from from impo	ort seaborn as sns ort matplotlib.pyplot as plt in sklearn.preprocessing import LabelEncoder, StandardScaler in sklearn.linear_model import LinearRegression, Lasso in sklearn.metrics import mean_squared_error, mean_absolute_error in sklearn.ensemble import RandomForestRegressor ort warnings inings.filterwarnings("ignore")  mattedData=pd.read_csv(r'C:\Users\21F22087\Desktop\formattedData.csv')  mattedData.head(5)
<ul><li>0 20</li><li>1 20</li><li>2 20</li><li>3 20</li></ul>	Make         Model         Kilometres         Body_Type         Engine         Transmission         Drivetrain         Exterior_Colour         Interior_Colour         Passengers         Doors         Fuel_Type         City         Highway         Price           14         Acura         RDX         290000.0         SUV         4         Automatic         AWD         Black         Black         5.0         5         Gas         11.336434         8.668992         11600           14         Acura         RDX         158868.0         SUV         6         Speed Automatic         AWD         White         Black         5.0         5         Gas         10.700000         7.300000         17998           19         Acura         MDX         226214.0         SUV         6         Automatic         AWD         White Diamond Pearl         Black         5.0         5         NaN         12.200000         9.000000         40588           21         Acura         RDX         NaN         SUV         4         10 Speed Automatic         AWD         Majestic Black Pearl         Black         5.0         5         Gas         11.000000         8.600000         41599
(186	nattedData.shape 47, 16) nattedData.isnull().sum()
Body Engi	metres 21 _Type 1
Exte Inte Pass Door Fuel City High	etrain 0 rior_Colour 0 rior_Colour 0 rengers 5 s 0 _Type 1 0 way 0
Pric dtyp	
Body Engi	L 0 metres 0 _Type 0
Driv Exte Inte Pass Door	etrain 0 rior_Colour 0 rior_Colour 0 engers 0 s 0 _Type 0
]: for	e 0 e: int64 nattedData.shape
Year Make Mode Kilo Body	metres float64 _Type object
Driv Exte Inte Pass Door Fuel	smission object etrain object rior_Colour object rior_Colour object engers float64 s int64 _Type object
impe	way float64
1.2 1.0 <u>9</u> 0.7	
0.5 0.2 0.0	
pea pri	n scipy import stats rson_coef,p_value=stats.pearsonr(formattedData['City'],formattedData['Price']) nt("The Pearson Correlation Coefficient is",pearson_coef,"with a P-value of P=",p_value) Pearson Correlation Coefficient is 0.39678696948232167 with a P-value of P= 0.0
1.5 1.2 1.0 2 0.7 0.5	
	sSubplot:xlabel='City', ylabel='Price'>
1.2 1.0 <u>9</u> 0.7	
0.5	
fori	City  mattedData.drop(['Year', 'Make', 'Model','Kilometres','Body_Type','Engine','Transmission'], axis = 1, inplace = True)  mattedData.shape
]: for:	nattedData.describe()  Passengers Doors City Highway Price
mean std min 25%	5.131850       3.734956       11.208205       8.401187       4.742887e+04         0.947508       0.729917       2.932372       2.095519       5.341182e+04         2.000000       2.000000       0.000000       2.000000e+03         5.000000       4.000000       9.300000       7.200000       2.485000e+04
75% max	5.000000 4.000000 12.900000 9.600000 5.791550e+04
coul uniqu to	e         6         1305         16         9           p         AWD         Black         Black         Gas
labe #for #for #for	n sklearn.preprocessing import LabelEncoder elencoder = LabelEncoder() rmattedData.Body_Type = labelencoder.fit_transform(formattedData.Body_Type) rmattedData.Make = labelencoder.fit_transform(formattedData.Make) rmattedData.Model = labelencoder.fit_transform(formattedData.Model) rmattedData.Transmission = labelencoder.fit_transform(formattedData.Transmission) mattedData.Drivetrain = labelencoder.fit_transform(formattedData.Drivetrain)
fori fori	hattedData.Exterior_Colour = labelencoder.fit_transform(formattedData.Exterior_Colour) hattedData.Interior_Colour = labelencoder.fit_transform(formattedData.Interior_Colour) hattedData.Fuel_Type = labelencoder.fit_transform(formattedData.Fuel_Type)  hattedData.head(10)
0 1 2 7	rivetrain         Exterior_Colour         Interior_Colour         Passengers         Doors         Fuel_Type         City         Highway         Price           3         116         1         5.0         5         3         11.336434         8.668992         11600           3         1056         1         5.0         5         3         10.700000         7.300000         17998           3         1254         1         7.0         5         3         12.700000         9.100000         17999           3         536         1         7.0         5         3         12.656604         9.261321         8995
8 9 10 11 12	3       116       1       5.0       5       3       10.400000       8.600000       28988         3       790       1       5.0       5       3       10.212500       7.128571       68917         3       498       1       5.0       5       3       13.700000       10.950000       96003         3       790       1       5.0       5       3       10.811111       8.533333       64921         3       708       1       5.0       5       3       10.811111       8.533333       54969
fori	3 116 1 5.0 5 3 10.212500 7.128571 59819  ort scipy.stats as stats nattedData = stats.zscore(formattedData) nattedData = stats.zscore(formattedData)
]:	Drivetrain         Exterior_Colour         Interior_Colour         Passengers         Doors         Fuel_Type         City         Highway         Price           -0.172438         -1.251028         -0.401947         -0.139159         1.733181         -0.017795         0.043730         0.127803         -0.670822           -0.172438         1.069340         -0.401947         -0.139159         1.733181         -0.017795         -0.173313         -0.525510         -0.551033           -0.172438         1.558099         -0.401947         1.971697         1.733181         -0.017795         0.508747         0.333489         -0.551014
7 8 	-0.172438       -0.214268       -0.401947       1.971697       1.733181       -0.017795       0.493948       0.410475       -0.719596         -0.172438       -1.251028       -0.401947       -0.139159       1.733181       -0.017795       -0.275622       0.094878       -0.345268                   -0.172438       -1.251028       0.270355       1.971697       0.363125       -0.017795       0.099511       0.524377       -0.363803
18645 18646	-0.172438
y_fox_fox_fox_fox_fox_fox_fox_fox_fox_fox	ormattedData=formattedData.iloc[:,0:7] ormattedData=formattedData.iloc[:,8] ormattedData=formattedData.iloc[:,0:7] ormattedData=formattedData.iloc[:,0:7] ormattedData=formattedData.iloc[:,8]
1	Drivetrain         Exterior_Colour         Interior_Colour         Passengers         Doors         Fuel_Type         City           -0.172438         -1.251028         -0.401947         -0.139159         1.733181         -0.017795         0.043730           -0.172438         1.069340         -0.401947         -0.139159         1.733181         -0.017795         -0.173313           -0.172438         1.558099         -0.401947         1.971697         1.733181         -0.017795         0.508747           -0.172438         -0.214268         -0.401947         1.971697         1.733181         -0.017795         0.493948
 18642 18643	-0.172438 -1.251028 -0.401947 -0.139159 1.733181 -0.017795 -0.275622
18645 18646 18612	-0.172438
mdl:	<pre>tinearRegression() rg.fit(x_formattedData,y_formattedData)  red1 = rg.predict(x_formattedData)  rt('The R-square for Multiple Linear regression is: ', rg.score(x_formattedData,y_formattedData))</pre>
The mae:	R-square for Multiple Linear regression is: 0.23225798157693855  L= mean_absolute_error(y_formattedData, y_pred1) nt('The mean absolute error for Multiple Linear Regression: ', mae1)  mean absolute error for Multiple Linear Regression: 0.42210709604029417
mse: pri	L = mean_squared_error(y_formattedData, y_pred1) nt('The mean square error for Multiple Linear Regression: ', mse1) mean square error for Multiple Linear Regression: 0.7677420184230614  figure(figsize=(10,6))
ax1 sns plt plt plt	= sns.distplot(y_formattedData, hist=False, color="r", label="Actual Value") distplot(y_pred1, hist=False, color="b", label="Fitted Values", ax=ax1)  title('Actual vs Fitted Values for Price') xlabel('Price (in dollars)') ylabel('Proportion of Cars')
plt	Show() close()  Actual vs Fitted Values for Price
Proportion of Cars 9.0	
€ 0.4 0.2 0.0	0 5 10 15 20 25 30
rf:	o 5 10 15 20 25 30 Price (in dollars)  RandomForestRegressor() el=rf.fit(x_formattedData,y_formattedData)  red2 = rf.predict(x_formattedData)
y_p printer the mse:	nt('The R-square for Random Forest is: ', rf.score(x_formattedData,y_formattedData)) R-square for Random Forest is: 0.940419181805703  R = mean_squared_error(y_formattedData, y_pred2)
The mae:	nean square error of price and predicted value is: ', mse2)  mean square error of price and predicted value is: 0.059580818194296996  Per mean_absolute_error(y_formattedData, y_pred2)  nt('The mean absolute error of price and predicted value is: ', mae2)  mean absolute error of price and predicted value is: 0.0966348475559992
plt ax1 sns	figure(figsize=(10,6))  = sns.distplot(y_formattedData, hist=False, color="r", label="Actual Value") distplot(y_pred2, hist=False, color="b", label="Fitted Values", ax=ax1)  title('Actual vs Fitted Values for Price') xlabel('Price (in dollars)')
plt plt plt	xlabel('Price (in dollars)') ylabel('Proportion of Cars') show() close()  Actual vs Fitted Values for Price
0.6 0.0 0.0	
0.6 Proportion of 0.4	
	O 5 10 15 20 25 30  Price (in dollars)  soModel=Lasso() .assoModel.fit(x_formattedData, y_formattedData)
]: y_p	red3 = lm.predict(x_formattedData)  nt('The R-square for LASSO is: ', lm.score(x_formattedData,y_formattedData))  R-square for LASSO is: 0.0
mae: pri	B= mean_absolute_error(y_formattedData, y_pred3) nt('The mean absolute error of price and predicted value is: ', mae3) mean absolute error of price and predicted value is: 0.48392371068875223  Tes = [('MLR', mae1),
mae mae	<pre>('Random Forest', mae2),    ('LASSO', mae3) ]  = pd.DataFrame(data = scores, columns=['Model', 'MAE Score'])</pre>
]:	Model         MAE Score           MLR         0.422107           Indom Forest         0.096635           LASSO         0.483924    Sort values (by=([-MAE Score-1]) ascending=Ealse_inplace=True)
2	sort_values(by=(['MAE Score']), ascending=False, inplace=True)  axe = plt.subplots(1,1, figsize=(10,7))
mae f, a sns axe axe	<pre>barplot(x = mae['Model'], y=mae['MAE Score'], ax = axe) set_xlabel('Mean Absolute Error', size=20) set_ylabel('Model', size=20) show()</pre>
mae f, a sns axe axe plt	<pre>barplot(x = mae['Model'], y=mae['MAE Score'], ax = axe) set_xlabel('Mean Absolute Error', size=20) set_ylabel('Model', size=20)</pre>
mae f, a sns axe axe plt	<pre>barplot(x = mae['Model'], y=mae['MAE Score'], ax = axe) set_xlabel('Mean Absolute Error', size=20) set_ylabel('Model', size=20) show()</pre>