In [61]:
```
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```

week04_Practical_03_Machine_Learning_Linear_Regression

Importing Libraries

In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

Why you want to apply regression on selected dataset?

Because our Y which is target variable is of continuous type so we can apply regression

In [2]:
```python
df = pd.read_csv('HousePrices_HalfMil.CSV')
df.head()
```

Out[2]:

	Area	Garage	FirePlace	Baths	White Marble	Black Marble	Indian Marble	Floors	City	Solar	Electric	Fiber	Glass Doors	Swiming Pool	Garden	Prices
0	164	2	0	2	0	1	0	0	3	1	1	1	1	0	0	43800
1	84	2	0	4	0	0	1	1	2	0	0	0	1	1	1	37550
2	190	2	4	4	1	0	0	0	2	0	0	1	0	0	0	49500
3	75	2	4	4	0	0	1	1	1	1	1	1	1	1	1	50075
4	148	1	4	2	1	0	0	1	2	1	0	0	1	1	1	52400

How many total observations in data?

The dimensionality of the dataset is the number of rows x columns in the dataset. The rows represent the observations and the columns represent the variables. The shape attribute of the DataFrame class returns a tuple representing rows x columns.There are 500000 observations (rows) and 16 variables (columns) in the dataset.

In [3]:
```python
print(len(df))
print(df.shape)
```

```
500000
(500000, 16)
```

How many independent variables?

In This dataset,we could say Area is the independent variables.

Which is dependent variable?

Prices is the dependent variable.

Which are most useful variable in estimation? Prove using correlation.

In this dataset there is only one independent variable. So there is no selection of most useful variable. But following is correlation between independent and dependent variable.

In [4]:
```python
df.corr()
```

Out[4]:

	Area	Garage	FirePlace	Baths	White Marble	Black Marble	Indian Marble	Floors	City	Solar	Electric	Fiber	Glass Doors	Swiming Pool	Garden	Prices
Area	1.000000	-0.000897	0.000374	-0.000398	0.002525	-0.001477	-0.001047	-0.000776	-0.003455	0.000526	-0.000128	0.000114	-0.001230	0.000610	0.001428	0.147717
Garage	-0.000897	1.000000	0.001307	-0.003647	0.000541	0.001847	-0.002385	-0.000931	0.000793	0.001480	0.000779	-0.000562	-0.002171	0.001088	-0.000669	0.100294
FirePlace	0.000374	0.001307	1.000000	0.000643	0.000952	-0.000922	-0.000030	0.000185	-0.000211	-0.000309	0.001342	0.001818	-0.000366	0.001295	0.000231	0.089139
Baths	-0.000398	-0.003647	0.000643	1.000000	0.002493	-0.002739	0.000246	-0.000880	-0.000858	-0.000755	0.001047	-0.000687	-0.001668	0.002212	0.001723	0.145087
White Marble	0.002525	0.000541	0.000952	0.002493	1.000000	-0.498893	-0.500723	0.000078	-0.000861	-0.001583	0.000558	-0.000576	-0.000402	-0.001898	0.000959	0.448154
Black Marble	-0.001477	0.001847	-0.000922	-0.002739	-0.498893	1.000000	-0.500383	-0.000368	-0.000324	0.001764	-0.000549	0.000073	0.000086	0.000713	0.000133	-0.078049
Indian Marble	-0.001047	-0.002385	-0.000030	0.000246	-0.500723	-0.500383	1.000000	0.000289	0.001184	-0.000180	-0.000010	0.000503	0.000316	0.001184	-0.001091	-0.369756
Floors	-0.000776	-0.000931	0.000185	-0.000880	0.000078	-0.000368	0.000289	1.000000	-0.000641	-0.002651	0.000082	0.001373	-0.000008	-0.000211	-0.000492	0.619451
City	-0.003455	0.000793	-0.000211	-0.000858	-0.000861	-0.000324	0.001184	-0.000641	1.000000	0.000488	0.000788	-0.002716	0.000770	0.000322	0.001207	0.233259
Solar	0.000526	0.001480	-0.000309	-0.000755	-0.001583	0.001764	-0.000180	-0.002651	0.000488	1.000000	0.001883	0.000238	-0.000817	-0.000466	-0.004263	0.008429
Electric	-0.000128	0.000779	0.001342	0.001047	0.000558	-0.000549	-0.000010	0.000082	0.000788	0.001883	1.000000	-0.000309	0.001088	0.000571	0.000772	0.052443
Fiber	0.000114	-0.000562	0.001818	-0.000687	-0.000576	0.000073	0.000503	0.001373	-0.002716	0.000238	-0.000309	1.000000	-0.002268	0.004127	-0.000023	0.484626
Glass Doors	-0.001230	-0.002171	-0.000366	-0.001668	-0.000402	0.000086	0.000316	-0.000008	0.000770	-0.000817	0.001088	-0.002268	1.000000	0.000396	0.003329	0.181973
Swiming Pool	0.000610	0.001088	0.001295	0.002212	-0.001898	0.000713	0.001184	-0.000211	0.000322	-0.000466	0.000571	0.004127	0.000396	1.000000	-0.000191	0.001787
Garden	0.001428	-0.000669	0.000231	0.001723	0.000959	0.000133	-0.001091	-0.000492	0.001207	-0.004263	0.000772	-0.000023	0.003329	-0.000191	1.000000	0.001540
Prices	0.147717	0.100294	0.089139	0.145087	0.448154	-0.078049	-0.369756	0.619451	0.233259	0.008429	0.052443	0.484626	0.181973	0.001787	0.001540	1.000000

Data Preparation

Finding Missing Values

In [5]:
```python
df.head()
```

Out[5]:

	Area	Garage	FirePlace	Baths	White Marble	Black Marble	Indian Marble	Floors	City	Solar	Electric	Fiber	Glass Doors	Swiming Pool	Garden	Prices
0	164	2	0	2	0	1	0	0	3	1	1	1	1	0	0	43800
1	84	2	0	4	0	0	1	1	2	0	0	0	1	1	1	37550
2	190	2	4	4	1	0	0	0	2	0	0	1	0	0	0	49500
3	75	2	4	4	0	0	1	1	1	1	1	1	1	1	1	50075
4	148	1	4	2	1	0	0	1	2	1	0	0	1	1	1	52400

In [6]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500000 entries, 0 to 499999
Data columns (total 16 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   Area           500000 non-null  int64
 1   Garage         500000 non-null  int64
 2   FirePlace      500000 non-null  int64
 3   Baths          500000 non-null  int64
 4   White Marble   500000 non-null  int64
 5   Black Marble   500000 non-null  int64
 6   Indian Marble  500000 non-null  int64
 7   Floors         500000 non-null  int64
 8   City           500000 non-null  int64
 9   Solar          500000 non-null  int64
 10  Electric       500000 non-null  int64
 11  Fiber          500000 non-null  int64
 12  Glass Doors    500000 non-null  int64
 13  Swiming Pool   500000 non-null  int64
 14  Garden         500000 non-null  int64
 15  Prices         500000 non-null  int64
dtypes: int64(16)
memory usage: 61.0 MB
```

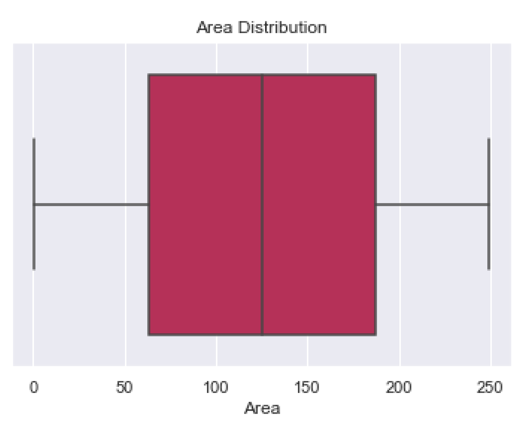
In [7]:
```python
df.isnull().sum()
```

Out[7]:
```
Area             0
Garage           0
FirePlace        0
Baths            0
White Marble     0
Black Marble     0
Indian Marble    0
Floors           0
City             0
Solar            0
Electric         0
Fiber            0
Glass Doors      0
Swiming Pool     0
Garden           0
Prices           0
dtype: int64
```

Area column

In [24]:
```python
import seaborn as sns

sns.set_theme(style="darkgrid")
sns.boxplot(x="Area", data=df, palette="rocket")
plt.title("Area Distribution")
```

Out[24]:
```
Text(0.5, 1.0, 'Area Distribution')
```



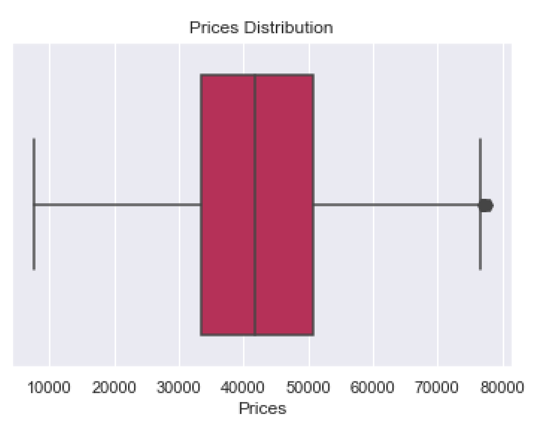
In [31]:
```python
df.Area.min(),df.Area.max()
```

Out[31]:
```
(1, 249)
```

Prices Column

In [32]:
```python
sns.set_theme(style="darkgrid")
sns.boxplot(x="Prices", data=df, palette="rocket")
plt.title("Prices Distribution")
```

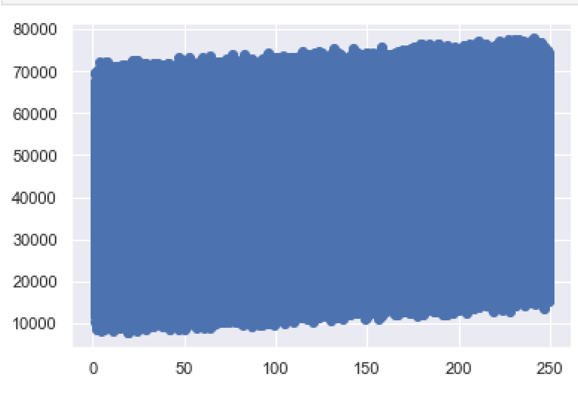
Out[32]:
```
Text(0.5, 1.0, 'Prices Distribution')
```



In [33]:
```python
df.Prices.min(),df.Prices.max()
```

Out[33]:
```
(7725, 77975)
```

In [34]:
```python
plt.scatter(df.Area, df.Prices)
plt.show()
```



In [38]:
```python
X = df['Area'].head(1000)
Y = df['Prices'].head(1000)
#print(X)
#print(Y)
```

Implement linear regression using OLS method

In [40]:
```python
x_bar = X.sum()/X.count()
y_bar = Y.sum()/Y.count()
print(x_bar,y_bar)
```

```
125.694 42074.3
```

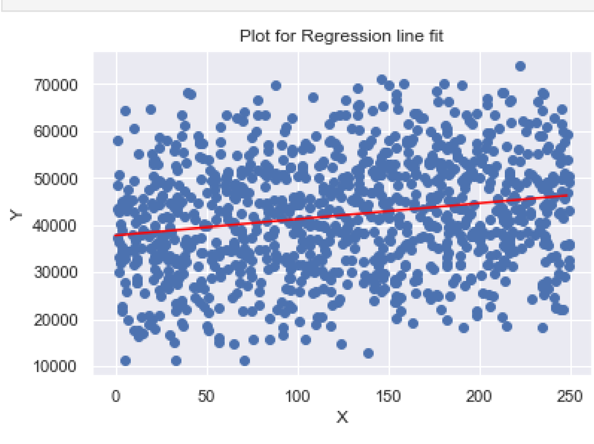
In [44]:
```python
#n = ((X-x_bar) * (Y-y_bar))
#print(n)
n = ((X-x_bar) * (Y-y_bar)).sum()
d = ((X-x_bar)**2).sum()
m = n/d
b = y_bar - m* x_bar
print(m, b)
```

```
33.97454508484849 37803.90353010506
```

In [49]:
```python
predicted_df = pd.DataFrame(data = range(0,int(X.max())), columns={'X'})

#print(predicted_df)
#print(predicted_df['X'])
#this above two statement print the same result because the predicted_df['Y'] is not added

predicted_df['Y'] = predicted_df.X*m + (b)

#print(predicted_df)
#print(predicted_df['Y'])
```

In [55]:
```python
x = predicted_df['X']
y = predicted_df['Y']
#print(x,y)
```

In [57]:
```python
plt.plot(x,y,c='red')
plt.scatter(X, Y)
plt.xlabel('X')
plt.ylabel('Y')
plt.title('Plot for Regression line fit')
#plt.legend()
plt.show()
```



Implement linear regression using Gradient Descent from scratch

In [58]:
```python
m = 0
c = 0

L      = 0.00001  # The learning Rate
epochs = 2500  # The number of iterations to perform gradient descent

n = float(len(X)) # Number of elements in X

# Performing Gradient Descent
for i in range(epochs):
    Y_pred = m*X + c  # The current predicted value of Y
    D_m = (-2/n) * sum(X * (Y - Y_pred))  # Derivative wrt m
    D_c = (-2/n) * sum(Y - Y_pred)  # Derivative wrt c
    m = m - L * D_m  # Update m
    c = c - L * D_c  # Update c
print (m, c)
```

```
258.428635231804 460.89669909759397
```

In [59]:
```python
from math import sqrt
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
Y_pred = m*X + c
print("RMSE: ", sqrt(mean_squared_error(Y,Y_pred)),"R2 score", r2_score(Y,Y_pred))
```

```
RMSE:  22067.243163314433 R2 score -2.2059483088350245
```

Implement linear regression using sklearn API

In [60]:
```python
from sklearn import linear_model
# This is using SKlearn API
X = pd.DataFrame(df.Area)
Y = df.Prices

# Create object of algorithm
rg = linear_model.LinearRegression()
# Create model by fitting data
rg.fit(X, Y)

# RMSE and R2 Score
print("RMSE: ", sqrt(mean_squared_error(Y,rg.predict(X))), "R2 Score:", r2_score(Y,rg.predict(X)))
```

```
RMSE:  11977.372439015693 R2 Score: 0.0218202278606604
```

Quantify goodness of your model and discuss steps taken for improvement (RMSE, MSE, R2Score).

Regression using SKlearn Api is good as it gives highest R2 score and low RMSE.

Discuss comparison of different methods.

The main reason why gradient descent is used for linear regression is the computational complexity: it's computationally cheaper (faster) to find the solution using the gradient descent in some cases.

The formula which you wrote looks very simple, even computationally, because it only works for univariate case, i.e. when you have only one variable. In the multivariate case, when you have many variables, the formulae is slightly more complicated on paper and requires much more calculations when you implement it in software: $\beta=(X'X)-1X'Y$ Here, you need to calculate the matrix X′X then invert it (see note below). It's an expensive calculation. For your reference, the (design) matrix X has K+1 columns where K is the number of predictors and N rows of observations. In a machine learning algorithm you can end up with K>1000 and N>1,000,000. The X′X matrix itself takes a little while to calculate, then you have to invert K×K matrix - this is expensive.

So, the gradient descent allows to save a lot of time on calculations. Moreover, the way it's done allows for a trivial parallelization, i.e. distributing the calculations across multiple processors or machines. The linear algebra solution can also be parallelized but it's more complicated and still expensive.

Additionally, there are versions of gradient descent when you keep only a piece of your data in memory, lowering the requirements for computer memory. Overall, for extra large problems it's more efficient than linear algebra solution.

This becomes even more important as the dimensionality increases, when you have thousands of variables like in machine learning.

In data analysis, we use OLS for estimating the unknown parameters in a linear regression model. The goal is minimizing the differences between the collected observations in some arbitrary dataset and the responses predicted by the linear approximation of the data. We can express the estimator by a simple formula. You can find the general OLS formula and its exact mathematical derivation.