Importing Libraries

In [1]:
```
import pandas as pd
import sklearn
import matplotlib.pyplot as plt
import numpy as np
import os
```

In [2]:
```
import tensorflow as tf
# from tf import keras

import keras
import visualkeras
from keras import Sequential
from keras.layers import Dropout , Dense, Flatten, Conv2D, MaxPool2D, BatchNo


from tensorflow.keras.optimizers import RMSprop, Adam, SGD, Adadelta
from tensorflow.python.keras.preprocessing.text import Tokenizer
from tensorflow.python.keras.preprocessing.sequence import pad_sequences
```

In [3]:
```
import nltk
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer, PorterStemmer

import string
from string import digits
import itertools
import collections
```

In [4]:
```
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\mphib\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Out[4]: True

In [5]:
```
nltk.download('punkt')
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\mphib\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

Out[5]: True

In [6]:
```
1 nltk.download('wordnet')
```

```
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\mphib\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Out[6]:
```
True
```

Importing Dataset

In [7]:
```
1 train = pd.read_csv("train.csv")
2 test = pd.read_csv("test.csv")
```

About the Data

Twitter has become a perfect platform for the global population to report any accident or disaster. However, there are also a large number of tweets that are simply bot generated or for advertisment purposes. Therefore, to differentiate between the actual and hoax, it has become impertive for the various disaster response agencies to monitor the feed while cleaning out the incorrect tweets from the actual ones to generate the subsequent response. The following dataset has been taken from kaggle to correctly identify the two type of tweets.

The dataset consists of train and test data. The former has **7613 observations on 5 features** and the latter has **3263 observations on 4 features**. The features include are 'id', 'keyword' , 'location', 'text' and 'target'. The tweets have been manually marked as **'1' meaning actual disaster** and **'0' indicating not a real disaster**.

Data Preprocessing

In [8]:
```
1 train.dtypes
```

Out[8]:
```
id           int64
keyword     object
location    object
text        object
target       int64
dtype: object
```

In [9]:
```
1 train.info
```

Out[9]:
```
<bound method DataFrame.info of          id keyword location  \
0         1     NaN      NaN
1         4     NaN      NaN
2         5     NaN      NaN
3         6     NaN      NaN
4         7     NaN      NaN
...     ...     ...      ...
7608  10869     NaN      NaN
7609  10870     NaN      NaN
7610  10871     NaN      NaN
7611  10872     NaN      NaN
7612  10873     NaN      NaN

                                                  text  target
0     Our Deeds are the Reason of this #earthquake M...       1
1                Forest fire near La Ronge Sask. Canada       1
2     All residents asked to 'shelter in place' are ...       1
3     13,000 people receive #wildfires evacuation or...       1
4     Just got sent this photo from Ruby #Alaska as ...       1
...                                                 ...     ...
7608  Two giant cranes holding a bridge collapse int...       1
7609  @aria_ahrary @TheTawniest The out of control w...       1
7610  M1.94 [01:04 UTC]?5km S of Volcano Hawaii. htt...       1
7611  Police investigating after an e-bike collided ...       1
7612  The Latest: More Homes Razed by Northern Calif...       1

[7613 rows x 5 columns]>
```

In [10]:
```
1 test.info
```

Out[10]:
```
<bound method DataFrame.info of          id keyword location  \
0         0     NaN      NaN
1         2     NaN      NaN
2         3     NaN      NaN
3         9     NaN      NaN
4        11     NaN      NaN
...     ...     ...      ...
3258  10861     NaN      NaN
3259  10865     NaN      NaN
3260  10868     NaN      NaN
3261  10874     NaN      NaN
3262  10875     NaN      NaN

                                                  text
0                    Just happened a terrible car crash
1     Heard about #earthquake is different cities, s...
2     there is a forest fire at spot pond, geese are...
3              Apocalypse lighting. #Spokane #wildfires
4         Typhoon Soudelor kills 28 in China and Taiwan
...                                                 ...
3258  EARTHQUAKE SAFETY LOS ANGELES  ÛÒ SAFETY FASTE...
3259  Storm in RI worse than last hurricane. My city...
3260  Green Line derailment in Chicago http://t.co/U... (http://t.co/U...)
3261  MEG issues Hazardous Weather Outlook (HWO) htt...
3262  #CityofCalgary has activated its Municipal Eme...

[3263 rows x 4 columns]>
```

Removing redundant columns

In [11]:
```
1 train = train.drop(['id','keyword','location'], axis = 1)
```

In [12]:
```
1 train.head()
```

Out[12]:

	text	target
0	Our Deeds are the Reason of this #earthquake M...	1
1	Forest fire near La Ronge Sask. Canada	1
2	All residents asked to 'shelter in place' are ...	1
3	13,000 people receive #wildfires evacuation or...	1
4	Just got sent this photo from Ruby #Alaska as ...	1

Cleaning the text

In [13]:
```
stop = set(nltk.corpus.stopwords.words('english'))
stop_words = stop.union({"http"}) ###IMPORTANT#################################


def cleaning(x):

    # converting to words
    tokens = word_tokenize(x)

    # convert to lower case
    words = [w.lower() for w in tokens]

    # removing alphanumerics
    words = [word for word in words if word.isalpha()]

    # removing punctuations
    table = str.maketrans('', '', string.punctuation)
    stripped = [w.translate(table) for w in words]

    # removing stopwords after modification
    words_mod = [w for w in stripped if not w in stop_words]

    # word lemmatization
    lemmatizer = WordNetLemmatizer()
    sentence = " ".join([lemmatizer.lemmatize(w) for w in words_mod])

    sen = " ".join(sentence.split())

    return (sen)
```

In [14]:
```
train_text = train.text.apply(lambda x: cleaning(x))
test_text = test.text.apply(lambda x: cleaning(x))

```

Summary Analysis

Since the objective of the project is to predict the tweets as real disaster or not based on the content, hence, we did not need to retain the additional columns and removed the columns named **'id' , 'location' and 'keyword' altogether**.

The second step involved the cleaning of the given data. For this, the following steps were performed:

1. Word Tokenization
2. Word Case to Lower
3. Removal of Punctuation
4. Removal of Alphanumerics
5. Removal of stopwords
6. Word Lemmatization

These steps to streamline the data were performed on both the train and test data.

EDA

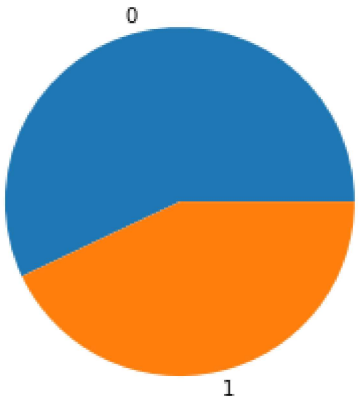
Checking Balancing

In [15]:
```
1 train.target.value_counts()
```

Out[15]:
```
0    4342
1    3271
Name: target, dtype: int64
```

In [16]:
```
1 plt.pie(train.target.value_counts(), labels = [0,1])
```

Out[16]:
```
([<matplotlib.patches.Wedge at 0x1da30bdfdf0>,
  <matplotlib.patches.Wedge at 0x1da31285370>],
 [Text(-0.24110481617711207, 1.0732513534192263, '0'),
  Text(0.24110481617711216, -1.0732513534192263, '1')])
```



Getting word frequencies of Classes

In [17]:
```
1 unreal = []
2 real  = []
3 for i in range(len(train.target)):
4     if train.target[i] == 1:
5         unreal.append(train_text[i])
6     else:
7         real.append(train_text[i])
```

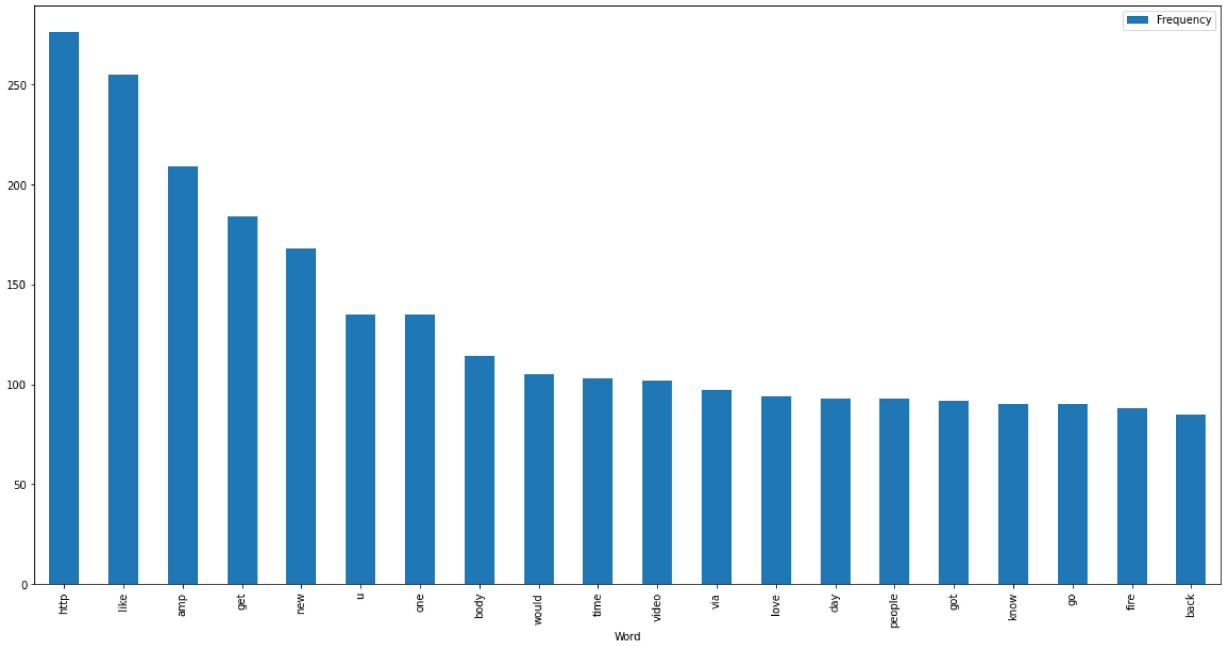
In [18]:
```
1  real_token = []
2  unreal_token = []
3
4  for i in range(len(real)):
5      real_token.append(real[i].split(" "))
6
7  for i in range(len(unreal)):
8      unreal_token.append(unreal[i].split(" "))
9
10 real_token_j = list(itertools.chain.from_iterable(real_token))
11 unreal_token_j = list(itertools.chain.from_iterable(unreal_token))
```

In [19]:
```
real_count = collections.Counter(real_token_j)
unreal_count = collections.Counter(unreal_token_j)
```

In [20]:
```
real_df = pd.DataFrame(real_count.most_common(20),columns=["Word", "Frequenc
unreal_df = pd.DataFrame(unreal_count.most_common(20),columns=["Word", "Freq

```

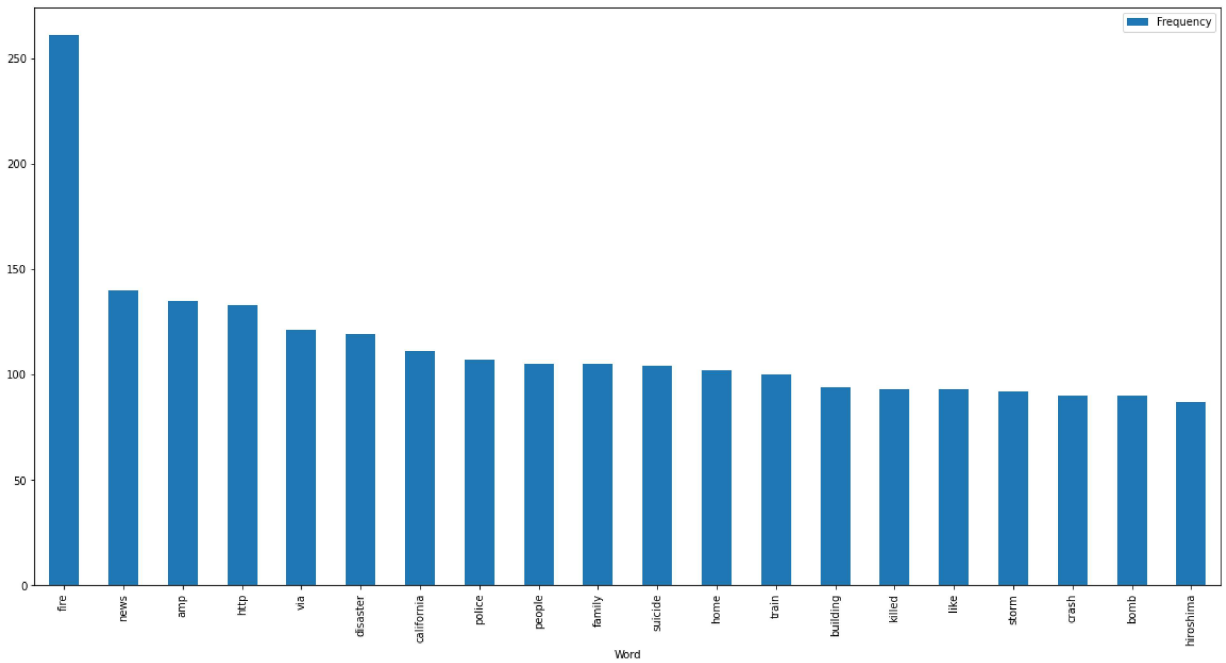
In [72]:
```
real_df.plot(x= "Word"  , y = "Frequency" ,kind = "bar", figsize=(20,10))
```

Out[72]: <AxesSubplot:xlabel='Word'>



In [73]:
```
unreal_df.plot(x= "Word"  , y = "Frequency" ,kind = "bar", figsize=(20,10))
```

Out[73]: <AxesSubplot:xlabel='Word'>



Analysis

The balancing of the data suggests that the amount of the fake tweets is less than then the actual ones. Since, the difference is not that much that it would skew the result much so we would leave it as it is.

The second part was to have a rough idea of the words that are occuring in the actual tweets to the fake ones. It reveals that the words http occurs the most in the hoax tweets followed words like, amp and get. The actual data seems to have words such fire, news and amp as the top most. It is however, pertinent to note here the words amp and http are occuring in both types albeit with different frequencies. Regardless, these words are bound to compromise the results in someway later on.

Model Training

In [23]:
```
## Tokening the cleaned tweets and converting them to a sequence for feeding
tokenizer = Tokenizer()
tokenizer.fit_on_texts(train_text.append(test_text))

train_seq = tokenizer.texts_to_sequences(train_text.values.reshape(len(train
test_seq = tokenizer.texts_to_sequences(test_text.values)
```

In [24]:
```
## Joining the two datasets to get the longest tweet for padding
joint_data = train_text.append(test_text)
joint_data = list(joint_data)
j_token = []
for i in range(len(joint_data)):
    j_token.append(joint_data[i].split(" "))

tok_j = list(itertools.chain.from_iterable(real_token))
```

In [25]:
```
len(joint_data)
```

Out[25]: 10876

In [26]:
```
len(tok_j)
```

Out[26]: 36058

In [27]:
```
max(len(x.split()) for x in joint_data)
```

Out[27]: 23

In [28]:
```
train_pad = pad_sequences(train_seq, maxlen=23, padding='post')
test_pad = pad_sequences(test_seq, maxlen=23, padding='post')
```

Model Architecture Design

The model architecture was designed to have 3 layers in total. We will be making and testing 3 models with the bidirectional which would enhance our model by giving it the ability to learn from both forward and backward way. We will change it **LSTM, GRU and a combination of LSTM & GRU**.

1. The initial layer with input length as 23 with padding, with LSTM(Long short term memory) gates on 100 hidden units. The drop out was set at 0.2 to reduce the probability of overfitting.
2. The second layer designed as dense with the activation set at relu.
3. The output layer was also taken as dense but with activation set to sigmoid now.

LSTM

In [29]:
```
embed_units = 100
hidden_units = 128
model1 = Sequential()


model1.add(Embedding(36059, embed_units, input_length = 23))
model1.add(Bidirectional(LSTM(hidden_units)))
model1.add(Dropout(0.2))


model1.add(Dense(256, activation='relu'))
model1.add(Dropout(0.2))
model1.add(Dense(1, activation='sigmoid'))

model1.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 23, 100)           3605900
_________________________________________________________________
bidirectional (Bidirectional (None, 256)               234496
_________________________________________________________________
dropout (Dropout)            (None, 256)               0
_________________________________________________________________
dense (Dense)                (None, 256)               65792
_________________________________________________________________
dropout_1 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 257
=================================================================
Total params: 3,906,445
Trainable params: 3,906,445
Non-trainable params: 0
_________________________________________________________________
```

In [30]:
```
learning_rate = 0.001
model1.compile(loss = 'binary_crossentropy',
               optimizer = 'adam',
               metrics = ['accuracy'])
```

In [31]:
```
model_hist1 = model1.fit((train_pad), (train.target),
                         epochs=5,
                         validation_split=0.2)
```

```
Epoch 1/5
191/191 [==============================] - 15s 57ms/step - loss: 0.5381 - accur
acy: 0.7259 - val_loss: 0.4690 - val_accuracy: 0.7879
Epoch 2/5
191/191 [==============================] - 10s 54ms/step - loss: 0.2976 - accur
acy: 0.8814 - val_loss: 0.4978 - val_accuracy: 0.7722
Epoch 3/5
191/191 [==============================] - 11s 58ms/step - loss: 0.1741 - accur
acy: 0.9356 - val_loss: 0.6098 - val_accuracy: 0.7275
Epoch 4/5
191/191 [==============================] - 10s 51ms/step - loss: 0.1141 - accur
acy: 0.9611 - val_loss: 0.7613 - val_accuracy: 0.7255
Epoch 5/5
191/191 [==============================] - 9s 49ms/step - loss: 0.0777 - accura
cy: 0.9714 - val_loss: 1.0191 - val_accuracy: 0.7295
```

GRU

In [32]:

```
embed_units = 100
hidden_units = 128

model2 = Sequential()


model2.add(Embedding(36059, embed_units, input_length = 23))
model2.add(Bidirectional(GRU(hidden_units)))
model2.add(Dropout(0.2))

model2.add(Dense(256, activation='relu'))
model2.add(Dropout(0.2))
model2.add(Dense(1, activation='sigmoid'))

model2.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 23, 100)           3605900
_________________________________________________________________
bidirectional_1 (Bidirection (None, 256)               176640
_________________________________________________________________
dropout_2 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_2 (Dense)              (None, 256)               65792
_________________________________________________________________
dropout_3 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 257
=================================================================
Total params: 3,848,589
Trainable params: 3,848,589
Non-trainable params: 0
_________________________________________________________________
```

In [33]:
```
learning_rate = 0.001
model2.compile(loss = 'binary_crossentropy',
               optimizer = 'adam',
               metrics = ['accuracy'])

model_hist_2 = model2.fit((train_pad), (train.target),
                          epochs=5,
                          validation_split=0.2)
```

```
Epoch 1/5
191/191 [==============================] - 15s 55ms/step - loss: 0.5288 - accur
acy: 0.7307 - val_loss: 0.4633 - val_accuracy: 0.7951
Epoch 2/5
191/191 [==============================] - 9s 48ms/step - loss: 0.2841 - accura
cy: 0.8852 - val_loss: 0.5103 - val_accuracy: 0.7623
Epoch 3/5
191/191 [==============================] - 9s 47ms/step - loss: 0.1627 - accura
cy: 0.9419 - val_loss: 0.5809 - val_accuracy: 0.7328
Epoch 4/5
191/191 [==============================] - 9s 49ms/step - loss: 0.1053 - accura
cy: 0.9634 - val_loss: 0.7373 - val_accuracy: 0.7104
Epoch 5/5
191/191 [==============================] - 10s 52ms/step - loss: 0.0830 - accur
acy: 0.9718 - val_loss: 0.7235 - val_accuracy: 0.7183
```

LSTM & GRU

In [36]:
```
embed_units = 100

model3 = Sequential()


model3.add(Embedding(36059, embed_units, input_length = 23))
model3.add(Bidirectional(GRU(256)))
model3.add(Dropout(0.2))

model3.add(Embedding(36059, embed_units))
model3.add(Bidirectional(LSTM(256)))
model3.add(Dropout(0.2))

model3.add(Dense(256, activation='relu'))
model3.add(Dropout(0.2))
model3.add(Dense(1, activation='sigmoid'))

model3.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_4 (Embedding)      (None, 23, 100)           3605900
_________________________________________________________________
bidirectional_4 (Bidirection (None, 512)               549888
_________________________________________________________________
dropout_7 (Dropout)          (None, 512)               0
_________________________________________________________________
embedding_5 (Embedding)      (None, 512, 100)          3605900
_________________________________________________________________
bidirectional_5 (Bidirection (None, 512)               731136
_________________________________________________________________
dropout_8 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_6 (Dense)              (None, 256)               131328
_________________________________________________________________
dropout_9 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_7 (Dense)              (None, 1)                 257
=================================================================
Total params: 8,624,409
Trainable params: 8,624,409
Non-trainable params: 0
_________________________________________________________________
```

In [38]:
```
learning_rate = 0.001
model3.compile(loss = 'binary_crossentropy',
               optimizer = 'adam',
               metrics = ['accuracy'])

model3.fit((train_pad), (train.target),
                           epochs=5,
                           validation_split=0.2)
```

```
Epoch 1/5
WARNING:tensorflow:Gradients do not exist for variables ['embedding_4/embedding
s:0', 'bidirectional_4/forward_gru_2/gru_cell_7/kernel:0', 'bidirectional_4/for
ward_gru_2/gru_cell_7/recurrent_kernel:0', 'bidirectional_4/forward_gru_2/gru_c
ell_7/bias:0', 'bidirectional_4/backward_gru_2/gru_cell_8/kernel:0', 'bidirecti
onal_4/backward_gru_2/gru_cell_8/recurrent_kernel:0', 'bidirectional_4/backward
_gru_2/gru_cell_8/bias:0'] when minimizing the loss.
WARNING:tensorflow:Gradients do not exist for variables ['embedding_4/embedding
s:0', 'bidirectional_4/forward_gru_2/gru_cell_7/kernel:0', 'bidirectional_4/for
ward_gru_2/gru_cell_7/recurrent_kernel:0', 'bidirectional_4/forward_gru_2/gru_c
ell_7/bias:0', 'bidirectional_4/backward_gru_2/gru_cell_8/kernel:0', 'bidirecti
onal_4/backward_gru_2/gru_cell_8/recurrent_kernel:0', 'bidirectional_4/backward
_gru_2/gru_cell_8/bias:0'] when minimizing the loss.
191/191 [==============================] - 277s 1s/step - loss: 0.6829 - accura
cy: 0.5788 - val_loss: 0.6936 - val_accuracy: 0.5345
Epoch 2/5
191/191 [==============================] - 247s 1s/step - loss: 0.6822 - accura
cy: 0.5793 - val_loss: 0.6934 - val_accuracy: 0.5345
Epoch 3/5
191/191 [==============================] - 267s 1s/step - loss: 0.6818 - accura
cy: 0.5793 - val_loss: 0.6922 - val_accuracy: 0.5345
Epoch 4/5
191/191 [==============================] - 318s 2s/step - loss: 0.6816 - accura
cy: 0.5793 - val_loss: 0.6934 - val_accuracy: 0.5345
Epoch 5/5
191/191 [==============================] - 373s 2s/step - loss: 0.6816 - accura
cy: 0.5793 - val_loss: 0.6933 - val_accuracy: 0.5345
```

Out[38]:
```
<keras.callbacks.History at 0x1da57fc9880>
```

Results

From the above results, we can broadly see that the LSTM is performing much better then the other two models. The difference against GRU is quite small with the GRU also generally faster and simpler then the LSTM. However, we will stick with the LSTM.

Optimizer Selection

After getting the general architecture, we will tweak the optimizers to get the best one. We will test 4 optimizers for the model that are:

1. Adam
2. RMSprop

3. Adagrad
4. Adadelta

Adam

In [39]:
```
embed_units = 100
hidden_units = 128

model2 = Sequential()


model2.add(Embedding(36059, embed_units, input_length = 23))
model2.add(Bidirectional(LSTM(hidden_units)))
model2.add(Dropout(0.2))

model2.add(Dense(256, activation='relu'))
model2.add(Dropout(0.2))
model2.add(Dense(1, activation='sigmoid'))

model2.summary()

learning_rate = 0.001
model2.compile(loss = 'binary_crossentropy',
               optimizer = 'adam',
               metrics = ['accuracy'])
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_6 (Embedding)      (None, 23, 100)           3605900
_________________________________________________________________
bidirectional_6 (Bidirection (None, 256)               234496
_________________________________________________________________
dropout_10 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_8 (Dense)              (None, 256)               65792
_________________________________________________________________
dropout_11 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_9 (Dense)              (None, 1)                 257
=================================================================
Total params: 3,906,445
Trainable params: 3,906,445
Non-trainable params: 0
_________________________________________________________________
```

In [40]:
```
model2.fit((train_pad), (train.target.values),
                           epochs=5,
                           validation_split=0.2)
```

```
Epoch 1/5
191/191 [==============================] - 12s 42ms/step - loss: 0.5341 - accur
acy: 0.7278 - val_loss: 0.4773 - val_accuracy: 0.7846
Epoch 2/5
191/191 [==============================] - 8s 41ms/step - loss: 0.2853 - accura
cy: 0.8854 - val_loss: 0.5011 - val_accuracy: 0.7840
Epoch 3/5
191/191 [==============================] - 7s 38ms/step - loss: 0.1696 - accura
cy: 0.9383 - val_loss: 0.5850 - val_accuracy: 0.7564
Epoch 4/5
191/191 [==============================] - 7s 38ms/step - loss: 0.1095 - accura
cy: 0.9621 - val_loss: 0.8344 - val_accuracy: 0.7538
Epoch 5/5
191/191 [==============================] - 7s 39ms/step - loss: 0.0756 - accura
cy: 0.9706 - val_loss: 0.8595 - val_accuracy: 0.7301
```

Out[40]: <keras.callbacks.History at 0x1da92a63850>

RMSprop

In [41]:
```
embed_units = 100
hidden_units = 128

model2 = Sequential()


model2.add(Embedding(36059, embed_units, input_length = 23))
model2.add(Bidirectional(LSTM(hidden_units)))
model2.add(Dropout(0.2))

model2.add(Dense(256, activation='relu'))
model2.add(Dropout(0.2))
model2.add(Dense(1, activation='sigmoid'))

learning_rate = 0.001
model2.compile(loss = 'binary_crossentropy',
               optimizer = 'RMSprop',
               metrics = ['accuracy'])
```

In [42]:
```
model2.fit((train_pad), (train.target.values),
                           epochs=5,
                           validation_split=0.2)
```

```
Epoch 1/5
191/191 [==============================] - 8s 29ms/step - loss: 0.5332 - accura
cy: 0.7343 - val_loss: 0.4712 - val_accuracy: 0.7827
Epoch 2/5
191/191 [==============================] - 5s 28ms/step - loss: 0.3624 - accura
cy: 0.8493 - val_loss: 0.4609 - val_accuracy: 0.7833
Epoch 3/5
191/191 [==============================] - 6s 29ms/step - loss: 0.3072 - accura
cy: 0.8805 - val_loss: 0.4875 - val_accuracy: 0.7820
Epoch 4/5
191/191 [==============================] - 6s 29ms/step - loss: 0.2526 - accura
cy: 0.9067 - val_loss: 0.4944 - val_accuracy: 0.7715
Epoch 5/5
191/191 [==============================] - 5s 28ms/step - loss: 0.2116 - accura
cy: 0.9251 - val_loss: 0.5760 - val_accuracy: 0.7571
```

Out[42]: <keras.callbacks.History at 0x1da98dfc9d0>

Adagrad

In [43]:
```
embed_units = 100
hidden_units = 128

model2 = Sequential()


model2.add(Embedding(36059, embed_units, input_length = 23))
model2.add(Bidirectional(LSTM(hidden_units)))
model2.add(Dropout(0.2))

model2.add(Dense(256, activation='relu'))
model2.add(Dropout(0.2))
model2.add(Dense(1, activation='sigmoid'))

learning_rate = 0.001
model2.compile(loss = 'binary_crossentropy',
               optimizer = 'Adagrad',
               metrics = ['accuracy'])
```

In [44]:
```
model2.fit((train_pad), (train.target.values),
                           epochs=5,
                           validation_split=0.2)
```

```
Epoch 1/5
191/191 [==============================] - 8s 25ms/step - loss: 0.6893 - accura
cy: 0.5775 - val_loss: 0.6910 - val_accuracy: 0.5345
Epoch 2/5
191/191 [==============================] - 4s 22ms/step - loss: 0.6854 - accura
cy: 0.5793 - val_loss: 0.6908 - val_accuracy: 0.5345
Epoch 3/5
191/191 [==============================] - 4s 23ms/step - loss: 0.6832 - accura
cy: 0.5793 - val_loss: 0.6912 - val_accuracy: 0.5345
Epoch 4/5
191/191 [==============================] - 4s 23ms/step - loss: 0.6823 - accura
cy: 0.5793 - val_loss: 0.6917 - val_accuracy: 0.5345
Epoch 5/5
191/191 [==============================] - 4s 22ms/step - loss: 0.6815 - accura
cy: 0.5793 - val_loss: 0.6922 - val_accuracy: 0.5345
```

Out[44]: <keras.callbacks.History at 0x1daa178fb50>

AdaDelta

In [45]:
```
embed_units = 100
hidden_units = 128

model2 = Sequential()


model2.add(Embedding(36059, embed_units, input_length = 23))
model2.add(Bidirectional(LSTM(hidden_units)))
model2.add(Dropout(0.2))

model2.add(Dense(256, activation='relu'))
model2.add(Dropout(0.2))
model2.add(Dense(1, activation='sigmoid'))

learning_rate = 0.001
model2.compile(loss = 'binary_crossentropy',
               optimizer = 'AdaDelta',
               metrics = ['accuracy'])
```

In [46]:
```
model2.fit((train_pad), (train.target.values),
                           epochs=5,
                           validation_split=0.2)
```

```
Epoch 1/5
191/191 [==============================] - 8s 26ms/step - loss: 0.6927 - accura
cy: 0.5299 - val_loss: 0.6930 - val_accuracy: 0.5279
Epoch 2/5
191/191 [==============================] - 4s 23ms/step - loss: 0.6925 - accura
cy: 0.5504 - val_loss: 0.6929 - val_accuracy: 0.5325
Epoch 3/5
191/191 [==============================] - 4s 22ms/step - loss: 0.6921 - accura
cy: 0.5673 - val_loss: 0.6928 - val_accuracy: 0.5345
Epoch 4/5
191/191 [==============================] - 5s 24ms/step - loss: 0.6918 - accura
cy: 0.5703 - val_loss: 0.6926 - val_accuracy: 0.5345
Epoch 5/5
191/191 [==============================] - 5s 25ms/step - loss: 0.6915 - accura
cy: 0.5765 - val_loss: 0.6925 - val_accuracy: 0.5345
```

Out[46]: <keras.callbacks.History at 0x1daa7360520>

Analysis

After our test, we can see that the RMSprop is the best choice amongst the 4. However, it is almsot at par with the Adam optimization. It was expected as these two are the most contemporary correcting the learning rates, bias and momentum rates from the 2 simpler optimizers as Adagrad and Adadelta.

Hyperparameter Tuning

Learning Rate

In [47]:
```
## Learning rate 0.005
embed_units = 100
hidden_units = 128

model2 = Sequential()


model2.add(Embedding(36059, embed_units, input_length = 23))
model2.add(Bidirectional(LSTM(hidden_units)))
model2.add(Dropout(0.2))

model2.add(Dense(256, activation='relu'))
model2.add(Dropout(0.2))
model2.add(Dense(1, activation='sigmoid'))

learning_rate = 0.005
model2.compile(loss = 'binary_crossentropy',
               optimizer = 'RMSprop',
               metrics = ['accuracy'])
```

In [48]:
```
model2.fit((train_pad), (train.target.values),
                          epochs=5,
                          validation_split=0.2)
```

```
Epoch 1/5
191/191 [==============================] - 8s 28ms/step - loss: 0.5319 - accura
cy: 0.7323 - val_loss: 0.4779 - val_accuracy: 0.7840
Epoch 2/5
191/191 [==============================] - 5s 25ms/step - loss: 0.3599 - accura
cy: 0.8499 - val_loss: 0.4709 - val_accuracy: 0.7925
Epoch 3/5
191/191 [==============================] - 5s 24ms/step - loss: 0.3018 - accura
cy: 0.8818 - val_loss: 0.4881 - val_accuracy: 0.7748
Epoch 4/5
191/191 [==============================] - 5s 25ms/step - loss: 0.2501 - accura
cy: 0.9071 - val_loss: 0.5208 - val_accuracy: 0.7577
Epoch 5/5
191/191 [==============================] - 5s 27ms/step - loss: 0.2025 - accura
cy: 0.9319 - val_loss: 0.6782 - val_accuracy: 0.6770
```

Out[48]: <keras.callbacks.History at 0x1daa6e6cee0>

In [ ]:
```

```

In [49]:
```
## Learning rate 0.008

embed_units = 100
hidden_units = 128

model2 = Sequential()


model2.add(Embedding(36059, embed_units, input_length = 23))
model2.add(Bidirectional(LSTM(hidden_units)))
model2.add(Dropout(0.2))

model2.add(Dense(256, activation='relu'))
model2.add(Dropout(0.2))
model2.add(Dense(1, activation='sigmoid'))

learning_rate = 0.008
model2.compile(loss = 'binary_crossentropy',
               optimizer = 'RMSprop',
               metrics = ['accuracy'])
```

In [50]:
```
model2.fit((train_pad), (train.target.values),
                          epochs=5,
                          validation_split=0.2)
```

```
Epoch 1/5
191/191 [==============================] - 9s 30ms/step - loss: 0.5261 - accura
cy: 0.7351 - val_loss: 0.4685 - val_accuracy: 0.7984
Epoch 2/5
191/191 [==============================] - 5s 28ms/step - loss: 0.3626 - accura
cy: 0.8525 - val_loss: 0.4746 - val_accuracy: 0.7912
Epoch 3/5
191/191 [==============================] - 5s 27ms/step - loss: 0.3036 - accura
cy: 0.8760 - val_loss: 0.4913 - val_accuracy: 0.7676
Epoch 4/5
191/191 [==============================] - 5s 27ms/step - loss: 0.2477 - accura
cy: 0.9077 - val_loss: 0.5156 - val_accuracy: 0.7623
Epoch 5/5
191/191 [==============================] - 5s 28ms/step - loss: 0.2035 - accura
cy: 0.9297 - val_loss: 0.5837 - val_accuracy: 0.7124
```

Out[50]: <keras.callbacks.History at 0x1dab6e0efd0>

In [ ]:
```

```

In [51]:
```
## Learning rate 0.003

embed_units = 100
hidden_units = 128

model2 = Sequential()


model2.add(Embedding(36059, embed_units, input_length = 23))
model2.add(Bidirectional(LSTM(hidden_units)))
model2.add(Dropout(0.2))

model2.add(Dense(256, activation='relu'))
model2.add(Dropout(0.2))
model2.add(Dense(1, activation='sigmoid'))

learning_rate = 0.003
model2.compile(loss = 'binary_crossentropy',
               optimizer = 'RMSprop',
               metrics = ['accuracy'])
```

In [52]:
```
model2.fit((train_pad), (train.target.values),
                          epochs=5,
                          validation_split=0.2)
```

```
Epoch 1/5
191/191 [==============================] - 10s 30ms/step - loss: 0.5353 - accur
acy: 0.7289 - val_loss: 0.4843 - val_accuracy: 0.7840
Epoch 2/5
191/191 [==============================] - 6s 30ms/step - loss: 0.3637 - accura
cy: 0.8470 - val_loss: 0.4784 - val_accuracy: 0.7873
Epoch 3/5
191/191 [==============================] - 5s 27ms/step - loss: 0.3099 - accura
cy: 0.8790 - val_loss: 0.4715 - val_accuracy: 0.7715
Epoch 4/5
191/191 [==============================] - 5s 27ms/step - loss: 0.2670 - accura
cy: 0.9010 - val_loss: 0.5403 - val_accuracy: 0.7505
Epoch 5/5
191/191 [==============================] - 5s 28ms/step - loss: 0.2180 - accura
cy: 0.9223 - val_loss: 0.5608 - val_accuracy: 0.7177
```

Out[52]:
```
<keras.callbacks.History at 0x1dabe9d9a00>
```

Analysis

The learning rates tweak gives us the best **learning rate as 0.005**.

Final Model

In [75]:
```
model_f = Sequential()


model_f.add(Embedding(36059, 100, input_length = 23))
model_f.add(Bidirectional(GRU(100)))
model_f.add(Dropout(0.2))

model_f.add(Dense(256, activation='relu'))
model_f.add(Dropout(0.2))
model_f.add(Dense(1, activation='sigmoid'))

learning_rate = 0.005
model_f.compile(loss = 'binary_crossentropy',
              optimizer = 'RMSprop',
              metrics = ['accuracy'])
```

In [76]:
```
model_f.fit((train_pad), (train.target.values),
                          epochs=5,
                          validation_split=0.2)
```

```
Epoch 1/5
191/191 [==============================] - 12s 39ms/step - loss: 0.5274 - accur
acy: 0.7346 - val_loss: 0.4897 - val_accuracy: 0.7827
Epoch 2/5
191/191 [==============================] - 6s 34ms/step - loss: 0.3616 - accura
cy: 0.8532 - val_loss: 0.4561 - val_accuracy: 0.7919
Epoch 3/5
191/191 [==============================] - 7s 36ms/step - loss: 0.3014 - accura
cy: 0.8833 - val_loss: 0.5253 - val_accuracy: 0.7347
Epoch 4/5
191/191 [==============================] - 8s 40ms/step - loss: 0.2478 - accura
cy: 0.9082 - val_loss: 0.5369 - val_accuracy: 0.7557
Epoch 5/5
191/191 [==============================] - 8s 42ms/step - loss: 0.2076 - accura
cy: 0.9269 - val_loss: 0.5767 - val_accuracy: 0.7085
```

Out[76]:
```
<keras.callbacks.History at 0x1dac72d4670>
```

Result & Analysis

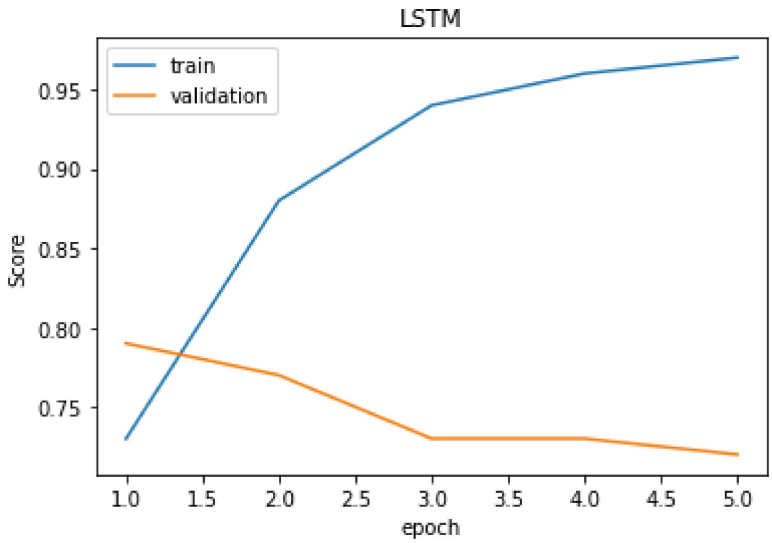
Model Architecture Comparison

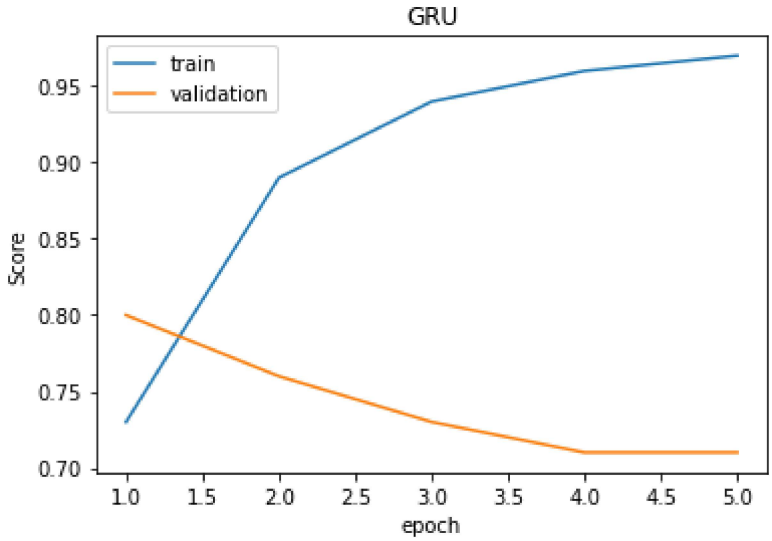
In [77]:

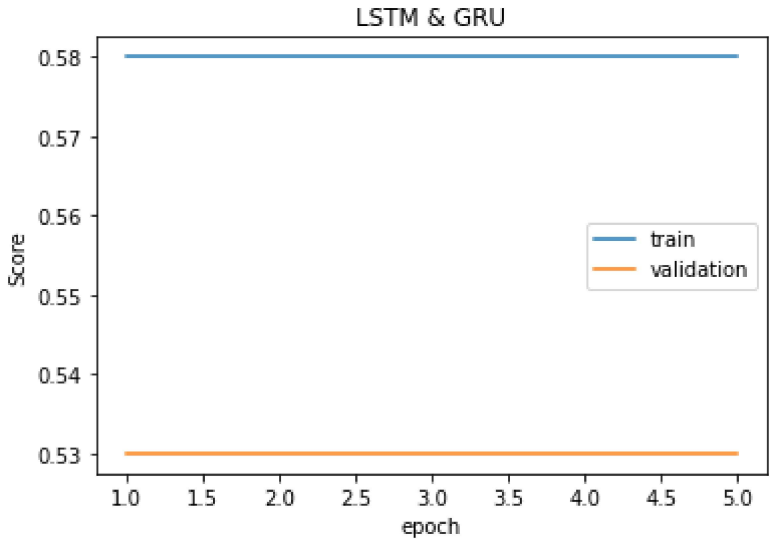
```
# LSTM
l_train_accuracy = [0.73,0.88,0.94,0.96,0.97]
l_val_accuracy = [0.79,0.77,0.73,0.73,0.72]
l_train_loss = [0.54,0.30,0.17,0.11,0.08]
l_val_loss = [0.47,0.50,0.61,0.76,1.0]

ep = [1,2,3,4,5]
dict1 = {'epoch': ep, 'tr_loss': l_train_loss, 'tr_score': l_train_accuracy,
         'val_loss': l_val_loss, 'val_score': l_val_accuracy}
df_lstm = pd.DataFrame(dict1)

# GRU
g_train_accuracy = [0.73,0.89,0.94,0.96,0.97]
g_val_accuracy = [0.80,0.76,0.73,0.71,0.71]
g_train_loss = [0.52,0.28,0.16,0.11,0.08]
g_val_loss = [0.46,0.51,0.58,0.74,0.72]

dict2 = {'epoch': ep, 'tr_loss': g_train_loss, 'tr_score': g_train_accuracy,
         'val_loss': g_val_loss, 'val_score': g_val_accuracy}
df_gru= pd.DataFrame(dict2)

# LSTM + GRU
j_train_accuracy = [0.58,0.58,0.58,0.58,0.58]
j_val_accuracy = [0.53,0.53,0.53,0.53,0.53]
j_train_loss = [0.68,0.68,0.68,0.68,0.68]
j_val_loss = [0.69,0.69,0.69,0.69,0.69]

dict3 = {'epoch': ep, 'tr_loss': j_train_loss, 'tr_score': j_train_accuracy,
         'val_loss': j_val_loss, 'val_score': j_val_accuracy}
df_joint = pd.DataFrame(dict3)
```

In [78]:

```
# LSTM
plt.plot(ep , l_train_accuracy)
plt.plot(ep , l_val_accuracy)
plt.title("LSTM")
plt.xlabel("epoch")
plt.ylabel("Score")
plt.legend(['train', 'validation'])
plt.show()

# GRU
plt.plot(ep , g_train_accuracy)
plt.plot(ep , g_val_accuracy)
plt.title("GRU")
plt.xlabel("epoch")
plt.ylabel("Score")
plt.legend(['train', 'validation'])
plt.show()

# LSTM + GRU
plt.plot(ep , j_train_accuracy)
plt.plot(ep , j_val_accuracy)
plt.title("LSTM & GRU")
plt.xlabel("epoch")
plt.ylabel("Score")
plt.legend(['train', 'validation'])
plt.show()
```







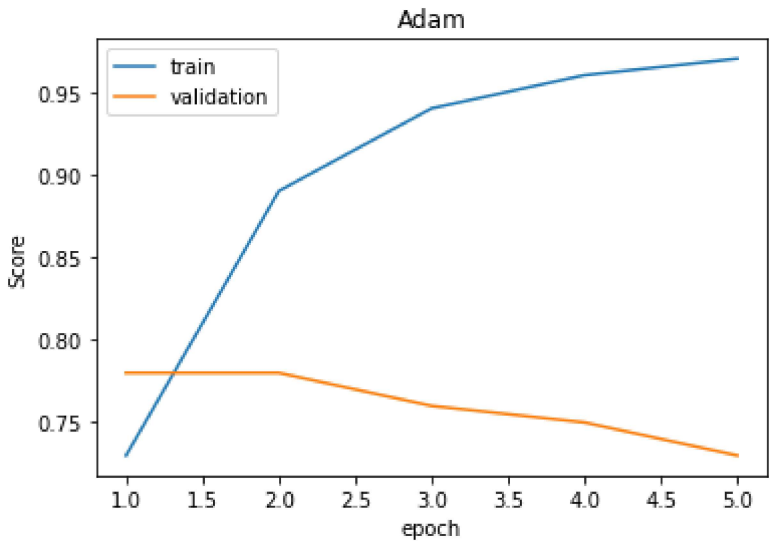
Optimizer Comparison

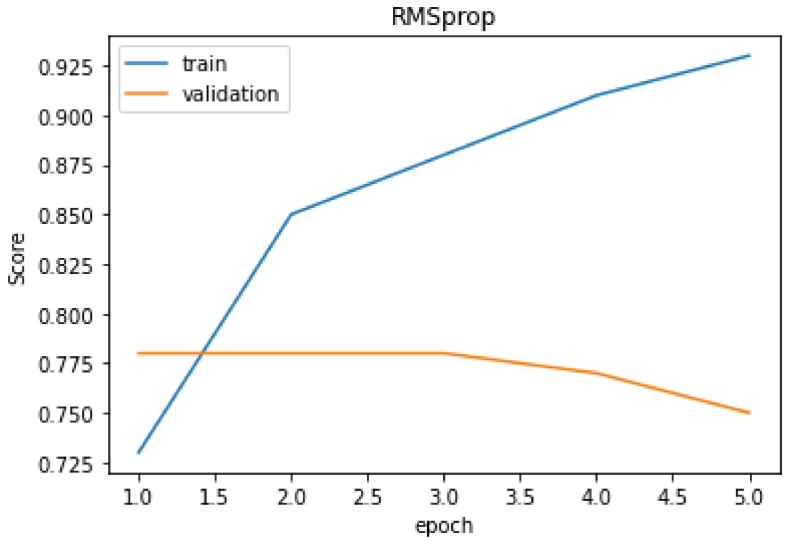
In [83]:

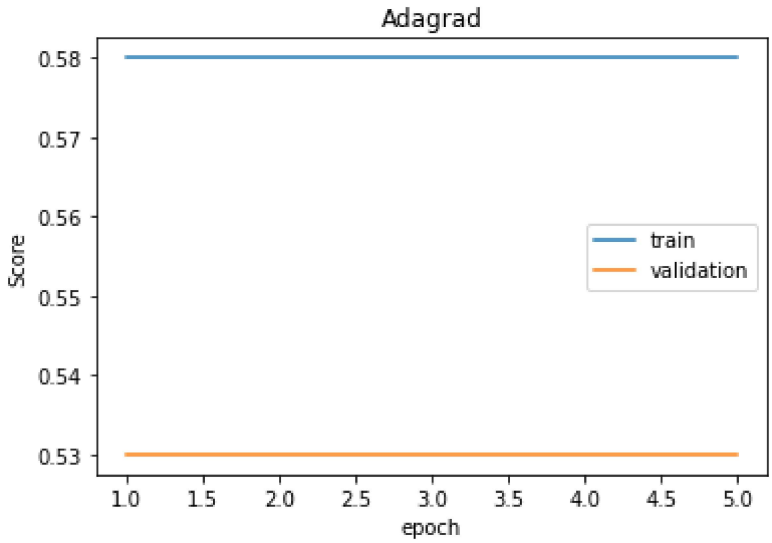
```
# Adam
a_train_accuracy = [0.73,0.89,0.94,0.96,0.97]
a_val_accuracy = [0.78,0.78,0.76,0.75,0.73]
a_train_loss = [0.53,0.29,0.17,0.11,0.08]
a_val_loss = [0.48,0.50,0.59,0.83,0.86]

dict1 = {'epoch': ep, 'tr_loss': a_train_loss, 'tr_score': a_train_accuracy,
         'val_loss': a_val_loss, 'val_score': a_val_accuracy}
df_adam= pd.DataFrame(dict1)

# RMSprop
rms_train_accuracy = [0.73,0.85,0.88,0.91,0.93]
rms_val_accuracy = [0.78,0.78,0.78,0.77,0.75]
rms_train_loss = [0.53,0.36,0.31,0.25,0.21]
rms_val_loss = [0.47,0.46,0.49,0.49,0.58]

dict2 = {'epoch': ep, 'tr_loss': rms_train_loss, 'tr_score': rms_train_accur
         'val_loss': rms_val_loss, 'val_score': rms_val_accuracy}
df_prop = pd.DataFrame(dict2)

# Adagrad
agrad_train_accuracy = [0.58,0.58,0.58,0.58,0.58]
agrad_val_accuracy = [0.53,0.53,0.53,0.53,0.53]
agrad_train_loss = [0.69,0.69,0.68,0.68,0.68]
agrad_val_loss = [0.69,0.69,0.69,0.69,0.69]

dict3 = {'epoch': ep, 'tr_loss': agrad_train_loss, 'tr_score': agrad_train_a
         'val_loss': agrad_val_loss, 'val_score': agrad_val_accuracy}
df_agrad = pd.DataFrame(dict3)

# Adadelta
ad_train_accuracy = [0.53,0.55,0.57,0.57,0.58]
ad_val_accuracy = [0.53,0.53,0.53,0.53,0.53]
ad_train_loss = [0.69,0.69,0.69,0.69,0.69]
ad_val_loss = [0.69,0.69,0.69,0.69,0.69]

dict4 = {'epoch': ep, 'tr_loss': ad_train_loss, 'tr_score': ad_train_accurac
         'val_loss': ad_val_loss, 'val_score': ad_val_accuracy}
df_ad = pd.DataFrame(dict4)
```

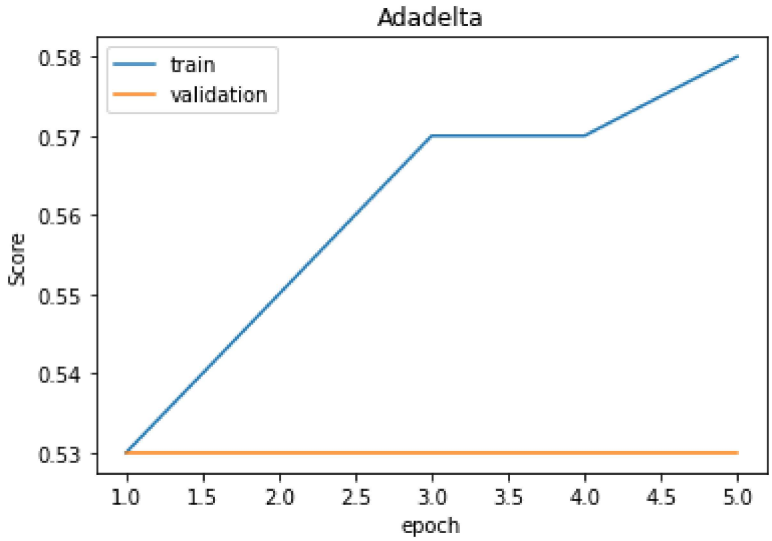
In [84]:

```
# Adam
plt.plot(ep , a_train_accuracy)
plt.plot(ep , a_val_accuracy)
plt.title("Adam")
plt.xlabel("epoch")
plt.ylabel("Score")
plt.legend(['train', 'validation'])
plt.show()

# RMSprop
plt.plot(ep , rms_train_accuracy)
plt.plot(ep , rms_val_accuracy)
plt.title("RMSprop")
plt.xlabel("epoch")
plt.ylabel("Score")
plt.legend(['train', 'validation'])
plt.show()

# Adagrad
plt.plot(ep , agrad_train_accuracy)
plt.plot(ep , agrad_val_accuracy)
plt.title("Adagrad")
plt.xlabel("epoch")
plt.ylabel("Score")
plt.legend(['train', 'validation'])
plt.show()

# Adadelta
plt.plot(ep , ad_train_accuracy)
plt.plot(ep , ad_val_accuracy)
plt.title("Adadelta")
plt.xlabel("epoch")
plt.ylabel("Score")
plt.legend(['train', 'validation'])
plt.show()
```




RMSprop
train
validation
Score
epoch
0.925
0.900
0.875
0.850
0.825
0.800
0.775
0.750
0.725
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0





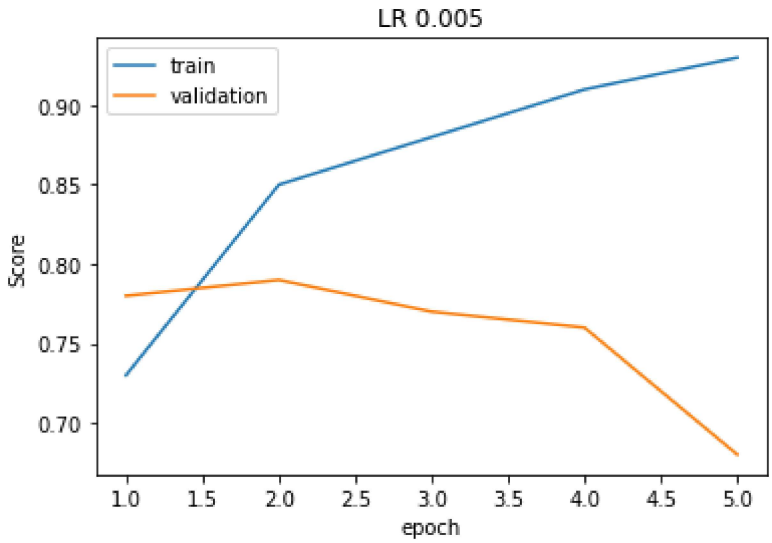
Learning Rate Comparison

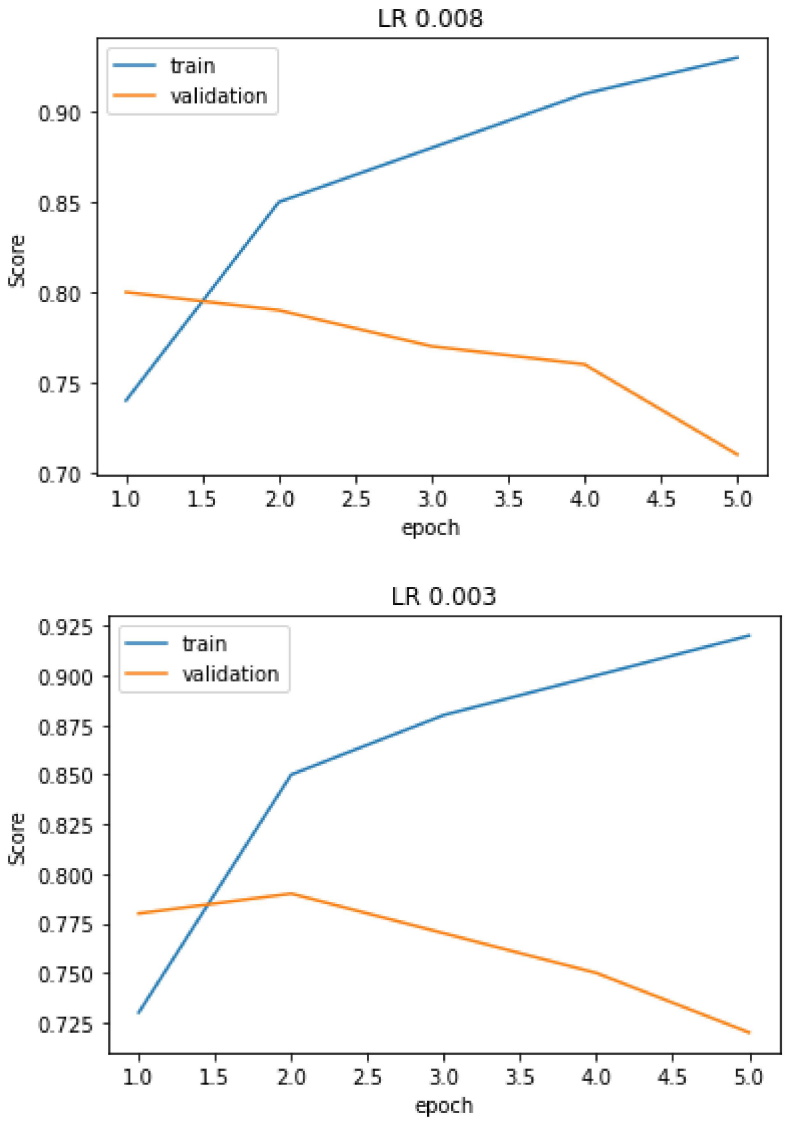
In [81]:

```
# lr 0.005
train_accuracy_5 = [0.73,0.85,0.88,0.91,0.93]
val_accuracy_5 = [0.78,0.79,0.77,0.76,0.68]
train_loss_5 = [0.53,0.36,0.30,0.25,0.2]
val_loss_5 = [0.48,0.47,0.49,0.52,0.67]

ep = [1,2,3,4,5]
dict1 = {'epoch': ep, 'tr_loss': train_loss_5, 'tr_score': train_accuracy_5,
         'val_loss': val_loss_5, 'val_score': val_accuracy_5}
df_5 = pd.DataFrame(dict1)

# lr 0.008
train_accuracy_8 = [0.74,0.85,0.88,0.91,0.93]
val_accuracy_8 = [0.8,0.79,0.77,0.76,0.71]
train_loss_8 = [0.53,0.36,0.3,0.25,0.2]
val_loss_8 = [0.47,0.47,0.49,0.52,0.58]

dict2 = {'epoch': ep, 'tr_loss': train_loss_8, 'tr_score': train_accuracy_8,
         'val_loss': val_loss_8, 'val_score': val_accuracy_8}
df_8 = pd.DataFrame(dict2)

# lr 0.003
train_accuracy_3 = [0.73,0.85,0.88,0.9,0.92]
val_accuracy_3 = [0.78,0.79,0.77,0.75,0.72]
train_loss_3 = [0.54,0.36,0.31,0.27,0.22]
val_loss_3 = [0.48,0.48,0.47,0.54,0.56]

dict3 = {'epoch': ep, 'tr_loss': train_loss_3, 'tr_score': train_accuracy_3,
         'val_loss': val_loss_3, 'val_score': val_accuracy_3}
df_3 = pd.DataFrame(dict3)
```

In [82]:

```
# Learning rate 0.005
plt.plot(ep , train_accuracy_5)
plt.plot(ep , val_accuracy_5)
plt.title("LR 0.005")
plt.xlabel("epoch")
plt.ylabel("Score")
plt.legend(['train', 'validation'])
plt.show()

# Learning rate 0.008
plt.plot(ep , train_accuracy_8)
plt.plot(ep , val_accuracy_8)
plt.title("LR 0.008")
plt.xlabel("epoch")
plt.ylabel("Score")
plt.legend(['train', 'validation'])
plt.show()

# Learning rate 0.003
plt.plot(ep , train_accuracy_3)
plt.plot(ep , val_accuracy_3)
plt.title("LR 0.003")
plt.xlabel("epoch")
plt.ylabel("Score")
plt.legend(['train', 'validation'])
plt.show()
```





Analysis

As the graph suggests that the LSTM and GRU are performing quite the same with a slight average better result shown by LSTM. The joint model between the two is somewhat straigt line between the accuracies of the train and validation. The reason for this is that GRU constitutes 2 gates while LSTM constitutes 3 gates so a combination between the two makes it an incorrect model to begin with. However, it was done to merely test the result with a combination of the two.

The optimizer graphs suggests that the Adam and RMSprop seems to be performing quite close to each other whereas the latter two seem to be quite bad. The reason for this is the ability for the Adam and RMSprop to tackle for more variables such as momentum, bias etc. We selected the RMSprop as the optimizer for our final model since it was giving us the best average result as compared to Adam optimizer.

The variation in the learning rates seems to suggest the 0.005 learning is sufficient enough to catter for the model most effectively.

The structure for our final model after summing up the above results comes out to be as follows:

1. Initial layer with embedding, input set at 23(longest tweet) and 100 hidden units with bidirectional using LSTM and drop out rate set at 0.2.
2. The second layer was taken as Dense layer with activation Relu.
3. The output layer was also taken as Dense but with the activation set to Sigmoid.

Kaggle Submission

In [88]:
```
pred = model_f.predict(test_pad)
temp = pd.read_csv("sample_submission.csv")
temp["target"] = pred
temp["target"] = temp["target"].apply(lambda x : 0 if x<=.5 else 1)
sub.to_csv("final_submit_kaggle.csv", index=False)
```

Conclusion

The RNN is quite an effective technique in text classification with the simple model we designed doing substantially well. The most important takeaway from the project is that the selection of the right parameters and hyperparamters can vary the output quite a lot. It can be understood from the example the selection of the optimizer where some optimizers produced quite poor results. Another important takeaway was the need to convert the data to sequencing with the padding to be able to add it into the the model. The bidirectional gates was also a major understanding in the sense to use GRU was simpler and smaller dataset and LSTM for larger and complex data since it allows more tweaking. The model may be further improved even by testing complex architectures with additional layers or tweaking the current ones even.

In [ ]:
```

```