Disaster Tweets

Description

This is notebook to build RNN for disaster tweet classification. The intention is use this RNN to classify tweet (text) if it's a about a real disaster or not. Our aim is get classification model with the most accuracy possible.

source : https://www.kaggle.com/competitions/nlp-getting-started/data

data type : CSV (5 columns)

data size : 7613 rows (988 KB)

Describe for each column

- id : a unique identifier for each tweet
- text : the text of the tweet
- location : the location the tweet was sent from (may be blank)
- keyword : a particular keyword from the tweet (may be blank)
- target : this denotes whether a tweet is about a real disaster (1) or not (0)

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from collections import Counter
from sklearn.model_selection import train_test_split
from tensorflow.keras import layers
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.models import Sequential
```

In [2]:
```
data = pd.read_csv('./nlp-getting-started/train.csv')
test_data = pd.read_csv('./nlp-getting-started/test.csv')
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7613 entries, 0 to 7612
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   id        7613 non-null   int64 
 1   keyword   7552 non-null   object
 2   location  5080 non-null   object
 3   text      7613 non-null   object
 4   target    7613 non-null   int64 
dtypes: int64(2), object(3)
memory usage: 297.5+ KB
```

In [3]:
```
data.head()
```

Out[3]:

	id	keyword	location	text	target
0	1	NaN	NaN	Our Deeds are the Reason of this #earthquake M...	1
1	4	NaN	NaN	Forest fire near La Ronge Sask. Canada	1
2	5	NaN	NaN	All residents asked to 'shelter in place' are ...	1
3	6	NaN	NaN	13,000 people receive #wildfires evacuation or...	1
4	7	NaN	NaN	Just got sent this photo from Ruby #Alaska as ...	1

In [4]:
```
data.describe()
```

Out[4]:

	id	target
count	7613.000000	7613.00000
mean	5441.934848	0.42966
std	3137.116090	0.49506
min	1.000000	0.00000
25%	2734.000000	0.00000
50%	5408.000000	0.00000
75%	8146.000000	1.00000
max	10873.000000	1.00000

In [5]:
```
data.isna().sum()
```

Out[5]:
```
id             0
keyword       61
location    2533
text           0
target         0
dtype: int64
```

In [6]:
```
test_data.isna().sum()
```

Out[6]:
```
id             0
keyword       26
location    1105
text           0
dtype: int64
```

Since test data have empty keyword and location. So, I will use only text data to train the model.

In [7]:
```
print(data['text'].nunique())
```

```
7503
```

We have duplicated data. Let's see if same text have the same target or class or not.

In [8]:
```
groupped = data.groupby('text')
c = 1
for k,v in groupped:
```

```
    if v.shape[0]>1:
        if v['target'].nunique() > 1:
          print(c, ' target nunique = ', v['target'].nunique(), ' id nuni
        c=c+1
```

```
1  target nunique =  2  id nunique =  3
8  target nunique =  2  id nunique =  3
12  target nunique =  2  id nunique =  4
25  target nunique =  2  id nunique =  3
26  target nunique =  2  id nunique =  2
33  target nunique =  2  id nunique =  6
34  target nunique =  2  id nunique =  3
36  target nunique =  2  id nunique =  2
38  target nunique =  2  id nunique =  2
40  target nunique =  2  id nunique =  2
45  target nunique =  2  id nunique =  2
49  target nunique =  2  id nunique =  2
53  target nunique =  2  id nunique =  6
54  target nunique =  2  id nunique =  4
61  target nunique =  2  id nunique =  3
66  target nunique =  2  id nunique =  2
68  target nunique =  2  id nunique =  4
69  target nunique =  2  id nunique =  2
```

There are 69 set of duplication and some of them have 2 classes (target). We must clean up this mess.

Clean Up

I will remove all data in duplication in set with 2 classes and for duplication set with 1 class I will keep only one row from each set and remove the rest.

In [9]:

```
toDel = []
for k,v in groupped:
    if v.shape[0]>1:
      if v['target'].nunique() > 1:
        toDel.extend(v['id'])
      else:
        toDel.extend(v['id'][1:])
data = data[~data['id'].isin(toDel)]
print('deleted ', len(toDel), 'rows')
```

```
deleted  128 rows
```

In [10]:

```
print('cleaned data = ', data.shape[0], ' rows')
```

```
cleaned data =  7485  rows
```

In [11]:

```
labels, labels_count = np.unique(data['target'], return_counts=True)
print(labels)
print(labels_count)
```

```
[0 1]
[4297 3188]
```

We have 4,297 negative data and 3,188 positive data.

In [12]:

```
tokenizer = Tokenizer()
tokenizer.fit_on_texts(data.text)
```

```
word_index = tokenizer.word_index
```

In [13]:
```
len(word_index)
```

Out[13]:
```
22675
```

We have 22,675 unique words.

In [14]:
```
# map word to index
data_seq = tokenizer.texts_to_sequences(data.text)
```

In [15]:
```
# count word for each text to df
words = list(word_index.keys())
wc = tokenizer.texts_to_matrix(data.text, mode='count')
wcdf = pd.DataFrame(wc, columns=['<oov>'] + words)
```

In [16]:
```
wcdf.sum().describe()
```

Out[16]:
```
count    22676.000000
mean         5.551111
std         66.981731
min          0.000000
25%          1.000000
50%          1.000000
75%          2.000000
max       4709.000000
dtype: float64
```

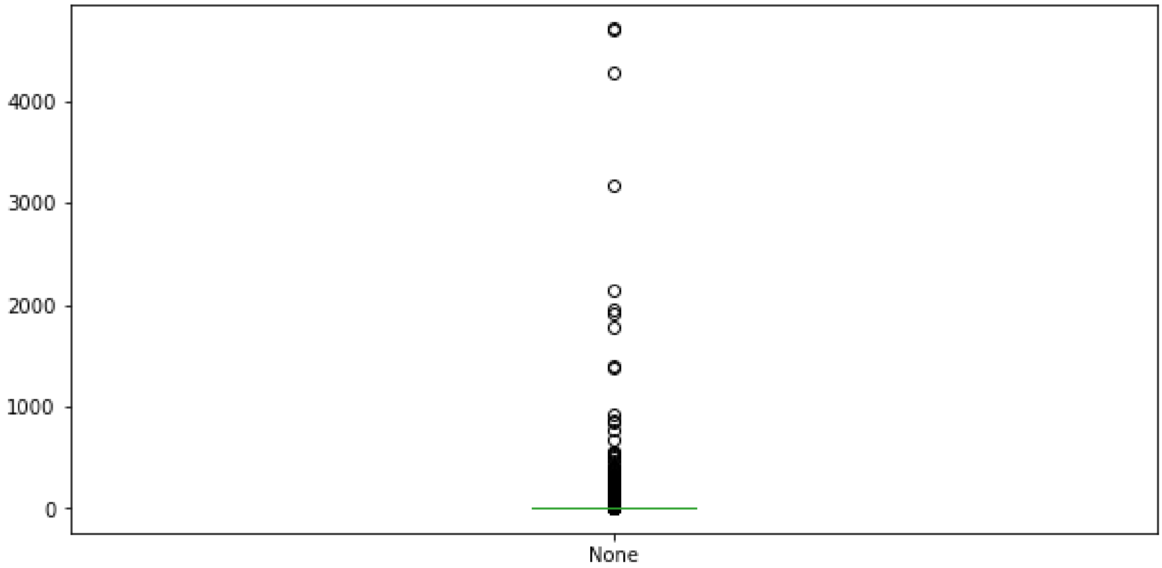
In [17]:
```
wcdf.sum().sort_values(ascending=False).head()
```

Out[17]:
```
t       4709.0
co      4700.0
http    4273.0
the     3180.0
a       2151.0
dtype: float64
```

Those are top words in training data.

In [18]:
```
wcdf.sum().plot(kind="box", subplots=True, figsize =(10, 5))
```

Out[18]:
```
None    AxesSubplot(0.125,0.125;0.775x0.755)
dtype: object
```



From boxplot above, we can see that most of tweet have less than 1,000 words.

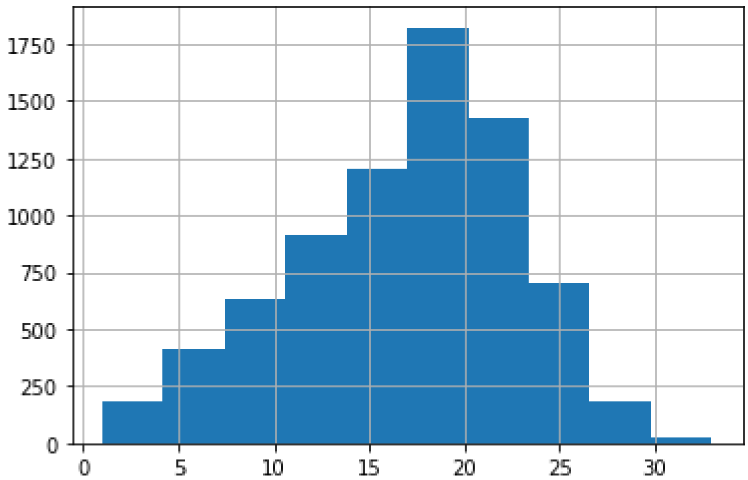
In [19]:
```
wcdf.sum(axis=1).describe()
```

Out[19]:
```
count    7485.000000
mean       16.817234
std         5.926167
min         1.000000
25%        13.000000
50%        17.000000
75%        21.000000
max        33.000000
dtype: float64
```

We have avearge around 17 words per tweet.

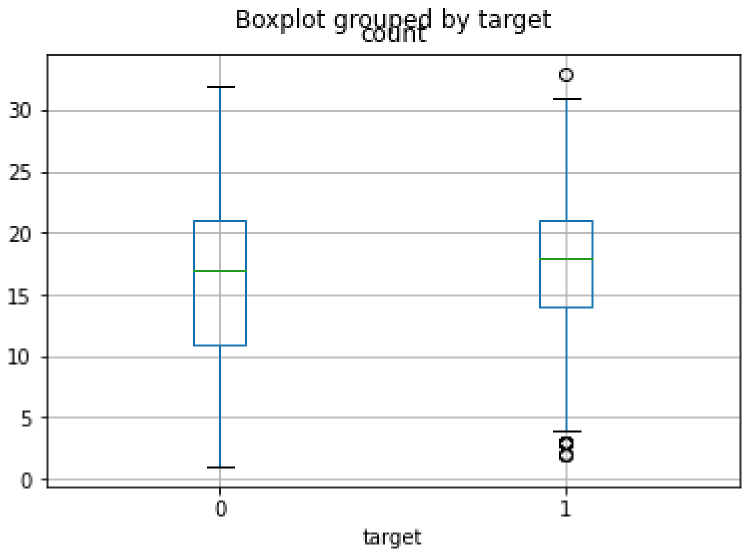
In [20]:
```
wcdf.sum(axis=1).hist(bins=10)
```

Out[20]: <AxesSubplot:>



In [21]:
```
pwcdf = pd.concat([wcdf.sum(axis=1), data['target'].reset_index(drop=True
pwcdf.boxplot(column=['count'], by='target')
```

Out[21]: <AxesSubplot:title={'center':'count'}, xlabel='target'>



Analysis

We have 22,675 unique words which too much for training So, I would reduce it before reed to the model. The largest of tweet have 33 words. So, I think we can crate CNN with 33 features.

Classification

First, I will try with simple CNN model as based line. Then, We will add more complexity to the model. I will also, try with small vocab size.

Spliting data in to train and validation (validation for 20%).

In [22]:
```
x_train, x_val, y_train, y_val = train_test_split(data.text, data.target,
```

In [23]:
```
# create vocab only from train data
tokenizer = Tokenizer()
tokenizer.fit_on_texts(x_train)
word_index = tokenizer.word_index
```

In [24]:
```
len(word_index)
```

Out[24]:
```
19300
```

In [25]:
```
x_train_seq = tokenizer.texts_to_sequences(x_train)
x_val_seq = tokenizer.texts_to_sequences(x_val)
```

We are going to padding. Therefore We must check longest of test data before doing it.

In [26]:
```
test_data_seq = tokenizer.texts_to_sequences(test_data.text)
```

In [27]:
```
max = 0
for s in test_data_seq:
  if max<len(s):
```

```
    max = len(s)
max
```

Out[27]:

```
30
```

So, We will pad to 33 words.

In [28]:

```
pad_x_train = tf.keras.utils.pad_sequences(x_train_seq, maxlen = 33)
pad_x_val = tf.keras.utils.pad_sequences(x_val_seq, maxlen = 33)
pad_x_test = tf.keras.utils.pad_sequences(test_data_seq, maxlen = 33)
```

Next, we will build simple model as based line.

In [29]:

```
model0 = Sequential()
model0.add(layers.Embedding(22675, 64, input_length = 33))
model0.add(layers.SimpleRNN(128))
model0.add(layers.Dense(1, activation = 'sigmoid'))
model0.compile(optimizer="adam", loss="mse", metrics=["accuracy"])
model0.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding (Embedding)       (None, 33, 64)            1451200   
                                                                 
 simple_rnn (SimpleRNN)      (None, 128)               24704     
                                                                 
 dense (Dense)               (None, 1)                 129       
                                                                 
=================================================================
Total params: 1476033 (5.63 MB)
Trainable params: 1476033 (5.63 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [30]:

```
history = model0.fit(pad_x_train, y_train, validation_data = (pad_x_val,
```

```
Epoch 1/20
188/188 [==============================] - 2s 7ms/step - loss: 0.2274 - ac
curacy: 0.6353 - val_loss: 0.2445 - val_accuracy: 0.5925
Epoch 2/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0857 - ac
curacy: 0.8960 - val_loss: 0.2884 - val_accuracy: 0.5939
Epoch 3/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0199 - ac
curacy: 0.9775 - val_loss: 0.2948 - val_accuracy: 0.5972
Epoch 4/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0112 - ac
curacy: 0.9883 - val_loss: 0.2784 - val_accuracy: 0.6032
Epoch 5/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0084 - ac
curacy: 0.9910 - val_loss: 0.2782 - val_accuracy: 0.5972
Epoch 6/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0056 - ac
curacy: 0.9937 - val_loss: 0.2591 - val_accuracy: 0.6239
Epoch 7/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0035 - ac
curacy: 0.9962 - val_loss: 0.2845 - val_accuracy: 0.6039
Epoch 8/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0029 - ac
curacy: 0.9968 - val_loss: 0.2824 - val_accuracy: 0.6086
Epoch 9/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0017 - ac
curacy: 0.9980 - val_loss: 0.2750 - val_accuracy: 0.6166
Epoch 10/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0016 - ac
curacy: 0.9985 - val_loss: 0.2850 - val_accuracy: 0.6025
Epoch 11/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0028 - ac
curacy: 0.9972 - val_loss: 0.3118 - val_accuracy: 0.5752
Epoch 12/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0011 - ac
curacy: 0.9988 - val_loss: 0.2803 - val_accuracy: 0.6239
Epoch 13/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0013 - ac
curacy: 0.9988 - val_loss: 0.2939 - val_accuracy: 0.5959
Epoch 14/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0015 - ac
curacy: 0.9985 - val_loss: 0.2898 - val_accuracy: 0.6005
Epoch 15/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0020 - ac
curacy: 0.9983 - val_loss: 0.2994 - val_accuracy: 0.6226
Epoch 16/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0018 - ac
curacy: 0.9983 - val_loss: 0.2771 - val_accuracy: 0.6319
Epoch 17/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0012 - ac
curacy: 0.9990 - val_loss: 0.3129 - val_accuracy: 0.5925
Epoch 18/20
188/188 [==============================] - 1s 7ms/step - loss: 9.8723e-04
- accuracy: 0.9990 - val_loss: 0.3118 - val_accuracy: 0.5872
Epoch 19/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0013 - ac
curacy: 0.9987 - val_loss: 0.2989 - val_accuracy: 0.6019
Epoch 20/20
188/188 [==============================] - 1s 7ms/step - loss: 0.0020 - ac
curacy: 0.9978 - val_loss: 0.3219 - val_accuracy: 0.5711
```

Now we have our first model which simple but not working well. So, I will try to change to LSTM wihich make model more complex.

In [31]:
```
model1 = Sequential()
model1.add(layers.Embedding(22675, 64, input_length = 33))
model1.add(layers.LSTM(128))
model1.add(layers.Dense(1, activation = 'sigmoid'))
model1.compile(optimizer="adam", loss="mse", metrics=["accuracy"])
model1.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_1 (Embedding)     (None, 33, 64)            1451200

 lstm (LSTM)                 (None, 128)               98816

 dense_1 (Dense)             (None, 1)                 129

=================================================================
Total params: 1550145 (5.91 MB)
Trainable params: 1550145 (5.91 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [32]:
```
history = model1.fit(pad_x_train, y_train, validation_data = (pad_x_val,
```

```
Epoch 1/20
188/188 [==============================] - 4s 19ms/step - loss: 0.1806 - a
ccuracy: 0.7244 - val_loss: 0.1436 - val_accuracy: 0.8043
Epoch 2/20
188/188 [==============================] - 4s 19ms/step - loss: 0.0841 - a
ccuracy: 0.8928 - val_loss: 0.1521 - val_accuracy: 0.7969
Epoch 3/20
188/188 [==============================] - 4s 19ms/step - loss: 0.0381 - a
ccuracy: 0.9532 - val_loss: 0.1633 - val_accuracy: 0.7889
Epoch 4/20
188/188 [==============================] - 3s 18ms/step - loss: 0.0171 - a
ccuracy: 0.9806 - val_loss: 0.1717 - val_accuracy: 0.7816
Epoch 5/20
188/188 [==============================] - 3s 18ms/step - loss: 0.0091 - a
ccuracy: 0.9906 - val_loss: 0.1815 - val_accuracy: 0.7735
Epoch 6/20
188/188 [==============================] - 3s 18ms/step - loss: 0.0063 - a
ccuracy: 0.9933 - val_loss: 0.1911 - val_accuracy: 0.7555
Epoch 7/20
188/188 [==============================] - 3s 19ms/step - loss: 0.0052 - a
ccuracy: 0.9947 - val_loss: 0.2056 - val_accuracy: 0.7355
Epoch 8/20
188/188 [==============================] - 3s 18ms/step - loss: 0.0035 - a
ccuracy: 0.9967 - val_loss: 0.2262 - val_accuracy: 0.7261
Epoch 9/20
188/188 [==============================] - 4s 19ms/step - loss: 0.0051 - a
ccuracy: 0.9948 - val_loss: 0.2274 - val_accuracy: 0.7121
Epoch 10/20
188/188 [==============================] - 4s 19ms/step - loss: 0.0038 - a
ccuracy: 0.9958 - val_loss: 0.2279 - val_accuracy: 0.7094
Epoch 11/20
188/188 [==============================] - 4s 19ms/step - loss: 0.0029 - a
ccuracy: 0.9970 - val_loss: 0.2101 - val_accuracy: 0.7475
Epoch 12/20
188/188 [==============================] - 4s 20ms/step - loss: 0.0106 - a
ccuracy: 0.9885 - val_loss: 0.2288 - val_accuracy: 0.6954
Epoch 13/20
188/188 [==============================] - 4s 20ms/step - loss: 0.0051 - a
ccuracy: 0.9943 - val_loss: 0.2517 - val_accuracy: 0.6814
Epoch 14/20
188/188 [==============================] - 4s 19ms/step - loss: 0.0038 - a
ccuracy: 0.9960 - val_loss: 0.2610 - val_accuracy: 0.6840
Epoch 15/20
188/188 [==============================] - 4s 20ms/step - loss: 0.0022 - a
ccuracy: 0.9975 - val_loss: 0.2018 - val_accuracy: 0.7482
Epoch 16/20
188/188 [==============================] - 4s 20ms/step - loss: 0.0020 - a
ccuracy: 0.9975 - val_loss: 0.2218 - val_accuracy: 0.7275
Epoch 17/20
188/188 [==============================] - 4s 20ms/step - loss: 0.0026 - a
ccuracy: 0.9970 - val_loss: 0.2044 - val_accuracy: 0.7582
Epoch 18/20
188/188 [==============================] - 4s 20ms/step - loss: 0.0024 - a
ccuracy: 0.9972 - val_loss: 0.2224 - val_accuracy: 0.7301
Epoch 19/20
188/188 [==============================] - 4s 20ms/step - loss: 0.0029 - a
ccuracy: 0.9968 - val_loss: 0.2898 - val_accuracy: 0.6493
Epoch 20/20
188/188 [==============================] - 4s 20ms/step - loss: 0.0022 - a
ccuracy: 0.9978 - val_loss: 0.2360 - val_accuracy: 0.7174
```

From result above I think it's overfitted. Because validation accuracy is not increase when test accuracy is increase.

So, I will try to reduce vocab size which might fix overfitted issue.

I think we can use only 1500 words to train.

In [33]:
```
# new tokenizer with num_words = 1500
vocab = 1500
tokenizer = Tokenizer(num_words = vocab)
tokenizer.fit_on_texts(x_train)
word_index = tokenizer.word_index
```

In [34]:
```
# convert to sequences
x_train_seq = tokenizer.texts_to_sequences(x_train)
x_val_seq = tokenizer.texts_to_sequences(x_val)
test_data_seq = tokenizer.texts_to_sequences(test_data.text)
```

In [35]:
```
# padding
pad_x_train = tf.keras.utils.pad_sequences(x_train_seq, maxlen = 33)
pad_x_val = tf.keras.utils.pad_sequences(x_val_seq, maxlen = 33)
pad_x_test = tf.keras.utils.pad_sequences(test_data_seq, maxlen = 33)
```

Create new model to fit new data with vocab size 1500.

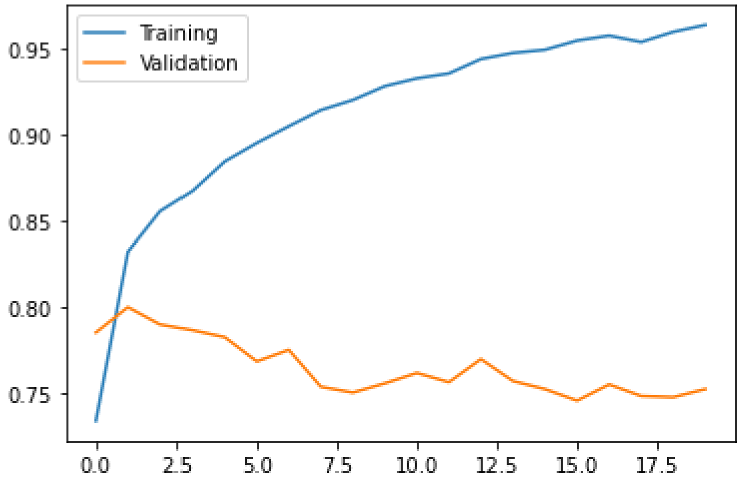
In [36]:
```
model2 = Sequential()
model2.add(layers.Embedding(vocab, 64, input_length = 33))
model2.add(layers.LSTM(128))
model2.add(layers.Dense(1, activation = 'sigmoid'))
model2.compile(optimizer="adam", loss="mse", metrics=["accuracy"])
model2.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_2 (Embedding)     (None, 33, 64)            96000

 lstm_1 (LSTM)               (None, 128)               98816

 dense_2 (Dense)             (None, 1)                 129

=================================================================
Total params: 194945 (761.50 KB)
Trainable params: 194945 (761.50 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [37]:
```
epochs = 20
history = model2.fit(pad_x_train, y_train, validation_data = (pad_x_val,
```

```
Epoch 1/20
188/188 [==============================] - 3s 15ms/step - loss: 0.1797 - a
ccuracy: 0.7345 - val_loss: 0.1488 - val_accuracy: 0.7856
Epoch 2/20
188/188 [==============================] - 3s 15ms/step - loss: 0.1240 - a
ccuracy: 0.8322 - val_loss: 0.1444 - val_accuracy: 0.8003
Epoch 3/20
188/188 [==============================] - 3s 15ms/step - loss: 0.1101 - a
ccuracy: 0.8555 - val_loss: 0.1603 - val_accuracy: 0.7902
Epoch 4/20
188/188 [==============================] - 3s 15ms/step - loss: 0.1021 - a
ccuracy: 0.8672 - val_loss: 0.1521 - val_accuracy: 0.7869
Epoch 5/20
188/188 [==============================] - 3s 16ms/step - loss: 0.0920 - a
ccuracy: 0.8843 - val_loss: 0.1575 - val_accuracy: 0.7829
Epoch 6/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0838 - a
ccuracy: 0.8950 - val_loss: 0.1796 - val_accuracy: 0.7689
Epoch 7/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0782 - a
ccuracy: 0.9046 - val_loss: 0.1772 - val_accuracy: 0.7756
Epoch 8/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0703 - a
ccuracy: 0.9140 - val_loss: 0.1970 - val_accuracy: 0.7542
Epoch 9/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0669 - a
ccuracy: 0.9198 - val_loss: 0.2058 - val_accuracy: 0.7508
Epoch 10/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0623 - a
ccuracy: 0.9279 - val_loss: 0.2082 - val_accuracy: 0.7562
Epoch 11/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0577 - a
ccuracy: 0.9324 - val_loss: 0.1982 - val_accuracy: 0.7622
Epoch 12/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0549 - a
ccuracy: 0.9352 - val_loss: 0.2043 - val_accuracy: 0.7568
Epoch 13/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0504 - a
ccuracy: 0.9436 - val_loss: 0.1984 - val_accuracy: 0.7702
Epoch 14/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0469 - a
ccuracy: 0.9471 - val_loss: 0.2080 - val_accuracy: 0.7575
Epoch 15/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0447 - a
ccuracy: 0.9489 - val_loss: 0.2130 - val_accuracy: 0.7528
Epoch 16/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0404 - a
ccuracy: 0.9542 - val_loss: 0.2204 - val_accuracy: 0.7462
Epoch 17/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0388 - a
ccuracy: 0.9571 - val_loss: 0.2182 - val_accuracy: 0.7555
Epoch 18/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0402 - a
ccuracy: 0.9534 - val_loss: 0.2174 - val_accuracy: 0.7488
Epoch 19/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0360 - a
ccuracy: 0.9593 - val_loss: 0.2259 - val_accuracy: 0.7482
Epoch 20/20
188/188 [==============================] - 3s 15ms/step - loss: 0.0339 - a
ccuracy: 0.9633 - val_loss: 0.2240 - val_accuracy: 0.7528
```

In [38]:
```
epochs_range = range(epochs)

plt.plot(epochs_range, history.history['accuracy'], label='Training')
plt.plot(epochs_range, history.history['val_accuracy'], label='Validation
plt.legend()
plt.show()
```



This model seems overfitted. So, I will add dropout and regularizer.

In [39]:
```
model3 = Sequential()
model3.add(layers.Embedding(vocab, 64, input_length = 33, embeddings_regu
model3.add(layers.LSTM(64))
model3.add(layers.Dense(64, activation = 'relu'))
model3.add(layers.Dropout(0.2))
model3.add(layers.Dense(1, activation = 'sigmoid'))
model3.compile(optimizer="adam", loss="mse", metrics=["accuracy"])
model3.summary()
```

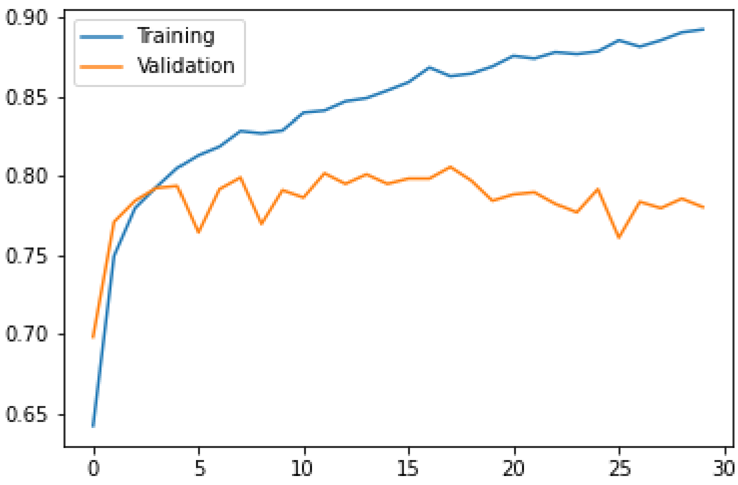
```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_3 (Embedding)     (None, 33, 64)            96000

 lstm_2 (LSTM)               (None, 64)                33024

 dense_3 (Dense)             (None, 64)                4160

 dropout (Dropout)           (None, 64)                0

 dense_4 (Dense)             (None, 1)                 65

=================================================================
Total params: 133249 (520.50 KB)
Trainable params: 133249 (520.50 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [40]:
```
epochs = 30
history = model3.fit(pad_x_train, y_train, validation_data = (pad_x_val,
```

```
Epoch 1/30
188/188 [==============================] - 2s 8ms/step - loss: 0.2907 - ac
curacy: 0.6421 - val_loss: 0.2183 - val_accuracy: 0.6981
Epoch 2/30
188/188 [==============================] - 1s 7ms/step - loss: 0.2109 - ac
curacy: 0.7493 - val_loss: 0.2016 - val_accuracy: 0.7709
Epoch 3/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1945 - ac
curacy: 0.7796 - val_loss: 0.1908 - val_accuracy: 0.7842
Epoch 4/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1834 - ac
curacy: 0.7928 - val_loss: 0.1804 - val_accuracy: 0.7923
Epoch 5/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1740 - ac
curacy: 0.8049 - val_loss: 0.1768 - val_accuracy: 0.7936
Epoch 6/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1676 - ac
curacy: 0.8130 - val_loss: 0.1902 - val_accuracy: 0.7642
Epoch 7/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1646 - ac
curacy: 0.8185 - val_loss: 0.1780 - val_accuracy: 0.7916
Epoch 8/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1583 - ac
curacy: 0.8283 - val_loss: 0.1721 - val_accuracy: 0.7989
Epoch 9/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1551 - ac
curacy: 0.8268 - val_loss: 0.1846 - val_accuracy: 0.7695
Epoch 10/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1519 - ac
curacy: 0.8287 - val_loss: 0.1739 - val_accuracy: 0.7909
Epoch 11/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1458 - ac
curacy: 0.8397 - val_loss: 0.1744 - val_accuracy: 0.7862
Epoch 12/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1422 - ac
curacy: 0.8410 - val_loss: 0.1706 - val_accuracy: 0.8016
Epoch 13/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1409 - ac
curacy: 0.8469 - val_loss: 0.1716 - val_accuracy: 0.7949
Epoch 14/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1381 - ac
curacy: 0.8489 - val_loss: 0.1716 - val_accuracy: 0.8009
Epoch 15/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1381 - ac
curacy: 0.8537 - val_loss: 0.1738 - val_accuracy: 0.7949
Epoch 16/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1335 - ac
curacy: 0.8589 - val_loss: 0.1752 - val_accuracy: 0.7983
Epoch 17/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1296 - ac
curacy: 0.8682 - val_loss: 0.1749 - val_accuracy: 0.7983
Epoch 18/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1321 - ac
curacy: 0.8627 - val_loss: 0.1736 - val_accuracy: 0.8056
Epoch 19/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1305 - ac
curacy: 0.8644 - val_loss: 0.1806 - val_accuracy: 0.7969
Epoch 20/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1309 - ac
curacy: 0.8689 - val_loss: 0.1825 - val_accuracy: 0.7842
```

```
Epoch 21/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1248 - ac
curacy: 0.8756 - val_loss: 0.1844 - val_accuracy: 0.7882
Epoch 22/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1260 - ac
curacy: 0.8739 - val_loss: 0.1854 - val_accuracy: 0.7896
Epoch 23/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1241 - ac
curacy: 0.8779 - val_loss: 0.1954 - val_accuracy: 0.7822
Epoch 24/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1249 - ac
curacy: 0.8768 - val_loss: 0.1982 - val_accuracy: 0.7769
Epoch 25/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1240 - ac
curacy: 0.8784 - val_loss: 0.1874 - val_accuracy: 0.7916
Epoch 26/30
188/188 [==============================] - 1s 8ms/step - loss: 0.1210 - ac
curacy: 0.8854 - val_loss: 0.2108 - val_accuracy: 0.7609
Epoch 27/30
188/188 [==============================] - 1s 8ms/step - loss: 0.1214 - ac
curacy: 0.8814 - val_loss: 0.1937 - val_accuracy: 0.7836
Epoch 28/30
188/188 [==============================] - 1s 8ms/step - loss: 0.1160 - ac
curacy: 0.8854 - val_loss: 0.1935 - val_accuracy: 0.7796
Epoch 29/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1160 - ac
curacy: 0.8904 - val_loss: 0.1983 - val_accuracy: 0.7856
Epoch 30/30
188/188 [==============================] - 1s 7ms/step - loss: 0.1185 - ac
curacy: 0.8923 - val_loss: 0.1984 - val_accuracy: 0.7802
```

In [41]:
```
epochs_range = range(epochs)

plt.plot(epochs_range, history.history['accuracy'], label='Training')
plt.plot(epochs_range, history.history['val_accuracy'], label='Validation
plt.legend()
plt.show()
```



Overfitted issue seems to be better. But still not total resolved. So, I will add more dropout.

In [42]:
```
model4 = Sequential()
model4.add(layers.Embedding(vocab, 64, input_length = 33, embeddings_regu
model4.add(layers.GRU(128, dropout=0.2))
```

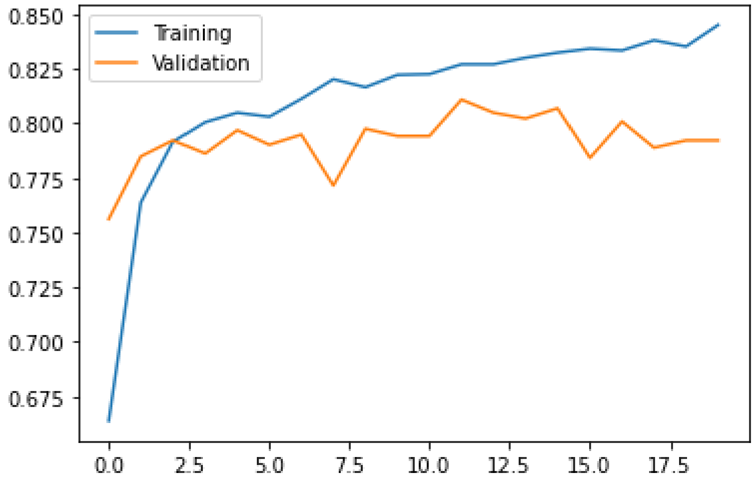
```python
model4.add(layers.Dense(128, activation = 'relu'))
model4.add(layers.Dropout(0.2))
model4.add(layers.Dense(1, activation = 'sigmoid'))
model4.compile(optimizer="adam", loss="mse", metrics=["accuracy"])
model4.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_4 (Embedding)     (None, 33, 64)            96000     
                                                                 
 gru (GRU)                   (None, 128)               74496     
                                                                 
 dense_5 (Dense)             (None, 128)               16512     
                                                                 
 dropout_1 (Dropout)         (None, 128)               0         
                                                                 
 dense_6 (Dense)             (None, 1)                 129       
                                                                 
=================================================================
Total params: 187137 (731.00 KB)
Trainable params: 187137 (731.00 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [43]:
```python
epochs = 20
history = model4.fit(pad_x_train, y_train, validation_data = (pad_x_val,
```

```
Epoch 1/20
188/188 [==============================] - 3s 14ms/step - loss: 0.2875 - a
ccuracy: 0.6638 - val_loss: 0.2067 - val_accuracy: 0.7562
Epoch 2/20
188/188 [==============================] - 3s 14ms/step - loss: 0.2080 - a
ccuracy: 0.7637 - val_loss: 0.1973 - val_accuracy: 0.7849
Epoch 3/20
188/188 [==============================] - 3s 14ms/step - loss: 0.1914 - a
ccuracy: 0.7916 - val_loss: 0.1914 - val_accuracy: 0.7923
Epoch 4/20
188/188 [==============================] - 3s 14ms/step - loss: 0.1847 - a
ccuracy: 0.8006 - val_loss: 0.1830 - val_accuracy: 0.7862
Epoch 5/20
188/188 [==============================] - 3s 14ms/step - loss: 0.1799 - a
ccuracy: 0.8049 - val_loss: 0.1831 - val_accuracy: 0.7969
Epoch 6/20
188/188 [==============================] - 3s 13ms/step - loss: 0.1796 - a
ccuracy: 0.8031 - val_loss: 0.1835 - val_accuracy: 0.7902
Epoch 7/20
188/188 [==============================] - 3s 14ms/step - loss: 0.1731 - a
ccuracy: 0.8113 - val_loss: 0.1863 - val_accuracy: 0.7949
Epoch 8/20
188/188 [==============================] - 3s 13ms/step - loss: 0.1678 - a
ccuracy: 0.8203 - val_loss: 0.1920 - val_accuracy: 0.7715
Epoch 9/20
188/188 [==============================] - 3s 13ms/step - loss: 0.1697 - a
ccuracy: 0.8166 - val_loss: 0.1781 - val_accuracy: 0.7976
Epoch 10/20
188/188 [==============================] - 3s 14ms/step - loss: 0.1640 - a
ccuracy: 0.8223 - val_loss: 0.1808 - val_accuracy: 0.7943
Epoch 11/20
188/188 [==============================] - 3s 14ms/step - loss: 0.1663 - a
ccuracy: 0.8226 - val_loss: 0.1828 - val_accuracy: 0.7943
Epoch 12/20
188/188 [==============================] - 3s 14ms/step - loss: 0.1597 - a
ccuracy: 0.8272 - val_loss: 0.1732 - val_accuracy: 0.8110
Epoch 13/20
188/188 [==============================] - 3s 14ms/step - loss: 0.1613 - a
ccuracy: 0.8272 - val_loss: 0.1797 - val_accuracy: 0.8049
Epoch 14/20
188/188 [==============================] - 3s 14ms/step - loss: 0.1615 - a
ccuracy: 0.8302 - val_loss: 0.1782 - val_accuracy: 0.8023
Epoch 15/20
188/188 [==============================] - 3s 13ms/step - loss: 0.1590 - a
ccuracy: 0.8325 - val_loss: 0.1785 - val_accuracy: 0.8069
Epoch 16/20
188/188 [==============================] - 3s 13ms/step - loss: 0.1586 - a
ccuracy: 0.8343 - val_loss: 0.1884 - val_accuracy: 0.7842
Epoch 17/20
188/188 [==============================] - 3s 14ms/step - loss: 0.1582 - a
ccuracy: 0.8335 - val_loss: 0.1826 - val_accuracy: 0.8009
Epoch 18/20
188/188 [==============================] - 3s 14ms/step - loss: 0.1567 - a
ccuracy: 0.8382 - val_loss: 0.1955 - val_accuracy: 0.7889
Epoch 19/20
188/188 [==============================] - 3s 14ms/step - loss: 0.1589 - a
ccuracy: 0.8353 - val_loss: 0.1891 - val_accuracy: 0.7923
Epoch 20/20
188/188 [==============================] - 3s 14ms/step - loss: 0.1563 - a
ccuracy: 0.8452 - val_loss: 0.1896 - val_accuracy: 0.7923
```

In [44]:
```
epochs_range = range(epochs)

plt.plot(epochs_range, history.history['accuracy'], label='Training')
plt.plot(epochs_range, history.history['val_accuracy'], label='Validation
plt.legend()
plt.show()
```



This model looking good for me. So, I will use it to perdict test data. and submit to kaggle.

In [45]:
```
predictions = model4.predict(pad_x_test)
pre_bi = (predictions.flatten() >= 0.5).astype(int)
output = pd.DataFrame({'id': test_data.id, 'target': pre_bi})
output.to_csv('submission.csv', index=False)
print("Your submission was successfully saved!")
```

```
102/102 [==============================] - 0s 3ms/step
Your submission was successfully saved!
```

This model has score 0.78332. This model still a overfitted. I will try a new model with more dropout.

In [46]:
```
model5 = Sequential()
model5.add(layers.Embedding(vocab, 256, input_length = 33, embeddings_reg
model5.add(layers.GRU(128, dropout=0.5))
model5.add(layers.Dense(128, activation = 'relu'))
model5.add(layers.Dropout(0.3))
model5.add(layers.Dense(1, activation = 'sigmoid'))
model5.compile(optimizer="adam", loss="mse", metrics=["accuracy"])
model5.summary()
```

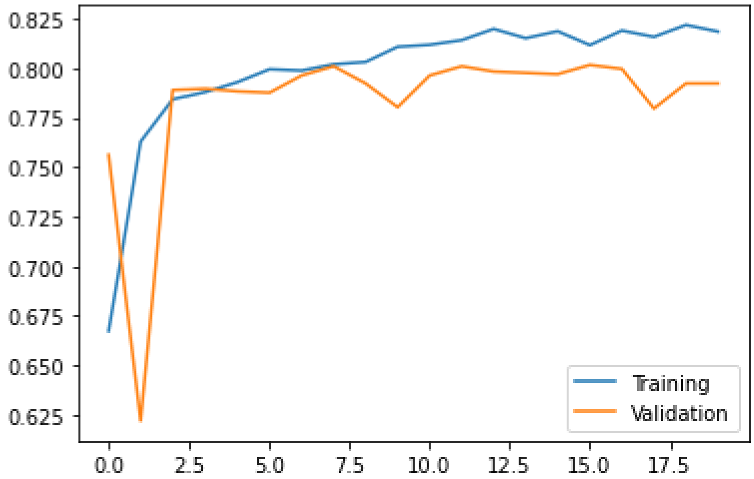
```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_5 (Embedding)     (None, 33, 256)           384000

 gru_1 (GRU)                 (None, 128)               148224

 dense_7 (Dense)             (None, 128)               16512

 dropout_2 (Dropout)         (None, 128)               0

 dense_8 (Dense)             (None, 1)                 129

=================================================================
Total params: 548865 (2.09 MB)
Trainable params: 548865 (2.09 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [47]:

```
epochs = 20
history = model5.fit(pad_x_train, y_train, validation_data = (pad_x_val,
```

```
Epoch 1/20
188/188 [==============================] - 5s 23ms/step - loss: 0.4773 - a
ccuracy: 0.6673 - val_loss: 0.2377 - val_accuracy: 0.7562
Epoch 2/20
188/188 [==============================] - 4s 24ms/step - loss: 0.2425 - a
ccuracy: 0.7629 - val_loss: 0.3137 - val_accuracy: 0.6219
Epoch 3/20
188/188 [==============================] - 4s 23ms/step - loss: 0.2291 - a
ccuracy: 0.7842 - val_loss: 0.2175 - val_accuracy: 0.7889
Epoch 4/20
188/188 [==============================] - 4s 22ms/step - loss: 0.2165 - a
ccuracy: 0.7879 - val_loss: 0.2139 - val_accuracy: 0.7896
Epoch 5/20
188/188 [==============================] - 4s 23ms/step - loss: 0.2127 - a
ccuracy: 0.7929 - val_loss: 0.2139 - val_accuracy: 0.7882
Epoch 6/20
188/188 [==============================] - 4s 24ms/step - loss: 0.2048 - a
ccuracy: 0.7994 - val_loss: 0.2056 - val_accuracy: 0.7876
Epoch 7/20
188/188 [==============================] - 4s 24ms/step - loss: 0.2063 - a
ccuracy: 0.7988 - val_loss: 0.2030 - val_accuracy: 0.7963
Epoch 8/20
188/188 [==============================] - 4s 24ms/step - loss: 0.2044 - a
ccuracy: 0.8019 - val_loss: 0.2042 - val_accuracy: 0.8009
Epoch 9/20
188/188 [==============================] - 5s 25ms/step - loss: 0.2024 - a
ccuracy: 0.8031 - val_loss: 0.2079 - val_accuracy: 0.7923
Epoch 10/20
188/188 [==============================] - 5s 25ms/step - loss: 0.1998 - a
ccuracy: 0.8108 - val_loss: 0.2125 - val_accuracy: 0.7802
Epoch 11/20
188/188 [==============================] - 5s 25ms/step - loss: 0.1996 - a
ccuracy: 0.8118 - val_loss: 0.2048 - val_accuracy: 0.7963
Epoch 12/20
188/188 [==============================] - 5s 25ms/step - loss: 0.1975 - a
ccuracy: 0.8141 - val_loss: 0.1994 - val_accuracy: 0.8009
Epoch 13/20
188/188 [==============================] - 5s 26ms/step - loss: 0.1976 - a
ccuracy: 0.8198 - val_loss: 0.2083 - val_accuracy: 0.7983
Epoch 14/20
188/188 [==============================] - 5s 26ms/step - loss: 0.1993 - a
ccuracy: 0.8151 - val_loss: 0.2052 - val_accuracy: 0.7976
Epoch 15/20
188/188 [==============================] - 5s 26ms/step - loss: 0.1965 - a
ccuracy: 0.8186 - val_loss: 0.2039 - val_accuracy: 0.7969
Epoch 16/20
188/188 [==============================] - 5s 27ms/step - loss: 0.1938 - a
ccuracy: 0.8116 - val_loss: 0.1990 - val_accuracy: 0.8016
Epoch 17/20
188/188 [==============================] - 5s 26ms/step - loss: 0.1931 - a
ccuracy: 0.8190 - val_loss: 0.2062 - val_accuracy: 0.7996
Epoch 18/20
188/188 [==============================] - 5s 27ms/step - loss: 0.1986 - a
ccuracy: 0.8158 - val_loss: 0.2141 - val_accuracy: 0.7796
Epoch 19/20
188/188 [==============================] - 5s 27ms/step - loss: 0.1952 - a
ccuracy: 0.8218 - val_loss: 0.2073 - val_accuracy: 0.7923
Epoch 20/20
188/188 [==============================] - 5s 26ms/step - loss: 0.1948 - a
ccuracy: 0.8185 - val_loss: 0.2053 - val_accuracy: 0.7923
```

In [48]:
```
epochs_range = range(epochs)

plt.plot(epochs_range, history.history['accuracy'], label='Training')
plt.plot(epochs_range, history.history['val_accuracy'], label='Validation
plt.legend()
plt.show()
```



This looks better. So, I will submit again.

In [49]:
```
predictions = model5.predict(pad_x_test)
pre_bi = (predictions.flatten() >= 0.5).astype(int)
output = pd.DataFrame({'id': test_data.id, 'target': pre_bi})
output.to_csv('submission5.csv', index=False)
print("Your submission was successfully saved!")
```

```
102/102 [==============================] - 1s 5ms/step
Your submission was successfully saved!
```

This model has score 0.78577 which is better a bit.

I want to get better score. So, I try tuning hyperparameter around and comeup with this last model.

P.S. I tried many thing off this notebook. But I think it's a bit too much. Therefore, I did not include those model in this notebook.

In [54]:
```
model6 = Sequential()
model6.add(layers.Embedding(vocab, 64, input_length = 33, embeddings_regu
model6.add(layers.GRU(32, dropout=0.1, return_sequences= True))
model6.add(layers.GRU(32, dropout=0.1))
model6.add(layers.Dense(32, activation = 'relu'))
model6.add(layers.Dropout(0.1))
model6.add(layers.Dense(1, activation = 'sigmoid'))
model6.compile(optimizer="adam", loss="mse", metrics=["accuracy"])
model6.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_7 (Embedding)     (None, 33, 64)            96000     
                                                                 
 gru_4 (GRU)                 (None, 33, 32)            9408      
                                                                 
 gru_5 (GRU)                 (None, 32)                6336      
                                                                 
 dense_11 (Dense)            (None, 32)                1056      
                                                                 
 dropout_4 (Dropout)         (None, 32)                0         
                                                                 
 dense_12 (Dense)            (None, 1)                 33        
                                                                 
=================================================================
Total params: 112833 (440.75 KB)
Trainable params: 112833 (440.75 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

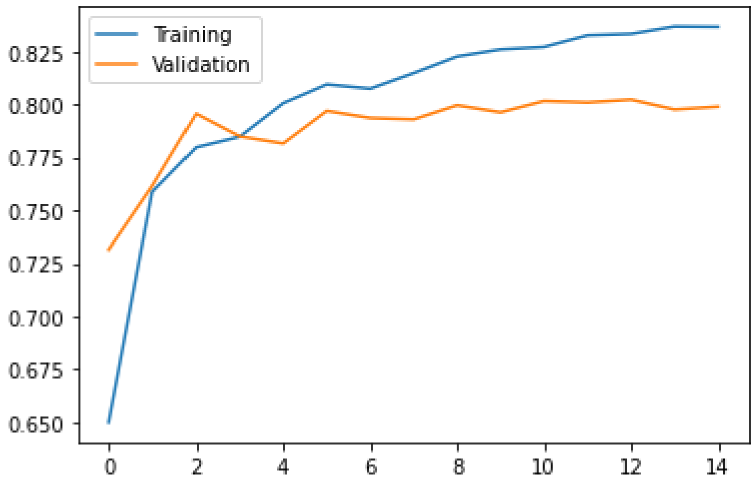
In [55]:

```
epochs = 15
history = model6.fit(pad_x_train, y_train, validation_data = (pad_x_val,
```

```
Epoch 1/15
188/188 [==============================] - 3s 9ms/step - loss: 0.2897 - ac
curacy: 0.6500 - val_loss: 0.2179 - val_accuracy: 0.7315
Epoch 2/15
188/188 [==============================] - 2s 9ms/step - loss: 0.2124 - ac
curacy: 0.7587 - val_loss: 0.2043 - val_accuracy: 0.7615
Epoch 3/15
188/188 [==============================] - 2s 9ms/step - loss: 0.1969 - ac
curacy: 0.7797 - val_loss: 0.1854 - val_accuracy: 0.7956
Epoch 4/15
188/188 [==============================] - 2s 9ms/step - loss: 0.1892 - ac
curacy: 0.7847 - val_loss: 0.1888 - val_accuracy: 0.7849
Epoch 5/15
188/188 [==============================] - 2s 9ms/step - loss: 0.1801 - ac
curacy: 0.8006 - val_loss: 0.1866 - val_accuracy: 0.7816
Epoch 6/15
188/188 [==============================] - 2s 9ms/step - loss: 0.1728 - ac
curacy: 0.8095 - val_loss: 0.1803 - val_accuracy: 0.7969
Epoch 7/15
188/188 [==============================] - 2s 9ms/step - loss: 0.1705 - ac
curacy: 0.8074 - val_loss: 0.1757 - val_accuracy: 0.7936
Epoch 8/15
188/188 [==============================] - 2s 9ms/step - loss: 0.1665 - ac
curacy: 0.8148 - val_loss: 0.1744 - val_accuracy: 0.7929
Epoch 9/15
188/188 [==============================] - 2s 9ms/step - loss: 0.1623 - ac
curacy: 0.8226 - val_loss: 0.1696 - val_accuracy: 0.7996
Epoch 10/15
188/188 [==============================] - 2s 9ms/step - loss: 0.1574 - ac
curacy: 0.8260 - val_loss: 0.1737 - val_accuracy: 0.7963
Epoch 11/15
188/188 [==============================] - 2s 10ms/step - loss: 0.1568 - a
ccuracy: 0.8272 - val_loss: 0.1742 - val_accuracy: 0.8016
Epoch 12/15
188/188 [==============================] - 2s 9ms/step - loss: 0.1523 - ac
curacy: 0.8327 - val_loss: 0.1703 - val_accuracy: 0.8009
Epoch 13/15
188/188 [==============================] - 2s 9ms/step - loss: 0.1529 - ac
curacy: 0.8333 - val_loss: 0.1734 - val_accuracy: 0.8023
Epoch 14/15
188/188 [==============================] - 2s 9ms/step - loss: 0.1490 - ac
curacy: 0.8368 - val_loss: 0.1707 - val_accuracy: 0.7976
Epoch 15/15
188/188 [==============================] - 2s 9ms/step - loss: 0.1509 - ac
curacy: 0.8367 - val_loss: 0.1714 - val_accuracy: 0.7989
```

In [56]:

```
epochs_range = range(epochs)

plt.plot(epochs_range, history.history['accuracy'], label='Training')
plt.plot(epochs_range, history.history['val_accuracy'], label='Validation
plt.legend()
plt.show()
```



In [57]:
```
predictions = model6.predict(pad_x_test)
pre_bi = (predictions.flatten() >= 0.5).astype(int)
output = pd.DataFrame({'id': test_data.id, 'target': pre_bi})
output.to_csv('submission6.csv', index=False)
print("Your submission was successfully saved!")
```

```
102/102 [==============================] - 0s 2ms/step
Your submission was successfully saved!
```

Score for submit this prediction to Kaggle = 0.78486

Conclusion

For this problem first we look at overview of the data. We did analysis based on our visualizations. Then, we clean it up (remove dulicate data). Then, we build classification model with RNN and tune it to get the best model (based on score from Kaggle our best model has score = 0.78577).

Most of my models suffer from overfitted problem. I did tried a lot of thing to remove it. I can't remove it, but it's getting better with dropout, reduced vocab size and regularization. Future Improvement would be study new way to reduce overfitted and apply it the our models.

From all of this I know how to do the classification from scratch with python and how to use kaggle.

github : https://github.com/Satjarporn/Disaster