

Introduction to Data Science

Clustering



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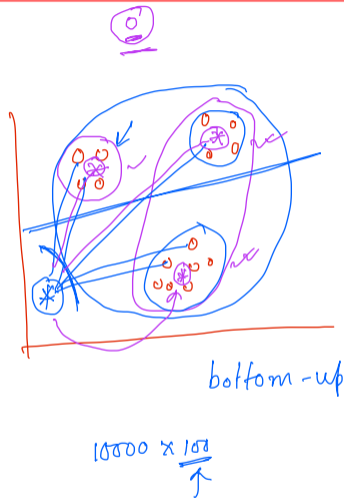
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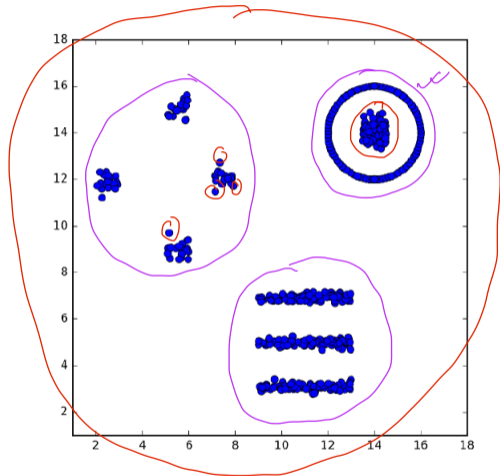
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Introduction

- Clustering is the problem of grouping of points by similarity.
- Splitting of points based on similarity
- Applications
 - Hypothesis development ✓
 - Modeling over smaller subset of data |
 - Data reduction ✓
 - Outliers detection



Example

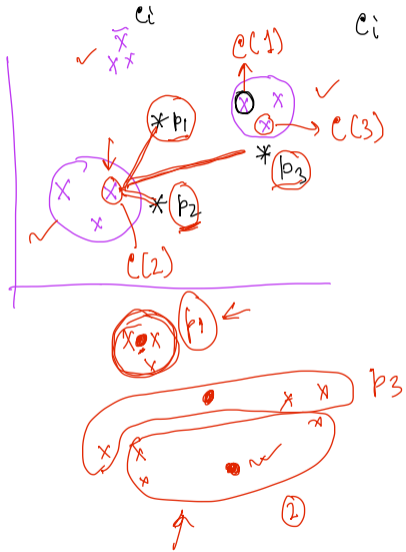


$\frac{9}{8}$ $\frac{3}{4}$
Many

1 - 2

(k)

k-means Clustering



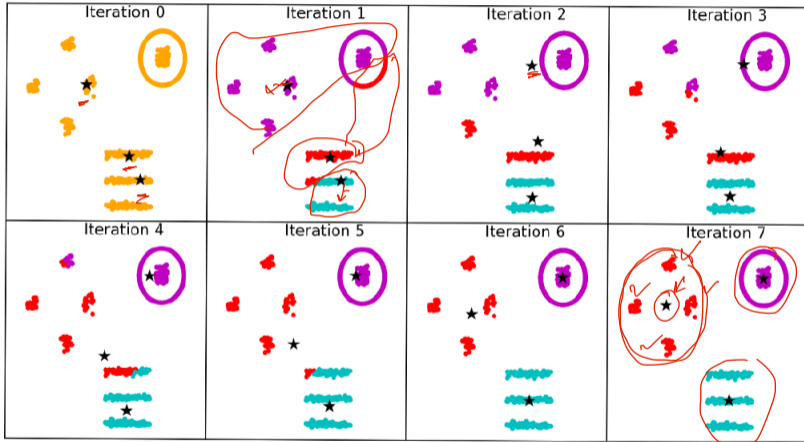
$k=1$
 $k=2$
 $\boxed{k=3}$

$$\min \left\{ \underbrace{d(c_i, p_1)}_{(p_1)}, \underbrace{d(c_i, p_2)}, \underbrace{d(c_i, p_3)} \right\}$$

label c_i with the class of p_j which is closest to c_i

$p_i \leftarrow$ Average of the points in the current cluster

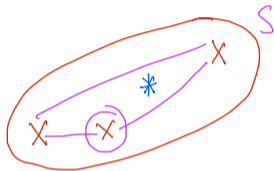
Example



Centers vs Centroids

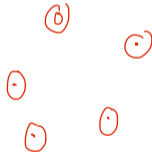
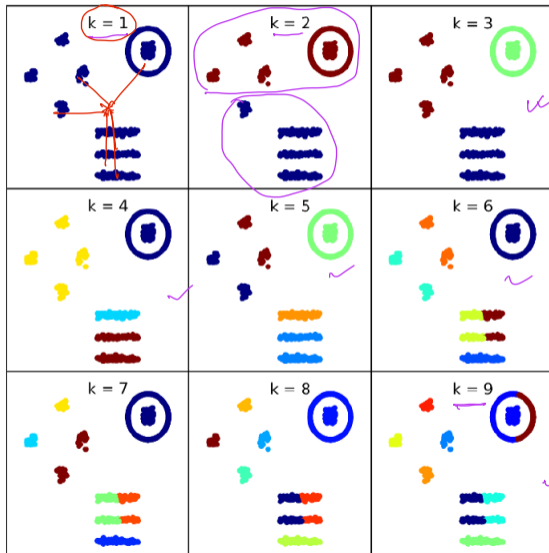
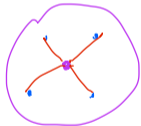
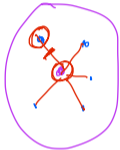
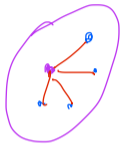
• Centroids: $C_d = \frac{1}{|S|} \sum_{p \in S} p[d]$ ✓ ✓

• Centers: $\arg \min_{c \in S} \sum_{i=1}^n d(c, p_i)$ ✓

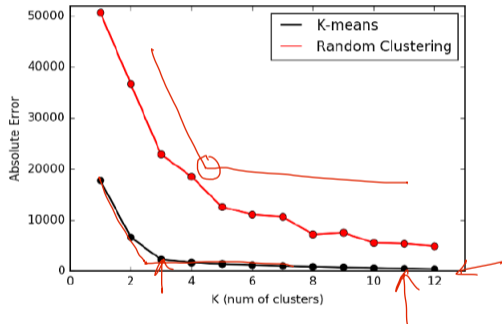


Number of clusters

$$F = \sum d_i$$



Number of clusters

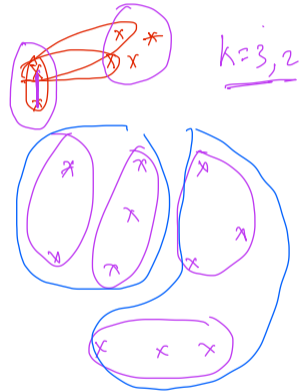


Hand-drawn diagrams and text illustrating the relationship between error and the number of clusters:

- A blue circle containing two 'X' marks, representing a cluster.
- A blue circle containing two 'X' marks, representing a cluster.
- A blue circle containing one 'X' mark, representing a cluster.
- Text: Black \rightarrow $E = 0$
- Text: ~~Red~~ Blue \rightarrow $E > 0$

Agglomerative clustering

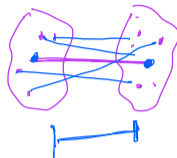
- A bottom-up approach
- Combining similar items
- Distance measures - C_1, C_2 are some clusters



Agglomerative clustering

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- Nearest neighbor - $d(C_1, C_2) = \min_{x \in C_1, y \in C_2} \|x - y\|$



Agglomerative clustering

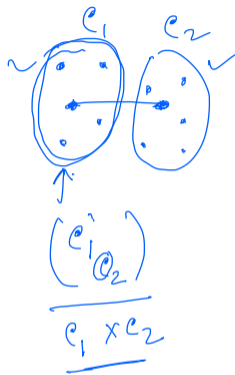
- A bottom-up approach
- Combining similar items
- Distance measures - C_1, C_2 are some clusters

- Nearest neighbor - $d(C_1, C_2) = \min_{x \in C_1, y \in C_2} \|x - y\|$

- Average link - $d(C_1, C_2) = \frac{1}{|C_1| \cdot |C_2|} \sum_{x \in C_1} \sum_{y \in C_2} \|x - y\|$

Agglomerative clustering

- A bottom-up approach
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- Distance measures - C_1, C_2 are some clusters
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 - Nearest centroid - closest centroids, $|C_1| \cdot |C_2|$ point-pairs

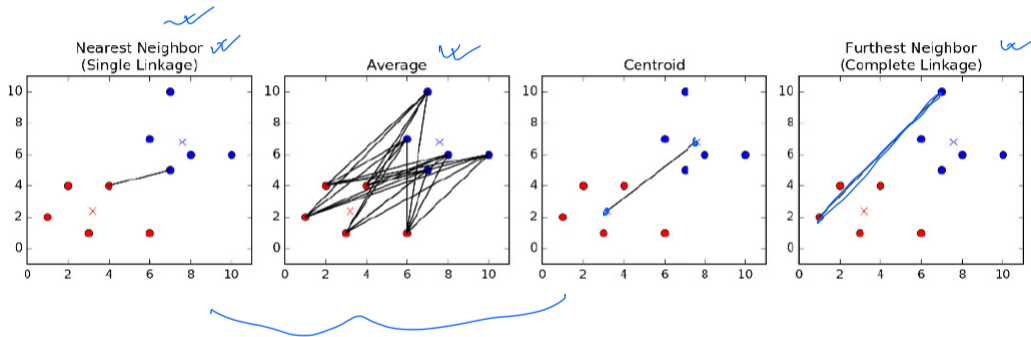


Agglomerative clustering

- A bottom-up approach
- Combining similar items
- Distance measures - C_1, C_2 are some clusters
 - Nearest neighbor - $d(C_1, C_2) = \min_{x \in C_1, y \in C_2} \|x - y\|$
 - Average link - $d(C_1, C_2) = \frac{1}{|C_1| \cdot |C_2|} \sum_{x \in C_1} \sum_{y \in C_2} \|x - y\|$
 - Nearest centroid - closest centroids, $|C_1| \cdot |C_2|$ point-pairs
 - Furthest link - $d(C_1, C_2) = \max_{x \in C_1, y \in C_2} \|x - y\|$

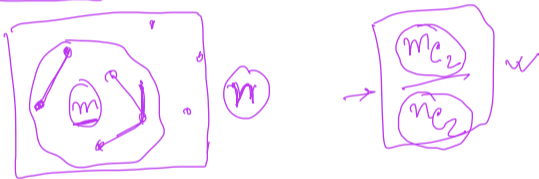


Distance measures



Comparing clustering

- Jaccard similarity: Similarity between two sets, $J(s_1, s_2) = \frac{|s_1 \cap s_2|}{|s_1 \cup s_2|} \rightarrow \left. \begin{array}{l} \text{common} \\ \text{Union} \end{array} \right\}$
- Jaccard distance: $1 - J(s_1, s_2)$. It is distance metric
- Rand index: ratio of compatible pairs to all possible pairs



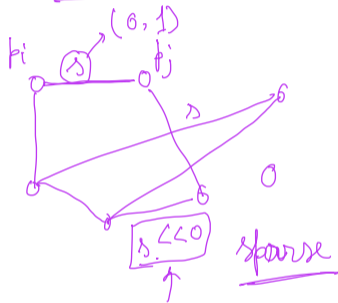
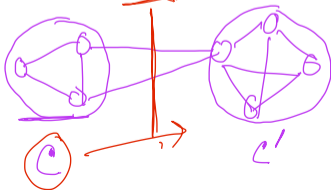
Similarity & Cuts

- Similarity measure - $S[i, j] = e^{-\beta \|p_i - p_j\|}$
- Similarity graph - It is based on similarity measure. Can be made sparse by applying thresholding on similarity values

• Cluster weight - $W(C) = \sum_{x \in C} \sum_{y \in C} S[i, j]$

• Cut weight - $W(C) = \sum_{x \in C} \sum_{y \in V - C} S[i, j]$

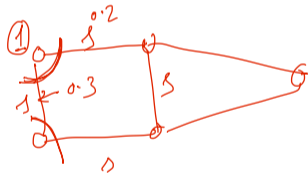
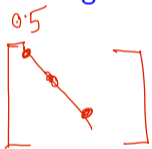
• Conductance of cluster C is $\frac{W'(C)}{W(C)}$



$e^{-x} \rightarrow 1$ when $x = 0$
 $e^{-x} \rightarrow 0$ when $x \rightarrow \infty$

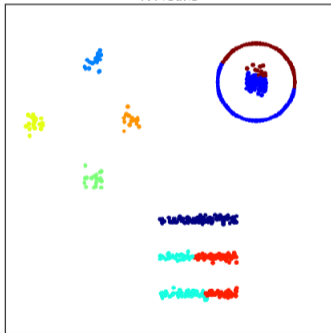
Spectral clustering

- Construct the Laplacian matrix $L = D - S$
 - S - similarity matrix
 - D - degree-weighted identity matrix, $D[i, i] = \sum_j S[i, j]$
- The most valuable eigenvectors for clustering here turn out to have the smallest non-zero eigenvalues
- Applying k -means clustering in this feature space produces connected clusters



Spectral clustering

K-Means



Spectral Clustering

