Chapter NLP:IV

IV. Text Representation Models

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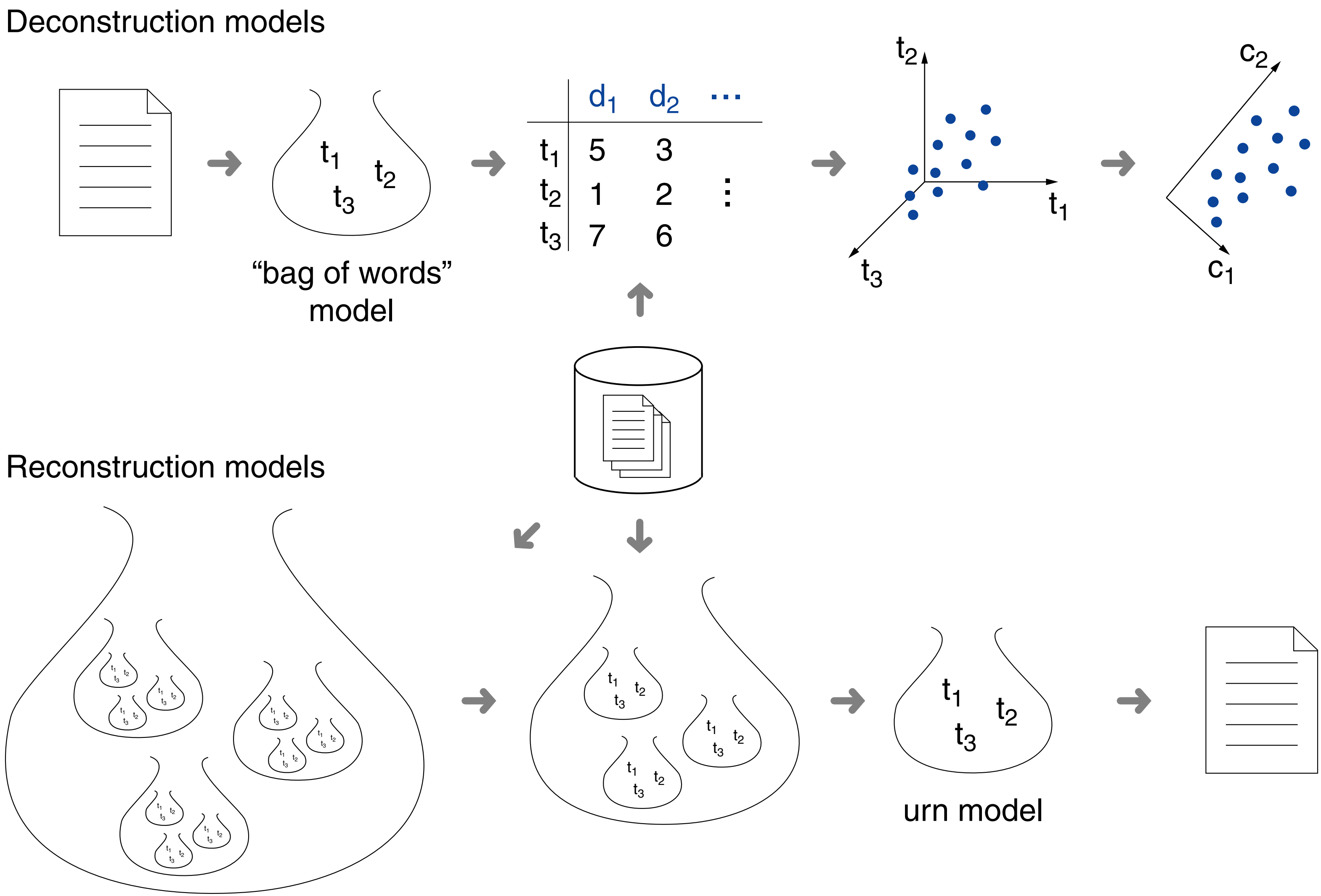
Introduction to Text Representation Models

How to represent Text? Digitally available texts



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Introduction to Text Representation Models

Bag of words

Bag of words hypothesis: “The frequencies of words in a document tend to indicate the relevance of the document to a query” [Turney, Pantel 2010]

Bag metaphor

- frequency is important
- order can be neglected

Example word list from presidential speech: `shall(12), amendment(7), states(7), constitution (6), congress (4), united (4)`

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Chapter NLP:IV

IV. Text Representation Models

- Introduction to Text Representation Models
- Bag of Words / Vector Space Model
- Similarity Measures in Natural Language Processing

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Vector Space Model [Salton et. al. 1975]

How to represent Text with the Bag of Words assumption?

Idea: Encode textual

- documents in **vectors**
- corpora in **matrices**

Data = event counts for applications like machine learning and statistics

Example corpus:

- D_1: Kim is leaving home.
- D_2: Kim is at home.
- D_3: Karen is leaving.

Dimensionality of vector space

- $|D| \times |V|$ where $|D|$: Number of documents, $|V|$: Vocabulary
- Example matrix dimensions: 3×7

	Kim	is	leaving	home	.	at	Karen
D_1	1	1	1	1	1	0	0
D_2	1	1	0	1	1	1	0
D_3	0	1	1	0	1	0	1

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Vector Space Model [Salton et. al. 1975]

Document-Term-Matrix

$$|D| \quad \begin{pmatrix} 1 & 0 & 5 & 1 & \cdots \\ 0 & 0 & 0 & 2 & \\ 1 & 3 & 0 & 1 & \\ 0 & 0 & 0 & 0 & \\ \vdots & & & & \ddots \end{pmatrix}$$

$$|V|$$

- DTM's may get very large
- Events: Frequency counts of word types in each document
- 100% Bag-of-Words
- Very sparse (contains approx. 95% zeros)
- variations:
  - Binary event counts
  - paragraphs as documents
  - sentences as documents
  - additional n-grams (n > 1) as events
  - . . .

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Vector Space Model [Salton et. al. 1975]

Special case for encoding sequences of text

One Hot coding: A finite sequence of binary numbers where only one number gets the high value (1) and the others are low (0).

- In case of text we have a sequence $\delta_{i,j} = \begin{cases} 1, & \text{if } w_j = w_i \\ 0, & \text{else} \end{cases}$
- where i is the word position, j is the index in the vocabulary.
- Example:

	Kim	is	leaving	home	.	at	Karen
D_1.1	1	0	0	0	0	0	0
D_1.2	0	1	0	0	0	0	0
D_...	...	...	...	...	...	...	...
D_1.5	0	0	0	0	1	0	0

- The Binary encoding for a single word has the dimensionality of the vocabulary.

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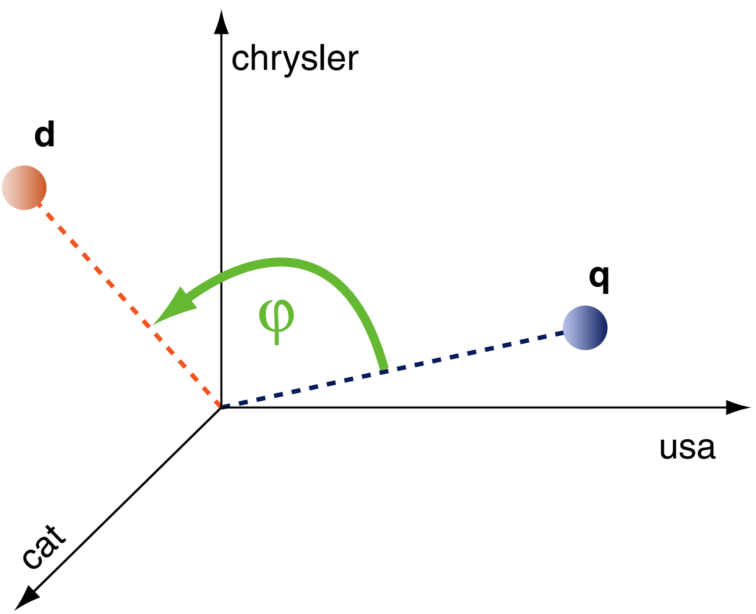
Vector Space Model

Document representations $\mathbf{D}$.

The set of index terms $T = \{t_1, \ldots, t_m\}$ is typically composed of the word stems of the vocabulary of a document collection, excluding stop words.

The representation $\mathbf{d}$ of a document d is a $|T|$-dimensional vector, where the i-th vector component of $\mathbf{d}$ corresponds to a term weight w_i of term $t_i \in T$, indicating its importance for d. Various term weighting schemes have been proposed.

Example Similarity Function ρ for a document: Cosine Similarity



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Vector Space Model

Example

$$\mathbf{d} = \begin{pmatrix} \texttt{chrysler} & w_1 \\ \texttt{usa} & w_2 \\ \texttt{cat} & w_3 \\ \texttt{dog} & w_4 \\ \texttt{mouse} & w_5 \end{pmatrix} = \begin{pmatrix} \texttt{chrysler} & 1 \\ \texttt{usa} & 4 \\ \texttt{cat} & 3 \\ \texttt{dog} & 7 \\ \texttt{mouse} & 5 \end{pmatrix}$$

$$\mathbf{d_i} = \begin{pmatrix} \texttt{chrysler} & 0.1 \\ \texttt{usa} & 0.4 \\ \texttt{cat} & 0.3 \\ \texttt{dog} & 0.7 \\ \texttt{mouse} & 0.5 \end{pmatrix}, \qquad \mathbf{d_j} = \begin{pmatrix} \texttt{chrysler} & 0.2 \\ \texttt{usa} & 0.1 \\ \texttt{cat} & 0.5 \\ \texttt{dog} & 0.0 \\ \texttt{mouse} & 0.0 \end{pmatrix}$$

The angle φ between $\mathbf{d_i}$ and $\mathbf{d_j}$ is about $67°$, $\cos(\varphi) \approx 0.38$.

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Vector Space Model

Example Term Weighting: *tf* · *idf*

To compute the weight w for a term t from document d under the vector space model, the most commonly employed term weighting scheme $\omega(t)$ is *tf* · *idf*:

- *tf*(t, d) denotes the normalized *term frequency* of term t in document d.
  The basic idea is that the importance of term t is proportional to its frequency in document d. However, t's importance does not increase linearly: the raw frequency must be normalized.

- *df*(t, D) denotes the *document frequency* of term t in document collection D.
  It counts the number of documents that contain t at least once.

- *idf*(t, D) denotes the *inverse document frequency*:

$$\mathit{idf}(t, D) = \log \frac{|D|}{\mathit{df}(t, D)}$$

  The importance of term t in general is inversely proportional to its document frequency.

A term weight w for term t in document $d \in D$ is computed as follows:

$$\omega(t) = \mathit{tf}(t, d) \cdot \mathit{idf}(t, D).$$

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Vector Space Model

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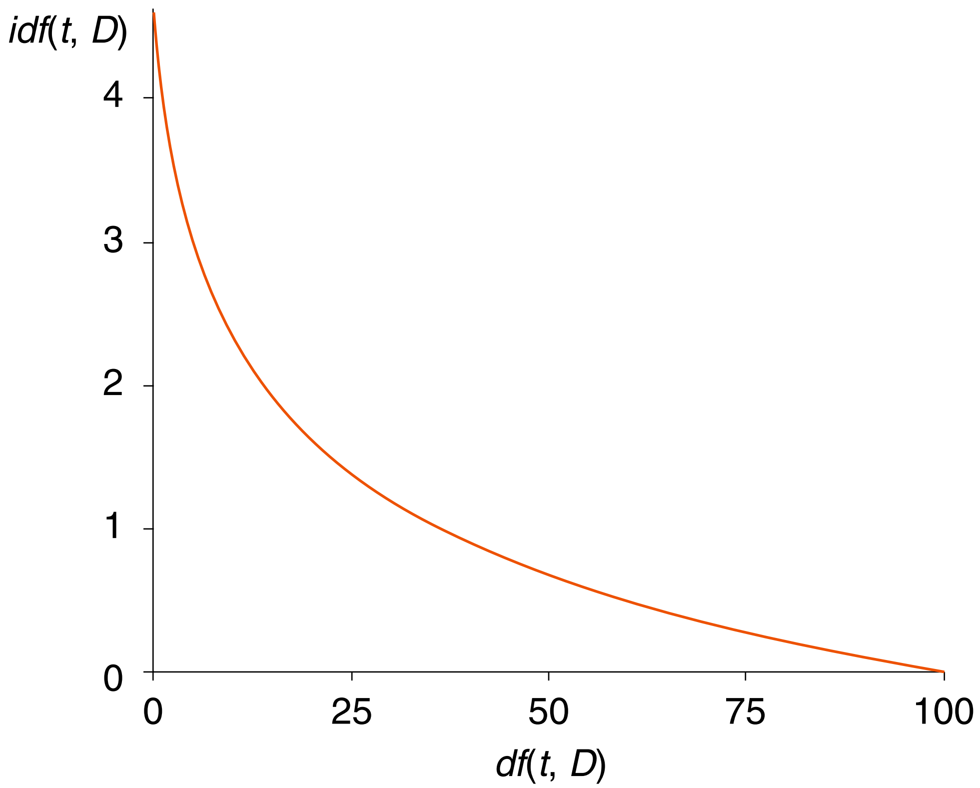
Vector Space Model

Term Weighting: *tf* · *idf*

Plot of the function $\textit{idf}(t, D) = \log \frac{|D|}{\textit{df}(t, D)}$ for $|D| = 100$.



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Remarks:

- Term frequency weighting was invented by Hans Peter Luhn: “There is also the probability that the more frequently a notion and combination of notions occur, the more importance the author attaches to them as reflecting the essence of his overall idea.” [Luhn 1957]

- The importance of a term t for a document d is not linearly correlated with its frequency. Several normalization factors have been proposed [Wikipedia]:
  - $\mathit{tf}(t,d)/|d|$
  - $1+\log(\mathit{tf}(t,d))$ for $\mathit{tf}(t,d)>0$
  - $k+(1-k)\dfrac{\mathit{tf}(t,d)}{\max_{t'\in d}(\mathit{tf}(t',d))}$, where k serves as smoothing term; typically $k=0.4$

- Inverse document frequency weighting was invented by Karen Spärck Jones: “it seems we should treat matches on non-frequent terms as more valuable than ones on frequent terms, without disregarding the latter altogether. The natural solution is to correlate a term’s matching value with its collection frequency.” [Spärck Jones 1972]

- Spärck Jones gives little theoretical justification for her intuition. Given the success of *idf* in practice, over the decades, numerous attempts at a theoretical justification have been made. A comprehensive overview has been compiled by [Robertson 2004].

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Vector Space Model

Pruning of vocabulary in Vector Space Model

Vocabularies even of small collections can get very large (5.000 German newspaper documents $\rightarrow |V|$ > 300.000 types)

- performance issue in machine learning tasks
- meaningful semantics

Pruning = filtering the vocabulary of a collection by minimum / maximum thresholds of token occurrence

Very useful preprocessing step to reduce vocabulary size:

- Count occurrence of types in the complete corpus
- keep only those terms which occur above / below a well-defined threshold

Term Frequency

- absolute pruning
- sum all term occurrences in all documents filter terms which occur e.g. $count(term) > 1$ AND $count(term) < 1000$

Document Frequency

- relative pruning
- for each term count number of documents in which it is contained allows for filters like: terms which occur e.g. in
  - more than 99% OR
  - less than 1%

  of all documents

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Remarks:

- Linguistic Preprocessing shall reduce / unify data for application specific purpose (See slides about text preprocessing)
- May contain various steps in row:
  - Data cleaning: encoding, spelling correction, duplicate filtering
  - Removing uninformative data: noise, duplicates, stopwords, dictionary lists
  - Unification: punctuation, capitalization, stemming, lemmatization
  - Pruning: remove low/high frequent terms
- Best setup dependent on final analysis task requirements
  - to be derived experimentally
  - or by analyst experience
- **Caution: order of steps influences results!**

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