Management Science Final Report _ Group2

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I: Background

1. Chosen subject:

   We chose the dataset "California Housing Prices Data" from Kaggle. The data pertains to the houses found in a given California district and some summary about them based on the 1990 census data.

2. Dataset Columns:

   The dataset provides 10 columns, below are the ten columns:

   a. Median House Value: Median house value for households within a block, measured in US Dollars ($).
   b. Median Income: Median income for households within a block of houses, measured in tens of thousands of US Dollars ($10,000).
   c. Median Age: Median age of a house within a block, where a lower number indicates a newer building, measured in years.
   d. Total Rooms: Total number of rooms within a block.
   e. Total Bedrooms: Total number of bedrooms within a block.
   f. Population: Total number of people residing within a block.
   g. Households: Total number of households, which represents a group of people residing within a home unit, for a block.
   h. Latitude: A measure of how far north a house is, where a higher value indicates a location farther north, measured in degrees (°).
   i. Longitude: A measure of how far west a house is, where a higher value indicates a location farther west, measured in degrees (°).
   j. Distance to coast: Distance to the nearest coastal point, is a categorical instance.

   The dataset contains information about various housing attributes and their respective values. These attributes provide insights into the housing market, demographics, and geographic location within California. By analyzing this dataset, we can explore relationships between the median house value and factors such as income, age, size of the property, population, and proximity to the coast.

3. Motivation:

The dataset on California housing prices provides valuable insights into the housing market in a specific region. Through making predictions and building models, we could understand housing trends to make informed decisions related to real estate investments, market analysis, and urban planning.

Understanding housing trends is crucial for individuals and organizations involved in the real estate industry.This information is essential for real estate agents, investors, and developers to make informed decisions about buying, selling, or developing properties.

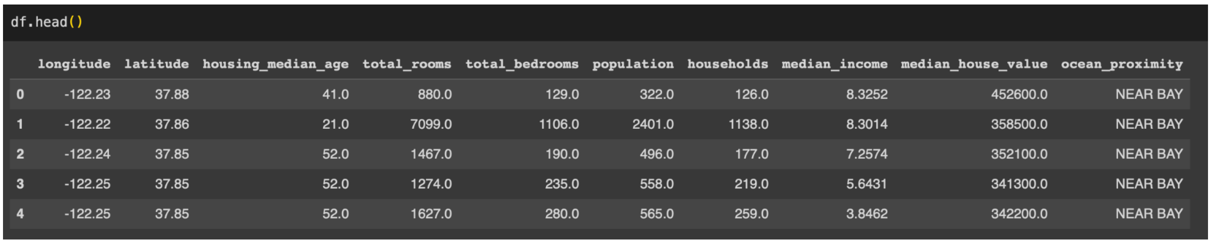
Market analysis, based on the dataset, provides insights into the dynamics of the housing market in California. By examining the relationships between housing prices and demographic factors, we can gain a deeper understanding of the market demand, identify target segments, and develop effective marketing and sales strategies.

The dataset also offers insights relevant to urban planning. By analyzing the relationship between housing prices and geographical factors such as latitude, longitude, and proximity to the coast, urban planners can identify areas with high or low housing affordability, assess the impact of development projects, and make informed decisions regarding housing policies and infrastructure development.

In conclusion, the results derived from analyzing the California housing prices dataset can have a broad impact on professionals working in real estate, finance, market analysis, urban planning, and data science. The insights obtained from this dataset enable informed decision-making, strategic planning, and optimization of various processes in these industries.

II: Preprocess Dataset

1. Initial Dataset:
    a. Number of initial rows: 20640
    Number of initial columns: 10
    b. Top five rows of the dataset:

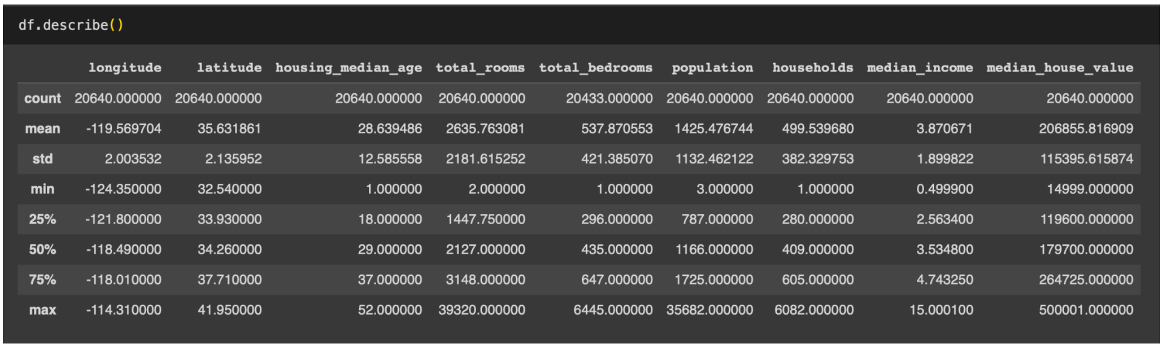


```
df.head()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY

    c. Descriptive statistics of a DataFrame:

Such as count, mean, standard deviation, minimum value, quartiles, and maximum value. Count is the number of non-missing values in each column. Worth noticing that due to the fact that ocean_proximity does not have a numeric value, so it is not incorporated.

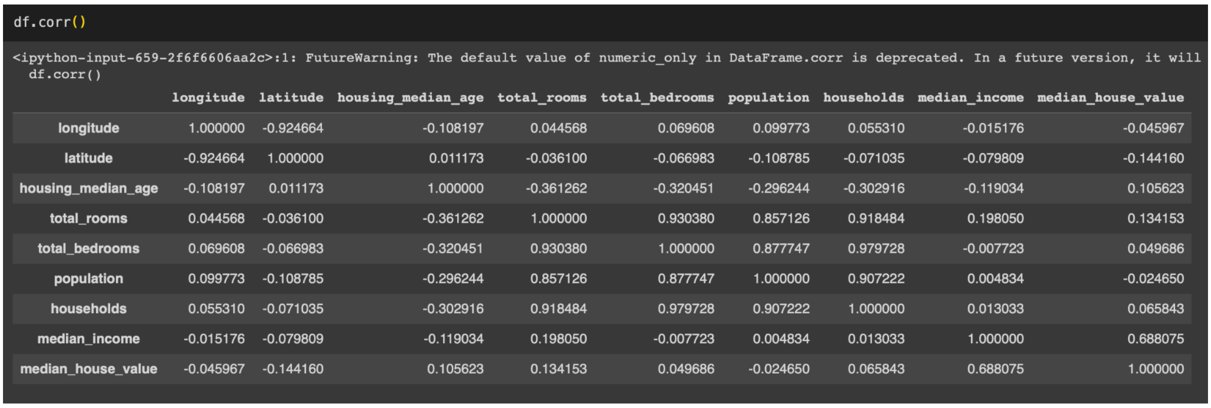


```
df.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680	3.870671	206855.816909
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329753	1.899822	115395.615874
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000000	0.499900	14999.000000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000000	2.563400	119600.000000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000000	3.534800	179700.000000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000000	4.743250	264725.000000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000000	15.000100	500001.000000

d. Correlations:

It calculates the correlation coefficient between every pair of numeric columns in the DataFrame.The correlation coefficient is a statistical measure that quantifies the strength and direction of the linear relationship between two variables. Worth noticing that due to the fact that ocean_proximity does not have a numeric value, so it is not incorporated.



```
df.corr()
```

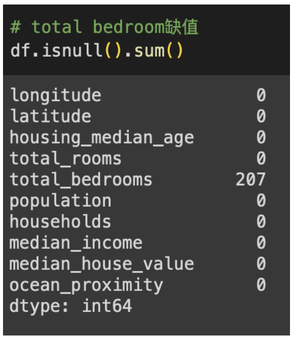
```
<ipython-input-659-2f6f6606aa2c>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will
  df.corr()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value
longitude	1.000000	-0.924664	-0.108197	0.044568	0.069608	0.099773	0.055310	-0.015176	-0.045967
latitude	-0.924664	1.000000	0.011173	-0.036100	-0.066983	-0.108785	-0.071035	-0.079809	-0.144160
housing_median_age	-0.108197	0.011173	1.000000	-0.361262	-0.320451	-0.296244	-0.302916	-0.119034	0.105623
total_rooms	0.044568	-0.036100	-0.361262	1.000000	0.930380	0.857126	0.918484	0.198050	0.134153
total_bedrooms	0.069608	-0.066983	-0.320451	0.930380	1.000000	0.877747	0.979728	-0.007723	0.049686
population	0.099773	-0.108785	-0.296244	0.857126	0.877747	1.000000	0.907222	0.004834	-0.024650
households	0.055310	-0.071035	-0.302916	0.918484	0.979728	0.907222	1.000000	0.013033	0.065843
median_income	-0.015176	-0.079809	-0.119034	0.198050	-0.007723	0.004834	0.013033	1.000000	0.688075
median_house_value	-0.045967	-0.144160	0.105623	0.134153	0.049686	-0.024650	0.065843	0.688075	1.000000

2. Process Dataset Method1:

a. Find missing values:

We found out that the column "total_bedrooms" has 207 missing values in the DataFrame. All other columns, including "longitude", "latitude", "housing_median_age", "total_rooms", "population", "households", "median_income", "median_house_value", and "ocean_proximity" have no missing values (count of missing values is 0).



```
# total bedroom缺值
df.isnull().sum()
```

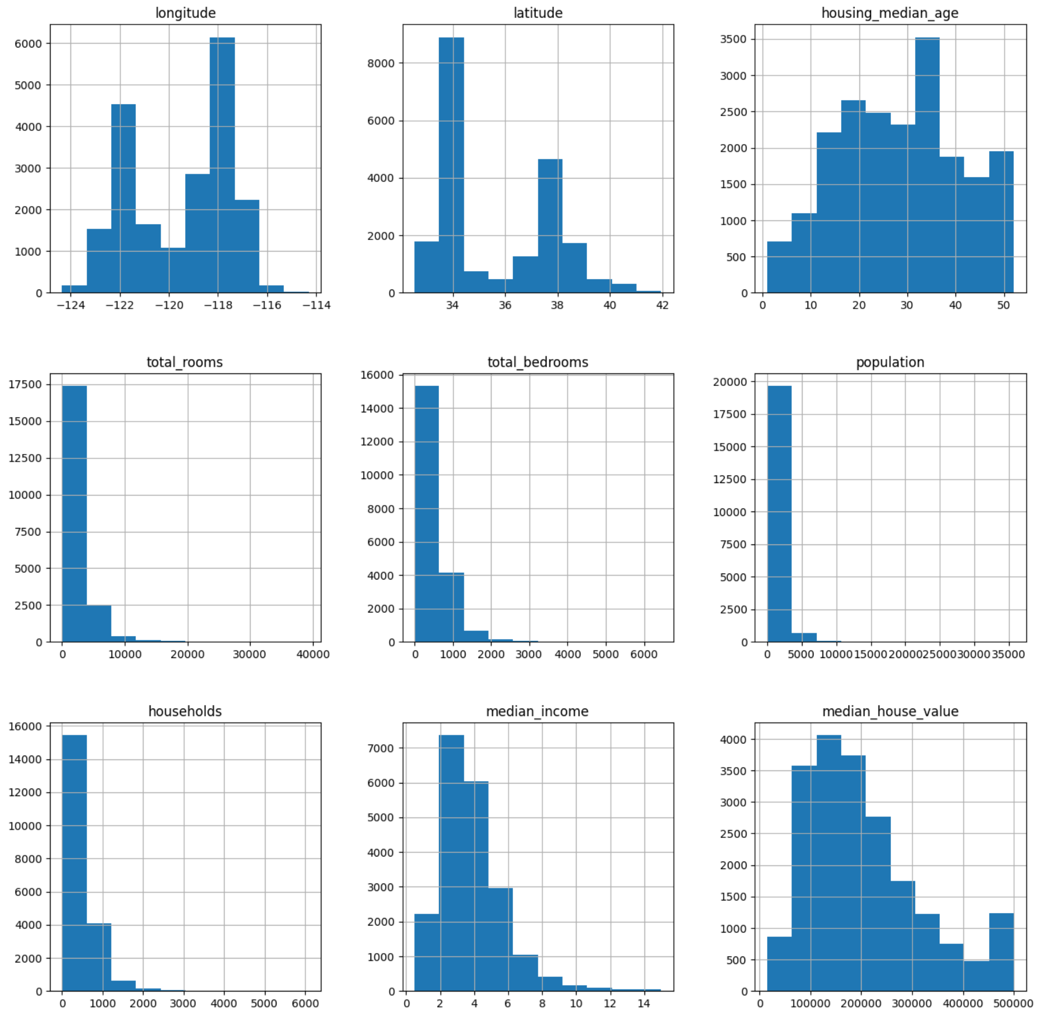
```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
median_house_value      0
ocean_proximity         0
dtype: int64
```

b. Remove missing data:

Any row containing at least one missing value will be dropped.

c. Draw Histogram:

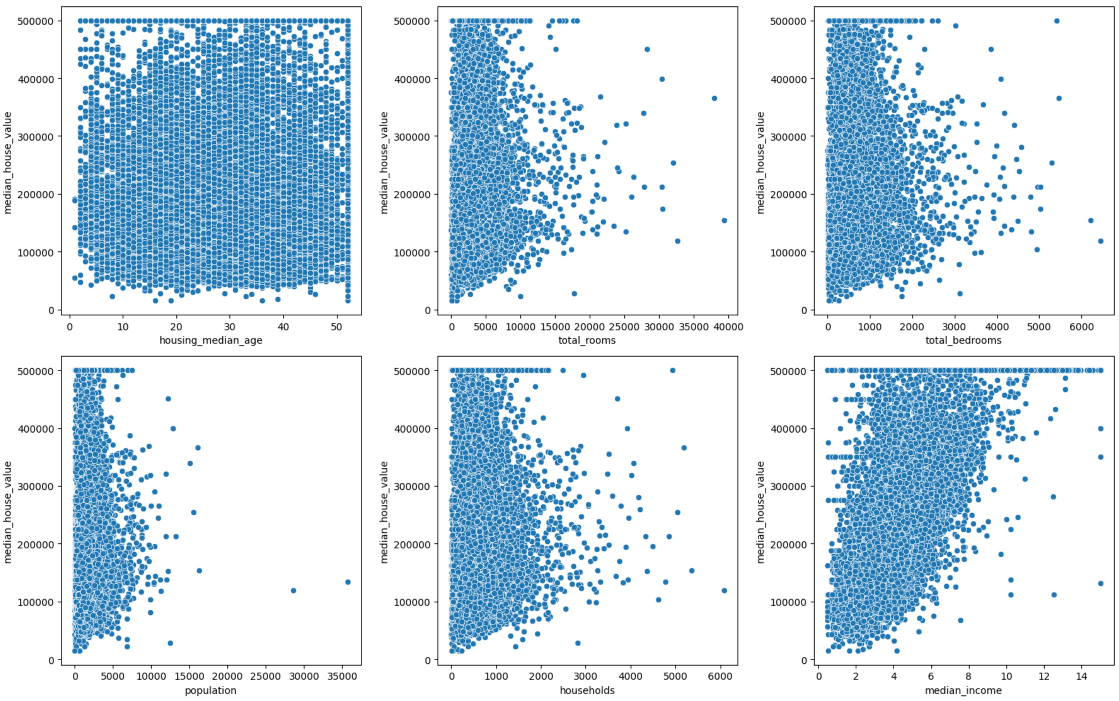
Create a histogram for each numeric column in the DataFrame . It visualizes the distribution of values in each column using a set of bins.figsize=(16, 16) is an optional parameter that specifies the size of the figure in inches. It determines the width and height of the resulting histogram plot.By setting figsize=(16, 16), the resulting plot will have a larger size, making it easier to view and analyze the histograms.



3. Process Dataset Method2:

a. Find outliers:

Creating a scatter plot for each selected variable against the "median_house_value" column in the DataFrame. This allows us to visually identify potential outliers or extreme values.



b. Remove outliers:

Remove rows where the values in the "total_rooms" column are less than or equal to 20000, the values in the "total_bedrooms" column are less than or equal to 3800, the values in the "population" column are less than or equal to 12000, and the values in the "households" column are less than or equal to 3000. After removing, we have a remaining of 20379 columns.

4. Process Dataset Method3:

a. Add new column "bedroom_percentage" :

This column represents the percentage of bedrooms in relation to the total number of rooms in each row.After executing the code, the DataFrame df will have a new column called "bedroom_percentage" that contains the calculated bedroom percentages for each row. This column can be used for further analysis, visualization, or modeling tasks.

Note that this calculation assumes that both the "total_bedrooms" and "total_rooms" columns contain valid numerical values and have been appropriately handled for missing or erroneous data.

5. Process Dataset Method4:

a. Encoding categorical variables into numeric labels:

By using LabelEncoder, the code converts the categorical values in the "ocean_proximity" column into numeric labels. Each unique category in the column is assigned a different integer label. After executing the code, the "ocean_proximity" column in df will be replaced with the encoded numeric labels obtained from the LabelEncoder transformation.

III: Models Building:

1. Linear Regression Model:
    a. Setting X and Y:

    X will contain the independent variables, excluding 'median_house_value' and 'total_bedrooms'. Y will contain the dependent variable, which is 'median_house_value'.

    b. Splits the data:

    Splits data into training and testing sets for both the independent variables (x) and the dependent variable (y) using the train_test_split function from scikit-learn. 30% of the data will be allocated to the testing set, and the remaining 70% will be used for training. Random_state=42 sets the random seed to ensure reproducibility.

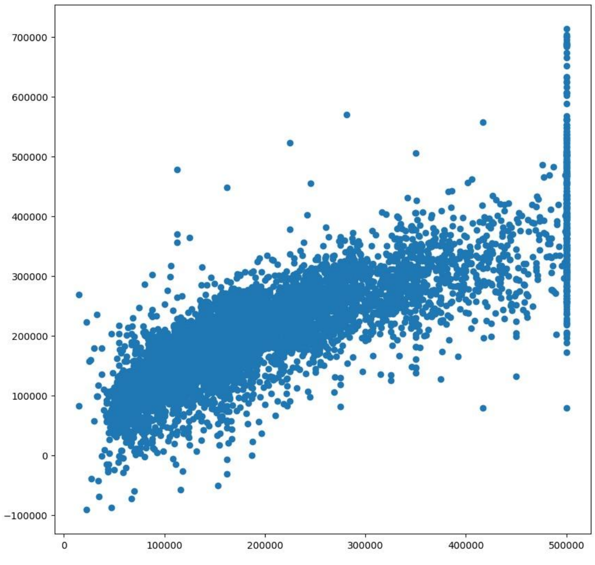
    The train_test_split function then returns four sets of data: x_train and y_train represent the training sets for the independent variables and dependent variable, respectively. These sets will be used to train the machine learning model. x_test and y_test represent the testing sets for the independent variables and dependent variable, respectively. These sets will be used to evaluate the performance of the trained model on unseen data.

    c. Calculate the coefficient of determination (R-squared) => Score: 0.6654808607029031. A higher R-squared score indicates that the linear regression model provides a better fit to the test data, with a higher proportion of the variance explained by the independent variables.

2. L0 Regression Model:
    a. Find best intercept and coefficient estimates:

    Applying L0_regression to the x_train and y_train datasets with a specified random seed of 10101. The function in the code L0_regression() will search for the best number of non-zero coefficients to consider and return the intercept and coefficient estimates for that model.

    b. Draw the plot:



Creates a scatter plot to visualize the relationship between the actual house prices and the predicted house prices using the L0 regression model. The plot helps in evaluating the performance of the model by comparing the predicted values to the actual values.

If the points in the scatter plot lie close to a diagonal line (y = x), it indicates that the model's predictions are in good agreement with the actual values. On the other hand, if the points are scattered far from the diagonal line, it suggests that the model's predictions deviate from the actual values.

3. Lasso (L1) Regression Model:
    a. Find alpha value:

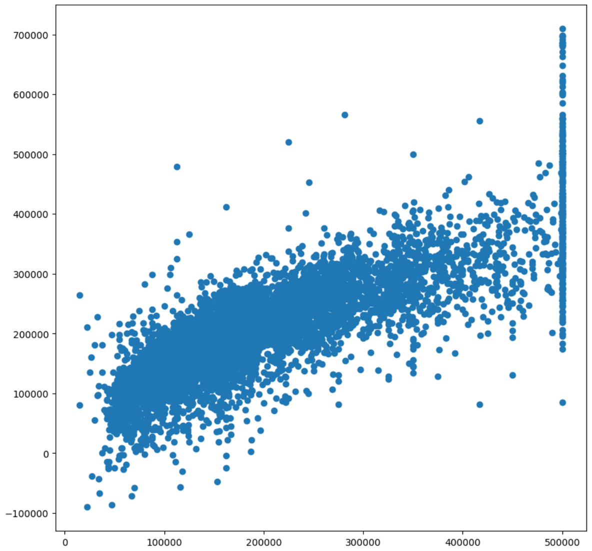
    Obtain the optimal value of the regularization parameter (alpha) selected by the LassoCV model using cross-validation. We use 5-fold cross-validation. This value is crucial for controlling the amount of regularization applied in the subsequent Lasso regression model.

    Random_state=0 sets the random seed to ensure reproducibility of the cross-validation process. Max_iter=10000 sets the maximum number of iterations for the Lasso algorithm to converge. This parameter determines the maximum number of iterations the algorithm will perform if it does not converge earlier.

    b. Calculate the coefficient of determination (R-squared) :

    After fitting the data, we calculate the R-squared score. We get => Score: 0.6656716894638972.

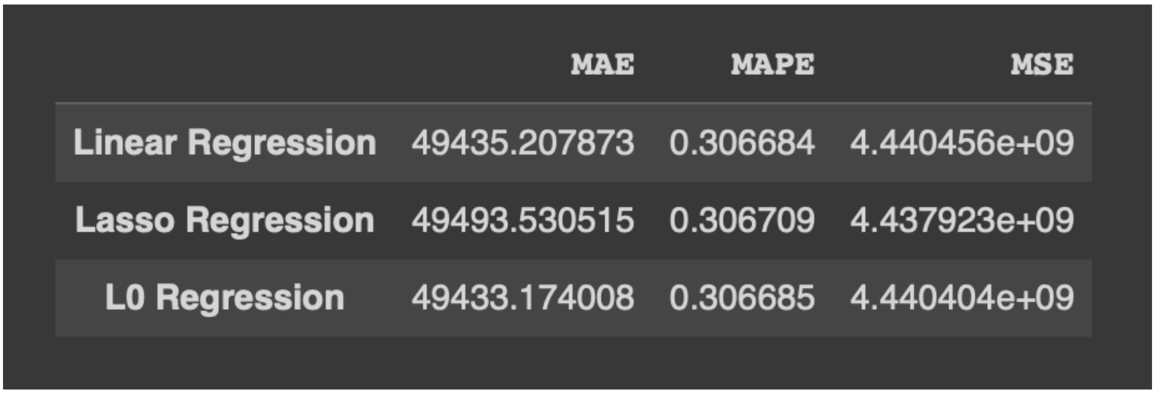
    c. Draw the plot:



Creates a scatter plot to visualize the relationship between the actual house prices (y_test) and the predicted house prices (lasso_predict) using the Lasso regression model. The plot helps in evaluating the performance of the model by comparing the predicted values to the actual values.

If the points in the scatter plot lie close to a diagonal line (y = x), it indicates that the model's predictions are in good agreement with the actual values. On the other hand, if the points are scattered far from the diagonal line, it suggests that the model's predictions deviate from the actual values.

IV: Models Evaluation



	MAE	MAPE	MSE
Linear Regression	49435.207873	0.306684	4.440456e+09
Lasso Regression	49493.530515	0.306709	4.437923e+09
L0 Regression	49433.174008	0.306685	4.440404e+09

From the evaluation metrics, we can observe that all three regression models have similar performance in terms of MAE, MAPE, and MSE. The differences between the models in these metrics are minimal.

Therefore, based on these results, we can conclude that the three regression models, namely Linear Regression, Lasso Regression, and L0 Regression, perform similarly in predicting the median house values. It is recommended to consider other factors such as model complexity, interpretability, and computational efficiency when choosing the best model for the specific application.

V: Conclusions

Based on the three regression models and their evaluation metrics in predicting the median house values for the California housing dataset, we can draw the following conclusions:

1. All three models, namely Linear Regression, Lasso Regression, and L0 Regression, provide reasonably similar performance in predicting house prices.
2. The mean absolute error (MAE) for all models is around 49,000 USD, indicating an average absolute difference between the predicted and actual house prices.
3. The mean absolute percentage error (MAPE) for all models is approximately 0.3067, suggesting an average percentage difference between the predicted and actual house prices. This indicates that, on average, the predictions deviate from the actual values by around 30.67%.
4. The mean squared error (MSE) for all models is on the order of 10^9, representing the average squared difference between the predicted and actual house prices. This metric gives higher weight to larger errors.
5. The Lasso Regression and L0 Regression models, which incorporate regularization techniques, do not significantly outperform the Linear Regression model in this scenario.

6. The evaluation metrics suggest that the chosen predictors in the models may not capture the full complexity and variability of the California housing prices.
7. Additional factors, such as geographic location, specific neighborhood characteristics, housing market trends, and other socioeconomic variables, may need to be considered to improve the accuracy of the models.
8. It is recommended to further explore and refine the feature selection process, consider alternative regression techniques, and potentially incorporate domain knowledge or additional data sources to enhance the predictive performance for the California house price dataset.