Quantitative Text Analysis – Essex Summer School

Word embeddings

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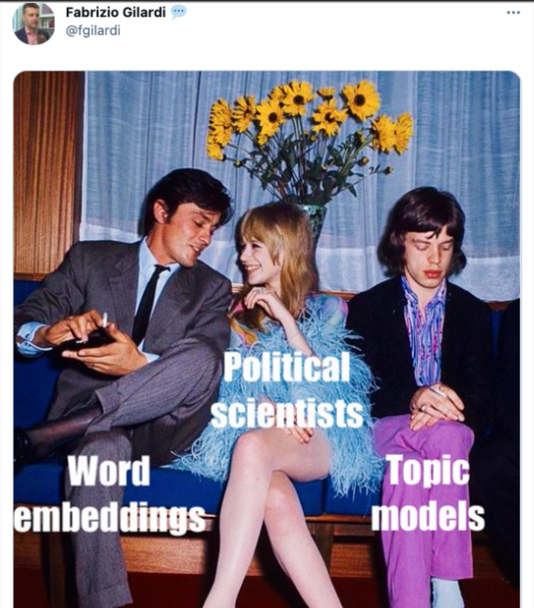
Today's class

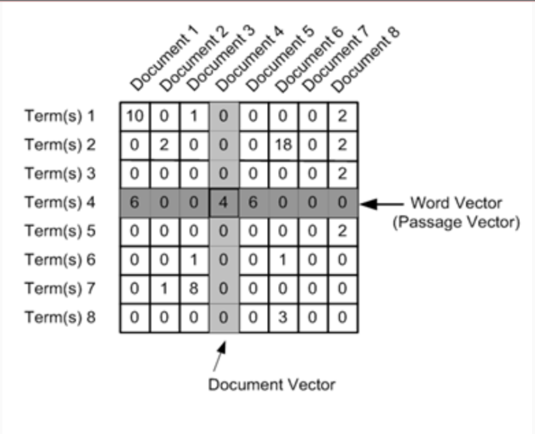
- Word embeddings
- Lab session
- Flash talks: Theresia and Vanessa

Word Embeddings



Word Embeddings

- Most applications of text as data in political science: bag of words
  - Context largely ignored (but remember: collocations)
- Word embeddings: different representation of text; words as a represented as a, real-valued vector of of numbers
  - The length of this vector "corresponds to the nature and complexity of the multidimensional space in which we are seeking to 'embed' the word" (Rodriguez & Spirling, 2022)



	Document 1	Document 2	Document 3	Document 4	Document 5	Document 6	Document 7	Document 8
Term(s) 1	10	0	1	0	0	0	0	2
Term(s) 2	0	2	0	0	0	18	0	2
Term(s) 3	0	0	0	0	0	0	0	2
Term(s) 4	6	0	0	4	6	0	0	0
Term(s) 5	0	0	0	0	0	0	0	2
Term(s) 6	0	0	1	0	0	1	0	0
Term(s) 7	0	1	8	0	0	0	0	0
Term(s) 8	0	0	0	0	0	3	0	0

- Words are counts in documents. We can calculate word similarities on this matrix using cosine similarity or euclidian distance
- Problem: usually many zeros, very sparse (curse of dimensionality)

What are word embeddings

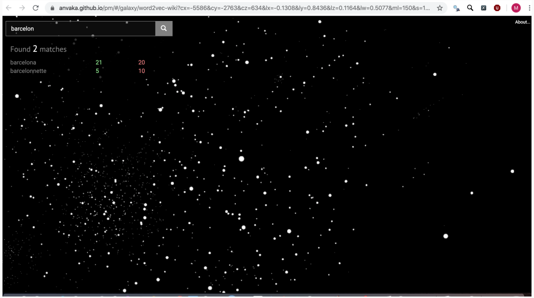
You shall know a word by the company it keeps (Firth, 1957)

Distributional hypothesis – meaning of a word can be extracted by looking, over many texts, by the words that occur around it

This may have exciting substantive implications:

- 'if the distance between "immigrants" and "hard-working" is smaller for liberals than for conservatives, we learn something about their relative worldviews' (Rodriguez & Spirling, 2022)

Visualizing word embeddings



`https://bit.ly/35WkD7K`

The dataset used for this visualization comes from GloVe, and has 6B tokens, 400K vocabulary, 300-dimensional vectors

What are word embeddings

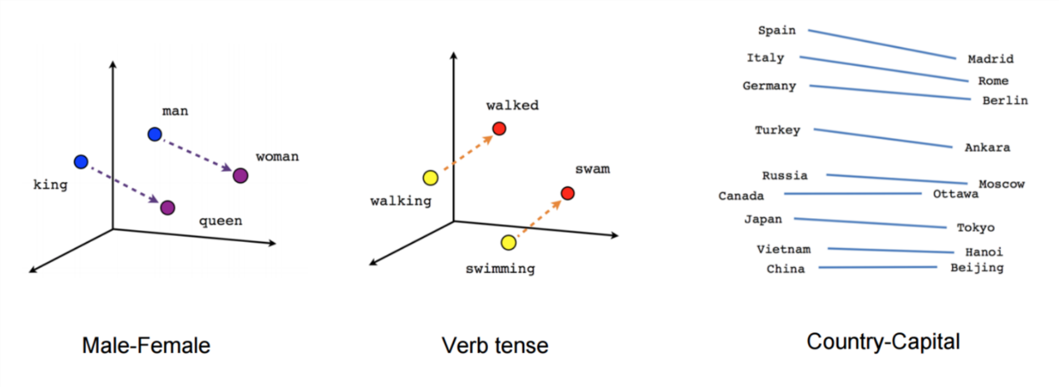
Word embeddings gained fame in NLP when it was demonstrated that they could be used to identify analogies.

- These analogical relationships can be expressed mathematically in terms of their word vectors:

$$\text{V(woman) - V(man)} + \text{V(king)} \approx \text{V(queen)}.$$

1. Start with the vector for "woman";
2. Subtract from it the vector for "man", leaving behind only what is unique about V(woman) as distinct from V(man);
3. Then, add this distinct difference to V(king).
4. You end up with a new vector position: V(woman-man+king). Which word vector, out of thousands of other words, is closest to V(woman-man+king)? In most word embedding models: V(queen).

Word Embeddings



Source:: https://cbail.github.io/textasdata/word2vec/rmarkdown/word2vec.html

Word Representations

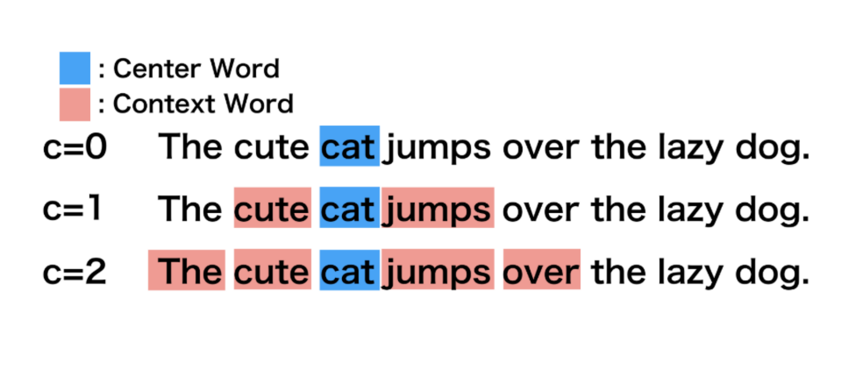
Bag of Words	Word embeddings
One-hot encoding	Vector in a semantic space
DxN	*NxV*
No context	Estimated from context
Meaning exogenous	Meaning learned
Input to a model	Output from a model

D = number of documents

N = number of words

V = number of embedding dimensions

Context Window



Source:: https://cbail.github.io/textasdata/word2vec/rmarkdown/word2vec.html

Learning word embeddings

There are various algorithms to learn word embeddings vectors:

- Word2Vec (Mikolov *et al.* 2013)
- GloVe (Pennington, Socher, Manning, 2014)

Important to keep in mind: researcher determines the size of the context window, the length of the word embeddings vector and whether to use pre-trained word embeddings or not (see Spirling & Rodriguez, 2022)

Some applications of word embeddings for social science

- Detecting emergency rhetoric among EU executives (Rauh, 2021)
- Develop domain-specific sentiment dictionaries dictionaries (Rheault *et al.* 2016)

Normality-emergency in executive speeches

Procedure in Rauh (2021):

1. Identify a short list of key words:
   - emergency: *crisis, danger, peril, hazard, threat, risk, disaster, uncertainty, uncertain*
   - normality: *normal, safety, stability, regularity, routine, calm, usual, certainty, certain*.
2. Learn a word embeddings model (GloVe) on the 100 years of House of Commons speeches
3. Identify an additional set of 250 crisis and emergency words closest the average vectors of normality and emergency
4. Use these words to scale EU executive speeches on a normality - emergency dimension (LSS)

Normality-emergency in executive speeches

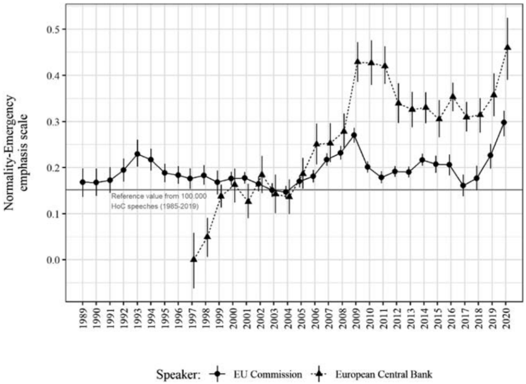


Figure 2. Emergency emphasis in public speeches of supranational executives over time.

Normality-emergency in executive speeches

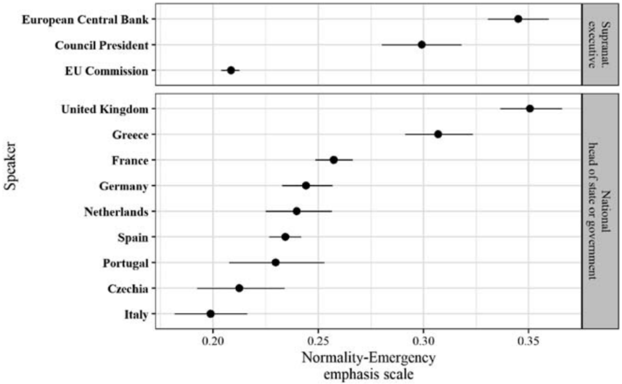


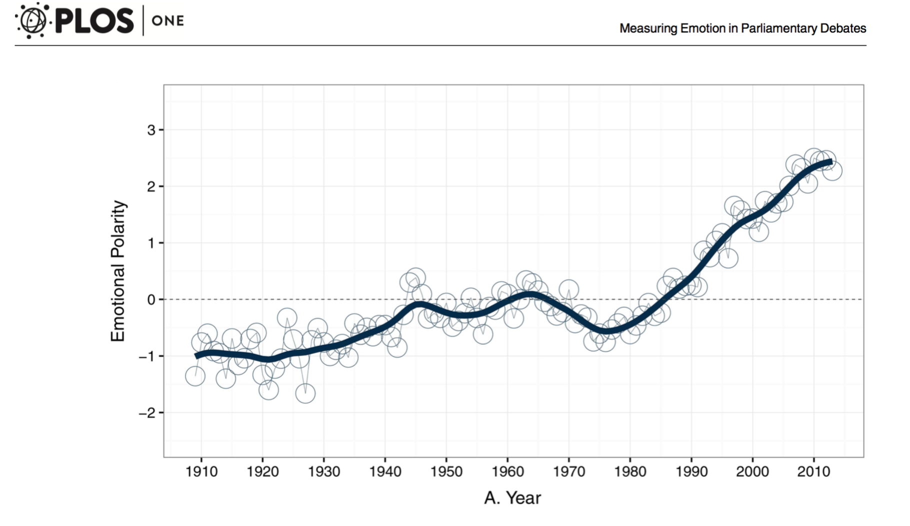
Figure 3. Emergency emphasis in executives' public speeches during the Eurocrisis (2009–2015).

Rheault et al. (2016)

Sentiment analysis – use word embeddings to develop a "domain specific sentiment dictionary"

- British House of Commons speeches between 1909 and 2013
  - After preprocessing, total of 108,506 unique tokens
  - Create a feature co-occurrence matrix
  - Use GloVe to learn word embeddings
  - Then locate 200 positive and negative 'seed' words in this space
  - With these words located, they can locate other words nearby, leading to a total of 4200 words denoting positive and negative sentiment

Overall sentiment in the HoC



Government and opposition sentiment in the HoC

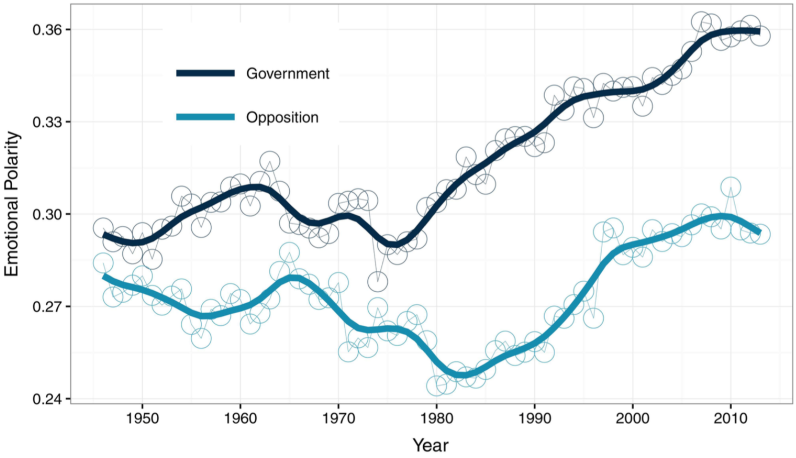


Fig 2. Emotional Polarity of Government and Opposition in Britain, 1946-2013.

doi:10.1371/journal.pone.0168843.g002

Word Embeddings

- Lots of cool possibilities: For example, how does the semantic meaning of words change over time (e.g., liberal and conservative)?
- Do parties shift in *how* they use particular words? For example, does debate vocabulary change over time?
  - See, e.g., work by Milan van Lange and Ralf Futselaar on War debates in Dutch parliament `https://github.com/MilanvanL/debating_evil`

Validation

For on a discussion on validation strategies for word embeddings models in political science, see Spirling & Rodriguez (2022)

Turing test:

1. Generate human-generated nearest neighbors for a concept of interest
2. Generate model-produced nearest neighbors for a concept of interest
3. Let coders rate which nearest fit better the definition of a context word
4. Calculate whether coders are equally likely to choose human-generated or model-produced vectors