

✓ Credit Card Fraud Detection

✓ Importing the libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import PowerTransformer
from imblearn.over_sampling import SMOTE
from collections import Counter
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix
%matplotlib inline
```

✓ Importing the dataset

```
df = pd.read_csv('/content/creditcard.csv')
df.head()
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	
0	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.
1	0.0	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.
2	1.0	-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.
3	1.0	-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.
4	2.0	-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.

5 rows × 31 columns

✓ Checking the discrepancies in the data and performing exploratory data analysis

```
df.isna().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

df.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

len(df)

284807

df.describe()

      Time      V1      V2      V3      V4      V5      V6      V7      V8
count 284807.000000  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  2
mean  94813.859575  1.168375e-15  3.416908e-16  -1.379537e-15  2.074095e-15  9.604066e-16  1.487313e-15  -5.556467e-16  1.213481e-16  -2.4
std   47488.145955  1.958696e+00  1.651309e+00  1.516255e+00  1.415869e+00  1.380247e+00  1.332271e+00  1.237094e+00  1.194353e+00  1
min      0.000000  -5.640751e+01  -7.271573e+01  -4.832559e+01  -5.683171e+00  -1.137433e+02  -2.616051e+01  -4.355724e+01  -7.321672e+01  -1
25%   54201.500000  -9.203734e-01  -5.985499e-01  -8.903648e-01  -8.486401e-01  -6.915971e-01  -7.682956e-01  -5.540759e-01  -2.086297e-01  -6
50%   84692.000000  1.810880e-02  6.548556e-02  1.798463e-01  -1.984653e-02  -5.433583e-02  -2.741871e-01  4.010308e-02  2.235804e-02  -3
75%  139320.500000  1.315642e+00  8.037239e-01  1.027196e+00  7.433413e-01  6.119264e-01  3.985649e-01  5.704361e-01  3.273459e-01  3
max  172792.000000  2.454930e+00  2.205773e+01  9.382558e+00  1.687534e+01  3.480167e+01  7.330163e+01  1.205895e+02  2.000721e+01  1

8 rows x 31 columns

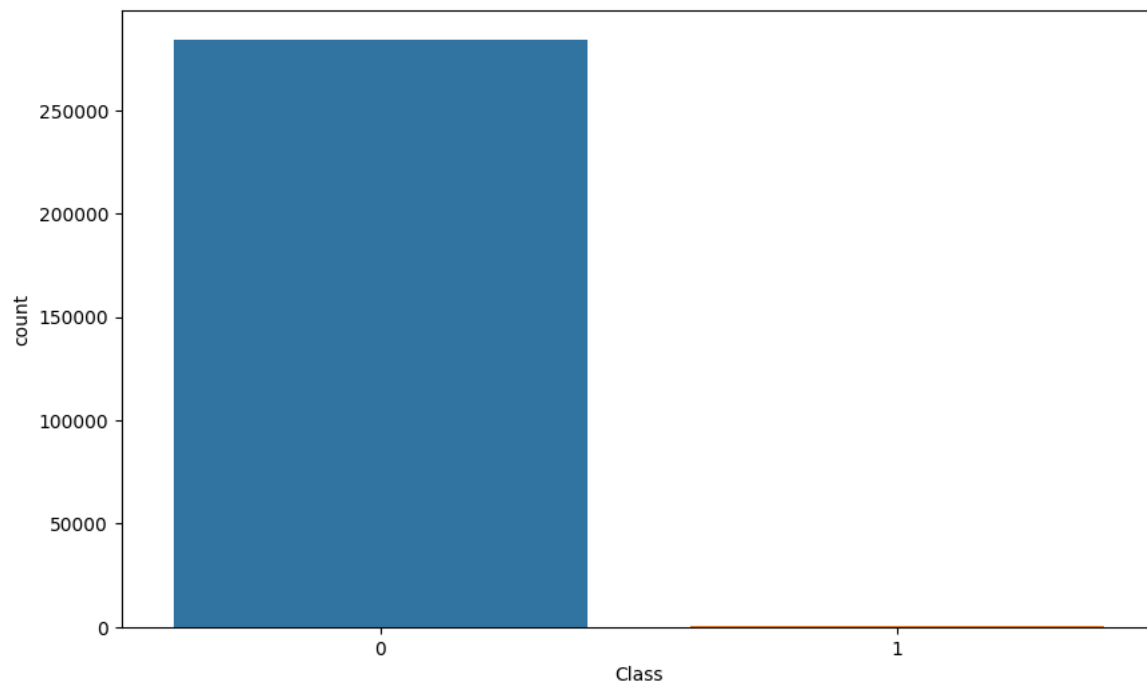
# The classes are heavily skewed we need to solve this issue later.
print('No Frauds', round(df['Class'].value_counts()[0]/len(df) * 100,2), '% of the dataset')
print('Frauds', round(df['Class'].value_counts()[1]/len(df) * 100,2), '% of the dataset')
```

No Frauds 99.83 % of the dataset
Frauds 0.17 % of the dataset

✓ Checking the distribution of data

```
plt.figure(dpi=100, figsize=(10,6))  
sns.countplot(data=df, x='Class')
```

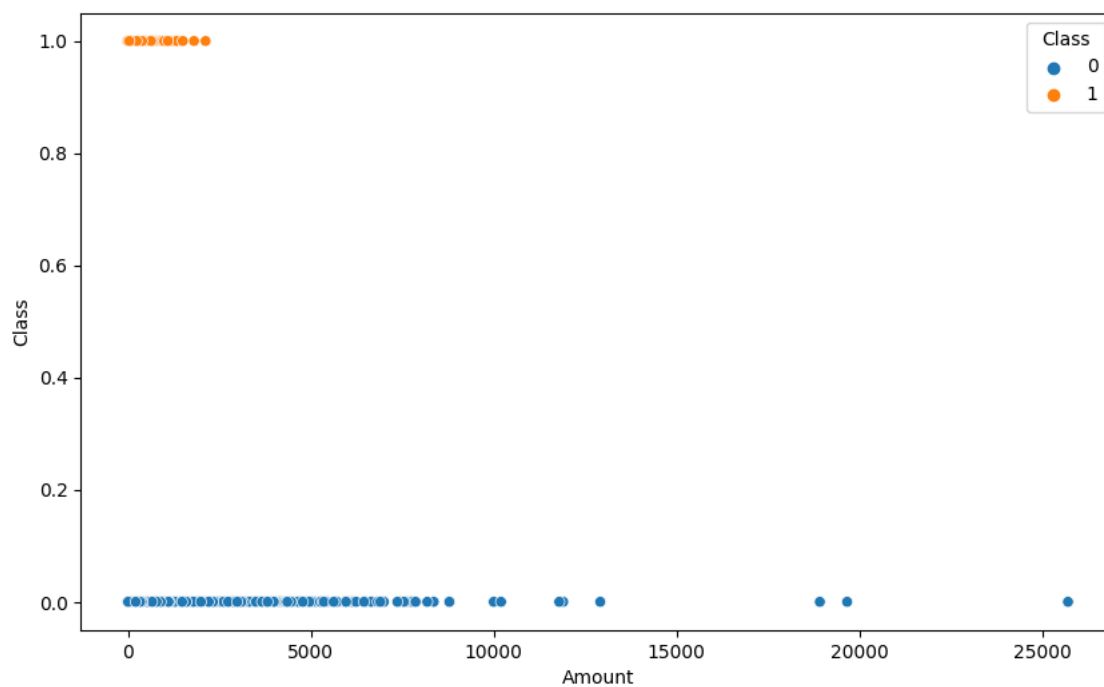
<Axes: xlabel='Class', ylabel='count'>



✓ Checking the effect of Amount and Time columns of the dataset on Class

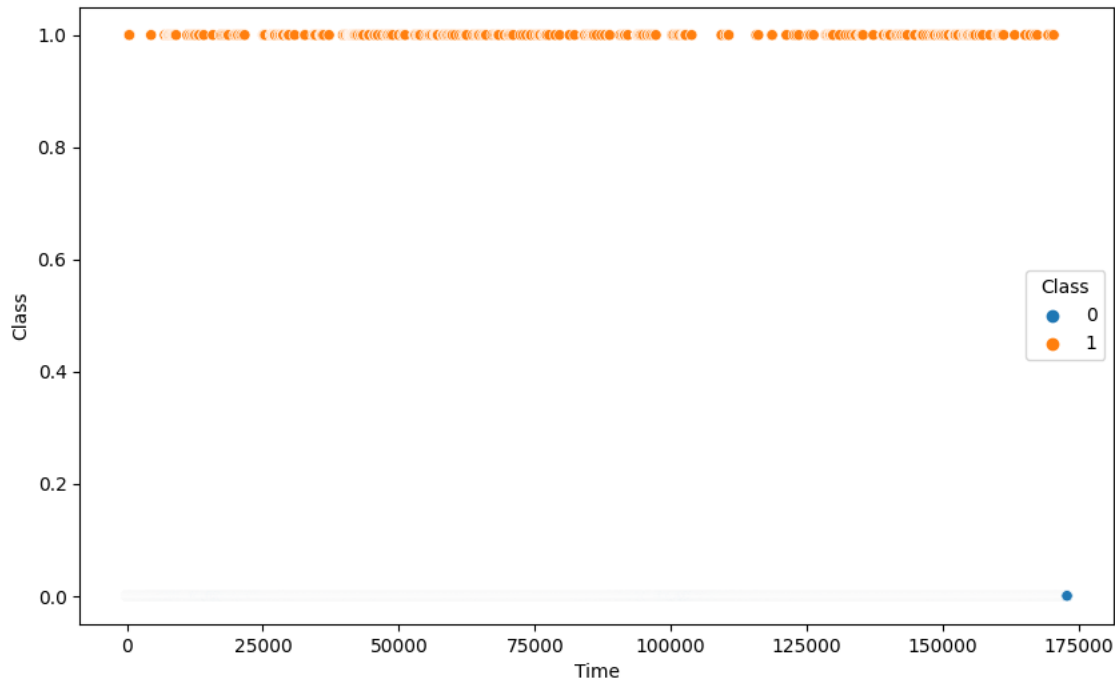
```
plt.figure(dpi=100, figsize=(10,6))  
sns.scatterplot(data=df, x='Amount', y='Class', hue='Class')
```

<Axes: xlabel='Amount', ylabel='Class'>



```
plt.figure(dpi=100, figsize=(10,6))
sns.scatterplot(data=df, x='Time', y='Class', hue='Class', )
```

<Axes: xlabel='Time', ylabel='Class'>



✓ Dropping the non impactful columns

```
df = df.drop(['Time'], axis=1)
df.head()
```

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	...	V21	V22	V23
0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	0.090794	...	-0.018307	0.277838	-0.110474
1	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	-0.166974	...	-0.225775	-0.638672	0.101288
2	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	0.207643	...	0.247998	0.771679	0.909412
3	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	-0.054952	...	-0.108300	0.005274	-0.190321
4	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	0.753074	...	-0.009431	0.798278	-0.137458

5 rows x 30 columns

✓ Scaling Amount feature for better results

```
sc = StandardScaler()
amount = df['Amount'].values

df['Amount'] = sc.fit_transform(amount.reshape(-1, 1))
df.head()
```

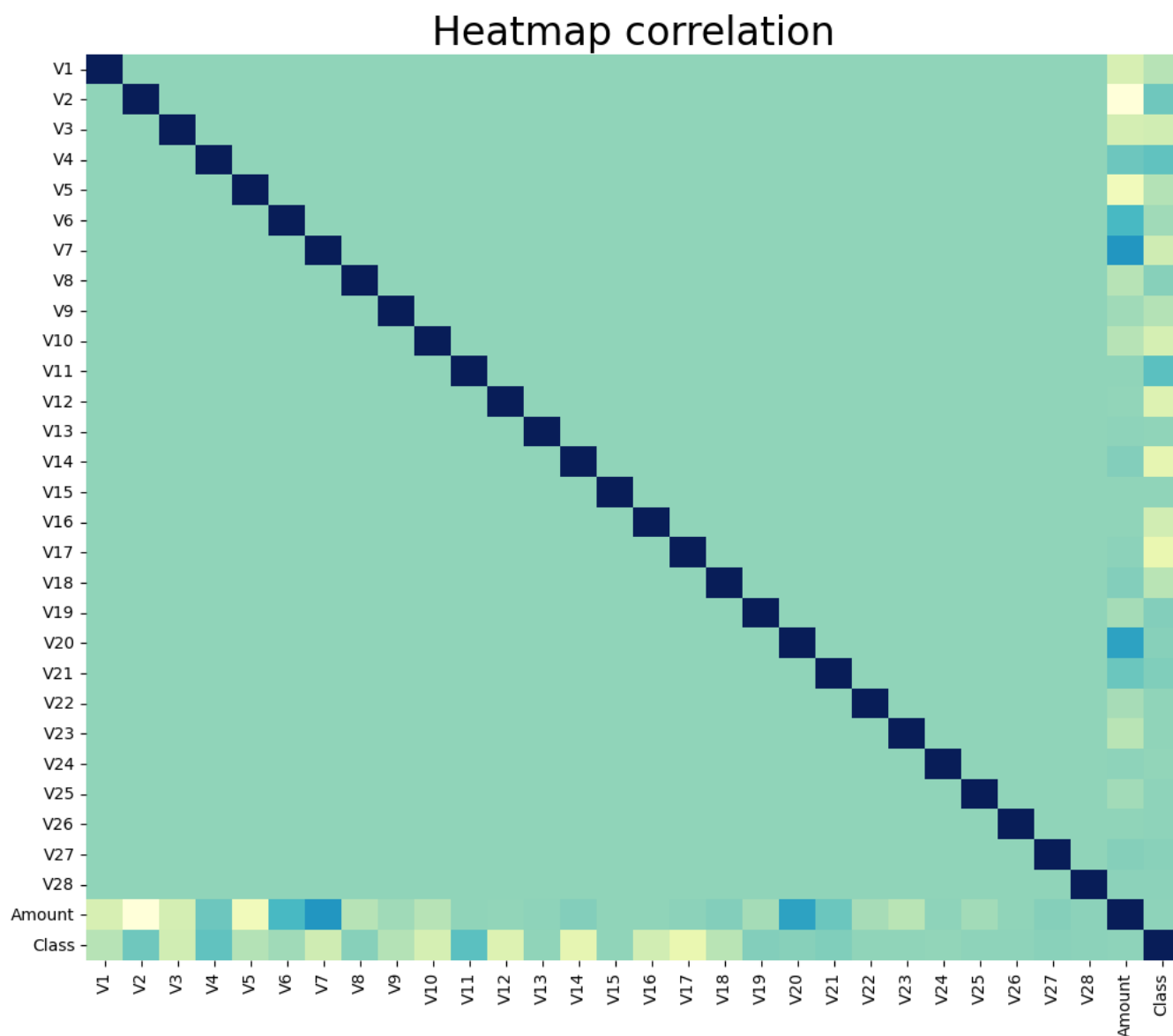
	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	...	V21	V22	V23
0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	0.090794	...	-0.018307	0.277838	-0.110474
1	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	-0.166974	...	-0.225775	-0.638672	0.101288
2	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	0.207643	...	0.247998	0.771679	0.909412
3	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	-0.054952	...	-0.108300	0.005274	-0.190321
4	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	0.753074	...	-0.009431	0.798278	-0.137458

5 rows x 30 columns

✓ Checking the Distribution of various features of our dataset

```
df_corr = df.corr() # Calculation of the correlation coefficients in pairs,
plt.figure(figsize=(15,10))
sns.heatmap(df_corr, cmap="YlGnBu") # Displaying the Heatmap
sns.set(font_scale=2,style='white')

plt.title('Heatmap correlation')
plt.show()
```

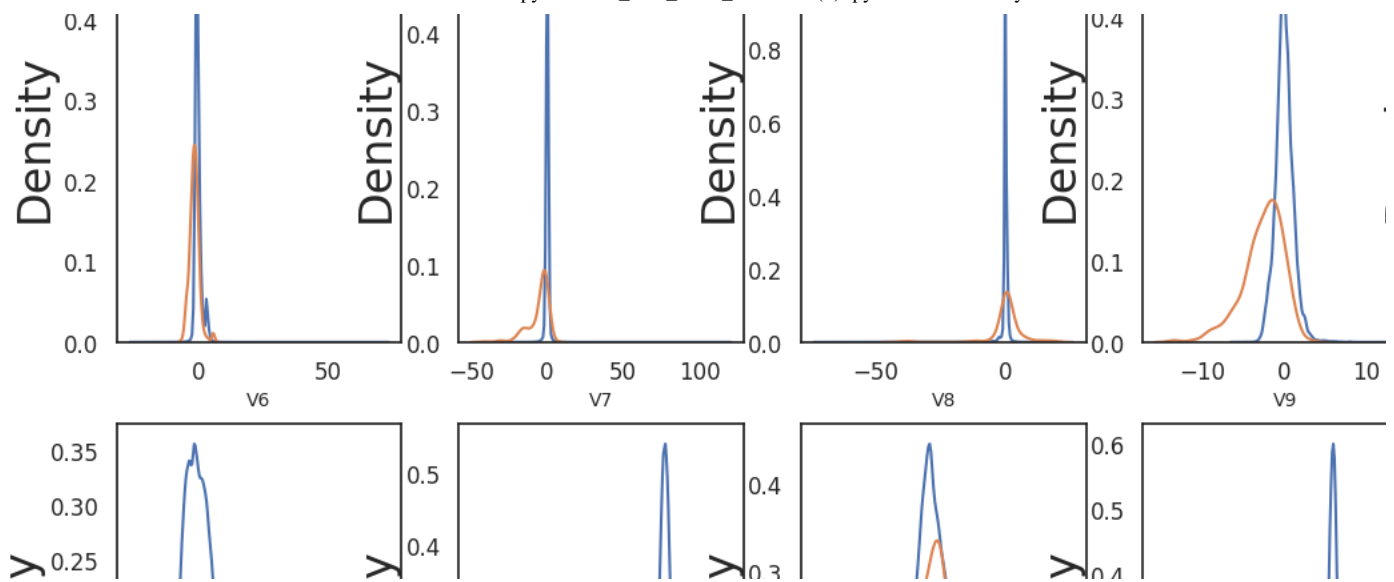


```
columns = list(df.columns.values)
columns.remove("Class")
n = 1
t0 = df.loc[df['Class'] == 0]
t1 = df.loc[df['Class'] == 1]

plt.figure()
fig, ax = plt.subplots(12,7,figsize=(16,28))

for i in columns:
    plt.subplot(6,5,n)
    sns.kdeplot(t0[i],label="0")
    sns.kdeplot(t1[i],label="1")
    plt.xlabel(i, fontsize=10)
    locs, labels = plt.xticks()
    plt.tick_params(axis='both', which='major', labelsize=12)
```

```
n = n + 1  
plt.show();
```

✓ Preparing the dataset for training

```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

✓ Splitting the dataset into training and validation sets

```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=7, test_size=0.4)
len(X_train)
```

170884

✓ Creating synthetic data using SMOTE (Since the dataset is imbalanced)

```
smote = SMOTE()
X_train_smote, y_train_smote = smote.fit_resample(X_train.astype('float'), y_train)
print("Before performing smote : ", Counter(y_train))
print("After performing smote : ", Counter(y_train_smote))
```

Before performing smote : Counter({0: 170580, 1: 304})
After performing smote : Counter({0: 170580, 1: 170580})

```
from sklearn.preprocessing import StandardScaler
# Create a StandardScaler object
scaler = StandardScaler() #check if it already save the mean, and std
```

```
# Fit and transform the scaler on the training data
X_train_smote = scaler.fit_transform(X_train_smote)
```

```
# Use the same mean and std to transform the testing data
X_test = scaler.transform(X_test)
```

```
print("X_train - ",X_train.shape)
print("y_train - ",y_train.shape)
print("X_train_smote - ",X_train_smote.shape)
print("y_train_smote - ",y_train_smote.shape)
print("X_test - ",X_test.shape)
print("y_test - ",y_test.shape)
```

```
X_train - (170884, 29)
y_train - (170884,)
X_train_smote - (341160, 29)
y_train_smote - (341160,)
X_test - (113923, 29)
y_test - (113923,)
```


✓ Testing various models on the dataset

✓ 1.1. Logistic Regression without synthetic data

```
model_ws_1 = LogisticRegression(solver='lbfgs', max_iter=1000)
model_ws_1.fit(X_train, y_train)
y_pred_ws_1 = model_ws_1.predict(X_test)
acc_ws_1 = accuracy_score(y_test, y_pred_ws_1)
acc_ws_1
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but LogisticR
warnings.warn(
0.9983936518525671
```

Logistic Regression CV without synthetic data

```
from sklearn.linear_model import LogisticRegressionCV
from sklearn.metrics import classification_report, mean_squared_error
from sklearn.model_selection import train_test_split, KFold
model_ws_1b = LogisticRegressionCV(Cs=30, cv=10, penalty="l1", n_jobs=8, max_iter=1000, solver="liblinear")
fit = model_ws_1b.fit(X_train, y_train)
```

```
y_pred_ws_1b = model_ws_1b.predict(X_test)
acc_ws_1b = accuracy_score(y_test, y_pred_ws_1b)
acc_ws_1b
```

```
/usr/local/lib/python3.10/dist-packages/joblib/externals/loky/process_executor.py:752: UserWarning: A worker stopped while s
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but LogisticR
warnings.warn(
0.9983936518525671
```

✓ Accuracy, f1Score, precision and recall of the model

```
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
# Prepare data (X, Y), build a model, and predict into Yh
res11 = accuracy_score(y_test, y_pred_ws_1b)
```

```
print("\n", "Accuracy: ".format(format(res11, '.3f')))
print("\n", "CFM: \n", confusion_matrix(y_test, y_pred_ws_1b))
print("\n", "Classification report: \n", classification_report(y_test, y_pred_ws_1b))
```

Accuracy:

```
CFM:
[[113731    4]
 [   180    8]]
```

Classification report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	113735
1	0.67	0.04	0.08	188
accuracy			1.00	113923
macro avg	0.83	0.52	0.54	113923
weighted avg	1.00	1.00	1.00	113923

✓ 1.2 Logistic Regression with synthetic data

```
model_s_1 = LogisticRegression(solver='lbfgs', max_iter=1000)
model_s_1.fit(X_train_smote, y_train_smote)
y_pred_s_1 = model_s_1.predict(X_test)
acc_s_1 = accuracy_score(y_test, y_pred_s_1)
acc_s_1
```

```
0.9725955250476199
```

✓ Accuracy, f1Score, precision and recall of the model

```
res12 = accuracy_score(y_test, y_pred_s_1)

print("\n", "Accuracy: ".format(format(res12, '.3f')))
print("\n", "CFM: \n", confusion_matrix(y_test, y_pred_s_1))
print("\n", "Classification report: \n", classification_report(y_test, y_pred_s_1))
```

Accuracy:

CFM:

```
[[110631  3104]
 [    18   170]]
```

Classification report:

	precision	recall	f1-score	support
0	1.00	0.97	0.99	113735
1	0.05	0.90	0.10	188
accuracy			0.97	113923
macro avg	0.53	0.94	0.54	113923
weighted avg	1.00	0.97	0.98	113923

✓ 2.1. Decision Tree Classifier without synthetic data

```
model_ws_2 = DecisionTreeClassifier(criterion='entropy', max_depth=5)
model_ws_2.fit(X_train, y_train)
y_pred_ws_2 = model_ws_2.predict(X_test)
acc_ws_2 = accuracy_score(y_test, y_pred_ws_2)
acc_ws_2
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but DecisionT
warnings.warn(
0.9983936518525671
```

✓ Accuracy, f1Score, precision and recall of the model

Confusion Matrix,

```
res21 = accuracy_score(y_test, y_pred_ws_2)

print("\n", "Accuracy: ".format(format(res21, '.3f')))
print("\n", "CFM: \n", confusion_matrix(y_test, y_pred_ws_2))
print("\n", "Classification report: \n", classification_report(y_test, y_pred_ws_2))
```

Accuracy:

CFM:

```
[[113735    0]
 [   183    5]]
```

Classification report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	113735
1	1.00	0.03	0.05	188
accuracy			1.00	113923
macro avg	1.00	0.51	0.53	113923
weighted avg	1.00	1.00	1.00	113923

✓ 2.2. Decision Tree Classifier with synthetic data

```
model_s_2 = DecisionTreeClassifier(criterion='entropy', max_depth=5)
model_s_2.fit(X_train_smote, y_train_smote)
y_pred_s_2 = model_s_2.predict(X_test)
```

```
acc_s_2 = accuracy_score(y_test, y_pred_s_2)
acc_s_2
```

```
0.9429439182605795
```

✓ Accuracy, f1Score, precision and recall of the model

```
res22 = accuracy_score(y_test, y_pred_s_2)
```

```
print("\n", "Accuracy: ".format(format(res22, '.3f')))
print("\n", "CFM: \n", confusion_matrix(y_test, y_pred_s_2))
print("\n", "Classification report: \n", classification_report(y_test, y_pred_s_2))
```

Accuracy:

CFM:

```
[[107248  6487]
 [   13   175]]
```

Classification report:

	precision	recall	f1-score	support
0	1.00	0.94	0.97	113735
1	0.03	0.93	0.05	188
accuracy			0.94	113923
macro avg	0.51	0.94	0.51	113923
weighted avg	1.00	0.94	0.97	113923

✓ 3.1. K Nearest Neighbors Classifier without synthetic data

```
model_ws_3 = KNeighborsClassifier(n_neighbors=3)
model_ws_3.fit(X_train, y_train)
y_pred_ws_3 = model_ws_3.predict(X_test)
acc_ws_3 = accuracy_score(y_test, y_pred_ws_3)
acc_ws_3
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but KNeighbor
warnings.warn(
0.9984902082985876
```

✓ Accuracy, f1Score, precision and recall of the model

```
res31 = accuracy_score(y_test, y_pred_ws_3)
```

```
print("\n", "Accuracy: ".format(format(res31, '.3f')))
print("\n", "CFM: \n", confusion_matrix(y_test, y_pred_ws_3))
print("\n", "Classification report: \n", classification_report(y_test, y_pred_ws_3))
```

Accuracy:

CFM:

```
[[113735    0]
 [   172   16]]
```

Classification report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	113735
1	1.00	0.09	0.16	188
accuracy			1.00	113923
macro avg	1.00	0.54	0.58	113923
weighted avg	1.00	1.00	1.00	113923

✓ 3.2. K Nearest Neighbors Classifier with synthetic data

```

model_s_3 = KNeighborsClassifier(n_neighbors=3)
model_s_3.fit(X_train_smote, y_train_smote)
y_pred_s_3 = model_s_3.predict(X_test)
acc_s_3 = accuracy_score(y_test, y_pred_s_3)
acc_s_3

```

0.9974105316749032

✓ Accuracy, f1Score, precision and recall of the model

```

res32 = accuracy_score(y_test, y_pred_s_3)

print("\n", "Accuracy: ".format(format(res32, '.3f')))
print("\n", "CFM: \n", confusion_matrix(y_test, y_pred_s_3))
print("\n", "Classification report: \n", classification_report(y_test, y_pred_s_3))

```

Accuracy:

CFM:
[[113470 265]
[30 158]]

Classification report:


	precision	recall	f1-score	support
0	1.00	1.00	1.00	113735
1	0.37	0.84	0.52	188
accuracy			1.00	113923
macro avg	0.69	0.92	0.76	113923
weighted avg	1.00	1.00	1.00	113923

✓ 4.1. Random Forest Classifier without synthetic data

```

model_ws_5 = RandomForestClassifier(max_depth=5, criterion='entropy')
model_ws_5.fit(X_train, y_train)
y_pred_ws_5 = model_ws_5.predict(X_test)
acc_ws_5 = accuracy_score(y_test, y_pred_ws_5)
acc_ws_5

```

 /usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
0.9983497625589214

✓ Accuracy, f1Score, precision and recall of the model

```

res41 = accuracy_score(y_test, y_pred_ws_5)

print("\n", "Accuracy: ".format(format(res41, '.3f')))
print("\n", "CFM: \n", confusion_matrix(y_test, y_pred_ws_5))
print("\n", "Classification report: \n", classification_report(y_test, y_pred_ws_5))

```

Accuracy:

CFM:
[[113735 0]
[188 0]]

Classification report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	113735
1	0.00	0.00	0.00	188
accuracy			1.00	113923
macro avg	0.50	0.50	0.50	113923
weighted avg	1.00	1.00	1.00	113923

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score

```
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score
_warn_prf(average, modifier, msg_start, len(result))
```

4.2. Random Forest Classifier with synthetic data

```
model_s_5 = RandomForestClassifier(max_depth=5, criterion='entropy')
model_s_5.fit(X_train_smote, y_train_smote)
y_pred_s_5 = model_s_5.predict(X_test)
acc_s_5 = accuracy_score(y_test, y_pred_s_5)
acc_s_5
```

```
0.993618496703914
```

Accuracy, f1Score, precision and recall of the model

```
res42 = accuracy_score(y_test, y_pred_s_5)

print("\n", "Accuracy: ".format(format(res42, '.3f')))
print("\n", "CFM: \n", confusion_matrix(y_test, y_pred_s_5))
print("\n", "Classification report: \n", classification_report(y_test, y_pred_s_5))
```

Accuracy:

```
CFM:
[[113028   707]
 [    20   168]]
```

Classification report:

	precision	recall	f1-score	support
0	1.00	0.99	1.00	113735
1	0.19	0.89	0.32	188
accuracy			0.99	113923
macro avg	0.60	0.94	0.66	113923
weighted avg	1.00	0.99	1.00	113923

5.1. Support Vector Classifier without synthetic data

```
model_ws_6 = SVC()
model_ws_6.fit(X_train, y_train)
y_pred_ws_6 = model_ws_6.predict(X_test)
acc_ws_6 = accuracy_score(y_test, y_pred_ws_6)
acc_ws_6
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but SVC was f
warnings.warn(
0.9983673182763797
```

Accuracy, f1Score, precision and recall of the model

```
res51 = accuracy_score(y_test, y_pred_ws_6)

print("\n", "Accuracy: ".format(format(res51, '.3f')))
print("\n", "CFM: \n", confusion_matrix(y_test, y_pred_ws_6))
print("\n", "Classification report: \n", classification_report(y_test, y_pred_ws_6))
```

Accuracy:

```
CFM:
[[113735    0]
 [   186    2]]
```

Classification report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	113735
1	1.00	0.01	0.02	188

accuracy			1.00	113923
macro avg	1.00	0.51	0.51	113923
weighted avg	1.00	1.00	1.00	113923

5.2. Support Vector Classifier with synthetic data

```
model_s_6 = SVC()
model_s_6.fit(X_train_smote, y_train_smote)
y_pred_s_6 = model_s_6.predict(X_test)
acc_s_6 = accuracy_score(y_test, y_pred_s_6)
acc_s_6
```

0.9921701500136056

Confusion Matrix

Accuracy, f1Score, precision and recall of the model

```
res52 = accuracy_score(y_test, y_pred_ws_6)

print("\n", "Accuracy: ".format(format(res52, '.3f')))
print("\n", "CFM: \n", confusion_matrix(y_test, y_pred_ws_6))
print("\n", "Classification report: \n", classification_report(y_test, y_pred_ws_6))
```

Accuracy:

CFM:
[[113735 0]
[186 2]]

Classification report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	113735
1	1.00	0.01	0.02	188

accuracy			1.00	113923
macro avg	1.00	0.51	0.51	113923
weighted avg	1.00	1.00	1.00	113923

Comparing precision, accuracy f1 score and recall of all the models

```
dp = pd.DataFrame([res11, res12, res21, res22, res31, res32, res41, res42, res51, res52], index=['1.1', '1.2', '2.1', '2.2', '3.1', '3.2', '4.1', '4.2', '5.1', '5.2'])
```

dp

	0
1.1	0.998385
1.2	0.972596
2.1	0.998394
2.2	0.942944
3.1	0.998490
3.2	0.997411
4.1	0.998350
4.2	0.993618
5.1	0.998367
5.2	0.998367