IMPORTING PACKAGES

In [3]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
#from sklearn.feature_selection import SelectKBest,f_classif,mutual_info_classif
from sklearn.model_selection import cross_validate,train_test_split
from sklearn.metrics import classification_report,confusion_matrix
from sklearn.naive_bayes import GaussianNB
#from scikitplot.metrics import plot_confusion_matrix
#from sklearn.metrics import plot_confusion_matrix
from sklearn.linear_model import LogisticRegression
import seaborn as sns
```

LOADING DATASET

In [4]:

```
data=pd.read_csv("C:/Users/DELL/Downloads/creditcard.csv")
data
```

Out[4]:

	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
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
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
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
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
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	7.305334	1.914428	...	0.213454	0.111864	1.014480
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	0.294869	0.584800	...	0.214205	0.924384	0.012463
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	0.708417	0.432454	...	0.232045	0.578229	-0.037501
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	0.679145	0.392087	...	0.265245	0.800049	-0.163298
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006	-0.414650	0.486180	...	0.261057	0.643078	0.376777

284807 rows × 31 columns

In [5]:

```
data.head()
```

Out[5]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24
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	0.066928
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	-0.339846
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	-0.689281
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	-1.175575
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	0.141267

5 rows × 31 columns

DATA EXPLORATION

In [6]:
```
data.shape
```
Out[6]: (284807, 31)

In [7]:
```
data.describe()
```
Out[7]:

	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	2.848070e
mean	94813.859575	3.919560e-15	5.688174e-16	-8.769071e-15	2.782312e-15	-1.552563e-15	2.010663e-15	-1.694249e-15	-1.927028e-16	-3.137024e
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	1.098632e
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	-1.343407e
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	-6.430976e
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	-5.142873e
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	5.971390e
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	1.559499e

8 rows × 31 columns

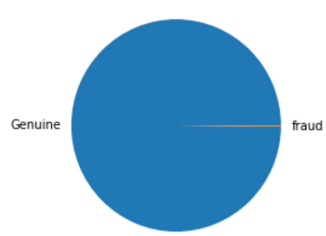
In [8]:
```
#printing the columns
print('Columns Name:',list(data))
print('Total Number of Columns: ',len(list(data)))
```
```
Columns Name: ['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10', 'V11', 'V12', 'V13', 'V14', 'V15', 'V1
6', 'V17', 'V18', 'V19', 'V20', 'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount', 'Class']
Total Number of Columns:  31
```

In [9]:
```
#counting the number of genuine and fradulent Transactions
n_genuine=data[data['Class']==0]
n_fraud=data[data['Class']==1]

#displaying the number of genuine and fraudulent Transcations
print(' Genuine Transactions: ',len(n_genuine))
print(' Fradulent Transactions: ',len(n_fraud))
```
```
 Genuine Transactions:  284315
 Fradulent Transactions:  492
```

In [10]:
```
outlierfraction=float(len(n_fraud))/float(len(n_genuine))
print(outlierfraction)
```
```
0.0017304750013189597
```

In [11]:
```
#plotting the pie plot of genuine and fraudulent transactions
plt.pie([len(n_genuine),len(n_fraud)],labels=['Genuine','fraud'],radius=1)
plt.show()
```



In [12]:
```
n_fraud.Amount.describe()
```
Out[12]:
```
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
```

In [13]:
```
n_genuine.Amount.describe()
```
Out[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
```

SEPERATING DATA INTO X AND Y

In [14]:
```
#here we put training data in x variable and target value in y variable
x,y=data.iloc[:,:-1],data.iloc[:,-1]
```

In [15]:
```
x.head()
```
Out[15]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V20	V21	V22	V23
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	0.251412	-0.018307	0.277838	-0.110474
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.069083	-0.225775	-0.638672	0.101288
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.524980	0.247998	0.771679	0.909412
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.208038	-0.108300	0.005274	-0.190321
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	0.408542	-0.009431	0.798278	-0.137458

5 rows × 30 columns

In [16]:
```
y.head()
```
Out[16]:
```
0    0
1    0
2    0
3    0
4    0
Name: Class, dtype: int64
```

SPLITTING OF DATA INTO TRAINING AND TESTING DATA

In [17]:

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_state=42)
```

Building a Random Forest Classifier

In [18]:

```
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
y_pred=rfc.predict(x_test)
```

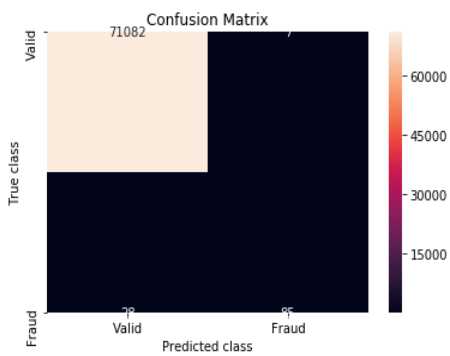
```
C:\Users\DELL\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:245: FutureWarning: The default value of n_estimators w
ill change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

EVALUATING THE MODEL

In [19]:

```
lables=['Valid','Fraud']
conf_matrix=confusion_matrix(y_test,y_pred)

sns.heatmap(conf_matrix,xticklabels=lables,yticklabels=lables,annot=True,fmt='d')
plt.title("Confusion Matrix")
plt.ylabel("True class")
plt.xlabel("Predicted class")
plt.show()
```



In [20]:

```
from sklearn.metrics import classification_report,accuracy_score,precision_score,recall_score,f1_score
print("The model used is random Forest classifier")
acc=accuracy_score(y_test,y_pred)
print("The accuracy Score is {}".format(acc))
prec=precision_score(y_test,y_pred)
print("The precision Score is {}".format(prec))
rec=recall_score(y_test,y_pred)
print("The recall Score is {}".format(rec))
f1=f1_score(y_test,y_pred)
print("The f1 Score is {}".format(f1))
```

```
The model used is random Forest classifier
The accuracy Score is 0.9995084407741356
The precision Score is 0.9239130434782609
The recall Score is 0.7522123893805309
The f1 Score is 0.8292682926829267
```

LOGISTIC REGRESSION

In [21]:
```
lr=LogisticRegression()
lr.fit(x_train,y_train)
```

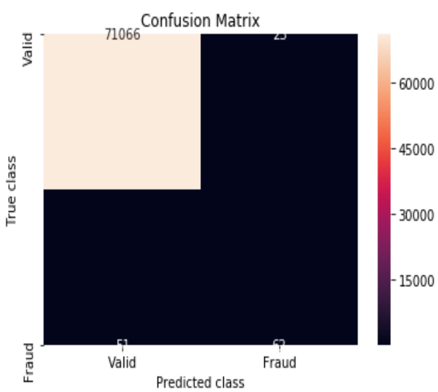
```
C:\Users\DELL\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:432: FutureWarning: Default solver will be change
d to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

Out[21]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [22]:
```
pred=lr.predict(x_test)
```

In [23]:
```
lables=['Valid','Fraud']
conf_matrix=confusion_matrix(y_test,pred)

sns.heatmap(conf_matrix,xticklabels=lables,yticklabels=lables,annot=True,fmt='d')
plt.title("Confusion Matrix")
plt.ylabel("True class")
plt.xlabel("Predicted class")
plt.show()
```



In [24]:
```
from sklearn.metrics import classification_report,accuracy_score,precision_score,recall_score,f1_score
print("The model used is logistic regression classifier")
acc=accuracy_score(y_test,pred)
print("The accuracy Score is {}".format(acc))
prec=precision_score(y_test,pred)
print("The precision Score is {}".format(prec))
rec=recall_score(y_test,pred)
print("The recall Score is {}".format(rec))
f1=f1_score(y_test,pred)
print("The f1 Score is {}".format(f1))
```

```
The model used is logistic regression classifier
The accuracy Score is 0.9989607033510295
The precision Score is 0.7294117647058823
The recall Score is 0.5486725663716814
The f1 Score is 0.6262626262626262
```

LINEAR SVM

In [25]:
```python
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.svm import LinearSVC
```

In [26]:
```python
svm_clf=LinearSVC()
```

In [27]:
```python
svm_clf.fit(x_train,y_train)
```

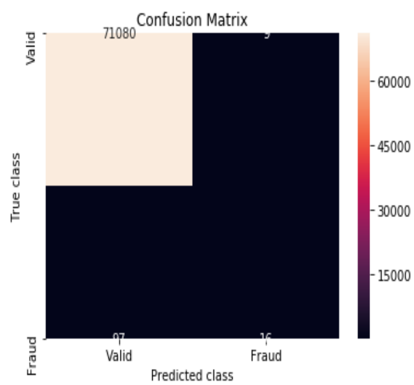
```
C:\Users\DELL\Anaconda3\lib\site-packages\sklearn\svm\base.py:929: ConvergenceWarning: Liblinear failed to converge, increas
e the number of iterations.
  "the number of iterations.", ConvergenceWarning)
```

Out[27]:
```
LinearSVC(C=1.0, class_weight=None, dual=True, fit_intercept=True,
          intercept_scaling=1, loss='squared_hinge', max_iter=1000,
          multi_class='ovr', penalty='l2', random_state=None, tol=0.0001,
          verbose=0)
```

In [28]:
```python
y_predi=svm_clf.predict(x_test)
```

In [29]:
```python
lables=['Valid','Fraud']
conf_matrix=confusion_matrix(y_test,y_predi)

sns.heatmap(conf_matrix,xticklabels=lables,yticklabels=lables,annot=True,fmt='d')
plt.title("Confusion Matrix")
plt.ylabel("True class")
plt.xlabel("Predicted class")
plt.show()
```



In [30]:
```python
from sklearn.metrics import classification_report,accuracy_score,precision_score,recall_score,f1_score
print("The model used is LinearSVC")
acc=accuracy_score(y_test,y_predi)
print("The accuracy Score is {}".format(acc))
prec=precision_score(y_test,y_predi)
print("The precision Score is {}".format(prec))
rec=recall_score(y_test,y_predi)
print("The recall Score is {}".format(rec))
f1=f1_score(y_test,y_predi)
print("The f1 Score is {}".format(f1))
```

```
The model used is LinearSVC
The accuracy Score is 0.9985112777730962
The precision Score is 0.64
The recall Score is 0.1415929203539823
The f1 Score is 0.2318840579710145
```

In [31]:
```
Algorithms=['RandomForest','Logisticregression','LinearSVM']
Accuracy=[0.995,0.9987,0.9984]
Precision=[0.946,0.611,0.6190]
recall=[0.786,0.584,0.1150]
final=pd.DataFrame({'Accuracy':Accuracy,'Algorithm':Algorithms,'Precision':Precision,'recall':recall})
final
```

Out[31]:

	Accuracy	Algorithm	Precision	recall
0	0.9950	RandomForest	0.946	0.786
1	0.9987	Logisticregression	0.611	0.584
2	0.9984	LinearSVM	0.619	0.115

In [32]:
```
sns.lineplot(x='Algorithm',y='Accuracy',data=final,palette='hot',label='Accuracy')
sns.lineplot(x='Algorithm',y='Precision',data=final,palette='hot',label='Precision')
sns.lineplot(x='Algorithm',y='recall',data=final,palette='hot',label='recall')
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x17f2924c8c8>