Natural Language Processing (NLP) with Deep NLP

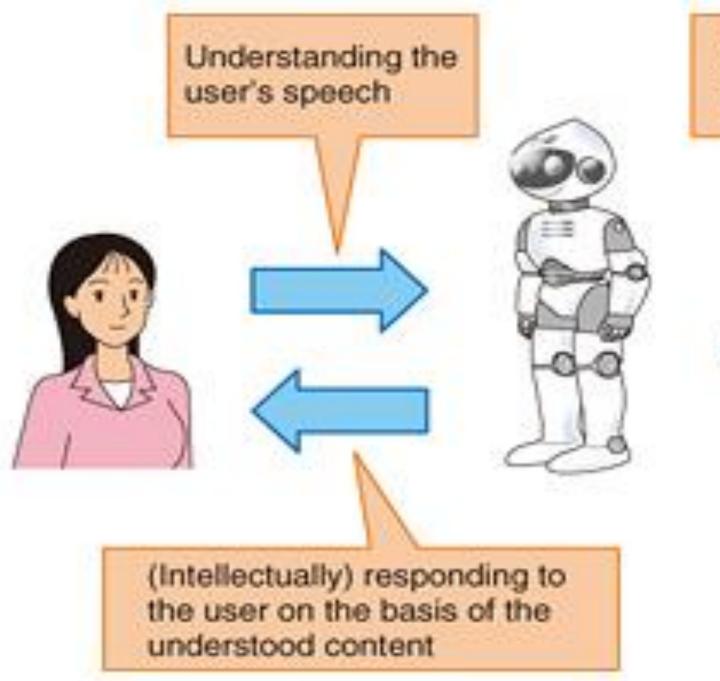
AMIT DHOMNE

Computer Science Instructor

Machine Learning and Deep learning Practitioner

Prerequisite for Natural language processing

- Python
- Basic Concept of Machine Learning and Deep Learning



Understanding written material by reading it

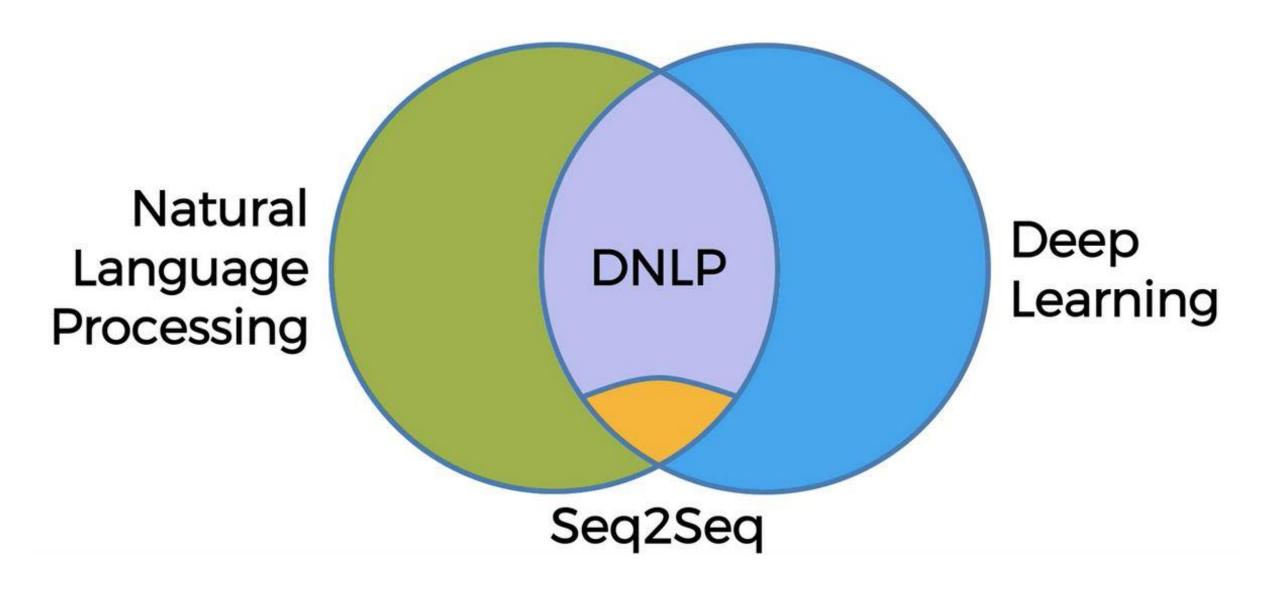


Natural language processing

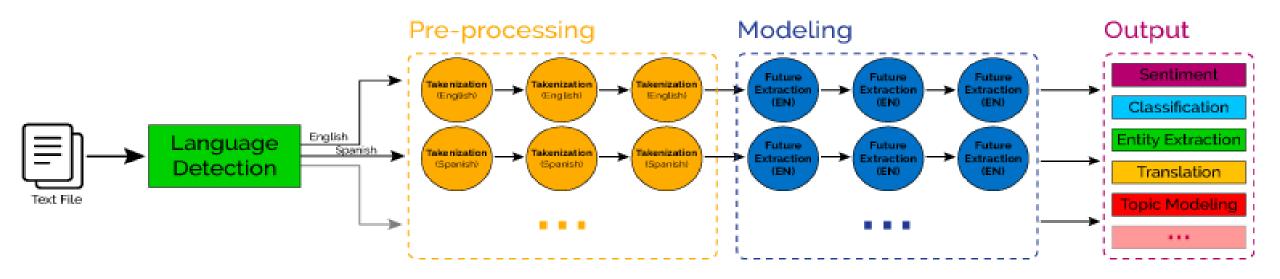
Natural language processing (NLP) is a subfield of linguistics, computer science, information engineering, and artificial intelligence concerned with the interactions between computers and human (natural) languages, in particular how to program computers to process and analyze large amounts of natural language data.

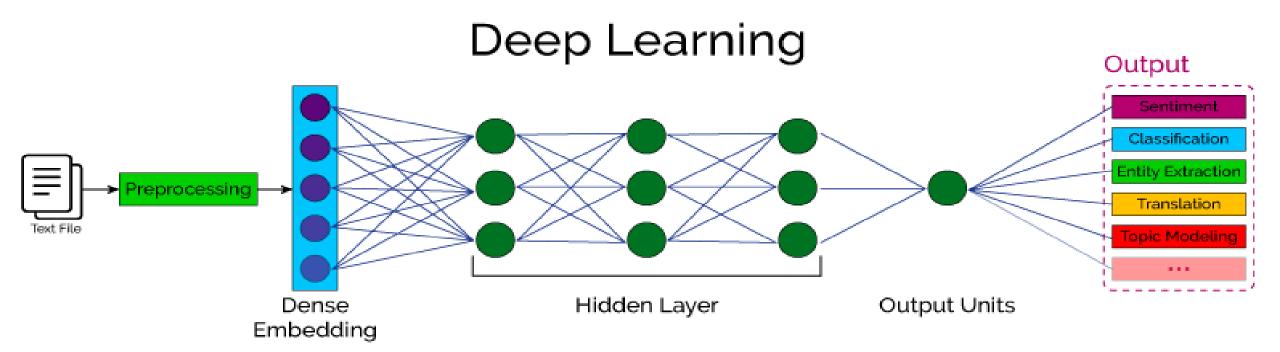
Challenges in natural language processing frequently involve speech recognition, natural language understanding, and natural language generation.

Types of NLP

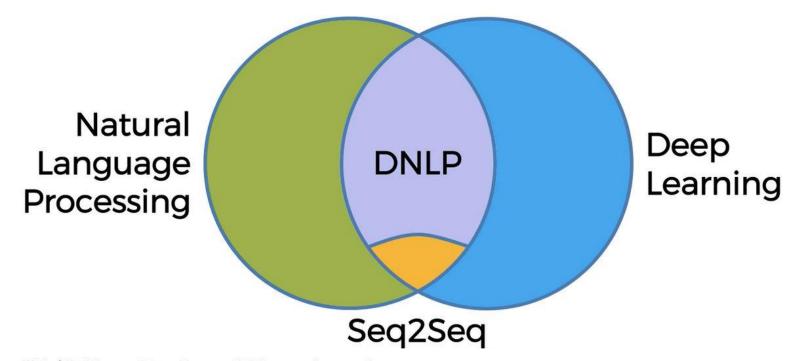


Classical NLP



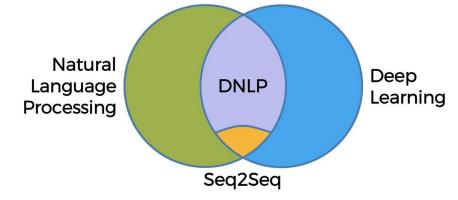


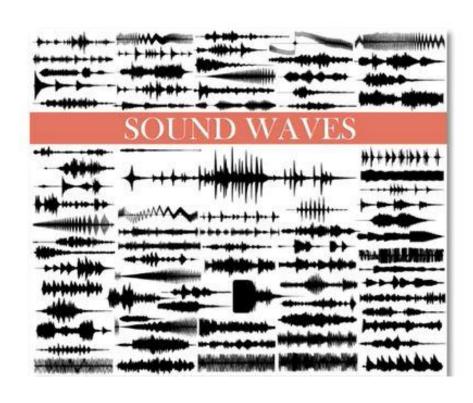
How NLP, DNLP and DL involves in!!!

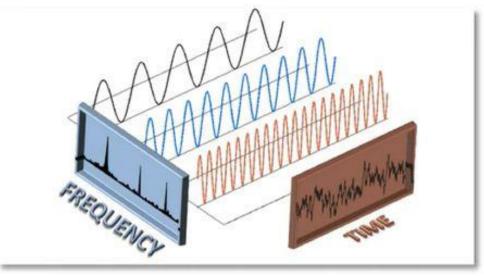


- 1. If / Else Rules (Chatbot)
- 2. Audio frequency components analysis (Speech Recognition)
- 3. Bag-of-words model (Classification)
- 4. CNN for text Recognition (Classification)
- 5. Seq2Seq (many applications)

How NLP, DNLP and DL involves in!!!







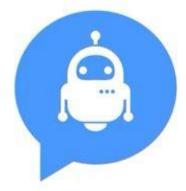
Applications



Speech Transcription



Neural Machine Translation (NMT)



Chatbots



Q&A



Text Summarization



Image Captioning



Video Captioning

Used by

















NLP Working

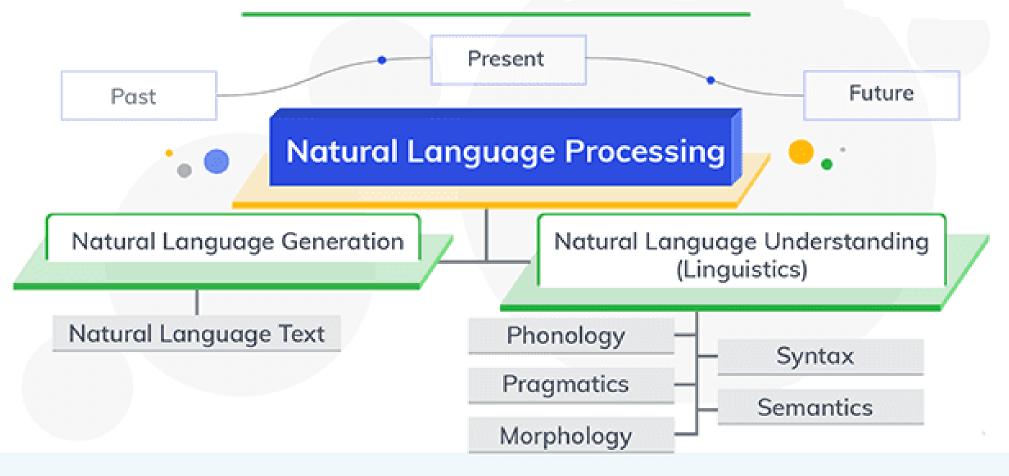


language

Amazon Alexa.

NLP Working

Evolution of NLP



Natural Language Understanding

Ambiguity:

Lexical Ambiguity: The Tank is full of water.

Syntactic Ambiguity: ill men and women get to hospital.

Semantic Ambiguity: The Bike hit the pole while it was running.

Pragmatic Ambiguity: The Army is coming.

Phonology – This science helps to deal with patterns present in the sound and speeches related to the sound as a physical entity.

Pragmatics – This science studies the different uses of language.

Morphology – This science deals with the structure of the words and the systematic relations between them.

Syntax – This science deal with the structure of the sentences.

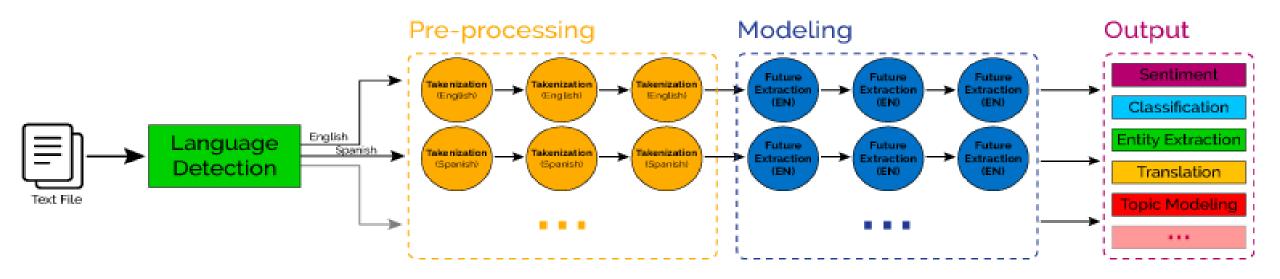
Semantics – This science deals with the literal meaning of the words, phrases as well as sentences.

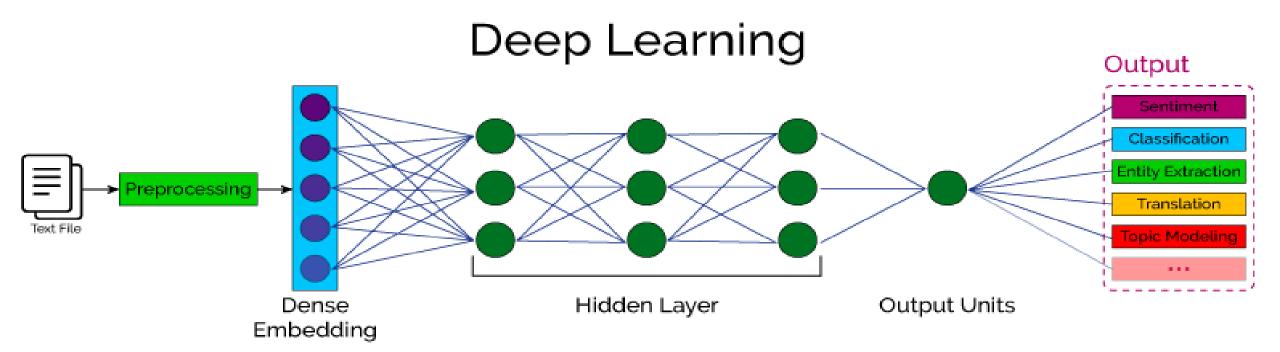
Natural Language Generation

Based on NL-Understanding, it will suggest about:

- What should say to user.
- Should be Intelligent and Covervational as like human
- Usage of Structured data.
- With text and Sentence like planning.

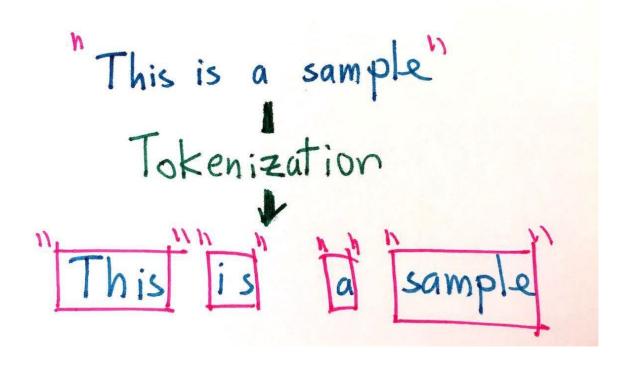
Classical NLP





Tokenization

Tokenization is the process of replacing sensitive data with unique identification symbols that retain all the essential information about the data without compromising its security.



Tokenization

There are many library / framework for NLP problem solution

- 1. Natural Language Toolkit (NLTK)
- 2. TextBlob
- 3. CoreNLP
- 4. Gensim
- 5. spaCy
- 6. polyglot
- 7. scikit-learn
- 8. Pattern

Stemming and Lemmatization

Before understanding Stemming and Lemmatization, first let's understand the following...

Prefix: Character(s) at the beginning ▶ \$ (" ¿

Suffix: Character(s) at the end ▶ km),.!"

Infix: Character(s) in between ▶ - -- / ...

Exception: Special-case rule to split a string into several tokens or prevent a token from being split when punctuation rules are applied St. U.S.

Stemming

Stemming is the process of reducing a word to its word stem that affixes to suffixes and prefixes or to the roots of words known as a lemma. **Stemming** is important in natural language understanding (NLU) and **natural language processing** (NLP).

Rule				Example		
SSES	\rightarrow	SS		caresses	\rightarrow	caress
IES	\rightarrow	Ι		ponies	\rightarrow	poni
SS	\rightarrow	SS		caress	\rightarrow	caress
S	\rightarrow			cats	\rightarrow	cat
	SSES IES SS	$\begin{array}{ccc} \text{SSES} & \rightarrow \\ \text{IES} & \rightarrow \\ \text{SS} & \rightarrow \end{array}$	$\begin{array}{ccc} \text{SSES} & \rightarrow & \text{SS} \\ \text{IES} & \rightarrow & \text{I} \\ \text{SS} & \rightarrow & \text{SS} \end{array}$	$\begin{array}{ccc} \text{SSES} & \rightarrow & \text{SS} \\ \text{IES} & \rightarrow & \text{I} \\ \text{SS} & \rightarrow & \text{SS} \end{array}$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

Form	Suffix	Stem	
studi <mark>es</mark>	-es	studi	
studying	-ing	study	
niñ <mark>as</mark>	-as	niñ	
niñ <mark>ez</mark>	-ez	niñ	

Porter Stemming

One of the most common - and effective - stemming tools is <u>Porter's Algorithm</u> developed by Martin Porter in <u>1980</u>. The algorithm employs five phases of word reduction, each with its own set of mapping rules

e.g: caresses reduces to caress but not cares

Snowball Stemming

Snowball is a small string processing language designed for creating **stemming** algorithms for use in Information Retrieval. This site describes **Snowball**, and presents several useful **stemmers** which have been implemented using it

Useful link for additional reading...

https://nlp.stanford.edu/IR-book/html/htmledition/stemming-and-lemmatization-1.html

Lemmatization

Lemmatization usually refers to doing things properly with the use of a vocabulary and morphological analysis of words, normally aiming to remove inflectional endings only and to return the base or dictionary form of a word, which is known as the lemma.

The lemma of 'was' is 'be' and the lemma of 'mice' is 'mouse'. Further, the lemma of 'meeting' might be 'meet' or 'meeting' depending on its use in a sentence.

Lemmatization Lemmatization

Mapping from text-word to lemma help (verb)

text-word	to	lemma
help		help (v)
helps		help (v)
helping		help (v)
helped		help (v)

https://nlp.stanford.edu/IR-book/html/htmledition/stemming-and-lemmatization-1.html

Recurrent Neural Network

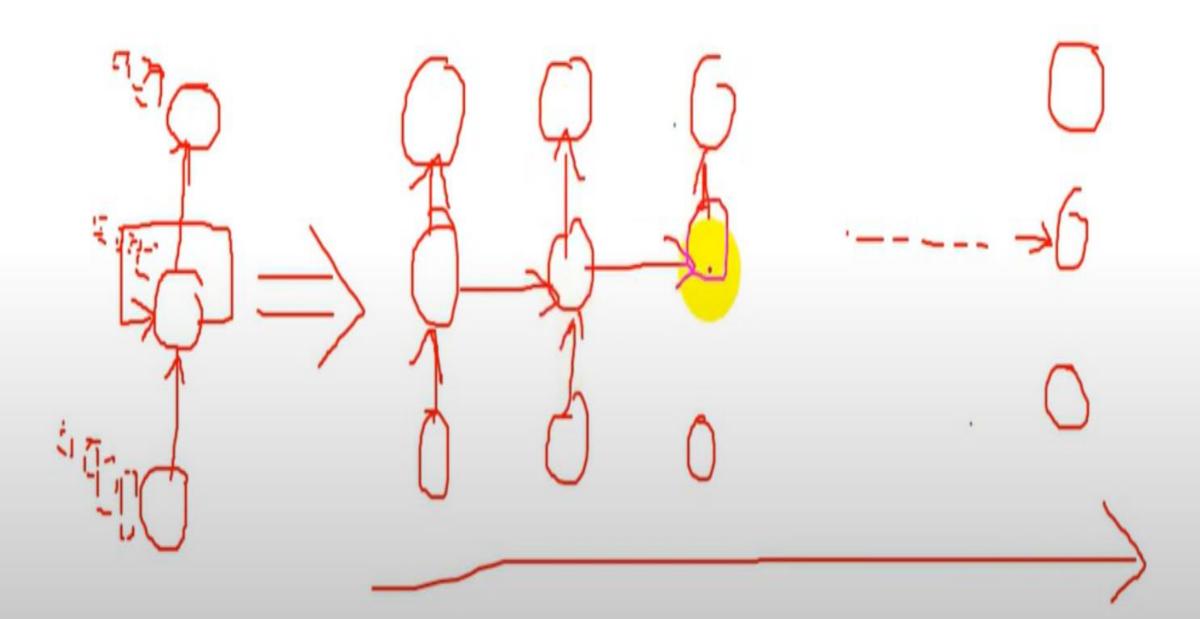
Tutorial 30: What are Recurrent Neural Networks (RNN) in Hindi using basic Example with LSTM concept NN)

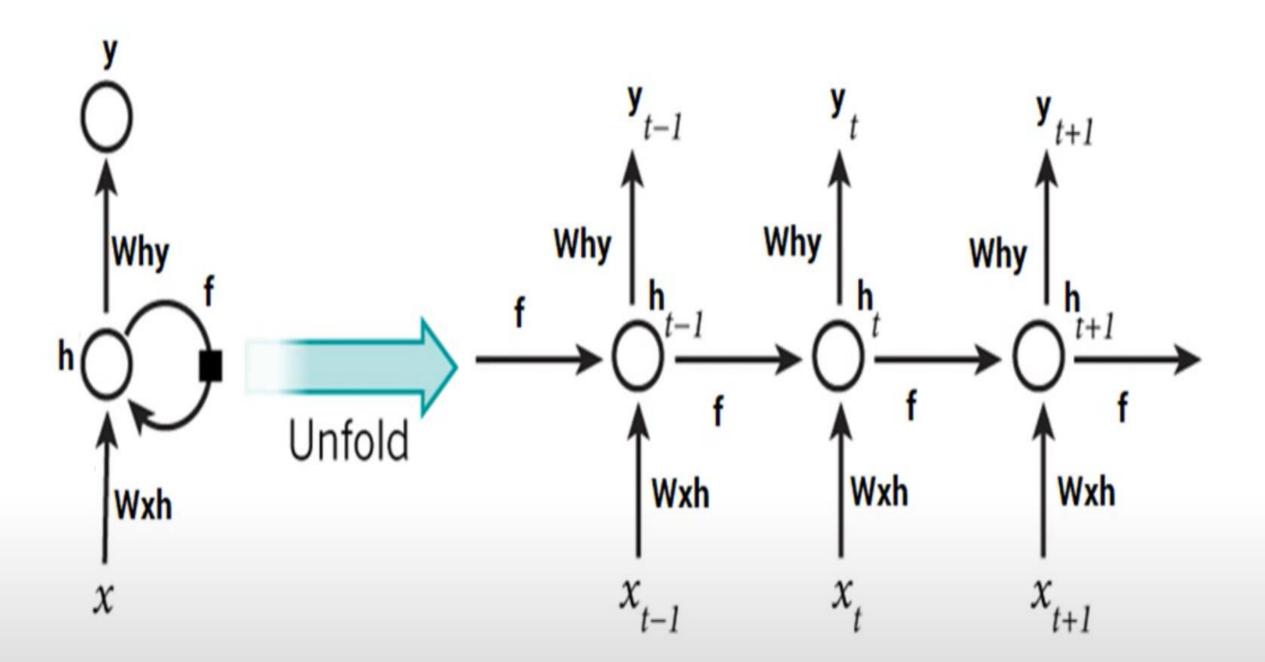
Recurrent Neural Network is a generalization of feedforward neural network that has an internal memory. RNN is recurrent in nature as it performs the same function for every input of data while the output of the current input depends on the past one computation. After producing the output, it is copied and sent back into the recurrent network. For making a decision, it considers the current input and the output that it has learned from the previous input.

Unlike feedforward neural networks, RNNs can use their internal state (memory) to process sequences of inputs. This makes them applicable to tasks such as unsegmented, connected handwriting recognition or speech recognition. In other neural networks, all the inputs are independent of each other. But in RNN, all the inputs are related to each other.

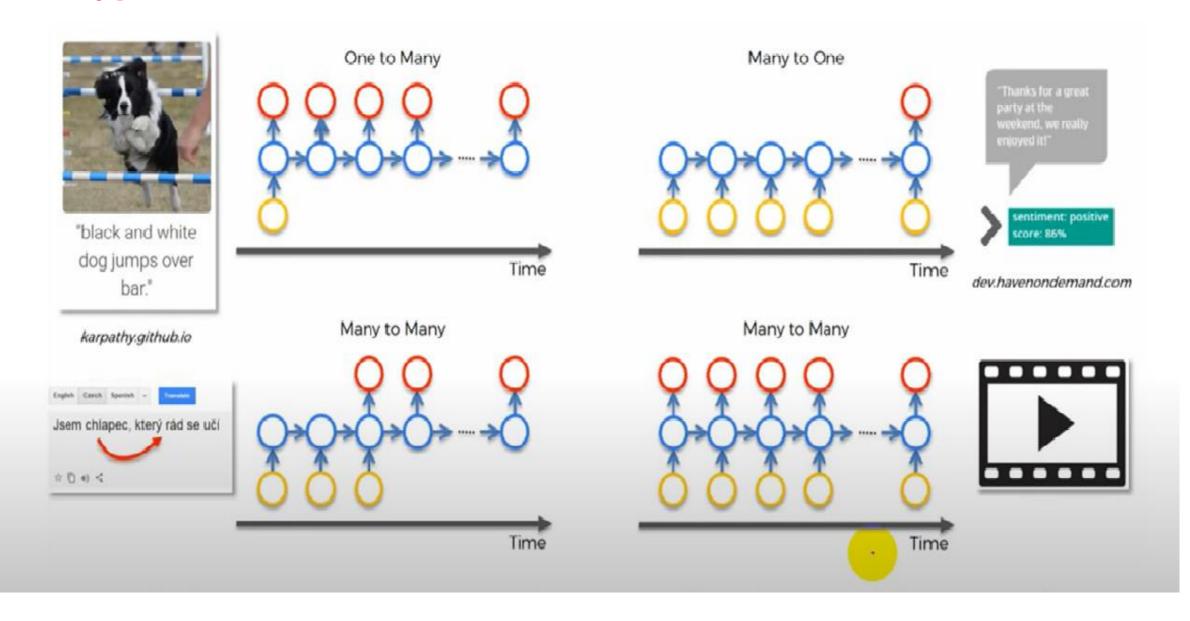
For further assistance, code and slide https://fahadhussaincs.blogspot.com/







Types of RNN

















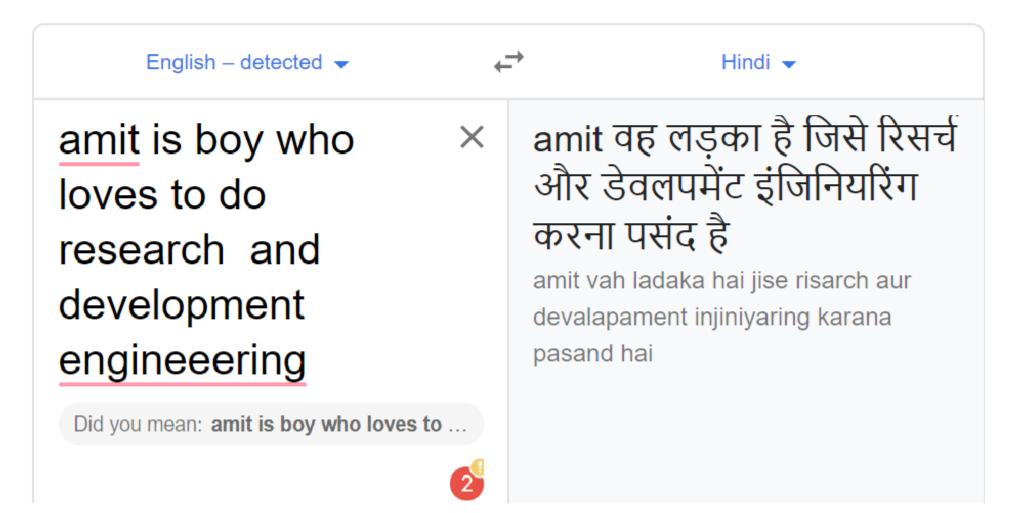


More

Settings

Tools

About 61,90,00,000 results (0.37 seconds)



What is Time series Analysis, How relate it is RNN to

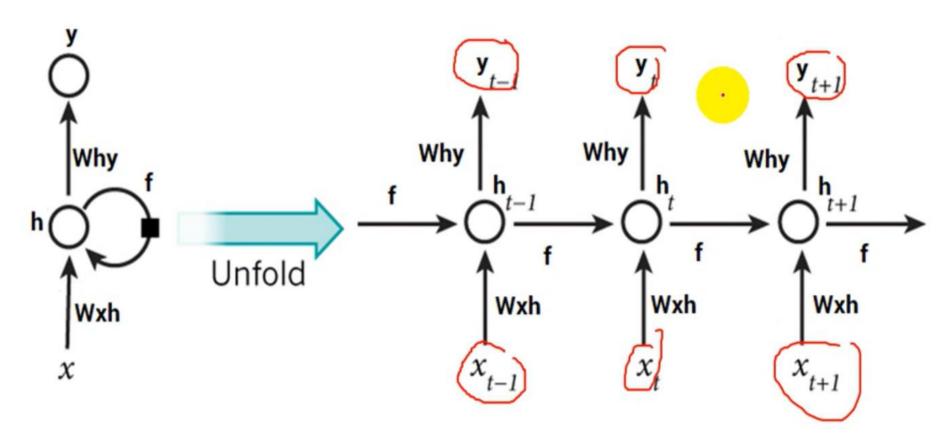
A time series is a series of data points indexed in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time. Thus it is a sequence of discrete-time data

4	A	В	С
1	Year	Quarter	Sales
2	2012	1	\$165,000.00
3		2	\$253,000.00
4		3	\$316,000.00
5		4	\$287,000.00
6	2013	1	\$257,000.00
7		2	\$308,000.00
8		3	\$376,000.00
9		4	\$351,000.00

Time series model is purely dependent on the idea that past behavior and price patterns can be used to predict future price behavior.

Vanishing gradient problem

The **vanishing gradient** makes the **gradient** very close to zero, so it's difficult to know where to move in the state space; the exploding **gradient** makes the **gradient** a very large value, so it makes learning unstable. This **problem** is more pronounced in recurrent networks since they use the same matrix at each time step.



Exploding Gradient:

The working of the exploding gradient is similar but the weights here change drastically instead of negligible change. Notice the small change.

Truncated BTT

Instead of starting backpropagation at the last time stamp, we can choose a smaller time stamp like 10 (we will lose the temporal context after 10 time stamps)

Clip gradients at threshold

Clip the gradient when it goes higher than a threshold

RMSprop to adjust learning rate

Vanishing Gradient:

When making use of backpropagation the goal is to calculate the error which is actually found out by finding out the difference between the actual output and the model output and raising.

ReLU activation function

We can use activation functions like ReLU, which gives output one while calculating gradient

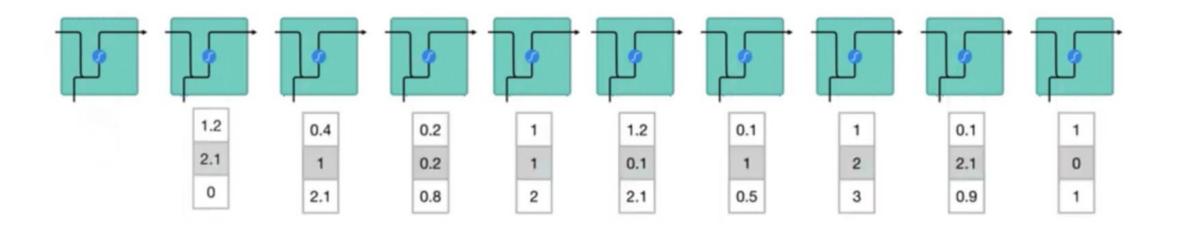
RMSprop

Clip the gradient when it goes higher than a threshold

LSTM, GRUs

Different network architectures that has been specially designed can be used to combat this problem

First Understand the RNN Works



This is a cat, and ____ is a good pet animal



Basic LSTM

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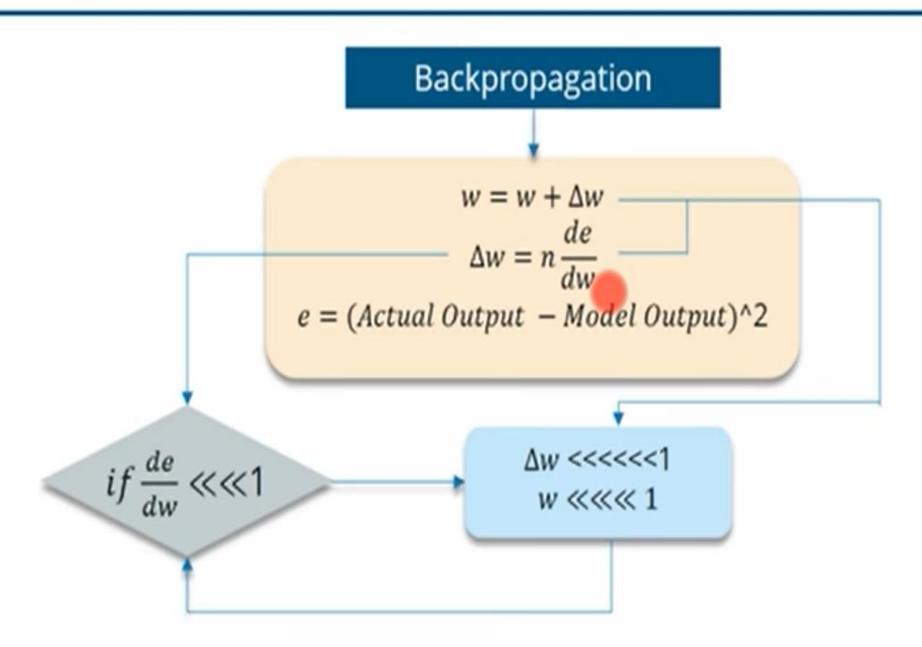
Long short-term memory network was first introduced in 1997 by Sepp Hochreiter and his supervisor for a Ph.D. thesis.

LSTM is a special kind of RNN, capable of learning long term dependencies.

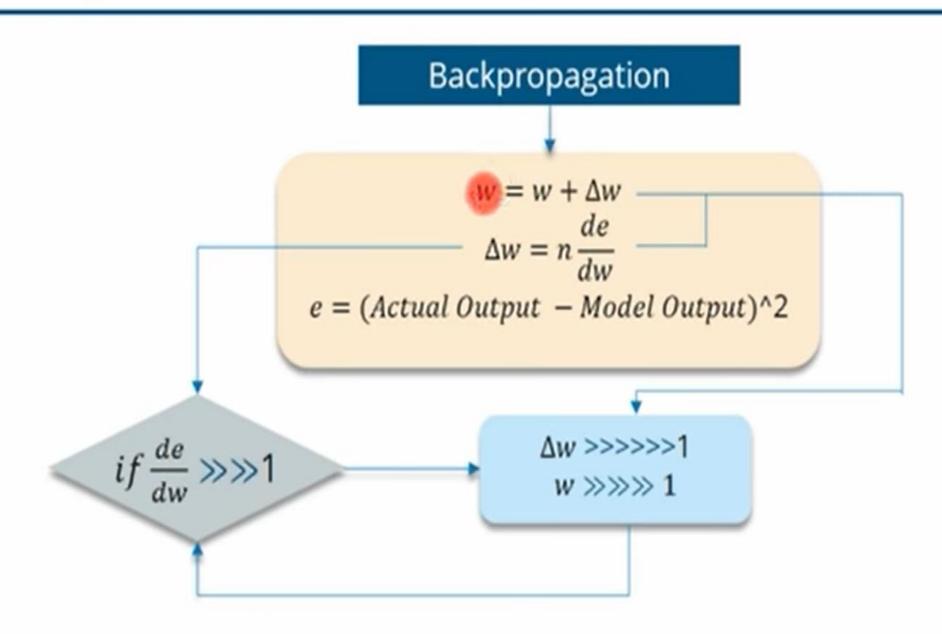
Remembering information for long period of time is it's default behaviour.

Long short-term memory (LSTM) network is the most popular solution to the vanishing gradient problem.

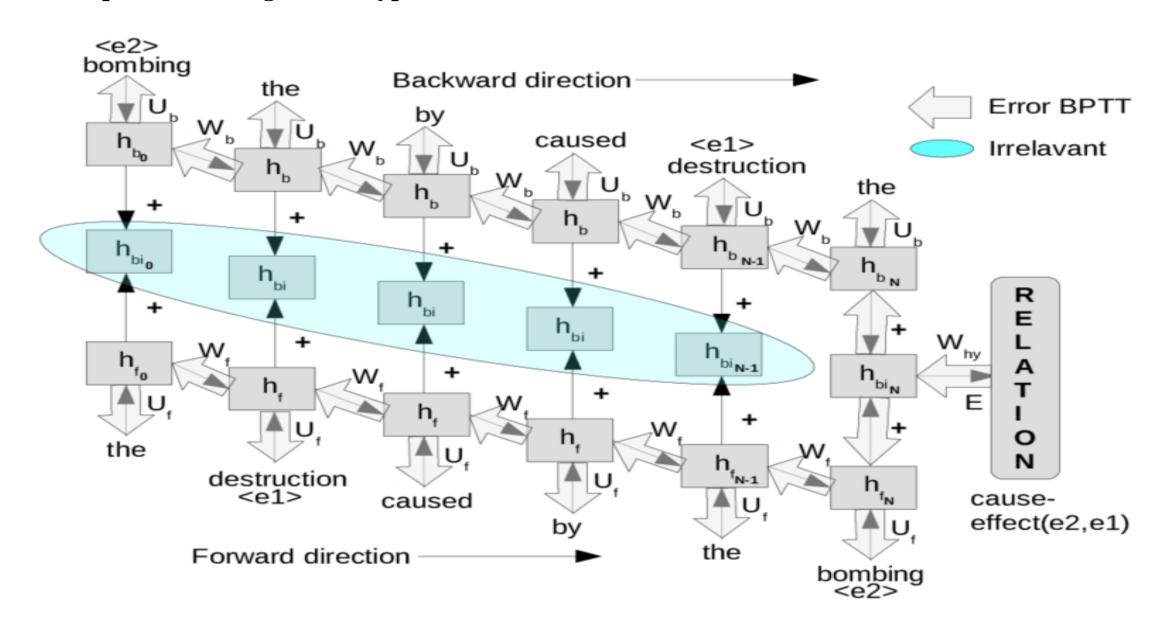
Vanishing Gradient



Exploding Gradient



Back Propagation Through Time(BTT): Backpropagation through time is a gradient-based technique for training certain types of recurrent neural networks.



How To Overcome These Challenges?

Exploding gradients

Truncated BTT

Instead of starting backpropagation at the last time stamp, we can choose a smaller time stamp like 10 (we will lose the temporal context after 10 time stamps)

- Clip gradients at threshold
 - Clip the gradient when it goes higher than a threshold
- RMSprop to adjust learning rate

Vanishing gradients

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We can use activation functions like ReLU, which gives output one while calculating gradient

RMSprop

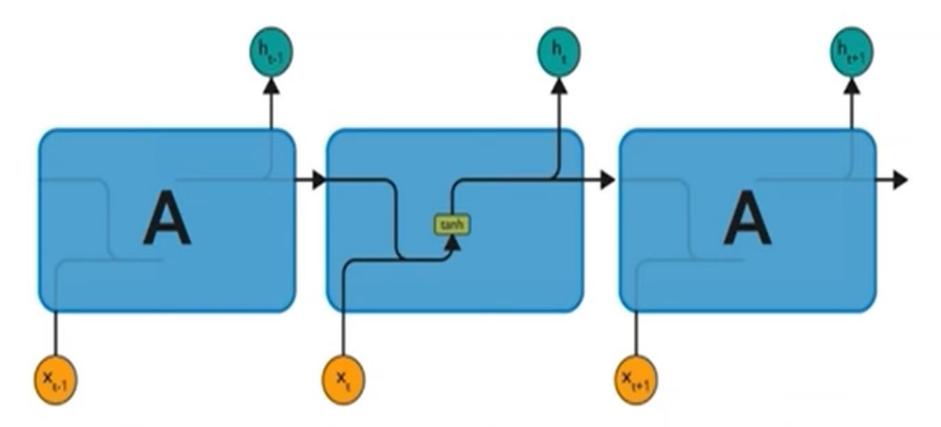
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LSTM, GRUs

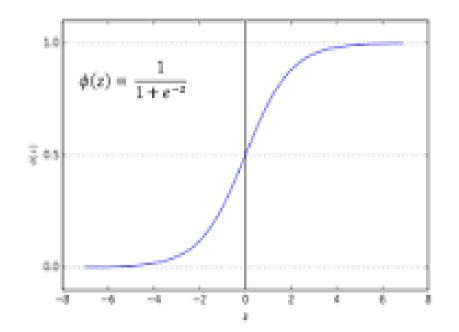
Different network architectures that has been specially designed can be used to combat this problem



- ✓ Long Short Term Memory networks usually just called "LSTMs" are a special kind of RNN.
- ✓ They are capable of learning long-term dependencies.



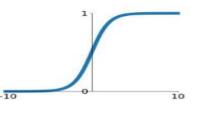
The repeating module in a standard RNN contains a single layer



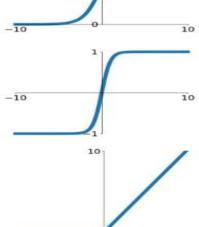
Sigmoid: -The **sigmoid activation function**, also called the logistic **function**, is traditionally a very popular **activation function** for neural networks. The input to the **function** is transformed into a value between 0.0 and 1.0 **Tanh:** The range of the **tanh function** is from (-1 to

Sigmoid

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

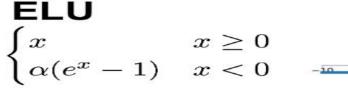


tanh



10

1)

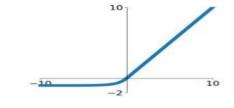


 $\max(w_1^T x + b_1, w_2^T x + b_2)$

Leaky ReLU

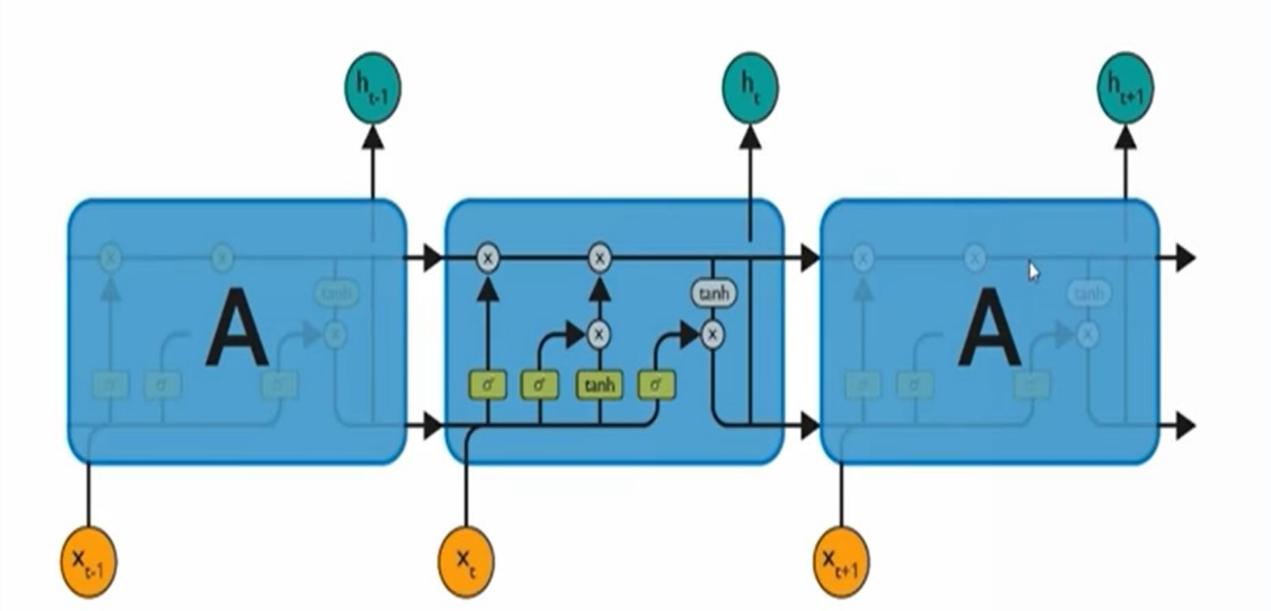
 $\max(0.1x, x)$

Maxout



ReLU 10

$$\max(0,x)$$

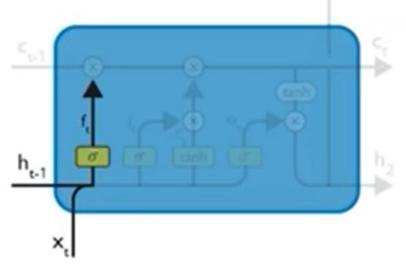


Step-1

The first step in the **LSTM** is to identify those information that are not required and will be thrown away from the cell state. This decision is made by a sigmoid layer called as forget gate layer.

$$w_f = Weight$$

 $h_{t-1} = Output \ from \ the \ previous \ time \ stamp$
 $x_t = New \ input$
 $b_f = Bias$



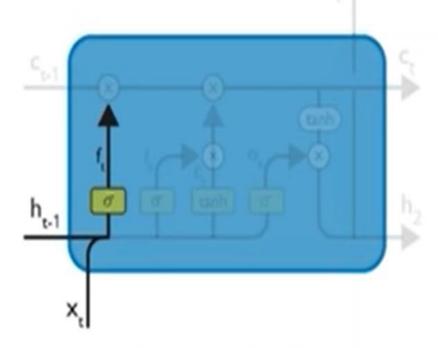
$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f)$$

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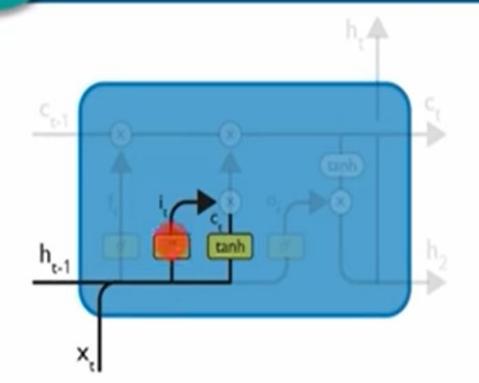
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$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f)$$

Step-2

The next step is to decide, what new information we're going to store in the cell state. This whole process comprises of following steps. A **sigmoid layer** called the "input gate layer" decides which values will be updated. Next, a **tanh layer** creates a vector of new candidate values, that could be added to the state.



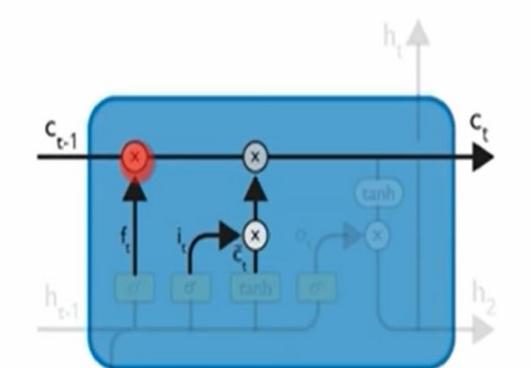
$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i)$$

$$\tilde{c}_t = tanh(w_c[h_{t-1}, x_t] + b_c)$$

In the next step, we'll combine these two to update the state.

Step-3

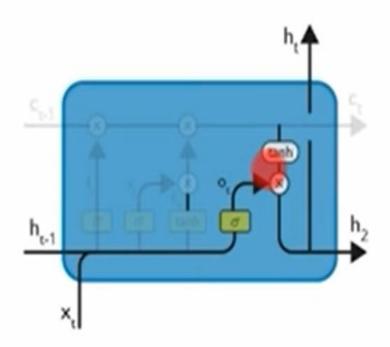
Now, we will update the old cell state, C_{t-1} , into the new cell state C_t . First, we multiply the old state (C_{t-1}) by f_t , forgetting the things we decided to forget earlier. Then, we add $i_t * c_t$. This is the new candidate values, scaled by how much we decided to update each state value.



$$c_t = f_t * c_{t-1} + i_t * c_t$$

Step-4

We will run a sigmoid layer which decides what parts of the cell state we're going to output. Then, we put the cell state through tanh (push the values to be between -1 and 1) and multiply it by the output of the sigmoid gate, so that we only output the parts we decided to.

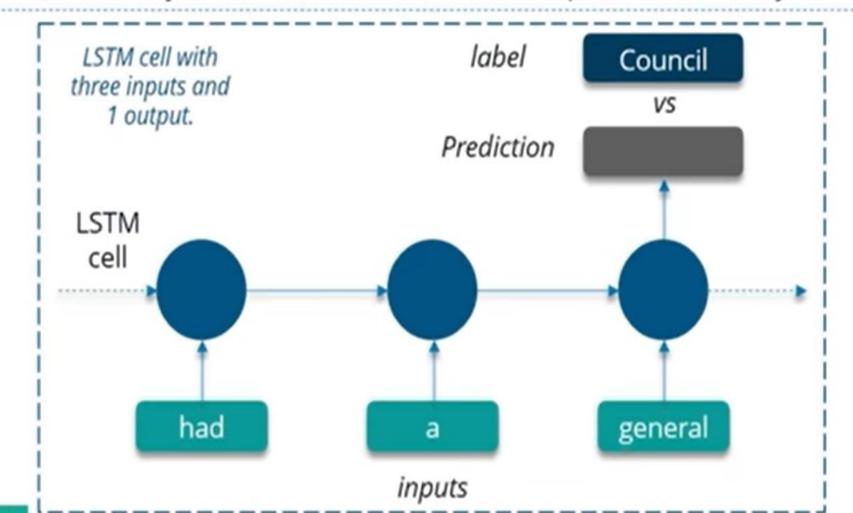


$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * tanh(c_t)$$

Long Short Term Memory Networks Use-Case

We will feed a LSTM with correct sequences from the text of 3 symbols as inputs and 1 labeled symbol, eventually the neural network will learn to predict the next symbol correctly



Long Short Term Memory Networks Use-Case



long ago , the mice had a general council to consider what measures they could take to outwit their common enemy, the cat. some said this, and some said that but at last a young mouse got up and said he had a proposal to make, which he thought would meet the case. you will all agree, said he, that our chief danger consists in the sly and treacherous manner in which the enemy approaches us . now , if we could receive some signal of her approach, we could easily escape from her . i venture , therefore , to propose that a small bell be procured, and attached by a ribbon round the neck of the cat. by this means we should always know when she was about, and could easily retire while she was in the neighborhood . this proposal met with general applause, until an old mouse got up and said that is all very well, but who is to bell the cat? the mice looked at one another and nobody spoke . then the old mouse said it is easy to propose impossible remedies.

A short story from Aesop's Fables with 112 unique symbols

Long Short Term Memory Networks Use-Case

A unique integer value is assigned to each symbol because LSTM inputs can only understand real numbers.

