Vehicle Price Prediction

Regression Model

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Introduction to the Dataset

For this project, I have chosen a dataset of sold vehicles in the last 12 months from a local car dealership. The dataset contains 2174 sold vehicles, each with several feature types, including; float, integer, and categorical. A regression model would be built to estimate a vehicle's sale price. This model can assist the dealership properly price their vehicles in active inventory.

Features in the data as follows;

Red/Black - Number of vehicles not appraised or booked out through the software

Carfax Has Report - vehicle has a carfax report generated

Carfax Has Manufacturer Recall - indicates if there is an OEM recall on the vehicle

Carfax Has Warnings - There is an alert on the vehicle report

Carfax Has Problems - vehicle has had major issues reported

Photos - vehicle has marketing photos

Year - Model year of the vehicle

Continued..

Vehicle - Model and trim/series of the vehicle

VIN - Vehicle identification number

Class - Vehicle body classification

Class_type - subcategories of the vehicle class

Certified - certified pre-owned vehicle

Deleted Date - sold date of vehicle

Status - if the vehicle was added via an appraisal or through the Dealer Management System

Recall Status - if the vehicle has an open or closed recall

Age - Vehicle Days in inventory

Body - number of vehicle doors and class

Color - vehicle color

Disp - Vehicle disposition

Price - Price vehicle was sold for

Book - vehicle book value depending on price guide selected

Cost - amount dealership paid for the vehicle

Odometer - the odometer reading when vehicle was sold

Overall - available supply of similarly configured vehicles

Like Mine - Days to sell vehicles like mine based on the market

First, lets load the dataset

In [260]:
```
excel_file = 'Deleted_report.xls'
data_original = pd.read_excel(excel_file)
data = pd.read_excel(excel_file)
data.head()
```

Out[260]:

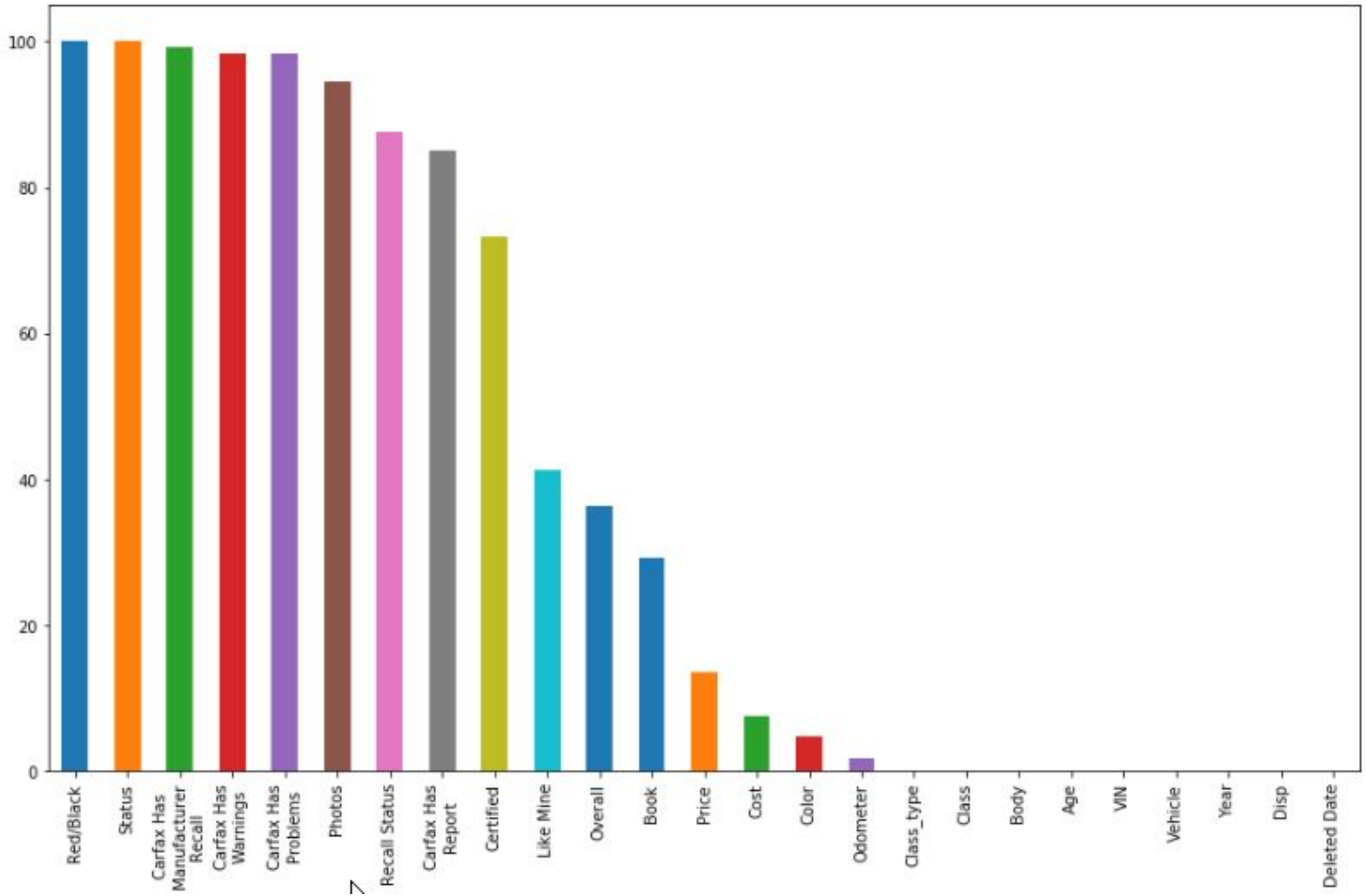
	Red/Black	Carfax Has Report	Carfax Has Manufacturer Recall	Carfax Has Warnings	Carfax Has Problems	Photos	Year	Vehicle	VIN	Class	...	Age	Body	Color	Disp	Pri
0	NaN	NaN	NaN	NaN	NaN	NaN	2018	Mercedes-Benz GLS 450 4MATIC®	4JGDF6EE8JB069995	SUV	...	1	4D Sport Utility	Obsidian Black	Retail	76164
1	NaN	Yes	NaN	NaN	NaN	NaN	2015	Mercedes-Benz C-Class C 300 4MATIC®	55SWF4KB3FU048731	Car	...	1	4D Sedan	Polar White	Retail	Na
2	NaN	NaN	NaN	NaN	NaN	NaN	2018	Mercedes-Benz S-Class S 450 4MATIC®	WDDUG6EB9JA374697	Car	...	1	4D Sedan	Gray Metallic	Retail	11614
								Mercedes-								

We took a look at the data types and the number of non-null values

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2174 entries, 0 to 2173
Data columns (total 25 columns):
Red/Black                        0 non-null float64
Carfax Has
Report                 326 non-null object
Carfax Has
Manufacturer
Recall    17 non-null object
Carfax Has
Warnings               36 non-null object
Carfax Has
Problems               36 non-null object
Photos                           120 non-null float64
Year                             2174 non-null int64
Vehicle                          2174 non-null object
VIN                              2174 non-null object
Class                            2171 non-null object
Class_type                       2171 non-null object
Certified                        582 non-null object
Deleted Date                     2174 non-null datetime64[ns]
Status                           0 non-null float64
Recall Status                    267 non-null object
Age                              2174 non-null int64
Body                             2173 non-null object
Color                            2068 non-null object
Disp                             2174 non-null object
Price                            1879 non-null float64
Book                             1536 non-null float64
Cost                             2009 non-null float64
Odometer                         2136 non-null float64
Overall                          1385 non-null float64
Like Mine                        1275 non-null float64
dtypes: datetime64[ns](1), float64(9), int64(2), object(13)
memory usage: 424.7+ KB
```

Visualization of the null values



About 9 columns are missing around 50% of their values. Some of the columns have features that allow the dealership manage their inventory against other dealerships in the area and therefore is not correlated with pricing the vehicle.

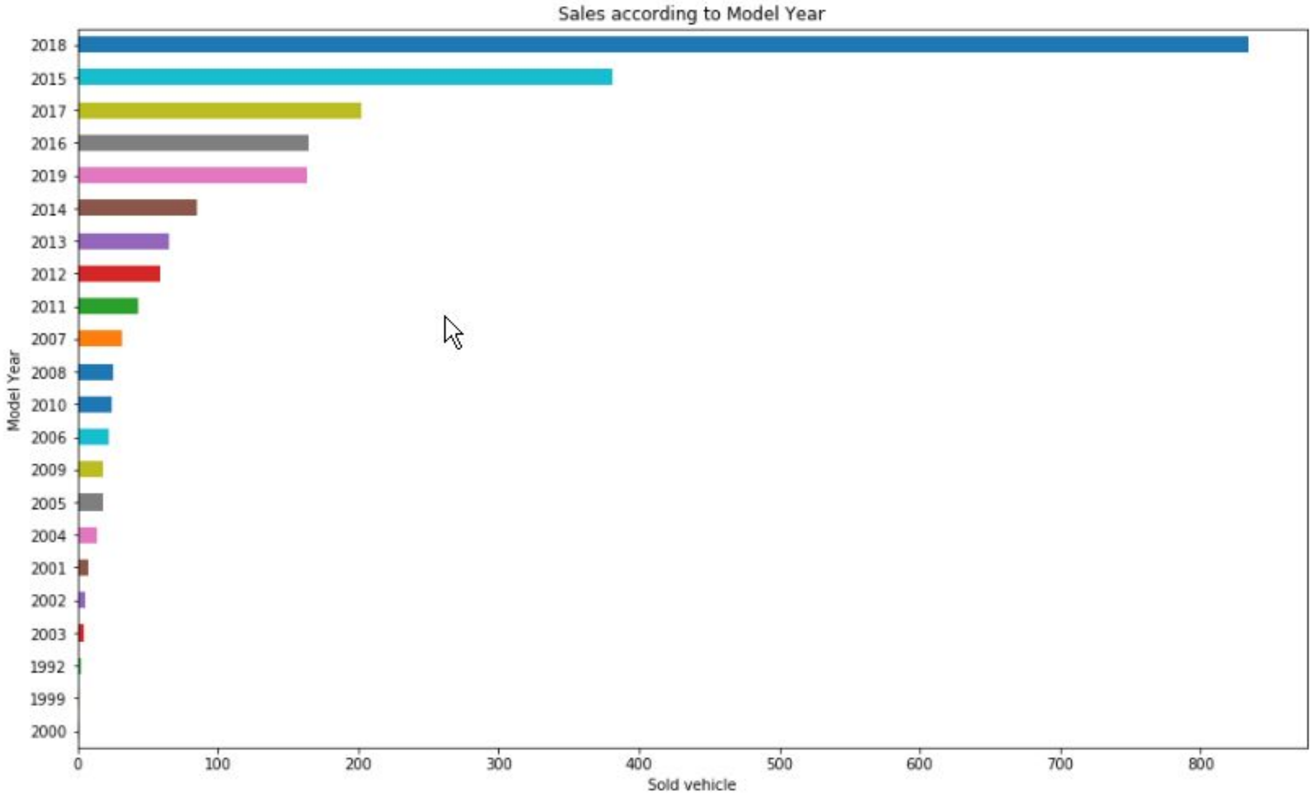
Red/Black
Status
Carfax Has Manufacturer Recall
Carfax Has Warnings
Carfax Has Problems
Photos
Recall Status
Carfax Has Report
Certified

Lets pull some statistics on the dataset...

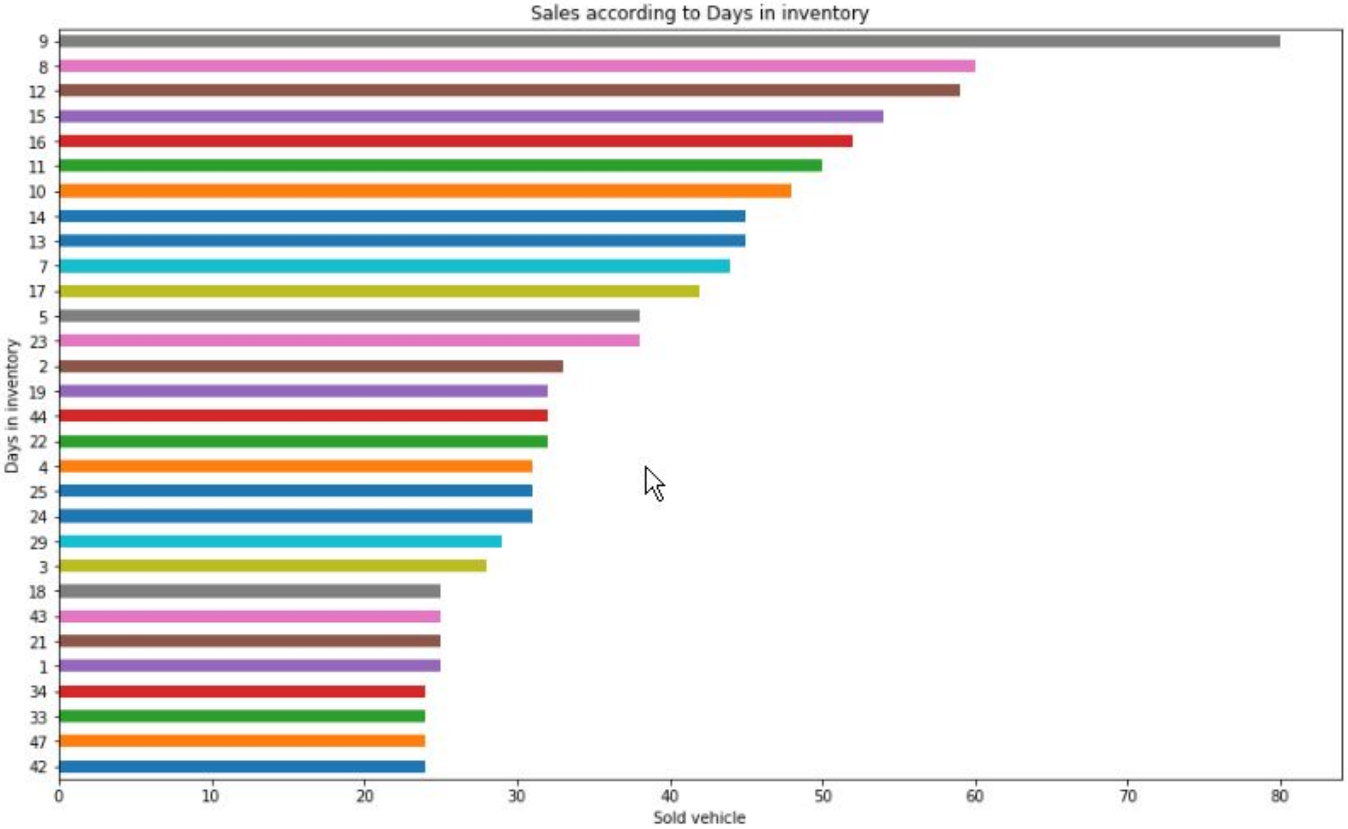
```
data.describe()
```

	Red/Black	Photos	Year	Status	Age	Price	Book	Cost	Odometer	Overall	Like Mine
count	0.0	120.000000	2174.000000	0.0	2174.000000	1879.000000	1536.000000	2009.000000	2136.000000	1385.000000	1275.000000
mean	NaN	37.741667	2015.756670	NaN	44.999540	47652.657265	29401.794271	41691.962668	25193.669944	75.168231	75.105882
std	NaN	1.803339	3.463057	NaN	48.331703	21481.115158	17054.939781	23689.764625	37088.196311	30.386715	44.660614
min	NaN	33.000000	1992.000000	NaN	1.000000	1302.000000	332.000000	-775.000000	3.000000	16.000000	16.000000
25%	NaN	37.000000	2015.000000	NaN	13.000000	32829.000000	19020.500000	27620.000000	13.000000	55.000000	47.000000
50%	NaN	38.000000	2017.000000	NaN	30.000000	44995.000000	28055.000000	42340.000000	6767.500000	70.000000	65.000000
75%	NaN	39.000000	2018.000000	NaN	60.000000	57603.000000	38835.000000	54578.000000	36021.750000	87.000000	90.000000
max	NaN	42.000000	2019.000000	NaN	503.000000	203000.000000	118469.000000	205250.000000	263738.000000	330.000000	653.000000

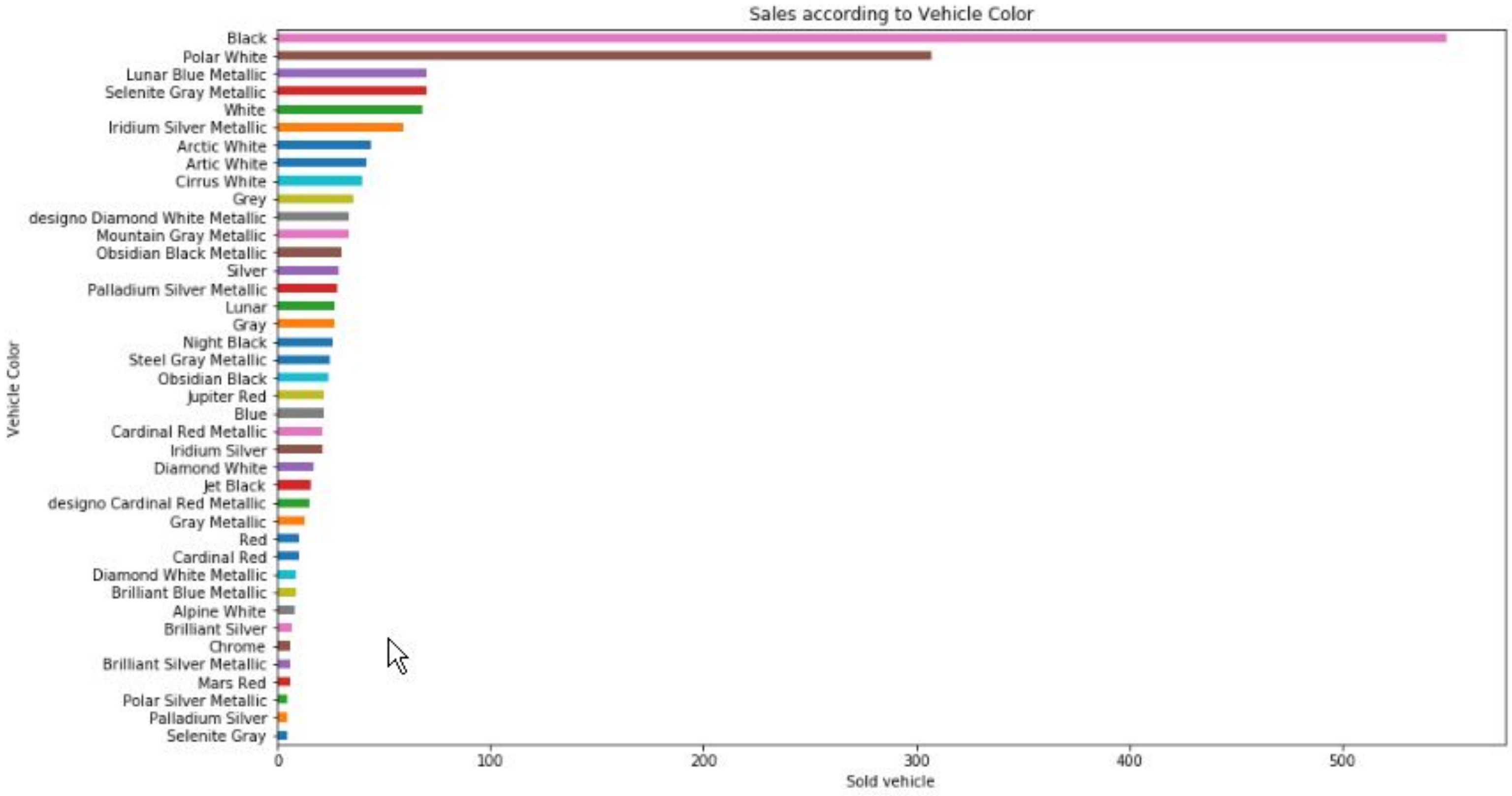
```python
data['Year'].value_counts().head(25).sort_values().plot(kind='barh', figsize=(15, 9))

plt.title('Sales according to Model Year')
plt.ylabel('Model Year')
plt.xlabel('Sold vehicle')
plt.show()
```



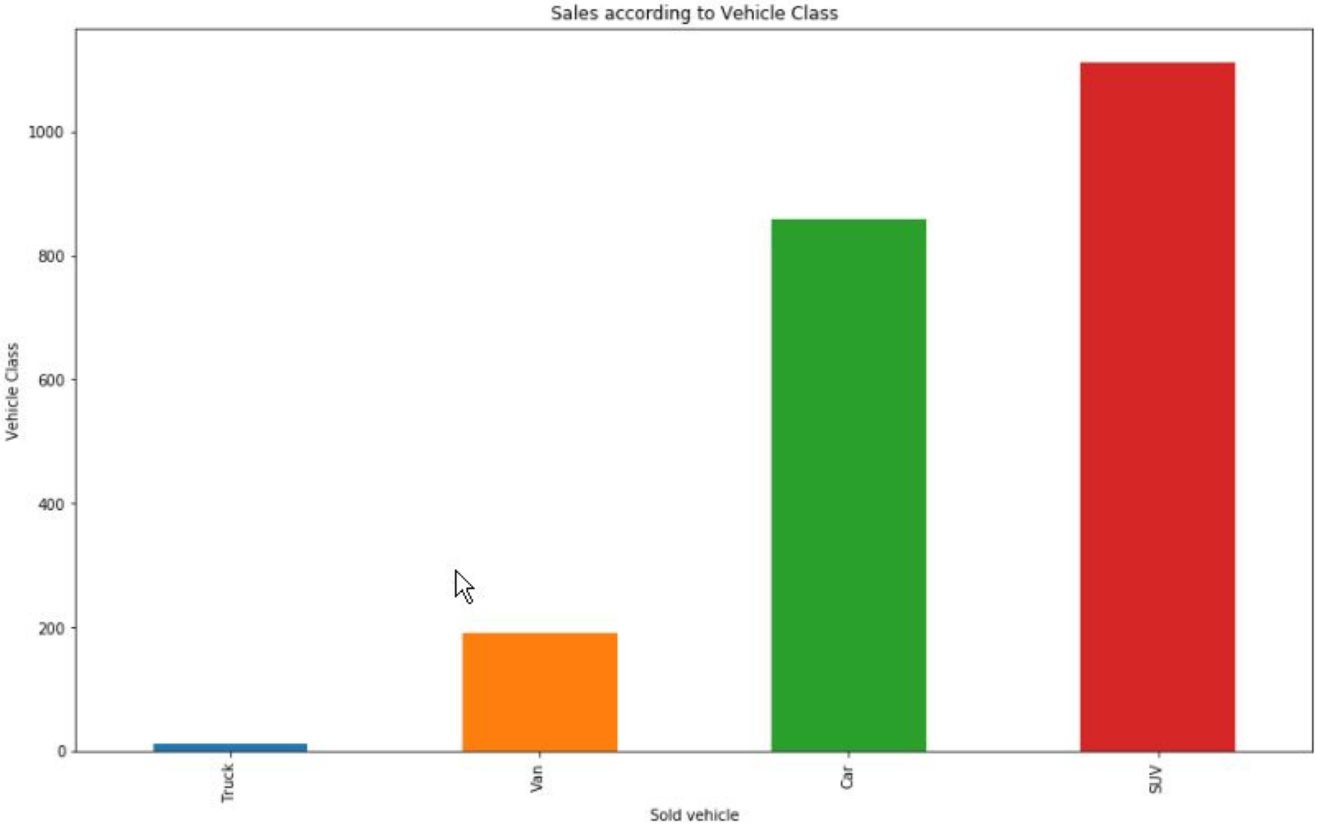
```
data['Age'].value_counts().head(30).sort_values().plot(kind='barh', figsize=(15, 9))
plt.title('Sales according to Days in inventory')
plt.ylabel('Days in inventory')
plt.xlabel('Sold vehicle')
plt.show()
```



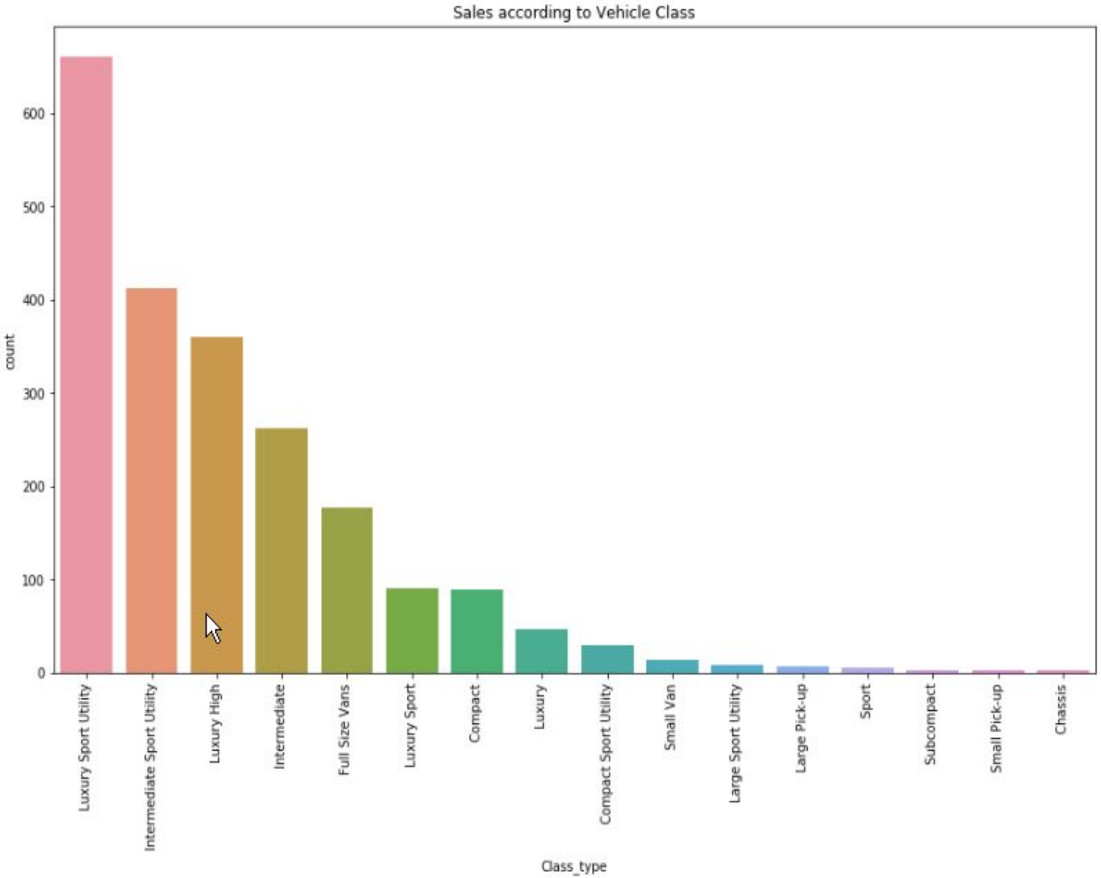
```
data['Color'].value_counts().head(40).sort_values().plot(kind='barh', figsize=(15, 9))
plt.title('Sales according to Vehicle Color')
plt.ylabel('Vehicle Color')
plt.xlabel('Sold vehicle')
plt.show()
```



```
data['Class'].value_counts().head(40).sort_values().plot(kind='bar', figsize=(15, 9))
plt.title('Sales according to Vehicle Class')
plt.ylabel('Vehicle Class')
plt.xlabel('Sold vehicle')
plt.show()
```

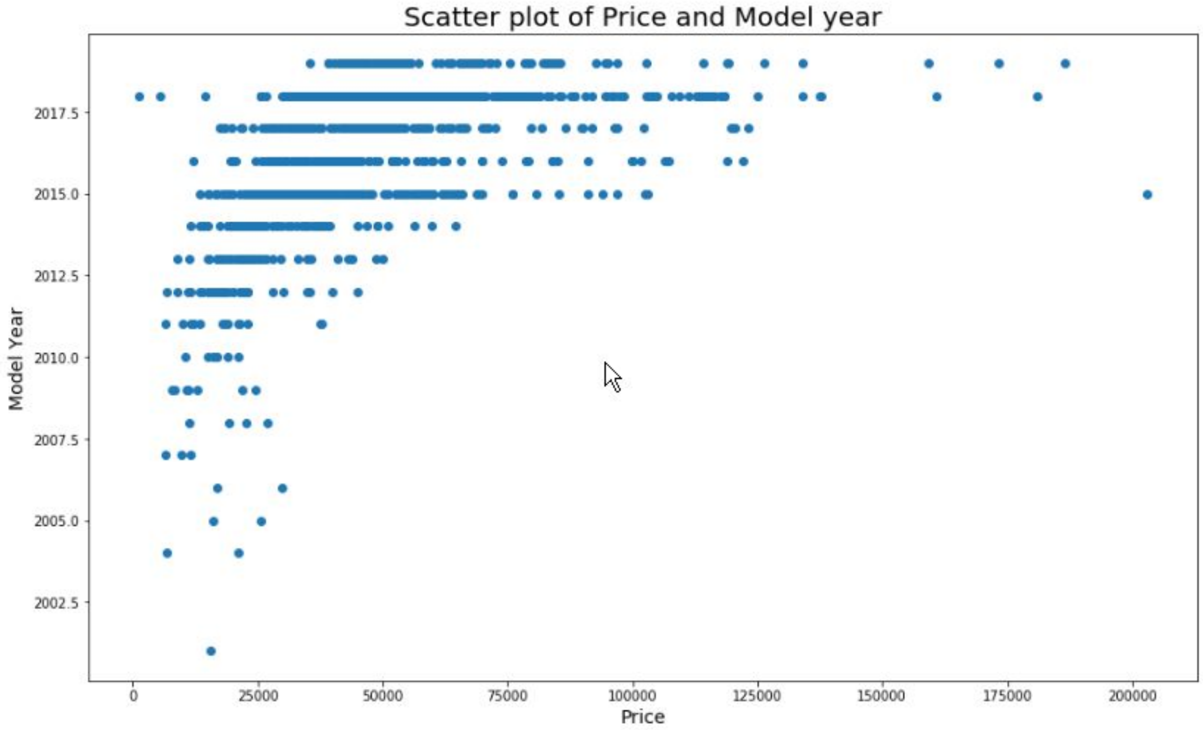


```
plt.figure(figsize=(15, 9))
plt.title('Sales according to Vehicle Class', fontsize=12)
plt.xticks(rotation=90)
sns.countplot(data['Class_type'], order = data['Class_type'].value_counts().index);
```



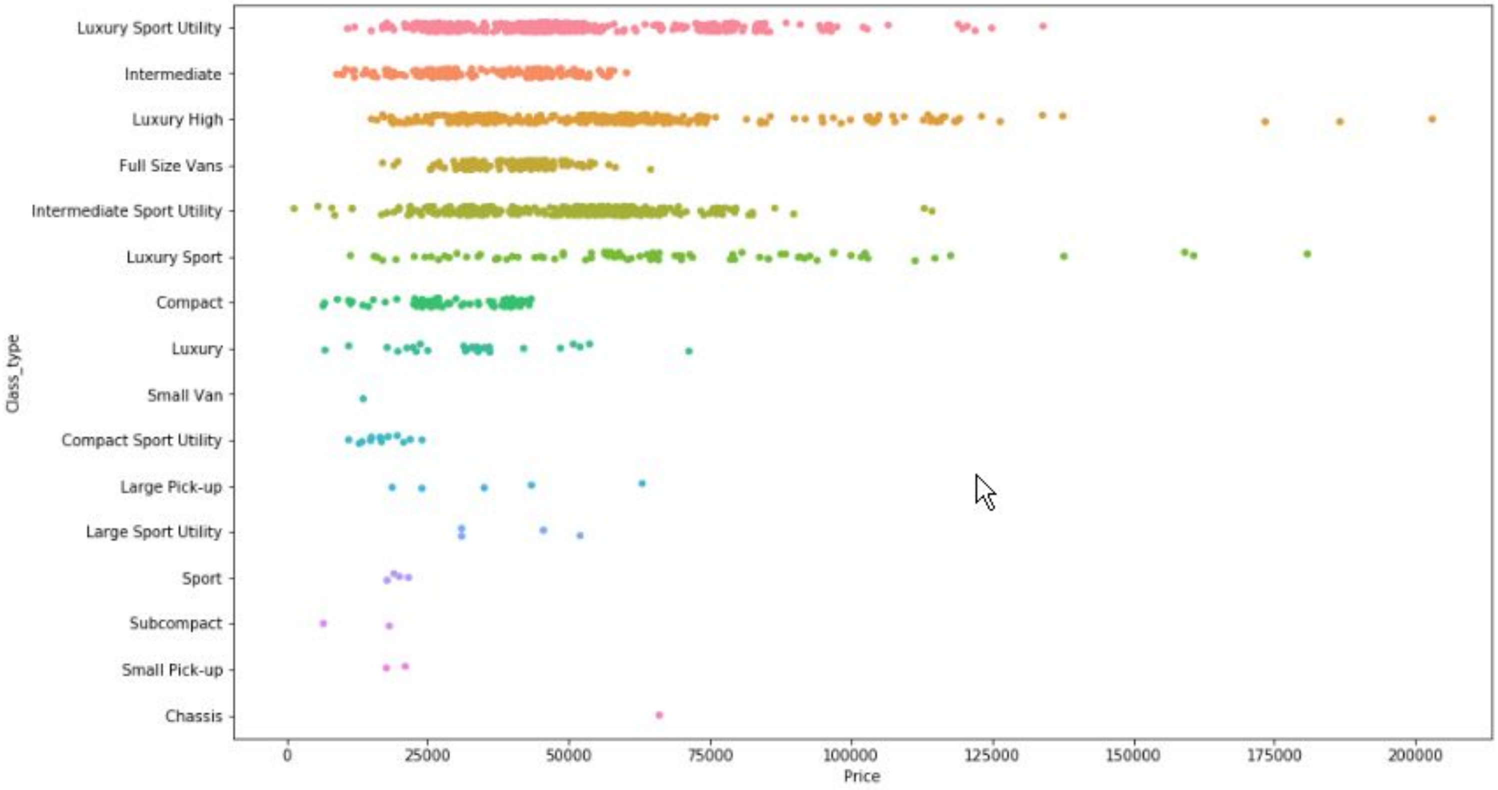
Below is a visualization of the distribution of Car Price by their Model Year.

```python

plt.figure(figsize=(15, 9))
# plot two values price per year_model
plt.scatter(data.Price, data.Year)
plt.xlabel("Price", fontsize=14)
plt.ylabel("Model Year", fontsize=14)
plt.title("Scatter plot of Price and Model year",fontsize=20)
plt.show()
```



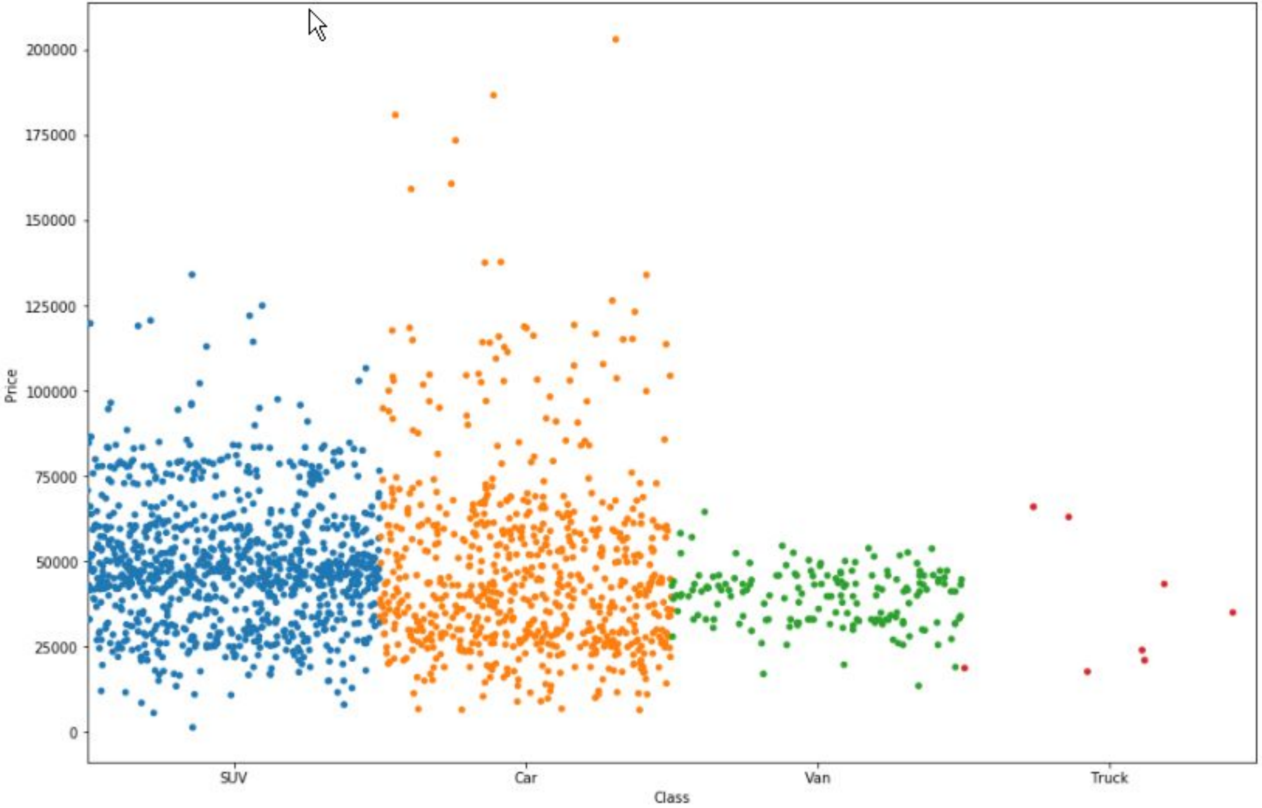
Looking to express the Cars Price according to Class Type

```
f, ax = plt.subplots(figsize=(15, 9))
sns.stripplot(data = data, x='Price', y='Class_type', jitter=.1)
plt.show()
```

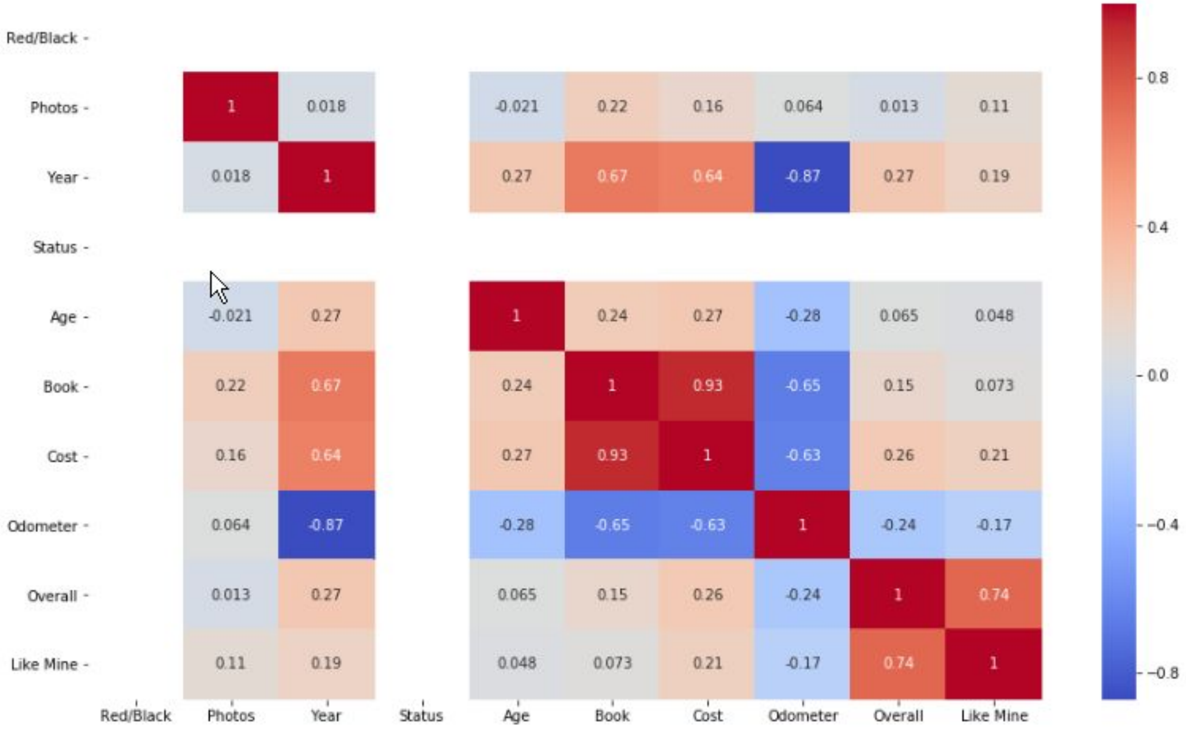


Price Distribution by Class

```
f, ax = plt.subplots(figsize=(15, 10))
sns.stripplot(data = data, x='Class', y='Price', jitter=.5)
plt.show()
```



It is important to understand possible correlations in your data, especially when building a regression model. Strongly correlated predictors, phenomenon referred to as multicollinearity, will cause coefficient estimates to be less reliable. As we see above, Cost and book are highly correlated, as well as Overall and Like Mine. There are no values for Status and Red/Black.



Let's do some Feature engineering by dropping columns that do not have any impact towards vehicle pricing.

Often, it is better to train your model with only significant features than to train it with all the features, including unnecessary ones.

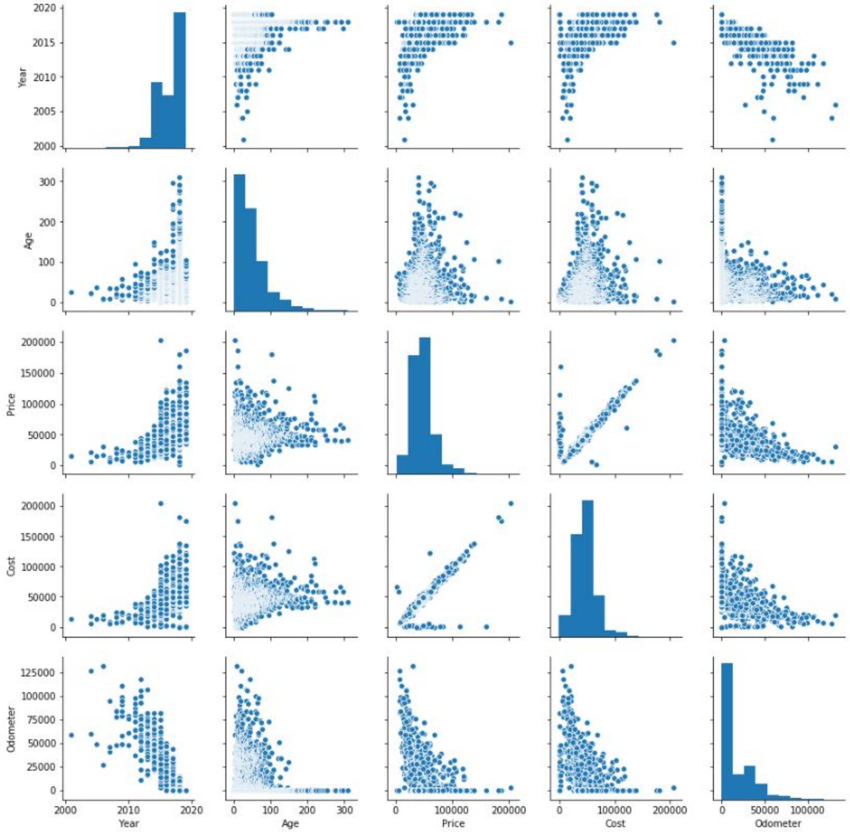
```
columns_to_drop = ['Red/Black', 'Deleted Date', 'Status', 'VIN', 'Recall Status','Disp', 'Book', 'Overall', 'Like Mine',
data.drop(labels=columns_to_drop, axis=1, inplace=True)
data.head()
```

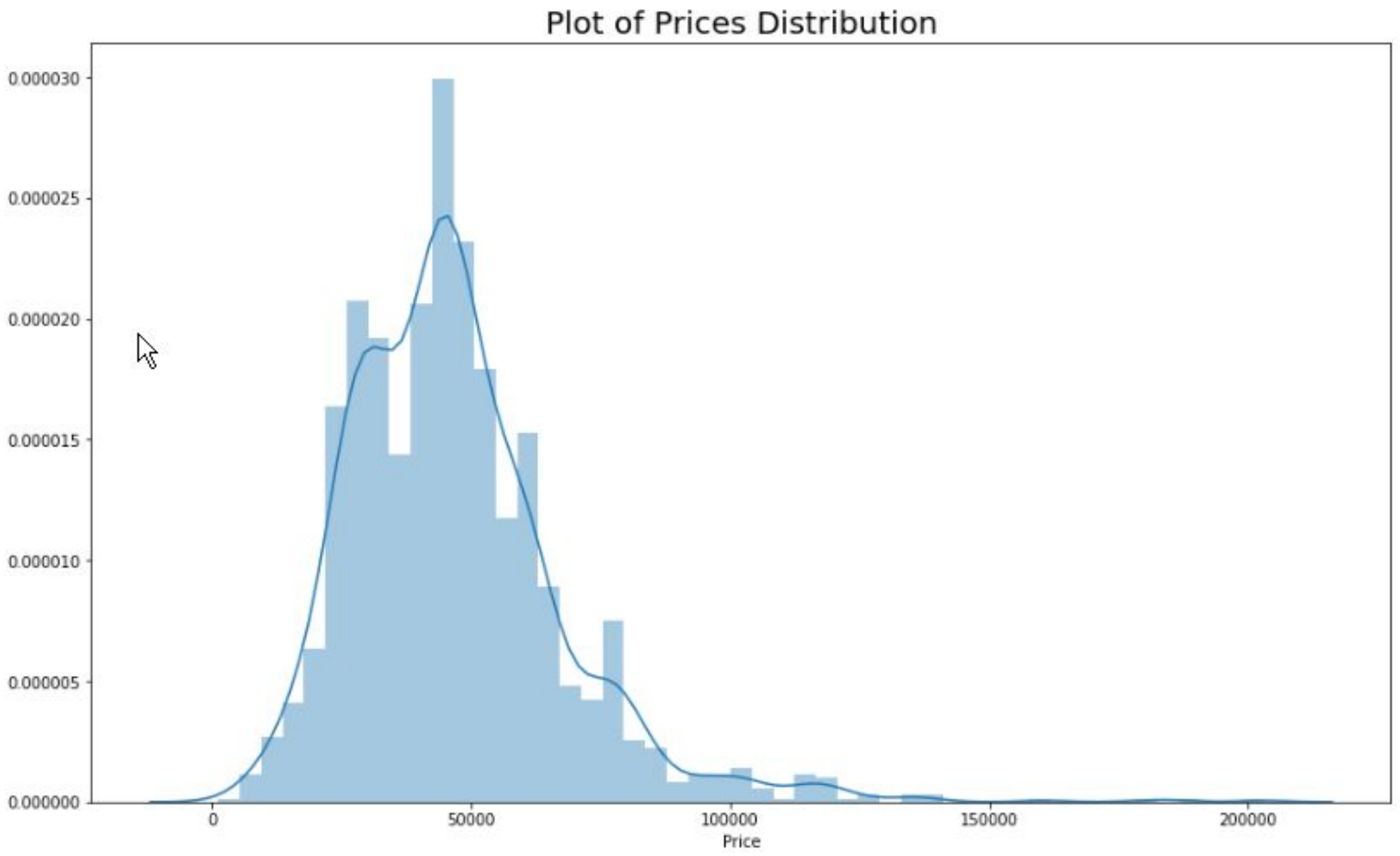
	Carfax Has Report	Carfax Has Manufacturer Recall	Carfax Has Warnings	Carfax Has Problems	Year	Vehicle	Class	Class_type	Certified	Age	Body	Color	Price	Cost	Odometer
0	NaN	NaN	NaN	NaN	2018	Mercedes-Benz GLS 450 4MATIC®	SUV	Luxury Sport Utility	NaN	1	4D Sport Utility	Obsidian Black	76164.0	76514.0	45.0
1	Yes	NaN	NaN	NaN	2015	Mercedes-Benz C-Class C 300 4MATIC®	Car	Intermediate	Yes	1	4D Sedan	Polar White	NaN	NaN	47525.0
2	NaN	NaN	NaN	NaN	2018	Mercedes-Benz S-Class S 450 4MATIC®	Car	Luxury High	NaN	1	4D Sedan	Gray Metallic	116148.0	NaN	42.0
3	NaN	NaN	NaN	NaN	2017	Mercedes-Benz Sprinter 3500	Van	Full Size Vans	NaN	1	3D Cargo Van	Arctic White	49526.0	NaN	5.0
4	NaN	NaN	NaN	NaN	2014	Mercedes-Benz M-Class ML 350 4MATIC®	SUV	Intermediate Sport Utility	NaN	1	4D Sport Utility	Brown	25117.0	NaN	45642.0

```python
# Now lets drop missing values for these important features since they missing values can not be assumed

data = data.dropna(subset=['Price','Odometer','Color','Cost']) #Drop null values
data.describe()
```

	Year	Age	Price	Cost	Odometer
count	1720.000000	1720.000000	1720.000000	1720.000000	1720.000000
mean	2016.602326	50.830233	46832.894767	45905.759302	15312.886628
std	2.054520	44.024799	20789.211542	21044.399419	20456.400584
min	2001.000000	1.000000	1302.000000	-775.000000	3.000000
25%	2015.000000	19.000000	31999.000000	32006.750000	12.000000
50%	2017.000000	40.000000	44548.000000	45269.000000	4454.500000
75%	2018.000000	67.000000	56801.000000	56499.500000	28263.750000
max	2019.000000	310.000000	203000.000000	205250.000000	132218.000000

Lets visualize pairwise relationships in the dataset. It creates a matrix of axes and shows the relationship for each pair of columns in our dataset. This also allows us to note outliers.
You can see there is no evidence of extreme outliers. You can see the vehicles with the highest price have lower odometer readings and are the newer model year vehicles.




Plot of Prices Distribution
0.000030
0.000025
0.000020
0.000015
0.000010
0.000005
0.000000
0
50000
100000
150000
200000
Price

```
# Lets turn the categorical features into numeric fields
data = pd.get_dummies(data)
data.head()
```

	Year	Age	Price	Cost	Odometer	Carfax Has Report_Yes	Carfax Has Manufacturer Recall_Yes	Carfax Has Warnings_Yes	Carfax Has Problems_Yes	Vehicle_Acura MDX 3.5L SH-AWD w/Advance Package	...	Color_designo Magno Alanite Gray (Matte Finish)	Color_designo Magno Night Black
0	2018	1	76164.0	76514.0	45.0	0	0	0	0	0	...	0	0
28	2018	2	62479.0	63004.0	41.0	0	0	0	0	0	...	0	0
31	2018	2	50347.0	50697.0	35.0	0	0	0	0	0	...	0	0
33	2018	2	77897.0	78247.0	9.0	0	0	0	0	0	...	0	0
38	2018	2	25510.0	25860.0	15.0	0	0	0	0	0	...	0	0

5 rows × 483 columns

```
data.describe()
```

	Year	Age	Price	Cost	Odometer	Carfax Has Report_Yes	Carfax Has Manufacturer Recall_Yes	Carfax Has Warnings_Yes	Carfax Has Problems_Yes	Vehicle_Acura MDX 3.5L SH-AWD w/Advance Package
count	1720.000000	1720.000000	1720.000000	1720.000000	1720.000000	1720.000000	1720.000000	1720.000000	1720.000000	1720.000000
mean	2016.602326	50.830233	46832.894767	45905.759302	15312.886628	0.156395	0.004070	0.008721	0.008721	0.000581
std	2.054520	44.024799	20789.211542	21044.399419	20456.400584	0.363335	0.063683	0.093005	0.093005	0.024112
min	2001.000000	1.000000	1302.000000	-775.000000	3.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	2015.000000	19.000000	31999.000000	32006.750000	12.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	2017.000000	40.000000	44548.000000	45269.000000	4454.500000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	2018.000000	67.000000	56801.000000	56499.500000	28263.750000	0.000000	0.000000	0.000000	0.000000	0.000000
max	2019.000000	310.000000	203000.000000	205250.000000	132218.000000	1.000000	1.000000	1.000000	1.000000	1.000000

8 rows × 483 columns

Splitting the Data

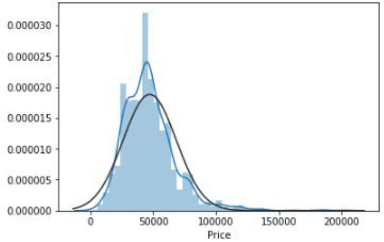
```python
#Create a new column that for each row, generates a random number between 0 and 1, and
#if that value is less than or equal to .75, then sets the value of that cell as True
#and false otherwise. This is a quick and dirty way of randomly assigning some rows to
#be used as the training data and some as the test data.

data['is_train'] = np.random.uniform(0, 1, len(data)) <= .75

#Create two new dataframes, one with the training rows, one with the test rows

train, test = data[data['is_train']==True], data[data['is_train']==False]

#Show the number of observations for the test and training dataframes
print('Number of observations in the training data:', len(train))
print('Number of observations in the test data:',len(test))
```

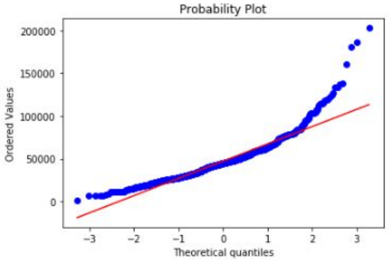
```
Number of observations in the training data: 1302
Number of observations in the test data: 418
```

Target Variable Analysis: Is it Normal?

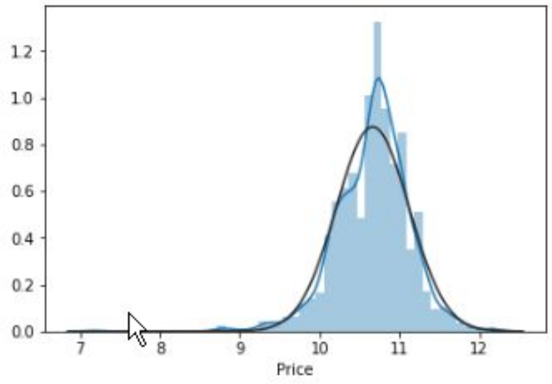
```
#histogram and normal probability plot to view the Target variable = Price
from scipy.stats import norm

sns.distplot(train['Price'],fit=norm);
fig = plt.figure()
res = stats.probplot(train['Price'], plot=plt)
```

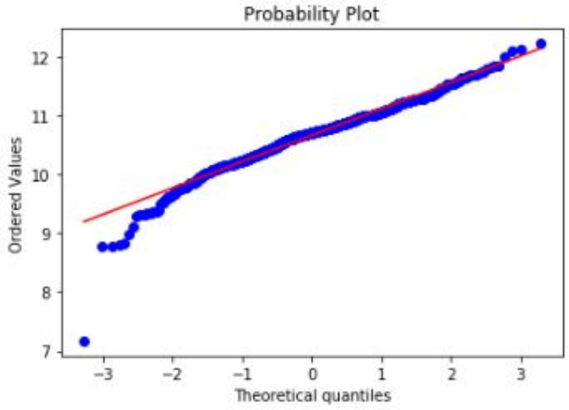
```
C:\Users\femis\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a non-tuple sequence for mult
ensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as
rray index, `arr[np.array(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```





The variable is certainly not normal: Let's apply a log transform on the data and see what happens...





The variable looks much better now.

Normalizing the features will hopefully improve the regressions. We just have to remember to transform the output data back using an exponentiation at the end of the model.

A Random Tree Regressor

To start off, let's try to train a simple model with a few of the features. Those features are:

Year, Age and Odometer

We will go for a very simple decision tree regression first. We can test for performance and overfitting using k-fold validation; here we take k=10 . First, we take the data and make it useful...

```
from sklearn.tree import DecisionTreeRegressor as dtr
# define the training data X...

X = train[['Year','Age','Cost','Odometer']]
Y = train[['Price']]

# and the data for the competition submission...
X_test = test[['Year','Age','Cost','Odometer']]
print(X.head())
print(Y.head())
```

```
    Year  Age     Cost  Odometer
0   2018    1  76514.0      45.0
28  2018    2  63004.0      41.0
31  2018    2  50697.0      35.0
33  2018    2  78247.0       9.0
47  2018    2  51350.0      18.0
        Price
0   11.240644
28  11.042586
31  10.826694
33  11.263143
47  10.836458
```

Explained Variance

Let's set up some cross-validation analysis to evaluate our model and later models...
In explained variance, the best possible result is 1. Values below 1 indicate error in the regression.

```
# Let's set up some cross-validation analysis to evaluate our model and later models...

from sklearn.model_selection import cross_val_score

# try fitting a decision tree regression model...
 # declare the regression model form. Let the depth be default.
DTR_1 = dtr(max_depth=None)

# fit the training data
scores_dtr = cross_val_score(DTR_1, X, Y, cv=10,scoring='explained_variance') # 10-fold cross validation
print('scores for k=10 fold validation:',scores_dtr)
print("Est. explained variance: %0.2f (+/- %0.2f)" % (scores_dtr.mean(), scores_dtr.std() * 2))
```

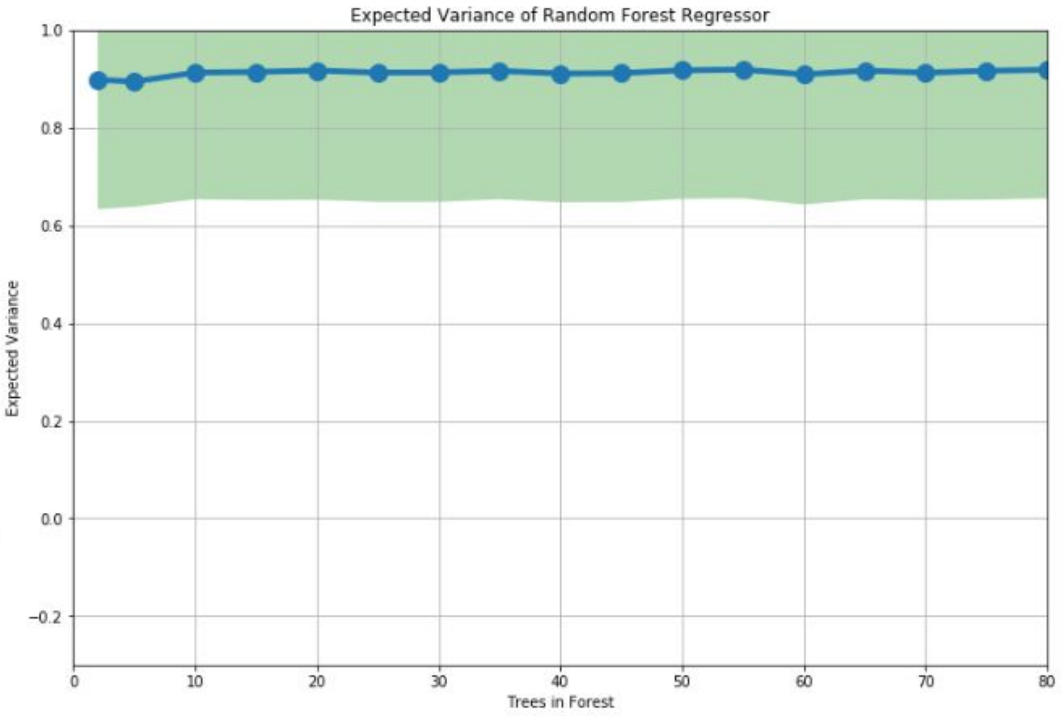
```
scores for k=10 fold validation: [0.91274071 0.87429349 0.87643702 0.95128801 0.93924753 0.95147265
 0.96283879 0.5172516  0.96503576 0.96001966]
Est. explained variance: 0.89 (+/- 0.26)
```

Let's use a random forest regressor instead. We will consider forests with varying numbers of trees (estimators), each of which provides a weak regression solution that can be averaged to get the overall regression output.

```
from sklearn.ensemble import RandomForestRegressor as rfr
estimators = [2, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80]
mean_rfrs = []
std_rfrs_upper = []
std_rfrs_lower = []
yt = [i for i in Y['Price']] # quick pre-processing of the target
np.random.seed(11111)
for i in estimators:
    model = rfr(n_estimators=i,max_depth=None)
    scores_rfr = cross_val_score(model,X,yt,cv=10,scoring='explained_variance')
    print('estimators:',i)
#     print('explained variance scores for k=10 fold validation:',scores_rfr)
    print("Est. explained variance: %0.2f (+/- %0.2f)" % (scores_rfr.mean(), scores_rfr.std() * 2))
    print('')
    mean_rfrs.append(scores_rfr.mean())
    std_rfrs_upper.append(scores_rfr.mean()+scores_rfr.std()*2) # for error plotting
    std_rfrs_lower.append(scores_rfr.mean()-scores_rfr.std()*2) # for error plotting
```

```
estimators: 2
Est. explained variance: 0.90 (+/- 0.26)

estimators: 5
Est. explained variance: 0.89 (+/- 0.26)

estimators: 10
Est. explained variance: 0.91 (+/- 0.26)

estimators: 15
Est. explained variance: 0.91 (+/- 0.26)

estimators: 20
Est. explained variance: 0.92 (+/- 0.26)

estimators: 25
Est. explained variance: 0.91 (+/- 0.26)
```

The results are acceptable.



Lets try using more features if there would be a difference.

Feature Ranking

A mutual information regression for feature ranking and selection will be used. This metric measures the dependence between two random variables, in this case each feature in the data set and the Price regression target.

```
included_features = [col for col in list(train)
                     if len([i for i in train[col].T.notnull() if i == True])==1302
                     and col!='Price']

X = train[included_features] # the feature data
Y = train[['Price']] # the target
yt = [i for i in Y['Price']] # the target list
# and the data for the test...
X_test = test[included_features]

X.head()
```

	Year	Age	Cost	Odometer	Carfax Has Report_Yes	Carfax Has Manufacturer Recall_Yes	Carfax Has Warnings_Yes	Carfax Has Problems_Yes	Vehicle_Acura MDX 3.5L SH-AWD w/Advance Package	Vehicle_Acura MDX 3.5L w/Technology & Entertainment Pkgs	...	Color_designo Magno Night Black	Color_desi Ma Platin (Matte Fini
0	2018	1	76514.0	45.0	0	0	0	0	0	0	...	0	
28	2018	2	63004.0	41.0	0	0	0	0	0	0	...	0	
31	2018	2	50697.0	35.0	0	0	0	0	0	0	...	0	
33	2018	2	78247.0	9.0	0	0	0	0	0	0	...	0	
47	2018	2	51350.0	18.0	0	0	0	0	0	0	...	0	

5 rows × 483 columns

Mutual Information Regression Metric for Feature Ranking

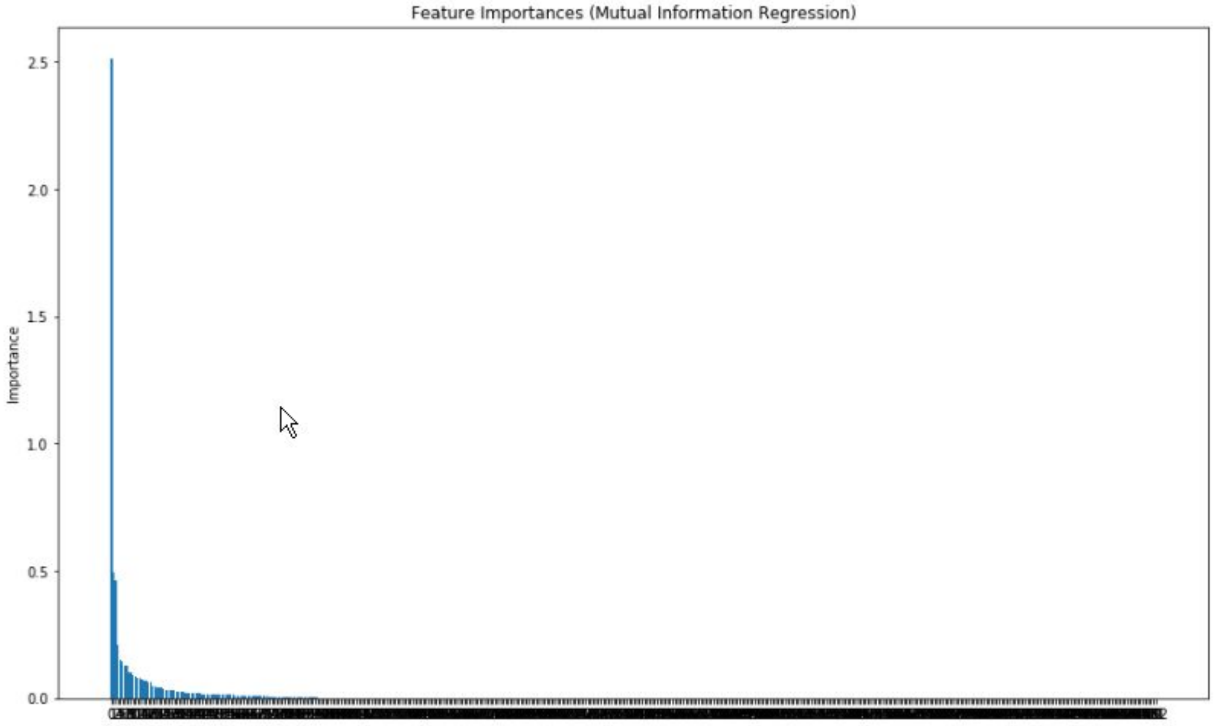
We will use mutual information regression for feature ranking and selection. This metric measures the dependence between two random variables, in this case each feature in the data set and the Price regression target.

```
import sklearn.feature_selection as fs

mir_result = fs.mutual_info_regression(X, yt) # mutual information regression feature ordering
feature_scores = []
for i in np.arange(len(included_features)):
    feature_scores.append([included_features[i],mir_result[i]])
sorted_scores = sorted(np.array(feature_scores), key=lambda s: float(s[1]), reverse=True)
print(np.array(sorted_scores))
```

```
[['Cost' '2.513674092717023']
 ['Odometer' '0.4936211292426828 7']
 ['Year' '0.465463228937 1934']
 ['Vehicle_Mercedes-Benz GLC 300 4MATIC®' '0.21016044454635474']
 ['Vehicle_Mercedes-Benz GLE 350 4MATIC®' '0.14945516152602356']
 ['Class_type_ Luxury Sport Utility' '0.14348095833780894']
 ['Certified_Yes' '0.1309328986878 5418']
 ['Vehicle_Mercedes-Benz GLS 450 4MATIC®' '0.12837635294044125']
 ['Class_type_ Full Size Vans' '0.10176353607005462']
 ['Class_Van' '0.09996731415604754']
 ['Class_type_ Intermediate Sport Utility' '0.08867553257504279']
```

Obviously, it determined that Cost, vehicle, odometer, year and Class type are the top 5 features. These seem like fairly intuitive results, at least for somebody with a distant notion of what matters when pricing a vehicle.

Let's plot the results next to each other for a better visualization...

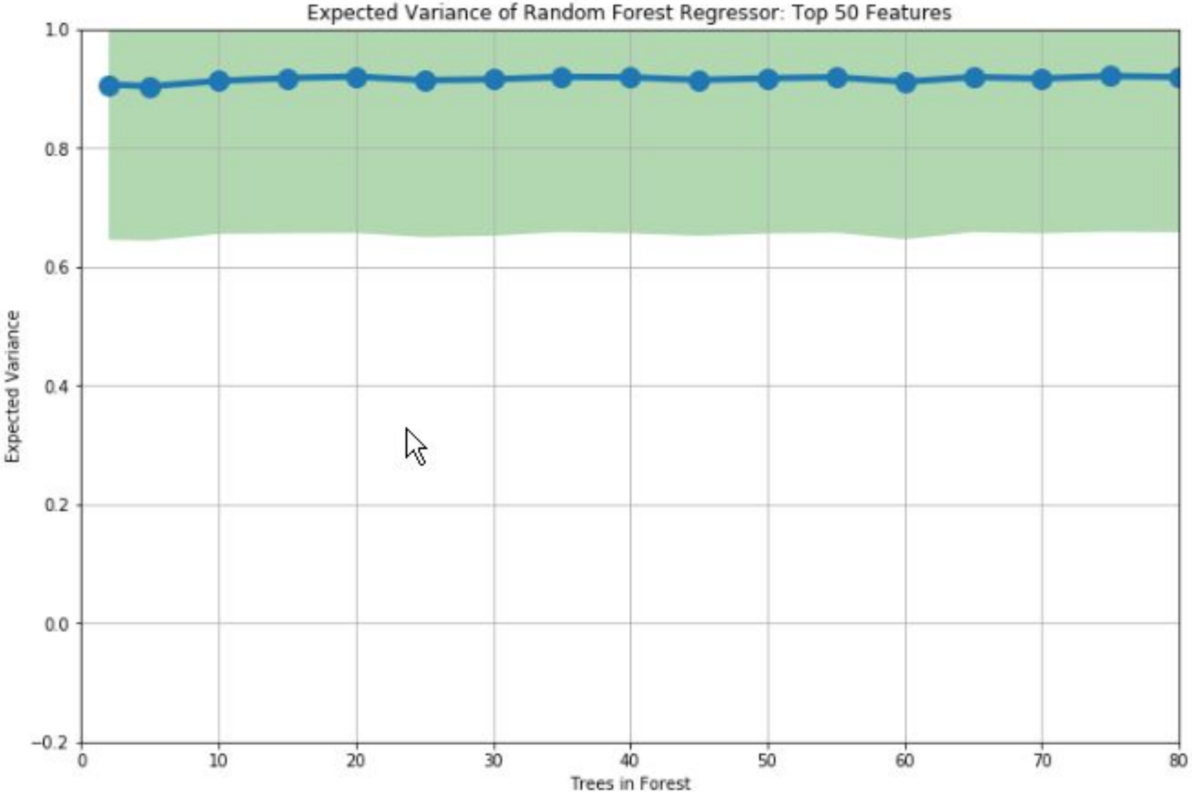


Feature Pruning

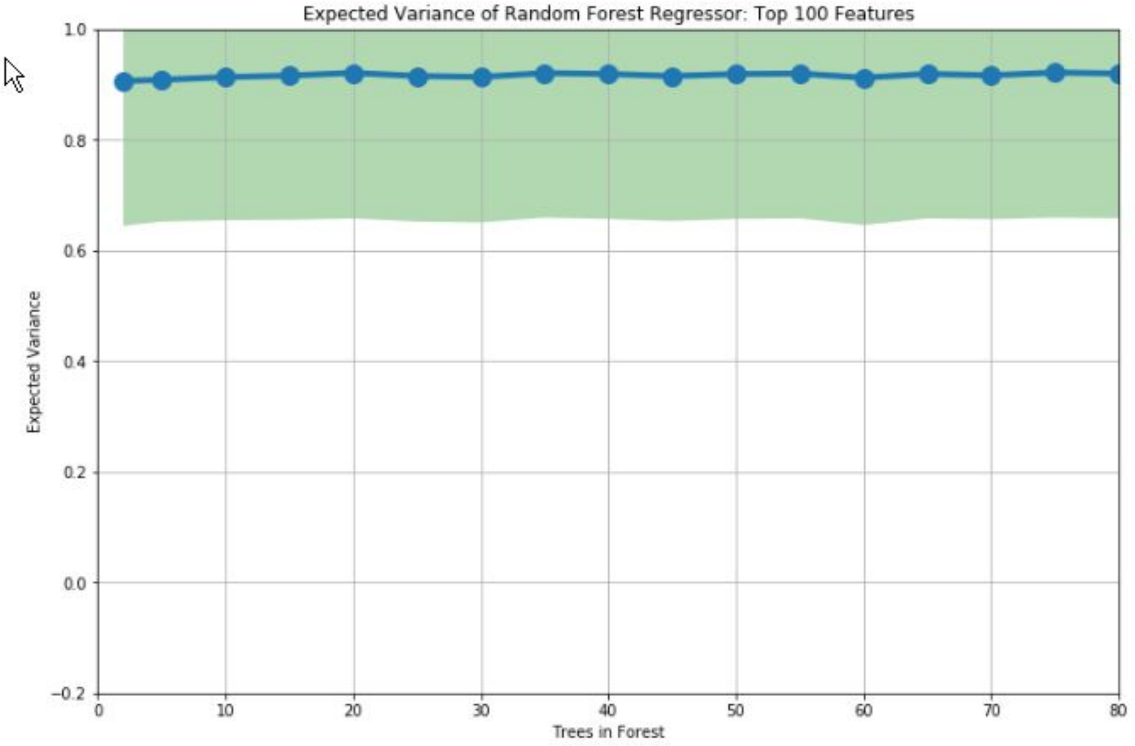
Let's take the top 50, 100, 150 and 200 features to train the random forest regressor model we've been working with. We will wrap the necessary model building and plotting code in functions first.

```
# define a function to do the necessary model building....
def getModel(sorted_scores,train,numFeatures):
    included_features = np.array(sorted_scores)[:,0][:numFeatures] # ordered list of important features
    # define the training data X...
    X = train[included_features]
    Y = train[['Price']]

    # define the number of estimators to consider
    estimators = [2, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80]
    mean_rfrs = []
    std_rfrs_upper = []
    std_rfrs_lower = []
    yt = [i for i in Y['Price']]
    np.random.seed(11111)

    # for each number of estimators, fit the model and find the results for 8-fold cross validation
    for i in estimators:
        model = rfr(n_estimators=i,max_depth=None)
        scores_rfr = cross_val_score(model,X,yt,cv=10,scoring='explained_variance')
        mean_rfrs.append(scores_rfr.mean())
        std_rfrs_upper.append(scores_rfr.mean()+scores_rfr.std()*2) # for error plotting
        std_rfrs_lower.append(scores_rfr.mean()-scores_rfr.std()*2) # for error plotting
    return mean_rfrs,std_rfrs_upper,std_rfrs_lower

# define a function to plot the model expected variance results...
def plotResults(mean_rfrs,std_rfrs_upper,std_rfrs_lower,numFeatures):
    fig = plt.figure(figsize=(12,8))
    ax = fig.add_subplot(111)
    ax.plot(estimators,mean_rfrs,marker='o',
           linewidth=4,markersize=12)
    ax.fill_between(estimators,std_rfrs_lower,std_rfrs_upper,
                    facecolor='green',alpha=0.3,interpolate=True)
    ax.set_ylim([-.2,1])
    ax.set_xlim([0,80])
    plt.title('Expected Variance of Random Forest Regressor: Top %d Features'%numFeatures)
    plt.ylabel('Expected Variance')
    plt.xlabel('Trees in Forest')
    plt.grid()
    plt.show()
    return
```

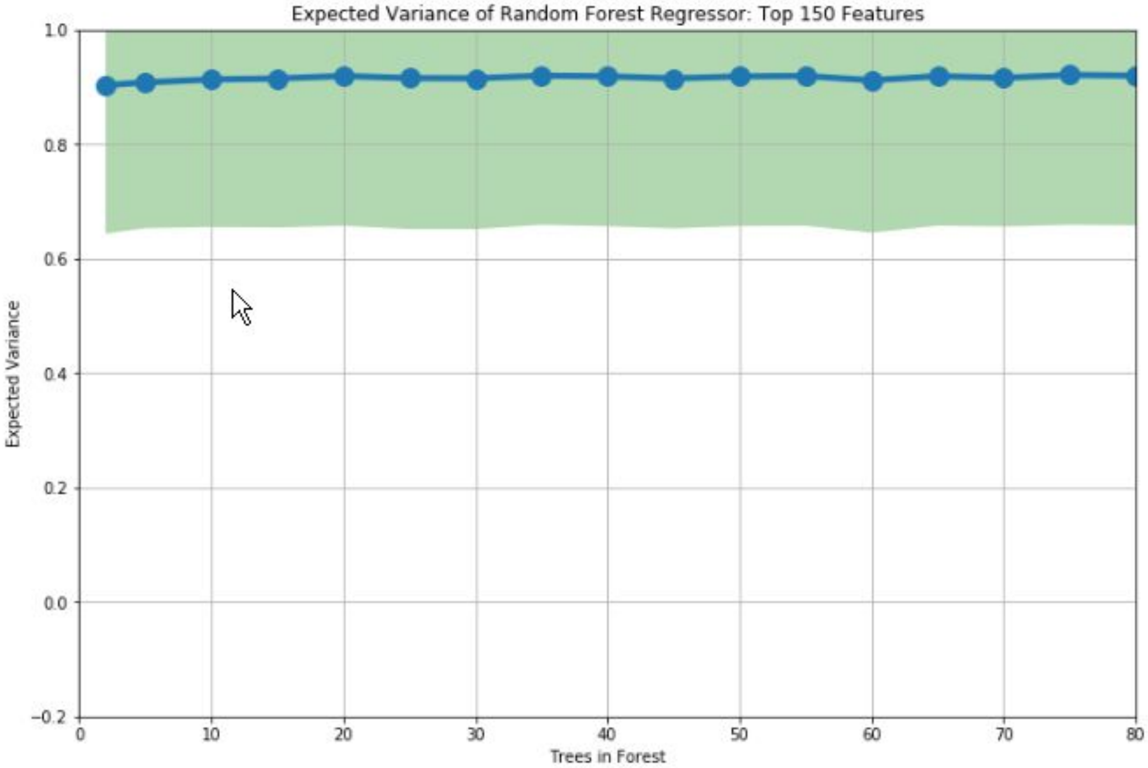
..and let's run the regression model fitting for each of the scenarios listed before...
top 50 features

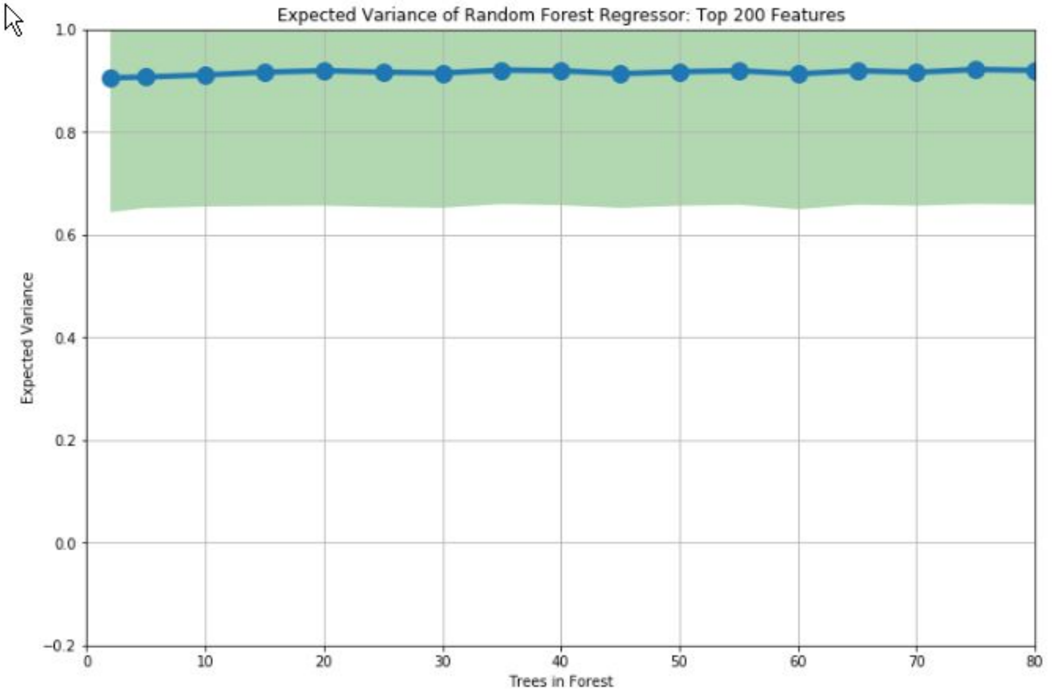


Top 100 features...



Top 150 features...





Random Forest Regression Impressions

It seems like the mean expected variance of the regressions stops improving at around 100 features. The deviation in the expected variance score decreases with increasing features, which is intuitive. The 150-feature and 200-feature results look almost identical, probably because the features are beginning to be insignificant. Let's only consider the top 100 features from here on out.

Building the Output

Now, let's take the best regression model we have and build the prediction output. For this model, we have:

A random forest regression model, incorporating the 100 most prominent features according to an MIR analysis, and 100 regressor trees per forest, and the default sklearn settings for the rest of the model parameters. So let's apply this model to the test data and generate the submission!

```
explained variance scores for k=10 fold validation: [0.9434265  0.90321735 0.94589638 0.98120699 0.98082264 0.97089864
 0.98713038 0.53367369 0.97895275 0.97145096]
Est. explained variance: 0.92 (+/- 0.26)

RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='auto', 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, n_estimators=100, n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False)
```

The explained variance with the top 100 feature selection is slightly better than the simple feature selection in the first model

Now we would apply the model to the test data and get the output..

```python
X_test = test[included_features]
# for col in list(X_test):
    # if X_test[col].dtype=='object':
        #  X_test = getObjectFeature(X_test, col, datalength=440)
# print(X_test.head(20))
y_output = model.predict(X_test.fillna(0)) # get the results and fill nan's with 0
print(y_output)
```

```
[10.20288951 11.1098845  11.27476247 10.613403   11.02980999 10.82989474
 10.36787285 10.40291664 10.66397638 10.9814766  11.27971609 10.42932844
 11.28237167 10.4272529  10.95729207 10.81932505 11.52082301 10.88847788
 10.80180224 10.27875295 10.5175694  10.14328043 10.71601961 10.75443587
 11.07037294 10.24513359 10.2127982  10.20198943 10.00216025 10.84052184
 10.24238159  9.47290421 10.3633731   9.91669954 10.97437297 11.04528181
 11.68073469 10.71957049 10.73237052 11.05889496 10.46141724 10.22806483
 10.43714389 10.80236551 10.68481017 10.76518316 10.4188083   9.99212869
 10.97921479 10.38850297 10.11238826  9.75875659 11.21013009 10.17636494
 10.22933957 10.98574416 10.96706768  9.91686282 10.89742758 10.23168242
 10.76494616 10.73386376 10.23328381 11.04994026  9.08965149 10.62851525
 10.51681298 10.86156545 10.71676382 10.15934737  9.35807367 10.31593605
  9.77572155 10.84649708 10.69193423 10.98123673 10.12340416 10.69249707
 10.53398837 10.21084233 10.411544   10.30327164 10.51763551 11.07078369
 11.28997065 10.75893916 10.78057482 10.08942901 10.54593092 10.07679079
```

We have to transform the data back because we applied a log transform earlier.

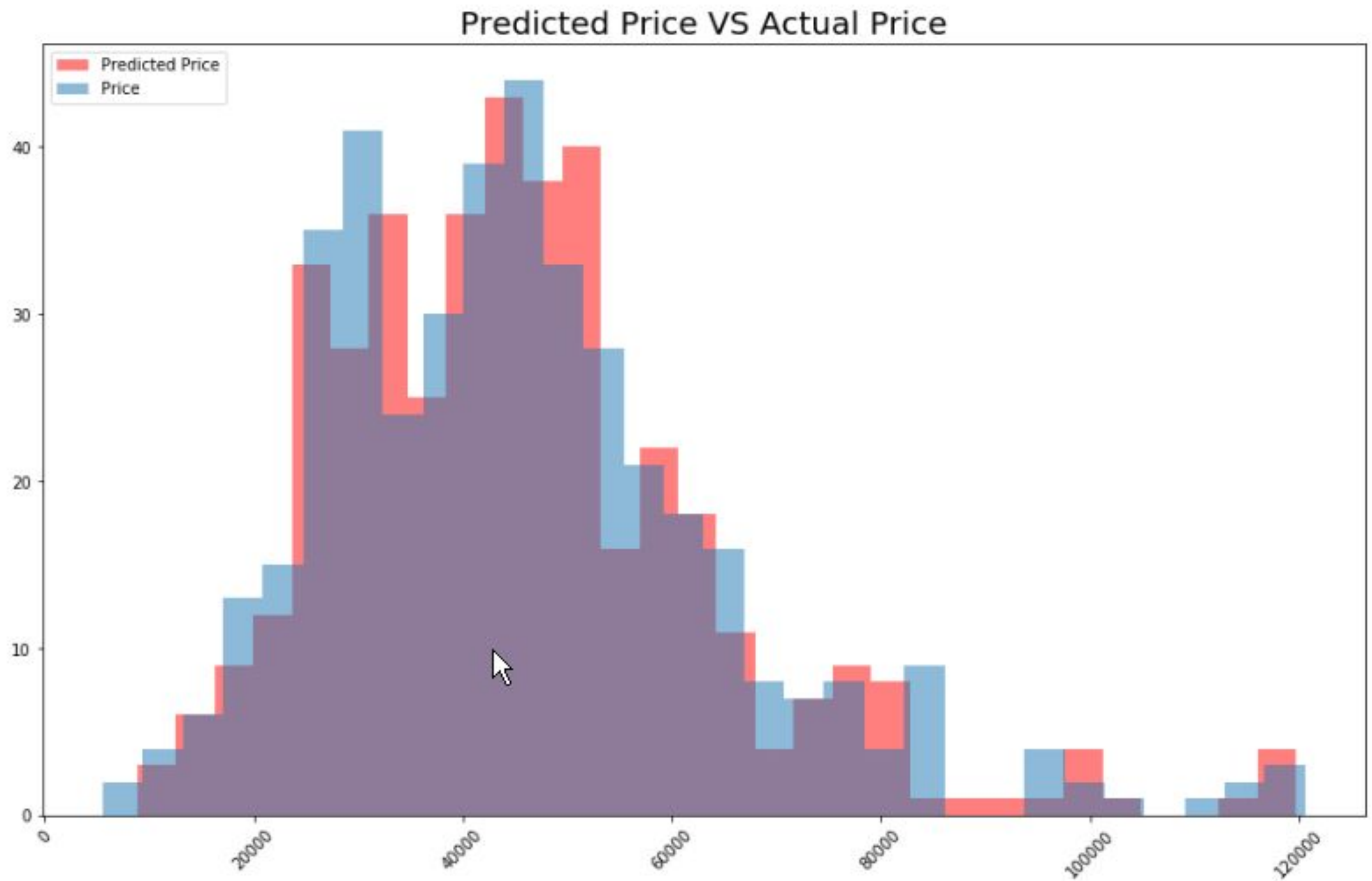
```
# transform the data

y_output = np.exp(y_output)
print(y_output)
```

```
[ 26981.0355376   66828.47217599  78807.42305632  40676.38560917
  61685.85847993  50508.38997451  31820.71741238  32955.60523554
  42786.43433578  58775.27785186  79198.77374548  33837.61879399
  79409.37123748  33767.46030056  57370.87604143  49977.34341443
 100792.8812588   53555.7198386   49109.22822312  29107.55228379
  36959.18215259  25419.71749508  45072.14077143  46837.33251939
  64239.45967805  28145.24172921  27249.71125646  26956.7613875
  22074.09994764  51048.01012892  28067.89260366  13002.59466044
  31677.85377725  20265.9929505   58359.23951829  62647.67274666
 118271.09562002  45232.47096387  45815.16913825  63506.33630012
  34941.03633319  27668.91415497  34103.1110273   49136.89755432
  43687.18850504  47343.42152951  33483.50813755  21853.7691375
  58642.48936518  32484.00091127  24646.45254664  17305.10099211
  73875.02513831  26274.78305523  27704.20734138  59026.640826
  57934.46192319  20269.30235124  54037.17842798  27769.19033605
  47332.20264311  45883.6332983   27813.69511446  62940.19442907
   8863.09668012  41295.76558248  36931.23617569  52133.62689676
  45105.69609834  25831.43326005  11592.03697627  30210.23484542
  17601.18566759  51353.9471901   43999.52982553  58761.18118867
```

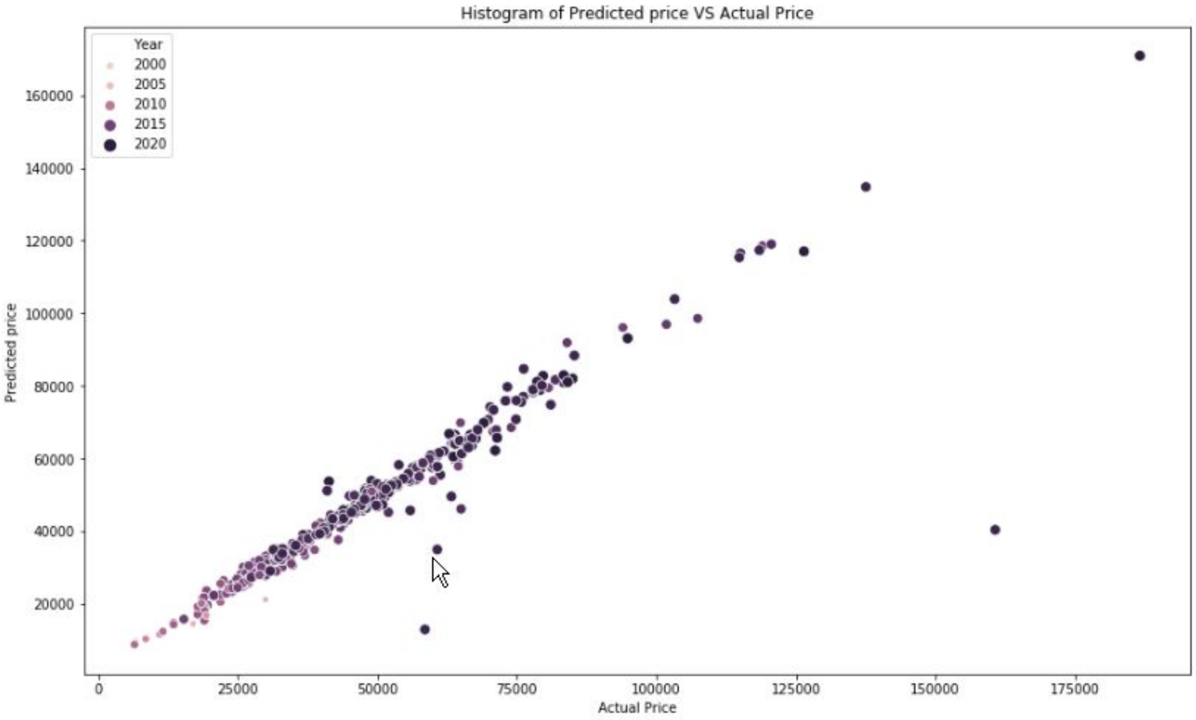
Now let's show a dataframe with the Predicted Price and the actual Price from the test data.

```python
# define the data frame for the results

Price = pd.DataFrame(y_output, columns=['Pred_Price'])

Test_ = test[['Price','Cost','Odometer', 'Year', 'Age']]
test_data = pd.DataFrame(Test_.reset_index(drop=True))

results = pd.concat([Price['Pred_Price'], test_data],axis=1)
results.head()
```

	Pred_Price	Price	Cost	Odometer	Year	Age
0	26981.035538	25510.0	25860.0	15.0	2018	2
1	66828.472176	68788.0	67589.0	59027.0	2015	3
2	78807.423056	78242.0	78592.0	8.0	2018	3
3	40676.385609	36048.0	36398.0	12.0	2018	3
4	61685.858480	61315.0	61665.0	9.0	2018	4


Predicted Price VS Actual Price
Predicted Price
Price
0
10
20
30
40
0
20000
40000
60000
80000
100000
120000

Lets create a scatterplot of the predicted price versus the actual price of the test data



Linear Regression

Lets try using linear regression to see if we can produce a better prediction model.

Run this cell

```python
# Load libraries
from sklearn import datasets, linear_model
from sklearn.metrics import mean_squared_error, r2_score
import warnings
# Suppress Warning
warnings.filterwarnings(action="ignore", module="scipy", message="^internal gelsd")
```

```python
# Lets define the independent variable and the target for both the training set and the test set.
# drop the target variable, Price, from the independent variables
included_features = [col for col in list(train)
                     if len([i for i in train[col].T.notnull() if i == True])==1291
                     and col!='Price']

X = train[included_features] # the feature data
Y = train[['Price']] # the target
# and the data for the test...
X_test = test[included_features]
Y_test = test[['Price']]

X.head()
```

46]:

	Year	Age	Cost	Odometer	Carfax Has Report_Yes	Carfax Has Manufacturer Recall_Yes	Carfax Has Warnings_Yes	Carfax Has Problems_Yes	Vehicle_Acura MDX 3.5L SH-AWD w/Advance Package	Vehicle_Acura MDX 3.5L w/Technology & Entertainment Pkgs	...	Color_designo Magno Night Black	Color_des Ma Plati (Matte Fi
28	2018	2	63004.0	41.0	0	0	0	0	0	0	...	0	
31	2018	2	50697.0	35.0	0	0	0	0	0	0	...	0	
33	2018	2	78247.0	9.0	0	0	0	0	0	0	...	0	
38	2018	2	25860.0	15.0	0	0	0	0	0	0	...	0	
50	2019	2	121714.0	14.0	0	0	0	0	0	0	...	0	

5 rows × 483 columns

Building the Output

The accuracy score of the linear regression is 91.84%

```
# Create linear regression object
regr = linear_model.LinearRegression()

# Train the model using the training sets
regr.fit(X, Y)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

```
# View the R-Squared score
# The closer to 1 the better
regr.score(X, Y)
```

```
0.9184132017076698
```

```
 # The coefficients
print('Coefficients: \n', regr.coef_)
```

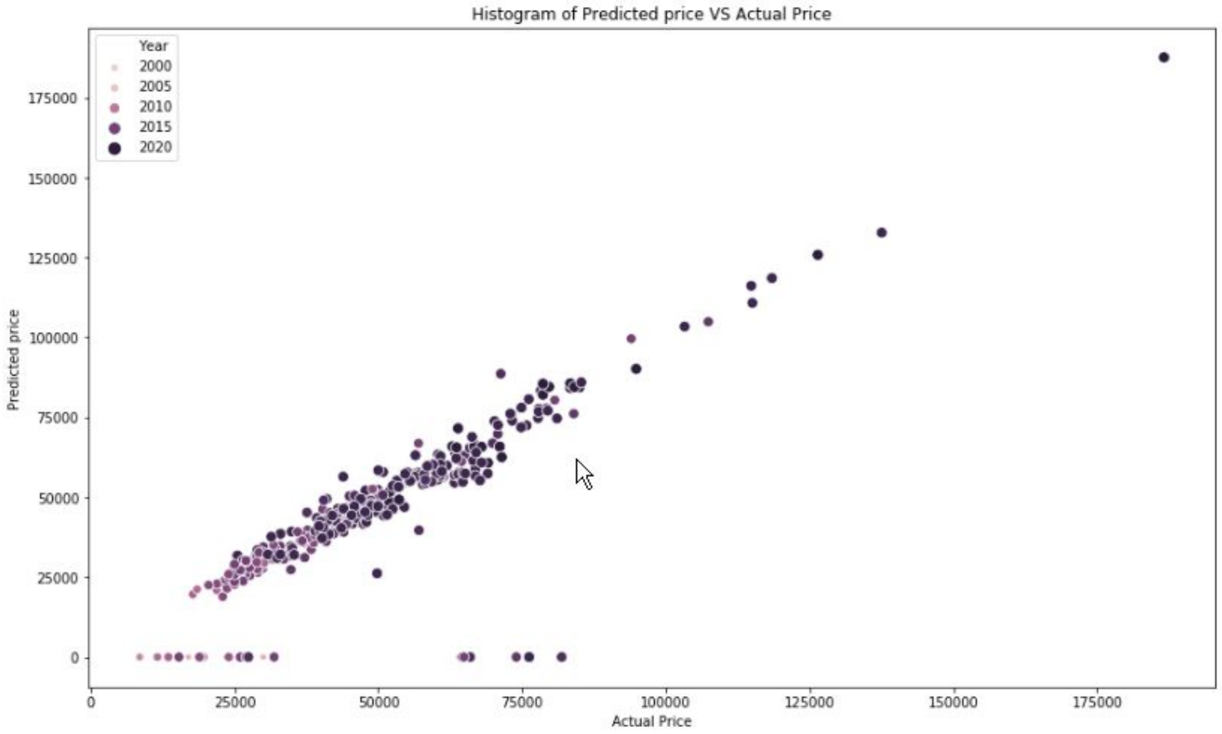
```
Coefficients:
 [[ 9.51415464e-02  7.54844194e-05  1.48134213e-06 -4.64722017e-06
  -4.52732674e-02  6.80607947e-02 -2.25570725e+06  2.25570721e+06
  -3.25431969e+05 -3.10992972e+05  1.02046159e+05 -9.93459144e+05
   3.16871493e+06 -5.01291095e+05 -2.54015126e+05 -2.54014790e+05
```

Now let's show a dataframe with the Predicted Price and the actual Price from the test data.

```
# define the data frame for the results

Price = pd.DataFrame(y_output, columns=['y_output'])

# Select features from the test data and create a new dataframe and reset the index
Test_ = test[['Price','Odometer', 'Year', 'Age']]
test_data = pd.DataFrame(Test_.reset_index(drop=True))

# Concatenate the Prediction and the new test dataframe
results = pd.concat([Price['y_output'], test_data],axis=1)
results.head()
```

	y_output	Price	Odometer	Year	Age
0	80670.922766	76164.0	45.0	2018	1
1	57867.400900	50841.0	18.0	2018	2
2	83342.022103	78242.0	8.0	2018	3
3	27741.127441	29888.0	28690.0	2015	4
4	57038.984789	55897.0	3812.0	2018	4

Lets create a scatterplot of the predicted price versus the actual price of the test data



The scatterplot of the regression model depicts a more accurate prediction

Conclusion

The predicted price in the random forest model was pretty close to the actual test dataset versus the linear regression. When I did the feature ranking of the dataset set, The best performing model was the random forest with 100 features and 100 trees, with an accuracy of 91%.

I believe the model can serve as a good pricing tool for the dealership because it follows in the dealership current pattern of pricing based on the recently sold inventory.

For this modeling, I chose the random forest regression model because it combines multiple decisions trees in determining the final output rather than relying on individual trees which i feel is perfect to create the model. I also chose to use linear regression because its a commonly used type of predictive analysis.

There were a few issues with the data, there was a lot of missing values in multiple fields which ended up causing a reduction in the data size when some of the fields and rows were dropped. Filling in the missing values in some of the fields would have skewed the data, which would affect the model.+

I believe if a model was created based on sold vehicle dataset from several other dealerships in the area, the model would be more robust and produce a more accurate predictive model.