Importing the dependencies

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Data Extraction and Data Preprocessing

Project: Credit Card Fraud Detection
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```
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, precision_score, recall_score, f1_score
from sklearn.metrics import confusion_matrix, classification_report, roc_curve, roc_auc_score
import seaborn as sns
import matplotlib.pyplot as plt
```

```
#loading the dataset to a pandas dataframe
credit_card_data = pd.read_csv('/content/drive/MyDrive/creditcard.csv')
```

```
credit_card_data.head()
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...

5 rows × 31 columns

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

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

Inference: Imbalanced dataset

```
#dataset information
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()
```

```
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
```

No null values

0 ---> Normal transactions

1 ---> Fraudulent transactions

```
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)
```

Data Analysis

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

```
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
```

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

```
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
```

```
# Compare the values for both transactions
```

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

Class	Time	V1	V2	V3	V4	V5	V6	V7	V8	
0	94838.202258	0.008258	-0.006271	0.012171	-0.007860	0.005453	0.002419	0.009637	-0.000987	0
1	80746.806911	-4.771948	3.623778	-7.033281	4.542029	-3.151225	-1.397737	-5.568731	0.570636	-2

2 rows × 30 columns

Dealing with Unbalanced Data using Undersampling

Build a sample dataset containing similar distribution of normal transactions and fraudulent transactions

number of fraudulenmt transactions are 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	V8	
88661	62235.0	1.254041	-0.377083	0.154381	-1.034386	-0.476982	-0.208320	-0.366712	0.055136	1.39
167084	118476.0	-0.838515	-0.687202	1.255584	-3.164715	-0.123387	0.067715	-0.240287	0.133879	-1.94
210158	137863.0	-0.563274	1.112728	0.634563	-0.054422	1.268482	-0.414805	0.969668	-0.129946	-0.87
33103	37092.0	1.198636	-0.489530	-0.372524	-0.298584	1.416174	3.962836	-1.179029	1.067166	0.79
234964	148187.0	1.922641	-1.595810	-0.616538	-1.100507	-0.957953	0.631334	-1.331910	0.209933	0.22

5 rows × 31 columns

```
new_dataset.tail()
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	
279863	169142.0	-1.927883	1.125653	-4.518331	1.749293	-1.566487	-2.010494	-0.882850	0.697211	-2.064
280143	169347.0	1.378559	1.289381	-5.004247	1.411850	0.442581	-1.326536	-1.413170	0.248525	-1.127
280149	169351.0	-0.676143	1.126366	-2.213700	0.468308	-1.120541	-0.003346	-2.234739	1.210158	-0.652
281144	169966.0	-3.113832	0.585864	-5.399730	1.817092	-0.840618	-2.943548	-2.208002	1.058733	-1.632
281674	170348.0	1.991976	0.158476	-2.583441	0.408670	1.151147	-0.096695	0.223050	-0.068384	0.577

5 rows × 31 columns

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

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

Spliting the data into features and target

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

```
print(x)
print(y)
```

```
            Time        V1        V2        V3        V4        V5        V6  \
88661    62235.0  1.254041 -0.377083  0.154381 -1.034386 -0.476982 -0.208320
167084  118476.0 -0.838515 -0.687202  1.255584 -3.164715 -0.123387  0.067715
210158  137863.0 -0.563274  1.112728  0.634563 -0.054422  1.268482 -0.414805
33103    37092.0  1.198636 -0.489530 -0.372524 -0.298584  1.416174  3.962836
234964  148187.0  1.922641 -1.595810 -0.616538 -1.100507 -0.957953  0.631334
...          ...       ...       ...       ...       ...       ...       ...
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  \
88661  -0.366712  0.055136  1.396761  ... -0.060218  0.000277  0.179921
167084 -0.240287  0.133879 -1.940176  ... -0.000806 -0.191606 -0.257967
210158  0.969668 -0.129946 -0.874451  ...  0.254919 -0.339831 -0.972655
33103  -1.179029  1.067166  0.795929  ...  0.063964 -0.132983 -0.385150
234964 -1.331910  0.209933  0.224904  ...  0.294199  0.280165  0.555601
...          ...       ...       ...  ...       ...       ...       ...
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
88661  -0.235146 -0.500162  0.753778 -0.591690  0.063676  0.010519   20.00
167084 -0.243214 -0.013493  0.783994 -0.107162  0.247747  0.119905   60.00
210158 -0.279093  0.419858  0.445326  0.482129 -0.004867  0.085759    4.49
33103  -0.021781  1.040540  0.406675  0.329932  0.015532  0.023939   28.75
234964 -0.017202 -1.429608 -0.363351 -0.196966  0.010813 -0.036520  142.20
...          ...       ...       ...       ...       ...       ...     ...
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]
88661     0
167084    0
210158    0
33103     0
234964    0
         ..
279863    1
280143    1
280149    1
281144    1
281674    1
Name: Class, Length: 984, dtype: int64
```

Splitting the data into training data and testing data

Double-click (or enter) to edit

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, stratify= y, random_state =2)
```

Using stratify =y , the data with 0 and 1 will be evenly distributed in both x_train and x_test

```
print(x.shape, x_train.shape, x_test.shape)
```

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

Model_Training

```
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('The Accuracy on training data: ', training_data_accuracy)
```

```
The Accuracy on training data:  0.951715374841169
```

```
# accuracy on test data
x_test_prediction = model.predict(x_test)
testing_data_accuracy = accuracy_score(x_test_prediction, y_test)
```

```
print('The Accuracy on testing data: ', testing_data_accuracy)
```

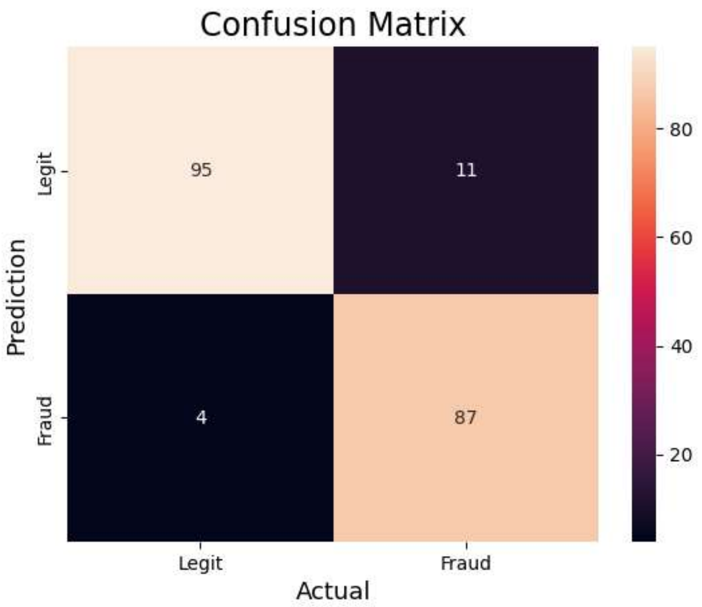
```
The Accuracy on testing data:  0.9238578680203046
```

Since the Accuracy of the training data and Testing data is very similar , there is no overfitting or underfitting

Confusion Matrix

```
cm = confusion_matrix(x_test_prediction , y_test)
```

```
sns.heatmap(cm, annot=True, fmt='g', xticklabels=['Legit', 'Fraud'], yticklabels=['Legit', 'Fraud'])
plt.ylabel('Prediction', fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix', fontsize =17)
plt.show()
```



print(classification_report(y_test, y_pred))

this is used to get the complete metric at one place

```
precision = precision_score(y_test, x_test_prediction)
print("Precision :", precision)
recall = recall_score(y_test, x_test_prediction)
print("Recall    :", recall)
F1_score = f1_score(y_test, x_test_prediction)
print("F1-score  :", F1_score)
```

```
Precision : 0.9560439560439561
Recall    : 0.8877551020408163
F1-score  : 0.9206349206349207
```

```
print(classification_report(y_test, x_test_prediction))
```

```
              precision    recall  f1-score   support

           0       0.90      0.96      0.93        99
           1       0.96      0.89      0.92        98

    accuracy                           0.92       197
   macro avg       0.93      0.92      0.92       197
weighted avg       0.93      0.92      0.92       197
```

ROC Curve

```
false_positive_rate, true_positive_rate, threshold = roc_curve(y_test, x_test_prediction, pos_label=1)
```

```
auc_score = roc_auc_score(y_test, x_test_prediction)
print(auc_score)
```

```
0.9236755308183879
```

Its a high Auc Score so Model is really good

```
plt.plot(true_positive_rate,false_positive_rate,  marker='.', label='Logistic')
plt.xlabel('True Positive Rate')
plt.ylabel('False Positive Rate')
# show the legend
plt.legend()
# show the plot
plt.show()
```