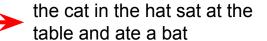
Recurrent Neural Networks III

Dr. Parlett-Pelleriti

Text Processing

Standardization

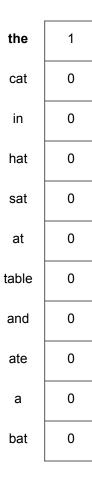
The cat in the hat sat at the table and ate a bat.



The cat in the hat sat at the table and ate a bat.

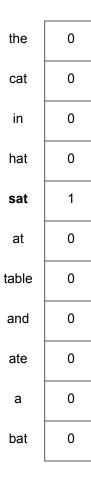
the cat in the hat sat at the table and ate a bat





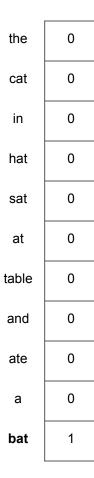
the cat in the hat sat at the table and ate a bat





the cat in the hat sat at the table and ate a bat





the cat in the hat sat at the table and ate a bat



Out of Vocab Token

the cat in the hat sat at the table and ate a **platypus**

Out of Vocab Token

the cat in the hat set the table and ate a platypus

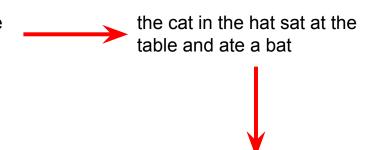
the 0 cat 0 0 in 0 hat 0 sat 0 at table 0 and 0 ate 0 0 а bat 0

the cat in the hat sat at the table and ate a **platypus**

the 0 cat 0 0 in 0 hat 0 sat 0 at table 0 and 0 ate 0 0 а bat 0 [UNK]

the cat in the hat sat at the table and ate a **platypus**

The cat in the hat sat at the table and ate a bat.



[1,0,0,0,0,0,0,0,0,0,0,0] [0,1,0,0,0,0,0,0,0,0,0] [0,0,1,0,0,0,0,0,0,0,0]

... [0,0,0,0,0,0,0,0,0,0,0,1]

Miscellaneous Text Processing

Stems

I was sitting on the bench and I thought that it was a nice place to sit and think about life.

I was [sit] on the bench and I [think] that it was a nice place to [sit] and [think] about life.

Bag-Of-Words

The cat in the hat sat at the table and ate a bat



Set vs. Sequence

The cat in the hat sat at the table and ate a bat

Sequence



```
['i', 'i was', 'was', 'was sitting', 'sitting', 'sitting on', 'on', 'on the', 'the', 'the bench', 'bench', 'bench and', 'and', 'and i', 'i', 'i thought', 'thought', 'thought', 'that', 'that it', 'it', 'it was', 'was', 'was a', 'a', 'a nice', 'nice', 'nice place', 'place', 'place to', 'to', 'to sit', 'sit', 'sit and', 'and', 'and think', 'think', 'think about', 'about' life']
```

TF-IDF

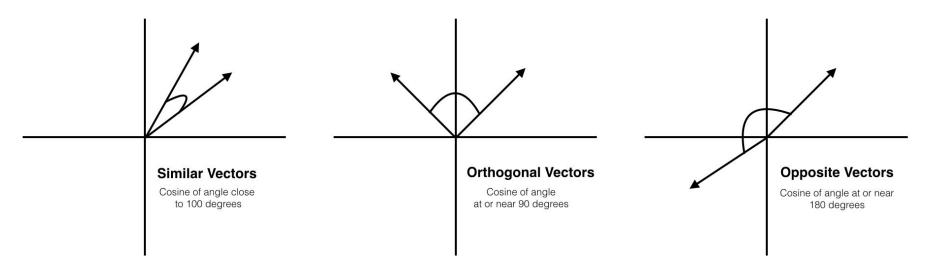
term frequency, inverse document frequency

$$tf = \frac{\text{frequency of word}}{\text{\# of words in document}}$$

$$idf = \frac{\text{\# of Documents}}{\text{\# of Documents that contain word}}$$

$$tfidf = tf * idf$$

Cosine Similarity of Word Counts



$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$

Image from: https://deepai.org/machine-learning-glossary-and-terms/cosine-similarity

Word Embeddings

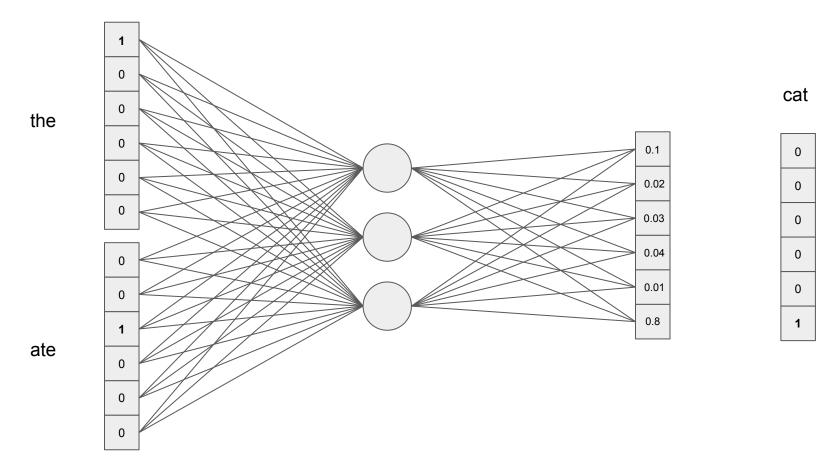
Embeddings

$\lceil 0.1 \rceil$		[0.2]
0.2		0.4
0.4		0.5
0.2		0.9
0.6		0.3
aoraeous	·	pvthon

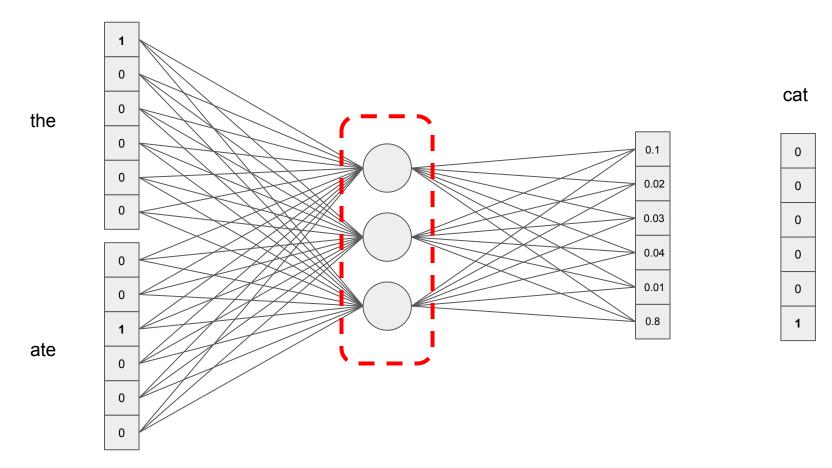
Word2Vec NN

- **Problem**: Fill in the Blank
- Use context to learn words' meanings
- Side Effect: Word Embeddings!

The cat ate



The cat ate



CBOW vs. Skip Gram

- Continuous Bag of Words: Predict target word from context words
- Skip Gram: Predict context words from target word

the The cat ate 0.4 0.2 0 0.05 0 0.05 0 0 0.2 0 0 0.1 0 0 cat 0 0.1 0 0 0.1 0 0.5 0.1 0 0.1 0 0.1 0

ate

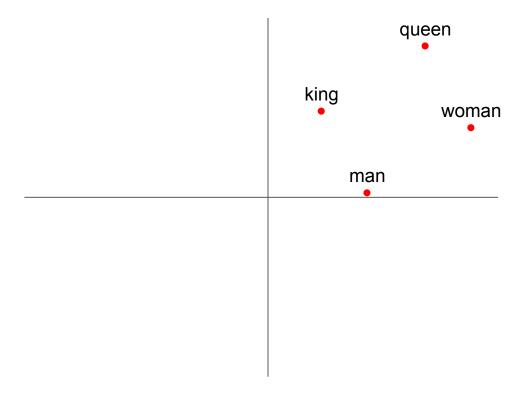
Word Embedding Example

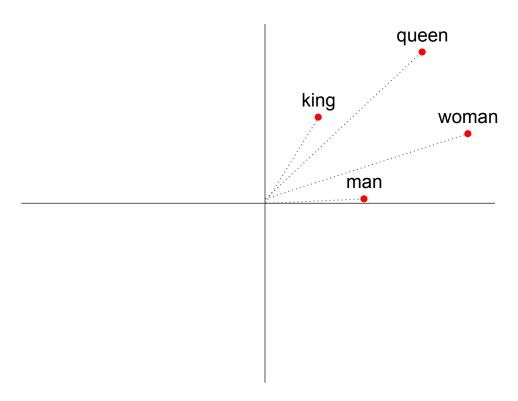
This is a word embedding for the word "king" (GloVe vector trained on Wikipedia):

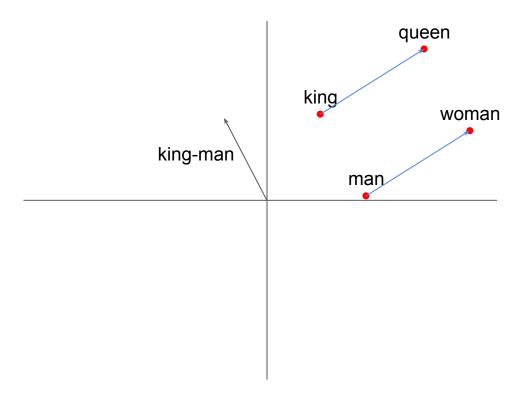
```
[ 0.50451 , 0.68607 , -0.59517 , -0.022801, 0.60046 , -0.13498 , -0.08813 , 0.47377 , -0.61798 , -0.31012 , -0.076666, 1.493 , -0.034189, -0.98173 , 0.68229 , 0.81722 , -0.51874 , -0.31503 , -0.55809 , 0.66421 , 0.1961 , -0.13495 , -0.11476 , -0.30344 , 0.41177 , -2.223 , -1.0756 , -1.0783 , -0.34354 , 0.33505 , 1.9927 , -0.04234 , -0.64319 , 0.71125 , 0.49159 , 0.16754 , 0.34344 , -0.25663 , -0.8523 , 0.1661 , 0.40102 , 1.1685 , -1.0137 , -0.21585 , -0.15155 , 0.78321 , -0.91241 , -1.6106 , -0.64426 , -0.51042 ]
```

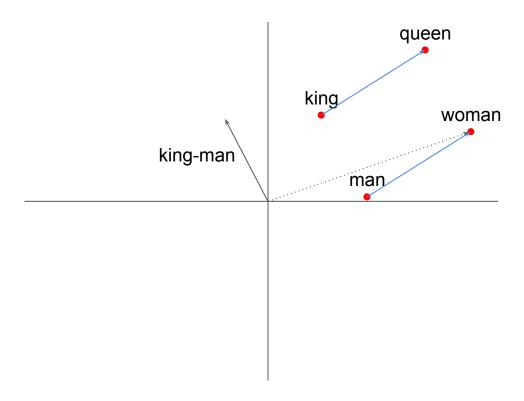
Word Embedding Example

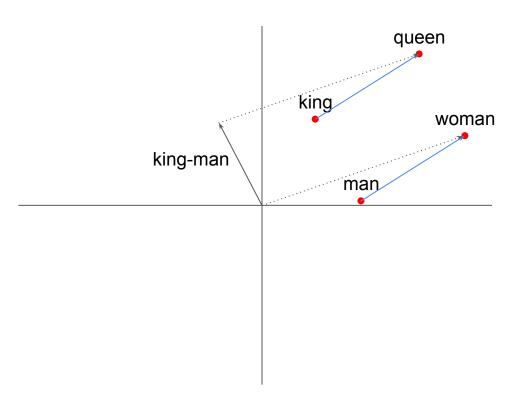
We need high dimensional embeddings so we have more set of the state o flexibility for words to be similar in different dimensions

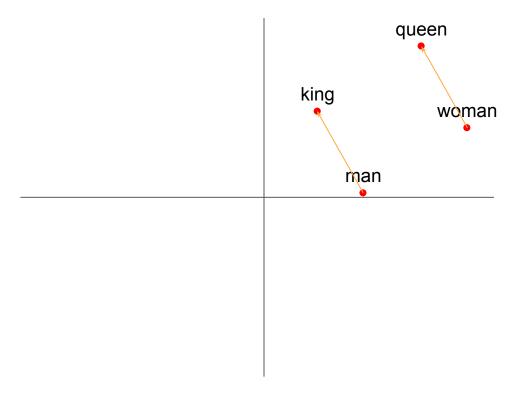


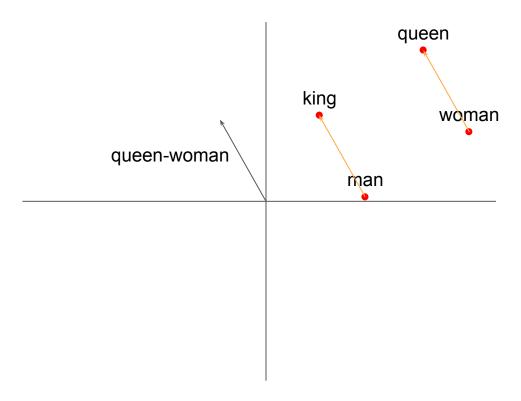


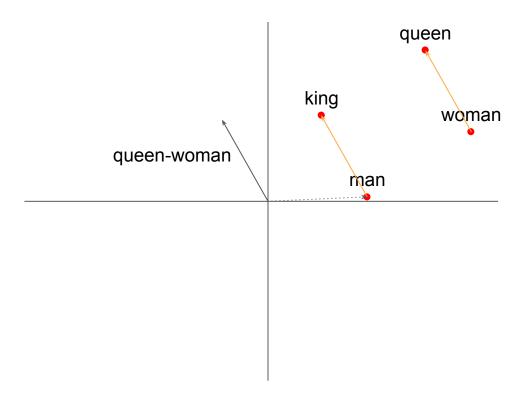


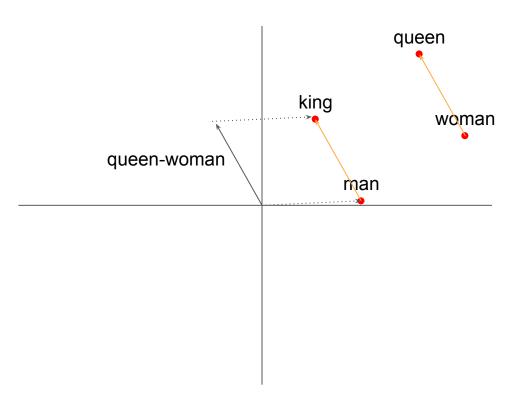


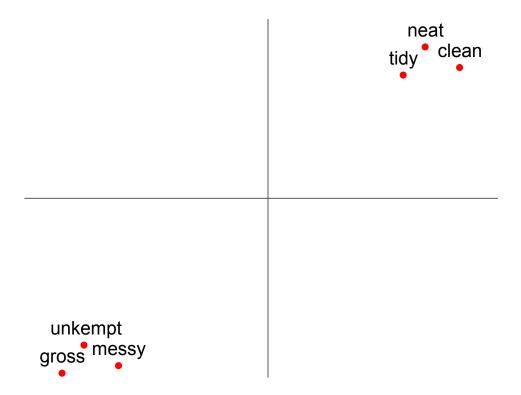












Other Word Embeddings

- Word2vec
- GloVe
- Train your own during GD

Transformer Models You Might Know

- BERT
- GPT
- Language Translations