Linear Regression Project

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Outlines

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Problem Statement

Our motivation is to select the best model using linear regression, which could assist in predicting the car price depending on the various features a car brand is offering. This could also help us understand why some car brands are very expensive while most others are in the affordable range.

Dataset Description

1. **Target column:** Price
2. **Number of features:** 25
3. **Number of observations:** 205

Variable description:

a) **15 numerical variables** (symboling, normalized-losses, wheel-base, length, width, height, curb-weight, engine-size, bore, stroke, compression-ratio, horsepower, peak-rpm, city-mpg, highway-mpg).

b) **10 categorical variables** (fuel-type, aspiration, num-of-doors, body-style, drive-wheels, engine-location, engine-type, num-of-cylinders, fuel-system, make)

Research questions

To get the best model we need to answer the following questions:

1. How many and what predictors are **correlated**?
2. Are there any **outliers/influential points** that are severely affecting the model?
3. Are there any **insignificant predictors**?
4. Are any **model assumptions** being violated?
5. Finally checking model performance.

Summary of methods

1. Exploratory Data Analysis
2. Checking for multicollinearity using VIF
3. External studentised t-tests and Cook’s distance
4. Breusch-Pagan test for heteroscedasticity and Jarque-Bera test for normality
5. T-test and ANOVA(typ=1)
6. Adj-R^2 and MSE

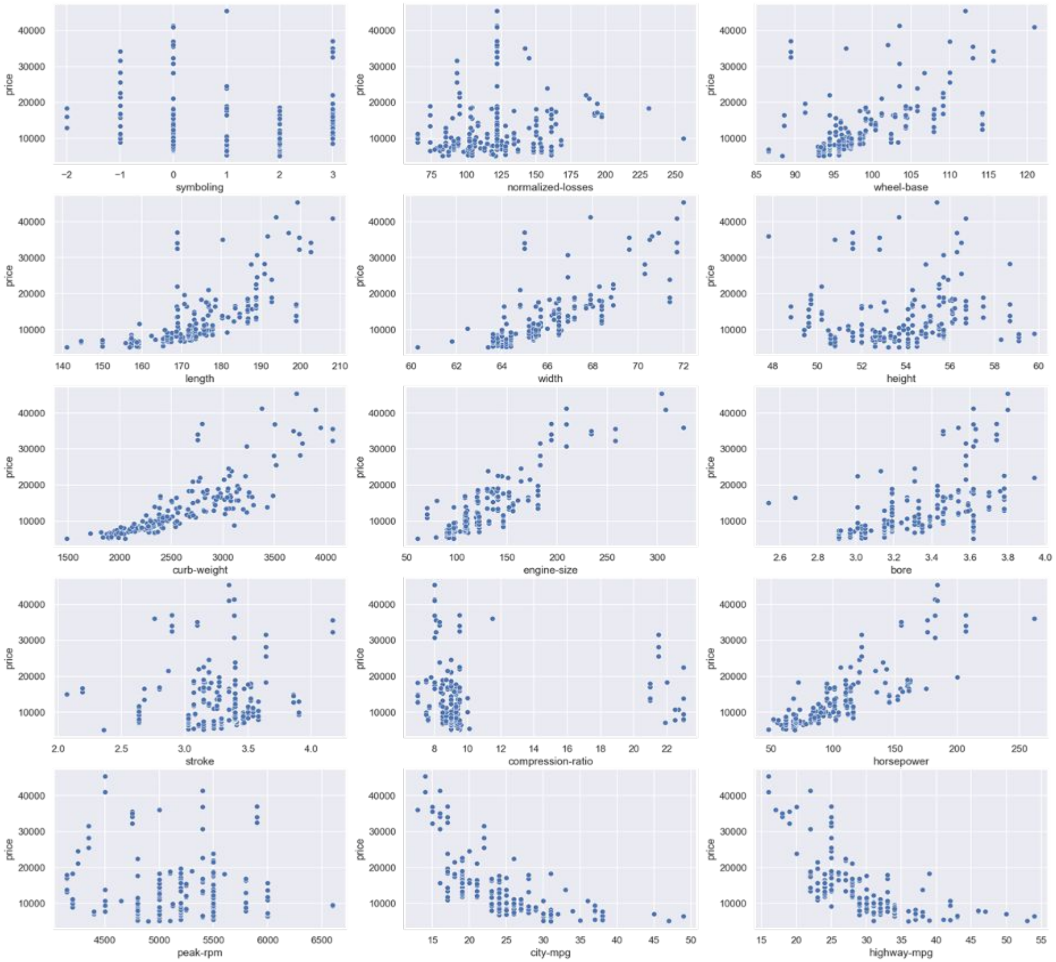
Exploratory Data Analysis

1. There were no null values but **few cells have '?'** which had to be replaced in columns like normalized-losses, num-of-doors, bore, stroke, horsepower, and peak-rpm variables.

2. The **null values were replaced by the mean value** of the respective columns. For num-of-doors null value was filled based on domain knowledge.

3. For target variable ‘price’, the unknown values were saved as test_data to check model accuracy.

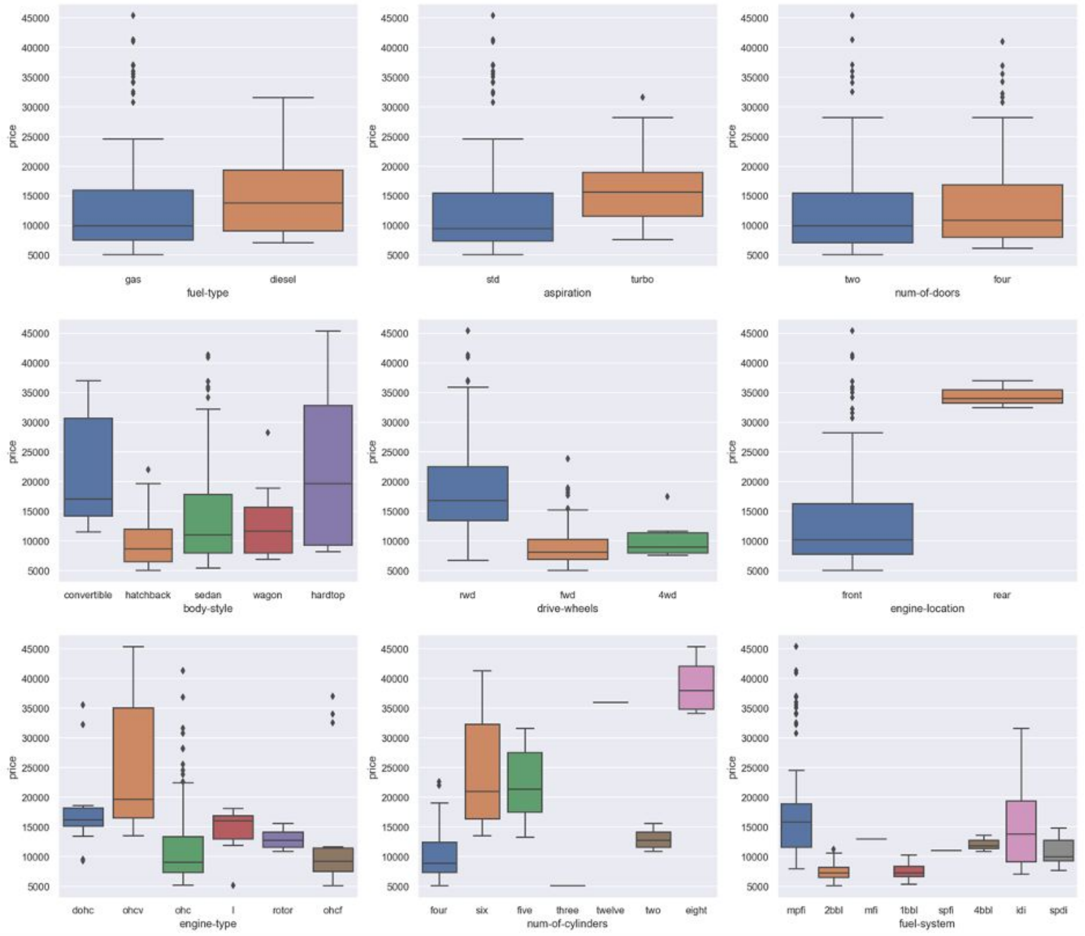
4. For numerical variables we plot scatterplots to understand their relationship with price.



- Columns - compression ratio, height, symboling, normalised-losses, stroke and peak-rpm attributes **has very less relation or no relation with price.**

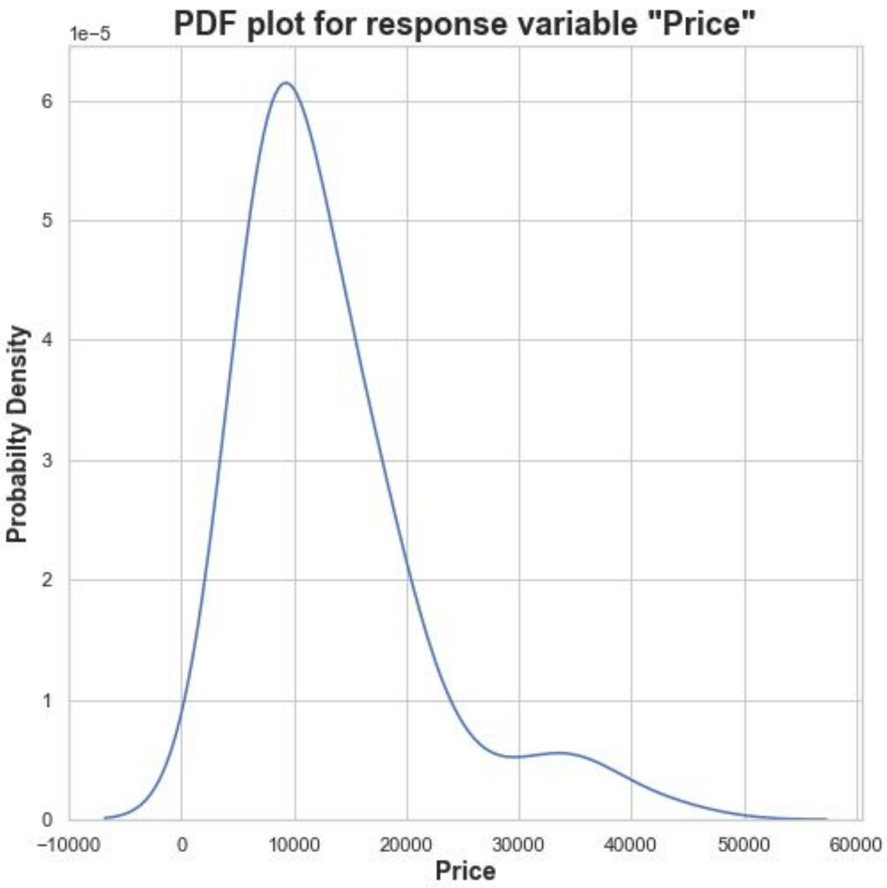
- Other columns have a **positive or negative relationship with price.**

5. For categorical variables we plotted boxplots to understand their relationship vs price.



- Rear wheel drive, rear engine location, eight number of cylinders **make the vehicles costlier.**
- **Multiple outliers** can be identified for each case.

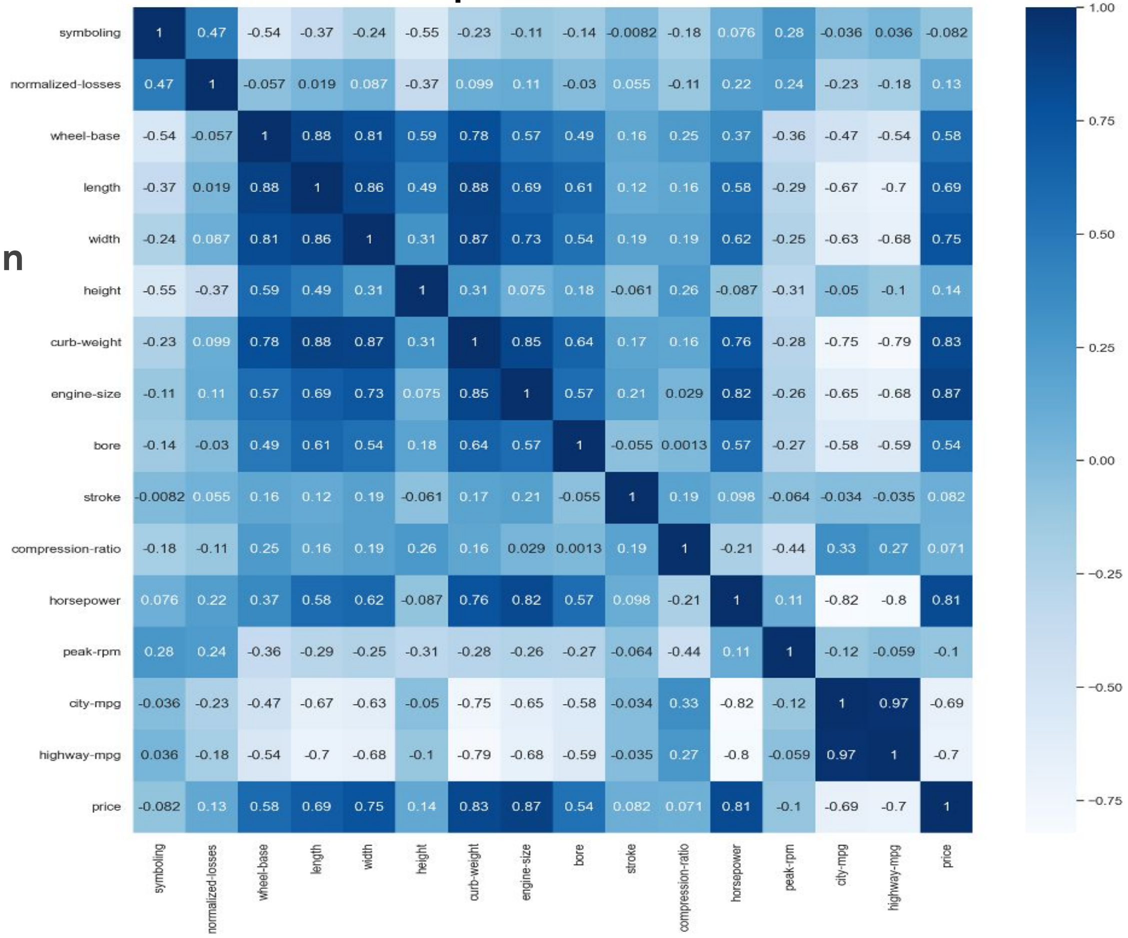
Target variable: “Price” PDF plot



Multicollinearity

We combined the length, width and height columns to create a new column "volume".

Heatmap for numerical variables



Variance Inflation Factor

1. After encoding the categorical features we get 72 features in our data set.

2. As we have only **22 columns out of 72 columns with VIF<10**, this isn't a reliable method to filter out predictors.

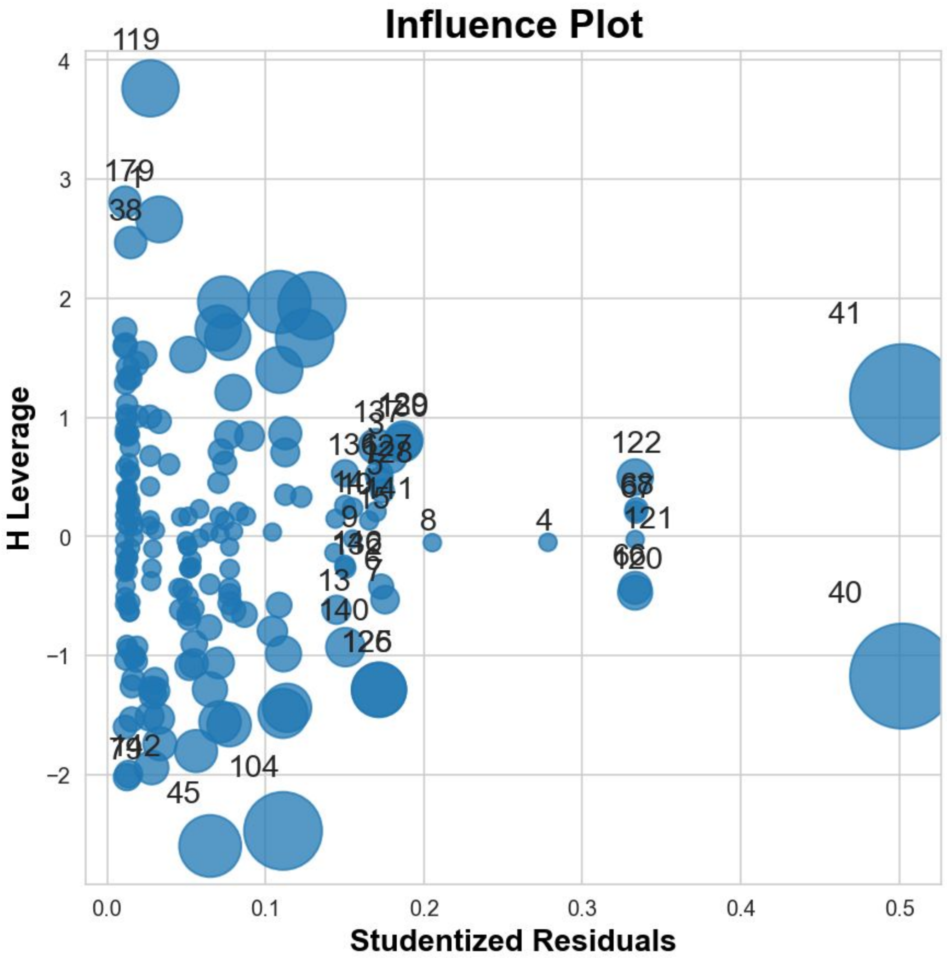
3. Figure beside shows the features which had VIF<10.

	VIF Factor	features
0	0.000000	Intercept
3	5.148115	make[T.chevrolet]
6	4.012004	make[T.isuzu]
7	7.706195	make[T.jaguar]
10	2.938450	make[T.mercury]
14	8.352246	make[T.plymouth]
16	3.468340	make[T.renault]
17	9.790689	make[T.saab]
23	6.483269	aspiration[T.turbo]
24	4.202776	num_of_doors[T.two]
25	3.572518	body_style[T.hardtop]
35	6.169138	engine_type[T.ohcv]
41	8.732602	num_of_cylinders[T.twelve]
44	6.311034	fuel_system[T.4bbl]
46	2.330516	fuel_system[T.mfi]
48	9.671580	fuel_system[T.spdi]
49	3.084567	fuel_system[T.spfi]
50	7.138638	symboling
51	3.864447	normalized_losses
55	8.596078	height
59	6.435681	stroke
62	6.367247	peak_rpm

Influential Points

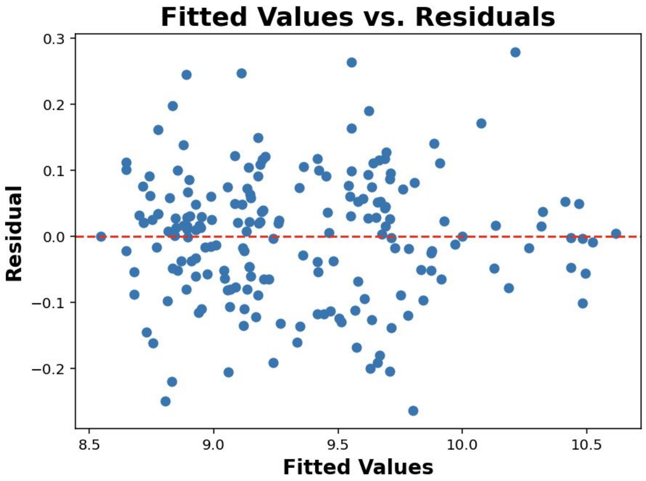
Observations

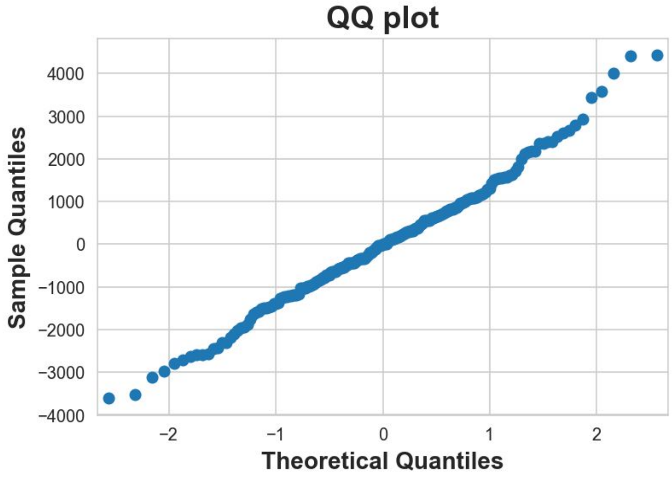
1. We remove the points which we get common in both **Cook's distance** and **studentized residual test results**.
2. **7 records are removed as outliers** (indexes: 40, 41, 119….).
3. Now we are **left with 194 observations.**



Model Assumptions

1. **Heteroscedasticity:**
   a. Initially found that heteroscedasticity existed.
   b. So, **applied log transformation** on the Price variable and performed **Breusch Pegan Test:** *LM-Test p-value:* 0.15 >0.05
   c. Hence, **resolved the issue of heteroscedasticity.**
2. **Normality:** From **QQ plot** we can observe the linear plot representing and performing **Jarque-Bera test:** *(0.406>alpha)*, normality assumption is not violated.
3. **E[ei] = 0**. We can observe that average mean of residuals is 0.





T-test and ANOVA(typ=1) Results

1. **Once the outliers and multicollinearity** is **handled,** model assumptions were agreed upon, We ran the the t test to select the significant features in the model.
2. To verify we are not missing any significance in the features, **we run ANOVA test type 1**.
3. Finally the table beside shows **few features selected** after doing t test and anova type 1.

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	7.7496	0.196	39.467	0.000	7.362	8.137
make_audi	0.3043	0.050	6.141	0.000	0.207	0.402
make_honda	0.0853	0.033	2.557	0.011	0.019	0.151
body_style_convertible	0.1550	0.049	3.191	0.002	0.059	0.251
make_saab	0.1344	0.049	2.732	0.007	0.037	0.231
curb_weight	0.0006	4.54e-05	14.309	0.000	0.001	0.001
make_bmw	0.4168	0.046	9.142	0.000	0.327	0.507
aspiration_turbo	0.0678	0.026	2.632	0.009	0.017	0.119
num_of_cylinders_two	0.1672	0.071	2.360	0.019	0.027	0.307
engine_location_rear	0.3865	0.125	3.093	0.002	0.140	0.633
num_of_cylinders_three	0.4153	0.124	3.347	0.001	0.170	0.660
make_isuzu	-0.2380	0.081	-2.942	0.004	-0.398	-0.078
fuel_system_mpfi	0.0779	0.024	3.213	0.002	0.030	0.126
make_porsche	0.4222	0.110	3.841	0.000	0.205	0.639
city_mpg	-0.0075	0.004	-1.992	0.048	-0.015	-6.98e-05
fuel_system_idi	0.1308	0.048	2.730	0.007	0.036	0.225
num_of_cylinders_eight	0.2034	0.071	2.864	0.005	0.063	0.344

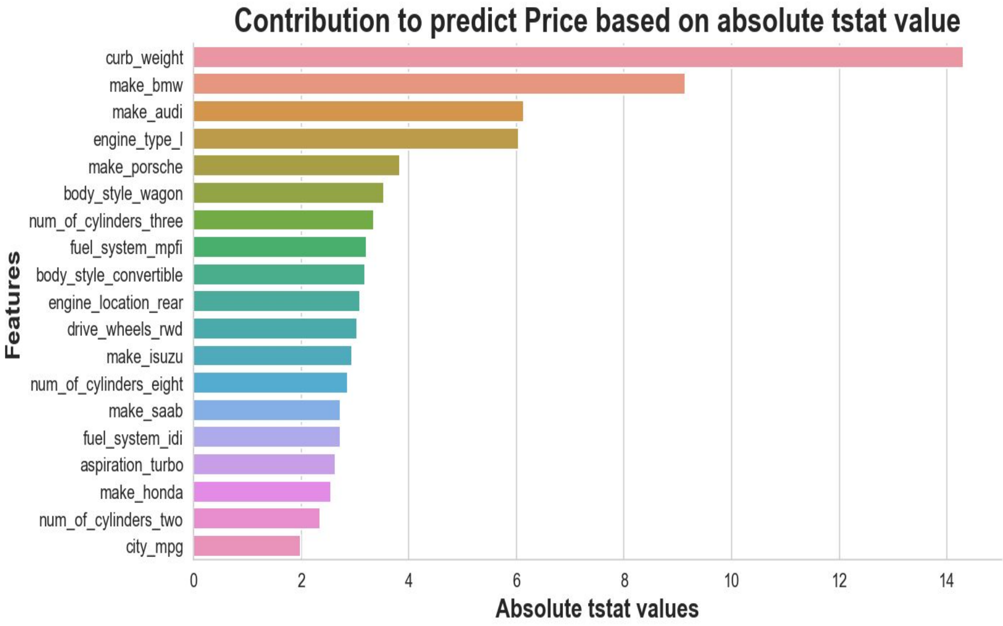
Final model summary

```
                        OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.956
Model:                            OLS   Adj. R-squared:                  0.951
Method:                 Least Squares   F-statistic:                     198.7
Date:                Sat, 15 Oct 2022   Prob (F-statistic):          2.96e-107
Time:                        16:40:01   Log-Likelihood:                 168.50
No. Observations:                 194   AIC:                            -297.0
Df Residuals:                     174   BIC:                            -231.7
Df Model:                          19
Covariance Type:            nonrobust
```

Final model selected achieves:

1. Adj.R2 = 95.1%
2. MSE: 0.0114

From the right graph, we can observe that ***car maker, curb weight, engine type, mpg*** are some major features contributing in **predicting the car price.**

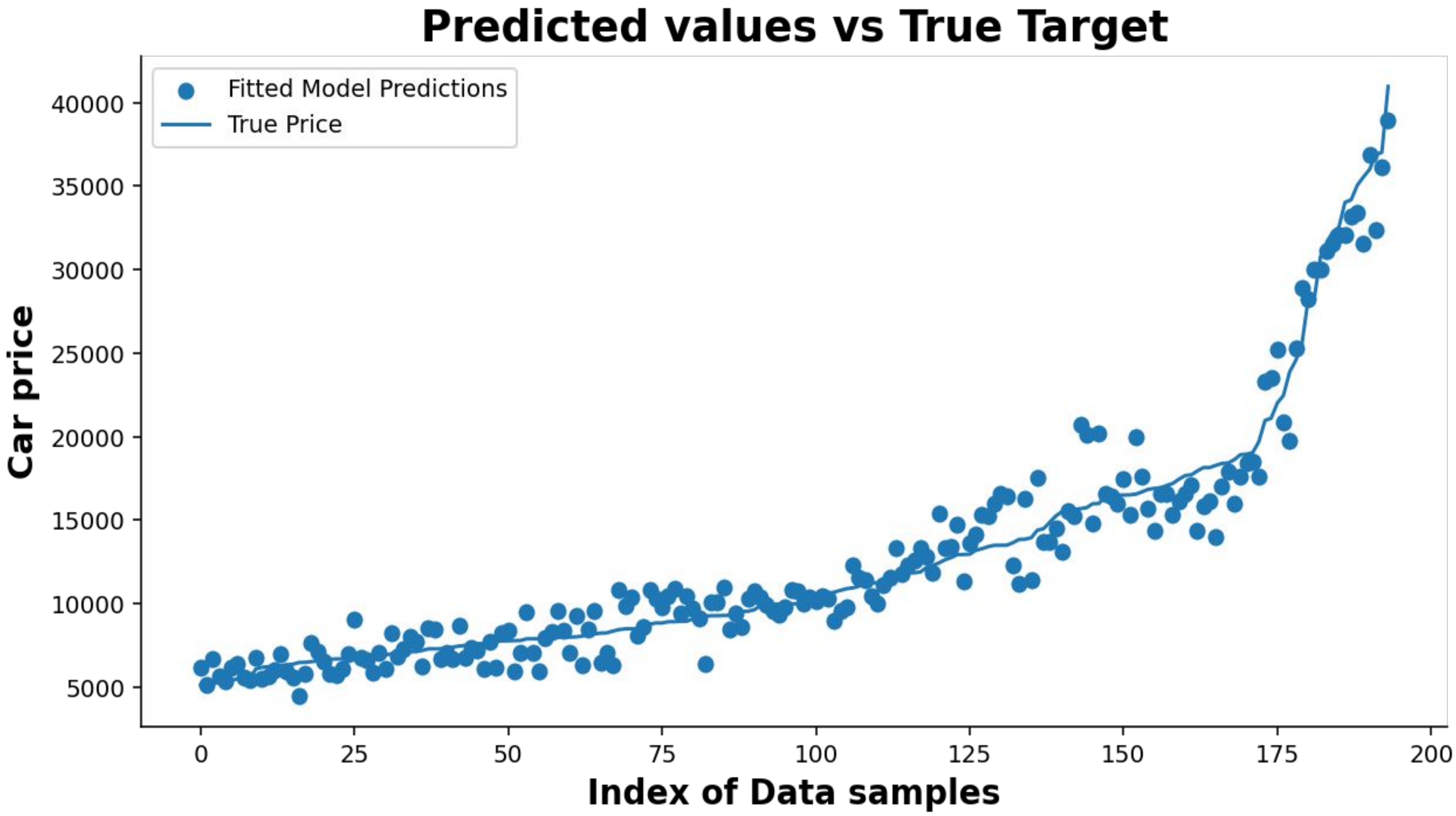


Final model in equation form:

Price~

engine_size+make_toyota+body_style_convertible+make_plymouth+'make_porsche+make_peugot+engine_type_rotor+make_bmw+engine_type_ohcv+curb_weight+stroke+num_of_cylinders_three+wheel_base+bore+make_dodge+horsepower+make_mercedes_benz+make_mitsubishi.

Model Performance Graph



Conclusion

- We observed that the data was too messy with many variables and null values.
- Once the data was cleaned we **performed statistical tests** and **resolved the problems** like:
    - Multicollinearity
    - Influential points
    - Statistical tests
    - Model assumptions and mitigated the violations.
- We came to know that the **car price depends on** the brand(car maker), engine type, mileage, body style whether it's convertible, fuel system etc..
- Models like decision tree or xgboost can perform better.