150B/355B
Introduction to Machine Learning for Social Science
TA Section 8

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March 2, 2018

Road Map

1. K-means clustering
2. Topic modeling
3. R Exercise

Clustering

Task: Partition a set of unlabeled documents into meaningful classes / clusters.

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This week: using these distance metrics, how do we find a good partition of documents?

K-Means Clustering

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   Q: What is the dimension of a centroid?

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   Stop when cluster assignments stop changing.

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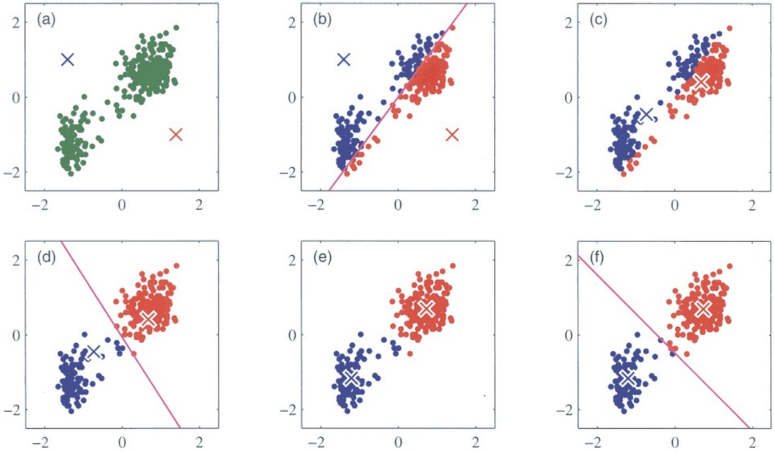

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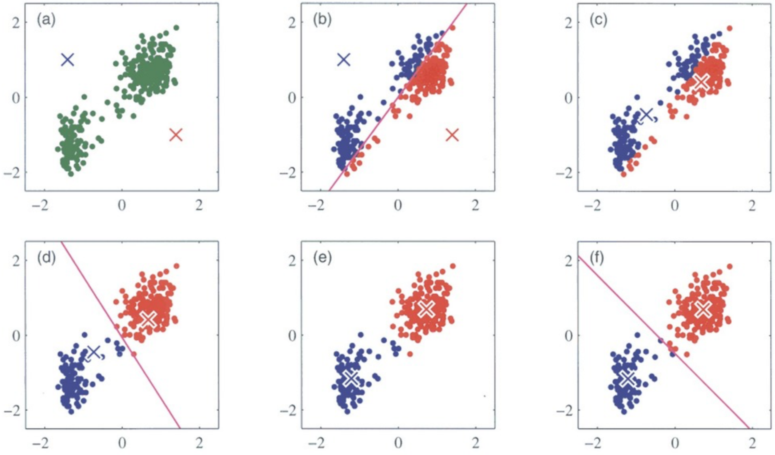

The algorithm stops when the partition boundary (red line) stops changing.

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Suppose we ran the algorithm using different starting values, given K and the preprocessing method, how can we know which starting value we should use?

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2. Qualitative evaluation:
   - A good clustering is one for which clusters are substantially / semantically interpretable.

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Sum of squared Euclidean distance

Step 1: For document $\boldsymbol{X}$, calculate its Euclidean distance with the centroid ($\boldsymbol{\mu_k}$) of the cluster it is assigned to:

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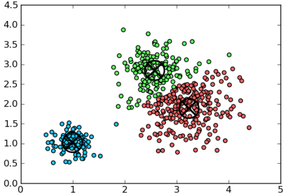

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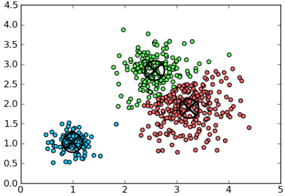

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Step 2: Repeat step 1 for each document and sum up all distances

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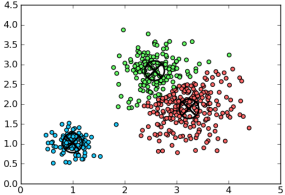

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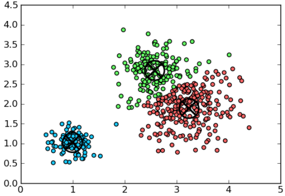

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We want to choose the clustering result that minimizes $\boldsymbol{W}$.

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Method: Latent Dirichlet Allocation (LDA); Structural Topic Modeling (STM)

Latent Dirichlet Allocation (LDA)

Inputs

1. A document term matrix (or any multidimensional dataset)
2. K: the desired number of topics.

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Outputs

1. π_k: Topic distribution over words - help us interpret each topic semantically

Topic	broccoli	banana	breakfast	kitten	cute	hamster	like	yesterday	*Total*
A	.30	.25	.20	.01	.01	.01	.12	.10	1
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2. θ_i: Document distribution over topics - help us identify representative documents in each topic

Document	Topic A Weight	Topic B Weight	Total
1	.99	.01	1
2	.99	.01	1
3	.01	99	1
4	.01	99	1
4	.60	.40	1

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Validation: run topic models with different k or random starting values multiple times, choose the model that yields the most substantially / semantically interpretable topics.

1. Look at top / distinctive words for each topic.
2. Read the most representative documents for each topic.

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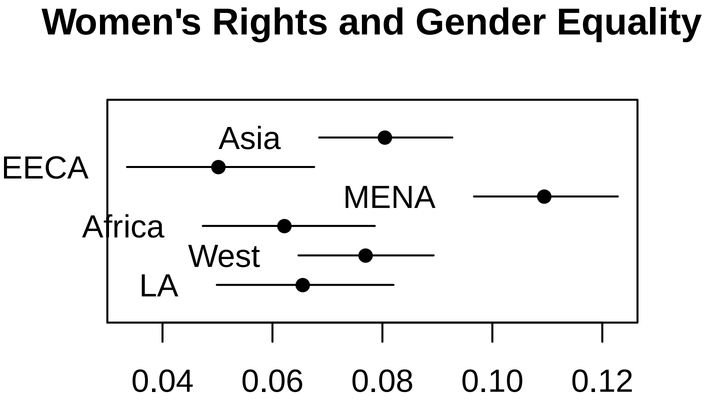
Example 2: In NYT articles, do articles on the Middle East talk more about women's rights and gender equality than articles on other regions do?

- Topic: women's rights and gender equality
- Covariate of document: region (Middle East, West, Asia, etc.)

Structural Topic Model



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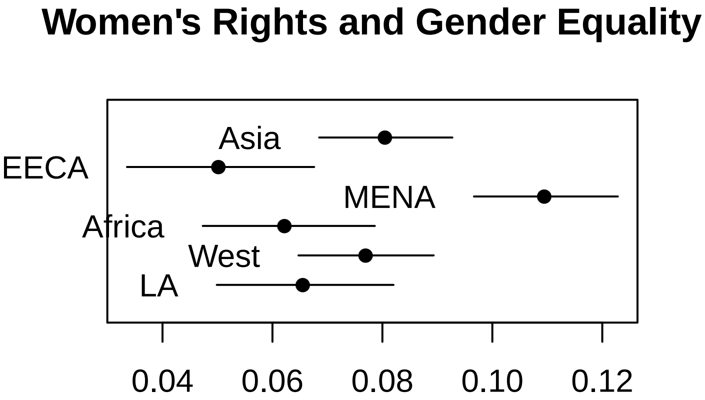

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