Fundamental of Data Science Mini Project

Car Price Prediction (Linear Regression)

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Business Understanding

> Target user:

Automobile company

> Define Problem:

Which variables are significant in predicting the price of a car

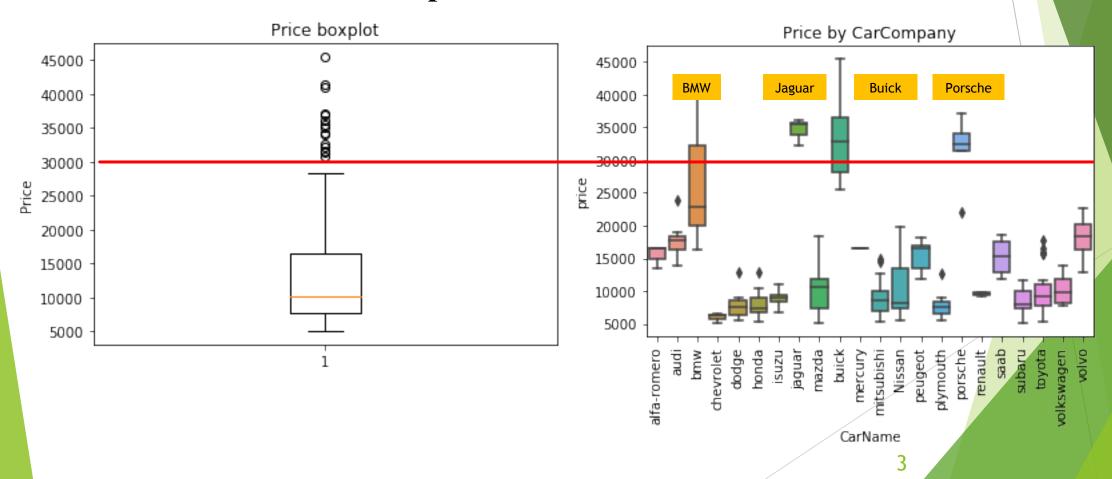
> Business Goal:

Company can design their cars and meet certain price based on the model

DATA DICTONARY			
1	Car_ID	Unique id of each observation (Interger)	
2	Symboling	Its assigned insurance risk rating, A value of +3 indicates that the auto is risky, -3 that it is probably pretty safe.(Categorical)	
3	carCompany	Name of car company (Categorical)	
4	fueltype	Car fuel type i.e gas or diesel (Categorical)	
5	aspiration	Aspiration Aspiration used in a car (Categorical)	
6	doornumber	Number of doors in a car (Categorical)	
7	carbody	body of car (Categorical)	
8	drivewheel	type of drive wheel (Categorical)	
9	enginelocation	Location of car engine (Categorical)	
10	wheelbase	Weelbase of car (Numeric)	
11	carlength	Length of car (Numeric)	
12	carwidth	Width of car (Numeric)	
13	carheight	height of car (Numeric)	
14	curbweight	The weight of a car without occupants or baggage. (Numeric)	
15	enginetype	enginetype Type of engine. (Categorical)	
16	cylindernumber	number cylinder placed in the car (Categorical)	
17	enginesize	Size of car (Numeric)	
18	fuelsystem	lsystem Fuel system of car (Categorical)	
19	boreratio	boreratio Boreratio of car (Numeric)	
20	stroke	Stroke or volume inside the engine (Numeric)	
21	compressionratio	compression ratio of car (Numeric)	
22	horsepower	Horsepower (Numeric)	
23	peakrpm	car peak rpm (Numeric)	
24	citympg	Mileage in city (Numeric)	
25	highwaympg	Mileage on highway (Numeric)	
26	price(Dependent variable	Price of car (Numeric)	

Data Understanding

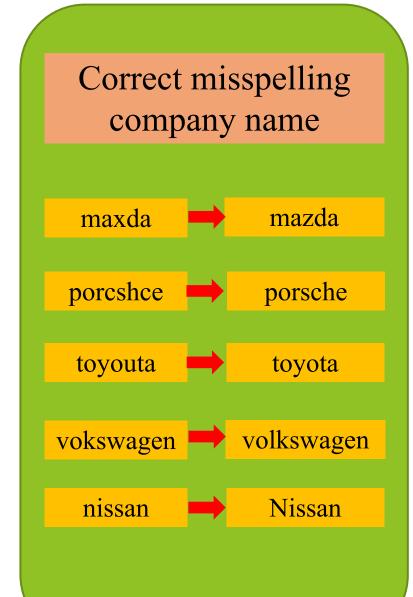
- Only 4 car company's car price over 30000 (BMW, Jaguar, Buick and Porsche)
- It is reasonable to keep these outliers



Data cleaning & Preprocessing

Detecting missing value

car ID symboling CarName fueltype aspiration doornumber carbody drivewheel enginelocation wheelbase carlength carwidth carheight curbweight enginetype cylindernumber enginesize fuelsystem boreratio stroke compressionratio horsepower peakrpm citympg highwaympg 0 price 0



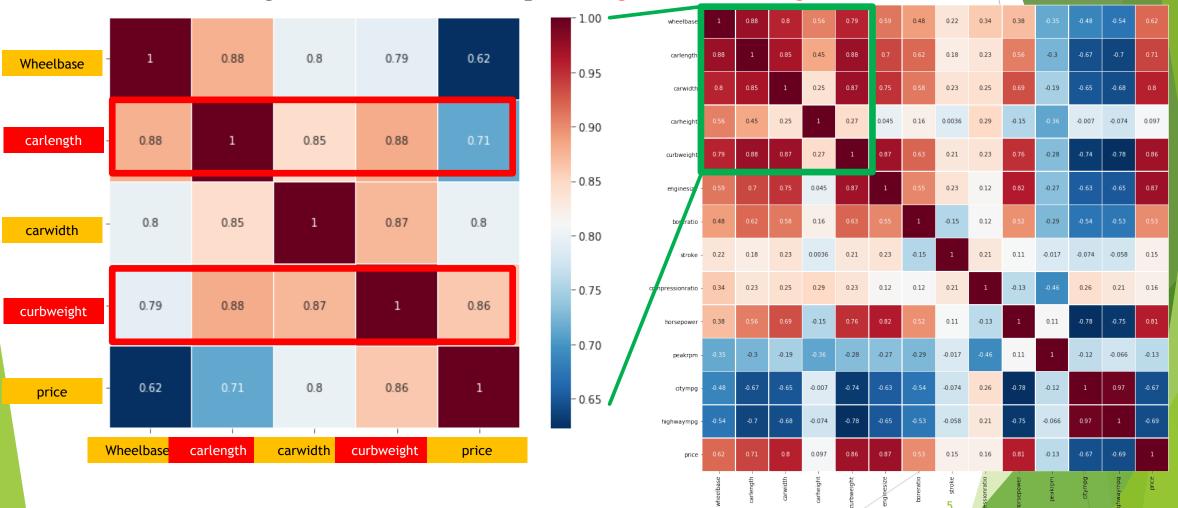
Splitting data

70% Training

30% Test

Feature Selection(Continuous)

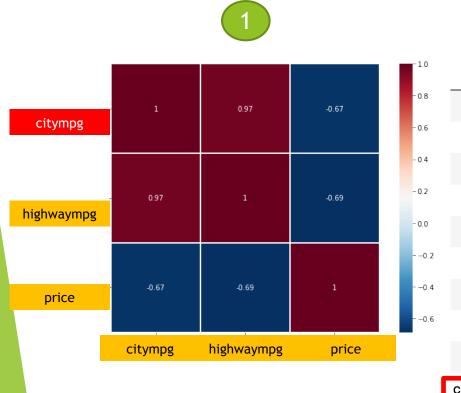
- Check correlation between each features
- According to the MSE result, drop carlength and curbweight



Feature Selection (Continuous)

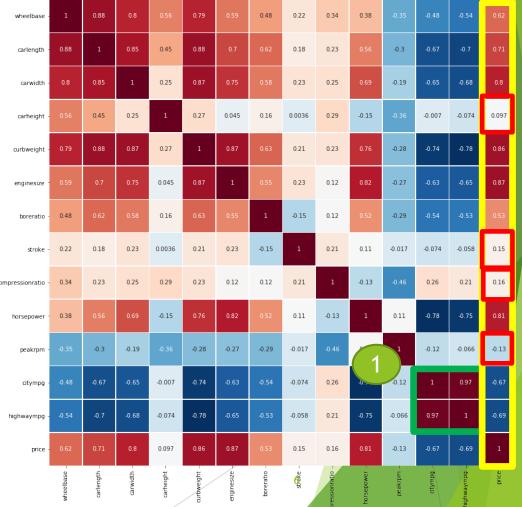
- Check correlation between each features
- Check F-score
- Drop the features with four lowest F-score

Drop



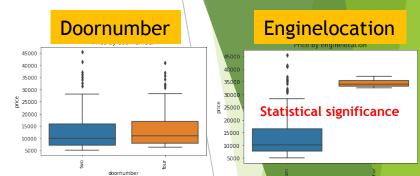
2

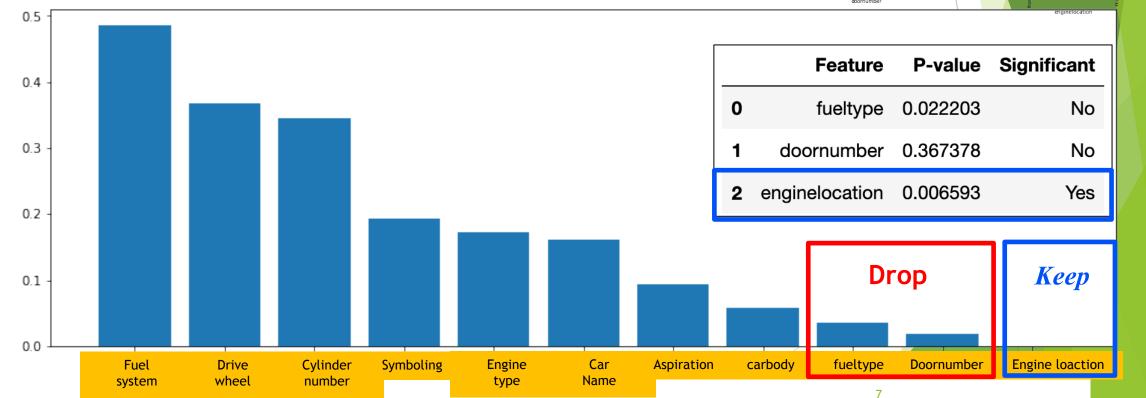
Feature	F-Score	
enginesize	430.488900	
curbweight	407.216278	
horsepower	261.777750	
carwidth	249.591029	
carlength	146.424930	
highwaympg	126.999719	0
citympg	117.557542	
wheelbase	89.248846	
boreratio	56.125469	
ompressionratio	3.744818	1
stroke	3.371650	
peakrpm	2.327430	
carheight	1.329005	



Feature Selection(Categorial)

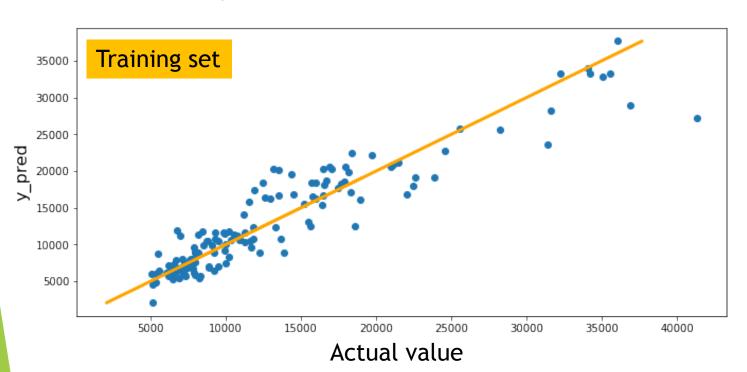
- Run mutual_info_test and P-value test
- Plot the feature versus Price
- Drop fueltype and doornumber and keep engineloaction

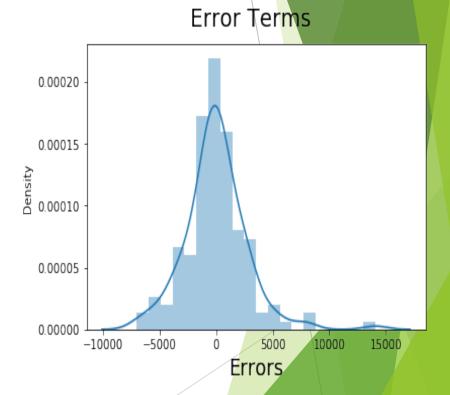




Result (training data)

- Training set: R-squared: 0.89, Mean Squared Error: 6939060.69
- Residual: $mean = \sim 0$, Standard deviation: 2643.46
- 90% confidence interval: ± 4348.49

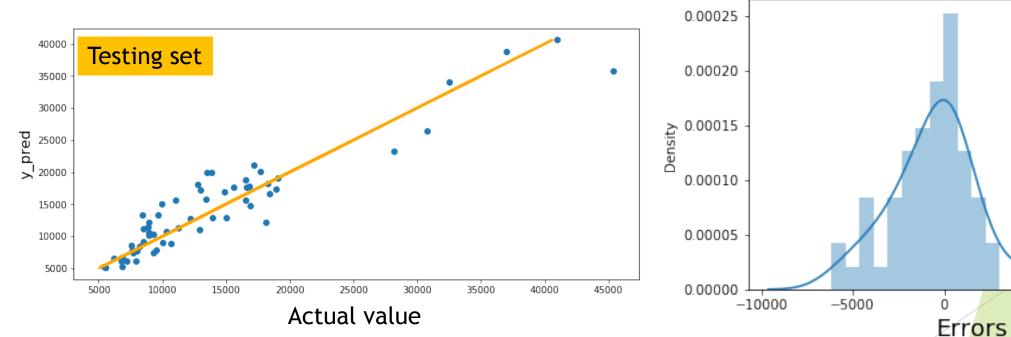




Result (testing data)

- Training set: R-squared: 0.89, Mean Squared Error: 7839580.17
- Residual: mean = -449.764, Standard deviation: 2799.92
- 90% confidence interval: ± 4605.87

Error Terms



5000

10000

Future work

- The model shows high variance in the medium price range. Since, we get the same R-squared values on training set and test set, we might try put more features to train the model.
- The model can't predict accurately the high-priced cars. I should collect more data to figure the issue should be high variance or high bias.
- When performing feature selection, use at least two methods to make the final decision.

Reference

Kaggle: https://www.kaggle.com/goyalshalini93/car-data