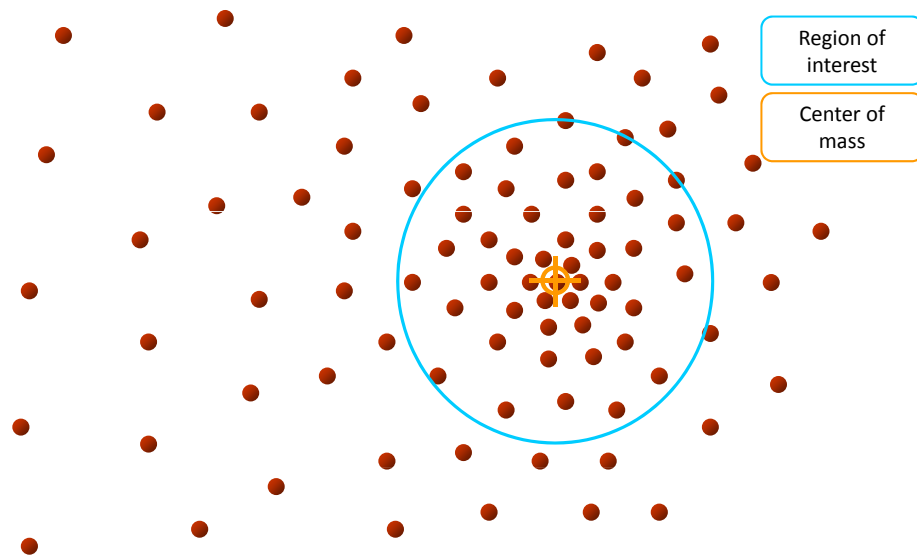


Slide by Y. Ukrainitz &amp; B. Sarel

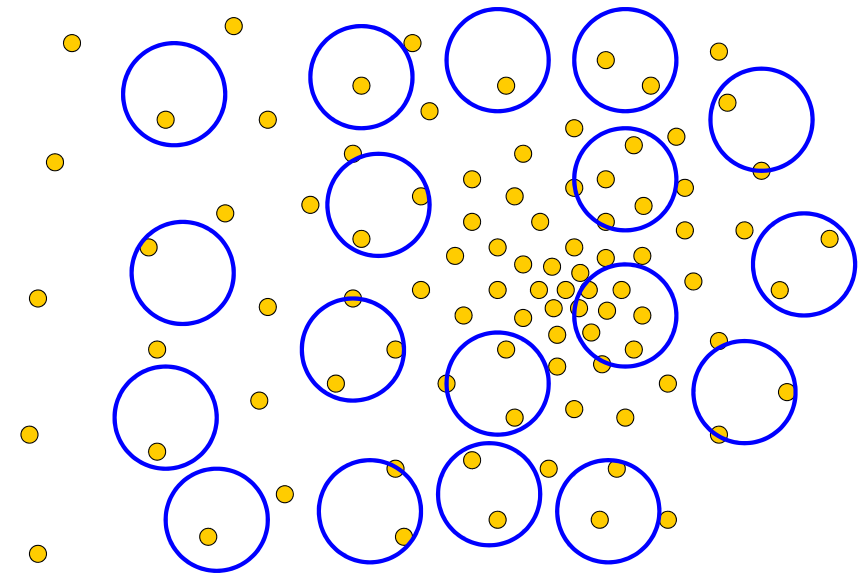
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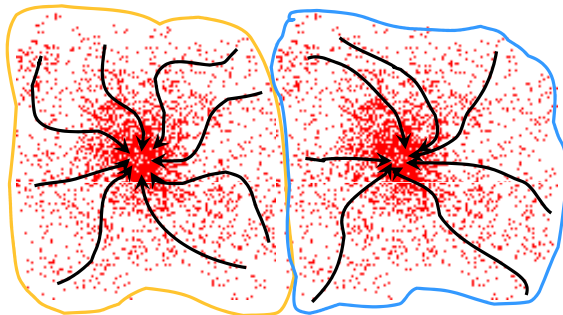


Slide by Y. Ukrainitz & B. Sarel

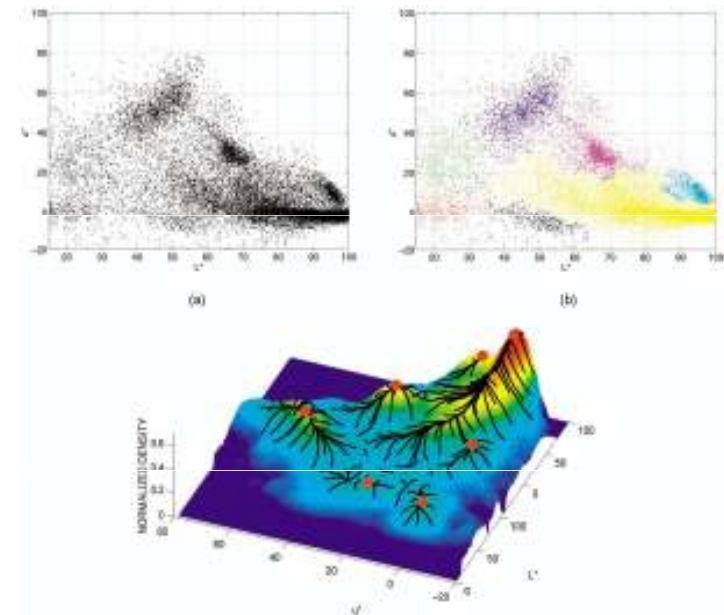


# Attraction Basin

- **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



# Mean-Shift Clustering

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- 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

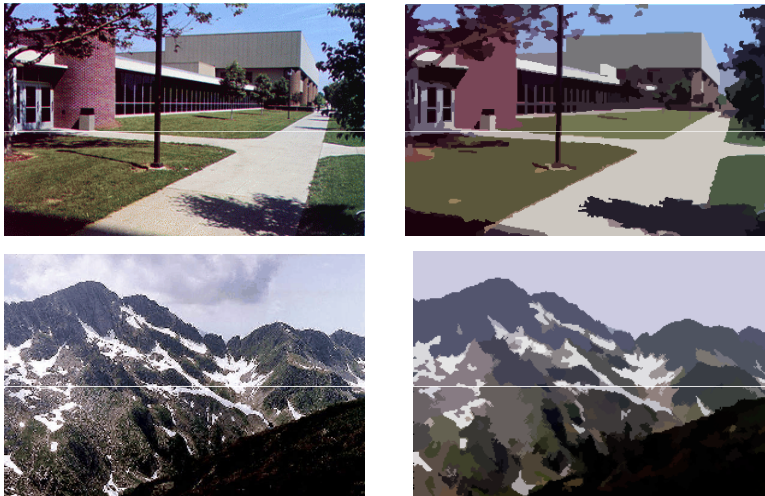
# Segmentation by Mean Shift

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- Compute features for each pixel (color, gradients, texture, etc); also store each pixel's position
- 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 modes that are within width of  $K_f$  and  $K_s$

# Mean-Shift Clustering

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# Mean-Shift Clustering

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# Mean Shift Pros and Cons

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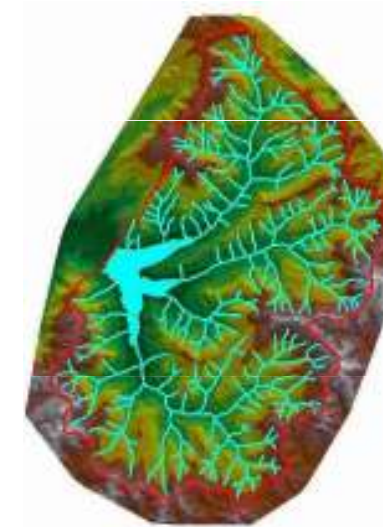
- Pros
  - Good general-purpose segmentation
  - Flexible in number and shape of regions
  - Robust to outliers
- Cons
  - Have to choose kernel size in advance
  - Not suitable for high-dimensional features
- When to use it
  - Oversegmentation
  - Multiple segmentations
  - Tracking, clustering, filtering applications
    - D. Comaniciu, V. Ramesh, P. Meer: [Real-Time Tracking of Non-Rigid Objects using Mean Shift](#), Best Paper Award, IEEE Conf. Computer Vision and Pattern Recognition (CVPR'00), Hilton Head Island, South Carolina, Vol. 2, 142-149, 2000

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# Watershed Algorithm

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# Watershed Segmentation

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Image

Gradient

Watershed  
Boundaries

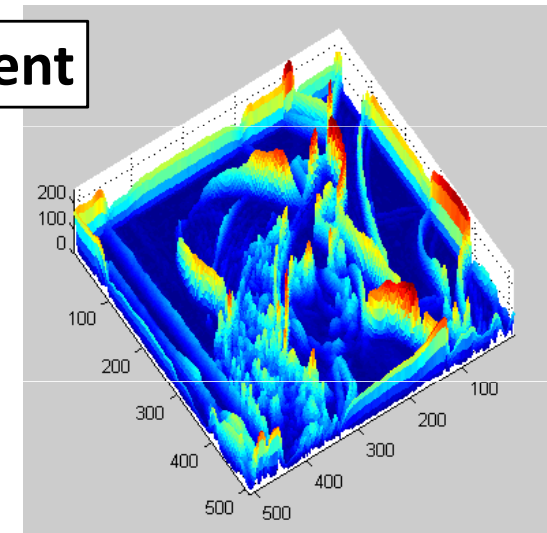
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# Watershed Segmentation

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Gradient



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# Watershed Segmentation

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1. Choose **local minima** as region seeds
2. Add neighbors to *priority queue*, sorted by value
3. Take top priority pixel from queue
  1. If all labeled neighbors have same label, assign that label to pixel
  2. Add all non-marked neighbors to queue
4. Repeat step 3 until finished (all remaining pixels in queue are on the boundary)

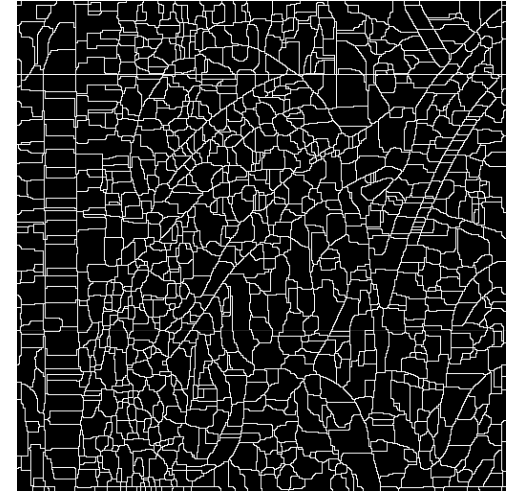
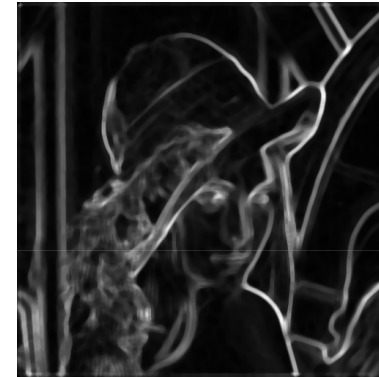
Meyer 1991

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Use Gaussian or median filter to reduce number of regions

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# Watershed Pros and Cons

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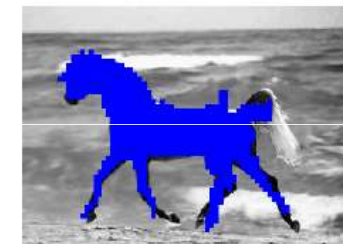
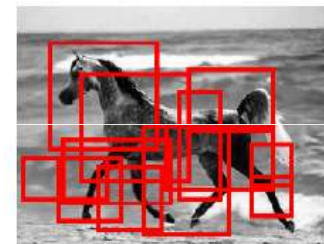
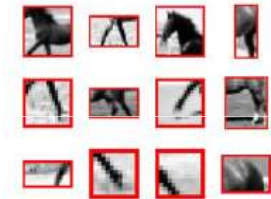
- Pros
  - Fast
  - Preserves boundaries
- Cons
  - Only as good as the soft boundaries
  - Not easy to get variety of regions for multiple segmentations
- Usage
  - Use as a starting point for hierarchical segmentation

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# Class-Specific Top-Down Segmentation

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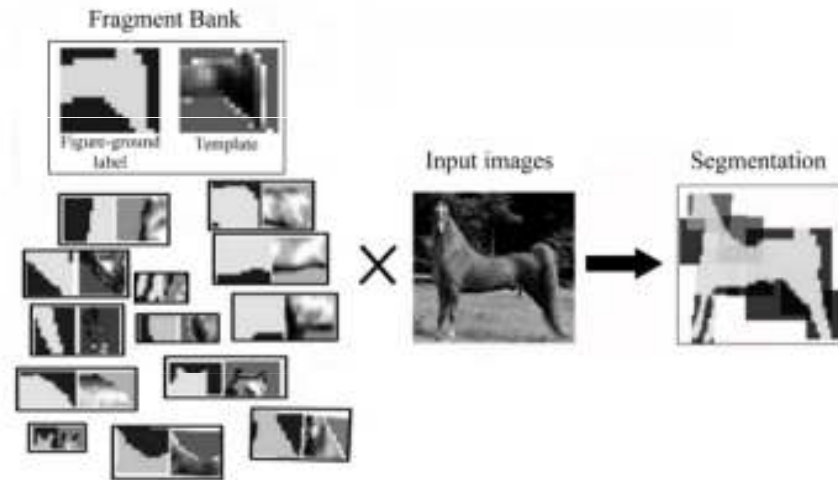


Eran Borenstein, et al.

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# Class-Specific Top-Down Segmentation



Eran Borenstein, et al.