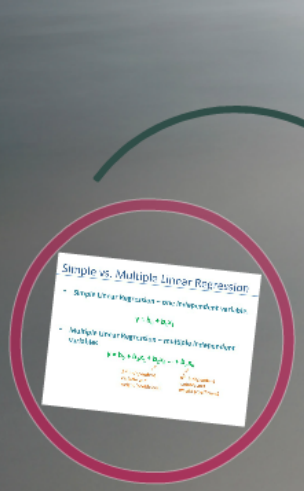
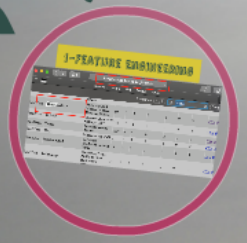
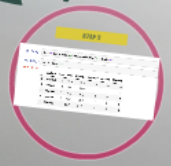
Predicticting Car Price by Using Multiple Linear Regression

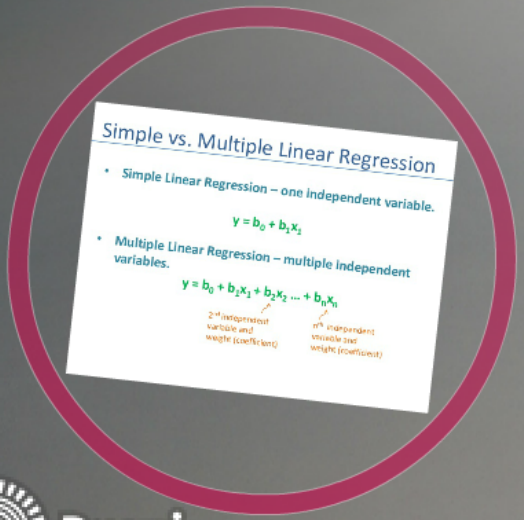


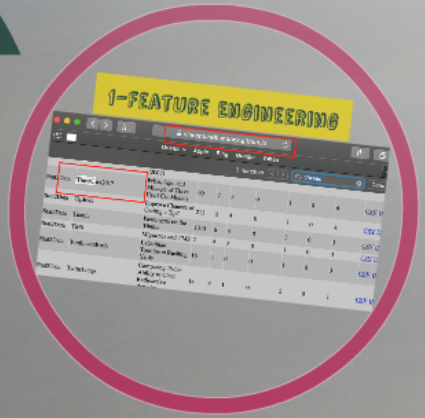


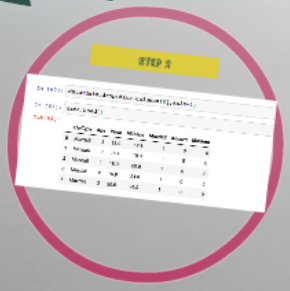


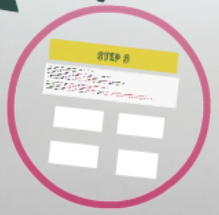
Thank You
Nilufer Metin
Data Science Tools-2
University of Denver

Predicticting Car Price by Using Multiple Linear Regression









Prezi

Simple vs. Multiple Linear Regression

- **Simple Linear Regression – one independent variable.**

$$y = b_0 + b_1x_1$$

- **Multiple Linear Regression – multiple independent variables.**

$$y = b_0 + b_1x_1 + b_2x_2 \ldots + b_nx_n$$

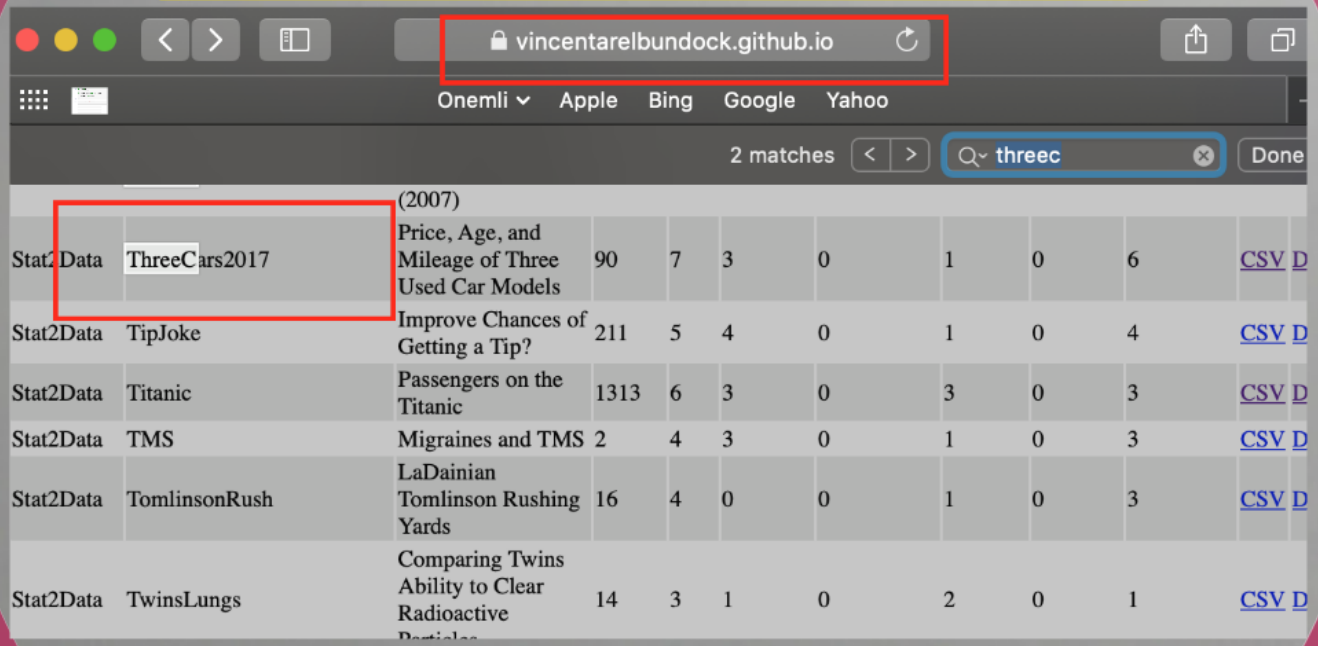
2^{nd} independent variable and weight (coefficient)

n^{th} independent variable and weight (coefficient)

In [61

Out[61

1-FEATURE ENGINEERING



		(2007)									
Stat2Data	ThreeCars2017	Price, Age, and Mileage of Three Used Car Models	90	7	3	0	1	0	6	CSV	D
Stat2Data	TipJoke	Improve Chances of Getting a Tip?	211	5	4	0	1	0	4	CSV	D
Stat2Data	Titanic	Passengers on the Titanic	1313	6	3	0	3	0	3	CSV	D
Stat2Data	TMS	Migraines and TMS	2	4	3	0	1	0	3	CSV	D
Stat2Data	TomlinsonRush	LaDainian Tomlinson Rushing Yards	16	4	0	0	1	0	3	CSV	D
Stat2Data	TwinsLungs	Comparing Twins Ability to Clear Radioactive	14	3	1	0	2	0	1	CSV	D

In [56]:
```
import pandas as pd
import numpy as np
import missingno as msno
import seaborn as sn
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
import statsmodels.formula.api as sm
```

In [57]:
```
#!pip install missingno
```

In [58]:
```
data = pd.read_csv("2-ThreeCars2017.csv")
```

In [59]:
```
data.head()
```

Out[59]:

	Unnamed: 0	CarType	Age	Price	Mileage	Mazda6	Accord	Maxima
0	1	Mazda6	3	15.9	17.8	1	0	0
1	2	Mazda6	2	16.4	19.0	1	0	0
2	3	Mazda6	1	18.9	20.9	1	0	0
3	4	Mazda6	2	16.9	24.0	1	0	0
4	5	Mazda6	2	20.5	24.0	1	0	0

STEP 2

```
In [60]: data=data.drop(data.columns[0],axis=1)
```

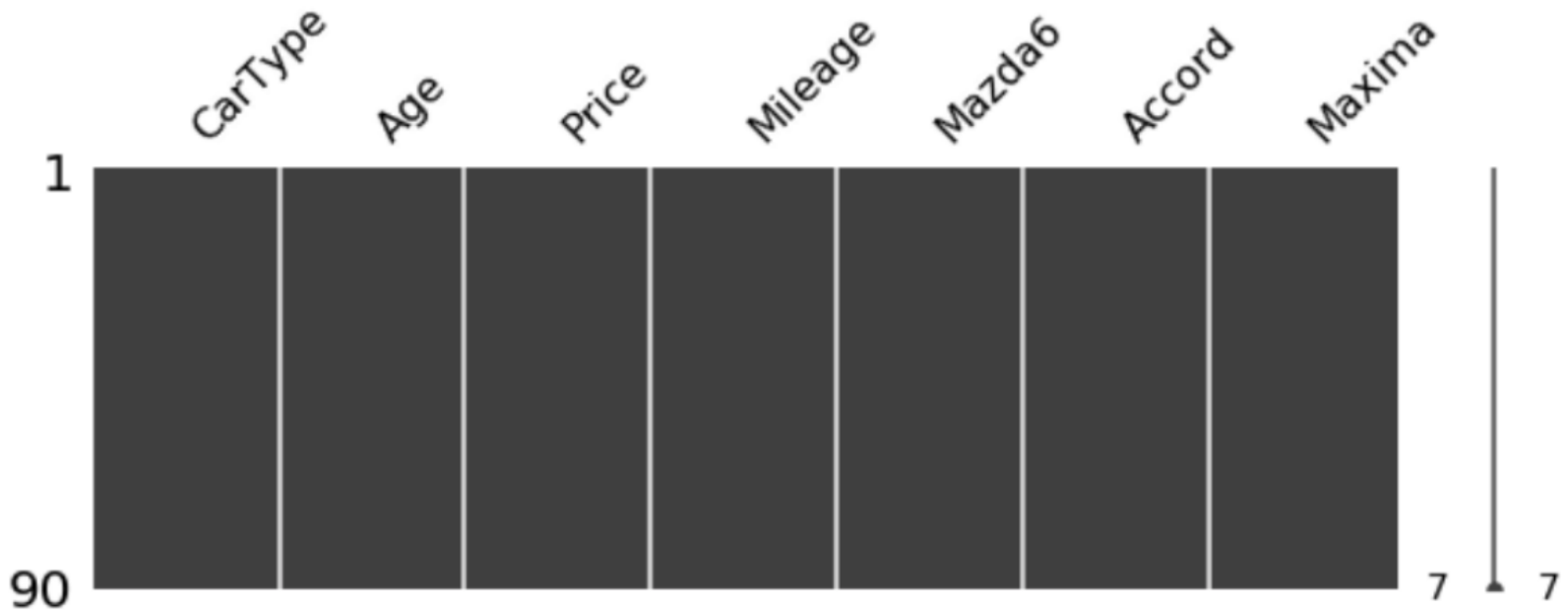
```
In [61]: data.head()
```

Out[61]:

	CarType	Age	Price	Mileage	Mazda6	Accord	Maxima
0	Mazda6	3	15.9	17.8	1	0	0
1	Mazda6	2	16.4	19.0	1	0	0
2	Mazda6	1	18.9	20.9	1	0	0
3	Mazda6	2	16.9	24.0	1	0	0
4	Mazda6	2	20.5	24.0	1	0	0

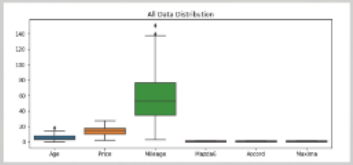
In [62]:
```
msno.matrix(data,figsize=(10,3))
```

Out[62]: <matplotlib.axes._subplots.AxesSubplot at 0x122b3fc18>



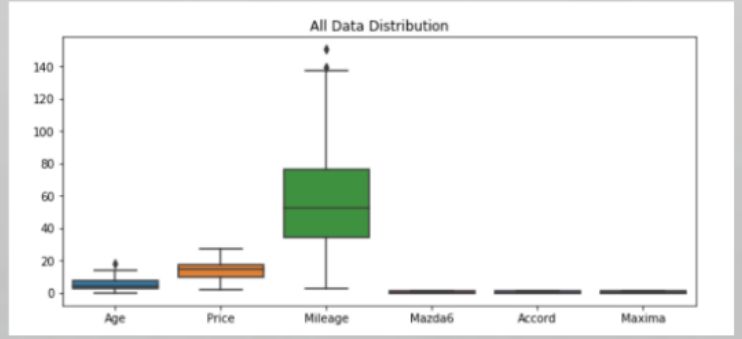
STEP 3

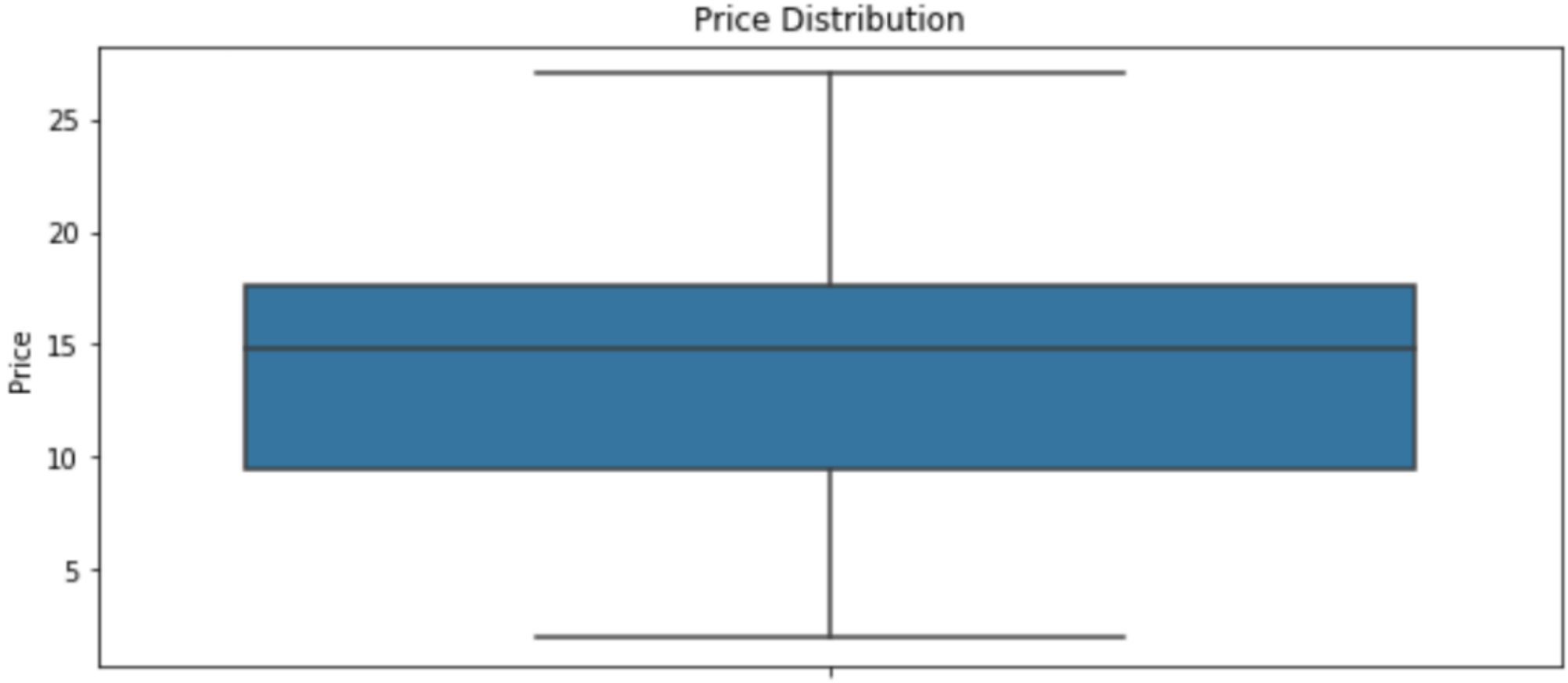
```
fig, axes = plt.subplots(nrows =4, ncols= 1)
fig.set_size_inches(10,20)
sn.boxplot(data=data, y='Price', orient="v", ax=axes[0])
sn.boxplot(data=data, orient="v", ax=axes[1])
sn.boxplot(data=data, y='Price', x="CarType", orient="v", ax=axes[2])
sn.boxplot(data=data, y='Price', x= "Age", orient="v", ax=axes[3])

axes[0].set(ylabel='Price', title='Price Distribution')
axes[1].set(title='All Data Distribution')
axes[2].set(ylabel='Price', xlabel='Cartype', title='Price Distribution based on CarType')
axes[3].set(ylabel='Price', xlabel = 'Age', title='Price Distribution based on the age of the Car')
```

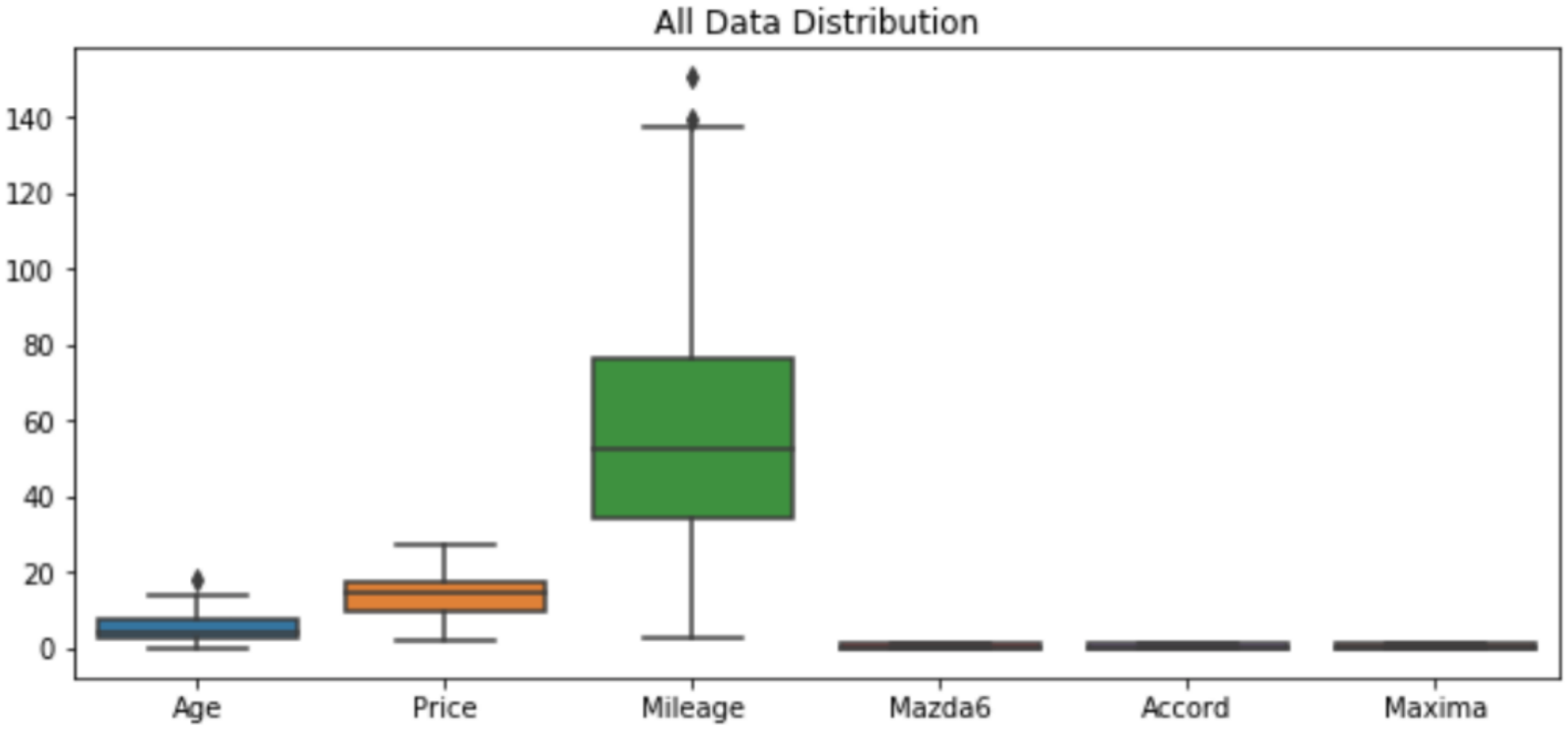


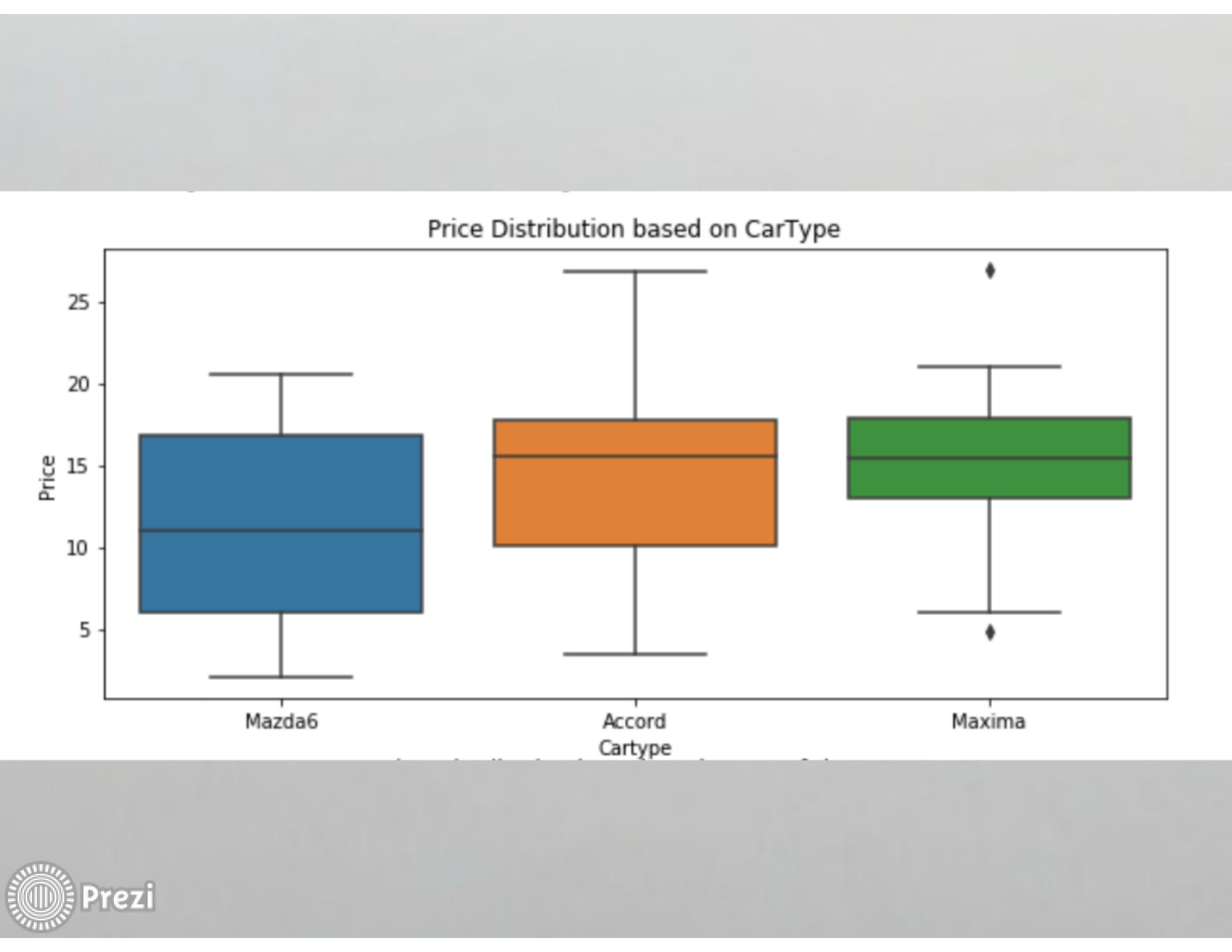
STEP 3

```
fig, axes = plt.subplots(nrows =4, ncols= 1)
fig.set_size_inches(10,20)
sn.boxplot(data=data, y='Price', orient="v", ax=axes[0])
sn.boxplot(data=data, orient="v", ax=axes[1])
sn.boxplot(data=data, y='Price', x="CarType", orient="v", ax=axes[2])
sn.boxplot(data=data, y='Price', x= "Age", orient="v", ax=axes[3])

axes[0].set(ylabel='Price', title='Price Distribution')
axes[1].set(title='All Data Distribution')
axes[2].set(ylabel='Price', xlabel='Cartype', title='Price Distribution based on CarType')
axes[3].set(ylabel='Price', xlabel = 'Age', title='Price Distribution based on the age of the Car')
```



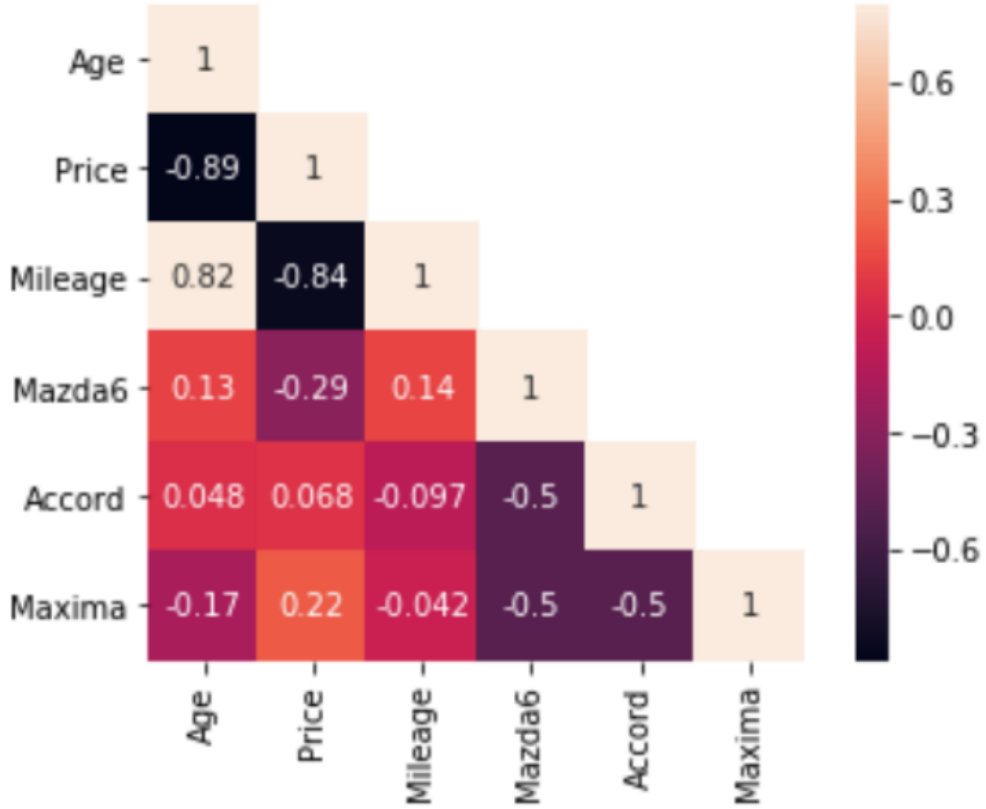



All Data Distribution
140
120
100
80
60
40
20
0
Age
Price
Mileage
Mazda6
Accord
Maxima


Price Distribution based on CarType
Price
25
20
15
10
5
Mazda6
Accord
Maxima
Cartype

In [146]:
```
corrMatt=data.corr()
mask = np.array(corrMatt)
mask[np.tril_indices_from(mask)]=False
fig.ax=plt.subplots()
fig.set_size_inches(20,10)
sn.heatmap(corrMatt, mask=mask, vmax=0.8, square=True, annot=True)
```

Out[146]: <matplotlib.axes._subplots.AxesSubplot at 0x12d0a8048>

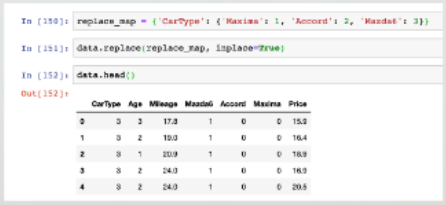


APPLYING LINEAR REGRESSION

```
In [147]: data = data[['CarType', 'Age', 'Mileage', 'Mazda6', 'Accord', 'Maxima', 'Price']]

In [148]: data.head()
```

Out[148]:

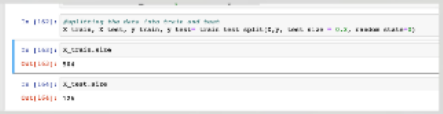
	CarType	Age	Mileage	Mazda6	Accord	Maxima	Price
0	Mazda6	3	17.0	1	0	0	15.0
1	Mazda6	3	19.0	1	0	0	16.4
2	Mazda6	1	20.9	1	0	0	18.9
3	Mazda6	2	24.0	1	0	0	16.9
4	Mazda6	2	24.0	1	0	0	20.5



```
In [150]: replace_map = {'CarType': {'Maxima': 1, 'Accord': 2, 'Mazda6': 3}}

In [151]: data.replace(replace_map, inplace=True)

In [152]: data.head()
```

Out[152]:

	CarType	Age	Mileage	Mazda6	Accord	Maxima	Price
0	3	3	17.0	1	0	0	15.0
1	3	2	19.0	1	0	0	16.4
2	3	1	20.9	1	0	0	18.9
3	3	2	24.0	1	0	0	16.9
4	3	2	24.0	1	0	0	20.5

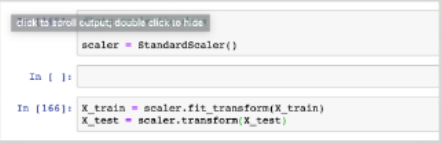


```
In [162]: X_train.size
```

Out[162]: 984

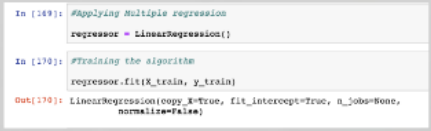
```
In [164]: X_test.size
```

Out[164]: 174



click to scroll output; double click to hide

```
scaler = StandardScaler()

In [ ]:

In [166]: X_train = scaler.fit_transform(X_train)
          X_test = scaler.transform(X_test)
```



```
In [169]: #Applying Multiple regression

          regressor = LinearRegression()

In [170]: #Training the algorithm

          regressor.fit(X_train, y_train)
```

Out[170]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                 normalize=False)
```

In [147]:
```
data = data[['CarType', 'Age', 'Mileage', 'Mazda6', 'Accord', 'Maxima', 'Price']]
```

In [148]:
```
data.head()
```

Out[148]:

	CarType	Age	Mileage	Mazda6	Accord	Maxima	Price
0	Mazda6	3	17.8	1	0	0	15.9
1	Mazda6	2	19.0	1	0	0	16.4
2	Mazda6	1	20.9	1	0	0	18.9
3	Mazda6	2	24.0	1	0	0	16.9
4	Mazda6	2	24.0	1	0	0	20.5

[150]:
```
replace_map = {'CarType': {'Maxima': 1, 'Accord': 2, 'Mazda
```

In [150]:
```
replace_map = {'CarType': {'Maxima': 1, 'Accord': 2, 'Mazda6': 3}}
```

In [151]:
```
data.replace(replace_map, inplace=True)
```

In [152]:
```
data.head()
```

Out[152]:

	CarType	Age	Mileage	Mazda6	Accord	Maxima	Price
0	3	3	17.8	1	0	0	15.9
1	3	2	19.0	1	0	0	16.4
2	3	1	20.9	1	0	0	18.9
3	3	2	24.0	1	0	0	16.9
4	3	2	24.0	1	0	0	20.5

2	3	1	20.9	1	0	0	18.9
3	3	2	24.0	1	0	0	16.9
4	3	2	24.0	1	0	0	20.5

In [162]:
```
#splitting the data into train and test
X_train, X_test, y_train, y_test= train_test_split(X,y, test_size = 0.2, random_state=0)
```

In [163]:
```
X_train.size
```

Out[163]: 504

In [164]:
```
X_test.size
```

Out[164]: 126

Out[164]: 126

click to scroll output; double click to hide

```
scaler = StandardScaler()
```

In [ ]:

In [166]:
```
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [169]:
```
#Applying Multiple regression

regressor = LinearRegression()
```

In [170]:
```
#Training the algorithm

regressor.fit(X_train, y_train)
```

Out[170]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

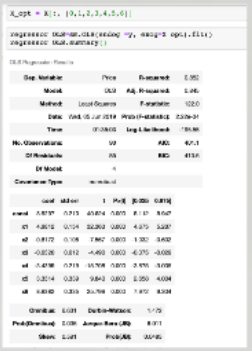
RESULTS OF PREDICTION MODEL

```
In [173]: predictions = regressor.predict(X_test)
          predictions

Out[173]: array([18.08828616, 14.88035618, 18.77602685, 20.14803392, 16.9452516 ,
                 12.39109463, 19.25628456, 19.0646856 , 16.5956154 ,  7.65135739,
                 15.89581643,  2.82007337, 13.66944052, 17.07411711, 15.75148706,
                 10.89232251,  3.82006976, 17.5079902 ])

In [174]: y_test

Out[174]: 2     18.9
          13    16.0
          53    21.0
          41    19.5
          66    21.0
          30    12.0
          45    17.5
          43    17.4
          78    16.9
          89     4.8
          7     18.0
          26     5.2
          33    12.5
          63    15.7
          8     13.6
          16     8.0
          24     2.0
          56    16.0
          Name: Price, dtype: float64
```

```
In [176]: df = pd.DataFrame({'Actual': y_test , 'Predicted' : predictions})
          df

Out[176]:
```

	Actual	Predicted
2	18.9	18.088286
13	16.0	14.880356
53	21.0	18.776027
41	19.5	20.148034
66	21.0	16.945252
30	12.0	12.391095
45	17.5	19.256285
43	17.4	19.064686
78	16.9	16.595615
89	4.8	7.651357
7	18.0	15.895816
26	5.2	2.820073
33	12.5	13.669441
63	15.7	17.074117
8	13.6	15.751487
16	8.0	10.892323
24	2.0	3.820070
56	16.0	17.507902

```
In [177]: r2_score(y_test, predictions)

Out[177]: 0.8749853622053401
```



In [173]:
```
predictions = regressor.predict(X_test)
predictions
```

Out[173]:
```
array([18.08828616, 14.88035618, 18.77602685, 20.14803392, 16.9452516 ,
       12.39109463, 19.25628456, 19.0646856 , 16.5956154 ,  7.65135739,
       15.89581643,  2.82007337, 13.66944052, 17.07411711, 15.75148706,
       10.89232251,  3.82006976, 17.5079902 ])
```

In [174]:
```
y_test
```

Out[174]:
```
2     18.9
13    16.0
53    21.0
41    19.5
66    21.0
30    12.0
45    17.5
43    17.4
78    16.9
89     4.8
7     18.0
26     5.2
33    12.5
63    15.7
8     13.6
16     8.0
24     2.0
56    16.0
Name: Price, dtype: float64
```

In [176]:
```
df = pd.DataFrame({'Actual': y_test , 'Predicted': predictions})
df
```

Out[176]:

	Actual	Predicted
2	18.9	18.088286
13	16.0	14.880356
53	21.0	18.776027
41	19.5	20.148034
66	21.0	16.945252
30	12.0	12.391095
45	17.5	19.256285
43	17.4	19.064686
78	16.9	16.595615
89	4.8	7.651357
7	18.0	15.895816
26	5.2	2.820073
33	12.5	13.669441
63	15.7	17.074117
8	13.6	15.751487
16	8.0	10.892323
24	2.0	3.820070
56	16.0	17.507990

```
In [177]: r2_score(y_test, predictions)

Out[177]: 0.8749853622053401
```

```
X_opt = X[:, [0,1,2,3,4,5,6]]
```

```
regressor_OLS=sm.OLS(endog =y, exog=X_opt).fit()
regressor_OLS.summary()
```

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.852
Model:	OLS	**Adj. R-squared:**	0.845
Method:	Least Squares	**F-statistic:**	122.0
Date:	Wed, 05 Jun 2019	**Prob (F-statistic):**	2.22e-34
Time:	01:35:03	**Log-Likelihood:**	-195.56
No. Observations:	90	**AIC:**	401.1
Df Residuals:	85	**BIC:**	413.6
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	8.5297	0.210	40.624	0.000	8.112	8.947
x1	4.9812	0.154	32.363	0.000	4.675	5.287
x2	-0.8172	0.108	-7.567	0.000	-1.032	-0.602
x3	-0.0520	0.012	-4.490	0.000	-0.075	-0.029
x4	-3.4399	0.219	-15.708	0.000	-3.875	-3.005
x5	3.3314	0.339	9.840	0.000	2.658	4.004
x6	8.6382	0.335	25.796	0.000	7.972	9.304

Omnibus:	6.631	**Durbin-Watson:**	1.472
Prob(Omnibus):	0.036	**Jarque-Bera (JB):**	6.011
Skew:	0.591	**Prob(JB):**	0.0495

SUMMARY

-Data is explored and problem is defined.

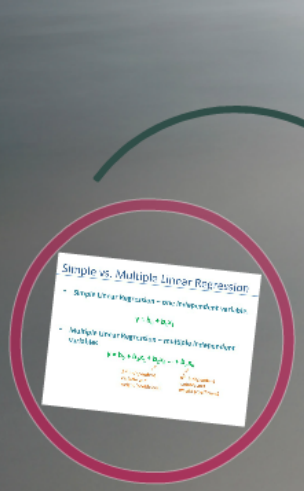
-Multiple Linear Regression model is selected to create a prediction model to predict Price of a car based on independent variables.

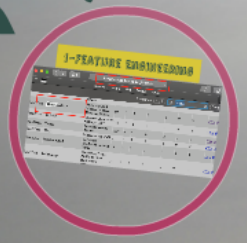
-Solution is implemented.

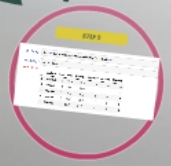
-Model is evaluated and result is analysed.

-As a result; prediction model is successful for about %87.

Predicticting Car Price by Using Multiple Linear Regression







Thank You
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