# Day42_SRL_House_Price_Prediction_Project

July 11, 2025

**Simple Linear Regression: House Price Prediction Project**

**Project Description**

This project uses **Simple Linear Regression** to predict house prices based on the **square footage of living area (`sqft_living`)** using a real dataset.

We'll go through:

- Data loading and exploration
- Feature selection
- Visualizing the relationship
- Training a Linear Regression model
- Evaluating model performance
- Making predictions on unseen data

**Objective**

Build a regression model to understand the relationship between square footage and price, and use it to predict prices for new, unseen homes.

## 1 Import Required Libraries

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
```

## 2 Load the Dataset

We are loading the dataset from the given path using pandas.read_csv() and displaying the first few rows using df.head().

[2]:
```
df = pd.read_csv(r"D:\Assignment Practice\M3\08 July\08 July\7th- slr\SLR -␣
↪House price prediction\House_data.csv")
df.head()
```

[2]:
```
           id             date     price  bedrooms  bathrooms  sqft_living  \
0  7129300520  20141013T000000  221900.0         3       1.00         1180
1  6414100192  20141209T000000  538000.0         3       2.25         2570
2  5631500400  20150225T000000  180000.0         2       1.00          770
3  2487200875  20141209T000000  604000.0         4       3.00         1960
4  1954400510  20150218T000000  510000.0         3       2.00         1680

   sqft_lot  floors  waterfront  view  …  grade  sqft_above  sqft_basement  \
0      5650     1.0           0     0  …      7        1180              0
1      7242     2.0           0     0  …      7        2170            400
2     10000     1.0           0     0  …      6         770              0
3      5000     1.0           0     0  …      7        1050            910
4      8080     1.0           0     0  …      8        1680              0

   yr_built  yr_renovated  zipcode      lat     long  sqft_living15  \
0      1955             0    98178  47.5112 -122.257           1340
1      1951          1991    98125  47.7210 -122.319           1690
2      1933             0    98028  47.7379 -122.233           2720
3      1965             0    98136  47.5208 -122.393           1360
4      1987             0    98074  47.6168 -122.045           1800

   sqft_lot15
0        5650
1        7639
2        8062
3        5000
4        7503

[5 rows x 21 columns]
```

# 3 Understand the Data

info() gives an overview of column types and non-null counts.

[3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21613 non-null  int64
 1   date           21613 non-null  object
 2   price          21613 non-null  float64
 3   bedrooms       21613 non-null  int64
 4   bathrooms      21613 non-null  float64
 5   sqft_living    21613 non-null  int64
 6   sqft_lot       21613 non-null  int64
```

```
 7   floors         21613 non-null  float64
 8   waterfront     21613 non-null  int64
 9   view           21613 non-null  int64
 10  condition      21613 non-null  int64
 11  grade          21613 non-null  int64
 12  sqft_above     21613 non-null  int64
 13  sqft_basement  21613 non-null  int64
 14  yr_built       21613 non-null  int64
 15  yr_renovated   21613 non-null  int64
 16  zipcode        21613 non-null  int64
 17  lat            21613 non-null  float64
 18  long           21613 non-null  float64
 19  sqft_living15  21613 non-null  int64
 20  sqft_lot15     21613 non-null  int64
dtypes: float64(5), int64(15), object(1)
memory usage: 3.5+ MB
```

describe() gives statistical summary of numerical features.

[4]:
```
df.describe()
```

[4]:
```
                 id         price      bedrooms     bathrooms   sqft_living  \
count  2.161300e+04  2.161300e+04  21613.000000  21613.000000  21613.000000
mean   4.580302e+09  5.401822e+05      3.370842      2.114757   2079.899736
std    2.876566e+09  3.673622e+05      0.930062      0.770163    918.440897
min    1.000102e+06  7.500000e+04      0.000000      0.000000    290.000000
25%    2.123049e+09  3.219500e+05      3.000000      1.750000   1427.000000
50%    3.904930e+09  4.500000e+05      3.000000      2.250000   1910.000000
75%    7.308900e+09  6.450000e+05      4.000000      2.500000   2550.000000
max    9.900000e+09  7.700000e+06     33.000000      8.000000  13540.000000

           sqft_lot        floors    waterfront          view     condition  \
count  2.161300e+04  21613.000000  21613.000000  21613.000000  21613.000000
mean   1.510697e+04      1.494309      0.007542      0.234303      3.409430
std    4.142051e+04      0.539989      0.086517      0.766318      0.650743
min    5.200000e+02      1.000000      0.000000      0.000000      1.000000
25%    5.040000e+03      1.000000      0.000000      0.000000      3.000000
50%    7.618000e+03      1.500000      0.000000      0.000000      3.000000
75%    1.068800e+04      2.000000      0.000000      0.000000      4.000000
max    1.651359e+06      3.500000      1.000000      4.000000      5.000000

              grade    sqft_above  sqft_basement      yr_built  yr_renovated  \
count  21613.000000  21613.000000   21613.000000  21613.000000  21613.000000
mean       7.656873   1788.390691     291.509045   1971.005136     84.402258
std        1.175459    828.090978     442.575043     29.373411    401.679240
min        1.000000    290.000000       0.000000   1900.000000      0.000000
25%        7.000000   1190.000000       0.000000   1951.000000      0.000000
50%        7.000000   1560.000000       0.000000   1975.000000      0.000000
```

```
75%        8.000000   2210.000000    560.000000   1997.000000      0.000000
max       13.000000   9410.000000   4820.000000   2015.000000   2015.000000

            zipcode           lat          long  sqft_living15     sqft_lot15
count  21613.000000  21613.000000  21613.000000   21613.000000   21613.000000
mean   98077.939805     47.560053   -122.213896    1986.552492   12768.455652
std       53.505026      0.138564      0.140828     685.391304   27304.179631
min    98001.000000     47.155900   -122.519000     399.000000     651.000000
25%    98033.000000     47.471000   -122.328000    1490.000000    5100.000000
50%    98065.000000     47.571800   -122.230000    1840.000000    7620.000000
75%    98118.000000     47.678000   -122.125000    2360.000000   10083.000000
max    98199.000000     47.777600   -121.315000    6210.000000  871200.000000
```

# 4 Select Features for Simple Linear Regression

We're using only one feature sqft_living to predict the house price, hence it's a Simple Linear Regression.

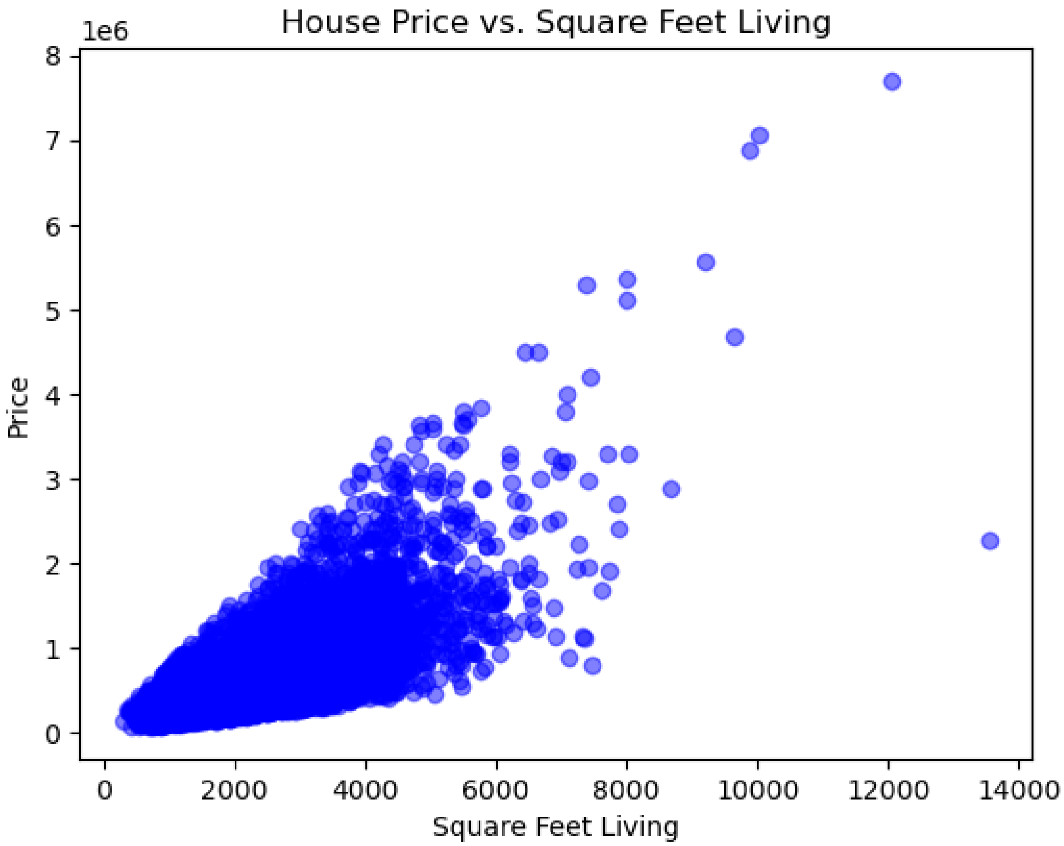
[5]:
```
X = np.array(df['sqft_living']).reshape(-1, 1)   # Independent variable
y = np.array(df['price'])                        # Dependent variable
```

- sklearn models expect X to be a 2D array → shape (n_samples, n_features)
- .reshape(-1, 1) converts a 1D array to 2D
- -1 lets NumPy figure out the number of rows
- 1 means one feature (column)
- y can stay 1D — it only contains target values.

# 5 Visualize the Relationship

A scatter plot helps to visualize whether there's a linear relationship between sqft_living and price.

[6]:
```
plt.scatter(X, y, color='blue', alpha=0.5)
plt.title("House Price vs. Square Feet Living")
plt.xlabel("Square Feet Living")
plt.ylabel("Price")
plt.show()
```




## 6 Split the Data

We split the data into training and testing sets (80-20 split) so that we can evaluate the model's performance on unseen data.

[7]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

## 7 Build and Train the Model

We create a Linear Regression model and fit it using the training data.

[8]:
```
model = LinearRegression()
model.fit(X_train, y_train)
```

[8]:
```
LinearRegression()
```

## 8 Get Model Parameters

- **Intercept** ( ): The constant term — it's the value of the price when `sqft_living = 0`.
- **Coefficient** ( ): The slope — it tells how much the price increases for each additional square foot.

**Equation of the model**:

$$\text{Predicted Price} = b_0 + b_1 \times \text{sqft\_living}$$

[9]:
```
print("Intercept (b ):", model.intercept_)
print("Coefficient (b ):", model.coef_[0])
```

```
Intercept (b ): -42291.12839802564
Coefficient (b ): 279.7397784623452
```

## 9 Predict and Evaluate the Model

- MSE measures average squared difference between actual and predicted values.
- $R^2$ Score tells how well the model explains the variation in the target variable.

[10]:
```
y_pred = model.predict(X_test)
print(y_pred)
```

```
[ 536770.21301903  768954.22914278 1012327.83640502 …  638595.49237932
  587123.37314225  676640.1022502 ]
```

### 9.1 Metrics

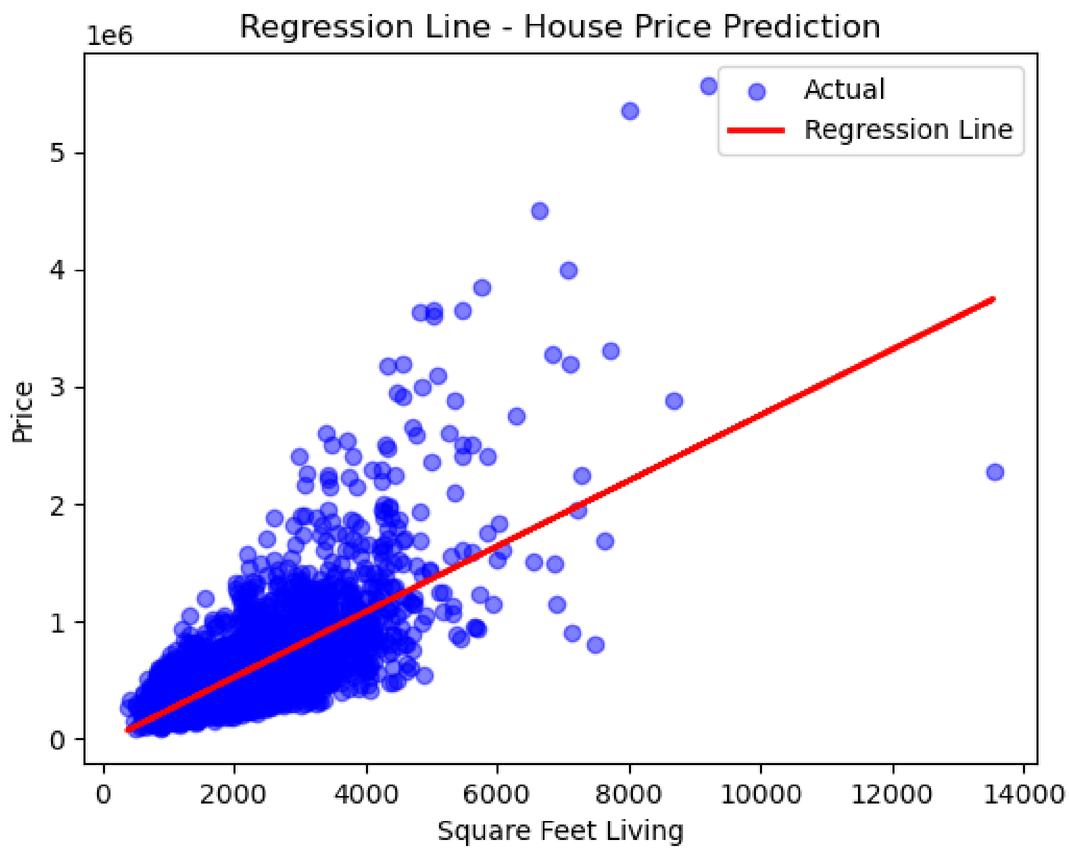
[11]:
```
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

[12]:
```
print("Mean Squared Error:", mse)
print("R² Score:", r2)
```

```
Mean Squared Error: 76570251342.04109
R² Score: 0.4941006145983624
```

## 10 Plot the Regression Line

[13]:
```
plt.scatter(X_test, y_test, color='blue', alpha=0.5, label="Actual")
plt.plot(X_test, y_pred, color='red', linewidth=2, label="Regression Line")
plt.title("Regression Line - House Price Prediction")
plt.xlabel("Square Feet Living")
plt.ylabel("Price")
plt.legend()
plt.show()
```




## 11 Predict on New (Unseen) Data

We use the trained model to predict house prices for unseen data points.

[14]:
```python
# Example: Predict price for 2000, 2500, and 3000 square feet
new_sqft = np.array([[2000], [2500], [3000]])
predicted_price = model.predict(new_sqft)

for sqft, price in zip(new_sqft, predicted_price):
    print(f"Predicted price for {sqft[0]} sqft = ${price:,.2f}")
```

```
Predicted price for 2000 sqft = $517,188.43
Predicted price for 2500 sqft = $657,058.32
Predicted price for 3000 sqft = $796,928.21
```

## 12 Conclusion

- We built a Simple Linear Regression model using sqft_living to predict house prices.
- Evaluated it using metrics like MSE and $R^2$.

- Plotted the regression line and predicted new values.

```
[ ]:
```