

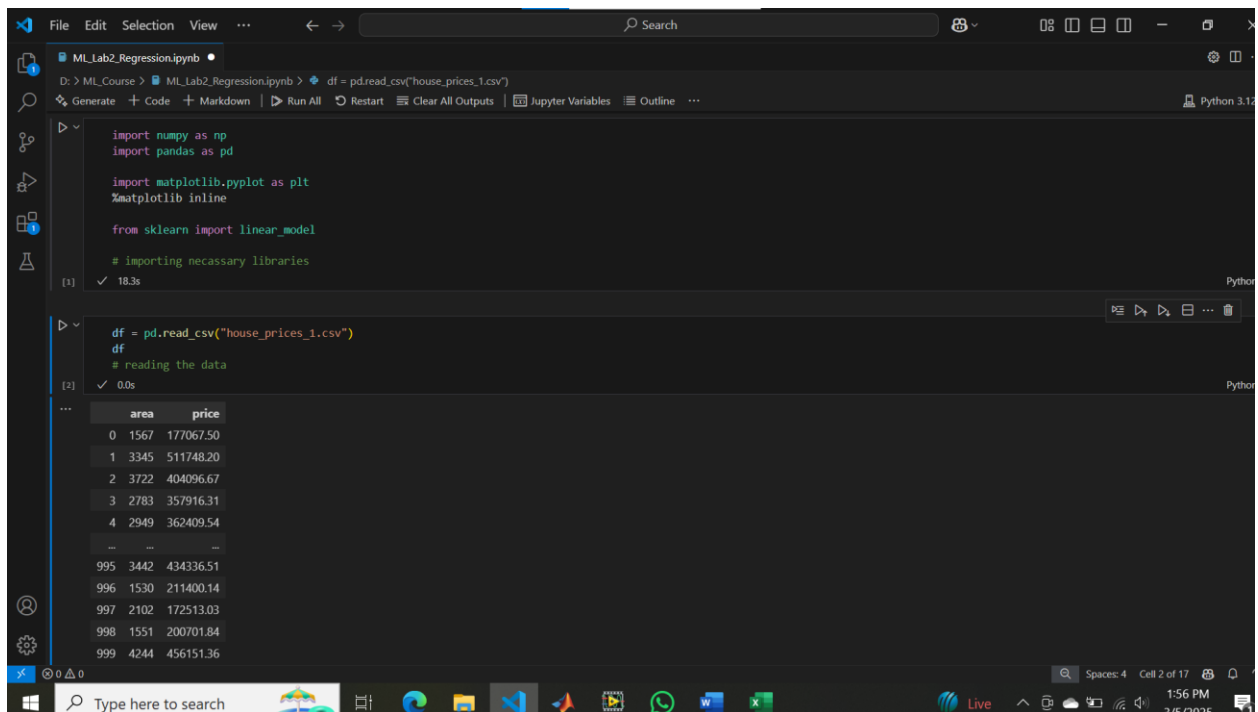
ML_Lab2_Regression

Student Name: Abdul Malik

Student Number: 2211011098

Objective:

Make a Linear Regression model that predicts the house price given a specific feature i.e. area in square feet.



```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
%matplotlib inline

from sklearn import linear_model

# importing necessary libraries
```

```
df = pd.read_csv("house_prices_1.csv")
df
# reading the data
```

	area	price
0	1567	177067.50
1	3345	511748.20
2	3722	404096.67
3	2783	357916.31
4	2949	362409.54
...
995	3442	434336.51
996	1530	211400.14
997	2102	172513.03
998	1551	200701.84
999	4244	456151.36

The above two cells of jupyter notebook show the necessary libraries which are firstly the famous ones, numpy, panda, matplotlib (for plotting the data) and scikit learn (famous for having packages for linear regression, logistic regression, classification and clustering etc) ([scikit-learn: machine learning in Python — scikit-learn 1.6.1 documentation](https://scikit-learn.org/stable/)).

Panda's **read_csv** reads the data from the saved **dataset house_prices_1.csv** and then prints the elements of csv file.

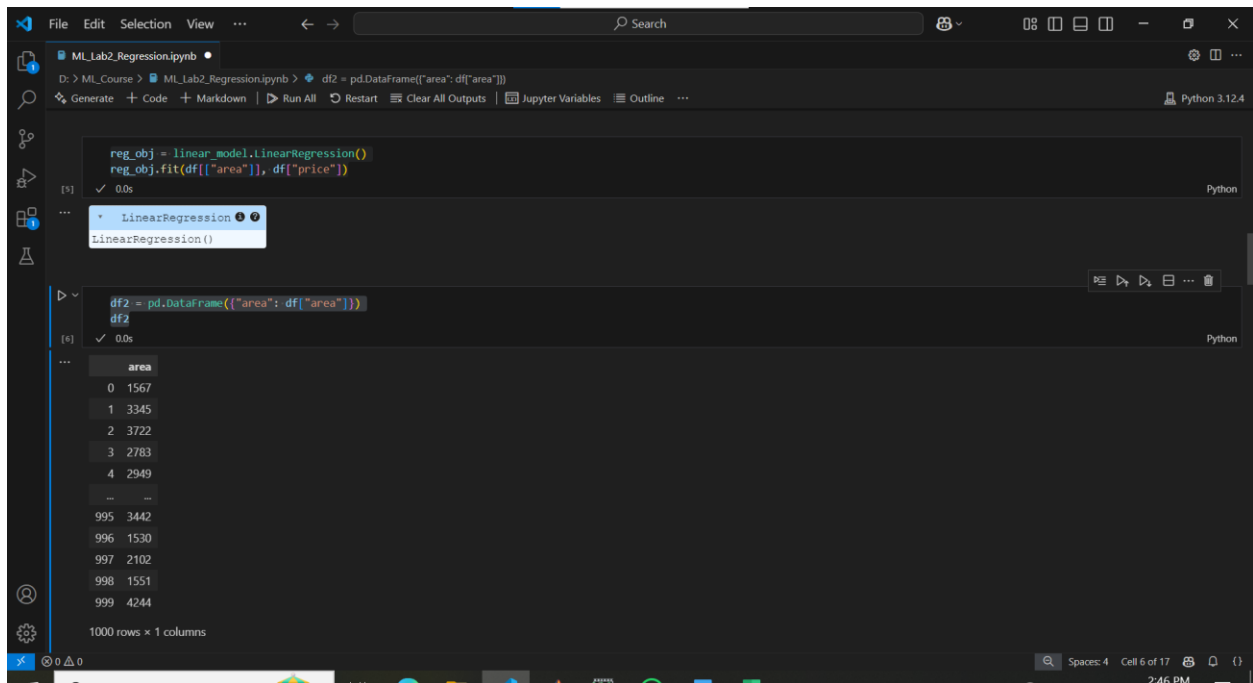
```
File Edit Selection View ... Search
ML_Lab2_Regression.ipynb
D:\ML_Course > ML_Lab2_Regression.ipynb > plt.scatter(df["area"], df["price"], color="red", marker="+")
Generate + Code + Markdown | Run All | Restart | Clear All Outputs | Jupyter Variables | Outline ... Python 3.12.4

df.dtypes
# checking the data types of the columns
[3]: ✓ 0.0s
...
area    int64
price   float64
dtype: object
```

Now the datatypes of the elements inside csv (df variable defined) are shown using **dtypes** from Pandas.



Here we scatter plot the elements of datasets which are area (square feet) and price (\$) using **plt** function from **matplotlib**.



The screenshot shows a Jupyter Notebook interface within a VS Code editor. The notebook file is named 'ML_Lab2_Regression.ipynb'. The current cell contains the following Python code:

```
reg_obj = linear_model.LinearRegression()
reg_obj.fit(df[["area"]], df["price"])
```

The output of the cell is a `LinearRegression` object, displayed as:

```
LinearRegression()
```

Below the code cell, the variable `df2` is shown, which is a `DataFrame` containing the 'area' column. The first few rows of the DataFrame are visible:

	area
0	1567
1	3345
2	3722
3	2783
4	2949
...	...
995	3442
996	1530
997	2102
998	1551
999	4244

The DataFrame has 1000 rows and 1 column. The bottom status bar indicates 'Spaces: 4', 'Cell 6 of 17', and the time '2:45 PM'.

Here we load the features (area in our case) to our linear regression model form scikit learn.

```
ML_Lab2_Regression.ipynb
D: > ML_Course > ML_Lab2_Regression.ipynb > c = reg_obj.intercept_ # outputs the value of intercept(c)
1000 rows x 1 columns

predicted_arr = reg_obj.predict(df2)

print(predicted_arr[:10], end=", ")
print("...", end=", ")
print(predicted_arr[-10:])

[7] ✓ 0.0s Python
... [212322.90487091 384074.21961441 420491.68061458 329786.12125342
345821.39585827 405712.18052698 266417.80715232 360600.89594587
484342.98491461 276657.19936988], ..., [378857.92546585 212709.29703006 416724.35706284 393251.0333943
468597.50442913 393444.22947387 208748.77739874 264002.85615762
210777.33623429 470915.85738405]

> m = reg_obj.coef_ # outputs the value of slope(m)
[8] ✓ 0.0s Python
... array([96.59803979])

> c = reg_obj.intercept_ # outputs the value of intercept(c)
[9] ✓ 0.0s Python
... 60953.776522719534

x = df2.to_numpy(df["area"])

x = df2.to_numpy(df["area"])

[12] ✓ 0.0s Python

# y = w * x + b
using_formula_arr = np.empty(1000)
for i in range(len(x)):
    using_formula_arr[i] = w * x[i] + b
    # print(m * x[i] + c, end=", ")

print(using_formula_arr[:10], end=", ")
print("...", end=", ")
print(using_formula_arr[-10:])

[13] ✓ 0.0s Python
... [212322.90487091 384074.21961441 420491.68061458 329786.12125342
345821.39585827 405712.18052698 266417.80715232 360600.89594587
484342.98491461 276657.19936988], ..., [378857.92546585 212709.29703006 416724.35706284 393251.0333943
468597.50442913 393444.22947387 208748.77739874 264002.85615762
210777.33623429 470915.85738405]
C:\Users\DELL\AppData\Local\Temp\ipykernel_17788\3950902830.py:5: DeprecationWarning: Conversion of an array with ndim > 0 to a scalar is deprecated, and will error in future. Ensure y
using_formula_arr[i] = w * x[i] + b

np.array_equal(predicted_arr, using_formula_arr)

[14] ✓ 0.0s Python
... True
```

Using the prediction equation $y' = w * x + b$, we calculate prediction inside a for loop by running it from i to number of features which is **len(x)** and saving each iteration inside `using_formula_arr[i]` array.

```
File Edit Selection View ... Search
ML_Lab2_Regression.ipynb
D: > ML_Course > ML_Lab2_Regression.ipynb > df["predicted_price"] = predicted_arr
Generate + Code + Markdown | Run All | Restart | Clear All Outputs | Jupyter Variables | Outline ... Python 3.12.4

[14] ✓ 0.0s
... True

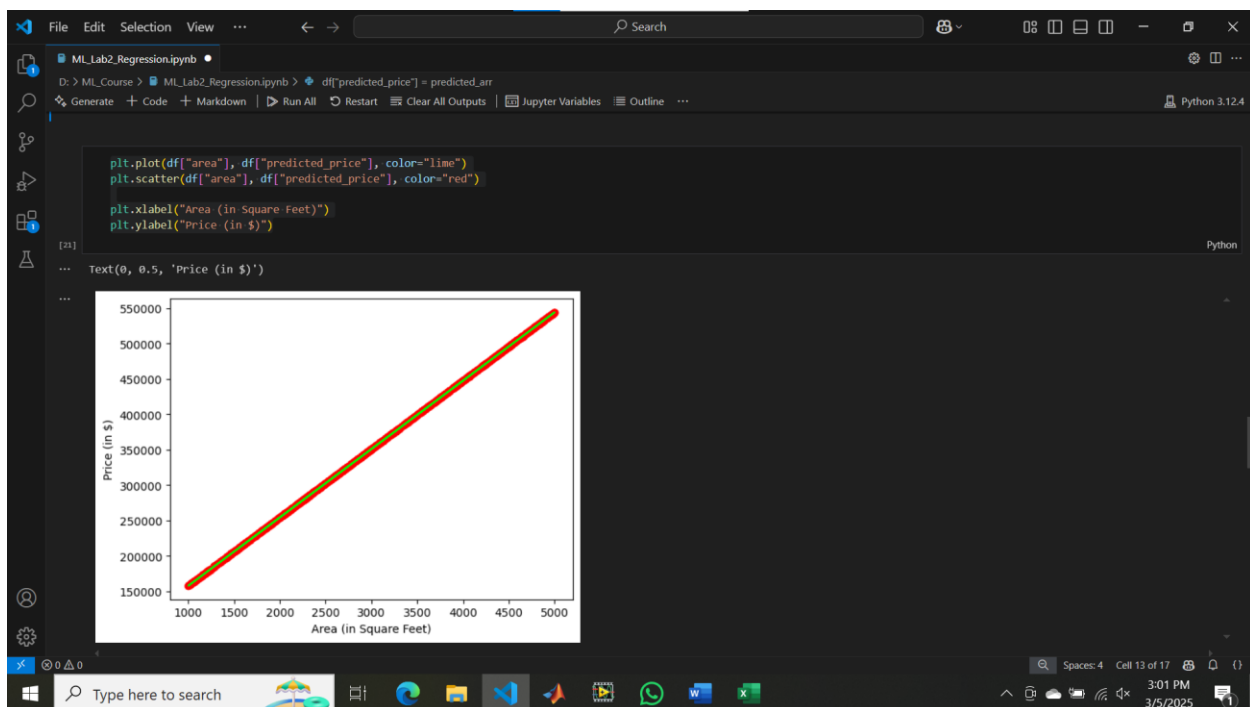
[15] ✓ 0.0s
df["predicted_price"] = predicted_arr
display(df)

...
   area  price  predicted_price
0  1567  177067.50  212322.904871
1  3345  511748.20  384074.219614
2  3722  404096.67  420491.680615
3  2783  357916.31  329786.121253
4  2949  362409.54  345821.395858
...    ...    ...
995 3442  434336.51  393444.229474
996 1530  211400.14  208748.777399
997 2102  172513.03  264002.856158
998 1551  200701.84  210777.336234
999 4244  456151.36  470915.857384

1000 rows x 3 columns

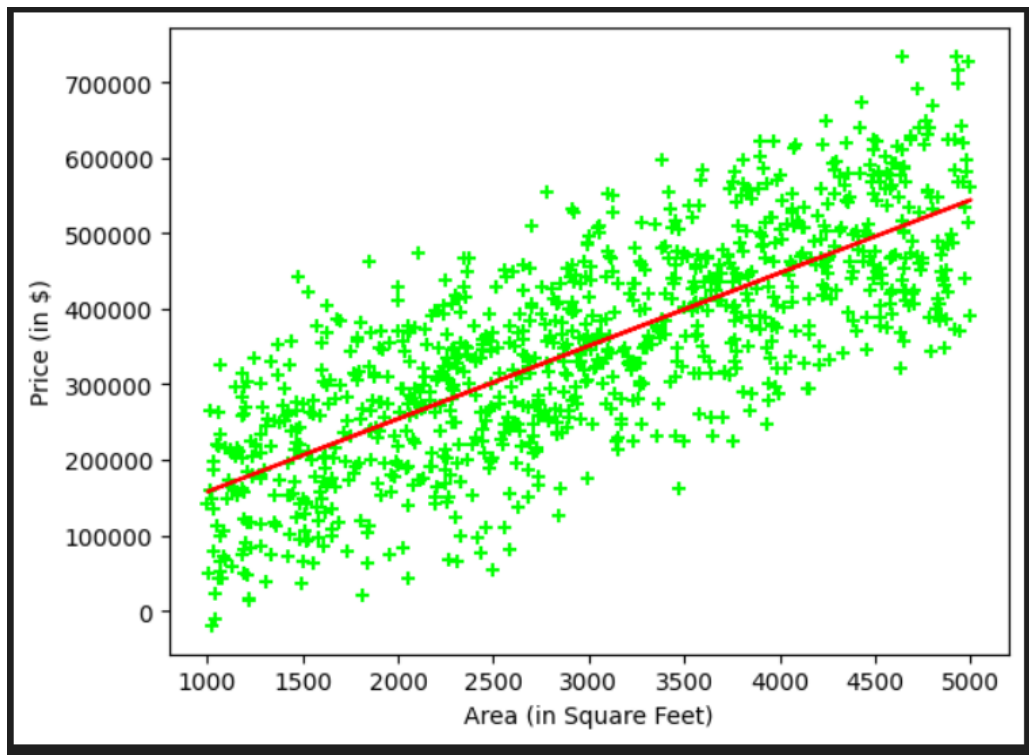
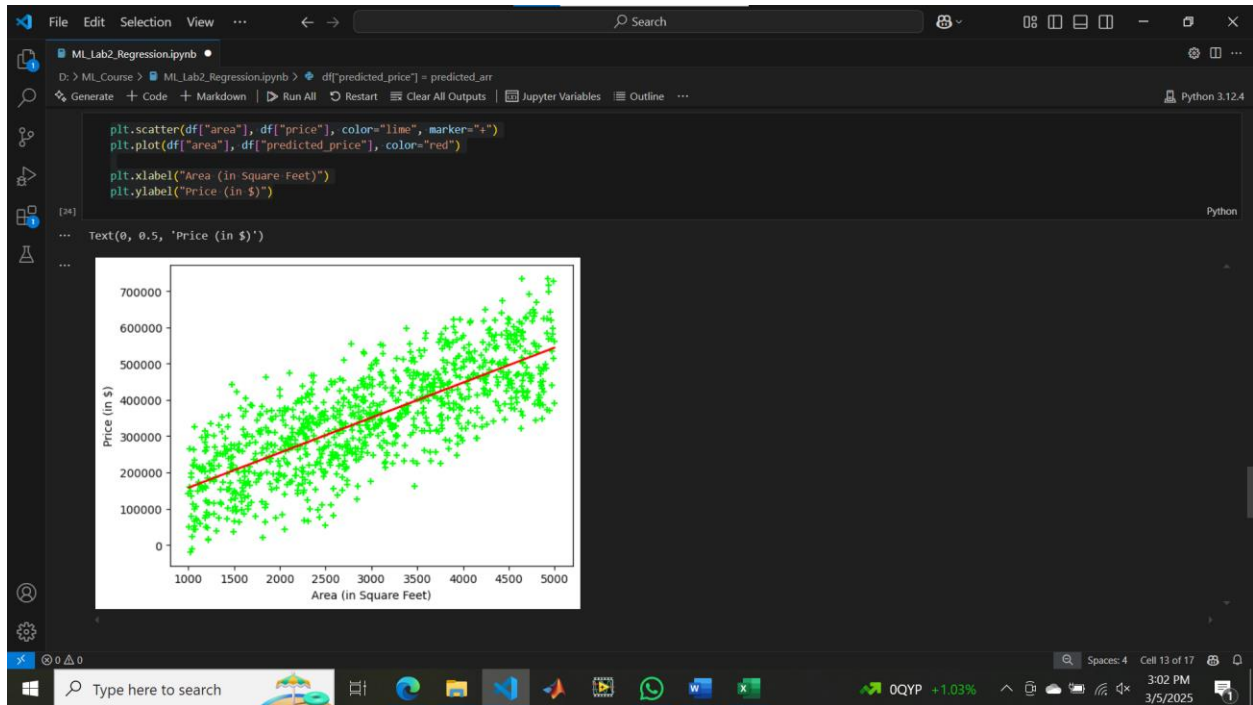
plt.plot(df["area"], df["predicted_price"], color="lime")
plt.scatter(df["area"], df["predicted_price"], color="red")
```

Now we pass the using_formula_arr[i] and predicted_arr (predicted value) to a numpy array and display the predicted_prices (\$) together with our feature (area) and price (\$).

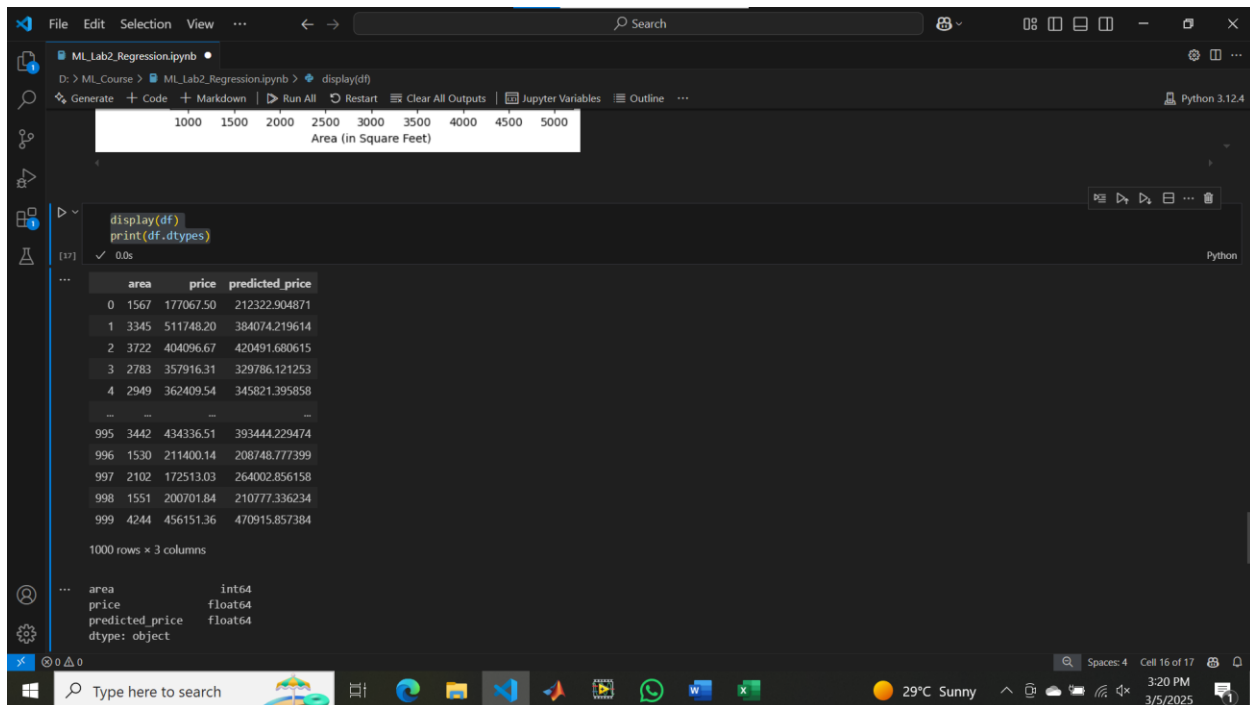


As shown above, plotting the linear regression best fit line. Why we choose the lime-colored line here? It is because we are calculating errors which is the vertical distance between our actual values and predicted values. We squared the errors that we found, taking their squares and

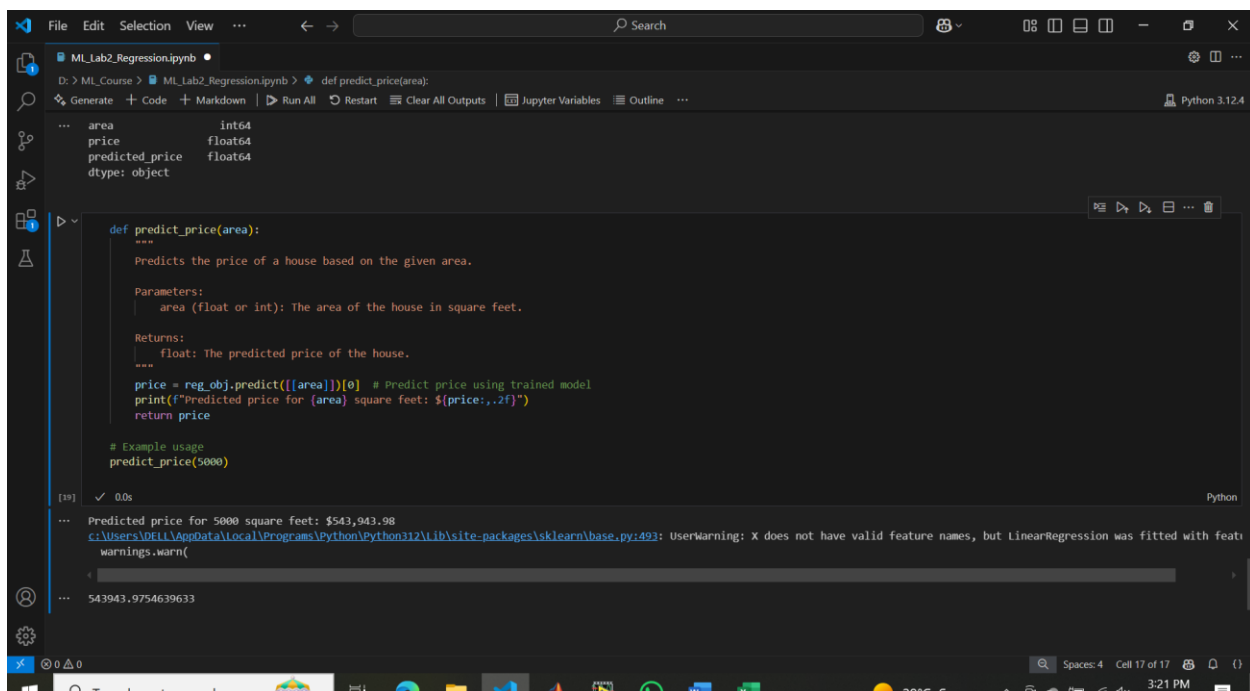
summing them up and making sure we minimize that error. So my lime-colored line actually represents the minimum sum value.



Now in a single scatter plot, we combine the regression line and the dataset values that we have to get the prediction model.



Displaying predicted price.



Here we are creating a function **predict_price** and giving it the **area** as a parameter. Here we can pass a certain value of our choice for the area that we want to predict the price for. As we can

see when an area of **5000 square feet** is passed to the function, it predicts the price of **543943.98\$**. It can be verified with the table given above as well.

Conclusion:

Our model gave us good results at the end. We implemented the simple linear regression model and got pretty close values to our actual values with almost 82% accuracy. If we train it with more datasets and different features we will get a more accurate result.