Data Source

Reference: *E. A. Lopez-Rojas, A. Elmir, and S. Axelsson*
Title: *PaySim: A Financial Mobile Money Simulator for Fraud Detection*
Conference: *The 28th European Modeling and Simulation Symposium (EMSS), Larnaca, Cyprus, 2016*
Link: Kaggle - PaySim Dataset

Project Context

This dataset has been utilized for a university internship project aimed at detecting fraud in bank money transactions. The data was carefully edited and cleaned to fit the specific requirements of the project.

About the Author

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Year: *2024*

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import plotly.express as px
```

In [ ]:
```
# Load the dataset
data = pd.read_csv("data.csv")

# Display the first few rows of the dataset
print("First 5 rows of the dataset:")
data.head(5)
```

```
First 5 rows of the dataset:
```

Out[ ]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFr
0	1	PAYMENT	9839.64	C1231006815	170136.0	160296.36	M1979787155	0.0	0.0	
1	1	PAYMENT	1864.28	C1666544295	21249.0	19384.72	M2044282225	0.0	0.0	
2	1	TRANSFER	181.00	C1305486145	181.0	0.00	C553264065	0.0	0.0	
3	1	CASH_OUT	181.00	C840083671	181.0	0.00	C38997010	21182.0	0.0	
4	1	PAYMENT	11668.14	C2048537720	41554.0	29885.86	M1230701703	0.0	0.0	

In [ ]:
```
# Checking for null values
print("\nChecking for null values in the dataset:")
print(data.isnull().sum())
```

```
Checking for null values in the dataset:
step              0
type              0
amount            0
nameOrig          0
oldbalanceOrg     0
newbalanceOrig    0
nameDest          0
oldbalanceDest    0
newbalanceDest    0
isFraud           0
isFlaggedFraud    0
dtype: int64
```

In [ ]:
```
# Information about the dataset
print("\nInformation about the dataset:")
data.info()
```

```
Information about the dataset:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6362620 entries, 0 to 6362619
Data columns (total 11 columns):
 #   Column          Dtype
---  ------          -----
 0   step            int64
 1   type            object
 2   amount          float64
 3   nameOrig        object
 4   oldbalanceOrg   float64
 5   newbalanceOrig  float64
 6   nameDest        object
 7   oldbalanceDest  float64
 8   newbalanceDest  float64
 9   isFraud         int64
 10  isFlaggedFraud  int64
dtypes: float64(5), int64(3), object(3)
memory usage: 534.0+ MB
```

In [ ]:
```
# Exploring transaction type
data.type.value_counts()
```

Out[ ]:
```
type
CASH_OUT    2237500
PAYMENT     2151495
CASH_IN     1399284
TRANSFER     532909
DEBIT         41432
Name: count, dtype: int64
```

In [ ]:
```
# Exploratory Data Analysis (EDA)
## Visualizing the distribution of transaction types
type_counts = data['type'].value_counts()
transactions = type_counts.index
quantity = type_counts.values

print("\nDistribution of Transaction Types:")
figure = px.pie(data,
                values=quantity,
                names=transactions,
                hole=0.5,
                title="Distribution of Transaction Types")
figure.show()
```

```
Distribution of Transaction Types:
```

In [ ]:
```
# Map existing types to new categories
data['type'] = data['type'].map({
    'PAYMENT': 1,        # PAYMENT
    'CASH_IN': 2,        # DEPOSIT
    'DEBIT': 2,          # DEPOSIT
    'CASH_OUT': 3,       # WITHDRAWAL
    'TRANSFER': 3        # WITHDRAWAL
})
```

In [ ]:
```
# Visualizing the Distribution of Transaction Types
type_counts = data['type'].value_counts()
transactions = type_counts.index
quantity = type_counts.values

figure = px.pie(data,
                values=quantity,
                names=['PAYMENT', 'DEPOSIT', 'WITHDRAWAL'],
                hole=0.5,
                title="Distribution of Transaction Type")
figure.show()
```

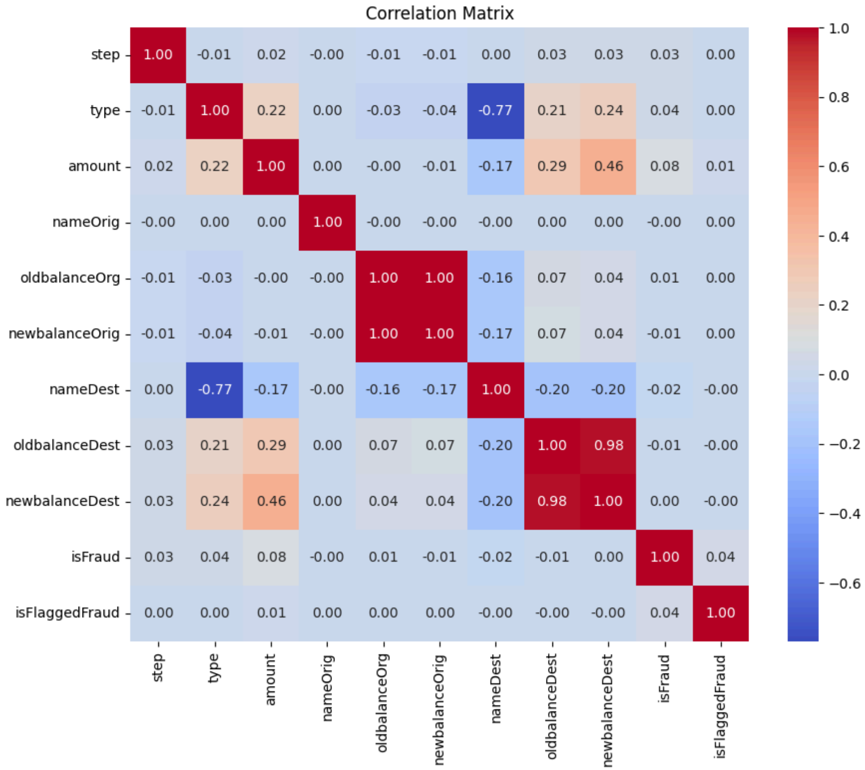
In [ ]:
```
from sklearn.preprocessing import LabelEncoder
# Create a label encoder object
label_encoder = LabelEncoder()

# Iterate over each column in the DataFrame
for column in data.columns:
    # Check if the column data type is object (string)
    if data[column].dtype == 'object':
        # Use label encoder to convert the string values to numerical values
        data[column] = label_encoder.fit_transform(data[column])

# Calculate the correlation matrix
correlation = data.corr()

# Plot the correlation matrix
```

```python
correlation = data.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Matrix")
plt.show()
```



In [ ]:
```python
# Display correlation with 'isFraud'
print(correlation["isFraud"].sort_values(ascending=False))
```

```
isFraud           1.000000
amount            0.076688
isFlaggedFraud    0.044109
type              0.037127
step              0.031578
oldbalanceOrg     0.010154
newbalanceDest    0.000535
nameOrig         -0.000464
oldbalanceDest   -0.005885
newbalanceOrig   -0.008148
nameDest         -0.021963
Name: isFraud, dtype: float64
```

In [ ]:
```python
# Mapping transaction types to integers for model training
data['isFraud'] = data['isFraud'].map({0: "No Fraud", 1: "Fraud"})
```

In [ ]:
```python
# Displaying the first few rows after transformation
data.head()
```

Out[ ]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlagg
0	1	1	9839.64	757869	170136.0	160296.36	1662094	0.0	0.0	No Fraud	
1	1	1	1864.28	2188998	21249.0	19384.72	1733924	0.0	0.0	No Fraud	
2	1	3	181.00	1002156	181.0	0.00	439685	0.0	0.0	Fraud	
3	1	3	181.00	5828262	181.0	0.00	391696	21182.0	0.0	Fraud	
4	1	1	11668.14	3445981	41554.0	29885.86	828919	0.0	0.0	No Fraud	

In [ ]:
```python
# Splitting the dataset into features and labels
X = data[["type", "amount", "oldbalanceOrg", "newbalanceOrig"]]
y = data["isFraud"]
```

In [ ]:
```python
# training a machine learning model
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42)
```

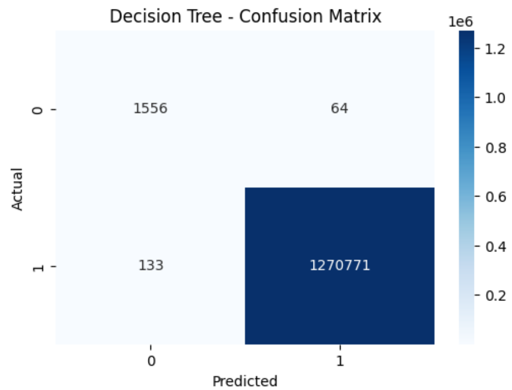
In [ ]:
```python
# Feature scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Model 1: Decision Tree Classifier

In [ ]:
```python
dt_model = DecisionTreeClassifier(random_state=42)
dt_model.fit(X_train_scaled, y_train)
dt_predictions = dt_model.predict(X_test_scaled)
dt_accuracy = dt_model.score(X_test_scaled, y_test)
```

In [ ]:
```python
print("Decision Tree Classifier Report:\n")
print(classification_report(y_test, dt_predictions))
```

In [ ]:
```python
# Visualizing the Confusion Matrix for Decision Tree
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, dt_predictions), annot=True, fmt='d', cmap='Blues')
plt.title("Decision Tree - Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

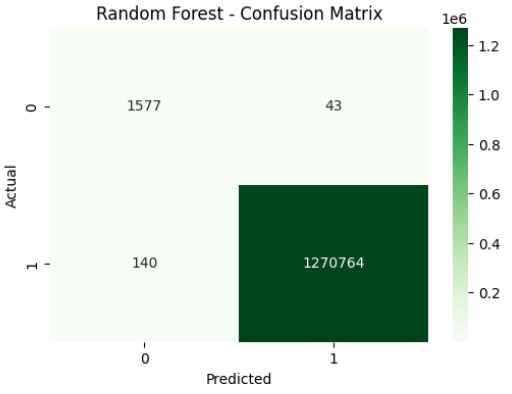


Model 2 : Random Forest Classifier

In [ ]:
```python
from sklearn.ensemble import RandomForestClassifier
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train_scaled, y_train)
rf_predictions = rf_model.predict(X_test_scaled)
rf_accuracy = rf_model.score(X_test_scaled, y_test)
```

In [ ]:
```python
print("Random Forest Classifier Report:\n")
print(classification_report(y_test, rf_predictions))
```

In [ ]:
```python
# Visualizing the Confusion Matrix for Random Forest
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, rf_predictions), annot=True, fmt='d', cmap='Greens')
plt.title("Random Forest - Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



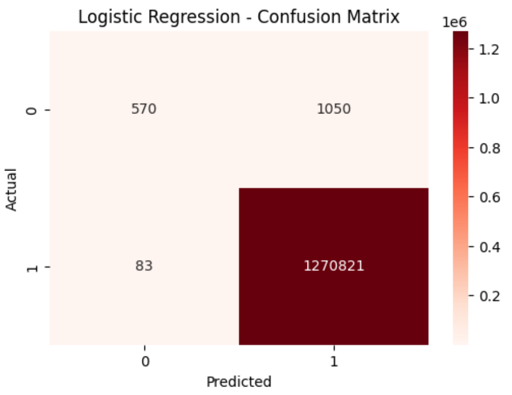
Model 3 : Logistic Regression

In [ ]:
```python
from sklearn.linear_model import LogisticRegression

lr_model = LogisticRegression(random_state=42)
lr_model.fit(X_train_scaled, y_train)
lr_predictions = lr_model.predict(X_test_scaled)
lr_accuracy = lr_model.score(X_test_scaled, y_test)

print("Logistic Regression Report:\n")
print(classification_report(y_test, lr_predictions))
```

In [ ]:
```python
# Visualizing the Confusion Matrix for Logistic Regression
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, lr_predictions), annot=True, fmt='d', cmap='Reds')
plt.title("Logistic Regression - Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



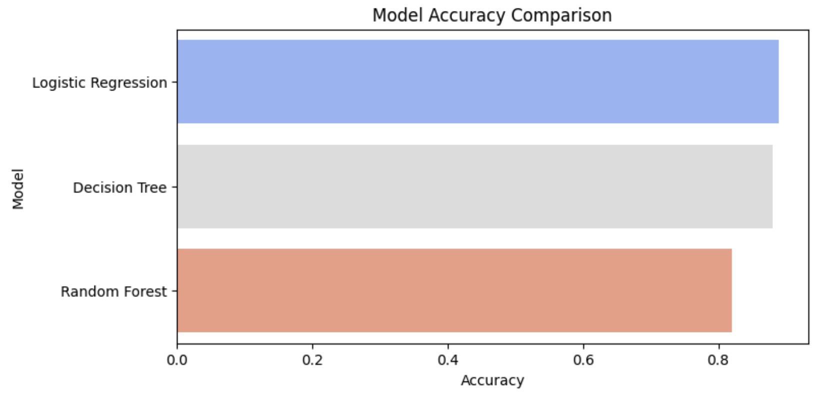
Model Accuracy Comparison

In [ ]:
```python
# Creating a summary table to compare the accuracy of each model
models_summary = pd.DataFrame({
    'Model': ['Decision Tree', 'Random Forest', 'Logistic Regression'],
    'Accuracy': [dt_accuracy, rf_accuracy, lr_accuracy]
})
```

In [ ]:
```python
# Sorting the models by accuracy
models_summary = models_summary.sort_values(by='Accuracy', ascending=False)

# Displaying the summary table
plt.figure(figsize=(8, 4))
sns.barplot(x='Accuracy', y='Model', data=models_summary, palette="coolwarm")
plt.title("Model Accuracy Comparison")
plt.xlabel("Accuracy")
plt.ylabel("Model")
plt.show()

models_summary
```



Out[ ]:

	Model	Accuracy
2	Logistic Regression	0.889110
0	Decision Tree	0.879845
1	Random Forest	0.819856

Model Selection and Saving

From the above models, we choose the model with the highest performance metrics.

In [ ]:
```python
import joblib
joblib.dump(lr_model, "fraud_detection_model.pkl")

print("Model saved as fraud_detection_model.pkl")
```

```
Model saved as fraud_detection_model.pkl
```

In [ ]:
```python
# Example of Loading the model and making a prediction
loaded_model = joblib.load("fraud_detection_model.pkl")

#features = [type, amount, oldbalanceOrg, newbalanceOrig]
example_transaction = np.array([[3, 9000.88, 1000, 100.89]])  # Example input
example_transaction_scaled = scaler.transform(example_transaction)
prediction = loaded_model.predict(example_transaction_scaled)
print("Prediction for the example transaction:", prediction)
```

```
Prediction for the example transaction: ['Fraud']
```