Deep Learning for Natural Language Processing

Lecture 4 – Word embeddings

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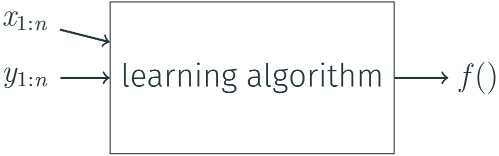
What's the problem



Input to neural models $f()$: numerical vector but NLP work with texts

How can we represent texts via numerical vectors?

This lecture

"Classic" features for text representation

Word embeddings

Count-based embeddings

Continuous bag of words and Skip-Gram

Evalution

Text Representation

Vector representation of a text should ideally reflect various linguistic properties of the text

$$\text{text} \longrightarrow \boxed{\text{feature function}} \longrightarrow x \longrightarrow f()$$

In this lecture we focus on feature functions rather than learning algorithms

Terminology

Letters: smallest units in a language $\rightarrow$ a,b,c,...

Tokens and **words**: tokens are outputs of a tokenizer and words are meaning-bearing units

- note: in this course we use the terms “word” and “token” interchangeably

Terminology

Lemma: the dictionary entry of the word $\rightarrow$ “book” is the lemma of “booking”, “booked”, and “books”

- How to obtain lemmas? Use morphological analyzers
- Available for many languages
- Lemmatization may not work for any sequence of letters, e.g., for mis-spelling

Stems: a shorter venison of a word defined based on some language-specific heuristic $\rightarrow$ “pictur” is the stem of “pictures”, “pictured”, and “picture”

- Stemmer’s output need not be a valid word

lexical resources

Lexical resources: provide information about words and their relations

Dictionaries

WordNet for English

- Semantic knowledge about words
- Each word is associated with one or several synsets
- Synsets are linked to each other according to semantic relations between their words
- Semantic relations are: hypernym (more specific), hyponym (less specific), antonyms, etc.
- Contains nouns, verbs, adjectives, and adverbs
- Manually created

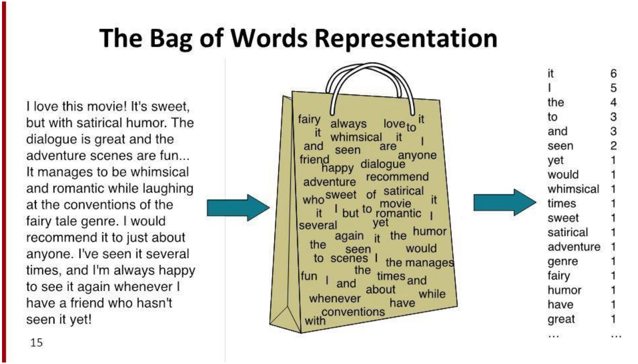
”Classic” features for text representation

Common Features for Textual Data

What information can we extract directly from a word

- Letters comprising a word and their order
- Length of word
- Is the first letter capitalized?
- Does word include hyphen?

Bag-of-Words (BoW): histogram of words as a feature vector



BOW does not care about the order of words

(Taken from: https://www.programmersought.com/article/4304366575/)

TF-IDF

TF-IDF: Term Frequency - Inverse Document Frequency

Let d be a document from a given corpus D

Map word w of d to a number as follows:

$$\frac{\#(w,d)}{\sum_{w'} \#(w',d)} \times \log \frac{|D|}{|\{d \in D : w \in d\}|}$$

N-grams: instead of using the frequency of a word, we use the frequency of N sequence of words

N=2 $\rightarrow$ bi-gram; N=3 $\rightarrow$ tri-gram

Common Features for Textual Data

Context: each piece of a text occurs within a larger text which is known as context

How to encode contextual information?

Using position of a word within a sentence or a document

Using the words that appear in an immediate context of a word

- Immediate context: a window of k words surrounding the target word
- "the cat sat on the mat" , k=2 $\rightarrow$ { word-minus-2=the, word-minus-1=cat, word-plus-1=on, word-plus-2=the }

Common Features for Textual Data

what information can we extract from the relation of text with external source of information?

- is a word in a list of common person names in Germany?
- is a word a female or male person name?
- what is the lemma of the word?
- what is the stem of the word?
- what information do lexical resources give us about the word?

Different Types of Features

Numerical features

- Value of a feature is a number, e.g., the frequency of a word in a text

Categorical features

- Value of a feature is from a set of values
- ”What is the POS of a word? ”

How to encode categorical features?

- One-hot encoding
- Dense embedding

One-hot Encoding

Assume that values of a feature is in categories $\{v_0, v_1, v_2\}$

Encode the space of feature values via vectors in which

- each entry is either 0 or 1
- each entry is associated with one of the categories
- only one item in a vector can be 1, the rest is 0

Example:

- $v_0 = [1, 0, 0]$
- $v_1 = [0, 1, 0]$
- $v_2 = [0, 0, 1]$

Example: Categorical Labels

Fet $f()$ take a vector x which encodes a text and also return a vector $\hat{y}$ representing the topic of the text which can be from $\{$news, sport, science, politic$\}$

How can we represent topic labels using one-hot encoding?

- news = $[1, 0, 0, 0]$
- sport = $[0, 1, 0, 0]$
- science = $[0, 0, 1, 0]$
- politic = $[0, 0, 0, 1]$

What is the length of one-hot vectors for a feature with k categories?

Example: Word Encodings

Let V be vocabulary of a language

We take V as categories a word can take in a text

Let $V = \{v_0, v_1, v_2, ..., v_{|V|-1}\}$

- $v_0 = [1, 0, 0, ..., 0]$
- $v_1 = [0, 1, 0, ..., 0]$
- $v_2 = [0, 0, 1, ..., 0]$
- $\ldots$
- $v_{|V|-1} = [0, 0, 0, ..., 1]$

We can easily represent a text via BOW and then represent each word in BOW with its one-hot vector

How can we define vocabulary V given a corpus D?

One-hot Encodings

- word vectors are very sparse
- semantic relations between words are not encoded in word vectors
- it's better to use one-hot representations for a few distinct features where we expect no correlation between features

Dense Encodings

- a categorical feature is embedded as a vector in a d dimensional space
- assuming categories $C = \{c_0, c_1, ..., c_{|C|-1}\}$, $d = 4$
  - $c_0 = [+0.1, -0.2, +0.3, +0.5]$
  - $c_1 = [-0.2 - 0.1, +0.1, +0.2]$
  - ...
  - $c_{|C|-1} = [+0.2, -0.2, -0.1, +0.3]$

Example: Word Encodings

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  - ...
  - $v_{|V|-1} = [+0.2, -0.2, -0.1, +0.3]$
- in the one-hot method we represent each word with a sparse vector of size $|V|$
- in dense encoding method we represent each word with a dense vector with a small size d

Dense Encodings

- dimensionality of vectors is d
- model training will cause similar features to have similar vectors
- it's mainly useful when we expect some correlations between features $\rightarrow$ "cat" and "dog" are semantically related
- is also useful when we have a large number of features $\rightarrow$ for example vocabulary

Word embeddings

Word Embeddings

- dense representations of words in an embedding space is known as word embeddings
- how to obtain word embeddings?

Random Initizalization

- we initialize the embedding vectors to random values
- values are uniformly sampled from numbers in the range
    - $[-\frac{1}{2d}, +\frac{1}{2d}]$ where d is the number of dimensions (Mikolov et al., 2013)
    - $[-\frac{\sqrt{6}}{\sqrt{d}}, +\frac{\sqrt{6}}{\sqrt{d}}]$ (xavier initialization)

Word Embeddings

- dense representations of words in an embedding space is known as word embeddings
- these vectors can be obtained by random initialization and tuned for any NLP task
- however, we as human beings can define semantic relations between words independent of any NLP task
    - e.g., “blue” and ’black” are colors
    - e.g., “dog” is more similar to “cat” than to “chair”
    - e.g., “easy” is the opposite of “difficult”
- how can we find word embeddings such that vectors of words with similar meaning be close to each other in the embedding space?

Distributional Hypothesis

- words that occur in the same contexts tend to have similar meanings (Harris, 1945)
- how can we model the distributional hypothesis?

Word-Context Matrix

- we count how often a word has occurred with a context in texts from a large corpus
- context is defined by a window over words
- let V be the set of words in vocabulary and C be the set of possible contexts
- word-context matrix M is a two dimensional matrix whose rows are associated with V and columns with C
- each entry of the matrix indicates how often a word co-occurs with a context in the given corpus
- this matrix is also known as co-occurrence matrix

Count-based embeddings

Word-Context Matrix

- corpus:
  - I like DL
  - I like NLP
  - I love ML
  - I love NLP
- window size = 1

	I	like	love	DL	NLP	ML
I	0	2	2	0	0	0
like	2	0	0	1	1	0
love	2	0	0	0	1	1
DL	0	1	0	0	0	0
NLP	0	1	1	0	0	0
ML	0	0	1	0	0	0

Word-Context Matrix

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ML	0	0	1	0	0	0

Count-based Embeddings

- for a large corpus, the size of matrix is very large
- the matrix could be sparse too
- to encounter this, we may use dimensionality reduction techniques
- however, for adding a new word we need to enlarge the matrix and apply dimensionality reduction again

CBoW Method

- CBoW stands for Continuous Bag of Words
- task: given a context $\rightarrow$ predict a missing word from the context

  input: "I _ NLP" $\rightarrow$ output: "like"

  input: ("I _ NLP", "like") $\rightarrow$ output: 1 and
  input: ("I _ NLP", "apple") $\rightarrow$ output: 0

Continuous bag of words and Skip-Gram

CBoW Method

- given a corpus, we create two sets:
  - positive set (D): consisting of pairs (c, w) where c is a context and w is the correct value for the missing word
  - negative set (D'): consisting of pairs (c, w) where c is a context and w is a random value for the missing word
- we compute the score estimating similarity between context c and word w given context-word pair (c, w)

$$s(c, w) = e(w) \sum_{w_i \in c} e(w_i)$$

where e is a function that maps each word to its embeddings

CBoW Method

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- Example

$$s(\text{I \_ NLP}, \text{like}) = e(\text{like})(e(\text{I}) + e(\text{NLP}))$$

CBoW Method

Use the sigmoid function to map the score to a probability

$$P(y = 1|(c, w)) = \frac{1}{1 + e^{-s(c,w)}}$$

Minimize the following loss

$$\begin{aligned} L(\Theta) = &- \frac{1}{|D|} \sum_{(c,w) \in D} \log \Pr(y = 1|(c, w)) \\ &- \frac{1}{|D'|} \sum_{(c,w) \in D'} \log \Pr(y = 0|(c, w)) \end{aligned}$$

Skip-Gram Method

Treat words of a context independent from each other

$$P(y = 1|(c, w)) = \prod_{c_i \in c} P(y = 1|(w, c_i)) = \prod_{c_i \in c} \frac{1}{1 + e^{-e(w)e(c_i)}}$$

Loss in Skip-Gram is identical to that in CBoW

We fine-tune parameters (word embeddings) using SGD

CBoW and Skip-Gram

- CBoW loses the order information between context's elements
- CBoW allows the use of variable-length contexts
- Skip-Gram decouples the dependence between context elements even further than CBoW
- Skip-Gram treats each context's element as an independent context

Context Matters!

- context of a word translates to its surrounding words in a sentence or paragraph
- window-based context: for a word we consider all words in a window of length $2m+1$ centred on the word as context
- the size of window: large windows tend to capture more topical similarities and small windows capture syntactic similarities

Context Matters!

- contexts can be defined based on text units, for example, words that occur in the same sentence, paragraph, or text
- contexts can also be defined based on syntax of a sentence for example using parse tree or dependency tree of a sentence
- contexts of a word can be foreign words that are aligned to the word in multilingual corpora

Word2Vec Software Package

- the implementations of CBoW and Skip-Gram methods exist in Word2Vec
- `https://code.google.com/archive/p/word2vec/`
- Skip-Gram is more effective in practice

GLoVe (Pennington et al., 2014)

- GloVe: Global Vectors for Word Representation
- GloVe is an unsupervised method for obtaining word embeddings
- GloVe aims at reconciling the advantages of corpus-wide co-occurrence counts and local context windows
- `https://nlp.stanford.edu/projects/glove/`

Evaluating Word Embeddings

- intrinsic
  - word similarity tasks
  - word analogy tasks
- extrinsic
  - on a downstream NLP task, we compare the performance of two models that differ only in the word embeddings they use
  - named entity recognition (NER): accuracy
  - machine translation (MT): BLEU score
  - summarization: ROUGE score
  - information retrieval (IR): precision - recall - F1 score

Evalution

Word Similarity Tasks

- similar words should have similar representations
- dataset: `http://alfonseca.org/eng/research/wordsim353.html`
- word-1 and word-2 $\rightarrow$ similarity score $\in [0, 10]$
- our function $f()$ should map two words to a similarity score using the distance between the word vectors of the words
- cosine similarity

$$\text{sim}(w_i, w_j) = \frac{e(w_i) \cdot e(w_j)}{\|e(w_i)\| \|e(w_j)\|}$$

Word Analogy Tasks

- A is to B as C to ?
- Germany is to Berlin as France is to ?
- dataset: `http://download.tensorflow.org/data/questions-words.txt`
- capital-common-countries
    - Athens Greece Baghdad $\rightarrow$ Iraq
    - Athens Greece Berlin $\rightarrow$ Germany
- family
    - boy girl brother $\rightarrow$ sister
    - brother sister dad $\rightarrow$ mom
- currency, adj-to-adverb, comparative, ...

Finding the Prototype of a Group of Words

- if we have a group of words $g = \{w_1, w_2, ..., w_k\}$
- the prototype of this group can be computed as follows

$$\text{proto}(g) = \frac{1}{k} \sum_{i \in 1..k} e(w_i)$$

  where e maps a word to its embeddings

Finding Similar Words

- cosine similarity

$$\text{sim}(w_i, w_j) = \frac{e(w_i) \cdot e(w_j)}{\|e(w_i)\|\|e(w_j)\|}$$

- words found by embedding-based similarities can be filtered with other types of word similarities

Short Text Similarities

$d_1 = \{w_1^1, w_2^1, ..., w_m^1\}$ and $d_2 = \{w_1^2, w_2^2, ..., w_n^2\}$

$$\text{sim}(d_1, d_2) = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} \cos\left(e(w_i^1), e(w_j^2)\right)$$

Pre-Trained Embeddings

- Word2Vec
  - trained on Google News (100 billion tokens)
- GloVe
  - trained on Wikipedia (6 billion tokens)
  - trained on CommonCrawl (42 and 840 billion tokens)
  - trained on Twitter (27 million tokens)
- many other pre-trained embeddings for different languages
  - `https://fasttext.cc/docs/en/crawl-vectors.html`

Practical Hints

- always try out different word embeddings (consider them as a hyperparameter)
- results may vary drastically with different embeddings
- consider source of corpora used to train word embeddings (larger is not always better, a smaller but more domain-focused can be more effective)
- consider what contexts were used to define similarities
- it's better to use the same tokenization and text normalization methods that were used for creating word embeddings

Limitations

- the algorithms discussed provide very little control over the kind of similarity they include
  - “cat” is more similar to “dog” than to “tiger” as they both are pets
  - “cat” is more similar to “tiger” than to “dog” as they both as felines
- many of the trivial properties of words are ignored because people are less likely to mention known information than they are to mention novel one

Limitations

- text corpora can easily be biased for better or worse
  $\rightarrow$ so word embeddings can become biased too
    - gender and racial biases are very common
- these word vectors are context independent
    - in reality, there is no such a thing to have context independent word meaning
    - some words have multiple sense e.g., “bank” may refer to a financial institution or to the side of a river

Summary

Common features used for converting textual data into numerical vectors

Basics of word embeddings

- How to get them?
- Where to use them?
- How to use them?

Limitations

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Credits

Ivan Habernal, Mohsen Mesgar, Steffen Eger

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