text-classification-cs4395

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1 Text Classification and Analysis using Naive Bayes, Logistic Regression, and Neural Networks

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Section: CS 4395.001

*** Before executing this notebook, ensure all necessary libraries/modules are installed. Simply run the notebook from top to bottom.** The dataset is used to solve a multi-class classification problem, classifying emails as fraud, commerical spam, phishing, or none (false-positive). This dataset is dervied from Kaggle, and is called "Phishing Email Data by Type." In this notebook, we will try to train our model using various algorithms, such as Naive Bayes, Logistic Regression, and a Neural Network to be able to predict whether a given email message is fraud, commerical spam, phishing, or none (false-positive). The dataset has 3 columns: 'Subject', 'Text', and 'Type.'The 'Text' column holds the entire email message. The subject of the emails is also another attribute in the dataset, however, in this notebook we will only be using the "Text" and "Type" columns. We will vectorize the "Text" column to derive the features for the model and the "Type" will represent our target class. Here is the link to the dataset: https://www.kaggle.com/datasets/charlottehall/phishing-email-data-by-type

1. Import Libraries and Preprocessing

[1]:
```
# import libraries
import pandas as pd
import seaborn as sns
import nltk
from nltk.corpus import stopwords
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('wordnet')

from sklearn.model_selection import train_test_split
from sklearn.feature_extraction import text
from sklearn.feature_extraction.text import TfidfVectorizer
from nltk import word_tokenize
from nltk.stem import WordNetLemmatizer
```

```
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score, confusion_matrix
```

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

[2]:
```
# get a text classification dataset (hosted on a public url via github)
data_url = "https://raw.githubusercontent.com/shreyavala/
 ↪nlp_text_classification_data/main/phishing_data_by_type.csv"
df=pd.read_csv(data_url)
df
```

[2]:

	Subject	Text	Type
0	URGENT BUSINESS ASSISTANCE AND PARTNERSHIP	URGENT BUSINESS ASSISTANCE AND PARTNERSHIP.\n\…	Fraud
1	URGENT ASSISTANCE /RELATIONSHIP (P)	Dear Friend,\n\nI am Mr. Ben Suleman a custom …	Fraud
2	GOOD DAY TO YOU	FROM HIS ROYAL MAJESTY (HRM) CROWN RULER OF EL…	Fraud
3	from Mrs.Johnson	Goodday Dear\n\n\nI know this mail will come t…	Fraud
4	Co-Operation	FROM MR. GODWIN AKWESI\nTEL: +233 208216645\nF…	Fraud
..	…	…	…
154	These Bags Just Arrived For Spring	Bags so perfect-you'll never want to be withou…	Commercial Spam
155	POTUS Comes to Broadway this April! Get Ticket…	INAUGURAL BROADWAY PERFORMANCE APRIL 14\r\nA N…	Commercial Spam
156	Let’s talk about Bridgerton!	GET THE BEST OF EVERYTHING IN THE APP\n\nSTARB…	Commercial Spam
157	MONDAY MIX: All eyes on Ukraine	Hi!\n \nSpring forward with our newest noPac c…	Commercial Spam
158	The DOTD is back on with 15% off a lightning-f…	Hi, | PLAYER MEMBER | 0 Points\n\nEarn And Sa…	Commercial Spam

[159 rows x 3 columns]

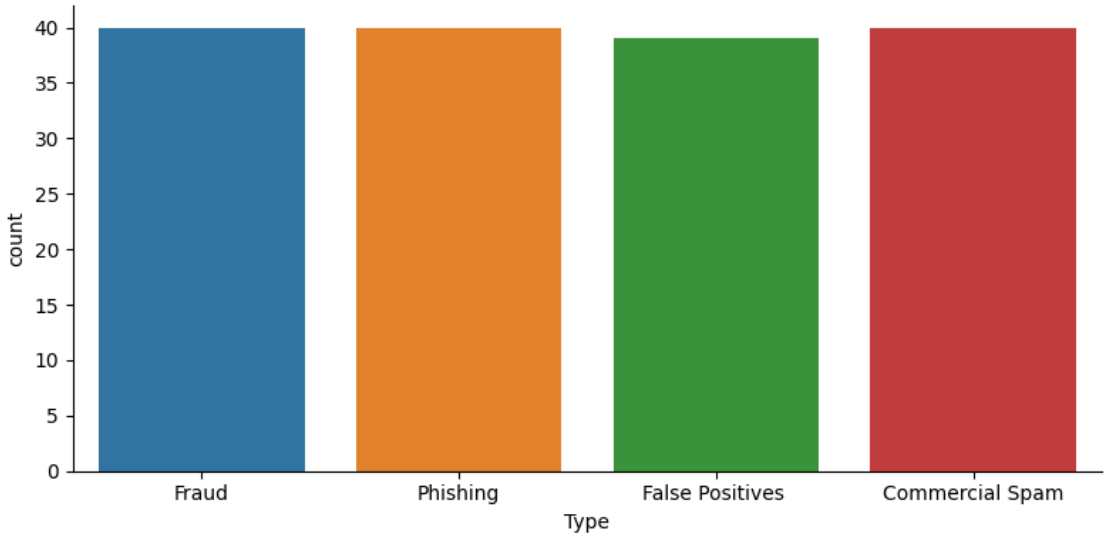
[3]:
```
print("Shape(Rows, Columns): ",df.shape)
```

```
Shape(Rows, Columns):  (159, 3)
```

[4]:
```
# creates a graph showing the distribution of the target classes

sns.catplot(data=df, kind='count', x='Type', height=4, aspect=2)
```

[4]:
```
<seaborn.axisgrid.FacetGrid at 0x7feca0b34b50>
```



From this distribution we can see that the classes are fairly balanced. There is a proportional number of instances between Fraud, Phishing, False Positives, and Commerical Spam emails. We do not need to undersample or oversample any class in this dataset. This dataset it relatively small, with 159 instances and 3 attributes.

[5]:
```
# preprocess the 'Text' column (lowercase, remove punctuation and numbers)
df['Text'] = df['Text'].str.lower() # lower
df['Text'] = df['Text'].str.replace('[^\w\s]','') # remove punctuation
df['Text'] = df['Text'].str.replace('\n','') # remove newlines
df['Text'] = df['Text'].str.replace('\t','') # remove tabs
df['Text'] = df['Text'].str.replace('\d+', '') # remove numbers
df
```

```
<ipython-input-5-a91182193439>:3: FutureWarning: The default value of regex will
change from True to False in a future version.
  df['Text'] = df['Text'].str.replace('[^\w\s]','') # remove punctuation
<ipython-input-5-a91182193439>:6: FutureWarning: The default value of regex will
change from True to False in a future version.
  df['Text'] = df['Text'].str.replace('\d+', '') # remove numbers
```

[5]:
```
                                              Subject  \
0           URGENT BUSINESS ASSISTANCE AND PARTNERSHIP
1                  URGENT ASSISTANCE /RELATIONSHIP (P)
```

```
2                                        GOOD DAY TO YOU
3                                       from Mrs.Johnson
4                                          Co-Operation
..                                                   …
154                    These Bags Just Arrived For Spring
155  POTUS Comes to Broadway this April! Get Ticket…
156                          Let’s talk about Bridgerton!
157                       MONDAY MIX: All eyes on Ukraine
158  The DOTD is back on with 15% off a lightning-f…

                                                  Text              Type
0    urgent business assistance and partnershipdear…             Fraud
1    dear friendi am mr ben suleman a custom office…             Fraud
2    from his royal majesty hrm crown ruler of elem…             Fraud
3    goodday deari know this mail will come to you …             Fraud
4    from mr godwin akwesitel  fax  before i introd…             Fraud
..                                                   …                 …
154  bags so perfectyoull never want to be without …  Commercial Spam
155  inaugural broadway performance april \ra new c…  Commercial Spam
156  get the best of everything in the appstarbucks…  Commercial Spam
157  hi spring forward with our newest nopac course…  Commercial Spam
158  hi   player member   pointsearn and save moreb…  Commercial Spam

[159 rows x 3 columns]
```

[6]:
```
# use tf-idf vectorization to extract features (tf-idf frequencies) and␣
 ↪preprocess by lemmatization
class LemmaTokenizer:
     def __init__(self):
         self.wnl = WordNetLemmatizer()
     def __call__(self, doc):
         return [self.wnl.lemmatize(t) for t in word_tokenize(doc)]

vectorizer = TfidfVectorizer(stop_words =␣
 ↪'english',tokenizer=LemmaTokenizer(),min_df=3) # intitialize a tf-idf␣
 ↪vectorizer (with stopwords removal and lemmatization)

vectorized_data = vectorizer.fit_transform(df['Text'].values.astype('U')) #␣
 ↪tell the vectorizer to read our data

# construct a dataframe with vectorized words (dataframe will be large)
df_vectorized= pd.DataFrame(vectorized_data.toarray(), columns=vectorizer.
 ↪get_feature_names_out())
df_vectorized.head()
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/feature_extraction/text.py:528:
UserWarning: The parameter 'token_pattern' will not be used since 'tokenizer' is
```

```
not None'
  warnings.warn(
/usr/local/lib/python3.9/dist-packages/sklearn/feature_extraction/text.py:409:
UserWarning: Your stop_words may be inconsistent with your preprocessing.
Tokenizing the stop words generated tokens ['ha', 'le', 'u', 'wa'] not in
stop_words.
  warnings.warn(
```

[6]:

	abacha	abandoned	abidjan	able	abroad	academic	accept	accepted	\
0	0.00000	0.0	0.0	0.0	0.000000	0.0	0.000000	0.0	
1	0.14028	0.0	0.0	0.0	0.000000	0.0	0.000000	0.0	
2	0.00000	0.0	0.0	0.0	0.070671	0.0	0.000000	0.0	
3	0.00000	0.0	0.0	0.0	0.200996	0.0	0.000000	0.0	
4	0.00000	0.0	0.0	0.0	0.000000	0.0	0.068949	0.0	

	access	accordance	…	youas	youi	youll	young	youre	youth	\
0	0.0	0.0	…	0.000000	0.000000	0.0	0.0	0.0	0.0	
1	0.0	0.0	…	0.000000	0.000000	0.0	0.0	0.0	0.0	
2	0.0	0.0	…	0.000000	0.000000	0.0	0.0	0.0	0.0	
3	0.0	0.0	…	0.000000	0.000000	0.0	0.0	0.0	0.0	
4	0.0	0.0	…	0.083368	0.065382	0.0	0.0	0.0	0.0	

	youtube	youve	zip	
0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0

[5 rows x 1251 columns]

2. Train/Test Split and Distribution of Data

[7]:
```
# train/test split
X = df_vectorized  # drop any other columns/features deemed unecessary for the X
y = df["Type"] # target class


x_train, x_test, y_train, y_test = train_test_split(X, y,test_size = 0.25) #␣
 ↪split data into 75% train, 25% test

print("X shape: ", x_train.shape, x_test.shape)
print("y shape: ", y_train.shape, y_test.shape)
```

```
X shape:  (119, 1251) (40, 1251)
y shape:  (119,) (40,)
```

3. Run and Evaluate Naive Bayes, Logistic Regression, Neural Network

Naive Bayes

[8]:
```
# Naive Bayes
from sklearn.naive_bayes import MultinomialNB

naive_bayes = MultinomialNB()
naive_bayes.fit(x_train, y_train)
```

[8]:
```
MultinomialNB()
```

[9]:
```
# test the naive bayes model by predicting
y_pred = naive_bayes.predict(x_test)
```

[10]:
```
#score the model printing accuracy, precision, and recall curves
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
                  precision    recall  f1-score   support

 Commercial Spam       0.75      0.90      0.82        10
False Positives        0.86      0.75      0.80         8
           Fraud       1.00      1.00      1.00        13
        Phishing       0.88      0.78      0.82         9

        accuracy                           0.88        40
       macro avg       0.87      0.86      0.86        40
    weighted avg       0.88      0.88      0.87        40
```

Logistic Regression

[11]:
```
# Logistic Regression
from sklearn.linear_model import LogisticRegression

logreg_model = LogisticRegression(multi_class='multinomial', solver = 'lbfgs')
logreg_model.fit(x_train,y_train)
```

[11]:
```
LogisticRegression(multi_class='multinomial')
```

[12]:
```
# test the logistic regression model by predicting
y_pred = logreg_model.predict(x_test)
```

[13]:
```
#score the model and print accuracy, precision, and recall curves
print(classification_report(y_test, y_pred))
```

```
                  precision    recall  f1-score   support

 Commercial Spam       0.80      0.80      0.80        10
False Positives        0.86      0.75      0.80         8
```

```
              Fraud       1.00      1.00      1.00        13
           Phishing       0.80      0.89      0.84         9

           accuracy                           0.88        40
          macro avg       0.86      0.86      0.86        40
       weighted avg       0.88      0.88      0.87        40
```

Neural Network

[14]:
```
# Neural Networks
from sklearn.neural_network import MLPClassifier

neural_net = MLPClassifier(activation = 'relu',random_state=1,␣
 ↪learning_rate='constant', learning_rate_init=0.001)
neural_net.fit(x_train, y_train)
```

```
/usr/local/lib/python3.9/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:686:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

[14]:
```
MLPClassifier(random_state=1)
```

[15]:
```
# test the neural network by predicting
y_pred = neural_net.predict(x_test)
```

[16]:
```
print(classification_report(y_test, y_pred))
```

```
                precision    recall  f1-score   support

 Commercial Spam       0.77      1.00      0.87        10
False Positives        0.78      0.88      0.82         8
          Fraud        1.00      0.92      0.96        13
       Phishing        1.00      0.67      0.80         9

       accuracy                           0.88        40
      macro avg       0.89      0.87      0.86        40
   weighted avg       0.90      0.88      0.87        40
```

1.0.1 4. Analysis

From running the three algorithms, we can see that the accuracy is fairly high and consistent across all with 88%.

When running naive bayes, it performed best at detecting fraud. Interestingly, it perfomed the same for detecting commerical spam as logistic regression. Additionally, it has a relatively low

precision and high recall for commerical spam, but a higher recall than precision for phishing, which is oppsite to what logitic regression had in terms of results.

For logistic regression, accuracy was once again sitting at 88%. For correctly detecting commerical spam, false positives, and fraud, the algorithm had a relatively high precision and high recall. It perfomed the worst at detecting false positives with precision at 0.86 and recall at 0.75. These differences are not concerning, but could be due to the fact that the number of actual false positive instances were lower than the other 3 types at 8. In general a very low precision rate means that the model predicts a lot of phishing emails even if they aren't. A low recall and high precision means that the model fails to detect many instances of a type emails, but when it does, it's fairly believable. This doesn't apply to our model because logistic regression performed well across all classes.

Lastly, using a neural network, in our case sklearn's MLPClassifier, accuracy was tied with the highest at 88%. Similarly, it perfomed very well detecting fraud. All across, the model perfomed well in detecting commerical spam, false positives, and phishing all with high recalls and precision. However, it had a high precision and lower recall for phishing, and a low precision and high recall for false positives. These results can be explained by the lower numbers of actual instances of those classes and by the explanation given above.

Overall, all 3 models performed very well, especially at detecting fraud emails. However, precision, recall, f1, and accuracy for all classes for all 3 models were relatively high but slight differences between classes.