# California Housing Price Prediction

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## Objective

The project aims at building a model of housing prices to predict median house values in California using the provided dataset. This model should learn from the data and be able to predict the median housing price in any district, given all the other metrics.

## Data handling

### Import required libraries

[109]:
```
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.compose import ColumnTransformer
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.lines import Line2D
```

### Load data

[110]:
```
## Assign the data frame as housing
housing = pd.read_excel('/Users/schinlfc/data-science-Python/
↪california_housing_price_prediction/data/housing.xlsx')
```

[111]:
```
## View the first 5 rows
housing.head()
```

[111]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                  41          880           129.0
1    -122.22     37.86                  21         7099          1106.0
2    -122.24     37.85                  52         1467           190.0
```

```
3    -122.25     37.85                  52         1274           235.0
4    -122.25     37.85                  52         1627           280.0

   population  households  median_income ocean_proximity  median_house_value
0         322         126         8.3252        NEAR BAY              452600
1        2401        1138         8.3014        NEAR BAY              358500
2         496         177         7.2574        NEAR BAY              352100
3         558         219         5.6431        NEAR BAY              341300
4         565         259         3.8462        NEAR BAY              342200
```

[112]:
```
## Get the number of rows and columns
housing.shape
```

[112]:
```
(20640, 10)
```

[113]:
```
## Get data types for each column
housing.dtypes
```

[113]:
```
longitude              float64
latitude               float64
housing_median_age       int64
total_rooms              int64
total_bedrooms         float64
population               int64
households               int64
median_income          float64
ocean_proximity         object
median_house_value       int64
dtype: object
```

[114]:
```
## Get basic summary statistics for float and integer column types
housing.describe()
```

[114]:
```
          longitude      latitude  housing_median_age   total_rooms  \
count  20640.000000  20640.000000        20640.000000  20640.000000
mean    -119.569704     35.631861           28.639486   2635.763081
std        2.003532      2.135952           12.585558   2181.615252
min     -124.350000     32.540000            1.000000      2.000000
25%     -121.800000     33.930000           18.000000   1447.750000
50%     -118.490000     34.260000           29.000000   2127.000000
75%     -118.010000     37.710000           37.000000   3148.000000
max     -114.310000     41.950000           52.000000  39320.000000

       total_bedrooms    population    households  median_income  \
count    20433.000000  20640.000000  20640.000000   20640.000000
mean       537.870553   1425.476744    499.539680       3.870671
std        421.385070   1132.462122    382.329753       1.899822
```

```
min          1.000000      3.000000      1.000000        0.499900
25%        296.000000    787.000000    280.000000        2.563400
50%        435.000000   1166.000000    409.000000        3.534800
75%        647.000000   1725.000000    605.000000        4.743250
max       6445.000000  35682.000000   6082.000000       15.000100

       median_house_value
count        20640.000000
mean        206855.816909
std         115395.615874
min          14999.000000
25%         119600.000000
50%         179700.000000
75%         264725.000000
max         500001.000000
```

[115]:
```python
## Check for the sum of missing values for each column
housing.isnull().sum()
```

[115]:
```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
ocean_proximity         0
median_house_value      0
dtype: int64
```

[116]:
```python
## Fill the missing values of the 'total_bedrooms' column with its mean value
housing['total_bedrooms'].fillna((housing['total_bedrooms'].mean()),␣
 ↪inplace=True)
```

[117]:
```python
## Check whether the missing values are filled
housing.isnull().sum()
```

[117]:
```
longitude             0
latitude              0
housing_median_age    0
total_rooms           0
total_bedrooms        0
population            0
households            0
median_income         0
ocean_proximity       0
```

```
median_house_value    0
dtype: int64
```

[118]:
```
## Convert categorical column 'ocean_proximity' in the dataset to numerical data
housing = pd.get_dummies(housing, columns=['ocean_proximity'])
```

[119]:
```
## Get name of all columns
print(housing.columns)
```

```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'median_house_value', 'ocean_proximity_<1H OCEAN',
       'ocean_proximity_INLAND', 'ocean_proximity_ISLAND',
       'ocean_proximity_NEAR BAY', 'ocean_proximity_NEAR OCEAN'],
      dtype='object')
```

[120]:
```
## Rename columns

# Strip any white space
housing = housing.rename(columns=lambda x: x.strip())

# Define a dictionary of columns we want to rename
col_map = {'ocean_proximity_<1H OCEAN': '1h_ocean',
           'ocean_proximity_INLAND': 'inland',
           'ocean_proximity_ISLAND': 'island',
           'ocean_proximity_NEAR BAY': 'near_bay',
           'ocean_proximity_NEAR OCEAN': 'near_ocean'}
# Rename columns with inplace=True
housing.rename(columns=col_map, inplace=True)
```

[121]:
```
## Check to see if columns are successfully renamed
print(housing.columns)
```

```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'median_house_value', '1h_ocean', 'inland', 'island', 'near_bay',
       'near_ocean'],
      dtype='object')
```

[122]:
```
## Check the data type of each column
housing.dtypes
```

[122]:
```
longitude             float64
latitude              float64
housing_median_age      int64
total_rooms             int64
total_bedrooms        float64
```

```
population             int64
households             int64
median_income        float64
median_house_value     int64
1h_ocean               uint8
inland                 uint8
island                 uint8
near_bay               uint8
near_ocean             uint8
dtype: object
```

[123]:
```
housing.columns
```

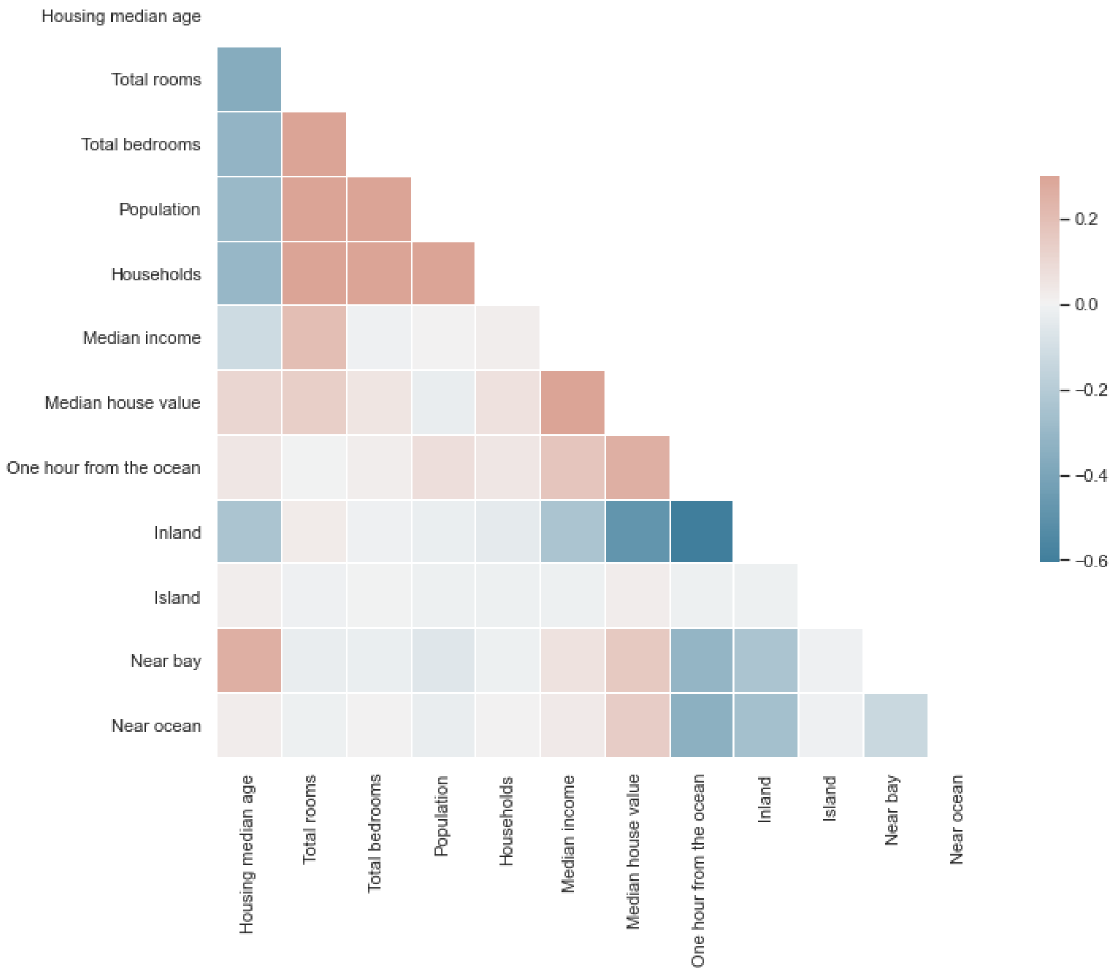
[123]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'median_house_value', '1h_ocean', 'inland', 'island', 'near_bay',
       'near_ocean'],
      dtype='object')
```

## Model building

[124]:
```
## Compute the crrelation matrix

# Set the theme
sns.set_theme(style="white")

# Rename columns for this correlation matrix plot only
col_map2 = {'housing_median_age': 'Housing median age',
            'total_rooms': 'Total rooms',
            'total_bedrooms': 'Total bedrooms',
            'population': 'Population',
            'households': 'Households',
            'median_income': 'Median income',
            'median_house_value': 'Median house value',
            '1h_ocean': 'One hour from the ocean',
            'inland': 'Inland',
            'island': 'Island',
            'near_bay': 'Near bay',
            'near_ocean': 'Near ocean'}

housing_corr = housing.rename(columns=col_map2)

# Compute the correlation matrix without lon and lat variables
corr = housing_corr[['Housing median age',
                     'Total rooms',
                     'Total bedrooms',
```

```
                      'Population',
                      'Households',
                      'Median income',
                      'Median house value',
                      'One hour from the ocean',
                      'Inland',
                      'Island',
                      'Near bay',
                      'Near ocean']].corr()

# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(corr, dtype=bool))

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

[124]: <AxesSubplot:>




[125]:
```
# Split the data into 80% training dataset and 20% test dataset
X = housing[['housing_median_age',
             'total_rooms',
             'median_income',
             'inland',
             'near_bay',
             'near_ocean']]
Y = housing[['median_house_value']]
x_train,x_test,y_train,y_test = train_test_split(X, Y, test_size=0.2,␣
 ↪random_state=0)
```

[126]:
```
## Check to see if the if the split is correct
print(f"The number of rows of the train dataset are: {x_train.shape[0]}")
print(f"The number of rows of the test dataset are: {x_test.shape[0]}")
```

```
The number of rows of the train dataset are: 16512
```

```
The number of rows of the test dataset are: 4128
```

[127]:
```python
## Standardize training and test datasets

# Note: Standardize features by removing the mean and scaling to unit variance
# The standard score of a sample x is calculated as:
# z = (x - u) / s
# where u is the mean of the training samples or zero if with_mean=False,
# and s is the standard deviation of the training samples or one if␣
↪with_std=False.

# Define a scaler object
scaler = StandardScaler()
```

[128]:
```python
# Standardize training dataset
x_train[['housing_median_age', 'total_rooms', 'median_income']] = scaler.
↪fit_transform(x_train[['housing_median_age',
                                                                              ␣
↪              'total_rooms',
                                                                              ␣
↪              'median_income']])
x_train.head()
```

[128]:

| | housing_median_age | total_rooms | median_income | inland | near_bay | near_ocean |
|---|---|---|---|---|---|---|
| 12069 | -1.795076 | -0.977736 | 0.190012 | 1 | 0 | 0 |
| 15925 | 1.855539 | -0.118501 | 0.269311 | 0 | 1 | 0 |
| 11162 | -0.207852 | -0.421680 | 0.029895 | 0 | 0 | 0 |
| 4904 | 0.744482 | -0.888566 | -1.264470 | 0 | 0 | 0 |
| 4683 | 1.855539 | -0.122159 | -0.367016 | 0 | 0 | 0 |

[129]:
```python
# Standardize test dataset of x_test
x_test[['housing_median_age', 'total_rooms', 'median_income']] = scaler.
↪fit_transform(x_test[['housing_median_age',
                                                                              ␣
↪             'total_rooms',
                                                                              ␣
↪             'median_income']])
x_test.head()
```

[129]:
```
       housing_median_age  total_rooms  median_income  inland  near_bay  \
14740           -0.536695    -0.239438       0.162239       0         0
10101            0.261819     0.000808       1.032000       0         0
20566            0.022265     0.254015       0.267446       1         0
2670             0.661075    -0.883797      -0.746474       1         0
15709           -0.297141    -0.454224       0.618065       0         1

       near_ocean
14740           1
10101           0
20566           0
2670            0
15709           0
```

[130]:
```python
# Standardize test dataset of y_train
y_train[['median_house_value']] = scaler.
 ↪fit_transform(y_train[['median_house_value']])
y_train.head()
```

[130]:
```
       median_house_value
12069            2.530522
15925            0.542408
11162           -0.096379
4904            -0.764555
4683             0.153431
```

[131]:
```python
# Standardize test dataset of y_test
y_test[['median_house_value']] = scaler.
 ↪fit_transform(y_test[['median_house_value']])
y_test.head()
```

[131]:
```
       median_house_value
14740           -0.598818
10101            0.315441
20566           -0.040104
2670            -1.162786
15709            2.230656
```

[132]:
```python
## Perform Linear Regression on training data

# Define a linear regression object
reg = LinearRegression()

# Fit the model
reg.fit(x_train, y_train)
```

[132]:
```
LinearRegression()
```

[133]:
```
# Get the coefficients
reg.fit(x_train, y_train).coef_
```

[133]:
```
array([[ 0.12585266,  0.06522436,  0.62116224, -0.61022652,  0.09936045,
         0.15727489]])
```

[134]:
```
# Get the intercept
reg.fit(x_train, y_train).intercept_
```

[134]:
```
array([0.16175561])
```

[135]:
```
# Predict output for test dataset using the fitted model
y_pred = reg.predict(x_test)
```

[136]:
```
# Get Root Mean Squared Error (RMSE) from the model
print(f"Root Mean Squared Error (RMSE): {mean_squared_error(y_test, y_pred,␣
 ↪squared=False)}")
```

```
Root Mean Squared Error (RMSE): 0.6426217852518341
```

**Bonus exercise: Perform Linear Regression with one independent variable**

[137]:
```
## Extract just the median_income column from the independent variables (from␣
 ↪x_train and x_test)

# Extract only the median_income column from x_train and return a pandas data␣
 ↪frame
x_train_mi = x_train[['median_income']]
x_train_mi.head()
```

[137]:

| | median_income |
|---|---|
| 12069 | 0.190012 |
| 15925 | 0.269311 |
| 11162 | 0.029895 |
| 4904 | -1.264470 |
| 4683 | -0.367016 |

[138]:
```
# Extract only the median_income column from x_test and return a pandas data␣
 ↪frame
x_test_mi = x_test[['median_income']]
x_test_mi.head()
```

[138]:

| | median_income |
|---|---|
| 14740 | 0.162239 |
| 10101 | 1.032000 |
| 20566 | 0.267446 |
| 2670 | -0.746474 |

```
15709       0.618065
```

[139]:
```
## Perform Linear Regression to predict housing values based on median_income

# Define a linear regression object
reg_mi = LinearRegression()

# Fit the model
reg_mi.fit(x_train_mi, y_train)
```

[139]:
```
LinearRegression()
```

[140]:
```
# Get the coefficient
reg_mi.fit(x_train_mi, y_train).coef_
```

[140]:
```
array([[0.69275835]])
```

[141]:
```
# Get the intercept
reg_mi.fit(x_train_mi, y_train).intercept_
```

[141]:
```
array([-4.65633805e-18])
```

[142]:
```
## Predict output for test dataset using the fitted model
y_pred_mi = reg_mi.predict(x_test_mi)
```

[143]:
```
## Get Root Mean Squared Error (RMSE) from the model with only median_income as␣
↪an independent variable
print(f"Root Mean Squared Error (RMSE): {mean_squared_error(y_test, y_pred_mi,␣
↪squared=False)}")
```

```
Root Mean Squared Error (RMSE): 0.7439347363418634
```

[144]:
```
## Plot the fitted model for training data as well as for test data to
#  check if the fitted model satisfies the test data
fig, ax = plt.subplots(figsize=(25,8))

legend_elements = [Line2D([0], [0], marker='*', color='w', label='Test Data',
                          markerfacecolor='r', markersize=15),
                   Line2D([0], [0], marker='o', color='w', label='Training Data',
                          markerfacecolor='g', markersize=15)]

scatter1 = ax.scatter(y_test,
            y_pred_mi,
            marker="*",
            color="r",
            s=80)
```

```
scatter2 = ax.scatter(y_train,
            reg_mi.predict(x_train_mi),
            marker="o",
            color="g",
            s=50,
            alpha=0.1)

ax.legend(handles=legend_elements, loc='upper left')
plt.title('Actual VS. Predicted Median House Value Using both Training and Test␣
 ↪Datasets', fontsize=20)
plt.xlabel('Actual Median House Value', fontsize=16)
plt.ylabel('Predicted Median House Value', fontsize=16)

plt.show()
```