1 Natural Language Processing with Disaster Tweets

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2 Overview

Business Problem

```
Our local emergency department want to use social media to trace emergency
occur. For example, when people post a tweet online, local police or 911 can
read the news and come out for help immediately. However, there are too many
text info online to sort by human, so we need to generate a sufficient machine
learning approach.
```

2.2 Business proposal

Twitter has become an important communication channel in times of emergency. The ubiquitousness of smartphones enables people to announce an emergency they're observing in real-time. Because of this, more agencies are interested in programatically monitoring Twitter (i.e. disaster relief organizations and news agencies).

2.3 Business solution

```
By using Natual language Processing model, we can recognize tweets and get
real disaster from social media. In this way, we may able to help emergency
ambulance locate and rescue on time.
```

3 Data Loading and cleaning

In [1]:

```
from distutils.version import LooseVersion
import warnings
import tensorflow as tf

# Check TensorFlow Version
assert LooseVersion(tf.__version__) >= LooseVersion('1.0'), 'Please use TensorF
print('TensorFlow Version: {}'.format(tf.__version__))

# Check for a GPU
if not tf.test.gpu_device_name():
    warnings.warn('No GPU found. Please ensure you have installed TensorFlow co
else:
    print('Default GPU Device: {}'.format(tf.test.gpu_device_name()))
```

```
TensorFlow Version: 2.7.0
Default GPU Device: /device:GPU:0
```

3.1 Import data

In [2]:

```
import sys
```

In [3]:
```
#need to install worlcloud on local pc by:
#conda install -c conda-forge wordcloud=1.6.0
#need to install: pip install transformers
import warnings
warnings.filterwarnings('ignore')
%config Completer.use_jedi = False

import os
import numpy as np
import pandas as pd

import text_hammer as th
import seaborn as sns
import matplotlib.pyplot as plt
import re
import en_core_web_sm
import pydot
from wordcloud import WordCloud
from wordcloud import STOPWORDS
from nltk.corpus import stopwords
from collections import defaultdict

from tqdm._tqdm_notebook import tqdm_notebook
tqdm_notebook.pandas()
from transformers import AutoTokenizer,TFBertModel
from sklearn.model_selection import train_test_split, KFold
from sklearn.metrics import accuracy_score, plot_roc_curve, plot_confusion_matr
from sklearn.metrics import f1_score, confusion_matrix, recall_score, precision
from sklearn import metrics

max_len = 36

import tensorflow as tf
tf.config.experimental.list_physical_devices('GPU')

from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.initializers import TruncatedNormal
from tensorflow.keras.losses import CategoricalCrossentropy,BinaryCrossentropy
from tensorflow.keras.metrics import CategoricalAccuracy,BinaryAccuracy
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.utils import plot_model
from tensorflow.keras.layers import Input, Dense
from keras.preprocessing.text import Tokenizer

from keras.layers import (LSTM,
                          Embedding,
                          BatchNormalization,
                          Dense,
                          TimeDistributed,
                          Dropout,
                          Bidirectional,
                          Flatten,
                          GlobalMaxPool1D)
from keras.callbacks import ModelCheckpoint, ReduceLROnPlateau
```

In [4]:
```
train_data = pd.read_csv('train.csv',usecols=['id','text','target'])
test_data = pd.read_csv('test.csv',usecols=['id','text'])
sample_data = pd.read_csv('sample_submission.csv')
```

In [5]:
```
test_data.head()
```

Out[5]:

	id	text
0	0	Just happened a terrible car crash
1	2	Heard about #earthquake is different cities, s...
2	3	there is a forest fire at spot pond, geese are...
3	9	Apocalypse lighting. #Spokane #wildfires
4	11	Typhoon Soudelor kills 28 in China and Taiwan

In [6]:
```
train_data.head()
```

Out[6]:

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

In [7]:
```
train_data.shape
```

Out[7]: (7613, 3)

In [8]:
```
test_data.shape
```

Out[8]: (3263, 2)

In [9]:
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7613 entries, 0 to 7612
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   id      7613 non-null   int64 
 1   text    7613 non-null   object
 2   target  7613 non-null   int64 
dtypes: int64(2), object(1)
memory usage: 178.6+ KB
```

In [10]:
```
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3263 entries, 0 to 3262
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   id      3263 non-null   int64 
 1   text    3263 non-null   object
dtypes: int64(1), object(1)
memory usage: 51.1+ KB
```

In [11]:
```
train_data.isnull().sum()
```

Out[11]:
```
id        0
text      0
target    0
dtype: int64
```

In [12]:
```
test_data.isnull().sum()
```

Out[12]:
```
id      0
text    0
dtype: int64
```

3.2 data cleaning

In [13]:
```
#data cleaning
def text_preprocessing(df,col_name):
    column = col_name
    df[column] = df[column].progress_apply(lambda x:str(x).lower())
#     df[column] = df[column].progress_apply(lambda x: th.cont_exp(x)) #you're
    df[column] = df[column].progress_apply(lambda x: th.remove_emails(x))
    df[column] = df[column].progress_apply(lambda x: th.remove_html_tags(x))
#     df[column] = df[column].progress_apply(lambda x: ps.remove_stopwords(x))
    df[column] = df[column].progress_apply(lambda x: th.remove_special_chars(x)
    df[column] = df[column].progress_apply(lambda x: th.remove_accented_chars(x
#     df[column] = df[column].progress_apply(lambda x: th.make_base(x)) #ran ->
    return(df)
```

In [14]:
```
train_cleaned_data = text_preprocessing(train_data,'text')
```

100% 7613/7613 [00:00<00:00, 447397.91it/s]

100% 7613/7613 [00:00<00:00, 205570.31it/s]

100% 7613/7613 [00:00<00:00, 9111.55it/s]

100% 7613/7613 [00:00<00:00, 185514.06it/s]

100% 7613/7613 [00:00<00:00, 362196.42it/s]

In [15]:
```
test_cleaned_data = text_preprocessing(test_data,'text')
```

100% 3263/3263 [00:00<00:00, 232854.34it/s]

100% 3263/3263 [00:00<00:00, 155237.11it/s]

100% 3263/3263 [00:00<00:00, 8887.89it/s]

100% 3263/3263 [00:00<00:00, 141740.26it/s]

100% 3263/3263 [00:00<00:00, 232866.23it/s]

In [16]:
```
train_cleaned_data.head(30)
```

Out[16]:

	id	text	target
0	1	our deeds are the reason of this earthquake ma...	1
1	4	forest fire near la ronge sask canada	1
2	5	all residents asked to shelter in place are be...	1
3	6	13000 people receive wildfires evacuation orde...	1
4	7	just got sent this photo from ruby alaska as s...	1
5	8	rockyfire update california hwy 20 closed in b...	1
6	10	flood disaster heavy rain causes flash floodin...	1
7	13	im on top of the hill and i can see a fire in ...	1
8	14	theres an emergency evacuation happening now i...	1
9	15	im afraid that the tornado is coming to our area	1
10	16	three people died from the heat wave so far	1
11	17	haha south tampa is getting flooded hah wait a...	1
12	18	raining flooding florida tampabay tampa 18 or ...	1
13	19	flood in bago myanmar we arrived bago	1
14	20	damage to school bus on 80 in multi car crash ...	1
15	23	whats up man	0
16	24	i love fruits	0
17	25	summer is lovely	0
18	26	my car is so fast	0
19	28	what a goooooooaaaaaal	0
20	31	this is ridiculous	0
21	32	london is cool	0
22	33	love skiing	0
23	34	what a wonderful day	0
24	36	looooool	0
25	37	no wayi cant eat that shit	0
26	38	was in nyc last week	0
27	39	love my girlfriend	0
28	40	cooool	0
29	41	do you like pasta	0

In [17]:
```
stop_words = set(stopwords.words('english'))
train_data['text'] = train_data['text'].apply(lambda x: ' '.join([word for word
```

4 EDA

4.1 Disaster Tweets wordcloud

In [18]:
```
disaster_tweets = train_data[train_data.target == 1]
disaster_string = []
for t in disaster_tweets.text:
    disaster_string.append(t)
disaster_string = pd.Series(disaster_string).str.cat(sep=' ')
wordcloud = WordCloud(width=1600, height=800,max_font_size=100, background_colo
plt.figure(figsize=(12,10))
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

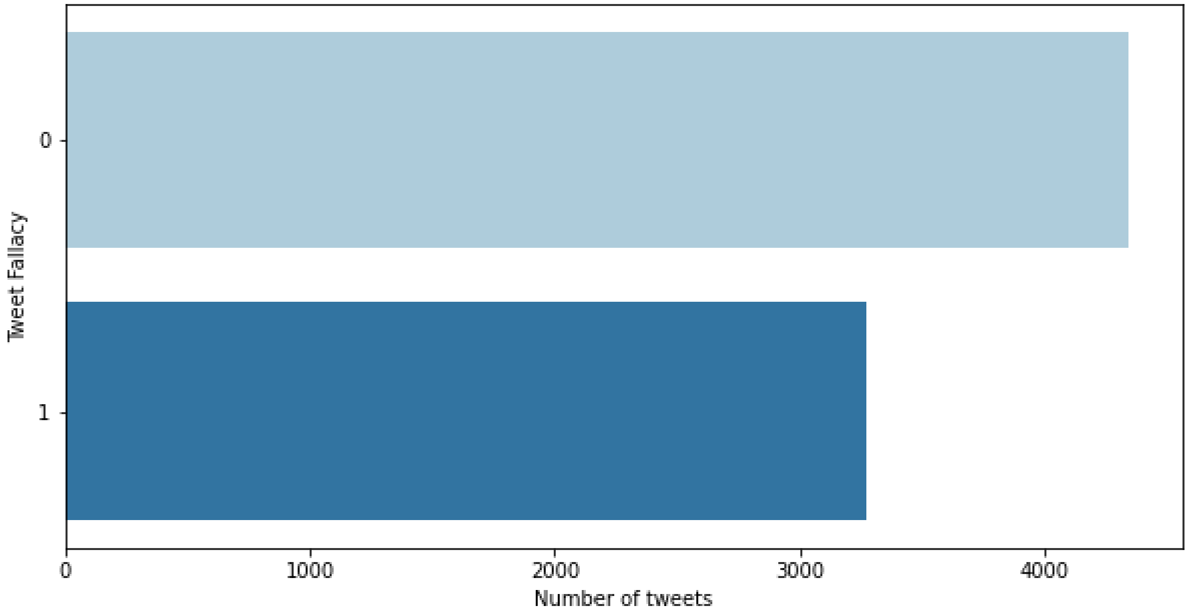
4.2 Positive tweets wordcloud

In [19]:

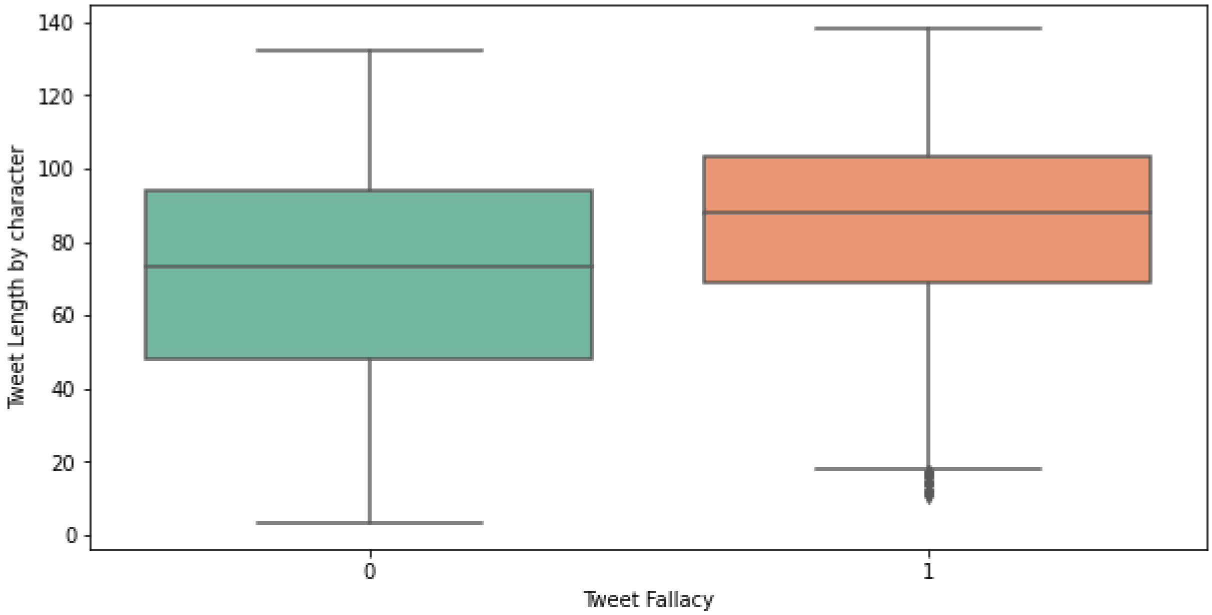
```
# Positive tweets wordcloud
formal_tweets = train_data[train_data.target == 0]
formal_string = []
for t in formal_tweets.text:
    formal_string.append(t)
formal_string = pd.Series(formal_string).str.cat(sep=' ')
wordcloud = WordCloud(width=1600, height=800,max_font_size=100, background_colo
plt.figure(figsize=(12,10))
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

4.3 Visualizing data distribution

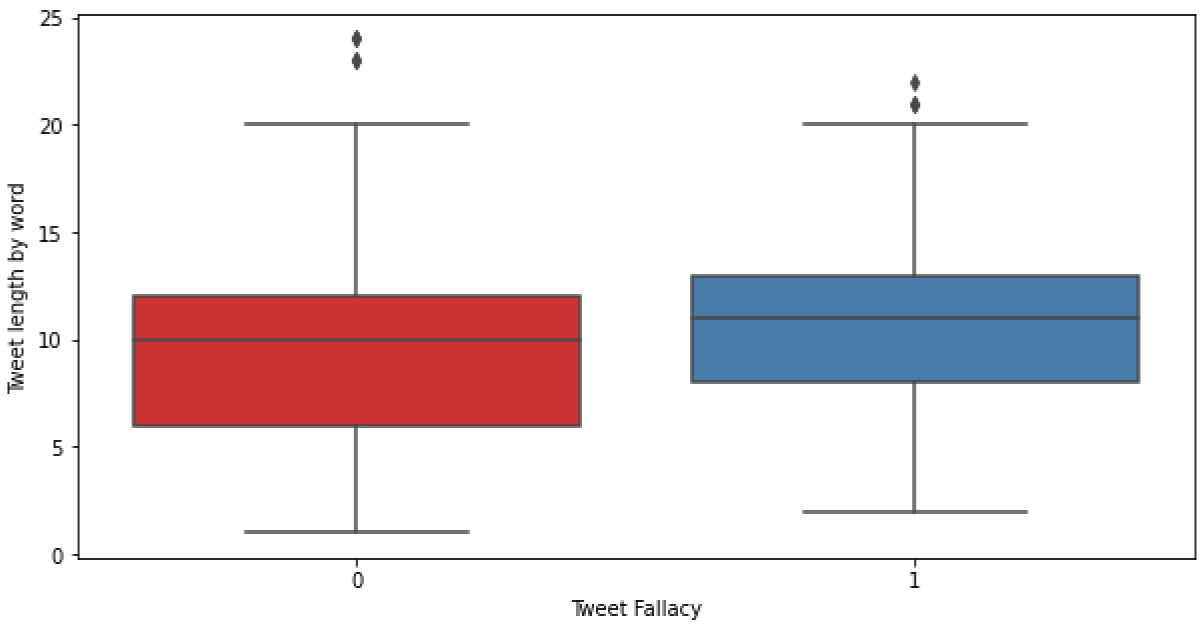
In [20]:
```
#Visualizing class distribution
plt.figure(figsize=(10,5))
sns.countplot(y='target',data = train_data,palette="Paired")
plt.ylabel("Tweet Fallacy")
plt.xlabel("Number of tweets")
plt.show()
```



In [21]:
```
#Visualizing tweet length by characaters
plt.figure(figsize=(10,5))
train_sent = train_data['text'].str.len()
sns.boxplot(x="target",y=train_sent,data=train_data,palette="Set2")
plt.xlabel("Tweet Fallacy")
plt.ylabel("Tweet Length by character")
plt.show()
```

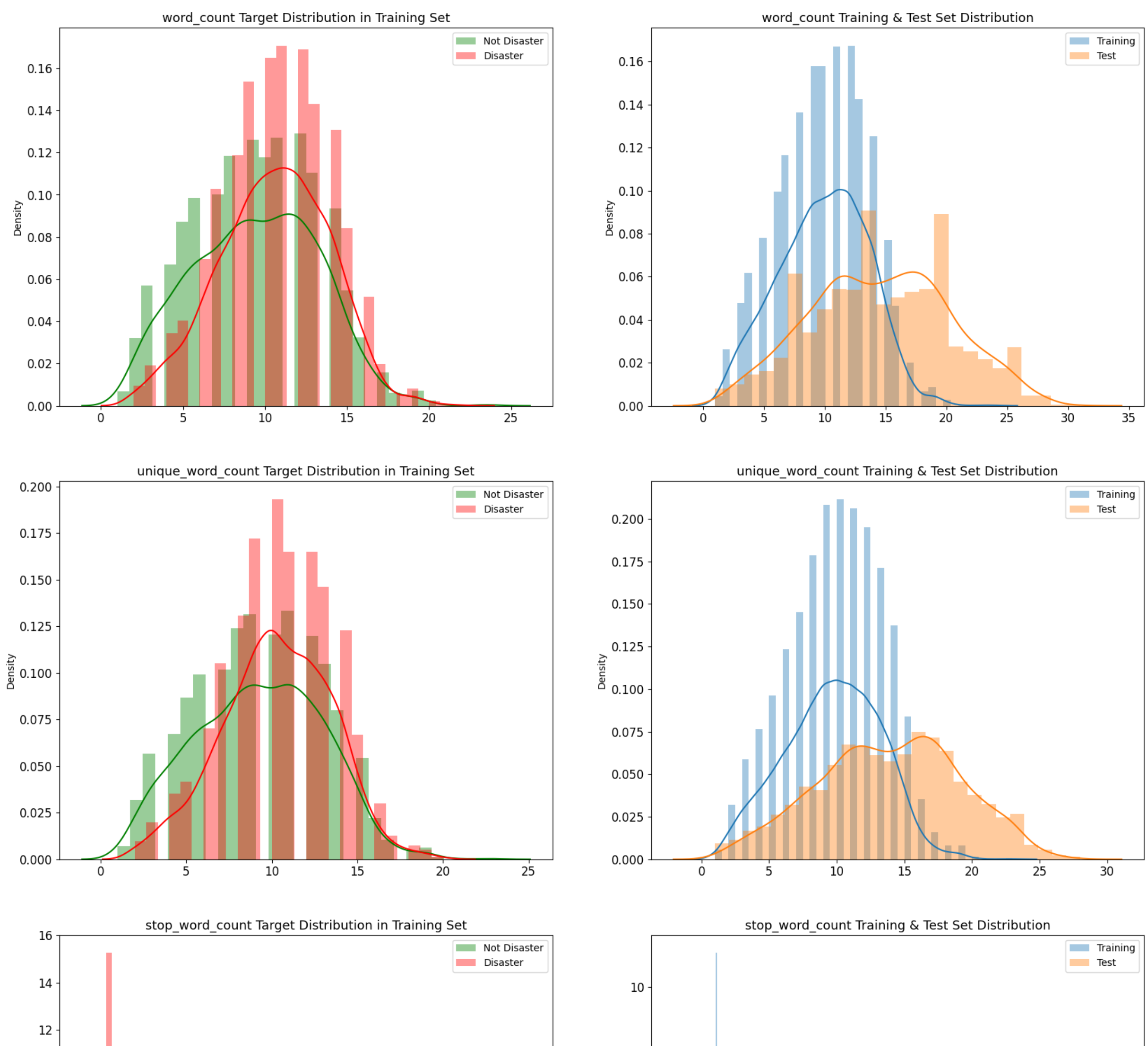


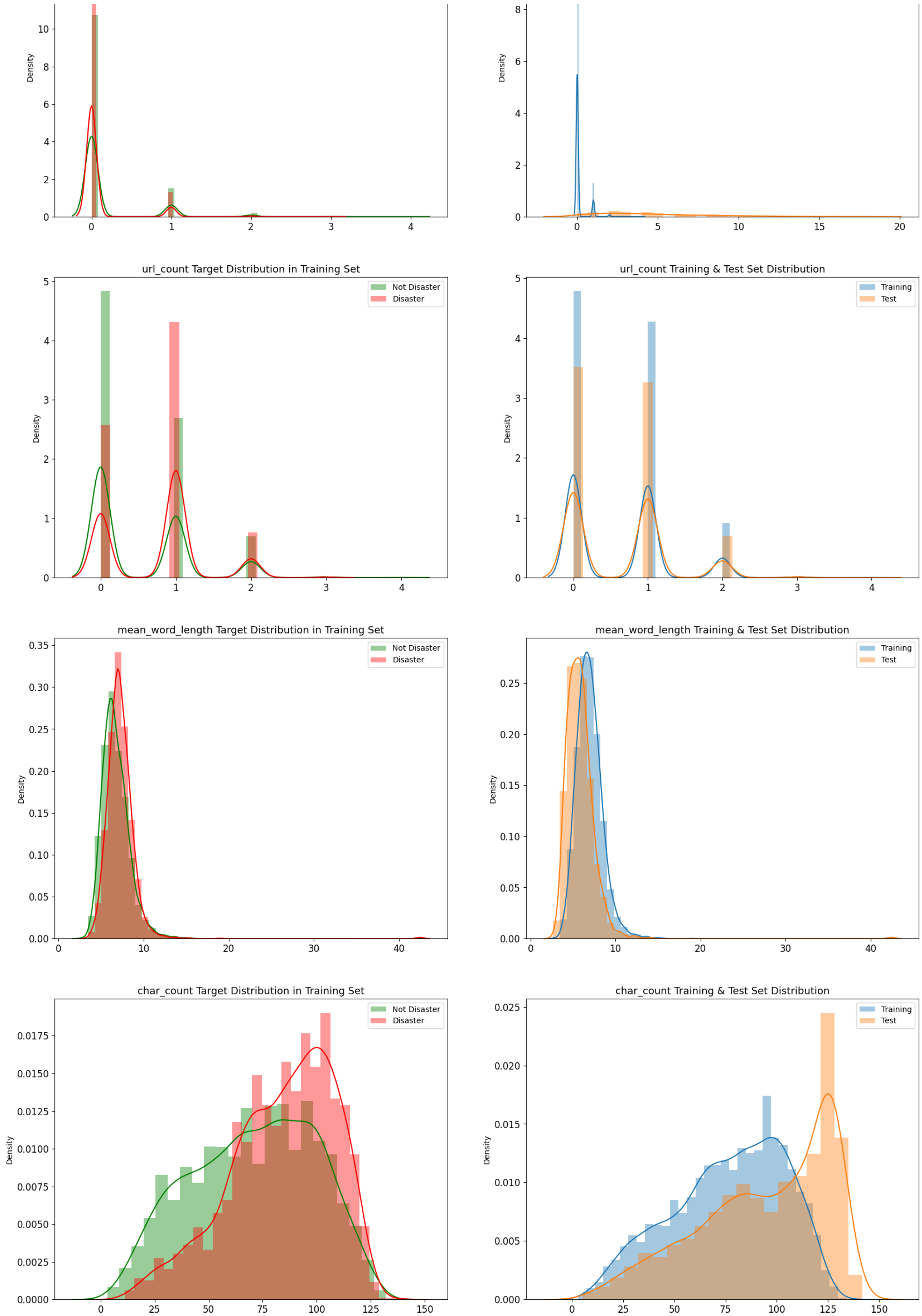
In [22]:
```
#Visualizing tweet length by words
plt.figure(figsize=(10,5))
train_sent = train_data['text'].str.split().map(lambda x : len(x))
sns.boxplot(x="target",y=train_sent,data=train_data,palette="Set1")
plt.xlabel("Tweet Fallacy")
plt.ylabel("Tweet length by word")
plt.show()
```



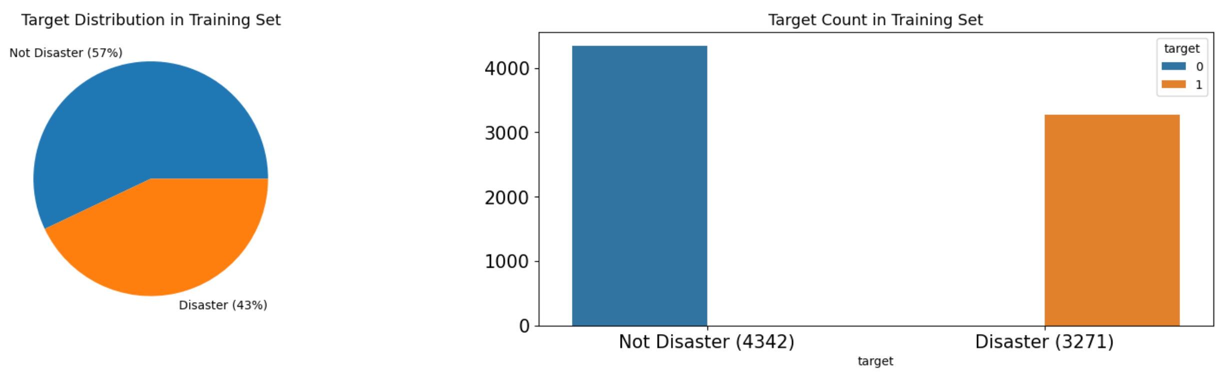
In [23]:
```
# word_count
train_data['word_count'] = train_data['text'].apply(lambda x: len(str(x).split(
test_data['word_count'] = test_data['text'].apply(lambda x: len(str(x).split())

# unique_word_count
train_data['unique_word_count'] = train_data['text'].apply(lambda x: len(set(st
test_data['unique_word_count'] = test_data['text'].apply(lambda x: len(set(str(

# stop_word_count
#Stopwords are the English words which does not add much meaning to a sentence.

train_data['stop_word_count'] = train_data['text'].apply(lambda x: len([w for w
test_data['stop_word_count'] = test_data['text'].apply(lambda x: len([w for w i

# url_count
train_data['url_count'] = train_data['text'].apply(lambda x: len([w for w in st
test_data['url_count'] = test_data['text'].apply(lambda x: len([w for w in str(

# mean_word_length
train_data['mean_word_length'] = train_data['text'].apply(lambda x: np.mean([le
test_data['mean_word_length'] = test_data['text'].apply(lambda x: np.mean([len(

# char_count
train_data['char_count'] = train_data['text'].apply(lambda x: len(str(x)))
test_data['char_count'] = test_data['text'].apply(lambda x: len(str(x)))
```

In [24]:
```python
METAFEATURES = ['word_count', 'unique_word_count', 'stop_word_count', 'url_cour
                'char_count']
DISASTER_TWEETS = train_data['target'] == 1

fig, axes = plt.subplots(ncols=2, nrows=len(METAFEATURES), figsize=(20, 50), dp

for i, feature in enumerate(METAFEATURES):
    sns.distplot(train_data.loc[~DISASTER_TWEETS][feature], label='Not Disaster
    sns.distplot(train_data.loc[DISASTER_TWEETS][feature], label='Disaster', ax

    sns.distplot(train_data[feature], label='Training', ax=axes[i][1])
    sns.distplot(test_data[feature], label='Test', ax=axes[i][1])

    for j in range(2):
        axes[i][j].set_xlabel('')
        axes[i][j].tick_params(axis='x', labelsize=12)
        axes[i][j].tick_params(axis='y', labelsize=12)
        axes[i][j].legend()

    axes[i][0].set_title(f'{feature} Target Distribution in Training Set', font
    axes[i][1].set_title(f'{feature} Training & Test Set Distribution', fontsiz

plt.show()
```




Density
url_count Target Distribution in Training Set
Not Disaster
Disaster
url_count Training & Test Set Distribution
Training
Test
mean_word_length Target Distribution in Training Set
Not Disaster
Disaster
mean_word_length Training & Test Set Distribution
Training
Test
char_count Target Distribution in Training Set
Not Disaster
Disaster
char_count Training & Test Set Distribution
Training
Test

In [25]:
```
fig, axes = plt.subplots(ncols=2, figsize=(17, 4), dpi=100)
plt.tight_layout()

train_data.groupby('target').count()['id'].plot(kind='pie', ax=axes[0], labels=
sns.countplot(x=train_data['target'], hue=train_data['target'], ax=axes[1])

axes[0].set_ylabel('')
axes[1].set_ylabel('')
axes[1].set_xticklabels(['Not Disaster (4342)', 'Disaster (3271)'])
axes[0].tick_params(axis='x', labelsize=15)
axes[0].tick_params(axis='y', labelsize=15)
axes[1].tick_params(axis='x', labelsize=15)
axes[1].tick_params(axis='y', labelsize=15)

axes[0].set_title('Target Distribution in Training Set', fontsize=13)
axes[1].set_title('Target Count in Training Set', fontsize=13)

plt.show()
```



5 LSTM MODEL

In [26]:
```
train_data.head()
```

Out[26]:

	id	text	target	word_count	unique_word_count	stop_word_count	url_count	mean_word
0	1	deeds reason earthquake may allah forgive us	1	7	7	0	0	5
1	4	forest fire near la ronge sask canada	1	7	7	0	0	4
2	5	residents asked shelter place notified officer...	1	11	9	0	0	7
3	6	13000 people receive wildfires evacuation orde...	1	7	7	0	0	7
4	7	got sent photo ruby alaska smoke wildfires pou...	1	9	9	0	0	5

In [27]:
```
train_tweets = train_data['text'].values
train_target = train_data['target'].values
test_tweets = test_data['text'].values
# test_tweets  = test_data['text'].values
# test_target = train_data['target'].values
```

In [28]:
```
# def embed for model
def embed(corpus):
    return word_tokenizer.texts_to_sequences(corpus)
```

In [29]:
```
import nltk
nltk.download('punkt')
from nltk.tokenize import word_tokenize
from keras.preprocessing.sequence import pad_sequences

texts = train_data['text']
target = train_data['target']

word_tokenizer = Tokenizer()
word_tokenizer.fit_on_texts(texts)

longest_train = max(texts, key=lambda sentence: len(word_tokenize(sentence)))
length_long_sentence = len(word_tokenize(longest_train))

train_padded_sentences = pad_sequences(
    embed(texts),
    length_long_sentence,
    padding='post'
)

train_padded_sentences
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\xu663\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

Out[29]:
```
array([[4388,  753,  149, ...,    0,    0,    0],
       [  96,    3,  131, ...,    0,    0,    0],
       [1573, 1445, 1948, ...,    0,    0,    0],
       ...,
       [3191, 4380, 6674, ...,    0,    0,    0],
       [  17,  982, 3026, ...,    0,    0,    0],
       [ 116,  113,  408, ...,    0,    0,    0]])
```

In [30]:
```
# Now we will load embedding vectors of those words that appear in the
# Glove dictionary. Others will be initialized to 0.

word_tokenizer = Tokenizer()
word_tokenizer.fit_on_texts(train_tweets)

vocab_length = len(word_tokenizer.word_index) + 1
embedding_dim = 100
embeddings_dictionary = dict()

embedding_matrix = np.zeros((vocab_length, embedding_dim))

for word, index in word_tokenizer.word_index.items():
    embedding_vector = embeddings_dictionary.get(word)
    if embedding_vector is not None:
        embedding_matrix[index] = embedding_vector
```

In [31]:
```
# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    train_padded_sentences,
    train_target,
    test_size=0.25
)
```

In [32]:

```
from keras.models import Sequential
def glove_lstm():
    model = Sequential()

    model.add(Embedding(
        input_dim=embedding_matrix.shape[0],
        output_dim=embedding_matrix.shape[1],
        weights = [embedding_matrix],
        input_length=length_long_sentence
    ))

    model.add(Bidirectional(LSTM(
        length_long_sentence,
        return_sequences = True,
        recurrent_dropout=0.2
    )))

    model.add(GlobalMaxPool1D())
    model.add(BatchNormalization())
    model.add(Dropout(0.5))
    model.add(Dense(length_long_sentence, activation = "relu"))
    model.add(Dropout(0.5))
    model.add(Dense(length_long_sentence, activation = "relu"))
    model.add(Dropout(0.5))
    model.add(Dense(1, activation = 'sigmoid'))
    model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['ac

    return model

model = glove_lstm()
model.summary()
```

```
WARNING:tensorflow:Layer lstm will not use cuDNN kernels since it doesn't me
et the criteria. It will use a generic GPU kernel as fallback when running o
n GPU.
WARNING:tensorflow:Layer lstm will not use cuDNN kernels since it doesn't me
et the criteria. It will use a generic GPU kernel as fallback when running o
n GPU.
WARNING:tensorflow:Layer lstm will not use cuDNN kernels since it doesn't me
et the criteria. It will use a generic GPU kernel as fallback when running o
n GPU.
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 24, 100)           2273000

 bidirectional (Bidirectiona  (None, 24, 48)           24000
 l)

 global_max_pooling1d (Globa  (None, 48)               0
 lMaxPooling1D)

 batch_normalization (BatchN  (None, 48)               192
 ormalization)
```

```
 dropout (Dropout)           (None, 48)                0

 dense (Dense)               (None, 24)                1176

 dropout_1 (Dropout)         (None, 24)                0

 dense_1 (Dense)             (None, 24)                600

 dropout_2 (Dropout)         (None, 24)                0

 dense_2 (Dense)             (None, 1)                 25

=================================================================
Total params: 2,298,993
Trainable params: 2,298,897
Non-trainable params: 96
_________________________________________________________________
```

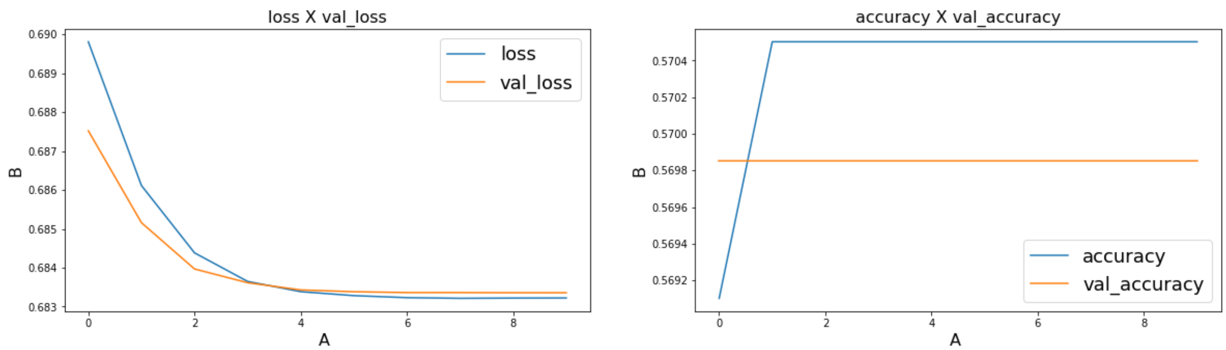
In [33]:
```
# Train the model

model = glove_lstm()

checkpoint = ModelCheckpoint(
    'model.h5',
    monitor = 'val_loss',
    verbose = 1,
    save_best_only = True
)
reduce_lr = ReduceLROnPlateau(
    monitor = 'val_loss',
    factor = 0.2,
    verbose = 1,
    patience = 5,
    min_lr = 0.001
)
history = model.fit(
    X_train,
    y_train,
    epochs = 10,
    batch_size = 32,
    validation_data = (X_test, y_test),
    verbose = 1,
    callbacks = [reduce_lr, checkpoint]
)
```

```
WARNING:tensorflow:Layer lstm_1 will not use cuDNN kernels since it doesn't mee
t the criteria. It will use a generic GPU kernel as fallback when running on GP
U.
WARNING:tensorflow:Layer lstm_1 will not use cuDNN kernels since it doesn't mee
t the criteria. It will use a generic GPU kernel as fallback when running on GP
U.
WARNING:tensorflow:Layer lstm_1 will not use cuDNN kernels since it doesn't mee
t the criteria. It will use a generic GPU kernel as fallback when running on GP
U.
Epoch 1/10
179/179 [==============================] - ETA: 0s - loss: 0.6898 - accuracy:
0.5691
Epoch 00001: val_loss improved from inf to 0.68752, saving model to model.h5
179/179 [==============================] - 28s 140ms/step - loss: 0.6898 - accu
racy: 0.5691 - val_loss: 0.6875 - val_accuracy: 0.5699 - lr: 0.0010
Epoch 2/10
179/179 [==============================] - ETA: 0s - loss: 0.6861 - accuracy:
0.5705
Epoch 00002: val_loss improved from 0.68752 to 0.68516, saving model to model.h
5
179/179 [==============================] - 25s 140ms/step - loss: 0.6861 - accu
racy: 0.5705 - val_loss: 0.6852 - val_accuracy: 0.5699 - lr: 0.0010
Epoch 3/10
179/179 [==============================] - ETA: 0s - loss: 0.6844 - accuracy:
0.5705
Epoch 00003: val_loss improved from 0.68516 to 0.68397, saving model to model.h
5
179/179 [==============================] - 25s 142ms/step - loss: 0.6844 - accu
racy: 0.5705 - val_loss: 0.6840 - val_accuracy: 0.5699 - lr: 0.0010
```

```
Epoch 4/10
179/179 [==============================] - ETA: 0s - loss: 0.6836 - accuracy:
0.5705
Epoch 00004: val_loss improved from 0.68397 to 0.68361, saving model to model.h
5
179/179 [==============================] - 25s 138ms/step - loss: 0.6836 - accu
racy: 0.5705 - val_loss: 0.6836 - val_accuracy: 0.5699 - lr: 0.0010
Epoch 5/10
179/179 [==============================] - ETA: 0s - loss: 0.6834 - accuracy:
0.5705
Epoch 00005: val_loss improved from 0.68361 to 0.68343, saving model to model.h
5
179/179 [==============================] - 25s 138ms/step - loss: 0.6834 - accu
racy: 0.5705 - val_loss: 0.6834 - val_accuracy: 0.5699 - lr: 0.0010
Epoch 6/10
179/179 [==============================] - ETA: 0s - loss: 0.6833 - accuracy:
0.5705
Epoch 00006: val_loss improved from 0.68343 to 0.68338, saving model to model.h
5
179/179 [==============================] - 25s 139ms/step - loss: 0.6833 - accu
racy: 0.5705 - val_loss: 0.6834 - val_accuracy: 0.5699 - lr: 0.0010
Epoch 7/10
179/179 [==============================] - ETA: 0s - loss: 0.6832 - accuracy:
0.5705
Epoch 00007: val_loss improved from 0.68338 to 0.68336, saving model to model.h
5
179/179 [==============================] - 25s 140ms/step - loss: 0.6832 - accu
racy: 0.5705 - val_loss: 0.6834 - val_accuracy: 0.5699 - lr: 0.0010
Epoch 8/10
179/179 [==============================] - ETA: 0s - loss: 0.6832 - accuracy:
0.5705
Epoch 00008: val_loss improved from 0.68336 to 0.68336, saving model to model.h
5
179/179 [==============================] - 25s 140ms/step - loss: 0.6832 - accu
racy: 0.5705 - val_loss: 0.6834 - val_accuracy: 0.5699 - lr: 0.0010
Epoch 9/10
179/179 [==============================] - ETA: 0s - loss: 0.6832 - accuracy:
0.5705
Epoch 00009: val_loss improved from 0.68336 to 0.68336, saving model to model.h
5
179/179 [==============================] - 25s 140ms/step - loss: 0.6832 - accu
racy: 0.5705 - val_loss: 0.6834 - val_accuracy: 0.5699 - lr: 0.0010
Epoch 10/10
179/179 [==============================] - ETA: 0s - loss: 0.6832 - accuracy:
0.5705
Epoch 00010: val_loss improved from 0.68336 to 0.68336, saving model to model.h
5
179/179 [==============================] - 25s 137ms/step - loss: 0.6832 - accu
racy: 0.5705 - val_loss: 0.6834 - val_accuracy: 0.5699 - lr: 0.0010
```

In [34]:
```
def plot_learning_curves(history, arr):
    fig, ax = plt.subplots(1, 2, figsize=(20, 5))
    for idx in range(2):
        ax[idx].plot(history.history[arr[idx][0]])
        ax[idx].plot(history.history[arr[idx][1]])
        ax[idx].legend([arr[idx][0], arr[idx][1]],fontsize=18)
        ax[idx].set_xlabel('A ',fontsize=16)
        ax[idx].set_ylabel('B',fontsize=16)
        ax[idx].set_title(arr[idx][0] + ' X ' + arr[idx][1],fontsize=16)
```

In [35]:
```
plot_learning_curves(history, [['loss', 'val_loss'],['accuracy', 'val_accuracy'
```



In [36]:
```
# visual_accuracy_and_loss(history)
```

In [37]:
```
yhat = (model.predict(X_test) > 0.5).astype("int32")
acc=[]
f1=[]
recall=[]
precision=[]
score_accuracy = accuracy_score(y_test, yhat)
score_f1 = f1_score(y_test, yhat)
score_recall = recall_score(y_test, yhat)
score_precision = precision_score(y_test, yhat)
acc.append(score_accuracy)
f1.append(score_f1)
# f1_score(y_test, yhat)
# lstm_score=metrics.accuracy_score(y_test, yhat)
print("LSTM's Accuracy:{0}".format(metrics.accuracy_score(y_test, yhat)))
print("LSTM's f1_score:{0}".format(metrics.f1_score(y_test, yhat)))
print("LSTM's recall:{0}".format(metrics.recall_score(y_test, yhat)))
print("LSTM's precision:{0}".format(metrics.precision_score(y_test, yhat)))
```

```
LSTM's Accuracy:0.5698529411764706
LSTM's f1_score:0.0
LSTM's recall:0.0
LSTM's precision:0.0
```

6 BERT MODEL

BERT - Bidirectional Encoder Representations from Transformers

LOADING BERT MODEL

In [38]:
```
tokenizer = AutoTokenizer.from_pretrained('bert-large-uncased')
bert = TFBertModel.from_pretrained('bert-large-uncased')
```

```
Some layers from the model checkpoint at bert-large-uncased were not used when
initializing TFBertModel: ['mlm___cls', 'nsp___cls']
- This IS expected if you are initializing TFBertModel from the checkpoint of a
model trained on another task or with another architecture (e.g. initializing a
BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing TFBertModel from the checkpoint
of a model that you expect to be exactly identical (initializing a BertForSeque
nceClassification model from a BertForSequenceClassification model).
All the layers of TFBertModel were initialized from the model checkpoint at ber
t-large-uncased.
If your task is similar to the task the model of the checkpoint was trained on,
you can already use TFBertModel for predictions without further training.
```

In [39]:
```
tokenizer('onl01-dtsc-pt-062821')
```

Out[39]:
```
{'input_ids': [101, 2006, 2140, 24096, 1011, 26718, 11020, 1011, 13866, 1011, 5
757, 22407, 17465, 102], 'token_type_ids': [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0], 'attention_mask': [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]}
```

In [40]:
```
print("max len of tweets",max([len(x.split()) for x in train_data.text]))
max_length = 36
```

```
max len of tweets 24
```

In [41]:
```
x_train = tokenizer(
    text=train_data.text.tolist(),
    add_special_tokens=True,
    max_length=36,
    truncation=True,
    padding=True,
    return_tensors='tf',
    return_token_type_ids = False,
    return_attention_mask = True,
    verbose = True)
```

In [42]:
```
y_train = train_data.target.values
```

In [43]:
```
train_data.target.value_counts()
```

Out[43]:
```
0    4342
1    3271
Name: target, dtype: int64
```

Import data in model

In [44]:
```
input_ids = Input(shape=(max_len,), dtype=tf.int32, name="input_ids")
input_mask = Input(shape=(max_len,), dtype=tf.int32, name="attention_mask")
# embeddings = dbert_model(input_ids,attention_mask = input_mask)[0]


embeddings = bert(input_ids,attention_mask = input_mask)[1] #(0 is the last hid
# out = tf.keras.layers.GlobalMaxPool1D()(embeddings)
out = tf.keras.layers.Dropout(0.1)(embeddings)

out = Dense(128, activation='relu')(out)
out = tf.keras.layers.Dropout(0.1)(out)
out = Dense(32,activation = 'relu')(out)

y = Dense(1,activation = 'sigmoid')(out)

model = tf.keras.Model(inputs=[input_ids, input_mask], outputs=y)
model.layers[2].trainable = True

# for training bert our lr must be so small
```

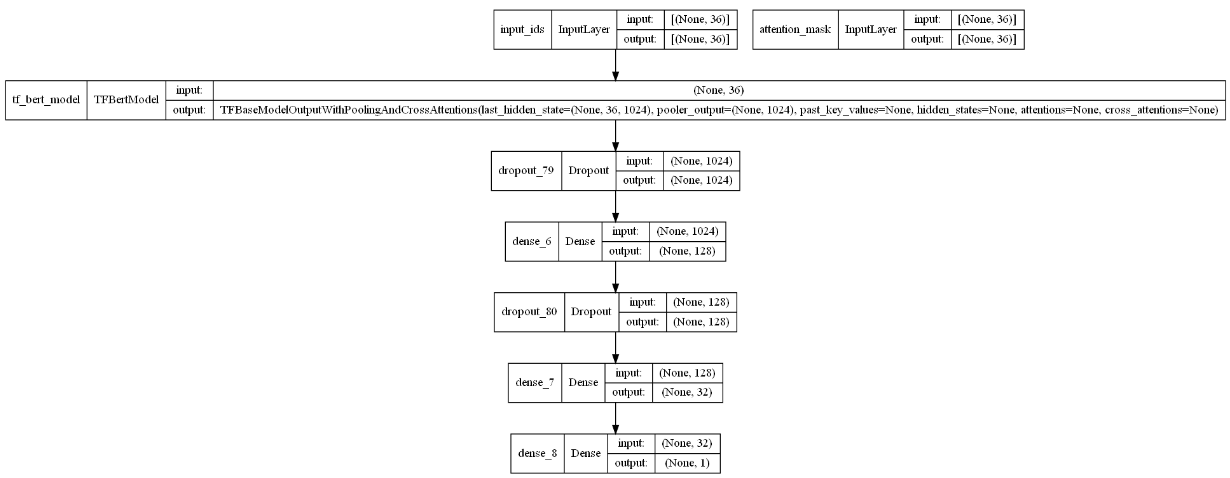
In [45]:
```
model.summary()
```

```
Model: "model"
________________________________________________________________________________
___________________
 Layer (type)                   Output Shape         Param #     Connected to
================================================================================
===================
 input_ids (InputLayer)         [(None, 36)]         0           []

 attention_mask (InputLayer)    [(None, 36)]         0           []

 tf_bert_model (TFBertModel)    TFBaseModelOutputWi  335141888   ['input_ids[0]
[0]',
                                thPoolingAndCrossAt               'attention_ma
sk[0][0]']
                                tentions(last_hidde
                                n_state=(None, 36,
                                1024),
                                 pooler_output=(Non
                                e, 1024),
                                 past_key_values=No
                                ne, hidden_states=N
                                one, attentions=Non
                                e, cross_attentions
                                =None)

 dropout_79 (Dropout)           (None, 1024)         0           ['tf_bert_mode
l[0][1]']

 dense_6 (Dense)                (None, 128)          131200      ['dropout_79
[0][0]']

 dropout_80 (Dropout)           (None, 128)          0           ['dense_6[0]
[0]']

 dense_7 (Dense)                (None, 32)           4128        ['dropout_80
[0][0]']

 dense_8 (Dense)                (None, 1)            33          ['dense_7[0]
[0]']

================================================================================
===================
Total params: 335,277,249
Trainable params: 335,277,249
Non-trainable params: 0
________________________________________________________________________________
___________________
```

In [46]:
```
optimizer = Adam(
    learning_rate=6e-06, # this learning rate is for bert model.
    epsilon=1e-08,
    decay=0.01,
    clipnorm=1.0)

# Set loss and metrics
loss = BinaryCrossentropy(from_logits = True)
metric = BinaryAccuracy('accuracy'),
# Compile the model
model.compile(
    optimizer = optimizer,
    loss = loss,
    metrics = metric)
```

In [47]:
```
plot_model(model, show_shapes = True)
```

Out[47]:



6.1 Fit the model

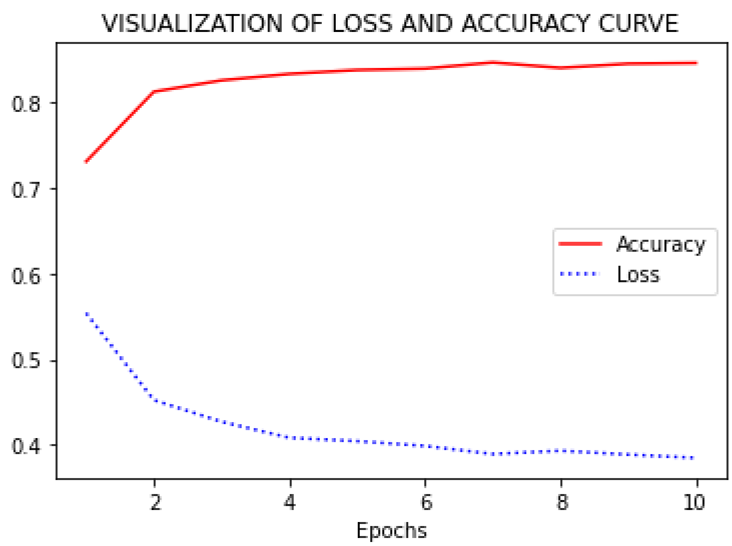
In [48]:
```
# Fit the model
final = model.fit(
    x ={'input_ids':x_train['input_ids'],'attention_mask':x_train['attention_ma
    y = y_train,
    validation_split=0.2,
#     epochs=1,
    epochs=10,
    batch_size=10
)
```

```
Epoch 1/10
609/609 [==============================] - 96s 134ms/step - loss: 0.5541 - accu
racy: 0.7312 - val_loss: 0.4566 - val_accuracy: 0.8122
Epoch 2/10
609/609 [==============================] - 80s 131ms/step - loss: 0.4522 - accu
racy: 0.8130 - val_loss: 0.4395 - val_accuracy: 0.8175
Epoch 3/10
609/609 [==============================] - 80s 132ms/step - loss: 0.4268 - accu
racy: 0.8263 - val_loss: 0.4300 - val_accuracy: 0.8221
Epoch 4/10
609/609 [==============================] - 80s 132ms/step - loss: 0.4080 - accu
racy: 0.8338 - val_loss: 0.4372 - val_accuracy: 0.8168
Epoch 5/10
609/609 [==============================] - 81s 133ms/step - loss: 0.4040 - accu
racy: 0.8384 - val_loss: 0.4337 - val_accuracy: 0.8181
Epoch 6/10
609/609 [==============================] - 80s 132ms/step - loss: 0.3984 - accu
racy: 0.8401 - val_loss: 0.4348 - val_accuracy: 0.8188
Epoch 7/10
609/609 [==============================] - 80s 131ms/step - loss: 0.3889 - accu
racy: 0.8473 - val_loss: 0.4313 - val_accuracy: 0.8253
Epoch 8/10
609/609 [==============================] - 81s 133ms/step - loss: 0.3928 - accu
racy: 0.8409 - val_loss: 0.4332 - val_accuracy: 0.8227
Epoch 9/10
609/609 [==============================] - 81s 134ms/step - loss: 0.3883 - accu
racy: 0.8458 - val_loss: 0.4368 - val_accuracy: 0.8188
Epoch 10/10
609/609 [==============================] - 79s 130ms/step - loss: 0.3844 - accu
racy: 0.8466 - val_loss: 0.4350 - val_accuracy: 0.8214
```

This is running results showing below: Epoch 1/9 762/762 [==============================] - 127s 139ms/step - loss: 0.5276 - accuracy: 0.7609 Epoch 2/9 762/762 [==============================] - 106s 139ms/step - loss: 0.4376 - accuracy: 0.8223 Epoch 3/9 762/762 [==============================] - 107s 141ms/step - loss: 0.4161 - accuracy: 0.8290 Epoch 4/9 762/762 [==============================] - 107s 141ms/step - loss: 0.4069 - accuracy: 0.8337 Epoch 5/9 762/762 [==============================] - 109s 144ms/step - loss: 0.3987 - accuracy: 0.8373 Epoch 6/9 762/762 [==============================] - 106s 140ms/step - loss: 0.3891 - accuracy: 0.8430 Epoch 7/9 762/762 [==============================] - 107s 140ms/step - loss: 0.3884 - accuracy: 0.8403 Epoch 8/9 762/762 [==============================] - 107s 140ms/step - loss: 0.3898 - accuracy: 0.8463 Epoch 9/9 762/762 [==============================] - 108s 142ms/step - loss: 0.3789 - accuracy: 0.8518

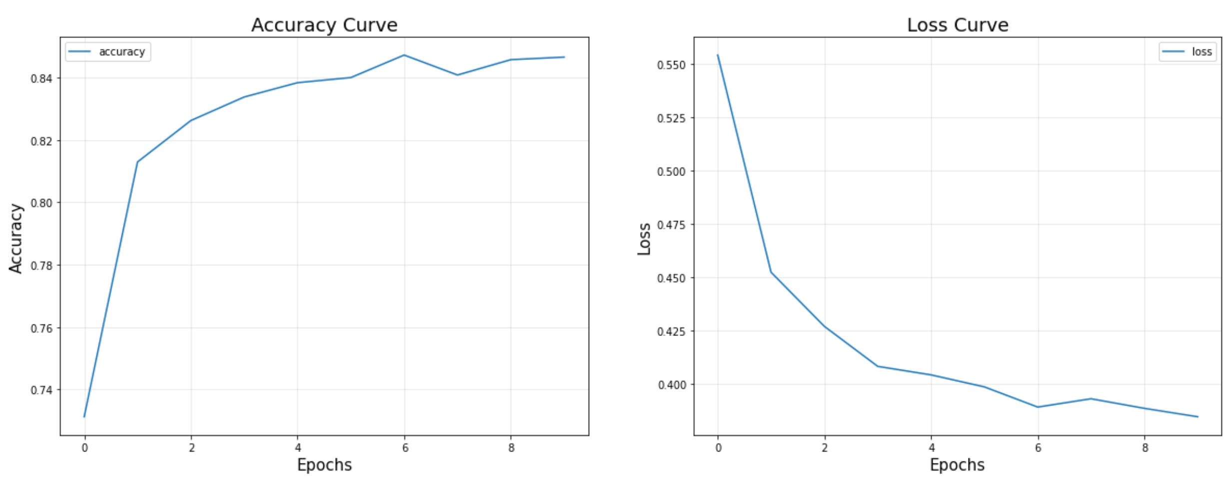
In [50]:
```
def visual_accuracy_and_loss(final):
    acc = final.history['accuracy']
    loss = final.history['loss']
    epochs_plot = np.arange(1, len(loss) + 1)
    plt.clf()
    plt.plot(epochs_plot, acc, 'r', label='Accuracy')
    plt.plot(epochs_plot, loss, 'b:', label='Loss')
    plt.title('VISUALIZATION OF LOSS AND ACCURACY CURVE')
    plt.xlabel('Epochs')
    plt.legend()
    plt.show()
```

In [51]:
```
visual_accuracy_and_loss(final)
```



6.2 Plot the loss and accuracy curves

In [52]:
```
# Plot the loss and accuracy curves

#Diffining Figure
f = plt.figure(figsize=(20,7))

#Adding Subplot 1 (For Accuracy)
f.add_subplot(121)

plt.plot(final.epoch,final.history['accuracy'],label = "accuracy") # Accuracy c


plt.title("Accuracy Curve",fontsize=18)
plt.xlabel("Epochs",fontsize=15)
plt.ylabel("Accuracy",fontsize=15)
plt.grid(alpha=0.3)
plt.legend()

#Adding Subplot 1 (For Loss)
f.add_subplot(122)

plt.plot(final.epoch,final.history['loss'],label="loss") # Loss curve


plt.title("Loss Curve",fontsize=18)
plt.xlabel("Epochs",fontsize=15)
plt.ylabel("Loss",fontsize=15)
plt.grid(alpha=0.3)
plt.legend()

plt.show()
```



7 Conclusion

After analysis, my team believe this BERT is suitable for NLP on Twitter. And accuracy can be improved to 0.85 through iteration.

We come into conclusion as below：

Bert generate better accuracy results compared to LSTM with same iteration times, even though Bert cost more calculation time.

By using our model, we successfully help tracing the emergency event by NLP.

In order to increasing accuracy, we can adding more balanced features like time, location, and etc.

8 Future work

1. With more time, I would like to dig into relationship between NLP models and make a clear comparison.
2. For other media content, we can try to fit the model and find results as well.
3. I want to see if we can add image processing to capture the emergency.