Next Word Prediction

Made by :-

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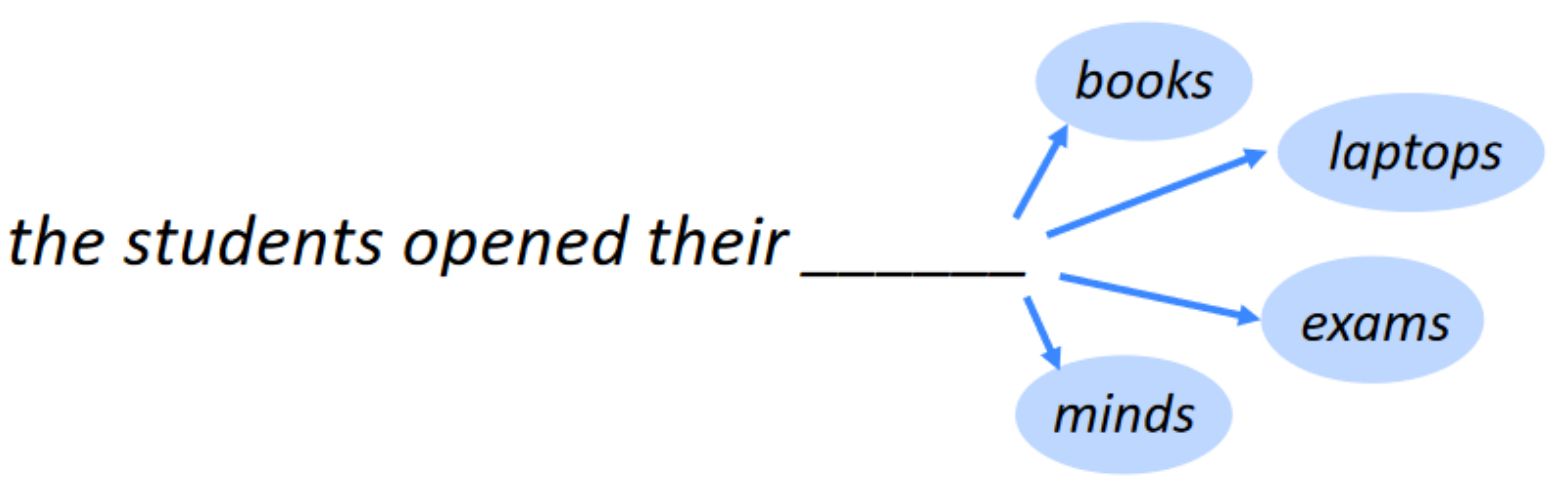
Introduction

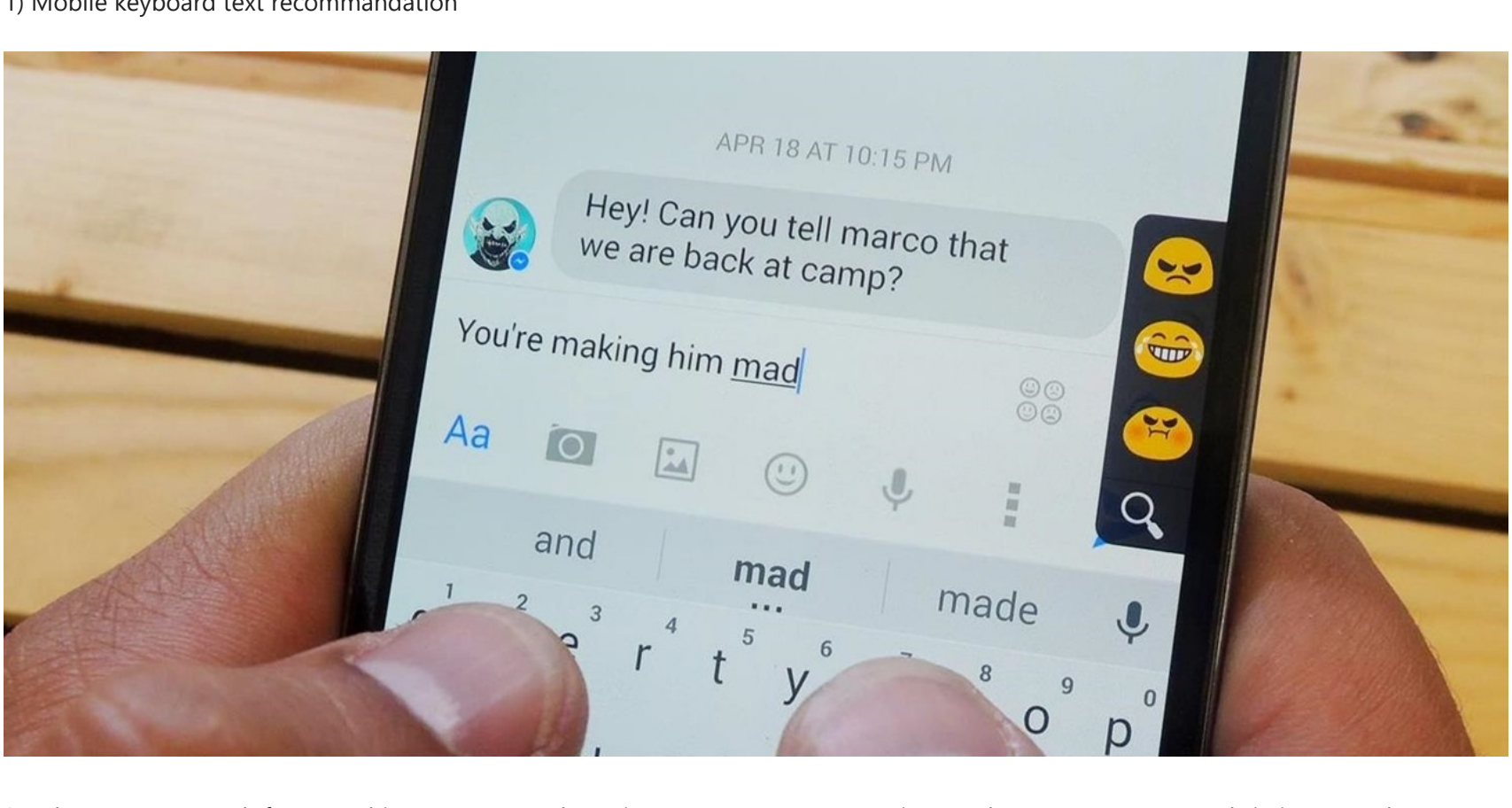
Next Word Prediction (also called Language Modeling) is the task of predicting what word comes next. It is one of the fundamental tasks of NLP.

Image reference: https://medium.com/@antonio.lopardo/the-basics-of-language-modeling-1c8832f21079



Application Language Modelling

1) Mobile keyboard text recommandation



2) Whenever we search for something on any search engine, we get many suggestions and, as we type new words in it, we get better recommendations according to our searching context. So, how will it happen???

It is possible through natural language processing (NLP) technique. Here, we will use NLP and try to make a prediction model using Bidirectional LSTM (Long short-term memory) model that will predict next words of sentence.

More about the dataset , check

https://www.kaggle.com/datasets/dorianlazar/medium-articles-dataset

About the program :

https://www.kaggle.com/code/ysthehurricane/next-word-prediction-bi-lstm-tutorial-easy-way

Import necessary libraries and packages

In [1]:
```
import numpy as np  # Using for different problems related to numericals operations
import pandas as pd  # Using to the read the csv dataset
import tensorflow as tf
from colorama import Back, Fore
from tensorflow.keras.layers import LSTM, Bidirectional, Dense, Embedding
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.preprocessing.text import Tokenizer
from termcolor import colored, cprint
```

Dataset information¶

Import Medium-articles-dataset:

This dataset contains information about randomly chosen medium articles published in 2019 from these 7 publications:

```
Towards Data Science
UX Collective
The Startup
The Writing Cooperative
Data Driven Investor
Better Humans
Better Marketing
```

In [2]:
```
df = pd.read_csv("medium_data.csv")
df.head()
```

Out[2]:

	id	url	title	subtitle	image	claps	responses	reading_time	publication	date
0	1	https://towardsdatascience.com/a-beginners-gui...	A Beginner's Guide to Word Embedding with Gens...	NaN	1.png	850	8	8	Towards Data Science	2019-05-30
1	2	https://towardsdatascience.com/hands-on-graph-...	Hands-on Graph Neural Networks with PyTorch & ...	NaN	2.png	1100	11	9	Towards Data Science	2019-05-30
2	3	https://towardsdatascience.com/how-to-use-ggpl...	How to Use ggplot2 in Python	A Grammar of Graphics for Python	3.png	767	1	5	Towards Data Science	2019-05-30
3	4	https://towardsdatascience.com/databricks-how-...	Databricks: How to Save Files in CSV on Your L...	When I work on Python projects dealing...	4.jpeg	354	0	4	Towards Data Science	2019-05-30
4	5	https://towardsdatascience.com/a-step-by-step-...	A Step-by-Step Implementation of Gradient Desc...	One example of building neural...	5.jpeg	211	3	4	Towards Data Science	2019-05-30

Checking the shape of the dataset

In [3]:
```
print("Number of records: ", df.shape[0])
print("Number of fields: ", df.shape[1])
```

```
Number of records:  6508
Number of fields:  10
```

Here, we have a 10 different fields and 6508 records but we will only use title field for predicting next word.

Display titles of various articles and preprocess them

In [4]:
```
df["title"]
```

Out[4]:
```
0       A Beginner's Guide to Word Embedding with Gen...
1       Hands-on Graph Neural Networks with PyTorch & ...
2                            How to Use ggplot2 in Python
3       Databricks: How to Save Files in CSV on Your L...
4       A Step-by-Step Implementation of Gradient Desc...
                              ...
6503    "We" vs "I" — How Should You Talk About Yourse...
6504                     How Donald Trump Markets Himself
6505        Content and Marketing Beyond Mass Consumption
6506    5 Questions All Copywriters Should Ask Clients...
6507               How To Write a Good Business Blog Post
Name: title, Length: 6508, dtype: object
```

Checking of any Null values

In [5]:
```
df["title"].isna().sum()
```

Out[5]: 0

Removing unwanted characters and words in titles

Looking at titles, we can see there are some of unwanted characters and words in it which can not be useful for us to predict infact it might decrease our model accuracy so we have to remove it.

In [6]:
```
df["title"] = df["title"].apply(lambda x: x.replace("\xa0", " "))
df["title"] = df["title"].apply(lambda x: x.replace("\u200a", " "))
```

In [7]:
```
df["title"]
```

Out[7]:
```
0       A Beginner's Guide to Word Embedding with Gen...
1       Hands-on Graph Neural Networks with PyTorch & ...
2                            How to Use ggplot2 in Python
3       Databricks: How to Save Files in CSV on Your L...
4       A Step-by-Step Implementation of Gradient Desc...
                              ...
6503    "We" vs "I" — How Should You Talk About Yourse...
6504                     How Donald Trump Markets Himself
6505        Content and Marketing Beyond Mass Consumption
6506    5 Questions All Copywriters Should Ask Clients...
6507               How To Write a Good Business Blog Post
Name: title, Length: 6508, dtype: object
```

Tokenzation

Tokenzaion is the process in which we provide an unique id to all the words and make a word index or we can say vocabulary.

In [8]:
```
from tensorflow.keras.preprocessing.text import Tokenizer
```

In [9]:
```
tokenizer = Tokenizer(
    oov_token="<oov>"
)  # For those words which are not found in word_index
tokenizer.fit_on_texts(df["title"])
total_words = len(tokenizer.word_index) + 1

print("Total number of words: ", total_words)
print("Word: ID")
print("------------")
print("<oov>: ", tokenizer.word_index["<oov>"])
print("Strong: ", tokenizer.word_index["strong"])
print("And: ", tokenizer.word_index["and"])
print("Consumption: ", tokenizer.word_index["consumption"])
print("------------")
print("Example how the data is stored :-\n", list(tokenizer.word_index.items())[:5])
```

```
Total number of words:  8238
Word: ID
------------
<oov>:  1
Strong:  4
And:  8
Consumption:  8237
------------
Example how the data is stored :-
 [('<oov>', 1), ('to', 2), ('the', 3), ('strong', 4), ('a', 5)]
```

Titles text into sequences and make n_gram model

suppose, we have sentence like "I am Yash" and this will convert into a sequence with their respective tokens {'I': 1,'am': 2,'Yash': 3}. Thus, output will be ['1','2','3']

Likewise, our all titles will be converted into sequences.

Then, we will make a n_gram model for good prediction.

Below image explain about everything.

Example of N-gram Model

Sentence: I am a Data Scientist

Word index: {'I': 1, 'am': 2, 'a': 3, 'Data': 4, 'scientist': 5}

Text Sequence: [1,2,3,4,5]

N_gram model for this sentence:

[1,2,3,4,5] = ['I', 'am', 'a', 'Data', 'Scientist']

[1,2,3,4] = ['I', 'am', 'a', 'Data']

[1,2,3] = ['I', 'am', 'a']

[1,2] = ['I', 'am']

In [19]:
```
token_list
```

Out[19]: [7, 2, 45, 5, 85, 56, 730, 550]

In [88]:
```
input_sequences = []
for line in df["title"]:
    token_list = tokenizer.texts_to_sequences([line])[0]
    # print(token_list)

    for i in range(1, len(token_list)):
        n_gram_sequence = token_list[: i + 1]
        input_sequences.append(n_gram_sequence)

print("This is What token list looks like :-", token_list)
cprint("-----------", "yellow")
# print(input_sequences)
print("Total input sequences: ", len(input_sequences))
cprint("-----------", "yellow")
print(list(tokenizer.word_index.items())[4])
print(list(tokenizer.word_index.items())[675])
print(list(tokenizer.word_index.items())[67])
print(list(tokenizer.word_index.items())[1])
print(list(tokenizer.word_index.items())[451])
print(list(tokenizer.word_index.items())[1517])
cprint("-----------", "yellow")
print("This sentence is converted into the below sequence :-")
cprint(df["title"][0], ...)
# print(len(list(tokenizer.word_index.items())))
input_sequences[:9]
```

```
This is What token list looks like :- [7, 2, 45, 5, 85, 56, 730, 550]
-----------
Total input sequences:  48461
-----------
('a', 5)
('beginner's', 676)
('guide', 68)
('to', 2)
('word', 452)
('embedding', 1518)
-----------
This sentence is converted into the below sequence :-
A Beginner's Guide to Word Embedding with Gensim Word2Vec Model
```

Out[88]:
```
[[5, 676],
 [5, 676, 68],
 [5, 676, 68, 2],
 [5, 676, 68, 2, 452],
 [5, 676, 68, 2, 452, 1518],
 [5, 676, 68, 2, 452, 1518, 14],
 [5, 676, 68, 2, 452, 1518, 14, 2455],
 [5, 676, 68, 2, 452, 1518, 14, 2455, 3653],
 [5, 676, 68, 2, 452, 1518, 14, 2455, 3653, 99]]
```

In [83]:
```
import pickle

# saving
with open("tokenizer.pickle", "wb") as handle:
    pickle.dump(tokenizer, handle, protocol=pickle.HIGHEST_PROTOCOL)
```

Make all titles with same length by using padding

The length of every title has to be the same. To make it, we need to find a title that has a maximum length, and based on that length, we have to pad rest of titles.

In [84]:
```
from tensorflow.keras.preprocessing.sequence import pad_sequences

max_sequence_len = max([len(x) for x in input_sequences])
# get the maximum length sequence
max_sequence_len
```

Out[84]: 40

In [21]:
```
input_sequences = np.array(
    pad_sequences(input_sequences, maxlen=max_sequence_len, padding="pre")
)
input_sequences[8]
```

Out[21]:
```
array([   0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,
          0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,
          0,    0,    0,    0,    0,    0,    0,    0,    5,  676,   68,
          2,  452, 1518,   14, 2455, 3653,   99])
```

Prepare features and labels

Here, we consider last element of all sequences as a label.Then, We need to perform onehot encoding on labels corresponding to total_words.

In [22]:
```
input_sequences[:, :]  # This is the original sequences
```

Out[22]:
```
array([[  0,   0,   0, ...,   0,   5, 676],
       [  0,   0,   0, ...,   5, 676,  68],
       [  0,   0,   0, ..., 676,  68,   2],
       ...,
       [  0,   0,   0, ...,   5,  85,  56],
       [  0,   0,   0, ...,  85,  56, 730],
       [  0,   0,   0, ...,  56, 730, 550]])
```

In [23]:
```
input_sequences[:, :-1]  # This is the sequences leaving the last element
```

Out[23]:
```
array([[  0,   0,   0, ...,   0,   0,   5],
       [  0,   0,   0, ...,   0,   5, 676],
       [  0,   0,   0, ...,   5, 676,  68],
       ...,
       [  0,   0,   0, ...,  65,   5,  85],
       [  0,   0,   0, ...,   5,  85,  56],
       [  0,   0,   0, ...,  85,  56, 730]])
```

In [24]:
```
input_sequences[:, -1]  # This is the last element which was omitted
```

Out[24]:
```
array([676,  68,   2, ...,  56, 730, 550])
```

In [25]:
```
xs, labels = input_sequences[:, :-1], input_sequences[:, -1]
print(xs[5])
print(labels[5])
```

```
[   0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    0    0    0    0    0    0    0    0    0
    0    0    0    0    0    5  676   68    2  452 1518]
14
```

In [26]:
```
cprint("Performing ONE-HOT ENCODING.....", "green")
ys = tf.keras.utils.to_categorical(labels, num_classes=total_words)
print("At row-5 and col-14 ==", ys[5][14])
pd.DataFrame(ys).head(6)
```

```
Performing ONE-HOT ENCODING.....
At row-5 and col-14 == 1.0
```

Out[26]:

	0	1	2	3	4	5	6	7	8	9	...	8228	8229	8230	8231	8232	8233	8234	8235	8236	8237
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

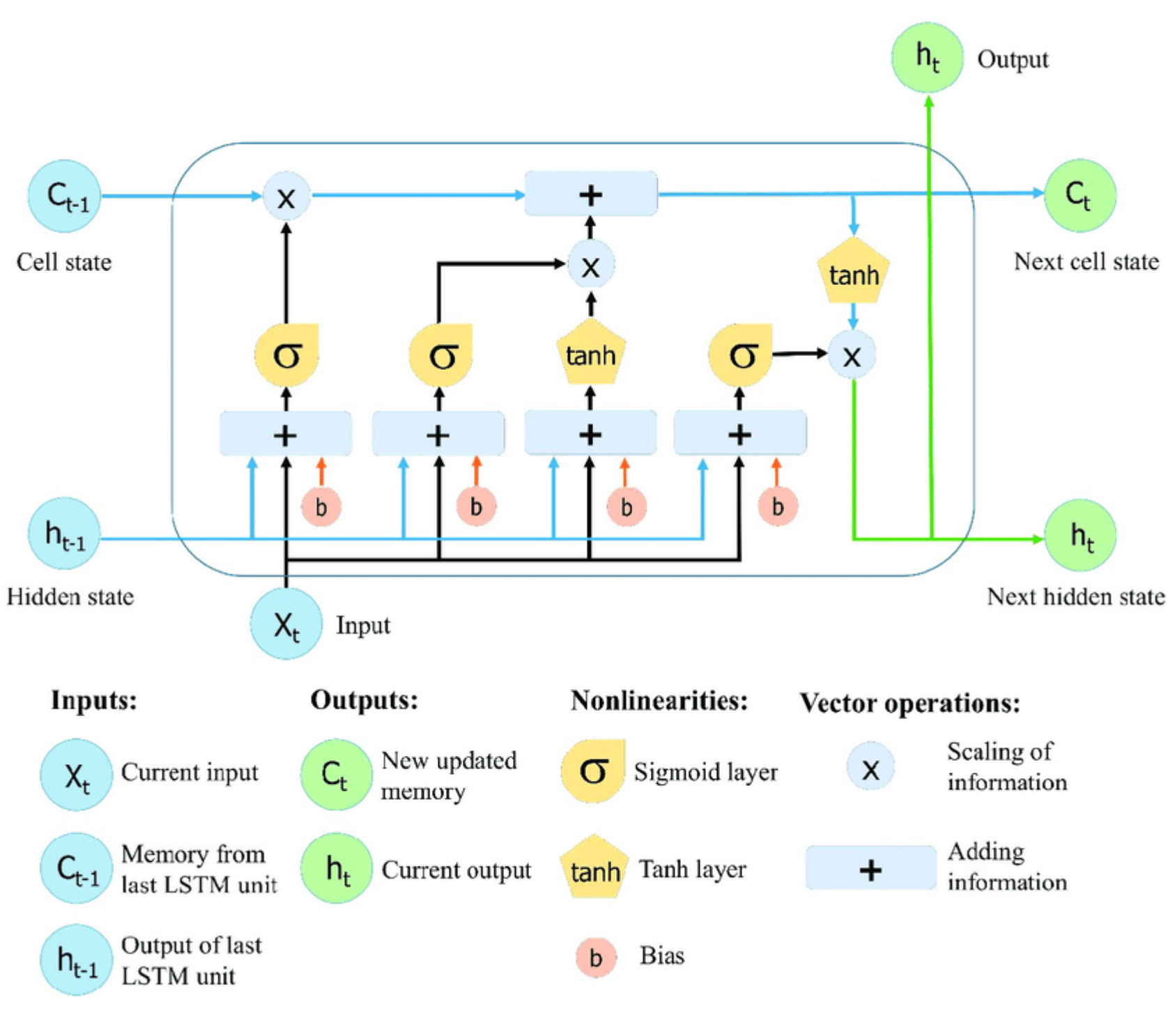
6 rows × 8238 columns

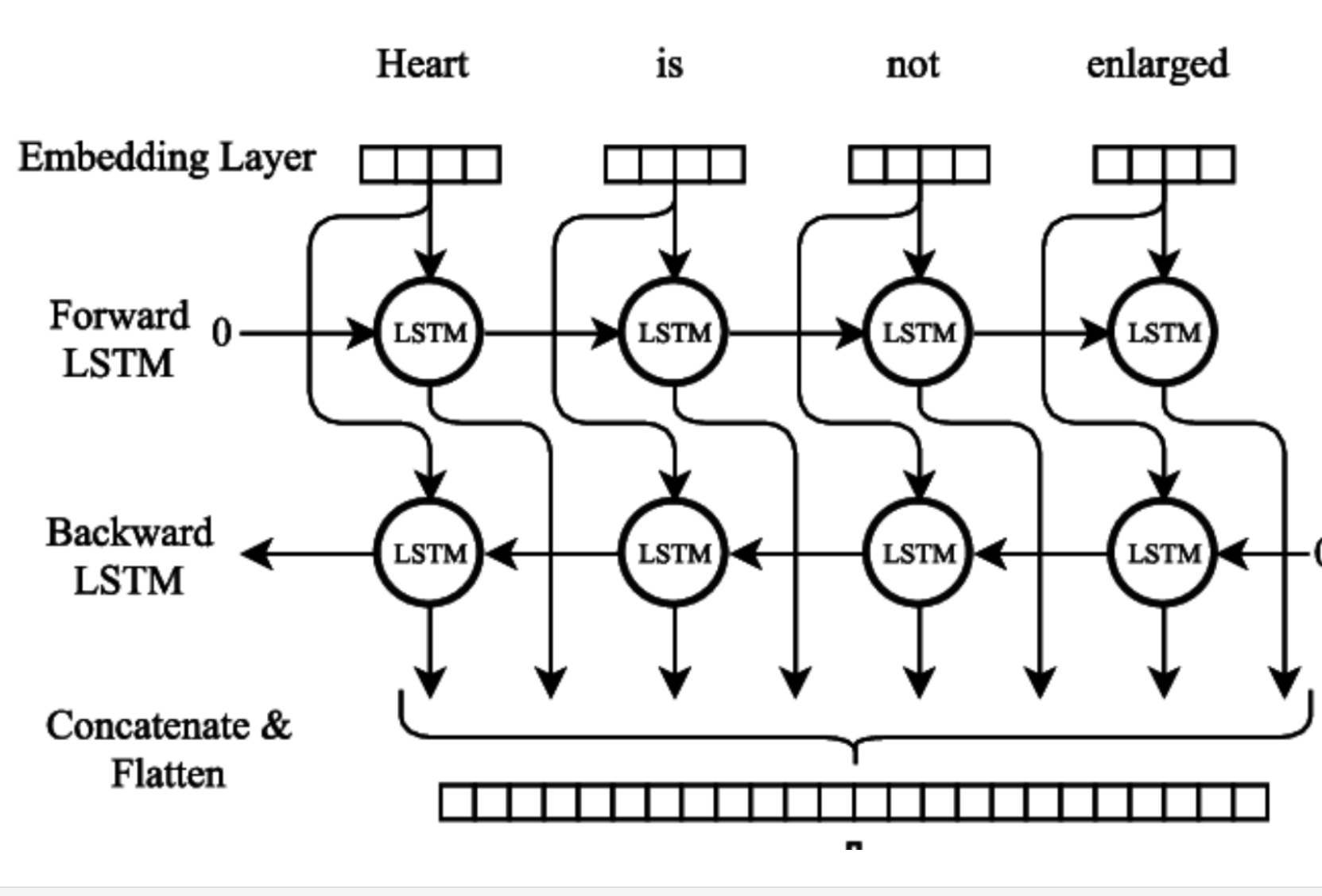
Architechture of Bidirectional LSTM Neural Network

Long Short-Term Memory (LSTM) networks is an advance recurrent neural network which is apable to store order states by using its cell state feature.

Image reference: https://www.researchgate.net/figure/The-structure-of-the-Long-Short-Term-Memory-LSTM-neural-network-Reproduced-from-Yan_fig8_334268507

Bidirectional LSTM Image reference: https://paperswithcode.com/method/bilstm





In [27]:
```
model = Sequential()
model.add(Embedding(total_words, 100, input_length=max_sequence_len - 1))
model.add(Bidirectional(LSTM(150)))
model.add(Dense(total_words, activation="softmax"))
adam = Adam(lr=0.01)
model.compile(loss="categorical_crossentropy", optimizer=adam, metrics=["accuracy"])
history = model.fit(xs, ys, epochs=50, verbose=1)
# print model.summary()
print(model)
```

```
C:\Users\sriva\AppData\Local\Programs\Python\Python310\lib\site-packages\keras\optimizers\optimizer_v2\adam.py:
110: UserWarning: The `lr` argument is deprecated, use `learning_rate` instead.
  super(Adam, self).__init__(name, **kwargs)
Epoch 1/50
1515/1515 [==============================] - 45s 16ms/step - loss: 6.9505 - accuracy: 0.1222
Epoch 2/50
1515/1515 [==============================] - 26s 17ms/step - loss: 6.1998 - accuracy: 0.1652
Epoch 3/50
1515/1515 [==============================] - 29s 19ms/step - loss: 4.9790 - accuracy: 0.2004
Epoch 4/50
1515/1515 [==============================] - 30s 20ms/step - loss: 4.2112 - accuracy: 0.2448
Epoch 5/50
1515/1515 [==============================] - 29s 19ms/step - loss: 3.6351 - accuracy: 0.2962
Epoch 6/50
1515/1515 [==============================] - 29s 19ms/step - loss: 3.2361 - accuracy: 0.3411
Epoch 7/50
1515/1515 [==============================] - 29s 19ms/step - loss: 2.9748 - accuracy: 0.3738
Epoch 8/50
1515/1515 [==============================] - 26s 17ms/step - loss: 2.7781 - accuracy: 0.4006
Epoch 9/50
1515/1515 [==============================] - 26s 17ms/step - loss: 2.6418 - accuracy: 0.4225
Epoch 10/50
1515/1515 [==============================] - 26s 17ms/step - loss: 2.5531 - accuracy: 0.4369
Epoch 11/50
1515/1515 [==============================] - 25s 16ms/step - loss: 2.4498 - accuracy: 0.4532
Epoch 12/50
1515/1515 [==============================] - 29s 19ms/step - loss: 2.3724 - accuracy: 0.4655
Epoch 13/50
1515/1515 [==============================] - 27s 18ms/step - loss: 2.3152 - accuracy: 0.4799
Epoch 14/50
1515/1515 [==============================] - 25s 17ms/step - loss: 2.3263 - accuracy: 0.4779
Epoch 15/50
1515/1515 [==============================] - 24s 16ms/step - loss: 2.2738 - accuracy: 0.4835
Epoch 16/50
1515/1515 [==============================] - 25s 17ms/step - loss: 2.2388 - accuracy: 0.4916
Epoch 17/50
1515/1515 [==============================] - 26s 17ms/step - loss: 2.1988 - accuracy: 0.4963
Epoch 18/50
1515/1515 [==============================] - 24s 16ms/step - loss: 2.1838 - accuracy: 0.5028
Epoch 19/50
1515/1515 [==============================] - 25s 16ms/step - loss: 2.1603 - accuracy: 0.5048
Epoch 20/50
1515/1515 [==============================] - 25s 17ms/step - loss: 2.1628 - accuracy: 0.5034
Epoch 21/50
1515/1515 [==============================] - 24s 16ms/step - loss: 2.1308 - accuracy: 0.5131
Epoch 22/50
1515/1515 [==============================] - 25s 16ms/step - loss: 2.1170 - accuracy: 0.5150
Epoch 23/50
1515/1515 [==============================] - 26s 17ms/step - loss: 2.1233 - accuracy: 0.5121
Epoch 24/50
1515/1515 [==============================] - 26s 17ms/step - loss: 2.0915 - accuracy: 0.5173
Epoch 25/50
1515/1515 [==============================] - 24s 16ms/step - loss: 2.1077 - accuracy: 0.5169
Epoch 26/50
1515/1515 [==============================] - 24s 16ms/step - loss: 2.1099 - accuracy: 0.5159
Epoch 27/50
1515/1515 [==============================] - 25s 17ms/step - loss: 2.1329 - accuracy: 0.5153
Epoch 28/50
1515/1515 [==============================] - 25s 16ms/step - loss: 2.0923 - accuracy: 0.5233
Epoch 29/50
1515/1515 [==============================] - 25s 17ms/step - loss: 2.2426 - accuracy: 0.5104
Epoch 30/50
1515/1515 [==============================] - 25s 17ms/step - loss: 2.1969 - accuracy: 0.5074
Epoch 31/50
1515/1515 [==============================] - 26s 17ms/step - loss: 2.1216 - accuracy: 0.5174
Epoch 32/50
1515/1515 [==============================] - 25s 17ms/step - loss: 2.0989 - accuracy: 0.5211
Epoch 33/50
1515/1515 [==============================] - 26s 17ms/step - loss: 2.0926 - accuracy: 0.5251
Epoch 34/50
1515/1515 [==============================] - 25s 17ms/step - loss: 2.0827 - accuracy: 0.5263
Epoch 35/50
1515/1515 [==============================] - 27s 18ms/step - loss: 2.0538 - accuracy: 0.5320
Epoch 36/50
1515/1515 [==============================] - 27s 18ms/step - loss: 2.0494 - accuracy: 0.5335
Epoch 37/50
1515/1515 [==============================] - 26s 17ms/step - loss: 2.0236 - accuracy: 0.5385
Epoch 38/50
1515/1515 [==============================] - 25s 17ms/step - loss: 2.0200 - accuracy: 0.5372
Epoch 39/50
1515/1515 [==============================] - 25s 17ms/step - loss: 2.0337 - accuracy: 0.5327
Epoch 40/50
1515/1515 [==============================] - 25s 16ms/step - loss: 2.0854 - accuracy: 0.5289
Epoch 41/50
1515/1515 [==============================] - 26s 17ms/step - loss: 2.0251 - accuracy: 0.5425
Epoch 42/50
1515/1515 [==============================] - 27s 18ms/step - loss: 1.9921 - accuracy: 0.5467
Epoch 43/50
1515/1515 [==============================] - 27s 18ms/step - loss: 1.9924 - accuracy: 0.5455
Epoch 44/50
1515/1515 [==============================] - 25s 16ms/step - loss: 2.0093 - accuracy: 0.5430
Epoch 45/50
1515/1515 [==============================] - 29s 19ms/step - loss: 2.0005 - accuracy: 0.5450
Epoch 46/50
1515/1515 [==============================] - 26s 17ms/step - loss: 1.9946 - accuracy: 0.5431
Epoch 47/50
1515/1515 [==============================] - 25s 17ms/step - loss: 2.0057 - accuracy: 0.5466
Epoch 48/50
1515/1515 [==============================] - 25s 16ms/step - loss: 2.0251 - accuracy: 0.5446
Epoch 49/50
1515/1515 [==============================] - 25s 16ms/step - loss: 2.0464 - accuracy: 0.5439
Epoch 50/50
1515/1515 [==============================] - 25s 16ms/step - loss: 2.0090 - accuracy: 0.5460
<keras.engine.sequential.Sequential object at 0x000001B9C5E6B1C0>
```

In [67]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 39, 100)           823800

 bidirectional (Bidirectiona  (None, 300)              301200
 l)

 dense (Dense)               (None, 8238)              2479638

=================================================================
Total params: 3,604,638
Trainable params: 3,604,638
Non-trainable params: 0
_________________________________________________________________
```

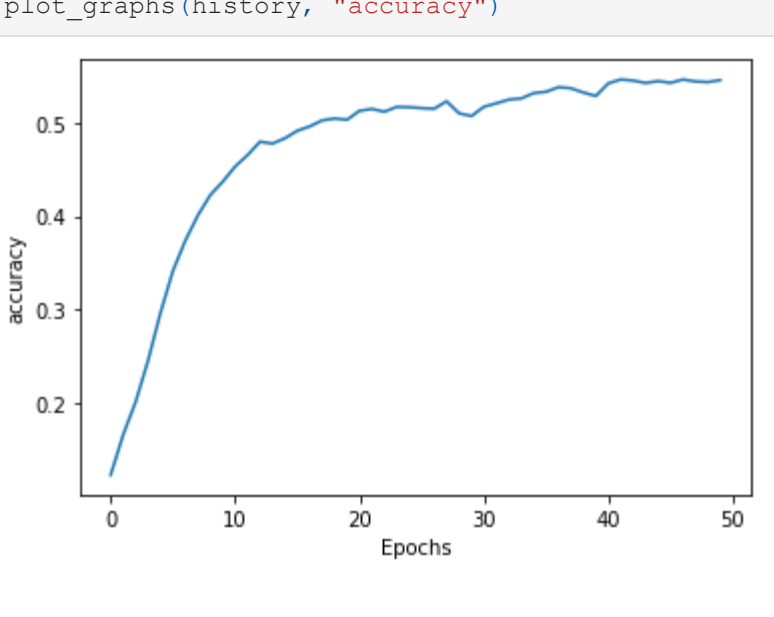
Plotting model accuracy and loss

In [61]:
```
import matplotlib.pyplot as plt


def plot_graphs(history, string):
    plt.plot(history.history[string])
    plt.xlabel("Epochs")
    plt.ylabel(string)
    plt.show()
```

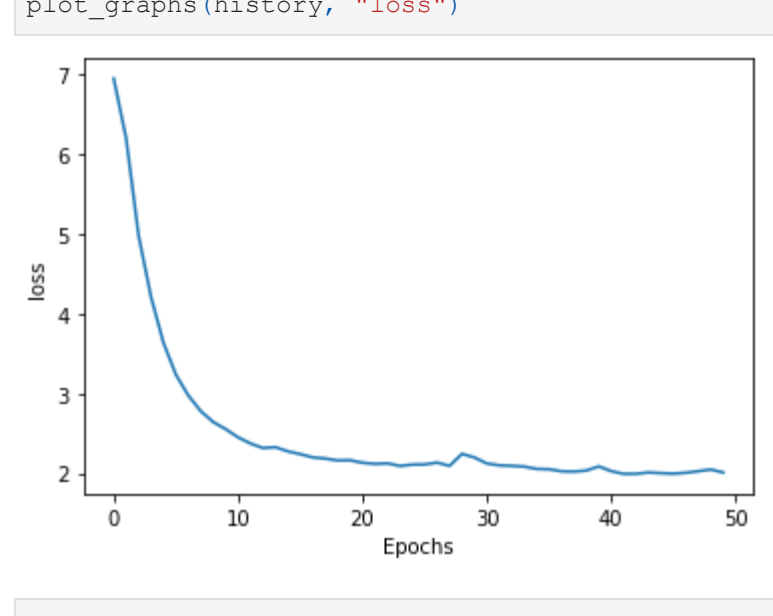
Graph of Accuracy

In [62]:
```
plot_graphs(history, "accuracy")
```



Graph of Loss

In [33]:
```
plot_graphs(history, "loss")
```



In [51]:
```
def output(text):
    seed_text = text
    next_words = 5

    for _ in range(next_words):
        token_list = tokenizer.texts_to_sequences([seed_text])[0]
        token_list = pad_sequences(
            [token_list], maxlen=max_sequence_len - 1, padding="pre"
        )
        predicted = np.argmax(model.predict(token_list), axis=-1)
        # model.predict_classes(token_list, verbose=0)
        cprint(predicted, "red")
        output_word = ""
        for word, index in tokenizer.word_index.items():
            if index == predicted:
                output_word = word
                break
        seed_text += " " + output_word
    print(seed_text)


output("implementation of")
```

```
1/1 [==============================] - 0s 34ms/step
[2529]
1/1 [==============================] - 0s 112ms/step
[759]
1/1 [==============================] - 0s 65ms/step
[236]
1/1 [==============================] - 0s 95ms/step
[2657]
1/1 [==============================] - 0s 62ms/step
[344]
implementation of rnn lstm based handwriting recognition
```

In [92]:
```
output("python for")
```

```
1/1 [==============================] - 0s 38ms/step
[499]
1/1 [==============================] - 0s 47ms/step
[1135]
1/1 [==============================] - 0s 68ms/step
[1487]
1/1 [==============================] - 0s 95ms/step
[158]
1/1 [==============================] - 0s 78ms/step
[2908]
python for beginners cleaning preprocessing web scraped
```

In [73]:
```
model.save("my_model.h5")
```

In [74]:
```
new_model = tf.keras.models.load_model("my_model.h5")
new_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 39, 100)           823800

 bidirectional (Bidirectiona  (None, 300)              301200
 l)

 dense (Dense)               (None, 8238)              2479638

=================================================================
Total params: 3,604,638
Trainable params: 3,604,638
Non-trainable params: 0
_________________________________________________________________
```

In [86]:
```
def output_2(text):
    seed_text = text
    next_words = 5

    for _ in range(next_words):
        token_list = tokenizer.texts_to_sequences([seed_text])[0]
        print(token_list)
        token_list = pad_sequences(
            [token_list], maxlen=max_sequence_len - 1, padding="pre"
        )

        predicted = np.argmax(new_model.predict(token_list), axis=-1)
        # model.predict_classes(token_list, verbose=0)
        cprint(predicted, "red")
        output_word = ""
        for word, index in tokenizer.word_index.items():
            if index == predicted:
                output_word = word
                break
        seed_text += " " + output_word
    print(seed_text)


output_2("implementation")
```