Deep Learning for NLP
Lecture 4: Text Representations I

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This lecture

- 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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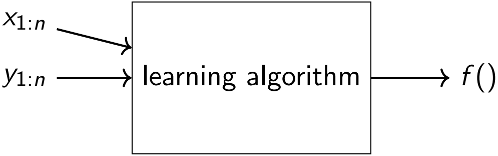

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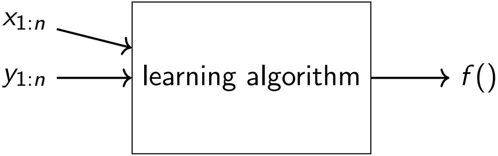

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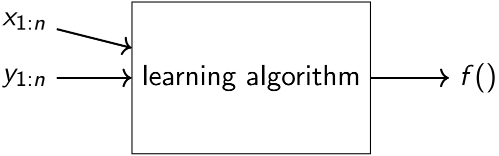

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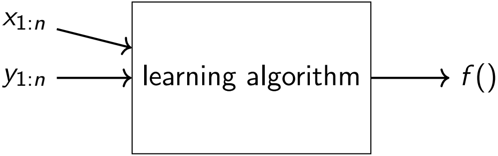

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- how can we represent texts via numerical vectors?

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- in this lecture we focus on feature functions rather than learning algorithms

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- stems: a shorter venison of a word defined based on some language-specific heuristic → "pictur" is the stem of "pictures", "pictured", and "picture"
  - the output of a stemmer need not be a valid word

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- does word include hyphen?

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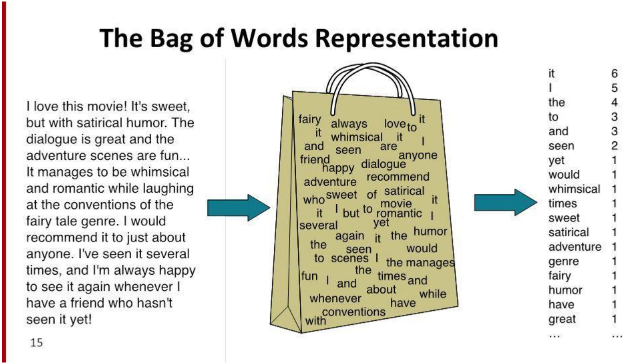

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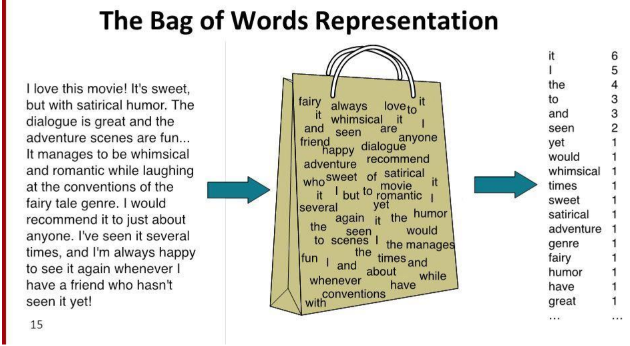

- BOW does not care about the order of words

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- N=3 $\rightarrow$ tri-gram

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  - "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 }

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- what information do lexical resources give us about the word?

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- how can we map textual features to a vector?

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- for example:
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- what is the length of one-hot vectors for a feature with k categories?

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

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  - $v_2 = [0, 0, 1, ..., 0]$
  - ...
  - $v_{|V|-1} = [0, 0, 0, ..., 1]$
- 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?

Comment

pause

One-hot Encodings

- word vectors are very sparse

One-hot Encodings

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- it's better to use one-hot representations for a few distinct features where we expect no correlation between features

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- 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

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- is also useful when we have a large number of features $\rightarrow$ for example vocabulary

Embeddings

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- how should we define these dense vectors or embeddings?

Word Embeddings

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

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  - $[-\frac{\sqrt{6}}{\sqrt{d}}, +\frac{\sqrt{6}}{\sqrt{d}}]$ (xavier initialization)

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  - 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?

Word Meaning

- "you should know a word by the company it keeps" (Frith, 1957)

Distributional Hypothesis

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- how can we model the distributional hypothesis?

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- corpus:
  - I like DL
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- however, for adding a new word we need to enlarge the matrix and apply dimensionality reduction again

CBoW Method

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

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- example

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

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or minimize the following loss

$$L(\Theta) = -\frac{1}{|D|} \sum_{(c,w) \in D} \log P(y = 1|(c, w)) - \frac{1}{|D'|} \sum_{(c,w) \in D'} \log P(y = 0|(c, w))$$

Skip-Gram Method

- we treat words of a context independent from each other

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- loss in Skip-Gram is identical to that in CBoW
- we fine-tune parameters (word embeddings) using SGD

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- 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/`

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  - information retrieval (IR): precision - recall - F1 score

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- family
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- currency, adj-to-adverb, comparative, ...

Finding the Prototype of a Group of Words

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- 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

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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`

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- 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

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- it uses a lookup table, which is a matrix with size $|V| \times d_{emb}$
- the i'th row of this matrix contains embeddings of i'th word in vocabulary V
- so the only thing we need to do is to replace a word with its index in vocabulary $\rightarrow$ a dictionary does this easily (word_to_ix)

Embedding Layers in PyTorch


```python
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim

torch.manual_seed(1)

word_to_ix = {"hello": 0, "world": 1}

embeds = nn.Embedding(2, 5)

lookup_tensor = torch.tensor([word_to_ix["hello"]], dtype=torch.long)

hello_embed = embeds(lookup_tensor)

print(hello_embed)
```

Embedding Layers in PyTorch

```
import torch
import torch.nn as nn

class EmbeddingLayer(nn.Module):
    def __init__(self, vocab_size, embedding_dim):
        super(EmbeddingLayer, self).__init__()
        self.embeddings = nn.Embedding(vocab_size, embedding_dim)

    def forward(self, inputs):
        embeds = self.embeddings(inputs)
        return embeds
```

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if __name__ == '__main__':
    model = EmbeddingLayer(voc_size=10, emb_size=3)
    inputs = [1,5]
    inputs_tenseor = torch.tensor(inputs, dtype=torch.long)

    emb_vectors = model(inputs_tenseor)

    print(f"the shape of emb vectors is {emb_vectors.shape}")
```

Using Pretrained Embedding Layers in PyTorch

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```
import torch
import torch.nn as nn

class EmbeddingLayer(nn.Module):
    def __init__(self, vocab_size, embedding_dim, weights_matrix):
        super(EmbeddingLayer, self).__init__()
        self.embeddings = nn.Embedding(vocab_size, embedding_dim)

        self.embeddings.load_state_dict({'weight': weights_matrix})


    def forward(self, inputs):
        embeds = self.embeddings(inputs)
        return embeds
```

Freezing Embedding Layers in PyTorch


```
import torch
import torch.nn as nn

class EmbeddingLayer(nn.Module):
    def __init__(self, vocab_size, embedding_dim, weights_matrix, freeze=False):
        super(EmbeddingLayer, self).__init__()
        self.embeddings = nn.Embedding(vocab_size, embedding_dim)

        self.embeddings.load_state_dict({'weight': weights_matrix})


        if freeze:
            self.embeddings.weight.requires_grad = False


    def forward(self, inputs):
        embeds = self.embeddings(inputs)
        return embeds
```

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  - a model trained on texts only might easily misled by this

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  - 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

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- 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

Thank You!