Text Data in Business and Economics

Basel University – Autumn 2023

5. Topic Models

Different Goals, Different Methods

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- Both strategies amplify human effort, each in different ways.
- Distinctions are not clear-cut:
  - supervised learning models can be used to discover themes/patterns
  - unsupervised learning models can be used in service of prediction or known goals.

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4. Empirical analysis
   - Produce statistics or predictions with the trained model.
   - **Answer the research question.**

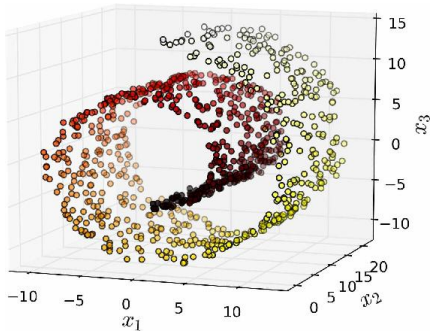
Outline

Dimensionality Reduction

Topic Models

- Datasets are not distributed uniformly across the feature space.
- They have a lower-dimensional latent structure – a **manifold** – that can be learned.

"The Swiss Roll"



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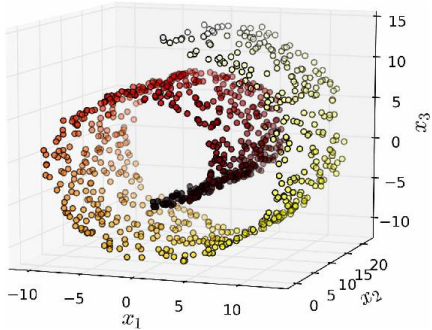

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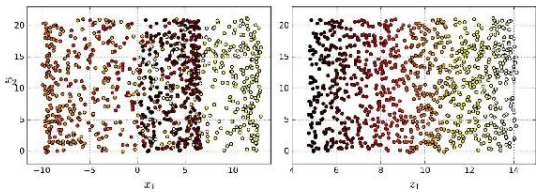

- **Dimensonality reduction** makes data more interpretable – for example by projecting down to two dimensions for visualization.
- improves computational tractability.
- can improve model performance.

What dimension reductions have you already tried in this class?

The Document-Term Matrix is high-dimensional

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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$\rightarrow \boldsymbol{X}$ often has billions of cells.

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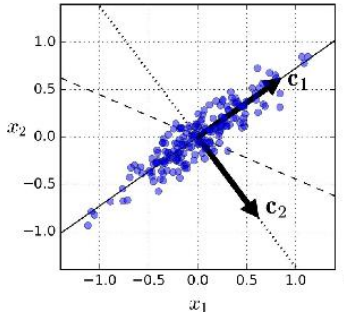

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from sklearn.decomposition import PCA
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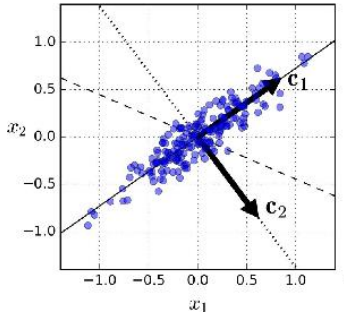

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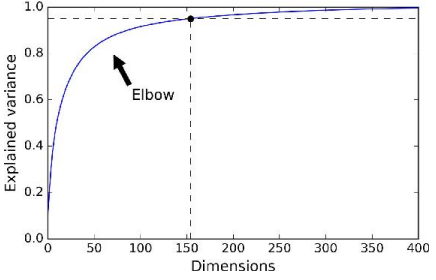

- after the first component, subsequent components learn the (orthogonal) dimensions explaining most variance in dataset after projecting out first component.

PCA and LSA

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- PCA factors are not interpretable.
  - Hoffman (1999) fixes this and puts LSA on firmer foundations by assuming a generative model of text – the word counts in a document are generated by a multinomial distribution.
  - For non-negative data (e.g. counts or frequencies), **Non-negative Matrix Factorization (NMF)** provides more interpretable factors than PCA.

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- Social scientists use topics as a form of measurement
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  - tell a story not just about what, but how and why
  - **topic models are more interpretable** than other dimension reduction methods, such as PCA.

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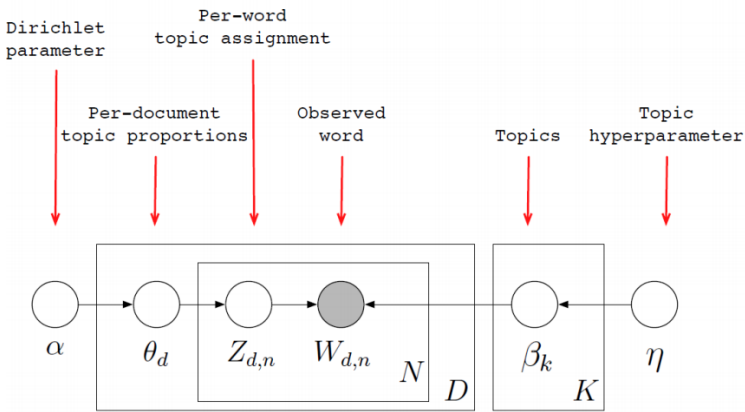

The Stata Journal (*yyyy*) *vv*, Number *ii*, pp. 1–16

ldagibbs: A command for Topic Modeling in Stata using Latent Dirichlet Allocation

Carlo Schwarz
University of Warwick
Coventry, United Kingdom
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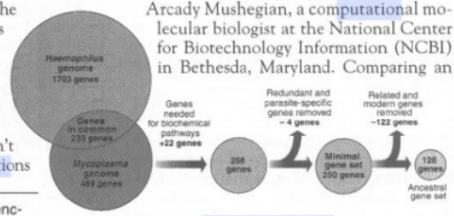
```
ldagibbs varname[ , topics(integer) burnin_iter(integer) alpha(real)
   beta(real) samples(integer) sampling_iter(integer) seed(integer)
   likelihood min_char(integer) stopwords(string) name_new_var(string)
   normalize mat_save path(string) ]
```

A statistical highlighter

Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK— How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions "are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genome," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an



Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

Image from Hanna Wallach

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Can then use the topic proportions as variables in a social science analysis.

- e.g., Catalinac (2016) shows that after a Japanese political reform that reduced intraparty competition, candidate platforms reduced pork-barrel policies and increased national ones.

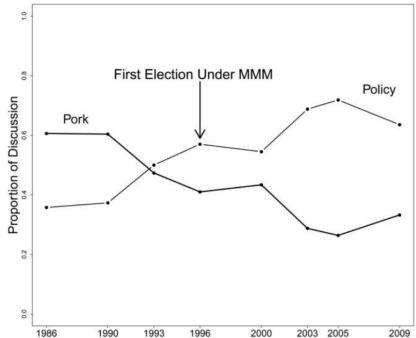

TABLE 1 **A Summary of Common Assumptions and Relative Costs Across Different Methods of Discrete Text Categorization**

	Method				
A. Assumptions	***Reading***	***Human Coding***	***Dictionaries***	***Supervised Learning***	***Topic Model***
Categories are known	No	Yes	Yes	Yes	No
Category nesting, if any, is known	No	Yes	Yes	Yes	No
Relevant text features are known	No	No	Yes	Yes	Yes
Mapping is known	No	No	Yes	No	No
Coding can be automated	No	No	Yes	Yes	Yes
B. Costs					
Preanalysis Costs					
Person-hours spent conceptualizing	Low	High	High	High	Low
Level of substantive knowledge	Moderate/High	High	High	High	Low
Analysis Costs					
Person hours spent per text	High	High	Low	Low	Low
Level of substantive knowledge	Moderate/High	Moderate	Low	Low	Low
Postanalysis Costs					
Person-hours spent interpreting	High	Low	Low	Low	Moderate
Level of substantive knowledge	High	High	High	High	High

Recommended: read this part of Quinn, Monroe, Colaresi, Crespin, and Radev (2010).

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Roberts, Stewart, and Tingley

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  - it will tell you which topics or features correlate with an outcome, but it will not provide an in-sample or out-of-sample prediction for an outcome
- The main implementation is in R. gensim has a light-weight version called "author topic model".