PEACHES AND LEMONS

**Predicting whether
a vehicle will be 'kicked back'
to the auction.**

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MOTIVATION & BACKGROUND

(In American slang, a lemon is a car that is found to be defective only after it has been bought.)

The Lemons Problem

In Economics, the Lemons Problem refers to issues that arise regarding the value of a product due to asymmetric information between the buyer and the seller.

This information asymmetry leads a degradation in the quality of products in a given market.

The subject even has laws named after it.

PROPOSED FLOW

- Overview of the Problem
- Objective
- The Data
- Feature Engineering
- Modeling & Feature Selection
- Tuning and Evaluating the Model
- Conclusion

Overview of the Problem

From kaggle:

"One of the biggest challenges of an auto dealership purchasing a used car at an auto auction is the risk of that the vehicle might have serious issues that prevent it from being sold to customers. The auto community calls these unfortunate purchases "kicks".

Asymmetric Information

Kicked cars often result when there are tampered odometers, mechanical issues the dealer is not able to address, issues with getting the vehicle title from the seller, or some other unforeseen problem. Kick cars can be very costly to dealers after transportation cost, throw-away repair work, and market losses in reselling the vehicle.

Preventing quality degredation

Modelers who can figure out which cars have a higher risk of being kick can provide real value to dealerships trying to provide the best inventory selection possible to their customers.

The challenge of this competition is to predict if the car purchased at the Auction is a Kick (bad buy)."

TL;DR:

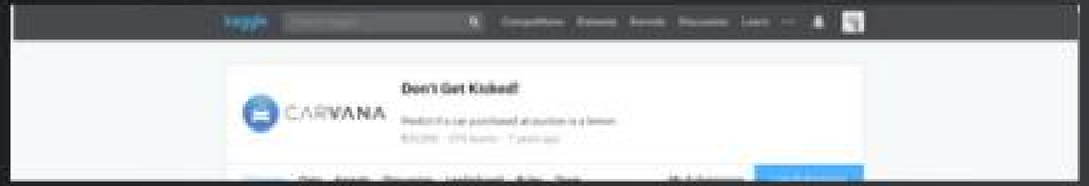
Vehicles that are returned to an auction are called kicks (lemons), and they can become a huge cost for dealers.

OBJECTIVE

The objective of the Kaggle competition is to predict which cars will be lemons.

In addition to predicting lemons, the data can also be used in an attempt to maximize the expected profit margins of the inventory.

Click Me!



THE DATA:

The data comes from Carvana, contains a list of vehicles purchased across two auctions (and other sources)

I used the training data and split it to train my model.

```
In [32]:
df.shape

Out[32]:
(72983, 34)
```

The test data does not contain the outcome attribute.

```
Class Balance:
Number of Lemons: 8976
Number of Peaches: 64007
Occurance Rate: 12.3%
```

The data is imbalanced.

THE DATA

Original Attributes

```
In [57]: df.dtypes

Out[57]: RefId                                int64
         IsBadBuy                             int64
         PurchDate                           object
         Auction                             object
         VehYear                              int64
         VehicleAge                           int64
         Make                                object
         Model                               object
         Trim                                object
         SubModel                            object
         Color                               object
         Transmission                        object
         WheelTypeID                        float64
         WheelType                           object
         VehOdo                               int64
         Nationality                         object
         Size                                object
         TopThreeAmericanName                object
         MMRAcquisitionAuctionAveragePrice  float64
         MMRAcquisitionAuctionCleanPrice    float64
         MMRAcquisitionRetailAveragePrice   float64
         MMRAcquisitonRetailCleanPrice      float64
         MMRCurrentAuctionAveragePrice      float64
         MMRCurrentAuctionCleanPrice        float64
         MMRCurrentRetailAveragePrice       float64
         MMRCurrentRetailCleanPrice         float64
         PRIMEUNIT                           object
         AUCGUART                            object
         BYRNO                                int64
         VNZIP1                               int64
         VNST                                object
         VehBCost                           float64
         IsOnlineSale                         int64
         WarrantyCost                         int64
         dtype: object
```

Attributes Dropped (a prior i)

['RefId', 'BYRNO', 'AUCGUART', 'PRIMEUNIT','VNZIP','WheelType', 'VehYear']

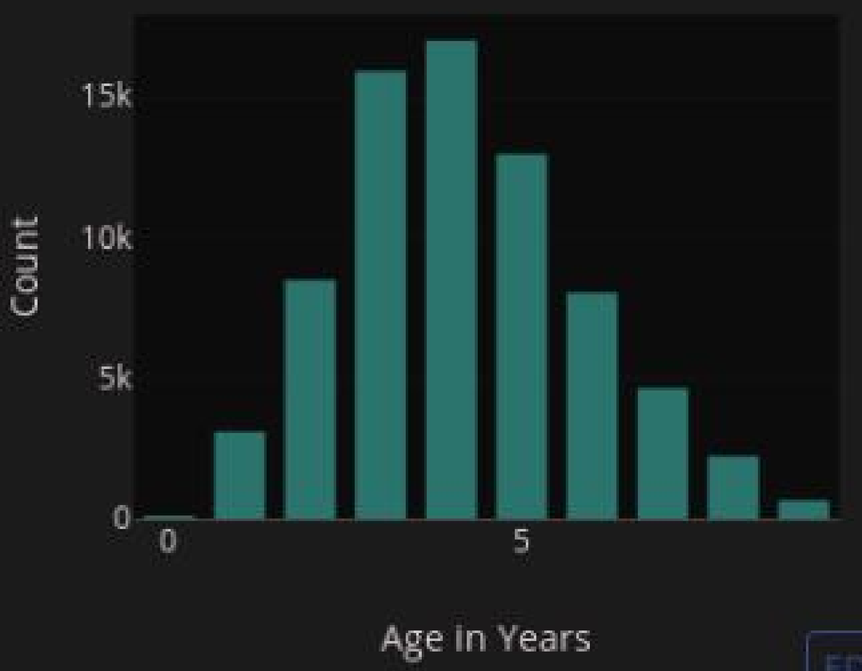
Continuous Attributes

```
Index(['VehYear', 'VehicleAge',  'VehOdo', 'VehBCost',
       'MMRAcquisitionAuctionAveragePrice', 'MMRAcquisitionAuctionCleanPrice',
       'MMRAcquisitionRetailAveragePrice', 'MMRAcquisitonRetailCleanPrice',
       'MMRCurrentAuctionAveragePrice', 'MMRCurrentAuctionCleanPrice',
       'MMRCurrentRetailAveragePrice', 'MMRCurrentRetailCleanPrice',
        'WarrantyCost']
```

Categorical/Binary Attributes

```
Index(['Auction','PurchDate 'Make', 'Model', 'Trim', 'SubModel', 'Color',
       'Transmission','VNST', 'WheelTypeID', 'Nationality','Size',
       'TopThreeAmericanName', 'IsOnlineSale']
```

Distribution of Vehicle Age



EDIT CHART

Distribution of Milage

EDIT CHART

THE DATA: Continuous Attributes

'VehicleAge' - Age of Vehicle in Years

'VehOdo' - Vehicle Odometer Reading

'VehBCost - Price paid at the time of acquisition

'MMRAcquisitionAuctionAveragePrice' - Acquisition Average Auction Price

'MMRAcquisitionAuctionCleanPrice' - Acquisition Good Condition Auction Price

'MMRAcquisitionRetailAveragePrice' - Acquisition Average Retail Price

'MMRAcquisitonRetailCleanPrice' - Acquisition Good Condition Auction Price

'MMRCurrentAuctionAveragePrice' - Current Average Auction Price

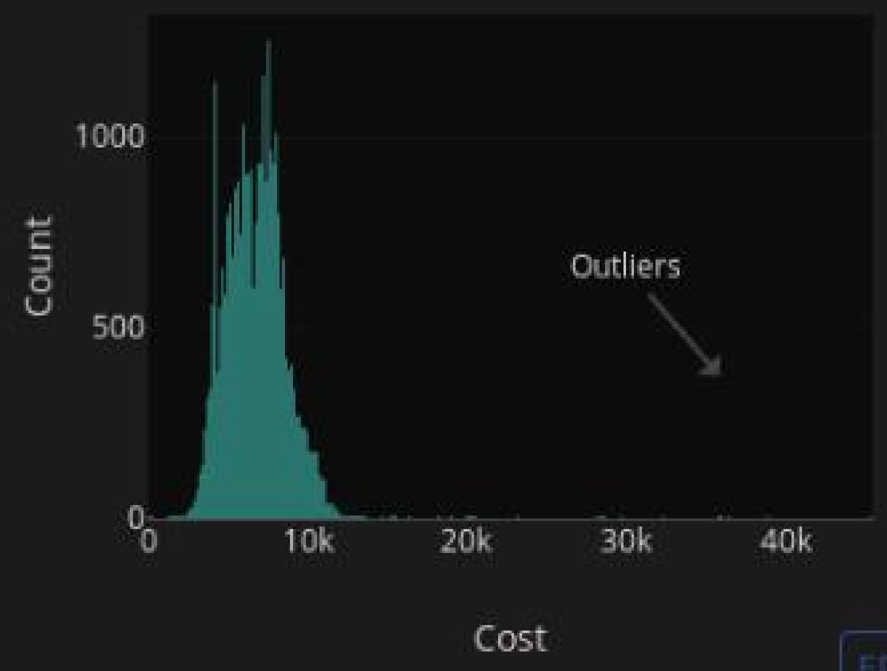
'MMRCurrentAuctionCleanPrice' - Current Good Condition Auction Price

'MMRCurrentRetailAveragePrice' - Current Average Retail Price

'MMRCurrentRetailCleanPrice' - Current Retail Good Condition Price

'WarrantyCost' - Cost of the warranty (36k mi, 36 mo)

Acquisition Price



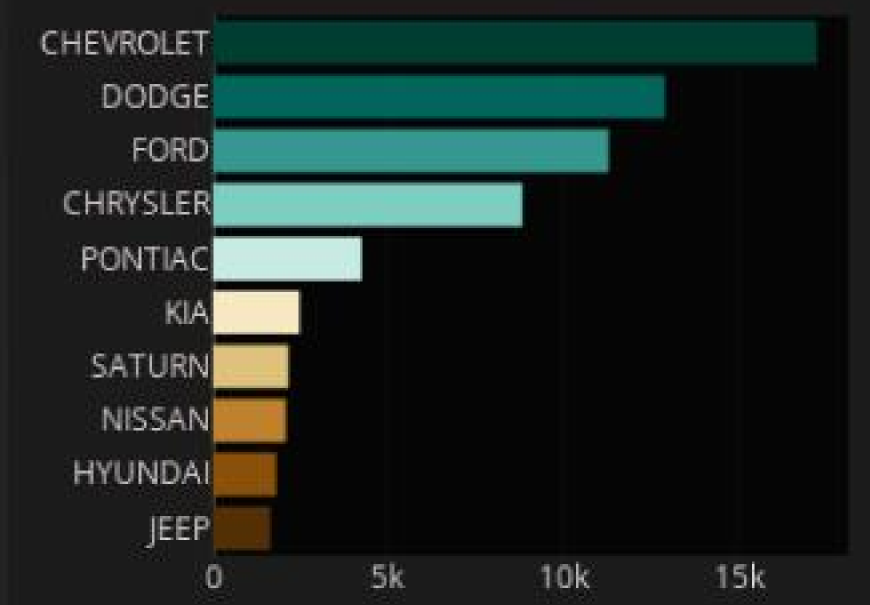
EDIT CHART

Distribution of Warrenty Cost

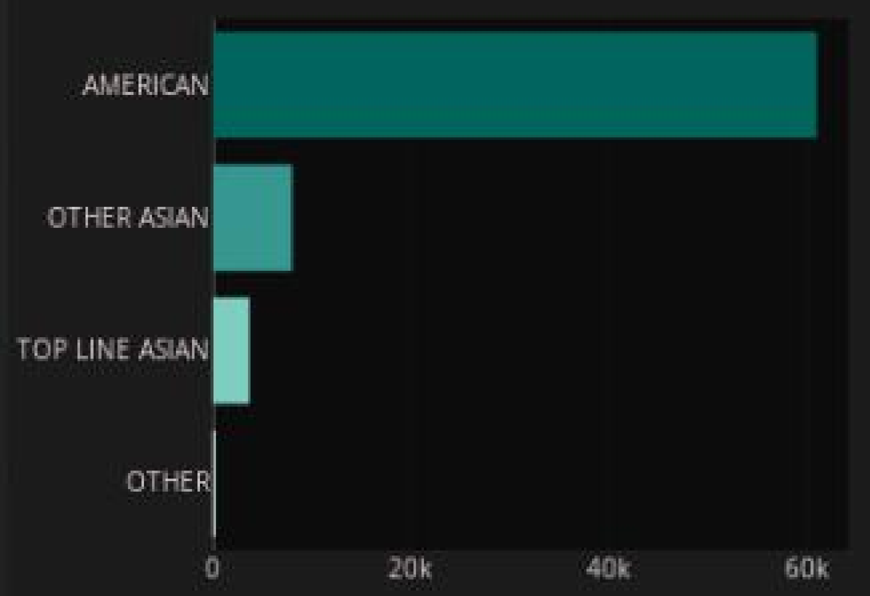
EDIT CHART

THE DATA: Categorical Attributes

Top 10 Vehicles by Make



Vehicle by Origin



- 'Auction' - Vehicle Source
- 'PurchDate' - Purchase Date
- 'Make' - Make
- 'Model'* - Model Type
- 'Trim'* - Style of the Vehicle
- 'SubModel'* - Additional specifications
- 'Color' - Color
- 'Transmission' - Transmission Type
- 'WheelTypeID' - Wheel Type
- 'Nationality' - Manufacturing Nation
- 'Size' - Size
- 'TopThreeAmericanName' - GM, Ford, Chrysler, other
- 'VNST' - State where Vehivle was Purchased
- 'IsOnlineSale' - The vehicle was purchased online (binary)

'IsBadBuy' (outcome) - The vehicle is a lemon (binary)

*Category is Problematic

```
for col in cats:
    print(col,len(df[col].unique()))
```

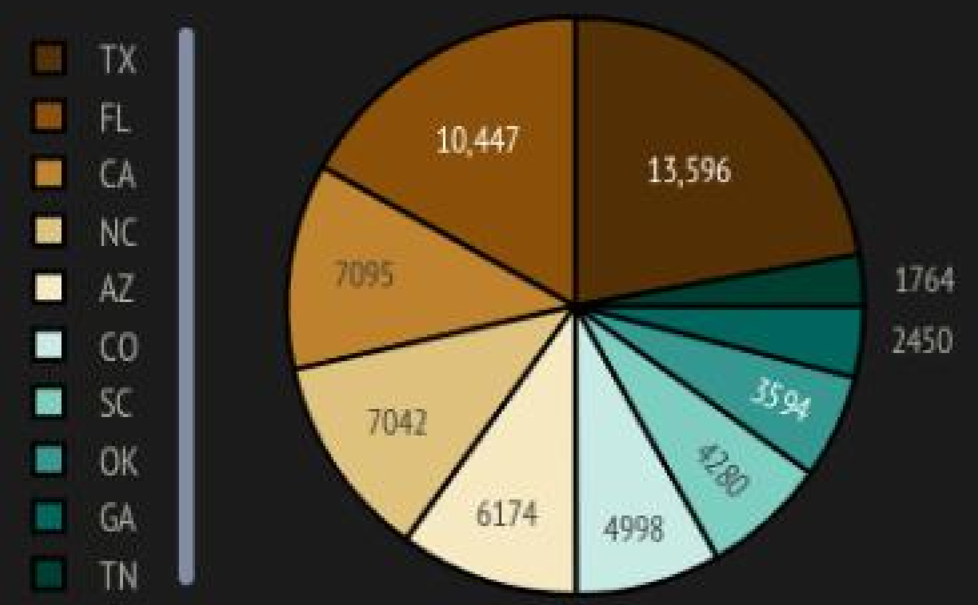
```
Auction 3
Make 33
Model 1063
Trim 135
SubModel 864
Color 17
Transmission 4
WheelTypeID 5
Nationality 5
Size 13
TopThreeAmericanName 5
VNST 37
IsOnlineSale 2
IsBadBuy 2
```

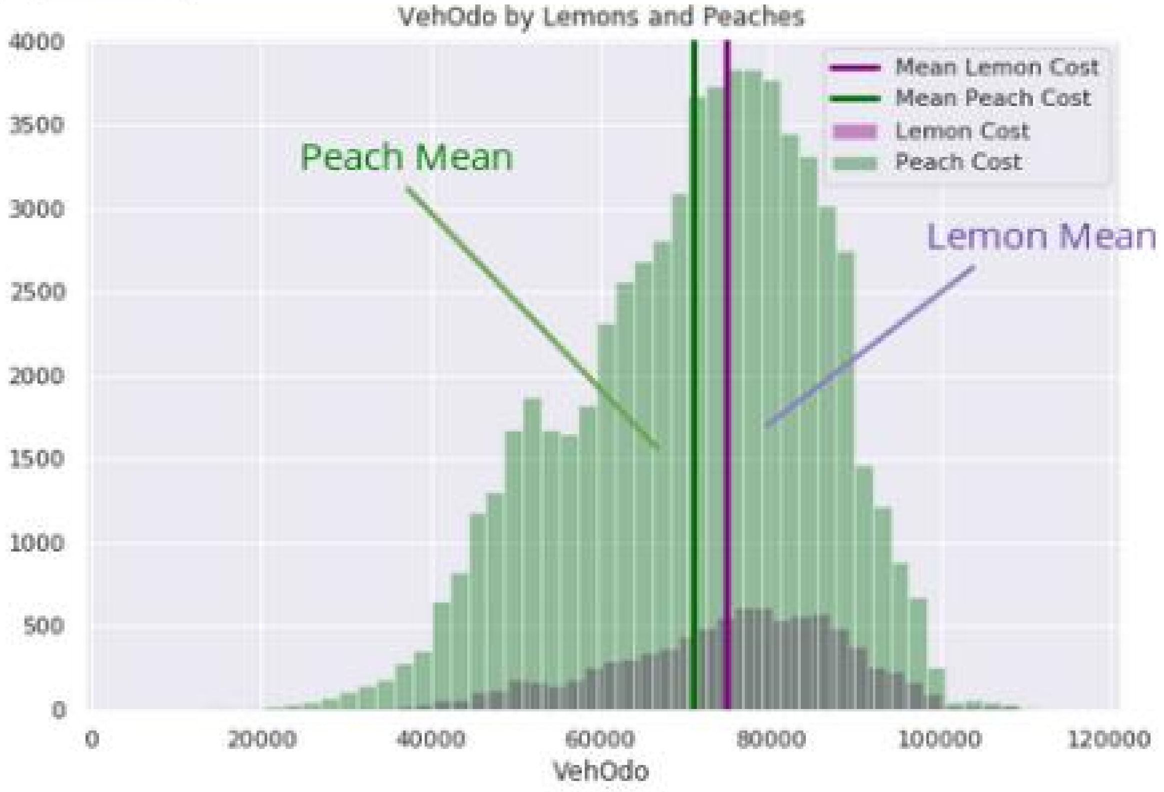
```
df.Color.unique()
```

```
array(['RED', 'WHITE', 'MAROON', 'SILVER', 'BLACK', 'GOLD', 'GREY',
       'BLUE', 'BEIGE', 'PURPLE', 'ORANGE', 'GREEN', 'BROWN', 'YELLOW',
       'NOT AVAIL', 'OTHER'], dtype=object)
```

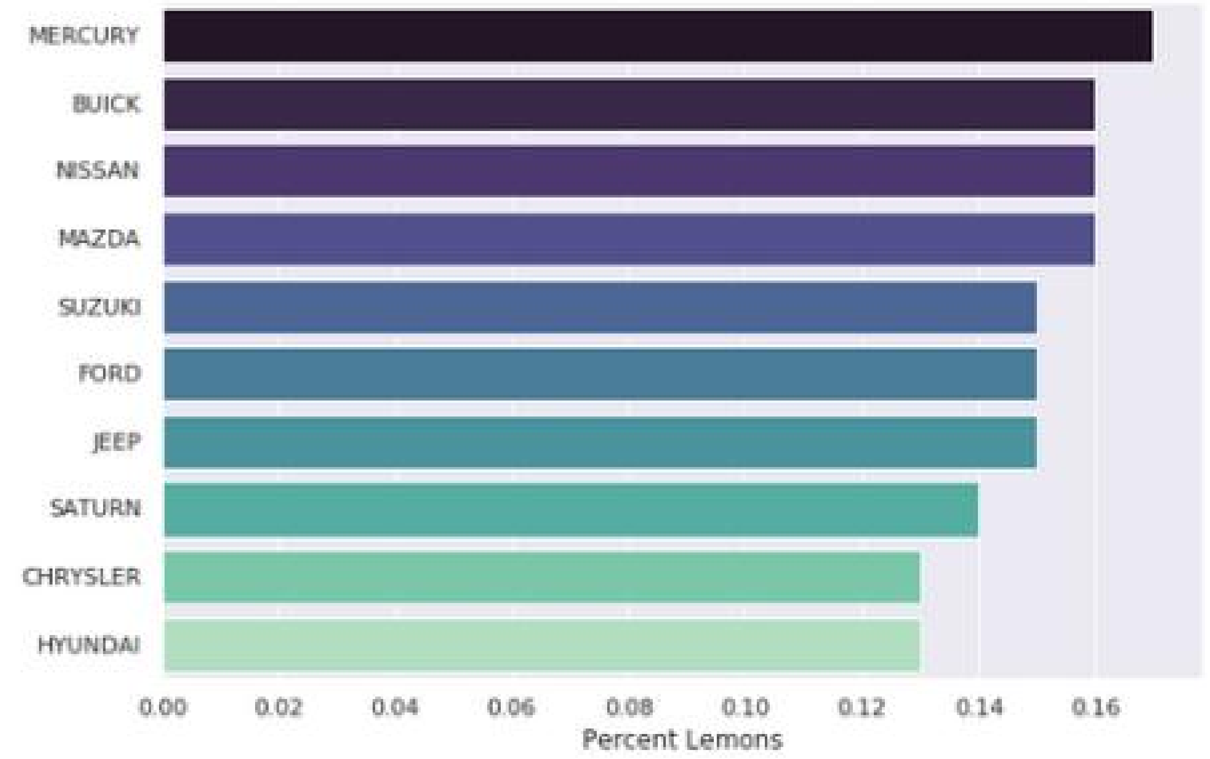
```
IsOnlineSale:
Number of Vehicles Purcahsed Online: 1845
Number of Vehicles Purchased not Online: 71138
Occurance Rate: 2.53%
```

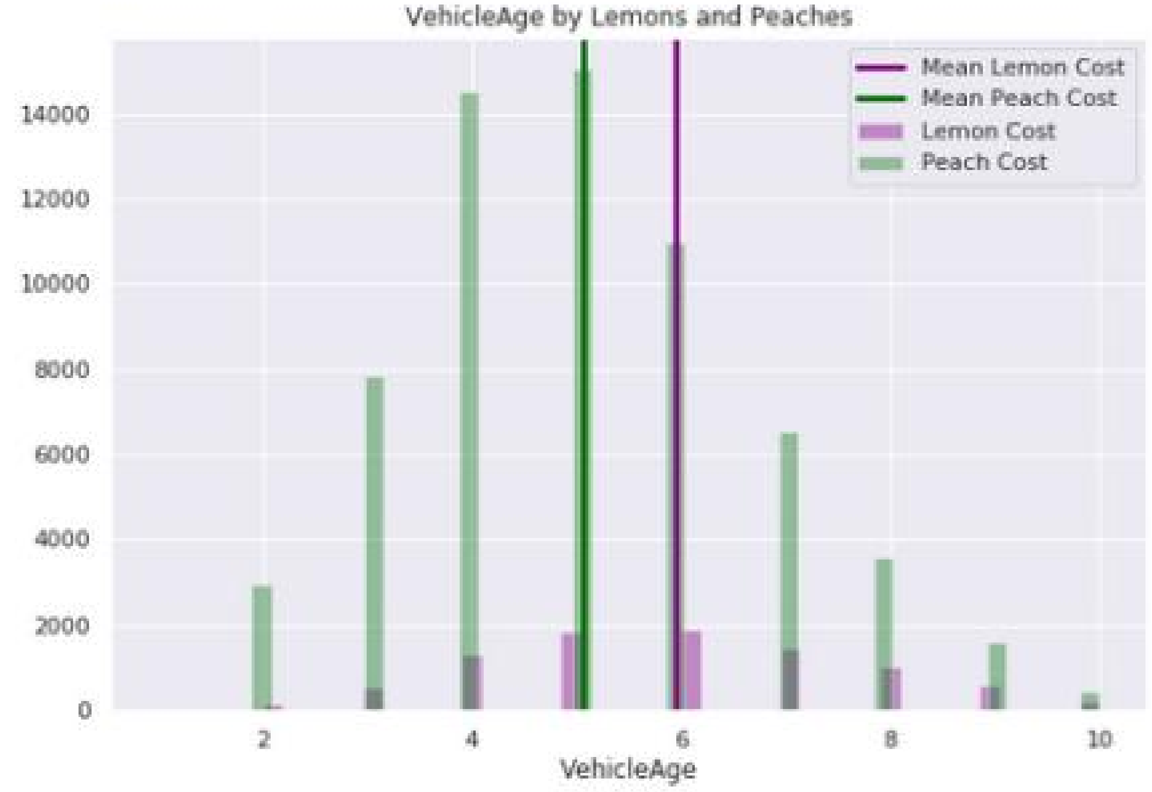
Top 10 Purchase States

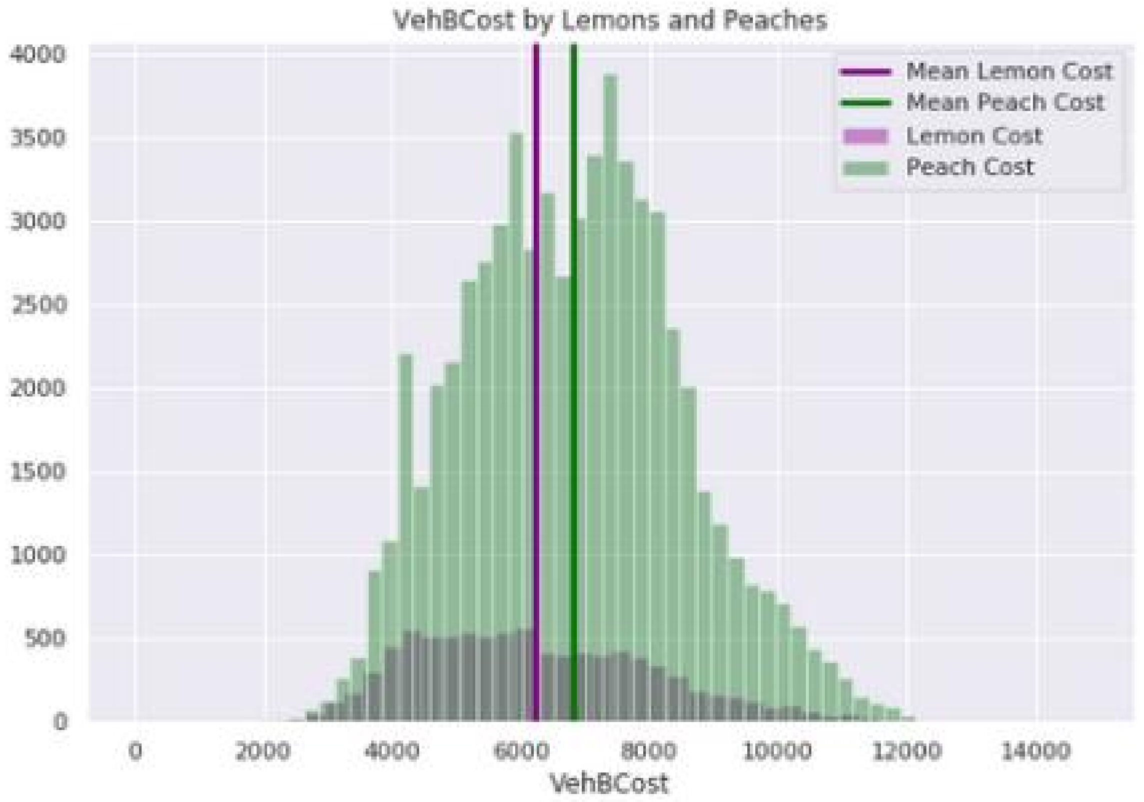



VehOdo by Lemons and Peaches
Mean Lemon Cost
Mean Peach Cost
Lemon Cost
Peach Cost
Peach Mean
Lemon Mean
VehOdo

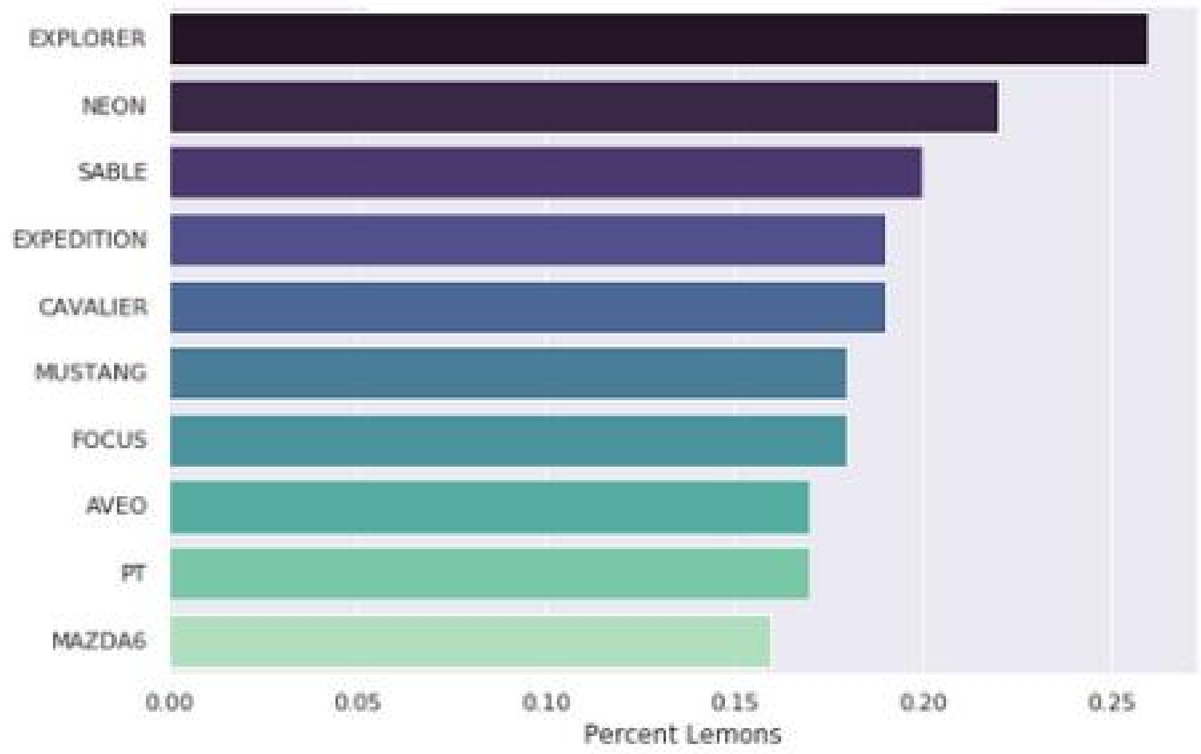
MAKE

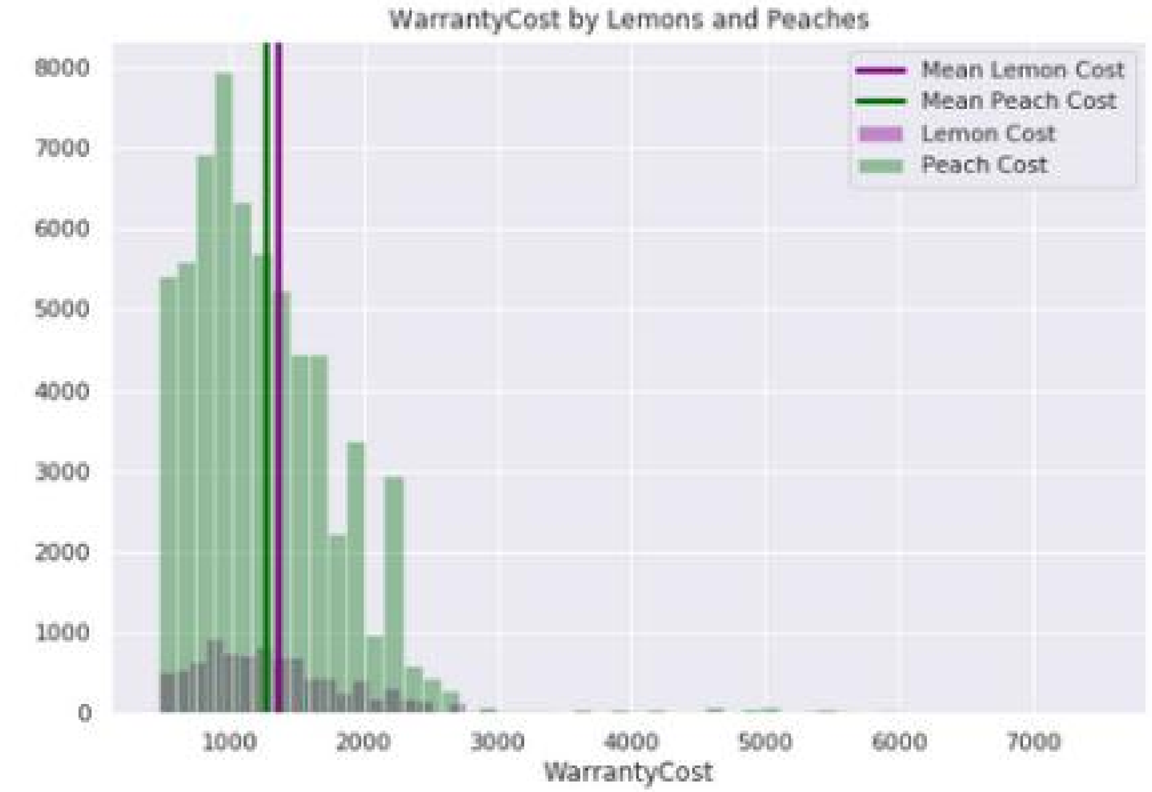

MERCURY
BUICK
NISSAN
MAZDA
SUZUKI
FORD
JEEP
SATURN
CHRYSLER
HYUNDAI
Percent Lemons


VehicleAge by Lemons and Peaches
Mean Lemon Cost
Mean Peach Cost
Lemon Cost
Peach Cost
VehicleAge


VehBCost by Lemons and Peaches
Mean Lemon Cost
Mean Peach Cost
Lemon Cost
Peach Cost
VehBCost

MODEL


EXPLORER
NEON
SABLE
EXPEDITION
CAVALIER
MUSTANG
FOCUS
AVEO
PT
MAZDA6
Percent Lemons


WarrantyCost by Lemons and Peaches
Mean Lemon Cost
Mean Peach Cost
Lemon Cost
Peach Cost
WarrantyCost

Market Rate Attributes

'CurrentRetailCleanPrice' - Current Retail Good Condition

'AcquisitonRetailCleanPrice' - Acquisition Retail Good Condition

'CurrentRetailAveragePrice' - Current Average Retail

'AcquisitionRetailAveragePrice' - Acquisition Average Retail

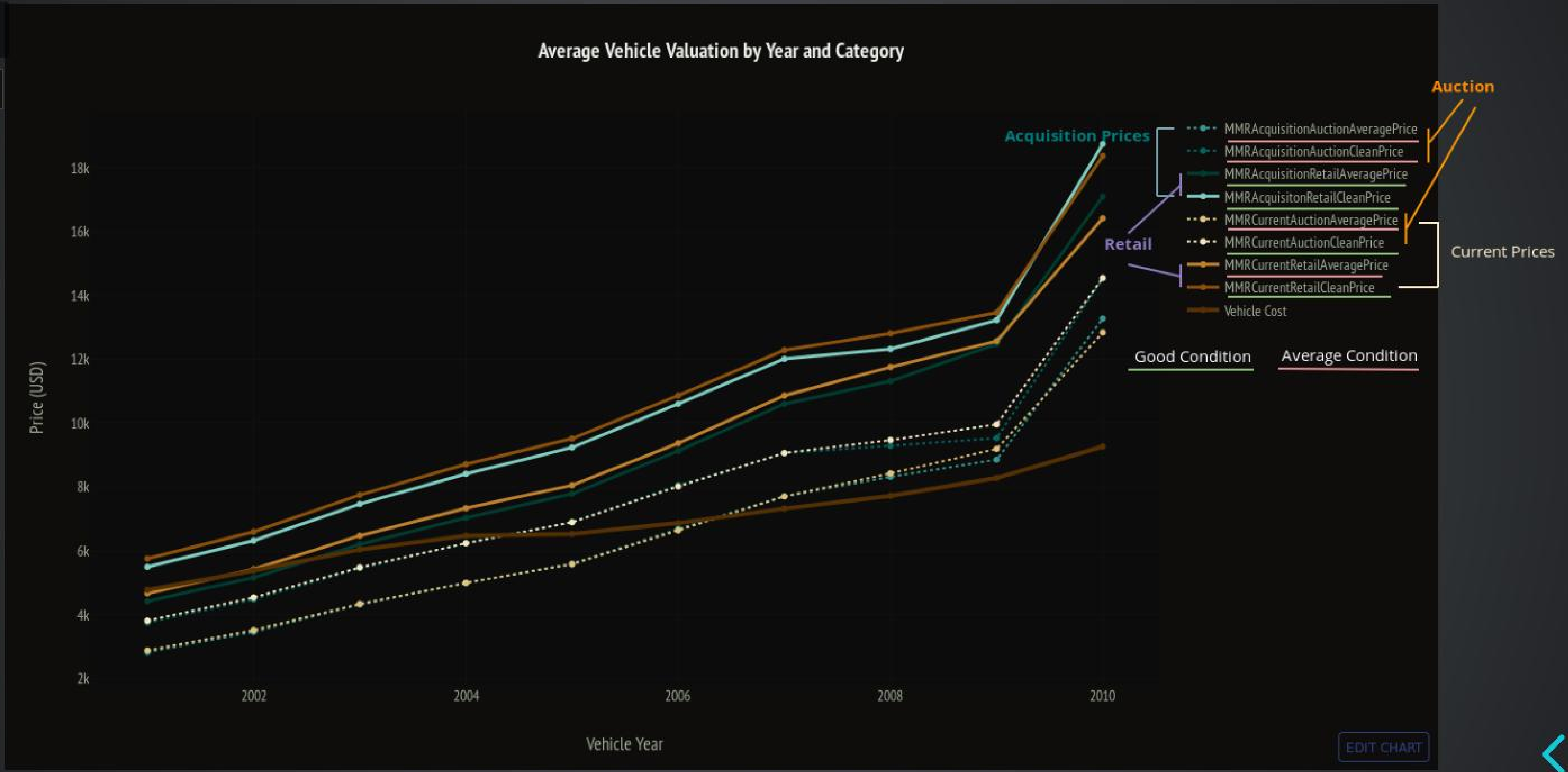
'CurrentAuctionCleanPrice' - Current Good Condition Auction

'AcquisitionAuctionCleanPrice' - Acquisition Good Condition Auction

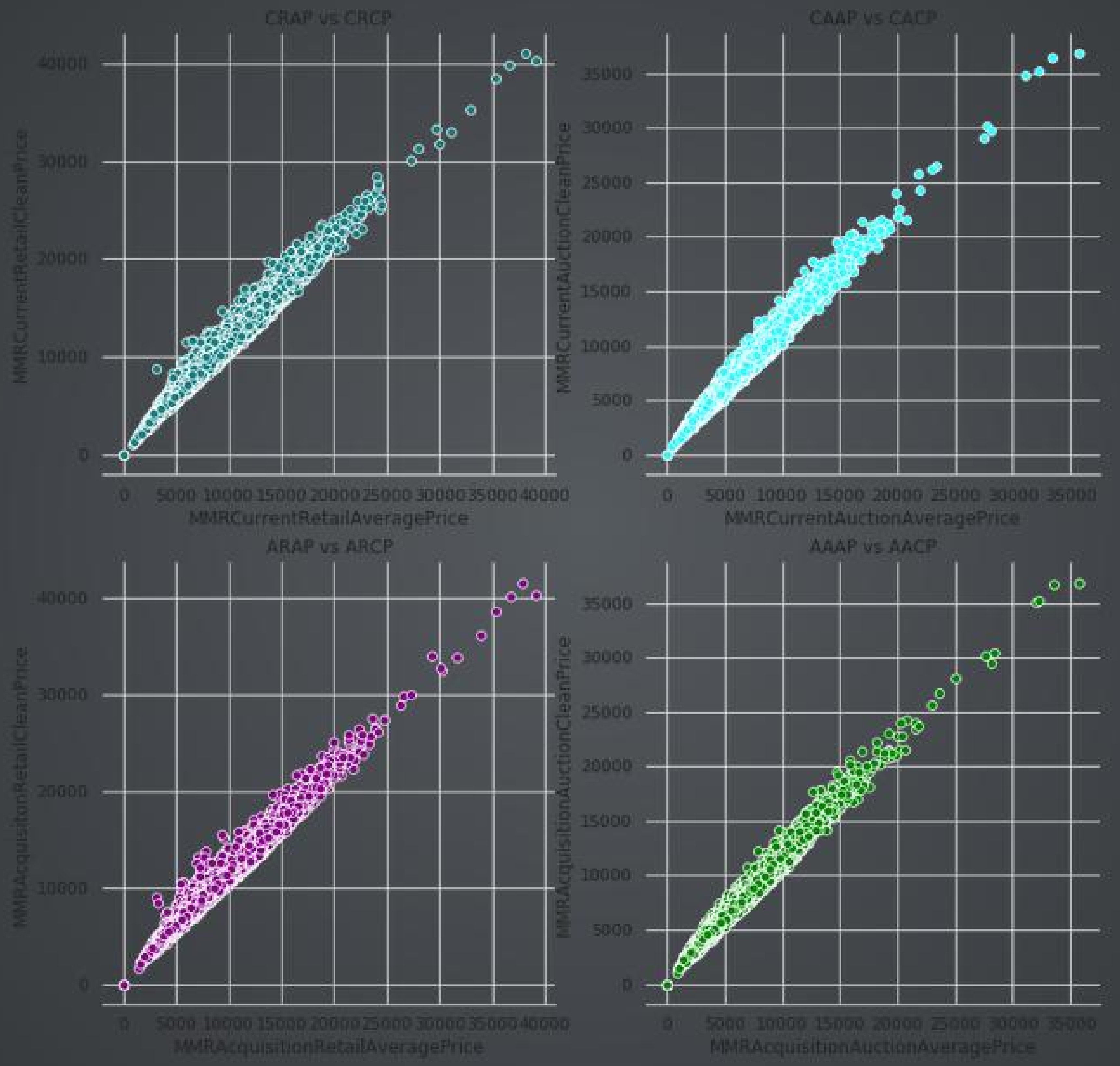
'CurrentAuctionAveragePrice' - Current Average Auction

'AcquisitionAuctionAveragePrice' - Acquisition Average Auction

Resume editing



Correlation Between Prices

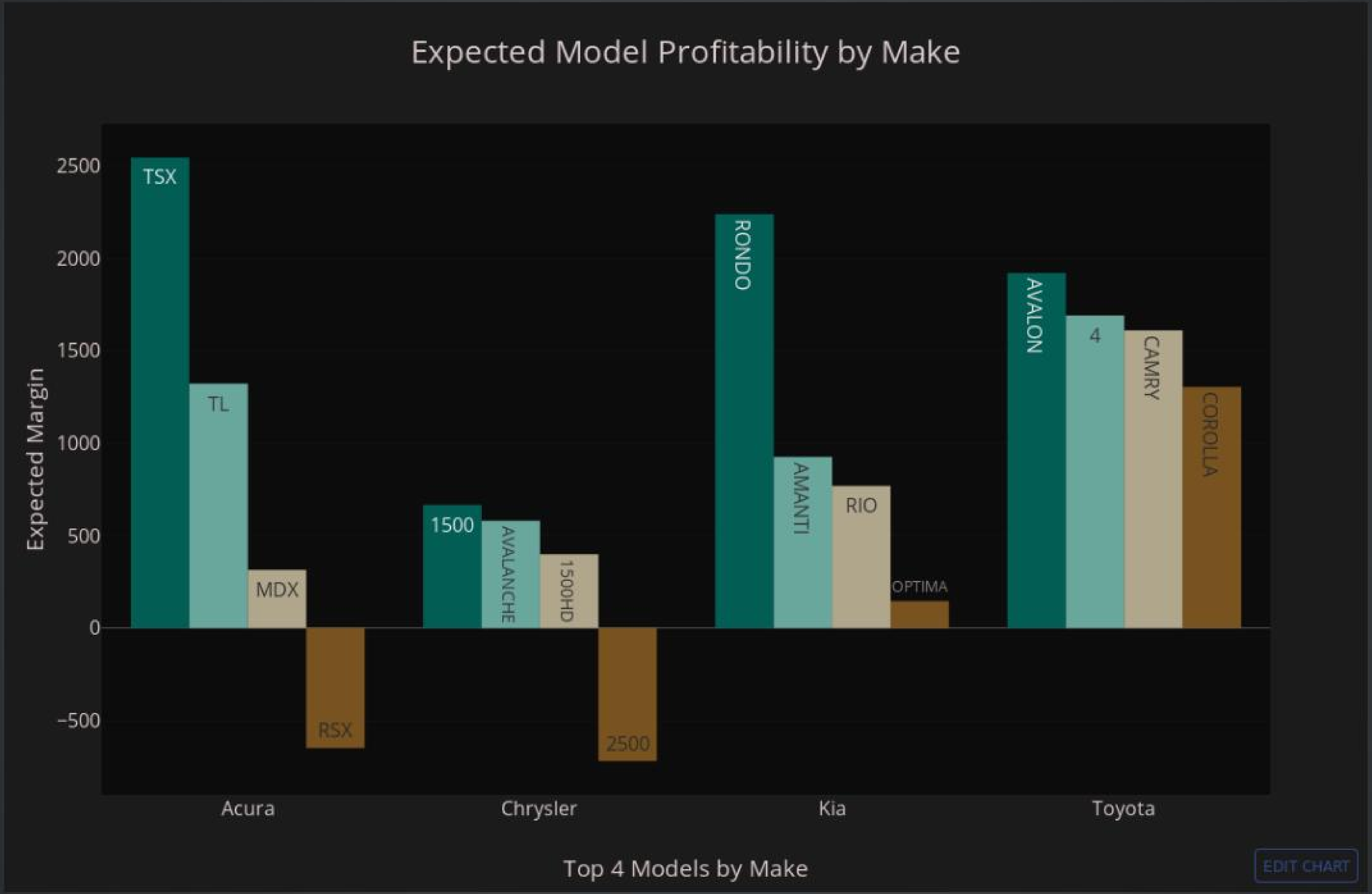


Expected Margin

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$$

'Average Price'

Average Price - Vehicle Cost = Expected Profit Margin



Expected Model Profitability by Make
Expected Margin
2500
2000
1500
1000
500
0
−500
TSX
TL
MDX
RSX
1500
AVALANCHE
1500HD
2500
RONDO
AMANTI
RIO
OPTIMA
AVALON
4
CAMRY
COROLLA
Acura
Chrysler
Kia
Toyota
Top 4 Models by Make
EDIT CHART

FEATURE ENGINEERING

Dealing with the categorical features

```
In [13]: characteristics = df[['Model','SubModel','Trim']]

In [14]: characteristics.head(10)
Out[14]:
                    Model              SubModel  Trim
0                  MAZDA3           4D SEDAN I     i
1  1500 RAM PICKUP 2WD    QUAD CAB 4.7L SLT     ST
2           STRATUS V6     4D SEDAN SXT FFV    SXT
3                   NEON             4D SEDAN    SXT
4                  FOCUS        2D COUPE ZX3    ZX3
5            GALANT 4C          4D SEDAN ES     ES
6              SPECTRA          4D SEDAN EX     EX
7               TAURUS          4D SEDAN SE     SE
8              SPECTRA          4D SEDAN EX     EX
9         FIVE HUNDRED         4D SEDAN SEL    SEL
```

```
df.PurchDate = pd.to_datetime(df.PurchDate)
```

pyear	pmonth	pday
2009	12	7
2009	12	7
2009	12	7
2009	12	7
2009	12	7

```
for col in cats:
    print(col,len(df[col].unique()))

Auction 3
Make 33
Model 1063
Trim 135
SubModel 864
Color 17
Transmission 4
WheelTypeID 5
Nationality 5
Size 13
TopThreeAmericanName 5
VNST 37
IsOnlineSale 2
IsBadBuy 2
```

FEATURE ENGINEERING

Dealing with the categorical features

'Model'

Before

```
In [16]: characteristics.Model.head(25)
Out[16]:
0                    MAZDA3
1        1500 RAM PICKUP 2WD
2                 STRATUS V6
3                       NEON
4                      FOCUS
5                  GALANT 4C
6                    SPECTRA
7                     TAURUS
8                    SPECTRA
9               FIVE HUNDRED
10     1500 SIERRA PICKUP 2
11       F150 PICKUP 2WD V6
12     CARAVAN GRAND FWD V6
13                    ALTIMA
14     CARAVAN GRAND FWD V6
15              CAVALIER 4C
16        TRAILBLAZER 2WD 6C
17               VUE 2WD 4C
18                    IMPALA
19          ENVOY XL 2WD 6C
20           VOYAGER FWD V6
21              MONTE CARLO
22           VENTURE FWD V6
23                       HHR
24                       HHR
Name: Model, dtype: object
```

After

```
In [18]: characteristics.Model.str.split().str[0].str.strip().head(25)
Out[18]:
0          MAZDA3
1            1500
2         STRATUS
3            NEON
4           FOCUS
5          GALANT
6         SPECTRA
7          TAURUS
8         SPECTRA
9            FIVE
10           1500
11           F150
12        CARAVAN
13         ALTIMA
14        CARAVAN
15       CAVALIER
16    TRAILBLAZER
17            VUE
18         IMPALA
19          ENVOY
20        VOYAGER
21          MONTE
22        VENTURE
23            HHR
24            HHR
Name: Model, dtype: object
```

This is a quick way to remove the additional information after the model name. However, some mix ups will occur. Such as makers having similar models like the Chevy and Dodge.The Sierra and Ram are both identified as 1500 and 'Monte Carlo' is truncated.

'Model' and 'SubModel'

Identify distinguishing features

```
In [13]: characteristics = df[['Model','SubModel','Trim']]

In [14]: characteristics.head(10)
Out[14]:
                Model             SubModel Trim
0             MAZDA3             4D SEDAN    i
1  1500 RAM PICKUP 2WD  QUAD CAB 4.7L SLT   ST
2         STRATUS V6     4D SEDAN SXT FFV  SXT
3               NEON             4D SEDAN  SXT
4              FOCUS         2D COUPE ZX3  ZX3
5         GALANT 4C          4D SEDAN ES   ES
6            SPECTRA          4D SEDAN EX   EX
7             TAURUS          4D SEDAN SE   SE
8            SPECTRA          4D SEDAN EX   EX
9       FIVE HUNDRED         4D SEDAN SEL  SEL
```

```
mod_chars = ['2WD','V6','4C','PICKUP','6C','FWD',
             '4WD','AWD','SFI','EFI','DOHC','I4','MPI']
```

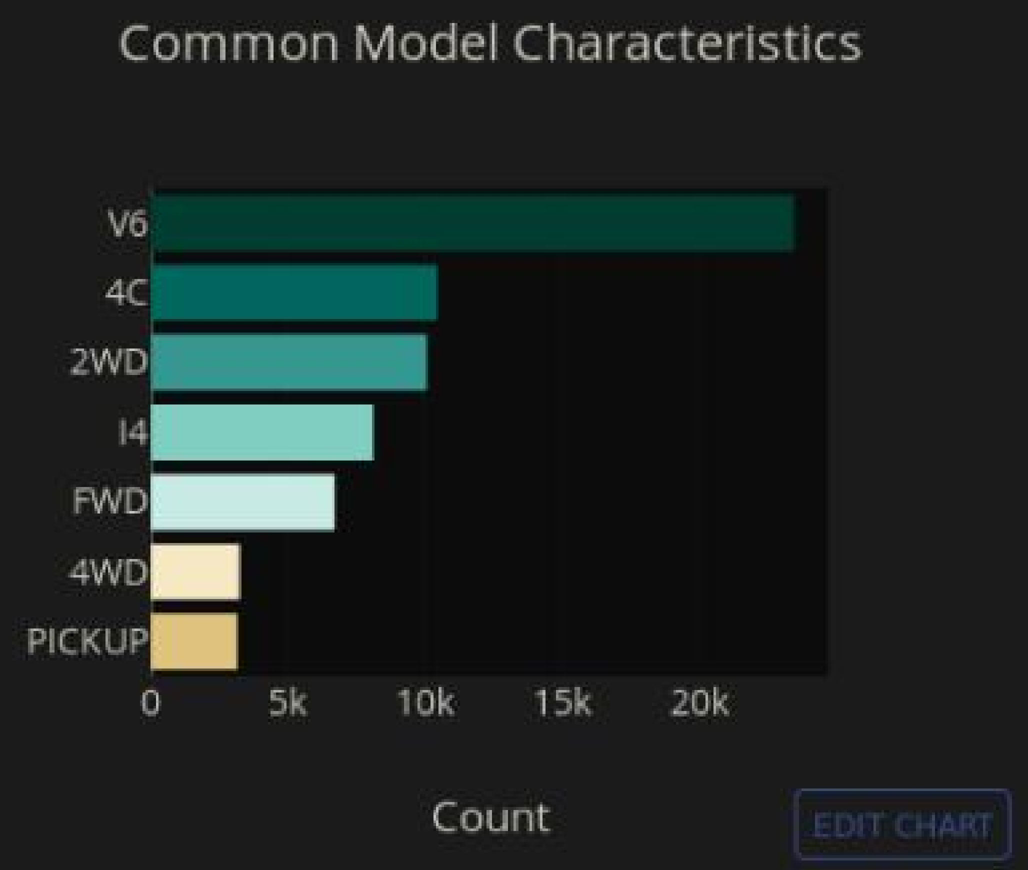
```
submod_chars = ['SEDAN','4D','EXT','CAB','2D','CAB','WAGON',
                'REG','FFV','PASSENGER','SUV','SPORT',
                'UTILITY','QUAD','COUPE','MINIVAN','CUV']
```

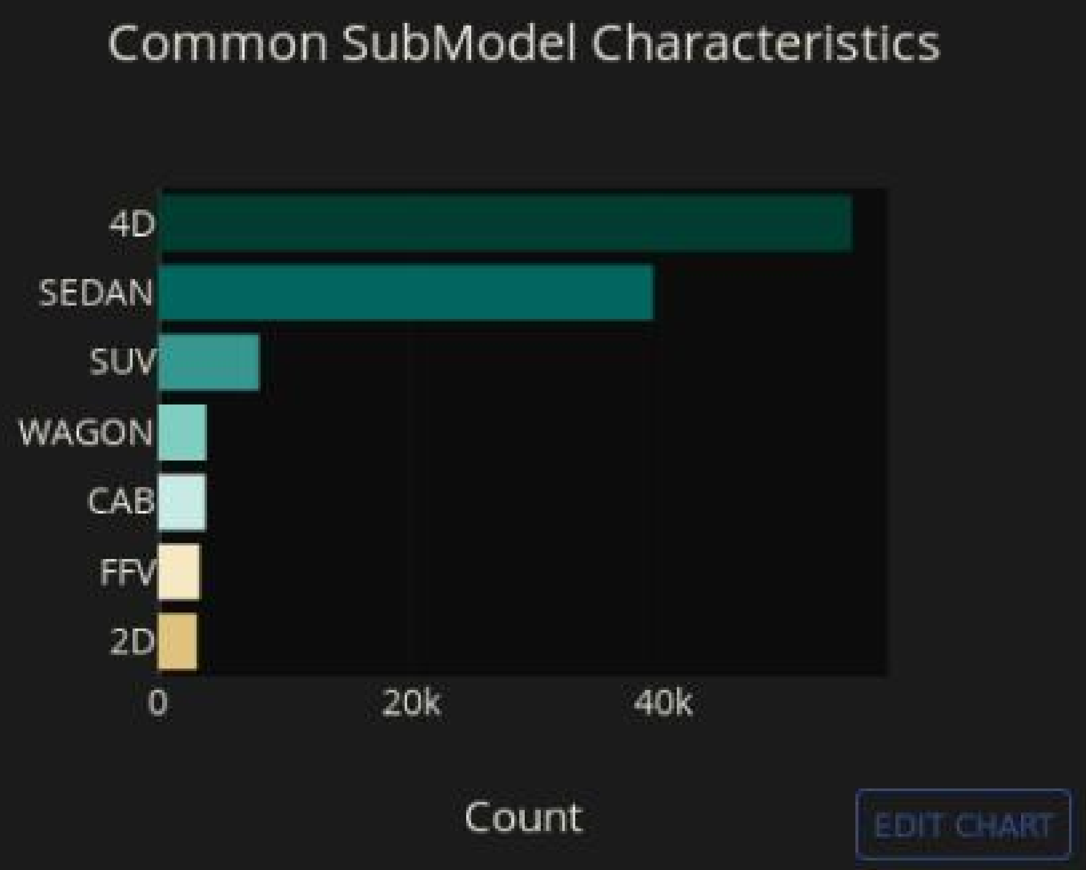
```
In [29]: mod_val_sets.head(10)
Out[29]:
   2WD  V6  4C  PICKUP  6C  FWD  4WD
0    0   0   0       0   0    0    0
1    1   0   0       1   0    0    0
2    0   1   0       0   0    0    0
3    0   0   0       0   0    0    0
4    0   0   0       0   0    0    0
5    0   0   1       0   0    0    0
6    0   0   0       0   0    0    0
7    0   0   0       0   0    0    0
8    0   0   0       0   0    0    0
9    0   0   0       0   0    0    0
```

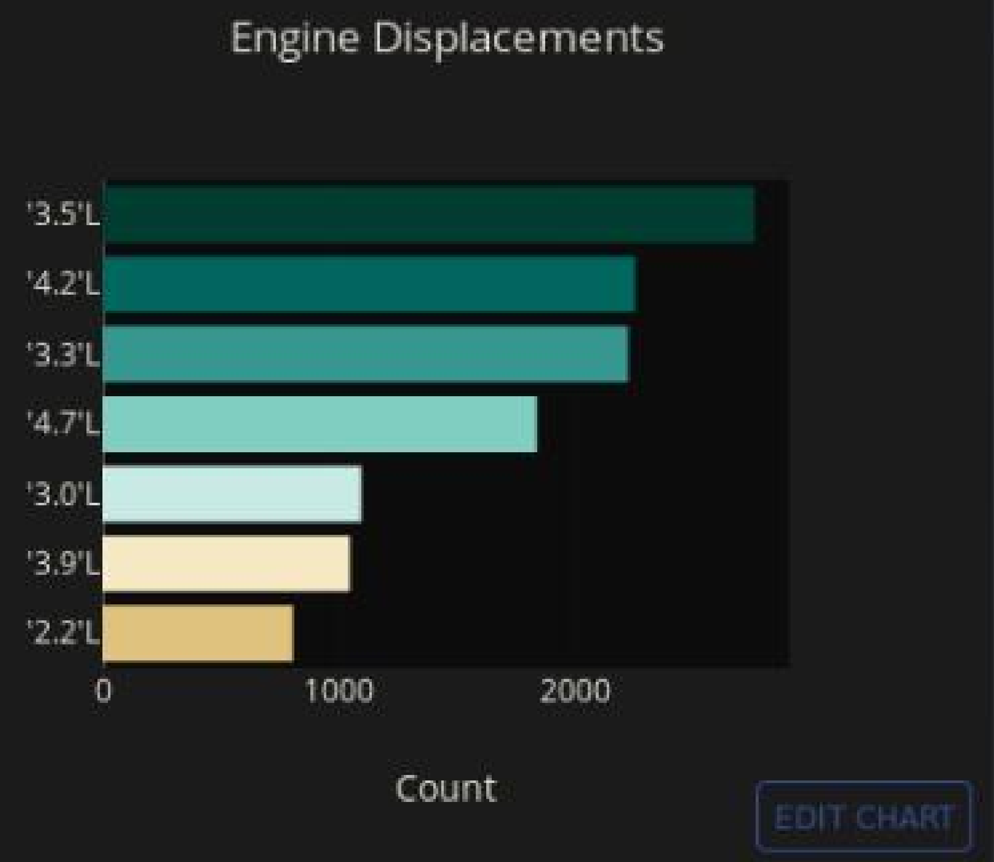
```
In [27]: sub_val_sets.head(10)
Out[27]:
   SEDAN  4D  EXT  CAB  2D  WAGON
0      1   1    0    0   0      0
1      0   0    0    1   0      0
2      1   1    0    0   0      0
3      1   1    0    0   0      0
4      0   0    0    0   1      0
5      1   1    0    0   0      0
6      1   1    0    0   0      0
7      1   1    0    0   0      0
8      1   1    0    0   0      0
9      1   1    0    0   0      0
```

```
In [42]: displacements[:10]
Out[42]: ['4.7', '4.3', '4.2', '3.3', '3.8', '4.2', '4.2', '3.3', '3.4', '2.2']
```

```
Total Number of Model Characteristic matches: 75219
Total Number of SubModel Charatistic matches: 134395
Total number of Displacement matches: 20247
```

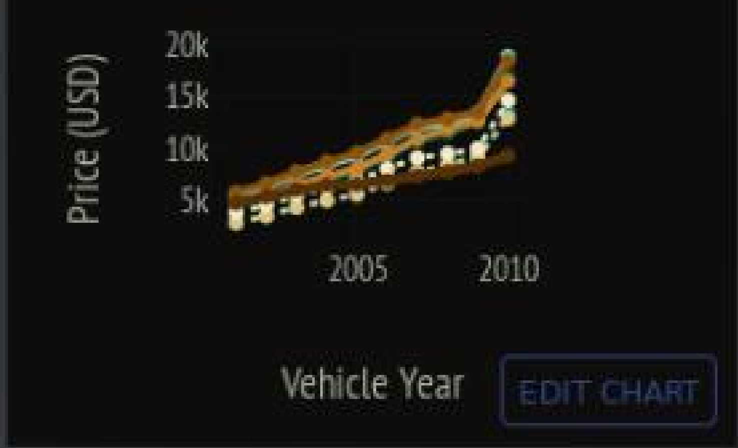






FEATURE ENGINEERING

```
plodf= df[['MMRAcquisitionAuctionAveragePrice', 'MMRAcquisitionAuctionCleanPrice',
 'MMRAcquisitionRetailAveragePrice', 'MMRAcquisitonRetailCleanPrice',
 'MMRCurrentAuctionAveragePrice', 'MMRCurrentAuctionCleanPrice',
 'MMRCurrentRetailAveragePrice', 'MMRCurrentRetailCleanPrice',
 'VehicleAge','VehOdo','WarrantyCost','IsBadBuy']].copy()
plodf.dropna(inplace=True)
```

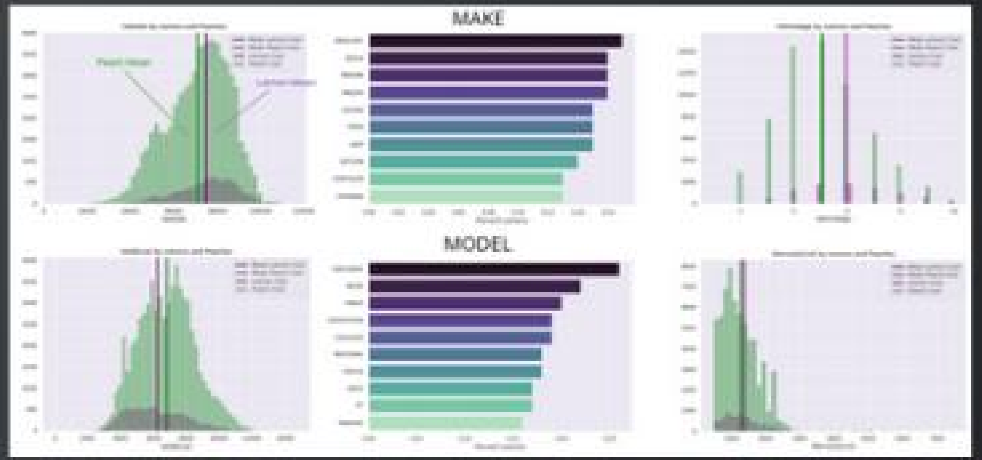


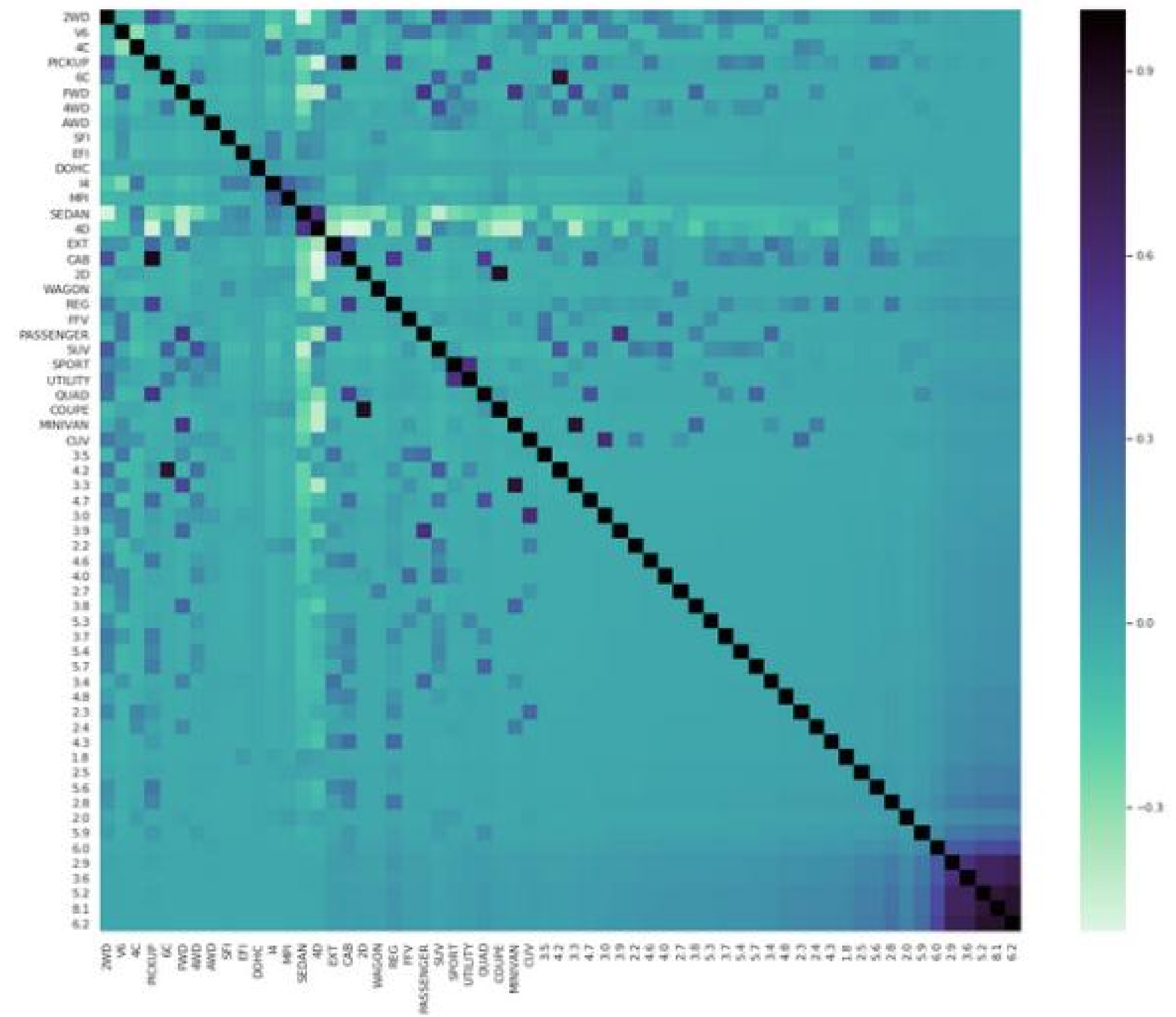

```
In [62]: list(plodf.columns[:20])
Out[62]:
['MMRAcquisitionAuctionAveragePrice',
 'MMRAcquisitionAuctionCleanPrice',
 'MMRAcquisitionRetailAveragePrice',
 'MMRAcquisitonRetailCleanPrice',
 'MMRCurrentAuctionAveragePrice',
 'MMRCurrentAuctionCleanPrice',
 'MMRCurrentRetailAveragePrice',
 'MMRCurrentRetailCleanPrice',
 'VehicleAge',
 'VehOdo',
 'WarrantyCost',
 'IsBadBuy',
 'crcp_cacp',
 'arcp_aacp',
 'crap_caap',
 'arap_aaap',
 'caap_aaap',
 'cacp_aacp',
 'crap_arap',
 'crcp_arcp']
```

```
In [63]: plodf.shape
Out[63]: (67275, 46)
```

```
In [70]: price_pvals.sort_values(by='pvalues')
Out[70]:
                                price       pvalues
8                          VehicleAge  0.000000e+00
11                           IsBadBuy  0.000000e+00
4       MMRCurrentAuctionAveragePrice  3.613714e-177
0   MMRAcquisitionAuctionAveragePrice  8.336208e-177
5         MMRCurrentAuctionCleanPrice  2.236708e-157
1     MMRAcquisitionAuctionCleanPrice  9.032533e-155
6        MMRCurrentRetailAveragePrice  2.946974e-146
7          MMRCurrentRetailCleanPrice  5.401022e-134
2    MMRAcquisitionRetailAveragePrice  2.777969e-114
9                              VehOdo  1.225459e-111
3       MMRAcquisitonRetailCleanPrice  5.123667e-104
10                       WarrantyCost  9.440349e-41
39                crap_caap_arap_aaap  3.615944e-19
24                          crcp_caap  1.769231e-17
38                crcp_cacp_arcp_aacp  1.293532e-16
40                crcp_caap_arcp_aaap  1.706332e-16
44                crcp_aacp_arcp_cacp  1.706332e-16
41                crap_cacp_arap_aacp  2.844209e-16
```

Very low p-values on t-tests for prices between lemons and non lemons





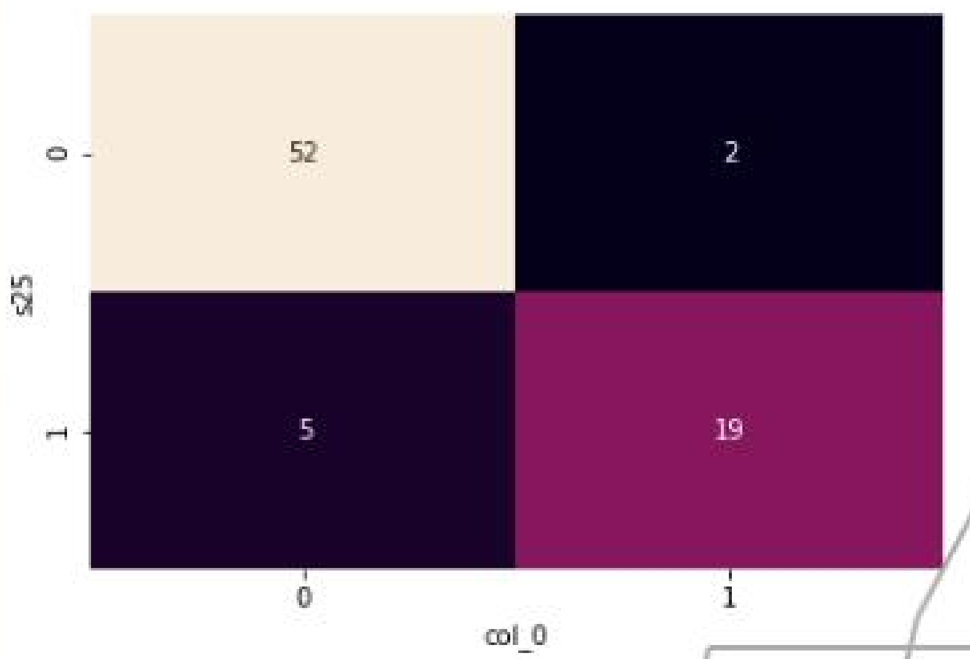
	level_0	level_1	0
199	PICKUP	CAB	0.911014
979	CAB	PICKUP	0.911014
1063	2D	COUPE	0.874932
1603	COUPE	2D	0.874932
3598	8.1	6.2	0.843254
3718	6.2	8.1	0.843254
3659	5.2	6.2	0.843254
3719	6.2	5.2	0.843254
274	6C	4.2	0.828402
1834	4.2	6C	0.828402
1678	MINIVAN	3.3	0.826839
1918	3.3	MINIVAN	0.826839
3597	8.1	5.2	0.799973
3657	5.2	8.1	0.799973

I dropped a few of the newly created features based on their correlation after reviewing how frequently each feature appeared in the data. e.g. 'CAB' has 3,916 occurrences while 'PICKUP' has 3,280.

Confusion Matrix

Metrics for Evaluating the Model

```
ROC_AUC score: 0.8773148148148148
 0,0 : Correctly Classified Negatives
 0,1 : False Positives (Type I Error)
 1,0 : False Negatives (Type II Error)
 1,1 : Correctly Classified Positives
```




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

          0       0.91      0.96      0.94        54
          1       0.90      0.79      0.84        24

avg / total       0.91      0.91      0.91        78
```

What percent of your predictions were correct?

You answer: the "accuracy" was (52+19) out of 78 = 91%

What percent of the positive cases did you catch?

You answer: the "recall" was 19 out of 24 = 79%

What percent of positive predictions were correct?

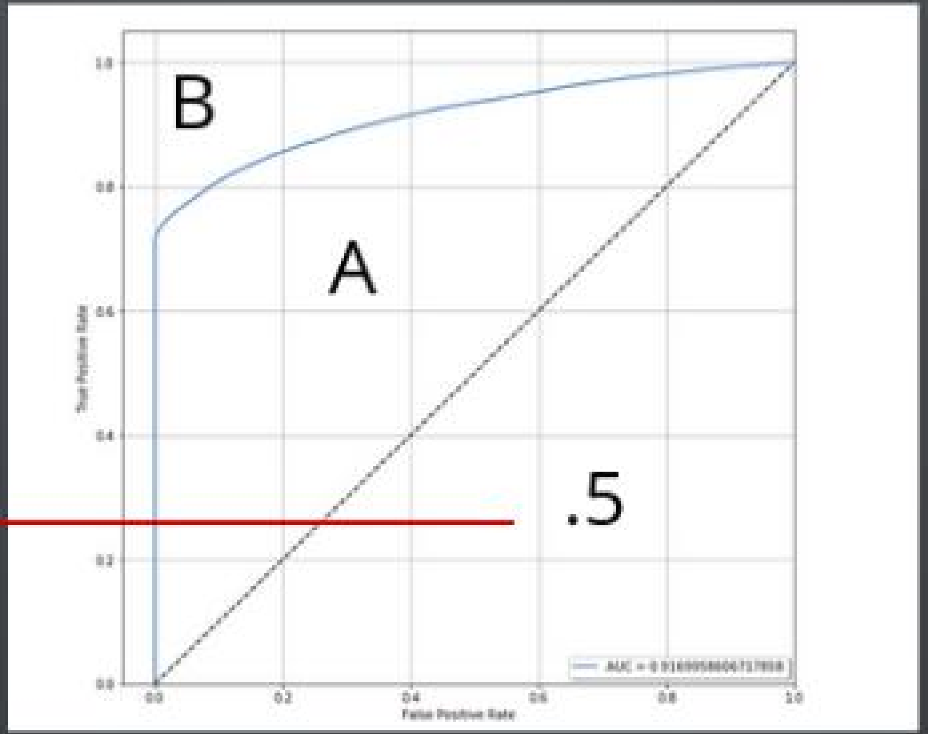
You answer: the "precision" was 19 out of 21 = 90%

A = $\boxed{.87}$ - $\boxed{.5}$ = .37

B = .5 - A = .13

G = .37/.5 ~ **.74**

ROC & AUC



Area under the curve (AUC)

.5 + A

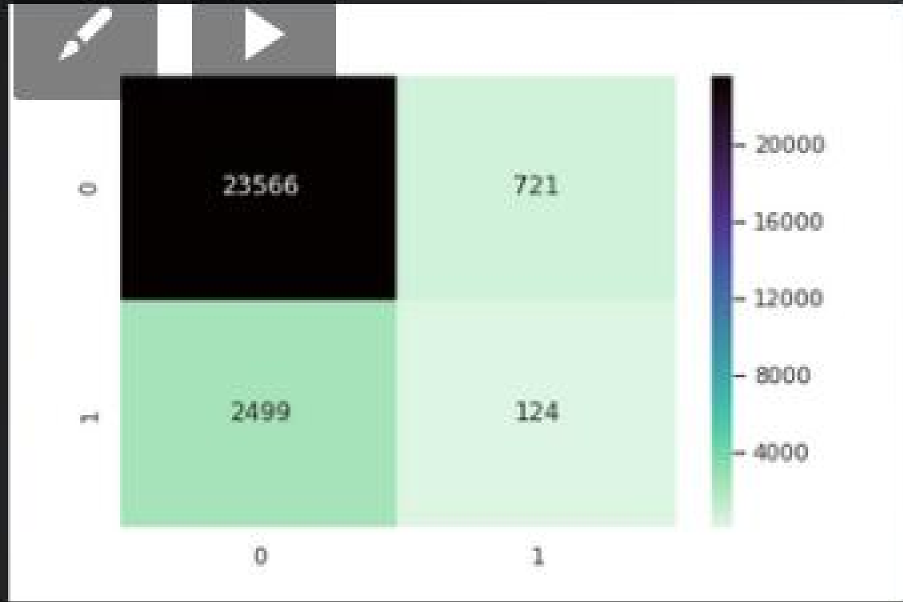
Gini Index

$$\frac{A}{A + B} = 2*A$$

PRELIMINARY MODEL

```
In [21]: mod_val_sets.shape,sub_val_sets.shape,disp_keys.shape,cont_df.shape
Out[21]: ((67275, 13), (67275, 16), (67275, 31), (67275, 3))

In [44]: model_df = pd.concat([df,add_feats],axis=1)

In [45]: model_df.drop(['SubModel'],1,inplace=True)
    ...: model_df.Model = model_df.Model.str.split().str[0].str.strip()
    ...:
    ...:

In [46]: model_df = pd.get_dummies(model_df)

In [47]: model_df.shape
Out[47]: (67275, 534)
```

KNN Classifier

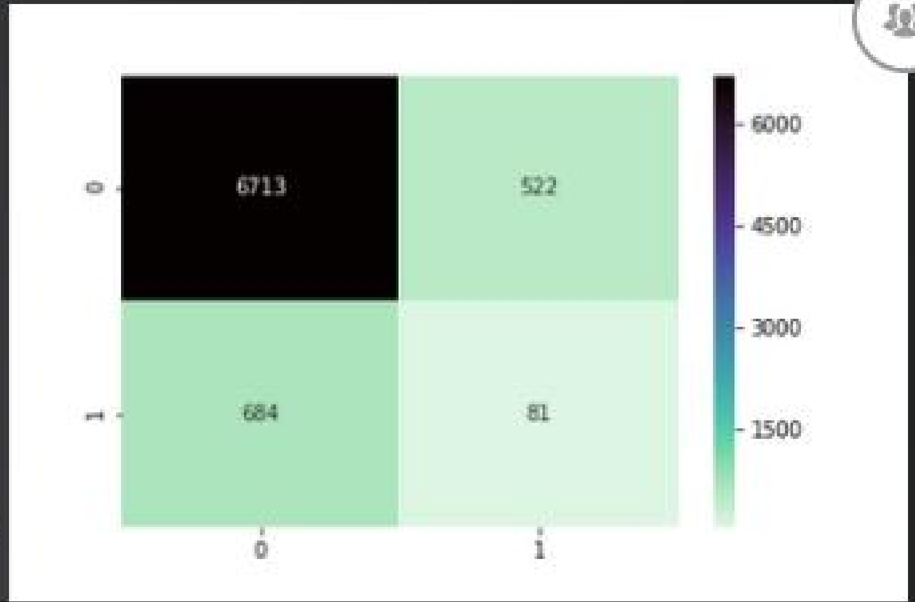


Classification Report: KNN k=4

	precision	recall	f1-score	support
0	0.91	0.97	0.94	24305
1	0.17	0.06	0.09	2605
micro avg	0.88	0.88	0.88	26910
macro avg	0.54	0.51	0.51	26910
weighted avg	0.83	0.88	0.85	26910

ROC_AUC SCORE: 0.51

SVC



Classification Report: SVC (rbf)

	precision	recall	f1-score	support
0	0.91	0.93	0.92	7235
1	0.13	0.11	0.12	765
micro avg	0.85	0.85	0.85	8000
macro avg	0.52	0.52	0.52	8000
weighted avg	0.83	0.85	0.84	8000

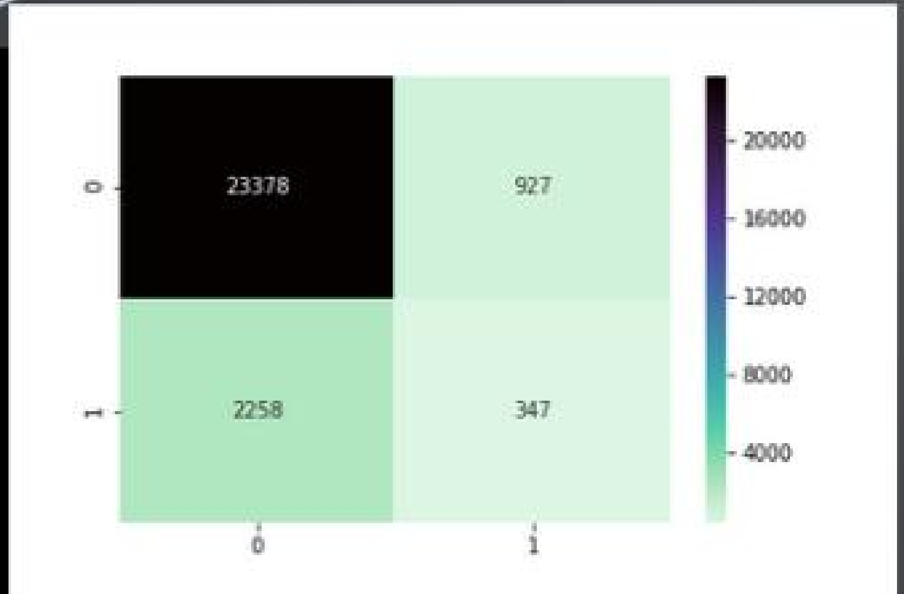
ROC_AUC SCORE: 0.52

Logistic Regression (lasso)

Classification Report: LRC (l1)

	precision	recall	f1-score	support
0	0.91	0.96	0.94	24305
1	0.27	0.13	0.18	2605
micro avg	0.88	0.88	0.88	26910
macro avg	0.59	0.55	0.56	26910
weighted avg	0.85	0.88	0.86	26910

ROC_AUC SCORE: 0.55

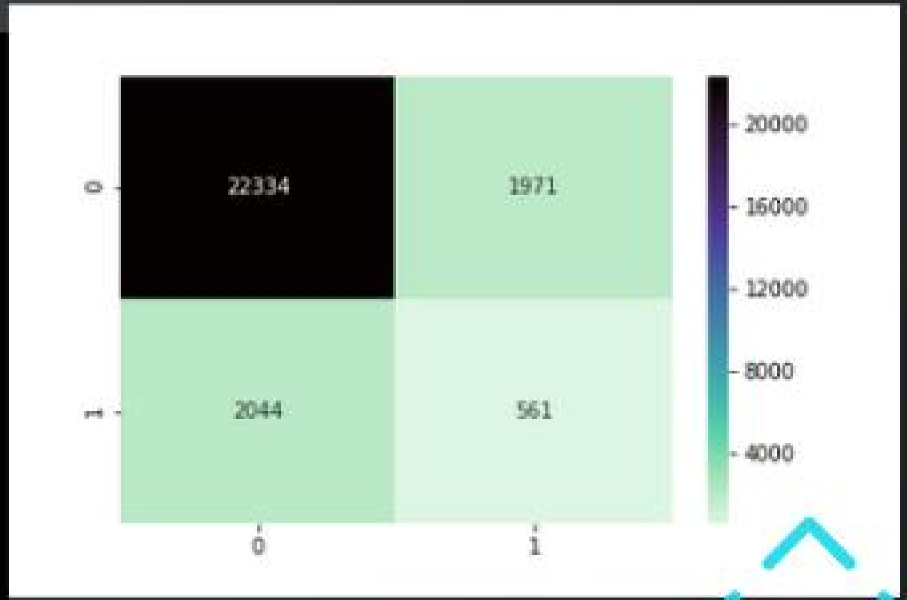


Random Forest

Classification Report: Random Forest

	precision	recall	f1-score	support
0	0.92	0.91	0.91	24305
1	0.22	0.23	0.22	2605
micro avg	0.85	0.85	0.85	26910
macro avg	0.57	0.57	0.57	26910
weighted avg	0.85	0.85	0.85	26910

ROC_AUC SCORE: 0.57



Yikes!

Why are the scores so low?

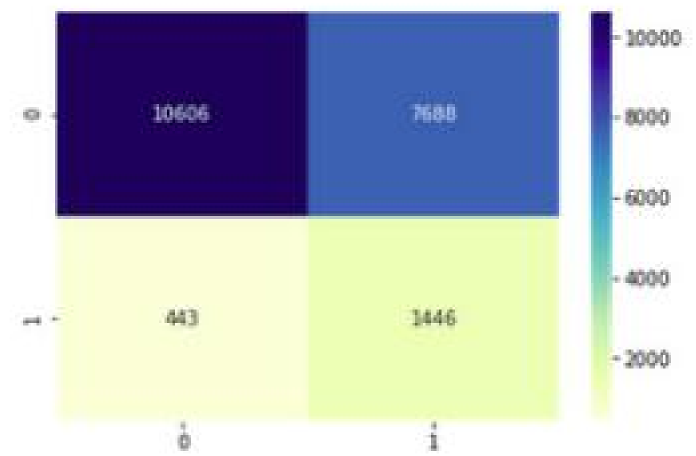
ROC_AUC SCORE: 0.52
ROC_AUC SCORE: 0.57
ROC_AUC SCORE: 0.55
ROC_AUC SCORE: 0.51

Whats going on?

What can we do about this?

FEATURE SELECTION & SMOTE

```
Classification Report: RFC with Tuned Parameters
              precision    recall  f1-score   support

           0       0.96      0.58      0.72     18294
           1       0.16      0.77      0.26      1889

   micro avg       0.60      0.60      0.60     20183
   macro avg       0.56      0.67      0.49     20183
weighted avg       0.88      0.60      0.68     20183

ROC_AUC SCORE: 0.67
```




```
sig_feats = feature_sigs[feature_sigs[0]>0][1]
len(sig_feats)
```

245

	Feature	Significance
0	VehicleAge	0.0442
1	TopThreeAmericanName_GM	0.0428
2	Auction_MANHEIM	0.0361
3	pyear	0.0352
4	WheelTypeID	0.0352
5	TopThreeAmericanName_CHRYSLER	0.0349
6	Make_CHEVROLET	0.0334
7	V6	0.0278
8	SEDAN	0.0264
9	Size_MEDIUM	0.0241

```
new_model = pd.get_dummies(model_df)
new_model = new_model[sig_feats]
```

Keep significant features from Random Forest Classifier.

Use SMOTE to mitigate the class imbalance in the outcome variable

Oversampling and Undersampling

Lemons Before

```
print(model_df.IsBadBuy.describe())
```

```
count    67275.000000
mean         0.095637
std          0.294095
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          1.000000
Name: IsBadBuy, dtype: float64
```

Lemons After

```
print(resampled_y.describe())
```

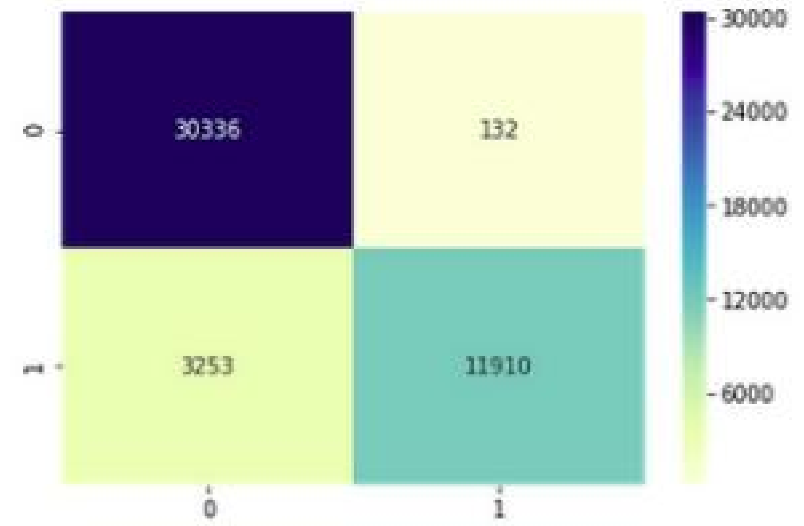
```
count    103429.000000
mean          0.411761
std           0.492155
min           0.000000
25%           0.000000
50%           0.000000
75%           1.000000
max           1.000000
dtype: float64
```

#1. Gradient Bootsting

Classification Report: Gradient Boosting

	precision	recall	f1-score	support
0	0.90	1.00	0.95	30468
1	0.99	0.79	0.88	15163
micro avg	0.93	0.93	0.93	45631
macro avg	0.95	0.89	0.91	45631
weighted avg	0.93	0.93	0.92	45631

ROC_AUC SCORE: 0.89



After eliminating some features and performing SMOTE on the data, the results improved dramatically.

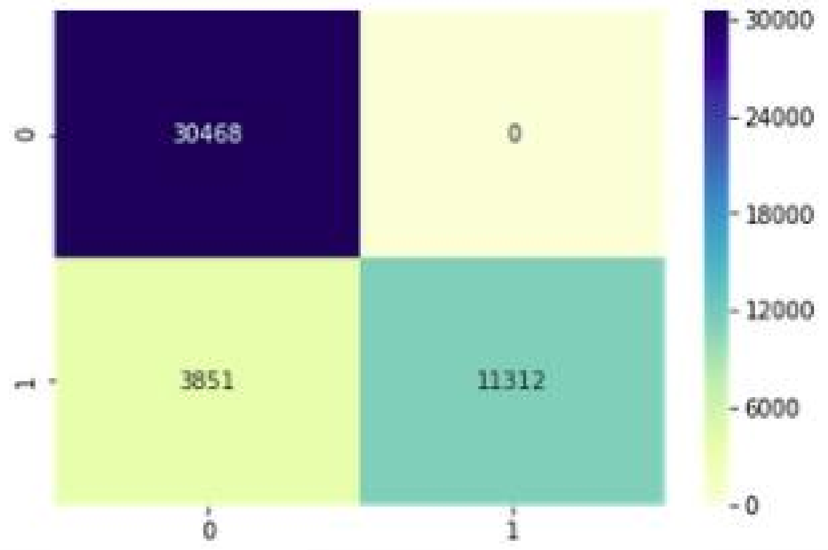
But how would this model do if it was given new, imbalanced information?

2. Random Forest

Classification Report: Optimized Random Forest

	precision	recall	f1-score	support
0	0.89	1.00	0.94	30468
1	1.00	0.75	0.85	15163
micro avg	0.92	0.92	0.92	45631
macro avg	0.94	0.87	0.90	45631
weighted avg	0.93	0.92	0.91	45631

ROC_AUC SCORE: 0.87

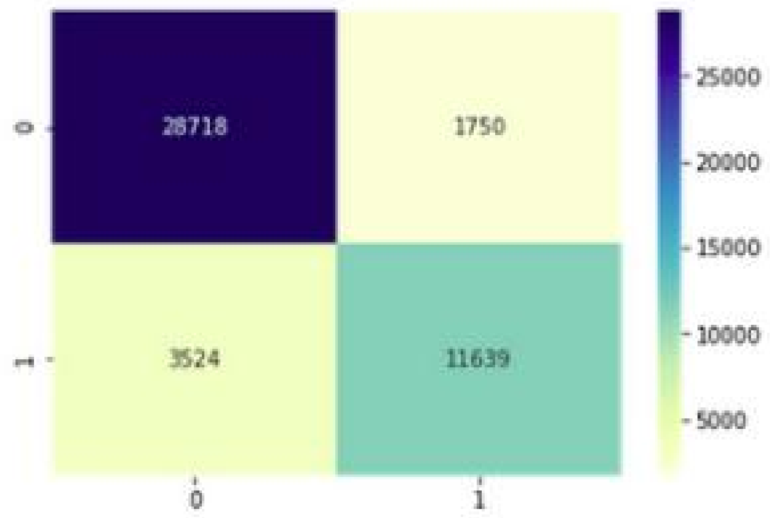


#3. Logistic Regression (lasso)

Classification Report: LRC (l1)

	precision	recall	f1-score	support
0	0.89	0.94	0.92	30468
1	0.87	0.77	0.82	15163
micro avg	0.88	0.88	0.88	45631
macro avg	0.88	0.86	0.87	45631
weighted avg	0.88	0.88	0.88	45631

ROC_AUC SCORE: 0.86



Original Data

Training Set

SMOTE Data Here

Train Model Here

SMOTE Training Set

SMOTE Testing Set

Test Set

Gini

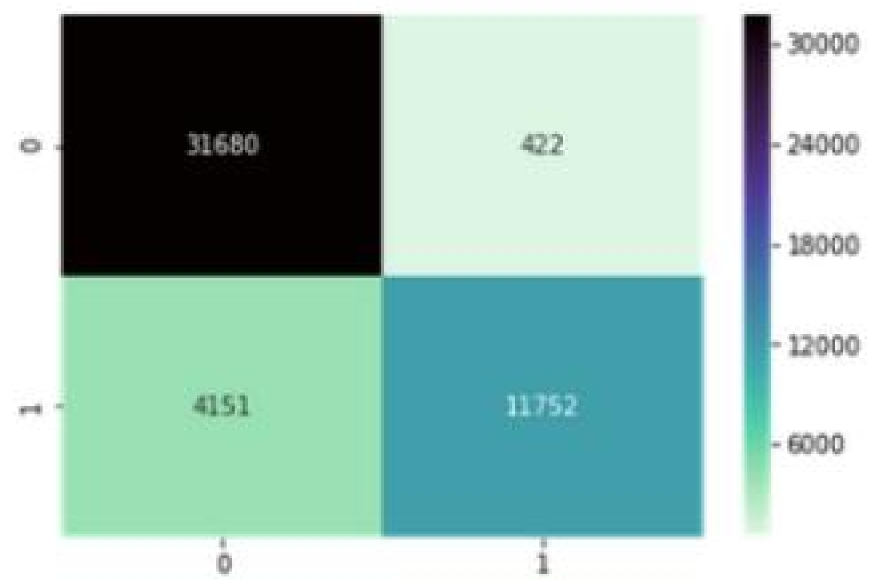
Top Kaggle Entries

Team Members	Score	Entries	Last
	0.27038	210	7y
	0.26929	119	7y
	0.26905	120	7y
	0.26884	57	7y

Classification Report: RFC

	precision	recall	f1-score	support
0	0.88	0.99	0.93	32102
1	0.97	0.74	0.84	15903
micro avg	0.90	0.90	0.90	48005
macro avg	0.92	0.86	0.88	48005
weighted avg	0.91	0.90	0.90	48005

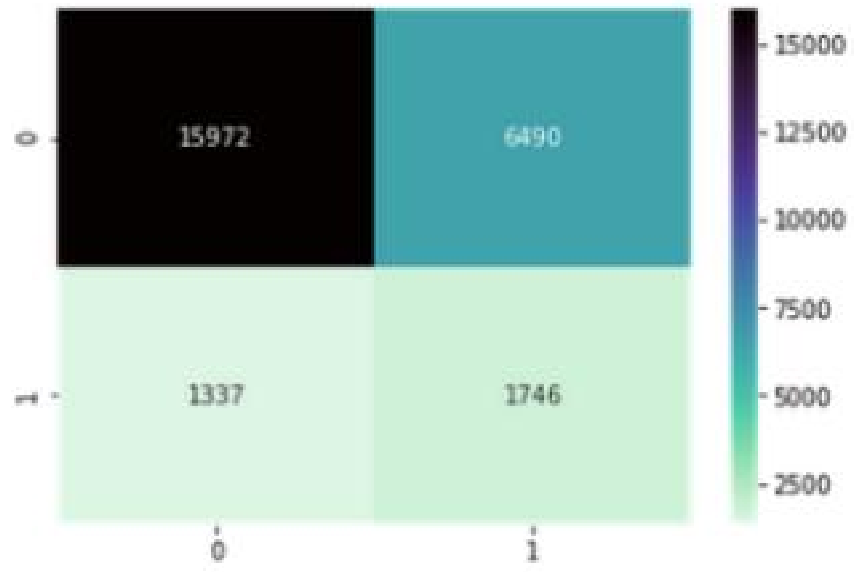
ROC_AUC SCORE: 0.86
Gini Index:0.7239



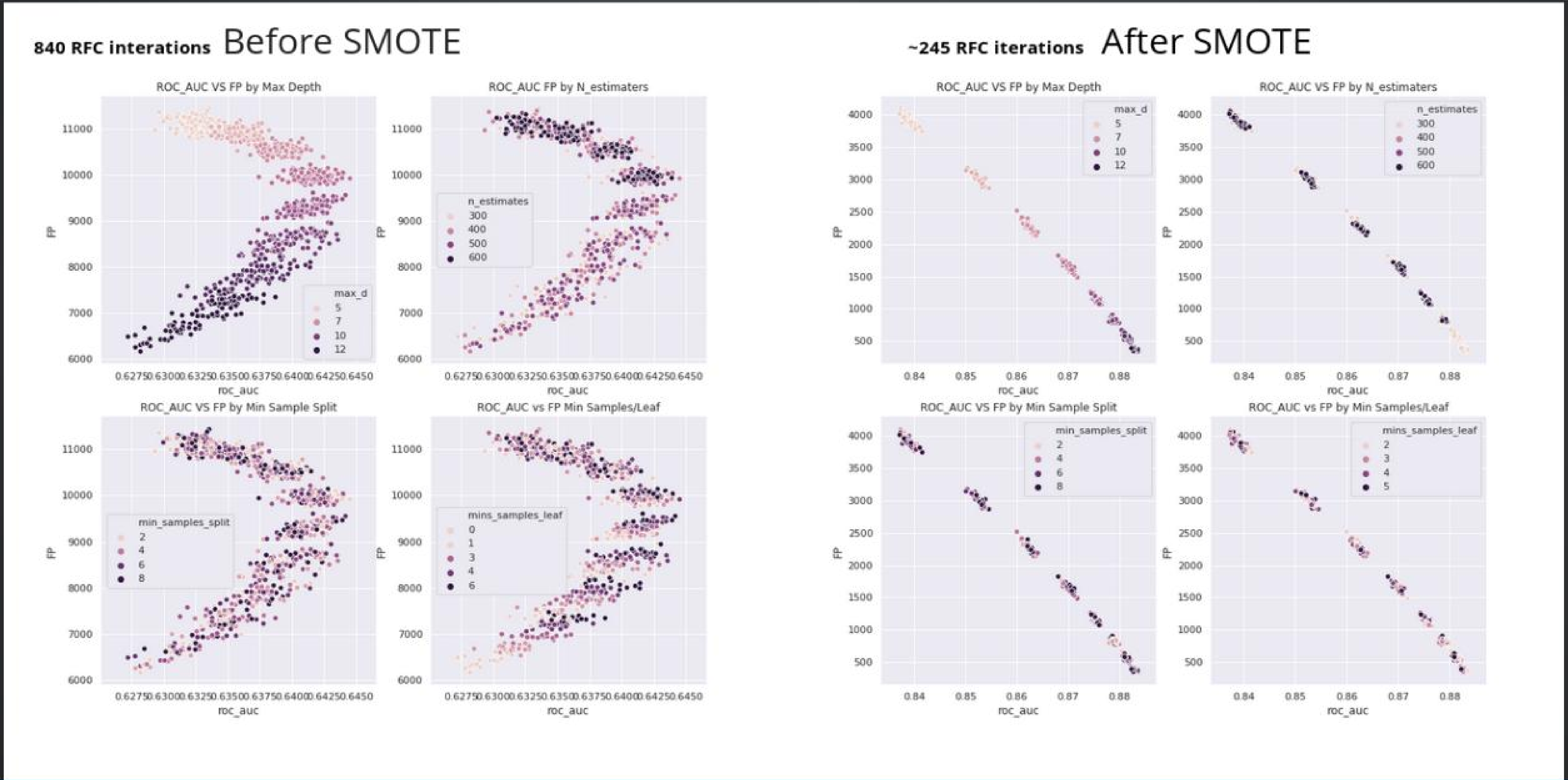
Classification Report: RFC

	precision	recall	f1-score	support
0	0.92	0.71	0.80	22462
1	0.21	0.57	0.31	3083
micro avg	0.69	0.69	0.69	25545
macro avg	0.57	0.64	0.56	25545
weighted avg	0.84	0.69	0.74	25545

ROC_AUC SCORE: 0.64
Gini Index:0.2802



SMOTE &HYPERPARAMETERS



Conclusion

The model performed extremely well after performing SMOTE on the data.

However, the complexity of the model became apparent after an average score of 76% in a 5-CV cross validation. (recall-macro)

The idea of the model being too complex is further supported by the scores from the leader board on Kaggle.

While the gap in information symmetry may never fully be bridged, this model shows that it is capable of helping car dealers avoid lemons...

But at what cost?

Next Steps

1. Continue to reduce attributes in order to reduce the complexity of the model.
2. Increase Gini index by tuning hyperparameters
3. Subscribe to carfax and use the incident reports to add information to dataset.

Industry Application

Through exploratory analysis it is possible to attempt to maximize the profitability of the inventory.

Using a chosen inventory goal, the model could used to avoid a fair amount of lemons and minimizing the opportunity cost.

Sources

Lemons - Definition

The Market for Lemons

The Data

kdnuggets

Lemon laws

This publication is for non-commercial educational purposes.

Code:
https://github.com/ExtraLime/lemons

Host
https://slides.com/will-m/lemons/

Will Morgan Nov 2, 2018
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