Text Analysis for Social Sciences in Python

Week 10: Text as Data – Topic Models

WINTER SEMESTER 21/22

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Last week…

Word Embeddings

…any questions with the materials and exercises?

Thank you to everyone who sent me the codes for the Bonus Exercise 1!

Final presentation date

Monday 31.01: 14.00 – 18.00 (20-25' presentation/group + 10' Q&A)

(i.e. code & slides submission by Thursday 27.01 23.59 to Open Olat folder)

Slot allocation (Google sheet link on your Slack channel #group_matching):

https://docs.google.com/spreadsheets/d/1E-IFBNDNk7-5GxALoYRfK-P8GO5aYJ8v9j0uEjUsZ5M/edit#gid=548845839

Today's agenda

Word Embedding (cont)

- Cosine Similarity
- Collocation

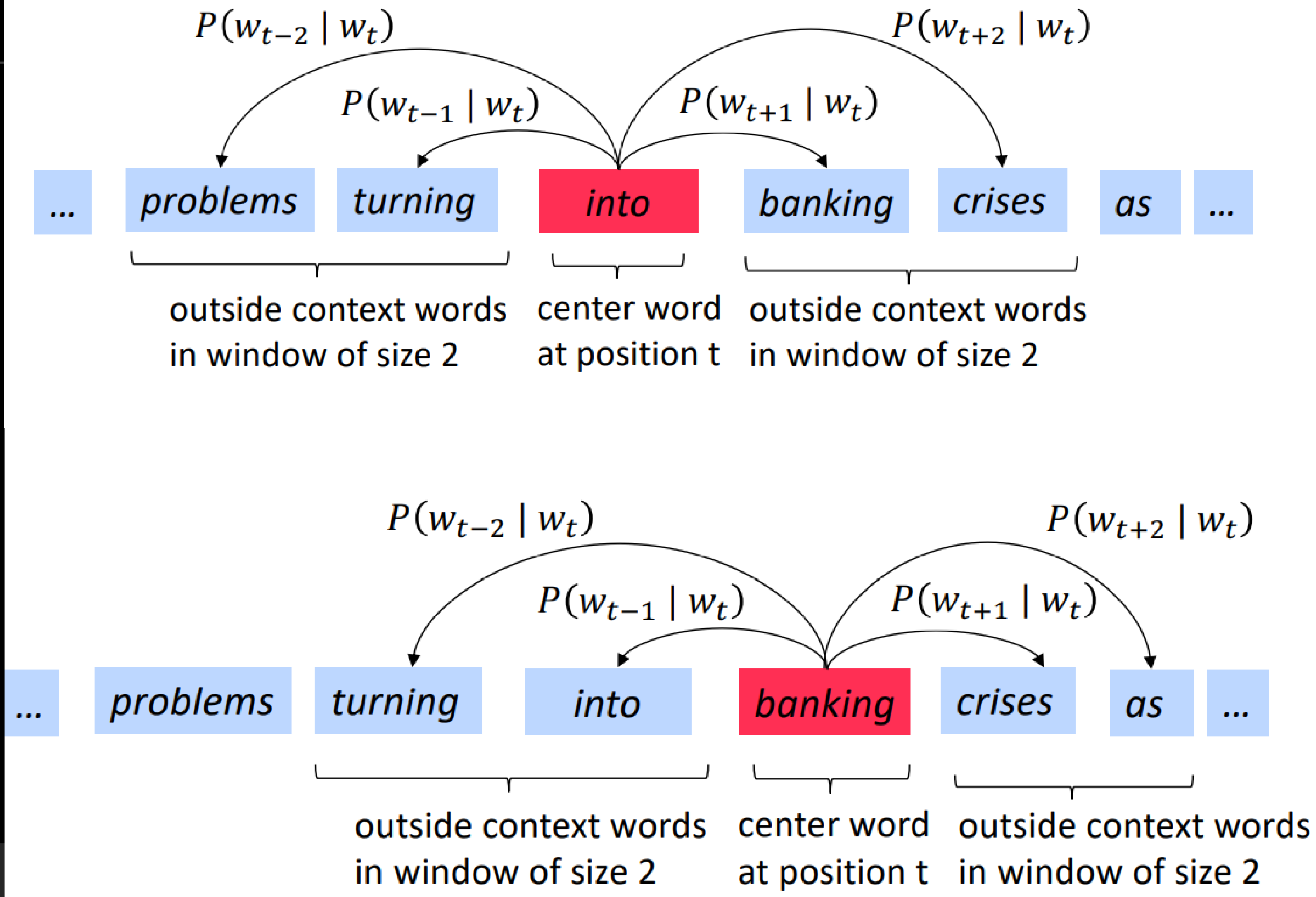
Topic models

- Word Embeddings vs. Topic Models?
- Topic models in Social Sciences
- Latent Dirichlet Allocation (LDA)
- Co-occurrence
- Structural Topic Model (STM)

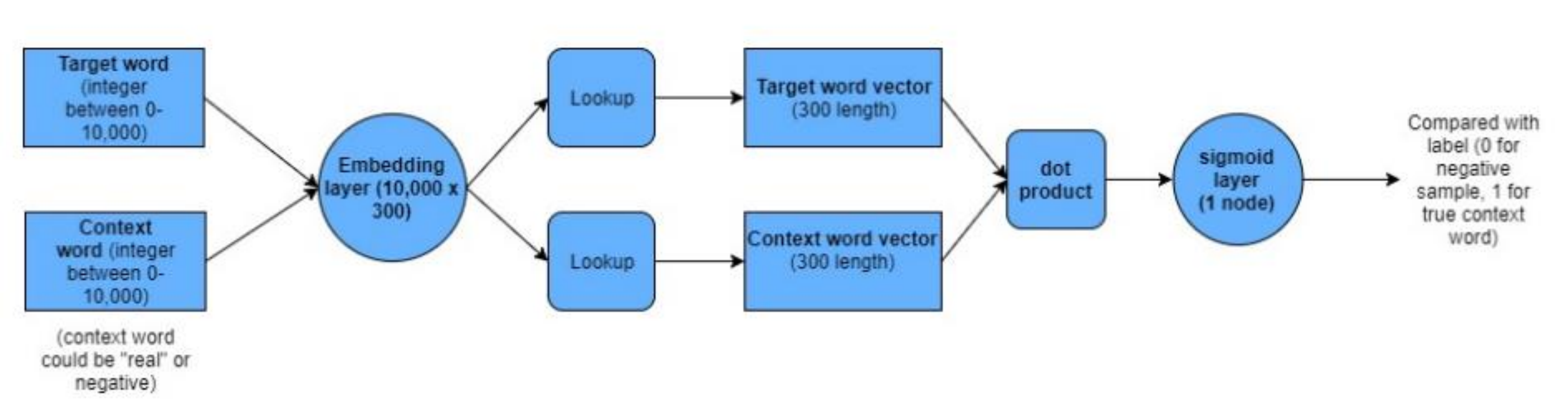
Word meaning as a neural word vector – visualization

$$\textit{expect} = \begin{pmatrix} 0.286 \\ 0.792 \\ -0.177 \\ -0.107 \\ 0.109 \\ -0.542 \\ 0.349 \\ 0.271 \\ 0.487 \end{pmatrix}$$

Example windows and process for computing $P(w_{t+j} \mid w_t)$



Word2vec schema



CBOW or Skip-gram Word2Vec?

CBOW is several times faster than skip gram and provides a better frequency for frequent words

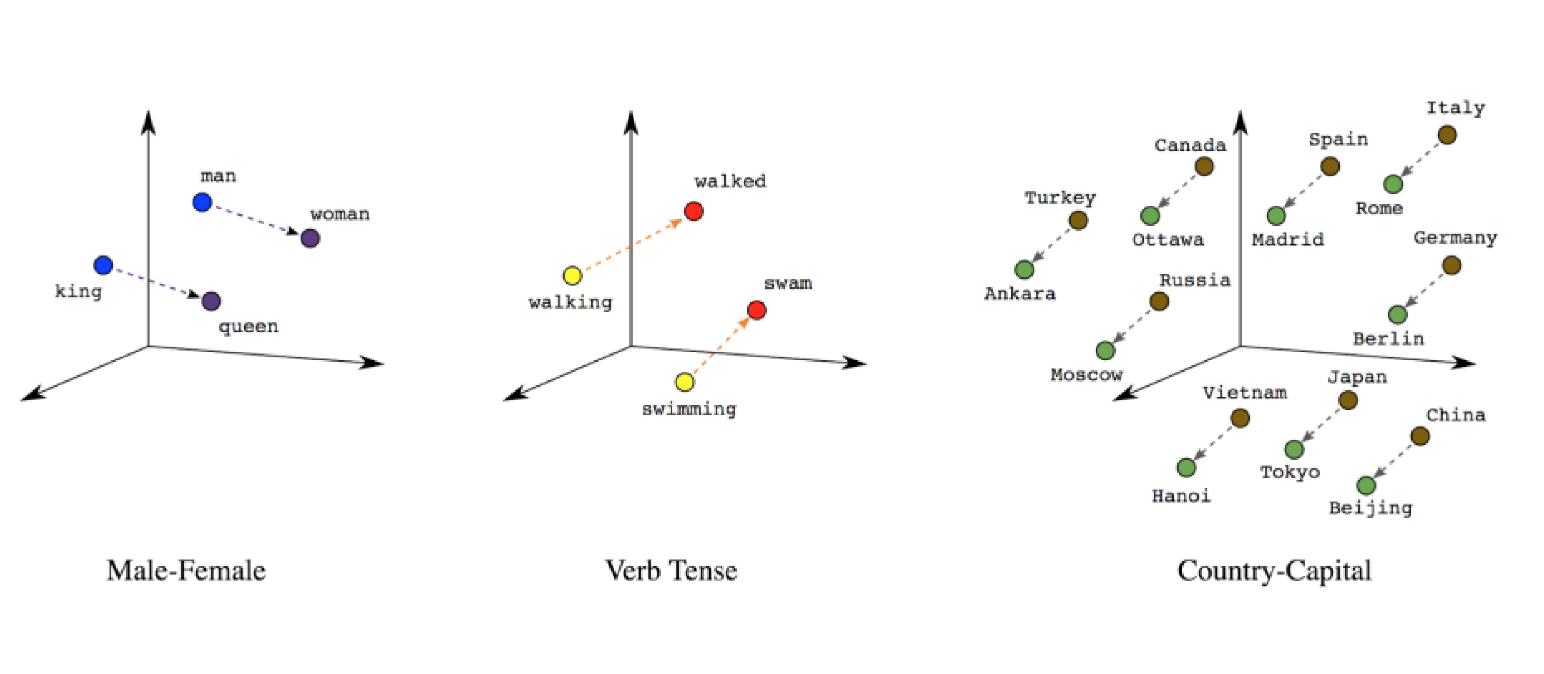
BUT skip gram needs a small amount of training data and represents even rare words or phrases.

→ Choose the model that works best for your data set.

How to measure cosine similarity?

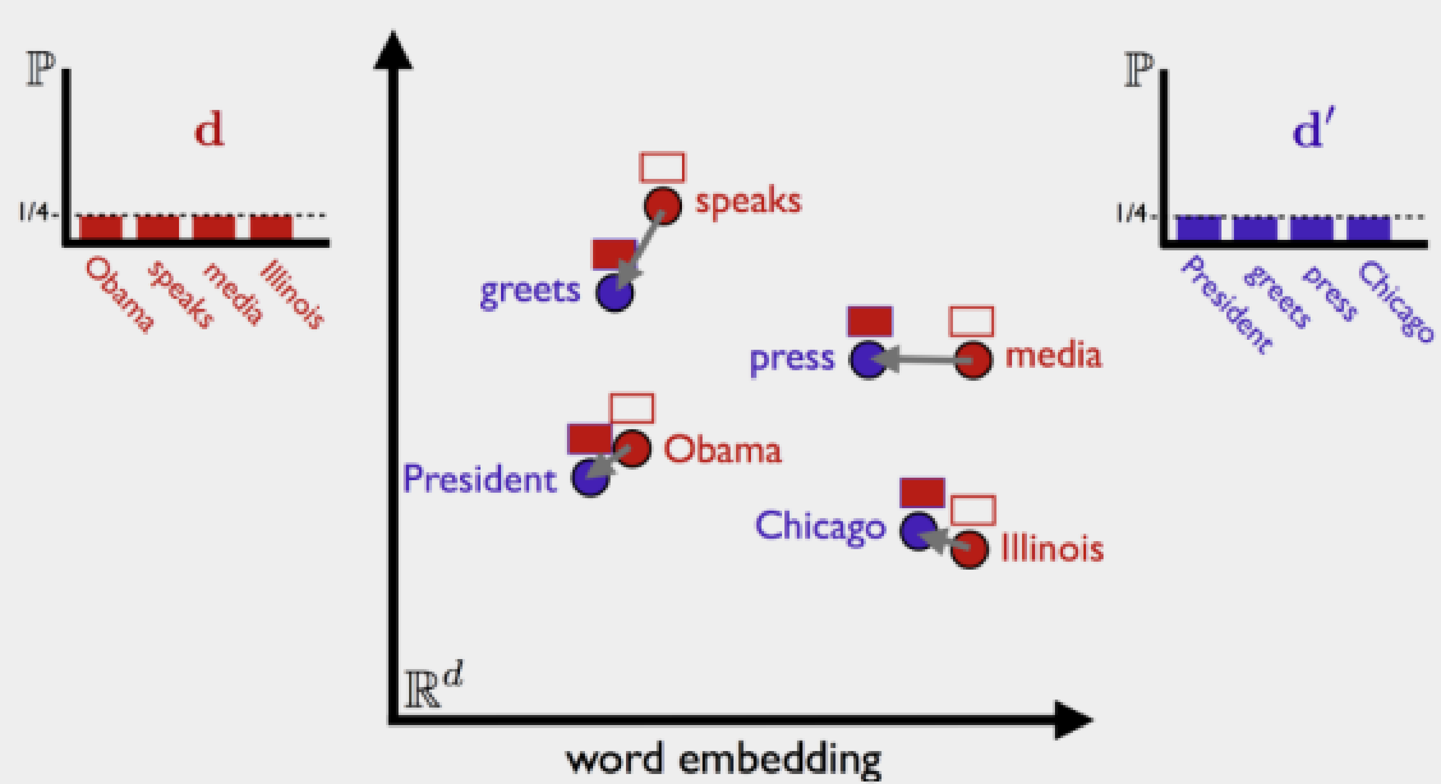
$$cos\theta = \frac{v_1 . v_2}{\|v_1\| \|v_2\|}$$

where v1 and v2 are vectors representing words (Word Embeddings/ documents (topic models).



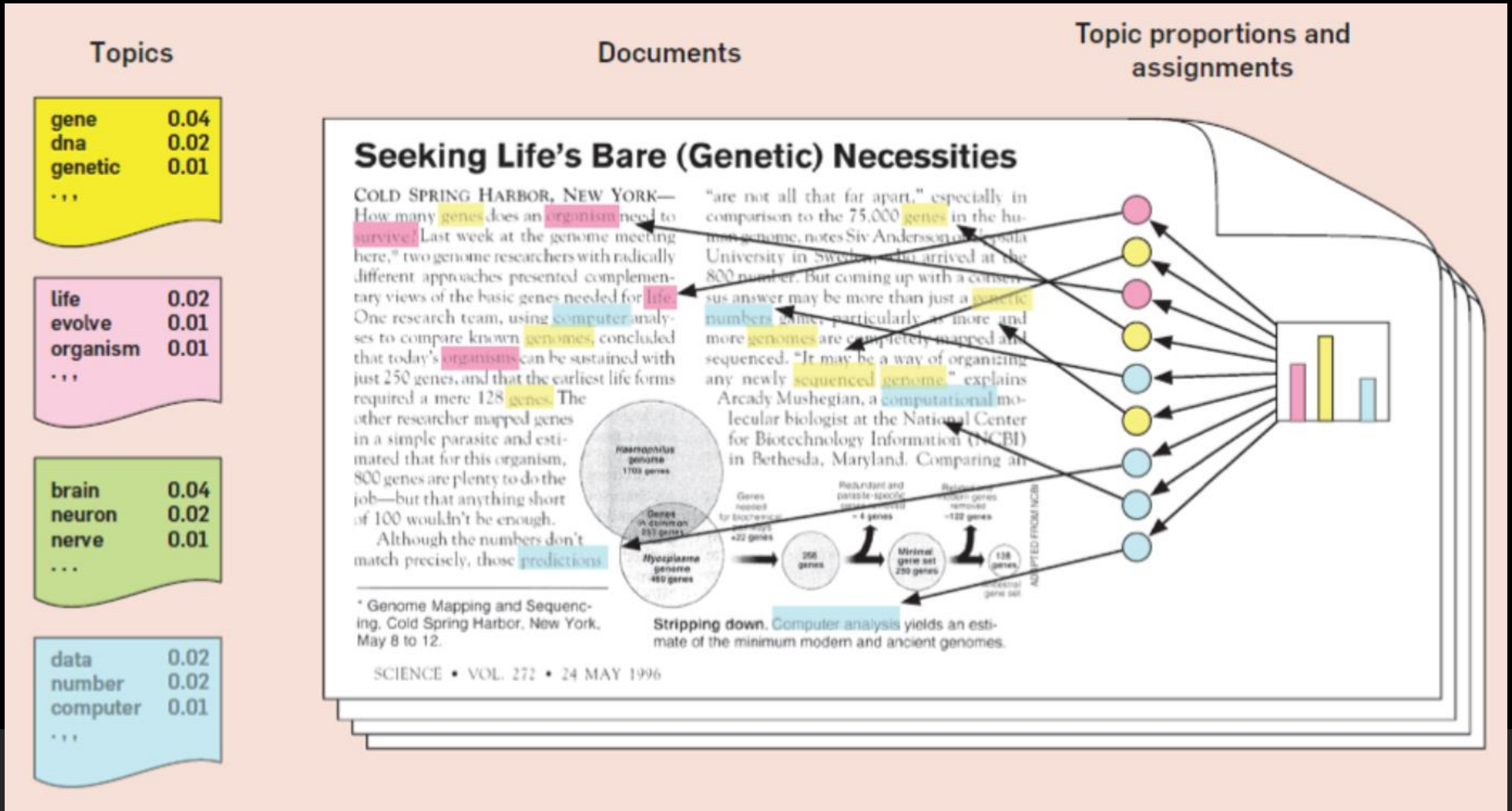
Word embeddings vs. topic models?

Word embedding models ignore information about individual documents → better understand the relationships between words.



Word embeddings vs. topic models?

Topic models reduce words to core meanings → understand documents more clearly.



Topic Models in Social Sciences

Core methods for topic models were developed in computer science and statistics to…

- summarize unstructured text
- use words within document to infer its subject
- reduce dimensionality

How are they used in social sciences?

- use topics as a form of measurement
- check how observed covariates drive trends in language
- tell a story not just about what, but how and why I topic models are more interpretable than other methods, e.g. PCA

Some example research papers

- How do senators present their work to the public? What explains variation in representational style? (Grimmer 2013)
- Do presidential candidates move to the center/left/right in their political speeches? (Sim et al 2013)
- How do central bankers respond to an increase in transparency over their discussions? (Hansen, McMahon, and Prat 2018)

Document-term Matrix X

	W1	W2	W3	Wm
D1	0	2	1	3
D2	1	4	0	0
D3	0	2	3	1
Dn	1	1	3	0

- A corpus of N documents D1, D2, D3,....Dn
- Vocabulary of M words W1, W2, W3,..... Wn
- The value of i, j cell gives the frequency count of word Wj in Document Di.

Matrix Factoring

LDA converts the document-term matrix into two lower-dimensional matrices, M1 and M2:

	K1	K2	K3	K
D1	1	0	0	1
D2	1	1	0	0
D3	1	0	0	1
Dn	1	0	1	0

	W1	W2	W3	Wm
K1	0	1	1	1
K2	1	1	1	0
K3	1	0	0	1
K	1	1	0	0

M1 is a N ×K document-topic matrix.

M2 is a K ×M topic-term matrix.

Latent Dirichlet Allocation (LDA)

Idea: documents exhibit each topic in some proportion.

- Each document is a distribution over topics.
- Each topic is a distribution over words.

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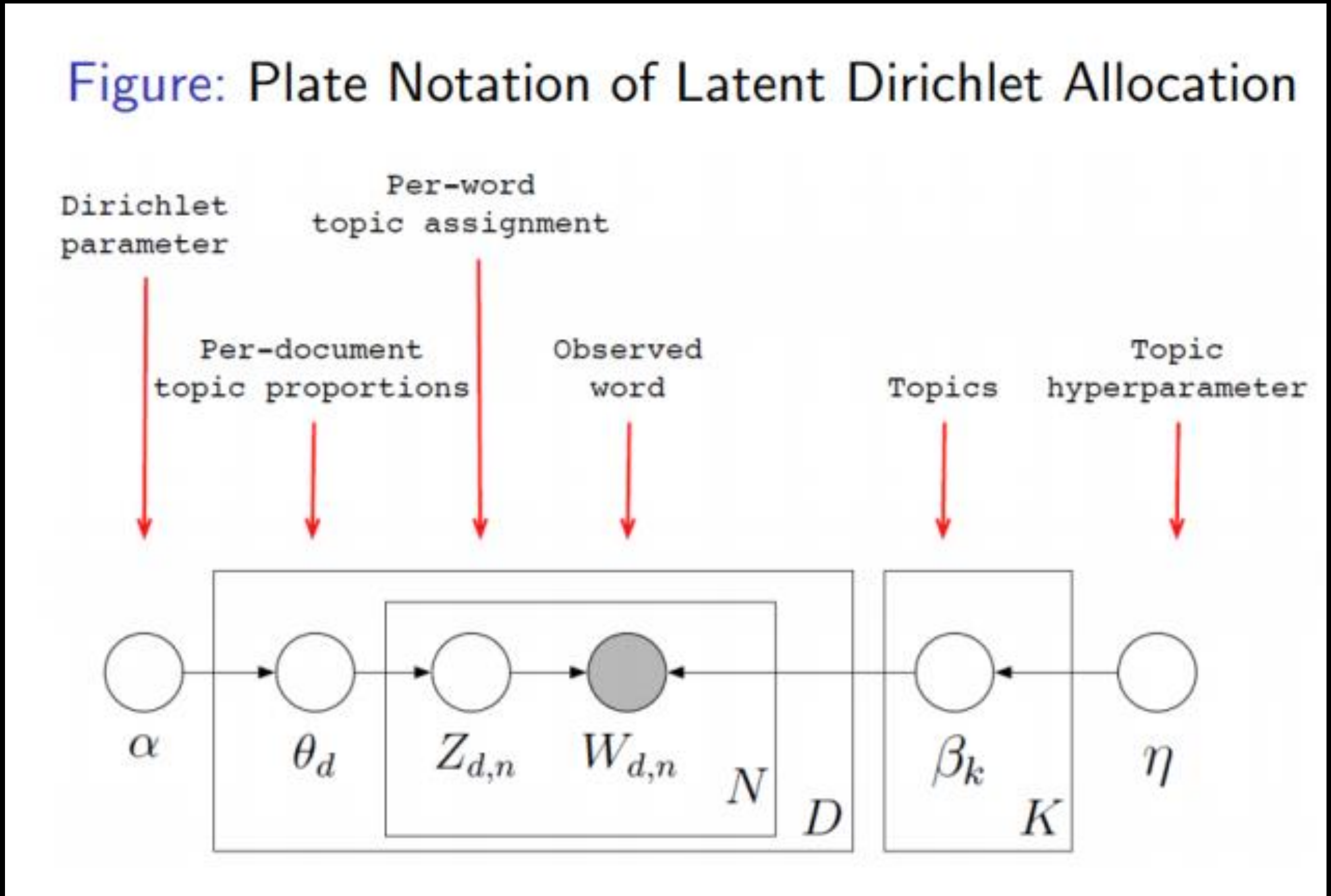
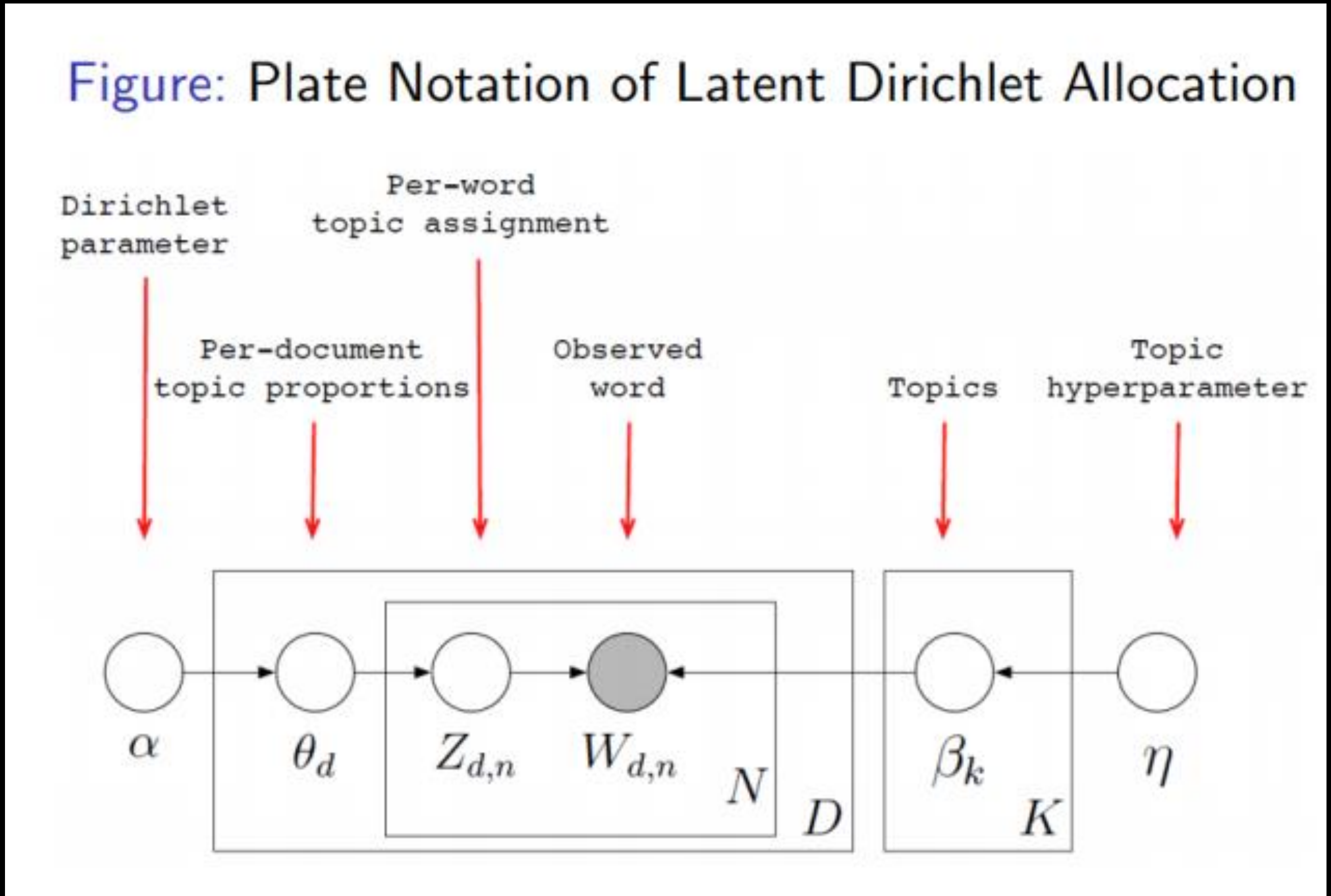
Key assumptions: Bag of words/phrases, and fix number of topics ex ante.

A Bayesian model



A Bayesian model



α : document-topic density
↑↓ α = documents have ↑↓ topics

β: topic-word density
↑↓ β = topics have ↑↓ words

Number of topics:

- this is specified in advance, or can be chosen to optimize model fit.
- the “statistically optimal” topic count is usually too high for the topics to be interpretable/useful.

Why does it work? Co-occurrence

- Where is the information for each word's topic?
- We are learning the pattern of what words <u>occur together</u>.
- The model wants a topic to contain as few words as possible, but a document to contain as few topics as possible.
- This tension is what makes the model work.

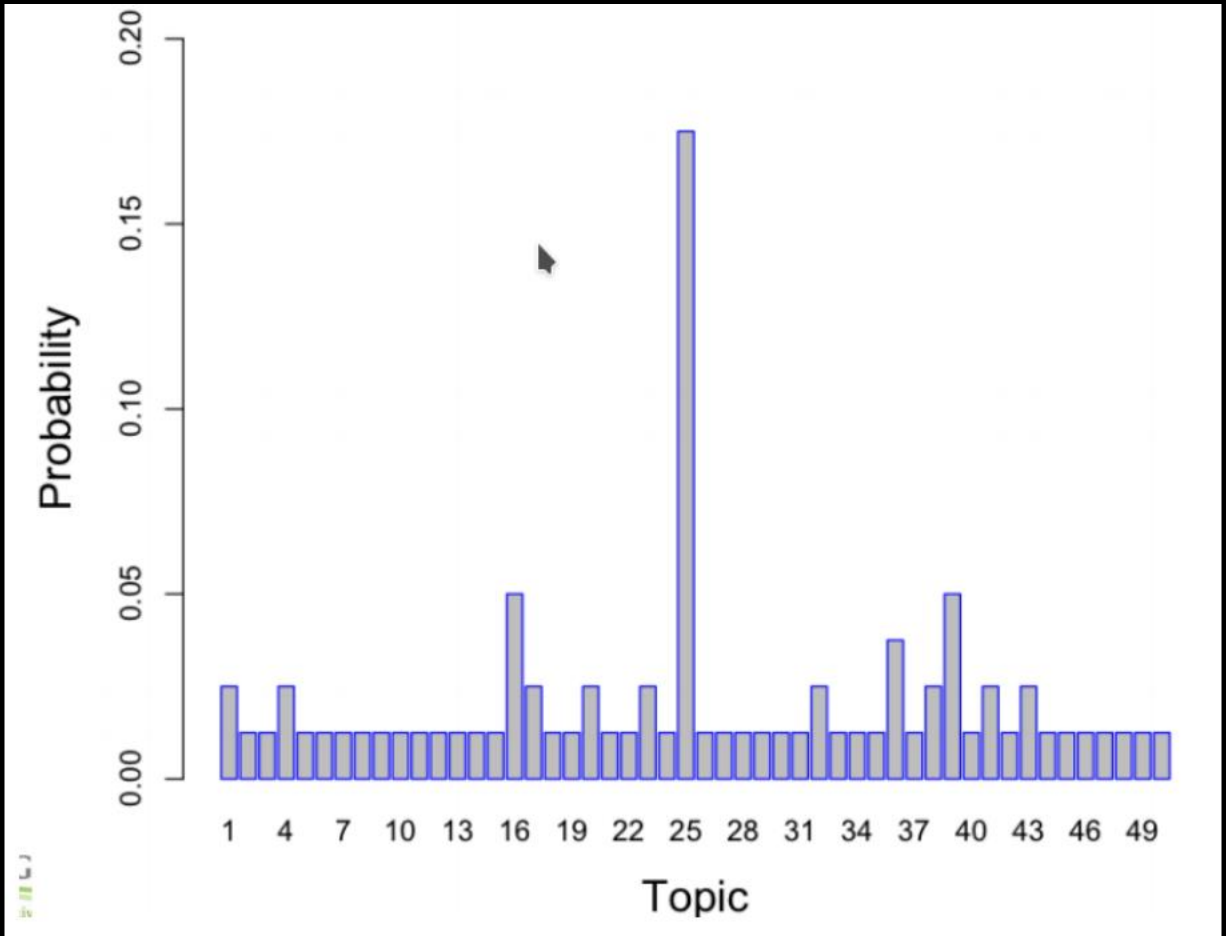
LDA in text application: An example (FOMC)

Hansen, McMahon, and Prat 2018 use LDA to analyze speech at the FOMC (Federal Open Market Committee).

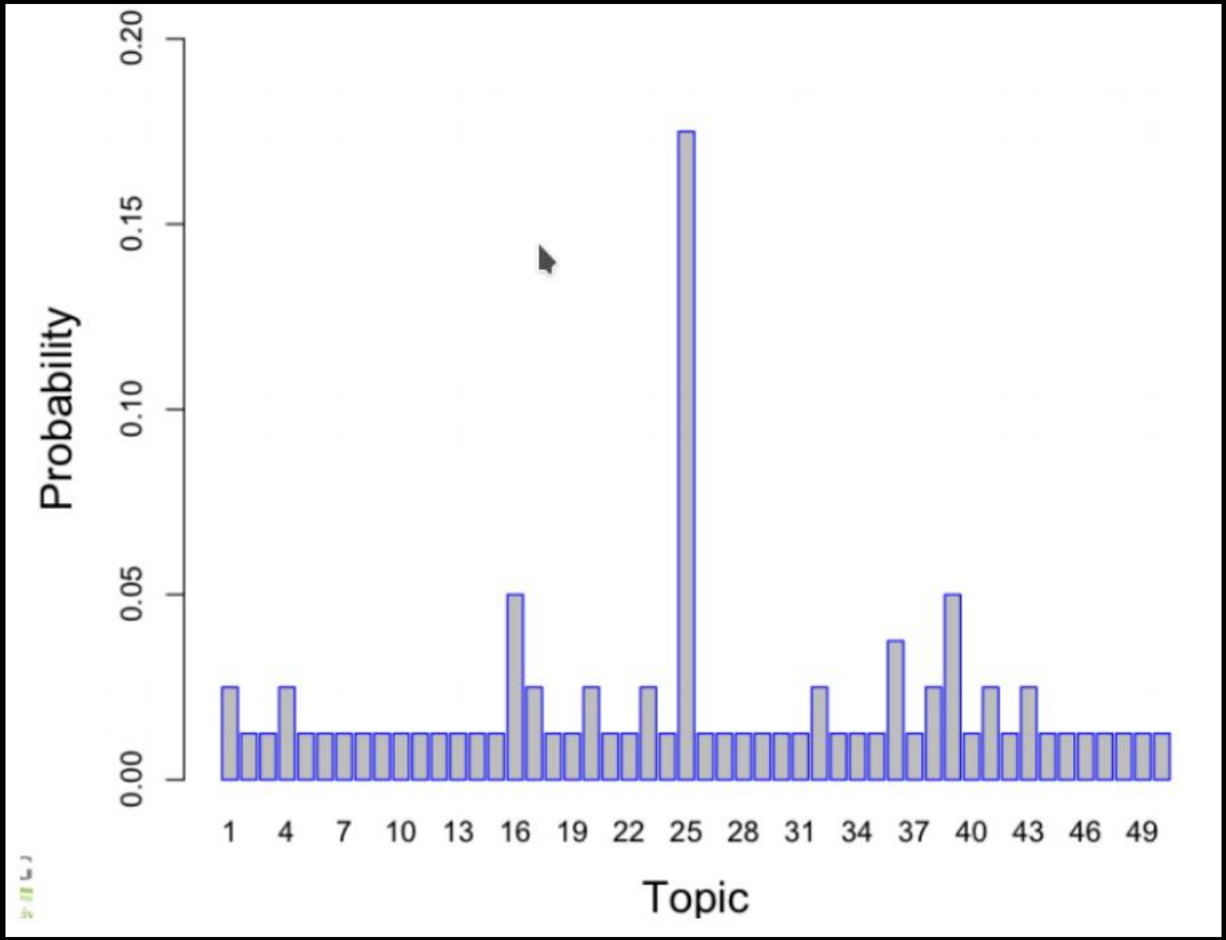
- 150 meetings, 20 years, 46000 speeches

They take the standard pre-processing steps and train LDA.

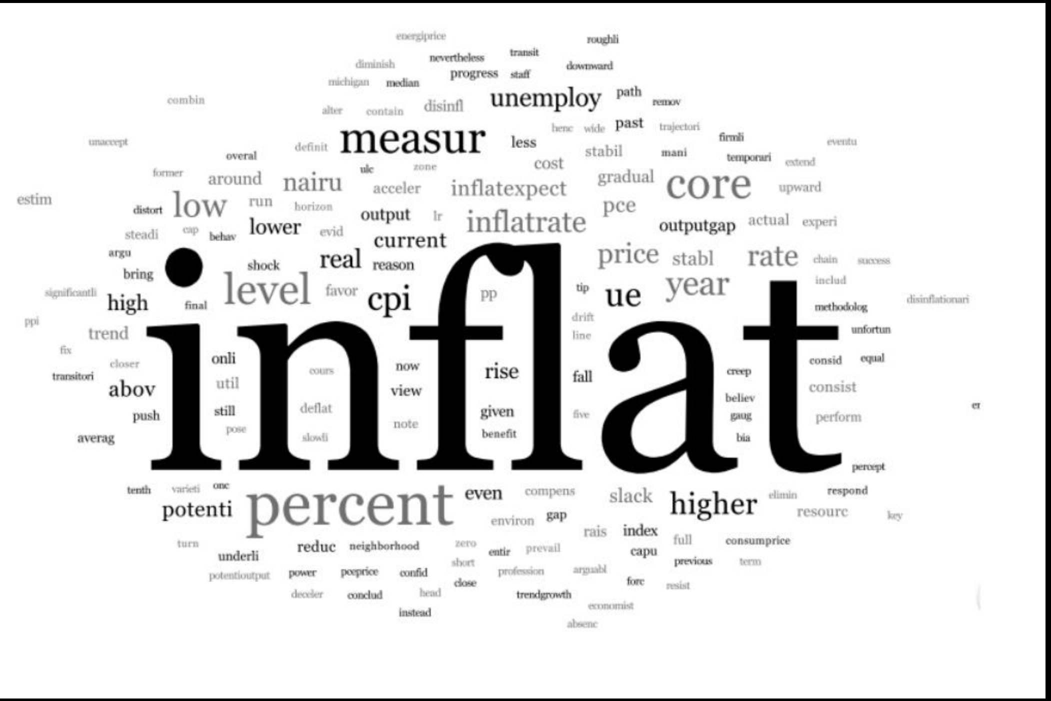
FOMC distribution of attention



FOMC distribution of attention



Topic 25 is…



What is their conclusion?

- Increasing transparency results in:
  - higher discipline / technocratic language (which is beneficial)
  - higher conformity (which is costly)

- Highlights tradeoffs from transparency in bureaucratic organizations

LDA on non-text applications?

LDA can be used on any type of co-occurence data. E.g:

- [Bandiera, Hansen, Prat, and Sadun (2017)]
  - use LDA to do dimension reduction on CEO tasks using time allocation data.
  - model endogenously identifies a “leader” CEO topic, and a “micro-manager” CEO topic
- [Draca and Schwarz (2018)]
  - use LDA to reduce dimensions of the features of political attitudes
  - model endogenously identifies “conservative” and “liberal” attitudes clusters.
- [Draca and Schwarz (2021)]
  - identify the underlying ideologies of citizens using LDA in political survey data.
  - evidence of a `disappearing centre' in a sub-group of countries: citizens shift away from centrist ideologies into anti-establishment `anarchist' ideologies over time, especially in the US.

Structural Topic Model = LDA + metadata

STM provides two ways to include contextual information:

- Topic prevalence can vary by metadata
- e.g. Republicans talk about military issues more then Democrats

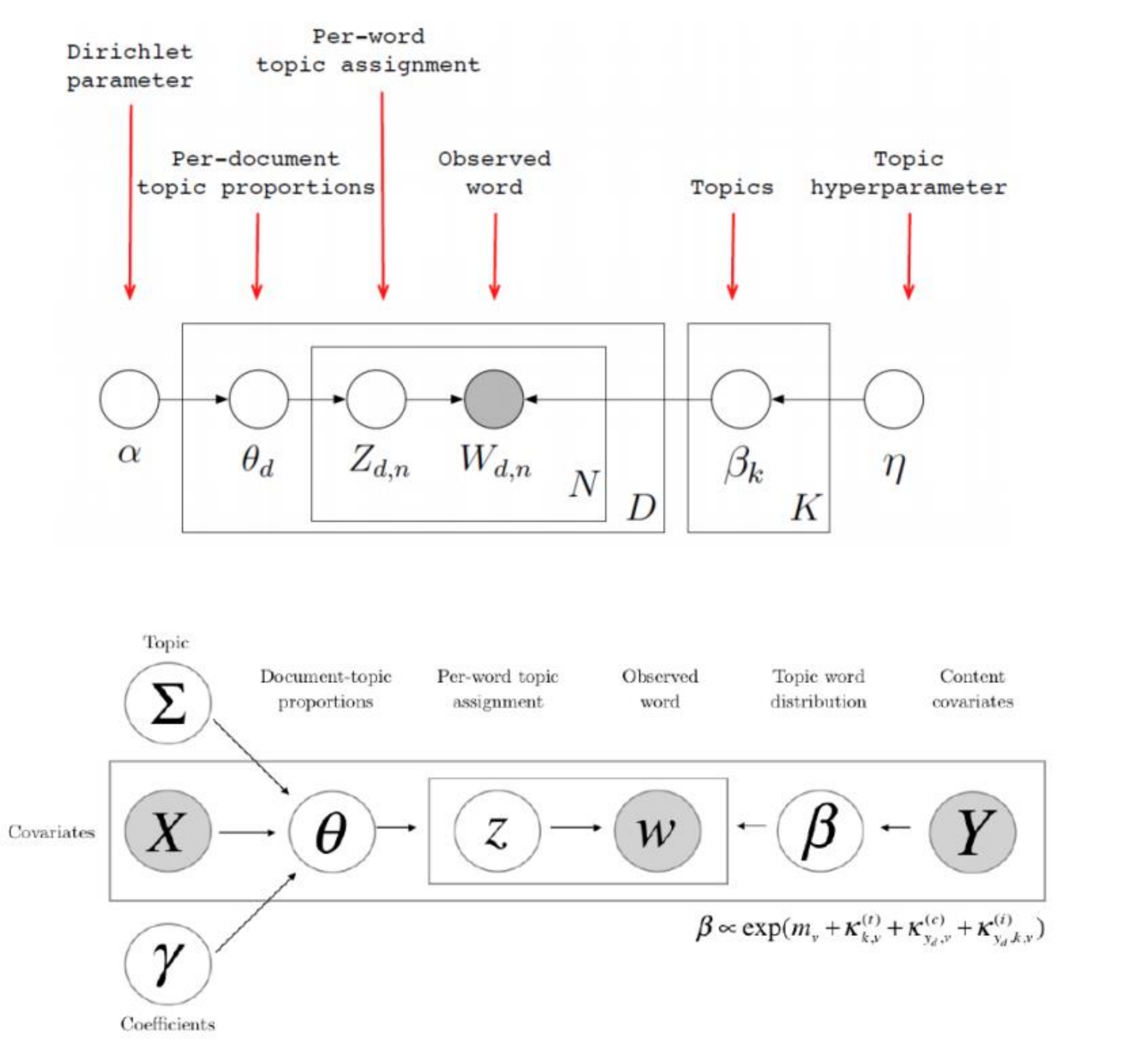
Topic content can vary by metadata

- e.g. Republicans talk about military issues differently from Democrats

Caveat: Structural topic model is not a prediction model.

- 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.

LDA vs. STM illustration



Practice time ☺

Open your Google Colab/ Jupyter Notebook

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https://github.com/httn21uhh/Text-Analysis-for-Social-Sciences-in-Python

→ W10_topic_model.ipynb + utils.py + txt_utils.py + death-penalty-cases.csv + X.pkl + X_tfidf.pkl

- Download and put them in the same directory/environment where you store other packages
- IMPORTANT: For txt_utils.py, open it first with Jupyter Notebook/Spyder/Pycharm and change the line of code WORKING_DIR to your own current working directory
- If none of these methods work, copy and run the relevant function code lines in these utils.py and txt_util.py into your own .ipynb. Then run them as usual.

This week…

- Topic models in action
- Follow closely the illustrated examples and replicate yourself as the session proceeds.
- Unmute yourself to ask questions at any point, including when you think things go too fast/slow for you.