A Practical Introduction to Machine Learning in Python Day 1 - Monday afternoon »From text to features«

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Today

From text to features: vectorizers

General idea

Pruning

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 a test test test"
```

like this:

- from collections import Counter
- print(Counter(t.split()))

```
1 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 (!!!)

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From vector to matrix

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

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

t2 = "This is an example"

	а	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

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But are all terms equally important?

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- 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)

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tf·idf

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

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

Is tf.idf always better?

It depends.

- ullet Ultimately, it's an empirical question which works better (o 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)
- TfidfVectorizer (word counts ("term frequency") weighted by number of documents in which the word occurs at all ("inverse document frequency"))

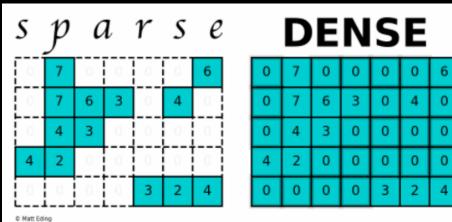
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Internal representations

Sparse vs dense matrices

- ullet o 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/

From text to features: vectorizers

Tomorrow we discuss how we can 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

```
1 from sklearn.feature_extraction.text import CountVectorizer
```

```
cv = CountVectorizer()
```

3 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

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Best of both worlds

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

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From text to features: vectorizers

Pruning

- 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
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CountVectorizer, only stopword removal

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

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 togehter: 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?