NLP: Spam Detection in SMS (text) data using Deep Learning

Text classification using Dense network, LSTM and Bi-LSTM architectures in TensorFlow2

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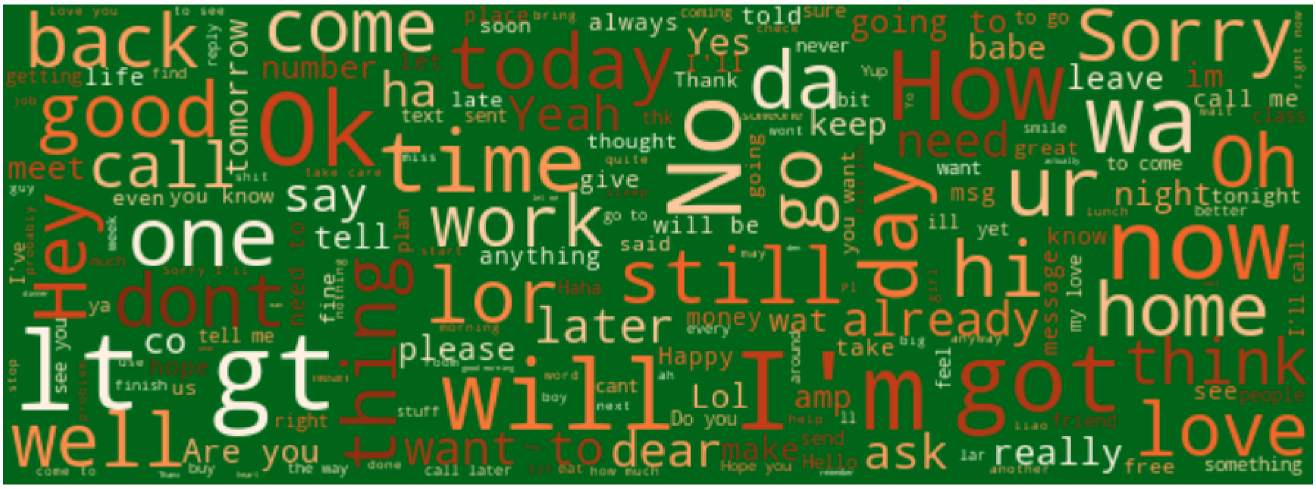


Image by Author

Introduction

Today, internet and social media have become the fastest and easiest ways to get information. In this age, reviews, opinions, feedbacks, messages and recommendations have become significant source of information. Thanks to advancement in technologies, we are now able to extract meaningful information from such data using various Natural Language Processing (NLP) techniques. NLP , a branch of Artificial Intelligence (AI), makes use of computers and human natural language to output classification.

Purpose

The purpose of this article is to understand how we can use TensorFlow2 to build SMS spam detection model. Particularly, we will build a binary classification model to detect whether a text message is spam or not (aka Ham). Moreover, we'll learn how to implement Dense, Long Short Term Memory (LSTM) and Bidirectional-LSTM (Bi-LSTM) deep learning models in TensorFlow2 Keras API.

Data

The SMS (text) data was downloaded from UCI datasets. It contains 5,574 SMS phone messages. The data were collected for the purpose of mobile phone spam research and have already been labeled as either spam or ham.

Method

We will use Dense text classifier , LSTM and Bi-LSTM and compare these methods in terms of performance and select a final one.

Below are the sections that we cover in this article:

- Load and explore the spam data
- Prepare train test data
- Train the spam detection model using the three approaches mentioned above
- Compare and select a final model
- Use the final trained classifier to classify the new messages

Let's get started, first making sure the version of TensrFlow.

```
import tensorflow as tf
print(tf.__version__)
2.2.0
```

Import required packages

```
# import libraries for reading data, exploring and plotting
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
%matplotlib inline

# library for train test split
from sklearn.model_selection import train_test_split

# deep learning libraries for text pre-processing
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Modeling
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding,
GlobalAveragePooling1D, Dense, Dropout, LSTM, Bidirectional
```

Load and explore the spam data

The data can be dowloaded from UCI datasets and saved in a local folder. The text file (and a complete Jupyter notebook) is also provided in my github location hence can be read using below syntax. The text file is a tab separated (\t) file hence, we can use pandas to read data as a dataframe. We can also provide the columns name by passing *names*, call it label and message.

```
url =
'https://raw.githubusercontent.com/ShresthaSudip/SMS_Spam_Detection_
DNN_LSTM_BiLSTM/master/SMSSpamCollection'
messages = pd.read_csv(url, sep ='\t',names=["label", "message"])
messages[:3]
```

	label	message
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...

Let's get the summary statistics and visualize the data. The *describe()* method from pandas provide a summary statistics. Such as, there are 5,572 labels and messages. There are two unique labels indicating for "ham" and "spam". We can also observe that there are less unique messages (5,169) than total message count(5,572) indicating some repeated messages. The top label is "ham" and the top message in the data is "Sorry, I'll call later". The *duplicatedRow* below shows, there are 403 duplicated messages.

```
messages.describe()
```

	label	message
count	5572	5572
unique	2	5169
top	ham	Sorry, I'll call later
freq	4825	30

Summary statistics

```
duplicatedRow = messages[messages.duplicated()]
print(duplicatedRow[:5])
```

```
    label                                            message
103   ham  As per your request 'Melle Melle (Oru Minnamin...
154   ham  As per your request 'Melle Melle (Oru Minnamin...
207   ham  As I entered my cabin my PA said, '' Happy B'd...
223   ham                             Sorry, I'll call later
326   ham                  No calls..messages..missed calls
```

Duplicated row

There are 4,825 ham compared to 747 spam messages. This indicates the **imbalanced** data which we will fix later. The most popular ham message is "Sorry, I'll call later", whereas the most popular spam message is "Please call our customer service…" which occurred 30 and 4 times, respectively.

	label	ham	spam
message	count	4825	747
	unique	4516	653
	top	Sorry, I'll call later	Please call our customer service representativ...
	freq	30	4

Summary statistic by labels (ham or spam)

Below, we further explore the data by label groups by creating a **WordCloud** and a **bar chart**. First, let's create a separate dataframe for ham and spam message and convert it to numpy array to generate WordCloud.

```
# Get all the ham and spam emails
ham_msg = messages[messages.label =='ham']
spam_msg = messages[messages.label=='spam']

# Create numpy list to visualize using wordcloud
ham_msg_text = " ".join(ham_msg.message.to_numpy().tolist())
spam_msg_text = " ".join(spam_msg.message.to_numpy().tolist())
```

To visualize using *WordCloud()*, we extract words most commonly found in ham and spam messages, remove meaningless stop words such as "the", "a" , "is" etc, and plot it. The WordCloud visualizes the most frequent words in the given text.

```
# wordcloud of ham messages
ham_msg_cloud = WordCloud(width =520, height =260,
stopwords=STOPWORDS,max_font_size=50, background_color ="black",
colormap='Blues').generate(ham_msg_text)
plt.figure(figsize=(16,10))
plt.imshow(ham_msg_cloud, interpolation='bilinear')
plt.axis('off') # turn off axis
plt.show()
```

The ham message WordCloud below shows that "now", "work", "How", "Ok" and "Sorry" are the most commonly appeared word in ham messages.

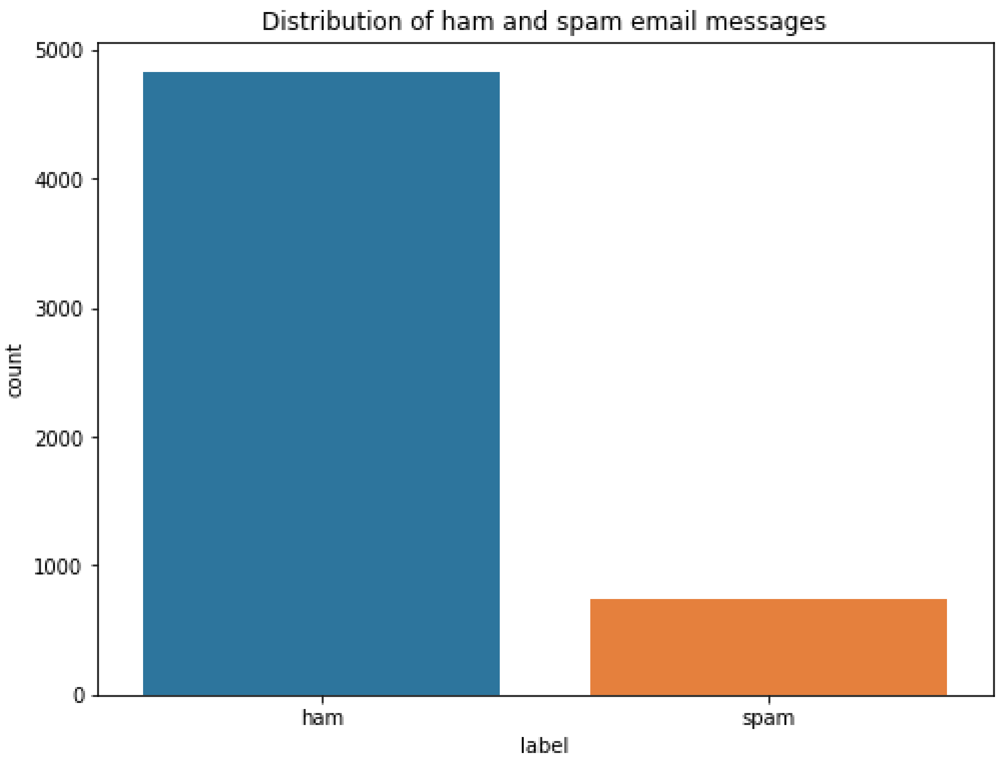
WordCould for ham messages

The spam message WordCloud below shows that “Free”, “call”, “text”, “claim” and“reply” are most commonly appeared words in spam messages.

```
# wordcloud of spam messages
spam_msg_cloud = WordCloud(width =520, height =260,
stopwords=STOPWORDS,max_font_size=50, background_color ="black",
colormap='Blues').generate(spam_msg_text)
plt.figure(figsize=(16,10))
plt.imshow(spam_msg_cloud, interpolation='bilinear')
plt.axis('off') # turn off axis
plt.show()
```

Now, let's further explore the imbalanced data. Below, the bar chart shows that the classes are imbalanced. There are most frequent ham messages (85%) than spam (15%).

```
# we can observe imbalance data here
plt.figure(figsize=(8,6))
sns.countplot(messages.label)
# Percentage of spam messages
(len(spam_msg)/len(ham_msg))*100 # 15.48%
```



Bar chart showing imbalanced data

There are several ways to handle the imbalance data, for instance

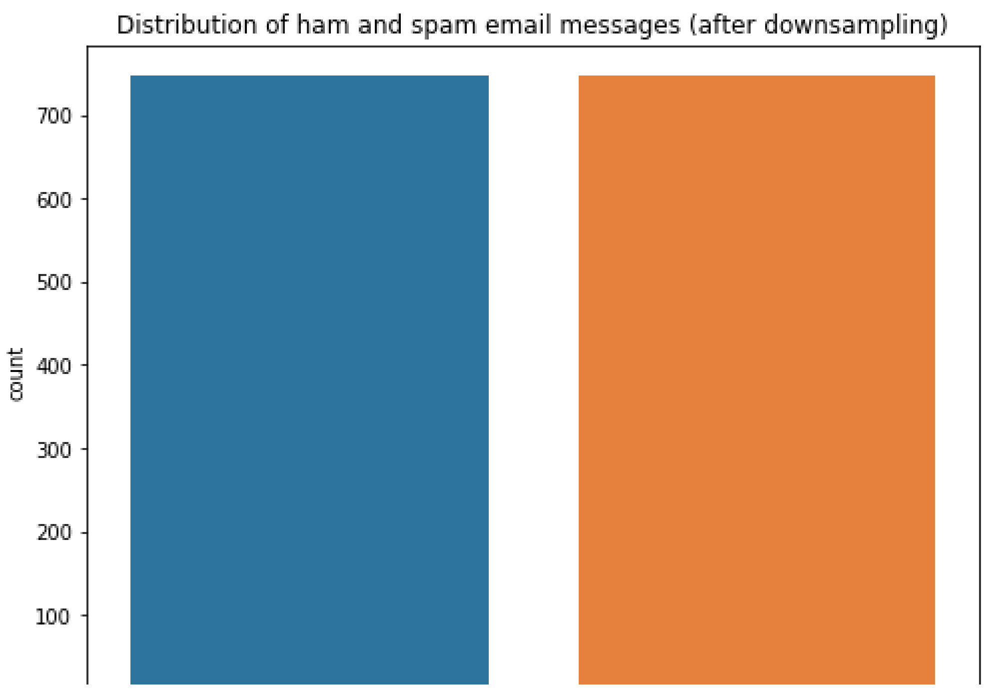
- use of appropriate evaluation metrics
- resampling the training set : oversampling/upsampling or undersampling/downsampling
- ensemble different resample datasets

Downsampling is a process where you randomly delete some of the observations from the majority class so that the numbers in majority and minority classes are matched. Below, we have downsampled the ham messages (majority class). There are now 747 messages in each class.

```
# one way to fix it is to downsample the ham msg
ham_msg_df = ham_msg.sample(n = len(spam_msg), random_state = 44)
spam_msg_df = spam_msg
print(ham_msg_df.shape, spam_msg_df.shape)

(747, 2) (747, 2)
```

Below chart shows a similar distribution across message types after accounting for the imbalanced data.

```
# Create a dataframe with these ham and spam msg
msg_df = ham_msg_df.append(spam_msg_df).reset_index(drop=True)
plt.figure(figsize=(8,6))
sns.countplot(msg_df.label)
plt.title('Distribution of ham and spam email messages (after
downsampling)')
plt.xlabel('Message types')
```



Bar chart after accounting for imbalanced data

Furthermore, on average, the ham message has length of 73 words whereas spam message has 138. The length information may be useful when we set *maxlen* parameter later.

```
# Get length column for each text
msg_df['text_length'] = msg_df['message'].apply(len)

#Calculate average length by label types
labels = msg_df.groupby('label').mean()
labels
```

label	text_length	msg_type
ham	73.238286	0.0
spam	138.670683	1.0

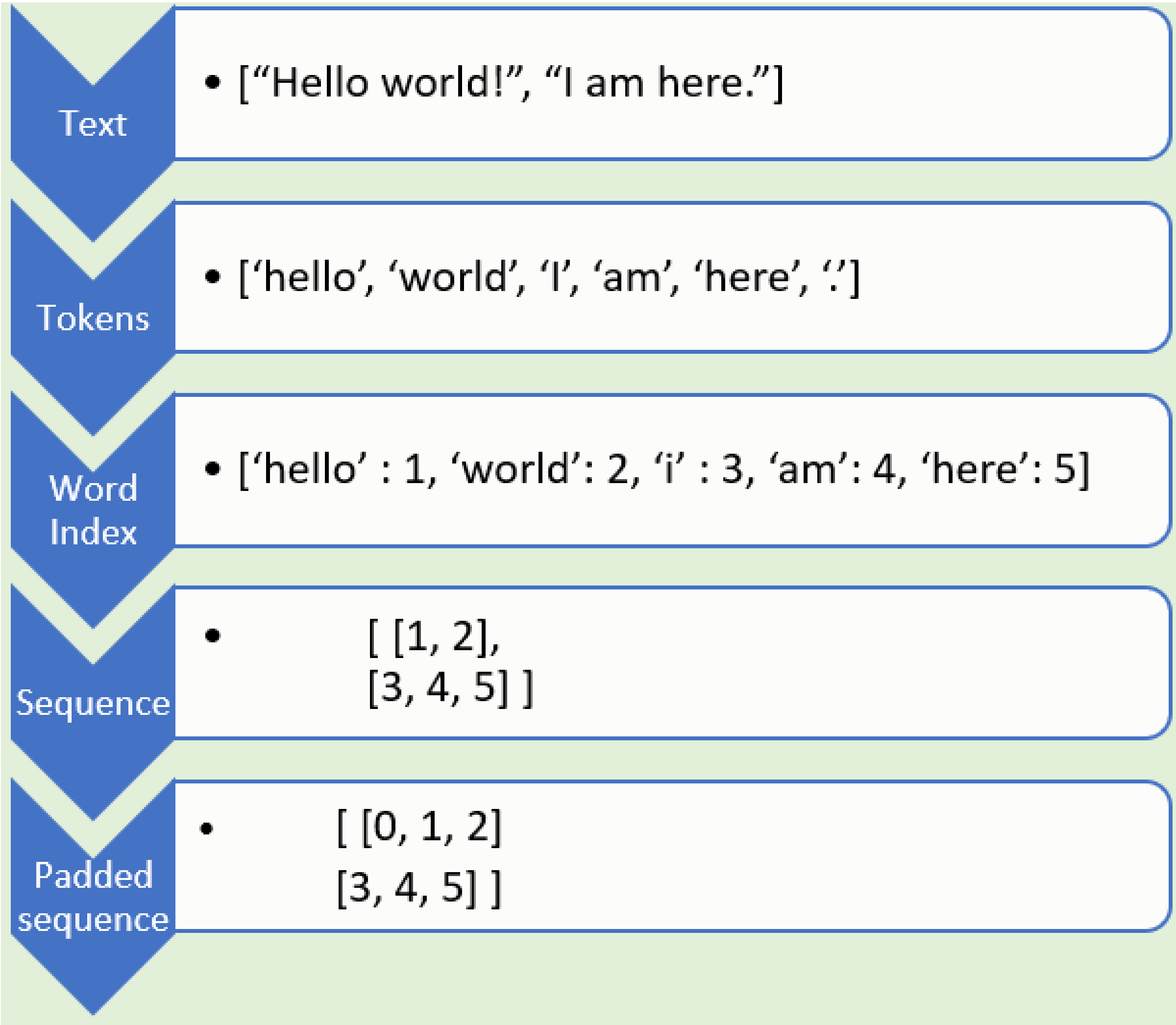
Table shows the text length by ham and spam messages

Prepare train/test data and pre-process text

After exploring and accounting for imbalanced data, next let's convert the text label to numeric and split the data into training set and testing set. Also, convert label to numpy arrays to fit deep learning models. 80% of data were used for training and 20% for testing purposes.

```
# Map ham label as 0 and spam as 1
msg_df['msg_type']= msg_df['label'].map({'ham': 0, 'spam': 1})
msg_label = msg_df['msg_type'].values

# Split data into train and test
train_msg, test_msg, train_labels, test_labels =
train_test_split(msg_df['message'], msg_label, test_size=0.2,
random_state=434)
```

Now, let's use text pre-processing which includes Tokenization, Sequencing and Padding.



For basic understanding on pre-processing text data using TensorFlow2, please refer to my previous article on *pre-processing data for deep learning model.*

Tokenization

As deep learning models do not understand text, let’s convert text into numerical representation. For this purpose, a first step is Tokenization. The Tokenizer API from TensorFlow Keras splits sentences into words and encodes these into integers. *Tokenizer()* does all the required pre-processing such as

- tokenize into word or character — here we use at word level
- num_words for maximum number of unique tokens hence we can filter out rare words

- convert all words to lower case
- convert all words to integer index

First, define hyper-parameters used for pre-processing. We'll describe these hyper-parameters later.

```
# Defining pre-processing hyperparameters
max_len = 50
trunc_type = "post"
padding_type = "post"
oov_tok = "<OOV>"
vocab_size = 500
```

Below, we used *Tokenizer()* to tokenize the words.

```
tokenizer = Tokenizer(num_words = vocab_size, char_level=False,
oov_token = oov_tok)
tokenizer.fit_on_texts(train_msg)
```

Hyper-parameters used in Tokenizer object are: num_words and oov_token, char_level.

- num_words: Indicate how many unique words to load in training and testing data. For our purpose, we selected 500 words (vocab_size)
- oov_token: When its used, out of vocabulary token will be added to word index in the corpus which is used to build the model. This is used to replace out of vocabulary words (words that are not in our corpus) during text_to_sequence calls (see below).
- char_level: If it is "True" then every *character* will be treated as a token. We set it as "False", hence every *word* will be treated as a token.

We can get the word_index using *tokenizer.word_index*. A snapshot of word_index is printed below.

```
word_index
```

```
{'<OOV>': 1,
 'to': 2,
 'you': 3,
 'a': 4,
 'i': 5,
 'call': 6,
 'the': 7,
 'u': 8,
 'your': 9,
 'for': 10,
 'is': 11,
 '2': 12,
 'and': 13,
 'now': 14,
 'free': 15,
 'or': 16,
 'on': 17,
 'in': 18,
 'ur': 19,
```

A snapshot of printed word index

```
# check how many words
tot_words = len(word_index)
print('There are %s unique tokens in training data. ' % tot_words)

There are 4169 unique tokens in training data.
```

Sequencing and Padding

After tokenization, we represent each sentence by sequences of numbers using *texts_to_sequences()* from tokenizer object. Subsequently, we use *pad_sequences()* so that each sequence will have same length. Sequencing and padding are done for both training and testing data.

```
# Sequencing and padding on training and testing
training_sequences = tokenizer.texts_to_sequences(train_msg)
training_padded = pad_sequences (training_sequences, maxlen =
max_len, padding = padding_type, truncating = trunc_type )

testing_sequences = tokenizer.texts_to_sequences(test_msg)
testing_padded = pad_sequences(testing_sequences, maxlen = max_len,
```

- padding = 'pre' or 'post (default pre). By using pre, we pad before each sequence and by using post we pad after each sequence.
- maxlen = maximum length of all sequences. Here max_len=50 hence, we are only going to use 50 words in a sentence. If not provided, by default it will use the maximum length of the longest sentence.
- truncating = 'pre' or 'post' (default 'pre'). If a sequence length is larger than the provided maxlen value then, these values will be truncated to maxlen. 'pre' option will truncate at the beginning where as 'post' will truncate at the end of the sequences.

```
# Shape of train tensor
print('Shape of training tensor: ', training_padded.shape)
print('Shape of testing tensor: ', testing_padded.shape)

Shape of training tensor:  (1195, 50)
Shape of testing tensor:  (299, 50)
```

Before padding, first sequence is 27 word long where as second one is 24. Once the padding was applied, both sequences have length of 50.

```
# Before padding
len(training_sequences[0]), len(training_sequences[1])

Output:
(27, 24)

# After padding
len(training_padded[0]), len(training_padded[1])

Output:
(50, 50)
```

As depicted below, the padded sequence has length of 50.

```
print(training_padded[0])
```

Padded sequence of a first sentence

Dense Spam Detection Model

With our data loaded and preprocessed, we're now well prepared to use neural network architecture to classify the text message. Let's train the model using a Dense architecture followed by LSTM and Bi-LSTM.

Define hyper-parameters:

```
vocab_size = 500 # As defined earlier
embeding_dim = 16
drop_value = 0.2 # dropout
n_dense = 24
```

Below is a model **architecture of dense spam detection model**.

```
#Dense model architecture
model = Sequential()
model.add(Embedding(vocab_size, embeding_dim, input_length=max_len))
model.add(GlobalAveragePooling1D())
model.add(Dense(24, activation='relu'))
model.add(Dropout(drop_value))
model.add(Dense(1, activation='sigmoid'))
```

- Sequential calls for Keras sequential model in which layers are added in a sequence
- The first layer i.e. embedding layer maps each word to a N-dimensional vector of real numbers. The embeding_dim is the size of this vector which is 16 in our case. The embedding layer indicates that the two words with a similar meaning tend to have very close vectors. Because, the embedding layer is the first hidden layer in our model network, we need to pass shape of our input layer as defined by input_length (max_len =50).
- The pooling layer helps to reduce the number of parameters in the model hence helps to avoid overfitting. We have used average pooling here and converted layer to 1 dimension.

As there are only two classes (ham or spam) to classify, we use only a single output neuron. The sigmoid activation function outputs probabilities between 0 and 1.

Here, we use fairly a shallow neural network architecture, however, you can make it more dense adding more layers.

The *model.summary()* below, provides the layer, shape and number of parameters used in each layer. In the embedding layer, the 8000 parameter comes from 500 words (vocab_size), each one with a 16 dimensional word-vector space (500 X 16 =8000). The embedding layer is passed through *GlobalAveragePooling1D* and into dense layers have shape of 16 (due to the average pooling along 16 embedding dimension). We selected 24 neurons for the dense hidden layer. Each of the 24 neurons in the dense layer gets input from each of the 16 values coming from the GlobalAveragePooling1D layer, for a total of 384 (16 X 24) weights and 24 biases (one for each 24 neurons). Hence the total parameter is 408. Finally, the output layer has 24 weights (one for each neuron) and its one bias term resulting 25 parameters in total.

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 50, 16)            8000
_________________________________________________________________
global_average_pooling1d (Gl (None, 16)                0
_________________________________________________________________
dense (Dense)                (None, 24)                408
_________________________________________________________________
dropout (Dropout)            (None, 24)                0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 25
=================================================================
Total params: 8,433
Trainable params: 8,433
Non-trainable params: 0
_________________________________________________________________
```

Model summary of Dense model architecture

Compiling the Dense model

momentum to avoid local minima and 'accuracy' as a measure of model performance.

```
model.compile(loss='binary_crossentropy',optimizer='adam' ,metrics=
['accuracy'])
```

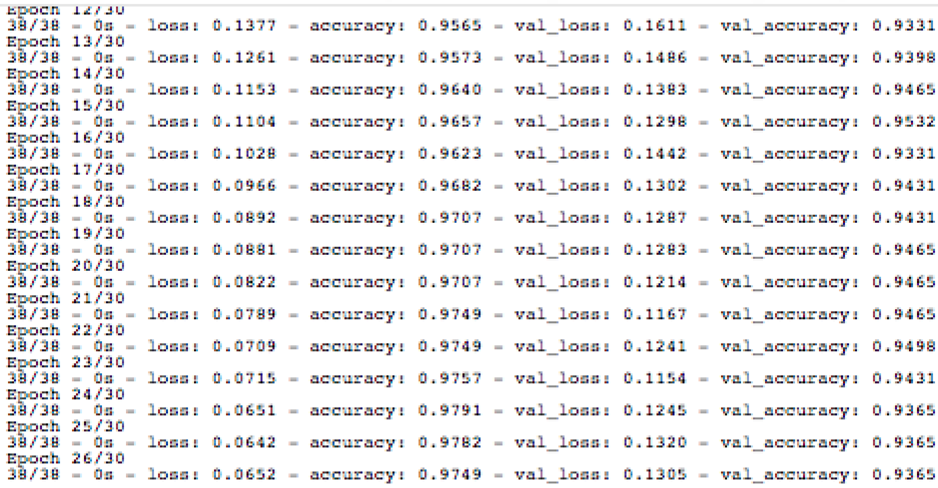
Training and evaluating the Dense model

Next, let's fit our dense classifier using *model.fit()* argument. It uses padded training data and training labels for training the model and validation data for validating.

- epoch: Number of times the learning algorithm will work through the entire training data set. We set it to be 20.
- callbacks: callbacks is used to pass the early stopping parameter. EarlyStopping(monitor='val_loss', patience=2) is used to define that we want to monitor the validation loss and if the validation loss is not improved after two epochs, then the model training is stopped. It helps to avoid overfitting problem and indicates when to stop training before the learner begins over-fit. As depicted in the history results below, the validation loss is increased (i.e. not improved), continuously for 2 epochs (epoch 24: 0.12, and epoch 25: 0.13) after epoch 23, hence the model fitting has stopped at epoch 26.
- verbose =2: lets to print loss and accuracy on each epoch

```
# fitting a dense spam detector model
num_epochs = 30
early_stop = EarlyStopping(monitor='val_loss', patience=3)

history = model.fit(training_padded, train_labels,
epochs=num_epochs, validation_data=(testing_padded,
test_labels),callbacks =[early_stop], verbose=2)
```

```
Epoch 1/30
38/38 - 0s - loss: 0.6875 - accuracy: 0.6628 - val_loss: 0.6794 - val_accuracy: 0.8227
Epoch 2/30
38/38 - 0s - loss: 0.6595 - accuracy: 0.8577 - val_loss: 0.6384 - val_accuracy: 0.8395
Epoch 3/30
38/38 - 0s - loss: 0.5977 - accuracy: 0.8695 - val_loss: 0.5619 - val_accuracy: 0.8462
Epoch 4/30
38/38 - 0s - loss: 0.5020 - accuracy: 0.8837 - val_loss: 0.4658 - val_accuracy: 0.8528
Epoch 5/30
38/38 - 0s - loss: 0.4005 - accuracy: 0.8962 - val_loss: 0.3799 - val_accuracy: 0.8729
Epoch 6/30
38/38 - 0s - loss: 0.3204 - accuracy: 0.9029 - val_loss: 0.3182 - val_accuracy: 0.8896
Epoch 7/30
38/38 - 0s - loss: 0.2659 - accuracy: 0.9146 - val_loss: 0.2783 - val_accuracy: 0.8963
```



```
Epoch 12/30
38/38 - 0s - loss: 0.1377 - accuracy: 0.9565 - val_loss: 0.1611 - val_accuracy: 0.9331
Epoch 13/30
38/38 - 0s - loss: 0.1261 - accuracy: 0.9573 - val_loss: 0.1486 - val_accuracy: 0.9398
Epoch 14/30
38/38 - 0s - loss: 0.1153 - accuracy: 0.9640 - val_loss: 0.1383 - val_accuracy: 0.9465
Epoch 15/30
38/38 - 0s - loss: 0.1104 - accuracy: 0.9657 - val_loss: 0.1298 - val_accuracy: 0.9532
Epoch 16/30
38/38 - 0s - loss: 0.1028 - accuracy: 0.9623 - val_loss: 0.1442 - val_accuracy: 0.9331
Epoch 17/30
38/38 - 0s - loss: 0.0966 - accuracy: 0.9682 - val_loss: 0.1302 - val_accuracy: 0.9431
Epoch 18/30
38/38 - 0s - loss: 0.0892 - accuracy: 0.9707 - val_loss: 0.1287 - val_accuracy: 0.9431
Epoch 19/30
38/38 - 0s - loss: 0.0881 - accuracy: 0.9707 - val_loss: 0.1283 - val_accuracy: 0.9465
Epoch 20/30
38/38 - 0s - loss: 0.0822 - accuracy: 0.9707 - val_loss: 0.1214 - val_accuracy: 0.9465
Epoch 21/30
38/38 - 0s - loss: 0.0789 - accuracy: 0.9749 - val_loss: 0.1167 - val_accuracy: 0.9465
Epoch 22/30
38/38 - 0s - loss: 0.0709 - accuracy: 0.9749 - val_loss: 0.1241 - val_accuracy: 0.9498
Epoch 23/30
38/38 - 0s - loss: 0.0715 - accuracy: 0.9757 - val_loss: 0.1154 - val_accuracy: 0.9431
Epoch 24/30
38/38 - 0s - loss: 0.0651 - accuracy: 0.9791 - val_loss: 0.1245 - val_accuracy: 0.9365
Epoch 25/30
38/38 - 0s - loss: 0.0642 - accuracy: 0.9782 - val_loss: 0.1320 - val_accuracy: 0.9365
Epoch 26/30
38/38 - 0s - loss: 0.0652 - accuracy: 0.9749 - val_loss: 0.1305 - val_accuracy: 0.9365
```

Accuracy and loss over epochs: Dense Classifier

The model resulted , training loss: 0.07, training accuracy: 97%, validation loss: 0.13 and validation accuracy: 94%.

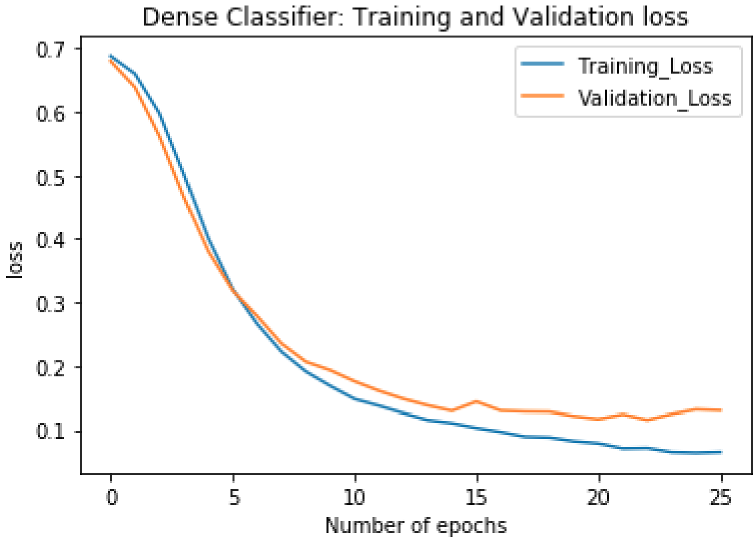
```
# Model performance on test data
model.evaluate(testing_padded, test_labels)

Output: loss: 0.13 - accuracy: 0.94
```

We can further visualize the history results by plotting loss and accuracy by number of epochs.

```
# Read as a dataframe
metrics = pd.DataFrame(history.history)
# Rename column
metrics.rename(columns = {'loss': 'Training_Loss', 'accuracy':
'Training_Accuracy', 'val_loss': 'Validation_Loss', 'val_accuracy':
'Validation_Accuracy'}, inplace = True)

def plot_graphs1(var1, var2, string):
    metrics[[var1, var2]].plot()
    plt.title('Training and Validation ' + string)
    plt.xlabel ('Number of epochs')
    plt.ylabel(string)
    plt.legend([var1, var2])
```

loss is higher than training loss after around 5 epochs and the difference is more pronounced with increase in epochs.

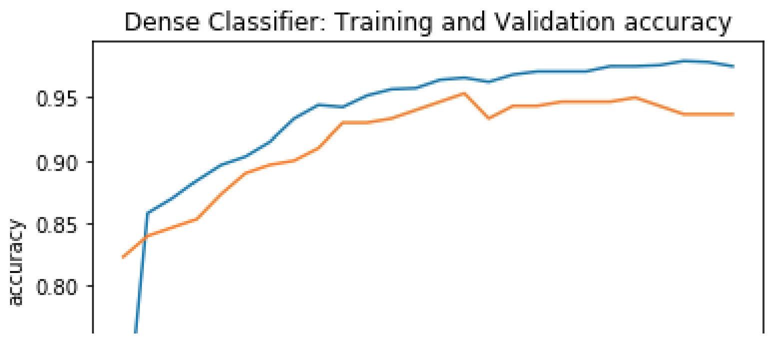
```
plot_graphs1('Training_Loss', 'Validation_Loss', 'loss')
```

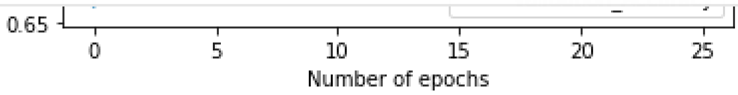


Keeping track of loss over epochs: Dense Classifier

The accuracy plot below shows, the accuracy is increasing over epochs. As expected, the model is performing better in training set than the validation set. If the model performs very well on training data however, its performance is worse in testing data, then it is an indication of overfitting. In our model, we don't see a significant issue with over-fitting. Moreover, we have accounted for over-fitting problem by using dropout layer and callback earlier.

```
plot_graphs1('Training_Accuracy', 'Validation_Accuracy', 'accuracy')
```





Keeping track of accuracy over epochs: Dense Classifier

Long Short Term Memory (LSTM) Model

Below, we fit the spam detection model using LSTM. Some new hyper-parameters used in LSTM below are *n_lstm* and *return_sequences*.

- n_lstm = 20 is the number of nodes in the hidden layers within the LSTM cell
- return_sequences=True ensures that the LSTM cell returns all of the outputs from the unrolled LSTM cell through time. If this argument is not used, the LSTM cell will simply provide the output of the LSTM cell from the previous step.

Below are hyper-parameters used for LSTM model.

```
#LSTM hyperparameters
n_lstm = 20
drop_lstm =0.2
```

Let’s define **LSTM spam detection model architecture**. In Keras, by simply adding LSTM we can fit the LSTM model.

```
#LSTM Spam detection architecture
model1 = Sequential()
model1.add(Embedding(vocab_size, embeding_dim,
input_length=max_len))
model1.add(LSTM(n_lstm, dropout=drop_lstm, return_sequences=True))
model1.add(LSTM(n_lstm, dropout=drop_lstm, return_sequences=True))
model1.add(Dense(1, activation='sigmoid'))
```

Compiling the LSTM model

```
model1.compile(loss = 'binary_crossentropy', optimizer = 'adam',
metrics=['accuracy'])
```

The training and evaluations are same as we did for Dense model above.

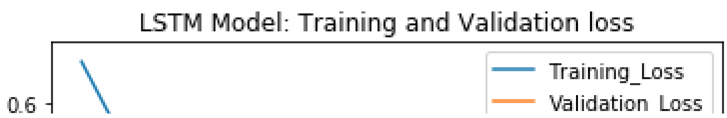
```
num_epochs = 30
early_stop = EarlyStopping(monitor='val_loss', patience=2)
history = model1.fit(training_padded, train_labels,
epochs=num_epochs, validation_data=(testing_padded,
test_labels),callbacks =[early_stop], verbose=2)
```

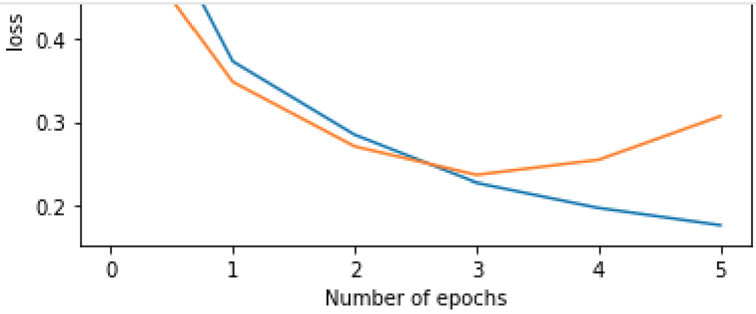
The validation loss and accuracy from LSTM are 0.31 and 91%, respectively.

```
Epoch 1/30
38/38 - 5s - loss: 0.6503 - accuracy: 0.6553 - val_loss: 0.5459 - val_accuracy: 0.7132
Epoch 2/30
38/38 - 3s - loss: 0.3723 - accuracy: 0.8709 - val_loss: 0.3477 - val_accuracy: 0.8910
Epoch 3/30
38/38 - 3s - loss: 0.2847 - accuracy: 0.9118 - val_loss: 0.2708 - val_accuracy: 0.9166
Epoch 4/30
38/38 - 3s - loss: 0.2278 - accuracy: 0.9339 - val_loss: 0.2367 - val_accuracy: 0.9240
Epoch 5/30
38/38 - 3s - loss: 0.1979 - accuracy: 0.9405 - val_loss: 0.2547 - val_accuracy: 0.9190
Epoch 6/30
38/38 - 3s - loss: 0.1772 - accuracy: 0.9467 - val_loss: 0.3068 - val_accuracy: 0.9070
```

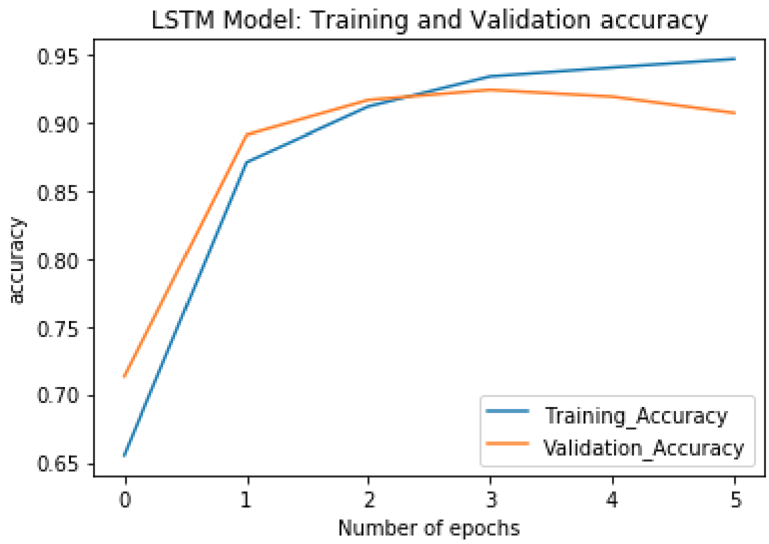
Accuracy and loss over epochs: LSTM

```
# Create a dataframe
metrics = pd.DataFrame(history.history)

# Rename column
metrics.rename(columns = {'loss': 'Training_Loss', 'accuracy':
'Training_Accuracy',
                         'val_loss': 'Validation_Loss',
'val_accuracy': 'Validation_Accuracy'}, inplace = True)
def plot_graphs1(var1, var2, string):
    metrics[[var1, var2]].plot()
    plt.title('LSTM Model: Training and Validation ' + string)
    plt.xlabel ('Number of epochs')
    plt.ylabel(string)
    plt.legend([var1, var2])

plot_graphs1('Training_Loss', 'Validation_Loss', 'loss')
plot_graphs1('Training_Accuracy', 'Validation_Accuracy', 'accuracy')
```





Keeping track of loss over epochs: LSTM



Keeping track of accuracy over epochs: LSTM

Bi-directional Long Short Term Memory (BiLSTM) Model

Unlike in LSTM, the Bi-LSTM learns patterns from both before and after a given token within a document. The Bi-LSTM back-propagates in both backward and forward directions in time. Due to this, the computational time is increased compared to LSTM. However, in most of the cases Bi-LSTM results in better accuracy.

Below, we can see the **Bi-directional LSTM architecture,** where only difference than LSTM is that we use *Bidirectional* wrapper to LSTM.

```
# Biderectional LSTM Spam detection architecture
model2 = Sequential()
model2.add(Embedding(vocab_size, embeding_dim,
input_length=max_len))
model2.add(Bidirectional(LSTM(n_lstm, dropout=drop_lstm,
return_sequences=True)))
model2.add(Dense(1, activation='sigmoid'))
```

```
model2.compile(loss = 'binary_crossentropy', optimizer = 'adam',
metrics=['accuracy'])
```

Training and evaluation BiLSTM model

```
# Training
num_epochs = 30
early_stop = EarlyStopping(monitor='val_loss', patience=2)
history = model2.fit(training_padded, train_labels,
epochs=num_epochs,
                    validation_data=(testing_padded,
test_labels),callbacks =[early_stop], verbose=2)
```

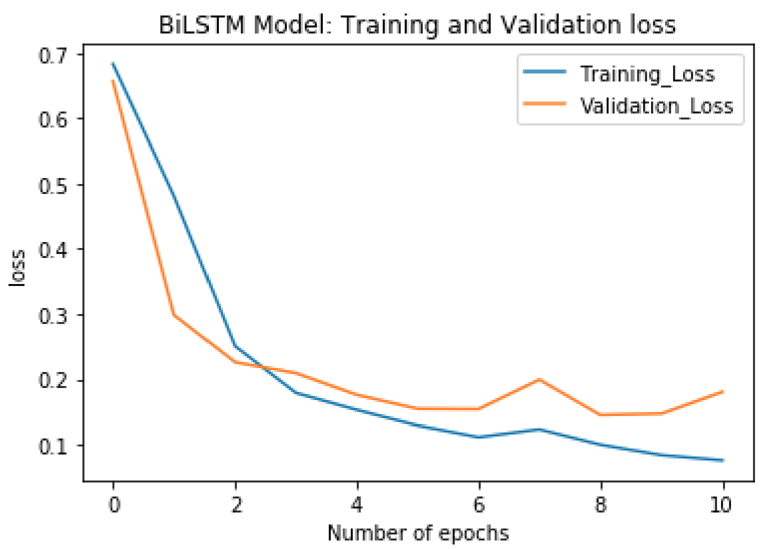
The validation loss and accuracy from BiLSTM are 0.18 and 95%, respectively.

```
Epoch 1/30
38/38 - 3s - loss: 0.6831 - accuracy: 0.5830 - val_loss: 0.6565 - val_accuracy: 0.6334
Epoch 2/30
38/38 - 1s - loss: 0.4813 - accuracy: 0.8033 - val_loss: 0.2986 - val_accuracy: 0.9104
Epoch 3/30
38/38 - 2s - loss: 0.2507 - accuracy: 0.9265 - val_loss: 0.2260 - val_accuracy: 0.9318
Epoch 4/30
38/38 - 2s - loss: 0.1789 - accuracy: 0.9523 - val_loss: 0.2093 - val_accuracy: 0.9389
Epoch 5/30
38/38 - 2s - loss: 0.1530 - accuracy: 0.9600 - val_loss: 0.1759 - val_accuracy: 0.9504
Epoch 6/30
38/38 - 2s - loss: 0.1292 - accuracy: 0.9671 - val_loss: 0.1547 - val_accuracy: 0.9569
Epoch 7/30
38/38 - 2s - loss: 0.1114 - accuracy: 0.9714 - val_loss: 0.1543 - val_accuracy: 0.9579
Epoch 8/30
38/38 - 2s - loss: 0.1234 - accuracy: 0.9632 - val_loss: 0.1993 - val_accuracy: 0.9514
Epoch 9/30
38/38 - 2s - loss: 0.1001 - accuracy: 0.9735 - val_loss: 0.1451 - val_accuracy: 0.9585
Epoch 10/30
38/38 - 2s - loss: 0.0841 - accuracy: 0.9781 - val_loss: 0.1472 - val_accuracy: 0.9600
Epoch 11/30
38/38 - 2s - loss: 0.0761 - accuracy: 0.9809 - val_loss: 0.1805 - val_accuracy: 0.9514
```

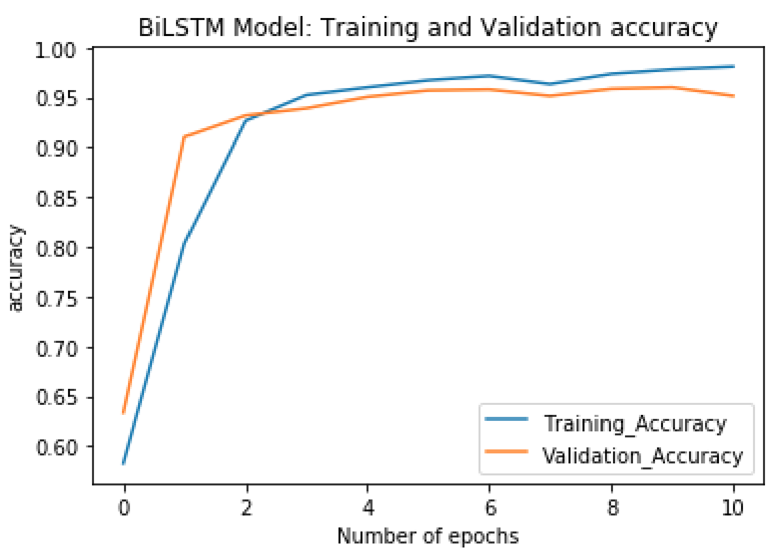
Accuracy and loss over epochs: BiLSTM

```
# Create a dataframe
metrics = pd.DataFrame(history.history)

# Rename column
metrics.rename(columns = {'loss': 'Training_Loss', 'accuracy':
'Training_Accuracy',
```

```
    metrics[[var1, var2]].plot()
    plt.title('BiLSTM Model: Training and Validation ' + string)
    plt.xlabel ('Number of epochs')
    plt.ylabel(string)
    plt.legend([var1, var2])

# Plot
plot_graphs1('Training_Loss', 'Validation_Loss', 'loss')
plot_graphs1('Training_Accuracy', 'Validation_Accuracy', 'accuracy')
```



Keeping track of loss over epochs: BiLSTM



Keeping track of accuracy over epochs: BiLSTM

Compare three different models and select a final one

the validation accuracy are 94%, 91% and 95%, respectively.

Among all, both Dense and BiLSTM outperformed the LSTM. Based on loss, accuracy and the plots above, we select Dense architecture as a final model for classifying the text messages for spam or ham. The dense classifier has simple structure and the loss and accuracy over epochs are more stable than in BiLSTM.

```
# Comparing three different models
print(f"Dense architecture loss and accuracy:
{model.evaluate(testing_padded, test_labels)} " )
print(f"LSTM architecture loss and accuracy:
{model1.evaluate(testing_padded, test_labels)} " )
print(f"Bi-LSTM architecture loss and accuracy:
{model2.evaluate(testing_padded, test_labels)} " )
```

```
10/10 [==============================] - 0s 2ms/step - loss: 0.1305 - accuracy: 0.9365
Dense architecture loss and accuracy: [0.13050097227096558, 0.9364548325538635]
10/10 [==============================] - 0s 15ms/step - loss: 0.3068 - accuracy: 0.9070
LSTM architecture loss and accuracy: [0.3067699074745178, 0.9070233702659607]
10/10 [==============================] - 0s 9ms/step - loss: 0.1805 - accuracy: 0.9514
Bi-LSTM architecture loss and accuracy: [0.18049846589565277, 0.9514381885528564]
```

Validation Loss and Accuracy from 3 models

Predict spam/ham on new messages

Scenario 1: Using raw text from our data:

Let’s evaluate how our Dense spam detection model predicts/classifies whether its spam or ham given the text from our original data. First and second messages below are ham whereas the third one is a spam message. We’ve used the same tokenizer that we created earlier in the code to convert them into the sequences. This makes sure the new words will have the same token as in the training set. Once tokenized, we use padding as we did earlier and provide the same dimension as in training set.

```
# display long string
pd.options.display.max_colwidth=100
messages[:3]
```

label message

2	spam	Free entry in 2 a wkly comp to win FA Cup final tkts 21st May 2005. Text FA to 87121 to receive ...

First 3 observations from our raw data

```
predict_msg = ["Go until jurong point, crazy.. Available only in
bugis n great world la e buffet... Cine there got amore wat...",
          "Ok lar... Joking wif u oni...",
          "Free entry in 2 a wkly comp to win FA Cup final tkts 21st
May 2005. Text FA to 87121 to receive entry question(std txt
rate)T&C's apply 08452810075over18's"]
```

predict_spam function is defined as below.

```
# Defining prediction function

def predict_spam(predict_msg):
    new_seq = tokenizer.texts_to_sequences(predict_msg)
    padded = pad_sequences(new_seq, maxlen =max_len,
                      padding = padding_type,
                      truncating=trunc_type)
    return (model.predict(padded))

predict_spam(predict_msg)
```

As shown below, the model correctly predicts first two sentences as not spam where as the third one as spam. There is 99% chance that the third sentence is spam.

```
array([[0.01329055],
       [0.00859618],
       [0.9998981 ]], dtype=float32)
```

Predicted outcome for raw data

Scenario 2: Using newly created text message and see how the model classifies them.

Below, first sentence is more like a spam whereas the rest of the two sentences are more like ham.

```
            "call me",
            "What's up?"]
predict_spam(predict_msg)
```

Our model correctly classifies the first message as spam (94% chance to be spam) were as the rest as ham.

```
array([[0.94021654],
       [0.06316207],
       [0.02721775]], dtype=float32)
```

Predicted outcome for new text messages

Summary

We used the text messages from UCI datasets and fit deep learning models such as Dense architecture, LSTM and Bi-LSTM and compared the accuracy and loss on validation set across these models. Finally, we selected the Dense architectural deep learning model to classify text messages as spam or ham and used it to classify new text messages. This article, provides an overview of using different architectural deep learning models to NLP problem using TensorFlow2 Keras.

Next Step/Improvement

Next, we can explore more sampling approaches such as upsampling, SMOTE, overall sample. We can also try using different hyper-parameters, increase the sample size to improve the model further.

Acknowledgement!

I would like to thank Jon Krohn for his book “Deep Learning Illustrated”, Lazy programmer Inc for their excellent course “Tensorflow 2.0: Deep Learning and Artificial Intelligence” and Jose Portilla for an awesome course “Complete Tensorflow 2 and Keras Deep Learning Bootcamp” on Udemy.

Thank you!

Thank you all for reading and please feel free to leave comments/suggestions.

Happy Learning!!!

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