Computational Communication Science 2 Week 3 - Lecture »Bottom up approaches to text analysis«

Anne Kroon

a.c.kroon@uva.nl, @annekroon

April 17, 2023

Digital Society Minor, University of Amsterdam

Today

From text to features: vectorizers

From text to features: 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)

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

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

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)

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)

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

$$w_{i,j} = tf_{i,j} \times \log\left(\frac{N}{df_i}\right)$$

$$\begin{aligned} tf_{i,j} = & \text{ number of occurrences of } i \text{ in } j \\ df_i = & \text{ number of documents containing } i \\ N = & \text{ total number of documents} \end{aligned}$$

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”))

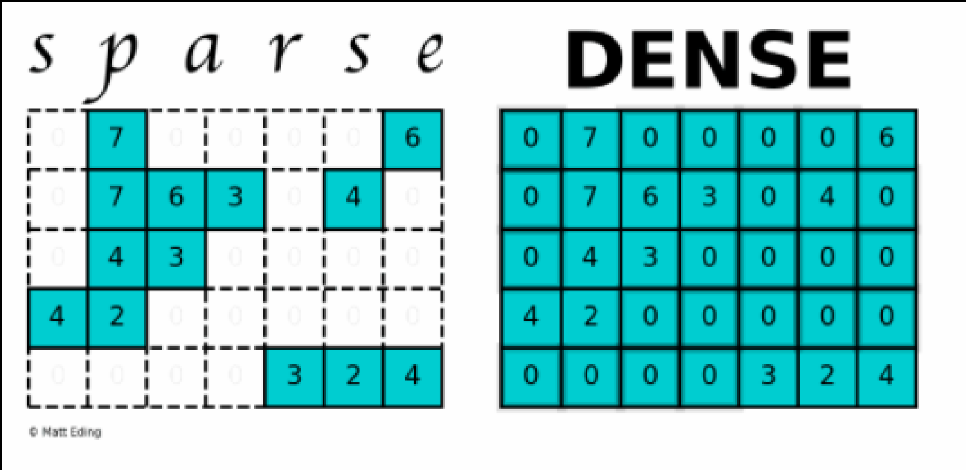
Different vectorizers

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 justed learned how to tokenize with a list comprehension (and that's often a good idea!). 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)

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)

From text to features: 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

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

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

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

```python
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!):

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

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

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

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

```python
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?

Cosine Similarity

Cosine Similarity

Cosine Similarity

- A measure that helps you determine how similar two documents are, irrespective of their size

Applications in Communication Science

- For example, to map *linguistic alignment* of romantic couples over time (Brinberg and Ram (2021))
- Or, in the political domain, agenda overlap between public opinion and political speech (Hager and Hilbig (2020))

Cosine Similarity

Cosine Similarity

- A measure that helps you determine how similar two documents are, irrespective of their size

Applications in Communication Science

- For example, to map *linguistic alignment* of romantic couples over time (Brinberg and Ram (2021))
- Or, in the political domain, agenda overlap between public opinion and political speech (Hager and Hilbig (2020))

Cosine Similarity

Cosine Similarity

- A measure that helps you determine how similar two documents are, irrespective of their size

Applications in Communication Science

- For example, to map *linguistic alignment* of romantic couples over time (Brinberg and Ram (2021))
- Or, in the political domain, agenda overlap between public opinion and political speech (Hager and Hilbig (2020))

Cosine Similarity

$$\text{similarity} = \cos(\theta) = \frac{\mathrm{A} \cdot \mathrm{B}}{\|\mathrm{A}\| \|\mathrm{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$

- It measures the cosine of the angle between two vectors projected in a multi-dimensional space.
- 0 means orthogonal vectors (90 degrees), very dissimilar
- 1 means vectors are the same (0 degrees), similar

Cosine Similarity

$$\text{similarity} = \cos(\theta) = \frac{\mathrm{A} \cdot \mathrm{B}}{\|\mathrm{A}\|\|\mathrm{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

- It measures the cosine of the angle between two vectors projected in a multi-dimensional space.
- 0 means orthogonal vectors (90 degrees); very dissimal
- 1 means vectors are the same (0 degrees); similar

Cosine Similarity

$$\text{similarity} = \cos(\theta) = \frac{\mathrm{A} \cdot \mathrm{B}}{\|\mathrm{A}\|\|\mathrm{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

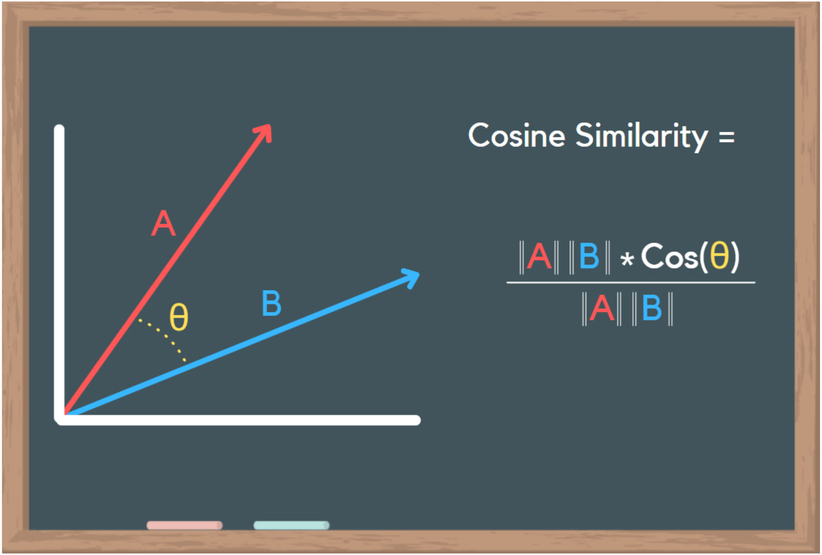
- It measures the cosine of the angle between two vectors projected in a multi-dimensional space.
- 0 means orthogonal vectors (90 degrees); very dissimal
- 1 means vectors are the same (0 degrees); similar

Cosine Similarity

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

- It measures the cosine of the angle between two vectors projected in a multi-dimensional space.
- 0 means orthogonal vectors (90 degrees); very dissimal
- 1 means vectors are the same (0 degrees); similar

Cosine Similarity



2

how can we calculate this in python?

Let's review a practical application [3].

[3] https://github.com/uva-cw-ccs2/2223s2/blob/master/week03/exercises/OPTIONAL_overtime_similarity.ipynb

```python
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
import pandas as pd

doc1 = "When I eat breakfast, I usually drink some tea".lower()
doc2 = "I like my tea with my breakfast".lower()
doc3 = "She likes cereal and coffee".lower()

vec = CountVectorizer(stop_words='english')
count_matrix = vec.fit_transform([doc1, doc2, doc3])

print(pd.DataFrame(count_matrix.A, columns=vec.get_feature_names_out()).to_string())
```

```
   breakfast  cereal  coffee  drink  eat  like  likes  tea  usually
0          1       0       0      1    1     0      0    1        1
1          1       0       0      0    0     1      0    1        0
2          0       1       1      0    0     0      1    0        0
```

```python
from sklearn.feature_extraction.text import CountVectorizer,
↪  TfidfVectorizer
import pandas as pd

doc1 = "When I eat breakfast, I usually drink some tea".lower()
doc2 = "I like my tea with my breakfast".lower()
doc3 = "She likes cereal and coffee".lower()

vec = CountVectorizer(stop_words='english')
count_matrix = vec.fit_transform([doc1, doc2, doc3])

print(pd.DataFrame(count_matrix.A,
↪  columns=vec.get_feature_names_out()).to_string())
```

```
   breakfast  cereal  coffee  drink  eat  like  likes  tea  usually
0          1       0       0      1    1     0      0    1        1
1          1       0       0      0    0     1      0    1        0
2          0       1       1      0    0     0      1    0        0
```

Implementation in Python

```python
doc1_vector = pd.DataFrame(count_matrix.A, columns=vec.get_feature_names_out()).T[0].to_list()
doc2_vector = pd.DataFrame(count_matrix.A, columns=vec.get_feature_names_out()).T[1].to_list()

print(f"The vector belonging to doc1: {doc1_vector}")
print(f"The vector belonging to doc2: {doc2_vector}")
```

```
The vector belonging to doc1: [1, 0, 0, 1, 1, 0, 0, 1, 1]
The vector belonging to doc2: [1, 0, 0, 0, 0, 1, 0, 1, 0]
```

Implementation in Python

```python
doc1_vector = pd.DataFrame(count_matrix.A,
    columns=vec.get_feature_names_out()).T[0].to_list()
doc2_vector = pd.DataFrame(count_matrix.A,
    columns=vec.get_feature_names_out()).T[1].to_list()

print(f"The vector belonging to doc1: {doc1_vector}")
print(f"The vector belonging to doc2: {doc2_vector}")
```

```
The vector belonging to doc1: [1, 0, 0, 1, 1, 0, 0, 1, 1]
The vector belonging to doc2: [1, 0, 0, 0, 0, 1, 0, 1, 0]
```

Implementation in Python

Now, lets populate the formula. 1.Execute the part of the formula in the numerator. Specifically, take the dot product of the vectors:

$$\sum_{i=1}^{n} A_i B_i$$

```
doc1: [1, 0, 0, 1, 1, 0, 0, 1, 1]
doc2: [1, 0, 0, 0, 0, 1, 0, 1, 0]
```

$$dot\_product = (1 \cdot 1) + (0 \cdot 0) + (0 \cdot 0) + (1 \cdot 0) + (1 \cdot 0) + (0 \cdot 0) + (1 \cdot 1) + (1 \cdot 0)$$

Or, using Python:

```
dot_product = sum([num1 * num2 for num1, num2 in zip(doc1_vector,
    doc2_vector)])
print(dot_product)
```

```
2
```

Implementation in Python

Now, lets populate the formula. 1.Execute the part of the formula in the numerator. Specifically, take the dot product of the vectors:

$$\sum_{i=1}^{n} A_i B_i$$

```
doc1: [1, 0, 0, 1, 1, 0, 0, 1, 1]
doc2: [1, 0, 0, 0, 0, 1, 0, 1, 0]
```

$$dot\_product = (1 \cdot 1) + (0 \cdot 0) + (0 \cdot 0) + (1 \cdot 0) + (1 \cdot 0) + (0 \cdot 0) + (1 \cdot 1) + (1 \cdot 0)$$

Or, using Python:

```
dot_product = sum([num1 * num2 for num1, num2 in zip(doc1_vector,
↪  doc2_vector)])
print(dot_product)
```

```
2
```

Implementation in Python

Now, lets populate the formula. 1.Execute the part of the formula in the numerator. Specifically, take the dot product of the vectors:

$$\sum_{i=1}^{n} A_i B_i$$

```
doc1: [1, 0, 0, 1, 1, 0, 0, 1, 1]
doc2: [1, 0, 0, 0, 0, 1, 0, 1, 0]
```

$$dot\_product = (1 \cdot 1)+(0 \cdot 0)+(0 \cdot 0)+(1 \cdot 0)+(1 \cdot 0)+(0 \cdot 0)+(1 \cdot 1)+(1 \cdot 0)$$

Or, using Python:

```
dot_product = sum([num1 * num2 for num1, num2 in zip(doc1_vector,
↪  doc2_vector)])
print(dot_product)
```

```
2
```

Implementation in Python

2.Execute the part of the formula in the denumerator. Take the cross product of the two vectors.

$$\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}$$

Calculate this by hand:

$$doc1_{=}\sqrt{1^2+0^2+0^2+1^2+1^2+0^2+1^2+1^2}$$

$$doc1_{=}\sqrt{1^2+0^2+0^2+0^2+1^2+0^2+1^2+0^2}$$

Implementation in Python:

```
import math
doc1_ = math.sqrt(sum( [i**2 for i in doc1_vector]) )
doc2_ = math.sqrt(sum( [i**2 for i in doc2_vector]) )

doc1_ * doc2_
```

Implementation in Python

2.Execute the part of the formula in the denumerator. Take the cross product of the two vectors.

$$\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}$$

Calculate this by hand:

$$doc1_{=}\sqrt{1^2+0^2+0^2+1^2+1^2+0^2+1^2+1^2}$$

$$doc1_{=}\sqrt{1^2+0^2+0^2+0^2+1^2+0^2+1^2+0^2}$$

Implementation in Python:

```
import math
doc1_ = math.sqrt(sum( [i**2 for i in doc1_vector]) )
doc2_ = math.sqrt(sum( [i**2 for i in doc2_vector]) )

doc1_ * doc2_
```

Implementation in Python

2.Execute the part of the formula in the denumerator. Take the cross product of the two vectors.

$$\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}$$

Calculate this by hand:

$$doc1_{=}\sqrt{1^2+0^2+0^2+1^2+1^2+0^2+1^2+1^2}$$

$$doc1_{=}\sqrt{1^2+0^2+0^2+0^2+1^2+0^2+1^2+0^2}$$

Implementation in Python:

```
import math
doc1_ = math.sqrt(sum( [i**2 for i in doc1_vector]) )
doc2_ = math.sqrt(sum( [i**2 for i in doc2_vector]) )

doc1_ * doc2_
```

Implementation in Python

3.Finally:

```
cos_sim = dot_product / (doc1_ * doc2_)
print(cos_sim)
```

```
0.5163977794943222
```

Implementation in Python

3.Finally:

```
cos_sim = dot_product / (doc1_ * doc2_)
print(cos_sim)
```

```
0.5163977794943222
```

Implementation in Python

We can, however, do this much faster using sklearn's `cosine_similarity`.

```
from sklearn.metrics.pairwise import cosine_similarity
cosine_similarity([doc1_vector, doc2_vector])
```

```
array([[1.        , 0.51639778],
[0.51639778, 1.        ]])
```

Implementation in Python

We can, however, do this much faster using sklearn's `cosine_similarity`.

```
from sklearn.metrics.pairwise import cosine_similarity
cosine_similarity([doc1_vector, doc2_vector])
```

```
array([[1.        , 0.51639778],
[0.51639778, 1.        ]])
```

How to use this in practice

What can you do with this?

- This is especially powerful if you want to compare different news articles, movies, song texts, etc.
- For example, which movies are most similair in terms of genre composition?

How to use this in practice

What can you do with this?

- This is especially powerful if you want to compare different news articles, movies, song texts, etc.
- For example, which movies are most similair in terms of genre composition?

	title	Avatar	Pirates of the Caribbean: At World's End	Spectre	The Dark Knight Rises	John Carter
	genre	action adventure fantasy science fiction	adventure fantasy action	action adventure crime	action crime drama thriller	action adventure science fiction
title	genres					
Avatar	action adventure fantasy science fiction	1.000000	0.691870	0.315126	0.084696	0.859850
Pirates of the Caribbean: At World's End	adventure fantasy action	0.691870	1.000000	0.455470	0.122417	0.366490
Spectre	action adventure crime	0.315126	0.455470	1.000000	0.473354	0.366490
The Dark Knight Rises	action crime drama thriller	0.084696	0.122417	0.473354	1.000000	0.098501
John Carter	action adventure science fiction	0.859850	0.366490	0.366490	0.098501	1.000000

Indentify movies that are similar in terms of genre [4]

[4] https://www.learndatasci.com/glossary/cosine-similarity/

Considering Cosine Similarity

Things to consider

- What type of overlap are you interested in?
- What is the meaning of n-grams, stems, stopwords when considering your RQ? How you should preproces, depends on your RQ and aim.
- Computationally cheap and fast; works well in e.g., recommender systems (next week!)

Drawbacks

- An *exact* match in terms of words is needed. Is that realistic?

Considering Cosine Similarity

Things to consider

- What type of overlap are you interested in?
- What is the meaning of n-grams, stems, stopwords when considering your RQ? How you should preproces, depends on your RQ and aim.
- Computationally cheap and fast; works well in e.g., recommender systems (next week!)

Drawbacks

- An *exact* match in terms of words is needed. Is that realistic?

Considering Cosine Similarity

Things to consider

- What type of overlap are you interested in?
- What is the meaning of n-grams, stems, stopwords when considering your RQ? How you should preproces, depends on your RQ and aim.
- Computationally cheap and fast; works well in e.g., recommender systems (next week!)

Drawbacks

- An *exact* match in terms of words is needed. Is that realistic?

Considering Cosine Similarity

Things to consider

- What type of overlap are you interested in?
- What is the meaning of n-grams, stems, stopwords when considering your RQ? How you should preproces, depends on your RQ and aim.
- Computationally cheap and fast; works well in e.g., recommender systems (next week!)

Drawbacks

- An *exact* match in terms of words is needed. Is that realistic?

Implementation in Python

```python
doc1 = "When I eat breakfast, I usually drink some tea".lower()
doc2 = "I like my tea with my breakfast".lower()
doc3 = "She likes cereal and coffee".lower()
```

What do you expect here? Should there be some level of overlap?

Implementation in Python

```python
doc1 = "When I eat breakfast, I usually drink some tea".lower()
doc2 = "I like my tea with my breakfast".lower()
doc3 = "She likes cereal and coffee".lower()
```

```python
print(cosine_similarity([doc1_vector, doc2_vector, doc3_vector]))
```

```
[[1.         0.51639778 0.        ]
 [0.51639778 1.         0.        ]
 [0.         0.         1.        ]]
```

Zero overlap between doc3 and the other documents. Is that correct?

Implementation in Python

```
doc1 = "When I eat breakfast, I usually drink some tea".lower()
doc2 = "I like my tea with my breakfast".lower()
doc3 = "She likes cereal and coffee".lower()
```

```
print(cosine_similarity([doc1_vector, doc2_vector, doc3_vector]))
```

```
[[1.         0.51639778 0.        ]
[0.51639778 1.         0.        ]
[0.         0.         1.        ]]
```

Zero overlap between doc3 and the other documents. Is that correct?

Implementation in Python

```
doc1 = "When I eat breakfast, I usually drink some tea".lower()
doc2 = "I like my tea with my breakfast".lower()
doc3 = "She likes cereal and coffee".lower()
```

```
print(cosine_similarity([doc1_vector, doc2_vector, doc3_vector]))
```

```
[[1.         0.51639778 0.        ]
 [0.51639778 1.         0.        ]
 [0.         0.         1.        ]]
```

Zero overlap between doc3 and the other documents. Is that correct?

Soft cosine similarity

Soft cosine similarity

...enter soft cosine similarty Sidorov et al. (2014)

"Soft Cosine Measure (SCM) is a method that allows us to assess the similarity between two documents in a meaningful way, even when they have no words in common. It uses a measure of similarity between words, which can be derived using [word2vec] vector embeddings of words." [5]

[5] https://radimrehurek.com/gensim//auto_examples/tutorials/run_scm.html

Soft cosine similarity

...enter soft cosine similarty Sidorov et al. (2014)

"Soft Cosine Measure (SCM) is a method that allows us to assess the similarity between two documents in a meaningful way, even when they have no words in common. It uses a measure of similarity between words, which can be derived using [word2vec] vector embeddings of words." [5]

[5] https://radimrehurek.com/gensim//auto_examples/tutorials/run_scm.html

Soft Cosine Measure (SCM)

SCM

- Even if two sentences do not share the same words, we can calculate similarity by modelling *synonym*
- For example, the words 'play' and 'game' are different but related Sidorov et al. (2014) [6]
- How can we capture 'semantic' meaning?

How?

- Convert words to *word vectors* and then compute similarities [7]

[6] http://www.scielo.org.mx/pdf/cys/v18n3/v18n3a7.pdf

[7] https://www.machinelearningplus.com/nlp/cosine-similarity/

Soft Cosine Measure (SCM)

SCM

- Even if two sentences do not share the same words, we can calculate similarity by modelling *synonym*
- For example, the words 'play' and 'game' are different but related Sidorov et al. (2014) [6]
- How can we capture 'semantic' meaning?

How?

- Convert words to *word vectors* and then compute similarities [7]

[6] http://www.scielo.org.mx/pdf/cys/v18n3/v18n3a7.pdf
[7] https://www.machinelearningplus.com/nlp/cosine-similarity/

Soft Cosine Measure (SCM)

SCM

- Even if two sentences do not share the same words, we can calculate similarity by modelling *synonym*
- For example, the words 'play' and 'game' are different but related Sidorov et al. (2014) [6]
- How can we capture 'semantic' meaning?

How?

- Convert words to *word vectors* and then compute similarities [7]

[6] http://www.scielo.org.mx/pdf/cys/v18n3/v18n3a7.pdf
[7] https://www.machinelearningplus.com/nlp/cosine-similarity/

Soft Cosine Measure (SCM)

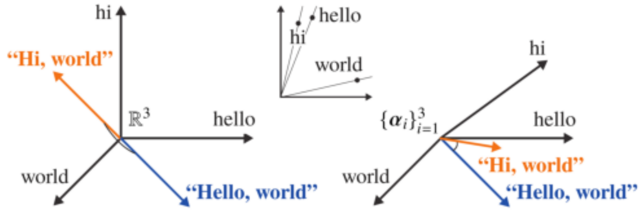
SCM

- Even if two sentences do not share the same words, we can calculate similarity by modelling *synonym*
- For example, the words 'play' and 'game' are different but related Sidorov et al. (2014) [6]
- How can we capture 'semantic' meaning?

How?

- Convert words to *word vectors* and then compute similarities [7]

[6] http://www.scielo.org.mx/pdf/cys/v18n3/v18n3a7.pdf
[7] https://www.machinelearningplus.com/nlp/cosine-similarity/



Soft cosine similarity [8]

[8] https://radimrehurek.com/gensim//auto_examples/tutorials/run_scm.html

Word embeddings

Word embeddings

- To use the SCM, you need word embeddings.

Soft cosine similarity

Word embeddings

Understanding SCM

SCM estimates extracts similarity from word embeddings.

What are word embeddings?

- No technical details here, just the general idea
- Word embeddings help capturing 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)

Understanding SCM

SCM estimates extracts similarity from word embeddings.

What are word embeddings?

- No technical details here, just the general idea
- Word embeddings help capturing 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)

Understanding SCM

SCM estimates extracts similarity from word embeddings.

What are word embeddings?

- No technical details here, just the general idea
- Word embeddings help capturing 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)

Understanding SCM

SCM estimates extracts similarity from word embeddings.

What are word embeddings?

- No technical details here, just the general idea
- Word embeddings help capturing 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)

Understanding SCM

SCM estimates extracts similarity from word embeddings.

What are word embeddings?

- No technical details here, just the general idea
- Word embeddings help capturing 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)

Soft cosine similarity

Implemention in Python

SCM in Python

Calculating Soft Cosine Measure

- To use the SCM, you need embeddings.
- We *can* train embeddings on our own corpus (if we had a lot of data) ...
- But for now we will use pre-trained models [9]. ...

```
import gensim.downloader as api

fasttext_model300 = api.load('fasttext-wiki-news-subwords-300')
```

[9] https://github.com/uva-cw-ccs2/2223s2/blob/master/week03/exercises/cosine-similarity-basics.ipynb

SCM in Python

Calculating Soft Cosine Measure

- To use the SCM, you need embeddings.
- We *can* train embeddings on our own corpus (if we had a lot of data) ...
- But for now we will use pre-trained models [9]. ...

```
import gensim.downloader as api

fasttext_model300 = api.load('fasttext-wiki-news-subwords-300')
```

[9] https://github.com/uva-cw-ccs2/2223s2/blob/master/week03/exercises/cosine-similarity-basics.ipynb

SCM in Python

Calculating Soft Cosine Measure

- To use the SCM, you need embeddings.
- We *can* train embeddings on our own corpus (if we had a lot of data) . . .
- But for now we will use pre-trained models [9]. . . .

```
import gensim.downloader as api

fasttext_model300 = api.load('fasttext-wiki-news-subwords-300')
```

[9] https://github.com/uva-cw-ccs2/2223s2/blob/master/week03/exercises/cosine-similarity-basics.ipynb

SCM in Python

Calculating Soft Cosine Measure

- To use the SCM, you need embeddings.
- We *can* train embeddings on our own corpus (if we had a lot of data) ...
- But for now we will use pre-trained models [9]. ...

```
import gensim.downloader as api

fasttext_model300 = api.load('fasttext-wiki-news-subwords-300')
```

[9] https://github.com/uva-cw-ccs2/2223s2/blob/master/week03/exercises/cosine-similarity-basics.ipynb

Create a dictionary

Let's review our 3 documents:

```
doc1 = "When I eat breakfast, I usually drink some tea".lower()
doc2 = "I like my tea with my breakfast".lower()
doc3 = "She likes cereal and coffee".lower()
```

Initialize a Dictionary. This step assigns a token_id to each word:

```
from gensim.utils import simple_preprocess
from gensim.corpora import Dictionary
dictionary = corpora.Dictionary([simple_preprocess(doc) for doc in [doc1, doc2, doc3]])
```

Now, let's check whether a specific word–for example coffee–is in our dictionary:

```
'coffee' in dictionary.token2id
```

```
True
```

Create a dictionary

Let's review our 3 documents:

```
doc1 = "When I eat breakfast, I usually drink some tea".lower()
doc2 = "I like my tea with my breakfast".lower()
doc3 = "She likes cereal and coffee".lower()
```

Initialize a Dictionary. This step assigns a `token_id` to each word:

```
from gensim.utils import simple_preprocess
from gensim.corpora import Dictionary
dictionary = corpora.Dictionary([simple_preprocess(doc) for doc in [doc1, doc2, doc3]])
```

Now, let's check whether a specific word–for example `coffee`–is in our `dictionary`:

```
'coffee' in dictionary.token2id
```

```
True
```

Create a dictionary

Let's review our 3 documents:

```
doc1 = "When I eat breakfast, I usually drink some tea".lower()
doc2 = "I like my tea with my breakfast".lower()
doc3 = "She likes cereal and coffee".lower()
```

Initialize a Dictionary. This step assigns a `token_id` to each word:

```
from gensim.utils import simple_preprocess
from gensim.corpora import Dictionary
dictionary = corpora.Dictionary([simple_preprocess(doc) for doc in [doc1, doc2, doc3]])
```

Now, let's check whether a specific word–for example `coffee`–is in our `dictionary`:

```
'coffee' in dictionary.token2id
```

```
True
```

Create a dictionary

Let's review our 3 documents:

```
doc1 = "When I eat breakfast, I usually drink some tea".lower()
doc2 = "I like my tea with my breakfast".lower()
doc3 = "She likes cereal and coffee".lower()
```

Initialize a Dictionary. This step assigns a `token_id` to each word:

```
from gensim.utils import simple_preprocess
from gensim.corpora import Dictionary
dictionary = corpora.Dictionary([simple_preprocess(doc) for doc in [doc1, doc2, doc3]])
```

Now, let's check whether a specific word–for example `coffee`–is in our `dictionary`:

```
'coffee' in dictionary.token2id
```

```
True
```

Create a bag-of-words representation

Next, let's represent each document by `(token_id, token_count)` tuples:

```
bag_of_words_vectors = [ dictionary.doc2bow(simple_preprocess(doc)) for doc in [doc1, doc2, doc3]]
```

Build a term similarity matrix and compute a sparse term similarity matrix:

```
from gensim.similarities import SparseTermSimilarityMatrix
from gensim.similarities import WordEmbeddingSimilarityIndex

similarity_index = WordEmbeddingSimilarityIndex(fasttext_model300)
similarity_matrix = SparseTermSimilarityMatrix(similarity_index, dictionary)
```

Create a bag-of-words representation

Next, let's represent each document by `(token_id, token_count)` tuples:

```
bag_of_words_vectors = [ dictionary.doc2bow(simple_preprocess(doc))
↪  for doc in [doc1, doc2, doc3]]
```

Build a term similarity matrix and compute a sparse term similarity matrix:

```
from gensim.similarities import SparseTermSimilarityMatrix
from gensim.similarities import WordEmbeddingSimilarityIndex

similarity_index = WordEmbeddingSimilarityIndex(fasttext_model300)
similarity_matrix = SparseTermSimilarityMatrix(similarity_index,
↪  dictionary)
```

Inspect results

Get SCM using `.inner_product()`: :

```
#between doc1 and doc2:
scm_doc1_doc2 = similarity_matrix.inner_product(bag_of_words_vectors[0], bag_of_words_vectors[1], normalized=(True, True))

#between doc1 and doc3:
scm_doc1_doc3 = similarity_matrix.inner_product(bag_of_words_vectors[0], bag_of_words_vectors[2], normalized=(True, True))

#between doc2 and doc3;
scm_doc2_doc3 = similarity_matrix.inner_product(bag_of_words_vectors[1], bag_of_words_vectors[2], normalized=(True, True))

print(f"SCM between:\ndoc1 <-> doc2: {scm_doc1_doc2:.2f}\ndoc1 <-> doc3: {scm_doc1_doc3:.2f}\ndoc2 <-> doc3: {scm_doc2_doc3:.2f}")
```

Inspect results

Do the results make more sense?:

```
doc1 = "When I eat breakfast, I usually drink some tea".lower()
doc2 = "I like my tea with my breakfast".lower()
doc3 = "She likes cereal and coffee".lower()
```

```
SCM between:
doc1 <-> doc2: 0.29
doc1 <-> doc3: 0.15
doc2 <-> doc3: 0.28
```

Inspect results

Do the results make more sense?:

```
doc1 = "When I eat breakfast, I usually drink some tea".lower()
doc2 = "I like my tea with my breakfast".lower()
doc3 = "She likes cereal and coffee".lower()
```

```
SCM between:
doc1 <-> doc2: 0.29
doc1 <-> doc3: 0.15
doc2 <-> doc3: 0.28
```

Applications of cosine and soft cosine similarity

Applications of *cosine* and *soft cosine* in the field of Communication Science generally involve some overtime dynamics.

Trace convergence or agenda setting dynamics over time

- Beyond the scope this course to discuss it here, but if you are interested in how you can apply cosine and soft cosine in an overtime analysis, we have prepared a notebook that will help you do just that.
- https://github.com/uva-cw-ccs2/2223s2/main/week03/exercises/OPTIONAL_overtime_similarity.ipynb

From test to large-scale

General approach

1. Take a single string and test your idea

```python
t = "This is a test test test."
print(t.count("test"))
```

2a. You'd assume it to return 3. If so, scale it up:

```python
results = []
for t in listwithallmytexts:
    r = t.count("test")
    print(f"{t} contains the substring {r} times")
        results.append(r)
```

2b. If you *only* need to get the list of results, a list comprehension is more elegant:

```python
results = [t.count("test") for t in listwithallmytexts]
```

General approach

1. Take a single string and test your idea

```
t = "This is a test test test."
print(t.count("test"))
```

2a. You'd assume it to return 3. If so, scale it up:

```
results = []
for t in listwithallmytexts:
    r = t.count("test")
    print(f"{t} contains the substring {r} times")
        results.append(r)
```

2b. If you *only* need to get the list of results, a list comprehension is more elegant:

```
results = [t.count("test") for t in listwithallmytexts]
```

General approach

Test on a single string, then make a for loop or list comprehension!

Own functions

If it gets more complex, you can write your ow= function and then use it in the list comprehension:

```
def mycleanup(t):
    # do sth with string t here, create new string t2
    return t2

results = [mycleanup(t) for t in allmytexts]
```

General approach

Test on a single string, then make a for loop or list comprehension!

Own functions

If it gets more complex, you can write your ow= function and then use it in the list comprehension:

```
def mycleanup(t):
    # do sth with string t here, create new string t2
    return t2

results = [mycleanup(t) for t in allmytexts]
```

Pandas string methods as alternative

If you select column with strings from a pandas dataframe, pandas offers a collection of string methods (via `.str.`) that largely mirror standard Python string methods:

```
df['newcoloumnwithresults'] = df['columnwithtext'].str.count("bla")
```

To pandas or not to pandas for text?

Partly a matter of taste.

Not-too-large dataset with a lot of extra columns? Advanced statistical analysis planned? Sounds like pandas.

It's mainly a lot of text? Wanna do some machine learning later on anyway? It's large and (potentially) messy? Doesn't sound like pandas is a good idea.

Pandas string methods as alternative

If you select column with strings from a pandas dataframe, pandas offers a collection of string methods (via `.str.`) that largely mirror standard Python string methods:

```
df['newcoloumnwithresults'] = df['columnwithtext'].str.count("bla")
```

To pandas or not to pandas for text?

Partly a matter of taste.

Not-too-large dataset with a lot of extra columns? Advanced statistical analysis planned? Sounds like pandas.

It's mainly a lot of text? Wanna do some machine learning later on anyway? It's large and (potentially) messy? Doesn't sound like pandas is a good idea.

Thank you!!

Thank you for your attention!

- Questions? Comments?

References

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

Hager, A., & Hilbig, H. (2020). Does public opinion affect political speech? *American Journal of Political Science*, *64*(4), 921–937. https://doi.org/10.1111/ajps.12516

Sidorov, G., Gelbukh, A., Gómez-Adorno, H., & Pinto, D. (2014). Soft similarity and soft cosine measure: Similarity of features in vector space model. *Computacion y Sistemas*, *18*(3), 491–504. https://doi.org/10.13053/CyS-18-3-2043