Unit 5: Clustering

BigSurv Text Analysis

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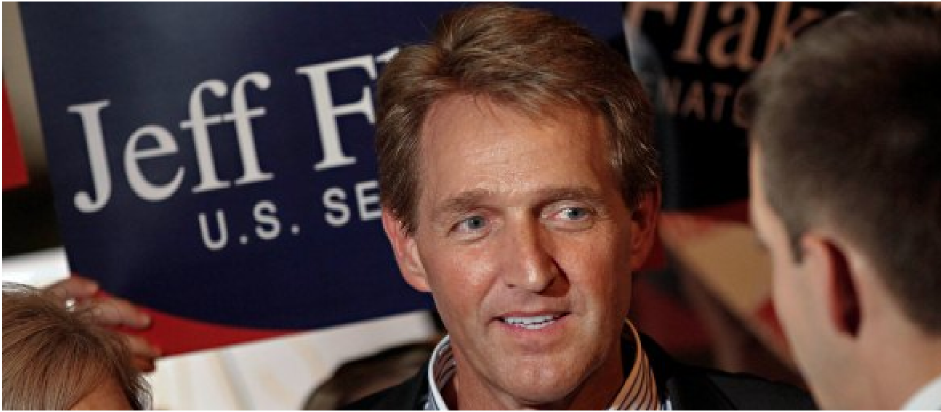

Jeff F
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Today: Cluster press releases

Goal: partition documents such that:

- similar documents are together
- dissimilar documents are apart

Method: Clustering methods

Game Plan:

1) What makes two data points (i.e. documents) similar?
2) How do we find a good partition?
3) How do we interpret the clusters?

Key Terms:

- (Multidimensional) Space
- Distance
- Euclidean Distance
- Cosine Distance
- Cluster Analysis / Clustering
- K-means
- Centroid

K-Means Clustering

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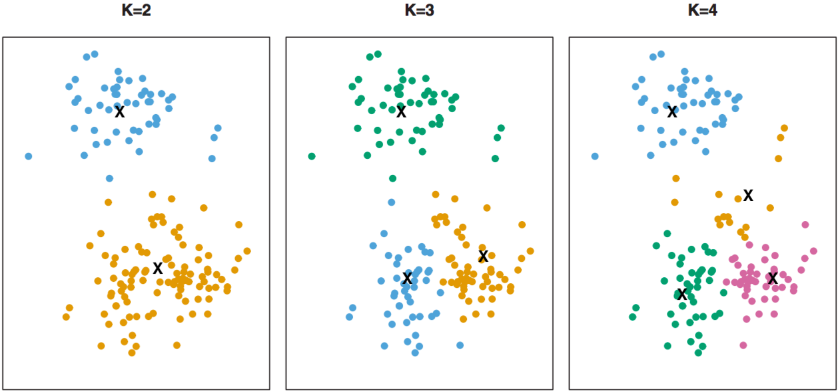
Outputs

1. C_k: The set of observations assigned to each cluster.
2. μ_k: The mean for each K – a vector representing the average values of all observations in that cluster. Also called centroid.

K-Means Clustering



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Then its mean is:

$$\mu = [\text{mean}(X_{1,1}, X_{2,1}), \text{mean}(X_{1,2}, X_{2,2}), \text{mean}(X_{1,3}, X_{2,3})]$$

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The K-means algorithm will assign each observation to the cluster with the closest mean.

K-Means Clustering: Example

Goal: Cluster the following documents:

- `I like to eat broccoli and bananas.`
- `I eat a banana smoothie for breakfast.`
- `Hamsters and kittens are cute.`
- `She adopted a cute kitten.`

K-Means Clustering: Example

Inputs

1. A document term matrix

	adopt	banana	breakfast	broccoli	cute	eat	hamster	kitten	like	smoothi
1	0	1	0	1	0	1	0	0	1	0
2	0	1	1	0	0	1	0	0	0	1
3	0	0	0	0	1	0	1	1	0	0
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Outputs

1. C_k: Cluster assignment:
   - $\boldsymbol{C_1}$: [1, 2]
   - $\boldsymbol{C_2}$: [3, 4]

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Outputs

1. C_k: Cluster assignment:
   - $\boldsymbol{C_1}$: [1, 2]
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2. μ_k: Cluster means / centroids:

	adopt	banana	breakfast	broccoli	cute	eat	hamster	kitten	like	smoothi
μ_1	0.0	1.0	0.5	0.5	0.0	1.0	0.0	0.0	0.5	0.5
μ_2	0.5	0.0	0.0	0.0	1.0	0.0	0.5	1.0	0.0	0.0

K-Means Clustering

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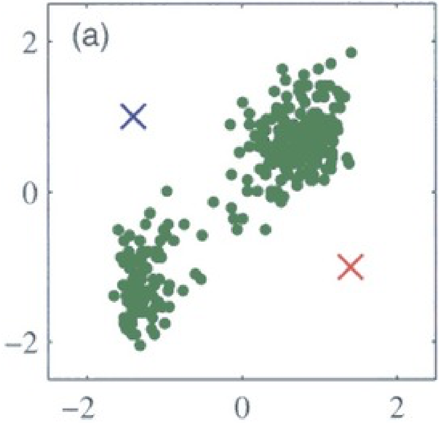
How do we find a good partition?

K-Means Clustering: Algorithm

1) Randomly initialize K cluster centroids $(\mu_1, \mu_2, \cdots, \mu_k)$ in random locations.
2) Repeat:
   - Assignment: Assign each observation $\boldsymbol{X}$ to cluster with closest mean μ_k.
   - Update: Calculate new centroids μ_k by averaging all points assigned to each cluster.

   Stop when cluster assignments stop changing.

K-Means Clustering: Algorithm



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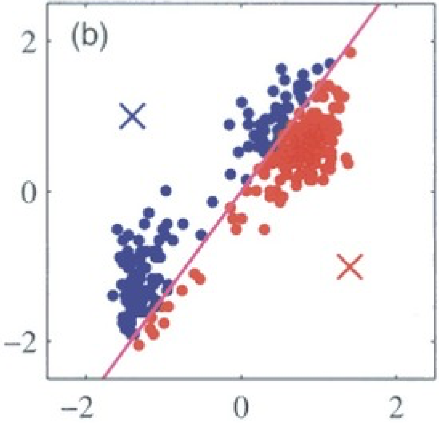

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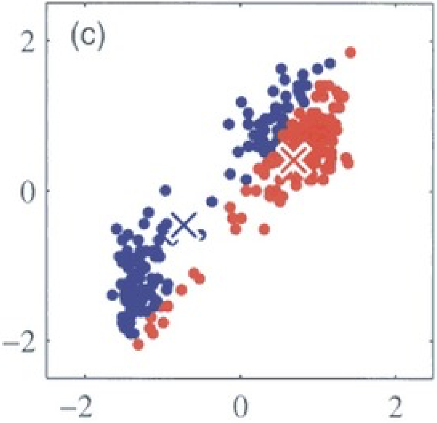

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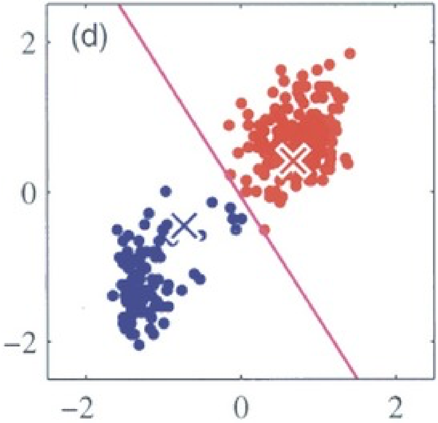

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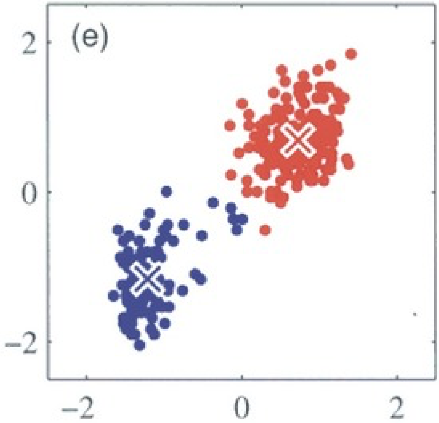

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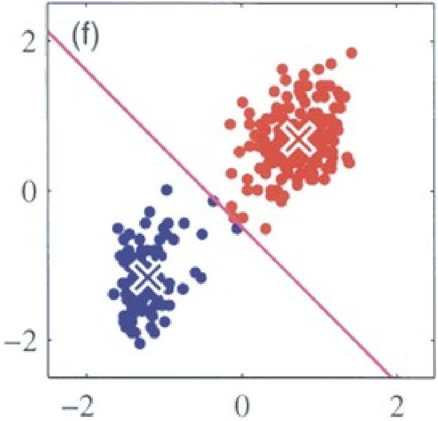

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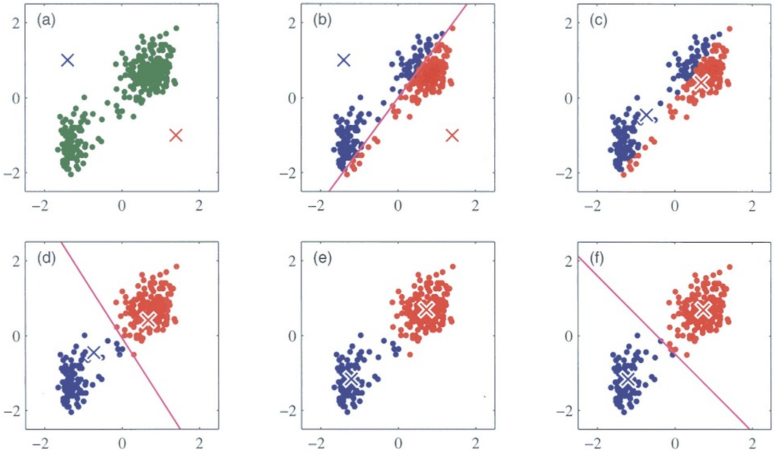

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1) How should we preprocess the data?
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Two kinds of validation criteria:

1. Quantitative evaluation:
   - A good clustering is one for which the within-cluster variation is as small as possible.
2. Qualitative evaluation:
   - A good clustering is one for which clusters are substantially / semantically interpretable.

Quantitative evaluation: within-cluster variation is as small as possible.

- Within-cluster variation: a measure of the amount by which the observations within a cluster differ from each other.
- Common metric: Sum of Squared Euclidean Distance

For a given document $\boldsymbol{X}$ in cluster k, the squared Euclidean distance is:

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Thus our goal is to minimize the total within-cluster sum of squares:

$$\sum_{k=1}^{K} W(C_k)$$

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1. Manual identification
    - Sample set of documents from same cluster
    - Read documents
    - Assign cluster "label" by hand
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3. Be Transparent
   - Provide documents + code
   - Detail labeling procedures
   - Acknowledge ambiguity

To the `R` code!