# Test.ipynb

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## Objective: Use different Classical Machine Learning Methods on a given Kaggle Dataset to predict whether or not a Credit Card Transaction is Fraudulent

### Methods Currently Used:

1. Logistic Regression
2. K Nearest Neighbors
3. Ridge Regularization
4. Support Vector Machine

### Kaggle Dataset:

https://www.kaggle.com/datasets/neharoychoudhury/credit-card-fraud-data/data

### Code Sources

1. SKLearn, Matplotlib, Seaborn Documentation
2. Previous HW's and a HW from a Data Science Class
3. Help from AI tools for boiler-plate code and debugging

```python
# Tons of imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.ticker import ScalarFormatter
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_squared_error, r2_score, f1_score,
accuracy_score, roc_curve, auc, confusion_matrix
from sklearn.linear_model import Ridge, LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn import svm

import seaborn as sns # For confusion matrix -- I know we have plt but
this is better for that specific situation
import warnings


#Global variables -- random state is for train_test split and thres is
the threshold for the confidence score (if x > thres, then it IS fraud
```

```
(1))
#In reality, we would want to not use a random state, but this is for
reproducibility for the sake of this project
RANDOM_STATE = 42
THRES = 0.5
SAVE = True # This is just a variable I used to save all the plots
instead of showing them
SAVE_DIR = 'Data/Figs/' # Directory to save the plots (Only works if
SAVE is True, obviously)

# read the data (obviously change this if you're not using the same
directory)
data = pd.read_csv('Data/fraud_data.csv')

# Suppress warnings
warnings.filterwarnings("ignore")

data

      trans_date_trans_time                          merchant
category  \
0          04-01-2019 00:58  "Stokes, Christiansen and Sipes"
grocery_net
1          04-01-2019 15:06                      Predovic Inc
shopping_net
2          04-01-2019 22:37                    Wisozk and Sons
misc_pos
3          04-01-2019 23:06                    Murray-Smitham
grocery_pos
4          04-01-2019 23:59                        Friesen Lt
health_fitness
...                     ...                               ...
...
14441      22-01-2019 00:37                      Hudson-Grady
shopping_pos
14442      22-01-2019 00:41    "Nienow, Ankunding and Collie"
misc_pos
14443      22-01-2019 00:42                   Pacocha-O'Reilly
grocery_pos
14444      22-01-2019 00:48     "Bins, Balistreri and Beatty"
shopping_pos
14445      22-01-2019 00:55                 Daugherty-Thompson
food_dining

          amt        city state      lat      long  city_pop  \
0       14.37       Wales    AK  64.7556 -165.6723       145
1      966.11       Wales    AK  64.7556 -165.6723       145
2       49.61       Wales    AK  64.7556 -165.6723       145
3      295.26       Wales    AK  64.7556 -165.6723       145
4       18.17       Wales    AK  64.7556 -165.6723       145
```

```
...        ...          ...   ...       ...        ...        ...
14441  122.00       Athena    OR  45.8289 -118.4971       1302
14442    9.07     Gardiner    OR  43.7857 -124.1437        260
14443  104.84         Alva    WY  44.6873 -104.4414        110
14444  268.16        Wales    AK  64.7556 -165.6723        145
14445   50.09   Unionville    MO  40.4815  -92.9951       3805

                                     job         dob  \
0              "Administrator, education"  09-11-1939
1              "Administrator, education"  09-11-1939
2              "Administrator, education"  09-11-1939
3              "Administrator, education"  09-11-1939
4              "Administrator, education"  09-11-1939
...                                   ...         ...
14441                              Dealer  18-10-1976
14442             "Engineer, maintenance"  01-09-1956
14443  "Administrator, local government"  16-05-1973
14444          "Administrator, education"  09-11-1939
14445     "Investment banker, corporate"  15-09-1950

                              trans_num  merch_lat  merch_long
is_fraud
0      a3806e984cec6ac0096d8184c64ad3a1  65.654142 -164.722603
1
1      a59185fe1b9ccf21323f581d7477573f  65.468863 -165.473127
1
2      86ba3a888b42cd3925881fa34177b4e0  65.347667 -165.914542
1
3      3a068fe1d856f0ecedbed33e4b5f4496  64.445035 -166.080207
1
4      891cdd1191028759dc20dc224347a0ff  65.447094 -165.446843
1
...                                 ...        ...         ...       ..
.
14441  699a4c06b22711bf3e0d8ef91232d356  46.442439 -118.524214
0
14442  080d620d24815c7d6c637cf0b71dde8e  42.901265 -124.995317
0
14443  3c346c8cd627c5fe3ed57430db2e9ae7  45.538062 -104.542117
0
14444  e66ffcc95ba7fc490486242af1205d04  64.081462 -165.898698
0
14445  65e7370f473f9b9d75796c8033a7c929  40.387243  -92.224871
0

[14446 rows x 15 columns]
```

# Data Normalization Step

1. Drop any rows with NaN/missing values

2. Make sure that the dependent variable is a binary "1" or "0"
3. Make sure that the independent variables are all numerical (for now, we are omitting categorical variables)
4. Split into training and testing data and use a Standard Scaler to normalize the data

```
#Oops! The data somehow is not cleaned properly. Let's clean it first.
# drop the rows with missing values
data = data.dropna()

#Make sure is_fraud is a binary variable. Remove those that aren't 0
or 1

data = data[(data["is_fraud"] == "0") | (data["is_fraud"] == "1")]

data["is_fraud"] = data["is_fraud"].astype(int)

data["is_fraud"].unique()

array([1, 0])

# Features and target variable
X = data[['lat', 'long', 'amt', 'city_pop', 'merch_lat',
'merch_long']]
y = data['is_fraud'].astype(int)

# Split the data into training and testing sets (80% training, 20%
testing)
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=RANDOM_STATE) #I'm filling a random seed
here just to make testing code consistent

print(f"X_train shape: {X_train.shape}")
print(f"X_test shape: {X_test.shape}")
print(f"y_train shape: {y_train.shape}")
print(f"y_test shape: {y_test.shape}")

X_train shape: (11555, 6)
X_test shape: (2889, 6)
y_train shape: (11555,)
y_test shape: (2889,)

#Let's scale the data -- this is just basically using the same code
from the HW's
scaler = StandardScaler()

# Scale the training data
X_train_scaled = scaler.fit_transform(X_train)

# Scale the test data
X_test_scaled = scaler.fit_transform(X_test)
```

# K-Nearest Neighbors

1. Find the optimal number of neighbors using a for loop -- the metric we are using is the R2 score (as done in previous homeworks)
2. Plot Confusion Matrix and ROC Curve as well as the different scores used for the midterm report.

```
# Define the values for n_neighbors to be tested
n_neighbors_list = [1, 3, 5, 10, 50, 100, 110]
best_r2 = -float('inf')
best_k = None

# Iterate over each value of n_neighbors
for k in n_neighbors_list:

    # Create and train the KNN
    knn = KNeighborsRegressor(n_neighbors=k)
    knn.fit(X_train_scaled, y_train)

    # Make predictions on the test set
    y_pred = knn.predict(X_test_scaled)

    # Calculate the R^2 score
    r2 = r2_score(y_test, y_pred)

    # Print the R^2 score for the current value of n_neighbors
    print(f"n_neighbors: {k}, R^2 Score: {r2:.2f}")

    # Update the best R^2 score and best value of n_neighbors
    if r2 > best_r2:
        best_r2 = r2
        best_k = k

print(f"Best n_neighbors: {best_k}, Best R^2 Score: {best_r2:.2f}")
```

```
n_neighbors: 1, R^2 Score: 0.40
n_neighbors: 3, R^2 Score: 0.55
n_neighbors: 5, R^2 Score: 0.60
n_neighbors: 10, R^2 Score: 0.60
n_neighbors: 50, R^2 Score: 0.56
n_neighbors: 100, R^2 Score: 0.52
n_neighbors: 110, R^2 Score: 0.52
Best n_neighbors: 10, Best R^2 Score: 0.60
```

Note: This block of code is used multiple times throughout the notebook to plot whatever is needed (with a few changes here and there). Here is the gist of this code:

1. Initializes and Fits the model.
2. Does predictions on the test data.
3. Gets BOTH binary representations of the predictions (>THRES is a 1 and <= is a 0, see THRES above) and the probabilities of the predictions (simple lambda function for this).

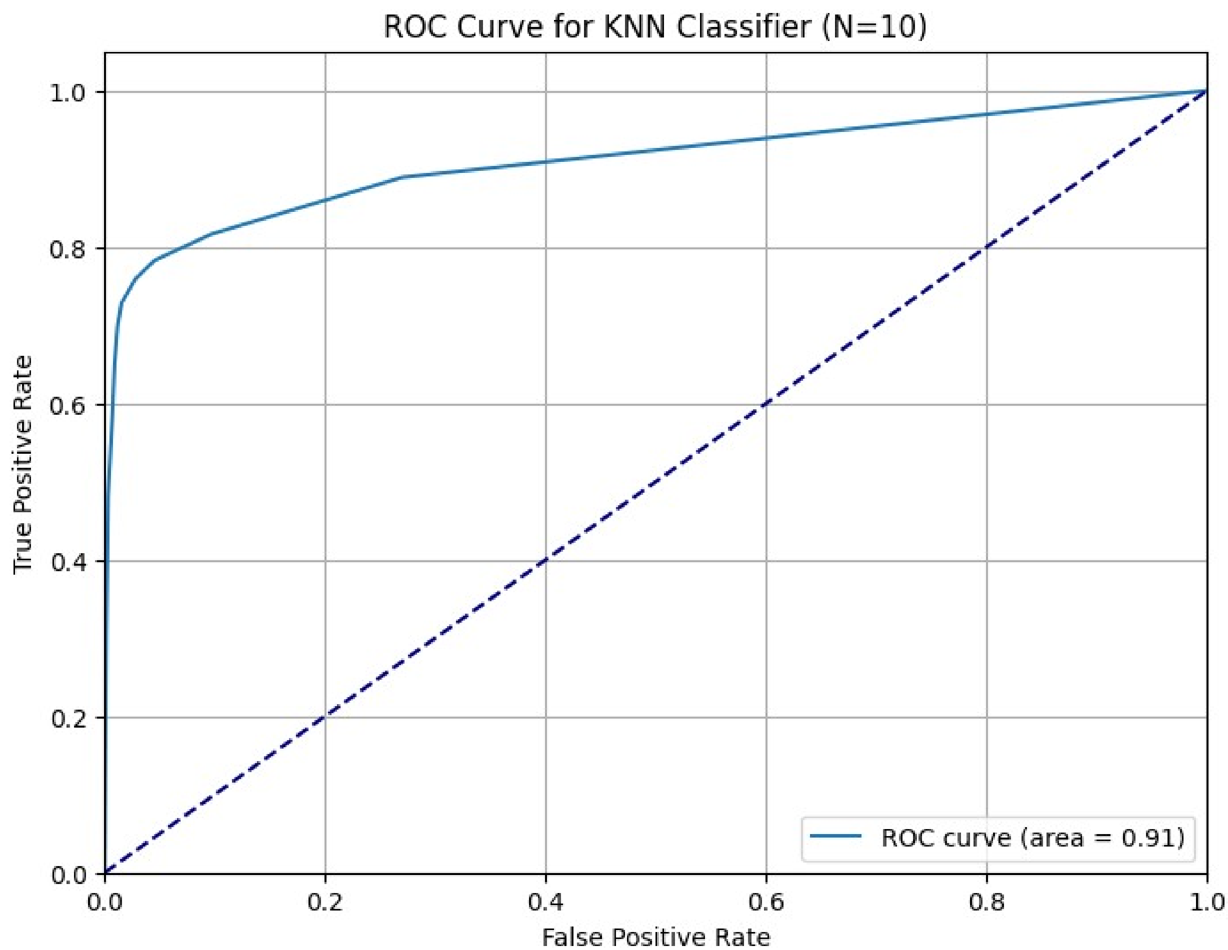
Binary predictions must be used for the confusion matrix as well as the f1 scores and accuracy scores, but the probabilities are used for a smoother ROC curve as well as the $R^2$ score.

4. Finally, the corresponding plots are made and scores are calculated. Most of this code was directly from previous homeworks, but we added the ROC curve plots. We hope the code is relatively straightforward to understand, since most of it is just using the sklearn library.

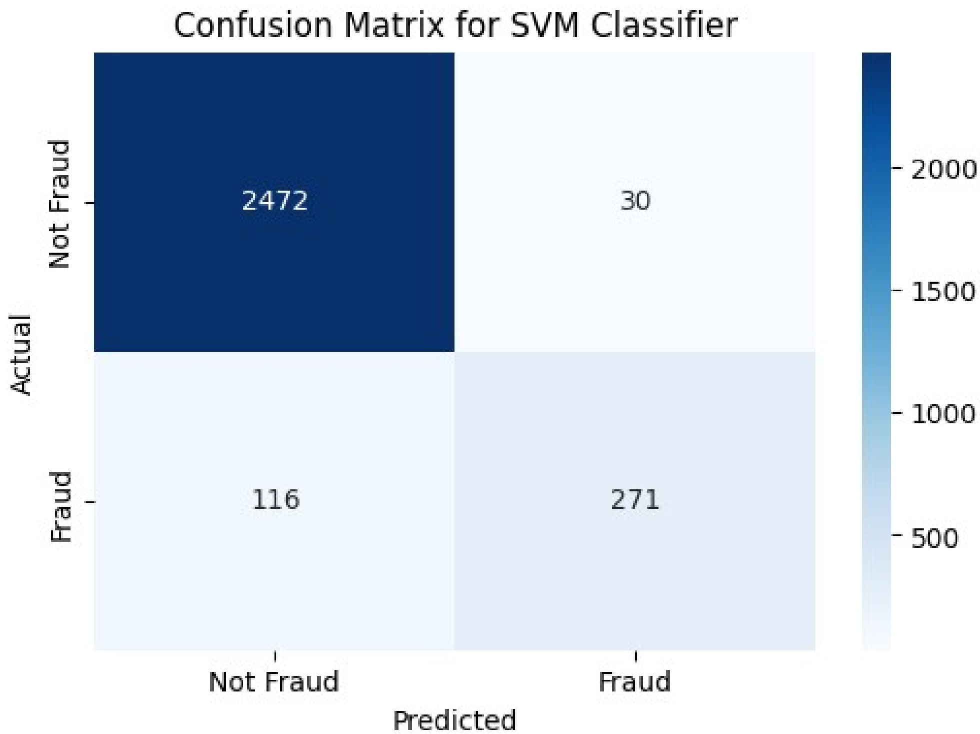
```
# Initialize the K-Nearest Neighbors Regressor with the best k value
best_model = KNeighborsRegressor(n_neighbors=best_k)

# Fit the model using the scaled training data
best_model.fit(X_train_scaled, y_train)

# Make predictions on the scaled test data using the trained KNN model
y_pred = best_model.predict(X_test_scaled)

# Calculate the Mean Squared Error (MSE) between the predicted and
actual values
mse_knn = mean_squared_error(y_test, y_pred)

# Calculate the R^2 score for the model
r2_knn = r2_score(y_test, y_pred)

#Convert y_pred to a series of 0s and 1s
y_pred_bin = pd.Series(y_pred).apply(lambda x: 1 if x > THRES else 0)

# f1 and accuracy score
f1_knn = f1_score(y_test, y_pred_bin)
acc_knn = accuracy_score(y_test, y_pred_bin)

# Print the MSE and R^2 score rounded to 2 decimal places
print(f"Mean Squared Error: {mse_knn:,.2f}")
print(f"R² Score: {r2_knn:.2f}")
print(f"F1 Score: {f1_knn:.2f}")
print(f"Accuracy Score: {acc_knn:.2f}")

# Calculate the ROC curve
fpr, tpr, _ = roc_curve(y_test, y_pred)
roc_auc = auc(fpr, tpr)

# Plot the ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', 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'ROC Curve for KNN Classifier (N={best_k})')
plt.legend(loc='lower right')
```

```
plt.grid(True)
if not SAVE:
    plt.show()
else:
    plt.savefig(SAVE_DIR + 'roc_curve_knn.png')

# Generate the confusion matrix
cm = confusion_matrix(y_test, y_pred_bin)

# Plot the confusion matrix using seaborn
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Not
Fraud', 'Fraud'], yticklabels=['Not Fraud', 'Fraud'])
plt.title('Confusion Matrix for SVM Classifier')
plt.xlabel('Predicted')
plt.ylabel('Actual')
if not SAVE:
    plt.show()
else:
    plt.savefig(SAVE_DIR + 'confusion_matrix_knn.png')
```

```
Mean Squared Error: 0.05
R² Score: 0.60
F1 Score: 0.79
Accuracy Score: 0.95
```



ROC Curve for KNN Classifier (N=10)
True Positive Rate
False Positive Rate
ROC curve (area = 0.91)
0.0
0.2
0.4
0.6
0.8
1.0

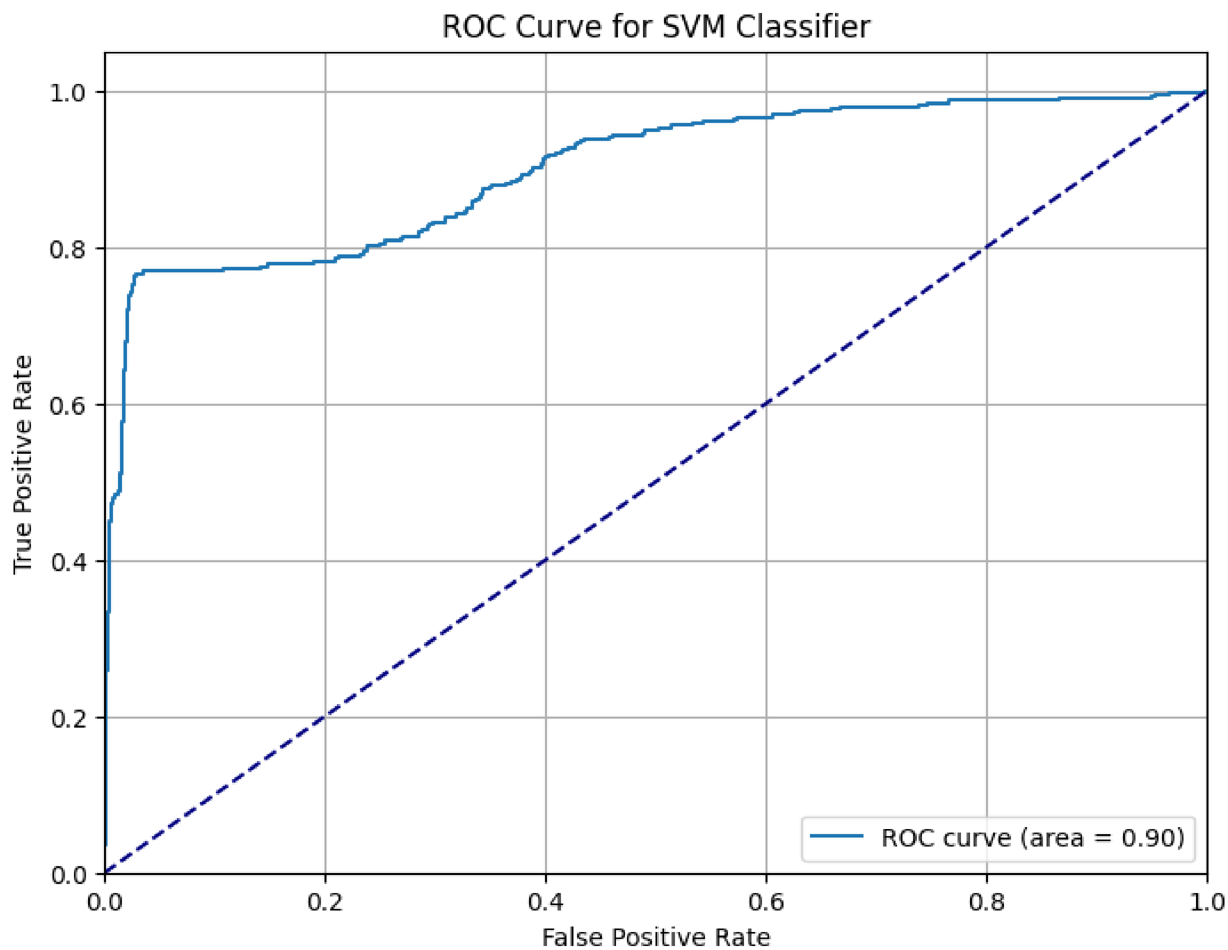



## Simple Vector Machine (SVM)

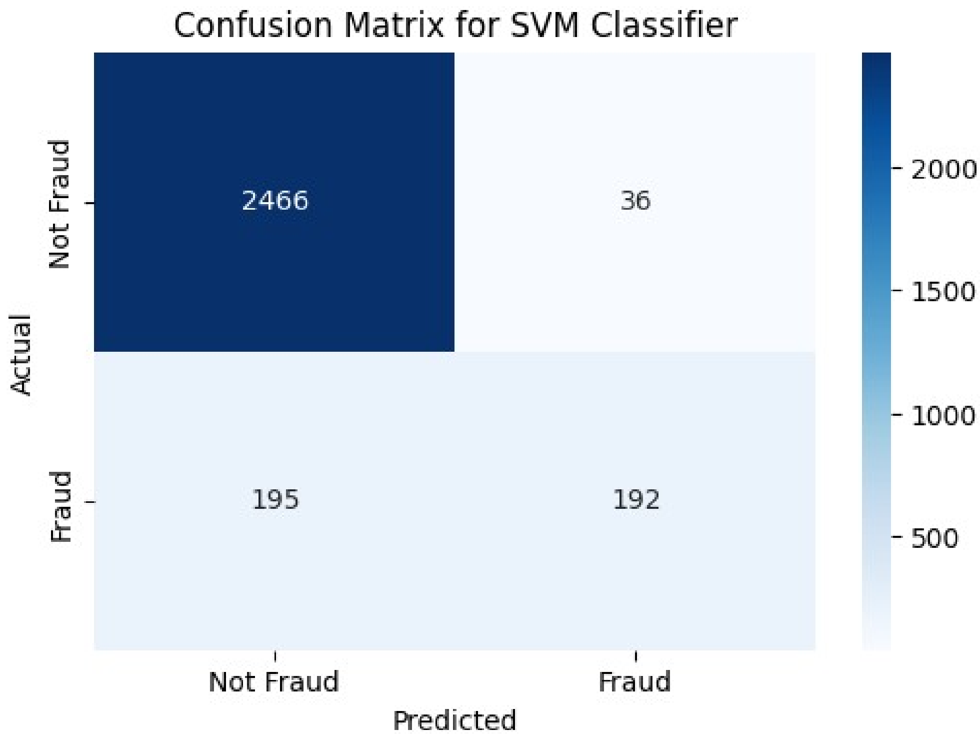
```
# using the svm method on the data now

clf = svm.SVC()
# Fit the SVM model using the scaled training data
clf.fit(X_train_scaled, y_train)

# Make predictions on the scaled test data
y_pred_svm = clf.predict(X_test_scaled)

# Calculate MSE
mse_svm = mean_squared_error(y_test, y_pred_svm)
print(f"Mean Squared Error (MSE): {mse_svm:.2f}")

# Calculate R² score
r2_svm = r2_score(y_test, y_pred_svm)
print(f"R² Score: {r2_svm:.2f}")

#Get the accuracy and f1 score
accuracy = clf.score(X_test_scaled, y_test)
f1 = f1_score(y_test, y_pred_svm)
print(f"Accuracy: {accuracy:.2f}")
print(f"F1 Score: {f1:.2f}")

# Get probability estimates from the SVM model (use
`decision_function` for SVMs) (basically the confidence of the model,
```

```
and the opposite of what we had to do with KNN)
y_prob_svm = clf.decision_function(X_test_scaled)

# Calculate the ROC curve
fpr, tpr, _ = roc_curve(y_test, y_prob_svm)
roc_auc = auc(fpr, tpr)

# Plot the ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', 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('ROC Curve for SVM Classifier')
plt.legend(loc='lower right')
plt.grid(True)
if not SAVE:
    plt.show()
else:
    plt.savefig(SAVE_DIR + 'roc_curve_svm.png')

# Generate the confusion matrix
cm = confusion_matrix(y_test, y_pred_svm)

# Plot the confusion matrix using seaborn
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Not
Fraud', 'Fraud'], yticklabels=['Not Fraud', 'Fraud'])
plt.title('Confusion Matrix for SVM Classifier')
plt.xlabel('Predicted')
plt.ylabel('Actual')
if not SAVE:
    plt.show()
else:
    plt.savefig(SAVE_DIR + 'confusion_matrix_svm.png')
```

```
Mean Squared Error (MSE): 0.08
R² Score: 0.31
Accuracy: 0.92
F1 Score: 0.62
```



ROC Curve for SVM Classifier
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (area = 0.90)

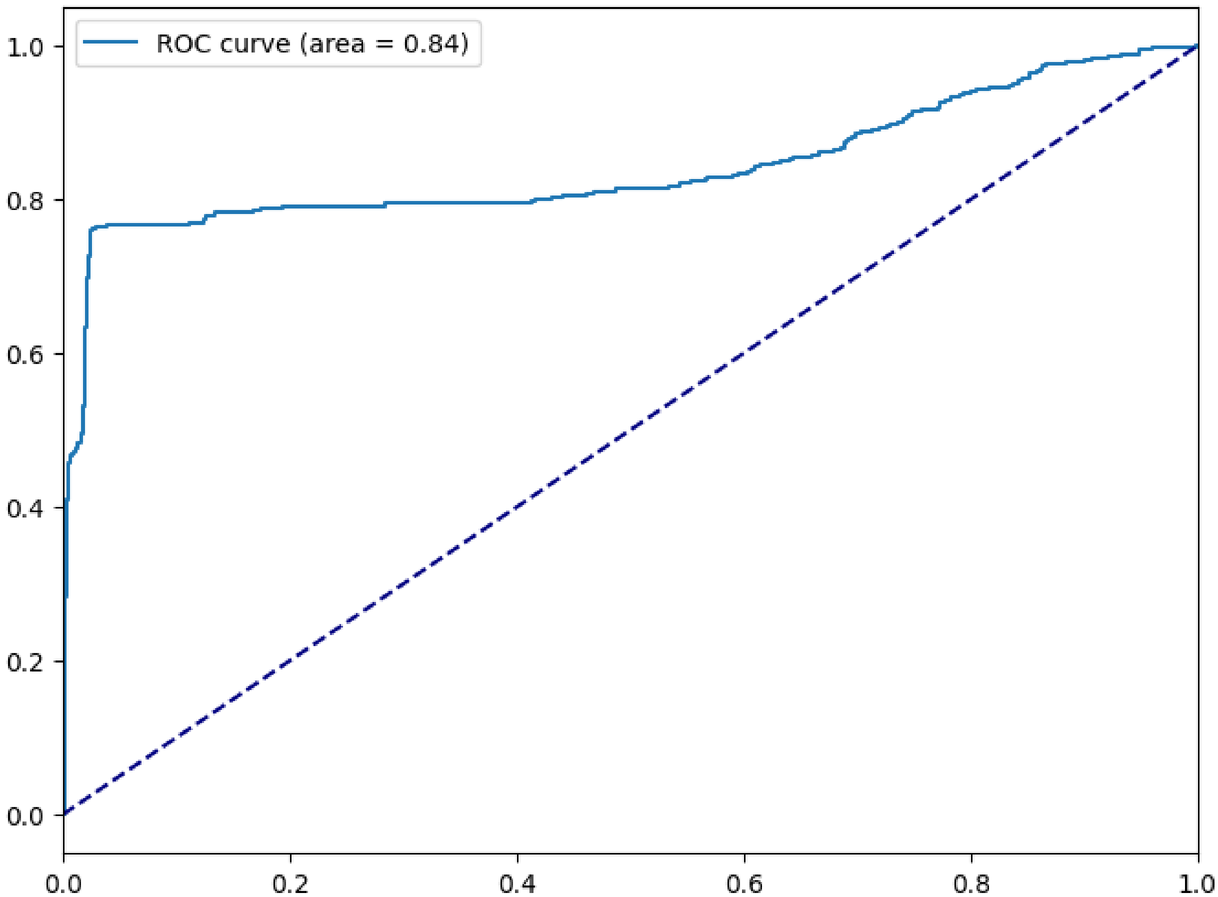


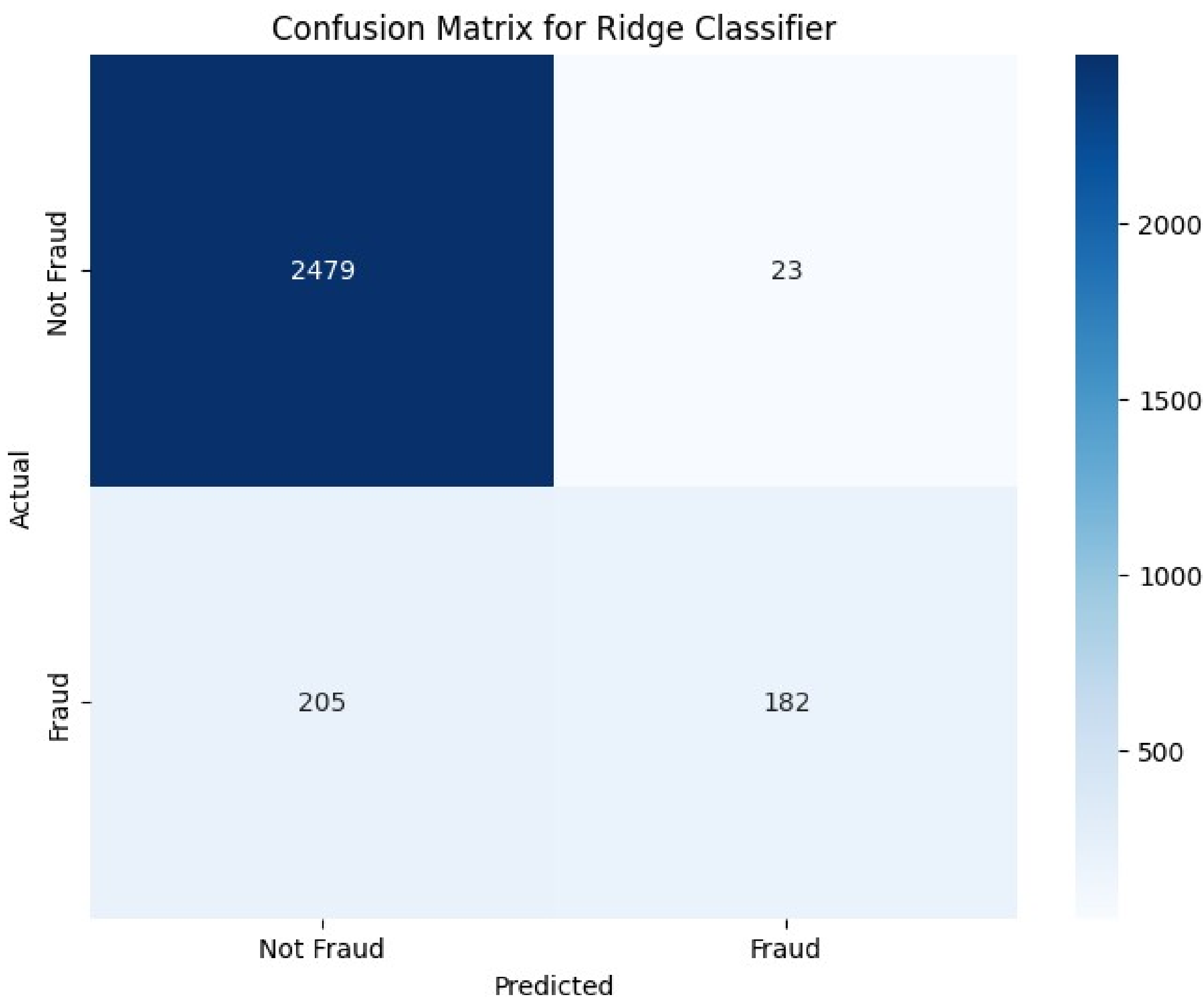

## Ridge (L2) Regularization

```
#Now that we have two models and initial results, let's use
regularization
# We should use L2 (Ridge) regularization for both models, since we do
not have very many dimensions in our data -- L1 (Lasso) regularization
is better suited for high-dimensional data.

# Initialize the Ridge model
ridge = Ridge(alpha=1.0)

# Fit the Ridge model using the scaled training data
ridge.fit(X_train_scaled, y_train)

# Make predictions on the scaled test data using the Ridge model
y_pred = ridge.predict(X_test_scaled)

# Calculate the Mean Squared Error (MSE) between the predicted and
actual values for Ridge
mse = mean_squared_error(y_test, y_pred)

# Calculate the R^2 score for the Ridge and Lasso models
r2_ridge = r2_score(y_test, y_pred)

#convert to either 0 or 1
y_pred_bin = pd.Series(y_pred).apply(lambda x: 1 if x > THRES else 0)
```

```python
#get f1 and accuracy score
f1 = f1_score(y_test, y_pred_bin)
accuracy = accuracy_score(y_test, y_pred_bin)

# Print the MSE and R^2 score for Ridge and Lasso models
print(f"Mean Squared Error: {mse:.2f}")
print(f"R² Score: {r2:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"Accuracy Score: {accuracy:.2f}")

# Calculate the ROC curve for Ridge and Lasso models
fpr, tpr, _ = roc_curve(y_test, y_pred)
roc_auc_ridge = auc(fpr, tpr)

# Plot the ROC curve for Ridge and Lasso models
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'ROC curve (area = {roc_auc_ridge:.2f})')
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlim([0.0, 1.0])
plt.legend()
if not SAVE:
    plt.show()
else:
    plt.savefig(SAVE_DIR + 'roc_curve_ridge.png')

# Generate the confusion matrix for Ridge and Lasso models
cm_ridge = confusion_matrix(y_test, y_pred_bin)

# Plot the confusion matrix using seaborn for Ridge and Lasso models
plt.figure(figsize=(8, 6))
sns.heatmap(cm_ridge, annot=True, fmt='d', cmap='Blues',
xticklabels=['Not Fraud', 'Fraud'], yticklabels=['Not Fraud',
'Fraud'])
plt.title('Confusion Matrix for Ridge Classifier')
plt.xlabel('Predicted')
plt.ylabel('Actual')
if not SAVE:
    plt.show()
else:
    plt.savefig(SAVE_DIR + 'confusion_matrix_ridge.png')
```

```
Mean Squared Error: 0.07
R² Score: 0.52
F1 Score: 0.61
Accuracy Score: 0.92
```


ROC curve (area = 0.84)
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0



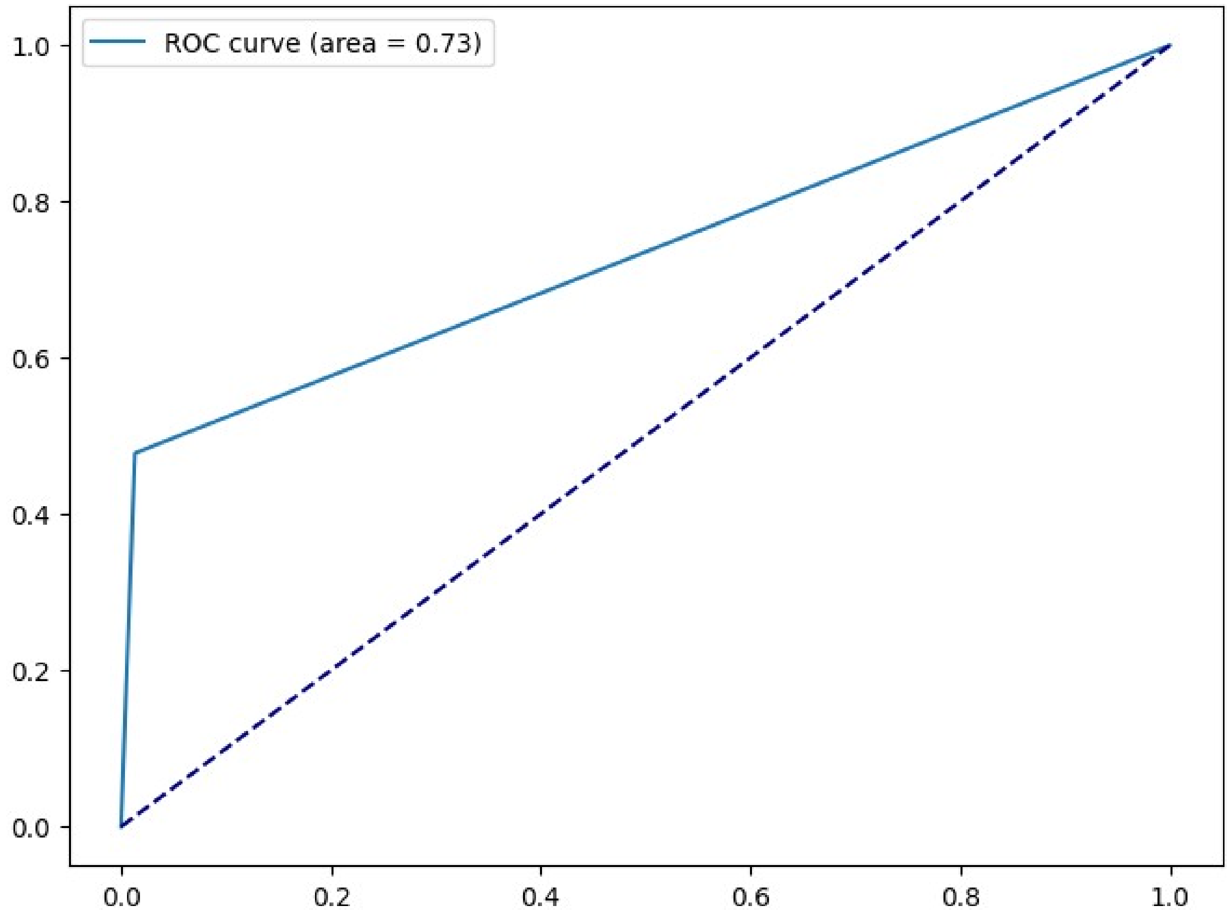

## Logistic Regression

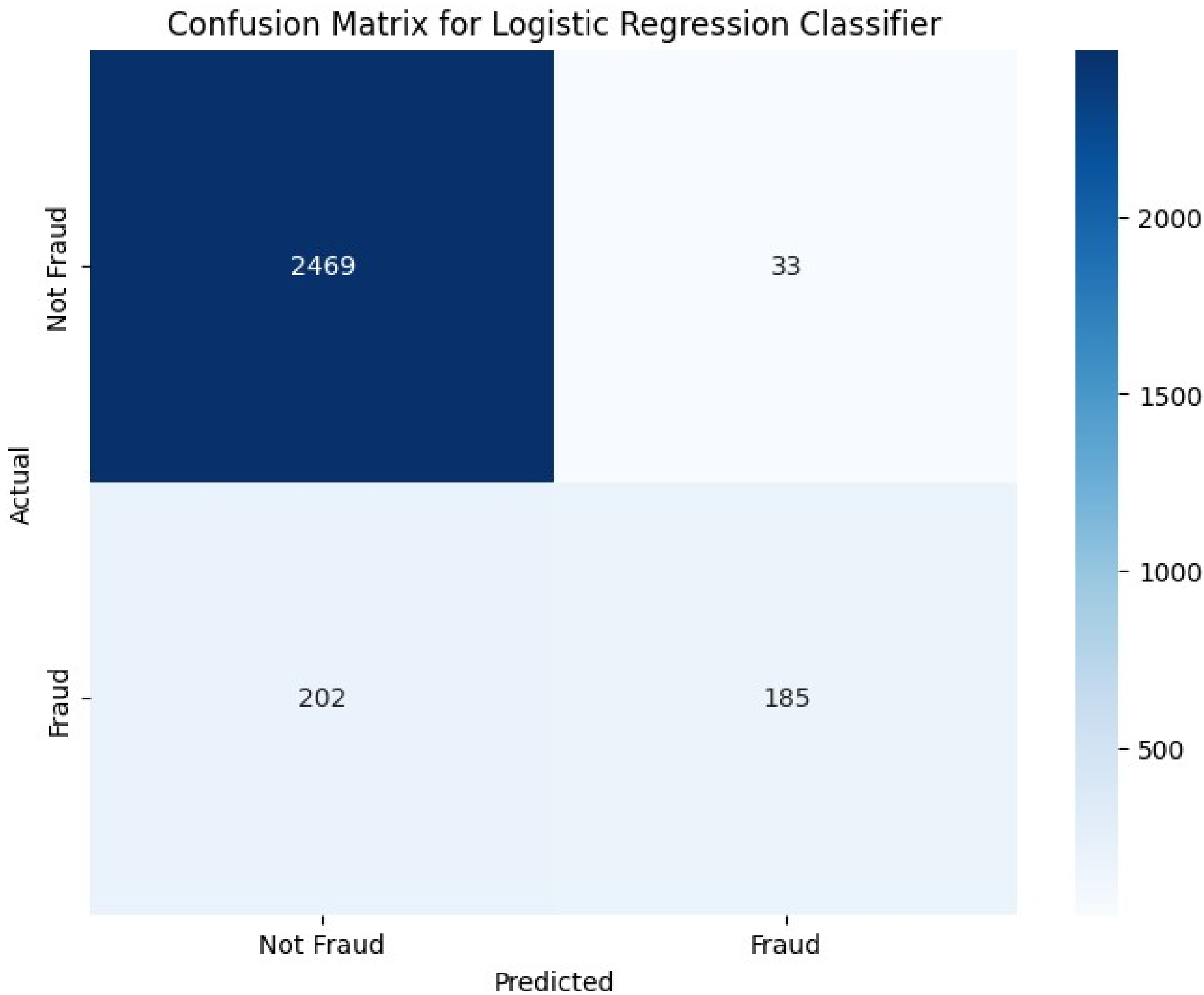
```
# Finally, let's do a logistic regression model

# Initialize the Logistic Regression model
log_reg = LogisticRegression()

# Fit the Logistic Regression model using the scaled training data
log_reg.fit(X_train_scaled, y_train)

# Make predictions on the scaled test data using the Logistic
Regression model
y_pred = log_reg.predict(X_test_scaled)

# Calculate the Mean Squared Error (MSE) between the predicted and
actual values for Logistic Regression
mse = mean_squared_error(y_test, y_pred)

# Calculate the R^2 score for the Logistic Regression model
```

```
r2_log_reg = r2_score(y_test, y_pred)

#convert to either 0 or 1

y_pred_bin = pd.Series(y_pred).apply(lambda x: 1 if x > THRES else 0)

#get f1 and accuracy score
f1 = f1_score(y_test, y_pred_bin)
accuracy = accuracy_score(y_test, y_pred_bin)

# Print the scores for Logistic Regression model
print(f"Mean Squared Error: {mse:.2f}")
print(f"R² Score: {r2:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"Accuracy Score: {accuracy:.2f}")

# Calculate the ROC curve for Logistic Regression model
fpr, tpr, _ = roc_curve(y_test, y_pred)

roc_auc = auc(fpr, tpr)

# Plot the ROC curve for Logistic Regression model
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.legend()
if not SAVE:
    plt.show()
else:
    plt.savefig(SAVE_DIR + 'roc_curve_log_reg.png')

# Plot the confusion matrix using seaborn for Logistic Regression
model
cm = confusion_matrix(y_test, y_pred_bin)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Not
Fraud', 'Fraud'], yticklabels=['Not Fraud', 'Fraud'])
plt.title('Confusion Matrix for Logistic Regression Classifier')
plt.xlabel('Predicted')
plt.ylabel('Actual')

if not SAVE:
    plt.show()
else:
    plt.savefig(SAVE_DIR + 'confusion_matrix_log_reg.png')
```

```
Mean Squared Error: 0.08
R² Score: 0.52
```

```
F1 Score: 0.61
Accuracy Score: 0.92
```






## One More Unique Plot

One more thing that we want to show is some sort of plot that almost shows "clusters" that SHOULD BE formed by a model in an optimal setting. However, we can really only display three variables out of the six that we have. Therefore, we have to get creative and choose three of the six variables that we think are the most important. The idea is to choose the three variables that have the highest correlation with the dependent variable. We will then plot these three variables in a 3D plot and color the points based on whether or not they are fraudulent. This will give us a good idea of how the model should be clustering the data, as well as which variables are most important. After consulting the internet and some AI assistance, we found that the best way to choose the variables is to do a simple Random Forest Classifier and then look at the feature importances. We will then choose the three variables with the highest feature importances and plot them in a 3D plot.

To reiterate, we are plotting the GROUND TRUTHS in the test data here. This is merely to get an idea of which factors are most important in determining whether or not a transaction is fraudulent. We are not plotting the predictions of any model.

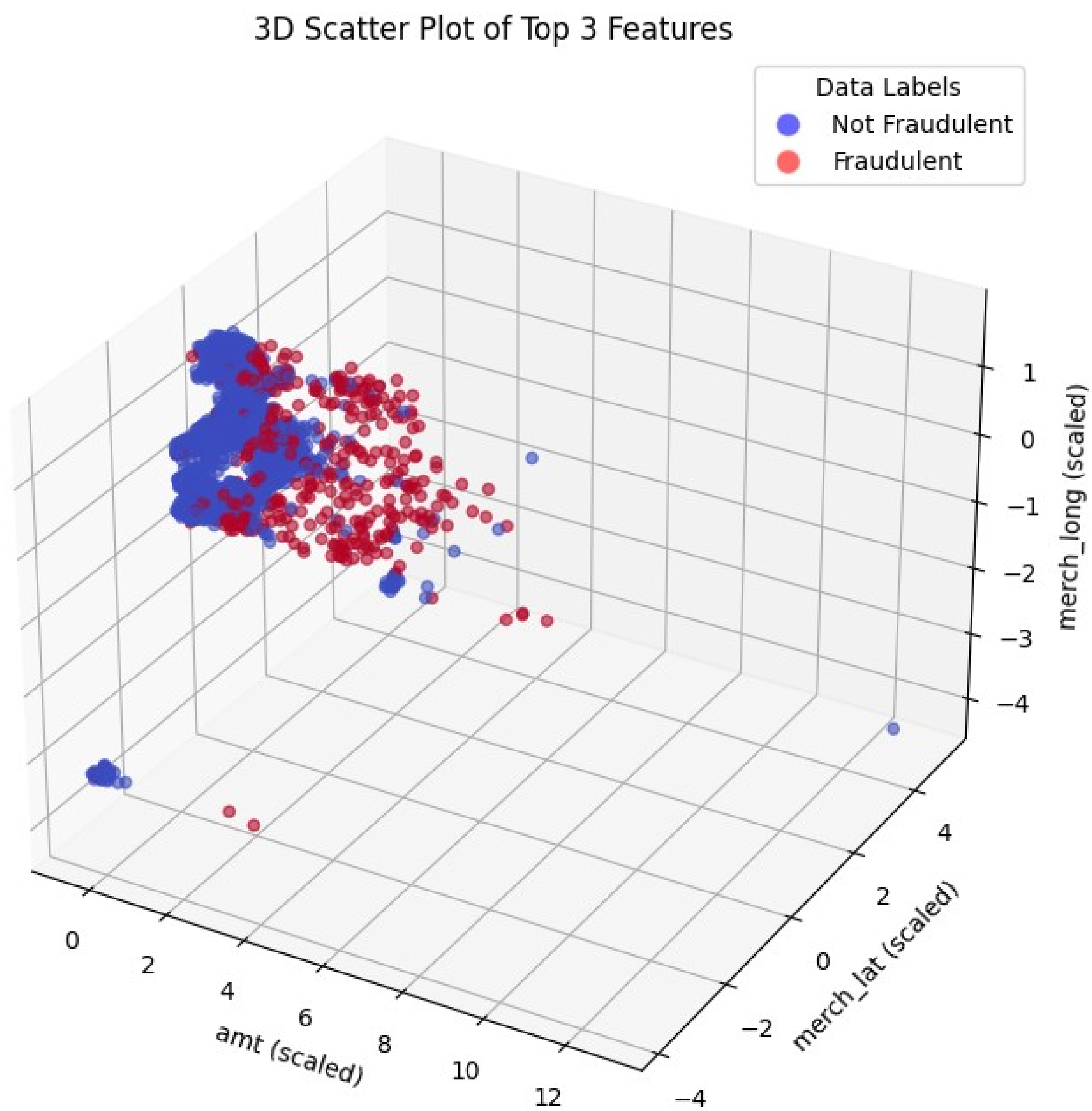
1. Declare the feature names in the correct order.

2. Fit the Random Forest Classifier and get the feature importances.
3. Choose the three variables with the highest feature importances.
4. Plot the 3D plot with the colors based on whether or not the data is fraudulent.

```
# Grab the names of the features
feature_names = X.columns

# Train a Random Forest model purely to get feature importances
rf = RandomForestClassifier(n_estimators=100,
random_state=RANDOM_STATE)
rf.fit(X_train_scaled, y_train)

importances = rf.feature_importances_
indices = np.argsort(importances)[::-1][:3]  # Get the indices of the
top 3 features

# Print the names of the top 3 features
top_features = [feature_names[i] for i in indices]
print(f"Top 3 features: {top_features}")

# For convenience in plotting the labels, let's acknowledge that the
top 3 features are scaled

for i, feat in enumerate(top_features):
    top_features[i] = f"{feat} (scaled)"

# Plot the data using the top 3 features

# I (Ryan) have plotted 3D plots before in another class, so I mainly
copied the code from there.
plt.figure(figsize=(10, 8))
ax = plt.axes(projection='3d')
ax.scatter3D(X_test_scaled[:, indices[0]], X_test_scaled[:,
indices[1]], X_test_scaled[:, indices[2]], c=y_test, cmap='coolwarm',
alpha=0.6)
ax.set_xlabel(top_features[0])
ax.set_ylabel(top_features[1])
ax.set_zlabel(top_features[2])
ax.set_title('3D Scatter Plot of Top 3 Features')

# Create a custom legend (I tried to automate this, but it was too
much of a hassle, so I have approximated the colors for the legend)
handles = [plt.Line2D([0], [0], marker='o', color='w',
markerfacecolor="blue", markersize=10, label="Not Fraudulent",
alpha=0.6),
           plt.Line2D([0], [0], marker='o', color='w',
markerfacecolor="red", markersize=10, label="Fraudulent", alpha=0.6),]
ax.legend(handles=handles, title='Data Labels')

if not SAVE:
    plt.show()
```

```
else:
    plt.savefig(SAVE_DIR + '3d_scatter_plot.png')
```

```
Top 3 features: ['amt', 'merch_lat', 'merch_long']
```




As we can see, the "amt" feature seems to be the most important feature, as the low amounts are typically not fraudulent and the high amounts are typically fraudulent.

## Future Prospects

```
#From all of this data, we can see that each model has its own
strengths and weaknesses.
#Thus, it's time to ensemble these models and, potentially, look into
```

```
something like Majority Voting
#Also, we should look into encoding categorical variables to get
better results.
```