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 = 'ros' #['ros', 'rus']
if NEW_STATEGY:
    print("Using New Preprocessing Strategy")
    using_cat = True
    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
MINI            19
ACURA           19
CADILLAC        17
SUBARU          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
UT     165
IL     165
WV     137
OR     136
WA     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]]
```

```
    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
                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
In the Column: Auction : 0, ?have been replaced by null
Preprocess the col: VehYear
Preprocess the col: Make
Preprocess the col: Color
In the Column: Color : 6, ?have been replaced by null
Preprocess the col: Transmission
In the Column: Transmission : 6, ?have been replaced by null
Preprocess the col: WheelTypeID
Preprocess the col: WheelType
Preprocess the col: VehOdo
Preprocess the col: Nationality
In the Column: Nationality : 3, ?have been replaced by null
Preprocess the col: Size
In the Column: Size : 3, ?have been replaced by null
Preprocess the col: TopThreeAmericanName
In the Column: TopThreeAmericanName : 3, ?have been replaced by null
Preprocess the col: MMRAcquisitionAuctionAveragePrice
In the Column: MMRAcquisitionAuctionAveragePrice : 7, ?have been rep
laced by null
Preprocess the col: MMRAcquisitionAuctionCleanPrice
In the Column: MMRAcquisitionAuctionCleanPrice : 7, ?have been repla
ced by null
Preprocess the col: MMRAcquisitionRetailAveragePrice
In the Column: MMRAcquisitionRetailAveragePrice : 7, ?have been repl
aced by null
Preprocess the col: MMRAcquisitonRetailCleanPrice
In the Column: MMRAcquisitonRetailCleanPrice : 7, ?have been replace
d by null
Preprocess the col: MMRCurrentAuctionAveragePrice
Preprocess the col: MMRCurrentAuctionCleanPrice
Preprocess the col: MMRCurrentRetailAveragePrice
Preprocess the col: MMRCurrentRetailCleanPrice
Preprocess the col: MMRCurrentRetailRatio
Preprocess the col: PRIMEUNIT
Preprocess the col: AUCGUART
Preprocess the col: VNST
Preprocess the col: VehBCost
In the Column: VehBCost : 29, ?have been replaced by null
Preprocess the col: IsOnlineSale
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
Preprocess the col: WarrantyCost
Preprocess the col: ForSale
In the Column: ForSale : 3, ?have been replaced by null
In the Column: ForSale : 0, 0have been replaced by null
Preprocess the col: IsBadBuy
```

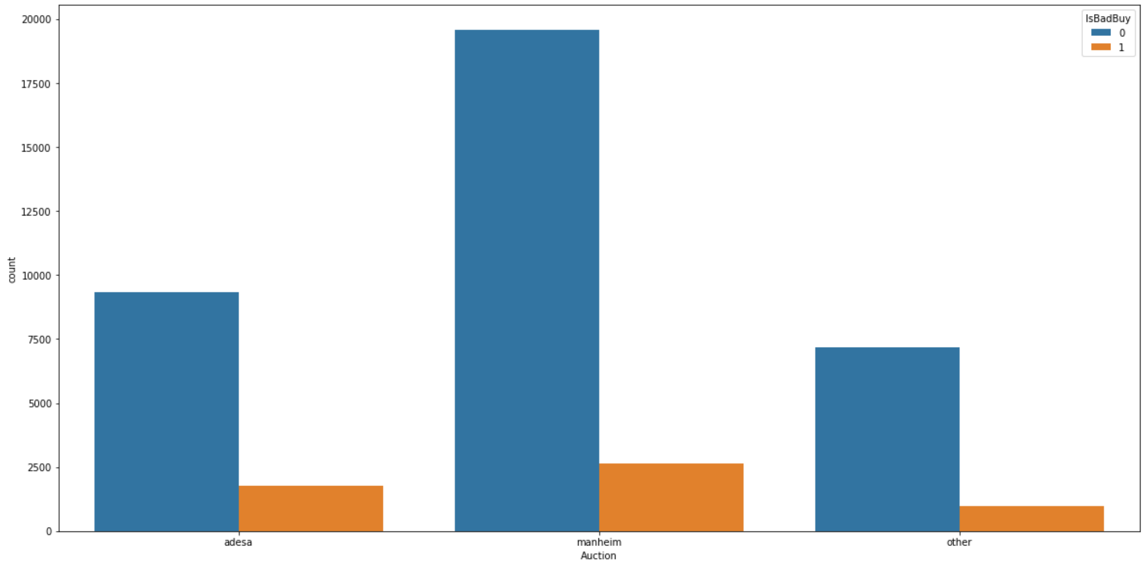
3. Can you identify any clear patterns by initial exploration of the data using histogram or box plot?

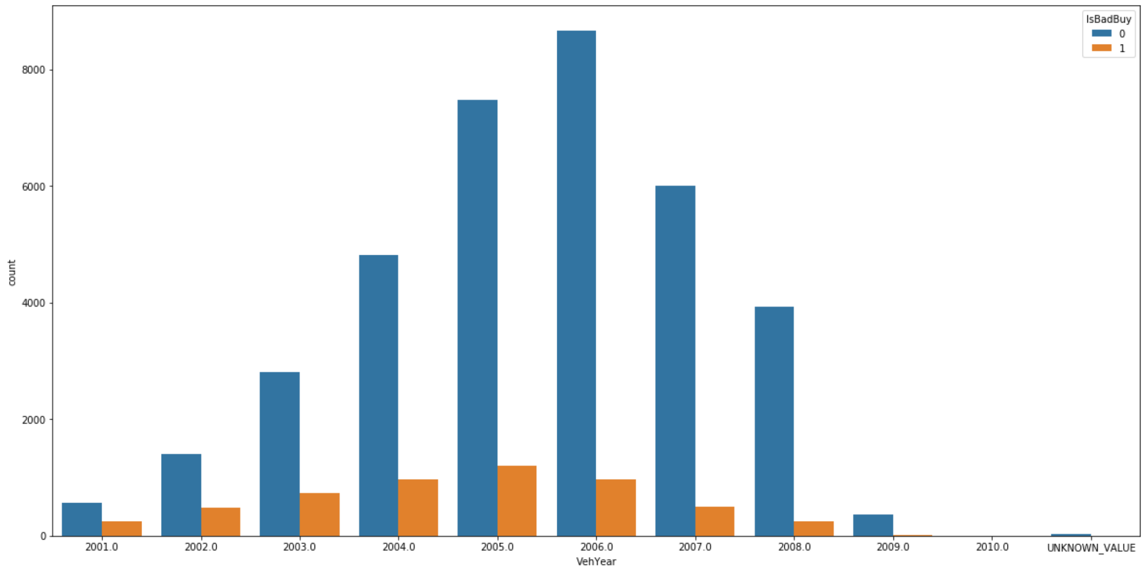
In [9]:

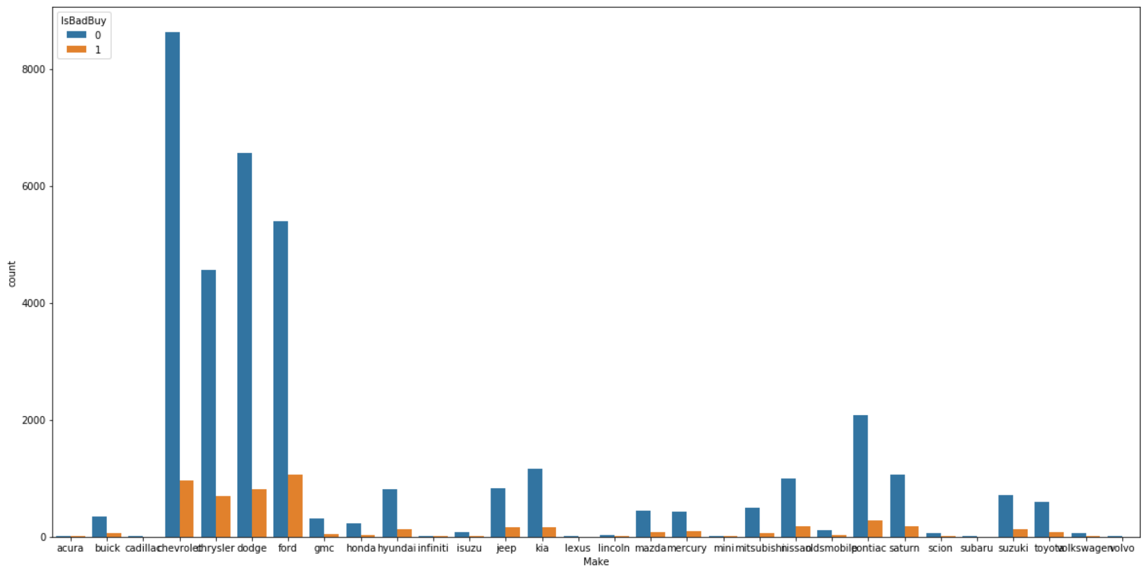
```
def plotAllCols (df):
    for colName in df.columns:
        plt.figure(figsize=(20,10))
        if colName in categorial_cols:
            ### if it's categorial column, plot hist diagram
            sns.countplot(x=colName, data = df, hue="IsBadBuy")
        elif colName in interval_cols:
    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

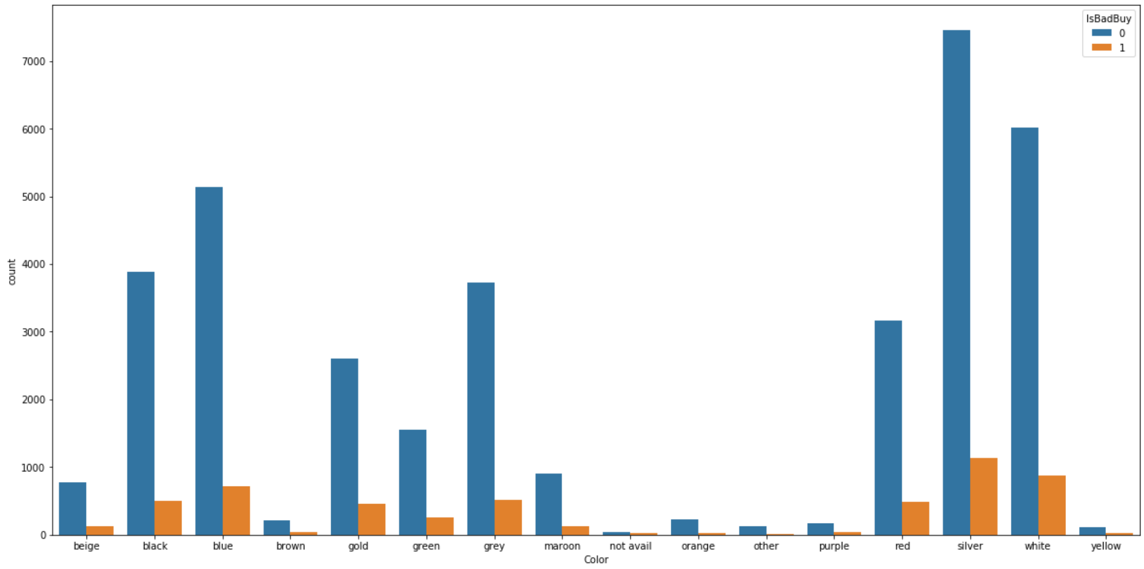
In [10]:

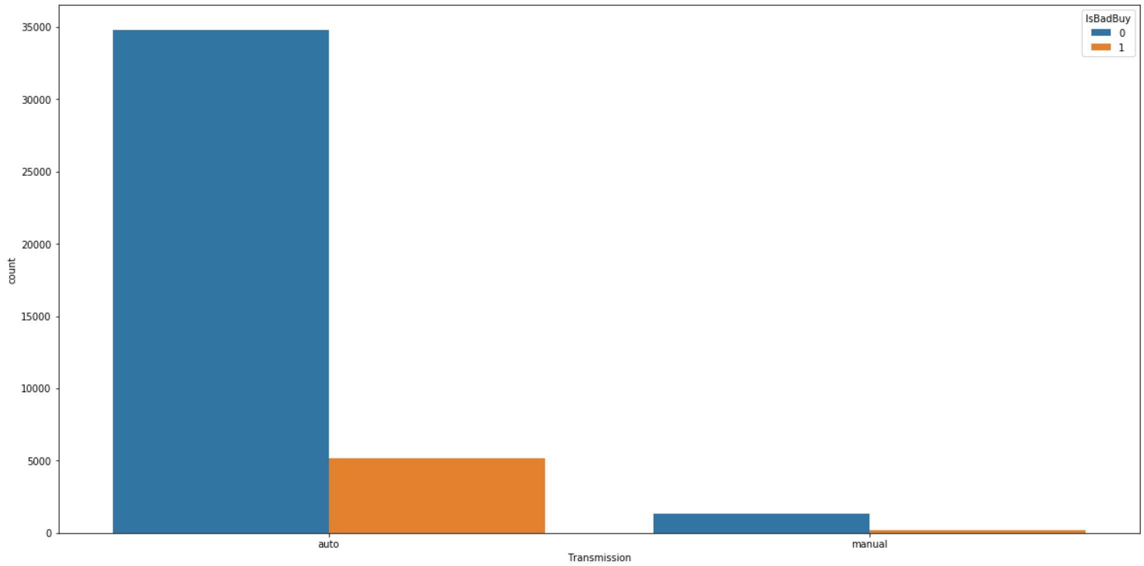
```
plotAllCols(df)
```

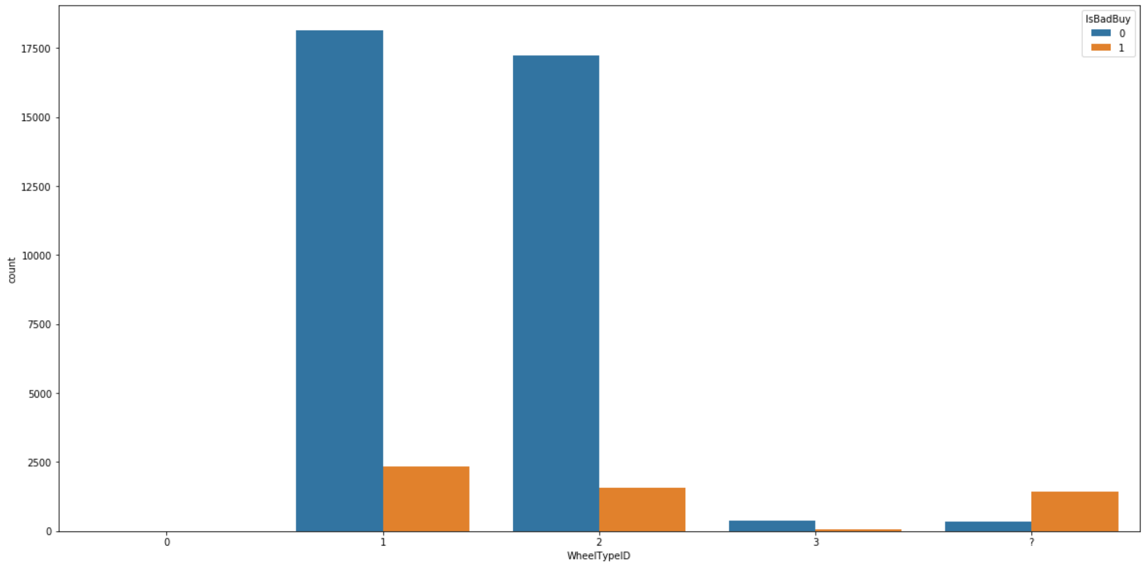

IsBadBuy
0
1
count
0
2500
5000
7500
10000
12500
15000
17500
20000
adesa
manheim
other
Auction

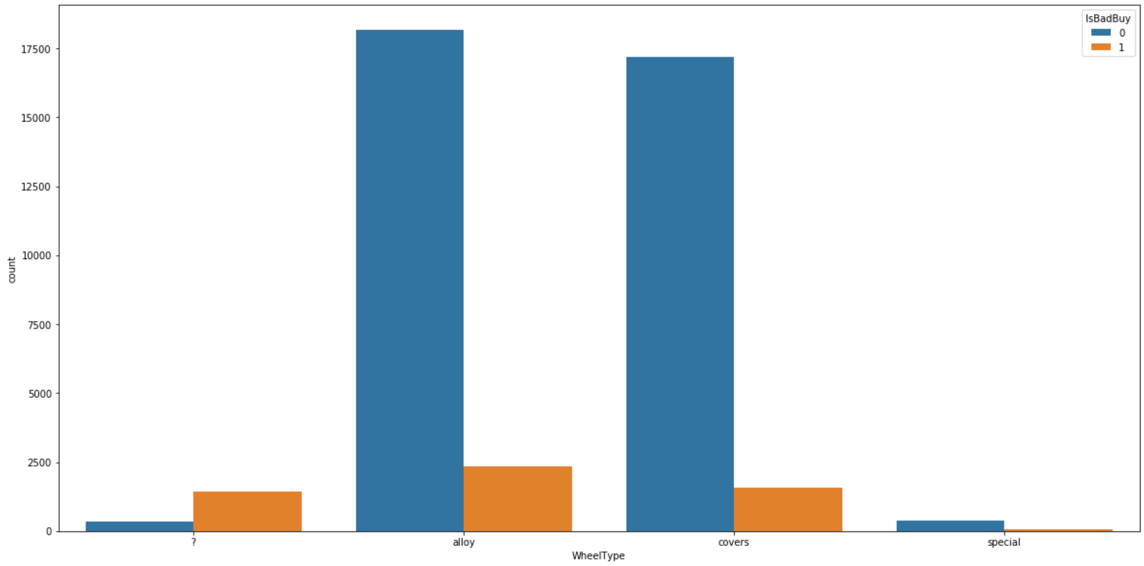

IsBadBuy
0
1
count
0
2000
4000
6000
8000
2001.0
2002.0
2003.0
2004.0
2005.0
2006.0
2007.0
2008.0
2009.0
2010.0
UNKNOWN_VALUE
VehYear

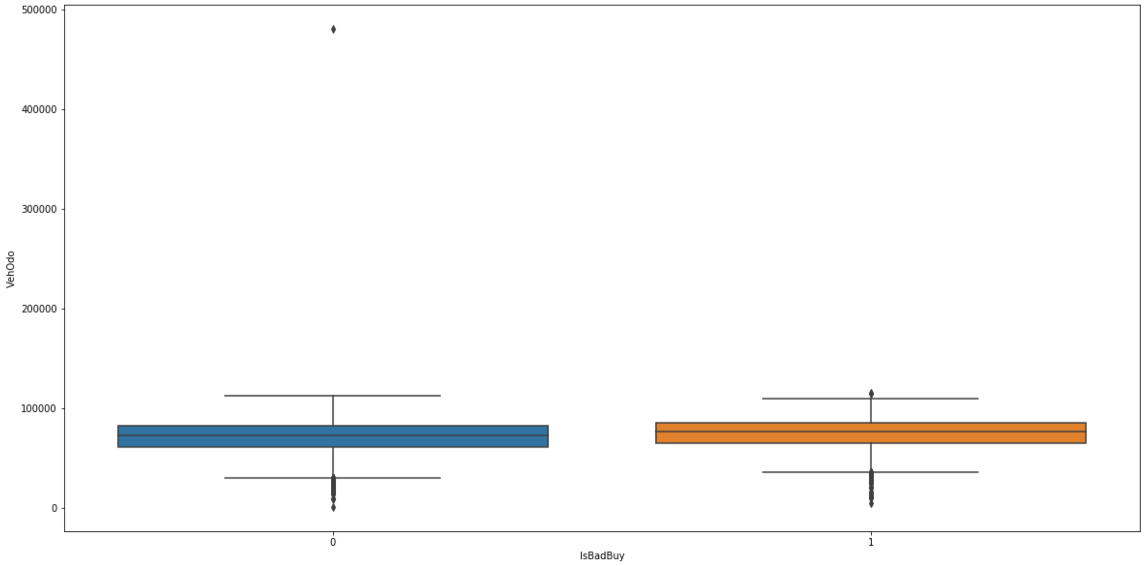

IsBadBuy
0
1
count
0
2000
4000
6000
8000
acura
buick
cadillac
chevrolet
chrysler
dodge
ford
gmc
honda
hyundai
infiniti
isuzu
jeep
kia
lexus
lincoln
mazda
mercury
mini
mitsubishi
nissan
oldsmobile
pontiac
saturn
scion
subaru
suzuki
toyota
volkswagen
volvo
Make

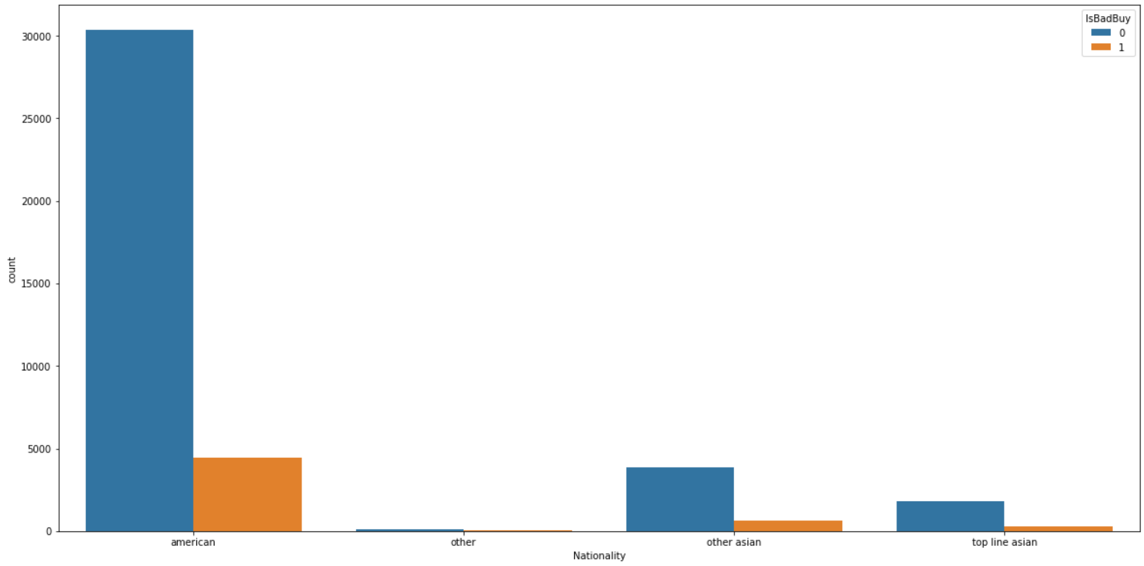

IsBadBuy
0
1
7000
6000
5000
4000
3000
2000
1000
0
count
beige
black
blue
brown
gold
green
grey
maroon
not avail
orange
other
purple
red
silver
white
yellow
Color

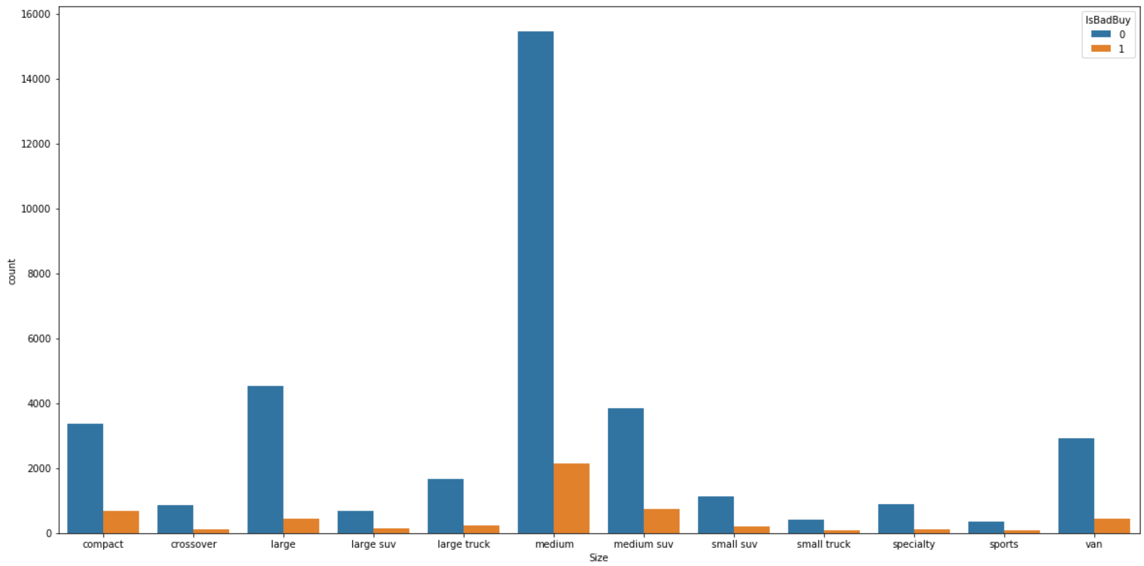

IsBadBuy
0
1
35000
30000
25000
20000
15000
10000
5000
0
count
auto
manual
Transmission

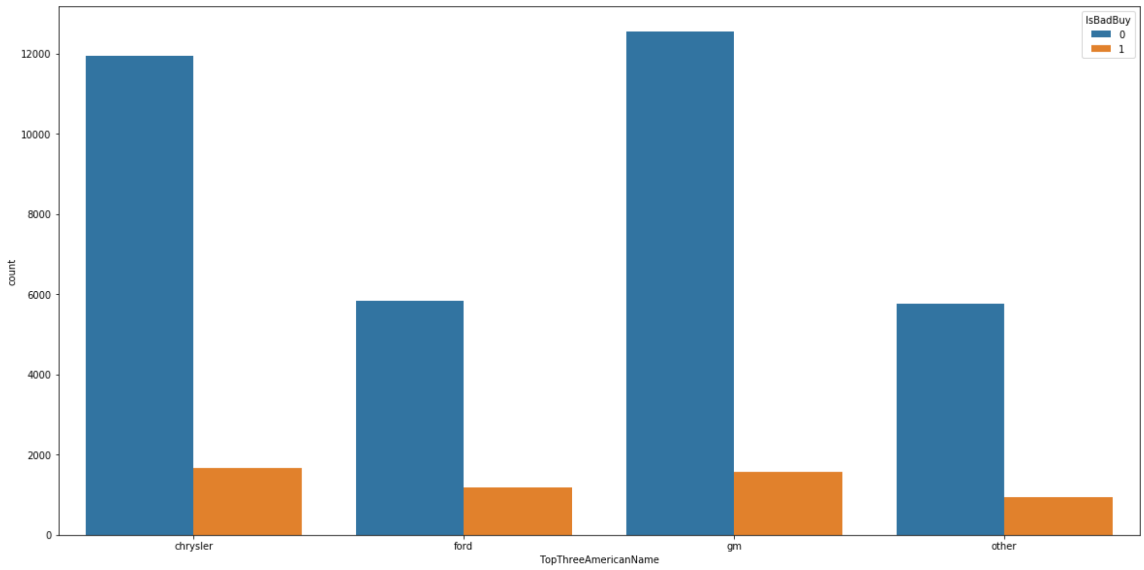

IsBadBuy
0
1
17500
15000
12500
10000
7500
5000
2500
0
count
0
1
2
3
?
WheelTypeID

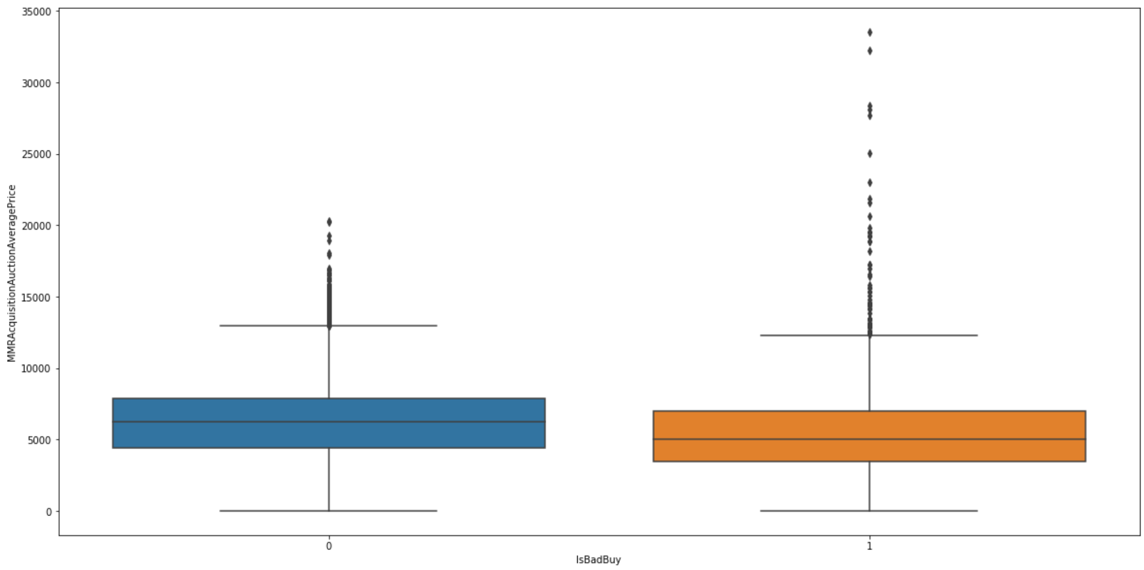

IsBadBuy
0
1
count
WheelType
?
alloy
covers
special
0
2500
5000
7500
10000
12500
15000
17500

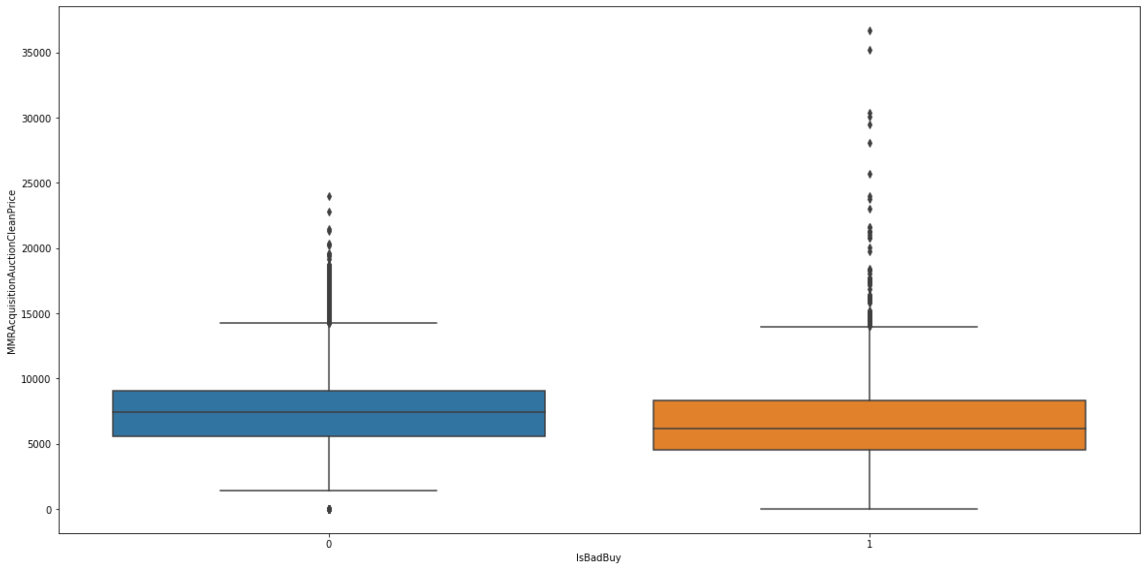

VehOdo
IsBadBuy
0
1
0
100000
200000
300000
400000
500000

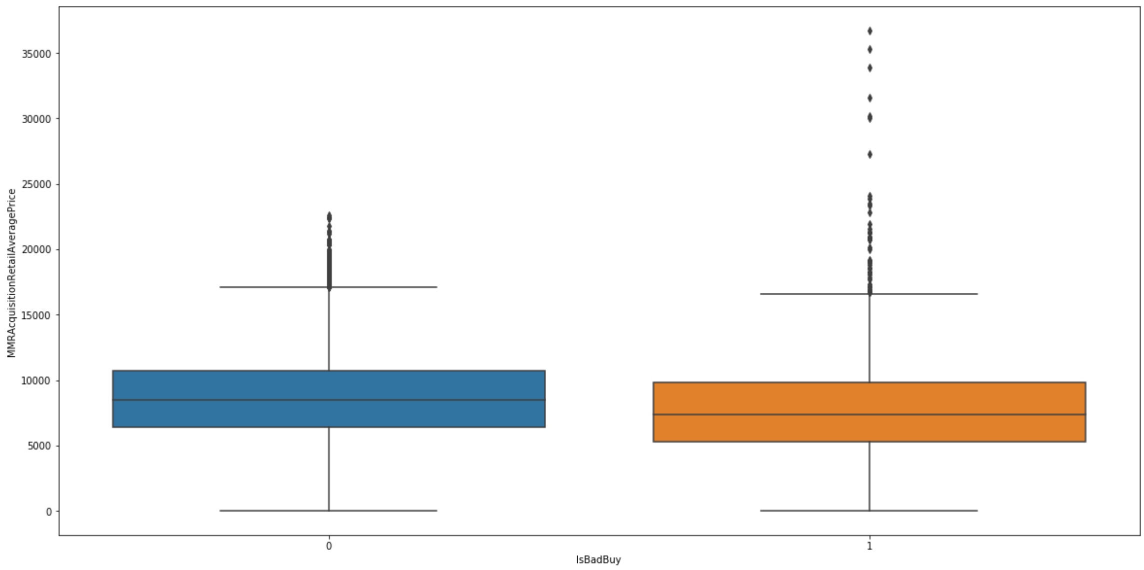

IsBadBuy
0
1
count
Nationality
american
other
other asian
top line asian
0
5000
10000
15000
20000
25000
30000

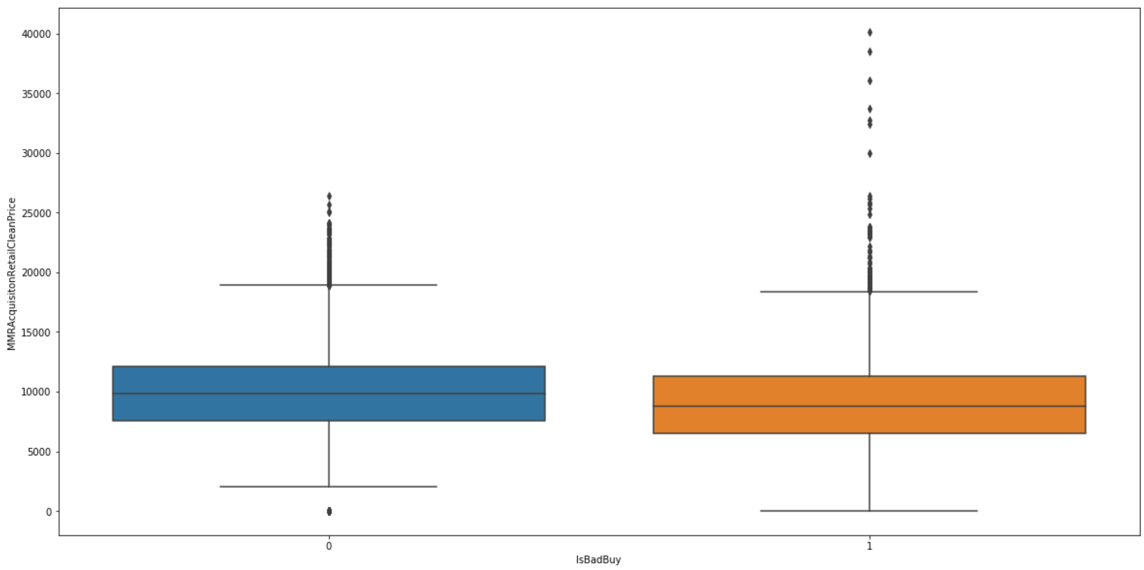

IsBadBuy
0
1
count
Size
compact
crossover
large
large suv
large truck
medium
medium suv
small suv
small truck
specialty
sports
van

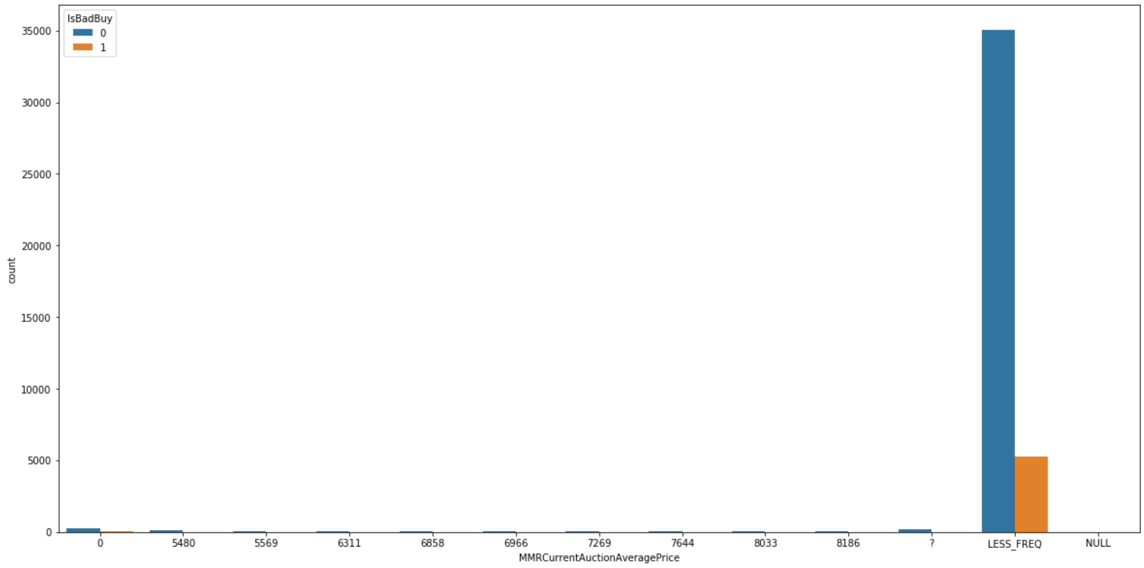

IsBadBuy
0
1
count
TopThreeAmericanName
chrysler
ford
gm
other

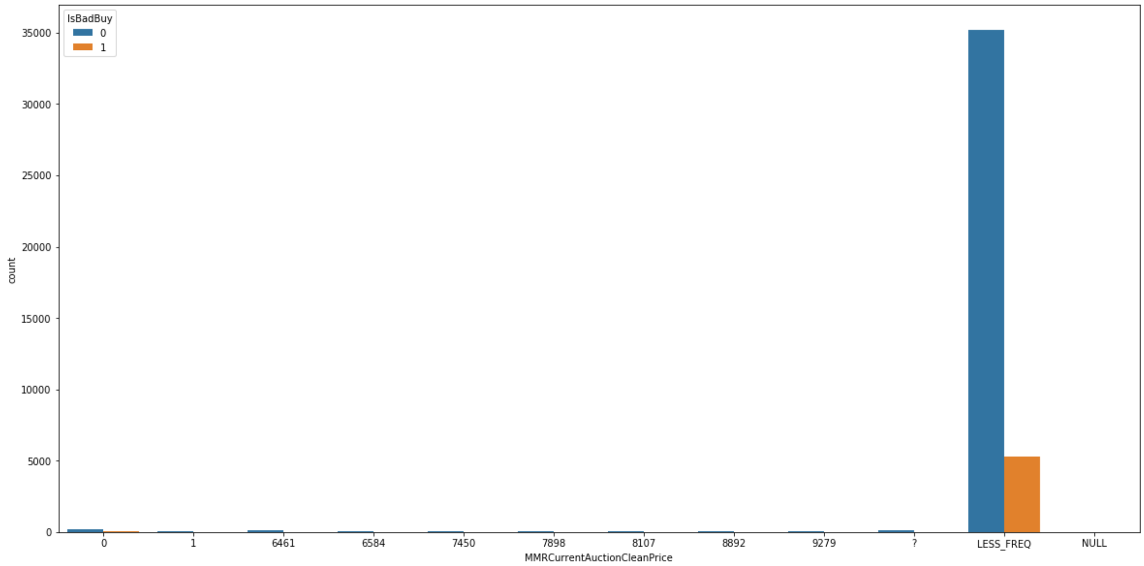

MMRAcquisitionAuctionAveragePrice
IsBadBuy

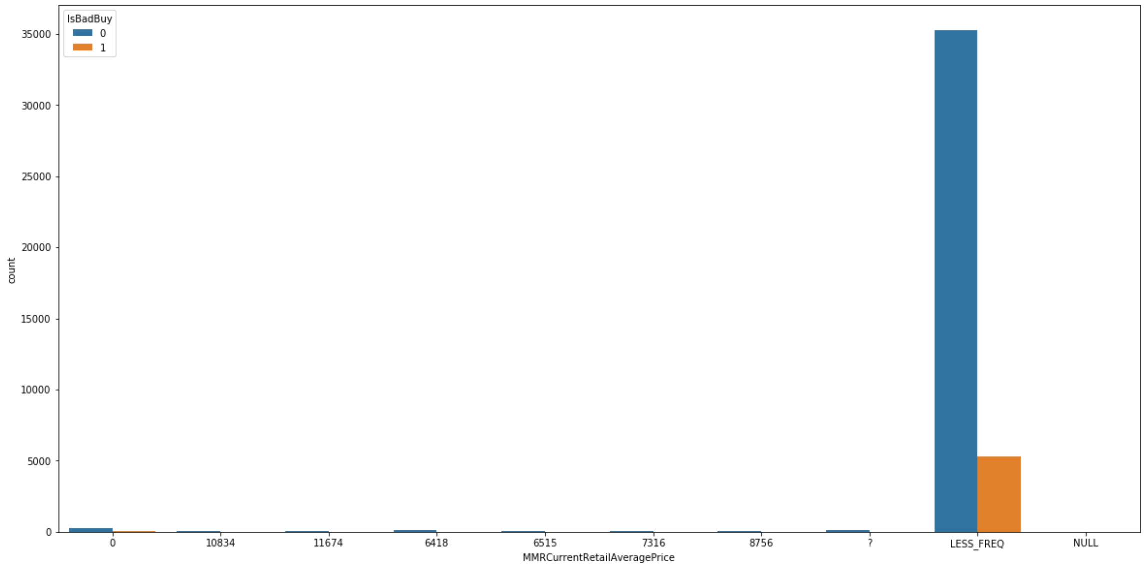

MMRAcquisitionAuctionCleanPrice
0
5000
10000
15000
20000
25000
30000
35000
0
1
IsBadBuy

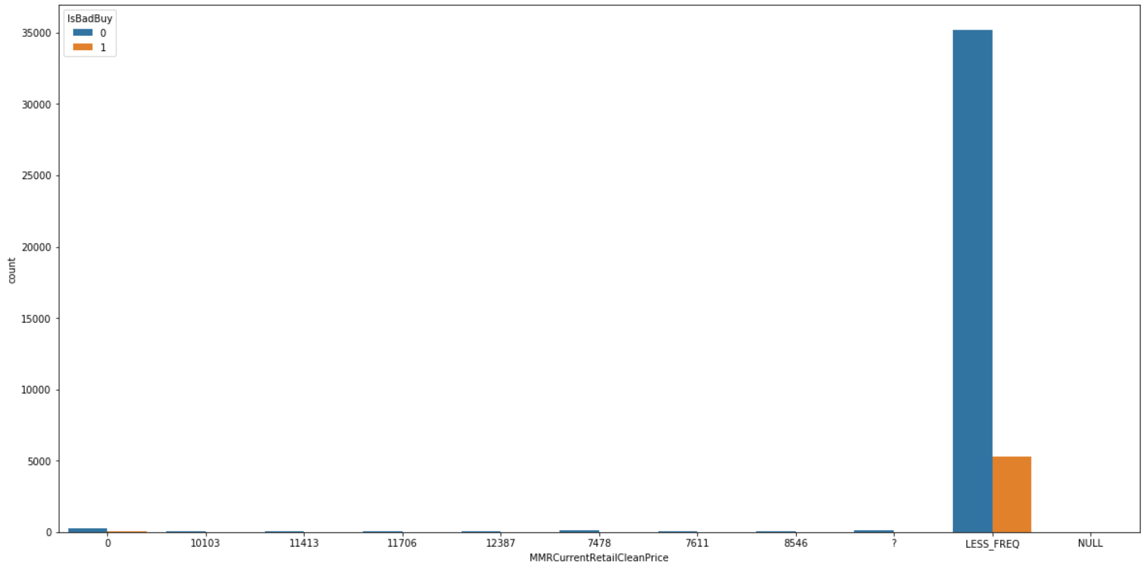

MMRAcquisitionRetailAveragePrice
0
5000
10000
15000
20000
25000
30000
35000
0
1
IsBadBuy

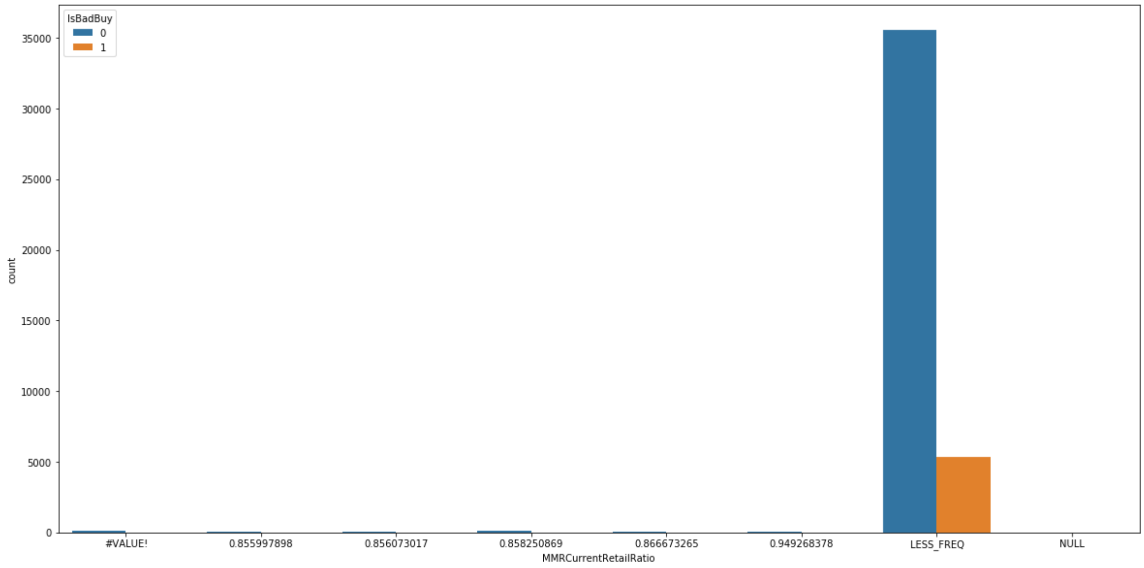

MMRAcquisitonRetailCleanPrice
0
5000
10000
15000
20000
25000
30000
35000
40000
0
1
IsBadBuy

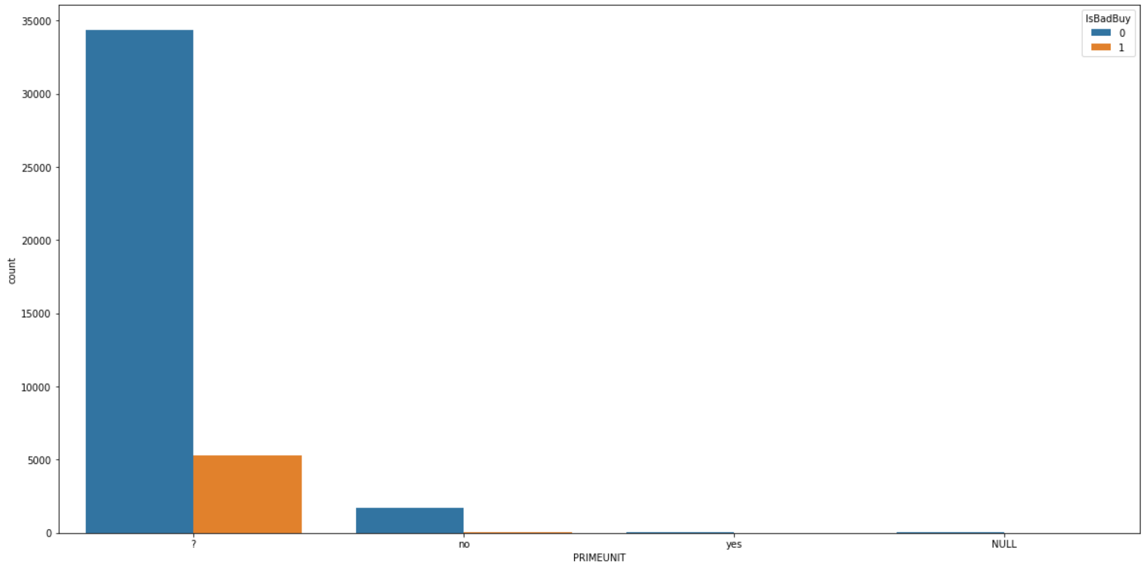

IsBadBuy
0
1
count
0
5000
10000
15000
20000
25000
30000
35000
0
5480
5569
6311
6858
6966
7269
7644
8033
8186
?
LESS_FREQ
NULL
MMRCurrentAuctionAveragePrice

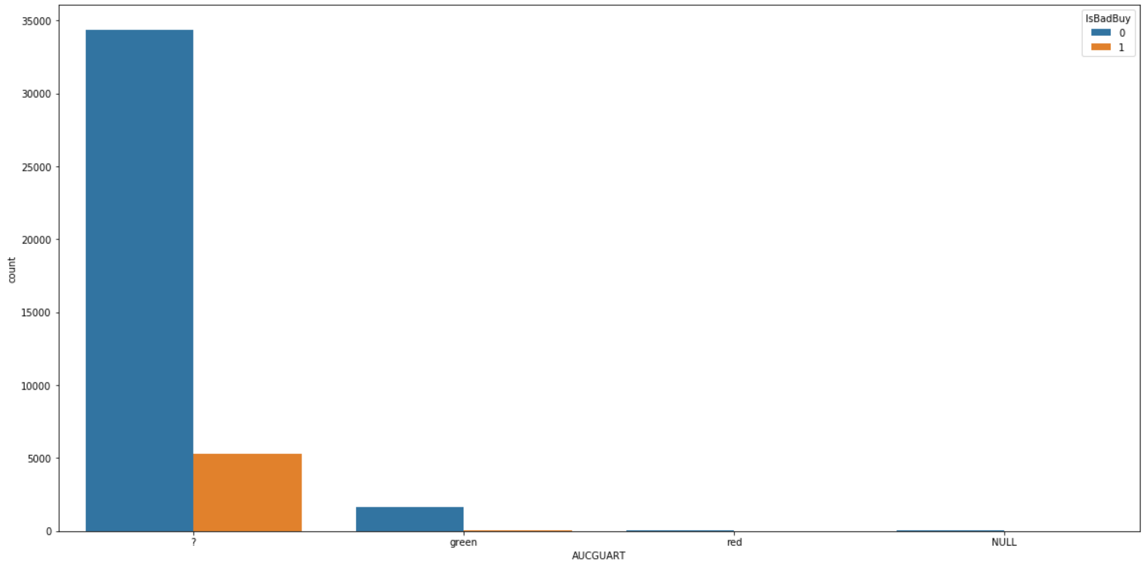

IsBadBuy
0
1
count
0
5000
10000
15000
20000
25000
30000
35000
0
1
6461
6584
7450
7898
8107
8892
9279
?
LESS_FREQ
NULL
MMRCurrentAuctionCleanPrice

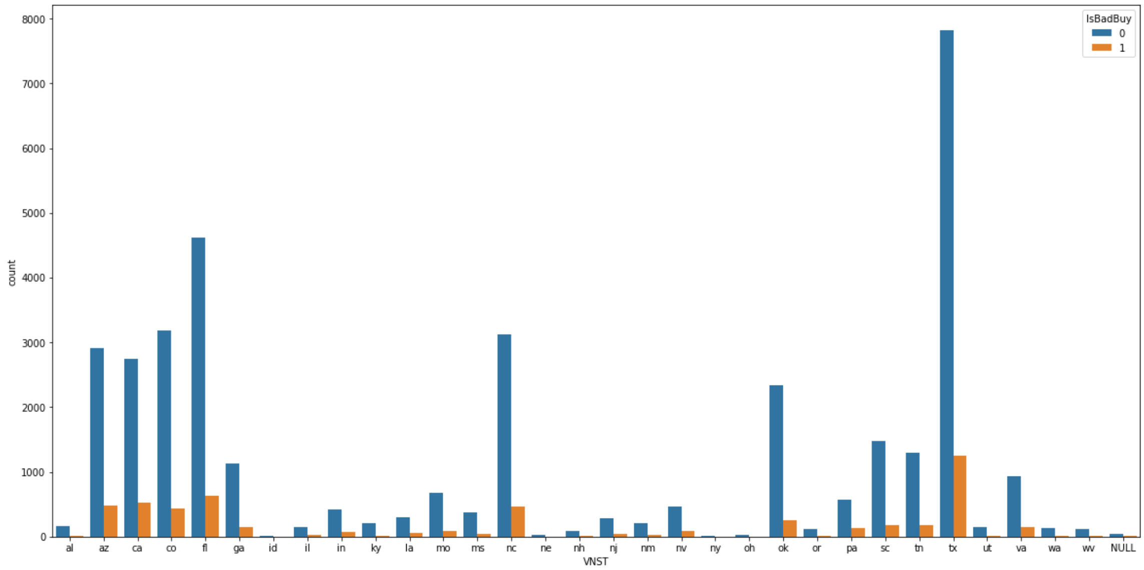

IsBadBuy
0
1
count
0
5000
10000
15000
20000
25000
30000
35000
0
10834
11674
6418
6515
7316
8756
?
LESS_FREQ
NULL
MMRCurrentRetailAveragePrice

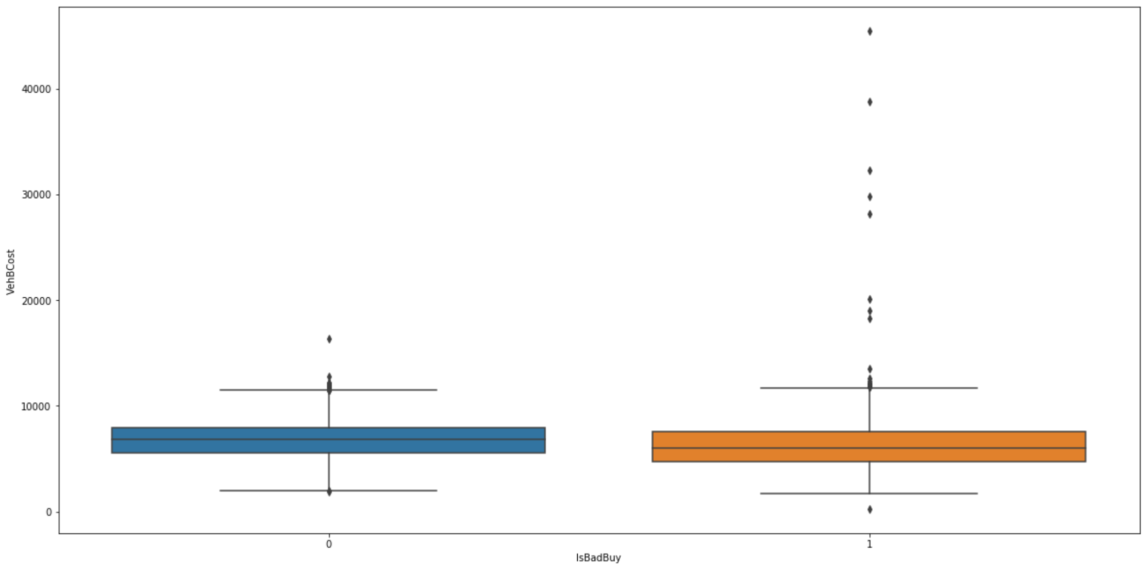

IsBadBuy
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
0
10103
11413
11706
12387
7478
7611
8546
?
LESS_FREQ
NULL
MMRCurrentRetailCleanPrice

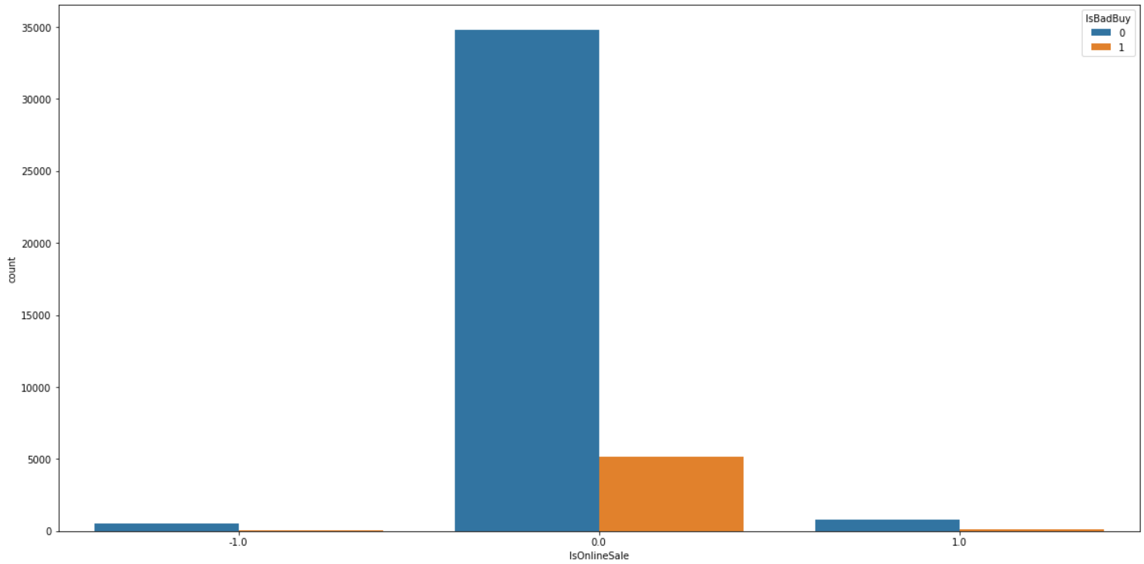

IsBadBuy
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
#VALUE!
0.855997898
0.856073017
0.858250869
0.866673265
0.949268378
LESS_FREQ
NULL
MMRCurrentRetailRatio

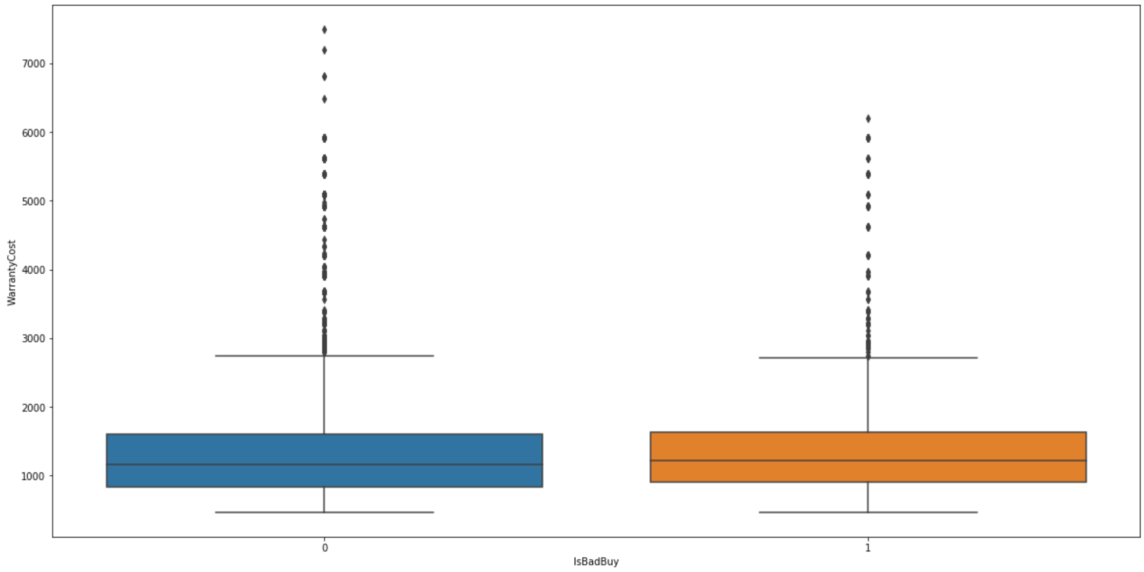

IsBadBuy
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
?
no
yes
NULL
PRIMEUNIT

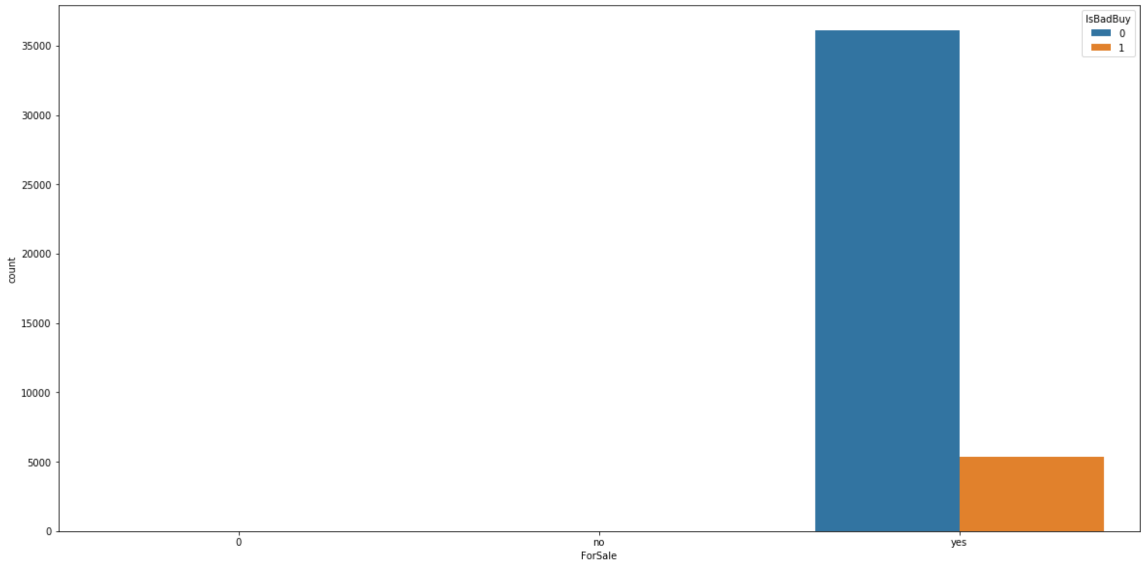

IsBadBuy
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
?
green
red
NULL
AUCGUART


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








```
<Figure size 1440x720 with 0 Axes>
```

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:", len(feature_names))

### 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: 198
Using ROS Resmapling
```

In [12]:

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

```
Number of Training:  50546
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: 0.9994856170616864
Test accuracy: 0.8256047576950896
              precision    recall  f1-score   support

           0       0.90      0.90      0.90     10832
           1       0.33      0.33      0.33      1611

   micro avg       0.83      0.83      0.83     12443
   macro avg       0.61      0.61      0.61     12443
weighted avg       0.83      0.83      0.83     12443
```

Out[15]:

```
array([[9742, 1090],
       [1080,  531]])
```

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:  7451
```

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_? : 0.13551426074337208
VehBCost : 0.12697398520218173
VehOdo : 0.09322697324736888
MMRAcquisitionAuctionCleanPrice : 0.0728830956066675
MMRAcquisitionRetailAveragePrice : 0.06240815240105831
```

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(2,7)) +[200, 500] + 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':
[2, 3, 4, 5, 6, 200, 500, 1, 1001, 2001, 3001, 4001, 5001, None], 's
plitter': ['best', 'random'], 'min_samples_leaf': range(1, 4), 'min_
samples_split': [2, 0.5, 0.3], 'max_features': ['auto', 'sqrt', 'log
2', None], 'class_weight': ['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: 0.9994856170616864
Test accuracy: 0.8243188941573576
              precision    recall  f1-score   support

           0       0.90      0.90      0.90     10832
           1       0.33      0.33      0.33      1611

   micro avg       0.82      0.82      0.82     12443
   macro avg       0.61      0.62      0.61     12443
weighted avg       0.83      0.82      0.83     12443

{'class_weight': 'balanced', 'criterion': 'entropy', 'max_depth': 20
0, 'max_features': 'auto', 'min_samples_leaf': 1, 'min_samples_spli
t': 2, '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:  13663
```

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)
```

```
MMRAcquisitionAuctionAveragePrice : 0.07556813524312803
MMRAcquisitionRetailAveragePrice : 0.07453858047632252
VehOdo : 0.07357030511029244
MMRAcquisitionAuctionCleanPrice : 0.07355390254270788
MMRAcquisitonRetailCleanPrice : 0.0672916389998756
```

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)


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



# 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)
```

```
Using ROS Resmapling
```

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: 0.6967910418232897
Test accuracy: 0.7531945672265531
GridSearch Train accuracy: 0.6972460728841056
GridSearch Test accuracy: 0.7545607972353934
```

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': 0.1, 'class_weight': 'balanced',
'max_iter': 50, 'solver': 'lbfgs', '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 : -1.2096083923720427
MMRAcquisitionRetailAveragePrice : 1.172070760190353
WheelTypeID_? : 0.7771546187078459
WheelTypeID_1 : -0.6112154370497105
WheelType_covers : -0.517388271054883
```

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       0.93      0.78      0.85     10832
           1       0.29      0.60      0.39      1611

   micro avg       0.75      0.75      0.75     12443
   macro avg       0.61      0.69      0.62     12443
weighted avg       0.85      0.75      0.79     12443

GridSearch Classification Report: 

              precision    recall  f1-score   support

           0       0.93      0.78      0.85     10832
           1       0.29      0.60      0.39      1611

   micro avg       0.75      0.75      0.75     12443
   macro avg       0.61      0.69      0.62     12443
weighted avg       0.85      0.75      0.79     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:  90
Number of selectFromModel features:  38
```

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', 'MMRAcquisitionReta
ilAveragePrice', 'MMRAcquisitonRetailCleanPrice', 'VehBCost', 'Warra
ntyCost', 'Auction_adesa', 'VehYear_2001.0', 'VehYear_2002.0', 'VehY
ear_2003.0', 'VehYear_2004.0', 'VehYear_2006.0', 'VehYear_2007.0',
'VehYear_2008.0', 'VehYear_2009.0', 'Make_acura', 'Make_chrysler',
'Make_dodge', 'Make_ford', 'Make_honda', 'Make_infiniti', 'Make_jee
p', 'Make_lexus', 'Make_nissan', 'Make_pontiac', 'Make_suzuki', 'Mak
e_toyota', 'Make_volvo', 'WheelTypeID_0', 'WheelTypeID_1', 'WheelTyp
eID_3', 'WheelTypeID_?', 'WheelType_?', 'WheelType_alloy', 'WheelTyp
e_covers', 'WheelType_special', 'Nationality_other asian', 'National
ity_top line asian', 'Size_large', 'Size_large suv', 'Size_medium',
'Size_medium suv', 'Size_van', 'TopThreeAmericanName_chrysler', 'Top
ThreeAmericanName_gm', 'MMRCurrentAuctionAveragePrice_5480', 'MMRCur
rentAuctionAveragePrice_5569', 'MMRCurrentAuctionAveragePrice_6311',
'MMRCurrentAuctionAveragePrice_7269', 'MMRCurrentAuctionAveragePrice
_7644', 'MMRCurrentAuctionAveragePrice_8186', 'MMRCurrentAuctionAver
agePrice_LESS_FREQ', 'MMRCurrentAuctionCleanPrice_6461', 'MMRCurrent
AuctionCleanPrice_6584', 'MMRCurrentAuctionCleanPrice_7450', 'MMRCur
rentAuctionCleanPrice_7898', 'MMRCurrentAuctionCleanPrice_LESS_FRE
Q', 'MMRCurrentRetailAveragePrice_10834', 'MMRCurrentRetailAveragePr
ice_11674', 'MMRCurrentRetailAveragePrice_6418', 'MMRCurrentRetailAv
eragePrice_6515', 'MMRCurrentRetailAveragePrice_7316', 'MMRCurrentRe
tailAveragePrice_8756', 'MMRCurrentRetailAveragePrice_LESS_FREQ', 'M
MRCurrentRetailCleanPrice_10103', 'MMRCurrentRetailCleanPrice_1141
3', 'MMRCurrentRetailCleanPrice_12387', 'MMRCurrentRetailCleanPrice_
7478', 'MMRCurrentRetailCleanPrice_7611', 'MMRCurrentRetailCleanPric
e_8546', 'MMRCurrentRetailCleanPrice_LESS_FREQ', 'MMRCurrentRetailRa
tio_#VALUE!', 'MMRCurrentRetailRatio_0.855997898', 'MMRCurrentRetail
Ratio_0.856073017', 'MMRCurrentRetailRatio_0.858250869', 'MMRCurrent
RetailRatio_0.866673265', 'MMRCurrentRetailRatio_0.949268378', 'MMRC
urrentRetailRatio_LESS_FREQ', 'PRIMEUNIT_?', 'PRIMEUNIT_no', 'VNST_i
d', 'VNST_ky', 'VNST_nc', 'VNST_ne', 'VNST_nh', 'VNST_ny', 'VNST_o
r', 'VNST_pa', 'VNST_tn', 'VNST_tx']



The SelectFromModel features:

 ['VehOdo', 'MMRAcquisitionAuctionAveragePrice', 'MMRAcquisitionAuct
ionCleanPrice', 'MMRAcquisitionRetailAveragePrice', 'MMRAcquisitonRe
tailCleanPrice', 'VehBCost', 'WarrantyCost', 'Auction_adesa', 'Aucti
on_manheim', 'Auction_other', 'VehYear_2003.0', 'VehYear_2004.0', 'V
ehYear_2005.0', 'VehYear_2006.0', 'Make_chevrolet', 'Make_chrysler',
'Make_dodge', 'Make_ford', 'Color_black', 'Color_blue', 'Color_gol
d', 'Color_grey', 'Color_red', 'Color_silver', 'Color_white', 'Wheel
TypeID_?', 'WheelType_?', 'WheelType_alloy', 'WheelType_covers', 'Si
ze_medium', 'TopThreeAmericanName_chrysler', 'TopThreeAmericanName_g
m', 'VNST_az', 'VNST_ca', 'VNST_co', 'VNST_fl', 'VNST_nc', 'VNST_t
x']
```

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:    2.6s finishe
d
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurr
ent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.4s finishe
d
```

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:

MMRAcquisitionAuctionAveragePrice : -0.9620067587313315
MMRAcquisitionAuctionCleanPrice : 0.858021895106162
Make_infiniti : 0.5946791320209158
Make_honda : -0.4498818947004017
Make_isuzu : 0.44302155083592776



Top-5 important variables for selectModel

MMRAcquisitionAuctionAveragePrice : -1.307036409153068
MMRAcquisitonRetailCleanPrice : 1.0802608352180163
Make_chrysler : 0.6273796723439636
Make_dodge : 0.540067113709443
MMRAcquisitionAuctionCleanPrice : 0.3335244152330805
```

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': 0.1, 'class_weight': 'balanced', 'm
ax_iter': 30, 'solver': 'newton-cg', 'warm_start': True}
Optimal Parameters for selectModel {'C': 1, 'class_weight': 'balance
d', 'max_iter': 50, 'solver': 'lbfgs', '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: 0.6972460728841056
GridSearch Test accuracy: 0.7545607972353934


RFE:

Train accuracy: 0.7000158271673327
Test accuracy: 0.7536767660532026


selectModel:

Train accuracy: 0.6827444308154949
Test accuracy: 0.7653299043638994
```

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       0.93      0.78      0.85     10832
           1       0.29      0.60      0.39      1611

   micro avg       0.75      0.75      0.75     12443
   macro avg       0.61      0.69      0.62     12443
weighted avg       0.85      0.75      0.79     12443




selectModel classification report:
               precision    recall  f1-score   support

           0       0.93      0.79      0.85     10832
           1       0.29      0.57      0.39      1611

   micro avg       0.77      0.77      0.77     12443
   macro avg       0.61      0.68      0.62     12443
weighted avg       0.84      0.77      0.79     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")
```

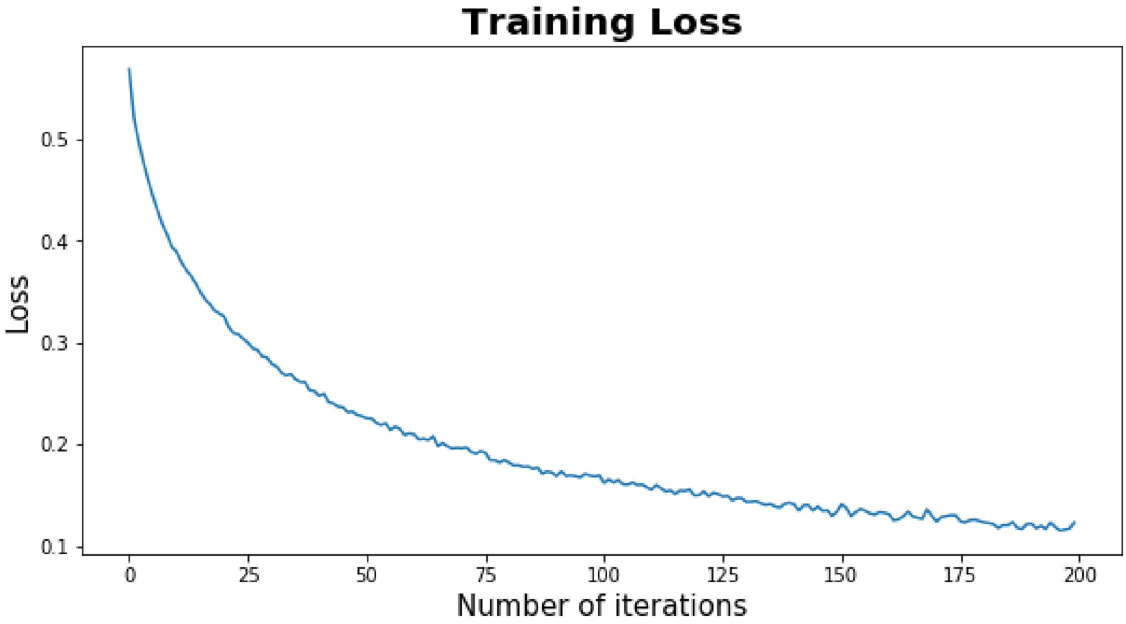
d. Did the training process converge and resulted in the best model?

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 0x7fceb132edd8>]
```



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: 0.4818383254856962
MLP Test accuracy: 0.7743309491280238



MLP classification report: 
               precision    recall  f1-score   support

           0       0.87      0.88      0.87     10832
           1       0.09      0.09      0.09      1611

   micro avg       0.77      0.77      0.77     12443
   macro avg       0.48      0.48      0.48     12443
weighted avg       0.77      0.77      0.77     12443
```

2. Refine this network by tuning it with GridSearchCV.

In [ ]:

```

```

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, 64, 32, 16)],
        'activation': ['relu'],
        'solver' : ['adam',],
        'batch_size': [64],
        'shuffle': [True],
        'learning_rate_init': [0.001],
        'n_iter_no_change': [10],
        'max_iter':[200],
        'warm_start': [True],
        'early_stopping': [True],
        'alpha': [0.01, 0.001],
    },
]


cv = GridSearchCV(param_grid=params, estimator=MLPClassifier(random_state=rs, ve
rbose=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 = 0.54856218
Validation score: 0.731751
Iteration 2, loss = 0.47211536
Validation score: 0.771316
Iteration 3, loss = 0.40356883
Validation score: 0.799011
Iteration 4, loss = 0.34348921
Validation score: 0.834817
Iteration 5, loss = 0.29075779
Validation score: 0.851236
Iteration 6, loss = 0.24983120
Validation score: 0.860534
Iteration 7, loss = 0.22284442
Validation score: 0.876558
Iteration 8, loss = 0.20155821
Validation score: 0.888625
Iteration 9, loss = 0.18602661
Validation score: 0.882690
Iteration 10, loss = 0.16979396
Validation score: 0.898516
Iteration 11, loss = 0.15977150
Validation score: 0.896736
Iteration 12, loss = 0.15176313
Validation score: 0.895351
Iteration 13, loss = 0.14464423
Validation score: 0.905836
Iteration 14, loss = 0.13999550
Validation score: 0.907023
Iteration 15, loss = 0.12720528
Validation score: 0.906034
Iteration 16, loss = 0.12930383
Validation score: 0.907023
Iteration 17, loss = 0.12255444
Validation score: 0.910386
Iteration 18, loss = 0.12068214
Validation score: 0.911771
Iteration 19, loss = 0.11399424
Validation score: 0.908803
Iteration 20, loss = 0.11282158
Validation score: 0.915331
Iteration 21, loss = 0.10661677
Validation score: 0.922057
Iteration 22, loss = 0.10446701
Validation score: 0.916518
Iteration 23, loss = 0.10589664
Validation score: 0.909792
Iteration 24, loss = 0.10556269
Validation score: 0.918497
Iteration 25, loss = 0.09938828
Validation score: 0.918299
Iteration 26, loss = 0.09541842
Validation score: 0.912760
Iteration 27, loss = 0.10113910
Validation score: 0.919683
Iteration 28, loss = 0.09432959
Validation score: 0.909792
Iteration 29, loss = 0.09296471
Validation score: 0.923046
Iteration 30, loss = 0.09169923
Validation score: 0.924036
Iteration 31, loss = 0.08993748
```

```
Validation score: 0.919288
Iteration 32, loss = 0.08603412
Validation score: 0.921662
Iteration 33, loss = 0.08854639
Validation score: 0.922453
Iteration 34, loss = 0.08351747
Validation score: 0.922849
Iteration 35, loss = 0.08777318
Validation score: 0.917112
Iteration 36, loss = 0.08058952
Validation score: 0.928190
Iteration 37, loss = 0.08469264
Validation score: 0.923640
Iteration 38, loss = 0.08402573
Validation score: 0.931157
Iteration 39, loss = 0.07430225
Validation score: 0.926607
Iteration 40, loss = 0.07893320
Validation score: 0.917903
Iteration 41, loss = 0.07689212
Validation score: 0.925223
Iteration 42, loss = 0.07355570
Validation score: 0.922057
Iteration 43, loss = 0.08132868
Validation score: 0.927399
Iteration 44, loss = 0.07889856
Validation score: 0.923838
Iteration 45, loss = 0.07490265
Validation score: 0.927596
Iteration 46, loss = 0.07099558
Validation score: 0.928388
Iteration 47, loss = 0.06990805
Validation score: 0.931157
Iteration 48, loss = 0.07486228
Validation score: 0.929179
Iteration 49, loss = 0.07158638
Validation score: 0.931355
Iteration 50, loss = 0.06874335
Validation score: 0.923046
Iteration 51, loss = 0.07661840
Validation score: 0.924431
Iteration 52, loss = 0.06855482
Validation score: 0.918101
Iteration 53, loss = 0.07291045
Validation score: 0.927596
Iteration 54, loss = 0.06441686
Validation score: 0.918892
Iteration 55, loss = 0.06992323
Validation score: 0.934520
Iteration 56, loss = 0.07443742
Validation score: 0.929970
Iteration 57, loss = 0.06685328
Validation score: 0.930366
Iteration 58, loss = 0.06478549
Validation score: 0.928586
Iteration 59, loss = 0.06425201
Validation score: 0.920079
Iteration 60, loss = 0.06606451
Validation score: 0.926805
Iteration 61, loss = 0.06558700
Validation score: 0.917507
```

```
Iteration 62, loss = 0.06666644
Validation score: 0.928586
Iteration 63, loss = 0.06158633
Validation score: 0.933927
Iteration 64, loss = 0.06551972
Validation score: 0.928190
Iteration 65, loss = 0.06410788
Validation score: 0.933927
Iteration 66, loss = 0.06246794
Validation score: 0.931355
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=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=True, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid=[{'hidden_layer_sizes': [(128, 64, 32, 16)], 'acti
vation': ['relu'], 'solver': ['adam'], 'batch_size': [64], 'shuffl
e': [True], 'learning_rate_init': [0.001], 'n_iter_no_change': [10],
'max_iter': [200], 'warm_start': [True], 'early_stopping': [True],
'alpha': [0.01, 0.001]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='war
n',
       scoring=None, verbose=0)
```

a. What is the network architecture?

In [53]:

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

```
Number of Layers:  6
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 64
4 Layer with hidden size 32
5 Layer with hidden size 16
6 Layer with hidden size 1
The activation function:  relu
```

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

In [54]:

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

```
Number of iterations it ran:  66
```

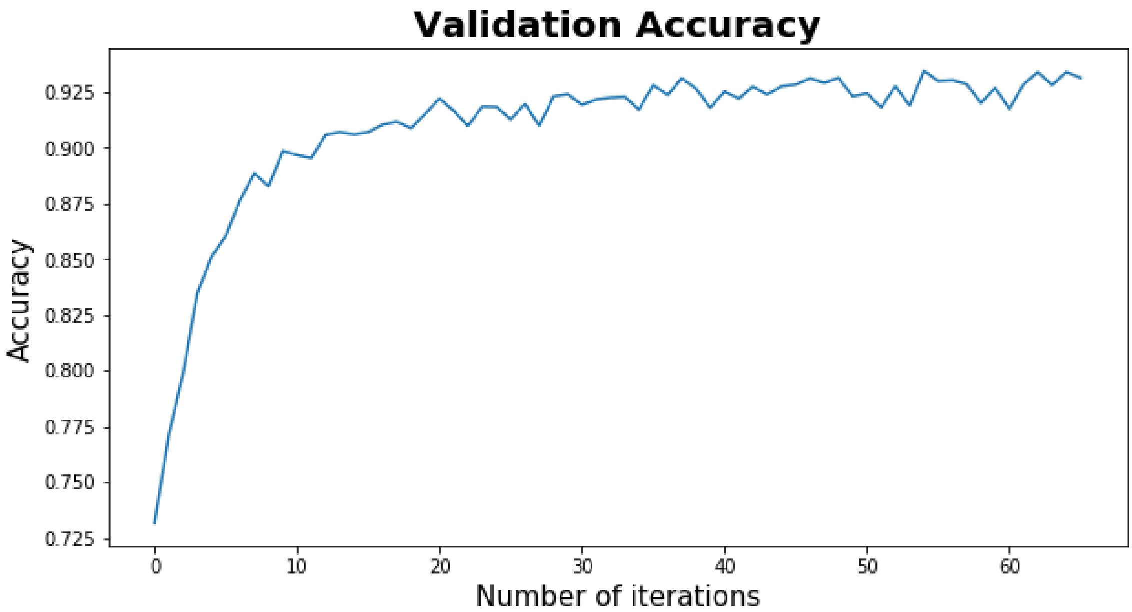
c. Sign of overfitting?

In [55]:

```
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[55]:

```
[<matplotlib.lines.Line2D at 0x7fceb73ae240>]
```



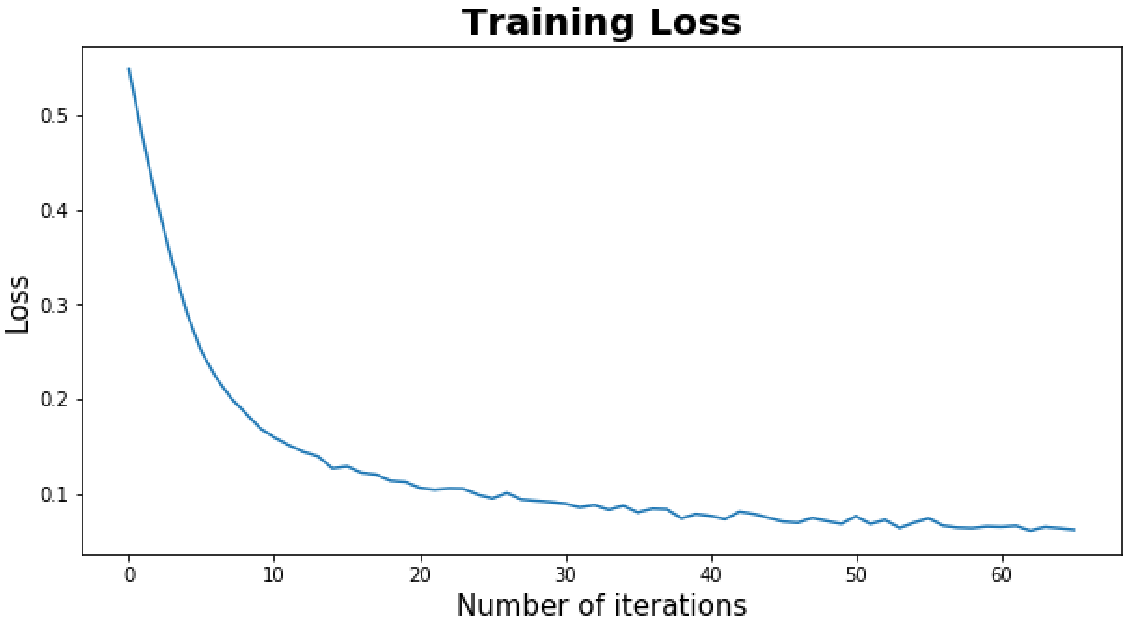
d. Did the training process converge and resulted in the best model?

In [56]:

```
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[56]:

```
[<matplotlib.lines.Line2D at 0x7fcee981feb8>]
```



e. 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("\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: 0.975843785858426
GridSearch NN Test accuracy: 0.8350880012858636



GridSearch NN Classification Report: 
               precision    recall  f1-score   support

           0       0.90      0.91      0.91     10832
           1       0.36      0.35      0.36      1611

   micro avg       0.84      0.84      0.84     12443
   macro avg       0.63      0.63      0.63     12443
weighted avg       0.83      0.84      0.83     12443

Best Parameters of NN:  {'activation': 'relu', 'alpha': 0.001, 'batc
h_size': 64, 'early_stopping': True, 'hidden_layer_sizes': (128, 64,
32, 16), 'learning_rate_init': 0.001, 'max_iter': 200, 'n_iter_no_ch
ange': 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 [58]:

```
params = [
    {
        'hidden_layer_sizes': [(128, 64, 32, 16)],
        'activation': ['relu'],
        'solver' : ['adam',],
        'batch_size': [64],
        'shuffle': [True],
        'learning_rate_init': [0.001],
        'n_iter_no_change': [10],
        'max_iter':[200],
        'warm_start': [True],
        'early_stopping': [True],
        'alpha': [0.01, 0.001],
    },
]



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 = 0.55920437
Validation score: 0.701088
Iteration 2, loss = 0.52882666
Validation score: 0.718497
Iteration 3, loss = 0.50945268
Validation score: 0.724431
Iteration 4, loss = 0.49081665
Validation score: 0.733729
Iteration 5, loss = 0.47221045
Validation score: 0.748764
Iteration 6, loss = 0.45545179
Validation score: 0.756874
Iteration 7, loss = 0.43961116
Validation score: 0.762413
Iteration 8, loss = 0.42345590
Validation score: 0.776855
Iteration 9, loss = 0.40902212
Validation score: 0.774085
Iteration 10, loss = 0.39399478
Validation score: 0.782987
Iteration 11, loss = 0.38196869
Validation score: 0.791691
Iteration 12, loss = 0.37132417
Validation score: 0.802770
Iteration 13, loss = 0.35926943
Validation score: 0.802374
Iteration 14, loss = 0.35237085
Validation score: 0.807913
Iteration 15, loss = 0.34211636
Validation score: 0.815430
Iteration 16, loss = 0.33492760
Validation score: 0.819980
Iteration 17, loss = 0.32979855
Validation score: 0.813452
Iteration 18, loss = 0.32135280
Validation score: 0.821761
Iteration 19, loss = 0.31107574
Validation score: 0.820772
Iteration 20, loss = 0.30655272
Validation score: 0.828487
Iteration 21, loss = 0.30055642
Validation score: 0.834619
Iteration 22, loss = 0.29370566
Validation score: 0.839763
Iteration 23, loss = 0.29085304
Validation score: 0.840752
Iteration 24, loss = 0.28560413
Validation score: 0.839565
Iteration 25, loss = 0.27783852
Validation score: 0.848467
Iteration 26, loss = 0.27460390
Validation score: 0.843126
Iteration 27, loss = 0.26903037
Validation score: 0.849654
Iteration 28, loss = 0.26691435
Validation score: 0.846093
Iteration 29, loss = 0.26184186
Validation score: 0.855391
Iteration 30, loss = 0.25517697
Validation score: 0.857765
Iteration 31, loss = 0.25043793
```

```
Validation score: 0.860732
Iteration 32, loss = 0.24956826
Validation score: 0.867458
Iteration 33, loss = 0.24653509
Validation score: 0.864095
Iteration 34, loss = 0.24232718
Validation score: 0.864095
Iteration 35, loss = 0.23811419
Validation score: 0.856578
Iteration 36, loss = 0.23480829
Validation score: 0.867458
Iteration 37, loss = 0.23060738
Validation score: 0.871217
Iteration 38, loss = 0.23409495
Validation score: 0.864688
Iteration 39, loss = 0.22532895
Validation score: 0.878734
Iteration 40, loss = 0.22178624
Validation score: 0.876558
Iteration 41, loss = 0.22148049
Validation score: 0.876558
Iteration 42, loss = 0.21450477
Validation score: 0.865084
Iteration 43, loss = 0.21584733
Validation score: 0.874777
Iteration 44, loss = 0.20695801
Validation score: 0.869436
Iteration 45, loss = 0.21020165
Validation score: 0.871414
Iteration 46, loss = 0.20530024
Validation score: 0.883284
Iteration 47, loss = 0.20353714
Validation score: 0.883086
Iteration 48, loss = 0.20482862
Validation score: 0.875964
Iteration 49, loss = 0.19887822
Validation score: 0.877151
Iteration 50, loss = 0.19629105
Validation score: 0.877745
Iteration 51, loss = 0.19356330
Validation score: 0.884866
Iteration 52, loss = 0.19437609
Validation score: 0.885460
Iteration 53, loss = 0.18961563
Validation score: 0.879130
Iteration 54, loss = 0.19083436
Validation score: 0.884075
Iteration 55, loss = 0.18806997
Validation score: 0.887240
Iteration 56, loss = 0.18442706
Validation score: 0.889416
Iteration 57, loss = 0.18377619
Validation score: 0.883482
Iteration 58, loss = 0.18678629
Validation score: 0.889021
Iteration 59, loss = 0.18137343
Validation score: 0.887438
Iteration 60, loss = 0.18123354
Validation score: 0.888823
Iteration 61, loss = 0.17177968
Validation score: 0.885064
```

```
Iteration 62, loss = 0.17651974
Validation score: 0.884669
Iteration 63, loss = 0.17674598
Validation score: 0.886053
Iteration 64, loss = 0.17642252
Validation score: 0.881701
Iteration 65, loss = 0.17523190
Validation score: 0.890406
Iteration 66, loss = 0.16765737
Validation score: 0.882493
Iteration 67, loss = 0.17072475
Validation score: 0.882097
Iteration 68, loss = 0.17133876
Validation score: 0.885064
Iteration 69, loss = 0.16613050
Validation score: 0.889614
Iteration 70, loss = 0.16533149
Validation score: 0.897527
Iteration 71, loss = 0.16759448
Validation score: 0.899703
Iteration 72, loss = 0.16446430
Validation score: 0.897132
Iteration 73, loss = 0.16026355
Validation score: 0.900890
Iteration 74, loss = 0.16050879
Validation score: 0.895153
Iteration 75, loss = 0.15964436
Validation score: 0.890406
Iteration 76, loss = 0.16012514
Validation score: 0.898912
Iteration 77, loss = 0.16244396
Validation score: 0.895549
Iteration 78, loss = 0.15592813
Validation score: 0.895945
Iteration 79, loss = 0.15615357
Validation score: 0.892384
Iteration 80, loss = 0.15800574
Validation score: 0.895747
Iteration 81, loss = 0.15256501
Validation score: 0.904649
Iteration 82, loss = 0.15300054
Validation score: 0.902671
Iteration 83, loss = 0.15487216
Validation score: 0.896934
Iteration 84, loss = 0.14603086
Validation score: 0.908012
Iteration 85, loss = 0.15403320
Validation score: 0.899703
Iteration 86, loss = 0.15071394
Validation score: 0.894758
Iteration 87, loss = 0.14822653
Validation score: 0.898121
Iteration 88, loss = 0.14979554
Validation score: 0.893769
Iteration 89, loss = 0.15398114
Validation score: 0.899308
Iteration 90, loss = 0.14342492
Validation score: 0.904451
Iteration 91, loss = 0.13827129
Validation score: 0.908012
Iteration 92, loss = 0.13878313
```

```
Validation score: 0.901682
Iteration 93, loss = 0.14959304
Validation score: 0.901484
Iteration 94, loss = 0.14540613
Validation score: 0.901286
Iteration 95, loss = 0.13803944
Validation score: 0.899703
Validation score did not improve more than tol=0.000100 for 10 conse
cutive epochs. Stopping.
Iteration 1, loss = 0.56758633
Validation score: 0.708803
Iteration 2, loss = 0.52061289
Validation score: 0.742235
Iteration 3, loss = 0.47988162
Validation score: 0.765381
Iteration 4, loss = 0.43770721
Validation score: 0.789515
Iteration 5, loss = 0.40139163
Validation score: 0.802967
Iteration 6, loss = 0.36874125
Validation score: 0.822354
Iteration 7, loss = 0.33961134
Validation score: 0.837389
Iteration 8, loss = 0.31134099
Validation score: 0.835015
Iteration 9, loss = 0.29042468
Validation score: 0.857567
Iteration 10, loss = 0.27402650
Validation score: 0.854995
Iteration 11, loss = 0.25834679
Validation score: 0.853017
Iteration 12, loss = 0.24560960
Validation score: 0.865282
Iteration 13, loss = 0.23563915
Validation score: 0.868249
Iteration 14, loss = 0.22484281
Validation score: 0.871019
Iteration 15, loss = 0.21206894
Validation score: 0.876558
Iteration 16, loss = 0.20650296
Validation score: 0.881108
Iteration 17, loss = 0.19491230
Validation score: 0.889219
Iteration 18, loss = 0.19157948
Validation score: 0.891395
Iteration 19, loss = 0.18691339
Validation score: 0.898714
Iteration 20, loss = 0.17542886
Validation score: 0.890801
Iteration 21, loss = 0.16974231
Validation score: 0.895153
Iteration 22, loss = 0.16926681
Validation score: 0.885262
Iteration 23, loss = 0.16494753
Validation score: 0.896340
Iteration 24, loss = 0.15958589
Validation score: 0.893373
Iteration 25, loss = 0.15443237
Validation score: 0.896340
Iteration 26, loss = 0.15332352
Validation score: 0.905242
```

```
Iteration 27, loss = 0.14638877
Validation score: 0.902473
Iteration 28, loss = 0.14652707
Validation score: 0.896736
Iteration 29, loss = 0.13801102
Validation score: 0.905045
Iteration 30, loss = 0.13734004
Validation score: 0.904055
Iteration 31, loss = 0.13424590
Validation score: 0.909001
Iteration 32, loss = 0.13010395
Validation score: 0.909001
Iteration 33, loss = 0.13167964
Validation score: 0.904055
Iteration 34, loss = 0.12470479
Validation score: 0.908803
Iteration 35, loss = 0.12287827
Validation score: 0.916518
Iteration 36, loss = 0.12482632
Validation score: 0.909792
Iteration 37, loss = 0.12250820
Validation score: 0.910386
Iteration 38, loss = 0.11735599
Validation score: 0.919090
Iteration 39, loss = 0.11516125
Validation score: 0.916518
Iteration 40, loss = 0.11587339
Validation score: 0.915727
Iteration 41, loss = 0.11253537
Validation score: 0.913155
Iteration 42, loss = 0.11271207
Validation score: 0.912957
Iteration 43, loss = 0.10741468
Validation score: 0.918497
Iteration 44, loss = 0.10654170
Validation score: 0.907616
Iteration 45, loss = 0.11138189
Validation score: 0.912166
Iteration 46, loss = 0.10459638
Validation score: 0.914342
Iteration 47, loss = 0.10066200
Validation score: 0.919683
Iteration 48, loss = 0.10282604
Validation score: 0.919881
Iteration 49, loss = 0.10288856
Validation score: 0.919090
Iteration 50, loss = 0.09895830
Validation score: 0.916518
Iteration 51, loss = 0.10345620
Validation score: 0.921464
Iteration 52, loss = 0.09593454
Validation score: 0.914936
Iteration 53, loss = 0.09924745
Validation score: 0.912562
Iteration 54, loss = 0.09504412
Validation score: 0.924629
Iteration 55, loss = 0.09313935
Validation score: 0.920673
Iteration 56, loss = 0.09394586
Validation score: 0.917507
Iteration 57, loss = 0.09315643
```

```
Validation score: 0.913947
Iteration 58, loss = 0.09688742
Validation score: 0.920870
Iteration 59, loss = 0.09098033
Validation score: 0.926805
Iteration 60, loss = 0.08448669
Validation score: 0.913947
Iteration 61, loss = 0.09126251
Validation score: 0.920870
Iteration 62, loss = 0.08467944
Validation score: 0.917903
Iteration 63, loss = 0.08991536
Validation score: 0.923244
Iteration 64, loss = 0.08036737
Validation score: 0.916320
Iteration 65, loss = 0.09312787
Validation score: 0.929773
Iteration 66, loss = 0.08405142
Validation score: 0.924036
Iteration 67, loss = 0.08724836
Validation score: 0.927201
Iteration 68, loss = 0.08187973
Validation score: 0.928586
Iteration 69, loss = 0.08966199
Validation score: 0.927992
Iteration 70, loss = 0.08373264
Validation score: 0.920277
Iteration 71, loss = 0.08257443
Validation score: 0.924431
Iteration 72, loss = 0.07883727
Validation score: 0.924036
Iteration 73, loss = 0.07999067
Validation score: 0.922651
Iteration 74, loss = 0.08826804
Validation score: 0.924233
Iteration 75, loss = 0.07661485
Validation score: 0.912166
Iteration 76, loss = 0.08053650
Validation score: 0.918497
Validation score did not improve more than tol=0.000100 for 10 conse
cutive epochs. Stopping.
```

Out[58]:

```
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, 64, 32, 16)], 'acti
vation': ['relu'], 'solver': ['adam'], 'batch_size': [64], 'shuffl
e': [True], 'learning_rate_init': [0.001], 'n_iter_no_change': [10],
'max_iter': [200], 'warm_start': [True], 'early_stopping': [True],
'alpha': [0.01, 0.001]}],
       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 [59]:

```
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': 'relu', 'alpha': 0.001, 'batc
h_size': 64, 'early_stopping': True, 'hidden_layer_sizes': (128, 64,
32, 16), 'learning_rate_init': 0.001, 'max_iter': 200, 'n_iter_no_ch
ange': 10, 'shuffle': True, 'solver': 'adam', 'warm_start': True}
Best Parameters of RFE NN:  {'activation': 'relu', 'alpha': 0.001,
'batch_size': 64, 'early_stopping': True, 'hidden_layer_sizes': (12
8, 64, 32, 16), 'learning_rate_init': 0.001, 'max_iter': 200, 'n_ite
r_no_change': 10, 'shuffle': True, 'solver': 'adam', 'warm_start': T
rue}
Best Parameters of modelSelect NN:  {'activation': 'relu', 'alpha':
0.001, 'batch_size': 64, 'early_stopping': True, 'hidden_layer_size
s': (128, 64, 32, 16), 'learning_rate_init': 0.001, 'max_iter': 200,
'n_iter_no_change': 10, 'shuffle': True, 'solver': 'adam', 'warm_sta
rt': True}



GridSearch:
Number of Layers:  6
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 64
4 Layer with hidden size 32
5 Layer with hidden size 16
6 Layer with hidden size 1
The activation function:  relu


RFE:
Number of Layers:  6
The First layer is Input Layer, and the last layer is the output lay
er
1 Layer with hidden size 90
2 Layer with hidden size 128
3 Layer with hidden size 64
4 Layer with hidden size 32
5 Layer with hidden size 16
6 Layer with hidden size 1
The activation function:  relu


modelSelect:
Number of Layers:  6
The First layer is Input Layer, and the last layer is the output lay
er
1 Layer with hidden size 38
2 Layer with hidden size 128
3 Layer with hidden size 64
4 Layer with hidden size 32
5 Layer with hidden size 16
6 Layer with hidden size 1
The activation function:  relu
```

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

In [60]:

```
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: 0.975843785858426
GridSearch NN Test accuracy: 0.8350880012858636
RFE NN Train accuracy: 0.9499267993510861
RFE NNTest accuracy: 0.8128264887888773
modelSelect NN Train accuracy: 0.974102797451826
modelSelect NN Test accuracmodelSelect_cvy: 0.8151571164510166
```

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

In [61]:

```
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:  66
Number of iterations rfe ran:  95
Number of iterations modelSelect ran:  76
```

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

In [ ]:

```

```

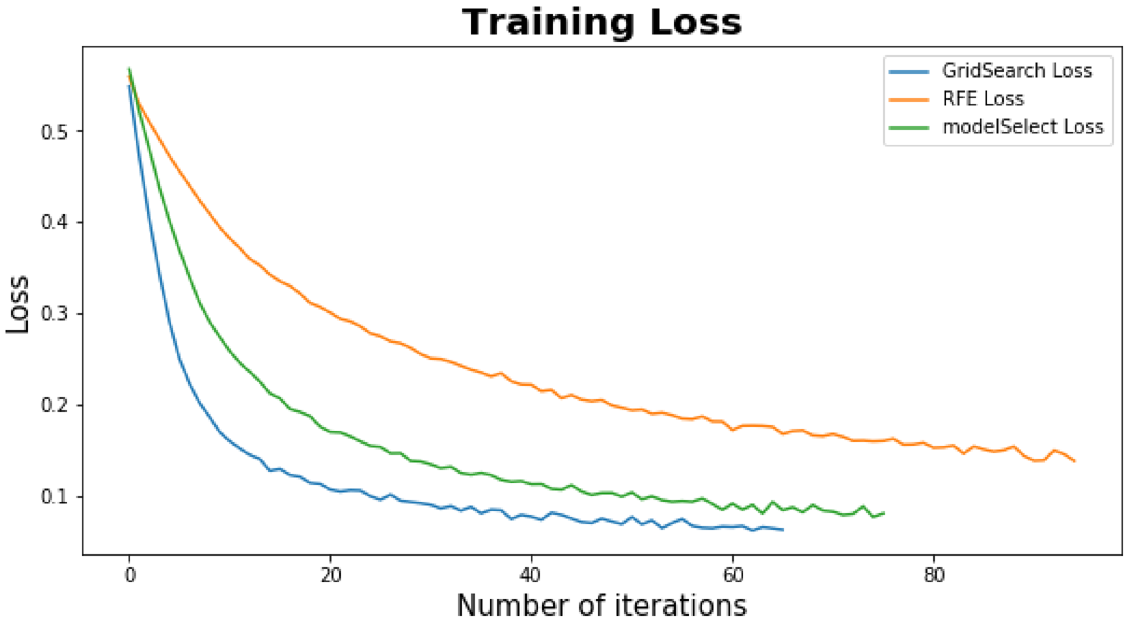
e. Did the training process converge and resulted in the best model?

In [62]:

```
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[62]:

```
<matplotlib.legend.Legend at 0x7fcea6f45470>
```



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 [63]:

```
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      0.91      0.91     10832
           1       0.36      0.35      0.36      1611

   micro avg       0.84      0.84      0.84     12443
   macro avg       0.63      0.63      0.63     12443
weighted avg       0.83      0.84      0.83     12443



RFE Classification Report: 
              precision    recall  f1-score   support

           0       0.91      0.88      0.89     10832
           1       0.32      0.39      0.35      1611

   micro avg       0.81      0.81      0.81     12443
   macro avg       0.61      0.63      0.62     12443
weighted avg       0.83      0.81      0.82     12443



modelSelect Classification Report: 
              precision    recall  f1-score   support

           0       0.90      0.89      0.89     10832
           1       0.31      0.34      0.32      1611

   micro avg       0.82      0.82      0.82     12443
   macro avg       0.60      0.61      0.61     12443
weighted avg       0.82      0.82      0.82     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 [64]:

```
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 = 0.54856218
Validation score: 0.731751
Iteration 2, loss = 0.47211536
Validation score: 0.771316
Iteration 3, loss = 0.40356883
Validation score: 0.799011
Iteration 4, loss = 0.34348921
Validation score: 0.834817
Iteration 5, loss = 0.29075779
Validation score: 0.851236
Iteration 6, loss = 0.24983120
Validation score: 0.860534
Iteration 7, loss = 0.22284442
Validation score: 0.876558
Iteration 8, loss = 0.20155821
Validation score: 0.888625
Iteration 9, loss = 0.18602661
Validation score: 0.882690
Iteration 10, loss = 0.16979396
Validation score: 0.898516
Iteration 11, loss = 0.15977150
Validation score: 0.896736
Iteration 12, loss = 0.15176313
Validation score: 0.895351
Iteration 13, loss = 0.14464423
Validation score: 0.905836
Iteration 14, loss = 0.13999550
Validation score: 0.907023
Iteration 15, loss = 0.12720528
Validation score: 0.906034
Iteration 16, loss = 0.12930383
Validation score: 0.907023
Iteration 17, loss = 0.12255444
Validation score: 0.910386
Iteration 18, loss = 0.12068214
Validation score: 0.911771
Iteration 19, loss = 0.11399424
Validation score: 0.908803
Iteration 20, loss = 0.11282158
Validation score: 0.915331
Iteration 21, loss = 0.10661677
Validation score: 0.922057
Iteration 22, loss = 0.10446701
Validation score: 0.916518
Iteration 23, loss = 0.10589664
Validation score: 0.909792
Iteration 24, loss = 0.10556269
Validation score: 0.918497
Iteration 25, loss = 0.09938828
Validation score: 0.918299
Iteration 26, loss = 0.09541842
Validation score: 0.912760
Iteration 27, loss = 0.10113910
Validation score: 0.919683
Iteration 28, loss = 0.09432959
Validation score: 0.909792
Iteration 29, loss = 0.09296471
Validation score: 0.923046
Iteration 30, loss = 0.09169923
Validation score: 0.924036
Iteration 31, loss = 0.08993748
```

```
Validation score: 0.919288
Iteration 32, loss = 0.08603412
Validation score: 0.921662
Iteration 33, loss = 0.08854639
Validation score: 0.922453
Iteration 34, loss = 0.08351747
Validation score: 0.922849
Iteration 35, loss = 0.08777318
Validation score: 0.917112
Iteration 36, loss = 0.08058952
Validation score: 0.928190
Iteration 37, loss = 0.08469264
Validation score: 0.923640
Iteration 38, loss = 0.08402573
Validation score: 0.931157
Iteration 39, loss = 0.07430225
Validation score: 0.926607
Iteration 40, loss = 0.07893320
Validation score: 0.917903
Iteration 41, loss = 0.07689212
Validation score: 0.925223
Iteration 42, loss = 0.07355570
Validation score: 0.922057
Iteration 43, loss = 0.08132868
Validation score: 0.927399
Iteration 44, loss = 0.07889856
Validation score: 0.923838
Iteration 45, loss = 0.07490265
Validation score: 0.927596
Iteration 46, loss = 0.07099558
Validation score: 0.928388
Iteration 47, loss = 0.06990805
Validation score: 0.931157
Iteration 48, loss = 0.07486228
Validation score: 0.929179
Iteration 49, loss = 0.07158638
Validation score: 0.931355
Iteration 50, loss = 0.06874335
Validation score: 0.923046
Iteration 51, loss = 0.07661840
Validation score: 0.924431
Iteration 52, loss = 0.06855482
Validation score: 0.918101
Iteration 53, loss = 0.07291045
Validation score: 0.927596
Iteration 54, loss = 0.06441686
Validation score: 0.918892
Iteration 55, loss = 0.06992323
Validation score: 0.934520
Iteration 56, loss = 0.07443742
Validation score: 0.929970
Iteration 57, loss = 0.06685328
Validation score: 0.930366
Iteration 58, loss = 0.06478549
Validation score: 0.928586
Iteration 59, loss = 0.06425201
Validation score: 0.920079
Iteration 60, loss = 0.06606451
Validation score: 0.926805
Iteration 61, loss = 0.06558700
Validation score: 0.917507
```

```
Iteration 62, loss = 0.06666644
Validation score: 0.928586
Iteration 63, loss = 0.06158633
Validation score: 0.933927
Iteration 64, loss = 0.06551972
Validation score: 0.928190
Iteration 65, loss = 0.06410788
Validation score: 0.933927
Iteration 66, loss = 0.06246794
Validation score: 0.931355
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 [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       0.88      1.00      0.93     10832
           1       0.80      0.05      0.09      1611

   micro avg       0.88      0.88      0.88     12443
   macro avg       0.84      0.52      0.51     12443
weighted avg       0.87      0.88      0.82     12443


Report for Logistic Regression: 
               precision    recall  f1-score   support

           0       0.93      0.78      0.85     10832
           1       0.29      0.60      0.39      1611

   micro avg       0.75      0.75      0.75     12443
   macro avg       0.61      0.69      0.62     12443
weighted avg       0.85      0.75      0.79     12443


Report for NN: 
               precision    recall  f1-score   support

           0       0.90      0.91      0.91     10832
           1       0.36      0.35      0.36      1611

   micro avg       0.84      0.84      0.84     12443
   macro avg       0.63      0.63      0.63     12443
weighted avg       0.83      0.84      0.83     12443


Report for Ensemble: 
               precision    recall  f1-score   support

           0       0.91      0.93      0.92     10832
           1       0.43      0.37      0.40      1611

   micro avg       0.85      0.85      0.85     12443
   macro avg       0.67      0.65      0.66     12443
weighted avg       0.85      0.85      0.85     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.

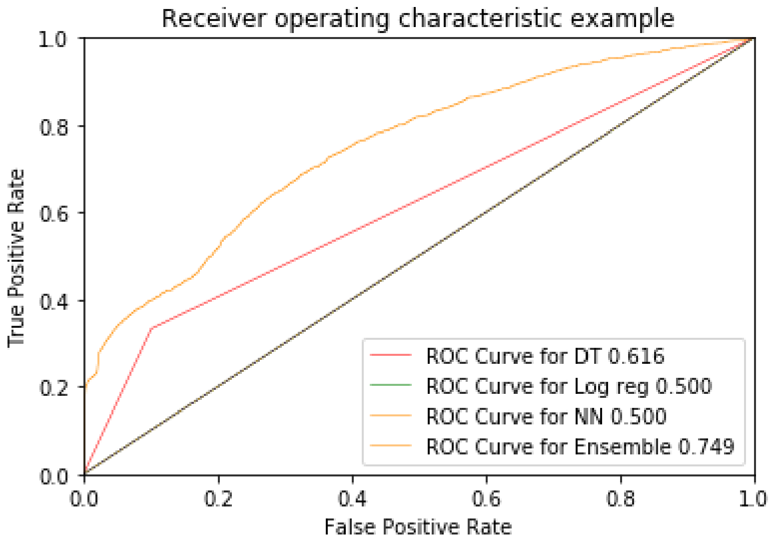
a. Discuss the findings led by (a) ROC Chart (and Index); (b) Score Ranking (or Accuracy Score); (c) Fit Statistics; (or Classification report) and (4) Output.

(a) ROC Chart (and Index)

In [66]:

```
#### 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: 0.6157864609264042
ROC index on test for logistic regression: 0.4997357932951725
ROC index on test for NN: 0.49995384047267355
ROC index on voting classifier: 0.7489632873881283
```



(b) Score Ranking (or Accuracy Score)

In [67]:

```
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: 0.8751105038977739
Accuracy score on test for Logistic Regression: 0.7545607972353934
Accuracy score on test for NN: 0.8350880012858636
Accuracy score on test for Ensemble: 0.8535722896407619
```

(c) Classification report

In [68]:

```
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       0.88      1.00      0.93     10832
           1       0.80      0.05      0.09      1611

   micro avg       0.88      0.88      0.88     12443
   macro avg       0.84      0.52      0.51     12443
weighted avg       0.87      0.88      0.82     12443


Report for Logistic Regression:
               precision    recall  f1-score   support

           0       0.93      0.78      0.85     10832
           1       0.29      0.60      0.39      1611

   micro avg       0.75      0.75      0.75     12443
   macro avg       0.61      0.69      0.62     12443
weighted avg       0.85      0.75      0.79     12443


Report for NN:
               precision    recall  f1-score   support

           0       0.90      0.91      0.91     10832
           1       0.36      0.35      0.36      1611

   micro avg       0.84      0.84      0.84     12443
   macro avg       0.63      0.63      0.63     12443
weighted avg       0.83      0.84      0.83     12443


Report for Ensemble:
               precision    recall  f1-score   support

           0       0.91      0.93      0.92     10832
           1       0.43      0.37      0.40      1611

   micro avg       0.85      0.85      0.85     12443
   macro avg       0.67      0.65      0.66     12443
weighted avg       0.85      0.85      0.85     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 [ ]:

```

```