Andrew Pfeifer Final Project Code

November 16, 2024

[37]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import random

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, accuracy_score, roc_curve,auc
from sklearn import metrics
%matplotlib inline


import warnings
warnings.filterwarnings("ignore")
```

1 Data Preparation

[38]:
```python
# Import the data.
df = pd.read_csv("creditcard.csv")

# Ensure the data loaded in properly.
df.head()
```

[38]:
```
   Time        V1        V2        V3        V4        V5        V6        V7  \
0   0.0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        V9  …       V21       V22       V23       V24       V25  \
0  0.098698  0.363787  … -0.018307  0.277838 -0.110474  0.066928  0.128539
1  0.085102 -0.255425  … -0.225775 -0.638672  0.101288 -0.339846  0.167170
2  0.247676 -1.514654  …  0.247998  0.771679  0.909412 -0.689281 -0.327642
3  0.377436 -1.387024  … -0.108300  0.005274 -0.190321 -1.175575  0.647376
```

```
4 -0.270533  0.817739  … -0.009431  0.798278 -0.137458  0.141267 -0.206010

        V26       V27       V28  Amount  Class
0 -0.189115  0.133558 -0.021053  149.62      0
1  0.125895 -0.008983  0.014724    2.69      0
2 -0.139097 -0.055353 -0.059752  378.66      0
3 -0.221929  0.062723  0.061458  123.50      0
4  0.502292  0.219422  0.215153   69.99      0

[5 rows x 31 columns]
```

[39]:
```
# Checking the shape of the data set.
df.shape
```

[39]:
```
(284807, 31)
```

[40]:
```
# Get counts of the fraud and non-fraud cases.
df['Class'].value_counts()
```

[40]:
```
Class
0    284315
1       492
Name: count, dtype: int64
```

[41]:
```
# Code maked as comments to save space on the paper.
# Using fig and axs set up the dimensions of the subplots.
#fig, axs = plt.subplots(len(df.columns), 1, figsize = (8, 40))
# Loop through the data to plot a histogram.
# Enumerate keeps track of the i value.
#for i, ax in enumerate(axs):
    #ax.hist(df.iloc[:,i])
    #ax.set_title(df.columns[i].title() + ' Histogram', fontsize =
 ↪12,fontweight= "bold")
# Tight layout prints the plots close together.
#plt.tight_layout()
# Use show to display the plots.
#plt.show()
```

[42]:
```
# Check for any NA values.
df.isna().sum().sum()
```

[42]:
```
0
```

[43]:
```
# Seperate the fraud and non fraud transactions.

nonFraud = df[df.Class==0]
fraud = df[df.Class==1]
```

[44]:
```python
# Compare the statistics for both transaction types.
df.groupby("Class").mean()
```

[44]:
```
               Time        V1        V2        V3        V4        V5  \
Class
0      94838.202258  0.008258 -0.006271  0.012171 -0.007860  0.005453
1      80746.806911 -4.771948  3.623778 -7.033281  4.542029 -3.151225

             V6        V7        V8        V9  …       V20       V21  \
Class                                          …
0      0.002419  0.009637 -0.000987  0.004467  … -0.000644 -0.001235
1     -1.397737 -5.568731  0.570636 -2.581123  …  0.372319  0.713588

            V22       V23       V24       V25       V26       V27       V28  \
Class
0     -0.000024  0.000070  0.000182 -0.000072 -0.000089 -0.000295 -0.000131
1      0.014049 -0.040308 -0.105130  0.041449  0.051648  0.170575  0.075667

           Amount
Class
0       88.291022
1      122.211321

[2 rows x 30 columns]
```

[45]:
```python
# build a dataset containing silimlar ditributions of the non-fraud and fraud␣
↪transactions.

np.random.seed(6)
nonFraud_sample = nonFraud.sample(n=492)
```

[46]:
```python
# concatenate the sample df and the fraud df.

new_DF = pd.concat([nonFraud_sample, fraud], axis=0)
```

[47]:
```python
# Check the value counts of the new dataframe.
new_DF["Class"].value_counts()
```

[47]:
```
Class
0    492
1    492
Name: count, dtype: int64
```

[48]:
```python
# Make sure the mean of class is simialr to the original df.
new_DF.groupby("Class").mean()
```

[48]:

```
                  Time        V1        V2        V3        V4        V5  \
Class
0      94148.357724 -0.102618 -0.020529 -0.080178 -0.058466  0.047008
1      80746.806911 -4.771948  3.623778 -7.033281  4.542029 -3.151225

             V6        V7        V8        V9  …       V20       V21  \
Class                                          …
0      0.041238 -0.035174 -0.059097  0.098234  …  0.028975  0.023641
1     -1.397737 -5.568731  0.570636 -2.581123  …  0.372319  0.713588

            V22       V23       V24       V25       V26       V27       V28  \
Class
0      0.042368  0.022010 -0.001911 -0.025868  0.027440  0.019331 -0.030460
1      0.014049 -0.040308 -0.105130  0.041449  0.051648  0.170575  0.075667

           Amount
Class
0       91.196443
1      122.211321

[2 rows x 30 columns]
```

[49]:

```
# Make a correlation matrix with the dataframe.
matrix = df.corr().abs()
# Save only the values above the diagonal to a variable.
upper = matrix.where(np.triu(np.ones(matrix.shape), k=1).astype(np.bool_))
# Loop through the columns to remove columns with coorelations above 0.9.
toRemove = [column for column in upper.columns if any (upper[column]> 0.9)]
# Print out the columns to remove.
print(toRemove)
```

```
[]
```

2 Building and evaluating models

[50]:

```
# Assign the regression function to a variable.
logr = LogisticRegression()
scaler = StandardScaler()
```

[51]:

```
# The target values are in Class.
target = 'Class'
# The features are the remaining columns minus Class.
features = new_DF.drop(target, axis=1)
features = scaler.fit_transform(features)
#Split the data into testing and training sets.
X_train, X_test, y_train, y_test = train_test_split(features,
 ↪new_DF[target],test_size=0.2, random_state = 32)
```

[52]:
```python
# Fit the training data to make the model.
logr.fit(X_train, y_train)
```

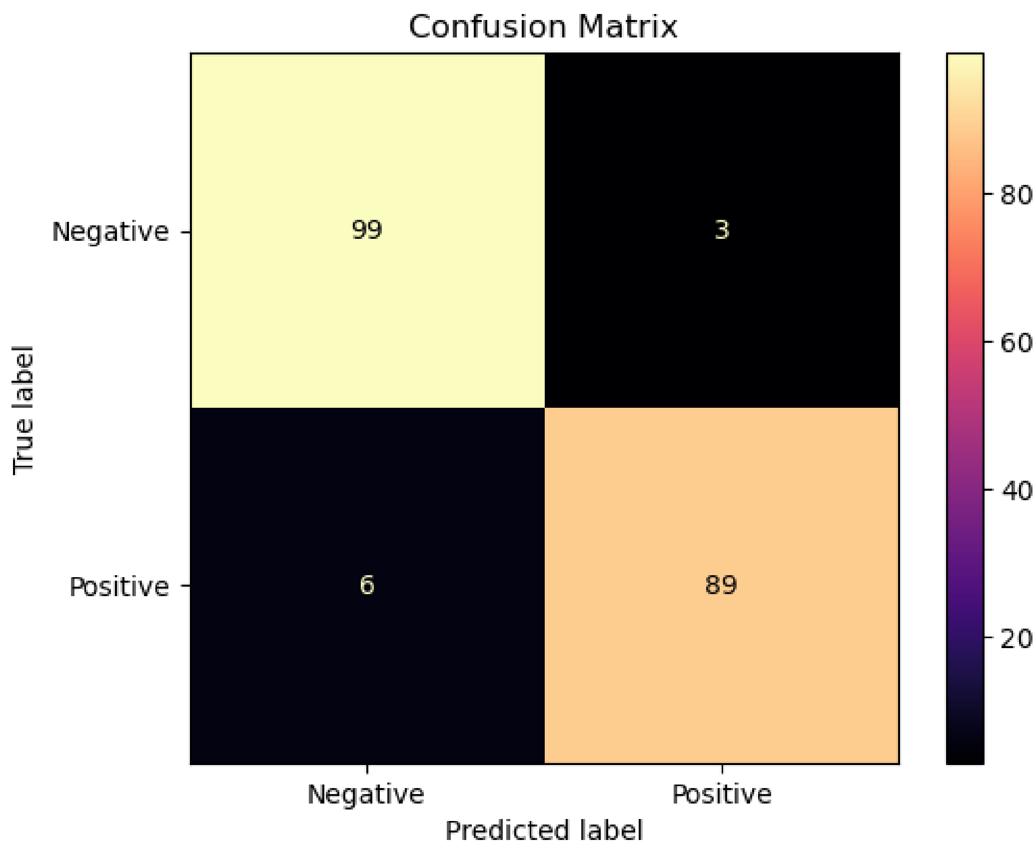
[52]: LogisticRegression()

[53]:
```python
# Get Predictions.
prediction = logr.predict(X_test)
```

[54]:
```python
# Test Accuracy.
X_train_pred = logr.predict(X_train)
training_accuracy = accuracy_score(X_train_pred, y_train)*100
accuracy = accuracy_score(y_test, prediction)*100
print('The accuracy on training data:', training_accuracy, '%')
print('The accuracy on testing data:', accuracy, '%')
```

```
The accuracy on training data: 94.66327827191868 %
The accuracy on testing data: 95.43147208121827 %
```

[55]:
```python
confusion_matrix = metrics.confusion_matrix(y_test, prediction)
# Set up the confusion matrix using Sklearn confusion matrix display.
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix,
                                            display_labels =␣
 ↪['Negative','Positive'])
# Plot can be used to set up the matrix.
cm_display.plot(cmap='magma')
# Changes the outside of the matrix can be done through pyplot.
plt.title('Confusion Matrix')
plt.show()
```

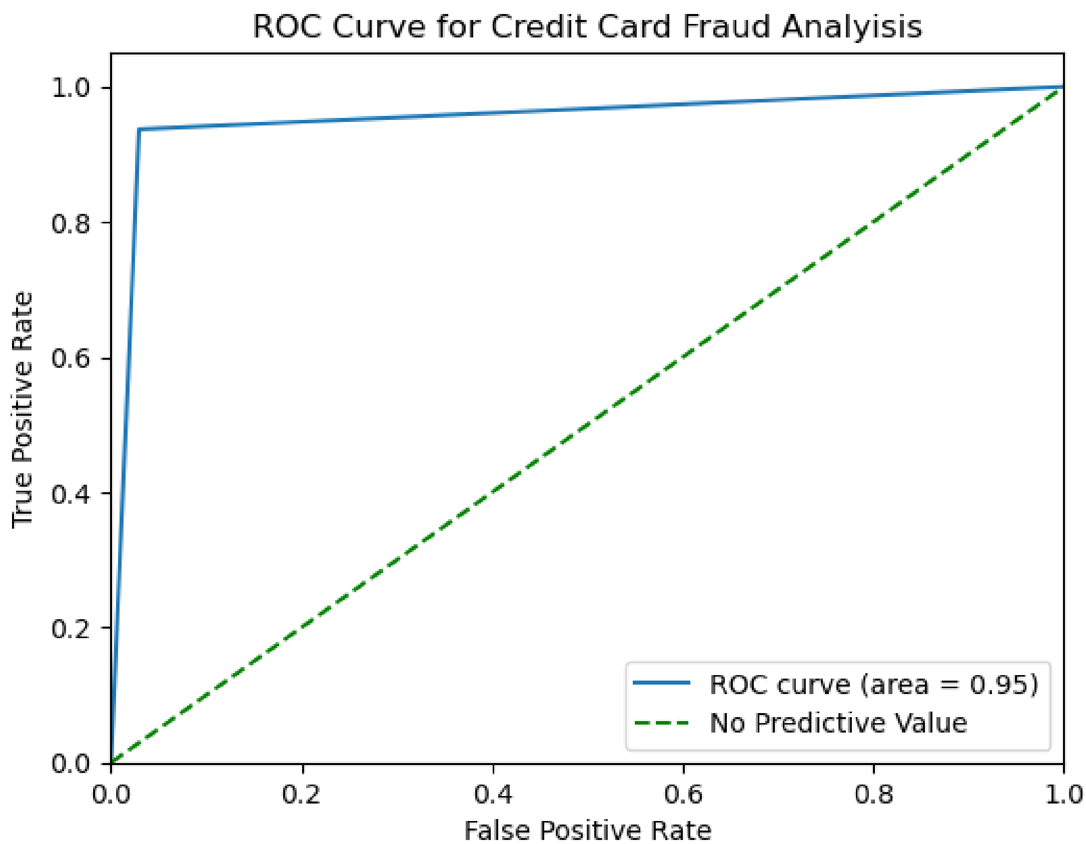


[56]:
```
print(classification_report(y_test, prediction))
```

```
              precision    recall  f1-score   support

           0       0.94      0.97      0.96       102
           1       0.97      0.94      0.95        95

    accuracy                           0.95       197
   macro avg       0.96      0.95      0.95       197
weighted avg       0.95      0.95      0.95       197
```

[57]:
```
# Calculate ROC curve
fpr, tpr, thresholds = roc_curve(y_test, prediction)
# Calculate the Area under curve(AUC)
roc_auc = auc(fpr, tpr)
# Plot the ROC curve
plt.figure()
plt.plot(fpr, tpr, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], 'g--', label='No Predictive Value')
```

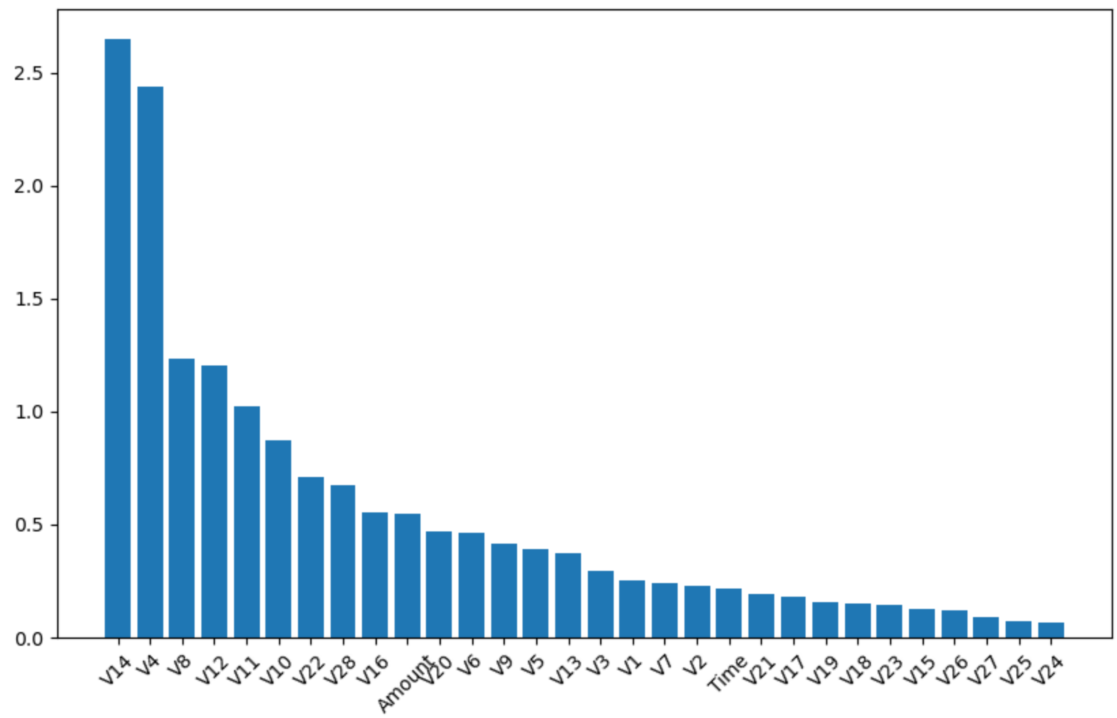
```python
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Credit Card Fraud Analyisis')
plt.legend()
plt.show()
```



[58]:
```python
# Make a new data frame for the features.
featureData = df.drop('Class', axis=1)

# Obtain the column naes from the data frame.
names = featureData.columns
```

[59]:
```python
# Calculate the feature importance.
importance = abs(logr.coef_[0])

# Build the feature's importance data frame.
data = list(zip(names, importance))
```

```
new_df = pd.DataFrame(data, columns =['Feature', 'Importance']).sort_values(by␣
↪= "Importance", ascending = False)

# Plot the features importance.
plt.figure(figsize=(10, 6))
plt.bar(new_df["Feature"], new_df["Importance"])
plt.xticks(rotation=45)
plt.show()
```



2.1 Random Forest Model

[60]:
```
# Assign the random forrest function to a variable.
randomforest = RandomForestClassifier(random_state=20, n_jobs=-1)
```

[61]:
```
# Make the model with the training data.
randomforest.fit(X_train, y_train)
```

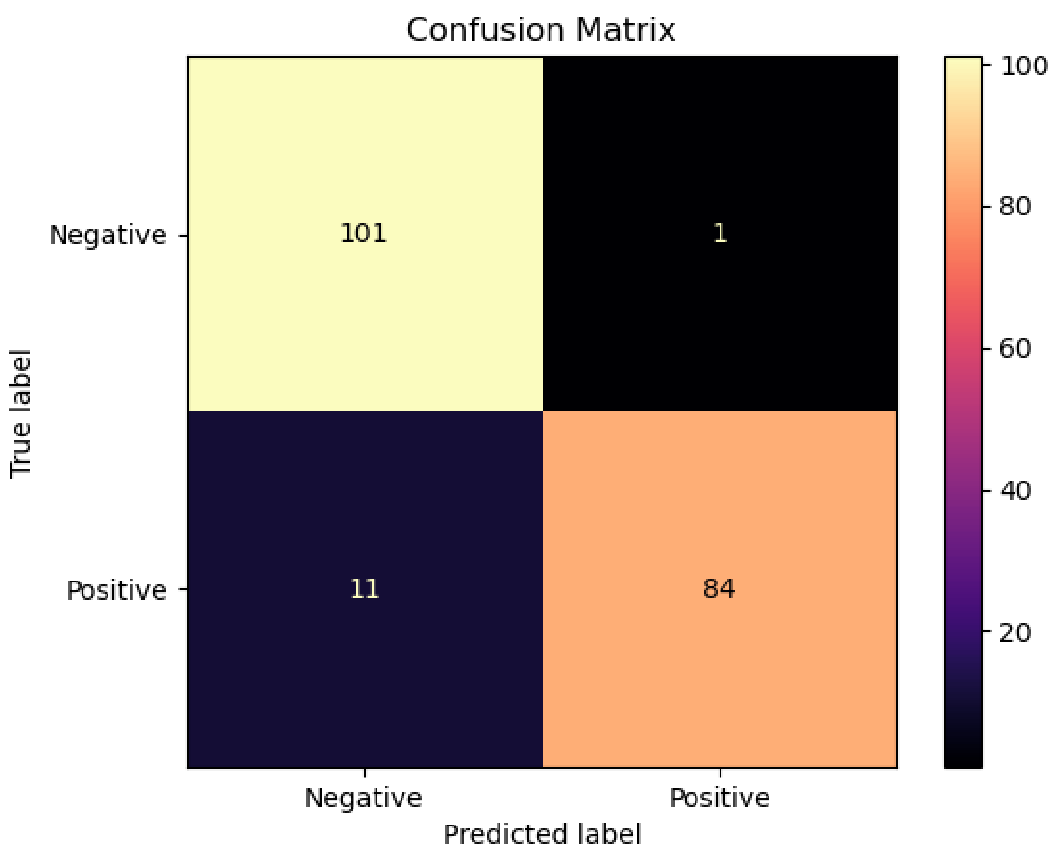
[61]: RandomForestClassifier(n_jobs=-1, random_state=20)

[62]:
```
# Get predictions.
prediction = randomforest.predict(X_test)
```

[63]:
```python
# Check accuracy.
accuracy = accuracy_score(y_test, prediction)*100
print('The accuracy is:', accuracy, '%')
```

```
The accuracy is: 93.90862944162437 %
```

[64]:
```python
confusion_matrix = metrics.confusion_matrix(y_test, prediction)
# Set up the confusion matrix using Sklearn confusion matrix display.
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix,
display_labels = ['Negative','Positive'])
# Plot can be used to set up the matrix.
cm_display.plot(cmap='magma')
# Changes f the outside of the matrix can be done through pyplot.
plt.title('Confusion Matrix')
plt.show()
```



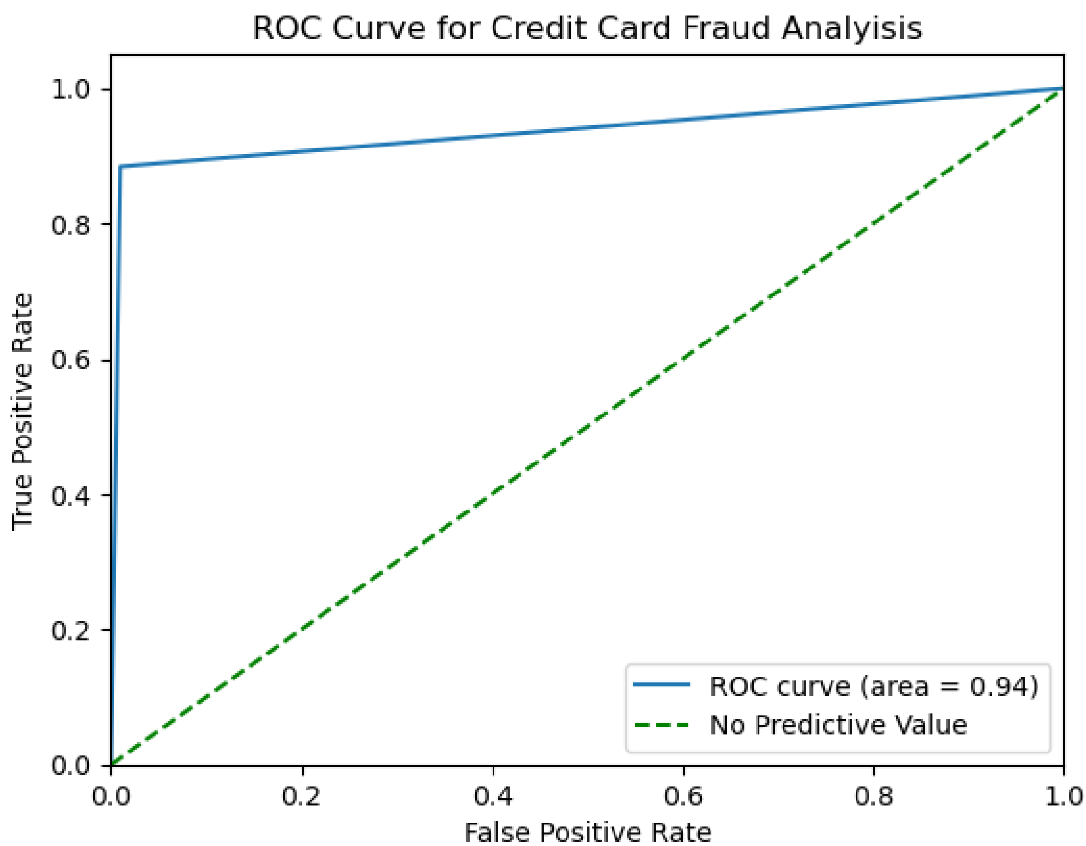
[65]:
```python
print(classification_report(y_test, prediction))
```

```
              precision    recall  f1-score   support

           0       0.90      0.99      0.94       102
```

```
           1       0.99      0.88      0.93        95

    accuracy                           0.94       197
   macro avg       0.95      0.94      0.94       197
weighted avg       0.94      0.94      0.94       197
```

[66]:
```python
# Calculate ROC curve
fpr, tpr, thresholds = roc_curve(y_test, prediction)
# Calculate the Area under curve(AUC)
roc_auc = auc(fpr, tpr)
# Plot the ROC curve
plt.figure()
plt.plot(fpr, tpr, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], 'g--', label='No Predictive Value')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Credit Card Fraud Analyisis')
plt.legend()
```

[66]:
```
<matplotlib.legend.Legend at 0x15bd4d250>
```



3 Adding unseen data to check for overfitting

[67]:
```
new_data = pd.read_csv("creditcard_2023.csv")
new_data.head()
```

[67]:
```
   id        V1        V2        V3        V4        V5        V6        V7  \
0   0 -0.260648 -0.469648  2.496266 -0.083724  0.129681  0.732898  0.519014
1   1  0.985100 -0.356045  0.558056 -0.429654  0.277140  0.428605  0.406466
2   2 -0.260272 -0.949385  1.728538 -0.457986  0.074062  1.419481  0.743511
3   3 -0.152152 -0.508959  1.746840 -1.090178  0.249486  1.143312  0.518269
4   4 -0.206820 -0.165280  1.527053 -0.448293  0.106125  0.530549  0.658849

         V8        V9  …       V21       V22       V23       V24       V25  \
0 -0.130006  0.727159  … -0.110552  0.217606 -0.134794  0.165959  0.126280
1 -0.133118  0.347452  … -0.194936 -0.605761  0.079469 -0.577395  0.190090
2 -0.095576 -0.261297  … -0.005020  0.702906  0.945045 -1.154666 -0.605564
3 -0.065130 -0.205698  … -0.146927 -0.038212 -0.214048 -1.893131  1.003963
4 -0.212660  1.049921  … -0.106984  0.729727 -0.161666  0.312561 -0.414116

        V26       V27       V28    Amount  Class
0 -0.434824 -0.081230 -0.151045  17982.10      0
1  0.296503 -0.248052 -0.064512   6531.37      0
2 -0.312895 -0.300258 -0.244718   2513.54      0
3 -0.515950 -0.165316  0.048424   5384.44      0
4  1.071126  0.023712  0.419117  14278.97      0

[5 rows x 31 columns]
```

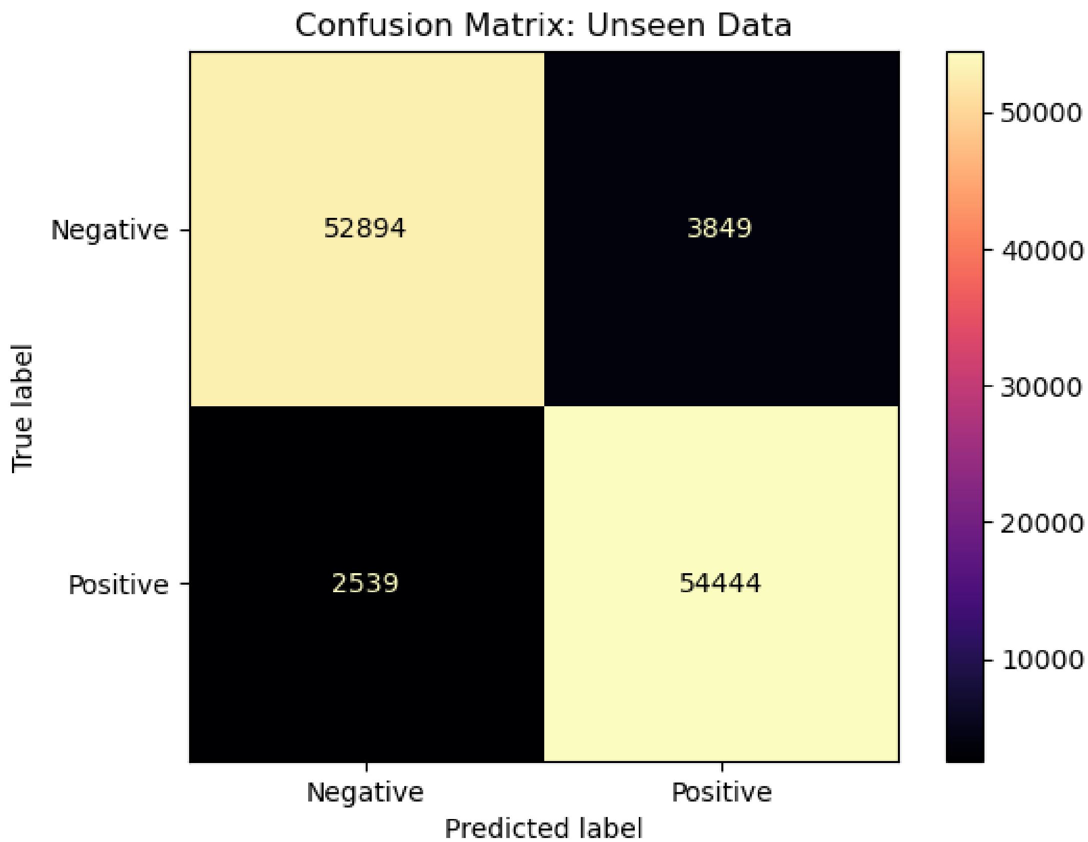
[68]:
```
# The target values are in Class.
target = 'Class'
# The features are the remaining columns minus Class.
features = new_data.drop(target, axis=1)
features = scaler.fit_transform(features)
#Split the data into testing and training sets.
X_train, X_test, y_train, y_test = train_test_split(features,␣
↪new_data[target],test_size=0.2, random_state = 32)
```

[69]:
```
prediction = logr.predict(X_test)
```

[70]:
```
# Check accuracy.
accuracy = accuracy_score(y_test, prediction)*100
print('The accuracy is:', accuracy, '%')
```

```
The accuracy is: 94.38299069693825 %
```

[71]:
```python
confusion_matrix = metrics.confusion_matrix(y_test, prediction)
# Set up the confusion matrix using Sklearn confusion matrix display.
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix,
display_labels = ['Negative','Positive'])
# Plot can be used to set up the matrix.
cm_display.plot(cmap='magma')
# Changes f the outside of the matrix can be done through pyplot.
plt.title('Confusion Matrix: Unseen Data')
plt.show()
```



[ ]:
```python

```