Quantitative text analysis: Describing and Comparing Text

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MY 459: Quantitative Text Analysis

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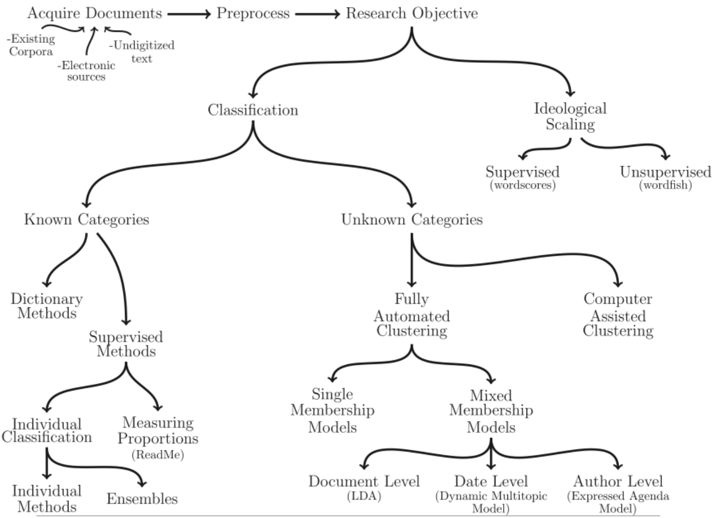
Course website: lse-my459.github.io

1. Overview and Fundamentals
2. Descriptive Statistical Methods for Text Analysis
3. Automated Dictionary Methods
4. Machine Learning for Texts
5. Supervised Scaling Models for Texts
6. *Reading Week*
7. Unsupervised Models for Scaling Texts
8. Similarity and Clustering Methods
9. Topic models
10. Word embeddings
11. Working with Social Media

Overview of text as data methods



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Readability statistics Use a combination of syllables and sentence length to indicate "readability" in terms of complexity

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- A document's vector for us is simply (for us) the row of the document-feature matrix
- The question is: how do we measure distance or similarity between the vector representation of two (or more) different documents?

Characteristics of similarity measures

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4. $d(A, C) \leq d(A, B) + d(B, C)$ (the measure must satisfy the triangle inequality)

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- Can be performed for any number of features J (where J is the number of columns in of the dfm, same as the number of feature types in the corpus)

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- Ranges from -1.0 to 1.0 for term frequencies, or 0 to 1.0 for normalized term frequencies (or tf-idf)

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- Not common, as at a textual level this is hard to implement and possibly meaningless

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- Some but not many applications in social sciences to measure substantive similarity — scaling models are generally preferred
- Can be used to generalize or represent features in machine learning, by computing similarities between textual (sub)sequences without extracting the features explicitly (as we will do in a second)

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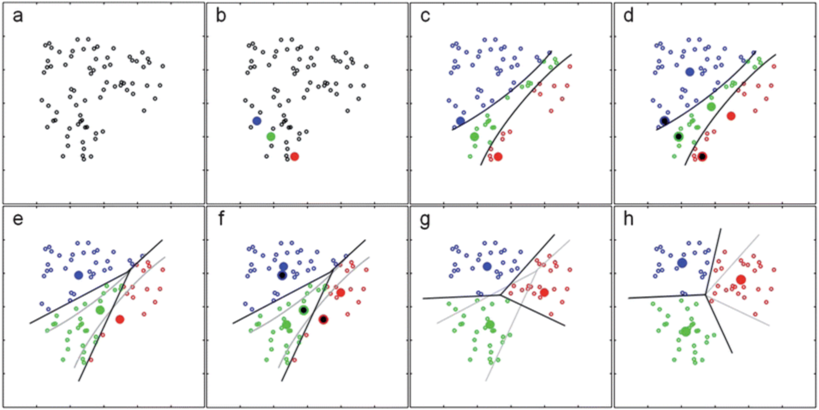
   - e.g. when no items are reclassified following update of centroids

k-means clustering illustrated



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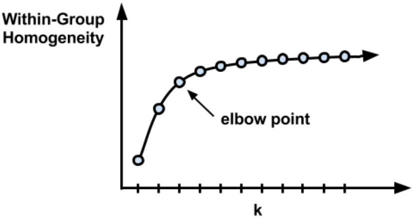
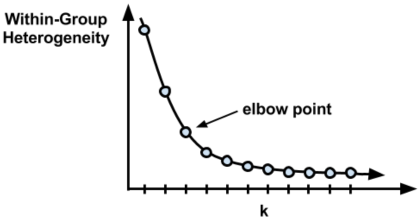
- "elbow plots": fit multiple clusters with different k values, and choose k beyond which are diminishing gains





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- Can be done at the document level, but also at the feature level (creating clusters of features)

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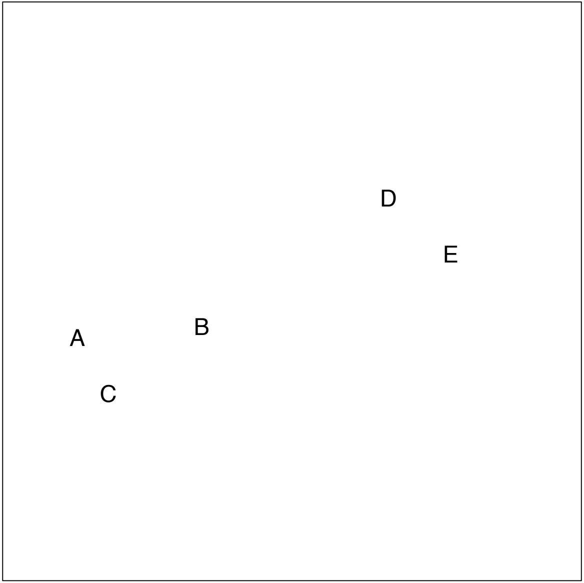
- In this section, we describe bottom-up or agglomerative clustering. This is the most common type of hierarchical clustering, and refers to the fact that a dendrogram is built starting from the leaves and combining clusters up to the trunk.

Hierarchical Clustering: the idea



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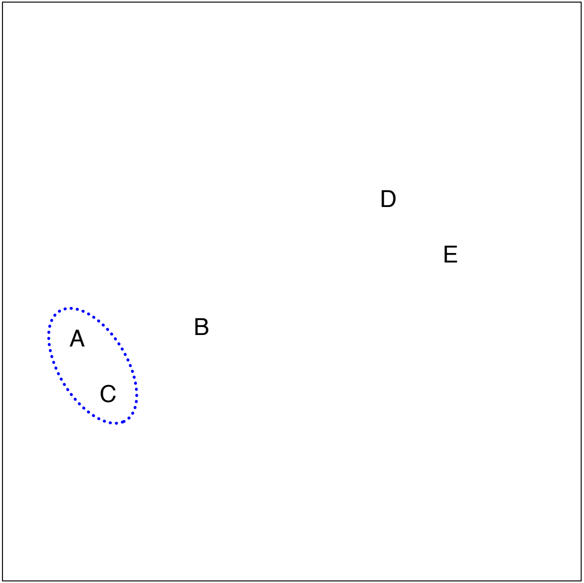

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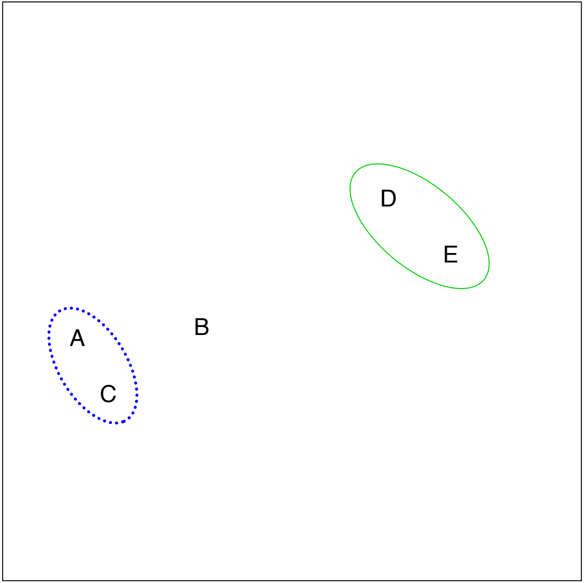

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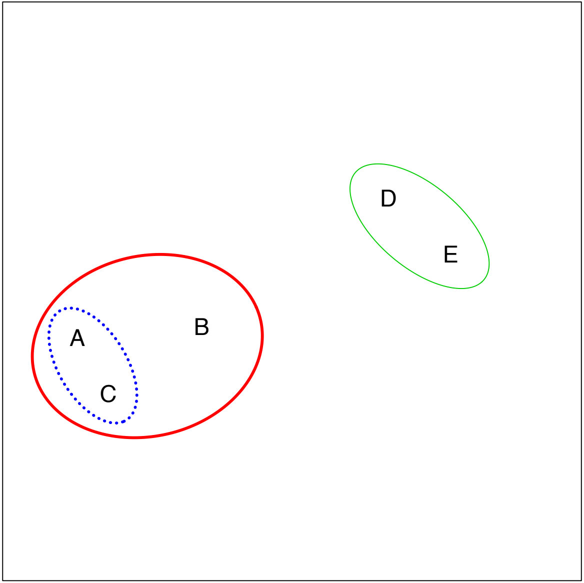

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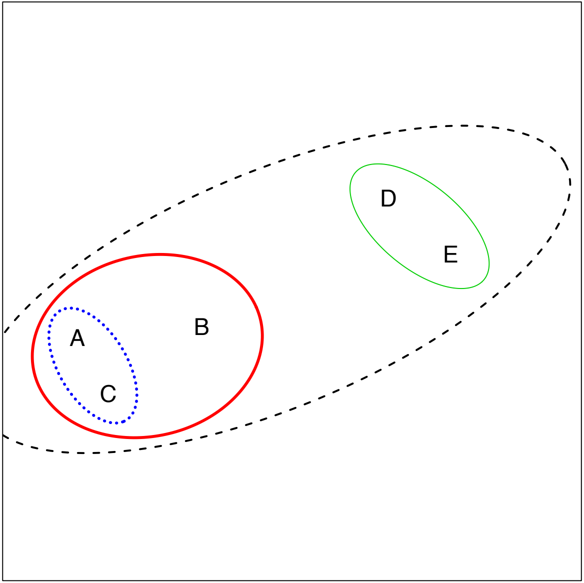
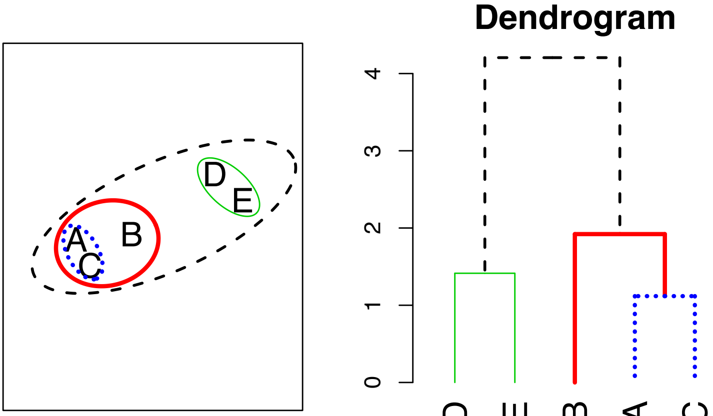


Hierarchical Clustering Algorithm

The approach in words:

- Start with each point in its own cluster.



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- Start with each point in its own cluster.
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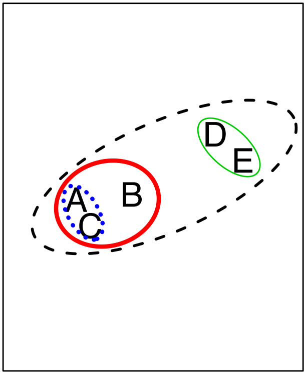
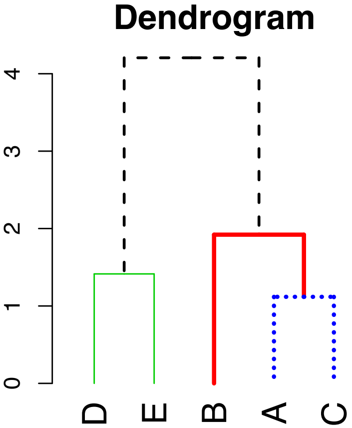
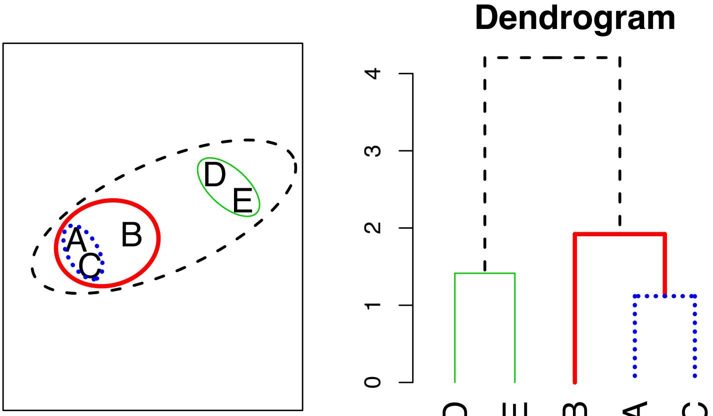




Hierarchical Clustering Algorithm

The approach in words:

- Start with each point in its own cluster.
- Identify the closest two clusters and merge them. -Repeat.
- Ends when all points are in a single cluster.



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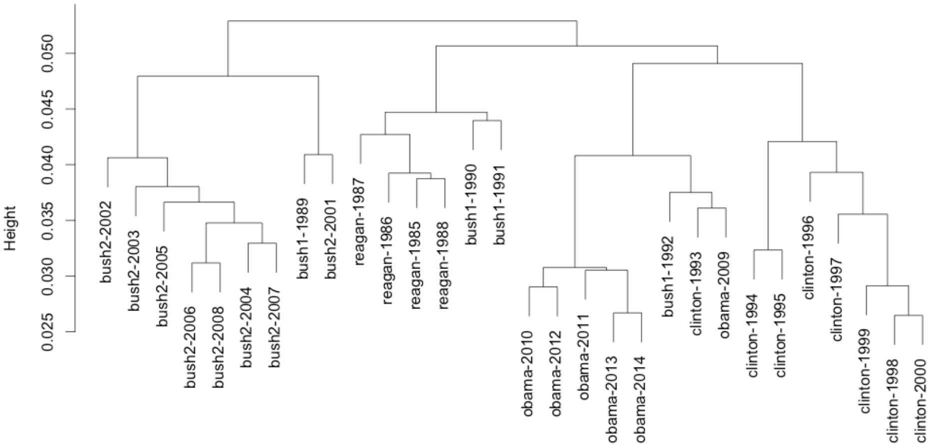
6. to plot the *dendrograms*, need decisions on ordering, since there are $2^{(N-1)}$ possible orderings

Dendrogram: Presidential State of the Union addresses



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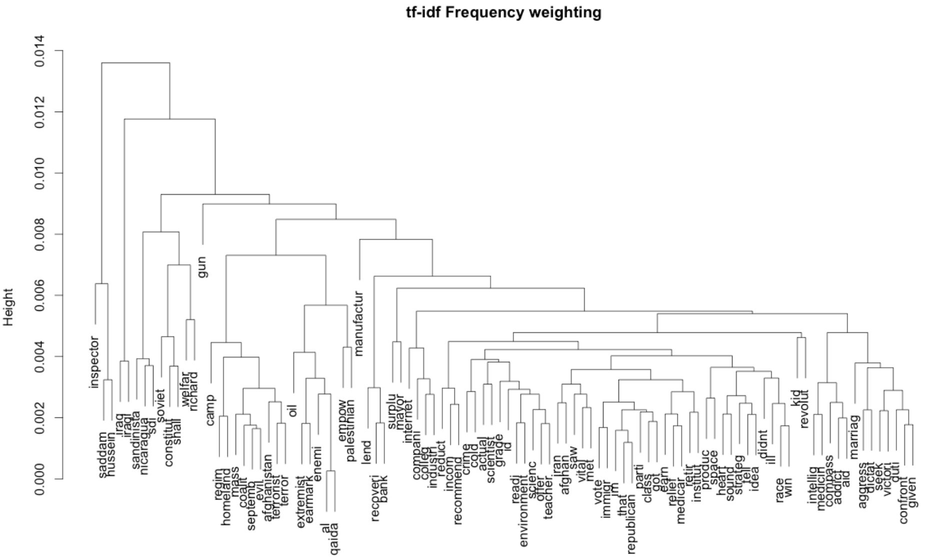

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  - for words, tends to identify collocations as base-level clusters (e.g. "saddam" and "hussein")

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