Buisness problem

```
In [ ]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.metrics import log_loss
        from sklearn.metrics import confusion_matrix
        from sklearn.model_selection import train_test_split
        from sklearn.linear_model import LogisticRegression
        from sklearn.ensemble import RandomForestClassifier
        from xgboost import XGBClassifier
        from sklearn.model_selection import RandomizedSearchCV
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.calibration import CalibratedClassifierCV
        from sklearn.linear_model import SGDClassifier
        from sklearn.preprocessing import StandardScaler
        import warnings
        warnings.filterwarnings("ignore")
```

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

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

Project Objectives

Provider Fraud is one of the biggest problems facing Medicare. According to the government, the total Medicare spending increased exponentially due to frauds in Medicare claims. Healthcare fraud is an organized crime which involves peers of providers, physicians, beneficiaries acting together to make fraud claims.

Rigorous analysis of Medicare data has yielded many physicians who indulge in fraud. They adopt ways in which an ambiguous diagnosis code is used to adopt costliest procedures and drugs. Insurance companies are the most vulnerable institutions impacted due to these bad practices. Due to this reason, insurance companies increased their insurance premiums and as result healthcare is becoming costly matter day by day.

Types of frauds

Healthcare fraud and abuse take many forms. Some of the most common types of frauds by providers are:

a) Billing for services that were not provided.

b) Duplicate submission of a claim for the same service.

c) Misrepresenting the service provided.

d) Charging for a more complex or expensive service than was actually provided.

e) Billing for a covered service when the service actually provided was not covered.

Objective

The goal of this project is to " predict the potentially fraudulent providers " based on the claims filed by them.along with this, we will also discover important variables helpful in detecting the behaviour of potentially fraud providers. further, we will study fraudulent patterns in the provider's claims to understand the future behaviour of providers.

Data we will be working with

For the purpose of this project, we are considering Inpatient claims, Outpatient claims and Beneficiary details of each provider. Lets s see their details :

A) Inpatient Data

This data provides insights about the claims filed for those patients who are admitted in the hospitals. It also provides additional details like their admission and discharge dates and admit d diagnosis code.

B) Outpatient Data

This data provides details about the claims filed for those patients who visit hospitals and not admitted in it.

C) Beneficiary Details Data

This data contains beneficiary KYC details like health conditions,regioregion they belong to etc.

D)Train Data:

Data containing provider id's and whether they are fraud or not.

Approach:

We are given with no details about the health care provider except for the *provider id*. But in inpatient and out paient files we have *provider id* as feature. So we can leverage that and generate information about the provider based on the details of patients.

```
In [ ]: #importing dependencies
        import pandas as pd
import numpy as np
from datetime import datetime
import matplotlib.pyplot as plt
import seaborn as sns
import random
```

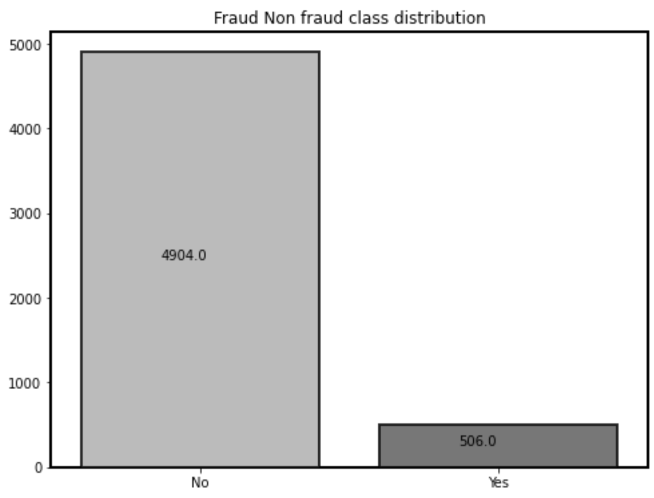
In [ ]:
```
ben_data=pd.read_csv('/content/drive/MyDrive/Train_Beneficiarydata-1542865627584.csv')
inp_data=pd.read_csv('/content/drive/MyDrive/Train_Inpatientdata-1542865627584.csv')
out_data=pd.read_csv('/content/drive/MyDrive/Train_Outpatientdata-1542865627584.csv')
train_data=pd.read_csv('/content/drive/MyDrive/Train-1542865627584.csv')
```

EDA

Train data

In [ ]:
```
def bar_plot(x,y,xlab=None,ylab=None,title=None,annotate=False):
  '''This function generates an annotated barplot'''
  fig,ax=plt.subplots(figsize=(8,6))
  custom_palette=['dark:salmon_r','ocean','inferno','BrBG','binary','winter']
  choice=random.choice(custom_palette)
  if title is not None:
    ax.set_title(title)
  else:
    ax.set_title('No title')
  sns.barplot(x=x,
            y=y,palette=choice,alpha=0.8,edgecolor='black',linewidth=2)
  ax.patch.set_edgecolor('black')
  ax.patch.set_linewidth('2')
  plt.xlabel(xlab)
  plt.ylabel(ylab)
  if annotate==True:
    for p in ax.patches:
      ax.annotate(p.get_height(), (p.get_x()+p.get_width()/3. * 1.005, p.get_height() * .5))
  plt.show()
```

In [ ]:
```
bar_plot(train_data.PotentialFraud.value_counts().index,train_data.PotentialFraud.value_counts().values,title='Fraud Non
plt.show()
print('Only {0:.2f}% of healthcare providers are fraudulent '.format(train_data.PotentialFraud.value_counts()[1]/5410*10
```

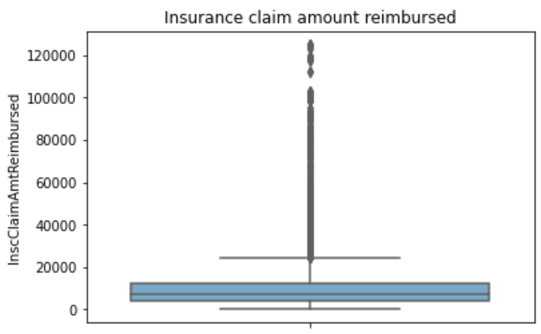


```
Only 9.35% of healthcare providers are fraudulent
```

From above plot we observe that there is a severe class imbalance.

Inp data

In [ ]:
```
#Insurance claim reimbursed
plt.title('Insurance claim amount reimbursed')
sns.boxplot(y=inp_data.InscClaimAmtReimbursed,palette='Blues')
plt.show()
```



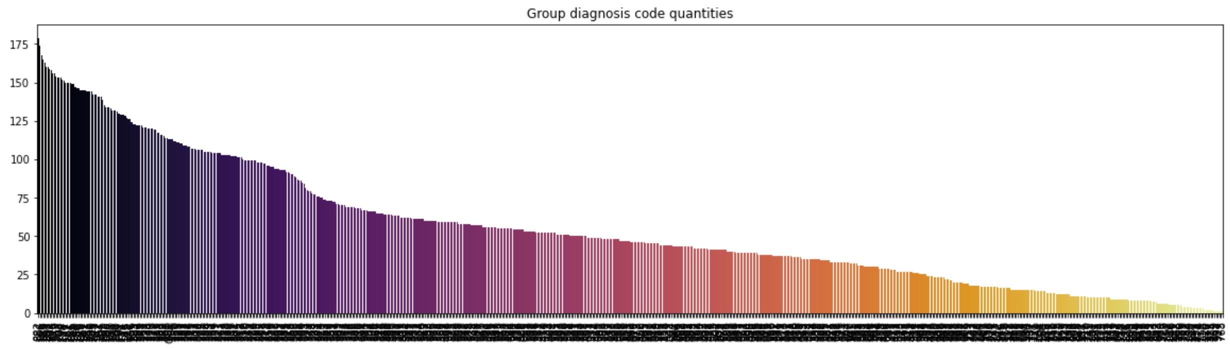
We see a large amount of outliers in this data.Most patients seem to have humble claim amounts while some having huge claims.

In [ ]:
```
#Physician data
print('Missing values in attending physician',inp_data.AttendingPhysician.isnull().sum())
print('Missing values in operating physician',inp_data.OperatingPhysician.isnull().sum())
print('Missing values in other physician',inp_data.OtherPhysician.isnull().sum())
```

```
Missing values in attending physician 112
Missing values in operating physician 16644
Missing values in other physician 35784
```

Most patients might not require a operation procedure i.e it seems for most patients the attending physician is sufficient. We will treat it as such while handling missing values.

In [ ]:
```
# Group diagnosis code
plt.figure(figsize=(20,5))
plt.title('Group diagnosis code quantities')
sns.barplot(x=inp_data.DiagnosisGroupCode.value_counts().index,y=inp_data.DiagnosisGroupCode.value_counts().values,palet
plt.xticks(rotation=90)
plt.show()
print('Top 10 diagnosis codes are \n',inp_data.DiagnosisGroupCode.value_counts()[:10])
```

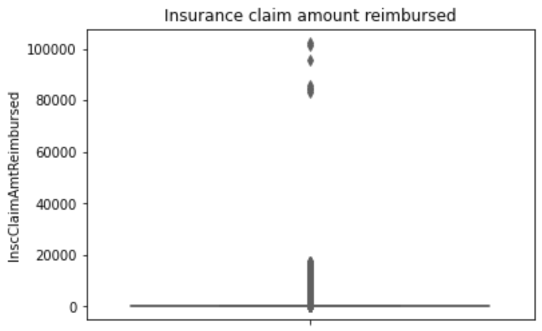


```
Top 10 diagnosis codes are
 882    179
884    174
166    168
183    165
939    163
168    160
883    160
887    159
204    158
945    156
Name: DiagnosisGroupCode, dtype: int64
```

Outpatient data

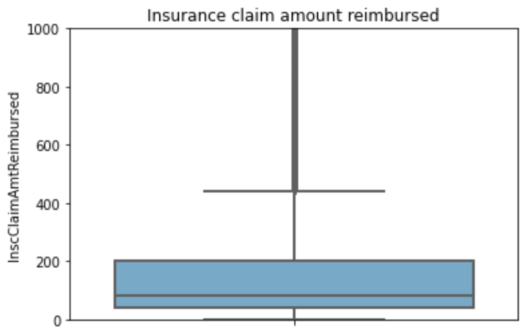
Much more outpatient claims than inpatient. Similar reducing trend is also observed here.

In [ ]:
```
#Outpatient InsclaimReimb
plt.title('Insurance claim amount reimbursed')
sns.boxplot(y=out_data.InscClaimAmtReimbursed,palette='Blues')
# plt.ylim(0,1000)
plt.show()
```



Outliers seem to be very separated from frequently occuring data but not much is clear..

In [ ]:
```
plt.title('Insurance claim amount reimbursed')
sns.boxplot(y=out_data.InscClaimAmtReimbursed,palette='Blues',linewidth=2)
plt.ylim(0,1000)
plt.show()
```

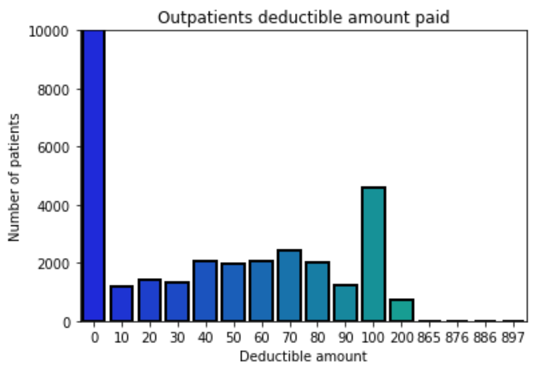


Most outdoor patients seem to have claims under 400

```
In [ ]: print('Missing values in attending physician',out_data.AttendingPhysician.isnull().sum())
        print('Missing values in operating physician',out_data.OperatingPhysician.isnull().sum())
        print('Missing values in other physician',out_data.OtherPhysician.isnull().sum())
```

```
Missing values in attending physician 1396
Missing values in operating physician 427120
Missing values in other physician 322691
```

```
In [ ]: plt.title('Outpatients deductible amount paid')
        sns.barplot(x=out_data.DeductibleAmtPaid.value_counts().index,y=out_data.DeductibleAmtPaid.value_counts().values,palette
        plt.xlabel('Deductible amount')
        plt.ylabel('Number of patients')
        plt.ylim(0,10000)
        plt.show()
        print('Total number of patients who not paid deductible amount',out_data.DeductibleAmtPaid.value_counts()[0])
```

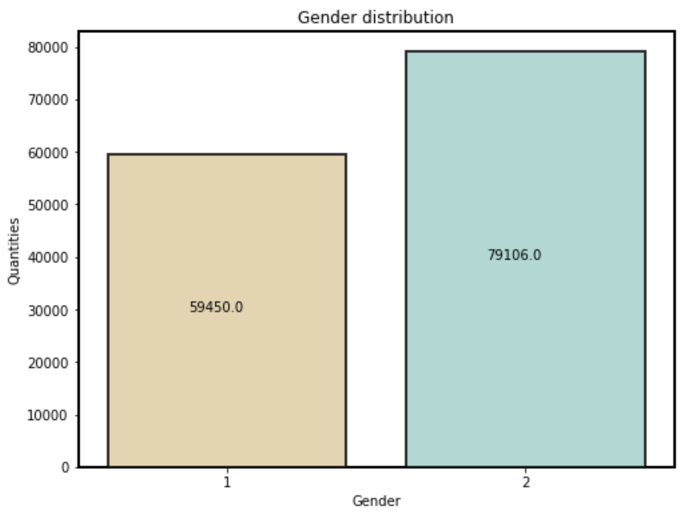


```
Total number of patients who not paid deductible amount 496701
```

Most patients do not have to pay any kind of deductible amount.This amount is probably be paid by the government.

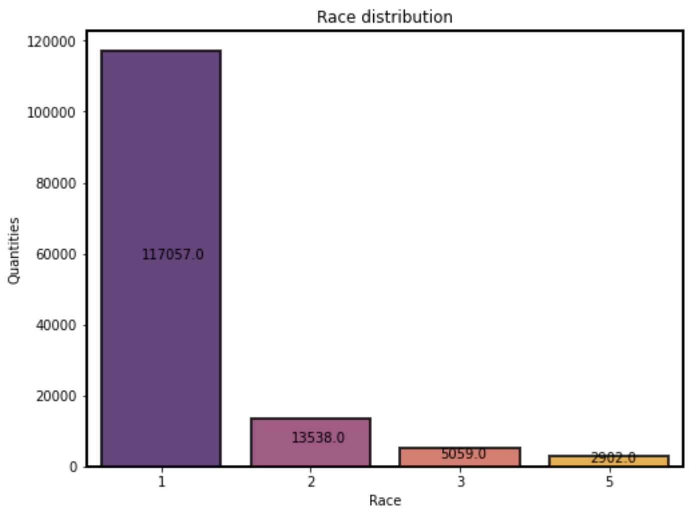
Benefeciary data

```
In [ ]: bar_plot(ben_data.Gender.value_counts().index,ben_data.Gender.value_counts().values,'Gender','Quantities','Gender distri
```



We see a minor imbalance between genders nothing to worry about.

```
In [ ]: bar_plot(ben_data.Race.value_counts().index,ben_data.Race.value_counts().values,xlab='Race',ylab='Quantities',title='Rac
```



Merging inpatient+outpatient+benefeciary+provider

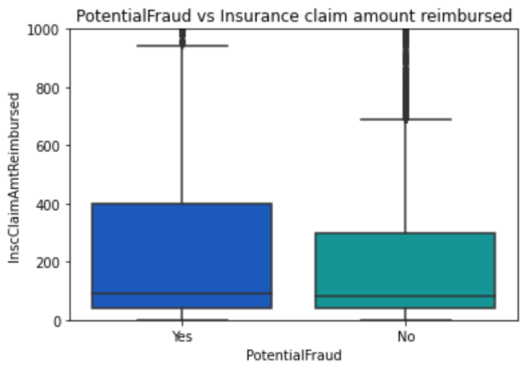
In [ ]:
```
#merging inpatient and outpatient data
cols=list(set(inp_data.columns).intersection(set(out_data.columns)))
patient=inp_data.merge(out_data,how='outer',on=cols)
```

In [ ]:
```
patient_int=ben_data.merge(patient,how='outer',on='BeneID')
```

In [ ]:
```
patient_fin=patient_int.merge(train_data,how='outer',on='Provider')
```

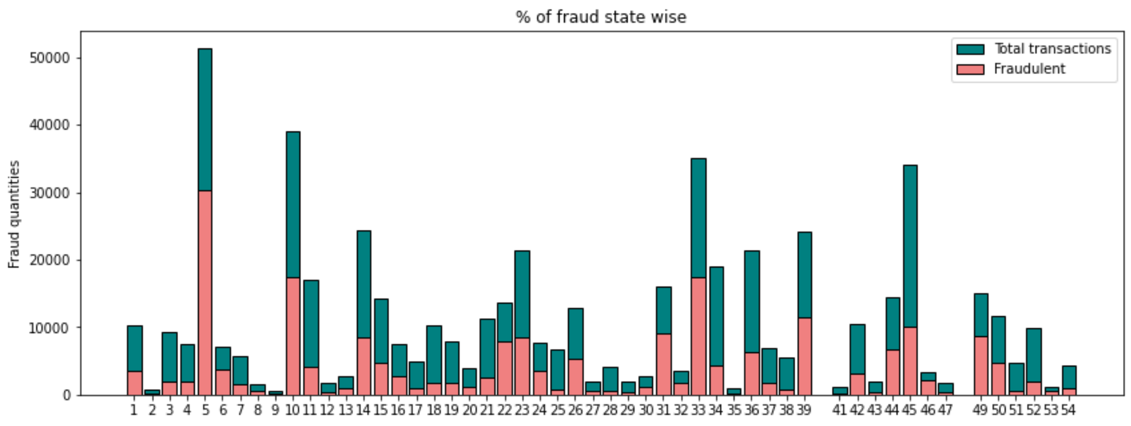
Now we have the target variable so we can visualize interaction features.

In [ ]:
```
plt.title('PotentialFraud vs Insurance claim amount reimbursed')
sns.boxplot(y='InscClaimAmtReimbursed',x='PotentialFraud',data=patient_fin,palette='winter')
plt.ylim(0,1000)
plt.show()
```



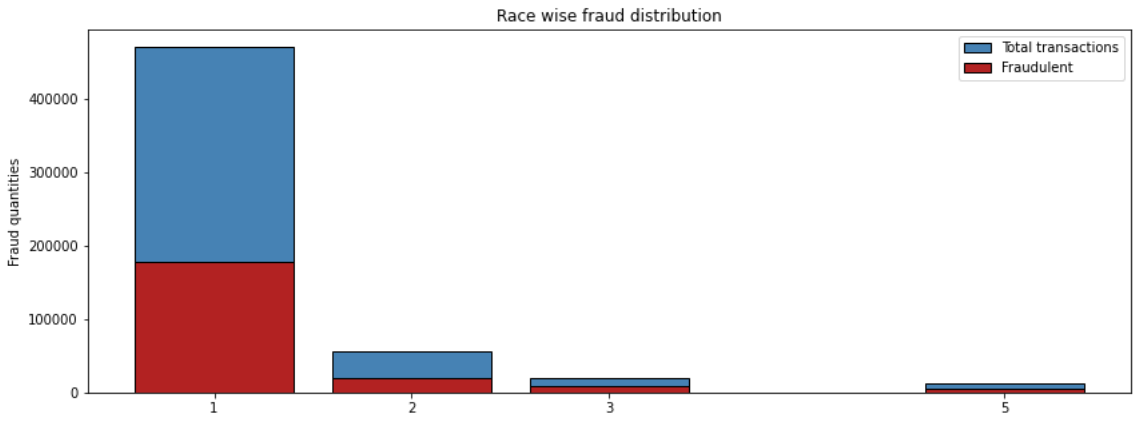
The upper whisker in the boxplot is higher for fraudulent transaction than non fraudulent.

In [ ]:
```
temp1=patient_fin.groupby('State')['PotentialFraud'].agg(lambda x:x.eq('Yes').sum()).reset_index() #aggregates state wis
temp2=patient_fin.groupby('State')['PotentialFraud'].agg(lambda x:x.eq('No').sum()).reset_index()
temp3=temp1['PotentialFraud']+temp2['PotentialFraud']
plt.figure(figsize=(14,5))
plt.title('State vs Potential Fraud')
p1=plt.bar(temp1['State'],temp3,edgecolor='black',color='teal')
p2=plt.bar(temp1['State'],temp1['PotentialFraud'],edgecolor='black',color='lightcoral')
plt.ylabel('Fraud quantities')
plt.title('% of fraud state wise')
plt.xticks(temp1['State'], list(temp1['State'].values))
plt.legend((p1[0], p2[0]), ('Total transactions', 'Fraudulent'))
plt.show()
#code for simple annotation
# for p in ax.patches:
#    ax.annotate(p.get_height(), (p.get_x()+p.get_width()/3. * 1.005, p.get_height() * 1.005))
```



In states 5,10,33 & 45 transactions are high and fraudulent transactions are also high.

In [ ]:
```
temp1=patient_fin.groupby('Race')['PotentialFraud'].agg(lambda x:x.eq('Yes').sum()).reset_index()
temp2=patient_fin.groupby('Race')['PotentialFraud'].agg(lambda x:x.eq('No').sum()).reset_index()
temp3=temp1['PotentialFraud']+temp2['PotentialFraud']
plt.figure(figsize=(14,5))
plt.title('Race vs Potential Fraud')
p1=plt.bar(temp1['Race'],temp3,edgecolor='black',color='steelblue')
p2=plt.bar(temp1['Race'],temp1['PotentialFraud'],edgecolor='black',color='firebrick')
plt.ylabel('Fraud quantities')
plt.title('Race wise fraud distribution')
plt.xticks(temp1['Race'], list(temp1['Race'].values))
plt.legend((p1[0], p2[0]), ('Total transactions', 'Fraudulent'))
plt.show()
print('% fraud transactions racewise')
[(temp1['Race'].loc[i],temp1['PotentialFraud'].loc[i]/temp3[i]) for i in range(len(temp1['PotentialFraud']))]
```



```
% fraud transactions racewise
```

```
Out[ ]: [(1, 0.37862286534362555),
         (2, 0.36455787203450757),
         (3, 0.45457773269084456),
         (5, 0.4403553299492386)]
```

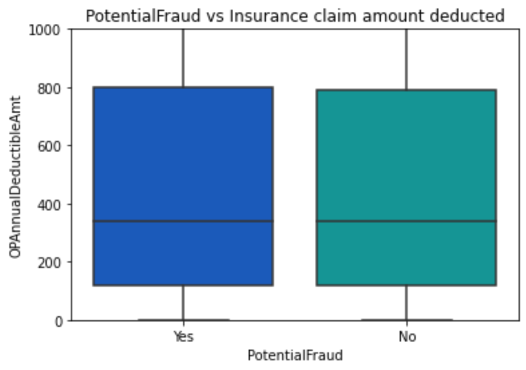
-There are no race 4 persons in dataset.

-Patients of race 3 and 5 are more susceptible to fraud

```
In [ ]: #label coding binary features
        cols=['ChronicCond_Alzheimer','ChronicCond_Heartfailure','ChronicCond_KidneyDisease',
              'ChronicCond_Cancer','ChronicCond_ObstrPulmonary','ChronicCond_Depression','ChronicCond_Diabetes',
              'ChronicCond_IschemicHeart','ChronicCond_Osteoporasis','ChronicCond_rheumatoidarthritis',
              'ChronicCond_stroke']
        for i in cols:
          patient_fin[i]=patient_fin[i].map({1:0,2:1})
```

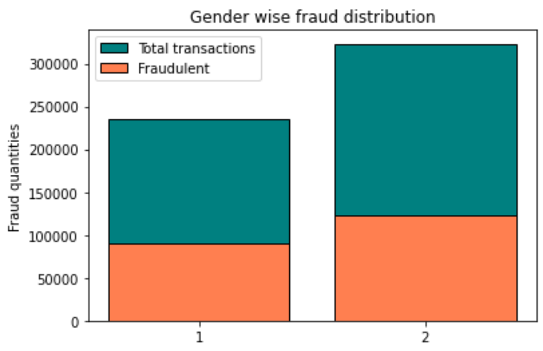
```
In [ ]: patient_fin.RenalDiseaseIndicator=patient_fin.RenalDiseaseIndicator.map({'0':0,'Y':1})
```

```
In [ ]: plt.title('PotentialFraud vs Insurance claim amount deducted')
        sns.boxplot(y='OPAnnualDeductibleAmt',x='PotentialFraud',data=patient_fin,palette='winter')
        plt.ylim(0,1000)
        plt.show()
```



Deductible amount is very similar for fraud and non fraud.

```
In [ ]: temp1=patient_fin.groupby('Gender')['PotentialFraud'].agg(lambda x:x.eq('Yes').sum()).reset_index()
        temp2=patient_fin.groupby('Gender')['PotentialFraud'].agg(lambda x:x.eq('No').sum()).reset_index()
        temp3=temp1['PotentialFraud']+temp2['PotentialFraud']
        plt.figure(figsize=(6,4))
        plt.title('Gender vs Potential Fraud')
        p1=plt.bar(temp1['Gender'],temp3,edgecolor='black',color='teal')
        p2=plt.bar(temp1['Gender'],temp1['PotentialFraud'],edgecolor='black',color='coral')
        plt.ylabel('Fraud quantities')
        plt.title('Gender wise fraud distribution')
        plt.xticks(temp1['Gender'], list(temp1['Gender'].values))
        plt.legend((p1[0], p2[0]), ('Total transactions', 'Fraudulent'))
        plt.show()
        print('% fraud transactions Genderwise')
        [(temp1['Gender'].loc[i],temp1['PotentialFraud'].loc[i]/temp3[i]) for i in range(len(temp1['PotentialFraud']))]
```



```
% fraud transactions Genderwise
```

Out[ ]:
```
[(1, 0.38147232844315326), (2, 0.38102032100125655)]
```

In [ ]:
```
patient_fin.to_csv('patient_fin.csv')
```

Both genders are equally prone to fraud.

This concludes our EDA. Next on to feature engineering.