Buisness Objective:

- An US Electrical company wants to analyse their sales and productivity by prediciting a particular report to be Suspicious
- The reports collected by the firm where each SalesPerson reports at a certain periodicity on which product was sold,how much quantity and totalAmount . The past data also contains Suspicious column to determine the target .
- For statergic planning they also want to segment salesPerson to 3 levels

Machine Learning Objective:

- The business objective expects us to create a fraud detecting system for each of their report based on their past data.
- It is a Supervised learning - classifcation problem with Suspicious Column as our dependent variable.
- Segmentation of SalesPerson is Unsupervised Learning - clustering problem with respect to SalesPerson

The ML model could help the company to understand the amount of fraud reports being given by the salesperson and also remove those reports and do a complete study on non supsicious reports for Sales and productivity analysis

The segmentation of salespersons would make them know that a few of the salesperson are completely different from the rest and they could look into their sales more or even remove them from the job if they are high risk salesperson

Loading required libraries

In [1]:
```
import os
import numpy as np
import os
import pandas as pd
import statistics
from statistics import *
from xgboost import XGBClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import AdaBoostClassifier,RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier, export_graphviz,DecisionTreeRegressor
from sklearn.metrics import accuracy_score,classification_report, recall_score, precision_score,confusion_matrix,mean_absolute_error,mean_squared_error, f1
_score

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, roc_curve, auc

from sklearn import tree
from sklearn.model_selection import GridSearchCV
import graphviz
import matplotlib.pyplot as plt

#from imblearn.over_sampling import SMOTE


path = os.getcwd()
```

In [2]:
```
## visualizations
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sns
import plotly
import plotly.offline as pyoff ## if not we have to login to their websit and do
import plotly.figure_factory as ff
from plotly.offline import init_notebook_mode, iplot, plot
import plotly.graph_objs as go
#import squarify # for tree maps
%matplotlib inline
from plotly.offline import plot
init_notebook_mode(connected=True)
```

In [3]:
```
import warnings
warnings.filterwarnings('ignore')
```

Reading and Understanding the data

In [4]:
```
data = pd.read_excel("../data/Train.xlsx")
```

- Understanding the Data

In [5]:
```
data.shape
```

Out[5]:
```
(42582, 6)
```

In [6]:
```
data.head(5)
```

Out[6]:

	ReportID	SalesPersonID	ProductID	Quantity	TotalSalesValue	Suspicious
0	Rep10101	C21116	PR6112	182	1665	indeterminate
1	Rep10102	C21116	PR6112	182	1740	indeterminate
2	Rep10103	C21116	PR6253	101	1040	indeterminate
3	Rep10104	C21116	PR6253	283	4495	No
4	Rep10105	C21116	PR6294	108	1465	indeterminate

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

Out[7]:
```
Index(['ReportID', 'SalesPersonID', 'ProductID', 'Quantity', 'TotalSalesValue',
       'Suspicious'],
      dtype='object')
```

In [8]:
```
data.dtypes
```

Out[8]:
```
ReportID            object
SalesPersonID       object
ProductID           object
Quantity             int64
TotalSalesValue      int64
Suspicious          object
dtype: object
```

Expoloratory Analysis

In [9]:
```
data.describe(include="all")
```

Out[9]:

	ReportID	SalesPersonID	ProductID	Quantity	TotalSalesValue	Suspicious
count	42582	42582	42582	4.258200e+04	4.258200e+04	42582
unique	42582	992	593	NaN	NaN	3
top	Rep18415	C21976	PR6253	NaN	NaN	indeterminate
freq	1	1359	2590	NaN	NaN	39846
mean	NaN	NaN	NaN	4.910048e+03	1.620923e+04	NaN
std	NaN	NaN	NaN	9.833621e+04	5.997195e+04	NaN
min	NaN	NaN	NaN	3.300000e+01	5.980000e+02	NaN
25%	NaN	NaN	NaN	1.110000e+02	1.345000e+03	NaN
50%	NaN	NaN	NaN	2.060000e+02	2.980000e+03	NaN
75%	NaN	NaN	NaN	1.136000e+03	1.076500e+04	NaN
max	NaN	NaN	NaN	1.970813e+07	3.953985e+06	NaN

- By observing the summary we can see that Quantity's mean is being driven by its huge outliers
- there is a huge differnece between the 75% and the max
- The totalSalesValue is slightly being influenced by some outliers as well but not as much as Quantity
- The Suspicious column have 3 levels with the most being indeterminate

Checking the median of Quantity and TotalSalesValue to see the difference it makes without outliers

In [10]:
```
median(data.Quantity)
```

Out[10]: 206.0

In [11]:
```
median(data.TotalSalesValue)
```

Out[11]: 2980.0

Checking if there are any NA values in the dataset

In [12]:
```
data.isnull().sum()
```

Out[12]:
```
ReportID           0
SalesPersonID      0
ProductID          0
Quantity           0
TotalSalesValue    0
Suspicious         0
dtype: int64
```

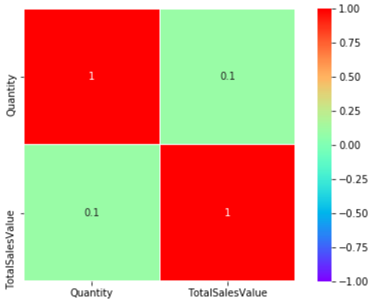
In [ ]:

In [ ]:

Correlation Plot between numerical attributes

In [13]:
```
import seaborn as sns
from pandas import ExcelWriter
from pandas import ExcelFile

corr = data.corr()

#writer=ExcelWriter('CorrelationMith.xlsx')
#corr.to_excel(writer,'Sheet1',index=False)
#writer.save()

plt.figure(figsize=(8, 5))
sns.heatmap(corr,cmap='rainbow', vmax=1.0, vmin=-1.0, linewidths=0.1,
            annot=True, annot_kws={"size": 10}, square=True)
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd18f19d8d0>



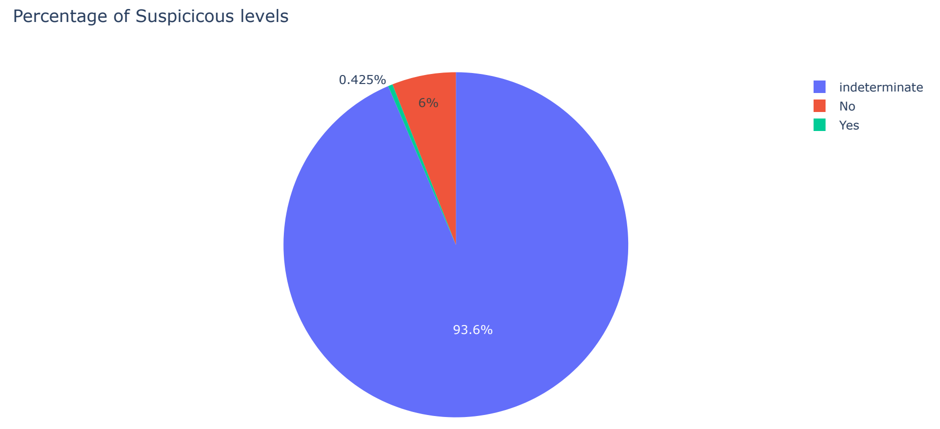
- there is no correlation within attributes in the dataset

In [ ]:

In [ ]:

Distribution of Target Column

In [14]:
```
d_temp=data.Suspicious.value_counts()
trace = go.Pie(values=d_temp,labels=d_temp.index)

layout = go.Layout(title = 'Percentage of Suspicicous levels')
data1 = [trace]
fig = go.Figure(data= data1,layout=layout)
iplot(fig)
```

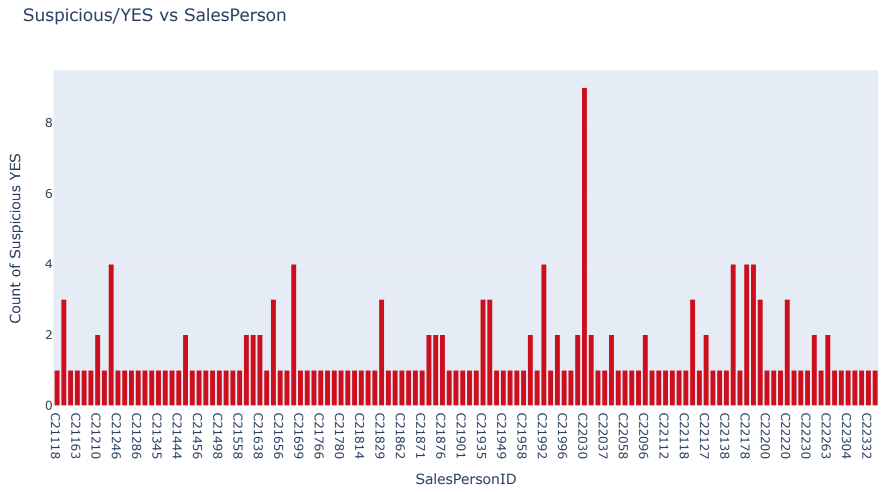


In [ ]:

The count of Suspicious reports with respect to a SalesPerson

In [15]:
```
d_S=data[data.Suspicious=="Yes"].groupby("SalesPersonID")["Suspicious"].count()
```

In [16]:
```
data_plot = [go.Bar(x=d_S.index,
                    y=d_S.values.astype(float),
       marker=dict(
        color="#CC0E1D",# Lava (#CC0E1D)
#          color = 'rgb(200,0,0)'   `
    ))]
layout = go.Layout(title = "Suspicious/YES vs SalesPerson",xaxis=dict(title="SalesPersonID"),yaxis=dict(title="Count of Suspicious YES"))

fig = go.Figure(data= data_plot, layout=layout)
iplot(fig)
```



C22030 is the salesperson giving most Suscipious Transcations with a count of 9 Suspicious records

In [ ]:

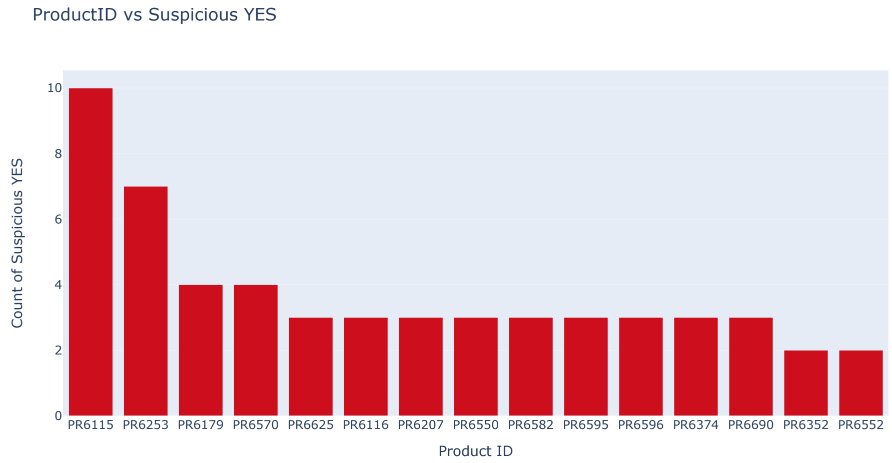
The count of Suspicious reports with respect to a ProductID

In [17]:
```
# grouping the records of suspicious reports with respect to productID and counting the nunber of records per Product
d_8=data[data.Suspicious=="Yes"].groupby("ProductID")["Suspicious"].count()
print("The number of products which have Suspicious reports is - ",d_8.shape[0])
```

```
The number of products which have Suspicious reports is -  115
```

In [18]:
```
# sorting and selecting only top 15 products with highest Suspicious reports
d_8.sort_values(ascending=False, axis =0, inplace = True)
d_8f=d_8.head(15)
```

In [19]:
```
data_plot = [go.Bar(x=d_8f.index,
                          y=d_8f.values.astype(float),
       marker=dict(
        color="#CC0E1D",# Lava (#CC0E1D)
#         color = 'rgb(200,0,0)'   `
    ))]
layout = go.Layout(title = "ProductID vs Suspicious YES ",xaxis=dict(title="Product ID"),yaxis=dict(title="Count of Suspicious YES"))
fig = go.Figure(data= data_plot, layout=layout)
iplot(fig)
```



- Showing only top 15 products arranged in descending order of their count of suspicious reports

PR6115 product is the one with most Suspicous Transcations

In [ ]:

In [ ]:

SalesPerson with the maximum SalesValue also segregated with Suspicious column

In [20]:
```
d_7=data.groupby(["SalesPersonID","Suspicious"]).agg({"TotalSalesValue":np.sum},axis=0)
```

In [21]:
```
d_7.head()
```

Out[21]:

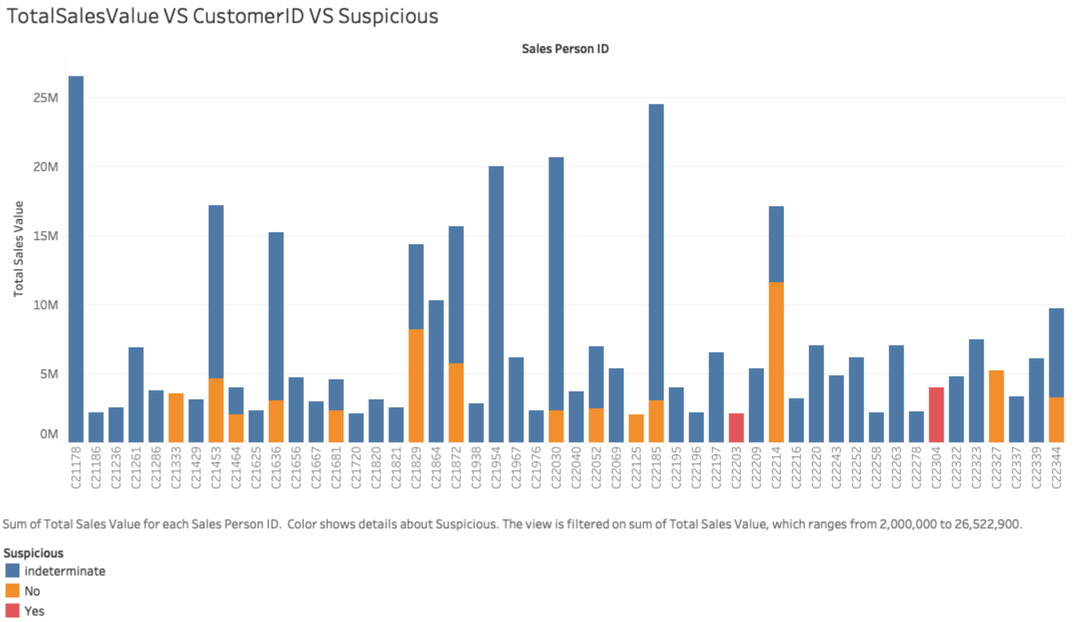
SalesPersonID	Suspicious	TotalSalesValue
C21116	No	4495
	indeterminate	19585
C21118	No	1222090
	Yes	23790
	indeterminate	746080

In [22]:
```
## the maximum sales value
print(d_7.max())
```

```
TotalSalesValue    26522900
dtype: int64
```

In [23]:
```
from IPython.display import Image
Image("TotalSalesValue VS CustomerID VS Suspicious1.png")
## table done on tableau Considering TotalSales > 2M
```

Out[23]:



In [24]:
```
d_7.loc[("C21178",),"TotalSalesValue"] ## Sales Person C21178 is highest sales
```

Out[24]:
```
Suspicious
indeterminate    26522900
Name: TotalSalesValue, dtype: int64
```

Sales Person C21178 has the highest TotalSalesValue across all SalesPersons

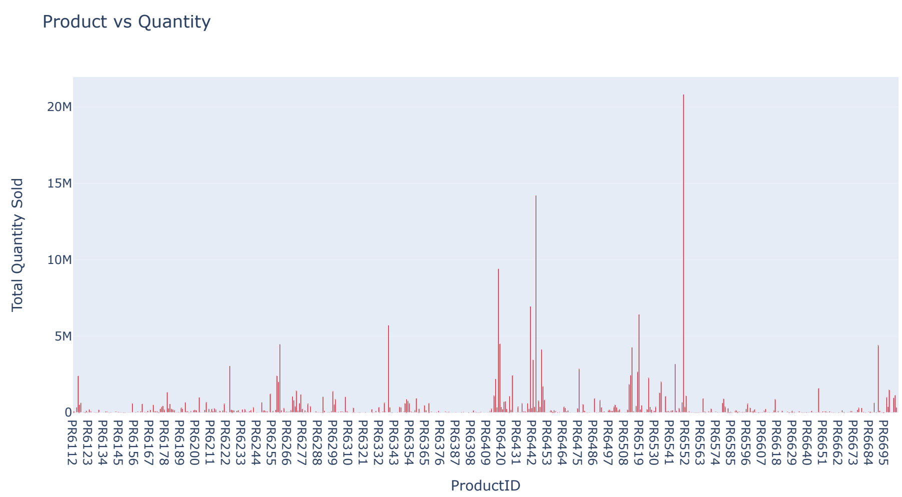
- with all his sales reports being indeterminate on suspicious(target)

In [ ]:

Product which has sold the most Quantity

In [25]:
```
## group by productID and sum the Quantity sold across reports based on that productID
d_5=data.groupby("ProductID").agg({'Quantity':np.sum},axis=0)
```

In [26]:
```
data_plot = [go.Bar(x=d_5.index,
                    y=d_5.Quantity.astype(float),
       marker=dict(
        color="#CC0E1D",# Lava (#CC0E1D)
#          color = 'rgb(200,0,0)'    `
    ))]
layout = go.Layout(title = "Product vs Quantity",xaxis=dict(title="ProductID"),yaxis=dict(title="Total Quantity Sold"))
fig = go.Figure(data= data_plot, layout=layout)
iplot(fig)
```



- ProductID PR6550 is shown as the highest Quantity Sold

- Lets look at that particular productID in detail

In [27]:
```
data[(data.ProductID=="PR6550")&(data.ReportID=="Rep34193")]
## This Report ID was found on seeing all PR6550 records , this Record was found to be Errornous or Big Outlier
## Therefore, why PR6550 was compartively very high on quantity
```

Out[27]:

	ReportID	SalesPersonID	ProductID	Quantity	TotalSalesValue	Suspicious
24092	Rep34193	C21992	PR6550	19708130	136860	Yes

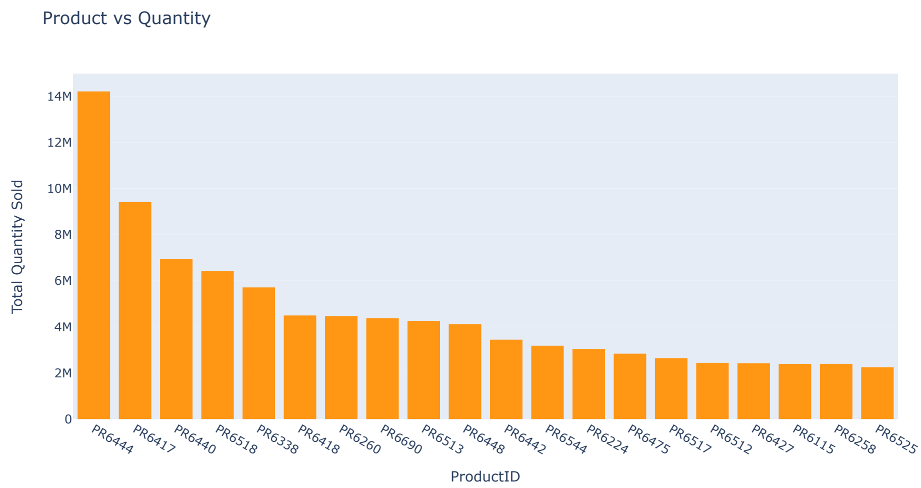
REMOVING THAT ONE TUPLE AND PLOTTING AGAIN

In [28]:
```
d_Rem=data[~((data.ProductID=="PR6550")&(data.ReportID=="Rep34193"))]
d_5Rem=d_Rem.groupby("ProductID").agg({'Quantity':np.sum},axis=0)
```

In [29]:
```
d_51=d_5Rem.sort_values(ascending=False,by="Quantity", axis =0)
```

In [30]:
```
d_51=d_51.head(20) ## showing only top 20 ProductID s with most Quantity Sold
```

In [31]:
```
data_plot = [go.Bar(x=d_51.index,
                             y=d_51.Quantity.astype(float),
       marker=dict(
        color="rgb(300,150,20)",# Lava (#CC0E1D)
#         color = 'rgb(200,0,0)'   `
    ))]
layout = go.Layout(title = "Product vs Quantity",xaxis=dict(title="ProductID"),yaxis=dict(title="Total Quantity Sold"))
fig = go.Figure(data= data_plot, layout=layout)
iplot(fig)
```



In [32]:
```
## therefore the second highest is checked for Suspicious Transcations which are of high quantity
data[(data.ProductID=="PR6444")&(data.Suspicious=="Yes")]
## we find that the quantity is less compared to TOTAL quantity
```

Out[32]:

	ReportID	SalesPersonID	ProductID	Quantity	TotalSalesValue	Suspicious
39296	Rep49397	C21636	PR6444	662	382890	Yes
39521	Rep49622	C21636	PR6444	470	270320	Yes

Therefore, product PR6444 genineuly sold most quantity

In [ ]:

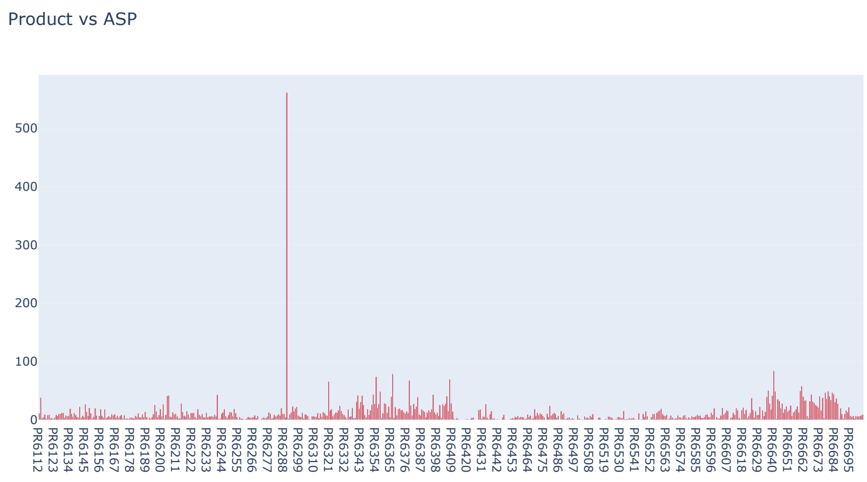
In [ ]:

Average Selling Price of a Product across all Reports

In [33]:
```
d1=data.groupby("ProductID")
```

In [34]:
```
d1=d1.agg({'Quantity': np.sum,'TotalSalesValue':np.sum},axis=0)
d1['ASP']=d1.TotalSalesValue/d1.Quantity ## selling price is Sales/Quantity
```

In [35]:
```
data_plot = [go.Bar(x=d1.index,
                          y=d1.ASP.astype(float),
       marker=dict(
        color="#CC0E1D",# Lava (#CC0E1D)
#         color = 'rgb(200,0,0)'   `
    ))]
layout = go.Layout(title = "Product vs ASP")
fig = go.Figure(data= data_plot, layout=layout)
iplot(fig)
```



- Product PR6290 is found to have compartively very high Average Selling Price Across Products
- On Observing the records which have PR6290 as product in the records
- This record was found which was outlier and also Suspicious

In [36]:
```
data[(data.ProductID=='PR6290')&(data.ReportID=="Rep38829")]
## this was after going through the full productID PR6290 which was HIHGEST
## that one fraudlent row was causing PR 6290 to be highest ASP ( Average Selling Price)
```

Out[36]:

	ReportID	SalesPersonID	ProductID	Quantity	TotalSalesValue	Suspicious
28728	Rep38829	C22304	PR6290	350	3953985	Yes

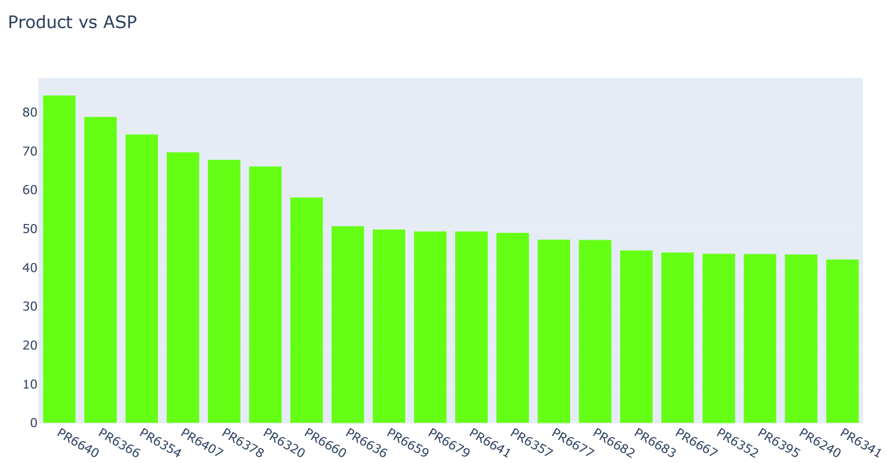
REMOVING THAT ONE TUPLE AND PLOTTING AGAIN

In [37]:
```
d_rev_ASP=data[~((data.ProductID=='PR6290')&(data.ReportID=="Rep38829"))]
```

In [38]:
```
d_rev1=d_rev_ASP.groupby("ProductID").agg({'Quantity': np.sum,'TotalSalesValue':np.sum},axis=0)
d_rev1['ASP']=d_rev1.TotalSalesValue/d_rev1.Quantity
```

In [39]:
```
d_rev1.sort_values(ascending=False,by="ASP", axis =0, inplace = True)
d_rev1=d_rev1.head(20) ## taking onlu top 20 products with high Average Selling Price
```

In [40]:
```
data_plot = [go.Bar(x=d_rev1.index,
                          y=d_rev1.ASP.astype(float),
       marker=dict(
        color='rgb(100,400,20)',# Lava (#CC0E1D)
#         color = 'rgb(200,0,0)'   `
    ))]
layout = go.Layout(title = "Product vs ASP")
fig = go.Figure(data= data_plot, layout=layout)
iplot(fig)
```



therefore PR6640 has the highest Average Selling Price in Complete Dataset.

In [41]:
```
d_rev1.ASP.mean()
# Also the mean selling price across products is 55 therefore PR6440 of being 80 isnt a huge difference
```

Out[41]: 55.14772787295895

In [ ]:

In [ ]:

Data Pre-Processing

In [42]:
```
data2=data.copy() # making a copy of the orginal data for santity purpose
```

In [43]:
```
# making a new column SellingPrice for each reportID
data2['SellingPrice']=data2.TotalSalesValue/data2.Quantity
```

In [44]:
```
data2.head()
```

Out[44]:

	ReportID	SalesPersonID	ProductID	Quantity	TotalSalesValue	Suspicious	SellingPrice
0	Rep10101	C21116	PR6112	182	1665	indeterminate	9.148352
1	Rep10102	C21116	PR6112	182	1740	indeterminate	9.560440
2	Rep10103	C21116	PR6253	101	1040	indeterminate	10.297030
3	Rep10104	C21116	PR6253	283	4495	No	15.883392
4	Rep10105	C21116	PR6294	108	1465	indeterminate	13.564815

In [45]:
```
# remvoing the 2 tuples found on exploratory data analysis which is a huge outlier
data2=data2[~(data2.ReportID=="Rep34193")]
data2=data2[~(data2.ReportID=="Rep38829")]
```

In [ ]:

- On understanding the problem statement each SalesPerson could sell Products at different prices across transcations
- My understanding of the problem is that there should be features of a particular product of a particular Sales Person
- The differences and ratios on a productID by a particular SalesPerson would create a profile for ProductID and SalesPersonID and helps us judge on how a salesperson sells a particular product.

In [46]:
```
# this gives us the Average Selling Price of each product sold by a SalesPerson across all his transcations.

d_10=data2.groupby(["SalesPersonID","ProductID"]).agg({"Quantity":np.sum,"TotalSalesValue":np.sum},axis=0)

d_10['ASP_CP']=d_10.TotalSalesValue/d_10.Quantity
```

In [47]:
```
d_10.shape
```

Out[47]: (7304, 3)

In [48]:
```
d_10.head()
```

Out[48]:

		Quantity	TotalSalesValue	ASP_CP
SalesPersonID	**ProductID**			
C21116	**PR6112**	546	5145	9.423077
	PR6253	908	13310	14.658590
	PR6294	225	3325	14.777778
	PR6297	150	2300	15.333333
C21118	**PR6202**	966939	1991960	2.060068

In [49]:
```
dcheck=d_10.reset_index()
dcheck.head()
```

Out[49]:

	SalesPersonID	ProductID	Quantity	TotalSalesValue	ASP_CP
0	C21116	PR6112	546	5145	9.423077
1	C21116	PR6253	908	13310	14.658590
2	C21116	PR6294	225	3325	14.777778
3	C21116	PR6297	150	2300	15.333333
4	C21118	PR6202	966939	1991960	2.060068

- Performing a inner JOIN operation on dataset so that each transcation gets its Average Selling price of that product sold by that respective SalesPerson

In [50]:
```
data3=pd.merge(data2,dcheck[['SalesPersonID','ProductID','ASP_CP']],
               left_on=['SalesPersonID','ProductID'],
               right_on=['SalesPersonID','ProductID'],how='inner')
```

In [51]:
```
print(data3.shape) # to show the number of rows have not increased

data3.head(5)
```

(42580, 8)

Out[51]:

	ReportID	SalesPersonID	ProductID	Quantity	TotalSalesValue	Suspicious	SellingPrice	ASP_CP
0	Rep10101	C21116	PR6112	182	1665	indeterminate	9.148352	9.423077
1	Rep10102	C21116	PR6112	182	1740	indeterminate	9.560440	9.423077
2	Rep10109	C21116	PR6112	182	1740	indeterminate	9.560440	9.423077
3	Rep10103	C21116	PR6253	101	1040	indeterminate	10.297030	14.658590
4	Rep10104	C21116	PR6253	283	4495	No	15.883392	14.658590

In [ ]:

In [ ]:

Various attributes were made but a few which are commented here did not contribute but only resulted in more noise

d_12=data2.groupby("SalesPersonID").agg({"Quantity":np.sum,"TotalSalesValue":np.sum},axis=0) d_12['ASP_C']=d_12.TotalSalesValue/d_12.Quantity

dcheck=d_12.reset_index()

dcheck.head()

data3=pd.merge(data3,dcheck[['SalesPersonID','ASP_C']], left_on='SalesPersonID', right_on='SalesPersonID',how='inner')

In [ ]:

d_13=data2.groupby("ProductID").agg({"Quantity":np.sum,"TotalSalesValue":np.sum},axis=0)

d_13['ASP_P']=d_13.TotalSalesValue/d_13.Quantity

dcheck=d_13.reset_index()

dcheck.head()

data3=pd.merge(data3,dcheck[['ProductID','ASP_P']], left_on='ProductID', right_on='ProductID',how='inner')

In [ ]:

Adding 2 new columns MedianQuantity and MedianTotalSalesValue of each product sold by a particular SalesPerson across all his transcations

In [52]:
```
d_11=data2.groupby(["SalesPersonID","ProductID"]).agg({"Quantity":np.median,"TotalSalesValue":np.median},axis=0)
d_11.head()
```

Out[52]:

SalesPersonID	ProductID	Quantity	TotalSalesValue
C21116	PR6112	182.0	1740.0
	PR6253	193.0	2807.5
	PR6294	112.5	1662.5
	PR6297	150.0	2300.0
C21118	PR6202	70950.0	136240.0

In [ ]:

In [53]:
```
d_11=d_11.reset_index()
d_11=d_11.rename(index=str,columns={"Quantity":"MedianQuantity",'TotalSalesValue':"MedianTotalSales"})

# join operation performed on main data
data4=pd.merge(data3,d_11[['SalesPersonID','ProductID','MedianQuantity','MedianTotalSales']],
               left_on=['SalesPersonID','ProductID'],
               right_on=['SalesPersonID','ProductID'],how='inner')
```

In [54]:
```
data4.head()
```

Out[54]:

	ReportID	SalesPersonID	ProductID	Quantity	TotalSalesValue	Suspicious	SellingPrice	ASP_CP	MedianQuantity	MedianTotalSales
0	Rep10101	C21116	PR6112	182	1665	indeterminate	9.148352	9.423077	182.0	1740.0
1	Rep10102	C21116	PR6112	182	1740	indeterminate	9.560440	9.423077	182.0	1740.0
2	Rep10109	C21116	PR6112	182	1740	indeterminate	9.560440	9.423077	182.0	1740.0
3	Rep10103	C21116	PR6253	101	1040	indeterminate	10.297030	14.658590	193.0	2807.5
4	Rep10104	C21116	PR6253	283	4495	No	15.883392	14.658590	193.0	2807.5

In [ ]:

Obtaining more columns from generated columns

In [55]:
```
data4['QuantityMargin']=data4.Quantity/data4.MedianQuantity
```

In [56]:
```
data4['TotalSalesMargin']=data4.TotalSalesValue/data4.MedianTotalSales
```

In [57]:
```
data4['SellingPriceDiff']=data4.ASP_CP-data4.SellingPrice
```

In [58]:
```
data4['SellingPriceMargin_CP']=data4.SellingPrice/data4.ASP_CP
```

In [59]:
```
data4['QuantityDiff']=data4.MedianQuantity-data4.Quantity
```

- Note: that the following attributes didnt contribute much so was removed

In [60]:
```
#data4['SellingPriceMargin_P']=data4.SellingPrice/data4.ASP_P

#data4['SellingPriceMargin_C']=data4.SellingPrice/data4.ASP_C

#data4["TotalSalesDiff"]=data4.MedianTotalSales-data4.TotalSalesValue
```

The final data after feautre engineering

In [61]:
```
data4.head()
```

Out[61]:

	ReportID	SalesPersonID	ProductID	Quantity	TotalSalesValue	Suspicious	SellingPrice	ASP_CP	MedianQuantity	MedianTotalSales	QuantityMargin	TotalSalesMargin	SellingPriceDiff	SellingPriceMargin_C
0	Rep10101	C21116	PR6112	182	1665	indeterminate	9.148352	9.423077	182.0	1740.0	1.000000	0.956897	0.274725	0.97084
1	Rep10102	C21116	PR6112	182	1740	indeterminate	9.560440	9.423077	182.0	1740.0	1.000000	1.000000	-0.137363	1.01457
2	Rep10109	C21116	PR6112	182	1740	indeterminate	9.560440	9.423077	182.0	1740.0	1.000000	1.000000	-0.137363	1.01457
3	Rep10103	C21116	PR6253	101	1040	indeterminate	10.297030	14.658590	193.0	2807.5	0.523316	0.370436	4.361561	0.70245
4	Rep10104	C21116	PR6253	283	4495	No	15.883392	14.658590	193.0	2807.5	1.466321	1.601069	-1.224802	1.08355

In [ ]:

In [62]:
```
data4.describe(include="all")
```

Out[62]:

	ReportID	SalesPersonID	ProductID	Quantity	TotalSalesValue	Suspicious	SellingPrice	ASP_CP	MedianQuantity	MedianTotalSales	QuantityMargin	TotalSalesMargin	SellingPriceDiff	Sellin
count	42580	42580	42580	4.258000e+04	4.258000e+04	42580	42580.000000	42580.000000	42580.000000	4.258000e+04	42580.000000	42580.000000	42580.000000	
unique	42580	992	593	NaN	NaN	3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
top	Rep18415	C21976	PR6253	NaN	NaN	indeterminate	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
freq	1	1359	2590	NaN	NaN	39846	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
mean	NaN	NaN	NaN	4.447421e+03	1.611392e+04	NaN	16.108425	15.855494	3357.779779	1.285908e+04	1.508774	1.440910	-0.252931	
std	NaN	NaN	NaN	2.350923e+04	5.685315e+04	NaN	57.783137	19.838360	14826.259704	4.023651e+04	8.336727	3.135102	54.729136	
min	NaN	NaN	NaN	3.300000e+01	5.980000e+02	NaN	0.005320	0.043424	35.000000	5.980000e+02	0.001060	0.003106	-8670.411113	
25%	NaN	NaN	NaN	1.110000e+02	1.345000e+03	NaN	6.781874	6.337962	113.000000	1.454375e+03	0.887029	0.835218	-1.040293	
50%	NaN	NaN	NaN	2.060000e+02	2.980000e+03	NaN	10.742574	10.999512	213.000000	3.200000e+03	1.000000	1.000000	0.000000	
75%	NaN	NaN	NaN	1.136000e+03	1.076125e+04	NaN	16.385542	19.005971	1066.000000	9.945000e+03	1.176146	1.259902	1.360031	
max	NaN	NaN	NaN	1.331792e+06	2.265400e+06	NaN	8755.900901	862.026144	492249.500000	1.165615e+06	1001.504854	341.200658	848.263768	

- Converting the target column Suspicious to 1,2,3 from Yes,No,Indeterminate as specified in problem statement

In [63]:
```
data4.Suspicious.replace(['Yes','No','indeterminate'],['1','2','3'],inplace=True)
```

Removing unnecesary attributes

- Dropping the ReportID as it is unique for every row
- Dropping SalesPersonID and ProductID as it has more than 900 and 500 levels each

In [64]:
```
dataUnn=data4.copy() # saving it into another variable , which is used later for cluster analysis.
```

In [65]:
```
data4.drop(["ProductID","SalesPersonID","ReportID"],axis=1,inplace=True)
```

Converting to necessary datatypes

In [66]:
```
## since all the other colums are already in int and float it is not needed to convert
data4["Suspicious"] = data4["Suspicious"].astype('category')
```

In [67]:
```
data4.dtypes
```

Out[67]:
```
Quantity                   int64
TotalSalesValue            int64
Suspicious              category
SellingPrice             float64
ASP_CP                   float64
MedianQuantity           float64
MedianTotalSales         float64
QuantityMargin           float64
TotalSalesMargin         float64
SellingPriceDiff         float64
SellingPriceMargin_CP    float64
QuantityDiff             float64
dtype: object
```

In [ ]:

In [68]:
```
data4.head()
```

Out[68]:

	Quantity	TotalSalesValue	Suspicious	SellingPrice	ASP_CP	MedianQuantity	MedianTotalSales	QuantityMargin	TotalSalesMargin	SellingPriceDiff	SellingPriceMargin_CP	QuantityDiff
0	182	1665	3	9.148352	9.423077	182.0	1740.0	1.000000	0.956897	0.274725	0.970845	0.0
1	182	1740	3	9.560440	9.423077	182.0	1740.0	1.000000	1.000000	-0.137363	1.014577	0.0
2	182	1740	3	9.560440	9.423077	182.0	1740.0	1.000000	1.000000	-0.137363	1.014577	0.0
3	101	1040	3	10.297030	14.658590	193.0	2807.5	0.523316	0.370436	4.361561	0.702457	92.0
4	283	4495	2	15.883392	14.658590	193.0	2807.5	1.466321	1.601069	-1.224802	1.083555	-90.0

In [ ]:

Train/Test Split

- 70/30 - Train/Test split
- Also mantaining the class imbalance across train/test split

In [69]:
```
#Performing train test split on the data
y=data4["Suspicious"]
X=data4.drop('Suspicious', axis=1)
```

In [70]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=123,stratify=y)
```

In [71]:
```
X_train.head()
```

Out[71]:

	Quantity	TotalSalesValue	SellingPrice	ASP_CP	MedianQuantity	MedianTotalSales	QuantityMargin	TotalSalesMargin	SellingPriceDiff	SellingPriceMargin_CP	QuantityDiff
40076	184775	128635	0.696171	0.510196	153776.0	76145.0	1.201585	1.689343	-0.185975	1.364517	-30999.0
4870	106	1515	14.292453	14.073499	106.0	1515.0	1.000000	1.000000	-0.218954	1.015558	0.0
6695	120	3670	30.583333	39.362851	120.0	3670.0	1.000000	1.000000	8.779518	0.776959	0.0
31170	279	9060	32.473118	20.294118	164.5	2715.0	1.696049	3.337017	-12.179001	1.600125	-114.5
12892	41912	117200	2.796335	3.619772	10742.0	45765.0	3.901694	2.560909	0.823437	0.772517	-31170.0

In [72]:
```
X_train.shape
```

Out[72]:
```
(29806, 11)
```

In [73]:
```
X_test.shape
```

Out[73]:
```
(12774, 11)
```

In [74]:
```
y_train.value_counts()
```

Out[74]:
```
3    27892
2     1789
1      125
Name: Suspicious, dtype: int64
```

In [75]:
```
y_test.value_counts()
```

Out[75]:
```
3    11954
2      766
1       54
Name: Suspicious, dtype: int64
```

- The ratio of 1 (yes) is same across the splits

A basic Decision tree model was built on which the recall for Yes was 75% .

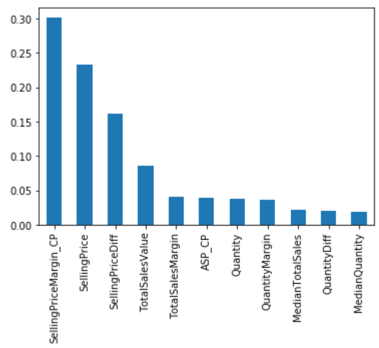
Shown here is a RandomForest model built on all features to find out important features across multiple Trees

In [76]:
```
clf_check = RandomForestClassifier(n_estimators=500,class_weight="balanced",max_depth=5,
                             max_features=4,min_samples_leaf=50,min_samples_split=10)

clf_check.fit(X=X_train, y=y_train)
y_pred = clf_check.predict(X_test)
y1_pred_=clf_check.predict(X_train)

print(accuracy_score(y_train,y1_pred_))
print(classification_report(y_train,y1_pred_,digits=4))
print("\n")


print(accuracy_score(y_test,y_pred))
print(classification_report(y_test,y_pred,digits=4))
```

```
0.736663758974703
              precision    recall  f1-score   support

           1     0.2620    0.8720    0.4030       125
           2     0.1381    0.6160    0.2256      1789
           3     0.9690    0.7438    0.8416     27892

    accuracy                         0.7367     29806
   macro avg     0.4564    0.7439    0.4901     29806
weighted avg     0.9162    0.7367    0.8028     29806



0.7343040551119462
              precision    recall  f1-score   support

           1     0.2299    0.7407    0.3509        54
           2     0.1355    0.6057    0.2214       766
           3     0.9674    0.7425    0.8402     11954

    accuracy                         0.7343     12774
   macro avg     0.4443    0.6963    0.4708     12774
weighted avg     0.9144    0.7343    0.8010     12774
```

In [77]:
```
feat_importances_rf = pd.Series(clf_check.feature_importances_, index = X_train.columns)
feat_importances_ordered = feat_importances_rf.nlargest(n=len(feat_importances_rf))
feat_importances_ordered.plot(kind='bar')
```

Out[77]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd18b19a160>
```



In [ ]:

Considering only the top 4 features for our futher models

In [78]:
```
X_train1=X_train[["SellingPriceMargin_CP","SellingPrice","SellingPriceDiff","TotalSalesValue"]]
X_test1=X_test[["SellingPriceMargin_CP","SellingPrice","SellingPriceDiff","TotalSalesValue"]]
```

In [79]:
```
X_train1.shape
```

Out[79]:
```
(29806, 4)
```

In [ ]:

In [80]:
```
X_train1.describe()
```

Out[80]:

	SellingPriceMargin_CP	SellingPrice	SellingPriceDiff	TotalSalesValue
count	29806.000000	29806.000000	29806.000000	2.980600e+04
mean	1.374702	16.353082	-0.410632	1.620022e+04
std	10.122271	65.868893	62.364994	5.736714e+04
min	0.003946	0.005320	-8670.411113	5.980000e+02
25%	0.863539	6.785857	-1.032198	1.340000e+03
50%	1.000000	10.756390	0.000000	2.975000e+03
75%	1.119464	16.504854	1.374703	1.066500e+04
max	839.862636	8755.900901	846.976639	2.170265e+06

NOTE : outliers were removed and tried but since the results didnt improve it was added back

X_train1_D=X_train1[~((X_train1<(-3))|(X_train1>3)).any(axis=1)] rown=X_train1[~((X_train1<(-3))|(X_train1>3)).any(axis=1)].index rown y_train1=y_train[rown] print(y_train1.shape) print(X_train1_D.shape)

Decision Tree and Random Forest with 4 important features

In [81]:
```
estimator_DT = DecisionTreeClassifier(max_depth=5,class_weight="balanced",random_state=123)
estimator_DT.fit(X_train1, y_train)

y1_pred_ = estimator_DT.predict(X_train1)
y_pred_ = estimator_DT.predict(X_test1)

print(accuracy_score(y_train,y1_pred_))
print(classification_report(y_train,y1_pred_,digits=4))
print("\n")

print(accuracy_score(y_test,y_pred_))
print(classification_report(y_test,y_pred_,digits=4))
```

```
0.6120244246124942
              precision    recall  f1-score   support

           1     0.1363    0.9040    0.2369       125
           2     0.1124    0.7367    0.1950      1789
           3     0.9746    0.6027    0.7448     27892

    accuracy                         0.6120     29806
   macro avg     0.4078    0.7478    0.3922     29806
weighted avg     0.9193    0.6120    0.7097     29806



0.6131204008141538
              precision    recall  f1-score   support

           1     0.1296    0.8519    0.2249        54
           2     0.1110    0.7232    0.1925       766
           3     0.9734    0.6050    0.7462     11954

    accuracy                         0.6131     12774
   macro avg     0.4047    0.7267    0.3879     12774
weighted avg     0.9181    0.6131    0.7108     12774
```

- for explanation of root and leaves in digramatic format

a=y_train.value_counts().reset_index()

dot_data = tree.export_graphviz(estimator_DT, out_file=None, feature_names=X_train1.columns, class_names=a["index"], filled=True, rounded=True, special_characters=True) graph = graphviz.Source(dot_data) graph

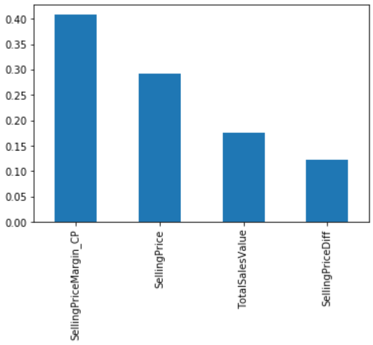
Random Forest

In [82]:
```
clf_RF = RandomForestClassifier(n_estimators=500,class_weight="balanced",max_depth=5,random_state=222,max_features=4
                                ,min_samples_leaf=50,min_samples_split=10)

clf_RF.fit(X=X_train1, y=y_train)
y_pred = clf_RF.predict(X_test1)
y1_pred_=clf_RF.predict(X_train1)

print(accuracy_score(y_train,y1_pred_))
print(classification_report(y_train,y1_pred_,digits=4))
print("\n")


print(accuracy_score(y_test,y_pred))
print(classification_report(y_test,y_pred,digits=4))
```

```
0.6735892102261289
              precision    recall  f1-score   support

           1     0.1836    0.8960    0.3048       125
           2     0.1206    0.6646    0.2042      1789
           3     0.9710    0.6732    0.7951     27892

    accuracy                         0.6736     29806
   macro avg     0.4251    0.7446    0.4347     29806
weighted avg     0.9166    0.6736    0.7576     29806



0.6798966651009863
              precision    recall  f1-score   support

           1     0.1800    0.8333    0.2961        54
           2     0.1250    0.6815    0.2113       766
           3     0.9724    0.6791    0.7997     11954

    accuracy                         0.6799     12774
   macro avg     0.4258    0.7313    0.4357     12774
weighted avg     0.9183    0.6799    0.7623     12774
```

In [83]:
```
feat_importances_rf = pd.Series(clf_RF.feature_importances_, index = X_train1.columns)
feat_importances_ordered = feat_importances_rf.nlargest(n=len(feat_importances_rf))
feat_importances_ordered.plot(kind='bar')
```

Out[83]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd174ba87b8>



In [ ]:

In [ ]:

CODE showing on how to save model using pickle

In [84]:
```
from sklearn import model_selection
import pickle
```

filename="RandomForest90.sav" pickle.dump(clf_RF,open(filename,"wb"))filename="DecisionTree86.sav" pickle.dump(estimator_DT,open(filename,"wb"))loaded_model=pickle.load(open(filename,"rb"))

In [ ]:

In [ ]:

Neural NEt and autoencoders

- Standarizing data to pass to nerual net

In [85]:
```
num_atr=X_train1.select_dtypes(['int64','float64']).columns
print(num_atr)

scaler = StandardScaler() ## object intitation
scaler.fit(X_train1[num_atr])

X_train1[num_atr]=scaler.transform(X_train1[num_atr])
X_test1[num_atr]=scaler.transform(X_test1[num_atr])
```

```
Index(['SellingPriceMargin_CP', 'SellingPrice', 'SellingPriceDiff',
       'TotalSalesValue'],
      dtype='object')
```

In [86]:
```
X_train1.describe()
```

Out[86]:

	SellingPriceMargin_CP	SellingPrice	SellingPriceDiff	TotalSalesValue
count	2.980600e+04	2.980600e+04	2.980600e+04	2.980600e+04
mean	-8.377505e-17	2.649006e-17	-2.896824e-17	2.178095e-18
std	1.000017e+00	1.000017e+00	1.000017e+00	1.000017e+00
min	-1.354221e-01	-2.481905e-01	-1.390226e+02	-2.719759e-01
25%	-5.049977e-02	-1.452489e-01	-9.966757e-03	-2.590415e-01
50%	-3.701825e-02	-8.496857e-02	6.584449e-03	-2.305404e-01
75%	-2.521593e-02	2.304200e-03	2.862768e-02	-9.648923e-02
max	8.283734e+01	1.326832e+02	1.358777e+01	3.754939e+01

In [ ]:

loading packages for neural networks from keras

In [87]:
```
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Dense, Input
from keras.layers.normalization import BatchNormalization
from tensorflow.keras.utils import to_categorical
```

```
Using TensorFlow backend.
```

In [88]:
```
X_train1.shape
```

Out[88]:
```
(29806, 4)
```

Building an autoencoder to generate new non linear features from existing ones

In [89]:
```
# The size of encoded and actual representations
encoding_dim = 1
actual_dim = X_train1.shape[1]

## MINE
# Input placeholder
input_img = Input(shape=(actual_dim,))

# "encoded" is the encoded representation of the input
encoded = Dense(encoding_dim, activation='relu')(input_img)

# "decoded" is the lossy reconstruction of the input
decoded = Dense(actual_dim, activation='sigmoid')(encoded)
```

In [90]:
```
# this model maps an input to its reconstruction
autoencoder = Model(input_img, decoded)

print(autoencoder.summary())

autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')

autoencoder.fit(X_train1, X_train1, epochs=30, batch_size=32)
```

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 4)]               0
_________________________________________________________________
dense (Dense)                (None, 1)                 5
_________________________________________________________________
dense_1 (Dense)              (None, 4)                 8
=================================================================
Total params: 13
Trainable params: 13
Non-trainable params: 0
_________________________________________________________________
None
WARNING:tensorflow:Falling back from v2 loop because of error: Failed to find data adapter that can handle input: <class 'pandas.core.frame.DataFrame'>, <
class 'NoneType'>
Train on 29806 samples
Epoch 1/30
29806/29806 [==============================] - 1s 19us/sample - loss: 0.5828
Epoch 2/30
29806/29806 [==============================] - 1s 18us/sample - loss: 0.5817
Epoch 3/30
29806/29806 [==============================] - 1s 20us/sample - loss: 0.5806
Epoch 4/30
29806/29806 [==============================] - 1s 18us/sample - loss: 0.5793
Epoch 5/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5779
Epoch 6/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5765
Epoch 7/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5751
Epoch 8/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5736
Epoch 9/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5720
Epoch 10/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5705
Epoch 11/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5689
Epoch 12/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5674
Epoch 13/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5659
Epoch 14/30
29806/29806 [==============================] - 1s 20us/sample - loss: 0.5643
Epoch 15/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5627
Epoch 16/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5611
Epoch 17/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5594
Epoch 18/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5579
Epoch 19/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5562
Epoch 20/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5546
Epoch 21/30
29806/29806 [==============================] - 0s 17us/sample - loss: 0.5530
Epoch 22/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5513
Epoch 23/30
29806/29806 [==============================] - 1s 19us/sample - loss: 0.5497
Epoch 24/30
29806/29806 [==============================] - 1s 20us/sample - loss: 0.5480
Epoch 25/30
29806/29806 [==============================] - 1s 21us/sample - loss: 0.5464
Epoch 26/30
29806/29806 [==============================] - 1s 18us/sample - loss: 0.5448
Epoch 27/30
29806/29806 [==============================] - 0s 17us/sample - loss: 0.5431
Epoch 28/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5415
Epoch 29/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5398
Epoch 30/30
29806/29806 [==============================] - 1s 17us/sample - loss: 0.5381
```

Out[90]:
```
<tensorflow.python.keras.callbacks.History at 0x7fd179f1e0b8>
```

In [91]:
```
# MIne
# this model maps an input to its encoded representation
encoder = Model(input_img, encoded)
```

In [92]:
```
print(encoder.summary())

#### derive new non-linear features

X_train_nonLinear_features = encoder.predict(X_train1)
X_test_nonLinear_features = encoder.predict(X_test1)

#### Combining new non-linear features to X_train and X_test respectively

X_train1_np=np.concatenate((X_train1, X_train_nonLinear_features), axis=1)
X_test1_np=np.concatenate((X_test1, X_test_nonLinear_features), axis=1)
```

```
Model: "model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 4)]               0
_________________________________________________________________
dense (Dense)                (None, 1)                 5
=================================================================
Total params: 5
Trainable params: 5
Non-trainable params: 0
_________________________________________________________________
None
```

building Decision tree and random Forest on concatenated old and new feature

In [93]:
```
estimator = DecisionTreeClassifier(max_depth=5,random_state=123,class_weight="balanced")
estimator.fit(X_train1_np, y_train)

y1_pred_ = estimator.predict(X_train1_np)
y_pred_ = estimator.predict(X_test1_np)

print(accuracy_score(y_train,y1_pred_))
print(classification_report(y_train,y1_pred_,digits=4))
print("\n")

print(accuracy_score(y_test,y_pred_))
print(classification_report(y_test,y_pred_,digits=4))
```

```
0.6125276789908072
              precision    recall  f1-score   support

           1     0.1388    0.9040    0.2407       125
           2     0.1124    0.7367    0.1950      1789
           3     0.9746    0.6033    0.7452     27892

    accuracy                         0.6125     29806
   macro avg     0.4086    0.7480    0.3936     29806
weighted avg     0.9194    0.6125    0.7101     29806



0.6136683889149835
              precision    recall  f1-score   support

           1     0.1322    0.8519    0.2289        54
           2     0.1110    0.7232    0.1925       766
           3     0.9734    0.6056    0.7466     11954

    accuracy                         0.6137     12774
   macro avg     0.4055    0.7269    0.3893     12774
weighted avg     0.9181    0.6137    0.7112     12774
```

In [ ]:

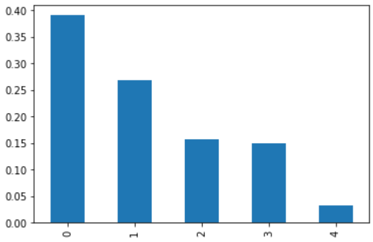
Random Forest

In [94]:
```
clf = RandomForestClassifier(n_estimators=500,class_weight="balanced",random_state=123,max_depth=6,max_features=4,
                             min_samples_leaf=50,min_samples_split=10)

clf.fit(X=X_train1_np, y=y_train)
y_pred = clf.predict(X_test1_np)
y1_pred_=clf.predict(X_train1_np)

print(accuracy_score(y_train,y1_pred_))
print(classification_report(y_train,y1_pred_,digits=4))
print("\n")


print(accuracy_score(y_test,y_pred))
print(classification_report(y_test,y_pred,digits=4))
```

```
0.6899953029591357
              precision    recall  f1-score   support

           1     0.1934    0.8960    0.3182       125
           2     0.1266    0.6652    0.2127      1789
           3     0.9716    0.6907    0.8074     27892

    accuracy                         0.6900     29806
   macro avg     0.4305    0.7506    0.4461     29806
weighted avg     0.9176    0.6900    0.7696     29806



0.6966494441834977
              precision    recall  f1-score   support

           1     0.1774    0.8148    0.2914        54
           2     0.1308    0.6749    0.2192       766
           3     0.9725    0.6975    0.8124     11954

    accuracy                         0.6966     12774
   macro avg     0.4269    0.7291    0.4410     12774
weighted avg     0.9186    0.6966    0.7746     12774
```

In [95]:
```
feat_importances_rf = pd.Series(clf.feature_importances_, index = pd.DataFrame(X_train1_np).columns)
feat_importances_ordered = feat_importances_rf.nlargest(n=len(feat_importances_rf))
feat_importances_ordered.plot(kind='bar')
```

Out[95]: `<matplotlib.axes._subplots.AxesSubplot at 0x7fd176daa780>`



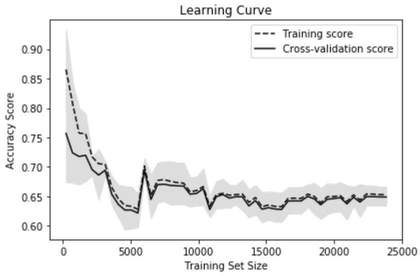
From the above feature importance graph we can find that the new non linear feature is not contributing much and could even be adding some noise

In [ ]:

In [ ]:

Learning curves for various models

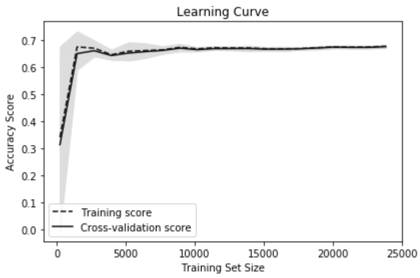
In [96]:
```
from sklearn.model_selection import learning_curve

from sklearn.model_selection import learning_curve
train_sizes, train_scores, test_scores = learning_curve(DecisionTreeClassifier(max_depth=5,random_state=123,class_weight="balanced"),
                                                        X_train1,
                                                        y_train,
                                                        # Number of folds in cross-validation
                                                        cv=5,
                                                        # Use all computer cores
                                                        n_jobs=-1,
                                                        # 50 different sizes of the training set
                                                        train_sizes=np.linspace(0.01, 1.0, 50))

# Create means and standard deviations of training set scores
train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)

# Create means and standard deviations of test set scores
test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

# Draw lines
plt.plot(train_sizes, train_mean, '--', color="#111111",  label="Training score")
plt.plot(train_sizes, test_mean, color="#111111", label="Cross-validation score")

# Draw bands
plt.fill_between(train_sizes, train_mean - train_std, train_mean + train_std, color="#DDDDDD")
plt.fill_between(train_sizes, test_mean - test_std, test_mean + test_std, color="#DDDDDD")

# Create plot
plt.title("Learning Curve")
plt.xlabel("Training Set Size"), plt.ylabel("Accuracy Score"), plt.legend(loc="best")
plt.tight_layout()
plt.show()
```



this model was not finalized as there is a lot of fluctuations on different cross validation folds and once number of sample size increases the model slowly becomes stable

In [97]:
```
from sklearn.model_selection import learning_curve

from sklearn.model_selection import learning_curve
train_sizes, train_scores, test_scores = learning_curve(RandomForestClassifier(n_estimators=50,class_weight="balanced",max_depth=5,
                             max_features=4,min_samples_leaf=50,min_samples_split=10),
                                                        X_train1,
                                                        y_train,
                                                        # Number of folds in cross-validation
                                                        cv=5,
                                                        # Use all computer cores
                                                        n_jobs=-1,
                                                        # 50 different sizes of the training set
                                                        train_sizes=np.linspace(.01, 1.0, 20))
```

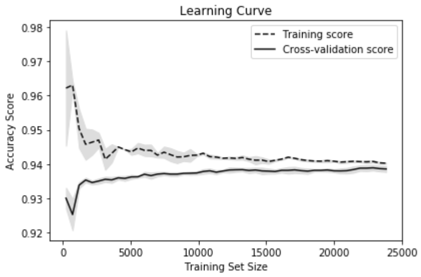
In [98]:
```
# Create means and standard deviations of training set scores
train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)

# Create means and standard deviations of test set scores
test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

# Draw lines
plt.plot(train_sizes, train_mean, '--', color="#111111",  label="Training score")
plt.plot(train_sizes, test_mean, color="#111111", label="Cross-validation score")

# Draw bands
plt.fill_between(train_sizes, train_mean - train_std, train_mean + train_std, color="#DDDDDD")
plt.fill_between(train_sizes, test_mean - test_std, test_mean + test_std, color="#DDDDDD")

# Create plot
plt.title("Learning Curve")
plt.xlabel("Training Set Size"), plt.ylabel("Accuracy Score"), plt.legend(loc="best")
plt.tight_layout()
plt.show()
```



As you can see the training score and cross- validation score are very close to eachother even in small training set and continue to be close to eachother as sample size increases - Therefore low bias and low variance model

XGboost not shown above but executed which yielded poor results

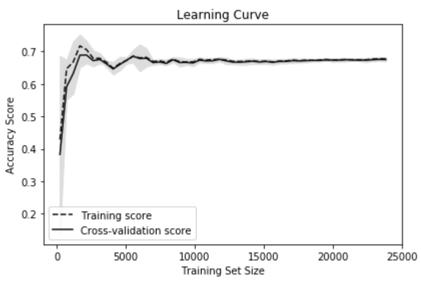
In [99]:
```
from sklearn.model_selection import learning_curve

from sklearn.model_selection import learning_curve
train_sizes, train_scores, test_scores = learning_curve(XGBClassifier(n_estimators=30,class_weight="balanced",max_depth=4),
                                                        X_train1,
                                                        y_train,
                                                        cv=5,
                                                        # Use all computer cores
                                                        n_jobs=-1,
                                                        # 50 different sizes of the training set
                                                        train_sizes=np.linspace(0.01, 1.0, 50))

# Create means and standard deviations of training set scores
train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)

# Create means and standard deviations of test set scores
test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

# Draw lines
plt.plot(train_sizes, train_mean, '--', color="#111111",  label="Training score")
plt.plot(train_sizes, test_mean, color="#111111", label="Cross-validation score")

# Draw bands
plt.fill_between(train_sizes, train_mean - train_std, train_mean + train_std, color="#DDDDDD")
plt.fill_between(train_sizes, test_mean - test_std, test_mean + test_std, color="#DDDDDD")

# Create plot
plt.title("Learning Curve")
plt.xlabel("Training Set Size"), plt.ylabel("Accuracy Score"), plt.legend(loc="best")
plt.tight_layout()
plt.show()
```



This model is suffering from a high bias problem

Random Forest with non linear features

In [100]:
```
from sklearn.model_selection import learning_curve

from sklearn.model_selection import learning_curve
train_sizes, train_scores, test_scores = learning_curve(RandomForestClassifier(n_estimators=50,class_weight="balanced",max_depth=5,
                             max_features=4,min_samples_leaf=50,min_samples_split=10),
                                                        X_train1_np,
                                                        y_train,
                                                        # Number of folds in cross-validation
                                                        cv=5,
                                                        # Use all computer cores
                                                        n_jobs=-1,
                                                        # 50 different sizes of the training set
                                                        train_sizes=np.linspace(0.01, 1.0, 50))

# Create means and standard deviations of training set scores
train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)

# Create means and standard deviations of test set scores
test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

# Draw lines
plt.plot(train_sizes, train_mean, '--', color="#111111",  label="Training score")
plt.plot(train_sizes, test_mean, color="#111111", label="Cross-validation score")

# Draw bands
plt.fill_between(train_sizes, train_mean - train_std, train_mean + train_std, color="#DDDDDD")
plt.fill_between(train_sizes, test_mean - test_std, test_mean + test_std, color="#DDDDDD")

# Create plot
plt.title("Learning Curve")
plt.xlabel("Training Set Size"), plt.ylabel("Accuracy Score"), plt.legend(loc="best")
plt.tight_layout()
plt.show()
```



In [ ]:

In [ ]:

CLUSTERING

In [101]:
```
# Using the copy of the data which was created after all new features were added
dataUnn.shape
```
Out[101]:
```
(42580, 15)
```

In [102]:
```
dataUnn.head()
```
Out[102]:

	ReportID	SalesPersonID	ProductID	Quantity	TotalSalesValue	Suspicious	SellingPrice	ASP_CP	MedianQuantity	MedianTotalSales	QuantityMargin	TotalSalesMargin	SellingPriceDiff	SellingPriceMargin_CP
0	Rep10101	C21116	PR6112	182	1665	3	9.148352	9.423077	182.0	1740.0	1.000000	0.956897	0.274725	0.970845
1	Rep10102	C21116	PR6112	182	1740	3	9.560440	9.423077	182.0	1740.0	1.000000	1.000000	-0.137363	1.014577
2	Rep10109	C21116	PR6112	182	1740	3	9.560440	9.423077	182.0	1740.0	1.000000	1.000000	-0.137363	1.014577
3	Rep10103	C21116	PR6253	101	1040	3	10.297030	14.658590	193.0	2807.5	0.523316	0.370436	4.361561	0.702457
4	Rep10104	C21116	PR6253	283	4495	2	15.883392	14.658590	193.0	2807.5	1.466321	1.601069	-1.224802	1.083555

Grouping the data SalesPerson wise do to segment SalesPerson

In [103]:
```
d1=dataUnn.groupby("SalesPersonID").agg({"TotalSalesValue":np.median,"Quantity":np.median,"SellingPriceMargin_CP":np.mean,"ReportID":np.count_nonzero},axis
=0)
```

In [104]:
```
d1.head()
```
Out[104]:

	TotalSalesValue	Quantity	SellingPriceMargin_CP	ReportID
SalesPersonID				
C21116	1740.0	166.0	0.959989	10
C21118	136240.0	70950.0	11.405030	10
C21119	1115.0	102.0	1.000000	4
C21121	5622.5	312.0	2.370057	32
C21122	1185.0	103.5	1.047227	28

In [105]:
```
d1.reset_index(inplace=True)
SalesPersonID=d1.SalesPersonID
```

In [106]:
```
d1.drop("SalesPersonID",axis=1,inplace=True)
```

In [107]:
```
d1.head()
```
Out[107]:

	TotalSalesValue	Quantity	SellingPriceMargin_CP	ReportID
0	1740.0	166.0	0.959989	10
1	136240.0	70950.0	11.405030	10
2	1115.0	102.0	1.000000	4
3	5622.5	312.0	2.370057	32
4	1185.0	103.5	1.047227	28

In [108]:
```
d1.shape
```
Out[108]:
```
(992, 4)
```

In [ ]:

In [109]:
```
d2=d1.copy() ## creating a copy so that actual values can be used for analyzing after assigning labels
```

In [110]:
```
d1.head()
```
Out[110]:

	TotalSalesValue	Quantity	SellingPriceMargin_CP	ReportID
0	1740.0	166.0	0.959989	10
1	136240.0	70950.0	11.405030	10
2	1115.0	102.0	1.000000	4
3	5622.5	312.0	2.370057	32
4	1185.0	103.5	1.047227	28

Standarizing data for clustering

In [111]:
```
num_atr=d1.select_dtypes(['int64','float64']).columns
print(num_atr)

scaler = StandardScaler() ## object intitation
scaler.fit(d1[num_atr])

d1[num_atr]=scaler.transform(d1[num_atr])
d1[num_atr]=scaler.transform(d1[num_atr])
```
```
Index(['TotalSalesValue', 'Quantity', 'SellingPriceMargin_CP', 'ReportID'], dtype='object')
```

In [ ]:

In [ ]:

ELBOW curve to find the optimal cluster number which will define the particular dataset

In [112]:
```
from sklearn.cluster import KMeans
```

In [113]:
```python
## Build K Means with the 2 clusters
kmeans = KMeans(n_clusters=2).fit(d1)

## Derive Centroids
centroids = kmeans.cluster_centers_

## Derive Labels
labels = kmeans.labels_

## Print Centroids
print(centroids)

## Print Labels
print(labels)

## Experiment/Build K means for different K values, from 1 to 20
K = range(1,20)
KM = [KMeans(n_clusters=k).fit(d1) for k in K]
centroids = [k.cluster_centers_ for k in KM]
#labelsk = [kmeans.labels_ for k in KM]

## Find with in sum of squared error
from scipy.spatial.distance import cdist, pdist

D_k = [cdist(d1, cent, 'euclidean') for cent in centroids]
cIdx = [np.argmin(D,axis=1) for D in D_k]
dist = [np.min(D,axis=1) for D in D_k]
sumWithinSS = [sum(d) for d in dist]
#silhouetteSS=[silhouette_score(d,labels=labelsk) for d in dist]


## Elbow curve
#1
# maring k=3
kIdx = 2
fig = plt.figure()
ax = fig.add_subplot(111)
ax.plot(K, sumWithinSS, 'b*-')
ax.plot(K[kIdx], sumWithinSS[kIdx], marker='o', markersize=12,
markeredgewidth=2, markeredgecolor='r', markerfacecolor='None')
plt.grid(True)
plt.xlabel('Number of clusters')
plt.ylabel('within-cluster sum of squares')
plt.title('Elbow for KMeans clustering')
```

```
[[-0.35857122 -0.17550655 -0.3961721  -0.56448472]
 [-0.35850918 -0.17519505  3.03682879 -0.56942075]]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
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 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
```
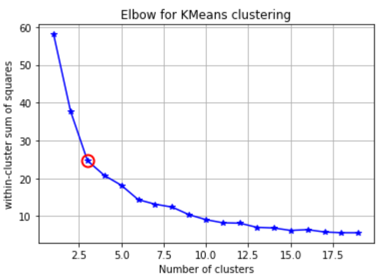

Out[113]: Text(0.5, 1.0, 'Elbow for KMeans clustering')



In [ ]:

In [114]:
```python
## Build K Means with the 3 clusters
kmeans = KMeans(n_clusters=3).fit(d1)
```

In [115]:
```python
## Derive Centroids
centroids = kmeans.cluster_centers_
```

In [116]:
```python
labels = kmeans.labels_
```

In [117]:
```python
# adding labels to the actual values
d2["label"]=labels
```

In [118]:
```python
d2["label"] = d2["label"].astype('category')
```

In [ ]:

In [119]:
```python
# for 4 clusters
# 0 - 976
# 1 - 12
# 3 - 3
# 2 - 1
```

In [120]:
```
d2.label.value_counts()
```
Out[120]:
```
0    976
2     12
1      4
Name: label, dtype: int64
```

In [121]:
```
# for 2 clusters
# 0 - 988
# 1 - 4
```

In [122]:
```
d2["SalesPersonID"]=SalesPersonID
```

In [123]:
```
d2[d2.label==1]
```
Out[123]:

	TotalSalesValue	Quantity	SellingPriceMargin_CP	ReportID	label	SalesPersonID
349	4210.0	217.0	44.349369	11	1	C21553
354	7617.5	286.5	45.083315	18	1	C21558
435	264400.0	492249.5	87.343926	8	1	C21659
849	19215.0	26817.0	45.960275	21	1	C22168

In [ ]:

In [ ]:

In [124]:
```
## to show the SalesPersom with most supicious Yes is not a high risk SalesPerson
d2[d2.SalesPersonID=="C22030"]
```
Out[124]:

	TotalSalesValue	Quantity	SellingPriceMargin_CP	ReportID	label	SalesPersonID
739	10520.0	1773.0	1.088686	525	0	C22030

In [125]:
```
dataUnn[(dataUnn.SalesPersonID=="C21659")&(dataUnn.Suspicious=='1')]
```
Out[125]:

	ReportID	SalesPersonID	ProductID	Quantity	TotalSalesValue	Suspicious	SellingPrice	ASP_CP	MedianQuantity	MedianTotalSales	QuantityMargin	TotalSalesMargin	SellingPriceDiff	SellingPriceMargin_
40243	Rep50346	C21659	PR6518	1125	539145	1	479.24	0.691168	492249.5	264400.0	0.002285	2.039126	-478.548832	693.377

In [126]:
```
# C22030 - 497NO 19 Indeterminate 9Yes
# C21659 - 6 NO 1 Int 1 Yes
```

In [127]:
```
d2[d2.label==0].describe(include="all")
```
Out[127]:

	TotalSalesValue	Quantity	SellingPriceMargin_CP	ReportID	label	SalesPersonID
count	976.000000	976.000000	976.000000	976.000000	976.0	976
unique	NaN	NaN	NaN	NaN	1.0	976
top	NaN	NaN	NaN	NaN	0.0	C22192
freq	NaN	NaN	NaN	NaN	976.0	1
mean	10864.276127	2914.058914	1.143966	43.319672	NaN	NaN
std	30561.452720	12760.344991	0.557911	76.612661	NaN	NaN
min	1005.000000	85.000000	0.690233	1.000000	NaN	NaN
25%	1607.500000	118.500000	0.984118	10.000000	NaN	NaN
50%	3435.000000	228.500000	1.004324	22.000000	NaN	NaN
75%	8613.750000	1035.750000	1.090198	45.000000	NaN	NaN
max	566000.000000	232820.000000	7.396199	1359.000000	NaN	NaN

In [128]:
```
d2[d2.label==1].describe(include="all")
```
Out[128]:

	TotalSalesValue	Quantity	SellingPriceMargin_CP	ReportID	label	SalesPersonID
count	4.000000	4.000000	4.000000	4.000000	4.0	4
unique	NaN	NaN	NaN	NaN	1.0	4
top	NaN	NaN	NaN	NaN	1.0	C21659
freq	NaN	NaN	NaN	NaN	4.0	1
mean	73860.625000	129892.500000	55.684221	14.500000	NaN	NaN
std	127188.520092	241895.710783	21.116740	6.027714	NaN	NaN
min	4210.000000	217.000000	44.349369	8.000000	NaN	NaN
25%	6765.625000	269.125000	44.899829	10.250000	NaN	NaN
50%	13416.250000	13551.750000	45.521795	14.500000	NaN	NaN
75%	80511.250000	143175.125000	56.306188	18.750000	NaN	NaN
max	264400.000000	492249.500000	87.343926	21.000000	NaN	NaN

In [ ]:

In [129]:
```
d2[d2.label==2].describe(include="all")
```
Out[129]:

	TotalSalesValue	Quantity	SellingPriceMargin_CP	ReportID	label	SalesPersonID
count	12.000000	12.000000	12.000000	12.000000	12.0	12
unique	NaN	NaN	NaN	NaN	1.0	12
top	NaN	NaN	NaN	NaN	2.0	C22178
freq	NaN	NaN	NaN	NaN	12.0	1
mean	34140.416667	12480.625000	14.189453	20.166667	NaN	NaN
std	44108.901504	20223.205256	4.988150	16.353111	NaN	NaN
min	1675.000000	148.000000	8.329741	5.000000	NaN	NaN
25%	3533.750000	490.375000	11.140478	8.500000	NaN	NaN
50%	12666.250000	5850.750000	12.329318	15.000000	NaN	NaN
75%	43638.125000	12703.500000	16.295548	23.500000	NaN	NaN
max	136240.000000	70950.000000	23.400621	53.000000	NaN	NaN

if we observe here the difference in clusters are their SellingPriceMargin will he is low , medium and very high respectively

- We could conclude that the ones with High SellingPriceMargin to be High Risk Salesperson

In [ ]:

In [ ]:

Functions to use pipeline in Pandas

In [130]:
```
def feature_eng(dataframe):
    dataframe['SellingPrice']=dataframe.TotalSalesValue/dataframe.Quantity
    d_10=dataframe.groupby(["SalesPersonID","ProductID"]).agg({"Quantity":np.sum,"TotalSalesValue":np.sum},axis=0)
    d_10['ASP_CP']=d_10.TotalSalesValue/d_10.Quantity
    dcheck=d_10.reset_index()
    dataframe=pd.merge(dataframe,dcheck[['SalesPersonID','ProductID','ASP_CP']],
              left_on=['SalesPersonID','ProductID'],
              right_on=['SalesPersonID','ProductID'],how='inner')
    d_11=dataframe.groupby(["SalesPersonID","ProductID"]).agg({"Quantity":np.median,"TotalSalesValue":np.median},axis=0)
    d_11=d_11.reset_index()
    d_11=d_11.rename(index=str,columns={"Quantity":"MedianQuantity",'TotalSalesValue':"MedianTotalSales"})
    # join operation performed on main data
    dataframe=pd.merge(dataframe,d_11[['SalesPersonID','ProductID','MedianQuantity','MedianTotalSales']],
              left_on=['SalesPersonID','ProductID'],
              right_on=['SalesPersonID','ProductID'],how='inner')
    return dataframe
```

In [131]:
```
def Ratios(data4):
    data4['QuantityMargin']=data4.Quantity/data4.MedianQuantity
    data4['TotalSalesMargin']=data4.TotalSalesValue/data4.MedianTotalSales
    data4['SellingPriceDiff']=data4.ASP_CP-data4.SellingPrice
    data4['SellingPriceMargin_CP']=data4.SellingPrice/data4.ASP_CP
    data4['QuantityDiff']=data4.MedianQuantity-data4.Quantity
    return data4
```

In [132]:
```
def selection(dataset):
    ReportID=dataset.ReportID
    dataset.drop(["ProductID","SalesPersonID","ReportID"],axis=1,inplace=True)
    dataset1=dataset[["SellingPriceMargin_CP","SellingPrice","SellingPriceDiff","TotalSalesValue"]]
    return dataset1,ReportID
```

In [ ]:

In [ ]:

Prediction for test Data SCT

In [133]:
```
tdata=pd.read_excel("../data/Test.xlsx")
```

In [134]:
```
tdata.head()
```

Out[134]:

	ReportID	SalesPersonID	ProductID	Quantity	TotalSalesValue
0	Rep70101	C21844	PR6483	102	1115
1	Rep70102	C21844	PR6251	102	1050
2	Rep70103	C21844	PR6253	344	3490
3	Rep70104	C21844	PR6378	108	1095
4	Rep70105	C21844	PR6463	146	1055

In [135]:
```
tdata.shape
```

Out[135]:
```
(9135, 5)
```

In [136]:
```
# defining a pipeline of functions
tfinal,ReportID=(tdata.pipe(func=feature_eng).pipe(func=Ratios).pipe(func=selection))
```

In [137]:
```
tfinal.head()
```

Out[137]:

	SellingPriceMargin_CP	SellingPrice	SellingPriceDiff	TotalSalesValue
0	1.0	10.931373	0.0	1115
1	1.0	10.931373	0.0	1115
2	1.0	10.931373	0.0	1115
3	1.0	10.931373	0.0	1115
4	1.0	10.294118	0.0	1050

- Predicting from best model on the test data

In [138]:
```
test_pred = clf_RF.predict(tfinal)
```

In [139]:
```
dataT1={'ReportID':ReportID,'Suspicious':test_pred}
d1f=pd.DataFrame(dataT1)
```

In [140]:
```
d1f.Suspicious.value_counts()
```

Out[140]:
```
3    5529
2    3486
1     120
Name: Suspicious, dtype: int64
```

In [141]:
```
#d1f.to_csv("Submission_RF_NN_1Auto.csv",index=False)
```

loading model using pickle and predicting

from sklearn import model_selection import pickleloaded_model=pickle.load(open("RandomForest90.sav","rb"))test_pred1 = loaded_model.predict(tfinal) dataT1={'ReportID':tdata3['ReportID'],'Suspicious':test_pred1} d1f=pd.DataFrame(dataT1)

In [ ]:

Adding non Linear features for test Data

In [142]:
```
tfinal.describe()
```

Out[142]:

	SellingPriceMargin_CP	SellingPrice	SellingPriceDiff	TotalSalesValue
count	9135.000000	9135.000000	9135.000000	9.135000e+03
mean	1.610482	14.322076	-0.162717	1.154211e+04
std	8.919273	23.025443	20.268518	3.671294e+04
min	0.060848	0.006659	-1035.817189	9.350000e+02
25%	0.900752	7.903282	-0.968012	1.205000e+03
50%	1.000000	10.643087	0.000000	2.235000e+03
75%	1.102152	14.750187	0.943065	7.817500e+03
max	231.406671	1190.875706	145.623489	1.298690e+06

In [143]:
```
t_final=tfinal.copy()
```

In [144]:
```
num_atr=t_final.select_dtypes(['int64','float64']).columns
print(num_atr)

#scaler = StandardScaler() ## object intitation
#scaler.fit(t_final[num_atr])

t_final[num_atr]=scaler.transform(t_final[num_atr])
```

```
Index(['SellingPriceMargin_CP', 'SellingPrice', 'SellingPriceDiff',
       'TotalSalesValue'],
      dtype='object')
```

In [145]:
```
print(encoder.summary())

#### derive new non-linear features

t_final_nonLinear_features = encoder.predict(t_final)

#### Combining new non-linear features to Test

t_final_np=np.concatenate((t_final, t_final_nonLinear_features), axis=1)
```

```
Model: "model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 4)]               0
_________________________________________________________________
dense (Dense)                (None, 1)                 5
=================================================================
Total params: 5
Trainable params: 5
Non-trainable params: 0
_________________________________________________________________
None
```

In [ ]:

In [ ]:

FINAL MODEL

The model using non linear features yielded same 90% in SCT and therefore OCCAM razor , a simpler model is chosen as no improvement in results

RandomForest without non linear features

Conclusion

- Succesfully built a ML model to predict Supicious Reports with a recall of 83% on Yes and an accuracy of 70% on all classes
- The model achieved a recall of 90% in SCT for unseen data
- Segemented salesperson into 3 clusters using k means clustering algorithm
- The business could collect more attributes to improve the performance of the model
- The business could impose a maximum Quantity and minimum price at which to be sold for a product , a bare minimum would atleast throw out highly faults reports

In [ ]:

In [ ]: