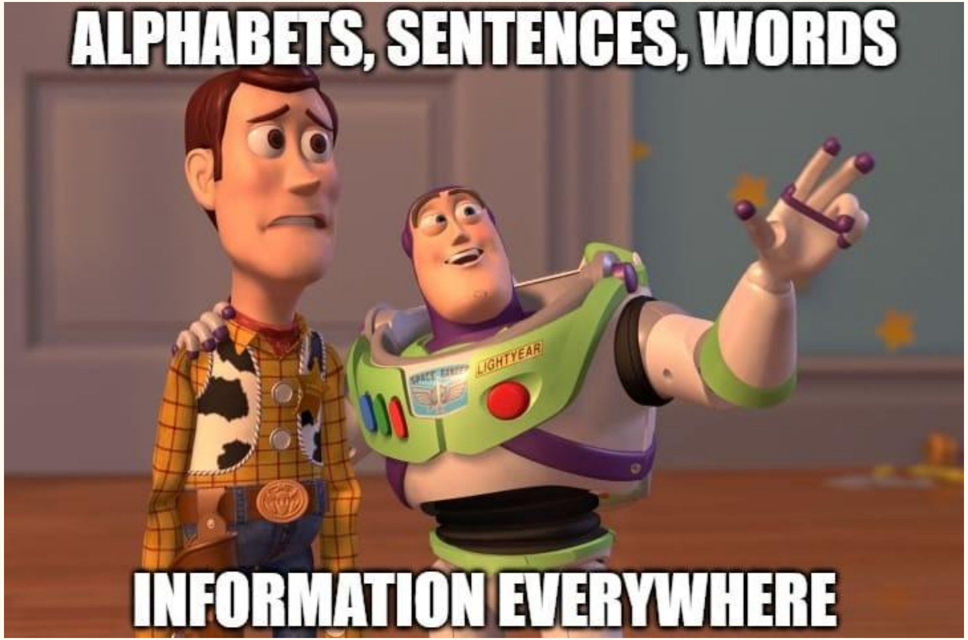
Natural Language Processing

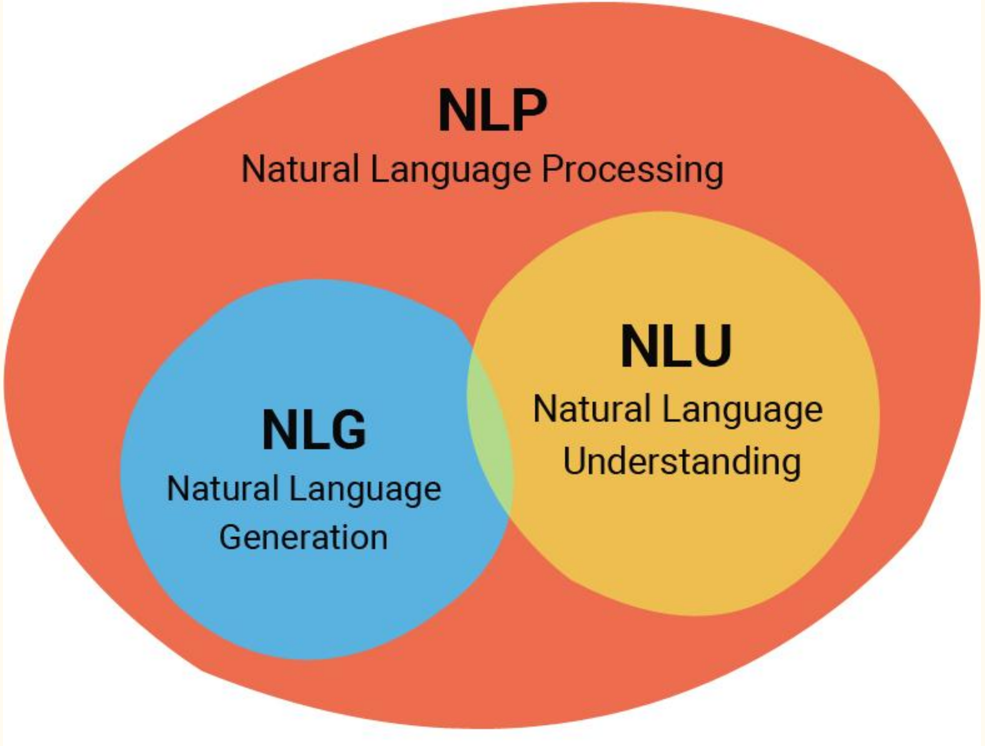
Tinkerers' Lab IITH

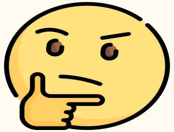
Welcome to the World of Natural Language Processing!



Natural Language Processing

- Subfield of AI, specializing in understanding and generating texts that “makes sense” to humans.
- It has 2 sub categories: Natural Language Understanding (NLU) and Natural Language Generation (NLG)
- Wide range of applications like: Text-to-Speech, Generative Text, Chatbots, Language Translation, etc.



But Why is NLP so important? 

- ★ Smart Assistants such as **Siri**, **Alexa** and **Google Assistant**
- ★ Suggesting **replies/autocorrect** in messaging apps
- ★ **Language translation** from one language to another
- ★ **Spam Filtering**
- ★ Content Summarization: **Inshorts**
- ★ **Voice-to-Text** conversion
- ★ **Chatbots**
- ★ ….. and many more!!

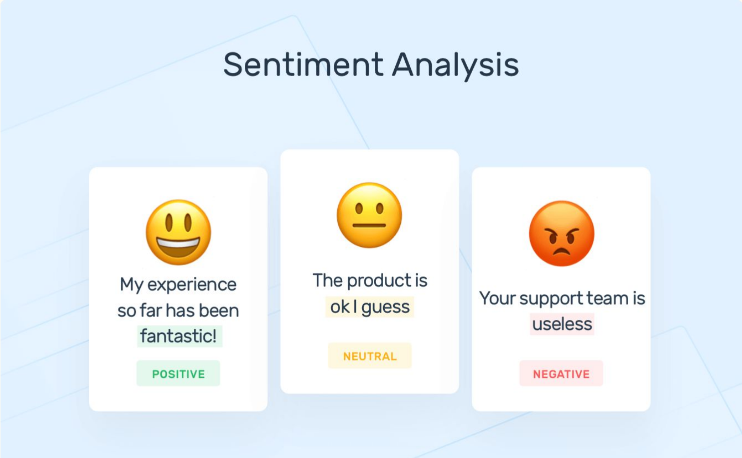
Some NLP related Tools to Play With

- Typeset.io is an AI chatbot/summarizer for scientific Papers which can be used to summarize a research paper and can also be used to ask questions related to that research paper.
- MonkeyLearn is an online text analysis tool. This can be used to predict the sentiment of a text.

Domains in NLP

Sentiment Analysis: Analyzing and determining the sentiment expressed by a text.

Applications: Customer reviews, social media monitoring



Named Entity Recognition: Identifying and classifying entities in text (such as names, locations, etc)

Applications: Information extraction, knowledge graph construction

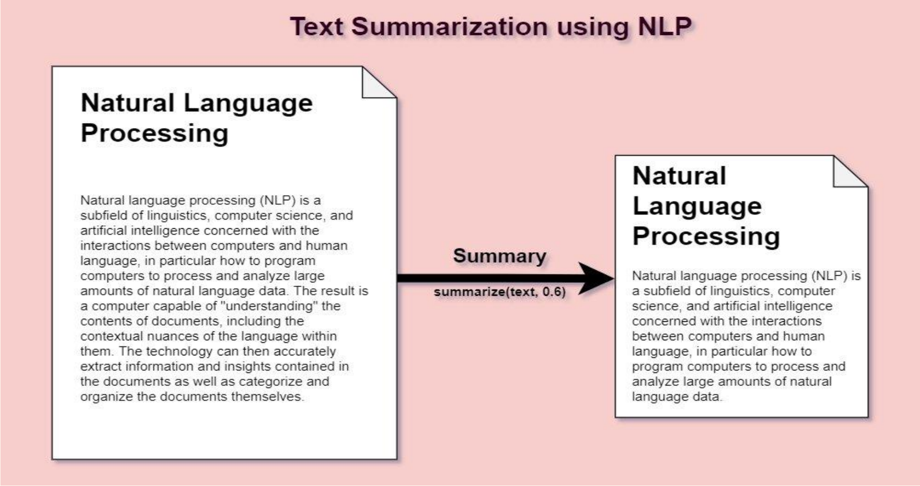
Domains in NLP

Chatbots: Building systems that can engage in natural language conversations.

Applications: Customer service, online support

Text Summarization: Generating concise summaries of longer texts while retaining essential information.

Applications: News summarization, document summarization



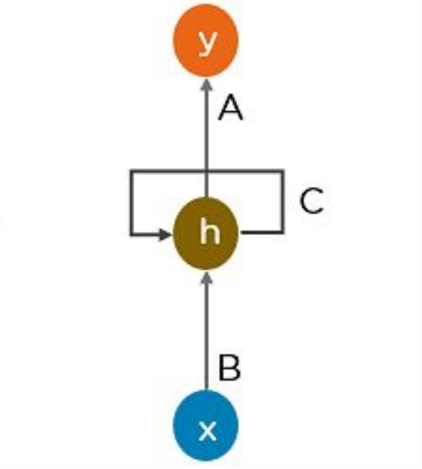
Sequential Data

- Whenever the points in the dataset are dependent on the other points in the dataset the data is said to be Sequential data.
- A common example of this is a Time Series such as a day-to-day weather forecast.

Day 1 Day 2 Day 3 Day 4 Day 5

RNNs

How do RNNs actually handle sequential input?

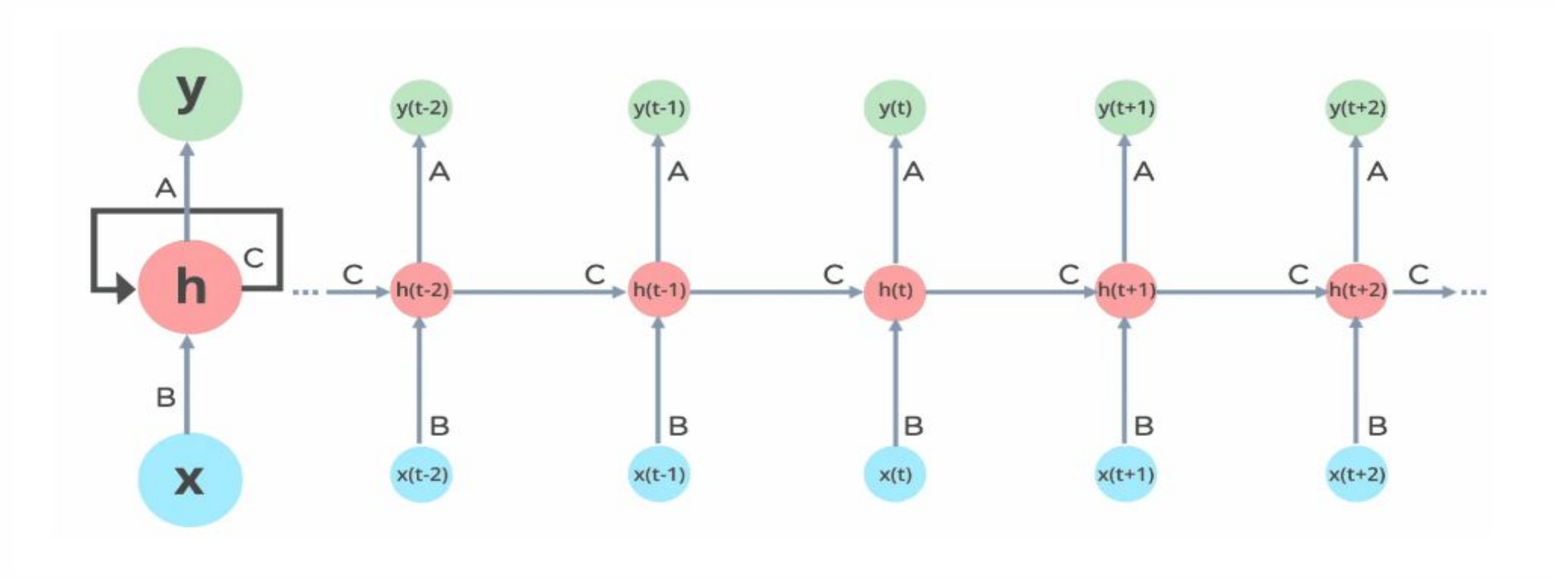


$$h(t) = f_c(h(t-1), x(t))$$

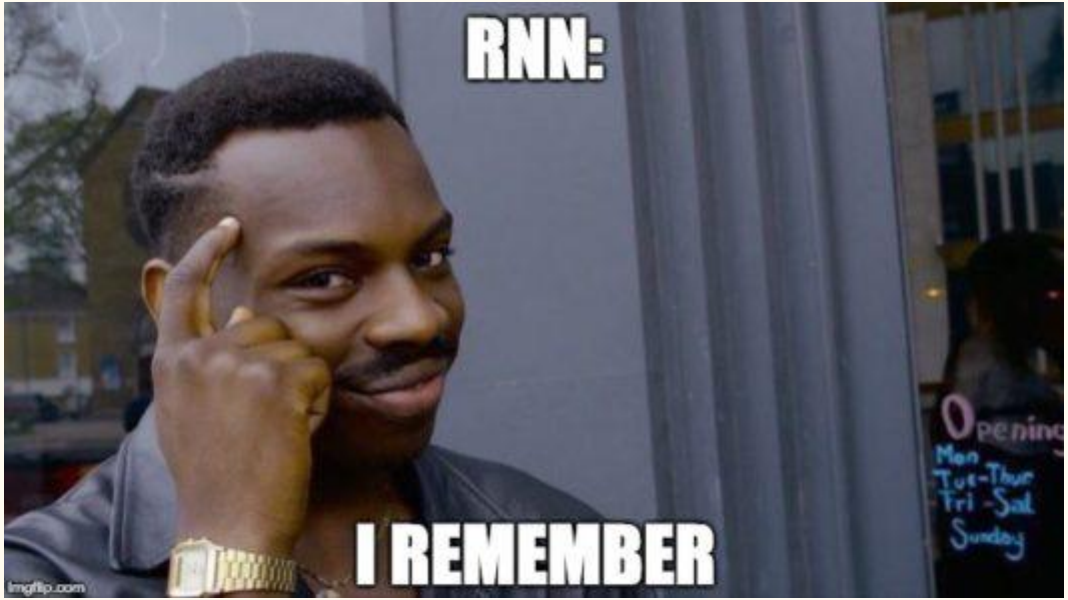
where,
$h(t)$ is the new state function
f_c is a function with parameter c
$h(t-1)$ is the previous state
$x(t)$ is the input vector at time-stamp t

RNNs

How do RNNs actually handle sequential input?



RNNs



Model Long-Term Dependence

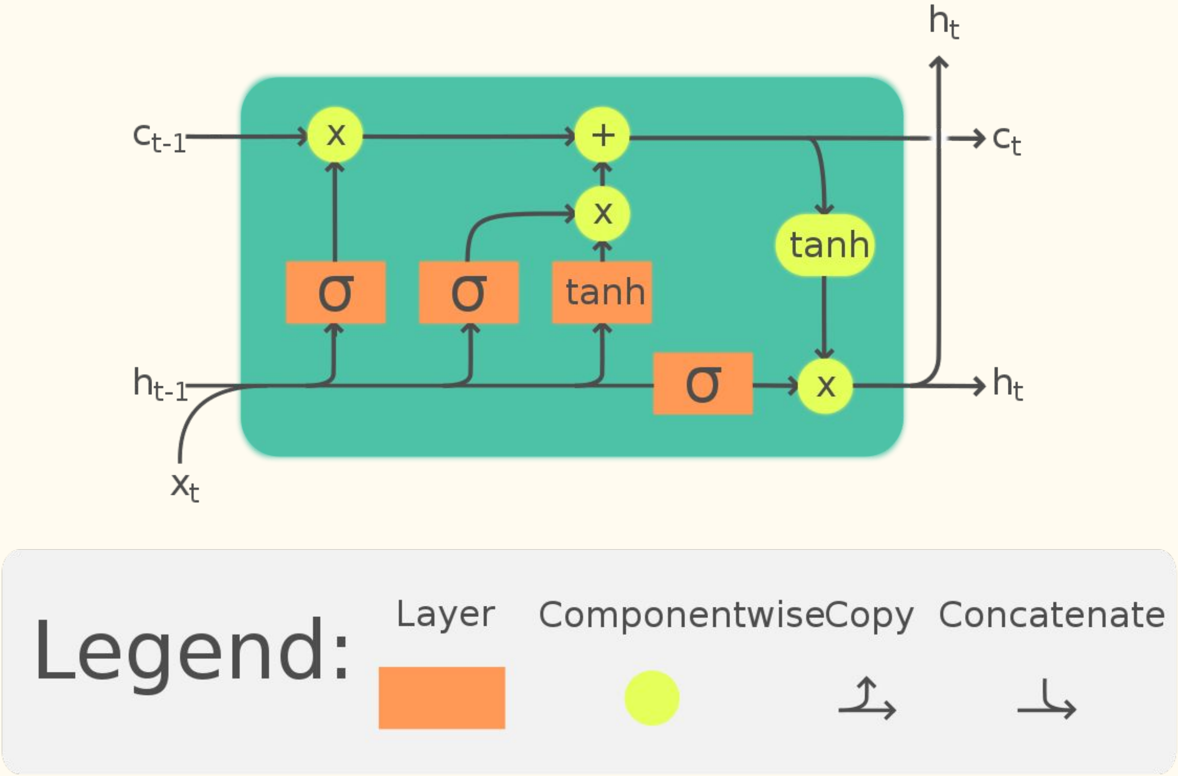
“I was born in **France** but I live in **Spain.** I speak fluent _____.”

French or **Spanish?**

In-order to get useful information we need to fix weights for both **long-term memorise** and **short-term memories**

This is what **LSTM(Long-Short Term Memory)** units are for!!!

LSTMs



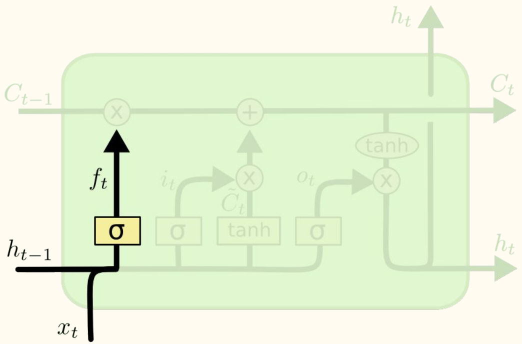
x_t Input Vector

h_t Cell Output

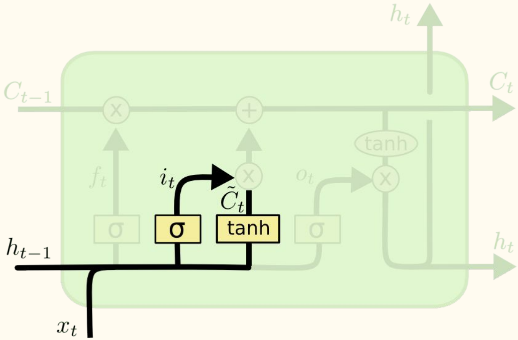
c_t Cell State

LSTMs

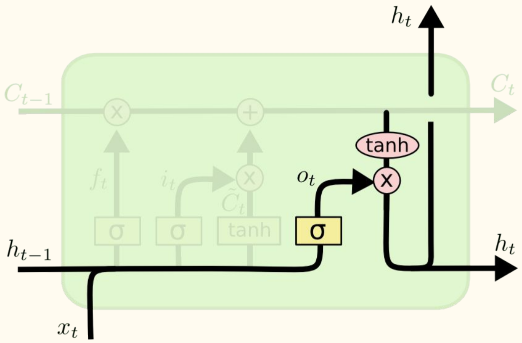
- The key to LSTMs is the cell state.
- LSTMs have the ability to remove or add information to the cell state
- The dataflow in LSTMs can be divided into 3 steps.



Forget Step

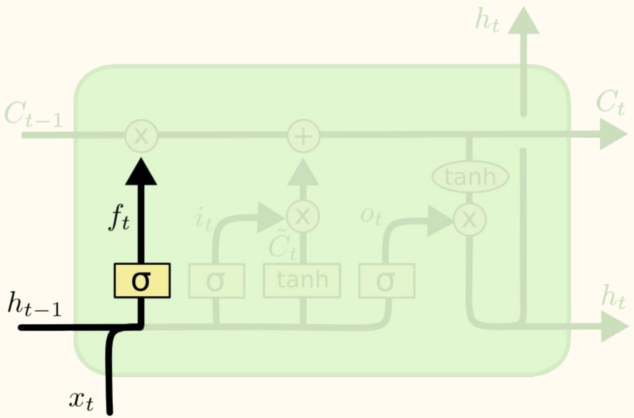


Input/Store Step



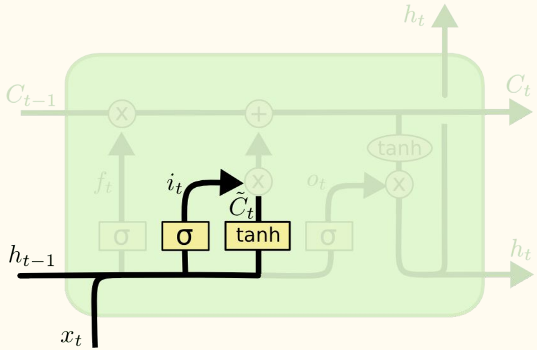
Output Step

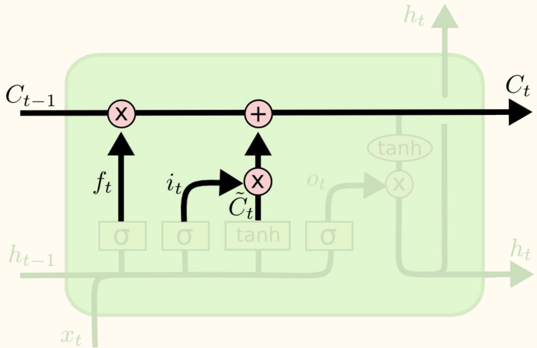
LSTMs: Forget Step



- The first step is to decide which information we're going to throw away from the **cell state.**
- This decision is taken by looking at h_{t-1} and x_t.

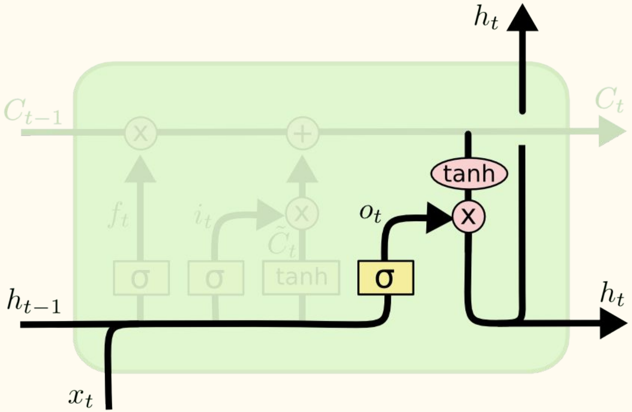
LSTMs: Input/Store Step





- The next step is to decide what new information we're going to store in the new cell state.
- This has two parts
- First the input layer we decide which values we'll update using h_{t-1} and x_t.
- Next we update the **previous cell state** using the output of the previous state $\tilde{C}_t$ and C_{t-1}.

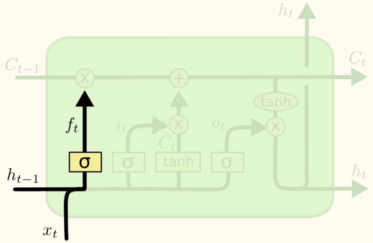
LSTMs: Output Step



- Finally our unit needs to give an output which is based on our cell state and the input.

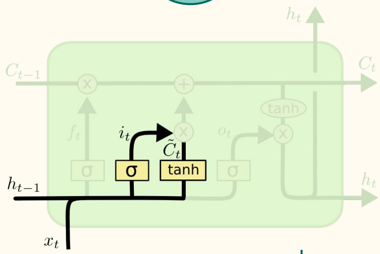
LSTMs: Maths :)

1



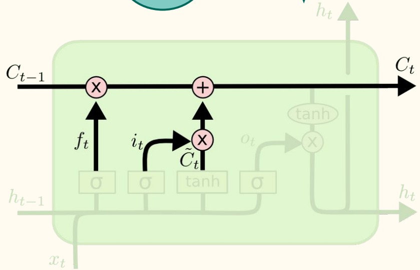
$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

2



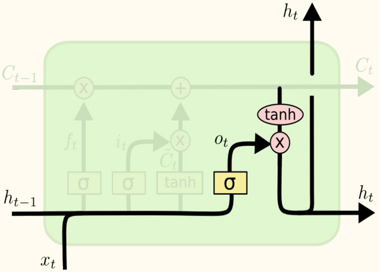
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

3



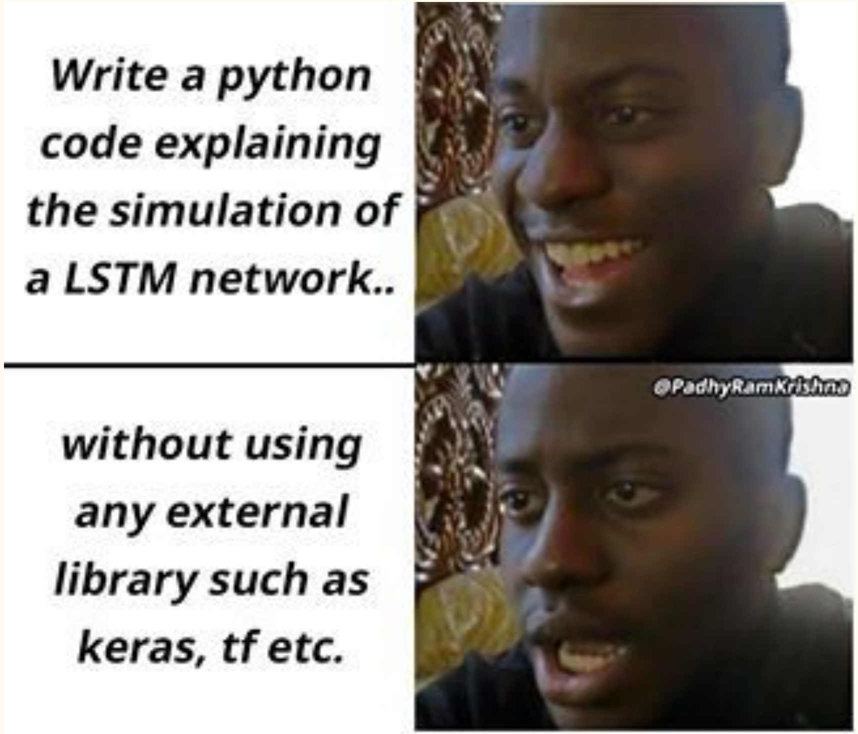
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

4



$$o_t = \sigma\left(W_o \; [h_{t-1}, x_t] \; + \; b_o\right)$$
$$h_t = o_t * \tanh\left(C_t\right)$$

LSTMs


Write a python code explaining the simulation of a LSTM network..
@PadhyRamKrishna
without using any external library such as keras, tf etc.

How to Process Language? Basic Units

Challenges of Natural Language:

- Words as such are not numbers to process directly.
- Sequence of words is very important unlike classification/recognition tasks.
- Necessity for means to remember sequence of words that followed before.
- Same meaning conveyed in different forms.
  Ex: 1. Dogs are barking because of cold.

  2. Chilly weather is making the dogs bark.

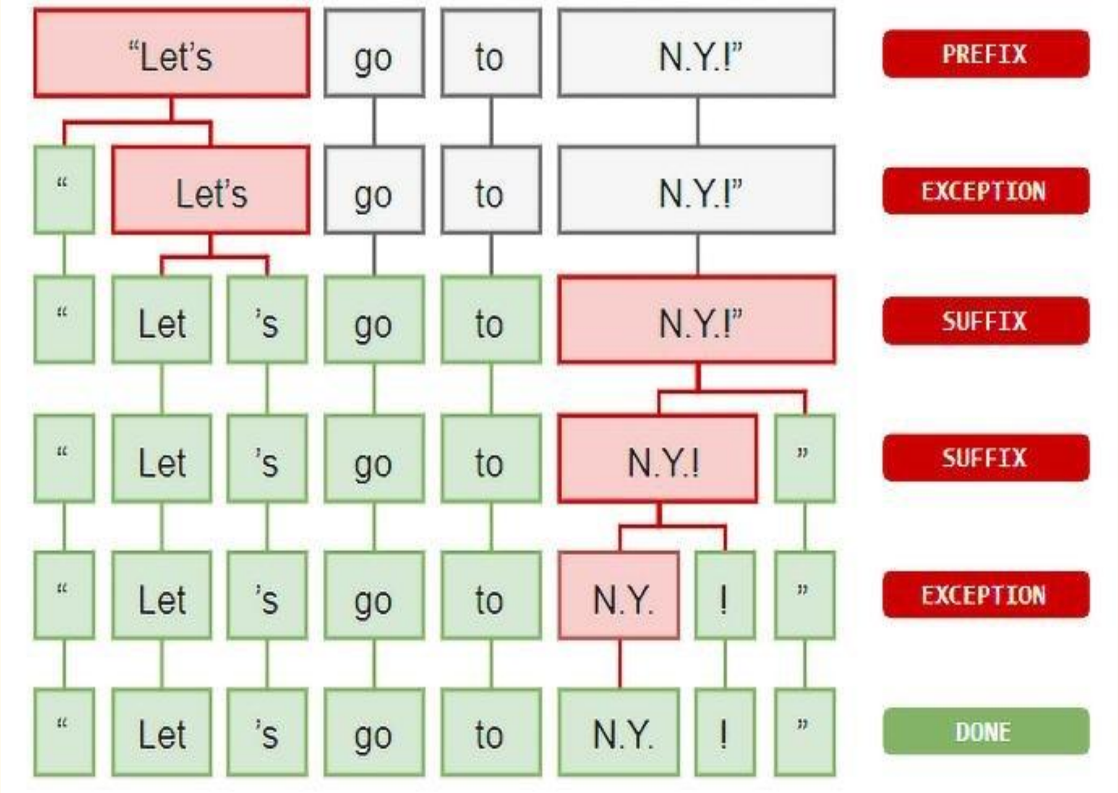
- Grammatical rules to be followed for a certain language.

Solution:

- Tokenization converts sentences to small chunks of words.
- Word-to-Vec can convert similar words into real vector.
- RNNs like LSTM or GRU which can have memory for solving the problem of sequencing.
- Huge dataset that can provide enough examples of variation of sentence structure for same meaning.
- We call them LLMs (Large Language Models)

Tokenization

- It is the process of **converting a large sentence into small chunks** of words.
- But why break a sentence into chunks?
- **High level Answer:** This helps to **assign numbers** to the chunks because numbers is what computer understands.



Types of Tokenization

Character Tokenization: Breaks text into individual characters

Original text: ‘Character Tokenization’

Tokenized: [‘C’, ‘h’, ‘a’, ‘r’, ‘a’, ‘c’, ‘t’, ‘e’, ‘r’, ‘T’, ‘o’, ‘k’, ‘e’, ‘n’, ‘i’, ‘z’, ‘a’, ‘t’, ‘i’, ‘o’, ‘n’]

Sentence Tokenization: Splits text into sentences

Original text: ‘Sentence tokenization splits text into sentences. Here is an example.’

Tokenized: [‘Sentence tokenization splits text into sentences’, ‘Here is an example’]

Word Tokenization: Splits text into words

Original Text: ‘Word tokenization is an important step in NLP’

Tokenized : [‘Word’, ‘tokenization’, ‘is’, ‘an’, ‘important’, ‘step’, ‘in’, ‘NLP’]

Subword Tokenization: Splits words into sub-words. Helps with out-of-vocabulary tokens.

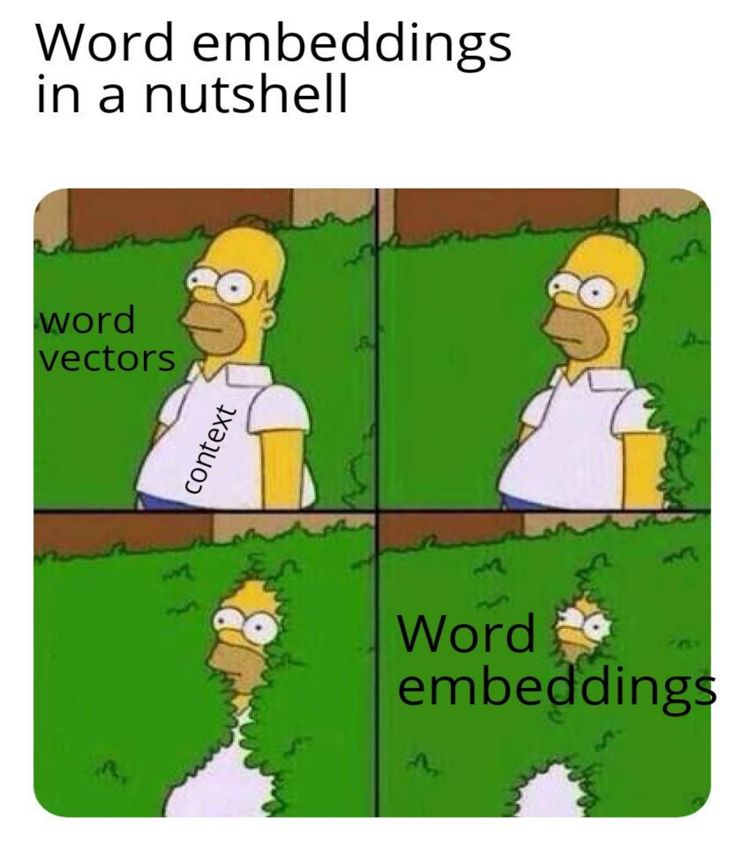
Original Text: ‘Tokenization’

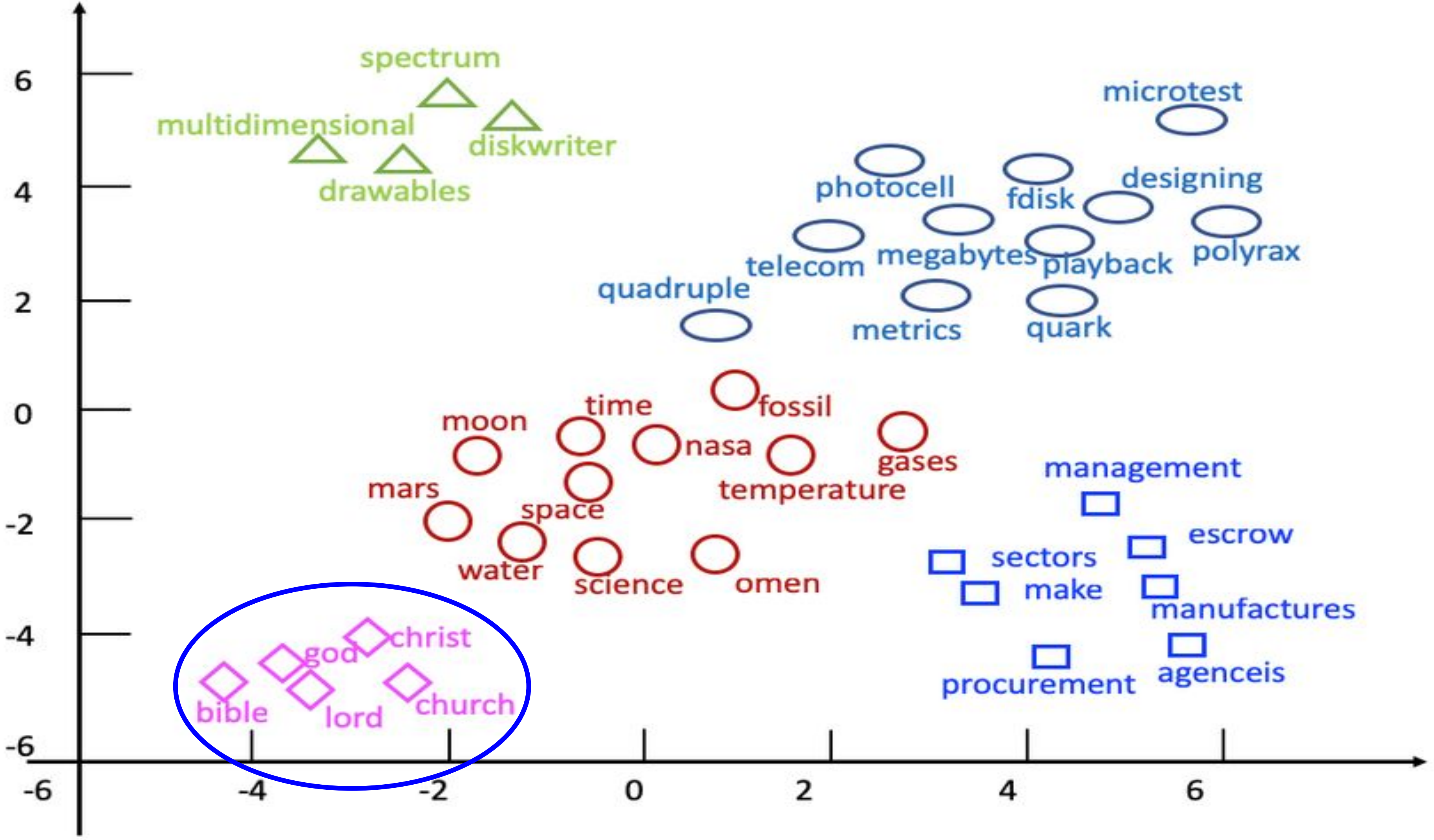
Tokenized: [‘Token’, ‘ization’]

Word Embedding

- It is the process of converting tokens into numerical data because character data is multi-dimensional!

- Word embeddings allows us to reduce data dimensionality and capture the importance of the word in the sentence based on its neighbours and context in the sentence.




spectrum
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fossil
moon
nasa
gases
mars
temperature
space
water
science
omen
management
escrow
sectors
make
manufactures
procurement
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god
bible
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6

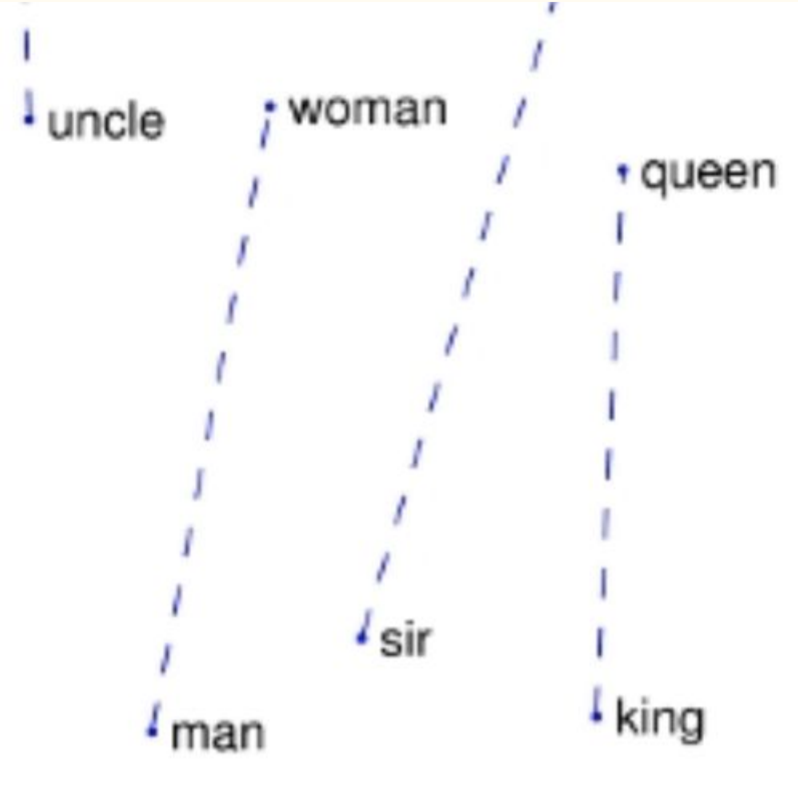
Obvious Question

- In general, word embedding can be thought of assigning “similar” words a “near-same” real value.
- Look at the picture, in the last slide and then at the blue marker at the bottom-left
- You may see that “God”, “Christ”, “Lord” are placed near each other because they possess almost same meaning.
- What word-embedding does is the same job at a much higher dimension.

- Well, you don't need to it exactly. Spacy and many other libraries are there for you!
- The techniques used are of many types, but the most common one is TF-IDF, GloVE, BERT and Word2Vec
- These are some mind-boggling jargons which you don't need to worry about now.

GloVe (Global Vector for Word Representation)

GloVe is a word vector technique that encode the co-occurrence probability ratio between two words as vector differences. GloVe uses a weighted least squares objective that minimizes the difference between the dot product of the vectors of two words and the logarithm of their number of co-occurrences.
GloVe is capable of finding linear sub-structures and nearest-neighbours in its embedding vector space.



Further Readings

- **Text Generation With RNNs:**
  - https://blog.paperspace.com/recurrent-neural-networks-part-1-2/
  - https://karpathy.github.io/2015/05/21/rnn-effectiveness/?ref=blog.paperspace.com
- **LSTMs:**
  - https://colah.github.io/posts/2015-08-Understanding-LSTMs/?ref=blog.paperspace.com
- **Roadmap for NLP:**
  - https://medium.com/aimonks/roadmap-to-learn-natural-language-processing-in-2023-6e3a9372b8cc

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