# IN_SYS - SW06 - Multiple Linear Regression - California Housing Data

## 30/10/2025 - Eugen Rodel - v2

### Goals:

- Deepen understanding of Multiple Linear Regression using California Housing Data
- Repeat old topics as importing data from CSV file into Pandas, exploring and visualization of data, train model, make predictions

# 1. California Housing Dataset Explanation

The **California_Housing.csv** dataset contains information about housing features in California, such as median income, number of rooms, and house prices. Below is a description of each column in the dataset:

1. **Median Income**:
    - Median income of households in the area, measured in tens of thousands of USD.
    - This feature is an indicator of the economic status of the neighborhood.
2. **Age of House**:
    - Age of the house in years.
    - Represents the average age of houses in the neighborhood.
3. **Average Rooms**:
    - Average number of rooms per household in the area.
    - Includes all rooms such as bedrooms, living rooms, kitchens, etc.
4. **Average Bedrooms**:
    - Average number of bedrooms per household in the area.
    - Represents the number of bedrooms available in homes, on average.
5. **Population**:
    - Total population of the area.
    - Indicates the number of people residing in the neighborhood.
6. **Average Occupancy**:
    - Average occupancy per household in the area.
    - Represents how many people live in each household, on average.
7. **Latitude**:
    - Latitude of the location.

- Represents the geographic coordinate for the neighborhood.

8. **Longitude**:

   - Longitude of the location.
   - Represents the geographic coordinate for the neighborhood.

9. **Price**:

   - Price of the house in hundreds of thousands of USD.
   - This is the **dependent variable** that we are trying to predict in our regression model. It represents the average housing price for the neighborhood.

The goal of this dataset is to predict the **Price** based on various features related to the property and the surrounding area. This dataset provides a practical use case for understanding how different factors, such as house size, age, and income, impact housing prices.

# 2. Import libraries

Hint: no new libraries are needed, just what we used in the lecture for the advertising Multiple Linear Regression.

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

# Set Seaborn style for plots
sns.set_style('whitegrid')
```

# 3. Load the Dataset

In [2]:
```
# Load the 'California_Housing.csv' file into a Pandas DataFrame called 'housing_
#housing_df = pd.read_csv('California_Housing.csv')
housing_df = pd.read_csv('California_Housing.csv')

# Display the first few rows of the DataFrame to verify that the import worked
housing_df.head()
```

Out[2]:

| | Median Income | Age of House | Average Rooms | Average Bedrooms | Population | Average Occupancy | Latitude | Longitude | I |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 8.3252 | 41.0 | 6.984127 | 1.023810 | 322.0 | 2.555556 | 37.88 | -122.23 | 4 |
| **1** | 8.3014 | 21.0 | 6.238137 | 0.971880 | 2401.0 | 2.109842 | 37.86 | -122.22 | 3 |
| **2** | 7.2574 | 52.0 | 8.288136 | 1.073446 | 496.0 | 2.802260 | 37.85 | -122.24 | 3 |
| **3** | 5.6431 | 52.0 | 5.817352 | 1.073059 | 558.0 | 2.547945 | 37.85 | -122.25 | 3 |
| **4** | 3.8462 | 52.0 | 6.281853 | 1.081081 | 565.0 | 2.181467 | 37.85 | -122.25 | 3 |

# 4. Data Exploration and Visualization

In [3]:

```
# Display shape of the DataFrame
housing_df.shape
```

Out[3]: (20640, 9)

In [4]:

```
# Display column names
housing_df.columns
```

Out[4]:

```
Index(['Median Income', 'Age of House', 'Average Rooms', 'Average Bedrooms',
       'Population', 'Average Occupancy', 'Latitude', 'Longitude', 'Price'],
      dtype='object')
```

In [5]:

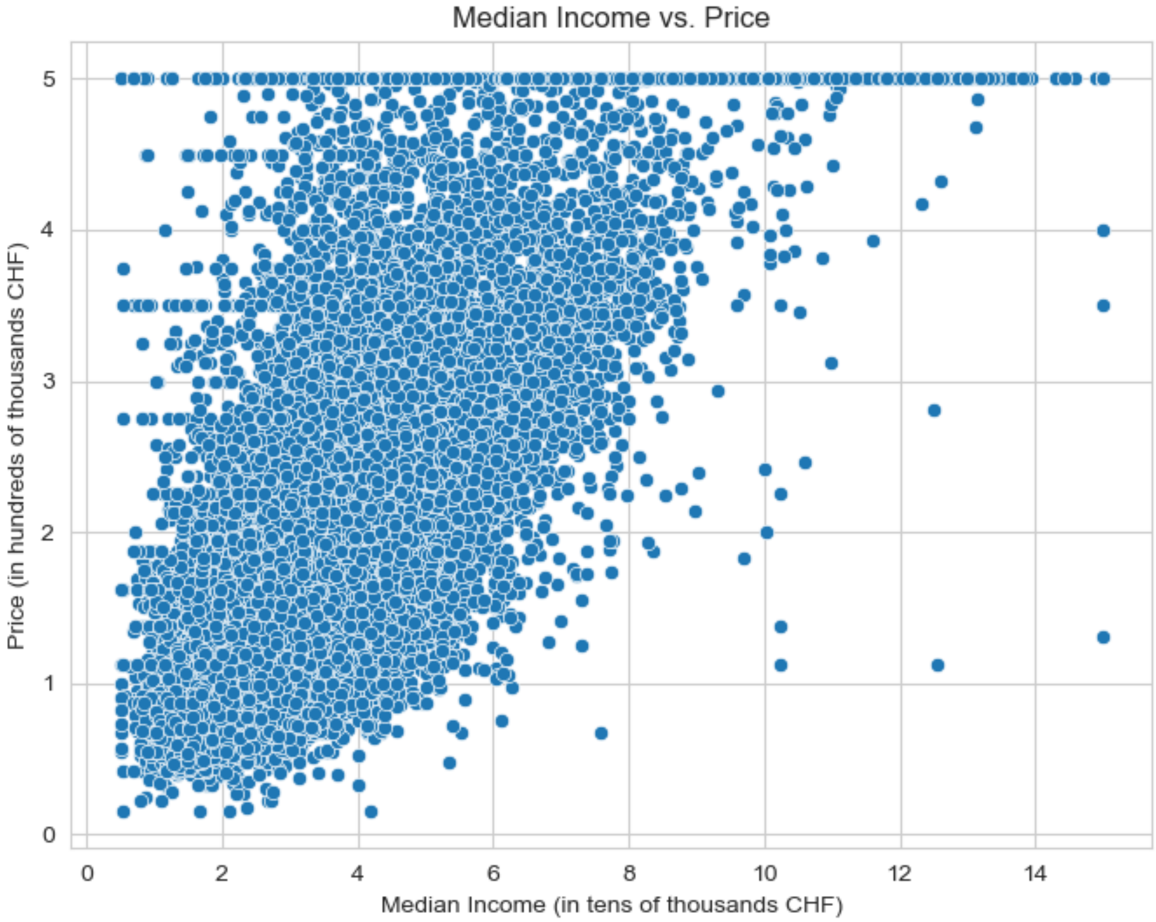
```
# Display summary statistics
housing_df.describe()
```

Out[5]:

| | Median Income | Age of House | Average Rooms | Average Bedrooms | Population | Aver Occupa |
|---|---|---|---|---|---|---|
| **count** | 20640.000000 | 20640.000000 | 20640.000000 | 20640.000000 | 20640.000000 | 20640.000 |
| **mean** | 3.870671 | 28.639486 | 5.429000 | 1.096675 | 1425.476744 | 3.070 |
| **std** | 1.899822 | 12.585558 | 2.474173 | 0.473911 | 1132.462122 | 10.386 |
| **min** | 0.499900 | 1.000000 | 0.846154 | 0.333333 | 3.000000 | 0.692 |
| **25%** | 2.563400 | 18.000000 | 4.440716 | 1.006079 | 787.000000 | 2.429 |
| **50%** | 3.534800 | 29.000000 | 5.229129 | 1.048780 | 1166.000000 | 2.818 |
| **75%** | 4.743250 | 37.000000 | 6.052381 | 1.099526 | 1725.000000 | 3.282 |
| **max** | 15.000100 | 52.000000 | 141.909091 | 34.066667 | 35682.000000 | 1243.333 |

In [6]:

```
# Scatter plot of Median Income vs Price
plt.figure(figsize=(8, 6))
sns.scatterplot(data=housing_df, x='Median Income', y='Price', marker='o')
plt.title('Median Income vs. Price')
plt.xlabel('Median Income (in tens of thousands CHF)')
plt.ylabel('Price (in hundreds of thousands CHF)')
plt.show()
```




# 5. Data "Cutting"

In the preceding scatter plot, we can see that the data has not been cleaned (e.g. where the price is constant and independent of income). A quick and dirty solution is to only use data where the price is < 3.

In [7]:
```
# copy the data
housing_cut_df = housing_df.copy()

# filter the data
housing_cut_df = housing_cut_df[housing_cut_df['Price'] < 3]
```

In [8]:
```
# describe data
housing_cut_df.describe()
```

Out[8]:

| | Median Income | Age of House | Average Rooms | Average Bedrooms | Population | Aver Occupa |
|---|---|---|---|---|---|---|
| **count** | 16774.000000 | 16774.000000 | 16774.000000 | 16774.000000 | 16774.000000 | 16774.000 |
| **mean** | 3.383996 | 27.979790 | 5.263933 | 1.101897 | 1457.075176 | 3.153 |
| **std** | 1.312453 | 12.307397 | 2.329034 | 0.477026 | 1148.226896 | 10.844 |
| **min** | 0.499900 | 1.000000 | 0.846154 | 0.333333 | 5.000000 | 0.692 |
| **25%** | 2.392900 | 18.000000 | 4.370574 | 1.006734 | 804.000000 | 2.495 |
| **50%** | 3.221600 | 28.000000 | 5.103504 | 1.050108 | 1196.000000 | 2.894 |
| **75%** | 4.208100 | 36.000000 | 5.821055 | 1.102007 | 1771.000000 | 3.374 |
| **max** | 15.000100 | 52.000000 | 132.533333 | 34.066667 | 35682.000000 | 1243.333 |

In [9]:

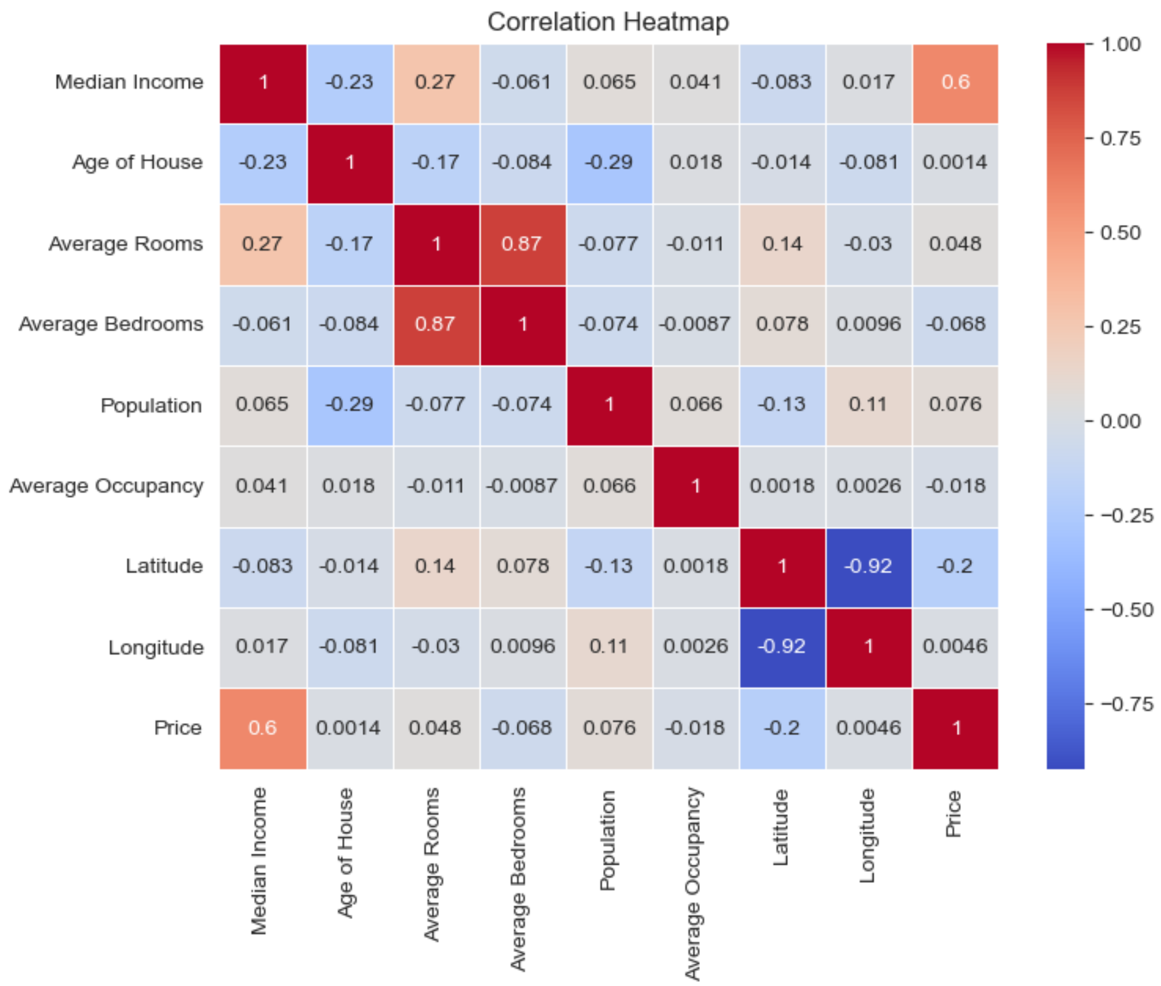
```
# Scatter plot of Median Income vs Price
plt.figure(figsize=(8, 6))
sns.scatterplot(data=housing_cut_df, x='Median Income', y='Price', marker='o')
plt.title('Median Income vs. Price')
plt.xlabel('Median Income (in tens of thousands CHF)')
plt.ylabel('Price (in hundreds of thousands CHF)')
plt.show()
```

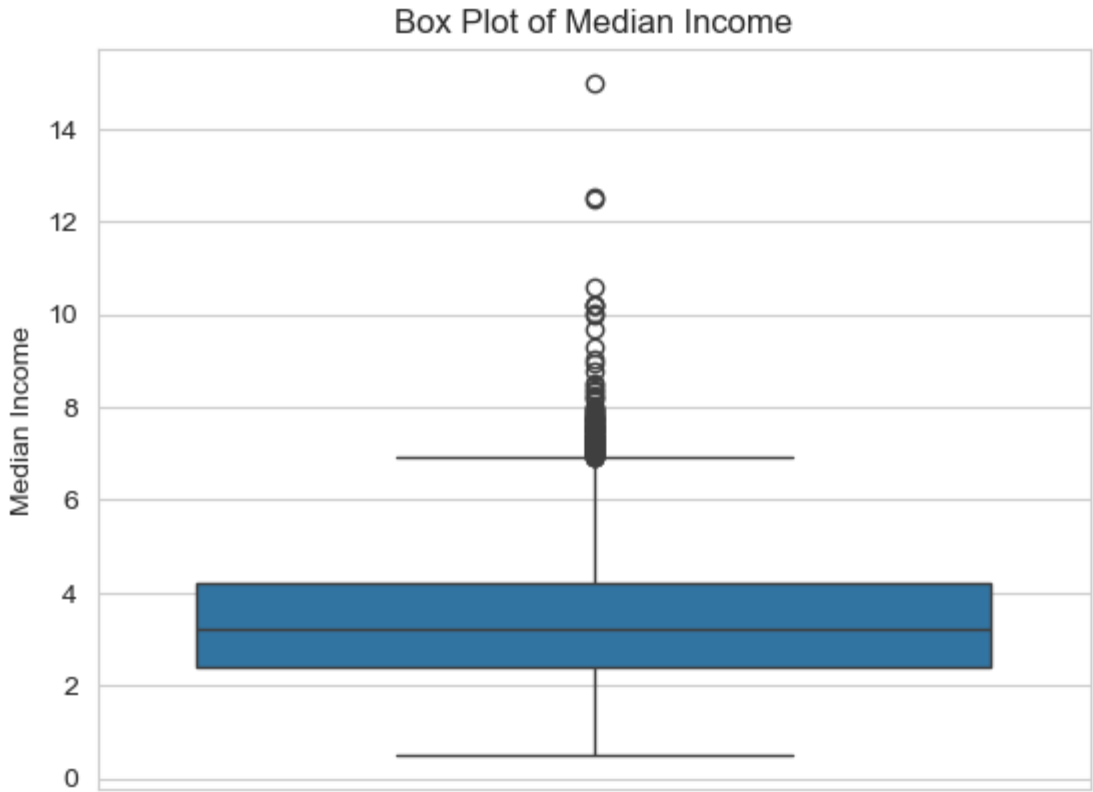

In [10]:

```
# Create a heatmap to show correlations between features
plt.figure(figsize=(8, 6))   # Set the plot size in inch: figsize(width, height)
sns.heatmap(housing_cut_df.corr(), annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Heatmap')
```

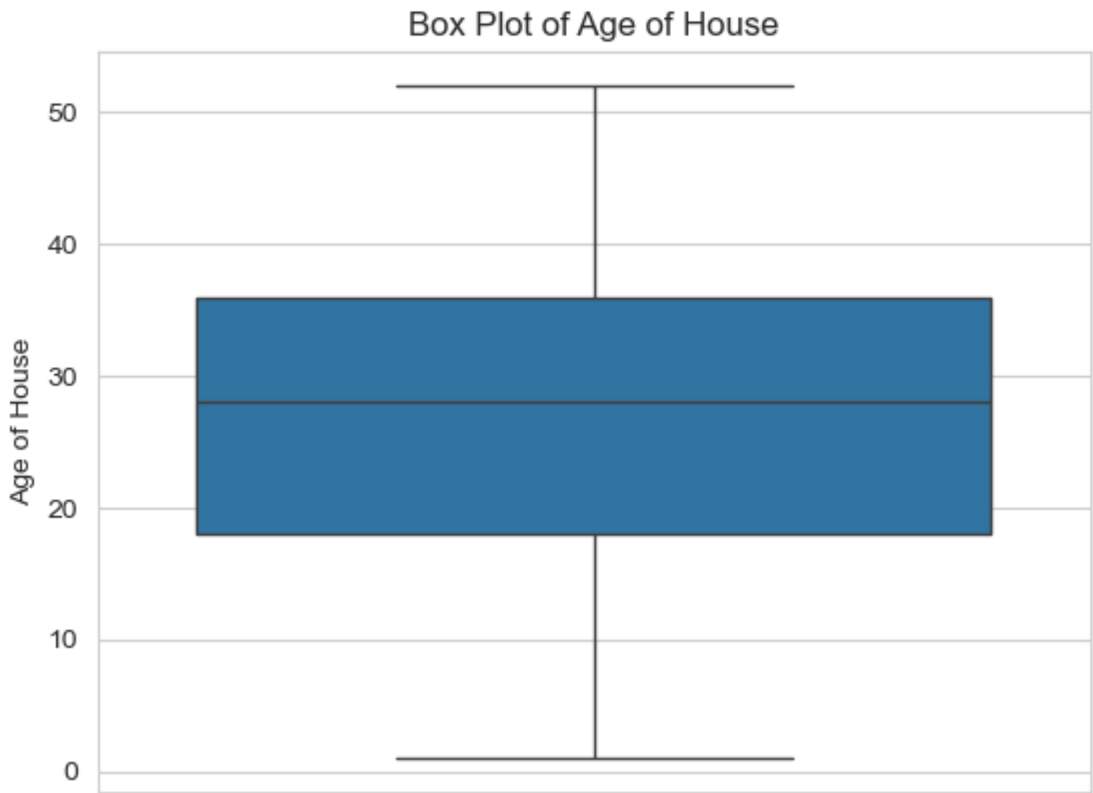
```python
# Box plot for "Median Income"
plt.figure()
sns.boxplot(data=housing_cut_df, y='Median Income')
plt.title('Box Plot of Median Income')
plt.ylabel('Median Income')

# Box plot for "Age of House"
plt.figure()
sns.boxplot(data=housing_cut_df, y='Age of House')
plt.title('Box Plot of Age of House')
plt.ylabel('Age of House')

# Box plot for "Price"
plt.figure()
sns.boxplot(data=housing_cut_df, y='Price')
plt.title('Box Plot of Price')
plt.ylabel('Price')
```

Out[10]: Text(0, 0.5, 'Price')

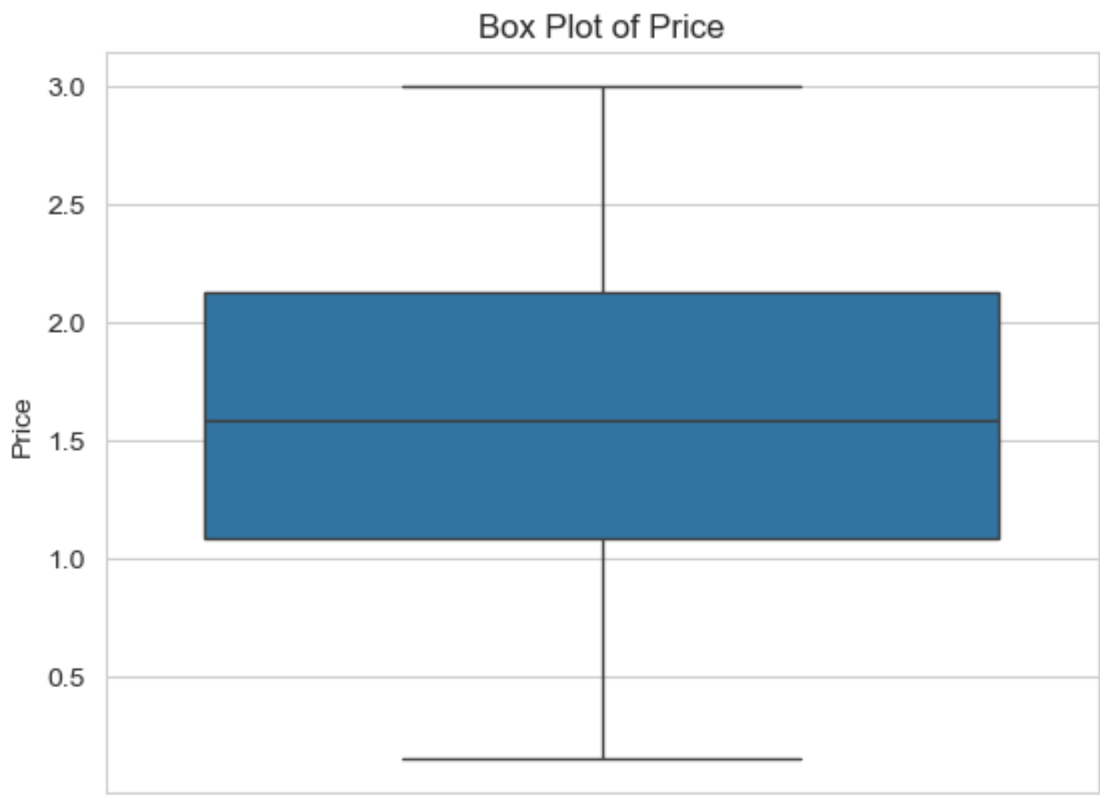




Box Plot of Median Income
Median Income
0
2
4
6
8
10
12
14

Box Plot of Age of House
Age of House
0
10
20
30
40
50




# 6. Prepare the Data for Modeling

In [11]:
```
# Define independent input features (X) and dependend output target - the sales ,
X = housing_cut_df[['Median Income', 'Age of House', 'Average Rooms', 'Average B
y = housing_cut_df['Price']
```

In [12]:
```
# Split the data into training and testing sets (80% training, 20% testing), wit
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

# 7. Train the Multiple Linear Regression Model

In [13]:
```
# Initialize and train the Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[13]:
```
▾ LinearRegression   i ?

LinearRegression()
```

# 8. Get the intercept and the coefficients of the model

In [14]:
```
print("Intercept:", model.intercept_)
print("Coefficients:", model.coef_)
```

```
Intercept: -26.27626898612006
Coefficients: [ 3.03026185e-01  2.19061719e-03 -5.79309274e-02  3.23577722e-01
  1.66894340e-05 -2.33109315e-03 -3.05992790e-01 -3.15074964e-01]
```

# 9. Make Predictions using the test data

In [15]:
```python
# Make predictions on the test set
# Make predictions on the test set
y_pred = model.predict(X_test)
```

# 9. Compare Predictions with Actual Values

In [16]:
```python
# Create a DataFrame including the test data, and "Actual Price" and "Predicted 
# name the new created DataFrame "results_df"

# Create a DataFrame from X_test
results_df = X_test.copy()

# Add the actual price values to the new DataFrame results_df into a new column 
results_df['Actual Price'] = y_test

# Add the predicted price values to the new DataFrame results_df into a new colu
results_df['Predicted Price'] = y_pred

# sort results (and display data frame)
results_df.sort_index()
```

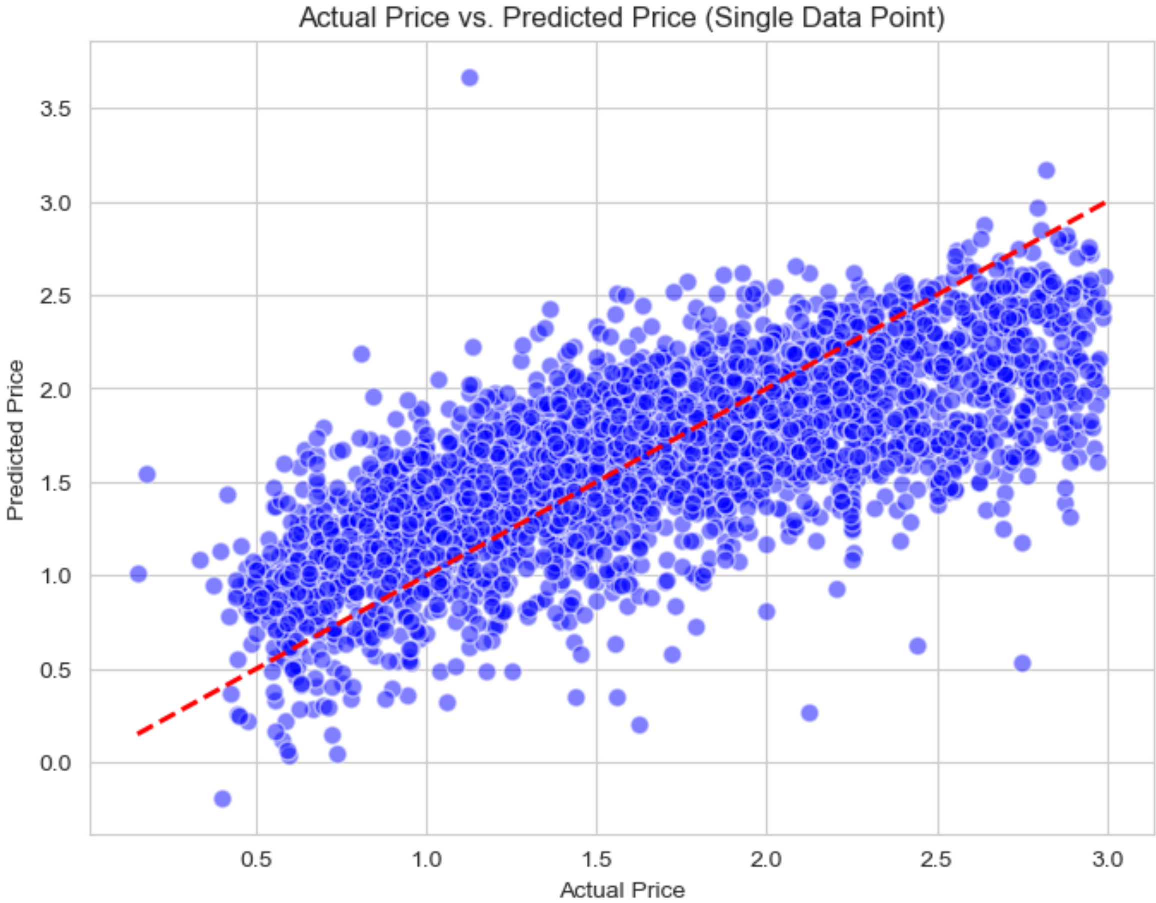
Out[16]:

| | Median Income | Age of House | Average Rooms | Average Bedrooms | Population | Average Occupancy | Latitude | Longitu |
|---|---|---|---|---|---|---|---|---|
| **5** | 4.0368 | 52.0 | 4.761658 | 1.103627 | 413.0 | 2.139896 | 37.85 | -122. |
| **8** | 2.0804 | 42.0 | 4.294118 | 1.117647 | 1206.0 | 2.026891 | 37.84 | -122. |
| **13** | 2.6736 | 52.0 | 4.000000 | 1.097701 | 345.0 | 1.982759 | 37.84 | -122. |
| **19** | 2.6033 | 52.0 | 5.465455 | 1.083636 | 690.0 | 2.509091 | 37.84 | -122. |
| **24** | 2.6000 | 52.0 | 5.270142 | 1.035545 | 1006.0 | 2.383886 | 37.84 | -122. |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **20616** | 2.0469 | 15.0 | 4.826667 | 1.176000 | 1157.0 | 3.085333 | 39.08 | -121. |
| **20617** | 3.3021 | 20.0 | 4.921053 | 0.956140 | 308.0 | 2.701754 | 39.06 | -121. |
| **20630** | 3.5673 | 11.0 | 5.932584 | 1.134831 | 1257.0 | 2.824719 | 39.29 | -121. |
| **20635** | 1.5603 | 25.0 | 5.045455 | 1.133333 | 845.0 | 2.560606 | 39.48 | -121. |
| **20638** | 1.8672 | 18.0 | 5.329513 | 1.171920 | 741.0 | 2.123209 | 39.43 | -121. |

3355 rows × 10 columns

# 10. Visualization of Actual vs Prodicted Values

In [17]:
```
# Scatter plot: Actual Price vs. Predicted Price
plt.figure(figsize=(8, 6))
plt.scatter(data=results_df, x='Actual Price', y='Predicted Price', s=60, color=
plt.plot([results_df['Actual Price'].min(), results_df['Actual Price'].max()],
         [results_df['Actual Price'].min(), results_df['Actual Price'].max()],
         color='red', linestyle='--', linewidth=2)  # 45-degree reference line
plt.title('Actual Price vs. Predicted Price (Single Data Point)')
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.show()
```




# 11. Model Evaluation

In [18]:
```
# Evaluate the model by calculating mse and r2
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Print the model evaluation results (mse and r2)
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"R² Score: {r2:.2f}")
```

```
Mean Squared Error (MSE): 0.19
R² Score: 0.55
```

In [ ]:

In [ ]: