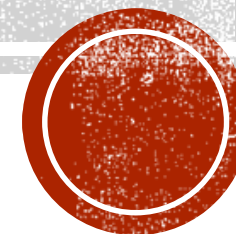




# NATURAL LANGUAGE PROCESSING WITH DEEP LEARNING

Dr.Minaei, IUST, Fall 2020

Presenting by Sara Rajaei



Most materials of this mini-course are provided by “Natural Language Processing with Deep Learning” course, Stanford, Winter 2020 and “Natural Language Processing” course, Mohammad Taher Pilehvar, IUST, Fall 2019

# IN THIS MINI-COURSE

- A big picture understanding of human languages
- An introduction to different tasks in NLP
- Advanced methods used in NLP: Recurrent Neural Networks, LSTMs, Attention mechanism, Transformers, etc.



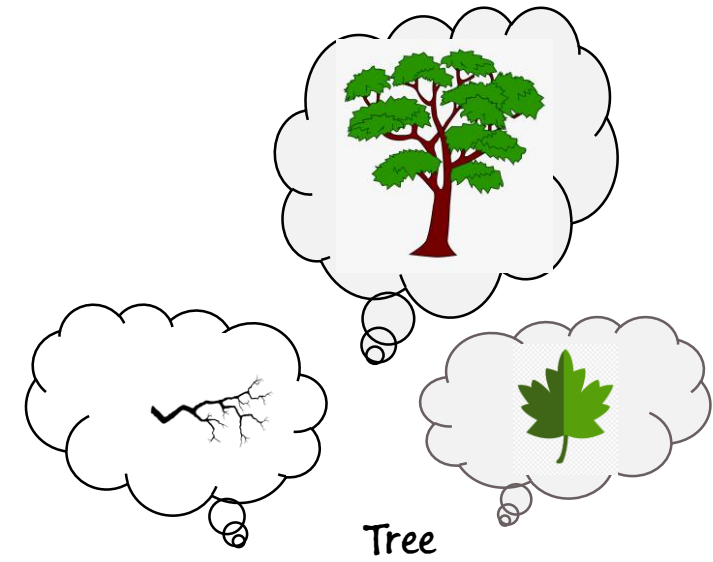
# PRESUMPTION

- You should be familiar with Python and Numpy. If you have a lot of programming experience but in a different language(e.g. C, C++, Matlab), you'll have an easy way to learn python.
- You should be comfortable with taking (multivariable) derivatives and understanding matrix/vector notation and operations.



# HUMAN LANGUAGE

- Word as a symbol



# HUMAN LANGUAGE

- Word as a symbol
- Why understanding of human languages are so hard for machine?
  - Ambiguity!  
A word's meaning depends on its context.
  - External Knowledge



Bank



# DIFFERENT TASKS IN NLP

- Downstream tasks are problems designed by experts to evaluate a model on different linguistic features
- Consider an NLP model as a black box(we'll explain a model in the next session)
- We want to train a model that can answer to the problems(Downstream tasks)



# DIFFERENT TASKS IN NLP

- Part-of-speech tagging
- Dependency parsing
- Semantic role labeling
- Sentiment analysis / opinion mining
- Word sense disambiguation/induction
- Named-entity recognition/classification
- Co-reference resolution
- Summarizing
- Textual entailment
- Question answering
- Machine translation
- ❖ Language Model
- ❖ Masked Language Model



# DIFFERENT TASKS IN NLP

- Part-of-speech tagging
- Dependency parsing
- Word sense disambiguation/induction
- Machine translation
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- Sentiment analysis / opinion mining
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```
1 sen = sp("I like to play football. I hated it in my childhood though")
2 tmp = ''
3 for j in range(len(sen)):
4     tmp = tmp + ' ' + sen[j].pos_
5 print(tmp)
```

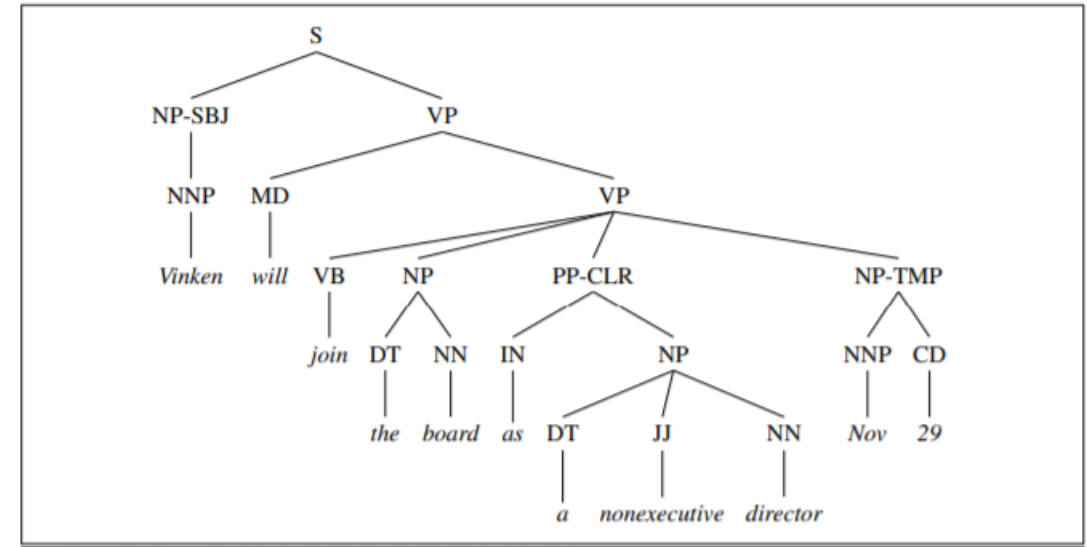
PRON VERB PART VERB NOUN PUNCT PRON VERB PRON ADP DET NOUN ADV





# DIFFERENT TASKS IN NLP

- Part-of-speech tagging
- **Dependency parsing**
- Word sense disambiguation/induction
- Machine translation
- Semantic role labeling
- Sentiment analysis / opinion mining
- Named-entity recognition/classification
- Co-reference resolution
- Textual entailment
- Question answering
- ❖ Language Model
- ❖ Masked Language Model



# DIFFERENT TASKS IN NLP

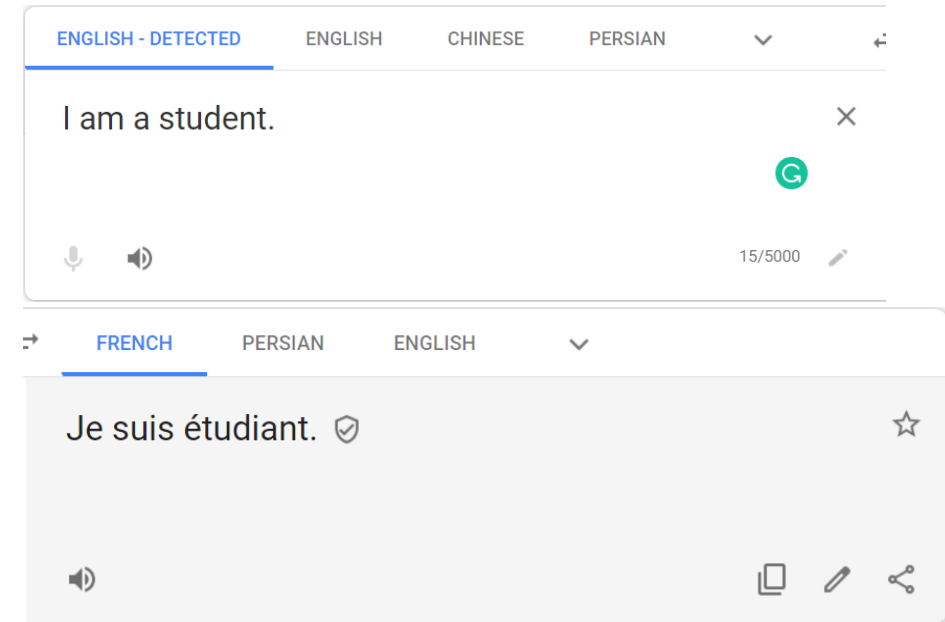
- Part-of-speech tagging
- Dependency parsing
- Word sense disambiguation
- Machine translation
- Semantic role labeling
- Sentiment analysis / opinion mining
- Named-entity recognition/classification
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The car hit the pole while it was moving



# DIFFERENT TASKS IN NLP

- Part-of-speech tagging
- Dependency parsing
- Word sense disambiguation
- **Machine translation**
- Semantic role labeling
- Sentiment analysis / opinion mining
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# DIFFERENT TASKS IN NLP

- Part-of-speech tagging
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Allen NLP demo



# REPRESENTING WORDS AS VECTORS

- Neural networks and deep models accept numbers(tensors) as inputs, So we need to convert raw texts to vectors.
- Text Segmentation
  - Word-level

Segment text into words, and transform each word into a vector.
  - Character-level

Segment text into characters, and transform each character into a vector.
  - SubWord-level

Segment text into subwords, and transform each subword into a vector.



# TOKENIZATION

Tokenization is a way of separating a piece of text into smaller units called tokens. Here, tokens can be either words, characters, or subwords.

- **Words**

- In English, you can consider space as a delimiter.

**The biggest box**

**“the”, “biggest”, “box”**

- **Characters**

**T-h-e-b-i-g-g-e-s-t-b-o-x**

- **Subwords**

**“the”, “big”, “est”, “box”**



# ONE-HOT ENCODING

Representing each token with an unique index, and then turning this index to a vector of size N.

- Advantages
  - Simple
- Disadvantages
  - Inefficient in using memory.
  - Do not reflect the words' meanings
  - ...

The biggest box

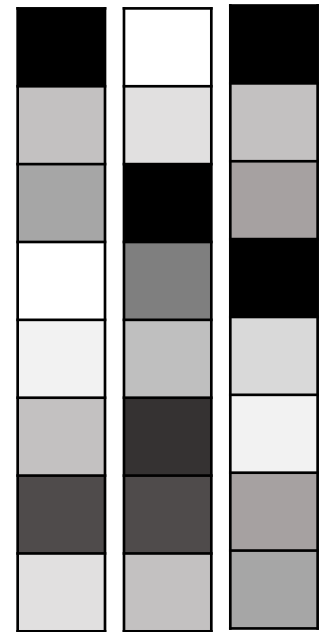
|         | 1 | 2 | 3 |
|---------|---|---|---|
| The     | 1 | 0 | 0 |
| biggest | 0 | 1 | 0 |
| box     | 0 | 0 | 1 |



# WORD EMBEDDING

Representing each token with a low dimensional vector which has useful traits

- Embed more information in lower dimensions
- Can jointly be learned with the target task. In this approach, word embeddings are initialized randomly and learned while neural network's weights are being set.
- Or you can use pre-trained word embeddings as the initial weights of word embeddings.





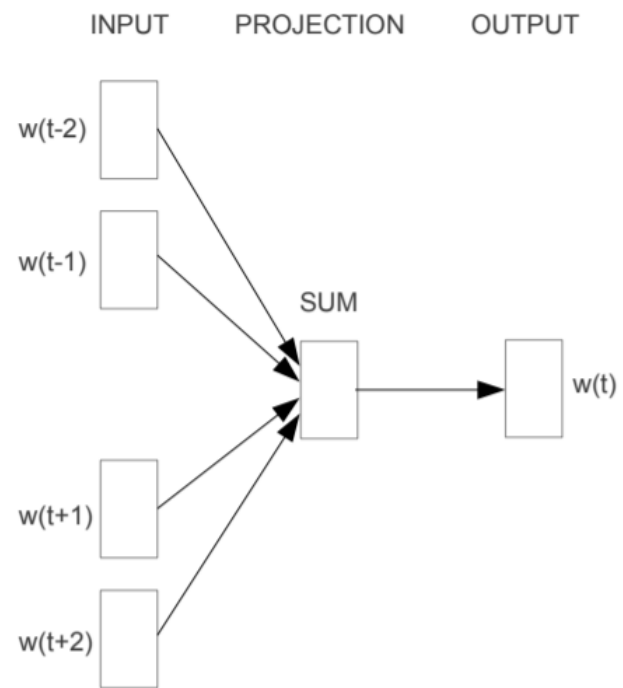
# PRE-TRAINED WORD EMBEDDING

Pre-trained word embeddings are trained on huge datasets with a specific target task and then are used in other tasks.

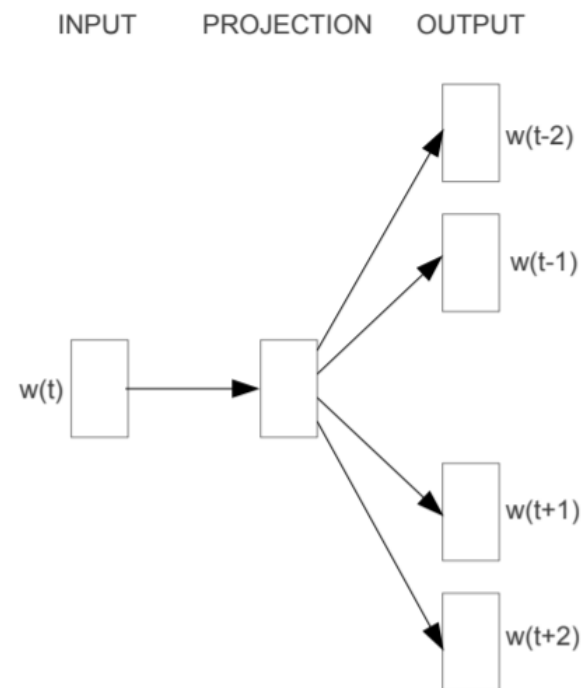
- A form of transfer learning
- Why they are useful?



# PRE-TRAINED WORD EMBEDDING – WORD2VEC



**CBOW**

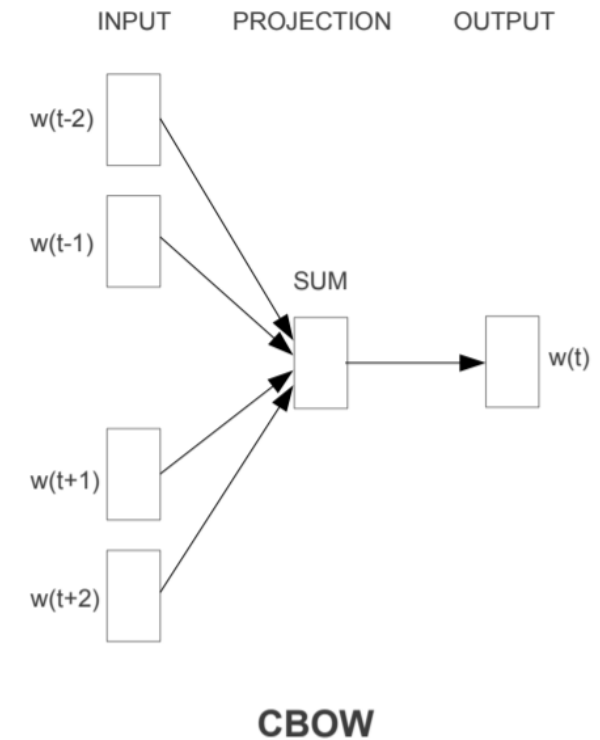


**Skip-gram**



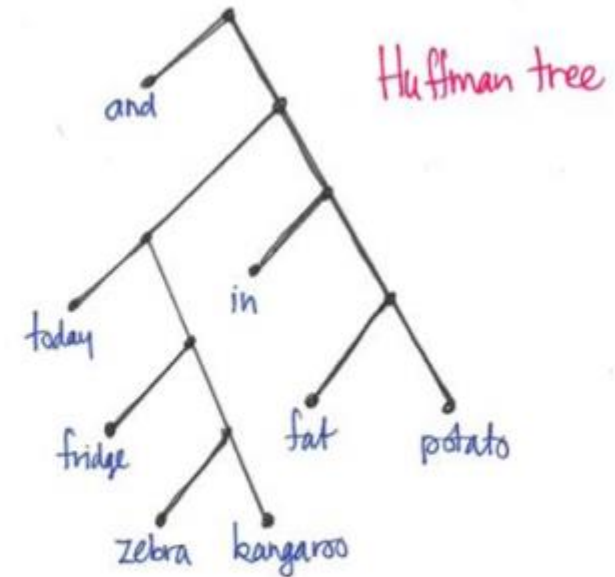
# WORD2VEC – NEGATIVE SAMPLING

- Instead of updating whole neural network's weights, we modify a small percentage of the weights
- In other words, instead of updating whole words in vocabulary, we update a small subset of words.
- These chosen words are called negative words

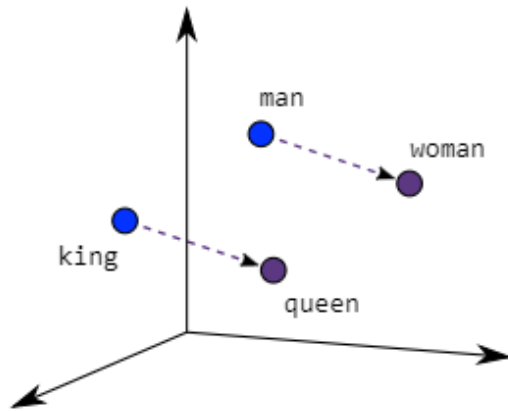


# WORD2VEC – HIERARCHICAL SOFTMAX

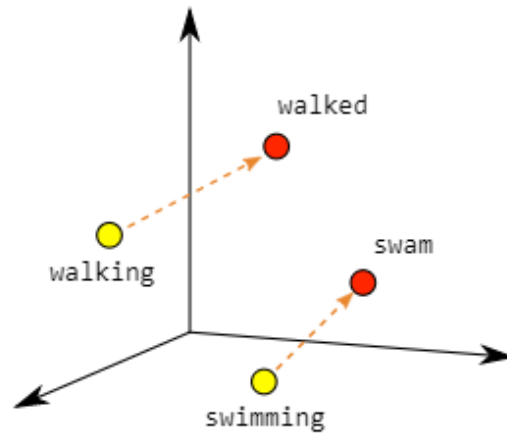
| word     | count |
|----------|-------|
| fat      | 3     |
| fridge   | 2     |
| zebra    | 1     |
| potato   | 3     |
| and      | 14    |
| in       | 7     |
| today    | 4     |
| kangaroo | 2     |



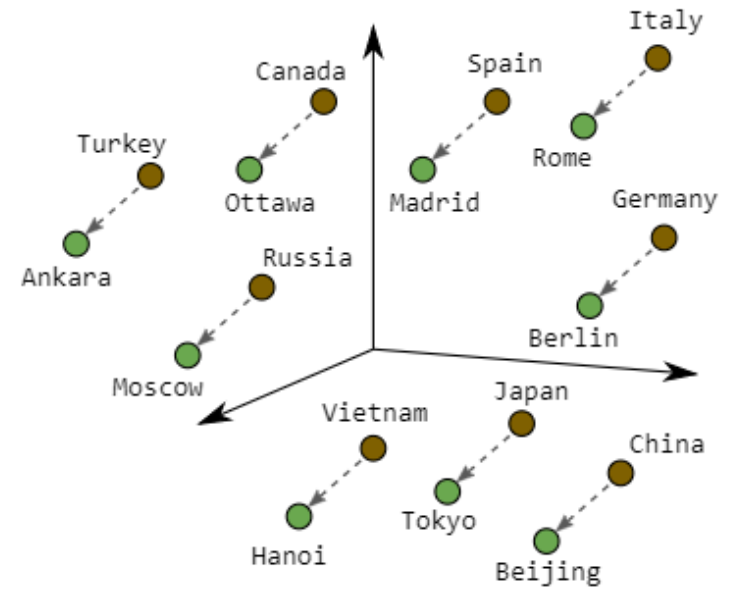
# WORD2VEC FEATURES



Male-Female



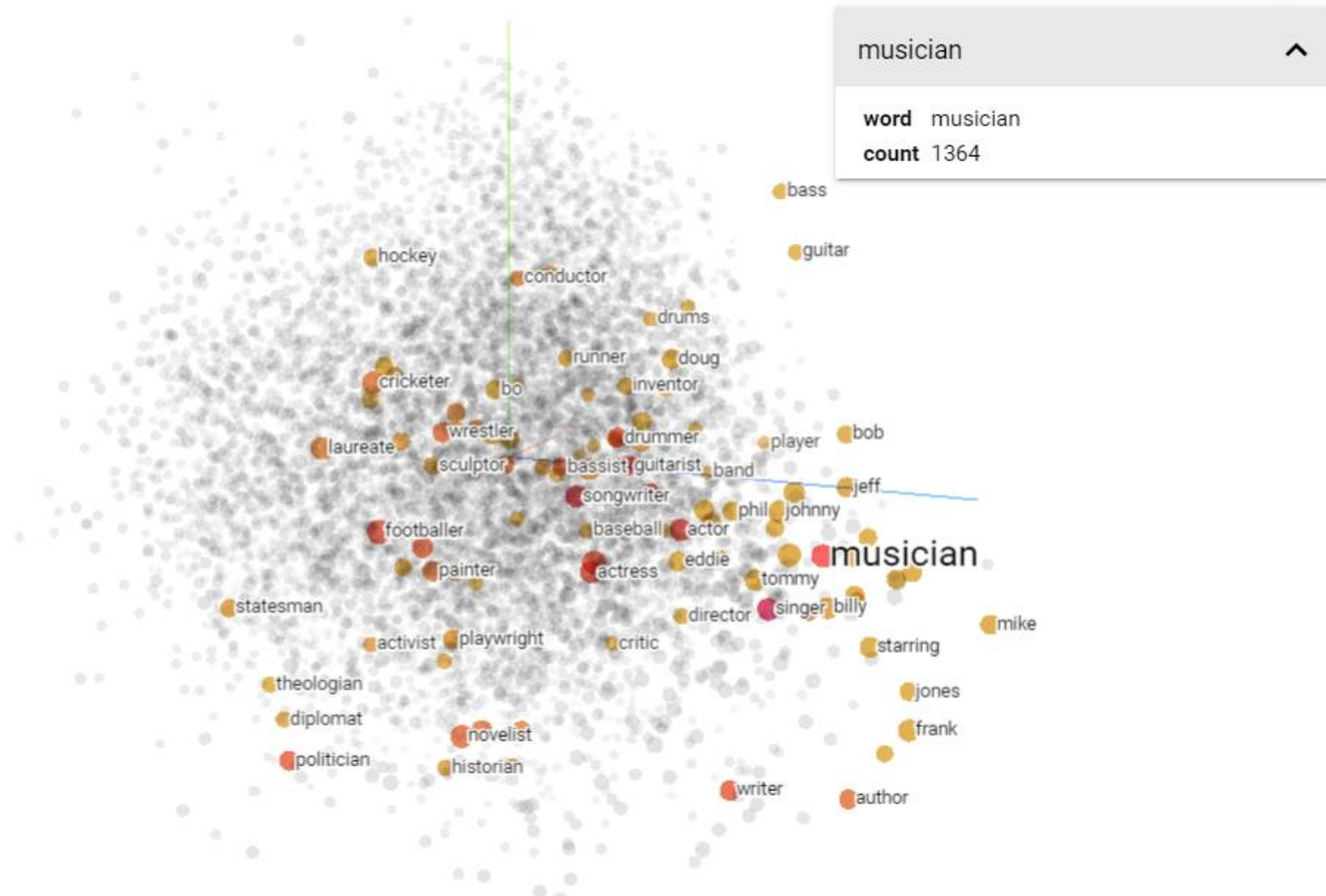
Verb Tense



Country-Capital



# WORD2VEC FEATURES



# PRE-TRAINED WORD EMBEDDING - GLOVE

- Using local information (like Word2Vec) and global information (word co-occurrence)

## The biggest box

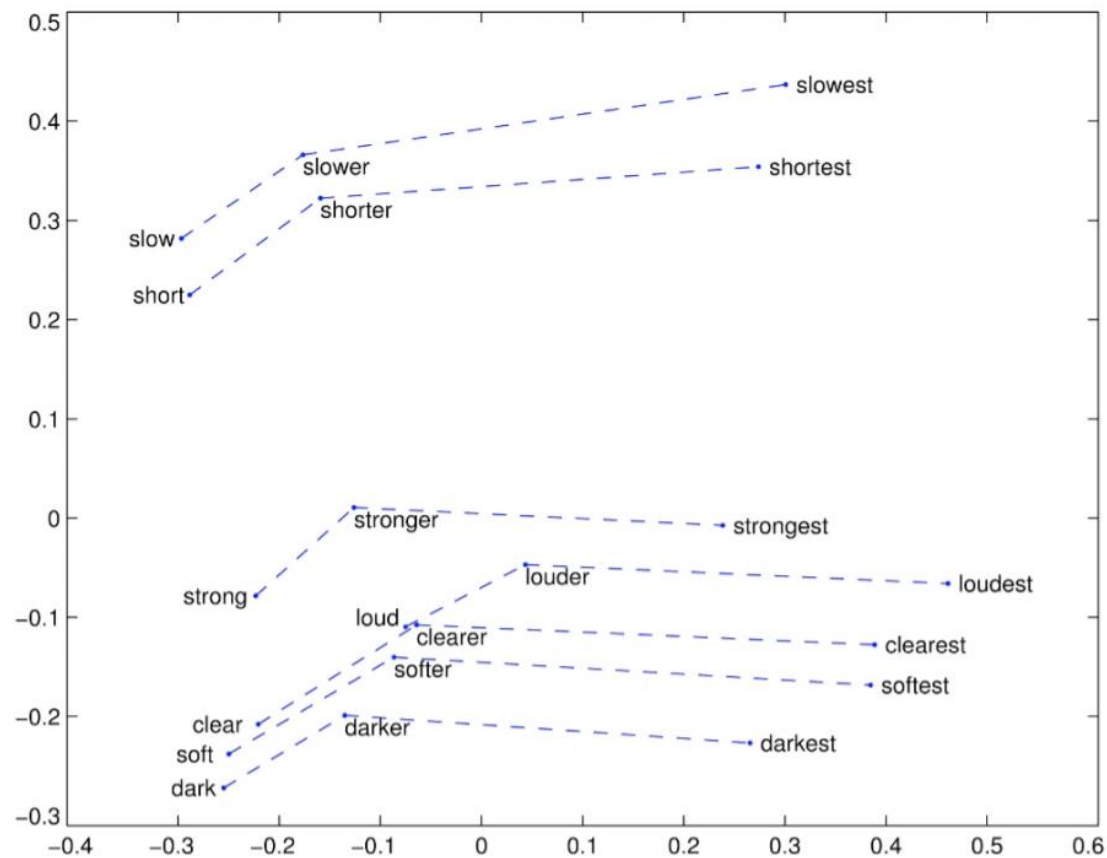
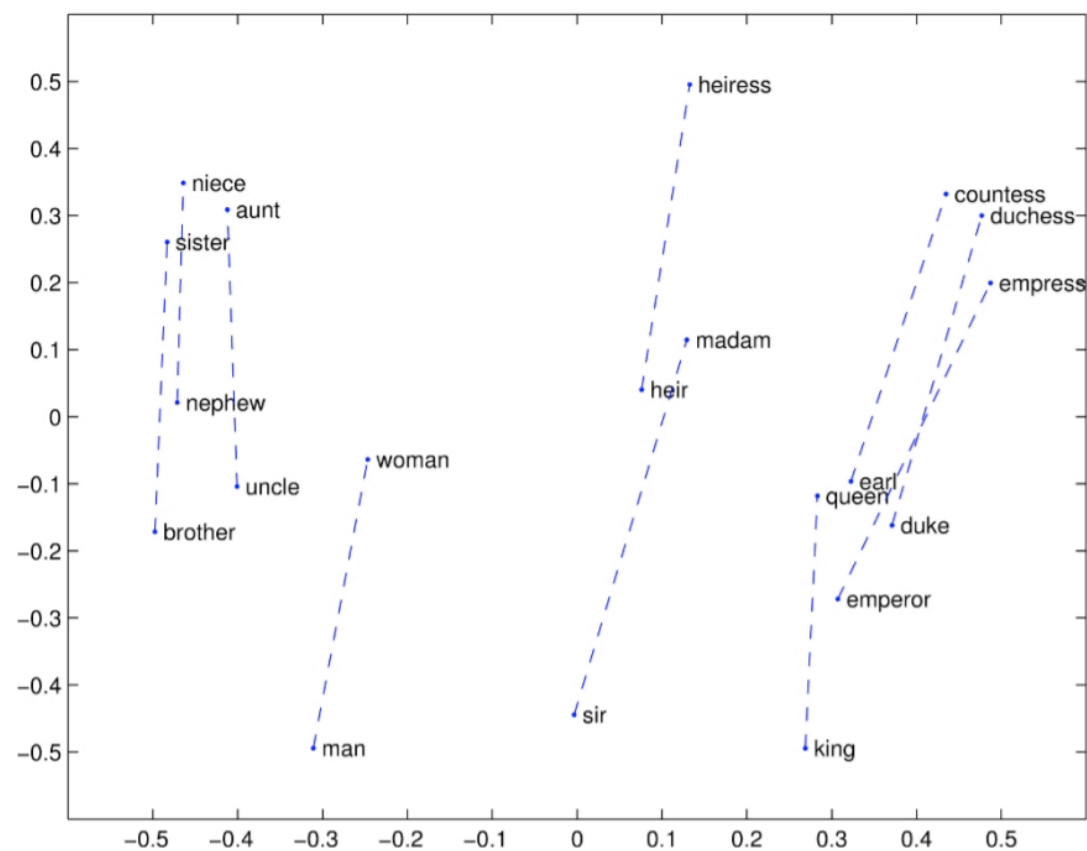
- Is “The” a special context for “box” or it is just a stopword?

Word2Vec cannot answer to this question!

- Glove uses a co-occurrence matrix representing how often word  $i$  appears in context of word  $j$
- Using a cost function which help us to prevent learning only from extremely common word pairs. (stopwords)



# GLOVE





# REFERENCES AND FURTHER RESOURCES

## Websites:

1. <http://nlpprogress.com/>
2. <https://demo.allennlp.org/reading-comprehension>
3. <https://www.analyticsvidhya.com/blog/2020/05/what-is-tokenization-nlp/>
4. <https://towardsdatascience.com/word-embeddings-for-nlp-5b72991e01d4>
5. <https://nlp.stanford.edu/projects/glove/>
6. <https://towardsdatascience.com/light-on-math-ml-intuitive-guide-to-understanding-glove-embeddings-b13b4f19c010>

## Papers and Books:

1. [Efficient Estimation of Word Representations in Vector Space](#)
2. [GloVe: Global Vectors for Word Representation](#)
3. [Embedding in Natural Language Processing](#)
4. [From Frequency to Meaning: Vector Space Models of Semantics](#)

