Clustering for Change Detection

CS 510
Lecture #10
February 8, 2017

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Discuss PA2

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Where are we?

- We can attend to still "objects" (interesting patches)
  - Geometric transformations
  - Fourier Analysis / Aliasing
  - DoG (Difference of Gaussians)
- Motion grabs attention
  - Far more than any other cue
  - Think of foveal/peripheral vision
- Next task: motion segmentation/attention
  - Phase 1: still camera
  - Phase 2: moving camera

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Change Detection

- Detecting moving objects in videos with still cameras is easy:
  - If a pixel changes, something has moved!
- Or is it? Why might a pixel change?
  - A moving object obscures a background pixel
  - An object moves, revealing a background pixel
    - Ghosting
  - Repeated variation (multi-state pixels)
    - Model variation pattern

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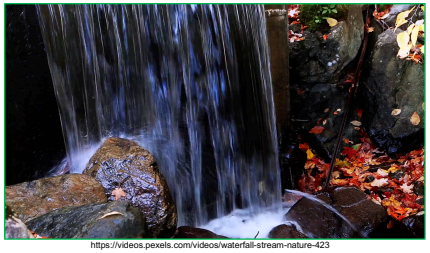
Repeated Variation (obvious)



https://videos.pexels.com/videos/waterfall-stream-nature-423

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Repeated Variation (subtle)

https://www.shutterstock.com/video/

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Motion from Still Cameras

1. Detect meaningfully changed pixels
   - Model individual pixels: 2 methods
     - Mixture of Gaussians (Stauffer & Grimson)
     - Statistical sampling (Barnich & Van Droogenbroeck)
   - Both grounded in clustering
2. Track detected regions
   - Again, 2 methods (still camera simplifies)
     - Kalman filters
     - Particle filters (Isard & Blake)
   - Eliminate ghost regions
   - Eliminate fragmentation
   - Determine trajectory

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Clustering

- Assumptions
  - K : the number of clusters
  - Every descriptor is a point in feature space
- Implicit Approach
  - Fit K statistical distributions (clusters) that are most likely to explain the data
    - K-Means (in OpenCV)
    - Expectation Maximization (EM) (in OpenCV)

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K-Means

- Select K samples as random, make them cluster centers
  - There are useful variations on this step
- Iterate until no change:
  - Assign every sample to the nearest cluster center
  - Move every cluster center to the mean of the samples assigned to it

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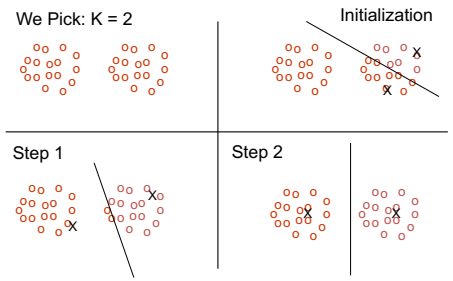
K-Means Illustration



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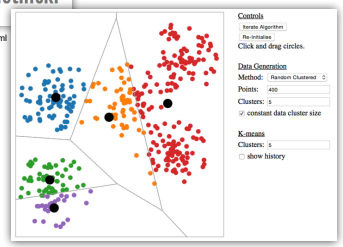
Excellent Online Visualization

Aleksey Nozdryn-Plotnicki
blog, portfolio, etc.

http://alekseynp.com/portfolio/k-means.html



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Analysis of K-Means

- K-Means minimizes $\sum_{s \in S} \| s - C(s) \|_{L2}$
  - Where 'S' is the set of samples
  - C(s) is the cluster center that sample 's' is assigned to
- The assignment step reduces the value by changing the assignments C(s)
- The mean computation step reduces the value by centering the means
- Together, they hill climb to a *local* optima

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Probabilistic Interpretation

- Every cluster center can be viewed as the mean of a Gaussian random process
  - St. Dev. is the same in every direction
  - St. Dev. is the same for every process
  - Samples are assigned to the process that was most likely to create them
- This interpretation supports
  - Estimating the likelihood of a sample
  - If K-Means is run more than once, select the solution most likely to generate the observed data