Exploring the Feasibility of Predicting California Housing Prices in 1990 Using Different Explanatory Variables

1. Introduction

The objective of this project is to explore the feasibility of predicting California housing prices in 1990 using different explanatory variables. The project aims to identify the variables that have the most significant impact on housing prices. The California Housing Prices dataset is collected from the 1990 California Census. It provides a wealth of information on housing prices, housing locations, housing structures, and demographic factors in the state, making it an ideal candidate for this type of study. The source of this dataset is the second chapter of Aurélien Géron's recent book 'Hands-On Machine learning with Scikit-Learn and TensorFlow', which contains information from the 1990 California census.

This project will analyze the relationship between the demographic and housing structures data with the housing price data, to investigate the explanatory variable that can best predict house prices. This dataset uses information collected from different neighborhood blocks, therefore each row of data displays the features of a specific neighborhood block. The five X variables used in this project are “Median Income”, “Number of Households”, “Population”, “Total Rooms”, and “Median Age”. The Y variable used in this project is “Median House Value”.

This project will contribute to a deeper understanding of the housing market in California in 1990. The result of this project provides an intuitive explanation for our problem; the best predicting variable is income because it has the strongest correlation to housing prices, which is very understandable as higher income groups can afford more expensive housing.

2. Data Loading and Cleaning

In [191…
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
```

In [192…
```
df_houseprice=pd.read_csv("/Users/frankzhong/Downloads/ECO225/ECO225PROJECT/Data/housing
print("Number of rows: ", len(df_houseprice))
```

```
Number of rows:  20640
```

Step 1: Check for missing values

In [193…
```
df_houseprice.isnull().sum()
```

Out[193]:
```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
median_house_value      0
```

```
ocean_proximity          0
dtype: int64
```

We found there to be 207 missing data in the "total_bedrooms".

Step 2: Impute the missing values using the average based on location of the house with respect to ocean

In [194…
```
print("The different categories of ocean proximity to be used:", df_houseprice['ocean_pr
```

```
The different categories of ocean proximity to be used: ['NEAR BAY' '<1H OCEAN' 'INLAND'
'NEAR OCEAN' 'ISLAND']
```

We will create a new dataframe called "new_house" with only columns of 'total_bedrooms' and 'ocean_proximity' to find the average of 'total_bedrooms' categorized by 'ocean_proximity', and impute the missing data with this average.

In [195…
```
new_house = df_houseprice[['total_bedrooms', 'ocean_proximity']]
new_house
```

Out[195]:

	total_bedrooms	ocean_proximity
0	129.0	NEAR BAY
1	1106.0	NEAR BAY
2	190.0	NEAR BAY
3	235.0	NEAR BAY
4	280.0	NEAR BAY
...	...	...
20635	374.0	INLAND
20636	150.0	INLAND
20637	485.0	INLAND
20638	409.0	INLAND
20639	616.0	INLAND

20640 rows × 2 columns

Computing the average total bedrooms within a block based on location of the house with respect to ocean.

In [196…
```
result = new_house.groupby('ocean_proximity').mean()
result
```

Out[196]:

	total_bedrooms
ocean_proximity	
<1H OCEAN	546.539185
INLAND	533.881619
ISLAND	420.400000
NEAR BAY	514.182819
NEAR OCEAN	538.615677

Imputing the average to the new_house dataframe

In [237…
```
for i in range(len(new_house)):
    if pd.isnull(new_house['total_bedrooms'][i]):
        new_house['total_bedrooms'][i] = result['total_bedrooms'][new_house['ocean_proxi
```

Checking the missing data in the "new_house" dataframe have been imputed.

In [198…
```
new_house.isnull().sum()
```

Out[198]:
```
total_bedrooms      0
ocean_proximity     0
dtype: int64
```

Merging the imputed column to the original dataframe and it no longer has any missing data.

In [199…
```
df_houseprice['total_bedrooms'] = new_house['total_bedrooms']
df_houseprice.isnull().sum()
```

Out[199]:
```
longitude             0
latitude              0
housing_median_age    0
total_rooms           0
total_bedrooms        0
population            0
households            0
median_income         0
median_house_value    0
ocean_proximity       0
dtype: int64
```

Step 3: Dropping the geographic columns and conduct house value analysis using the rest of the explanetory variables

The geographic variables are dropped because of the complexity nature in their units and scales, therefore it is challenging to include them in the analysis.

In [200…
```
df_predict_price = df_houseprice.drop(columns=['longitude', 'latitude', 'ocean_proximity
df_predict_price
```

Out[200]:

	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	media
0	41	880	129.0	322	126	8.3252	
1	21	7099	1106.0	2401	1138	8.3014	
2	52	1467	190.0	496	177	7.2574	
3	52	1274	235.0	558	219	5.6431	
4	52	1627	280.0	565	259	3.8462	
...	...	...	...	...	...	...	
20635	25	1665	374.0	845	330	1.5603	
20636	18	697	150.0	356	114	2.5568	
20637	17	2254	485.0	1007	433	1.7000	
20638	18	1860	409.0	741	349	1.8672	
20639	16	2785	616.0	1387	530	2.3886	

20640 rows × 7 columns

Step 4: Dropping the "total_bedrooms" column because of its collinearity with the "total_rooms" column

In [201…

```
room_correlation = df_predict_price['total_rooms'].corr(df_predict_price['total_bedrooms
print("The correlation between total_rooms and total_bedrooms is: ", room_correlation)
```

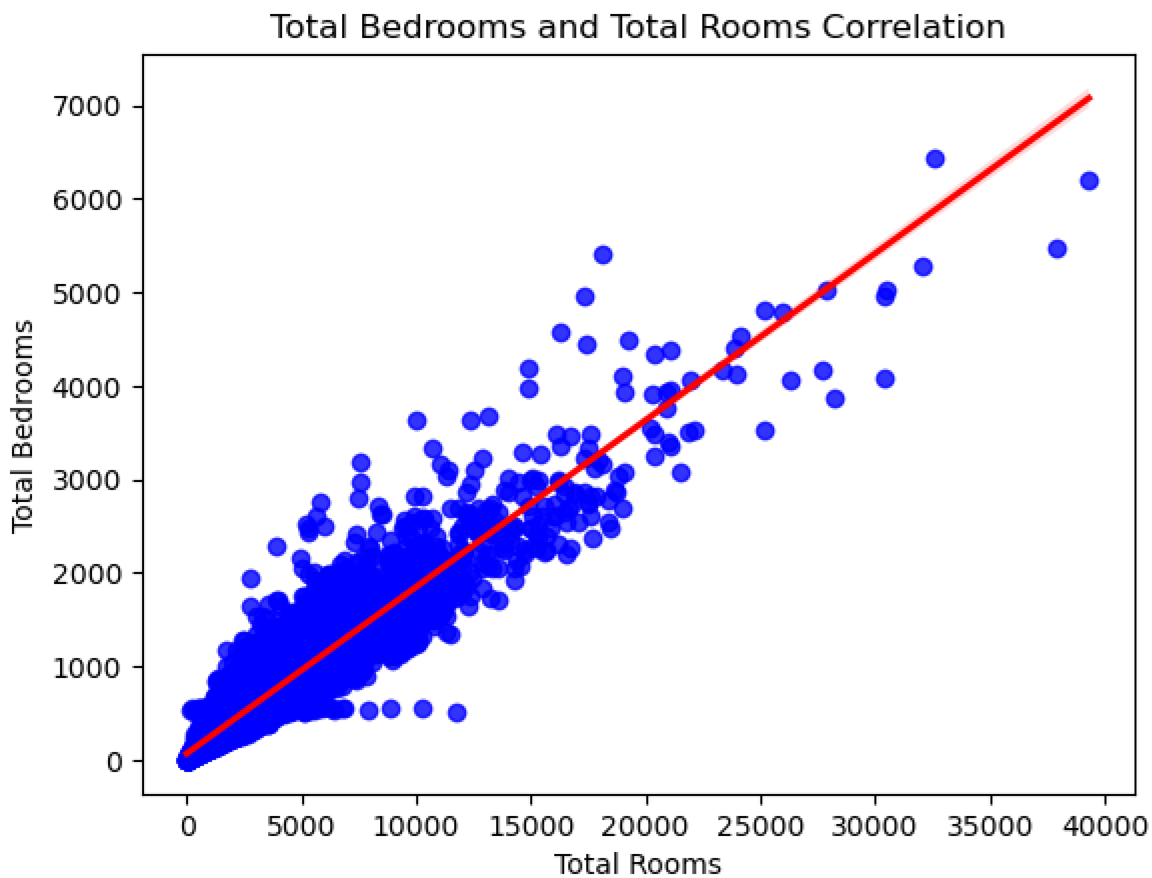
```
The correlation between total_rooms and total_bedrooms is:  0.9272521715028144
```

In [202…

```
rooms_cor = sns.regplot(x=df_predict_price.total_rooms, y=df_predict_price.total_bedroom
rooms_cor.set_title('Total Bedrooms and Total Rooms Correlation')
rooms_cor.set_xlabel('Total Rooms')
rooms_cor.set_ylabel('Total Bedrooms')
rooms_cor
```

Out[202]:

```
<AxesSubplot: title={'center': 'Total Bedrooms and Total Rooms Correlation'}, xlabel='T
otal Rooms', ylabel='Total Bedrooms'>
```



In [203…

```
df_prepared = df_predict_price.drop(columns = ['total_bedrooms'])
df_prepared
```

Out[203]:

	housing_median_age	total_rooms	population	households	median_income	median_house_value
0	41	880	322	126	8.3252	452600
1	21	7099	2401	1138	8.3014	358500
2	52	1467	496	177	7.2574	352100
3	52	1274	558	219	5.6431	341300
4	52	1627	565	259	3.8462	342200
...	...	...	...	...	...	...
20635	25	1665	845	330	1.5603	78100
20636	18	697	356	114	2.5568	77100
20637	17	2254	1007	433	1.7000	92300

20638	18	1860	741	349	1.8672	84700
20639	16	2785	1387	530	2.3886	89400

20640 rows × 6 columns

We have now finalized what explanatory variables we want to keep for this project.

Step 5: Removing Outliers

We have created a function to check for outliers within a dataframe, and used that function to remove the standardized dataframe. Once the outliers are dropped, we have created an unstandardized dataframe by making a copy of the "prepared" dataframe named "df_finalized" and keeping the same indexes that hold the remaining rows that have no outliers values. As a result, the new dataframe has 894 less entries.

In [220…

```
#Standardize dataframe
standardized = (df_predict_price - df_predict_price.mean()) / df_predict_price.std()

#Check for outliers
def check_outliers(df, threshold=3):
    mean = df.mean()
    std = df.std()
    z = (df - mean) / std
    outliers = df[(np.abs(z) > threshold).any(axis=1)]
    return outliers

outliers = check_outliers(standardized)

#Drop outliers
df_no_outliers = standardized.drop(outliers.index, axis=0)

#Unstandardize dataframe
keep = df_no_outliers.index
df_finalized = df_prepared.loc[keep]

print("Number of rows before: ", len(standardized))
print("Number of rows after:", len(df_finalized))
```

```
Number of rows before:  20640
Number of rows after: 19746
```

This concludes our data cleaning process and the "df_finalized" dataframe is ready to be used for our analysis.

3. Summary Statistic

In [205…

```
summary = df_finalized.describe()

print('Summary Statistics for the 1990 California Census:')
summary
```

```
Summary Statistics for the 1990 California Census:
```

Out[205]:

	housing_median_age	total_rooms	population	households	median_income	median_house_va
count	19746.000000	19746.000000	19746.000000	19746.000000	19746.000000	19746.000(
mean	29.020055	2391.087208	1311.810088	460.504153	3.724951	201820.017

std	12.416867	1434.521943	772.867946	267.598163	1.601798	110647.6692
min	1.000000	2.000000	3.000000	2.000000	0.499900	14999.0000
25%	19.000000	1430.000000	782.000000	278.000000	2.541700	117800.0000
50%	29.000000	2082.000000	1151.000000	404.000000	3.491250	177000.0000
75%	37.000000	3026.750000	1672.000000	585.000000	4.648400	258300.0000
max	52.000000	9179.000000	4818.000000	1644.000000	9.556100	500001.0000

After cleaning the 1990 California Census data, the summary statistics table shows that we have 19,746 observations remaining for us to analyze.

We can see that we are conducting a study on 1990 California housing in the price range of $15,000 to \$500,000 with most of the houses being less than the $250,000 price point. The houses' age varies from being recently constructed less than a year ago to 52 years ago and the houses have an average age of 29 years. The census also covers a vast variety of income groups from the lower spectrum household income of less than \$5,000 to wealthy families making more than $90,000 in household income. It is important to note that the majority of the observations make around \$35,000 in household income.

Some interesting insights found from looking at the table are that there are observations from possibly unconstructed or undeveloped regions that are unpopulated. The minimum value shows that in this census, there are neighborhood blocks with only 2 rooms, 2 households, or only 3 people residing.

The broad range of data in each column shows that we can conduct a detailed correlation analysis between each explanatory variable and the response variable to find which variables are the biggest factor affecting the 1990 house value in California.

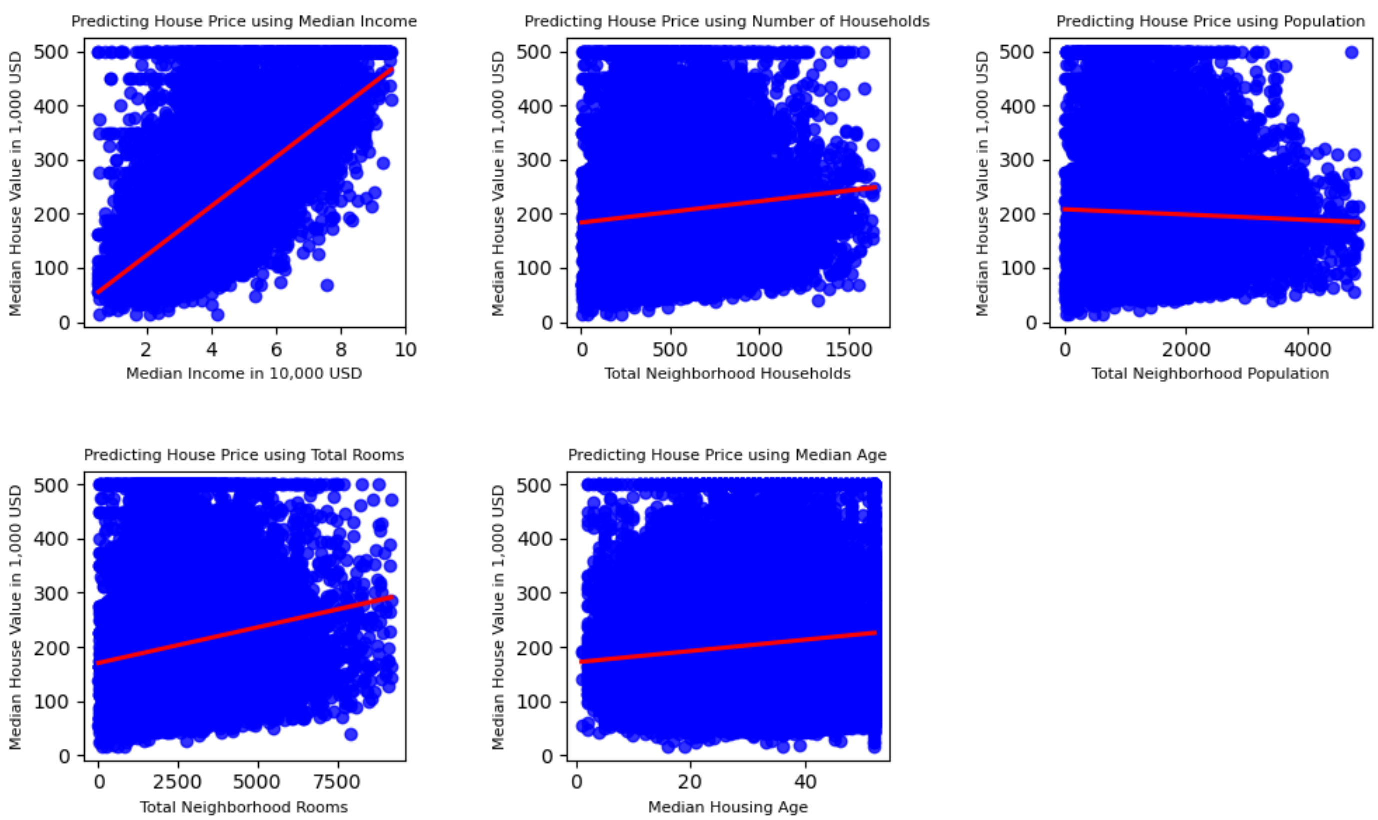
4. Plots, Histograms, Figures

Scatter Plots to display each x variable's relationship with the median house price

In [214…
```
price_thousands = pd.DataFrame()
price_thousands['median_house_value'] = df_finalized['median_house_value'] / 1000
```

In [221…
```
import seaborn as sns

fig, ax = plt.subplots(2, 3, figsize=(10, 6))



sns.regplot(x=df_finalized.median_income, y=price_thousands.median_house_value, scatter_


sns.regplot(x=df_finalized.households, y=price_thousands.median_house_value, scatter_kws


sns.regplot(x=df_finalized.population, y=price_thousands.median_house_value, scatter_kws


sns.regplot(x=df_finalized.total_rooms, y=price_thousands.median_house_value, scatter_kw


sns.regplot(x=df_finalized.housing_median_age, y=price_thousands.median_house_value, sca
```

```
fig.delaxes(ax[1][2])

ax[0][0].set_title('Predicting House Price using Median Income', fontsize=8)
ax[0][1].set_title('Predicting House Price using Number of Households', fontsize=8)
ax[0][2].set_title('Predicting House Price using Population', fontsize=8)
ax[1][0].set_title('Predicting House Price using Total Rooms', fontsize=8)
ax[1][1].set_title('Predicting House Price using Median Age', fontsize=8)

ax[0][0].set_ylabel('Median House Value in 1,000 USD', fontsize=8)
ax[0][1].set_ylabel('Median House Value in 1,000 USD', fontsize=8)
ax[0][2].set_ylabel('Median House Value in 1,000 USD', fontsize=8)
ax[1][0].set_ylabel('Median House Value in 1,000 USD', fontsize=8)
ax[1][1].set_ylabel('Median House Value in 1,000 USD', fontsize=8)


ax[0][0].set_xlabel('Median Income in 10,000 USD', fontsize=8)
ax[0][1].set_xlabel('Total Neighborhood Households', fontsize=8)
ax[0][2].set_xlabel('Total Neighborhood Population', fontsize=8)
ax[1][0].set_xlabel('Total Neighborhood Rooms', fontsize=8)
ax[1][1].set_xlabel('Median Housing Age', fontsize=8)


fig.tight_layout()
fig.subplots_adjust(wspace=0.5, hspace=0.5)

plt.show()
```



It is apparent that the median income has the strongest positive correlation with the median house value which is quite obvious because households with a higher income can afford higher-priced houses. The neighborhood rooms also have a decent positive correlation to the median house value, and it can infer that more expensive houses tend to be larger than the less expensive houses, therefore having a larger number of rooms as well. However, a larger number of rooms in a neighborhood does not necessarily represent a neighborhood with fancy large houses, it could simply be an observation of a densily populated neighborhood with inadequate housing.

The total households and total population will be regarded as ineffective predictors because they show a weak correlation with house value. In addition to their weak correlation, the two explanatory variables also produce a conflicting result. The neighborhood household scatterplot suggests that when there are more households in a block, the higher its median house value in that block will be. A higher number of households will typically infer a higher population. However, the neighborhood population scatterplot suggests that a higher population leads to a lower median house value. The issue between these two variables may be caused by hidden confounding variables or nonresponse errors.

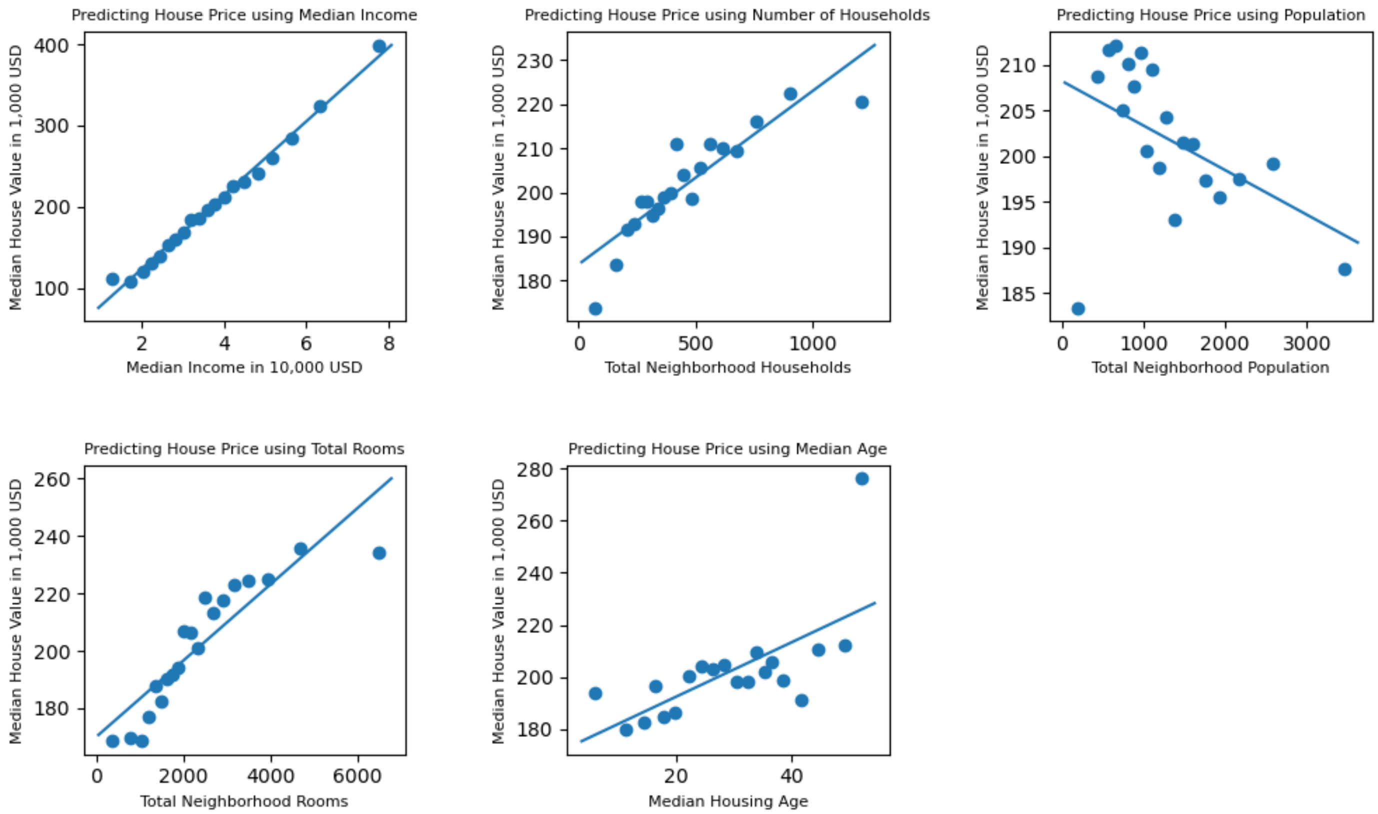
The median housing age scatterplot suggests that older houses tend to be more expensive the newer houses. This variable will also be disregarded as it does not provide a clear correlation with median house value.

Reduce scatters by using the binscatter method

*Source code provided by Elizabeth Santorella, originally written for STATA by Prof. Michael Stepner at UofT

In [222…

```
#Elizabeth Santorella bin scatter original
import binscatter
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt

fig, ax = plt.subplots(2, 3, figsize=(10, 6))

#Create plots
ax[0][0].binscatter(df_finalized["median_income"], price_thousands["median_house_value"]
ax[0][1].binscatter(df_finalized["households"], price_thousands["median_house_value"])
ax[0][2].binscatter(df_finalized["population"], price_thousands["median_house_value"])
ax[1][0].binscatter(df_finalized["total_rooms"], price_thousands["median_house_value"])
ax[1][1].binscatter(df_finalized["housing_median_age"], price_thousands["median_house_va

#Create plot titles
ax[0][0].set_title('Predicting House Price using Median Income', fontsize=8)
ax[0][1].set_title('Predicting House Price using Number of Households', fontsize=8)
ax[0][2].set_title('Predicting House Price using Population', fontsize=8)
ax[1][0].set_title('Predicting House Price using Total Rooms', fontsize=8)
ax[1][1].set_title('Predicting House Price using Median Age', fontsize=8)


ax[0][0].set_ylabel('Median House Value in 1,000 USD', fontsize=8)
ax[0][1].set_ylabel('Median House Value in 1,000 USD', fontsize=8)
ax[0][2].set_ylabel('Median House Value in 1,000 USD', fontsize=8)
ax[1][0].set_ylabel('Median House Value in 1,000 USD', fontsize=8)
ax[1][1].set_ylabel('Median House Value in 1,000 USD', fontsize=8)


ax[0][0].set_xlabel('Median Income in 10,000 USD', fontsize=8)
ax[0][1].set_xlabel('Total Neighborhood Households', fontsize=8)
ax[0][2].set_xlabel('Total Neighborhood Population', fontsize=8)
ax[1][0].set_xlabel('Total Neighborhood Rooms', fontsize=8)
ax[1][1].set_xlabel('Median Housing Age', fontsize=8)
fig.delaxes(ax[1][2])

plt.tight_layout()
fig.subplots_adjust(wspace=0.5, hspace=0.5)

plt.show()
```



The binscatter method groups x variables into equal sized bins to provide more readable scatterplots that originally hold an enormous set of obersvations. The binscatter scatterplots produce a stronger visualization of the correlation between the explanatory variable with the median house value and further strengthens our findings from above.

Finding the OLS slope of the scatterplots for Median Income and Total Rooms

In [232…

```
from scipy.stats import linregress

slope, intercept, r_value, p_value, std_err = linregress(df_finalized["median_income"],


print("Median Income - Median House Value OLS Slope: ",slope)
```

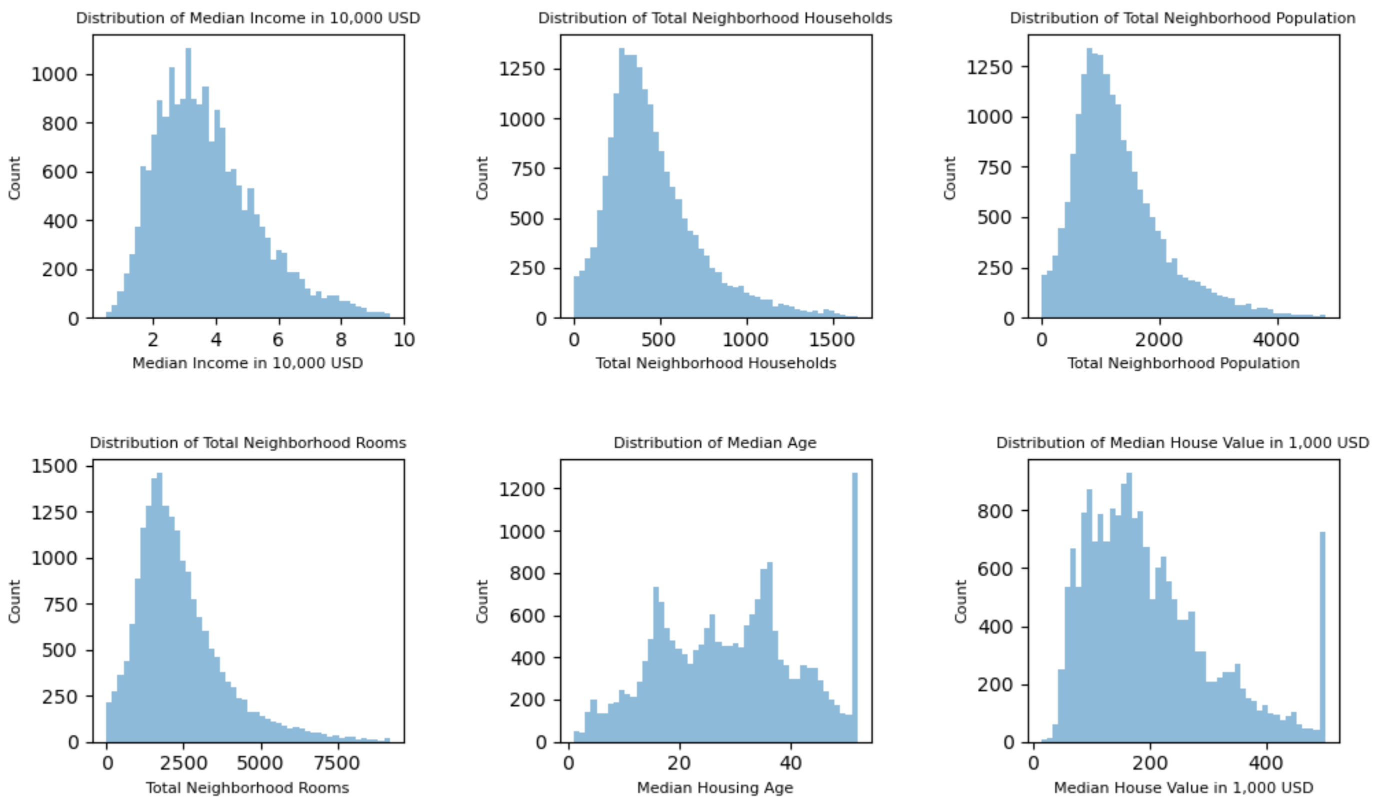
```
Median Income - Median House Value OLS Slope:  45.39114336817376
```

Histograms to show the distribution of each variable

In [223…

```
fig, ax = plt.subplots(2, 3, figsize=(10, 6))

ax[0][0].hist(df_finalized['median_income'], bins=50, alpha=0.5)
ax[0][1].hist(df_finalized['households'], bins=50, alpha=0.5)
ax[0][2].hist(df_finalized['population'], bins=50, alpha=0.5)
ax[1][0].hist(df_finalized['total_rooms'], bins=50, alpha=0.5)
ax[1][1].hist(df_finalized['housing_median_age'], bins=50, alpha=0.5)
ax[1][2].hist(price_thousands['median_house_value'], bins=50, alpha=0.5)


ax[0][0].set_title('Distribution of Median Income in 10,000 USD', fontsize=8)
ax[0][1].set_title('Distribution of Total Neighborhood Households', fontsize=8)
ax[0][2].set_title('Distribution of Total Neighborhood Population', fontsize=8)
ax[1][0].set_title('Distribution of Total Neighborhood Rooms', fontsize=8)
ax[1][1].set_title('Distribution of Median Age', fontsize=8)
ax[1][2].set_title('Distribution of Median House Value in 1,000 USD', fontsize=8)
```

```
ax[0][0].set_xlabel('Median Income in 10,000 USD', fontsize=8)
ax[0][1].set_xlabel('Total Neighborhood Households', fontsize=8)
ax[0][2].set_xlabel('Total Neighborhood Population', fontsize=8)
ax[1][0].set_xlabel('Total Neighborhood Rooms', fontsize=8)
ax[1][1].set_xlabel('Median Housing Age', fontsize=8)
ax[1][2].set_xlabel('Median House Value in 1,000 USD', fontsize=8)

ax[0][0].set_ylabel('Count', fontsize=8)
ax[0][1].set_ylabel('Count', fontsize=8)
ax[0][2].set_ylabel('Count', fontsize=8)
ax[1][0].set_ylabel('Count', fontsize=8)
ax[1][1].set_ylabel('Count', fontsize=8)
ax[1][2].set_ylabel('Count', fontsize=8)

plt.tight_layout()
fig.subplots_adjust(wspace=0.5, hspace=0.5)

plt.show()
```



We can see that the 1990 median housing age in California has a bimodal distribution around 15 years and 35 years, and it also shows that the mode of the median housing age is old houses above the age of 50. It may be interesting to conduct further studies on why there is a large number of data concentrated at that range.

The other 5 variables share a right-skewed distribution with an exception of median house value having a peak around the $500,000 price point. This peak at its tail corresponds to the peak in the median housing age histogram, which may suggest that in 1990, the oldest houses in California are also the most expensive houses.

Conclusion

We have analyzed the individual relationship between each housing variable and the housing price and we explored the feasibility of using them to predict the 1990 California housing price. The project found interesting insights such as the conflicting trend between total households and total population in relation to housing price, the expensiveness of the oldest houses in California, and median income's influence on housing price.

Comparing the correlation and regression between our explanatory variables with our response variable, we have concluded that the median household income in a block and the total number of rooms in a block are the best estimator for California housing prices in 1990. We estimate that households making $4,500 more in household income tend to on average live in houses that that are \$10,000 more expensive. This shows a strong positive relationship between household income and housing prices, which is in line with our assumption of wealthy households being able to afford expensive houses.

In future studies, including a categorical variable to describe the quality of each neighorhood block may provide better accuracy for this study. Generalizing each observation into different types of neighborhoods may explain some issues such as the number of rooms' influence on housing prices. It will also describe each explanatory variable more precisely.

Reference

"Binscatter." Binscatter: a Stata Program to Generate Binned Scatterplots, https://michaelstepner.com/binscatter/.

Esantorella. "Esantorella/Binscatter." GitHub, https://github.com/esantorella/binscatter.