predictive-potential-spammer

February 8, 2024

1 Model For Predictive Potential Spammer

[3]:
```
# Enable GPU in Colab
from tensorflow.python.client import device_lib
device_lib.list_local_devices()
```

[3]:
```
[name: "/device:CPU:0"
 device_type: "CPU"
 memory_limit: 268435456
 locality {
 }
 incarnation: 3496969768930533623
 xla_global_id: -1]
```

[1]:
```
from IPython.display import display, Image

# Specify the URL of your image
image_url = 'https://st3.depositphotos.com/7652440/14222/v/1600/
 ↪depositphotos_142221644-stock-illustration-spammer-rubber-stamp.jpg'

# Display the image in the notebook
display(Image(url=image_url))
```

```
<IPython.core.display.Image object>
```

[4]:
```
#Importing the Libraries.
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

[5]:
```
#Importing the data
PPS_df = pd.read_csv("/content/fiverr_data.csv")
```

2 Data Exploration

[16]:
```
#See the data using head function.
PPS_df.head(10).T
```

[16]:

	0	1	2	3	4	5	6	\
label	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
user_id	1.0	2.0	3.0	4.0	5.0	6.0	7.0	
X1	20972.0	7362.0	21216.0	2261.0	4543.0	7353.0	13668.0	
X2	14.0	213.0	215.0	212.0	213.0	213.0	213.0	
X3	13.0	71.0	71.0	71.0	71.0	13.0	71.0	
X4	3.0	3.0	3.0	2.0	2.0	3.0	2.0	
X5	11.0	11.0	11.0	8.0	8.0	11.0	8.0	
X6	1.0	1.0	1.0	1.0	1.0	1.0	1.0	
X7	2.0	2.0	2.0	2.0	2.0	2.0	2.0	
X8	15.0	15.0	15.0	15.0	15.0	15.0	15.0	
X9	26.0	26.0	14.0	14.0	14.0	36.0	26.0	
X10	48955.0	48955.0	48955.0	48909.0	48955.0	1.0	48955.0	
X11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X12	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X13	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X14	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X15	0.0	0.0	1.0	0.0	0.0	0.0	0.0	
X16	10.0	10.0	14.0	11.0	13.0	10.0	10.0	
X17	2.0	2.0	0.0	0.0	1.0	2.0	7.0	
X18	7.0	9.0	11.0	7.0	11.0	8.0	7.0	
X19	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X20	1.0	1.0	1.0	1.0	1.0	0.0	1.0	
X21	12.0	12.0	11.0	13.0	25.0	19.0	15.0	
X22	11.0	12.0	11.0	13.0	19.0	15.0	12.0	
X23	1.0	2.0	1.0	0.0	5.0	2.0	1.0	
X24	0.0	0.0	0.0	1.0	0.0	0.0	2.0	
X25	0.0	0.0	0.0	0.0	1.0	0.0	0.0	
X26	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X27	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X28	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X29	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X30	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X31	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X32	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X33	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X34	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X35	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X36	1.0	1.0	1.0	1.0	1.0	1.0	1.0	
X37	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
X38	1.0	0.0	0.0	0.0	0.0	0.0	0.0	
X39	0.0	0.0	0.0	0.0	0.0	0.0	1.0	

X40	0.0	0.0	0.0	0.0	0.0	0.0	0.0
X41	0.0	0.0	0.0	0.0	0.0	0.0	0.0
X42	0.0	0.0	0.0	0.0	0.0	1.0	0.0
X43	0.0	0.0	0.0	0.0	0.0	0.0	0.0
X44	0.0	0.0	0.0	0.0	0.0	0.0	0.0
X45	0.0	0.0	0.0	0.0	0.0	0.0	0.0
X46	0.0	0.0	0.0	0.0	0.0	0.0	0.0
X47	0.0	0.0	0.0	0.0	0.0	0.0	0.0
X48	0.0	0.0	0.0	0.0	0.0	0.0	0.0
X49	0.0	0.0	0.0	1.0	0.0	1.0	1.0
X50	1.0	0.0	0.0	0.0	0.0	0.0	0.0
X51	0.0	0.0	0.0	0.0	0.0	0.0	0.0

	7	8	9
label	0.0	0.0	0.0
user_id	8.0	9.0	10.0
X1	6139.0	19774.0	2730.0
X2	211.0	211.0	46.0
X3	71.0	13.0	71.0
X4	3.0	3.0	3.0
X5	11.0	17.0	11.0
X6	1.0	1.0	1.0
X7	2.0	2.0	2.0
X8	15.0	15.0	15.0
X9	18.0	26.0	36.0
X10	48955.0	48955.0	48955.0
X11	0.0	0.0	0.0
X12	0.0	0.0	0.0
X13	0.0	0.0	0.0
X14	0.0	0.0	0.0
X15	0.0	0.0	0.0
X16	12.0	10.0	11.0
X17	0.0	2.0	0.0
X18	7.0	9.0	9.0
X19	0.0	0.0	0.0
X20	1.0	1.0	1.0
X21	11.0	18.0	14.0
X22	11.0	13.0	14.0
X23	1.0	1.0	0.0
X24	0.0	0.0	1.0
X25	0.0	0.0	0.0
X26	0.0	0.0	0.0
X27	0.0	0.0	0.0
X28	0.0	2.0	0.0
X29	0.0	0.0	0.0
X30	0.0	0.0	0.0
X31	0.0	0.0	0.0

X32	0.0	0.0	0.0
X33	0.0	0.0	0.0
X34	0.0	0.0	0.0
X35	0.0	0.0	0.0
X36	1.0	1.0	1.0
X37	0.0	0.0	0.0
X38	0.0	0.0	0.0
X39	0.0	0.0	0.0
X40	0.0	0.0	0.0
X41	0.0	0.0	0.0
X42	0.0	0.0	0.0
X43	0.0	0.0	0.0
X44	0.0	0.0	0.0
X45	0.0	0.0	0.0
X46	0.0	0.0	0.0
X47	0.0	0.0	0.0
X48	0.0	0.0	0.0
X49	0.0	0.0	1.0
X50	1.0	1.0	0.0
X51	0.0	0.0	0.0

[17]:
```
#See the data using tail function.
PPS_df.tail(5).T
```

[17]:

	458793	458794	458795	458796	458797
label	0.0	0.0	0.0	0.0	0.0
user_id	482931.0	482932.0	482933.0	482934.0	482935.0
X1	1.0	6139.0	1164.0	187.0	19901.0
X2	213.0	211.0	213.0	137.0	213.0
X3	13.0	13.0	13.0	14.0	13.0
X4	3.0	3.0	3.0	2.0	3.0
X5	16.0	11.0	11.0	2.0	11.0
X6	4.0	4.0	4.0	4.0	4.0
X7	4.0	4.0	4.0	4.0	4.0
X8	22.0	22.0	22.0	22.0	22.0
X9	27.0	28.0	26.0	14.0	14.0
X10	47159.0	43936.0	1.0	7193.0	49496.0
X11	0.0	0.0	0.0	0.0	0.0
X12	0.0	0.0	0.0	0.0	0.0
X13	0.0	0.0	0.0	0.0	0.0
X14	0.0	0.0	0.0	0.0	0.0
X15	0.0	0.0	1.0	0.0	0.0
X16	12.0	7.0	10.0	15.0	8.0
X17	3.0	0.0	0.0	0.0	0.0
X18	11.0	5.0	10.0	11.0	7.0
X19	4.0	1.0	0.0	0.0	0.0
X20	1.0	1.0	0.0	1.0	1.0

X21	16.0	16.0	39.0	17.0	12.0
X22	14.0	14.0	27.0	12.0	11.0
X23	5.0	9.0	3.0	1.0	0.0
X24	0.0	0.0	1.0	0.0	0.0
X25	0.0	0.0	1.0	0.0	1.0
X26	0.0	0.0	0.0	0.0	0.0
X27	0.0	0.0	0.0	0.0	0.0
X28	0.0	1.0	1.0	0.0	0.0
X29	0.0	0.0	0.0	0.0	0.0
X30	0.0	0.0	0.0	0.0	0.0
X31	1.0	2.0	1.0	1.0	2.0
X32	0.0	1.0	1.0	1.0	1.0
X33	0.0	0.0	0.0	0.0	0.0
X34	1.0	1.0	1.0	1.0	1.0
X35	1.0	1.0	1.0	1.0	1.0
X36	0.0	0.0	0.0	0.0	0.0
X37	0.0	0.0	0.0	0.0	0.0
X38	0.0	0.0	0.0	0.0	0.0
X39	0.0	0.0	0.0	1.0	0.0
X40	0.0	0.0	0.0	0.0	0.0
X41	0.0	0.0	0.0	0.0	0.0
X42	0.0	0.0	2.0	0.0	0.0
X43	0.0	0.0	0.0	0.0	0.0
X44	0.0	1.0	0.0	0.0	0.0
X45	0.0	0.0	0.0	0.0	0.0
X46	0.0	0.0	0.0	0.0	0.0
X47	0.0	0.0	0.0	0.0	0.0
X48	0.0	0.0	0.0	0.0	0.0
X49	0.0	0.0	1.0	0.0	0.0
X50	1.0	1.0	1.0	1.0	0.0
X51	0.0	0.0	0.0	0.0	0.0

[18]:
```
#See the random Rows present in the data.
PPS_df.sample(5).T
```

[18]:

	284378	254449	204596	119390	37842
label	0.0	0.0	0.0	0.0	0.0
user_id	299199.0	267630.0	215073.0	125546.0	39839.0
X1	17716.0	1.0	14435.0	12509.0	8835.0
X2	212.0	213.0	78.0	213.0	222.0
X3	13.0	51.0	33.0	13.0	14.0
X4	3.0	2.0	3.0	3.0	2.0
X5	11.0	8.0	16.0	17.0	2.0
X6	4.0	2.0	3.0	3.0	3.0
X7	2.0	9.0	3.0	11.0	2.0
X8	15.0	22.0	15.0	14.0	15.0
X9	14.0	14.0	14.0	14.0	14.0

X10	48955.0	48955.0	48955.0	47124.0	1.0
X11	0.0	0.0	0.0	0.0	0.0
X12	0.0	0.0	0.0	0.0	0.0
X13	0.0	0.0	0.0	0.0	0.0
X14	0.0	0.0	0.0	0.0	0.0
X15	0.0	1.0	0.0	0.0	0.0
X16	15.0	9.0	21.0	9.0	15.0
X17	2.0	2.0	0.0	6.0	0.0
X18	14.0	7.0	12.0	7.0	11.0
X19	0.0	0.0	0.0	1.0	0.0
X20	1.0	1.0	1.0	1.0	0.0
X21	75.0	29.0	14.0	16.0	13.0
X22	17.0	19.0	14.0	16.0	12.0
X23	1.0	2.0	0.0	4.0	0.0
X24	3.0	2.0	0.0	0.0	0.0
X25	1.0	0.0	0.0	0.0	1.0
X26	0.0	0.0	0.0	0.0	0.0
X27	0.0	0.0	0.0	0.0	0.0
X28	0.0	0.0	0.0	0.0	0.0
X29	0.0	0.0	0.0	0.0	0.0
X30	0.0	0.0	0.0	0.0	0.0
X31	1.0	0.0	0.0	0.0	0.0
X32	1.0	0.0	0.0	0.0	0.0
X33	0.0	0.0	0.0	0.0	0.0
X34	1.0	0.0	0.0	0.0	0.0
X35	1.0	0.0	0.0	0.0	0.0
X36	0.0	1.0	1.0	1.0	1.0
X37	0.0	0.0	0.0	0.0	0.0
X38	0.0	1.0	0.0	0.0	0.0
X39	0.0	0.0	1.0	1.0	1.0
X40	0.0	0.0	0.0	0.0	0.0
X41	0.0	0.0	0.0	0.0	0.0
X42	0.0	0.0	0.0	0.0	0.0
X43	0.0	0.0	0.0	0.0	0.0
X44	0.0	0.0	0.0	0.0	0.0
X45	0.0	0.0	0.0	0.0	0.0
X46	0.0	0.0	0.0	0.0	0.0
X47	0.0	0.0	0.0	0.0	0.0
X48	0.0	0.0	0.0	0.0	0.0
X49	1.0	1.0	0.0	0.0	0.0
X50	0.0	0.0	1.0	1.0	0.0
X51	0.0	0.0	0.0	0.0	0.0

[6]:
```
#using shape funnction to get data size(Rows,columns) of the data.
PPS_df.shape
```

[6]: (458798, 53)

[20]:
```
#getting the all names of the columns.
PPS_df.columns
```

[20]:
```
Index(['label', 'user_id', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X7', 'X8',
       'X9', 'X10', 'X11', 'X12', 'X13', 'X14', 'X15', 'X16', 'X17', 'X18',
       'X19', 'X20', 'X21', 'X22', 'X23', 'X24', 'X25', 'X26', 'X27', 'X28',
       'X29', 'X30', 'X31', 'X32', 'X33', 'X34', 'X35', 'X36', 'X37', 'X38',
       'X39', 'X40', 'X41', 'X42', 'X43', 'X44', 'X45', 'X46', 'X47', 'X48',
       'X49', 'X50', 'X51'],
      dtype='object')
```

[21]:
```
#using info method to see how my model looks like.
PPS_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 458798 entries, 0 to 458797
Data columns (total 53 columns):
 #   Column   Non-Null Count   Dtype
---  ------   --------------   -----
 0   label    458798 non-null  int64
 1   user_id  458798 non-null  int64
 2   X1       458798 non-null  int64
 3   X2       458798 non-null  int64
 4   X3       458798 non-null  int64
 5   X4       458798 non-null  int64
 6   X5       458798 non-null  int64
 7   X6       458798 non-null  int64
 8   X7       458798 non-null  int64
 9   X8       458798 non-null  int64
 10  X9       458798 non-null  int64
 11  X10      458798 non-null  int64
 12  X11      458798 non-null  int64
 13  X12      458798 non-null  int64
 14  X13      458792 non-null  float64
 15  X14      458798 non-null  int64
 16  X15      458798 non-null  int64
 17  X16      458798 non-null  int64
 18  X17      458798 non-null  int64
 19  X18      458798 non-null  int64
 20  X19      458798 non-null  int64
 21  X20      458798 non-null  int64
 22  X21      458798 non-null  int64
 23  X22      458798 non-null  int64
 24  X23      458798 non-null  int64
 25  X24      458798 non-null  int64
 26  X25      458798 non-null  int64
 27  X26      458798 non-null  int64
```

```
 28  X27      458798 non-null  int64
 29  X28      458798 non-null  int64
 30  X29      458798 non-null  int64
 31  X30      458798 non-null  int64
 32  X31      458798 non-null  int64
 33  X32      458798 non-null  int64
 34  X33      458798 non-null  int64
 35  X34      458798 non-null  int64
 36  X35      458798 non-null  int64
 37  X36      458798 non-null  int64
 38  X37      458798 non-null  int64
 39  X38      458798 non-null  int64
 40  X39      458798 non-null  int64
 41  X40      458798 non-null  int64
 42  X41      458798 non-null  int64
 43  X42      458798 non-null  int64
 44  X43      458798 non-null  int64
 45  X44      458798 non-null  int64
 46  X45      458798 non-null  int64
 47  X46      458798 non-null  int64
 48  X47      458798 non-null  int64
 49  X48      458798 non-null  int64
 50  X49      458798 non-null  int64
 51  X50      458798 non-null  int64
 52  X51      458798 non-null  int64
dtypes: float64(1), int64(52)
memory usage: 185.5 MB
```

[22]:
```
#lets check the null values present in the data.
PPS_df.isnull().sum()
```

[22]:
```
label      0
user_id    0
X1         0
X2         0
X3         0
X4         0
X5         0
X6         0
X7         0
X8         0
X9         0
X10        0
X11        0
X12        0
X13        6
X14        0
```

```
X15        0
X16        0
X17        0
X18        0
X19        0
X20        0
X21        0
X22        0
X23        0
X24        0
X25        0
X26        0
X27        0
X28        0
X29        0
X30        0
X31        0
X32        0
X33        0
X34        0
X35        0
X36        0
X37        0
X38        0
X39        0
X40        0
X41        0
X42        0
X43        0
X44        0
X45        0
X46        0
X47        0
X48        0
X49        0
X50        0
X51        0
dtype: int64
```

[2]:
```
#by using isnull ---> we clearly see that, there are null values present in the␣
 ↪data.
#columns which contains null values{X13}.
```

[24]:
```
#lets check the data type of the column variables wheather it contain integer,␣
 ↪float, or objects type of data.
PPS_df.dtypes
```

[24]:
```
label        int64
user_id      int64
X1           int64
X2           int64
X3           int64
X4           int64
X5           int64
X6           int64
X7           int64
X8           int64
X9           int64
X10          int64
X11          int64
X12          int64
X13        float64
X14          int64
X15          int64
X16          int64
X17          int64
X18          int64
X19          int64
X20          int64
X21          int64
X22          int64
X23          int64
X24          int64
X25          int64
X26          int64
X27          int64
X28          int64
X29          int64
X30          int64
X31          int64
X32          int64
X33          int64
X34          int64
X35          int64
X36          int64
X37          int64
X38          int64
X39          int64
X40          int64
X41          int64
X42          int64
X43          int64
X44          int64
X45          int64
```

```
X46          int64
X47          int64
X48          int64
X49          int64
X50          int64
X51          int64
dtype: object
```

[3]:
```
#Data is containing integer and float type of data.
```

[26]:
```
#checking the statistical measures of the data.  eg: mean , median , 50th␣
 ↪percentile, 75% or max etc.
PPS_df.describe().T
```

[26]:

	count	mean	std	min	25%	50%	\
label	458798.0	0.026855	0.161660	0.0	0.00	0.0	
user_id	458798.0	241363.771411	139440.017203	1.0	120595.25	241234.5	
X1	458798.0	10850.591243	7078.656632	1.0	4692.00	11574.0	
X2	458798.0	154.947696	67.952267	1.0	95.00	189.0	
X3	458798.0	28.107965	19.227303	1.0	13.00	14.0	
X4	458798.0	2.407831	0.800163	1.0	2.00	3.0	
X5	458798.0	10.985176	5.527487	1.0	8.00	11.0	
X6	458798.0	3.215446	0.811902	1.0	3.00	3.0	
X7	458798.0	5.082675	3.302548	1.0	2.00	5.0	
X8	458798.0	15.654039	4.993260	1.0	14.00	15.0	
X9	458798.0	17.663438	6.338223	1.0	14.00	14.0	
X10	458798.0	20368.205770	22837.166285	1.0	1.00	4378.5	
X11	458798.0	0.001796	0.042341	0.0	0.00	0.0	
X12	458798.0	0.007971	0.088923	0.0	0.00	0.0	
X13	458792.0	0.087454	0.310598	0.0	0.00	0.0	
X14	458798.0	0.019340	0.149538	0.0	0.00	0.0	
X15	458798.0	0.179563	0.479321	0.0	0.00	0.0	
X16	458798.0	11.909082	3.889814	1.0	9.00	12.0	
X17	458798.0	1.510190	1.867473	0.0	0.00	1.0	
X18	458798.0	9.116648	2.541091	1.0	7.00	9.0	
X19	458798.0	0.304940	3.552758	0.0	0.00	0.0	
X20	458798.0	0.512358	0.499848	0.0	0.00	1.0	
X21	458798.0	29.257200	32.999054	1.0	13.00	18.0	
X22	458798.0	16.166404	6.705688	1.0	12.00	14.0	
X23	458798.0	3.186806	4.143823	0.0	0.00	1.0	
X24	458798.0	0.203510	0.846675	0.0	0.00	0.0	
X25	458798.0	0.783177	2.852496	0.0	0.00	0.0	
X26	458798.0	0.022993	0.491043	0.0	0.00	0.0	
X27	458798.0	0.000000	0.000000	0.0	0.00	0.0	
X28	458798.0	0.444897	0.782575	0.0	0.00	0.0	
X29	458798.0	0.000000	0.000000	0.0	0.00	0.0	
X30	458798.0	0.000000	0.000000	0.0	0.00	0.0	

X31	458798.0	0.464124	0.900999	0.0	0.00	0.0
X32	458798.0	0.536768	1.486929	0.0	0.00	0.0
X33	458798.0	0.000000	0.000000	0.0	0.00	0.0
X34	458798.0	0.398201	0.635505	0.0	0.00	0.0
X35	458798.0	0.381710	0.626832	0.0	0.00	0.0
X36	458798.0	0.483285	0.551332	0.0	0.00	0.0
X37	458798.0	0.000532	0.031383	0.0	0.00	0.0
X38	458798.0	0.086814	0.355296	0.0	0.00	0.0
X39	458798.0	0.469900	0.721578	0.0	0.00	0.0
X40	458798.0	0.019344	0.152753	0.0	0.00	0.0
X41	458798.0	0.065436	0.392297	0.0	0.00	0.0
X42	458798.0	0.519900	1.557607	0.0	0.00	0.0
X43	458798.0	0.041033	0.253398	0.0	0.00	0.0
X44	458798.0	0.074793	0.432161	0.0	0.00	0.0
X45	458798.0	0.008123	0.089763	0.0	0.00	0.0
X46	458798.0	0.000000	0.000000	0.0	0.00	0.0
X47	458798.0	0.000000	0.000000	0.0	0.00	0.0
X48	458798.0	0.000000	0.000000	0.0	0.00	0.0
X49	458798.0	0.299703	0.458128	0.0	0.00	0.0
X50	458798.0	0.512291	0.499849	0.0	0.00	1.0
X51	458798.0	0.000072	0.008481	0.0	0.00	0.0

	75%	max
label	0.00	1.0
user_id	362157.75	482935.0
X1	16425.00	24234.0
X2	213.00	222.0
X3	37.00	94.0
X4	3.00	3.0
X5	16.00	17.0
X6	4.00	4.0
X7	8.00	11.0
X8	21.00	29.0
X9	23.00	38.0
X10	48955.00	49637.0
X11	0.00	1.0
X12	0.00	1.0
X13	0.00	10.0
X14	0.00	5.0
X15	0.00	14.0
X16	14.00	48.0
X17	3.00	26.0
X18	11.00	25.0
X19	0.00	213.0
X20	1.00	1.0
X21	32.00	913.0
X22	20.00	55.0

X23	4.00	15.0
X24	0.00	40.0
X25	1.00	688.0
X26	0.00	63.0
X27	0.00	0.0
X28	1.00	42.0
X29	0.00	0.0
X30	0.00	0.0
X31	1.00	201.0
X32	1.00	333.0
X33	0.00	0.0
X34	1.00	11.0
X35	1.00	10.0
X36	1.00	8.0
X37	0.00	10.0
X38	0.00	38.0
X39	1.00	32.0
X40	0.00	6.0
X41	0.00	56.0
X42	0.00	97.0
X43	0.00	33.0
X44	0.00	56.0
X45	0.00	1.0
X46	0.00	0.0
X47	0.00	0.0
X48	0.00	0.0
X49	1.00	1.0
X50	1.00	1.0
X51	0.00	1.0

1. Label (Target Variable):

The mean of the label is 0.026855, indicating that it is a highly imbalanced binary classification problem, as the mean is close to zero.

The maximum value is 1.0, suggesting that this is a binary classification task.

2. User ID:

The mean user ID is approximately 241363.771, indicating a potential large user base.

3. Features X1 to X51:

The features X1 to X51 have varying ranges and scales.

Some features, like X11, X12, X27, X29, X30, and X33, have a mean and standard deviation close to zero, suggesting that they might be mostly zeros.

Features like X10, X21, and X22 have a wide range, with a large standard deviation.

4. Highly Imbalanced Features:

Some features, like X27, X29, X30, X33, X46, X47, and X48, seem to be highly imbalanced with mean and standard deviation close to zero.

5. Outliers:

Features like X21, X22, X23, and X28 have higher maximum values compared to their 75th percentiles, suggesting potential outliers.

6. Missing Values: If X13 has a count of 42083 while other features have a count of 458792.0, it suggests that there might be one missing value in X13.

[27]:
```
#null values can also is different form eg.@,#,$,%,^,&,*,@,! etc. if there is␣
 ↪any null values present in this form we will use replace function with NaN␣
 ↪so that my function easily read the null values.
# Specify the characters to check
specified_chars = ['@', '#', '$', '%', '^', '&', '*', '@', '!']

# Create a boolean DataFrame indicating whether any of the specified characters␣
 ↪are present
contains_special_chars = PPS_df.isin(specified_chars)

# Check if any cell in the DataFrame contains the specified characters
contains_special_chars_anywhere = contains_special_chars.any().any()

# Display the result
if contains_special_chars_anywhere:
    print("The specified characters are present in your data.")
else:
    print("The specified characters are not present in your data.")
```

```
The specified characters are not present in your data.
```

[28]:
```
#checking the correlation of the data with each other.
PPS_df.corr()
```

[28]:

	label	user_id	X1	X2	X3	X4	X5	\
label	1.000000	0.061876	-0.032693	0.013588	0.029224	-0.160983	-0.120901	
user_id	0.061876	1.000000	0.013957	0.014969	-0.138243	0.295803	0.222938	
X1	-0.032693	0.013957	1.000000	-0.007159	-0.005513	0.074084	0.074294	
X2	0.013588	0.014969	-0.007159	1.000000	0.047257	0.011539	0.040342	
X3	0.029224	-0.138243	-0.005513	0.047257	1.000000	-0.334795	-0.318808	
X4	-0.160983	0.295803	0.074084	0.011539	-0.334795	1.000000	0.777915	
X5	-0.120901	0.222938	0.074294	0.040342	-0.318808	0.777915	1.000000	
X6	0.118793	0.723465	0.001220	0.018339	-0.157905	0.219334	0.147991	
X7	-0.119792	0.221098	0.016307	0.042581	-0.188255	0.490346	0.306014	
X8	0.048605	-0.114807	-0.011004	-0.042068	0.080587	-0.339239	-0.251238	
X9	-0.022055	0.190853	0.027944	0.059326	0.045473	0.075179	0.102487	
X10	-0.100047	0.069658	0.035474	-0.022699	-0.149559	0.322633	0.164281	
X11	0.120644	0.036195	-0.009772	0.006603	-0.005574	0.004757	0.008942	

```
X12      0.019983  0.031783 -0.078111  0.076462 -0.031508  0.029884  0.041073
X13     -0.010180  0.105058 -0.009566 -0.034400 -0.024930  0.035121  0.044008
X14     -0.017878  0.069924  0.003011 -0.011188  0.027997 -0.002490  0.003569
X15      0.062969  0.032686  0.017542 -0.047919 -0.005814  0.037062  0.028913
X16      0.057109 -0.040611 -0.029454 -0.045124  0.004233 -0.089475 -0.082818
X17      0.059880 -0.063109 -0.041145 -0.018894 -0.005007 -0.129450 -0.098735
X18      0.068317 -0.034246 -0.028100 -0.036959  0.012730 -0.081208 -0.063470
X19      0.255836  0.037780 -0.007009  0.019319  0.006929 -0.066074 -0.045547
X20     -0.108509  0.131372  0.043343 -0.029288 -0.160554  0.386188  0.216258
X21     -0.060306  0.038227  0.030616 -0.026332 -0.002741  0.119419  0.074735
X22     -0.137752 -0.026355  0.038910 -0.027644 -0.001407  0.171565  0.073889
X23     -0.012464  0.145683  0.003540 -0.024808 -0.013997  0.075210  0.047369
X24     -0.034945  0.004683  0.015655 -0.004497  0.012065  0.098003  0.043827
X25     -0.041365  0.010408  0.018310 -0.002501  0.019129  0.053826  0.025115
X26     -0.006049 -0.025403  0.000837  0.004643  0.019882 -0.082384 -0.037007
X27           NaN       NaN       NaN       NaN       NaN       NaN       NaN
X28     -0.052109  0.177716  0.026855 -0.042228 -0.091970  0.284021  0.182814
X29           NaN       NaN       NaN       NaN       NaN       NaN       NaN
X30           NaN       NaN       NaN       NaN       NaN       NaN       NaN
X31     -0.015480  0.516205  0.008644  0.009816 -0.084937  0.248845  0.170889
X32     -0.015020  0.394026 -0.001395 -0.018198 -0.053815  0.159760  0.094940
X33           NaN       NaN       NaN       NaN       NaN       NaN       NaN
X34     -0.028180  0.675787  0.018706  0.024032 -0.110252  0.317630  0.235063
X35     -0.024651  0.664375  0.016886  0.020590 -0.102802  0.306514  0.225344
X36     -0.125662 -0.495886  0.032489 -0.017314 -0.078314  0.347744  0.161736
X37     -0.002815  0.010361  0.000421 -0.003702 -0.006640  0.003254 -0.005759
X38     -0.036264  0.043413  0.009324 -0.029243  0.013163  0.059893 -0.006792
X39     -0.088430 -0.315717  0.019376 -0.018848 -0.136520  0.290729  0.163475
X40     -0.011593  0.000083  0.005827 -0.004527 -0.015763  0.059373  0.031833
X41     -0.022142  0.016208  0.012042 -0.009253 -0.006906  0.072874  0.041236
X42     -0.046576 -0.001015  0.021797 -0.001674  0.016148  0.049450  0.038266
X43     -0.023761  0.007723  0.001440 -0.013477 -0.001081  0.040131 -0.010210
X44     -0.022635  0.021242  0.012040 -0.011569 -0.010851  0.077870  0.046910
X45     -0.010978  0.039277 -0.007417 -0.032602 -0.038949  0.056899  0.049953
X46           NaN       NaN       NaN       NaN       NaN       NaN       NaN
X47           NaN       NaN       NaN       NaN       NaN       NaN       NaN
X48           NaN       NaN       NaN       NaN       NaN       NaN       NaN
X49     -0.098286 -0.013521  0.043650  0.021256  0.032632  0.258472  0.114467
X50     -0.076360  0.258356  0.015712  0.008627 -0.191943  0.492168  0.339178
X51      0.001771 -0.002797  0.000003 -0.000243  0.003013 -0.013637 -0.006208

               X6        X7        X8  …       X42       X43       X44  \
label    0.118793 -0.119792  0.048605  … -0.046576 -0.023761 -0.022635
user_id  0.723465  0.221098 -0.114807  … -0.001015  0.007723  0.021242
X1       0.001220  0.016307 -0.011004  …  0.021797  0.001440  0.012040
X2       0.018339  0.042581 -0.042068  … -0.001674 -0.013477 -0.011569
X3      -0.157905 -0.188255  0.080587  …  0.016148 -0.001081 -0.010851
```

X4	0.219334	0.490346	-0.339239	…	0.049450	0.040131	0.077870
X5	0.147991	0.306014	-0.251238	…	0.038266	-0.010210	0.046910
X6	1.000000	0.094531	-0.236773	…	-0.021187	-0.011643	0.012672
X7	0.094531	1.000000	-0.032051	…	0.000013	0.022997	0.058733
X8	-0.236773	-0.032051	1.000000	…	-0.008536	-0.017078	-0.017547
X9	0.012006	0.062717	-0.031472	…	0.006032	-0.010235	0.002008
X10	-0.022370	0.076571	-0.002275	…	0.087460	0.078391	0.021574
X11	0.034078	0.001120	-0.024505	…	-0.006292	-0.005650	0.001593
X12	0.035114	0.053673	-0.010121	…	-0.014970	-0.007164	-0.001901
X13	0.085747	0.018180	-0.035911	…	-0.004165	-0.006018	0.004580
X14	-0.010496	-0.008935	0.015800	…	0.009067	0.005517	0.004734
X15	0.046749	-0.008829	-0.007868	…	0.013310	0.001087	0.011052
X16	0.009670	-0.036996	0.017667	…	-0.026766	-0.001465	-0.014199
X17	-0.055560	0.017353	0.036490	…	-0.044289	-0.008889	-0.027197
X18	0.004857	-0.033064	-0.000272	…	-0.030143	-0.006191	-0.017106
X19	0.058725	-0.023610	0.033935	…	-0.017318	-0.012681	-0.004466
X20	0.013789	0.113875	-0.024958	…	0.099390	0.078269	0.051201
X21	0.010126	0.005061	-0.005906	…	0.525284	0.126166	0.195281
X22	-0.064821	0.056143	-0.008600	…	0.479763	0.144484	0.211701
X23	0.120450	0.024161	-0.015422	…	0.322421	0.088473	0.139351
X24	-0.003041	0.015110	-0.019007	…	0.022704	0.283643	0.058470
X25	-0.001970	0.014621	-0.005112	…	0.359683	0.044716	0.091343
X26	-0.016433	-0.052697	0.032308	…	0.190582	-0.007582	-0.008104
X27	NaN	NaN	NaN	…	NaN	NaN	NaN
X28	0.139227	0.131305	-0.106219	…	0.166095	0.046420	0.143766
X29	NaN	NaN	NaN	…	NaN	NaN	NaN
X30	NaN	NaN	NaN	…	NaN	NaN	NaN
X31	0.429778	0.141532	-0.167007	…	0.012169	0.018400	0.035134
X32	0.330691	0.106679	-0.105813	…	-0.002067	0.021431	0.019683
X33	NaN	NaN	NaN	…	NaN	NaN	NaN
X34	0.573770	0.199198	-0.187852	…	0.006977	0.013081	0.036727
X35	0.561880	0.175255	-0.209151	…	0.011939	0.015162	0.037065
X36	-0.479080	0.213791	-0.047218	…	0.058091	0.063758	0.049354
X37	0.008506	0.008156	0.000006	…	-0.003605	-0.000277	-0.000040
X38	-0.237015	0.094247	0.122487	…	0.017437	0.036790	0.026758
X39	-0.130184	0.143455	-0.128272	…	0.041458	0.038225	0.056835
X40	-0.000827	0.042857	0.000830	…	0.024825	0.010014	0.366336
X41	0.007233	0.053929	-0.016864	…	0.081369	0.024516	0.931156
X42	-0.021187	0.000013	-0.008536	…	1.000000	0.026807	0.072688
X43	-0.011643	0.022997	-0.017078	…	0.026807	1.000000	0.024679
X44	0.012672	0.058733	-0.017547	…	0.072688	0.024679	1.000000
X45	0.029101	0.039702	-0.019372	…	-0.008195	0.021951	0.005295
X46	NaN	NaN	NaN	…	NaN	NaN	NaN
X47	NaN	NaN	NaN	…	NaN	NaN	NaN
X48	NaN	NaN	NaN	…	NaN	NaN	NaN
X49	-0.046905	0.109300	-0.075918	…	0.409815	0.120854	0.069188
X50	0.139608	0.388176	-0.239834	…	0.060822	0.036785	-0.025137

```
X51     -0.000984 -0.008928  0.006455  …  0.016474 -0.001373 -0.001468
```

	X45	X46	X47	X48	X49	X50	X51
label	-0.010978	NaN	NaN	NaN	-0.098286	-0.076360	0.001771
user_id	0.039277	NaN	NaN	NaN	-0.013521	0.258356	-0.002797
X1	-0.007417	NaN	NaN	NaN	0.043650	0.015712	0.000003
X2	-0.032602	NaN	NaN	NaN	0.021256	0.008627	-0.000243
X3	-0.038949	NaN	NaN	NaN	0.032632	-0.191943	0.003013
X4	0.056899	NaN	NaN	NaN	0.258472	0.492168	-0.013637
X5	0.049953	NaN	NaN	NaN	0.114467	0.339178	-0.006208
X6	0.029101	NaN	NaN	NaN	-0.046905	0.139608	-0.000984
X7	0.039702	NaN	NaN	NaN	0.109300	0.388176	-0.008928
X8	-0.019372	NaN	NaN	NaN	-0.075918	-0.239834	0.006455
X9	-0.026352	NaN	NaN	NaN	0.008226	0.029524	-0.002712
X10	0.030394	NaN	NaN	NaN	0.256533	0.216750	-0.002546
X11	-0.001545	NaN	NaN	NaN	-0.019883	0.014920	-0.000360
X12	-0.006474	NaN	NaN	NaN	-0.025950	0.033961	-0.000760
X13	0.037530	NaN	NaN	NaN	-0.031199	0.017977	-0.001561
X14	-0.004397	NaN	NaN	NaN	0.022676	-0.014655	-0.001097
X15	-0.005179	NaN	NaN	NaN	0.030002	-0.007269	-0.001032
X16	0.020668	NaN	NaN	NaN	-0.052592	-0.006665	-0.000396
X17	0.019680	NaN	NaN	NaN	-0.114951	0.006267	0.000435
X18	0.015119	NaN	NaN	NaN	-0.061601	0.007379	-0.000288
X19	-0.002731	NaN	NaN	NaN	-0.047781	-0.029838	0.002310
X20	0.031695	NaN	NaN	NaN	0.251406	0.152389	-0.003552
X21	0.008827	NaN	NaN	NaN	0.437517	-0.026602	0.006375
X22	0.024358	NaN	NaN	NaN	0.613288	0.064402	0.007417
X23	0.039622	NaN	NaN	NaN	0.252197	-0.072636	0.007246
X24	-0.000186	NaN	NaN	NaN	0.365113	-0.038465	-0.002039
X25	-0.010146	NaN	NaN	NaN	0.248120	-0.052625	0.009384
X26	-0.004238	NaN	NaN	NaN	-0.030632	-0.047990	0.024202
X27	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X28	0.085292	NaN	NaN	NaN	0.225757	0.053259	-0.004165
X29	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X30	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X31	0.051318	NaN	NaN	NaN	0.052079	0.157334	-0.004369
X32	0.039919	NaN	NaN	NaN	0.020519	0.094928	-0.003062
X33	NaN	NaN	NaN	NaN	NaN	NaN	NaN
X34	0.050241	NaN	NaN	NaN	0.042613	0.183268	-0.005314
X35	0.049017	NaN	NaN	NaN	0.053347	0.174875	-0.005165
X36	0.001533	NaN	NaN	NaN	0.240422	0.191303	-0.006502
X37	0.002335	NaN	NaN	NaN	-0.005780	-0.006669	-0.000144
X38	0.000919	NaN	NaN	NaN	0.085189	0.032860	-0.002072
X39	0.023579	NaN	NaN	NaN	0.143666	0.179036	-0.004811
X40	-0.006850	NaN	NaN	NaN	0.030870	-0.046690	-0.001074
X41	-0.003087	NaN	NaN	NaN	0.079210	-0.047796	-0.001415
X42	-0.008195	NaN	NaN	NaN	0.409815	0.060822	0.016474

```
X43      0.021951  NaN  NaN  NaN  0.120854  0.036785 -0.001373
X44      0.005295  NaN  NaN  NaN  0.069188 -0.025137 -0.001468
X45      1.000000  NaN  NaN  NaN -0.017331  0.050798 -0.000768
X46           NaN  NaN  NaN  NaN       NaN       NaN       NaN
X47           NaN  NaN  NaN  NaN       NaN       NaN       NaN
X48           NaN  NaN  NaN  NaN       NaN       NaN       NaN
X49     -0.017331  NaN  NaN  NaN  1.000000  0.144081 -0.004426
X50      0.050798  NaN  NaN  NaN  0.144081  1.000000 -0.007664
X51     -0.000768  NaN  NaN  NaN -0.004426 -0.007664  1.000000

[53 rows x 53 columns]
```

A correlation coefficient close to 1 indicates a strong positive correlation, while a value close to -1 indicates a strong negative correlation.

1. Correlation Direction:

Positive correlation means that as one variable increases, the other tends to increase.

Negative correlation means that as one variable increases, the other tends to decrease.

For instance, in the label row, the correlation with X1 is -0.032693, indicating a slight negative correlation.

2. Missing Values:

The presence of NaN (Not a Number) values in the correlation matrix indicates missing or undefined values for some pairs of variables.

3. Highly Correlated Variables:

Identifying pairs of variables with high correlation (close to 1 or -1) may indicate redundancy.

For example, X6 and user_id have a correlation coefficient of 0.723465, suggesting a strong positive correlation.

4. Correlation Magnitude:

The magnitude of the correlation coefficient indicates the strength of the relationship.

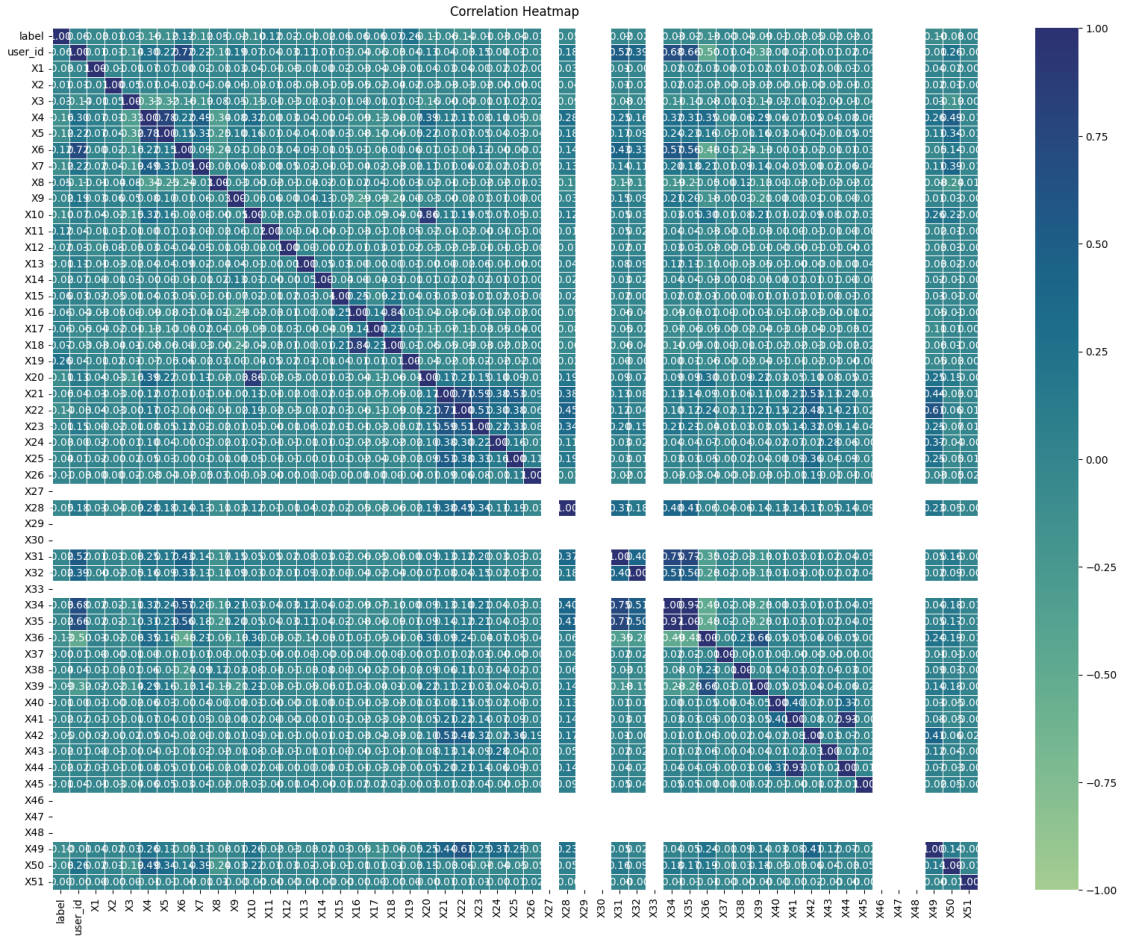
A correlation coefficient close to 0 suggests a weak or no linear relationship.

In the X42 row, the correlation between X3 and X9 is 0.045473 , suggesting a relatively weak positive correlation.

[7]:
```
PPS_df['X13']=PPS_df['X13'].fillna(PPS_df['X13'].mode())
```

[30]:
```
#visualizing the data using Heatmap.
plt.figure(figsize=(20,15))
heatmap = sns.heatmap(PPS_df.corr(), vmin=-1, vmax=1, annot=True, fmt=".2f",␣
 ↪linewidth=.5, cmap="crest")
heatmap.set_title('Correlation Heatmap', fontdict={'fontsize':12}, pad=12)
```

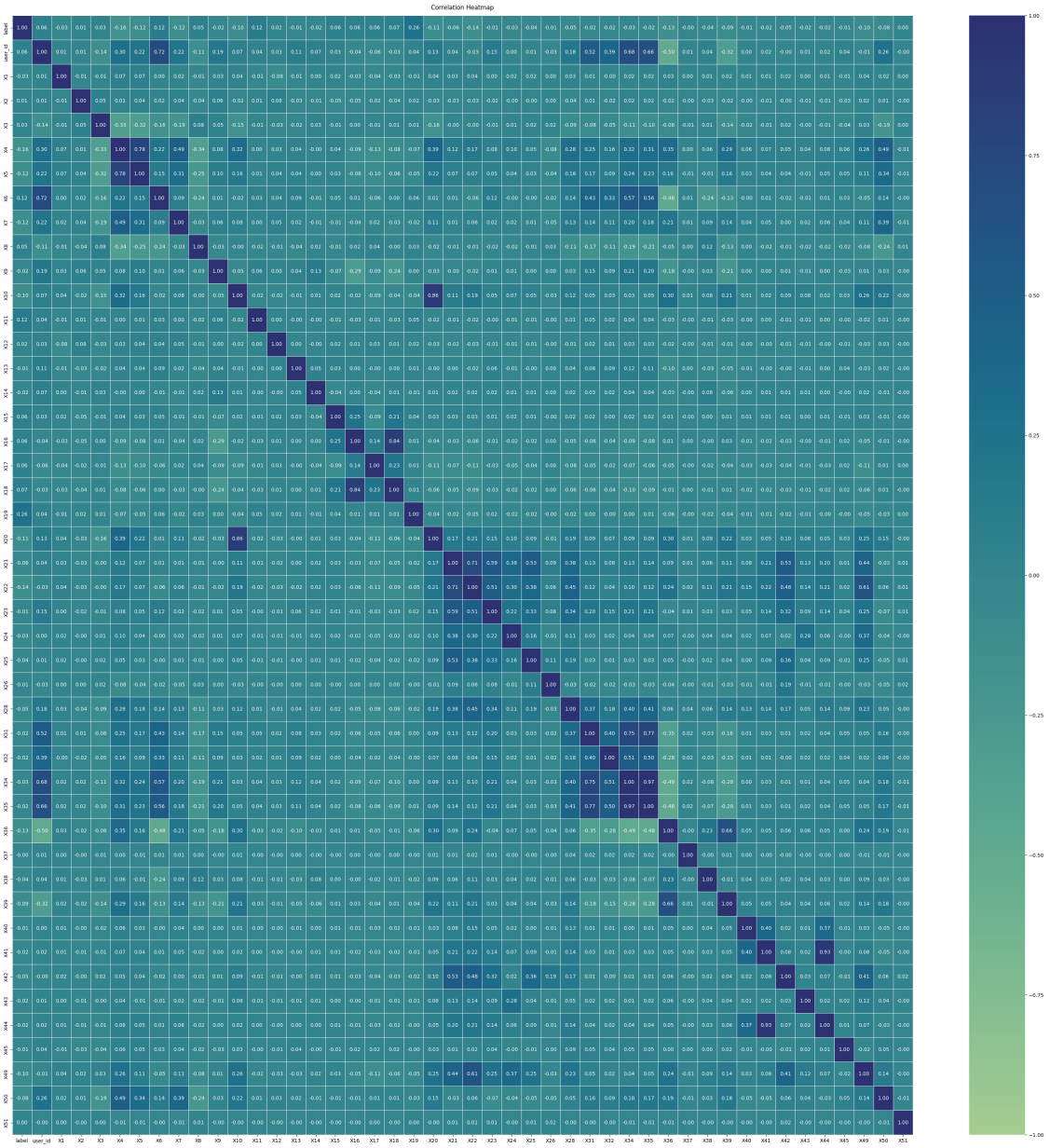
[30]:
```
Text(0.5, 1.0, 'Correlation Heatmap')
```



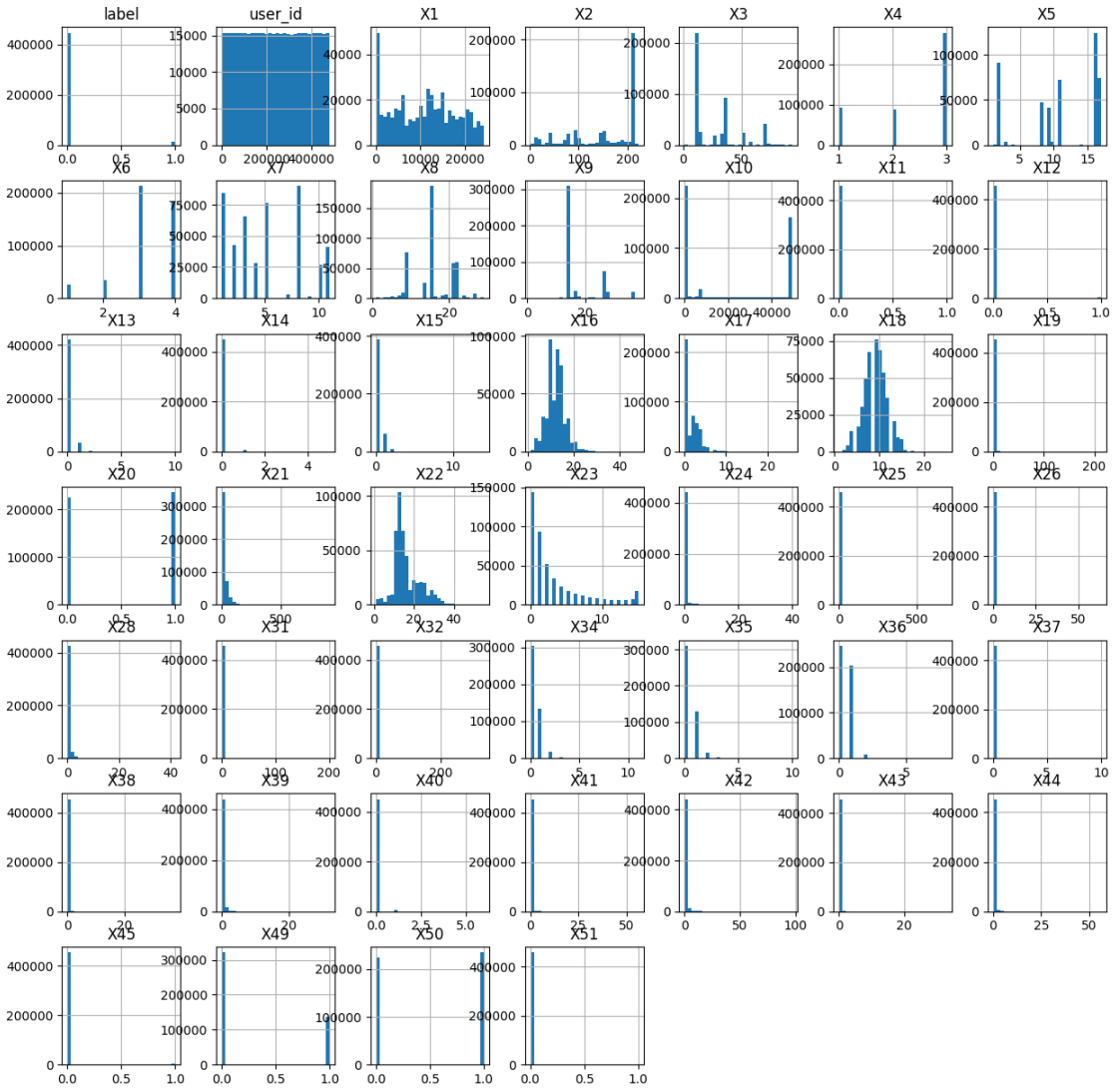
[8]:
```
#Dropping the unwanted columns having NAN values.
PPS_df.drop(columns=['X27','X29', 'X30', 'X33', 'X46', 'X47', 'X48'],␣
↪inplace=True)
```

[11]:
```
#Again visualizing the data to check wheather the NAN values is removed or not.
plt.figure(figsize=(40,40))
heatmap = sns.heatmap(PPS_df.corr(), vmin=-1, vmax=1, annot=True, fmt=".2f",␣
↪linewidth=.5, cmap="crest")
heatmap.set_title('Correlation Heatmap', fontdict={'fontsize':12}, pad=12)
```

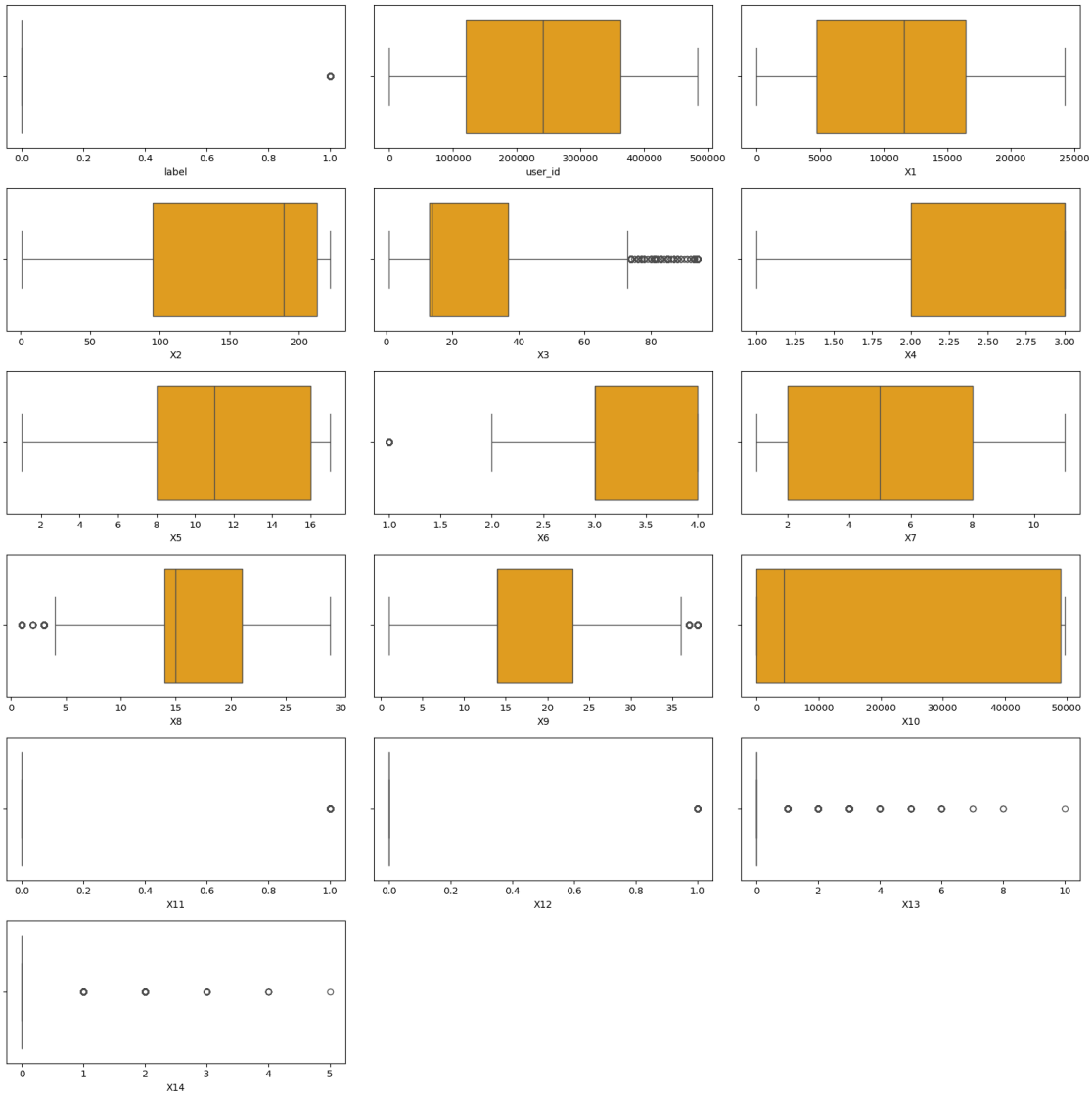
[11]:
```
Text(0.5, 1.0, 'Correlation Heatmap')
```



[33]:
```
#Multivariate Analysis
#visualizing the data using histogram chart.
PPS_df.hist(bins=30, figsize=(15,15))
plt.show()
```



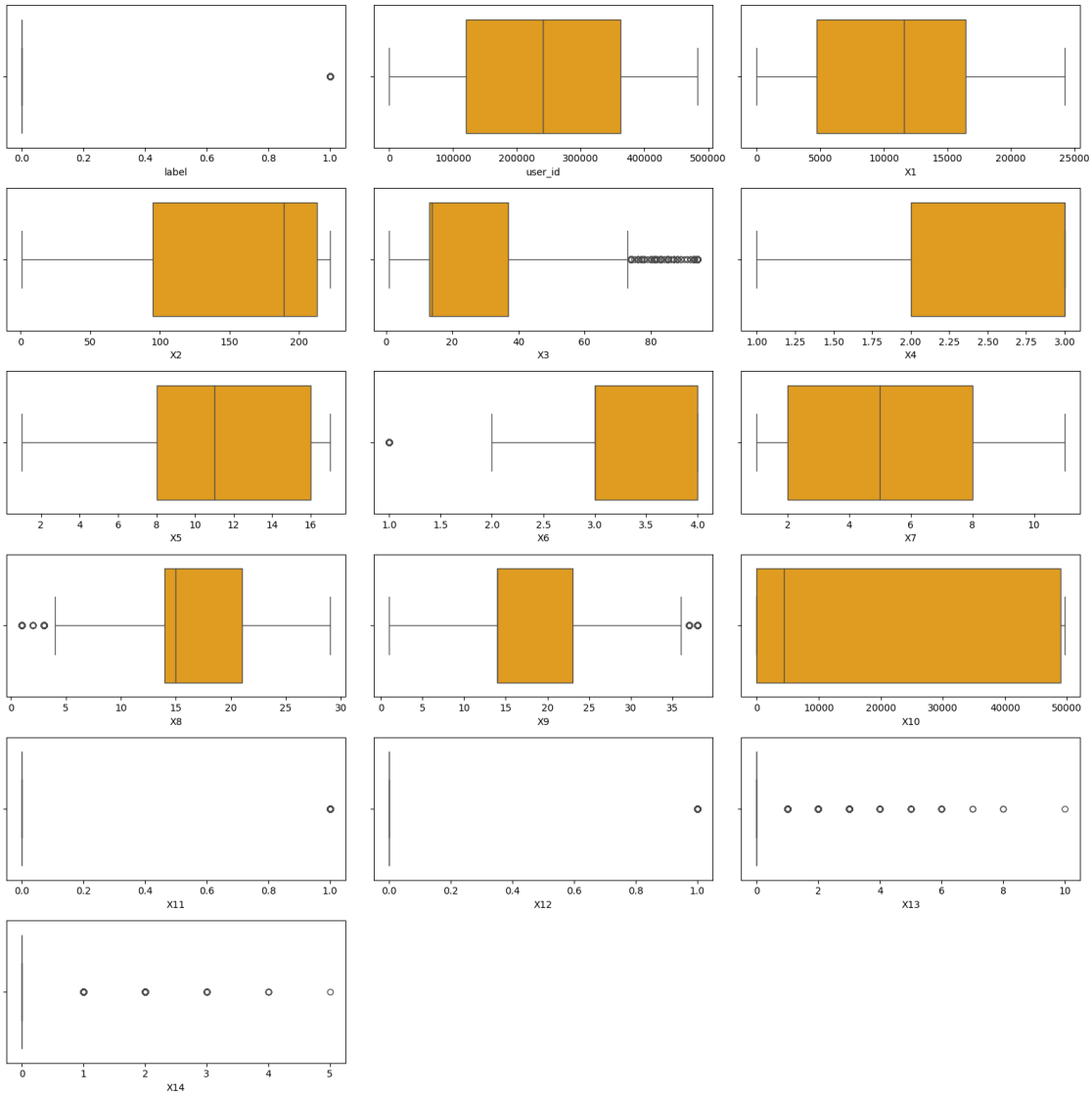
[34]:
```
#lets check the outliers by using box plot.
plt.figure(figsize=(16,16),facecolor='white')
pltnum =1
for column in PPS_df:
    if pltnum <= 16:
        ax = plt.subplot(6,3,pltnum)
        sns.boxplot(x=column,data=PPS_df,color='orange')
    pltnum +=1
plt.tight_layout()
plt.show()
```



[9]:
```python
# Function to treat outliers using the IQR method
def treat_outliers_iqr(PPS_df, factor = 1.5):
    Q1 = PPS_df.quantile(0.25)
    Q3 = PPS_df.quantile(0.75)
    IQR = Q3 - Q1

    lower_bound = Q1 - factor * IQR
    upper_bound = Q3 + factor * IQR

    # Cap outliers beyond the threshold
    PPS = PPS_df.apply(lambda x: min(max(x, lower_bound), upper_bound))

    return PPS_df
```

```
# Apply the IQR method to treat outliers for each numerical column
for column in PPS_df.select_dtypes(include=['number']).columns:
    PPS_df[column] = treat_outliers_iqr(PPS_df[column])
```

[10]:
```
#lets check the outliers by using box plot.
plt.figure(figsize=(16,16),facecolor='white')
pltnum =1
for column in PPS_df:
    if pltnum <= 16:
        ax = plt.subplot(6,3,pltnum)
        sns.boxplot(x=column,data=PPS_df,color='orange')
    pltnum +=1
plt.tight_layout()
plt.show()
```



[37]:
```
#Scaling the data.
```

[11]:
```
x_scale = PPS_df.iloc[:,1:]   #scaling independent variables of the data.
```

[12]:
```
#scaling data using Min Max scalar.
from sklearn.preprocessing import MinMaxScaler
scale = MinMaxScaler()
```

[13]:
```
PPS_scaled = scale.fit_transform(x_scale)
```

[14]:
```
PPS_scaled
```

[14]:
```
array([[0.00000000e+00, 8.65390170e-01, 5.88235294e-02, …,
        0.00000000e+00, 1.00000000e+00, 0.00000000e+00],
       [2.07067632e-06, 3.03759336e-01, 9.59276018e-01, …,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       [4.14135265e-06, 8.75459085e-01, 9.68325792e-01, …,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       …,
       [9.99995859e-01, 4.79924070e-02, 9.59276018e-01, …,
        1.00000000e+00, 1.00000000e+00, 0.00000000e+00],
       [9.99997929e-01, 7.67548384e-03, 6.15384615e-01, …,
        0.00000000e+00, 1.00000000e+00, 0.00000000e+00],
       [1.00000000e+00, 8.21194239e-01, 9.59276018e-01, …,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00]])
```

[15]:
```
PPS_sc = pd.DataFrame(PPS_scaled,columns=[ 'user_id', 'X1', 'X2', 'X3', 'X4',␣
 ↪'X5', 'X6', 'X7', 'X8',
       'X9', 'X10', 'X11', 'X12','X13', 'X14', 'X15', 'X16', 'X17', 'X18',␣
 ↪'X19',
       'X20', 'X21', 'X22', 'X23', 'X24', 'X25', 'X26', 'X28', 'X31', 'X32',
       'X34', 'X35', 'X36', 'X37', 'X38', 'X39', 'X40', 'X41', 'X42', 'X43',
       'X44', 'X45', 'X49', 'X50','X51'])
PPS_sc.head(5).T
```

[15]:

	0	1	2	3	4
user_id	0.000000	0.000002	0.000004	0.000006	0.000008
X1	0.865390	0.303759	0.875459	0.093261	0.187430
X2	0.058824	0.959276	0.968326	0.954751	0.959276
X3	0.129032	0.752688	0.752688	0.752688	0.752688
X4	1.000000	1.000000	1.000000	0.500000	0.500000
X5	0.625000	0.625000	0.625000	0.437500	0.437500
X6	0.000000	0.000000	0.000000	0.000000	0.000000
X7	0.100000	0.100000	0.100000	0.100000	0.100000

X8	0.500000	0.500000	0.500000	0.500000	0.500000
X9	0.675676	0.675676	0.351351	0.351351	0.351351
X10	0.986260	0.986260	0.986260	0.985333	0.986260
X11	0.000000	0.000000	0.000000	0.000000	0.000000
X12	0.000000	0.000000	0.000000	0.000000	0.000000
X13	0.000000	0.000000	0.000000	0.000000	0.000000
X14	0.000000	0.000000	0.000000	0.000000	0.000000
X15	0.000000	0.000000	0.071429	0.000000	0.000000
X16	0.191489	0.191489	0.276596	0.212766	0.255319
X17	0.076923	0.076923	0.000000	0.000000	0.038462
X18	0.250000	0.333333	0.416667	0.250000	0.416667
X19	0.000000	0.000000	0.000000	0.000000	0.000000
X20	1.000000	1.000000	1.000000	1.000000	1.000000
X21	0.012061	0.012061	0.010965	0.013158	0.026316
X22	0.185185	0.203704	0.185185	0.222222	0.333333
X23	0.066667	0.133333	0.066667	0.000000	0.333333
X24	0.000000	0.000000	0.000000	0.025000	0.000000
X25	0.000000	0.000000	0.000000	0.000000	0.001453
X26	0.000000	0.000000	0.000000	0.000000	0.000000
X28	0.000000	0.000000	0.000000	0.000000	0.000000
X31	0.000000	0.000000	0.000000	0.000000	0.000000
X32	0.000000	0.000000	0.000000	0.000000	0.000000
X34	0.000000	0.000000	0.000000	0.000000	0.000000
X35	0.000000	0.000000	0.000000	0.000000	0.000000
X36	0.125000	0.125000	0.125000	0.125000	0.125000
X37	0.000000	0.000000	0.000000	0.000000	0.000000
X38	0.026316	0.000000	0.000000	0.000000	0.000000
X39	0.000000	0.000000	0.000000	0.000000	0.000000
X40	0.000000	0.000000	0.000000	0.000000	0.000000
X41	0.000000	0.000000	0.000000	0.000000	0.000000
X42	0.000000	0.000000	0.000000	0.000000	0.000000
X43	0.000000	0.000000	0.000000	0.000000	0.000000
X44	0.000000	0.000000	0.000000	0.000000	0.000000
X45	0.000000	0.000000	0.000000	0.000000	0.000000
X49	0.000000	0.000000	0.000000	1.000000	0.000000
X50	1.000000	0.000000	0.000000	0.000000	0.000000
X51	0.000000	0.000000	0.000000	0.000000	0.000000

[43]:
```
#lets visualize our scaled data.
plt.figure(figsize=(40,40))
sns.heatmap(PPS_sc.corr(),annot=True,cmap=sns.cubehelix_palette(as_cmap=True))
```

[43]: <Axes: >

#Splitting independent and dependent data.

[16]:
```
X=PPS_sc
y=PPS_df["label"]
```

[17]:
```
X.T
```

[17]:

	0	1	2	3	4	5	6	\
user_id	0.000000	0.000002	0.000004	0.000006	0.000008	0.000010	0.000012	
X1	0.865390	0.303759	0.875459	0.093261	0.187430	0.303388	0.563983	

X2	0.058824	0.959276	0.968326	0.954751	0.959276	0.959276	0.959276
X3	0.129032	0.752688	0.752688	0.752688	0.752688	0.129032	0.752688
X4	1.000000	1.000000	1.000000	0.500000	0.500000	1.000000	0.500000
X5	0.625000	0.625000	0.625000	0.437500	0.437500	0.625000	0.437500
X6	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X7	0.100000	0.100000	0.100000	0.100000	0.100000	0.100000	0.100000
X8	0.500000	0.500000	0.500000	0.500000	0.500000	0.500000	0.500000
X9	0.675676	0.675676	0.351351	0.351351	0.351351	0.945946	0.675676
X10	0.986260	0.986260	0.986260	0.985333	0.986260	0.000000	0.986260
X11	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X12	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X13	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X14	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X15	0.000000	0.000000	0.071429	0.000000	0.000000	0.000000	0.000000
X16	0.191489	0.191489	0.276596	0.212766	0.255319	0.191489	0.191489
X17	0.076923	0.076923	0.000000	0.000000	0.038462	0.076923	0.269231
X18	0.250000	0.333333	0.416667	0.250000	0.416667	0.291667	0.250000
X19	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X20	1.000000	1.000000	1.000000	1.000000	1.000000	0.000000	1.000000
X21	0.012061	0.012061	0.010965	0.013158	0.026316	0.019737	0.015351
X22	0.185185	0.203704	0.185185	0.222222	0.333333	0.259259	0.203704
X23	0.066667	0.133333	0.066667	0.000000	0.333333	0.133333	0.066667
X24	0.000000	0.000000	0.000000	0.025000	0.000000	0.000000	0.050000
X25	0.000000	0.000000	0.000000	0.000000	0.001453	0.000000	0.000000
X26	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X28	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X31	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X32	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X34	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X35	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X36	0.125000	0.125000	0.125000	0.125000	0.125000	0.125000	0.125000
X37	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X38	0.026316	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X39	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.031250
X40	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X41	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X42	0.000000	0.000000	0.000000	0.000000	0.000000	0.010309	0.000000
X43	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X44	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X45	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X49	0.000000	0.000000	0.000000	1.000000	0.000000	1.000000	1.000000
X50	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
X51	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

	7	8	9	…	458788	458789	458790	\
user_id	0.000014	0.000017	0.000019	…	0.999981	0.999983	0.999986	
X1	0.253291	0.815953	0.112615	…	0.647547	0.617835	0.226509	

X2	0.950226	0.950226	0.203620	…	0.959276	0.959276	0.959276
X3	0.752688	0.129032	0.752688	…	0.440860	0.698925	0.129032
X4	1.000000	1.000000	1.000000	…	0.500000	0.500000	1.000000
X5	0.625000	1.000000	0.625000	…	0.437500	0.437500	0.937500
X6	0.000000	0.000000	0.000000	…	1.000000	1.000000	1.000000
X7	0.100000	0.100000	0.100000	…	0.300000	0.300000	0.300000
X8	0.500000	0.500000	0.500000	…	0.750000	0.750000	0.750000
X9	0.459459	0.675676	0.945946	…	0.351351	0.351351	0.432432
X10	0.986260	0.986260	0.986260	…	0.000000	0.991357	0.121041
X11	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X12	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X13	0.000000	0.000000	0.000000	…	0.000000	0.100000	0.000000
X14	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X15	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X16	0.234043	0.191489	0.212766	…	0.191489	0.170213	0.446809
X17	0.000000	0.076923	0.000000	…	0.153846	0.000000	0.153846
X18	0.250000	0.333333	0.333333	…	0.291667	0.250000	0.500000
X19	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X20	1.000000	1.000000	1.000000	…	0.000000	1.000000	1.000000
X21	0.010965	0.018640	0.014254	…	0.015351	0.013158	0.010965
X22	0.185185	0.222222	0.240741	…	0.166667	0.185185	0.166667
X23	0.066667	0.066667	0.000000	…	0.000000	0.066667	0.000000
X24	0.000000	0.000000	0.025000	…	0.000000	0.025000	0.000000
X25	0.000000	0.000000	0.000000	…	0.002907	0.000000	0.000000
X26	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X28	0.000000	0.047619	0.000000	…	0.000000	0.000000	0.000000
X31	0.000000	0.000000	0.000000	…	0.004975	0.004975	0.004975
X32	0.000000	0.000000	0.000000	…	0.003003	0.006006	0.003003
X34	0.000000	0.000000	0.000000	…	0.090909	0.090909	0.090909
X35	0.000000	0.000000	0.000000	…	0.100000	0.100000	0.100000
X36	0.125000	0.125000	0.125000	…	0.000000	0.000000	0.000000
X37	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X38	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X39	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X40	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X41	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X42	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X43	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X44	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X45	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000
X49	0.000000	0.000000	1.000000	…	0.000000	1.000000	0.000000
X50	1.000000	1.000000	0.000000	…	0.000000	0.000000	1.000000
X51	0.000000	0.000000	0.000000	…	0.000000	0.000000	0.000000

	458791	458792	458793	458794	458795	458796	458797
user_id	0.999988	0.999990	0.999992	0.999994	0.999996	0.999998	1.000000
X1	0.614781	0.000000	0.000000	0.253291	0.047992	0.007675	0.821194

```
X2      0.425339  0.959276  0.959276  0.950226  0.959276  0.615385  0.959276
X3      0.129032  0.129032  0.129032  0.129032  0.129032  0.139785  0.129032
X4      1.000000  1.000000  1.000000  1.000000  1.000000  0.500000  1.000000
X5      0.937500  0.625000  0.937500  0.625000  0.625000  0.062500  0.625000
X6      1.000000  1.000000  1.000000  1.000000  1.000000  1.000000  1.000000
X7      0.300000  0.300000  0.300000  0.300000  0.300000  0.300000  0.300000
X8      0.750000  0.750000  0.750000  0.750000  0.750000  0.750000  0.750000
X9      0.351351  0.702703  0.702703  0.729730  0.675676  0.351351  0.351351
X10     0.170662  0.000000  0.950077  0.885144  0.000000  0.144895  0.997159
X11     0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
X12     0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
X13     0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
X14     0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
X15     0.071429  0.000000  0.000000  0.000000  0.071429  0.000000  0.000000
X16     0.404255  0.148936  0.234043  0.127660  0.191489  0.297872  0.148936
X17     0.000000  0.115385  0.115385  0.000000  0.000000  0.000000  0.000000
X18     0.458333  0.291667  0.416667  0.166667  0.375000  0.416667  0.250000
X19     0.000000  0.000000  0.018779  0.004695  0.000000  0.000000  0.000000
X20     1.000000  0.000000  1.000000  1.000000  0.000000  1.000000  1.000000
X21     0.004386  0.014254  0.016447  0.016447  0.041667  0.017544  0.012061
X22     0.074074  0.203704  0.240741  0.240741  0.481481  0.203704  0.185185
X23     0.000000  0.000000  0.333333  0.600000  0.200000  0.066667  0.000000
X24     0.000000  0.000000  0.000000  0.000000  0.025000  0.000000  0.000000
X25     0.000000  0.000000  0.000000  0.000000  0.001453  0.000000  0.001453
X26     0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
X28     0.000000  0.023810  0.000000  0.023810  0.023810  0.000000  0.000000
X31     0.004975  0.004975  0.004975  0.009950  0.004975  0.004975  0.009950
X32     0.003003  0.003003  0.000000  0.003003  0.003003  0.003003  0.003003
X34     0.090909  0.090909  0.090909  0.090909  0.090909  0.090909  0.090909
X35     0.100000  0.100000  0.100000  0.100000  0.100000  0.100000  0.100000
X36     0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
X37     0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
X38     0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
X39     0.000000  0.000000  0.000000  0.000000  0.000000  0.031250  0.000000
X40     0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
X41     0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
X42     0.000000  0.000000  0.000000  0.000000  0.020619  0.000000  0.000000
X43     0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
X44     0.000000  0.000000  0.000000  0.017857  0.000000  0.000000  0.000000
X45     0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
X49     0.000000  0.000000  0.000000  0.000000  1.000000  0.000000  0.000000
X50     0.000000  1.000000  1.000000  1.000000  1.000000  1.000000  0.000000
X51     0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000

[45 rows x 458798 columns]
```

[18]:
```
y
```

[18]:
```
0         0
1         0
2         0
3         0
4         0
          ..
458793    0
458794    0
458795    0
458796    0
458797    0
Name: label, Length: 458798, dtype: int64
```

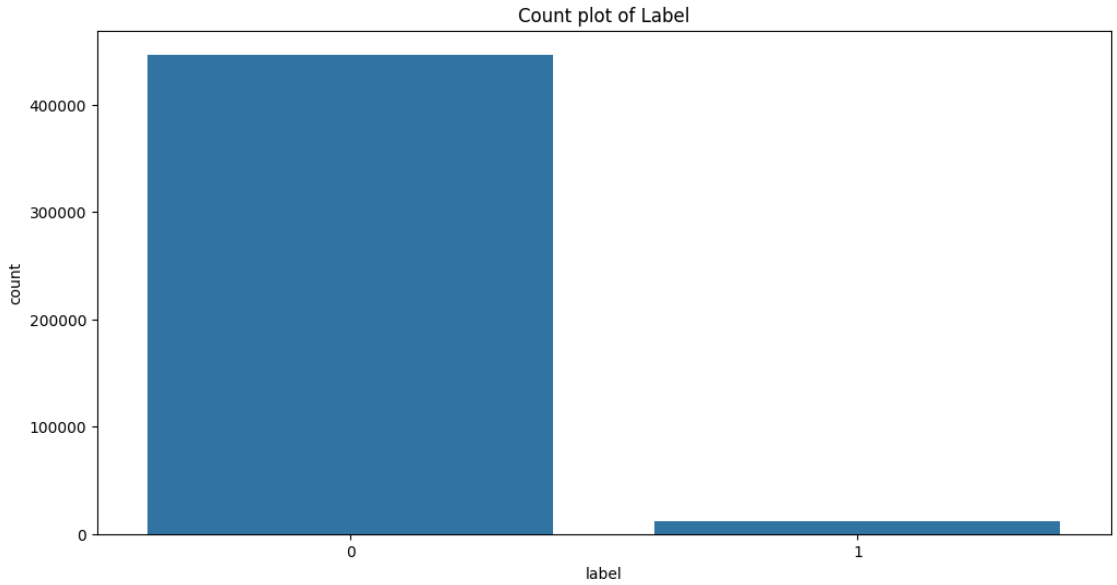
[19]:
```
#Creating Logistic model and impoting the libraries.
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
```

[20]:
```
#first check whether the dependent variables is labeled or not.
```

[21]:
```
PPS_df.label.value_counts()
```

[21]:
```
0    446477
1     12321
Name: label, dtype: int64
```

[22]:
```
# VISUALIZE target variable
plt.figure(figsize=(12,6))
sns.countplot(data=PPS_df, x = 'label')
plt.title('Count plot of Label')
plt.show()
```



[51]:
```
#dependent variable is not labeled. lets label is first.
```

[23]:
```
#this step i done here because there is a error come which tell me that there␣
 ↪are NAN values are present in the X_train data.
#checking the NAN values present in the X_train data.
nan_count = pd.DataFrame(X_train).isna().sum().sum()

if nan_count > 0:
    print("X_train contains NaN values.")
else:
    print("X_train does not contain NaN values.")
```

```
X_train contains NaN values.
```

[24]:
```
#there are NAN values present in the data.
#handeling NAN values by using impute method and replace NAN values by the mean.
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy="mean")
X_train = imputer.fit_transform(X_train)
```

[27]:
```
#now after handelling the NAN values, we are able to perform the labeling step␣
 ↪to labele the data.
#labelling the data by using SMOTE method.
```

[25]:
```
from imblearn.over_sampling import SMOTE
```

[26]:
```
oversample = SMOTE(random_state=42)

x_sampled,y_sampled = oversample.fit_resample(X_train,y_train)
```

[27]:
```
x_sampled.shape
```

[27]:
```
(714248, 45)
```

[28]:
```
y_sampled.value_counts()
```

[28]:
```
0    357124
1    357124
Name: label, dtype: int64
```

3 logistic model

[29]:
```
# Train a logistic regression model
logimodel = LogisticRegression()
logimodel.fit(X_train, y_train)
```

[29]:
```
LogisticRegression()
```

[30]:
```
# Make predictions on the training set
logi_train_pred = logimodel.predict(X_train)
```

[31]:
```
imputer = SimpleImputer(strategy="mean")
X_test = imputer.fit_transform(X_test)
```

[32]:
```
# Make predictions on the test set
logi_pred = logimodel.predict(X_test)
```

[33]:
```
# Evaluate accuracy on training and test sets
logi_train_accuracy = accuracy_score(y_train, logi_train_pred)
logi_test_accuracy = accuracy_score(y_test, logi_pred)
```

[34]:
```
print(f"Training Accuracy: {logi_train_accuracy}")
print(f"Test Accuracy: {logi_test_accuracy}")
```

```
Training Accuracy: 0.9770650450362088
Test Accuracy: 0.9778007846556234
```

[35]:
```
# Check for overfitting
if logi_train_accuracy > logi_test_accuracy:
    print("Warning: Model may be overfitting the training data.")
```

[36]:
```
logi_pred =logimodel.predict(X_test)
```

[37]:
```
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix
# Evaluate the model
logi_test_accuracy = accuracy_score(y_test, logi_pred)
logi_conf_matrix = confusion_matrix(y_test, logi_pred )
logi_classification_rep = classification_report(y_test, logi_pred )

# Display results
print(f'logi_test_accuracy: {logi_test_accuracy}')
print('\nlogi_Confusion Matrix:')
print(logi_conf_matrix)
print('\nlogi_Classification Report:')
print(logi_classification_rep)
```

```
logi_test_accuracy: 0.9778007846556234

logi_Confusion Matrix:
[[89219   134]
 [ 1903   504]]

logi_Classification Report:
              precision    recall  f1-score   support

           0       0.98      1.00      0.99     89353
           1       0.79      0.21      0.33      2407

    accuracy                           0.98     91760
   macro avg       0.88      0.60      0.66     91760
weighted avg       0.97      0.98      0.97     91760
```

1. Insights interpret from Confusion matrix -:

True Positive (TP): 89219

True Negative (TN): 504

False Positive (FP): 134

False Negative (FN): 1903

Insights:

1. Accuracy:

The overall accuracy of the model is 98%, indicating that it correctly predicts the class label for approximately 98% of the samples.

2. Precision:

Precision for class 0 (Negative class) is high (98%), indicating that when the model predicts the class as 0, it is correct 98% of the time. Precision for class 1 (Positive class) is lower (79%),

indicating that when the model predicts the class as 1, it is correct only 79% of the time.

3. Recall (Sensitivity):

Recall for class 0 is very high (100%), indicating that the model correctly identifies nearly all instances of class 0. Recall for class 1 is low (21%), indicating that the model fails to identify a significant portion of instances of class 1.

4. F1-Score:

The F1-score for class 0 is high (99%), reflecting a good balance between precision and recall for class 0. The F1-score for class 1 is relatively low (33%), indicating a lower balance between precision and recall for class 1.

5. Support:

The support represents the number of actual occurrences of each class in the dataset. Class 0 has much higher support (89353) compared to class 1 (2407), indicating class imbalance.

4 Decision tree model

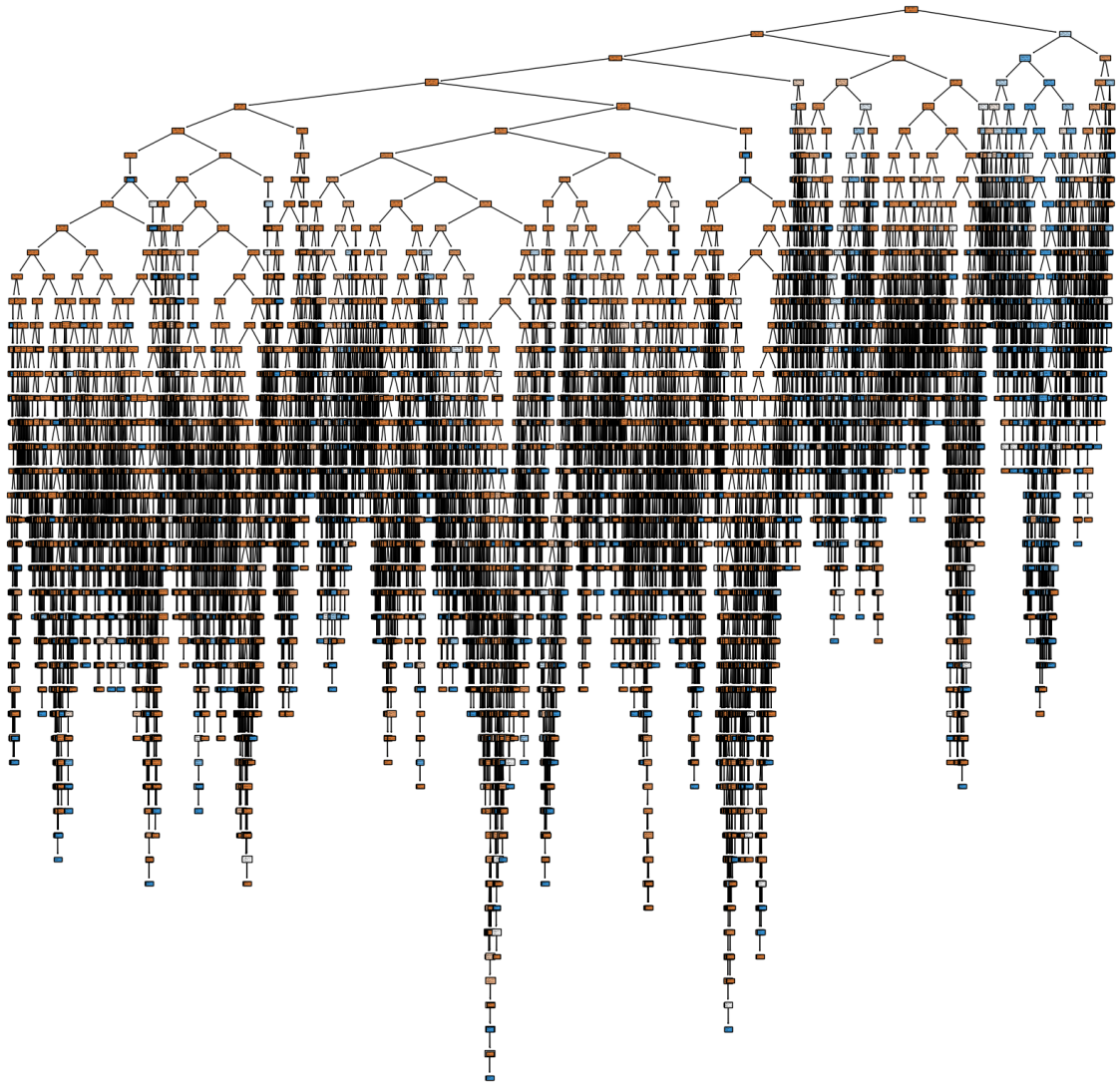
[38]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
```

[39]:
```
decision_model= DecisionTreeClassifier()
```

[40]:
```
decision_model.fit(X_train, y_train)
```

[40]:
```
DecisionTreeClassifier()
```

[ ]:
```
plt.figure(figsize=(20,20))
tree.plot_tree(decision_model,filled=True,class_names=[str(i) for i in set(y)],␣
 ↪feature_names=X.columns)
plt.savefig('decision_model')
```



[41]:
```
dt_pred = decision_model.predict(X_test)
```

[42]:
```
dt_score = accuracy_score(y_test,dt_pred)
```

[43]:
```
dt_score = decision_model.score(X_test, y_test)
```

[44]:
```
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix
# Evaluate the model
dt_score = accuracy_score(y_test, dt_pred )
dt_conf_matrix = confusion_matrix(y_test, dt_pred )
dt_classification_rep = classification_report(y_test, dt_pred )
```

```python
# Display results
print(f'Accuracy: {dt_score}')
print('\ndt_Confusion Matrix:')
print(dt_conf_matrix)
print('\nClassification Report:')
print(dt_classification_rep)
```

```
Accuracy: 0.9752397558849172

dt_Confusion Matrix:
[[88089  1264]
 [ 1008  1399]]

Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.99      0.99     89353
           1       0.53      0.58      0.55      2407

    accuracy                           0.98     91760
   macro avg       0.76      0.78      0.77     91760
weighted avg       0.98      0.98      0.98     91760
```

Precision:

Precision for class 0 is 99%, indicating that when the model predicts the class as 0, it is correct 99% of the time. For class 1, precision is 53%, meaning that 53% of instances predicted as class 1 are indeed class 1.

Recall (Sensitivity):

Recall for class 0 is 99%, meaning that the model correctly identifies 99% of instances of class 0. However, recall for class 1 is 58%, indicating that the model fails to identify 42% of class 1 instances.

F1-score:

The F1-score is the harmonic mean of precision and recall. F1-score for class 0 is 99%, reflecting a good balance between precision and recall. For class 1, F1-score is 55%, indicating a lower balance between precision and recall.

Support:

Support represents the number of actual occurrences of each class in the dataset. Class 0 has a much higher support (89353) compared to class 1 (2407), indicating class imbalance.

5 Random forest model

[45]:
```
# Import necessary libraries
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
```

[46]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=0)
```

[47]:
```
nan_count = pd.DataFrame(X_train).isna().sum().sum()

if nan_count > 0:
    print("X_train contains NaN values.")
else:
    print("X_train does not contain NaN values.")
```

```
X_train contains NaN values.
```

[48]:
```
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy="mean")
X_train = imputer.fit_transform(X_train)
```

[49]:
```
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy="mean")
X_test = imputer.fit_transform(X_test)
```

[50]:
```
# Apply SMOTE for oversampling
smote = SMOTE(random_state=0)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
```

[51]:
```
# Create a Random Forest classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=0)
```

[52]:
```
# Train the classifier on the training data
rf_classifier.fit(X_train, y_train)
```

[52]:
```
RandomForestClassifier(random_state=0)
```

[53]:
```
# Make predictions on the test data
rf_pred = rf_classifier.predict(X_test)
```

[54]:
```
# Evaluate the accuracy of the model
rf_testing_accuracy = accuracy_score(y_test, rf_pred)
```

```
print(f"rf_testing_accuracy: {rf_testing_accuracy}")
```

```
rf_testing_accuracy: 0.9858653007846556
```

[55]:
```
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix
# Evaluate the model
rf_testing_accuracy = accuracy_score(y_test, rf_pred )
rf_conf_matrix = confusion_matrix(y_test, rf_pred )
rf_classification_rep = classification_report(y_test, rf_pred )

# Display results
print(f'rf_testing_accuracy: {rf_testing_accuracy}')
print('\nrf_Confusion Matrix:')
print(rf_conf_matrix)
print('\nrf_Classification Report:')
print(rf_classification_rep)
```

```
rf_testing_accuracy: 0.9858653007846556

rf_Confusion Matrix:
[[89120   177]
 [ 1120  1343]]

rf_Classification Report:
              precision    recall  f1-score   support

           0       0.99      1.00      0.99     89297
           1       0.88      0.55      0.67      2463

    accuracy                           0.99     91760
   macro avg       0.94      0.77      0.83     91760
weighted avg       0.98      0.99      0.98     91760
```

Overall Accuracy: The random forest model achieves an accuracy of approximately 98.59% on the testing data, indicating that it correctly classifies the majority of instances.

Confusion Matrix: The confusion matrix reveals that the model predicts class 0 (negative class) with high accuracy, as evidenced by the large number of true negatives (89120) and the small number of false positives (177). However, it is less accurate in predicting class 1 (positive class), as indicated by the moderate number of false negatives (1120) and true positives (1343).

Precision and Recall: The precision for class 0 is very high (99%), indicating a low false positive rate. However, the precision for class 1 is slightly lower (88%), suggesting that there is a relatively higher false positive rate for this class. The recall for class 0 is excellent (100%), indicating that the model correctly identifies nearly all instances of class 0. In contrast, the recall for class 1 is moderate (55%), indicating that the model misses a significant portion of class 1 instances.

F1-score: The F1-score, which considers both precision and recall, is high for class 0 (99%), indicating a good balance between precision and recall. However, for class 1, the F1-score is lower (67%), indicating a less balanced performance between precision and recall.

Class Imbalance: The support values in the classification report indicate a significant class imbalance, with a much larger number of instances for class 0 (89297) compared to class 1 (2463). This class imbalance could impact the model's performance, particularly in terms of its ability to correctly classify instances of the minority class (class 1).

Note —-> The median is a robust statistic, meaning that it is not affected by outliers. This makes it a good choice for imputing missing values when the data is skewed or contains outliers.

There are other methods that can be used to handle missing values, such as:

Mean imputation:

This replaces missing values with the mean of the non-missing values.

Mode imputation:

This replaces missing values with the most frequent value.

K-nearest neighbors imputation:

This replaces missing values with the average of the k nearest neighbors. The choice of imputation method depends on the data and the assumptions made about the missing values.

In this case, since the data is skewed and may contain outliers, using the median imputation method is a good choice.

from sklearn.impute import SimpleImputer imputer = SimpleImputer(strategy="median") data = imputer.fit_transform(data)

[86]:

6 SVM model

[106]:
```
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
from sklearn.impute import SimpleImputer
```

[107]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[108]:
```
nan_count = pd.DataFrame(X_train).isna().sum().sum()

if nan_count > 0:
    print("X_train contains NaN values.")
else:
    print("X_train does not contain NaN values.")
```

X_train contains NaN values.

[109]:
```
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy="mean")
X_train = imputer.fit_transform(X_train)
```

[110]:
```
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy="mean")
X_test = imputer.fit_transform(X_test)
```

[111]:
```
# Apply SMOTE for oversampling
smote = SMOTE(random_state=0)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
```

[112]:
```
# Create a Support Vector Machine classifier
svm_classifier = SVC(kernel='rbf', C=1.0, random_state=42)
```

[114]:
```
svm_classifier.fit(X_train, y_train)
```

[114]:
```
SVC(random_state=42)
```

[115]:
```
svc_pred = svm_classifier.predict(X_test)
```

[118]:
```
svc_pred
```

[118]:
```
array([0, 0, 0, …, 0, 0, 0])
```

[117]:
```
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix
# Evaluate the model
svc_testing_accuracy = accuracy_score(y_test, svc_pred )
svc_conf_matrix = confusion_matrix(y_test, svc_pred )
svc_classification_rep = classification_report(y_test, svc_pred)

# Display results
print(f'svc_testing_accuracy: {svc_testing_accuracy}')
print('\nsvc_Confusion Matrix:')
print(svc_conf_matrix)
print('\nsvc_Classification Report:')
print(svc_classification_rep)
```

```
svc_testing_accuracy: 0.9795117698343505

svc_Confusion Matrix:
[[89270    83]
 [ 1797   610]]
```

```
svc_Classification Report:
              precision    recall  f1-score   support

           0       0.98      1.00      0.99     89353
           1       0.88      0.25      0.39      2407

    accuracy                           0.98     91760
   macro avg       0.93      0.63      0.69     91760
weighted avg       0.98      0.98      0.97     91760
```

7 KNeighbors model

[56]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
```

[57]:
```
k = 3
```

[58]:
```
knn_classifier = KNeighborsClassifier(n_neighbors=k)
```

[59]:
```
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy="mean")
X_train = imputer.fit_transform(X_train)
```

[60]:
```
knn_classifier.fit(X_train, y_train)
```

[60]:
```
KNeighborsClassifier(n_neighbors=3)
```

[61]:
```
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy="mean")
X_test = imputer.fit_transform(X_test)
```

[62]:
```
kn_pred = knn_classifier.predict(X_test)
```

[63]:
```
kn_testing_accuracy = accuracy_score(y_test, kn_pred)
print(f"Accuracy: {kn_testing_accuracy}")
```

```
Accuracy: 0.9792284219703574
```

[64]:
```
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix
# Evaluate the model
kn_testing_accuracy = accuracy_score(y_test, kn_pred )
kn_conf_matrix = confusion_matrix(y_test, kn_pred )
```

```
kn_classification_rep = classification_report(y_test, kn_pred )

# Display results
print(f'Accuracy: {kn_testing_accuracy}')
print('\nConfusion Matrix:')
print(kn_conf_matrix)
print('\nClassification Report:')
print(kn_classification_rep)
```

```
Accuracy: 0.9792284219703574

Confusion Matrix:
[[88708   589]
 [ 1317  1146]]

Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.99      0.99     89297
           1       0.66      0.47      0.55      2463

    accuracy                           0.98     91760
   macro avg       0.82      0.73      0.77     91760
weighted avg       0.98      0.98      0.98     91760
```

8 Gaussian naive_bayes

[65]:
```
from sklearn.naive_bayes import GaussianNB
```

[66]:
```
naive_bayes_classifier = GaussianNB()
```

[67]:
```
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy="mean")
X_train = imputer.fit_transform(X_train)
```

[68]:
```
naive_bayes_classifier.fit(X_train, y_train)
```

[68]:
```
GaussianNB()
```

[69]:
```
# Make predictions on the test data
nb_pred = naive_bayes_classifier.predict(X_test)
```

[70]:
```
nb_testing_accuracy = accuracy_score(y_test, nb_pred)
print(f"Accuracy: {nb_testing_accuracy}")
```

```
Accuracy: 0.6711857018308631
```

[71]:
```
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix
# Evaluate the model
nb_testing_accuracy = accuracy_score(y_test, nb_pred)
nb_conf_matrix = confusion_matrix(y_test, nb_pred )
nb_classification_rep = classification_report(y_test, nb_pred )

# Display results
print(f'Accuracy: {nb_testing_accuracy}')
print('\nConfusion Matrix:')
print(nb_conf_matrix)
print('\nClassification Report:')
print(nb_classification_rep)
```

```
Accuracy: 0.6711857018308631

Confusion Matrix:
[[59381 29916]
 [  256  2207]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.66      0.80     89297
           1       0.07      0.90      0.13      2463

    accuracy                           0.67     91760
   macro avg       0.53      0.78      0.46     91760
weighted avg       0.97      0.67      0.78     91760
```

9 XGBOOST

[72]:
```
# Import necessary libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix
```

[73]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
```

[74]:
```
# Create an XGBoost classifier
xgb_model = XGBClassifier(objective='binary:logistic', random_state=42)
```

[75]:
```
# Train the model
xgb_model.fit(X_train, y_train)
```

[75]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=42, …)
```

[76]:
```
# Make predictions on the test set
xg_pred = xgb_model.predict(X_test)
```

[77]:
```
# Evaluate the model
xg_testing_accuracy = accuracy_score(y_test, xg_pred)
xg_conf_matrix = confusion_matrix(y_test, xg_pred)
xg_classification_rep = classification_report(y_test, xg_pred)

# Display the results
print("XGBoost Model:")
print("Accuracy:", xg_testing_accuracy)
print("\nConfusion Matrix:\n", xg_conf_matrix)
print("\nClassification Report:\n", xg_classification_rep)
```

```
XGBoost Model:
Accuracy: 0.987216652136007

Confusion Matrix:
 [[89114   239]
 [  934  1473]]

Classification Report:
              precision    recall  f1-score   support

           0       0.99      1.00      0.99     89353
           1       0.86      0.61      0.72      2407

    accuracy                           0.99     91760
   macro avg       0.93      0.80      0.85     91760
```

```
weighted avg       0.99      0.99      0.99     91760
```

Accuracy: The model achieves an accuracy of approximately 98.72%, indicating that it correctly classifies the majority of instances.

Confusion Matrix:

True negatives (TN): 1473

False positives (FP): 239

False negatives (FN): 934

True positives (TP): 89114

This matrix demonstrates that the model is particularly effective at correctly identifying instances of the majority class (0), but it does have some false negatives for the minority class (1).

Precision and Recall:

Precision for class 0 is 99%, indicating a low false positive rate. Precision for class 1 is 86%, indicating that when the model predicts class 1, it is correct 86% of the time.

Recall for class 0 is 100%, suggesting the model effectively captures all instances of class 0. Recall for class 1 is 61%, indicating that the model identifies 61% of actual instances of class 1.

F1-score: The F1-score, which balances precision and recall, is high for class 0 (99%) and moderate for class 1 (72%).

Support: The support values indicate a significant class imbalance, with a much larger number of instances for class 0 compared to class 1.

Let's make data frame of all the models which one is giving good accuracy.

[123]:
```
models = pd.DataFrame({'Model': ['Logistic Regression','Random␣
↪Forest','Decision Tree','XGBoost Classifier', 'KNeighbors model','Gaussian␣
↪naive_bayse','svm'],
                       'Score': [logi_test_accuracy*100 ,␣
↪rf_testing_accuracy*100, dt_score *100, xg_testing_accuracy␣
↪*100,kn_testing_accuracy*100, nb_testing_accuracy*100,␣
↪svc_testing_accuracy*100]}).round(2)
```

[124]:
```
models
```

[124]:

	Model	Score
0	Logistic Regression	97.78
1	Random Forest	98.59
2	Decision Tree	97.52
3	XGBoost Classifier	98.72
4	KNeighbors model	97.92
5	Gaussian naive_bayse	67.12
6	svm	97.95

As we can see that xgboost and random forest is the algorithms which gives good accuracies.

[ ]: