Computational Communication Science 2 Week 2 - Lecture

Bottom-up approaches to text analysis: From preprocessing to vectorization

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Today's Agenda

Recap

Review of key concepts

- **Text preprocessing:** Cleaning and preparing raw text for analysis.
- **Core techniques:**
  - tokenization
  - Stopword removal
  - Using built-in string methods for text cleaning
- **Methodological approaches:** Combining *bottom-up* (data-driven) and *top-down* (theory-driven) approaches.

Typical preprocessing steps

Preprocessing steps

tokenization How do we (best) split a sentence into tokens (terms, words)?

pruning How can we remove unneccessary words/ punctuation?

lemmatization and stemming How can we make sure that slight variations of the same word are not counted differently?

ngrams Neighbouring terms

Simple Tokenization using .split()

Tokenization: Splitting text into words or subwords is essential for many NLP tasks.

Simple Tokenization with .split(): Python's built-in 'split()' method is a simple way to break a text into tokens by spaces.

```
text = "This is an example sentence."
tokens = text.split()
print(tokens)  # Output: ['This', 'is', 'an', 'example', 'sentence.']
```

Advanced Tokenization with TreebankWordTokenizer

For more sophisticated tokenization that handles punctuation, contractions, etc., we use ‘TreebankWordTokenizer‘ from NLTK.

```
from nltk.tokenize import TreebankWordTokenizer

docs = ["This is an example sentence."]
tokens = [TreebankWordTokenizer().tokenize(d) for d in docs]
print(tokens)  # Output: [['This', 'is', 'an', 'example', 'sentence',
↪  '.']]
```

Understanding N-grams

- An n-gram is a sequence of *n* words treated as a single feature.
- Examples:
  - Unigrams (1-word units): “science”
  - Bigrams (2-word units): “data science”
  - Trigrams (3-word units): “machine learning model”
- **Why use n-grams?** Captures context and word relationships beyond single words.
- **Collocations:** Identifying n-grams that occur frequently and naturally together (e.g., "data science," "machine learning") helps uncover meaningful word patterns in text.

Generating N-grams with Python

Code Example: Generating n-grams using Python's NLTK library.

```python
import nltk
from nltk.util import ngrams
from nltk.tokenize import word_tokenize

# Sample text
text = "Machine learning is a powerful tool for data science."

# Tokenize the text
tokens = word_tokenize(text)

# Create bigrams and trigrams
bigrams = list(ngrams(tokens, 2))
trigrams = list(ngrams(tokens, 3))

# Count the frequency of n-grams
print("Bigrams:", bigrams)
print("Trigrams:", trigrams)
```

Identifying collocations

Code Example: Finding collocations using NLTK's BigramCollocationFinder.

```
from nltk.collocations import BigramCollocationFinder,
↪  BigramAssocMeasures
from collections import Counter

# Find bigram collocations using NLTK's BigramCollocationFinder
bigram_finder = BigramCollocationFinder.from_words(tokens)
bigram_collocations =
↪  bigram_finder.nbest(BigramAssocMeasures.likelihood_ratio, 5)

print("Collocations (Bigram):", bigram_collocations)

```

Stemming: Reducing Words to Their Root

- **Stemming** chops off word endings to reduce words to a common root.
- It's fast and simple, but may produce non-dictionary words.
- Example: "running" → "run", "flies" → "fli"

Code example (PorterStemmer):

```python
from nltk.stem import PorterStemmer

stemmer = PorterStemmer()
words = ["running", "flies", "easily", "fairly"]
stems = [stemmer.stem(word) for word in words]

print(stems)
# Output: ['run', 'fli', 'easili', 'fairli']
```

Lemmatization: Getting the Dictionary Form

- **Lemmatization** maps words to their base (dictionary) form.
- More accurate than stemming, but slower and requires POS tagging for best results.
- Example: "better" → "good", "running" → "run"

Code Example (WordNetLemmatizer):

```python
from nltk.stem import WordNetLemmatizer
from nltk.corpus import wordnet
from nltk import pos_tag, word_tokenize

lemmatizer = WordNetLemmatizer()
words = ["running", "flies", "better"]
lemmas = [lemmatizer.lemmatize(word) for word in words]

print(lemmas)
# Output: ['running', 'flies', 'better']
```

Building text representations: vectorizers

Building text representations: vectorizers

General idea

A text as a collections of word

Let us represent a string

```
t = "This this is is is a test test test"
# like this:
print(Counter(t.split()))
```

```
Counter({'is': 3, 'test': 3, 'This': 1, 'this': 1, 'a': 1})
```

Compared to the original string, this representation

- is less repetitive
- preserves word frequencies
- but does *not* preserve word order
- can be interpreted as a vector to calculate with (!!!)

Of course, still a lot of stuff to fine-tune... (for example, This/this)

From vector to matrix

If we do this for multiple texts, we can arrange the vectors in a table.

t1 = "This this is is is a test test test"

t2 = "This is an example"

	a	an	example	is	this	This	test
t1	1	0	0	3	1	1	3
t2	0	1	1	1	0	1	0

What can you do with such a matrix? Why would you want to represent a collection of texts in such a way?

What is a vectorizer

- Transforms a list of texts into a sparse (!) matrix (of word frequencies)
- Vectorizer needs to be "fitted" to the training data (learn which words (features) exist in the dataset and assign them to columns in the matrix)
- Vectorizer can then be re-used to transform other datasets

The cell entries: raw counts versus tf·idf scores

- In the example, we entered simple counts (the "term frequency")

But are all terms equally important?

The cell entries: raw counts versus tf·idf scores

- In the example, we entered simple counts (the "term frequency")
- But does a word that occurs in almost all documents contain much information?
- And isn't the presence of a word that occurs in very few documents a pretty strong hint?
- **Solution: Weigh by *the number of documents in which the term occurs at least once) (the "document frequency")***

⇒ we multiply the "term frequency" (tf) by the inverse document frequency (idf)

(usually with some additional logarithmic transformation and normalization applied, see https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfTransformer.html)

TF-IDF: Weighted Importance of Words

$$\text{tf-idf} = \text{tf}_{i,j} \times \log\left(\frac{N}{\text{df}_i}\right)$$

- $\text{tf}_{i,j}$ = term frequency of term i in document j
- df_i = number of documents containing the term i
- N = total number of documents in the corpus

- **Term Frequency (TF)**: Measures how often a term appears in a document. More frequent terms in a document receive a higher TF score.
- **Inverse Document Frequency (IDF)**: Downscales terms that appear in many documents and boosts those that are rare but important.

Is tf·idf always better?

It depends.

- Ultimately, it's an empirical question which works better ($\rightarrow$ machine learning)
- In many scenarios, "discounting" too frequent words and "boosting" rare words makes a lot of sense (most frequent words in a text can be highly un-informative)
- Beauty of raw tf counts, though: interpretability + describes document in itself, not in relation to other documents

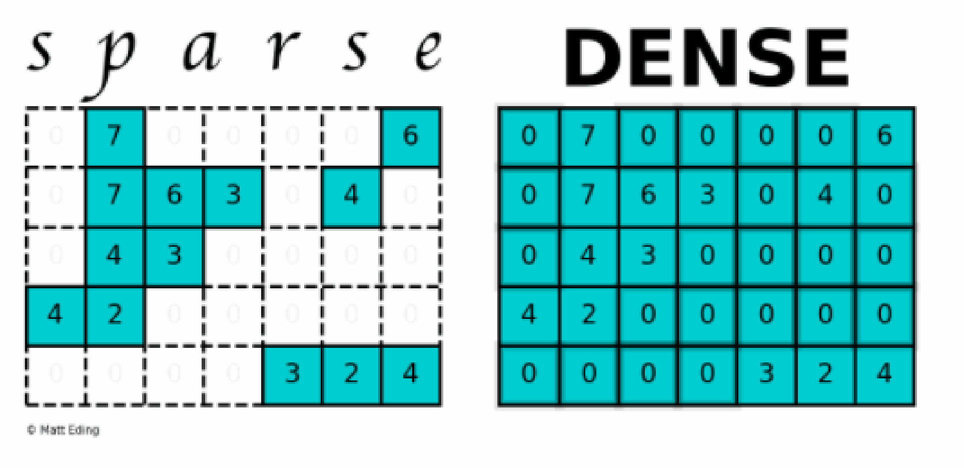
Different vectorizers

1. CountVectorizer (=simple word counts)
2. TfidfVectorizer (word counts ("term frequency") weighted by number of documents in which the word occurs at all ("inverse document frequency"))

Internal representations

Sparse vs dense matrices

- $\rightarrow$ tens of thousands of columns (terms), and one row per document
- Filling all cells is inefficient *and* can make the matrix too large to fit in memory (!!!)
- Solution: store only non-zero values with their coordinates! (sparse matrix)
- dense matrix (or dataframes) not advisable, only for toy examples



https://matteding.github.io/2019/04/25/sparse-matrices/

We learned in week 1 how to tokenize with a list comprehension (and that's often a good idea!).

```
from nltk.tokenize import TreebankWordTokenizer
tokens = [TreebankWordTokenizer().tokenize(d) for d in docs]
```

But what if we want to *directly* get a DTM instead of lists of tokens?

OK, good enough, perfect?

scikit-learn's CountVectorizer (default settings)

- applies lowercasing
- deals with punctuation etc. itself
- minimum word length > 1
- more technically, tokenizes using this regular expression: `r"(?u)\b\w\w+\b"` [1]

```
from sklearn.feature_extraction.text import CountVectorizer
cv = CountVectorizer()
dtm_sparse = cv.fit_transform(docs)
```

[1] ?u = support unicode, \b = word boundary

OK, good enough, perfect?

CountVectorizer supports more

- stopword removal
- custom regular expression
- or even using an external tokenizer
- ngrams instead of unigrams

see
https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html

Best of both worlds

Use the Count vectorizer with a NLTK-based external tokenizer! (see book)

This notebook might help to better your understanding of vectorizers!

Building text representations: vectorizers

Pruning

General idea

- Idea behind both stopword removal and tf·idf: too frequent words are uninformative
- (possible) downside stopword removal: a priori list, does not take empirical frequencies in dataset into account
- (possible) downside tf·idf: does not reduce number of features

Pruning: remove all features (tokens) that occur in less than X or more than X of the documents

CountVectorizer, only stopword removal

```
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
myvectorizer = CountVectorizer(stop_words=mystopwords)
```

CountVectorizer, better tokenization, stopword removal (pay attention that stopword list uses same tokenization!):

```
myvectorizer = CountVectorizer(tokenizer = TreebankWordTokenizer().tokenize, stop_words=mystopwords)
```

Additionally remove words that occur in more than 75% or less than $n = 2$ documents:

```
myvectorizer = CountVectorizer(tokenizer = TreebankWordTokenizer().tokenize, stop_words=mystopwords, max_df=.75, min_df=2)
```

All together: tf·idf, explicit stopword removal, pruning

```
myvectorizer = TfidfVectorizer(tokenizer = TreebankWordTokenizer().tokenize, stop_words=mystopwords, max_df=.75, min_df=2)
```

What is “best”? Which (combination of) techniques to use, and how to decide?

Exercise time: Word cloud

Let's put this into practice!

- Follow the instructions in the exercise material.
- You will create a word cloud from text data.
- Apply preprocessing techniques such as tokenization, stopword removal, and normalization.

Exercise Link: GitHub: Word cloud exercise *Think about how*

different preprocessing choices impact the resulting word cloud

From text to features

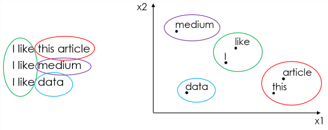
- Text needs to be transformed into numerical representations for computational analysis.
- Tokenization breaks text into meaningful units (words, phrases, n-grams).
- Frequency-based representations allow us to quantify text characteristics.

Introducing embeddings

Why move beyond TF-IDF?

Limitations of TF-IDF and CountVectorizer:

- Create **sparse**, high-dimensional representations.
- Ignore **semantic meaning**—similar words have different vectors.
- Cannot capture **contextual relationships**.



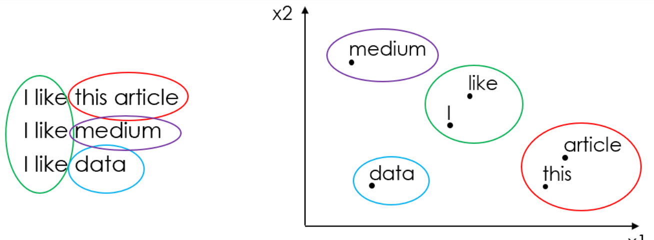
Solution: Word embeddings

Embeddings create **dense**, low-dimensional representations that retain meaning and context.

What are embeddings?

- Map words or documents into **continuous vector spaces**.
- Words with similar meanings have **similar vectors**.
- **Learned** from large text corpora using machine learning models.

Popular Examples: Word2Vec, GloVe, fastText, BERT embeddings.



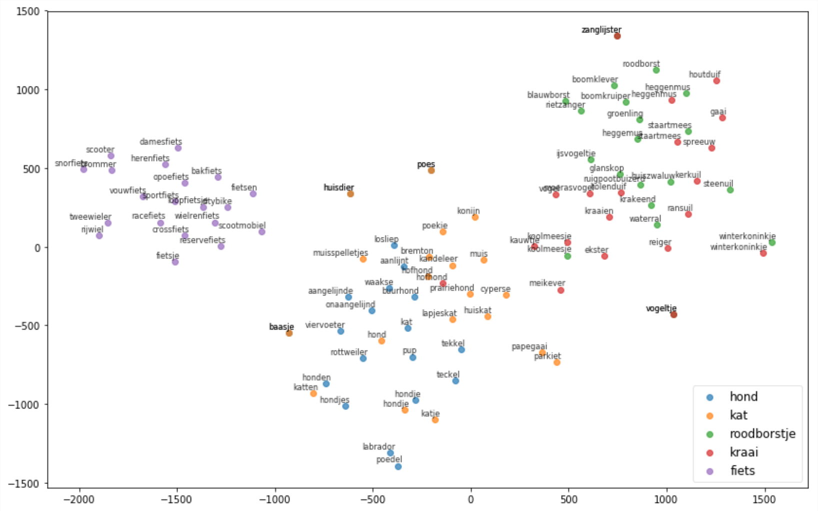
Introducing embeddings

Word embeddings

Understanding embeddings

What are word embeddings?

- No technical details here, just the general idea
- Word embeddings help capture the meaning of text
- Word embeddings are low-dimensional vector representations that capture semantic meaning
- Used to be state-of-the-art in NLP (but now: contextualized embeddings, e.g., BERT or GPT)
- *"...a word is characterized by the company it keeps..."* (Firth, 1957)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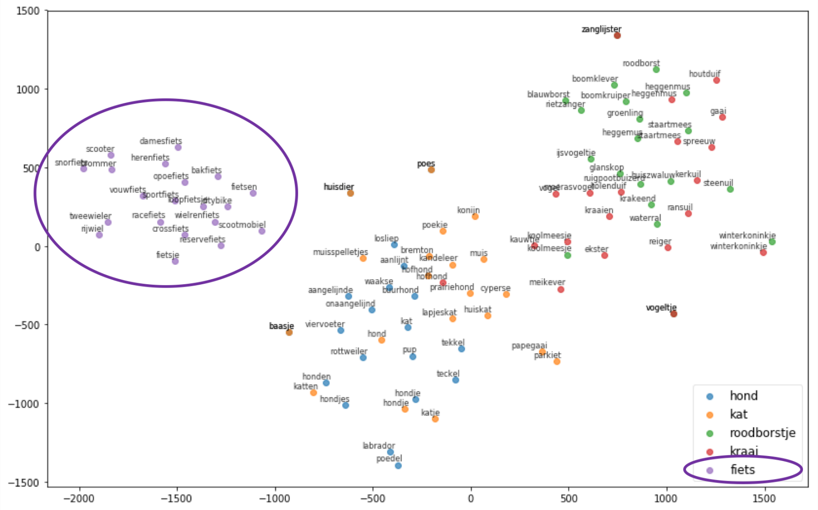
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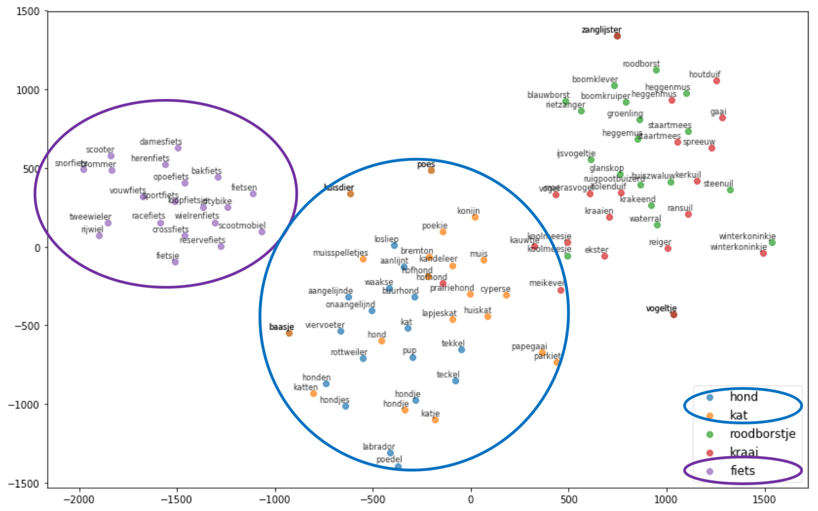
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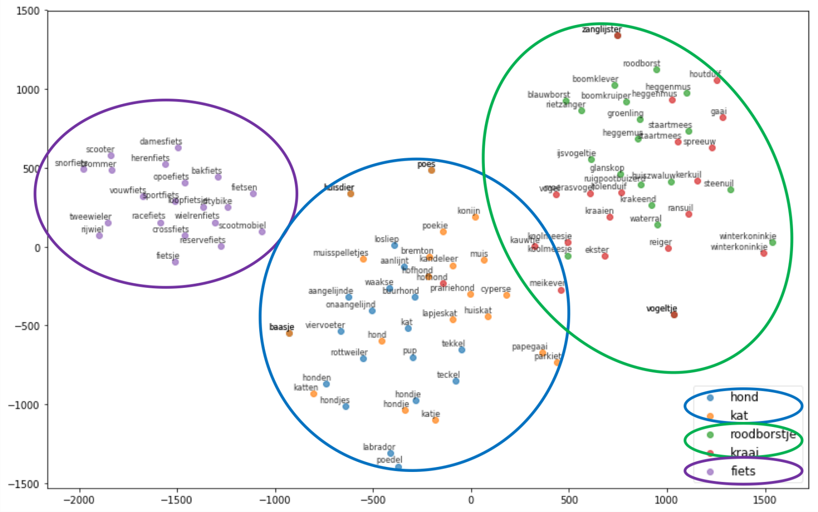


- Explore word embeddings interactively using the TensorFlow Projector.
- Click here to access the TensorFlow Projector.

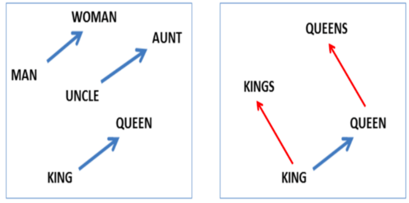
How embeddings work

- Each word (or document) is represented by a **vector** in a high-dimensional space.
- The model learns these vectors by predicting word co-occurrences in text.
- Example: **Word2Vec** uses a neural network to predict surrounding words.

Example: Word similarity with embeddings

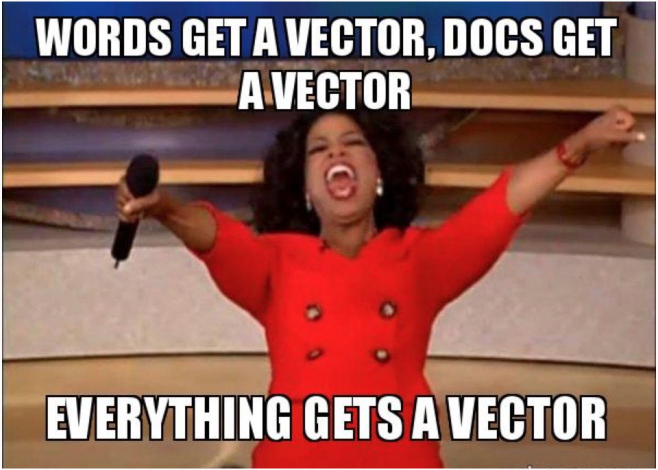
Word2Vec analogy:

- `vec("king") - vec("man") + vec("woman") = vec("queen")`
- Captures **semantic relationships** automatically.
- Unlike TF-IDF, embeddings **understand meaning**.



Example: Getting word embeddings with spaCy

Try it out yourself.. Visualize your embeddings



Embeddings in communication science

Applications:

- **Sentiment analysis:** Understanding audience reactions on social media (Rudkowsky et al., 2018)
- **Topic modeling**: cross-lingual topics
- **Recommender Systems:** Suggesting content based on user preferences (Loecherbach and Trilling, 2020)
- **Text similarity:** Measuring the similarity between texts (Brinberg and Ram, 2021)

Note: We will discuss this next week.

Using pretrained embeddings

Why use pretrained models?

- Trained on massive datasets (Google News, Wikipedia, etc.).
- Capture **rich linguistic structures**.
- Reduce training time and improve performance.

Popular choices:

- Word2Vec (Google News)
- GloVe (Common Crawl, Wikipedia)
- BERT (contextualized embeddings)
- fastText (subword information)

Why Use Embeddings?

- Capture **semantic meaning** of words.
- Handle **synonyms** and **related words** effectively.
- Work well in NLP applications: **text classification, clustering, sentiment analysis**.
- Used in communication science for **media analysis, misinformation detection, and social network studies**.

Key takeaways

- Traditional methods (TF-IDF) are **limited in capturing meaning**.
- Word embeddings create **dense vectors** that capture relationships.
- Pretrained models like **Word2Vec, GloVe, and BERT** help analyze text effectively.
- Embeddings are **widely used** in NLP and communication science.

Thank you!!

Thank you for your attention!

- Questions? Comments?

References i

References

Brinberg, M., & Ram, N. (2021).**Do new romantic couples use more similar language over time? Evidence from intensive longitudinal text messages.** *Journal of Communication*, *71*(3), 454–477. https://doi.org/10.1093/joc/jqab012

Loecherbach, F., & Trilling, D. (2020).**3bij3 – Developing a framework for researching recommender systems and their effects.** *Computational Communication Research*, *2*(1), 53–79. https://doi.org/10.5117/ccr2020.1.003.loec

References ii

Rudkowsky, E., Haselmayer, M., Wastian, M., Jenny, M., Emrich, Š., & Sedlmair, M. (2018).**More than bags of words: Sentiment analysis with word embeddings.** *Communication Methods and Measures*, *12*(2-3), 140–157.