# Credit Card Fraud Detection with Decision Trees and SVM

Problem Statement:- Imagine that you work for a financial institution and part of your job is to build a model that predicts if a credit card transaction is fraudulent or not. You can model the problem as a binary classification problem. A transaction belongs to the positive class (1) if it is a fraud, otherwise it belongs to the negative class (0).

You have access to transactions that occured over a certain period of time. The majority of the transactions are normally legitimate and only a small fraction are non-legitimate. Thus, typically you have access to a dataset that is highly unbalanced. This is also the case of the current dataset: only 492 transactions out of 284,807 are fraudulent (the positive class - the frauds - accounts for 0.172% of all transactions).

## Importing Dataset from Kaggle

```
import os
os.environ['KAGGLE_USERNAME'] = 'ibrahimahmed05'
os.environ['KAGGLE_KEY'] = '1bfa1b55ce18364f2bc02bb78f531b63'
```

```
!kaggle datasets download -d mlg-ulb/creditcardfraud
```

```
Dataset URL: https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud
License(s): DbCL-1.0
```

```
!unzip creditcardfraud.zip
```

```
Archive:  creditcardfraud.zip
  inflating: creditcard.csv
```

## Importing libraries

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import normalize, StandardScaler
from sklearn.utils.class_weight import compute_sample_weight
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import roc_auc_score
from sklearn.svm import LinearSVC
```

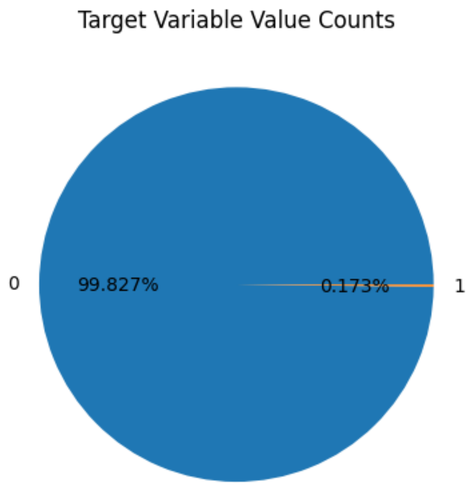
```
data= pd.read_csv('creditcard.csv')
data.head()
```

| | Time | V1 | V2 | V3 | V4 | V5 | V6 | V7 | V8 | V9 | ... | V21 | V22 | V23 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.0 | -1.359807 | -0.072781 | 2.536347 | 1.378155 | -0.338321 | 0.462388 | 0.239599 | 0.098698 | 0.363787 | ... | -0.018307 | 0.277838 | -0.110474 | 0 |
| 1 | 0.0 | 1.191857 | 0.266151 | 0.166480 | 0.448154 | 0.060018 | -0.082361 | -0.078803 | 0.085102 | -0.255425 | ... | -0.225775 | -0.638672 | 0.101288 | -0 |
| 2 | 1.0 | -1.358354 | -1.340163 | 1.773209 | 0.379780 | -0.503198 | 1.800499 | 0.791461 | 0.247676 | -1.514654 | ... | 0.247998 | 0.771679 | 0.909412 | -0 |
| 3 | 1.0 | -0.966272 | -0.185226 | 1.792993 | -0.863291 | -0.010309 | 1.247203 | 0.237609 | 0.377436 | -1.387024 | ... | -0.108300 | 0.005274 | -0.190321 | -1 |
| 4 | 2.0 | -1.158233 | 0.877737 | 1.548718 | 0.403034 | -0.407193 | 0.095921 | 0.592941 | -0.270533 | 0.817739 | ... | -0.009431 | 0.798278 | -0.137458 | 0 |

5 rows × 31 columns

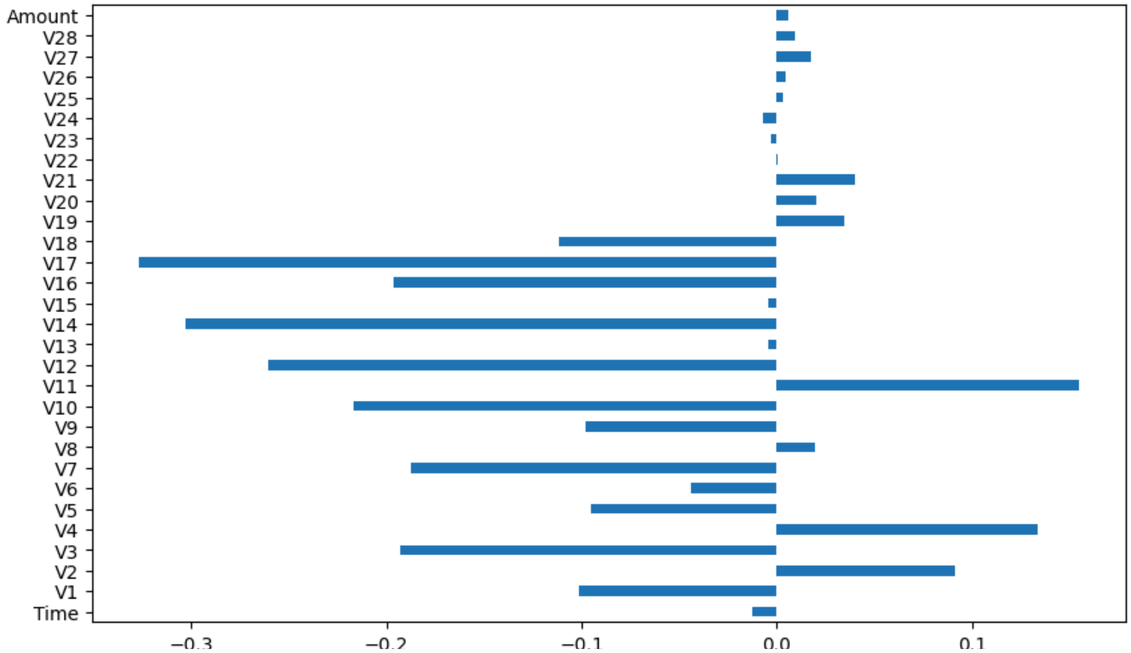
## Data Preprocessing

```
labels = data.Class.unique()
sizes = data.Class.value_counts().values
fig, ax = plt.subplots()
ax.pie(sizes, labels=labels, autopct='%1.3f%%')
ax.set_title('Target Variable Value Counts')
plt.show()
```



```
correlation_values = data.corr()['Class'].drop('Class')
correlation_values.plot(kind='barh', figsize=(10, 6))
```

```
<Axes: >
```



```
X= data.drop('Class', axis=1)
y= data['Class']
X= StandardScaler().fit_transform(X)
X = normalize(X, norm="l1")
```

## Feature Extraction

```
correlated_values= abs(data.corr()['Class'].drop('Class'))
correlated_values= correlated_values.sort_values(ascending=False)
correlated_cols= correlated_values.head(6).index.tolist()
X= data[correlated_cols]
X.head()
```

|   | V17 | V14 | V12 | V10 | V16 | V3 |
|---|---|---|---|---|---|---|
| 0 | 0.207971 | -0.311169 | -0.617801 | 0.090794 | -0.470401 | 2.536347 |
| 1 | -0.114805 | -0.143772 | 1.065235 | -0.166974 | 0.463917 | 0.166480 |
| 2 | 1.109969 | -0.165946 | 0.066084 | 0.207643 | -2.890083 | 1.773209 |
| 3 | -0.684093 | -0.287924 | 0.178228 | -0.054952 | -1.059647 | 1.792993 |
| 4 | -0.237033 | -1.119670 | 0.538196 | 0.753074 | -0.451449 | 1.548718 |

## Train Test Split

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

## Decission Tree Classifier

```
w_train = compute_sample_weight('balanced', y_train)
dt = DecisionTreeClassifier(max_depth=4, random_state=35)
dt.fit(X_train, y_train, sample_weight=w_train)
y_pred= dt.predict(X_test)
dt_auc= roc_auc_score(y_test, y_pred)
print(f'AUC Score of decision tree algorithm is: {dt_auc}')
```

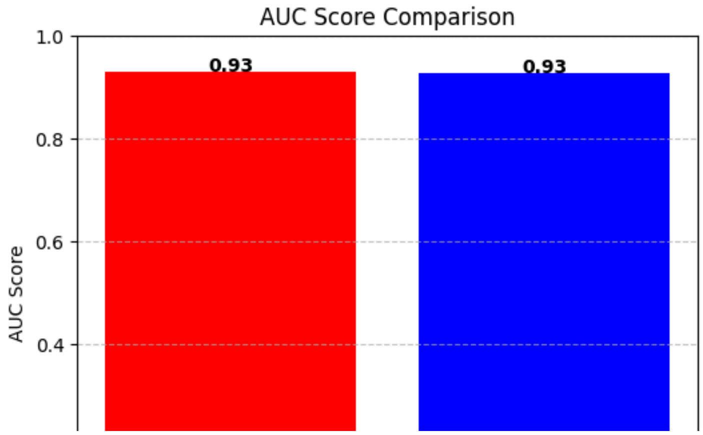
```
AUC Score of decision tree algorithm is: 0.9269754257921514
```

```
svm= LinearSVC(class_weight='balanced', random_state=35)
svm.fit(X_train, y_train)
y_pred= svm.predict(X_test)
svm_auc= roc_auc_score(y_test, y_pred)
print(f'AUC Score of SVM algorithm is: {svm_auc}')
```

```
AUC Score of SVM algorithm is: 0.9301496660847794
```

```
models = ['SVM', 'Decision Tree']
auc_scores = [svm_auc, dt_auc]

plt.figure(figsize=(6,5))
plt.bar(models, auc_scores, color=['red', 'blue'])
plt.title('AUC Score Comparison')
plt.ylabel('AUC Score')
plt.ylim(0, 1)
for i, v in enumerate(auc_scores):
    plt.text(i, v , f'{v:.2f}', ha='center', fontweight='bold')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```


AUC Score Comparison
1.0
0.8
0.6
0.4
AUC Score
0.93
0.93