Project – Credit Card Fraud Detection

Problem Statement:

1. A credit card is a small thin plastic or fiber card that incorporates information about the person such as a picture or signature and the person's name on it to charge purchases and services to his linked account. Charges are debited regularly. Nowadays, card data is read by ATMs, swiping machines, store readers, banks and online transactions.
2. Each card has a unique card number which is very important. Its security mainly relies on the physical security of the card and also the privacy of the credit card number. There is a rapid growth in credit card transactions which has led to substantial growth in scam cases.
3. Credit card fraud is expanding heavily because fraud financial loss is increasing drastically. Multiple data mining and statistical techniques are used to catch fraud. Therefore the detection of fraud using efficient and secured methods are very important.

Tasks To Be Performed:

1. Load the dataset using the pandas module.

In [195…
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import *
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

In [196…
```
df = pd.read_csv('creditcard.csv')
df
```

Out[196]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	V28	Amount	Class
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	0.066928	0.128539	-0.189115	0.133558	-0.021053	149.62	0.0
1	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	-0.339846	0.167170	0.125895	-0.008983	0.014724	2.69	0.0
2	1	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.689281	-0.327642	-0.139097	-0.055353	-0.059752	378.66	0.0
3	1	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.175575	0.647376	-0.221929	0.062723	0.061458	123.50	0.0
4	2	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.141267	-0.206010	0.502292	0.219422	0.215153	69.99	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
11660	19915	1.294875	-0.645847	0.689549	-0.351634	-1.026884	-0.129811	-0.928101	0.114172	0.804717	...	-0.097462	-0.020893	0.040297	0.159282	0.350705	-0.278351	-0.010354	-0.008003	10.00	0.0
11661	19915	1.404683	-0.554883	0.612239	-0.234956	-1.190992	-0.816824	-0.775771	-0.142637	1.121638	...	-0.196110	-0.303562	0.005661	0.313352	0.473813	-0.276618	-0.024026	0.002106	5.00	0.0
11662	19915	-0.945541	0.479754	1.521916	-1.298658	-0.852548	-0.604029	-0.354686	0.498106	0.407159	...	-0.050745	0.056031	-0.055584	0.312195	0.026299	-0.413466	0.189152	0.086360	10.00	0.0
11663	19915	-0.087909	0.184093	1.683910	-0.837378	-0.682605	-0.669907	-0.056222	-0.120669	0.409636	...	-0.109428	-0.054760	-0.139329	0.333267	0.072695	-0.320292	0.006423	0.010148	10.00	0.0
11664	19915	1.504229	-0.499337	0.052377	-0.576345	-0.393971	0.015149	-0.718603	-0.125852	1.023281	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

11665 rows × 31 columns

2. Perform missing value analysis on the dataset.

In [197…
```
df.isna().sum()
```

Out[197]:
```
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       1
V13       1
V14       1
V15       1
V16       1
V17       1
V18       1
V19       1
V20       1
V21       1
V22       1
V23       1
V24       1
V25       1
V26       1
V27       1
V28       1
Amount    1
Class     1
dtype: int64
```

In [198…
```
df[df['Amount'].isnull()].T
```

Out[198]:

	11664
Time	19915.000000
V1	1.504229
V2	-0.499337
V3	0.052377
V4	-0.576345
V5	-0.393971
V6	0.015149
V7	-0.718603
V8	-0.125852
V9	1.023281
V10	0.141308
V11	-0.993422
V12	NaN
V13	NaN
V14	NaN
V15	NaN
V16	NaN
V17	NaN
V18	NaN
V19	NaN
V20	NaN
V21	NaN
V22	NaN
V23	NaN
V24	NaN
V25	NaN
V26	NaN
V27	NaN
V28	NaN
Amount	NaN
Class	NaN

All null values are in one row. So it's best to just remove that row.

In [199…
```
df.dropna(inplace=True)
```

In [200…
```
df
```

Out[200]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	V28	Amount	Class
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	0.066928	0.128539	-0.189115	0.133558	-0.021053	149.62	0.0
1	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	-0.339846	0.167170	0.125895	-0.008983	0.014724	2.69	0.0
2	1	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.689281	-0.327642	-0.139097	-0.055353	-0.059752	378.66	0.0
3	1	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.175575	0.647376	-0.221929	0.062723	0.061458	123.50	0.0
4	2	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.141267	-0.206010	0.502292	0.219422	0.215153	69.99	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
11659	19914	1.348167	-0.531813	0.737667	-0.312410	-1.147767	-0.585711	-0.810412	-0.062116	0.705208	...	-0.120215	-0.076450	0.006995	0.489243	0.448523	-0.309831	-0.021411	-0.003987	5.00	0.0
11660	19915	1.294875	-0.645847	0.689549	-0.351634	-1.026884	-0.129811	-0.928101	0.114172	0.804717	...	-0.097462	-0.020893	0.040297	0.159282	0.350705	-0.278351	-0.010354	-0.008003	10.00	0.0
11661	19915	1.404683	-0.554883	0.612239	-0.234956	-1.190992	-0.816824	-0.775771	-0.142637	1.121638	...	-0.196110	-0.303562	0.005661	0.313352	0.473813	-0.276618	-0.024026	0.002106	5.00	0.0
11662	19915	-0.945541	0.479754	1.521916	-1.298658	-0.852548	-0.604029	-0.354686	0.498106	0.407159	...	-0.050745	0.056031	-0.055584	0.312195	0.026299	-0.413466	0.189152	0.086360	10.00	0.0
11663	19915	-0.087909	0.184093	1.683910	-0.837378	-0.682605	-0.669907	-0.056222	-0.120669	0.409636	...	-0.109428	-0.054760	-0.139329	0.333267	0.072695	-0.320292	0.006423	0.010148	10.00	0.0

11664 rows × 31 columns

3. From the dataset, calculate the number of genuine transactions, number of fraud transactions and the percentage of fraud transactions.

In [201…
```
df['Class'].value_counts()
```

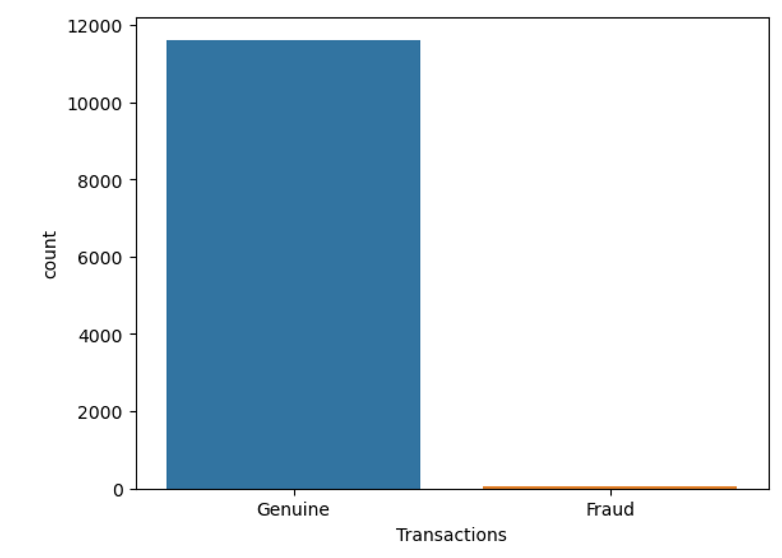
Out[201]:
```
0.0    11615
1.0       49
Name: Class, dtype: int64
```

In [202…
```
genuine_transactions = df['Class'].value_counts()[0]
fraud_transactions = df['Class'].value_counts()[1]
percentage_fraud_transactions = fraud_transactions/(genuine_transactions+fraud_transactions)
print('Genuine Transactions: ', genuine_transactions)
print('Fraud Transactions: ', fraud_transactions)
print('Percentage Fraud Transactions: ', percentage_fraud_transactions*100,'%')
```

```
Genuine Transactions:  11615
Fraud Transactions:  49
Percentage Fraud Transactions:  0.4200960219478738 %
```

4. Using the visualization module, visualize the genuine and fraudulent transactions using a bar graph.

In [203…
```
sns.countplot(data=df, x='Class', hue_order=['A', 'B'])
plt.xticks(ticks=[0, 1], labels=['Genuine', 'Fraud'])
plt.xlabel('Transactions')
plt.show()
```



5. Using the Standard Scaler module, normalize the amount column and store the new values in the NormalizedAmount column.

In [204…
```
sc = StandardScaler()
df['NormalizedAmount'] = sc.fit_transform(df['Amount'].values.reshape(-1, 1))
```

In [205…
```
df
```

Out[205]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V22	V23	V24	V25	V26	V27	V28	Amount	Class	NormalizedAmount
0	0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	0.277838	-0.110474	0.066928	0.128539	-0.189115	0.133558	-0.021053	149.62	0.0	0.482873
1	0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.638672	0.101288	-0.339846	0.167170	0.125895	-0.008983	0.014724	2.69	0.0	-0.334272
2	1	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.771679	0.909412	-0.689281	-0.327642	-0.139097	-0.055353	-0.059752	378.66	0.0	1.756668
3	1	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	0.005274	-0.190321	-1.175575	0.647376	-0.221929	0.062723	0.061458	123.50	0.0	0.337607
4	2	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	0.798278	-0.137458	0.141267	-0.206010	0.502292	0.219422	0.215153	69.99	0.0	0.040014
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
11659	19914	1.348167	-0.531813	0.737667	-0.312410	-1.147767	-0.585711	-0.810412	-0.062116	0.705208	...	-0.076450	0.006995	0.489243	0.448523	-0.309831	-0.021411	-0.003987	5.00	0.0	-0.321425
11660	19915	1.294875	-0.645847	0.689549	-0.351634	-1.026884	-0.129811	-0.928101	0.114172	0.804717	...	-0.020893	0.040297	0.159282	0.350705	-0.278351	-0.010354	-0.008003	10.00	0.0	-0.293618
11661	19915	1.404683	-0.554883	0.612239	-0.234956	-1.190992	-0.816824	-0.775771	-0.142637	1.121638	...	-0.303562	0.005661	0.313352	0.473813	-0.276618	-0.024026	0.002106	5.00	0.0	-0.321425
11662	19915	-0.945541	0.479754	1.521916	-1.298658	-0.852548	-0.604029	-0.354686	0.498106	0.407159	...	0.056031	-0.055584	0.312195	0.026299	-0.413466	0.189152	0.086360	10.00	0.0	-0.293618
11663	19915	-0.087909	0.184093	1.683910	-0.837378	-0.682605	-0.669907	-0.056222	-0.120669	0.409636	...	-0.054760	-0.139329	0.333267	0.072695	-0.320292	0.006423	0.010148	10.00	0.0	-0.293618

11664 rows × 32 columns

6. Split the dataset in train and test set and have a 70:30 split ratio for the model.

In [206…
```
X = df.drop(columns=['Class'])
y = df['Class']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.30, random_state=42)
```

7. Now use a decision tree and random forest model for training on top of the train set.

Decision Tree

In [207…
```
dt = DecisionTreeClassifier()
dt.fit(X_train,y_train)
```

Out[207]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [208…
```
dt_y_pred = dt.predict(X_test)
```

In [209…
```
dt_cf = confusion_matrix(y_test,dt_y_pred)
dt_cf
```

Out[209]:
```
array([[3482,    2],
       [   2,   14]], dtype=int64)
```

In [210…
```
dt_score = dt.score(X_test,y_test)
dt_score
```

Out[210]:
```
0.9988571428571429
```

Random Forest

In [211…
```
rf = RandomForestClassifier()
rf.fit(X_train,y_train)
```

Out[211]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [212…
```
rf_y_pred = rf.predict(X_test)
```

In [213…
```
rf_cf = confusion_matrix(y_test,rf_y_pred)
rf_cf
```

Out[213]:
```
array([[3483,    1],
       [   2,   14]], dtype=int64)
```

In [214…
```
rf_score = rf.score(X_test,y_test)
rf_score
```

Out[214]:
```
0.9991428571428571
```

In [215…
```
print('Decision Tree score: ', dt_score)
print ('Random Forest score: ', rf_score)
```

```
Decision Tree score:  0.9988571428571429
Random Forest score:  0.9991428571428571
```

`Observation: Random Forest model is slightly better`

10. Check the performance matrix of both models and compare which model is having the highest performance.

Decision Tree

In [216…
```
dt_cf
```

Out[216]:
```
array([[3482,    2],
       [   2,   14]], dtype=int64)
```

In [217…
```
print(classification_report(y_test, dt_y_pred))
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      3484
         1.0       0.88      0.88      0.88        16

    accuracy                           1.00      3500
   macro avg       0.94      0.94      0.94      3500
weighted avg       1.00      1.00      1.00      3500
```

In [218…
```
print('Accuracy: ', accuracy_score(y_test, dt_y_pred))
print('Precision: ', precision_score(y_test, dt_y_pred))
print('Recall: ', recall_score(y_test, dt_y_pred))
print('F1 score: ', f1_score(y_test, dt_y_pred))
```

```
Accuracy:  0.9988571428571429
Precision:  0.875
Recall:  0.875
F1 score:  0.875
```

Random Forest

In [219…
```
rf_cf
```

Out[219]:
```
array([[3483,    1],
       [   2,   14]], dtype=int64)
```

In [220…
```
print(classification_report(y_test, rf_y_pred))
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      3484
         1.0       0.93      0.88      0.90        16

    accuracy                           1.00      3500
   macro avg       0.97      0.94      0.95      3500
weighted avg       1.00      1.00      1.00      3500
```

In [221…
```
print('Accuracy: ', accuracy_score(y_test, rf_y_pred))
print('Precision: ', precision_score(y_test, rf_y_pred))
print('Recall: ', recall_score(y_test, rf_y_pred))
print('F1 score: ', f1_score(y_test, rf_y_pred))
```

```
Accuracy:  0.9991428571428571
Precision:  0.9333333333333333
Recall:  0.875
F1 score:  0.9032258064516129
```

It is safe to say, Random Forest model has the highest performance.

In [ ]: