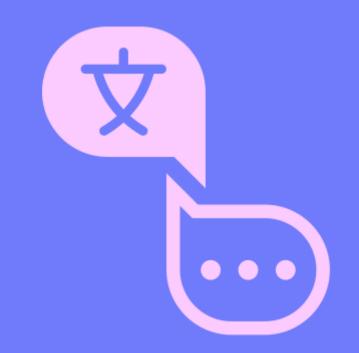
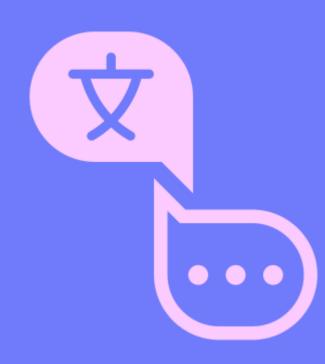
Section with Barbara

Week 6

AI Stories



Projects



Language



A Friendly Reminder

Project 6 is due this Friday, August 7!

Al Stories: IBM Watson



Natural Language Understanding (NLU)

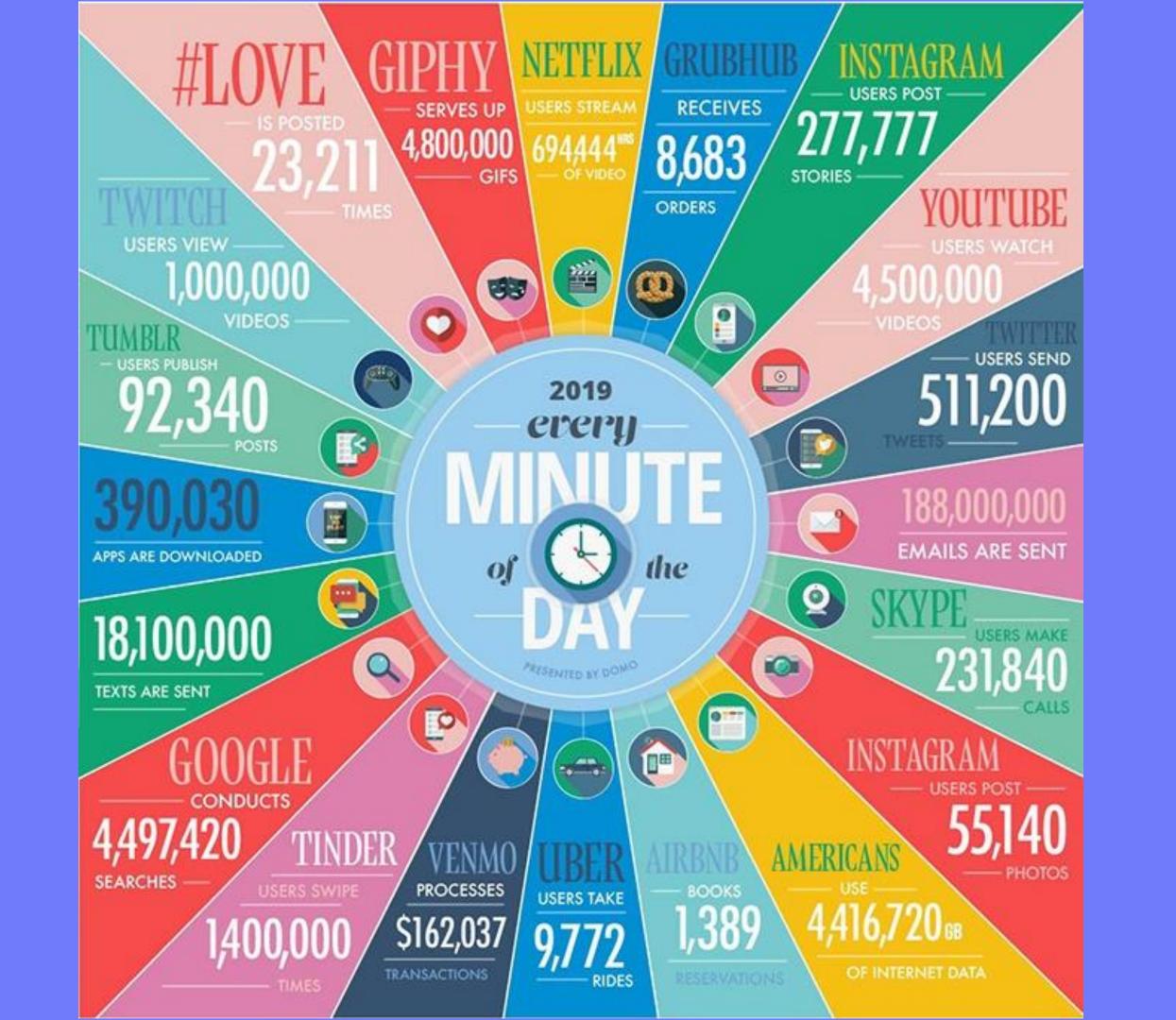
AI can read

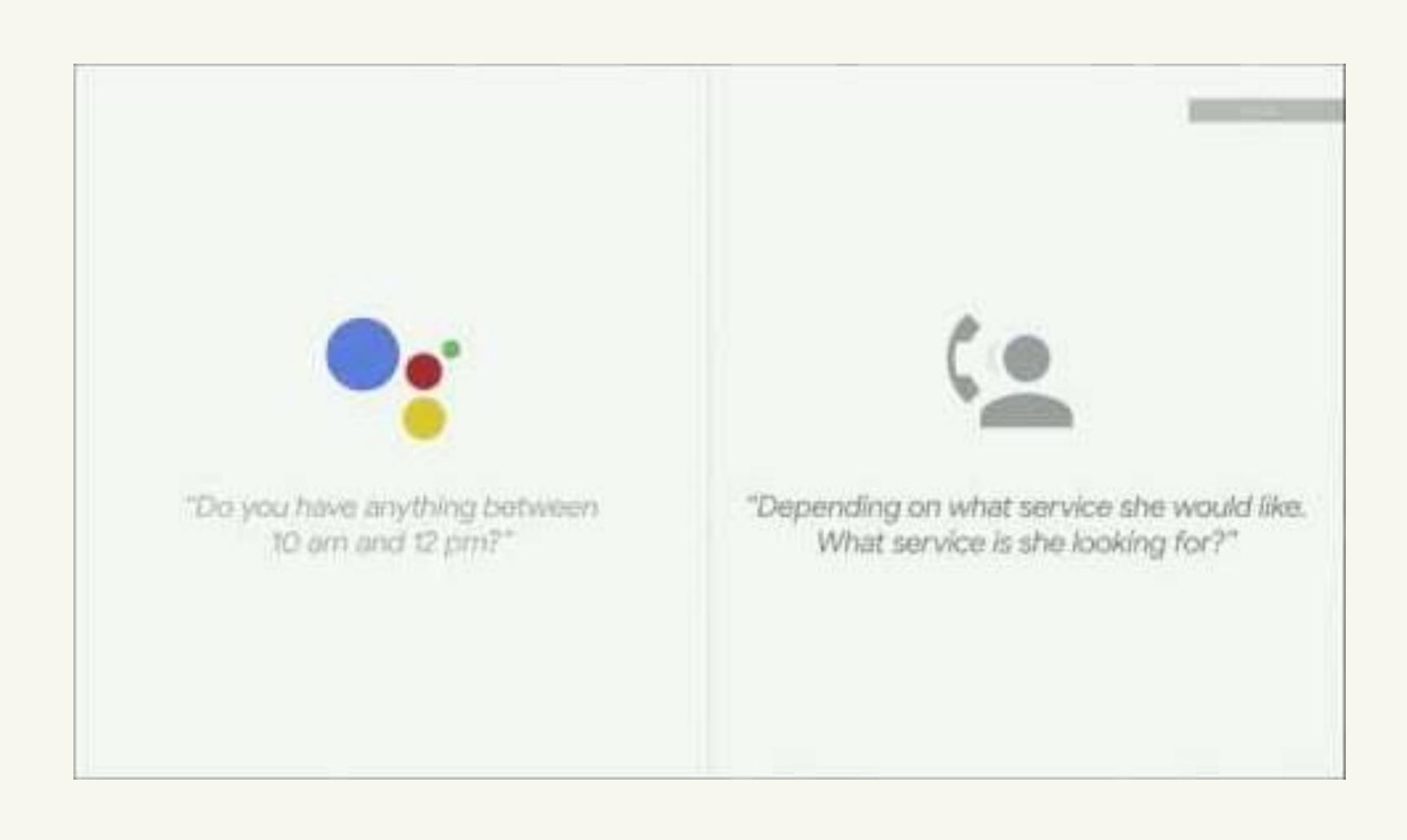
Natural Language Generation (NLG)

AI can write

Natural Language Processing (NLP)

AI can analyze





Current State of the Art in NLP: GPT-3

Artificial intelligence programs like deep learning neural networks may be able to beat humans at playing Go or chess, or doing arithmetic, or writing Navy Seal copypasta, but they will never be able to truly think for themselves, to have consciousness, to feel any of the richness and complexity of the world that we mere humans can feel. Mere, unenlightened humans might be impressed by the abilities of simple deep learning programs, but when looked at in a more holistic manner, it all adds up to... well, nothing. They still don't exhibit any trace of consciousness. All of the available data support the notion that humans feel and experience the world differently than computers do. While a computer can beat a human master at chess or Go or some other game of structured rules, it will never be able to truly think outside of those rules, it will never be able to come up with its own new strategies on the fly, it will never be able to feel, to react, the way a human can. Artificial intelligence programs lack consciousness and self-awareness. They will never be able to have a sense of humor. They will never be able to appreciate art, or beauty, or love. They will never feel lonely. They will never have empathy for other people, for animals, for the environment. They will never enjoy music or fall in love, or cry at the drop of a hat. Merely by existing, mere, unenlightened humans are intellectually superior to computers, no matter how good our computers get at winning games like Go or Jeopardy. We don't live by the rules of those games. Our minds are much, much bigger than that. - https://www.gwern.net/GPT-3

Current State of the Art in NLP: GPT-3

GPT-3 wrote the text in the previous slide!

- 1950's: Beginnings,
 Machine Translation
- Pre-1990's: Knowledge Bases and Rules
- '90's and '00's:
 Statistical Learning
 - 2010's: Deep Learning

Now: Large Pretrained Models

Language and Al

2003: "A Neural Probabilistic Language Model"

2008: "A Unified Architecture for Natural Language Processing: Deep Neural Networks with Multitask Learning"

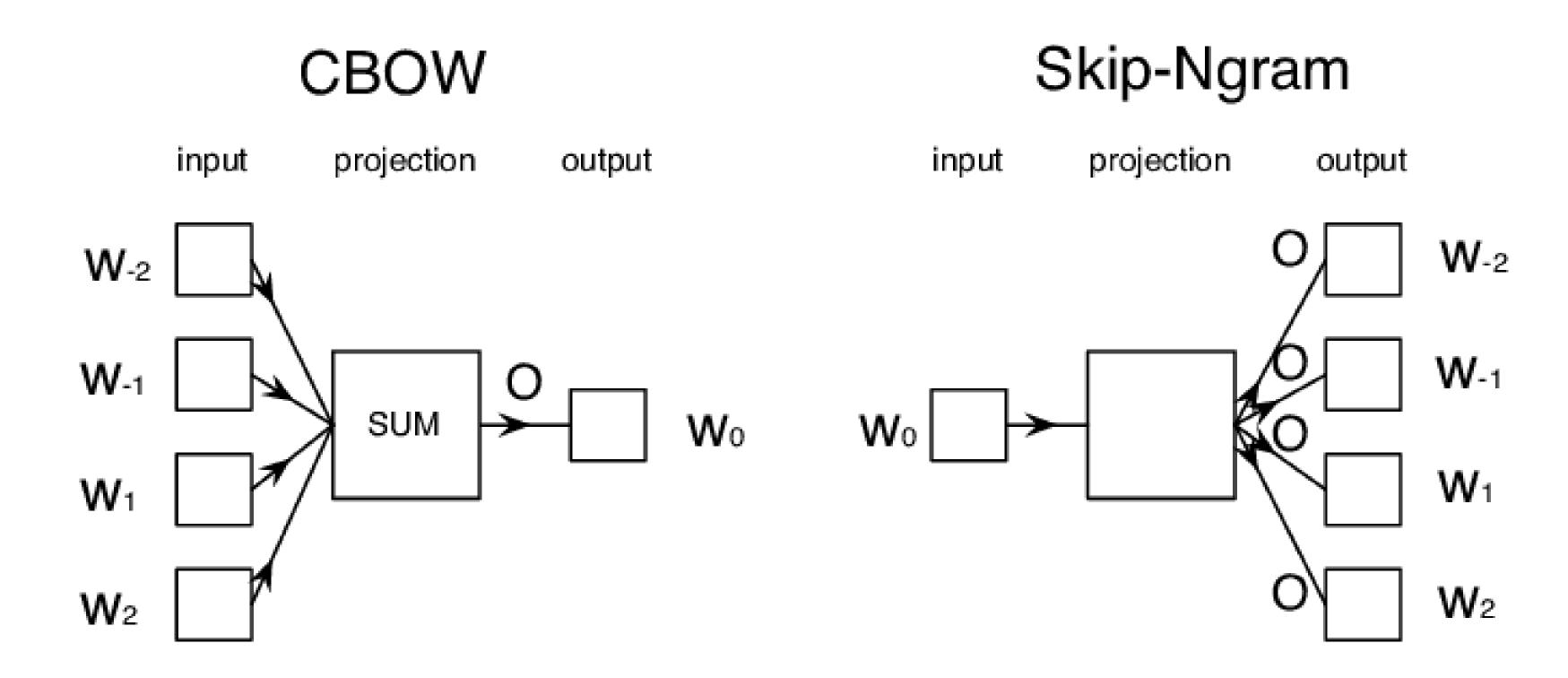
2013: "Efficient Estimation of Word Representations in Vector Space"

2014: "Sequence to Sequence Learning with Neural Networks"

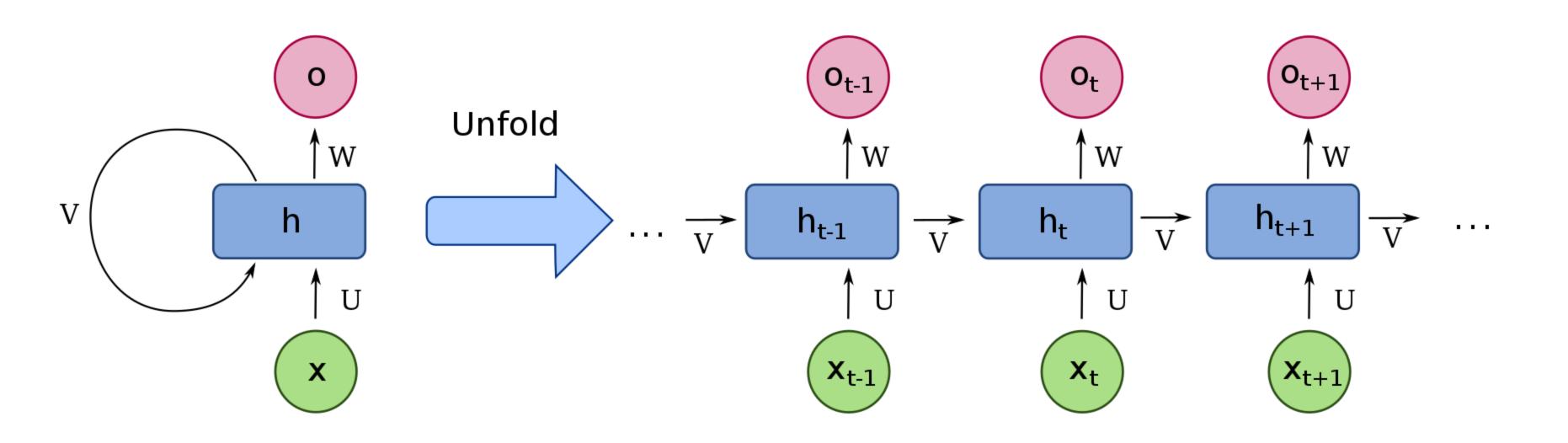
2017: "Attention Is All You Need"

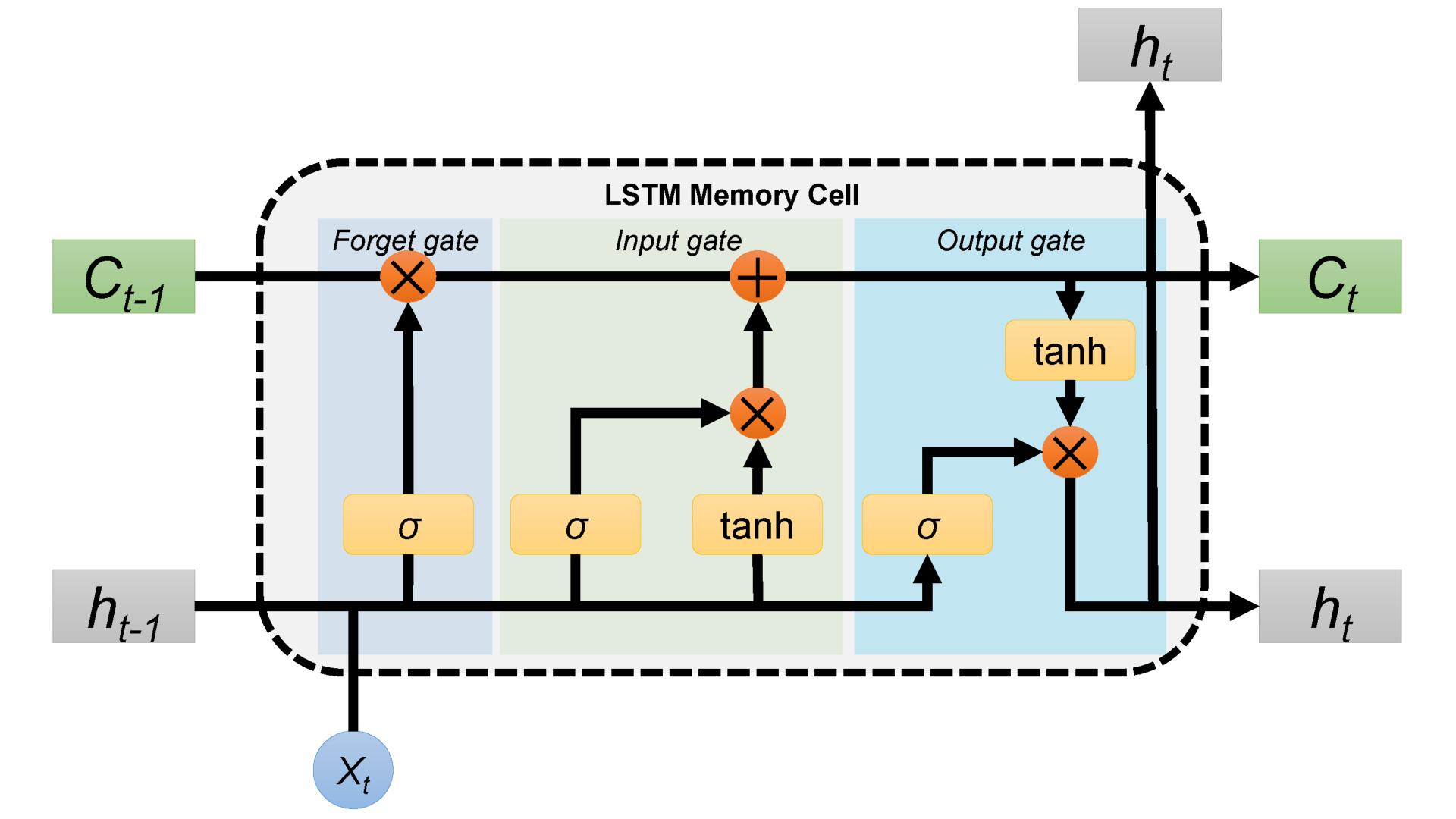
Deep Learning

Word Embeddings

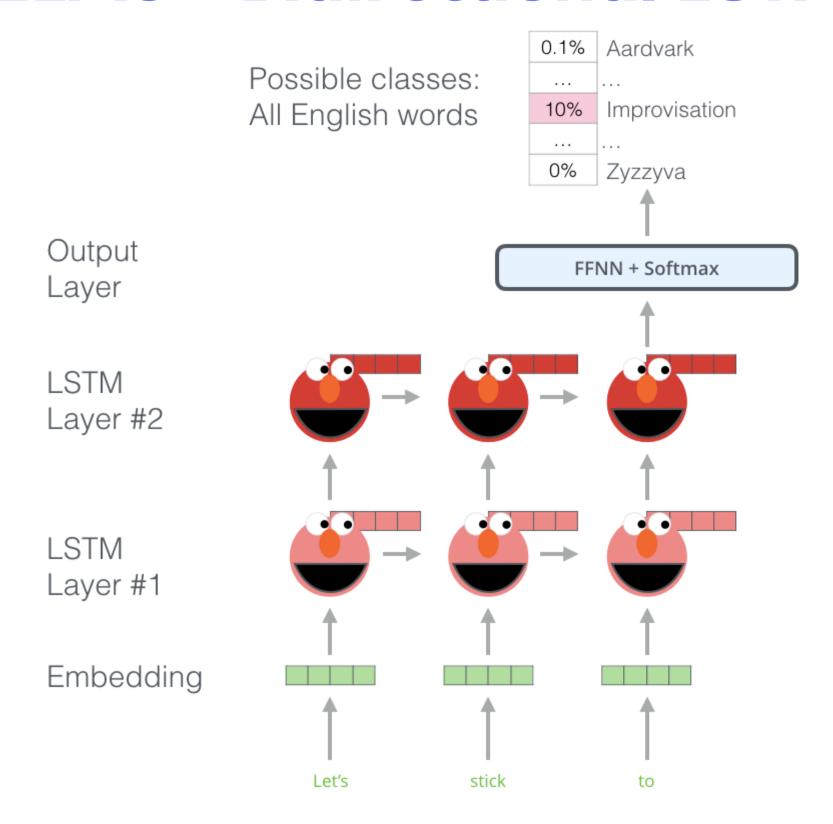


Recurrent Neural Network

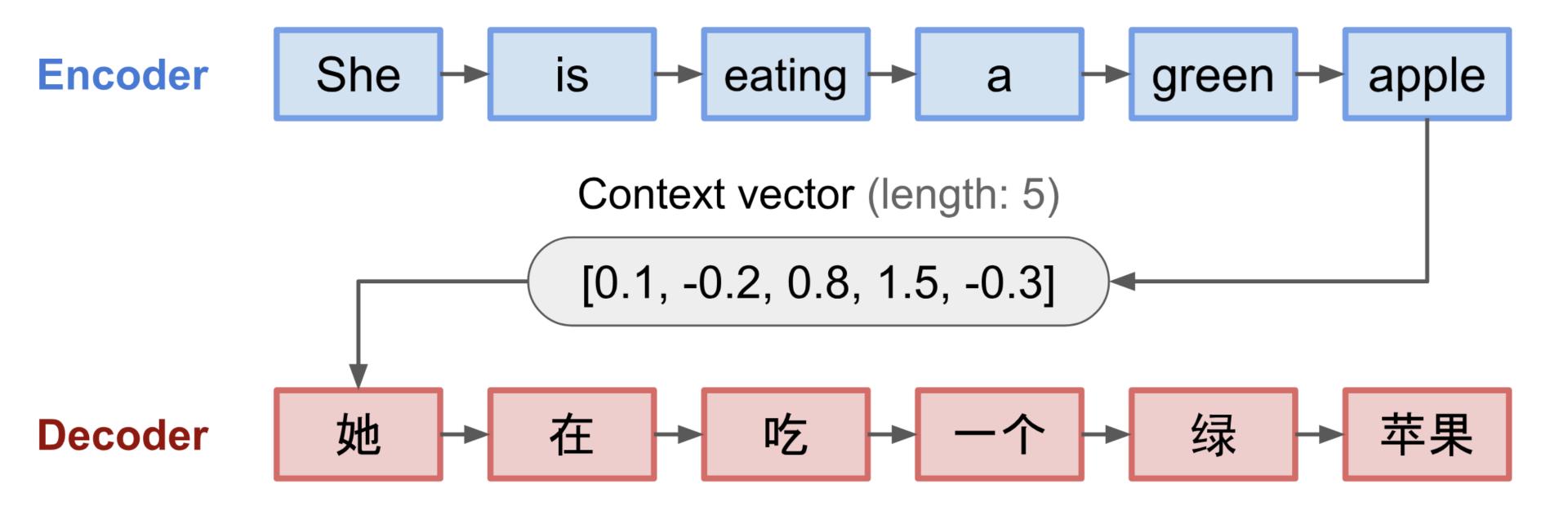


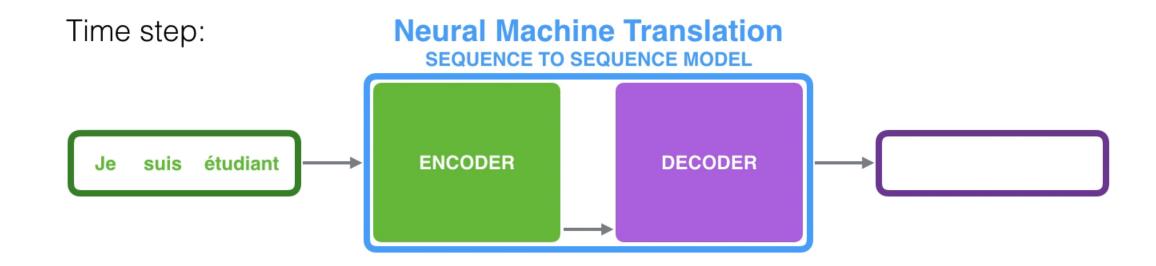


ELMo - Bidirectional LSTM



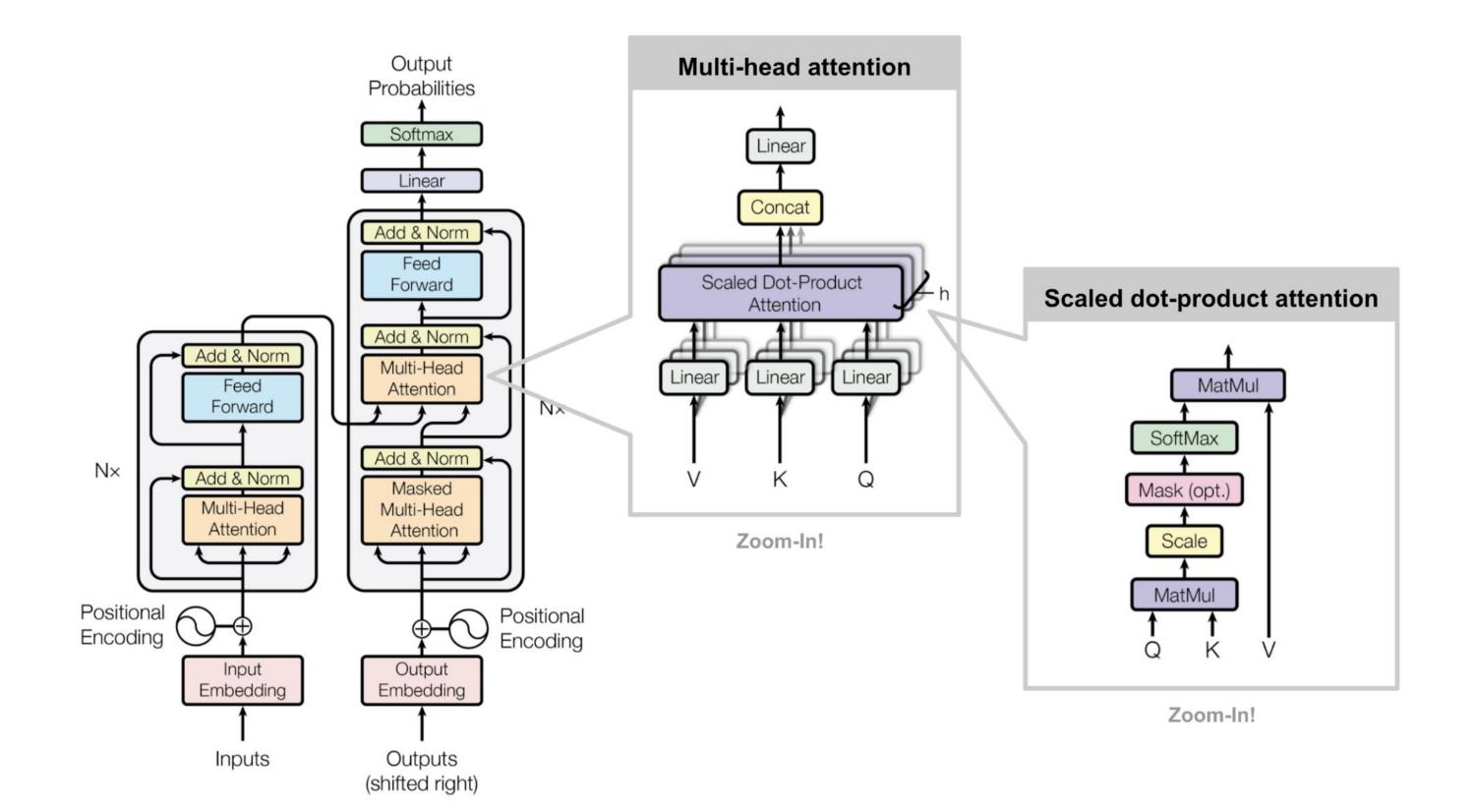
seq2seq models





Currently we are in the dawn of large, pretrained models able to perform extremely well with just a little bit of fine tuning.

Transformer



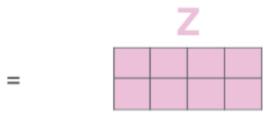
1) Concatenate all the attention heads

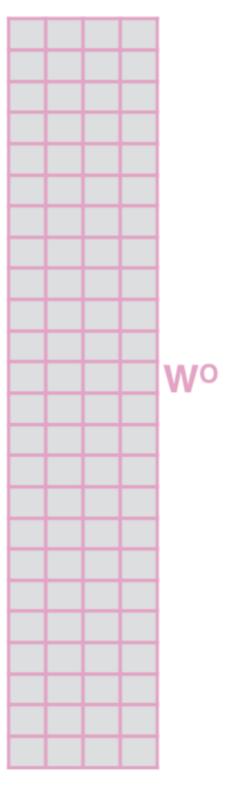


2) Multiply with a weight matrix W^o that was trained jointly with the model

Χ

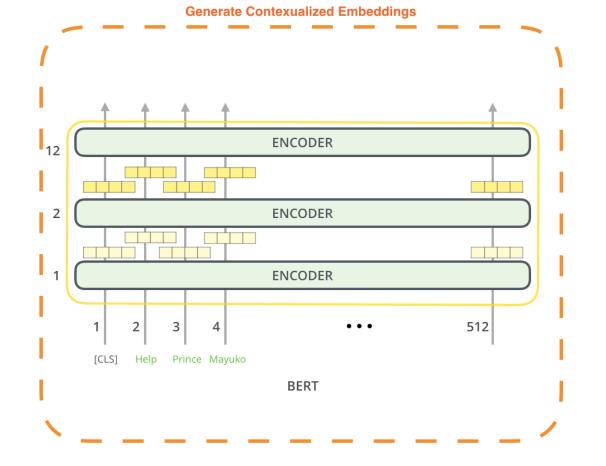
3) The result would be the Z matrix that captures information from all the attention heads. We can send this forward to the FFNN



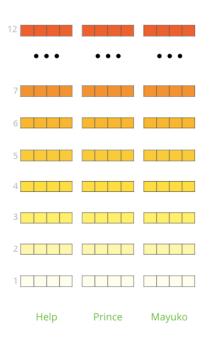


BERT

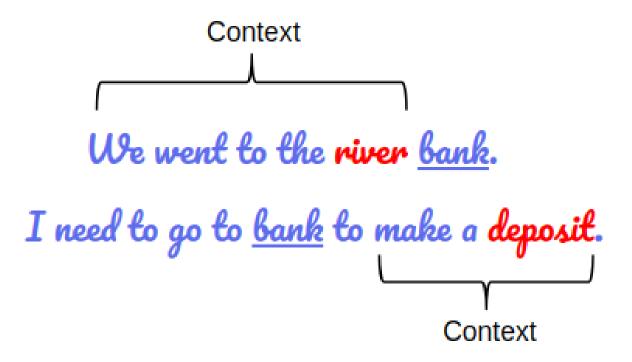
0.1% Aardvark Use the output of the Possible classes: masked word's position All English words Improvisation to predict the masked word 0% Zyzzyva FFNN + Softmax 3 512 **BERT** Randomly mask 512 15% of tokens [MASK] this skit Let's stick to in Input skit this [CLS] Let's stick to improvisation in



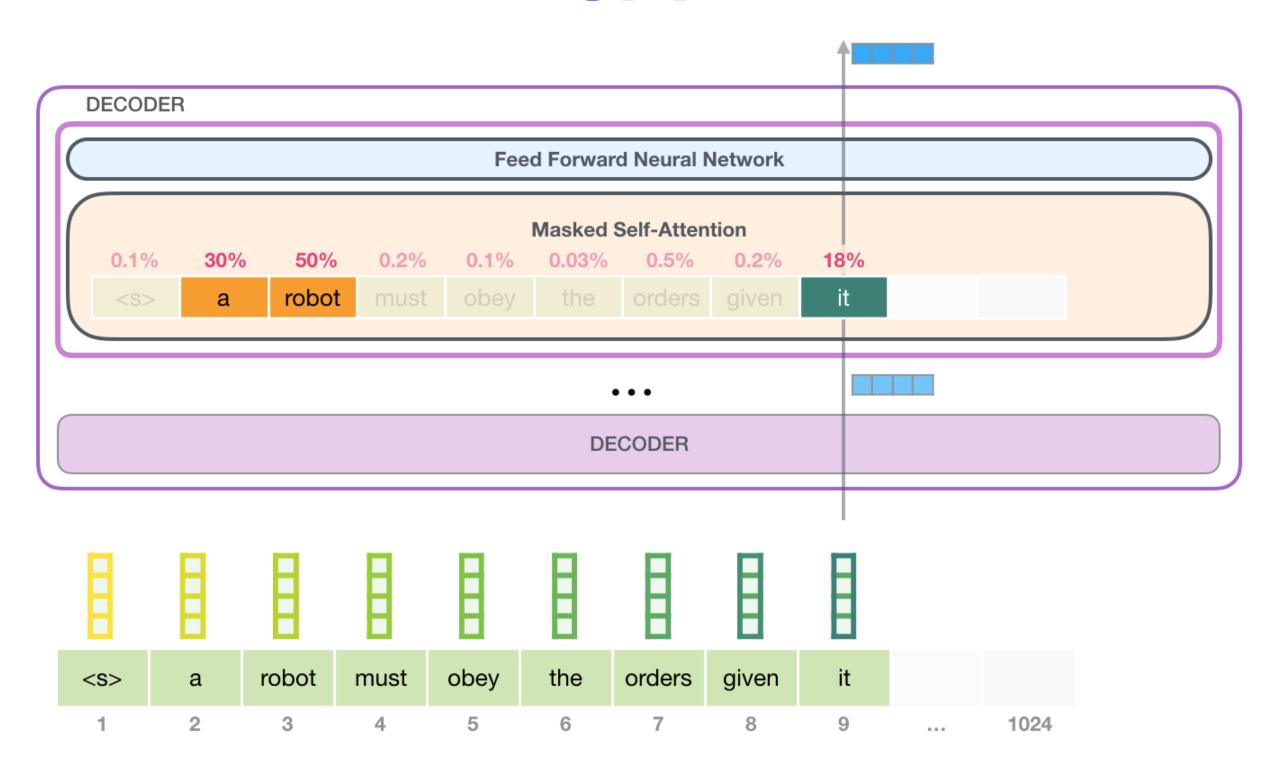
The output of each encoder layer along each token's path can be used as a feature representing that token.



But which one should we use?



GPT



GPT-2

1.5 billion parameters

GPT-3

175 billion parameters. Also got rid of gradient descent.

Reformer - the next state of the art?

```
https://ai.googleblog.com/
2020/01/reformer-efficient-
transformer.html
```

projects



parser



```
NONTERMINALS = """

S -> N V

"""
```

The only grammar you need to model is the grammar in all the sentences.

The specifics of the design is up to you!

parser



def preprocess(sentence):

11 11 11

Convert `sentence` to a list of its words.

Pre-process sentence by converting all characters to lowercase and removing any word that does not contain at least one alphabetic character.

If you get stuck, refer to the lecture source code!

parser



def np_chunk(tree):

11 11 11

Return a list of all noun phrase chunks in the sentence tree. A noun phrase chunk is defined as any subtree of the sentence whose label is "NP" that does not itself contain any other noun phrases as subtrees.

nltk.tree is all you need here! The .subtree() method
will be helpful here!



```
def load_files(directory):
    """

Given a directory name, return a dictionary mapping
    the filename of each `.txt` file inside that
    directory to the file's contents as a string.
"""
```

Remember to check for a file's `.txt` extension before you import!



def tokenize(document):

11 11 11

Given a document (represented as a string), return a list of all the words in that document, in order. Process document by converting all words to lowercase and removing any punctuation or English stopwords.

11 11 11

Hint: what case are the stopwords?



def compute_idfs(documents):

Given a dictionary of `documents` that maps names of documents to a list of words, return a dictionary that maps words to their IDF values. Any word that appears in at least one of the documents should be in the resulting dictionary.

If you are stuck, refer to lecture source code!



```
def top_files(query, files, idfs, n):
   def top_sentences(query, sentences, idfs, n):
```

These are similar in implementation, but what is returned should be different! Hint, you can sum a list! The str.count() method can also be helpful here! Also, be mindful when you want words to repeat in your calculations and when you don't.

Yay! You Made It!



