Natural Language and Processing

Utkarsh Agiwal

July 15, 2022

Mentor : Samyak Shah

Contents

1 Introduction

What is Natural Language Processing or usually called NLP? We use it all the time without even knowing it. Each time while texting on WhatsApp, using the auto-correct features, our email filters for spam/non-spam, subtitles/transcript in live videos, lectures etc. everything is an application of NLP.
One of the reasons I am interested in NLP is its growing boom and research in the recent years. Currently our world revolves around automation. These automations wouldn't be possible if it weren't for Artificial Intelligence and one of its major branches, Natural Language Processing (NLP). The world is getting **data rich**. Data is now a commodity for most businesses and a lot of this data is unstructured. This means there is a need for such applications. Here is a report on my learnings of NLP.

2 Basics of NLP

2.1 Regular Expression (RE)

This is a language for specifying text search strings. For example to search for a *word*, we type */word/*. Regex (short for Regular Expression) is case sensitive. So the above expression differentiates between *word* and *Word*. This problem is solved by using []. Now */[Ww]ord/* will not differentiate for the earlier. Similarly in regex there are a lot of syntax rules that solve many such string operation problems in NLP. A gist of them:

RE	Example	Match
[]	/[1234567890]/	any digit
-	/[A-Z]/	an upper case letter
^	/[^A-Z]/	not an upper case letter
*	/a*/	any string of zero or more aa's
+	/a+/	one or more occurrences of a
$	/$/	end of line
()	/pupp(y|ies)/	puppy or puppies
|	/cat|dog/	occurrence of word cat or dog

2.2 Word Tokenization

It is the task of segmenting text into words. For many NLP applications, we need to decide about keeping punctuation and other grammatical tools since they might help the training algorithm, for example in sentiment analysis. Most tokenization schemes have two parts: a token learner, and a token segmenter. The token learner takes a raw training corpus (sometimes roughly pre-separated into words, for example by white-space) and induces a vocabulary, a set of tokens. The token segmenter takes a raw test sentence and segments it into the tokens in the vocabulary. In python this is usually done using *word_tokenize* function imported from **NLTK** library.

2.3 Word Normalization, Lemmatization and Stemming

Word Normalization is the task of putting words/tokens in a standard format so that there are no discrepancies in different datasets used for training. Case folding is one of its kind. Mapping all words to lowercase helps in generalising words.
Lemmatization is the task of determining that two words have the same root, despite their surface differences. For example, 'eat' and 'eating' have the same root eat. Lemmatization algorithms are complex. They involve **morphological parsing** of the word. So, idea of **stemming** was introduced which is a naive way of parsing. It involves chopping of word-final affixes. In python this is usually done using *porter_stemmer* function.

3 Classification Models for Sentiment Analysis

The most basic classification model is the Logisitic Regression. It is a statistical analysis method to predict a binary outcome, such as yes or no, based on prior observations of a data set.

3.1 Logisitic Regression

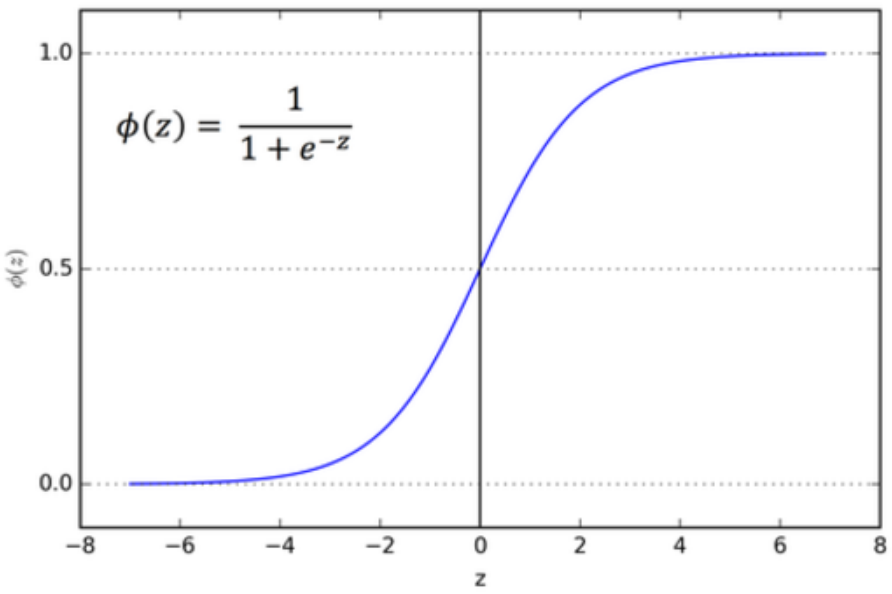


Figure 1: Logistic Regression

$$h_\theta(x) = g(\theta^T x) \tag{1}$$

$$g(z) = \frac{1}{1+e^{-z}} \tag{2}$$

$$\text{Predict y} = 1 \text{ if } h_\theta(x) \geq 0.5 \Rightarrow \theta^T x \geq 0$$
$$\text{Predict y} = 0 \text{ if } h_\theta(x) \leq 0.5 \Rightarrow \theta^T x \leq 0$$

$$J(\theta) = \frac{1}{m} \sum_{i=1}^{m} Cost(h_\theta(x^i), y^i) \tag{3}$$

$$Cost(h_\theta(x), y) = \begin{cases} \text{-log}(\text{h}_\theta(x)) \text{ if y} = 1 \\ \text{-log}(\text{1-h}_\theta(x)) \text{ if y} = 0 \end{cases} \tag{4}$$

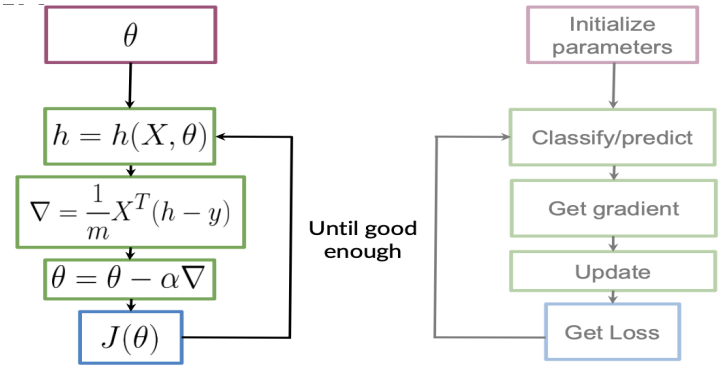


Figure 2: Training LR

Given a tweet/sentence, we need a way to classify if its positively(1) or negatively(0) sentimented. Given a sentence in english(WLG) corpus, the first step is to mathematically represent any input so that it can be fed into the algorithm.

How to mathematically represent tweets?

After preprocessing the tweets as explained in the basics of NLP using tokenization and lemmatization, we create a vocabulary of all the unique words we have counting their frequency in positive/negative tweets as shown in figure.

Vocabulary	PosFreq (1)	NegFreq (0)
I	3	3
am	3	3
happy	2	0
because	1	0
learning	1	1
NLP	1	1
sad	0	2
not	0	1

Figure 3: Frequency Table

For each tweet, we calculate the positive and negative frequency using the vocabulary table just shown above. For example: If the tweet is : "I am sad." It can be represented in vectorial form as:

$$\begin{bmatrix} 1 & 6 & 8 \end{bmatrix}$$

$$\begin{bmatrix} bias\_vector & sum\_of\_positive\_freq & sum\_of\_neg\_freq \end{bmatrix}$$

Hence after converting each tweet into a vector of 1x3, the training set is put into the logistic regressor and accuracy is tested out.

3.2 Naive Bayes

It is based upon the Bayes' rule (conditional probability).

$$P\left(\frac{X}{Y}\right) = P\left(\frac{Y}{X}\right) * \frac{P(X)}{P(Y)} \tag{5}$$

Lets look at usage of this algorithm in sentiment classification.
Using the table in Figure 3, a probability table is created with each value corresponding to the value $P\left(\frac{w_i}{class}\right)$.

Word	Pos	Neg
I	0.24	0.25
am	0.24	0.25
happy	0.15	0.08
because	0.08	0
learning	0.08	0.08
NLP	0.08	0.08
sad	0.08	0.08
not	0.08	0.17

Tweet : I am happy today; I am learning. To classify this tweet, ratio of it being positive to negative is calculated. If its > 1, the tweet is positive or else the opposite. For example, for this tweet:

$$\prod_{i=1}^{m} \frac{P(w_i|pos)}{P(w_i|neg)} = \frac{0.14}{0.10} = 1.4 \quad > 1$$

$$\frac{0.20}{0.20} * \frac{0.20}{0.20} * \boxed{\frac{0.14}{0.10}} * \frac{0.20}{0.20} * \frac{0.20}{0.20} * \frac{0.10}{0.10}$$

Figure 4: Naive Bayes classification

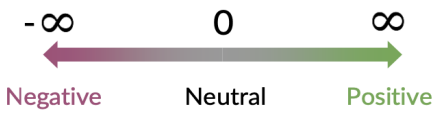
As it is visible in the table of probabilities that some probabilities can turn out to be zero. That might create problems in the equation we used to classify the tweet. That's where **smoothing** jumps in.

Laplace Smoothing

$$P\left(\frac{w_i}{class}\right) = \frac{freq(w_i, class) + 1}{N_{class} + V_{class}} \tag{6}$$

where, N_{class} = frequency of all words in class
V_{class} = number of unique words in class
To get better scaling logarithm of the conditions is taken which produces the results:

$$\sum_{i=1}^{m} log \frac{P(w_i|pos)}{P(w_i|neg)} > 0$$



Naive Bayes Assumptions and Errors

- Independence - Often the words are not independent, they are connected to each other. Naive Bayes doesn't include the effect of previous words.
- Relative frequencies in corpus
- Adversarial Attacks (Sarcasm and Irony) - 'This is a ridiculously movie. The plot was gripping and I cried through till the ending!' Processed tweet: [ridicul, power, movi, plot, grip, cry, end] would classify this tweet as negative and in fact its positively sentimented.

4 Vector Space Models

Vector space models help in designating similarity to sentences which have same meaning. This model represents words as vectors as a representation that captures relative meaning.

Word by Word design - Construction of vector spaces

Idea: Number of times two words occur together within a certain distance k. Consider two sentences:

- I like simple data
- I prefer simple raw data

Taking k=2 in the given example, vector space would look like:

	simple	raw	like	I
data	2	1	1	0

Since 'data' is within 2 words distance of 'simple' 2 times and similarly for other pairs.

Word by Document design - Construction of vector spaces

Idea: Number of times a word occurs within a certain category. For example:

	Entertainment	Economy	Machine Learning
data	500	6620	9320
film	7000	4000	1000

Vector Space visualization

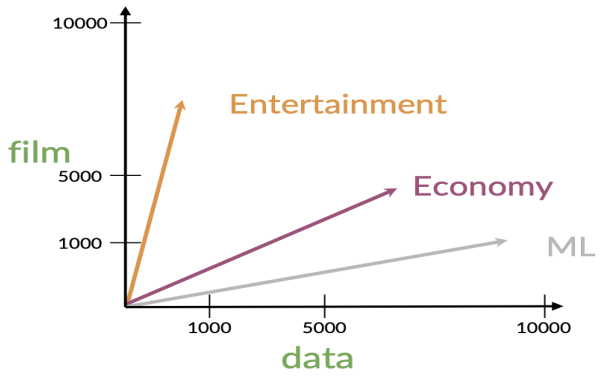


Figure 5: Vector space

4.1 Euclidean distance for n-dimensional vectors

$$d(\vec{v}, \vec{w}) = \sqrt{\sum_{i=1}^{n}(v_i - w_i)^2} \tag{7}$$

It is basically the length of straight line joining two points. Also called as the **norm** of the difference between two vectors.

4.2 Cosine Similarity

There are certain drawbacks with the euclidean distance. It doesn't properly classify corpus related to each other. Cosine of the angle between two vectors is observed to be more accurate as shown in the figure.

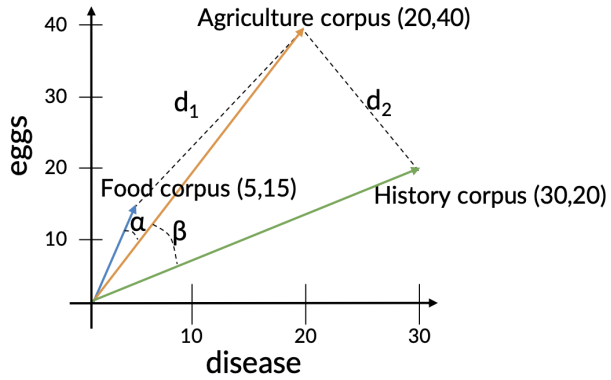


Figure 6: Cosine similarity

Euclidean distance : $d_2 > d_1$
Angles : $\alpha < \beta$

$$\cos\theta = \frac{\vec{v} \cdot \vec{w}}{||\vec{v}||||\vec{w}||} \tag{8}$$

The cosine similarity idea can be used to find words with similar relations. For example: India : Delhi :: Japan : ?
In vector language: $\vec{Delhi} - \vec{India} = \vec{?} - \vec{Japan}$. In a given corpus, the maximum value of the cosine similarity between the unknown word and $\vec{Delhi} - \vec{India} + \vec{Japan}$ would give the related word.

5 Minimum Edit Distance - Auto-correct

Autocorrect is one of the applications of NLP which is widely used in everyday life. For example, autocorrect for graffe can be giraffe, grail or graf. We observe that each of these corrections involve a certain number of edits. **Edit Distance** gives us a way to quantify both of these intuitions about string similarity. The **minimum edit distance** between two strings is defined as the minimum number of editing operations needed to transform one string to another.

5.1 Edit operations

- Insert (add a letter) ⇒ 'to' : 'top', 'two'
- Delete (remove a letter) ⇒ 'hat' : 'ha', 'at'
- Switch (swap two adjacent letters) ⇒ 'eta': 'eat'
- Replace (change one letter to another) ⇒ 'jaw':'jar'

5.2 Finding the minimum distance

Given two strings, the source string X of length n, and target string Y of length m, $D[i,j]$ is defined as the edit distance between $X[1...i]$ and $Y[1...j]$ i.e the first i characters of X and the first j characters of Y. The edit distance between X and Y is thus $D[n,m]$.Dynamic programming is used to compute $D[n,m]$ bottom up, combining solutions to subproblems.
In the base case, with a source substring of length i but an empty target string, going from i characters to 0 requires i deletes. With a target substring of length j but an empty source going from 0 characters to j characters requires j inserts. Having computed $D[i,j]$ for small i,j we then compute larger $D[i,j]$ based on previously computed smaller values. The value of $D[i,j]$ is computed by taking the minimum of the three possible paths through the matrix which arrive there:

$$D[i,j] = min \begin{cases} D[i-1,j]+1 \\ D[i,j-1]+1 \\ D[i-1,j-1] + \begin{cases} 2; \text{ if } source[i] \neq target[j] \\ 0; \text{ if } source[i] = target[j] \end{cases} \end{cases} \tag{9}$$

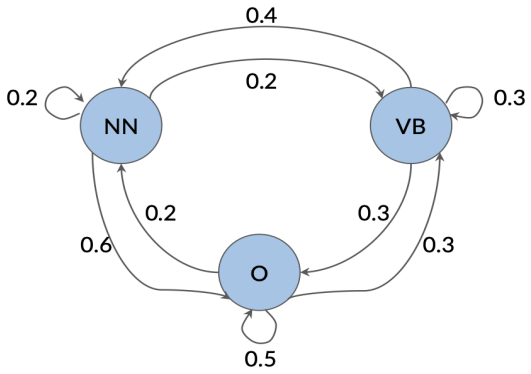
The assumptions involve insertion and deletion having cost of 1 and substitutions with a cost of 2. An example of the matrix $D[i,j]$ (# represents empty string):

		0	1	2	3	4
		#	s	t	a	y
0	#	0	1	2	3	4
1	p	1	2	3	4	5
2	l	2	3	4	5	6
3	a	3	4	5	4	5
4	y	4	5	6	5	4

6 Part of Speech Tagging

It involves tagging of words with parts of speech (noun, adverb, adjective etc.). The applications involve:

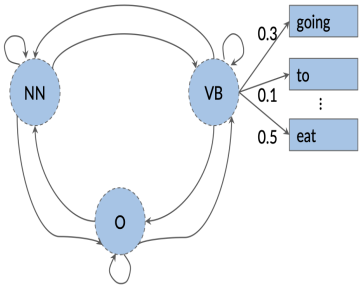
- Named entities
- Co-reference resolution
- Speech recognition

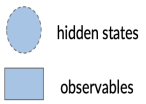


Transition matrix

$$A = \begin{pmatrix} a_{1,1} & \cdots & a_{1,N} \\ \vdots & \ddots & \vdots \\ a_{N+1,1} & \cdots & a_{N+1,N} \end{pmatrix}$$

Figure 7: Transition matrix





Emission matrix

$$B = \begin{pmatrix} b_{11} & \cdots & b_{1V} \\ \vdots & \ddots & \vdots \\ b_{N1} & \cdots & b_{NV} \end{pmatrix}$$

Figure 8: Emission matrix

6.1 Markov Chains

A Markov chain or Markov process is a stochastic model describing a sequence of possible events in which the probability of each event depends only on the state attained in the previous event. POS tags are represented as states with transition probabilities as shown in the figure 7.

$$P(t_i|t_{i-1}) = \frac{C(t_{i-1}, t_i)}{\sum_{j=1}^{N} C(t_{i-1}, t_j)} \tag{10}$$

These probabilities are used to create the transition matrix. where $C(t_{i-1}, t_i)$ represents the count of occurences of the tag pairs. Smoothing is applied to these probabilities in similar fashion as in case of Naive Bayes.

Emission Probabilities

This is used to create the emission matrix. The transition matrix denotes the probability for going from one hidden state to another (Tags).

6.2 The Viterbi Algorithm

As an instance of dynamic programming, Viterbi resembles the dynamic programming minimum edit distance algorithm. The Viterbi algorithm first sets up a probability matrix or lattice, with one column for each observation o_t and one row for each state in the state graph. Each column thus has a cell for each state q_i in the single combined automaton.
Each cell of the lattice, $v_t(j)$, represents the probability that the HMM is in state j after seeing the first t observations and passing through the most probable state sequence $q_1, ..., q_{t1}$, given the HMM (Hidden Markov Model) λ . The value of each cell $v_t(j)$ is computed by recursively taking the most probable path that could lead us to this cell. Formally, each cell expresses the probability:

$$v_t(j) = \max_{\{q_1 \dots q_{t-1}\}} P(q_1 ... q_{t-1}, o_1 ... o_t, q_t = j|\lambda) \tag{11}$$

We represent the most probable path by taking the maximum over all possible previous state sequences $\max_{\{q_1 \dots q_{t-1}\}}$. Viterbi fills each cell recursively. Given that we had already computed the probability of being in every state at time $t-1$, we compute the Viterbi probability by taking the most probable of the extensions of the paths that lead to the current cell. For a given state q_j at time t, the value $v_t(j)$ is computed as:

$$v_t(j) = \max_{\{i=1\}}^{N} v_{t-1}(i) a_{ij} b_j(o_t) \tag{12}$$

where $v_{t-1}(i)$ denote the previous Viterbi path probability from the previous step, a_{ij} is the transition probability from previous state q_i to current state q_j and $b_j(o_t)$ is the state observation likelihood of the observation symbol o_t given the current state j.

7 N-grams and Probabilities

An N-gram is a sequence of N words. Lets see some starter grams. Corpus: 'I am happy because I am learning'. Size of corpus m = 7.

Unigram Probability: $P(w) = \frac{C(w)}{m}$
Bigram Probability: $P(y|x) = \frac{C(xy)}{C(x)}$
Trigram Probability: P(happy | I am) $= \frac{C(Iamhappy)}{C(Iam)} = 1/2 \Rightarrow P(w_3|w_1^2) = \frac{C(w_1^2 w_3)}{C(w_1^2)}$
Probability of N-gram: $P(w_N|w_1^N - 1) = \frac{C(w_1^{N-1} w_N)}{C(w_1^{N-1})}$
where C is the count.
The assumption that the probability of a word depends only on the previous word is

called a **Markov assumption**. Markov models are the class of probabilistic models that assume we can predict the probability of some future unit without looking too far into the past. We can generalize the bigram (which looks one word into the past) to the trigram (which looks two words into the past) and thus to the n-gram (which looks $n1$ words into the past) as in the N-gram probability above.

7.1 Starting and Ending sentences

Each sentence need to be augmented with a special symbol $< s >$ at the beginning of the sentence, to give us the bigram context of the first word. We also need a special end-symbol $< /s >$. An example for bigram is shown in the figure.

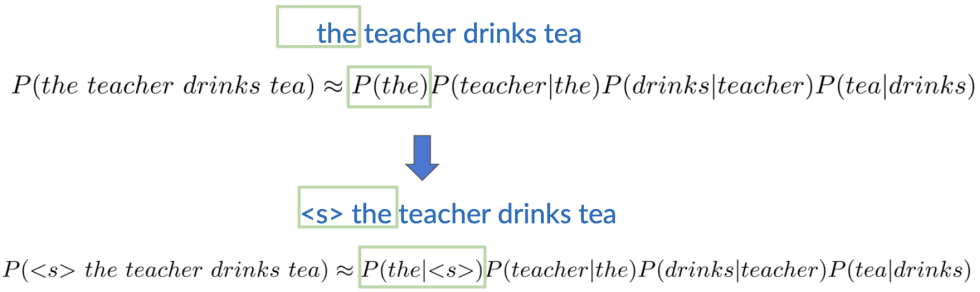


Figure 9: Bigram Updation

N-gram model: add $N - 1$ start tokens $< s >$

7.2 Model Outline

Count Matrix

The rows and columns each contain unique corpus words along with start tokens.

Probability Matrix

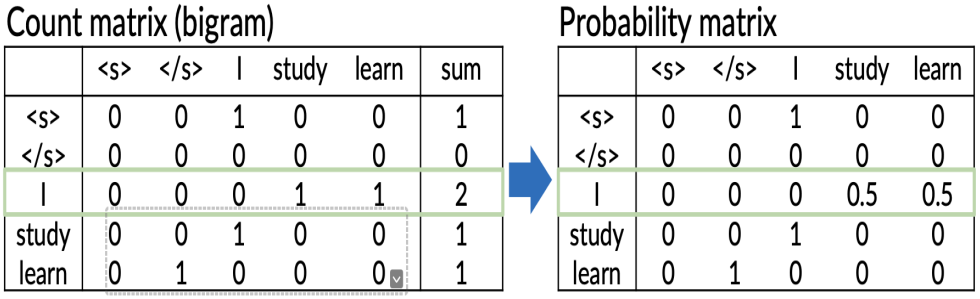
Obtained by dividing each cell by its row sum. For example: Let corpus be 'I study I learn'. An example of the matrix is shown in Figure 10.

Language Model

Let's say we want to find the probability of the sentence: $< s >$ I learn $< /s >$

$$P(sentence) = P(I| < s >)P(learn|I)P(< /s > |learn) = 1 * 0.5 * 1 = 0.5$$

For N-grams as N becomes larger the probability values tend to shrink. Therefore, log of probabilities is taken as it is easier for machines to carry out calculations with larger numbers.



	<s>	</s>	I	study	learn	sum
<s>	0	0	1	0	0	1
</s>	0	0	0	0	0	0
I	0	0	0	1	1	2
study	0	0	1	0	0	1
learn	0	1	0	0	0	1

	<s>	</s>	I	study	learn
<s>	0	0	1	0	0
</s>	0	0	0	0	0
I	0	0	0	0.5	0.5
study	0	0	1	0	0
learn	0	1	0	0	0

Figure 10: Bigram Count and Probability Matrix

7.3 Evaluating Language Models

The best way to evaluate the performance of a language model is to embed it in an application and measure how much the application improves. Such end-to-end evaluation is called **extrinsic evaluation**.
Unfortunately, running big NLP systems end-to-end is often very expensive. Instead, it would be nice to have a metric that can be used to quickly evaluate potential improvements in a language model. An **intrinsic evaluation** metric is one that measures the quality of a model independent of any application.
For an intrinsic evaluation of a language model we need a **test set**. As with many of the statistical models in our field, the probabilities of an n-gram model come from the corpus it is trained on, the training set or training corpus. We can then measure the quality of an n-gram model by its performance on some unseen data called the test set or test corpus. Given two probabilistic models, the better model is the one that has a tighter fit to the test data or that better predicts the details of the test data, and hence will assign a higher probability to the test data.
But sometimes, we let the training set get induce into the test set. This introduces a bias that makes probabilities look high and huge inaccuracies in perplexity.

Perplexity

In practice we don't use raw probability as our metric for evaluating language models, but a variant called perplexity. The perplexity (sometimes called PP for short) of a language model on a test set is the inverse probability of the test set, normalized by the number of words. For a test set $W = w_1 w_2 ... w_N, :$

$$\sqrt[m]{\prod_{i=1}^{m} \frac{1}{P(w_i|w_{i-1})}} \tag{13}$$

Perplexity can also be mathematically taken with logarithm. Smaller is the perplexity, better is the model.

7.4 Out of Vocabulary Words

In some cases, we deal with words, we haven't seen before which we call **unknown words** or **out of vocabulary**. An open vocabulary system is one in which we model these potential unknown words in the test set by adding a pseudo-word called $< UNK >$.

Common ways to train the probabilities of the unknown word model:

- Choose a vocabulary (word list) that is fixed in advance.
- Convert in the training set any word that is not in this set (any OOV word) to the unknown word token $< UNK >$ in a text normalization step.
- Estimate the probabilities for $< UNK >$ from its counts just like any other regular word in the training set.

8 Word Embeddings

This section explores vector semantics, which instantiates this linguistic hypothesis by learning representations of the meaning of words, called **embeddings**, directly from their distributions in texts.
Vectors for representing words are called embeddings, although the term is sometimes more strictly applied only to dense vectors like **word2vec**, rather than sparse **TF-IDF or PPMI** vectors. The word "embedding" derives from its mathematical sense as a mapping from one space or structure to another. The Figure 11 shows a visualization of embeddings learned for sentiment analysis, showing the location of selected words projected down from 60-dimensional space into a two dimensional space. Notice the distinct regions containing positive words, negative words, and neutral function words.

Figure 11: Visualization of embeddings

8.1 CBOW Model

It stands for Continuous Bag of Words model, an embedding method. In the CBOW model, the distributed representations of context (or surrounding words) are combined

to predict the word in the middle using a Neural Network. A prerequisite for any neural network or any supervised training technique is to have labeled training data. How do you a train a neural network to predict word embedding when you don't have any labeled data i.e words and their corresponding word embedding?
We do so by creating a "fake" task for the neural network to train. We won't be interested in the inputs and outputs of this network, rather the goal is actually just to learn the **weights** of the **hidden layer** that are actually the "word vectors" that we're trying to learn.
The fake task is to take into account context words and predict the target word and teach the model that they co-occur. A figure might help to understand this better. The

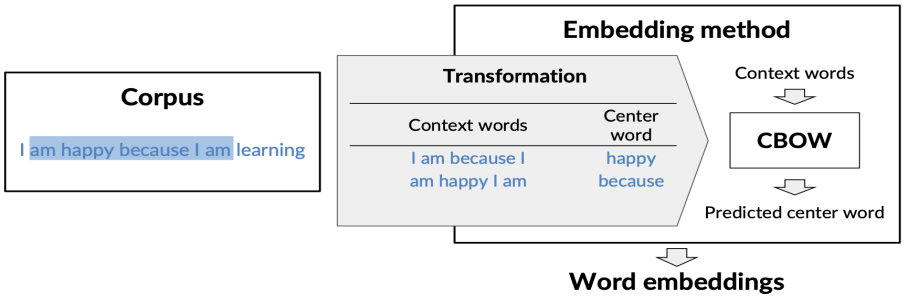


Figure 12: CBOW overview

dimension of hidden layer and output layer will remain the same. Only the dimension of input layer and the calculation of hidden layer activations will change, if we have 4 context words for a single target word, we will have 4 1xV input vectors. Each will be multiplied with the VxE hidden layer returning 1xE vectors. All 4 1xE vectors will be averaged element-wise to obtain the final activation which then will be fed into the softmax layer.

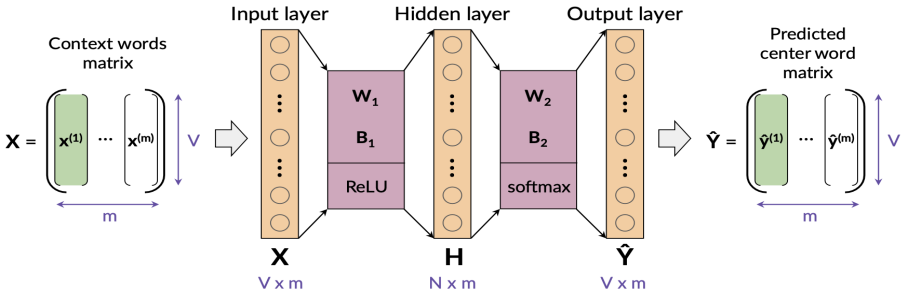


Figure 13: CBOW architecture

8.2 TF-IDF

This section will describe tf-idf algorithm, usually used when dimensions are documents. The tf-idf algorithm (the '-' here is a hyphen, not a minus sign :p) is the

product of two terms, each term capturing one of these two intuitions:
The first is the **term frequency**: the frequency of the word t in the document d. We can just use the raw count as the term frequency:

$$tf_{t,d} = count(t, d) \tag{14}$$

More commonly we squash the raw frequency a bit, by using the log_{10} of the fre- quency instead. The intuition is that a word appearing 100 times in a document doesn't make that word 100 times more likely to be relevant to the meaning of the document. Because we can't take the log of 0, we normally add 1 to the count:

$$tf_{t,d} = \log_{10}(count(t, d) + 1) \tag{15}$$

The second factor in tf-idf is used to give a higher weight to words that occur only in a few documents. Terms that are limited to a few documents are useful for discriminating those documents from the rest of the collection; terms that occur frequently across the entire collection aren't as helpful. The document frequency df_t of a term t is the number of documents it occurs in. The idf is defined using the fraction N/df_t, where N is the total number of documents in the collection, and df_t is the number of documents in which term t occurs. The fewer documents in which a term occurs, the higher this weight. The lowest weight of 1 is assigned to terms that occur in all the documents. The tf-idf weighted value $w_{t,d}$ for word t in document d thus combines term frequency $tf_{t,d}$ with idf to give:

$$w_{t,d} = tf_{t,d} * idf_t \tag{16}$$

8.3 Word2Vec

This section describes one method for computing embeddings: skip-gram with negative sampling, sometimes called SGNS. The skip-gram algorithm is one of two algorithms in a software package called word2vec, and so sometimes the algorithm is loosely referred to as word2vec. Word2vec embeddings are static embeddings, meaning that the method learns one fixed embedding for each word in the vocabulary.
The intuition of word2vec is that instead of counting how often each word w occurs near, say, *apricot*, we'll instead train a classifier on a binary prediction task: "Is word w likely to show up near *apricot*?" We don't actually care about this prediction task; instead we'll take the learned classifier **weights** as the word embeddings. The intuition behind is:

- Treat the target word and a neighboring context word as positive examples.

- Randomly sample other words in the lexicon to get negative samples.
- Use logistic regression to train a classifier to distinguish those two cases.
- Use the learned weights as the embeddings.

Classifier

Imagine a sentence like the following, with a target word apricot, and assume we're using a window of ±2 context words:

$$\begin{bmatrix} tablespoon & of & apricot & jam & a \end{bmatrix}$$

$$\begin{bmatrix} c1 & c2 & w & c3 & c4 \end{bmatrix}$$

Our goal is to train a classifier such that, given a tuple (w, c) of a target word w paired with a candidate context word c (for example (apricot, jam), or perhaps (apricot, aardvark)) it will return the probability that c is a real context word.

How does the classifier compute the probability P?

The intuition of the skip-gram model is to base this probability on embedding similarity: a word is likely to occur near the target if its embedding is similar to the target embedding. To compute similarity between these dense embeddings, we rely on the intuition that two vectors are similar if they have a high dot product (after all, cosine is just a normalized dot product :p). To turn the dot product into a probability, we use the **sigmoid** function.

9 Recurrent Neural Networks (RNN)

A recurrent neural network (RNN) is any network that contains a cycle within its network connections. That is, any network where the value of a unit is directly, or indirectly, dependent on its own earlier outputs as an input. While powerful, such networks are difficult to reason about and to train. Simple Recurrent Networks serve as a basis for complex models such as LSTM. The key difference from a feedforward network lies in the recurrent link shown in the figure with the dashed line. This link augments the input to the computation at the hidden layer with the value of the hidden layer from the preceding point in time.
The hidden states $h^{<t>}$ propagate information through time. Each recurrent unit has two inputs at each time : $h^{<t>}$ $x^{<t>}$. As with feedforward networks, it uses a training set, a loss function, and backpropagation to obtain the gradients needed to adjust the weights in these recurrent networks. To compute the loss function for the output at time t we need the hidden layer from time $t1$. Second, the hidden layer at time t influences both the output at time t and the hidden layer at time $t + 1$ (and hence the output and loss at $t + 1$). It follows from this that to assess the error accruing to h_t,

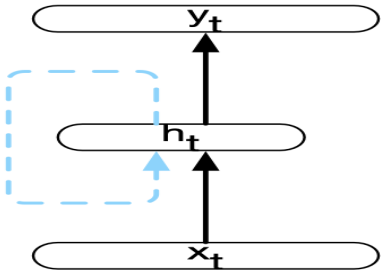


Figure 14: Simple RNN

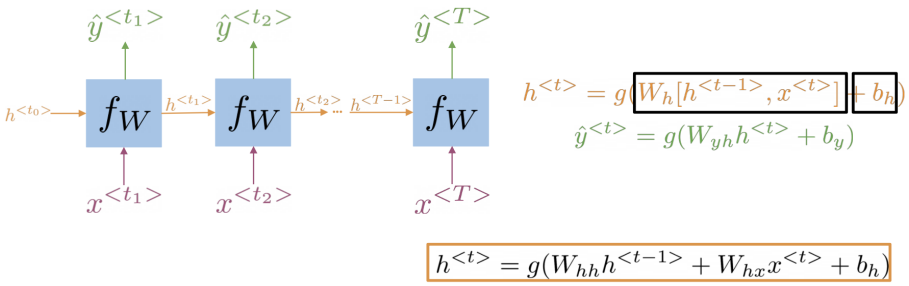


Figure 15: RNN Architecture

we'll need to know its influence on both the current output as well as the ones that follow.

Tailoring the backpropagation algorithm to this situation leads to a two-pass algorithm for training the weights in RNNs. In the first pass, we perform forward inference, computing h_t , y_t, accumulating the loss at each step in time, saving the value of the hidden layer at each step for use at the next time step. In the second phase, we process the sequence in reverse, computing the required gradients as we go, computing and saving the error term for use in the hidden layer for each step backward in time. This general approach is commonly referred to as Backpropagation through time.

9.1 Stacked RNNs

Stacked RNNs consist of multiple networks where the output of one layer serves as the input to a subsequent layer, as shown in Fig. 16. Stacked RNN's outperform single-layer networks because they have the ability to induce representations at differing levels of abstraction across layers.

9.2 Bidirectional RNNs

In a simple RNN, the hidden state at a given time t represents everything the network knows about the sequence up to that point in the sequence. That is, the hidden state

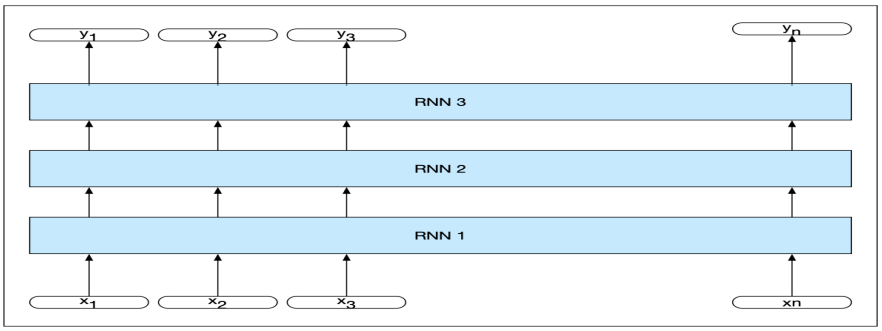


Figure 16: Stacked RNN

at time t is the result of a function of the inputs from the start up through time t. But, in many applications we have access to the entire input sequence at once. It might be helpful to take advantage of the context to the right of the current input as well. One way to recover such information is to train an RNN on an input sequence in reverse, using exactly the same kind of network.
Combining the forward and backward networks results in a bidirectional RNN. A Bi-RNN consists of two independent RNNs, one where the input is processed from the start to the end, and the other from the end to the start. We then combine the outputs of the two networks into a single representation that captures both the left and right contexts of an input at each point in time. Bidirectional RNNs have proven to be quite effective for sequence classification.

$$h_t^f = RNN_{forward}(x_1^t) \tag{17}$$

$$h_t^b = RNN_{backward}(x_t^n) \tag{18}$$

$$h_t = h_t^f \oplus h_t^b \tag{19}$$

9.3 LSTM's and GRU's

Despite having access to complete sequence, the information encoded in hidden states still tends to be quite local, influenced by nearby time states much more as compared to other. It is often the case, however, that distant information is critical to many language applications.
Lets consider an example, the statement : 'The flights the airline was cancelling were full.' Assigning a high probability to was following airline is straightforward since airline provides a strong local context for the singular agreement. However, assigning an appropriate probability to were is quite difficult, not only because the plural flights is quite distant, but also because the intervening context involves singular constituents. To address these issues, more complex network architectures have been designed to explicitly manage the task of maintaining relevant context over time.

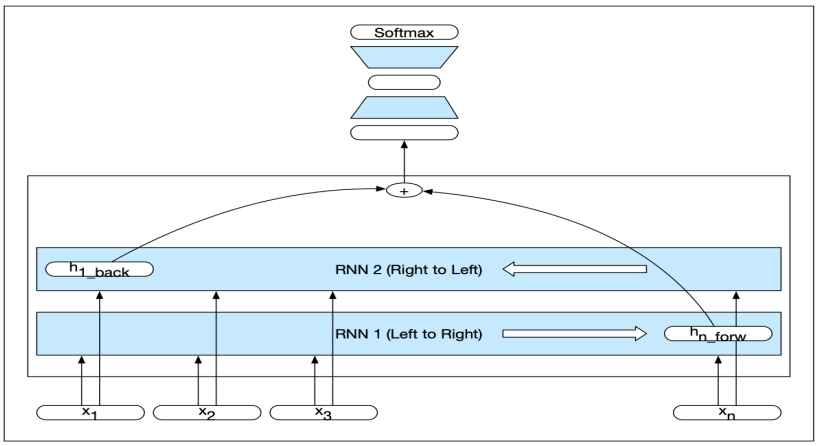


Figure 17: Bi-RNN

LSTM - Long Short-term Memory

Long short-term memory (LSTM) networks divide the context management problem into two sub-problems: removing information no longer needed from the context, and adding information likely to be needed for later decision making. LSTMs accomplish this by first adding an explicit **context layer** to the architecture (in addition to the usual recurrent hidden layer), and through the use of specialized neural units that make use of gates to control the flow of information into and out of the units that comprise the network layers. These gates are implemented through the use of additional weights that operate sequentially on the input, and previous hidden layer, and previous context layers.
Basic anatomy:

- A cell state
- A hidden state
- Multiple gates

The gates in an LSTM share a common design pattern; each consists of a feed-forward layer, followed by a sigmoid activation function, followed by a pointwise multiplication with the layer being gated. The choice of the sigmoid as the activation function arises from its tendency to push its outputs to either 0 or 1. Combining this with a pointwise multiplication has an effect similar to that of a binary mask.

- Forget gate: The purpose of a forget gate is to delete information from the context that is no longer needed. The forget gate computes a weighted sum of the previous state's hidden layer and the current input and passes that through a sigmoid. This mask is then multiplied by the context vector to remove the information from context that is no longer required.

$$f_t = \sigma(U_f h_{t-1} + W_f x_t) \tag{20}$$

$$k_t = c_{t-1t} \tag{21}$$

The next task is compute the actual information we need to extract from the previous hidden state and current inputs — the same basic computation used for recurrent networks.

$$g_t = tanh(U_g h_{t-1} + W_g x_t) \tag{22}$$

Next, we generate the mask for the add gate to select the information to add to the current context.

$$i_t = \sigma(U_i h_{t-1} + W_i x_t) \tag{23}$$

$$j_t = g_t \odot i_t \tag{24}$$

Next, we add this to the modified context vector to get our new context vector.

$$c_t = j_t + k_t \tag{25}$$

The final gate used is the output gate which is used to decide what information is required for the current hidden state.

$$o_t = \sigma(U_o h_{t-1} + W_o x_t) \tag{26}$$

$$h_t = o_t \odot tanh(c_t) \tag{27}$$

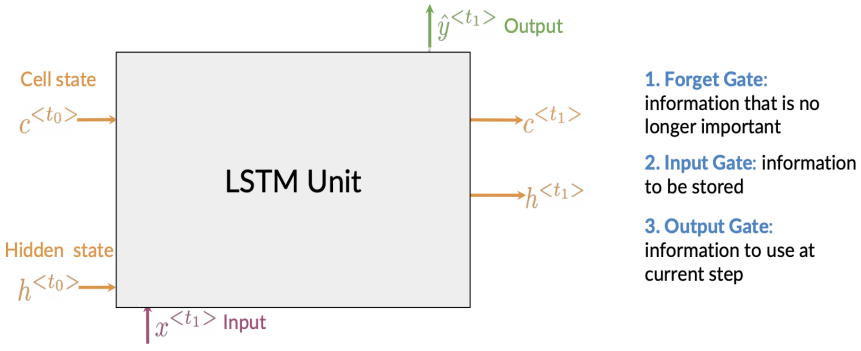


Figure 18: Gates in LSTM

GRU - Gated Recurrent Units

The problem with LSTM's is a large number of parameters to be trained upon. Training these additional parameters imposes a much significantly higher training cost. Gated Recurrent Units (GRU's) ease this burden by dispensing with the use of a separate context vector and by reducing the number of gates to 2 — a reset gate, r and an update gate, z.

$$r_t = \sigma(U_r h_{t-1} + W_r x_t) \tag{28}$$

$$z_t = \sigma(U_z h_{t-1} + W_z x_t) \tag{29}$$

10 Siamese Networks

Often while asking questions on websites like Quora, Stackoverflow, etc. you tend to get substitutes for your question, or questions similar to yours. This is done with the help of siamese networks. They identify similarity between things. For example, 'What is your age' and 'How old are you?' actually are question duplicates.

Model Architecture

In Siamese network the basic network for getting features of entities(images/text) is kept same and the two entities we want to compare are passed through the exact same network. By the exact same network it is meant that both the entities are passed through the same architecture having same weights as shown in the figure. At the end of common network a vectored representation of the input is obtained which can then be used for measuring or quantifying the similarity between them.

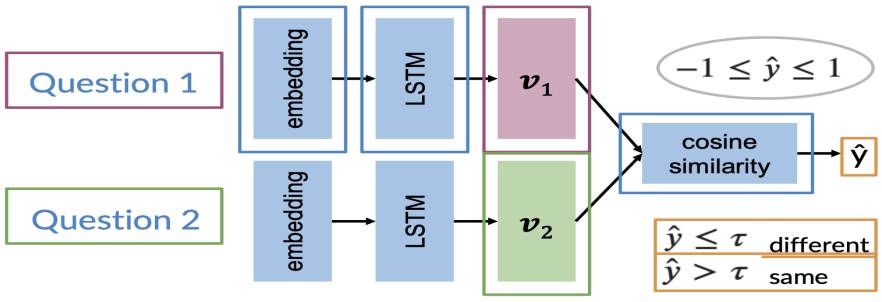


Figure 19: Siamese Architecture

Loss Function

An anchor statement is chosen to which we want to designate similarity to sentences.

- Anchor : How old are you?
- Positive : What is your age?
- Negative : Where are you from?

Similarity between anchor and positive statements $s(A, P)$ as well as between anchor and negative statements $s(A, N)$ is calculated using the cosine similarity function described in 4.2. The loss function is defined as:

$$diff = s(A, N) - s(A, P) \tag{30}$$

Triplet Loss

$$L = \begin{cases} 0 \text{ if diff} + \alpha \leq 0 \\ \text{diff if diff} + \alpha > 0 \end{cases} \tag{31}$$

The triplet loss adds a margin since we want our model to train more over examples which have diff close to zero, since these are examples which are highly correlated and might be important.

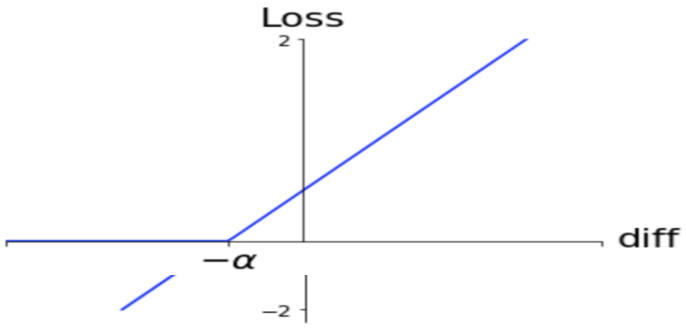


Figure 20: Triplet Loss

Cost Function

$$J = \sum_{i=1}^{m} L(A^{(i)}, P^{(i)}, N^{(i)}) \tag{32}$$

Training/Testing

First step is to prepare two batches such that a question in one batch doesn't match to any other question in the same batch but is similar to the same indexed in the second batch.
Second step involves creating a subnetwork :

- Embedding
- LSTM
- Vectors
- Cosine Similarity

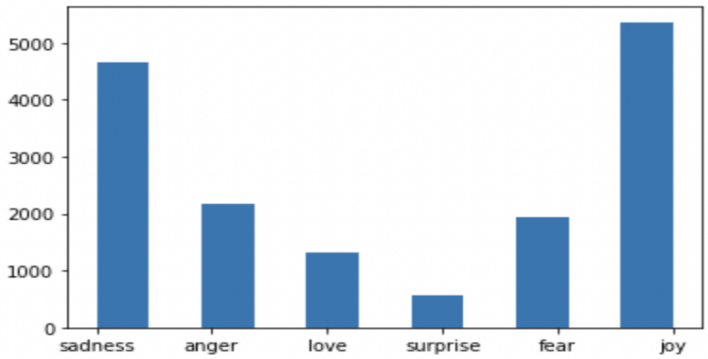
Third step involves testing which includes:

- Convert each input into an array of numbers
- Feed arrays into your model
- Compare v_i, v_2 using cosine similarity
- Test again a threshold

11 Hobby Project

Tweet Emotion Recognition

The Colab file can be found here. The dataset used is from the NLP library itself. It consists of training data of size 16000 whereas 2000 tweets for validation and testing. The first step is to convert each input into an array of numbers which was done using tokenizer function. Now since, we want all sequences of same length, padding is necessary so that an input of constant shape can be fed into the model. The dataset after labelling :



Data oversampling can be done in order to produce a balanced dataset but as we will see, the model performed well even without that. As discussed a bi-directional RNN is generally very useful for sentiment analysis. The model summary is as follows with 175k parameters. Model Statistics after 8 epochs since it was monitored on basis of validation accuracy checking overfitting (Fig 21).
Now it's time for the model to get tested upon. It gives an accuracy of 88.65%. The confusion matrix shows that the model has certain wrong labels/outputs between love and joy (Figure 22).

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                 Output Shape              Param #
=================================================================
 embedding_1 (Embedding)      (None, 50, 16)            160000

 bidirectional_2 (Bidirectio  (None, 50, 40)            5920
 nal)

 bidirectional_3 (Bidirectio  (None, 40)              9760
 nal)

 dense_1 (Dense)              (None, 6)                 246

=================================================================
Total params: 175,926
Trainable params: 175,926
Non-trainable params: 0
```

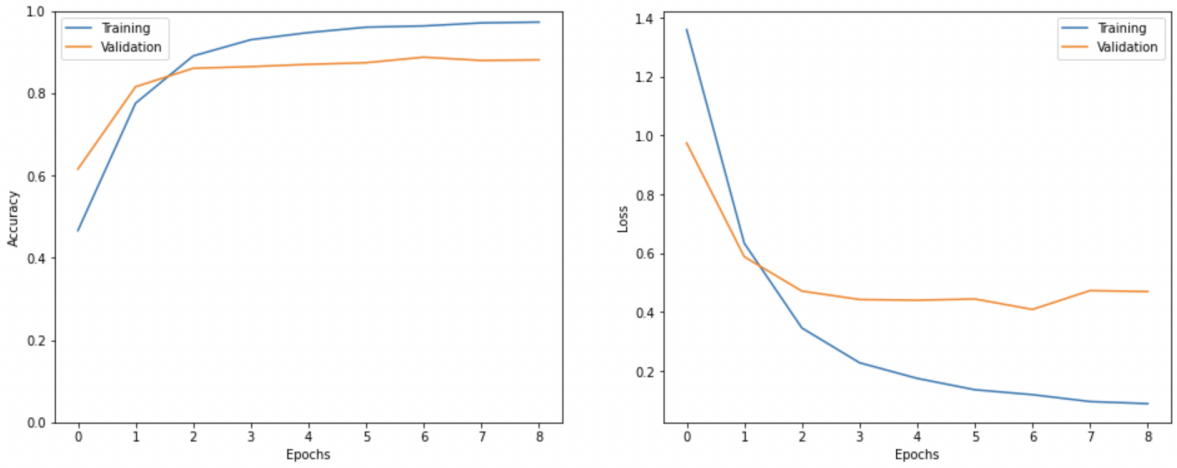


Figure 21: Model history

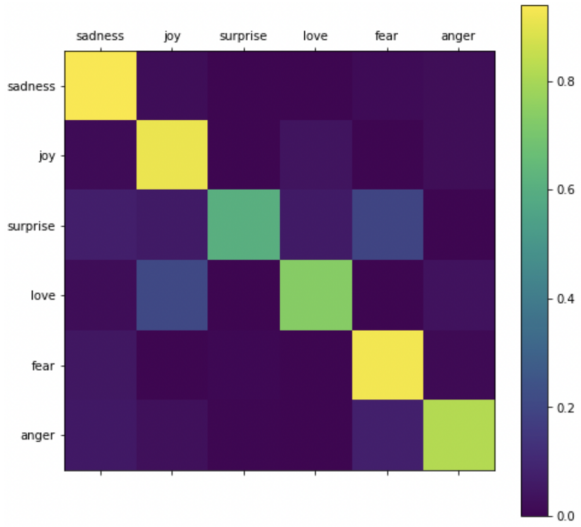


Figure 22: Confusion Matrix

Acknowlegdements

This work was done as a part of the Summer Of Science, 2022 by the MnP Club, IIT Bombay. I have followed the course Natural Language Specialization by DeepLearning.AI. The course instructors were Younes Bensouda Mourri and Łukasz Kaiser. All the content here is highly inspired by this course as well the book by Daniel Jurafsky and James H. Martin. S on NLP. I have tried to compress the contents, skipping a few details while keeping the important ones. At the end, I also did a small hobby project which is just a tiny part of the learning. Also, I would like to acknowledge the help of my mentor, Samyak Shah, for his help and support.

References

1. Daniel Jurafsky and James H. Martin. Speech and Language Processing
2. DeepLearning.AI, NLP Specialisation Course
3. DeepLearning.AI, Sequence Models
4. https://stackoverflow.com/