Credit Card Fraud Detection - Logistic Regression

Importing Libraries

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
```

```
# loading the dataset to a Pandas DataFrame
credit_card_data = pd.read_csv('creditcard.csv')
```

```
# first 5 rows of the dataset
credit_card_data.head()
```

	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

```
credit_card_data.tail()
```

	Time	V1	V2	V3	V4	V5	V6	V7
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006

5 rows × 31 columns

```
# dataset informations
credit_card_data.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
```

```
# checking the number of missing values in each column
credit_card_data.isnull().sum()
```

	0
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

```
# distribution of legit transactions & fraudulent transactions
credit_card_data['Class'].value_counts()
```

Class	count
0	284315
1	492

dtype: int64

```
# separating the data for analysis
legit = credit_card_data[credit_card_data.Class == 0]
fraud = credit_card_data[credit_card_data.Class == 1]
```

```
print(legit.shape)
print(fraud.shape)
```

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

```
# statistical measures of the data
legit.Amount.describe()
```

	Amount
count	284315.000000
mean	88.291022
std	250.105092
min	0.000000
25%	5.650000
50%	22.000000
75%	77.050000
max	25691.160000

dtype: float64

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

	Amount
count	492.000000
mean	122.211321
std	256.683288
min	0.000000
25%	1.000000
50%	9.250000
75%	105.890000
max	2125.870000

dtype: float64

```
# compare the values for both transactions
credit_card_data.groupby('Class').mean()
```

	Time	V1	V2	V3	V4	V5	V6	
Class								
0	94838.202258	0.008258	-0.006271	0.012171	-0.007860	0.005453	0.002419	0.0096
1	80746.806911	-4.771948	3.623778	-7.033281	4.542029	-3.151225	-1.397737	-5.5687

2 rows × 30 columns

Under-Sampling Build a sample dataset containing similar distribution of normal transactions and Fraudulent Transactions Number of Fraudulent Transactions --> 492

```
legit_sample = legit.sample(n=492)
```

Concatenating two DataFrames

```
new_dataset = pd.concat([legit_sample, fraud], axis=0)
```

```
new_dataset.head()
```

	Time	V1	V2	V3	V4	V5	V6	V7
222644	143064.0	-0.204156	0.789728	0.676419	-0.702966	0.646070	-1.062063	1.261606
170948	120421.0	-0.907712	-0.236815	0.907539	-2.955275	-0.168306	1.180725	-0.707736
22404	32227.0	-1.113087	1.379736	1.213365	1.055965	0.181941	0.334371	0.534518
20513	31093.0	-1.192693	0.567001	1.018639	-2.027937	0.195278	-0.084362	0.468799
63843	50889.0	-0.653976	1.318063	1.506234	0.211357	0.025224	-0.798924	0.946490

5 rows × 31 columns

```
new_dataset.tail()
```

	Time	V1	V2	V3	V4	V5	V6	V7
279863	169142.0	-1.927883	1.125653	-4.518331	1.749293	-1.566487	-2.010494	-0.882850
280143	169347.0	1.378559	1.289381	-5.004247	1.411850	0.442581	-1.326536	-1.413170
280149	169351.0	-0.676143	1.126366	-2.213700	0.468308	-1.120541	-0.003346	-2.234739
281144	169966.0	-3.113832	0.585864	-5.399730	1.817092	-0.840618	-2.943548	-2.208002
281674	170348.0	1.991976	0.158476	-2.583441	0.408670	1.151147	-0.096695	0.223050

5 rows × 31 columns

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

	count
Class	
0	492
1	492

dtype: int64

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

Class	Time	V1	V2	V3	V4	V5	V6	V
0	93213.233740	0.129194	-0.141559	0.093879	0.010826	-0.007418	-0.054803	-0.07346
1	80746.806911	-4.771948	3.623778	-7.033281	4.542029	-3.151225	-1.397737	-5.5687

2 rows × 30 columns

Splitting the data into Features & Targets

```
X = new_dataset.drop(columns='Class', axis=1)
Y = new_dataset['Class']
```

```
print(X)
```

```
            Time        V1        V2        V3        V4        V5        V6  \
222644  143064.0 -0.204156  0.789728  0.676419 -0.702966  0.646070 -1.062063
170948  120421.0 -0.907712 -0.236815  0.907539 -2.955275 -0.168306  1.180725
22404    32227.0 -1.113087  1.379736  1.213365  1.055965  0.181941  0.334371
20513    31093.0 -1.192693  0.567001  1.018639 -2.027937  0.195278 -0.084362
63843    50889.0 -0.653976  1.318063  1.506234  0.211357  0.025224 -0.798924
...          ...       ...       ...       ...       ...       ...       ...
279863  169142.0 -1.927883  1.125653 -4.518331  1.749293 -1.566487 -2.010494
280143  169347.0  1.378559  1.289381 -5.004247  1.411850  0.442581 -1.326536
280149  169351.0 -0.676143  1.126366 -2.213700  0.468308 -1.120541 -0.003346
281144  169966.0 -3.113832  0.585864 -5.399730  1.817092 -0.840618 -2.943548
281674  170348.0  1.991976  0.158476 -2.583441  0.408670  1.151147 -0.096695

              V7        V8        V9  ...       V20       V21       V22  \
222644  1.261606 -0.382036  0.066857  ...  0.037529 -0.287439 -0.528936
170948 -0.707736  0.888734 -2.719511  ... -0.516192 -0.014660  0.275362
22404   0.534518  0.244474 -0.078077  ...  0.408270 -0.116449  0.404205
20513   0.468799  0.076647  1.302181  ... -0.189550  0.118729  0.648605
63843   0.946490 -0.347420 -0.803105  ...  0.080555 -0.405211 -1.338554
...          ...       ...       ...  ...       ...       ...       ...
279863 -0.882850  0.697211 -2.064945  ...  1.252967  0.778584 -0.319189
280143 -1.413170  0.248525 -1.127396  ...  0.226138  0.370612  0.028234
280149 -2.234739  1.210158 -0.652250  ...  0.247968  0.751826  0.834108
281144 -2.208002  1.058733 -1.632333  ...  0.306271  0.583276 -0.269209
281674  0.223050 -0.068384  0.577829  ... -0.017652 -0.164350 -0.295135

             V23       V24       V25       V26       V27       V28  Amount
222644 -0.012390 -0.044981 -0.644623  0.110487  0.182384  0.013292    6.79
170948 -0.307543 -1.442482  0.431331  0.066443 -0.043824 -0.049160   10.00
22404  -0.164734  0.031346 -0.033780 -0.284219  0.208148 -0.206163    9.00
20513  -0.206028 -0.266573  0.160577 -0.770116 -0.093414  0.193993    5.50
63843   0.025747  0.386570 -0.020912  0.071301 -0.453309 -0.017510   18.00
...          ...       ...       ...       ...       ...       ...     ...
279863  0.639419 -0.294885  0.537503  0.788395  0.292680  0.147968  390.00
```

```
280143 -0.145640 -0.081049  0.521875  0.739467  0.389152  0.186637    0.76
280149  0.190944  0.032070 -0.739695  0.471111  0.385107  0.194361   77.89
281144 -0.456108 -0.183659 -0.328168  0.606116  0.884876 -0.253700  245.00
281674 -0.072173 -0.450261  0.313267 -0.289617  0.002988 -0.015309   42.53

[984 rows x 30 columns]
```

```
print(Y)
```

```
222644    0
170948    0
22404     0
20513     0
63843     0
         ..
279863    1
280143    1
280149    1
281144    1
281674    1
Name: Class, Length: 984, dtype: int64
```

Split the data into Training data & Testing Data

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, stratify=Y, random_
```

```
print(X.shape, X_train.shape, X_test.shape)
```

```
(984, 30) (787, 30) (197, 30)
```

Model Training

Logistic Regression

```
model = LogisticRegression()
```

```
# training the Logistic Regression Model with Training Data
model.fit(X_train, Y_train)
```

```
▾ LogisticRegression
LogisticRegression()
```

Model Evaluation

Accuracy Score

```
# accuracy on training data
X_train_prediction = model.predict(X_train)
training_data_accuracy = accuracy_score(X_train_prediction, Y_train)
```

```
print('Accuracy on Training data : ', training_data_accuracy)
```

```
Accuracy on Training data :  0.9250317662007624
```

```
# accuracy on test data
X_test_prediction = model.predict(X_test)
test_data_accuracy = accuracy_score(X_test_prediction, Y_test)
```

```
print('Accuracy score on Test Data : ', test_data_accuracy)
```

```
Accuracy score on Test Data :  0.9187817258883249
```

Start coding or generate with AI.