```
In [105]: import pandas as pd
    import seaborn as sns
    import numpy as np
    import sklearn
    import scipy
    import matplotlib.pyplot as plt
    from sklearn.metrics import classification_report,accuracy_score
    from sklearn.ensemble import IsolationForest
    from sklearn.eighbors import LocalOutlierFactor
    from sklearn.svm import OneClassSVM
    from pylab import rcParams

from sklearn.model_selection import train_test_split
    rcParams['figure.figsize']=14,8
    RANDOM_SEED=42
    LABELS=["Normal","Fraud"]
```

In [74]: data=pd.read_csv("C:/Users/Rakesh Kumar/Desktop/creditcard.csv")

In [75]: data.head()

Out[75]:

	Time	V 1	V2	V3	V4	V5	V6	V7	V8
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533

5 rows × 31 columns

<

```
fraud_detection - Jupyter Notebook
In [76]:
         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
              V3
          3
                       284807 non-null
                                        float64
          4
              V4
                       284807 non-null
                                        float64
          5
              V5
                       284807 non-null
                                        float64
          6
                                       float64
              ۷6
                       284807 non-null
          7
              ٧7
                       284807 non-null float64
          8
              ٧8
                       284807 non-null float64
          9
              V9
                       284807 non-null
                                        float64
              V10
                                       float64
          10
                       284807 non-null
                       284807 non-null float64
          11
              V11
          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
                       284807 non-null
          25
                                        float64
              V25
          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
```

```
In [77]:
         #get the fraud and normal dataset
         fraud=data.loc[data['Class']==1]
         normal=data.loc[data['Class']==0]
```

```
In [78]: print(fraud.shape,normal.shape)
```

(492, 31) (284315, 31)

##we need more information from transaction data In [79]: #how different are the amount of money used in different transaction classes fraud.Amount.describe()

492.000000 Out[79]: count 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

In [80]: fraud.Amount.describe()

Out[80]: count 492.000000 mean 122.211321 std 256.683288 min 0.000000 25% 1.000000 50% 9.250000 75% 105.890000 2125.870000 max

Name: Amount, dtype: float64

In [81]: | fraud

Out[81]:

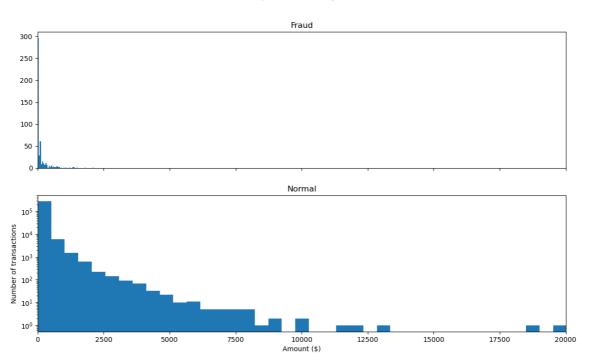
	Time	V1	V2	V3	V4	V5	V6	V7	
541	406.0	-2.312227	1.951992	-1.609851	3.997906	-0.522188	-1.426545	-2.537387	_
623	472.0	-3.043541	-3.157307	1.088463	2.288644	1.359805	-1.064823	0.325574	-
4920	4462.0	-2.303350	1.759247	-0.359745	2.330243	-0.821628	-0.075788	0.562320	-
6108	6986.0	-4.397974	1.358367	-2.592844	2.679787	-1.128131	-1.706536	-3.496197	-
6329	7519.0	1.234235	3.019740	-4.304597	4.732795	3.624201	-1.357746	1.713445	-
279863	169142.0	-1.927883	1.125653	-4.518331	1.749293	-1.566487	-2.010494	-0.882850	
280143	169347.0	1.378559	1.289381	-5.004247	1.411850	0.442581	-1.326536	-1.413170	
280149	169351.0	-0.676143	1.126366	-2.213700	0.468308	-1.120541	-0.003346	-2.234739	
281144	169966.0	-3.113832	0.585864	-5.399730	1.817092	-0.840618	-2.943548	-2.208002	
281674	170348.0	1.991976	0.158476	-2.583441	0.408670	1.151147	-0.096695	0.223050	-

492 rows × 31 columns

<

```
In [82]: f,(ax1,ax2)=plt.subplots(2,1,sharex=True)
    f.suptitle("Amount per transaction 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 ($)')
    plt.ylabel("Number of transactions")
    plt.xlim(0,20000)
    plt.yscale('log')
    plt.show();
```

Amount per transaction by class



In [83]: len(fraud)

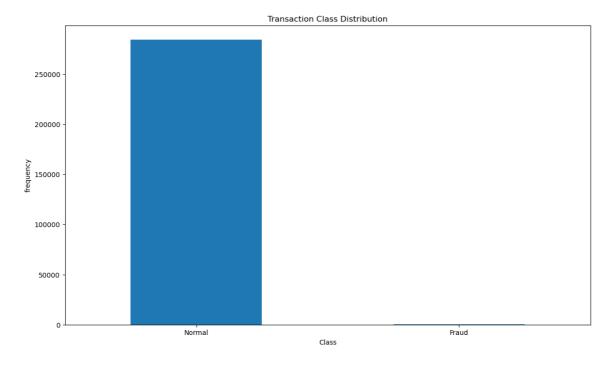
Out[83]: 492

```
fraud.sum()
In [84]:
Out[84]: Time
                    3.972743e+07
          ۷1
                   -2.347799e+03
          V2
                    1.782899e+03
         V3
                   -3.460374e+03
         ۷4
                    2.234678e+03
         ۷5
                   -1.550403e+03
         ۷6
                   -6.876865e+02
         V7
                   -2.739816e+03
         ٧8
                    2.807529e+02
                   -1.269912e+03
         ۷9
         V10
                   -2.793026e+03
         V11
                    1.869685e+03
         V12
                   -3.079621e+03
         V13
                   -5.379224e+01
         V14
                   -3.430088e+03
         V15
                   -4.572094e+01
         V16
                   -2.036853e+03
         V17
                   -3.279592e+03
         V18
                   -1.105184e+03
         V19
                    3.348844e+02
         V20
                    1.831811e+02
         V21
                    3.510855e+02
                    6.912050e+00
         V22
         V23
                   -1.983152e+01
         V24
                   -5.172411e+01
         V25
                    2.039285e+01
         V26
                    2.541088e+01
         V27
                    8.392280e+01
         V28
                    3.722831e+01
         Amount
                    6.012797e+04
                    4.920000e+02
         Class
         dtype: float64
In [85]:
         len(normal)
Out[85]: 284315
In [86]: X=data.iloc[:,:-1]
         y=data['Class']
In [87]:
         X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.35)
         clf=linear_model.LogisticRegression(C=1e5)
In [88]:
```

```
In [89]:
         clf.fit(X_train,y_train)
         C:\Users\Rakesh Kumar\anaconda3\anaconda\lib\site-packages\sklearn\linear_
         model\_logistic.py:814: ConvergenceWarning: lbfgs failed to converge (stat
         us=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max_iter) or scale the data as shown i
         n:
             https://scikit-learn.org/stable/modules/preprocessing.html (https://sc
         ikit-learn.org/stable/modules/preprocessing.html)
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear model.html#logistic-reg
         ression (https://scikit-learn.org/stable/modules/linear_model.html#logisti
         c-regression)
           n_iter_i = _check_optimize_result(
Out[89]: LogisticRegression(C=100000.0)
In [90]:
         y_pred=np.array(clf.predict(X_test))
         y=np.array(y_test)
         from sklearn.metrics import confusion_matrix,classification_report,accuracy
In [91]:
         print(confusion_matrix(y,y_pred))
In [92]:
         [[99444
                    48]
                   128]]
              63
In [93]:
         print(accuracy_score(y,y_pred))
         0.9988864701102494
In [94]:
         print(classification_report(y,y_pred))
                        precision
                                     recall f1-score
                                                        support
                                                          99492
                    0
                             1.00
                                       1.00
                                                 1.00
                    1
                             0.73
                                       0.67
                                                 0.70
                                                            191
                                                 1.00
                                                          99683
             accuracy
                             0.86
                                       0.83
                                                 0.85
                                                          99683
            macro avg
         weighted avg
                             1.00
                                       1.00
                                                 1.00
                                                          99683
In [95]:
         #EXPLORATORY DATA ANALYSIS
         data.isnull().values.any()
Out[95]: False
```

```
In [96]: count_classes=pd.value_counts(data['Class'],sort=True)
    count_classes.plot(kind='bar',rot=0)
    plt.title("Transaction Class Distribution")
    plt.xticks(range(2),LABELS)
    plt.xlabel("Class")
    plt.ylabel("frequency")
```

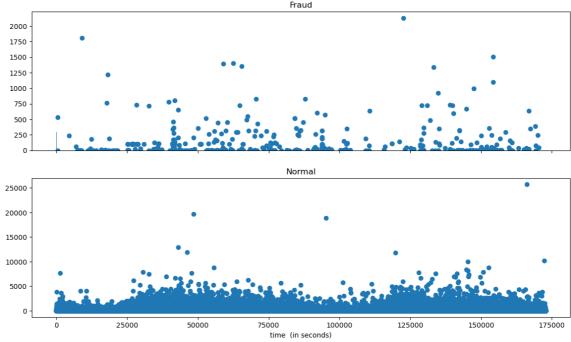
Out[96]: Text(0, 0.5, 'frequency')



```
In [97]: # we will check do fraudulent transactions occur more often during certain t
f, (ax1,ax2)=plt.subplots(2,1,sharex=True)

f.suptitle("time pf transaction vs Amount by class")
ax1.scatter(fraud.Time,fraud.Amount)
ax1.hist(fraud.Amount,bins=bins)
ax1.set_title('Fraud')
ax2.scatter(normal.Time,normal.Amount)
ax2.set_title('Normal')
plt.xlabel('time (in seconds)')
```

time pf transaction vs Amount by class



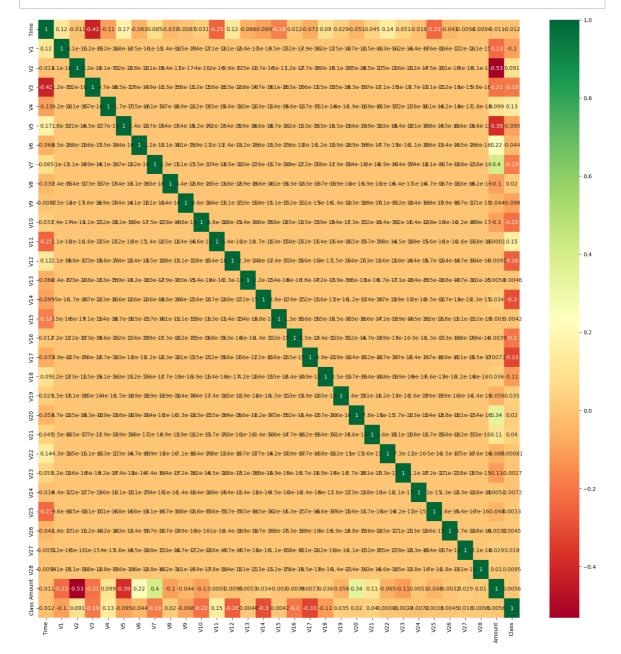
```
In [101]: print(outlier_fraction)
    print("Fraud Cases:{}".format(len(Fraud)))
    print("Valid Cases:{}".format(len(Valid)))
```

0.0017234102419808666

Fraud Cases:49 Valid Cases:28432

In [102]:

```
##correlation
import seaborn as sns
corrmat=data1.corr()
top_corr_features=corrmat.index
plt.figure(figsize=(20,20))
g=sns.heatmap(data[top_corr_features].corr(),annot=True,cmap="RdYlGn")
```



```
#create dependent and independent features
In [103]:
          columns=data.columns.tolist()
          columns=[c for c in columns if c not in ["Class"]]
          target="Class"
          state=np.random.RandomState(42)
          X=data1[columns]
          Y=data1[target]
          X_outliers=state.uniform(low=0,high=1,size=(X.shape[0],X.shape[1]))
          print(X.shape)
          print(Y.shape)
           (28481, 30)
          (28481,)
In [116]: from sklearn.svm import OneClassSVM
          from sklearn.ensemble import IsolationForest
          from sklearn.neighbors import LocalOutlierFactor
          classifiers = {
              "Isolation Forest": IsolationForest(n estimators=100, max samples=len(X)
                                                   contamination=outlier_fraction, ver
              "Local Outlier Factor": LocalOutlierFactor(n_neighbors=20, algorithm='a
                                                          contamination=outlier_fraction
              "Support Vector Machine": OneClassSVM(kernel='rbf', degree=3, gamma=0.1]
          }
In [117]: type(classifiers)
Out[117]: dict
 In [*]: n_outliers=len(Fraud)
          for i,(clf_name,clf) in enumerate(classifiers.items()):
              if clf_name=="Local Outlier Factor":
                  y_pred==clf.fit_predict(X)
                  scores prediction=clf.negative outlier factor
              elif clf_name=="Support Vector Machine":
                  clf.fit(X)
                  y_pred=clf.predict(X)
              else:
                  clf.fit(X)
                  scores prediction=clf.decision function(X)
                  y_pred=clf.predict(X)
          y_pred[y_pred==1]=0
          y_pred[y_pred==-1]=1
          n_errors=(y_pred!=Y).sum()
          print("{}:{}".format(clf name, n errors))
          print("Accuracy Score :")
          print(accuracy_score(Y,y_pred))
          print("Classification Report :")
          print(classification_report(Y,y_pred))
```

In []]:	
In []]:	
In []]:	