Text factorisation — I: Bag-of-words methods

Course "Text-as-data analysis of international trade"

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Course outline

1. Preferential Trade Agreements and International Economic Order
2. Gravity and Gravitas
3. **Text factorisation — I: Bag-of-words methods**
4. Text factorisation — II: Distributive semantics
5. Welfare effects of Preferential Trade Agreements

Outline

1. What's in a bag?
   - BOW representation
   - BOW applications
2. Improvements
   - Tokenisation
   - Re-weighting of DTM
3. DTM Factorisation
   - Latent Semantic Analysis

Outline

Bag-of-words

- A simple yet versatile way to quantify any text is a *bag of words*:
  - `John likes to watch movies. Mary likes movies too.`
    $\Updownarrow$
    `"John", "likes", "to", "watch", "movies", "Mary", "likes", "movies", "too"`
  - `John also likes to watch football games.`
    $\Updownarrow$
    `"John", "also", "likes", "to", "watch", "football", "games"`
- In itself, it is of limited use. However, one can build a vocabulary of unique terms and store their counts:

	John	likes	to	watch	movies	Mary	too	also	football	games
doc1	1	2	1	1	2	1	1	0	0	0
doc2	1	1	1	1	0	0	0	1	1	1

- This is a unigram document-term matrix

Bag-of-words & DTMs

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- This is a unigram document-term matrix (DTM)

Unigrams vs. *n*-grams vs. *q*-grams

- One can put more than one word in a bag — bigram here, *n*-gram in general:
  - `"John_likes", "likes_to", "to_watch", "watch_movies", "movies_Mary", "Mary_likes", "likes_movies", "movies_too", ...`
- Or capitalise on character-level information — *q*-gram:
  - `"jo", "hn", "n_l", "li", "ik", "ke", "es", "s_", ...`
- Variance-bias trade-off: larger n, q leads to lower generalisability of the language model
  - need for sparse representations: most *n*-grams are never used
- What shall one do with punctuation?

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Figure 1: Relative counts in Google *n*-grams (Michel et al., 2011) from Pechenick et al. (2015, fig. 2)

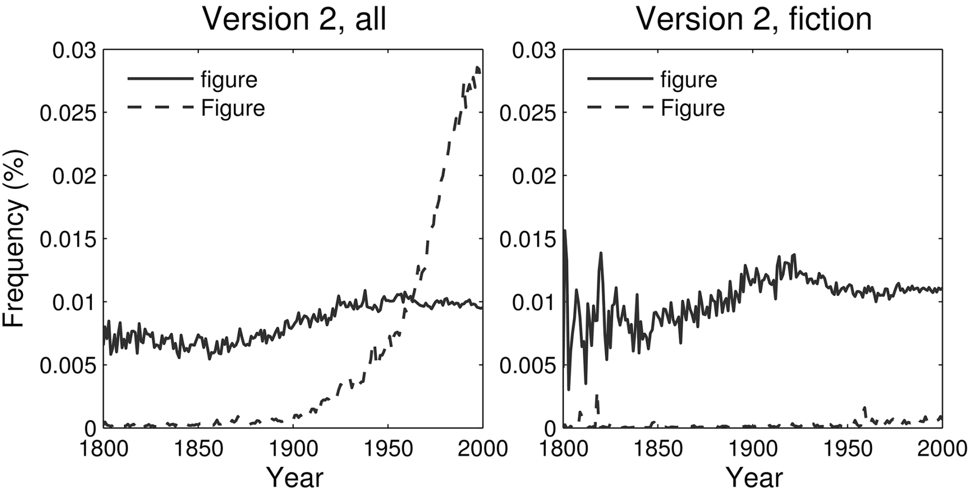

Figure 2: Dendrogram for *n*-gram distances between languages (Feinerer et al., 2013, fig. 4)

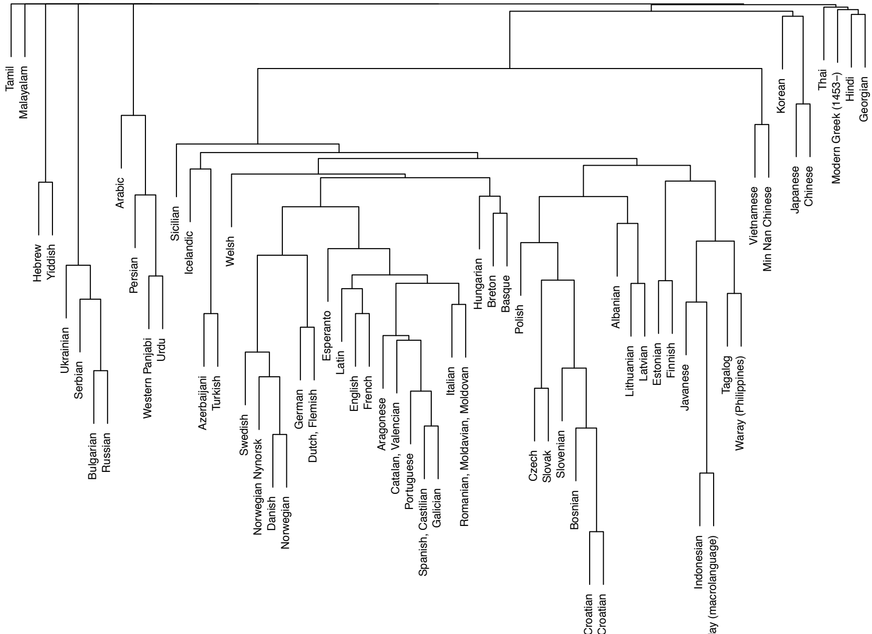

Figure 3: TDM of select terms in Shakespeare plays (Jurafsky and Martin, 2017, fig. 15.1)

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	1	8	15
soldier	2	2	12	36
fool	37	58	1	5
clown	5	117	0	0

Figure 4: 2 dimensions of Shakespeare TDM (Jurafsky and Martin, 2017, fig. 15.3)

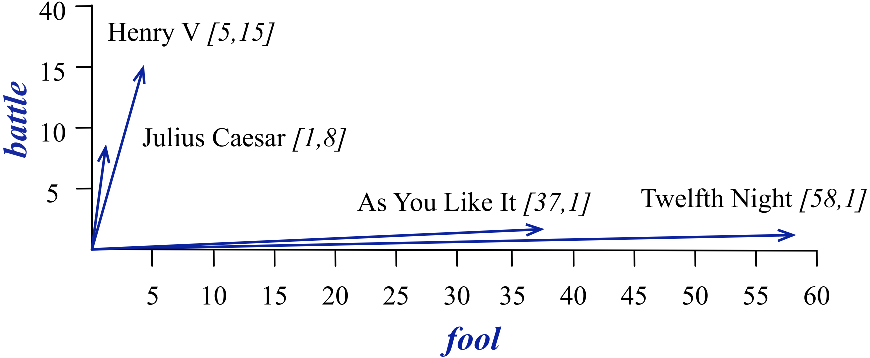

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Figure 5: Partition examples of Dickens's "*Tale of Two Cities*" (Williams et al., 2015, fig. 1A): clause, phrase, word, grapheme, letter

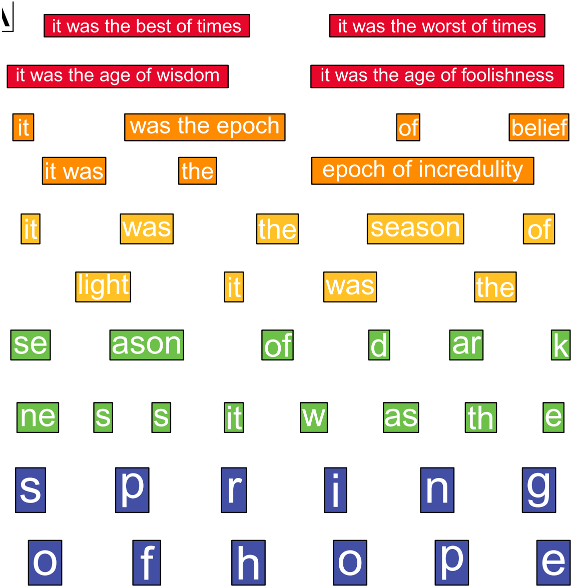


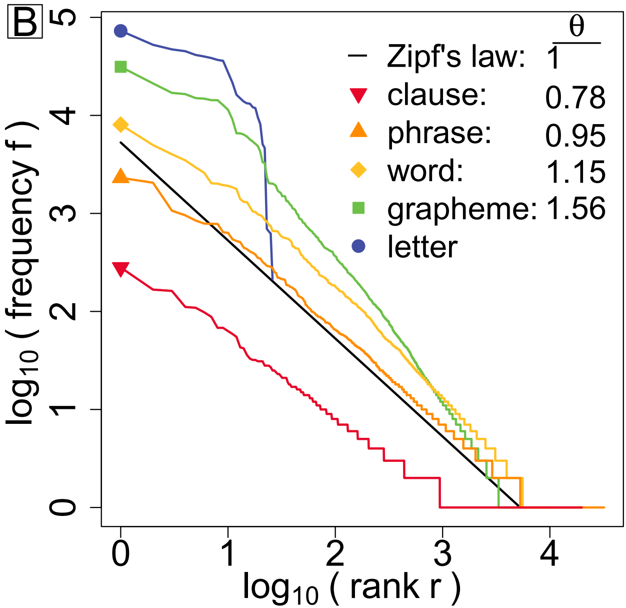
Table 1: Tokenisation is not as easy as it seems (`https://www.ibm.com/developerworks/community/blogs/nlp/entry/tokenization`)

“I said, ’what’re you? Crazy?”’ said Sandowsky.

	Naïve whitespace	Apache Open NLP	Stanford	Custom	Ideal
1		“	“	“	“
2	“i	i	i	i	i
3	said,	said	said	said	said
4		,	,	,	,
5	what’re	what	‘		
6			what	what’re	what
7		re	re		are
8	you?	you	you	you	you
9		?	?	?	?
10	crazy?’”	crazy	crazy	crazy	crazy
11		?	?	?	?
12					
13	said	said	said	said	said
14	sandowsky.	sandowsky	sandowsky	sandowsky	sandowsky
15		.	.	.	.

Outline

Figure 6: Zipf's law ($F(w) \propto rank(w)^{-\theta}$) at various token level (Williams et al., 2015, fig. 1B): clause, phrase, word, grapheme, letter



Dealing with Zipf's law

- Zipf's law suggests that word frequency counts are very skewed
- At the same time, frequent words are not necessarily discriminative "the" vs "a"
- Solution 1: "stopwords" remove such stop words
  - problem: influence word order and any *n*-/*q*-gram measures
- Solution 2: term frequency-inverse document frequency weighting (tf-idf):

$$\mathrm{tf}\left(token\right)_i = \frac{\#occurences\ in\ document\ i}{\#tokens\ in\ document\ i}$$

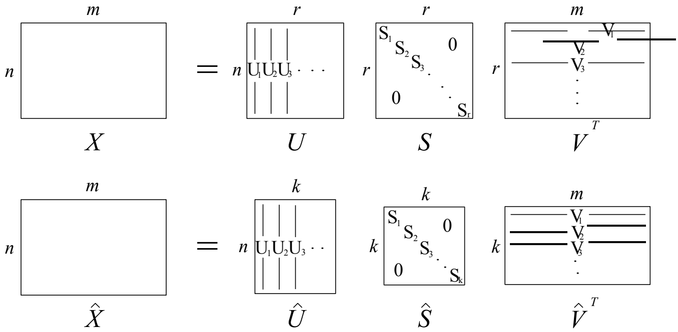
$$\mathrm{idf}\left(token\right) = \ln \frac{\#documents}{\#documents\ with\ token + 1}$$

Outline

How to extract meaning from DTMs

- Widely known way to extract meaning is to apply singular value decomposition to (tf-idf-weighted) DTM (Deerwester et al., 1990):

Figure 7: SVD example (from Radinsky, 2017)



See also: `https://en.wikipedia.org/wiki/File:Topic_model_scheme.webm`

LSA in practice

- In practice, LSA has large computational cost — $O\left(mn^2\right)$ — not always scaleable
- Need to reduce the resulting still-high-dimensional LSA output further, e.g. with PCA
- tf-idf makes a huge difference

Take-aways

- BOW model is a powerful albeit limited way to quantify texts
- Tokenisation is often overlooked but can be a large problem in practice
- Simply applying SVD to DTM can take you a long way

Thank you for your attention!

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