Ford car price prediction using linear regression

In this project we are going to perform Ford car price prediction using linear regression by following steps

1. Data Loading
2. EDA (Exploratory data Analysis)
3. Data cleaning
4. Data processing
5. Splitting the Dataset
6. Model training
7. Model testing
8. Model evaluation

About this Dataset

1.model - > Ford Car Brands 2.year - >Production Year 3.price - >Price of car in $ 4.transmission - > Automatic,Manual, Semi-Auto 5.mileage -> Number of miles traveled 6.fuel_Type -> Petrol,Diesel,Hybrid,Electric,Other 7.tax -> Annual Tax 8.mpg - > Miles per Gallon 9.engineSize - > Car's Engine Size

In [199…
```
## Importing important libraries
import numpy as np
import  pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [200…
```
## Loading the Dataset
df = pd.read_csv("ford.csv")
```

EDA

In [201…
```
df.shape ## Dataset has 17966 rows & 9 columns
```

Out[201…
```
(17966, 9)
```

In [202…
```
df.columns
```

Out[202…
```
Index(['model', 'year', 'price', 'transmission', 'mileage', 'fuelType', 'tax',
       'mpg', 'engineSize'],
      dtype='object')
```

Here price is Dependent variable & Other columns will be Independent variables. Now, we have to select which columns to use in our model by checking correlation of each column with price through EDA.

In [203…
```
df.info() ## Checking null values & datatype of each column
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17966 entries, 0 to 17965
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   model         17966 non-null  object 
 1   year          17966 non-null  int64  
 2   price         17966 non-null  int64  
 3   transmission  17966 non-null  object 
 4   mileage       17966 non-null  int64  
 5   fuelType      17966 non-null  object 
 6   tax           17966 non-null  int64  
 7   mpg           17966 non-null  float64
 8   engineSize    17966 non-null  float64
dtypes: float64(2), int64(4), object(3)
memory usage: 1.2+ MB
```

In [204…
```
df.describe() ## Statistical Analysis of each numeric column
```

Out[204…

	year	price	mileage	tax	mpg	engineSize
count	17966.000000	17966.000000	17966.000000	17966.000000	17966.000000	17966.000000
mean	2016.866470	12279.534844	23362.608761	113.329456	57.906980	1.350807
std	2.050336	4741.343657	19472.054349	62.012456	10.125696	0.432367
min	1996.000000	495.000000	1.000000	0.000000	20.800000	0.000000
25%	2016.000000	8999.000000	9987.000000	30.000000	52.300000	1.000000
50%	2017.000000	11291.000000	18242.500000	145.000000	58.900000	1.200000
75%	2018.000000	15299.000000	31060.000000	145.000000	65.700000	1.500000
max	2060.000000	54995.000000	177644.000000	580.000000	201.800000	5.000000

In [205…

```
df.isnull().sum().sum() ## There are no null values
```

Out[205…

```
np.int64(0)
```

In [206…

```
df.isna().sum().sum() ## There are no na values
```

Out[206…

```
np.int64(0)
```

In [207…

```
df.duplicated().sum() ## Dataset has 154 duplicate rows
```

Out[207…

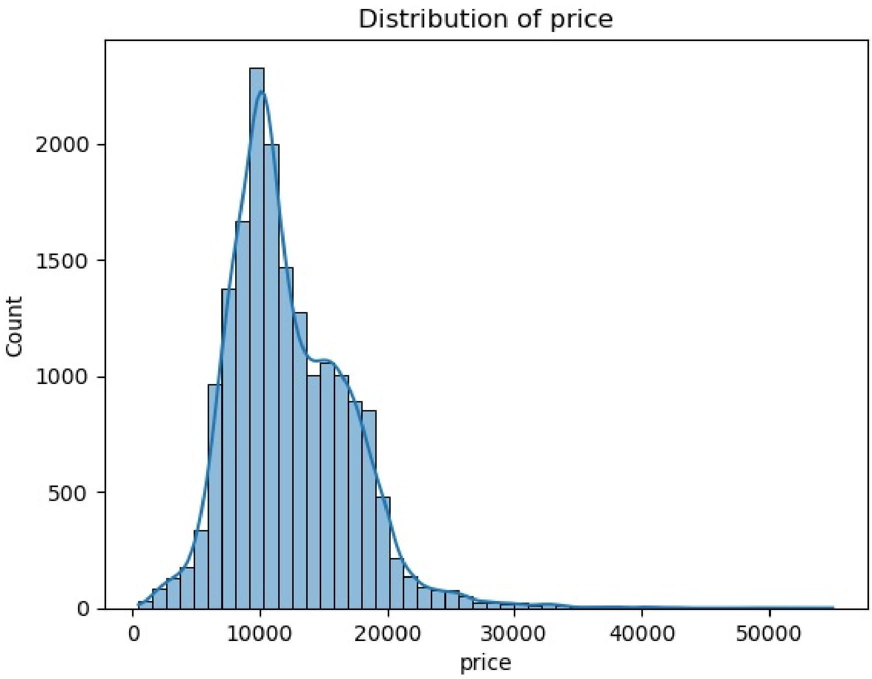
```
np.int64(154)
```

In [208…

```
## Checking the Distribution of prices by histogram
sns.histplot(data=df,x="price",bins=50,kde=True)
plt.title("Distribution of price")
'''The distribution of price has outliers on the right side which means
 there are few cars with very price'''
```

Out[208…

```
'The distribution of price has outliers on the right side which means\n there are few cars with very price'
```

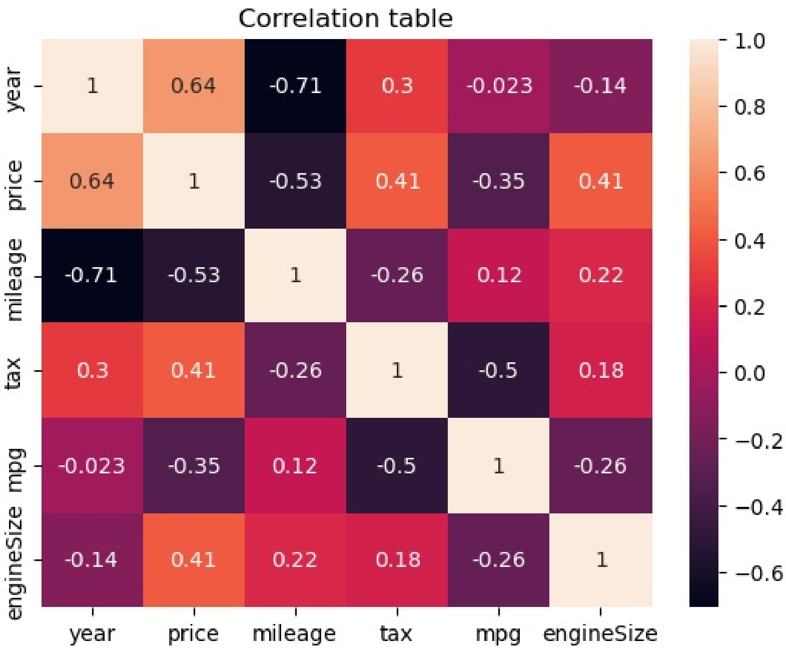


In [209…

```
## Plotting the correlation between numerical variable using heatmap
sns.heatmap(df.corr(numeric_only=True),annot=True)
plt.title("Correlation table")
'''year,tax,enginesize are positively correlated to price
whereas, mileage & mpg are negetively correllated'''
```

Out[209…

```
'year,tax,enginesize are positively correlated to price\nwhereas, mileage & mpg are negetively correllated'
```



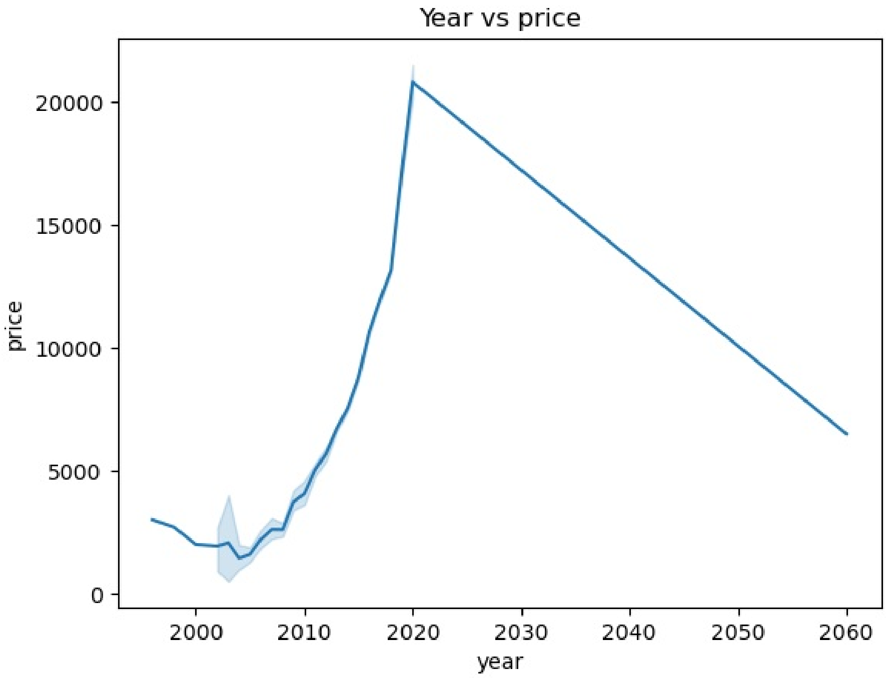
	year	price	mileage	tax	mpg	engineSize
year	1	0.64	-0.71	0.3	-0.023	-0.14
price	0.64	1	-0.53	0.41	-0.35	0.41
mileage	-0.71	-0.53	1	-0.26	0.12	0.22
tax	0.3	0.41	-0.26	1	-0.5	0.18
mpg	-0.023	-0.35	0.12	-0.5	1	-0.26
engineSize	-0.14	0.41	0.22	0.18	-0.26	1

In [210…

```
## Checking relation between year & price through line chart
sns.lineplot(x="year",y="price",data=df)
plt.title("Year vs price")
''' Here we can see there are entries with year (year of release)
in 2060 as well which is impractical & should be removed from datset
Year has high posituve correlation with price & should be used in model'''
```

Out[210…

```
' Here we can see there are entries with year (year of release) \nin 2060 as well which is impractical & should be removed from datset\nYear has high posituve correlation with price & should be used in model'
```

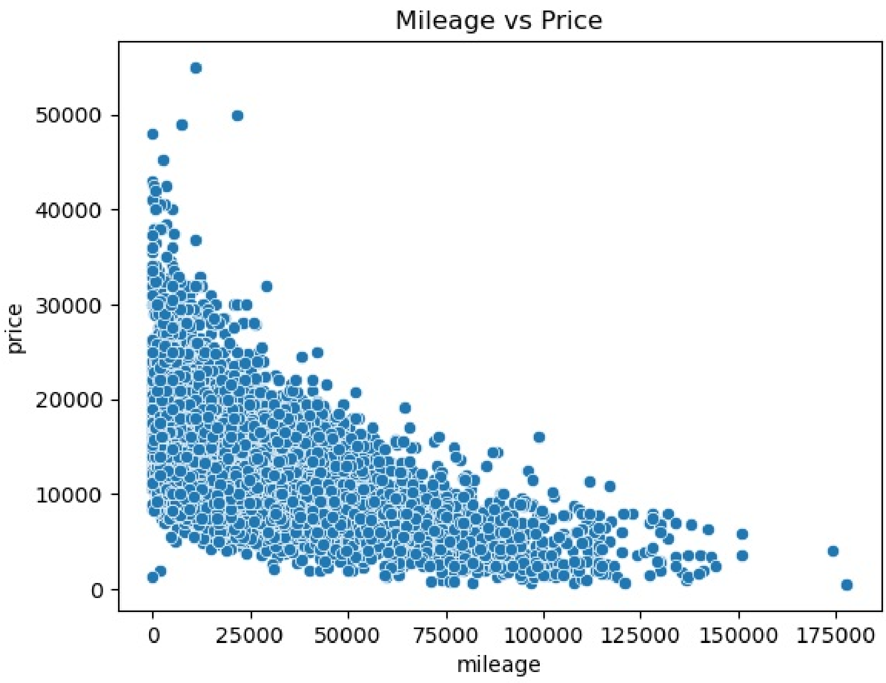


In [211…

```
## Checking the relation between mileage & price using scatter plot
sns.scatterplot(data=df,x="mileage",y="price")
plt.title("Mileage vs Price")
'''Mileage has clear negetive correlation with price & Should be used in model'''
```

Out[211…

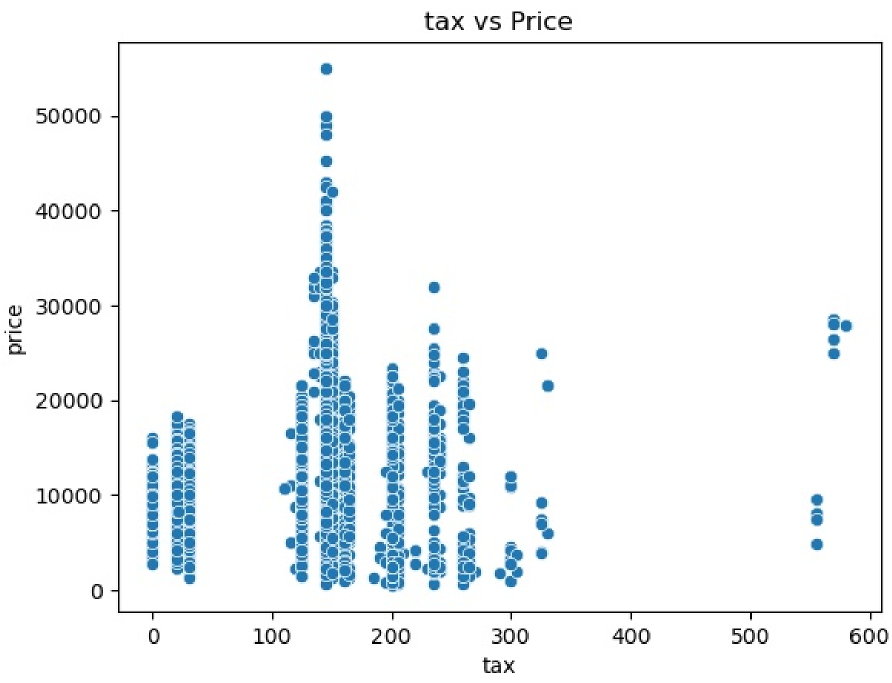
```
'Mileage has clear negetive correlation with price & Should be used in model'
```



In [212…

```
## Checking the relation between tax & price using scatter plot
sns.scatterplot(data=df,x="tax",y="price")
plt.title("tax vs Price")
'''Tax has clear positive correlation with price & Should be used in model'''
```

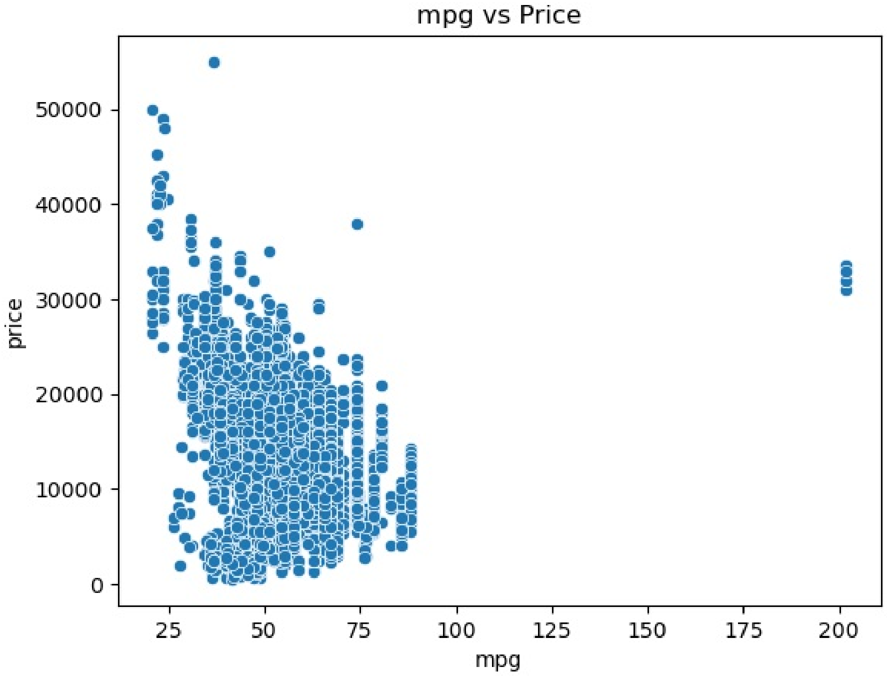
Out[212… 'Tax has clear positive correlation with price & Should be used in model'



In [213…

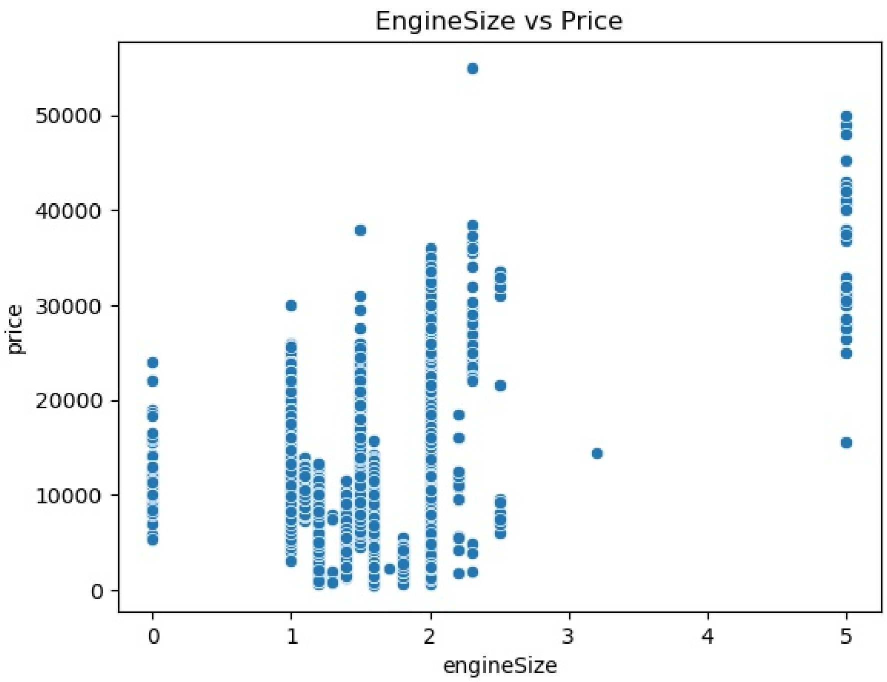
```
## Checking the relation between mpg & price using scatter plot
sns.scatterplot(data=df,x="mpg",y="price")
plt.title("mpg vs Price")
'''mpg has clear negetive correlation with price & Should be used in model'''
```

Out[213… 'mpg has clear negetive correlation with price & Should be used in model'




```
In [214…  ## Checking the relation between engineSize & price using scatter plot
sns.scatterplot(data=df,x="engineSize",y="price")
plt.title("EngineSize vs Price")
'''EngineSize has clear positive correlation with price & Should be used in model'''
```

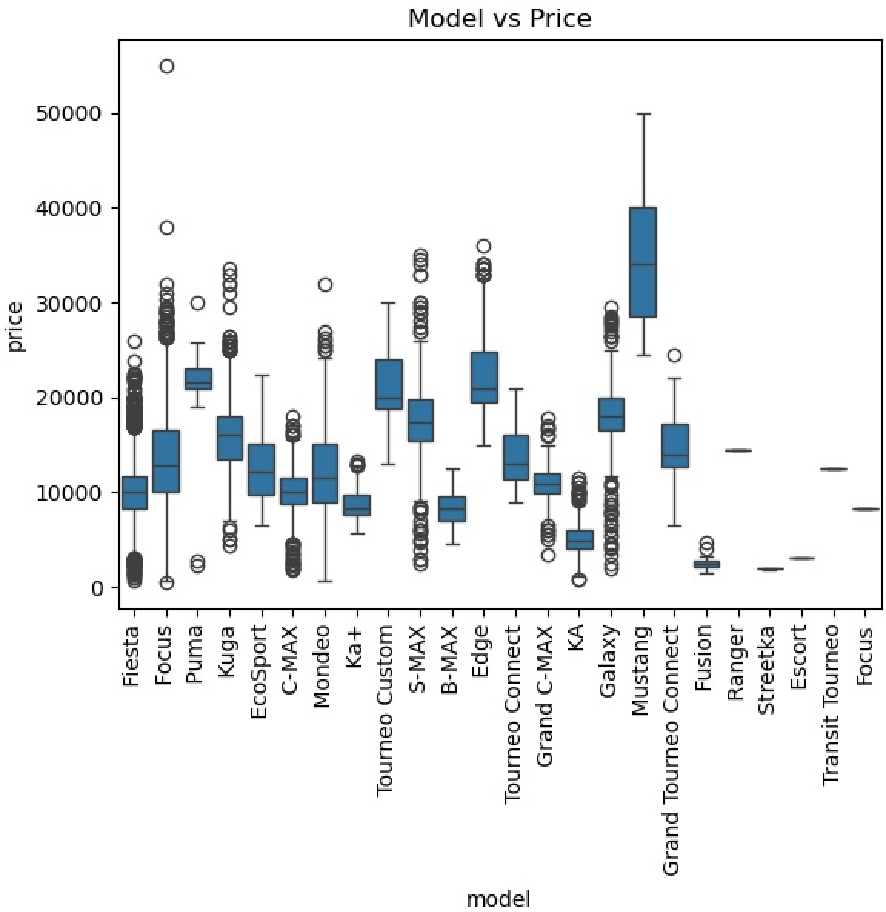
```
Out[214…  'EngineSize has clear positive correlation with price & Should be used in model'
```



Now Let us compare the relation of price with categorical variable

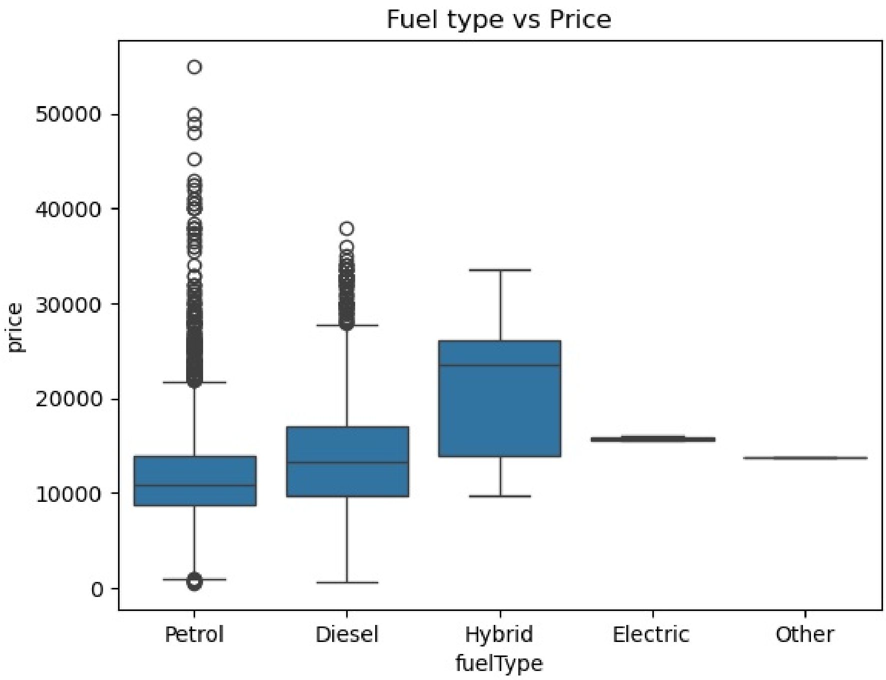
```
In [215…  ## Checking the relation of model with price
sns.boxplot(data=df,x="model",y="price")
plt.xticks(rotation =90)
plt.title("Model vs Price")
'''Some models like Mustang has very high price
so its better to use the variable in model'''
```

Out[215… 'Some models like Mustang has very high price \nso its better to use the variable in model'



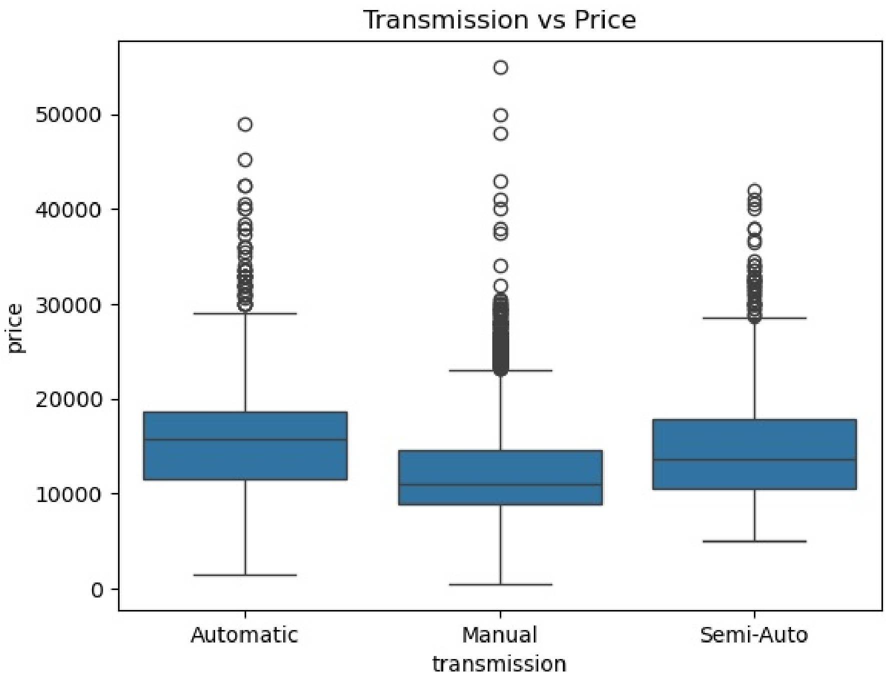
In [216…
```python
## Checking the relation of Fueltype with price
sns.boxplot(data=df,x="fuelType",y="price")
plt.title("Fuel type vs Price")
'''Some Fuel types like Petrol has very high price
so its better to use the variable in model'''
```

Out[216… 'Some Fuel types like Petrol has very high price \nso its better to use the variable in model'



In [217…
```python
## Checking the relation of transmission with price
sns.boxplot(data=df,x="transmission",y="price")
plt.title("Transmission vs Price")
''' There iss no much relation beetween the transmission & price
so this variable can be dropped'''
```

Out[217… ' There iss no much relation beetween the transmission & price\nso this variable can be dropped'



Data Cleaning & processing

In [218…
```
## Dropping duplicate records
df.drop_duplicates(inplace=True)
```

In [219…
```
##Dropping the record with year as 2060 from the dataset
data = df[df["year"]!=2060]
```

In [220…
```
data
```

Out[220…

	model	year	price	transmission	mileage	fuelType	tax	mpg	engineSize
0	Fiesta	2017	12000	Automatic	15944	Petrol	150	57.7	1.0
1	Focus	2018	14000	Manual	9083	Petrol	150	57.7	1.0
2	Focus	2017	13000	Manual	12456	Petrol	150	57.7	1.0
3	Fiesta	2019	17500	Manual	10460	Petrol	145	40.3	1.5
4	Fiesta	2019	16500	Automatic	1482	Petrol	145	48.7	1.0
...	...	...	...	...	...	...	...	...	...
17961	B-MAX	2017	8999	Manual	16700	Petrol	150	47.1	1.4
17962	B-MAX	2014	7499	Manual	40700	Petrol	30	57.7	1.0
17963	Focus	2015	9999	Manual	7010	Diesel	20	67.3	1.6
17964	KA	2018	8299	Manual	5007	Petrol	145	57.7	1.2
17965	Focus	2015	8299	Manual	5007	Petrol	22	57.7	1.0

17811 rows × 9 columns

In [221…
```
## Defining X & y variables for model
X = data.drop(columns=["price","transmission"])
y = data["price"]
```

Now we are going to perform encoding on categorical variable & Standardisation of numerical variable in X

In [222…
```
## Creating X version with hot one encoding
X_hot_one = pd.get_dummies(data=X,columns=["model","fuelType"])
```

In [223…
```
X_hot_one = X_hot_one.astype(int)
```

In [224…
```
X_hot_one
```

Out[224…

	year	mileage	tax	mpg	engineSize	model_ B-MAX	model_ C-MAX	model_ EcoSport	model_ Edge	model_ Escort	...	model_ Streetka	model_ Tourneo Connect	model_ Tourneo Custom	mode Tran Tourn
0	2017	15944	150	57	1	0	0	0	0	0	...	0	0	0	
1	2018	9083	150	57	1	0	0	0	0	0	...	0	0	0	
2	2017	12456	150	57	1	0	0	0	0	0	...	0	0	0	
3	2019	10460	145	40	1	0	0	0	0	0	...	0	0	0	
4	2019	1482	145	48	1	0	0	0	0	0	...	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
17961	2017	16700	150	47	1	1	0	0	0	0	...	0	0	0	
17962	2014	40700	30	57	1	1	0	0	0	0	...	0	0	0	
17963	2015	7010	20	67	1	0	0	0	0	0	...	0	0	0	
17964	2018	5007	145	57	1	0	0	0	0	0	...	0	0	0	
17965	2015	5007	22	57	1	0	0	0	0	0	...	0	0	0	

17811 rows × 34 columns

In [225…

```python
from sklearn.preprocessing import StandardScaler
```

In [226…

```python
numerical_cols = ['year', 'mileage', 'tax', 'mpg', 'engineSize']
scaler = StandardScaler()
X_hot_one[numerical_cols] = scaler.fit_transform(X_hot_one[numerical_cols])
```

In [227…

```python
X_hot_one
```

Out[227…

	year	mileage	tax	mpg	engineSize	model_ B-MAX	model_ C-MAX	model_ EcoSport	model_ Edge	model_ Escort	...	model_ Streetka	model_ Tourneo Connect
0	0.069100	-0.382920	0.591483	-0.042378	-0.446973	0	0	0	0	0	...	0	0
1	0.562581	-0.736260	0.591483	-0.042378	-0.446973	0	0	0	0	0	...	0	0
2	0.069100	-0.562551	0.591483	-0.042378	-0.446973	0	0	0	0	0	...	0	0
3	1.056062	-0.665344	0.510877	-1.720342	-0.446973	0	0	0	0	0	...	0	0
4	1.056062	-1.127709	0.510877	-0.930712	-0.446973	0	0	0	0	0	...	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
17961	0.069100	-0.343986	0.591483	-1.029415	-0.446973	1	0	0	0	0	...	0	0
17962	-1.411343	0.892007	-1.343040	-0.042378	-0.446973	1	0	0	0	0	...	0	0
17963	-0.917862	-0.843019	-1.504251	0.944660	-0.446973	0	0	0	0	0	...	0	0
17964	0.562581	-0.946172	0.510877	-0.042378	-0.446973	0	0	0	0	0	...	0	0
17965	-0.917862	-0.946172	-1.472009	-0.042378	-0.446973	0	0	0	0	0	...	0	0

17811 rows × 34 columns

In [228…

```python
## Creating X version with Label encoding
from sklearn.preprocessing import LabelEncoder

columns = ['model', 'fuelType']

Xlable = X.copy()  # make a safe copy
label_encoders = {}

for col in columns:
    le = LabelEncoder()
    Xlable[col] = le.fit_transform(Xlable[col].astype(str))  # Convert to string in case of nulls
    label_encoders[col] = le
```

In [229…

```python
Xlable
```

Out[229...

	model	year	mileage	fuelType	tax	mpg	engineSize
0	5	2017	15944	4	150	57.7	1.0
1	6	2018	9083	4	150	57.7	1.0
2	6	2017	12456	4	150	57.7	1.0
3	5	2019	10460	4	145	40.3	1.5
4	5	2019	1482	4	145	48.7	1.0
...	...	...	...	...	...	...	...
17961	0	2017	16700	4	150	47.1	1.4
17962	0	2014	40700	4	30	57.7	1.0
17963	6	2015	7010	0	20	67.3	1.6
17964	11	2018	5007	4	145	57.7	1.2
17965	23	2015	5007	4	22	57.7	1.0

17811 rows × 7 columns

In [230...
```
Xlable[numerical_cols] = scaler.fit_transform(Xlable[numerical_cols])
```

In [231...
```
Xlable
```

Out[231...

	model	year	mileage	fuelType	tax	mpg	engineSize
0	5	0.069100	-0.382920	4	0.591483	-0.020681	-0.810532
1	6	0.562581	-0.736260	4	0.591483	-0.020681	-0.810532
2	6	0.069100	-0.562551	4	0.591483	-0.020681	-0.810532
3	5	1.056062	-0.665344	4	0.510877	-1.738002	0.345322
4	5	1.056062	-1.127709	4	0.510877	-0.908951	-0.810532
...	...	...	...	...	...	...	...
17961	0	0.069100	-0.343986	4	0.591483	-1.066865	0.114151
17962	0	-1.411343	0.892007	4	-1.343040	-0.020681	-0.810532
17963	6	-0.917862	-0.843019	0	-1.504251	0.926806	0.576493
17964	11	0.562581	-0.946172	4	0.510877	-0.020681	-0.348190
17965	23	-0.917862	-0.946172	4	-1.472009	-0.020681	-0.810532

17811 rows × 7 columns

In [232...
```
## Importing important modules from sklearn
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

Splitting the data into Train & test data

In [233...
```
X_train,X_test,y_train,y_test = \
train_test_split(X_hot_one,y,test_size=20,random_state=42)
```

Model training

In [234...
```
model = LinearRegression()
```

In [235...
```
model.fit(X_train,y_train)
```

Out[235...

▾ LinearRegression

```
LinearRegression()
```

Model testing

In [236...
```
y_pred = model.predict(X_test)
```

In [237...
```
y_pred
```

Out[237…
```
array([17255.8291468 ,  -258.90153969, 15822.83122526, 16122.86655283,
       13214.33020384,  7048.56930921,  8123.58768652, 21173.34691016,
       10028.78941924, 12673.46656022,  9818.80385982,  8326.57555118,
       14001.43870078, 13394.62752121, 11262.32902156, 11342.00820294,
       13983.66323611,  9970.40532827, 20608.46891876, -1549.87156206])
```

In [238…
```
y_test
```

Out[238…
```
1034     14995
16978     2295
2864     14950
11569    17890
10089    11795
11049     8263
15446     8000
2314     20500
17894    10999
13953    15000
9067      9995
15144     7800
8948     16500
17555    13500
8702     10000
3684      7850
14848    14999
3477      9200
10585    23179
16278     3295
Name: price, dtype: int64
```

Model Evaluation

In [239…
```
r2 = r2_score(y_test,y_pred)
r2
```

Out[239…
```
0.8562273030053025
```

In [240…
```
n = X_test.shape[0]
p = X_test.shape[1]
adjusted_r2 = 1 - ((1 - r2) * (n - 1)) / (n - p - 1)
print("Adjusted R² Score:", adjusted_r2)
```

```
Adjusted R² Score: 1.18211208285995
```

Now, Conducting model training, testing & evaluation with data with Label encoding

In [241…
```
X_train,X_test,y_train,y_test = \
train_test_split(Xlable,y,test_size=20,random_state=42)
```

In [242…
```
model2 = LinearRegression()
model2.fit(X_train,y_train)
```

Out[242…
```
▾ LinearRegression
LinearRegression()
```

In [243…
```
y_pred = model2.predict(X_test)
y_pred
```

Out[243…
```
array([14693.18196576, -1839.36254128, 15852.54453998, 16363.83844554,
       11409.55501502,  6534.9917188 ,  7799.25074846, 21681.35225796,
       11619.97196514, 12514.85508919,  9320.29965613,  7981.38354938,
       12110.55889048, 13665.13001164, 11366.75900015, 12182.34904331,
       14005.54529017,  9812.09574047, 18812.69429352,  -919.47645557])
```

In [244…
```
y_test
```

Out[244…
```
1034      14995
16978      2295
2864      14950
11569     17890
10089     11795
11049      8263
15446      8000
2314      20500
17894     10999
13953     15000
9067       9995
15144      7800
8948      16500
17555     13500
8702      10000
3684       7850
14848     14999
3477       9200
10585     23179
16278      3295
Name: price, dtype: int64
```

In [245…
```
r2 = r2_score(y_test,y_pred)
r2
```

Out[245…
```
0.7968195008602432
```

In [246…
```
n = X_test.shape[0]
p = X_test.shape[1]
adjusted_r2 = 1 - ((1 - r2) * (n - 1)) / (n - p - 1)
print("Adjusted R² Score:", adjusted_r2)
```

```
Adjusted R² Score: 0.6782975430287184
```

Conclusion

R2 & Adjusted R2 with one hot encode data = R2 Score-0.86,Adjusted R^2 Score: 1.82 R2 & Adjusted R2 with label encode data = R2 Score-0.80,Adjusted R^2 Score: 0.67

Model gives better results with one hot encoding

Thank you