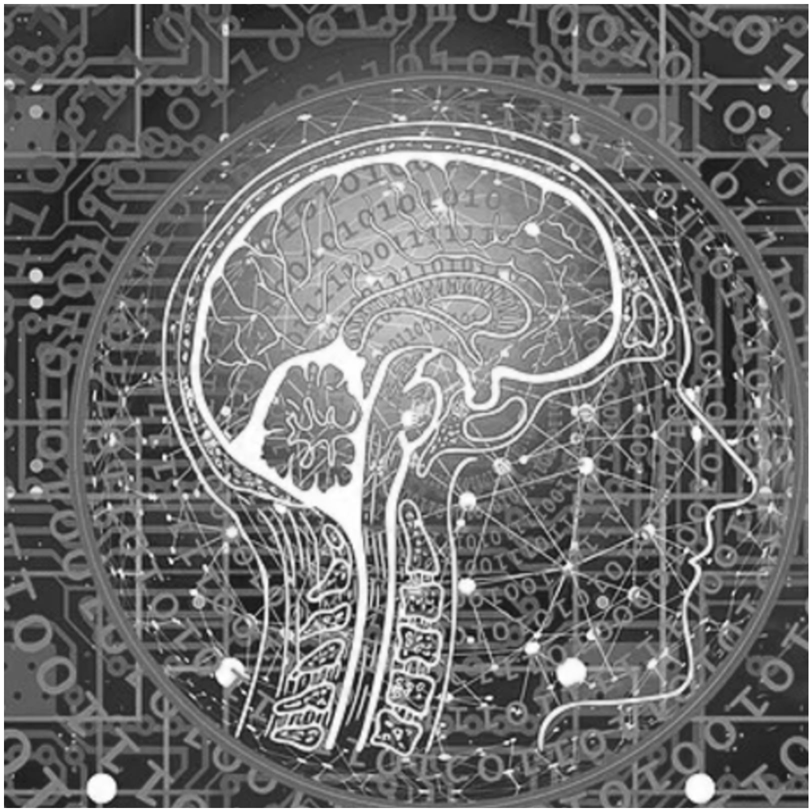


Coursera IBM-- Deep Learning: Final Project
By: Liam Webster
8/11/2022

Introduction:

The main objective of this analysis was to continue research on my previous project regarding Fake News. Previously I used clustering algorithms to build a fake news filter. I was able to get decent results. The models predicted the correct classification 80 percent of the time but also relayed good interpretability. In this analysis I aimed to use deep learning to improve upon these results. This model could be used in applications where filtering untruthful news is pertinent such as in educational settings.

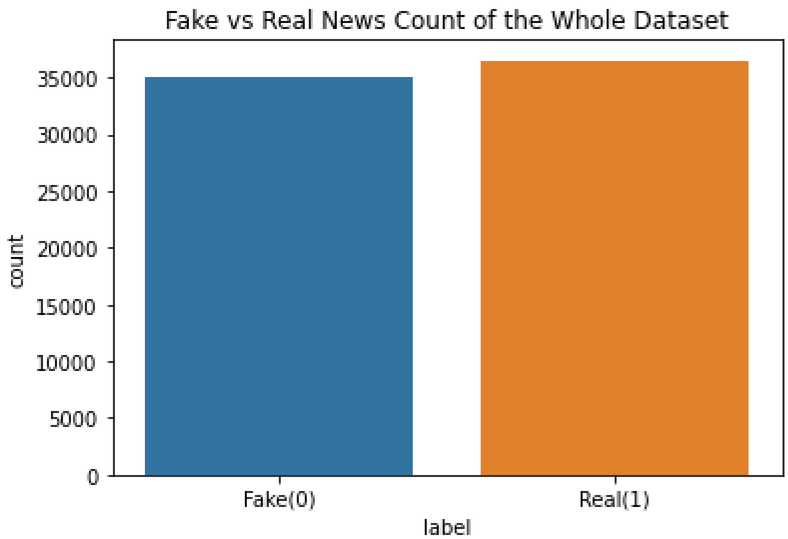
Dataset:

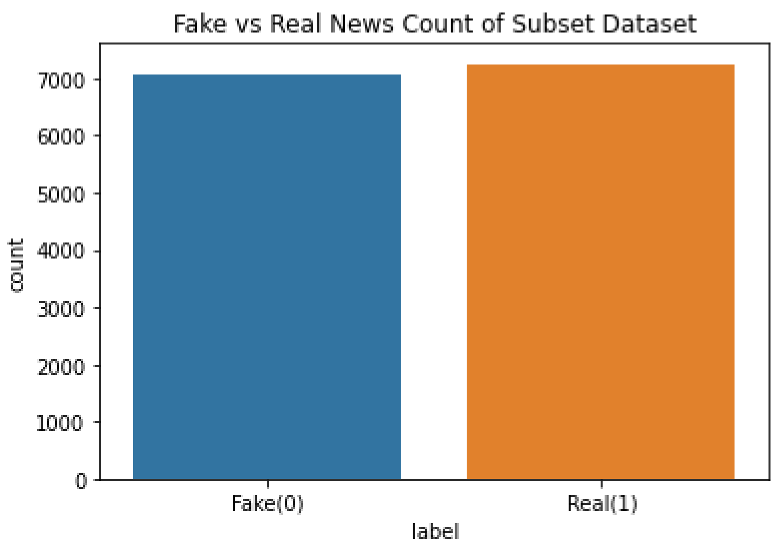
The dataset used in this analysis contains 72 thousand rows and four columns. Three feature columns– “Index”, “Title”, and “Text” – containing the index, the title of the news article, and a keyword summary of the article, respectively. The last column being “label” which indicates whether the article is fake or real. The dataset is a combination of 4 other datasets thus amassing a total of 72 thousand observations.

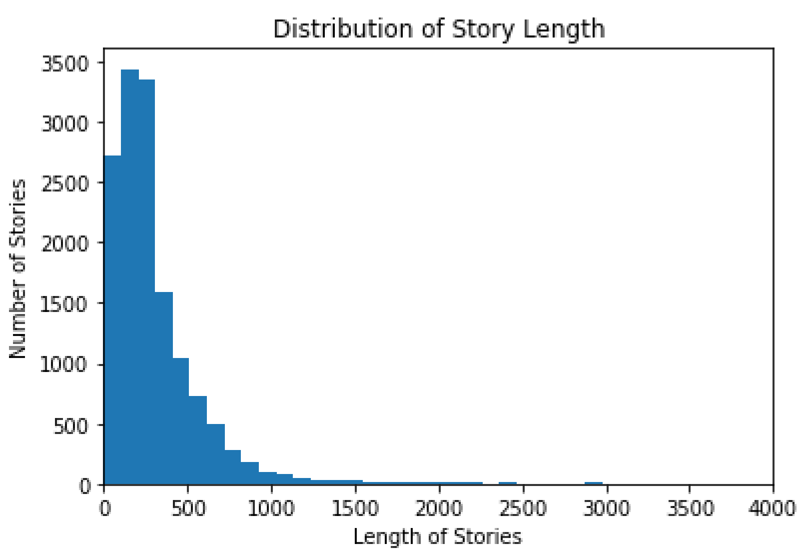
	title	text	label
0	LAW ENFORCEMENT ON HIGH ALERT Following Threat...	No comment is expected from Barack Obama Membe...	1
1	NaN	Did they post their votes for Hillary already?	1
2	UNBELIEVABLE! OBAMA'S ATTORNEY GENERAL SAYS MO...	Now, most of the demonstrators gathered last ...	1
3	Bobby Jindal, raised Hindu, uses story of Chri...	A dozen politically active pastors came here f...	0
4	SATAN 2: Russia unvelis an image of its terrif...	The RS-28 Sarmat missile, dubbed Satan 2, will...	1

EDA:

After previously working with this dataset I was pretty familiar with it. In this exploration I decided to initially investigate a subset of 20 percent of the full dataset. This was in hopes to reveal general trends on the smaller dataset thus decreasing general training times. Later the full dataset was tested on the final model. The subset was checked for any skewing but it was found to have a normal distribution. Before building the models a corpus had to be generated from the article’s text. In doing so, all words were lowercased, numbers were excluded, punctuation was removed, and all stop words were removed. From this corpus the articles were vectorized and then fed into the models.


Fake vs Real News Count of the Whole Dataset
count
35000
30000
25000
20000
15000
10000
5000
0
Fake(0)
Real(1)
label


Fake vs Real News Count of Subset Dataset
count
7000
6000
5000
4000
3000
2000
1000
0
Fake(0)
Real(1)
label


Distribution of Story Length
Number of Stories
3500
3000
2500
2000
1500
1000
500
0
0
500
1000
1500
2000
2500
3000
3500
4000
Length of Stories

Models:

The first model created was a sequential three layer recurrent neural network, utilizing a kera's embedding, a LSTM, and a dense layer. An RMSprop optimizer was used and the loss function implemented was a binary cross entropy function. This model predicted the correct classification 82 percent of the time.

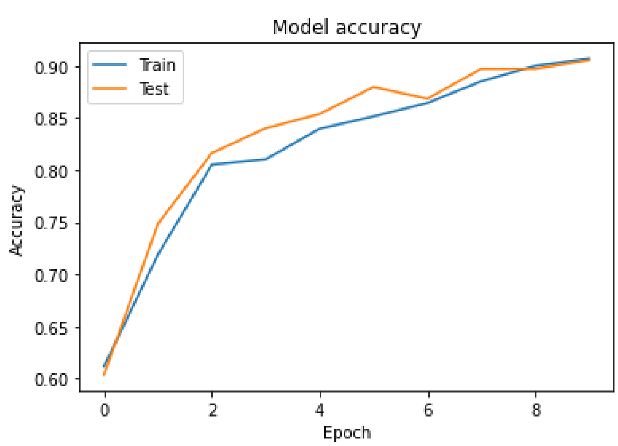
The second model trained was a six layer sequential model. Composed of one embedding layer, one LSTM layer, two dropout layers and two dense layers. This again used an RMSprop optimizer and used a binary cross entropy loss function. This model predicted the correct classification 92% of the time.

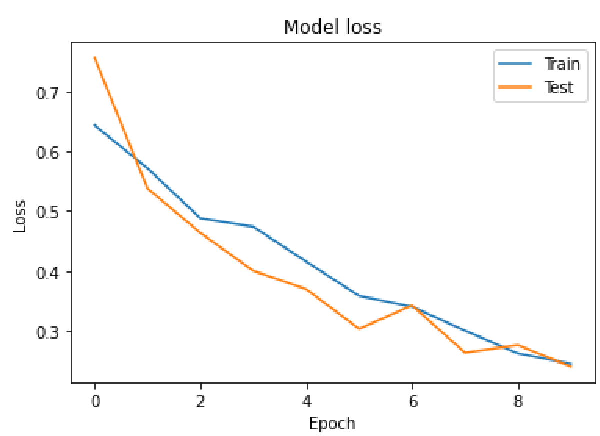
The third model trained was an 11 layer sequential model. Composed of one embedding layer, one MaxPooling layer, one Conv1D layer, two LSTM layers, a couple dropout layers and dense layers. The model used an Adam optimizer and a binary cross entropy loss function. This model predicted the correct classification 91 percent of the time.

Final Model:

It is recommended to use model two as the final deliverable. It produced the best result while also reducing complexity in comparison to model three.

	Model 1	Model 2	Model 3
Accuracy	81.89	91.87	90.68





Key Findings and Insights

Working with large data requires a lot of computing power and patience. Creating the data corpus from the 70 thousand articles took an hour. Words such as ‘Trump’, ‘President’, and ‘people’ were commonly found in both real and fake articles. While words such as ‘Clinton’, ‘think’, and ‘reality’ were commonly found in real articles and words such as ‘Government’, ‘illegal’, and ‘Reuters’ were commonly found in fake articles.

Suggestions:

In this analysis just the text of each article was analyzed, to further this research the title could be incorporated into the model. More sophisticated natural language preprocessing techniques could be performed.

In [37]:

```python
# External Library Imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import keras
import tensorflow as tf
from keras.preprocessing.text import Tokenizer
from tensorflow.keras.utils import pad_sequences
from keras.models import Sequential
from keras.layers import Activation, Dropout, Flatten, Dense, BatchNormalization, LSTM,
from keras import initializers
from sklearn.model_selection import train_test_split
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
import re

def warn(*args, **kwargs):
    pass
import warnings
warnings.warn = warn
warnings.filterwarnings('ignore')
```

In [49]:

```python
# Functions

def CountPlot(data, title):
    plot = plt.axes()
    plot.set_title(title)
    sns.countplot(data)
    plot.set_xlabel('label')
    plot.set_xticklabels(['Fake(0)','Real(1)'])
    return plot

def CorpusGen(text):
    # Removes numbers, lowercases words, removes stopwords, word tokenizes, and finally
    lemmatizer = WordNetLemmatizer()
    nltk.download('stopwords')
    nltk.download('punkt')
    nltk.download('wordnet')
    nltk.download('omw-1.4')

    corpus = list()
    for i in range(0,len(text)):
        message = re.sub('[^a-zA-Z]', ' ', text.iloc[i])
        message = message.lower()
        message = word_tokenize(message)
        message = list(lemmatizer.lemmatize(w) for w in message if not w in stopwords.wo
        message = ' '.join(message)
        corpus.append(message)
    return corpus

def plot(history):
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.title('Model accuracy')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.legend(['Train', 'Test'], loc='upper left')
    plt.show()

    plt.plot(history.history['loss'])
```

```
    plt.plot(history.history['val_loss'])
    plt.title('Model loss')
    plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.legend(['Train', 'Test'], loc='upper right')
    plt.show()
```

In [13]:
```
# Import Data
filepath = "Data\WELFake_Dataset.csv\WELFake_Dataset.csv"

raw_data = pd.read_csv(filepath)
```

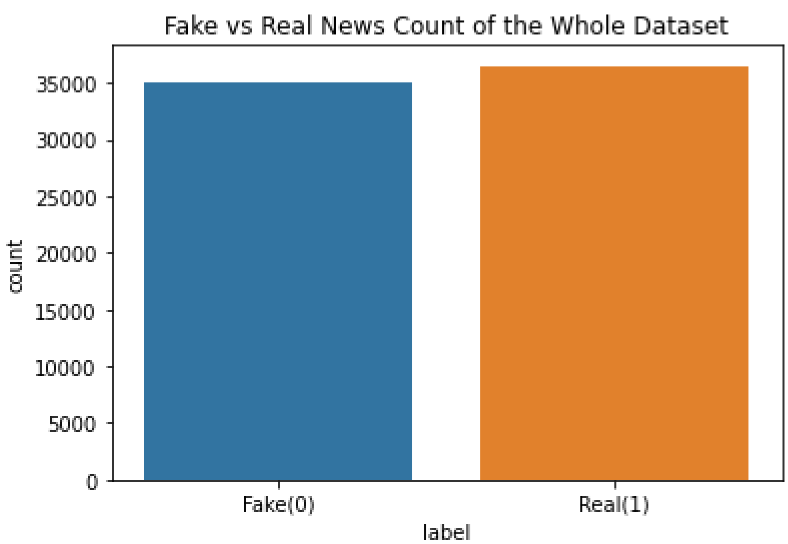
In [14]:
```
# Data Cleaning
cols = [x for x in raw_data.columns if x in ['title', 'text', 'label']]
clean_data = raw_data[cols]
clean_data.dropna(axis=0, inplace=True)
print(clean_data.shape)
clean_data.head()
```

```
(71537, 3)
```

Out[14]:

	title	text	label
0	LAW ENFORCEMENT ON HIGH ALERT Following Threat...	No comment is expected from Barack Obama Membe...	1
2	UNBELIEVABLE! OBAMA'S ATTORNEY GENERAL SAYS MO...	Now, most of the demonstrators gathered last ...	1
3	Bobby Jindal, raised Hindu, uses story of Chri...	A dozen politically active pastors came here f...	0
4	SATAN 2: Russia unvelis an image of its terrif...	The RS-28 Sarmat missile, dubbed Satan 2, will...	1
5	About Time! Christian Group Sues Amazon and SP...	All we can say on this one is it s about time ...	1

In [50]:
```
fulldata_countplot = CountPlot(clean_data['label'], 'Fake vs Real News Count of the Whol
```



In [16]:
```
# I want to initially work with a smaller subset of the data
subset_data_one = clean_data.sample(frac = 0.2)
print(subset_data_one.shape)
subset_data_one.head()
```

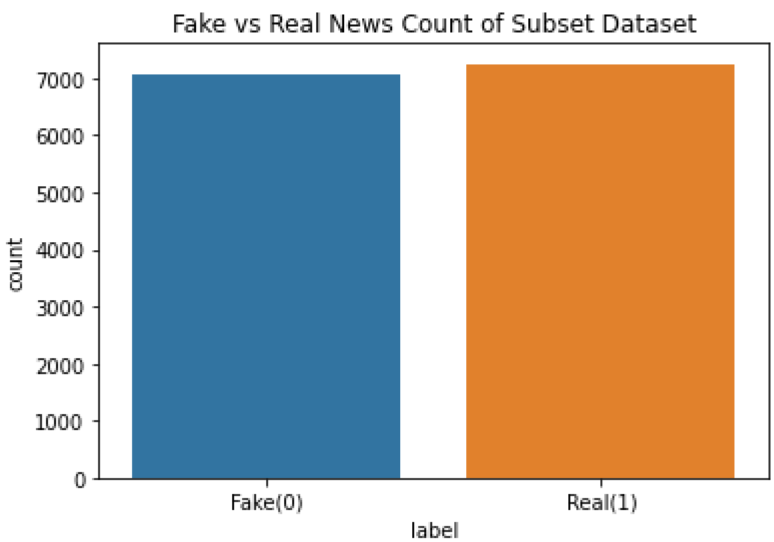
```
(14307, 3)
```

Out[16]:

	title	text	label
9277	Obama to Veto Bill Allowing 9/11 Lawsuits Agai...	WASHINGTON — The White House said on Monday...	0

54537	COLLEGE CAMPUS BANS Chalk, Fears Students Migh...	Remember when college campuses were considered...	1
35895	What Will Happen to Your Guns Under President ...	21st Century Wire says Legacy note to Obama s ...	1
40553	HILLARY'S CHICKENS ARE COMIN' HOME TO ROOST: N...	Hillary may have gotten away with lying to the...	1
27656	Ex-British spy paid $168,000 for Trump dossier...	WASHINGTON (Reuters) - A Washington research f...	0

In [51]:
```
subsetdata_countplot = CountPlot(subset_data_one['label'], 'Fake vs Real News Count of S
```



In [18]:
```
# Model 1
```

In [19]:
```
corpus_one = CorpusGen(subset_data_one['text'])
```

```
[nltk_data] Downloading package stopwords to C:\Users\Liam's
[nltk_data]     Computer\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to C:\Users\Liam's
[nltk_data]     Computer\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to C:\Users\Liam's
[nltk_data]     Computer\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package omw-1.4 to C:\Users\Liam's
[nltk_data]     Computer\AppData\Roaming\nltk_data...
[nltk_data]   Package omw-1.4 is already up-to-date!
```

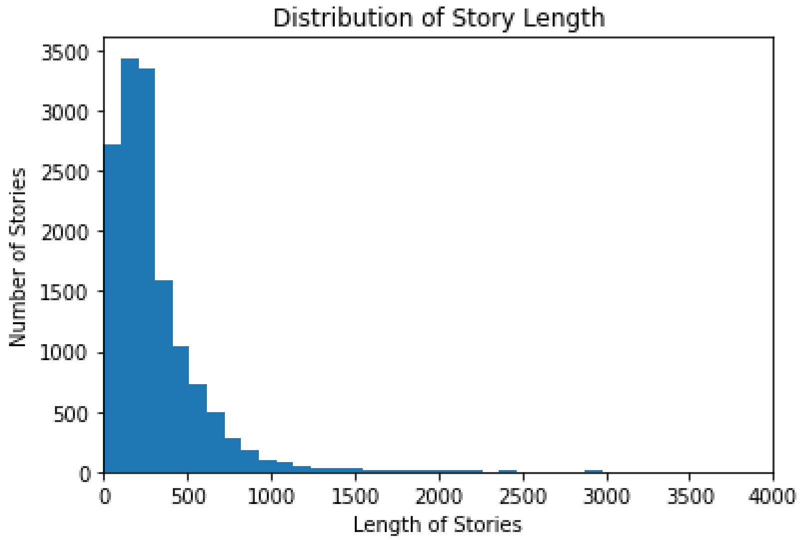
In [20]:
```
# Tokenize text

tokenizer = Tokenizer()
tokenizer.fit_on_texts(corpus_one)
word_index = tokenizer.word_index
vocab_size=len(word_index)
sequences = tokenizer.texts_to_sequences(corpus_one)
```

In [21]:
```
list = []
count = 0
for i in range(14307):
    length = len(sequences[i])
    list.append(length)
    if length <= 600:
        count += 1
```

```
plt.hist(list, bins=100)
plt.xlim(0,4000)
plt.xlabel('Length of Stories')
plt.ylabel('Number of Stories')
plt.title('Distribution of Story Length')
percent = count / len(sequences)
print('Percentage of Articles with length less than 600 words:  ' + str((count / len(seq
```

```
Percentage of Articles with length less than 600 words:  89.23603830292863
```



In [22]:

```
padded = pad_sequences(sequences, maxlen=600, padding='post', truncating='post')
X_train, X_test, y_train, y_test = train_test_split(padded,subset_data_one['label'], tes
```

In [23]:

```
embeddings_index = {};
with open('glove.6B\glove.6B.100d.txt', encoding="utf8") as f:
    for line in f:
        values = line.split();
        word = values[0];
        coefs = np.asarray(values[1:], dtype='float32');
        embeddings_index[word] = coefs;
print(len(coefs))

embeddings_matrix = np.zeros((vocab_size+1, 100));
for word, i in word_index.items():
    embedding_vector = embeddings_index.get(word);
    if embedding_vector is not None:
        embeddings_matrix[i] = embedding_vector;
```

```
100
```

In [45]:

```
rnn_hidden_dim = 10
model_rnn1 = Sequential()
model_rnn1.add(Embedding(vocab_size + 1, 100, weights=[embeddings_matrix], trainable=Fal
model_rnn1.add(LSTM(rnn_hidden_dim, return_sequences=True))
model_rnn1.add(Dense(1, activation='sigmoid'))
```

In [46]:

```
rmsprop = keras.optimizers.RMSprop(lr = .01)

model_rnn1.compile(loss='binary_crossentropy', optimizer=rmsprop, metrics=['accuracy'])
```

In [47]:

```
model_rnn1.fit(X_train, y_train,
          batch_size=64,
          epochs=5,
          validation_data=(X_test, y_test))
```

```
Epoch 1/5
179/179 [==============================] - 22s 115ms/step - loss: 0.5088 - accuracy: 0.7
494 - val_loss: 0.4860 - val_accuracy: 0.7434
```

```
Epoch 2/5
179/179 [==============================] - 20s 110ms/step - loss: 0.3592 - accuracy: 0.8
463 - val_loss: 0.3188 - val_accuracy: 0.8723
Epoch 3/5
179/179 [==============================] - 20s 112ms/step - loss: 0.3182 - accuracy: 0.8
702 - val_loss: 0.3323 - val_accuracy: 0.8758
Epoch 4/5
179/179 [==============================] - 20s 111ms/step - loss: 0.2708 - accuracy: 0.8
875 - val_loss: 0.2546 - val_accuracy: 0.8902
Epoch 5/5
179/179 [==============================] - 20s 112ms/step - loss: 0.2385 - accuracy: 0.9
008 - val_loss: 0.2447 - val_accuracy: 0.8920
```

Out[47]:

```
<keras.callbacks.History at 0x2b38aa10790>
```

In [28]:

```
# Model 2
```

In [43]:

```
rnn_hidden_dim = 20
model_rnn2 = Sequential()
model_rnn2.add(Embedding(vocab_size + 1, 100, weights=[embeddings_matrix], trainable=Fal
model_rnn2.add(Dropout(0.2))
model_rnn2.add(LSTM(rnn_hidden_dim, return_sequences=True))
model_rnn2.add(Dropout(0.2))
model_rnn2.add(Dense(256))
model_rnn2.add(Dense(1, activation='sigmoid'))
```

In [44]:

```
rmsprop = keras.optimizers.RMSprop(lr = .01)

model_rnn2.compile(loss='binary_crossentropy', optimizer=rmsprop, metrics=['accuracy'])
```

In [42]:

```
model_rnn2.fit(X_train, y_train,
          batch_size=64,
          epochs=10,
          validation_data=(X_test, y_test))
```

```
Epoch 1/10
179/179 [==============================] - 33s 177ms/step - loss: 0.5682 - accuracy: 0.7
261 - val_loss: 0.4205 - val_accuracy: 0.8475
Epoch 2/10
179/179 [==============================] - 31s 173ms/step - loss: 0.4077 - accuracy: 0.8
392 - val_loss: 0.3275 - val_accuracy: 0.8728
Epoch 3/10
179/179 [==============================] - 31s 174ms/step - loss: 0.3346 - accuracy: 0.8
680 - val_loss: 0.3217 - val_accuracy: 0.8817
Epoch 4/10
179/179 [==============================] - 31s 175ms/step - loss: 0.3097 - accuracy: 0.8
828 - val_loss: 0.4629 - val_accuracy: 0.8117
Epoch 5/10
179/179 [==============================] - 31s 174ms/step - loss: 0.2821 - accuracy: 0.8
925 - val_loss: 0.2562 - val_accuracy: 0.9065
Epoch 6/10
179/179 [==============================] - 31s 174ms/step - loss: 0.2407 - accuracy: 0.9
056 - val_loss: 0.2403 - val_accuracy: 0.9079
Epoch 7/10
179/179 [==============================] - 32s 180ms/step - loss: 0.2461 - accuracy: 0.9
063 - val_loss: 0.2323 - val_accuracy: 0.9134
Epoch 8/10
179/179 [==============================] - 33s 187ms/step - loss: 0.2285 - accuracy: 0.9
135 - val_loss: 0.2567 - val_accuracy: 0.8907
Epoch 9/10
179/179 [==============================] - 34s 189ms/step - loss: 0.2228 - accuracy: 0.9
147 - val_loss: 0.3041 - val_accuracy: 0.8698
Epoch 10/10
179/179 [==============================] - 34s 188ms/step - loss: 0.2099 - accuracy: 0.9
187 - val_loss: 0.2124 - val_accuracy: 0.9167
```

Out[42]: <keras.callbacks.History at 0x2b3907a9ea0>

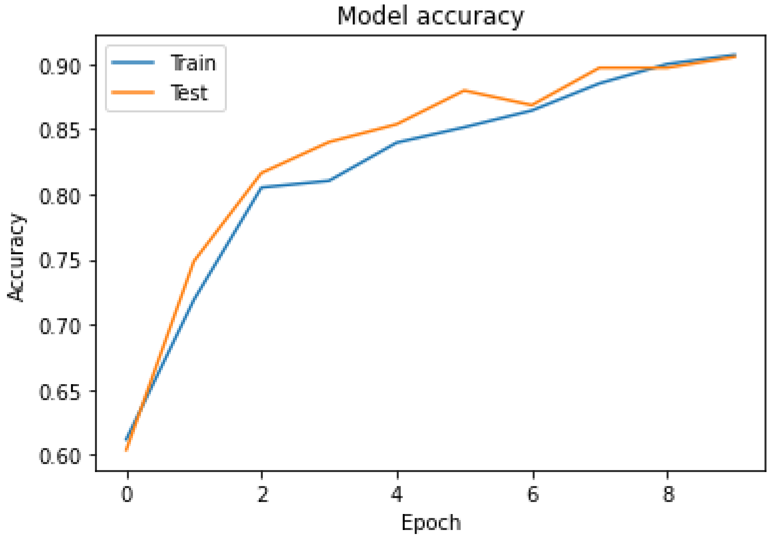
In [32]:
```
# Model 3
```

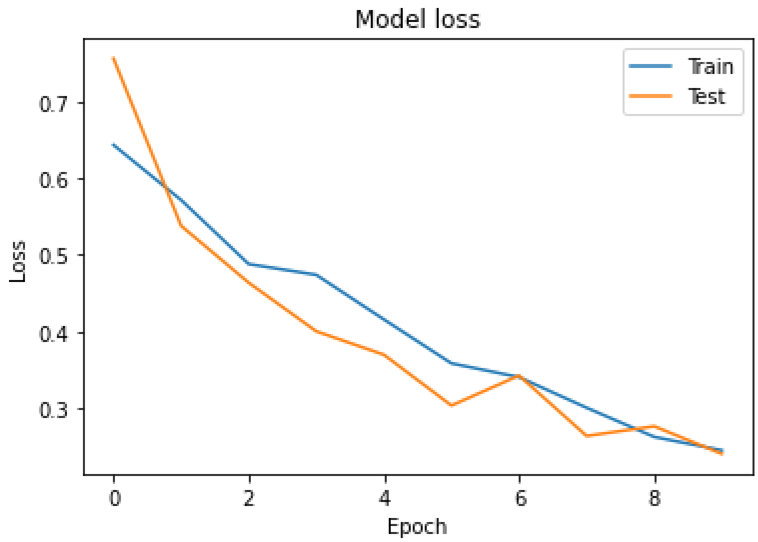
In [38]:
```
rnn_hidden_dim = 20
model_rnn3 = Sequential()
model_rnn3.add(Embedding(vocab_size+1, 100, weights=[embeddings_matrix], trainable=False
model_rnn3.add(Dropout(0.2))
model_rnn3.add(Conv1D(64, 5, activation='relu'))
model_rnn3.add(MaxPooling1D(pool_size=4))
model_rnn3.add(LSTM(20, return_sequences=True))
model_rnn3.add(LSTM(20))
model_rnn3.add(Dropout(0.2))
model_rnn3.add(Dense(512))
model_rnn3.add(Dropout(0.3))
model_rnn3.add(Dense(256))
model_rnn3.add(Dense(1, activation='sigmoid'))
```

In [39]:
```
model_rnn3.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])

history = model_rnn3.fit(X_train, y_train,
                    epochs=10,
                    batch_size=100,
                    validation_data=(X_test, y_test))
plot(history)
```

```
Epoch 1/10
115/115 [==============================] - 22s 169ms/step - loss: 0.6437 - accuracy: 0.6
119 - val_loss: 0.7567 - val_accuracy: 0.6038
Epoch 2/10
115/115 [==============================] - 20s 178ms/step - loss: 0.5717 - accuracy: 0.7
188 - val_loss: 0.5380 - val_accuracy: 0.7484
Epoch 3/10
115/115 [==============================] - 23s 198ms/step - loss: 0.4880 - accuracy: 0.8
051 - val_loss: 0.4636 - val_accuracy: 0.8162
Epoch 4/10
115/115 [==============================] - 24s 212ms/step - loss: 0.4739 - accuracy: 0.8
102 - val_loss: 0.4001 - val_accuracy: 0.8400
Epoch 5/10
115/115 [==============================] - 24s 207ms/step - loss: 0.4156 - accuracy: 0.8
395 - val_loss: 0.3694 - val_accuracy: 0.8536
Epoch 6/10
115/115 [==============================] - 23s 205ms/step - loss: 0.3581 - accuracy: 0.8
513 - val_loss: 0.3030 - val_accuracy: 0.8795
Epoch 7/10
115/115 [==============================] - 24s 209ms/step - loss: 0.3401 - accuracy: 0.8
641 - val_loss: 0.3422 - val_accuracy: 0.8683
Epoch 8/10
115/115 [==============================] - 24s 209ms/step - loss: 0.3001 - accuracy: 0.8
849 - val_loss: 0.2632 - val_accuracy: 0.8969
Epoch 9/10
115/115 [==============================] - 24s 212ms/step - loss: 0.2620 - accuracy: 0.8
998 - val_loss: 0.2759 - val_accuracy: 0.8969
Epoch 10/10
115/115 [==============================] - 25s 214ms/step - loss: 0.2445 - accuracy: 0.9
068 - val_loss: 0.2399 - val_accuracy: 0.9053
```


Model accuracy
Train
Test
Accuracy
Epoch


Model loss
Train
Test
Loss
Epoch

In [ ]: