# Fraud Detection - Credit Card

## About Dataset

The dataset has a time column which shows the transaction in seconds. The dataset have more columns from V1 to V28 which represents some feature about the transaction but as the transactions of credit cards are sensitive, the columns are presented by numbers. Moreover the data has 'Amount' column which is shows the transaction amount in dollars and 'Class' column shows whether the transaction is fraud or not.

Kaggle link for the Dataset - [https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud (https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud)](https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud)

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

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

In [2]:

```
credit_card = pd.read_csv('creditcard.csv')
```

In [3]:

```
credit_card.head()
```

Out[3]:

| | Time | V1 | V2 | V3 | V4 | V5 | V6 | V7 | V8 |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.0 | -1.359807 | -0.072781 | 2.536347 | 1.378155 | -0.338321 | 0.462388 | 0.239599 | 0.098698 |
| **1** | 0.0 | 1.191857 | 0.266151 | 0.166480 | 0.448154 | 0.060018 | -0.082361 | -0.078803 | 0.085102 |
| **2** | 1.0 | -1.358354 | -1.340163 | 1.773209 | 0.379780 | -0.503198 | 1.800499 | 0.791461 | 0.247676 |
| **3** | 1.0 | -0.966272 | -0.185226 | 1.792993 | -0.863291 | -0.010309 | 1.247203 | 0.237609 | 0.377436 |
| **4** | 2.0 | -1.158233 | 0.877737 | 1.548718 | 0.403034 | -0.407193 | 0.095921 | 0.592941 | -0.270533 |

5 rows × 31 columns

In [4]:

```
credit_card.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64  
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

In [5]:

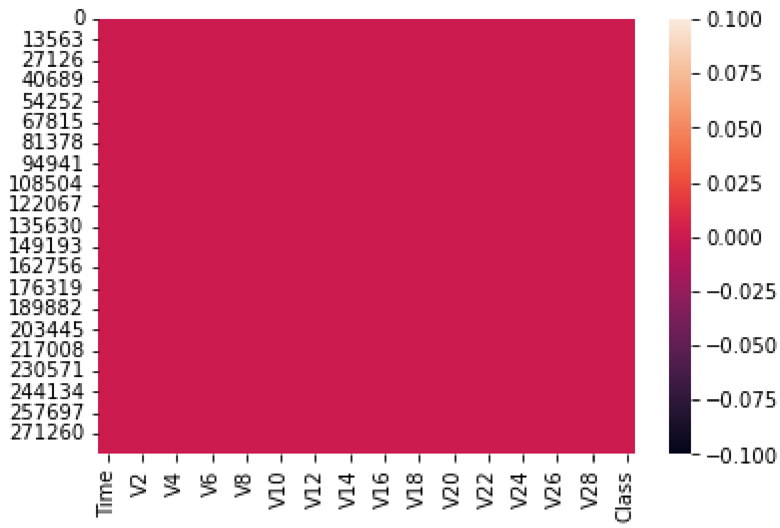
```
credit_card.isnull().sum()
```

Out[5]:

```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

In [6]:

```
sns.heatmap(credit_card.isnull())
plt.show()
```



In [7]:

```
cc = credit_card.copy()
```

In [8]:

```
cc.head()
```

Out[8]:

| | Time | V1 | V2 | V3 | V4 | V5 | V6 | V7 | V8 |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.0 | -1.359807 | -0.072781 | 2.536347 | 1.378155 | -0.338321 | 0.462388 | 0.239599 | 0.098698 |
| **1** | 0.0 | 1.191857 | 0.266151 | 0.166480 | 0.448154 | 0.060018 | -0.082361 | -0.078803 | 0.085102 |
| **2** | 1.0 | -1.358354 | -1.340163 | 1.773209 | 0.379780 | -0.503198 | 1.800499 | 0.791461 | 0.247676 |
| **3** | 1.0 | -0.966272 | -0.185226 | 1.792993 | -0.863291 | -0.010309 | 1.247203 | 0.237609 | 0.377436 |
| **4** | 2.0 | -1.158233 | 0.877737 | 1.548718 | 0.403034 | -0.407193 | 0.095921 | 0.592941 | -0.270533 |

5 rows × 31 columns

In [9]:

```
cc['Class'].value_counts()
```

Out[9]:

```
0    284315
1       492
Name: Class, dtype: int64
```

In [10]:

```
cc.groupby('Class').mean()
```

Out[10]:

| | Time | V1 | V2 | V3 | V4 | V5 | V6 | V7 |
|---|---|---|---|---|---|---|---|---|
| **Class** | | | | | | | | |
| **0** | 94838.202258 | 0.008258 | -0.006271 | 0.012171 | -0.007860 | 0.005453 | 0.002419 | 0.009637 |
| **1** | 80746.806911 | -4.771948 | 3.623778 | -7.033281 | 4.542029 | -3.151225 | -1.397737 | -5.568731 |

2 rows × 30 columns

In [11]:

```
normal = cc[cc.Class == 0]
fraud = cc[cc.Class == 1]
```

In [12]:

```
normal.shape , fraud.shape
```

Out[12]:

```
((284315, 31), (492, 31))
```

In [13]:

```
normal.Amount.describe()
```

Out[13]:

```
count    284315.000000
mean         88.291022
std         250.105092
min           0.000000
25%           5.650000
50%          22.000000
75%          77.050000
max       25691.160000
Name: Amount, dtype: float64
```

In [14]:

```
fraud.Amount.describe()
```

Out[14]:

```
count     492.000000
mean      122.211321
std       256.683288
min         0.000000
25%         1.000000
50%         9.250000
75%       105.890000
max      2125.870000
Name: Amount, dtype: float64
```

In [15]:

```
#As the data is not distributed evenly, we must try to disribute evenly
normal_sample = normal.sample(n = 492)
```

In [16]:

```
cc_final = pd.concat([normal_sample, fraud], axis = 0)
```

In [17]:

```
cc_final.sample(5)
```

Out[17]:

| | Time | V1 | V2 | V3 | V4 | V5 | V6 | V7 |
|---|---|---|---|---|---|---|---|---|
| **238127** | 149534.0 | 1.984559 | -1.930051 | -1.088922 | -1.675583 | -1.137633 | 0.197087 | -1.172027 |
| **86001** | 61038.0 | -1.120009 | 0.750977 | 2.561013 | -0.030162 | -0.294961 | 0.376599 | 0.342202 |
| **18773** | 29753.0 | 0.269614 | 3.549755 | -5.810353 | 5.809370 | 1.538808 | -2.269219 | -0.824203 |
| **135718** | 81372.0 | -0.885254 | 1.790649 | -0.945149 | 3.853433 | -1.543510 | 0.188582 | -2.988383 |
| **53794** | 46149.0 | -1.346509 | 2.132431 | -1.854355 | 2.116998 | -1.070378 | -1.092671 | -2.230986 |

5 rows × 31 columns

In [18]:

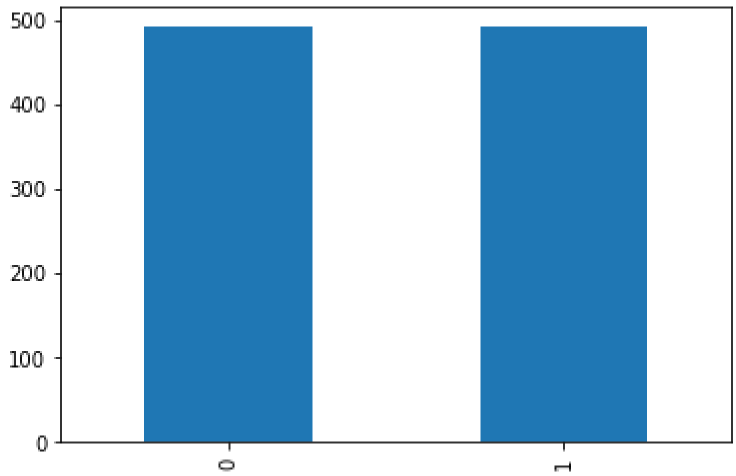
```
#Checking if the data is evenly distributed or not
dis = cc_final['Class'].value_counts()
dis
```

Out[18]:

```
0    492
1    492
Name: Class, dtype: int64
```

In [19]:

```
dis.plot(kind = 'bar')
plt.show()
```



In [20]:

```
cc_final.groupby('Class').mean()
```

Out[20]:

| | Time | V1 | V2 | V3 | V4 | V5 | V6 | V7 |
|---|---|---|---|---|---|---|---|---|
| **Class** | | | | | | | | |
| **0** | 94732.664634 | -0.085919 | -0.019114 | -0.053619 | 0.006691 | -0.050785 | -0.012492 | 0.024236 |
| **1** | 80746.806911 | -4.771948 | 3.623778 | -7.033281 | 4.542029 | -3.151225 | -1.397737 | -5.568731 |

2 rows × 30 columns

In [21]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
```

In [22]:

```
x = cc_final.drop(['Class'], axis = 1)
y = cc_final['Class']
```

In [23]:

```
x.head()
```

Out[23]:

| | Time | V1 | V2 | V3 | V4 | V5 | V6 | V7 |
|---|---|---|---|---|---|---|---|---|
| **270265** | 163994.0 | -5.808461 | 5.392370 | -5.774109 | -0.357545 | -2.558459 | -1.157350 | -3.267030 |
| **33592** | 37297.0 | 0.566593 | -1.377684 | 0.438796 | 0.458684 | -1.453851 | -0.477246 | -0.165218 |
| **107181** | 70320.0 | -1.672614 | -4.918784 | -1.770582 | 1.282633 | -1.757134 | -0.065947 | 2.060316 |
| **146920** | 87962.0 | -2.956152 | 2.569305 | -1.167447 | -2.839101 | -0.504506 | -1.310978 | 0.040740 |
| **154360** | 101272.0 | 1.263040 | -1.097398 | -0.603314 | 1.863709 | -0.381287 | 0.407999 | 0.049589 |

5 rows × 30 columns

In [24]:

```
y.head()
```

Out[24]:

```
270265    0
33592     0
107181    0
146920    0
154360    0
Name: Class, dtype: int64
```

In [25]:

```
X_train, X_test, y_train, y_test = train_test_split (x, y, test_size=0.3, random_state=0)
```

In [26]:

```
lg = LogisticRegression()
```

In [27]:

```
lg.fit(X_train, y_train)
```

Out[27]:

```
LogisticRegression()
```

In [28]:

```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[28]:

```
((688, 30), (296, 30), (688,), (296,))
```

In [29]:

```
y_train = y_train.values.reshape(-1,1)
y_test = y_test.values.reshape(-1,1)
```

In [30]:

```
y_train.shape, y_test.shape
```

Out[30]:

```
((688, 1), (296, 1))
```

In [31]:

```
lg.score(X_test, y_test)
```

Out[31]:

```
0.9222972972972973
```

In [32]:

```
y_train_pred = lg.predict(X_train)
y_train_pred
```

Out[32]:

```
array([0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0,
       0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1,
       1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1,
       0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0,
       1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1,
       0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0,
       1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1,
       0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1,
       0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1,
       0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0,
       1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1,
       0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1,
       0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0,
       1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1,
       0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1,
       1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0,
       0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
       1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0,
       0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1,
       0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0,
       0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0,
       0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0,
       0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1,
       1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1,
       1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1,
       1, 1, 0, 1, 1, 1], dtype=int64)
```

In [33]:

```
y_test_pred = lg.predict(X_test)
y_test_pred
```

Out[33]:

```
array([0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1,
       1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0,
       1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1,
       0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0,
       0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0,
       1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0,
       0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1,
       1, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0,
       1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1,
       0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0,
       1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1,
       0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0,
       1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0,
       0, 1, 0, 0, 1, 0, 1, 1, 1, 1], dtype=int64)
```

In [34]:

```
from sklearn.metrics import mean_absolute_error, mean_squared_error,r2_score
```

In [35]:

```
print("R2Score : " ,r2_score(y_test, y_test_pred))
print("mean_absolute_error : ",mean_absolute_error(y_test, y_test_pred))
print("mean_squared_error : " ,mean_squared_error(y_test, y_test_pred))
print("Root mean_squared_error : ",np.sqrt(mean_squared_error(y_test, y_test_pred)))
```

```
R2Score :  0.6891749988586038
mean_absolute_error :  0.0777027027027027
mean_squared_error :  0.0777027027027027
Root mean_squared_error :  0.27875204519913876
```

In [36]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train_std = sc.fit_transform(X_train)
X_test_std = sc.transform(X_test)
```

In [37]:

```
from sklearn.ensemble import RandomForestRegressor

rf_tree = RandomForestRegressor(random_state=0)
rf_tree.fit(X_train_std,y_train)
rf_tree_y_pred = rf_tree.predict(X_train_std)
print("Accuracy: {}".format(rf_tree.score(X_train_std,y_train)))
print("R squared: {}".format(r2_score(y_true=y_train,y_pred=rf_tree_y_pred)))
```

```
Accuracy: 0.9734927992563485
R squared: 0.9734927992563485
```

In [38]:

```
print ('Logistic Regression Accuracy: {}'.format(lg.score(X_test, y_test)))
print ('Random Forest Accuracy: {}'.format(rf_tree.score(X_train_std,y_train)))
```

```
Logistic Regression Accuracy: 0.9222972972972973
Random Forest Accuracy: 0.9734927992563485
```

### Conclusion

Random Forest Regressor has more accuracy than Logistic Regression. So we can use Random Forest Regressor to detect the fraud in credit transaction.