HEALTHCARE PROVIDER FRAUD DETECTION ANALYSIS

Introduction:

Healthcare Insurance is provided by the insurance companies to the insurance holder to cover his/her medical expenses depending upon the plan the policy holder selects. The amount depends on the diagnosis done by the doctor . but some holders or insurance providers misuse this and try to file fake claims by giving fake details. According to Govt total medicare increases exponentially due to frauds ,by which the company as well as insurance holder suffer . The approach to this problem is using Machine Learning and Deep Learning Algorithms to detect healthcare frauds.

Problem Statement

We have to find/detect/predict these claims into fraud provided/filed by the fradulents. Which will save a very huge amount of money from frauds. And also discover the important variables helpful in detecting the behaviour of fraud providers.

ML formulation of business problem:

This is a binary classification problem , We need to classify whether the data points are fraudulent or real claims.

Performance metric:

1. Confusion Matrix : for visualization the reults of TP,TN,FP,FN
2. Precision:
    A. The formula to calculate the Precision is TP/(TP+FP). i.e it checks for out of the predicted Positve how many are actual positive and it only care for false positive and not False negaative
    B. also the insurance companies will try to preserve the coustmer i.e if the fraud claim is classifed into non fraud claim then it ok as they have to reimburse the money but if the Non Fraud Claim classified in Fraud Claim then they might loose the coustmer.
    C. As the data is slightly imbalanced the Precision is a great metrics and .
    D. And from The averaged precision i will be choosing micro-averaged because for imbalance datasets it assigns different wieghts of different classes.

Business constraints:

The Misclassification rate must be very low.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [ ]:
```
from google.colab import drive
drive.mount("/content/drive/")
```

```
Mounted at /content/drive/
```

Loading Data

In [ ]:
```
df_inpatient=pd.read_csv("/content/drive/My Drive/CASE Studies/healthcare/archive_fraud/Train_Inpatientdata.csv")
print("The shape of the Inpatient Data:",df_inpatient.shape)
print("The columns of the Inpatient Data are :",df_inpatient.columns)
```

```
The shape of the Inpatient Data: (40474, 30)
The columns of the Inpatient Data are : Index(['BeneID', 'ClaimID', 'ClaimStartDt', 'ClaimEndDt', 'Provider',
       'InscClaimAmtReimbursed', 'AttendingPhysician', 'OperatingPhysician',
       'OtherPhysician', 'AdmissionDt', 'ClmAdmitDiagnosisCode',
       'DeductibleAmtPaid', 'DischargeDt', 'DiagnosisGroupCode',
       'ClmDiagnosisCode_1', 'ClmDiagnosisCode_2', 'ClmDiagnosisCode_3',
       'ClmDiagnosisCode_4', 'ClmDiagnosisCode_5', 'ClmDiagnosisCode_6',
       'ClmDiagnosisCode_7', 'ClmDiagnosisCode_8', 'ClmDiagnosisCode_9',
       'ClmDiagnosisCode_10', 'ClmProcedureCode_1', 'ClmProcedureCode_2',
       'ClmProcedureCode_3', 'ClmProcedureCode_4', 'ClmProcedureCode_5',
       'ClmProcedureCode_6'],
      dtype='object')
```

In [ ]:
```
df_outpatient=pd.read_csv("/content/drive/My Drive/CASE Studies/healthcare/archive_fraud/Train_Outpatientdata.csv")
print("The shape of the Outpatient Data:",df_outpatient.shape)
print("The columns of the Outpatient Data are :",df_outpatient.columns)
```

```
The shape of the Outpatient Data: (517737, 27)
The columns of the Outpatient Data are : Index(['BeneID', 'ClaimID', 'ClaimStartDt', 'ClaimEndDt', 'Provider',
       'InscClaimAmtReimbursed', 'AttendingPhysician', 'OperatingPhysician',
       'OtherPhysician', 'ClmDiagnosisCode_1', 'ClmDiagnosisCode_2',
       'ClmDiagnosisCode_3', 'ClmDiagnosisCode_4', 'ClmDiagnosisCode_5',
       'ClmDiagnosisCode_6', 'ClmDiagnosisCode_7', 'ClmDiagnosisCode_8',
       'ClmDiagnosisCode_9', 'ClmDiagnosisCode_10', 'ClmProcedureCode_1',
       'ClmProcedureCode_2', 'ClmProcedureCode_3', 'ClmProcedureCode_4',
       'ClmProcedureCode_5', 'ClmProcedureCode_6', 'DeductibleAmtPaid',
       'ClmAdmitDiagnosisCode'],
      dtype='object')
```

In [ ]:
```
df_beneficiary=pd.read_csv("/content/drive/My Drive/CASE Studies/healthcare/archive_fraud/Train_Beneficiarydata.csv")
print("The shape of the Beneficary Data:",df_beneficiary.shape)
print("The columns of the Beneficary Data are :",df_beneficiary.columns)
```

```
The shape of the Beneficary Data: (138556, 25)
The columns of the Beneficary Data are : Index(['BeneID', 'DOB', 'DOD', 'Gender', 'Race', 'RenalDiseaseIndicator',
       'State', 'County', 'NoOfMonths_PartACov', 'NoOfMonths_PartBCov',
       'ChronicCond_Alzheimer', 'ChronicCond_Heartfailure',
       'ChronicCond_KidneyDisease', 'ChronicCond_Cancer',
       'ChronicCond_ObstrPulmonary', 'ChronicCond_Depression',
       'ChronicCond_Diabetes', 'ChronicCond_IschemicHeart',
       'ChronicCond_Osteoporasis', 'ChronicCond_rheumatoidarthritis',
       'ChronicCond_stroke', 'IPAnnualReimbursementAmt',
       'IPAnnualDeductibleAmt', 'OPAnnualReimbursementAmt',
       'OPAnnualDeductibleAmt'],
      dtype='object')
```

In [ ]:
```
# Loading Target File
df_train=pd.read_csv("/content/drive/My Drive/CASE Studies/healthcare/archive_fraud/Train.csv")
print("The shape of the Target file:",df_train.shape)
print("The columns of the Target file are :",df_train.columns)
```

```
The shape of the Target file: (5410, 2)
The columns of the Target file are : Index(['Provider', 'PotentialFraud'], dtype='object')
```

Merging all Data

In [ ]:
```
# Merging Inpatient_data and OutPatient_data
cols=[i for i in df_outpatient.columns if i in df_inpatient.columns ]
df=pd.merge(df_inpatient,df_outpatient,
            left_on=cols,
            right_on=cols,
            how="outer")

# Merging df and Benificiary data
df=pd.merge(df_beneficiary,df,
            on="BeneID",
            how="outer")

# Merging df and target_data
df=pd.merge(df_train,df,
            on="Provider",
            how="outer")
df.head()
```

Out[ ]:

	Provider	PotentialFraud	BeneID	DOB	DOD	Gender	Race	RenalDiseaseIndicator	Sta
0	PRV51001	No	BENE11727	1930-05-01	NaN	1	1	Y	
1	PRV51001	No	BENE24646	1943-03-01	NaN	1	1	0	
2	PRV51001	No	BENE31617	1933-08-01	NaN	2	1	0	
3	PRV51001	No	BENE32715	1936-03-01	NaN	1	1	0	
4	PRV51001	No	BENE36012	1940-07-01	NaN	1	1	0	

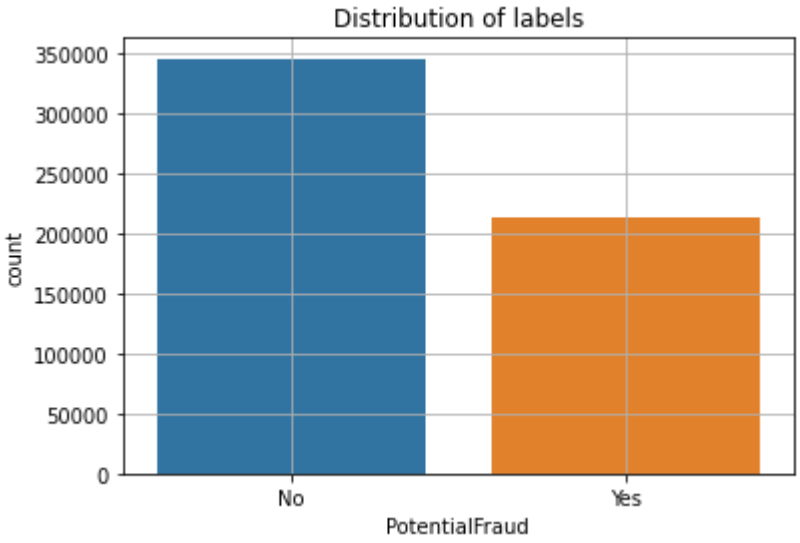
In [ ]:

EDA

1.1Checking The Distribution of labels(Imbalance)

In [ ]:
```
# Cecking Distribution for whole dataset
#plt.style.use("seaborn-whitegrid")
sns.countplot(df["PotentialFraud"])
plt.title("Distribution of labels")
plt.grid("whitegrid")

print("Percentage of No(No fraud) Labels present is ",(df["PotentialFraud"].va
lue_counts()[0]*100)/df["PotentialFraud"].count(),"%")
print("Percentage of Yes(Fraud) Labels present is ",(df["PotentialFraud"].valu
e_counts()[1]*100)/df["PotentialFraud"].count(),"%")
```

```
Percentage of No(No fraud) Labels present is  61.878931085198964 %
Percentage of Yes(Fraud) Labels present is  38.121068914801036 %
```

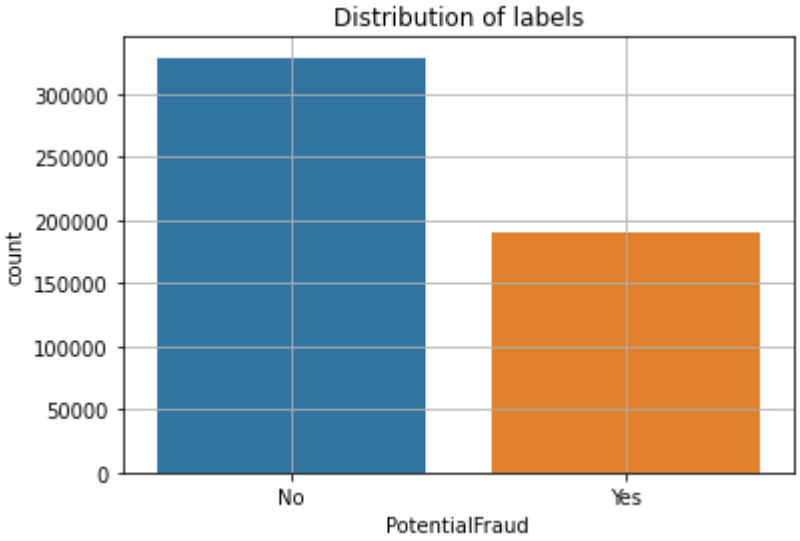


Observation

1. In The whole data there are 345415 non fraud claims, 212796 fraud claim
2. percentage of No class is 61.87%, Yes class is 38.12%

In [ ]:
```
# Cecking Distribution for Outpatient dataset
out=pd.merge(df_train,df_outpatient,
             on="Provider",
             how="outer")
sns.countplot(out["PotentialFraud"])
plt.title("Distribution of labels")
plt.grid("whitegrid")

print("Percentage of No(No fraud) Labels present is ",(out["PotentialFraud"].v
alue_counts()[0]*100)/out["PotentialFraud"].count(),"%")
print("Percentage of Yes(Fraud) Labels present is ",(out["PotentialFraud"].val
ue_counts()[1]*100)/out["PotentialFraud"].count(),"%")
```

```
Percentage of No(No fraud) Labels present is  63.43848610883264 %
Percentage of Yes(Fraud) Labels present is  36.56151389116736 %
```

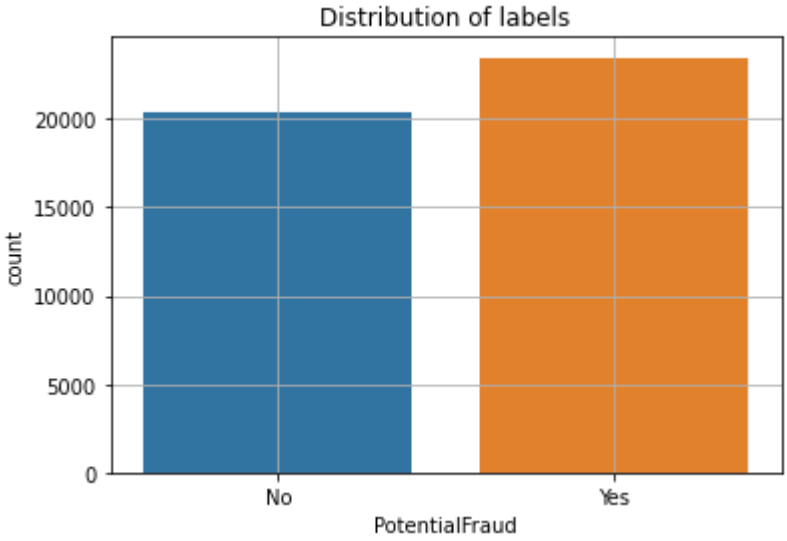


Observation

1. In Outpatient file there are 328697 non fraud, 189438 fraud claim
2. Percentage of No class is 63.43%, Yes class is 36.56%

In [ ]:
```
# Cecking Distribution for INpatient dataset
In=pd.merge(df_train,df_inpatient,
            on="Provider",
            how="outer")
sns.countplot(In["PotentialFraud"])
plt.title("Distribution of labels")
plt.grid("whitegrid")

print("Percentage of No(No fraud) Labels present is ",(In["PotentialFraud"].va
lue_counts()[0]*100)/In["PotentialFraud"].count(),"%")
print("Percentage of Yes(Fraud) Labels present is ",(In["PotentialFraud"].valu
e_counts()[1]*100)/In["PotentialFraud"].count(),"%")
```

```
Percentage of No(No fraud) Labels present is  53.58969674826452 %
Percentage of Yes(Fraud) Labels present is  46.41030325173548 %
```



Observation

1. In train outpatient file there are 20324 non fraud, 23468 fraud claim
2. percentage of No class is 53.58%, Yes class is 46.56%

CONCLUSION

1.Maximum Frauds Happens when the Patient Gets admitted to Hospital,This because the patient can claim more amount

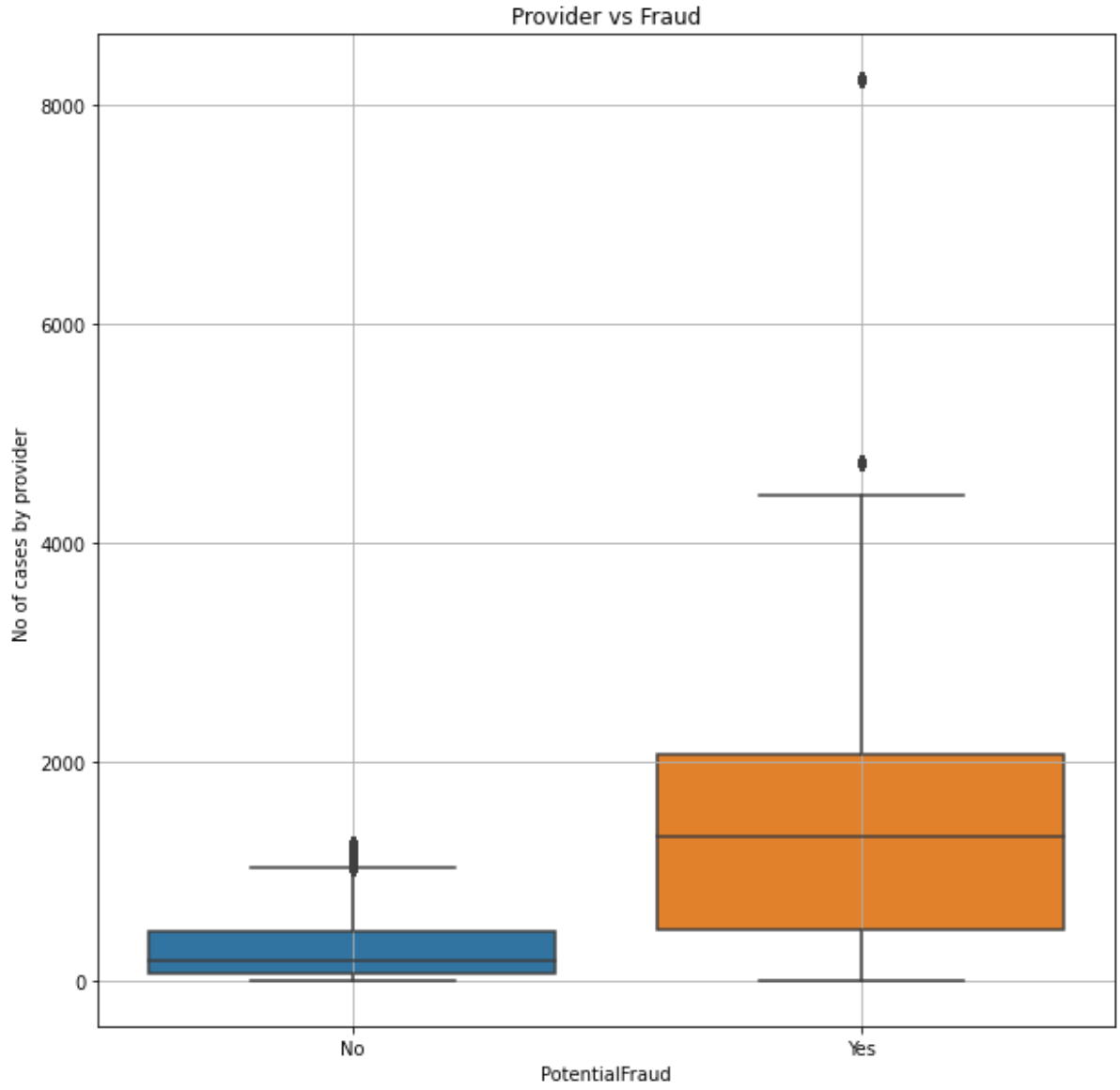
In [ ]:
```
```

1.2 Feature Provider vs Fraud

In [ ]:
```
# checking for the  Whole Data set
print("The number of Providers present are :",df["Provider"].value_counts().co
unt())
print("Top 5 Providers are ",df["Provider"].value_counts()[:5])

provider_dict= df["Provider"].value_counts().to_dict()
count=df["Provider"].map(provider_dict)

plt.figure(figsize=(10,10))
sns.boxplot(data=df,y=count,x="PotentialFraud")
plt.grid("whitegrid")
plt.ylabel("No of cases by provider ")
plt.title("Provider vs Fraud")
```

```
The number of Providers present are : 5410
Top 5 Providers are  PRV51459    8240
PRV53797    4739
PRV51574    4444
PRV53918    3588
PRV54895    3436
Name: Provider, dtype: int64
```

Out[ ]: Text(0.5, 1.0, 'Provider vs Fraud')



In [ ]:
```
# checking for fraud/non fraud cases handled by each provider
# calculating number of fraud and non fraud cases from the each provider
def check(df,provider ):
  yes=0
  no=0
  g=df.groupby("Provider")
  data=g.get_group(provider)
  if data["PotentialFraud"].value_counts().keys()[0]=="Yes":
    yes=data["PotentialFraud"].value_counts()[0]
  if data["PotentialFraud"].value_counts().keys()[0]=="No":
    no=data["PotentialFraud"].value_counts()[0]
  return yes,no

print("Top 1 provider has Classes(yes,no) :",check(df,df["Provider"].value_cou
nts().keys()[0]))
print("Top 2 provider has Classes(yes,no) :",check(df,df["Provider"].value_cou
nts().keys()[1]))
print("Top 3 provider has Classes(yes,no) :",check(df,df["Provider"].value_cou
nts().keys()[2]))
print("Top 93 provider has Classes(yes,no) :",check(df,df["Provider"].value_co
unts().keys()[93]))
print("Top 100 provider has Classes(yes,no) :",check(df,df["Provider"].value_c
ounts().keys()[100]))
```

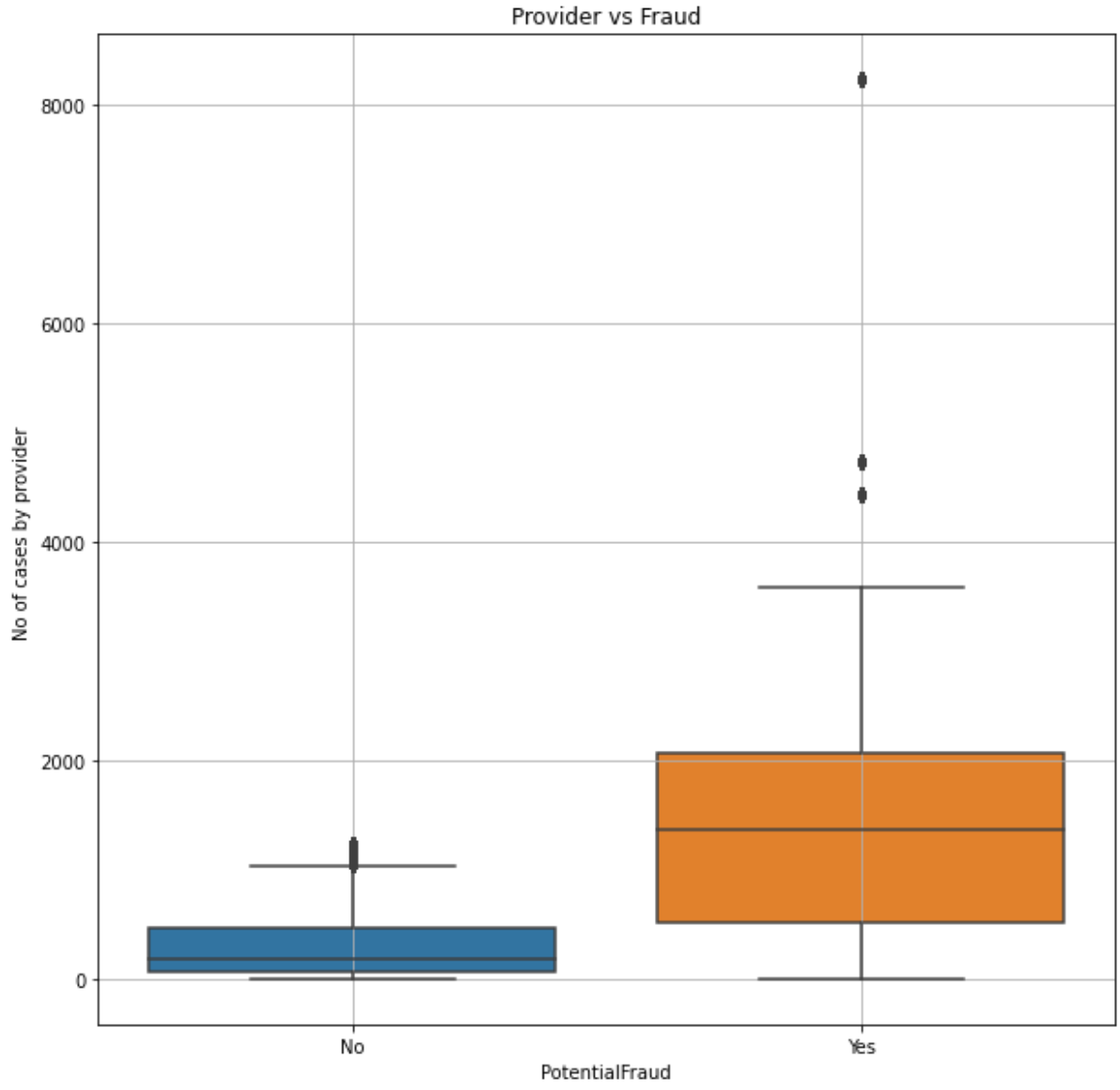
```
Top 1 provider has Classes(yes,no) : (8240, 0)
Top 2 provider has Classes(yes,no) : (4739, 0)
Top 3 provider has Classes(yes,no) : (4444, 0)
Top 93 provider has Classes(yes,no) : (0, 861)
Top 100 provider has Classes(yes,no) : (0, 828)
```

Observation

1. This analysis shows that the provider handling more number of cases tends to commit fraud whereas the provider handling less cases do not commit any fraud
2. The Top Provider handles 8240 cases and least amount of cases handled by Provider are 1 3.also from the box plot if the Provider is handling more than 1800-2000 cases he/she may be involved in commiting Fraud

In [ ]:
```
# OUTPATIENT DATA
print("*"*50)
print("The number of Providers present are :",out["Provider"].value_counts().c
ount())
print("Top 5 Providers are ",out["Provider"].value_counts()[:5])
print("*"*50)
print("\n\n")

#**********************************************************************
*******************************
provider_dict= out["Provider"].value_counts().to_dict()
count=out["Provider"].map(provider_dict)

plt.figure(figsize=(10,10))
sns.boxplot(data=out,y=count,x="PotentialFraud")
plt.grid("whitegrid")
plt.ylabel("No of cases by provider ")
plt.title("Provider vs Fraud")
plt.show()


#**********************************************************************
*******************************
print("\n\n")
print("*"*50)
print("Top 1 provider has Classes(yes,no) :",check(out,out["Provider"].value_c
ounts().keys()[0]))
print("Top 2 provider has Classes(yes,no) :",check(out,out["Provider"].value_c
ounts().keys()[1]))
print("Top 3 provider has Classes(yes,no) :",check(out,out["Provider"].value_c
ounts().keys()[2]))
print("Top 93 provider has Classes(yes,no) :",check(out,out["Provider"].value_
counts().keys()[93]))
print("Top 100 provider has Classes(yes,no) :",check(out,out["Provider"].value
_counts().keys()[100]))
```

```
************************************************
The number of Providers present are : 5410
Top 5 Providers are  PRV51459    8240
PRV53797    4739
PRV51574    4444
PRV53918    3588
PRV54895    3433
Name: Provider, dtype: int64
************************************************
```



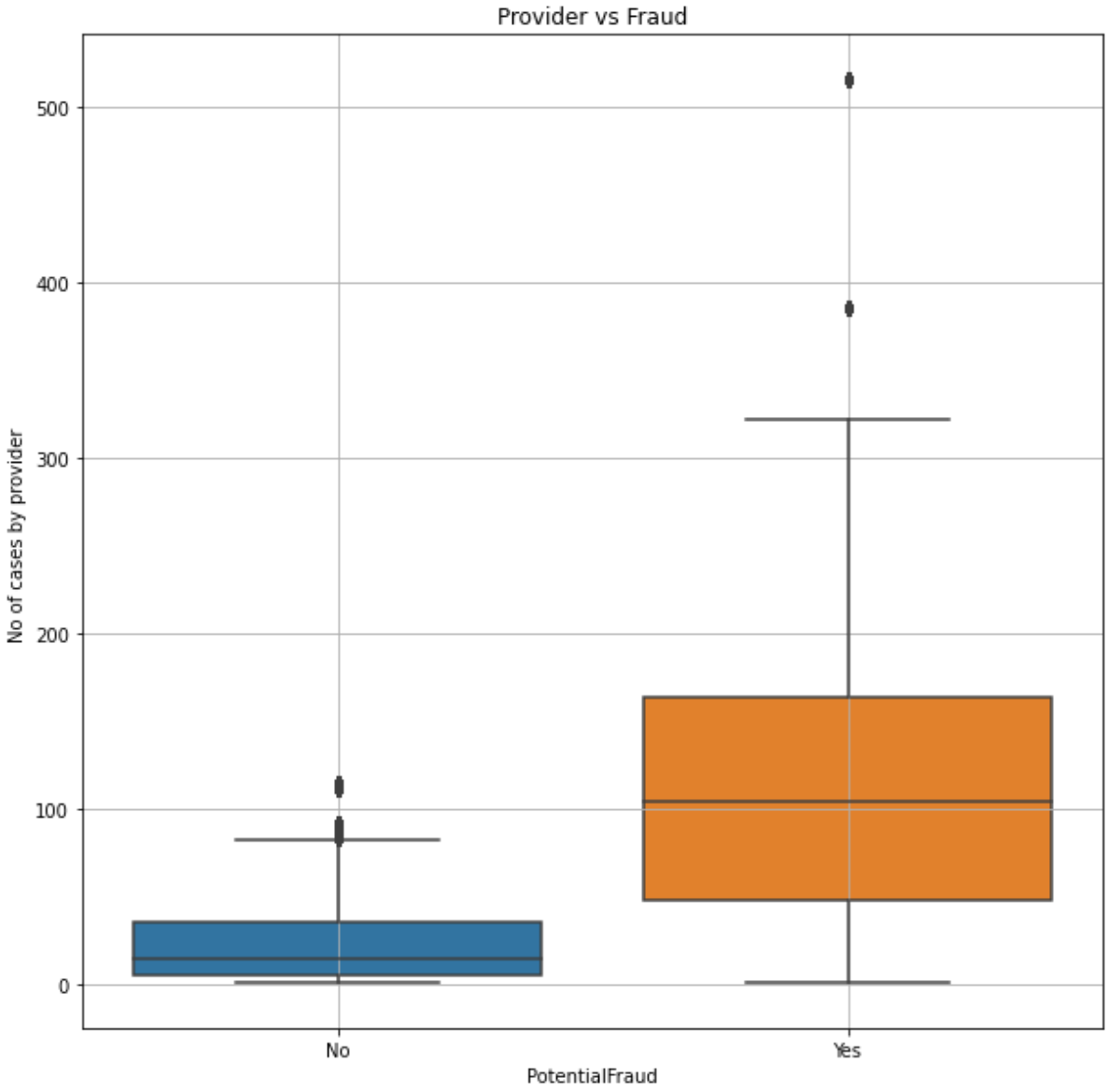

```
************************************************
Top 1 provider has Classes(yes,no) : (8240, 0)
Top 2 provider has Classes(yes,no) : (4739, 0)
Top 3 provider has Classes(yes,no) : (4444, 0)
Top 93 provider has Classes(yes,no) : (842, 0)
Top 100 provider has Classes(yes,no) : (0, 818)
```

Observation

1. This analysis shows that the provider handling more number of cases tends to commit fraud whereas the provider handling less cases do not commit any fraud
2. The Top Provider handles 8240 cases and least amount of cases handled by Provider are 1 3.also from the box plot if the Provider is handling more than 1800-2000 outpatient cases he/she may be involved in commiting Fraud

In [ ]:
```
# INPPATIENT DATA

print("*"*50)
print("The number of Providers present are :",In["Provider"].value_counts().co
unt())
print("Top 5 Providers are ",In["Provider"].value_counts()[:5])
print("*"*50)
print("\n\n")

#*************************************************************************
*******************************
provider_dict= In["Provider"].value_counts().to_dict()
count=In["Provider"].map(provider_dict)
plt.figure(figsize=(10,10))
sns.boxplot(data=In,y=count,x="PotentialFraud")
plt.grid("whitegrid")
plt.ylabel("No of cases by provider ")
plt.title("Provider vs Fraud")
plt.show()

#*************************************************************************
*******************************
print("\n\n")
print("*"*50)
print("Top 1 provider has Classes(yes,no) :",check(In,In["Provider"].value_cou
nts().keys()[0]))
print("Top 2 provider has Classes(yes,no) :",check(In,In["Provider"].value_cou
nts().keys()[1]))
print("Top 3 provider has Classes(yes,no) :",check(In,In["Provider"].value_cou
nts().keys()[2]))
print("Top 93 provider has Classes(yes,no) :",check(In,In["Provider"].value_co
unts().keys()[93]))
print("Top 100 provider has Classes(yes,no) :",check(In,In["Provider"].value_c
ounts().keys()[100]))
```

```
**************************************************
The number of Providers present are : 5410
Top 5 Providers are  PRV52019    516
PRV55462    386
PRV54367    322
PRV53706    282
PRV55209    275
Name: Provider, dtype: int64
**************************************************
```




```
**************************************************
Top 1 provider has Classes(yes,no) : (516, 0)
Top 2 provider has Classes(yes,no) : (386, 0)
Top 3 provider has Classes(yes,no) : (322, 0)
Top 93 provider has Classes(yes,no) : (0, 86)
Top 100 provider has Classes(yes,no) : (0, 82)
```

Observation

1. This analysis shows that the provider handling more number of cases tends to commit fraud whereas the provider handling less cases do not commit any fraud
2. The Top Provider handles 516 cases and least amount of cases handled by Provider are 1
3. also from the box plot if the Provider is handling more than 120-150 Inpatient cases he/she may be involved in commiting Fraud

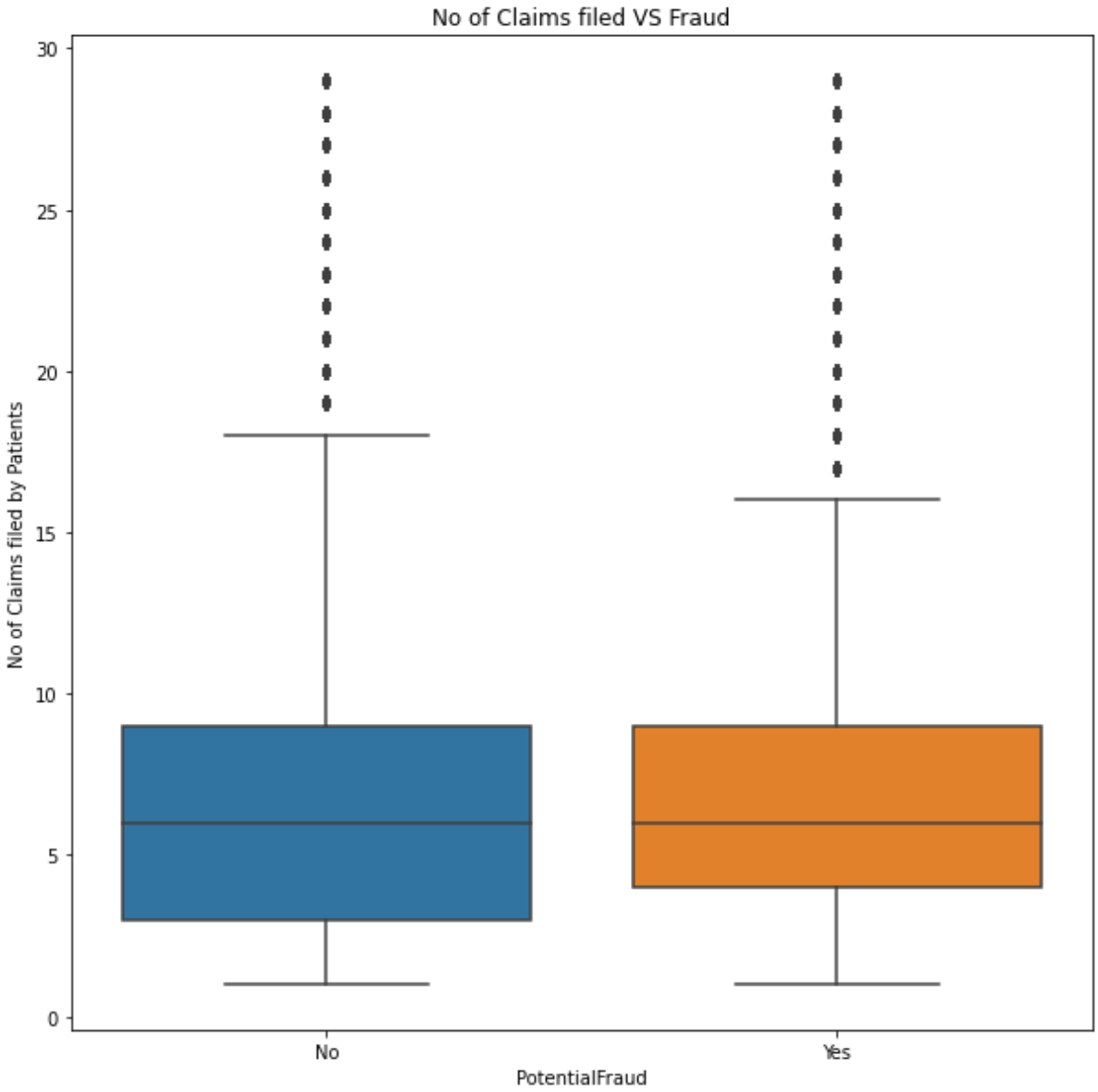
In [ ]:

1.3 BeneID vs Fraud

In [ ]:
```
# WHOLE DATASET
print("*"*50)
print("The number of patients are :",df["BeneID"].value_counts().count())
print("The Top 5 Patients with maximum number of claims are :\n",df["BeneID"].
value_counts()[:5])
print("*"*50)
print("\n\n")
plt.figure(figsize=(10,10))
bene=df["BeneID"].value_counts().to_dict()
count=df["BeneID"].map(bene)
sns.boxplot(data=df,y=count,x="PotentialFraud")
plt.ylabel("No of Claims filed by Patients")
plt.title("No of Claims filed VS Fraud")
```

```
**************************************************
The number of patients are : 138556
The Top 5 Patients with maximum number of claims are :
 BENE42721     29
BENE59303     29
BENE118316    29
BENE44241     28
BENE80977     28
Name: BeneID, dtype: int64
**************************************************
```

Out[ ]: Text(0.5, 1.0, 'No of Claims filed VS Fraud')



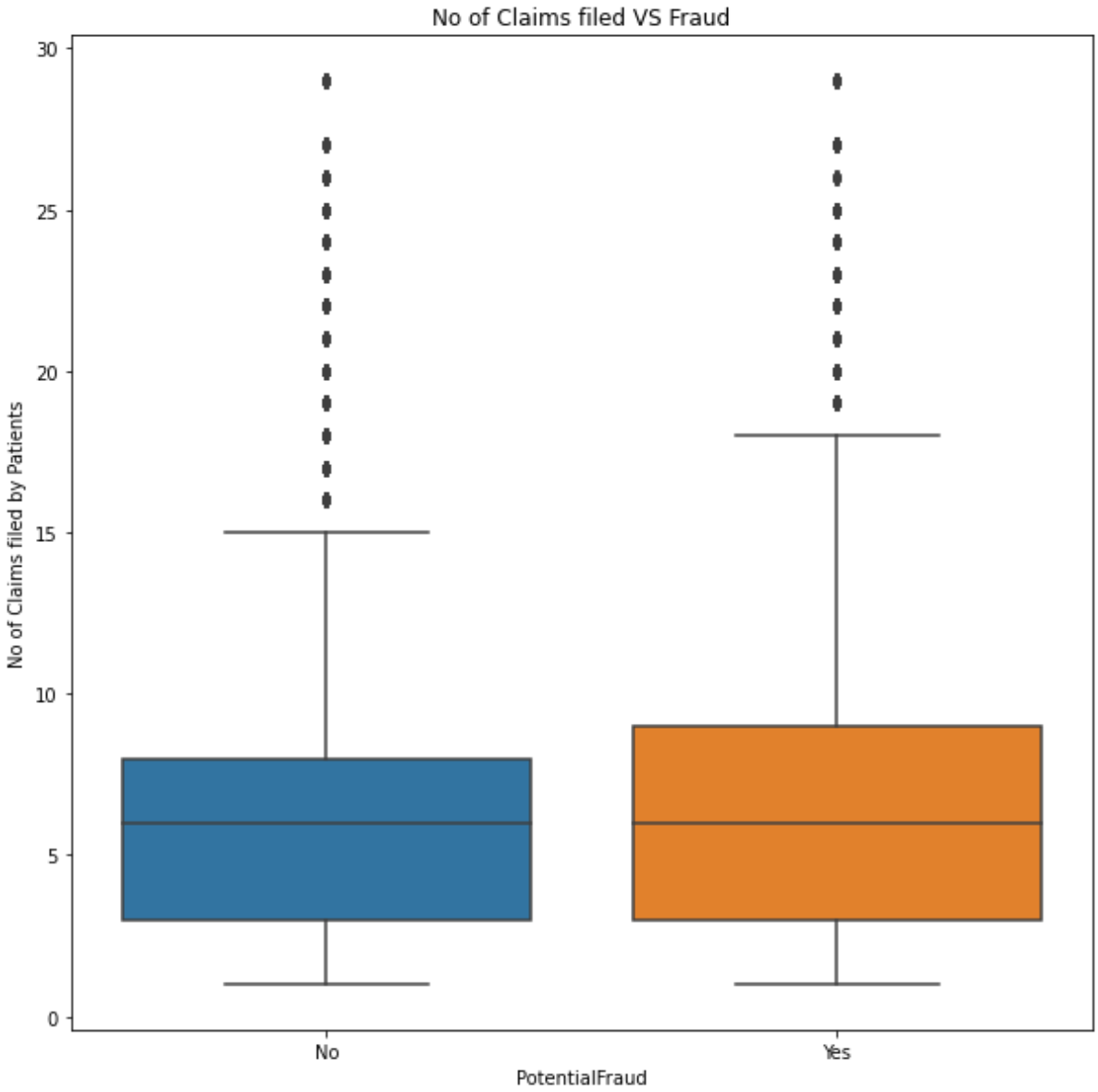
Observation

1. The total Number Of patients are 138556
2. The Maximum claims filed by a patient is 29 and minimum is 1

In [ ]:
```
# OUTPATIENT DATASET
print("*"*50)
print("The number of patients are :",out["BeneID"].value_counts().count())
print("The Top 5 Patients with maximum number of claims are :\n",out["BeneID"]
.value_counts()[:5])
print("*"*50)
print("\n\n")
plt.figure(figsize=(10,10))
bene=out["BeneID"].value_counts().to_dict()
count=out["BeneID"].map(bene)
sns.boxplot(data=out,y=count,x="PotentialFraud")
plt.ylabel("No of Claims filed by Patients")
plt.title("No of Claims filed VS Fraud")
```

```
**************************************************
The number of patients are : 133980
The Top 5 Patients with maximum number of claims are :
 BENE42721     29
BENE118316    29
BENE59303     27
BENE63544     27
BENE143400    27
Name: BeneID, dtype: int64
**************************************************
```

Out[ ]: Text(0.5, 1.0, 'No of Claims filed VS Fraud')



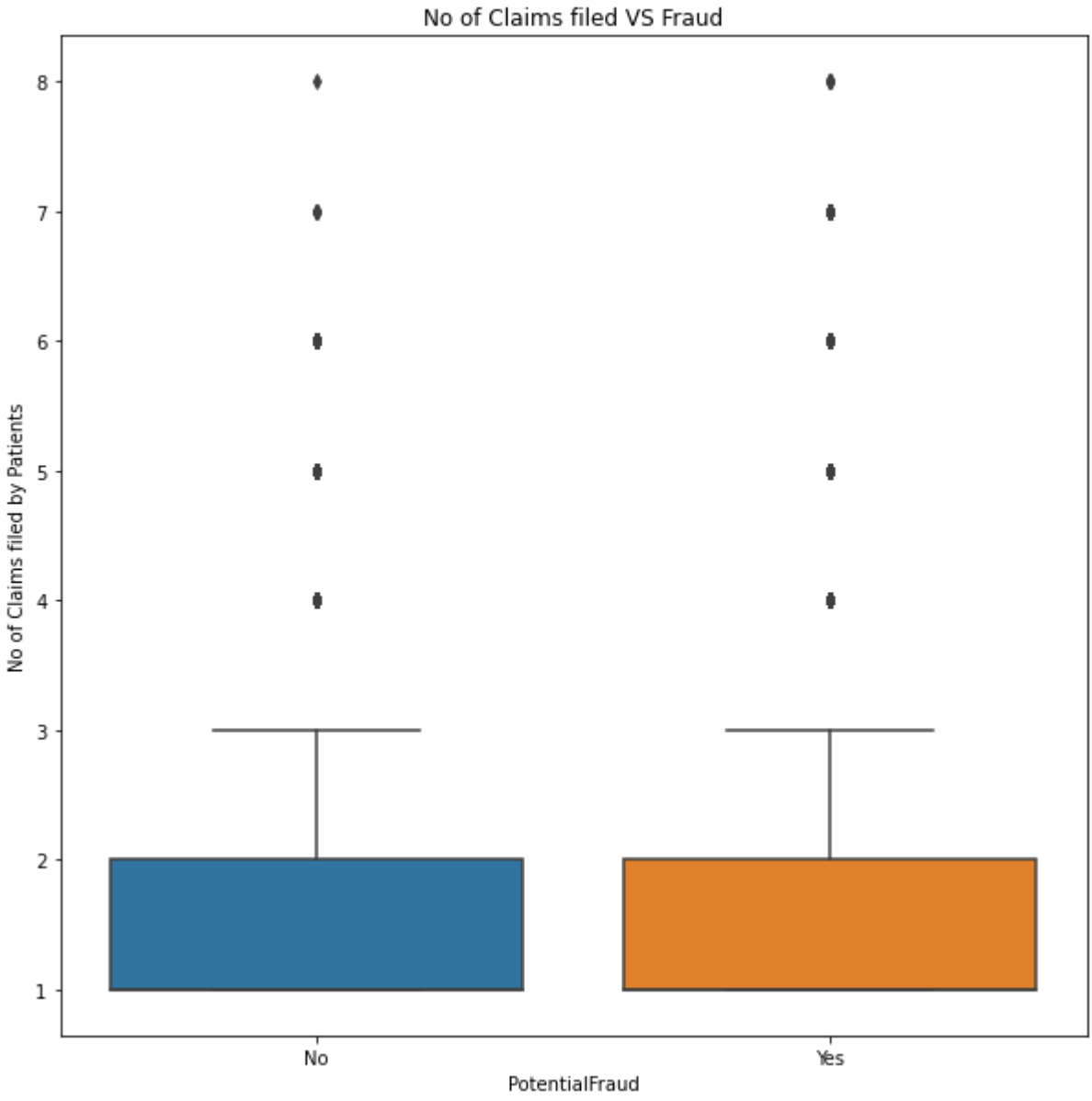
Observation

1. The total Number Of patients are 133980
2. The Maximum claims filed by a patient is 29 and minimum is 1

In [ ]:
```
# INPATIENT DATASET
print("*"*50)
print("The number of patients are :",In["BeneID"].value_counts().count())
print("The Top 5 Patients with maximum number of claims are :\n",In["BeneID"].
value_counts()[:5])
print("*"*50)
print("\n\n")
plt.figure(figsize=(10,10))
bene=In["BeneID"].value_counts().to_dict()
count=In["BeneID"].map(bene)
sns.boxplot(data=In,y=count,x="PotentialFraud")
plt.ylabel("No of Claims filed by Patients")
plt.title("No of Claims filed VS Fraud")
```

```
**************************************************
The number of patients are : 31289
The Top 5 Patients with maximum number of claims are :
 BENE134170    8
BENE119457    7
BENE121796    7
BENE64791     7
BENE62091     7
Name: BeneID, dtype: int64
**************************************************
```

Out[ ]: Text(0.5, 1.0, 'No of Claims filed VS Fraud')



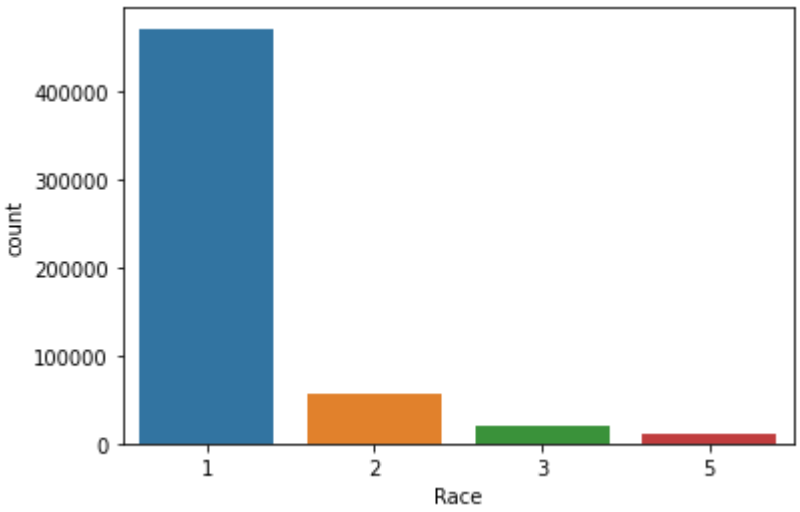
Observation

1. The total Number Of patients are 31289
2. The Maximum claims filed by a patient is 8 and minimum is 1

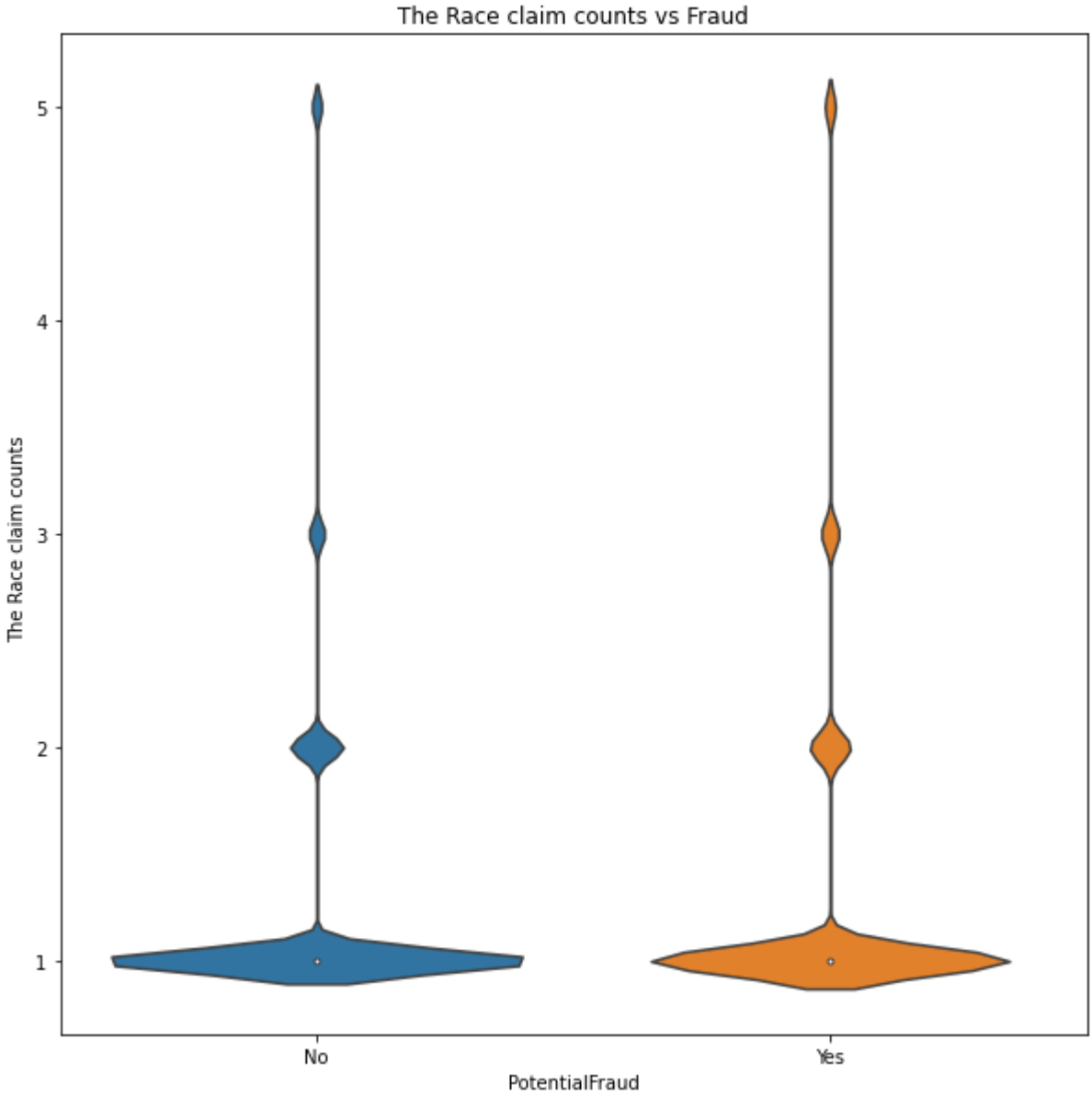
1.4 Race vs Fraud

In [ ]:
```
# Whole Data
print("*"*50)
print("The Number Of Race Categoreis Present are:",df["Race"].value_counts().c
ount())
print("The Categories and their claim counts are:\n",df["Race"].value_counts
())
sns.countplot(x=df["Race"])
plt.show()
print("*"*50)
print("\n\n")
plt.figure(figsize=(10,10))
sns.violinplot(x="PotentialFraud",y="Race",data=df)
plt.title("The Race claim counts vs Fraud")
plt.ylabel("The Race claim counts ")
plt.show()
```

```
**************************************************
The Number Of Race Categoreis Present are: 4
The Categories and their claim counts are:
 1    471036
2     55640
3     19715
5     11820
Name: Race, dtype: int64
```




```
**************************************************
```



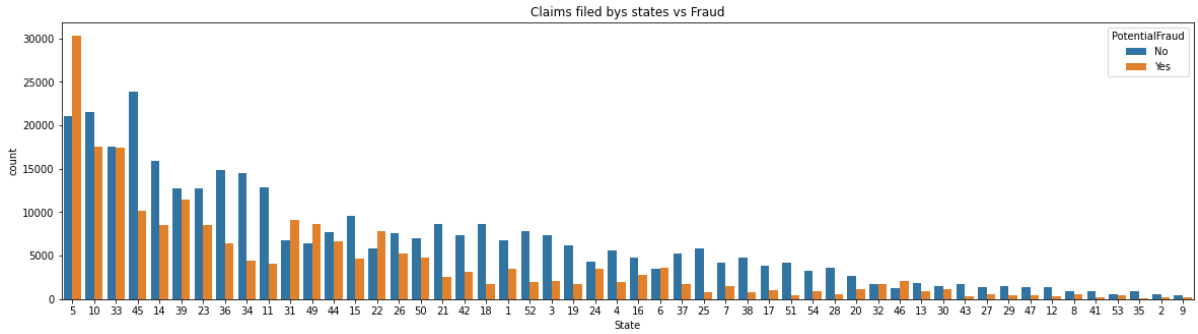
Observation

1. The total Number Of Race Categories are 4
2. The People belonging to category 1 have filed maximum claims
3. From the Violin plot The Category 1 people are more involved in commiting fraud than other categories

1.5 State vs Fraud

In [ ]:
```
print("*"*50)
print("The Number Of States are :",df["State"].value_counts().count())
print("Top 5 States With Maximum Claims are :\n",df["State"].value_counts()[:5
])
print("*"*50)
print("\n\n")
plt.figure(figsize=(20,5))
sns.countplot(x=df["State"],hue=df["PotentialFraud"],order=df["State"].value_c
ounts().keys())
plt.title("Claims filed bys states vs Fraud")
plt.show()
```

```
**************************************************
The Number Of States are : 52
Top 5 States With Maximum Claims are :
 5     51350
10     39073
33     35024
45     34022
14     24417
Name: State, dtype: int64
**************************************************
```

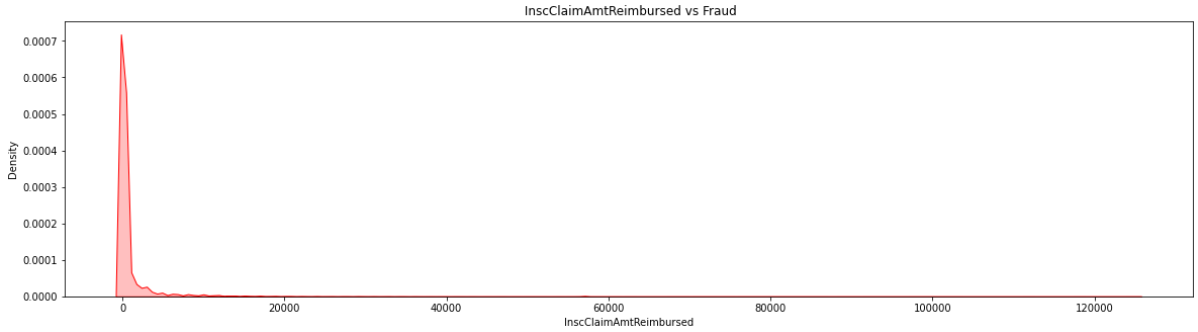


Observation

1. The total Number Of States are 52
2. The State which filed maximum claims is state 5 with 51350 Claims
3. The State which filed maximum claims is state 9 with 617 Claims

1.6 InscClaimAmtReimbursed vs Fraud

In [ ]:
```
# Whole Dataset
plt.figure(figsize=(20,5))
sns.kdeplot(df["InscClaimAmtReimbursed"],shade=True,color="R")
plt.title(" InscClaimAmtReimbursed vs Fraud")
plt.show()

print("\n\n")
print("The 25 Percentile values is ",np.percentile(df["InscClaimAmtReimbursed"
],25))
print("The 50 Percentile values is ",np.percentile(df["InscClaimAmtReimbursed"
],50))
print("The 75 Percentile values is ",np.percentile(df["InscClaimAmtReimbursed"
],75))
print("The 90 Percentile values is ",np.percentile(df["InscClaimAmtReimbursed"
],90))
print("The 99 Percentile values is ",np.percentile(df["InscClaimAmtReimbursed"
],99))
for i in range(1,10):
  a=99
  b=i/10
  a=a+b
  print(f"The {a} Percentile values is {np.percentile(df['InscClaimAmtReimburs
ed'],a)}")
print("The 100 Percentile values is ",np.percentile(df["InscClaimAmtReimburse
d"],100))
```

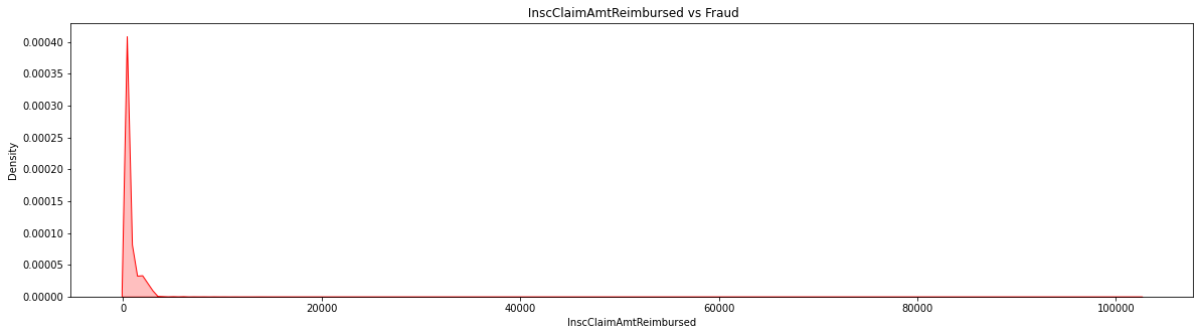



```
The 25 Percentile values is  40.0
The 50 Percentile values is  80.0
The 75 Percentile values is  300.0
The 90 Percentile values is  2000.0
The 99 Percentile values is  17000.0
The 99.1 Percentile values is 18000.0
The 99.2 Percentile values is 19000.0
The 99.3 Percentile values is 21000.0
The 99.4 Percentile values is 23000.0
The 99.5 Percentile values is 25000.0
The 99.6 Percentile values is 29000.0
The 99.7 Percentile values is 33000.0
The 99.8 Percentile values is 39000.0
The 99.9 Percentile values is 55000.0
The 100 Percentile values is  125000.0
```

Observation

1. The Maximum amount Reimbursed is 125000
2. The 90% of claims has reimbursed amount to be less than 2000
3. There is Huge difference between 99 and 100 percentile may be it is fraud claim

In [ ]:
```
# OutPatient Dataset
plt.figure(figsize=(20,5))
sns.kdeplot(out["InscClaimAmtReimbursed"],shade=True,color="R")
plt.title(" InscClaimAmtReimbursed vs Fraud")
plt.show()

print("\n\n")
print("The 25 Percentile values is ",np.percentile(out["InscClaimAmtReimburse
d"].dropna(),25))
print("The 50 Percentile values is ",np.percentile(out["InscClaimAmtReimburse
d"].dropna(),50))
print("The 75 Percentile values is ",np.percentile(out["InscClaimAmtReimburse
d"].dropna(),75))
print("The 90 Percentile values is ",np.percentile(out["InscClaimAmtReimburse
d"].dropna(),90))
print("The 99 Percentile values is ",np.percentile(out["InscClaimAmtReimburse
d"].dropna(),99))
for i in range(1,10):
  a=99
  b=i/10
  a=a+b
  print(f"The {a} Percentile values is {np.percentile(out['InscClaimAmtReimbur
sed'].dropna(),a)}")
print("The 100 Percentile values is ",np.percentile(out["InscClaimAmtReimburse
d"].dropna(),100))
```

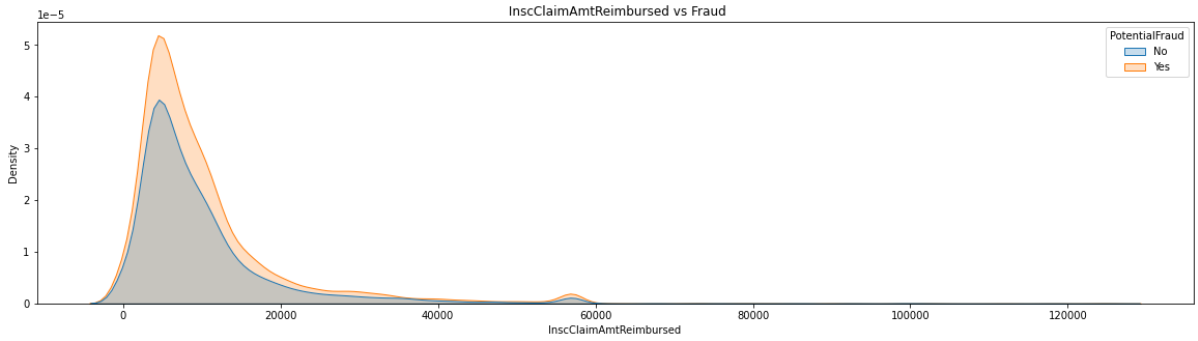



```
The 25 Percentile values is  40.0
The 50 Percentile values is  80.0
The 75 Percentile values is  200.0
The 90 Percentile values is  700.0
The 99 Percentile values is  3300.0
The 99.1 Percentile values is 3300.0
The 99.2 Percentile values is 3300.0
The 99.3 Percentile values is 3300.0
The 99.4 Percentile values is 3300.0
The 99.5 Percentile values is 3300.0
The 99.6 Percentile values is 3300.0
The 99.7 Percentile values is 3300.0
The 99.8 Percentile values is 3300.0
The 99.9 Percentile values is 3500.0
The 100 Percentile values is  102500.0
```

Observation

1. The Maximum amount Reimbursed is 102500
2. The 90% of claims has reimbursed amount to be less than 700
3. There is Huge difference between 99 and 100 percentile may be it is fraud claim

In [ ]:
```
# INPatient Dataset
plt.figure(figsize=(20,5))
sns.kdeplot(In["InscClaimAmtReimbursed"],hue=In["PotentialFraud"],shade=True,color="R")
plt.title(" InscClaimAmtReimbursed vs Fraud")
plt.show()

print("\n\n")
print("The 25 Percentile values is ",np.percentile(In["InscClaimAmtReimbursed"].dropna(),25))
print("The 50 Percentile values is ",np.percentile(In["InscClaimAmtReimbursed"].dropna(),50))
print("The 75 Percentile values is ",np.percentile(In["InscClaimAmtReimbursed"].dropna(),75))
print("The 90 Percentile values is ",np.percentile(In["InscClaimAmtReimbursed"].dropna(),90))
print("The 99 Percentile values is ",np.percentile(In["InscClaimAmtReimbursed"].dropna(),99))
for i in range(1,10):
  a=99
  b=i/10
  a=a+b
  print(f"The {a} Percentile values is {np.percentile(In['InscClaimAmtReimbursed'].dropna(),a)}")
print("The 100 Percentile values is ",np.percentile(In["InscClaimAmtReimbursed"].dropna(),100))
```



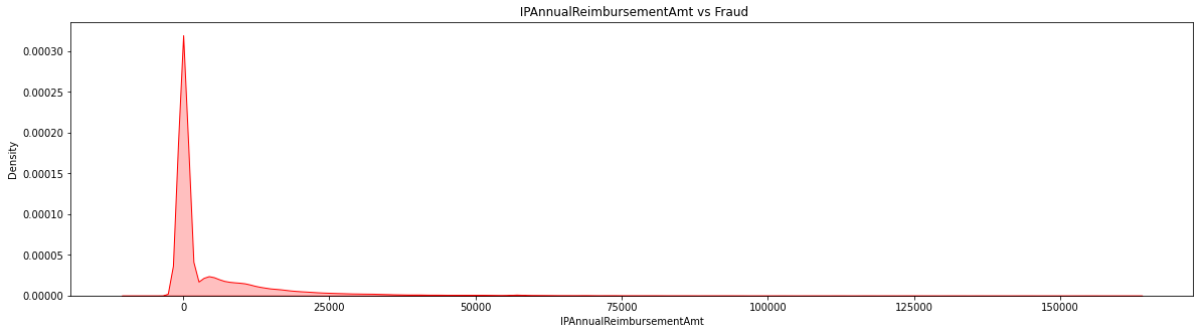

```
The 25 Percentile values is  4000.0
The 50 Percentile values is  7000.0
The 75 Percentile values is  12000.0
The 90 Percentile values is  20000.0
The 99 Percentile values is  57000.0
The 99.1 Percentile values is 57000.0
The 99.2 Percentile values is 57000.0
The 99.3 Percentile values is 57000.0
The 99.4 Percentile values is 57000.0
The 99.5 Percentile values is 57000.0
The 99.6 Percentile values is 57000.0
The 99.7 Percentile values is 57000.0
The 99.8 Percentile values is 72053.99999999645
The 99.9 Percentile values is 90000.0
The 100 Percentile values is  125000.0
```

Observation

1. The Maximum amount Reimbursed is 125000
2. The 90% of claims has reimbursed amount to be less than 20000.0

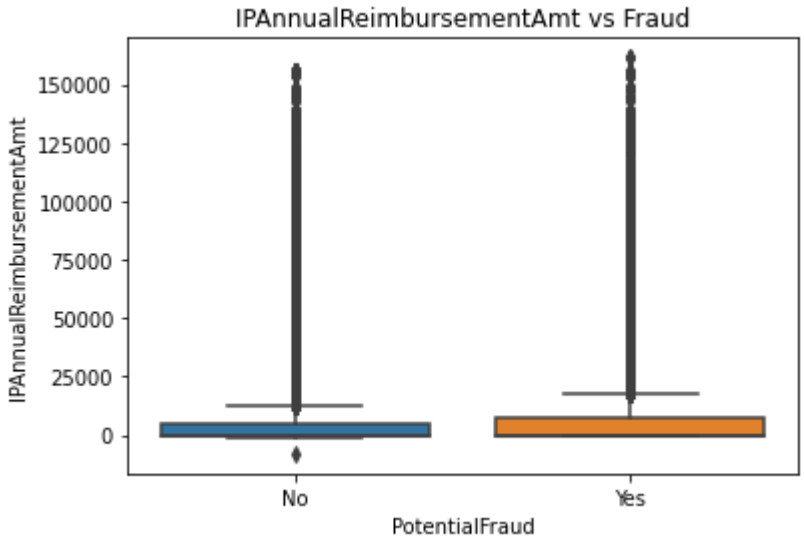
1.7 IPAnnualReimbursementAmt vs Fraud

In [ ]:
```
# Whole Dataset
plt.figure(figsize=(20,5))
sns.kdeplot(df["IPAnnualReimbursementAmt"],shade=True,color="R")
plt.title(" IPAnnualReimbursementAmt vs Fraud")
plt.show()

print("\n\n")
print("The 25 Percentile values is ",np.percentile(df["IPAnnualReimbursementAmt"],25))
print("The 50 Percentile values is ",np.percentile(df["IPAnnualReimbursementAmt"],50))
print("The 75 Percentile values is ",np.percentile(df["IPAnnualReimbursementAmt"],75))
print("The 90 Percentile values is ",np.percentile(df["IPAnnualReimbursementAmt"],90))
print("The 99 Percentile values is ",np.percentile(df["IPAnnualReimbursementAmt"],99))
for i in range(1,10):
  a=99
  b=i/10
  a=a+b
  print(f"The {a} Percentile values is {np.percentile(df['IPAnnualReimbursementAmt'],a)}")
print("The 100 Percentile values is ",np.percentile(df["IPAnnualReimbursementAmt"],100))
print("\n\n")

sns.boxplot(y='IPAnnualReimbursementAmt',x="PotentialFraud",data=df)
plt.title("IPAnnualReimbursementAmt vs Fraud")
```




```
The 25 Percentile values is  0.0
The 50 Percentile values is  0.0
The 75 Percentile values is  6000.0
The 90 Percentile values is  17000.0
The 99 Percentile values is  57200.0
The 99.1 Percentile values is 58610.0
The 99.2 Percentile values is 60620.0
The 99.3 Percentile values is 63000.0
The 99.4 Percentile values is 66000.0
The 99.5 Percentile values is 69020.0
The 99.6 Percentile values is 73210.0
The 99.7 Percentile values is 79000.0
The 99.8 Percentile values is 86894.99999998952
The 99.9 Percentile values is 103000.0
The 100 Percentile values is  161470.0
```

Out[ ]: Text(0.5, 1.0, 'IPAnnualReimbursementAmt vs Fraud')

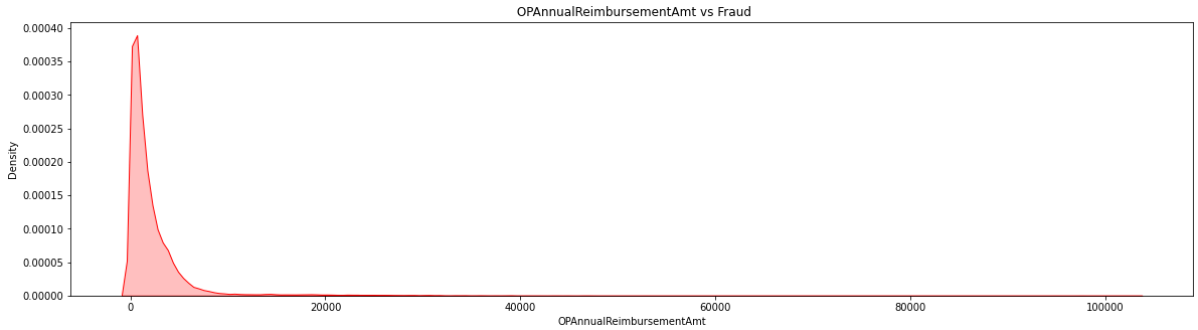


Observation

1. The Maximum amount Reimbursed for Inpatient is 161470
2. The 90% of claims has reimbursed amount to be less than 17000.0
3. From Box plot both the categories No and Yes are have same range for amount to reimbursed but for fraud case the highest amount to claim.

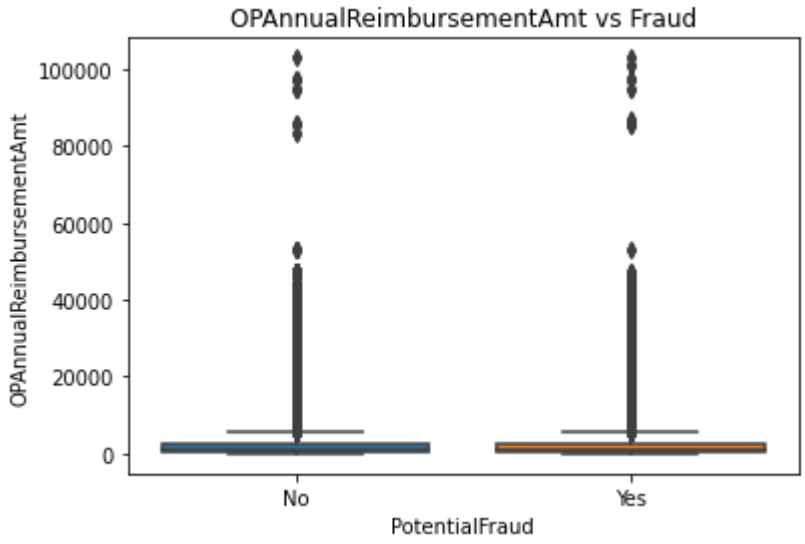
1.8 OPAnnualReimbursementAmt vs Fraud

In [ ]:
```
# Whole Dataset
plt.figure(figsize=(20,5))
sns.kdeplot(df["OPAnnualReimbursementAmt"],shade=True,color="R")
plt.title(" OPAnnualReimbursementAmt vs Fraud")
plt.show()

print("\n\n")
print("The 25 Percentile values is ",np.percentile(df["OPAnnualReimbursementAmt"],25))
print("The 50 Percentile values is ",np.percentile(df["OPAnnualReimbursementAmt"],50))
print("The 75 Percentile values is ",np.percentile(df["OPAnnualReimbursementAmt"],75))
print("The 90 Percentile values is ",np.percentile(df["OPAnnualReimbursementAmt"],90))
print("The 99 Percentile values is ",np.percentile(df["OPAnnualReimbursementAmt"],99))
for i in range(1,10):
  a=99
  b=i/10
  a=a+b
  print(f"The {a} Percentile values is {np.percentile(df['OPAnnualReimbursementAmt'],a)}")
print("The 100 Percentile values is ",np.percentile(df["OPAnnualReimbursementAmt"],100))
print("\n\n")

sns.boxplot(y='OPAnnualReimbursementAmt',x="PotentialFraud",data=df)
plt.title("OPAnnualReimbursementAmt vs Fraud")
```




```
The 25 Percentile values is  460.0
The 50 Percentile values is  1170.0
The 75 Percentile values is  2590.0
The 90 Percentile values is  4700.0
The 99 Percentile values is  22080.0
The 99.1 Percentile values is 22740.0
The 99.2 Percentile values is 23530.0
The 99.3 Percentile values is 24580.0
The 99.4 Percentile values is 25560.0
The 99.5 Percentile values is 26900.0
The 99.6 Percentile values is 28560.0
The 99.7 Percentile values is 30200.0
The 99.8 Percentile values is 32240.0
The 99.9 Percentile values is 36340.0
The 100 Percentile values is  102960.0
```

Out[ ]: Text(0.5, 1.0, 'OPAnnualReimbursementAmt vs Fraud')



Observation

1. The Maximum amount Reimbursed for Inpatient is 102960.0
2. The 90% of claims has reimbursed amount to be less than 4700
3. From Box plot both the categories No and Yes are have same range for amount to reimbursed .

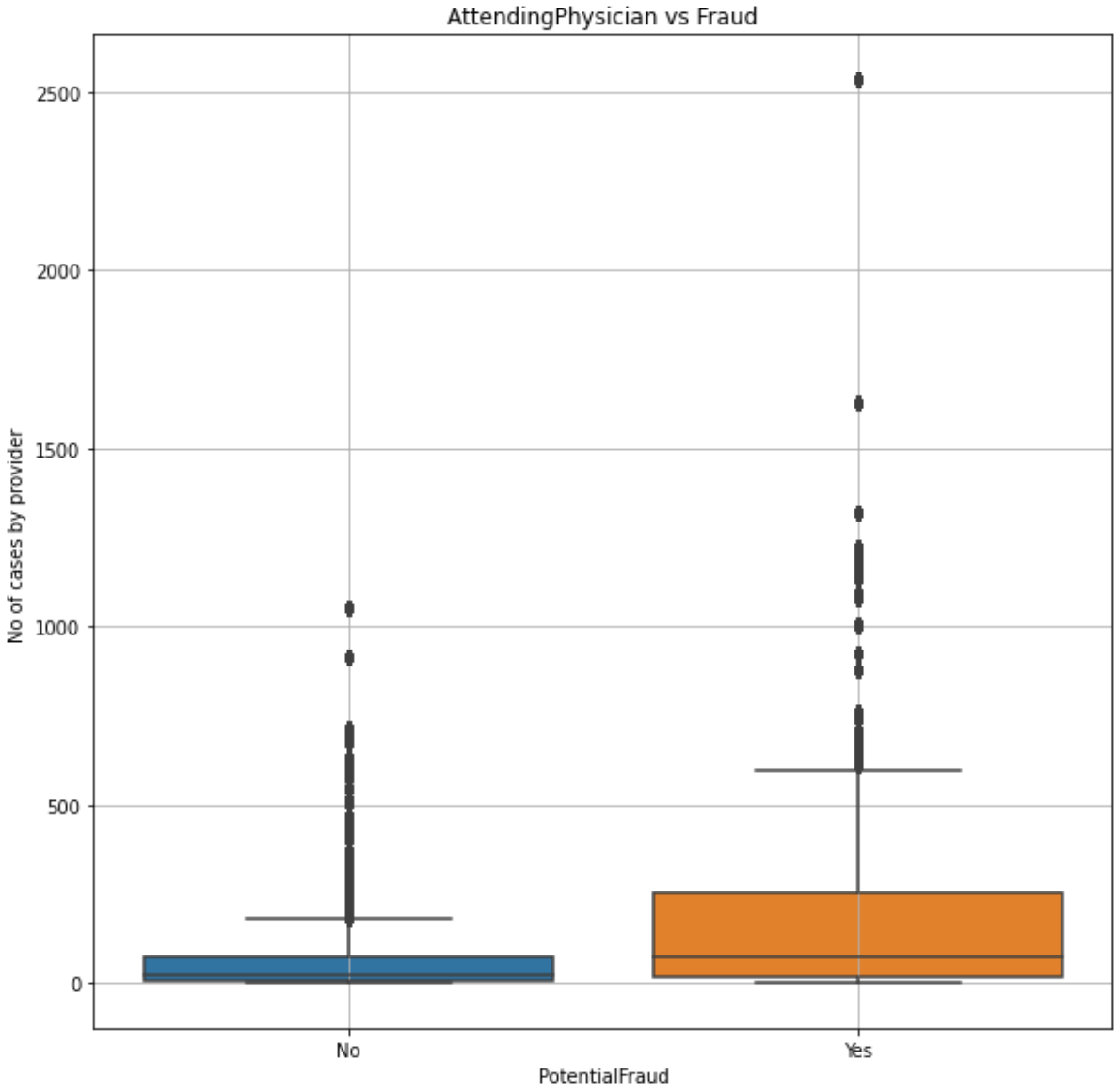
In [ ]:

1.9 AttendingPhysician vs Fraud

In [ ]:
```
# Whole Data set
print("The number of AttendingPhysician present are :",df["AttendingPhysician"
].value_counts().count())
print("Top 5 AttendingPhysician are ",df["AttendingPhysician"].value_counts()
[:5])

provider_dict= df["AttendingPhysician"].value_counts().to_dict()
count=df["AttendingPhysician"].map(provider_dict)

plt.figure(figsize=(10,10))
sns.boxplot(data=df,y=count,x="PotentialFraud")
plt.grid("whitegrid")
plt.ylabel("No of cases by provider ")
plt.title("AttendingPhysician vs Fraud")
```

```
The number of AttendingPhysician present are : 82063
Top 5 AttendingPhysician are  PHY330576    2534
PHY350277    1628
PHY412132    1321
PHY423534    1223
PHY314027    1200
Name: AttendingPhysician, dtype: int64
```

Out[ ]: Text(0.5, 1.0, 'AttendingPhysician vs Fraud')



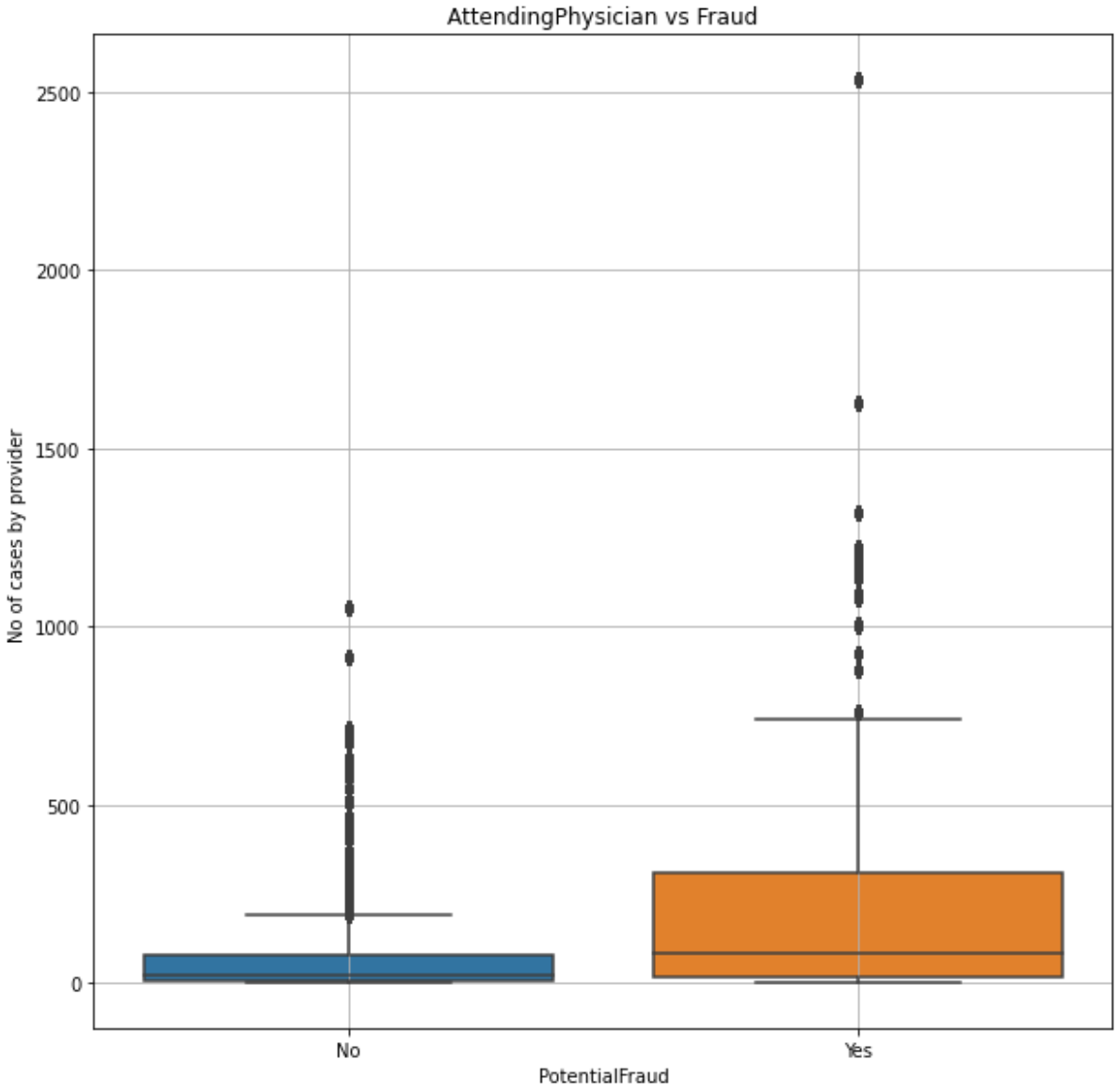
Observation

1. The Total Number Of attending Physican are 82063
2. From The box plot if the Physician attending more cases then may be he is invloved in commiting fraud and if it is handling less number of cases make non fraud.
3. The maximum number of handled cases are 2534

In [ ]:
```
# Outpatient Data set
print("The number of AttendingPhysician present are :",out["AttendingPhysicia
n"].value_counts().count())
print("Top 5 AttendingPhysician are ",out["AttendingPhysician"].value_counts()
[:5])

provider_dict= out["AttendingPhysician"].value_counts().to_dict()
count=out["AttendingPhysician"].map(provider_dict)

plt.figure(figsize=(10,10))
sns.boxplot(data=out,y=count,x="PotentialFraud")
plt.grid("whitegrid")
plt.ylabel("No of cases by provider ")
plt.title("AttendingPhysician vs Fraud")
```

```
The number of AttendingPhysician present are : 74109
Top 5 AttendingPhysician are  PHY330576    2534
PHY350277    1628
PHY412132    1321
PHY423534    1223
PHY314027    1200
Name: AttendingPhysician, dtype: int64
```

Out[ ]: Text(0.5, 1.0, 'AttendingPhysician vs Fraud')



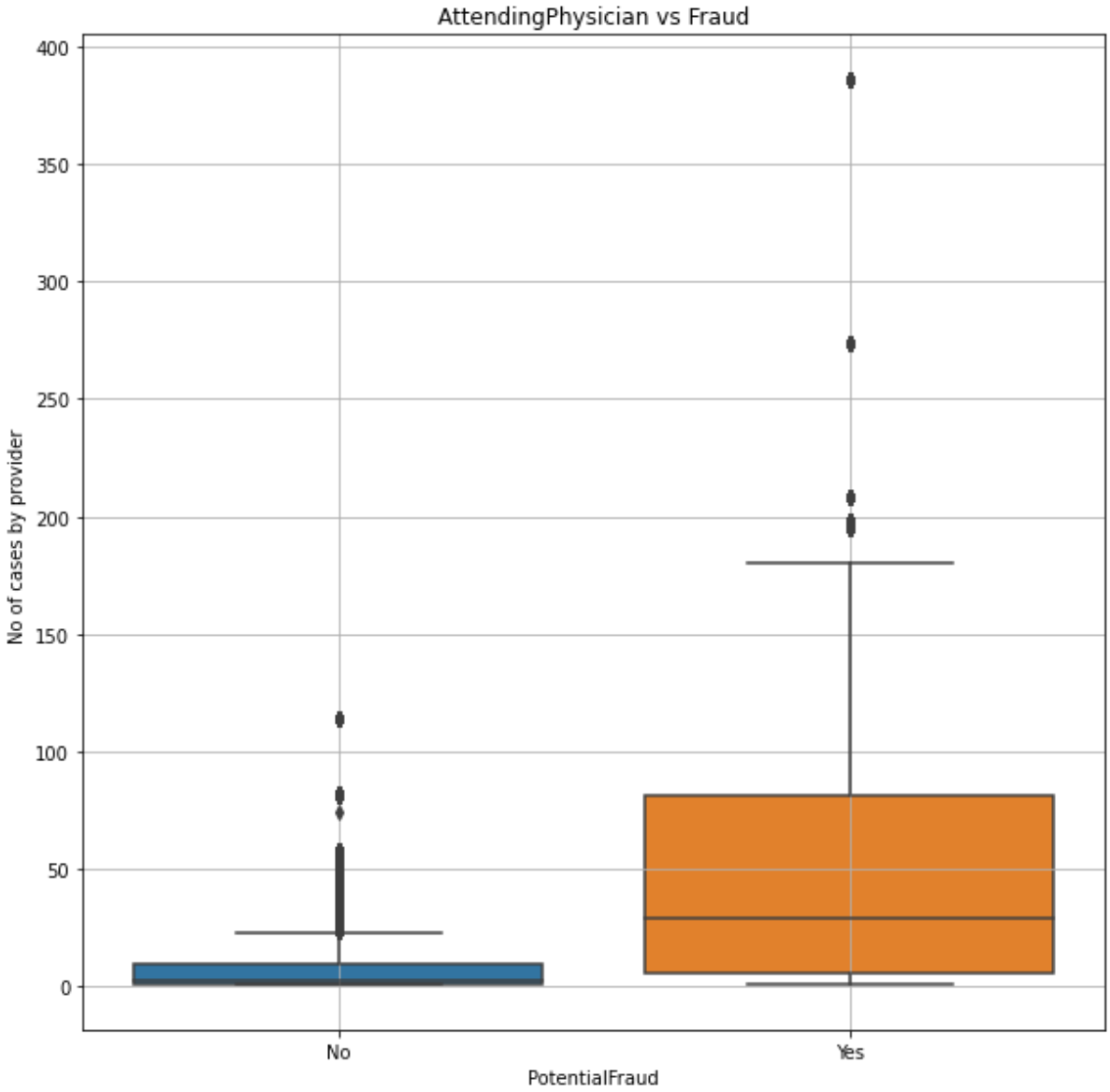
Observation

1. The Total Number Of attending Physican are 74109
2. From The box plot if the Physician attending more cases then may be he is invloved in commiting fraud and if it is handling less number of cases make non fraud.
3. The maximum number of handled cases are 2534

In [ ]:
```
# Inpatient Data set
print("The number of AttendingPhysician present are :",In["AttendingPhysician"
].value_counts().count())
print("Top 5 AttendingPhysician are ",In["AttendingPhysician"].value_counts()
[:5])

provider_dict= In["AttendingPhysician"].value_counts().to_dict()
count=In["AttendingPhysician"].map(provider_dict)

plt.figure(figsize=(10,10))
sns.boxplot(data=In,y=count,x="PotentialFraud")
plt.grid("whitegrid")
plt.ylabel("No of cases by provider ")
plt.title("AttendingPhysician vs Fraud")
```

```
The number of AttendingPhysician present are : 11604
Top 5 AttendingPhysician are  PHY422134    386
PHY341560    274
PHY315112    208
PHY411541    198
PHY362864    195
Name: AttendingPhysician, dtype: int64
```

Out[ ]: Text(0.5, 1.0, 'AttendingPhysician vs Fraud')



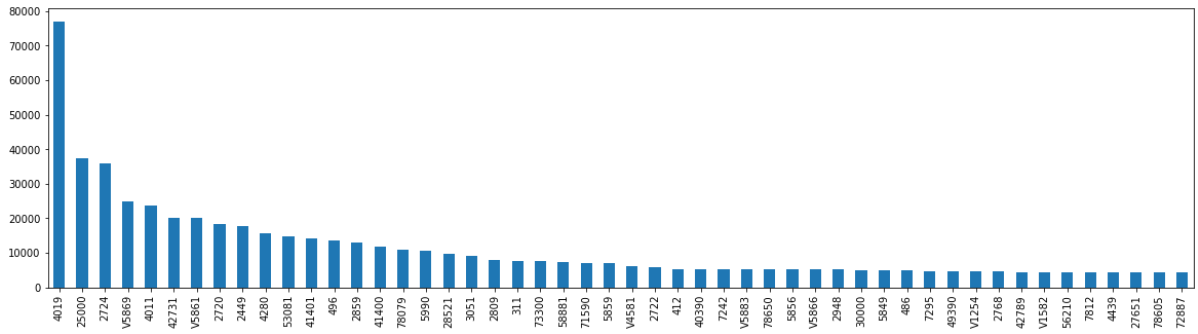
Observation

1. The Total Number Of attending Physican are 11604
2. From The box plot if the Physician attending more cases then may be he is invloved in commiting fraud and if it is handling less number of cases make non fraud.
3. The maximum number of handled cases are 386

1.10 DiagnoiseCode vs Fraud

In [ ]:
```
#Concating all the DiagnosisCode
data = pd.DataFrame(columns = ['DiagnosisCode'])
data['DiagnosisCode'] = pd.concat([df["ClmDiagnosisCode_1"],df["ClmDiagnosisCode_2"],df["ClmDiagnosisCode_3"],df["ClmDiagnosisCode_4"],df["ClmDiagnosisCode_5"],
                           df["ClmDiagnosisCode_6"],df["ClmDiagnosisCode_7"],df["ClmDiagnosisCode_8"],df["ClmDiagnosisCode_9"],
                           df["ClmDiagnosisCode_10"]], axis=0)
print("The Null values Present are",  data["DiagnosisCode"].isnull().sum())
data.dropna(inplace=True)
print("The Shape   after droping nullvalues Present are", data["DiagnosisCode"].shape[0])

print("The number of categories of code present are: ",data["DiagnosisCode"].value_counts().count())
codes=data["DiagnosisCode"].value_counts()[:50]
plt.figure(figsize=(20,5))
codes.plot(kind="bar")
plt.show()
print("\n\n")
print("The number of categories of code present are: ",data["DiagnosisCode"].value_counts()[:10])
```

```
The Null values Present are 3901394
The Shape   after droping nullvalues Present are 1680716
The number of categories of code present are:  11014
```




```
The number of categories of code present are:  4019     77056
25000    37356
2724     35763
V5869    24904
4011     23773
42731    20138
V5861    20001
2720     18268
2449     17600
4280     15507
Name: DiagnosisCode, dtype: int64
```

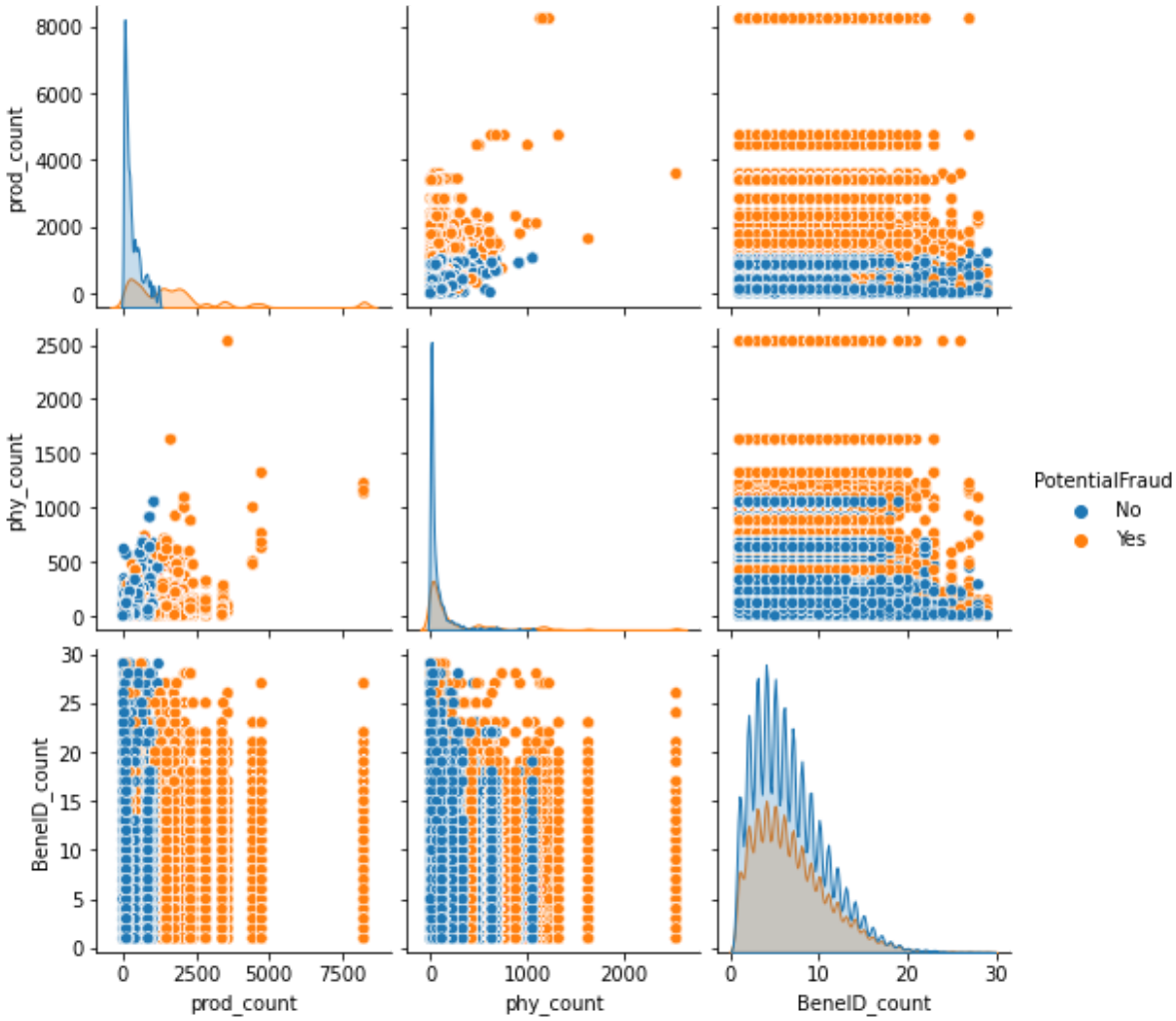
Observation

1. The Number of Unique Code are 11014
2. The most common codes used is 4019 with count of 77056

1.10 Bivariate Analysis of Provider and AttendingPhysican

In [ ]:
```
phy_dict= df["AttendingPhysician"].value_counts().to_dict()
df["phy_count"]=df["AttendingPhysician"].map(phy_dict)

prod_dict= df["Provider"].value_counts().to_dict()
df["prod_count"]=df["Provider"].map(prod_dict)

bene_dict= df["BeneID"].value_counts().to_dict()
df["BeneID_count"]=df["BeneID"].map(bene_dict)

sns.pairplot(data=df,hue='PotentialFraud',vars=["prod_count","phy_count","BeneID_count"])
```

Out[ ]:
```
<seaborn.axisgrid.PairGrid at 0x7f85ab839dd0>
```



In [ ]:
```
print("The Top 5 Patients with maximum claims are \n",df["BeneID"].value_count
s()[:5])
top_patients=df["BeneID"].value_counts().keys()[:50]
print("**"*50)
print("The Top 5 Provider with maximum claims are \n",df["Provider"].value_cou
nts()[:5])
top_provider=df["Provider"].value_counts().keys()[:50]
print("**"*50)
print("The Top 5 AttendingPhysician with maximum claims are \n",df["AttendingP
hysician"].value_counts()[:5])
top_physican=df["AttendingPhysician"].value_counts().keys()[:50]
print("**"*50)

pp1=[]
for i in range(5):
  g=df.groupby("Provider")
  data=g.get_group(top_provider[i])
  for j in range(5):
    if any(data[(data["AttendingPhysician"]==top_physican[j])&(data["Potential
Fraud"]=="Yes")]):
      pp1.append(((top_provider[i],top_physican[j]),"Yes"))


pb1=[]
for i in range(5):
  g=df.groupby("BeneID")
  data=g.get_group(top_patients[i])
  for j in range(5):
    if any(data[(data["AttendingPhysician"]==top_physican[j])&(data["Potential
Fraud"]=="Yes")]):
      pb1.append(((top_patients[i],top_physican[j]),"Yes"))
print("**"*50)
print("The top 10 Provider and Physcian that are involved in Commiting Fraud a
re:\n")
for i in pp1:
  print(i)
print("The top 10 Patients and Physcian that are involved in Commiting Fraud a
re:")
for i in pb1:
  print(i)
```

```
The Top 5 Patients with maximum claims are
 BENE42721     29
BENE59303     29
BENE118316    29
BENE44241     28
BENE80977     28
Name: BeneID, dtype: int64
**************************************************************************
**********************
The Top 5 Provider with maximum claims are
 PRV51459    8240
PRV53797    4739
PRV51574    4444
PRV53918    3588
PRV54895    3436
Name: Provider, dtype: int64
**************************************************************************
**********************
The Top 5 AttendingPhysician with maximum claims are
 PHY330576    2534
PHY350277    1628
PHY412132    1321
PHY423534    1223
PHY314027    1200
Name: AttendingPhysician, dtype: int64
**************************************************************************
**********************
**************************************************************************
**********************
The top 10 Provider and Physcian that are involved in Commiting Fraud are:

(('PRV51459', 'PHY330576'), 'Yes')
(('PRV51459', 'PHY350277'), 'Yes')
(('PRV51459', 'PHY412132'), 'Yes')
(('PRV51459', 'PHY423534'), 'Yes')
(('PRV51459', 'PHY314027'), 'Yes')
(('PRV53797', 'PHY330576'), 'Yes')
(('PRV53797', 'PHY350277'), 'Yes')
(('PRV53797', 'PHY412132'), 'Yes')
(('PRV53797', 'PHY423534'), 'Yes')
(('PRV53797', 'PHY314027'), 'Yes')
(('PRV51574', 'PHY330576'), 'Yes')
(('PRV51574', 'PHY350277'), 'Yes')
(('PRV51574', 'PHY412132'), 'Yes')
(('PRV51574', 'PHY423534'), 'Yes')
(('PRV51574', 'PHY314027'), 'Yes')
(('PRV53918', 'PHY330576'), 'Yes')
(('PRV53918', 'PHY350277'), 'Yes')
(('PRV53918', 'PHY412132'), 'Yes')
(('PRV53918', 'PHY423534'), 'Yes')
(('PRV53918', 'PHY314027'), 'Yes')
(('PRV54895', 'PHY330576'), 'Yes')
(('PRV54895', 'PHY350277'), 'Yes')
(('PRV54895', 'PHY412132'), 'Yes')
(('PRV54895', 'PHY423534'), 'Yes')
(('PRV54895', 'PHY314027'), 'Yes')
The top 10 Patients and Physcian that are involved in Commiting Fraud are:
```

```
(('BENE42721', 'PHY330576'), 'Yes')
(('BENE42721', 'PHY350277'), 'Yes')
(('BENE42721', 'PHY412132'), 'Yes')
(('BENE42721', 'PHY423534'), 'Yes')
(('BENE42721', 'PHY314027'), 'Yes')
(('BENE59303', 'PHY330576'), 'Yes')
(('BENE59303', 'PHY350277'), 'Yes')
(('BENE59303', 'PHY412132'), 'Yes')
(('BENE59303', 'PHY423534'), 'Yes')
(('BENE59303', 'PHY314027'), 'Yes')
(('BENE118316', 'PHY330576'), 'Yes')
(('BENE118316', 'PHY350277'), 'Yes')
(('BENE118316', 'PHY412132'), 'Yes')
(('BENE118316', 'PHY423534'), 'Yes')
(('BENE118316', 'PHY314027'), 'Yes')
(('BENE44241', 'PHY330576'), 'Yes')
(('BENE44241', 'PHY350277'), 'Yes')
(('BENE44241', 'PHY412132'), 'Yes')
(('BENE44241', 'PHY423534'), 'Yes')
(('BENE44241', 'PHY314027'), 'Yes')
(('BENE80977', 'PHY330576'), 'Yes')
(('BENE80977', 'PHY350277'), 'Yes')
(('BENE80977', 'PHY412132'), 'Yes')
(('BENE80977', 'PHY423534'), 'Yes')
(('BENE80977', 'PHY314027'), 'Yes')
```

In [ ]:
```
df.drop(columns=["prod_count","phy_count","BeneID_count"],inplace=True,axis=1)
```

Observation

1. From the Analysis The top 5 Provider combinations with Physican are involved in fraud this conclude that all the Provider and Physican who handle more cases are involved in Fraud
2. From the Analysis The top 5 Patients combinations with Physican are involved in fraud this conclude that all the Patients and Physican who handle more cases are involved in Fraud

1.10 Gender vs Fraud

In [ ]:
```
sns.violinplot(y="Gender",x="PotentialFraud",data=df)
plt.title("Gender vs Fraud")
```

Out[ ]:
```
Text(0.5, 1.0, 'Gender vs Fraud')
```

Observation

1. From the Plot the gender 2 are more involved in the Fraud

In [ ]:

SUMMARY

1. The Distribution of Data Points are 61.87% of them are not Fraud Claims, 38.12% are Fraud claims
2. If the provider is handling more number of cases tends to commit fraud whereas the provider handling less cases do not commit any fraud.
3. If The patient files more claims he/she is involved in Fraud.
4. The people belong Race Category 1 are involved in fraud most of the time
5. The states like 5,10,34 have more than 15000 fraud cases
6. for the 90% of claims the reimbursed amt is less(2000) and if the amout is too big may it falls under fraud claim
7. if the Physician attending more cases then may be he is invloved in commiting fraud and if it is handling less number of cases make non fraud.
8. If the most attended physician and most cases handled provider files claim together then they are involved in fraud
9. If the most attended physician and Top patient files claim together then they are involved in fraud
10. Rest of the columns are containg most of Null values and not interpreting any reult

In [ ]:

Data Preprocessing

In [ ]:
```
# The Potential Fraud has 2 cateories Yes/No coverting it to 1/0
df["PotentialFraud"]=np.where(df["PotentialFraud"]=="Yes",1,0)
df["PotentialFraud"].value_counts()
```

Out[ ]:
```
0    345415
1    212796
Name: PotentialFraud, dtype: int64
```

In [ ]:
```
# The Column RenalDiseaseIndicator has 2 categories Y/0 converting to 1/0
df["RenalDiseaseIndicator"]=np.where(df["RenalDiseaseIndicator"]=="Y",1,0)
df["RenalDiseaseIndicator"].value_counts()
```

Out[ ]:
```
0    448363
1    109848
Name: RenalDiseaseIndicator, dtype: int64
```

In [ ]:
```
# Checking for the NULL Values
df.isnull().sum()
```

Out[ ]:

Provider	0
PotentialFraud	0
BeneID	0
DOB	0
DOD	554080
Gender	0
Race	0
RenalDiseaseIndicator	0
State	0
County	0
NoOfMonths_PartACov	0
NoOfMonths_PartBCov	0
ChronicCond_Alzheimer	0
ChronicCond_Heartfailure	0
ChronicCond_KidneyDisease	0
ChronicCond_Cancer	0
ChronicCond_ObstrPulmonary	0
ChronicCond_Depression	0
ChronicCond_Diabetes	0
ChronicCond_IschemicHeart	0
ChronicCond_Osteoporasis	0
ChronicCond_rheumatoidarthritis	0
ChronicCond_stroke	0
IPAnnualReimbursementAmt	0
IPAnnualDeductibleAmt	0
OPAnnualReimbursementAmt	0
OPAnnualDeductibleAmt	0
ClaimID	0
ClaimStartDt	0
ClaimEndDt	0
InscClaimAmtReimbursed	0
AttendingPhysician	1508
OperatingPhysician	443764
OtherPhysician	358475
AdmissionDt	517737
ClmAdmitDiagnosisCode	412312
DeductibleAmtPaid	899
DischargeDt	517737
DiagnosisGroupCode	517737
ClmDiagnosisCode_1	10453
ClmDiagnosisCode_2	195606
ClmDiagnosisCode_3	315156
ClmDiagnosisCode_4	393675
ClmDiagnosisCode_5	446287
ClmDiagnosisCode_6	473819
ClmDiagnosisCode_7	492034
ClmDiagnosisCode_8	504767
ClmDiagnosisCode_9	516396
ClmDiagnosisCode_10	553201
ClmProcedureCode_1	534901
ClmProcedureCode_2	552721
ClmProcedureCode_3	557242
ClmProcedureCode_4	558093
ClmProcedureCode_5	558202
ClmProcedureCode_6	558211

dtype: int64

In [ ]:
```
# The columns ClmProcedureCode_4 ,ClmProcedureCode_5 ,ClmProcedureCode_6  have all null values AND NoOfMonths_PartACov', 'NoOfMonths_PartBCov' have same values so droping them
df.drop(columns=["ClmProcedureCode_4","ClmProcedureCode_5","ClmProcedureCode_6","NoOfMonths_PartACov", "NoOfMonths_PartBCov"],inplace=True, axis=1 )
```

In [ ]:
```
#Replacing all the null values with 0
imp = ['ClmDiagnosisCode_1','ClmDiagnosisCode_2','ClmDiagnosisCode_3','ClmDiagnosisCode_4',
            'ClmDiagnosisCode_5','ClmDiagnosisCode_6','ClmDiagnosisCode_7','ClmDiagnosisCode_8',
            'ClmDiagnosisCode_9','ClmDiagnosisCode_10','ClmProcedureCode_1','ClmProcedureCode_2'
            ,'ClmProcedureCode_3','DiagnosisGroupCode','ClmAdmitDiagnosisCode']
for i in imp:
  df[i]=df[i].replace({np.nan:0})
```

In [ ]:
```
df
```

Out[ ]:

	Provider	PotentialFraud	BeneID	DOB	DOD	Gender	Race	RenalDiseaseIndicat
0	PRV51001	0	BENE11727	1930-05-01	NaN	1	1	
1	PRV51001	0	BENE24646	1943-03-01	NaN	1	1	
2	PRV51001	0	BENE31617	1933-08-01	NaN	2	1	
3	PRV51001	0	BENE32715	1936-03-01	NaN	1	1	
4	PRV51001	0	BENE36012	1940-07-01	NaN	1	1	
...	...	...	...	...	...	...	...	
558206	PRV57763	0	BENE148535	1940-02-01	NaN	2	2	
558207	PRV57763	0	BENE150998	1958-12-01	NaN	1	2	
558208	PRV57763	0	BENE151006	1963-08-01	NaN	2	1	
558209	PRV57763	0	BENE158531	1952-02-01	NaN	2	2	
558210	PRV57763	0	BENE158531	1952-02-01	NaN	2	2	

558211 rows × 50 columns

In [ ]:
```
df.isnull().sum()
```

Out[ ]:
```
Provider                            0
PotentialFraud                      0
BeneID                              0
DOB                                 0
DOD                            554080
Gender                              0
Race                                0
RenalDiseaseIndicator               0
State                               0
County                              0
ChronicCond_Alzheimer               0
ChronicCond_Heartfailure            0
ChronicCond_KidneyDisease           0
ChronicCond_Cancer                  0
ChronicCond_ObstrPulmonary          0
ChronicCond_Depression              0
ChronicCond_Diabetes                0
ChronicCond_IschemicHeart           0
ChronicCond_Osteoporasis            0
ChronicCond_rheumatoidarthritis     0
ChronicCond_stroke                  0
IPAnnualReimbursementAmt            0
IPAnnualDeductibleAmt               0
OPAnnualReimbursementAmt            0
OPAnnualDeductibleAmt               0
ClaimID                             0
ClaimStartDt                        0
ClaimEndDt                          0
InscClaimAmtReimbursed              0
AttendingPhysician               1508
OperatingPhysician             443764
OtherPhysician                 358475
AdmissionDt                    517737
ClmAdmitDiagnosisCode               0
DeductibleAmtPaid                 899
DischargeDt                    517737
DiagnosisGroupCode                  0
ClmDiagnosisCode_1                  0
ClmDiagnosisCode_2                  0
ClmDiagnosisCode_3                  0
ClmDiagnosisCode_4                  0
ClmDiagnosisCode_5                  0
ClmDiagnosisCode_6                  0
ClmDiagnosisCode_7                  0
ClmDiagnosisCode_8                  0
ClmDiagnosisCode_9                  0
ClmDiagnosisCode_10                 0
ClmProcedureCode_1                  0
ClmProcedureCode_2                  0
ClmProcedureCode_3                  0
dtype: int64
```

Feature Engineering

In [ ]:
```
# handling BeneID:  Relpacing the categories by the count
count=df["BeneID"].value_counts().to_dict()
df["BeneID"]=df["BeneID"].map(count)
with open('/content/drive/My Drive/CASE Studies/healthcare/patient_count.json'
, 'wb') as fp:
    pickle.dump(count, fp)
```

In [ ]:
```
#handling Provider replacing The categories by the count
count=df["Provider"].value_counts().to_dict()
df["Provider"]=df["Provider"].map(count)

with open('/content/drive/My Drive/CASE Studies/healthcare/provider_count.jso
n', 'wb') as fp:
    pickle.dump(count, fp)
```

In [ ]:
```
# Creating new feature as total amount to reimbursed
# 1 there are four features IPAnnualReimbursementAmt ,oPAnnualReimbursementAmt
,IPAnnualDeductibleAmt,OPAnnualDeductibleAmt
# 2 so we can calculate the total amount to be reimbursed
reimb_amount=df["IPAnnualReimbursementAmt"]+df["OPAnnualReimbursementAmt"]
deduct_amt=df["IPAnnualDeductibleAmt"]+df["OPAnnualDeductibleAmt"]
df["amount_to_reimbursed"]=reimb_amount-deduct_amt
df.drop(columns=["IPAnnualReimbursementAmt" ,"OPAnnualReimbursementAmt" ,"IPAn
nualDeductibleAmt","OPAnnualDeductibleAmt"],inplace=True,axis=1)
```

In [ ]:
```
# handling AttendingPhysician replacing The  categories with count
count=df["AttendingPhysician"].value_counts().to_dict()
df["AttendingPhysician"]=df["AttendingPhysician"].map(count)
df["AttendingPhysician"].fillna(0)
with open('/content/drive/My Drive/CASE Studies/healthcare/attending_phy_coun
t.json', 'wb') as fp:
    pickle.dump(count, fp)
```

In [ ]:
```
# creating New feature how many physican are involved in treating the patients
# 1 there are 3 columns OperatingPhysician , OtherPhysician ,AttendingPhysicia
n
# 2 so we can count how many physican were treating the patients and can  drop
these operating and otherphyscian
count_of_physician=df[['AttendingPhysician','OperatingPhysician','OtherPhysici
an']].fillna(0).values
count=[]
for i in range(len(count_of_physician)):
  count.append(np.count_nonzero(count_of_physician[i]))    #https://stackoverf
low.com/questions/26053849/counting-non-zero-values-in-each-column-of-a-datafr
ame-in-python

df["Physician_count"]=count
df.drop(columns=["OtherPhysician","OperatingPhysician"],inplace=True,axis=1)
```

In [ ]:
```
# creating column like number of days took to complete the Claim
strt_date=pd.to_datetime(df["ClaimStartDt"]).dt.day
end_date=pd.to_datetime(df["ClaimEndDt"]).dt.day
df["Claim_duration"]=end_date-strt_date
df.drop(columns=["ClaimStartDt","ClaimEndDt"],inplace=True,axis=1)
```

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 558211 entries, 0 to 558210
Data columns (total 45 columns):
 #   Column                            Non-Null Count   Dtype  
---  ------                            --------------   -----  
 0   Provider                          558211 non-null  int64  
 1   PotentialFraud                    558211 non-null  int64  
 2   BeneID                            558211 non-null  int64  
 3   DOB                               558211 non-null  object 
 4   DOD                               4131 non-null    object 
 5   Gender                            558211 non-null  int64  
 6   Race                              558211 non-null  int64  
 7   RenalDiseaseIndicator             558211 non-null  int64  
 8   State                             558211 non-null  int64  
 9   County                            558211 non-null  int64  
 10  ChronicCond_Alzheimer             558211 non-null  int64  
 11  ChronicCond_Heartfailure          558211 non-null  int64  
 12  ChronicCond_KidneyDisease         558211 non-null  int64  
 13  ChronicCond_Cancer                558211 non-null  int64  
 14  ChronicCond_ObstrPulmonary        558211 non-null  int64  
 15  ChronicCond_Depression            558211 non-null  int64  
 16  ChronicCond_Diabetes              558211 non-null  int64  
 17  ChronicCond_IschemicHeart         558211 non-null  int64  
 18  ChronicCond_Osteoporasis          558211 non-null  int64  
 19  ChronicCond_rheumatoidarthritis   558211 non-null  int64  
 20  ChronicCond_stroke                558211 non-null  int64  
 21  ClaimID                           558211 non-null  object 
 22  InscClaimAmtReimbursed            558211 non-null  int64  
 23  AttendingPhysician                556703 non-null  float64
 24  AdmissionDt                       40474 non-null   object 
 25  ClmAdmitDiagnosisCode             558211 non-null  object 
 26  DeductibleAmtPaid                 557312 non-null  float64
 27  DischargeDt                       40474 non-null   object 
 28  DiagnosisGroupCode                558211 non-null  object 
 29  ClmDiagnosisCode_1                558211 non-null  object 
 30  ClmDiagnosisCode_2                558211 non-null  object 
 31  ClmDiagnosisCode_3                558211 non-null  object 
 32  ClmDiagnosisCode_4                558211 non-null  object 
 33  ClmDiagnosisCode_5                558211 non-null  object 
 34  ClmDiagnosisCode_6                558211 non-null  object 
 35  ClmDiagnosisCode_7                558211 non-null  object 
 36  ClmDiagnosisCode_8                558211 non-null  object 
 37  ClmDiagnosisCode_9                558211 non-null  object 
 38  ClmDiagnosisCode_10               558211 non-null  object 
 39  ClmProcedureCode_1                558211 non-null  float64
 40  ClmProcedureCode_2                558211 non-null  float64
 41  ClmProcedureCode_3                558211 non-null  float64
 42  amount_to_reimbursed              558211 non-null  int64  
 43  Physician_count                   558211 non-null  int64  
 44  Claim_duration                    558211 non-null  int64  
dtypes: float64(5), int64(23), object(17)
memory usage: 195.9+ MB
```

In [ ]:
```
df2=df.copy()
```

In [ ]:
```
# selecting only five Diagosis code
data = pd.DataFrame(columns = ['DiagnosisCode'])
data['DiagnosisCode'] = pd.concat([df["ClmDiagnosisCode_1"],df["ClmDiagnosisCo
de_2"],df["ClmDiagnosisCode_3"],df["ClmDiagnosisCode_4"],df["ClmDiagnosisCode_
5"],
                           df["ClmDiagnosisCode_6"],df["ClmDiagnosisCode_7"],df
["ClmDiagnosisCode_8"],df["ClmDiagnosisCode_9"],
                           df["ClmDiagnosisCode_10"]], axis=0)
print("The total categories of codes are",data["DiagnosisCode"].value_counts()
.count())
codes=data["DiagnosisCode"].value_counts()[1:6].keys()
print("The top5 categories are :",data["DiagnosisCode"].value_counts()[1:6])

# taking 5 top Codes and coverting it to column
# for each code we will check wether the the code is present or not if yes rep
lace with 1 and if no replace with 0
# we do this for all the ClmDiagnosisCode columns
# from ClmDiagnosisCode_2 onwords we will check if the code is present if yes
 replcae with 1 or else replace the value of the column with code

for i in codes:
  df["D_"+str(i)]=np.where(df["ClmDiagnosisCode_1"]==i,1,0)
  for j in range(2,11):
    df["D_"+str(i)]=np.where(df["ClmDiagnosisCode_"+str(j)]==i,1,np.where(df[
'D_'+str(i)]==1,1,0))

  df['D_'+str(i)] = np.where(df['DiagnosisGroupCode']==i,1,np.where(df['D_'+st
r(i)]==1,1,0 ))
  df['D_'+str(i)] = np.where(df['ClmAdmitDiagnosisCode']==i,1,np.where(df['D_'
+str(i)]==1,1,0 ))

df.drop(columns=["ClmDiagnosisCode_1","ClmDiagnosisCode_2","ClmDiagnosisCode_
3","ClmDiagnosisCode_4","ClmDiagnosisCode_5","ClmDiagnosisCode_6"
                 ,"ClmDiagnosisCode_7","ClmDiagnosisCode_8","ClmDiagnosisCode
_9","ClmDiagnosisCode_10","DiagnosisGroupCode","ClmAdmitDiagnosisCode"],inplac
e=True,axis=1)
```

```
The total categories of codes are 11015
The top5 categories are : 4019     77056
25000    37356
2724     35763
V5869    24904
4011     23773
Name: DiagnosisCode, dtype: int64
```

In [ ]:
```
# selecting only Top five Procedure code
data = pd.DataFrame(columns = ['ProcedureCode'])
data["ProcedureCode"]=pd.concat([df['ClmProcedureCode_1'], df['ClmProcedureCod
e_2'],df['ClmProcedureCode_3']],axis=0).dropna()
print("The total categories of Procedure codes are",data["ProcedureCode"].valu
e_counts().count())
codes=data["ProcedureCode"].value_counts()
codes=codes.index[1:6]
print("The top5 categories are :",data["ProcedureCode"].value_counts().index[1
:6])

for i in codes:
  df["P_"+str(i)]=np.where(df["ClmProcedureCode_1"]==i,1,0)
  for j in range(2,4):
    df["P_"+str(i)]=np.where(df["ClmProcedureCode_"+str(j)]==i,1,np.where(df[
'P_'+str(i)]==1,1,0))

df.drop(columns=["ClmProcedureCode_1","ClmProcedureCode_2","ClmProcedureCode_
3"],inplace=True,axis=1)
```

```
The total categories of Procedure codes are 1323
The top5 categories are : Float64Index([4019.0, 9904.0, 2724.0, 8154.0, 66.
0], dtype='float64')
```

In [ ]:
```
# droping unwanted columns
df.drop(columns=["DOD","AdmissionDt","DischargeDt","DOB","ClaimID"],inplace=Tr
ue,axis=1)
```

In [ ]:
```
df.fillna(0,inplace=True)
```

In [ ]:
```
df.to_csv("/content/drive/My Drive/CASE Studies/healthcare/data.csv")
```

In [2]:
```
import pandas as pd
df=pd.read_csv("data.csv")
df.shape
```

Out[2]:
```
(558211, 36)
```

In [3]:
```
df.columns
```

Out[3]:
```
Index(['Unnamed: 0', 'Provider', 'PotentialFraud', 'BeneID', 'Gender', 'Rac
e',
       'RenalDiseaseIndicator', 'State', 'County', 'ChronicCond_Alzheimer',
       'ChronicCond_Heartfailure', 'ChronicCond_KidneyDisease',
       'ChronicCond_Cancer', 'ChronicCond_ObstrPulmonary',
       'ChronicCond_Depression', 'ChronicCond_Diabetes',
       'ChronicCond_IschemicHeart', 'ChronicCond_Osteoporasis',
       'ChronicCond_rheumatoidarthritis', 'ChronicCond_stroke',
       'InscClaimAmtReimbursed', 'AttendingPhysician', 'DeductibleAmtPaid',
       'amount_to_reimbursed', 'Physician_count', 'Claim_duration', 'D_4019',
       'D_25000', 'D_2724', 'D_V5869', 'D_4011', 'P_4019.0', 'P_9904.0',
       'P_2724.0', 'P_8154.0', 'P_66.0'],
      dtype='object')
```

In [4]:
```
df.drop(["Unnamed: 0"],inplace=True,axis=1)
```

In [5]:
```
x=df.drop(["PotentialFraud"],axis=1)
y=df["PotentialFraud"]
```

In [6]:
```
#Train Test Split
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,stratify=y,ra
ndom_state=0)
```

In [7]:
```
x_train.columns
```

Out[7]:
```
Index(['Provider', 'BeneID', 'Gender', 'Race', 'RenalDiseaseIndicator',
       'State', 'County', 'ChronicCond_Alzheimer', 'ChronicCond_Heartfailur
e',
       'ChronicCond_KidneyDisease', 'ChronicCond_Cancer',
       'ChronicCond_ObstrPulmonary', 'ChronicCond_Depression',
       'ChronicCond_Diabetes', 'ChronicCond_IschemicHeart',
       'ChronicCond_Osteoporasis', 'ChronicCond_rheumatoidarthritis',
       'ChronicCond_stroke', 'InscClaimAmtReimbursed', 'AttendingPhysician',
       'DeductibleAmtPaid', 'amount_to_reimbursed', 'Physician_count',
       'Claim_duration', 'D_4019', 'D_25000', 'D_2724', 'D_V5869', 'D_4011',
       'P_4019.0', 'P_9904.0', 'P_2724.0', 'P_8154.0', 'P_66.0'],
      dtype='object')
```

In [8]:
```
#Normalizing data
from sklearn.preprocessing import MinMaxScaler
sccale_cols=["DeductibleAmtPaid",'InscClaimAmtReimbursed' , 'Race','State', 'C
ounty','AttendingPhysician','BeneID','Provider',
'Claim_duration', 'amount_to_reimbursed',  'Physician_count']

ss=MinMaxScaler()
```

In [9]:
```
#from sklearn.externals.joblib import dump, load
def scale(train,test,col):

  ss.fit(train[col].values.reshape(-1,1))
  #dump(ss, '/content/drive/My Drive/CASE Studies/healthcare/scaling/'+col+'_s
td_scaler.bin', compress=True)

  s_tr=ss.transform(train[col].values.reshape(-1,1))
  s_te=ss.transform(test[col].values.reshape(-1,1))

  return s_tr,s_te
```

In [10]:
```
for i in sccale_cols:
  x_train[i],x_test[i]=scale(x_train,x_test,i)
```

LINEAR MODEL

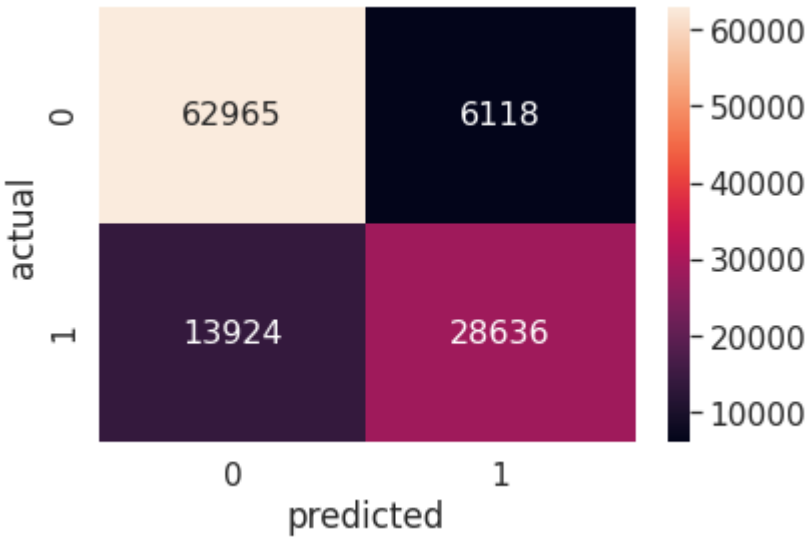
In [ ]:
```
# SGD CLASSIFIER
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import SGDClassifier
alpha=[0.0001,0.001,0.01,0.1,1,10,100]
p=["l1","l2"]
lr=SGDClassifier(class_weight='balanced',loss="log" )
param={ 'alpha':alpha,
          'penalty':p}
cv=RandomizedSearchCV(lr,param_distributions=param ,cv=5 ,n_iter=10,n_jobs=-1,
verbose=2)
cv.fit(x_train,y_train)
print("best_parameters",cv.best_params_)
lr_model=cv.best_estimator_
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed:   49.5s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:  1.0min finished

best_parameters {'penalty': 'l1', 'alpha': 0.01}
```

In [ ]:
```
from sklearn.metrics import confusion_matrix,classification_report,precision_score ,average_precision_score as aps
#import pickle
#lr_model = pickle.load(open("/content/drive/My Drive/CASE Studies/healthcare/model_linear.pkl", 'rb'))

lr_model.fit(x_train,y_train)
pred=lr_model.predict(x_test)
score=precision_score(y_test,pred)
report=classification_report(y_test,pred)
micro_precision=precision_score(y_test,pred,average='micro')
macro_precision=precision_score(y_test,pred,average='macro')

print(f"Precision_score={score}, micro_precision={micro_precision} ,macro_precision={macro_precision}")

print("CLASSIFICATION REPORT",report)


conf_matr_train = pd.DataFrame(confusion_matrix(y_test, pred), range(2),range(2))
sns.set(font_scale=1.4)
sns.heatmap(conf_matr_train, annot=True,annot_kws={"size": 16}, fmt='g')
plt.xlabel("predicted")
plt.ylabel("actual")
```

```
Precision_score=0.8239627093284226, micro_precision=0.8204813557500247 ,macro_precision=0.8214352427366274
CLASSIFICATION REPORT               precision    recall  f1-score   support

           0       0.82      0.91      0.86     69083
           1       0.82      0.67      0.74     42560

    accuracy                           0.82    111643
   macro avg       0.82      0.79      0.80    111643
weighted avg       0.82      0.82      0.82    111643
```

Out[ ]:
```
Text(25.5, 0.5, 'actual')
```



In [ ]:
```
import pickle
with open("/content/drive/My Drive/CASE Studies/healthcare/model_linear.pkl",
'wb') as file:
    pickle.dump(lr_model, file)
```

In [11]:
```
# Decision Tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import RandomizedSearchCV
params={'max_depth':[5,10,30,50],
'min_samples_split':[2,3,5,10],
'criterion':['gini','entropy']}
dt=DecisionTreeClassifier(class_weight="balanced")

cv=RandomizedSearchCV(dt,param_distributions=params ,cv=5 ,n_iter=10,n_jobs=-1
,verbose=2)
cv.fit(x_train,y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  1.6min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:  2.4min finished
```

Out[11]:
```
RandomizedSearchCV(cv=5,
                   estimator=DecisionTreeClassifier(class_weight='balanced'),
                   n_jobs=-1,
                   param_distributions={'criterion': ['gini', 'entropy'],
                                        'max_depth': [5, 10, 30, 50],
                                        'min_samples_split': [2, 3, 5, 10]},
                   verbose=2)
```

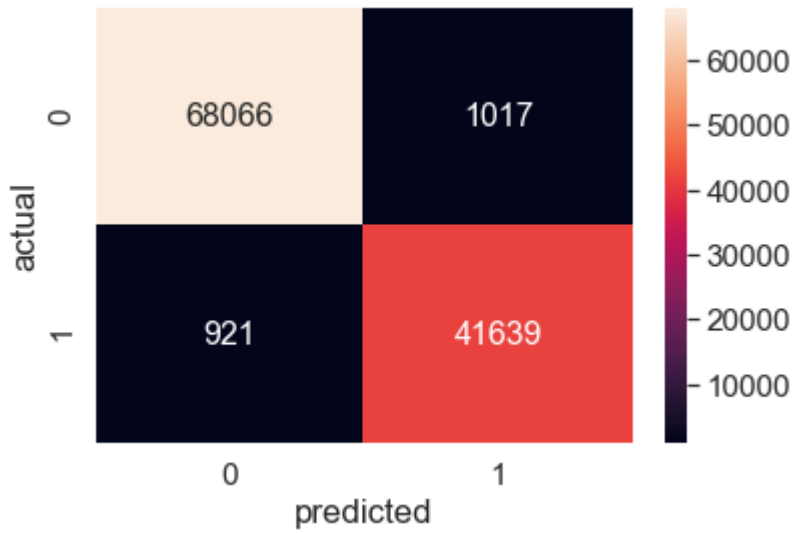
In [12]:
```
print("The best parameters are ",cv.best_params_)
tree_model=cv.best_estimator_
```

```
The best parameters are  {'min_samples_split': 5, 'max_depth': 30, 'criterio
n': 'entropy'}
```

In [13]:
```
import seaborn as sns
#tree_model = pickle.load(open("/content/drive/My Drive/CASE Studies/healthcare/tree_model.pkl", 'rb'))
from sklearn.metrics import confusion_matrix,classification_report,precision_score ,average_precision_score as aps

pred=tree_model.predict(x_test)
score=precision_score(y_test,pred)

report=classification_report(y_test,pred)
micro_precision=precision_score(y_test,pred,average='micro')
macro_precision=precision_score(y_test,pred,average='macro')
print(f"Precision_score={score}, micro_precision={micro_precision},macro_precision={macro_precision}")


print("CLASSIFICATION REPORT",report)

conf_matr_train = pd.DataFrame(confusion_matrix(y_test, pred), range(2),range(2))
sns.set(font_scale=1.4)
sns.heatmap(conf_matr_train, annot=True,annot_kws={"size": 16}, fmt='g')
plt.xlabel("predicted")
plt.ylabel("actual")
```

```
Precision_score=0.9761581020255063, micro_precision=0.9826410970683339,macro_
precision=0.9814038803284213
CLASSIFICATION REPORT               precision    recall  f1-score   support

           0       0.99      0.99      0.99     69083
           1       0.98      0.98      0.98     42560

    accuracy                           0.98    111643
   macro avg       0.98      0.98      0.98    111643
weighted avg       0.98      0.98      0.98    111643
```

Out[13]: Text(26.5, 0.5, 'actual')



In [14]:
```
import pickle
with open("Dtree.pkl", 'wb') as file:
    pickle.dump(tree_model, file)
```

XGBoostClassifier

In [ ]:
```
from xgboost import XGBClassifier
from sklearn.model_selection import RandomizedSearchCV
xgb = XGBClassifier()
param = {'learning_rate':[0.01,0.03,00.05,0.1],'n_estimators':[10,50,100,500,1
000],'max_depth':[3,5,10],'colsample_bytree':[0.1,0.3,0.5,1],'subsample':[0.1,
0.3,0.5,1] }
cv = RandomizedSearchCV(xgb,param,cv=5,n_jobs=-1,verbose=10)
cv.fit(x_train,y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done   1 tasks      | elapsed:  3.9min
[Parallel(n_jobs=-1)]: Done   4 tasks      | elapsed:  7.8min
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:  9.2min
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed: 19.4min
[Parallel(n_jobs=-1)]: Done  21 tasks      | elapsed: 61.5min
[Parallel(n_jobs=-1)]: Done  28 tasks      | elapsed: 67.4min
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed: 124.2min
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed: 164.9min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed: 211.9min finished
```

Out[ ]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                           colsample_bylevel=1,
                                           colsample_bynode=1,
                                           colsample_bytree=1, gamma=0,
                                           learning_rate=0.1, max_delta_step=
0,
                                           max_depth=3, min_child_weight=1,
                                           missing=None, n_estimators=100,
                                           n_jobs=1, nthread=None,
                                           objective='binary:logistic',
                                           random_state=0, reg_alpha=0,
                                           reg_lambda=1, sc...
                                           seed=None, silent=None, subsample=
1,
                                           verbosity=1),
                   iid='deprecated', n_iter=10, n_jobs=-1,
                   param_distributions={'colsample_bytree': [0.1, 0.3, 0.5,
1],
                                        'learning_rate': [0.01, 0.03, 0.05,
                                                          0.1],
                                        'max_depth': [3, 5, 10],
                                        'n_estimators': [10, 50, 100, 500,
                                                         1000],
                                        'subsample': [0.1, 0.3, 0.5, 1]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=False, scoring=None, verbose=10)
```

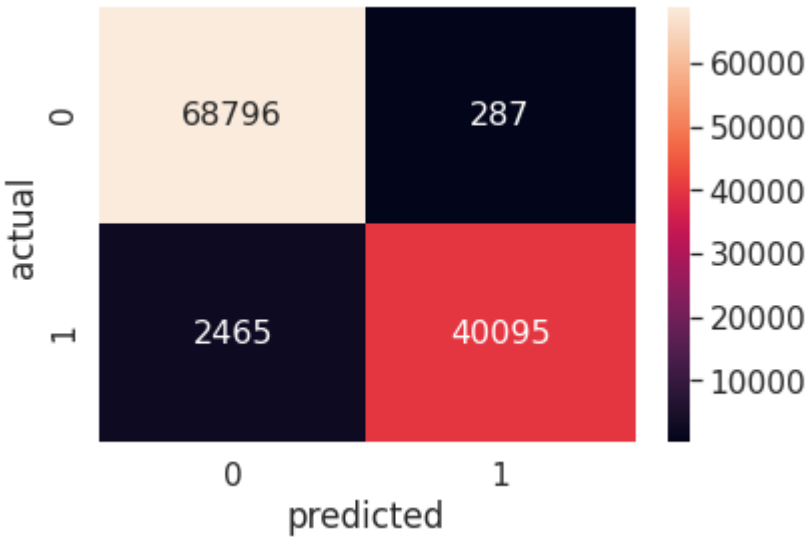
In [ ]:
```
print("The best parameters are ",cv.best_params_)
model_xgb=cv.best_estimator_
```

```
The best parameters are  {'subsample': 0.3, 'n_estimators': 1000, 'max_dept
h': 10, 'learning_rate': 0.1, 'colsample_bytree': 0.3}
```

In [ ]:
```
from sklearn.metrics import confusion_matrix,classification_report,precision_score ,average_precision_score as aps ,plot_confusion_matrix
import pickle
model_xgb = pickle.load(open("/content/drive/My Drive/CASE Studies/healthcare/XGB_model.pkl", 'rb'))

pred=model_xgb.predict(x_test)
score=precision_score(y_test,pred)

report=classification_report(y_test,pred)
micro_precision=precision_score(y_test,pred,average='micro')
macro_precision=precision_score(y_test,pred,average='macro')

print(f"Precision_score={score}, micro_precision={micro_precision} , macro_precision={macro_precision}")

print("CLASSIFICATION REPORT",report)

conf_matr_train = pd.DataFrame(confusion_matrix(y_test, pred), range(2),range(2))
sns.set(font_scale=1.4)
sns.heatmap(conf_matr_train, annot=True,annot_kws={"size": 16}, fmt='g')
plt.xlabel("predicted")
plt.ylabel("actual")
```

```
Precision_score=0.9928928730622555, micro_precision=0.9753499995521439 , macro_precision=0.9791508611111925
CLASSIFICATION REPORT               precision    recall  f1-score   support

           0       0.97      1.00      0.98     69083
           1       0.99      0.94      0.97     42560

    accuracy                           0.98    111643
   macro avg       0.98      0.97      0.97    111643
weighted avg       0.98      0.98      0.98    111643
```

Out[ ]:
```
Text(25.5, 0.5, 'actual')
```



In [ ]:
```
import pickle
with open("/content/drive/My Drive/CASE Studies/healthcare/XGB_model.pkl", 'wb') as file:
    pickle.dump(model_xgb, file)
```

CUSTOM MODELS

In [ ]:
```
#1 splitting the dataset in (80-20)
#2 splitting traing data into (50-50)
train_d1,train_d2,test_d1,test_d2=train_test_split(x_train,y_train,test_size=0.5)
```

In [ ]:
```
import random
def generating_samples(input_data, target_data):

  row_samples=random.sample(range(0,input_data.shape[0]),int((60/100)*(input_data.shape[0])))
  row_repl=random.sample(row_samples,int((40/100)*(input_data.shape[0])))
  rows=row_samples+row_repl
  cols=random.sample(range(0,input_data.shape[1]),random.randrange(3,34))

  a=input_data.iloc[rows]
  a=a.iloc[:,cols]
  b=target_data.iloc[rows]

  return a,b,rows,cols
```

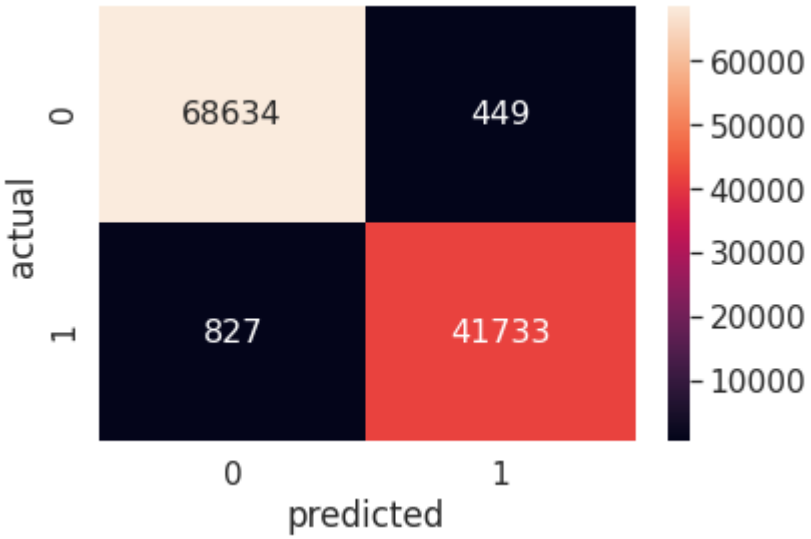
In [ ]:
```
from sklearn.metrics import confusion_matrix,classification_report,precision_s
core ,average_precision_score as aps
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBClassifier
def custom_model(samples,m):
  input=[]
  output=[]
  rows=[]
  cols=[]
  for i in range(samples):
    a,b,r,c=generating_samples(train_d1,test_d1)   # generating samples
    input.append(a)
    output.append(b)
    rows.append(r)
    cols.append(c)

  base_models=[]
  for i in range(samples):
    x_tr=input[i]
    y_tr=output[i]
    dt=DecisionTreeClassifier(criterion="entropy",max_depth=50,min_samples_spl
it=10)# creating k base models
    dt.fit(x_tr,y_tr)
    base_models.append(dt)

  # passing D2 to these k models
  prediction_for_d2=[]
  for i in range(samples):
    pred=base_models[i].predict(train_d2.iloc[:,cols[i]])
    prediction_for_d2.append(pred)
  prediction_for_d2 = np.array(prediction_for_d2).transpose()

  # predicting X_test data using k models
  prediction_for_x_test=[]
  for i in range(samples):
    p=base_models[i].predict(x_test.iloc[:,cols[i]])
    prediction_for_x_test.append(p)
  prediction_for_x_test = np.array(prediction_for_x_test).transpose()


  if m==1:
    # meta model as SGD
    lr=SGDClassifier(class_weight='balanced',loss="log" )
    param={ 'alpha':[0.0001,0.001,0.01,0.1,1,10,100],
          'penalty':["l1","l2"]}
    cv=RandomizedSearchCV(lr,param_distributions=param ,cv=5 ,n_iter=10,n_jobs
=-1,verbose=2)
    cv.fit(prediction_for_d2,test_d2)
    print("\n Bestparameters are :",cv.best_params_)

  if m==2:
    # meta model as DecisionTree
    params={'max_depth':[5,10,30,50],
            'min_samples_split':[2,3,5,10],
```

```
            'criterion':['gini','entropy']}
    dt=DecisionTreeClassifier(class_weight="balanced")
    cv=RandomizedSearchCV(dt,param_distributions=params ,cv=10 ,n_iter=10,n_jo
bs=-1,verbose=2)
    cv.fit(prediction_for_d2,test_d2)
    print("\n Bestparameters are :",cv.best_params_)

  if m==3:
    # meta model as XGBoost
    xgb = XGBClassifier()
    param = {'learning_rate':[0.01,0.03,00.05,0.1],
             'n_estimators':[10,50,100,500,1000],
             'max_depth':[3,5,10],
             'colsample_bytree':[0.1,0.3,0.5,1],
             'subsample':[0.1,0.3,0.5,1] }
    cv = RandomizedSearchCV(xgb,param,cv=5,n_jobs=-1,verbose=10)
    cv.fit(prediction_for_d2,test_d2)
    print("\n Bestparameters are :",cv.best_params_)


  model=cv.best_estimator_
  pred=model.predict(prediction_for_x_test)
  score=precision_score(y_test,pred)
  report=classification_report(y_test,pred)
  micro_precision=precision_score(y_test,pred,average='micro')
  macro_precision=precision_score(y_test,pred,average='macro')

  print(f"\n Precision_score={score}, micro_precision={micro_precision} ,macro
_precision={macro_precision}")

  print("\n CLASSIFICATION REPORT",report)

  conf_matr_train = pd.DataFrame(confusion_matrix(y_test, pred), range(2),rang
e(2))
  sns.set(font_scale=1.4)
  sns.heatmap(conf_matr_train, annot=True,annot_kws={"size": 16}, fmt='g')
  plt.xlabel("predicted")
  plt.ylabel("actual")

  return model ,base_models,cols
```

SGD as Meta Model with 30 samples

In [ ]:
```
m,models,cols=custom_model(30,1)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed:   17.9s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:   24.3s finished

 Bestparameters are : {'penalty': 'l1', 'alpha': 0.001}

 Precision_score=0.9893556493290977, micro_precision=0.9885707120016481 ,macr
o_precision=0.9887248438551738

 CLASSIFICATION REPORT               precision    recall  f1-score   support

           0       0.99      0.99      0.99     69083
           1       0.99      0.98      0.98     42560

    accuracy                           0.99    111643
   macro avg       0.99      0.99      0.99    111643
weighted avg       0.99      0.99      0.99    111643
```

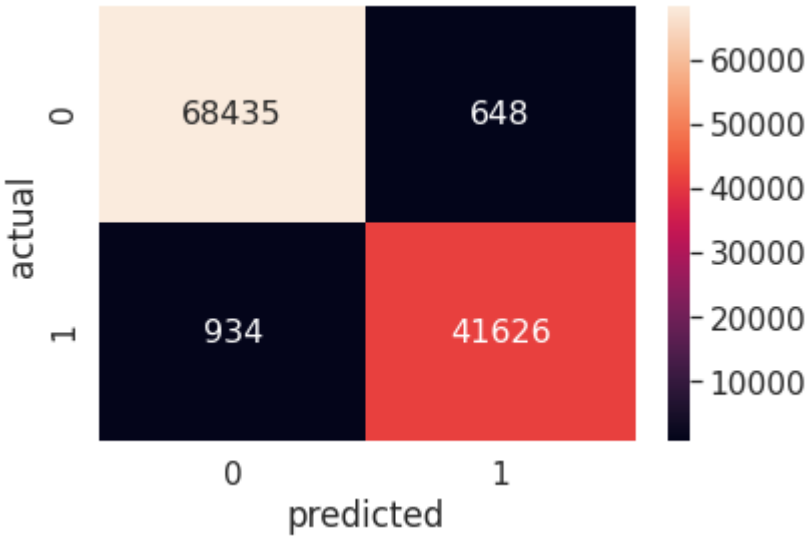


In [ ]:
```
import pickle
with open("/content/drive/My Drive/CASE Studies/healthcare/lr_meta_model.pkl",
'wb') as file:
    pickle.dump(m, file)
```

DecisionTreeClassifier as meta model with 30 samples

In [ ]:
```
tree,models,columns=custom_model(30,2)
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed:   30.5s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  1.7min finished

 Bestparameters are : {'min_samples_split': 5, 'max_depth': 10, 'criterion':
'entropy'}

 Precision_score=0.9846714292472915, micro_precision=0.985829832591385 ,macro
_precision=0.9856036008552478

 CLASSIFICATION REPORT              precision    recall  f1-score   support

           0       0.99      0.99      0.99     69083
           1       0.98      0.98      0.98     42560

    accuracy                           0.99    111643
   macro avg       0.99      0.98      0.98    111643
weighted avg       0.99      0.99      0.99    111643
```

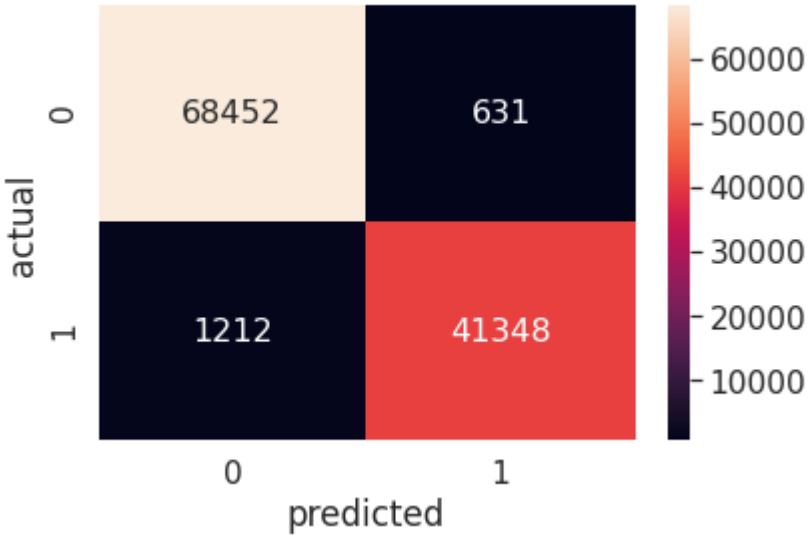


In [ ]:
```
import pickle
with open("/content/drive/My Drive/CASE Studies/healthcare/tree_meta_model.pk
l", 'wb') as file:
    pickle.dump(tree, file)
```

XGBClassifier as meta model with 30 samples

In [ ]:
```
xg,models,cols=custom_model(30,3)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done   1 tasks      | elapsed:  1.7min
[Parallel(n_jobs=-1)]: Done   4 tasks      | elapsed:  3.3min
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed: 12.1min
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed: 12.6min
[Parallel(n_jobs=-1)]: Done  21 tasks      | elapsed: 13.5min
[Parallel(n_jobs=-1)]: Done  28 tasks      | elapsed: 16.2min
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed: 22.9min
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed: 29.1min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed: 32.1min finished

 Bestparameters are : {'subsample': 0.1, 'n_estimators': 500, 'max_depth': 1
0, 'learning_rate': 0.01, 'colsample_bytree': 1}

 Precision_score=0.9849686748135973, micro_precision=0.9834920236826312 ,macr
o_precision=0.9837854398413416

 CLASSIFICATION REPORT              precision    recall  f1-score   support

           0       0.98      0.99      0.99     69083
           1       0.98      0.97      0.98     42560

    accuracy                           0.98    111643
   macro avg       0.98      0.98      0.98    111643
weighted avg       0.98      0.98      0.98    111643
```

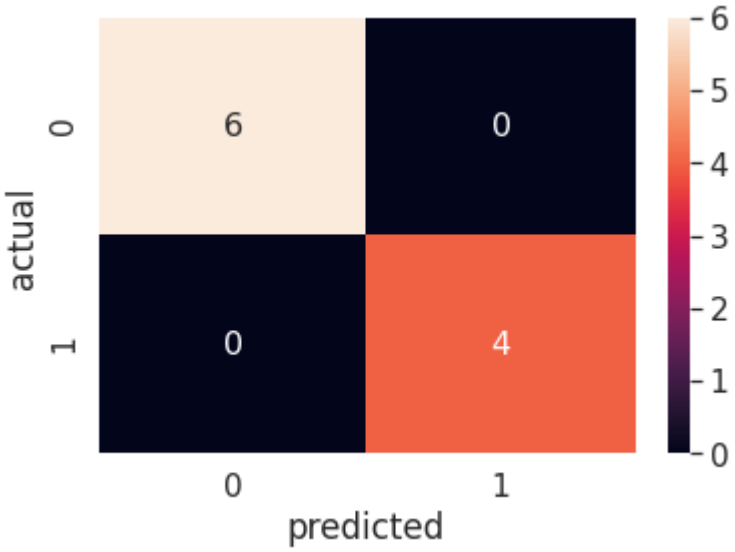


for testing Data using Decision tree as Meta model

In [ ]:
```
#This function takes the x and y the data i.e independent variables and depend
ent variables

def make_pred(data_train,data_test):
  meta = pickle.load(open("/content/drive/My Drive/CASE Studies/healthcare/tre
e_meta_model.pkl", 'rb'))
  samples=30
  test_data_pred=[]
  for i in range(samples):
    p=models[i].predict(data_train.iloc[:,columns[i]])
    test_data_pred.append(p)
  test_data_pred = np.array(test_data_pred).transpose()

  pred=meta.predict(test_data_pred)
  score=precision_score(data_test,pred)
  report=classification_report(data_test,pred)
  micro_precision=precision_score(data_test,pred,average='micro')
  macro_precision=precision_score(data_test,pred,average='macro')

  print(f"\n Precision_score={score}, micro_precision={micro_precision} ,macro
_precision={macro_precision}")
  print("\n CLASSIFICATION REPORT",report)

  conf_matr_train = pd.DataFrame(confusion_matrix(data_test, pred), range(2),r
ange(2))
  sns.set(font_scale=1.4)
  sns.heatmap(conf_matr_train, annot=True,annot_kws={"size": 16}, fmt='g')
  plt.xlabel("predicted")
  plt.ylabel("actual")

  return pred
```

In [ ]:
```
import pickle
data_train=x_test.iloc[10:20]
data_test=y_test.iloc[10:20]
out=make_pred(data_train,data_test)
```

```
Precision_score=1.0, micro_precision=1.0 ,macro_precision=1.0

CLASSIFICATION REPORT              precision    recall  f1-score   support

           0       1.00      1.00      1.00         6
           1       1.00      1.00      1.00         4

    accuracy                           1.00        10
   macro avg       1.00      1.00      1.00        10
weighted avg       1.00      1.00      1.00        10
```



In [ ]:
```
out
```

Out[ ]:
```
array([1, 0, 0, 1, 1, 0, 0, 0, 1, 0])
```

In [ ]:
```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Model", "Precision", "Micro_Precision"]
x.add_row(["SGD CLASSIFIER",0.82 , 0.82])
x.add_row(["Decision Tree Classifier", 0.98, 0.98])
x.add_row(["XGBoost Classifier", 0.99, 0.97])
x.add_row(["Meta model as SGD",0.98,0.98])
x.add_row(["Meta model as DT",0.98,0.98])
x.add_row(["Meta model as XGB",0.98,0.98])
print(x)
```

```
+--------------------------+-----------+-----------------+
|          Model           | Precision | Micro_Precision |
+--------------------------+-----------+-----------------+
|      SGD CLASSIFIER      |    0.82   |       0.82      |
| Decision Tree Classifier |    0.97   |       0.98      |
|    XGBoost Classifier    |    0.99   |       0.97      |
|    Meta model as SGD     |    0.98   |       0.98      |
|     Meta model as DT     |    0.98   |       0.98      |
|    Meta model as XGB     |    0.98   |       0.98      |
+--------------------------+-----------+-----------------+
```

In [ ]:

In [ ]: