Importing Necessary Libraries

In [1]:

```
import pandas as pd
import numpy as np
import sklearn
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, accuracy_score
from sklearn.metrics import confusion_matrix
import numpy as np
from collections import defaultdict
import pydot
from io import StringIO
from sklearn.tree import export_graphviz
from sklearn.model_selection import GridSearchCV
from sklearn.neural_network import MLPClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import SelectFromModel
from sklearn.metrics import roc_auc_score
from sklearn.ensemble import VotingClassifier
from sklearn.feature_selection import RFECV
from sklearn.metrics import roc_curve
from itertools import compress
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import RandomOverSampler
import warnings
warnings.filterwarnings('ignore')

'''
TODO:

1. Try to improve

2. Desing the replace_val for each column

3. Creat preprocess procedure for every class.
'''


%matplotlib inline

rs = 101
```

Task 1. Data Selection and Distribution.

In [2]:

```
## Read Data
df = pd.read_csv("CaseStudyData.csv")
```

1. What is the proportion of cars who can be classified as a “kick”?

In [3]:

```
## Exploring the features in this dataset
print("Number of Columns: ", len(df.columns))
print("Columns: ",list(df.columns))
```

```
Number of Columns:  31
Columns:  ['PurchaseID', 'PurchaseTimestamp', 'PurchaseDate', 'Aucti
on', 'VehYear', 'Make', 'Color', 'Transmission', 'WheelTypeID', 'Whe
elType', 'VehOdo', 'Nationality', 'Size', 'TopThreeAmericanName', 'M
MRAcquisitionAuctionAveragePrice', 'MMRAcquisitionAuctionCleanPric
e', 'MMRAcquisitionRetailAveragePrice', 'MMRAcquisitonRetailCleanPri
ce', 'MMRCurrentAuctionAveragePrice', 'MMRCurrentAuctionCleanPrice',
'MMRCurrentRetailAveragePrice', 'MMRCurrentRetailCleanPrice', 'MMRCu
rrentRetailRatio', 'PRIMEUNIT', 'AUCGUART', 'VNST', 'VehBCost', 'IsO
nlineSale', 'WarrantyCost', 'ForSale', 'IsBadBuy']
```

In [4]:

```
print("Number of Observations: ", len(df))
```

```
Number of Observations:  41476
```

In [5]:

```
proportionOfKicks = len(df[df['IsBadBuy'] == 1]) / len(list(df['IsBadBuy']))
print("The proportion of kicks: ", proportionOfKicks)
```

```
The proportion of kicks:  0.1294965763333012
```

2. Did you have to fix any data quality problems? Detail them.

In [6]:

```
#### PREPROCESSING STATEGY
NEW_STATEGY = True
ResamplingMethod = 'rus' #['ros', 'rus']
if NEW_STATEGY:
    print("Using New Preprocessing Strategy")
    using_cat = False
    categorial_cols = ['Auction', 'VehYear', 'Make', 'Color', 'Transmission','Wh
eelTypeID', 'WheelType', 'Nationality', 'Size', 'TopThreeAmericanName','PRIMEUNI
T','AUCGUART','VNST','IsOnlineSale','ForSale' ] # Replaced by the most common
    interval_cols = ['VehOdo','MMRAcquisitionAuctionAveragePrice','MMRAcquisitio
nAuctionCleanPrice','MMRAcquisitionRetailAveragePrice','MMRAcquisitonRetailClean
Price','VehBCost','WarrantyCost' ]
    drop_cols = ['PurchaseID','PurchaseDate','PurchaseTimestamp']
    questionMark_data = ['MMRCurrentAuctionAveragePrice','MMRCurrentAuctionClean
Price','MMRCurrentRetailAveragePrice','MMRCurrentRetailCleanPrice','MMRCurrentRe
tailRatio']
    replaced_vals = ['?', '#VALUE!']
    if using_cat:
        categorial_cols += questionMark_data
        print("See [MMRCurrentAuctionAveragePrice" +
              "MMRCurrentAuctionCleanPrice, MMRCurrentRetailAveragePrice," +
              " MMRCurrentRetailCleanPrice, MMRCurrentRetailRatio] as Categorial
Data")
    else:
        interval_cols += questionMark_data
        print("See [MMRCurrentAuctionAveragePrice" +
              "MMRCurrentAuctionCleanPrice, MMRCurrentRetailAveragePrice," +
              " MMRCurrentRetailCleanPrice, MMRCurrentRetailRatio] as Interval D
ata")
else:
    print("Using Old Preprocessing Strategy")
    drop_cols = ['PurchaseID','PurchaseDate']
    categorial_cols = ['Auction', 'VehYear', 'Make', 'Color', 'Transmission','Wh
eelTypeID', 'WheelType', 'Nationality', 'Size', 'TopThreeAmericanName','PRIMEUNI
T','AUCGUART','VNST','IsOnlineSale','ForSale' ] # Replaced by the most common
    interval_cols = ['PurchaseTimestamp', 'VehOdo','MMRAcquisitionAuctionAverage
Price','MMRAcquisitionAuctionCleanPrice','MMRAcquisitionRetailAveragePrice','MMR
AcquisitonRetailCleanPrice','MMRCurrentAuctionAveragePrice','MMRCurrentAuctionCl
eanPrice','MMRCurrentRetailAveragePrice','MMRCurrentRetailCleanPrice','MMRCurren
tRetailRatio','VehBCost','WarrantyCost' ] # Replaced by the mean
    replaced_vals = ['?', '#VALUE!']

print("Total null before Replacing: ", df.isnull().sum().sum())
```

```
Using New Preprocessing Strategy
See [MMRCurrentAuctionAveragePriceMMRCurrentAuctionCleanPrice, MMRCu
rrentRetailAveragePrice, MMRCurrentRetailCleanPrice, MMRCurrentRetai
lRatio] as Categorial Data
Total null before Replacing:  1691
```

In [7]:

```
def printColumnInfo():

    '''
    Display the information of this Dataframe
    '''

    for colName in df.columns:
        print("====================== " + str(colName) + " ====================
===")
        print("---------------------- FIRST FIVE ----------------------")
        print(df[colName][:5])
        print("---------------------- DESCIRBE ----------------------")
        print(df[colName].describe())
        print("---------------------- COUNTS ----------------------")
        commonList = list(df[colName].value_counts().keys())
        if len(commonList) > 100:
            print("Five Most Common: ", commonList[:5])
        else:
            print("Count List: \n", df[colName].value_counts())
        print("Num of NULL: ", df[colName].isnull().sum())
        for rep in replaced_vals:
            print("Number of "+str(rep)+" : " + str(len(df[df[colName] == rep
])))
printColumnInfo()
```

```
======================= PurchaseID =======================
----------------------- FIRST FIVE -----------------------
0    0
1    1
2    2
3    3
4    4
Name: PurchaseID, dtype: int64
----------------------- DESCIRBE -----------------------
count    41476.000000
mean     20737.500000
std      11973.234219
min          0.000000
25%      10368.750000
50%      20737.500000
75%      31106.250000
max      41475.000000
Name: PurchaseID, dtype: float64
----------------------- COUNTS -----------------------
Five Most Common:  [2047, 11567, 15693, 13644, 3403]
Num of NULL:  0
Number of ? : 0
Number of #VALUE! : 0
======================= PurchaseTimestamp =======================
----------------------- FIRST FIVE -----------------------
0    1253232000
1    1253232000
2    1253232000
3    1253232000
4    1253232000
Name: PurchaseTimestamp, dtype: int64
----------------------- DESCIRBE -----------------------
count    4.147600e+04
mean     1.262260e+09
std      1.796895e+07
min      1.231114e+09
25%      1.247530e+09
50%      1.262045e+09
75%      1.277770e+09
max      1.293667e+09
Name: PurchaseTimestamp, dtype: float64
----------------------- COUNTS -----------------------
Five Most Common:  [1235520000, 1259020800, 1234396800, 1264032000,
1287014400]
Num of NULL:  0
Number of ? : 0
Number of #VALUE! : 0
======================= PurchaseDate =======================
----------------------- FIRST FIVE -----------------------
0    18/09/2009 10:00
1    18/09/2009 10:00
2    18/09/2009 10:00
3    18/09/2009 10:00
4    18/09/2009 10:00
Name: PurchaseDate, dtype: object
----------------------- DESCIRBE -----------------------
count                41476
unique                 497
top       12/02/2009 10:00
freq                   242
Name: PurchaseDate, dtype: object
```

```
----------------------- COUNTS -----------------------
Five Most Common:  ['12/02/2009 10:00', '24/11/2009 10:00', '25/02/2
009 10:00', '21/01/2010 10:00', '14/10/2010 10:00']
Num of NULL:  0
Number of ? : 0
Number of #VALUE! : 0
======================= Auction =======================
----------------------- FIRST FIVE -----------------------
0    OTHER
1    OTHER
2    OTHER
3    OTHER
4    OTHER
Name: Auction, dtype: object
----------------------- DESCIRBE -----------------------
count       41432
unique          3
top       MANHEIM
freq        22168
Name: Auction, dtype: object
----------------------- COUNTS -----------------------
Count List:
 MANHEIM    22168
ADESA      11086
OTHER       8178
Name: Auction, dtype: int64
Num of NULL:  44
Number of ? : 0
Number of #VALUE! : 0
======================= VehYear =======================
----------------------- FIRST FIVE -----------------------
0    2008.0
1    2008.0
2    2008.0
3    2008.0
4    2008.0
Name: VehYear, dtype: float64
----------------------- DESCIRBE -----------------------
count    41432.000000
mean      2005.360615
std          1.730587
min       2001.000000
25%       2004.000000
50%       2005.000000
75%       2007.000000
max       2010.000000
Name: VehYear, dtype: float64
----------------------- COUNTS -----------------------
Count List:
 2006.0    9630
2005.0    8682
2007.0    6514
2004.0    5792
2008.0    4177
2003.0    3554
2002.0    1879
2001.0     816
2009.0     387
2010.0       1
Name: VehYear, dtype: int64
Num of NULL:  44
```

```
Number of ? : 0
Number of #VALUE! : 0
====================== Make ======================
---------------------- FIRST FIVE ----------------------
0        DODGE
1        DODGE
2     CHRYSLER
3    CHEVROLET
4        DODGE
Name: Make, dtype: object
---------------------- DESCIRBE ----------------------
count         41432
unique           30
top       CHEVROLET
freq           9548
Name: Make, dtype: object
---------------------- COUNTS ----------------------
Count List:
 CHEVROLET     9548
DODGE         7385
FORD          6458
CHRYSLER      5259
PONTIAC       2355
KIA           1337
SATURN        1245
NISSAN        1186
JEEP           985
HYUNDAI        957
SUZUKI         842
TOYOTA         664
MITSUBISHI     569
MAZDA          532
MERCURY        527
BUICK          413
GMC            351
HONDA          263
OLDSMOBILE     146
ISUZU           82
SCION           77
VOLKSWAGEN      73
LINCOLN         54
INFINITI        27
ACURA           19
MINI            19
SUBARU          17
CADILLAC        17
LEXUS           13
VOLVO           12
Name: Make, dtype: int64
Num of NULL:  44
Number of ? : 0
Number of #VALUE! : 0
====================== Color ======================
---------------------- FIRST FIVE ----------------------
0       RED
1       RED
2    SILVER
3       RED
4    SILVER
Name: Color, dtype: object
---------------------- DESCIRBE ----------------------
```

```
count      41432
unique        17
top       SILVER
freq        8541
Name: Color, dtype: object
----------------------- COUNTS -----------------------
Count List:
 SILVER       8541
WHITE        6890
BLUE         5855
BLACK        4392
GREY         4248
RED          3661
GOLD         3059
GREEN        1796
MAROON       1039
BEIGE         894
ORANGE        255
BROWN         249
PURPLE        205
YELLOW        141
OTHER         136
NOT AVAIL      65
?               6
Name: Color, dtype: int64
Num of NULL:  44
Number of ? : 6
Number of #VALUE! : 0
======================= Transmission =======================
----------------------- FIRST FIVE -----------------------
0    AUTO
1    AUTO
2    AUTO
3    AUTO
4    AUTO
Name: Transmission, dtype: object
----------------------- DESCIRBE -----------------------
count     41432
unique        4
top        AUTO
freq      39930
Name: Transmission, dtype: object
----------------------- COUNTS -----------------------
Count List:
 AUTO      39930
MANUAL     1495
?             6
Manual        1
Name: Transmission, dtype: int64
Num of NULL:  44
Number of ? : 6
Number of #VALUE! : 0
======================= WheelTypeID =======================
----------------------- FIRST FIVE -----------------------
0    2
1    2
2    2
3    2
4    2
Name: WheelTypeID, dtype: object
----------------------- DESCIRBE -----------------------
```

```
count     41432
unique        5
top           1
freq      20426
Name: WheelTypeID, dtype: object
----------------------- COUNTS -----------------------
Count List:
 1    20426
2    18791
?     1775
3      437
0        3
Name: WheelTypeID, dtype: int64
Num of NULL:  44
Number of ? : 1775
Number of #VALUE! : 0
======================= WheelType =======================
----------------------- FIRST FIVE -----------------------
0    Covers
1    Covers
2    Covers
3    Covers
4    Covers
Name: WheelType, dtype: object
----------------------- DESCIRBE -----------------------
count     41380
unique        4
top       Alloy
freq      20406
Name: WheelType, dtype: object
----------------------- COUNTS -----------------------
Count List:
 Alloy      20406
Covers     18761
?           1777
Special      436
Name: WheelType, dtype: int64
Num of NULL:  96
Number of ? : 1777
Number of #VALUE! : 0
======================= VehOdo =======================
----------------------- FIRST FIVE -----------------------
0    51099.0
1    48542.0
2    46318.0
3    50413.0
4    50199.0
Name: VehOdo, dtype: float64
----------------------- DESCIRBE -----------------------
count     41432.000000
mean      71300.010427
std       14724.041171
min         577.000000
25%       61578.000000
50%       73128.500000
75%       82259.250000
max      480444.000000
Name: VehOdo, dtype: float64
----------------------- COUNTS -----------------------
Five Most Common:  [84675.0, 85884.0, 67464.0, 72101.0, 79600.0]
Num of NULL:  44
```

```
Number of ? : 0
Number of #VALUE! : 0
======================= Nationality =======================
----------------------- FIRST FIVE -----------------------
0    AMERICAN
1    AMERICAN
2    AMERICAN
3    AMERICAN
4    AMERICAN
Name: Nationality, dtype: object
----------------------- DESCIRBE -----------------------
count        41432
unique           6
top       AMERICAN
freq         34616
Name: Nationality, dtype: object
----------------------- COUNTS -----------------------
Count List:
 AMERICAN          34616
OTHER ASIAN        4474
TOP LINE ASIAN     2110
USA                 125
OTHER               104
?                     3
Name: Nationality, dtype: int64
Num of NULL:  44
Number of ? : 3
Number of #VALUE! : 0
======================= Size =======================
----------------------- FIRST FIVE -----------------------
0     MEDIUM
1     MEDIUM
2     MEDIUM
3    COMPACT
4     MEDIUM
Name: Size, dtype: object
----------------------- DESCIRBE -----------------------
count      41432
unique        13
top       MEDIUM
freq       17540
Name: Size, dtype: object
----------------------- COUNTS -----------------------
Count List:
 MEDIUM         17540
LARGE           4968
MEDIUM SUV      4569
COMPACT         4035
VAN             3367
LARGE TRUCK     1897
SMALL SUV       1332
SPECIALTY        998
CROSSOVER        974
LARGE SUV        830
SMALL TRUCK      494
SPORTS           425
?                  3
Name: Size, dtype: int64
Num of NULL:  44
Number of ? : 3
Number of #VALUE! : 0
```

```
======================= TopThreeAmericanName =======================
----------------------- FIRST FIVE -----------------------
0    CHRYSLER
1    CHRYSLER
2    CHRYSLER
3          GM
4    CHRYSLER
Name: TopThreeAmericanName, dtype: object
----------------------- DESCIRBE -----------------------
count     41432
unique        5
top          GM
freq      14075
Name: TopThreeAmericanName, dtype: object
----------------------- COUNTS -----------------------
Count List:
 GM          14075
CHRYSLER    13627
FORD         7039
OTHER        6688
?               3
Name: TopThreeAmericanName, dtype: int64
Num of NULL:  44
Number of ? : 3
Number of #VALUE! : 0
======================= MMRAcquisitionAuctionAveragePrice ==========
=============
----------------------- FIRST FIVE -----------------------
0    8566
1    8566
2    8835
3    7165
4    8566
Name: MMRAcquisitionAuctionAveragePrice, dtype: object
----------------------- DESCIRBE -----------------------
count     41416
unique     9271
top           0
freq        502
Name: MMRAcquisitionAuctionAveragePrice, dtype: object
----------------------- COUNTS -----------------------
Five Most Common:  ['0', '5480', '6311', '7811', '7644']
Num of NULL:  60
Number of ? : 7
Number of #VALUE! : 0
======================= MMRAcquisitionAuctionCleanPrice ============
===========
----------------------- FIRST FIVE -----------------------
0    9325
1    9325
2    9428
3    7770
4    9325
Name: MMRAcquisitionAuctionCleanPrice, dtype: object
----------------------- DESCIRBE -----------------------
count     41429
unique    10010
top           0
freq        415
Name: MMRAcquisitionAuctionCleanPrice, dtype: object
----------------------- COUNTS -----------------------
```

```
Five Most Common:  ['0', '6461', '7450', '1', '8258']
Num of NULL:  47
Number of ? : 7
Number of #VALUE! : 0
====================== MMRAcquisitionRetailAveragePrice ===========
============
----------------------- FIRST FIVE -----------------------
0     9751
1     9751
2    10042
3     8238
4     9751
Name: MMRAcquisitionRetailAveragePrice, dtype: object
----------------------- DESCIRBE -----------------------
count     41429
unique    11070
top           0
freq        502
Name: MMRAcquisitionRetailAveragePrice, dtype: object
----------------------- COUNTS -----------------------
Five Most Common:  ['0', '6418', '7316', '11114', '8756']
Num of NULL:  47
Number of ? : 7
Number of #VALUE! : 0
====================== MMRAcquisitonRetailCleanPrice ==============
=========
----------------------- FIRST FIVE -----------------------
0    10571
1    10571
2    10682
3     8892
4    10571
Name: MMRAcquisitonRetailCleanPrice, dtype: object
----------------------- DESCIRBE -----------------------
count     41327
unique    11583
top           0
freq        501
Name: MMRAcquisitonRetailCleanPrice, dtype: object
----------------------- COUNTS -----------------------
Five Most Common:  ['0', '7478', '8546', '11562', '10103']
Num of NULL:  149
Number of ? : 7
Number of #VALUE! : 0
====================== MMRCurrentAuctionAveragePrice ==============
=========
----------------------- FIRST FIVE -----------------------
0    7781
1    8568
2    8137
3    7074
4    7857
Name: MMRCurrentAuctionAveragePrice, dtype: object
----------------------- DESCIRBE -----------------------
count     41429
unique     9183
top           0
freq        287
Name: MMRCurrentAuctionAveragePrice, dtype: object
----------------------- COUNTS -----------------------
Five Most Common:  ['0', '?', '5480', '6311', '7269']
```

```
Num of NULL:  47
Number of ? : 184
Number of #VALUE! : 0
====================== MMRCurrentAuctionCleanPrice ================
=======
----------------------- FIRST FIVE -----------------------
0    8545
1    9325
2    8733
3    7629
4    8711
Name: MMRCurrentAuctionCleanPrice, dtype: object
----------------------- DESCIRBE -----------------------
count     41429
unique     9890
top           0
freq        206
Name: MMRCurrentAuctionCleanPrice, dtype: object
----------------------- COUNTS -----------------------
Five Most Common:  ['0', '?', '6461', '1', '7450']
Num of NULL:  47
Number of ? : 184
Number of #VALUE! : 0
====================== MMRCurrentRetailAveragePrice ===============
========
----------------------- FIRST FIVE -----------------------
0    11777
1     9753
2     9288
3     8140
4     8986
Name: MMRCurrentRetailAveragePrice, dtype: object
----------------------- DESCIRBE -----------------------
count     41409
unique    10935
top           0
freq        287
Name: MMRCurrentRetailAveragePrice, dtype: object
----------------------- COUNTS -----------------------
Five Most Common:  ['0', '?', '6418', '7316', '8756']
Num of NULL:  67
Number of ? : 184
Number of #VALUE! : 0
====================== MMRCurrentRetailCleanPrice =================
======
----------------------- FIRST FIVE -----------------------
0    12505
1    10571
2     9932
3     8739
4     9908
Name: MMRCurrentRetailCleanPrice, dtype: object
----------------------- DESCIRBE -----------------------
count     41409
unique    11363
top           0
freq        287
Name: MMRCurrentRetailCleanPrice, dtype: object
----------------------- COUNTS -----------------------
Five Most Common:  ['0', '?', '7478', '8546', '10103']
Num of NULL:  67
```

```
Number of ? : 184
Number of #VALUE! : 0
====================== MMRCurrentRetailRatio ======================
=
---------------------- FIRST FIVE ----------------------
0    0.941783287
1    0.922618485
2    0.935159082
3    0.931456688
4    0.906943884
Name: MMRCurrentRetailRatio, dtype: object
---------------------- DESCIRBE ----------------------
count       41116
unique      25870
top        #VALUE!
freq          178
Name: MMRCurrentRetailRatio, dtype: object
---------------------- COUNTS ----------------------
Five Most Common:  ['#VALUE!', '0.858250869', '0.856073017', '0.8666
73265', '0.949268378']
Num of NULL:  360
Number of ? : 0
Number of #VALUE! : 178
====================== PRIMEUNIT ======================
---------------------- FIRST FIVE ----------------------
0    ?
1    ?
2    ?
3    ?
4    ?
Name: PRIMEUNIT, dtype: object
---------------------- DESCIRBE ----------------------
count     41432
unique        3
top           ?
freq      39634
Name: PRIMEUNIT, dtype: object
---------------------- COUNTS ----------------------
Count List:
 ?      39634
NO      1764
YES       34
Name: PRIMEUNIT, dtype: int64
Num of NULL:  44
Number of ? : 39634
Number of #VALUE! : 0
====================== AUCGUART ======================
---------------------- FIRST FIVE ----------------------
0    ?
1    ?
2    ?
3    ?
4    ?
Name: AUCGUART, dtype: object
---------------------- DESCIRBE ----------------------
count     41432
unique        3
top           ?
freq      39634
Name: AUCGUART, dtype: object
---------------------- COUNTS ----------------------
```

```
Count List:
 ?        39634
GREEN     1754
RED         44
Name: AUCGUART, dtype: int64
Num of NULL:  44
Number of ? : 39634
Number of #VALUE! : 0
======================= VNST =======================
----------------------- FIRST FIVE -----------------------
0    NC
1    NC
2    NC
3    NC
4    NC
Name: VNST, dtype: object
----------------------- DESCIRBE -----------------------
count     41432
unique       31
top          TX
freq       9076
Name: VNST, dtype: object
----------------------- COUNTS -----------------------
Count List:
 TX    9076
FL    5250
CO    3623
NC    3594
AZ    3383
CA    3268
OK    2595
SC    1662
TN    1471
GA    1287
VA    1093
MO     758
PA     700
NV     553
IN     486
MS     412
LA     349
NJ     317
NM     239
KY     230
AL     179
IL     165
UT     165
WV     137
WA     136
OR     136
NH      97
NE      26
OH      25
ID      14
NY       6
Name: VNST, dtype: int64
Num of NULL:  44
Number of ? : 0
Number of #VALUE! : 0
======================= VehBCost =======================
----------------------- FIRST FIVE -----------------------
```

```
0    7800
1    7800
2    7800
3    6000
4    7800
Name: VehBCost, dtype: object
----------------------- DESCIRBE -----------------------
count     41432
unique     1869
top        7500
freq        459
Name: VehBCost, dtype: object
----------------------- COUNTS ----------------------
Five Most Common:  ['7500', '6500', '7800', '7200', '7000']
Num of NULL:  44
Number of ? : 29
Number of #VALUE! : 0
======================= IsOnlineSale =======================
----------------------- FIRST FIVE ----------------------
0    0
1    0
2    0
3    0
4    0
Name: IsOnlineSale, dtype: object
----------------------- DESCIRBE -----------------------
count     41432.0
unique        8.0
top           0.0
freq      31368.0
Name: IsOnlineSale, dtype: float64
----------------------- COUNTS ----------------------
Count List:
 0.0     31368
0        8572
1.0       753
-1.0      601
1         134
?           2
4.0         1
2.0         1
Name: IsOnlineSale, dtype: int64
Num of NULL:  44
Number of ? : 2
Number of #VALUE! : 0
======================= WarrantyCost =======================
----------------------- FIRST FIVE ----------------------
0    920.0
1    834.0
2    834.0
3    671.0
4    920.0
Name: WarrantyCost, dtype: float64
----------------------- DESCIRBE -----------------------
count    41432.000000
mean      1273.050758
std        599.188662
min        462.000000
25%        834.000000
50%       1155.000000
75%       1623.000000
```

```
max       7498.000000
Name: WarrantyCost, dtype: float64
----------------------- COUNTS -----------------------
Five Most Common:  [920.0, 1974.0, 2152.0, 1215.0, 1389.0]
Num of NULL:  44
Number of ? : 0
Number of #VALUE! : 0
======================= ForSale =======================
----------------------- FIRST FIVE -----------------------
0    Yes
1    Yes
2    Yes
3    Yes
4    Yes
Name: ForSale, dtype: object
----------------------- DESCIRBE -----------------------
count     41476
unique        6
top         Yes
freq      27402
Name: ForSale, dtype: object
----------------------- COUNTS -----------------------
Count List:
 Yes    27402
YES     8544
yes     5524
?          3
No         2
0          1
Name: ForSale, dtype: int64
Num of NULL:  0
Number of ? : 3
Number of #VALUE! : 0
======================= IsBadBuy =======================
----------------------- FIRST FIVE -----------------------
0    0
1    0
2    0
3    0
4    0
Name: IsBadBuy, dtype: int64
----------------------- DESCIRBE -----------------------
count    41476.000000
mean         0.129497
std          0.335753
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          1.000000
Name: IsBadBuy, dtype: float64
----------------------- COUNTS -----------------------
Count List:
 0    36105
1     5371
Name: IsBadBuy, dtype: int64
Num of NULL:  0
Number of ? : 0
Number of #VALUE! : 0
```

In [8]:

```
if NEW_STATEGY:

    class filling_method():
        MOST_COMMON = "MOST_COMMON"
        MEAN = "MEAN"
        CERTAIN_VALUE = "CERTAIN_VALUE"

    def replaceFunc(colName):
        for replaced, target in preprocessStrategy[colName]['replace_pairs']:
            df[colName].replace(replaced, target, inplace=True)

    def removeOutlier(colName):  # FOR THE INTERVAL ONLY
        global df
        df = df[df[colName] < df[colName].quantile(0.999)]

    def replacingValueCol(colName):
        for replaced in preprocessStrategy[colName]['replaced_vals']:
            print("In the Column: " + str(colName) + " : " + str(len(
                df[df[colName] == replaced])) + ", " + str(replaced) + "have bee
n replaced by null")
            # Replacing the null in this process #Inplacing for saving the memor
y
            df[colName].replace(replaced, float('nan'), inplace=True)

    def loweringCol(colName):
        df[colName] = df[colName].str.lower()

    def fillingTheNullValue(colName):  # method can be ["MEAN", "MOST_COMMON"]
        if preprocessStrategy[colName]['filling_method'] == filling_method.MEAN:
            df[colName] = df[colName].astype('float')
            df[colName].fillna(df[colName].astype(
                'float').mean(), inplace=True)
        elif preprocessStrategy[colName]['filling_method'] == filling_method.MOS
T_COMMON:
            df[colName] = df[colName].astype('category')
            df[colName].fillna(df[colName].astype(
                'category').describe()['top'], inplace=True)
        elif preprocessStrategy[colName]['filling_method'] == filling_method.CER
TAIN_VALUE:
            df[colName] = df[colName].astype('category')
            df[colName] = df[colName].cat.add_categories(
                [preprocessStrategy[colName]['filling_value']])
            df[colName].fillna(preprocessStrategy[colName]
                               ['filling_value'], inplace=True)

    def filterOutRareValue(colName):

        def checkingKeepValue(v, savingValues):
            if v in savingValues:
                return v
            return "LESS_FREQ"

        k = [v for v in df[colName].value_counts().values if v >
             preprocessStrategy[colName]['min_freq']]
        savingValues = df[colName].value_counts().keys()[:len(k)]

        df[colName] = [checkingKeepValue(v, savingValues) for v in df[colName]]
```

```python
    def changeToType(colName):
        df[colName] = df[colName].astype(
            preprocessStrategy[colName]['changeToType'])

    def newData_prep(df):
        '''
        For Preprocessing through the whole dictionary
        '''
        df.drop(drop_cols, axis=1, inplace=True)

        for colName in df.columns:  # df.columns:

            print("Preprocess the col: " + colName)

            for stra in preprocessStrategy[colName]['strategies']:
                if not stra:
                    continue
                print(stra)
                stra(colName)

        if not using_cat:
            df['MMRCurrentRetailRatio'] = df['MMRCurrentRetailAveragePrice'] / \
                (df['MMRCurrentRetailCleanPrice']+1e-8)  # Prvent divided by 0

        return df

    preprocessStrategy = defaultdict(dict)

    preprocessStrategy['Auction'] = {
        "strategies":
            [
                replacingValueCol,
                loweringCol,
                fillingTheNullValue,
            ],
        "replaced_vals": ['?'],
        "filling_method": filling_method.MOST_COMMON
    }

    preprocessStrategy['VehYear'] = {
        "strategies":
            [
                fillingTheNullValue,
            ],
        "filling_method": filling_method.CERTAIN_VALUE,
        "filling_value": "UNKNOWN_VALUE"
    }

    preprocessStrategy['Make'] = {
        "strategies":
            [
                loweringCol,
                fillingTheNullValue,
            ],
        "filling_method": filling_method.MOST_COMMON
    }

    preprocessStrategy['Color'] = {
        "strategies":
            [
                loweringCol,
```

```
                replacingValueCol,
                fillingTheNullValue,
            ],
        "replaced_vals": ['?'],
        "filling_method": filling_method.MOST_COMMON
    }

    preprocessStrategy['Transmission'] = {
        "strategies":
            [
                loweringCol,
                replacingValueCol,
                fillingTheNullValue,
            ],
        "replaced_vals": ['?'],
        "filling_method": filling_method.MOST_COMMON
    }

    preprocessStrategy['WheelTypeID'] = {
        "strategies":
            [
                fillingTheNullValue,
            ],
        "filling_method": filling_method.MOST_COMMON
    }

    preprocessStrategy['WheelType'] = {
        "strategies":
            [
                loweringCol,
                fillingTheNullValue,
            ],
        "filling_method": filling_method.MOST_COMMON
    }

    preprocessStrategy['VehOdo'] = {
        "strategies":
            [
                fillingTheNullValue,
            ],
        "filling_method": filling_method.MEAN
    }

    preprocessStrategy['Nationality'] = {  # Should I merge USA with AMERICAN?
        "strategies":
            [
                replaceFunc,
                loweringCol,
                replacingValueCol,
                fillingTheNullValue,
            ],
        "replaced_vals": ['?'],
        "filling_method": filling_method.MOST_COMMON,
        "replace_pairs": [("USA", "AMERICAN")]

    }

    preprocessStrategy['Size'] = {
        "strategies":
            [
                loweringCol,
```

```
                replacingValueCol,
                fillingTheNullValue,
            ],
        "replaced_vals": ['?'],
        "filling_method": filling_method.MOST_COMMON

    }

    preprocessStrategy['TopThreeAmericanName'] = {
        "strategies":
            [
                loweringCol,
                replacingValueCol,
                fillingTheNullValue,
            ],
        "replaced_vals": ['?'],
        "filling_method": filling_method.MOST_COMMON
    }

    preprocessStrategy['TopThreeAmericanName'] = {
        "strategies":
            [
                loweringCol,
                replacingValueCol,
                fillingTheNullValue,
            ],
        "replaced_vals": ['?'],
        "filling_method": filling_method.MOST_COMMON
    }

    preprocessStrategy['MMRAcquisitionAuctionAveragePrice'] = {
        "strategies":
            [
                replacingValueCol,
                fillingTheNullValue,
            ],
        "replaced_vals": ['?'],
        "filling_method": filling_method.MEAN
    }

    preprocessStrategy['MMRAcquisitionAuctionCleanPrice'] = {
        "strategies":
            [
                replacingValueCol,
                fillingTheNullValue,
            ],
        "replaced_vals": ['?'],
        "filling_method": filling_method.MEAN
    }

    preprocessStrategy['MMRAcquisitionRetailAveragePrice'] = {
        "strategies":
            [
                replacingValueCol,
                fillingTheNullValue,
            ],
        "replaced_vals": ['?'],
        "filling_method": filling_method.MEAN
    }

    preprocessStrategy['MMRAcquisitonRetailCleanPrice'] = {
```

```
        "strategies":
            [
                replacingValueCol,
                fillingTheNullValue,
            ],
        "replaced_vals": ['?'],
        "filling_method": filling_method.MEAN
    }

    ###############################################################

    int_stra = {
        "strategies":
            [
                replacingValueCol,
                fillingTheNullValue,
            ],
        "replaced_vals": ['?', '#VALUE!'],  # GOT 184 '?'
        "filling_method": filling_method.MEAN,
    }

    cat_stra = {  # HOW DO WE DEAL WITH ? in this column
        "strategies":
            [
                filterOutRareValue,
                fillingTheNullValue,
            ],
        #     "replaced_vals": ['?'], # GOT 184 '?'
        "filling_method": filling_method.CERTAIN_VALUE,
        "filling_value": 'NULL',
        "min_freq": 50
    }

    preprocessStrategy['MMRCurrentAuctionAveragePrice'] \
        = preprocessStrategy['MMRCurrentAuctionCleanPrice'] \
        = preprocessStrategy['MMRCurrentRetailAveragePrice'] \
        = preprocessStrategy['MMRCurrentRetailCleanPrice'] \
        = preprocessStrategy['MMRCurrentRetailRatio'] \
        = cat_stra if using_cat else int_stra

    ###############################################################

    preprocessStrategy['PRIMEUNIT'] = {  # HOW DO WE DEAL WITH ? in this column
        "strategies":
            [
                loweringCol,
                fillingTheNullValue,
            ],
        #     "replaced_vals": ['?'], # GOT 184 '?'
        "filling_method": filling_method.CERTAIN_VALUE,
        "filling_value": 'NULL',
    }

    preprocessStrategy['AUCGUART'] = {  # HOW DO WE DEAL WITH ? in this column
        "strategies":
            [
                loweringCol,
                fillingTheNullValue,
            ],
        #     "replaced_vals": ['?'], # GOT 184 '?'
        "filling_method": filling_method.CERTAIN_VALUE,
```

```
        "filling_value": 'NULL',
    }

    preprocessStrategy['VNST'] = {  # HOW DO WE DEAL WITH ? in this column
        "strategies":
            [
                loweringCol,
                fillingTheNullValue,
            ],
        #     "replaced_vals": ['?'], # GOT 184 '?'
        "filling_method": filling_method.CERTAIN_VALUE,
        "filling_value": 'NULL',
    }

    preprocessStrategy['VehBCost'] = {  # HOW DO WE DEAL WITH ? in this column
        "strategies":
            [
                replacingValueCol,

                fillingTheNullValue,
            ],
        "replaced_vals": ['?'],  # GOT 184 '?'
        "filling_method": filling_method.MEAN
    }

    preprocessStrategy['IsOnlineSale'] = {  # HOW DO WE DEAL WITH ? in this colu
mn
        "strategies":
            [
                replacingValueCol,
                changeToType,
                fillingTheNullValue,
            ],
        "replaced_vals": ['?', 2.0, 4.0],  # GOT 184 '?'
        "filling_method": filling_method.MOST_COMMON,
        "changeToType": 'float'
    }

    preprocessStrategy['WarrantyCost'] = {  # HOW DO WE DEAL WITH ? in this colu
mn
        "strategies":
            [
                fillingTheNullValue,
            ],
        "replaced_vals": ['?'],  # GOT 184 '?'
        "filling_method": filling_method.MEAN,
    }

    preprocessStrategy['ForSale'] = {  # HOW DO WE DEAL WITH ? in this column
        "strategies":
            [
                loweringCol,
                replacingValueCol,
                fillingTheNullValue,
            ],
        "replaced_vals": ['?', 0],  # GOT 184 '?'
        "filling_method": filling_method.MOST_COMMON,
    }

    # HOW DO WE DEAL WITH ? in this column
    preprocessStrategy['IsBadBuy'] = {"strategies": [None]}
```

```
        newData_prep(df)


else:

    def data_prep(df):
        '''
        For Preprocessing the Data (OLD_METHOD)
        '''

        # Check the replaced values are not in the dataset

        for colName in df.columns:

            if colName in categorial_cols:

                if colName == "IsOnlineSale":
                    df[colName] = df[colName].astype(
                        'float').astype('category')
                    df[colName].fillna(df[colName].astype(
                        'category').describe()['top'], inplace=True)

                # Try to lower the data if the data type is string
                try:
                    df[colName] = df[colName].str.lower()
                except:
                    print(colName, " can't be lowered")

                for replaced in replaced_vals:
                    print("In the Column: " + str(colName) + ": " +
                          str(len(df[df[colName] == replaced])) + " -> " + str(r
eplaced))
                    df[colName].replace(replaced, float('nan'), inplace=True)

                df[colName] = df[colName].astype('category')

                # Replacing the null by the most common category
                df[colName].fillna(df[colName].astype(
                    'category').describe()['top'], inplace=True)

            if colName in interval_cols:

                if colName == "MMRCurrentRetailRatio":  # Dealing with this calc
ulated value at the last
                    continue

                for replaced in replaced_vals:
                    print("In the Column: " + str(colName) + ": " +
                          str(len(df[df[colName] == replaced])) + " -> " + str(r
eplaced))
                    df[colName].replace(replaced, float('nan'), inplace=True)

                df[colName] = df[colName].astype('float')

                # Removing outlier
                df = df[df[colName] < df[colName].quantile(0.999)]

                # Replacing the null by the mean
                df[colName].fillna(df[colName].astype(
                    'float').mean(), inplace=True)
```

```
    df['MMRCurrentRetailRatio'] = df['MMRCurrentRetailAveragePrice'] / \
        (df['MMRCurrentRetailCleanPrice']+1e-8)  # Prvent divided by 0

    df.drop(drop_cols, axis=1, inplace=True)

    return df

df = data_prep(df)
```

```
Preprocess the col: Auction
<function replacingValueCol at 0x7fbaaa726158>
In the Column: Auction : 0, ?have been replaced by null
<function loweringCol at 0x7fbaaa726d90>
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: VehYear
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: Make
<function loweringCol at 0x7fbaaa726d90>
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: Color
<function loweringCol at 0x7fbaaa726d90>
<function replacingValueCol at 0x7fbaaa726158>
In the Column: Color : 6, ?have been replaced by null
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: Transmission
<function loweringCol at 0x7fbaaa726d90>
<function replacingValueCol at 0x7fbaaa726158>
In the Column: Transmission : 6, ?have been replaced by null
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: WheelTypeID
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: WheelType
<function loweringCol at 0x7fbaaa726d90>
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: VehOdo
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: Nationality
<function replaceFunc at 0x7fbaaa726488>
<function loweringCol at 0x7fbaaa726d90>
<function replacingValueCol at 0x7fbaaa726158>
In the Column: Nationality : 3, ?have been replaced by null
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: Size
<function loweringCol at 0x7fbaaa726d90>
<function replacingValueCol at 0x7fbaaa726158>
In the Column: Size : 3, ?have been replaced by null
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: TopThreeAmericanName
<function loweringCol at 0x7fbaaa726d90>
<function replacingValueCol at 0x7fbaaa726158>
In the Column: TopThreeAmericanName : 3, ?have been replaced by null
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: MMRAcquisitionAuctionAveragePrice
<function replacingValueCol at 0x7fbaaa726158>
In the Column: MMRAcquisitionAuctionAveragePrice : 7, ?have been rep
laced by null
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: MMRAcquisitionAuctionCleanPrice
<function replacingValueCol at 0x7fbaaa726158>
In the Column: MMRAcquisitionAuctionCleanPrice : 7, ?have been repla
ced by null
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: MMRAcquisitionRetailAveragePrice
<function replacingValueCol at 0x7fbaaa726158>
In the Column: MMRAcquisitionRetailAveragePrice : 7, ?have been repl
aced by null
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: MMRAcquisitonRetailCleanPrice
<function replacingValueCol at 0x7fbaaa726158>
In the Column: MMRAcquisitonRetailCleanPrice : 7, ?have been replace
```

```
d by null
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: MMRCurrentAuctionAveragePrice
<function filterOutRareValue at 0x7fbaaaf3a8c8>
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: MMRCurrentAuctionCleanPrice
<function filterOutRareValue at 0x7fbaaaf3a8c8>
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: MMRCurrentRetailAveragePrice
<function filterOutRareValue at 0x7fbaaaf3a8c8>
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: MMRCurrentRetailCleanPrice
<function filterOutRareValue at 0x7fbaaaf3a8c8>
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: MMRCurrentRetailRatio
<function filterOutRareValue at 0x7fbaaaf3a8c8>
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: PRIMEUNIT
<function loweringCol at 0x7fbaaa726d90>
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: AUCGUART
<function loweringCol at 0x7fbaaa726d90>
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: VNST
<function loweringCol at 0x7fbaaa726d90>
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: VehBCost
<function replacingValueCol at 0x7fbaaa726158>
In the Column: VehBCost : 29, ?have been replaced by null
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: IsOnlineSale
<function replacingValueCol at 0x7fbaaa726158>
In the Column: IsOnlineSale : 2, ?have been replaced by null
In the Column: IsOnlineSale : 1, 2.0have been replaced by null
In the Column: IsOnlineSale : 1, 4.0have been replaced by null
<function changeToType at 0x7fbaaaf3a9d8>
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: WarrantyCost
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: ForSale
<function loweringCol at 0x7fbaaa726d90>
<function replacingValueCol at 0x7fbaaa726158>
In the Column: ForSale : 3, ?have been replaced by null
In the Column: ForSale : 0, 0have been replaced by null
<function fillingTheNullValue at 0x7fbaaa7260d0>
Preprocess the col: IsBadBuy
```

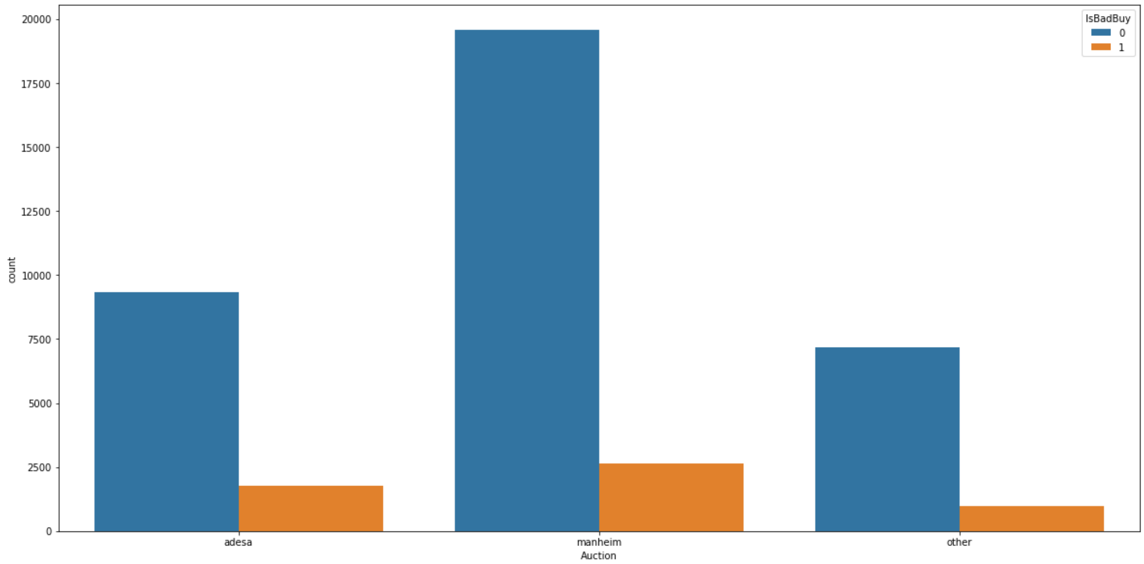
3. Can you identify any clear patterns by initial exploration of the data using histogram or box plot?

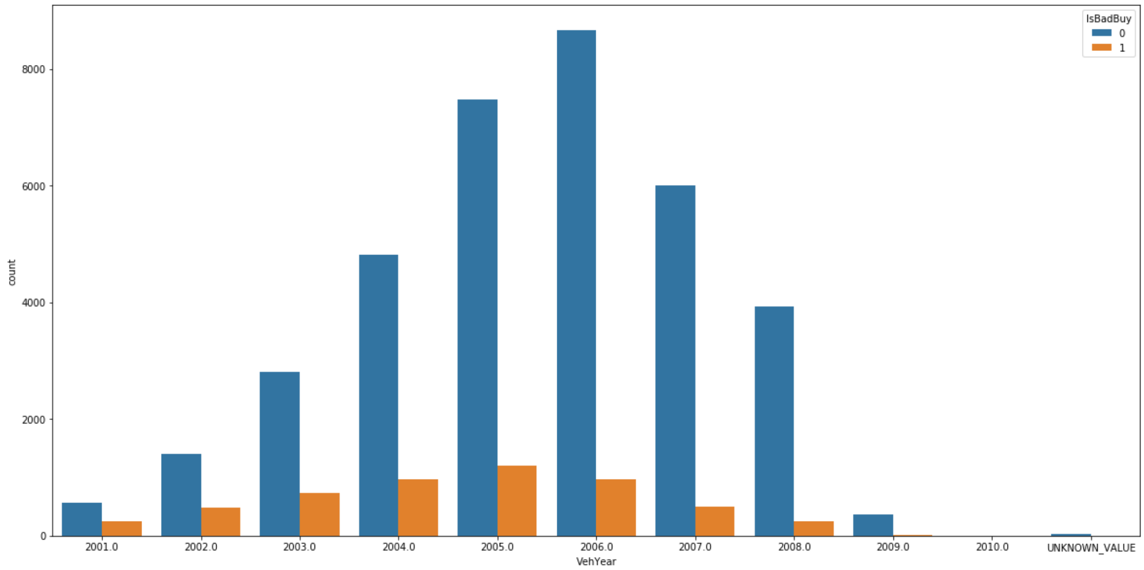
In [9]:

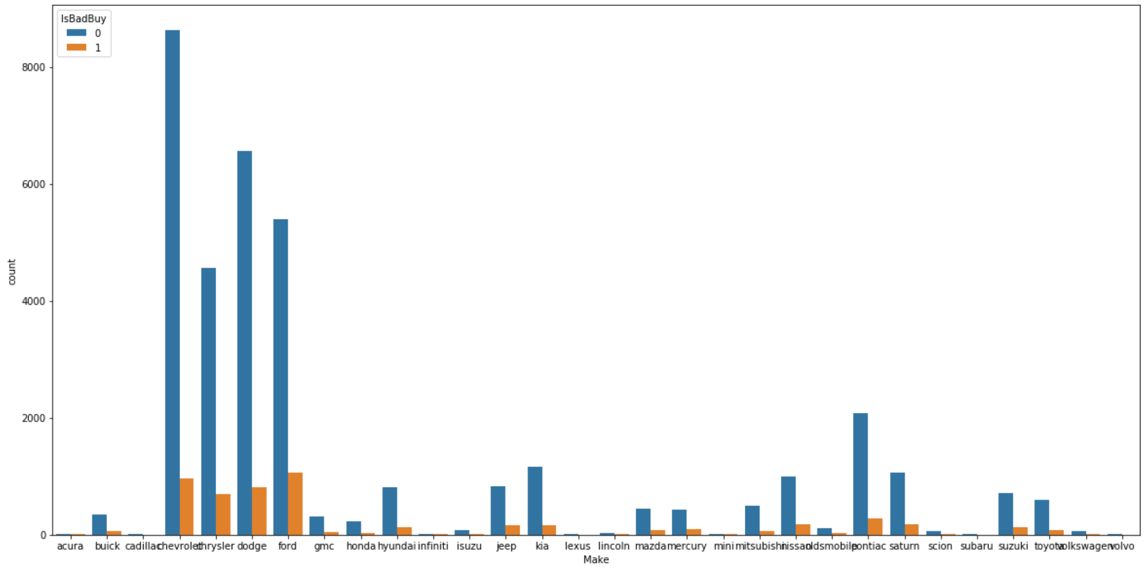
```
def plotAllCols (df):
    for colName in df.columns:
        plt.figure(figsize=(20,10))
        if colName in categorial_cols:
            ### if it's categorial column, plot hist diagram
            sns.countplot(x=colName, data = df, hue="IsBadBuy")
        elif colName in interval_cols:
            ### if it's interval column, plot box diagram
            sns.boxplot(x="IsBadBuy", y=colName, data = df )
```

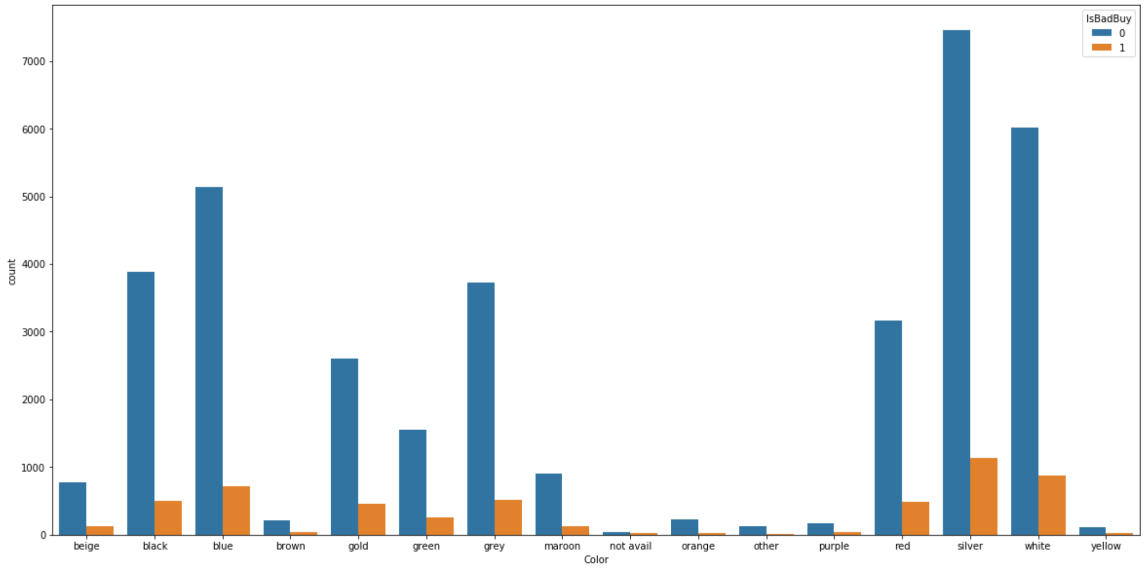
In [10]:

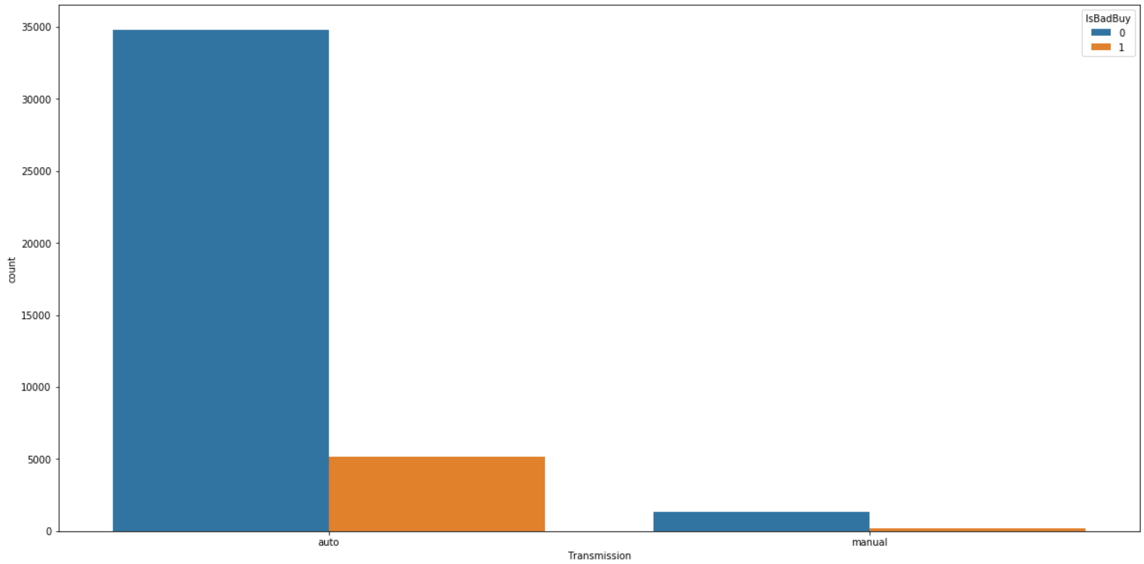
```
plotAllCols(df)
```

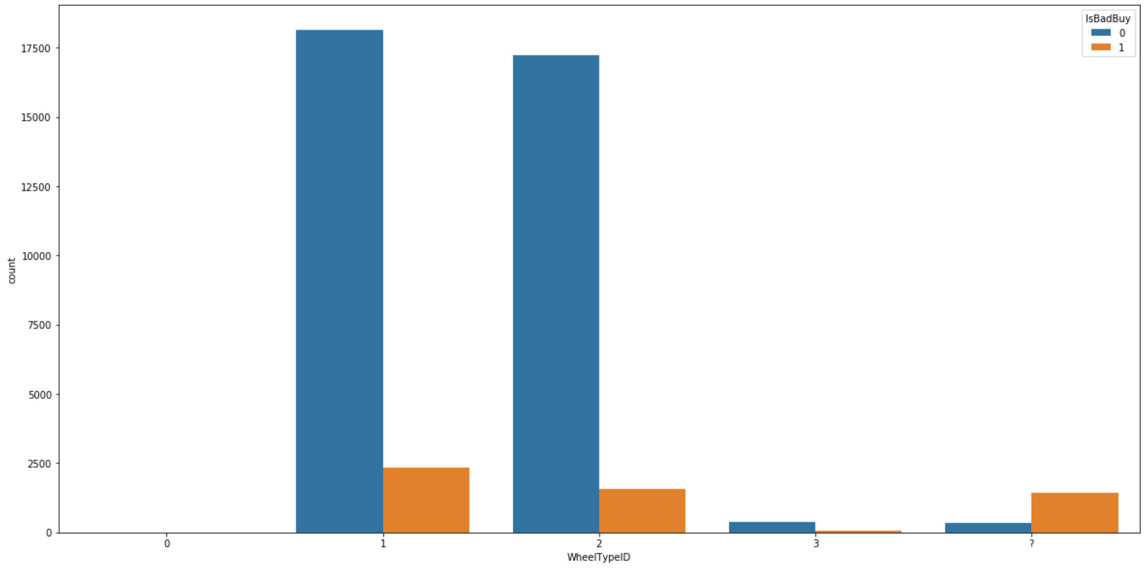

IsBadBuy
0
1
count
20000
17500
15000
12500
10000
7500
5000
2500
0
adesa
manheim
other
Auction

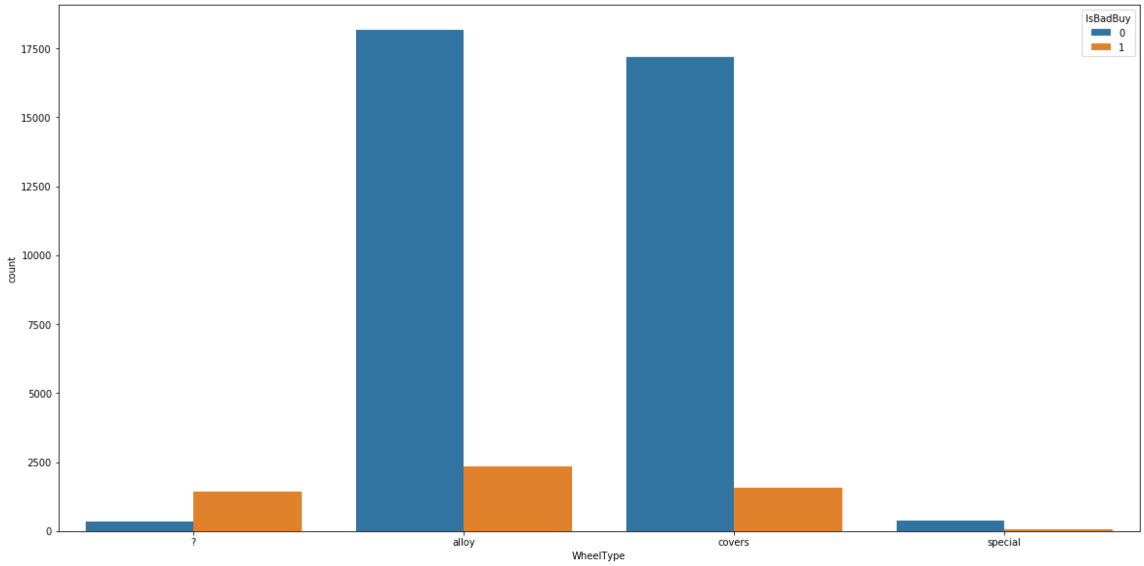

IsBadBuy
0
1
count
8000
6000
4000
2000
0
2001.0
2002.0
2003.0
2004.0
2005.0
2006.0
2007.0
2008.0
2009.0
2010.0
UNKNOWN_VALUE
VehYear

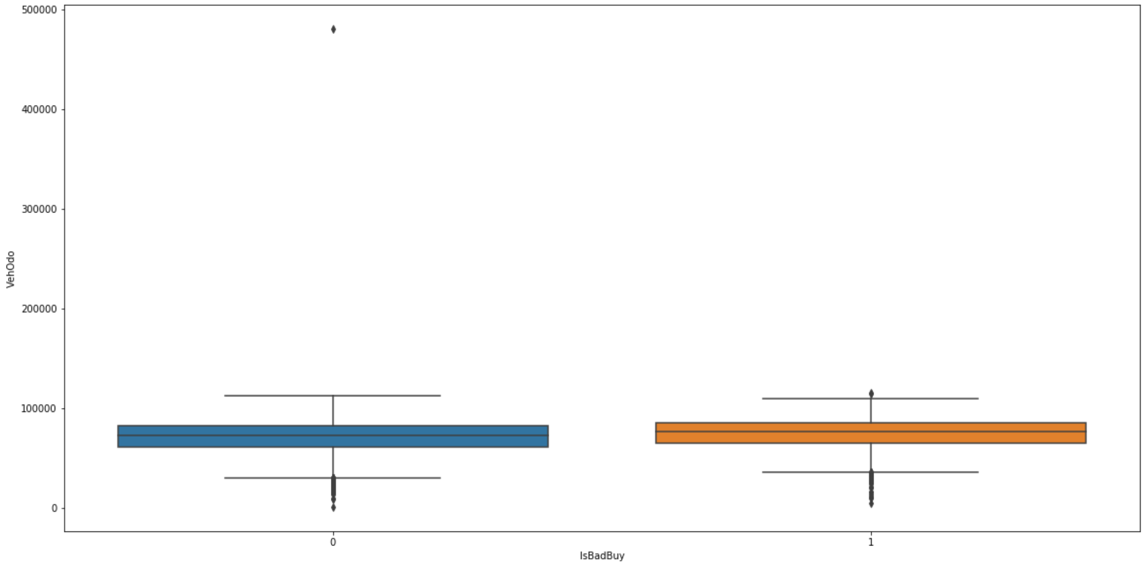

IsBadBuy
0
1
8000
6000
4000
2000
0
count
acura buick cadillac chevrolet chrysler dodge ford gmc honda hyundai infiniti isuzu jeep kia lexus lincoln mazda mercury mini mitsubishi nissan oldsmobile pontiac saturn scion subaru suzuki toyota volkswagen volvo
Make

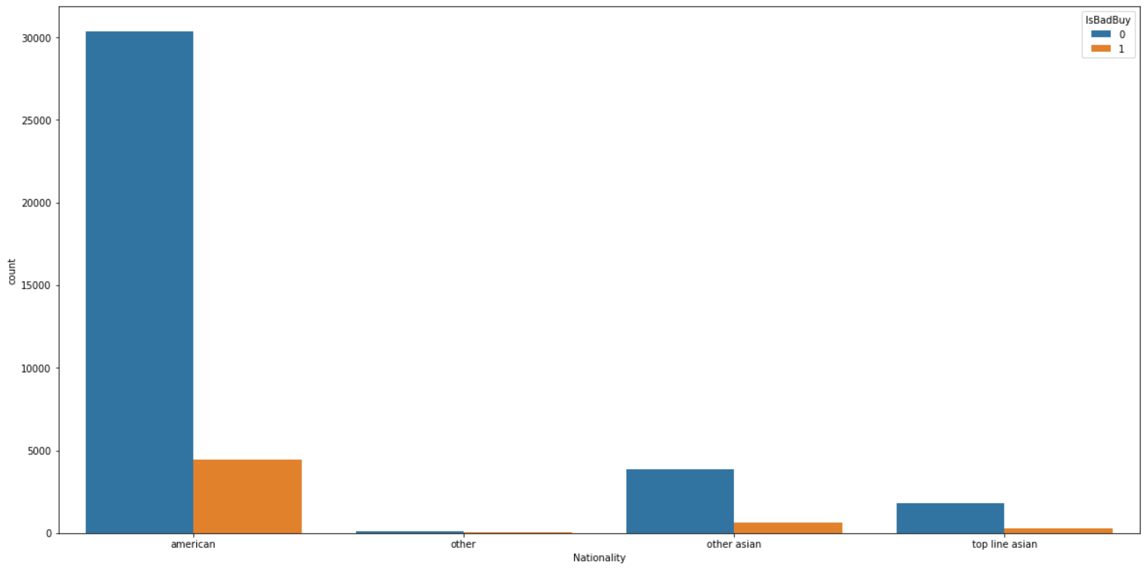

IsBadBuy
0
1
7000
6000
5000
4000
3000
2000
1000
0
count
beige black blue brown gold green grey maroon not avail orange other purple red silver white yellow
Color

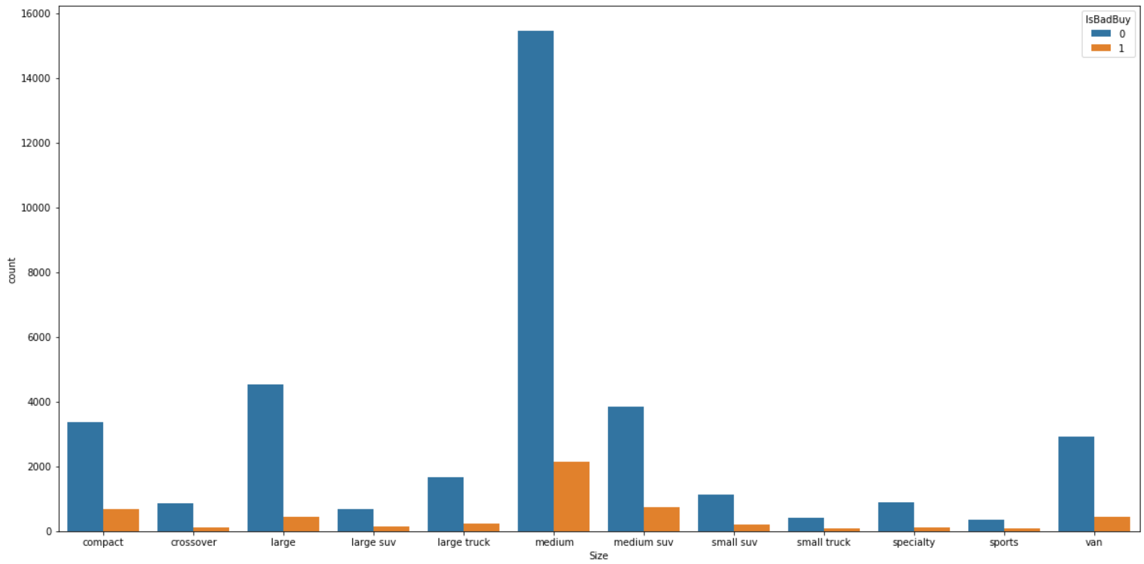

IsBadBuy
0
1
35000
30000
25000
20000
15000
10000
5000
0
count
auto
manual
Transmission

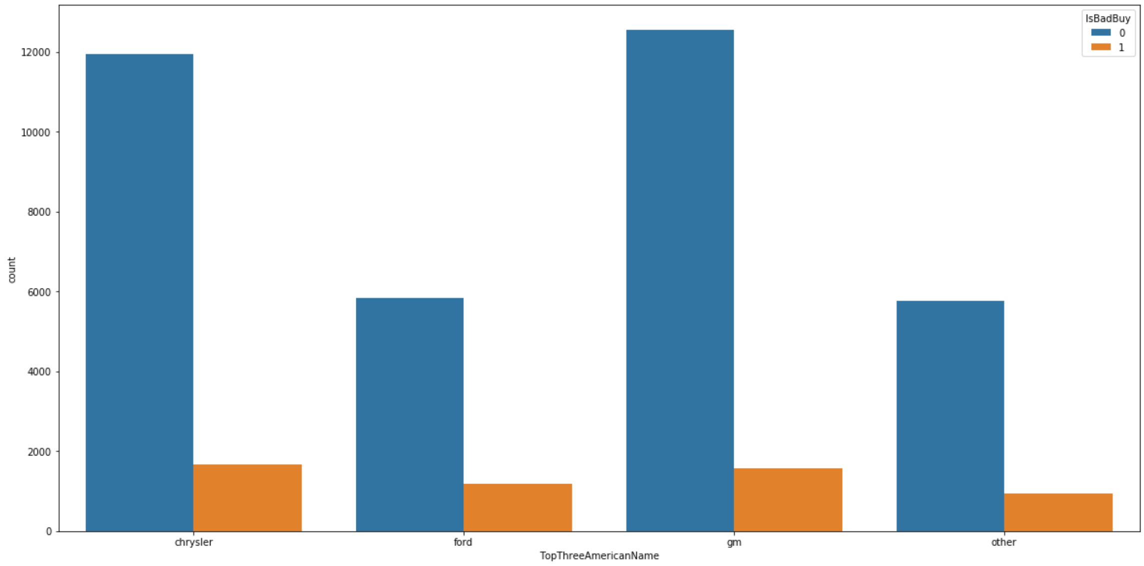

IsBadBuy
0
1
17500
15000
12500
10000
7500
5000
2500
0
count
0
1
2
3
?
WheelTypeID

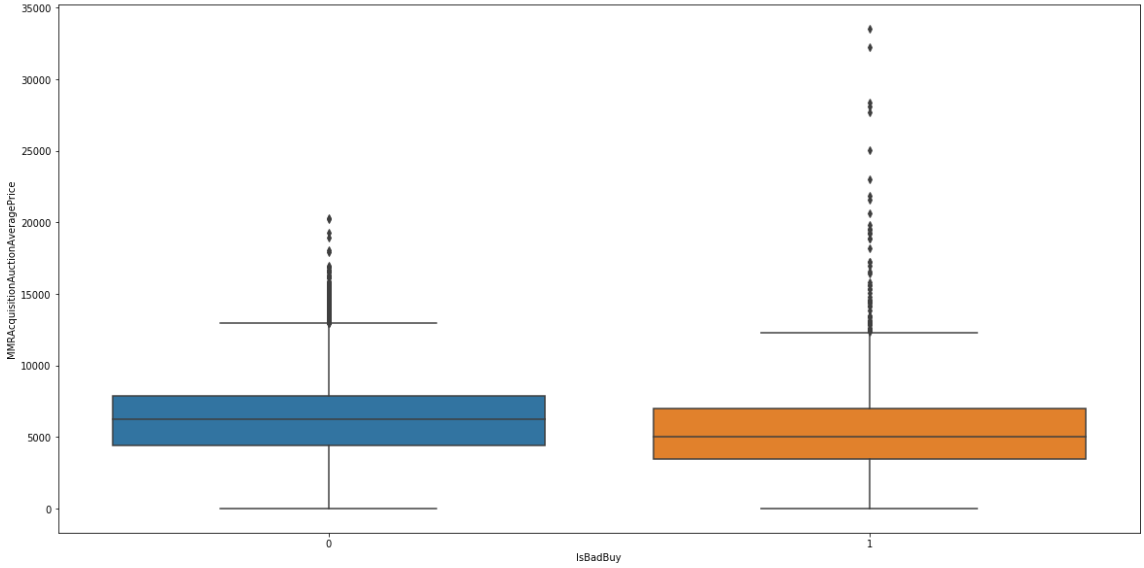

IsBadBuy
0
1
17500
15000
12500
10000
7500
5000
2500
0
count
?
alloy
covers
special
WheelType

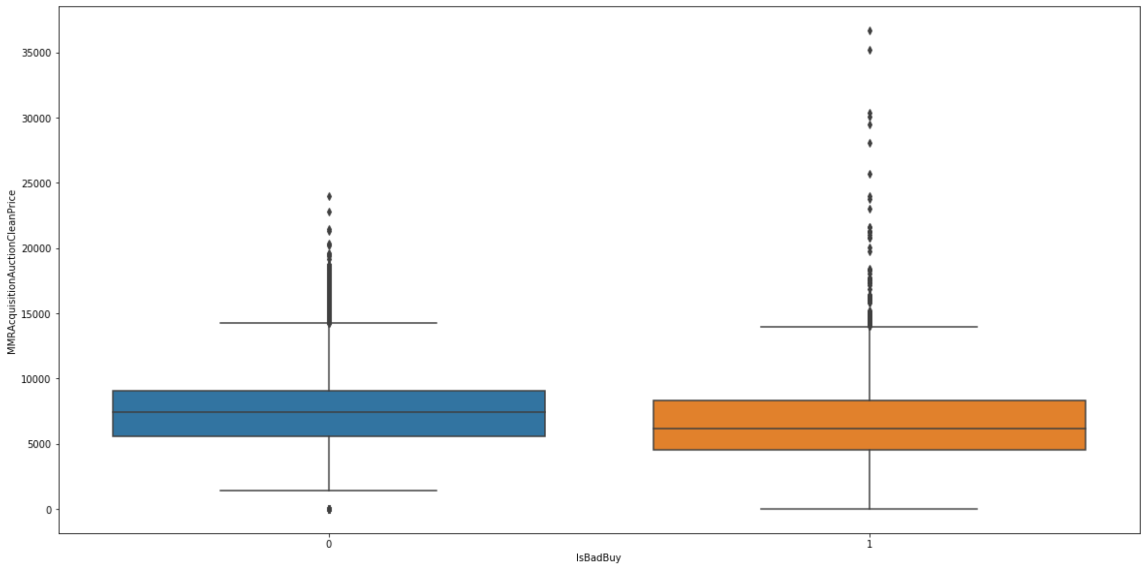

500000
400000
300000
200000
100000
0
VehOdo
0
1
IsBadBuy

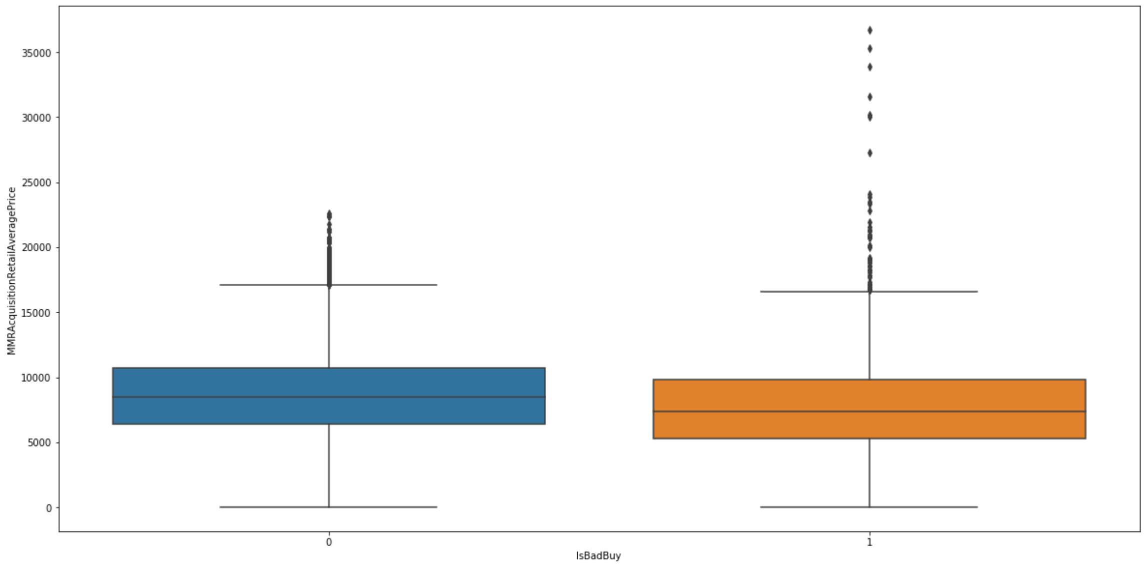

IsBadBuy
0
1
30000
25000
20000
15000
10000
5000
0
count
american
other
other asian
top line asian
Nationality

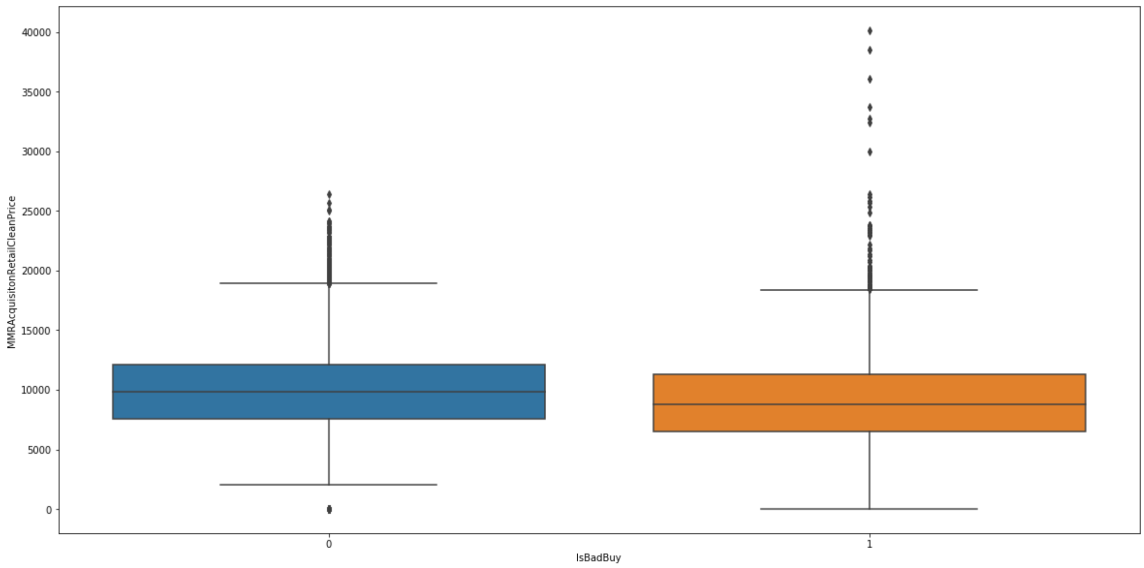

IsBadBuy
0
1
16000
14000
12000
10000
8000
6000
4000
2000
0
count
compact
crossover
large
large suv
large truck
medium
medium suv
small suv
small truck
specialty
sports
van
Size


IsBadBuy
0
1
count
0
2000
4000
6000
8000
10000
12000
chrysler
ford
gm
other
TopThreeAmericanName

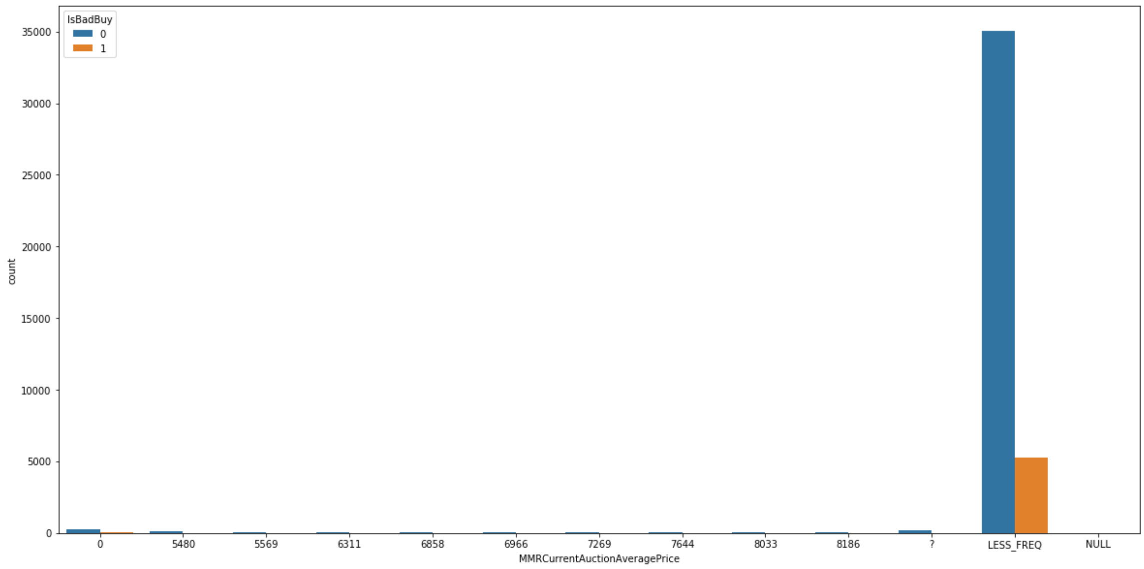

MMRAcquisitionAuctionAveragePrice
0
5000
10000
15000
20000
25000
30000
35000
0
1
IsBadBuy


35000
30000
25000
20000
15000
10000
5000
0
MMRAcquisitionAuctionCleanPrice
0
1
IsBadBuy

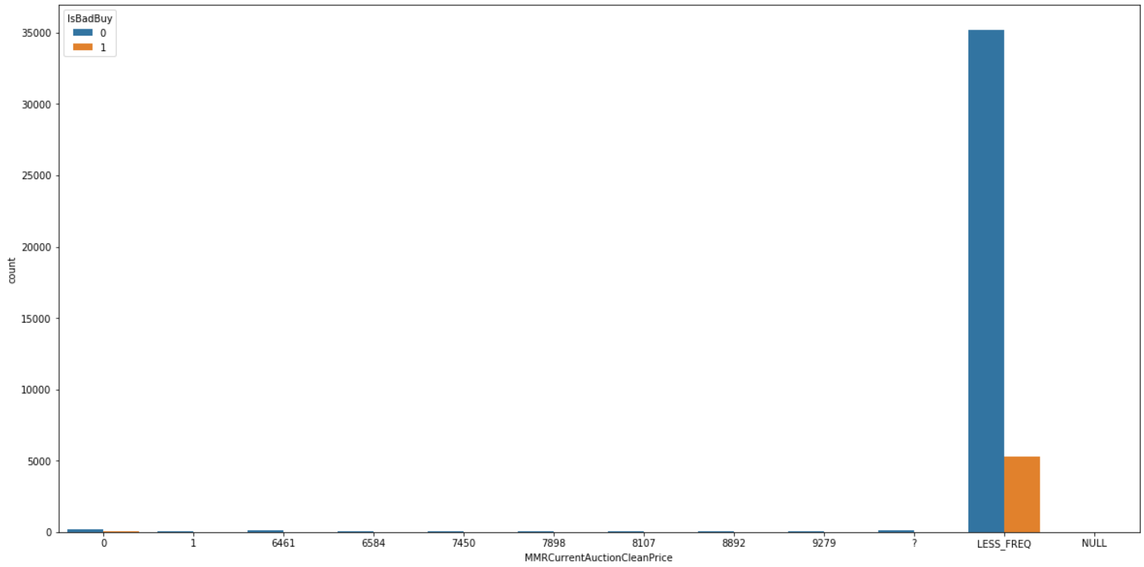

35000
30000
25000
20000
15000
10000
5000
0
MMRAcquisitionRetailAveragePrice
0
1
IsBadBuy

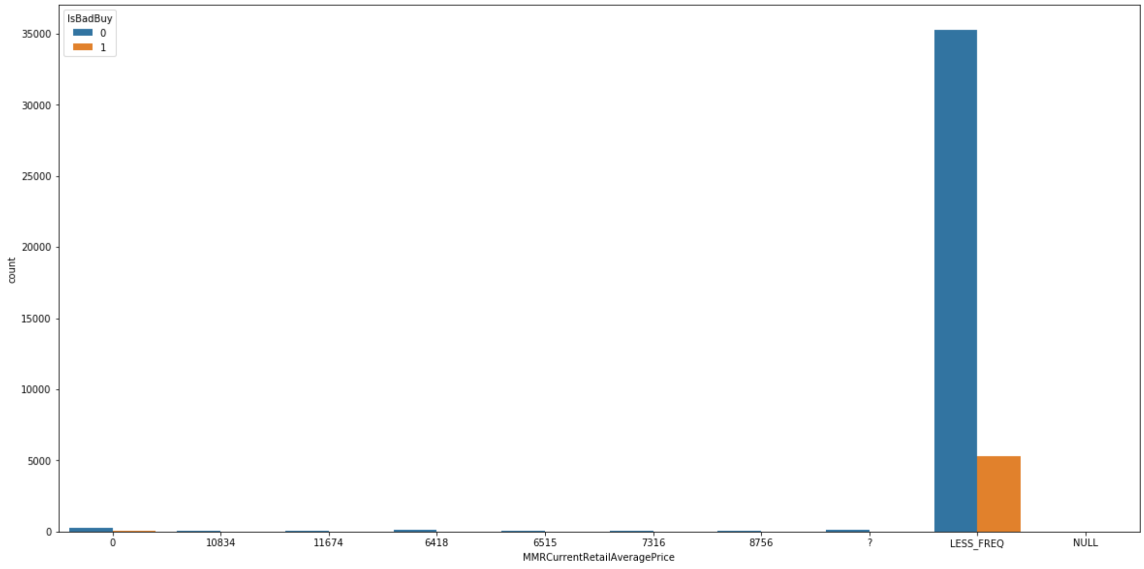


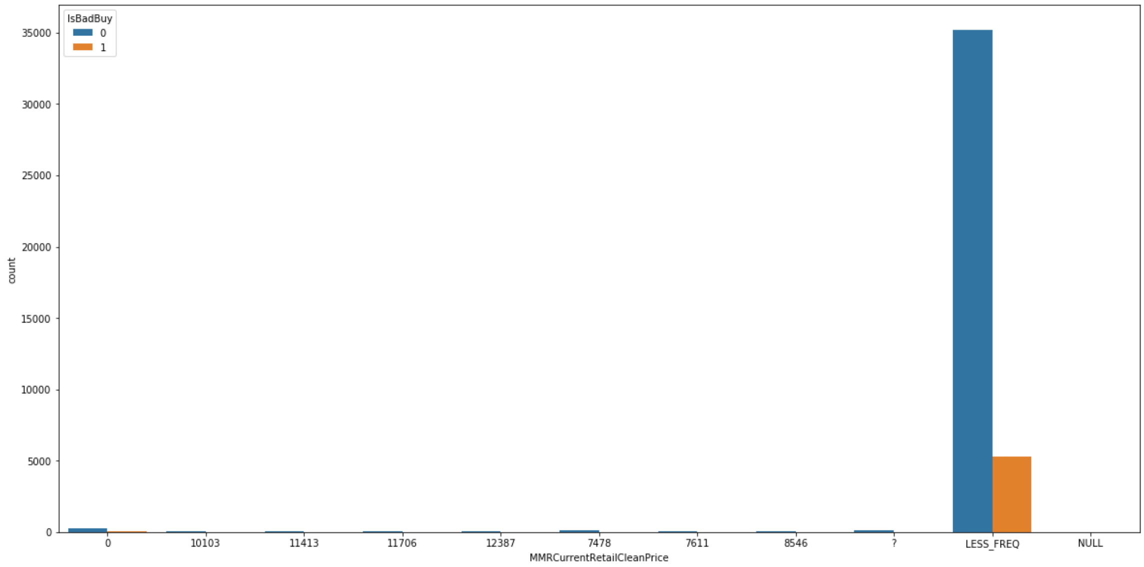
MMRAcquisitonRetailCleanPrice
40000
35000
30000
25000
20000
15000
10000
5000
0
0
1
IsBadBuy

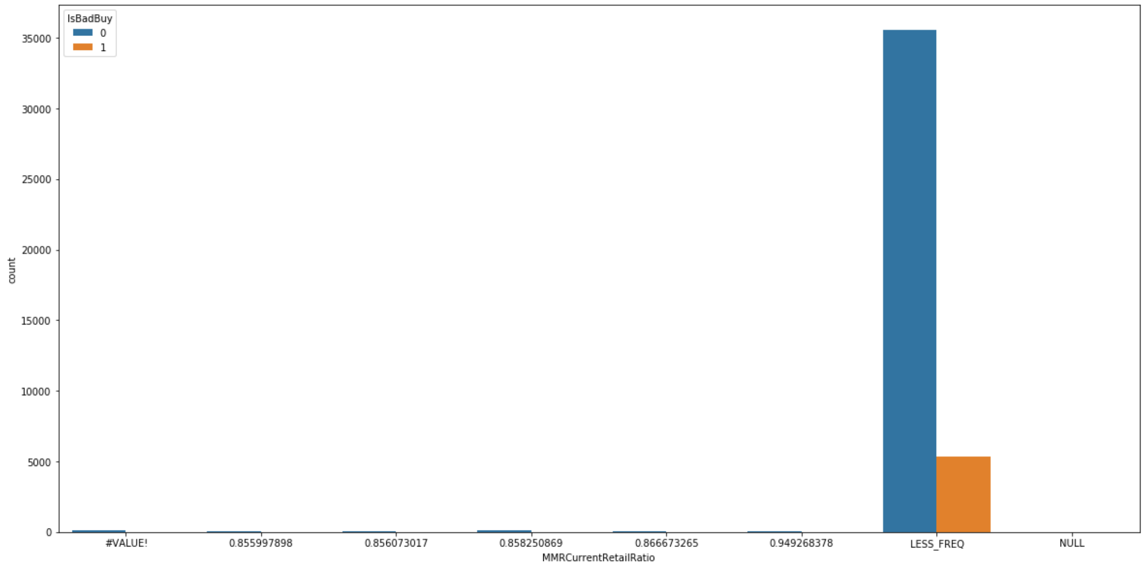


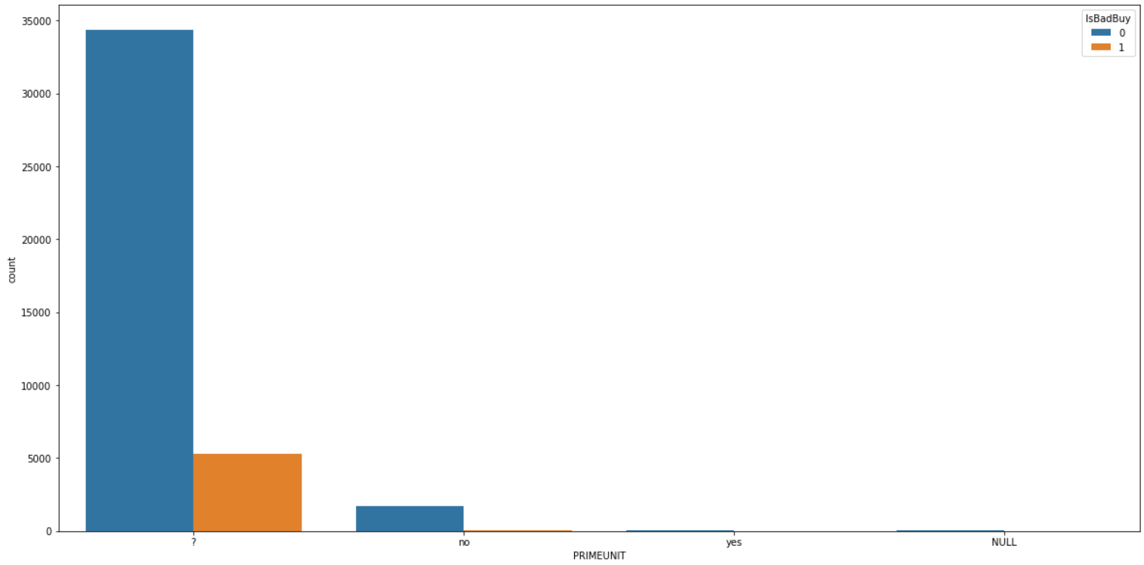
IsBadBuy
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
0
5480
5569
6311
6858
6966
7269
7644
8033
8186
?
LESS_FREQ
NULL
MMRCurrentAuctionAveragePrice

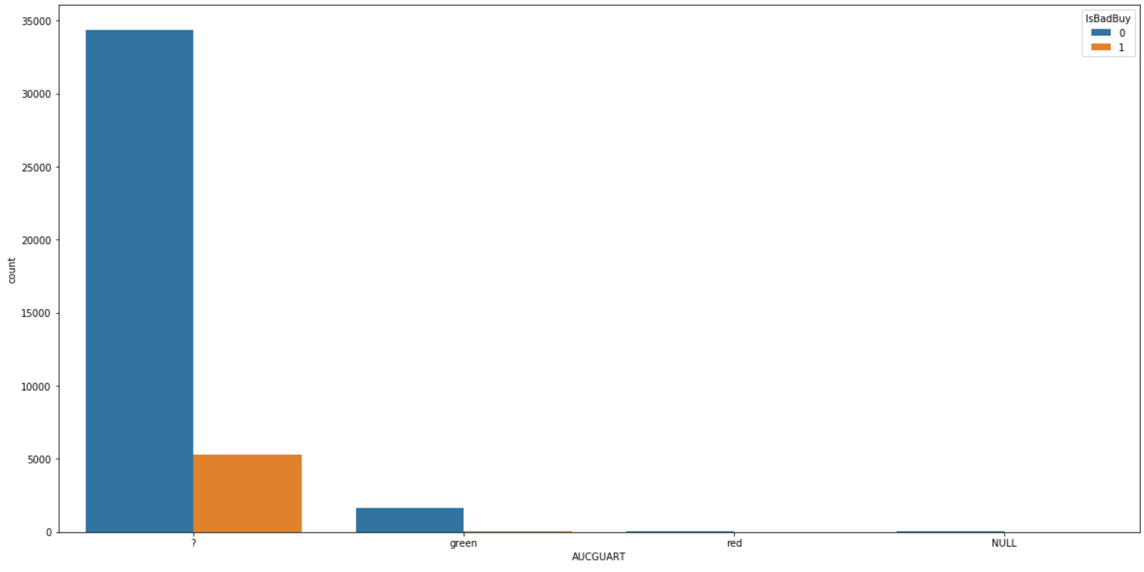

IsBadBuy
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
0
1
6461
6584
7450
7898
8107
8892
9279
?
LESS_FREQ
NULL
MMRCurrentAuctionCleanPrice

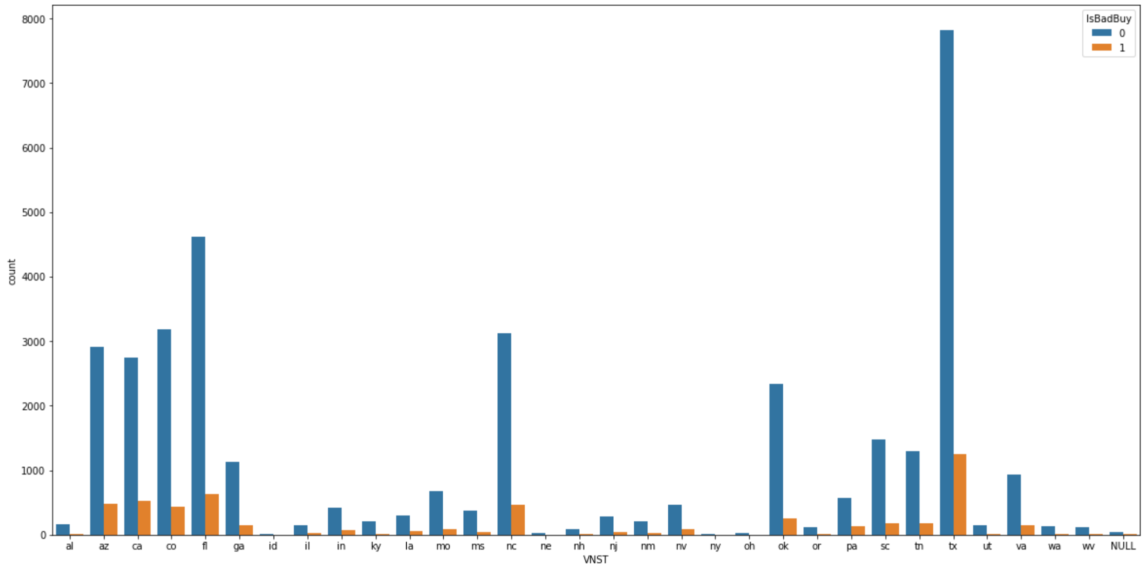

IsBadBuy
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
0
10834
11674
6418
6515
7316
8756
?
LESS_FREQ
NULL
MMRCurrentRetailAveragePrice

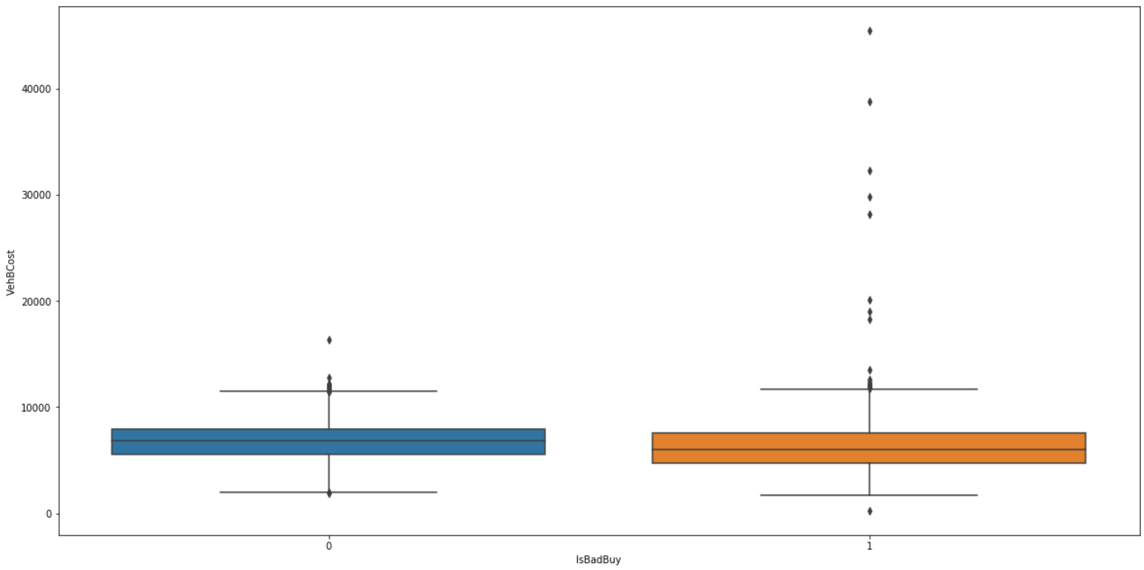

IsBadBuy
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
0
10103
11413
11706
12387
7478
7611
8546
?
LESS_FREQ
NULL
MMRCurrentRetailCleanPrice

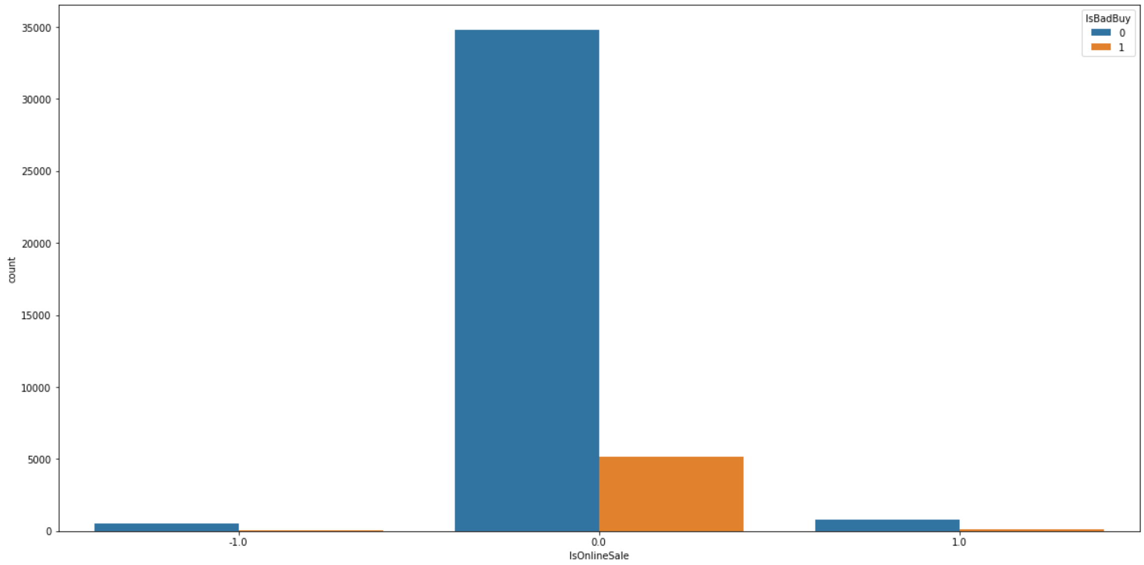

IsBadBuy
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
#VALUE!
0.855997898
0.856073017
0.858250869
0.866673265
0.949268378
LESS_FREQ
NULL
MMRCurrentRetailRatio

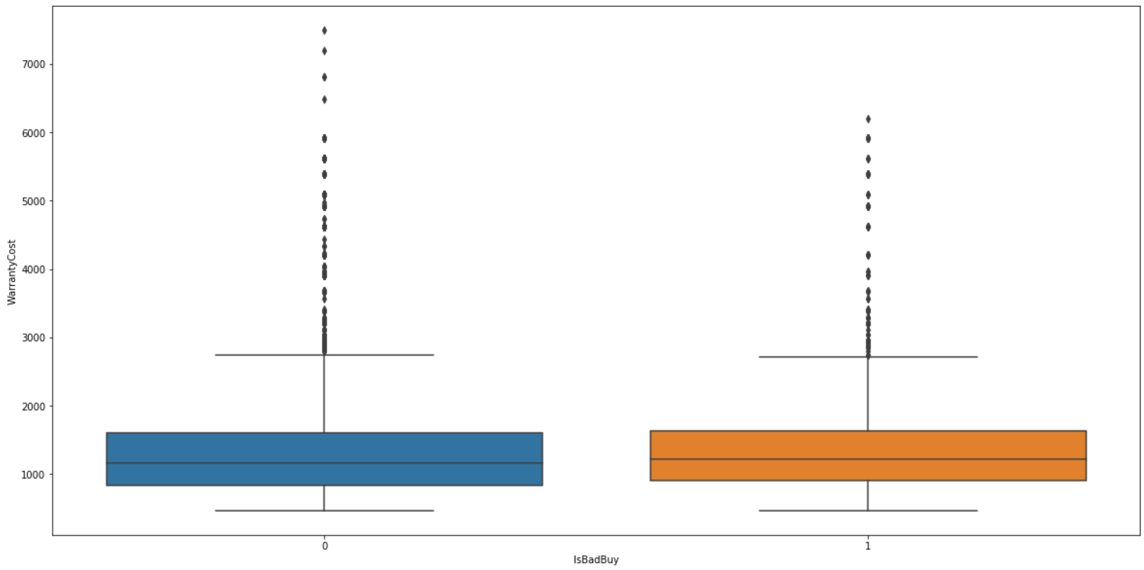

IsBadBuy
0
1
count
PRIMEUNIT
?
no
yes
NULL
35000
30000
25000
20000
15000
10000
5000
0

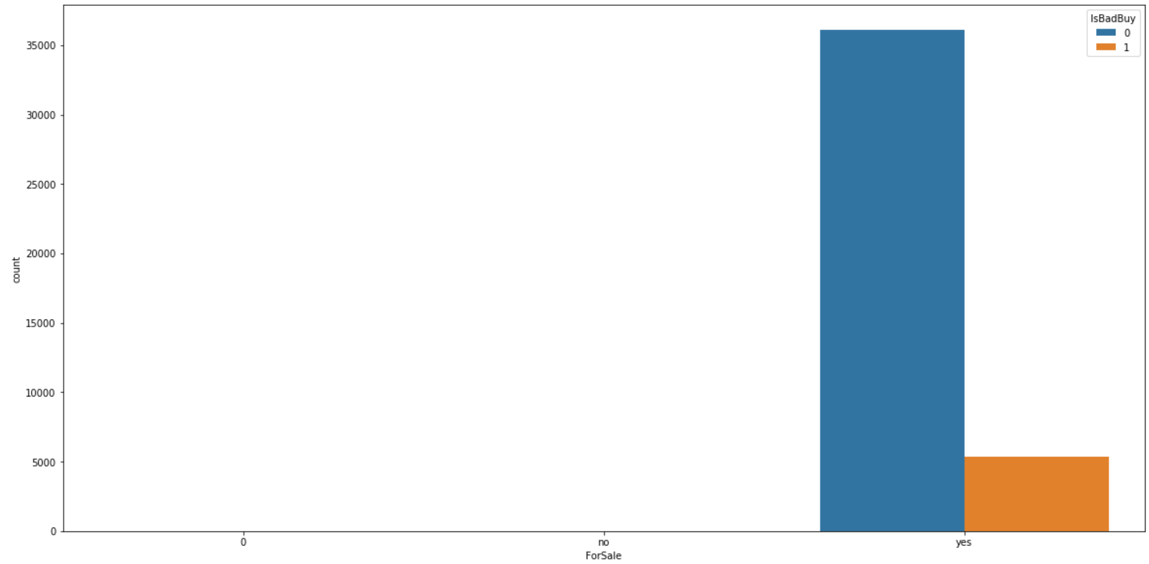

IsBadBuy
0
1
count
AUCGUART
?
green
red
NULL
35000
30000
25000
20000
15000
10000
5000
0


IsBadBuy
0
1
count
8000
7000
6000
5000
4000
3000
2000
1000
0
al az ca co fl ga id il in ky la mo ms nc ne nh nj nm nv ny oh ok or pa sc tn tx ut va wa wv NULL
VNST


VehBCost
40000
30000
20000
10000
0
0
1
IsBadBuy


IsBadBuy
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
-1.0
0.0
1.0
IsOnlineSale


WarrantyCost
7000
6000
5000
4000
3000
2000
1000
0
1
IsBadBuy




```
&lt;Figure size 1440x720 with 0 Axes&gt;
```

4. What variables did you include in the analysis and what were their roles and measurement level set? Justify your choice

In [ ]:

```

```

5. What distribution scheme did you use? What data partitioning allocation did you set? Explain your selection.

In [11]:

```
# Change to the dummy

df = pd.get_dummies(df)

feature_names = df.drop("IsBadBuy", axis=1).columns
print("Num of Features:")

### Split to the training and test set.
#  The test size is 3%

# y = df['IsBadBuy']
# X = df.drop(['IsBadBuy'], axis=1)
# X_mat = X.as_matrix()

# X_train, X_test, y_train, y_test = train_test_split(X_mat, y, test_size=0.3, s
tratify=y, random_state=rs)

X_train, X_test, y_train, y_test = train_test_split(df.drop("IsBadBuy", axis=1),
df['IsBadBuy'], test_size=0.3, stratify=df['IsBadBuy'], random_state=rs)

if ResamplingMethod == 'ros':
    print("Using ROS Resmapling")
    ros = RandomOverSampler(random_state=rs)
    X_train, y_train = ros.fit_resample(X_train, y_train)
elif  ResamplingMethod == 'rus':
    print("Using RUS Resmapling")
    rus = RandomUnderSampler(random_state=rs)
    X_train, y_train = rus.fit_resample(X_train, y_train)
else:
    print("No Resampling Method Used")
```

```
Num of Features:
Using RUS Resmapling
```

In [12]:

```
print("Number of Training: ", len(X_train))
print("Number of Test: ", len(X_test) )
```

```
Number of Training:  7520
Number of Test:  12443
```

Task 2. Predictive Modeling Using Decision Trees

1. Python: Build a decision tree using the default setting.

In [13]:

```
def printLRTopImportant(model, top = 5):

    coef = model.coef_[0]
    indices = np.argsort(np.absolute(coef))
    indices = np.flip(indices, axis=0)
    indices = indices[:top]
    for i in indices:
        print(feature_names[i], ':', coef[i])

def analyse_feature_importance(dm_model, feature_names, n_to_display=20):
    # grab feature importances from the model
    importances = dm_model.feature_importances_

    # sort them out in descending order
    indices = np.argsort(importances)
    indices = np.flip(indices, axis=0)

    # limit to 20 features, you can leave this out to print out everything
    indices = indices[:n_to_display]

    for i in indices:
        print(feature_names[i], ':', importances[i])

def visualize_decision_tree(dm_model, feature_names, save_name):
    dotfile = StringIO()
    export_graphviz(dm_model, out_file=dotfile, feature_names=feature_names)
    graph = pydot.graph_from_dot_data(dotfile.getvalue())
    graph[0].write_png(save_name) # saved in the following file
```

In [14]:

```
# simple decision tree training
model = DecisionTreeClassifier(random_state=rs)
model.fit(X_train, y_train)
```

Out[14]:

```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_dept
h=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_stat
e=101,
            splitter='best')
```

a. What is the classification accuracy on training and test datasets?

In [15]:

```
print("Train accuracy:", model.score(X_train, y_train))
print("Test accuracy:", model.score(X_test, y_test))
y_pred = model.predict(X_test)
print(classification_report(y_test, y_pred))
confusion_matrix(y_test, y_pred) ## Confusion Matrix on the TestSet
```

```
Train accuracy: 0.9998670212765958
Test accuracy: 0.629590934662059
              precision    recall  f1-score   support

           0       0.92      0.63      0.75     10832
           1       0.20      0.61      0.30      1611

   micro avg       0.63      0.63      0.63     12443
   macro avg       0.56      0.62      0.52     12443
weighted avg       0.82      0.63      0.69     12443
```

Out[15]:

```
array([[6852, 3980],
       [ 629,  982]])
```

b. What is the size of tree (i.e. number of nodes)?

In [16]:

```
print("Number of nodes: ",model.tree_.node_count)
```

```
Number of nodes:  3013
```

c. How many leaves are in the tree that is selected based on the validation dataset?

In [ ]:

```

```

d. Which variable is used for the first split? What are the competing splits for this first split?

In [17]:

```
visualize_decision_tree(model, df.drop("IsBadBuy", axis=1).columns, "Tree_Struc
t.png")
```

e. What are the 5 important variables in building the tree?

In [18]:

```
analyse_feature_importance(model, df.drop("IsBadBuy", axis=1).columns, 5)
```

```
WheelTypeID_? : 0.134805855052287
VehBCost : 0.1192484018329195
VehOdo : 0.10392404388384845
MMRAcquisitionAuctionCleanPrice : 0.06733362778563777
MMRAcquisitonRetailCleanPrice : 0.0669018736190701
```

f. Report if you see any evidence of model overfitting.

In [ ]:

```

```

g. Did changing the default setting (i.e., only focus on changing the setting of the number of splits to create a node) help improving the model? Answer the above questions on the best performing tree.

In [ ]:

```

```

2. Python: Build another decision tree tuned with GridSearchCV

In [ ]:

```

```

In [19]:

```
# grid search CV
params = {'criterion': ['gini', 'entropy'],
          'max_depth': list(range(1, 6000, 1000)) + [None],
          'splitter': ['best', 'random'],
          'min_samples_leaf': range(1,  4),
          'min_samples_split': [2, 0.5, 0.3],
          'max_features':['auto','sqrt','log2', None],
          'class_weight':['balanced', None]
         }

cv = GridSearchCV(param_grid=params, estimator=DecisionTreeClassifier(random_sta
te=rs), cv=3)
cv.fit(X_train, y_train)
```

Out[19]:

```
GridSearchCV(cv=3, error_score='raise-deprecating',
       estimator=DecisionTreeClassifier(class_weight=None, criterion
='gini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_stat
e=101,
            splitter='best'),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid={'criterion': ['gini', 'entropy'], 'max_depth':
[1, 1001, 2001, 3001, 4001, 5001, None], 'splitter': ['best', 'rando
m'], 'min_samples_leaf': range(1, 4), 'min_samples_split': [2, 0.5,
0.3], 'max_features': ['auto', 'sqrt', 'log2', None], 'class_weigh
t': ['balanced', None]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='war
n',
       scoring=None, verbose=0)
```

a. What is the classification accuracy on training and test datasets?

In [20]:

```
print("Train accuracy:", cv.score(X_train, y_train))
print("Test accuracy:", cv.score(X_test, y_test))

# test the best model
y_pred = cv.predict(X_test)
print(classification_report(y_test, y_pred))
# print parameters of the best model
print(cv.best_params_)

dt_model = cv.best_estimator_
```

```
Train accuracy: 0.6638297872340425
Test accuracy: 0.7328618500361649
              precision    recall  f1-score   support

           0       0.92      0.76      0.83     10832
           1       0.26      0.57      0.35      1611

   micro avg       0.73      0.73      0.73     12443
   macro avg       0.59      0.66      0.59     12443
weighted avg       0.84      0.73      0.77     12443

{'class_weight': 'balanced', 'criterion': 'entropy', 'max_depth': 10
01, 'max_features': None, 'min_samples_leaf': 1, 'min_samples_spli
t': 0.3, 'splitter': 'best'}
```

b. What is the size of tree (i.e. number of nodes)? Is the size different from the maximal tree or the tree in the previous step? Why?

In [21]:

```
print("Number of nodes: ", cv.best_estimator_.tree_.node_count)
```

```
Number of nodes:  11
```

c. How many leaves are in the tree that is selected based on the validation dataset?

In [ ]:

```

```

d. Which variable is used for the first split? What are the competing splits for this first split?

In [22]:

```
visualize_decision_tree(cv.best_estimator_, df.drop("IsBadBuy", axis=1).columns,
"Tree_Struct_CV.png")
```

e. What are the 5 important variables in building the tree?

In [23]:

```
analyse_feature_importance(cv.best_estimator_, df.drop("IsBadBuy", axis=1).colum
ns, 5)
```

```
WheelTypeID_? : 0.74893803336981
VehBCost : 0.14713461692795504
VehYear_2008.0 : 0.05033636957077116
VehYear_2006.0 : 0.028044983434325217
VehYear_2007.0 : 0.025545996697138425
```

f. Report if you see any evidence of model overfitting.

In [ ]:

g. What are the parameters used? Explain your choices.

In [ ]:

3. What is the significant difference do you see between these two decision tree models (steps 2.1 & 2.2)? How do they compare performance-wise? Explain why those changes may have happened.

In [ ]:

4. From the better model, can you identify which cars could potential be “kicks”? Can you provide some descriptive summary of those cars?

In [ ]:

In [ ]:

Task 3. Predictive Modeling Using Regression

1. In preparation for regression, is any imputation of missing values needed for this data set? List the variables that needed this.

In [24]:

```
# We've already done this in the prep_data function
```

2. Apply transformation method(s) to the variable(s) that need it. List the variables that needed it

In [25]:

```
## Doing the log transformation


### Q: It's enoguh?
columns_to_transform = interval_cols

def logTransformation(df):

    df_log = df.copy()


    for col in columns_to_transform:
        df_log[col] = df_log[col].apply(lambda x: x+1)
        df_log[col] = df_log[col].apply(np.log)


    return df_log

df_log = logTransformation(df)
X_train_log, X_test_log, y_train_log, y_test_log = train_test_split(df_log.drop
(['IsBadBuy'], axis=1), df_log['IsBadBuy'], test_size=0.3, stratify=df_log['IsBa
dBuy']
,random_state=rs)

# Standardise
scaler_log = StandardScaler()
X_train_log = scaler_log.fit_transform(X_train_log, y_train_log)
X_test_log = scaler_log.transform(X_test_log)
```

3. Build a regression model using the default regression method with all inputs. Once you done it, build another one and tune it using GridSearchCV. Answer the followings:

In [26]:

```
### Traing Logistic Regression
model = LogisticRegression(random_state=rs)
model.fit(X_train_log, y_train_log)
```

Out[26]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_interce
pt=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=101, solver='war
n',
          tol=0.0001, verbose=0, warm_start=False)
```

In [27]:

```
## GridSearch for Logistic Regression
params = {
    'C': [pow(10, x) for x in range(-4, 1)],
    'solver' : ['newton-cg',"lbfgs", "liblinear", "sag", "saga"],
    'max_iter': [30, 50, 100],
    'warm_start': [True, False],
    'class_weight':['balanced', None]
}

cv = GridSearchCV(param_grid=params, estimator=LogisticRegression(random_state=r
s), cv=3, n_jobs=-1)
cv.fit(X_train_log, y_train_log)
```

Out[27]:

```
GridSearchCV(cv=3, error_score='raise-deprecating',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=F
alse, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=101, solver='war
n',
          tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'C': [0.0001, 0.001, 0.01, 0.1, 1], 'solver': ['n
ewton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'], 'max_iter': [30, 5
0, 100], 'warm_start': [True, False], 'class_weight': ['balanced', N
one]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='war
n',
       scoring=None, verbose=0)
```

h. Name the regression function used.

In [ ]:

```

```

i. How much was the difference in performance of two models build, default and optimal?

In [28]:

```
print("Train accuracy:", model.score(X_train_log, y_train_log))
print("Test accuracy:", model.score(X_test_log, y_test_log))
print("GridSearch Train accuracy:", cv.score(X_train_log, y_train_log))
print("GridSearch Test accuracy:", cv.score(X_test_log, y_test_log))
```

```
Train accuracy: 0.8963593152619433
Test accuracy: 0.8982560475769509
GridSearch Train accuracy: 0.895945992491303
GridSearch Test accuracy: 0.8984167805191674
```

j. Show the set parameters for the best model. What are the parameters used? Explain your decision. What are the optimal parameters?

In [29]:

```
print("The best model parameters: ", cv.best_params_)
```

```
The best model parameters:  {'C': 0.001, 'class_weight': None, 'max_
iter': 30, 'solver': 'newton-cg', 'warm_start': True}
```

k. Report which variables are included in the regression model.

In [ ]:

```

```

l. Report the top-5 important variables (in the order) in the model.

In [30]:

```
def printLRTopImportant(model, top = 5):

    coef = model.coef_[0]
    indices = np.argsort(np.absolute(coef))
    indices = np.flip(indices, axis=0)
    indices = indices[:top]
    for i in indices:
        print(feature_names[i], ':', coef[i])
```

In [31]:

```
printLRTopImportant(model, 5)
```

```
MMRAcquisitionAuctionAveragePrice : -0.7971823901149314
MMRAcquisitionRetailAveragePrice : 0.7882376918654318
WheelTypeID_? : 0.590062075011876
WheelTypeID_1 : -0.42595465288544654
WheelType_covers : -0.3800420459666399
```

m. What is classification accuracy on training and test datasets?

In [32]:

```
y_pred = model.predict(X_test_log)
print("Classification Report: \n\n",classification_report(y_test_log, y_pred))

y_pred = cv.predict(X_test_log)
print("GridSearch Classification Report: \n\n",classification_report(y_test_log,
y_pred))
log_reg_model = cv.best_estimator_
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.90      0.99      0.94     10832
           1       0.84      0.27      0.40      1611

   micro avg       0.90      0.90      0.90     12443
   macro avg       0.87      0.63      0.67     12443
weighted avg       0.89      0.90      0.87     12443

GridSearch Classification Report:

              precision    recall  f1-score   support

           0       0.90      0.99      0.94     10832
           1       0.84      0.27      0.40      1611

   micro avg       0.90      0.90      0.90     12443
   macro avg       0.87      0.63      0.67     12443
weighted avg       0.89      0.90      0.87     12443
```

n. Report any sign of overfitting.

In [33]:

```
## The GridSearch Precision and Recall is weird
```

4. Build another regression model using the subset of inputs selected by RFE and selection by model method. Answer the followings:

In [34]:

```
rfe = RFECV(estimator = LogisticRegression(random_state=rs), cv=3)
rfe.fit(X_train_log, y_train_log)
X_train_rfe = rfe.transform(X_train_log)
X_test_rfe = rfe.transform(X_test_log)

selectmodel = SelectFromModel(dt_model, prefit=True)
X_train_sel_model = selectmodel.transform(X_train_log)
X_test_sel_model = selectmodel.transform(X_test_log)
```

a. Report which variables are included in the regression model.

In [35]:

```
print("Original feature set", X_train.shape[1])
print("Number of RFE-selected features: ", rfe.n_features_)
print("Number of selectFromModel features: ",  X_train_sel_model.shape[1])
```

```
Original feature set 198
Number of RFE-selected features:  69
Number of selectFromModel features:  5
```

In [36]:

```
print("The RFE-selected features: \n\n", list(compress(feature_names, rfe.suppor
t_)))
print("\n\n")
print("The SelectFromModel features: \n\n",list(compress(feature_names, selectmo
del.get_support())))
```

```
The RFE-selected features: 

 ['VehOdo', 'MMRAcquisitionAuctionAveragePrice', 'MMRAcquisitionAuct
ionCleanPrice', 'MMRAcquisitionRetailAveragePrice', 'MMRAcquisitonRe
tailCleanPrice', 'VehBCost', 'WarrantyCost', 'VehYear_2001.0', 'VehY
ear_2002.0', 'VehYear_2003.0', 'VehYear_2004.0', 'VehYear_2005.0',
'VehYear_2008.0', 'Make_honda', 'Make_nissan', 'Make_toyota', 'Make_
volvo', 'Color_other', 'WheelTypeID_1', 'WheelTypeID_3', 'WheelTypeI
D_?', 'WheelType_?', 'WheelType_alloy', 'WheelType_covers', 'WheelTy
pe_special', 'Nationality_top line asian', 'Size_large', 'Size_large
suv', 'Size_medium suv', 'Size_van', 'TopThreeAmericanName_gm', 'MMR
CurrentAuctionAveragePrice_5480', 'MMRCurrentAuctionAveragePrice_556
9', 'MMRCurrentAuctionAveragePrice_6311', 'MMRCurrentAuctionAverageP
rice_7269', 'MMRCurrentAuctionAveragePrice_7644', 'MMRCurrentAuction
AveragePrice_8186', 'MMRCurrentAuctionCleanPrice_6461', 'MMRCurrentA
uctionCleanPrice_6584', 'MMRCurrentAuctionCleanPrice_7898', 'MMRCurr
entRetailAveragePrice_10834', 'MMRCurrentRetailAveragePrice_11674',
'MMRCurrentRetailAveragePrice_6418', 'MMRCurrentRetailAveragePrice_6
515', 'MMRCurrentRetailAveragePrice_7316', 'MMRCurrentRetailAverageP
rice_8756', 'MMRCurrentRetailCleanPrice_10103', 'MMRCurrentRetailCle
anPrice_11413', 'MMRCurrentRetailCleanPrice_7478', 'MMRCurrentRetail
CleanPrice_7611', 'MMRCurrentRetailCleanPrice_8546', 'MMRCurrentReta
ilRatio_#VALUE!', 'MMRCurrentRetailRatio_0.855997898', 'MMRCurrentRe
tailRatio_0.856073017', 'MMRCurrentRetailRatio_0.858250869', 'MMRCur
rentRetailRatio_0.866673265', 'MMRCurrentRetailRatio_0.949268378',
'MMRCurrentRetailRatio_LESS_FREQ', 'PRIMEUNIT_?', 'PRIMEUNIT_no', 'A
UCGUART_?', 'VNST_fl', 'VNST_id', 'VNST_ky', 'VNST_nc', 'VNST_ne',
'VNST_or', 'VNST_pa', 'VNST_tn']



The SelectFromModel features: 

 ['VehBCost', 'VehYear_2006.0', 'VehYear_2007.0', 'VehYear_2008.0',
'WheelTypeID_?']
```

b. Report the top-5 important variables (in the order) in the model.

In [37]:

```
params = {
    'C': [pow(10, x) for x in range(-4, 1)],
    'solver' : ['newton-cg',"lbfgs", "liblinear", "sag", "saga"],
    'max_iter': [30, 50, 100],
    'warm_start': [True, False],
    'class_weight':['balanced', None]

}
rfe_cv = GridSearchCV(param_grid=params, estimator=LogisticRegression(random_sta
te=rs, verbose=True), cv=3, n_jobs=-1)
rfe_cv.fit(X_train_rfe, y_train_log)

selectModel_cv = GridSearchCV(param_grid=params, estimator=LogisticRegression(ra
ndom_state=rs, verbose=True), cv=3, n_jobs=-1)
selectModel_cv.fit(X_train_sel_model, y_train_log)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurr
ent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.3s finishe
d

[LibLinear]
```

Out[37]:

```
GridSearchCV(cv=3, error_score='raise-deprecating',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=F
alse, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=101, solver='war
n',
          tol=0.0001, verbose=True, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'C': [0.0001, 0.001, 0.01, 0.1, 1], 'solver': ['n
ewton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'], 'max_iter': [30, 5
0, 100], 'warm_start': [True, False], 'class_weight': ['balanced', N
one]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='war
n',
       scoring=None, verbose=0)
```

In [38]:

```
print("Top-5 important variables for RFE: \n")
printLRTopImportant(rfe_cv.best_estimator_, 5)
print("\n\n")
print("Top-5 important variables for selectModel \n")
printLRTopImportant(selectModel_cv.best_estimator_, 5)
```

```
Top-5 important variables for RFE:

MMRAcquisitionRetailAveragePrice : 0.5910445372774984
Color_not avail : -0.503177053104706
MMRAcquisitionAuctionAveragePrice : -0.4973269163098214
MMRAcquisitionAuctionCleanPrice : -0.4943539763541305
MMRAcquisitonRetailCleanPrice : 0.40966123480199057



Top-5 important variables for selectModel

MMRAcquisitonRetailCleanPrice : 0.23730179328439338
VehOdo : -0.06264868440183996
MMRAcquisitionRetailAveragePrice : -0.039661939311477705
MMRAcquisitionAuctionCleanPrice : -0.037192878242779864
MMRAcquisitionAuctionAveragePrice : -0.032088788617570585
```

c. What are the parameters used? Explain your choices. What are the optimal parameters? Which regression function is being used?

In [39]:

```
print("Optimal Parameters for RFE", rfe_cv.best_params_)
print("Optimal Parameters for selectModel", selectModel_cv.best_params_)
```

```
Optimal Parameters for RFE {'C': 1, 'class_weight': None, 'max_ite
r': 30, 'solver': 'lbfgs', 'warm_start': True}
Optimal Parameters for selectModel {'C': 0.0001, 'class_weight': Non
e, 'max_iter': 30, 'solver': 'liblinear', 'warm_start': True}
```

d. Report any sign of overfitting

In [ ]:

```

```

e. What is classification accuracy on training and test datasets?

In [40]:

```
print("GridSearch Train accuracy:", cv.score(X_train_log, y_train_log))
print("GridSearch Test accuracy:", cv.score(X_test_log, y_test_log))
print("\n\nRFE:\n")
print("Train accuracy:", rfe_cv.score(X_train_rfe, y_train_log))
print("Test accuracy:", rfe_cv.score(X_test_rfe, y_test_log))
print("\n\nselectModel:\n")
print("Train accuracy:", selectModel_cv.score(X_train_sel_model, y_train_log))
print("Test accuracy:", selectModel_cv.score(X_test_sel_model, y_test_log))
```

```
GridSearch Train accuracy: 0.895945992491303
GridSearch Test accuracy: 0.8984167805191674


RFE:

Train accuracy: 0.8965659766472635
Test accuracy: 0.8987382464036004


selectModel:

Train accuracy: 0.8954637825922226
Test accuracy: 0.8980953146347344
```

f. Did it improve/worsen the performance? Explain why those changes may have happened

In [41]:

```
y_pred = rfe_cv.predict(X_test_rfe)
print("REF classification report: \n",classification_report(y_test, y_pred))
print("\n\n")
y_pred = selectModel_cv.predict(X_test_sel_model)
print("selectModel classification report: \n",classification_report(y_test, y_pr
ed))
```

```
REF classification report:
               precision    recall  f1-score   support

           0       0.90      0.99      0.94     10832
           1       0.85      0.27      0.40      1611

   micro avg       0.90      0.90      0.90     12443
   macro avg       0.87      0.63      0.67     12443
weighted avg       0.89      0.90      0.87     12443




selectModel classification report:
               precision    recall  f1-score   support

           0       0.90      0.99      0.94     10832
           1       0.83      0.27      0.40      1611

   micro avg       0.90      0.90      0.90     12443
   macro avg       0.87      0.63      0.67     12443
weighted avg       0.89      0.90      0.87     12443
```

Task4 - Predicting using neural network

1. Build a Neural Network model using the default setting. Answer the following:

In [42]:

```
model = MLPClassifier(random_state=rs)
model.fit(X_train_log, y_train_log)
```

Out[42]:

```
MLPClassifier(activation='relu', alpha=0.0001, batch_size='auto', be
ta_1=0.9,
       beta_2=0.999, early_stopping=False, epsilon=1e-08,
       hidden_layer_sizes=(100,), learning_rate='constant',
       learning_rate_init=0.001, max_iter=200, momentum=0.9,
       n_iter_no_change=10, nesterovs_momentum=True, power_t=0.5,
       random_state=101, shuffle=True, solver='adam', tol=0.0001,
       validation_fraction=0.1, verbose=False, warm_start=False)
```

a. What is the network architecture?

In [43]:

```
def printMLPArchitecture(model):

    print("Number of Layers: ",model.n_layers_ )
    print("The First layer is Input Layer, and the last layer is the output laye
r")
    for i, w in enumerate(model.coefs_):
        print("{} Layer with hidden size {}".format(i+1, w.shape[0]))
        if (i+1) == len(model.coefs_):
            print("{} Layer with hidden size {}".format(i+2, w.shape[1]))

    print("The activation function: ", model.activation)

printMLPArchitecture(model)
```

```
Number of Layers:  3
The First layer is Input Layer, and the last layer is the output lay
er
1 Layer with hidden size 198
2 Layer with hidden size 100
3 Layer with hidden size 1
The activation function:  relu
```

b. How many iterations are needed to train this network?

In [44]:

```
print("Number of iterations it ran: ", model.n_iter_)
```

```
Number of iterations it ran:  200
```

c. Do you see any sign of over-fitting?

In [45]:

```
# fig = plt.figure(figsize=(10, 5))
# plt.ylabel('Accuracy',fontsize=15)
# plt.xlabel('Number of iterations',fontsize=15)
# plt.title('Validation Accuracy',fontsize=20,fontweight ="bold")
# plt.plot(model.validation_scores_, label="Validation Accuracy")
```

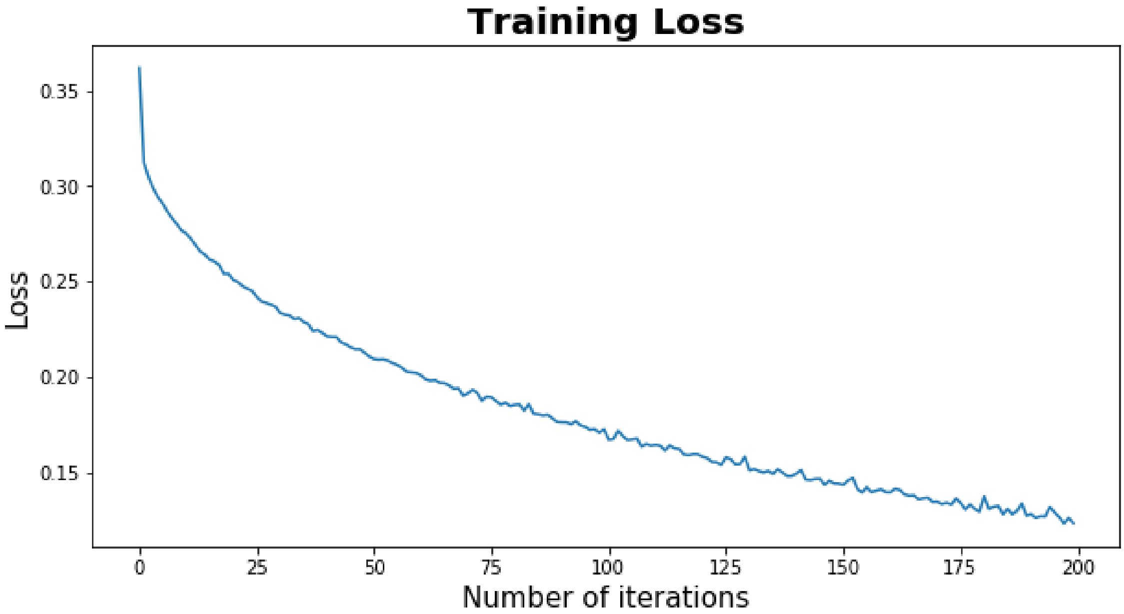
d. Did the training process converge and resulted in the best model?

In [46]:

```
fig = plt.figure(figsize=(10, 5))
plt.ylabel('Loss',fontsize=15)
plt.xlabel('Number of iterations',fontsize=15)
plt.title('Training Loss',fontsize=20,fontweight ="bold")
plt.plot(model.loss_curve_, label="Training Loss")

### The Loss curve is still decreasing
```

Out[46]:

```
[<matplotlib.lines.Line2D at 0x7fbacc5b2748>]
```



e. What is classification accuracy on training and test datasets?

In [47]:

```
print("MLP Train accuracy:", model.score(X_train, y_train))
print("MLP Test accuracy:", model.score(X_test, y_test))
print("\n\n")
y_pred = model.predict(X_test)
print("MLP classification report: \n",classification_report(y_test, y_pred))
```

```
MLP Train accuracy: 0.5002659574468085
MLP Test accuracy: 0.8704492485734951



MLP classification report: 
               precision    recall  f1-score   support

           0       0.87      1.00      0.93     10832
           1       0.00      0.00      0.00      1611

   micro avg       0.87      0.87      0.87     12443
   macro avg       0.44      0.50      0.47     12443
weighted avg       0.76      0.87      0.81     12443
```

2. Refine this network by tuning it with GridSearchCV.

In [48]:

```
# Default
# params = {'hidden_layer_sizes': [(3,), (5,), (7,), (9,)], 'alpha': [0.01,0.00
1, 0.0001, 0.00001]}


params = [
    {
        'hidden_layer_sizes': [(128,)],
        'activation': ['logistic', 'relu','identity'],
        'solver' : ['adam',],
        'batch_size': [ 64],
        'shuffle': [True],
        'learning_rate_init': [pow(10, x) for x in range(-4, -2)],
        'n_iter_no_change': [10],
        'max_iter':[200, 500],
        'warm_start': [True, False],
    },
    {
        'hidden_layer_sizes': [(128,)],
        'learning_rate' : ['constant', 'invscaling', 'adaptive'],
        'activation': ['logistic', 'relu','identity'],
        'solver' : ['sgd'],
        'shuffle': [True],
        'batch_size': [64],
        'max_iter':[200, 500],
        'learning_rate_init': [pow(10, x) for x in range(-4, -2)],
        'n_iter_no_change': [10],
        'warm_start': [True, False],
    },
    {
        'hidden_layer_sizes': [(128,)],
        'activation': ['logistic', 'relu','identity'],
        'solver' : ['lbfgs'],
        'max_iter':[200, 500],
        'batch_size': [64],
        'learning_rate_init': [pow(10, x) for x in range(-4, -2)],
        'n_iter_no_change': [10],
        'warm_start': [True, False],
    }

]


cv = GridSearchCV(param_grid=params, estimator=MLPClassifier(random_state=rs, ea
rly_stopping = True, verbose=True), cv=3, n_jobs=-1)
# cv = GridSearchCV(param_grid=params, estimator=MLPClassifier(random_state=rs,
 early_stopping=True, max_iter = max_iter, n_iter_no_change = max_iter ), cv=3,
 n_jobs=-1)
cv.fit(X_train_log, y_train_log)
```

```
Iteration 1, loss = 0.33406174
Validation score: 0.899449
Iteration 2, loss = 0.31403847
Validation score: 0.899449
Iteration 3, loss = 0.31255767
Validation score: 0.899449
Iteration 4, loss = 0.31177683
Validation score: 0.899449
Iteration 5, loss = 0.31103730
Validation score: 0.899449
Iteration 6, loss = 0.31010433
Validation score: 0.899449
Iteration 7, loss = 0.30906946
Validation score: 0.899449
Iteration 8, loss = 0.30817736
Validation score: 0.900138
Iteration 9, loss = 0.30726278
Validation score: 0.899449
Iteration 10, loss = 0.30637227
Validation score: 0.899449
Iteration 11, loss = 0.30483040
Validation score: 0.900138
Iteration 12, loss = 0.30360087
Validation score: 0.900482
Iteration 13, loss = 0.30294773
Validation score: 0.900138
Iteration 14, loss = 0.30116919
Validation score: 0.899793
Iteration 15, loss = 0.29985837
Validation score: 0.899105
Iteration 16, loss = 0.29817458
Validation score: 0.899793
Iteration 17, loss = 0.29671322
Validation score: 0.898416
Iteration 18, loss = 0.29506197
Validation score: 0.900138
Iteration 19, loss = 0.29314780
Validation score: 0.900482
Iteration 20, loss = 0.29144124
Validation score: 0.898416
Iteration 21, loss = 0.28907336
Validation score: 0.899793
Iteration 22, loss = 0.28694002
Validation score: 0.898416
Iteration 23, loss = 0.28437917
Validation score: 0.899449
Validation score did not improve more than tol=0.000100 for 10 conse
cutive epochs. Stopping.
```

Out[48]:

```
GridSearchCV(cv=3, error_score='raise-deprecating',
       estimator=MLPClassifier(activation='relu', alpha=0.0001, batc
h_size='auto', beta_1=0.9,
       beta_2=0.999, early_stopping=True, epsilon=1e-08,
       hidden_layer_sizes=(100,), learning_rate='constant',
       learning_rate_init=0.001, max_iter=200, momentum=0.9,
       n_iter_no_change=10, nesterovs_momentum=True, power_t=0.5,
       random_state=101, shuffle=True, solver='adam', tol=0.0001,
       validation_fraction=0.1, verbose=True, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid=[{'hidden_layer_sizes': [(128,)], 'activation':
['logistic', 'relu', 'identity'], 'solver': ['adam'], 'batch_size':
[64], 'shuffle': [True], 'learning_rate_init': [0.0001, 0.001], 'n_i
ter_no_change': [10], 'max_iter': [200, 500], 'warm_start': [True, F
alse]}, {'hidden_layer_sizes': [(128,...[64], 'learning_rate_init':
[0.0001, 0.001], 'n_iter_no_change': [10], 'warm_start': [True, Fals
e]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='war
n',
       scoring=None, verbose=0)
```

a. What is the network architecture?

In [49]:

```
print("Best Parameters of NN: ", cv.best_params_)
```

```
Best Parameters of NN:  {'activation': 'logistic', 'batch_size': 64,
'hidden_layer_sizes': (128,), 'learning_rate_init': 0.001, 'max_ite
r': 200, 'n_iter_no_change': 10, 'shuffle': True, 'solver': 'adam',
'warm_start': True}
```

In [50]:

```
printMLPArchitecture(cv.best_estimator_)
```

```
Number of Layers:  3
The First layer is Input Layer, and the last layer is the output lay
er
1 Layer with hidden size 198
2 Layer with hidden size 128
3 Layer with hidden size 1
The activation function:  logistic
```

b. How many iterations are needed to train this network?

In [51]:

```
print("Number of iterations it ran: ",cv.best_estimator_.n_iter_)
```

```
Number of iterations it ran:  23
```

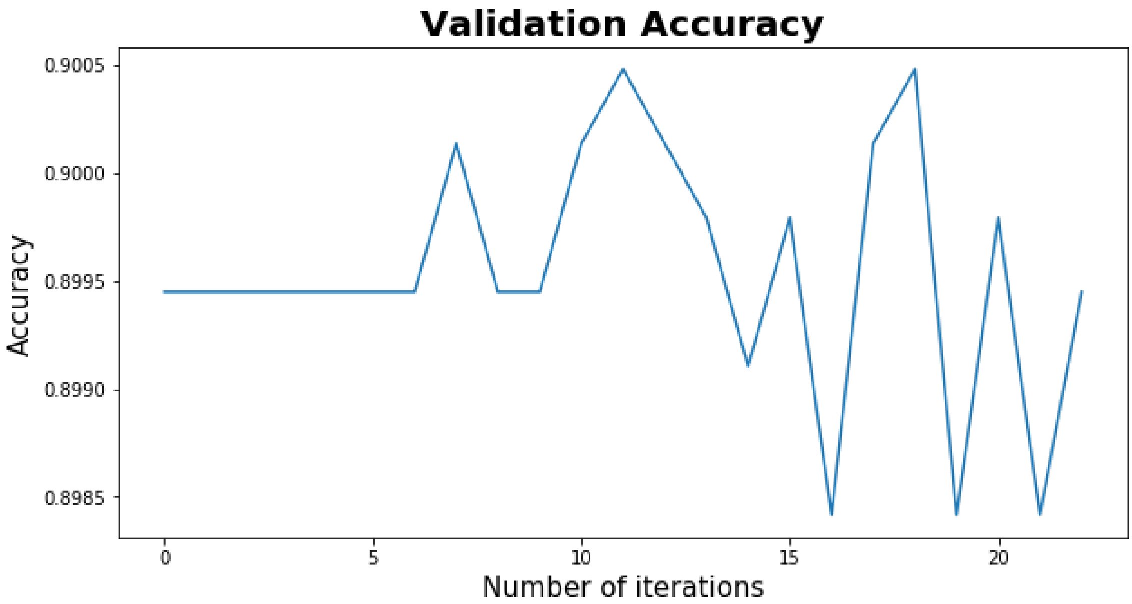
c. Sign of overfitting?

In [52]:

```
fig = plt.figure(figsize=(10, 5))
plt.ylabel('Accuracy',fontsize=15)
plt.xlabel('Number of iterations',fontsize=15)
plt.title('Validation Accuracy',fontsize=20,fontweight ="bold")
plt.plot(cv.best_estimator_.validation_scores_, label="Validation Accuracy")
```

Out[52]:

```
[<matplotlib.lines.Line2D at 0x7fbacc6306a0>]
```



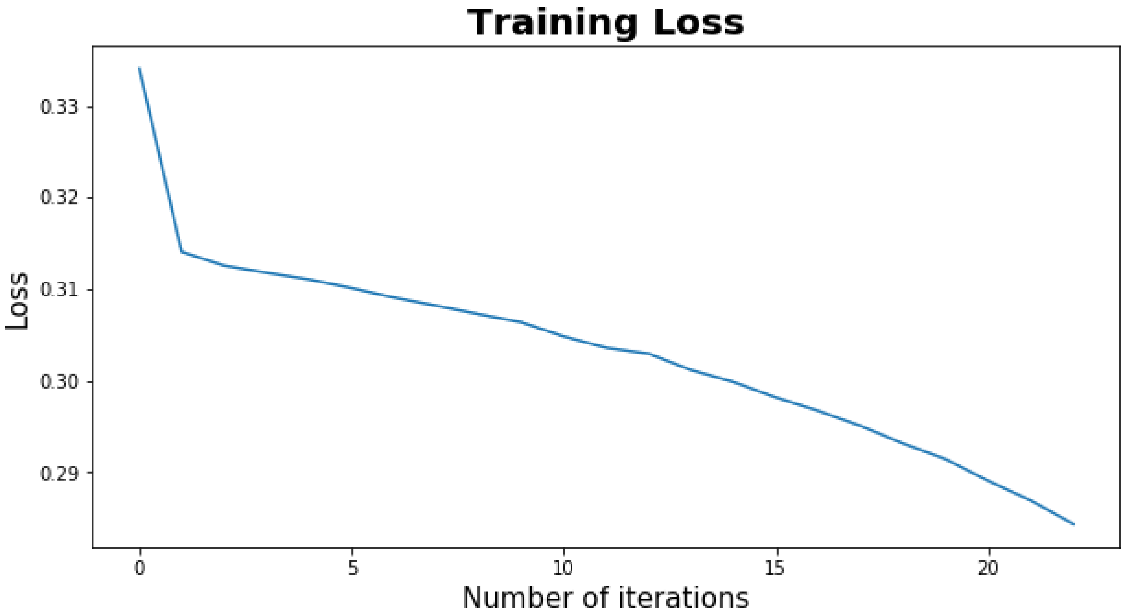
d. Did the training process converge and resulted in the best model?

In [53]:

```
fig = plt.figure(figsize=(10, 5))
plt.ylabel('Loss',fontsize=15)
plt.xlabel('Number of iterations',fontsize=15)
plt.title('Training Loss',fontsize=20,fontweight ="bold")
plt.plot(cv.best_estimator_.loss_curve_, label="Training Loss")
```

Out[53]:

```
[<matplotlib.lines.Line2D at 0x7fbacc5b8128>]
```



e. What is classification accuracy on training and test datasets? Is there any improvement in the outcome?

In [54]:

```
print("GridSearch NN Train accuracy:", cv.score(X_train_log, y_train_log))
print("GridSearch NN Test accuracy:", cv.score(X_test_log, y_test_log))

print("\n\n")
y_pred = cv.predict(X_test_log)
print("GridSearch NN Classification Report: \n",classification_report(y_test_log
, y_pred))

print("Best Parameters of NN: ", cv.best_params_)
nn_model = cv.best_estimator_
```

```
GridSearch NN Train accuracy: 0.8979781627802845
GridSearch NN Test accuracy: 0.8980149481636261



GridSearch NN Classification Report: 
               precision    recall  f1-score   support

           0       0.90      0.99      0.94     10832
           1       0.84      0.26      0.40      1611

   micro avg       0.90      0.90      0.90     12443
   macro avg       0.87      0.63      0.67     12443
weighted avg       0.89      0.90      0.87     12443

Best Parameters of NN:  {'activation': 'logistic', 'batch_size': 64,
'hidden_layer_sizes': (128,), 'learning_rate_init': 0.001, 'max_ite
r': 200, 'n_iter_no_change': 10, 'shuffle': True, 'solver': 'adam',
'warm_start': True}
```

3. Would feature selection help here? Build another Neural Network model with inputs selected from RFE with regression (use the best model generated in Task 3) and selection with decision tree (use the best model from Task 2).

In [55]:

```
params = [
    {
        'hidden_layer_sizes': [(3,),(128,)],
        'activation': ['logistic', 'relu','identity'],
        'solver' : ['adam',],
        'batch_size': [ 64],
        'shuffle': [True],
        'learning_rate_init': [pow(10, x) for x in range(-4, -2)],
        'n_iter_no_change': [10],
        'max_iter':[200, 500],
        'warm_start': [True, False],
    },
    {
        'hidden_layer_sizes': [(3,), (128,)],
        'learning_rate' : ['constant', 'invscaling', 'adaptive'],
        'activation': ['logistic', 'relu','identity'],
        'solver' : ['sgd'],
        'shuffle': [True],
        'batch_size': [64],
        'max_iter':[200, 500],
        'learning_rate_init': [pow(10, x) for x in range(-4, -2)],
        'n_iter_no_change': [10],
        'warm_start': [True, False],
    },
    {
        'hidden_layer_sizes': [(3,),(128,)],
        'activation': ['logistic', 'relu','identity'],
        'solver' : ['lbfgs'],
        'max_iter':[200, 500],
        'batch_size': [64],
        'learning_rate_init': [pow(10, x) for x in range(-4, -2)],
        'n_iter_no_change': [10],
        'warm_start': [True, False],
    }

]


rfe_cv = GridSearchCV(param_grid=params, estimator=MLPClassifier(random_state=rs
, early_stopping=True, verbose=True), cv=3, n_jobs=-1)
rfe_cv.fit(X_train_rfe, y_train_log)
modelSelect_cv = GridSearchCV(param_grid=params, estimator=MLPClassifier(random_
state=rs, early_stopping=True, verbose=True), cv=3, n_jobs=-1)
modelSelect_cv.fit(X_train_sel_model, y_train_log)
```

```
Iteration 1, loss = 0.38896433
Validation score: 0.871212
Iteration 2, loss = 0.36839117
Validation score: 0.871212
Iteration 3, loss = 0.35670821
Validation score: 0.871212
Iteration 4, loss = 0.34582363
Validation score: 0.871556
Iteration 5, loss = 0.33669776
Validation score: 0.878788
Iteration 6, loss = 0.32953443
Validation score: 0.892906
Iteration 7, loss = 0.32452803
Validation score: 0.898072
Iteration 8, loss = 0.32101373
Validation score: 0.898072
Iteration 9, loss = 0.31865502
Validation score: 0.897383
Iteration 10, loss = 0.31691035
Validation score: 0.897039
Iteration 11, loss = 0.31570717
Validation score: 0.896350
Iteration 12, loss = 0.31494236
Validation score: 0.896350
Iteration 13, loss = 0.31420999
Validation score: 0.897039
Iteration 14, loss = 0.31367637
Validation score: 0.896350
Iteration 15, loss = 0.31328425
Validation score: 0.896350
Iteration 16, loss = 0.31303482
Validation score: 0.896350
Iteration 17, loss = 0.31273916
Validation score: 0.896694
Iteration 18, loss = 0.31245818
Validation score: 0.896694
Validation score did not improve more than tol=0.000100 for 10 conse
cutive epochs. Stopping.
Iteration 1, loss = 0.35165876
Validation score: 0.900482
Iteration 2, loss = 0.32354225
Validation score: 0.899105
Iteration 3, loss = 0.32297835
Validation score: 0.900138
Iteration 4, loss = 0.32355480
Validation score: 0.900138
Iteration 5, loss = 0.32334681
Validation score: 0.900138
Iteration 6, loss = 0.32325016
Validation score: 0.900482
Iteration 7, loss = 0.32358188
Validation score: 0.900482
Iteration 8, loss = 0.32348756
Validation score: 0.899793
Iteration 9, loss = 0.32340600
Validation score: 0.900482
Iteration 10, loss = 0.32345076
Validation score: 0.900138
Iteration 11, loss = 0.32312515
Validation score: 0.900138
Iteration 12, loss = 0.32328606
```

```
Validation score: 0.900482
Validation score did not improve more than tol=0.000100 for 10 conse
cutive epochs. Stopping.
```

Out[55]:

```
GridSearchCV(cv=3, error_score='raise-deprecating',
       estimator=MLPClassifier(activation='relu', alpha=0.0001, batc
h_size='auto', beta_1=0.9,
       beta_2=0.999, early_stopping=True, epsilon=1e-08,
       hidden_layer_sizes=(100,), learning_rate='constant',
       learning_rate_init=0.001, max_iter=200, momentum=0.9,
       n_iter_no_change=10, nesterovs_momentum=True, power_t=0.5,
       random_state=101, shuffle=True, solver='adam', tol=0.0001,
       validation_fraction=0.1, verbose=True, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid=[{'hidden_layer_sizes': [(128,)], 'activation':
['logistic', 'relu', 'identity'], 'solver': ['adam'], 'batch_size':
[64], 'shuffle': [True], 'learning_rate_init': [0.0001, 0.001], 'n_i
ter_no_change': [10], 'max_iter': [200, 500], 'warm_start': [True, F
alse]}, {'hidden_layer_sizes': [(128,...[64], 'learning_rate_init':
[0.0001, 0.001], 'n_iter_no_change': [10], 'warm_start': [True, Fals
e]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='war
n',
       scoring=None, verbose=0)
```

a. Did feature selection help here? Any change in the network architecture? What inputs are being used as the network input?

In [56]:

```
print("Best Parameters of NN: ", cv.best_params_)
print("Best Parameters of RFE NN: ", rfe_cv.best_params_)
print("Best Parameters of modelSelect NN: ", modelSelect_cv.best_params_)
print("\n\n")

print("GridSearch:")
printMLPArchitecture(cv.best_estimator_)
print("\n")
print("RFE:")
printMLPArchitecture(rfe_cv.best_estimator_)
print("\n")
print("modelSelect:")
printMLPArchitecture(modelSelect_cv.best_estimator_)
print("\n")
```

```
Best Parameters of NN:  {'activation': 'logistic', 'batch_size': 64,
'hidden_layer_sizes': (128,), 'learning_rate_init': 0.001, 'max_ite
r': 200, 'n_iter_no_change': 10, 'shuffle': True, 'solver': 'adam',
'warm_start': True}
Best Parameters of RFE NN:  {'activation': 'logistic', 'batch_size':
64, 'hidden_layer_sizes': (128,), 'learning_rate': 'constant', 'lear
ning_rate_init': 0.001, 'max_iter': 200, 'n_iter_no_change': 10, 'sh
uffle': True, 'solver': 'sgd', 'warm_start': True}
Best Parameters of modelSelect NN:  {'activation': 'identity', 'batc
h_size': 64, 'hidden_layer_sizes': (128,), 'learning_rate_init': 0.0
01, 'max_iter': 200, 'n_iter_no_change': 10, 'shuffle': True, 'solve
r': 'adam', 'warm_start': True}



GridSearch:
Number of Layers:  3
The First layer is Input Layer, and the last layer is the output lay
er
1 Layer with hidden size 198
2 Layer with hidden size 128
3 Layer with hidden size 1
The activation function:  logistic


RFE:
Number of Layers:  3
The First layer is Input Layer, and the last layer is the output lay
er
1 Layer with hidden size 69
2 Layer with hidden size 128
3 Layer with hidden size 1
The activation function:  logistic


modelSelect:
Number of Layers:  3
The First layer is Input Layer, and the last layer is the output lay
er
1 Layer with hidden size 5
2 Layer with hidden size 128
3 Layer with hidden size 1
The activation function:  identity
```

b. What is classification accuracy on training and test datasets? Is there any improvement in the outcome?

In [57]:

```
print("GridSearch NN Train accuracy:", cv.score(X_train_log, y_train_log))
print("GridSearch NN Test accuracy:", cv.score(X_test_log, y_test_log))
print("RFE NN Train accuracy:", rfe_cv.score(X_train_rfe, y_train_log))
print("RFE NNTest accuracy:", rfe_cv.score(X_test_rfe, y_test_log))
print("modelSelect NN Train accuracy:", modelSelect_cv.score(X_train_sel_model,
y_train_log))
print("modelSelect NN Test accuracmodelSelect_cvy:", modelSelect_cv.score(X_test
_sel_model, y_test_log))
```

```
GridSearch NN Train accuracy: 0.8979781627802845
GridSearch NN Test accuracy: 0.8980149481636261
RFE NN Train accuracy: 0.8964282023903833
RFE NNTest accuracy: 0.8987382464036004
modelSelect NN Train accuracy: 0.8954293390280026
modelSelect NN Test accuracmodelSelect_cvy: 0.8980953146347344
```

c. How many iterations are now needed to train this network?

In [58]:

```
print("Number of iterations GS ran: ",cv.best_estimator_.n_iter_)
print("Number of iterations rfe ran: ",rfe_cv.best_estimator_.n_iter_)
print("Number of iterations modelSelect ran: ",modelSelect_cv.best_estimator_.n_
iter_)
```

```
Number of iterations GS ran:  23
Number of iterations rfe ran:  18
Number of iterations modelSelect ran:  12
```

d. Do you see any sign of over-fitting?

In [ ]:

```

```

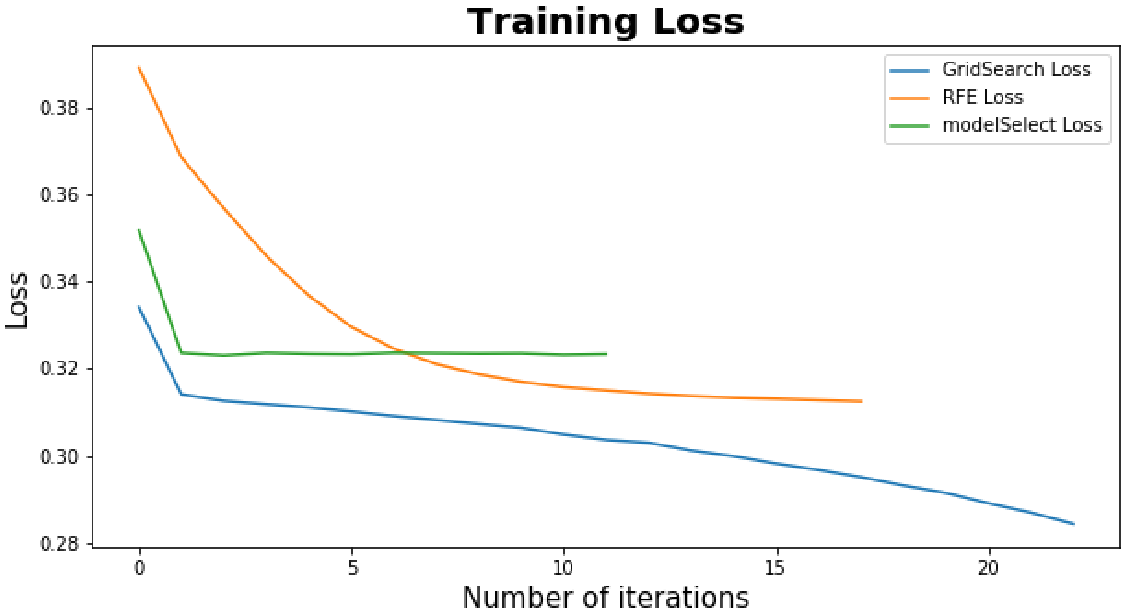
e. Did the training process converge and resulted in the best model?

In [59]:

```
fig = plt.figure(figsize=(10, 5))
plt.ylabel('Loss',fontsize=15)
plt.xlabel('Number of iterations',fontsize=15)
plt.title('Training Loss',fontsize=20,fontweight ="bold")
plt.plot(cv.best_estimator_.loss_curve_, label="GridSearch Loss")
plt.plot(rfe_cv.best_estimator_.loss_curve_, label="RFE Loss")
plt.plot(modelSelect_cv.best_estimator_.loss_curve_, label="modelSelect Loss")
plt.legend(loc='upper right')
```

Out[59]:

```
<matplotlib.legend.Legend at 0x7fbacc79e828>
```



4. Using the comparison methods, which of the models (i.e one with selected variables and another with all variables) appears to be better? From the better model, can you identify cars those could potential be “kicks”? Can you provide some descriptive summary of those cars? Is it easy to comprehend the performance of the best neural network model for decision making?

In [60]:

```
print("GridSearch Classification Report: ")
y_pred = cv.predict(X_test_log)
print(classification_report(y_test_log, y_pred))
print("\n\nRFE Classification Report: ")
y_pred = rfe_cv.predict(X_test_rfe)
print(classification_report(y_test_log, y_pred))
print("\n\nmodelSelect Classification Report: ")
y_pred = modelSelect_cv.predict(X_test_sel_model)
print(classification_report(y_test_log, y_pred))
```

```
GridSearch Classification Report: 
              precision    recall  f1-score   support

           0       0.90      0.99      0.94     10832
           1       0.84      0.26      0.40      1611

   micro avg       0.90      0.90      0.90     12443
   macro avg       0.87      0.63      0.67     12443
weighted avg       0.89      0.90      0.87     12443



RFE Classification Report: 
              precision    recall  f1-score   support

           0       0.90      0.99      0.94     10832
           1       0.85      0.26      0.40      1611

   micro avg       0.90      0.90      0.90     12443
   macro avg       0.88      0.63      0.67     12443
weighted avg       0.89      0.90      0.87     12443



modelSelect Classification Report: 
              precision    recall  f1-score   support

           0       0.90      0.99      0.94     10832
           1       0.83      0.27      0.40      1611

   micro avg       0.90      0.90      0.90     12443
   macro avg       0.87      0.63      0.67     12443
weighted avg       0.89      0.90      0.87     12443
```

Task 5. Generating an Ensemble Model and Comparing Models

1. Generate an ensemble model to include the best regression model, best decision tree model, and best neural network model.

In [61]:

```
voting = VotingClassifier(estimators=[('dt', dt_model), ('lr', log_reg_model), (
'nn', nn_model)], voting='soft')
voting.fit(X_train_log, y_train_log)

y_pred_dt = dt_model.predict(X_test_log)
y_pred_log_reg = log_reg_model.predict(X_test_log)
y_pred_nn = nn_model.predict(X_test_log)
y_pred_ensemble = voting.predict(X_test_log)
```

```
Iteration 1, loss = 0.33406174
Validation score: 0.899449
Iteration 2, loss = 0.31403847
Validation score: 0.899449
Iteration 3, loss = 0.31255767
Validation score: 0.899449
Iteration 4, loss = 0.31177683
Validation score: 0.899449
Iteration 5, loss = 0.31103730
Validation score: 0.899449
Iteration 6, loss = 0.31010433
Validation score: 0.899449
Iteration 7, loss = 0.30906946
Validation score: 0.899449
Iteration 8, loss = 0.30817736
Validation score: 0.900138
Iteration 9, loss = 0.30726278
Validation score: 0.899449
Iteration 10, loss = 0.30637227
Validation score: 0.899449
Iteration 11, loss = 0.30483040
Validation score: 0.900138
Iteration 12, loss = 0.30360087
Validation score: 0.900482
Iteration 13, loss = 0.30294773
Validation score: 0.900138
Iteration 14, loss = 0.30116919
Validation score: 0.899793
Iteration 15, loss = 0.29985837
Validation score: 0.899105
Iteration 16, loss = 0.29817458
Validation score: 0.899793
Iteration 17, loss = 0.29671322
Validation score: 0.898416
Iteration 18, loss = 0.29506197
Validation score: 0.900138
Iteration 19, loss = 0.29314780
Validation score: 0.900482
Iteration 20, loss = 0.29144124
Validation score: 0.898416
Iteration 21, loss = 0.28907336
Validation score: 0.899793
Iteration 22, loss = 0.28694002
Validation score: 0.898416
Iteration 23, loss = 0.28437917
Validation score: 0.899449
Validation score did not improve more than tol=0.000100 for 10 conse
cutive epochs. Stopping.
```

a. Does the Ensemble model outperform the underlying models? Resonate your answer.

In [62]:

```
print("Report for DT: \n",classification_report(y_test_log, y_pred_dt))
print("\nReport for Logistic Regression: \n",classification_report(y_test_log, y
_pred_log_reg))
print("\nReport for NN: \n",classification_report(y_test_log, y_pred_nn))
print("\nReport for Ensemble: \n",classification_report(y_test_log, y_pred_ensem
ble))
```

```
Report for DT: 
               precision    recall  f1-score   support

           0       0.00      0.00      0.00     10832
           1       0.13      1.00      0.23      1611

   micro avg       0.13      0.13      0.13     12443
   macro avg       0.06      0.50      0.11     12443
weighted avg       0.02      0.13      0.03     12443


Report for Logistic Regression: 
               precision    recall  f1-score   support

           0       0.90      0.99      0.94     10832
           1       0.84      0.27      0.40      1611

   micro avg       0.90      0.90      0.90     12443
   macro avg       0.87      0.63      0.67     12443
weighted avg       0.89      0.90      0.87     12443


Report for NN: 
               precision    recall  f1-score   support

           0       0.90      0.99      0.94     10832
           1       0.84      0.26      0.40      1611

   micro avg       0.90      0.90      0.90     12443
   macro avg       0.87      0.63      0.67     12443
weighted avg       0.89      0.90      0.87     12443


Report for Ensemble: 
               precision    recall  f1-score   support

           0       0.90      0.99      0.94     10832
           1       0.83      0.27      0.40      1611

   micro avg       0.90      0.90      0.90     12443
   macro avg       0.86      0.63      0.67     12443
weighted avg       0.89      0.90      0.87     12443
```

2. Use the comparison methods (or the comparison node) to compare the best decision tree model, the best regression model, the best neural network model and the ensemble model.

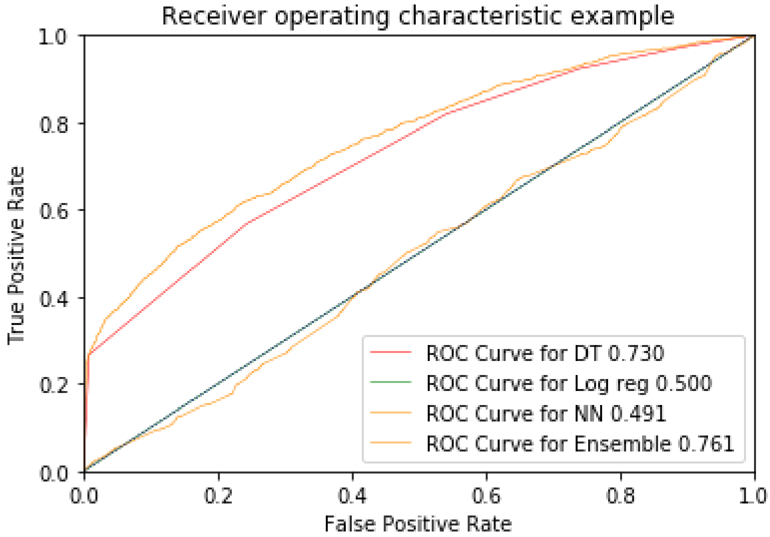
a. Discuss the findings led by (a) ROC Chart (and Index); (b) Score Ranking (or Accuracy Score); (c) Fit Statistics; (or Classification report) and (4) Output.

(a) ROC Chart (and Index)

In [63]:

```
#### ROC

y_pred_proba_dt = dt_model.predict_proba(X_test)
y_pred_proba_log_reg = log_reg_model.predict_proba(X_test)
y_pred_proba_nn = nn_model.predict_proba(X_test)
y_pred_proba_ensemble = voting.predict_proba(X_test_log)

roc_index_dt = roc_auc_score(y_test, y_pred_proba_dt[:, 1])
roc_index_log_reg = roc_auc_score(y_test, y_pred_proba_log_reg[:, 1])
roc_index_nn = roc_auc_score(y_test, y_pred_proba_nn[:, 1])
roc_index_ensemble = roc_auc_score(y_test_log, y_pred_proba_ensemble[:, 1])


print("ROC index on test for DT:", roc_index_dt)
print("ROC index on test for logistic regression:", roc_index_log_reg)
print("ROC index on test for NN:", roc_index_nn)
print("ROC index on voting classifier:", roc_index_ensemble)


fpr_dt, tpr_dt, thresholds_dt = roc_curve(y_test, y_pred_proba_dt[:,1])
fpr_log_reg, tpr_log_reg, thresholds_log_reg = roc_curve(y_test, y_pred_proba_lo
g_reg[:,1])
fpr_nn, tpr_nn, thresholds_nn = roc_curve(y_test, y_pred_proba_nn[:,1])
fpr_ensemble, tpr_ensemble, thresholds_ensemble = roc_curve(y_test, y_pred_proba
_ensemble[:,1])


plt.plot(fpr_dt, tpr_dt, label='ROC Curve for DT {:.3f}'.format(roc_index_dt), c
olor='red', lw=0.5)
plt.plot(fpr_log_reg, tpr_log_reg, label='ROC Curve for Log reg {:.3f}'.format(r
oc_index_log_reg), color='green', lw=0.5)
plt.plot(fpr_nn, tpr_nn, label='ROC Curve for NN {:.3f}'.format(roc_index_nn), c
olor='darkorange', lw=0.5)
plt.plot(fpr_ensemble, tpr_ensemble, label='ROC Curve for Ensemble {:.3f}'.forma
t(roc_index_ensemble), color='darkorange', lw=0.5)

plt.plot([0, 1], [0, 1], color='navy', lw=0.5, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```

```
ROC index on test for DT: 0.7296085202178155
ROC index on test for logistic regression: 0.49956381968684643
ROC index on test for NN: 0.4908949114608118
ROC index on voting classifier: 0.7610001792513986
```



(b) Score Ranking (or Accuracy Score)

In [64]:

```
print("Accuracy score on test for DT:", accuracy_score(y_test_log, y_pred_dt))
print("Accuracy score on test for Logistic Regression:", accuracy_score(y_test_l
og, y_pred_log_reg))
print("Accuracy score on test for NN:", accuracy_score(y_test_log, y_pred_nn))
print("Accuracy score on test for Ensemble:", accuracy_score(y_test_log, y_pred_
ensemble))
```

```
Accuracy score on test for DT: 0.12947038495539662
Accuracy score on test for Logistic Regression: 0.8984167805191674
Accuracy score on test for NN: 0.8980149481636261
Accuracy score on test for Ensemble: 0.8977738487503014
```

(c) Classification report

In [65]:

```
print("Report for DT: \n",classification_report(y_test_log, y_pred_dt))
print("\nReport for Logistic Regression: \n",classification_report(y_test_log, y
_pred_log_reg))
print("\nReport for NN: \n",classification_report(y_test_log, y_pred_nn))
print("\nReport for Ensemble: \n",classification_report(y_test_log, y_pred_ensem
ble))
```

```
Report for DT:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00     10832
           1       0.13      1.00      0.23      1611

   micro avg       0.13      0.13      0.13     12443
   macro avg       0.06      0.50      0.11     12443
weighted avg       0.02      0.13      0.03     12443


Report for Logistic Regression:
               precision    recall  f1-score   support

           0       0.90      0.99      0.94     10832
           1       0.84      0.27      0.40      1611

   micro avg       0.90      0.90      0.90     12443
   macro avg       0.87      0.63      0.67     12443
weighted avg       0.89      0.90      0.87     12443


Report for NN:
               precision    recall  f1-score   support

           0       0.90      0.99      0.94     10832
           1       0.84      0.26      0.40      1611

   micro avg       0.90      0.90      0.90     12443
   macro avg       0.87      0.63      0.67     12443
weighted avg       0.89      0.90      0.87     12443


Report for Ensemble:
               precision    recall  f1-score   support

           0       0.90      0.99      0.94     10832
           1       0.83      0.27      0.40      1611

   micro avg       0.90      0.90      0.90     12443
   macro avg       0.86      0.63      0.67     12443
weighted avg       0.89      0.90      0.87     12443
```

(d) Output

In [ ]:

```

```

b. Do all the models agree on the cars characteristics? How do they vary?

In [ ]:

Task 6. Final Remarks: Decision Making

1. Finally, based on all models and analysis, is there

2. Can you summarise positives and negatives of each predictive modelling method based on this analysis?

3. How the outcome of this study can be used by decision makers?

In [ ]:

In [ ]:

In [ ]: