1. Main objective of the analysis that specifies whether your model will be focused on prediction or interpretation.

- We want a model which can perform both good prediction and interpretation of different feature

In [1]:

```
import pandas as pd, numpy as np , matplotlib.pyplot as plt
```

1. Brief description of the data set you chose and a summary of its attributes.

In [2]:

```
data = pd.read_csv('ToyotaCorolla.csv')
data_copy = data.copy()
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1436 entries, 0 to 1435
Data columns (total 10 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   Price      1436 non-null   int64 
 1   Age        1436 non-null   int64 
 2   KM         1436 non-null   int64 
 3   FuelType   1436 non-null   object
 4   HP         1436 non-null   int64 
 5   MetColor   1436 non-null   int64 
 6   Automatic  1436 non-null   int64 
 7   CC         1436 non-null   int64 
 8   Doors      1436 non-null   int64 
 9   Weight     1436 non-null   int64 
dtypes: int64(9), object(1)
memory usage: 112.3+ KB
```

Brief Data Description

- Data is related to the car price of Toyota Brand car with different specification . As per the age of car and KM it is driven we have different prices of the car
- There are total 1436 car prices are given with respect to 9 features of the car
- Also here we have price of old cars whose age is ranging from 1-80 years

In [3]:

```
data.drop(columns = ['FuelType']).describe().loc[['min','max' ,'mean','count'],:].T
```

Out[3]:

	min	max	mean	count
Price	4350.0	32500.0	10730.824513	1436.0
Age	1.0	80.0	55.947075	1436.0
KM	1.0	243000.0	68533.259749	1436.0
HP	69.0	192.0	101.502089	1436.0
MetColor	0.0	1.0	0.674791	1436.0
Automatic	0.0	1.0	0.055710	1436.0
CC	1300.0	2000.0	1566.827994	1436.0
Doors	2.0	5.0	4.033426	1436.0
Weight	1000.0	1615.0	1072.459610	1436.0

From the above mean value of different variable we conclude that how each continuous variable differ in scale of measurement

In [4]:

```
data[['FuelType']].describe()
```

Out[4]:

	FuelType
count	1436
unique	3
top	Petrol
freq	1264

1. Brief summary of data exploration and actions taken for data cleaning and feature engineering.

- Converting categorical variable to their respective dummy variable . Here , all categorical variable other than Fuel type is al

In [5]:

```
data_tr = pd.get_dummies(data ,columns = ['FuelType'] ,drop_first = True)
data_tr.shape
```

Out[5]:

```
(1436, 11)
```

In [6]:

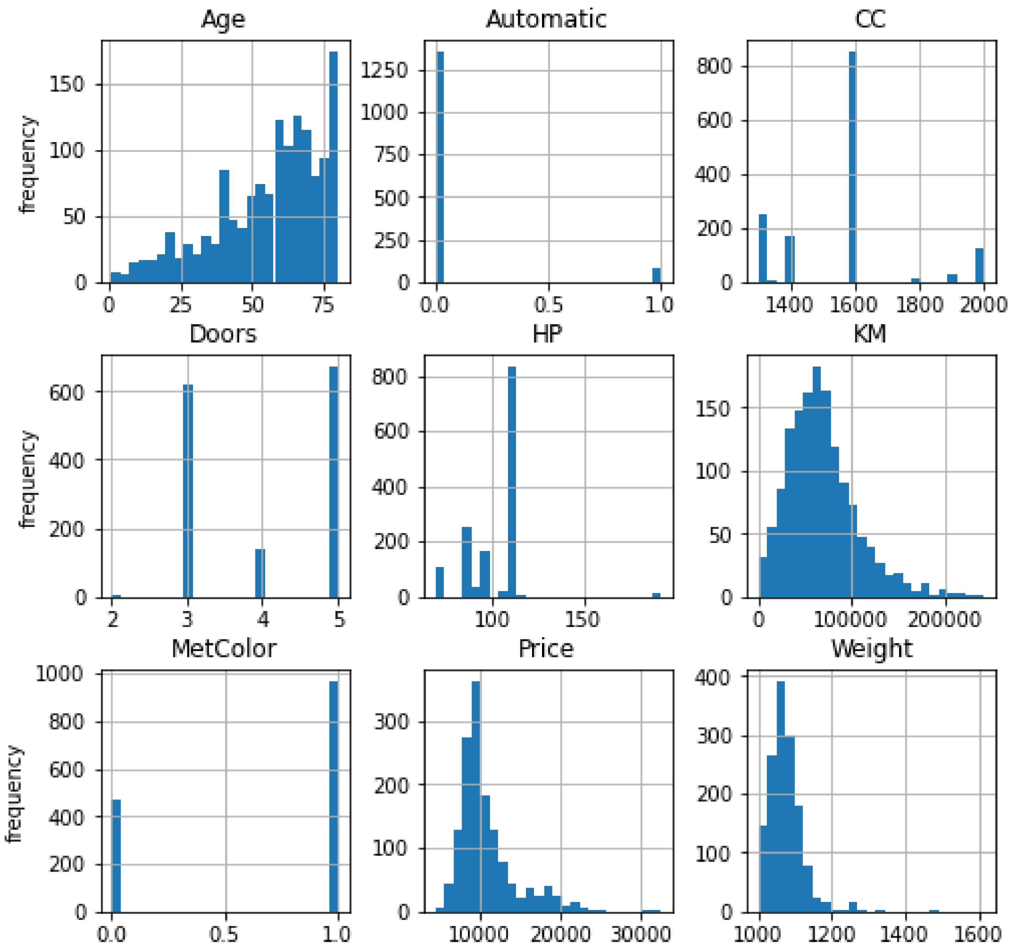
```
data_tr.dtypes
```

Out[6]:

```
Price              int64
Age                int64
KM                 int64
HP                 int64
MetColor           int64
Automatic          int64
CC                 int64
Doors              int64
Weight             int64
FuelType_Diesel    uint8
FuelType_Petrol    uint8
dtype: object
```

In [7]:

```
axList = data_tr[data_tr.columns[data_tr.dtypes==np.int64]].hist(bins=25 ,figsize = (8,8))
for ax in axList.flatten():
    if ax.is_first_col():
        ax.set_ylabel('frequency')
```



We get to know from the above plot that variable 'Automatic' , 'CC' , 'Doors' ,'HP' ,'MetColor' are categorical and are ordinal variable except 'MetColor' and 'Automatic'

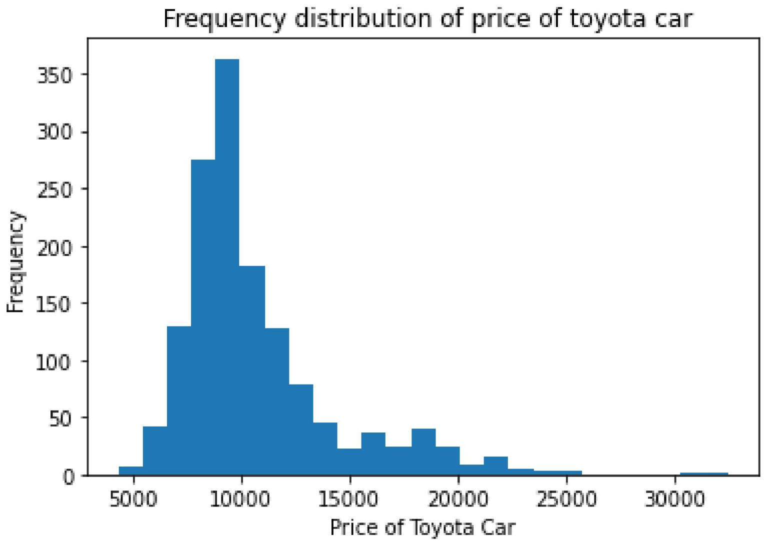
Here our target variable of interest is Price of car lets first check whether it is normally distributed or not

In [8]:

```
ax = data_tr['Price'].plot.hist(bins = 25)
ax.set(xlabel = 'Price of Toyota Car',
      title = " Frequency distribution of price of toyota car")
```

Out[8]:

```
[Text(0.5, 0, 'Price of Toyota Car'),
 Text(0.5, 1.0, ' Frequency distribution of price of toyota car')]
```



from the above plot it is clear that price of car is positively skewed. It is not normal distributed

In [9]:

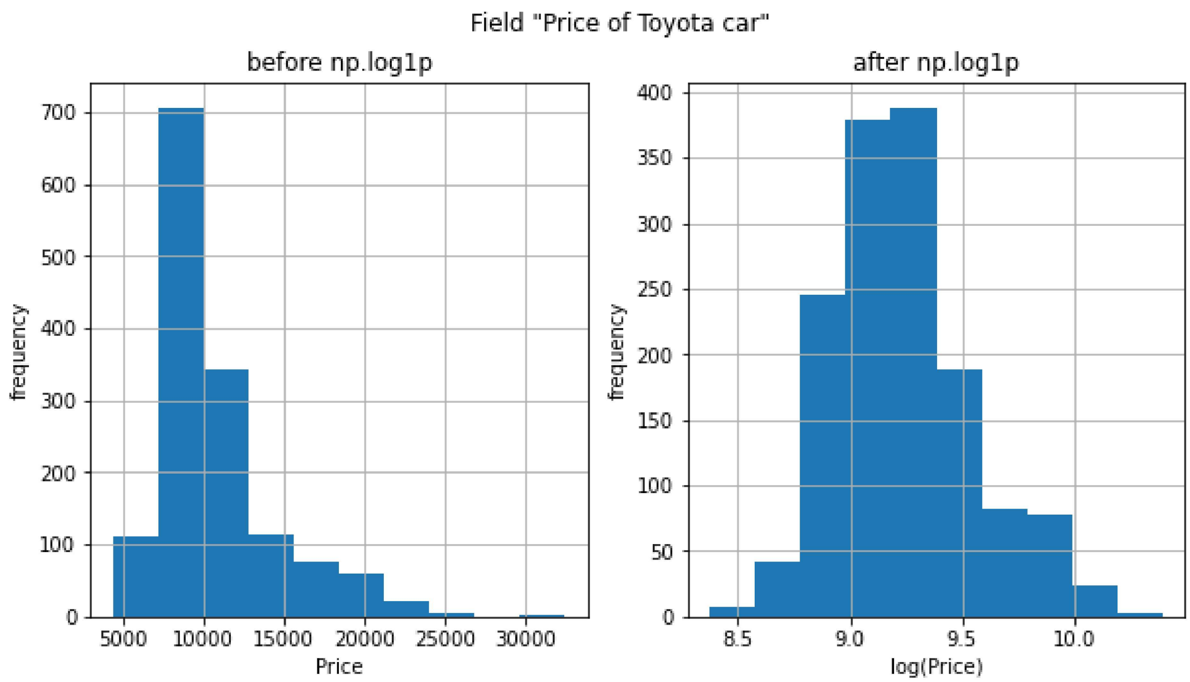
```
# Let's look at what happens to Price, when we apply np.log1p visually.

# Create two "subplots" and a "figure" using matplotlib
fig, (ax_before, ax_after) = plt.subplots(1, 2, figsize=(10, 5))

# Create a histogram on the "ax_before" subplot
data_tr['Price'].hist(ax=ax_before)

# Apply a log transformation (numpy syntax) to this column
data_tr['Price'].apply(np.log1p).hist(ax=ax_after)

# Formatting of titles etc. for each subplot
ax_before.set(title='before np.log1p', ylabel='frequency', xlabel='Price')
ax_after.set(title='after np.log1p', ylabel='frequency', xlabel='log(Price)')
fig.suptitle('Field "{}"'.format('Price of Toyota car'));
```



In [10]:

```
from scipy.stats import normaltest
statistics , p =normaltest(np.log1p(data_tr['Price']))
if (p > 0.05):
    print('Price of car is normally distributed after log transformation')
else :
    print('Price of car is not normally distributed after log transformation')
print('pvalue is :-',p)
```

```
Price of car is not normally distributed after log transformation
pvalue is :- 1.0018988063780995e-26
```

Thus also after the log transformation Price is not normal distributed lets try with boxcox transformation

In [11]:

```
from scipy.stats import boxcox
z,lamb = boxcox(data_tr['Price'])
statistics , p =normaltest(z)
if (p > 0.05):
    print('Price of car is normally distributed after boxcox transformation')
else :
    print('Price of car is not normally distributed after boxcox transformation')
print('pvalue is :-' ,p)
```

```
Price of car is not normally distributed after boxcox transformation
pvalue is :- 0.018972015148861304
```

From the above two transformation p value result we can say that boxcox transformation is working very well then the log transformation to transform the price of car in normal distributed variable . So , we can consider box cox transformation for our further model building

In [12]:

```
num_col = ['KM','Price','CC' , 'Weight' ,'Age' ,'HP']
```

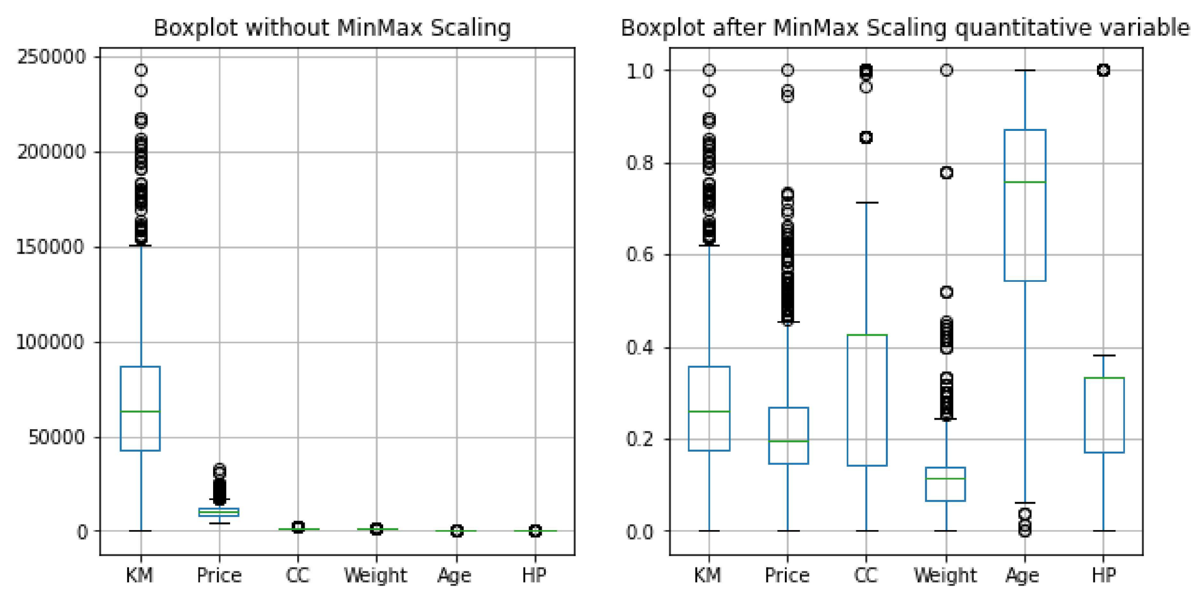
In [13]:

```
from sklearn.preprocessing import MinMaxScaler
MMS = MinMaxScaler()
MMS.fit(data_tr.loc[:,num_col])
tt = MMS.transform(data_tr.loc[:,num_col])
tt = pd.DataFrame(tt)
tt.columns = ['KM','Price','CC' , 'Weight' ,'Age' ,'HP']


# Checking for outliers in our data
fig ,(ax_before ,ax_after) = plt.subplots(1,2 ,figsize = (10,5))
tt.boxplot(ax = ax_after)
data_tr.loc[:,num_col].boxplot(ax = ax_before)
ax_before.set(title = 'Boxplot without MinMax Scaling ')
ax_after.set(title = 'Boxplot after MinMax Scaling quantitative variable')
```

Out[13]:

```
[Text(0.5, 1.0, 'Boxplot after MinMax Scaling quantitative variable')]
```



In [14]:

```
import seaborn as sns
(data_tr.drop(columns=num_col))
```

Out[14]:

	MetColor	Automatic	Doors	FuelType_Diesel	FuelType_Petrol
0	1	0	3	1	0
1	1	0	3	1	0
2	1	0	3	1	0
3	0	0	3	1	0
4	0	0	3	1	0
...	...	...	...	...	...
1431	1	0	3	0	1
1432	0	0	3	0	1
1433	0	0	3	0	1
1434	1	0	3	0	1
1435	0	0	5	0	1

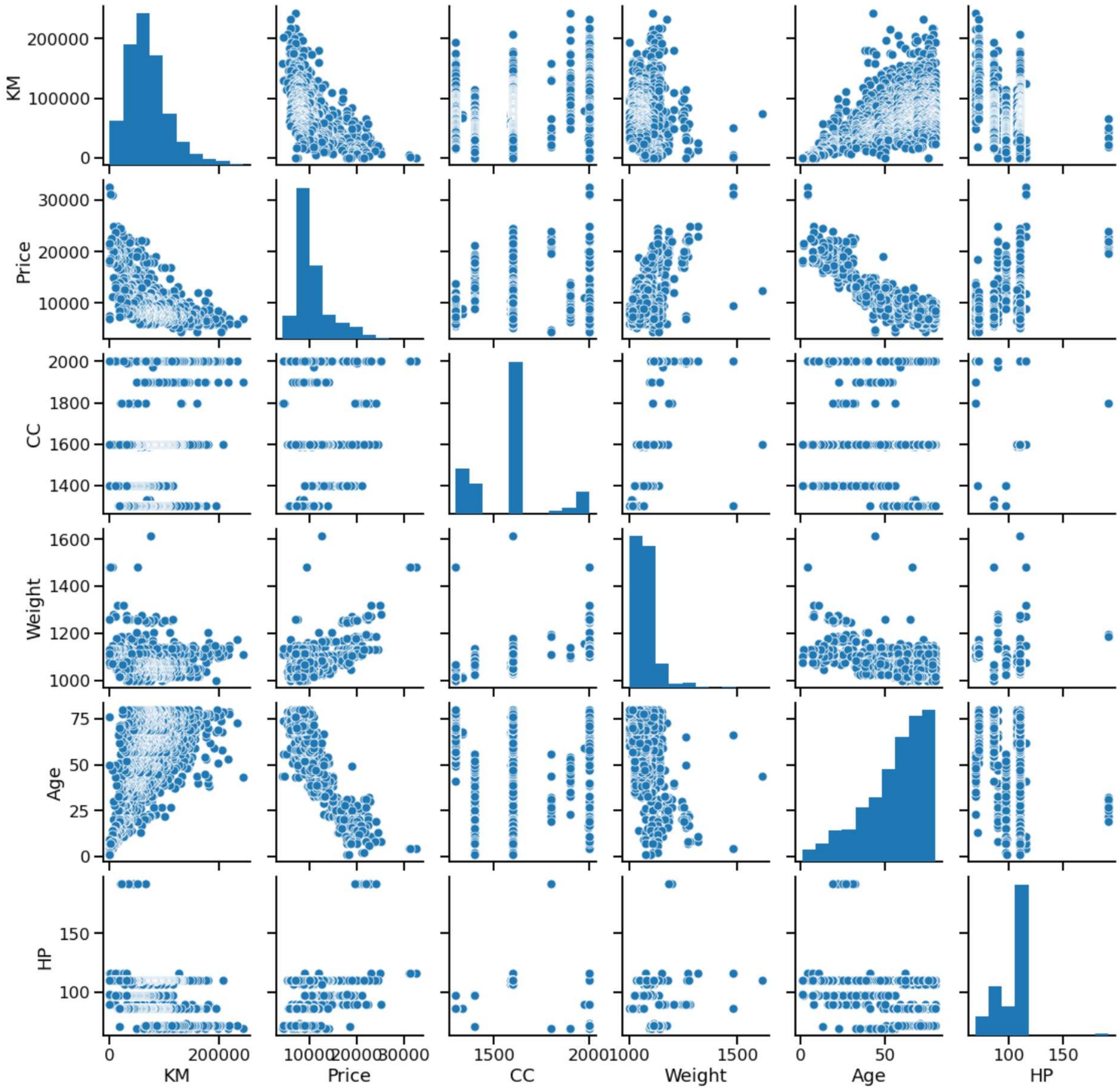
1436 rows × 5 columns

In [15]:

```
### BEGIN SOLUTION
sns.set_context('talk')
sns.pairplot(data_tr[num_col] )
```

Out[15]:

<seaborn.axisgrid.PairGrid at 0x16b37a8cf40>



In [16]:

```
data_tr.head()
```

Out[16]:

	Price	Age	KM	HP	MetColor	Automatic	CC	Doors	Weight	FuelType_Diesel	FuelTyp
0	13500	23	46986	90	1	0	2000	3	1165	1	
1	13750	23	72937	90	1	0	2000	3	1165	1	
2	13950	24	41711	90	1	0	2000	3	1165	1	
3	14950	26	48000	90	0	0	2000	3	1165	1	
4	13750	30	38500	90	0	0	2000	3	1170	1	

1. Summary of training at least three linear regression models which should be variations that cover using a simple linear regression as a baseline, adding polynomial effects, and using a regularization regression. Preferably, all use the same training and test splits, or the same cross-validation method.

(a.) Simple Linear Regression without polynomial features

In [17]:

```
X = data_tr.drop('Price', axis=1)
y = data_tr.Price
```

- Creating K Fold training and testing set

In [19]:

```
from sklearn.model_selection import KFold
kf  = KFold(n_splits = 5 , random_state = 42 ,shuffle = True)

for train_index, test_index in kf.split(X):
    print("Train index:", train_index[:10], len(train_index))
    print("Test index:",test_index[:10], len(test_index))
    print('')
```

```
Train index: [0 1 2 3 4 5 6 7 8 9] 1148
Test index: [15 23 29 30 32 43 44 49 51 56] 288

Train index: [ 0  1  2  4  6  7  8  9 11 13] 1149
Test index: [ 3  5 10 12 31 39 48 54 59 83] 287

Train index: [ 1  3  4  5  8 10 11 12 13 14] 1149
Test index: [ 0  2  6  7  9 25 27 33 45 47] 287

Train index: [ 0  1  2  3  5  6  7  8  9 10] 1149
Test index: [ 4 11 16 17 18 19 22 24 28 35] 287

Train index: [ 0  2  3  4  5  6  7  9 10 11] 1149
Test index: [ 1  8 13 14 20 21 26 34 37 40] 287
```

- Checking training error on different test set

In [20]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

scores_lr = []
lr = LinearRegression()

for train_index, test_index in kf.split(X):
    X_train, X_test, y_train, y_test = (X.iloc[train_index, :],
                                        X.iloc[test_index, :],
                                        y[train_index],
                                        y[test_index])

    lr.fit(X_train, y_train)

    y_pred = lr.predict(X_test)

    score = r2_score(y_test.values, y_pred)

    scores_lr.append(score)

scores_lr
```

Out[20]:

```
[0.8463009058053605,
 0.8516617085360746,
 0.8713216872861502,
 0.8734847611130779,
 0.8583923728040344]
```

(b.) Simple Linear Regression with all 2nd order polynomial features

- Adding Polynomial features

In [21]:

```
from sklearn.preprocessing import  PolynomialFeatures
pf = PolynomialFeatures(degree = 2 ,include_bias = False)
X_pf = pf.fit_transform(X)
X_pf = pd.DataFrame(X_pf)
X_pf.head()
```

Out[21]:

	0	1	2	3	4	5	6	7	8	9	...	55	56	57	58	5
0	23.0	46986.0	90.0	1.0	0.0	2000.0	3.0	1165.0	1.0	0.0	...	9.0	3495.0	3.0	0.0	1357225.
1	23.0	72937.0	90.0	1.0	0.0	2000.0	3.0	1165.0	1.0	0.0	...	9.0	3495.0	3.0	0.0	1357225.
2	24.0	41711.0	90.0	1.0	0.0	2000.0	3.0	1165.0	1.0	0.0	...	9.0	3495.0	3.0	0.0	1357225.
3	26.0	48000.0	90.0	0.0	0.0	2000.0	3.0	1165.0	1.0	0.0	...	9.0	3495.0	3.0	0.0	1357225.
4	30.0	38500.0	90.0	0.0	0.0	2000.0	3.0	1170.0	1.0	0.0	...	9.0	3510.0	3.0	0.0	1368900.

5 rows × 65 columns

- Checking Training error on different test set

In [22]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

scores_lr_pf = []
lr = LinearRegression()

for train_index, test_index in kf.split(X):
    X_train, X_test, y_train, y_test = (X_pf.iloc[train_index, :],
                                        X_pf.iloc[test_index, :],
                                        y[train_index],
                                        y[test_index])

    lr.fit(X_train, y_train)

    y_pred = lr.predict(X_test)

    score = r2_score(y_test.values, y_pred)

    scores_lr_pf.append(score)

scores_lr_pf
```

Out[22]:

```
[0.744794689714854,
 0.8923058597980359,
 0.8982241850460506,
 0.8940510680742745,
 0.7507977888929567]
```

(c) Lasso Regression with polynomial feature upto 2nd order

- Now we have to perform scaling of features as we are doing regularization using L1 penalty . We have not done scaling while performing vanila regression before as feature scaling does not matter in performance of model

In [27]:

```
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.linear_model import Lasso
from sklearn.model_selection import cross_val_predict

ls = Lasso(alpha = 1.0 , max_iter = 100000)
s = StandardScaler()
estimator = Pipeline([("scaler", s),
                      ("regression", ls)])
predictions = cross_val_predict(estimator, X_pf , y, cv=kf)
scores_ls = r2_score(y, predictions)
scores_ls
```

Out[27]:

```
0.8953217277670256
```

- Above I have arbitarily chosen the value of hyperparameter as 1 . One can hypertune this hyperparameter with best possible choice . I have taken 1.0 as there are lot feature in the data and I want to have descent penalty ,so, that the coefficient of irrelevant variable is exactly zero

1. A paragraph explaining which of your regressions you recommend as a final model that best fits your needs in terms of accuracy and explainability.

In [32]:

```
pd.DataFrame({'linear_regression': scores_lr , 'linear_regression_polynomial_feat': scores_lr_pf ,
              'lasso_regression': scores_ls})
```

Out[32]:

	linear_regression	linear_regression_polynomial_feat	lasso_regression
0	0.846301	0.744795	0.895322
1	0.851662	0.892306	0.895322
2	0.871322	0.898224	0.895322
3	0.873485	0.894051	0.895322
4	0.858392	0.750798	0.895322

- We can see from the above table that lasso regression is outperforming all other model in terms of explaining the variance of the variable 'Price of the Toyota Car' . 89.5% of the variability of the response is exlpained by the lasso regression model . Also , we have some advantage of model interpreatability

1. Summary Key Findings and Insights, which walks your reader through the main drivers of your model and insights from your data derived from your linear regression model.

Key Findings are as follows :-

- Price of car decreases as age of car decreases and vice versa
- Price of car is high if the car is automatic car
- Approx 90% of the variance in Price of the car is explained by the regression model

1. Suggestions for next steps in analyzing this data, which may include suggesting revisiting this model adding specific data features to achieve a better explanation or a better prediction.

- We can hypertune the parameter of the lasso regression in our next step to get the best possible result
- We can implment GridSearch or any other merhod to search the best hyper paramater
- We can try to get the coefficient of the features and we can analyse them further for model interpreatation part

In [ ]:

```

```