

From Bag-of-Words to Large Language Models: Recent Advances in Topic Modelling

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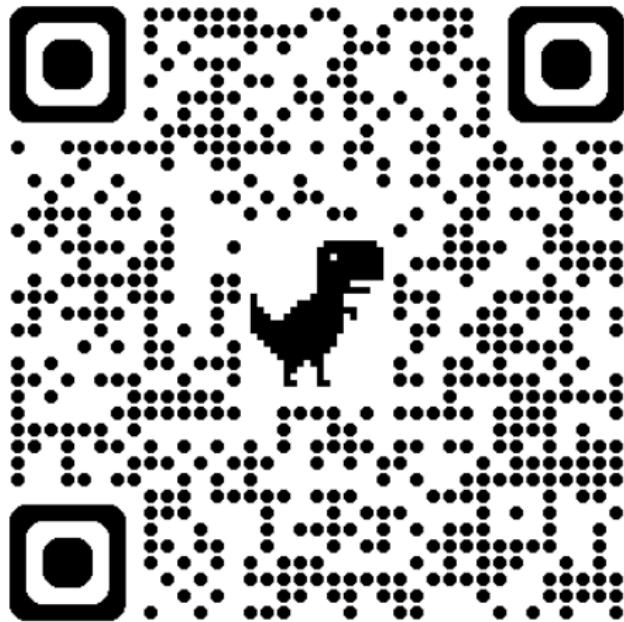


Figure: <https://github.com/RafaelGottardo/Topic-Modelling>

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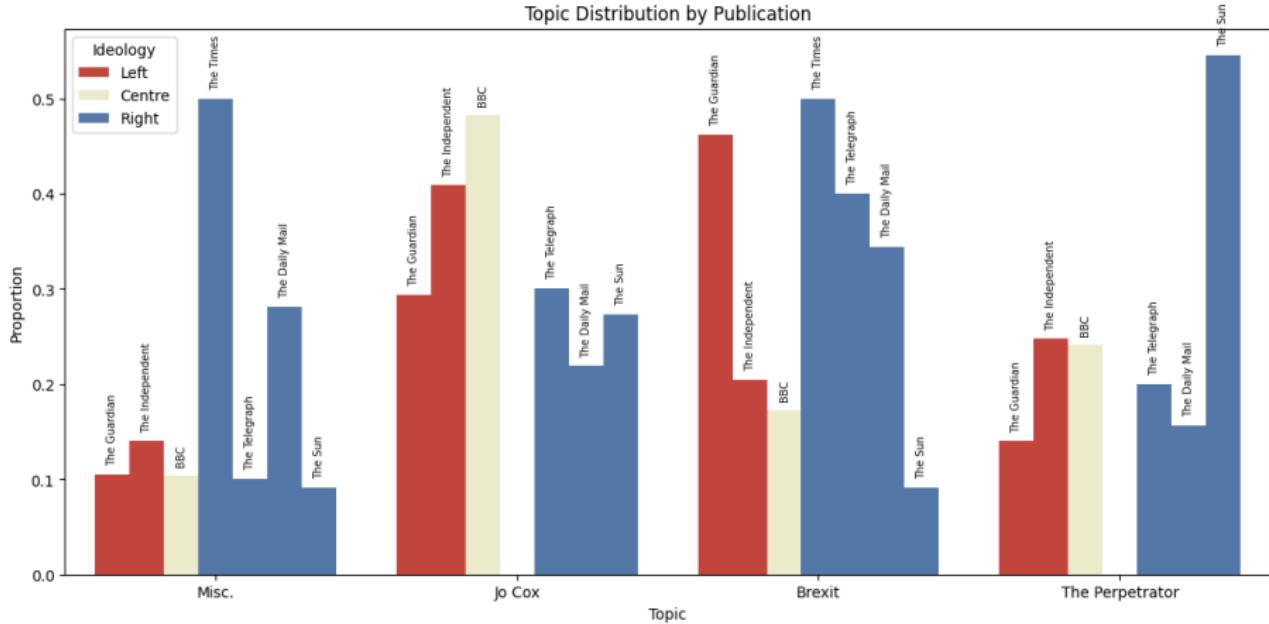
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- Topics are a collection of words that co-occur together.
 - Can be used to identify themes in text (Erlich et al. 2024)

Uses of Topic Modelling

Topic Distribution by Publication



Uses of Topic Modelling

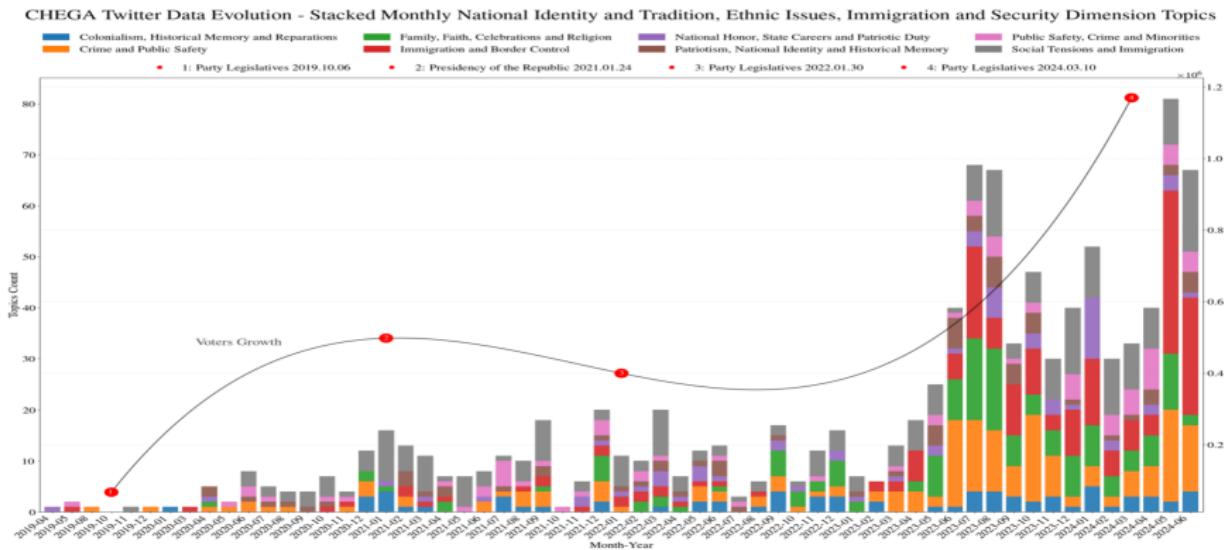


Figure 5 Monthly Evolution of Topics Related to National Identity, Tradition, Ethnic Issues, Immigration, and Security Dimensions (2019-2024).

Figure: Source: Cardoso et al. (2025)

Uses of Topic Modelling

Figure 3: Percentages and Counts of Hostile Responses by Topic

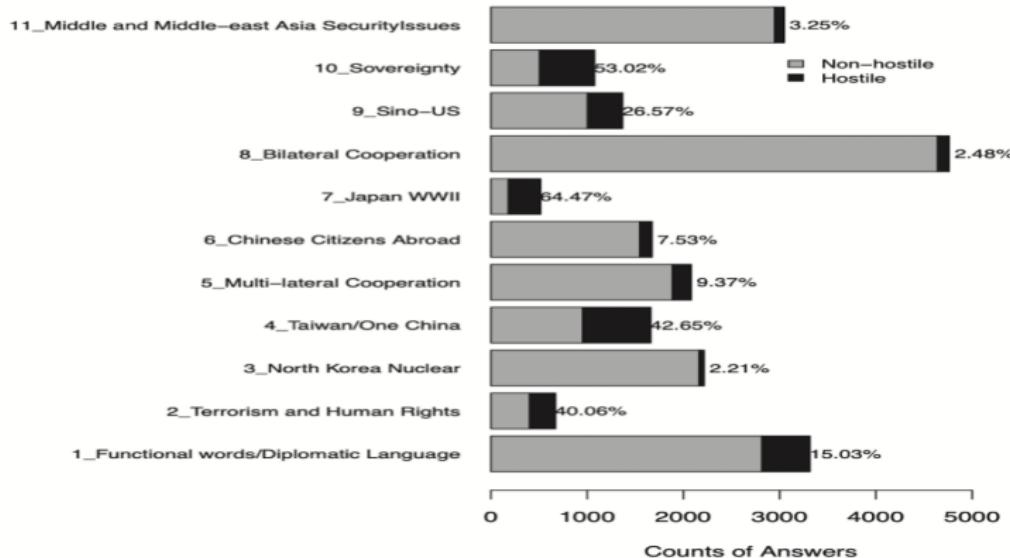


Figure: Source: Dai and Luqiu (2022)

Uses of Topic Modelling

Table 2: Topic Labels and Most Likely Terms within Each Topic

Number	Label	Most Relevant Term	Most Relevant Term Translated
1	Functional Words/ Diplomatic Language	中國，問題，是否，不，沒 有，有關，會，進行，一， 這個，情況，說，一些，方 面，中方	China, question, whether, no, not, relevant, will, ongoing, one, this, situation, say, some, aspect
2	Terrorism and Human Rights	中國，組織，國際，人權， 恐怖主義，打擊，反恐，恐 怖，社會，合作，政府，反 對，國家，人民，宗教	China, organization, international, human rights, terrorism, strike, anti-terrorism, terror, society, cooperation, government, against, nation, people, religion
3	North Korea Nuclear	朝鮮，會談，問題，六， 方，中方，半島，各方，解 決，對話有關，希望，朝， 和平，努力	Korea (N.), talks, problem, six-party, China, peninsula, each party, solve, dialogue, relevant, hope, Korea (N.), peace, strive
4	Taiwan/One China	中國，美，美國，臺灣， 關係，問題，中，美方， 不，中方，一個，和平，發 展，對此，國家	China, America, U.S., Taiwan, relationship, issue, China, America, no, Chinese side, one, peace, development, regarding, country
5	Multilateral Cooperation	中國，國家，合作，國際 ，發展，經濟，世界，中方 ，組織，會議，將，非洲， 積極，歐盟，社會	China, country, cooperation, international, development, economic, world, China side, organization, conference, will, Africa, active, E.U., society

Figure: Source: Dai and Luqiu (2022)

Workshop Outline

- Data Pre-processing
 - Bag-of-words
 - Word embeddings
- Topic Modelling
 - Latent Dirichlet Allocation (LDA)
 - BERTopic
 - LLMs for Topic Modelling
- Lab Component
 - BERTopic in R

Data Pre-processing

Data pre-processing Bag-of-words

- Each document is represented by the number of times each word appear in the document.
- Documents are represented in a document feature matrix.

Document Feature Matrix

- *Officials in Minneapolis on Friday accused federal authorities of "hiding the facts" over the shooting of a United States citizen by an officer with the Immigration and Customs Enforcement (ICE) agency.*
- *Jacob Frey, the mayor of Minneapolis, criticized the response of the federal authorities to the shooting in Minneapolis.*

Document	Officials	Minneapolis	Friday	accused	federal	authorities	hiding	facts	shooting	United States	citizen	officer	Immigration	Customs	Enforcement	ICE	agency	Jacob	Frey	mayor	criticized	response
Doc 1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	
Doc 2	0	2	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	1	1	1	1	1

Table: Document-Feature Matrix

Step 1: Tokenize

- Officials in Minneapolis on Friday accused federal authorities of ``hiding the facts'' over the shooting of a United States citizen by an officer with the Immigration and Customs Enforcement (ICE) agency.
- Jacob Frey, the mayor of Minneapolis, criticized the response of the federal authorities to the shooting in Minneapolis.

Step 2: Reduce Complexity

- make text lowercase
- remove punctuation
- remove stop words (e.g. the, and, it, or; le, la, et, ou).

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Weaknesses of Bag-of-words

- Sometimes it is important to analyze stop words (e.g. determining authorship).
- Assumes that words that share the same base have the same meaning (e.g. car and cars; good and better)
- Ignores semantics: similar words in semantic space are treated differently (e.g. barrister and solicitor).
- Ignores order of the sentence.

Alternatives to Bag-of-words: Word Embedding

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 - The *usage* of a word suggests the *meaning* of a word.
- Stopwords are not removed because they are needed to encode meaning.
- Advantages:
 - Encode similarity
 - Allow for automatic generalization (learning about one word automatically tells us about another word)
 - provide a measure of meaning (similar meaning when used in similar contexts)
 - Fewer pre-processing steps required.

Estimating Word Embedding

- Word embeddings need to be trained.
- The most common training method is self-supervision.
- There exist a number of pre-trained embeddings, that can be drawn on for topic modelling.
 - word2vec
 - doc2vec
 - GloVe
 - MTEB-French
 - and more available from huggingface.co

Training Word Embedding (word2vec)

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- Context words can predict centre word (“mother,” “sister,” “friend”) (continuous bag-of-words).

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- King – Man + Woman = Queen
- Montreal Canadians – Montreal + Toronto =
Toronto Maple Leafs

An example from Grimmer et al. (2022)

- Two 300-dimensional vectors for the word manufacturing (pre-1960 and post-1960).
- Use cosine difference to compare the closest neighbours in each time period.
- **Pre-1960:**
 - exportation, oil-related, concomitant, detriment, war-relate.
- **Post-1960:**
 - retool*, jobs, downtowns, offshoring.

Word Embedding in R

```
# load data
data("movie_review", package = "text2vec")

# prepare data for doc2vec
df <- data.frame(#create a unique id variable for each review
                  doc_id = paste0("movie_", movie_review$id),
                  # use a cleaning function from word2vec
                  text = txt_clean_word2vec(movie_review$review),
                  stringsAsFactors = FALSE)

# train the doc2vec model
model <- paragraph2vec(x = df, type = "PV-DBOW",
                        dim = 100, iter = 10, min_count = 5,
                        lr = 0.05, threads = 4)

# extract the document embeddings
embedding <- as.matrix(model, which = "docs")
```

Topic Modelling

Latent Dirichlet Allocation (LDA)

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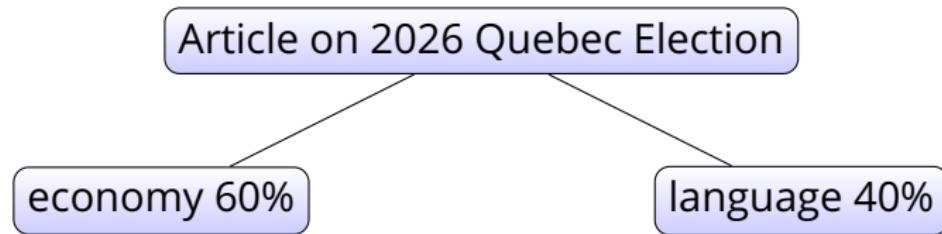
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- When writing a text the author first draws on a topic and then conditional on the topic draws the specific words.

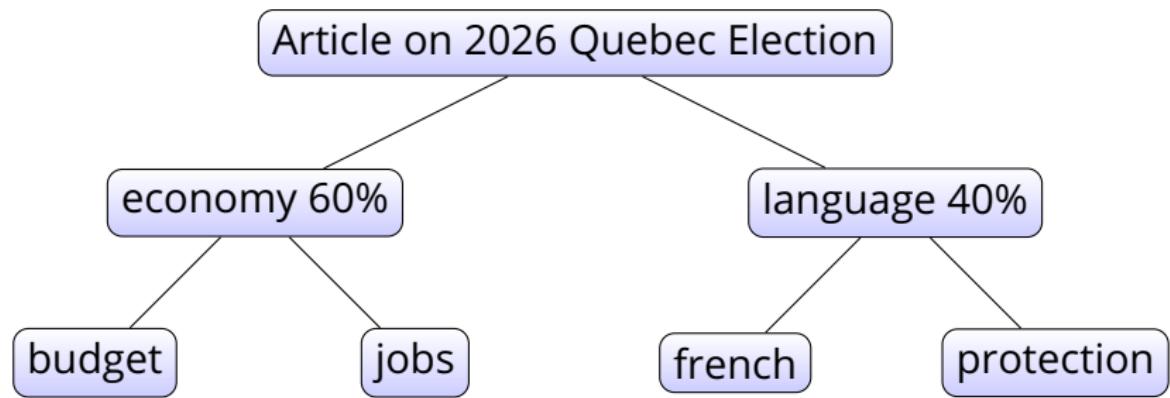
Visualization of LDA Theory

Article on 2026 Quebec Election

Visualization of LDA Theory



Visualization of LDA Theory



LDA in R

```
library(quanteda)

ON_22$text <- as.character(ON_22$text)
ON_22_corp <- corpus(ON_22, text_field = "text")

toks <- tokens(ON_22_corp,
                what = "word",
                remove_punct = TRUE,
                remove_symbols = TRUE,
                remove_numbers = TRUE) %>%
tokens_tolower() %>%
tokens_remove(stopwords("english"))

dfm <- dfm(toks)
```

LDA in R

```
library(topicmodels)
library(tidytext)

lda_model <- LDA(
    # specify the pre-processed data
    dfm,
    # specify the number of topics
    k = 10,
    # seed for replicability
    control = list(seed = 1998)
)
```

LDA in R

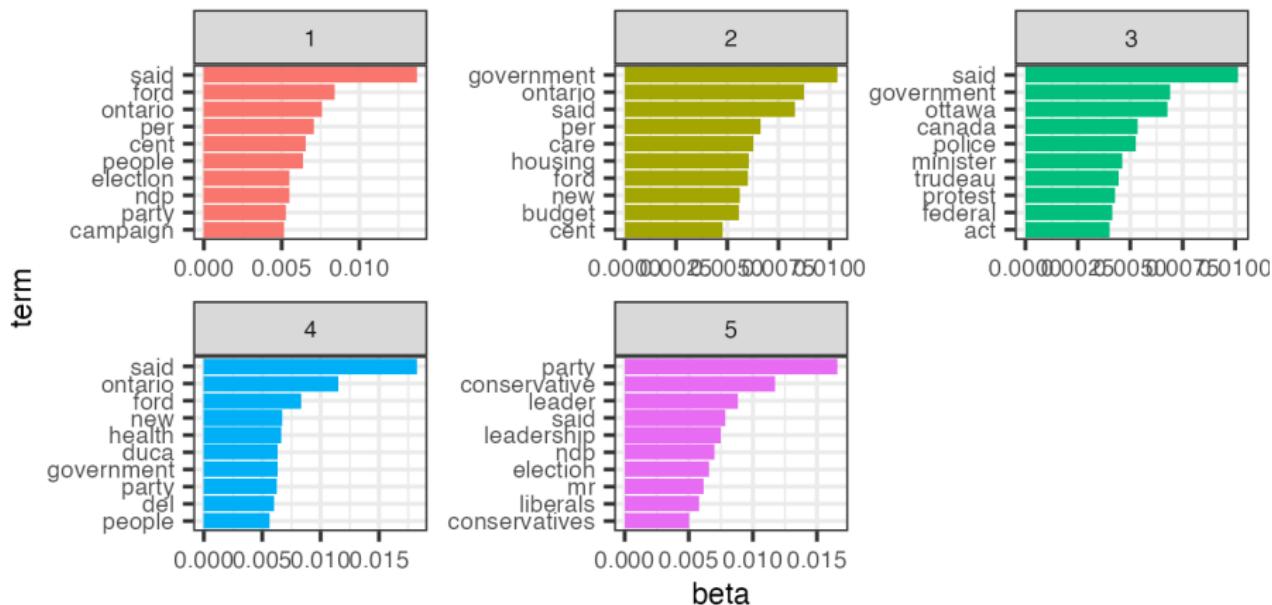
- Extract the per-topic word probabilities β

```
topics <- tidy(lda_model, matrix = "beta")  
topics
```

topic	term	beta
1	ndp's	0.000609
2	ndp's	0.000008
3	ndp's	0.000000
4	ndp's	0.000280
5	ndp's	0.000388
6	ndp's	0.000000
7	ndp's	0.000039
8	ndp's	0.000000
1	sandy	0.000091
2	sandy	0.000000

LDA in R

- We can use the `slice_max()` function to extract the terms with the highest probability of being generated by each topic



Weaknesses of LDA

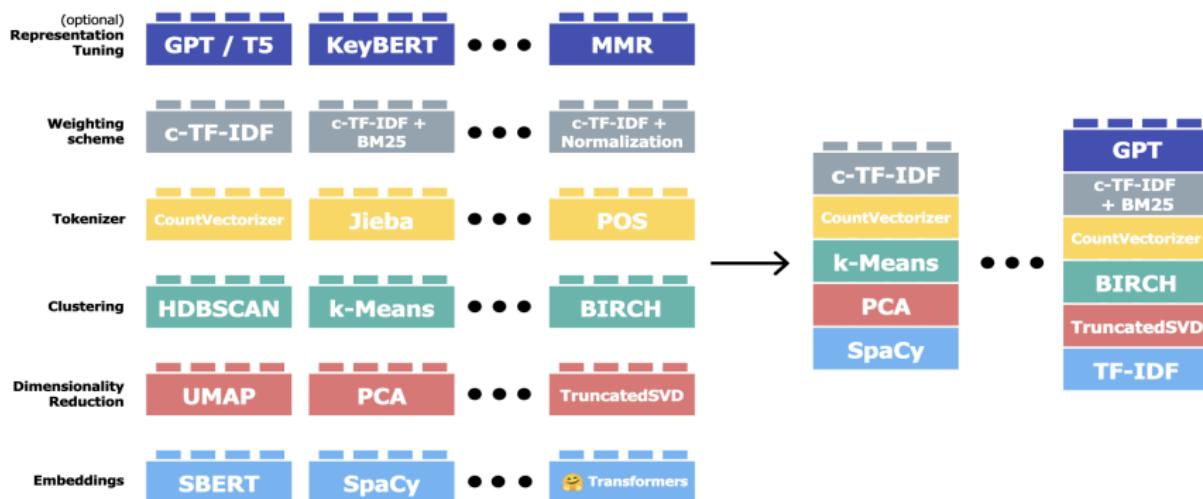
- LDA requires the number of topics to be pre-specified.
- Often relies on “Bag-of-Words” representation.
- Struggles with short texts where there is limited variations in words.

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- A sequence of steps that create topic representations.
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 - ③ Cluster documents using a clustering algorithm hierarchical density-based clustering approach (HDBSCAN).

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Document Embedding

- Uses sentence BERT to create sentence embeddings that are compared using cosine similarity to locate sentences with similar meaning.
- Create vector space representations to be compared semantically.
- Assumes that documents on the same topic are semantically similar.

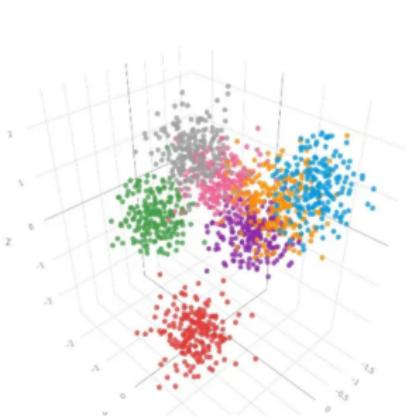
Dimensionality Reduction

- In high dimensional data the distance to the nearest data point approaches the distance to the furthest data point.
- The concept of spatial locality does not work well.
- Many methods: PCA, t-SNE, **UMAP**.

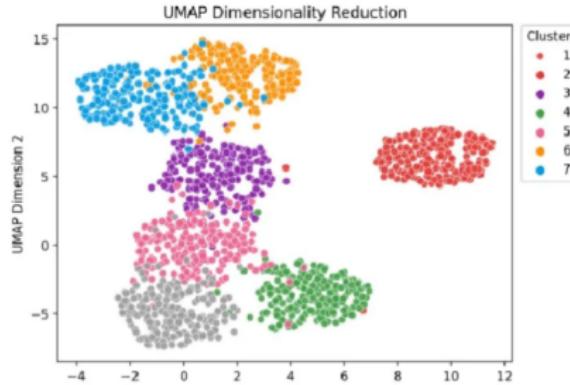
Uniform Manifold Approximation and Projection (UMAP)

- Preserves local and global features of high-dimensional data (McInnes et al. 2020).

Point cloud in a 3-dimensional space



Clusters

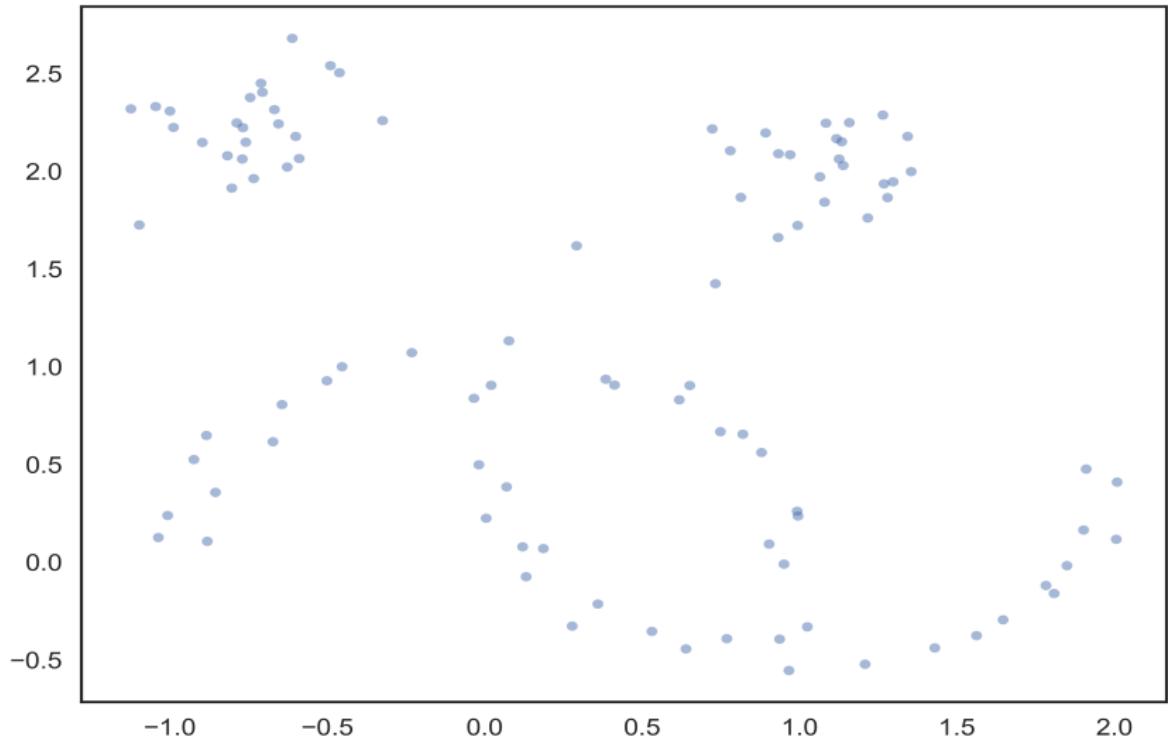


(Luna 2023)

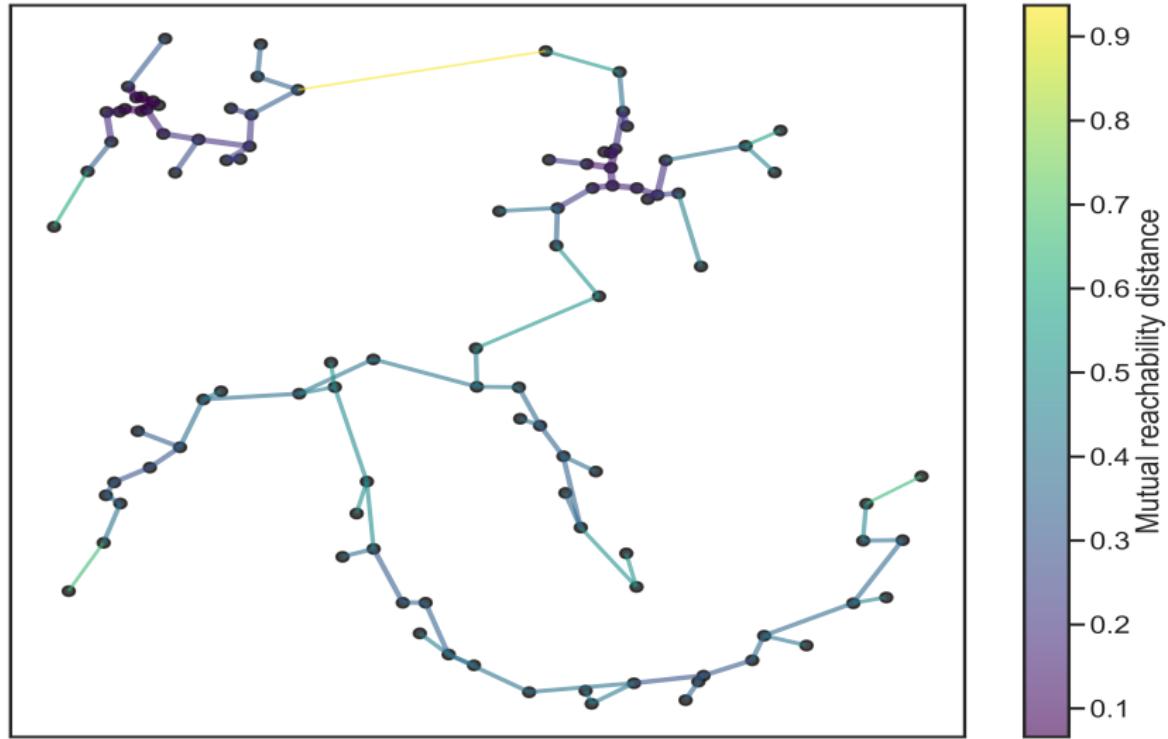
Cluster Documents

- Hierarchical density-based clustering approach (HDBSCAN)
- Allows noise to be modelled as outliers.

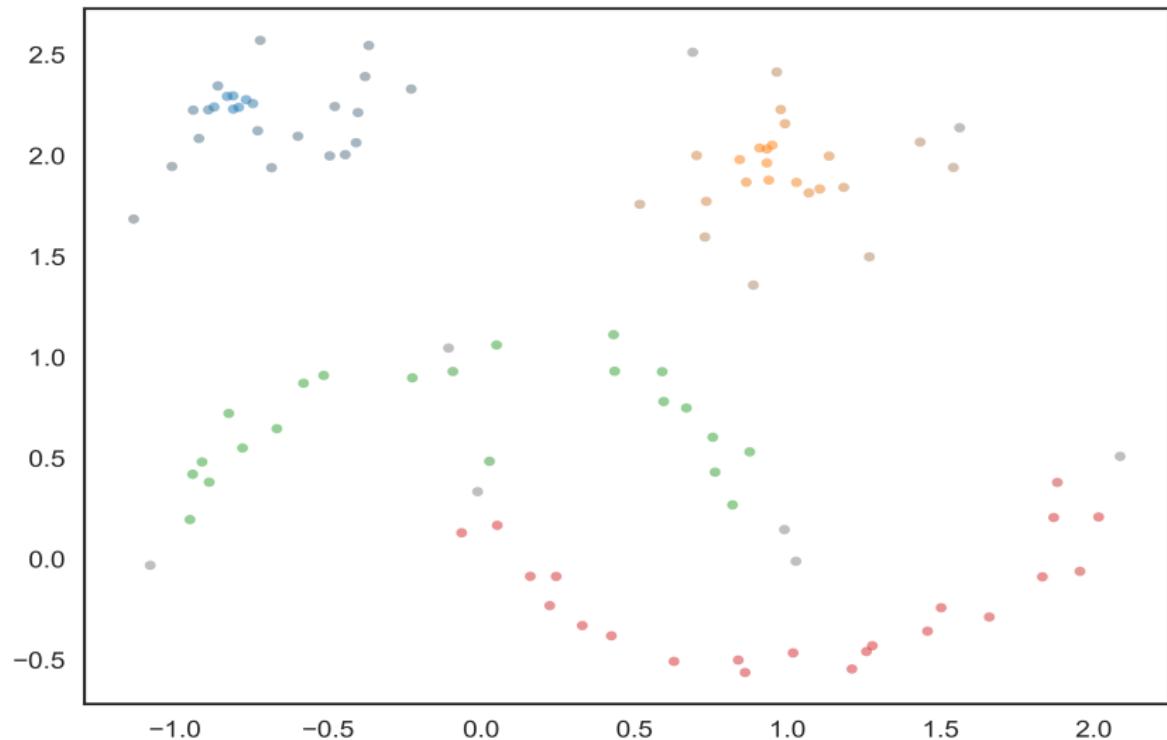
Visualizing HDBSCAN - Data



Minimum Spanning Tree - Mutually Reachability



HBDSCAN Clustered Data



Topic Representation

- TF-IDF measures the importance of a word to a document.

$$W_{t,d} = tf_{t,d} \cdot \log\left(\frac{N}{df_t}\right) \quad (1)$$

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Topic Representation

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$$W_{t,d} = tf_{t,d} \cdot \log\left(\frac{N}{df_t}\right) \quad (1)$$

- How can we do this for topics (clusters)?

$$W_{t,c} = tf_{t,c} \cdot \log\left(1 + \frac{A}{tf_t}\right) \quad (2)$$

Where frequency is the frequency of a term t in a class (cluster) c .
The inference class frequency is calculated as the logarithm of the average number of words in class A divided by the frequency of the term t across all classes. What makes one cluster different from another

TF-IDF in Practice

Word	df	idf
Romeo	1	1.57
salad	2	1.27
Falstaff	4	0.966
forest	12	0.489
battle	21	0.246
wit	34	0.037
fool	36	0.012
good	37	0
sweet	37	0

Table: Document frequency (df) and inverse document frequency (idf) by word (source Wikipedia)

cTF-IDF in Practice

$$W_{t,c} = tf_{t,c} \cdot \log\left(1 + \frac{A}{tf_t}\right) \quad (3)$$

The teacher went to **school** and taught the students. Attending **school** is important for students learning and growth. **(A)**

The mayoral candidate promised to invest \$20 billion to prevent **school** closures and \$50 billion in hospitals. **(B)**

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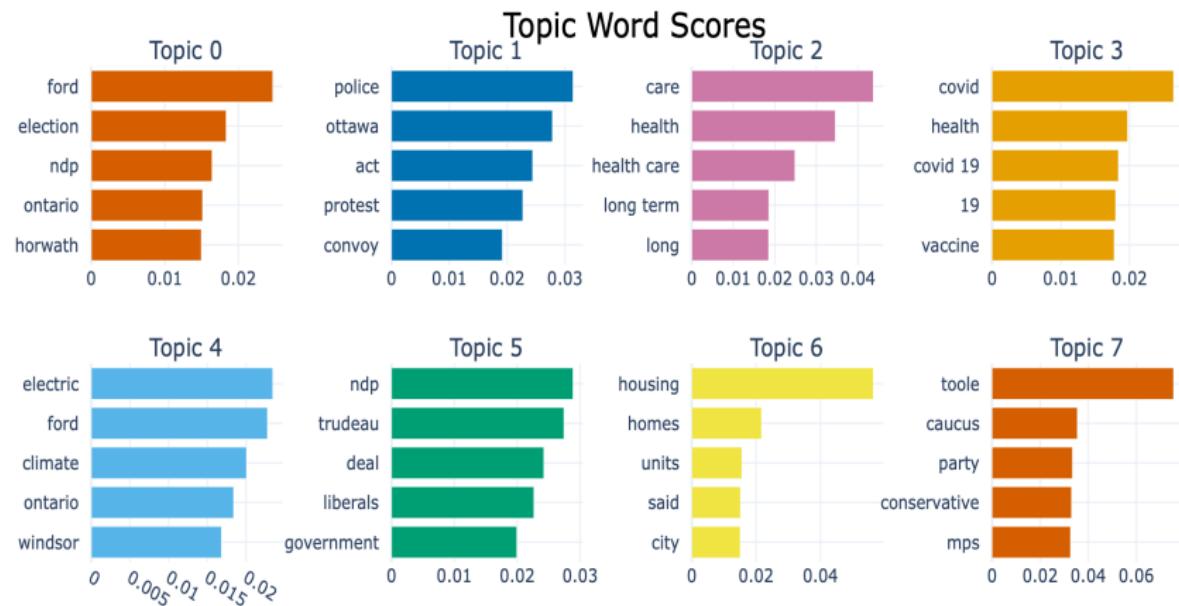
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- **Cluster B:** $W_{t,c} = 1 \cdot \log\left(1 + \frac{17.5}{3}\right)$
- $W_{t,c} = 0.834$

BERTopic in R

- BERTopic is designed for Python but there is an R version using reticulate.
- We will go over using BERT Topic in R in the lab component.

BERTopic in R



LLMs for Topic Modelling

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- **Strengths:**

- Recent research has shown that generative large language models produce topics that are more closely aligned with the human coded ground truth (e.g. GPT based models).
- Topics have natural language labels.
- More customizable than other methods.

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- **Weaknesses**

- Relies on closed models making replicability difficult.
- "Zero-shot" topic modelling can often produce mis-specified topics.
- The models do not provide information on the underlying process to generate topics.
- Specific prompt engineering is required to ensure that models do not hallucinate.

One workflow TopicGPT

① Topic Generation

- Prompt an LLM to generate topics from a data set.
- Provide new document and prompt LLM to assign it to an existing topic or create a new topic.
- Refine topics by identifying duplicate topics and prompting LLMs to remove these topics.

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2 Topic Assignment

- Provide the LLM with the topics, descriptions and examples.
- Ask the LLM to assign the one or more topics to each document.
- Provide a quote to justify the assignment.

Lab Time

Rafael Campos-Gottardo
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