Segmentation and Clustering (Part 3)

This Lecture

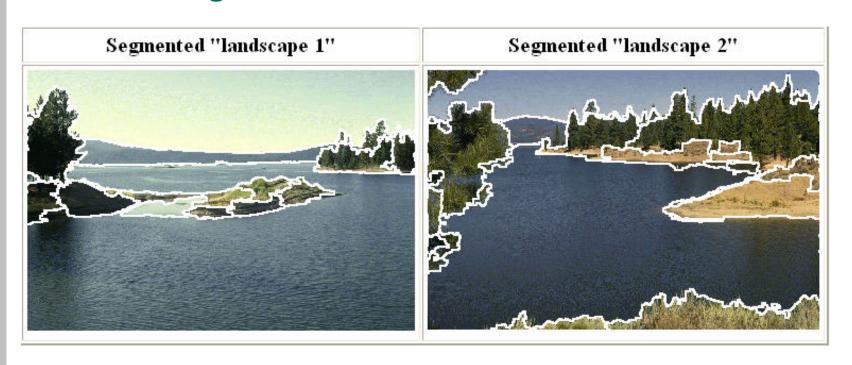
- Segmentation and grouping
 - Gestalt principles
 - Image segmentation
- Segmentation as clustering
 - k-Means
 - Feature spaces
- Probabilistic clustering
 - Mixture of Gaussians, EM
- Model-free clustering
 - Mean-Shift clustering
- Graph theoretic segmentation
 - Normalised cuts



The University of Manchester

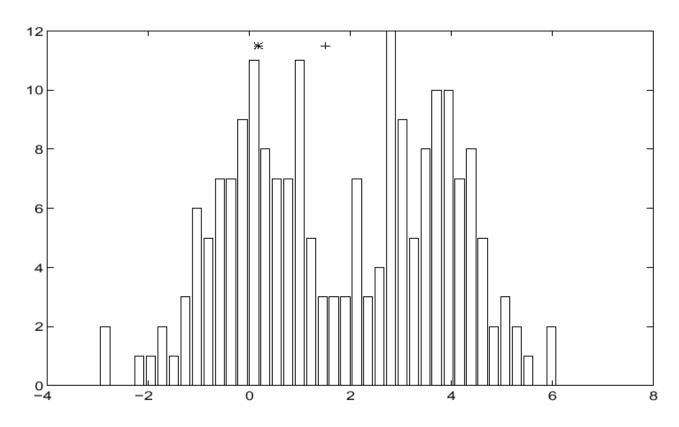
Mean-Shift Segmentation

 An advanced and versatile technique for clusteringbased segmentation



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

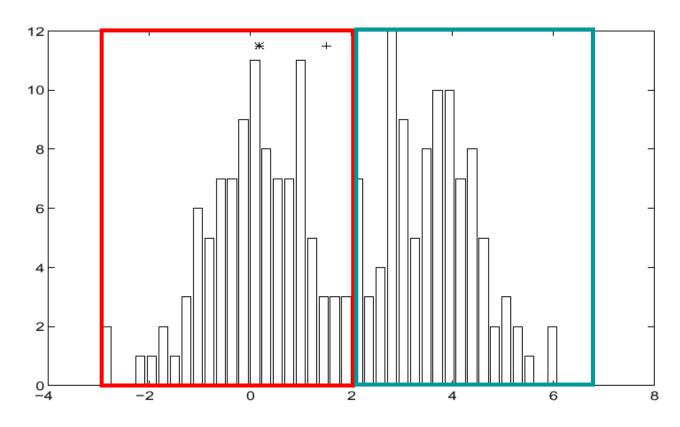
Finding Modes in a Histogram



• How many modes are there?

- Mode = local maximum of the density of a given distribution
- Easy to see, hard to compute

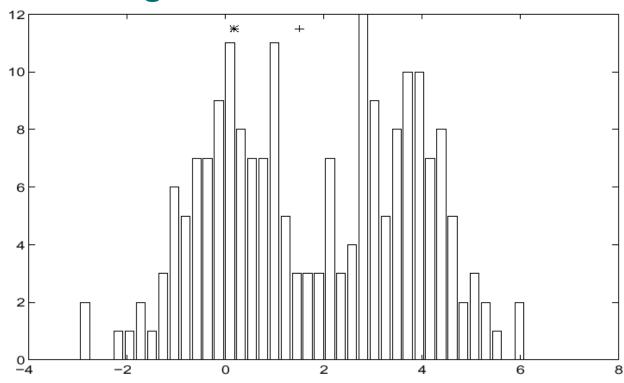
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Mean-Shift Algorithm

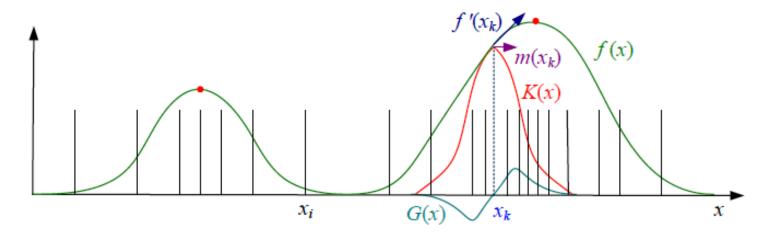


Iterative Mode Search

- Initialise random seed, and window W
- $\sum xH(x)$ Calculate centre of gravity (the "mean") of W: $x \in W$
- Shift the search window to the "mean"
- Repeat Step 2 until convergence



Mean-Shift and mode finding

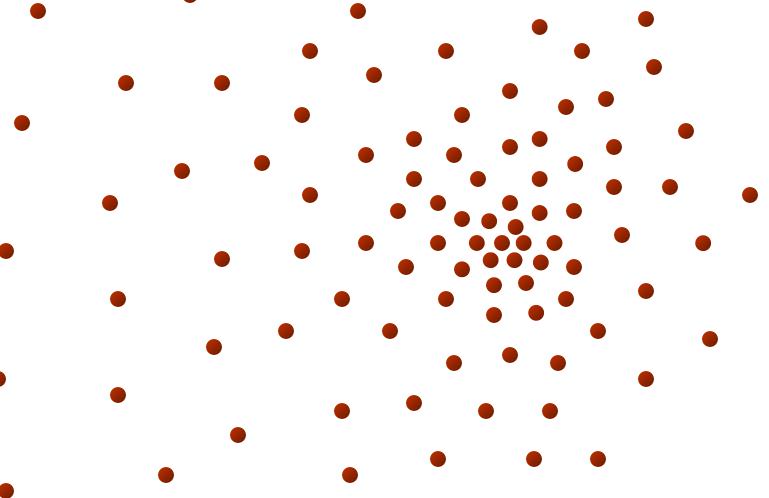


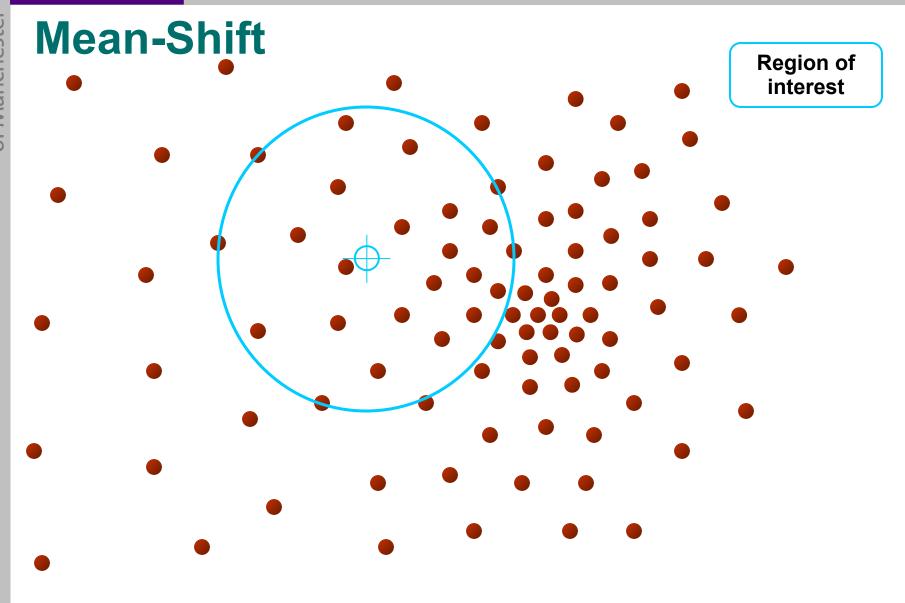
One-dimensional visualization of kernel density estimate, its derivative, and a mean shift.

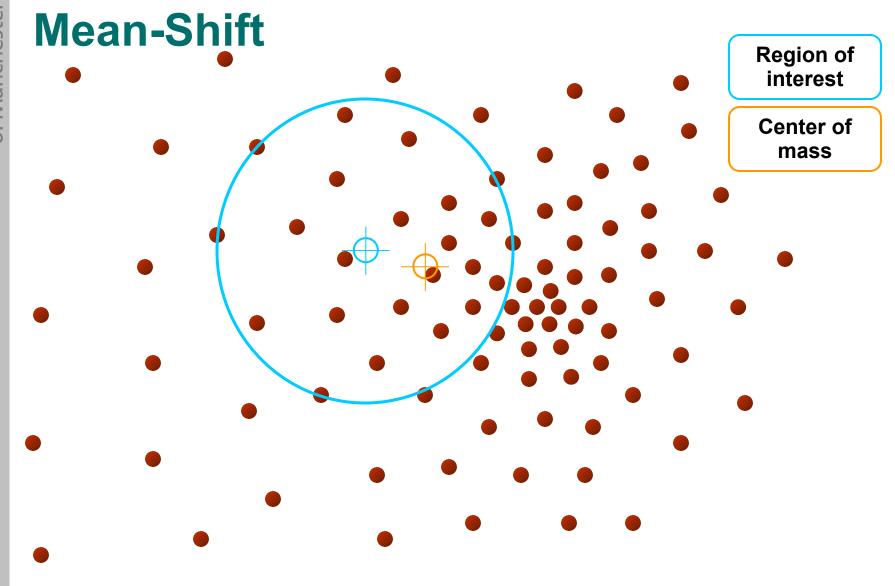
Further details:

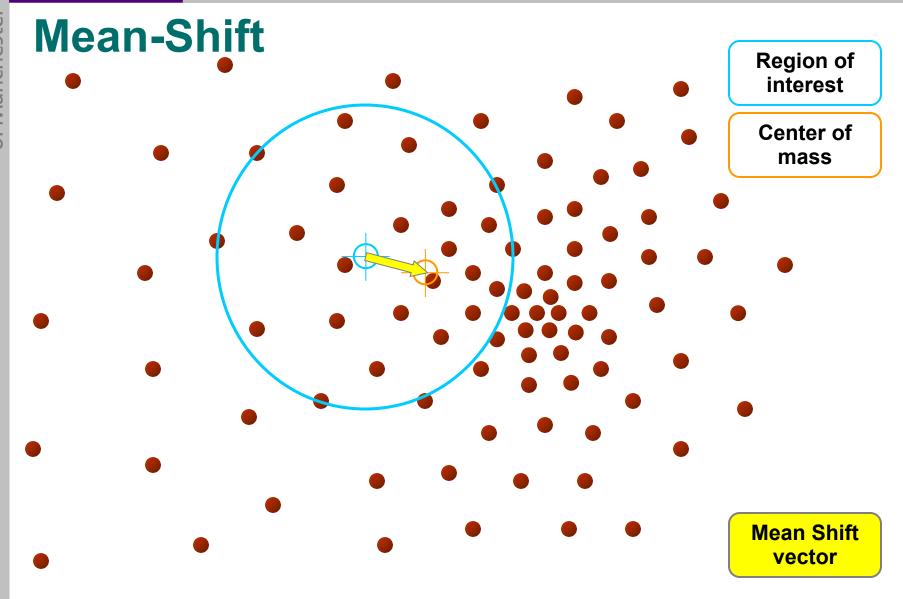
- Parzen window or kernel approach to probability density estimation:
 - Duda, Hart, and stork 2001, section 4.3
 - Bishop 2006, section 2.5.1
- D. Comaniciu and P. Meer, <u>Mean Shift: A Robust Approach toward Feature Space</u> <u>Analysis</u>, PAMI 2002 (copy on blackboard)

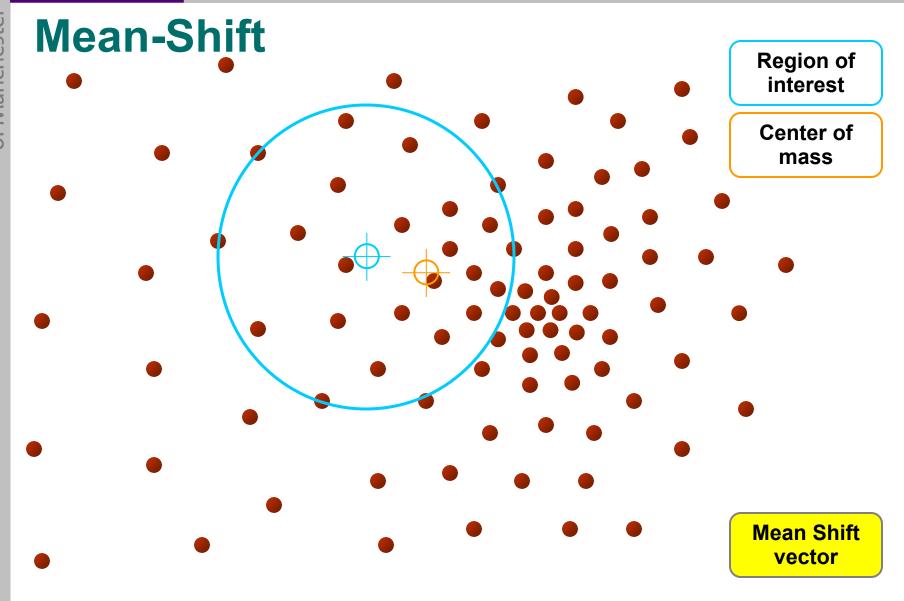
Mean-Shift

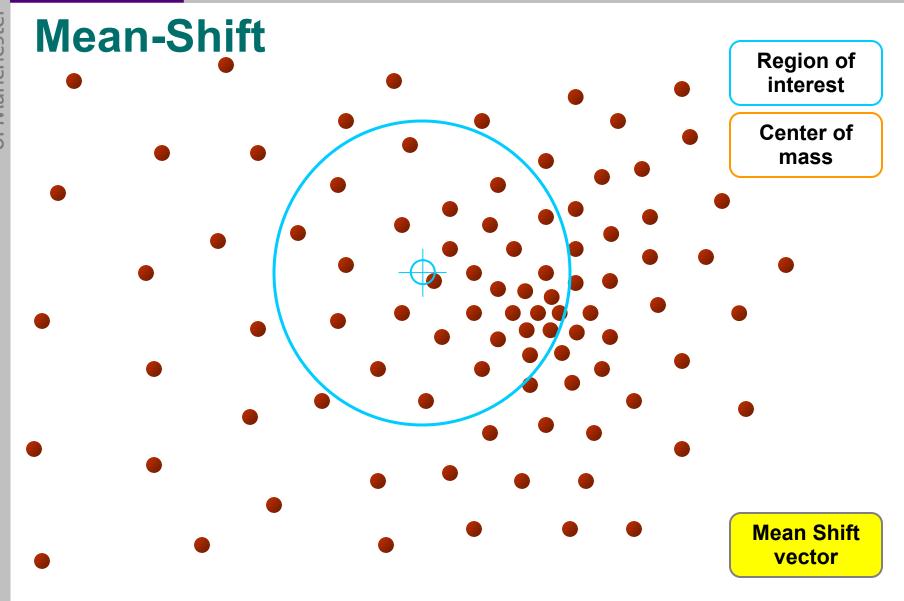


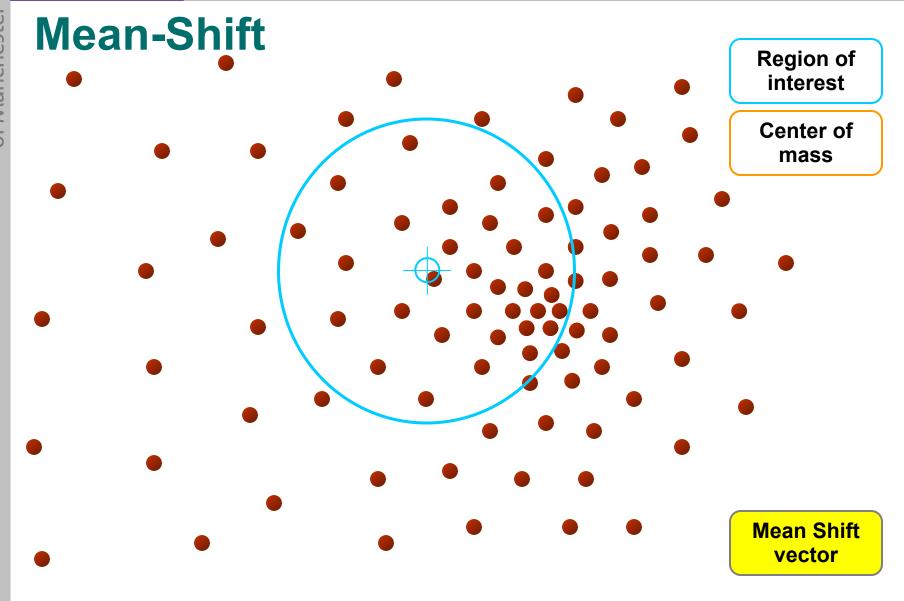


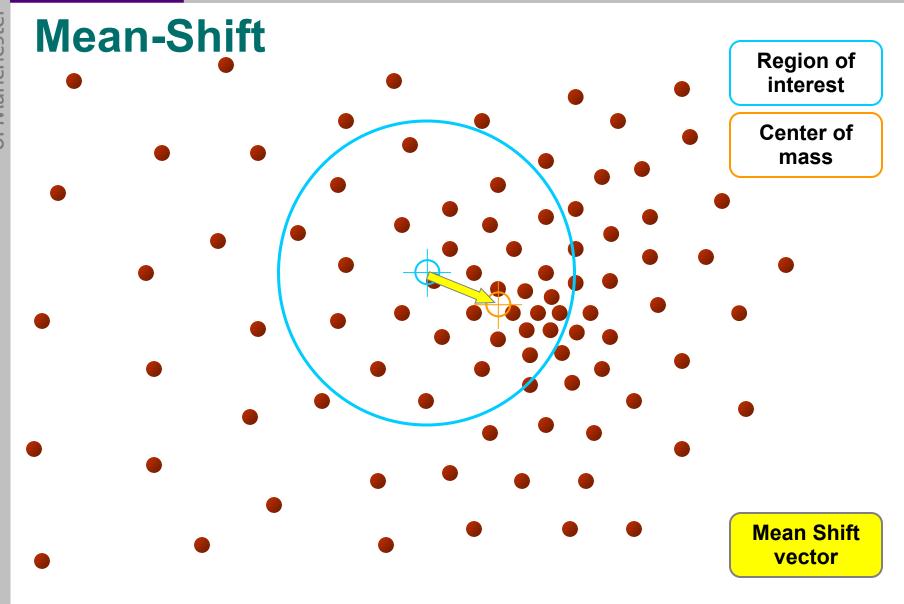


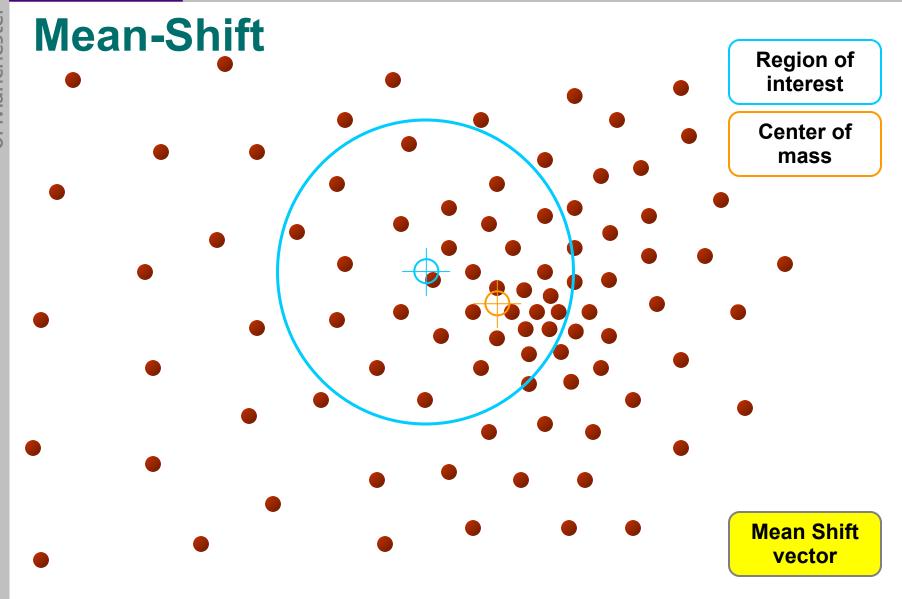


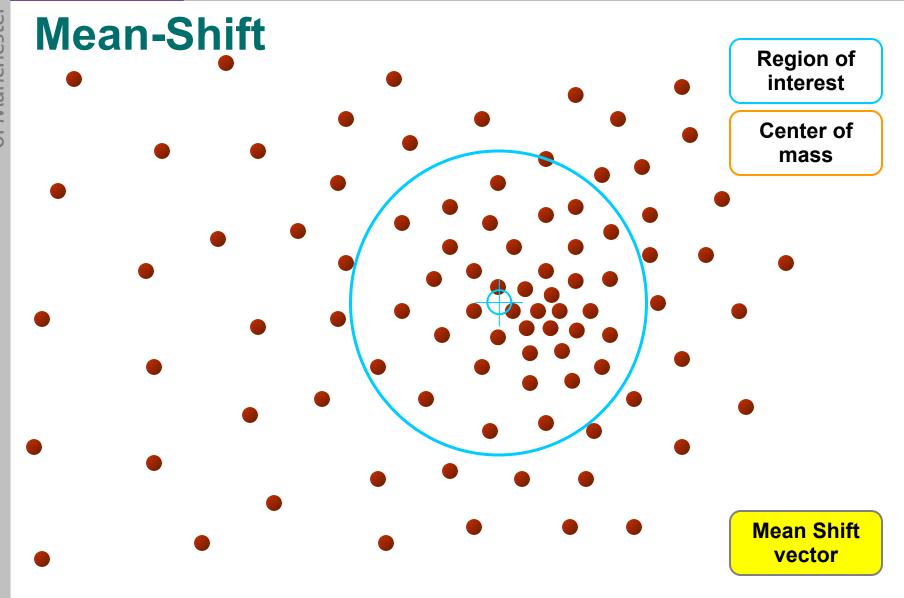


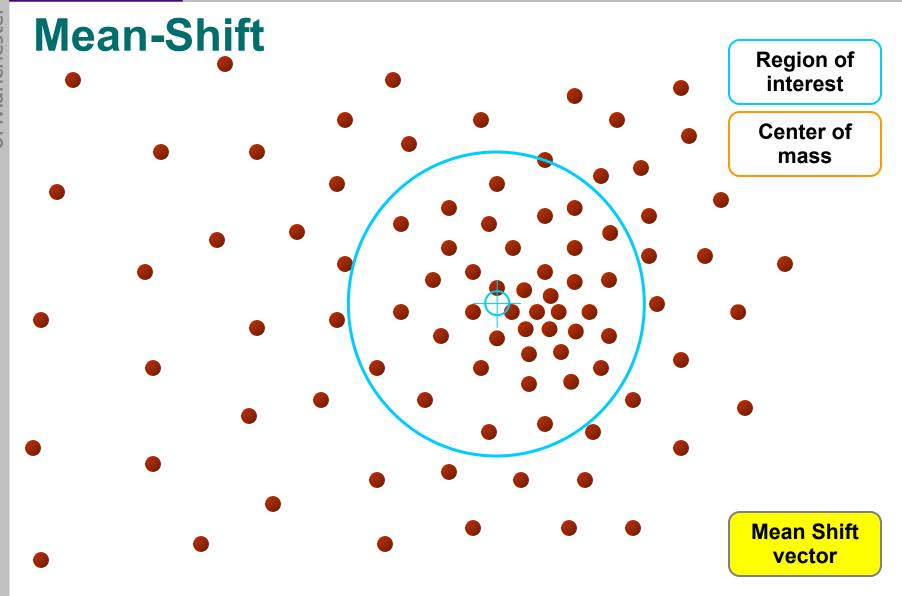


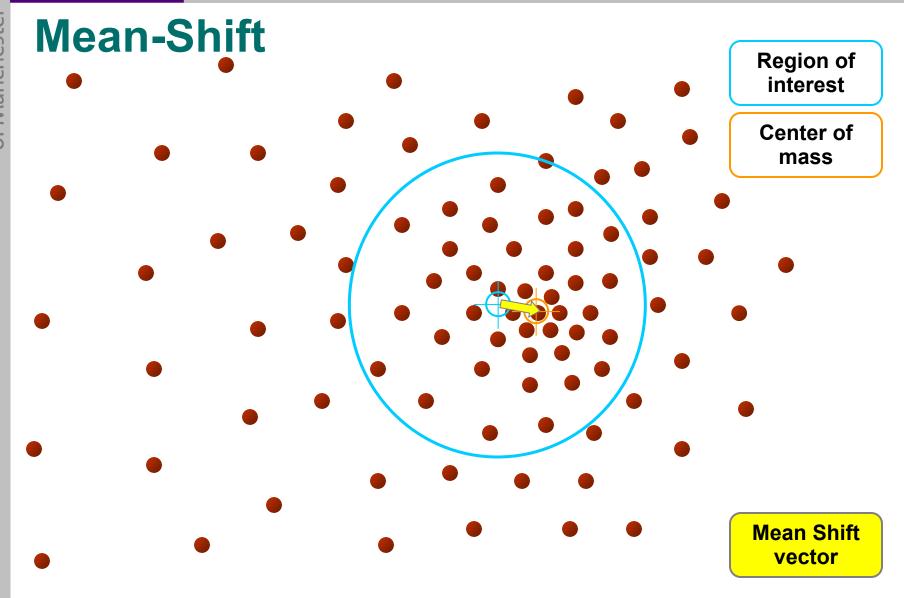


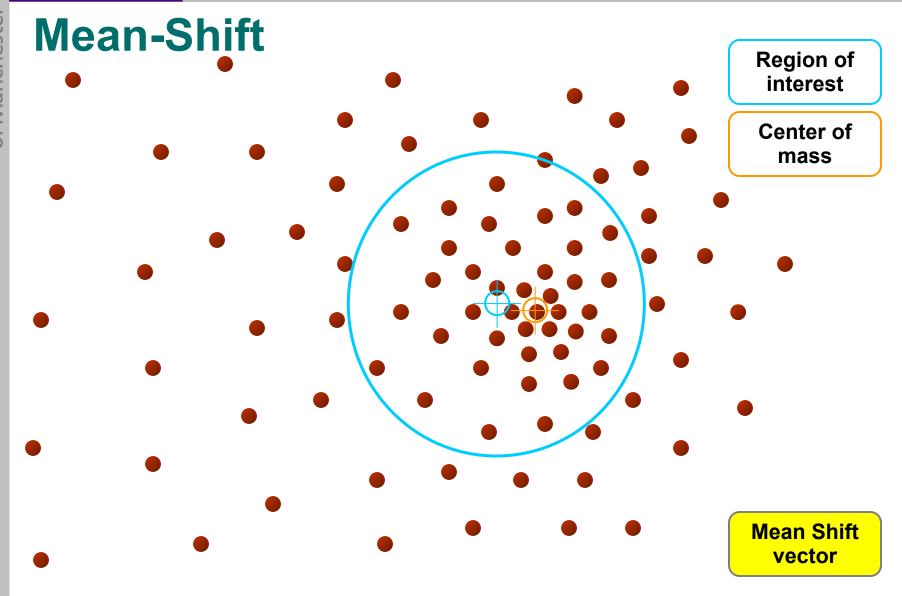


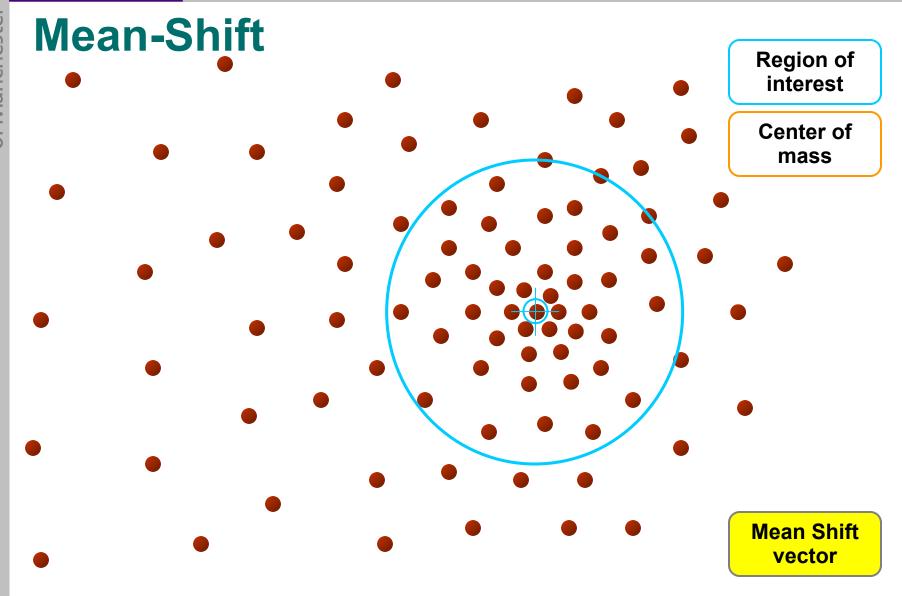


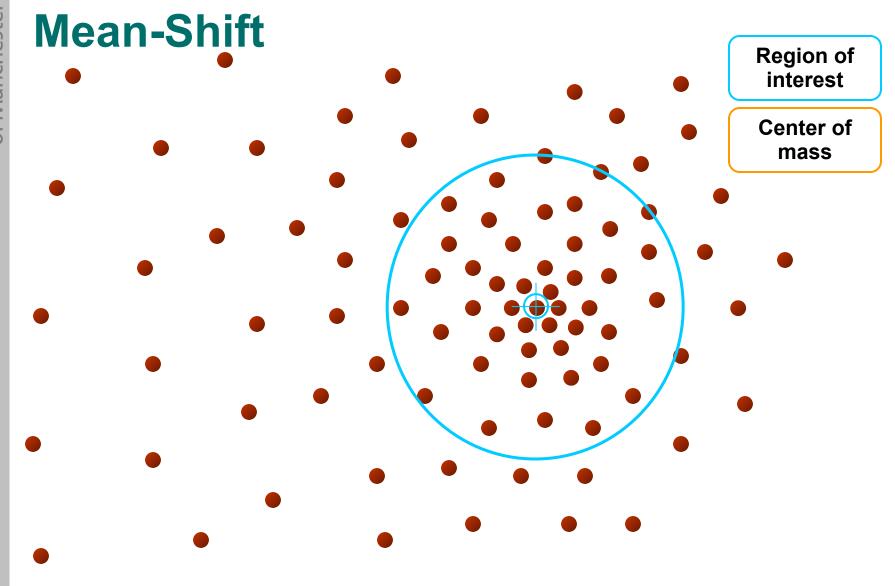


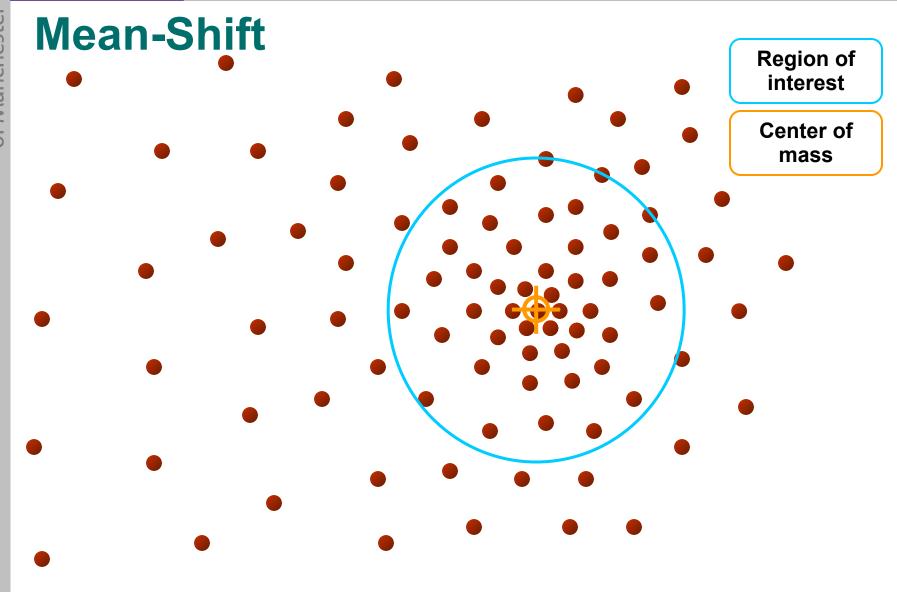




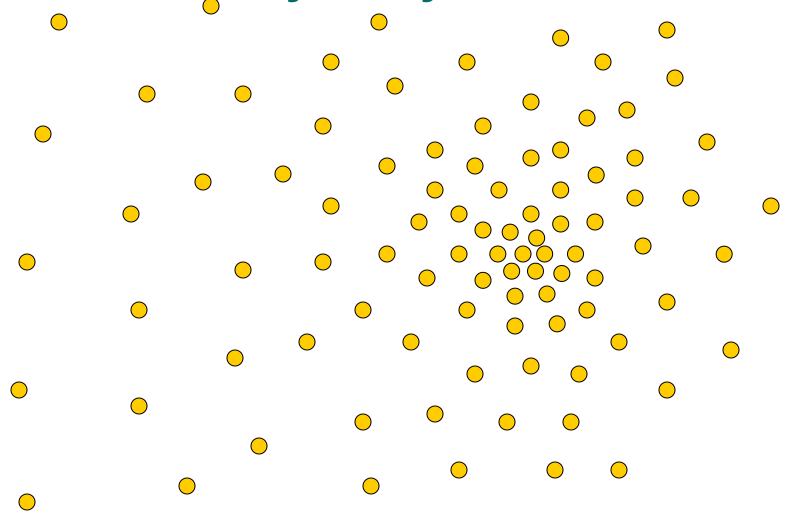


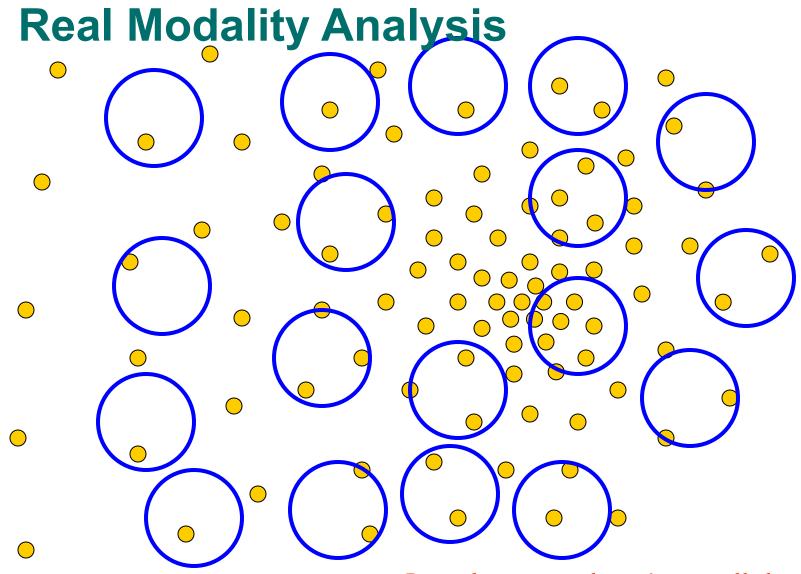




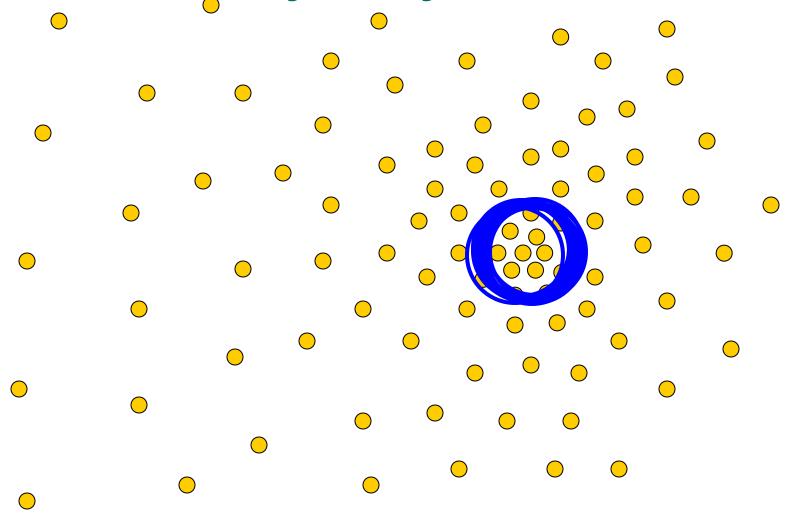






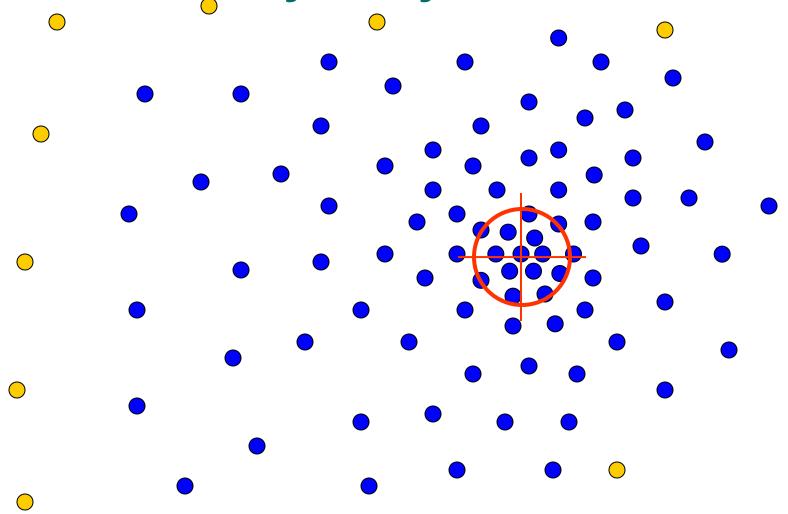


Run the procedure in parallel



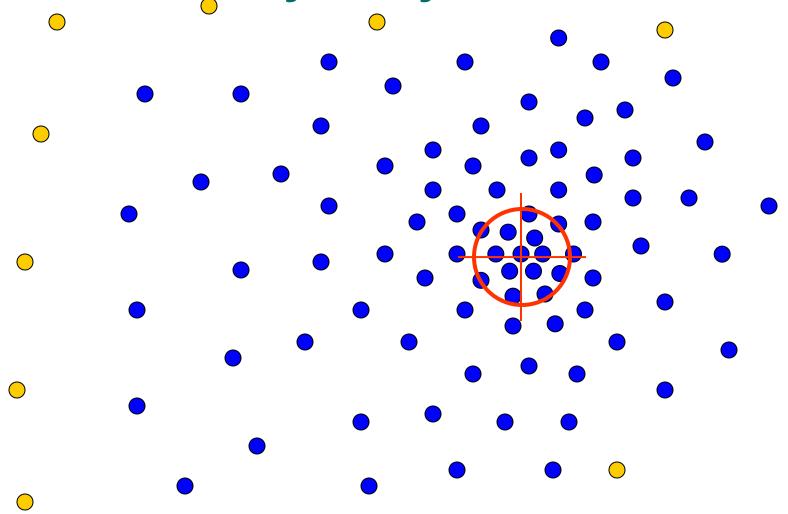
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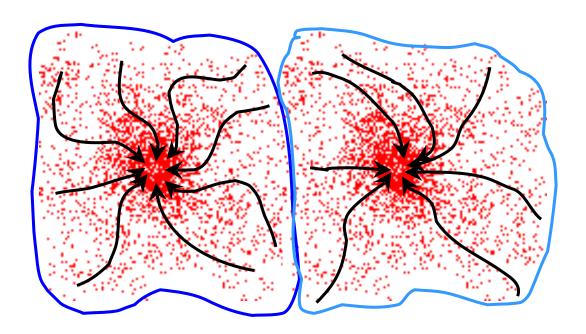




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Mean-Shift Clustering

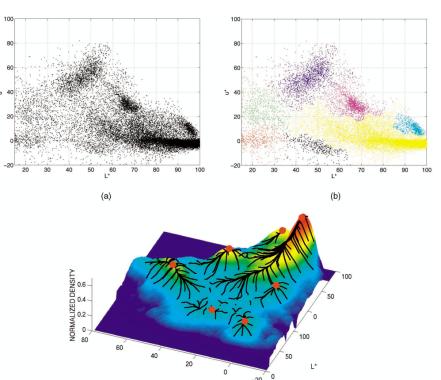
- Cluster: all data points in the attraction basin of a mode
- Attraction basin: the region for which all trajectories lead to the same mode



Mean-Shift Clustering/Segmentation

- Find features (colour, 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









D. Comaniciu and P. Meer, <u>Mean Shift: A Robust Approach toward Feature Space</u>
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- Does not scale well with dimension of feature space

Today's Lecture

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 - Gestalt principles
 - Image segmentation
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Reading



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Forsyth, Ponce: Chapter 14

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- D. Comaniciu and P. Meer, <u>Mean Shift: A Robust Approach toward</u> <u>Feature Space Analysis</u>, PAMI 2002 (copy on blackboard)