

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")
```

```
/home/chihcheng/python3env/lib/python3.6/site-packages/IPython/core/
interactiveshell.py:3044: DtypeWarning: Columns (27) have mixed type
s. Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

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 STRATEGY
NEW_STRATEGY = True
ResamplingMethod = 'ros' #['ros', 'rus']
if NEW_STRATEGY:
    print("Using New Preprocessing Strategy")
    using_cat = False
    categorial_cols = ['Auction', 'VehYear', 'Make', 'Color', 'Transmission', 'WheelTypeID', 'WheelType', 'Nationality', 'Size', 'TopThreeAmericanName', 'PRIMEUNIT', 'AUCGUART', 'VNST', 'IsOnlineSale', 'ForSale' ] # Replaced by the most common
    interval_cols = ['VehOdo', 'MMRAcquisitionAuctionAveragePrice', 'MMRAcquisitionAuctionCleanPrice', 'MMRAcquisitionRetailAveragePrice', 'MMRAcquisitionRetailCleanPrice', 'VehBCost', 'WarrantyCost' ]
    drop_cols = ['PurchaseID', 'PurchaseDate', 'PurchaseTimestamp']
    questionMark_data = ['MMRCurrentAuctionAveragePrice', 'MMRCurrentAuctionCleanPrice', 'MMRCurrentRetailAveragePrice', 'MMRCurrentRetailCleanPrice', 'MMRCurrentRetailRatio']
    replaced_vals = ['?', '#VALUE!']
    if using_cat:
        categorial_cols += questionMark_data
        print("See [MMRCurrentAuctionAveragePrice" +
              "MMRCurrentAuctionCleanPrice, MMRCurrentRetailAveragePrice," +
              " MMRCurrentRetailCleanPrice, MMRCurrentRetailRatio] as Categorical
Data")
    else:
        interval_cols += questionMark_data
        print("See [MMRCurrentAuctionAveragePrice" +
              "MMRCurrentAuctionCleanPrice, MMRCurrentRetailAveragePrice," +
              " MMRCurrentRetailCleanPrice, MMRCurrentRetailRatio] as Interval
Data")
    else:
        print("Using Old Preprocessing Strategy")
        drop_cols = ['PurchaseID', 'PurchaseDate']
        categorial_cols = ['Auction', 'VehYear', 'Make', 'Color', 'Transmission', 'WheelTypeID', 'WheelType', 'Nationality', 'Size', 'TopThreeAmericanName', 'PRIMEUNIT', 'AUCGUART', 'VNST', 'IsOnlineSale', 'ForSale' ] # Replaced by the most common
        interval_cols = ['PurchaseTimestamp', 'VehOdo', 'MMRAcquisitionAuctionAveragePrice', 'MMRAcquisitionAuctionCleanPrice', 'MMRAcquisitionRetailAveragePrice', 'MMRAcquisitionRetailCleanPrice', 'MMRCurrentAuctionAveragePrice', 'MMRCurrentAuctionCleanPrice', 'MMRCurrentRetailAveragePrice', 'MMRCurrentRetailCleanPrice', 'MMRCurrentRetailRatio', 'VehBCost', 'WarrantyCost' ] # Replaced by the mean
        replaced_vals = ['?', '#VALUE!']

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

Using New Preprocessing Strategy

See [MMRCurrentAuctionAveragePriceMMRCurrentAuctionCleanPrice, MMRCurrentRetailAveragePrice, MMRCurrentRetailCleanPrice, MMRCurrentRetailRatio] as Interval 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("----- DESCRIBE -----")
        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()

```

```
/home/chihcheng/python3env/lib/python3.6/site-packages/pandas/core/ops.py:1649: FutureWarning: elementwise comparison failed; returning scalar instead, but in the future will perform elementwise comparison
    result = method(y)
```

```
===== PurchaseID =====
----- FIRST FIVE -----
0      0
1      1
2      2
3      3
4      4
```

Name: PurchaseID, dtype: int64

```
----- DESCRIBE -----
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

```
----- DESCRIBE -----
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

```
----- DESCRIBE -----
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', '25/02/2009 10:00', '24/11/2
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
----- DESCRIBE -----
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
----- DESCRIBE -----
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

----- DESCRIBE -----

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

MINI 569

MAZDA 532

MERCURY 527

BUICK 413

GMC 351

HONDA 263

OLDSMOBILE 146

ISUZU 82

SCION 77

VOLKSWAGEN 73

LINCOLN 54

INFINITI 27

ACURA 19

MINI 19

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

----- DESCRIBE -----


```
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

----- DESCRIBE -----

```
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

----- DESCRIBE -----

```
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

----- DESCRIBE -----

```
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

===== Veh0do =====

----- FIRST FIVE -----

```
0      51099.0
1      48542.0
2      46318.0
3      50413.0
4      50199.0
```

Name: Veh0do, dtype: float64

----- DESCRIBE -----

```
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: Veh0do, 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

----- DESCRIBE -----

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

----- DESCRIBE -----

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
----- DESCRIBE -----
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
----- DESCRIBE -----
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
----- DESCRIBE -----
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

----- DESCRIBE -----

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

----- DESCRIBE -----

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

----- DESCRIBE -----

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

----- DESCRIBE -----

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

----- DESCRIBE -----

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

----- DESCRIBE -----

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

----- DESCRIBE -----

count 41116

unique 25870

top #VALUE!

freq 178

Name: MMRCurrentRetailRatio, dtype: object

----- COUNTS -----

Five Most Common: ['#VALUE!', '0.858250869', '0.856073017', '0.866673265', '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

----- DESCRIBE -----

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

----- DESCRIBE -----

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

----- DESCRIBE -----

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

WA 136

OR 136

NH 97

NE 26

OH 25

ID 14

NY 6

Name: VNST, dtype: int64

Num of NULL: 44

Number of ? : 0

Number of #VALUE! : 0

===== VehBCost =====

----- FIRST FIVE -----


```
0    7800
1    7800
2    7800
3    6000
4    7800
```

Name: VehBCost, dtype: object

----- DESCRIBE -----

```
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

----- DESCRIBE -----

```
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

----- DESCRIBE -----

```
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
----- DESCRIBE -----
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
----- DESCRIBE -----
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_STRATEGY:

    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 been
n replaced by null")
            # Replacing the null in this process #Inplacing for saving the memory
            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.MOST
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
            print(stra)
            stra(colName)

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

    return df

preprocessStrategy = defaultdict(dict)

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

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

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

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

```

```

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

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

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

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

preprocessStrategy['Veh0do'] = {
    "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 column
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 column
mn
        "strategies":
            [
                fillingTheNullValue,
            ],
        "replaced_vals": ['?'], # GOT 184 '?'
        "filling_method": filling_method.MEAN,
    }

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

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

```



```

newData_prep(df)

else:

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

        # Check the replaced values are not in the dataset

        for colName in df.columns:

            if colName in categorial_cols:

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

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

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

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

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

            if colName in interval_cols:

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

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

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

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

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

```

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

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

return df

df = data_prep(df)
```

```
Preprocess the col: Auction
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: Auction : 0, ?have been replaced by null
<function loweringCol at 0x7fdb75fb1ae8>
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: VehYear
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: Make
<function loweringCol at 0x7fdb75fb1ae8>
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: Color
<function loweringCol at 0x7fdb75fb1ae8>
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: Color : 6, ?have been replaced by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: Transmission
<function loweringCol at 0x7fdb75fb1ae8>
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: Transmission : 6, ?have been replaced by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: WheelTypeID
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: WheelType
<function loweringCol at 0x7fdb75fb1ae8>
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: Veh0do
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: Nationality
<function replaceFunc at 0x7fdb760006a8>
<function loweringCol at 0x7fdb75fb1ae8>
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: Nationality : 3, ?have been replaced by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: Size
<function loweringCol at 0x7fdb75fb1ae8>
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: Size : 3, ?have been replaced by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: TopThreeAmericanName
<function loweringCol at 0x7fdb75fb1ae8>
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: TopThreeAmericanName : 3, ?have been replaced by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: MMRAcquisitionAuctionAveragePrice
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: MMRAcquisitionAuctionAveragePrice : 7, ?have been replaced by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: MMRAcquisitionAuctionCleanPrice
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: MMRAcquisitionAuctionCleanPrice : 7, ?have been replaced by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: MMRAcquisitionRetailAveragePrice
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: MMRAcquisitionRetailAveragePrice : 7, ?have been replaced by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: MMRAcquisitionRetailCleanPrice
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: MMRAcquisitionRetailCleanPrice : 7, ?have been replaced
```

```
d by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: MMRCurrentAuctionAveragePrice
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: MMRCurrentAuctionAveragePrice : 184, ?have been repla
ced by null
In the Column: MMRCurrentAuctionAveragePrice : 0, #VALUE!have been r
eplaced by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: MMRCurrentAuctionCleanPrice
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: MMRCurrentAuctionCleanPrice : 184, ?have been replace
d by null
In the Column: MMRCurrentAuctionCleanPrice : 0, #VALUE!have been rep
laced by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: MMRCurrentRetailAveragePrice
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: MMRCurrentRetailAveragePrice : 184, ?have been replac
ed by null
In the Column: MMRCurrentRetailAveragePrice : 0, #VALUE!have been re
placed by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: MMRCurrentRetailCleanPrice
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: MMRCurrentRetailCleanPrice : 184, ?have been replaced
by null
In the Column: MMRCurrentRetailCleanPrice : 0, #VALUE!have been repl
aced by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: MMRCurrentRetailRatio
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: MMRCurrentRetailRatio : 0, ?have been replaced by nul
l
In the Column: MMRCurrentRetailRatio : 178, #VALUE!have been replace
d by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: PRIMEUNIT
<function loweringCol at 0x7fdb75fb1ae8>
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: AUCGUART
<function loweringCol at 0x7fdb75fb1ae8>
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: VNST
<function loweringCol at 0x7fdb75fb1ae8>
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: VehBCost
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: VehBCost : 29, ?have been replaced by null
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: IsOnlineSale
<function replacingValueCol at 0x7fdbcd8d9840>
In the Column: IsOnlineSale : 2, ?have been replaced by null
In the Column: IsOnlineSale : 1, 2.0have been replaced by null
In the Column: IsOnlineSale : 1, 4.0have been replaced by null
<function changeToType at 0x7fdb75fb1d08>
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: WarrantyCost
<function fillingTheNullValue at 0x7fdb75fb1e18>
Preprocess the col: ForSale
<function loweringCol at 0x7fdb75fb1ae8>
```

```
<function replacingValueCol at 0x7fdbcd8d9840>  
In the Column: ForSale : 3, ?have been replaced by null  
In the Column: ForSale : 0, 0have been replaced by null  
<function fillingTheNullValue at 0x7fdb75fb1e18>  
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]:

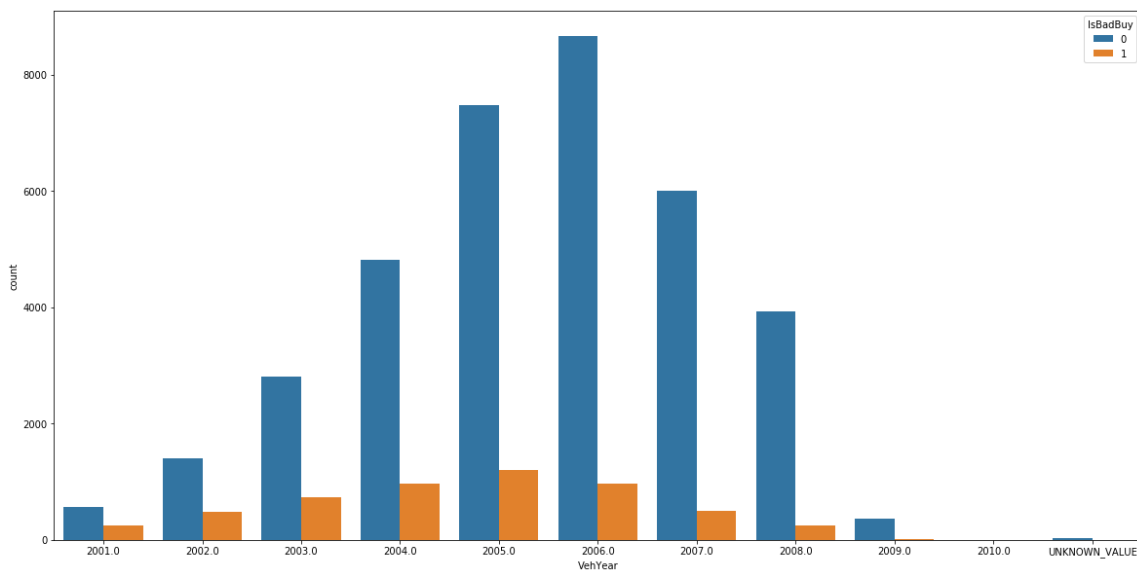
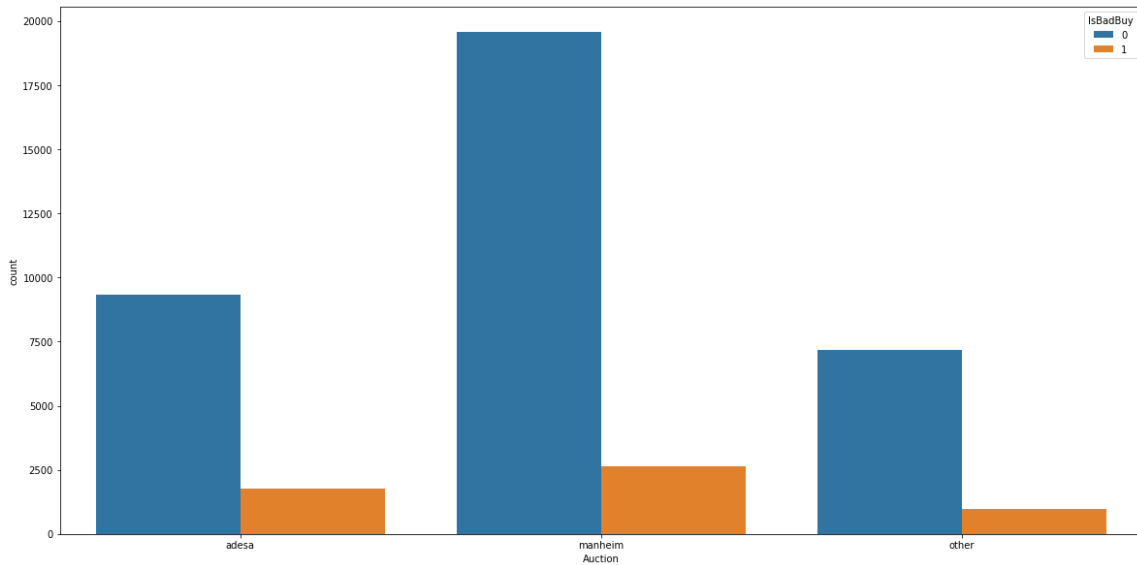
```
plotAllCols(df)
```

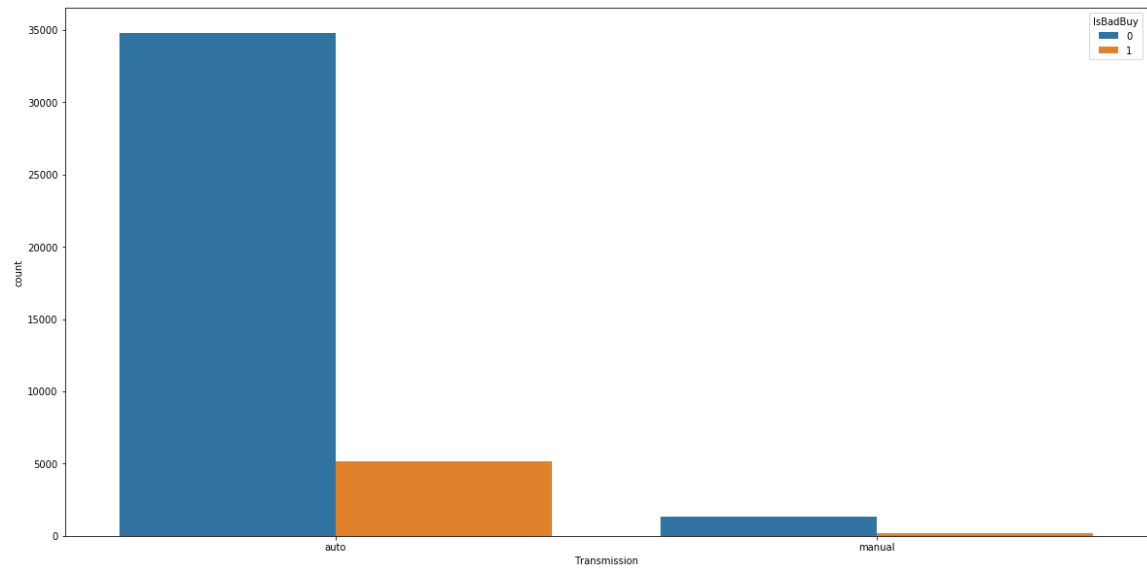
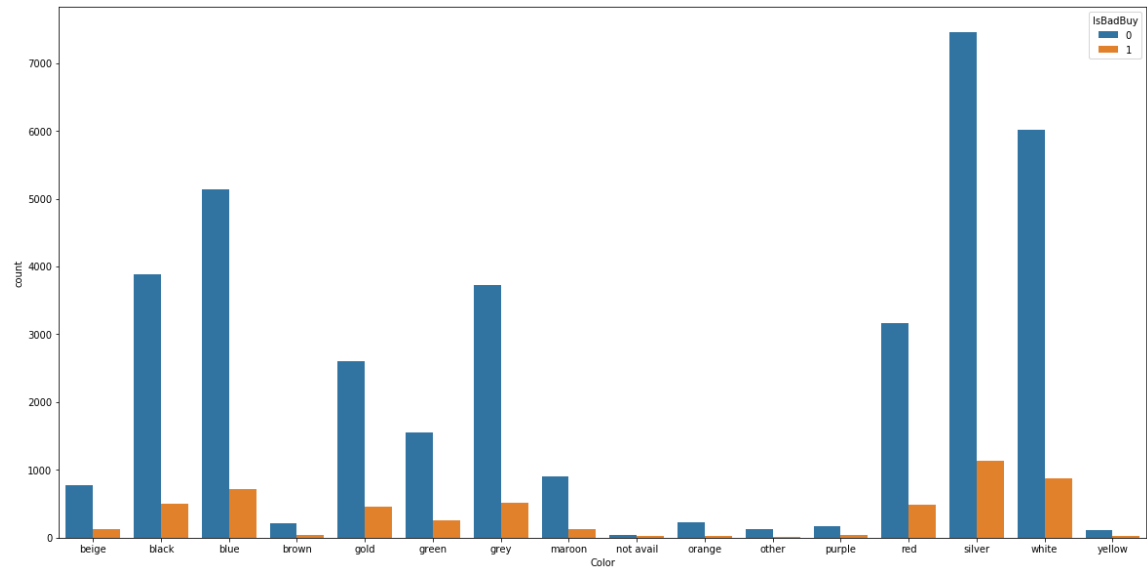
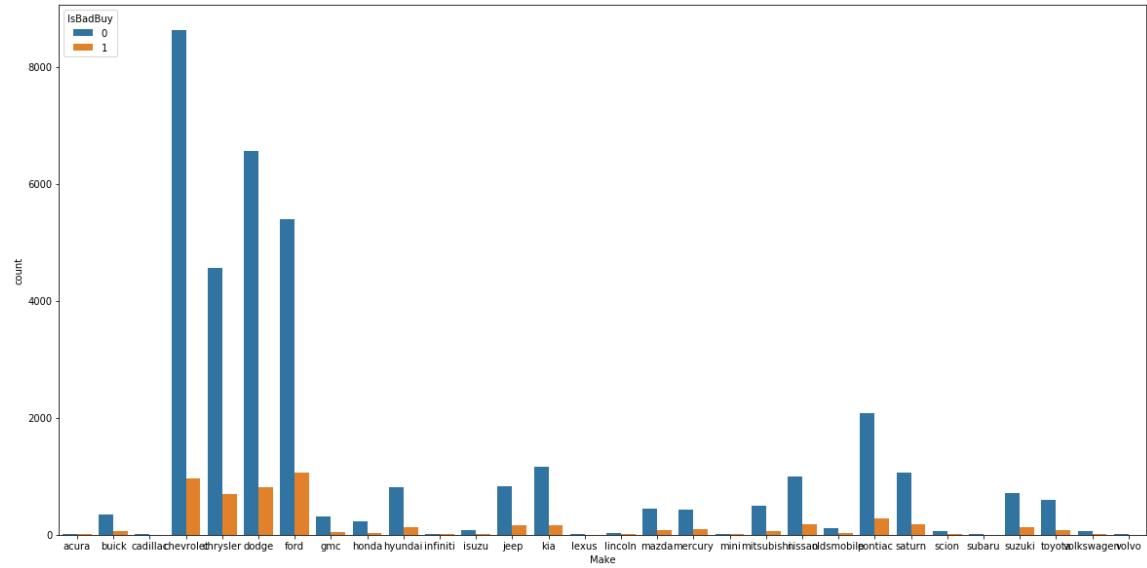
```
/home/chihcheng/python3env/lib/python3.6/site-packages/matplotlib/py
plot.py:514: RuntimeWarning: More than 20 figures have been opened.
Figures created through the pyplot interface (`matplotlib.pyplot.fig
ure`) are retained until explicitly closed and may consume too much
memory. (To control this warning, see the rcParam `figure.max_open_w
arning`).
```

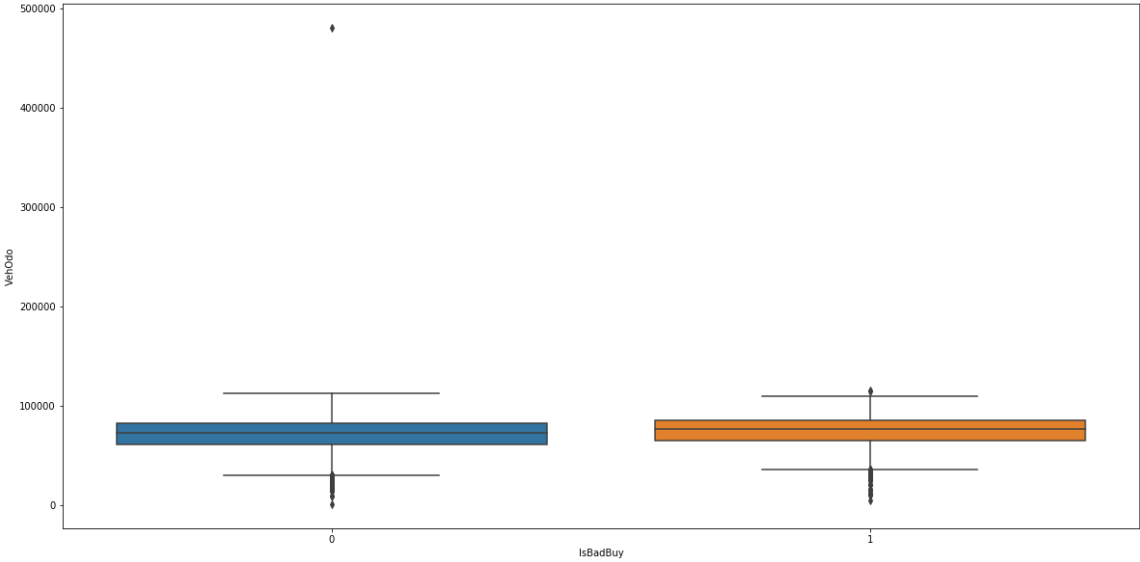
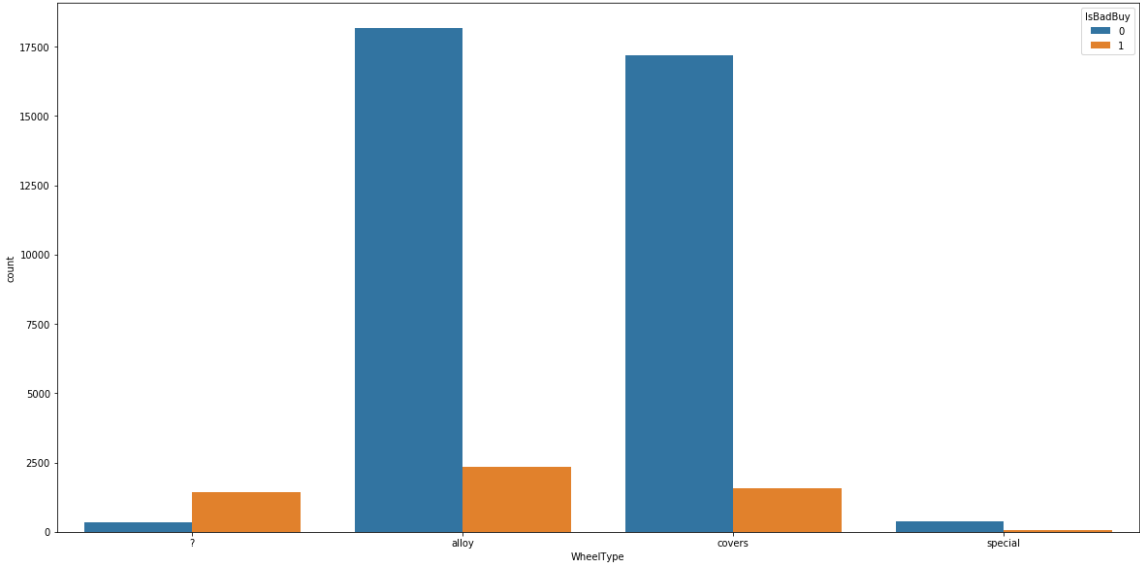
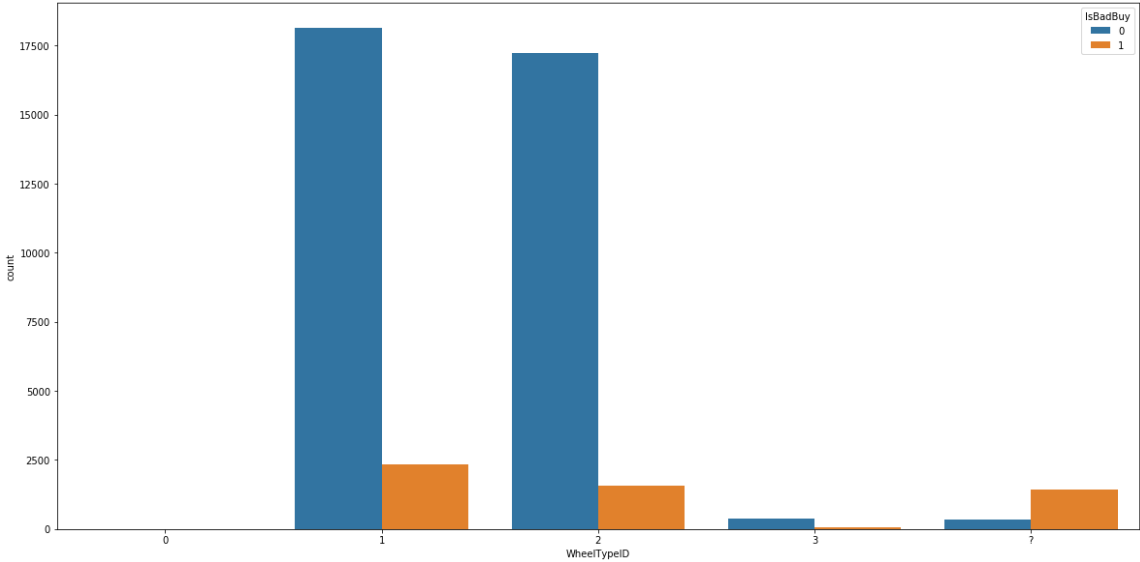
```
max_open_warning, RuntimeWarning)
```

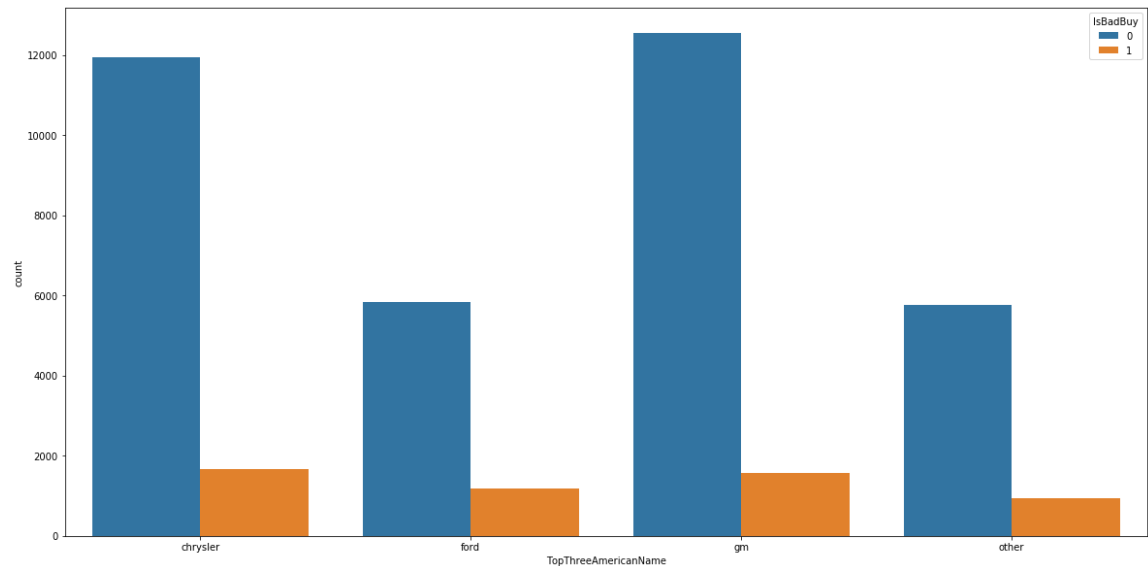
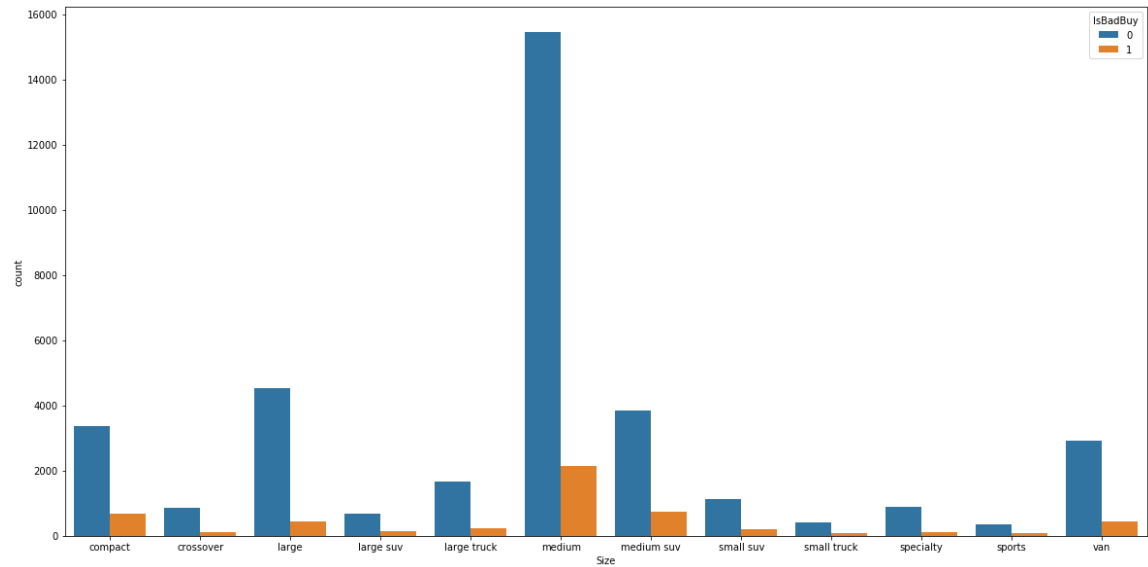
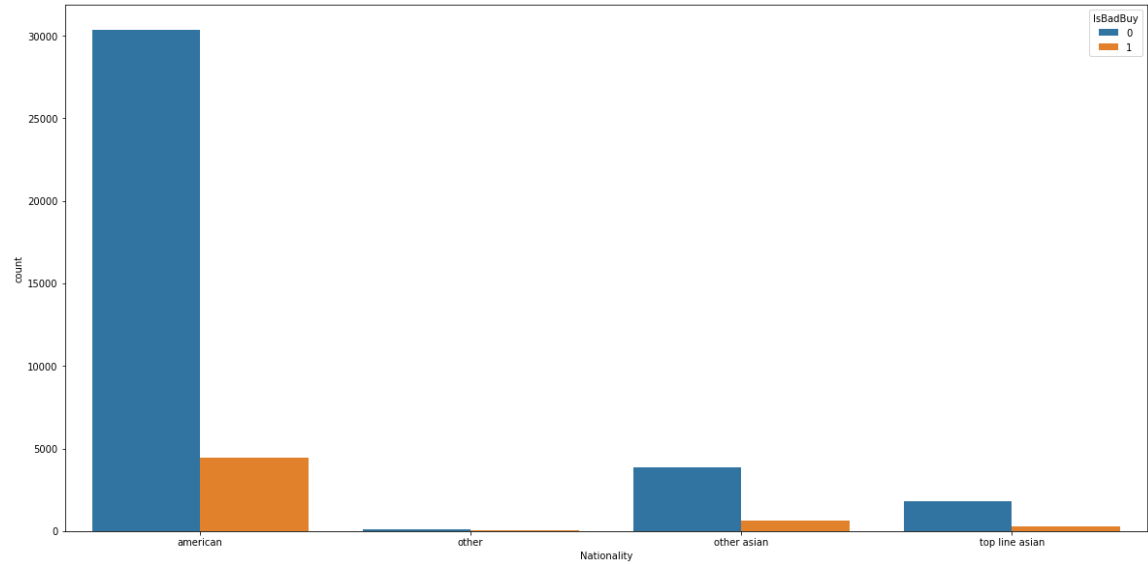
```
/home/chihcheng/python3env/lib/python3.6/site-packages/matplotlib/py
plot.py:514: RuntimeWarning: More than 20 figures have been opened.
Figures created through the pyplot interface (`matplotlib.pyplot.fig
ure`) are retained until explicitly closed and may consume too much
memory. (To control this warning, see the rcParam `figure.max_open_w
arning`).
```

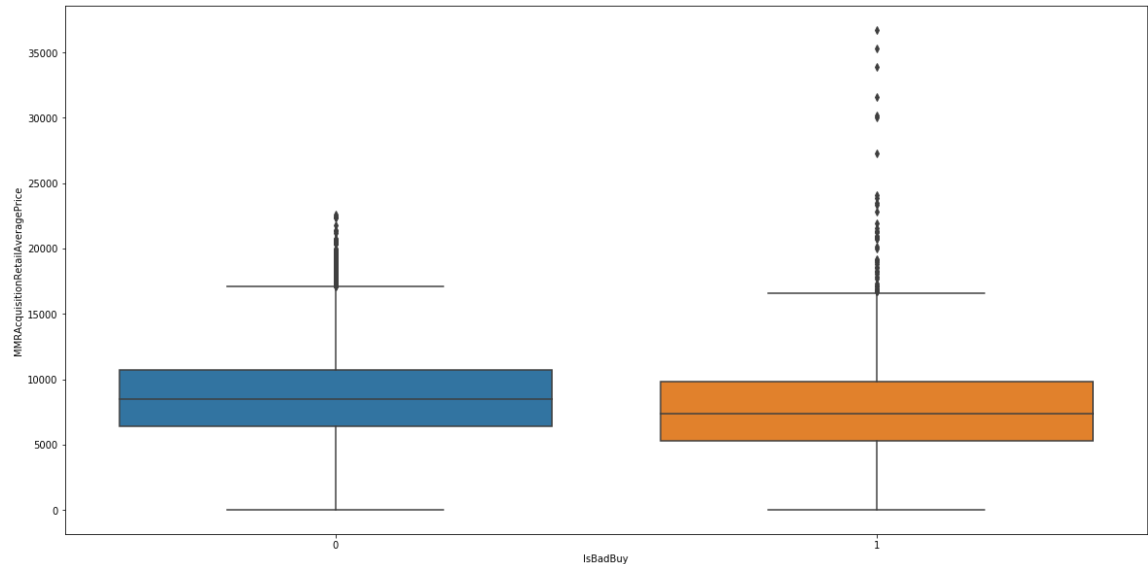
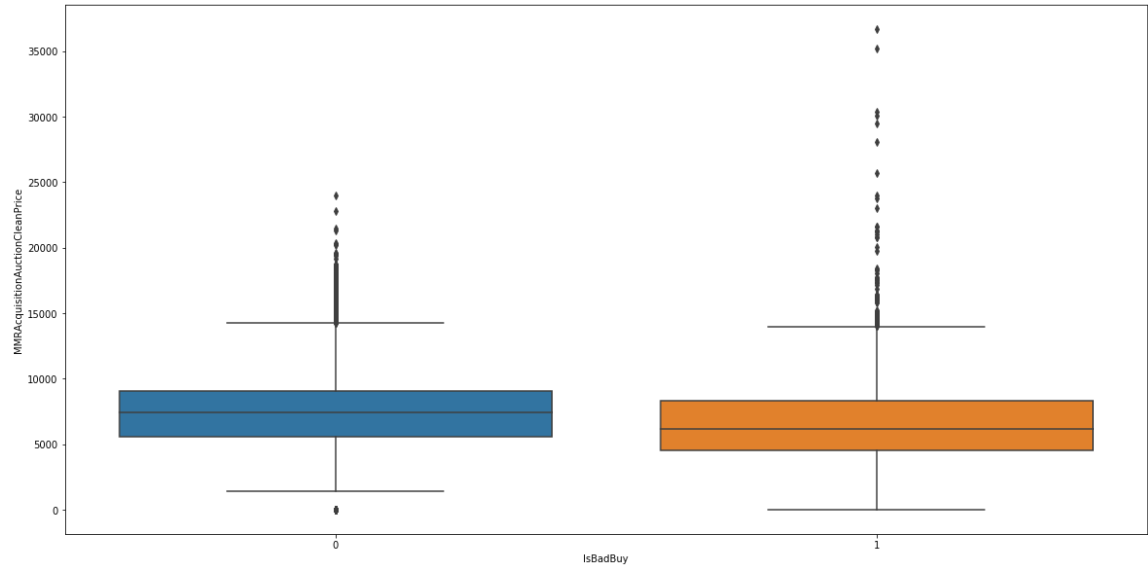
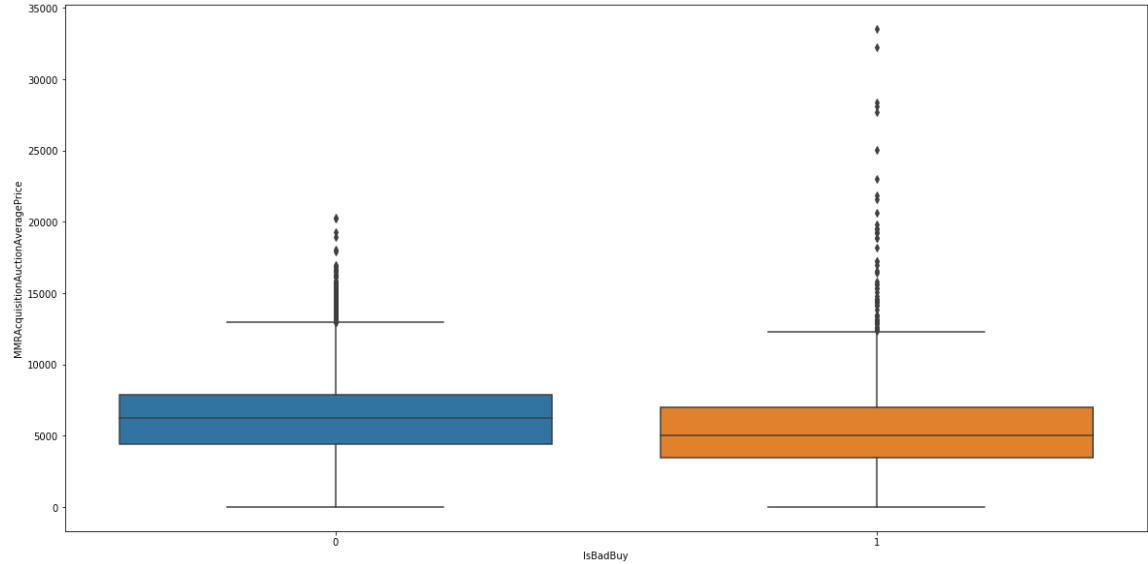
```
max_open_warning, RuntimeWarning)
```

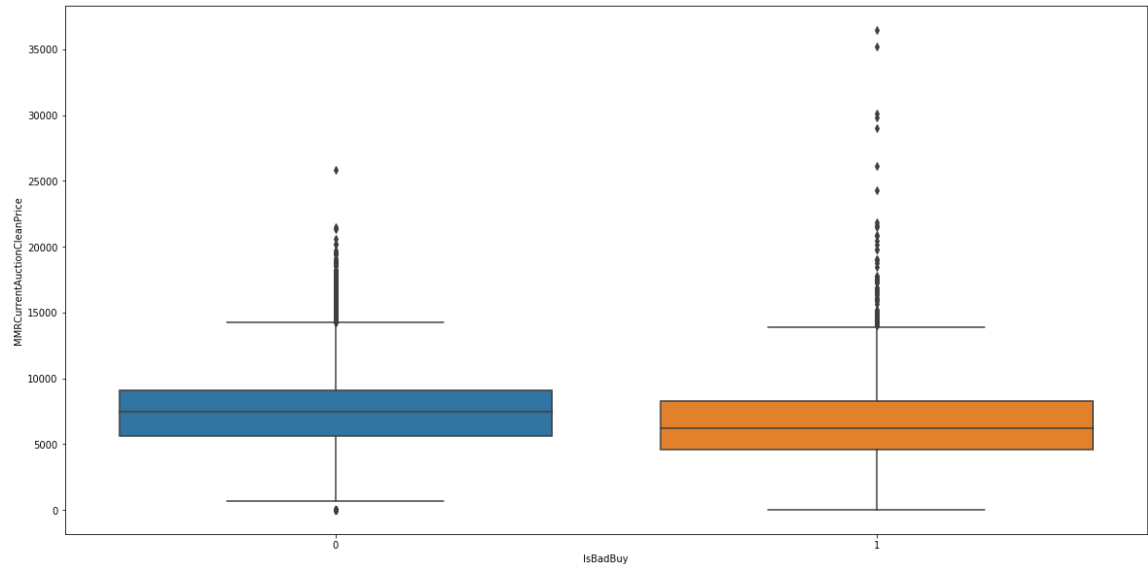
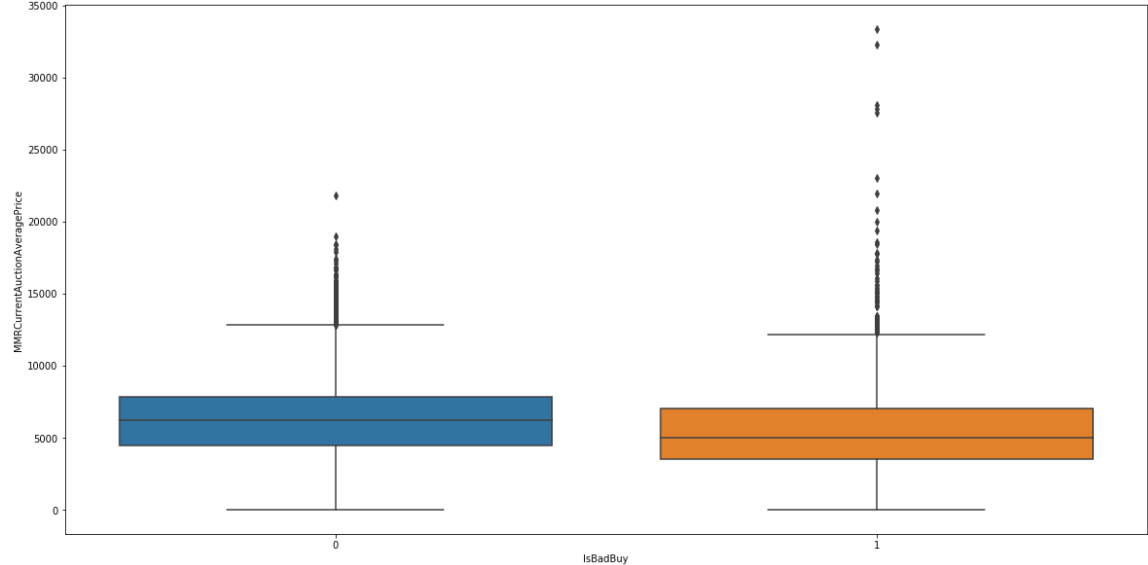
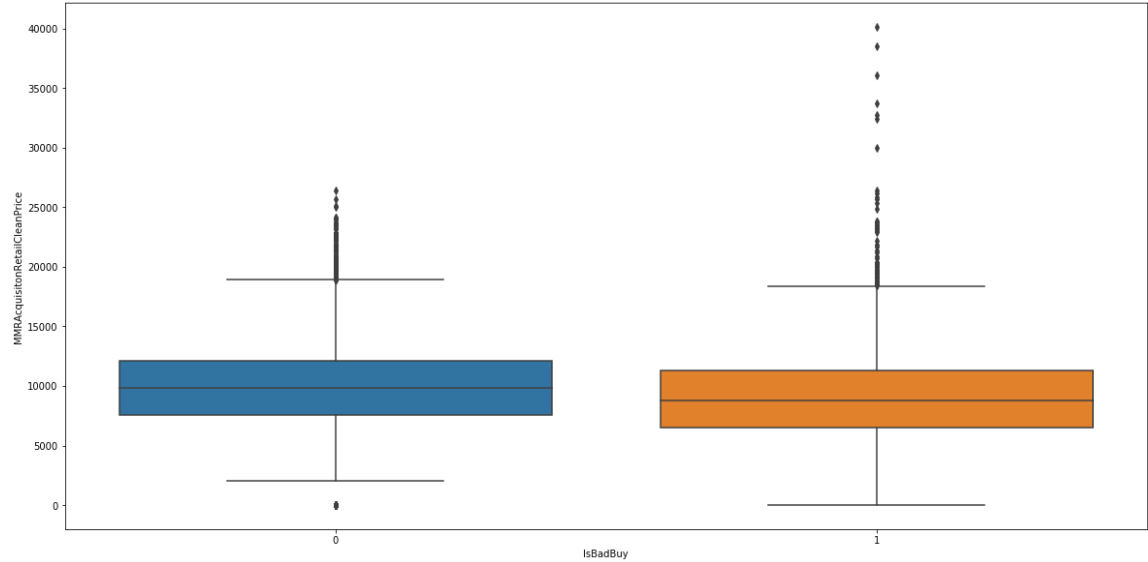


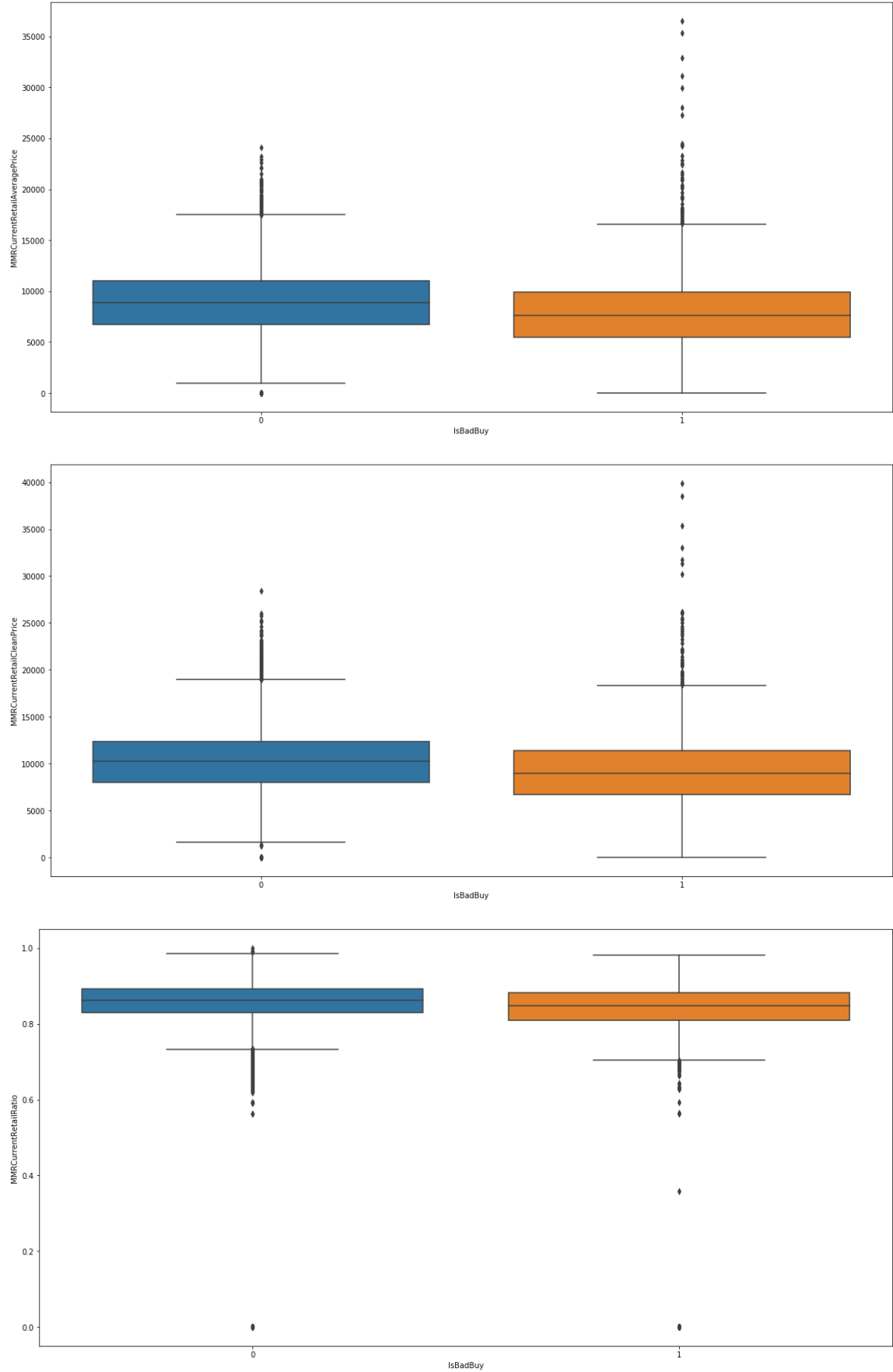


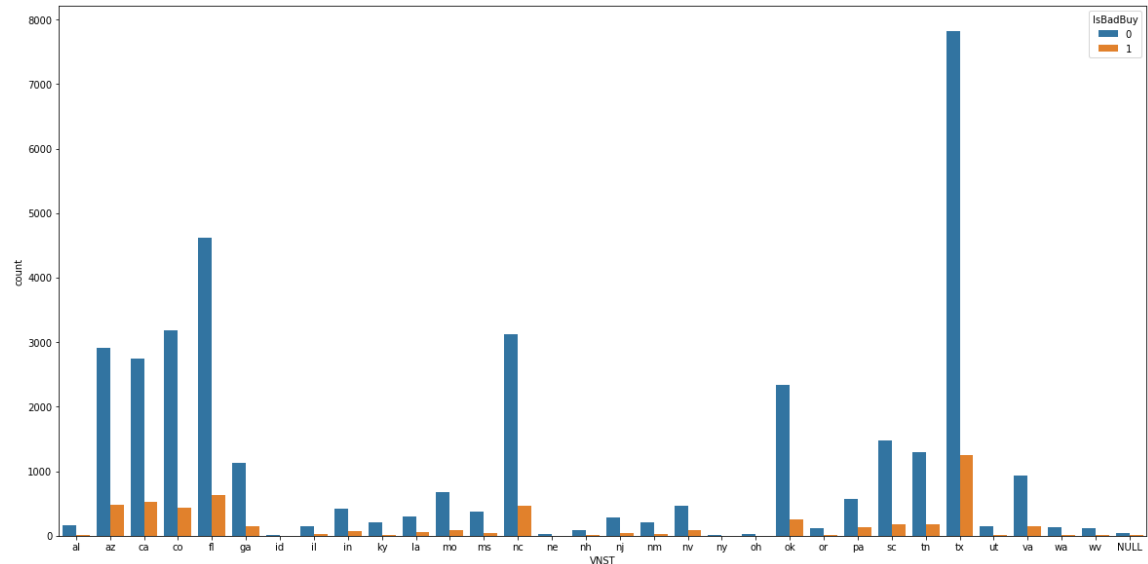
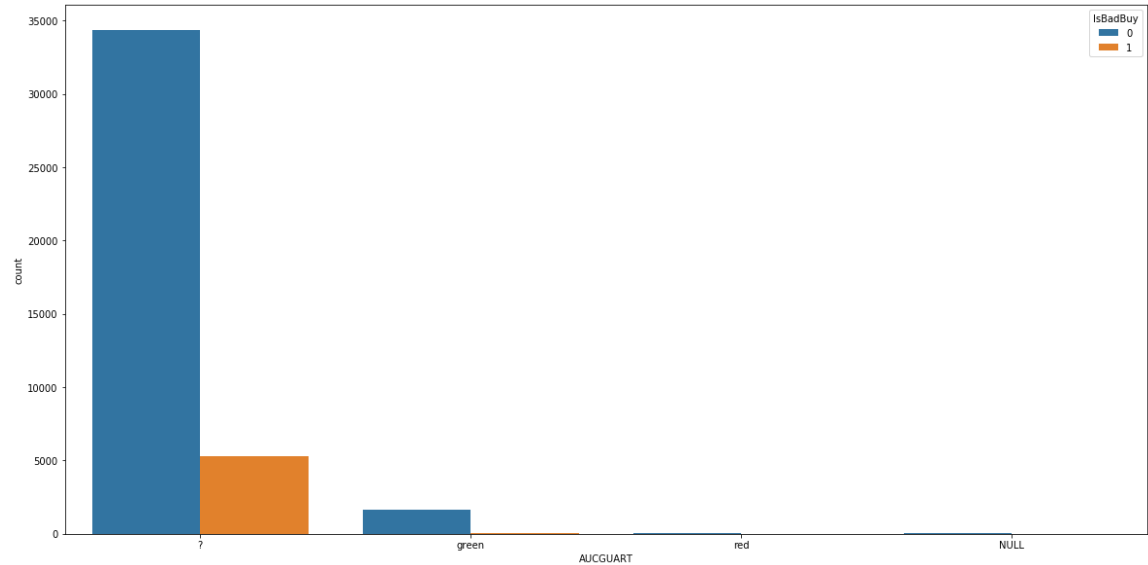
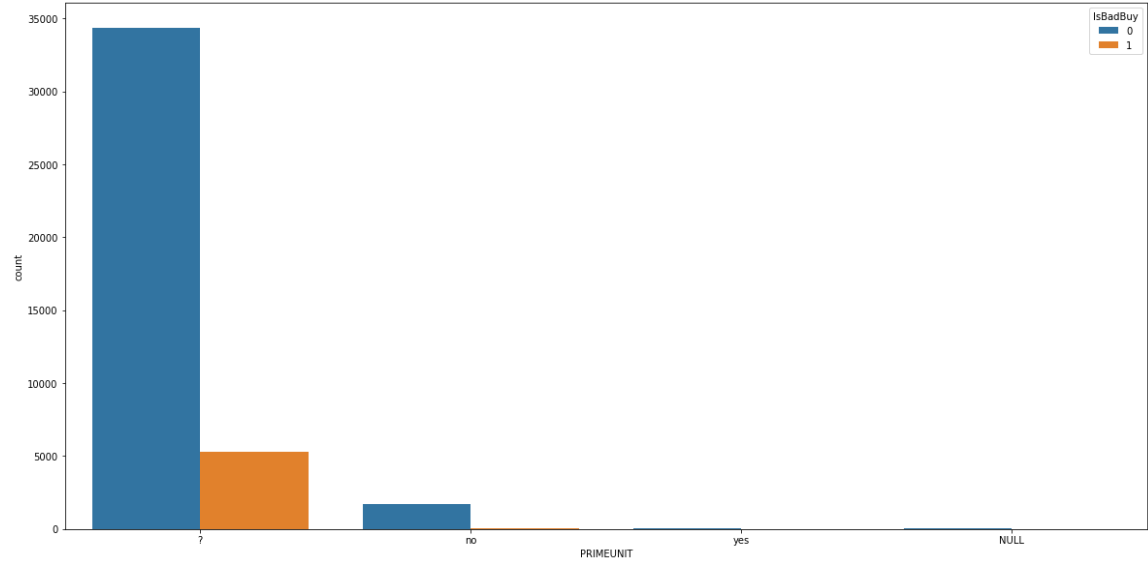


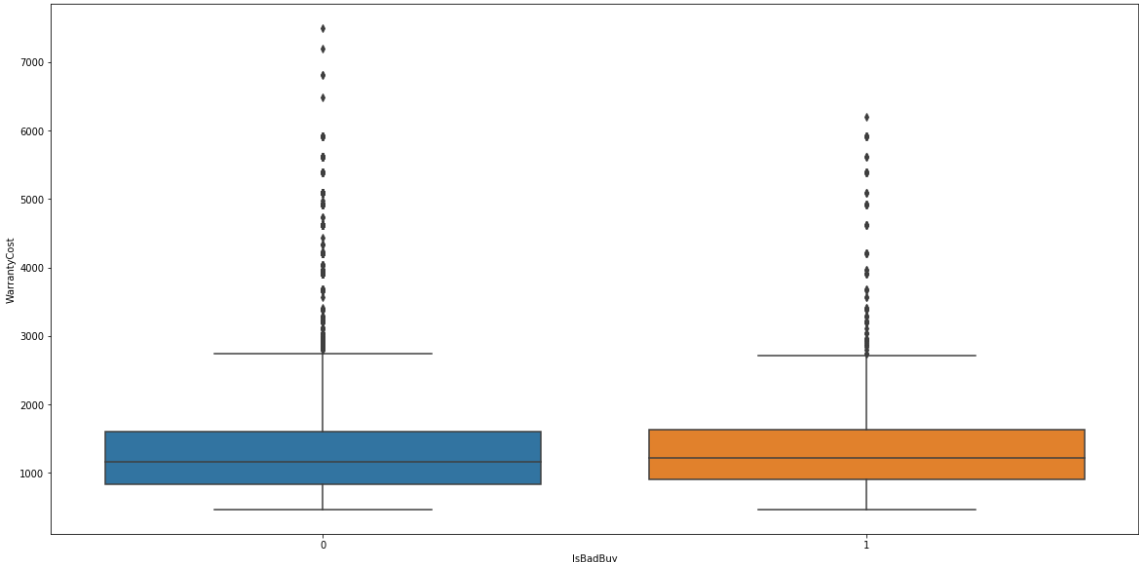
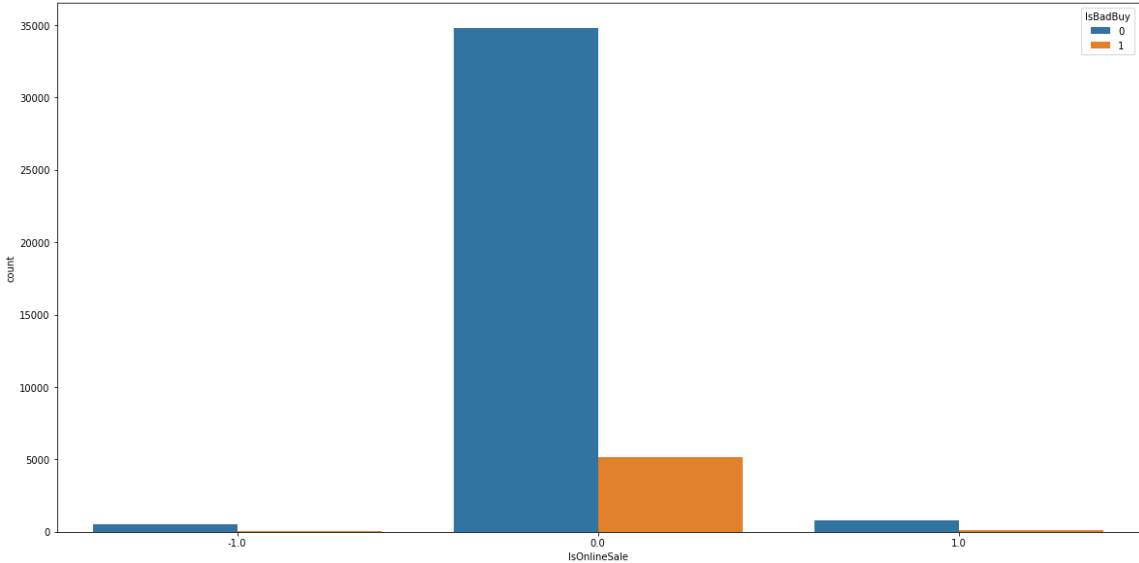
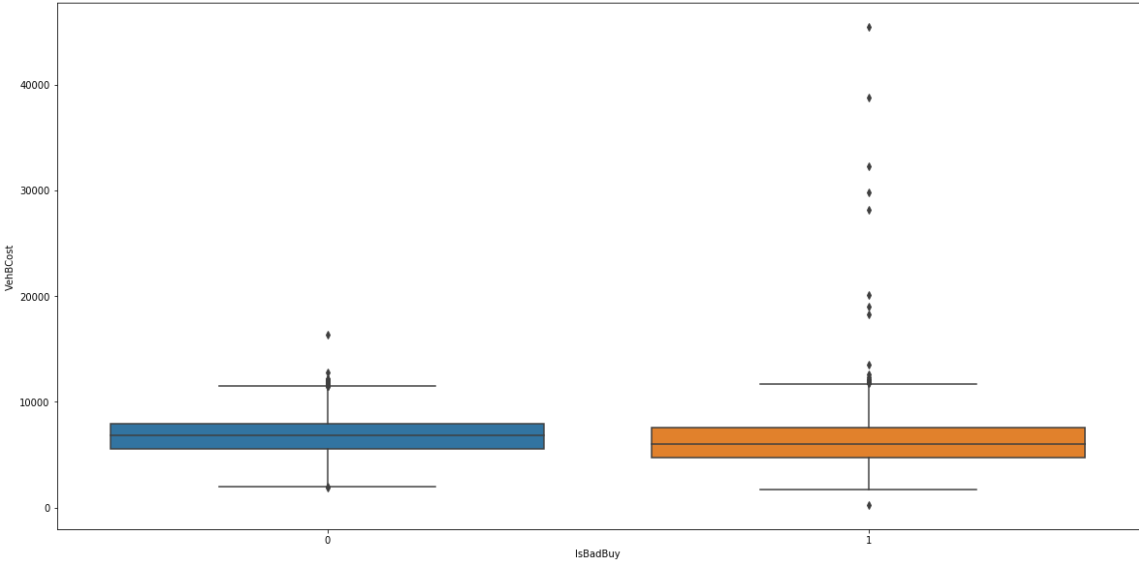


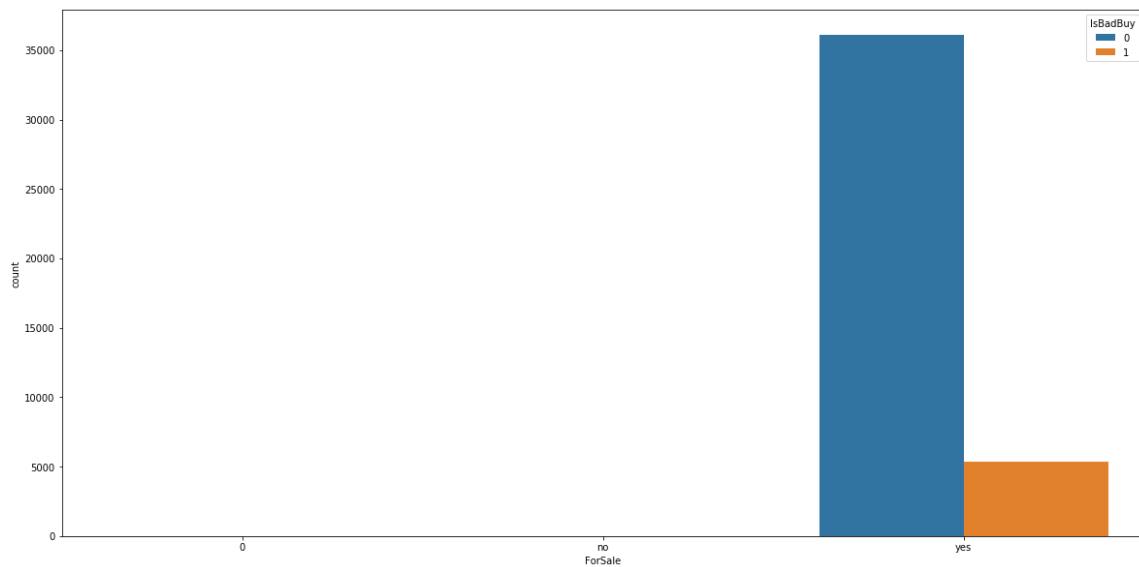












<Figure size 1440x720 with 0 Axes>

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:")

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

Using ROS Resampling

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_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_state=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: 0.8286586835972033

	precision	recall	f1-score	support
0	0.91	0.90	0.90	10832
1	0.35	0.37	0.36	1611
micro avg	0.83	0.83	0.83	12443
macro avg	0.63	0.63	0.63	12443
weighted avg	0.83	0.83	0.83	12443

Out[15]:

```
array([[9714, 1118],
       [1014, 597]])
```

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: 6703

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_Struct.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

MMRCurrentAuctionAveragePrice : 0.07916633374386034

VehOdo : 0.06681157785792576

VehBCost : 0.06493159964208899

MMRCurrentRetailRatio : 0.06347311733157501

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

In []:

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

In []:

2. Python: Build another decision tree tuned with GridSearchCV

In []:

In [19]:

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

cv = GridSearchCV(param_grid=params, estimator=DecisionTreeClassifier(random_state=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_state=101,
             splitter='best'),
             fit_params=None, iid='warn', n_jobs=None,
             param_grid={'criterion': ['gini', 'entropy'], 'max_depth':
[1, 1001, 2001, 3001, 4001, 5001, None], 'splitter': ['best', '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]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
             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: 0.8236759623884915

	precision	recall	f1-score	support
0	0.90	0.90	0.90	10832
1	0.32	0.32	0.32	1611
micro avg	0.82	0.82	0.82	12443
macro avg	0.61	0.61	0.61	12443
weighted avg	0.82	0.82	0.82	12443

```
{'class_weight': 'balanced', 'criterion': 'gini', 'max_depth': 1001,
 'max_features': 'log2', 'min_samples_leaf': 1, 'min_samples_split':
 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: 13743

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).columns, 5)
```

```
WheelType_? : 0.10196726739090486  
VehBCost : 0.07747480575066952  
VehOdo : 0.04975026240861232  
MMRAcquisitionAuctionCleanPrice : 0.04953950838542224  
MMRCurrentAuctionAveragePrice : 0.04898870588447332
```

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 enough?
columns_to_transform = interval_cols

def logTransformation(df):

    df_log = df.copy()

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

    return df_log

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

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

```
/home/chihcheng/python3env/lib/python3.6/site-packages/sklearn/prepr
ocessing/data.py:645: DataConversionWarning: Data with input dtype u
int8, float64 were all converted to float64 by StandardScaler.
```

```
return self.partial_fit(X, y)
/home/chihcheng/python3env/lib/python3.6/site-packages/sklearn/base.
py:467: DataConversionWarning: Data with input dtype uint8, float64
were all converted to float64 by StandardScaler.
```

```
return self.fit(X, y, **fit_params).transform(X)
/home/chihcheng/python3env/lib/python3.6/site-packages/ipykernel_lau
ncher.py:26: DataConversionWarning: Data with input dtype uint8, flo
at64 were all converted to float64 by StandardScaler.
```


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]:

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

```
/home/chihcheng/python3env/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

Out[26]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                    intercept_scaling=1, max_iter=100, multi_class='warn',
                    n_jobs=None, penalty='l2', random_state=101, solver='warn',
                    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=rs), 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=False, fit_intercept=True,
             intercept_scaling=1, max_iter=100, multi_class='warn',
             n_jobs=None, penalty='l2', random_state=101, solver='warn',
             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': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'], 'max_iter': [30, 50, 100], 'warm_start': [True, False], 'class_weight': ['balanced', None]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
             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: 0.8966348637757036
Test accuracy: 0.8982560475769509
GridSearch Train accuracy: 0.8961526538766231
GridSearch Test accuracy: 0.8984167805191674
```

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

In [29]:

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

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

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

In []:

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

In [30]:

```
def printLRTopImportant(model, top = 5):
    coef = model.coef_[0]
    indices = np.argsort(np.absolute(coef))
    indices = np.flip(indices, axis=0)
    indices = indices[:top]
    for i in indices:
        print(feature_names[i], ': ', coef[i])
```

In [31]:

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

```
MMRAcquisitionAuctionAveragePrice : -1.3421704081048444
MMRAcquisitionRetailAveragePrice : 1.1753374313929883
MMRCurrentAuctionAveragePrice : 0.7514553467571049
MMRCurrentRetailCleanPrice : -0.6579437881110104
MMRAcquisitonRetailCleanPrice : 0.6566173157712023
```

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

In [32]:

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

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

Classification Report:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	10832
1	0.84	0.26	0.40	1611
micro avg	0.90	0.90	0.90	12443
macro avg	0.87	0.63	0.67	12443
weighted avg	0.89	0.90	0.87	12443

GridSearch Classification Report:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	10832
1	0.84	0.27	0.40	1611
micro avg	0.90	0.90	0.90	12443
macro avg	0.87	0.63	0.67	12443
weighted avg	0.89	0.90	0.87	12443

n. Report any sign of overfitting.

In [33]:

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

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

In [34]:

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

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

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```
/home/chihcheng/python3env/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
```

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```
/home/chihcheng/python3env/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
```

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```
/home/chihcheng/python3env/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
```

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```
/home/chihcheng/python3env/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
```

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[illegible]

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```
/home/chihcheng/python3env/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
```

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```
/home/chihcheng/python3env/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
```

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```
/home/chihcheng/python3env/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
```

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```
/home/chihcheng/python3env/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
```

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file:///home/chihcheng/Downloads/Assignment1-NewStraUsingCat.html

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 149

Number of RFE-selected features: 80

Number of selectFromModel features: 24

In [36]:

```
print("The RFE-selected features: \n\n", list(compress(feature_names, rfe.support_)))
print("\n\n")
print("The SelectFromModel features: \n\n", list(compress(feature_names, selectmodel.get_support())))
```

The RFE-selected features:

```
['VehOdo', 'MMRAcquisitionAuctionAveragePrice', 'MMRAcquisitionAuctionCleanPrice', 'MMRAcquisitionRetailAveragePrice', 'MMRAcquisitionRetailCleanPrice', 'MMRCurrentAuctionAveragePrice', 'MMRCurrentAuctionCleanPrice', 'MMRCurrentRetailCleanPrice', 'MMRCurrentRetailRatio', 'VehBCost', 'WarrantyCost', 'Auction_adesa', 'Auction_manheim', 'VehYear_2001.0', 'VehYear_2002.0', 'VehYear_2003.0', 'VehYear_2004.0', 'VehYear_2005.0', 'VehYear_2006.0', 'VehYear_2007.0', 'VehYear_2008.0', 'VehYear_2009.0', 'VehYear_UNKNOWN_VALUE', 'Make_acura', 'Make_dodge', 'Make_honda', 'Make_infiniti', 'Make_isuzu', 'Make_lincoln', 'Make_mini', 'Make_nissan', 'Make_pontiac', 'Make_subaru', 'Make_suzuki', 'Make_toyota', 'Make_volvo', 'Color_green', 'Color_other', 'Color_white', 'WheelTypeID_0', 'WheelTypeID_1', 'WheelTypeID_2', 'WheelTypeID_3', 'WheelTypeID_?', 'WheelType_?', 'WheelType_alloy', 'WheelType_covers', 'WheelType_special', 'Nationality_other_asian', 'Nationality_top_line_asian', 'Size_large', 'Size_large_suv', 'Size_medium', 'Size_medium_suv', 'Size_van', 'TopThreeAmericanName_chrysler', 'TopThreeAmericanName_gm', 'PRIMEUNIT_?', 'PRIMEUNIT_no', 'PRIMEUNIT_yes', 'PRIMEUNIT_NULL', 'AUCGUART_?', 'VNST_co', 'VNST_fl', 'VNST_ga', 'VNST_id', 'VNST_ky', 'VNST_la', 'VNST_nc', 'VNST_ne', 'VNST_nh', 'VNST_ny', 'VNST_or', 'VNST_pa', 'VNST_sc', 'VNST_tn', 'VNST_ut', 'VNST_wa', 'IsOnlineSale_1.0', 'ForSale_yes']
```

The SelectFromModel features:

```
['VehOdo', 'MMRAcquisitionAuctionAveragePrice', 'MMRAcquisitionAuctionCleanPrice', 'MMRAcquisitionRetailAveragePrice', 'MMRAcquisitionRetailCleanPrice', 'MMRCurrentAuctionAveragePrice', 'MMRCurrentAuctionCleanPrice', 'MMRCurrentRetailAveragePrice', 'MMRCurrentRetailCleanPrice', 'MMRCurrentRetailRatio', 'VehBCost', 'WarrantyCost', 'Auction_manheim', 'VehYear_2004.0', 'Make_chevrolet', 'Make_dodge', 'Color_silver', 'Color_white', 'WheelTypeID_2', 'WheelType_?', 'WheelType_covers', 'TopThreeAmericanName_chrysler', 'TopThreeAmericanName_gm', 'VNST_tx']
```

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_state=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(random_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 concurrent workers.

[Parallel(n_jobs=1)]: Done 1 out of 1 | elapsed: 0.3s finished

[LibLinear]

Out[37]:

```
GridSearchCV(cv=3, error_score='raise-deprecating',
             estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
             intercept_scaling=1, max_iter=100, multi_class='warn',
             n_jobs=None, penalty='l2', random_state=101, solver='warn',
             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': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'], 'max_iter': [30, 50, 100], 'warm_start': [True, False], 'class_weight': ['balanced', None]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
             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:

Make_mercury : 0.35873351247562235
 Make_mini : 0.337853228316747
 MMRCurrentRetailRatio : -0.2582420901617004
 MMRAcquisitionRetailAveragePrice : 0.2432460273505872
 MMRAcquisitionAuctionAveragePrice : -0.24047249906816362

Top-5 important variables for selectModel

VehYear_2005.0 : 0.5481306536486824
 VehBCost : -0.18772050826489606
 VehYear_2008.0 : -0.07471605543299463
 VehOdo : 0.0727959318884104
 WarrantyCost : 0.0697723208892288

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': 0.01, 'class_weight': None, 'max_iter': 50, 'solver': 'lbfgs', 'warm_start': True}
 Optimal Parameters for selectModel {'C': 0.001, 'class_weight': None, 'max_iter': 30, 'solver': 'liblinear', 'warm_start': True}

d. Report any sign of overfitting

In []:

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

In [40]:

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

GridSearch Train accuracy: 0.8961526538766231
GridSearch Test accuracy: 0.8984167805191674

RFE:

Train accuracy: 0.8965659766472635
Test accuracy: 0.8984971469902756

selectModel:

Train accuracy: 0.8954637825922226
Test accuracy: 0.8979345816925178

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_pred))
```

REF classification report:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	10832
1	0.85	0.26	0.40	1611
micro avg	0.90	0.90	0.90	12443
macro avg	0.87	0.63	0.67	12443
weighted avg	0.89	0.90	0.87	12443

selectModel classification report:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	10832
1	0.83	0.27	0.40	1611
micro avg	0.90	0.90	0.90	12443
macro avg	0.87	0.63	0.67	12443
weighted avg	0.89	0.90	0.87	12443

Task4 - Predicting using neural network

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

In [42]:

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

```
/home/chihcheng/python3env/lib/python3.6/site-packages/sklearn/neural_network/multilayer_perceptron.py:562: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
```

```
% self.max_iter, ConvergenceWarning)
```

Out[42]:

```
MLPClassifier(activation='relu', alpha=0.0001, batch_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=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 layer")
    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 layer
```

```
1 Layer with hidden size 149
```

```
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?

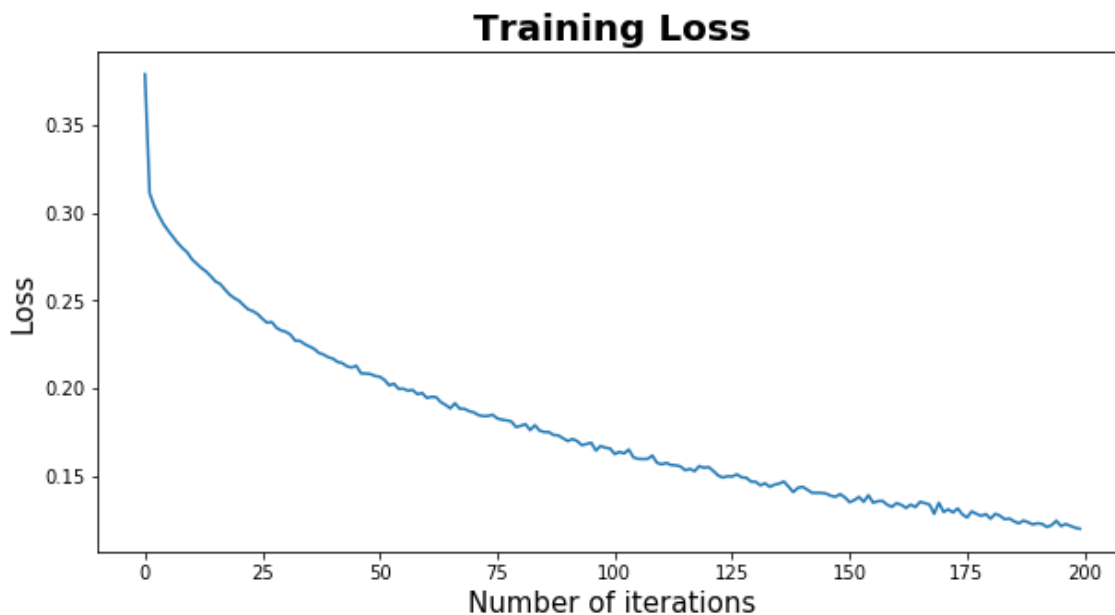
In [46]:

```
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 0x7fdb41ae2588>]



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: 0.5001384877141614

MLP Test accuracy: 0.8705296150446034

MLP classification report:

	precision	recall	f1-score	support
0	0.87	1.00	0.93	10832
1	0.00	0.00	0.00	1611
micro avg	0.87	0.87	0.87	12443
macro avg	0.44	0.50	0.47	12443
weighted avg	0.76	0.87	0.81	12443

/home/chihcheng/python3env/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples.

'precision', 'predicted', average, warn_for)

2. Refine this network by tuning it with GridSearchCV.

In [48]:

```
# Default
# params = {'hidden_layer_sizes': [(3,), (5,), (7,), (9,)], 'alpha': [0.01, 0.001, 0.0001]}

params = [
    {
        'hidden_layer_sizes': [(128,)],
        'activation': ['logistic', 'relu', 'identity'],
        'solver' : ['adam'],
        'batch_size': [32, 64],
        'shuffle': [True],
        'learning_rate_init': [pow(10, x) for x in range(-4, -2)],
        'n_iter_no_change': [10, 20],
        'warm_start': [True, False],
    },
    {
        'hidden_layer_sizes': [(128,)],
        'learning_rate' : ['constant', 'invscaling', 'adaptive'],
        'activation': ['logistic', 'relu', 'identity'],
        'solver' : ['sgd'],
        'shuffle': [True],
        'batch_size': [32, 64],
        'learning_rate_init': [pow(10, x) for x in range(-4, -2)],
        'n_iter_no_change': [10, 20],
        'warm_start': [True, False],
    },
    {
        'hidden_layer_sizes': [(128,)],
        'activation': ['logistic', 'relu', 'identity'],
        'solver' : ['lbfgs'],
        'batch_size': [32, 64],
        'learning_rate_init': [pow(10, x) for x in range(-4, -2)],
        'n_iter_no_change': [10, 20],
        'warm_start': [True, False],
    }
]

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

```
Iteration 1, loss = 0.32857511
Validation score: 0.890496
Iteration 2, loss = 0.31191295
Validation score: 0.890496
Iteration 3, loss = 0.31137095
Validation score: 0.891185
Iteration 4, loss = 0.31018978
Validation score: 0.890840
Iteration 5, loss = 0.30922495
Validation score: 0.891529
Iteration 6, loss = 0.30831522
Validation score: 0.891529
Iteration 7, loss = 0.30758839
Validation score: 0.891185
Iteration 8, loss = 0.30660339
Validation score: 0.891185
Iteration 9, loss = 0.30571344
Validation score: 0.891185
Iteration 10, loss = 0.30481675
Validation score: 0.891185
Iteration 11, loss = 0.30362134
Validation score: 0.891185
Iteration 12, loss = 0.30283829
Validation score: 0.892218
Iteration 13, loss = 0.30120792
Validation score: 0.892218
Iteration 14, loss = 0.29949388
Validation score: 0.892218
Iteration 15, loss = 0.29829281
Validation score: 0.892906
Iteration 16, loss = 0.29680944
Validation score: 0.893251
Iteration 17, loss = 0.29516226
Validation score: 0.892906
Iteration 18, loss = 0.29294147
Validation score: 0.892562
Iteration 19, loss = 0.29150188
Validation score: 0.892562
Iteration 20, loss = 0.28919079
Validation score: 0.892218
Iteration 21, loss = 0.28730894
Validation score: 0.892906
Iteration 22, loss = 0.28529079
Validation score: 0.891873
Iteration 23, loss = 0.28228859
Validation score: 0.892906
Iteration 24, loss = 0.27981098
Validation score: 0.892218
Iteration 25, loss = 0.27729154
Validation score: 0.892218
Iteration 26, loss = 0.27511337
Validation score: 0.892562
Iteration 27, loss = 0.27187226
Validation score: 0.892218
Validation score did not improve more than tol=0.000100 for 10 consecutive epochs. Stopping.
```


Out[48]:

```
GridSearchCV(cv=3, error_score='raise-deprecating',
             estimator=MLPClassifier(activation='relu', alpha=0.0001, batc
h_size='auto', beta_1=0.9,
             beta_2=0.999, early_stopping=True, epsilon=1e-08,
             hidden_layer_sizes=(100,), learning_rate='constant',
             learning_rate_init=0.001, max_iter=200, momentum=0.9,
             n_iter_no_change=10, nesterovs_momentum=True, power_t=0.5,
             random_state=101, shuffle=True, solver='adam', tol=0.0001,
             validation_fraction=0.1, verbose=True, warm_start=False),
             fit_params=None, iid='warn', n_jobs=-1,
             param_grid=[{'hidden_layer_sizes': [(128,)], 'activation':
['logistic', 'relu', 'identity'], 'solver': ['adam'], 'batch_size':
[32, 64], 'shuffle': [True], 'learning_rate_init': [0.0001, 0.001],
'n_iter_no_change': [10, 20], 'warm_start': [True, False]}, {'hidden
_layer_sizes': [(128,)], 'learning_ra...', 'learning_rate_init': [0.0
001, 0.001], 'n_iter_no_change': [10, 20], 'warm_start': [True, Fals
e]}],
             pre_dispatch='2*n_jobs', refit=True, return_train_score='war
n',
             scoring=None, verbose=0)
```

a. What is the network architecture?

In [49]:

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

```
Best Parameters of NN: {'activation': 'logistic', 'batch_size': 64,
'hidden_layer_sizes': (128,), 'learning_rate_init': 0.001, 'n_iter_n
o_change': 10, 'shuffle': True, 'solver': 'adam', 'warm_start': Tru
e}
```

In [50]:

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

```
Number of Layers: 3
The First layer is Input Layer, and the last layer is the output lay
er
1 Layer with hidden size 149
2 Layer with hidden size 128
3 Layer with hidden size 1
The activation function: logistic
```

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

In [51]:

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

```
Number of iterations it ran: 27
```

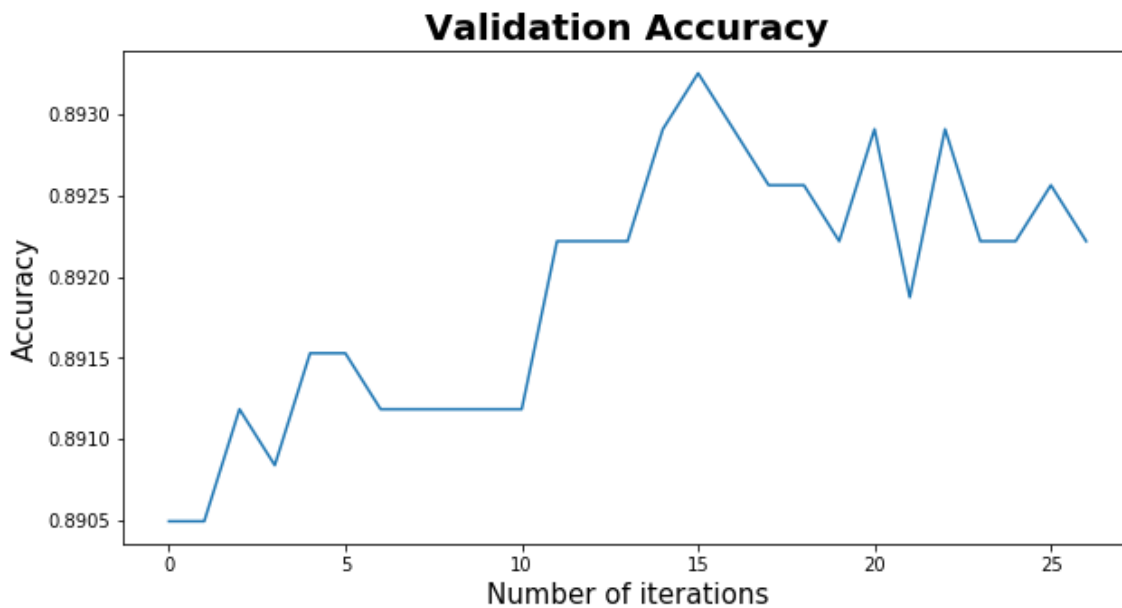
c. Sign of overfitting?

In [52]:

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

Out[52]:

[<matplotlib.lines.Line2D at 0x7fdb30159278>]



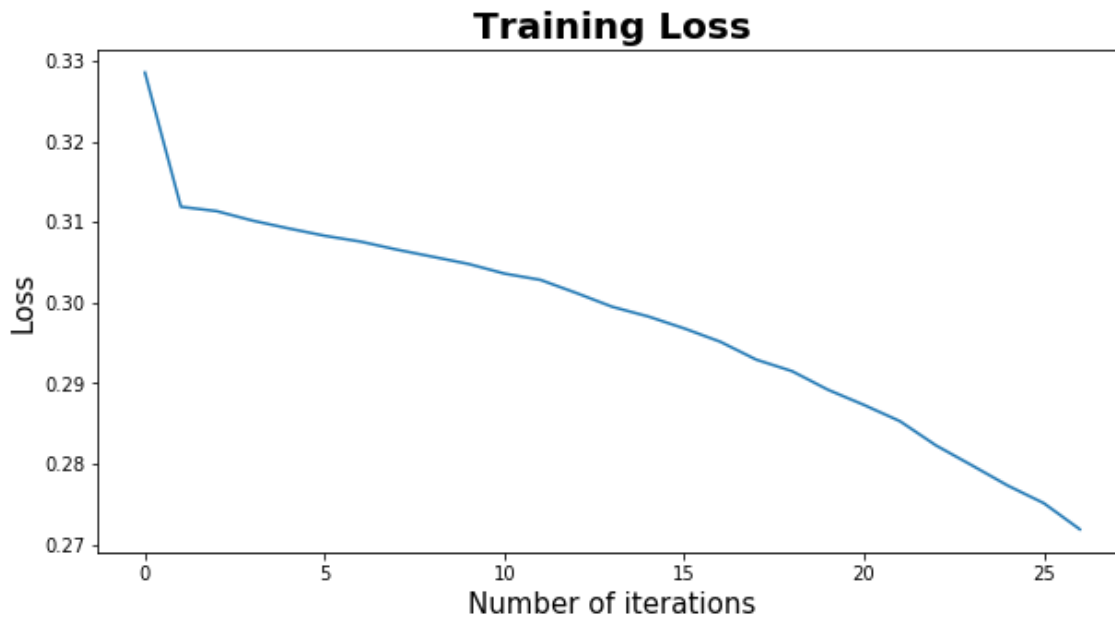
d. Did the training process converge and resulted in the best model?

In [53]:

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

Out[53]:

[<matplotlib.lines.Line2D at 0x7fdb2eb4a4a8>]



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

In [54]:

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

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

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

GridSearch NN Train accuracy: 0.8991836875279854

GridSearch NN Test accuracy: 0.8985775134613839

GridSearch NN Classification Report:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	10832
1	0.86	0.26	0.40	1611
micro avg	0.90	0.90	0.90	12443
macro avg	0.88	0.63	0.67	12443
weighted avg	0.90	0.90	0.87	12443

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

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

In [55]:

```

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

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

```

```
Iteration 1, loss = 0.32866056
Validation score: 0.899105
Iteration 2, loss = 0.30725139
Validation score: 0.899449
Iteration 3, loss = 0.30192863
Validation score: 0.898760
Iteration 4, loss = 0.29865307
Validation score: 0.895317
Iteration 5, loss = 0.29619341
Validation score: 0.899105
Iteration 6, loss = 0.29378594
Validation score: 0.896694
Iteration 7, loss = 0.29167638
Validation score: 0.895661
Iteration 8, loss = 0.29023446
Validation score: 0.895661
Iteration 9, loss = 0.28901530
Validation score: 0.895661
Iteration 10, loss = 0.28718890
Validation score: 0.896694
Iteration 11, loss = 0.28605909
Validation score: 0.895317
Iteration 12, loss = 0.28466641
Validation score: 0.897383
Iteration 13, loss = 0.28332199
Validation score: 0.898416
Validation score did not improve more than tol=0.000100 for 10 consecutive epochs. Stopping.
Iteration 1, loss = 0.37382535
Validation score: 0.904959
Iteration 2, loss = 0.31958283
Validation score: 0.906680
Iteration 3, loss = 0.31632059
Validation score: 0.907713
Iteration 4, loss = 0.31419681
Validation score: 0.907713
Iteration 5, loss = 0.31315285
Validation score: 0.907369
Iteration 6, loss = 0.31221688
Validation score: 0.907369
Iteration 7, loss = 0.31138924
Validation score: 0.907713
Iteration 8, loss = 0.31043667
Validation score: 0.902893
Iteration 9, loss = 0.30996280
Validation score: 0.907369
Iteration 10, loss = 0.30981473
Validation score: 0.907369
Iteration 11, loss = 0.30906495
Validation score: 0.906680
Iteration 12, loss = 0.30842626
Validation score: 0.907713
Iteration 13, loss = 0.30816527
Validation score: 0.907713
Iteration 14, loss = 0.30784851
Validation score: 0.907369
Validation score did not improve more than tol=0.000100 for 10 consecutive epochs. Stopping.
```

Out[55]:

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

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

In [56]:

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

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



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

GridSearch:

Number of Layers: 3

The First layer is Input Layer, and the last layer is the output layer

1 Layer with hidden size 149

2 Layer with hidden size 128

3 Layer with hidden size 1

The activation function: logistic

RFE:

Number of Layers: 3

The First layer is Input Layer, and the last layer is the output layer

1 Layer with hidden size 80

2 Layer with hidden size 128

3 Layer with hidden size 1

The activation function: relu

modelSelect:

Number of Layers: 3

The First layer is Input Layer, and the last layer is the output layer

1 Layer with hidden size 24

2 Layer with hidden size 128

3 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 [57]:

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

```
GridSearch NN Train accuracy: 0.8991836875279854
GridSearch NN Test accuracy: 0.8985775134613839
RFE NN Train accuracy: 0.8983570419867047
RFE NNTest accuracy: 0.8982560475769509
modelSelect NN Train accuracy: 0.8974959528812041
modelSelect NN Test accuracmodelSelect_cv: 0.8976934822791931
```

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

In [58]:

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

```
Number of iterations GS ran: 27
Number of iterations rfe ran: 13
Number of iterations modelSelect ran: 14
```

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

In []:

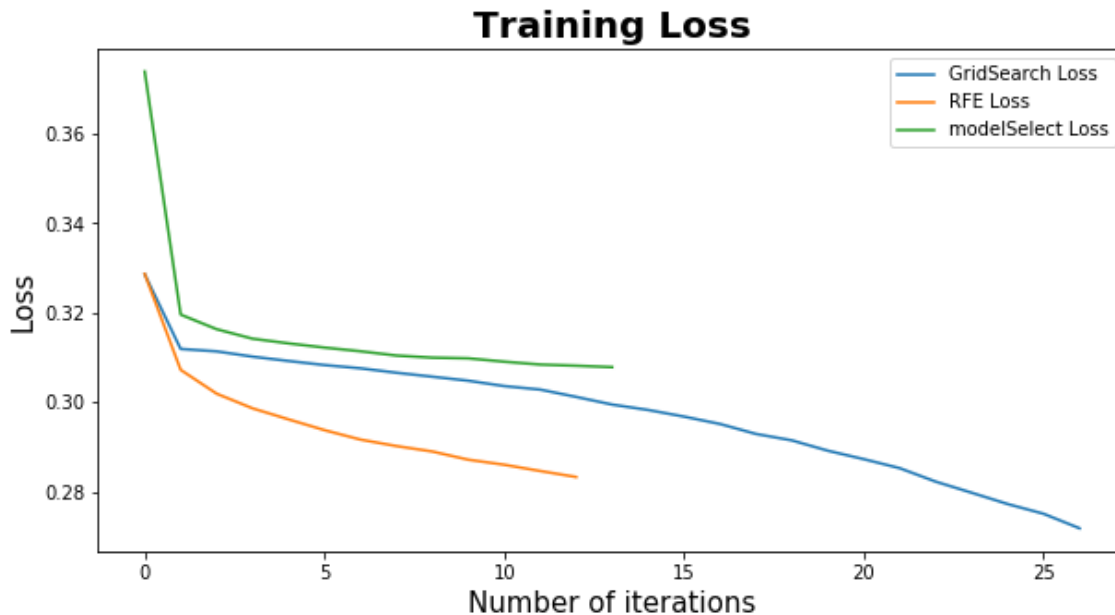
e. Did the training process converge and resulted in the best model?

In [59]:

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

Out[59]:

<matplotlib.legend.Legend at 0x7fdb2a1fa198>



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

In [60]:

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

GridSearch Classification Report:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	10832
1	0.86	0.26	0.40	1611
micro avg	0.90	0.90	0.90	12443
macro avg	0.88	0.63	0.67	12443
weighted avg	0.90	0.90	0.87	12443

RFE Classification Report:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	10832
1	0.87	0.25	0.39	1611
micro avg	0.90	0.90	0.90	12443
macro avg	0.88	0.62	0.67	12443
weighted avg	0.90	0.90	0.87	12443

modelSelect Classification Report:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	10832
1	0.86	0.25	0.39	1611
micro avg	0.90	0.90	0.90	12443
macro avg	0.88	0.62	0.67	12443
weighted avg	0.89	0.90	0.87	12443

Task 5. Generating an Ensemble Model and Comparing Models

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

In [61]:

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

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

```
Iteration 1, loss = 0.32857511
Validation score: 0.890496
Iteration 2, loss = 0.31191295
Validation score: 0.890496
Iteration 3, loss = 0.31137095
Validation score: 0.891185
Iteration 4, loss = 0.31018978
Validation score: 0.890840
Iteration 5, loss = 0.30922495
Validation score: 0.891529
Iteration 6, loss = 0.30831522
Validation score: 0.891529
Iteration 7, loss = 0.30758839
Validation score: 0.891185
Iteration 8, loss = 0.30660339
Validation score: 0.891185
Iteration 9, loss = 0.30571344
Validation score: 0.891185
Iteration 10, loss = 0.30481675
Validation score: 0.891185
Iteration 11, loss = 0.30362134
Validation score: 0.891185
Iteration 12, loss = 0.30283829
Validation score: 0.892218
Iteration 13, loss = 0.30120792
Validation score: 0.892218
Iteration 14, loss = 0.29949388
Validation score: 0.892218
Iteration 15, loss = 0.29829281
Validation score: 0.892906
Iteration 16, loss = 0.29680944
Validation score: 0.893251
Iteration 17, loss = 0.29516226
Validation score: 0.892906
Iteration 18, loss = 0.29294147
Validation score: 0.892562
Iteration 19, loss = 0.29150188
Validation score: 0.892562
Iteration 20, loss = 0.28919079
Validation score: 0.892218
Iteration 21, loss = 0.28730894
Validation score: 0.892906
Iteration 22, loss = 0.28529079
Validation score: 0.891873
Iteration 23, loss = 0.28228859
Validation score: 0.892906
Iteration 24, loss = 0.27981098
Validation score: 0.892218
Iteration 25, loss = 0.27729154
Validation score: 0.892218
Iteration 26, loss = 0.27511337
Validation score: 0.892562
Iteration 27, loss = 0.27187226
Validation score: 0.892218
Validation score did not improve more than tol=0.000100 for 10 consecutive epochs. Stopping.
```

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

In [62]:

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

Report for DT:

	precision	recall	f1-score	support
0	0.87	0.95	0.91	10832
1	0.16	0.07	0.10	1611
micro avg	0.83	0.83	0.83	12443
macro avg	0.52	0.51	0.50	12443
weighted avg	0.78	0.83	0.80	12443

Report for Logistic Regression:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	10832
1	0.84	0.27	0.40	1611
micro avg	0.90	0.90	0.90	12443
macro avg	0.87	0.63	0.67	12443
weighted avg	0.89	0.90	0.87	12443

Report for NN:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	10832
1	0.86	0.26	0.40	1611
micro avg	0.90	0.90	0.90	12443
macro avg	0.88	0.63	0.67	12443
weighted avg	0.90	0.90	0.87	12443

Report for Ensemble:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	10832
1	0.78	0.26	0.39	1611
micro avg	0.89	0.89	0.89	12443
macro avg	0.84	0.62	0.66	12443
weighted avg	0.88	0.89	0.87	12443

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

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

(a) ROC Chart (and Index)

In [63]:

ROC

```

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

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

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

fpr_dt, tpr_dt, thresholds_dt = roc_curve(y_test, y_pred_proba_dt[:,1])
fpr_log_reg, tpr_log_reg, thresholds_log_reg = roc_curve(y_test, y_pred_proba_log_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])

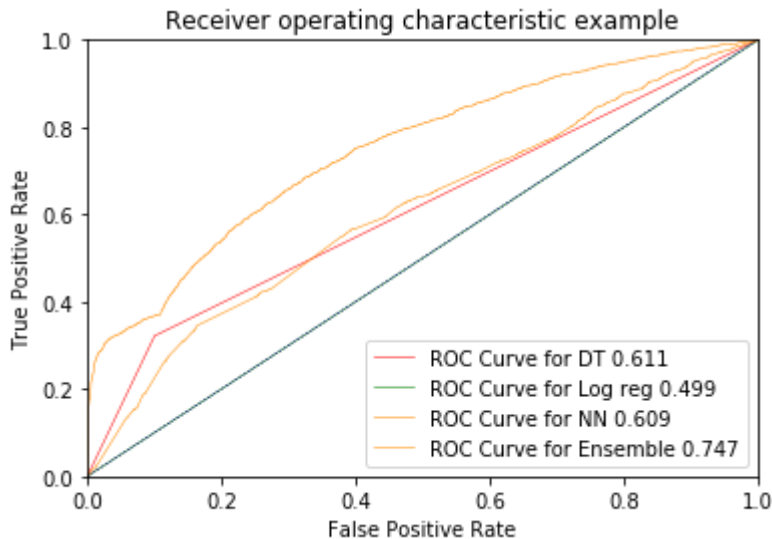
plt.plot(fpr_dt, tpr_dt, label='ROC Curve for DT {:.3f}'.format(roc_index_dt), color='red', lw=0.5)
plt.plot(fpr_log_reg, tpr_log_reg, label='ROC Curve for Log reg {:.3f}'.format(roc_index_log_reg), color='green', lw=0.5)
plt.plot(fpr_nn, tpr_nn, label='ROC Curve for NN {:.3f}'.format(roc_index_nn), color='darkorange', lw=0.5)
plt.plot(fpr_ensemble, tpr_ensemble, label='ROC Curve for Ensemble {:.3f}'.format(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: 0.6106552750339935
 ROC index on test for logistic regression: 0.49947161524306216
 ROC index on test for NN: 0.6089292640056774
 ROC index on voting classifier: 0.7474468709857544

/home/chihcheng/python3env/lib/python3.6/site-packages/sklearn/linear_model/base.py:297: RuntimeWarning: overflow encountered in exp
 np.exp(prob, prob)



(b) Score Ranking (or Accuracy Score)

In [64]:

```
print("Accuracy score on test for DT:", accuracy_score(y_test_log, y_pred_dt))
print("Accuracy score on test for Logistic Regression:", accuracy_score(y_test_log, 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: 0.8348469018725387
 Accuracy score on test for Logistic Regression: 0.8984167805191674
 Accuracy score on test for NN: 0.8985775134613839
 Accuracy score on test for Ensemble: 0.8943180904926464

(c) Classification report

In [65]:

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

Report for DT:

	precision	recall	f1-score	support
0	0.87	0.95	0.91	10832
1	0.16	0.07	0.10	1611
micro avg	0.83	0.83	0.83	12443
macro avg	0.52	0.51	0.50	12443
weighted avg	0.78	0.83	0.80	12443

Report for Logistic Regression:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	10832
1	0.84	0.27	0.40	1611
micro avg	0.90	0.90	0.90	12443
macro avg	0.87	0.63	0.67	12443
weighted avg	0.89	0.90	0.87	12443

Report for NN:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	10832
1	0.86	0.26	0.40	1611
micro avg	0.90	0.90	0.90	12443
macro avg	0.88	0.63	0.67	12443
weighted avg	0.90	0.90	0.87	12443

Report for Ensemble:

	precision	recall	f1-score	support
0	0.90	0.99	0.94	10832
1	0.78	0.26	0.39	1611
micro avg	0.89	0.89	0.89	12443
macro avg	0.84	0.62	0.66	12443
weighted avg	0.88	0.89	0.87	12443

(d) Output

In []:

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

In []:

Task 6. Final Remarks: Decision Making

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

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

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

In []:

In []:

In []: