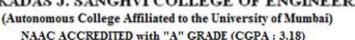


## SHRI VILEPARLE KELAVANI MANDAL'S DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING





### DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)

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**COURSE CODE: DJ19DSC501** 

COURSE NAME: Machine Learning - II CLASS: AY 2023-24

#### LAB EXPERIMENT NO.6

#### **AIM / OBJECTIVE:**

Implement LSTM Sentiment Analysis on text dataset to evaluate customer reviews.

#### **DESCRIPTION OF EXPERIMENT:**

Python sentiment analysis is a methodology for analyzing a piece of text to discover the sentiment hidden within it. It accomplishes this by combining machine learning and natural language processing (NLP). Sentiment analysis allows you to examine the feelings expressed in a piece of text. It is essential for businesses to gauge customer response.

### Preprocessing -

- Normalization Words which look different due to casing or written another way but are the same in meaning need to be process correctly. Normalisation processes ensure that these words are treated equally. For example, changing numbers to their word equivalents or converting the casing of all the text.
  - a) Casing the Characters Converting character to the same case so the same words are recognised as the same. (all lowercase)
  - b) Removing Stand alone punctuations, special characters and numerical tokens are removed as they do not contribute to sentiment which leaves only alphabetic characters. This step needs the use of tokenized words as they have been split appropriately for us to remove. We need to remove the special characters, numbers from the text. We can use the regular expression operations library of Python.
- 2) Tokenization Tokenization is the process of breaking down chunks of text into smaller pieces. It converts text into tokens before transforming it into vectors. It is also easier to filter out unnecessary tokens. spaCy comes with a default processing pipeline that begins with tokenization, making this process a snap. In spaCy, you can do either sentence tokenization or word tokenization:
  - Word tokenization breaks text down into individual words.
  - Sentence tokenization breaks text down into individual sentences.
- 3) Stopwords Stop words are the most commonly occurring words which are not relevant in the context of the data and do not contribute any deeper meaning to the phrase. In this case it contains no sentiment. We need to remove them as part of text preprocessing. nltk has a list of stopwords of every language.



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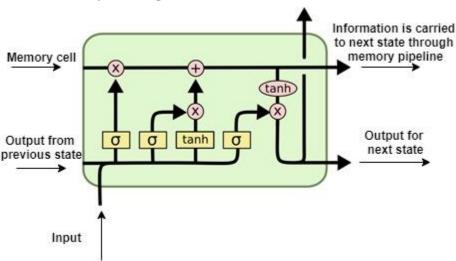
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4) Obtaining the stem words

A stem is a part of a word responsible for its lexical meaning. The two popular techniques of obtaining the root/stem words are Stemming and Lemmatization

- a) Stemming Stemming is a technique used to extract the base form of the words by removing affixes from them. It is just like cutting down the branches of a tree to its stems. For example, the stem of the words eating, eats, eaten is eat.
- b) Lemmitization This process finds the base or dictionary form of the word known as the lemma. This is done through the use of vocabulary (dictionary importance of words) and morphological analysis (word structure and grammar relations)
- 5) Vectorization use a count vectorizer from the Scikit-learn library to transform the text in data frame into a bag of words model, which will contain a sparse matrix of integers. The number of occurrences of each word will be counted.

## Sentiment Analysis using LSTM: Use Keras



## Hyperparameters to tune -

- 1. Layers Explore additional hierarchical learning capacity by adding more layers and varied numbers of neurons in each layer
- 2. Number of inputs in dense layer Dense layers improve overall accuracy and 5–10 units or nodes per layer is a good base
- 3. Dropout Slow down learning with regularization methods like dropout on the recurrent LSTM connections. A good starting point is 20% but the dropout value should be kept small (up to 50%). The 20% value is widely accepted as the best compromise between preventing model overfitting and retaining model accuracy.
- 4. Learning Rate This hyperparameter defines how quickly the network updates its parameters.
- 5. Decay Rate weight decay can be added in the weight update rule that makes the weights decay to zero exponentially, if no other weight update is scheduled. After each update, the weights are multiplied by a factor slightly less than 1, thereby preventing them from growing to huge. This specifies regularization in the network.



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6. Number of epochs

## **Sentiment Analysis using TextBlob:**

TextBlob is a Python library for processing textual data. It provides a consistent API for diving into common natural language processing (NLP) tasks such as part-of-speech tagging, noun phrase extraction, sentiment analysis, and more.

The two measures that are used to analyze the sentiment are:

- Polarity talks about how positive or negative the opinion is
- Subjectivity talks about how subjective the opinion is

TextBlob(text).sentiment gives us the Polarity, Subjectivity values.

Polarity ranges from -1 to 1 (1 is more positive, 0 is neutral, -1 is more negative)

Subjectivity ranges from 0 to 1(0 being very objective and 1 being very subjective)

```
res = TextBlob("I love horror films").sentiment
res
Sentiment(polarity=0.5, subjectivity=0.6)
```

Example of TextBlob sentiment

#### Workflow -

- 1. Preprocess data.
- 2. Split data into training and evaluation sets.
- 3. Select a model architecture.
- 4. Use training data to train model.
- 5. Use test data to evaluate the performance of model.
- 1. Apply preprocessing techniques and LSTM on the dataset. Show accuracy achieved on the test dataset by providing classification report.
- 2. Perform LSTM hyperparameter tuning to improve accuracy score.
- 3. Show how LSTM model compares to built-in classifier provided by TextBlob.
- 4. State the applications of sentiment analysis
- 5. State the challenges faced while performing sentiment analysis.

## LSTM model

```
import pandas as pd
In [3]:
          df = pd.read csv('/content/flipkart reviews.csv')
In [4]:
          df
In [5]:
Out[5]:
                    Reviewer
                                                                                                             Star
                                                                                                                     Review
                                                       Review Title
                                                                                      Review Paragraph
                       Name
                                                                                                          Rating
                                                                                                                       Date
              0
                   Nitin Singh
                                                      Great product
                                                                                                                   Mar, 2020
                                                                                                Great....
                                                                      It's another solid performer from the
                       Flipkart
                                                      Great product
                                                                                                                   Oct, 2016
                    Customer
                                                                                              apple st...
                                                                             Nice product . u will feel the
              2
                    Neeladri V
                                                      Great product
                                                                                                                5
                                                                                                                    Jul, 2020
                                                                                             difference.
                       Kishore
              3
                                                            Brilliant
                                                                             Perfect mobile for iOS lovers
                                                                                                                   Feb, 2020
                       Gagan
                       Flipkart
                                                                            On Time Delivery Best Part Of
              4
                                Amazing service from Apple & Flipkart
                                                                                                                5
                                                                                                                   Oct, 2016
                     Customer
                                                                                      Flipkart.\n\nAma...
                       Haresh
                                                                      Got the delivery on launch day itself.
          7022
                                        Delivered on launch day itself
                                                                                                                   Oct, 2016
                      Sachdev
                                                                                               Thanks ...
                         Ankit
                                                                        Last year Flipkart had lost me as a
          7023
                                                                                                                   Oct, 2016
                                               Flipkart made my day!
                      Ruparel
                                                                                            customer. ...
                                    Review of my purchase of iphone7
                                                                      I'm happy that I preordered iphone7
                  Swaroop SK
                                                                                                                   Oct, 2016
          7024
                                                     through flipkart
                                                                                             from flipk...
                                                                      IPhone 7 got it delivered much more
          7025
                 Zeelan Basha
                                                    Simply awesome
                                                                                                                   Oct, 2016
                                                                                             early than...
                                                                         Nicely packaged and before time
          7026
                  Rohit Ranjan
                                                Awesome experience
                                                                                                                   Oct, 2016
                                                                                               delivery.
         7027 rows × 5 columns
In [6]:
          import pandas as pd
          df['Review'] = ''
          for index, row in df.iterrows():
                if row['Star Rating'] <= 2:</pre>
                     df.at[index, 'Review'] = 'Negative'
                elif row['Star Rating'] == 3:
                     df.at[index, 'Review'] = 'Neutral'
                     df.at[index, 'Review'] = 'Positive'
          df
In [7]:
Out[7]:
                    Reviewer
                                                                                                     Star
                                                                                                            Review
```

**Review Title** 

Name

**Review Paragraph** 

Rating

Review

**Date** 

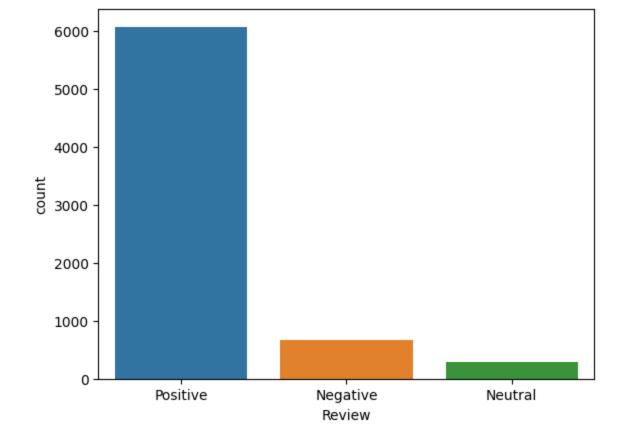
0	Nitin Singh	Great product	Great	5	Mar, 2020	Positive
1	Flipkart Customer	Great product	It's another solid performer from the apple st	5	Oct, 2016	Positive
2	Neeladri V	Great product	Nice product . u will feel the difference.	5	Jul, 2020	Positive
3	Kishore Gagan	Brilliant	Perfect mobile for iOS lovers	5	Feb, 2020	Positive
4	Flipkart Customer	Amazing service from Apple & Flipkart	On Time Delivery Best Part Of Flipkart.\n\nAma	5	Oct, 2016	Positive
•••						
7022	Haresh Sachdev	Delivered on launch day itself	Got the delivery on launch day itself. Thanks	5	Oct, 2016	Positive
7023	Ankit Ruparel	Flipkart made my day!	Last year Flipkart had lost me as a customer	5	Oct, 2016	Positive
7024	Swaroop SK	Review of my purchase of iphone7 through flipkart	I'm happy that I preordered iphone7 from flipk	5	Oct, 2016	Positive
7025	Zeelan Basha	Simply awesome	IPhone 7 got it delivered much more early than	5	Oct, 2016	Positive
7026	Rohit Ranjan	Awesome experience	Nicely packaged and before time delivery.	5	Oct, 2016	Positive

7027 rows × 6 columns

```
In [8]: df.isnull().values.any()
Out[8]:

False
In [9]: import seaborn as sns
    sns.countplot(x='Review', data = df)
```

Out[9]: <Axes: xlabel='Review', ylabel='count'>



In [10]:

Out[15]:

In [16]:

import nltk

```
nltk.download('stopwords')
         [nltk data] Downloading package stopwords to /root/nltk data...
         [nltk data] Unzipping corpora/stopwords.zip.
         True
Out[10]:
In [11]:
         from nltk.corpus import stopwords
         import regex as re
In [12]:
         def preprocess text(sen):
In [13]:
             sentence = sen.lower()
             sentence = re.sub('[^a-zA-Z]','', sentence)
             sentence = re.sub(r"\s+[^a-zA-Z]\s+",'',sentence)
             sentence = re.sub(r'\s+','', sentence)
             pattern = re.compile(r'\b(' + r'|'.join(stopwords.words('english')) + r')\b\s*')
             sentence = pattern.sub('', sentence)
             return ' '.join(sentence.split(' '))
In [14]:
         X = []
         sentences = list(df['Review Paragraph'])
         for sen in sentences :
           X.append(preprocess text(sen))
In [15]: X[1]
```

'itsanothersolidperformerfromtheapplestabletheunpackingwasmadespecialbyflipkartforthepre

orderedonesidontwanttoelaborateastonotruinthesurpriseforothersthephoneperformseffortless lyhavenothadanyissuessofarmigratingfromanearlieriphoneisquickandsimplebatterylifeisbette rthantheearlierphonesandthenewhomebuttonbeautifullyengineeredprovidinganenhanceduserexpe

rienceiwoulddefinitelyrecommendthisphone'

import numpy as np

```
In [17]: | y = df['Review']
         y = np.array(list(map(lambda x: 1 if x=="positive" else 0,y)))
In [18]: from keras import Sequential
         from keras import optimizers
         from keras.preprocessing.sequence import pad sequences
         from keras.models import Sequential, Model
         from keras.layers import LSTM, Dense, Bidirectional, Input, Dropout, BatchNormalization, E
         from keras import backend as K
         from keras import initializers, regularizers, constraints
         from sklearn.model selection import KFold, cross val score, train test split
In [19]: X_train, X_test , y_train,y_test = train_test_split(X,y,test size = 0.2 , random state =
In [20]: import nltk
         nltk.download('punkt')
         [nltk data] Downloading package punkt to /root/nltk data...
         [nltk data] Unzipping tokenizers/punkt.zip.
         True
Out[20]:
In [21]: from keras.preprocessing.text import Tokenizer
In [22]: word_tokenizer = Tokenizer()
         word tokenizer.fit on texts(X train)
         X train = word tokenizer.texts to sequences(X train)
         X test = word tokenizer.texts to sequences(X test)
In [23]: vocab length = len(word tokenizer.word index) + 1
         vocab length
         4574
Out[23]:
In [24]:
        maxlen = 100
         X train = pad sequences(X train,padding='post',maxlen = maxlen)
         X test = pad sequences(X test,padding='post',maxlen = maxlen)
In [25]: !pip install keras.utils.np utils
         ERROR: Could not find a version that satisfies the requirement keras.utils.np utils (fro
         m versions: none)
         ERROR: No matching distribution found for keras.utils.np utils
        import numpy as np # linear algebra
In [26]:
         import pandas as pd # data processing, CSV file I/O (e.g. pd.read csv)
         from sklearn.feature extraction.text import CountVectorizer
         from keras.preprocessing.text import Tokenizer
         from keras.preprocessing.sequence import pad sequences
         from keras.models import Sequential
         from keras.layers import Dense, Embedding, LSTM, SpatialDropout1D
         from sklearn.model selection import train test split
         import re
In [27]: df = df[['Review Paragraph','Review']]
In [28]: df
Out[28]:
                                   Review Paragraph Review
                                           Great.... Positive
```

```
4 On Time Delivery Best Part Of Flipkart.\n\nAma...
         7022
                 Got the delivery on launch day itself. Thanks ... Positive
         7023
                 Last year Flipkart had lost me as a customer. ...
                                                    Positive
         7024
               I'm happy that I preordered iphone7 from flipk... Positive
               IPhone 7 got it delivered much more early than...
                                                   Positive
         7026
                    Nicely packaged and before time delivery. Positive
        7027 rows \times 2 columns
In [29]:
         df = df[df.Review != "Neutral"]
         df['Review Paragraph'] = df['Review Paragraph'].apply(lambda x: x.lower())
         df['Review Paragraph'] = df['Review Paragraph'].apply((lambda x: re.sub('[^a-zA-z0-9\s]'
         print(df[ df['Review'] == 'Positive'].size)
         print(df[ df['Review'] == 'Negative'].size)
         for idx,row in df.iterrows():
             row[0] = row[0].replace('rt',' ')
         max fatures = 2000
         tokenizer = Tokenizer(num words=max fatures, split=' ')
         tokenizer.fit on texts(df['Review Paragraph'].values)
         X = tokenizer.texts to sequences(df['Review Paragraph'].values)
         X = pad sequences(X)
         12142
         1346
         <ipython-input-29-d4fca0560a36>:2: SettingWithCopyWarning:
         A value is trying to be set on a copy of a slice from a DataFrame.
         Try using .loc[row indexer,col indexer] = value instead
         See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user
         guide/indexing.html#returning-a-view-versus-a-copy
           df['Review Paragraph'] = df['Review Paragraph'].apply(lambda x: x.lower())
         <ipython-input-29-d4fca0560a36>:3: SettingWithCopyWarning:
         A value is trying to be set on a copy of a slice from a DataFrame.
         Try using .loc[row indexer, col indexer] = value instead
         See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user
         guide/indexing.html#returning-a-view-versus-a-copy
           df['Review Paragraph'] = df['Review Paragraph'].apply((lambda x: re.sub('[^a-zA-z0-9
         \s]','',x)))
In [30]:
         embed dim = 128
         lstm out = 196
         model = Sequential()
         model.add(Embedding(max fatures, embed dim,input length = X.shape[1]))
         model.add(SpatialDropout1D(0.4))
         model.add(LSTM(1stm out, dropout=0.2, recurrent dropout=0.2))
         model.add(Dense(2,activation='softmax'))
         model.compile(loss = 'categorical crossentropy', optimizer='adam', metrics = ['accuracy']
         print(model.summary())
```

It's another solid performer from the apple st... Positive

Nice product . u will feel the difference. Positive

Perfect mobile for iOS lovers Positive

2

3

WARNING:tensorflow:Layer lstm will not use cuDNN kernels since it doesn't meet the crite ria. It will use a generic GPU kernel as fallback when running on GPU.

Model: "sequential"

```
Layer (type)
                                  Output Shape
                                                          Param #
        ______
        embedding (Embedding) (None, 553, 128)
                                                          256000
         spatial dropout1d (Spatial (None, 553, 128)
         Dropout1D)
         lstm (LSTM)
                                   (None, 196)
                                                           254800
         dense (Dense)
                                                            394
                                   (None, 2)
        ______
        Total params: 511194 (1.95 MB)
        Trainable params: 511194 (1.95 MB)
        Non-trainable params: 0 (0.00 Byte)
        None
In [31]: Y = pd.get dummies(df['Review']).values
        X train, X test, Y train, Y test = train test split(X,Y, test size = 0.33, random state
        print(X train.shape, Y train.shape)
        print(X test.shape, Y test.shape)
        (4518, 553) (4518, 2)
        (2226, 553) (2226, 2)
In [32]: batch size = 32
        model.fit(X train, Y train, epochs = 7, batch size=batch size, verbose = 2)
        Epoch 1/7
        142/142 - 384s - loss: 0.2754 - accuracy: 0.9028 - 384s/epoch - 3s/step
        Epoch 2/7
        142/142 - 356s - loss: 0.1545 - accuracy: 0.9469 - 356s/epoch - 3s/step
        Epoch 3/7
        142/142 - 353s - loss: 0.1124 - accuracy: 0.9622 - 353s/epoch - 2s/step
        Epoch 4/7
        142/142 - 348s - loss: 0.0859 - accuracy: 0.9726 - 348s/epoch - 2s/step
        Epoch 5/7
        142/142 - 351s - loss: 0.0749 - accuracy: 0.9772 - 351s/epoch - 2s/step
        Epoch 6/7
        142/142 - 347s - loss: 0.0680 - accuracy: 0.9792 - 347s/epoch - 2s/step
        Epoch 7/7
        142/142 - 352s - loss: 0.0569 - accuracy: 0.9830 - 352s/epoch - 2s/step
        <keras.src.callbacks.History at 0x7d603582f8e0>
Out[32]:
In [33]: validation size = 1500
        X validate = X test[-validation size:]
        Y validate = Y test[-validation size:]
        X test = X test[:-validation size]
        Y test = Y test[:-validation_size]
        score,acc = model.evaluate(X test, Y test, verbose = 2, batch size = batch size)
        print("score: %.2f" % (score))
        print("acc: %.2f" % (acc))
        23/23 - 4s - loss: 0.2641 - accuracy: 0.9242 - 4s/epoch - 160ms/step
        score: 0.26
        acc: 0.92
```

In [34]: pos cnt, neg cnt, pos correct, neg correct = 0, 0, 0, 0

for x in range(len(X\_validate)):

```
result = model.predict(X validate[x].reshape(1, X test.shape[1]),batch size=1,verbose
    if np.argmax(result) == np.argmax(Y validate[x]):
        if np.argmax(Y validate[x]) == 0:
            neg correct += 1
        else:
            pos correct += 1
    if np.argmax(Y validate[x]) == 0:
        neg cnt += 1
    else:
        pos cnt += 1
print("pos acc", pos correct/pos cnt*100, "%")
print("neg acc", neg correct/neg cnt*100, "%")
1/1 - 1s - 604ms/epoch - 604ms/step
1/1 - 0s - 143ms/epoch - 143ms/step
1/1 - 0s - 154ms/epoch - 154ms/step
1/1 - 0s - 146ms/epoch - 146ms/step
1/1 - 0s - 140ms/epoch - 140ms/step
1/1 - 0s - 150ms/epoch - 150ms/step
1/1 - 0s - 154ms/epoch - 154ms/step
1/1 - 0s - 154ms/epoch - 154ms/step
1/1 - 0s - 168ms/epoch - 168ms/step
1/1 - 0s - 142ms/epoch - 142ms/step
1/1 - 0s - 151ms/epoch - 151ms/step
1/1 - 0s - 147ms/epoch - 147ms/step
1/1 - 0s - 146ms/epoch - 146ms/step
1/1 - 0s - 146ms/epoch - 146ms/step
1/1 - 0s - 143ms/epoch - 143ms/step
1/1 - 0s - 149ms/epoch - 149ms/step
1/1 - 0s - 145ms/epoch - 145ms/step
1/1 - 0s - 151ms/epoch - 151ms/step
1/1 - 0s - 141ms/epoch - 141ms/step
1/1 - 0s - 151ms/epoch - 151ms/step
1/1 - 0s - 148ms/epoch - 148ms/step
```

1/1 - 0s - 146ms/epoch - 146ms/step 1/1 - 0s - 142ms/epoch - 142ms/step 1/1 - 0s - 150ms/epoch - 150ms/step 1/1 - 0s - 146ms/epoch - 146ms/step 1/1 - 0s - 155ms/epoch - 155ms/step1/1 - 0s - 146ms/epoch - 146ms/step 1/1 - 0s - 146ms/epoch - 146ms/step 1/1 - 0s - 147ms/epoch - 147ms/step 1/1 - 0s - 145ms/epoch - 145ms/step1/1 - 0s - 146ms/epoch - 146ms/step 1/1 - 0s - 154ms/epoch - 154ms/step 1/1 - 0s - 173ms/epoch - 173ms/step1/1 - 0s - 261ms/epoch - 261ms/step 1/1 - 0s - 144ms/epoch - 144ms/step 1/1 - 0s - 163ms/epoch - 163ms/step 1/1 - 0s - 224ms/epoch - 224ms/step 1/1 - 0s - 234ms/epoch - 234ms/step 1/1 - 0s - 214ms/epoch - 214ms/step 1/1 - 0s - 261ms/epoch - 261ms/step 1/1 - 0s - 240ms/epoch - 240ms/step 1/1 - 0s - 254ms/epoch - 254ms/step 1/1 - 0s - 230ms/epoch - 230ms/step 1/1 - 0s - 225ms/epoch - 225ms/step1/1 - 0s - 146ms/epoch - 146ms/step 1/1 - 0s - 147ms/epoch - 147ms/step 1/1 - 0s - 143ms/epoch - 143ms/step

```
1/1 - 0s - 180ms/epoch - 180ms/step
1/1 - 0s - 150ms/epoch - 150ms/step
1/1 - 0s - 145ms/epoch - 145ms/step
1/1 - 0s - 145ms/epoch - 145ms/step
1/1 - 0s - 143ms/epoch - 143ms/step
1/1 - 0s - 147ms/epoch - 147ms/step
1/1 - 0s - 145ms/epoch - 145ms/step
1/1 - 0s - 144ms/epoch - 144ms/step
1/1 - 0s - 148ms/epoch - 148ms/step
1/1 - 0s - 150ms/epoch - 150ms/step
1/1 - 0s - 148ms/epoch - 148ms/step
1/1 - 0s - 147ms/epoch - 147ms/step
1/1 - 0s - 150ms/epoch - 150ms/step
1/1 - 0s - 151ms/epoch - 151ms/step
1/1 - 0s - 141ms/epoch - 141ms/step
1/1 - 0s - 153ms/epoch - 153ms/step
1/1 - 0s - 146ms/epoch - 146ms/step
1/1 - 0s - 150ms/epoch - 150ms/step
1/1 - 0s - 143ms/epoch - 143ms/step
1/1 - 0s - 148ms/epoch - 148ms/step
1/1 - 0s - 144ms/epoch - 144ms/step
1/1 - 0s - 143ms/epoch - 143ms/step
1/1 - 0s - 147ms/epoch - 147ms/step
1/1 - 0s - 149ms/epoch - 149ms/step
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1/1 - 0s - 144ms/epoch - 144ms/step
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1/1 - 0s - 144ms/epoch - 144ms/step
1/1 - 0s - 154ms/epoch - 154ms/step
1/1 - 0s - 151ms/epoch - 151ms/step
1/1 - 0s - 148ms/epoch - 148ms/step
1/1 - 0s - 144ms/epoch - 144ms/step
1/1 - 0s - 144ms/epoch - 144ms/step
1/1 - 0s - 147ms/epoch - 147ms/step
1/1 - 0s - 151ms/epoch - 151ms/step
1/1 - 0s - 147ms/epoch - 147ms/step
1/1 - 0s - 157ms/epoch - 157ms/step
1/1 - 0s - 143ms/epoch - 143ms/step
1/1 - 0s - 149ms/epoch - 149ms/step
1/1 - 0s - 144ms/epoch - 144ms/step
1/1 - 0s - 142ms/epoch - 142ms/step
1/1 - 0s - 151ms/epoch - 151ms/step
1/1 - 0s - 160ms/epoch - 160ms/step
1/1 - 0s - 150ms/epoch - 150ms/step
1/1 - 0s - 144ms/epoch - 144ms/step
1/1 - 0s - 202ms/epoch - 202ms/step
1/1 - 0s - 238ms/epoch - 238ms/step
1/1 - 0s - 231ms/epoch - 231ms/step
1/1 - 0s - 221ms/epoch - 221ms/step
1/1 - 0s - 265ms/epoch - 265ms/step
1/1 - 0s - 237ms/epoch - 237ms/step
1/1 - 0s - 230ms/epoch - 230ms/step
1/1 - 0s - 245ms/epoch - 245ms/step
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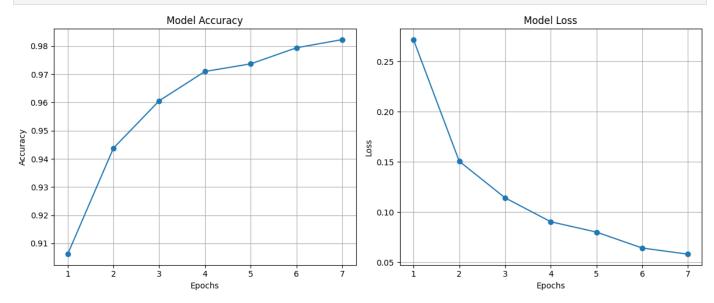
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1/1 - 0s - 147ms/epoch - 147ms/step 1/1 - 0s - 146ms/epoch - 146ms/step

```
neg acc 58.9041095890411 %
        # Import necessary libraries
In [35]:
         import matplotlib.pyplot as plt
         # Create lists with the same number of elements
         accuracy history = [0.9062, 0.9438, 0.9606, 0.9710, 0.9737, 0.9794, 0.9823]
         loss history = [0.2719, 0.1507, 0.1143, 0.0904, 0.0801, 0.0642, 0.0581]
         # Define the number of epochs
         epochs = len(accuracy history)
         # Plot accuracy
         plt.figure(figsize=(12, 5))
         plt.subplot(1, 2, 1)
        plt.plot(range(1, epochs + 1), accuracy history, marker='o', linestyle='-')
         plt.title('Model Accuracy')
         plt.xlabel('Epochs')
        plt.ylabel('Accuracy')
        plt.grid(True)
         # Plot loss
        plt.subplot(1, 2, 2)
         plt.plot(range(1, epochs + 1), loss history, marker='o', linestyle='-')
         plt.title('Model Loss')
         plt.xlabel('Epochs')
        plt.ylabel('Loss')
         plt.grid(True)
         # Show the plots
         plt.tight layout()
         plt.show()
```



# **TextBlob Sentiment Analysis**

1/1 - 0s - 146ms/epoch - 146ms/step

pos acc 98.3751846381093 %

```
In [36]: from textblob import TextBlob
In [38]: res=TextBlob("Wassup").sentiment
res.polarity
Out[38]: 0.0
```

```
Ο,
                                     0, ...,
                                                  4,
                                                        69,
                                                              111],
          array([[
Out[39]:
                       0,
                              0,
                                     0, ...,
                                               223, 106,
                                                               36],
                                     0, ...,
                                                 37, 1727,
                       0,
                              0,
                                                                8],
                       Ο,
                              0,
                                     0, ...,
                                                 Ο,
                                                        22,
                                                               9],
                                                        21,
                  [
                       0,
                              0,
                                     0, ...,
                                                Ο,
                                                               32],
                                                223,
                       0,
                              0,
                                     0, ...,
                                                        8,
                                                               62]], dtype=int32)
          df
In [40]:
Out[40]:
                                        Review Paragraph
             0
                                                   great
                                                        Positive
                  its another solid performer from the apple sta...
                                                         Positive
             2
                          nice product u will feel the difference
                                                         Positive
             3
                                 perfect mobile for ios lovers
                                                        Positive
                  on time delivery best pa of flipka \n\namazin... Positive
             4
          7022
                   got the delivery on launch day itself thanks f...
          7023
                   last year flipka had lost me as a customer i ... Positive
          7024 im happy that i preordered iphone7 from flipka...
                                                         Positive
          7025
                iphone 7 got it delivered much more early than... Positive
          7026
                      nicely packaged and before time delivery Positive
         6744 rows × 2 columns
          X=df['Review Paragraph'].values
In [41]:
          y=df['Review'].values
          pd.value counts(y)
In [42]:
          Positive
                        6071
Out[42]:
          Negative
                         673
          dtype: int64
          X train, X test, Y train, Y test = train test split(X,y, test size = 0.3, random state =
In [55]:
          X test
In [56]:
          array(['very good experience overall phone also working brilliantly',
Out[56]:
                   'excellent product and very good colou hanks flip ka for delivering before tim
          e',
                  'really its a very nice product dashing look professional features good battery b
          ackup etc have enjoyed it',
                  ..., 'very nice',
                  'when i received the product box seal was tempted previously',
                  'really good one'], dtype=object)
In [57]:
          y pred=[]
          for i in X test:
            res=TextBlob(i).sentiment
            if(res.polarity<=0.0):</pre>
              y pred.append(0)
```

X test

In [39]:

```
else:
           y pred.append(1)
In [58]: Y test
       array(['Positive', 'Positive', 'Positive', ..., 'Positive', 'Negative',
Out[58]:
              'Positive'], dtype=object)
In [59]: y_test=[]
        for i in Y test:
         if(i=="Positive"):
           y test.append(1)
         else:
           y test.append(0)
In [60]: pd.value_counts(y test)
          1808
Out[60]:
       0 216
       dtype: int64
In [62]: from sklearn.metrics import classification report
        print(classification report(y test,y pred))
                    precision recall f1-score support
                      0.45 0.75 0.56
                                                   216
                       0.97
                                0.89
                                         0.93
                                                  1808
                                          0.88 2024
           accuracy
                     0.71 0.82 0.75
                                                  2024
          macro avg
       weighted avg
                       0.91
                                0.88
                                         0.89
                                                  2024
```

Thus we see that the LSTM model performs better as it has an accuracy of 98% while the TextBlob Sentiment Analyzer gives us only a 88% accuracy