Importing the Dependencies

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn import metrics
```

Data Collection and Processing

car_dataset.head()

```
# loading the data from csv file to pandas dataframe
car_dataset = pd.read_csv('/content/car data.csv')
# inspecting the first 5 rows of the dataframe
```

1 to 5 of 5 entries	Filter		•
---------------------	--------	--	---

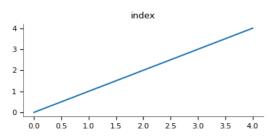
index	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual	0
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manual	0
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manual	0
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual	0
4	swift	2014	4.6	6.87	42450	Diesel	Dealer	Manual	0

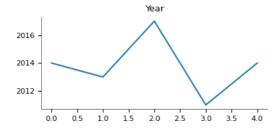
Show 25 ➤ per page



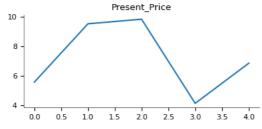
Like what you see? Visit the data table notebook to learn more about interactive tables.

Values

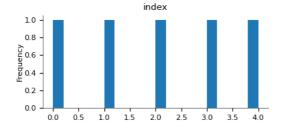




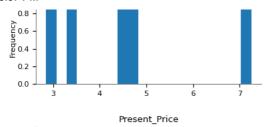


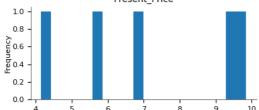


Distributions









Categorical distributions





checking the number of rows and columns
car_dataset.shape

```
(301, 9)
```

getting some information about the dataset
car_dataset.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300

Data	columns (total	9 columns):			
#	Column	Non-Null Count	Dtype		
0	Car_Name	301 non-null	object		
1	Year	301 non-null	int64		
2	Selling_Price	301 non-null	float64		
3	Present_Price	301 non-null	float64		
4	Kms_Driven	301 non-null	int64		
5	Fuel_Type	301 non-null	object		
6	Seller_Type	301 non-null	object		
7	Transmission	301 non-null	object		
8	Owner	301 non-null	int64		
dtypes: float64(2),		<pre>int64(3), object(4)</pre>			
memor	ry usage: 21.3+	KB			
-	_		_		

checking the number of missing values
car_dataset.isnull().sum()

```
Car_Name
                0
Year
                0
Selling_Price
                0
Present_Price
                0
Kms_Driven
Fuel_Type
                0
Seller_Type
Transmission
Owner
dtype: int64
             Car Name
```

checking the distribution of categorical data
print(car_dataset.Fuel_Type.value_counts())
print(car_dataset.Seller_Type.value_counts())
print(car_dataset.Transmission.value_counts())

```
Petrol 239
Diesel 60
CNG 2
Name: Fuel_Type, dtype: int64
Dealer 195
Individual 106
Name: Seller_Type, dtype: int64
Manual 261
```

Automatic 40 Name: Transmission, dtype: int64

Encoding the Categorical Data

```
# encoding "Fuel_Type" Column
car_dataset.replace({'Fuel_Type':{'Petrol':0,'Diesel':1,'CNG':2}},inplace=True)
# encoding "Seller_Type" Column
car_dataset.replace({'Seller_Type':{'Dealer':0,'Individual':1}},inplace=True)
# encoding "Transmission" Column
car_dataset.replace({'Transmission':{'Manual':0,'Automatic':1}},inplace=True)
car_dataset.head()
```

1 to 5 of 5 entries Filter						
า	Fuel_Type	Seller_Type	Transmission	Owner		
0	0	0	0	0		
0	1	0	0	0		
\sim	0	0	0	0		

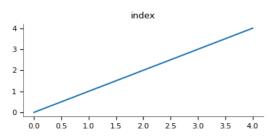
index	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner
0	ritz	2014	3.35	5.59	27000	0	0	0	0
1	sx4	2013	4.75	9.54	43000	1	0	0	0
2	ciaz	2017	7.25	9.85	6900	0	0	0	0
3	wagon r	2011	2.85	4.15	5200	0	0	0	0
4	swift	2014	4.6	6.87	42450	1	0	0	0

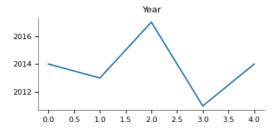
Show 25 v per page

ıl.

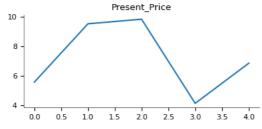
Like what you see? Visit the data table notebook to learn more about interactive tables.

Values

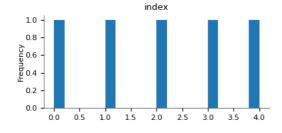








Distributions





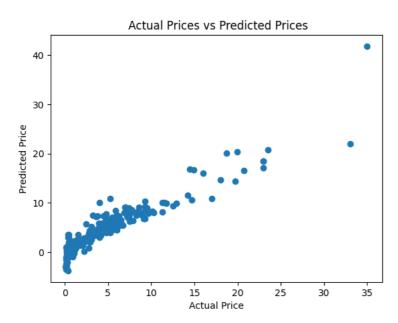
```
Splitting the data and Target
X = car_dataset.drop(['Car_Name', 'Selling_Price'], axis=1)
Y = car_dataset['Selling_Price']
print(X)
          Year Present_Price Kms_Driven Fuel_Type Seller_Type Transmission \
     0
          2014
                         5.59
                                    27000
     1
          2013
                         9.54
                                    43000
                                                   1
                                                                0
     2
          2017
                         9.85
                                     6900
                                                   0
          2011
     3
                                     5200
     4
          2014
                         6.87
                                    42450
                                                   1
                                                                0
                                                                              0
                                                  ...
     296
          2016
                        11.60
                                    33988
                                                                0
                                                                               0
     297
          2015
                        5.90
                                    60000
                                                   0
                                                                0
                                                                              0
                        11.00
     298
          2009
                                    87934
                                                   0
                                                                0
                                                                              a
     299
          2017
                        12.50
                                     9000
                                                   1
                                                                0
                                                                              0
     300
          2016
                         5.90
                                     5464
                                                                0
          Owner
     0
     1
     2
              0
     3
              0
     4
             0
     296
              а
     297
              0
     298
     299
              0
     [301 rows x 7 columns]
            print(Y)
     0
             3.35
     1
             4.75
     2
             7.25
     3
             2.85
     4
             4.60
     296
            9.50
     297
            4.00
     298
             3.35
     299
            11.50
     300
            5.30
     Name: Selling_Price, Length: 301, dtype: float64
           ritz -
Splitting Training and Test data
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.1, random_state=2)
Model Training
   1. Linear Regression
                       1
# loading the linear regression model
lin_reg_model = LinearRegression()
lin_reg_model.fit(X_train,Y_train)
      ▼ LinearRegression
     LinearRegression()
Model Evaluation
# prediction on Training data
training_data_prediction = lin_reg_model.predict(X_train)
# R squared Error
error_score = metrics.r2_score(Y_train, training_data_prediction)
print("R squared Error : ", error_score)
```

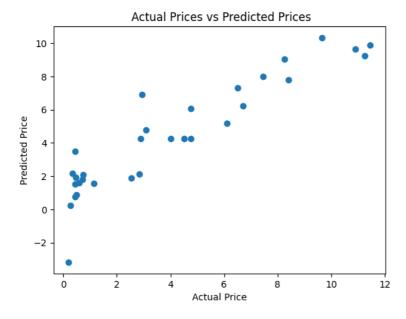
```
https://colab.research.google.com/drive/1qEJeY-6MILH0aQMjeHIPSjJ655yB-oVu#scrollTo=dGZ_kmRW5o85&printMode=true
```

R squared Error : 0.8799451660493711

Visualize the actual prices and Predicted prices

```
plt.scatter(Y_train, training_data_prediction)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title(" Actual Prices vs Predicted Prices")
plt.show()
```





2. Lasso Regression

```
# loading the linear regression model
lass_reg_model = Lasso()
lass_reg_model.fit(X_train,Y_train)

v Lasso
Lasso()
```

Model Evaluation

```
# prediction on Training data
training_data_prediction = lass_reg_model.predict(X_train)

# R squared Error
error_score = metrics.r2_score(Y_train, training_data_prediction)
print("R squared Error : ", error_score)

R squared Error : 0.8427856123435794
```

Visualize the actual prices and Predicted prices

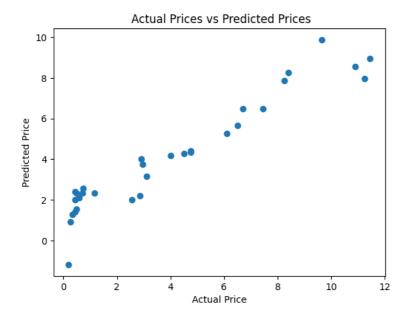
```
plt.scatter(Y_train, training_data_prediction)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title(" Actual Prices vs Predicted Prices")
plt.show()
```

Actual Prices vs Predicted Prices 40 30 10 0 5 10 15 20 25 30 35 Actual Price

```
# prediction on Training data
test_data_prediction = lass_reg_model.predict(X_test)

# R squared Error
error_score = metrics.r2_score(Y_test, test_data_prediction)
print("R squared Error : ", error_score)
    R squared Error : 0.8709167941173195

plt.scatter(Y_test, test_data_prediction)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title(" Actual Prices vs Predicted Prices")
plt.show()
```



✓ 0s completed at 3:35 PM