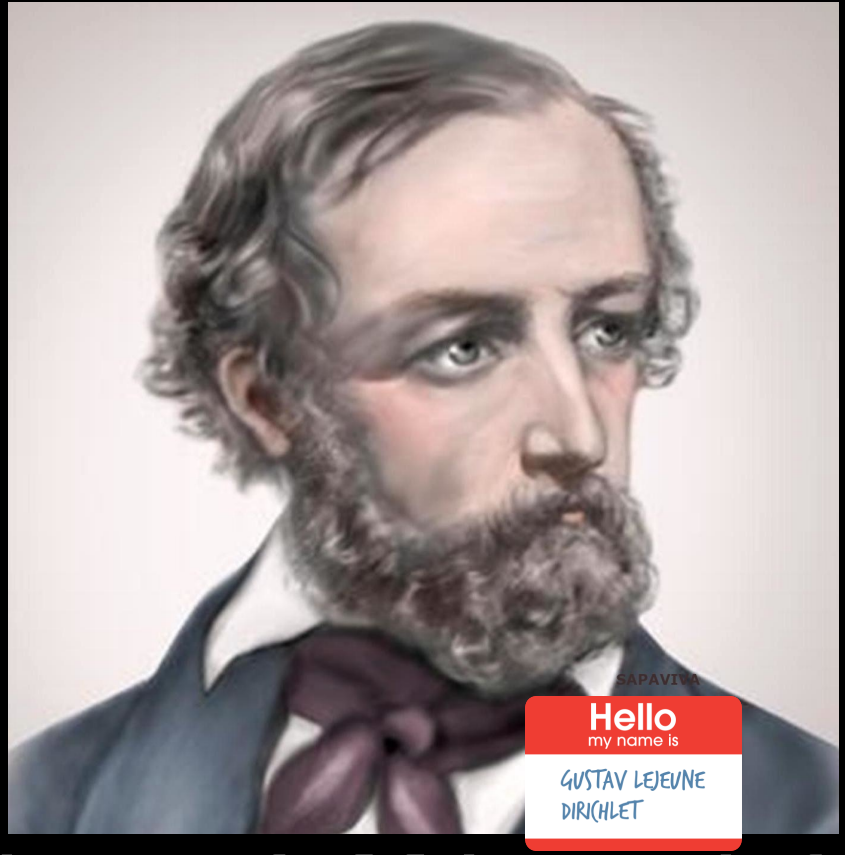

Topic Modelling with LDA

Instructor: Xandra Dave Cochran
April 3-10, 2024
Centre for Data, Culture & Society

Topic Modelling:

- Unsupervised Machine Learning

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- Unsupervised Machine Learning
- Identifies clusters of related words in text
- Does not require predefined categories – good for discovery and exploration of a dataset

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What is your previous experience with machine learning?

Why are you interested in topic modelling?

Have you used LLMs before?

Is there a dataset you have in mind to use for topic modelling in future?

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- But is it as good?

Latent Dirichlet Allocation

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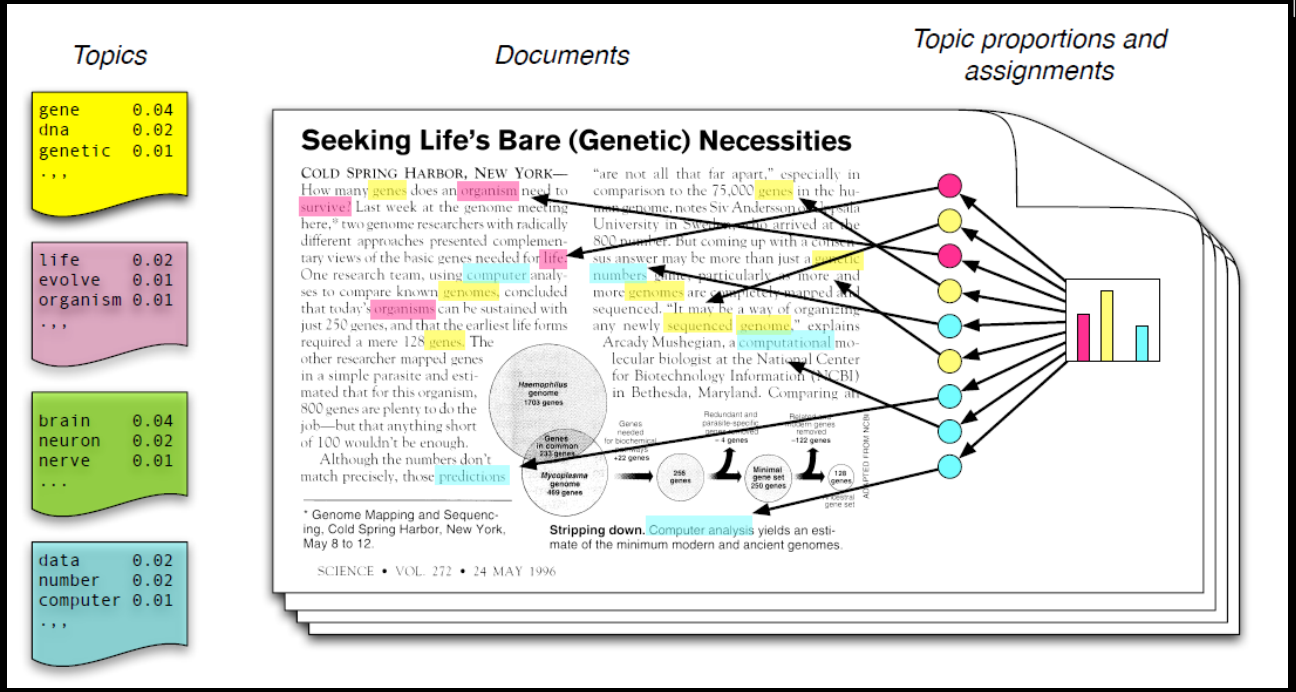

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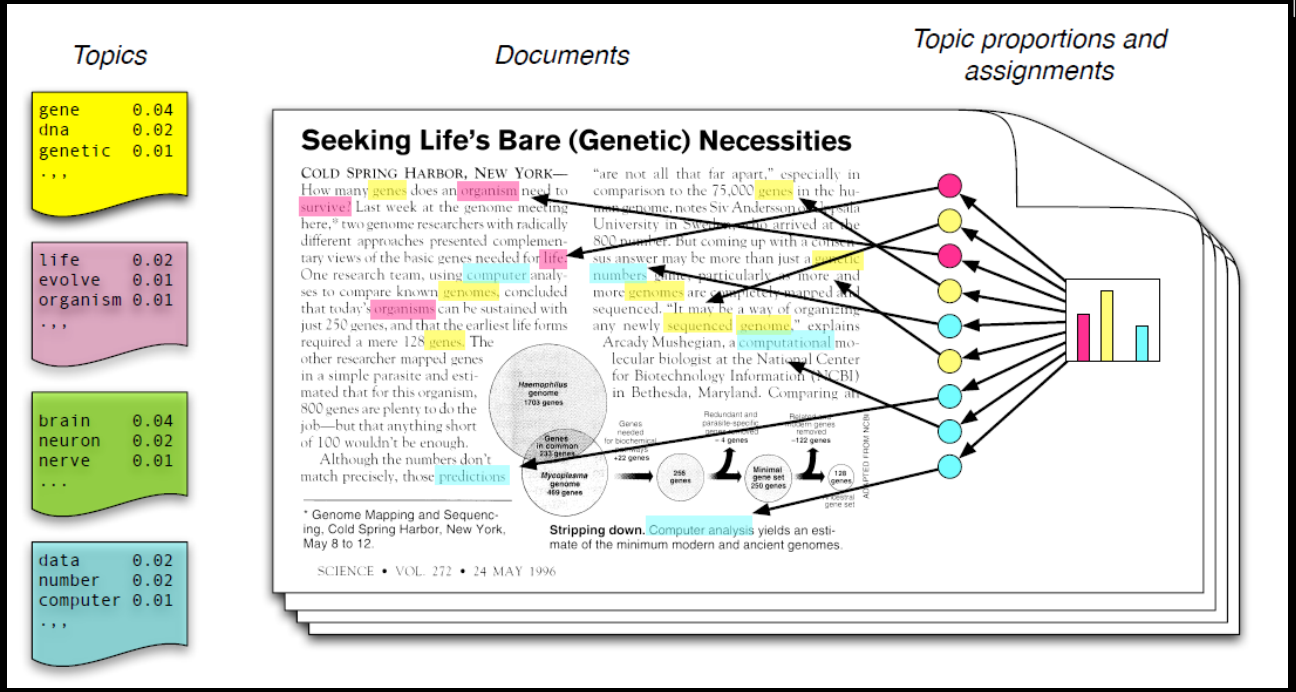

Latent Dirichlet Allocation

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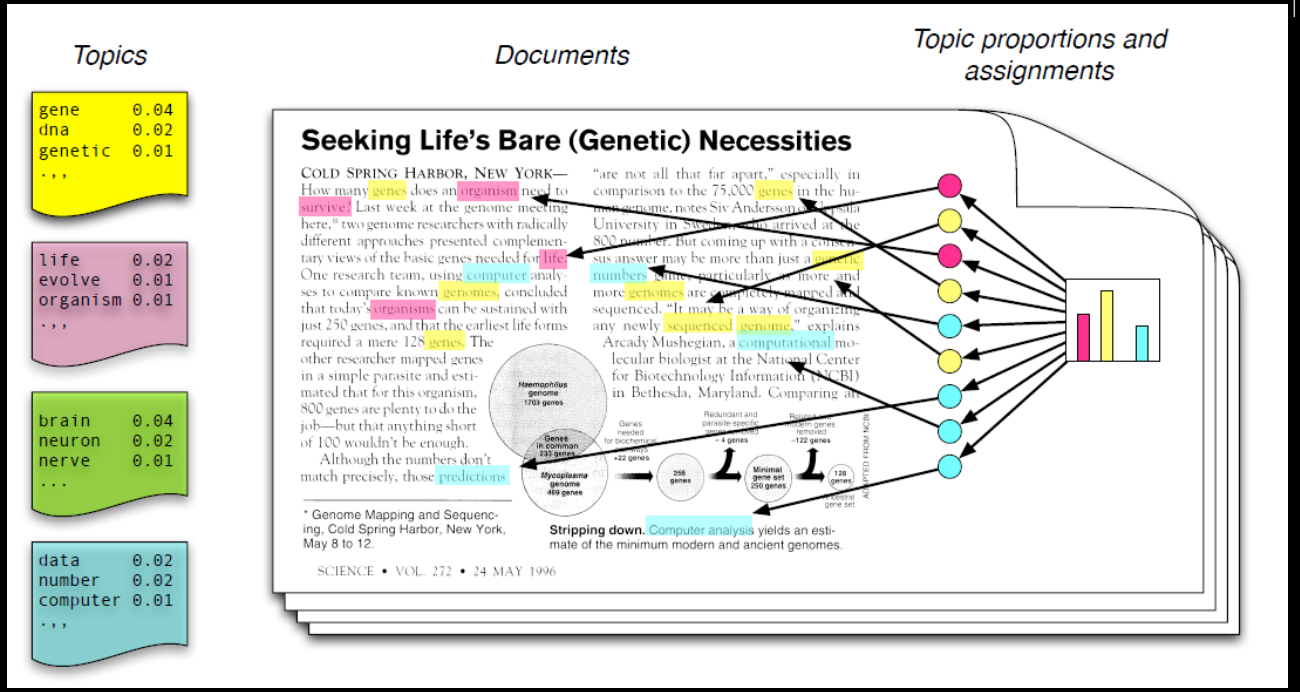
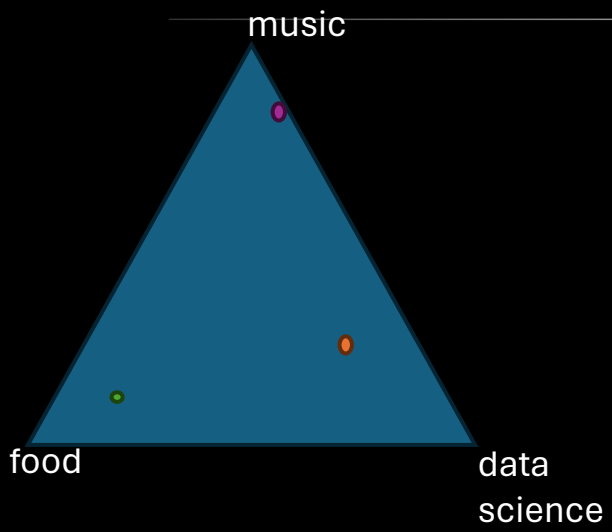
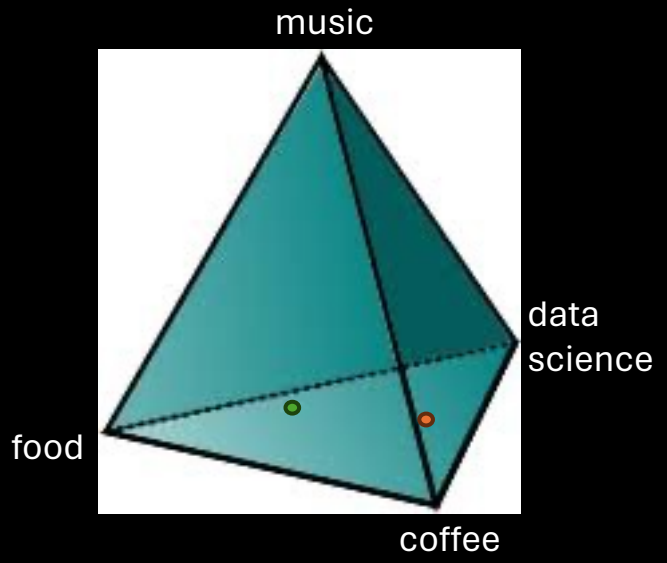
- A document may be a blend of multiple topics
- The model makes use of *Dirichlet Distributions* to model the relations from Topics to Documents and Words to Topics…



Latent Dirichlet Allocation

- A Dirichlet distribution a generative model...





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- We also ignore stop-words like ‘and’, ‘is’, etc
- Also numbers, links, punctuation, etc
- Also anything else we think is going to be frequent across all documents – like ‘UN’ in a corpus of UN tweets

DEMO

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- Agrees well with human evaluations of topic quality

DEMO

Compare to BERTopic…

- More pre-processing
- Uses only corpus data
- Instability
- Complexity

DEMO

Thanks Everyone!

Next step: Notebook 3, BYO Data with BERTopic

Will be released by the 12th

Complete in your own time, optional

Please message me on Teams for office hours to discuss!