D001 Economic Analysis of Non-Standard Data

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4. Document Distance

Outline

Document Distance/Proximity

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- In economics, we often want to compare documents to one another
- Example, how close is a political speech to the party leader?
- Today, we will focus on methods designed to measure document distance/proximity
- But almost everything we do in this class can be framed as measuring document distance in some way

Text Re-Use

- Text Re-Use algorithms (like "Smith-Waterman" or BLAST) measure similarity by finding and counting shared sequences in two texts above some minimum length, e.g. 5 words
  - useful for plagiarism detection, for example
- precise but slow
  - shortcut: look at proportion of shared (hashed) 5-grams across texts

Document-Term Matrix

The **document-term matrix** $\boldsymbol{X}$:

- each row d represents a **document,** while each column w represents a word (or term more generally, e.g. n-grams)
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  - these vectors have a **spatial interpretation** $\rightarrow$ geometric distances between document vectors reflect semantic distances between documents in terms of shared terms
- each word/column $\boldsymbol{X}_{[:,w]}$ is a distribution over documents
  - these vectors also have a spatial interpretation! geometric distances between word vectors reflect semantic distances between words in terms of showing up in the same documents

Cosine Similarity

- Each document is a vector x_d, e.g. term counts or TF-IDF frequencies
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Cosine similarity is computable as the normalized dot product between the vectors:

$$\text{cos\_sim}(x_1, x_2) = \frac{x_1 \cdot x_2}{||x_1||||x_2||}$$

```
from sklearn.metrics.pairwise import
cosine_similarity
# between two vectors:
sim = cosine_similarity(x, y)[0,0]
# between all rows of a matrix:
sims = cosine_similarity(X)
```

Notes on Cosine Similarity

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Alternative distance metrics:

- dot product and Euclidean distance (too sensitive to document length)
- Jensen-Shannon Divergence
- Jaccard distance
- etc.

Burgess et al, "Legislative Influence Detectors"

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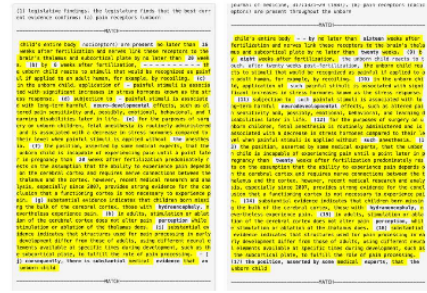

Figure 10: Match between Scott Walker’s bill and a highly similar bill from Louisiana. For a detailed view, please visit http://dssg.uchicago.edu/lid/.

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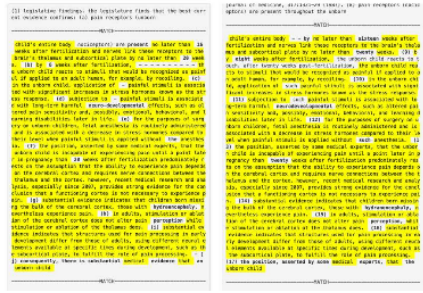

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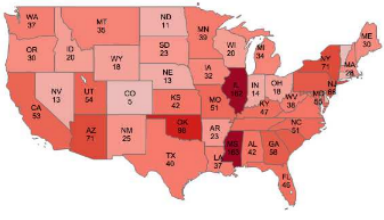
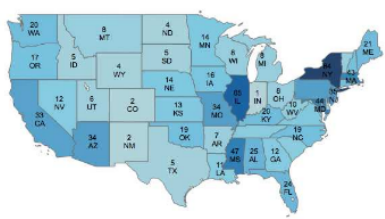


Figure 7: Introduced bills by state from ALEC model legislation



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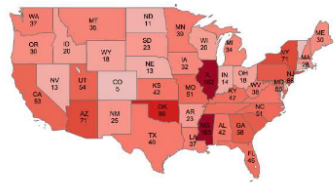
ABSTRACT

State legislatures introduce at least 45,000 bills each year. However, we lack a clear understanding of who is actually writing those bills. As legislators often lack the time and staff to draft each bill, they frequently copy text written by other states or interest groups.

However, existing approaches to detect text reuse are slow, biased, and incomplete. Journalists or researchers who want to know where a particular bill originated must perform a largely manual search. Watchdog organizations even hire armies of volunteers to monitor legislation for matches. Given the time-consuming nature of the analysis, journalists and researchers tend to limit their analysis to a subset of topics (e.g. abortion or gun control) or a few interest groups.

This paper presents the Legislative Influence Detector (LID). LID uses the Smith-Waterman local alignment algorithm to detect sequences of text that occur in model legislation and state bills. As it is computationally too expensive to run this algorithm on a large corpus of data, we use a search engine built using Elasticsearch to limit the number of comparisons. We show how LID has found 45,405 instances of bill-to-bill text reuse and 14,137 instances of model-legislation-to-bill text reuse. LID reduces the time it takes to manually find text reuse from days to seconds.



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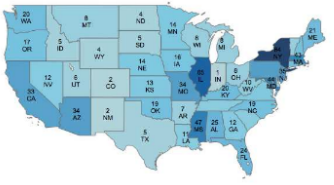

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1. What is the research question?
2. Why is it important?
3. What are the problems solved by the chosen methods?
4. What is being measured?
5. How does the measurement help answer the research question?

Outline

K-Means Clustering

- k-**means clustering**: divide documents $\boldsymbol{x}$ into sets $S_1, ..., S_k$ with associated centroids $\mu_1, ..., \mu_k$; each doc is in set with closest centroid

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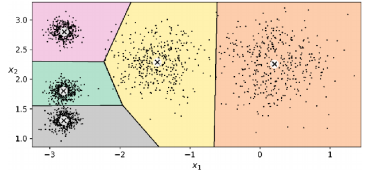

K-Means decision boundaries (Voronoi tessellation)

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assigned_cluster = kmeans.labels_
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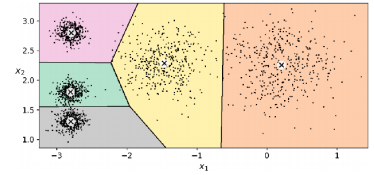

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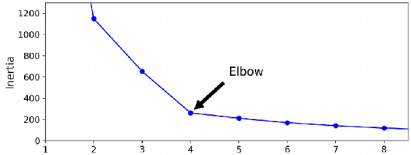
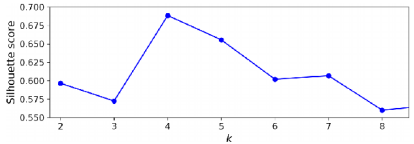
k (number of clusters) is the only hyperparameter, can select using:





Other clustering algorithms

- "k-medoid" clustering use L1 distance rather than Euclidean distance; produces the "medoid" (median vector) for each cluster rather than "centroid" (mean vector)
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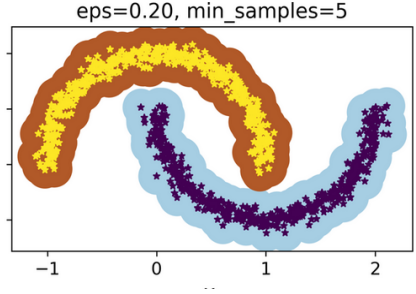
- **DBSCAN defines clusters as continuous regions of high density**
  - **detects and excludes outliers automatically**



- Agglomerative (hierarchical) clustering makes nested clusters

Note on terms and documents

- Recall that in $\boldsymbol{X}$,
  - each row / document $\boldsymbol{X}_{[d,:]}$ is a distribution over terms
  - each column / term $\boldsymbol{X}_{[:,w]}$ is a distribution over documents
- The same methods we used on the rows can be used on the columns:
  - apply cosine similarity to the columns to compare words (rather than compare documents)
  - apply k-means clustering to the columns to get clusters of similar words (rather than clusters of documents)