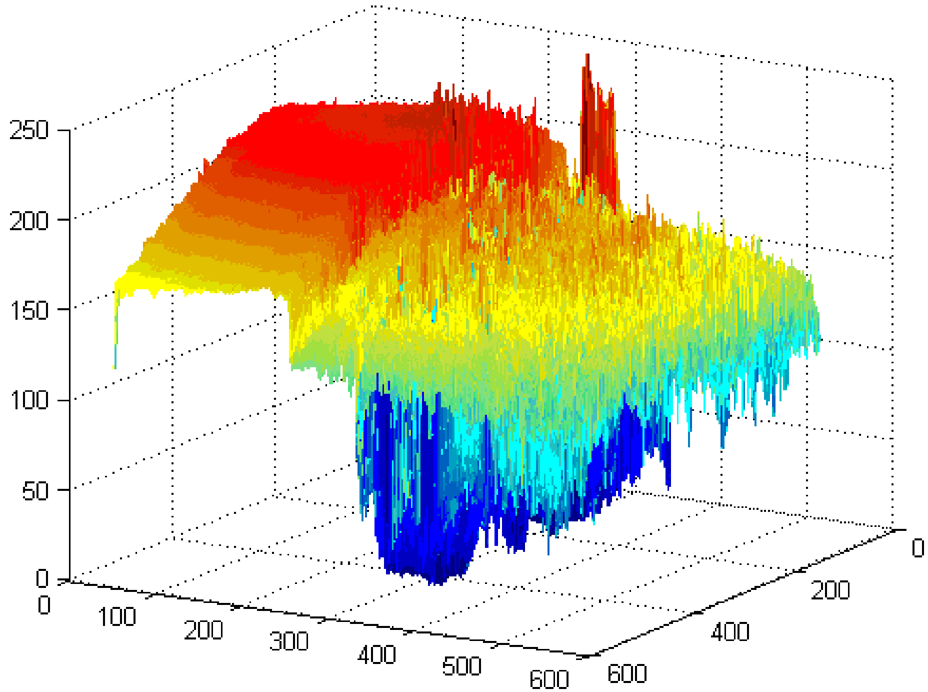
数字图像处理
Digital Image Processing

彩色图像分割
Color Image Segmentation

彩色图像分割及处理

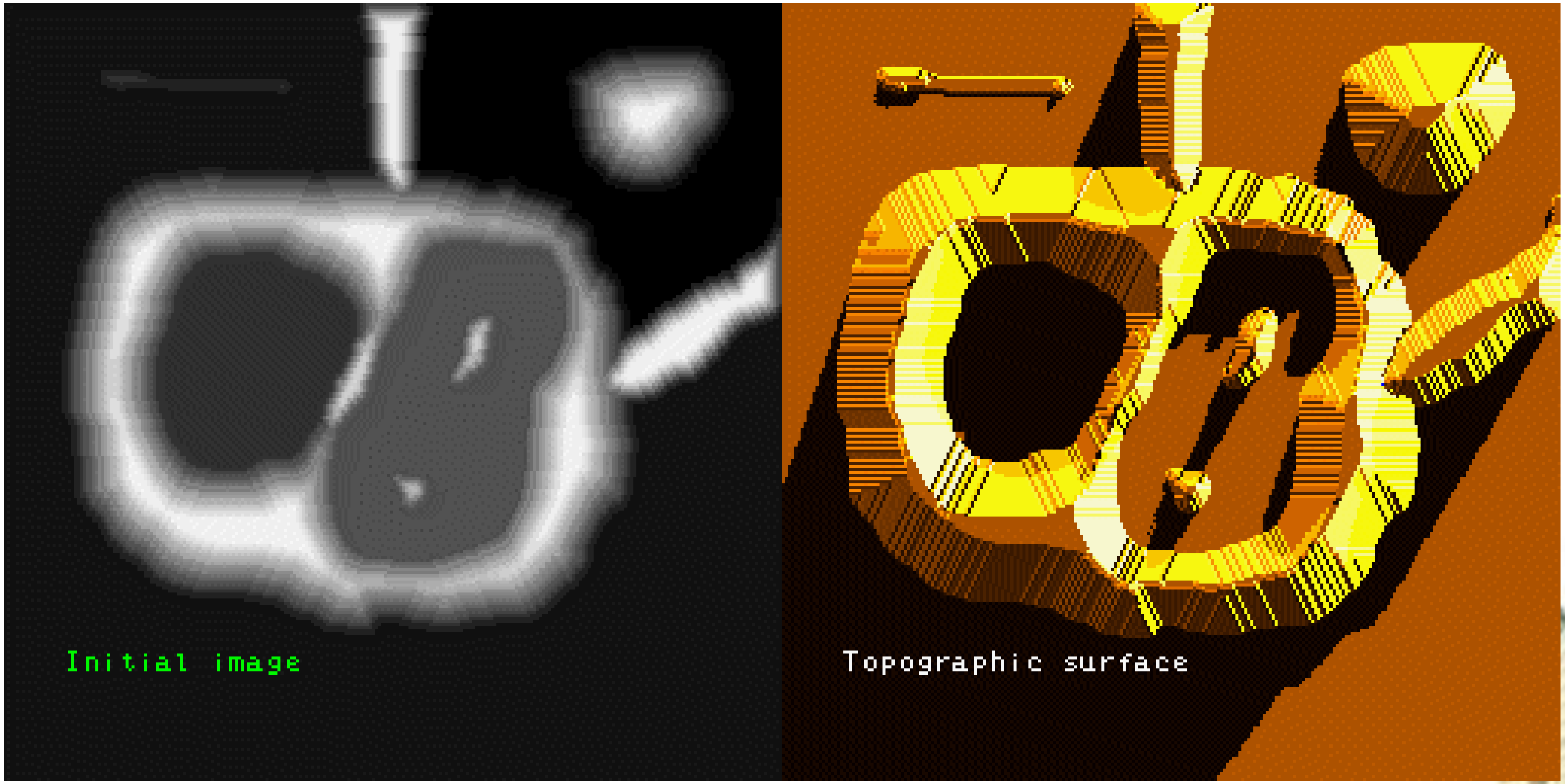
1. 分水岭算法
2. Mean shift分割
3. Normalized cuts(Ncuts)分割
4. Ncuts分割改进算法

分水岭算法
Watershed algorithm

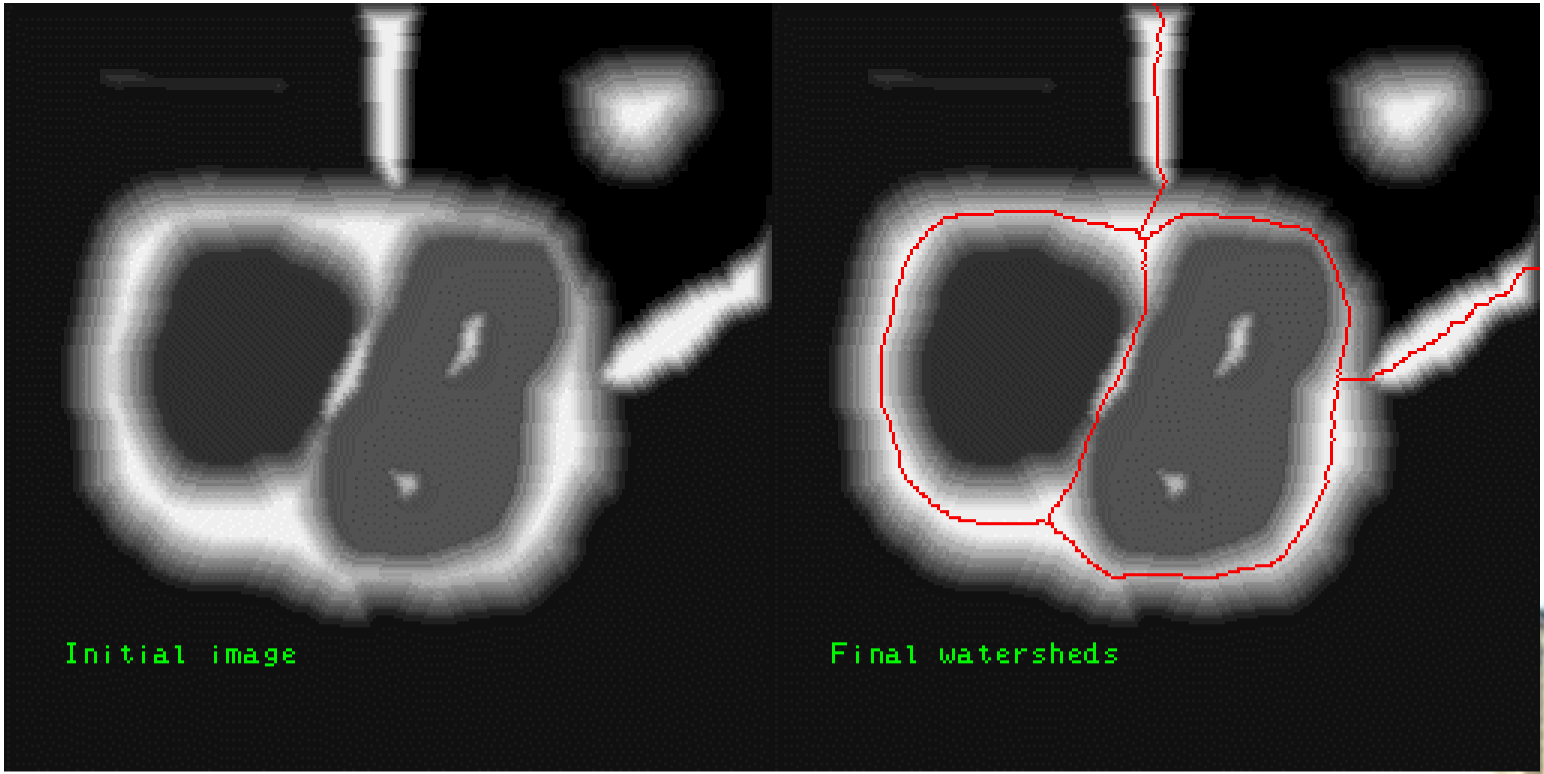


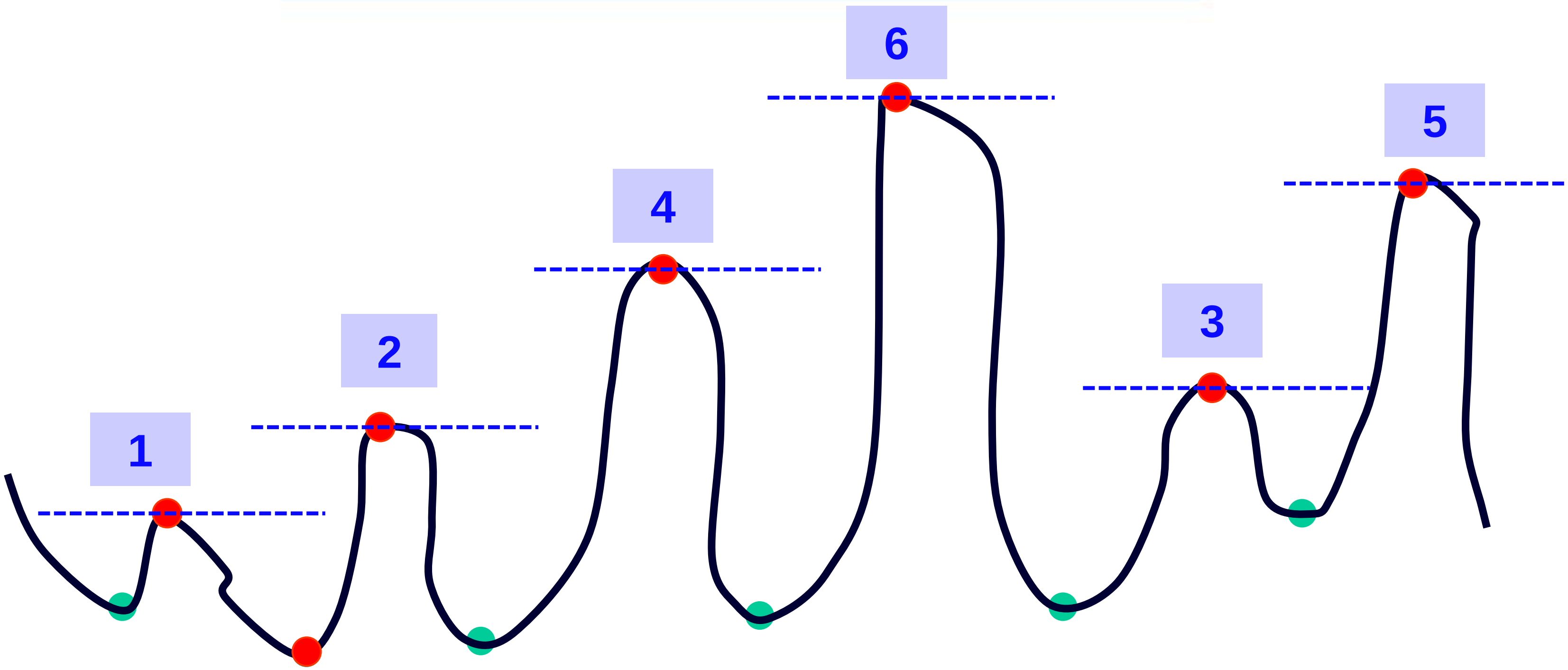
分割原理

(1) 任何的灰度级图像都可以被看做是一个地形图



(2) 假设我们在每个区域最小值位置地方打个洞, 让水以均匀的速度上升, 从低到高淹没整个地形. 当处在不同的汇聚盆地中的水将要聚合在一起时, 修建大坝将阻止聚合, 最后得到的水坝边界就是分水岭的分割线.





- 获取**局部极小**
- 统计**连通分量**
- 以最小的局部极小为基准**提升高度**
- 如果出现某两个连通分量合并，则**记录分界线**
- 逐渐提升高度，直至整个图像**合并一个连通分量**
- 记录的所有的分界线即为**分割边界**

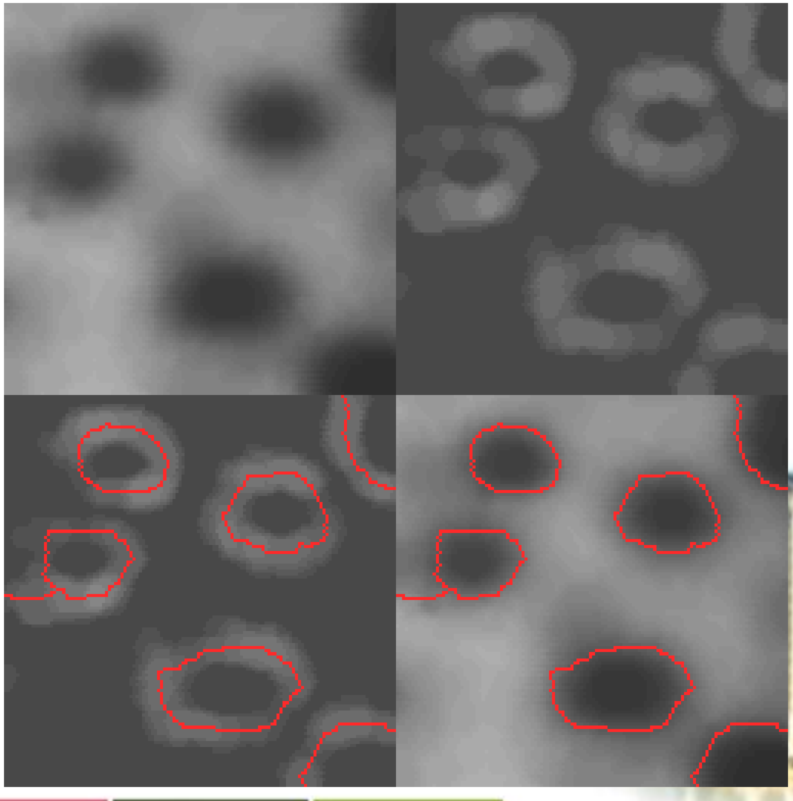
递归过程

◆ 分水岭算法用于梯度图像

分水岭方法应用在梯度图像，那么集水处对应灰度变化最小的区域，而分水岭对应灰度变化相对最大的区域。

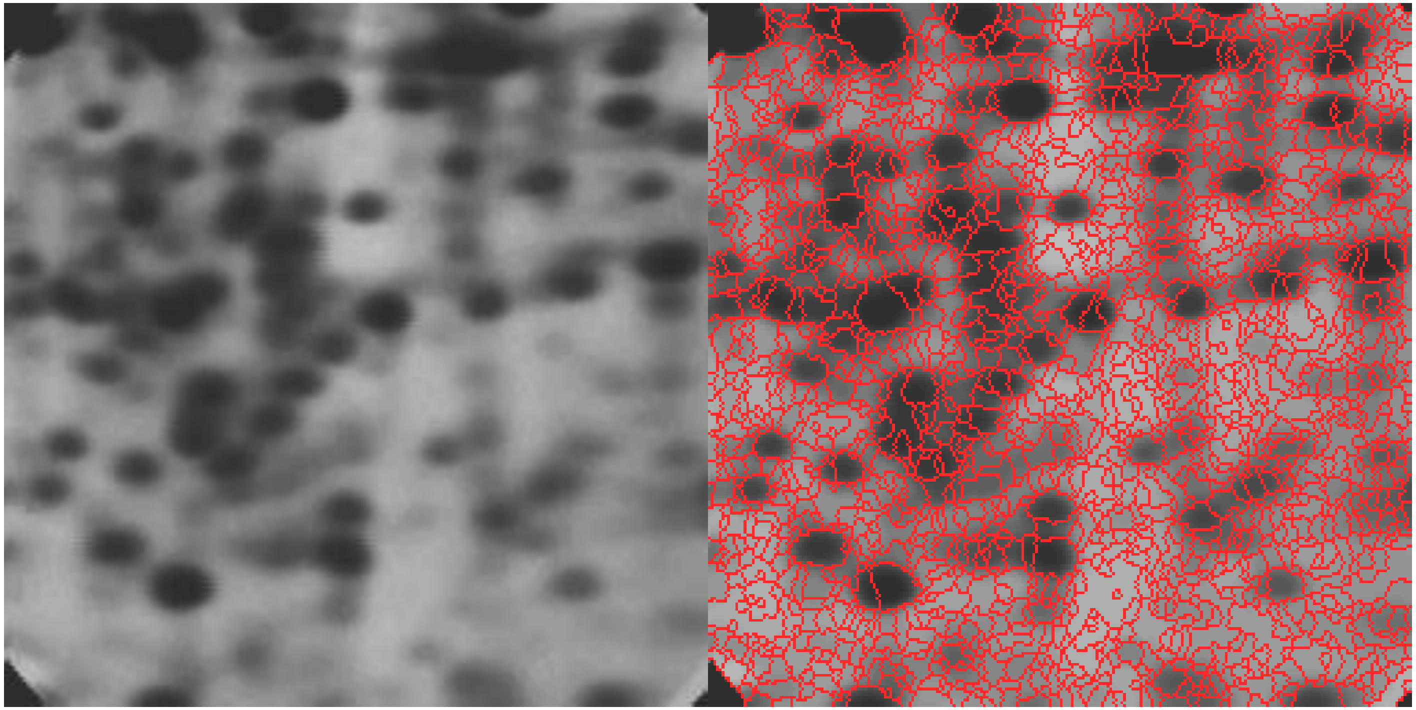
从上到下, 从右到左

- 原始图
- 梯度图
- 梯度图的分水岭
- 最终轮廓



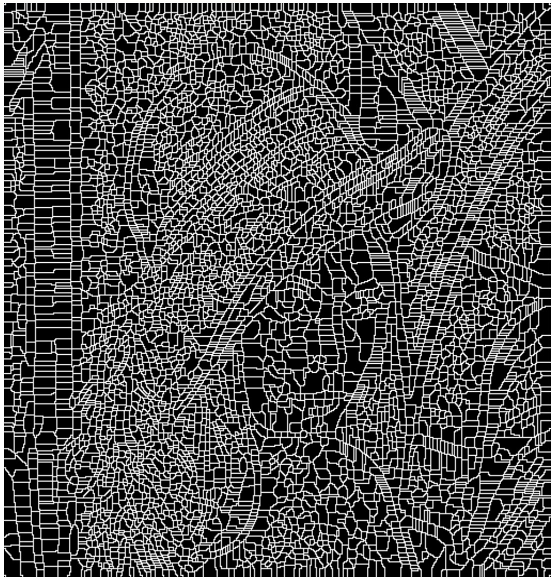
➢ 分水岭由于噪声或者局部不规则而引起”过度分割”

电泳凝胶图像与经过分水岭转变的分割图

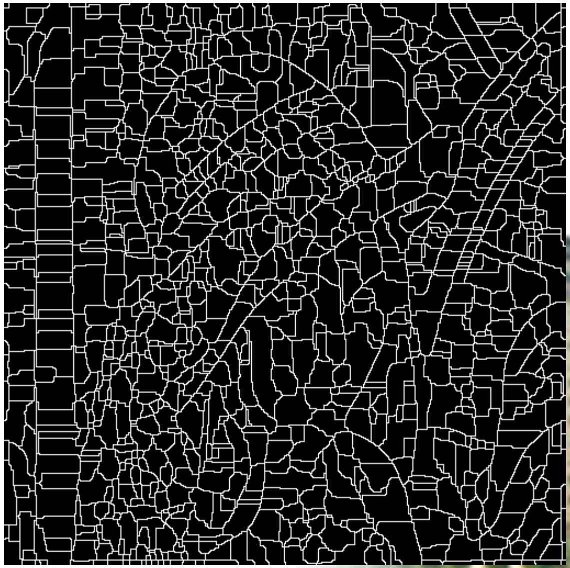


Image

Gradient



Old Watershed



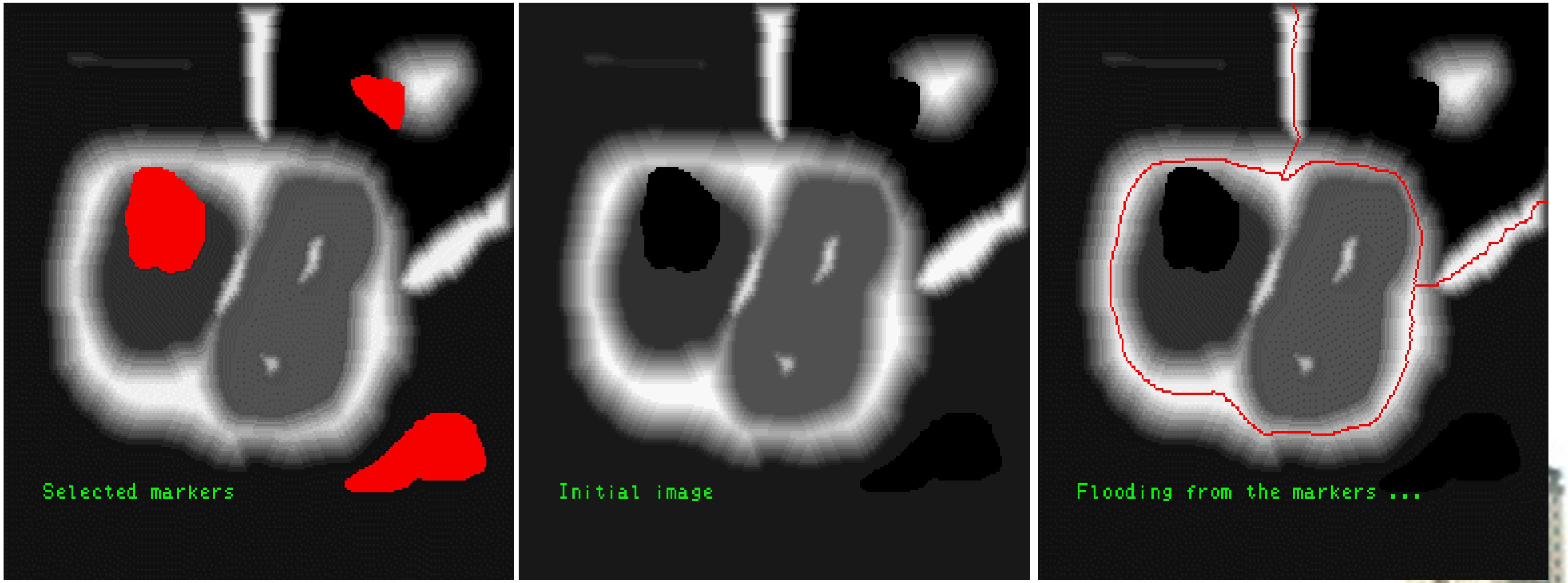
New Watershed

◆ 分水岭之前平滑去燥

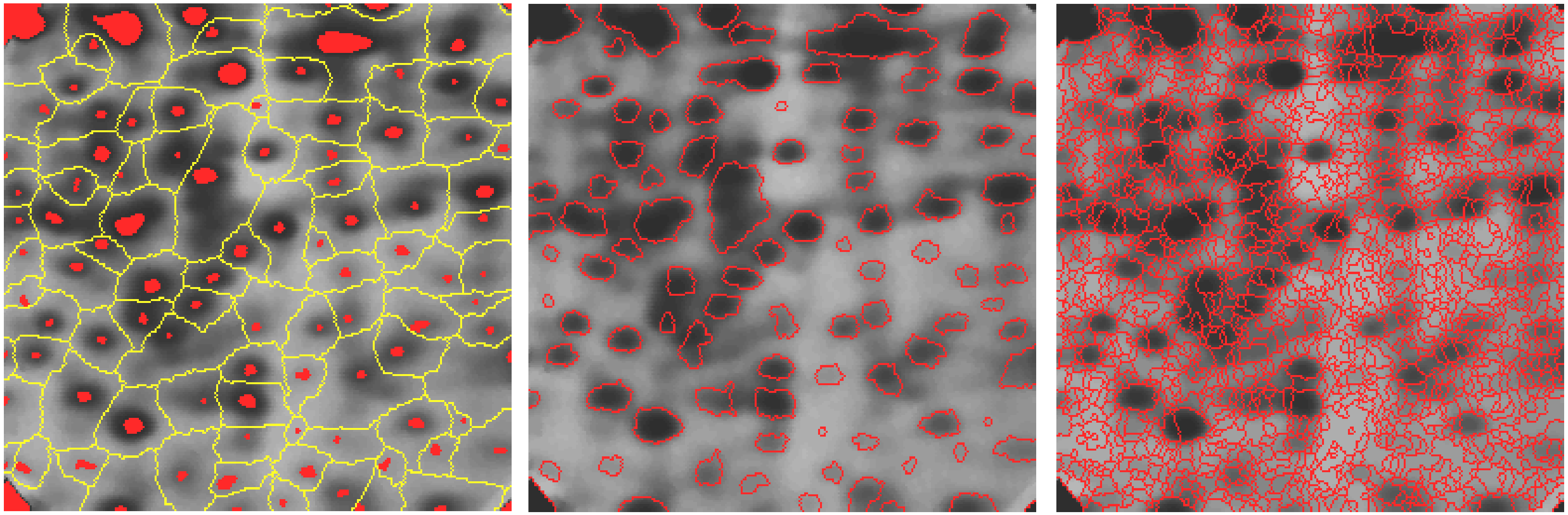
采用高斯滤波或者中值滤波先处理去掉一些局部极小，减少区域个数

◆ 标记约束分水岭算法

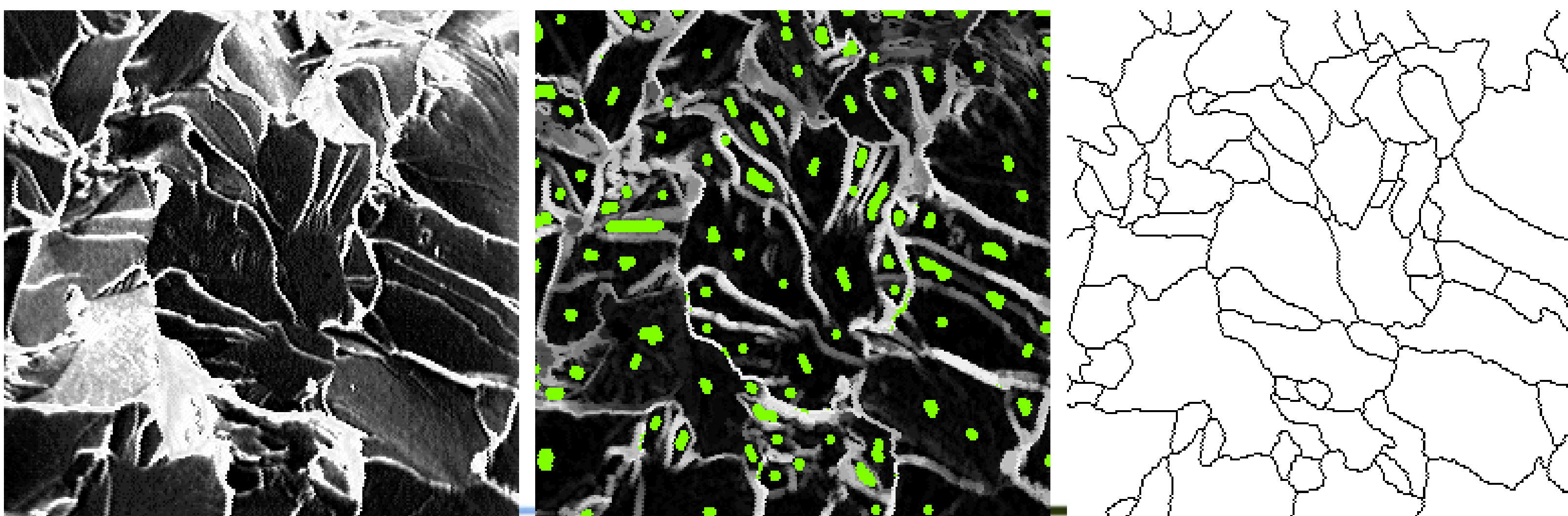
从先前已经定好的区域开始浸水，防止过度分割



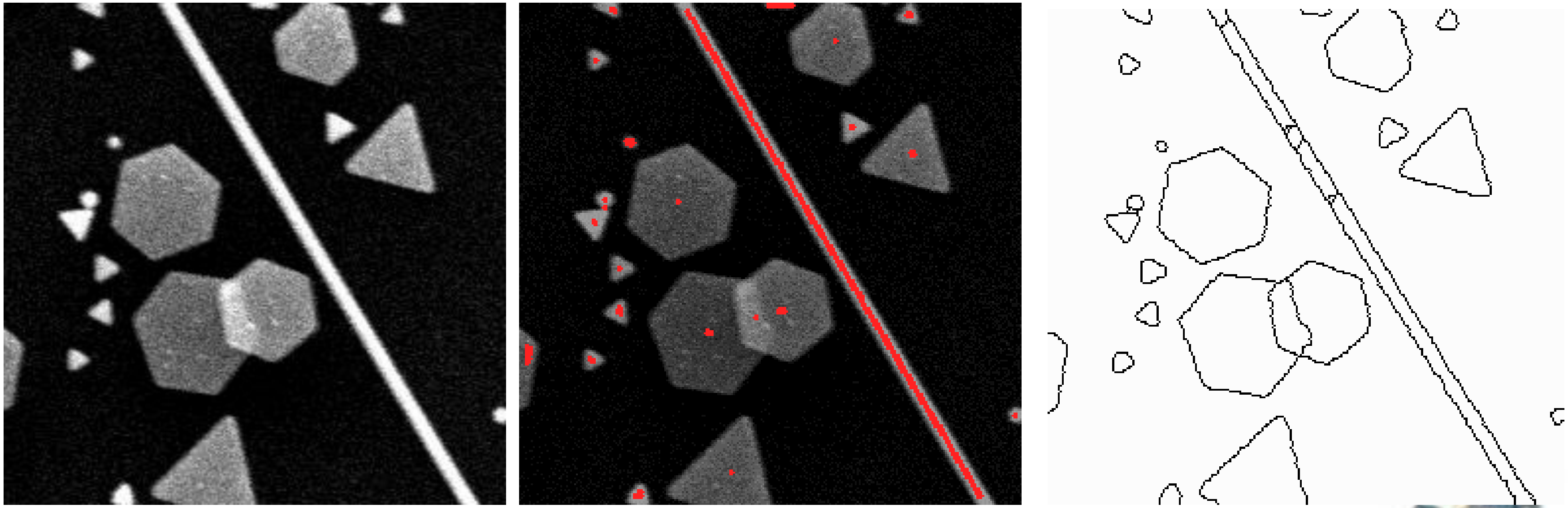
电泳凝胶图像与经过标记约束分水岭转变的分割图



钢的断裂面的提取



银色木纹的提取



◆ 分级分割

- 通过分分水岭算法，得到一张初始的分割图片

- 以这些相对高度为基础，再次用分水岭算法，可达下一级的分割图如下

Meyer(1991)分水岭分割算法

1. 选择所有局部最小作为区域种子
2. 将其所有邻域点加到优先级队列，按照值的大小排序
3. 从队列中取出优先级最高的像素点：
   1. 如果该像素所有的被标记的邻域点都有相同的标记，那么就把这个标记给该像素
   2. 将它的所有未被标记的点加入优先级队列
4. 重复步骤3直到结束

Matlab: seg = watershed(bnd_im)

分水岭分割算法的优点和缺点

- 优点
  - Fast (< 1 sec for 512x512 image)
  - Among best methods for hierarchical segmentation
- 缺点
  - 容易“过分割”
  - No top-down information
- Usage
  - Preferred algorithm for hierarchical segmentation

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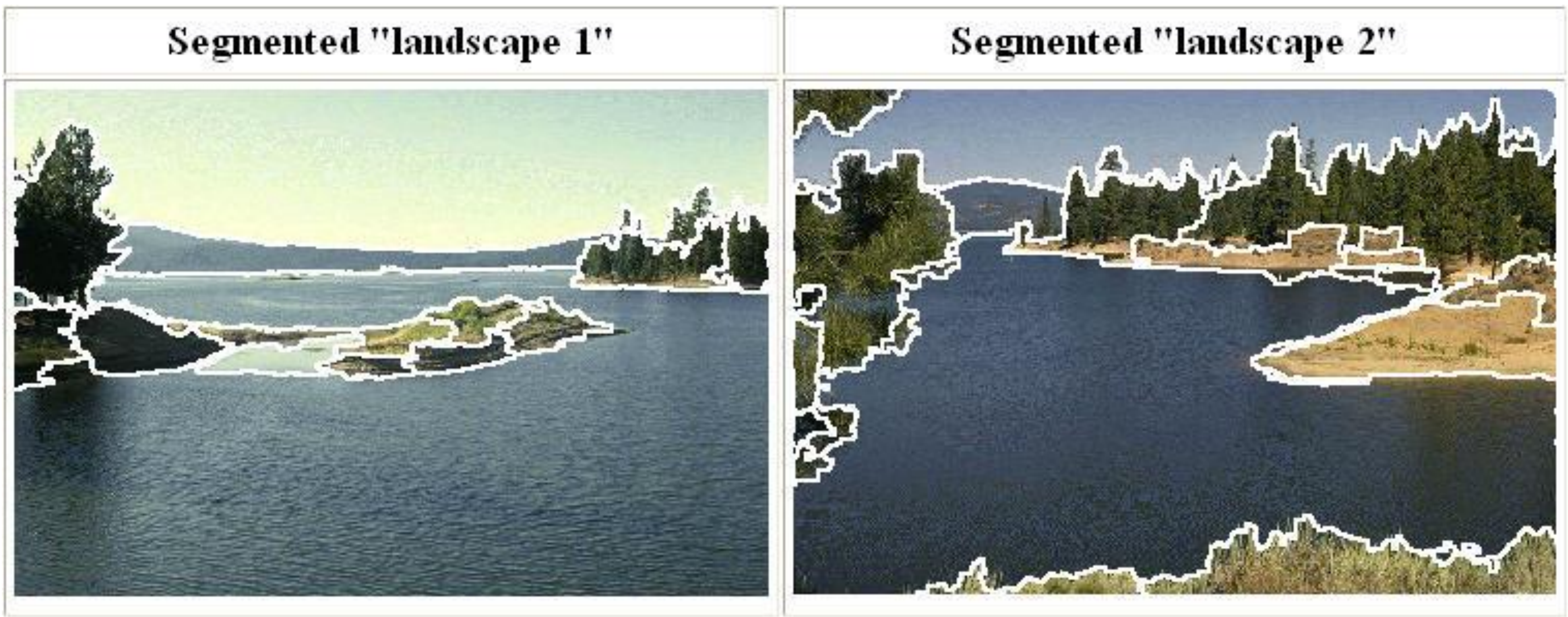
Mean shift segmentation

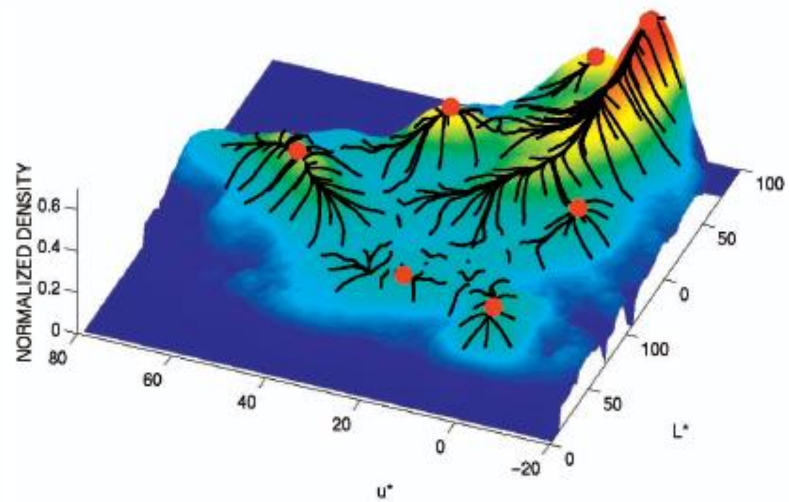
- Versatile technique for clustering-based segmentation

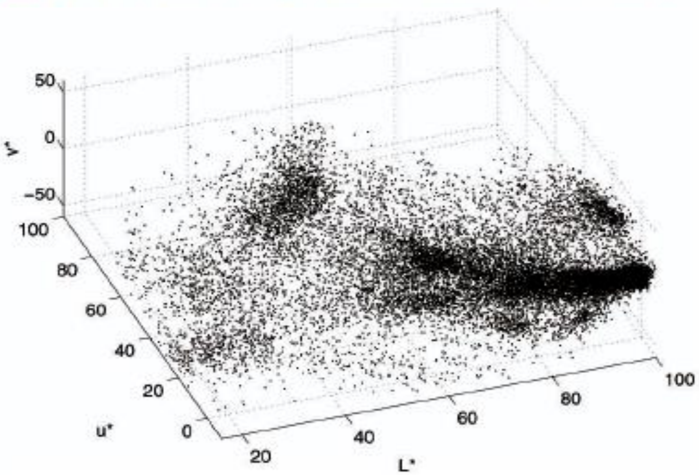


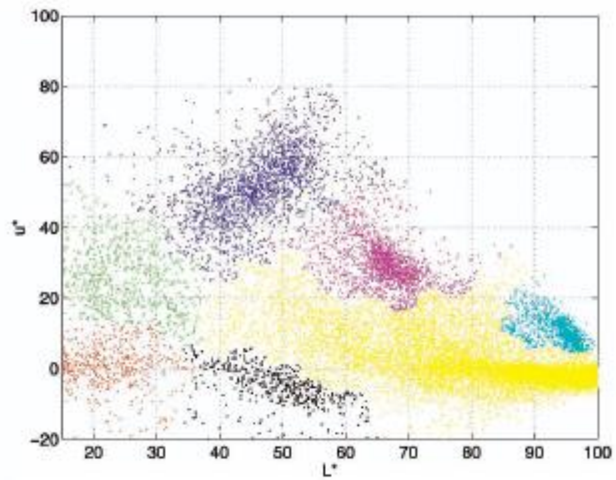
- D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

Mean shift algorithm

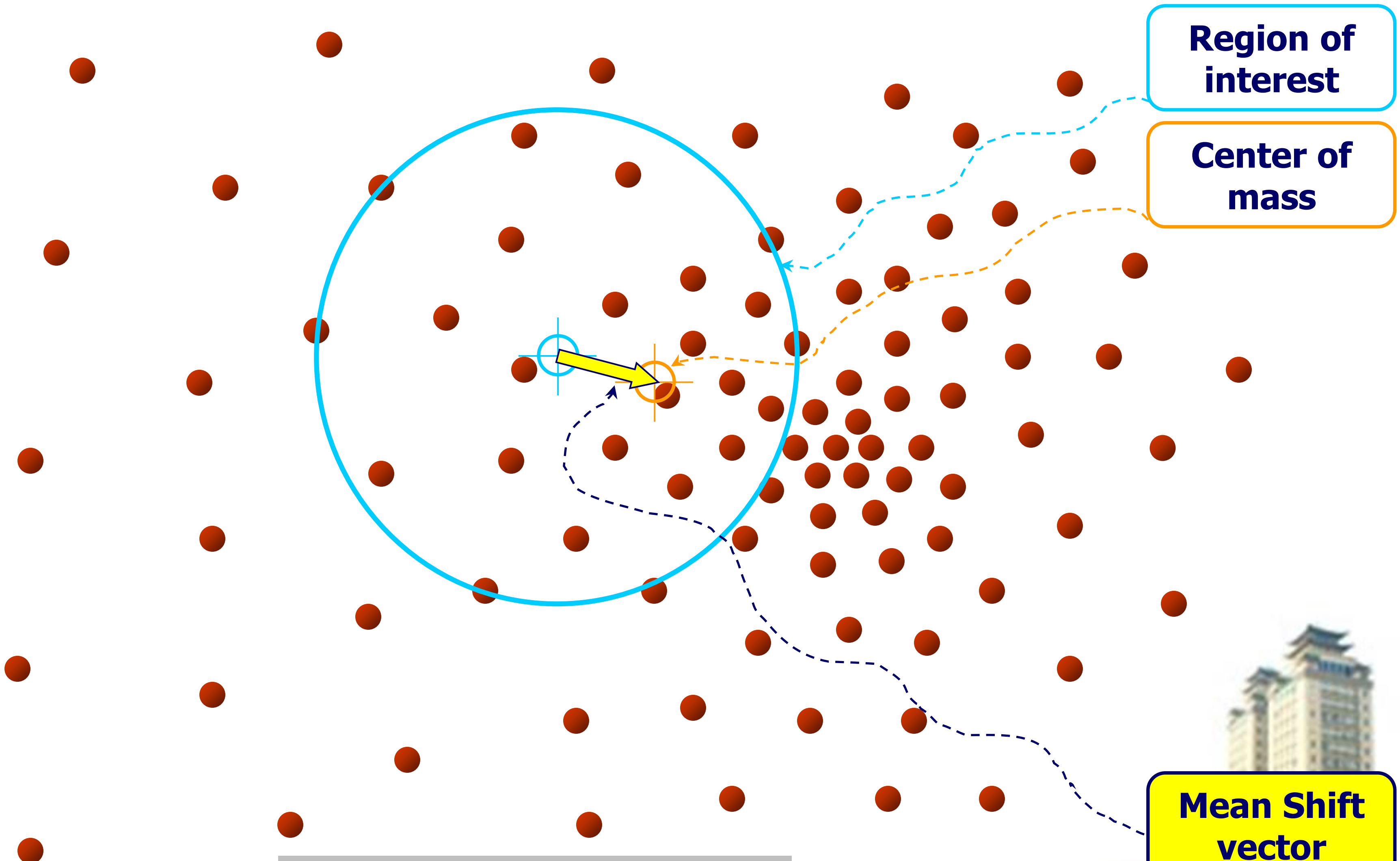
- Try to find ***modes*** of this non-parametric density





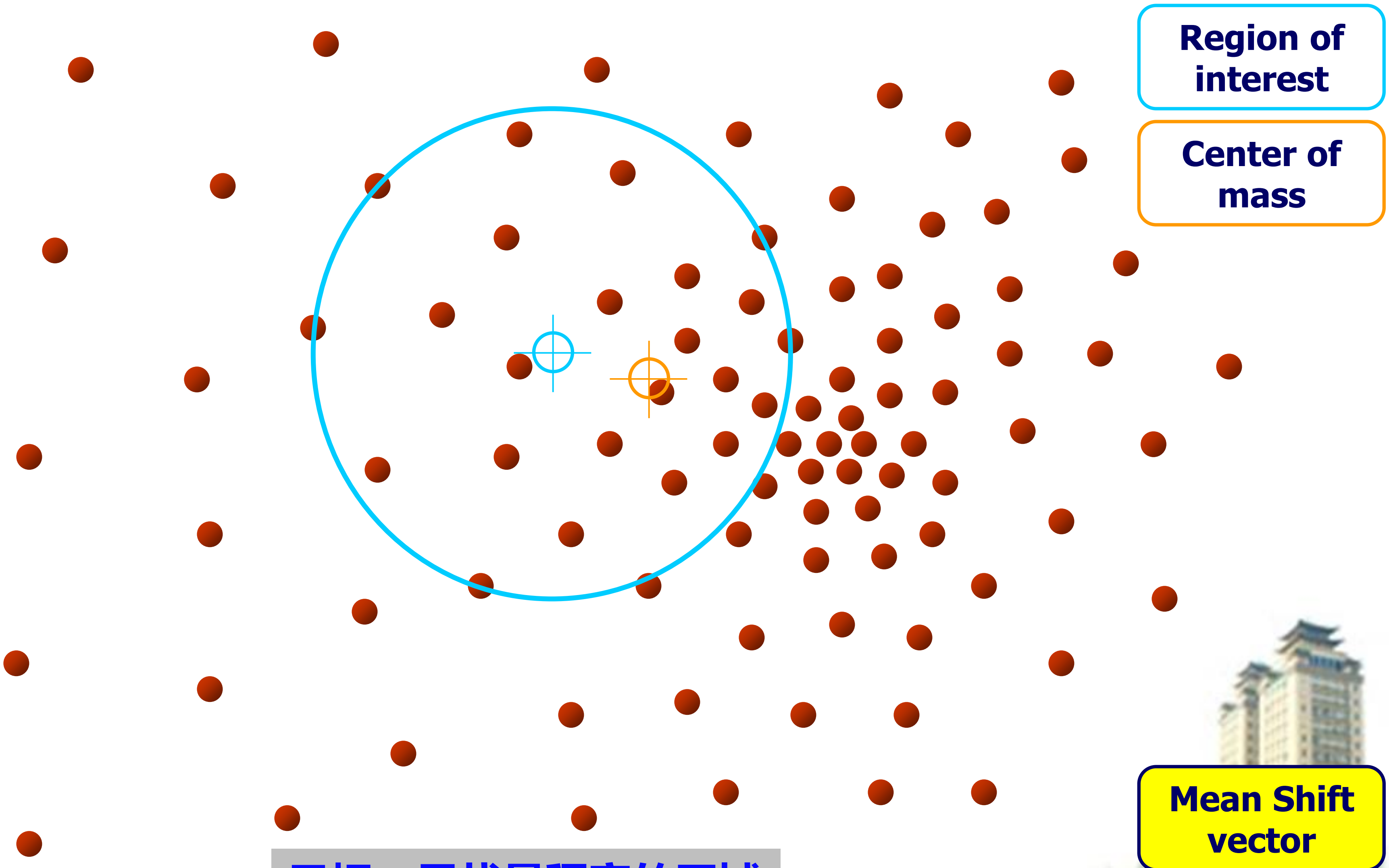


Intuitive Description



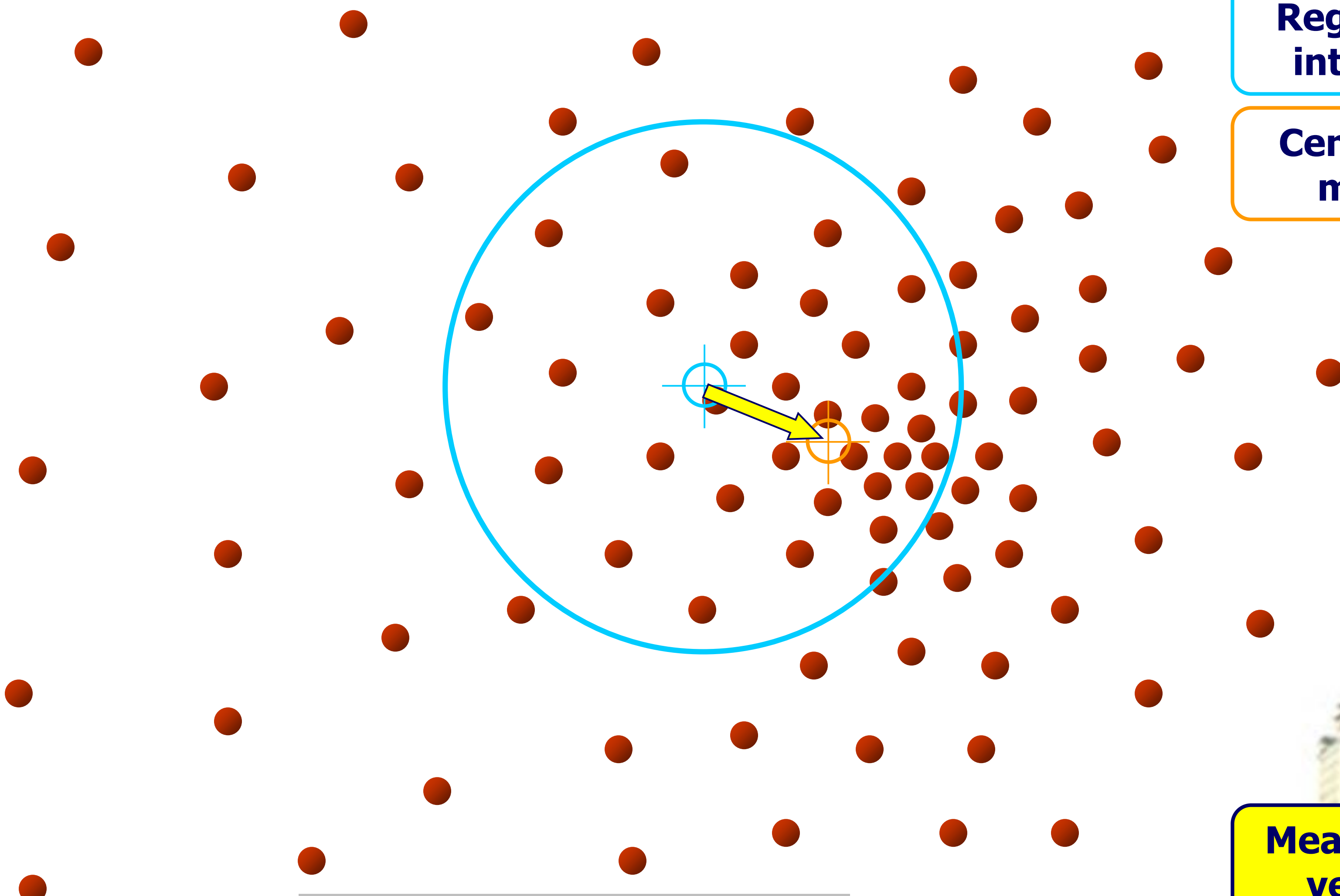
目标：寻找最稠密的区域

Intuitive Description



目标：寻找最稠密的区域

Intuitive Description



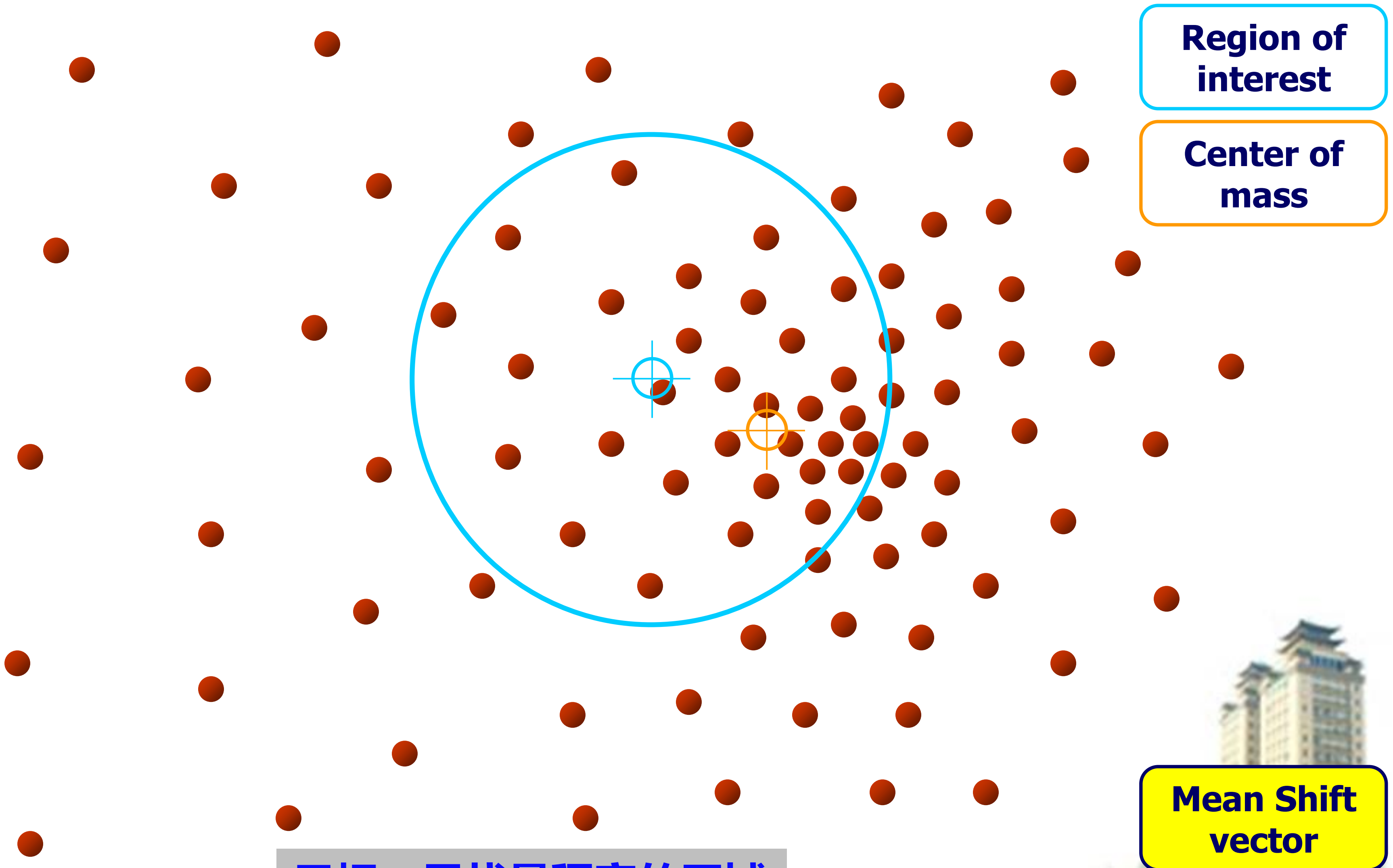
Region of interest

Center of mass

Mean Shift vector

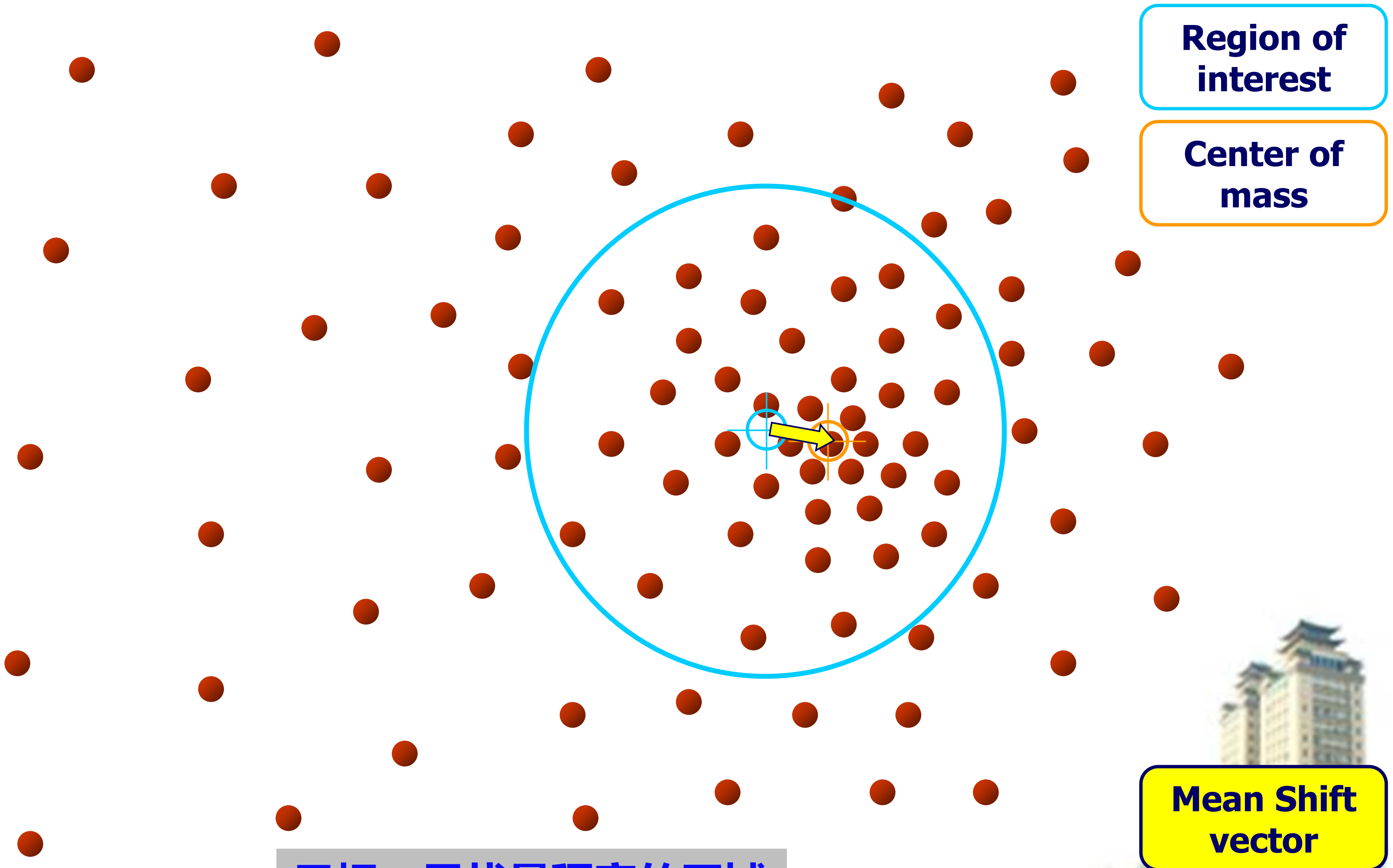
目标：寻找最稠密的区域

Intuitive Description



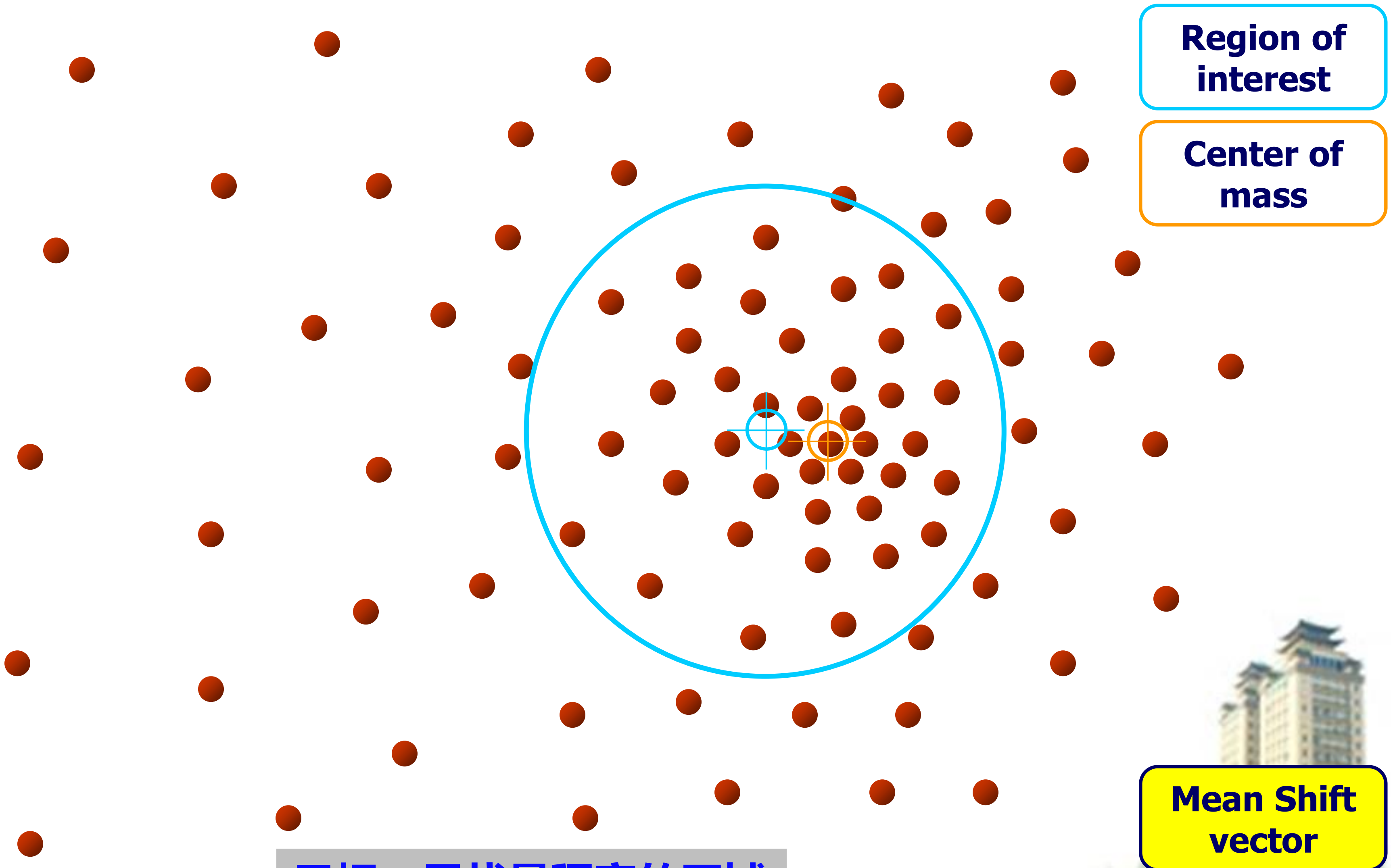
目标：寻找最稠密的区域

Intuitive Description



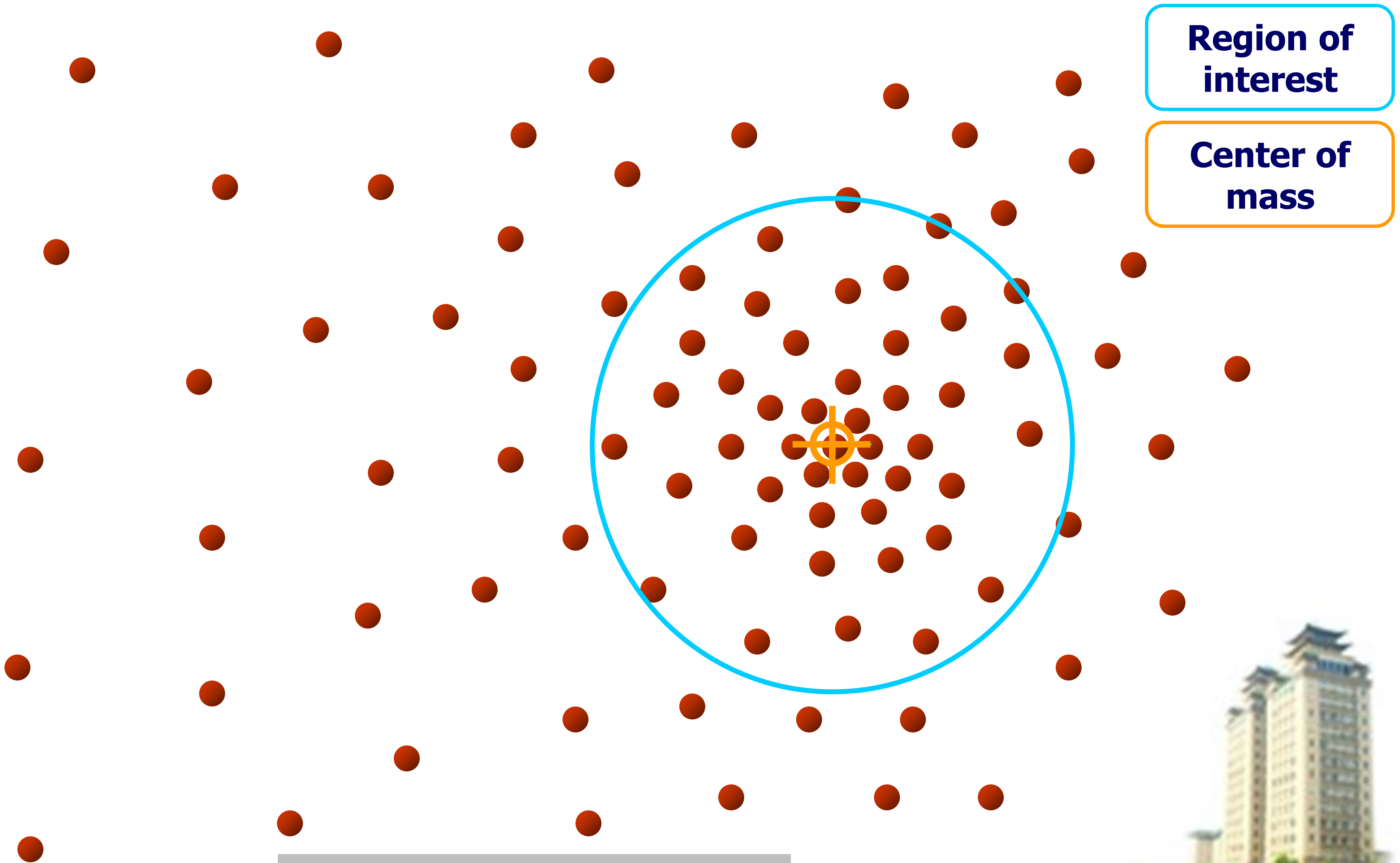
目标：寻找最稠密的区域

Intuitive Description



目标：寻找最稠密的区域

Intuitive Description



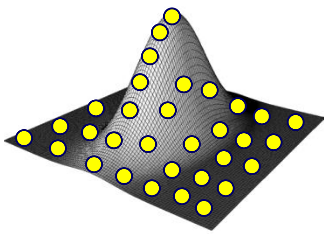
目标：寻找最稠密的区域

What is Mean Shift ?

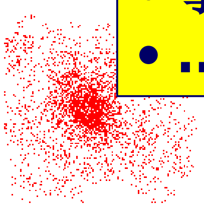
<u>A tool for</u>:
在样本集合中寻找模型，确定N维空间R^N里面一个潜在的概率密度函数
(PDF- probability density function)

<u>特征空间的概率密度函数</u>

- 颜色空间（**color spapce**）
- 尺度空间（**Scale space**）
- 事实上我们可以设想的任意特征空间
- **…**

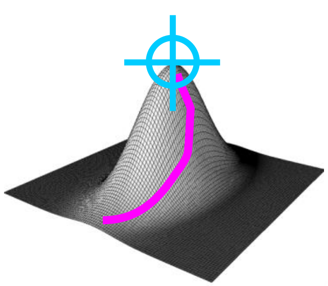


Discrete PDF Representation



Data

非参数密度梯度估计
Non-parametric
Density GRADIENT Estimation
(Mean Shift)

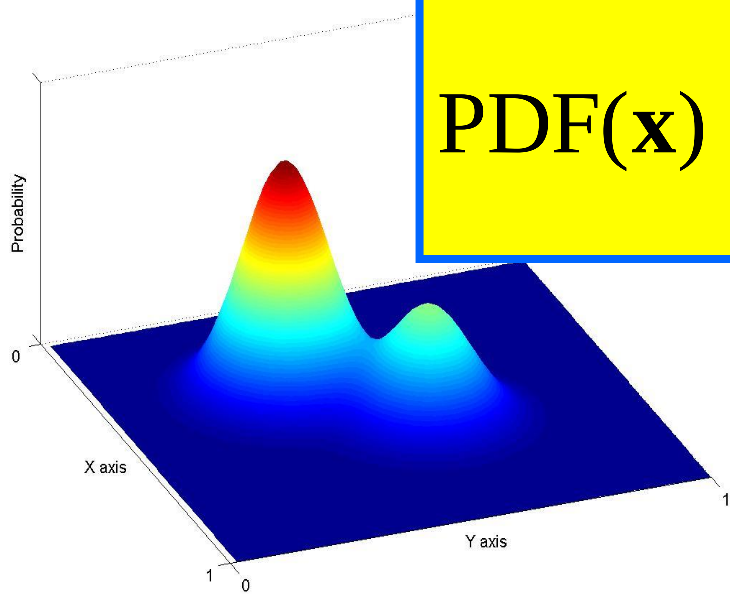


PDF Analysis

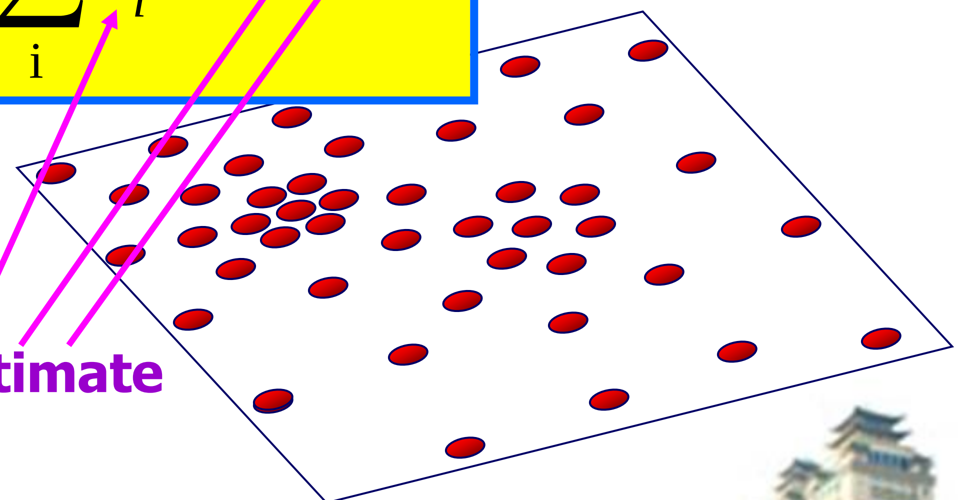
Parametric Density Estimation

Assumption : The data points are sampled from an underlying PDF

$$\mathrm{PDF}(\mathbf{x}) = \sum_{\mathrm{i}} c_i \cdot e^{-\frac{(\mathbf{x}-\mathbf{u}_i)^2}{2\sigma_i^2}}$$



Estimate

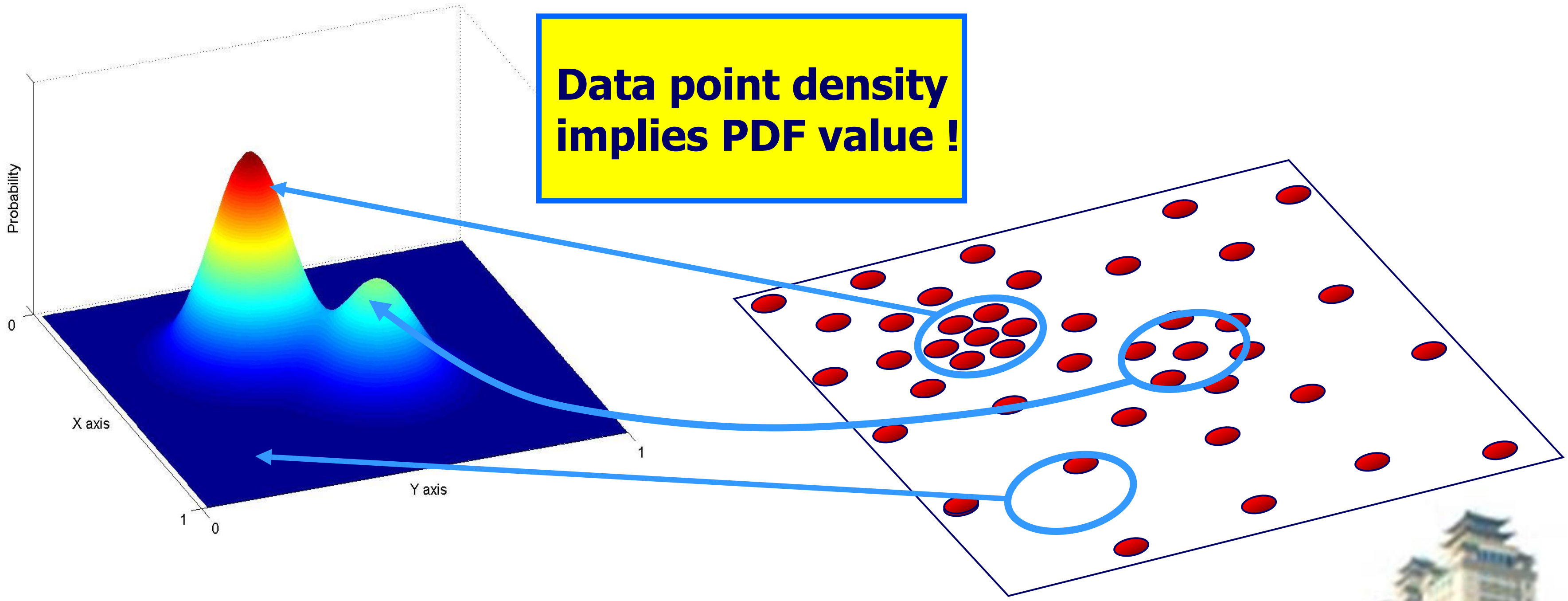


Assumed Underlying PDF

Real Data Samples

Non-Parametric Density Estimation

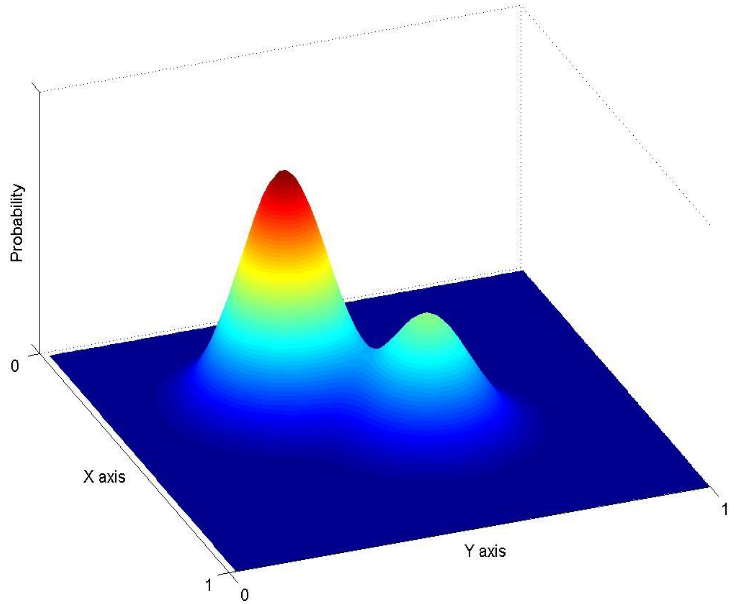
假设: 数据点是从一个隐含的概率密度函数PDF进行采样



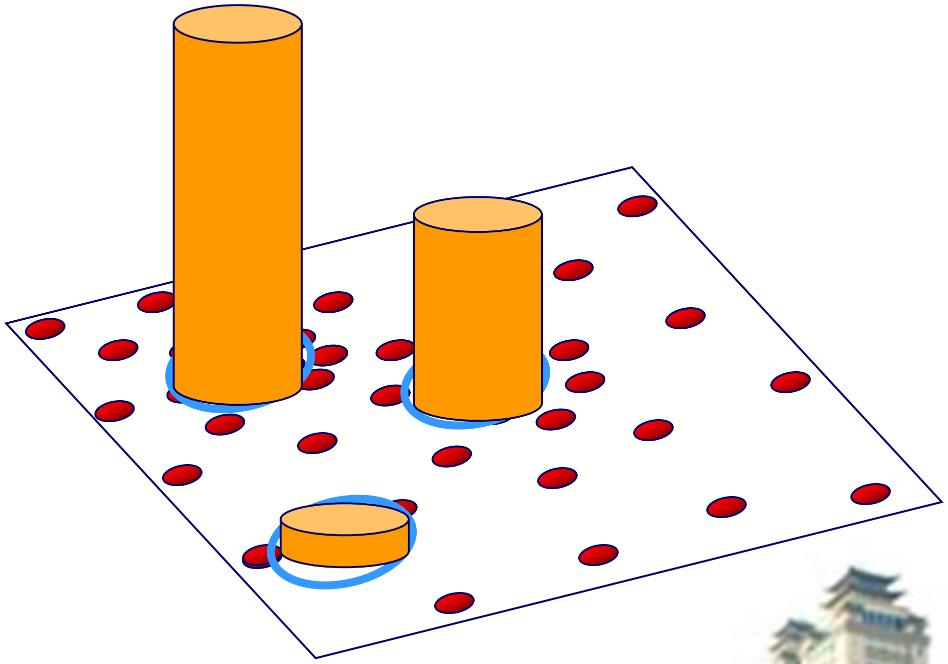
Assumed Underlying PDF

Real Data Samples

Non-Parametric Density Estimation

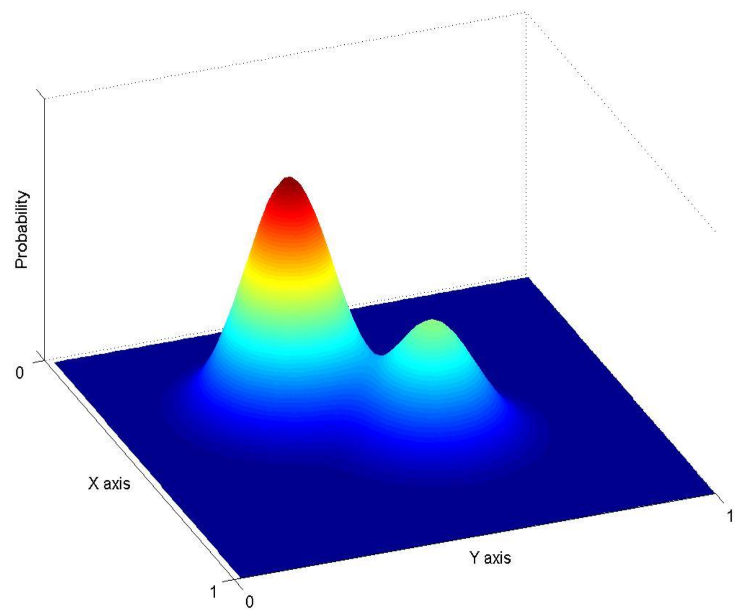


Assumed Underlying PDF

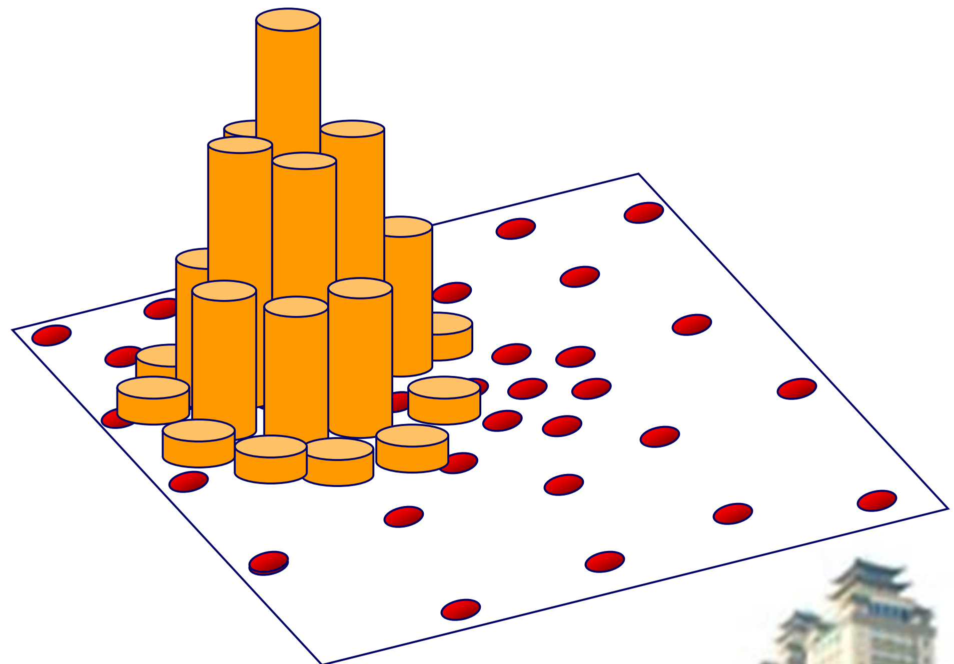


Real Data Samples

Non-Parametric ? Density Estimation



Assumed Underlying PDF



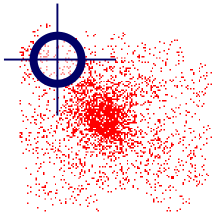
Real Data Samples

Kernel Density Estimation

Parzen Windows - General Framework

$$P(\mathbf{x}) = \frac{1}{n}\sum_{i=1}^{n} K(\mathbf{x} - \mathbf{x}_i)$$

A function of some finite number of data points $x_1 \ldots x_n$



Data

In practice one uses the forms:

$$K(\mathbf{x}) = c\prod_{i=1}^{d} k(x_i)$$ or $$K(\mathbf{x}) = ck\left(\|\mathbf{x}\|\right)$$

Same function on each dimension

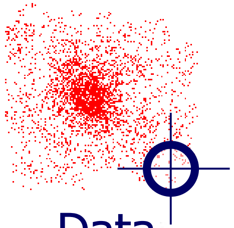
Function of vector length only

Kernel Density Estimation

Various Kernels

$$P(\mathbf{x}) = \frac{1}{n}\sum_{i=1}^{n} K(\mathbf{x}-\mathbf{x}_i)$$

A function of some finite number of data points $x_1 \ldots x_n$

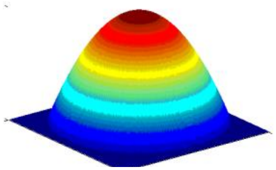


Data

Examples:

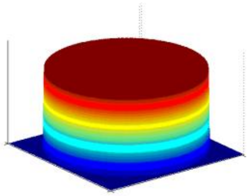
- **Epanechnikov Kernel**

$$K_E(\mathbf{x}) = \begin{cases} c\left(1-\|\mathbf{x}\|^2\right) & \|\mathbf{x}\| \le 1 \\ 0 & \text{otherwise} \end{cases}$$



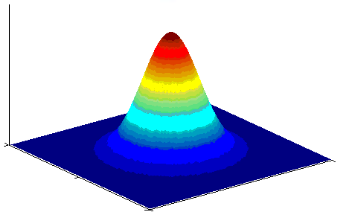
- **Uniform Kernel**

$$K_U(\mathbf{x}) = \begin{cases} c & \|\mathbf{x}\| \le 1 \\ 0 & \text{otherwise} \end{cases}$$



- **Normal Kernel**

$$K_N(\mathbf{x}) = c \cdot \exp\left(-\frac{1}{2}\|\mathbf{x}\|^2\right)$$



Kernel Density Estimation

Gradient

$$\nabla P(\mathbf{x}) = \frac{1}{n}\sum_{i=1}^{n} \nabla K(\mathbf{x}-\mathbf{x}_i)$$

Give up estimating the PDF !
Estimate **ONLY** the **gradient**

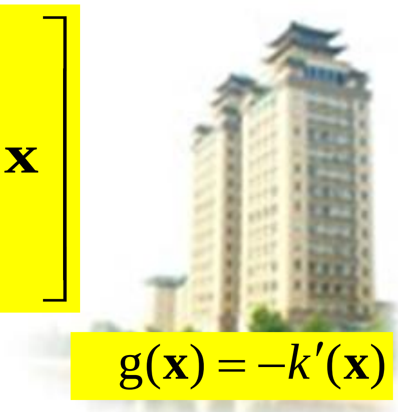
Using the Kernel form:

$$K(\mathbf{x}-\mathbf{x}_i) = ck\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{h}\right\|^2\right)$$

Size of window

We get :

$$\nabla P(\mathbf{x}) = \frac{c}{n}\sum_{i=1}^{n} \nabla k_i = \frac{c}{n}\left[\sum_{i=1}^{n} g_i\right] \bullet \left[\frac{\sum_{i=1}^{n} \mathbf{x}_i g_i}{\sum_{i=1}^{n} g_i} - \mathbf{x}\right]$$



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

Computing The Mean Shift

Kernel Density Estimation

Gradient

$$\nabla P(\mathbf{x}) = \frac{c}{n}\sum_{i=1}^{n}\nabla k_i = \frac{c}{n}\left[\sum_{i=1}^{n} g_i\right] \bullet \left[\frac{\sum_{i=1}^{n}\mathbf{x}_i g_i}{\sum_{i=1}^{n} g_i} - \mathbf{x}\right]$$

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

Computing The Mean Shift

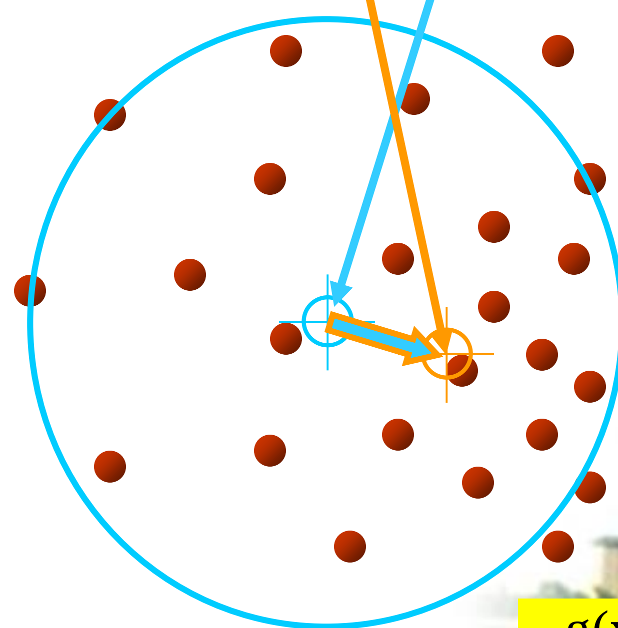
$$\nabla P(\mathbf{x}) = \frac{c}{n}\sum_{i=1}^{n}\nabla k_i = \frac{c}{n}\left[\sum_{i=1}^{n} g_i\right]\cdot\left[\frac{\sum_{i=1}^{n}\mathbf{x}_i g_i}{\sum_{i=1}^{n} g_i} - \mathbf{x}\right]$$

Yet another Kernel
density estimation !

Simple Mean Shift procedure:

- Compute mean shift vector

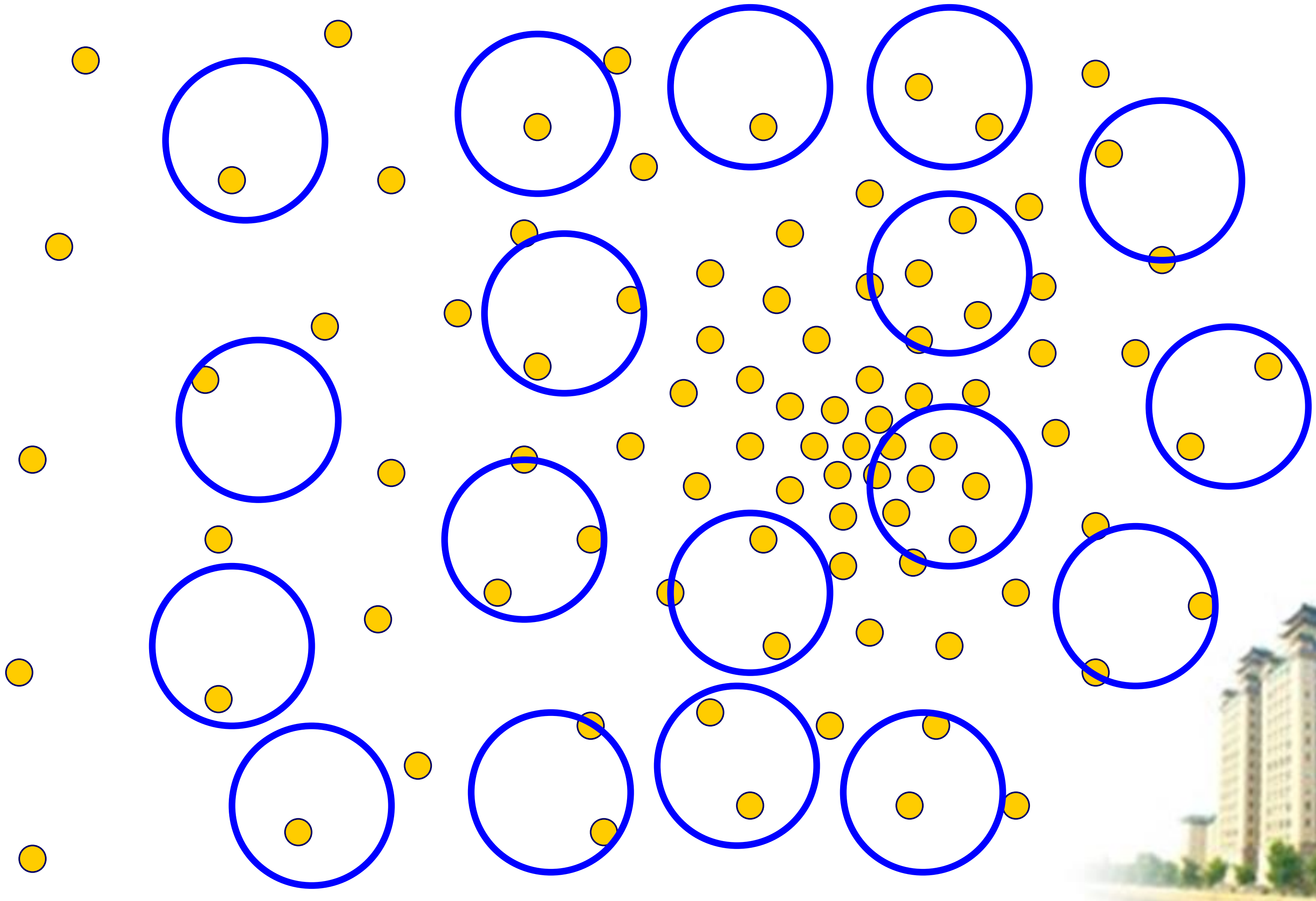
$$\mathbf{m}(\mathbf{x}) = \left[\frac{\sum_{i=1}^{n}\mathbf{x}_i g\left(\frac{\left\|\mathbf{x}-\mathbf{x}_i\right\|^2}{h}\right)}{\sum_{i=1}^{n} g\left(\frac{\left\|\mathbf{x}-\mathbf{x}_i\right\|^2}{h}\right)} - \mathbf{x}\right]$$



- Translate the Kernel window by **m(x)**

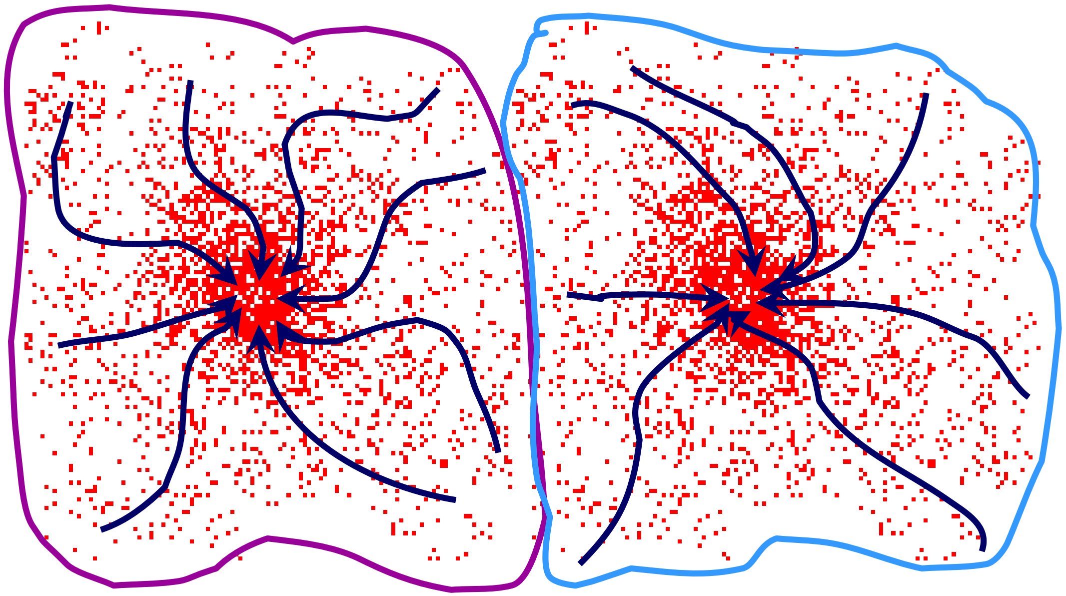
$$g(\mathbf{x}) = -k'(\mathbf{x})$$

Real Modality Analysis

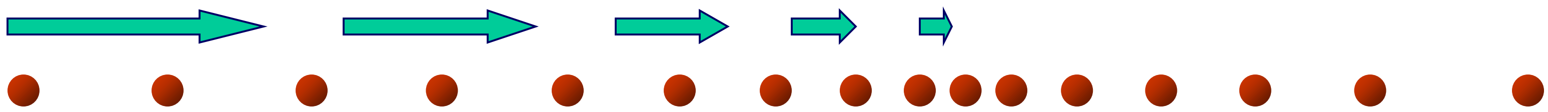


Attraction basin

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

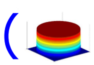
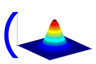
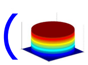


Mean Shift Properties

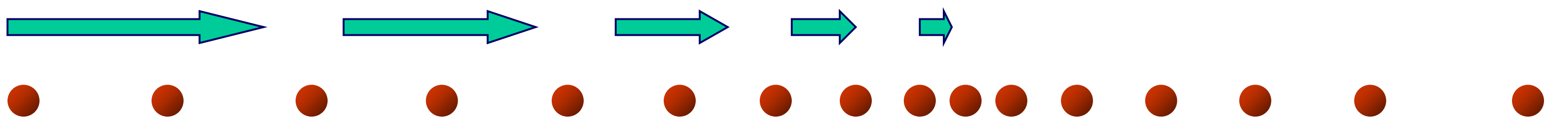


- Automatic convergence speed – the mean shift vector size depends on the gradient itself.
- Near maxima, the steps are small and refined

Adaptive Gradient Ascent

- Convergence is guaranteed for infinitesimal steps only ➔ infinitely convergent, (therefore set a lower bound)
- For Uniform Kernel (), convergence is achieved in a finite number of steps
- Normal Kernel () exhibits a smooth trajectory, but is slower than Uniform Kernel ().

Mean Shift Strengths & Weaknesses



Strengths :

- Application independent tool
- Suitable for real data analysis
- Does not assume any prior shape (e.g. elliptical) on data clusters
- Can handle arbitrary feature spaces
- Only ONE parameter to choose
- *h* (window size) has a physical meaning, unlike K-Means

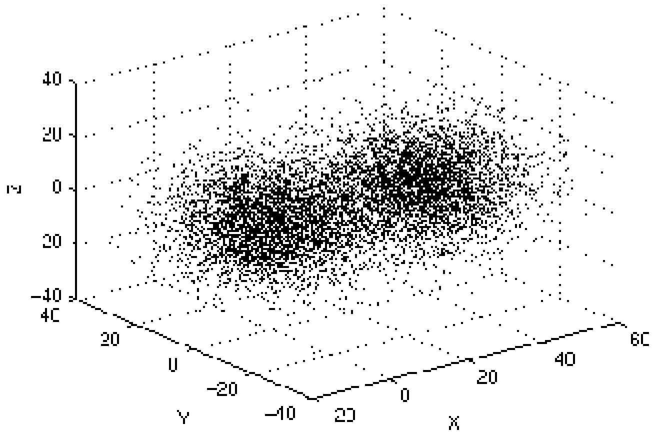
Weaknesses :

- The window size (bandwidth selection) is not trivial
- Inappropriate window size can cause modes to be merged, or generate additional “shallow” modes ➔ Use adaptive window size

Mean Shift 的收敛性？

Clustering

Synthetic Examples

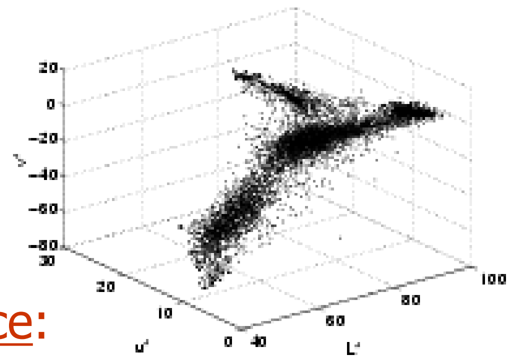


Simple Modal Structures

Complex Modal Structures

Clustering

Real Example



Feature space:
L*u*v representation (a)

Initial window
centers

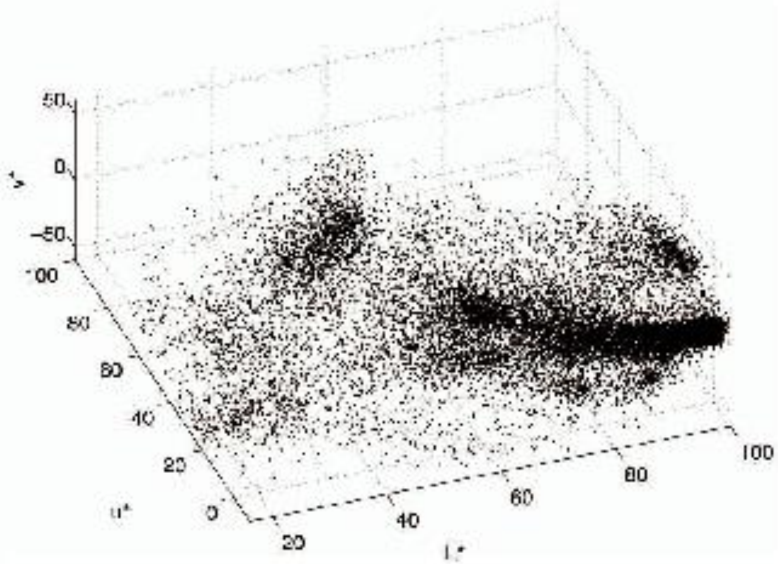
Modes found

Modes after
pruning

Final clusters

Clustering

Real Example



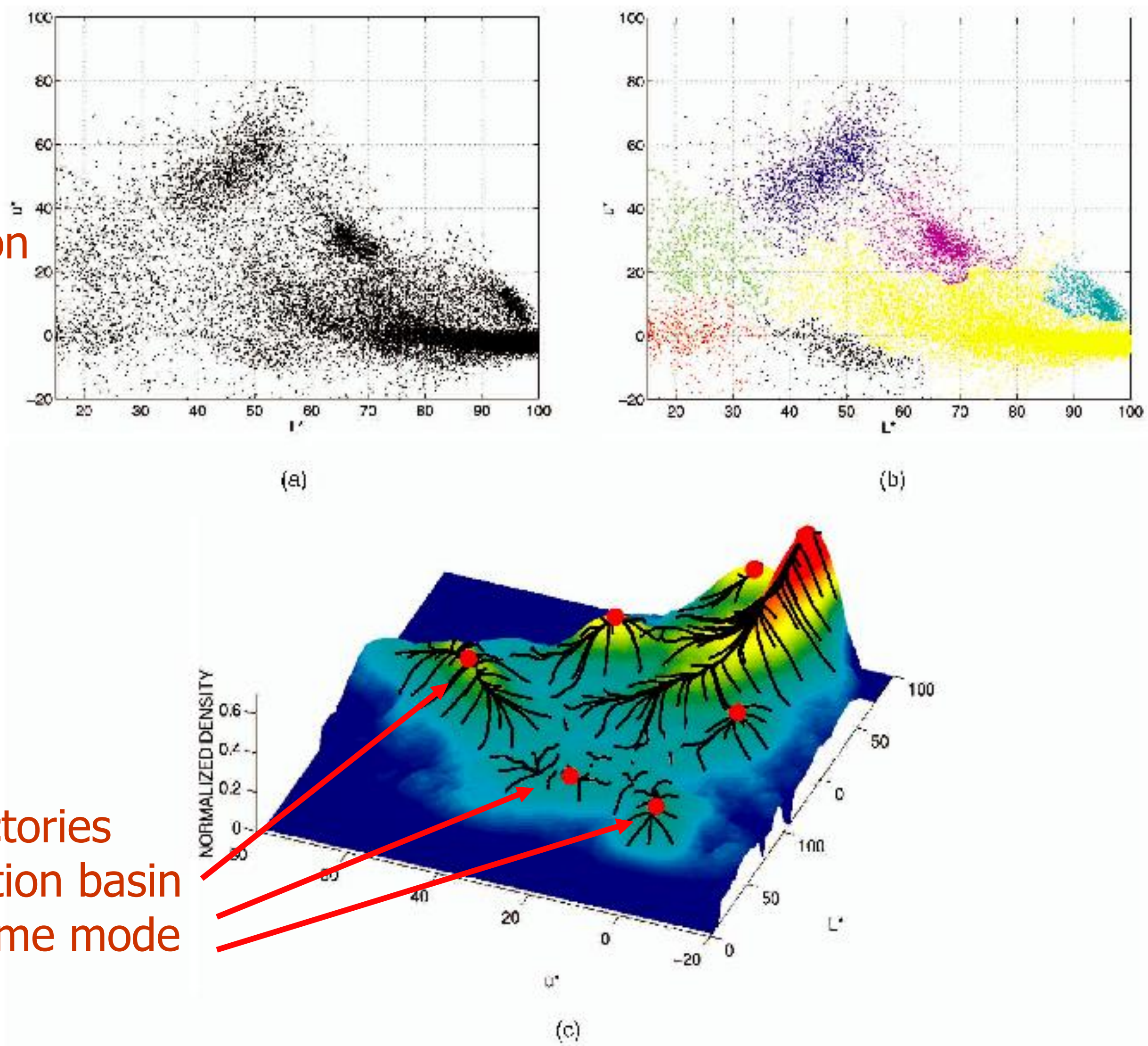
L*u*v space representation

Clustering

Real Example

2D (L*u)
space
representation

Final clusters



Not all trajectories
in the attraction basin
reach the same mode

Discontinuity Preserving Smoothing

Feature space : Joint domain = spatial coordinates + color space

$$K(\mathbf{x}) = C \cdot k_s\left(\left\|\frac{\mathbf{x}^s}{h_s}\right\|\right) \cdot k_r\left(\left\|\frac{\mathbf{x}^r}{h_r}\right\|\right)$$

Meaning : treat the image as data points in the spatial and gray level domain

Discontinuity Preserving Smoothing

Example

Segmentation

Segment = Cluster, or Cluster of Clusters

Algorithm:

- **Run Filtering (*discontinuity preserving smoothing*)**
- **Cluster the clusters which are closer than window size**

Things to remember

- Uses of segmentation
  - Efficiency
  - Better features
  - Want the segmented object
- Mean-shift segmentation
  - Good general-purpose segmentation method
  - Generally useful clustering, tracking technique
- Watershed segmentation
  - Good for hierarchical segmentation
  - Use in combination with boundary prediction