

# Language Model and Word Embeddings

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# Lecture Overview

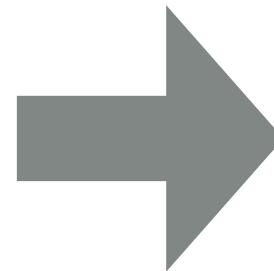
- ▶ Preprocessing
- ▶ word embeddings

# Tokenization

## ► Typical preprocessing steps of text data

- Tokenize text (from a long string to a list of token strings)

**“He’s spending 7 days in San  
Francisco.”**



“ He ”
“ ’ s ”
“ spending ”
“ 7 ”
“ days ”
“ in ”
“ San Francisco ”
“ . ”

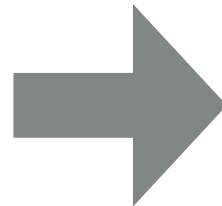
- For many datasets, this has already been done for you
- Splitting into tokens based on spaces and separating punctuation is good enough in English or French

# Lemmatization

## ► Lemmatize tokens

- Put into standard form

“ He ”
“ ’ s ”
“ spending ”
“ 7 ”
“ days ”
“ in ”
“ San Francisco ”
“ . ”



“ he ”
“ be ”
“ spend ”
“ NUMBER ”
“ day ”
“ in ”
“ San Francisco ”
“ . ”

- The specific lemmatization will depend on the problem we want to solve
  - ✓ we can remove variations of words that are not relevant to the task at hand

# vocabulary

## ► word to unique ID

- First, construct dictionary (vocabulary)
- Maps lemmatized words to a unique ID (position of word in dictionary)

## ► Selection of vocabulary

- Pick most frequent words
- Ignore uninformative words from a user-defined short list  
✓ ex. "the", "a", etc.

## ► All words not in the vocabulary will be mapped to a special "out-of-vocabulary" ID

# vocabulary

## ► Example

“ the ”
“ cat ”
“ and ”
“ the ”
“ dog ”
“ play ”
“ . ”

**Vocabulary**

Word	w
“ the ”	1
“ and ”	2
“ dog ”	3
“ . ”	4
“ oov ”	5



1	
5	
2	
1	
3	
5	
4	



# One-hot Encoding

► From its word ID, we get a basic representation of a word through the one-hot encoding of the ID

- The one-hot vector of an ID is a vector filled with 0s, except for a 1 at the position associated with the ID

- ✓ Ex: for vocabulary size  $D=10$ , the one-hot vector of word ID  $w=4$  is

- ✓  $e(w) = [0 \ 0 \ 0 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0]$

- A one-hot encoding makes no assumption about word similarity

- ✓ 두 개의 단어가 같으면 거리가 = 0

- ✓ 두 개의 단어가 서로 다른다면 거리가 무조건 = 2

► 단점

- word similarity 를 잘 나타내지 못함

- one-hot representation has very high-dimension

# Word Embeddings

## ► Learn a continuous representation of words

- 즉 각 단어의 representation 을 학습가능한 파라미터로 생각하여 학습함
- 앞에서 언급한 one-hot encoding 의 한계 극복 가능

Word	$w$	$C(w)$
" the "	1	[ 0.6762, -0.9607, 0.3626, -0.2410, 0.6636 ]
" a "	2	[ 0.6859, -0.9266, 0.3777, -0.2140, 0.6711 ]
" have "	3	[ 0.1656, -0.1530, 0.0310, -0.3321, -0.1342 ]
" be "	4	[ 0.1760, -0.1340, 0.0702, -0.2981, -0.1111 ]
" cat "	5	[ 0.5896, 0.9137, 0.0452, 0.7603, -0.6541 ]
" dog "	6	[ 0.5965, 0.9143, 0.0899, 0.7702, -0.6392 ]
" car "	7	[ -0.0069, 0.7995, 0.6433, 0.2898, 0.6359 ]
...	...	...

## ► How to do it?

- word embedding 은 one-hot encoding 을 input 으로 하는 NN의 weight matrix 학습하는 것과 같음



# Word Embeddings

