Segmentation:
Mean-shift & watershed

Dr. Tushar Sandhan

Introduction

- Number of segments?

Introduction

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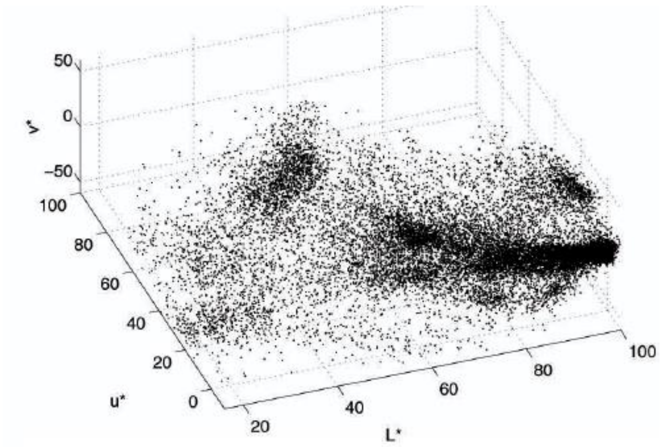
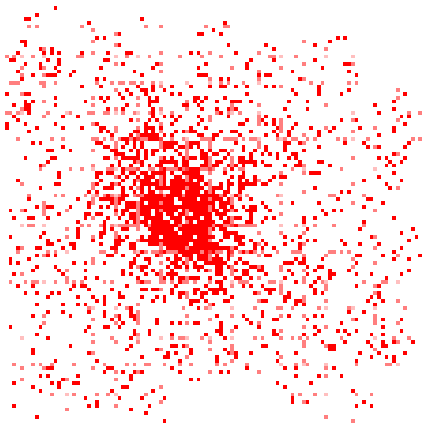
- Number of segments?

Mean-shift

- Mean-shift clustering
  - iterative steepest ascent method
  - seeks peaks of probability density in feature space
    - finds modes or local maxima
  - it tries to find all possible cluster centres
  - no need of initial guess of K clusters



Mean-shift



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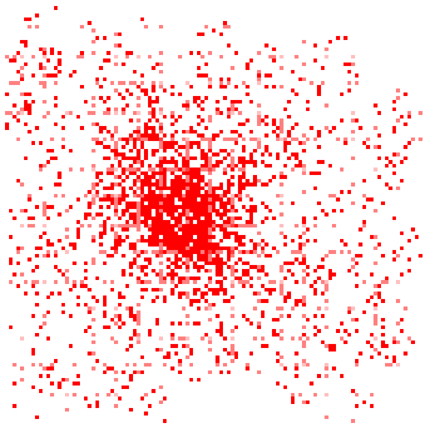

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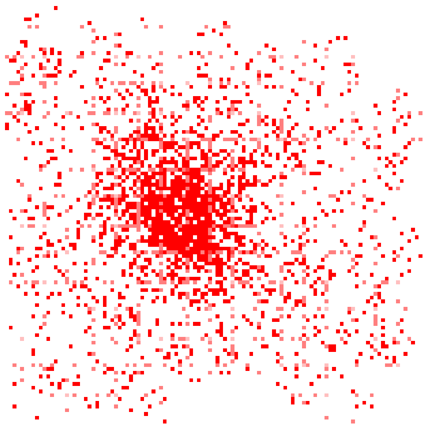
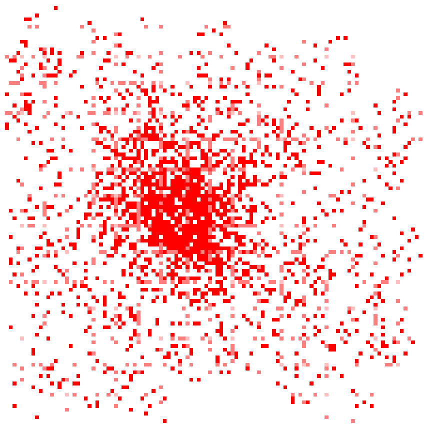


Non-parametric density estimation

Mean-shift



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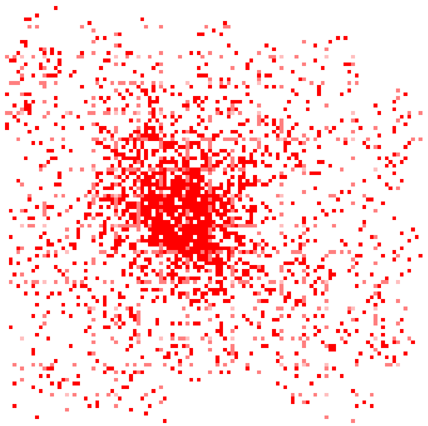

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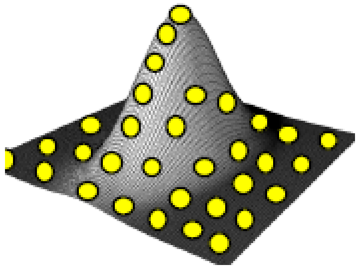

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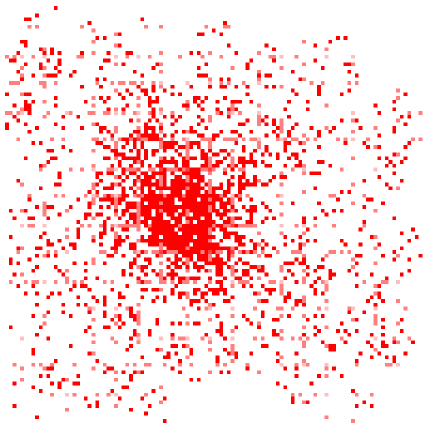
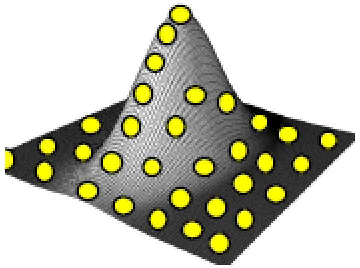


Non-parametric density estimation

Non-parametric density gradient estimation



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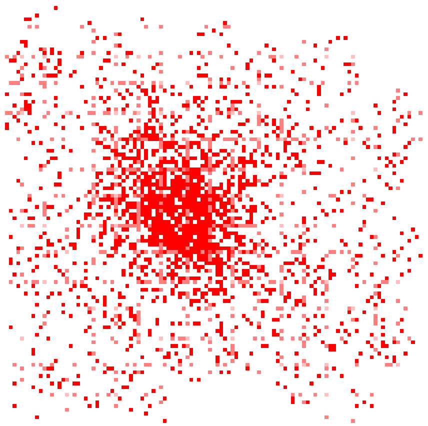

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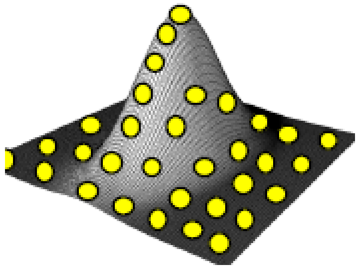

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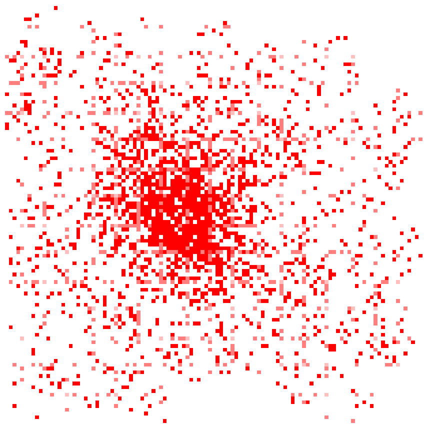

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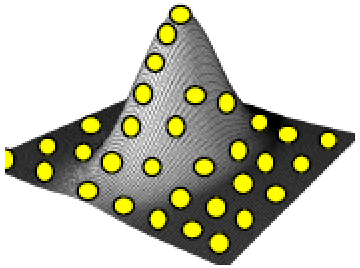

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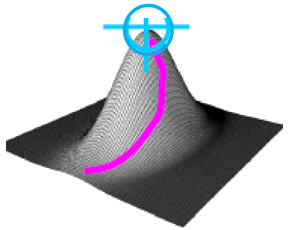

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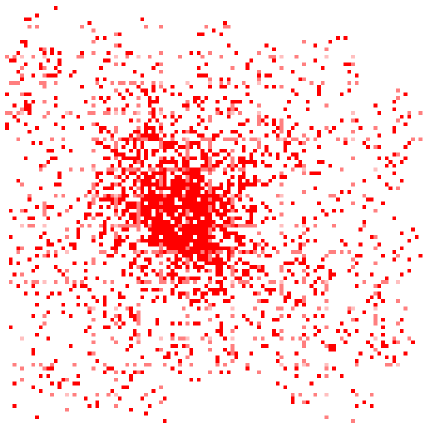

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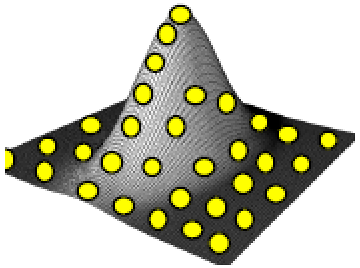
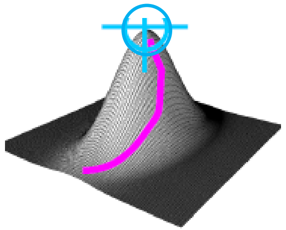


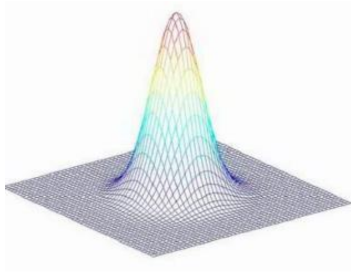
Non-parametric density gradient estimation

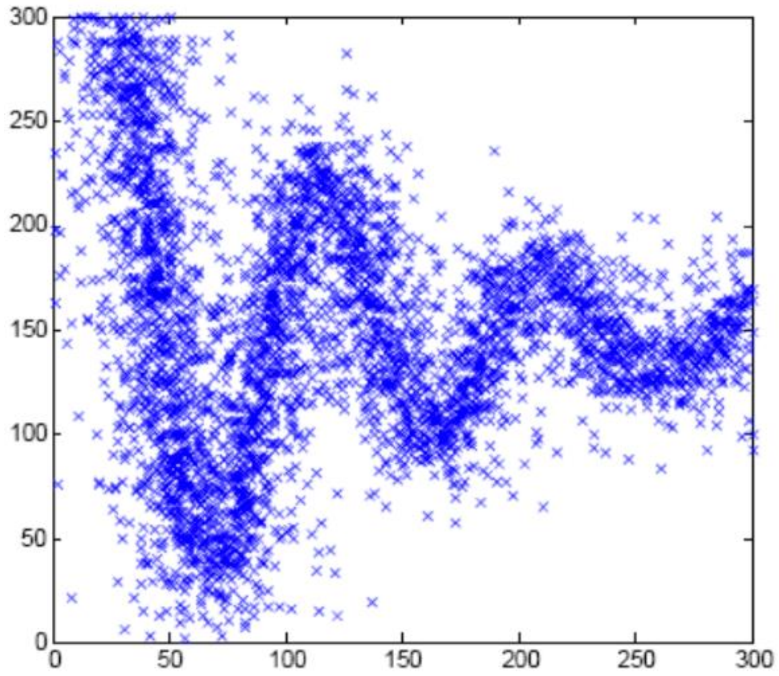
(Mean shift)



Mean-shift

- Density estimation
  - find the underlying distribution that generates the given data
- Non-parametric density estimation
  - use data points to define distribution
  - put a small probability mass around each data-point via kernel
  - e.g. Gaussian kernel





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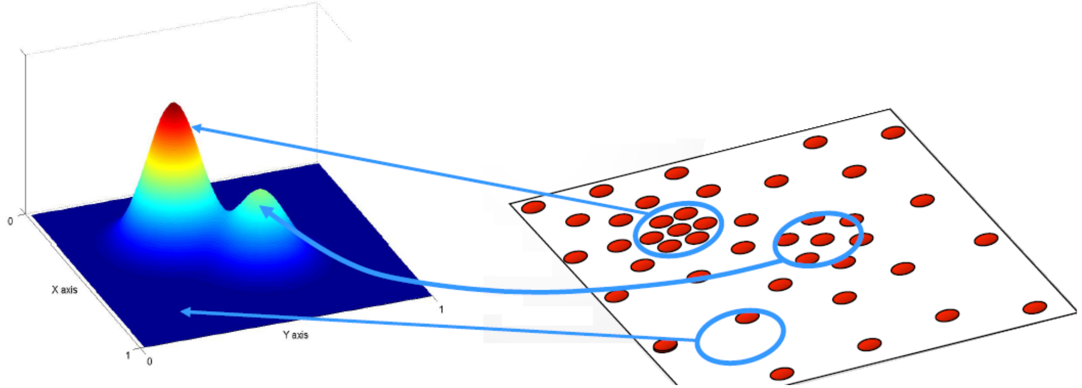
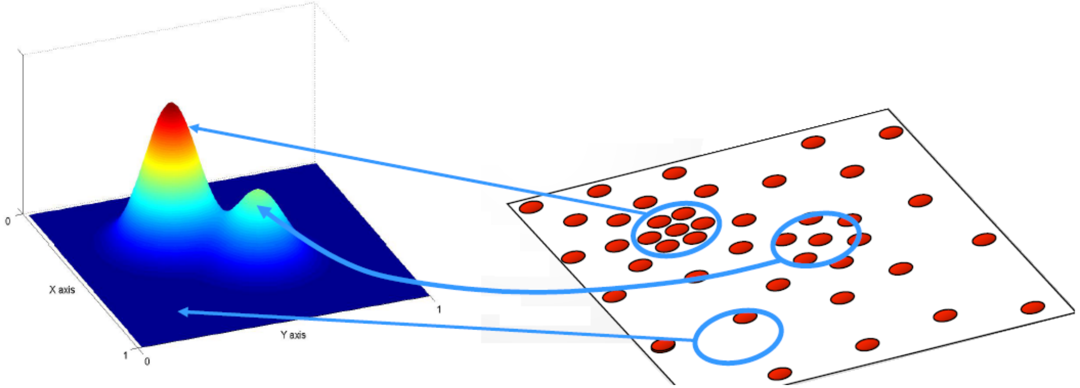


Data point density is similar to PDF value

Courtesy: T. Tappen

Mean-shift



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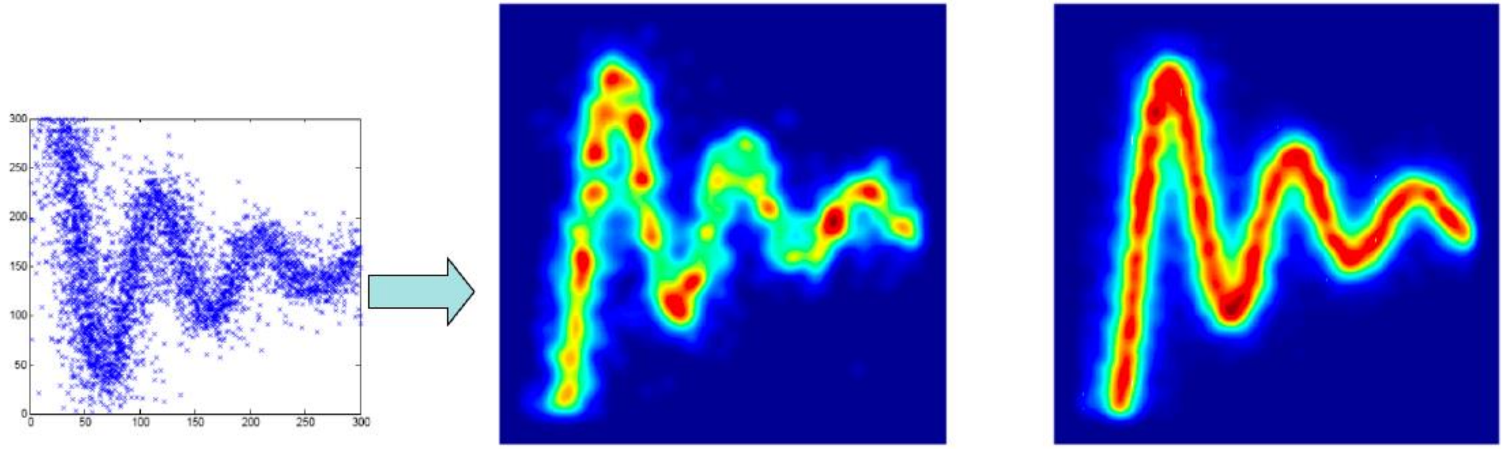

(a) 2000 Samples (b) 20000 Samples

Courtesy: T. Tappen

Mean-shift

$$x_1 = x_0 + \eta \nabla f(x_0)$$

$$\hat{f}(\mathbf{x}) = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{\mathbf{x} - \mathbf{x}_i}{h}\right)$$

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$c_{k,d}$ is volume of unit sphere $\in R^d$

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at the modes: $\nabla f(\mathbf{x}) = \mathbf{0}$

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Define a function of a kernel $g(x) = -k'(x)$

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$$= \frac{2c_{k,d}}{nh^{d+2}} \left[\sum_{i=1}^{n} g\left(\left\|\frac{\mathbf{x} - \mathbf{x}_i}{h}\right\|^2\right)\right] \left[\frac{\sum_{i=1}^{n} \mathbf{x}_i g\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{h}\right\|^2\right)} - \mathbf{x}\right]$$

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

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$$\begin{aligned}
&\hat{\nabla} f_{h,K}(\mathbf{x}) \\
&= \frac{2c_{k,d}}{nh^{d+2}}\sum_{i=1}^{n}(\mathbf{x}_i-\mathbf{x})g\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{h}\right\|^2\right) \\
&= \frac{2c_{k,d}}{nh^{d+2}}\left[\sum_{i=1}^{n} g\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{h}\right\|^2\right)\right]\left[\frac{\sum_{i=1}^{n}\mathbf{x}_i g\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{h}\right\|^2\right)} - \mathbf{x}\right]
\end{aligned}$$

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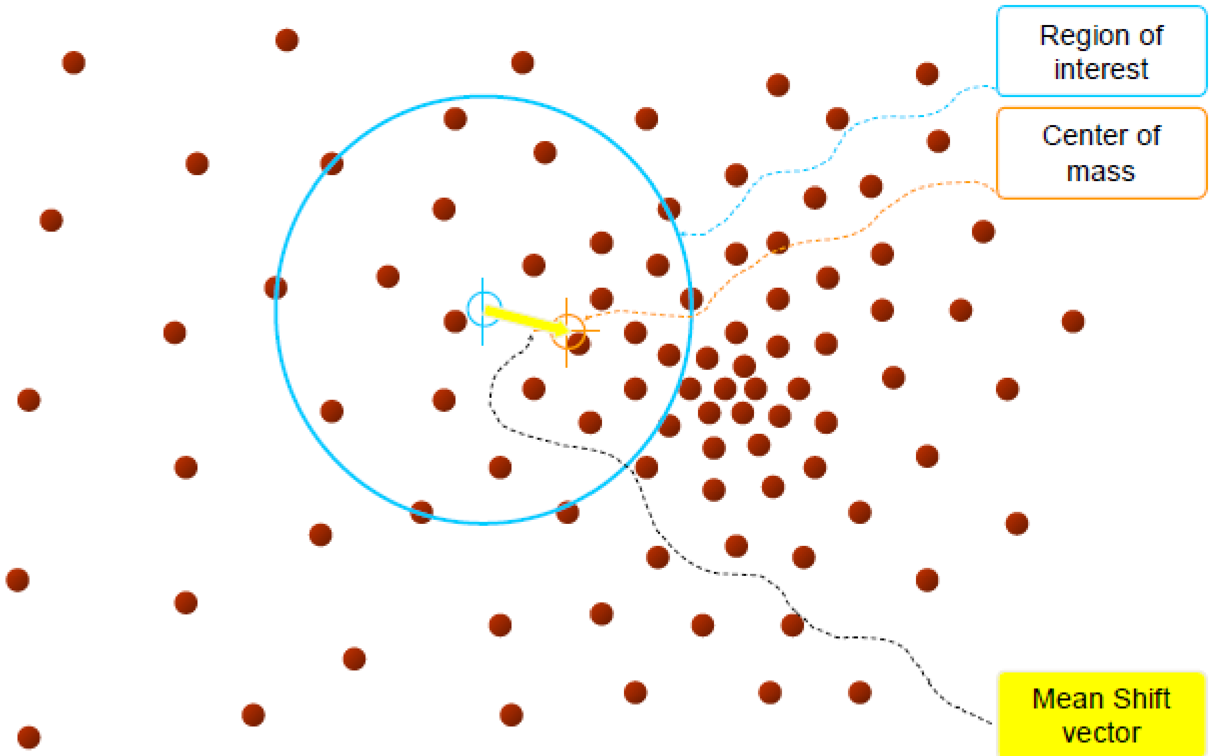
$$\hat{\nabla} f_{h,K}(\mathbf{x}) = \hat{f}_{h,G}(\mathbf{x})\frac{2c_{k,d}}{h^2 c_{g,d}}\mathbf{m}_{h,G}(\mathbf{x}) \qquad \mathbf{m}_{h,G}(\mathbf{x}) = \frac{1}{2}h^2 c\frac{\hat{\nabla} f_{h,K}(\mathbf{x})}{\hat{f}_{h,G}(\mathbf{x})}$$

Mean-shift



Courtesy: Y. Ukrainitz

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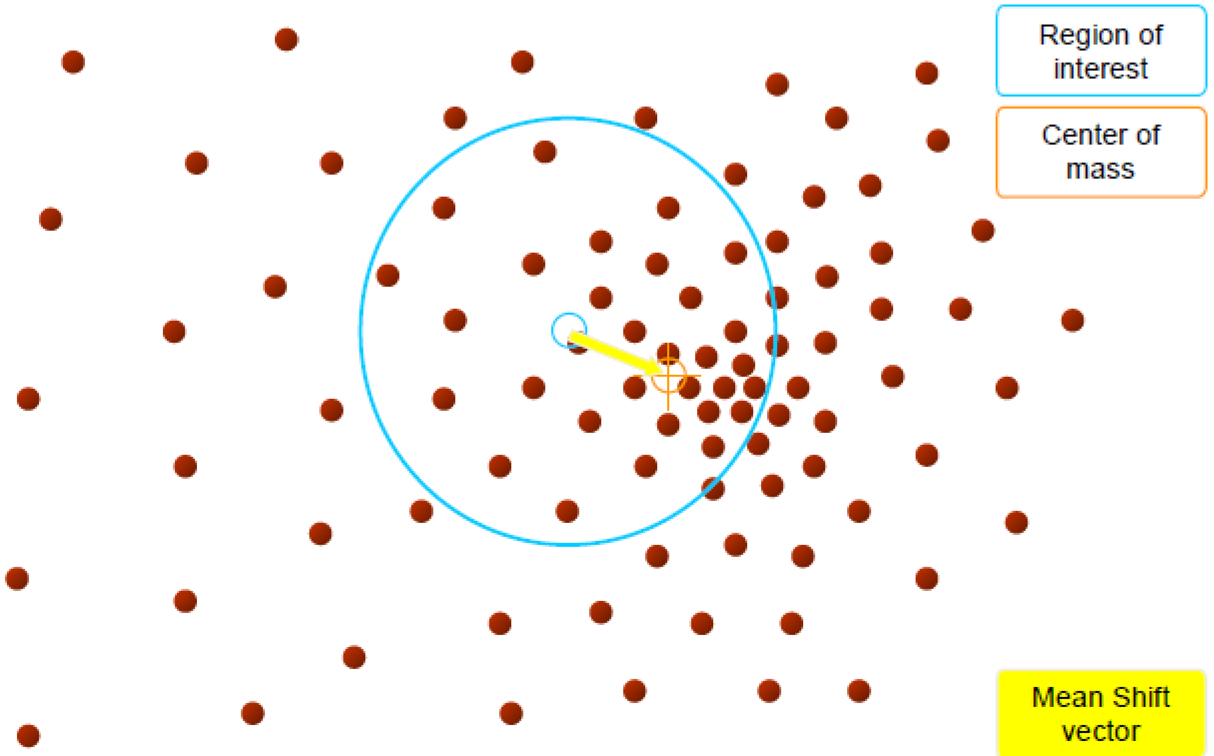

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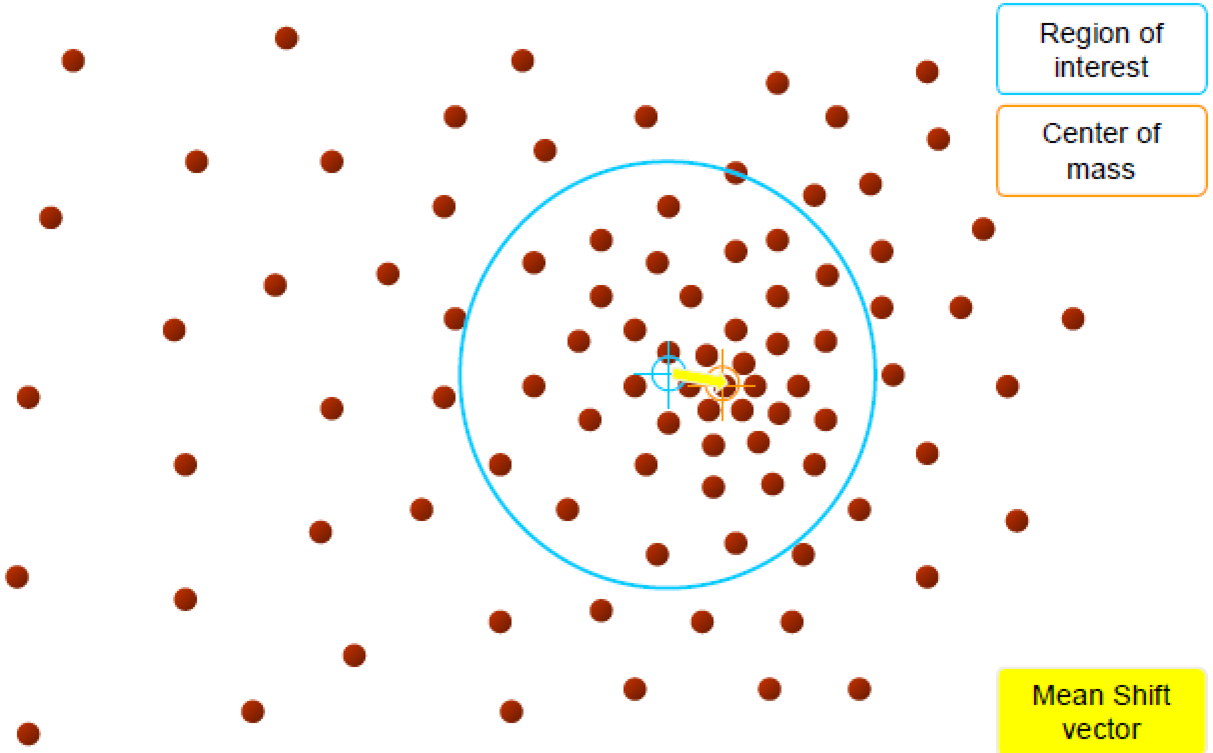

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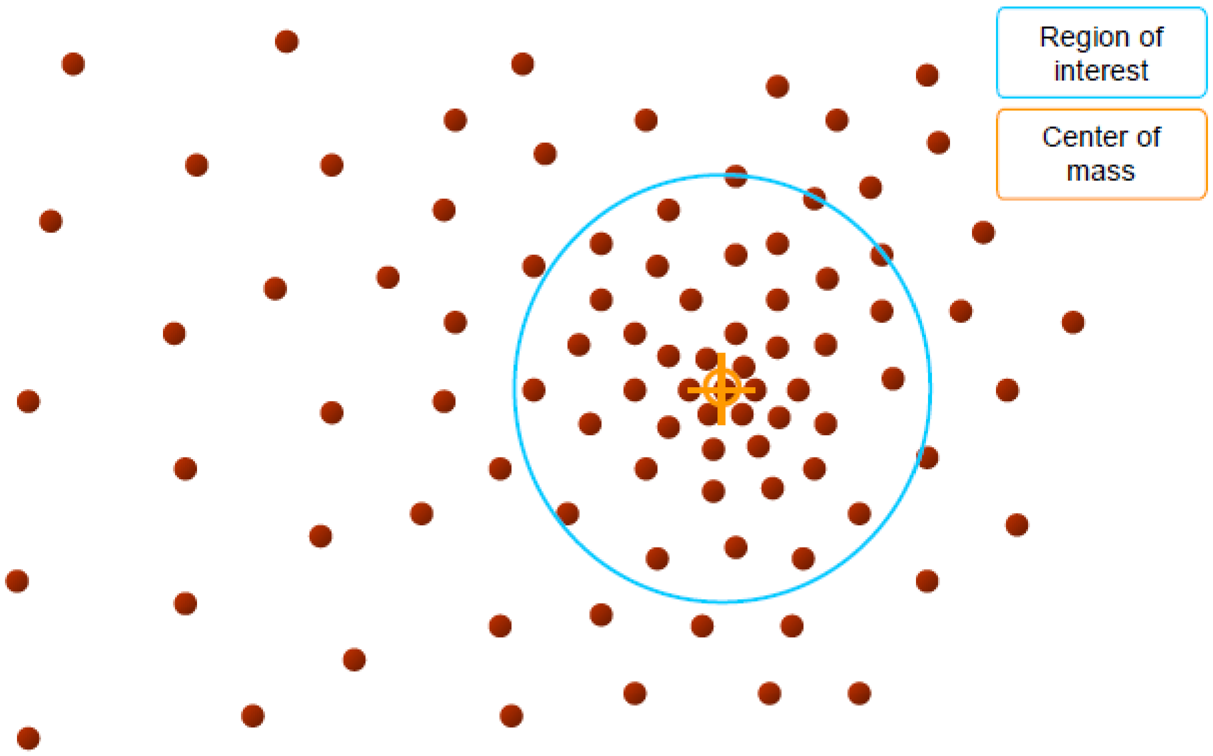

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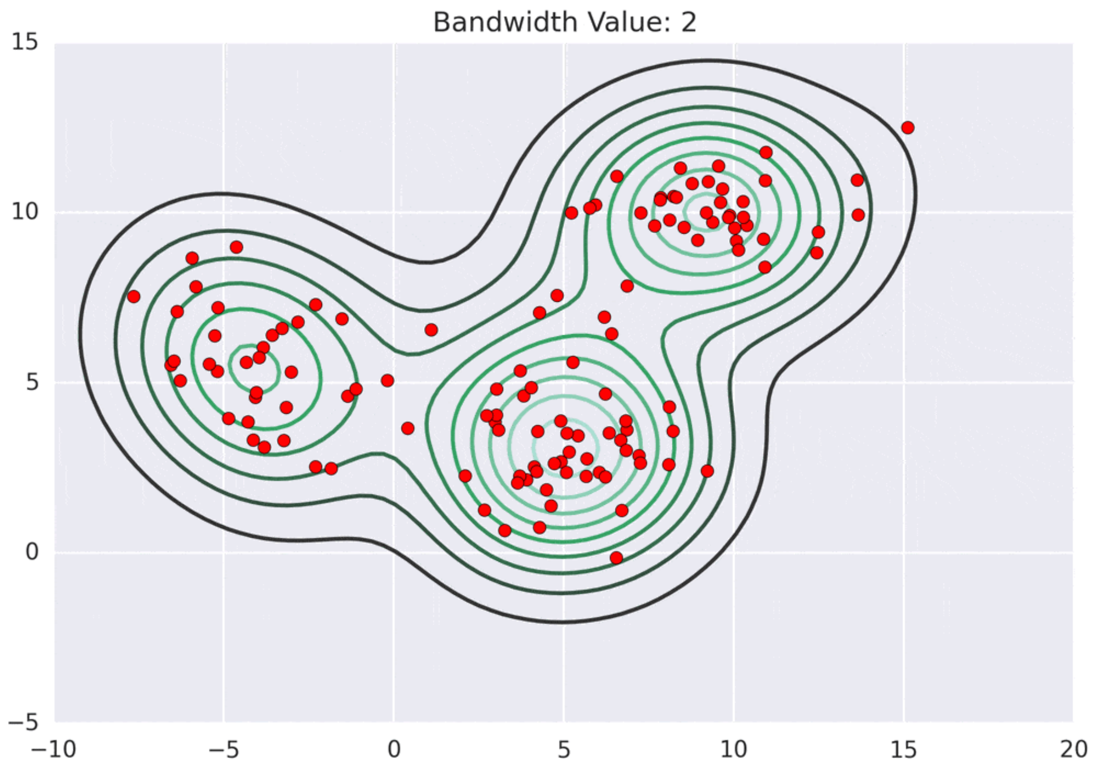

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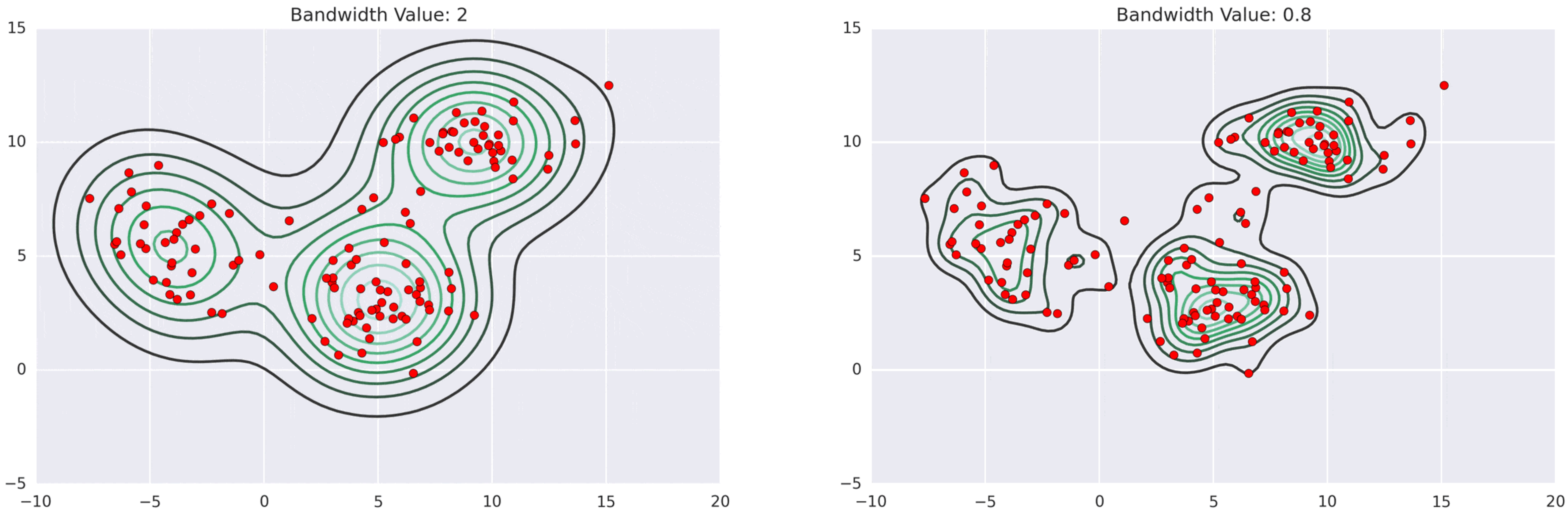


Mean-shift

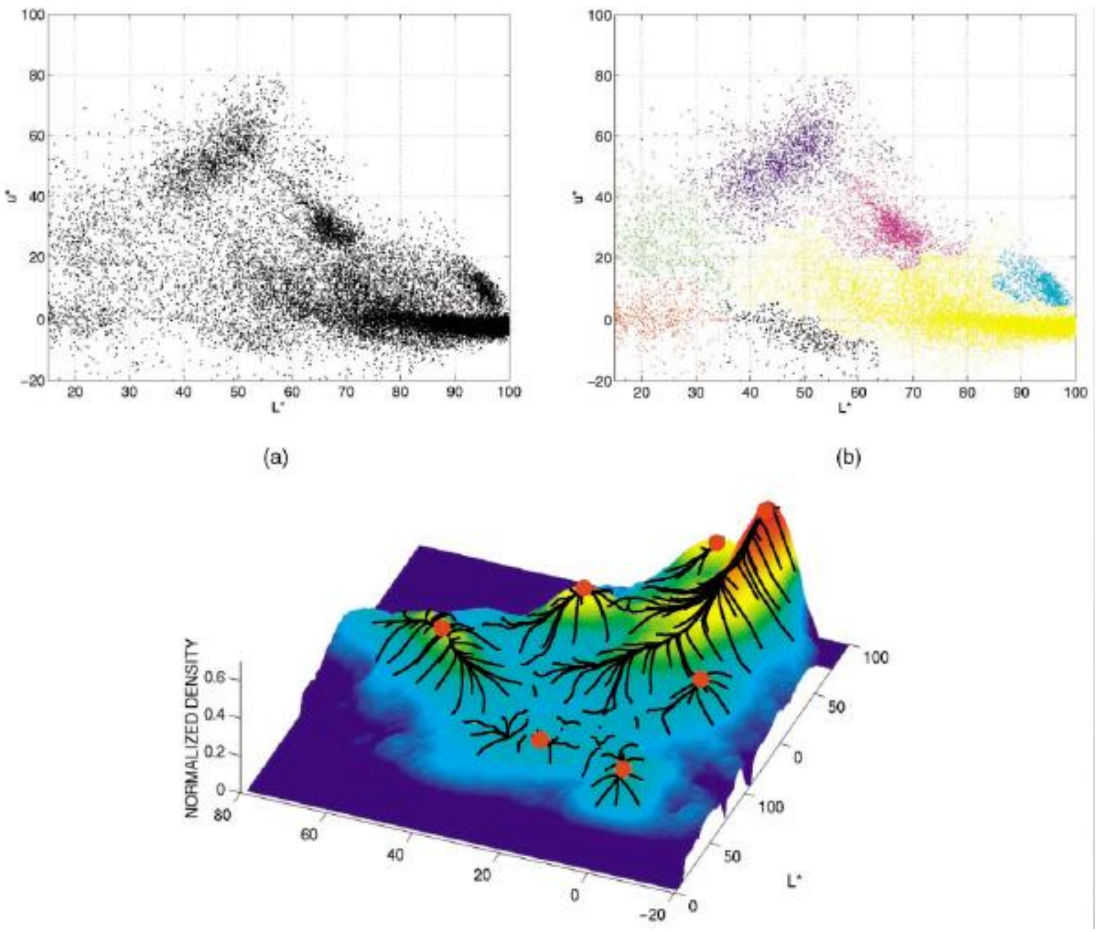
- Algorithm

  - transform image into feature space
  - initialize window at each feature point
  - for each window
    - compute mean shift vector $m(x)$
    - move density estimation window by $m(x)$
    - repeat till convergence
  - merge windows that end up near same peak

Mean-shift

- Pros
  - automatically finds various number of modes
  - no need of initial guessing of cluster centres
  - does not assume spherical clusters
  - robust to outliers
  - just a single para (window size w)
- Cons
  - bandwidth or windows size is an imp. Para
    - slight change in w, translates varied output
  - computationally expensive
    - complexity: $O(n^2T)$
  - not scalable with dimensionality

Mean-shift



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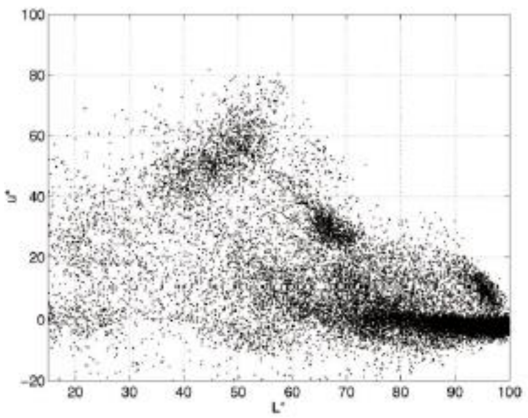
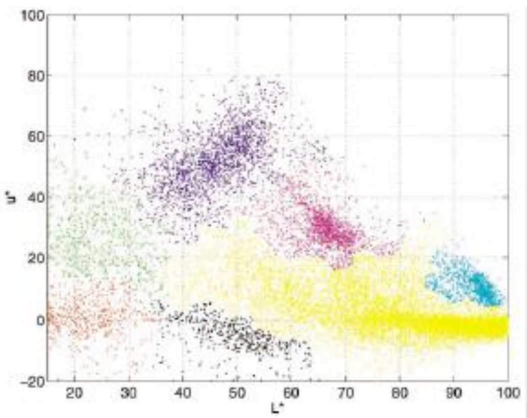
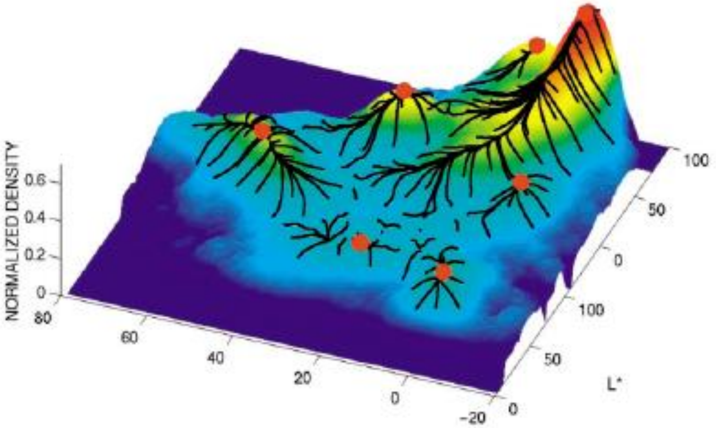


(a)

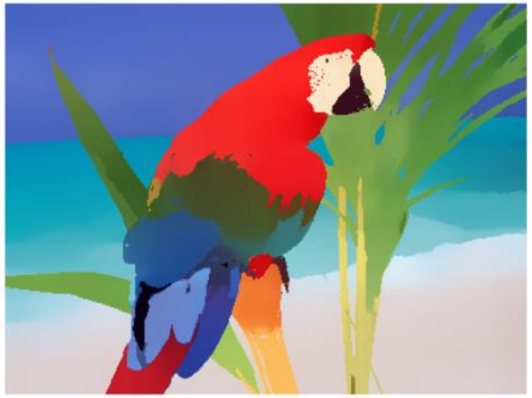


(b)



input image

output image



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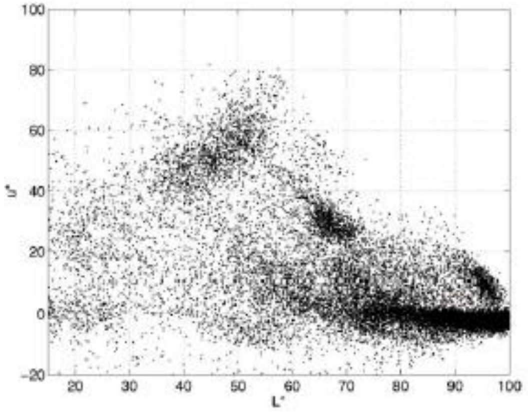

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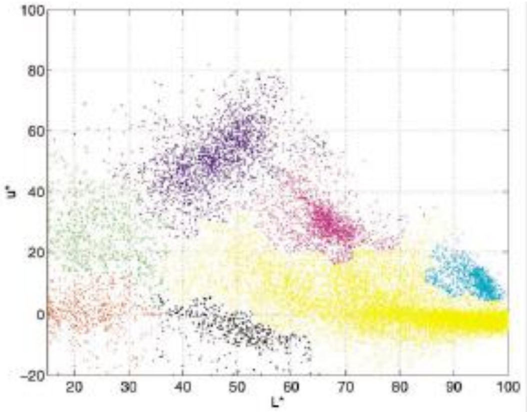

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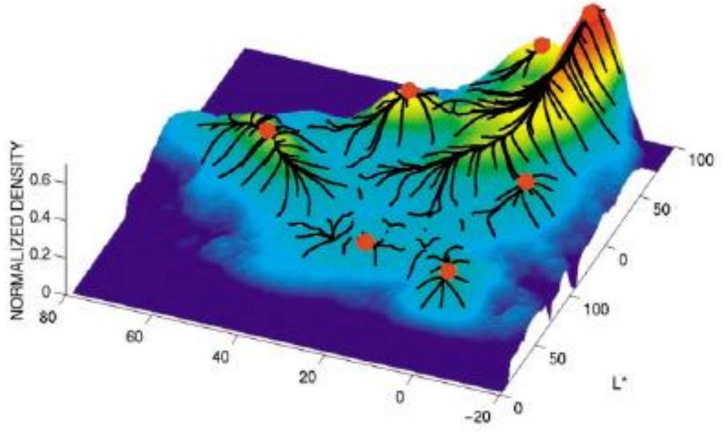
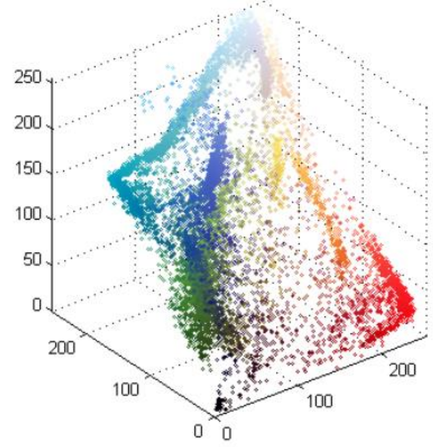
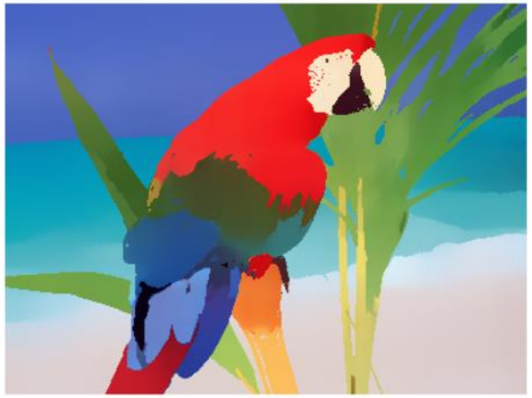


input image

Pixel Distribution Before Meanshift



output image



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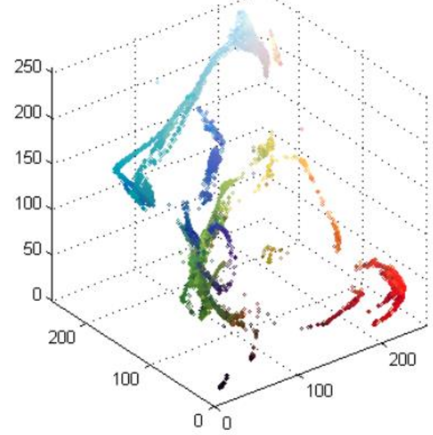
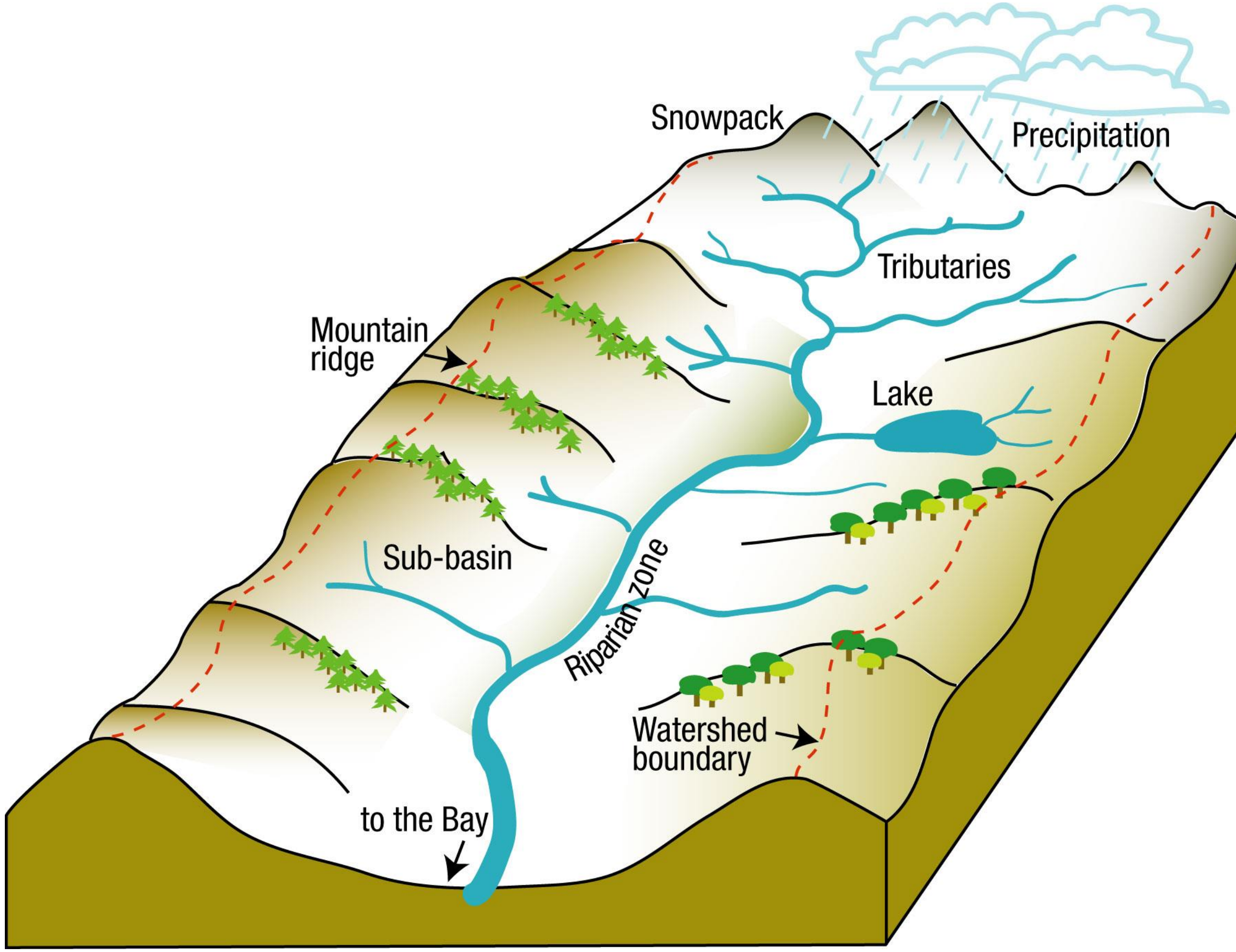
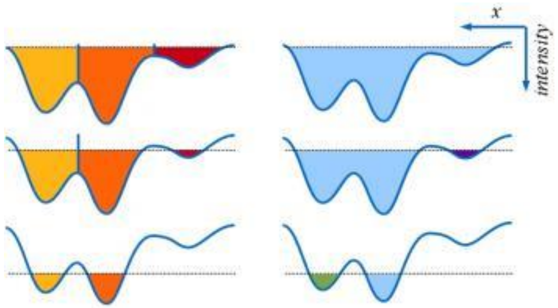


Watershed

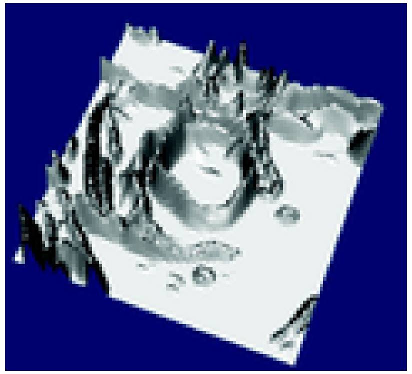

Snowpack
Precipitation
Tributaries
Mountain ridge
Lake
Sub-basin
Riparian zone
Watershed boundary
to the Bay

Watershed

- Watershed segmentation
  - considers an image as a topological surface
  - pixel intensities are heights (lowest level 0, highest peak 255)
  - segmenting overlapping objects
  - consider each waterbody as a separate object



waterbodies via watershed



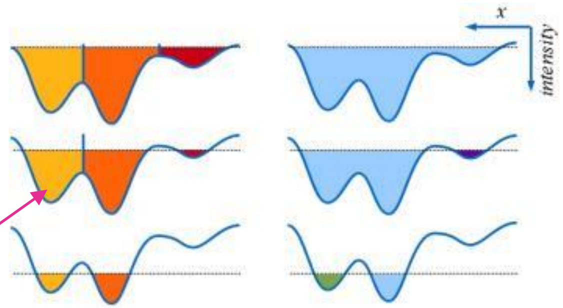
input

courtesy: wiki

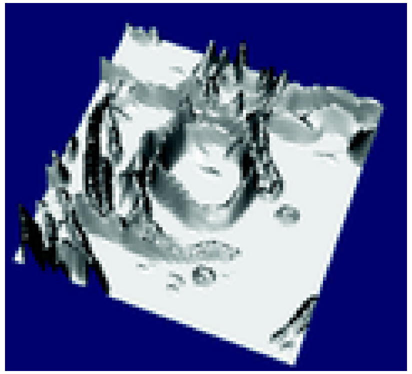
Watershed

- Watershed segmentation
  - considers an image as a topological surface
  - pixel intensities are heights (lowest level 0, highest peak 255)
  - segmenting overlapping objects
  - consider each waterbody as a separate object

catchment basins



waterbodies via watershed



input

courtesy: wiki

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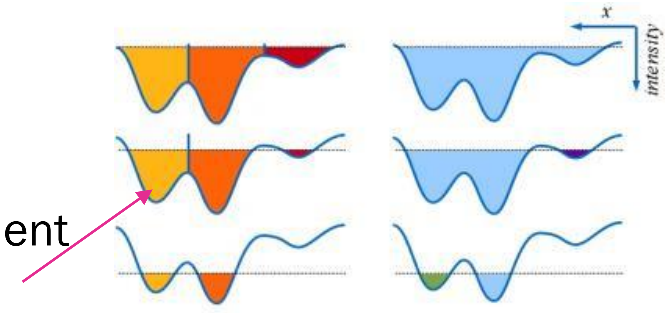
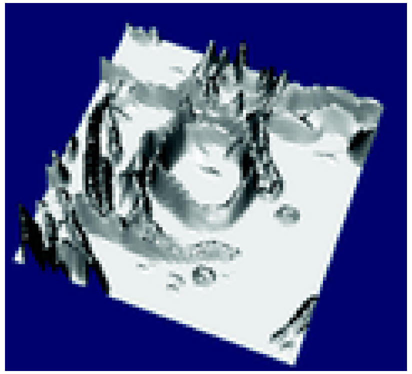
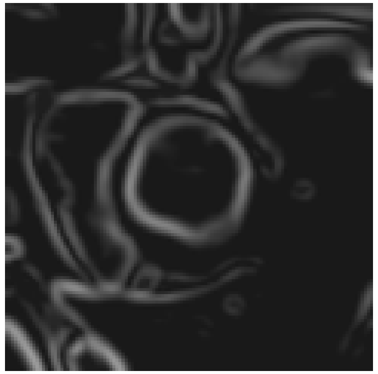


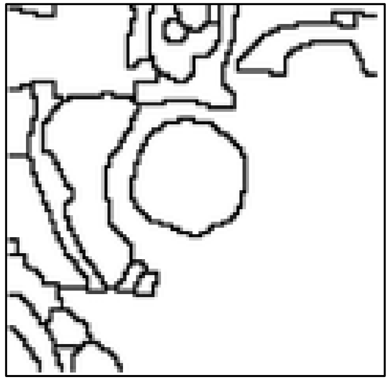
waterbodies via watershed



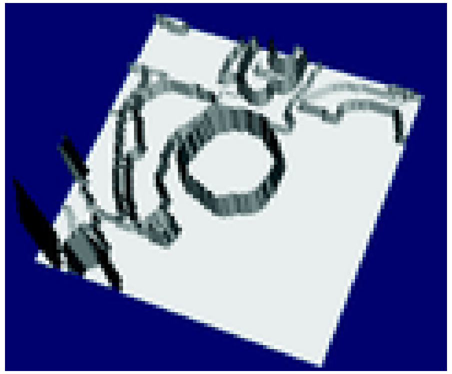
input



gradient



watershed 2D

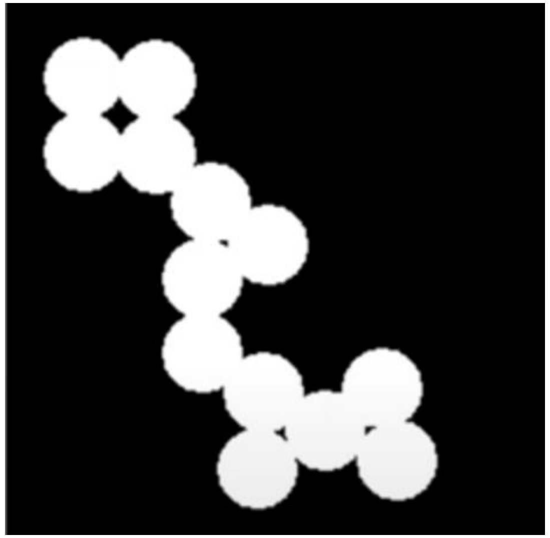


watershed 3D

courtesy: wiki

Watershed

- Watershed segmentation
  - overlapping objects



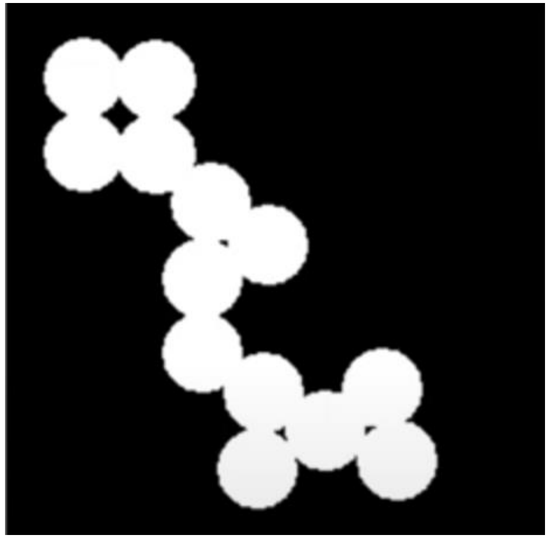
input

thresholding or clustering

courtesy: JW Tay

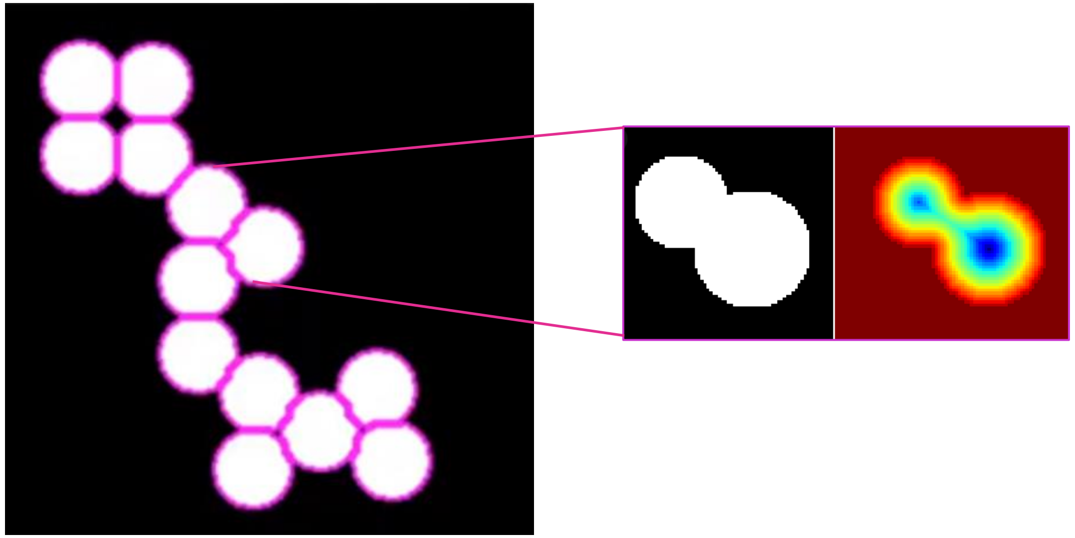
Watershed

- Watershed segmentation
  - overlapping objects



input

thresholding or clustering

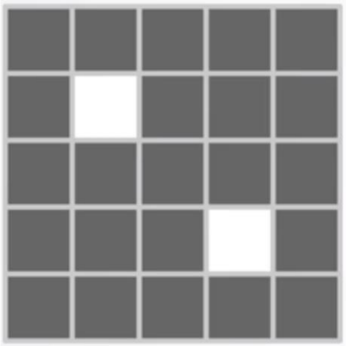


watershed

courtesy: JW Tay

Watershed

- Distance transform
  - computes the distance between each pix and nearest nonzero pix



1.41	1	1.41	2.24	3.16
1	0	1	2	2.24
1.41	1	1.41	1	1.41
2.24	2	1	0	1
3.16	2.24	1.41	1	1.41

courtesy: JW Tay

Watershed

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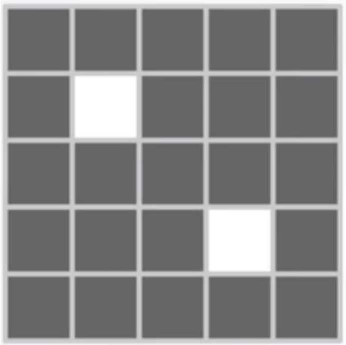
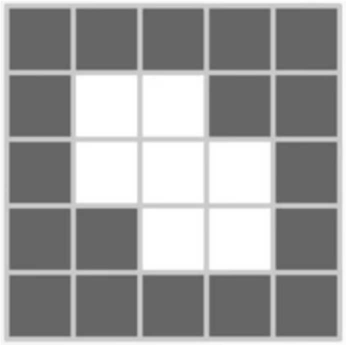


1.41	1	1.41	2.24	3.16
1	0	1	2	2.24
1.41	1	1.41	1	1.41
2.24	2	1	0	1
3.16	2.24	1.41	1	1.41



1.41	1	1	1.41	2.24
1	0	0	1	1.41
1	0	0	0	1
1.41	1	0	0	1
2.24	1.41	1	1	1.41

courtesy: JW Tay

Watershed

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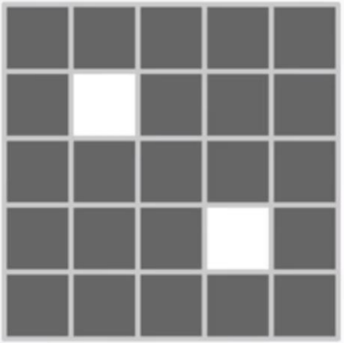
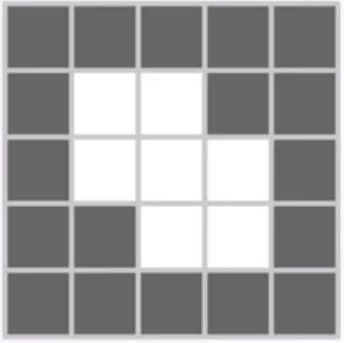
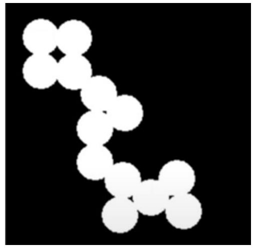
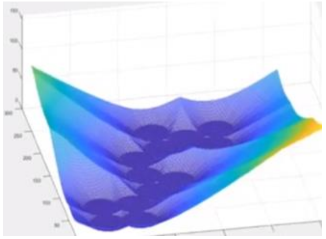


1.41	1	1.41	2.24	3.16
1	0	1	2	2.24
1.41	1	1.41	1	1.41
2.24	2	1	0	1
3.16	2.24	1.41	1	1.41



1.41	1	1	1.41	2.24
1	0	0	1	1.41
1	0	0	0	1
1.41	1	0	0	1
2.24	1.41	1	1	1.41

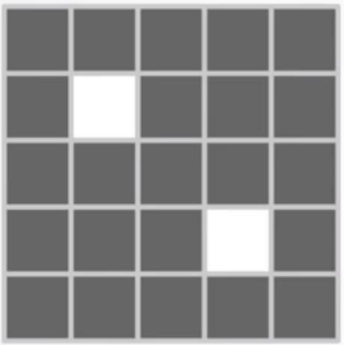




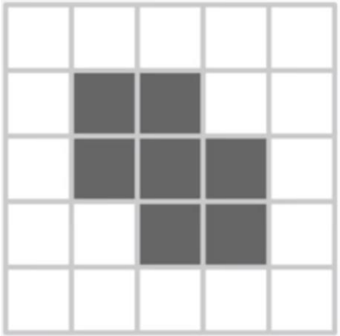
courtesy: JW Tay

Watershed

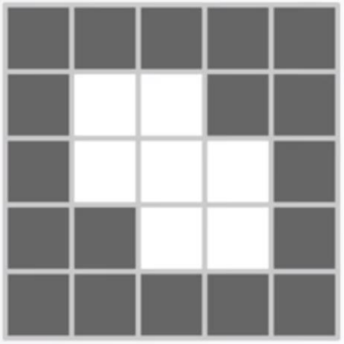
- Distance transform
  - computes the distance between each pix and nearest nonzero pix



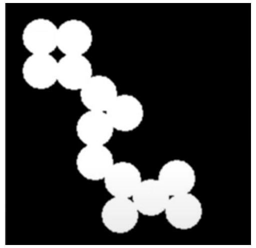
1.41	1	1.41	2.24	3.16
1	0	1	2	2.24
1.41	1	1.41	1	1.41
2.24	2	1	0	1
3.16	2.24	1.41	1	1.41

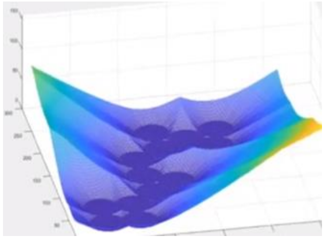


0	0	0	0	0
0	1	1	0	0
0	1	1.41	1	0
0	0	1	1	0
0	0	0	0	0



1.41	1	1	1.41	2.24
1	0	0	1	1.41
1	0	0	0	1
1.41	1	0	0	1
2.24	1.41	1	1	1.41





courtesy: JW Tay

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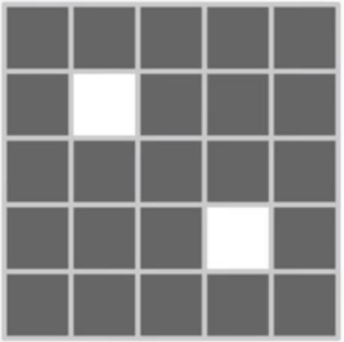

1.41	1	1.41	2.24	3.16
1	0	1	2	2.24
1.41	1	1.41	1	1.41
2.24	2	1	0	1
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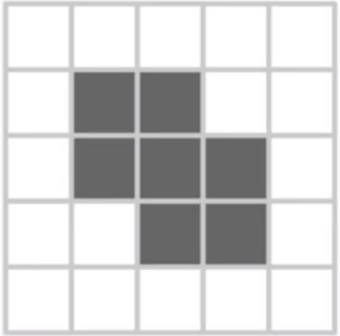
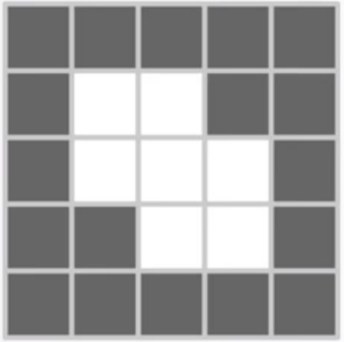
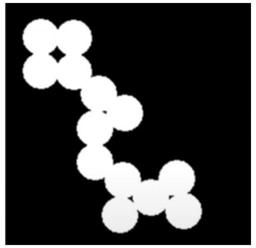


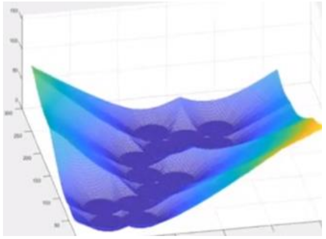
0	0	0	0	0
0	1	1	0	0
0	1	1.41	1	0
0	0	1	1	0
0	0	0	0	0

0	0	0	0	0
0	-1	-1	0	0
0	-1	-1.41	-1	0
0	0	-1	-1	0
0	0	0	0	0



1.41	1	1	1.41	2.24
1	0	0	1	1.41
1	0	0	0	1
1.41	1	0	0	1
2.24	1.41	1	1	1.41





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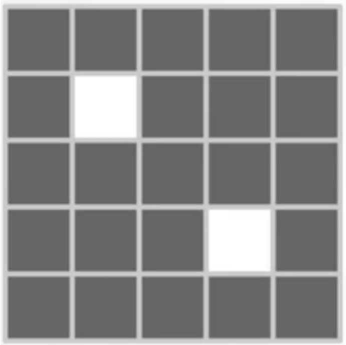
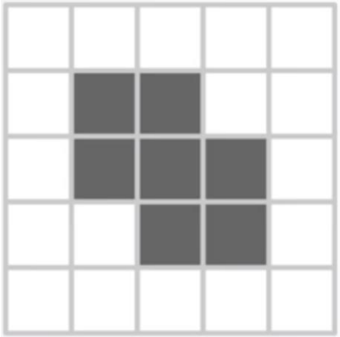
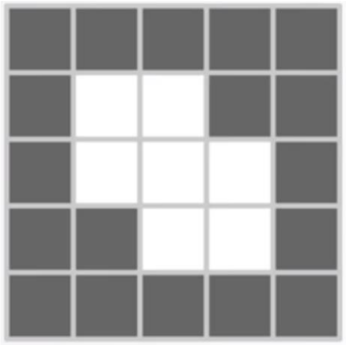


1.41	1	1.41	2.24	3.16
1	0	1	2	2.24
1.41	1	1.41	1	1.41
2.24	2	1	0	1
3.16	2.24	1.41	1	1.41



0	0	0	0	0
0	1	1	0	0
0	1	1.41	1	0
0	0	1	1	0
0	0	0	0	0

0	0	0	0	0
0	-1	-1	0	0
0	-1	-1.41	-1	0
0	0	-1	-1	0
0	0	0	0	0



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1	0	0	1	1.41
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1.41	1	0	0	1
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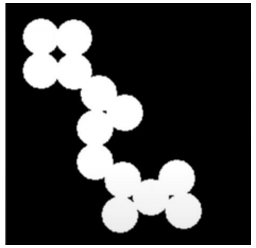

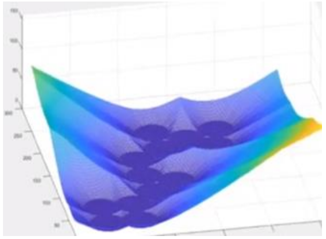

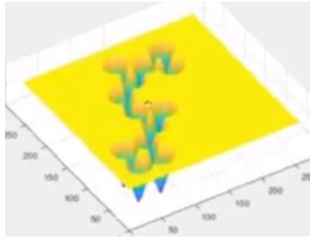

courtesy: JW Tay

Watershed

- Algorithm: outline

  - Requires:
    - each obj must be a basin, coinciding basin's bottom with approx obj center
  - Input: image I
  - convert I into inverted grey: $\hat{I} = L - grey(I)$
  - compute the negative distance transform of $\hat{I}$
  - non-max suppression over shallow minima
  - fill basins & get watersheds
  - update each segmented mask with watersheds

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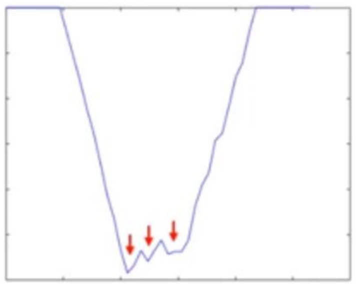
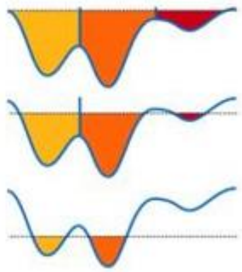
---

why non-max suppression?



Watershed



- Algorithm: getting watersheds

  - Initialize:

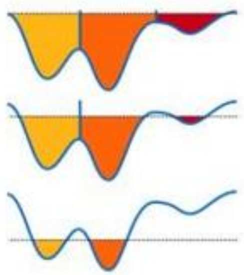
    - A $grey(I)$ having: $[h_{min}\ h_{max}]$
    - Minima points: $M_1, \ldots, M_R$
    - Thresholded set: $T_h = \{p \in I | I(p) \leq h\}$, where p is an pixel in I and h is some intensity level.
    - Let's define Influence set

$$C(M_i) = \text{cluster associated with } M_i$$

$$IZ_{h+1}(M_i) = \{p \in T_{h+1} | d(p, C(M_i)) < d(p, C(M_j))\} \quad \forall j,\ i \neq j$$

Watershed

- Algorithm: getting watersheds



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  - A $grey(I)$ having: $[\boldsymbol{h_{min}}\ \boldsymbol{h_{max}}]$
  - Minima points: $\boldsymbol{M_1, \ldots, M_R}$
  - Thresholded set: $T_h = \{p \in I | I(p) \leq h\}$, where $\boldsymbol{p}$ is an pixel in $\boldsymbol{I}$ and $\boldsymbol{h}$ is some intensity level.
  - Let's define Influence set

$$C(M_i) = \text{cluster associated with } M_i$$

$$IZ_{h+1}(M_i) = \{p \in T_{h+1} | d(p, C(M_i)) < d(p, C(M_j))\} \quad \forall j,\ i \neq j$$

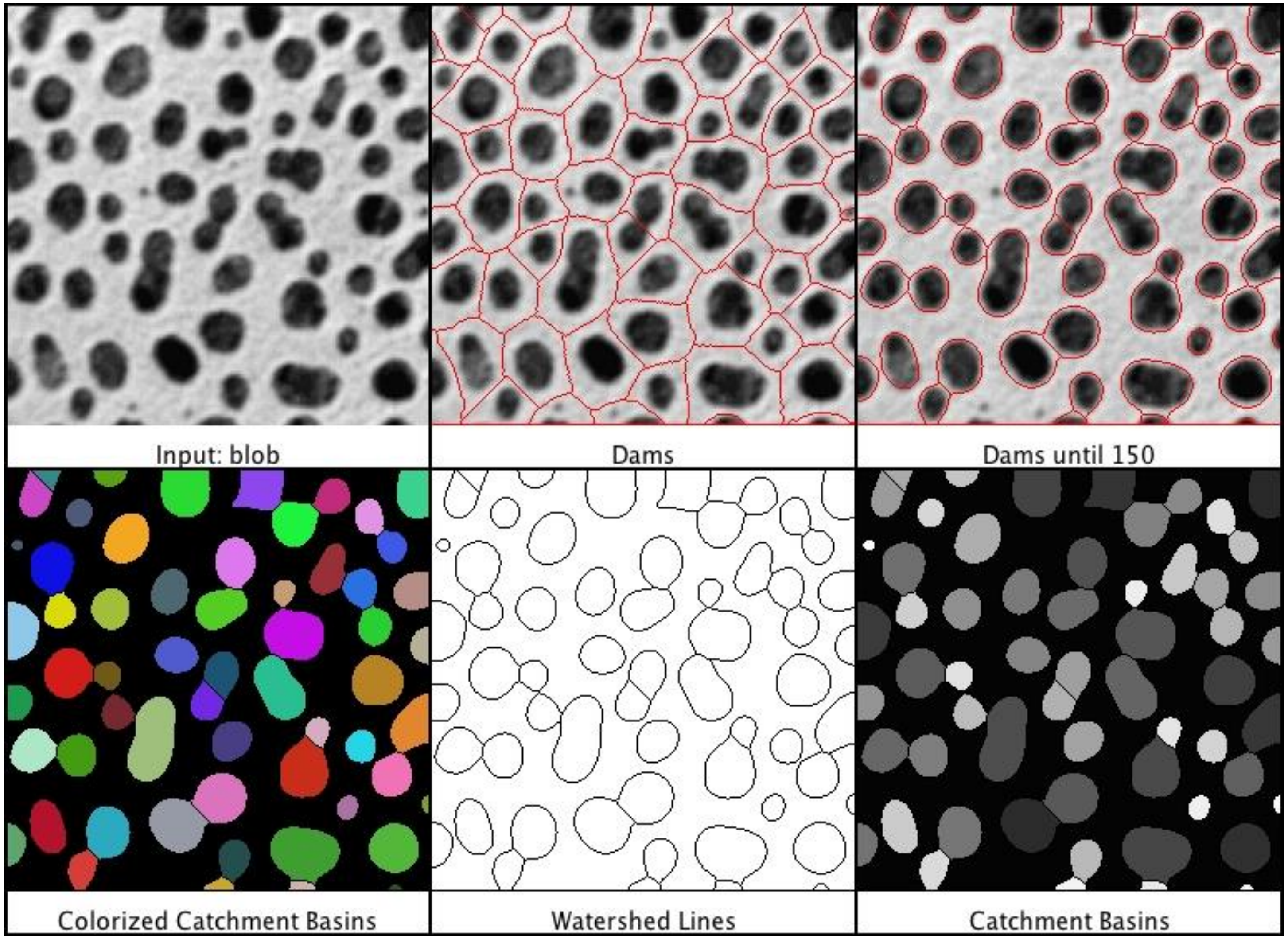
- Run:
  - $\boldsymbol{h = h_{min}}$
  - Immersed set: $X_h = X_{h_{min}} = T_{h_{min}} = \{p \in I | I(p) \leq h_{min}\}$
  - **Loop** until $\boldsymbol{h_{max}}$

$$X_{h+1} = X_h \bigcup \boxed{IZ_{h+1}(M_1)} \ldots \bigcup IZ_{h+1}(M_R)$$

Influence set of minima $\boldsymbol{M_1}$ at level $\boldsymbol{h+1}$

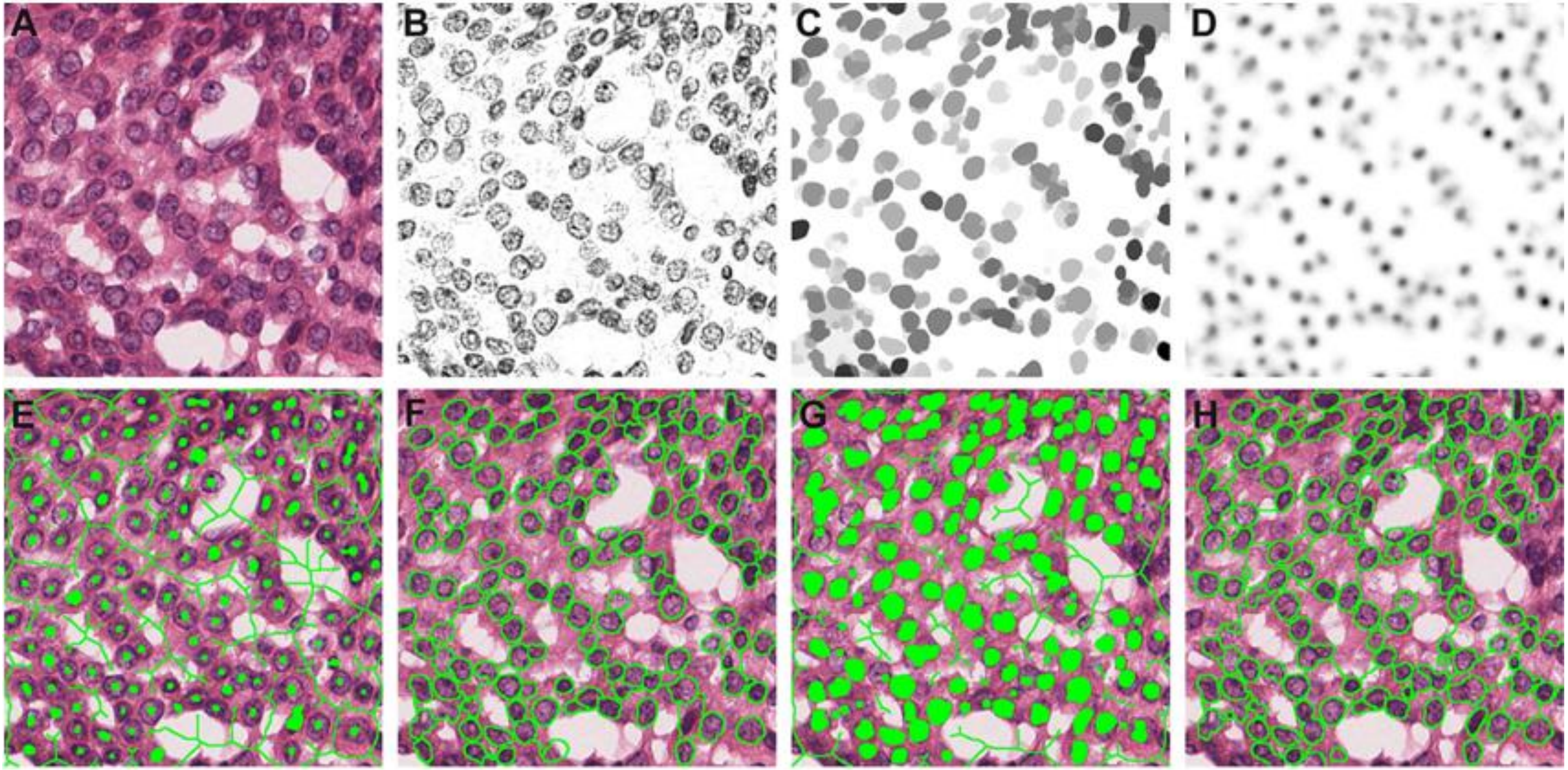
  - $Watershed(\boldsymbol{I})$ = Set of all pixels in $\boldsymbol{I} \setminus \boldsymbol{X_{hmax}}$

Watershed



courtesy: EPFL

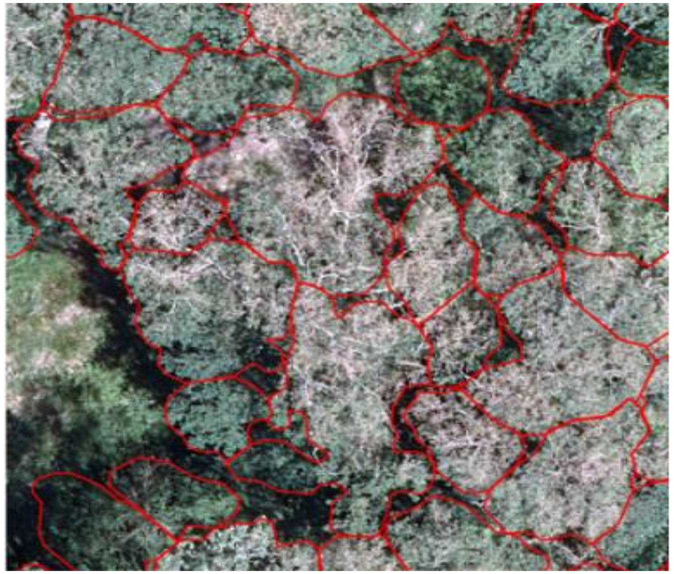
Watershed



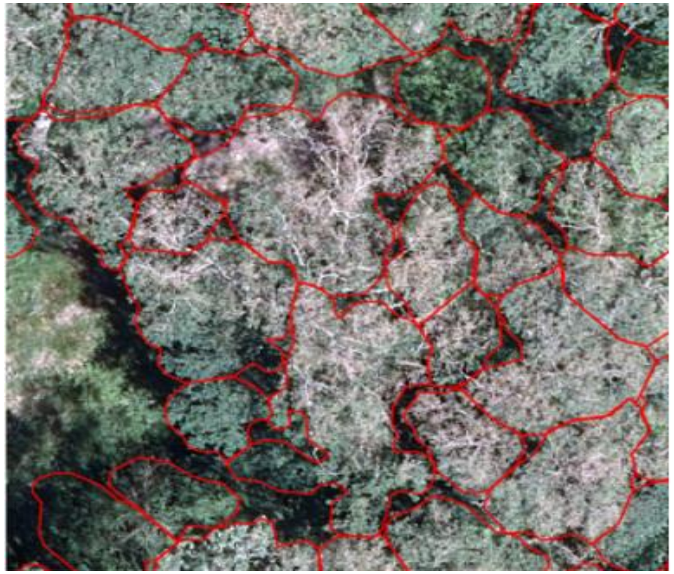
courtesy: M Veta

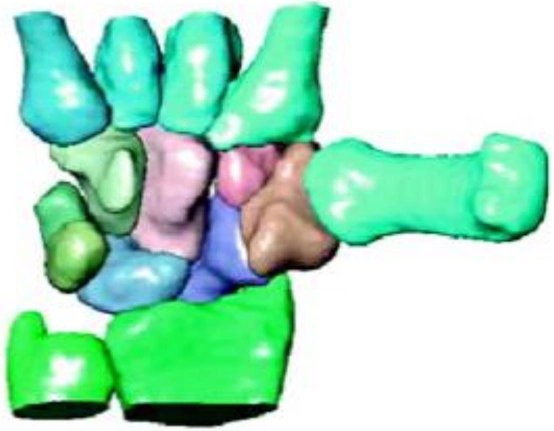
Watershed

Watershed



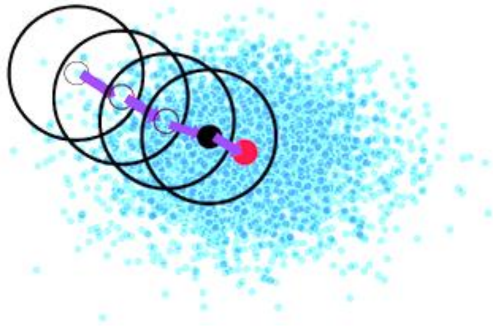
Watershed

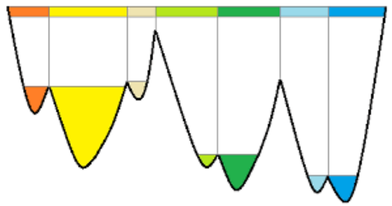




Conclusion

- Mean-shift
- Watershed



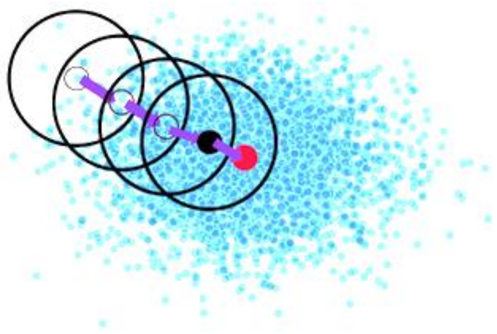


Conclusion

- Mean-shift
- Watershed

❑ Mean-shift

- Number of cluster specification is not needed
- Mode seeking algorithm
- Computationally expensive



❑ Watershed

- Precise boundaries even for overlapping similar objects
- Images treated as topological surfaces