```
# Load, explore and plot data
import numpy as np
import pandas as pd
import re
import string
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# suppress display of warnings
import warnings
warnings.filterwarnings("ignore")
```

```
C:\Users\mbkhn\AppData\Roaming\Python\Python39\site-packages\
matplotlib\projections\__init__.py:63: UserWarning: Unable to import
Axes3D. This may be due to multiple versions of Matplotlib being
installed (e.g. as a system package and as a pip package). As a
result, the 3D projection is not available.
  warnings.warn("Unable to import Axes3D. This may be due to multiple
versions of "
```

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

```
credit_card_data.head()
```

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

         V8        V9  ...       V21       V22       V23       V24
V25  \
0  0.098698  0.363787  ... -0.018307  0.277838 -0.110474  0.066928
0.128539
1  0.085102 -0.255425  ... -0.225775 -0.638672  0.101288 -0.339846
0.167170
2  0.247676 -1.514654  ...  0.247998  0.771679  0.909412 -0.689281 -
0.327642
3  0.377436 -1.387024  ... -0.108300  0.005274 -0.190321 -1.175575
0.647376
4 -0.270533  0.817739  ... -0.009431  0.798278 -0.137458  0.141267 -
0.206010
```

```
        V26       V27       V28  Amount  Class
0 -0.189115  0.133558 -0.021053  149.62      0
1  0.125895 -0.008983  0.014724    2.69      0
2 -0.139097 -0.055353 -0.059752  378.66      0
3 -0.221929  0.062723  0.061458  123.50      0
4  0.502292  0.219422  0.215153   69.99      0

[5 rows x 31 columns]
```

```
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
```

```
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
```

```
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)
```

```
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
```

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

```
               Time        V1        V2        V3        V4        V5
\
Class

0      94838.202258  0.008258 -0.006271  0.012171 -0.007860  0.005453

1      80746.806911 -4.771948  3.623778 -7.033281  4.542029 -3.151225


             V6        V7        V8        V9  ...       V20       V21
\
Class                                          ...

0      0.002419  0.009637 -0.000987  0.004467  ... -0.000644 -0.001235

1     -1.397737 -5.568731  0.570636 -2.581123  ...  0.372319  0.713588


            V22       V23       V24       V25       V26       V27
V28  \
Class

0     -0.000024  0.000070  0.000182 -0.000072 -0.000089 -0.000295 -
0.000131
1      0.014049 -0.040308 -0.105130  0.041449  0.051648  0.170575
0.075667

           Amount
Class
0       88.291022
1      122.211321
```

```
[2 rows x 30 columns]

legit_sample = legit.sample(n=492)

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

new_dataset.head()

            Time        V1        V2        V3        V4        V5
V6  \
267043  162588.0  2.076305  0.183539 -1.991667  0.451110  0.542355 -
1.009372
50697    44606.0 -0.646942  0.334413  1.501834 -1.271515  0.065255 -
0.845126
269602  163695.0 -1.513142  0.471152  1.762687 -1.088295  0.033669 -
0.586055
246968  153408.0  1.944373 -0.229404 -0.666059  1.671707 -0.347378 -
0.418573
39947    40033.0  1.068666 -0.215634  0.801594  0.013162 -0.688575 -
0.216140

              V7        V8        V9  ...       V21       V22
V23  \
267043  0.319117 -0.262955  0.432012  ... -0.236113 -0.570998
0.242137
50697   0.559335 -0.013064  0.023107  ... -0.040290 -0.340621 -
0.013481
269602 -0.087914  0.689651 -0.043542  ...  0.017152 -0.344239 -
0.258993
246968 -0.142945 -0.005186  1.362874  ... -0.350666 -0.680077
0.260252
39947  -0.341395  0.092139 -0.015976  ... -0.062973 -0.268102
0.145213

             V24       V25       V26       V27       V28  Amount
Class
267043  0.583720 -0.084671  0.339876 -0.075827 -0.037138    2.35
0
50697  -0.105770 -0.346627  0.733987 -0.010162  0.112136   38.67
0
269602 -0.062147  0.433706 -0.904888 -0.053161 -0.079799    1.00
0
246968 -0.090145 -0.011299 -0.810771  0.031751 -0.047261    7.48
0
39947   0.280072 -0.111974  0.780683 -0.053391  0.013355   53.53
0

[5 rows x 31 columns]

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

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

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

```
               Time        V1        V2        V3        V4        V5
\
Class

0      96186.827236  0.092076  0.046601 -0.089525  0.034670 -0.001328

1      80746.806911 -4.771948  3.623778 -7.033281  4.542029 -3.151225


             V6        V7        V8        V9  ...       V20       V21
\
Class                                        ...

0     -0.054238  0.126569  0.018107  0.023790  ...  0.029643 -0.003234

1     -1.397737 -5.568731  0.570636 -2.581123  ...  0.372319  0.713588


            V22       V23       V24       V25       V26       V27
V28  \
Class

0     -0.037585  0.004307  0.040286  0.024395 -0.007042  0.010295
0.015000
1      0.014049 -0.040308 -0.105130  0.041449  0.051648  0.170575
0.075667

           Amount
Class
0       97.454045
1      122.211321

[2 rows x 30 columns]
```

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

```
X
```

```
            Time        V1        V2        V3        V4        V5
V6  \
267043  162588.0  2.076305  0.183539 -1.991667  0.451110  0.542355 -
1.009372
50697    44606.0 -0.646942  0.334413  1.501834 -1.271515  0.065255 -
```

```
0.845126
269602  163695.0 -1.513142  0.471152  1.762687 -1.088295  0.033669 -
0.586055
246968  153408.0  1.944373 -0.229404 -0.666059  1.671707 -0.347378 -
0.418573
39947    40033.0  1.068666 -0.215634  0.801594  0.013162 -0.688575 -
0.216140
...          ...       ...       ...       ...       ...       ...
...
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  \
267043  0.319117 -0.262955  0.432012  ... -0.202033 -0.236113 -
0.570998
50697   0.559335 -0.013064  0.023107  ... -0.021141 -0.040290 -
0.340621
269602 -0.087914  0.689651 -0.043542  ... -0.191429  0.017152 -
0.344239
246968 -0.142945 -0.005186  1.362874  ... -0.419124 -0.350666 -
0.680077
39947  -0.341395  0.092139 -0.015976  ...  0.060770 -0.062973 -
0.268102
...          ...       ...       ...  ...       ...       ...       ..
.
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
267043  0.242137  0.583720 -0.084671  0.339876 -0.075827 -0.037138
2.35
```

```
50697  -0.013481 -0.105770 -0.346627  0.733987 -0.010162  0.112136
38.67
269602 -0.258993 -0.062147  0.433706 -0.904888 -0.053161 -0.079799
1.00
246968  0.260252 -0.090145 -0.011299 -0.810771  0.031751 -0.047261
7.48
39947   0.145213  0.280072 -0.111974  0.780683 -0.053391  0.013355
53.53
...          ...       ...       ...       ...       ...       ...
...
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]
```

```
Y
```

```
267043    0
50697     0
269602    0
246968    0
39947     0
         ..
279863    1
280143    1
280149    1
281144    1
281674    1
Name: Class, Length: 984, dtype: int64
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y,
test_size=0.2, stratify=Y, random_state=2)
```

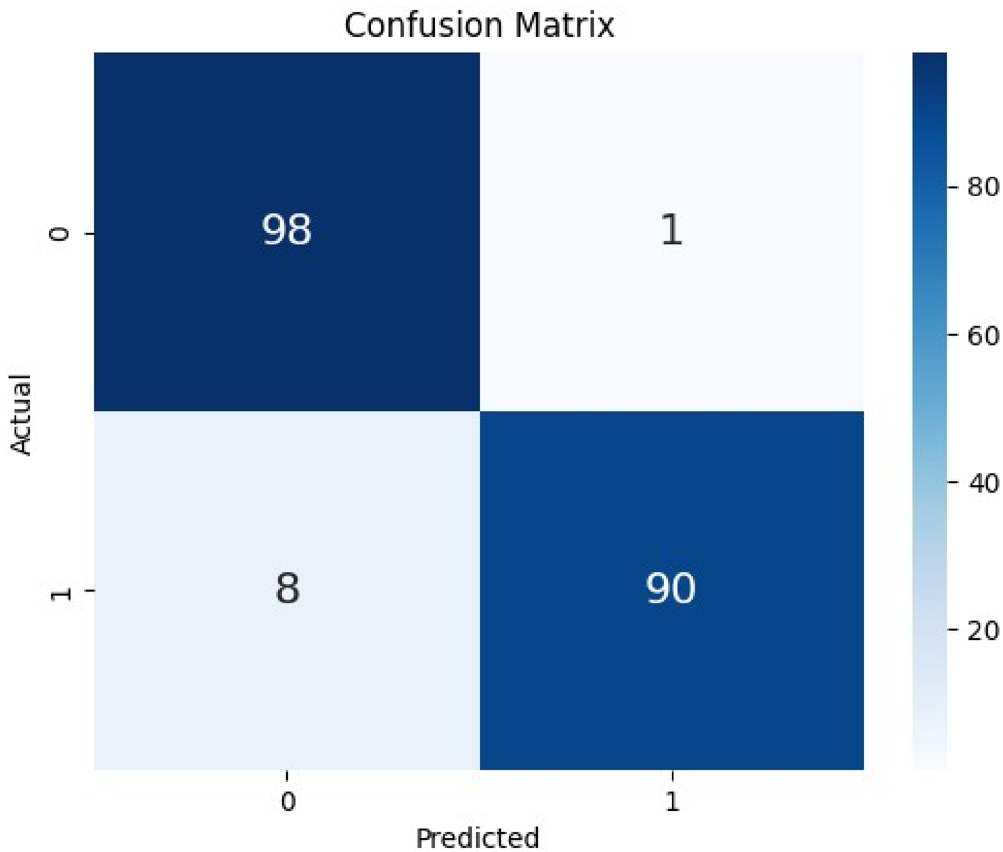
```
X.shape, X_train.shape, X_test.shape
```

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

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
```

```
model.fit(X_train, Y_train)
```

```
LogisticRegression()

from sklearn.metrics import accuracy_score
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 :  0.9466327827191868

# 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 :  0.9543147208121827

from sklearn.metrics import r2_score
Y_pred = model.predict(X_test)
r_squared = r2_score(Y_test, Y_pred)
print(f'R-squared: {r_squared}')

R-squared: 0.8172541743970316

from sklearn.metrics import confusion_matrix

Y_pred = model.predict(X_test)

# Calculate confusion matrix
cm = confusion_matrix(Y_test, Y_pred)

# Create a heatmap using seaborn
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', annot_kws={"size":
16})
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```




```
TP = 98
TN = 90
FP = 1
FN = 8

# Calculating metrics
accuracy = (TP + TN) / (TP + TN + FP + FN)
precision = TP / (TP + FP)
recall = TP / (TP + FN)
f1_score = 2 * (precision * recall) / (precision + recall)

# Displaying the results
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1 Score: {f1_score:.4f}")

Accuracy: 0.9543
Precision: 0.9899
Recall: 0.9245
F1 Score: 0.9561
```

These values will give you insights into the performance of your classification model. In practice, the interpretation of these metrics depends on the specific requirements and goals of your application. Higher values for accuracy, precision, recall, and F1 score are generally desirable

```
from sklearn.metrics import classification_report

# Assuming you've already trained the logistic regression model
(model.fit)
Y_pred = model.predict(X_test)
Y_proba = model.predict_proba(X_test)[:, 1]

# Classification Report
print("\nClassification Report:")
print(classification_report(Y_test, Y_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.99      0.96        99
           1       0.99      0.92      0.95        98

    accuracy                           0.95       197
   macro avg       0.96      0.95      0.95       197
weighted avg       0.96      0.95      0.95       197
```

```
from sklearn.model_selection import cross_val_score

cross_val_scores = cross_val_score(model, X, Y, cv=5,
scoring='accuracy')  # You can use other scoring metrics

# Display cross-validation scores
print("Cross-Validation Scores:", cross_val_scores)
print("Mean Accuracy:", cross_val_scores.mean())
```

```
Cross-Validation Scores: [0.95939086 0.94416244 0.9035533  0.94416244
0.91836735]
Mean Accuracy: 0.933927276494354
```

The cross-validation scores for each fold are quite high, ranging from 90.36% to 95.94%.

The mean accuracy across all folds is approximately 93.39%.

This indicates that your logistic regression model is performing well on different subsets of the data. The relatively consistent high scores suggest that the model generalizes well and is not overfitting or underfitting.

```
```