Simple Linear Regression

- one independent variable

X = independent, predictors, feature variables
y = dependent, target, output variable

In [13]:
```
# import required libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

prepare the dataset

In [19]:
```
sns.get_dataset_names()
```

Out[19]:
```
['anagrams',
 'anscombe',
 'attention',
 'brain_networks',
 'car_crashes',
 'diamonds',
 'dots',
 'exercise',
 'flights',
 'fmri',
 'gammas',
 'geyser',
 'iris',
 'mpg',
 'penguins',
 'planets',
 'taxis',
 'tips',
 'titanic']
```

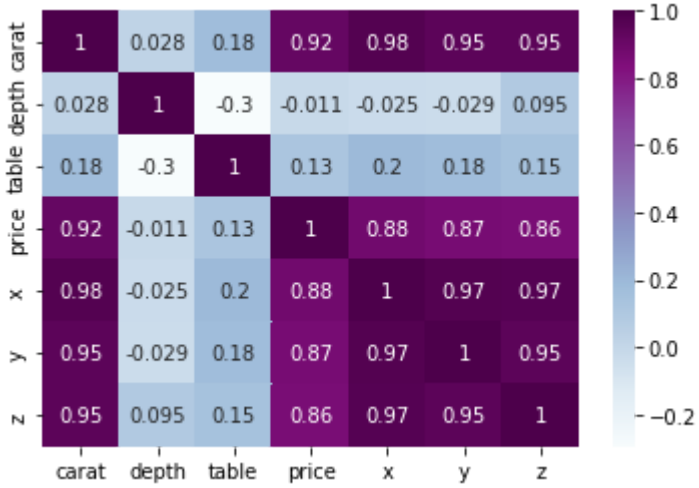
In [25]:
```
diamonds = sns.load_dataset('diamonds')
diamonds.head()
```

Out[25]:

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75

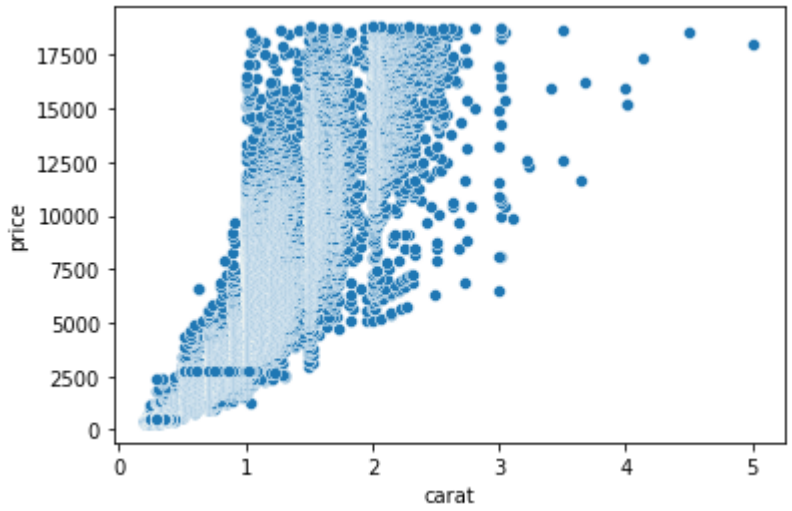
Visualization

In [32]:
```
sns.heatmap(diamonds.corr(), annot = True, cmap = 'BuPu')
plt.show()
```



From the above heatmap we find that carat and price column have good correlation between them and hence we can do simple linear regression using these two columns

In [39]:
```
sns.scatterplot(x = diamonds.carat, y = diamonds.price)
plt.show()
```



In [87]:
```
X = np.array(diamonds['carat'].values).reshape(-1,1) #converting into 2-d fo
y = diamonds['price'].values
```

In [88]:
```
len(X)
```

Out[88]: 53940

Train-Test-Split

In [89]:
```
from sklearn.model_selection import train_test_split
```

In [90]:
```
X_train, X_test,y_train, y_test = train_test_split(X,y,test_size = 0.3, rand
```

In [91]:
```
X_train.shape
```

Out[91]: (37758, 1)

In [92]:
```
y_train.shape
```

Out[92]: (37758,)

In [93]:
```
X_test.shape
```

Out[93]: (16182, 1)

In [94]:
```
y_test.shape
```

Out[94]: (16182,)

In [95]:
```
X_train
```

Out[95]:
```
array([[1.21],
       [0.31],
       [1.21],
       ...,
       [0.33],
       [0.9 ],
       [1.14]])
```

Model Building

In [96]:
```
from sklearn.linear_model import LinearRegression
```

In [97]:
```
slr_model = LinearRegression()   # creating LinearRegression object for trai

slr_model.fit(X_train,y_train)               # fit trains the model using X
```

Out[97]: LinearRegression()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Evaluation

r2 score

In [98]:
```
slr_model.score(X_test,y_test)
```

Out[98]: 0.8486858713767871

r2 score value is 0.85. Which means our model is able to explain 85% variance in the data

intercept

In [99]:
```
i = slr_model.intercept_
i
```

Out[99]: -2258.91865599418

slope

In [100]:
```
m = slr_model.coef_
m
```

Out[100]: array([7765.31828393])

Now we have intercept and slope value; we can make equation of the best fit line:

```
y = m*x + c i.e.,
y = 7765.318 * x + (-2258.918)
```

In [101]:
```
def prediction(x):
    y = (7765.318 * x) - 2258.918
    return y
```

Prediction

In [102]:
```
X_test[:5]
```

Out[102]:
```
array([[0.24],
       [0.58],
       [0.4 ],
       [0.43],
       [1.55]])
```

In [103]:
```
y_test[:5]
```

Out[103]: array([559, 2201, 1238, 1304, 6901], dtype=int64)

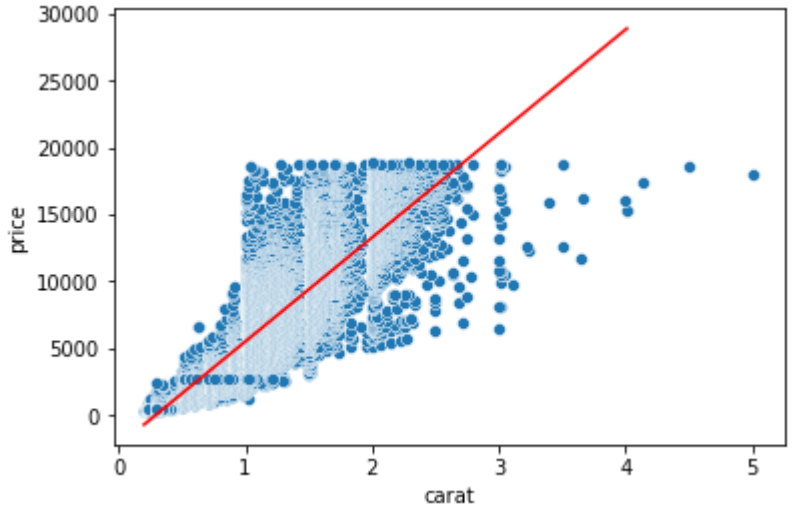
In [104]:
```
# prediction using the above prediction function

prediction(0.24)
```

Out[104]: -395.2416800000001

In [105]:
```
y_pred = slr_model.predict(X_test)
```

Visualization

In [115]:
```
sns.scatterplot(x=diamonds.carat,y=diamonds.price)
sns.lineplot(x = X_test.reshape(-1), y= y_pred, color = 'red')
plt.show()
```



What will be the price of a 2 carat diamond ?

In [118]:
```
# using predict function from the model to predict the values

slr_model.predict([[2]])
```

Out[118]:
```
array([13271.71791186])
```

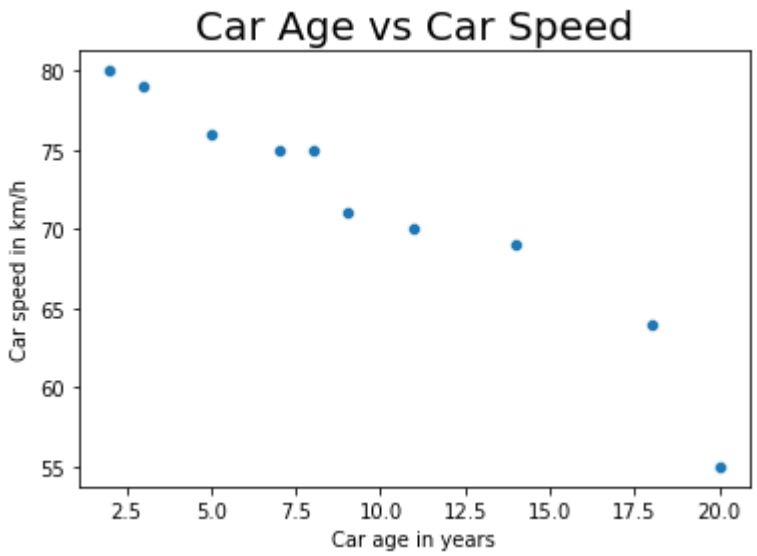
13271 dollar will be the price of a 2 carat diamond

In [ ]:
```
RRAJ
```

Example - 2

- Car age and Car speed prediction

In [123]:
```
car_age = [2,5,3,7,8,9,20,14,18,11]
car_speed = [80,76,79,75,75,71,55,69,64,70]


sns.scatterplot(x = car_age, y = car_speed)
plt.title("Car Age vs Car Speed", size = 20)
plt.xlabel('Car age in years')
plt.ylabel('Car speed in km/h')
plt.show()
```



Train a model with the given values

In [128]:
```
X = np.array(car_age).reshape(-1,1)
```

In [130]:
```
%%time

from sklearn.linear_model import LinearRegression

model = LinearRegression()
model.fit(X, car_speed)
```

```
Wall time: 997 µs
```

Out[130]:
```
LinearRegression()
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

prediction

In [134]:
```
model.predict([[2]])
```

Out[134]:
```
array([80.60012045])
```

In [136]:
```
y_pred = model.predict(X)
```

In [138]:
```
df = pd.DataFrame({'X':car_age,
                   'actual speed':car_speed,
                   'predicted speed':y_pred})
df
```

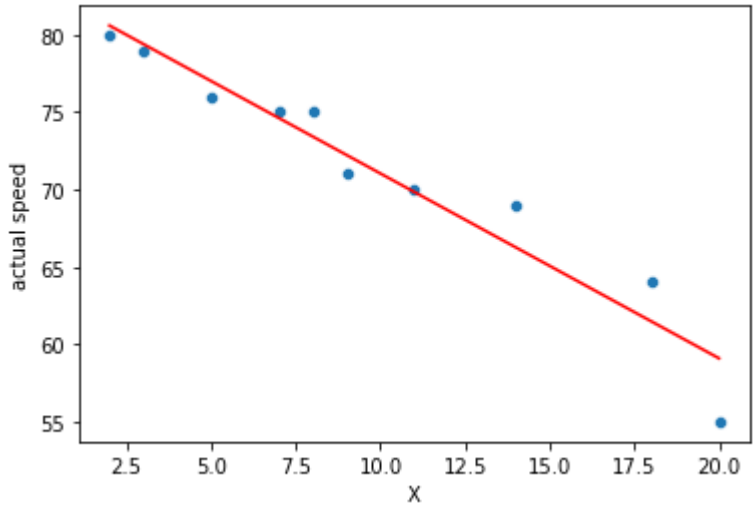
Out[138]:

	X	actual speed	predicted speed
0	2	80	80.600120
1	5	76	77.015658
2	3	79	79.405300
3	7	75	74.626016
4	8	75	73.431195
5	9	71	72.236375
6	20	55	59.093345
7	14	69	66.262270
8	18	64	61.482987
9	11	70	69.846733

Visualization

In [148]:
```
sns.scatterplot(df.X,df['actual speed'])
sns.lineplot(df.X,df['predicted speed'], color = 'red')
```

Out[148]: <AxesSubplot:xlabel='X', ylabel='actual speed'>



Evaluation

In [149]:
```
model.score(X, car_speed)
```

Out[149]: 0.9288889266461456

R2 value os 92.88 percent

In [156]:
```
from sklearn.metrics import r2_score,mean_squared_error, mean_absolute_error
```

In [157]:
```
r2_score(car_speed,y_pred)
```

Out[157]: 0.9288889266461456

R2 score value is 0.9288 which is a very good value obtained by the model.

It means our model is able to explain 92.8% variance in the data.

In [158]:
```
# mean absolute error

mean_absolute_error(car_speed,y_pred)
```

Out[158]: 1.4701595904847935

In [155]:
```
# mean square error

mean_squared_error(car_speed,y_pred)
```

Out[155]: 3.6295091839807263

In [159]:
```
# root mean squared error

np.sqrt(mean_squared_error(car_speed,y_pred))
```

Out[159]: 1.9051270781710932

Understanding the impact of outliers in errors

exactly same predictions

In [160]:
```
y_actual = [2,3,4,5,6,5,6,7]
y_pred = [2,3,4,5,6,5,6,7]
```

In [161]:
```
mean_absolute_error(y_actual, y_pred)
```

Out[161]: 0.0

In [162]:
```
mean_squared_error(y_actual, y_pred)
```

Out[162]: 0.0

In [163]:
```
np.sqrt(mean_squared_error(y_actual, y_pred))
```

Out[163]: 0.0

with some outliers in data

In [164]:
```
y_actual = [2,3,4,5,6,500,6,7]
y_pred = [2,3,4,5,6,5,6,7]
```

In [165]:
```
mean_absolute_error(y_actual, y_pred)
```

Out[165]: 61.875

In [166]:
```
mean_squared_error(y_actual, y_pred)
```

Out[166]: 30628.125

In [167]:
```
1 np.sqrt(mean_squared_error(y_actual, y_pred))
```

Out[167]:
```
175.0089283436705
```

In [ ]:
```
1
```

In [ ]:
```
1
```