Representing linguistic data

Statistical Methods in NLP 2
ISCL-BA-08

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Representing linguistic data

- Almost all machine learning methods require a fixed number of numeric predictors
- In most NLP task, our predictors are sequences of (categorical) units: letters/phonemes, words, sentences, documents
- Correct representations of these units have direct impact on the success of the ML methods
- We start with some basic methods of representations, and move on to *learning* these representations

Basics: how to represent categorical predictors?

binary case

- Representing binary predictors is relatively straightforward

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- Representing binary predictors is relatively straightforward

$$x = \begin{cases} 0 & \text{for male} \\ 1 & \text{for female} \end{cases}$$

$$x = \begin{cases} -1 & \text{positive} \\ +1 & \text{negative} \end{cases}$$

- 0 and 1 is the most common choice in practice
- The choice of the numbers is arbitrary, any two real numbers would do
- The order is also arbitrary, but sometimes good to pick a particular order for interpretability

Categorical predictors

with more than two categories

POS tag	code
NOUN	1
VERB	2
ADJ	3
ADV	4
PRON	5

Categorical predictors

with more than two categories

POS tag	code
NOUN	001
VERB	010
ADJ	011
ADV	100
PRON	101

Categorical predictors

with more than two categories

POS tag	code
NOUN	00001
VERB	00010
ADJ	00100
ADV	01000
PRON	10000

Categorical predictors

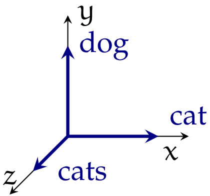
with more than two categories

- For categorical variables most common choice is the *one-hot* (or *one-of-k*) representation
- One-hot vectors are orthogonal, they do not indicate any (random) similarity or ordering
- Even for ordinal variables, it may often be better to use one-hot vectors
- They cannot represent any similarities between class values
- The vectors may become large if there are many values

POS tag	code
NOUN	00001
VERB	00010
ADJ	00100
ADV	01000
PRON	10000

Problem with one-hot representations

$$
\begin{aligned}
\text{cat} &= (0, \ldots, 1, 0, 0, \ldots, 0) \\
\text{cats} &= (0, \ldots, 0, 1, 0, \ldots, 0) \\
\text{dog} &= (0, \ldots, 0, 0, 1, \ldots, 0) \\
&\ldots
\end{aligned}
$$



- No notion of similarity
- It is particularly bad if the instances are not a closed class (e.g., documents)
- Large (but sparse) vectors

Properties of good representations

- Representations should allow measuring similarity: similar objects should be represented with similar vectors
- Representations should allow making distinctions required for the task
- Representations should be efficient to process
- Representations should be easy to obtain (automatically)

Bag of words (BoW) representation

The idea: use words that occur in text as features without paying attention to their order.

The document

It's a good thing most animated sci-fi movies come from Japan, because "titan a.e." is proof that Hollywood doesn't have a clue how to do it. I don't know what this film is supposed to be about.

BoW representation

how japan good n't I thing film what , proof titan a because . 's know does most hollywood is animated it do sci-fi a.e. " " supposed be come clue to this that from have movies about .

Bag of words representation

with binary features

The document

It’s a good thing most animated sci-fi movies come from Japan, because “titan a.e.” is proof that Hollywood doesn’t have a clue how to do it. I don’t know what this film is supposed to be about.

- If the word is in the document, the value of 1, otherwise 0
- The feature vector contains values for all words in our document collection

feature	value
to	1
do	1
a	1
thing	1
have	1
good	1
be	1
clue	1
great	0
pathetic	0
masterpiece	0
...	

Bag of words representation

with (document) frequencies

The document

It's a good thing most animated sci-fi movies come from Japan, because "titan a.e." is proof that Hollywood doesn't have a clue how to do it. I don't know what this film is supposed to be about.

- Use frequencies rather than binary vectors
- May help in some cases, but
  - effect of document length
  - frequent is not always good

feature	value
to	2
do	2
a	2
thing	1
have	1
good	1
be	1
clue	1
great	0
pathetic	0
masterpiece	0
...	

Bag of words representation

with relative frequencies

The document

It's a good thing most animated sci-fi movies come from Japan, because "titan a.e." is proof that Hollywood doesn't have a clue how to do it. I don't know what this film is supposed to be about.

- Relative frequencies are less sensitive to document length
- Still, high-frequency words dominate

feature	value
to	0.06
do	0.06
a	0.06
thing	0.03
have	0.03
good	0.03
be	0.03
clue	0.03
great	0.00
pathetic	0.00
masterpiece	0.00
...	

tf-idf weighting

- Intuition:
  - Words that appear multiple times in a document is important/representative for the document
  - Words that appear in many documents are not specific/useful
- tf-idf uses two components
  - tf term frequency - frequency of the word in the document
  - idf inverse document frequency - inverse of the ratio of documents that contain the term
- Both components are typically normalized

term count in doc number of docs

$$\text{tf-idf}_{t,d} = \frac{C_{t,d}}{|d|} \times \log \frac{N}{n_t}$$

doc length number of docs with t

tf-idf example

Document 1 (d_1)

the	5
good	2
bad	1

Document 2 (d_2)

the	2
a	2
book	1

Document 3 (d_3)

the	1
a	2
good	3

$$\text{tf-idf}(t, d) = \text{tf}(t, d) \times \text{idf}(t)$$

$$\text{tf-idf}(\text{good}, d_1) = ?$$

$$\text{tf-idf}(\text{the}, d_1) = ?$$

$$\text{tf-idf}(\text{bad}, d_1) = ?$$

$$\text{tf-idf}(\text{good}, d_3) = ?$$

tf-idf example

Document 1 (d_1)

the	5
good	2
bad	1

Document 2 (d_2)

the	2
a	2
book	1

Document 3 (d_3)

the	1
a	2
good	3

$$\text{tf-idf}(t, d) = \text{tf}(t, d) \times \text{idf}(t)$$

$$\text{tf-idf}(\text{good}, d_1) = \frac{2}{8} \times \log \frac{3}{2} = 0.15$$

$$\text{tf-idf}(\text{the}, d_1) = \frac{5}{8} \times \log \frac{3}{3} = 0.00$$

$$\text{tf-idf}(\text{bad}, d_1) = \frac{1}{8} \times \log \frac{3}{1} = 0.20$$

$$\text{tf-idf}(\text{good}, d_3) = \frac{3}{6} \times \log \frac{3}{2} = 0.29$$

Some notes on tf-idf

- tf-idf is an effective method for term weighting
- It was originally used for information retrieval, where it brought substantial improvements over other methods
- It is also very effective on text classification when using linear models
- There are some alternatives (e.g., BM25), and many variations: frequencies for TF, or use the $\log$ TF
- It has been difficult to improve over it (since 1970's)

Pointwise mutual information

for term weighting

- Another common weighting method is pointwise mutual information

$$\mathrm{PMI}(t, d) = \log \frac{P(t, d)}{P(t)P(d)}$$

- Besides normalizing for 'term frequency/probability', PMI also takes the 'document probability' into account
- Note that 'document' does not have to be a document, any definition of 'context' may result in useful representations (depending on the task)

A document is more than a BoW

The example document for sentiment analysis

It's a good thing most animated sci-fi movies come from Japan, because "titan a.e." is proof that Hollywood doesn't have a clue how to do it. I don't know what this film is supposed to be about.

- So far, we considered documents as simple BoW words
- BoW representations is surprisingly successful in many fields (IR, spam detection, …)
- However, word order matters
  - According to a sentiment dictionary, our example contains one positive and one negative word

A document is more than a BoW

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It’s a good thing most animated sci-fi movies come from Japan, because “titan a.e.” is proof that Hollywood doesn’t have a clue how to do it. I don’t know what this film is supposed to be about.

- So far, we considered documents as simple BoW words
- BoW representations is surprisingly successful in many fields (IR, spam detection, …)
- However, word order matters
  - According to a sentiment dictionary, our example contains one positive and one negative word
- Paying attention to longer sequences allows us to get better results

Bag of n-grams

- Using n-grams rather than words allows us to capture more information in the data
- We can still use the same weighting methods (tf-idf)
- It is a common practice to use a range of (overlapping) n-grams
- This results in large set of features (millions for most practical applications)
- Data sparsity is a problem for higher order n-grams

The unreasonable effectiveness of character n-grams

An example document

It's a good thing ...

- For a number of text classification tasks (authorship attribution, language detection), character n-gram features found to be effective
- The idea is to use a range of character n-grams

feature	value
`it`	2
`t'`	1
`'s`	2
`s␣`	3
`␣a`	4
`a␣`	5
`␣g`	2
`it's␣`	2
`t's␣a`	1
`'s␣a␣`	1
`s␣a␣g`	1
`␣a␣go`	2
`a␣goo`	2
...	

$$
\begin{array}{r c}
 & \begin{array}{ccccc} d_1 & d_2 & d_3 & \dots & d_m \end{array} \\
\begin{array}{r} \text{cat} \\ \text{dog} \\ \text{book} \\ \dots \end{array} &
\begin{bmatrix} 0 & 3 & 1 & \dots & 4 \\ 0 & 0 & 3 & \dots & 3 \\ 4 & 1 & 4 & \dots & 5 \\ \dots & \dots & \dots & \dots & \dots \end{bmatrix}
\end{array}
$$

- Rows of the matrix represent words: words that appear in the same set of documents will be similar to each other
- The columns represent documents: documents with overlapping sets of words will be similar to each other
- Terms do not have to be words, any sequence we can count can be a term
- Contexts do not have to be documents, and any meaningful context can be used instead of documents
- Data is highly correlated (lots of redundancy)
- For practical applications we need huge (but sparse) matrices

A toy example

A four-sentence corpus with *bag of words* (BOW) model.

The corpus:

```
S1: She likes cats and dogs
S2: He likes dogs and cats
S3: She likes books
S4: He reads books
```

Term-document (sentence) matrix

	S1	S2	S3	S4
she	1	0	1	0
he	0	1	0	1
likes	1	1	1	0
reads	0	0	0	1
cats	1	1	0	0
dogs	1	1	0	0
books	0	0	1	1
and	1	1	0	0

A toy example

A four-sentence corpus with *bag of words* (BOW) model.

The corpus:

```
S1: She likes cats and dogs
S2: He likes dogs and cats
S3: She likes books
S4: He reads books
```

Term-term (left-context) matrix

	#	she	he	likes	reads	cats	dogs	books	and
she	2	0	0	0	0	0	0	0	0
he	2	0	0	0	0	0	0	0	0
likes	0	2	1	0	0	0	0	0	0
reads	0	0	1	0	0	0	0	0	0
cats	0	0	0	1	0	0	0	0	1
dogs	0	0	0	1	0	0	0	0	1
books	0	0	0	1	1	0	0	0	0
and	0	0	0	0	0	1	1	0	0

What about the linguistic features?

- Linguistically-informed representations is one potential area where linguistics can help building NLP system
- For text classification, the use of 'lexicons' has been common
- Other linguistic features such as
  - lemmas
  - sequences of POS tags
  - parser output: dependency triplets, or partial trees

  are also used in some tasks

A simple example from phonetics/phonology

	Vowel	High	Back	Round	Voice	Labial	Nasal	...
i	1	1	0	0	1	0	0	...
ɑ	1	0	1	0	1	0	0	...
n	0	0	0	0	1	0	1	...
m	0	0	0	0	1	1	0	...
p	0	0	0	0	0	0	0	...
b	0	0	0	0	1	0	0	...

- Compared to one-hot representations, these type of representations help identifying similar units

Are linguistic features useful at all?

- It is often difficult to get improvements over simple features
- It also makes systems more complex and language dependent
- Linguistic features can particularly be useful if the amount of data is limited
- They are particularly interesting for interpretable and explainable ML/NLP
- Considering the types of linguistics features that help is useful for structuring your input

Final remarks

- Representation of inputs to a ML model is important
- More meaningful/useful representations are likely to improve the systems
- Modern ML methods learn these representations from the data
- Informed/clever ways to represent the data may still be important in some cases (e.g., low-resource scenarios)

Final remarks

- Representation of inputs to a ML model is important
- More meaningful/useful representations are likely to improve the systems
- Modern ML methods learn these representations from the data
- Informed/clever ways to represent the data may still be important in some cases (e.g., low-resource scenarios)

Next:

Fri/Mon Learning representations

Some sources of information

- Jurafsky and Martin (Chapter 6, 2025)

Jurafsky, Daniel and James H. Martin (2025). *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition with Language Models*. 3rd. Online manuscript released January 12, 2025. URL: `https://web.stanford.edu/~jurafsky/slp3/`.