Data and Artificial Intelligence

Cyber Shujaa Program

Week 1 Assignment

Web Scraping and Data Handling in Python

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Introduction

This week's assignment was to develop hands-on experience in building a **Linear Regression model** using Python. I explored a dataset, trained and tested my model, and visualized my results.

The purpose of the assignment was to gain hands-on practice in:

- Exploring a real-world dataset
- Preparing and splitting data for training and testing
- Building a simple linear regression model
- Evaluating the model using key metrics
- Visualizing predictions and regression lines
- Publishing your project as part of your portfolio collection

Tasks Completed

Part 1: simple linear regression

Step 1: exploring the data set given

In this step I imported the homeprices.csv data set as pandas' data frame. To get an overview of the data I ran the df. head() command.

Code

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from sklearn import linear_model

from google.colab import files

uploaded = files.upload()

df = pd.read_csv('homeprices.csv')
```

df.head()

Screenshot:

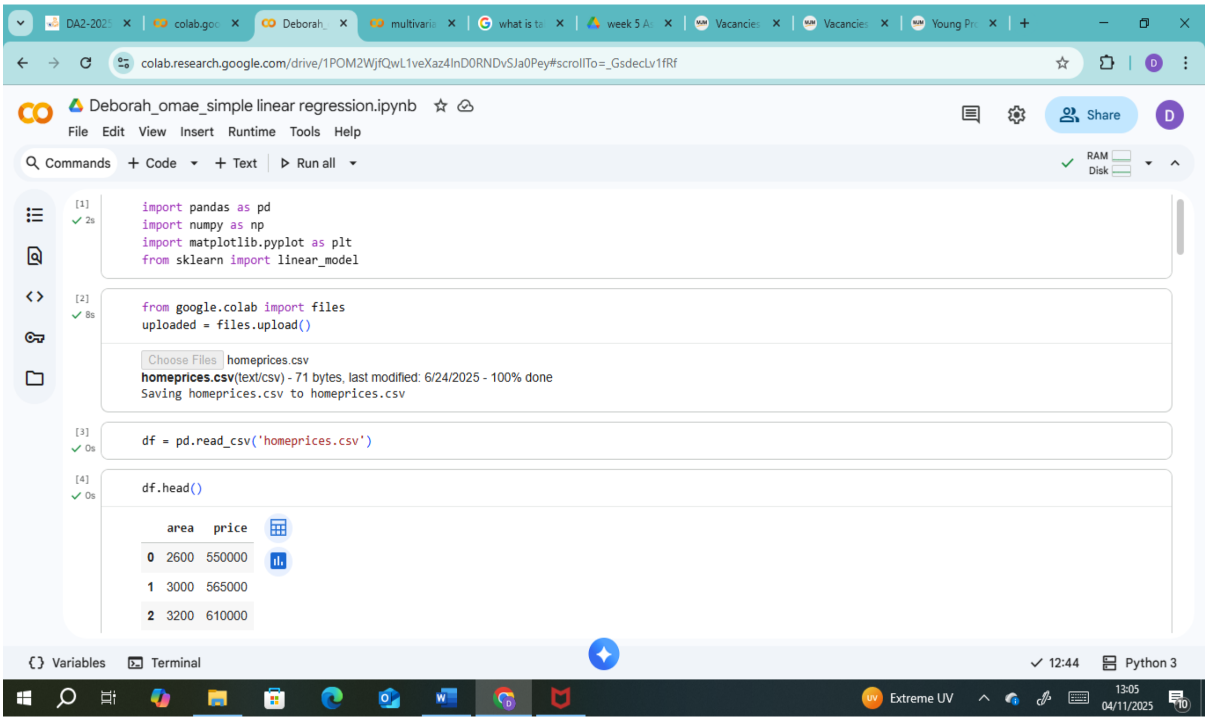


Figure 1: screenshot showing the imported dataset as a pandas data frame

Step 2: visualizing my data

I visualized the distribution of my dataset through a scatter plot.

Code:

plt.xlabel('area')

plt.ylabel('price')

plt.scatter(df.area,df.price,color='red',marker='+')

Screenshot:

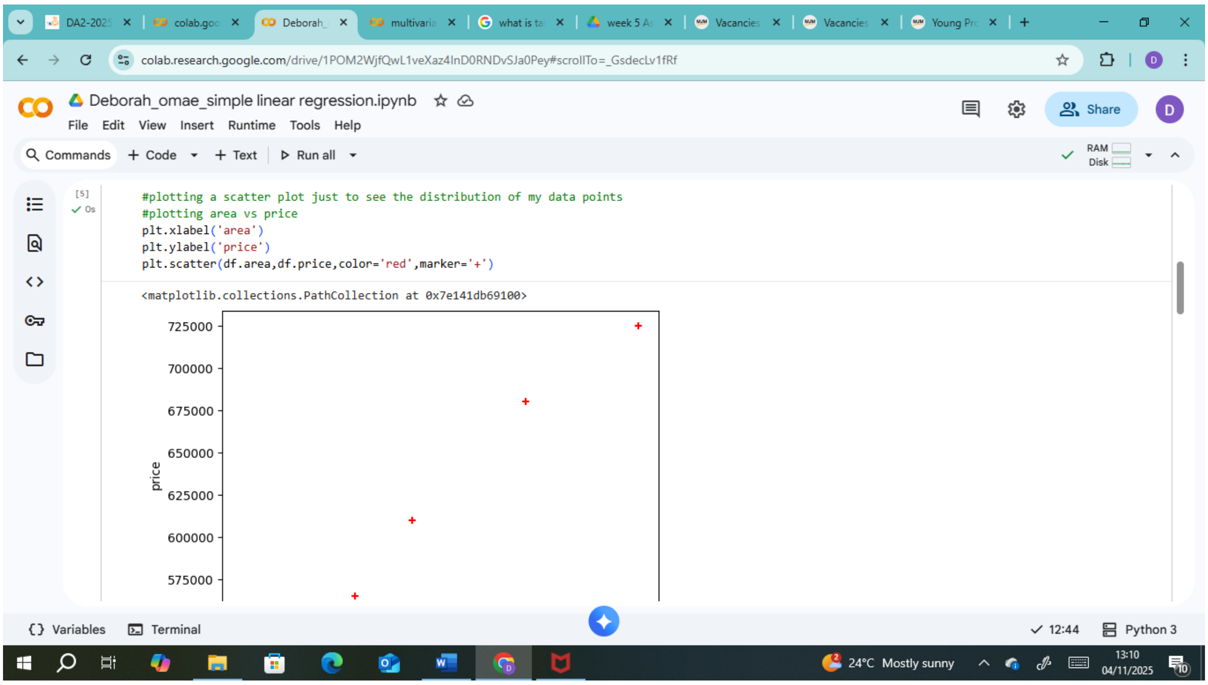


Figure 2: A scatter plot showing the area vs price

Step 3: preparing and splitting the data for training and testing

I used a linear regression model from Scikitlearn library. In order to train my regression model, I had to split my data set into 80% training and 20% testing. This is because we have to se how the model works on unseen data.

Code:

from sklearn.model_selection import train_test_split

 # drawing the linear regression line after seeing the distribution

reg = linear_model.LinearRegression()

 # Split the data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(df[['area']], df.price, test_size=0.2, random_state=0)

print ('x_test', X_test)

 # Fit the model using the training data

reg.fit(X_train, y_train)

y_pred = reg.predict(X_test)

display(y_pred)

Screenshot:

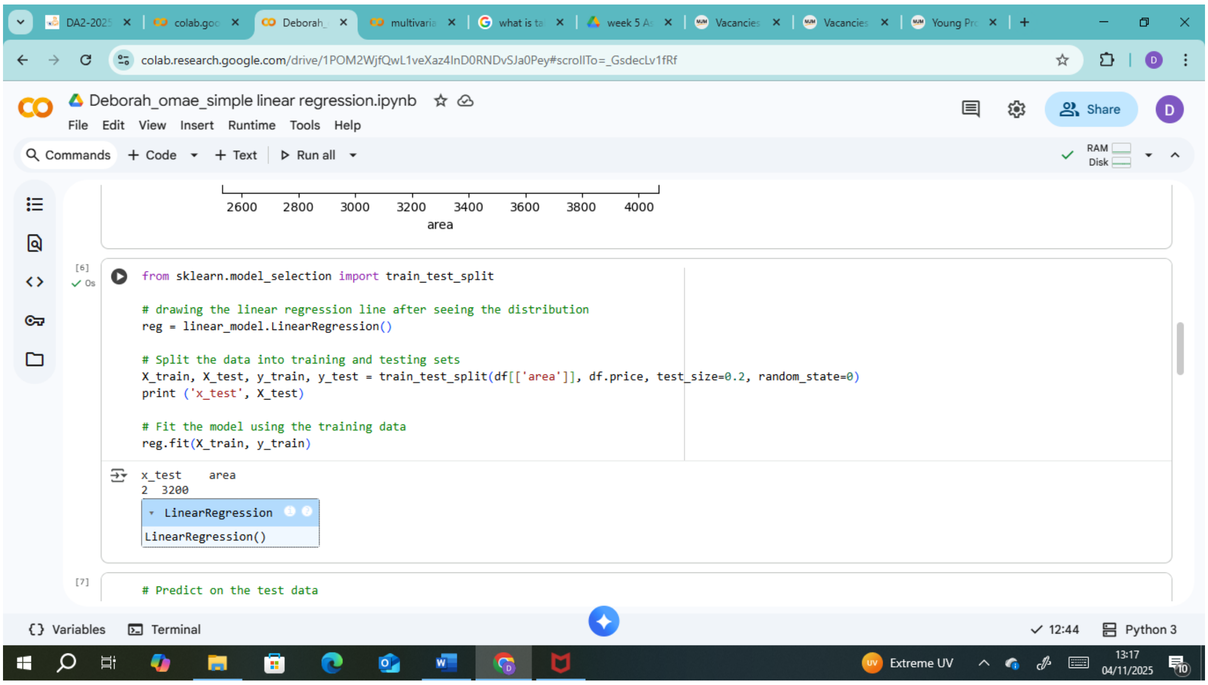


Figure 3: screenshot showing the code for splitting the data set. It can be seen that my testing data is 3200

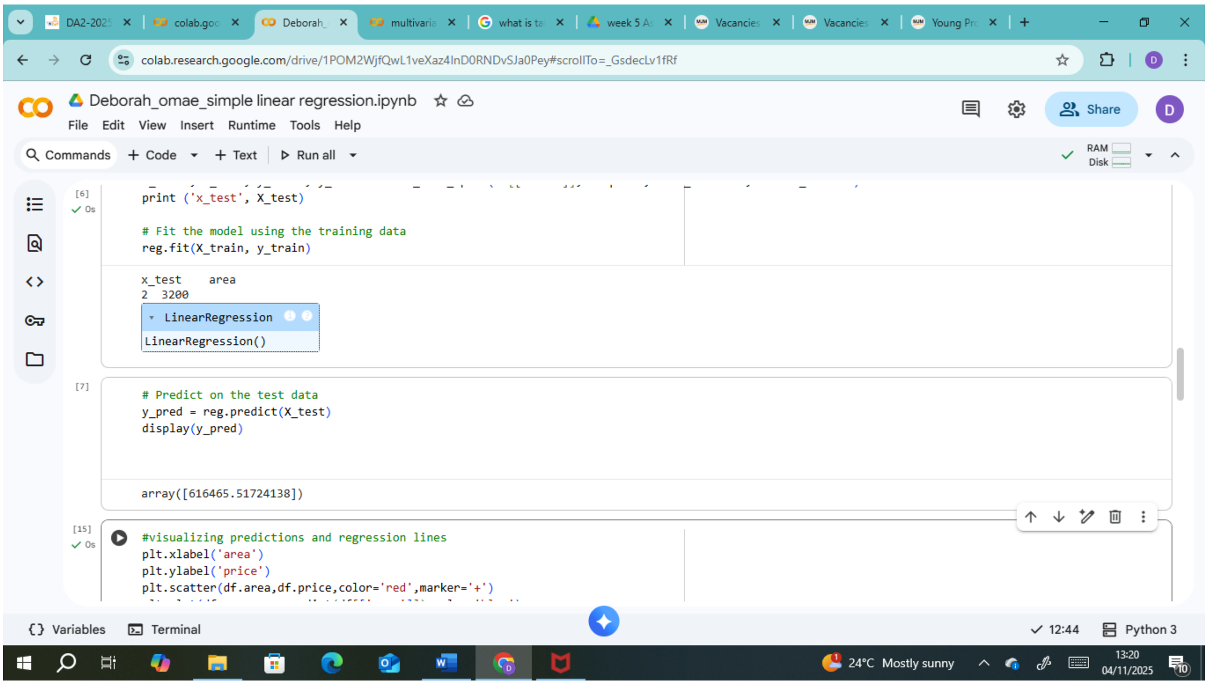


Figure 4: screenshot showing the predicted price for the area Of 3200

Step 4: visualizing predictions and regression lines

I visualized the predicted prices against the original prices

Code

#visualizing predictions and regression lines

plt.xlabel('area')

plt.ylabel('price')

plt.scatter(df.area,df.price,color='red',marker='+')

plt.plot(df.area,reg.predict(df[['area']]),color='blue')

 # Plot the predicted prices against the original areas

plt.scatter(df.area, reg.predict(df[['area']]), color='green', marker='x', label='Predicted Price')

plt.legend()

Screenshot:

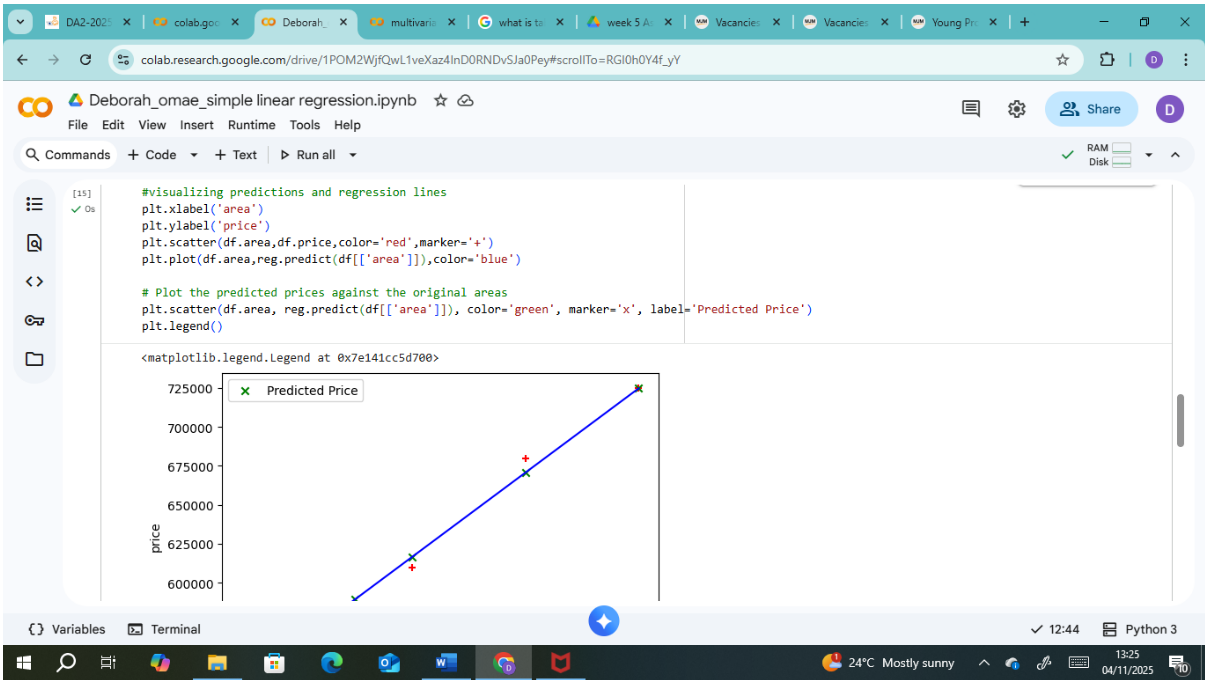


Figure 5: screenshot showing the visualized predictions

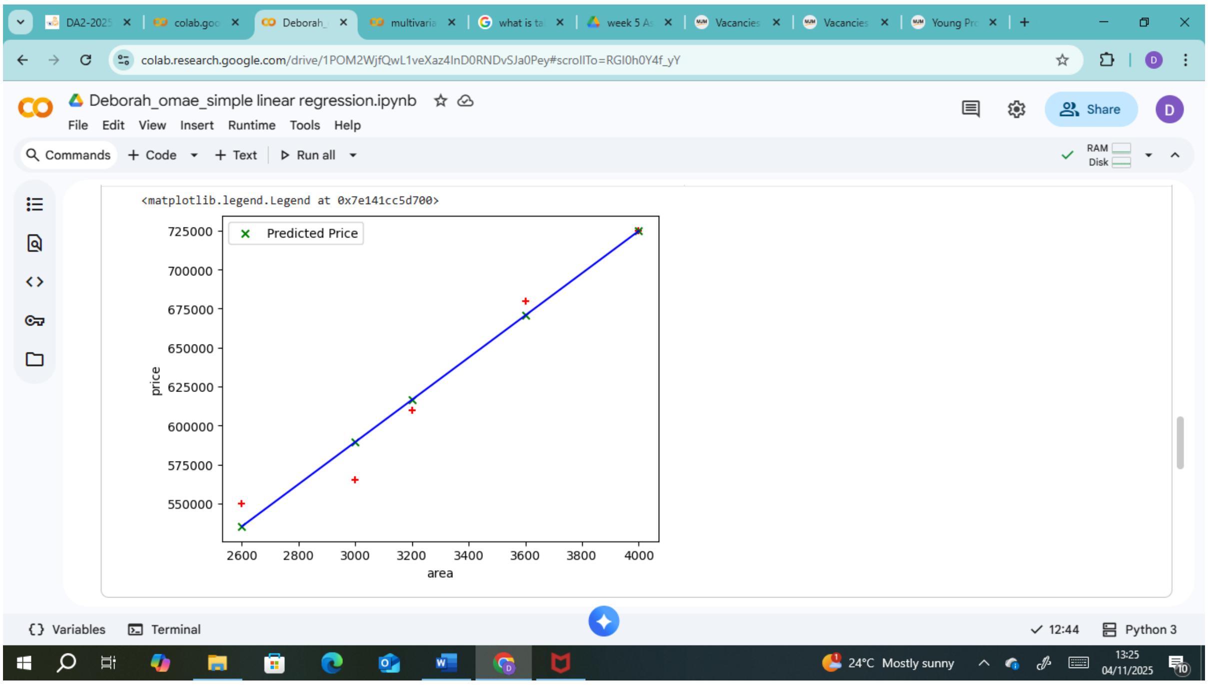


Figure 6: graph showing predicted and actual prices

Step 5: evaluating my model using key metrics

In this step I evaluated my model using regression metrics such as mean absolute error, mean squared error, root mean squared error, and R^2

MAE is the **average of the absolute differences** between actual and predicted values. It measures how far, on average, the predictions are from the real values.

MSE is the average of squared differences between actual and predicted values. By squaring the errors, it gives more weight to larger mistakes, making it useful when large errors are especially undesirable.

RMSE is the square root of the MSE**,** converting the result back to the same unit as the target variable. It represents the standard deviation of prediction errors. In other words, how much the predictions typically deviate from the actual values.

R^2 (coefficient of determination) measures the **proportion of the variance in the dependent variable** that is explained by the independent variables in the model. It compares how well your model performs against a simple baseline model that always predicts the mean.

Code

#evaluating this model using the regression metrics; MSE, RMSE, AME, R2

from sklearn.metrics import mean_squared_error, mean_absolute_error, root_mean_squared_error, r2_score

mae = mean_absolute_error(y_test, y_pred)

mse = mean_squared_error(y_test, y_pred)

rmse = root_mean_squared_error(y_test, y_pred)

r2 = r2_score(y_test, y_pred)

print('Mean Absolute Error:', mae)

print('Mean Squared Error:', mse)

print('Root Mean Squared Error:', rmse)

print('R-squared:', r2)

Screenshot:

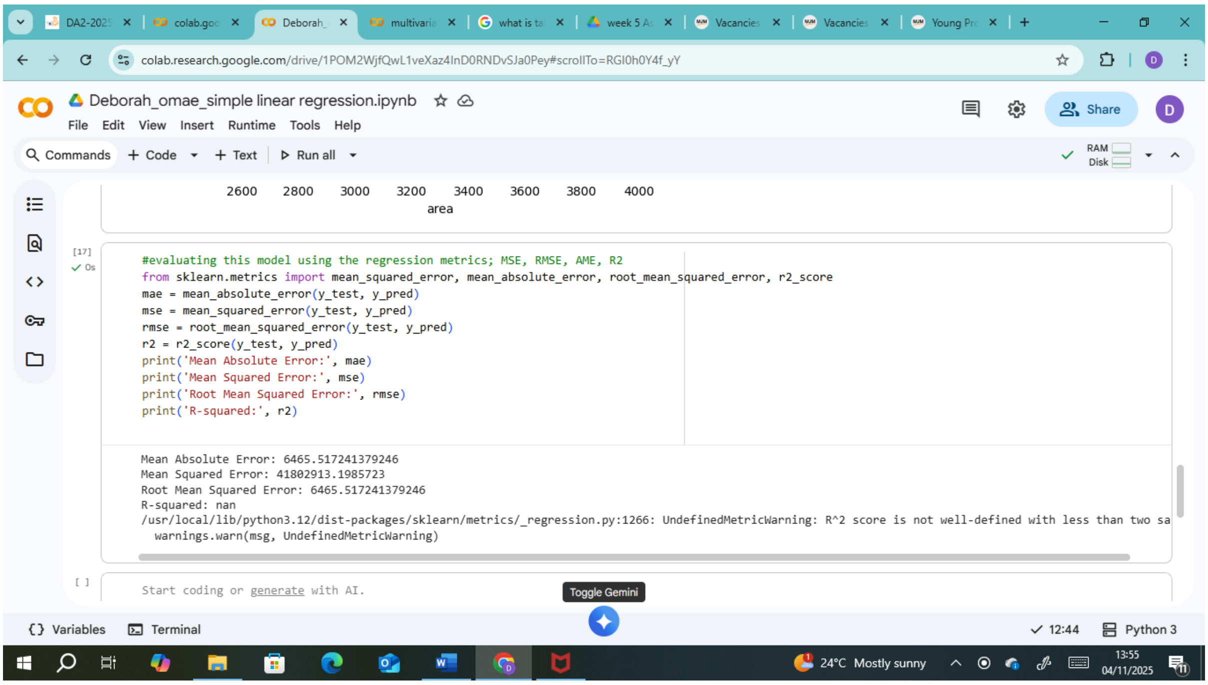


Figure 7: screenshot of model evaluation

Evaluation

The model has a mean absolute error and root mean square error of approximately 6465. This shows the error margin between our predicted value and actual value. Therefore, the predictions are reliable.

Part 2: linear regression with multiple variables

Step 1: exploring the dataset

I imported the homeprices-m .csv into a pandas' data frame and got an overview of the data.

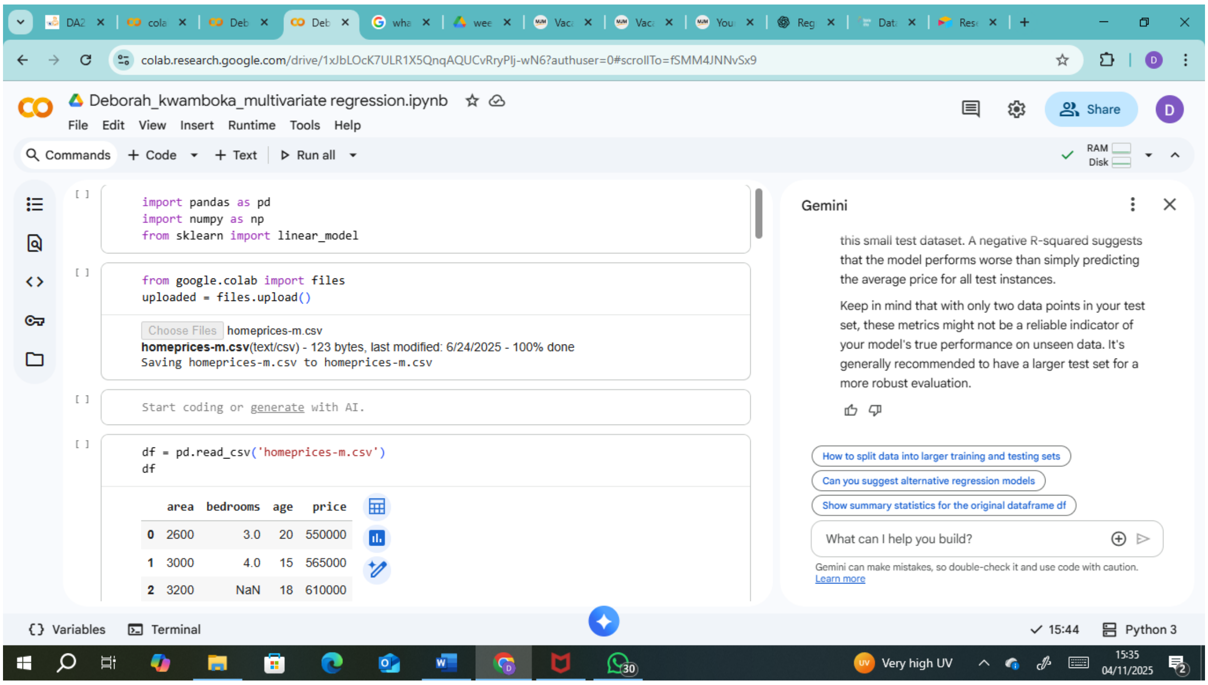


Figure 8: screenshot showing the dataset imported as pandas DataFrame

Step 2: data preparation and cleaning

My data set had one missing value in the bedroom's column. I imputed the missing value using the median of the bedroom's column.

The code:

df.bedrooms = df.bedrooms.fillna(df.bedrooms.median())

df

screenshot:

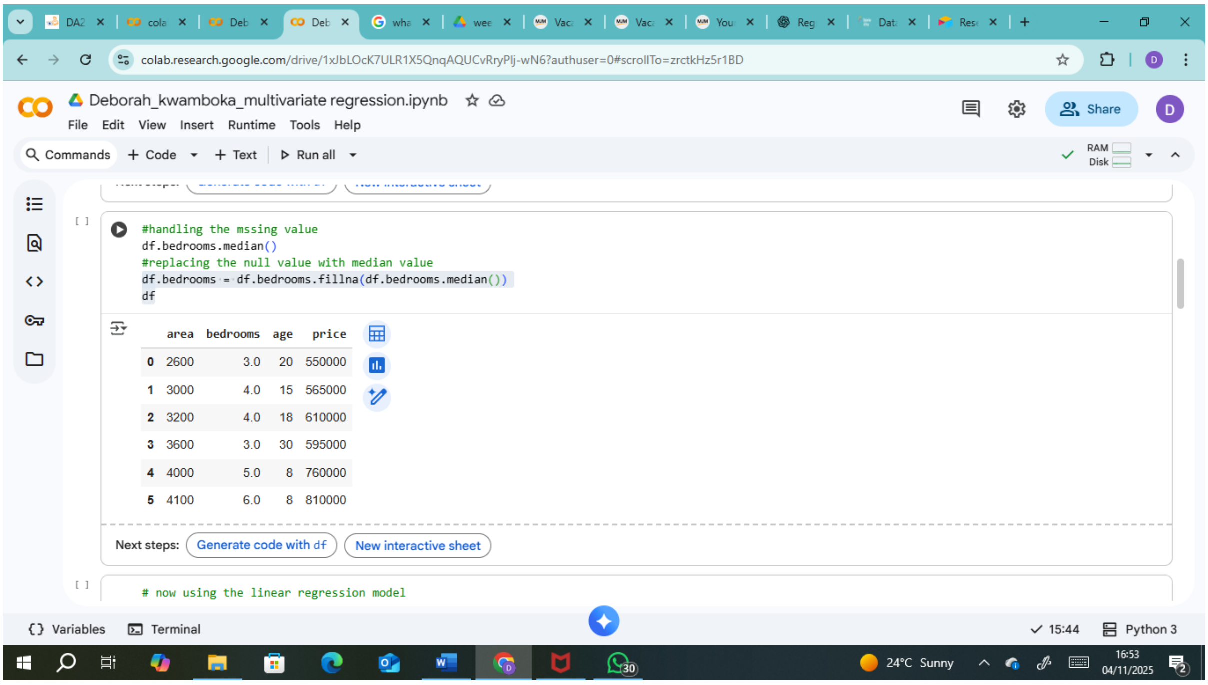


Figure 9: screenshot showing the handled missing value

step 3: splitting data into training and testing and fitting the regression model

In this step I had to split my data homeprices-m into training and testing data.

#80% training and 20% testing. I manually selected the data points for training and testing.

Code:

from sklearn.model_selection import train_test_split

from sklearn.metrics import mean_absolute_error, mean_squared_error, root_mean_squared_error, r2_score

p = df[['area', 'bedrooms', 'age']]

t = df['price']

print(p)

print('')

print(t)

 # Manually splitting the data with index 1 and 2 for testing

p_test = p.iloc[[1, 2]]

t_test = t.iloc[[1, 2]]

p_train = p.drop([1, 2])

t_train = t.drop([1, 2])

print(p_train)

print('')

print(p_test)

print('')

print(t_train)

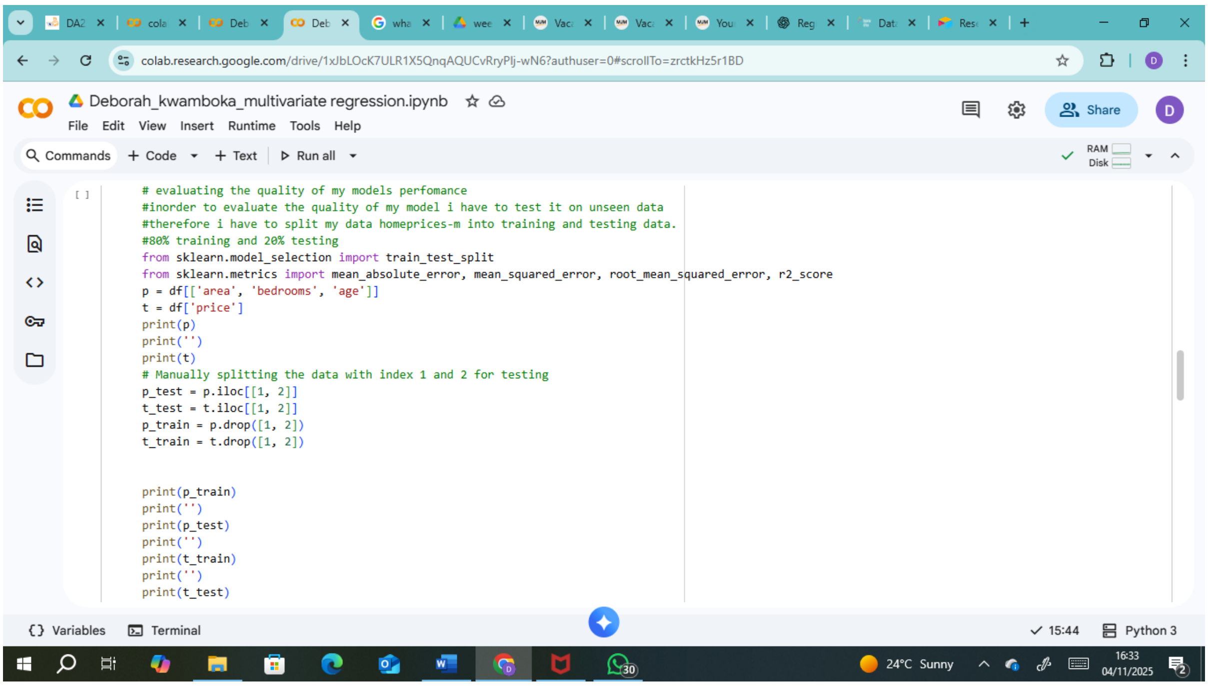
print('')

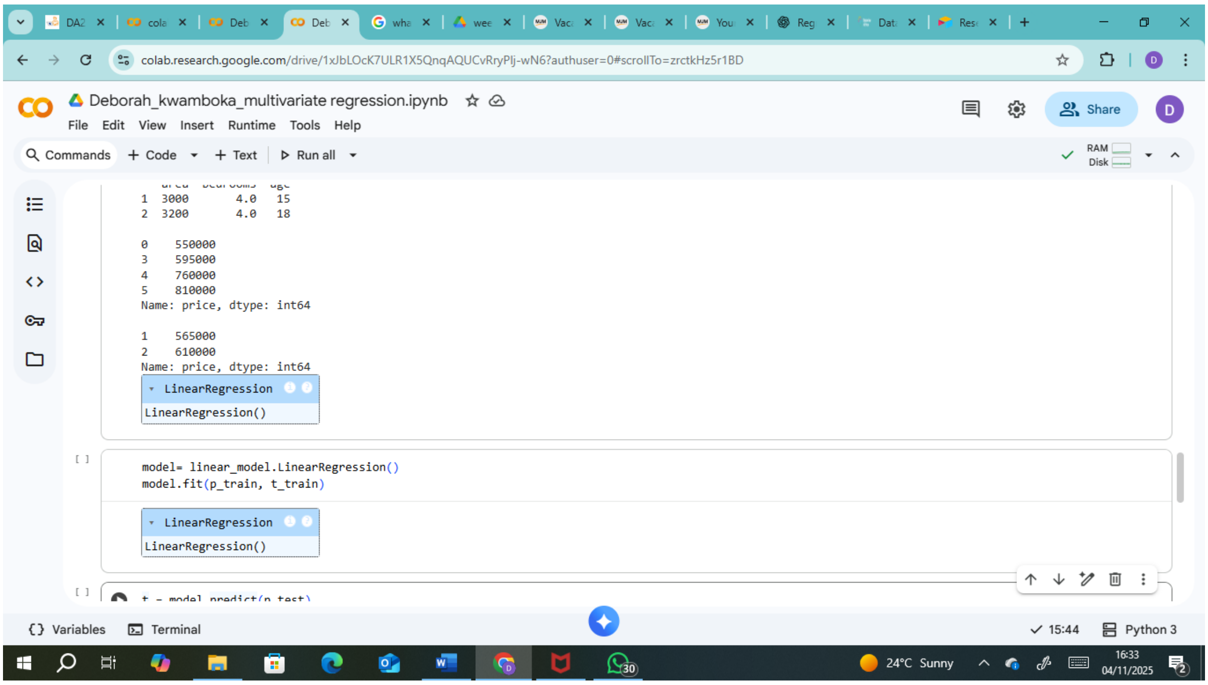
print(t_test)

model = linear_model.LinearRegression()

model.fit(p_train, t_train)

screenshot:





Step 4: evaluating the model

In this step I evaluated our regression model through regression metrics such as mean square error and mean absolute error.

Code:

 # getting the regression metrics

mae = mean_absolute_error(t_test, t)

mse = mean_squared_error(t_test, t)

rmse = root_mean_squared_error(t_test, t)

r2 = r2_score(t_test, t)

print(f"Mean Absolute Error (MAE): {mae}")

print(f"Mean Squared Error (MSE): {mse}")

print(f"Root Mean Squared Error (RMSE): {rmse}")

print(f"R-squared (R2): {r2}")

screenshot:

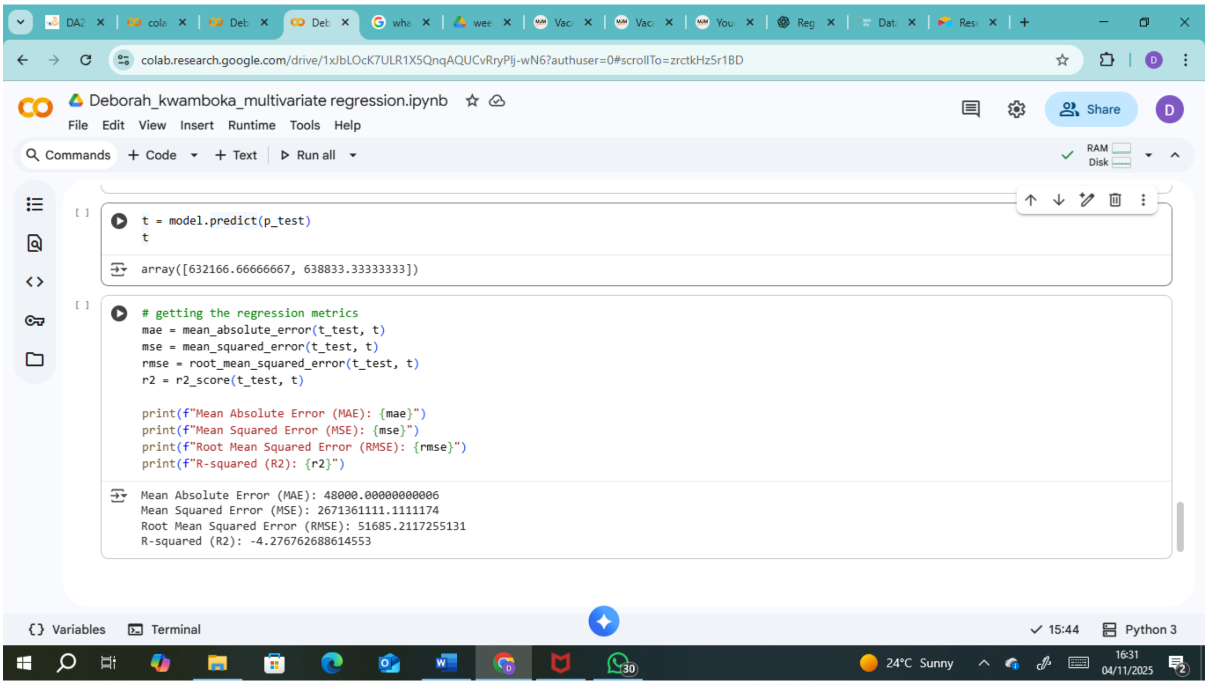


Figure 10: screenshot showing the evaluation of the model

Evaluation

The data set has a mean absolute error of approximately 48000 and R^2 is -4. This shows that our model is making poor predictions. Perhaps it needs training with a larger dataset.

Link to code

Link to Code:

Link 1(for simple linear regression):

https://colab.research.google.com/drive/1POM2WjfQwL1veXaz4InD0RNDvSJa0Pey?usp=sharing

Link 2(for linear regression with multiple variables):

https://colab.research.google.com/drive/1xJbLOcK7ULR1X5QnqAQUCvRryPlj-wN6?usp=sharing

Conclusion

In this task, a linear regression model was developed to predict house prices based on key features such as area (in square feet), number of bedrooms, and age of the house. The model was trained and evaluated using standard regression performance metrics including Mean Absolute Error (MAE)**,** Mean Squared Error (MSE)**,** Root Mean Squared Error (RMSE)**,** and the R^2 score. I can confidently say that a linear regression model is a good fit to make predictions and is more reliable with a larger dataset.