Problem Statement

To predict if the car purchased at an Auction is a good / bad buy.

The dependent variable (IsBadBuy) is binary and There are 32 Independent variables.

Data is divided in training.csv and test.csv. Use only training.csv to train the model

Variable:

RefID Unique (sequential) number assigned to vehicles

IsBadBuy Identifies if the kicked vehicle was an avoidable purchase

PurchDate The Date the vehicle was Purchased at Auction

Auction Auction provider at which the vehicle was purchased

VehYear The manufacturer's year of the vehicle

VehicleAge The Years elapsed since the manufacturer's year

Make Vehicle Manufacturer

Model Vehicle Model

Trim Vehicle Trim Level

SubModel Vehicle Submodel

Color Vehicle Color

Transmission Vehicles transmission type (Automatic, Manual)

WheelTypeID The type id of the vehicle wheel

WheelType The vehicle wheel type description (Alloy, Covers)

VehOdo The vehicles odometer reading

Nationality The Manufacturer's country

Size The size category of the vehicle (Compact, SUV, etc.)

TopThreeAmericanName Identifies if the manufacturer is one of the top three American manufacturers

MMRAcquisitionAuctionAveragePrice Acquisition price for this vehicle in average condition at time of purchase

MMRAcquisitionAuctionCleanPrice Acquisition price for this vehicle in the above Average condition at time of purchase

MMRAcquisitionRetailAveragePrice Acquisition price for this vehicle in the retail market in average condition at time of purchase

MMRAcquisitonRetailCleanPrice Acquisition price for this vehicle in the retail market in above average condition at time of purchase

MMRCurrentAuctionAveragePrice Acquisition price for this vehicle in average condition as of current day

MMRCurrentAuctionCleanPrice Acquisition price for this vehicle in the above condition as of current day

MMRCurrentRetailAveragePrice Acquisition price for this vehicle in the retail market in average condition as of current day

MMRCurrentRetailCleanPrice Acquisition price for this vehicle in the retail market in above average condition as of current day

PRIMEUNIT Identifies if the vehicle would have a higher demand than a standard purchase

AcquisitionType Identifies how the vehicle was aquired (Auction buy, trade in, etc)

AUCGUART The level guarntee provided by auction for the vehicle (Green light - Guaranteed/arbitratable, Yellow Light - caution/issue, red light - sold as is)

KickDate Date the vehicle was kicked back to the auction

BYRNO Unique number assigned to the buyer that purchased the vehicle

VNZIP Zipcode where the car was purchased

VNST State where the the car was purchased

VehBCost Acquisition cost paid for the vehicle at time of purchase

IsOnlineSale Identifies if the vehicle was originally purchased online

WarrantyCost Warranty price (term=36month and millage=36K)

Error Measurement

log loss- used for measure the loss

Confusion matrix, Precision and Recall matrix used to measure the accuracy

Solution Approach

1)Import dataset and library

2)EDA(univariate, bivariate, PDF, CDF) --variable selection

3) MIssing data filled using MICE (detail explained in respective section)

4) Data cleaning like removing space, punctuation etc.

5) Split dataset

6)One hot encoding of categorical variable and Normalization of Numerical Variable

7)Apply different model like (KNN, Naive base, Logistic, SVM, Random forest)

8) Stacking all above model in logistic regression

9) Conclusion

In [ ]:
```

```

Solution

Import dataset and library

In [669]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

import sqlite3
import pandas as pd
import numpy as np
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from tqdm import tqdm
import os

from plotly import plotly
import plotly.offline as offline
import plotly.graph_objs as go
offline.init_notebook_mode()
```

In [670]:
```
project_data = pd.read_csv('Buy_train.csv')
project_data_test = pd.read_csv('Buy_test.csv')
```

In [671]:
```
project_data.shape
```

Out[671]:
```
(72983, 34)
```

In [672]:
```
print("Number of data points in train data", project_data.shape)
print('-'*50)
print("The attributes of data :", project_data.columns.values)
```

```
Number of data points in train data (72983, 34)
--------------------------------------------------
The attributes of data : ['RefId' 'IsBadBuy' 'PurchDate' 'Auction' 'VehYear'
'VehicleAge' 'Make'
 'Model' 'Trim' 'SubModel' 'Color' 'Transmission' 'WheelTypeID'
 'WheelType' 'VehOdo' 'Nationality' 'Size' 'TopThreeAmericanName'
 'MMRAcquisitionAuctionAveragePrice' 'MMRAcquisitionAuctionCleanPrice'
 'MMRAcquisitionRetailAveragePrice' 'MMRAcquisitonRetailCleanPrice'
 'MMRCurrentAuctionAveragePrice' 'MMRCurrentAuctionCleanPrice'
 'MMRCurrentRetailAveragePrice' 'MMRCurrentRetailCleanPrice' 'PRIMEUNIT'
 'AUCGUART' 'BYRNO' 'VNZIP1' 'VNST' 'VehBCost' 'IsOnlineSale'
 'WarrantyCost']
```

In [673]:
```
print(project_data["IsBadBuy"].value_counts(normalize = True))
print("*"*50)
```

```
0    0.877012
1    0.122988
Name: IsBadBuy, dtype: float64
**************************************************
```

Dataset is Imbalance where 87% is not bad buy and 12% is bad buy

Sorted by time

In [674]:
```
#training

#https://stats.stackexchange.com/questions/341312/train-test-split-with-time-a
nd-person-indexed-data
# how to replace elements in list python: https://stackoverflow.com/a/2582163/
4084039
cols = ['Date' if x=='PurchDate' else x for x in list(project_data.columns)]


#sort dataframe based on time pandas python: https://stackoverflow.com/a/49702
492/4084039
project_data['Date'] = pd.to_datetime(project_data['PurchDate'])
project_data.drop('PurchDate', axis=1, inplace=True)
project_data.sort_values(by=['Date'], inplace=True)


# how to reorder columns pandas python: https://stackoverflow.com/a/13148611/4
084039
project_data = project_data[cols]
```

In [675]:
```
#test

#https://stats.stackexchange.com/questions/341312/train-test-split-with-time-a
nd-person-indexed-data
# how to replace elements in list python: https://stackoverflow.com/a/2582163/
4084039
cols = ['Date' if x=='PurchDate' else x for x in list(project_data_test.column
s)]


#sort dataframe based on time pandas python: https://stackoverflow.com/a/49702
492/4084039
project_data_test['Date'] = pd.to_datetime(project_data_test['PurchDate'])
project_data_test.drop('PurchDate', axis=1, inplace=True)
project_data_test.sort_values(by=['Date'], inplace=True)


# how to reorder columns pandas python: https://stackoverflow.com/a/13148611/4
084039
project_data_test = project_data_test[cols]
```

In [676]:
```
project_data.head(10)
```

Out[676]:

	RefId	IsBadBuy	Date	Auction	VehYear	VehicleAge	Make	Model	Tr
32367	32389	0	2009-01-05	MANHEIM	2007	2	CHRYSLER	PACIFICA FWD 3.8L V6	B
32384	32406	0	2009-01-05	MANHEIM	2005	4	FORD	FREESTAR FWD V6 3.9L	SI
32385	32407	0	2009-01-05	MANHEIM	2004	5	DODGE	STRATUS 4C 2.4L I4 M	
32386	32408	0	2009-01-05	MANHEIM	2006	3	CHEVROLET	TRAILBLAZER EXT 4WD	
32387	32409	0	2009-01-05	MANHEIM	2004	5	FORD	TAURUS 3.0L V6 EFI	SI
8875	8884	0	2009-01-05	MANHEIM	2005	4	CHEVROLET	IMPALA 3.4L V6 SFI	B
8874	8883	0	2009-01-05	MANHEIM	2003	6	FORD	MUSTANG V6 3.8L V6 E	B
8873	8882	0	2009-01-05	MANHEIM	2004	5	DODGE	STRATUS 4C 2.4L I4 M	S
8872	8881	0	2009-01-05	MANHEIM	2004	5	DODGE	DURANGO 4WD V8 4.7L	S
8871	8880	1	2009-01-05	MANHEIM	2006	3	FORD	FREESTYLE AWD V6 3.0	

10 rows × 34 columns

In [ ]:

Reindexing the dataset

In [677]:
```
project_data = project_data.reset_index(drop=True)
project_data_test = project_data_test.reset_index(drop=True)
```

In [678]:
```
project_data.head(10)
```

Out[678]:

	RefId	IsBadBuy	Date	Auction	VehYear	VehicleAge	Make	Model	Trim
0	32389	0	2009-01-05	MANHEIM	2007	2	CHRYSLER	PACIFICA FWD 3.8L V6	Bas
1	32406	0	2009-01-05	MANHEIM	2005	4	FORD	FREESTAR FWD V6 3.9L	SES
2	32407	0	2009-01-05	MANHEIM	2004	5	DODGE	STRATUS 4C 2.4L I4 M	SE
3	32408	0	2009-01-05	MANHEIM	2006	3	CHEVROLET	TRAILBLAZER EXT 4WD	LS
4	32409	0	2009-01-05	MANHEIM	2004	5	FORD	TAURUS 3.0L V6 EFI	SES
5	8884	0	2009-01-05	MANHEIM	2005	4	CHEVROLET	IMPALA 3.4L V6 SFI	Bas
6	8883	0	2009-01-05	MANHEIM	2003	6	FORD	MUSTANG V6 3.8L V6 E	Bas
7	8882	0	2009-01-05	MANHEIM	2004	5	DODGE	STRATUS 4C 2.4L I4 M	SXT
8	8881	0	2009-01-05	MANHEIM	2004	5	DODGE	DURANGO 4WD V8 4.7L	SLT
9	8880	1	2009-01-05	MANHEIM	2006	3	FORD	FREESTYLE AWD V6 3.0	SE

10 rows × 34 columns

In [679]:
```
project_data.info(10)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 72983 entries, 0 to 72982
Data columns (total 34 columns):
RefId                                72983 non-null int64
IsBadBuy                             72983 non-null int64
Date                                 72983 non-null datetime64[ns]
Auction                              72983 non-null object
VehYear                              72983 non-null int64
VehicleAge                           72983 non-null int64
Make                                 72983 non-null object
Model                                72983 non-null object
Trim                                 70623 non-null object
SubModel                             72975 non-null object
Color                                72975 non-null object
Transmission                         72974 non-null object
WheelTypeID                          69814 non-null float64
WheelType                            69809 non-null object
VehOdo                               72983 non-null int64
Nationality                          72978 non-null object
Size                                 72978 non-null object
TopThreeAmericanName                 72978 non-null object
MMRAcquisitionAuctionAveragePrice    72965 non-null float64
MMRAcquisitionAuctionCleanPrice      72965 non-null float64
MMRAcquisitionRetailAveragePrice     72965 non-null float64
MMRAcquisitonRetailCleanPrice        72965 non-null float64
MMRCurrentAuctionAveragePrice        72668 non-null float64
MMRCurrentAuctionCleanPrice          72668 non-null float64
MMRCurrentRetailAveragePrice         72668 non-null float64
MMRCurrentRetailCleanPrice           72668 non-null float64
PRIMEUNIT                            3419 non-null object
AUCGUART                             3419 non-null object
BYRNO                                72983 non-null int64
VNZIP1                               72983 non-null int64
VNST                                 72983 non-null object
VehBCost                             72983 non-null float64
IsOnlineSale                         72983 non-null int64
WarrantyCost                         72983 non-null int64
dtypes: datetime64[ns](1), float64(10), int64(9), object(14)
memory usage: 18.9+ MB
```

Here dataset have both categorical and numerical variable but having lot of missing value in some variable.

EDA

High level statistics

In [680]:
```
print(project_data.describe())
```

```
              RefId      IsBadBuy       VehYear    VehicleAge   WheelTypeID  \
count  72983.000000  72983.000000  72983.000000  72983.000000  69814.000000
mean   36511.428497      0.122988   2005.343052      4.176644      1.494299
std    21077.241302      0.328425      1.731252      1.712210      0.521290
min        1.000000      0.000000   2001.000000      0.000000      0.000000
25%    18257.500000      0.000000   2004.000000      3.000000      1.000000
50%    36514.000000      0.000000   2005.000000      4.000000      1.000000
75%    54764.500000      0.000000   2007.000000      5.000000      2.000000
max    73014.000000      1.000000   2010.000000      9.000000      3.000000

              VehOdo  MMRAcquisitionAuctionAveragePrice  \
count   72983.000000                       72965.000000
mean    71499.995917                        6128.909217
std     14578.913128                        2461.992768
min      4825.000000                           0.000000
25%     61837.000000                        4273.000000
50%     73361.000000                        6097.000000
75%     82436.000000                        7765.000000
max    115717.000000                       35722.000000

       MMRAcquisitionAuctionCleanPrice  MMRAcquisitionRetailAveragePrice  \
count                     72965.000000                      72965.000000
mean                       7373.636031                       8497.034332
std                        2722.491986                       3156.285284
min                           0.000000                          0.000000
25%                        5406.000000                       6280.000000
50%                        7303.000000                       8444.000000
75%                        9021.000000                      10651.000000
max                       36859.000000                      39080.000000

       MMRAcquisitonRetailCleanPrice  MMRCurrentAuctionAveragePrice  \
count                   72965.000000                   72668.000000
mean                     9850.928240                    6132.081287
std                      3385.789541                    2434.567723
min                         0.000000                       0.000000
25%                      7493.000000                    4275.000000
50%                      9789.000000                    6062.000000
75%                     12088.000000                    7736.000000
max                     41482.000000                   35722.000000

       MMRCurrentAuctionCleanPrice  MMRCurrentRetailAveragePrice  \
count                 72668.000000                  72668.000000
mean                   7390.681827                   8775.723331
std                    2686.248852                   3090.702941
min                       0.000000                      0.000000
25%                    5414.000000                   6536.000000
50%                    7313.000000                   8729.000000
75%                    9013.000000                  10911.000000
max                   36859.000000                  39080.000000

       MMRCurrentRetailCleanPrice         BYRNO        VNZIP1      VehBCost  \
count                72668.000000  72983.000000  72983.000000  72983.000000
mean                 10145.385314  26345.842155  58043.059945   6730.934326
std                   3310.254351  25717.351219  26151.640415   1767.846435
min                      0.000000    835.000000   2764.000000      1.000000
```

```
25%                      7784.000000  17212.000000  32124.000000   5435.000000
50%                     10103.000000  19662.000000  73108.000000   6700.000000
75%                     12309.000000  22808.000000  80022.000000   7900.000000
max                     41062.000000  99761.000000  99224.000000  45469.000000

       IsOnlineSale  WarrantyCost
count  72983.000000  72983.000000
mean       0.025280   1276.580985
std        0.156975    598.846788
min        0.000000    462.000000
25%        0.000000    837.000000
50%        0.000000   1155.000000
75%        0.000000   1623.000000
max        1.000000   7498.000000
```

Above table show the mean and deviation of numerical variable

In [681]:
```
import numpy as np
IsBadBuy_yes = project_data.loc[project_data["IsBadBuy"] == 1];
IsBadBuy_no = project_data.loc[project_data["IsBadBuy"] == 0];
```

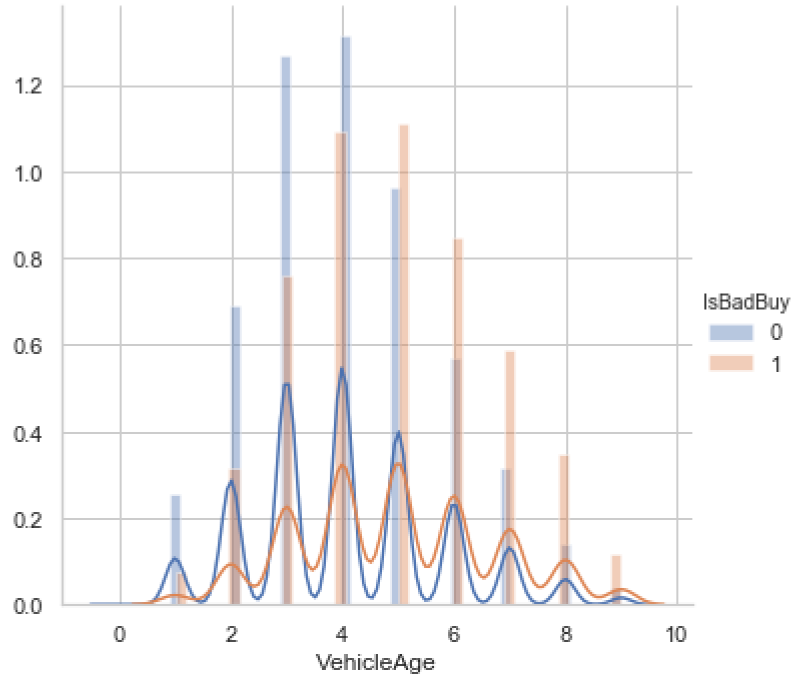
Univariate analysis(Histogram, PDF, CDF)

In [682]:
```
import numpy as np
import matplotlib.pyplot as plt
```

VehicleAge, WarrantyCost, VehBCost

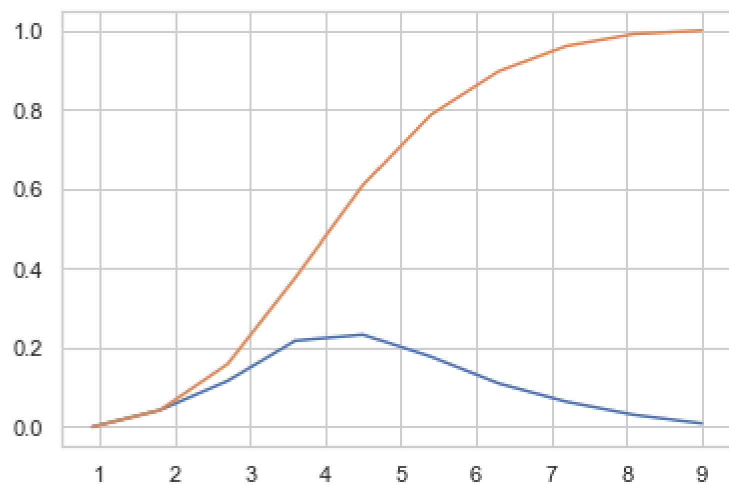
In [683]:
```
plt.figure(1)
#PDF of VehicleAge
#plt.subplot(1,2,1)
sns.FacetGrid(project_data, hue="IsBadBuy", size=5).map(sns.distplot, "Vehicle
Age").add_legend();
plt.show();

#plt.subplot(1,2,2)

plt.figure(2)
#------Plot CDF of age

counts, bin_edges = np.histogram(project_data['VehicleAge'], bins=10,density =
True)
pdf = counts/(sum(counts))
print(pdf);
print(bin_edges)
#compute CDF
cdf = np.cumsum(pdf)
plt.plot(bin_edges[1:],pdf)
plt.plot(bin_edges[1:], cdf)

#plt.show();
```

```
<Figure size 432x288 with 0 Axes>
```




```
[2.74036419e-05 4.23934341e-02 1.16218845e-01 2.17886357e-01
 2.33109080e-01 1.77520793e-01 1.09916008e-01 6.36586602e-02
 3.04180426e-02 8.85137635e-03]
[0.  0.9 1.8 2.7 3.6 4.5 5.4 6.3 7.2 8.1 9. ]
```

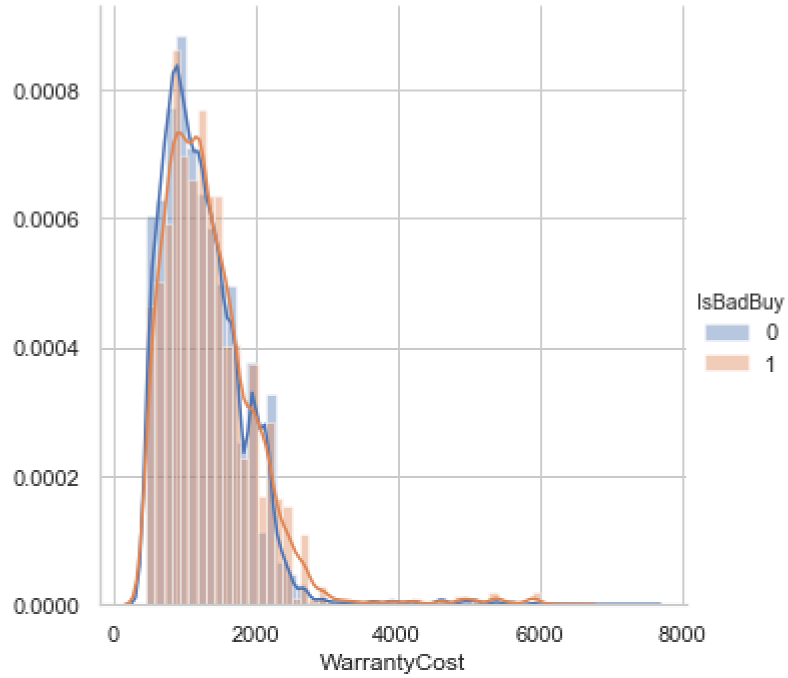
Out[683]: `[<matplotlib.lines.Line2D at 0x16d1926b780>]`



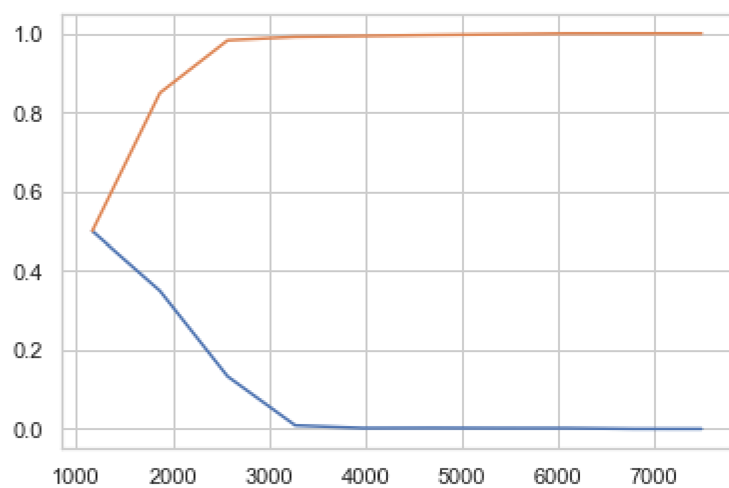
90% of the vahicle have age less than 7 year from manufacture year.

In [684]:
```
plt.figure(1)
#PDF of WarrantyCost
#plt.subplot(211)
sns.FacetGrid(project_data, hue="IsBadBuy", size=5).map(sns.distplot, "WarrantyCost").add_legend();
plt.show();

plt.figure(2)
#------Plot CDF of age

counts, bin_edges = np.histogram(project_data['WarrantyCost'], bins=10,density = True)
pdf = counts/(sum(counts))
print(pdf);
print(bin_edges)
#compute CDF
cdf = np.cumsum(pdf)
plt.plot(bin_edges[1:],pdf)
plt.plot(bin_edges[1:], cdf)

plt.show();
```

```
<Figure size 432x288 with 0 Axes>
```



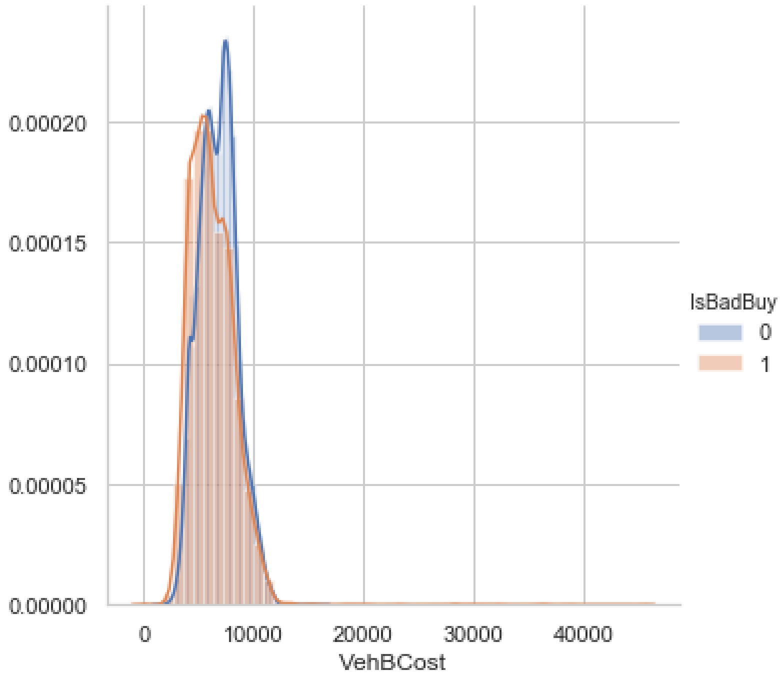

```
[5.00061658e-01 3.49506049e-01 1.33030980e-01 8.93358727e-03
 2.08267679e-03 2.39781867e-03 1.95936040e-03 1.87714947e-03
 9.59127468e-05 5.48072839e-05]
[ 462.   1165.6 1869.2 2572.8 3276.4 3980.  4683.6 5387.2 6090.8 6794.4
 7498. ]
```



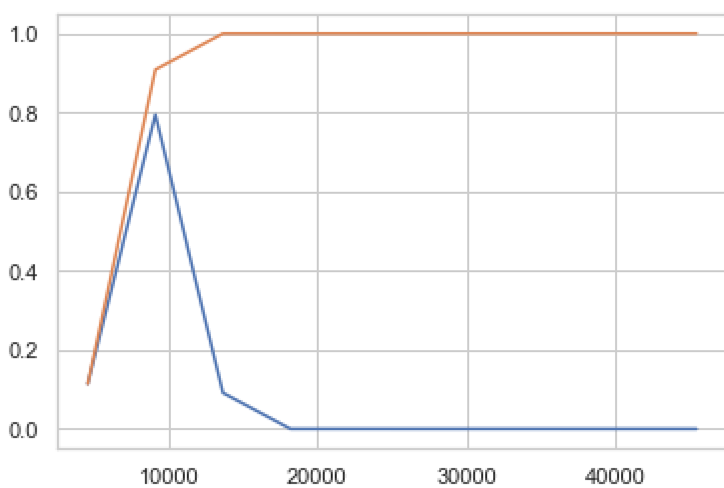
80% of buyer choice have less than 2000 WarrantyCost

In [685]:
```
plt.figure(1)
#PDF of VehBCost
#plt.subplot(211)
sns.FacetGrid(project_data, hue="IsBadBuy", size=5).map(sns.distplot, "VehBCost").add_legend();
plt.show();

plt.figure(2)
#------Plot CDF of age

counts, bin_edges = np.histogram(project_data['VehBCost'], bins=10,density = True)
pdf = counts/(sum(counts))
print(pdf);
print(bin_edges)
#compute CDF
cdf = np.cumsum(pdf)
plt.plot(bin_edges[1:],pdf)
plt.plot(bin_edges[1:], cdf)

plt.show();
```

```
<Figure size 432x288 with 0 Axes>
```




```
[1.14218380e-01 7.94267158e-01 9.12678295e-02 6.85091049e-05
 5.48072839e-05 1.37018210e-05 4.11054629e-05 2.74036419e-05
 2.74036419e-05 1.37018210e-05]
[1.00000e+00 4.54780e+03 9.09460e+03 1.36414e+04 1.81882e+04 2.27350e+04
 2.72818e+04 3.18286e+04 3.63754e+04 4.09222e+04 4.54690e+04]
```



Again 90% of buyerchoice have less than 10000 VehBCost

In [686]:
```
#Mean
print("Means:")
print(np.mean(IsBadBuy_yes["VehicleAge"]))
print(np.mean(IsBadBuy_yes["WarrantyCost"]))
print(np.mean(IsBadBuy_yes["VehBCost"]))
print("*"*50)
print(np.mean(IsBadBuy_no["VehicleAge"]))
print(np.mean(IsBadBuy_no["WarrantyCost"]))
print(np.mean(IsBadBuy_no["VehBCost"]))
```

```
Means:
4.940953654188949
1360.246546345811
6259.274156639928
**************************************************
4.069461152686425
1264.848172856094
6797.077430593529
```

In [687]:
```
#Variance, Std-deviation
print("Means:")
print(np.std(IsBadBuy_yes["VehicleAge"]))
print(np.std(IsBadBuy_yes["WarrantyCost"]))
print(np.std(IsBadBuy_yes["VehBCost"]))
print("*"*50)
print(np.std(IsBadBuy_no["VehicleAge"]))
print(np.std(IsBadBuy_no["WarrantyCost"]))
print(np.std(IsBadBuy_no["VehBCost"]))
```

```
Means:
1.7652034214401928
679.8566695004682
2078.839471386023
**************************************************
1.6770113350557971
585.6329973638996
1709.3561755837766
```

Observation:

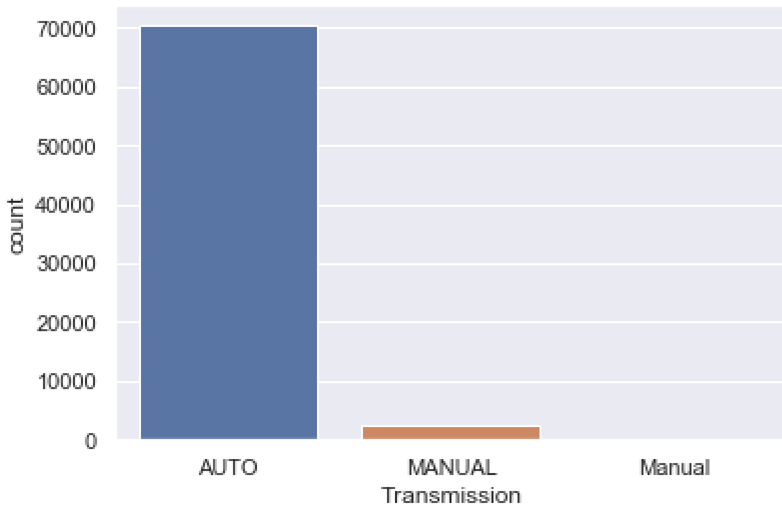
Mean of Vehicleage, vehiclecost and worrentycost are nearly same in both case of Buyer choice(yes,no).

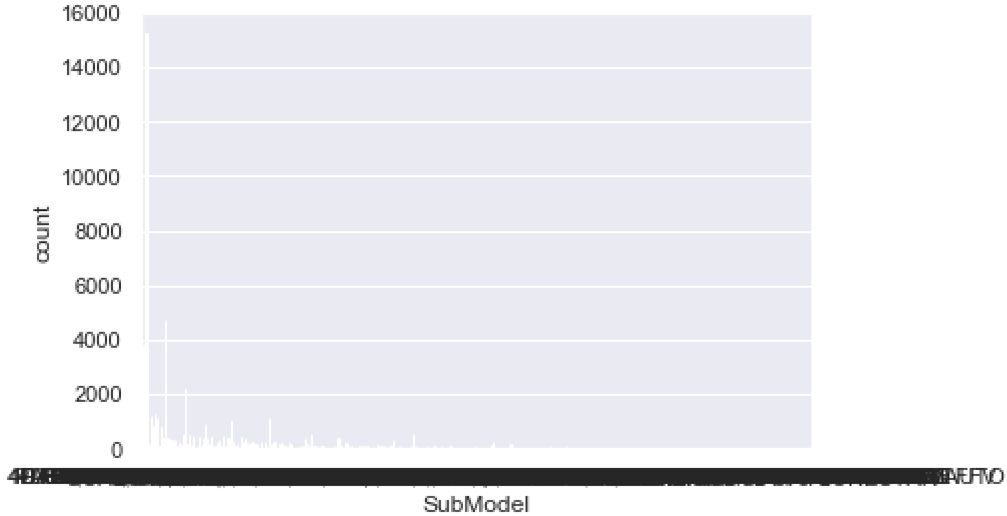
Spreadness of VehicleAge is nearly same in both case of choice but spreadness of WarrantyCost and VehBCost is wide when buyer buy the car as compare of Buyer dont buy the vehicle. means some buyer are very negotiable and some are straight buy the vehicle.

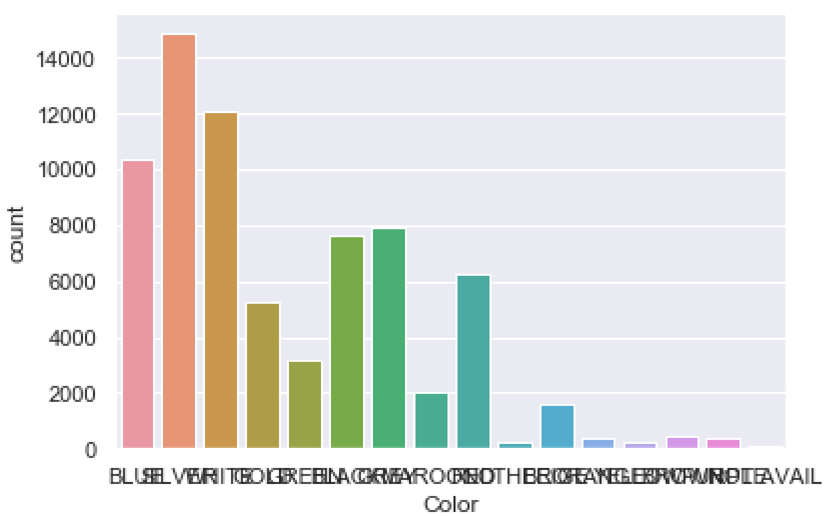
All above three variable are not able to classified or segrigate the Buyer choice but they have good overlap which is good for model.

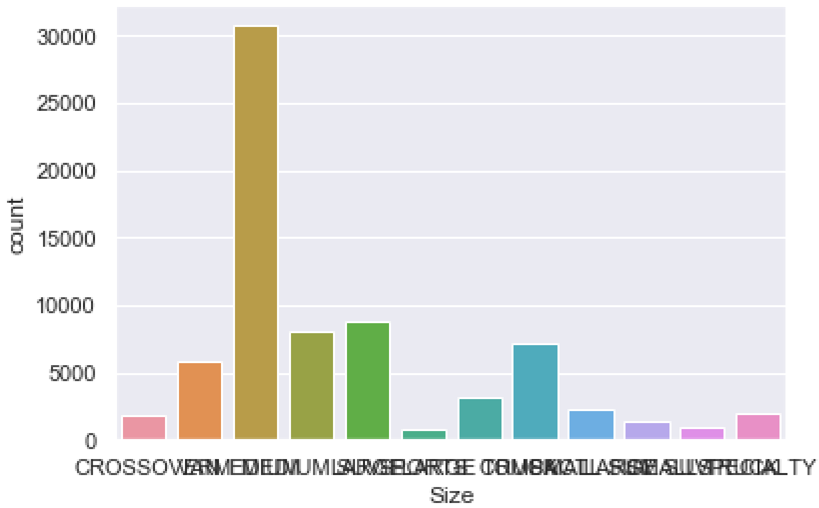
SubModel,Color,Size,WheelType,IsOnlineSale

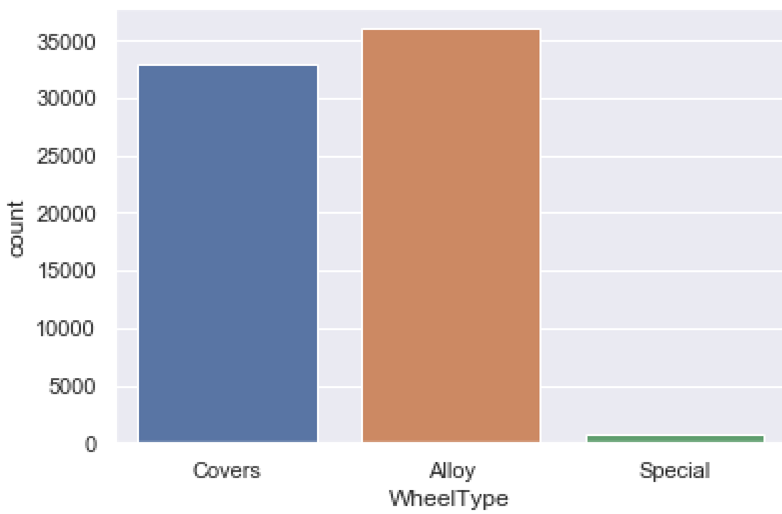
In [688]:
```
plt.figure(1)
import seaborn as sns
sns.set(style="darkgrid")
ax = sns.countplot(x="Transmission", data=project_data)

plt.figure(2)
import seaborn as sns
sns.set(style="darkgrid")
ax = sns.countplot(x="SubModel", data=project_data)

plt.figure(3)
import seaborn as sns
sns.set(style="darkgrid")
ax = sns.countplot(x="Color", data=project_data)

plt.figure(4)
import seaborn as sns
sns.set(style="darkgrid")
ax = sns.countplot(x="Size", data=project_data)

plt.figure(5)
import seaborn as sns
sns.set(style="darkgrid")
ax = sns.countplot(x="WheelType", data=project_data)

plt.figure(6)
import seaborn as sns
sns.set(style="darkgrid")
ax = sns.countplot(x="IsOnlineSale", data=project_data)
```

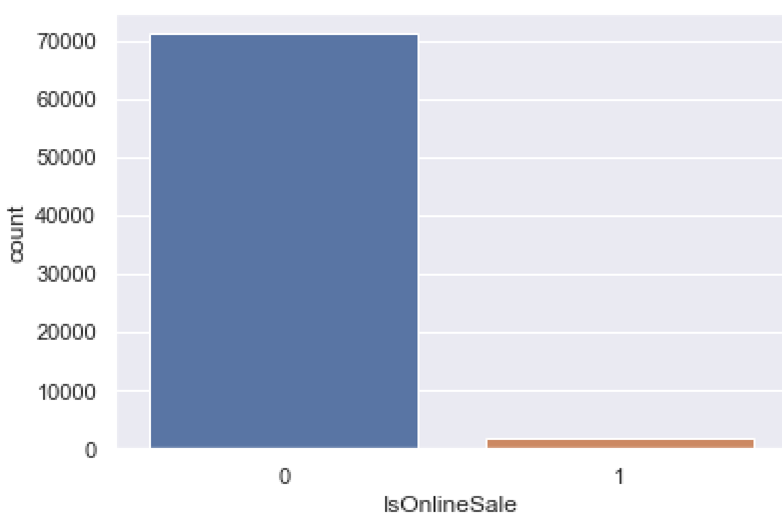

70000
60000
50000
40000
30000
20000
10000
0
count
AUTO
MANUAL
Manual
Transmission


16000
14000
12000
10000
8000
6000
4000
2000
0
count
SubModel


14000
12000
10000
8000
6000
4000
2000
0
count
Color


count
Size


count
Covers
Alloy
Special
WheelType


count
IsOnlineSale

Observation:

Most of Transmission done auto.

Most of sale happen offline because of its second hand product.

People prefer to take vehicle with alloywheel tyre vehicle

Silver and white color vehicle prefered.

Medium size vehicle prefered

Multivariate analysis

In [689]:
```
project_data.columns
```

Out[689]:
```
Index(['RefId', 'IsBadBuy', 'Date', 'Auction', 'VehYear', 'VehicleAge', 'Mak
e',
       'Model', 'Trim', 'SubModel', 'Color', 'Transmission', 'WheelTypeID',
       'WheelType', 'VehOdo', 'Nationality', 'Size', 'TopThreeAmericanName',
       'MMRAcquisitionAuctionAveragePrice', 'MMRAcquisitionAuctionCleanPric
e',
       'MMRAcquisitionRetailAveragePrice', 'MMRAcquisitonRetailCleanPrice',
       'MMRCurrentAuctionAveragePrice', 'MMRCurrentAuctionCleanPrice',
       'MMRCurrentRetailAveragePrice', 'MMRCurrentRetailCleanPrice',
       'PRIMEUNIT', 'AUCGUART', 'BYRNO', 'VNZIP1', 'VNST', 'VehBCost',
       'IsOnlineSale', 'WarrantyCost'],
      dtype='object')
```

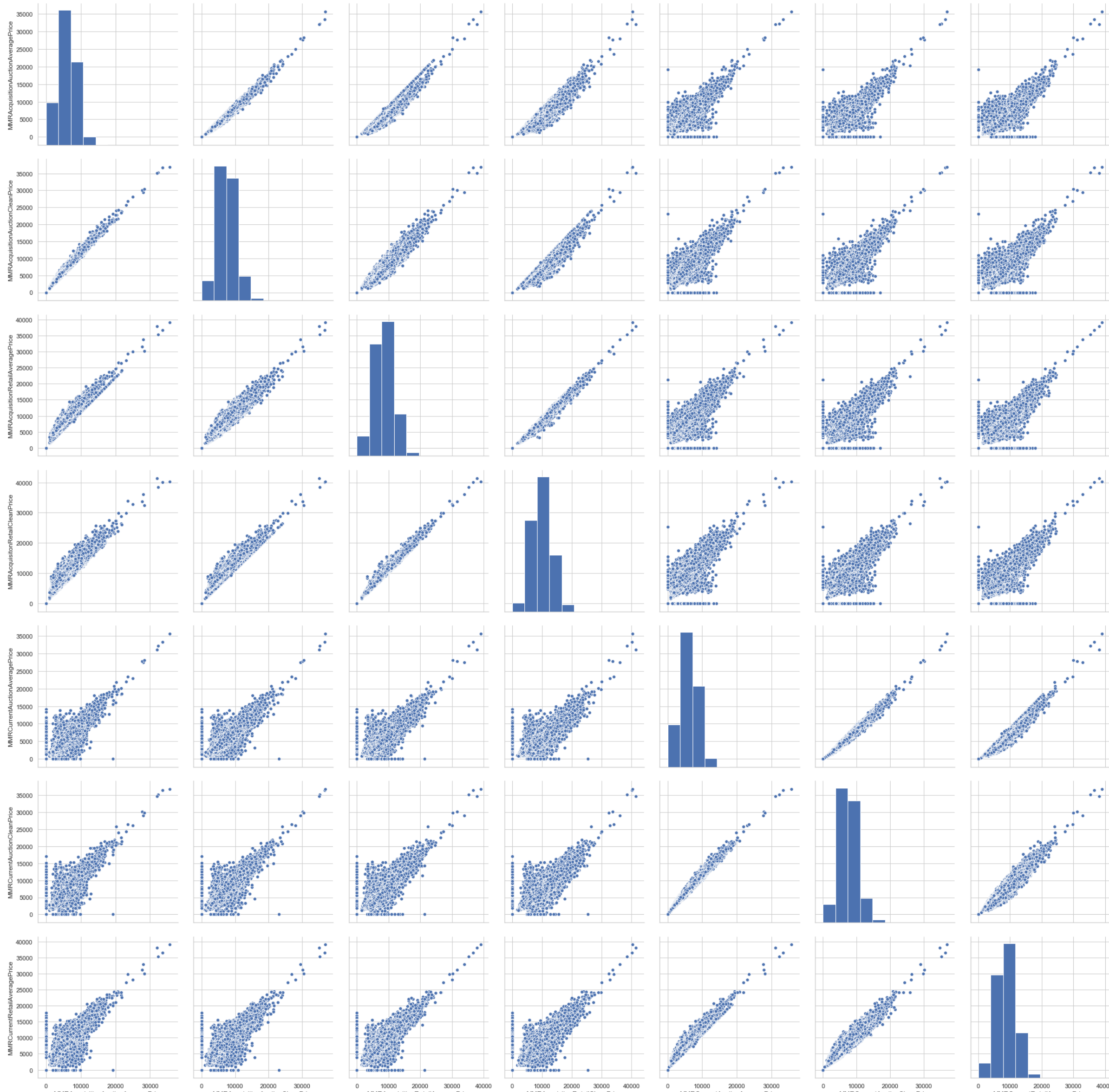
In [690]:
```
df1 = project_data.iloc[:, 17:25]
df2 = project_data.iloc[:, 1:2]
```

In [691]:
```
df2.columns
```

Out[691]:
```
Index(['IsBadBuy'], dtype='object')
```

In [692]:
```
df = pd.concat([df1, df2])
```

In [693]:
```
plt.close();
sns.set_style("whitegrid");
sns.pairplot(df1, size=4);
plt.show()
```



Most of numerical Cost variable have linear variation among them

There is high chance of buyer did not buy vehicles

Processing Missing value

In [694]:
```
project_data.head(5)
```

Out[694]:

	RefId	IsBadBuy	Date	Auction	VehYear	VehicleAge	Make	Model	Trim
0	32389	0	2009-01-05	MANHEIM	2007	2	CHRYSLER	PACIFICA FWD 3.8L V6	Bas
1	32406	0	2009-01-05	MANHEIM	2005	4	FORD	FREESTAR FWD V6 3.9L	SES
2	32407	0	2009-01-05	MANHEIM	2004	5	DODGE	STRATUS 4C 2.4L I4 M	SE
3	32408	0	2009-01-05	MANHEIM	2006	3	CHEVROLET	TRAILBLAZER EXT 4WD	LS
4	32409	0	2009-01-05	MANHEIM	2004	5	FORD	TAURUS 3.0L V6 EFI	SES

5 rows × 34 columns

In [695]:
```
project_data.columns[project_data.isnull().any()]
```

Out[695]:
```
Index(['Trim', 'SubModel', 'Color', 'Transmission', 'WheelTypeID', 'WheelTyp
e',
       'Nationality', 'Size', 'TopThreeAmericanName',
       'MMRAcquisitionAuctionAveragePrice', 'MMRAcquisitionAuctionCleanPric
e',
       'MMRAcquisitionRetailAveragePrice', 'MMRAcquisitonRetailCleanPrice',
       'MMRCurrentAuctionAveragePrice', 'MMRCurrentAuctionCleanPrice',
       'MMRCurrentRetailAveragePrice', 'MMRCurrentRetailCleanPrice',
       'PRIMEUNIT', 'AUCGUART'],
      dtype='object')
```

In [696]:
```
# variable having missing value
null_counts = project_data.isnull().sum()
null_counts[null_counts > 0].sort_values(ascending=False)
```

Out[696]:
```
AUCGUART                             69564
PRIMEUNIT                            69564
WheelType                             3174
WheelTypeID                           3169
Trim                                  2360
MMRCurrentAuctionAveragePrice          315
MMRCurrentAuctionCleanPrice            315
MMRCurrentRetailAveragePrice           315
MMRCurrentRetailCleanPrice             315
MMRAcquisitonRetailCleanPrice           18
MMRAcquisitionRetailAveragePrice        18
MMRAcquisitionAuctionCleanPrice         18
MMRAcquisitionAuctionAveragePrice       18
Transmission                             9
Color                                    8
SubModel                                 8
TopThreeAmericanName                     5
Size                                     5
Nationality                              5
dtype: int64
```

In [697]:
```
# variable having missing value
null_counts = project_data_test.isnull().sum()
null_counts[null_counts > 0].sort_values(ascending=False)
```

Out[697]:
```
AUCGUART                             46191
PRIMEUNIT                            46191
WheelTypeID                           2188
WheelType                             2188
Trim                                  1550
MMRCurrentAuctionAveragePrice          143
MMRCurrentAuctionCleanPrice            143
MMRCurrentRetailAveragePrice           143
MMRCurrentRetailCleanPrice             143
MMRAcquisitonRetailCleanPrice           10
MMRAcquisitionRetailAveragePrice        10
MMRAcquisitionAuctionCleanPrice         10
MMRAcquisitionAuctionAveragePrice       10
TopThreeAmericanName                     7
Size                                     7
Nationality                              7
SubModel                                 5
Color                                    4
Transmission                             3
dtype: int64
```

Preprocessing PRIMEUNIT and AUCGUART variable

In [698]:
```
project_data.info(10)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 72983 entries, 0 to 72982
Data columns (total 34 columns):
RefId                                72983 non-null int64
IsBadBuy                             72983 non-null int64
Date                                 72983 non-null datetime64[ns]
Auction                              72983 non-null object
VehYear                              72983 non-null int64
VehicleAge                           72983 non-null int64
Make                                 72983 non-null object
Model                                72983 non-null object
Trim                                 70623 non-null object
SubModel                             72975 non-null object
Color                                72975 non-null object
Transmission                         72974 non-null object
WheelTypeID                          69814 non-null float64
WheelType                            69809 non-null object
VehOdo                               72983 non-null int64
Nationality                          72978 non-null object
Size                                 72978 non-null object
TopThreeAmericanName                 72978 non-null object
MMRAcquisitionAuctionAveragePrice    72965 non-null float64
MMRAcquisitionAuctionCleanPrice      72965 non-null float64
MMRAcquisitionRetailAveragePrice     72965 non-null float64
MMRAcquisitonRetailCleanPrice        72965 non-null float64
MMRCurrentAuctionAveragePrice        72668 non-null float64
MMRCurrentAuctionCleanPrice          72668 non-null float64
MMRCurrentRetailAveragePrice         72668 non-null float64
MMRCurrentRetailCleanPrice           72668 non-null float64
PRIMEUNIT                            3419 non-null object
AUCGUART                             3419 non-null object
BYRNO                                72983 non-null int64
VNZIP1                               72983 non-null int64
VNST                                 72983 non-null object
VehBCost                             72983 non-null float64
IsOnlineSale                         72983 non-null int64
WarrantyCost                         72983 non-null int64
dtypes: datetime64[ns](1), float64(10), int64(9), object(14)
memory usage: 18.9+ MB
```

In [699]:
```
print(project_data["PRIMEUNIT"].value_counts(normalize = True))
print("*"*50)

print(project_data["AUCGUART"].value_counts(normalize = True))
print("*"*50)
```

```
NO     0.981866
YES    0.018134
Name: PRIMEUNIT, dtype: float64
**************************************************
GREEN    0.976894
RED      0.023106
Name: AUCGUART, dtype: float64
**************************************************
```

From above analysis, PRIMEUNIT and AUCGUART variable bith have very number of missing value and among present value they are highly imbalance so it will be better to remove both variable otherwise will create bias problem.

Notes:

```
Some of variable are not useful for model, like RefId,Date, VehYear,W,heelTypeID

VehYear already considered in VehicleAge variable

Data is sorted so PurchDate variable not usefulll.
```

Multiple Imputation using MICE (Multiple Imputation by Chained Equations)

Rest of missing value in both categorical as well as numerical variable filled with the MICE method.

https://pypi.org/project/fancyimpute/ (https://pypi.org/project/fancyimpute/)

https://medium.com/ibm-data-science-experience/missing-data-conundrum-exploration-and-imputation-techniques-9f40abe0fd87 (https://medium.com/ibm-data-science-experience/missing-data-conundrum-exploration-and-imputation-techniques-9f40abe0fd87)

Multiple imputation is a process where the missing values are filled multiple times to create “complete” datasets. Multiple imputation has a lot of advantages over traditional single imputation methods. Multiple Imputation by Chained Equations (MICE) is an imputation method that works with the assumption that the missing data are Missing at Random (MAR). Recall that for MAR, the nature of the missing data is related to the observed data but not the missing data. The MICE algorithm works by running multiple regression models and each missing value is modeled conditionally depending on the observed (non-missing) values. A complete explanation of the MICE algorithm can be seen here. fancyimpute.MICE().complete(data matrix) can be used for MICE implementation.

Usages:

```
from fancyimpute import KNN, NuclearNormMinimization, SoftImpute, BiScaler
```

X is the complete data matrix

X_incomplete has the same values as X except a subset have been replace with NaN

Use 3 nearest rows which have a feature to fill in each row's missing features

X_filled_knn = KNN(k=3).fit_transform(X_incomplete)

matrix completion using convex optimization to find low-rank solution

that still matches observed values. Slow!

X_filled_nnm = NuclearNormMinimization().fit_transform(X_incomplete)

Instead of solving the nuclear norm objective directly, instead

induce sparsity using singular value thresholding

X_incomplete_normalized = BiScaler().fit_transform(X_incomplete)

X_filled_softimpute = SoftImpute().fit_transform(X_incomplete_normalized)

print mean squared error for the imputation methods above

nnm_mse = ((X_filled_nnm[missing_mask] - X[missing_mask]) ** 2).mean()

print("Nuclear norm minimization MSE: %f" % nnm_mse)

softImpute_mse = ((X_filled_softimpute[missing_mask] - X[missing_mask]) ** 2).mean()

print("SoftImpute MSE: %f" % softImpute_mse)

knn_mse = ((X_filled_knn[missing_mask] - X[missing_mask]) ** 2).mean()

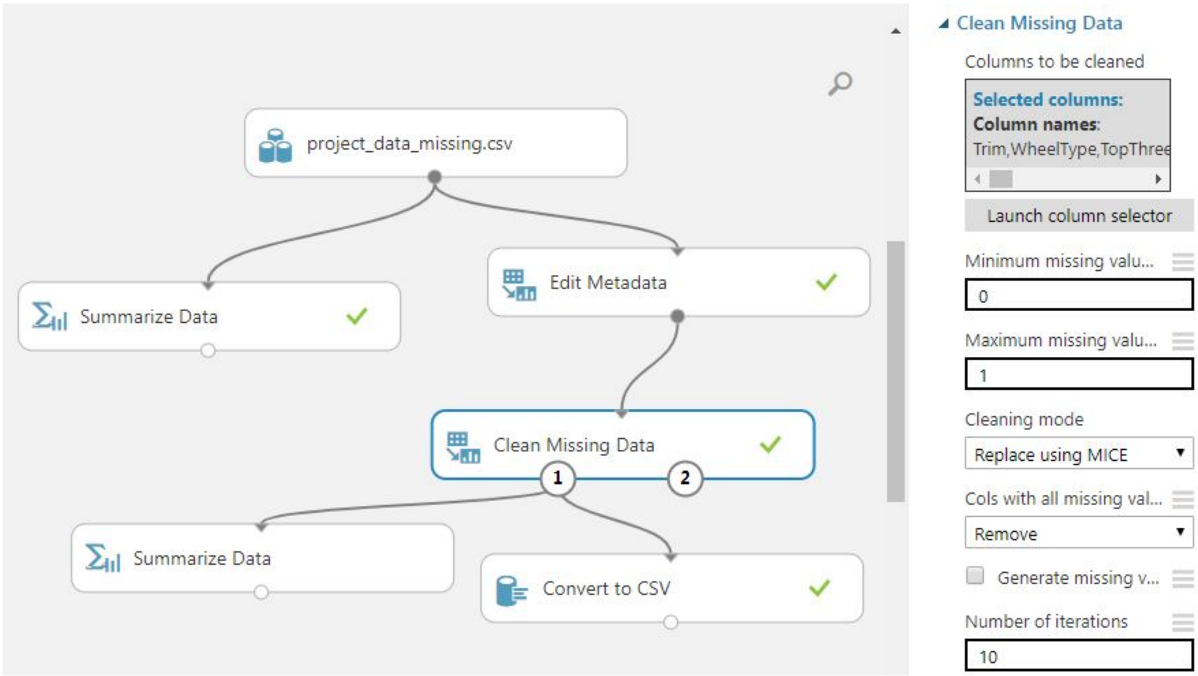
print("knnImpute MSE: %f" % knn_mse)

In [ ]:
```
project_data.to_csv("project_data_missing.csv", index=False)
project_data_test.to_csv("project_data_test_missing.csv", index=False)
```

The missing value filled using Microsoft AZURE Machine Learning studio platform

In [700]:
```
# for training dataset
#https://stackoverflow.com/questions/32370281/how-to-embed-image-or-picture-in
-jupyter-notebook-either-from-a-local-machine-o
from IPython.display import Image
Image("missing_train_azure.jpg")
#Number of iterations=10
```

Out[700]:



In [701]:
```
# for test dataset
#https://stackoverflow.com/questions/32370281/how-to-embed-image-or-picture-in
-jupyter-notebook-either-from-a-local-machine-o
from IPython.display import Image
Image("missing_test_azure.jpg")
#Number of iterations=10
```

Out[701]:

In [ ]:

```

```

Some basic preprocessing(Replacing space with underscore to consider as one value)

Importing dataset after filling Missing value in Azure ML Studio

In [702]:

```
project_data = pd.read_csv('project_data_clean_missing.csv')
project_data_test = pd.read_csv('project_data_test_clean_missing.csv')
```

Preprocessing Model column

In [703]:

```
project_data["Model"][0:5]
```

Out[703]:

```
0    PACIFICA FWD 3.8L V6
1    FREESTAR FWD V6 3.9L
2    STRATUS 4C 2.4L I4 M
3     TRAILBLAZER EXT 4WD
4      TAURUS 3.0L V6 EFI
Name: Model, dtype: object
```

In [704]:

```
project_data["Model"].unique()
```

Out[704]:

```
array(['PACIFICA FWD 3.8L V6', 'FREESTAR FWD V6 3.9L',
       'STRATUS 4C 2.4L I4 M', ..., 'LHS', 'ARMADA 4WD V8', 'S60'],
      dtype=object)
```

Since model is unique value, it will be useful to replace space with underscore

In [705]:

```
Model = []
for i in range(len(project_data)):
    a = project_data["Model"][i].replace(" ", "_")
    Model.append(a)
```

In [706]:

```
Model[0:5]
```

Out[706]:

```
['PACIFICA_FWD_3.8L_V6',
 'FREESTAR_FWD_V6_3.9L',
 'STRATUS_4C_2.4L_I4_M',
 'TRAILBLAZER_EXT_4WD',
 'TAURUS_3.0L_V6_EFI']
```

In [707]:

```
project_data.drop(['Model'], axis=1, inplace=True)
project_data["Model"] = Model
```

In [708]:
```
project_data["Model"].unique()
```

Out[708]:
```
array(['PACIFICA_FWD_3.8L_V6', 'FREESTAR_FWD_V6_3.9L',
       'STRATUS_4C_2.4L_I4_M', ..., 'LHS', 'ARMADA_4WD_V8', 'S60'],
      dtype=object)
```

In [709]:
```
#test
Model = []
for i in range(len(project_data_test)):
    a = project_data_test["Model"][i].replace(" ", "_")
    Model.append(a)
```

In [710]:
```
project_data_test.drop(['Model'], axis=1, inplace=True)
project_data_test["Model"] = Model
```

Preprocessing SubModel column

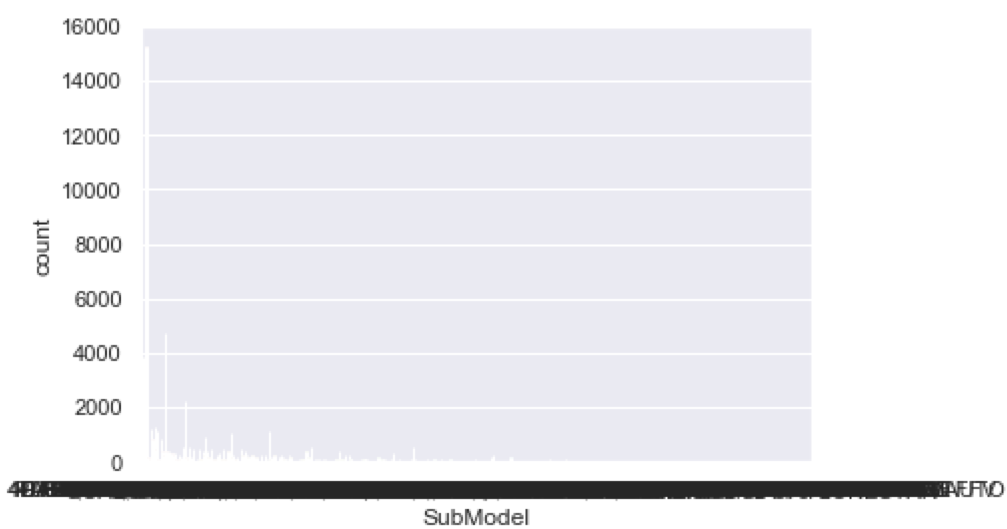
In [711]:
```
type(project_data["SubModel"])
```

Out[711]:
```
pandas.core.series.Series
```

In [712]:
```
project_data["SubModel"][0:5]
```

Out[712]:
```
0                  4D SPORT
1    4D PASSENGER 3.9L SES
2               4D SEDAN SE
3               4D SUV 4.2L
4     4D SEDAN SES DURATEC
Name: SubModel, dtype: object
```

In [713]:
```
import seaborn as sns
sns.set(style="darkgrid")
ax = sns.countplot(x="SubModel", data=project_data)
```



In [714]:
```
project_data['SubModel'] = project_data['SubModel'].astype(str).str.replace(" ", "_")
project_data["SubModel"][0:5]
```

Out[714]:
```
0                  4D_SPORT
1     4D_PASSENGER_3.9L_SES
2               4D_SEDAN_SE
3               4D_SUV_4.2L
4      4D_SEDAN_SES_DURATEC
Name: SubModel, dtype: object
```

In [715]:
```
project_data_test['SubModel'] = project_data_test['SubModel'].astype(str).str.replace(" ", "_")
project_data_test["SubModel"][0:5]
```

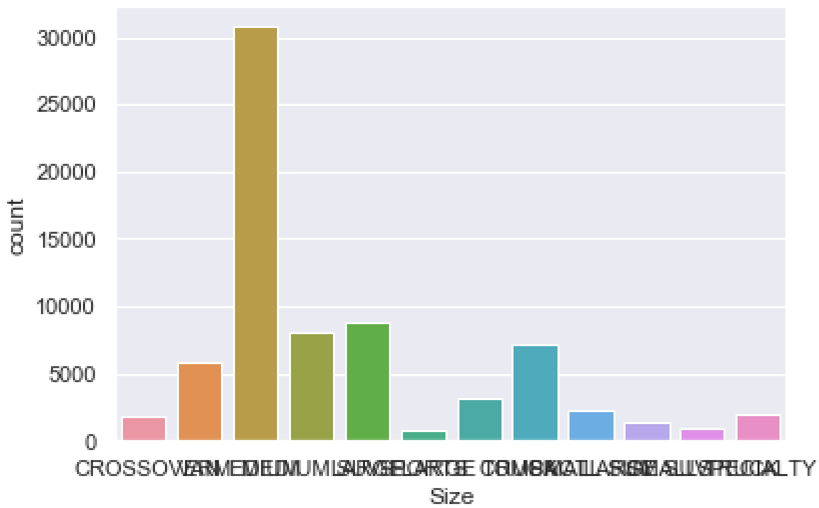
Out[715]:
```
0             4D_SEDAN
1             4D_SEDAN
2             4D_SEDAN
3             4D_SEDAN
4     4D_SEDAN_CLASSIC
Name: SubModel, dtype: object
```

Preprocessing Size column

In [716]:
```
project_data["Size"].value_counts()
```

Out[716]:
```
MEDIUM         30786
LARGE           8850
MEDIUM SUV      8091
COMPACT         7205
VAN             5854
LARGE TRUCK     3170
SMALL SUV       2278
SPECIALTY       1915
CROSSOVER       1759
LARGE SUV       1433
SMALL TRUCK      865
SPORTS           777
Name: Size, dtype: int64
```

In [717]:
```
import seaborn as sns
sns.set(style="darkgrid")
ax = sns.countplot(x="Size", data=project_data)
```



In [718]:
```
#filling missing value with mode value in train data
#project_data['Size'].fillna(project_data['Size'].mode()[0], inplace=True)
```

In [719]:
```
project_data['Size'] = project_data['Size'].astype(str).str.replace(" ", "_")
project_data["Size"].value_counts()
```

Out[719]:
```
MEDIUM          30786
LARGE            8850
MEDIUM_SUV       8091
COMPACT          7205
VAN              5854
LARGE_TRUCK      3170
SMALL_SUV        2278
SPECIALTY        1915
CROSSOVER        1759
LARGE_SUV        1433
SMALL_TRUCK       865
SPORTS            777
Name: Size, dtype: int64
```

In [720]:
```
project_data["Size"].unique()
```

Out[720]:
```
array(['CROSSOVER', 'VAN', 'MEDIUM', 'MEDIUM_SUV', 'LARGE', 'SPORTS',
       'LARGE_TRUCK', 'COMPACT', 'SMALL_SUV', 'LARGE_SUV', 'SMALL_TRUCK',
       'SPECIALTY'], dtype=object)
```

In [721]:
```
project_data_test['Size'] = project_data_test['Size'].astype(str).str.replace(
" ", "_")
project_data_test["Size"].value_counts()
```

Out[721]:
```
MEDIUM          20365
LARGE            5711
MEDIUM_SUV       5455
COMPACT          4882
VAN              4042
LARGE_TRUCK      2069
SMALL_SUV        1575
SPECIALTY        1446
CROSSOVER        1286
LARGE_SUV         868
SPORTS            516
SMALL_TRUCK       492
Name: Size, dtype: int64
```

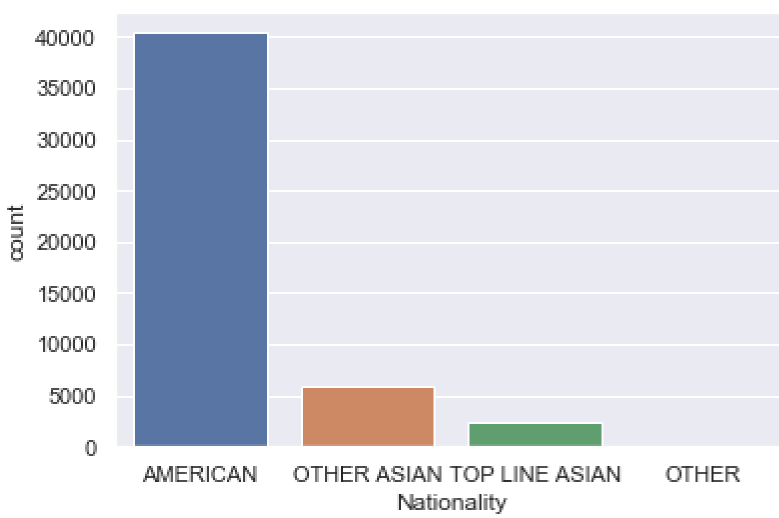
In [ ]:

Preprocessing Nationality column

In [722]:
```
project_data["Nationality"].value_counts()
```

Out[722]:
```
AMERICAN          61033
OTHER ASIAN        8033
TOP LINE ASIAN     3722
OTHER               195
Name: Nationality, dtype: int64
```

In [723]:
```
import seaborn as sns
sns.set(style="darkgrid")
ax = sns.countplot(x="Nationality", data=project_data_test)
```



In [724]:
```
#filling missing value with mode value in train
#project_data['Nationality'].fillna(project_data['Nationality'].mode()[0], inp
lace=True)
```

In [725]:
```
project_data['Nationality'] = project_data['Nationality'].astype(str).str.repl
ace(" ", "_")
project_data["Nationality"].value_counts()
```

Out[725]:
```
AMERICAN          61033
OTHER_ASIAN        8033
TOP_LINE_ASIAN     3722
OTHER               195
Name: Nationality, dtype: int64
```

In [726]:
```
project_data_test['Nationality'] = project_data_test['Nationality'].astype(str
).str.replace(" ", "_")
project_data_test["Nationality"].value_counts()
```

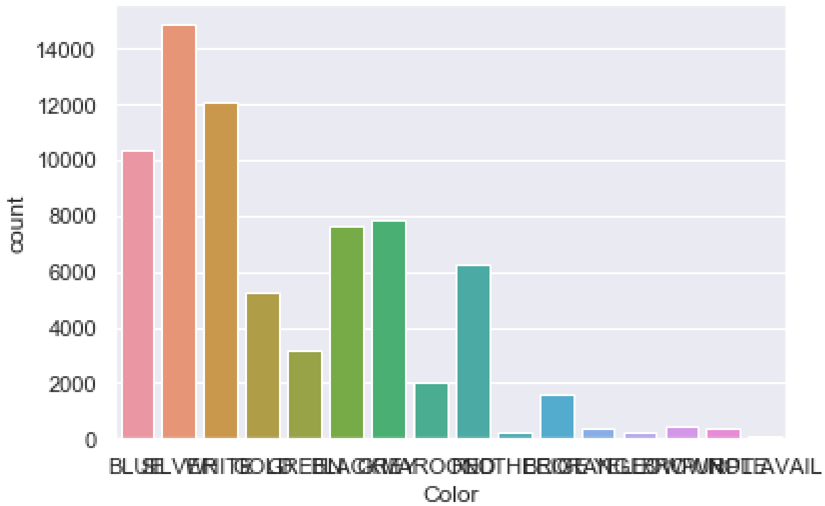
Out[726]:
```
AMERICAN          40420
OTHER_ASIAN        5838
TOP_LINE_ASIAN     2326
OTHER               123
Name: Nationality, dtype: int64
```

Preprocessing Color column

In [727]:
```
project_data["Color"].value_counts()
```

Out[727]:
```
SILVER       14877
WHITE        12125
BLUE         10349
GREY          7888
BLACK         7627
RED           6258
GOLD          5231
GREEN         3194
MAROON        2046
BEIGE         1584
BROWN          436
ORANGE         415
PURPLE         373
YELLOW         244
OTHER          242
NOT AVAIL       94
Name: Color, dtype: int64
```

In [728]:
```
import seaborn as sns
sns.set(style="darkgrid")
ax = sns.countplot(x="Color", data=project_data)
```



In [729]:
```
project_data['Color'] = project_data['Color'].astype(str).str.replace(" ", "_"
)
project_data["Color"].value_counts()
```

Out[729]:
```
SILVER       14877
WHITE        12125
BLUE         10349
GREY          7888
BLACK         7627
RED           6258
GOLD          5231
GREEN         3194
MAROON        2046
BEIGE         1584
BROWN          436
ORANGE         415
PURPLE         373
YELLOW         244
OTHER          242
NOT_AVAIL       94
Name: Color, dtype: int64
```

In [730]:
```
project_data_test['Color'] = project_data_test['Color'].astype(str).str.replac
e(" ", "_")
project_data_test["Color"].value_counts()
```

Out[730]:
```
SILVER       10084
WHITE         8056
BLUE          6840
BLACK         5177
GREY          5077
RED           4166
GOLD          3401
GREEN         2318
MAROON        1308
BEIGE         1070
PURPLE         295
BROWN          278
ORANGE         238
YELLOW         181
OTHER          128
NOT_AVAIL       89
PINK             1
Name: Color, dtype: int64
```

Preprocessing Make column

In [731]:
```
project_data["Make"].value_counts()
```

Out[731]:
```
CHEVROLET       17248
DODGE           12912
FORD            11305
CHRYSLER         8844
PONTIAC          4258
KIA              2484
SATURN           2163
NISSAN           2085
HYUNDAI          1811
JEEP             1644
SUZUKI           1328
TOYOTA           1144
MITSUBISHI       1030
MAZDA             979
MERCURY           913
BUICK             720
GMC               649
HONDA             497
OLDSMOBILE        243
ISUZU             134
VOLKSWAGEN        134
SCION             129
LINCOLN            97
INFINITI           42
VOLVO              37
ACURA              33
CADILLAC           33
LEXUS              31
SUBARU             28
MINI               24
PLYMOUTH            2
TOYOTA SCION        1
HUMMER              1
Name: Make, dtype: int64
```

In [732]:
```
project_data['Make'] = project_data['Make'].astype(str).str.replace(" ", "_")
project_data["Make"].value_counts()
```

Out[732]:
```
CHEVROLET       17248
DODGE           12912
FORD            11305
CHRYSLER         8844
PONTIAC          4258
KIA              2484
SATURN           2163
NISSAN           2085
HYUNDAI          1811
JEEP             1644
SUZUKI           1328
TOYOTA           1144
MITSUBISHI       1030
MAZDA             979
MERCURY           913
BUICK             720
GMC               649
HONDA             497
OLDSMOBILE        243
ISUZU             134
VOLKSWAGEN        134
SCION             129
LINCOLN            97
INFINITI           42
VOLVO              37
ACURA              33
CADILLAC           33
LEXUS              31
SUBARU             28
MINI               24
PLYMOUTH            2
TOYOTA_SCION        1
HUMMER              1
Name: Make, dtype: int64
```

In [733]:
```
project_data_test['Make'] = project_data_test['Make'].astype(str).str.replace(
" ", "_")
project_data_test["Make"].value_counts()
```

Out[733]:
```
CHEVROLET     11486
DODGE          8095
FORD           7441
CHRYSLER       6050
PONTIAC        3001
KIA            1914
SATURN         1392
HYUNDAI        1311
NISSAN         1228
JEEP           1187
SUZUKI          873
MITSUBISHI      783
TOYOTA          780
MAZDA           704
MERCURY         620
BUICK           500
GMC             388
HONDA           318
OLDSMOBILE      163
ISUZU            85
SCION            85
VOLKSWAGEN       71
LINCOLN          66
VOLVO            42
CADILLAC         29
INFINITI         28
ACURA            26
LEXUS            19
SUBARU           12
MINI             10
Name: Make, dtype: int64
```

In [ ]:

In [734]:
```
project_data.info(10)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 72983 entries, 0 to 72982
Data columns (total 34 columns):
RefId                                72983 non-null int64
IsBadBuy                             72983 non-null int64
Date                                 72983 non-null object
Auction                              72983 non-null object
VehYear                              72983 non-null int64
VehicleAge                           72983 non-null int64
Make                                 72983 non-null object
Trim                                 72983 non-null object
SubModel                             72983 non-null object
Color                                72983 non-null object
Transmission                         72983 non-null object
WheelTypeID                          69814 non-null float64
WheelType                            72983 non-null object
VehOdo                               72983 non-null int64
Nationality                          72983 non-null object
Size                                 72983 non-null object
TopThreeAmericanName                 72983 non-null object
MMRAcquisitionAuctionAveragePrice    72983 non-null float64
MMRAcquisitionAuctionCleanPrice      72983 non-null float64
MMRAcquisitionRetailAveragePrice     72983 non-null float64
MMRAcquisitonRetailCleanPrice        72983 non-null float64
MMRCurrentAuctionAveragePrice        72983 non-null float64
MMRCurrentAuctionCleanPrice          72983 non-null float64
MMRCurrentRetailAveragePrice         72983 non-null float64
MMRCurrentRetailCleanPrice           72983 non-null float64
PRIMEUNIT                            3419 non-null object
AUCGUART                             3419 non-null object
BYRNO                                72983 non-null int64
VNZIP1                               72983 non-null int64
VNST                                 72983 non-null object
VehBCost                             72983 non-null float64
IsOnlineSale                         72983 non-null int64
WarrantyCost                         72983 non-null int64
Model                                72983 non-null object
dtypes: float64(10), int64(9), object(15)
memory usage: 18.9+ MB
```

Processing Missing data

In [735]:
```
# variable having missing value
null_counts = project_data.isnull().sum()
null_counts[null_counts > 0].sort_values(ascending=False)
```

Out[735]:
```
AUCGUART       69564
PRIMEUNIT      69564
WheelTypeID     3169
dtype: int64
```

In [736]:
```
# variable having missing value
null_counts = project_data_test.isnull().sum()
null_counts[null_counts > 0].sort_values(ascending=False)
```

Out[736]:
```
AUCGUART       46191
PRIMEUNIT      46191
WheelTypeID     2188
dtype: int64
```

In [ ]:

Split dataset into test train and cv

In [432]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import model_selection
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score

from collections import Counter
from sklearn.metrics import accuracy_score

from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_validate

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
```

In [499]:
```
project_data.head(10)
```

Out[499]:

	RefId	IsBadBuy	Date	Auction	VehYear	VehicleAge	Make	Trim	
0	32389	0	1/5/2009 12:00:00 AM	MANHEIM	2007	2	CHRYSLER	Bas	
1	32406	0	1/5/2009 12:00:00 AM	MANHEIM	2005	4	FORD	SES	4D_PASSENG
2	32407	0	1/5/2009 12:00:00 AM	MANHEIM	2004	5	DODGE	SE	4
3	32408	0	1/5/2009 12:00:00 AM	MANHEIM	2006	3	CHEVROLET	LS	
4	32409	0	1/5/2009 12:00:00 AM	MANHEIM	2004	5	FORD	SES	4D_SEDAN_S
5	8884	0	1/5/2009 12:00:00 AM	MANHEIM	2005	4	CHEVROLET	Bas	
6	8883	0	1/5/2009 12:00:00 AM	MANHEIM	2003	6	FORD	Bas	
7	8882	0	1/5/2009 12:00:00 AM	MANHEIM	2004	5	DODGE	SXT	4
8	8881	0	1/5/2009 12:00:00 AM	MANHEIM	2004	5	DODGE	SLT	
9	8880	1	1/5/2009 12:00:00 AM	MANHEIM	2006	3	FORD	SE	4D_

10 rows × 34 columns

In [501]:
```
project_data["IsBadBuy"].value_counts()
```

Out[501]:
```
0    64007
1     8976
Name: IsBadBuy, dtype: int64
```

Dataset is highly imbalane so not possible to split on time base

In [502]:
```
y=project_data["IsBadBuy"]
```

In [503]:
```
x=project_data.drop(['IsBadBuy'], axis=1)
```

In [ ]:

In [504]:
```
from sklearn.model_selection import train_test_split
x_train, x_cv, y_train, y_cv = train_test_split(x, y,
                                                    stratify=y,
                                                    test_size=0.3)
```

In [505]:
```
x_test=project_data_test
```

In [506]:
```
x_train.head(5)
```

Out[506]:

	RefId	Date	Auction	VehYear	VehicleAge	Make	Trim	SubModel
70092	63302	11/30/2010 12:00:00 AM	MANHEIM	2005	5	FORD	XLT	4D_CUV_3.0L_XLT
61749	12950	9/27/2010 12:00:00 AM	MANHEIM	2008	2	CHEVROLET	LS	4D_SEDAN_LS
67834	4486	11/10/2010 12:00:00 AM	OTHER	2003	7	FORD	SE	4D_SEDAN_SE
45665	65805	4/15/2010 12:00:00 AM	MANHEIM	2002	8	FORD	SE	4D_WAGON_SE
44361	11399	4/2/2010 12:00:00 AM	MANHEIM	2006	4	FORD	SE	4D_SEDAN_SE

5 rows × 33 columns

In [507]:
```
x_train["IsOnlineSale"].value_counts()
```

Out[507]:
```
0    49783
1     1305
Name: IsOnlineSale, dtype: int64
```

In [508]:
```
y_train.head(10)
```

Out[508]:
```
70092    0
61749    0
67834    1
45665    0
44361    0
4058     0
6334     0
51259    0
2394     0
61451    1
Name: IsBadBuy, dtype: int64
```

In [509]:
```
y_train.value_counts()
```

Out[509]:
```
0    44805
1     6283
Name: IsBadBuy, dtype: int64
```

In [510]:
```
y_cv.value_counts()
```

Out[510]:
```
0    19202
1     2693
Name: IsBadBuy, dtype: int64
```

Now ratio is almost same in both case of 0 and 1

In [511]:
```
x_train.info(5)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 51088 entries, 70092 to 25710
Data columns (total 33 columns):
RefId                                    51088 non-null int64
Date                                     51088 non-null object
Auction                                  51088 non-null object
VehYear                                  51088 non-null int64
VehicleAge                               51088 non-null int64
Make                                     51088 non-null object
Trim                                     51088 non-null object
SubModel                                 51088 non-null object
Color                                    51088 non-null object
Transmission                             51088 non-null object
WheelTypeID                              48916 non-null float64
WheelType                                51088 non-null object
VehOdo                                   51088 non-null int64
Nationality                              51088 non-null object
Size                                     51088 non-null object
TopThreeAmericanName                     51088 non-null object
MMRAcquisitionAuctionAveragePrice        51088 non-null float64
MMRAcquisitionAuctionCleanPrice          51088 non-null float64
MMRAcquisitionRetailAveragePrice         51088 non-null float64
MMRAcquisitonRetailCleanPrice            51088 non-null float64
MMRCurrentAuctionAveragePrice            51088 non-null float64
MMRCurrentAuctionCleanPrice              51088 non-null float64
MMRCurrentRetailAveragePrice             51088 non-null float64
MMRCurrentRetailCleanPrice               51088 non-null float64
PRIMEUNIT                                2413 non-null object
AUCGUART                                 2413 non-null object
BYRNO                                    51088 non-null int64
VNZIP1                                   51088 non-null int64
VNST                                     51088 non-null object
VehBCost                                 51088 non-null float64
IsOnlineSale                             51088 non-null int64
WarrantyCost                             51088 non-null int64
Model                                    51088 non-null object
dtypes: float64(10), int64(8), object(15)
memory usage: 13.3+ MB
```

Data preprocessing(one hot encoding) for categorical data

In [512]:
```
#you can vectorize the Auction
# ______________________________
#https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.
text.CountVectorizer.html

vectorizer = CountVectorizer()
vectorizer.fit(x_train['Auction'].values)# fit has to apply only on train data

# we use fitted CountVectorizer to convert the text to vector
x_train_Auction = vectorizer.transform(x_train['Auction'].values)
x_cv_Auction = vectorizer.transform(x_cv['Auction'].values)
x_test_Auction = vectorizer.transform(x_test['Auction'].values)

print("Shape of matrix after one hot encodig ",x_train_Auction.shape, y_train.
shape)
print("Shape of matrix after one hot encodig ",x_cv_Auction.shape, y_cv.shape)
print("Shape of matrix after one hot encodig ",x_test_Auction.shape)
```

```
Shape of matrix after one hot encodig  (51088, 3) (51088,)
Shape of matrix after one hot encodig  (21895, 3) (21895,)
Shape of matrix after one hot encodig  (48707, 3)
```

In [513]:
```
#you can vectorize the Make
# ______________________________
#https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.
text.CountVectorizer.html

vectorizer = CountVectorizer()
vectorizer.fit(x_train['Make'].values)# fit has to apply only on train data

# we use fitted CountVectorizer to convert the text to vector
x_train_Make = vectorizer.transform(x_train['Make'].values)
x_cv_Make = vectorizer.transform(x_cv['Make'].values)
x_test_Make = vectorizer.transform(x_test['Make'].values)

print("Shape of matrix after one hot encodig ",x_train_Make.shape, y_train.sha
pe)
print("Shape of matrix after one hot encodig ",x_cv_Make.shape, y_cv.shape)
print("Shape of matrix after one hot encodig ",x_test_Make.shape)
```

```
Shape of matrix after one hot encodig  (51088, 33) (51088,)
Shape of matrix after one hot encodig  (21895, 33) (21895,)
Shape of matrix after one hot encodig  (48707, 33)
```

In [514]:
```
#you can vectorize the Trim
#______________________________
#https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.
text.CountVectorizer.html

vectorizer = CountVectorizer()
vectorizer.fit(x_train['Trim'].values)# fit has to apply only on train data

# we use fitted CountVectorizer to convert the text to vector
x_train_Trim = vectorizer.transform(x_train['Trim'].values)
x_cv_Trim = vectorizer.transform(x_cv['Trim'].values)
x_test_Trim = vectorizer.transform(x_test['Trim'].values)

print("Shape of matrix after one hot encodig ",x_train_Trim.shape, y_train.sha
pe)
print("Shape of matrix after one hot encodig ",x_cv_Trim.shape, y_cv.shape)
print("Shape of matrix after one hot encodig ",x_test_Trim.shape)
```

```
Shape of matrix after one hot encodig  (51088, 117) (51088,)
Shape of matrix after one hot encodig  (21895, 117) (21895,)
Shape of matrix after one hot encodig  (48707, 117)
```

In [515]:
```
#you can vectorize the SubModel
#______________________________
#https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.
text.CountVectorizer.html

vectorizer = CountVectorizer()
vectorizer.fit(x_train['SubModel'].values)# fit has to apply only on train dat
a

# we use fitted CountVectorizer to convert the text to vector
x_train_SubModel = vectorizer.transform(x_train['SubModel'].values)
x_cv_SubModel = vectorizer.transform(x_cv['SubModel'].values)
x_test_SubModel = vectorizer.transform(x_test['SubModel'].values)

print("Shape of matrix after one hot encodig ",x_train_SubModel.shape, y_train
.shape)
print("Shape of matrix after one hot encodig ",x_cv_SubModel.shape, y_cv.shape
)
print("Shape of matrix after one hot encodig ",x_test_SubModel.shape)
```

```
Shape of matrix after one hot encodig  (51088, 629) (51088,)
Shape of matrix after one hot encodig  (21895, 629) (21895,)
Shape of matrix after one hot encodig  (48707, 629)
```

In [ ]:

In [ ]:

In [516]:
```
#you can vectorize the Color
#______________________________
#https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.
text.CountVectorizer.html

vectorizer = CountVectorizer()
vectorizer.fit(x_train['Color'].values)# fit has to apply only on train data

# we use fitted CountVectorizer to convert the text to vector
x_train_Color = vectorizer.transform(x_train['Color'].values)
x_cv_Color = vectorizer.transform(x_cv['Color'].values)
x_test_Color = vectorizer.transform(x_test['Color'].values)

print("Shape of matrix after one hot encodig ",x_train_Color.shape, y_train.sh
ape)
print("Shape of matrix after one hot encodig ",x_cv_Color.shape, y_cv.shape)
print("Shape of matrix after one hot encodig ",x_test_Color.shape)
```

```
Shape of matrix after one hot encodig  (51088, 16) (51088,)
Shape of matrix after one hot encodig  (21895, 16) (21895,)
Shape of matrix after one hot encodig  (48707, 16)
```

In [517]:
```
#you can vectorize the Transmission
#______________________________
#https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.
text.CountVectorizer.html

vectorizer = CountVectorizer()
vectorizer.fit(x_train['Transmission'].values)# fit has to apply only on train
data

# we use fitted CountVectorizer to convert the text to vector
x_train_Transmission = vectorizer.transform(x_train['Transmission'].values)
x_cv_Transmission = vectorizer.transform(x_cv['Transmission'].values)
x_test_Transmission = vectorizer.transform(x_test['Transmission'].values)

print("Shape of matrix after one hot encodig ",x_train_Transmission.shape, y_t
rain.shape)
print("Shape of matrix after one hot encodig ",x_cv_Transmission.shape, y_cv.s
hape)
print("Shape of matrix after one hot encodig ",x_test_Transmission.shape)
```

```
Shape of matrix after one hot encodig  (51088, 2) (51088,)
Shape of matrix after one hot encodig  (21895, 2) (21895,)
Shape of matrix after one hot encodig  (48707, 2)
```

In [518]:
```
#you can vectorize the WheelType
#______________________________
#https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.
text.CountVectorizer.html

vectorizer = CountVectorizer()
vectorizer.fit(x_train['WheelType'].values)# fit has to apply only on train da
ta

# we use fitted CountVectorizer to convert the text to vector
x_train_WheelType = vectorizer.transform(x_train['WheelType'].values)
x_cv_WheelType = vectorizer.transform(x_cv['WheelType'].values)
x_test_WheelType = vectorizer.transform(x_test['WheelType'].values)

print("Shape of matrix after one hot encodig ",x_train_WheelType.shape, y_trai
n.shape)
print("Shape of matrix after one hot encodig ",x_cv_WheelType.shape, y_cv.shap
e)
print("Shape of matrix after one hot encodig ",x_test_WheelType.shape)
```

```
Shape of matrix after one hot encodig  (51088, 3) (51088,)
Shape of matrix after one hot encodig  (21895, 3) (21895,)
Shape of matrix after one hot encodig  (48707, 3)
```

In [519]:
```
#you can vectorize the Nationality
#______________________________
#https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.
text.CountVectorizer.html

vectorizer = CountVectorizer()
vectorizer.fit(x_train['Nationality'].values)# fit has to apply only on train
 data

# we use fitted CountVectorizer to convert the text to vector
x_train_Nationality = vectorizer.transform(x_train['Nationality'].values)
x_cv_Nationality = vectorizer.transform(x_cv['Nationality'].values)
x_test_Nationality = vectorizer.transform(x_test['Nationality'].values)

print("Shape of matrix after one hot encodig ",x_train_Nationality.shape, y_tr
ain.shape)
print("Shape of matrix after one hot encodig ",x_cv_Nationality.shape, y_cv.sh
ape)
print("Shape of matrix after one hot encodig ",x_test_Nationality.shape)
```

```
Shape of matrix after one hot encodig  (51088, 4) (51088,)
Shape of matrix after one hot encodig  (21895, 4) (21895,)
Shape of matrix after one hot encodig  (48707, 4)
```

In [520]:
```
#you can vectorize the Size
#_______________________________
#https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.
text.CountVectorizer.html

vectorizer = CountVectorizer()
vectorizer.fit(x_train['Size'].values)# fit has to apply only on train data

# we use fitted CountVectorizer to convert the text to vector
x_train_Size = vectorizer.transform(x_train['Size'].values)
x_cv_Size = vectorizer.transform(x_cv['Size'].values)
x_test_Size = vectorizer.transform(x_test['Size'].values)

print("Shape of matrix after one hot encodig ",x_train_Size.shape, y_train.sha
pe)
print("Shape of matrix after one hot encodig ",x_cv_Size.shape, y_cv.shape)
print("Shape of matrix after one hot encodig ",x_test_Size.shape)
```

```
Shape of matrix after one hot encodig  (51088, 12) (51088,)
Shape of matrix after one hot encodig  (21895, 12) (21895,)
Shape of matrix after one hot encodig  (48707, 12)
```

In [521]:
```
#you can vectorize the TopThreeAmericanName
#_______________________________
#https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.
text.CountVectorizer.html

vectorizer = CountVectorizer()
vectorizer.fit(x_train['TopThreeAmericanName'].values)# fit has to apply only
 on train data

# we use fitted CountVectorizer to convert the text to vector
x_train_TopThreeAmericanName = vectorizer.transform(x_train['TopThreeAmericanN
ame'].values)
x_cv_TopThreeAmericanName = vectorizer.transform(x_cv['TopThreeAmericanName'].
values)
x_test_TopThreeAmericanName = vectorizer.transform(x_test['TopThreeAmericanNam
e'].values)

print("Shape of matrix after one hot encodig ",x_train_TopThreeAmericanName.sh
ape, y_train.shape)
print("Shape of matrix after one hot encodig ",x_cv_TopThreeAmericanName.shape
, y_cv.shape)
print("Shape of matrix after one hot encodig ",x_test_TopThreeAmericanName.sha
pe)
```

```
Shape of matrix after one hot encodig  (51088, 4) (51088,)
Shape of matrix after one hot encodig  (21895, 4) (21895,)
Shape of matrix after one hot encodig  (48707, 4)
```

In [522]:
```
#you can vectorize the VNST
#______________________________
#https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.
text.CountVectorizer.html

vectorizer = CountVectorizer()
vectorizer.fit(x_train['VNST'].values)# fit has to apply only on train data

# we use fitted CountVectorizer to convert the text to vector
x_train_VNST = vectorizer.transform(x_train['VNST'].values)
x_cv_VNST = vectorizer.transform(x_cv['VNST'].values)
x_test_VNST = vectorizer.transform(x_test['VNST'].values)

print("Shape of matrix after one hot encodig ",x_train_VNST.shape, y_train.sha
pe)
print("Shape of matrix after one hot encodig ",x_cv_VNST.shape, y_cv.shape)
print("Shape of matrix after one hot encodig ",x_test_VNST.shape)
```

```
Shape of matrix after one hot encodig  (51088, 37) (51088,)
Shape of matrix after one hot encodig  (21895, 37) (21895,)
Shape of matrix after one hot encodig  (48707, 37)
```

In [523]:
```
#you can vectorize the Model
#______________________________
#https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.
text.CountVectorizer.html

vectorizer = CountVectorizer()
vectorizer.fit(x_train['Model'].values)# fit has to apply only on train data

# we use fitted CountVectorizer to convert the text to vector
x_train_Model = vectorizer.transform(x_train['Model'].values)
x_cv_Model = vectorizer.transform(x_cv['Model'].values)
x_test_Model = vectorizer.transform(x_test['Model'].values)

print("Shape of matrix after one hot encodig ",x_train_Model.shape, y_train.sh
ape)
print("Shape of matrix after one hot encodig ",x_cv_Model.shape, y_cv.shape)
print("Shape of matrix after one hot encodig ",x_test_Model.shape)
```

```
Shape of matrix after one hot encodig  (51088, 1030) (51088,)
Shape of matrix after one hot encodig  (21895, 1030) (21895,)
Shape of matrix after one hot encodig  (48707, 1030)
```

Merge categorical dataset

In [525]:
```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
# with the same hstack function we are concatinating a sparse matrix and a den
se matirx :)
x_train_categorical = hstack((x_train_Auction,x_train_Make,x_train_Trim,x_trai
n_SubModel,x_train_Color,x_train_Transmission,x_train_WheelType,x_train_Nation
ality,x_train_Size,x_train_TopThreeAmericanName,x_train_VNST,x_train_Model))
x_cv_categorical = hstack((x_cv_Auction,x_cv_Make,x_cv_Trim,x_cv_SubModel,x_cv
_Color,x_cv_Transmission,x_cv_WheelType,x_cv_Nationality,x_cv_Size,x_cv_TopThr
eeAmericanName,x_cv_VNST,x_cv_Model))
x_test_categorical = hstack((x_test_Auction,x_test_Make,x_test_Trim,x_test_Sub
Model,x_test_Color,x_test_Transmission,x_test_WheelType,x_test_Nationality,x_t
est_Size,x_test_TopThreeAmericanName,x_test_VNST,x_test_Model))

print(x_train_categorical.shape)
print(x_cv_categorical.shape)
print(x_test_categorical.shape)
```

```
(51088, 1890)
(21895, 1890)
(48707, 1890)
```

In [ ]:

Encoding numerical features(Normalize)

In [526]:
```
x_train.info(5)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 51088 entries, 70092 to 25710
Data columns (total 33 columns):
RefId                                 51088 non-null int64
Date                                  51088 non-null object
Auction                               51088 non-null object
VehYear                               51088 non-null int64
VehicleAge                            51088 non-null int64
Make                                  51088 non-null object
Trim                                  51088 non-null object
SubModel                              51088 non-null object
Color                                 51088 non-null object
Transmission                          51088 non-null object
WheelTypeID                           48916 non-null float64
WheelType                             51088 non-null object
VehOdo                                51088 non-null int64
Nationality                           51088 non-null object
Size                                  51088 non-null object
TopThreeAmericanName                  51088 non-null object
MMRAcquisitionAuctionAveragePrice     51088 non-null float64
MMRAcquisitionAuctionCleanPrice       51088 non-null float64
MMRAcquisitionRetailAveragePrice      51088 non-null float64
MMRAcquisitonRetailCleanPrice         51088 non-null float64
MMRCurrentAuctionAveragePrice         51088 non-null float64
MMRCurrentAuctionCleanPrice           51088 non-null float64
MMRCurrentRetailAveragePrice          51088 non-null float64
MMRCurrentRetailCleanPrice            51088 non-null float64
PRIMEUNIT                             2413 non-null object
AUCGUART                              2413 non-null object
BYRNO                                 51088 non-null int64
VNZIP1                                51088 non-null int64
VNST                                  51088 non-null object
VehBCost                              51088 non-null float64
IsOnlineSale                          51088 non-null int64
WarrantyCost                          51088 non-null int64
Model                                 51088 non-null object
dtypes: float64(10), int64(8), object(15)
memory usage: 13.3+ MB
```

In [527]:

```
#vectorize the VehOdo
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['VehOdo'].values.reshape(-1,1))

x_train_VehOdo = normalizer.transform(x_train['VehOdo'].values.reshape(-1,1))
x_cv_VehOdo = normalizer.transform(x_cv['VehOdo'].values.reshape(-1,1))
x_test_VehOdo = normalizer.transform(x_test['VehOdo'].values.reshape(-1,1))

print("After vectorizations")
print(x_train_VehOdo.shape, y_train.shape)
print(x_cv_VehOdo.shape, y_cv.shape)
print(x_test_VehOdo.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

In [528]:

```
#vectorize the VehicleAge
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['VehicleAge'].values.reshape(-1,1))

x_train_VehicleAge = normalizer.transform(x_train['VehicleAge'].values.reshape
(-1,1))
x_cv_VehicleAge = normalizer.transform(x_cv['VehicleAge'].values.reshape(-1,1
))
x_test_VehicleAge = normalizer.transform(x_test['VehicleAge'].values.reshape(-
1,1))

print("After vectorizations")
print(x_train_VehicleAge.shape, y_train.shape)
print(x_cv_VehicleAge.shape, y_cv.shape)
print(x_test_VehicleAge.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

In [529]:
```
#vectorize the MMRAcquisitionAuctionAveragePrice
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['MMRAcquisitionAuctionAveragePrice'].values.reshape(-1,
1))

x_train_MMRAcquisitionAuctionAveragePrice = normalizer.transform(x_train['MMRA
cquisitionAuctionAveragePrice'].values.reshape(-1,1))
x_cv_MMRAcquisitionAuctionAveragePrice = normalizer.transform(x_cv['MMRAcquisi
tionAuctionAveragePrice'].values.reshape(-1,1))
x_test_MMRAcquisitionAuctionAveragePrice = normalizer.transform(x_test['MMRAcq
uisitionAuctionAveragePrice'].values.reshape(-1,1))

print("After vectorizations")
print(x_train_MMRAcquisitionAuctionAveragePrice.shape, y_train.shape)
print(x_cv_MMRAcquisitionAuctionAveragePrice.shape, y_cv.shape)
print(x_test_MMRAcquisitionAuctionAveragePrice.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

In [530]:
```
#vectorize the MMRAcquisitionAuctionCleanPrice
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['MMRAcquisitionAuctionCleanPrice'].values.reshape(-1,1
))

x_train_MMRAcquisitionAuctionCleanPrice = normalizer.transform(x_train['MMRAcq
uisitionAuctionCleanPrice'].values.reshape(-1,1))
x_cv_MMRAcquisitionAuctionCleanPrice = normalizer.transform(x_cv['MMRAcquisiti
onAuctionCleanPrice'].values.reshape(-1,1))
x_test_MMRAcquisitionAuctionCleanPrice = normalizer.transform(x_test['MMRAcqui
sitionAuctionCleanPrice'].values.reshape(-1,1))

print("After vectorizations")
print(x_train_MMRAcquisitionAuctionCleanPrice.shape, y_train.shape)
print(x_cv_MMRAcquisitionAuctionCleanPrice.shape, y_cv.shape)
print(x_test_MMRAcquisitionAuctionCleanPrice.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

In [531]:
```
#vectorize the MMRAcquisitionRetailAveragePrice
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['MMRAcquisitionRetailAveragePrice'].values.reshape(-1,1
))

x_train_MMRAcquisitionRetailAveragePrice = normalizer.transform(x_train['MMRAc
quisitionRetailAveragePrice'].values.reshape(-1,1))
x_cv_MMRAcquisitionRetailAveragePrice = normalizer.transform(x_cv['MMRAcquisit
ionRetailAveragePrice'].values.reshape(-1,1))
x_test_MMRAcquisitionRetailAveragePrice = normalizer.transform(x_test['MMRAcqu
isitionRetailAveragePrice'].values.reshape(-1,1))

print("After vectorizations")
print(x_train_MMRAcquisitionRetailAveragePrice.shape, y_train.shape)
print(x_cv_MMRAcquisitionRetailAveragePrice.shape, y_cv.shape)
print(x_test_MMRAcquisitionRetailAveragePrice.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

In [ ]:

In [ ]:

In [532]:
```
#vectorize the MMRAcquisitonRetailCleanPrice
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['MMRAcquisitonRetailCleanPrice'].values.reshape(-1,1))

x_train_MMRAcquisitonRetailCleanPrice = normalizer.transform(x_train['MMRAcqui
sitonRetailCleanPrice'].values.reshape(-1,1))
x_cv_MMRAcquisitonRetailCleanPrice = normalizer.transform(x_cv['MMRAcquisitonR
etailCleanPrice'].values.reshape(-1,1))
x_test_MMRAcquisitonRetailCleanPrice = normalizer.transform(x_test['MMRAcquisi
tonRetailCleanPrice'].values.reshape(-1,1))

print("After vectorizations")
print(x_train_MMRAcquisitonRetailCleanPrice.shape, y_train.shape)
print(x_cv_MMRAcquisitonRetailCleanPrice.shape, y_cv.shape)
print(x_test_MMRAcquisitonRetailCleanPrice.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

In [533]:
```
#vectorize the MMRCurrentAuctionAveragePrice
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['MMRCurrentAuctionAveragePrice'].values.reshape(-1,1))

x_train_MMRCurrentAuctionAveragePrice = normalizer.transform(x_train['MMRCurrentAuctionAveragePrice'].values.reshape(-1,1))
x_cv_MMRCurrentAuctionAveragePrice = normalizer.transform(x_cv['MMRCurrentAuctionAveragePrice'].values.reshape(-1,1))
x_test_MMRCurrentAuctionAveragePrice = normalizer.transform(x_test['MMRCurrentAuctionAveragePrice'].values.reshape(-1,1))

print("After vectorizations")
print(x_train_MMRCurrentAuctionAveragePrice.shape, y_train.shape)
print(x_cv_MMRCurrentAuctionAveragePrice.shape, y_cv.shape)
print(x_test_MMRCurrentAuctionAveragePrice.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

In [534]:
```
#vectorize the MMRCurrentAuctionCleanPrice
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['MMRCurrentAuctionCleanPrice'].values.reshape(-1,1))

x_train_MMRCurrentAuctionCleanPrice = normalizer.transform(x_train['MMRCurrentAuctionCleanPrice'].values.reshape(-1,1))
x_cv_MMRCurrentAuctionCleanPrice = normalizer.transform(x_cv['MMRCurrentAuctionCleanPrice'].values.reshape(-1,1))
x_test_MMRCurrentAuctionCleanPrice = normalizer.transform(x_test['MMRCurrentAuctionCleanPrice'].values.reshape(-1,1))

print("After vectorizations")
print(x_train_MMRCurrentAuctionCleanPrice.shape, y_train.shape)
print(x_cv_MMRCurrentAuctionCleanPrice.shape, y_cv.shape)
print(x_test_MMRCurrentAuctionCleanPrice.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

In [535]:
```
#vectorize the MMRCurrentRetailAveragePrice
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['MMRCurrentRetailAveragePrice'].values.reshape(-1,1))

x_train_MMRCurrentRetailAveragePrice = normalizer.transform(x_train['MMRCurrentRetailAveragePrice'].values.reshape(-1,1))
x_cv_MMRCurrentRetailAveragePrice = normalizer.transform(x_cv['MMRCurrentRetailAveragePrice'].values.reshape(-1,1))
x_test_MMRCurrentRetailAveragePrice = normalizer.transform(x_test['MMRCurrentRetailAveragePrice'].values.reshape(-1,1))

print("After vectorizations")
print(x_train_MMRCurrentRetailAveragePrice.shape, y_train.shape)
print(x_cv_MMRCurrentRetailAveragePrice.shape, y_cv.shape)
print(x_test_MMRCurrentRetailAveragePrice.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

In [536]:
```
#vectorize the MMRCurrentRetailCleanPrice
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['MMRCurrentRetailCleanPrice'].values.reshape(-1,1))

x_train_MMRCurrentRetailCleanPrice = normalizer.transform(x_train['MMRCurrentRetailCleanPrice'].values.reshape(-1,1))
x_cv_MMRCurrentRetailCleanPrice = normalizer.transform(x_cv['MMRCurrentRetailCleanPrice'].values.reshape(-1,1))
x_test_MMRCurrentRetailCleanPrice = normalizer.transform(x_test['MMRCurrentRetailCleanPrice'].values.reshape(-1,1))

print("After vectorizations")
print(x_train_MMRCurrentRetailCleanPrice.shape, y_train.shape)
print(x_cv_MMRCurrentRetailCleanPrice.shape, y_cv.shape)
print(x_test_MMRCurrentRetailCleanPrice.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

In [537]:
```
#vectorize the BYRNO
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['BYRNO'].values.reshape(-1,1))

x_train_BYRNO = normalizer.transform(x_train['BYRNO'].values.reshape(-1,1))
x_cv_BYRNO = normalizer.transform(x_cv['BYRNO'].values.reshape(-1,1))
x_test_BYRNO = normalizer.transform(x_test['BYRNO'].values.reshape(-1,1))

print("After vectorizations")
print(x_train_BYRNO.shape, y_train.shape)
print(x_cv_BYRNO.shape, y_cv.shape)
print(x_test_BYRNO.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

In [538]:
```
#vectorize the VNZIP1
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['VNZIP1'].values.reshape(-1,1))

x_train_VNZIP1 = normalizer.transform(x_train['VNZIP1'].values.reshape(-1,1))
x_cv_VNZIP1 = normalizer.transform(x_cv['VNZIP1'].values.reshape(-1,1))
x_test_VNZIP1 = normalizer.transform(x_test['VNZIP1'].values.reshape(-1,1))

print("After vectorizations")
print(x_train_VNZIP1.shape, y_train.shape)
print(x_cv_VNZIP1.shape, y_cv.shape)
print(x_test_VNZIP1.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

In [539]:
```
#vectorize the VehBCost
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['VehBCost'].values.reshape(-1,1))

x_train_VehBCost = normalizer.transform(x_train['VehBCost'].values.reshape(-1,
1))
x_cv_VehBCost = normalizer.transform(x_cv['VehBCost'].values.reshape(-1,1))
x_test_VehBCost = normalizer.transform(x_test['VehBCost'].values.reshape(-1,1
))

print("After vectorizations")
print(x_train_VehBCost.shape, y_train.shape)
print(x_cv_VehBCost.shape, y_cv.shape)
print(x_test_VehBCost.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

In [540]:
```
#vectorize the WarrantyCost
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['WarrantyCost'].values.reshape(-1,1))

x_train_WarrantyCost = normalizer.transform(x_train['WarrantyCost'].values.res
hape(-1,1))
x_cv_WarrantyCost = normalizer.transform(x_cv['WarrantyCost'].values.reshape(-
1,1))
x_test_WarrantyCost = normalizer.transform(x_test['WarrantyCost'].values.resha
pe(-1,1))

print("After vectorizations")
print(x_train_WarrantyCost.shape, y_train.shape)
print(x_cv_WarrantyCost.shape, y_cv.shape)
print(x_test_WarrantyCost.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

In [543]:
```
#vectorize the IsOnlineSale
from sklearn.preprocessing import Normalizer

normalizer = Normalizer()
normalizer.fit(x_train['IsOnlineSale'].values.reshape(-1,1))

x_train_IsOnlineSale = normalizer.transform(x_train['IsOnlineSale'].values.res
hape(-1,1))
x_cv_IsOnlineSale = normalizer.transform(x_cv['IsOnlineSale'].values.reshape(-
1,1))
x_test_IsOnlineSale = normalizer.transform(x_test['IsOnlineSale'].values.resha
pe(-1,1))

print("After vectorizations")
print(x_train_IsOnlineSale.shape, y_train.shape)
print(x_cv_IsOnlineSale.shape, y_cv.shape)
print(x_test_IsOnlineSale.shape, )
```

```
After vectorizations
(51088, 1) (51088,)
(21895, 1) (21895,)
(48707, 1)
```

Merge numerical dataset

In [544]:
```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
# with the same hstack function we are concatinating a sparse matrix and a den
se matirx :)
x_train_numerical = np.hstack((x_train_VehOdo,x_train_VehicleAge,x_train_MMRAc
quisitionAuctionAveragePrice,x_train_MMRAcquisitionAuctionCleanPrice,x_train_M
MRAcquisitionRetailAveragePrice,x_train_MMRAcquisitonRetailCleanPrice,x_train_
MMRCurrentAuctionAveragePrice,x_train_MMRCurrentAuctionCleanPrice,x_train_MMRC
urrentRetailAveragePrice,x_train_MMRCurrentRetailCleanPrice,x_train_BYRNO,x_tr
ain_VNZIP1,x_train_VehBCost,x_train_WarrantyCost,x_train_IsOnlineSale))
x_cv_numerical = np.hstack((x_cv_VehOdo,x_cv_VehicleAge,x_cv_MMRAcquisitionAuc
tionAveragePrice,x_cv_MMRAcquisitionAuctionCleanPrice,x_cv_MMRAcquisitionRetai
lAveragePrice,x_cv_MMRAcquisitonRetailCleanPrice,x_cv_MMRCurrentAuctionAverage
Price,x_cv_MMRCurrentAuctionCleanPrice,x_cv_MMRCurrentRetailAveragePrice,x_cv_
MMRCurrentRetailCleanPrice,x_cv_BYRNO,x_cv_VNZIP1,x_cv_VehBCost,x_cv_WarrantyC
ost,x_cv_IsOnlineSale))
x_test_numerical = np.hstack((x_test_VehOdo,x_test_VehicleAge,x_test_MMRAcquis
itionAuctionAveragePrice,x_test_MMRAcquisitionAuctionCleanPrice,x_test_MMRAcqu
isitionRetailAveragePrice,x_test_MMRAcquisitonRetailCleanPrice,x_test_MMRCurre
ntAuctionAveragePrice,x_test_MMRCurrentAuctionCleanPrice,x_test_MMRCurrentReta
ilAveragePrice,x_test_MMRCurrentRetailCleanPrice,x_test_BYRNO,x_test_VNZIP1,x_
test_VehBCost,x_test_WarrantyCost,x_test_IsOnlineSale))

print(x_train_numerical.shape)
print(x_cv_numerical.shape)
print(x_test_numerical.shape)
```

```
(51088, 15)
(21895, 15)
(48707, 15)
```

In [ ]:

Merging all Categorical as well as numerical data

In [553]:
```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
x_train_bow= hstack((x_train_categorical,x_train_numerical)).tocsr()
x_cv_bow= hstack((x_cv_categorical,x_cv_numerical)).tocsr()
x_test_bow= hstack((x_test_categorical,x_test_numerical)).tocsr()

print(x_train_bow.shape)
print(x_cv_bow.shape)
print(x_test_bow.shape)
```

```
(51088, 1905)
(21895, 1905)
(48707, 1905)
```

Implementing different model Model

In [547]:

```
import pandas as pd
import matplotlib.pyplot as plt
import re
import time
import warnings
import numpy as np
from nltk.corpus import stopwords
from sklearn.decomposition import TruncatedSVD
from sklearn.preprocessing import normalize
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.manifold import TSNE
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics.classification import accuracy_score, log_loss
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import SGDClassifier
#from imblearn.over_sampling import SMOTE
from collections import Counter
from scipy.sparse import hstack
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC
from sklearn import model_selection
from sklearn.model_selection import StratifiedKFold
from collections import Counter, defaultdict
from sklearn.calibration import CalibratedClassifierCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
import math
from sklearn.metrics import normalized_mutual_info_score
from sklearn.ensemble import RandomForestClassifier
warnings.filterwarnings("ignore")

from mlxtend.classifier import StackingClassifier

from sklearn import model_selection
from sklearn.linear_model import LogisticRegression
```

In [548]:

```
def predict_and_plot_confusion_matrix(train_x, train_y,test_x, test_y, clf):
    clf.fit(train_x, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train_x, train_y)
    pred_y = sig_clf.predict(test_x)

    # for calculating log_loss we willl provide the array of probabilities bel
ongs to each class
    print("Log loss :",log_loss(test_y, sig_clf.predict_proba(test_x)))
    # calculating the number of data points that are misclassified
    print("Number of mis-classified points :", np.count_nonzero((pred_y- test_
y))/test_y.shape[0])
    plot_confusion_matrix(test_y, pred_y)
```

In [549]:
```
def report_log_loss(train_x, train_y, test_x, test_y,  clf):
    clf.fit(train_x, train_y)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(train_x, train_y)
    sig_clf_probs = sig_clf.predict_proba(test_x)
    return log_loss(test_y, sig_clf_probs, eps=1e-15)
```

In [572]:
```
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)

    A =(((C.T)/(C.sum(axis=1))).T)

    B =(C/C.sum(axis=0))

    labels = [1,0]
    # representing A in heatmap format
    print("-"*20, "Confusion matrix", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(C, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, y
ticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()

    print("-"*20, "Precision matrix (Columm Sum=1)", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(B, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, y
ticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()

    # representing B in heatmap format
    print("-"*20, "Recall matrix (Row sum=1)", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(A, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, y
ticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
```

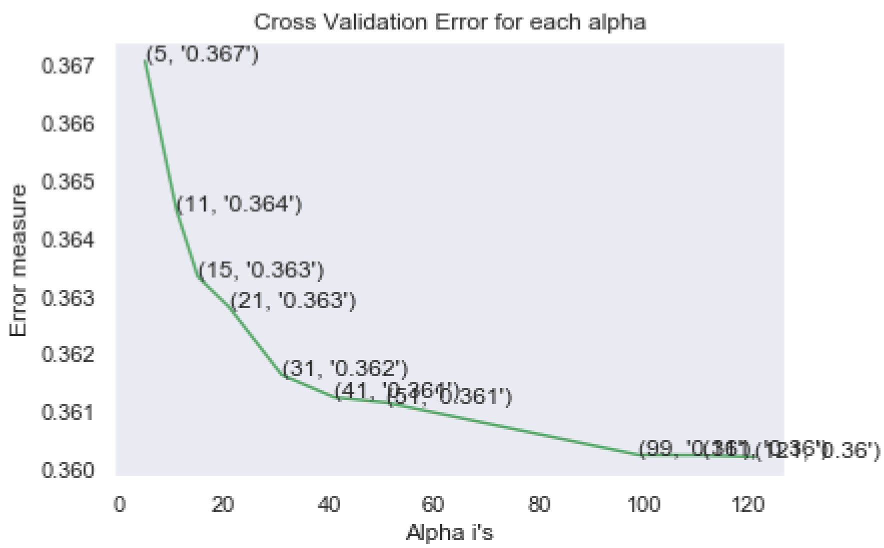
KNN

In [554]:
```
def batch_predict(clf, data):
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability e
stimates of the positive class
    # not the predicted outputs

    y_data_pred = []
    tr_loop = data.shape[0] - data.shape[0]%1000
    # consider you X_tr shape is 49041, then your tr_loop will be 49041 - 4904
1%1000 = 49000
    # in this for loop we will iterate unti the last 1000 multiplier
    for i in range(0, tr_loop, 1000):
        y_data_pred.extend(clf.predict_proba(data[i:i+1000])[:,1])
    # we will be predicting for the last data points
    if data.shape[0]%1000 !=0:
        y_data_pred.extend(clf.predict_proba(data[tr_loop:])[:,1])

    return y_data_pred
```

In [555]:

```
alpha = [5, 11, 15, 21, 31, 41, 51, 99,111,121]
cv_log_error_array = []
for i in alpha:
    print("for alpha =", i)
    clf = KNeighborsClassifier(n_neighbors=i)
    clf.fit(x_train_bow, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(x_train_bow, y_train)
    sig_clf_probs = sig_clf.predict_proba(x_cv_bow)
    cv_log_error_array.append(log_loss(y_cv, sig_clf_probs, labels=clf.classes
_, eps=1e-15))
    # to avoid rounding error while multiplying probabilites we use log-probab
ility estimates
    print("Log Loss :",log_loss(y_cv, sig_clf_probs))

fig, ax = plt.subplots()
ax.plot(alpha, cv_log_error_array,c='g')
for i, txt in enumerate(np.round(cv_log_error_array,3)):
    ax.annotate((alpha[i],str(txt)), (alpha[i],cv_log_error_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()


best_alpha = np.argmin(cv_log_error_array)
clf = KNeighborsClassifier(n_neighbors=alpha[best_alpha])
clf.fit(x_train_bow, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(x_train_bow, y_train)
```

```
for alpha = 5
Log Loss : 0.367068440131076
for alpha = 11
Log Loss : 0.3644791296666901
for alpha = 15
Log Loss : 0.3633420908180204
for alpha = 21
Log Loss : 0.362812876750281
for alpha = 31
Log Loss : 0.3616395492577407
for alpha = 41
Log Loss : 0.36124994781856506
for alpha = 51
Log Loss : 0.3611568676097378
for alpha = 99
Log Loss : 0.36025001303637827
for alpha = 111
Log Loss : 0.36024625501628077
for alpha = 121
Log Loss : 0.3602171886090073
```



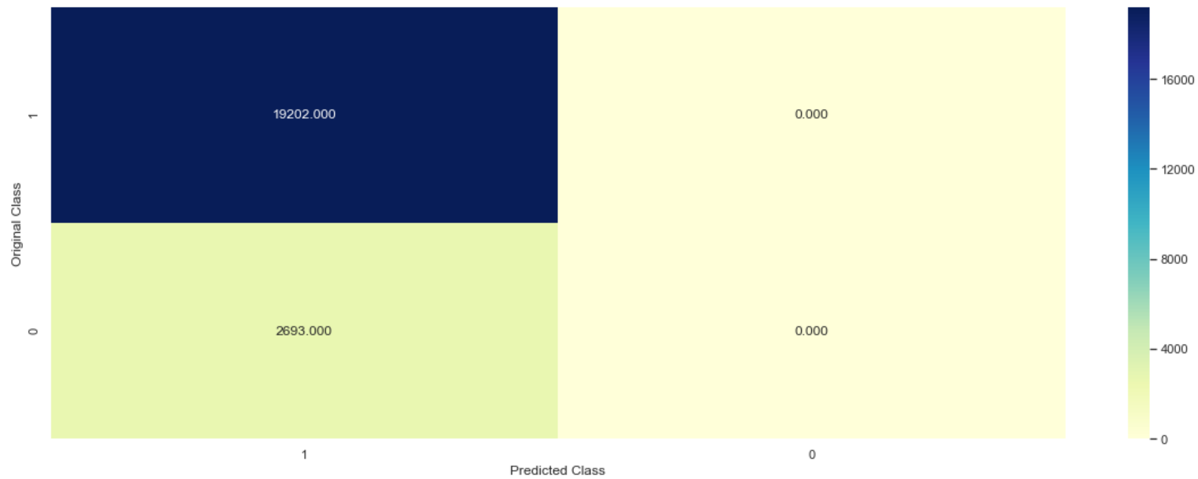
Out[555]:
```
CalibratedClassifierCV(base_estimator=KNeighborsClassifier(algorithm='auto',
                                                           leaf_size=30,
                                                           metric='minkowsk
i',
                                                           metric_params=Non
e,
                                                           n_jobs=None,
                                                           n_neighbors=121, p
=2,
                                                           weights='unifor
m'),
                       cv='warn', method='sigmoid')
```

In [556]:
```
predict_y = sig_clf.predict_proba(x_train_bow)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(x_cv_bow)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation log loss is:",log_loss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(x_test_bow)
#print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
```

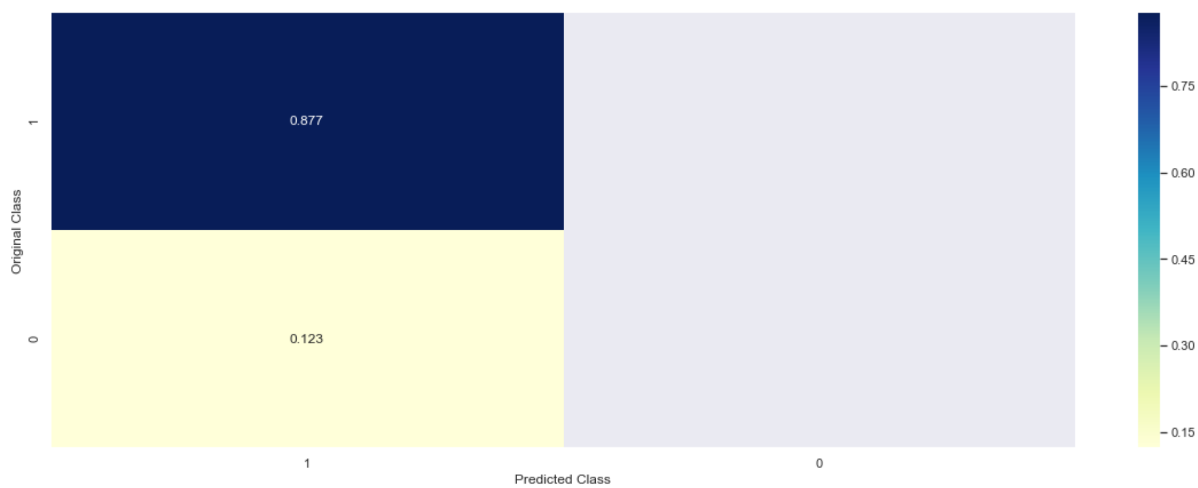
```
For values of best alpha =  121 The train log loss is: 0.35642527187290246
For values of best alpha =  121 The cross validation log loss is: 0.3602171886090073
```

In [611]:
```
clf = KNeighborsClassifier(n_neighbors=121)
predict_and_plot_confusion_matrix(x_train_bow, y_train, x_cv_bow, y_cv, clf)
```

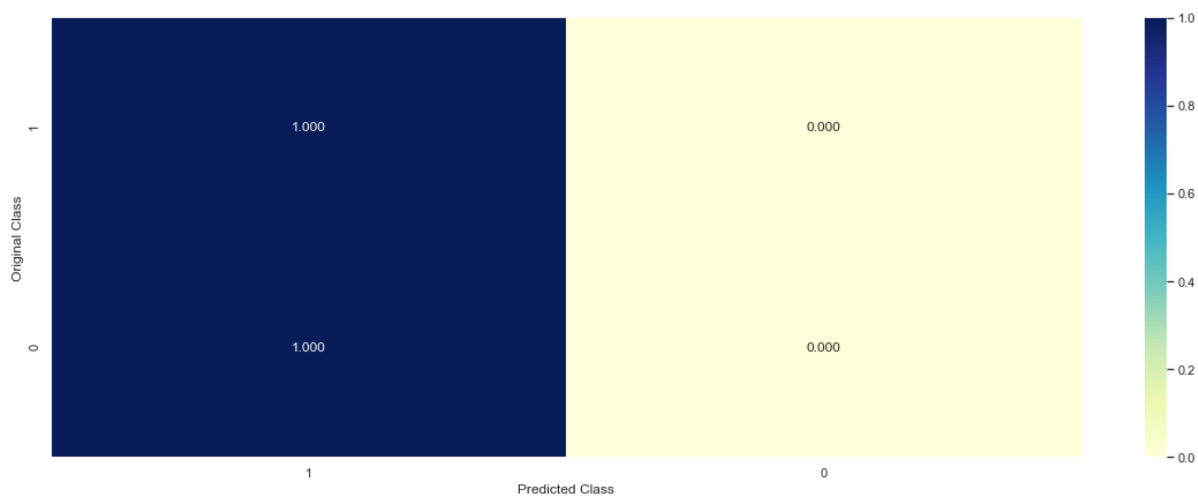
```
Log loss : 0.3602171886090073
Number of mis-classified points : 0.12299611783512217
-------------------- Confusion matrix --------------------
```




```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



In [612]:
```
predictions = clf.predict(x_test_bow)
print(predictions)
new_series = pd.Series(predictions)
new_series.value_counts()
```

```
[0 0 0 ... 0 0 0]
```

Out[612]:
```
0    48707
dtype: int64
```

In [613]:
```
predictions_knn = pd.DataFrame(new_series, columns=['IsBadBuy'])
predictions_knn.to_csv("predictions_knn.csv", index=False)
```

Notes:

most of the error occure in false negative cell in which original is 0 but predicted is 1.

of total available point 12.3% of point is misclassified using knn classifier.

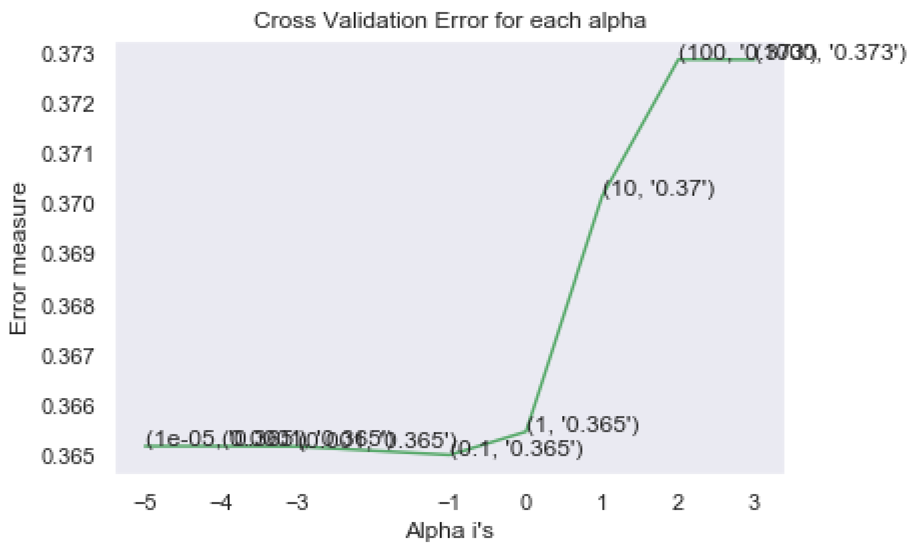
after number of iteration, we found the tuned value of k=121 with cross validation log loss of: 0.365, for loss = log_loss at which minimum loss occure.

true positive is desirable condition which have high value while false negative value is very less again support our model accuracy.

Naive base

In [558]:
```
from sklearn.calibration import CalibratedClassifierCV
alpha = [0.00001, 0.0001, 0.001, 0.1, 1, 10, 100,1000]
cv_log_error_array = []
for i in alpha:
    print("for alpha =", i)
    clf = MultinomialNB(alpha=i)
    clf.fit(x_train_bow, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(x_train_bow, y_train)
    sig_clf_probs = sig_clf.predict_proba(x_cv_bow)
    cv_log_error_array.append(log_loss(y_cv, sig_clf_probs, labels=clf.classes
_, eps=1e-15))
    # to avoid rounding error while multiplying probabilites we use log-probab
ility estimates
    print("Log Loss :",log_loss(y_cv, sig_clf_probs))

fig, ax = plt.subplots()
ax.plot(np.log10(alpha), cv_log_error_array,c='g')
for i, txt in enumerate(np.round(cv_log_error_array,3)):
    ax.annotate((alpha[i],str(txt)), (np.log10(alpha[i]),cv_log_error_array[i
]))
plt.grid()
plt.xticks(np.log10(alpha))
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()


best_alpha = np.argmin(cv_log_error_array)
clf = MultinomialNB(alpha=alpha[best_alpha])
clf.fit(x_train_bow, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(x_train_bow, y_train)


predict_y = sig_clf.predict_proba(x_train_bow)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss i
s:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(x_cv_bow)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation
 log loss is:",log_loss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(x_test_bow)
#print('For values of best alpha = ', alpha[best_alpha], "The test log loss i
s:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
```

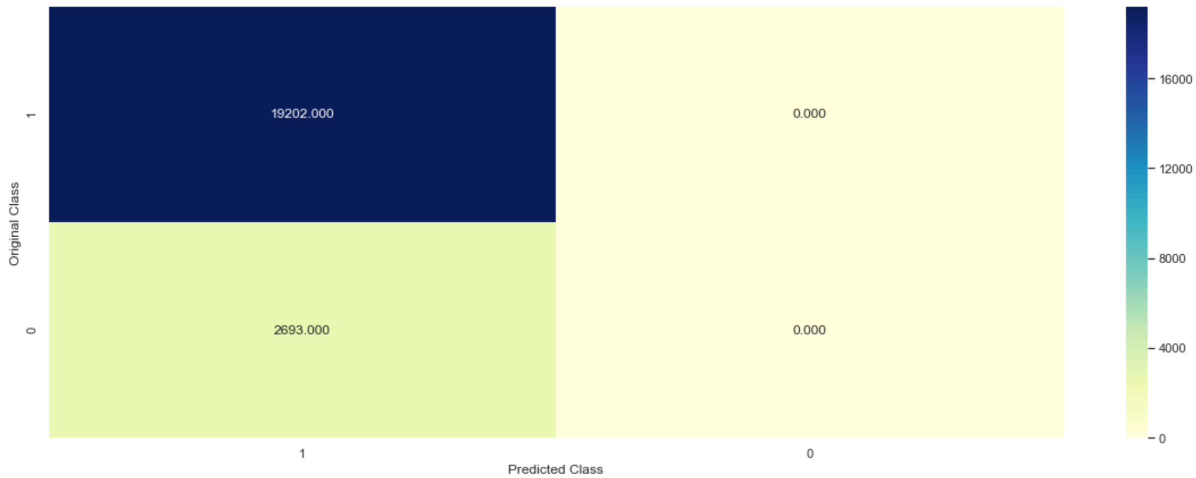
```
for alpha = 1e-05
Log Loss : 0.3651929991631001
for alpha = 0.0001
Log Loss : 0.3651923929310967
for alpha = 0.001
Log Loss : 0.36518661928419344
for alpha = 0.1
Log Loss : 0.36501906515357485
for alpha = 1
Log Loss : 0.3654812110901443
for alpha = 10
Log Loss : 0.37014654475195896
for alpha = 100
Log Loss : 0.37285660568029316
for alpha = 1000
Log Loss : 0.3728523457566167
```



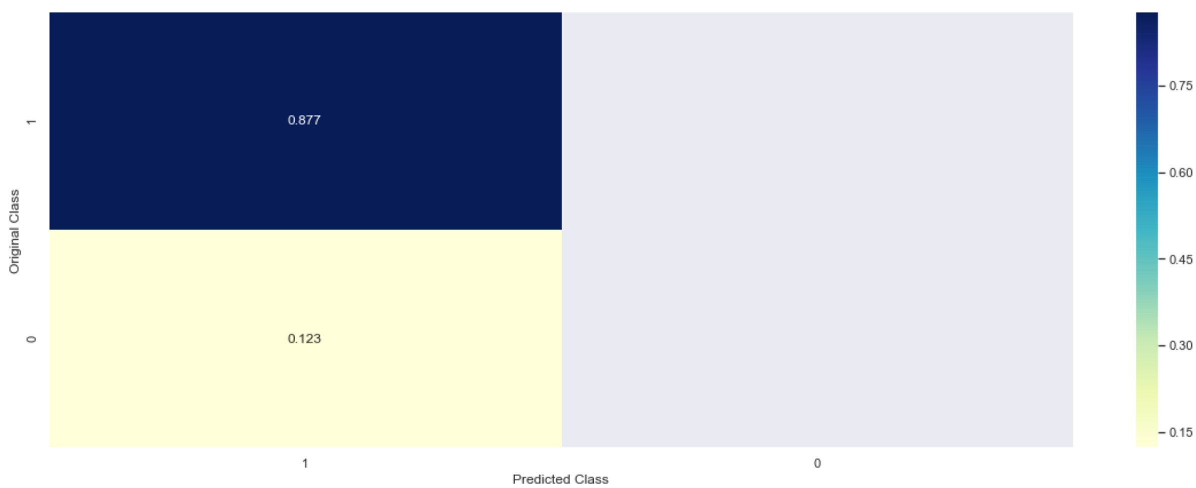

```
For values of best alpha =  0.1 The train log loss is: 0.3582251911752722
For values of best alpha =  0.1 The cross validation log loss is: 0.365019065
15357485
```

In [608]:
```
clf = MultinomialNB(alpha=0.1)
clf.fit(x_train_bow, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(x_train_bow, y_train)
sig_clf_probs = sig_clf.predict_proba(x_cv_bow)
# to avoid rounding error while multiplying probabilites we use log-probabilit
y estimates
print("Log Loss :",log_loss(y_cv, sig_clf_probs))
print("Number of missclassified point :", np.count_nonzero((sig_clf.predict(x_
cv_bow)- y_cv))/y_cv.shape[0])
plot_confusion_matrix(y_cv, sig_clf.predict(x_cv_bow.toarray()))
```

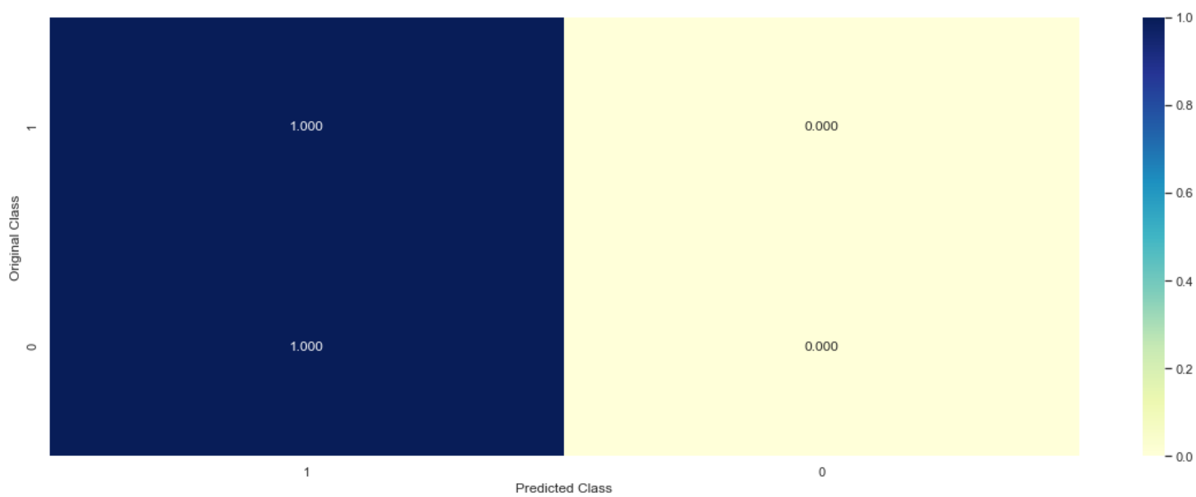
```
Log Loss : 0.365019065153574885
Number of missclassified point : 0.12299611783512217
-------------------- Confusion matrix --------------------
```




```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



In [609]:
```
predictions = clf.predict(x_test_bow)
print(predictions)
new_series = pd.Series(predictions)
new_series.value_counts()
```

```
[0 1 0 ... 0 0 0]
```

Out[609]:
```
0    44279
1     4428
dtype: int64
```

In [610]:
```
predictions_Naive = pd.DataFrame(new_series, columns=['IsBadBuy'])
predictions_Naive.to_csv("predictions_Naive.csv", index=False)
```

Notes:

most of the error occure in false negative cell in which original is 0 but predicted is 1.

of total available point 12.3% of point is misclassified using Naive base classifier.

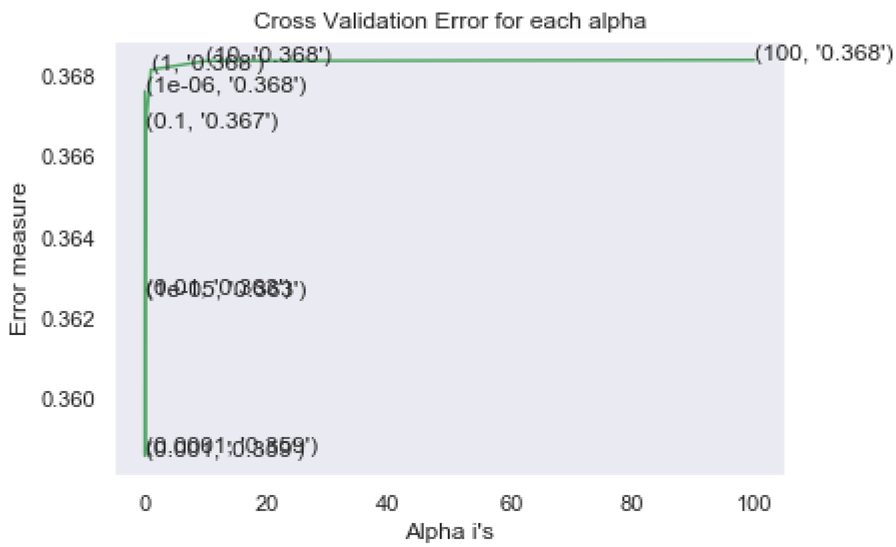
after number of iteration, we found the tuned value of alpha = 0.1 with cross validation log loss of: 0.365, for loss = log_loss at which minimum loss occure.

true positive is desirable condition which have high value while false negative value is very less again support our model accuracy.

Logistic Regression

In [560]:
```
alpha = [10 ** x for x in range(-6, 3)]
cv_log_error_array = []
for i in alpha:
    print("for alpha =", i)
    clf = SGDClassifier(class_weight='balanced', alpha=i, penalty='l2', loss=
'log', random_state=42)
    clf.fit(x_train_bow, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(x_train_bow, y_train)
    sig_clf_probs = sig_clf.predict_proba(x_cv_bow)
    cv_log_error_array.append(log_loss(y_cv, sig_clf_probs, labels=clf.classes
_, eps=1e-15))
    # to avoid rounding error while multiplying probabilites we use log-probab
ility estimates
    print("Log Loss :",log_loss(y_cv, sig_clf_probs))

fig, ax = plt.subplots()
ax.plot(alpha, cv_log_error_array,c='g')
for i, txt in enumerate(np.round(cv_log_error_array,3)):
    ax.annotate((alpha[i],str(txt)), (alpha[i],cv_log_error_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()


best_alpha = np.argmin(cv_log_error_array)
clf = SGDClassifier(class_weight='balanced', alpha=alpha[best_alpha], penalty=
'l2', loss='log', random_state=42)
clf.fit(x_train_bow, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(x_train_bow, y_train)

predict_y = sig_clf.predict_proba(x_train_bow)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss i
s:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(x_cv_bow)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation
 log loss is:",log_loss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(x_test_bow)
#print('For values of best alpha = ', alpha[best_alpha], "The test log loss i
s:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
```

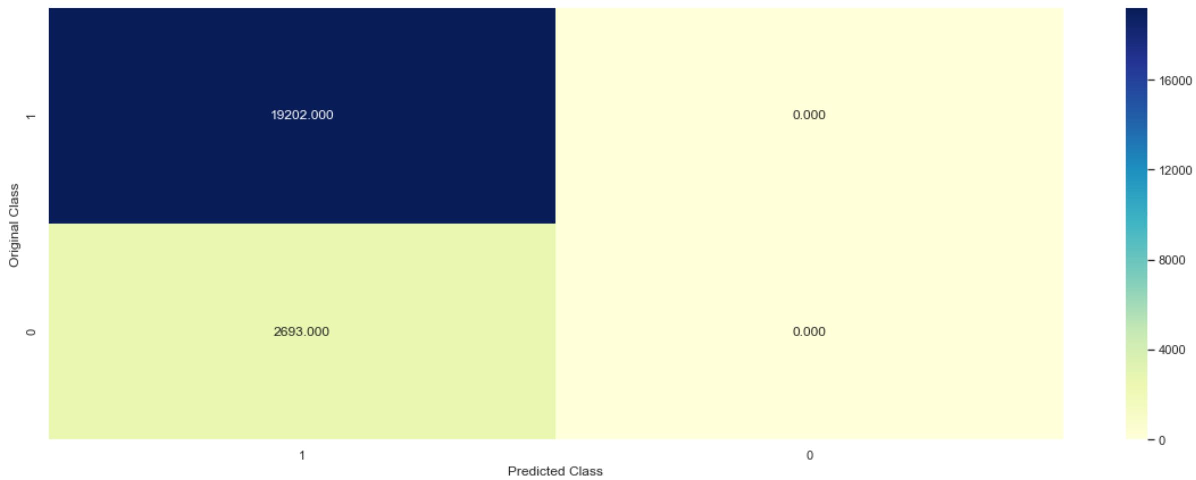
```
for alpha = 1e-06
Log Loss : 0.3676314401758066
for alpha = 1e-05
Log Loss : 0.36251254483515316
for alpha = 0.0001
Log Loss : 0.35866349623727756
for alpha = 0.001
Log Loss : 0.35855575022518626
for alpha = 0.01
Log Loss : 0.3626059779016653
for alpha = 0.1
Log Loss : 0.3667125409318471
for alpha = 1
Log Loss : 0.368163326987055
for alpha = 10
Log Loss : 0.3683816160086673
for alpha = 100
Log Loss : 0.36840622819475716
```



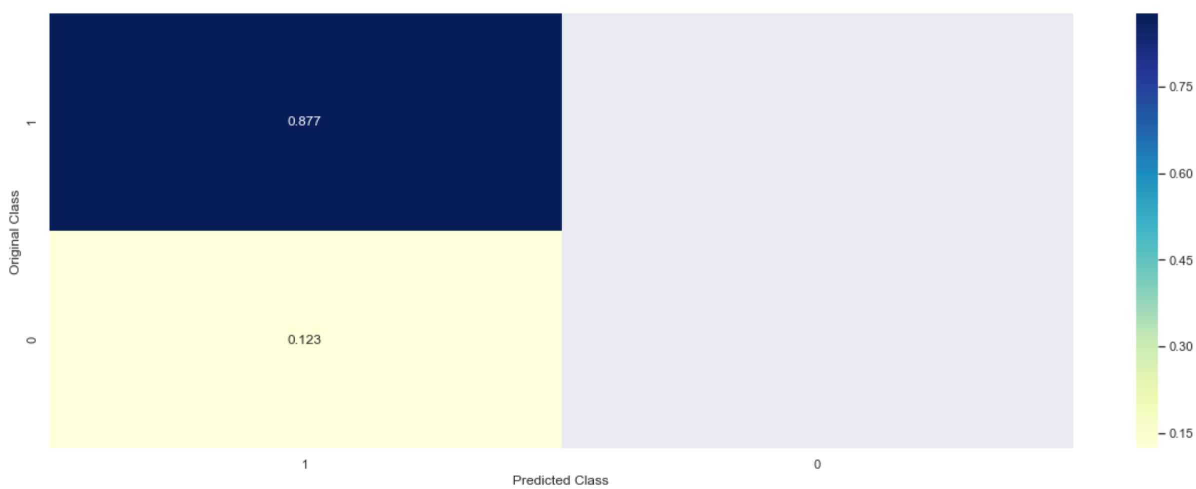

```
For values of best alpha =  0.001 The train log loss is: 0.3544213181694525
For values of best alpha =  0.001 The cross validation log loss is: 0.3585557
5022518626
```

In [605]:
```
clf = SGDClassifier(class_weight='balanced', alpha=0.001, penalty='l2', loss=
'log', random_state=42)
predict_and_plot_confusion_matrix(x_train_bow, y_train, x_cv_bow, y_cv, clf)
```

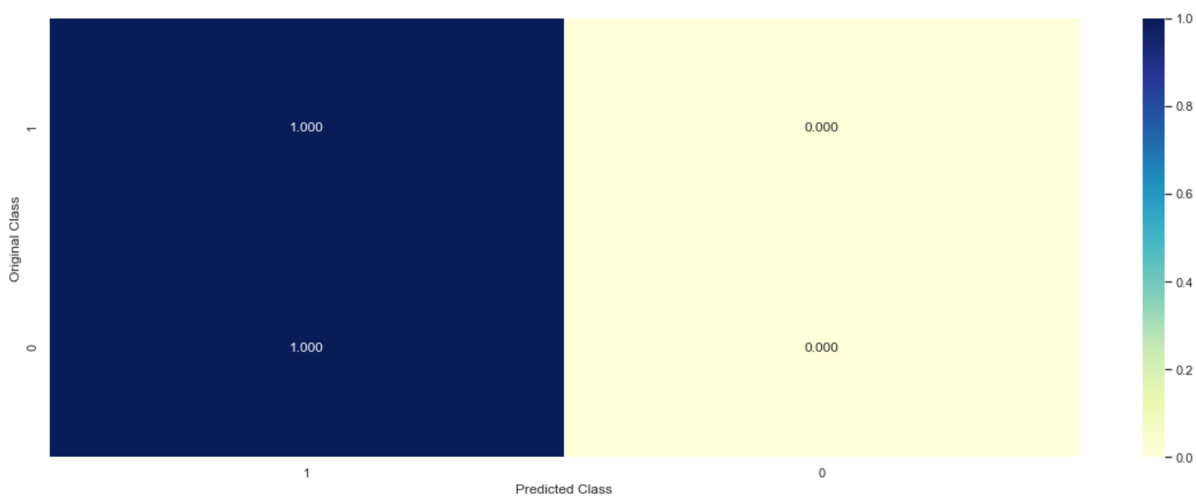
```
Log loss : 0.358555750225186626
Number of mis-classified points : 0.12299611783512217
-------------------- Confusion matrix --------------------
```




```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



In [606]:
```
predictions = clf.predict(x_test_bow)
print(predictions)
new_series = pd.Series(predictions)
new_series.value_counts()
```

```
[1 1 1 ... 0 0 0]
```

Out[606]:
```
1    34944
0    13763
dtype: int64
```

In [607]:
```
predictions_LOGISTIC = pd.DataFrame(new_series, columns=['IsBadBuy'])
predictions_LOGISTIC.to_csv("predictions_LOGISTIC.csv", index=False)
```

In [ ]:

Notes:

most of the error occure in false negative cell in which original is 0 but predicted is 1.

of total available point 12.3% of point is misclassified using logistic regression classifier.

after number of iteration, we found the tuned value of alpha = 0.001, for loss = log at which minimum loss occure.

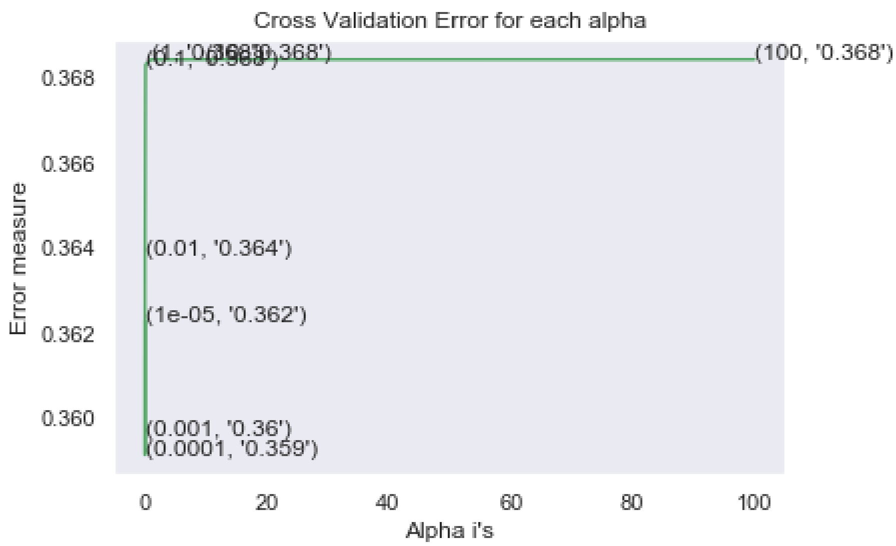
true positive is desirable condition which have high value while false negative value is very less again support our model accuracy.

Linear Support Vector Machines

In [562]:

```
alpha = [10 ** x for x in range(-5, 3)]
cv_log_error_array = []
for i in alpha:
    print("for C =", i)
#     clf = SVC(C=i,kernel='linear',probability=True, class_weight='balanced')
    clf = SGDClassifier( class_weight='balanced', alpha=i, penalty='l2', loss=
'hinge', random_state=42)
    clf.fit(x_train_bow, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(x_train_bow, y_train)
    sig_clf_probs = sig_clf.predict_proba(x_cv_bow)
    cv_log_error_array.append(log_loss(y_cv, sig_clf_probs, labels=clf.classes
_, eps=1e-15))
    print("Log Loss :",log_loss(y_cv, sig_clf_probs))

fig, ax = plt.subplots()
ax.plot(alpha, cv_log_error_array,c='g')
for i, txt in enumerate(np.round(cv_log_error_array,3)):
    ax.annotate((alpha[i],str(txt)), (alpha[i],cv_log_error_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()


best_alpha = np.argmin(cv_log_error_array)
# clf = SVC(C=i,kernel='linear',probability=True, class_weight='balanced')
clf = SGDClassifier(class_weight='balanced', alpha=alpha[best_alpha], penalty=
'l2', loss='hinge', random_state=42)
clf.fit(x_train_bow, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(x_train_bow, y_train)

predict_y = sig_clf.predict_proba(x_train_bow)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss i
s:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(x_cv_bow)
print('For values of best alpha = ', alpha[best_alpha], "The cross validation
 log loss is:",log_loss(y_cv, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(x_test_bow)
#print('For values of best alpha = ', alpha[best_alpha], "The test log loss i
s:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
```

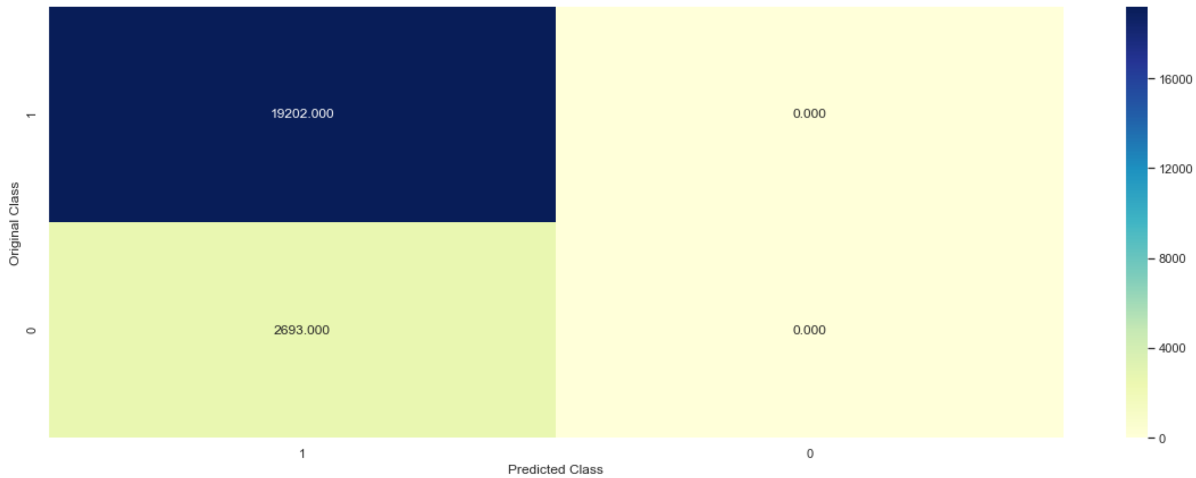
```
for C = 1e-05
Log Loss : 0.3622920360344007
for C = 0.0001
Log Loss : 0.35913680033100404
for C = 0.001
Log Loss : 0.3595764090979283
for C = 0.01
Log Loss : 0.3638379123403508
for C = 0.1
Log Loss : 0.3682899935179967
for C = 1
Log Loss : 0.3684071588943381
for C = 10
Log Loss : 0.3684099823356231
for C = 100
Log Loss : 0.3684103267978749
```



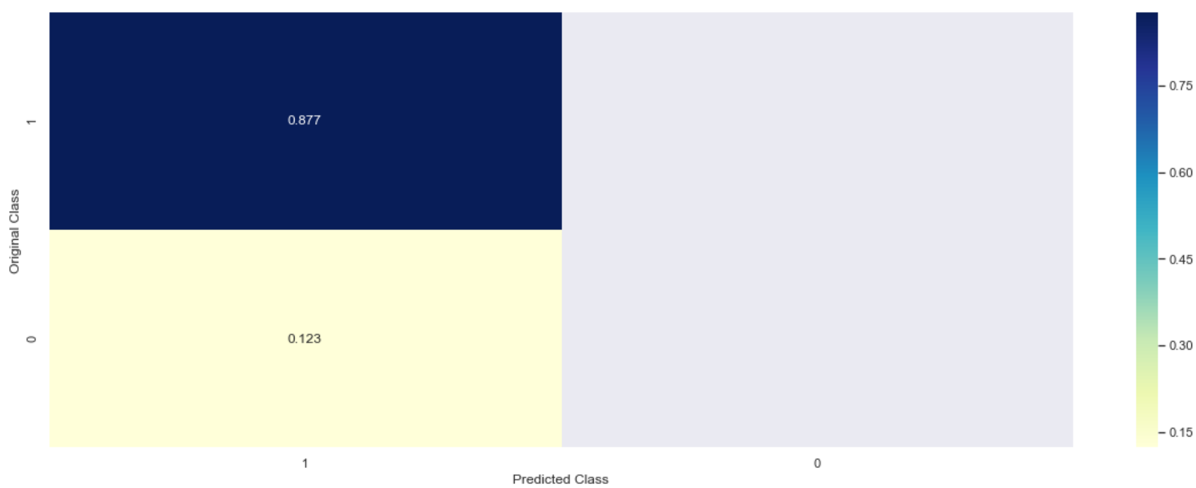

```
For values of best alpha =  0.0001 The train log loss is: 0.35204372222323355
For values of best alpha =  0.0001 The cross validation log loss is: 0.359136
80033100404
```

In [602]:
```
# clf = SVC(C=alpha[best_alpha],kernel='linear',probability=True, class_weight
='balanced')
clf = SGDClassifier(alpha=0.0001, penalty='l2', loss='hinge', random_state=42,
class_weight='balanced')
predict_and_plot_confusion_matrix(x_train_bow, y_train,x_cv_bow,y_cv, clf)
```

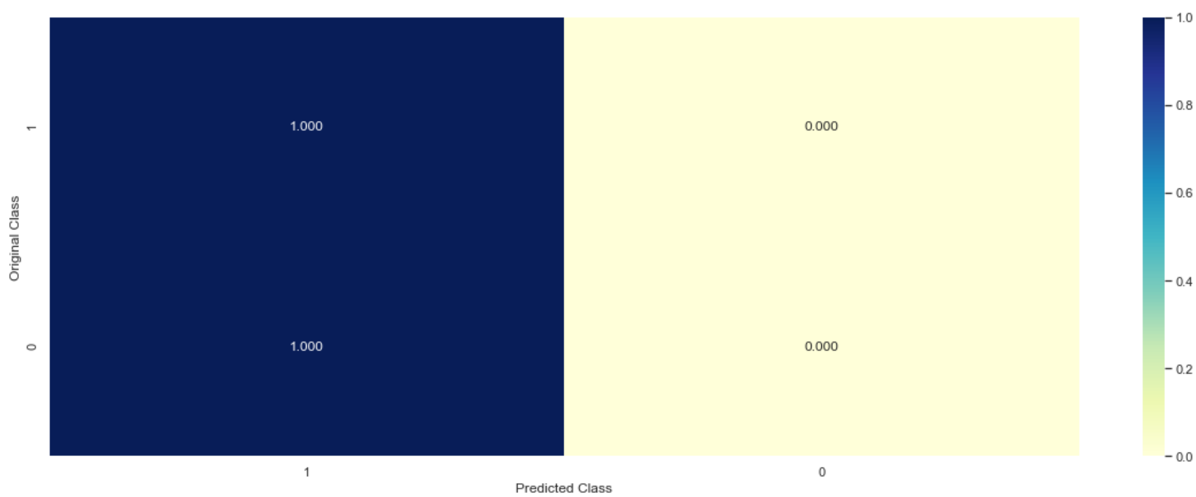
```
Log loss : 0.35913680033100404
Number of mis-classified points : 0.12299611783512217
-------------------- Confusion matrix --------------------
```




```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



In [603]:
```
predictions = clf.predict(x_test_bow)
print(predictions)
new_series = pd.Series(predictions)
new_series.value_counts()
```

```
[0 1 0 ... 0 0 0]
```

Out[603]:
```
0    37179
1    11528
dtype: int64
```

In [604]:
```
predictions_SVM = pd.DataFrame(new_series, columns=['IsBadBuy'])
predictions_SVM.to_csv("predictions_SVM.csv", index=False)
```

Notes:

most of the error occure in false negative cell in which original is 0 but predicted is 1.

of total available point 12.3% of point is misclassified using support vector machine classifier.

after number of iteration, we found the tuned value of alpha=0.0001, for loss = hinge.

true positive is desirable condition which have high value while false negative value is very less again support our model accuracy.

In [ ]:

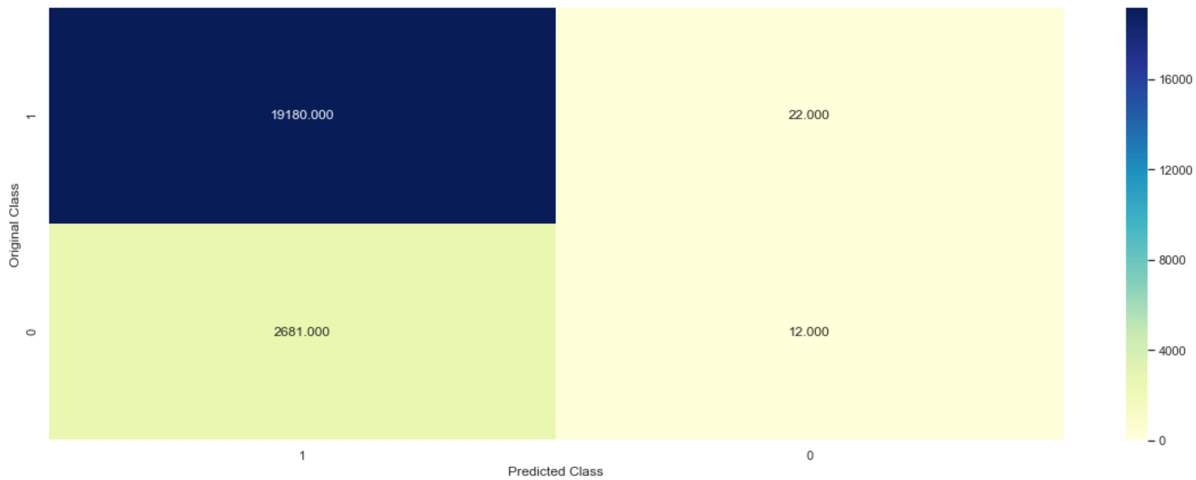
Random Forest Classifie

In [564]:
```
alpha = [100,200,500,1000,2000]
max_depth = [5, 10]
cv_log_error_array = []
for i in alpha:
    for j in max_depth:
        print("for n_estimators =", i,"and max depth = ", j)
        clf = RandomForestClassifier(n_estimators=i, criterion='gini', max_dep
th=j, random_state=42, n_jobs=-1)
        clf.fit(x_train_bow, y_train)
        sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
        sig_clf.fit(x_train_bow, y_train)
        sig_clf_probs = sig_clf.predict_proba(x_cv_bow)
        cv_log_error_array.append(log_loss(y_cv, sig_clf_probs, labels=clf.cla
sses_, eps=1e-15))
        print("Log Loss :",log_loss(y_cv, sig_clf_probs))

'''fig, ax = plt.subplots()
features = np.dot(np.array(alpha)[:,None],np.array(max_depth)[None]).ravel()
ax.plot(features, cv_log_error_array,c='g')
for i, txt in enumerate(np.round(cv_log_error_array,3)):
    ax.annotate((alpha[int(i/2)],max_depth[int(i%2)],str(txt)), (features[i],c
v_log_error_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()
'''

best_alpha = np.argmin(cv_log_error_array)
clf = RandomForestClassifier(n_estimators=alpha[int(best_alpha/2)], criterion=
'gini', max_depth=max_depth[int(best_alpha%2)], random_state=42, n_jobs=-1)
clf.fit(x_train_bow, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(x_train_bow, y_train)

predict_y = sig_clf.predict_proba(x_train_bow)
print('For values of best estimator = ', alpha[int(best_alpha/2)], "The train
 log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(x_cv_bow)
print('For values of best estimator = ', alpha[int(best_alpha/2)], "The cross
 validation log loss is:",log_loss(y_cv, predict_y, labels=clf.classes_, eps=1
e-15))
predict_y = sig_clf.predict_proba(x_test_bow)
#print('For values of best estimator = ', alpha[int(best_alpha/2)], "The test
 log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
```

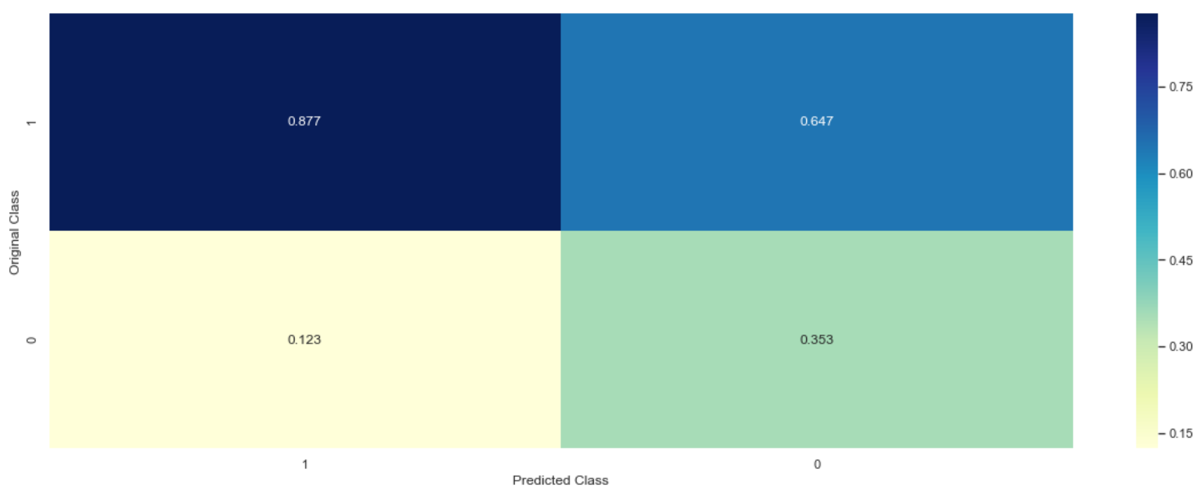
```
for n_estimators = 100 and max depth =  5
Log Loss : 0.36521456128006996
for n_estimators = 100 and max depth =  10
Log Loss : 0.3638449773032039
for n_estimators = 200 and max depth =  5
Log Loss : 0.36538038229699166
for n_estimators = 200 and max depth =  10
Log Loss : 0.3638092230242292
for n_estimators = 500 and max depth =  5
Log Loss : 0.365185416489371
for n_estimators = 500 and max depth =  10
Log Loss : 0.3636131280183961
for n_estimators = 1000 and max depth =  5
Log Loss : 0.3650757283865537
for n_estimators = 1000 and max depth =  10
Log Loss : 0.3635144143084634
for n_estimators = 2000 and max depth =  5
Log Loss : 0.36509527872669467
for n_estimators = 2000 and max depth =  10
Log Loss : 0.3635069086640479
For values of best estimator =  2000 The train log loss is: 0.350941839298182
9
For values of best estimator =  2000 The cross validation log loss is: 0.3635
069086648878
```

In [599]:
```
clf = RandomForestClassifier(n_estimators=2000, criterion='gini', max_depth=10
, random_state=42, n_jobs=-1)
predict_and_plot_confusion_matrix(x_train_bow, y_train,x_cv_bow,y_cv, clf)
```

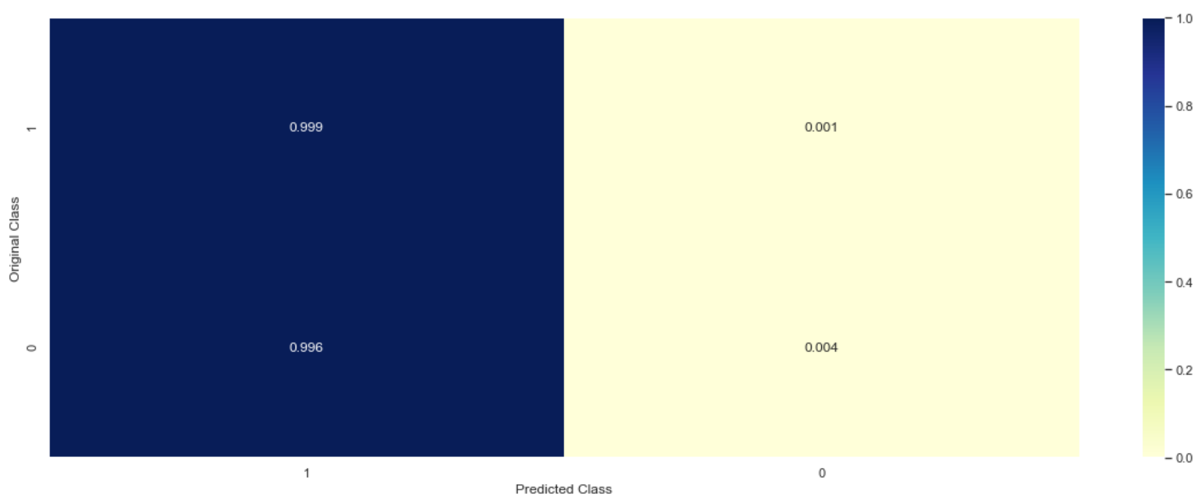
```
Log loss : 0.3635069086657385
Number of mis-classified points : 0.12345284311486641
-------------------- Confusion matrix --------------------
```




```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



In [600]:
```
predictions = clf.predict(x_test_bow)
print(predictions)
new_series = pd.Series(predictions)
new_series.value_counts()
```

```
[0 0 0 ... 0 0 0]
```

Out[600]:
```
0    48707
dtype: int64
```

In [601]:
```
predictions_RF = pd.DataFrame(new_series, columns=['IsBadBuy'])
predictions_RF.to_csv("predictions_RF.csv", index=False)
```

Notes:

```
most of the error occure in false negative cell in which original is 0 but predicte
d is 1.

of total available point 12.3% of point is misclassified using Random forest classi
fier.

after five set of iteration, we found the tuned value of n_estimators=2000,  max_de
pth=10 for criterion='gini' loss.

true positive is desirable condition which have high value while false negative val
ue is very less again support our model accuracy.
```

Stack the models

In [571]:

```
clf2 = KNeighborsClassifier(n_neighbors=121)
clf2.fit(x_train_bow, y_train)
sig_clf2 = CalibratedClassifierCV(clf2, method="sigmoid")
sig_clf2.fit(x_train_bow, y_train)

clf3 = MultinomialNB(alpha=0.1)
clf3.fit(x_train_bow, y_train)
sig_clf3 = CalibratedClassifierCV(clf3, method="sigmoid")
sig_clf3.fit(x_train_bow, y_train)

clf4 = SGDClassifier(class_weight='balanced', alpha=0.001, penalty='l2', loss=
'log', random_state=0)
clf4.fit(x_train_bow, y_train)
sig_clf4 = CalibratedClassifierCV(clf4, method="sigmoid")
sig_clf4.fit(x_train_bow, y_train)

clf5 = SGDClassifier(class_weight='balanced', alpha=0.0001, penalty='l2', loss
='hinge', random_state=0)
clf5.fit(x_train_bow, y_train)
sig_clf5 = CalibratedClassifierCV(clf5, method="sigmoid")
sig_clf5.fit(x_train_bow, y_train)

clf6 = RandomForestClassifier(n_estimators=2000, criterion='gini', max_depth=1
0, random_state=0, n_jobs=-1)
clf6.fit(x_train_bow, y_train)
sig_clf6 = CalibratedClassifierCV(clf6, method="sigmoid")
sig_clf6.fit(x_train_bow, y_train)


print("KNN :  Log Loss: %0.2f" % (log_loss(y_cv, sig_clf2.predict_proba(x_cv_b
ow))))

print("Logistic Regression :  Log Loss: %0.2f" % (log_loss(y_cv, sig_clf4.pred
ict_proba(x_cv_bow))))

print("Support vector machines : Log Loss: %0.2f" % (log_loss(y_cv, sig_clf5.p
redict_proba(x_cv_bow))))

print("Naive Bayes : Log Loss: %0.2f" % (log_loss(y_cv, sig_clf3.predict_proba
(x_cv_bow))))

print("Random Forest :  Log Loss: %0.2f" % (log_loss(y_cv, sig_clf6.predict_pr
oba(x_cv_bow))))

print("-"*50)
alpha = [0.0001,0.001,0.01,0.1,1,10]
best_alpha = 999
for i in alpha:
    lr = LogisticRegression(C=i)
    sclf = StackingClassifier(classifiers=[sig_clf2, sig_clf3, sig_clf4,sig_cl
f5,sig_clf6], meta_classifier=lr, use_probas=True)
    sclf.fit(x_train_bow, y_train)
    print("Stacking Classifer : for the value of alpha: %f Log Loss: %0.3f" %
(i, log_loss(y_cv, sclf.predict_proba(x_cv_bow))))
    log_error =log_loss(y_cv, sclf.predict_proba(x_cv_bow))
```

```
    if best_alpha > log_error:
        best_alpha = log_error
```

```
KNN :  Log Loss: 0.36
Logistic Regression :  Log Loss: 0.36
Support vector machines : Log Loss: 0.36
Naive Bayes : Log Loss: 0.37
Random Forest :  Log Loss: 0.36
--------------------------------------------------
Stacking Classifer : for the value of alpha: 0.000100 Log Loss: 0.383
Stacking Classifer : for the value of alpha: 0.001000 Log Loss: 0.368
Stacking Classifer : for the value of alpha: 0.010000 Log Loss: 0.361
Stacking Classifer : for the value of alpha: 0.100000 Log Loss: 0.361
Stacking Classifer : for the value of alpha: 1.000000 Log Loss: 0.368
Stacking Classifer : for the value of alpha: 10.000000 Log Loss: 0.373
```

the minimum log loss occure at alpha value of 0.01 and 0.1

In [573]:

```
lr = LogisticRegression(C=0.01)
sclf = StackingClassifier(classifiers=[sig_clf2, sig_clf3, sig_clf4,sig_clf5,sig_clf6], meta_classifier=lr, use_probas=True)
sclf.fit(x_train_bow, y_train)
```

Out[573]:

```
'log_error = log_loss(y_train, sclf.predict_proba(x_train_bow))\nprint("Log loss (train) on the stacking classifier :",log_error)\n\nlog_error = log_loss(y_cv, sclf.predict_proba(x_cv_bow))\nprint("Log loss (CV) on the stacking classifier :",log_error)\n\n#log_error = log_loss(y_test, sclf.predict_proba(x_test_bow))\n#print("Log loss (test) on the stacking classifier :",log_error)\n\nprint("Number of missclassified point :", np.count_nonzero((sclf.predict(x_test_bow)- y_test))/y_test.shape[0])\nplot_confusion_matrix(y_test=y_test, predict_y=sclf.predict(x_test_bow))'
```

Here im using logistic regression for all stacking classifier

In [597]:

```
predictions = sclf.predict(x_test_bow)
print(predictions)
new_series = pd.Series(predictions)
new_series.value_counts()
```

```
[0 0 0 ... 0 0 0]
```

Out[597]:

```
0    48698
1        9
dtype: int64
```

In [598]:

```
predictions_stack = pd.DataFrame(new_series, columns=['IsBadBuy'])
predictions_stack.to_csv("predictions_stack.csv", index=False)
```

Conclusion

Naive base , Logistic regreession and SVM shows better result for above problem.

KNN, Randome Forest, and Stacking Logistic regression are bias toward one class of buyer hence they have bias problem.

Random forest shows very good result on training data but one test data is's shows bias problem.