

credit-card-fraud-detection

July 19, 2024

```
[1]: # Import Library's.  
import pandas as pd  
import numpy as np  
import matplotlib.pyplot as plt
```

```
[4]: # Import Data Set.  
credit_card_data = pd.read_csv("C:\\Users\\Shreyas\\OneDrive\\Desktop\\Machine_\\  
Learning Project\\creditcard.csv")  
credit_card_data
```

```
[4]:
```

	Time	V1	V2	V3	V4	V5	\		
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321			
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018			
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198			
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309			
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193			
...			
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	\
0	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838		
1	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672		
2	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679		
3	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274		
4	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278		
...		
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	\

0	-0.110474	0.066928	0.128539	-0.189115	0.133558	-0.021053	149.62
1	0.101288	-0.339846	0.167170	0.125895	-0.008983	0.014724	2.69
2	0.909412	-0.689281	-0.327642	-0.139097	-0.055353	-0.059752	378.66
3	-0.190321	-1.175575	0.647376	-0.221929	0.062723	0.061458	123.50
4	-0.137458	0.141267	-0.206010	0.502292	0.219422	0.215153	69.99
...
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

0	0
1	0
2	0
3	0
4	0
...	...
284802	0
284803	0
284804	0
284805	0
284806	0

[284807 rows x 31 columns]

```
[5]: # First and last 5 rows of dataset
credit_card_data.head()
```

[5]:	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]

```
[6]: credit_card_data.tail()
```

```

[6]:      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]

```

[7]: # Data set Information.
      credit_card_data.isnull().sum()

```

```

[7]: 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

```

```
[8]: credit_card_data.describe()
```

```

[8]:
      count      Time      V1      V2      V3      V4  \
count  284807.000000  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean    94813.859575  1.168375e-15  3.416908e-16 -1.379537e-15  2.074095e-15
std     47488.145955  1.958696e+00  1.651309e+00  1.516255e+00  1.415869e+00
min         0.000000 -5.640751e+01 -7.271573e+01 -4.832559e+01 -5.683171e+00
25%     54201.500000 -9.203734e-01 -5.985499e-01 -8.903648e-01 -8.486401e-01
50%     84692.000000  1.810880e-02  6.548556e-02  1.798463e-01 -1.984653e-02
75%    139320.500000  1.315642e+00  8.037239e-01  1.027196e+00  7.433413e-01
max    172792.000000  2.454930e+00  2.205773e+01  9.382558e+00  1.687534e+01

      V5      V6      V7      V8      V9  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean    9.604066e-16  1.487313e-15 -5.556467e-16  1.213481e-16 -2.406331e-15
std     1.380247e+00  1.332271e+00  1.237094e+00  1.194353e+00  1.098632e+00
min    -1.137433e+02 -2.616051e+01 -4.355724e+01 -7.321672e+01 -1.343407e+01
25%    -6.915971e-01 -7.682956e-01 -5.540759e-01 -2.086297e-01 -6.430976e-01
50%    -5.433583e-02 -2.741871e-01  4.010308e-02  2.235804e-02 -5.142873e-02
75%     6.119264e-01  3.985649e-01  5.704361e-01  3.273459e-01  5.971390e-01

```

```
max      3.480167e+01  7.330163e+01  1.205895e+02  2.000721e+01  1.559499e+01
```

```

...      V21      V22      V23      V24  \
count    ...  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean      ...  1.654067e-16 -3.568593e-16  2.578648e-16  4.473266e-15
std        ...  7.345240e-01  7.257016e-01  6.244603e-01  6.056471e-01
min        ... -3.483038e+01 -1.093314e+01 -4.480774e+01 -2.836627e+00
25%        ... -2.283949e-01 -5.423504e-01 -1.618463e-01 -3.545861e-01
50%        ... -2.945017e-02  6.781943e-03 -1.119293e-02  4.097606e-02
75%        ...  1.863772e-01  5.285536e-01  1.476421e-01  4.395266e-01
max        ...  2.720284e+01  1.050309e+01  2.252841e+01  4.584549e+00
```

```

...      V25      V26      V27      V28      Amount  \
count    2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  284807.000000
mean      5.340915e-16  1.683437e-15 -3.660091e-16 -1.227390e-16      88.349619
std        5.212781e-01  4.822270e-01  4.036325e-01  3.300833e-01     250.120109
min       -1.029540e+01 -2.604551e+00 -2.256568e+01 -1.543008e+01      0.000000
25%       -3.171451e-01 -3.269839e-01 -7.083953e-02 -5.295979e-02      5.600000
50%        1.659350e-02 -5.213911e-02  1.342146e-03  1.124383e-02     22.000000
75%        3.507156e-01  2.409522e-01  9.104512e-02  7.827995e-02     77.165000
max        7.519589e+00  3.517346e+00  3.161220e+01  3.384781e+01    25691.160000
```

```

...      Class
count    284807.000000
mean      0.001727
std       0.041527
min       0.000000
25%       0.000000
50%       0.000000
75%       0.000000
max       1.000000
```

```
[8 rows x 31 columns]
```

```
[9]: 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

```

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

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

```
[11]: # sepration dataset for analysis.
legit = credit_card_data[credit_card_data.Class ==0]
fraud = credit_card_data[credit_card_data.Class ==1]
```

```
[12]: print(legit.shape)
print(fraud.shape)
```

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

```
[13]: # StASTICAL MEASUREMENT OF DATA SET
legit.Amount.describe()
```

```
[13]: 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
```

```
[14]: fraud.Amount.describe()
```

```
[14]: 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
```

```
[15]: # COMPARE THE VALUE FOR BOTH TRANSATION.
credit_card_data.groupby('Class').mean()
```

```
[15]:
```

	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]

```
[16]: legit_sample = legit.sample(n=492)
```

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

```
[18]: new_dataset.head()
```

```
[18]:
```

	Time	V1	V2	V3	V4	V5	V6	\
37629	39043.0	1.066100	-0.161069	1.118310	0.620694	-0.931990	-0.346915	
43389	41489.0	0.698122	-1.094558	0.412464	0.482848	-1.237461	-0.669810	
13580	24078.0	1.250127	0.060157	-0.752441	0.285687	2.030749	3.609633	
265846	162070.0	-0.486404	-0.138413	2.306777	-2.515815	-0.282440	0.231716	
281721	170378.0	-0.126513	1.176895	-0.326781	-0.492242	0.659229	-1.047616	

	V7	V8	V9	...	V21	V22	V23	\
37629	-0.450947	0.044601	0.381159	...	0.079557	0.203153	0.084861	
43389	-0.006946	-0.126056	0.721621	...	0.093262	-0.279385	-0.238308	
13580	-0.788806	0.801707	1.332631	...	-0.027853	0.052992	-0.159477	
265846	-0.007968	-0.438984	0.440198	...	0.278358	1.510426	-0.267723	
281721	0.922631	-0.082445	0.167155	...	-0.341945	-0.780615	0.167378	

	V24	V25	V26	V27	V28	Amount	Class
37629	0.454484	0.037353	0.394027	0.005238	0.035698	52.15	0
43389	0.457393	0.134987	0.986115	-0.116470	0.056533	292.00	0
13580	0.956027	0.753319	-0.246269	0.008765	0.016394	16.35	0
265846	0.715280	-0.358132	-0.324237	-0.080343	-0.364515	8.99	0
281721	0.970323	-0.458010	0.095416	0.332530	0.147018	2.69	0

[5 rows x 31 columns]

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

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

```
[21]: new_dataset.groupby('Class').mean()
```

```
[21]:
```

	Time	V1	V2	V3	V4	V5	\
Class							
0	97136.491870	-0.123785	0.130570	0.017336	-0.010601	-0.065660	
1	80746.806911	-4.771948	3.623778	-7.033281	4.542029	-3.151225	

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


```

Class
0      -0.030280  0.012729  0.015314  0.104237  ...  0.020087 -0.035464
1      -1.397737 -5.568731  0.570636 -2.581123  ...  0.372319  0.713588

      V22      V23      V24      V25      V26      V27      V28  \
Class
0      -0.000281  0.005424  0.015587  0.002499 -0.021452 -0.002072 -0.001191
1       0.014049 -0.040308 -0.105130  0.041449  0.051648  0.170575  0.075667

      Amount
Class
0       84.932297
1      122.211321

```

[2 rows x 30 columns]

```

[28]: # SEPRATING THE DATASET INTO FEATURES & TARGETS.
x = new_dataset.iloc[:
↪, [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29]]

```

```

[29]: x

```

```

[29]:
      Time      V1      V2      V3      V4      V5      V6  \
37629  39043.0  1.066100 -0.161069  1.118310  0.620694 -0.931990 -0.346915
43389  41489.0  0.698122 -1.094558  0.412464  0.482848 -1.237461 -0.669810
13580  24078.0  1.250127  0.060157 -0.752441  0.285687  2.030749  3.609633
265846 162070.0 -0.486404 -0.138413  2.306777 -2.515815 -0.282440  0.231716
281721 170378.0 -0.126513  1.176895 -0.326781 -0.492242  0.659229 -1.047616
...      ...      ...      ...      ...      ...      ...
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  \
37629 -0.450947  0.044601  0.381159  ...  0.009667  0.079557  0.203153
43389 -0.006946 -0.126056  0.721621  ...  0.459849  0.093262 -0.279385
13580 -0.788806  0.801707  1.332631  ... -0.026359 -0.027853  0.052992
265846 -0.007968 -0.438984  0.440198  ...  0.540062  0.278358  1.510426
281721  0.922631 -0.082445  0.167155  ...  0.097622 -0.341945 -0.780615
...      ...      ...      ...      ...      ...      ...
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
37629	0.084861	0.454484	0.037353	0.394027	0.005238	0.035698	52.15
43389	-0.238308	0.457393	0.134987	0.986115	-0.116470	0.056533	292.00
13580	-0.159477	0.956027	0.753319	-0.246269	0.008765	0.016394	16.35
265846	-0.267723	0.715280	-0.358132	-0.324237	-0.080343	-0.364515	8.99
281721	0.167378	0.970323	-0.458010	0.095416	0.332530	0.147018	2.69
...
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]

```
[30]: y = new_dataset.iloc[:,[30]]
```

```
[31]: y
```

```
[31]:      Class
37629      0
43389      0
13580      0
265846     0
281721     0
...
279863     1
280143     1
280149     1
281144     1
281674     1
```

[984 rows x 1 columns]

```
[32]: # TRAINING AND TESTING THE DATASET
from sklearn.model_selection import train_test_split
```

```
[34]: x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.
↪2,stratify=y,random_state=2)
```

```
[36]: print(x.shape,x_train.shape,x_test.shape)
```

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

```
[37]: # LOGISTIC REGRESSION ALGORITHM
from sklearn.linear_model import LogisticRegression
```

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

```
[41]: model.fit(x_train,y_train)
```

```
C:\Users\Shreyas\anaconda3\Lib\site-packages\sklearn\utils\validation.py:1143:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
    y = column_or_1d(y, warn=True)
```

```
[41]: LogisticRegression()
```

```
[45]: # REDICTITION
x_train_prediction = model.predict(x_train)
training_data_accuracy = accuracy_score(x_train_prediction, y_train)
```

```
[46]: print("Accuracy on training data : ", training_data_accuracy)
```

```
Accuracy on training data : 0.9453621346886912
```

```
[51]: # FIND THE ACCURACY
lr = LogisticRegression()
lr.fit(x_train,y_train)
lr.score(x_train,y_train)*100,lr.score(x_test,y_test)*100
```

```
C:\Users\Shreyas\anaconda3\Lib\site-packages\sklearn\utils\validation.py:1143:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
    y = column_or_1d(y, warn=True)
```

```
[51]: (94.53621346886912, 89.84771573604061)
```

```
[47]: x_test_prediction = model.predict(x_test)
test_data_accuracy = accuracy_score(x_test_prediction, y_test)
```

```
[48]: print("Accuracy on test data : ", test_data_accuracy)
```

```
Accuracy on test data : 0.8984771573604061
```

```
[49]: from sklearn.metrics import mean_absolute_error
```

```
[53]: lr.predict([[0, -1.359807134, -0.072781173, 2.536346738, 1.378155224, -0.
↪33832077, 0.462387778, 0.239598554, 0.098697901, 0.36378697, 0.090794172, -0.
↪551599533, -0.617800856, -0.991389847, -0.311169354, 1.468176972, -0.
↪470400525, 0.207971242, 0.02579058, 0.40399296, 0.251412098, -0.018306778, 0.
↪277837576, -0.11047391, 0.066928075, 0.128539358, -0.189114844, 0.133558377,
↪-0.021053053, 149.62]])
```

```
C:\Users\Shreyas\anaconda3\Lib\site-packages\sklearn\base.py:439: UserWarning: X
does not have valid feature names, but LogisticRegression was fitted with
feature names
  warnings.warn(
```

```
[53]: array([0], dtype=int64)
```

```
[ ]:
```