Clustering: Grouping Related Docs



CS229: Machine Learning Carlos Guestrin Stanford University Slides include content developed by and co-developed with Emily Fox

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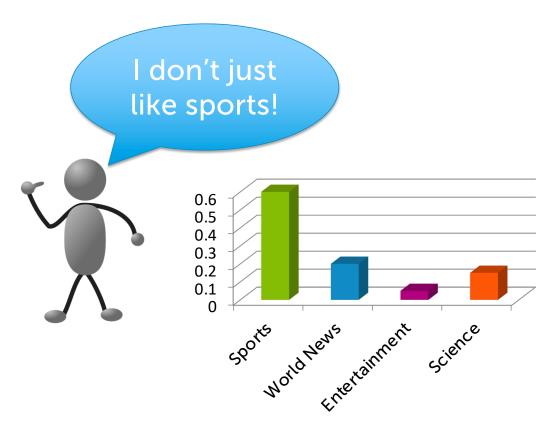
Motivating clustering approaches

Goal: Structure documents by topic

Discover groups (*clusters*) of related articles

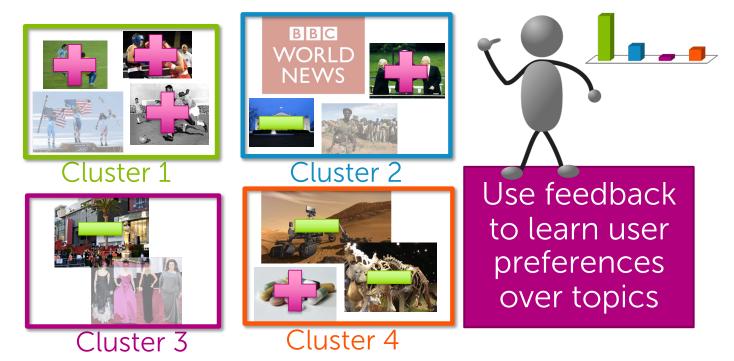


Why might clustering be useful?



Learn user preferences

Set of clustered documents read by user



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What if some of the labels are known?

Training set of labeled docs



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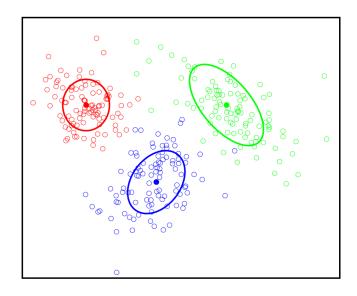
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Clustering

No labels provided ...uncover cluster structure from input alone

Input: docs as vectors \mathbf{x}_i Output: cluster labels \mathbf{z}_i

An unsupervised learning task

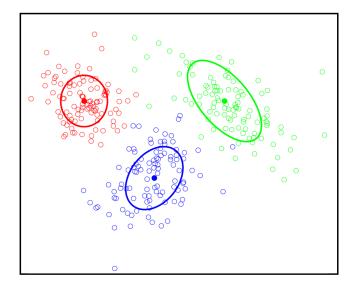


What defines a cluster?

Cluster defined by center & shape/spread

Assign observation x_i (doc) to cluster k (topic label) if

- Score under cluster k is higher than under others
- For simplicity, often define score as distance to cluster center (ignoring shape)

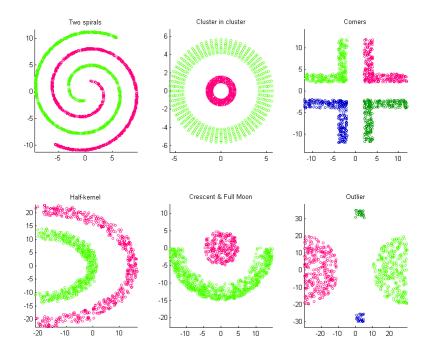


Hope for unsupervised learning

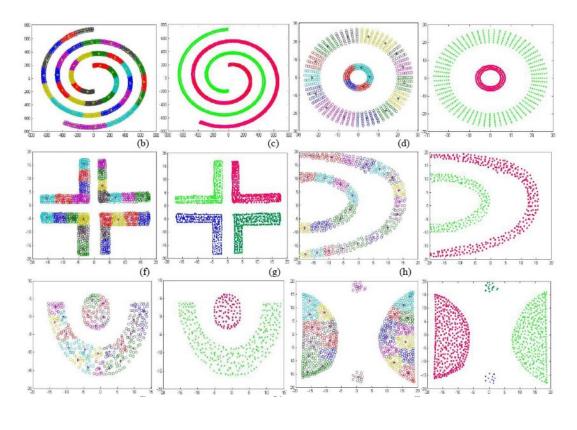


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Other (challenging!) clusters to discover...



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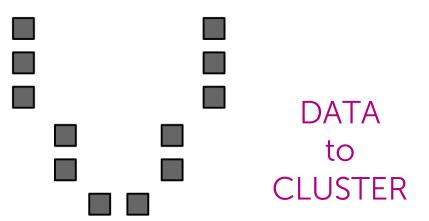




k-means

Assume

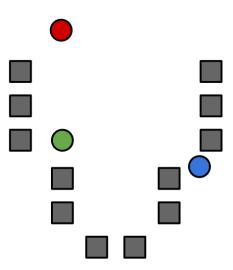
-Score= distance to cluster center (smaller better)



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0. Initialize cluster centers

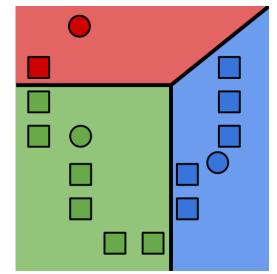
$$\mu_1, \mu_2, \ldots, \mu_k$$



- 0. Initialize cluster centers
- 1. Assign observations to closest cluster center

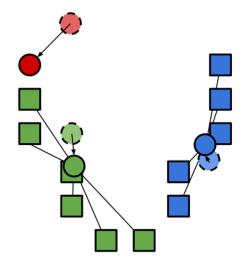
$$z_i \leftarrow \arg\min_j ||\mu_j - \mathbf{x}_i||_2^2$$

Inferred label for obs i, whereas supervised learning has given label y_i

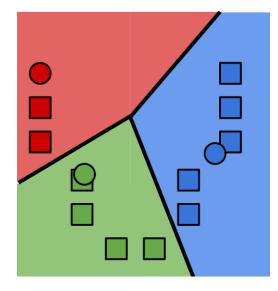


- O. Initialize cluster centers
- 1. Assign observations to closest cluster center
- 2. Revise cluster centers as mean of assigned observations

$$\mu_j = \frac{1}{n_j} \sum_{i: z_i = j} \mathbf{x}_i$$



- O. Initialize cluster centers
- 1. Assign observations to closest cluster center
- 2. Revise cluster centers as mean of assigned observations
- 3. Repeat 1.+2. until convergence



Why does K-means work???

- What's k-means optimizing?
- Does it always converge?

What is k-means optimizing?

• Potential function $F(\mu, \mathbf{z})$ of centers μ and point allocations \mathbf{z} :

• Optimal k-means:

Does K-means converge??? Part 1

Optimize potential function:

$$\min_{\mu} \min_{\mathbf{z}} F(\mu, \mathbf{z}) = \min_{\mu} \min_{\mathbf{z}} \sum_{j=1}^{N} \|\mu_{z_i} - x_i\|_{2}^{2}$$

• Fix μ and minimize z:

Does K-means converge??? Part 2

Optimize potential function:

$$\min_{\mu} \min_{\mathbf{z}} F(\mu, \mathbf{z}) = \min_{\mu} \min_{\mathbf{z}} \sum_{j=1}^{N} \|\mu_{z_i} - x_i\|_{2}^{2}$$

• Fix **z** and minimize μ :

Coordinate descent algorithms

$$\min_{\mu} \min_{\mathbf{z}} F(\mu, \mathbf{z}) = \min_{\mu} \min_{\mathbf{z}} \sum_{j=1}^{N} \|\mu_{z_{i}} - x_{i}\|_{2}^{2}$$

- Want: min_a min_b F(a,b)
- Coordinate descent:
 - fix a, minimize b
 - fix b, minimize a
 - repeat
- Converges!!!
 - if F is bounded
 - to a (often good) local optimum
 - as we saw in applet (play with it!)
 - (For LASSO it converged to the global optimum, because of convexity)

K-means is a coordinate descent algorithm!



Clustering images

- For search, group as:
 - Ocean
 - Pink flower
 - Dog
 - Sunset
 - Clouds
 - **–** ...





Limitations of k-means

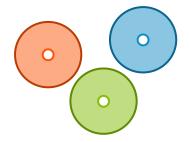
Assign observations to closest cluster center



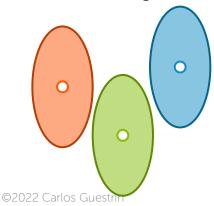
Can use weighted Euclidean, but requires *known* weights

Only center matters

Equivalent to assuming spherically symmetric clusters

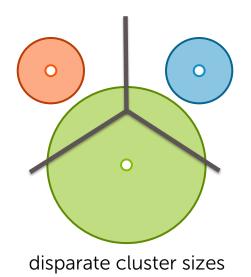


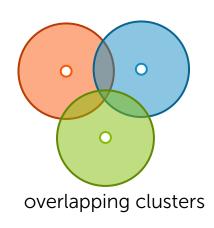
Still assumes all clusters have the same axis-aligned ellipses

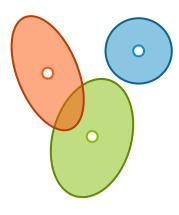


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Failure modes of k-means







different shaped/oriented clusters

What you can do now...

- Describe the input (unlabeled observations) and output (labels) of a clustering algorithm
- Determine whether a task is supervised or unsupervised
- Cluster documents using k-means
- Describe potential applications of clustering