credit-defaulter-analysis

July 27, 2023

[1]:
```
### library
from ISLP import load_data
import seaborn as sns
import pandas as pd
import sklearn.linear_model as skl
import numpy as np
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
```

[2]:
```
df=load_data("Default")  ### loading of Defaulter data
```

1 About the Data

[3]:
```
df
```

[3]:

	default	student	balance	income
0	No	No	729.526495	44361.625074
1	No	Yes	817.180407	12106.134700
2	No	No	1073.549164	31767.138947
3	No	No	529.250605	35704.493935
4	No	No	785.655883	38463.495879
…	…	…	…	…
9995	No	No	711.555020	52992.378914
9996	No	No	757.962918	19660.721768
9997	No	No	845.411989	58636.156984
9998	No	No	1569.009053	36669.112365
9999	No	Yes	200.922183	16862.952321

[10000 rows x 4 columns]

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 4 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
```

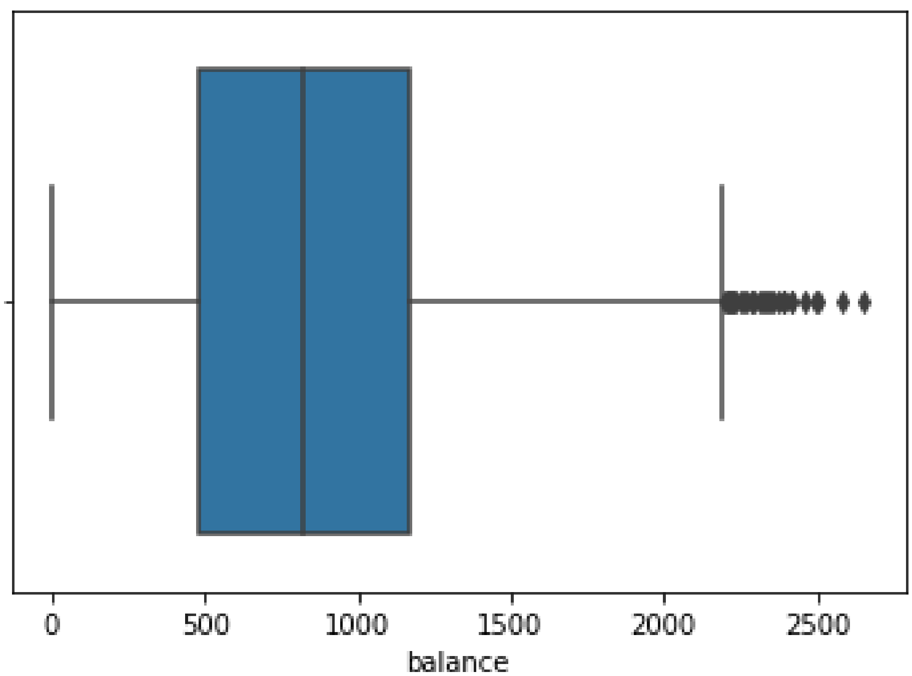
 0   default   10000 non-null   object
 1   student   10000 non-null   object
 2   balance   10000 non-null   float64
 3   income   10000 non-null   float64
dtypes: float64(2), object(2)
memory usage: 312.6+ KB

2 variables are categorical and other 2 are continous

2 Exploratory Data Analysis

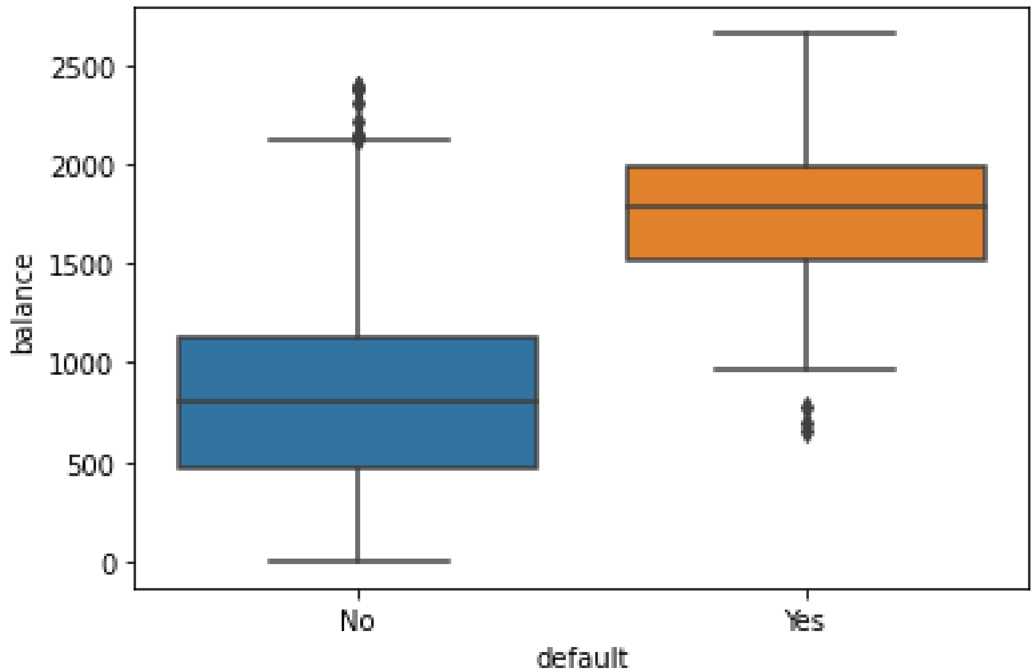
[5]:
```
sns.boxplot(x="balance", data=df)  ## boxplot of balance
```

[5]: <Axes: xlabel='balance'>



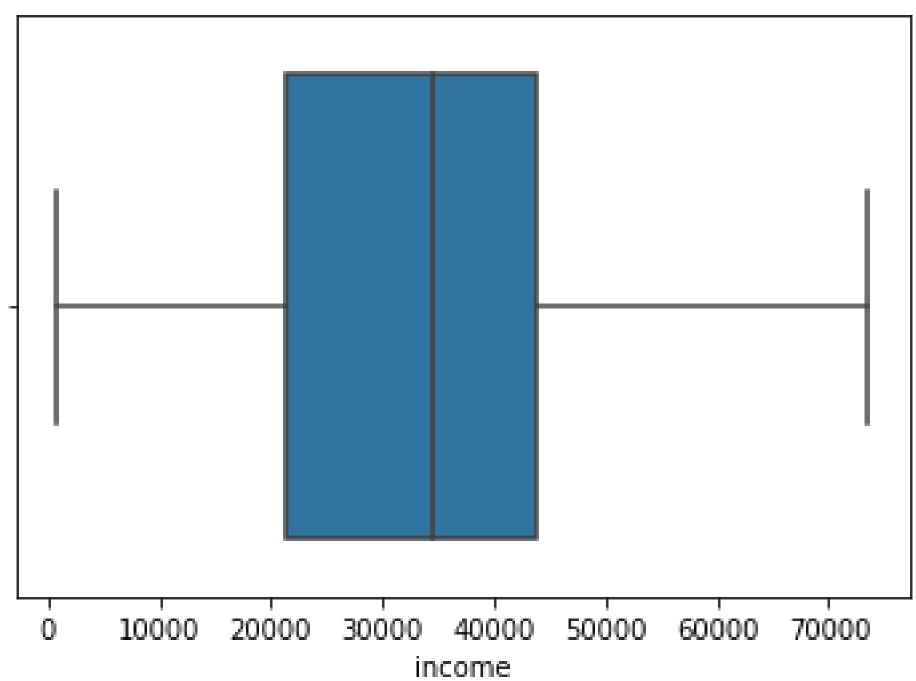
[6]:
```
sns.boxplot(y="balance", x='default', data=df)
```

[6]: <Axes: xlabel='default', ylabel='balance'>



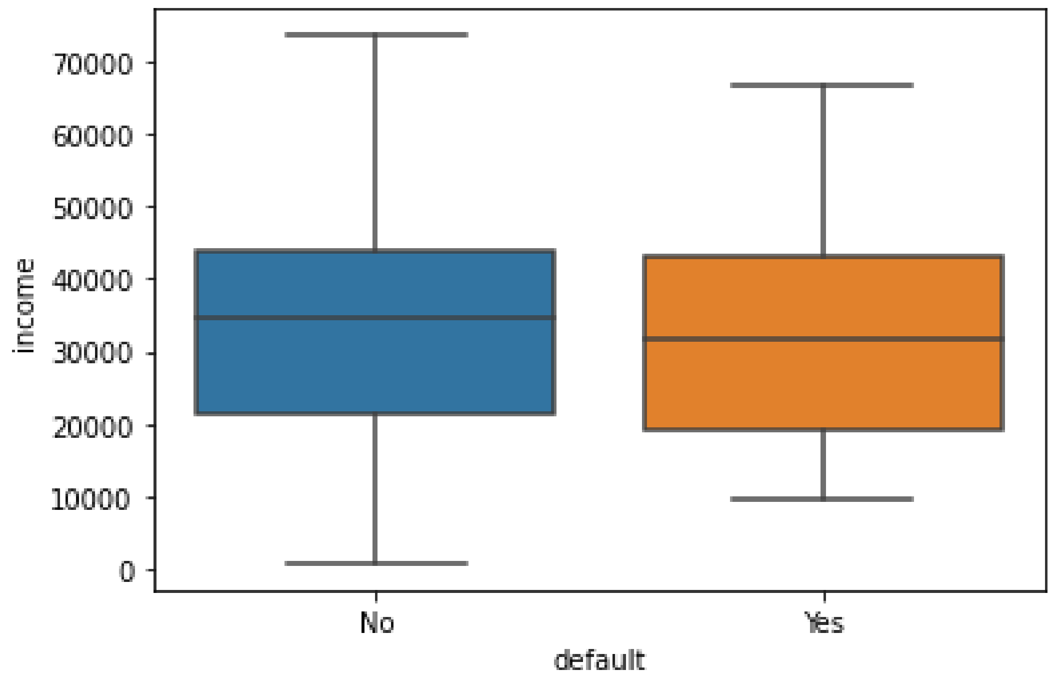
[7]:
```
sns.boxplot(x="income", data=df)
```

[7]: <Axes: xlabel='income'>



[8]:
```
sns.boxplot(y="income", x='default', data=df)
```

[8]: <Axes: xlabel='default', ylabel='income'>



Observation :

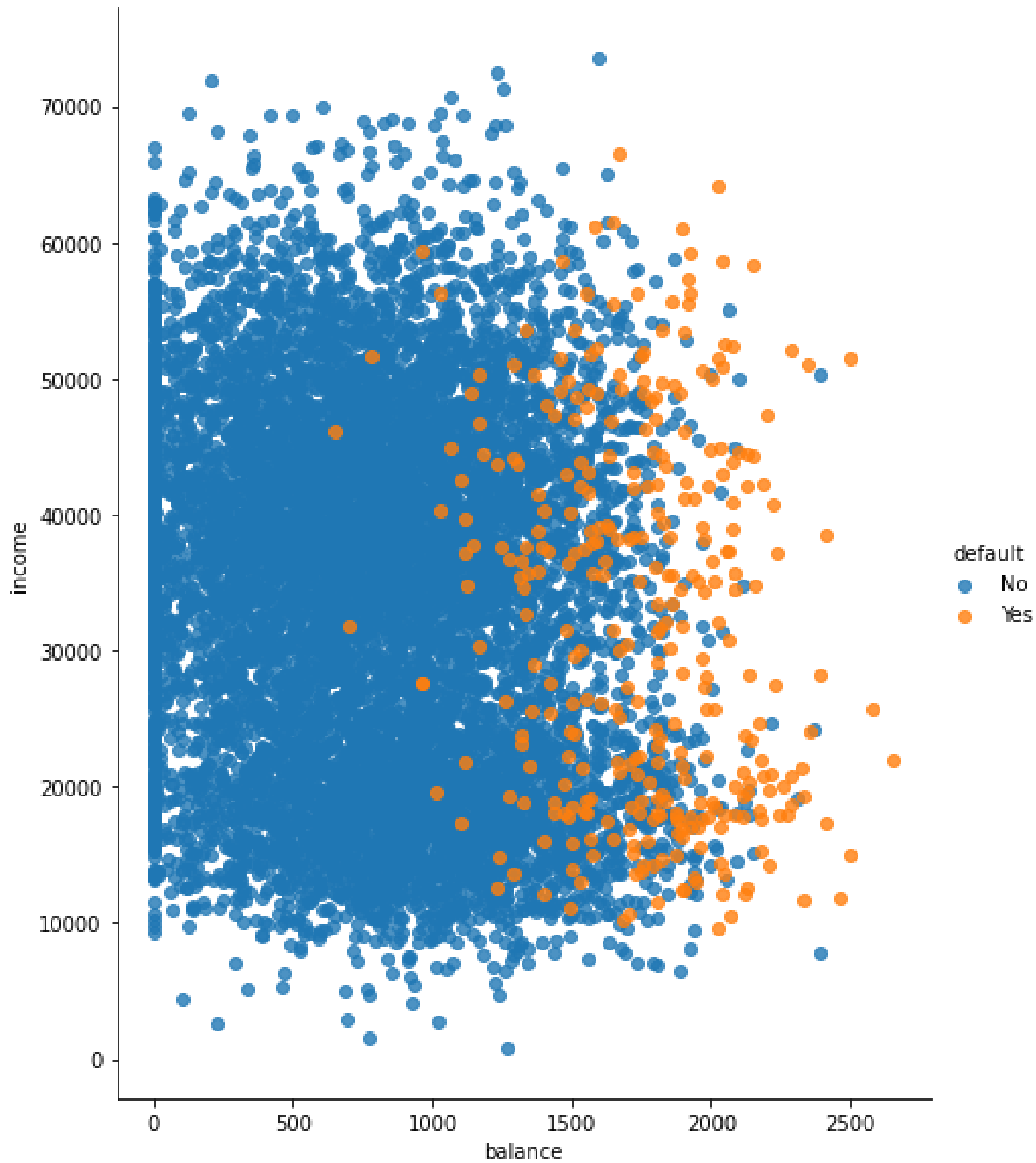
1> There are some outliers corresponding to the variable "balance". This variable ranges from 500 to 1200 (subject to the corresponding unit) in general. In the light of the given data, it seems that the defaulters have high balance in general.

2> There are no outliers corresponding to the variable "income". This variable ranges from 20000 to 43000 (subject to the corresponding unit) in general. In the light of the given data, it seems that the income status has no significant impact for the defaulters in general.

[9]:
```
sns.
 ↪lmplot(x="balance",y="income",data=df,hue="default",fit_reg=False,height=8,aspect=0.
 ↪8)
```

```
D:\Anaconda 1\lib\site-packages\seaborn\axisgrid.py:64: UserWarning: The figure
layout has changed to tight
  self.fig.tight_layout(*args, **kwargs)
```

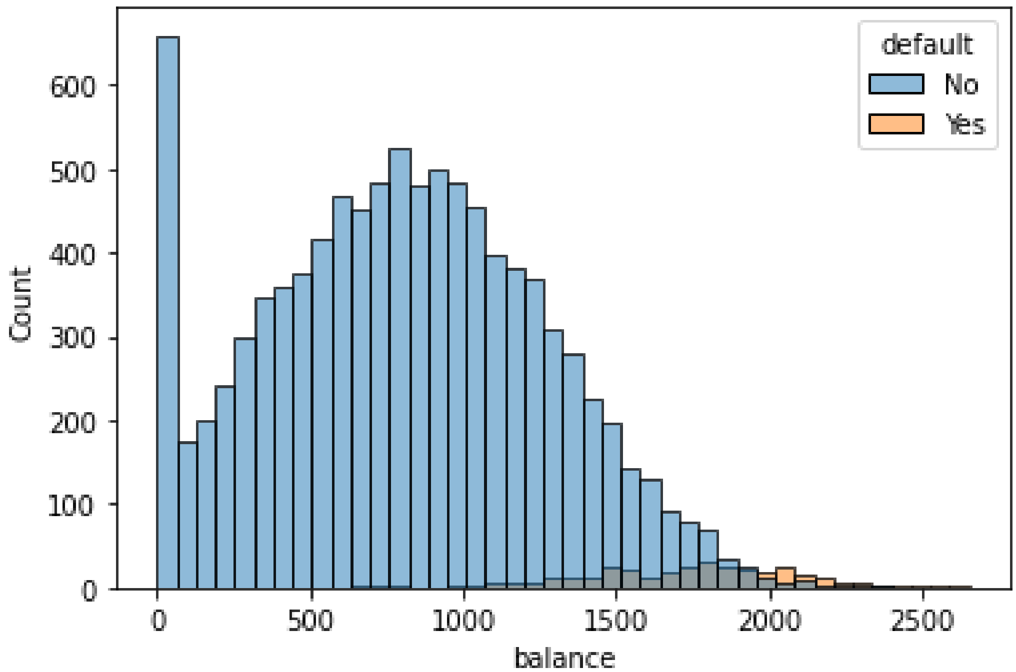
[9]: <seaborn.axisgrid.FacetGrid at 0x208b04f2af0>



It is very clear that balance for defaulters are higher than those of non-defaulter on average. This goes in line with the observation we made from the box plot. Moreover, there is no significant relationship between balance and income in light of the given data.

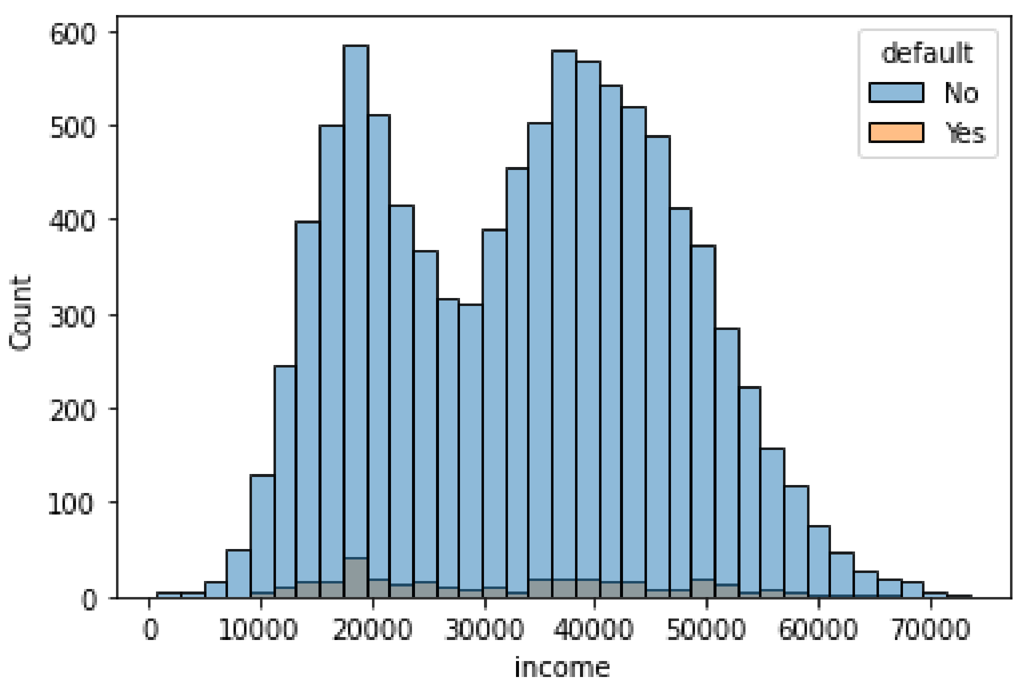
[10]:
```
sns.histplot(x="balance",data=df,hue="default")    ##### histogram of balance
```

[10]: <Axes: xlabel='balance', ylabel='Count'>



[11]:
```
sns.histplot(x="income",data=df,hue="default")
```

[11]: <Axes: xlabel='income', ylabel='Count'>



Observation :

1> For the non-defaulters we observe that many of them have balance 0, also there are a no. of people who have high balance.

2 > For the defaulters most of them have moderate or high balance.

3 > For the non-defaulters the income distribution seems to be bimodal. There is no significant difference in the income status which goes in line with the boxplot above.

4 > For the non-defaulters the balance has an inflation at 0. This seems to be the reason for the fact that the balance for non-defaulters are as a whole lower than those of defaulters which is the immediate consequence for boxplot of balance.

[12]:
```
pd.crosstab(index=df["default"],columns=df["student"])
```

[12]:
```
student     No   Yes
default
No        6850  2817
Yes        206   127
```

Observation :

1 > Percentage of student defaulter is higher than the non-student defaulters.

2 > Our data has more non-defaulter individuals compared to defaulter individuals. So it seems that the data is imbalanced.

3 Logistic Regression

[13]:
```
from sklearn.preprocessing import LabelEncoder   ### label encoding
lab=LabelEncoder()
df["student"]=lab.fit_transform(df["student"])
```

[14]:
```
x=df.drop("default",axis=1)
y=df["default"]

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=0)
```

[15]:
```
logistic_model=skl.LogisticRegression(max_iter=500)
logistic_model.fit(x_train,y_train)
```

[15]:
```
LogisticRegression(max_iter=500)
```

[16]:
```
logistic_model.intercept_
```

[16]:
```
array([-2.86828093])
```

[17]:
```
logistic_model.feature_names_in_
```

[17]:
```
array(['student', 'balance', 'income'], dtype=object)
```

[18]:
```
logistic_model.coef_
```

[18]:
```
array([[-3.79898798e+00,  4.06908863e-03, -1.37600242e-04]])
```

[19]:
```
y_pred_logistic=logistic_model.predict(x_test)
from sklearn.metrics import confusion_matrix as cm
c_logistic=cm(y_pred_logistic,y_test)
c_logistic
```

[19]:
```
array([[1915,   59],
       [  11,   15]], dtype=int64)
```

[20]:
```
# misclassification error
(c_logistic[1][0]+c_logistic[0][1])/c_logistic.sum()
```

[20]:
```
0.035
```

[21]:
```
## f1 score
pre=(c_logistic[0][0])/(c_logistic[0][0]+c_logistic[0][1])
re=(c_logistic[0][0])/(c_logistic[0][0]+c_logistic[1][0])
2*pre*re/(pre+re)
```

[21]:
```
0.982051282051282
```

On performing logistic regression, the misclassification error is 0.035 and F1 score is 0.98205.

4 Decision Tree

[22]:
```
from sklearn.tree import (DecisionTreeClassifier as DTC,export_graphviz)
Classifier=DTC(random_state=0,min_samples_split=50,max_depth=4)
Classifier.fit(x_train,y_train)
fn=['student', 'balance', 'income']
cn=["NO","YES"]
```

[23]:
```
export_graphviz(Classifier,out_file="credit.dot",
                     feature_names = fn,
                     class_names=cn,
                     filled = True)
```

[24]:
```
y_pred_dec=Classifier.predict(x_test)
c_dec=cm(y_pred_dec,y_test)
c_dec
```

[24]: array([[1918,   56],
       [8,   18]], dtype=int64)

[25]:
```
# misclassification error
(c_dec[1][0]+c_dec[0][1])/c_dec.sum()
```

[25]: 0.032

[26]:
```
## f1 score
pre=(c_dec[0][0])/(c_dec[0][0]+c_dec[0][1])
re=(c_dec[0][0])/(c_dec[0][0]+c_dec[1][0])
2*pre*re/(pre+re)
```

[26]: 0.9835897435897435

On applying decision tree algorithm for classification, the misclassification error is 0.032 and F1 score is 0.983589. Since we had 10000 data points, in order to prevent overfitting we fixed minimum no. of samples per leaf to 50 and max depth of the tree to 4.

5 Random Forest

[27]:
```
from sklearn.ensemble import RandomForestClassifier as RC
```

[28]:
```
Random_forest=RC(random_state=0,bootstrap=True,oob_score=True,max_features=2,max_depth=4,min_s
Random_forest.fit(x_train,y_train)
```

[28]: RandomForestClassifier(max_depth=4, max_features=2, max_samples=6000,
                       min_samples_leaf=50, oob_score=True, random_state=0)

[29]:
```
y_pred_rc=Random_forest.predict(x_test)
```

[30]:
```
c_rf=cm(y_pred_rc,y_test)
c_rf
```

[30]: array([[1921,   51],
       [5,   23]], dtype=int64)

[31]:
```
# misclassification error
(c_rf[1][0]+c_rf[0][1])/c_rf.sum()
```

[31]: 0.028

[32]:
```
## f1 score
pre=(c_rf[0][0])/(c_rf[0][0]+c_rf[0][1])
re=(c_rf[0][0])/(c_rf[0][0]+c_rf[1][0])
2*pre*re/(pre+re)
```

[32]: 0.9856336582863007

[33]:
```
Random_forest.oob_score_
```

[33]: 0.9735

On applying random forest algorithm for classification, the misclassification error is 0.028 and F1 score is 0.985633. In our training data we had 8000 data points, each time we obtained a bootstrapped dataset by choosing 6000 data points randomly with replacements. In each of the trees we had min samples per leaf 50 and max depth of the tree 4.

6 Comparison

Misclassification error : Random forest $<$ Decision tree $<$ Logistic Regression

F1 score : Random forest $>$ Decision tree $>$ Logistic Regression