DSC680T301_PhishingDetection_LincolnBrown

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[52]:
```
from collections import Counter
import matplotlib.pyplot as plt
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
import numpy as np
import pandas as pd
import re
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,␣
  ↪confusion_matrix, roc_auc_score, roc_curve
import torch
from torch.utils.data import DataLoader, TensorDataset
from torch.optim import AdamW
import torch.nn.functional as F
from transformers import BertTokenizer, BertForSequenceClassification,␣
  ↪get_scheduler
from textblob import TextBlob
```

[2]:
```
f = './Phishing_Email.csv'
df = pd.read_csv(f, index_col=0)
```

[3]:
```
df
```

[3]:
```
                                              Email Text      Email Type
0      re : 6 . 1100 , disc : uniformitarianism , re …      Safe Email
1      the other side of * galicismos * * galicismo *…      Safe Email
2      re : equistar deal tickets are you still avail…      Safe Email
3      \nHello I am your hot lil horny toy.\n    I am…  Phishing Email
4      software at incredibly low prices ( 86 % lower…  Phishing Email
…                                                  …               …
18646  date a lonely housewife always wanted to date …  Phishing Email
18647  request submitted : access request for anita …      Safe Email
18648  re : important - prc mtg hi dorn & john , as y…      Safe Email
18649  press clippings - letter on californian utilit…      Safe Email
```

```
18650                                                  empty  Phishing Email

[18650 rows x 2 columns]
```

0.1 Data Cleaning

[4]:
```python
# Get the number of null values in the dataset
df.isnull().sum()
```

[4]:
```
Email Text    16
Email Type     0
dtype: int64
```

[5]:
```python
# Drop the na's
clean_df = df.copy()
clean_df.dropna(inplace=True)
```

[6]:
```python
# Look for records that contain the text 'empty'
# These records will also be considered missing and dropped as well

len(clean_df.loc[clean_df['Email Text'] == 'empty'])
```

[6]:
```
533
```

[7]:
```python
# Select records that do not have the email text 'empty'
clean_df = clean_df[clean_df['Email Text'] != 'empty']
```

[8]:
```python
# View the shape after removing nulls
clean_df.shape
```

[8]:
```
(18101, 2)
```

[9]:
```python
# Binary Encode the Email Type
clean_df.loc[:, 'Email Type'] =  clean_df['Email Type'].map({'Phishing Email':␣
↪1, 'Safe Email': 0})
```

[10]:
```python
# Convert to int64
clean_df['Email Type'] = pd.to_numeric(clean_df['Email Type'])
clean_df['Email Type'].dtype
```

[10]:
```
dtype('int64')
```

[11]:
```python
# Download stopwords from nltk
nltk.download('stopwords')
nltk.download('punkt')
```

```
[nltk_data] Downloading package stopwords to /Users/x/nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

```
[nltk_data] Downloading package punkt to /Users/x/nltk_data…
[nltk_data]   Package punkt is already up-to-date!
```

[11]: True

0.2 Exploratory Data Analysis

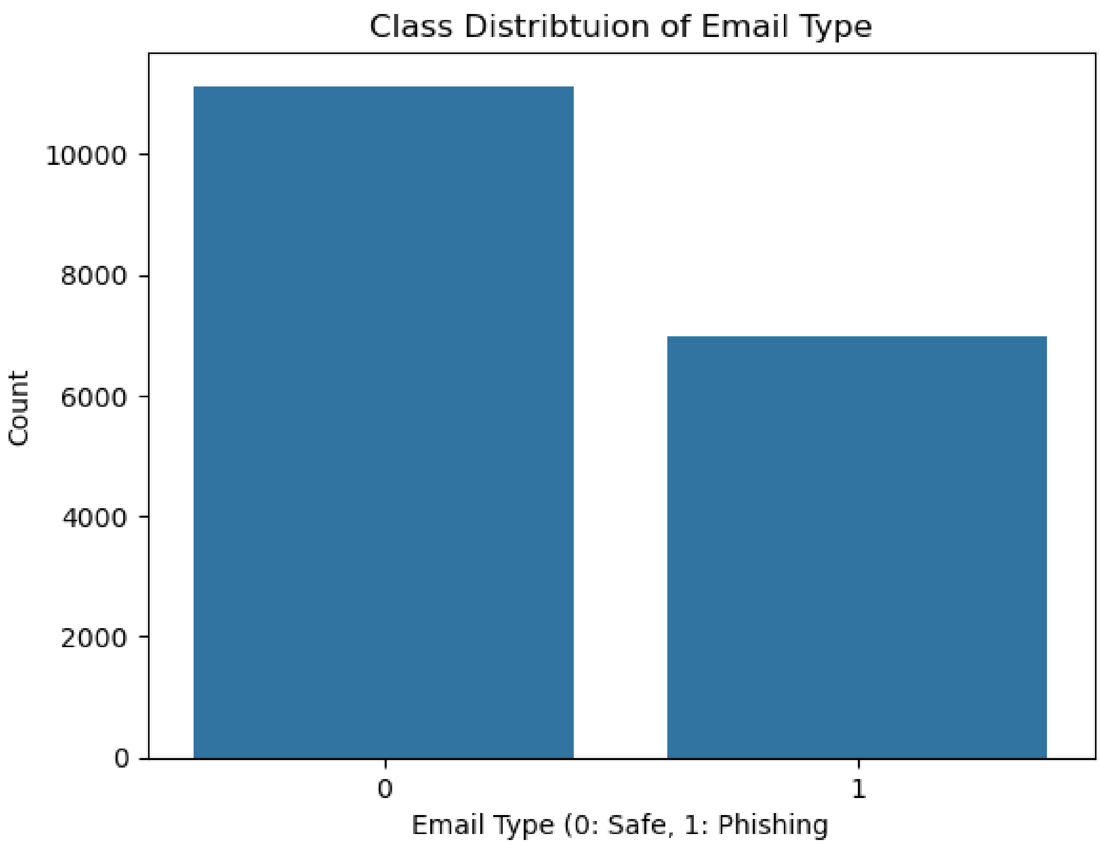
[12]:
```python
eda_df = clean_df.copy()
```

[13]:
```python
eda_df.describe()
```

[13]:

	Email Type
count	18101.000000
mean	0.385448
std	0.486714
min	0.000000
25%	0.000000
50%	0.000000
75%	1.000000
max	1.000000

[14]:
```python
# Create a count plot of the class distribution
sns.countplot(x=eda_df['Email Type'])
plt.title('Class Distribtuion of Email Type')
plt.xlabel('Email Type (0: Safe, 1: Phishing')
plt.ylabel('Count')
plt.show()
```



[15]:

```
# Get the word and character counts for the emails

eda_df['word_count'] = eda_df['Email Text'].apply(lambda x: len(x.split()))
eda_df['char_count'] = eda_df['Email Text'].apply(lambda x: len(x))
```

[16]:

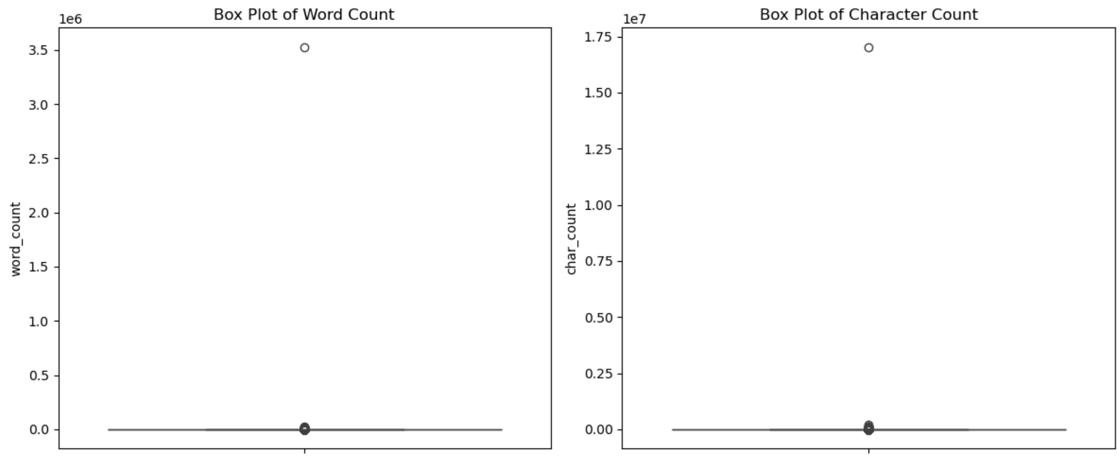
```
eda_df.describe()
```

[16]:

	Email Type	word_count	char_count
count	18101.000000	1.810100e+04	1.810100e+04
mean	0.385448	5.509090e+02	2.836649e+03
std	0.486714	2.622834e+04	1.266919e+05
min	0.000000	0.000000e+00	1.000000e+00
25%	0.000000	8.000000e+01	4.340000e+02
50%	0.000000	1.670000e+02	9.130000e+02
75%	1.000000	3.660000e+02	1.936000e+03
max	1.000000	3.527576e+06	1.703669e+07

From the descriptive statistics above, we can see that we have at least one email that contains no characters and at least one that is many magnitudes higher (e+07) than the median (e+02). Let's take a look at the distribution of word_count and char_count.

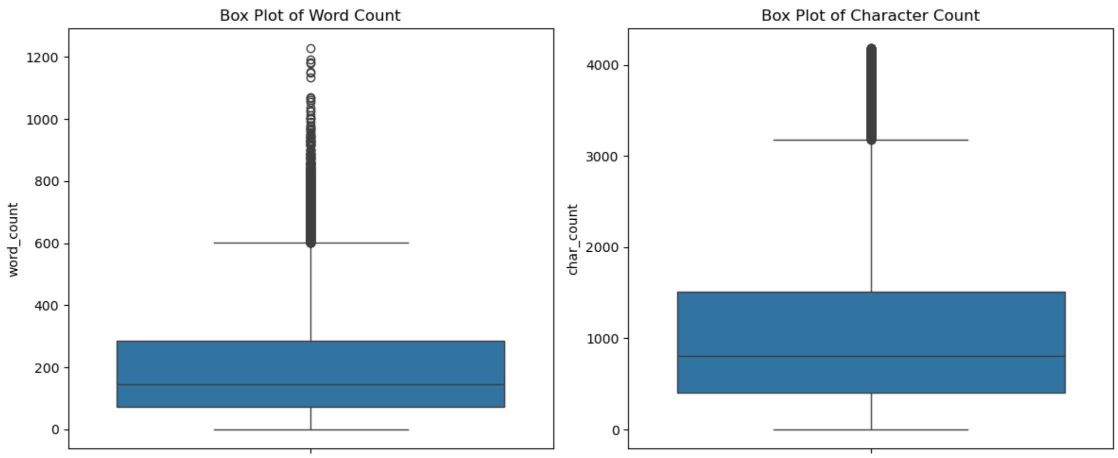
[17]:
```python
# Review the distributions using box plots
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Box plot of word_count
sns.boxplot(eda_df['word_count'], ax=axes[0])
axes[0].set_title('Box Plot of Word Count')

# Box plot of char_count
sns.boxplot(eda_df['char_count'], ax=axes[1])
axes[1].set_title('Box Plot of Character Count')

plt.tight_layout()
plt.show()
```



[18]:
```python
# Remove the outliers using IQR
q1 = eda_df['char_count'].quantile(0.25)
q3 = eda_df['char_count'].quantile(0.75)
iqr = q3 - q1

# Define bounds
lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr

# Filter the outliers
filtered_df = eda_df[(eda_df['char_count'] >= lower_bound) &␣
↪(eda_df['char_count'] <= upper_bound)].copy()
```

[19]:
```python
# Review the distributions after removing outliers
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Box plot of word_count
```

```
sns.boxplot(filtered_df['word_count'], ax=axes[0])
axes[0].set_title('Box Plot of Word Count')

# Box plot of char_count
sns.boxplot(filtered_df['char_count'], ax=axes[1])
axes[1].set_title('Box Plot of Character Count')

plt.tight_layout()
plt.show()
```

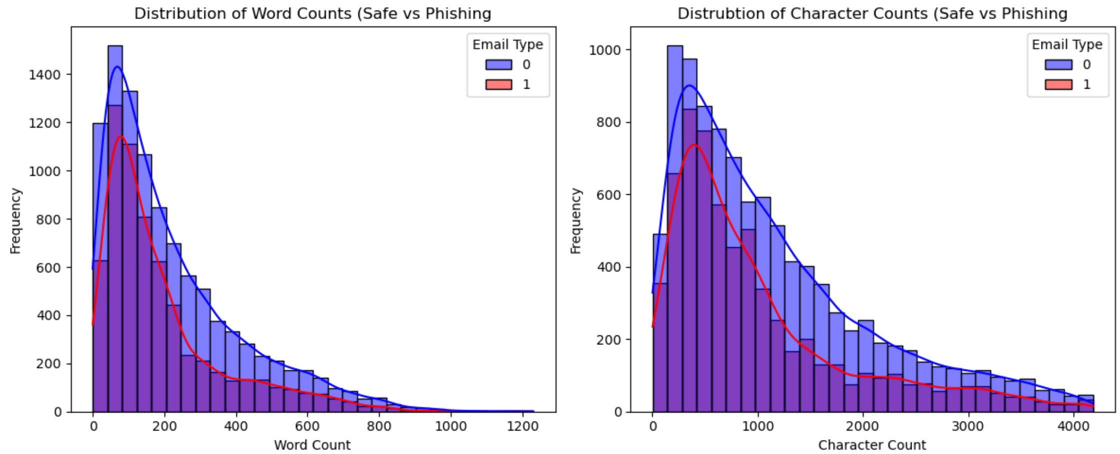


[20]:
```
# Determine the amount of outlier records removed
num_outliers_removed = eda_df.shape[0] - filtered_df.shape[0]

print(f'There were {num_outliers_removed} outlier records removed.')
print(f'The dataset now contains {filtered_df.shape[0]} rows and {filtered_df.
  ↪shape[1]} columns.')
```

```
There were 1662 outlier records removed.
The dataset now contains 16439 rows and 4 columns.
```

[21]:
```
# Check distributions of safe vs phishing emails for word and character counts

fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Plot word count
sns.histplot(data=filtered_df, x='word_count', hue='Email Type', bins=30,␣
  ↪kde=True, ax=axes[0], palette={0: 'blue', 1: 'red'})
axes[0].set_title('Distribution of Word Counts (Safe vs Phishing')
axes[0].set_xlabel('Word Count')
axes[0].set_ylabel('Frequency')
```

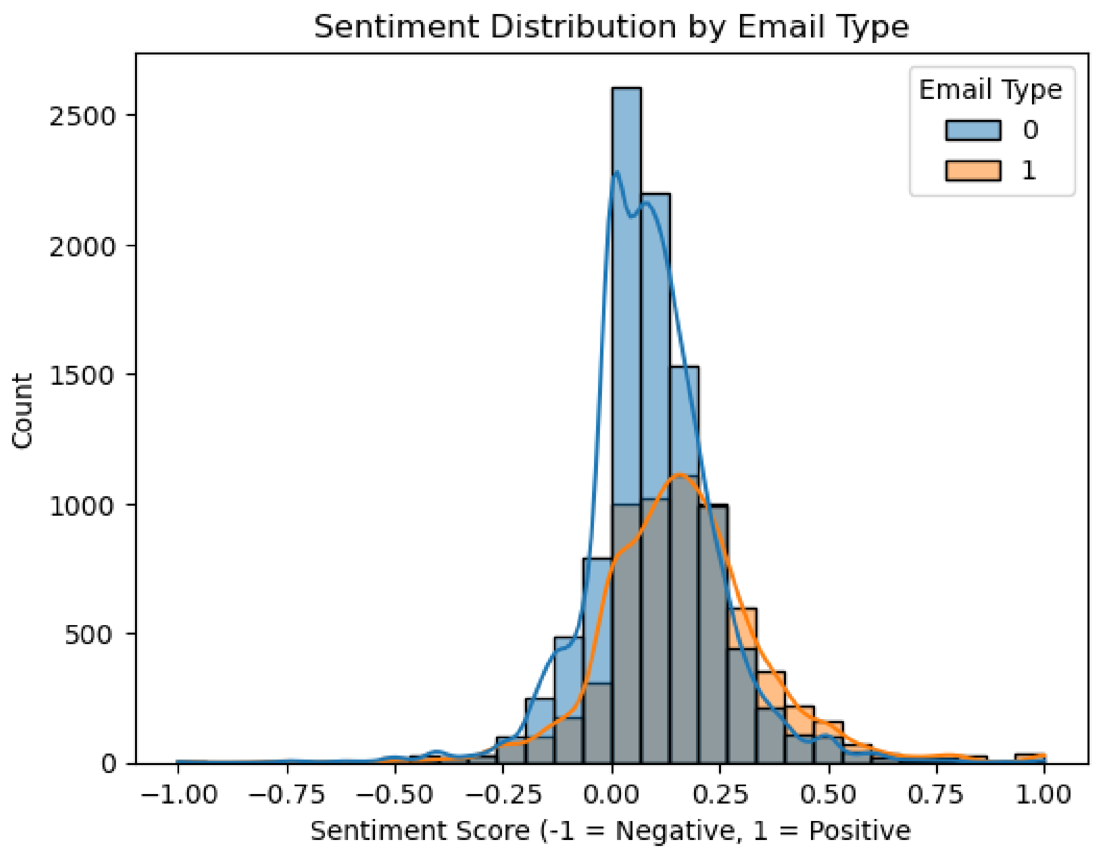
```
# Plot character count
sns.histplot(data=filtered_df, x='char_count', hue='Email Type', bins=30,␣
↪kde=True, ax=axes[1], palette={0: 'blue', 1: 'red'})
axes[1].set_title('Distrubtion of Character Counts (Safe vs Phishing')
axes[1].set_xlabel('Character Count')
axes[1].set_ylabel('Frequency')

plt.tight_layout()
plt.show()
```



0.3 Sentiment Analysis

[22]:
```
filtered_df['sentiment'] = filtered_df.loc[:,'Email Text'].apply(lambda x:␣
↪TextBlob(x).sentiment.polarity)
```

[23]:
```
# Plot sentiment distribution
sns.histplot(filtered_df, x='sentiment', hue='Email Type', bins=30, kde=True)
plt.title('Sentiment Distribution by Email Type')
plt.xlabel('Sentiment Score (-1 = Negative, 1 = Positive)')
plt.show()
```



0.4 Most Common Words in Safe vs Phishing Emails

[24]:
```
# Split phishing and safe emails
safe_text = ' '.join(filtered_df[filtered_df['Email Type'] == 0]['Email Text'])
phishing_text = ' '.join(filtered_df[filtered_df['Email Type'] == 1]['Email␣
↪Text'])
```

0.5 Bag of Words

[25]:
```
# Setup the function to clean the text

def bow_preprocess_text(text):
    text = re.sub(r'\W', ' ', text) # Remove special characters
    text = re.sub(r'\d+', ' ', text) # Remove numbers
    text = re.sub(r'\s_', ' ', text).strip() # Remove extra spaces
    text = text.lower()
    words = word_tokenize(text) # Tokenization
    words = [word for word in words if word not in stopwords.words('english')]␣
↪# Remove stop words
```

```
    return ' '.join(words)
```

[26]:
```
model_df = filtered_df.copy()
model_df
```

[26]:
```
                                              Email Text  Email Type  \
0      re : 6 . 1100 , disc : uniformitarianism , re …           0
1      the other side of * galicismos * * galicismo *…           0
2      re : equistar deal tickets are you still avail…           0
3      \nHello I am your hot lil horny toy.\n    I am…           1
4      software at incredibly low prices ( 86 % lower…           1
…                                                    …         …
18643  URL: http://diveintomark.org/archives/2002/09/…           0
18646  date a lonely housewife always wanted to date …           1
18647  request submitted : access request for anita …          0
18648  re : important - prc mtg hi dorn & john , as y…           0
18649  press clippings - letter on californian utilit…           0

       word_count  char_count  sentiment
0             230        1030   0.201493
1              91         479   0.009375
2             305        1245   0.091540
3              96         688   0.260069
4              91         441   0.152579
…             …          …        …
18643          62         429   0.000000
18646          45         237  -0.100000
18647          99         477  -0.183333
18648         253        1214   0.141250
18649          34         213   0.200000

[16439 rows x 5 columns]
```

[27]:
```
# Preprocess text
model_df['Cleaned Text'] = model_df['Email Text'].apply(bow_preprocess_text)
```

[28]:
```
model_df.drop(columns=['Email Text'], inplace=True)
```

[29]:
```
model_df
```

[29]:
```
       Email Type  word_count  char_count  sentiment  \
0               0         230        1030   0.201493
1               0          91         479   0.009375
2               0         305        1245   0.091540
3               1          96         688   0.260069
4               1          91         441   0.152579
…             …          …          …          …
```

```
18643          0          62          429   0.000000
18646          1          45          237  -0.100000
18647          0          99          477  -0.183333
18648          0         253         1214   0.141250
18649          0          34          213   0.200000

                                            Cleaned Text
0      disc uniformitarianism sex lang dick hudson ob…
1      side galicismos galicismo spanish term names i…
2      equistar deal tickets still available assist r…
3      hello hot lil horny toy one dream open minded …
4      software incredibly low prices lower drapery s…
…                                                   …
18643  url http diveintomark org archives html plan d…
18646  date lonely housewife always wanted date lonel…
18647  request submitted access request anita dupont …
18648  important prc mtg hi dorn john discovered rece…
18649  press clippings letter californian utilities p…

[16439 rows x 5 columns]
```

[30]:
```python
# Split the dataset
X_train, X_test, y_train, y_test = train_test_split(model_df['Cleaned Text'],
  model_df['Email Type'], test_size=0.2, random_state=42,
  stratify=model_df['Email Type'])
```

[31]:
```python
# Convert to TF-IDF features
vectorizer = TfidfVectorizer(max_features=5000)
X_train_tfidf = vectorizer.fit_transform(X_train)
X_test_tfidf = vectorizer.transform(X_test)
```

0.6 Logistic Regression Model

[32]:
```python
# Logistic Regression Model
# Create the LR model
lr_model = LogisticRegression()
# Train the LR Model
lr_model.fit(X_train_tfidf, y_train)

# Make predictions
y_pred_lr = lr_model.predict(X_test_tfidf)

# Evalute model performance
accuracy = accuracy_score(y_test, y_pred_lr)
print(f'Accuracy: {accuracy:.4f}')
print(f'Classification Report: \n{classification_report(y_test, y_pred_lr)}')
```

```
Accuracy: 0.9775
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.98      2008
           1       0.98      0.96      0.97      1280

    accuracy                           0.98      3288
   macro avg       0.98      0.97      0.98      3288
weighted avg       0.98      0.98      0.98      3288
```

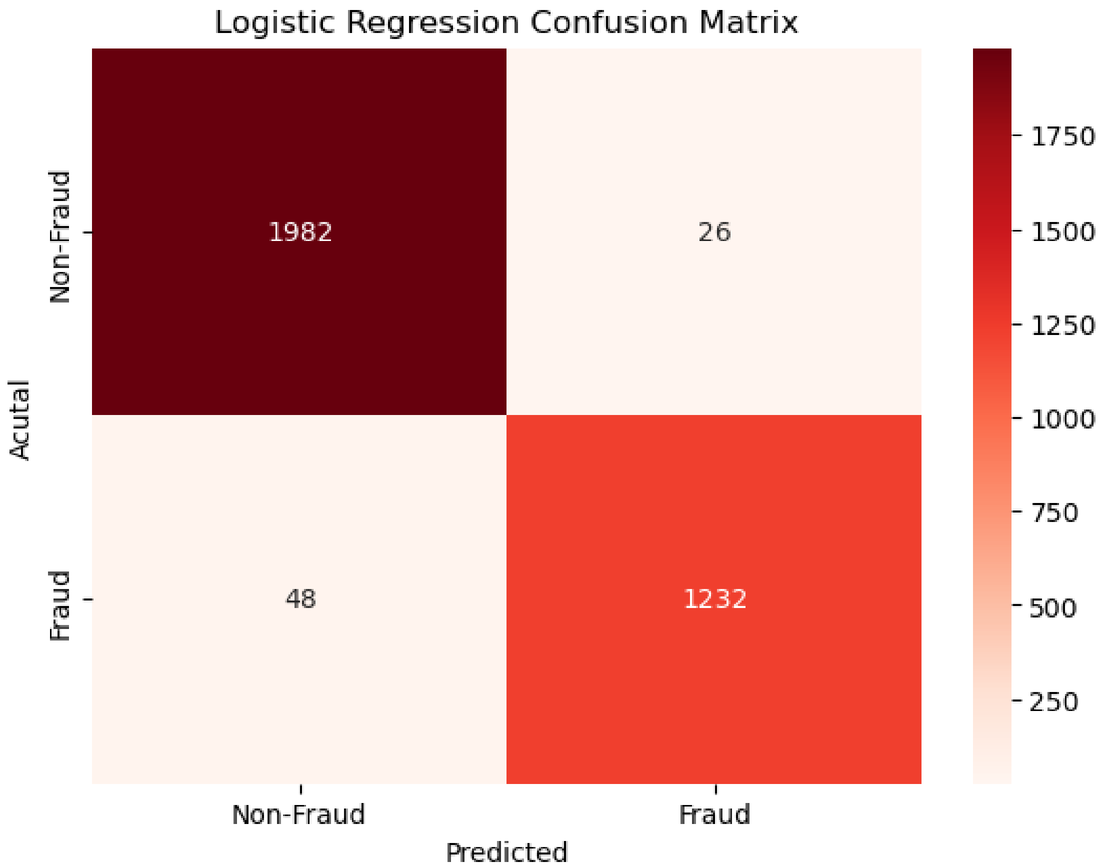
[33]:
```
feature_names = vectorizer.get_feature_names_out()
top_coefs = lr_model.coef_[0].argsort()[::-1][:20]
print([feature_names[i] for i in top_coefs])
```

```
['remove', 'click', 'sightings', 'free', 'money', 'site', 'email', 'save',
'life', 'removed', 'reply', 'hello', 'software', 'offer', 'want', 'viagra',
'best', 'online', 'quality', 'account']
```

[34]:
```
# Confusion Matrix
lr_cm = confusion_matrix(y_test, y_pred_lr)
lr_cm
```

[34]:
```
array([[1982,   26],
       [  48, 1232]])
```

[65]:
```
# Plot the LR model confusion matrix
plt.figure(figsize=(7,5))
annotations = [f'TN: {lr_cm[0,0]}', f'FP: {lr_cm[0,1]}'], [f'FN:{lr_cm[1,0]}',␣
 ↪f'TP: {lr_cm[1,1]}']
lr_hm = sns.heatmap(lr_cm, annot=True, fmt='d', cmap='Reds',␣
 ↪xticklabels=['Non-Fraud', 'Fraud'], yticklabels=['Non-Fraud', 'Fraud'])

plt.xlabel('Predicted')
plt.ylabel('Acutal')
plt.title('Logistic Regression Confusion Matrix')
bert_hm.text(0.1, 0.2, 'True Negative', color='white')
bert_hm.text(1.1, 0.2, 'False Positive')
bert_hm.text(0.1, 1.2, 'False Negative')
bert_hm.text(1.1, 1.2, 'True Positive')
plt.show()
```

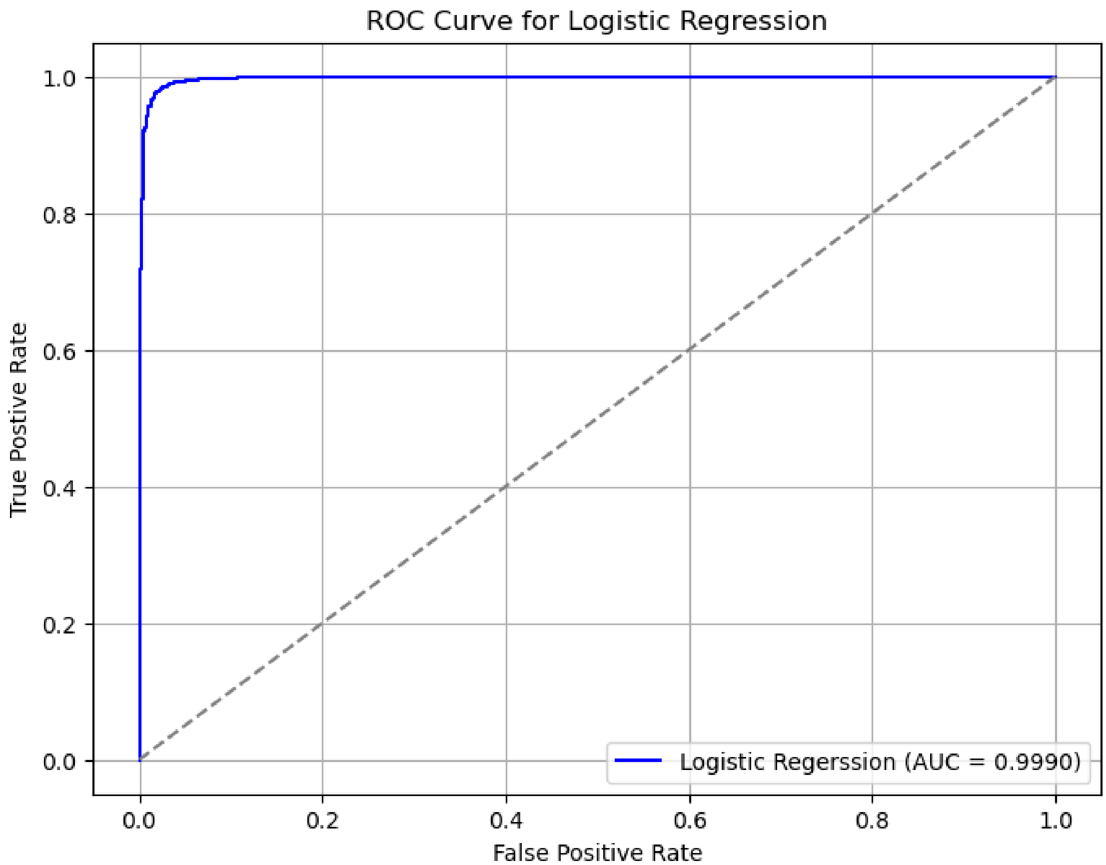


[36]:
```python
# Get the ROC AUC
# Get the probability for the phishing emails
y_probs = lr_model.predict_proba(X_test_tfidf)[:, 1]

roc_auc = roc_auc_score(y_test, y_probs)
roc_auc
```

[36]: 0.9973800112051793

[54]:
```python
# Plot the ROC curve
lr_fpr, lr_tpr, _ = roc_curve(y_test, y_probs)

plt.figure(figsize=(8,6))
plt.plot(lr_fpr, lr_tpr, label=f'Logistic Regerssion (AUC = {roc_auc:.4f})',␣
 ↪color='blue')
plt.plot([0,1], [0,1], linestyle='--', color='gray')
plt.xlabel('False Positive Rate')
plt.ylabel('True Postive Rate')
plt.title('ROC Curve for Logistic Regression')
```

```
plt.legend()
plt.grid()
plt.show()
```



0.7 BERT Model

[38]:
```
# Load the BERT Tokenizer
tokenizer = BertTokenizer.from_pretrained("bert-base-uncased")
```

[39]:
```
# Define tokenize function
def tokenize_function(texts):
    return tokenizer(texts.tolist(), padding=True, truncation=True,␣
 ↪max_length=512, return_tensors='pt')
```

[40]:
```
# Tokenize teh data and convert labels to tensors
train_encodings = tokenize_function(X_train)
test_encodings = tokenize_function(X_test)

train_labels = torch.tensor(y_train.tolist())
```

```
test_labels = torch.tensor(y_test.tolist())
```

[41]:
```
# Create the Bert Model
bert_model = BertForSequenceClassification.from_pretrained('bert-base-uncased',␣
↪num_labels=2)
```

```
Some weights of BertForSequenceClassification were not initialized from the
model checkpoint at bert-base-uncased and are newly initialized:
['classifier.bias', 'classifier.weight']
You should probably TRAIN this model on a down-stream task to be able to use it
for predictions and inference.
```

[48]:
```
# Create a TensorDataset for the input_ids and attention masks
train_dataset = TensorDataset(train_encodings['input_ids'],␣
↪train_encodings['attention_mask'], train_labels)
test_dataset = TensorDataset(test_encodings['input_ids'],␣
↪test_encodings['attention_mask'], test_labels)

# Create data loaders for batch processing
train_dataloader = DataLoader(train_dataset, batch_size=8, shuffle=True)
test_dataloader = DataLoader(test_dataset, batch_size=8, shuffle=False)
```

[43]:
```
# Use Apple GPU
device = torch.device('mps' if torch.backends.mps.is_available() else 'cpu')
bert_model.to(device)
```

[43]:
```
BertForSequenceClassification(
  (bert): BertModel(
    (embeddings): BertEmbeddings(
      (word_embeddings): Embedding(30522, 768, padding_idx=0)
      (position_embeddings): Embedding(512, 768)
      (token_type_embeddings): Embedding(2, 768)
      (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (encoder): BertEncoder(
      (layer): ModuleList(
        (0-11): 12 x BertLayer(
          (attention): BertAttention(
            (self): BertSdpaSelfAttention(
              (query): Linear(in_features=768, out_features=768, bias=True)
              (key): Linear(in_features=768, out_features=768, bias=True)
              (value): Linear(in_features=768, out_features=768, bias=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
            (output): BertSelfOutput(
              (dense): Linear(in_features=768, out_features=768, bias=True)
              (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
```

```
                (dropout): Dropout(p=0.1, inplace=False)
              )
            )
            (intermediate): BertIntermediate(
              (dense): Linear(in_features=768, out_features=3072, bias=True)
              (intermediate_act_fn): GELUActivation()
            )
            (output): BertOutput(
              (dense): Linear(in_features=3072, out_features=768, bias=True)
              (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
          )
        )
      )
      (pooler): BertPooler(
        (dense): Linear(in_features=768, out_features=768, bias=True)
        (activation): Tanh()
      )
    )
    (dropout): Dropout(p=0.1, inplace=False)
    (classifier): Linear(in_features=768, out_features=2, bias=True)
  )
```

[47]:

```
# Train the BERT model
# Set optimizer
optimizer = AdamW(bert_model.parameters(), lr=3e-5)

epochs = 3

num_training_steps = epochs * len(train_dataloader)
lr_scheduler = get_scheduler(
    "linear", optimizer=optimizer, num_warmup_steps=0,␣
 ↪num_training_steps=num_training_steps
)

for epoch in range(epochs):
    bert_model.train()
    total_loss = 0
    for batch in train_dataloader:
        input_ids, attention_mask, labels = [x.to(device) for x in batch]
        optimizer.zero_grad()
        outputs = bert_model(input_ids, attention_mask=attention_mask,␣
 ↪labels=labels)
        loss = outputs.loss
        total_loss += loss.item()
        loss.backward()
```

```
        optimizer.step()

    print(f'Epoch {epoch+1}, Loss: {total_loss:.4f}')
```

```
Epoch 1, Loss: 229.5264
Epoch 2, Loss: 64.3780
Epoch 3, Loss: 31.5956
```

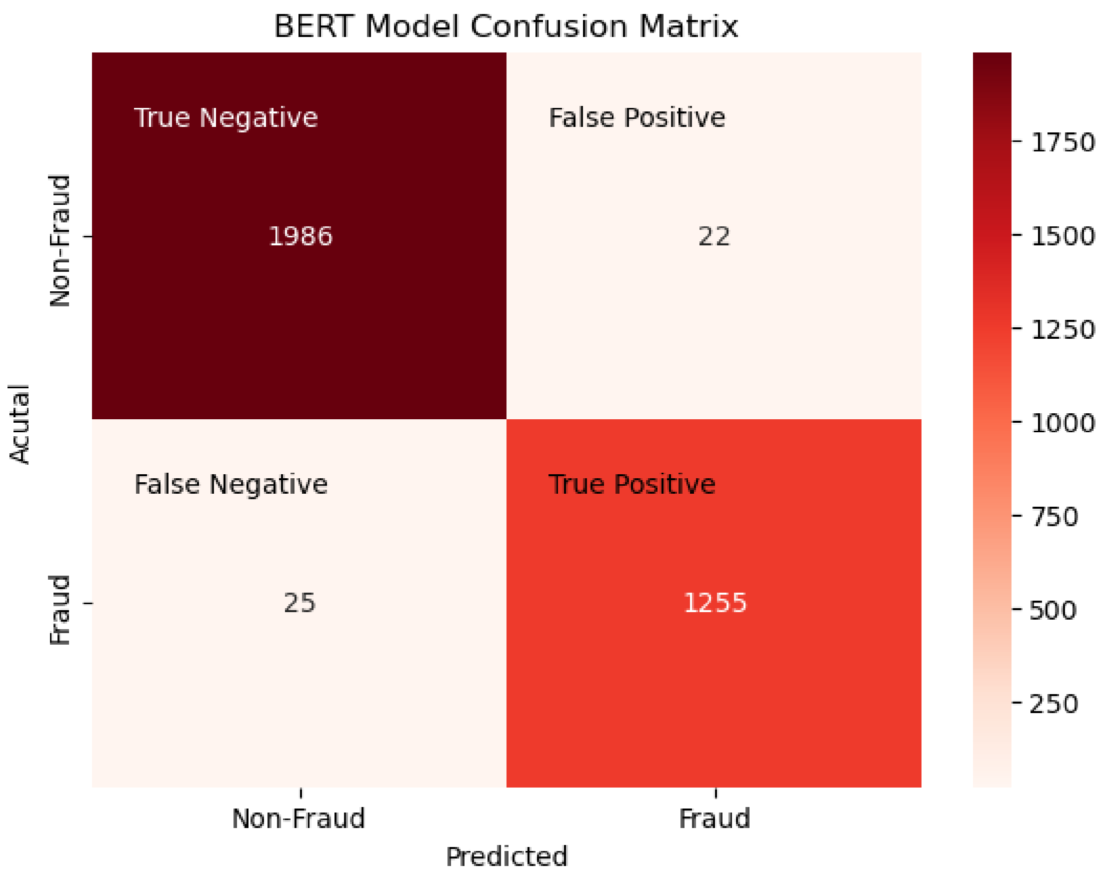
[49]:
```
# Get the BERT model results
bert_model.eval()
predictions, true_labels = [], []

with torch.no_grad():
    for batch in test_dataloader:
        input_ids, attention_mask, labels = [x.to(device) for x in batch]

        outputs = bert_model(input_ids, attention_mask=attention_mask)
        logits = outputs.logits
        preds = torch.argmax(logits, dim=1).cpu().numpy()

        predictions.extend(preds)
        true_labels.extend(labels.cpu().numpy())

# Print metrics
print(f'Accuracy: {accuracy_score(true_labels, predictions):.4f}')
print(classification_report(true_labels, predictions))
```

```
Accuracy: 0.9857
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      2008
           1       0.98      0.98      0.98      1280

    accuracy                           0.99      3288
   macro avg       0.99      0.98      0.98      3288
weighted avg       0.99      0.99      0.99      3288
```

[50]:
```
# BERT Model Confusion Matrix
bert_cm = confusion_matrix(true_labels, predictions)

bert_cm
```

[50]:
```
array([[1986,   22],
       [  25, 1255]])
```

[63]:
```
# Plot the BERT model confusion matrix
plt.figure(figsize=(7,5))
annotations = [f'TN: {bert_cm[0,0]}', f'FP: {bert_cm[0,1]}'], [f'FN:
↪{bert_cm[1,0]}', f'TP: {bert_cm[1,1]}']
bert_hm = sns.heatmap(bert_cm, annot=True, fmt='d', cmap='Reds',␣
↪xticklabels=['Non-Fraud', 'Fraud'], yticklabels=['Non-Fraud', 'Fraud'])

plt.xlabel('Predicted')
plt.ylabel('Acutal')
plt.title('BERT Model Confusion Matrix')
bert_hm.text(0.1, 0.2, 'True Negative', color='white')
bert_hm.text(1.1, 0.2, 'False Positive')
bert_hm.text(0.1, 1.2, 'False Negative')
bert_hm.text(1.1, 1.2, 'True Positive')
plt.show()
```



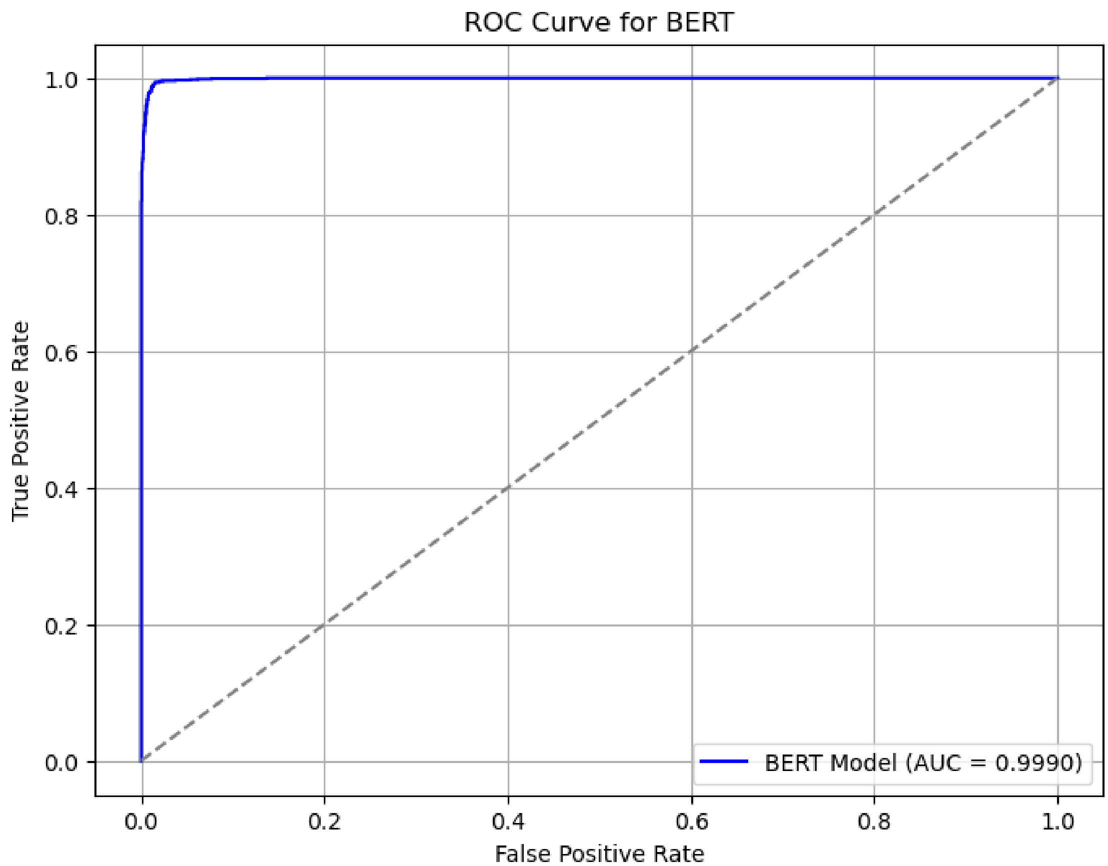
[53]:
```
# Convert logits to probabilities using softmax

with torch.no_grad():
```

```
    all_logits = []
    all_true_labels = []
    for batch in test_dataloader:
        input_ids, attention_mask, labels = [x.to(device) for x in batch]
        outputs = bert_model(input_ids, attention_mask=attention_mask)
        logits = outputs.logits
        probs = F.softmax(logits, dim=1)[:, 1].cpu().numpy()  # Probabilities␣
 ↪for the positive class
        all_logits.extend(probs)
        all_true_labels.extend(labels.cpu().numpy())

# Compute AUC-ROC Score
roc_auc = roc_auc_score(all_true_labels, all_logits)
print(f'ROC AUC Score: {roc_auc:.4f}')
```

```
ROC AUC Score: 0.9990
```

[57]:

```
# Plot the ROC curve
bert_fpr, bert_tpr, _ = roc_curve(all_true_labels, all_logits)

plt.figure(figsize=(8,6))
plt.plot(bert_fpr, bert_tpr, label=f'BERT Model (AUC = {roc_auc:.4f})',␣
 ↪color='blue')
plt.plot([0,1], [0,1], linestyle='--', color='gray')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for BERT')
plt.legend()
plt.grid()
plt.show()
```


ROC Curve for BERT
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
BERT Model (AUC = 0.9990)

```
[ ]:
```