```
import numpy as np
import pandas as pd
import math
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
import seaborn as sns
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
import warnings
from sklearn import linear_model, preprocessing
from sklearn.metrics import mean_squared_error, classification_report, precision_recall_fscore_support
from collections import Counter
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import SMOTE
from sklearn.neural_network import MLPClassifier
import itertools
warnings.filterwarnings('ignore')
%matplotlib inline
df = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Datasets/creditcard.csv')
df.head(n=10)
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	• • •	V21	V22
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
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
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
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
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
5	2.0	-0.425966	0.960523	1.141109	-0.168252	0.420987	-0.029728	0.476201	0.260314	-0.568671		-0.208254	-0.559825
6	4.0	1.229658	0.141004	0.045371	1.202613	0.191881	0.272708	-0.005159	0.081213	0.464960		-0.167716	-0.270710
7	7.0	-0.644269	1.417964	1.074380	-0.492199	0.948934	0.428118	1.120631	-3.807864	0.615375		1.943465	-1.015455
8	7.0	-0.894286	0.286157	-0.113192	-0.271526	2.669599	3.721818	0.370145	0.851084	-0.392048		-0.073425	-0.268092
9	9.0	-0.338262	1.119593	1.044367	-0.222187	0.499361	-0.246761	0.651583	0.069539	-0.736727		-0.246914	-0.633753
4.0		0.4											

10 rows × 31 columns

```
df.shape
```

(284807, 31)

## df.columns.tolist()

- ['Time',
- 'V1',
- 'V2',
- 'V3',

```
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           'V4',
           'V5',
           'V6',
           'V7',
           'V8',
           'V9',
           'V10',
           'V11',
           'V12',
           'V13',
           'V14',
           'V15',
           'V16',
           'V17',
           'V18',
           'V19',
           'V20',
           'V21',
           'V22',
           'V23',
           'V24',
           'V25',
           'V26',
           'V27',
           'V28',
           'Amount',
           'Class']
```

new\_df = df.sample(frac=1,random\_state=42).reset\_index(drop=True) new\_df.head()

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	•••	V21	V22	V23	V24	V25	V26	V27	
0	41505.0	-16.526507	8.584972	-18.649853	9.505594	-13.793819	-2.832404	-16.701694	7.517344	-8.507059		1.190739	-1.127670	-2.358579	0.673461	-1.413700	-0.462762	-2.018575	-1.04
1	44261.0	0.339812	-2.743745	-0.134070	-1.385729	-1.451413	1.015887	-0.524379	0.224060	0.899746		-0.213436	-0.942525	-0.526819	-1.156992	0.311211	-0.746647	0.040996	0.10
2	35484.0	1.399590	-0.590701	0.168619	-1.029950	-0.539806	0.040444	-0.712567	0.002299	-0.971747		0.102398	0.168269	-0.166639	-0.810250	0.505083	-0.232340	0.011409	0.00
3	167123.0	-0.432071	1.647895	-1.669361	-0.349504	0.785785	-0.630647	0.276990	0.586025	-0.484715		0.358932	0.873663	-0.178642	-0.017171	-0.207392	-0.157756	-0.237386	0.00
4	168473.0	2.014160	-0.137394	-1.015839	0.327269	-0.182179	-0.956571	0.043241	-0.160746	0.363241		-0.238644	-0.616400	0.347045	0.061561	-0.360196	0.174730	-0.078043	-0.07

5 rows × 31 columns

```
df_1 = new_df.iloc[:227845,:].reset_index(drop=True)
test = new_df.iloc[227845:,:].reset_index(drop=True)
train, valid = train_test_split(df_1,test_size=0.2)
```

```
train.info()
print('*'*100)
valid.info()
print('*'*100)
test.info()
      14 V14
                 45569 non-null float64
                 45569 non-null float64
```

```
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                    TOUCOT
            v + -
        16 V16
                    45569 non-null float64
        17
            V17
                    45569 non-null float64
        18 V18
                    45569 non-null float64
        19
            V19
                    45569 non-null float64
        20
            V20
                    45569 non-null float64
            V21
        21
                    45569 non-null float64
            V22
        22
                    45569 non-null float64
        23
            V23
                    45569 non-null float64
            V24
        24
                    45569 non-null float64
            V25
        25
                    45569 non-null float64
            V26
        26
                    45569 non-null float64
        27 V27
                    45569 non-null float64
            V28
                    45569 non-null float64
        28
            Amount 45569 non-null float64
        29
        30 Class 45569 non-null int64
        dtypes: float64(30), int64(1)
        memory usage: 11.1 MB
        *************************************
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 56962 entries, 0 to 56961
        Data columns (total 31 columns):
            Column Non-Null Count Dtype
        0
            Time
                    56962 non-null float64
        1
            ٧1
                    56962 non-null float64
        2
            V2
                    56962 non-null float64
        3
            V3
                    56962 non-null float64
            V4
        4
                    56962 non-null float64
        5
            V5
                    56962 non-null float64
        6
            ۷6
                    56962 non-null float64
        7
            V7
                    56962 non-null float64
        8
            ٧8
                    56962 non-null float64
        9
            V9
                    56962 non-null float64
            V10
        10
                    56962 non-null float64
        11 V11
                    56962 non-null float64
        12
            V12
                    56962 non-null float64
        13 V13
                    56962 non-null float64
        14 V14
                    56962 non-null float64
            V15
        15
                    56962 non-null float64
        16 V16
                    56962 non-null float64
        17 V17
                    56962 non-null float64
        18
            V18
                    56962 non-null float64
        19
            V19
                    56962 non-null float64
        20
            V20
                    56962 non-null float64
            V21
                    56962 non-null float64
        21
            V22
                    56962 non-null float64
        22
        23 V23
                    56962 non-null float64
            V24
        24
                    56962 non-null float64
        25
            V25
                    56962 non-null float64
            V26
        26
                    56962 non-null float64
            V27
                    56962 non-null float64
        27
        28
            V28
                    56962 non-null float64
        29
            Amount 56962 non-null float64
        30 Class 56962 non-null int64
        dtypes: float64(30), int64(1)
```

print(pd.isnull(train).sum())

memory usage: 13.5 MB

```
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   print('*'*100)
   print(pd.isnull(valid).sum())
   print('*'*100)
```

print(pd.isnull(test).sum())

Time 0 V1 0 V2 ٧3 0 V4 V5 ۷6 V7 ٧8 ۷9 0 V10 0 V11 V12 0 V13 0 0 V14 V15 0 V16 0 V17 0 V18 0 V19 0 V20 0 V21 0 V22 0 V23 0 V24 V25 0 V26 0 V27 V28 0 Amount 0 Class

dtype: int64 \*

Time V1 0 V2 0 V3 V4 V5 0 ۷6 ٧7 V8 V9 V10 0 V11 0 V12 0 V13 0 V14 0 V15 0 V16 0 V17 0 V18 0

0

0

V19

V20

0

```
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     V21
     V22
     V23
  print(train['Class'].value_counts())
  print('*'*100)
  print(valid['Class'].value_counts())
  print('*'*100)
  print(test['Class'].value_counts())
     0
         181968
           308
     1
     Name: Class, dtype: int64
     ************************************
         45490
          79
     1
     Name: Class, dtype: int64
     56857
     1
          105
     Name: Class, dtype: int64
```

0

0

```
train.columns
     Index(['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10',
```

```
'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20',
 'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount',
 'Class'],
dtype='object')
```

```
plt.figure(figsize=(10,6))
labels=['Not Fraud' , 'Frauds']
explode = [.01,.01]
color=['LightGreen' , 'Blue']
sizes=df.Class.value_counts().values
plt.pie(sizes,explode,labels,autopct="%1.1f%%", colors = color)
plt.show()
```

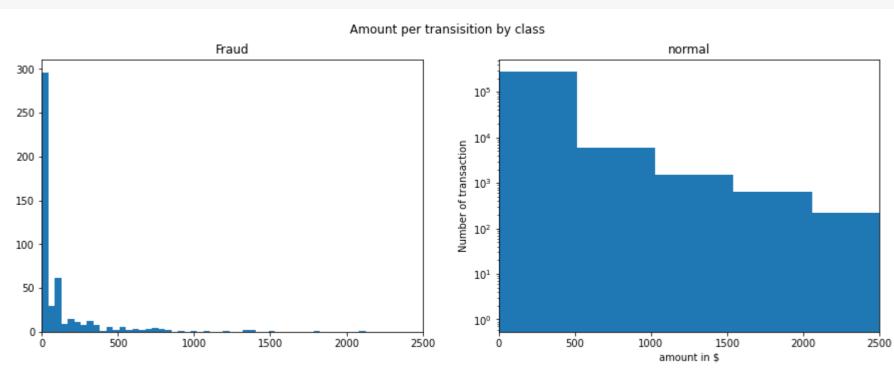
```
fraud=df[df['Class']==1]
normal=df[df['Class']==0]

f,(ax1,ax2)=plt.subplots(1,2,figsize=(15,5),sharex=True)
f.suptitle('Amount per transisition by class')
bins =50
ax1.hist(fraud.Amount , bins=bins)
ax1.set_title('Fraud')

ax2.hist(normal.Amount,bins=bins)
ax2.set_title('normal')

plt.xlabel('amount in $')
plt.ylabel('Number of transaction')

plt.xlim(0,2500)
plt.yscale('log')
plt.show()
```



df[df['Class']==0].describe().transpose()

	count	mean	std	min	25%	50%	75%	max
Time	284315.0	94838.202258	47484.015786	0.000000	54230.000000	84711.000000	139333.000000	172792.000000
V1	284315.0	0.008258	1.929814	-56.407510	-0.917544	0.020023	1.316218	2.454930
V2	284315.0	-0.006271	1.636146	-72.715728	-0.599473	0.064070	0.800446	18.902453
V3	284315.0	0.012171	1.459429	-48.325589	-0.884541	0.182158	1.028372	9.382558
V4	284315.0	-0.007860	1.399333	-5.683171	-0.850077	-0.022405	0.737624	16.875344
V5	284315.0	0.005453	1.356952	-113.743307	-0.689398	-0.053457	0.612181	34.801666
V6	284315.0	0.002419	1.329913	-26.160506	-0.766847	-0.273123	0.399619	73.301626
V7	284315.0	0.009637	1.178812	-31.764946	-0.551442	0.041138	0.571019	120.589494
V8	284315.0	-0.000987	1.161283	-73.216718	-0.208633	0.022041	0.326200	18.709255
V9	284315.0	0.004467	1.089372	-6.290730	-0.640412	-0.049964	0.598230	15.594995
V10	284315.0	0.009824	1.044204	-14.741096	-0.532880	-0.091872	0.455135	23.745136
V11	284315.0	-0.006576	1.003112	-4.797473	-0.763447	-0.034923	0.736362	10.002190
V12	284315.0	0.010832	0.945939	-15.144988	-0.402102	0.141679	0.619207	7.848392
V13	284315.0	0.000189	0.995067	-5.791881	-0.648067	-0.013547	0.662492	7.126883
V14	284315.0	0.012064	0.897007	-18.392091	-0.422453	0.051947	0.494104	10.526766
V15	284315.0	0.000161	0.915060	-4.391307	-0.582812	0.048294	0.648842	8.877742
V16	284315.0	0.007164	0.844772	-10.115560	-0.465543	0.067377	0.523738	17.315112
V17	284315.0	0.011535	0.749457	-17.098444	-0.482644	-0.064833	0.399922	9.253526
V18	284315.0	0.003887	0.824919	-5.366660	-0.497414	-0.002787	0.501103	5.041069
V19	284315.0	-0.001178	0.811733	-7.213527	-0.456366	0.003117	0.457499	5.591971
V20	284315.0	-0.000644	0.769404	-54.497720	-0.211764	-0.062646	0.132401	39.420904
V21	284315.0	-0.001235	0.716743	-34.830382	-0.228509	-0.029821	0.185626	22.614889
V22	284315.0	-0.000024	0.723668	-10.933144	-0.542403	0.006736	0.528407	10.503090
V23	284315.0	0.000070	0.621541	-44.807735	-0.161702	-0.011147	0.147522	22.528412
V24	284315.0	0.000182	0.605776	-2.836627	-0.354425	0.041082	0.439869	4.584549
V2E ['Class'	28/315 n ]==1].desc	_n nnnn72 ribe().transpo	n 520672 ose()	_10 205307	_∩ २171//5	0 016/17	በ 350504	7 510590

df[df['Class']==1].describe().transpose()

	count	mean	std	min	25%	50%	75%	max
Time	492.0	80746.806911	47835.365138	406.000000	41241.500000	75568.500000	128483.000000	170348.000000
V1	492.0	-4.771948	6.783687	-30.552380	-6.036063	-2.342497	-0.419200	2.132386
V2	492.0	3.623778	4.291216	-8.402154	1.188226	2.717869	4.971257	22.057729
V3	492.0	-7.033281	7.110937	-31.103685	-8.643489	-5.075257	-2.276185	2.250210
V4	492.0	4.542029	2.873318	-1.313275	2.373050	4.177147	6.348729	12.114672
V5	492.0	-3.151225	5.372468	-22.105532	-4.792835	-1.522962	0.214562	11.095089
V6	492.0	-1.397737	1.858124	-6.406267	-2.501511	-1.424616	-0.413216	6.474115
V7	492.0	-5.568731	7.206773	-43.557242	-7.965295	-3.034402	-0.945954	5.802537
V8	492.0	0.570636	6.797831	-41.044261	-0.195336	0.621508	1.764879	20.007208
V9	492.0	-2.581123	2.500896	-13.434066	-3.872383	-2.208768	-0.787850	3.353525
V10	492.0	-5.676883	4.897341	-24.588262	-7.756698	-4.578825	-2.614184	4.031435
V11	492.0	3.800173	2.678605	-1.702228	1.973397	3.586218	5.307078	12.018913
V12	492.0	-6.259393	4.654458	-18.683715	-8.688177	-5.502530	-2.974088	1.375941
V13	492.0	-0.109334	1.104518	-3.127795	-0.979117	-0.065566	0.672964	2.815440
V14	492.0	-6.971723	4.278940	-19.214325	-9.692723	-6.729720	-4.282821	3.442422
V15	492.0	-0.092929	1.049915	-4.498945	-0.643539	-0.057227	0.609189	2.471358
V16	492.0	-4.139946	3.865035	-14.129855	-6.562915	-3.549795	-1.226043	3.139656
V17	492.0	-6.665836	6.970618	-25.162799	-11.945057	-5.302949	-1.341940	6.739384
V18	492.0	-2.246308	2.899366	-9.498746	-4.664576	-1.664346	0.091772	3.790316
V19	492.0	0.680659	1.539853	-3.681904	-0.299423	0.646807	1.649318	5.228342
V20	492.0	0.372319	1.346635	-4.128186	-0.171760	0.284693	0.822445	11.059004
V21	492.0	0.713588	3.869304	-22.797604	0.041787	0.592146	1.244611	27.202839
V22	492.0	0.014049	1.494602	-8.887017	-0.533764	0.048434	0.617474	8.361985
V23	492.0	-0.040308	1.579642	-19.254328	-0.342175	-0.073135	0.308378	5.466230
V24	492.0	-0.105130	0.515577	-2.028024	-0.436809	-0.060795	0.285328	1.091435
V25	492.0	0.041449	0.797205	-4.781606	-0.314348	0.088371	0.456515	2.208209
1/00	100 0	0.051010		(0.4)	0.050440	2 22 422 4	0 000700	0.715001

scaler = preprocessing.MinMaxScaler(feature\_range=(0, 1))
names = train.columns

d = scaler.fit\_transform(train)

scaled\_df = pd.DataFrame(d, columns=names)

scaled\_df.head()

```
V1
                               V2
                                                                                            V9 ...
                                                                                                                                            V25
                                                                                                                                                     V26
            Time
                                        ٧3
                                                         ۷5
                                                                           ٧7
                                                                                                         V21
                                                                                                                 V22
                                                                                                                          V23
                                                                                                                                   V24
                                                                                                                                                             V27
                                                                                                                                                                      V28
                                                                                                                                                                            Amount
     0 0.357297 0.977844 0.735707 0.752364 0.196624 0.578518 0.560240 0.478895 0.793422
                                                                                                                              0.465269
                                                                                                    0.556878 0.426547
                                                                                                                      0.671011
     1 0.739479 0.984386
                         0.733790
                                  0.734158
                                           0.299318
                                                   0.569061
                                                            0.515456
                                                                     0.490651 0.786724
                                                                                       0.460816
                                                                                                    0.564843
                                                                                                             0.506589
                                                                                                                      0.668041
                                                                                                                              0.178131
                                                                                                                                       0.593288
                                                                                                                                                0.361145 0.650135
                                                                                                                                                                 0.339143 0.006744
     2 0.244166 0.976593 0.741837 0.778640 0.265097
                                                   0.556790 0.494146 0.485056 0.785245
                                                                                      0.454831
                                                                                                                     0.669361
                                                                                                                               0.288011
                                                                                                                                       0.598165 0.449564 0.649259
                                                                                                                                                                 0.341404 0.000047
                                                                                                    0.556532
                                                                                                             0.430576
     3 0.428405 0.975364 0.738307 0.789678
                                           0.280893 0.550457
                                                            0.492521
                                                                     0.484703 0.784267
                                                                                       0.478000
                                                                                                    0.556181
                                                                                                             0.435893
                                                                                                                      0.668979
                                                                                                                              0.353918
                                                                                                                                       0.604416 0.462570 0.649551
                                                                                                                                                                  0.341545 0.001586
     4 0.746834 0.944087 0.746032 0.777418 0.244498 0.570822 0.463398 0.497785 0.780291 0.463420
                                                                                                            0.565804
#Oversampling
X_train, y_train = train.drop(['Class'], axis = 1), train['Class']
sm = SMOTE(random_state = 42)
X_train, y_train = sm.fit_resample(X_train, y_train)#.ravel())
lg=LogisticRegression()
lg.fit(X_train,y_train)
lg_pred=lg.predict(valid.drop(['Class'],axis=1))
print(classification_report(valid['Class'],lg_pred))
                             recall f1-score
                 precision
                                               support
                                         0.99
                                                 45490
               0
                      1.00
                               0.98
                      0.08
               1
                               0.89
                                         0.14
                                                    79
        accuracy
                                         0.98
                                                 45569
       macro avg
                      0.54
                               0.93
                                         0.57
                                                 45569
     weighted avg
                      1.00
                               0.98
                                         0.99
                                                 45569
mlp_clf = MLPClassifier(hidden_layer_sizes=(10,2),
                      max_iter = 10,activation = 'relu',
                      solver = 'adam')
mlp_clf.fit(X_train, y_train)
    MLPClassifier(hidden_layer_sizes=(10, 2), max_iter=10)
mlp_pred = mlp_clf.predict(valid.drop(['Class'],axis=1))
print(classification_report(valid['Class'],mlp_pred))
                 precision
                             recall f1-score
                                               support
               0
                      1.00
                               1.00
                                        1.00
                                                 45490
                      0.00
               1
                               0.00
                                         0.00
                                                    79
                                                 45569
        accuracy
                                        1.00
       macro avg
                      0.50
                               0.50
                                         0.50
                                                 45569
     weighted avg
                      1.00
                               1.00
                                        1.00
                                                 45569
```

```
mlp_clf_iter25 = MLPClassifier(hidden_layer_sizes=(15,2),
                        max_iter = 25,activation = 'relu',
                        solver = 'adam')
mlp_clf_iter25.fit(X_train, y_train)
y_pred_25 = mlp_clf_iter25.predict(test.drop(['Class'],axis=1))
print('Accuracy: {:.2f}'.format(accuracy_score(test['Class'], y_pred_25)))
     Accuracy: 1.00
mlp_clf_iter50 = MLPClassifier(hidden_layer_sizes=(15,2),
                        max_iter = 50,activation = 'relu',
                        solver = 'adam')
mlp_clf_iter50.fit(X_train, y_train)
y_pred_50 = mlp_clf_iter50.predict(test.drop(['Class'],axis=1))
print('Accuracy: {:.2f}'.format(accuracy_score(test['Class'], y_pred_50)))
     Accuracy: 0.98
mlp_clf_iter75 = MLPClassifier(hidden_layer_sizes=(15,2),
                        max_iter = 75,activation = 'relu',
                        solver = 'adam')
mlp_clf_iter75.fit(X_train, y_train)
y_pred_75 = mlp_clf_iter75.predict(test.drop(['Class'],axis=1))
print('Accuracy: {:.2f}'.format(accuracy_score(test['Class'], y_pred_75)))
```

https://colab.research.google.com/drive/122NVowk40BdL5yGV\_wFaO7IHZ9l3yRIY#printMode=true

Accuracy: 0.00

11/15/22, 12:54 PM ML\_Lab-3.ipynb - Colaboratory

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