vitz_john_finaltermproj

Name: John Vitz

UCID: jhv6

Email Address: jhv6@njit.edu

Class: CS 634-101

Professor: Yasser Abdullah

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1. Final Project - Data Mining

Github Repository Link:

https://github.com/VitzJ/CS634-Data-Mining-Final-Project The dataset for this project is comprised of questions from the website https://www.quora.com/. Quora is an internet forum that allows users to ask and answer each other's questions. In 2019, the website submitted a dataset comprised of 1.3+ million unique different questions along with an attached target label to a kaggle competition with the goal of leveraging the power of the kaggle community to come up with machine learning and natural language processing solutions to the following problem: **How can we tell whether or not a question is sincere?**

For this project, I utilized 3 different machine learning algorithms in order to perform basic binary classification.

- a. Random Forest (Required)
- a. Bi-Directional LSTM (Additional Option: Deep Learning)
- a. Naive Bayes (Additional Option: Algorithms)

I also included a Logistic Regression model for comparison. The goal of utilizing these models was to examine various classification task metrics across models utilizing 10 fold cross validation in order to learn about their implementation as well as how to interpret them in the context of machine learning models.

The zip file folder **readme.txt** / the github **readme.md** contain a detailed tutorial on how to run the python source file **vitz_john_finaltermproj.py** in the command prompt terminal.

1.1 Data Source, Data Description, Data Loading, and Imports

Data Source: https://www.kaggle.com/c/quora-insincere-questions-classification/data

Important Data Pre-Processing Information:

The data was extremely large, so I was forced to cut the size down very substantially. I cut it down to a small subset utilizing the following code:

```
train = pd.read_csv('/content/train.csv')

# I want to get rid of questions that are below a choice groups of
characters long
# because I don't think they will be valuable for training models, I
want the
# limited data to contain at least 5 groups of characters.
min_chars = 5

num_train = 2500 # 2500 train values
num_test = int(num_train * 0.1) # 250 total test values

pos_neg_split = 0.5 # 50/50 class split

pos_train = int(num_train * pos_neg_split)
neg_train = num_train - pos_train

pos_test = int(num_test * pos_neg_split)
neg_test = num_test - pos_test

train['length'] = (train['question_text'].str.split().str.len())
train = train[train['length'] >= min_chars].copy()

test = pd.concat([train[train['target'] == 0][pos_train: pos_train +
pos_test].copy(),
                  train[train['target'] == 1][neg_train: neg_train +
neg_test].copy()],
                  axis=0)

train = pd.concat([train[train['target'] == 0][:pos_train].copy(),
                   train[train['target'] == 1][:neg_train].copy()],
                   axis=0)

train.to_csv(f'vitz_john_finaltermproj_train_set.csv', index=False)
test.to_csv(f'vitz_john_finaltermproj_test_set.csv', index=False)

train = pd.read_csv(f'vitz_john_finaltermproj_train_set.csv')
test = pd.read_csv(f'vitz_john_finaltermproj_test_set.csv')
```

The train.csv file from the previously mentioned source: https://www.kaggle.com/c/quora-insincere-questions-classification/data?select=train.csv

The data is filtered based on class membership, and then the number of training and testing points are selected from the subset. This is done in order to assure that the new subset will have balanced class membership.

Data Class and Fields Description

Dataset Overview

- **Number of questions in train:** 2500
- **Number of questions in test:** 250 (10% of amount of questions in the train data)

Target Values

There are two possible values for the `target` field:

- **0**: Indicates that the given question **is not** insincere.
- **1**: Indicates that the given question **is** insincere.

Data Fields

- **qid**: Unique question identifier
- **question_text**: Quora question text
- **target**: A question labeled "insincere" has a value of 1, otherwise 0

Required Imports

Package Name	Package Version	Website
pandas	2.2.2	https://pandas.pydata.org/
numpy	1.26.4	https://numpy.org/
matplotlib	3.8.0	https://matplotlib.org/
scikit-learn	1.5.2	https://scikit-learn.org/stable/
torch	2.5.1	https://pytorch.org/
nltk	3.9.1	https://www.nltk.org/

```python
# data structures/display methods imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import KFold
from sklearn.feature_extraction.text import TfidfVectorizer

# model imports
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import MultinomialNB
```

```
# neural network model imports
import torch
import torch.nn as nn
import torch.autograd as autograd
import torch.optim as optim
import torch.nn.functional as F

# metrics imports
from sklearn.metrics import roc_auc_score, roc_curve
from sklearn.metrics import auc

# string methods imports
import nltk # https://www.nltk.org/data.html
nltk.download('stopwords')
from nltk.corpus import stopwords
import re # regular expressions library builtin
import string # string library builtin
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

```
train = pd.read_csv(f'vitz_john_finaltermproj_train_set.csv')
test = pd.read_csv(f'vitz_john_finaltermproj_test_set.csv')
```

```
train.head()
```


```
{"summary":"{\n  \"name\": \"train\",\n  \"rows\": 2500,\n
\"fields\": [\n    {\n      \"column\": \"qid\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 2500,\n        \"samples\": [\n
\"0098e5b8335a62791abf\",\n          \"003ae8ef6c2b869b9a0c\",\n
\"00382fbffbeb071469ce\"\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"question_text\",\n      \"properties\": {\n
\"dtype\": \"string\",\n        \"num_unique_values\": 2500,\n
\"samples\": [\n          \"Is Dr. Steven Greer an extremely good
fraudster with his claims of ufo' s and aliens?\",\n          \"Where
in Abu Dhabi can I get all electronic components like resistors,
transistors, breadboards, etc.?\",\n          \"Has Nintendo ever made
a game in which Pauline from Donkey Kong meets Princess Peach?\"\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"target\",\n      \"properties\":
{\n        \"dtype\": \"number\",\n        \"std\": 0,\n
\"min\": 0,\n        \"max\": 1,\n        \"num_unique_values\": 2,\n
\"samples\": [\n          1,\n          0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"length\",\n      \"properties\":
{\n        \"dtype\": \"number\",\n        \"std\": 8,\n
\"min\": 5,\n        \"max\": 51,\n        \"num_unique_values\": 47,\
```

```
n        \"samples\": [\n          24,\n          49\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    }\n  ]\n}","type":"dataframe","variable_name":"train"}
```



```
grouped_lengths = train.groupby('target')['length'].agg(['count',
'min', 'max', 'median', 'mean', 'std'])
print(f'\nA comparison of the train set length of character groups
before cleaning: \n')
print(grouped_lengths, '\n')
```

```
A comparison of the train set length of character groups before
cleaning:

        count  min  max  median     mean       std
target
0        1250    5   50    11.0  12.6632  6.758514
1        1250    5   51    15.0  17.3864  9.341933
```

1.2 Data Handling and Cleaning Information

I utilized multiple techniques such as lowercasing, removing particular components of text, removing links, punctuation, and removing words containing numbers. I also removed stopwords through nltk and utilized a technique call stemming on the data. I applied both of these processes to the train set and the test set while maintaining their independence from each other. This was done with the purpose of standardizing the text to allow for more concentration into the vectorization.

```
# Special thanks to https://www.kaggle.com/tanulsingh077 for this
function

def clean_text(text):
    '''Make text lowercase, remove text in square brackets,remove
links,remove punctuation
    and remove words containing numbers.'''

    text = str(text).lower()
    text = re.sub('\[.*?\]', '', text)
    text = re.sub('https?://\S+|www\.\S+', '', text)
    text = re.sub('<.*?>+', '', text)
    text = re.sub('[%s]' % re.escape(string.punctuation), '', text)
    text = re.sub('\n', '', text)
    text = re.sub('\w*\d\w*', '', text)

    return text
```

Removal of Stopwords

Can try with and without. In an effort to reduce computational requirements for this project, I will try removing stopwords.

```
stop_words = list(set(stopwords.words('english'))) # uses nltk
#print(stop_words)

def remove_stopwords(text):
  text = ' '.join(word for word in text.split(' ') if word not in
stop_words)
  return text
```

Stemming

Stemming - chopping off the ends of words in hopes to remove derivational affixes, such as trying to get words like 'adjustably' and 'adjustable' to be recognized under the same umbrella 'adjust' which is the root word by removing terms such as 'ably' and 'able' from the word.

```
stemmer = nltk.SnowballStemmer("english")

def stemm_text(text):
    text = ' '.join(stemmer.stem(word) for word in text.split(' '))
    return text
```

Clean Punctuation, Remove Stopwords, and Stemm all words in the data.

```
def preprocess_data(text):
  # Clean puntuation, urls, and so on
  text = clean_text(text)
  # Remove stopwords
  text = ' '.join(word for word in text.split(' ') if word not in
stop_words)
  # Stemm all the words in the sentence
  text = ' '.join(stemmer.stem(word) for word in text.split(' '))

  return text

# Apply the cleaning to the train set
train['question_text'] = train['question_text'].apply(preprocess_data)

# Apply the same cleaning to the test set (without looking at it in
any way)
test['question_text'] = test['question_text'].apply(preprocess_data)

train['new_length'] = (train['question_text'].str.split().str.len())
grouped_newlengths = train.groupby('target')
['new_length'].agg(['count', 'min', 'max', 'median', 'mean', 'std'])
```

```
print(f'\nA comparison of the length of character groups after
cleaning: \n')
print(grouped_newlengths, '\n')
avg_words_removed = sum(train['length'] - train['new_length']) /
train.shape[0]
print(f'\nAverage number of words removed after cleaning:
{avg_words_removed}\n\n')
```

```
A comparison of the length of character groups after cleaning:
```

	count	min	max	median	mean	std
target						
0	1250	1	26	5.0	6.2712	3.393474
1	1250	2	27	8.0	9.0912	4.863189

```
Average number of words removed after cleaning: 7.3436
```

1.3 Data Loading and Metrics Helper Functions

I utilize sklearn KFold to generate a 10 fold split for 10 fold cross validation. I also declare a few helper functions.

K-Fold Cross Validation Splits

I have to make sure that when I use vectorizors / train models, I don't use the test fold to train the model, so I have to cut out the test data seperately each time.

```
X_train = train['question_text'].values
y_train = train['target'].values

X_test = test['question_text'].values
y_test = test['target'].values

K_fold_CV = KFold(n_splits=10, shuffle=True, random_state=42)
K_fold_CV.get_n_splits(X_train)
```

```
10
```

Helper Functions

Get Metrics For Models

The **get_metrics()** function processes y_test (groud truth vector), prediction (model prediction vector), prediction probabilities (model prediction probabilities vector), and nn_bool (boolean to handle neural network inputs). It returns a labeled pandas dataframe consisting of the various metrics computed through the function.

```
# Metrics from
https://njit.instructure.com/courses/42753/files/6730397?
module_item_id=1417132

def get_metrics(y_test, prediction, prediction_probabilities,
nn_bool=False):

  # TP: actual is 1, predicted is 1
  TP = sum(((np.array(y_test) == 1) & (np.array(prediction) == 1)) &
(np.array(y_test) == 1)) # True Positives

  # TN: actual is 0, predicted is 0
  TN = sum(((np.array(y_test) == 0) & (np.array(prediction) == 0)) &
(np.array(y_test) == 0)) # True Negatives

  # FP: actual is 0, predicted is 1, type II error
  FP = sum(((np.array(y_test) == 0) & (np.array(prediction) == 1)) &
(np.array(y_test) == 0)) # False Positives

  # FN: actual is 1, predicted is 0, type I error
  FN = sum(((np.array(y_test) == 1) & (np.array(prediction) == 0)) &
(np.array(y_test) == 1)) # False Negatives

  # Handle division by zero with 0 as default value

  TPR = 0 if (TP + FN) == 0 else TP / (TP + FN)  # True Positive Rate
| Recall / Sensitivity

  TNR = 0 if (TN + FP) == 0 else TN / (TN + FP)  # True Negative Rate
| Specificity

  FPR = 0 if (TN + FP) == 0 else FP / (TN + FP)  # False Positive Rate

  FNR = 0 if (TP + FN) == 0 else FN / (TP + FN)  # False Negative Rate

  Precision = 0 if (TP + FP) == 0 else TP / (TP + FP)  # Precision

  F1_measure = 0 if (((2 * TP) + FP + FN) == 0) else (2 * TP) / ((2 *
TP) + FP + FN)  # F1 Measure

  Accuracy = 0 if (TP + FP + TN + FN) == 0 else (TP + TN) / (TP + FP +
TN + FN)  # Accuracy

  Error_rate = 0 if (TP + FP + TN + FN) == 0 else (FP + FN) / (TP + FP
+ TN + FN)  # Error rate

  BACC = (TPR + TNR) / 2 # Balanced Accuracy

  TSS = TPR - FPR # True Skill Statistics

  HSS = (2 * ((TP * TN) - (FP * FN))) / (((TP + FN) * (FN + TN)) +
```

```
((TP + FP) * (FP + TN))) # Heidke Skill Score

  if nn_bool:
    ### FOR LSTM ###
    # The values are all close to 0.5, which means that the model has 
likely not actually learned anything
    # from the data and is just adding in random noise for the 
predictions. Our classes are balanced for the chopped
    # data, so the naive prediction from BS_Naive is actually equal to 
the class proportions (50% 0, 50% 1). What this
    # means is that when comparing in BSS we get close to 1 because 
our model's output is very close to being Naive
    # this basically means the model isn't really learning much if at 
all.

    # Brier_Score = MSE between expected probabilities and predicted 
probabilities
    BS = (1 / y_test.shape[0]) * torch.sum(((y_test - 
prediction_probabilities) ** 2)) # (1 / N) * sum((y_test - 
prediction_probabilities) ** 2)
    BS = BS.item()

    # Brier Skill Score = likelihood of an event to happen or BS / BS 
(Naive) where BS (Naive)
    # uses the average probability of class membership instead of 
prediction_probabilities
    BS_Naive = ((1 / y_test.shape[0])) * torch.sum((y_test - 
(torch.sum(y_test) / y_test.shape[0])) ** 2) # (1 / N) * (sum(y_test - 
mean(y_test) ** 2))
    BS_Naive = BS_Naive.item()

  else:
    # Brier_Score = MSE between expected probabilities and predicted 
probabilities
    BS = (1 / len(y_test)) * sum(((y_test - prediction_probabilities) 
** 2)) # (1 / N) * sum((y_test - prediction_probabilities) ** 2)

    # Brier Skill Score = likelihood of an event to happen or BS / BS 
(Naive) where BS (Naive)
    # uses the average probability of class membership instead of 
prediction_probabilities
    BS_Naive = ((1 / len(y_test))) * sum((y_test - (sum(y_test) / 
len(y_test))) ** 2) # (1 / N) * (sum(y_test - mean(y_test) ** 2))

  BSS = BS / BS_Naive

  NPV = 0 if (TN + FN) == 0 else TN / (TN + FN) # Negative Predictive 
Value

  FDR = 0 if (FP + TP) == 0 else FP / (FP + TP) # False Discovery Rate
```

```
  ROC_AUC_SCORE = roc_auc_score(y_test, prediction_probabilities)

  final_metrics = [TP, TN, FP, FN, TPR, TNR, FPR, FNR,
                   Precision, F1_measure, Accuracy, Error_rate,
                   BACC, TSS, HSS, BS, BSS, NPV, FDR, ROC_AUC_SCORE]

  final_metrics_labels = ['TP', 'TN', 'FP', 'FN', 'TPR', 'TNR', 'FPR',
'FNR',
                          'Precision', 'F1_measure', 'Accuracy',
'Error_rate',
                          'BACC', 'TSS', 'HSS', 'BS', 'BSS', 'NPV',
'FDR',
                          'ROC_AUC_SCORE']

  return pd.DataFrame(data=final_metrics, index=final_metrics_labels)
```

Metrics Per Iteration and Average Metrics

The function **metrics_per_iteration** reshapes the metrics stored in the pandas dataframes from **get_metrics()** into a format that arranges the metrics by model and then by fold.

```
def metrics_per_iteration(input_metrics, num_folds=10, verbose=True):
  #iterations = list(range(num_folds))
  columns = input_metrics[0].columns.to_list()

  new_dfs = []

  for model_col in columns:

    temp_df = pd.DataFrame()

    for k in range(num_folds):
      #print(input_metrics[k])
      temp_df[f'Fold{k + 1}'] = input_metrics[k][model_col]

    new_dfs.append(temp_df)

    if verbose:
      print(f'Metrics for {model_col}:')
      print(new_dfs[-1], '\n')

  return new_dfs
```

The function **average_metrics** simply returns the metrics for each model averaged across all of the folds.

```
def average_metrics(input_metrics, num_folds=10):
  avg_metrics = sum(input_metrics) / num_folds
  print('Average Metrics by Model')
```

```
    print(avg_metrics)
    return avg_metrics
```

1.4 Machine Learning Algorithms

For this project, I utilized 3 different machine learning algorithms in order to perform basic binary classification.

- a. Random Forest (Required)
- a. Bi-Directional LSTM (Additional Option: Deep Learning)
- a. Naive Bayes (Additional Option: Algorithms)

I also included a Logistic Regression model for comparison.

```
from sklearn.naive_bayes import MultinomialNB
```

Bi-Directional LSTM using pytorch

In this section, I construct a Bi-Directional LSTM using pytorch. The input is expanded tf-idf vectors. The model itself is extremely simple, because the training time is very long as is, and as I will explain in the final section, the input doesn't exactly return desireable results.

```
# Define a Bi-directional LSTM model for classification
class BiLSTMModel(nn.Module):

    def __init__(self, input_size, hidden_size, output_size):
        super(BiLSTMModel, self).__init__()
        # Bidirectional LSTM: set bidirectional=True
        self.lstm = nn.LSTM(input_size, hidden_size, batch_first=True, 
bidirectional=True)

        # Adjust the output size of the fully connected layer to 
account for the doubled hidden size
        self.fc = nn.Linear(hidden_size * 2, output_size)  # 
hidden_size * 2 because of bidirectional

    def forward(self, x):
        # LSTM layer
        lstm_out, (h_n, c_n) = self.lstm(x)  # lstm_out has shape 
(batch_size, seq_len, hidden_size * 2)

        # We use the output from the last timestep of the 
bidirectional LSTM
        out = lstm_out[:, -1, :]  # Get the output from the last 
timestep (for classification)
```

```
        # Apply fully connected layer
        out = self.fc(out)

        # Apply sigmoid for binary classification
        return torch.sigmoid(out)  # Sigmoid for binary 
classification, outputs range from [0, 1]

def fit_lstm(model, X_train_tensor, y_train_tensor, 
prediction_threshold=0.5, verbose=False):

  # Loss function and optimizer
  criterion = nn.BCELoss()  # Binary Cross-Entropy loss for binary 
classification
  optimizer = optim.Adam(model.parameters(), lr=0.001)

  # Training loop
  num_epochs = 5

  for epoch in range(num_epochs):
    model.train() # would be for if we had dropout/batch normalization 
layers
    optimizer.zero_grad() # clears gradients from previous epoch

    # Forward pass
    outputs = model(X_train_tensor) # Forward pass through the model
    loss = criterion(outputs, y_train_tensor) # Computes the loss 
between actual y and pred y

    # Backward pass and optimization
    loss.backward() # calculates the gradients (backprop)
    optimizer.step() # utilizes loss through the optimizer to update 
weights

    # Print loss every few epochs
    if verbose & ((epoch == 0) | ((epoch + 1) % 2 == 0) | ((epoch + 1) 
== num_epochs)):
        print(f"Epoch [{epoch+1}/{num_epochs}], Loss: 
{loss.item():.4f}")

  return model
```

1.5 TFIDF Vectorization output with All Machine Learning Models

The **all_models_tfidf_vectorize_10FoldCV()** function utilizes KFold splits to generate tf-idf vector representations of the train set from each respective split. It then passes the tfidf vector to each of the models, trains them, generates predictions, and the passes them to the **get_metrics** function.

all_models_tfidf_vectorize_10FoldCV() then records the metrics for each model for each fold, prints the metrics out for all models for the current fold, and repeats for each split until it finally returns a list of pandas dataframes (1 for each fold) on completion.

```
def all_models_tfidf_vectorize_10FoldCV():

  metrics = []

  for i, (train_index, test_index) in
enumerate(K_fold_CV.split(X=X_train, y=y_train)):
    # declare models
    print(f"Fold {i + 1}:")

    # get fold train subsets (Note that X and y are global variables)
    temp_X_train = X_train[train_index]
    temp_y_train = y_train[train_index]

    # get fold test subsets (Note that X and y are global variables)
    temp_X_test = X_train[test_index]
    temp_y_test = y_train[test_index]

    # instantiate and fit the tf-idf vectorizer
    tfidf_vector = TfidfVectorizer(stop_words='english',
                                   ngram_range=(1, 2),
                                   norm="l2",
                                   smooth_idf=True # prevents 0 divisions
                                   #min_df=30, # lowest number of occurences
required for words to be recorded in dtm
                                   #max_df=0.7, # highest percentage
threshold before words stop being recorded in dtm
                                   #max_features=100
                                   )

    tfidf_vector.fit(temp_X_train)

    # Transform the X_train/X_test folds
    X_train_tfidf_vector = tfidf_vector.transform(temp_X_train)
    X_test_tfidf_vector = tfidf_vector.transform(temp_X_test)

    # Transform for LSTM input
    x_train_dtm_l_LSTM =
np.expand_dims(X_train_tfidf_vector.toarray(), axis=1)  # Shape
becomes (n_samples, 1, n_features)
    x_test_dtm_l_LSTM = np.expand_dims(X_test_tfidf_vector.toarray(),
axis=1)

    # Convert data to PyTorch tensors for LSTM
    X_train_tensor = torch.tensor(x_train_dtm_l_LSTM,
dtype=torch.float32)
    X_test_tensor = torch.tensor(x_test_dtm_l_LSTM,
```

```
dtype=torch.float32)
    y_train_tensor = torch.tensor(temp_y_train,
dtype=torch.float32).view(-1, 1)  # Reshaping for binary
classification
    y_test_tensor = torch.tensor(temp_y_test,
dtype=torch.float32).view(-1, 1) # Reshaping for binary classification

    # Get various models
    log_reg_model = LogisticRegression()
    rfc_model = RandomForestClassifier()
    nb_model = MultinomialNB()
    biLSTM_model = BiLSTMModel(input_size=X_train_tensor.shape[2], #
This is the number of features (i.e., the TF-IDF size)
                               hidden_size=64, # Hidden units in LSTM
                               output_size=1 # Binary output (0 or 1)
                               )

    # arrange models for input into a loop
    models = [log_reg_model, rfc_model, nb_model, biLSTM_model]
    model_names = ['Logistic_Regression', 'Random_Forest_Classifier',
'Naive_Bayes', 'Bi-LSTM']

    iteration_i = []

    for k, temp_model in enumerate(models):

      # test if the model is a pytorch neural network
      if isinstance(temp_model, nn.Module):

        # fit model and predict for X_test
        temp_model = fit_lstm(temp_model, X_train_tensor,
y_train_tensor)

        # Evaluate the model on the test data
        temp_model.eval()  # Set the model to evaluation mode

        # Don't calculate gradients during prediction
        with torch.no_grad():

           # output is a probability of positive (1) class membership
from range [0, 1]
          temp_model_proba_prediction = temp_model(X_test_tensor)

          # Mask the model output with a threshold value to get binary
predictions
          temp_model_prediction = (temp_model_proba_prediction >=
0.5).float()

        # get metrics for current iteration for each neural network
model
```

```
        temp_model_metrics = get_metrics(y_test_tensor.view(-1),
                                         temp_model_prediction.view(-
1),

temp_model_proba_prediction.view(-1),
                                         nn_bool=True)

      else:

        # fit the model and predict for X_test
        temp_model.fit(X_train_tfidf_vector, temp_y_train) #
X_train_tfidf_vector is the transformed count vectorized X_train
matrix
        temp_model_prediction =
temp_model.predict(X_test_tfidf_vector) # X_test_tfidf_vector is the
transformed count vectorized X_test matrix

         # output is a probability of positive (1) class membership
from range [0, 1]
        temp_model_proba_prediction =
temp_model.predict_proba(X_test_tfidf_vector)[:, 1]

        # get metrics for current iteration for each non-neural
network model
        temp_model_metrics = get_metrics(temp_y_test,
                                         temp_model_prediction,
                                         temp_model_proba_prediction,
                                         nn_bool=False)

      temp_model_metrics.rename(columns={0: model_names[k]},
inplace=True)
      iteration_i.append(temp_model_metrics)

    # get a single table with metrics for current fold for every model
    metrics.append(pd.concat(iteration_i, axis=1))

    print(metrics[i], '\n')

  return metrics

print('Displaying Model Metrics by fold for 10 folds: \n')
final_metrics = all_models_tfidf_vectorize_10FoldCV()
```

```
Displaying Model Metrics by fold for 10 folds:

Fold 1:
               Logistic_Regression  Random_Forest_Classifier
Naive_Bayes  \
TP                      104.000000                 88.000000
112.000000
TN                       95.000000                108.000000
```

```
79.000000
FP                         29.000000                  16.000000
45.000000
FN                         22.000000                  38.000000
14.000000
TPR                         0.825397                   0.698413
0.888889
TNR                         0.766129                   0.870968
0.637097
FPR                         0.233871                   0.129032
0.362903
FNR                         0.174603                   0.301587
0.111111
Precision                   0.781955                   0.846154
0.713376
F1_measure                  0.803089                   0.765217
0.791519
Accuracy                    0.796000                   0.784000
0.764000
Error_rate                  0.204000                   0.216000
0.236000
BACC                        0.795763                   0.784690
0.762993
TSS                         0.591526                   0.569380
0.525986
HSS                         0.591791                   0.568580
0.527031
BS                          0.171899                   0.162701
0.171762
BSS                         0.687642                   0.650846
0.687091
NPV                         0.811966                   0.739726
0.849462
FDR                         0.218045                   0.153846
0.286624
ROC_AUC_SCORE               0.872056                   0.852375
0.864183

                  Bi-LSTM
TP             102.000000
TN              56.000000
FP              68.000000
FN              24.000000
TPR              0.809524
TNR              0.451613
FPR              0.548387
FNR              0.190476
Precision        0.600000
F1_measure       0.689189
```

```
Accuracy         0.632000
Error_rate       0.368000
BACC             0.630568
TSS              0.261137
HSS              0.261874
BS               0.248779
BSS              0.995178
NPV              0.700000
FDR              0.400000
ROC_AUC_SCORE    0.681324

Fold 2:
               Logistic_Regression  Random_Forest_Classifier
Naive_Bayes  \
TP                      112.000000                 89.000000
128.000000
TN                       87.000000                101.000000
80.000000
FP                       25.000000                 11.000000
32.000000
FN                       26.000000                 49.000000
10.000000
TPR                       0.811594                  0.644928
0.927536
TNR                       0.776786                  0.901786
0.714286
FPR                       0.223214                  0.098214
0.285714
FNR                       0.188406                  0.355072
0.072464
Precision                 0.817518                  0.890000
0.800000
F1_measure                0.814545                  0.747899
0.859060
Accuracy                  0.796000                  0.760000
0.832000
Error_rate                0.204000                  0.240000
0.168000
BACC                      0.794190                  0.773357
0.820911
TSS                       0.588380                  0.546713
0.641822
HSS                       0.587885                  0.529781
0.653922
BS                        0.166021                  0.175644
0.158891
BSS                       0.671347                  0.710257
0.642512
NPV                       0.769912                  0.673333
```

```
0.888889
FDR                               0.182482                  0.110000
0.200000
ROC_AUC_SCORE                     0.884252                  0.868498
0.888975

                  Bi-LSTM
TP               8.000000
TN             111.000000
FP               1.000000
FN             130.000000
TPR              0.057971
TNR              0.991071
FPR              0.008929
FNR              0.942029
Precision        0.888889
F1_measure       0.108844
Accuracy         0.476000
Error_rate       0.524000
BACC             0.524521
TSS              0.049042
HSS              0.044242
BS               0.249290
BSS              1.008063
NPV              0.460581
FDR              0.111111
ROC_AUC_SCORE    0.722438

Fold 3:
               Logistic_Regression  Random_Forest_Classifier
Naive_Bayes  \
TP                       96.000000                 83.000000
100.000000
TN                      102.000000                116.000000
84.000000
FP                       31.000000                 17.000000
49.000000
FN                       21.000000                 34.000000
17.000000
TPR                       0.820513                  0.709402
0.854701
TNR                       0.766917                  0.872180
0.631579
FPR                       0.233083                  0.127820
0.368421
FNR                       0.179487                  0.290598
0.145299
Precision                 0.755906                  0.830000
0.671141
```

```
F1_measure                     0.786885                        0.764977
0.751880
Accuracy                       0.792000                        0.796000
0.736000
Error_rate                     0.208000                        0.204000
0.264000
BACC                           0.793715                        0.790791
0.743140
TSS                            0.587430                        0.581582
0.486280
HSS                            0.584426                        0.586710
0.478409
BS                             0.171648                        0.142990
0.173728
BSS                            0.689416                        0.574311
0.697770
NPV                            0.829268                        0.773333
0.831683
FDR                            0.244094                        0.170000
0.328859
ROC_AUC_SCORE                  0.873401                        0.885740
0.869481

                  Bi-LSTM
TP               0.000000
TN             133.000000
FP               0.000000
FN             117.000000
TPR              0.000000
TNR              1.000000
FPR              0.000000
FNR              1.000000
Precision        0.000000
F1_measure       0.000000
Accuracy         0.532000
Error_rate       0.468000
BACC             0.500000
TSS              0.000000
HSS              0.000000
BS               0.247177
BSS              0.992773
NPV              0.532000
FDR              0.000000
ROC_AUC_SCORE    0.780348

Fold 4:
               Logistic_Regression  Random_Forest_Classifier
Naive_Bayes  \
TP                      103.000000                 92.000000
```

			111.000000
TN	99.000000	106.000000	88.000000
FP	28.000000	21.000000	39.000000
FN	20.000000	31.000000	12.000000
TPR	0.837398	0.747967	0.902439
TNR	0.779528	0.834646	0.692913
FPR	0.220472	0.165354	0.307087
FNR	0.162602	0.252033	0.097561
Precision	0.786260	0.814159	0.740000
F1_measure	0.811024	0.779661	0.813187
Accuracy	0.808000	0.792000	0.796000
Error_rate	0.192000	0.208000	0.204000
BACC	0.808463	0.791307	0.797676
TSS	0.616926	0.582613	0.595352
HSS	0.616295	0.583360	0.593301
BS	0.178376	0.157385	0.169174
BSS	0.713686	0.629702	0.676871
NPV	0.831933	0.773723	0.880000
FDR	0.213740	0.185841	0.260000
ROC_AUC_SCORE	0.846745	0.855995	0.866590

	Bi-LSTM
TP	86.000000
TN	94.000000
FP	33.000000
FN	37.000000
TPR	0.699187
TNR	0.740157
FPR	0.259843
FNR	0.300813

```
Precision       0.722689
F1_measure      0.710744
Accuracy        0.720000
Error_rate      0.280000
BACC            0.719672
TSS             0.439344
HSS             0.439570
BS              0.248200
BSS             0.993052
NPV             0.717557
FDR             0.277311
ROC_AUC_SCORE   0.779271

Fold 5:
               Logistic_Regression  Random_Forest_Classifier
Naive_Bayes  \
TP                      103.000000                 95.000000
109.000000
TN                      101.000000                112.000000
84.000000
FP                       26.000000                 15.000000
43.000000
FN                       20.000000                 28.000000
14.000000
TPR                       0.837398                  0.772358
0.886179
TNR                       0.795276                  0.881890
0.661417
FPR                       0.204724                  0.118110
0.338583
FNR                       0.162602                  0.227642
0.113821
Precision                 0.798450                  0.863636
0.717105
F1_measure                0.817460                  0.815451
0.792727
Accuracy                  0.816000                  0.828000
0.772000
Error_rate                0.184000                  0.172000
0.228000
BACC                      0.816337                  0.827124
0.773798
TSS                       0.632674                  0.654247
0.547596
HSS                       0.632188                  0.655338
0.545571
BS                        0.166142                  0.134012
0.168322
BSS                       0.664739                  0.536185
```

```
0.673461
NPV                         0.834711                  0.800000
0.857143
FDR                         0.201550                  0.136364
0.282895
ROC_AUC_SCORE               0.884386                  0.896870
0.878113

                 Bi-LSTM
TP             78.000000
TN             82.000000
FP             45.000000
FN             45.000000
TPR             0.634146
TNR             0.645669
FPR             0.354331
FNR             0.365854
Precision       0.634146
F1_measure      0.634146
Accuracy        0.640000
Error_rate      0.360000
BACC            0.639908
TSS             0.279816
HSS             0.279816
BS              0.248426
BSS             0.993960
NPV             0.645669
FDR             0.365854
ROC_AUC_SCORE   0.740862

Fold 6:
               Logistic_Regression  Random_Forest_Classifier
Naive_Bayes  \
TP                        106.000000                 87.000000
111.000000
TN                        101.000000                110.000000
87.000000
FP                         23.000000                 14.000000
37.000000
FN                         20.000000                 39.000000
15.000000
TPR                         0.841270                  0.690476
0.880952
TNR                         0.814516                  0.887097
0.701613
FPR                         0.185484                  0.112903
0.298387
FNR                         0.158730                  0.309524
0.119048
```

```
Precision                     0.821705                   0.861386
0.750000
F1_measure                    0.831373                   0.766520
0.810219
Accuracy                      0.828000                   0.788000
0.792000
Error_rate                    0.172000                   0.212000
0.208000
BACC                          0.827893                   0.788786
0.791283
TSS                           0.655786                   0.577573
0.582565
HSS                           0.655912                   0.576650
0.583387
BS                            0.168722                   0.158018
0.162347
BSS                           0.674930                   0.632112
0.649429
NPV                           0.834711                   0.738255
0.852941
FDR                           0.178295                   0.138614
0.250000
ROC_AUC_SCORE                 0.877752                   0.864855
0.891897

                  Bi-LSTM
TP             120.000000
TN              32.000000
FP              92.000000
FN               6.000000
TPR              0.952381
TNR              0.258065
FPR              0.741935
FNR              0.047619
Precision        0.566038
F1_measure       0.710059
Accuracy         0.608000
Error_rate       0.392000
BACC             0.605223
TSS              0.210445
HSS              0.211610
BS               0.248585
BSS              0.994405
NPV              0.842105
FDR              0.433962
ROC_AUC_SCORE    0.727407

Fold 7:
               Logistic_Regression  Random_Forest_Classifier
```

```
Naive_Bayes  \
TP                          105.000000                        85.000000
115.000000
TN                          102.000000                       111.000000
90.000000
FP                           23.000000                        14.000000
35.000000
FN                           20.000000                        40.000000
10.000000
TPR                           0.840000                         0.680000
0.920000
TNR                           0.816000                         0.888000
0.720000
FPR                           0.184000                         0.112000
0.280000
FNR                           0.160000                         0.320000
0.080000
Precision                     0.820312                         0.858586
0.766667
F1_measure                    0.830040                         0.758929
0.836364
Accuracy                      0.828000                         0.784000
0.820000
Error_rate                    0.172000                         0.216000
0.180000
BACC                          0.828000                         0.784000
0.820000
TSS                           0.656000                         0.568000
0.640000
HSS                           0.656000                         0.568000
0.640000
BS                            0.163457                         0.151408
0.161681
BSS                           0.653827                         0.605634
0.646723
NPV                           0.836066                         0.735099
0.900000
FDR                           0.179688                         0.141414
0.233333
ROC_AUC_SCORE                 0.888064                         0.876256
0.884992

                  Bi-LSTM
TP             125.000000
TN               4.000000
FP             121.000000
FN               0.000000
TPR              1.000000
TNR              0.032000
```

```
FPR              0.968000
FNR              0.000000
Precision        0.508130
F1_measure       0.673854
Accuracy         0.516000
Error_rate       0.484000
BACC             0.516000
TSS              0.032000
HSS              0.032000
BS               0.248941
BSS              0.995764
NPV              1.000000
FDR              0.491870
ROC_AUC_SCORE    0.693504

Fold 8:
               Logistic_Regression  Random_Forest_Classifier
Naive_Bayes  \
TP                      100.000000                 86.000000
113.000000
TN                      104.000000                112.000000
87.000000
FP                       21.000000                 13.000000
38.000000
FN                       25.000000                 39.000000
12.000000
TPR                       0.800000                  0.688000
0.904000
TNR                       0.832000                  0.896000
0.696000
FPR                       0.168000                  0.104000
0.304000
FNR                       0.200000                  0.312000
0.096000
Precision                 0.826446                  0.868687
0.748344
F1_measure                0.813008                  0.767857
0.818841
Accuracy                  0.816000                  0.792000
0.800000
Error_rate                0.184000                  0.208000
0.200000
BACC                      0.816000                  0.792000
0.800000
TSS                       0.632000                  0.584000
0.600000
HSS                       0.632000                  0.584000
0.600000
BS                        0.165513                  0.145247
0.159401
```

```
BSS                          0.662053                    0.580987
0.637604
NPV                          0.806202                    0.741722
0.878788
FDR                          0.173554                    0.131313
0.251656
ROC_AUC_SCORE                0.894144                    0.898336
0.899840

                  Bi-LSTM
TP              53.000000
TN             105.000000
FP              20.000000
FN              72.000000
TPR              0.424000
TNR              0.840000
FPR              0.160000
FNR              0.576000
Precision        0.726027
F1_measure       0.535354
Accuracy         0.632000
Error_rate       0.368000
BACC             0.632000
TSS              0.264000
HSS              0.264000
BS               0.248614
BSS              0.994457
NPV              0.593220
FDR              0.273973
ROC_AUC_SCORE    0.733760

Fold 9:
               Logistic_Regression  Random_Forest_Classifier
Naive_Bayes  \
TP                       86.000000                 67.000000
94.000000
TN                      113.000000                132.000000
99.000000
FP                       33.000000                 14.000000
47.000000
FN                       18.000000                 37.000000
10.000000
TPR                       0.826923                  0.644231
0.903846
TNR                       0.773973                  0.904110
0.678082
FPR                       0.226027                  0.095890
0.321918
FNR                       0.173077                  0.355769
```

```
0.096154
Precision                 0.722689                  0.827160
0.666667
F1_measure                0.771300                  0.724324
0.767347
Accuracy                  0.796000                  0.796000
0.772000
Error_rate                0.204000                  0.204000
0.228000
BACC                      0.800448                  0.774170
0.790964
TSS                       0.600896                  0.548340
0.581928
HSS                       0.588683                  0.566356
0.553599
BS                        0.172035                  0.136518
0.172657
BSS                       0.708127                  0.561930
0.710687
NPV                       0.862595                  0.781065
0.908257
FDR                       0.277311                  0.172840
0.333333
ROC_AUC_SCORE             0.888567                  0.890477
0.891596

                  Bi-LSTM
TP               0.000000
TN             146.000000
FP               0.000000
FN             104.000000
TPR              0.000000
TNR              1.000000
FPR              0.000000
FNR              1.000000
Precision        0.000000
F1_measure       0.000000
Accuracy         0.584000
Error_rate       0.416000
BACC             0.500000
TSS              0.000000
HSS              0.000000
BS               0.246830
BSS              1.015997
NPV              0.584000
FDR              0.000000
ROC_AUC_SCORE    0.745061

Fold 10:
```

```
               Logistic_Regression  Random_Forest_Classifier
Naive_Bayes  \
TP                      120.000000                104.000000
127.000000
TN                       76.000000                 88.000000
63.000000
FP                       31.000000                 19.000000
44.000000
FN                       23.000000                 39.000000
16.000000
TPR                       0.839161                  0.727273
0.888112
TNR                       0.710280                  0.822430
0.588785
FPR                       0.289720                  0.177570
0.411215
FNR                       0.160839                  0.272727
0.111888
Precision                 0.794702                  0.845528
0.742690
F1_measure                0.816327                  0.781955
0.808917
Accuracy                  0.784000                  0.768000
0.760000
Error_rate                0.216000                  0.232000
0.240000
BACC                      0.774721                  0.774851
0.738448
TSS                       0.549441                  0.549703
0.476897
HSS                       0.554661                  0.537067
0.493141
BS                        0.174873                  0.163189
0.166050
BSS                       0.714305                  0.666577
0.678265
NPV                       0.767677                  0.692913
0.797468
FDR                       0.205298                  0.154472
0.257310
ROC_AUC_SCORE             0.859029                  0.858016
0.869290

                 Bi-LSTM
TP             54.000000
TN             90.000000
FP             17.000000
FN             89.000000
TPR             0.377622
```

```
TNR                0.841121
FPR                0.158879
FNR                0.622378
Precision          0.760563
F1_measure         0.504673
Accuracy           0.576000
Error_rate         0.424000
BACC               0.609372
TSS                0.218744
HSS                0.201663
BS                 0.249195
BSS                1.017886
NPV                0.502793
FDR                0.239437
ROC_AUC_SCORE      0.683485
```

```
print('Displaying Model Metrics by model for 10 folds: \n')
final_metrics_per_iter = metrics_per_iteration(final_metrics)
```

```
Displaying Model Metrics by model for 10 folds:

Metrics for Logistic_Regression:
                         Fold1        Fold2        Fold3        Fold4
Fold5  \
TP               104.000000   112.000000    96.000000   103.000000
103.000000
TN                95.000000    87.000000   102.000000    99.000000
101.000000
FP                29.000000    25.000000    31.000000    28.000000
26.000000
FN                22.000000    26.000000    21.000000    20.000000
20.000000
TPR                0.825397     0.811594     0.820513     0.837398
0.837398
TNR                0.766129     0.776786     0.766917     0.779528
0.795276
FPR                0.233871     0.223214     0.233083     0.220472
0.204724
FNR                0.174603     0.188406     0.179487     0.162602
0.162602
Precision          0.781955     0.817518     0.755906     0.786260
0.798450
F1_measure         0.803089     0.814545     0.786885     0.811024
0.817460
Accuracy           0.796000     0.796000     0.792000     0.808000
0.816000
Error_rate         0.204000     0.204000     0.208000     0.192000
0.184000
BACC               0.795763     0.794190     0.793715     0.808463
```

```
0.816337
TSS                0.591526    0.588380    0.587430    0.616926
0.632674
HSS                0.591791    0.587885    0.584426    0.616295
0.632188
BS                 0.171899    0.166021    0.171648    0.178376
0.166142
BSS                0.687642    0.671347    0.689416    0.713686
0.664739
NPV                0.811966    0.769912    0.829268    0.831933
0.834711
FDR                0.218045    0.182482    0.244094    0.213740
0.201550
ROC_AUC_SCORE      0.872056    0.884252    0.873401    0.846745
0.884386

                      Fold6       Fold7       Fold8       Fold9
Fold10
TP               106.000000  105.000000  100.000000   86.000000
120.000000
TN               101.000000  102.000000  104.000000  113.000000
76.000000
FP                23.000000   23.000000   21.000000   33.000000
31.000000
FN                20.000000   20.000000   25.000000   18.000000
23.000000
TPR                0.841270    0.840000    0.800000    0.826923
0.839161
TNR                0.814516    0.816000    0.832000    0.773973
0.710280
FPR                0.185484    0.184000    0.168000    0.226027
0.289720
FNR                0.158730    0.160000    0.200000    0.173077
0.160839
Precision          0.821705    0.820312    0.826446    0.722689
0.794702
F1_measure         0.831373    0.830040    0.813008    0.771300
0.816327
Accuracy           0.828000    0.828000    0.816000    0.796000
0.784000
Error_rate         0.172000    0.172000    0.184000    0.204000
0.216000
BACC               0.827893    0.828000    0.816000    0.800448
0.774721
TSS                0.655786    0.656000    0.632000    0.600896
0.549441
HSS                0.655912    0.656000    0.632000    0.588683
0.554661
BS                 0.168722    0.163457    0.165513    0.172035
```

```
0.174873
BSS                 0.674930    0.653827    0.662053    0.708127
0.714305
NPV                 0.834711    0.836066    0.806202    0.862595
0.767677
FDR                 0.178295    0.179688    0.173554    0.277311
0.205298
ROC_AUC_SCORE       0.877752    0.888064    0.894144    0.888567
0.859029

Metrics for Random_Forest_Classifier:
                       Fold1       Fold2       Fold3       Fold4
Fold5  \
TP                 88.000000   89.000000   83.000000   92.000000
95.000000
TN                108.000000  101.000000  116.000000  106.000000
112.000000
FP                 16.000000   11.000000   17.000000   21.000000
15.000000
FN                 38.000000   49.000000   34.000000   31.000000
28.000000
TPR                 0.698413    0.644928    0.709402    0.747967
0.772358
TNR                 0.870968    0.901786    0.872180    0.834646
0.881890
FPR                 0.129032    0.098214    0.127820    0.165354
0.118110
FNR                 0.301587    0.355072    0.290598    0.252033
0.227642
Precision           0.846154    0.890000    0.830000    0.814159
0.863636
F1_measure          0.765217    0.747899    0.764977    0.779661
0.815451
Accuracy            0.784000    0.760000    0.796000    0.792000
0.828000
Error_rate          0.216000    0.240000    0.204000    0.208000
0.172000
BACC                0.784690    0.773357    0.790791    0.791307
0.827124
TSS                 0.569380    0.546713    0.581582    0.582613
0.654247
HSS                 0.568580    0.529781    0.586710    0.583360
0.655338
BS                  0.162701    0.175644    0.142990    0.157385
0.134012
BSS                 0.650846    0.710257    0.574311    0.629702
0.536185
NPV                 0.739726    0.673333    0.773333    0.773723
0.800000
```

```
FDR                0.153846    0.110000    0.170000    0.185841
0.136364
ROC_AUC_SCORE      0.852375    0.868498    0.885740    0.855995
0.896870

                      Fold6       Fold7       Fold8       Fold9
Fold10
TP                87.000000   85.000000   86.000000   67.000000
104.000000
TN               110.000000  111.000000  112.000000  132.000000
88.000000
FP                14.000000   14.000000   13.000000   14.000000
19.000000
FN                39.000000   40.000000   39.000000   37.000000
39.000000
TPR                0.690476    0.680000    0.688000    0.644231
0.727273
TNR                0.887097    0.888000    0.896000    0.904110
0.822430
FPR                0.112903    0.112000    0.104000    0.095890
0.177570
FNR                0.309524    0.320000    0.312000    0.355769
0.272727
Precision          0.861386    0.858586    0.868687    0.827160
0.845528
F1_measure         0.766520    0.758929    0.767857    0.724324
0.781955
Accuracy           0.788000    0.784000    0.792000    0.796000
0.768000
Error_rate         0.212000    0.216000    0.208000    0.204000
0.232000
BACC               0.788786    0.784000    0.792000    0.774170
0.774851
TSS                0.577573    0.568000    0.584000    0.548340
0.549703
HSS                0.576650    0.568000    0.584000    0.566356
0.537067
BS                 0.158018    0.151408    0.145247    0.136518
0.163189
BSS                0.632112    0.605634    0.580987    0.561930
0.666577
NPV                0.738255    0.735099    0.741722    0.781065
0.692913
FDR                0.138614    0.141414    0.131313    0.172840
0.154472
ROC_AUC_SCORE      0.864855    0.876256    0.898336    0.890477
0.858016

Metrics for Naive_Bayes:
```

	Fold1	Fold2	Fold3	Fold4	Fold5
TP	112.000000	128.000000	100.000000	111.000000	109.000000
TN	79.000000	80.000000	84.000000	88.000000	84.000000
FP	45.000000	32.000000	49.000000	39.000000	43.000000
FN	14.000000	10.000000	17.000000	12.000000	14.000000
TPR	0.888889	0.927536	0.854701	0.902439	0.886179
TNR	0.637097	0.714286	0.631579	0.692913	0.661417
FPR	0.362903	0.285714	0.368421	0.307087	0.338583
FNR	0.111111	0.072464	0.145299	0.097561	0.113821
Precision	0.713376	0.800000	0.671141	0.740000	0.717105
F1_measure	0.791519	0.859060	0.751880	0.813187	0.792727
Accuracy	0.764000	0.832000	0.736000	0.796000	0.772000
Error_rate	0.236000	0.168000	0.264000	0.204000	0.228000
BACC	0.762993	0.820911	0.743140	0.797676	0.773798
TSS	0.525986	0.641822	0.486280	0.595352	0.547596
HSS	0.527031	0.653922	0.478409	0.593301	0.545571
BS	0.171762	0.158891	0.173728	0.169174	0.168322
BSS	0.687091	0.642512	0.697770	0.676871	0.673461
NPV	0.849462	0.888889	0.831683	0.880000	0.857143
FDR	0.286624	0.200000	0.328859	0.260000	0.282895
ROC_AUC_SCORE	0.864183	0.888975	0.869481	0.866590	0.878113

	Fold6	Fold7	Fold8	Fold9	Fold10
TP	111.000000	115.000000	113.000000	94.000000	127.000000
TN	87.000000	90.000000	87.000000	99.000000	63.000000

```
FP                37.000000   35.000000   38.000000  47.000000
44.000000
FN                15.000000   10.000000   12.000000  10.000000
16.000000
TPR                0.880952    0.920000    0.904000   0.903846
0.888112
TNR                0.701613    0.720000    0.696000   0.678082
0.588785
FPR                0.298387    0.280000    0.304000   0.321918
0.411215
FNR                0.119048    0.080000    0.096000   0.096154
0.111888
Precision          0.750000    0.766667    0.748344   0.666667
0.742690
F1_measure         0.810219    0.836364    0.818841   0.767347
0.808917
Accuracy           0.792000    0.820000    0.800000   0.772000
0.760000
Error_rate         0.208000    0.180000    0.200000   0.228000
0.240000
BACC               0.791283    0.820000    0.800000   0.790964
0.738448
TSS                0.582565    0.640000    0.600000   0.581928
0.476897
HSS                0.583387    0.640000    0.600000   0.553599
0.493141
BS                 0.162347    0.161681    0.159401   0.172657
0.166050
BSS                0.649429    0.646723    0.637604   0.710687
0.678265
NPV                0.852941    0.900000    0.878788   0.908257
0.797468
FDR                0.250000    0.233333    0.251656   0.333333
0.257310
ROC_AUC_SCORE      0.891897    0.884992    0.899840   0.891596
0.869290

Metrics for Bi-LSTM:
                      Fold1       Fold2       Fold3      Fold4
Fold5  \
TP               102.000000    8.000000    0.000000  86.000000
78.000000
TN                56.000000  111.000000  133.000000  94.000000
82.000000
FP                68.000000    1.000000    0.000000  33.000000
45.000000
FN                24.000000  130.000000  117.000000  37.000000
45.000000
TPR                0.809524    0.057971    0.000000   0.699187
```

```
0.634146
TNR              0.451613    0.991071    1.000000   0.740157
0.645669
FPR              0.548387    0.008929    0.000000   0.259843
0.354331
FNR              0.190476    0.942029    1.000000   0.300813
0.365854
Precision        0.600000    0.888889    0.000000   0.722689
0.634146
F1_measure       0.689189    0.108844    0.000000   0.710744
0.634146
Accuracy         0.632000    0.476000    0.532000   0.720000
0.640000
Error_rate       0.368000    0.524000    0.468000   0.280000
0.360000
BACC             0.630568    0.524521    0.500000   0.719672
0.639908
TSS              0.261137    0.049042    0.000000   0.439344
0.279816
HSS              0.261874    0.044242    0.000000   0.439570
0.279816
BS               0.248779    0.249290    0.247177   0.248200
0.248426
BSS              0.995178    1.008063    0.992773   0.993052
0.993960
NPV              0.700000    0.460581    0.532000   0.717557
0.645669
FDR              0.400000    0.111111    0.000000   0.277311
0.365854
ROC_AUC_SCORE    0.681324    0.722438    0.780348   0.779271
0.740862

                    Fold6       Fold7       Fold8       Fold9
Fold10
TP             120.000000  125.000000   53.000000    0.000000
54.000000
TN              32.000000    4.000000  105.000000  146.000000
90.000000
FP              92.000000  121.000000   20.000000    0.000000
17.000000
FN               6.000000    0.000000   72.000000  104.000000
89.000000
TPR              0.952381    1.000000    0.424000    0.000000
0.377622
TNR              0.258065    0.032000    0.840000    1.000000
0.841121
FPR              0.741935    0.968000    0.160000    0.000000
0.158879
FNR              0.047619    0.000000    0.576000    1.000000
```

```
0.622378
Precision         0.566038    0.508130    0.726027    0.000000
0.760563
F1_measure        0.710059    0.673854    0.535354    0.000000
0.504673
Accuracy          0.608000    0.516000    0.632000    0.584000
0.576000
Error_rate        0.392000    0.484000    0.368000    0.416000
0.424000
BACC              0.605223    0.516000    0.632000    0.500000
0.609372
TSS               0.210445    0.032000    0.264000    0.000000
0.218744
HSS               0.211610    0.032000    0.264000    0.000000
0.201663
BS                0.248585    0.248941    0.248614    0.246830
0.249195
BSS               0.994405    0.995764    0.994457    1.015997
1.017886
NPV               0.842105    1.000000    0.593220    0.584000
0.502793
FDR               0.433962    0.491870    0.273973    0.000000
0.239437
ROC_AUC_SCORE     0.727407    0.693504    0.733760    0.745061
0.683485
```

```
print('Displaying Averaged Model Metrics: \n')
final_average_metrics = average_metrics(final_metrics)
```

```
Displaying Averaged Model Metrics:

Average Metrics by Model
              Logistic_Regression  Random_Forest_Classifier
Naive_Bayes  \
TP                     103.500000                 87.600000
112.000000
TN                      98.000000                109.600000
84.100000
FP                      27.000000                 15.400000
40.900000
FN                      21.500000                 37.400000
13.000000
TPR                      0.827965                  0.700305
0.895665
TNR                      0.783140                  0.875911
0.672177
FPR                      0.216860                  0.124089
0.327823
FNR                      0.172035                  0.299695
```

```
0.104335
Precision                  0.792594                  0.850530
0.731599
F1_measure                 0.809505                  0.767279
0.805006
Accuracy                   0.806000                  0.788800
0.784400
Error_rate                 0.194000                  0.211200
0.215600
BACC                       0.805553                  0.788108
0.783921
TSS                        0.611106                  0.576215
0.567843
HSS                        0.609984                  0.575584
0.566836
BS                         0.169869                  0.152711
0.166401
BSS                        0.684007                  0.614854
0.670041
NPV                        0.818504                  0.744917
0.864463
FDR                        0.207406                  0.149470
0.268401
ROC_AUC_SCORE              0.876840                  0.874742
0.880496

                 Bi-LSTM
TP             62.600000
TN             85.300000
FP             39.700000
FN             62.400000
TPR             0.495483
TNR             0.679970
FPR             0.320030
FNR             0.504517
Precision       0.540648
F1_measure      0.456686
Accuracy        0.591600
Error_rate      0.408400
BACC            0.587726
TSS             0.175453
HSS             0.173477
BS              0.248404
BSS             1.000154
NPV             0.657793
FDR             0.259352
ROC_AUC_SCORE   0.728746
```

1.6 ROC Curves and AUC scores on **test** dataset

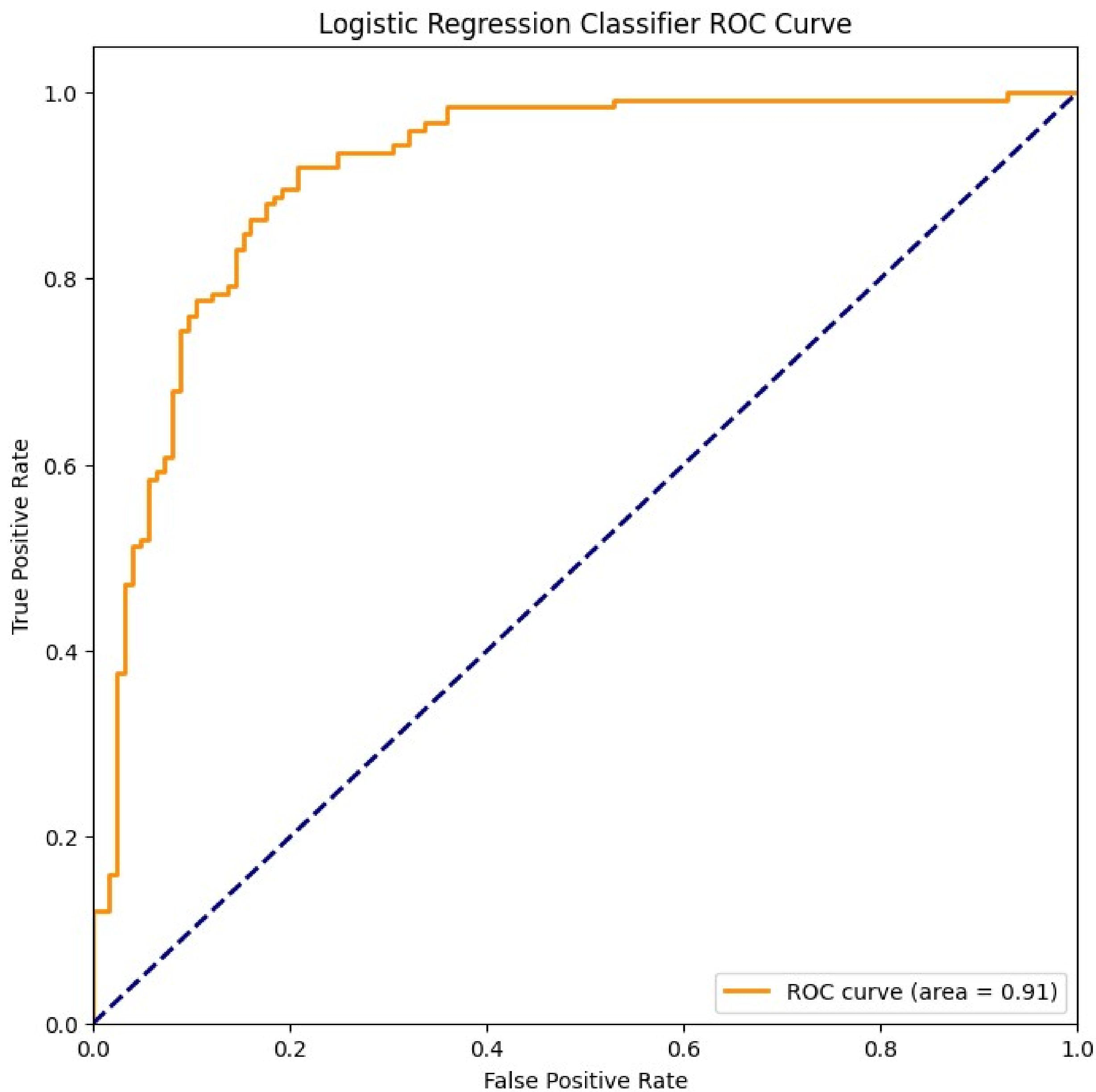
We now take each model and train them on the full **train** dataset so that we can evaluate them on the untouched **test** dataset. The training and evaluation process is the same as was in the **all_models_tfidf_vectorize_10FoldCV()** function.

We do this in order to generate plots of the ROC/AUC curves for each model.

```
# instantiate and fit the tf-idf vectorizer
tfidf_vector = TfidfVectorizer(stop_words='english',
                        ngram_range=(1, 2),
                        norm="l2",
                        smooth_idf=True # prevents 0 divisions
                        #min_df=30, # lowest number of occurences
required for words to be recorded in dtm
                        #max_df=0.7, # highest percentage threshold
before words stop being recorded in dtm
                        #max_features=100
                        )

tfidf_vector.fit(X_train)

# Transform the X_train/X_test folds
X_train_tfidf_vector = tfidf_vector.transform(X_train)
X_test_tfidf_vector = tfidf_vector.transform(X_test)

# Transform for LSTM input
x_train_dtm_l_LSTM = np.expand_dims(X_train_tfidf_vector.toarray(),
axis=1)  # Shape becomes (n_samples, 1, n_features)
x_test_dtm_l_LSTM = np.expand_dims(X_test_tfidf_vector.toarray(),
axis=1)

# Convert data to PyTorch tensors for LSTM
X_train_tensor = torch.tensor(x_train_dtm_l_LSTM, dtype=torch.float32)
X_test_tensor = torch.tensor(x_test_dtm_l_LSTM, dtype=torch.float32)
y_train_tensor = torch.tensor(y_train, dtype=torch.float32).view(-1,
1)  # Reshaping for binary classification
y_test_tensor = torch.tensor(y_test, dtype=torch.float32).view(-1, 1)
# Reshaping for binary classification

def get_AUC_ROC_curve(temp_model, model_name=''):

  # if the input model is a torch.nn module (Neural Network)
  if isinstance(temp_model, nn.Module):
    # fit model and predict for X_test
    temp_model = fit_lstm(temp_model, X_train_tensor, y_train_tensor)

    # Evaluate the model on the test data
    temp_model.eval()  # Set the model to evaluation mode
```

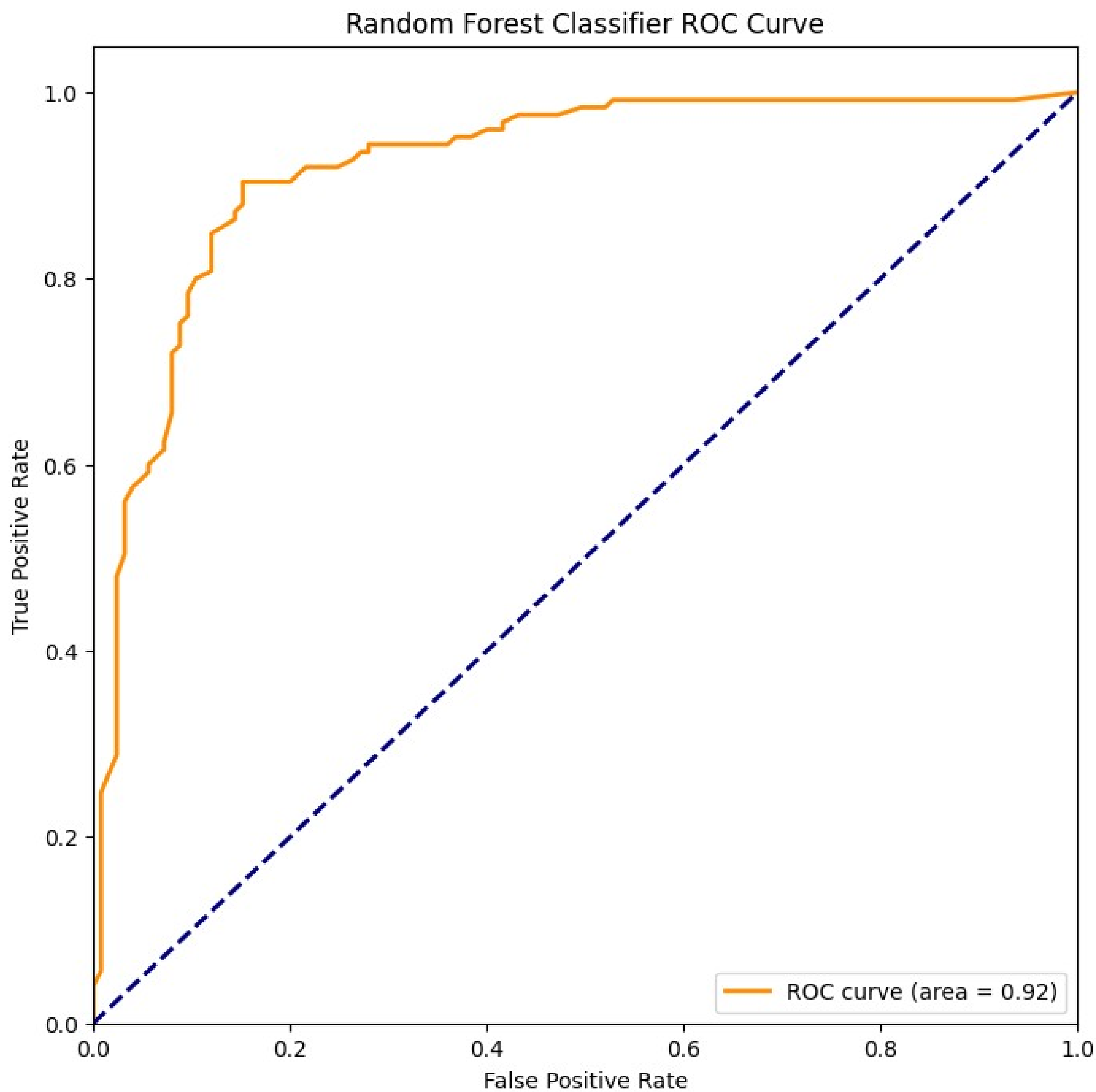
```
    with torch.no_grad():
      temp_model_proba_prediction = temp_model(X_test_tensor) #
outputs ranging between [0, 1]

    # our outputs are on a range from [0, 1] and in our case represent
relative probabilities
    # (this is our model's estimation) that each test question is
either a member of the
    # class (1) or a not a member of the class (0). So that means
these results are comperable
    # to what we get from predict_proba, and can be used in the AUC /
ROC plot.

  else:
    temp_model.fit(X_train_tfidf_vector, y_train)
    temp_model_proba_prediction =
temp_model.predict_proba(X_test_tfidf_vector)[:, 1]


  #return (X_test_tfidf_vector, temp_model_proba_prediction)
  # Compute ROC curve and ROC area
  fpr, tpr, _ = roc_curve(y_true=y_test,
                          y_score=temp_model_proba_prediction)

  roc_auc = auc(fpr, tpr)

  print('Please close the graphic to continue')

  # Plot ROC curve
  plt.figure(figsize=(8, 8))
  plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area
= {:.2f})'.format(roc_auc))
  plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
  plt.xlim([0.0, 1.0])
  plt.ylim([0.0, 1.05])
  plt.xlabel('False Positive Rate')
  plt.ylabel('True Positive Rate')
  plt.title(f'{model_name} ROC Curve')
  plt.legend(loc='lower right')
  plt.show()

  return # (X_test_tfidf_vector, temp_model_proba_prediction)

get_AUC_ROC_curve(LogisticRegression(), model_name='Logistic
Regression Classifier')
```

```
Please close the graphic to continue
```

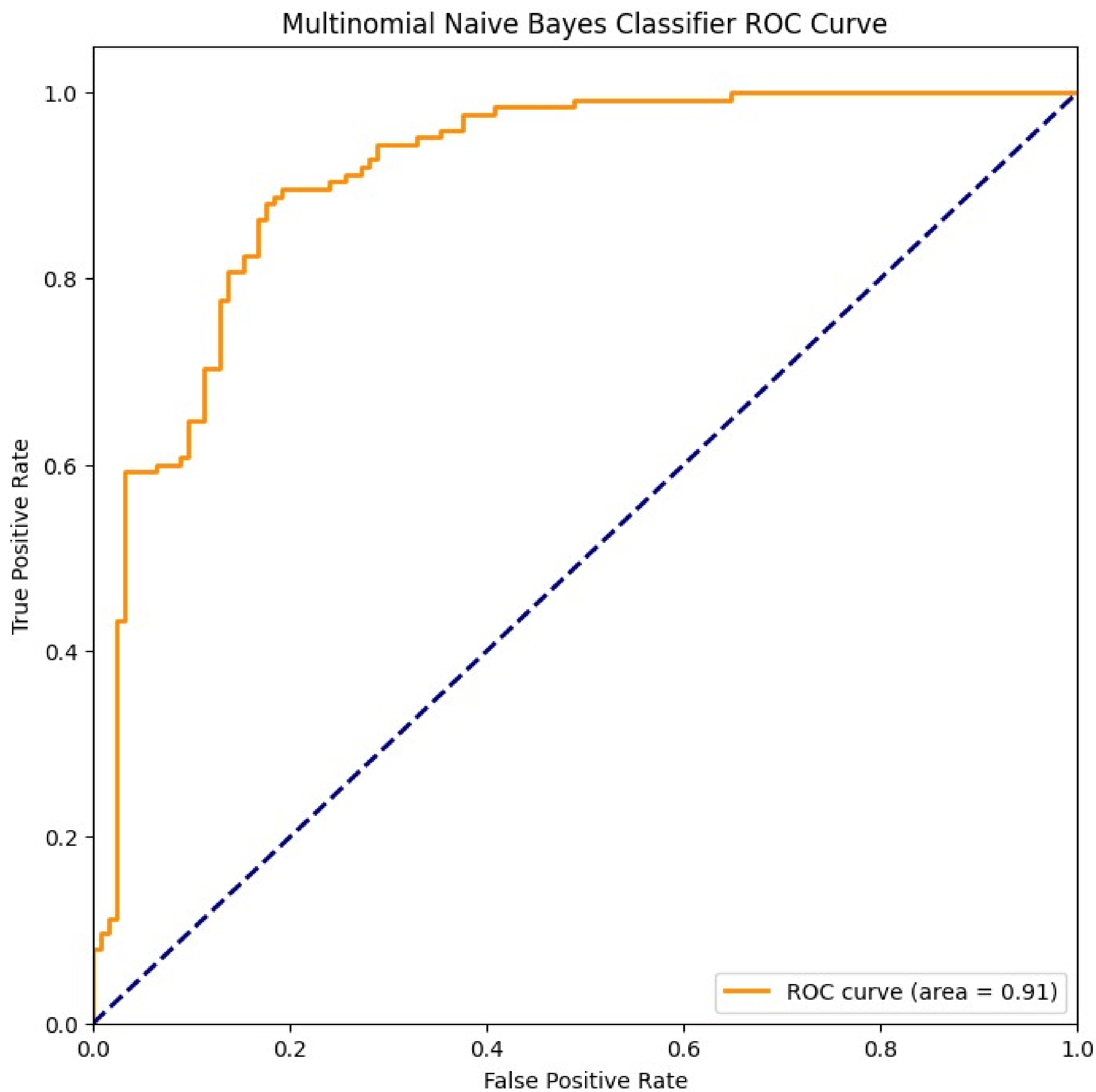



```
get_AUC_ROC_curve(RandomForestClassifier(), model_name='Random Forest Classifier')
```

```
Please close the graphic to continue
```

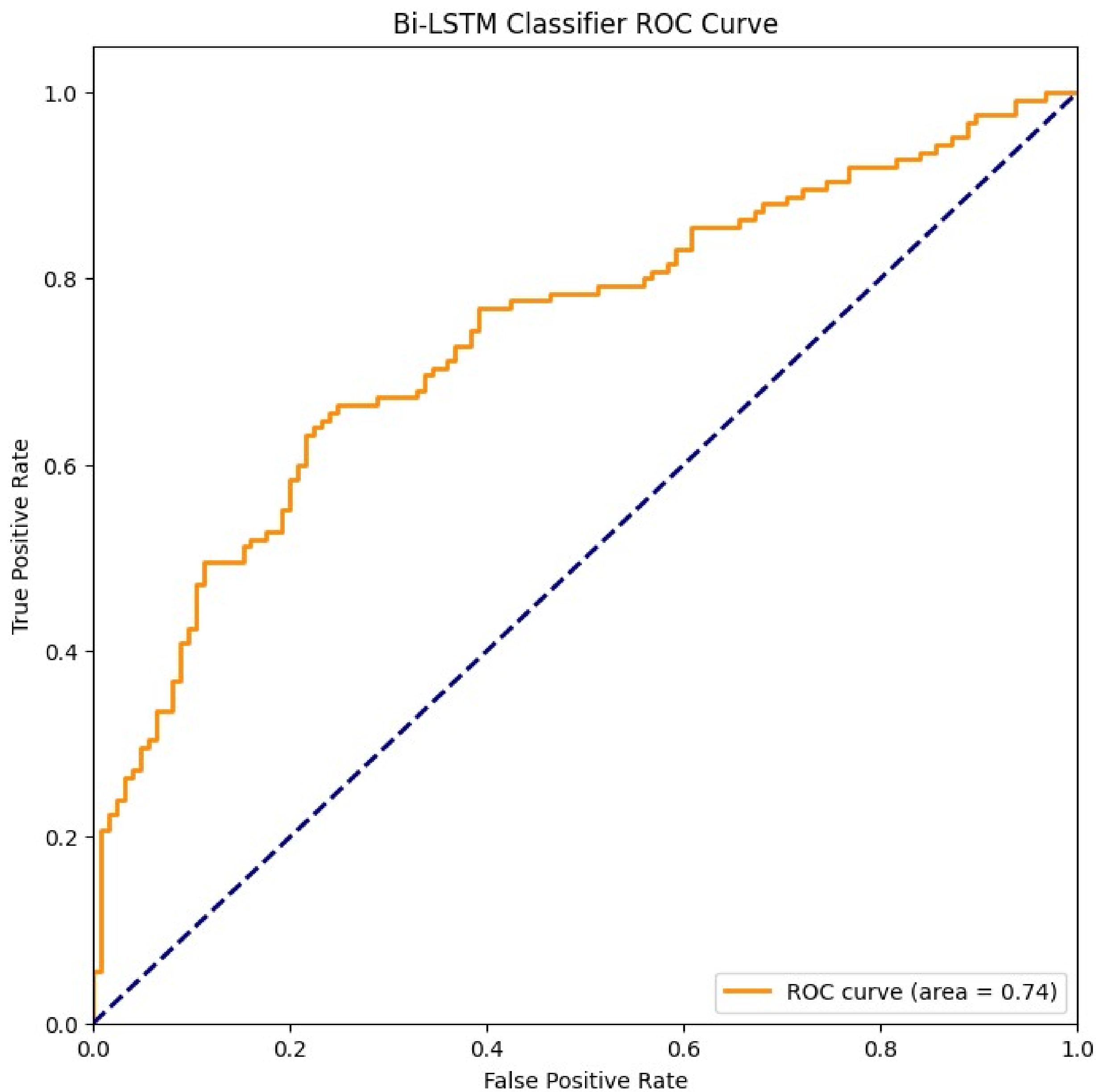



```
get_AUC_ROC_curve(MultinomialNB(), model_name='Multinomial Naive Bayes Classifier')

Please close the graphic to continue
```




```
biLSTM_model = BiLSTMModel(input_size=X_train_tensor.shape[2], # This
is the number of features (i.e., the TF-IDF size)
                            hidden_size=64, # Hidden units in LSTM
                            output_size=1 # Binary output (0 or 1)
                            )

get_AUC_ROC_curve(biLSTM_model, model_name='Bi-LSTM Classifier')
```

```
Please close the graphic to continue
```



1.7 Conclusion

For the purpose of the Conclusion, I think it is useful to visualize the average final metrics again. In particular I want to describe how this project helped me learn about the limitations and potential pitfalls of using neural networks, and why certain techniques are better than others regarding methods of vectorization.

```
print('Displaying Averaged Model Metrics: \n')
print(final_average_metrics)
```

```
Displaying Averaged Model Metrics:
```

	Logistic_Regression	Random_Forest_Classifier	Naive_Bayes
TP	103.500000	87.600000	112.000000
TN	98.000000	109.600000	84.100000
FP	27.000000	15.400000	40.900000
FN	21.500000	37.400000	13.000000
TPR	0.827965	0.700305	0.895665
TNR	0.783140	0.875911	0.672177
FPR	0.216860	0.124089	0.327823
FNR	0.172035	0.299695	0.104335
Precision	0.792594	0.850530	0.731599
F1_measure	0.809505	0.767279	0.805006
Accuracy	0.806000	0.788800	0.784400
Error_rate	0.194000	0.211200	0.215600
BACC	0.805553	0.788108	0.783921
TSS	0.611106	0.576215	0.567843
HSS	0.609984	0.575584	0.566836
BS	0.169869	0.152711	0.166401
BSS	0.684007	0.614854	0.670041
NPV	0.818504	0.744917	0.864463
FDR	0.207406	0.149470	0.268401
ROC_AUC_SCORE	0.876840	0.874742	0.880496

	Bi-LSTM
TP	62.600000
TN	85.300000
FP	39.700000
FN	62.400000
TPR	0.495483

```
TNR              0.679970
FPR              0.320030
FNR              0.504517
Precision        0.540648
F1_measure       0.456686
Accuracy         0.591600
Error_rate       0.408400
BACC             0.587726
TSS              0.175453
HSS              0.173477
BS               0.248404
BSS              1.000154
NPV              0.657793
FDR              0.259352
ROC_AUC_SCORE    0.728746
```

My Classes are balanced, so accuracy is not necessarily a bad measure here. Of the three models: Random_Forest_Classifier, Naive_Bayes, and Bi-LSTM, the non-neural network methods are much closer to ideal than the Bi-LSTM model tends to be.

Summary of Model Performance Metrics

Metric	Logistic Regression	Random Forest	Naive Bayes	Bi-LSTM
True Positives (TP)	103.5	87.6	112.0	62.6
True Negatives (TN)	98.0	109.6	84.1	85.3
False Positives (FP)	27.0	15.4	40.9	39.7
False Negatives (FN)	21.5	37.4	13.0	62.4
True Positive Rate (TPR)	0.828	0.700	0.896	0.495
True Negative Rate (TNR)	0.783	0.876	0.672	0.680
False Positive Rate (FPR)	0.217	0.124	0.328	0.320
False Negative Rate (FNR)	0.172	0.300	0.104	0.505
Precision	0.793	0.851	0.732	0.541
F1 Measure	0.810	0.767	0.805	0.457
Accuracy	0.806	0.789	0.784	0.592
Error Rate	0.194	0.211	0.216	0.408
Balanced Accuracy (BACC)	0.806	0.788	0.784	0.588
True Skill Statistic (TSS)	0.611	0.576	0.568	0.175
Heidke Skill Score (HSS)	0.610	0.576	0.567	0.173

Metric	Logistic Regression	Random Forest	Naive Bayes	Bi-LSTM
Brier Score (BS)	0.170	0.153	0.166	0.248
Brier Skill Score (BSS)	0.684	0.615	0.670	1.000
Negative Predictive Value (NPV)	0.819	0.745	0.864	0.658
False Discovery Rate (FDR)	0.207	0.149	0.268	0.259
ROC AUC Score	0.877	0.875	0.880	0.729

I think that false positives and false negatives are equally important in this data, because as a subset with equally distributed classes, we don't want to over-predict either, as it could result in missing a lot of insincere comments or potentially the deletion/removal of a lot of sincere questions. Neither is ideal, at least within the confines of the subset.

When relating it to the original dataset, however, there is a massive class imbalance. I believe it is something like over 90% of the original data consists of sincere questions. This presents quite a problem, because overpredicting False Positives would lead to many more unjustifiable question removals, and might end up hurting site engagement more than helping it (which is presumably the aim of trying to detect/remove insincere questions).

That means that in my opinion, a good classifier has to be balanced, if not slightly properly overpredicting True Negatives at the cost of underpredicting False Negatives.

Basically, a good classifier for this problem should prioritize allowing as many sincere questions through as it can whilst progressively seeking to discover insincere questions. This should be done without an marked increase in False Positives so that there is no sweeping mass auto-ban of people's valid, sincere questions.

With that in mind, I will look at a few key metrics:

Maximize TP: Naive Bayes

Minimize FP: Random Forest

Maximize TN: Random Forest

Minimize FN: Naive Bayes

TPR: Random Forest

TNR: Random Forest

Precision: Random Forest

Accuracy / BACC: Random Forest, Naive Bayes Tie (basically)

I think that in this case, because we want to minimize FP while gaining as much TP as we can, that means that we need to choose the classifier that performs the best at minimizing FP without costing TN, which means that in this case I would choose Random Forest.

Random Forest and Naive Bayes may basically tie on accuracy metrics, however they differ with respect to what they are able to detect. Random Forest is better at minimizing FP, which means that it more conservative with how it passes judgement on whether or not a question is insincere. Naive Bayes seems to be decent at maximizing the amount of positive classifications, which means that it is more aggressive than Random Forest. This might be okay if the original data was not so imbalanced, but given the imbalance this will be the worse choice, because in the context of the real world problem, this approach will result in many more detrimental total FP than it will advantageous total TP.

As a note; the reason that I did not even include the LSTM in this model is simple. My approach to this project utilizes tf-idf vectorization. This technique utilizes a generated voacbulary of sparse representations of word appearances to transform input sentences for model training.

This sparse representation works with models such as Naive Bayes and Random Forest, however it does not work with neural networks. This is because each of the vectors representing the sparse vocabulary term data has to be expanded into a dense vector before it can be utilized as input to a neural network. But this is the problem: when you expand a sparse vector/matrix, you make most of the values in the matrix/vector equal to zero. So I did this, and it basically results in a total loss of any discernable information for the input sentences. This obviously results in a total loss of ability for the neural network to learn any patterns, which is exactly what happens above. Upon closer examination of the neural network when computing the brier score / brier skill score, it becomes obvious that the model is not learning, because the probabilities that it outputs are basically the equivalent of a coin flip with added noise for every fold of training. I appreciate learning this here rather than in a professional setting.

1.8 END OF PROJECT