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Linear Regression of Used Toyota Cars in UK Project

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Introduction

This data set was collected from kaggle.com website which contains information of price, transmission, mileage, fuel type, road tax, miles per gallon (mpg), and engine size of used Toyota cars in United Kingdom.

Problem Statement:

- Find which factor has the most effect on car price?

- Which factor has more impact on car price drop?

- Find the best regression model to predict price with high accuracy?

Web Scraping

Web Scraping

```python
import csv
from bs4 import BeautifulSoup
```

```python
# opening html offline & parsing with BeautifulSoup
htm= open("UK_usedCars.html", 'r')
soup = BeautifulSoup(htm.read(), 'html.parser')

def extract_rows(soup,class_='sc-gAOGNj sc-bXGNvv eYELsP hTKZnU'):
    """ Extracting data from html based on div class """
    rows= soup.find_all('div',class_)

    return [rows[i].getText('div').split('div') for i in range(len(rows))]

def export_data(rows):
    """ Export data to csv file with headers """
    with open('toyota.csv', 'w') as csvfile:
        file_obj = csv.writer(csvfile)
        file_obj.writerow(['model', 'year','price','transmission','mileage','fuelType','tax','mpg', 'engineSize'])
        file_obj.writerows(rows)

data = extract_rows(soup,class_='sc-gAOGNj sc-bXGNvv eYELsP hTKZnU')
export_data(data)
```

```python
data[0:5]
```

```
[[' GT86', '2016', '16000', 'Manual', '24089', 'Petrol', '265', '36.2', '2.0'],
 [' GT86', '2017', '15995', 'Manual', '18615', 'Petrol', '145', '36.2', '2.0'],
 [' GT86', '2015', '13998', 'Manual', '27469', 'Petrol', '265', '36.2', '2.0'],
 [' GT86', '2017', '18998', 'Manual', '14736', 'Petrol', '150', '36.2', '2.0'],
 [' GT86', '2017', '17498', 'Manual', '36284', 'Petrol', '145', '36.2', '2.0']]
```

Data Structure

Before

	model	year	transmission	mileage	fuelType	tax	mpg	engineSize	price
0	GT86	2016	Manual	24089	Petrol	265	36.2	2.0	16000
1	GT86	2017	Manual	18615	Petrol	145	36.2	2.0	15995
2	GT86	2015	Manual	27469	Petrol	265	36.2	2.0	13998
3	GT86	2017	Manual	14736	Petrol	150	36.2	2.0	18998
4	GT86	2017	Manual	36284	Petrol	145	36.2	2.0	17498
...	...	...	...	...	...	...	...	...	...
6733	IQ	2011	Automatic	30000	Petrol	20	58.9	1.0	5500
6734	Urban Cruiser	2011	Manual	36154	Petrol	125	50.4	1.3	4985
6735	Urban Cruiser	2012	Manual	46000	Diesel	125	57.6	1.4	4995
6736	Urban Cruiser	2011	Manual	60700	Petrol	125	50.4	1.3	3995
6737	Urban Cruiser	2011	Manual	45128	Petrol	125	50.4	1.3	4495

6738 rows × 9 columns

After

	model	year	transmission	mileage	fuelType	tax	mpg	engineSize	price
0	GT86	2016	Manual	24089	Petrol	265	36.2	2.0	16000
1	GT86	2017	Manual	18615	Petrol	145	36.2	2.0	15995
2	GT86	2015	Manual	27469	Petrol	265	36.2	2.0	13998
3	GT86	2017	Manual	14736	Petrol	150	36.2	2.0	18998
4	GT86	2017	Manual	36284	Petrol	145	36.2	2.0	17498
...	...	...	...	...	...	...	...	...	...
5923	PROACE VERSO	2019	Manual	588	Diesel	145	40.4	2.0	24498
5924	PROACE VERSO	2019	Manual	7350	Diesel	145	40.4	2.0	24990
5925	PROACE VERSO	2019	Manual	9441	Diesel	145	40.4	2.0	24450
5926	PROACE VERSO	2019	Manual	6570	Diesel	145	40.4	2.0	23950
5927	Camry	2019	Automatic	5145	Hybrid	135	52.3	2.5	24990

5928 rows × 9 columns

Data Cleaning

```python
# searching for douplicate values
dataset.groupby(dataset.columns.tolist(),as_index=False).size().sort_values()
```

```
model   year  transmission  mileage  fuelType  tax  mpg   engineSize  price
 Auris  2007  Automatic     84000    Petrol    205  40.9  1.6         3395     1
 Verso  2011  Manual        67085    Petrol    200  41.5  1.6         5999     1
                            54000    Diesel    145  53.3  2.0         5995     1
                            47570    Petrol    200  41.5  1.6         6795     1
                            29761    Diesel    145  53.3  2.0         7995     1
                                                                              ..
 Aygo   2016  Manual        12935    Petrol    0    69.0  1.0         8450     2
        2019  Manual        2000     Petrol    145  57.7  1.0         10350    3
                            1500     Petrol    145  56.5  1.0         9999     3
                            25       Petrol    145  56.5  1.0         9995     3
 RAV4   2015  Manual        45757    Diesel    125  57.6  2.0         13500    3
Length: 6699, dtype: int64
```

```python
dataset = dataset.drop_duplicates()
dataset.shape
```

```
(6699, 9)
```

```python
dataset.groupby(dataset.columns.tolist(),as_index=False).size().sort_values()
```

```
model   year  transmission  mileage  fuelType  tax  mpg   engineSize  price
 Auris  2007  Automatic     84000    Petrol    205  40.9  1.6         3395     1
 Verso  2011  Manual        67085    Petrol    200  41.5  1.6         5999     1
                            54000    Diesel    145  53.3  2.0         5995     1
                            47570    Petrol    200  41.5  1.6         6795     1
                            29761    Diesel    145  53.3  2.0         7995     1
                                                                              ..
 Aygo   2018  Manual        14716    Petrol    145  56.5  1.0         8222     1
                            14696    Petrol    145  68.9  1.0         7995     1
                            14680    Petrol    145  69.0  1.0         6995     1
                            12987    Petrol    145  56.5  1.0         8295     1
 Yaris  2020  Manual        4895     Petrol    150  49.6  1.0         12495    1
Length: 6699, dtype: int64
```

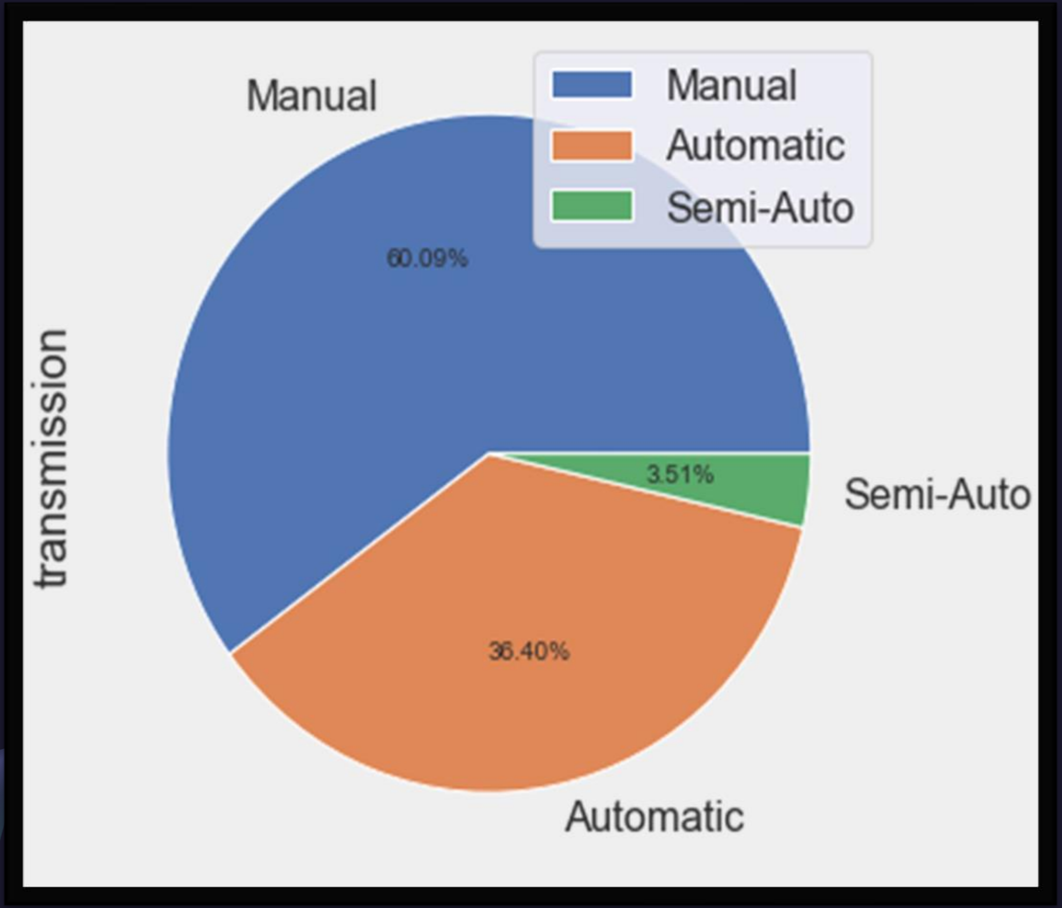
```python
df=df[~((df.transmission == "Other"))]
```

```python
df=df[~((df.fuelType == "Other"))]
```

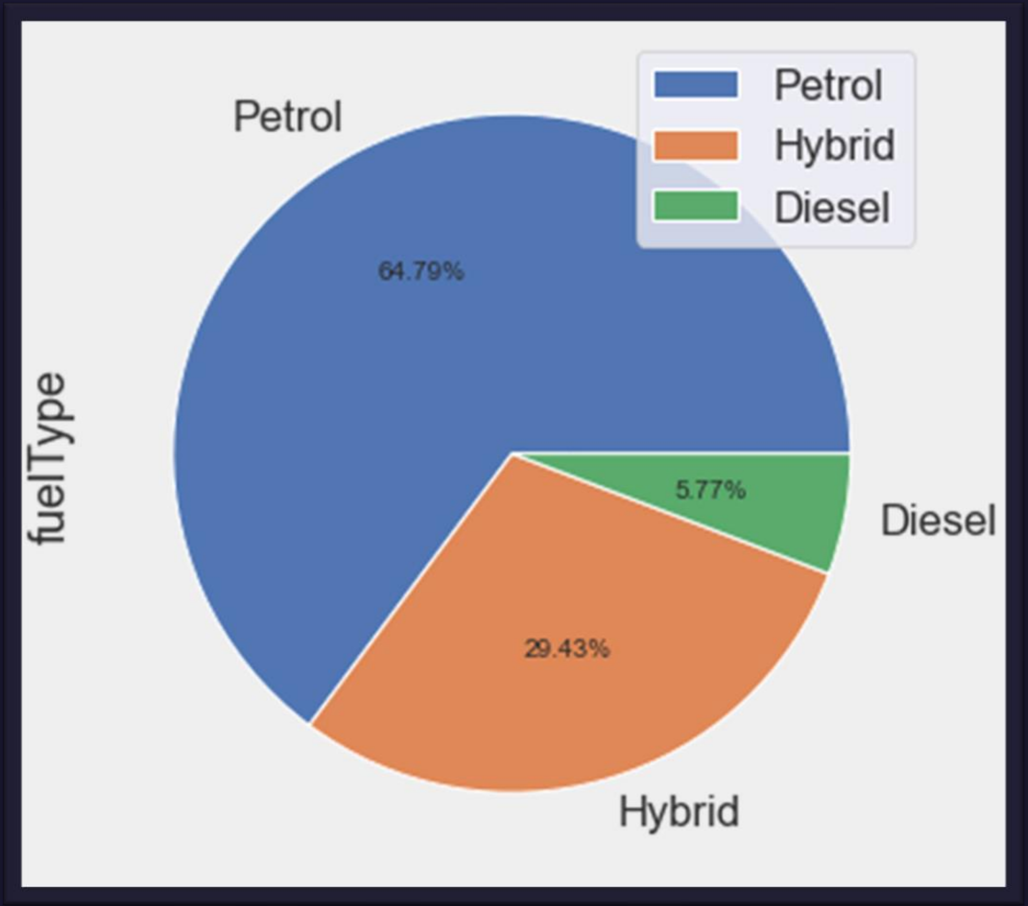
```python
df[df.columns[[1,3,5,6,7,8,]]].corr()
```

Visualization

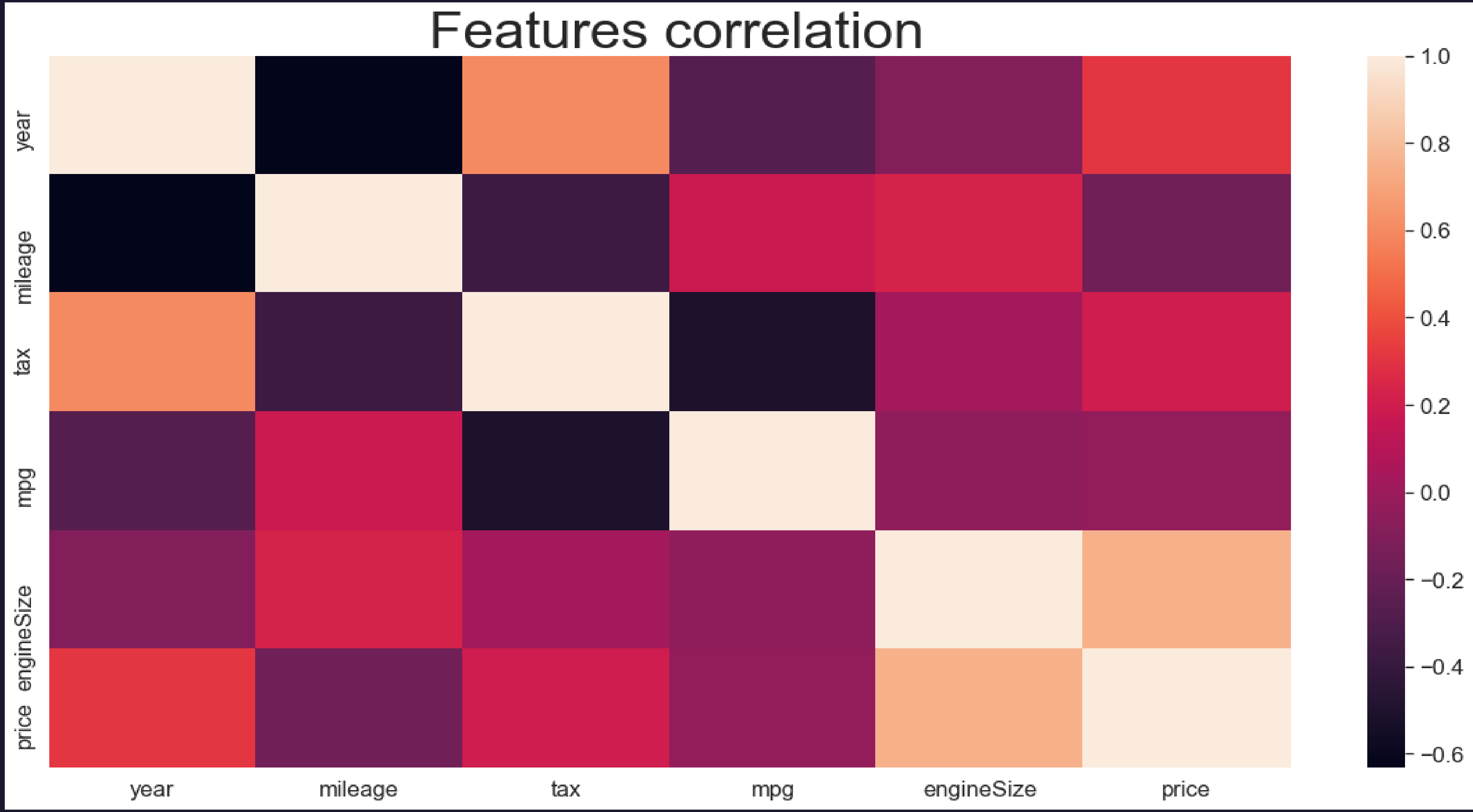
Frequency /counts of car transmission types



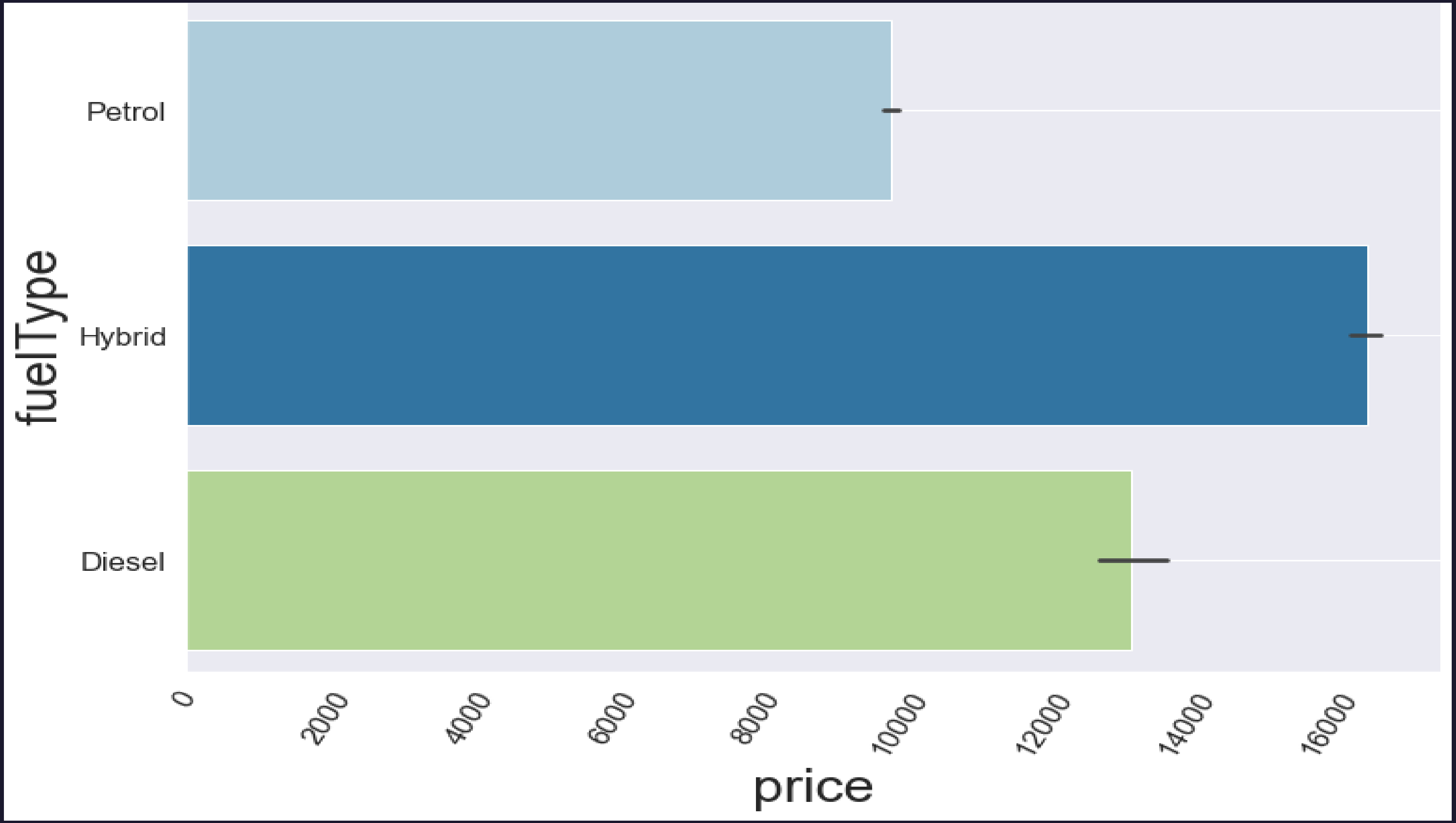
Frequency /counts of car based on fuel types



Heatmap


Features correlation
year
mileage
tax
mpg
engineSize
price
year
mileage
tax
mpg
engineSize
price
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

Price Based on Fuel Type



Linear Regression

```python
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.model_selection import cross_val_score
from sklearn.metrics import mean_squared_error
import sklearn.metrics as metrics
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from pylab import rcParams
rcParams['figure.figsize'] = 9, 5
```

```python
dataset = pd.read_csv('toyota_cleaned_dataset_v2.csv')
dataset.head(2)
```

	model	year	transmission	mileage	fuelType	tax	mpg	engineSize	price
0	GT86	2016	Manual	24089	Petrol	265	36.2	2.0	16000
1	GT86	2017	Manual	18615	Petrol	145	36.2	2.0	15995

```python
# up to 6 values are 0
# to solve this issue substitute with mean
dataset['engineSize'][dataset.engineSize == 0] = dataset.engineSize.median()
```

```python
dataset = pd.get_dummies(dataset, drop_first=True)
dataset.head(3)
```

	year	mileage	tax	mpg	engineSize	price	model_Avensis	model_Aygo	model_C-HR	model_Camry	...	model_Hilux	model_PROACE VERSO
0	2016	24089	265	36.2	2.0	16000	0	0	0	0	...	0	0
1	2017	18615	145	36.2	2.0	15995	0	0	0	0	...	0	0
2	2015	27469	265	36.2	2.0	13998	0	0	0	0	...	0	0

3 rows x 22 columns

```python
X, y = dataset.drop('price',axis=1), dataset['price']

# splitting data to 20/80 for testing and traning
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.2, random_state=10)
```

```python
print(X_train.shape, X_test.shape)
```

```
(4672, 21) (1169, 21)
```

Linear Regression

```python
# linear model
lm = LinearRegression()

# linear regression model cross validation
val_score = cross_val_score(lm, X_train, y_train, # estimator, features, target
                cv=5, # number of folds
                scoring='r2') # scoring metric
val_sc = round(val_score.mean(),4)

lm.fit(X_train, y_train)
y_pred_test = lm.predict(X_test)
r_2 = round(metrics.r2_score(y_test,y_pred_test),4)
mean_sq = round(mean_squared_error(y_test,y_pred_test),2 )
print(f'The average validation score is: {val_sc}\t AND R^2 = {r_2}')
print(f'Mean Squared Error: {mean_sq}')
```

```
The average validation score is: 0.9487  AND R^2 = 0.9452
Mean Squared Error: 1264586.81
```

```python
# lasso model
lm_laso = Lasso(alpha=0.7)

# lasso regression model cross validation
val_score = cross_val_score(lm_laso, X_train, y_train, # estimator, features, target
                cv=5, # number of folds
                scoring='r2') # scoring metric
val_sc = round(val_score.mean(),4)

lm_laso.fit(X_train, y_train)
y_pred_test = lm_laso.predict(X_test)
r_2 = round(metrics.r2_score(y_test,y_pred_test),4)
mean_sq = round(mean_squared_error(y_test,y_pred_test),2 )
print(f'The average validation score is: {val_sc}\t AND R^2 = {r_2}')
print(f'Mean Squared Error: {mean_sq}')
```

```
The average validation score is: 0.9486  AND R^2 = 0.9454
Mean Squared Error: 1260993.2
```

Linear Regression

```python
# Ridge model
lm_reg = Ridge(alpha=1)

# Ridge regression model cross validation
val_score = cross_val_score(lm_reg, X_train, y_train, # estimator, features, target
                cv=5, # number of folds
                scoring='r2') # scoring metric
val_sc = round(val_score.mean(),4)

lm_reg.fit(X_train, y_train)
y_pred_test = lm_reg.predict(X_test)
r_2 = round(metrics.r2_score(y_test,y_pred_test),4)
mean_sq = round(mean_squared_error(y_test,y_pred_test),2 )
print(f'The average validation score is: {val_sc}\t AND R^2 = {r_2}')
print(f'Mean Squared Error: {mean_sq}')
```

```
The average validation score is: 0.9483  AND R^2 = 0.9454
Mean Squared Error: 1260829.35
```

```python
# Feature scaling for train, val, and test so that we can run our ridge model on each
scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train.values)
X_test_scaled = scaler.transform(X_test.values)


# Ridge model
lm_reg = Ridge(alpha=1)

# Ridge regression model cross validation
val_score = cross_val_score(lm_reg, X_train_scaled, y_train, # estimator, features, target
                cv=5, # number of folds
                scoring='r2') # scoring metric
val_sc = round(val_score.mean(),4)

lm_reg.fit(X_train_scaled, y_train)
y_pred_test = lm_reg.predict(X_test_scaled)
r_2 = round(metrics.r2_score(y_test,y_pred_test),4)
mean_sq = round(mean_squared_error(y_test,y_pred_test),2 )

print(f'The average validation score is: {val_sc}\t AND R^2 = {r_2}')
print(f'Mean Squared Error: {mean_sq}')
```

```
The average validation score is: 0.9487  AND R^2 = 0.9452
Mean Squared Error: 1264357.72
```

Linear Regression

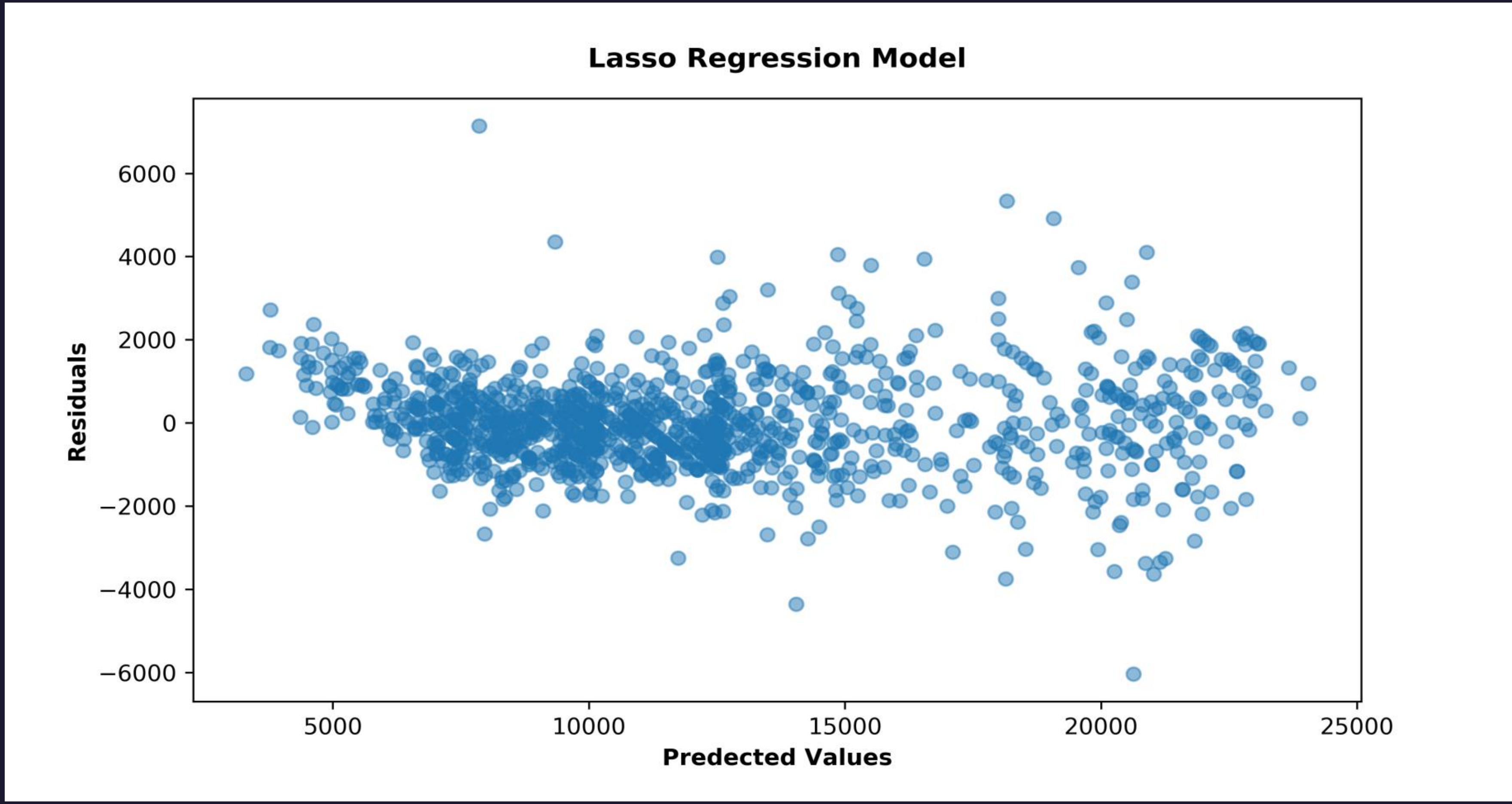
```
# polynomial model
# Feature transforms for train test so that we can run our poly model on each
poly = PolynomialFeatures(degree=2)

X_train_poly = poly.fit_transform(X_train.values)
X_test_poly = poly.transform(X_test.values)

lm_poly = LinearRegression()


# polynomial regression model cross validation
val_score = cross_val_score(lm_poly, X_train_scaled, y_train, # estimator, features, target
                cv=5, # number of folds
                scoring='r2') # scoring metric
val_sc = round(val_score.mean(),4)

lm_poly.fit(X_train_scaled, y_train)
y_pred_test = lm_poly.predict(X_test_scaled)
r_2 = round(metrics.r2_score(y_test,y_pred_test),4)
mean_sq = round(mean_squared_error(y_test,y_pred_test),2 )
print(f'The average validation score of Polynomial regression with degree 2 is: {val_sc}\t AND R^2 = {r_2}')
print(f'Mean Squared Error: {mean_sq}')
```

```
The average validation score of Polynomial regression with degree 2 is: 0.9487   AND R^2 = 0.9452
Mean Squared Error: 1264586.81
```

```
# mean sq error
# lasso Error: min => 1260993.2
print("Selected Model: Lasso Regression")
print('Model coefficients: %s'%(lm_laso.coef_))
print('Model intercept: ',round(lm_laso.intercept_),4)
```

```
Selected Model: Lasso Regression
Model coefficients: [ 7.99151974e+02 -5.20032320e-02 -3.48953929e+00 -2.69901292e+01
  2.86263477e+03  3.18919738e+02 -2.51605732e+03  5.21558343e+03
  1.58117349e+03  4.69229517e+03  4.81102119e+03  6.36237794e+03
  8.50522130e+03  5.07727276e+03  3.51444407e+03  7.18838980e+02
 -1.64006402e+03 -1.39089813e+03 -2.37771014e+02  2.40951966e+03
  5.59965688e+02]
Model intercept:  -1600765.0 4
```

Residual Error



Conclusion

We focused on mileage & engine size features as –/+ correlation to price.

We test 4 models of regression & based on R2 score we select Lasso Regression .

With 0.94 accuracy .

Minimum mean squared error .

Future work :

Applying deep learning algorithm to enhance the accuracy .

Thank you for listening

Any question ?