Capstone -1 Fraud Analysis Using ML Algorithms

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Problem Statement: In this capstone project, you are going to analyze customer's purchase data set and build a machine learning algorithm to detect fraud purchases. And also you are going to perform customer segmentation

Dataset: Purchase_Fraud_Data.csv

CAPSTONE PROJECT - 1 FRAUD ANALYSIS USING ML ALGORITHMS

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Dataset: Purchase_Fraud_Data.csv

Dataset Description: Every row in this dataset contains information about purchases from multiple customers. Along with purchase details, we also have customer basic details like gender, date of birth etc. Individual column description as follows

User_id: Customer unique id Signup_time: Date & Time at which the customer signup in the platform Purchase_time: The latest purchase date & time from a customer Purchase_value: Total purchase amount Device_id: Unique device ID from which purchase was done Source: Medium through which customers reached the platform Browser: Browser used while purchasing IP_address: IP Address from which purchase was done Class: 1 = Target class; Fraud transaction; 0=Regular transaction Category: Type of product purchased Dob: Date of birth of the customer

Exploratory Data Analysis

1. Summarize numerical, categorical and date columns separately and list down your inferences
2. Identify and perform missing value treatment using appropriate techniques
3. Univariate analysis: For each column perform appropriate univariate analysis. (i.e. perform distribution analysis on numerical columns and frequency analysis on categorical columns)
4. Multivariate analysis: Take combinations of multiple columns and identify the relationship between them. a. Categorical vs numerical columns – bar charts, boxplots b. Numerical vs numerical columns – scatter plot c. Categorical vs multiple numerical columns – scatter plot d. Correlation matrix e. …
5. Perform statistical hypothesis test to identify the relationship between input and target variables

Base Model for Benchmark

1. Convert all the input columns to numerical columns using one hot encoding
2. Make sure you temporarily ignore the date columns and id columns
3. Split the data in training and testing
4. Build a simple decision tree with max_depth=5 and identify accuracy and f1 score. Keep this as a bench mark values to explain the improvement post feature engineering

Feature Engineering

Using the original data, perform the following feature engineering techniques to create new columns for modelling

1. Using all the date columns, extract the following information wherever necessary a. Year, month, day, hour, day of the week (mon, tue, etc)
2. Using date of birth column, try to calculate the appropriate age of the customer. (Compute difference between purchase date and date of birth)
3. Using age column, identify age buckets using binning method
4. Compute no. of hours/days between purchase time and signup time

5. For all appropriate numerical variables, compute buckets using binning method

Model Building

1. Convert all the input variables to numeric
2. Split the new data in to training and testing
3. Build the following classification models using new data a. Decision Trees b. Random Forest c. Boosting techniques d. XGBoost
4. For all the above classifiers, make sure that you perform hyper parameter tuning to select optimal value hyper parameters
5. For all the above methods, report accuracy and f1 score
6. Also in a single plot, compare the ROC curves for all the above models
7. Choose an appropriate model based on above inferences and report the same

Customer Segmentation

The company would like to segment their customers using various attributes, so that they can perform targeted marketing campaign. Do the following to group the customers in the different clusters

1. In the original feature engineered dataset, exclude the following columns: ids, dates, class (target column)
2. Convert all the input variables to numeric
3. Using Elbow method identify optimal number of clusters required to group customers in to various clusters
4. Perform K-Means clustering using appropriate number of clusters
5. Tag each customer with a cluster
6. Cluster-wise report average values of all input variables

In [1]:
```
import numpy as np
import pandas as pd
from IPython.display import display, HTML
%matplotlib inline
import datetime
import seaborn as sns
from sklearn.model_selection import cross_val_score
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix,classification_report,accuracy_score,precision_sc
```

In [ ]:
```

```

In [ ]:
```
#reading the file
```

In [2]:
```
df = pd.read_csv('Purchase_Fraud_data.csv')
df.head(5)
```

Out[2]:

	user_id	signup_time	purchase_time	purchase_value	device_id	source	browser	sex	ip_address	cl
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	65278	QVPSPJUOCKZAR	SEO	Chrome	M	7.327584e+08	
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	96399	EOGFQPIZPYXFZ	Ads	Chrome	F	3.503114e+08	
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	57296	YSSKYOSJHPPLJ	SEO	Opera	M	2.621474e+09	
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	43650	ATGTXKYKUDUQN	SEO	Safari	M	3.840542e+09	
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	45016	NAUITBZFJKHWW	Ads	Safari	M	4.155831e+08	

In [3]:
```
df1=df.copy()
```

In [4]:
```
#Summarize numerical, categorical and date columns separately and list down your inferences
```

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

Out[5]:
```
(151112, 12)
```

In [6]:
```
df.count()
```

Out[6]:
```
user_id           151112
signup_time       151112
purchase_time     151112
purchase_value    151112
device_id         151112
source            151112
browser           151112
sex               146185
ip_address        151112
class             151112
category          151112
dob               146188
dtype: int64
```

In [7]:
```
df.describe()
```

Out[7]:

	user_id	purchase_value	ip_address	class
count	151112.000000	151112.000000	1.511120e+05	151112.000000
mean	200171.040970	50521.469003	2.152145e+09	0.093646
std	115369.285024	28533.667117	1.248497e+09	0.291336
min	2.000000	1016.000000	5.209350e+04	0.000000
25%	100642.500000	25919.000000	1.085934e+09	0.000000
50%	199958.000000	50484.000000	2.154770e+09	0.000000
75%	300054.000000	75296.250000	3.243258e+09	0.000000
max	400000.000000	100092.000000	4.294850e+09	1.000000

In [8]:
```
#Identify and perform missing value treatment using appropriate techniques
```

In [9]:
```
df.isna().sum()
```

Out[9]:
```
user_id              0
signup_time          0
purchase_time        0
purchase_value       0
device_id            0
source               0
browser              0
sex               4927
ip_address           0
class                0
category             0
dob               4924
dtype: int64
```

In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 151112 entries, 0 to 151111
Data columns (total 12 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   user_id         151112 non-null  int64  
 1   signup_time     151112 non-null  object 
 2   purchase_time   151112 non-null  object 
 3   purchase_value  151112 non-null  int64  
 4   device_id       151112 non-null  object 
 5   source          151112 non-null  object 
 6   browser         151112 non-null  object 
 7   sex             146185 non-null  object 
 8   ip_address      151112 non-null  float64
 9   class           151112 non-null  int64  
 10  category        151112 non-null  object 
 11  dob             146188 non-null  object 
dtypes: float64(1), int64(3), object(8)
memory usage: 13.8+ MB
```

In [11]:
```
df.isna().sum()/len(df)*100
#we can see the null values in Sex and Dob coulmns
```

Out[11]:
```
user_id           0.000000
signup_time       0.000000
purchase_time     0.000000
purchase_value    0.000000
device_id         0.000000
source            0.000000
browser           0.000000
sex               3.260496
ip_address        0.000000
class             0.000000
category          0.000000
dob               3.258510
dtype: float64
```

In [12]:
```
#Since it has null values less than 10 % we can drop null values of sex and dob columns.
```

In [13]:
```
df['class'].value_counts()
```

Out[13]:
```
0    136961
1     14151
Name: class, dtype: int64
```

In [14]:
```
df = df.dropna()
df.head()
```

Out[14]:

	user_id	signup_time	purchase_time	purchase_value	device_id	source	browser	sex	ip_address	cla
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	65278	QVPSPJUOCKZAR	SEO	Chrome	M	7.327584e+08	
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	96399	EOGFQPIZPYXFZ	Ads	Chrome	F	3.503114e+08	
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	57296	YSSKYOSJHPPLJ	SEO	Opera	M	2.621474e+09	
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	43650	ATGTXKYKUDUQN	SEO	Safari	M	3.840542e+09	
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	45016	NAUITBZFJKHWW	Ads	Safari	M	4.155831e+08	

In [15]:
```
df.columns
```

Out[15]:
```
Index(['user_id', 'signup_time', 'purchase_time', 'purchase_value',
       'device_id', 'source', 'browser', 'sex', 'ip_address', 'class',
       'category', 'dob'],
      dtype='object')
```

In [16]:
```
df['class'].value_counts()
```

Out[16]:
```
0    128164
1     13240
Name: class, dtype: int64
```

In [17]:
```
df.isna().sum()/len(df)*100
```

Out[17]:
```
user_id           0.0
signup_time       0.0
purchase_time     0.0
purchase_value    0.0
device_id         0.0
source            0.0
browser           0.0
sex               0.0
ip_address        0.0
class             0.0
category          0.0
dob               0.0
dtype: float64
```

In [18]:
```
df.skew()
```

```
C:\Users\asus\AppData\Local\Temp/ipykernel_13324/1665899112.py:1: FutureWarning: Dropping of
nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a futur
e version this will raise TypeError.  Select only valid columns before calling the reduction.
  df.skew()
```

Out[18]:
```
user_id           0.001247
purchase_value    0.000862
ip_address       -0.007756
class             2.789898
dtype: float64
```

In [19]:
```
df.std()
```

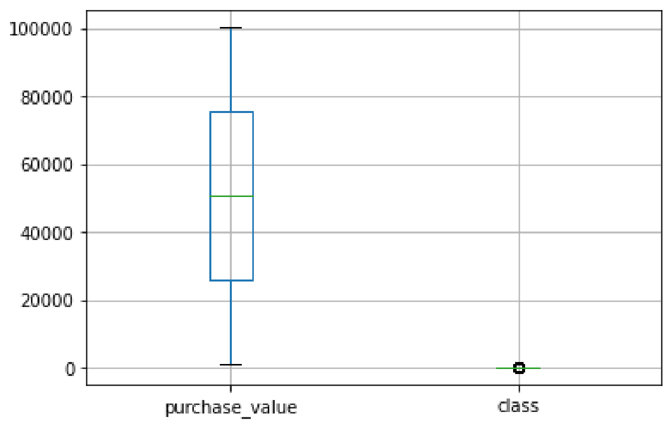
```
C:\Users\asus\AppData\Local\Temp/ipykernel_13324/3390915376.py:1: FutureWarning: Dropping of
nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a futur
e version this will raise TypeError.  Select only valid columns before calling the reduction.
  df.std()
```

Out[19]:
```
user_id           1.153234e+05
purchase_value    2.853566e+04
ip_address        1.248164e+09
class             2.913177e-01
dtype: float64
```

Outlier visualization

In [20]:
```
df.drop(['user_id','ip_address'],axis=1).boxplot()
# we can observe that no outlier present.
```

Out[20]: <AxesSubplot:>



In [21]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 141404 entries, 0 to 151111
Data columns (total 12 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   user_id         141404 non-null  int64  
 1   signup_time     141404 non-null  object 
 2   purchase_time   141404 non-null  object 
 3   purchase_value  141404 non-null  int64  
 4   device_id       141404 non-null  object 
 5   source          141404 non-null  object 
 6   browser         141404 non-null  object 
 7   sex             141404 non-null  object 
 8   ip_address      141404 non-null  float64
 9   class           141404 non-null  int64  
 10  category        141404 non-null  object 
 11  dob             141404 non-null  object 
dtypes: float64(1), int64(3), object(8)
memory usage: 14.0+ MB
```

In [22]:
```
obj=df.select_dtypes(include='object').columns
obj
```

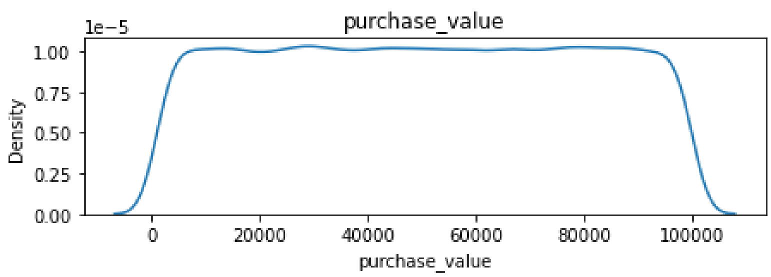
Out[22]:
```
Index(['signup_time', 'purchase_time', 'device_id', 'source', 'browser', 'sex',
       'category', 'dob'],
      dtype='object')
```

In [23]:
```
df1['class']=df1['class'].astype('object')
```

UNIVARIATE ANALYSIS OF NUMERICAL COLUMN

In [24]:
```
num=['purchase_value']
```

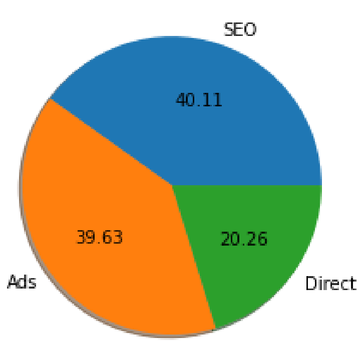
In [25]:
```
a = 4
b = 2
counter = 1
plt.figure(figsize = [12, 8])

for i in num:
    plt.subplot(a,b,counter)
    plt.title(i)
    sns.kdeplot(df1.loc[:, i])
    counter = counter+1
plt.tight_layout()
plt.show()
```



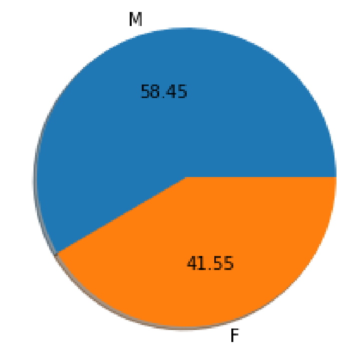
In [26]:
```
# Purchase value is highly skewed
```

UNIVARIATE ANALYSIS OF CATEGORICAL COLUMN

In [27]:
```
x=df1['source'].value_counts()
plt.pie(x,labels=x.index,autopct='%0.2f',shadow=True)
plt.show()
```

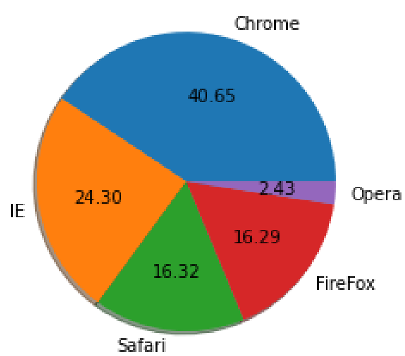


In [28]:
```
# SEO is highest in percentage followed by Ads and Direct.
x=df1['sex'].value_counts()
plt.pie(x,labels=x.index,autopct='%0.2f',shadow=True)
plt.show()
```



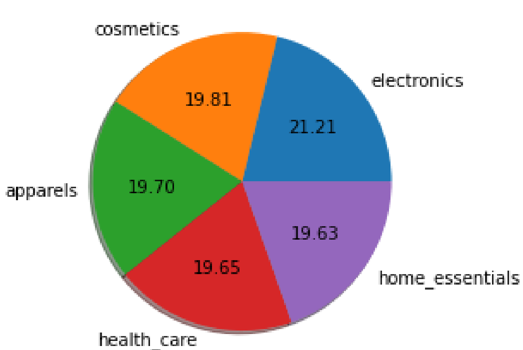
In [29]:
```
# In terms of gender the category of  Males are more in percentage as compared to females.
```

In [30]:
```
x=df1['browser'].value_counts()
plt.pie(x,labels=x.index,autopct='%0.2f',shadow=True)
plt.show()
```



In [31]:
```
#majority of the customers  are using Chrome followed by IE,Safari,Firefox and Opera.
```

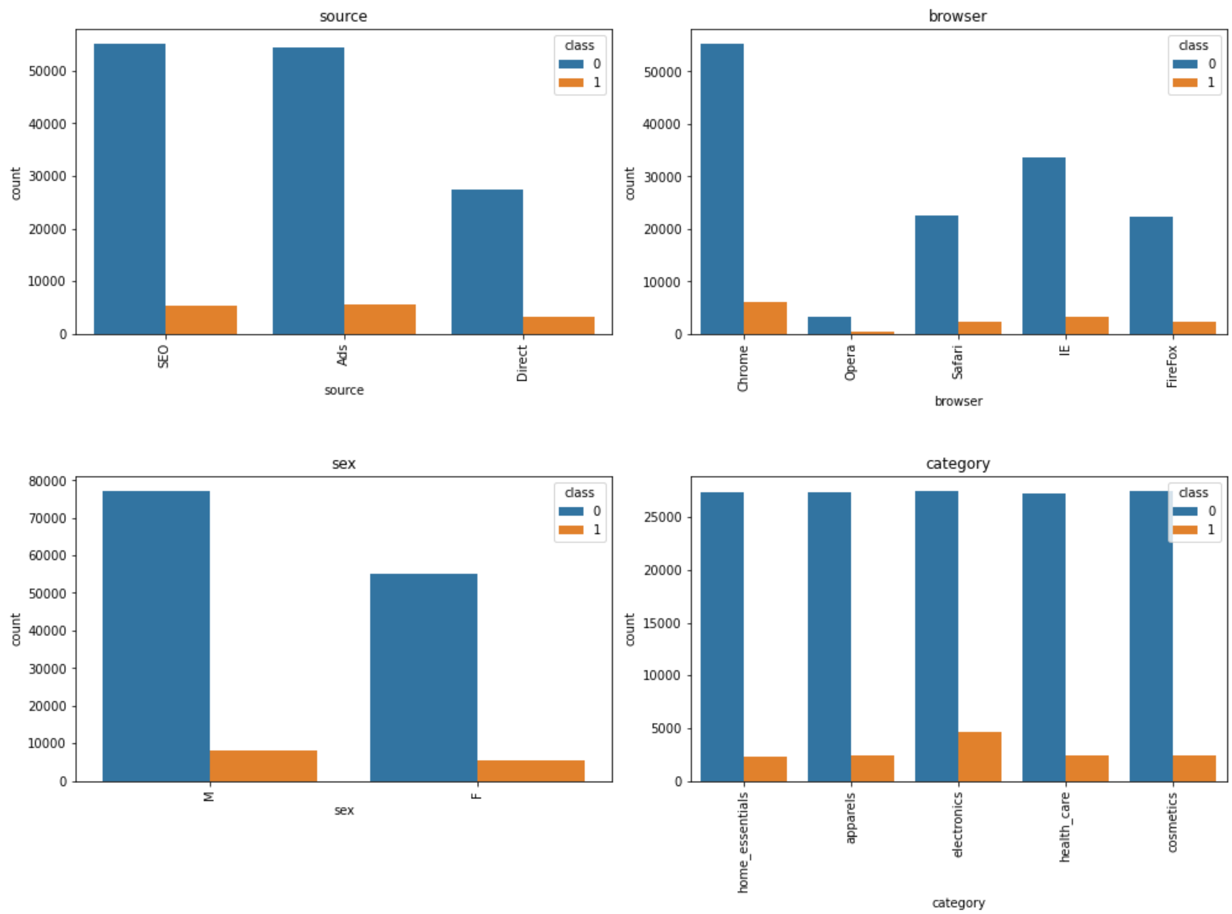
In [32]:
```
x=df1['category'].value_counts()
plt.pie(x,labels=x.index,autopct='%0.2f',shadow=True)
plt.show()
```



Bi variate analysis of the categorical columns.Customer segmentation on the basis of source,browser,sex,category

In [33]:
```
obj=[ 'source', 'browser', 'sex','category']
```

In [34]:
```
cols=obj
a = 3
b = 2
counter = 1
plt.figure(figsize = [14, 14])
for i in cols:
    plt.subplot(a,b,counter)
    plt.title(i)
    sns.countplot(x=df1[i],hue=df1['class'])
    counter = counter+1
    plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



Bi variate analysis of the continuous columns. Customer segmentation on the basis of purchase value

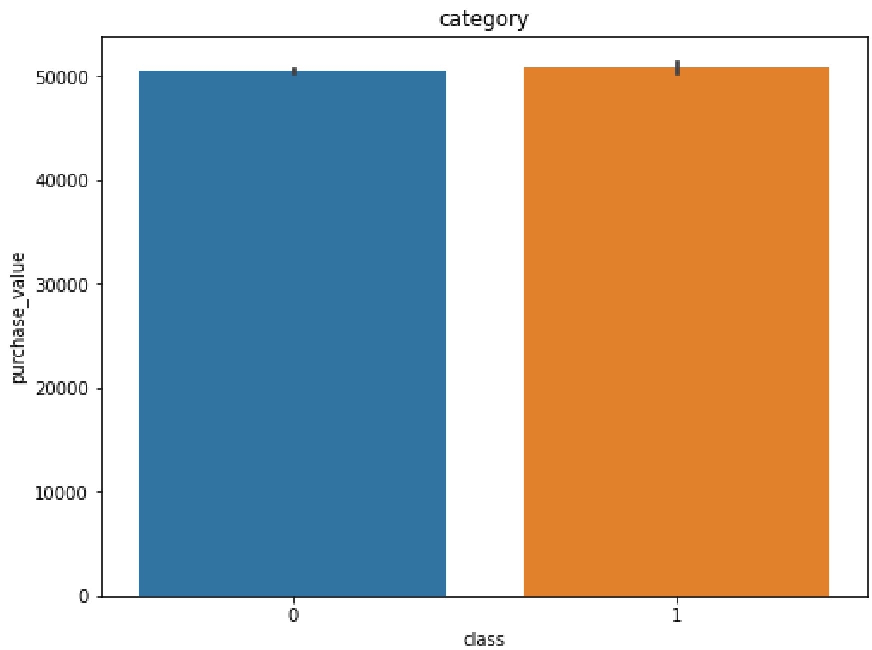
In [35]:
```
num=df1.select_dtypes(exclude='object').columns
```

In [36]:
```
num[1]
```

Out[36]:
```
'purchase_value'
```

In [37]:
```
cols=num[1]
plt.figure(figsize=[8,6])
plt.title(i)
sns.barplot(y=df1['purchase_value'],x=df1['class'])
```

Out[37]: <AxesSubplot:title={'center':'category'}, xlabel='class', ylabel='purchase_value'>



In [38]:
```
#from the above graph we can infer that approximately equal amount of Average purcahse is done
```

In [39]:
```
df1['purchase_value'].min()
```

Out[39]: 1016

In [40]:
```
df1['purchase_value'].median()
```

Out[40]: 50484.0

In [41]:
```
df1['purchase_value'].mean()
```

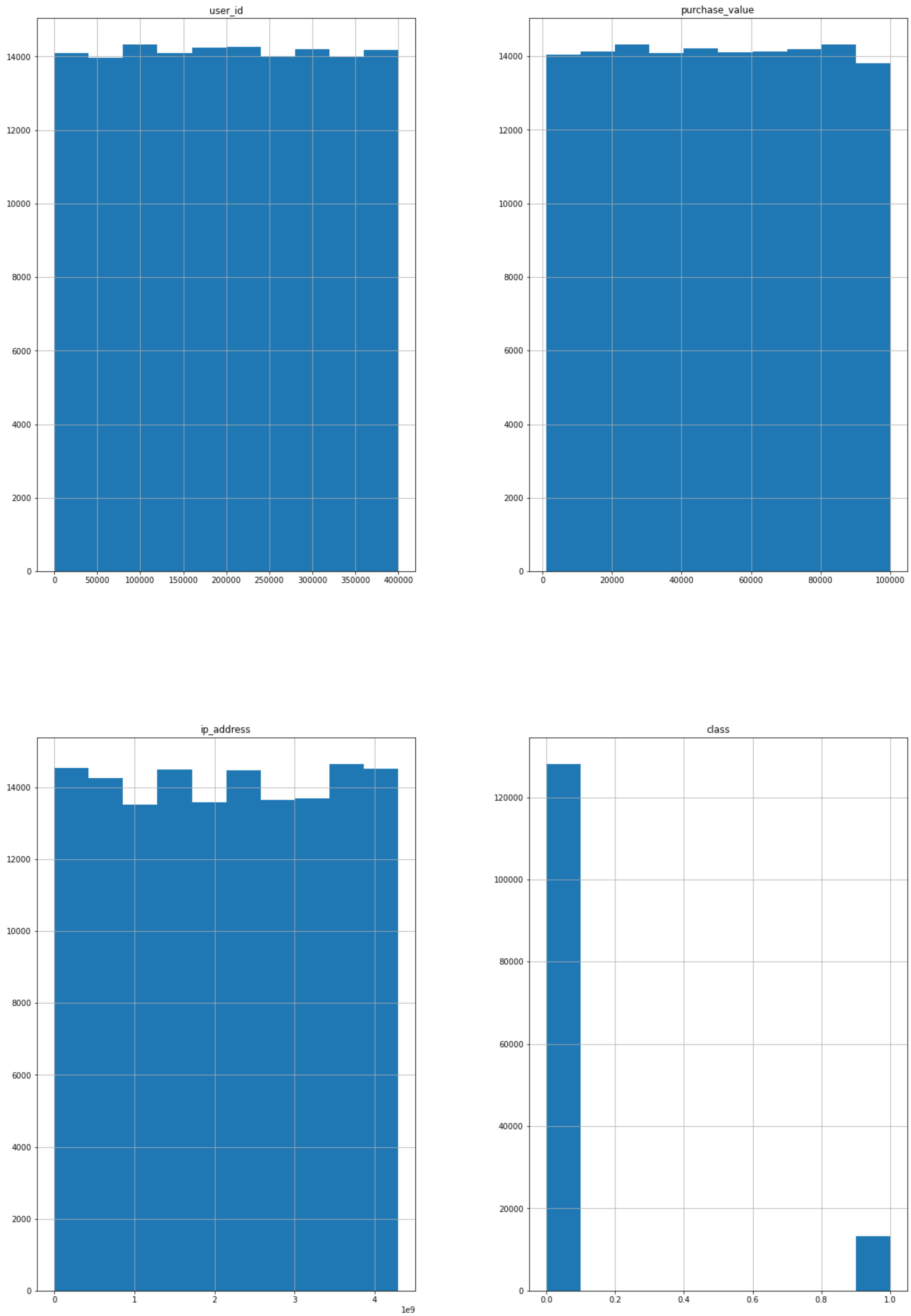
Out[41]: 50521.46900312351

In [42]:
```
df1['purchase_value'].max()
```

Out[42]: 100092

In [43]:
```
import matplotlib.pyplot as plt
%matplotlib inline

df.hist(figsize=(20,30))
```

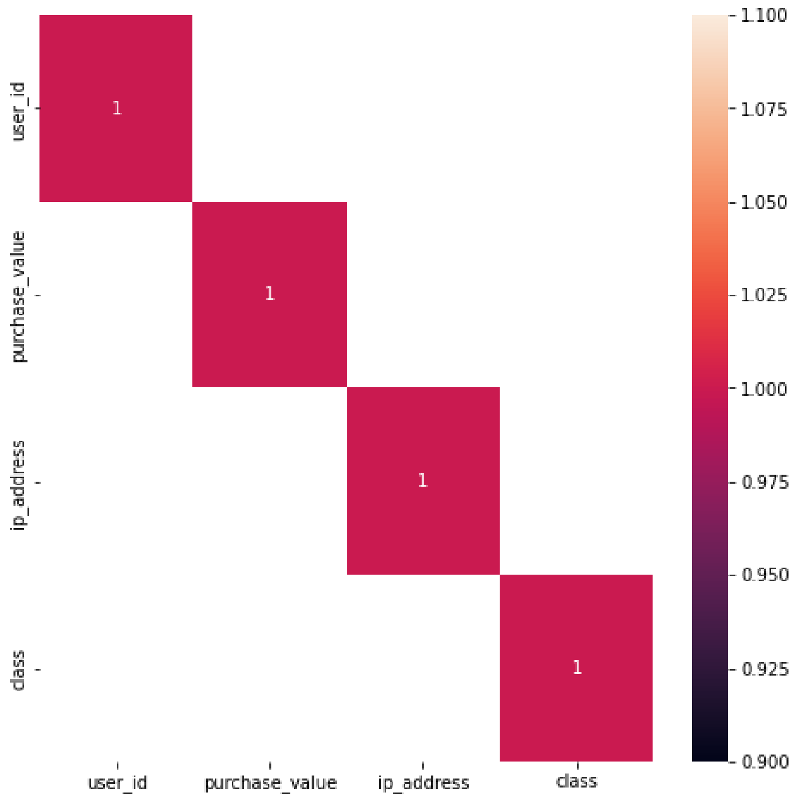
Out[43]:
```
array([[<AxesSubplot:title={'center':'user_id'}>,
        <AxesSubplot:title={'center':'purchase_value'}>],
       [<AxesSubplot:title={'center':'ip_address'}>,
        <AxesSubplot:title={'center':'class'}>]], dtype=object)
```



user_id
purchase_value
ip_address
class
1e9

In [44]:
```
plt.figure(figsize=[8,8])
sns.heatmap(df.corr()[df.corr()>0.5],annot=True)
```

Out[44]: <AxesSubplot:>



No strong co-relation with the target class

CREATING BASE MODEL FOR BENCH MARK

In [45]:
```
df['source'] = df['source'].replace({'SEO':0, 'Direct':1,'Ads':3})
```

In [46]:
```
df['browser'] = df['browser'].replace({'Chrome':0, 'Opera':1,'Safari':3,'IE':4,'FireFox':5})
```

In [47]:
```
df['sex'] = df['sex'].replace({'M':0, 'F':1})
```

In [48]:
```
df['category'] = df['category'].replace({'home_essentials':0, 'apparels':1,'electronics':3,'he
```

In [49]:
```
df1=df.drop(['user_id', 'signup_time','device_id', 'purchase_time',
       'ip_address',
        'dob'],axis=1)
```

In [50]:
```python
import pandas as pd
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, f1_score, confusion_matrix, auc, roc_curve
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
```

In [51]:
```python
df1
```

Out[51]:

	purchase_value	source	browser	sex	class	category
0	65278	0	0	0	0	0
1	96399	3	0	1	0	1
2	57296	0	1	0	1	3
3	43650	0	3	0	0	4
4	45016	3	3	0	0	0
...	...	...	...	...	...	...
151107	58549	0	0	0	1	1
151108	57952	0	3	0	0	3
151109	19003	0	4	1	0	4
151110	68296	0	0	0	0	3
151111	23622	1	4	0	0	1

141404 rows × 6 columns

In [52]:
```python
target_col = 'class'
input_cols =df1.drop(target_col, axis=1).columns
train_x, test_x, train_y, test_y = train_test_split(df1[input_cols],
                                                    df1[target_col],
                                                     test_size=0.2,
                                                     random_state=1)
train_x.shape, test_x.shape, train_y.shape, test_y.shape
```

Out[52]:
```
((113123, 5), (28281, 5), (113123,), (28281,))
```

In [53]:
```python
scaler = StandardScaler().fit(train_x)
train_x_scaled = pd.DataFrame(scaler.transform(train_x),
                              columns=train_x.columns,
                              index=train_x.index)
test_x_scaled = pd.DataFrame(scaler.transform(test_x),
                             columns=test_x.columns,
                             index=test_x.index)
```

In [54]:
```
def get_model_metrics(actual, predicted, classifier_name):
  acc = accuracy_score(actual, predicted)
  f1 = f1_score(actual, predicted)
  tn, fp, fn, tp = confusion_matrix(actual, predicted).ravel()
  sensitivity = tp / (tp + fn)
  specificity = tn / (tn + fp)
  fpr, tpr, thresholds = roc_curve(actual, predicted, pos_label=1)
  auc_value = auc(fpr, tpr)
  return {'accuracy': acc,
          'f1-score': f1,
          'classifier': classifier_name,
          'sensitivity': sensitivity,
          'specificity': specificity,
          'AUC': auc_value,
          'fpr_values': fpr,
          'tpr_values': tpr}
```

In [55]:
```
res_cols = ['classifier', 'f1-score', 'sensitivity', 'specificity', 'AUC', 'accuracy']
df_results = pd.DataFrame(columns=res_cols)
```

In [56]:
```
#USING SIMPLE DECISION TREE WITH MAX_DEPTH=5
```

In [57]:
```
# Decision Trees
classifier_name = 'Decision Tree'
model = DecisionTreeClassifier(max_depth=5, random_state=10).fit(train_x_scaled, train_y)
test_y_pred = model.predict(test_x_scaled)
dt_metrics = get_model_metrics(test_y, test_y_pred, classifier_name)
print(dt_metrics)
if classifier_name not in df_results['classifier'].values:
    df_results = df_results.append(dt_metrics, ignore_index=True)
```

```
{'accuracy': 0.9066157490894947, 'f1-score': 0.0, 'classifier': 'Decision Tree', 'sensitivit
y': 0.0, 'specificity': 0.999960999961, 'AUC': 0.4999804999805, 'fpr_values': array([0.000000
0e+00, 3.9000039e-05, 1.0000000e+00]), 'tpr_values': array([0., 0., 1.])}
```

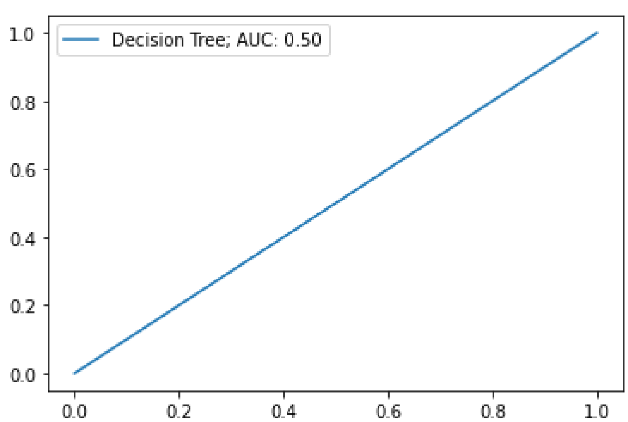
In [58]:
```
df_results.drop(['fpr_values', 'tpr_values'], axis=1)
```

Out[58]:

	classifier	f1-score	sensitivity	specificity	AUC	accuracy
0	Decision Tree	0.0	0.0	0.999961	0.49998	0.906616

In [59]:
```
plt.plot(dt_metrics['fpr_values'], dt_metrics['tpr_values'])
plt.legend(['Decision Tree; AUC: %.2f' % dt_metrics['AUC']])
```

Out[59]: <matplotlib.legend.Legend at 0x24e6855fe80>



In [ ]:

PERFORM FEATURE ENGINEERING

Using the original data, perform the following feature engineering techniques to create new columns for modelling

Using all the date columns, extract the following information wherever necessary a. Year, month, day, hour, day of the week (mon, tue, etc) Using date of birth column, try to calculate the appropriate age of the customer. (Compute difference between purchase date and date of birth) Using age column, identify age buckets using binning method Compute no. of hours/days between purchase time and signup time For all appropriate numerical variables, compute buckets using binning method

In [60]:
```
df2 = pd.read_csv('Purchase_Fraud_data.csv')
df2.head(5)
```

Out[60]:

	user_id	signup_time	purchase_time	purchase_value	device_id	source	browser	sex	ip_address	cl
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	65278	QVPSPJUOCKZAR	SEO	Chrome	M	7.327584e+08	
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	96399	EOGFQPIZPYXFZ	Ads	Chrome	F	3.503114e+08	
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	57296	YSSKYOSJHPPLJ	SEO	Opera	M	2.621474e+09	
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	43650	ATGTXKYKUDUQN	SEO	Safari	M	3.840542e+09	
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	45016	NAUITBZFJKHWW	Ads	Safari	M	4.155831e+08	

In [61]:
```
df2.isna().sum()
```

Out[61]:
```
user_id              0
signup_time          0
purchase_time        0
purchase_value       0
device_id            0
source               0
browser              0
sex               4927
ip_address           0
class                0
category             0
dob               4924
dtype: int64
```

In [62]:
```
df2.isna().sum()/len(df2)*100
#we can see the null values in Sex and Dob
```

Out[62]:
```
user_id           0.000000
signup_time       0.000000
purchase_time     0.000000
purchase_value    0.000000
device_id         0.000000
source            0.000000
browser           0.000000
sex               3.260496
ip_address        0.000000
class             0.000000
category          0.000000
dob               3.258510
dtype: float64
```

In [63]:
```
df2= df2.dropna()
df2.head()
```

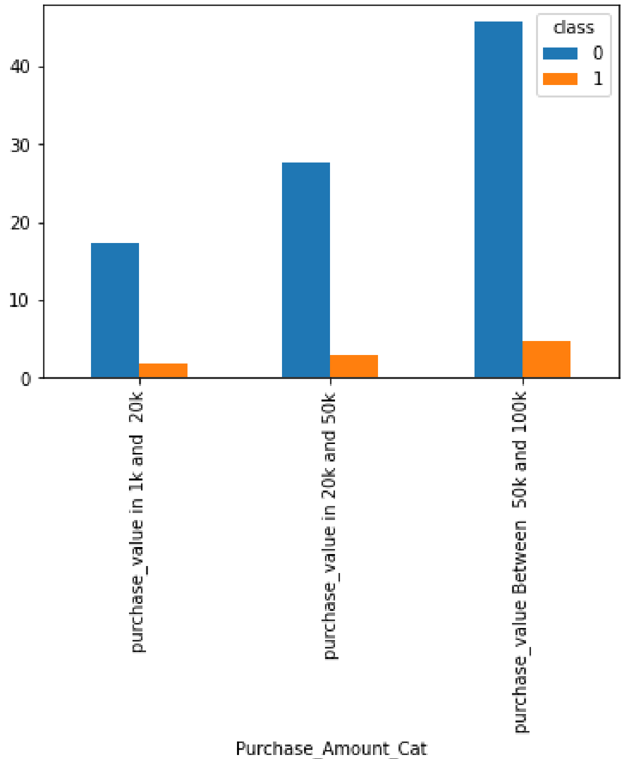
Out[63]:

	user_id	signup_time	purchase_time	purchase_value	device_id	source	browser	sex	ip_address	cl
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	65278	QVPSPJUOCKZAR	SEO	Chrome	M	7.327584e+08	
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	96399	EOGFQPIZPYXFZ	Ads	Chrome	F	3.503114e+08	
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	57296	YSSKYOSJHPPLJ	SEO	Opera	M	2.621474e+09	
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	43650	ATGTXKYKUDUQN	SEO	Safari	M	3.840542e+09	
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	45016	NAUITBZFJKHWW	Ads	Safari	M	4.155831e+08	

In [64]:
```
#Binning of Purchase Column
```

In [65]:
```
df2['Purchase_Amount_Cat']=pd.cut(df2['purchase_value'],bins=[1016 ,20000,50000,100092],
                                labels=['purchase_value in 1k and  20k','purchase_value in 20k
```

In [66]:
```
(pd.crosstab(df2['Purchase_Amount_Cat'],df2['class'],normalize=True)*100).plot(kind="bar")
plt.show()
```



In [67]:
```
# from the above graph we  can infer that Most of the regular transactions are taking place be
# Most Fraud Transaction are happening in range 50 k and 100 k
```

In [ ]:

In [68]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 141404 entries, 0 to 151111
Data columns (total 13 columns):
 #   Column               Non-Null Count   Dtype   
---  ------               --------------   -----   
 0   user_id              141404 non-null  int64   
 1   signup_time          141404 non-null  object  
 2   purchase_time        141404 non-null  object  
 3   purchase_value       141404 non-null  int64   
 4   device_id            141404 non-null  object  
 5   source               141404 non-null  object  
 6   browser              141404 non-null  object  
 7   sex                  141404 non-null  object  
 8   ip_address           141404 non-null  float64 
 9   class                141404 non-null  int64   
 10  category             141404 non-null  object  
 11  dob                  141404 non-null  object  
 12  Purchase_Amount_Cat  141403 non-null  category
dtypes: category(1), float64(1), int64(3), object(8)
memory usage: 14.2+ MB
```

In [69]:
```
df2.head()
```

Out[69]:

	user_id	signup_time	purchase_time	purchase_value	device_id	source	browser	sex	ip_address	cla
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	65278	QVPSPJUOCKZAR	SEO	Chrome	M	7.327584e+08	
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	96399	EOGFQPIZPYXFZ	Ads	Chrome	F	3.503114e+08	
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	57296	YSSKYOSJHPPLJ	SEO	Opera	M	2.621474e+09	
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	43650	ATGTXKYKUDUQN	SEO	Safari	M	3.840542e+09	
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	45016	NAUITBZFJKHWW	Ads	Safari	M	4.155831e+08	

In [70]:
```
df2['class'].value_counts()
```

Out[70]:
```
0    128164
1     13240
Name: class, dtype: int64
```

In [71]:
```
#We can see that our target class is imbalanced
```

In [ ]:

Conversion Of Date Time of Signup and Purchase Time

In [72]:
```
import datetime as dt
df2['tot_mins_diff']=pd.to_datetime(df2['purchase_time'])-pd.to_datetime(df2['signup_time'])

df2.head()

df2['tot_mins_diff'] = df2['tot_mins_diff'].dt.total_seconds()

# Conversion of Difference in Minutes

df2['tot_mins_diff']=df2['tot_mins_diff']/60

df2.head()
```

Out[72]:

	user_id	signup_time	purchase_time	purchase_value	device_id	source	browser	sex	ip_address	cla
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	65278	QVPSPJUOCKZAR	SEO	Chrome	M	7.327584e+08	
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	96399	EOGFQPIZPYXFZ	Ads	Chrome	F	3.503114e+08	
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	57296	YSSKYOSJHPPLJ	SEO	Opera	M	2.621474e+09	
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	43650	ATGTXKYKUDUQN	SEO	Safari	M	3.840542e+09	
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	45016	NAUITBZFJKHWW	Ads	Safari	M	4.155831e+08	

In [73]:
```
df2
```

Out[73]:

	user_id	signup_time	purchase_time	purchase_value	device_id	source	browser	sex	ip_addres
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	65278	QVPSPJUOCKZAR	SEO	Chrome	M	7.327584e+0
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	96399	EOGFQPIZPYXFZ	Ads	Chrome	F	3.503114e+0
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	57296	YSSKYOSJHPPLJ	SEO	Opera	M	2.621474e+0
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	43650	ATGTXKYKUDUQN	SEO	Safari	M	3.840542e+0
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	45016	NAUITBZFJKHWW	Ads	Safari	M	4.155831e+0
...	...	...	...	...	...	...	...	...	.
151107	345170	2015-01-27 03:03:34	2015-03-29 00:30:47	58549	XPSKTWGPWINLR	SEO	Chrome	M	3.451155e+0
151108	274471	2015-05-15 17:43:29	2015-05-26 12:24:39	57952	LYSFABUCPCGBA	SEO	Safari	M	2.439047e+0
151109	368416	2015-03-03 23:07:31	2015-05-20 07:07:47	19003	MEQHCSJUBRBFE	SEO	IE	F	2.748471e+0
151110	207709	2015-07-09 20:06:07	2015-09-07 09:34:46	68296	CMCXFGRHYSTVJ	SEO	Chrome	M	3.601175e+0
151111	138208	2015-06-10 07:02:20	2015-07-21 02:03:53	23622	ZINIADFCLHYPG	Direct	IE	M	4.103825e+0

141404 rows × 14 columns

In [74]:
```
#df2.drop(['signup_time','purchase_time'],axis=1,inplace=True)
```

Customer segmentation on the basis of difference between signup time and purchase time

In [75]:
```
df2['tot_mins_diff'].max()
```

Out[75]: 172799.53333333333

In [76]:
```
df2['tot_mins_diff'].min()
```

Out[76]: 0.016666666666666666

In [77]:
```
df2['tot_mins_diff'].mean()
```

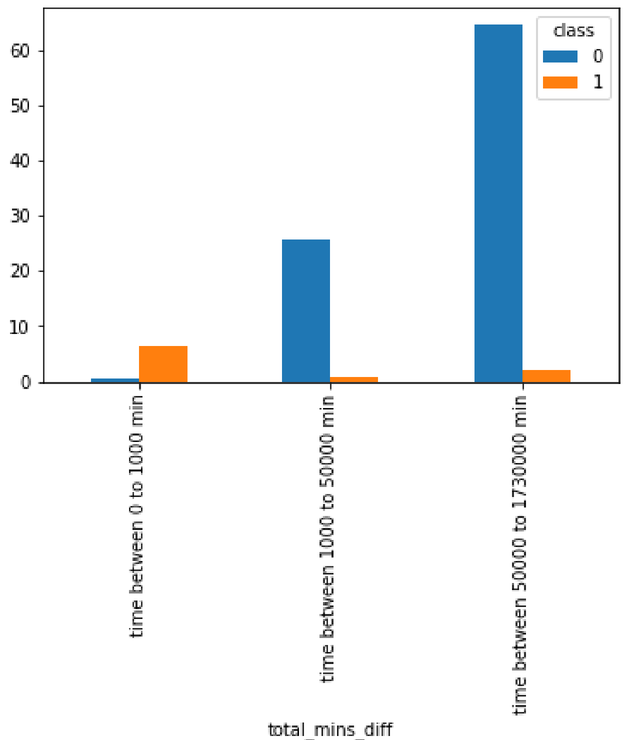
Out[77]: 81064.4638903388

In [78]:
```
df2['tot_mins_diff'].median()
```

Out[78]: 80805.4

In [79]:
```
df2['total_mins_diff']=pd.cut(df2['tot_mins_diff'],bins=[0.01 ,1000,50000,173000],
                              labels=['time between 0 to 1000 min','time between 1000 to 500
```

In [80]:
```
(pd.crosstab(df2['total_mins_diff'],df2['class'],normalize=True)*100).plot(kind="bar")
plt.show()
```



Most of the fraud transactions are betwwen to 0 to 1000 mins of interval.
We can also observe that fraud people are taking less time than people who are making regular transaction.
people who are making Regular transactions are taking more time than 1000 mins.

Customer segmentation on the basis of different age group

In [82]:
```
import datetime as dt
df2['dob'] = pd.to_datetime(df2['dob'], format = "%d-%m-%Y")
now = pd.Timestamp('now')
df2['age'] = (now - df2['dob'])
df2['age']  = df2['age'].astype(str)
df2[['age','age_waste']] = df2['age'].str.split("days",expand=True)
```

In [83]:
```
df2 = df2.drop(['age_waste'],axis = 1)
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 141404 entries, 0 to 151111
Data columns (total 16 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   user_id              141404 non-null  int64
 1   signup_time          141404 non-null  object
 2   purchase_time        141404 non-null  object
 3   purchase_value       141404 non-null  int64
 4   device_id            141404 non-null  object
 5   source               141404 non-null  object
 6   browser              141404 non-null  object
 7   sex                  141404 non-null  object
 8   ip_address           141404 non-null  float64
 9   class                141404 non-null  int64
 10  category             141404 non-null  object
 11  dob                  141404 non-null  datetime64[ns]
 12  Purchase_Amount_Cat  141403 non-null  category
 13  tot_mins_diff        141404 non-null  float64
 14  total_mins_diff      141404 non-null  category
 15  age                  141404 non-null  object
dtypes: category(2), datetime64[ns](1), float64(2), int64(3), object(8)
memory usage: 16.5+ MB
```

In [84]:
```
df2['age'] = pd.to_numeric(df2['age'], errors='coerce')
```

In [85]:
```
df2['age']=df2['age']/365
```

In [86]:
```
df2['age'].max()
```

Out[86]: 84.06027397260274

In [87]:
```
df2['age'].min()
```

Out[87]: 25.405479452054795

In [88]:
```
df2['age'].mean()
```

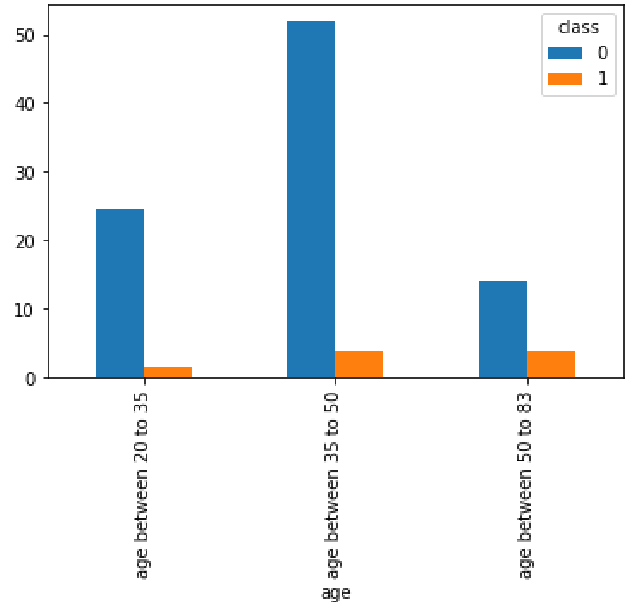
Out[88]: 41.74240983669481

In [89]:
```
df2['age'].median()
```

Out[89]: 40.772602739726025

In [90]:
```
df2['age']=pd.cut(df2['age'],bins=[20,35,50,83],
                                labels=['age between 20 to 35','age between 35 to 50','age bet
```

In [91]:
```python
(pd.crosstab(df2['age'],df2['class'],normalize=True)*100).plot(kind="bar")
plt.show()
```



Fraud transactions are higher between the ages of 50 to 83.

Most of the regular transactions are done by the age group of 35 to 50.

In [ ]:

In [92]:
```python
df2.drop(['signup_time','purchase_time',  'dob','device_id','ip_address','user_id','total_mins
```

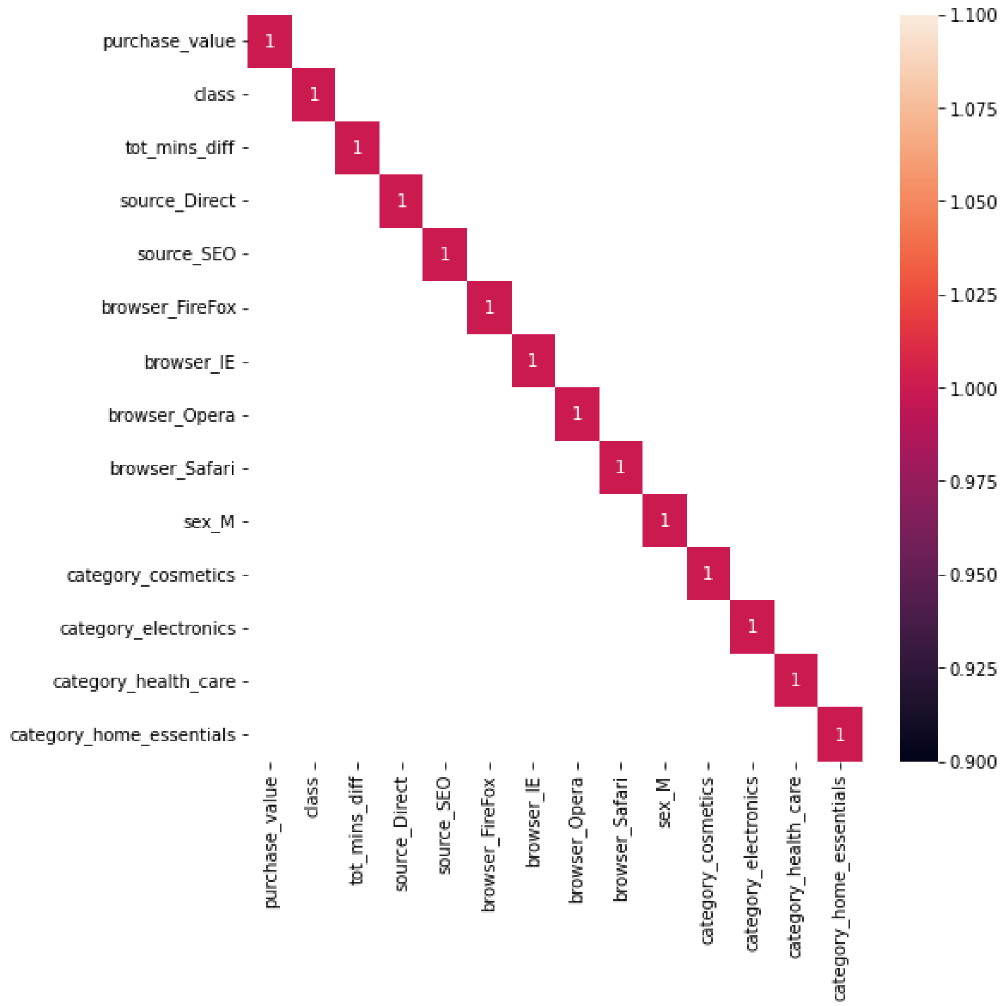
In [93]:
```python
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 141404 entries, 0 to 151111
Data columns (total 7 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   purchase_value  141404 non-null  int64  
 1   source          141404 non-null  object 
 2   browser         141404 non-null  object 
 3   sex             141404 non-null  object 
 4   class           141404 non-null  int64  
 5   category        141404 non-null  object 
 6   tot_mins_diff   141404 non-null  float64
dtypes: float64(1), int64(2), object(4)
memory usage: 8.6+ MB
```

In [94]:
```python
# Here We are converting categorical data into dummy or indicator variables.
df2=pd.get_dummies(df2,drop_first=True)
```

In [95]:
```
plt.figure(figsize=[8,8])
sns.heatmap(df2.corr()[df2.corr()>0.5],annot=True)
```

Out[95]: <AxesSubplot:>



In [96]:
```
# No strong co-relation with the target class
```

#Perform statistical hypothesis test to identify the relationship between input and target variables

Plotting Histogram for every columns

In [97]:
```python
import matplotlib.pyplot as plt
%matplotlib inline

df2.hist(figsize=(20,30))
```

Out[97]:
```
array([[<AxesSubplot:title={'center':'purchase_value'}>,
        <AxesSubplot:title={'center':'class'}>,
        <AxesSubplot:title={'center':'tot_mins_diff'}>,
        <AxesSubplot:title={'center':'source_Direct'}>],
       [<AxesSubplot:title={'center':'source_SEO'}>,
        <AxesSubplot:title={'center':'browser_FireFox'}>,
        <AxesSubplot:title={'center':'browser_IE'}>,
        <AxesSubplot:title={'center':'browser_Opera'}>],
       [<AxesSubplot:title={'center':'browser_Safari'}>,
        <AxesSubplot:title={'center':'sex_M'}>,
        <AxesSubplot:title={'center':'category_cosmetics'}>,
        <AxesSubplot:title={'center':'category_electronics'}>],
       [<AxesSubplot:title={'center':'category_health_care'}>,
        <AxesSubplot:title={'center':'category_home_essentials'}>,
        <AxesSubplot:>, <AxesSubplot:>]], dtype=object)
```


purchase_value
class
tot_mins_diff
source_Direct
source_SEO
browser_FireFox
browser_IE
browser_Opera
browser_Safari
sex_M
category_cosmetics
category_electronics
category_health_care
category_home_essentials

In [ ]:

In [ ]:

MODEL AFTER PERFORMING FEATURE ENGINEERING

Model Building

Convert all the input variables to numeric Split the new data in to training and testing Build the following classification models using new data a. Decision Trees b. Random Forest c. Boosting techniques d. XGBoost For all the above classifiers, make sure that you perform hyper parameter tuning to select optimal value hyper parameters For all the above methods, report accuracy and f1 score Also in a single plot, compare the ROC curves for all the above models Choose an appropriate model based on above inferences and report the same

In [98]:
```
from sklearn.model_selection import train_test_split
```

In [99]:
```
X=df2.drop('class',axis=1)
y=df2['class']
```

In [100]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=10)
```

In [101]:
```
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import LogisticRegression
```

In [102]:
```
df2['class'].value_counts()
```

Out[102]:
```
0    128164
1     13240
Name: class, dtype: int64
```

In [103]:
```
#Using Decision tree model
```

In [104]:
```
pip install imblearn
```

```
Requirement already satisfied: imblearn in c:\users\asus\anaconda3\lib\site-packages (0.0)
Requirement already satisfied: imbalanced-learn in c:\users\asus\anaconda3\lib\site-packages
(from imblearn) (0.10.1)
Requirement already satisfied: joblib>=1.1.1 in c:\users\asus\anaconda3\lib\site-packages (fr
om imbalanced-learn->imblearn) (1.2.0)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\asus\anaconda3\lib\site-packag
es (from imbalanced-learn->imblearn) (1.2.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\asus\anaconda3\lib\site-packa
ges (from imbalanced-learn->imblearn) (2.2.0)
Requirement already satisfied: scipy>=1.3.2 in c:\users\asus\anaconda3\lib\site-packages (fro
m imbalanced-learn->imblearn) (1.7.1)
Requirement already satisfied: numpy>=1.17.3 in c:\users\asus\anaconda3\lib\site-packages (fr
om imbalanced-learn->imblearn) (1.20.3)
Note: you may need to restart the kernel to use updated packages.
```

In [105]:
```
from imblearn.over_sampling import SMOTE
sm = SMOTE()
X_train_sm, y_train_sm= sm.fit_resample(X_train, y_train.astype('int'))
```

In [106]:
```
df2['class'].value_counts()
```

Out[106]:
```
0    128164
1     13240
Name: class, dtype: int64
```

In [107]:
```
y_train_sm.value_counts()
```

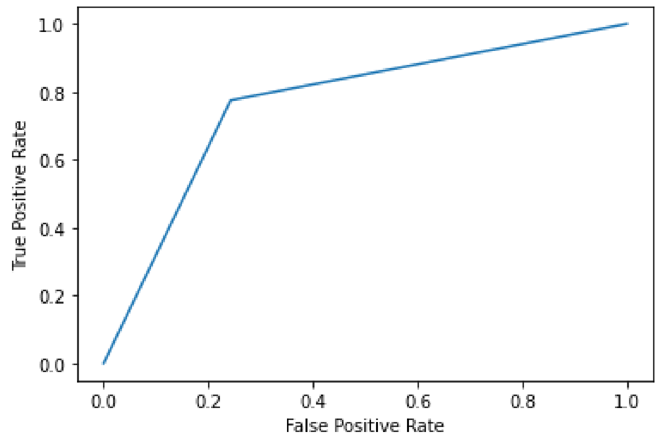
Out[107]:
```
0    102528
1    102528
Name: class, dtype: int64
```

In [108]:
```
lr=LogisticRegression(random_state=20,solver='liblinear')
lr_model=lr.fit(X_train_sm,y_train_sm)

y_pred_smote=lr_model.predict(X_test)

print(classification_report(y_test,y_pred_smote))
print()
print('RFC score ',np.mean(cross_val_score(lr,X_train_sm,y_train_sm,cv=5)))
print()
print(confusion_matrix(y_test,y_pred_smote))
print()
print('train score ',lr_model.score(X_train_sm,y_train_sm))
print()
print('test score ',lr_model.score(X_test,y_test))
```

```
              precision    recall  f1-score   support

           0       0.97      0.76      0.85     25636
           1       0.25      0.78      0.38      2645

    accuracy                           0.76     28281
   macro avg       0.61      0.77      0.61     28281
weighted avg       0.90      0.76      0.81     28281


RFC score  0.7516044333180225

[[19410  6226]
 [  595  2050]]

train score  0.7516629603620475

test score  0.7588133375764647
```

In [109]:
```
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import LogisticRegression
```

In [110]:
```
#create ROC curve
fpr, tpr, thresholds = roc_curve(y_test,  y_pred_smote)
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



Since our model has imporved for the Target class we can say that it has improved,but we will try with another models.
Train AND Test are not having equal score which means model is not underfitting.

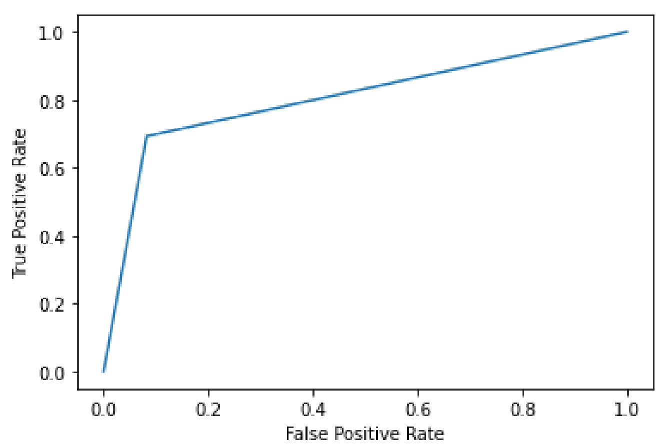
Using Decision tree model

In [ ]:

In [112]:
```
from sklearn.tree import DecisionTreeClassifier
dc=DecisionTreeClassifier(random_state=10)
dc_model=dc.fit(X_train_sm,y_train_sm)

y_pred_dc=dc_model.predict(X_test)

print(classification_report(y_test,y_pred_dc))
print()

print('RFC score ',np.mean(cross_val_score(dc,X_train_sm,y_train_sm,cv=5)))
print()
print(confusion_matrix(y_test,y_pred_dc))
print()
print('train score ',dc_model.score(X_train_sm,y_train_sm))
print()
print('test score ',dc_model.score(X_test,y_test))
```

```
              precision    recall  f1-score   support

           0       0.97      0.92      0.94     25636
           1       0.46      0.69      0.56      2645

    accuracy                           0.90     28281
   macro avg       0.72      0.81      0.75     28281
weighted avg       0.92      0.90      0.91     28281


RFC score  0.9164425949212175

[[23528  2108]
 [  813  1832]]

train score  1.0

test score  0.8967151090838372
```

In [113]:
```
#create ROC curve
fpr, tpr, thresholds = roc_curve(y_test,  y_pred_dc)
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



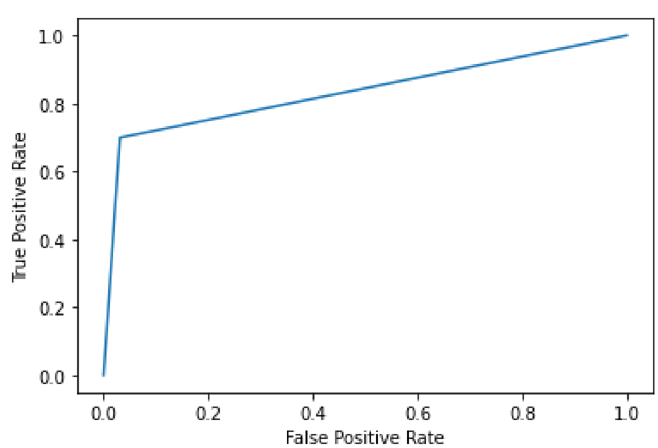

```
#Model is Overfitting
```

Tuned Random Forest Model

In [115]:
```
from sklearn.ensemble import GradientBoostingClassifier,RandomForestClassifier
Rfc=RandomForestClassifier(random_state=10,criterion='gini',max_depth= 5,min_samples_split= 2,
Rfc_modeltune=Rfc.fit(X_train_sm,y_train_sm)

y_pred_tune=Rfc_modeltune.predict(X_test)

print(classification_report(y_test,y_pred_tune))
print()
print('RFC score ',np.mean(cross_val_score(Rfc_modeltune,X_train_sm,y_train_sm,cv=5)))
print()
print(confusion_matrix(y_test,y_pred_tune))
print()
print('train score ',Rfc_modeltune.score(X_train_sm,y_train_sm))
print()
print('test score ',Rfc_modeltune.score(X_test,y_test))
```

```
              precision    recall  f1-score   support

           0       0.97      0.97      0.97     25636
           1       0.70      0.70      0.70      2645

    accuracy                           0.94     28281
   macro avg       0.83      0.83      0.83     28281
weighted avg       0.94      0.94      0.94     28281


RFC score  0.8812228159209845

[[24838   798]
 [  796  1849]]

train score  0.8812031835205992

test score  0.9436370708249354
```

In [116]:
```
#create ROC curve
fpr, tpr, thresholds = roc_curve(y_test,  y_pred_tune)
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



Using adaboost model

In [117]:
```
from sklearn.ensemble import AdaBoostClassifier
abc=AdaBoostClassifier(random_state=10)
abc_model=abc.fit(X_train_sm,y_train_sm)

y_pred_ada=abc_model.predict(X_test)

print(classification_report(y_test,y_pred_ada))
print()

print('RFC score ',np.mean(cross_val_score(abc,X_train_sm,y_train_sm,cv=5)))
print()
print(confusion_matrix(y_test,y_pred_ada))

print('train score ',abc_model.score(X_train_sm,y_train_sm))

print('test score ',abc_model.score(X_test,y_test))
```

```
              precision    recall  f1-score   support

           0       0.97      0.93      0.95     25636
           1       0.50      0.71      0.58      2645

    accuracy                           0.91     28281
   macro avg       0.73      0.82      0.77     28281
weighted avg       0.92      0.91      0.91     28281


RFC score  0.9038704119515975

[[23748  1888]
 [  772  1873]]
train score  0.9067230415106118
test score  0.9059439199462537
```

In [118]:
```
pip install parfit==0.220
```

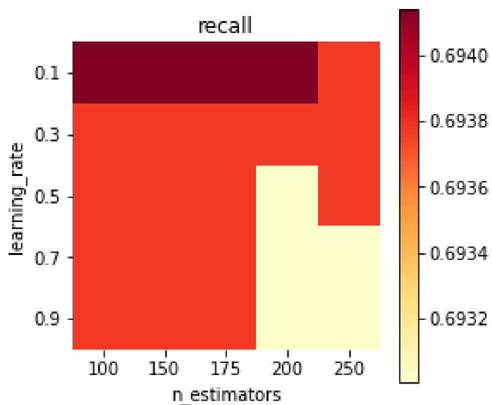
```
Requirement already satisfied: parfit==0.220 in c:\users\asus\anaconda3\lib\site-packages (0.
220)
Requirement already satisfied: matplotlib in c:\users\asus\anaconda3\lib\site-packages (from
parfit==0.220) (3.4.3)
Requirement already satisfied: numpy in c:\users\asus\anaconda3\lib\site-packages (from parfi
t==0.220) (1.20.3)
Requirement already satisfied: joblib in c:\users\asus\anaconda3\lib\site-packages (from parf
it==0.220) (1.2.0)
Requirement already satisfied: sklearn in c:\users\asus\anaconda3\lib\site-packages (from par
fit==0.220) (0.0)
Requirement already satisfied: cycler>=0.10 in c:\users\asus\anaconda3\lib\site-packages (fro
m matplotlib->parfit==0.220) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\asus\anaconda3\lib\site-packages
(from matplotlib->parfit==0.220) (1.3.1)
Requirement already satisfied: pillow>=6.2.0 in c:\users\asus\anaconda3\lib\site-packages (fr
om matplotlib->parfit==0.220) (8.4.0)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\asus\anaconda3\lib\site-packa
ges (from matplotlib->parfit==0.220) (2.8.2)
Requirement already satisfied: pyparsing>=2.2.1 in c:\users\asus\anaconda3\lib\site-packages
(from matplotlib->parfit==0.220) (3.0.4)
Requirement already satisfied: six in c:\users\asus\anaconda3\lib\site-packages (from cycler>
=0.10->matplotlib->parfit==0.220) (1.16.0)
Requirement already satisfied: scikit-learn in c:\users\asus\anaconda3\lib\site-packages (fro
m sklearn->parfit==0.220) (1.2.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\asus\anaconda3\lib\site-packa
ges (from scikit-learn->sklearn->parfit==0.220) (2.2.0)
Requirement already satisfied: scipy>=1.3.2 in c:\users\asus\anaconda3\lib\site-packages (fro
m scikit-learn->sklearn->parfit==0.220) (1.7.1)
Note: you may need to restart the kernel to use updated packages.
```

In [119]:
```
from sklearn.model_selection import ParameterGrid

import parfit.parfit as pf

from sklearn.metrics import roc_auc_score, recall_score
#Check first with Adaboost
ad = AdaBoostClassifier()

paramGrid = ParameterGrid({
    'n_estimators': [100,150,175,200,250],
    'learning_rate': [0.1,0.3,0.5,0.7,0.9]
})
```

In [ ]:

In [120]:
```
best_model, best_score, all_models, all_scores = pf.bestFit(ad, paramGrid,
     X_train,y_train,X_test, y_test,
     metric=recall_score, scoreLabel='recall')
```

```
-------------FITTING MODELS-------------

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done   5 tasks      | elapsed:   53.2s
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:  1.5min
[Parallel(n_jobs=-1)]: Done  17 tasks      | elapsed:  2.5min
[Parallel(n_jobs=-1)]: Done  21 out of  25 | elapsed:  3.1min remaining:   35.9s
[Parallel(n_jobs=-1)]: Done  25 out of  25 | elapsed:  3.7min finished
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.

-------------SCORING MODELS-------------

[Parallel(n_jobs=-1)]: Done  25 out of  25 | elapsed:   19.5s finished
```



In [121]:
```
#Tunned Adaboost
```

In [122]:
```
from sklearn.ensemble import AdaBoostClassifier
abc=AdaBoostClassifier(random_state=20,n_estimators=100,learning_rate=0.1)
abc_model_tune=abc.fit(X_train_sm,y_train_sm)

y_pred_ada_tune=abc_model.predict(X_test)

print(classification_report(y_test,y_pred_ada_tune))
print()

print('RFC score ',np.mean(cross_val_score(abc,X_train_sm,y_train_sm,cv=5)))
print()
print(confusion_matrix(y_test,y_pred_ada_tune))

print('train score ',abc_model_tune.score(X_train_sm,y_train_sm))

print('test score ',abc_model_tune.score(X_test,y_test))
```

```
              precision    recall  f1-score   support

           0       0.97      0.93      0.95     25636
           1       0.50      0.71      0.58      2645

    accuracy                           0.91     28281
   macro avg       0.73      0.82      0.77     28281
weighted avg       0.92      0.91      0.91     28281


RFC score  0.8822224988282183

[[23748  1888]
 [  772  1873]]
train score  0.8805106897627965
test score  0.9545277748311587
```

Gradient Boost Model

In [123]:
```
from sklearn.ensemble import GradientBoostingClassifier
gb = GradientBoostingClassifier(random_state=10)
pred_test_gb_sm = gb.fit(X_train_sm,y_train_sm).predict(X_test)

print(classification_report(y_test,pred_test_gb_sm))
print()

print('RFC score ',np.mean(cross_val_score(gb,X_train_sm,y_train_sm,cv=5)))
print()
print(confusion_matrix(y_test,pred_test_gb_sm))

print('train score ',gb.score(X_train_sm,y_train_sm))

print('test score ',gb.score(X_test,y_test))
```

```
              precision    recall  f1-score   support

           0       0.97      0.93      0.95     25636
           1       0.51      0.71      0.59      2645

    accuracy                           0.91     28281
   macro avg       0.74      0.82      0.77     28281
weighted avg       0.93      0.91      0.92     28281


RFC score  0.9064550333441357

[[23825  1811]
 [  771  1874]]
train score  0.9067132880774033
test score  0.9087019553764011
```

Using XGboost

In [124]:
```
pip install xgboost
```

```
Requirement already satisfied: xgboost in c:\users\asus\anaconda3\lib\site-packages (1.7.5)
Requirement already satisfied: scipy in c:\users\asus\anaconda3\lib\site-packages (from xgboo
st) (1.7.1)
Requirement already satisfied: numpy in c:\users\asus\anaconda3\lib\site-packages (from xgboo
st) (1.20.3)
Note: you may need to restart the kernel to use updated packages.
```

In [125]:

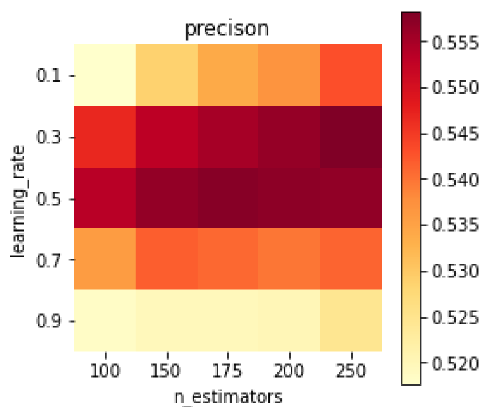
```
from xgboost import XGBClassifier
xgb=XGBClassifier(random_state=10,eval_metric='logloss',use_label_encoder=False)
xgb_model=xgb.fit(X_train_sm,y_train_sm)
y_pred_xgb=xgb_model.predict(X_test)

print(classification_report(y_test,y_pred_xgb))
print()

print('RFC score ',np.mean(cross_val_score(xgb,X_train_sm,y_train_sm,cv=5)))
print()
print(confusion_matrix(y_test,y_pred_xgb))

print('train score ',xgb_model.score(X_train_sm,y_train_sm))

print('test score ',xgb_model.score(X_test,y_test))
```

```
              precision    recall  f1-score   support

           0       0.97      0.94      0.95     25636
           1       0.55      0.70      0.62      2645

    accuracy                           0.92     28281
   macro avg       0.76      0.82      0.78     28281
weighted avg       0.93      0.92      0.92     28281


RFC score  0.9127899615573923

[[24091  1545]
 [  781  1864]]
train score  0.9221042056803995
test score  0.9177539690958594
```

Use of Parfit for model tuning

In [126]:
```python
from sklearn.model_selection import ParameterGrid

import parfit.parfit as pf

from sklearn.metrics import roc_auc_score, recall_score
xg = XGBClassifier()

paramGrid = ParameterGrid({
    'n_estimators': [100,150,175,200,250],
    'learning_rate': [0.1,0.3,0.5,0.7,0.9],

})
best_model, best_score, all_models, all_scores = pf.bestFit(xg, paramGrid,
     X_train_sm, y_train_sm, X_test, y_test,
     metric=precision_score, scoreLabel='precison')
```

```
-------------FITTING MODELS-------------

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done   5 tasks      | elapsed:  2.0min
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:  3.6min
[Parallel(n_jobs=-1)]: Done  17 tasks      | elapsed:  6.0min
[Parallel(n_jobs=-1)]: Done  21 out of  25 | elapsed:  7.7min remaining:  1.5min
[Parallel(n_jobs=-1)]: Done  25 out of  25 | elapsed:  8.8min finished
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.

-------------SCORING MODELS-------------

[Parallel(n_jobs=-1)]: Done  25 out of  25 | elapsed:    2.6s finished
```



Tunned XG Boost

In [127]:
```
from xgboost import XGBClassifier
xgb=XGBClassifier(random_state=10,eval_metric='logloss',use_label_encoder=False,n_estimators=2
xgb_model_tune=xgb.fit(X_train_sm,y_train_sm)
y_pred_xgb_tune=xgb_model.predict(X_test)

print(classification_report(y_test,y_pred_xgb_tune))
print()

print('RFC score ',np.mean(cross_val_score(xgb,X_train_sm,y_train_sm,cv=5)))
print()
print(confusion_matrix(y_test,y_pred_xgb_tune))

print('train score ',xgb_model_tune.score(X_train_sm,y_train_sm))

print('test score ',xgb_model_tune.score(X_test,y_test))
```

```
              precision    recall  f1-score   support

           0       0.97      0.94      0.95     25636
           1       0.55      0.70      0.62      2645

    accuracy                           0.92     28281
   macro avg       0.76      0.82      0.78     28281
weighted avg       0.93      0.92      0.92     28281


RFC score  0.9190809251450958

[[24091  1545]
 [  781  1864]]
train score  0.9348373127340824
test score  0.9202291290972738
```

In [ ]:

```
#CONCLUSIN
```

```
We want to pay special attention to accuracy, precision, recall, and the F1 score.  Accuracy
is a performance metric that is very intuitive: it is simply the ratio of all correctly
predicted cases whether positive or negative and all cases in the data.

Precision is the ratio of correctly predicted positive cases vs. all predicted positive
cases. It answers the following question: Of all people in the database we predicted as
defaulters (fraud), how many were actually fraud? If we think about it, high precision should
yield to a low false positive rate. This is important in terms of marketing ,the marketing
team has to focus the target customers who ar actually purchasing the products!  If we want
to maximize our profit, precision is key.

 Recall or sensitivity is the ratio of all correctly identified target class  divided by all
actually target cases.  It answers the following question: How well did our model perform in
correctly identifying fraud class of customers among all true  customers.  This is important
if we want to maximize overall response (call it revenue maximization)

The F1 Score is the weighted average of precision and recall, hence it takes both false
positives and false negatives into account. If data has an uneven class distribution, then
the F1 score is far more useful than accuracy.  Accuracy works best if false positives and
false negatives have similar values. If the value of false positives and false negatives are
very different, it’s better to look at both precision and recall.

ROC AUC:
```

```
ROC stands for Receiver Operating Characteristic,  used to evaluate the performance of model
.   sensitivity is the proportion of correctly predicted events (cases), while specificity is
the the proportion of correctly identified non-events (cases).  Ideally, both specificity and
sensitivity should be high.  The ROC curve represents the tradeoff between the two
constructs.

The ROC-AUC score provides us with information about how well a model is performing its job
of separating cases: in our case distinguishing fraud class from those who are actually
making a purchase . Example- 0.92 score means that there is a 92% chance that a model can
distinguish fraud from non fraud.
```

Accuracy: Tuned random forest model best accuracy with score of 94.00 followed by XG Boost Model and tuned XG Boost produced the accuracy with identical scores at 92.00

F1 Score: Tuned Random Forest gave best result

ROC Score: Adaptive Boosting achieved the best score followed by gradient boosting and then XG Boost.

FINAL INFERENCE

Tuned Random Forest model is probably a best choice as it provides the best accuracy and F1 Score It is the best model in separating fraud purchase from non-fraud purchase.

The company would like to segment their customers using various attributes, so that they can perform targeted marketing campaign. Do the following to group the customers in the different clusters

In the original feature engineered dataset, exclude the following columns: ids, dates, class (target column) Convert all the input variables to numeric Using Elbow method identify optimal number of clusters required to group customers in to various clusters Perform K-Means clustering using appropriate number of clusters Tag each customer with a cluster Cluster-wise report average values of all input variables

Using Elbow method identify optimal number of clusters required to group customers in to various clusters

Perform K-Means clustering using appropriate number of clusters Tag each customer with a cluster Cluster-wise report average values of all input variables

In [128]:
```
df3 = pd.read_csv('Purchase_Fraud_data.csv')
df3.head(5)
```

Out[128]:

	user_id	signup_time	purchase_time	purchase_value	device_id	source	browser	sex	ip_address	cla
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	65278	QVPSPJUOCKZAR	SEO	Chrome	M	7.327584e+08	
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	96399	EOGFQPIZPYXFZ	Ads	Chrome	F	3.503114e+08	
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	57296	YSSKYOSJHPPLJ	SEO	Opera	M	2.621474e+09	
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	43650	ATGTXKYKUDUQN	SEO	Safari	M	3.840542e+09	
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	45016	NAUITBZFJKHWW	Ads	Safari	M	4.155831e+08	

In [129]: df3

Out[129]:

	user_id	signup_time	purchase_time	purchase_value	device_id	source	browser	sex	ip_addres
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	65278	QVPSPJUOCKZAR	SEO	Chrome	M	7.327584e+0
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	96399	EOGFQPIZPYXFZ	Ads	Chrome	F	3.503114e+0
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	57296	YSSKYOSJHPPLJ	SEO	Opera	M	2.621474e+0
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	43650	ATGTXKYKUDUQN	SEO	Safari	M	3.840542e+0
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	45016	NAUITBZFJKHWW	Ads	Safari	M	4.155831e+0
...	...	...	...	...	...	...	...	...	.
151107	345170	2015-01-27 03:03:34	2015-03-29 00:30:47	58549	XPSKTWGPWINLR	SEO	Chrome	M	3.451155e+0
151108	274471	2015-05-15 17:43:29	2015-05-26 12:24:39	57952	LYSFABUCPCGBA	SEO	Safari	M	2.439047e+0
151109	368416	2015-03-03 23:07:31	2015-05-20 07:07:47	19003	MEQHCSJUBRBFE	SEO	IE	F	2.748471e+0
151110	207709	2015-07-09 20:06:07	2015-09-07 09:34:46	68296	CMCXFGRHYSTVJ	SEO	Chrome	M	3.601175e+0
151111	138208	2015-06-10 07:02:20	2015-07-21 02:03:53	23622	ZINIADFCLHYPG	Direct	IE	M	4.103825e+0

151112 rows × 12 columns

In [130]: df3.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 151112 entries, 0 to 151111
Data columns (total 12 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   user_id         151112 non-null  int64  
 1   signup_time     151112 non-null  object 
 2   purchase_time   151112 non-null  object 
 3   purchase_value  151112 non-null  int64  
 4   device_id       151112 non-null  object 
 5   source          151112 non-null  object 
 6   browser         151112 non-null  object 
 7   sex             146185 non-null  object 
 8   ip_address      151112 non-null  float64
 9   class           151112 non-null  int64  
 10  category        151112 non-null  object 
 11  dob             146188 non-null  object 
dtypes: float64(1), int64(3), object(8)
memory usage: 13.8+ MB
```

In [131]:
```
import datetime as dt
df3['dob'] = pd.to_datetime(df3['dob'], format = "%d-%m-%Y")
now = pd.Timestamp('now')
df3['age'] = (now - df3['dob'])
df3['age']  = df3['age'].astype(str)
df3[['age','age_waste']] = df3['age'].str.split("days",expand=True)
```

In [7]:
```
df3 = df3.drop(['age_waste'],axis = 1)
df3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 151112 entries, 0 to 151111
Data columns (total 13 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   user_id         151112 non-null  int64
 1   signup_time     151112 non-null  object
 2   purchase_time   151112 non-null  object
 3   purchase_value  151112 non-null  int64
 4   device_id       151112 non-null  object
 5   source          151112 non-null  object
 6   browser         151112 non-null  object
 7   sex             146185 non-null  object
 8   ip_address      151112 non-null  float64
 9   class           151112 non-null  int64
 10  category        151112 non-null  object
 11  dob             146188 non-null  datetime64[ns]
 12  age             151112 non-null  object
dtypes: datetime64[ns](1), float64(1), int64(3), object(8)
memory usage: 15.0+ MB
```

In [136]:
```
df3['age'] = pd.to_numeric(df3['age'], errors='coerce')
```

In [137]:
```
df3['age']=df3['age']/365
```

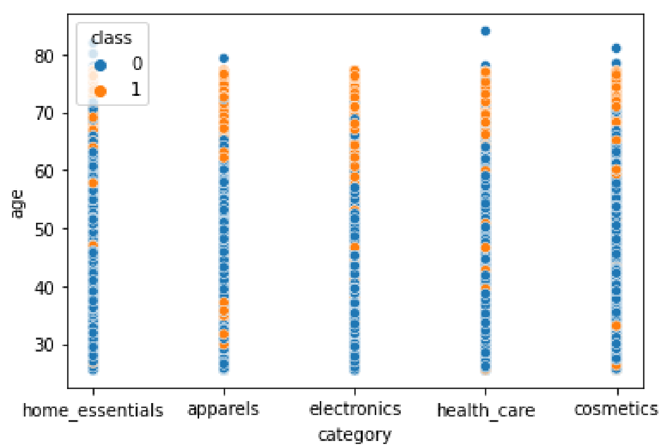
In [138]:
```
import datetime as dt
df3['tot_mins_diff']=pd.to_datetime(df3['purchase_time'])-pd.to_datetime(df3['signup_time'])

df3.head()

df3['tot_mins_diff'] = df3['tot_mins_diff'].dt.total_seconds()

# Conversion of Difference in Minutes

df3['tot_mins_diff']=df3['tot_mins_diff']/60

df3.head()
```

Out[138]:

	user_id	signup_time	purchase_time	purchase_value	device_id	source	browser	sex	ip_address	cl
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	65278	QVPSPJUOCKZAR	SEO	Chrome	M	7.327584e+08	
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	96399	EOGFQPIZPYXFZ	Ads	Chrome	F	3.503114e+08	
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	57296	YSSKYOSJHPPLJ	SEO	Opera	M	2.621474e+09	
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	43650	ATGTXKYKUDUQN	SEO	Safari	M	3.840542e+09	
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	45016	NAUITBZFJKHWW	Ads	Safari	M	4.155831e+08	

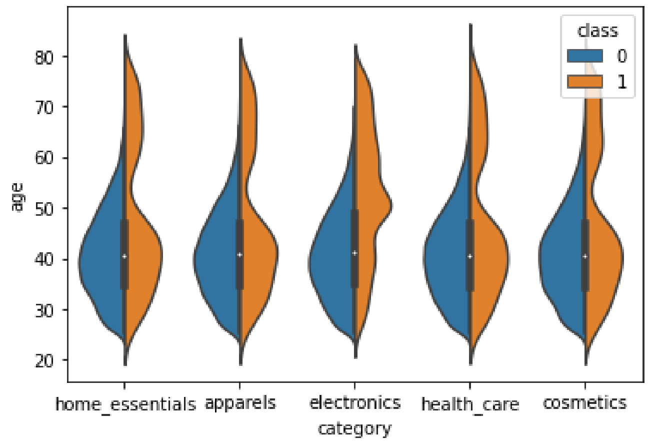
In [139]:
```
sns.scatterplot(data=df3, x="category", y="age",hue='class')
```

Out[139]: <AxesSubplot:xlabel='category', ylabel='age'>



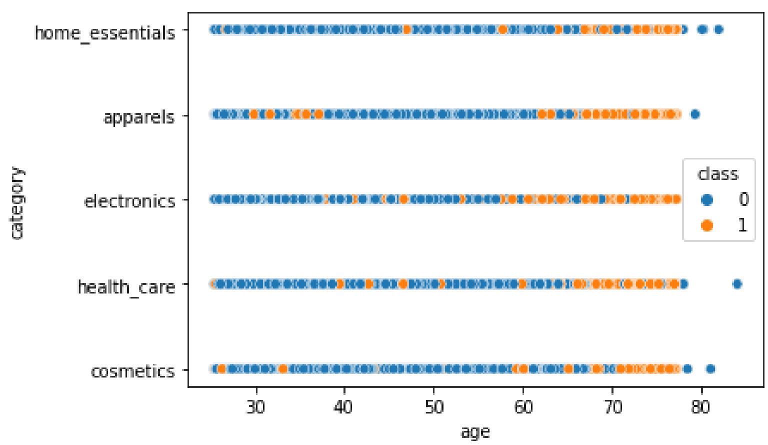
In [140]:
```
sns.violinplot(data=df3, x="category", y="age", hue="class", split=True)
```

Out[140]: <AxesSubplot:xlabel='category', ylabel='age'>



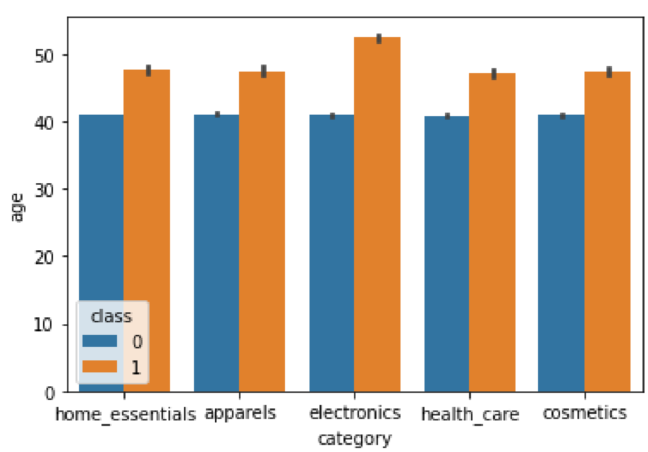
In [141]:
```
sns.scatterplot(data=df3, x="age", y="category",hue='class')
```

Out[141]: <AxesSubplot:xlabel='age', ylabel='category'>



In [142]:
```
sns.barplot(data=df3, x="category", y="age", hue="class")
```

Out[142]: <AxesSubplot:xlabel='category', ylabel='age'>



#We take three features for consideration of creating customer segemntation which are : 'purchase_value','age','tot_mins_diff'

In [143]:
```
features=pd.DataFrame(df3, columns = ['purchase_value','age','tot_mins_diff'])
```

In [144]:
```
features=pd.get_dummies(features,drop_first=True)
```

In [145]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

In [146]:
```
features.head(5)
```

Out[146]:

	purchase_value	age	tot_mins_diff
0	65278	47.183562	75111.366667
1	96399	61.331507	299.066667
2	57296	61.161644	0.016667
3	43650	48.824658	8201.416667
4	45016	52.682192	72691.016667

In [147]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

In [148]:
```
features = features.dropna()
```

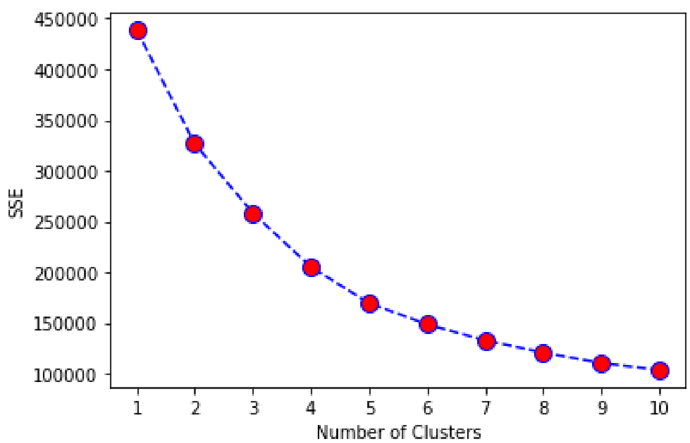
In [149]:
```
features.head(5)
```

Out[149]:

	purchase_value	age	tot_mins_diff
0	65278	47.183562	75111.366667
1	96399	61.331507	299.066667
2	57296	61.161644	0.016667
3	43650	48.824658	8201.416667
4	45016	52.682192	72691.016667

In [150]:
```
#create scaled DataFrame where each variable has mean of 0 and standard dev of 1
scaled_df = StandardScaler().fit_transform(features)
```

In [151]:
```
#initialize kmeans parameters
kmeans_kwargs = {
"init": "random",
"n_init": 10,
"random_state": 1,
}

#create list to hold SSE values for each k
sse = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
    kmeans.fit(scaled_df)
    sse.append(kmeans.inertia_)

#visualize results
plt.plot(range(1, 11), sse,color='blue', linestyle='dashed', marker='o',
         markerfacecolor='red', markersize=10)
plt.xticks(range(1, 11))
plt.xlabel("Number of Clusters")
plt.ylabel("SSE")
plt.show()
```



#Perform K-Means Clustering with Optimal K=4

In [153]:
```
#instantiate the k-means class, using optimal number of clusters
kmeans = KMeans(init="random", n_clusters=4, n_init=10, random_state=1)

#fit k-means algorithm to data
kmeans.fit(scaled_df)

#view cluster assignments for each observation
kmeans.labels_
```

Out[153]:
```
array([2, 3, 3, ..., 0, 2, 0])
```

In [154]:
```
#append cluster assingments to original DataFrame
features['cluster'] = kmeans.labels_

#view updated DataFrame
print(features)
```

```
        purchase_value        age  tot_mins_diff  cluster
0                65278  47.183562   75111.366667        2
1                96399  61.331507     299.066667        3
2                57296  61.161644       0.016667        3
3                43650  48.824658    8201.416667        3
4                45016  52.682192   72691.016667        3
...                ...        ...            ...      ...
151107           58549  35.720548   87687.216667        2
151108           57952  39.550685   15521.166667        1
151109           19003  33.605479  111360.266667        0
151110           68296  45.238356   85768.650000        2
151111           23622  45.857534   58741.550000        0

[146188 rows x 4 columns]
```

Getting the total count of the customers belonging to various clusters

In [173]:
```
cust1=features[features["cluster"]==0]
print('Number of customer in 1st group=', len(cust1))
```

```
Number of customer in 1st group= 40388
```

In [174]:
```
cust2=features[features["cluster"]==1]
print('Number of customer in 2nd group=', len(cust2))
```

```
Number of customer in 2nd group= 41896
```

In [175]:
```
cust3=features[features["cluster"]==2]
print('Number of customer in 3rd group=', len(cust3))
```

```
Number of customer in 3rd group= 39126
```

In [176]:
```
cust4=features[features["cluster"]==3]
print('Number of customer in 4th group=', len(cust4))
```

```
Number of customer in 4th group= 24778
```

In [165]:
```
x = features.values
```

In [166]:
```
WCSS = []
for i in range(1,11):
    model = KMeans(n_clusters = i,init = 'k-means++')
    model.fit(x)
    WCSS.append(model.inertia_)
fig = plt.figure(figsize = (7,7))
plt.plot(range(1,11),WCSS, linewidth=4, markersize=12,marker='o',color = 'red')
plt.xticks(np.arange(11))
plt.xlabel("Number of clusters")
plt.ylabel("WCSS")
plt.show()
```

```
C:\Users\asus\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The
default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` exp
licitly to suppress the warning
  warnings.warn(
C:\Users\asus\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The
default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` exp
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C:\Users\asus\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The
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licitly to suppress the warning
  warnings.warn(
C:\Users\asus\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The
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C:\Users\asus\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The
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C:\Users\asus\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The
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  warnings.warn(
C:\Users\asus\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The
default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` exp
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  warnings.warn(
C:\Users\asus\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The
default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` exp
licitly to suppress the warning
  warnings.warn(
C:\Users\asus\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The
default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` exp
licitly to suppress the warning
  warnings.warn(
C:\Users\asus\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The
default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` exp
licitly to suppress the warning
  warnings.warn(
```
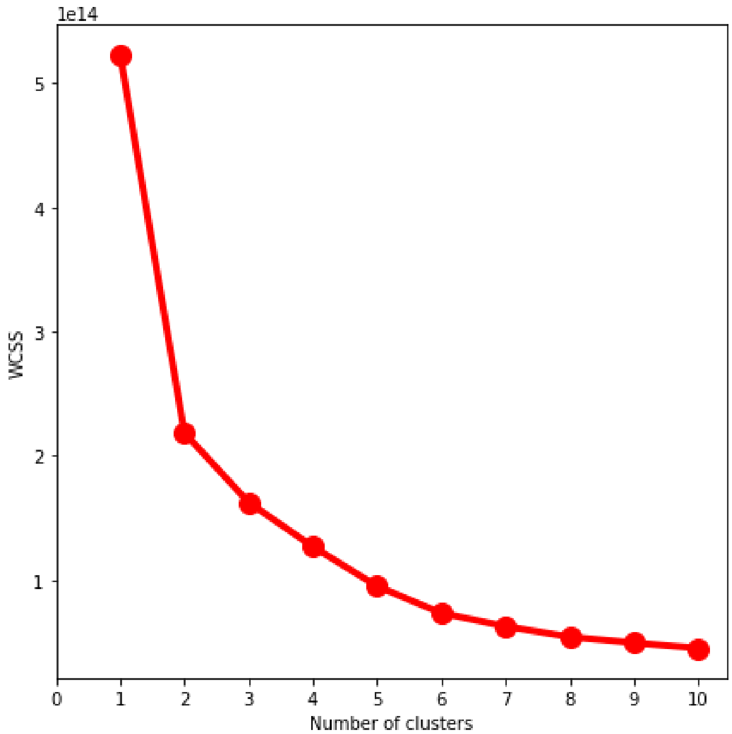
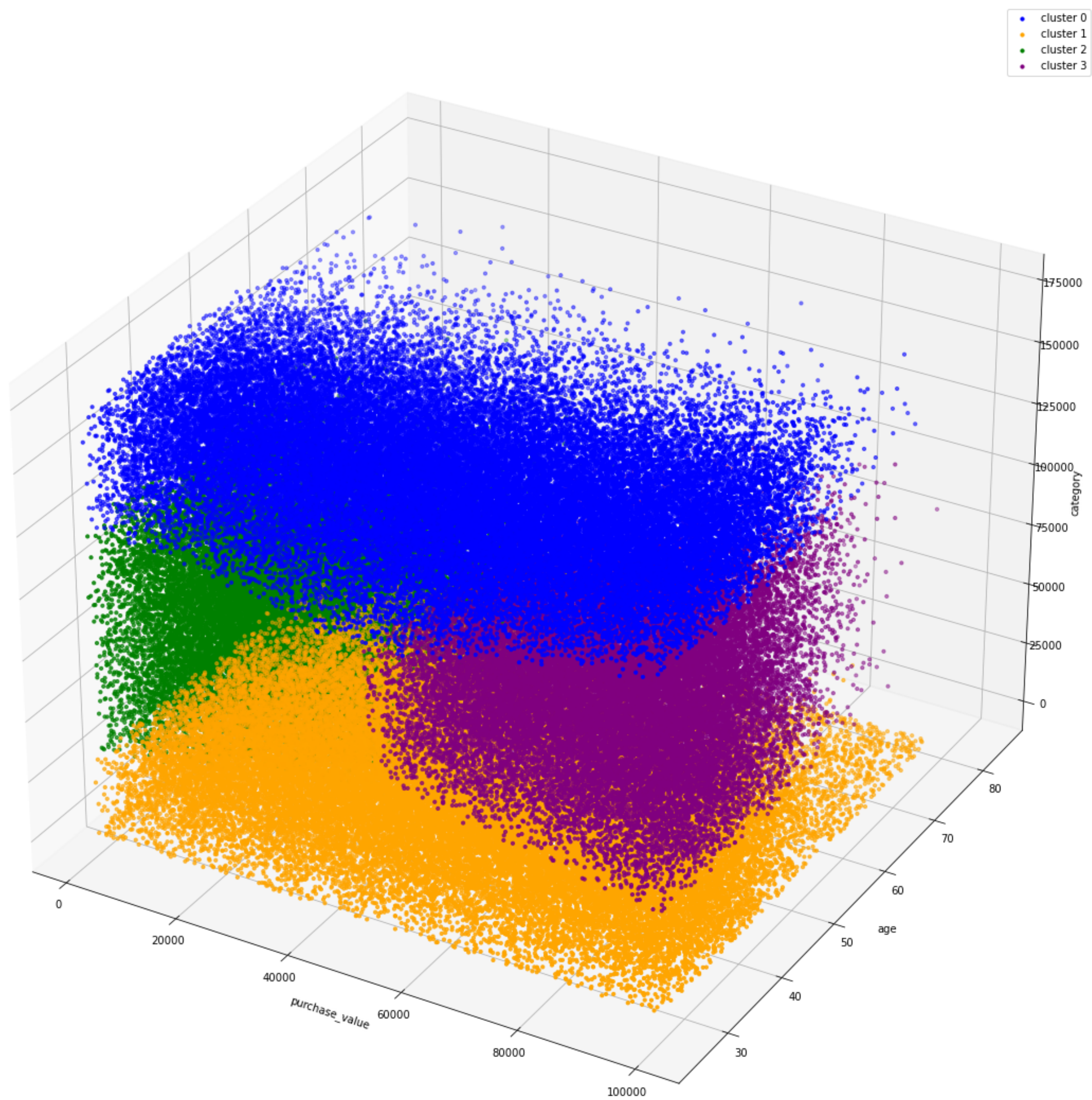



In [167]:
```
model = KMeans(n_clusters = 4, init = "k-means++", max_iter = 300, n_init = 10, random_state =
y_clusters = model.fit_predict(x)
```

In [168]:
```
fig = plt.figure(figsize = (20,20))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(x[y_clusters == 0,0],x[y_clusters == 0,1],x[y_clusters == 0,2], s = 10 , color = 'b
ax.scatter(x[y_clusters == 1,0],x[y_clusters == 1,1],x[y_clusters == 1,2], s = 10 , color = 'o
ax.scatter(x[y_clusters == 2,0],x[y_clusters == 2,1],x[y_clusters == 2,2], s = 10 , color = 'g
ax.scatter(x[y_clusters == 3,0],x[y_clusters == 3,1],x[y_clusters == 3,2], s = 10 , color = 'p
ax.set_xlabel('purchase_value')
ax.set_ylabel('age')
ax.set_zlabel('category')
ax.legend()
plt.show()
```



Customer clusters based on age group , purchase value and tot_mins_diff(difference between sign up time and purchase time)

Customer clusters based on age group , purchase value and tot_mins_diff(differnece between sign up time and purchase time
from the above graph we can infer :

```
cluster 0 indicated with blue has customer base in age group of 40- 80 years where there
tot_mins_diff is in range 50000 to 10000 mins and purchase value has high range 0-80000
The total count of customers in cluster 0 is 40388

cluster 1 indicated with orange color has customer base in age group of
30- 80 years where there tot_mins_diff is in range 0 to 25000 mins and purchase value has
range 0 to 85000
The total count of customers in cluster 1 is 41896

cluster 2 indicated with green color  has customer base in age group of
30- 60 years where there tot_mins_diff is in range 0 to 25000 mins and purchase value has
range 0-90000
The total count of customers in cluster 2 is 39126

cluster 3 indicated with purple color  has customer base in age group of
40- 90 years where there tot_mins_diff is in range 0 to approximately 80000 mins and purchase
value has high range 25000-90000
The total count of customers in cluster 3 is 24778
```

In [169]:

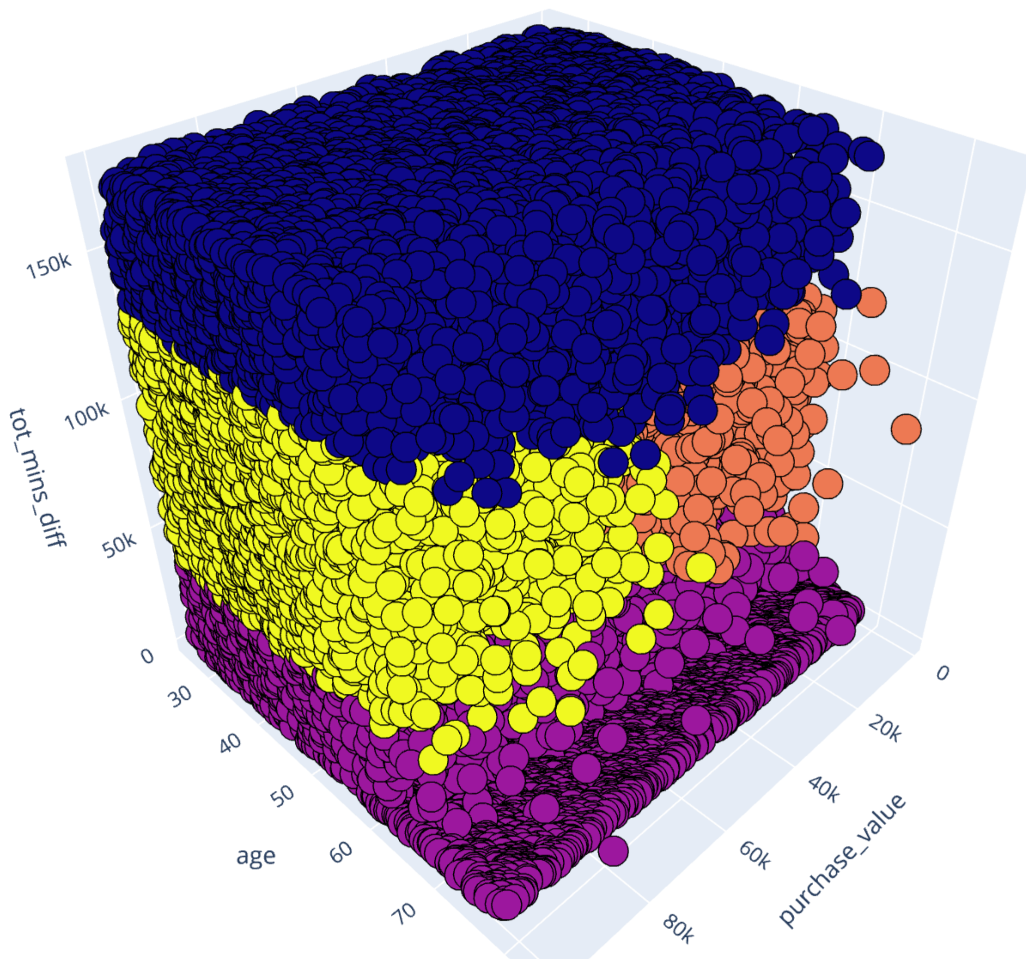
```
pip install plotly
```

```
Requirement already satisfied: plotly in c:\users\asus\anaconda3\lib\site-packages (5.14.1)
Requirement already satisfied: tenacity>=6.2.0 in c:\users\asus\anaconda3\lib\site-packages
(from plotly) (8.2.2)
Requirement already satisfied: packaging in c:\users\asus\anaconda3\lib\site-packages (from p
lotly) (21.0)
Requirement already satisfied: pyparsing>=2.0.2 in c:\users\asus\anaconda3\lib\site-packages
(from packaging->plotly) (3.0.4)
Note: you may need to restart the kernel to use updated packages.
```

In [170]:

```
from mpl_toolkits.mplot3d import Axes3D
import plotly.graph_objs as go
from plotly import tools
from plotly.subplots import make_subplots
import plotly.offline as py
```

In [177]:
```
Scene = dict(xaxis = dict(title  = 'purchase_value'),yaxis = dict(title  = 'age'),zaxis = dict

# model.labels_ is nothing but the predicted clusters i.e y_clusters
labels = model.labels_
trace = go.Scatter3d(x=x[:, 0], y=x[:, 1], z=x[:, 2], mode='markers',marker=dict(color = label
layout = go.Layout(margin=dict(l=0,r=0),scene = Scene,height = 800,width = 800)
data = [trace]
fig = go.Figure(data = data, layout = layout)
fig.show()
```



In [ ]: