In [47]:
```
#sara elmassry was here
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression,Lasso,Ridge
from sklearn.metrics import mean_absolute_error, mean_squared_error,r2_score,mean_a
```

In [15]:
```
house_data = pd.read_csv('California_Houses.csv')
house_data.head()
```

Out[15]:

	Median_House_Value	Median_Income	Median_Age	Tot_Rooms	Tot_Bedrooms	Populati
0	452600.0	8.3252	41	880	129	3
1	358500.0	8.3014	21	7099	1106	24
2	352100.0	7.2574	52	1467	190	4
3	341300.0	5.6431	52	1274	235	5
4	342200.0	3.8462	52	1627	280	5

In [16]:
```
house_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 14 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Median_House_Value        20640 non-null  float64
 1   Median_Income             20640 non-null  float64
 2   Median_Age                20640 non-null  int64
 3   Tot_Rooms                 20640 non-null  int64
 4   Tot_Bedrooms              20640 non-null  int64
 5   Population                20640 non-null  int64
 6   Households                20640 non-null  int64
 7   Latitude                  20640 non-null  float64
 8   Longitude                 20640 non-null  float64
 9   Distance_to_coast         20640 non-null  float64
 10  Distance_to_LA            20640 non-null  float64
 11  Distance_to_SanDiego      20640 non-null  float64
 12  Distance_to_SanJose       20640 non-null  float64
 13  Distance_to_SanFrancisco  20640 non-null  float64
dtypes: float64(9), int64(5)
memory usage: 2.2 MB
```

In [17]:
```
house_data.isna().sum()
```

Out[17]:
```
Median_House_Value          0
Median_Income               0
Median_Age                  0
Tot_Rooms                   0
Tot_Bedrooms                0
Population                  0
Households                  0
Latitude                    0
Longitude                   0
Distance_to_coast           0
Distance_to_LA              0
Distance_to_SanDiego        0
Distance_to_SanJose         0
Distance_to_SanFrancisco    0
dtype: int64
```

No nulls in dataset

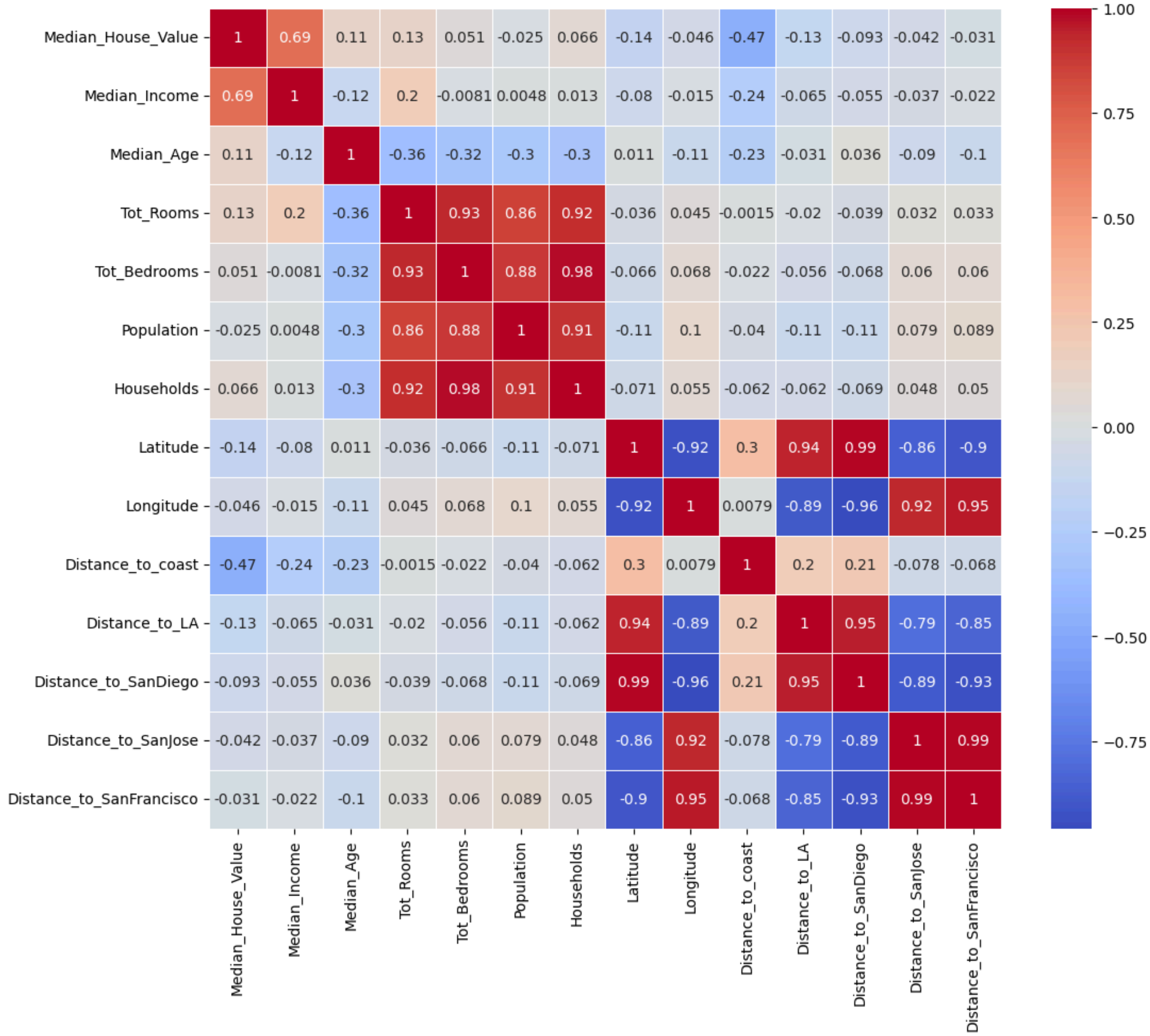
In [18]:
```
house_data.duplicated().sum()
```

Out[18]:
```
0
```

No duplicates

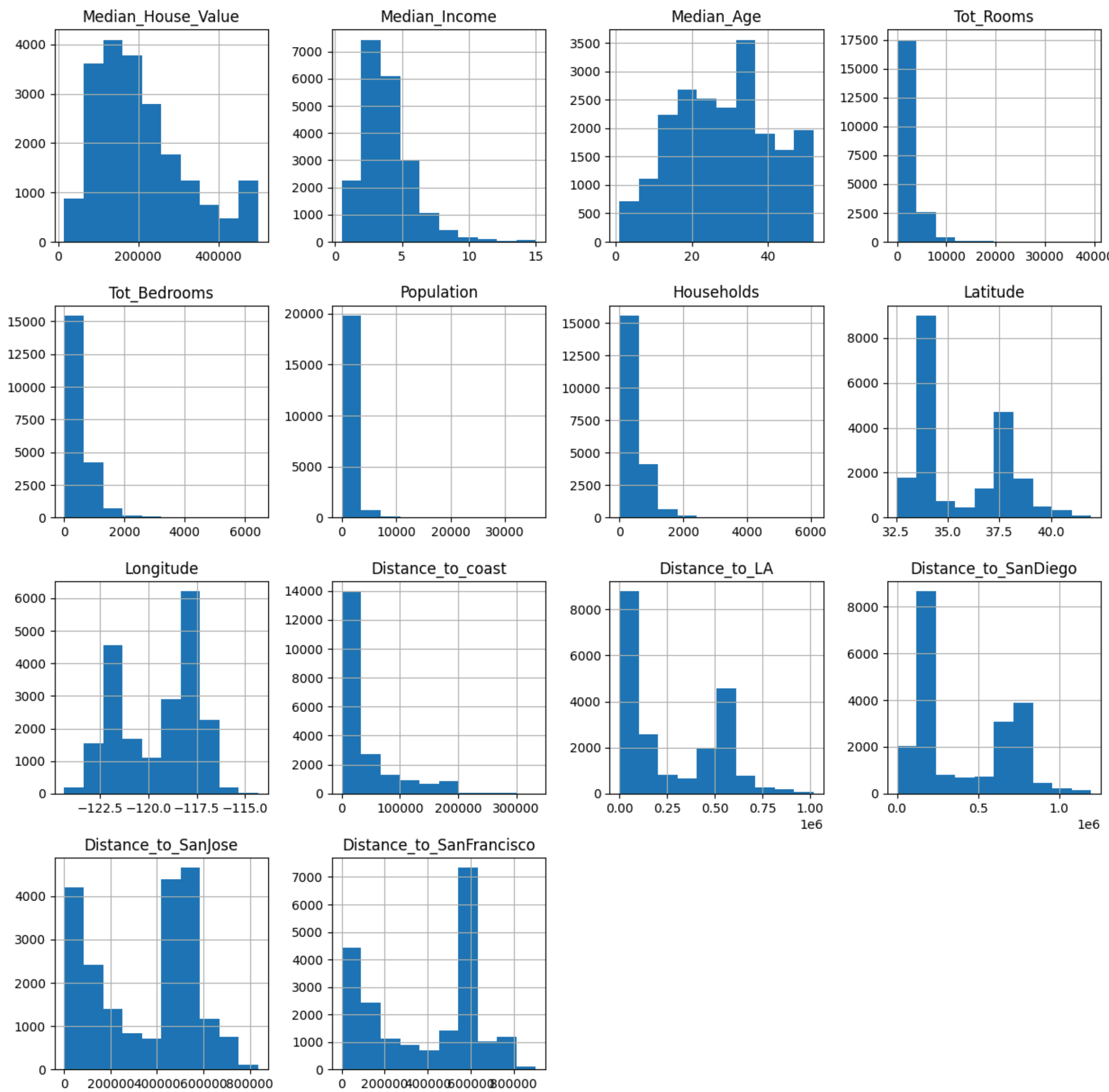
Visualization

In [19]:
```
correlation_matrix = house_data.corr()

plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.show()
```

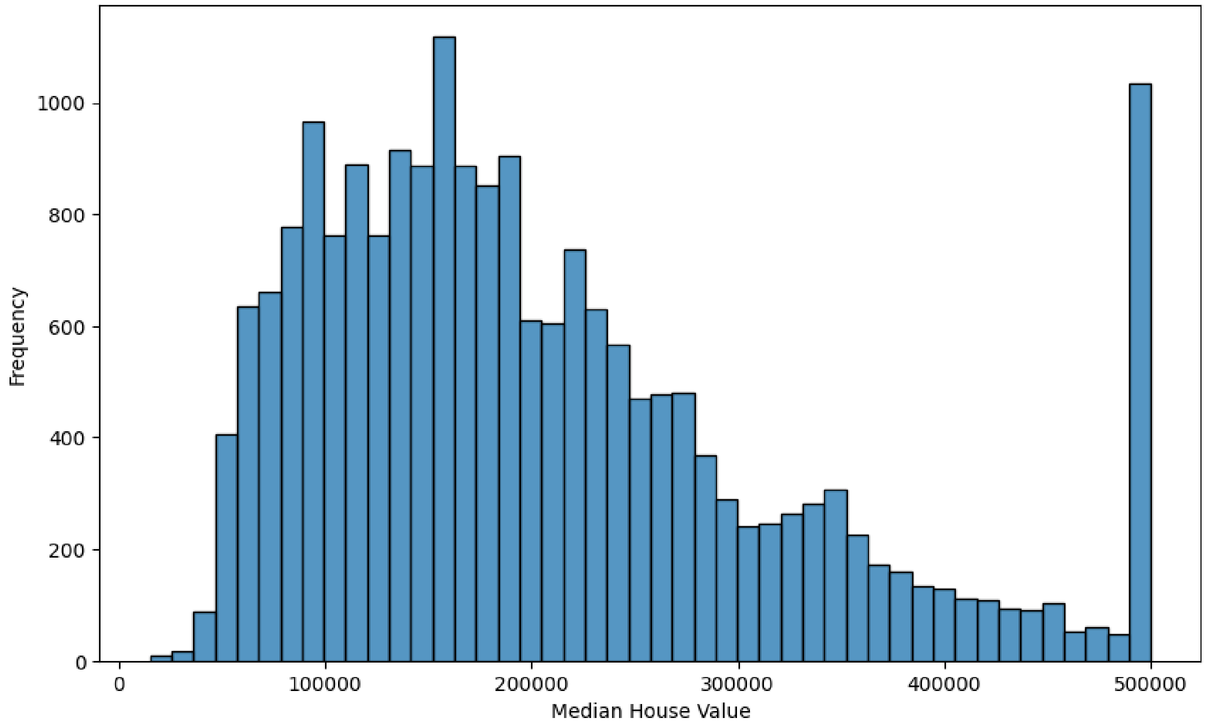


In [20]:
```
house_data.hist(figsize=(15, 15))
```

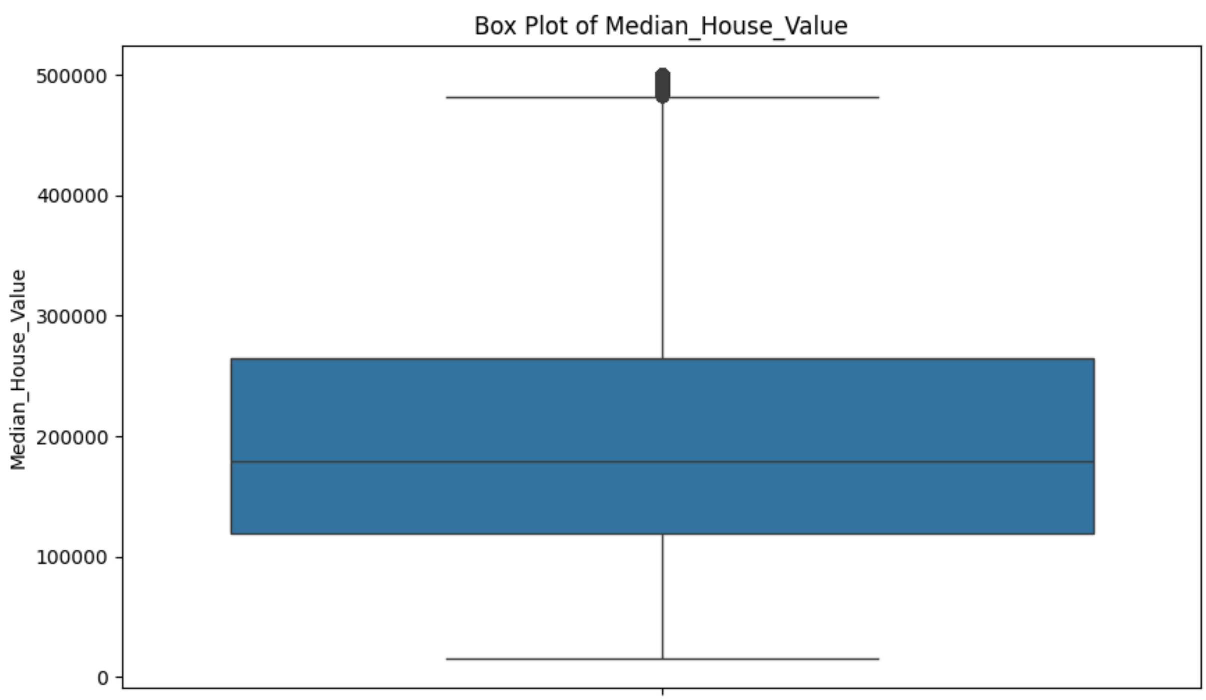
Out[20]:
```
array([[<Axes: title={'center': 'Median_House_Value'}>,
        <Axes: title={'center': 'Median_Income'}>,
        <Axes: title={'center': 'Median_Age'}>,
        <Axes: title={'center': 'Tot_Rooms'}>],
       [<Axes: title={'center': 'Tot_Bedrooms'}>,
        <Axes: title={'center': 'Population'}>,
        <Axes: title={'center': 'Households'}>,
        <Axes: title={'center': 'Latitude'}>],
       [<Axes: title={'center': 'Longitude'}>,
        <Axes: title={'center': 'Distance_to_coast'}>,
        <Axes: title={'center': 'Distance_to_LA'}>,
        <Axes: title={'center': 'Distance_to_SanDiego'}>],
       [<Axes: title={'center': 'Distance_to_SanJose'}>,
        <Axes: title={'center': 'Distance_to_SanFrancisco'}>, <Axes: >,
        <Axes: >]], dtype=object)
```

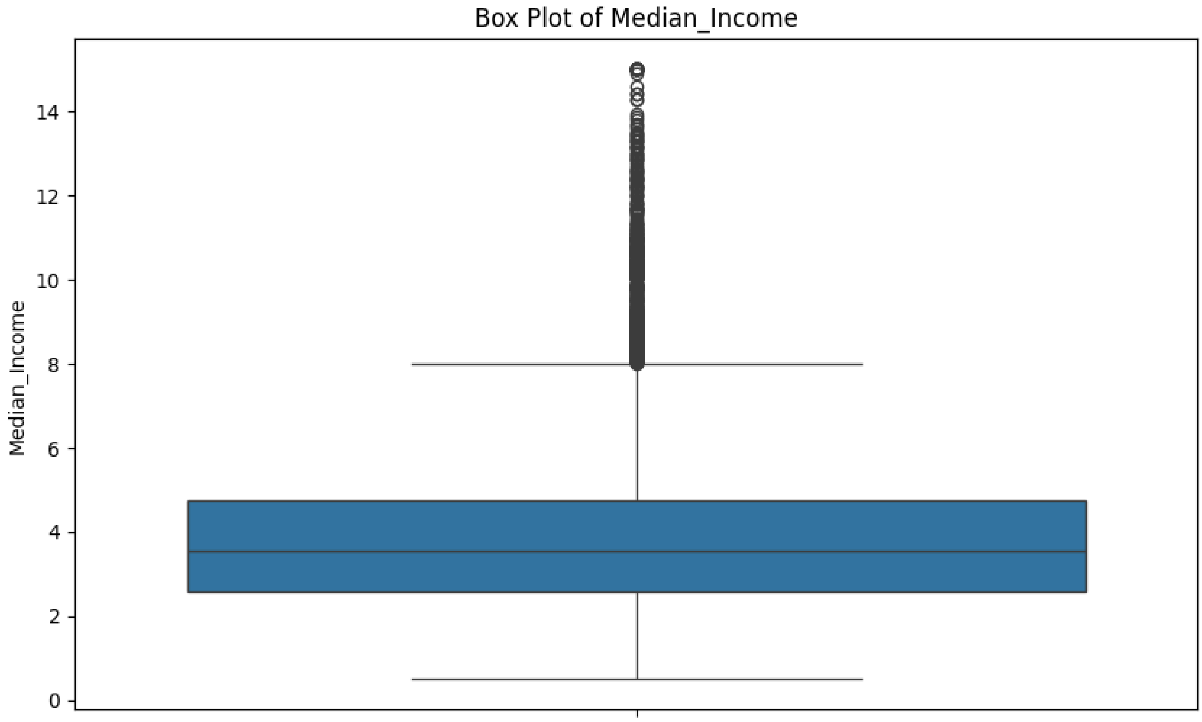


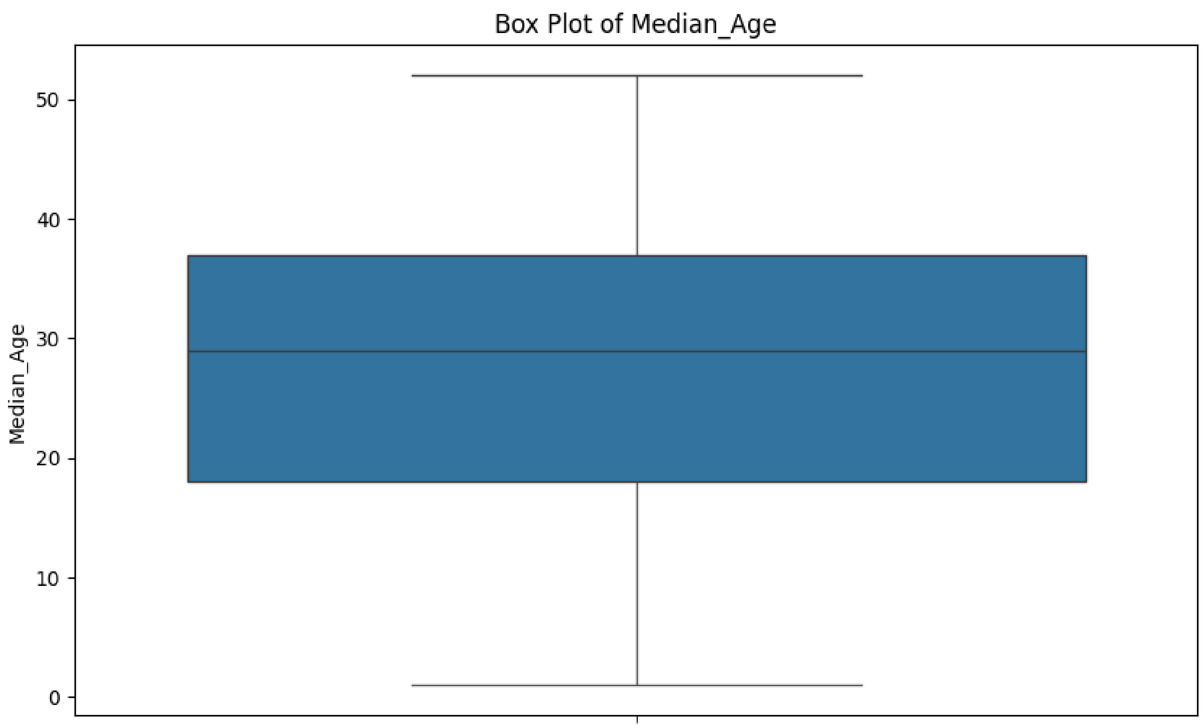
In [21]:
```python
plt.figure(figsize=(10, 6))
sns.histplot(house_data['Median_House_Value'])
plt.xlabel('Median House Value')
plt.ylabel('Frequency')
plt.show()
```

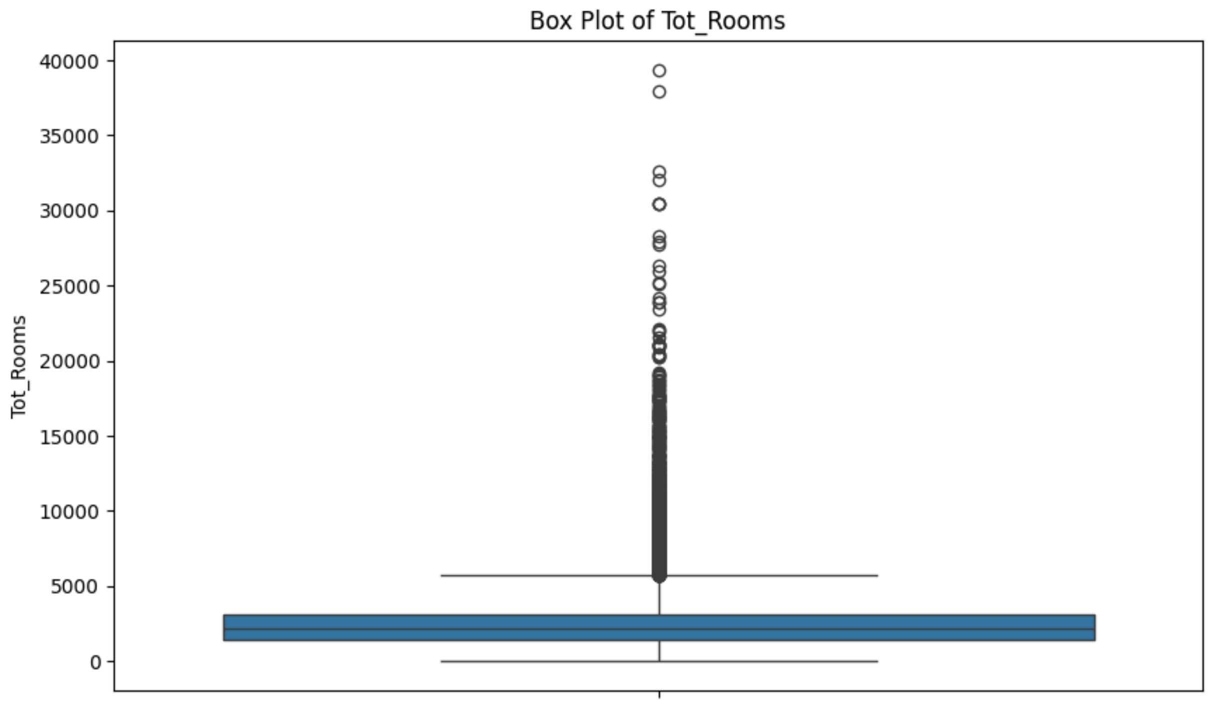


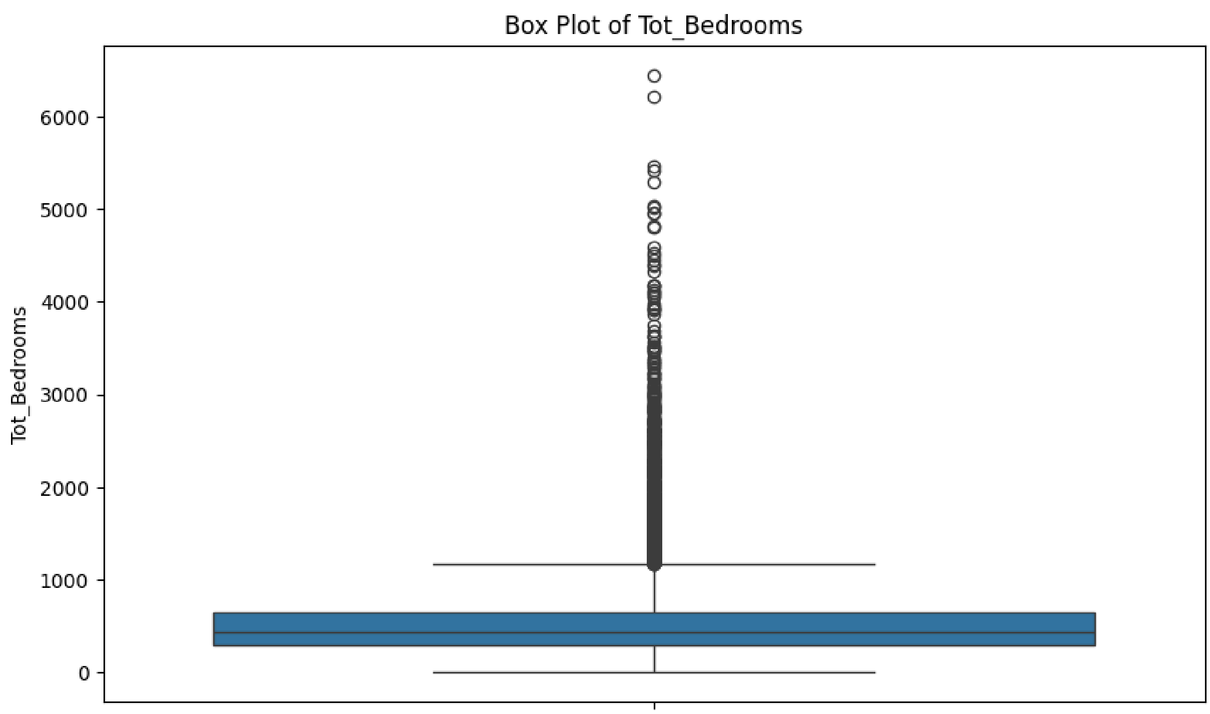
In [22]:
```
for column in house_data.columns:
    plt.figure(figsize=(10, 6))
    sns.boxplot(y=house_data[column])
    plt.title(f'Box Plot of {column}')
    plt.ylabel(column)
    plt.show()
```

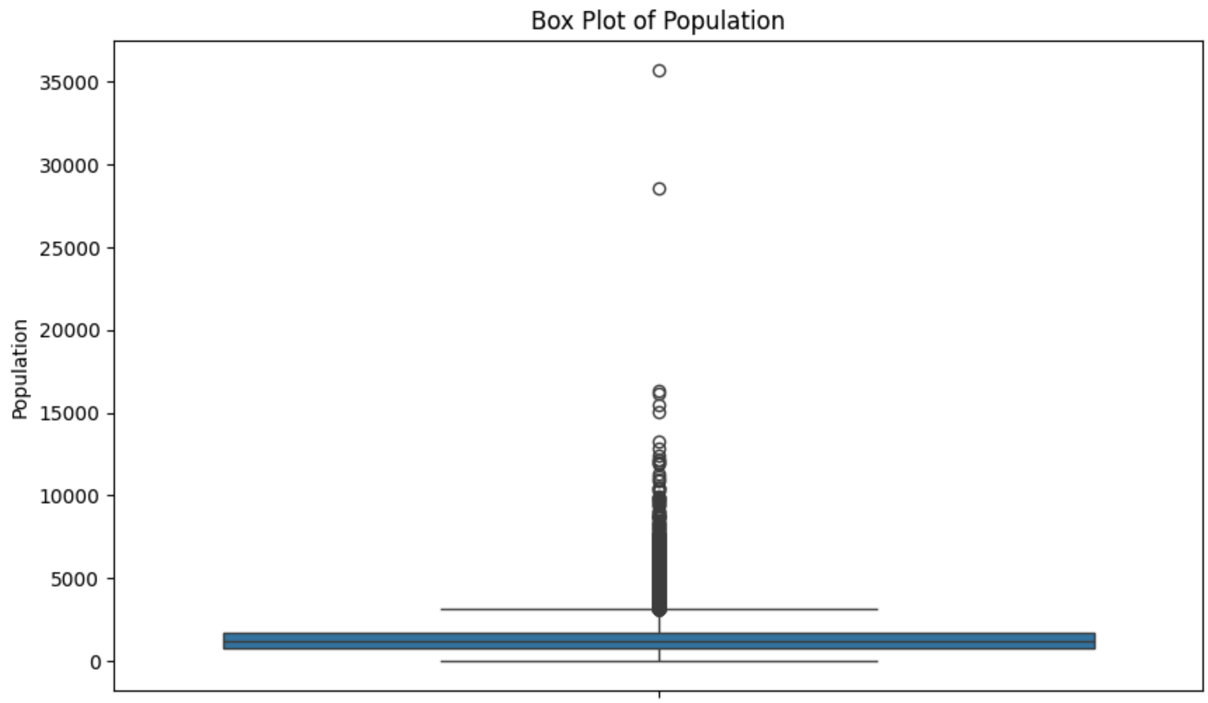


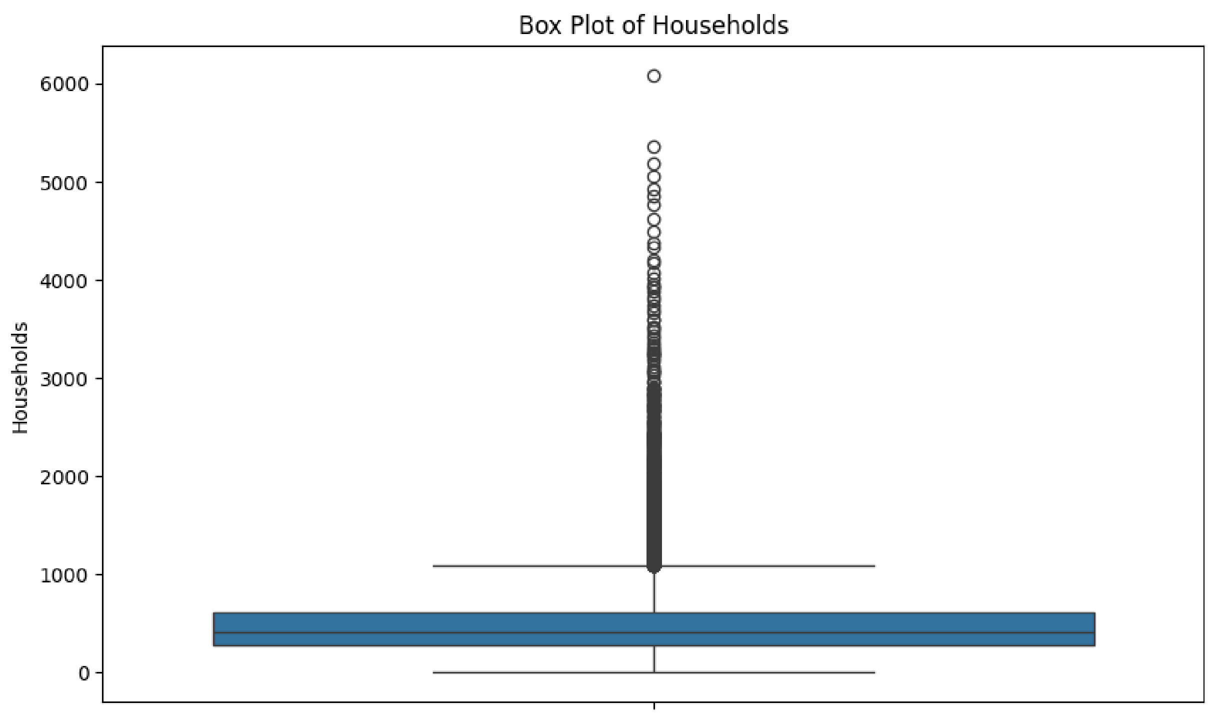

Box Plot of Median_Income
Median_Income
0
2
4
6
8
10
12
14

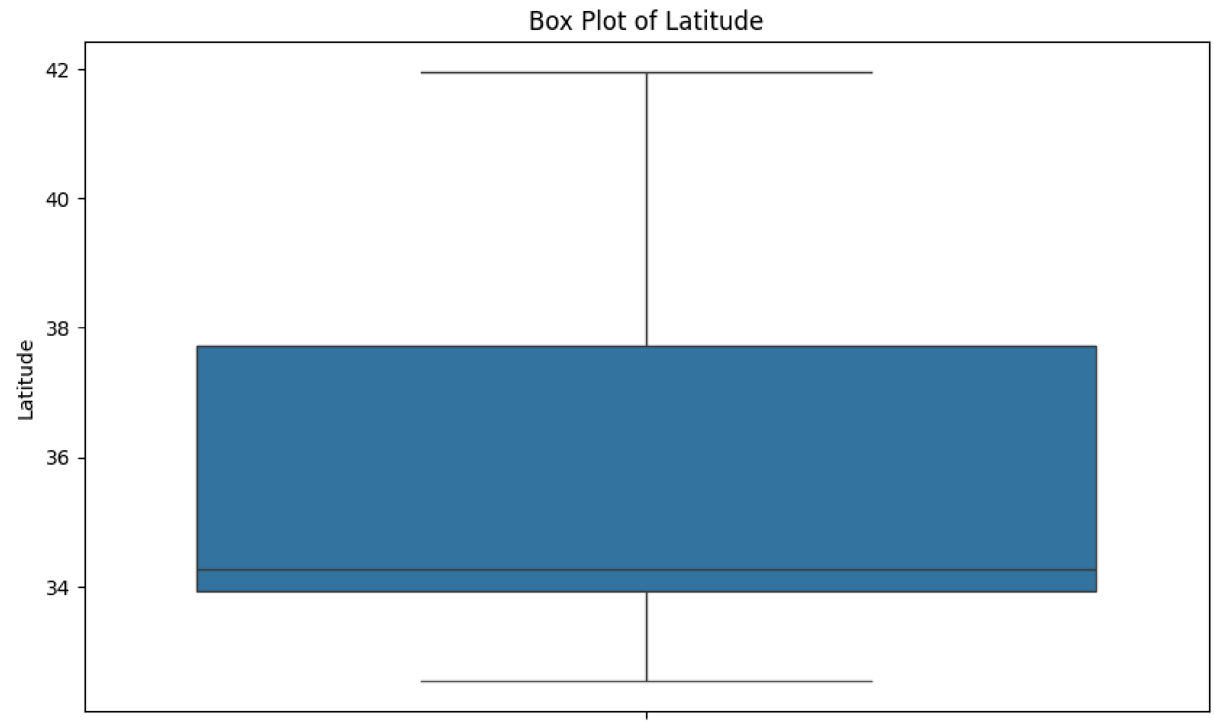

Box Plot of Median_Age
Median_Age
0
10
20
30
40
50

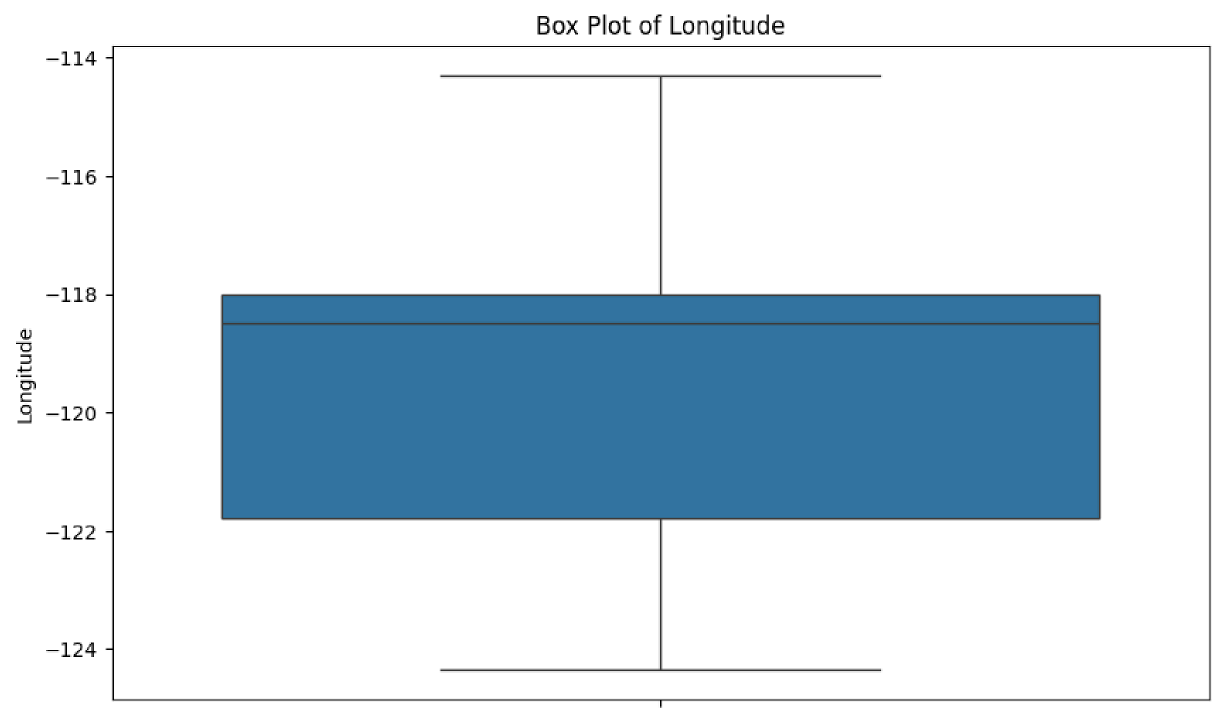

Box Plot of Tot_Rooms
Tot_Rooms
40000
35000
30000
25000
20000
15000
10000
5000
0

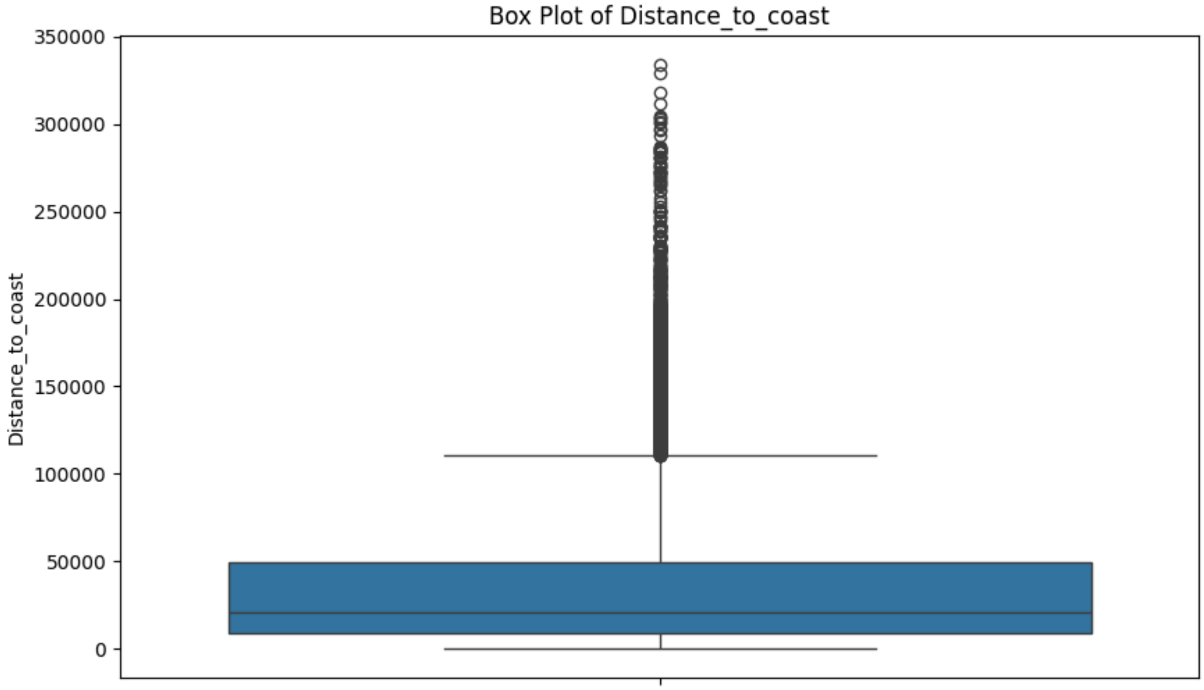

Box Plot of Tot_Bedrooms
Tot_Bedrooms
6000
5000
4000
3000
2000
1000
0

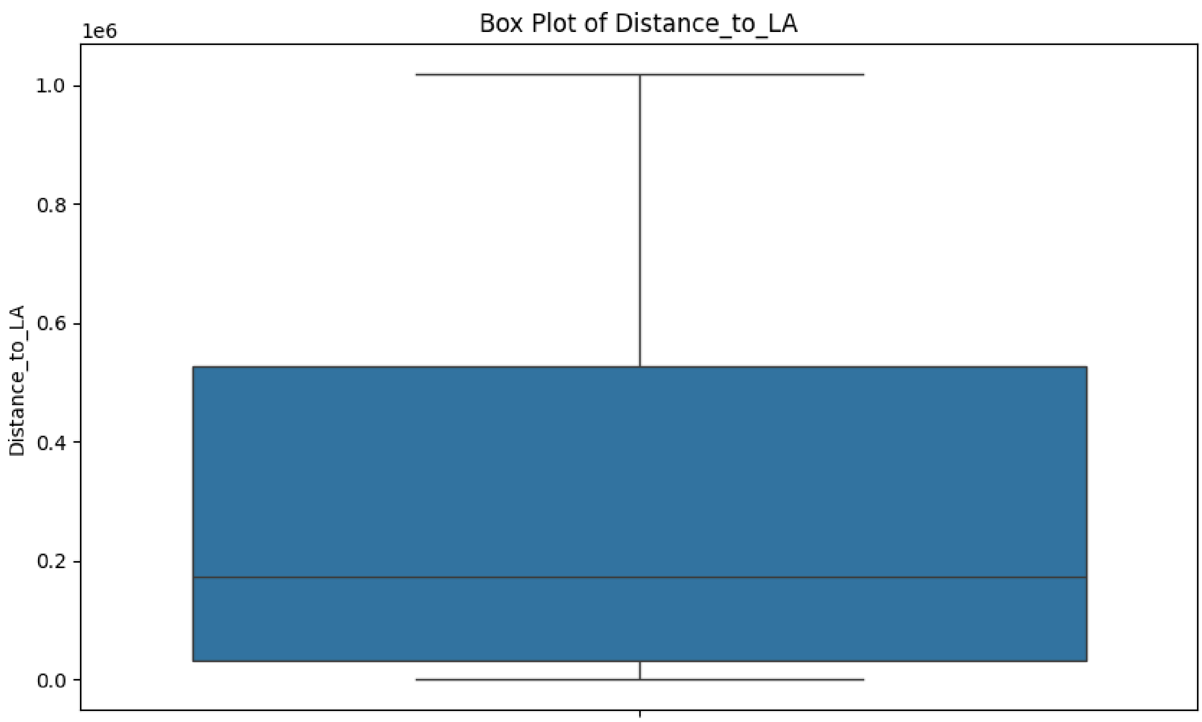

Box Plot of Population
Population
35000
30000
25000
20000
15000
10000
5000
0

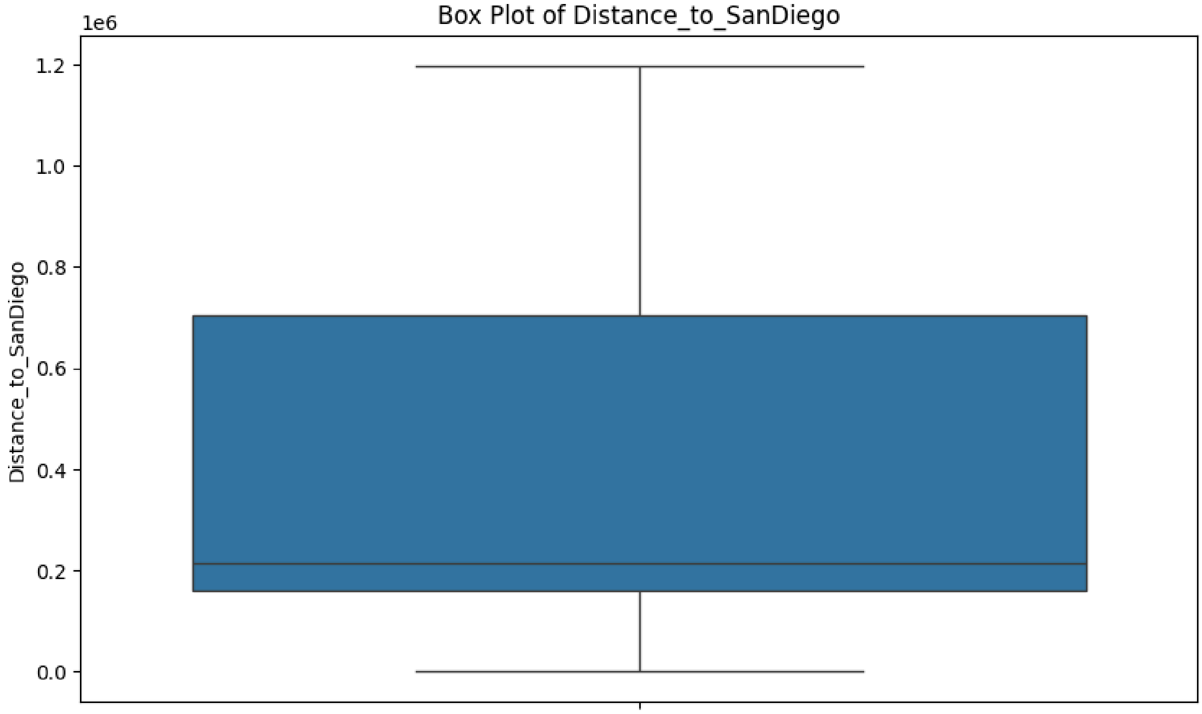

Box Plot of Households
Households
6000
5000
4000
3000
2000
1000
0

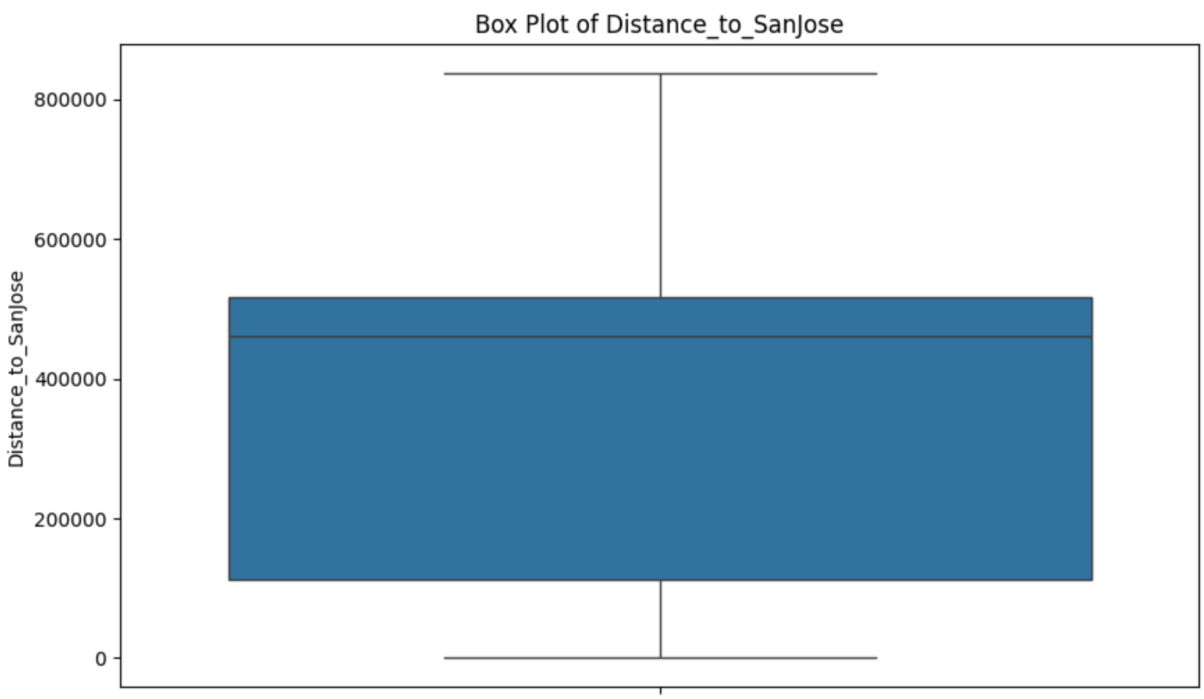

Box Plot of Latitude
Latitude
42
40
38
36
34

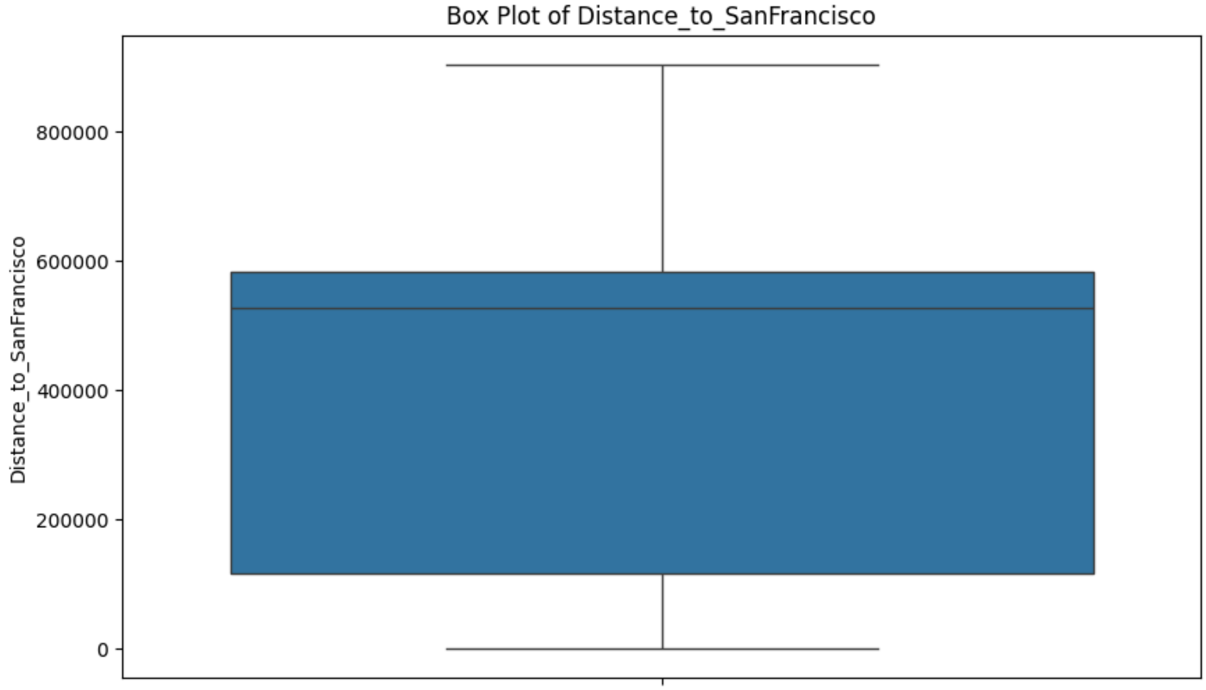

Box Plot of Longitude
Longitude
−114
−116
−118
−120
−122
−124


Box Plot of Distance_to_coast
Distance_to_coast
350000
300000
250000
200000
150000
100000
50000
0


Box Plot of Distance_to_LA
1e6
Distance_to_LA
1.0
0.8
0.6
0.4
0.2
0.0


Box Plot of Distance_to_SanDiego
1e6
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Distance_to_SanDiego


Box Plot of Distance_to_SanJose
800000
600000
400000
200000
0
Distance_to_SanJose



Reduce the outliers to perform a better model

In [23]:
```
def remove_outliers(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]
```

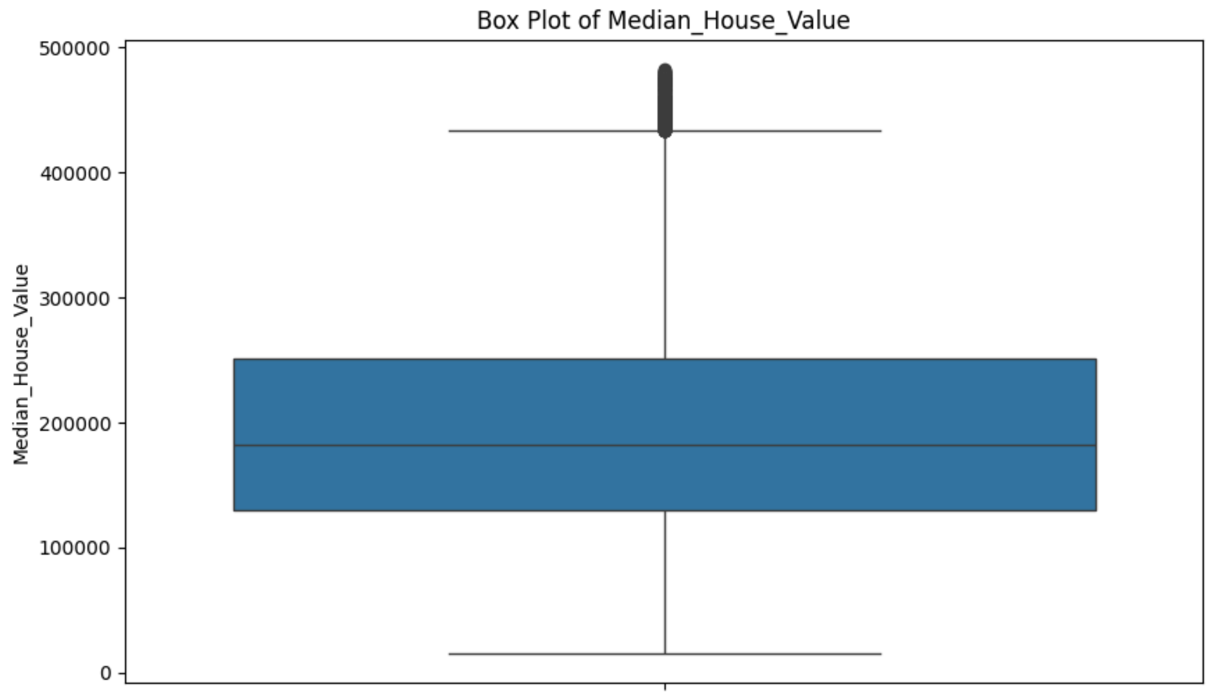
In [24]:
```
outlier_counts_list = []

for column in house_data.columns:
    count = remove_outliers(house_data, column).shape[0]
    outlier_counts_list.append({'Feature': column, 'Outlier Count': count})

outlier_counts = pd.DataFrame(outlier_counts_list)

outlier_counts
```

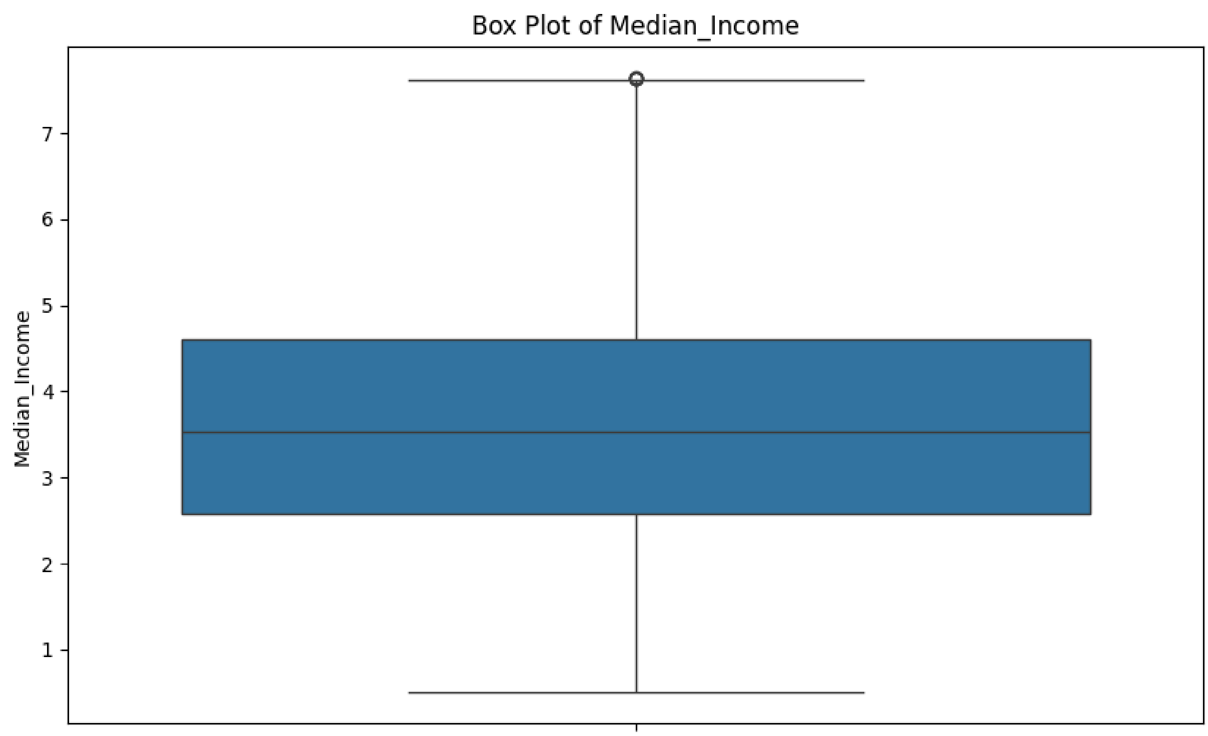
Out[24]:

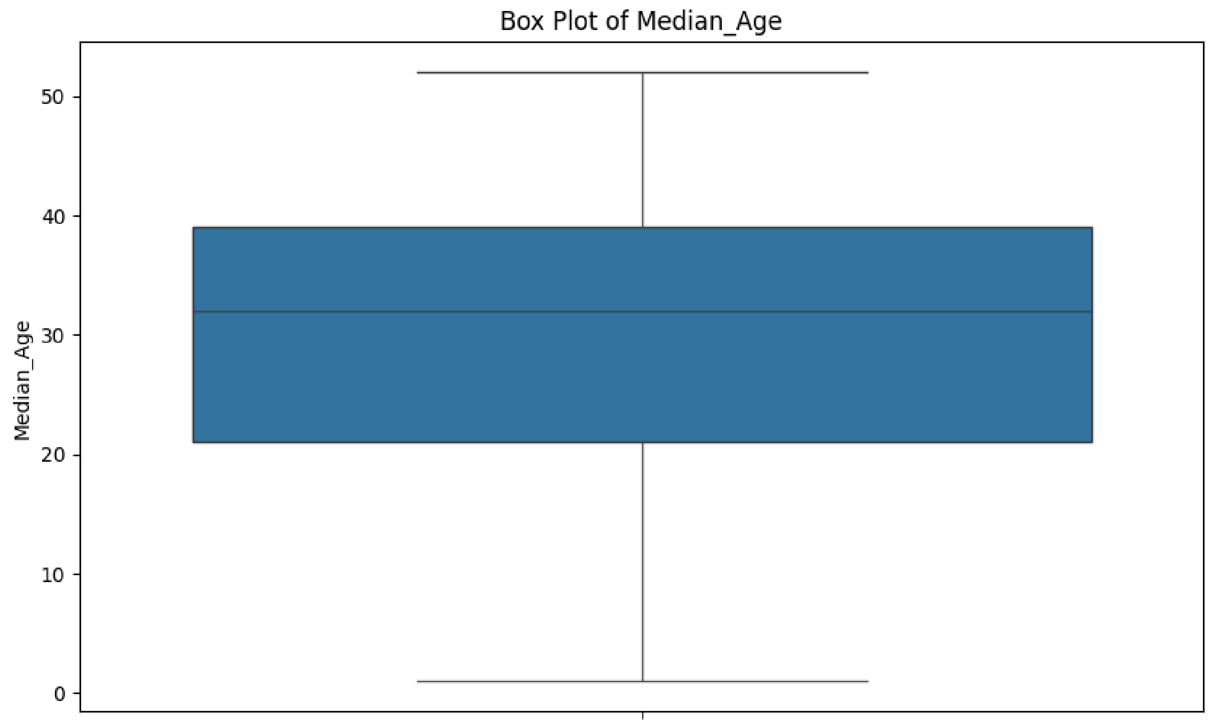
	Feature	Outlier Count
0	Median_House_Value	19569
1	Median_Income	19959
2	Median_Age	20640
3	Tot_Rooms	19353
4	Tot_Bedrooms	19358
5	Population	19444
6	Households	19420
7	Latitude	20640
8	Longitude	20640
9	Distance_to_coast	18264
10	Distance_to_LA	20640
11	Distance_to_SanDiego	20640
12	Distance_to_SanJose	20640
13	Distance_to_SanFrancisco	20640

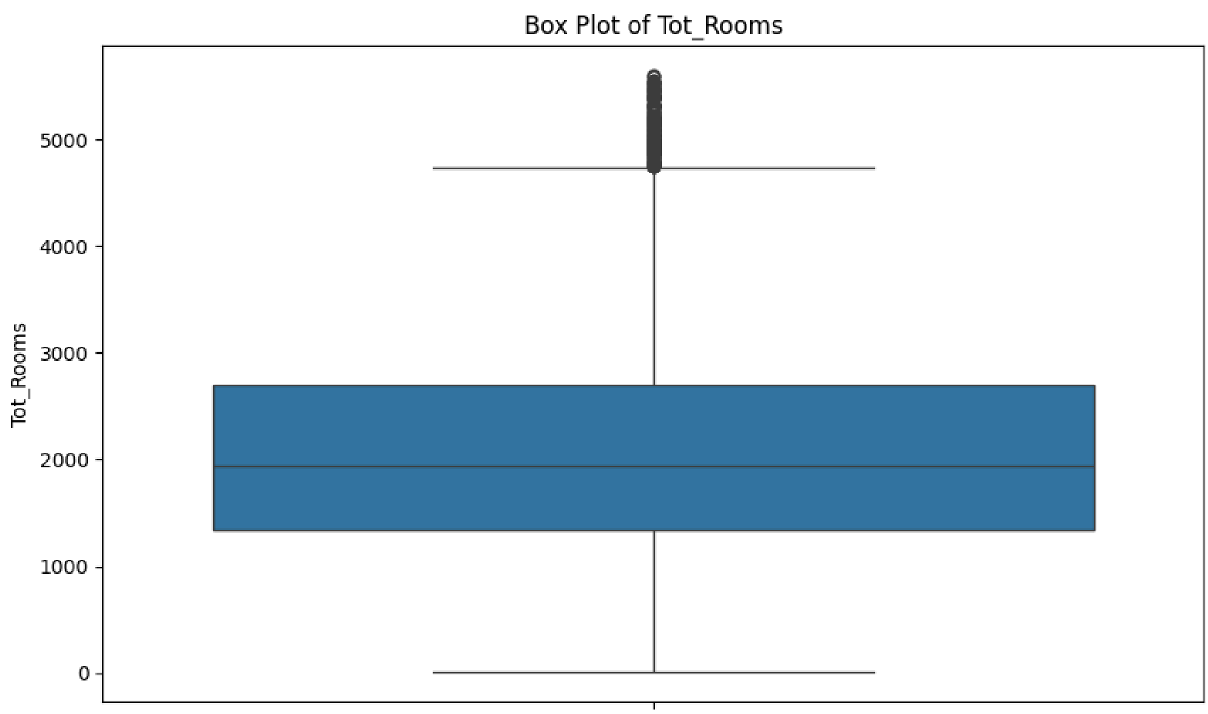
In [25]:

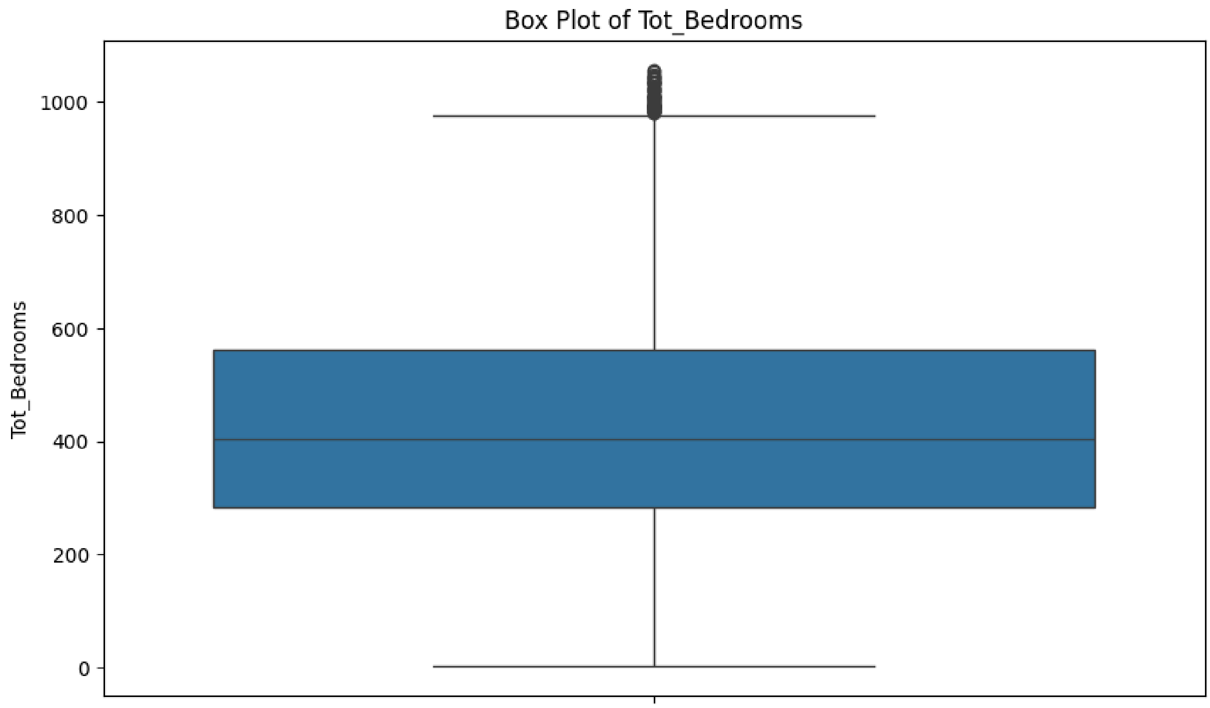
```
columns_to_clean = ['Median_House_Value', 'Median_Income', 'Tot_Rooms', 'Tot_Bedroo

for column in columns_to_clean:
    house_data = remove_outliers(house_data, column)

for column in house_data.columns:
    plt.figure(figsize=(10, 6))
    sns.boxplot(y=house_data[column])
    plt.title(f'Box Plot of {column}')
    plt.ylabel(column)
    plt.show()
```

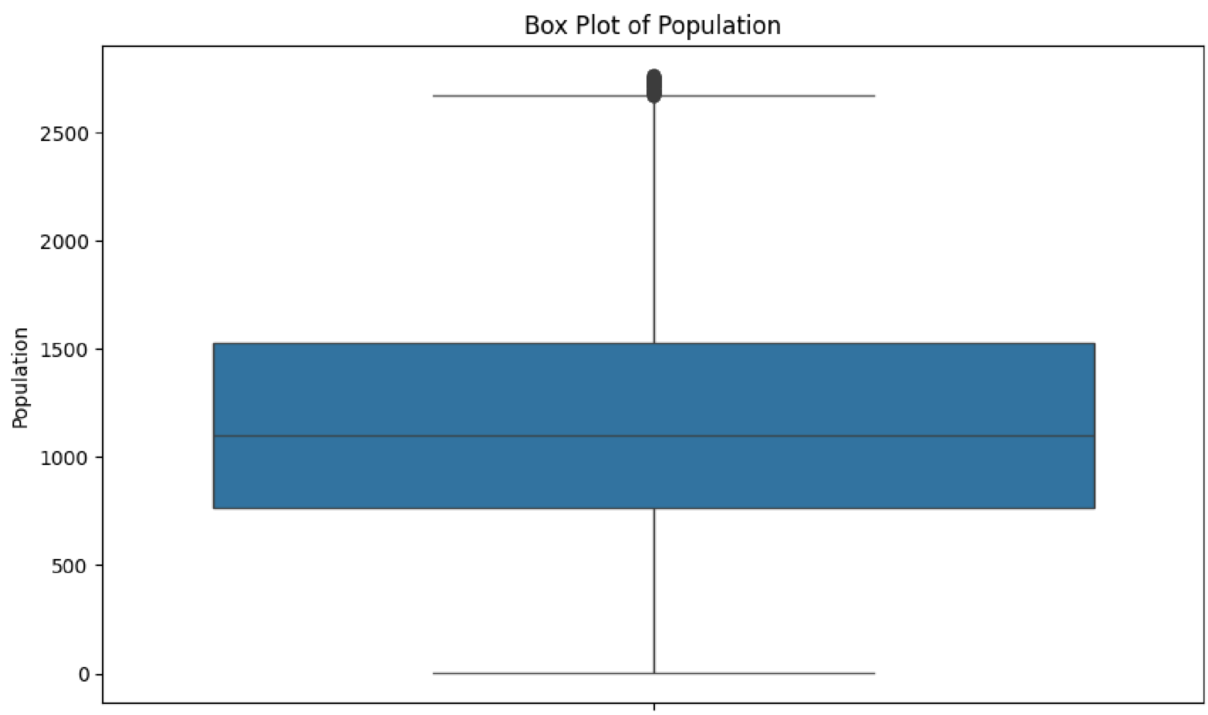

Box Plot of Median_House_Value
Median_House_Value
500000
400000
300000
200000
100000
0

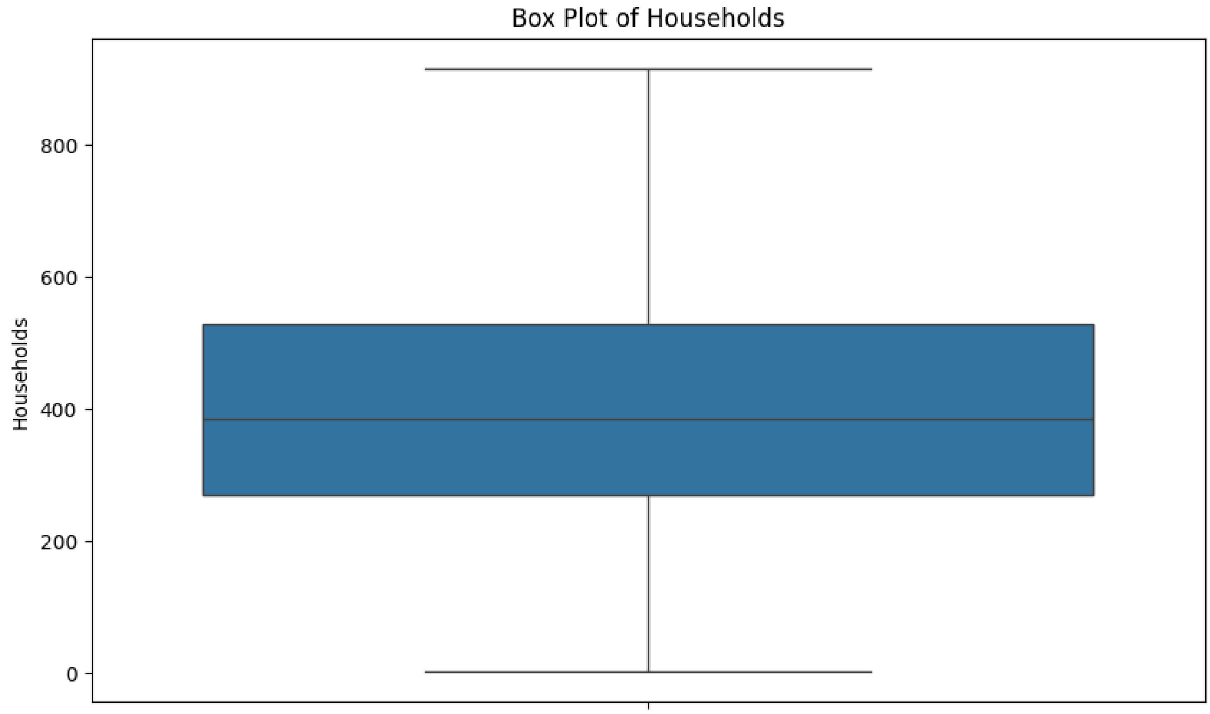

Box Plot of Median_Income
Median_Income
7
6
5
4
3
2
1

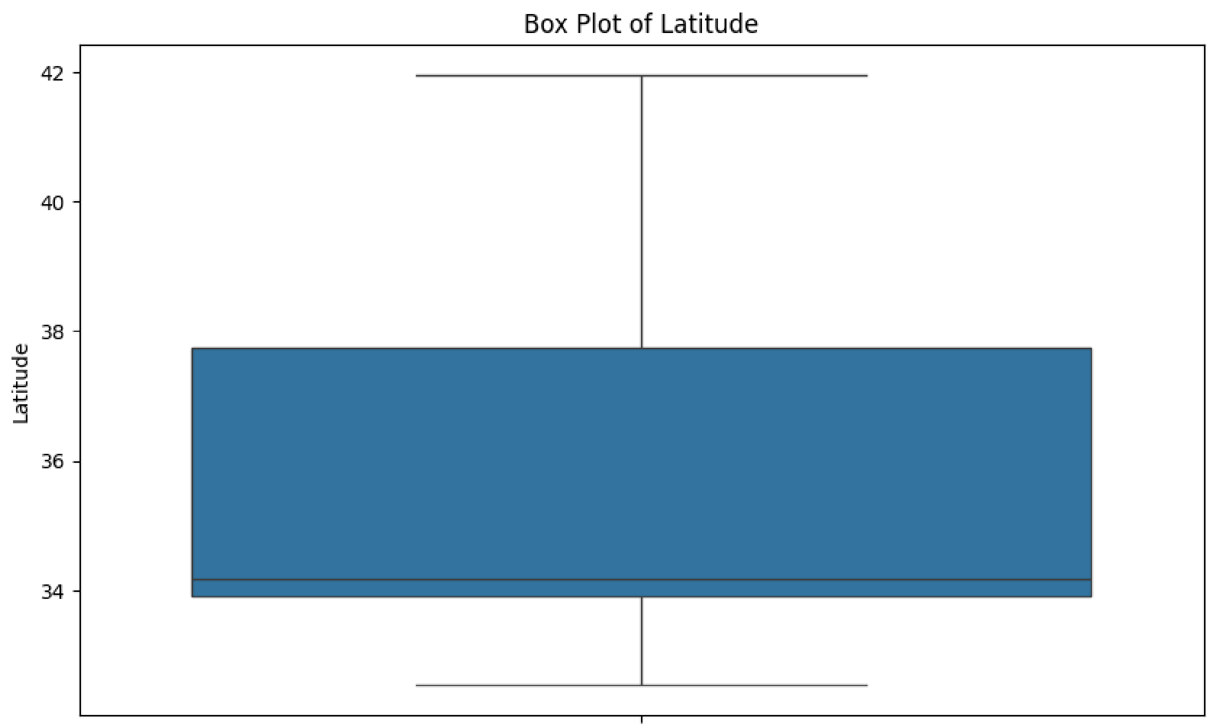

Box Plot of Median_Age
Median_Age
0
10
20
30
40
50

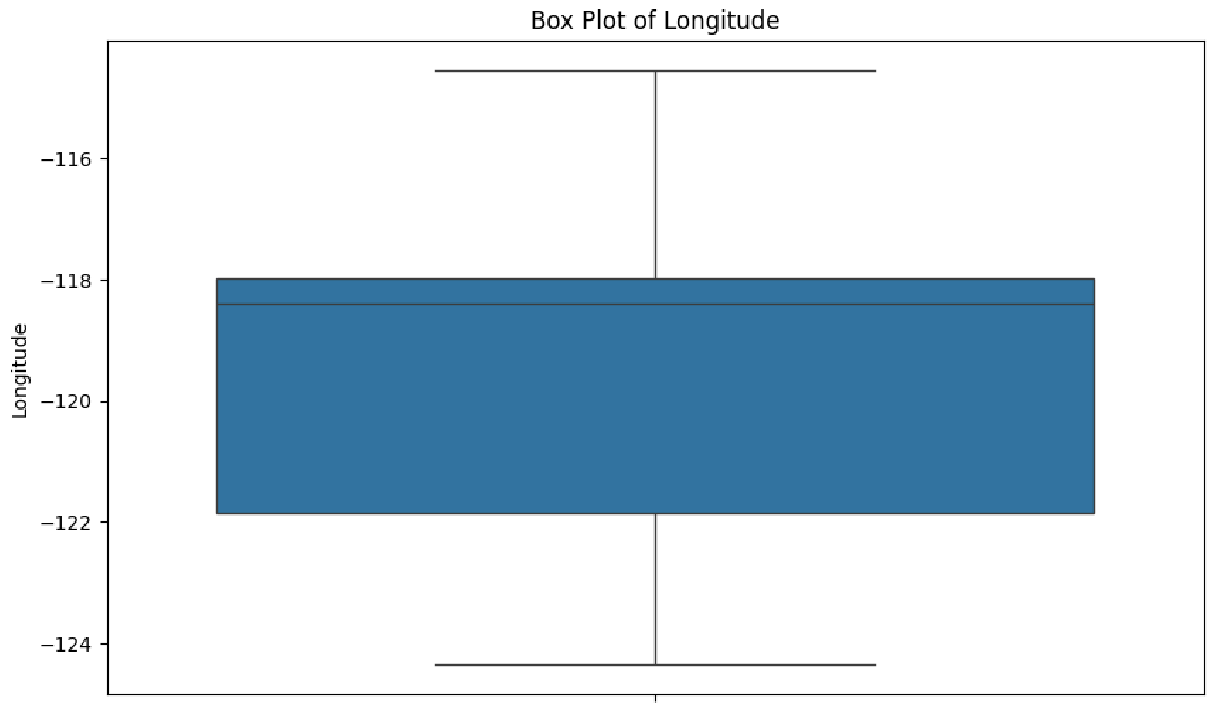

Box Plot of Tot_Rooms
Tot_Rooms
0
1000
2000
3000
4000
5000

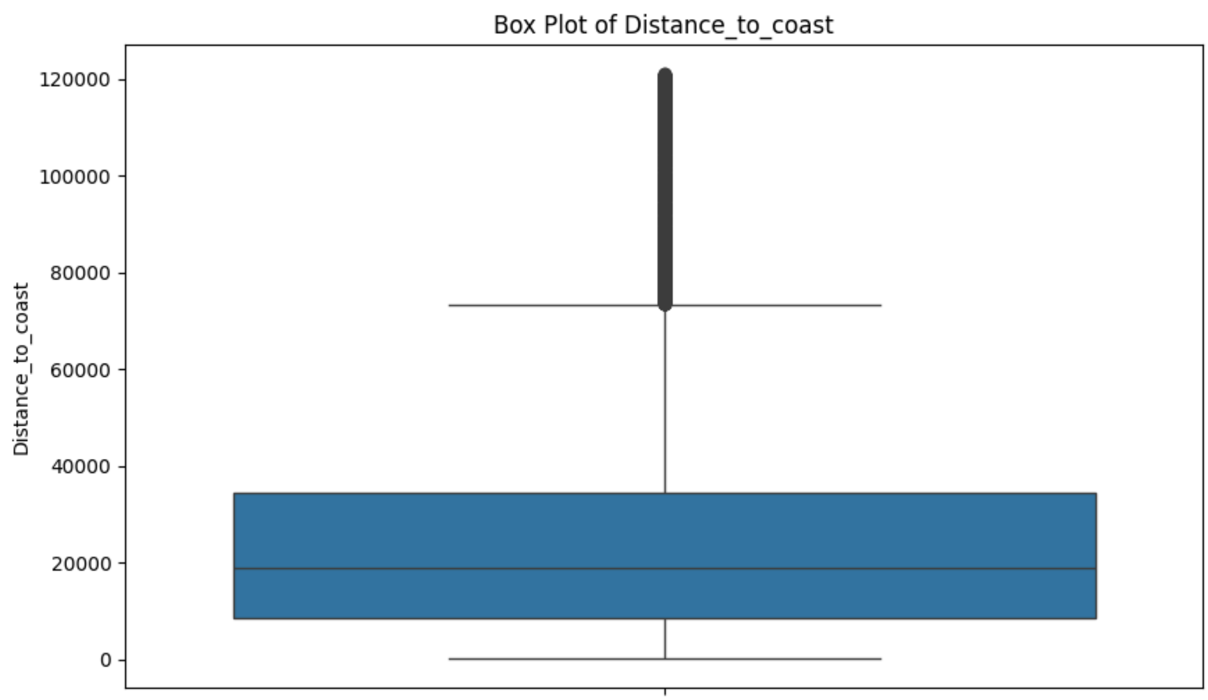

Box Plot of Tot_Bedrooms
Tot_Bedrooms
0
200
400
600
800
1000

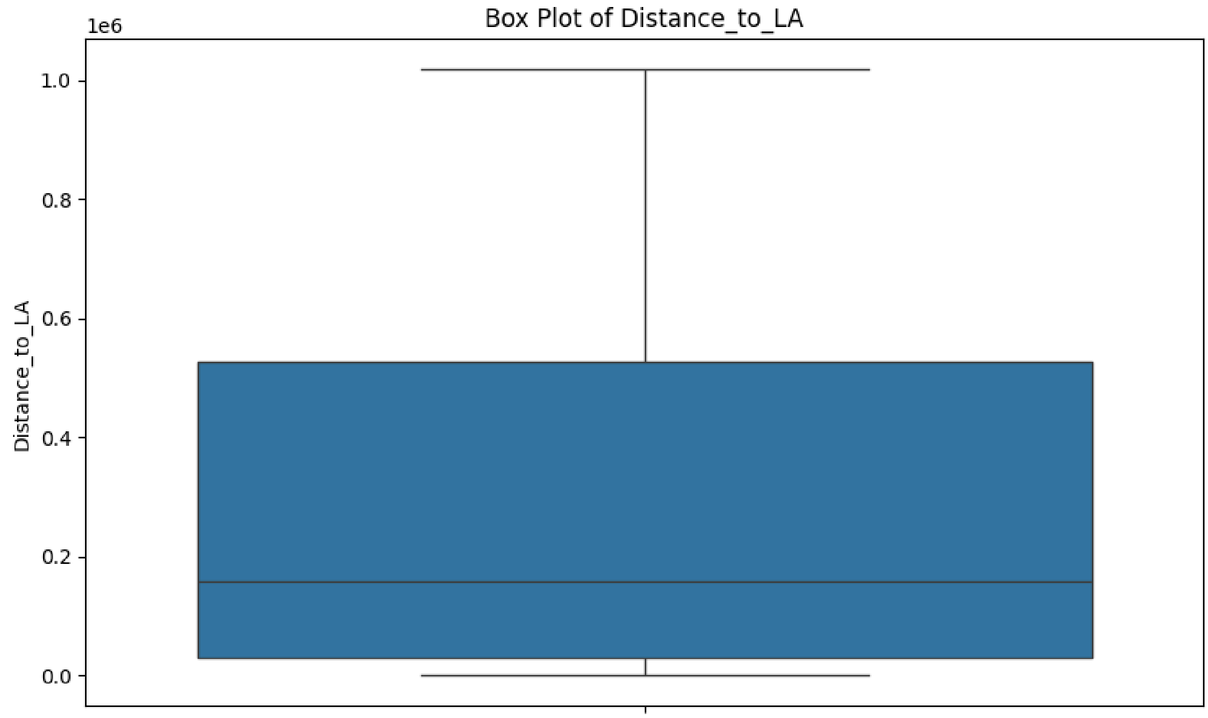

Box Plot of Population
Population
0
500
1000
1500
2000
2500

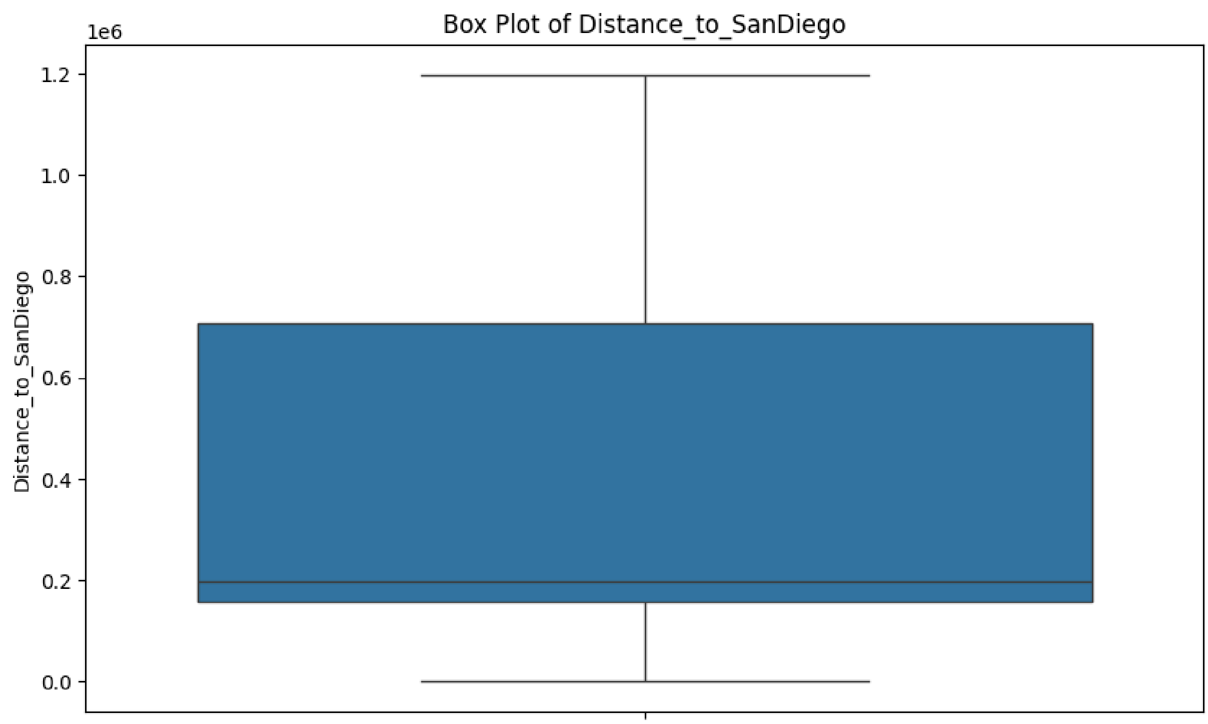

Box Plot of Households
Households
800
600
400
200
0

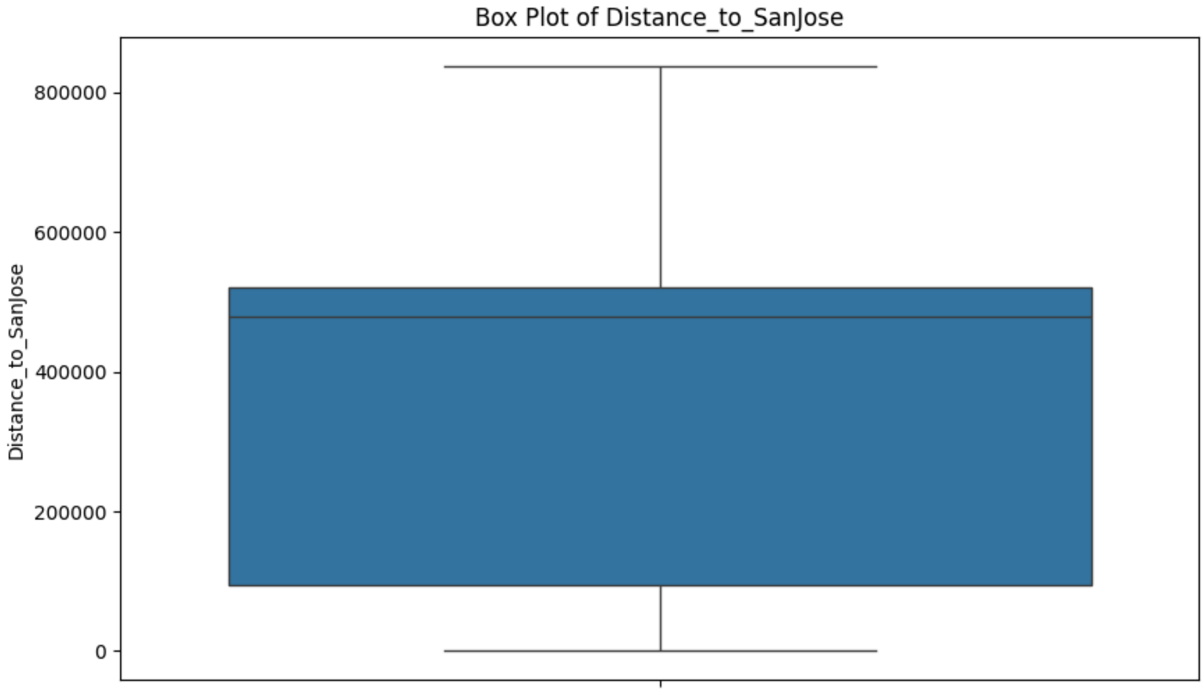

Box Plot of Latitude
Latitude
42
40
38
36
34

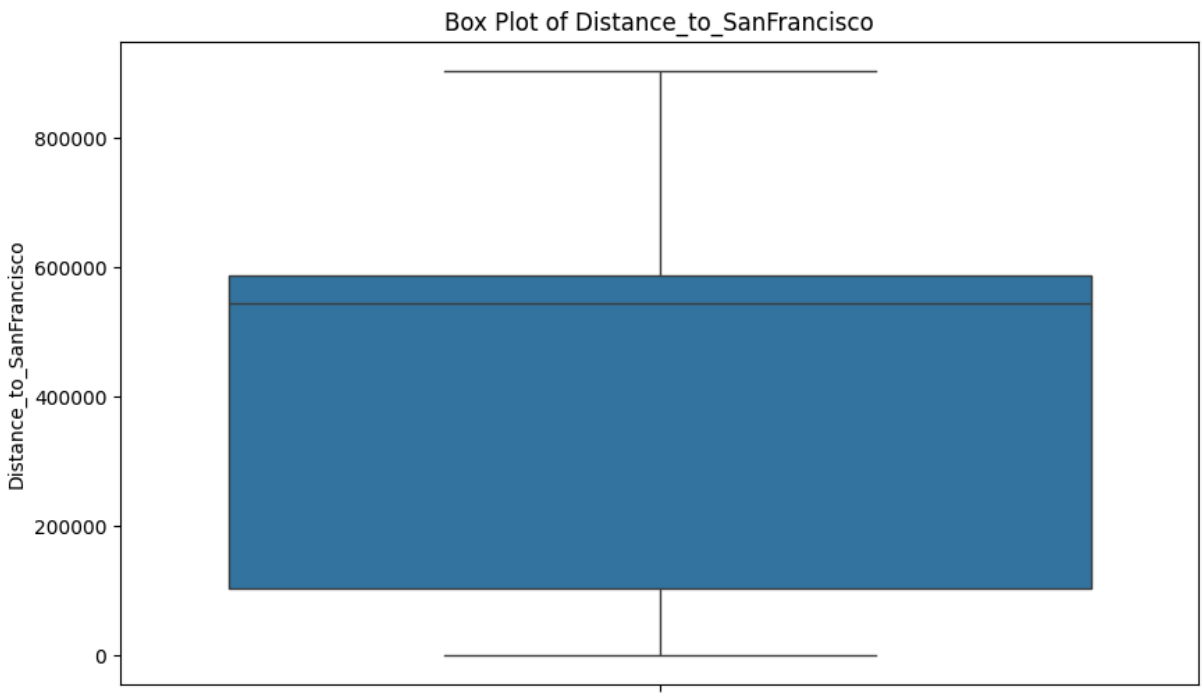

Box Plot of Longitude
Longitude
−116
−118
−120
−122
−124


Box Plot of Distance_to_coast
Distance_to_coast
120000
100000
80000
60000
40000
20000
0


Box Plot of Distance_to_LA
1e6
1.0
0.8
0.6
0.4
0.2
0.0
Distance_to_LA


Box Plot of Distance_to_SanDiego
1e6
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Distance_to_SanDiego



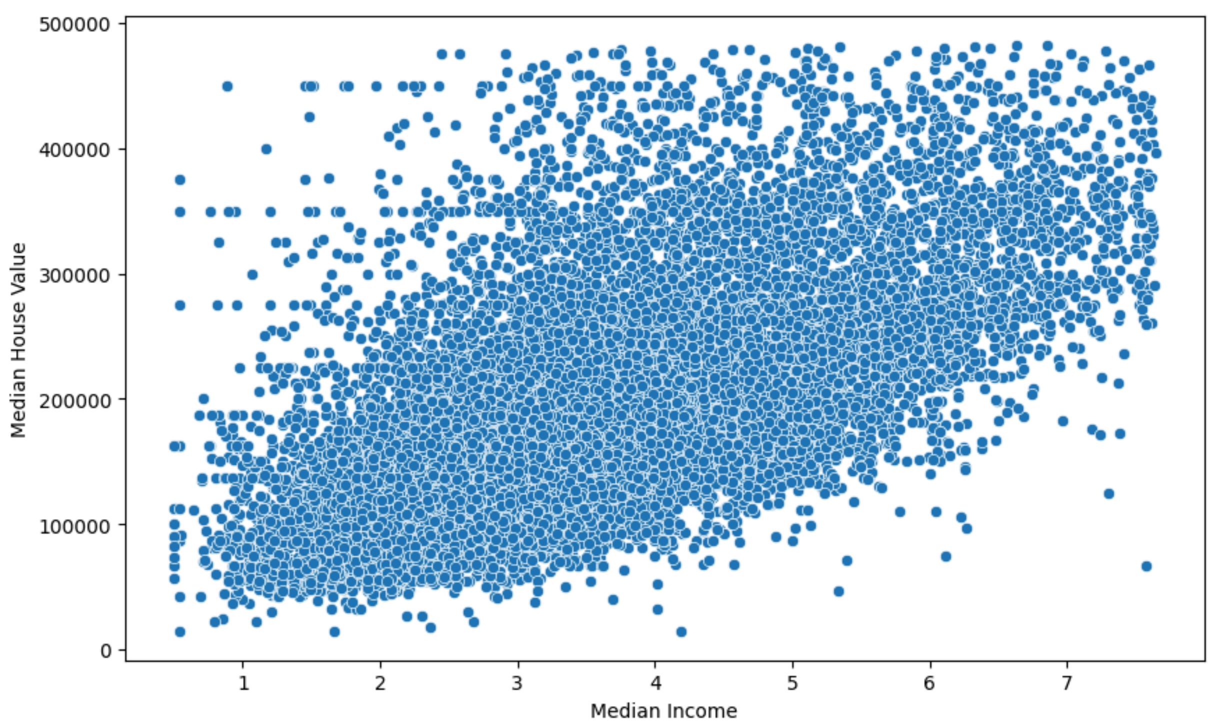


In [26]:
```
outlier_counts_list = []

for column in house_data.columns:
    count = remove_outliers(house_data, column).shape[0]
    outlier_counts_list.append({'Feature': column, 'Outlier Count': count})

outlier_counts = pd.DataFrame(outlier_counts_list)

outlier_counts
```

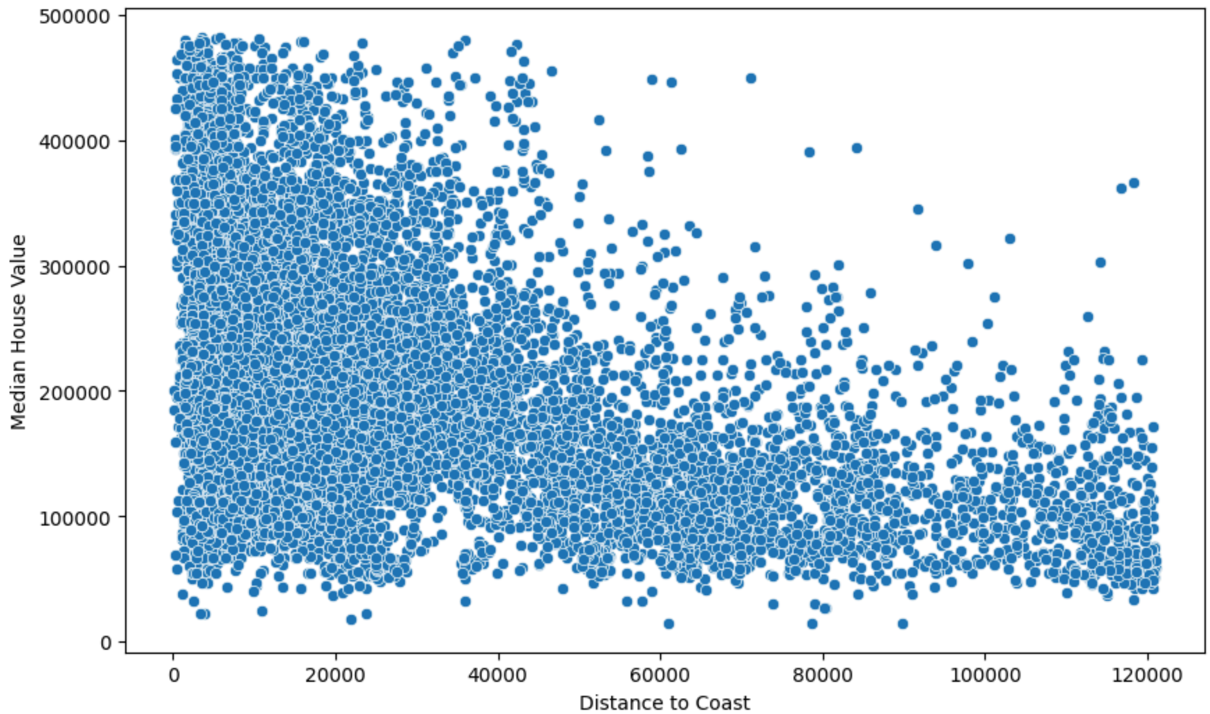
Out[26]:

	Feature	Outlier Count
0	Median_House_Value	14841
1	Median_Income	15081
2	Median_Age	15086
3	Tot_Rooms	14874
4	Tot_Bedrooms	15031
5	Population	15017
6	Households	15086
7	Latitude	15086
8	Longitude	15086
9	Distance_to_coast	13781
10	Distance_to_LA	15086
11	Distance_to_SanDiego	15086
12	Distance_to_SanJose	15086
13	Distance_to_SanFrancisco	15086

In [27]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(data=house_data, x='Median_Income', y='Median_House_Value')
plt.xlabel('Median Income')
plt.ylabel('Median House Value')
plt.show()
```



In [28]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(data=house_data, x='Distance_to_coast', y='Median_House_Value')
plt.xlabel('Distance to Coast')
plt.ylabel('Median House Value')
plt.show()
```



In [29]:
```
X = house_data.drop('Median_House_Value', axis=1)
y = house_data['Median_House_Value']

X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3, random_sta
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, rand
```

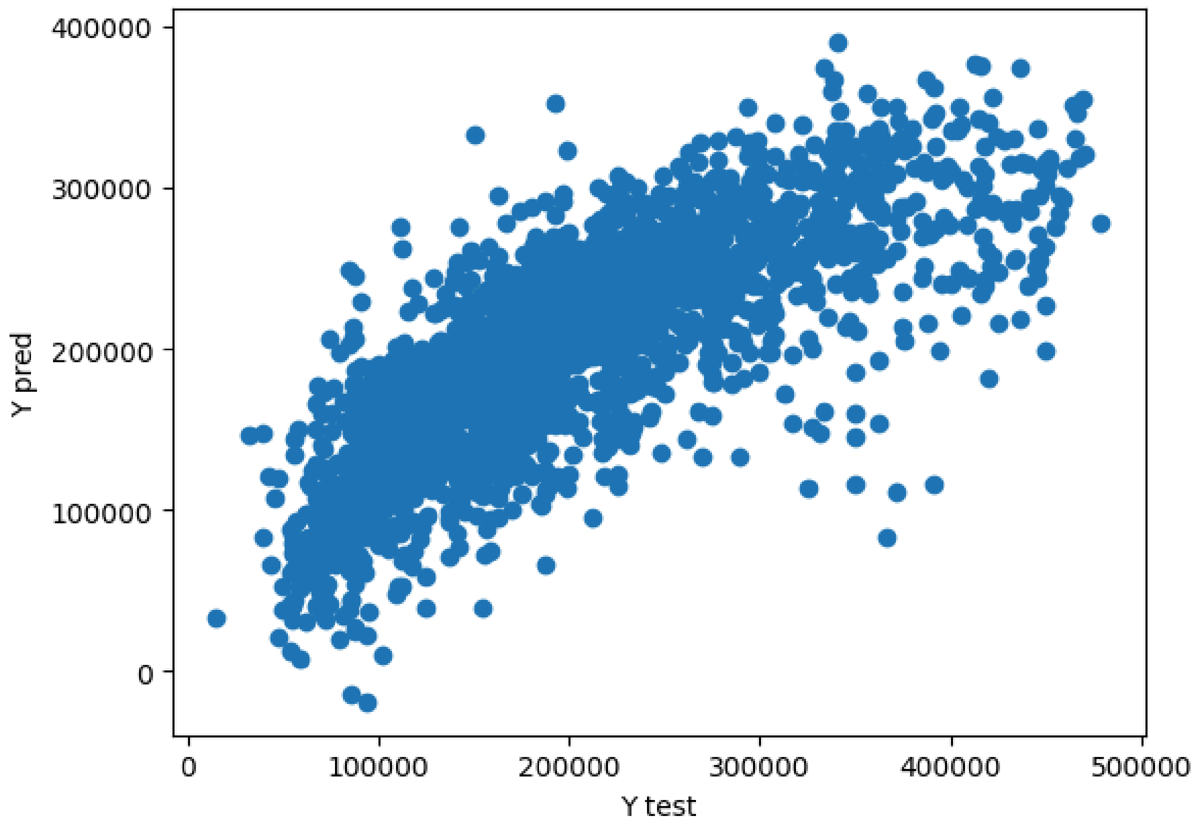
In [30]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
X_val_scaled = scaler.transform(X_val)
```

In [31]:
```
lr = LinearRegression()
lr.fit(X_train_scaled,y_train)
```

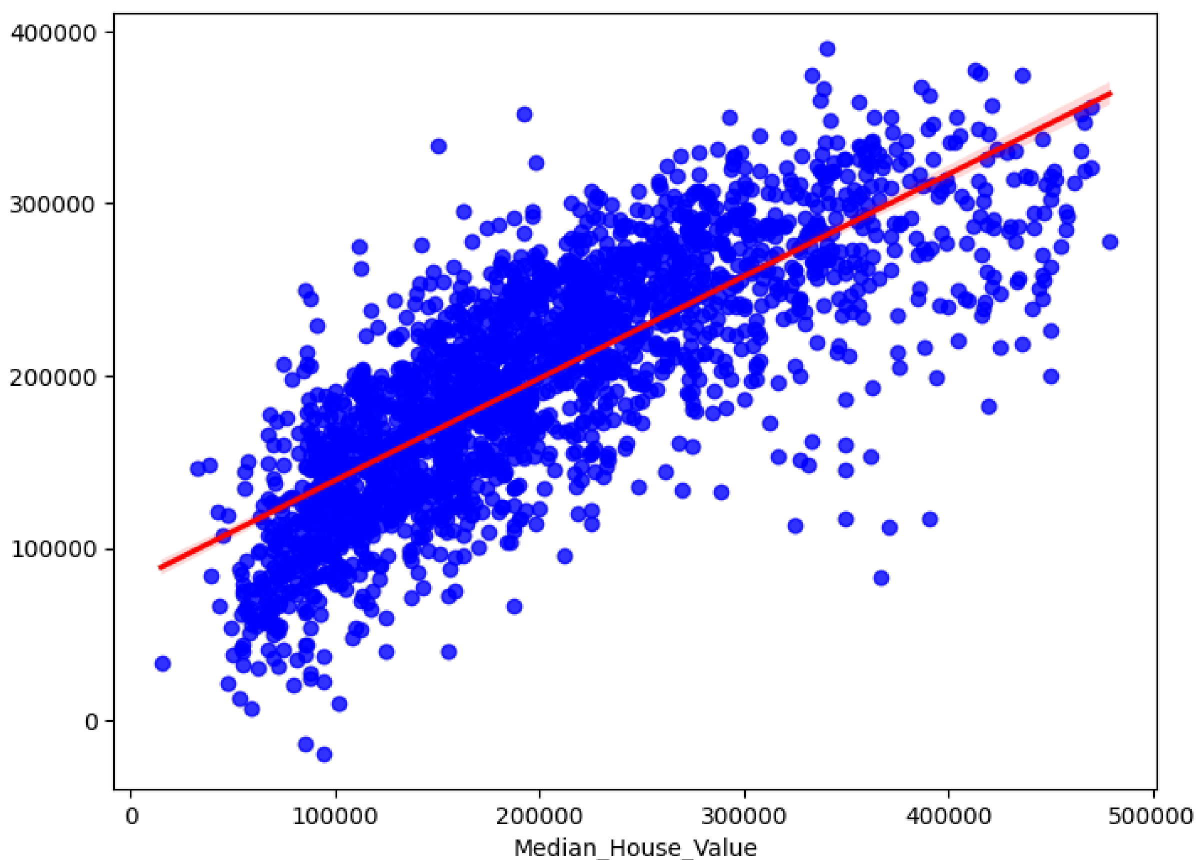
Out[31]:
```
▾ LinearRegression
LinearRegression()
```

In [32]:
```
y_pred_lr = lr.predict(X_test_scaled)
```

In [33]:
```
plt.scatter(y_test,y_pred_lr)
plt.xlabel('Y test')
plt.ylabel('Y pred')
plt.show()
```



In [34]:
```
plt.figure(figsize=(8, 6))
sns.regplot(x=y_test, y=y_pred_lr, scatter_kws={'color': 'blue'}, line_kws={'color'
plt.show()
```



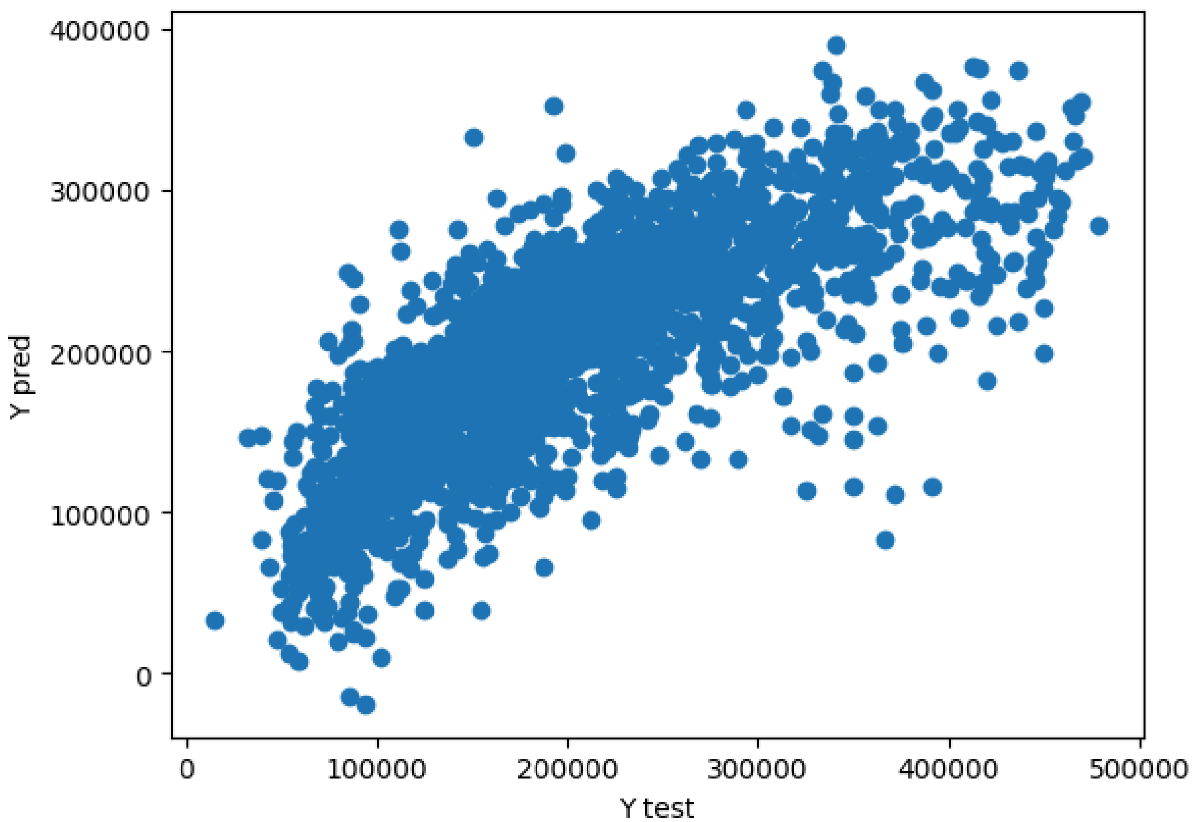
In [50]:
```
lasso = Lasso(alpha=0.4)
lasso.fit(X_train_scaled, y_train)
```

```
C:\Users\Kimo Store\AppData\Roaming\Python\Python312\site-packages\sklearn\linear_mo
del\_coordinate_descent.py:697: ConvergenceWarning: Objective did not converge. You
might want to increase the number of iterations, check the scale of the features or
consider increasing regularisation. Duality gap: 1.286e+13, tolerance: 8.674e+09
  model = cd_fast.enet_coordinate_descent(
```

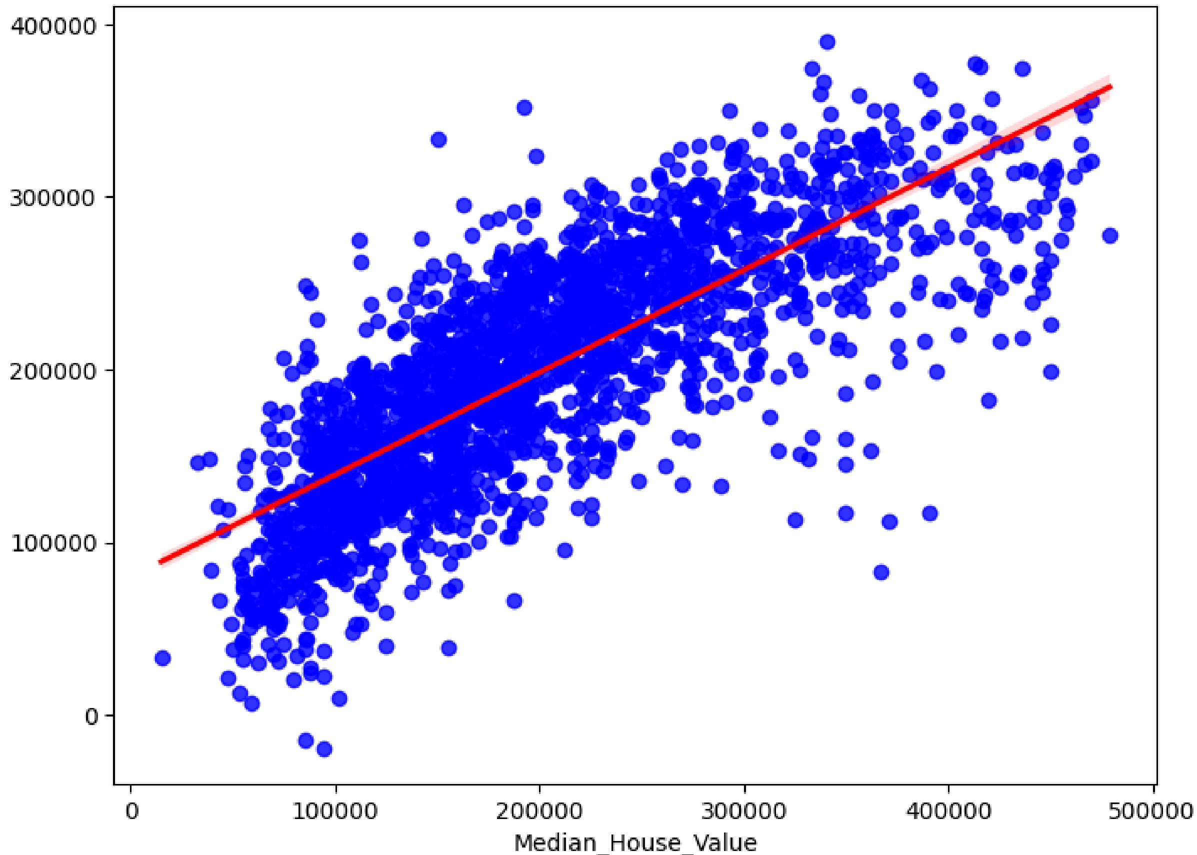
Out[50]:
```
▾ Lasso
Lasso(alpha=0.4)
```

In [51]:
```
y_pred_lasso = lasso.predict(X_test_scaled)
```

In [52]:
```
plt.scatter(y_test,y_pred_lasso)
plt.xlabel('Y test')
plt.ylabel('Y pred')
plt.show()
```



In [53]:
```
plt.figure(figsize=(8, 6))
sns.regplot(x=y_test, y=y_pred_lasso, scatter_kws={'color': 'blue'}, line_kws={'col
plt.show()
```

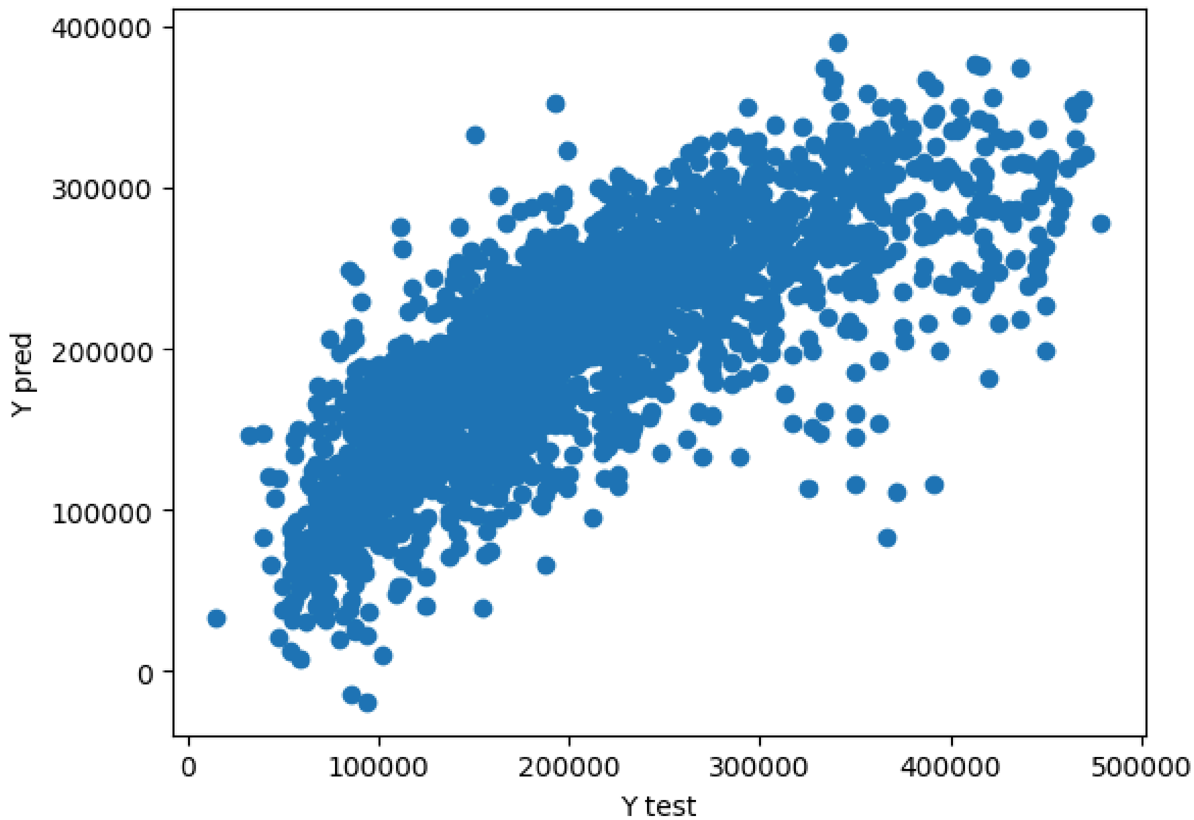


In [54]:
```
ridge = Ridge(alpha=0.4)
ridge.fit(X_train_scaled, y_train)
```

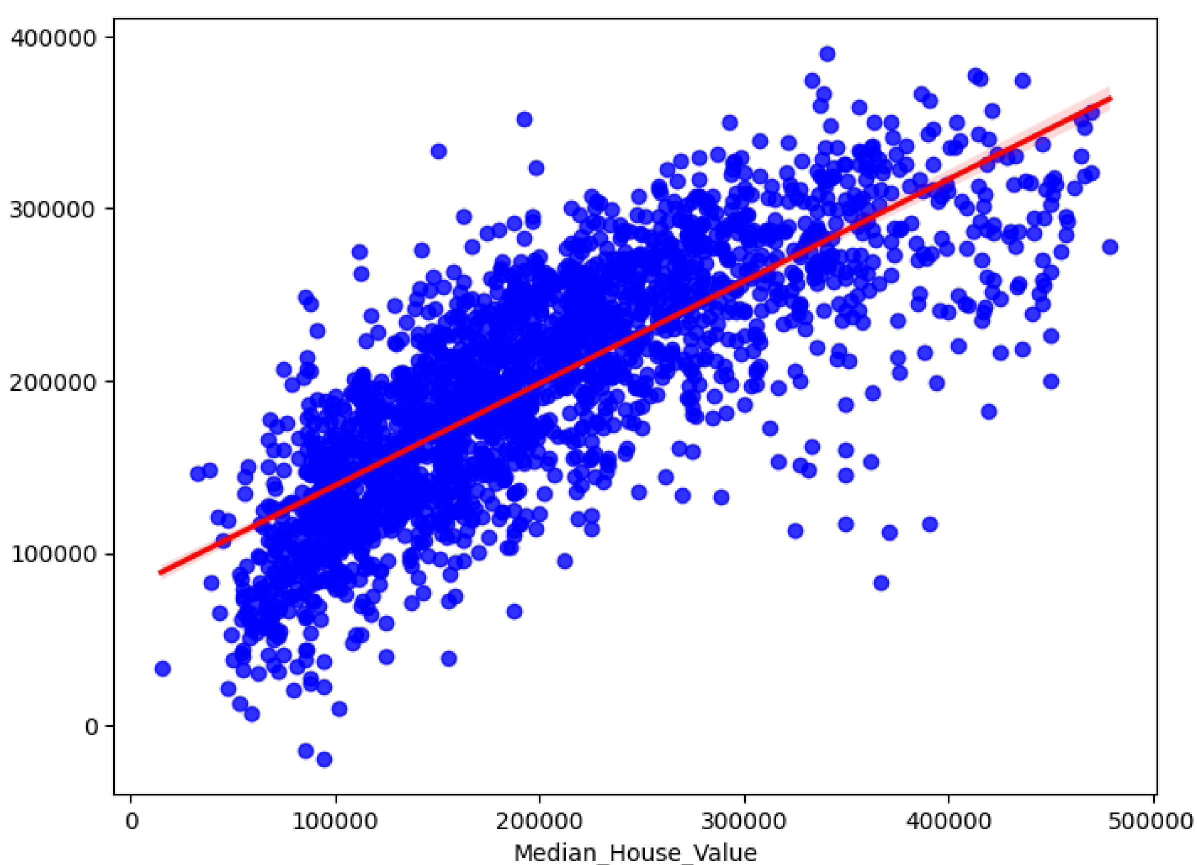
Out[54]:
```
Ridge
Ridge(alpha=0.4)
```

In [55]:
```
y_pred_ridge = ridge.predict(X_test_scaled)
```

In [56]:
```
plt.scatter(y_test,y_pred_ridge)
plt.xlabel('Y test')
plt.ylabel('Y pred')
plt.show()
```



In [57]:
```
plt.figure(figsize=(8, 6))
sns.regplot(x=y_test, y=y_pred_ridge, scatter_kws={'color': 'blue'}, line_kws={'col
plt.show()
```



In [58]:
```
mae_lr = mean_absolute_error(y_test, y_pred_lr)
mse_lr = mean_squared_error(y_test,y_pred_lr)
mae_lasso = mean_absolute_error(y_test, y_pred_lasso)
mse_lasso = mean_squared_error(y_test,y_pred_lasso)
mae_ridge = mean_absolute_error(y_test, y_pred_ridge)
mse_ridge = mean_squared_error(y_test,y_pred_ridge)
```

In [59]:
```
print('Mean Squared Error LR: ',mse_lr)
print('Mean Squared Error Lasso: ',mse_lasso)
print('Mean Squared Error Ridge: ',mse_ridge)
print('Mean absolute error LR: ', mae_lr)
print('Mean absolute error Lasso: ', mae_lasso)
print('Mean absolute error Ridge: ', mae_ridge)
```

```
Mean Squared Error LR:  3307228849.0476165
Mean Squared Error Lasso:  3307224286.6204267
Mean Squared Error Ridge:  3307279847.2781982
Mean absolute error LR:  42688.20200800906
Mean absolute error Lasso:  42689.38903502964
Mean absolute error Ridge:  42691.12100005777
```

In [60]:
```
r2_lr = r2_score(y_test,y_pred_lr)
r2_lasso = r2_score(y_test,y_pred_lasso)
r2_ridge = r2_score(y_test,y_pred_ridge)
print('R2 score LR: ',r2_lr)
print('R2 score Lasso: ',r2_lasso)
print('R2 score Ridge: ',r2_ridge)
```

```
R2 score LR:  0.6111302760884514
R2 score Lasso:  0.6111308125465807
R2 score Ridge:  0.6111242796277432
```

In [61]:
```
mape_lr = mean_absolute_percentage_error(y_test, y_pred_lr)
mspe_lr = np.mean(((y_test - y_pred_lr) / y_test) ** 2) * 100
mape_lasso = mean_absolute_percentage_error(y_test, y_pred_lasso)
mspe_lasso = np.mean(((y_test - y_pred_lasso) / y_test) ** 2) * 100
mape_ridge = mean_absolute_percentage_error(y_test, y_pred_ridge)
mspe_ridge = np.mean(((y_test - y_pred_ridge) / y_test) ** 2) * 100
```

In [62]:
```
print(f'MSPE_lr: {mspe_lr:.2f}%')
print(f'MAPE_lr: {mape_lr * 100:.2f}%')
print(f'MSPE_lasso: {mspe_lasso:.2f}%')
print(f'MAPE_lasso: {mape_lasso * 100:.2f}%')
print(f'MSPE_ridge: {mspe_ridge:.2f}%')
print(f'MAPE_ridge: {mape_ridge * 100:.2f}%')
```

```
MSPE_lr: 12.38%
MAPE_lr: 24.52%
MSPE_lasso: 12.37%
MAPE_lasso: 24.52%
MSPE_ridge: 12.37%
MAPE_ridge: 24.52%
```

we can say that Models used have approximatly the same mean absolute error and mean squared error

In [84]:
```
exclude_columns = [ 'Tot_Bedrooms', 'Population', 'Households']
X = house_data.drop(columns=exclude_columns + ['Median_House_Value'])
y = house_data['Median_House_Value']
```

In [85]:
```
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3, random_sta
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, rand
```

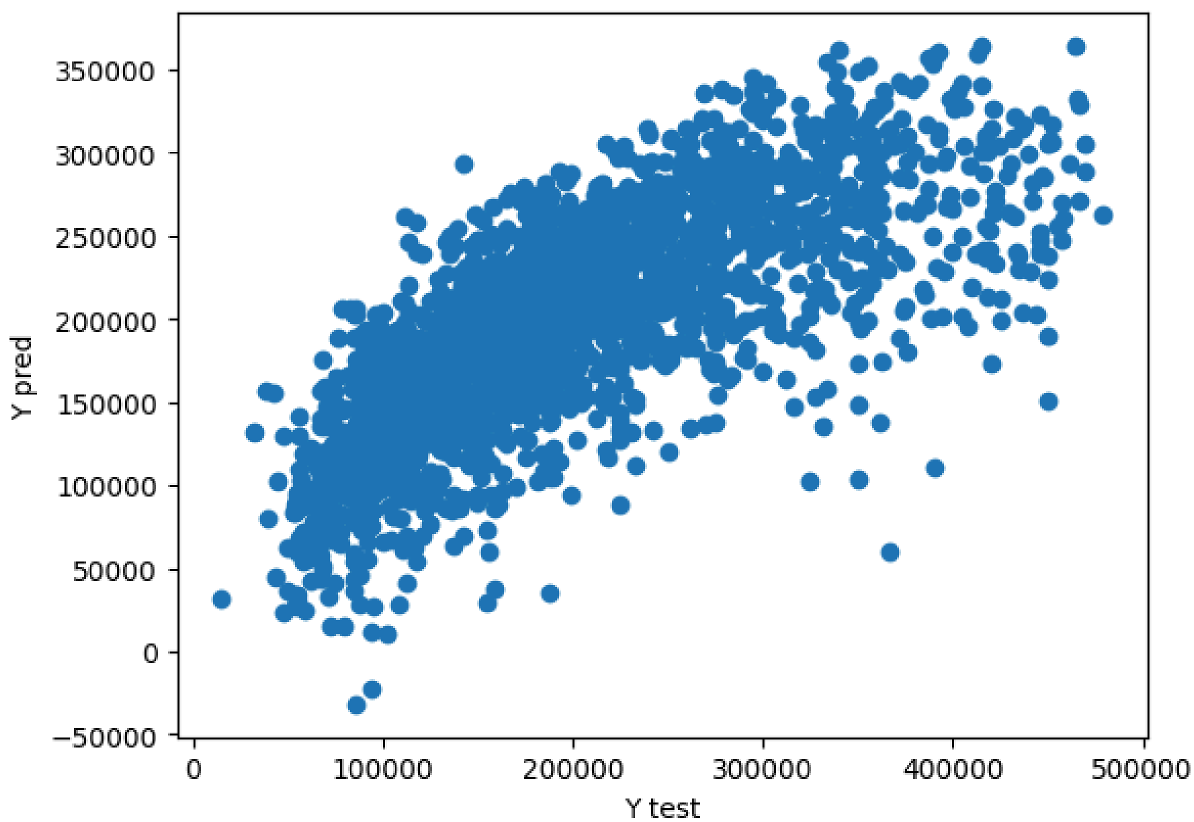
In [86]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
X_val_scaled = scaler.transform(X_val)
```

In [87]:
```
lr = LinearRegression()
lr.fit(X_train_scaled,y_train)
```

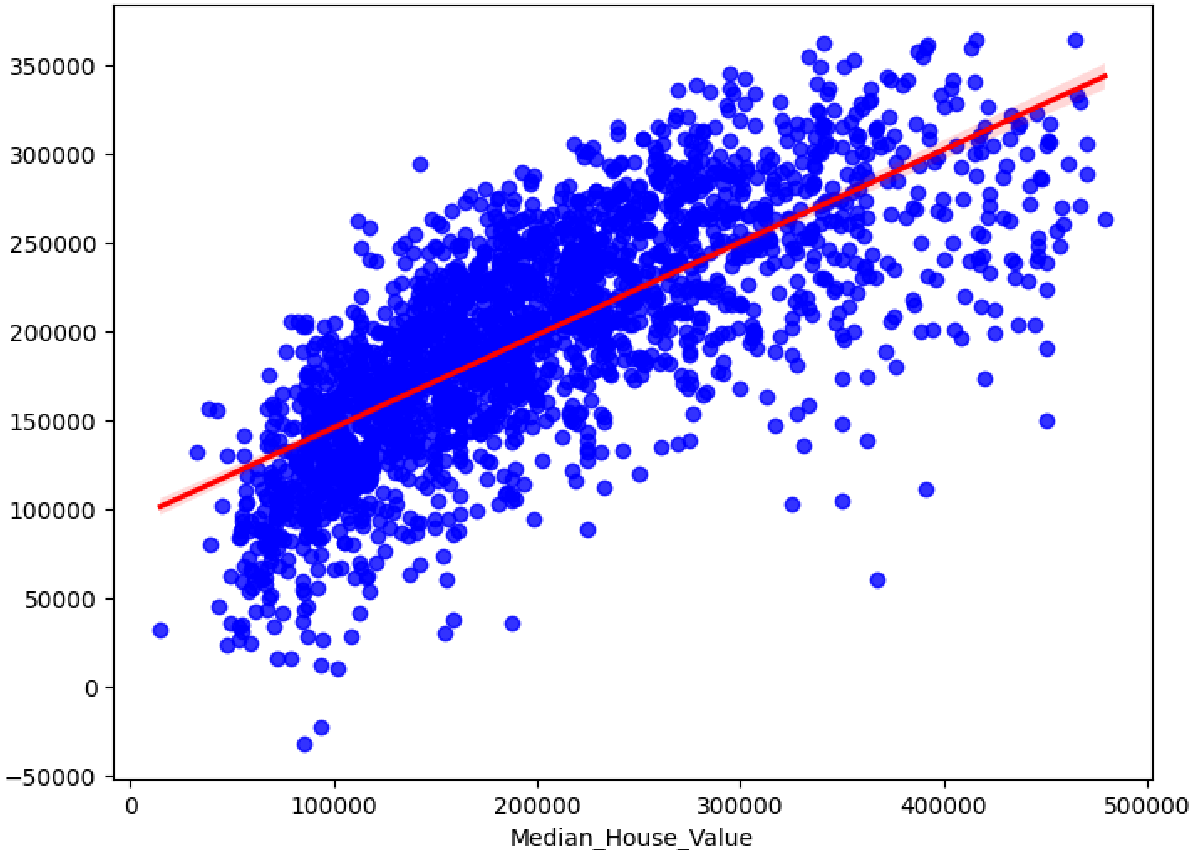
Out[87]:
```
▾ LinearRegression
LinearRegression()
```

In [88]:
```
y_pred_lr = lr.predict(X_test_scaled)
```

In [89]:
```
plt.scatter(y_test,y_pred_lr)
plt.xlabel('Y test')
plt.ylabel('Y pred')
plt.show()
```



In [90]:
```
plt.figure(figsize=(8, 6))
sns.regplot(x=y_test, y=y_pred_lr, scatter_kws={'color': 'blue'}, line_kws={'color'
plt.show()
```



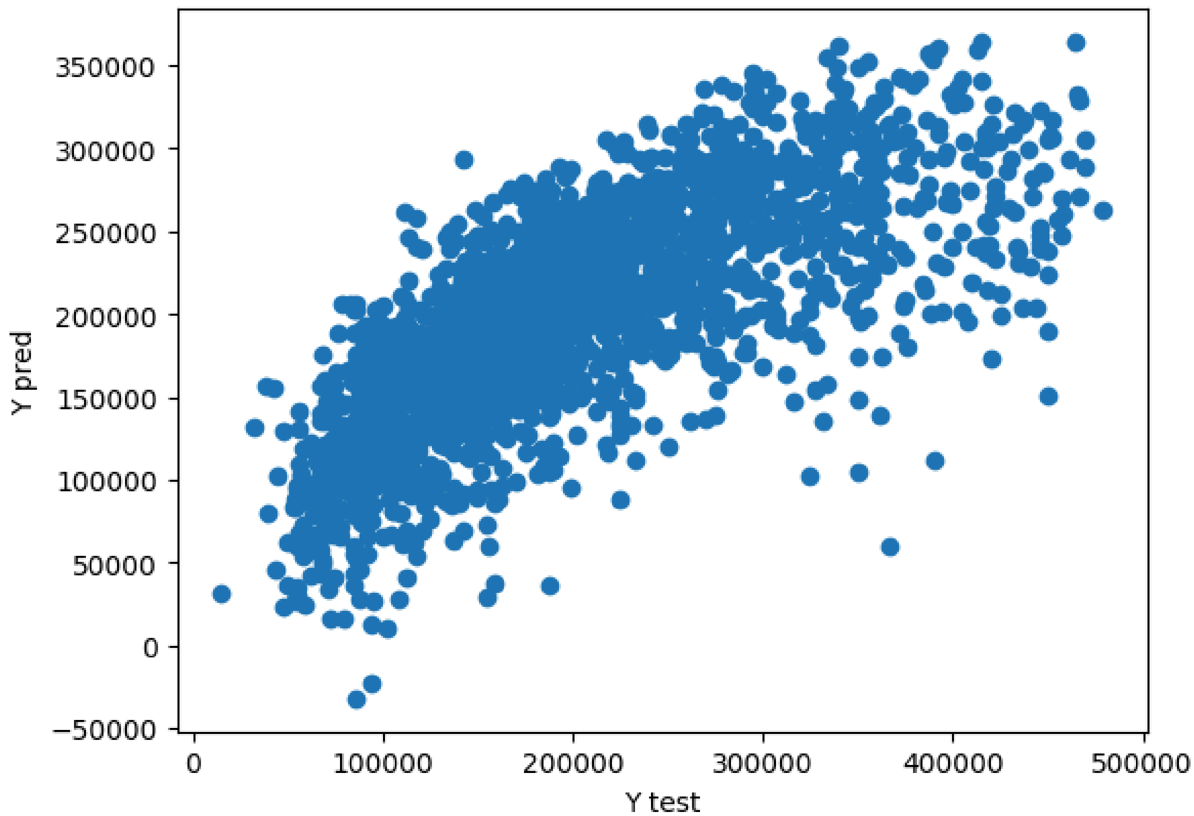
In [91]:
```
lasso = Lasso(alpha=0.4)
lasso.fit(X_train_scaled, y_train)
```

```
C:\Users\Kimo Store\AppData\Roaming\Python\Python312\site-packages\sklearn\linear_mo
del\_coordinate_descent.py:697: ConvergenceWarning: Objective did not converge. You
might want to increase the number of iterations, check the scale of the features or
consider increasing regularisation. Duality gap: 1.470e+13, tolerance: 8.674e+09
  model = cd_fast.enet_coordinate_descent(
```

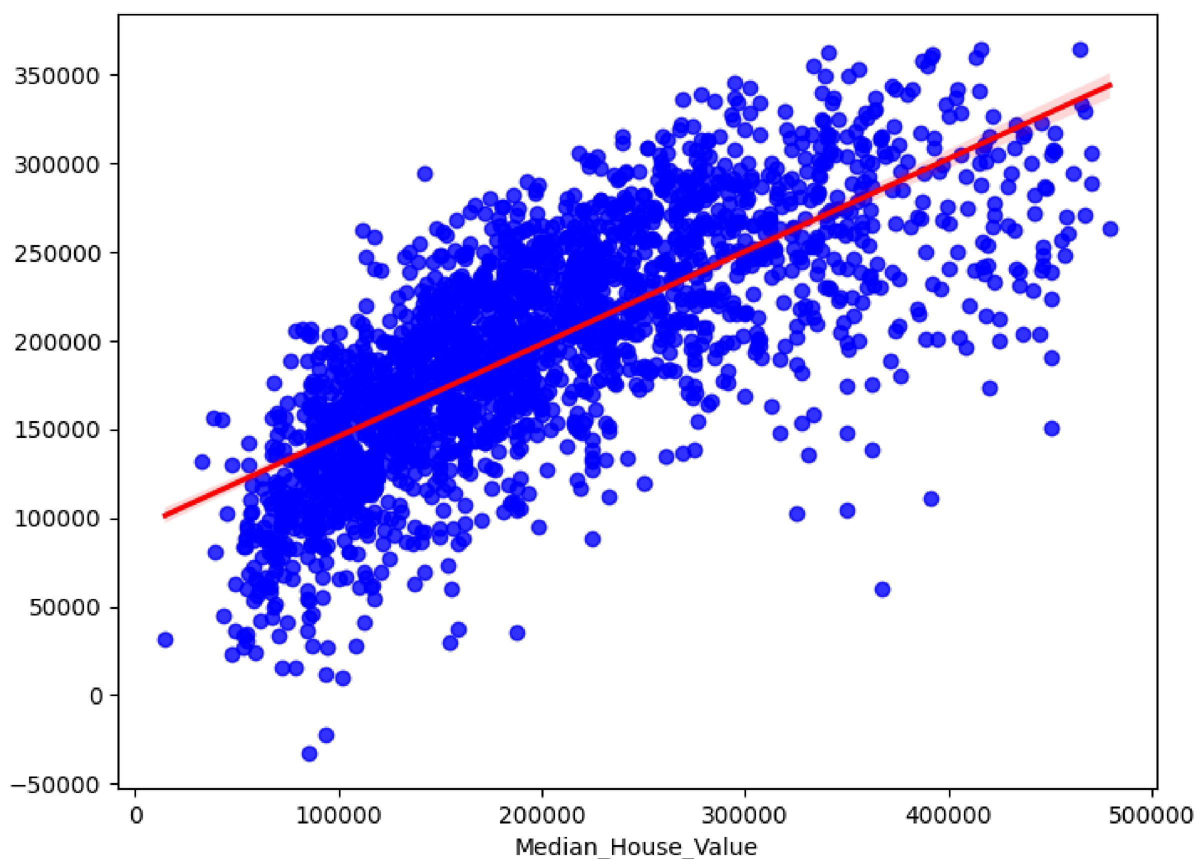
Out[91]:
```
▾ Lasso
Lasso(alpha=0.4)
```

In [92]:
```
y_pred_lasso = lasso.predict(X_test_scaled)
```

In [93]:
```
plt.scatter(y_test,y_pred_lasso)
plt.xlabel('Y test')
plt.ylabel('Y pred')
plt.show()
```



In [94]:
```
plt.figure(figsize=(8, 6))
sns.regplot(x=y_test, y=y_pred_lasso, scatter_kws={'color': 'blue'}, line_kws={'col
plt.show()
```

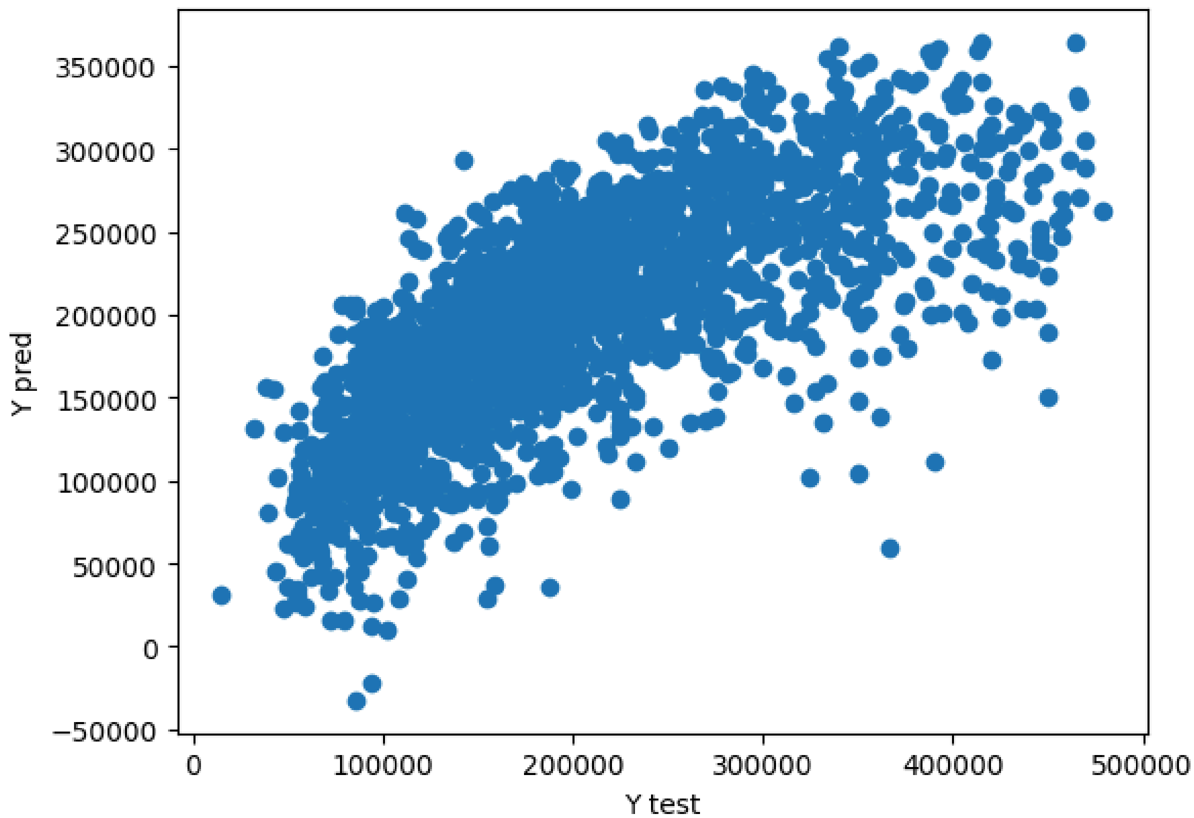


In [95]:
```
ridge = Ridge(alpha=0.4)
ridge.fit(X_train_scaled, y_train)
```

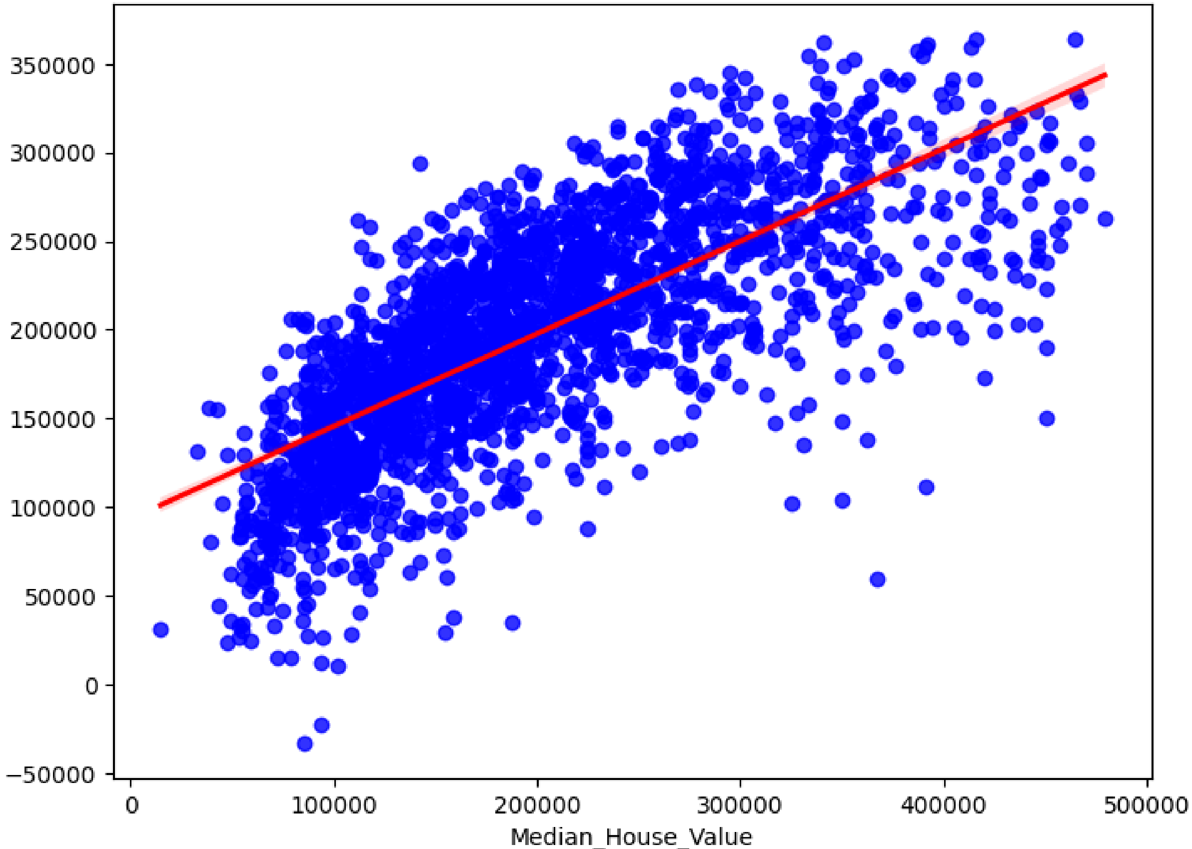
Out[95]:
```
▾ Ridge
Ridge(alpha=0.4)
```

In [96]:
```
y_pred_ridge = ridge.predict(X_test_scaled)
```

In [97]:
```
plt.scatter(y_test,y_pred_ridge)
plt.xlabel('Y test')
plt.ylabel('Y pred')
plt.show()
```



In [98]:
```
plt.figure(figsize=(8, 6))
sns.regplot(x=y_test, y=y_pred_ridge, scatter_kws={'color': 'blue'}, line_kws={'col
plt.show()
```



In [99]:
```
mae_lr = mean_absolute_error(y_test, y_pred_lr)
mse_lr = mean_squared_error(y_test,y_pred_lr)
mae_lasso = mean_absolute_error(y_test, y_pred_lasso)
mse_lasso = mean_squared_error(y_test,y_pred_lasso)
mae_ridge = mean_absolute_error(y_test, y_pred_ridge)
mse_ridge = mean_squared_error(y_test,y_pred_ridge)
```

In [100…
```
print('Mean Squared Error LR: ',mse_lr)
print('Mean Squared Error Lasso: ',mse_lasso)
print('Mean Squared Error Ridge: ',mse_ridge)
print('Mean absolute error LR: ', mae_lr)
print('Mean absolute error Lasso: ', mae_lasso)
print('Mean absolute error Ridge: ', mae_ridge)
```

```
Mean Squared Error LR:  3913803978.4021273
Mean Squared Error Lasso:  3913791250.9178443
Mean Squared Error Ridge:  3913817347.6407666
Mean absolute error LR:  46942.383558058646
Mean absolute error Lasso:  46943.34262435514
Mean absolute error Ridge:  46945.16537074284
```

In [101…
```
r2_lr = r2_score(y_test,y_pred_lr)
r2_lasso = r2_score(y_test,y_pred_lasso)
r2_ridge = r2_score(y_test,y_pred_ridge)
print('R2 score LR: ',r2_lr)
print('R2 score Lasso: ',r2_lasso)
print('R2 score Ridge: ',r2_ridge)
```

```
R2 score LR:  0.5398081167066999
R2 score Lasso:  0.5398096132264526
R2 score Ridge:  0.5398065447283531
```

In [102…

```
mape_lr = mean_absolute_percentage_error(y_test, y_pred_lr)
mspe_lr = np.mean(((y_test - y_pred_lr) / y_test) ** 2) * 100
mape_lasso = mean_absolute_percentage_error(y_test, y_pred_lasso)
mspe_lasso = np.mean(((y_test - y_pred_lasso) / y_test) ** 2) * 100
mape_ridge = mean_absolute_percentage_error(y_test, y_pred_ridge)
mspe_ridge = np.mean(((y_test - y_pred_ridge) / y_test) ** 2) * 100
```

In [103…

```
print(f'MSPE_lr: {mspe_lr:.2f}%')
print(f'MAPE_lr: {mape_lr * 100:.2f}%')
print(f'MSPE_lasso: {mspe_lasso:.2f}%')
print(f'MAPE_lasso: {mape_lasso * 100:.2f}%')
print(f'MSPE_ridge: {mspe_ridge:.2f}%')
print(f'MAPE_ridge: {mape_ridge * 100:.2f}%')
```

```
MSPE_lr: 13.75%
MAPE_lr: 26.88%
MSPE_lasso: 13.75%
MAPE_lasso: 26.88%
MSPE_ridge: 13.75%
MAPE_ridge: 26.88%
```

when we excluded the most uncorrelated column with the mean house value the error increased

In [ ]: