

rd-fraud-detection-codsoft-task-3

October 30, 2023

Credit Card Fraud Detection - Giriraju B

Importing libraries

```
[150]: 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.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
```

```
[151]: df=pd.read_csv('/content/creditcard.csv')
df.head()
```

```
[151]:
```

	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]

```
[152]: df.tail()
```

```
[152]:
```

	Time	V1	V2	V3	V4	V5	\
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	

	V6	V7	V8	V9	...	V21	V22	\
284802	-2.606837	-4.918215	7.305334	1.914428	...	0.213454	0.111864	
284803	1.058415	0.024330	0.294869	0.584800	...	0.214205	0.924384	
284804	3.031260	-0.296827	0.708417	0.432454	...	0.232045	0.578229	
284805	0.623708	-0.686180	0.679145	0.392087	...	0.265245	0.800049	
284806	-0.649617	1.577006	-0.414650	0.486180	...	0.261057	0.643078	

	V23	V24	V25	V26	V27	V28	Amount	\
284802	1.014480	-0.509348	1.436807	0.250034	0.943651	0.823731	0.77	
284803	0.012463	-1.016226	-0.606624	-0.395255	0.068472	-0.053527	24.79	
284804	-0.037501	0.640134	0.265745	-0.087371	0.004455	-0.026561	67.88	
284805	-0.163298	0.123205	-0.569159	0.546668	0.108821	0.104533	10.00	
284806	0.376777	0.008797	-0.473649	-0.818267	-0.002415	0.013649	217.00	

	Class
284802	0
284803	0
284804	0
284805	0
284806	0

[5 rows x 31 columns]

```
[153]: 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

```
[154]: df.isnull().sum()
```

```
[154]: 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
```

```
[155]: df['Class'].value_counts()
```

```
[155]: 0    284315
      1      492
      Name: Class, dtype: int64
```

```
[156]: labels = 'Not Fraud', 'Fraud'
      sizes = [df.Class[df['Class'] == 0].count(), df.Class[df['Class'] == 1].count()]
      fig1, ax1 = plt.subplots(figsize=(10, 6))
      ax1.pie(sizes, labels=labels, autopct='%1.2f%%', shadow=False, startangle=120)
      ax1.axis('equal')
      title = "Percentage of Fraud and Non-Fraud Transactions"
      plt.title(title, size=16, pad=20)
      plt.show()
```

Percentage of Fraud and Non-Fraud Transactions



```
[157]: sns.set(style="whitegrid")
ax = sns.countplot(x='Class', data=df, order=[0, 1], label='Count',
                  palette='pastel')
counts = df['Class'].value_counts()
for i, count in enumerate(counts):
    ax.text(i, count, str(count), ha='center', va='bottom', fontsize=12)
title = "Amount of Fraud and Non-Fraud Transactions"
ax.set_title(title, size=16)
plt.title(title, size=16, pad=20)
plt.show()
```

Amount of Fraud and Non-Fraud Transactions



This is highly unbalanced. 0 is Normal transaction and 1 is Fraudulent Transaction

```
[158]: Legit=df[df.Class==0]
      Fraud=df[df.Class==1]
```

```
[159]: print(Legit.shape)
      print(Fraud.shape)
```

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

```
[184]: sns.distplot(df['Time'])
      plt.show()
```

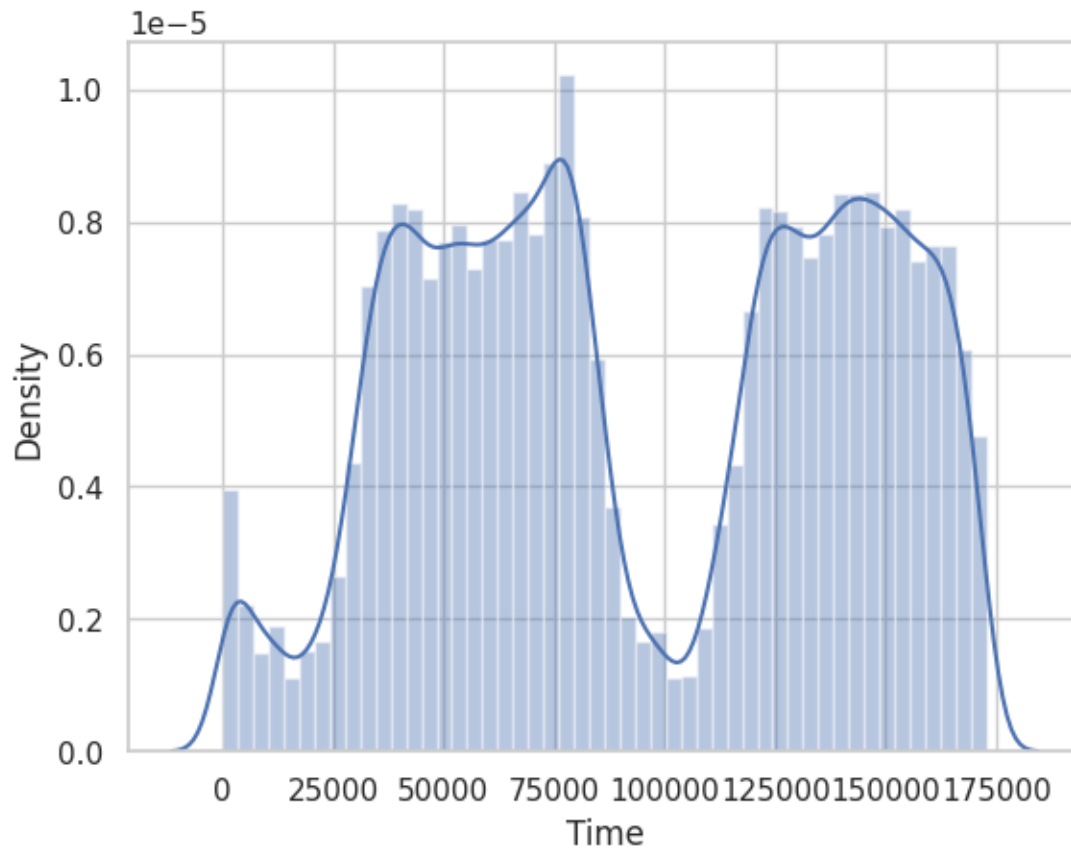
<ipython-input-184-8730e128497f>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

```
sns.distplot(df['Time'])
```



```
[160]: Legit.Amount.describe()
```

```
[160]: 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
```

```
[161]: Fraud.Amount.describe()
```

```
[161]: 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
```

```
[162]: df.groupby('Class').mean()
```

```
[162]:
```

	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	

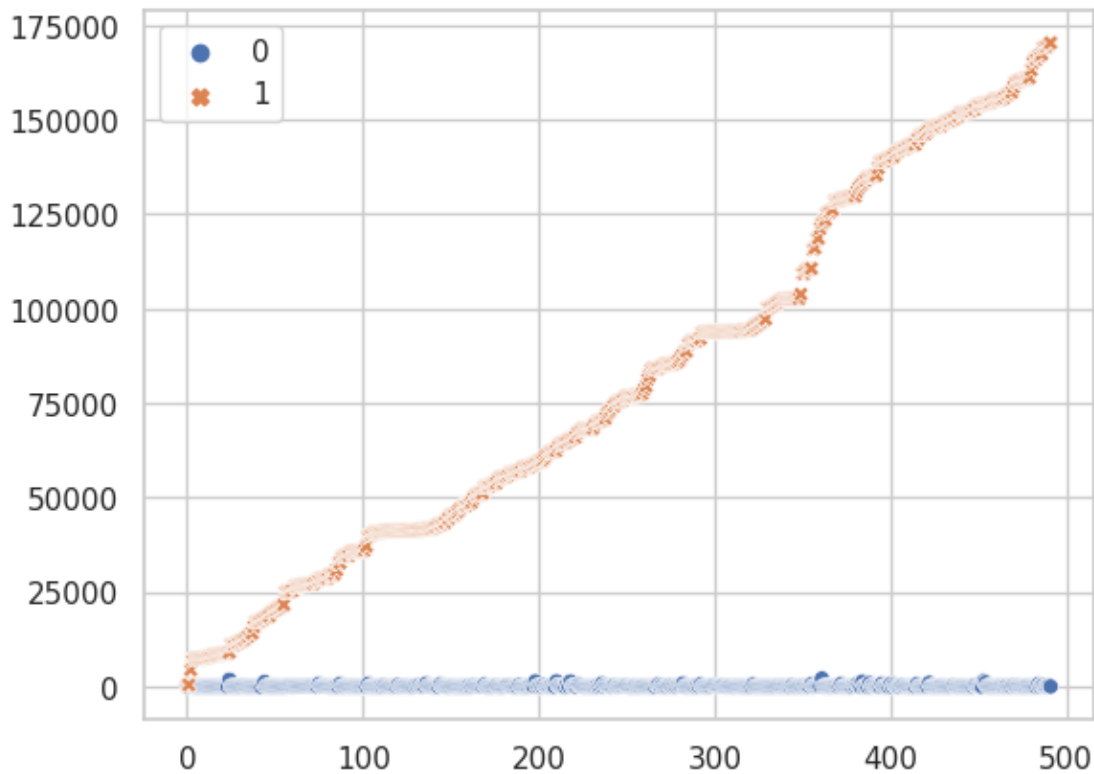
	V6	V7	V8	V9	...	V20	V21	\
Class					...			
0	0.002419	0.009637	-0.000987	0.004467	...	-0.000644	-0.001235	
1	-1.397737	-5.568731	0.570636	-2.581123	...	0.372319	0.713588	

	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]
```

```
[183]: sns.scatterplot(df[df['Class']==1][['Amount', 'Time']].values)
      plt.show()
```

Equaling the Fraud & Legit numbers

```
[163]: Legit_sample=Legit.sample(n=492)
```

Contatenating Two Dataframes

```
[164]: df.new=pd.concat([Legit_sample,Fraud],axis=0)
```

<ipython-input-164-31066150e47b>:1: UserWarning: Pandas doesn't allow columns to be created via a new attribute name - see <https://pandas.pydata.org/pandas-docs/stable/indexing.html#attribute-access>

```
df.new=pd.concat([Legit_sample,Fraud],axis=0)
```

Normal Transaction

```
[165]: df.new.head()
```

```
[165]:
```

	Time	V1	V2	V3	V4	V5	V6	\
25542	33659.0	0.768339	-1.528915	0.671929	-0.784746	-1.751015	-0.488586	
158281	111113.0	2.105250	0.185232	-1.394275	0.307472	0.541140	-0.681034	
162569	115219.0	2.110837	-1.115878	0.380569	-0.775945	-1.647459	-0.257212	
252408	155793.0	2.067731	0.177746	-1.684627	0.423875	0.430133	-0.890014	
278725	168388.0	1.991229	-0.032907	-2.047936	0.153355	0.634608	-0.323808	

	V7	V8	V9	...	V21	V22	V23	\
25542	-0.500464	0.014844	2.531866	...	0.133782	0.291348	-0.359974	
158281	0.166989	-0.441286	1.831992	...	0.112498	0.793382	-0.027106	
162569	-1.577400	0.026295	0.441391	...	0.442233	1.457486	0.177474	
252408	0.215259	-0.260619	0.434835	...	-0.356530	-0.909479	0.336941	
278725	0.058439	-0.083924	0.762592	...	-0.243854	-0.494031	0.023766	

	V24	V25	V26	V27	V28	Amount	Class
25542	0.489697	0.526475	0.147203	0.007573	0.059866	249.00	0
158281	0.476600	0.416848	-0.480340	-0.013822	-0.052981	1.00	0
162569	-0.011693	-0.380001	-0.088345	0.068258	-0.029552	9.99	0
252408	0.578458	-0.250807	0.168091	-0.060726	-0.028844	4.49	0
278725	-1.211285	0.033012	-0.043332	-0.008892	-0.033804	35.38	0

[5 rows x 31 columns]

Fraudulent Transaction

```
[166]: df.new.tail()
```

```
[166]:
```

	Time	V1	V2	V3	V4	V5	V6	\
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	...	V21	V22	V23	\
279863	-0.882850	0.697211	-2.064945	...	0.778584	-0.319189	0.639419	
280143	-1.413170	0.248525	-1.127396	...	0.370612	0.028234	-0.145640	
280149	-2.234739	1.210158	-0.652250	...	0.751826	0.834108	0.190944	
281144	-2.208002	1.058733	-1.632333	...	0.583276	-0.269209	-0.456108	
281674	0.223050	-0.068384	0.577829	...	-0.164350	-0.295135	-0.072173	

	V24	V25	V26	V27	V28	Amount	Class
279863	-0.294885	0.537503	0.788395	0.292680	0.147968	390.00	1
280143	-0.081049	0.521875	0.739467	0.389152	0.186637	0.76	1
280149	0.032070	-0.739695	0.471111	0.385107	0.194361	77.89	1
281144	-0.183659	-0.328168	0.606116	0.884876	-0.253700	245.00	1
281674	-0.450261	0.313267	-0.289617	0.002988	-0.015309	42.53	1

[5 rows x 31 columns]

```
[167]: df.new["Class"].value_counts()
```

```
[167]: 0    492
        1    492
        Name: Class, dtype: int64
```

```
[168]: df.new.groupby('Class').mean()
```

```
[168]:
```

	Time	V1	V2	V3	V4	V5	\
Class							
0	92404.668699	-0.097676	-0.017284	-0.021619	0.003334	-0.023866	
1	80746.806911	-4.771948	3.623778	-7.033281	4.542029	-3.151225	

	V6	V7	V8	V9	...	V20	V21	\
Class					...			
0	-0.085432	0.005330	-0.064021	-0.011526	...	-0.021644	-0.079637	
1	-1.397737	-5.568731	0.570636	-2.581123	...	0.372319	0.713588	

	V22	V23	V24	V25	V26	V27	V28	\
Class								
0	0.045524	-0.053218	0.029643	0.000817	0.003066	0.023885	0.017528	
1	0.014049	-0.040308	-0.105130	0.041449	0.051648	0.170575	0.075667	

	Amount
Class	
0	95.477276
1	122.211321

[2 rows x 30 columns]

Splitting the datas into Features and Targets

```
[169]: X= df.new.drop(columns='Class',axis=1)
        Y= df.new['Class']
```

```
[170]: print(X)
```

	Time	V1	V2	V3	V4	V5	V6	\
25542	33659.0	0.768339	-1.528915	0.671929	-0.784746	-1.751015	-0.488586	
158281	111113.0	2.105250	0.185232	-1.394275	0.307472	0.541140	-0.681034	
162569	115219.0	2.110837	-1.115878	0.380569	-0.775945	-1.647459	-0.257212	
252408	155793.0	2.067731	0.177746	-1.684627	0.423875	0.430133	-0.890014	
278725	168388.0	1.991229	-0.032907	-2.047936	0.153355	0.634608	-0.323808	
...	
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	\
25542	-0.500464	0.014844	2.531866	...	0.334264	0.133782	0.291348	
158281	0.166989	-0.441286	1.831992	...	-0.166055	0.112498	0.793382	
162569	-1.577400	0.026295	0.441391	...	0.066605	0.442233	1.457486	
252408	0.215259	-0.260619	0.434835	...	-0.127504	-0.356530	-0.909479	
278725	0.058439	-0.083924	0.762592	...	-0.064723	-0.243854	-0.494031	
...	
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
25542	-0.359974	0.489697	0.526475	0.147203	0.007573	0.059866	249.00
158281	-0.027106	0.476600	0.416848	-0.480340	-0.013822	-0.052981	1.00
162569	0.177474	-0.011693	-0.380001	-0.088345	0.068258	-0.029552	9.99
252408	0.336941	0.578458	-0.250807	0.168091	-0.060726	-0.028844	4.49
278725	0.023766	-1.211285	0.033012	-0.043332	-0.008892	-0.033804	35.38
...
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]

```
[171]: print(Y)
```

```
25542      0
158281      0
162569      0
252408      0
278725      0
...
279863      1
280143      1
280149      1
281144      1
281674      1
```

Name: Class, Length: 984, dtype: int64

Training & Testing Data

```
[172]: X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.
↳2,stratify=Y,random_state=2)
```

```
[173]: print(X.shape,X_train.shape, X_test.shape)
```

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

Model Training

Logistic Regression

```
[174]: model=LogisticRegression()
```

```
[175]: model.fit(X_train,Y_train)
```

```
[175]: LogisticRegression()
```

Model Evaluation

Accuracy Score

```
[176]: X_train_prediction=model.predict(X_train)
training_data_accuracy=accuracy_score(X_train_prediction, Y_train)
```

```
[177]: print("Accuracy Score is : ",training_data_accuracy)
```

```
Accuracy Score is :  0.9212198221092758
```

```
[178]: X_test_prediction = model.predict(X_test)
test_data_accuracy = accuracy_score(X_test_prediction, Y_test)
```

```
[179]: print("Accuracy Score is : ",test_data_accuracy)
```

```
Accuracy Score is :  0.8883248730964467
```

****Thank You !!****