Project Information

Project Title: Analyzing Key Factors Influencing US Home Prices Over the Last 20 Years

Project Overview: The objective of this project is to build a data science model that explains the impact of key factors on US home prices over the last two decades. The project involves finding publicly available data for these influencing factors and using the S&P Case-Schiller Home Price Index (CSUSHPIS) as a proxy for home prices.

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Project Plan

We will cover this entire project by dividing it in 4 sections :

1. **Data Collection** : I will collect data from various sources including US Govt offical websites and from different publicly available data. I will share links for each data source as and when required.
2. **Data Preparation** : After collecting data, i will consolidate all the data into a csv file and access the file.
3. **EDA** : I will analyse the prepared data using various plotting methods and how different factors are correlated to each other.
4. **Modeling** : With the help of all the above information , i will build a suitable model which will predict index prices in US real estate.

Data Collection

I have collected data mainly from https://fred.stlouisfed.org/

The website "https://fred.stlouisfed.org/" is an official website of the Federal Reserve Economic Data (FRED), which is maintained by the Federal Reserve Bank of St. Louis. FRED is an extensive online database of economic data and financial indicators

I have downloaded data from ***2001-01 to 2023-07*** in csv format. Here are the files details and source from where I have fetched data :

S&P/Case-Shiller U.S. National Home Price Index : https://fred.stlouisfed.org/series/CSUSHPISA

GDP : https://fred.stlouisfed.org/series/GDP

New Privately-Owned Housing Units Started: Total Units : https://fred.stlouisfed.org/series/HOUST

30-Year Fixed Rate Mortgage Average in the United States : https://fred.stlouisfed.org/series/MORTGAGE30US

Monthly Supply of New Houses in the United States : https://fred.stlouisfed.org/series/MSACSR

Personal Income : https://fred.stlouisfed.org/series/PI

Population : https://fred.stlouisfed.org/series/POPTHM

Personal Saving Rate : https://fred.stlouisfed.org/series/PSAVERT

Unemployment Rate : https://fred.stlouisfed.org/series/UNRATE

Target Data : S&P/Case-Shiller U.S. National Home Price Index

Feature Data : All other Data

Data Preparation

Let's clean our data now by changing column names, setting date as Index

```
import pandas as pd
```

```
target_data = pd.read_csv("/content/Project Data/ S&P:Case-Shiller U.S. National Home Price Index.csv")
target_data.head()
```

	DATE	CSUSHPISA
0	2000-01-01	100.551
1	2000-02-01	101.339
2	2000-03-01	102.127
3	2000-04-01	102.922
4	2000-05-01	103.678

```
target_data.set_index('DATE', inplace=True)
target_data.rename(columns={'CSUSHPISA': 'target'}, inplace=True)
target_data.index = pd.to_datetime(target_data.index)
target_data.head()
```

	target
DATE	
2000-01-01	100.551
2000-02-01	101.339
2000-03-01	102.127
2000-04-01	102.922
2000-05-01	103.678

```
target_data.to_csv("Cleaned Data/target.csv")
```

Lets follow the same process to rename columns and set date column as index for all other feature data

Personal Income

Personal Income is one of the key factors that influence US real estate prices as increase in personal income also led to increase in purchasing power which ultimately increases demand and prices of real estate

```
personal_income = pd.read_csv("/content/Project Data/Personal Income.csv")
personal_income.head()
```

	DATE	PI
0	2000-01-01	8348.0
1	2000-02-01	8408.8
2	2000-03-01	8468.3
3	2000-04-01	8506.8
4	2000-05-01	8544.5

```
personal_income.set_index('DATE', inplace=True)
personal_income.rename(columns={'PI': 'Personal Income'}, inplace=True)
personal_income.index = pd.to_datetime(personal_income.index)
personal_income.head()
```

	Personal Income
DATE	
2000-01-01	8348.0
2000-02-01	8408.8
2000-03-01	8468.3
2000-04-01	8506.8
2000-05-01	8544.5

```
personal_income.to_csv("Cleaned Data/Personal_Income.csv")
```

Population

As population increases, also grows the demand of houses to live which will fuel the demand and prices of real estate

```
population = pd.read_csv("/content/Project Data/Population.csv")
population.head()
```

	DATE	POPTHM
0	2000-01-01	281083.0
1	2000-02-01	281299.0
2	2000-03-01	281531.0
3	2000-04-01	281763.0
4	2000-05-01	281996.0

```
population.set_index('DATE', inplace=True)
population.rename(columns={'POPTHM': 'Population'}, inplace=True)
population.index = pd.to_datetime(population.index)
population.head()
```

	Population
DATE	
2000-01-01	281083.0
2000-02-01	281299.0
2000-03-01	281531.0
2000-04-01	281763.0
2000-05-01	281996.0

```
population.to_csv("Cleaned Data/Population.csv")
```

Unemployment Rate

Unemployment rate is one of the direct factor that impacts the prices of real estate as the more the unemployment, less the buying capacity, hence less demand led to less prices

```
unemployment_rate = pd.read_csv("/content/Project Data/Unemployment Rate.csv")
unemployment_rate.head()
```

	DATE	UNRATE
0	2000-01-01	4.0

```
unemployment_rate.set_index('DATE', inplace=True)
unemployment_rate.rename(columns={'UNRATE': 'Unemployment Rate'}, inplace=True)
unemployment_rate.index = pd.to_datetime(unemployment_rate.index)
unemployment_rate.head()
```

DATE	Unemployment Rate
2000-01-01	4.0
2000-02-01	4.1
2000-03-01	4.0
2000-04-01	3.8
2000-05-01	4.0

```
unemployment_rate.to_csv("Cleaned Data/Unemployment_Rate.csv")
```

GDP

GDP is the criteria which shows the development of a nation. The more the GDP is, the more developed nation is, which also directly impacts the prices of real estate

```
gdp_data = pd.read_csv("/content/Project Data/GDP.csv")
gdp_data.head()
```

	DATE	GDP
0	2000-01-01	10002.179
1	2000-04-01	10247.720
2	2000-07-01	10318.165
3	2000-10-01	10435.744
4	2001-01-01	10470.231

```
gdp_data.set_index('DATE', inplace=True)
gdp_data.index = pd.to_datetime(gdp_data.index)

# Resampling
gdp_data = gdp_data.resample('M').ffill() #this will resample the index to monthly and then fill extra created rows with la

# Set the day of the index to 1
gdp_data.index = gdp_data.index.map(lambda x: x.replace(day=1))
gdp_data = gdp_data["2000-01-01":"2023-07-01"]

gdp_data.head()
```

DATE	GDP
2000-01-01	10002.179
2000-02-01	10002.179
2000-03-01	10002.179
2000-04-01	10247.720
2000-05-01	10247.720

```
gdp_data.to_csv("/content/Cleaned Data/GDP.csv")
```

Mortgage Rate

A mortgage rate is the interest rate charged for a home loan. If mortgage rate is high, people will be less interested to take a loan for home, which will negatively impact the prices

```
mortgage_rate_monthly = pd.read_csv("/content/Project Data/Mortgage_monthly.csv")
mortgage_rate_monthly.head()
```

	DATE	MORTGAGE30US
0	2000-01-01	8.2100
1	2000-02-01	8.3250
2	2000-03-01	8.2400
3	2000-04-01	8.1525
4	2000-05-01	8.5150

```
mortgage_rate_monthly.set_index('DATE', inplace=True)
mortgage_rate_monthly.rename(columns={'MORTGAGE30US': 'Mortgage Rate Monthly'}, inplace=True)
mortgage_rate_monthly.index = pd.to_datetime(mortgage_rate_monthly.index)
mortgage_rate_monthly.head()
```

DATE	Mortgage Rate Monthly
2000-01-01	8.2100
2000-02-01	8.3250
2000-03-01	8.2400
2000-04-01	8.1525
2000-05-01	8.5150

```
mortgage_rate_monthly.to_csv("/content/Cleaned Data/Mortgage_Rate_monthly.csv")
```

Personal Saving Rate

The personal saving rate is a measure that reflects the portion of disposable income that households save rather than spend. As savings increases, it means people are spending less on investments such as real estate which slows the demand for buying new houses

```
personal_saving_rate = pd.read_csv("/content/Project Data/Personal Saving Rate.csv")
personal_saving_rate.head()
```

	DATE	PSAVERT
0	2000-01-01	4.5
1	2000-02-01	4.0
2	2000-03-01	3.8
3	2000-04-01	4.3
4	2000-05-01	4.3

```
personal_saving_rate.set_index('DATE', inplace=True)
personal_saving_rate.rename(columns={'PSAVERT': 'Personal Saving Rate'}, inplace=True)
personal_saving_rate.index = pd.to_datetime(personal_saving_rate.index)
personal_saving_rate.head()
```

DATE	Personal Saving Rate
2000-01-01	4.5
2000-02-01	4.0
2000-03-01	3.8
2000-04-01	4.3
2000-05-01	4.3

```
personal_saving_rate.to_csv("Cleaned Data/Personal_Saving_Rate.csv")
```

Inventory Level Impact

The balance between housing supply and demand in a particular market can influence home prices. Limited supply relative to demand tends to drive prices up. Lets clean our data related to Houses construction completed, under construction, monthly supply of new houses

```
# Monthly supply of new houses in US
monthly_supply_houses = pd.read_csv("/content/Project Data/Monthly Supply of New Houses in the United States.csv")
monthly_supply_houses.head()
```

	DATE	MSACSR
0	2000-01-01	4.3
1	2000-02-01	4.3
2	2000-03-01	4.3
3	2000-04-01	4.4
4	2000-05-01	4.4

```
monthly_supply_houses.set_index('DATE', inplace=True)
monthly_supply_houses.rename(columns={'MSACSR': 'ratio of new houses for sale to new houses sold'}, inplace=True)
monthly_supply_houses.index = pd.to_datetime(monthly_supply_houses.index)
monthly_supply_houses.head()
```

	ratio of new houses for sale to new houses sold
DATE	
2000-01-01	4.3
2000-02-01	4.3
2000-03-01	4.3
2000-04-01	4.4
2000-05-01	4.4

```
monthly_supply_houses.to_csv("Cleaned Data/Monthly_Supply_Houses.csv")
```

```
# New Housing Project started
new_housing_project_started = pd.read_csv("/content/Project Data/ New Privately-Owned Housing Units Started- Total Units.cs
new_housing_project_started.head()
```

	DATE	HOUST
0	2000-01-01	1636.0
1	2000-02-01	1737.0
2	2000-03-01	1604.0
3	2000-04-01	1626.0
4	2000-05-01	1575.0

```
new_housing_project_started.set_index('DATE', inplace=True)
new_housing_project_started.rename(columns={'HOUST': 'Housing unit started'}, inplace=True)
new_housing_project_started.index = pd.to_datetime(new_housing_project_started.index)
new_housing_project_started.head()
```

	Housing unit started
DATE	
2000-01-01	1636.0
2000-02-01	1737.0
2000-03-01	1604.0
2000-04-01	1626.0
2000-05-01	1575.0

```
new_housing_project_started.to_csv("Cleaned Data/New_Housing_Unit_Started.csv")
```

EDA

In this section, we will explore the data we have cleaned in last section and try to fetch meaningful comparison and correlation

```
import numpy as np #for feature engineering
import matplotlib.pyplot as plt #for various plotting
import seaborn as sns #for various plotting
import os
```

Lets join all our csv files into 1 csv file

```
path = '/content/Cleaned Data'

csv_files = [os.path.join(path, f) for f in os.listdir(path) if f.endswith('.csv')]

dfs = [pd.read_csv(f) for f in csv_files]

# Merging the dataframes on the 'DATE' column
final_df = pd.concat(dfs, ignore_index=False).groupby('DATE').sum()
```

```
# Lets save this new final df to a new csv file
final_df.to_csv("/content/Final Data/final_data.csv")
```

```
final_data = pd.read_csv("/content/Final Data/final_data.csv")
```

```
final_data.set_index('DATE', inplace=True)
final_data.index = pd.to_datetime(final_data.index)
```

```
final_data.head(15)
```

	Population	ratio of new houses for sale to new houses sold	Mortgage Rate Monthly	target	Housing unit started	Personal Saving Rate	Unemployment Rate	GDP	Personal Income
DATE									
2000-01-01	281083.0	4.3	8.2100	100.551	1636.0	4.5	4.0	10002.179	8348.0
2000-02-01	281299.0	4.3	8.3250	101.339	1737.0	4.0	4.1	10002.179	8408.8
2000-03-01	281531.0	4.3	8.2400	102.127	1604.0	3.8	4.0	10002.179	8468.3
2000-04-01	281763.0	4.4	8.1525	102.922	1626.0	4.3	3.8	10247.720	8506.8
2000-05-01	281996.0	4.4	8.5150	103.678	1575.0	4.3	4.0	10247.720	8544.5
2000-06-01	282247.0	4.8	8.2880	104.424	1559.0	4.3	4.0	10247.720	8597.8
2000-07-01	282504.0	4.1	8.1475	105.054	1463.0	4.7	4.0	10318.165	8665.3
2000-08-01	282769.0	4.4	8.0275	105.768	1541.0	4.8	4.1	10318.165	8712.2
2000-09-01	283033.0	4.0	7.9120	106.538	1507.0	4.1	3.9	10318.165	8757.7
2000-10-01	283285.0	4.0	7.7950	107.382	1549.0	4.3	3.9	10435.744	8792.1
2000-11-01	283523.0	4.2	7.7450	108.302	1551.0	4.3	3.9	10435.744	8809.9
2000-12-01	283748.0	3.6	7.3820	109.140	1532.0	4.1	3.9	10435.744	8844.0
2001-01-01	283960.0	3.8	7.0325	109.846	1600.0	4.5	4.2	10470.231	8940.9
2001-02-01	284166.0	3.7	7.0500	110.500	1625.0	4.6	4.2	10470.231	8975.8
2001-	284380.0	3.8	6.9520	111.100	1590.0	4.9	4.3	10470.231	9009.4

```
final_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 283 entries, 2000-01-01 to 2023-07-01
```

```
Data columns (total 9 columns):
 #   Column                                       Non-Null Count  Dtype  
---  ------                                       --------------  -----  
 0   Population                                   283 non-null    float64
 1   ratio of new houses for sale to new houses sold  283 non-null    float64
 2   Mortgage Rate Monthly                        283 non-null    float64
 3   target                                       283 non-null    float64
 4   Housing unit started                         283 non-null    float64
 5   Personal Saving Rate                         283 non-null    float64
 6   Unemployment Rate                            283 non-null    float64
 7   GDP                                          283 non-null    float64
 8   Personal Income                              283 non-null    float64
dtypes: float64(9)
memory usage: 22.1 KB
```

```
final_data.describe()
```

	Population	ratio of new houses for sale to new houses sold	Mortgage Rate Monthly	target	Housing unit started	Personal Saving Rate	Unemployment Rate	GDP	Personal Income
count	283.000000	283.000000	283.000000	283.000000	283.000000	283.000000	283.000000	283.000000	283.000000
mean	311546.162544	5.920141	5.046721	175.080618	1301.286219	5.758304	5.800353	16652.775551	14130.734276
std	16478.919037	1.943360	1.363965	48.539426	444.109060	3.302067	1.968664	4471.798668	4051.141788
min	281083.000000	3.300000	2.684000	100.551000	478.000000	1.400000	3.400000	10002.179000	8348.000000
25%	297200.000000	4.400000	3.907500	142.405000	980.000000	4.300000	4.400000	13324.204000	10834.250000
50%	313060.000000	5.400000	4.857500	167.335000	1288.000000	5.400000	5.300000	15842.259000	13406.400000
75%	327241.000000	7.000000	6.168000	193.212000	1627.500000	6.300000	6.700000	19692.595000	16787.800000

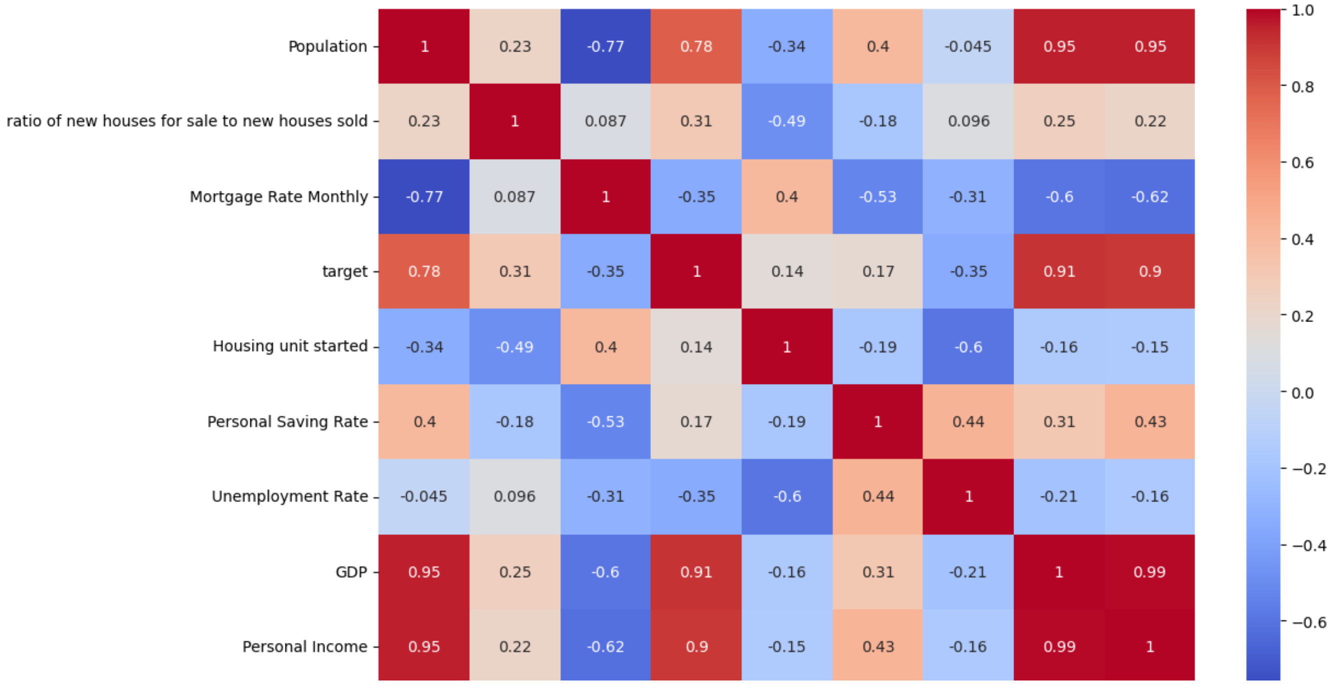
```
# Missing values
print(final_data.isnull().sum())
```

```
Population                                         0
ratio of new houses for sale to new houses sold    0
Mortgage Rate Monthly                              0
target                                             0
Housing unit started                               0
Personal Saving Rate                               0
Unemployment Rate                                  0
GDP                                                0
Personal Income                                    0
dtype: int64
```

As we can see , there is no missing data in our dataset so we are good to proceed with next step

```
# Correlation matrix
correlation_matrix = final_data.corr()

# Heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
```



The heatmap shows that the target variable (housing price) is strongly correlated with several other variables, including:

Population (0.78)

Personal income (0.9)

GDP (0.91)

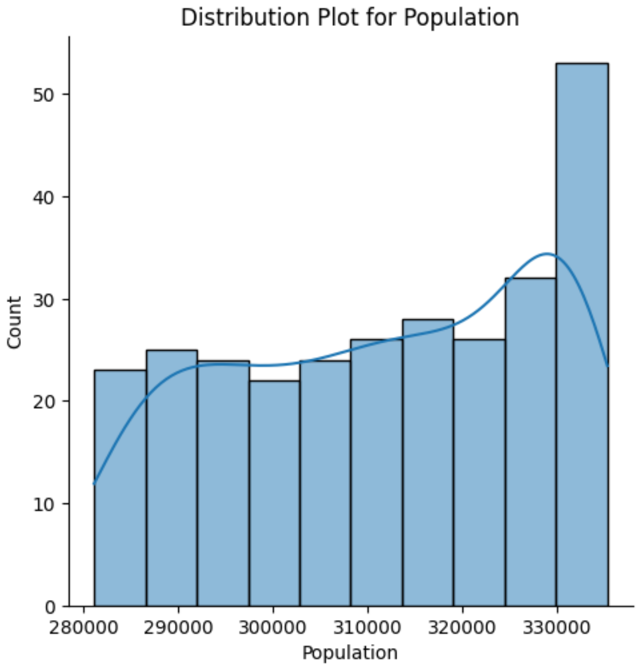
Mortgage rate monthly (-0.35)

This means that these variables are likely to have a significant impact on housing prices. For example, if personal income or GDP increases, housing prices are also likely to increase. Conversely, if mortgage rates increase, housing prices are likely to decrease.

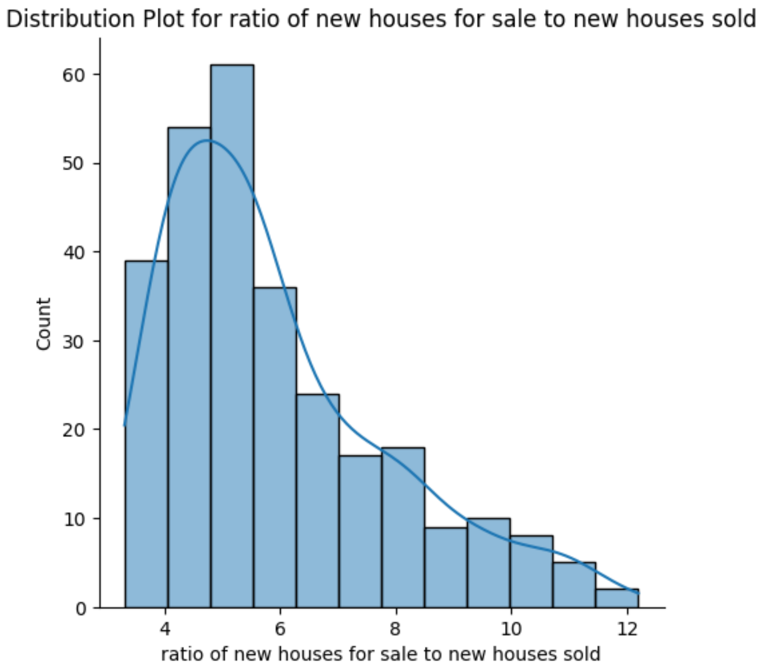
```
# Lets plot density plot

plt.figure(figsize=(12, 6))
for col in final_data.columns.tolist():
    plt.figure(figsize=(6, 4))
    sns.displot(data=final_data, x=col, kde =True)
    plt.xlabel(f"{col}")
    plt.ylabel("Count")
    plt.title(f'Distribution Plot for {col}')
    plt.show()
```

```
<Figure size 1200x600 with 0 Axes>
<Figure size 600x400 with 0 Axes>
```




```
<Figure size 600x400 with 0 Axes>
```




```
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```

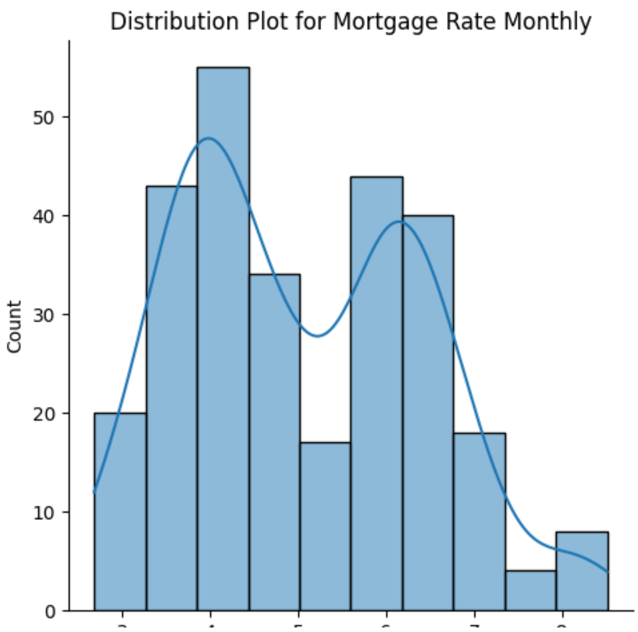

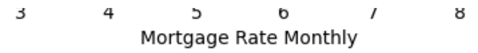

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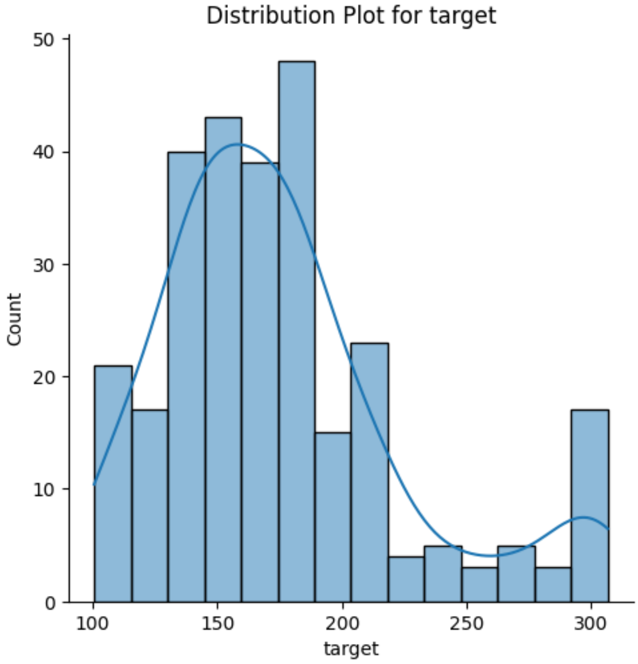
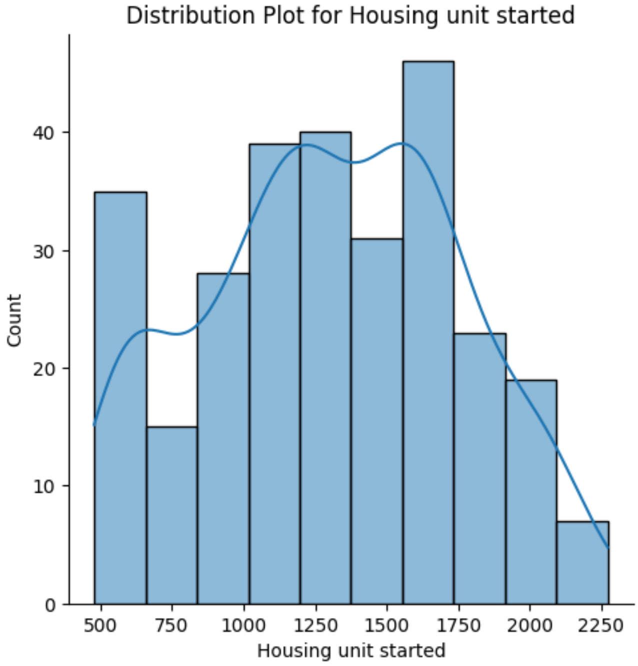
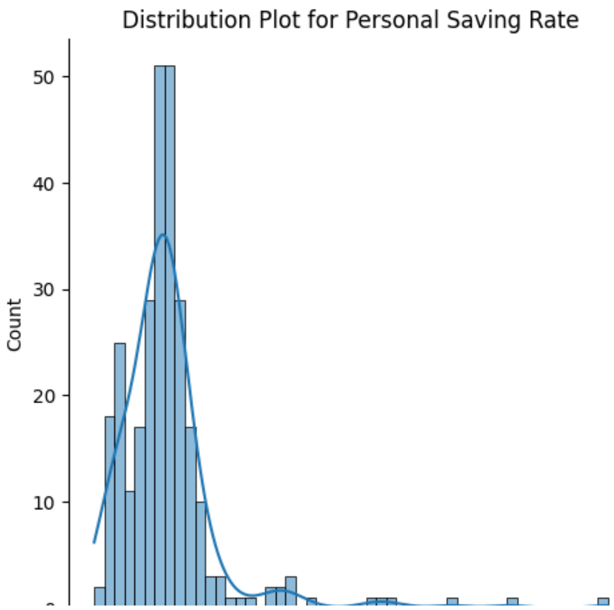
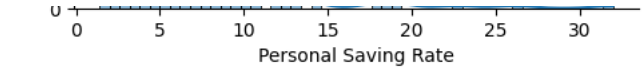


<Figure size 600x400 with 0 Axes>

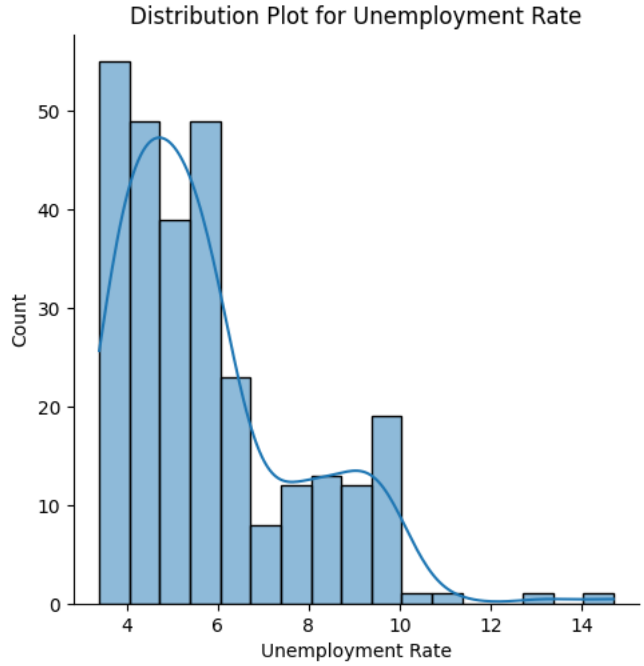


<Figure size 600x400 with 0 Axes>

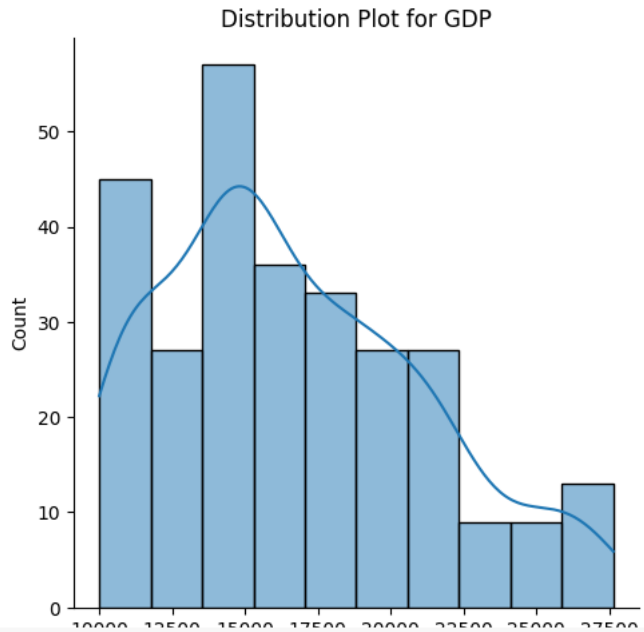




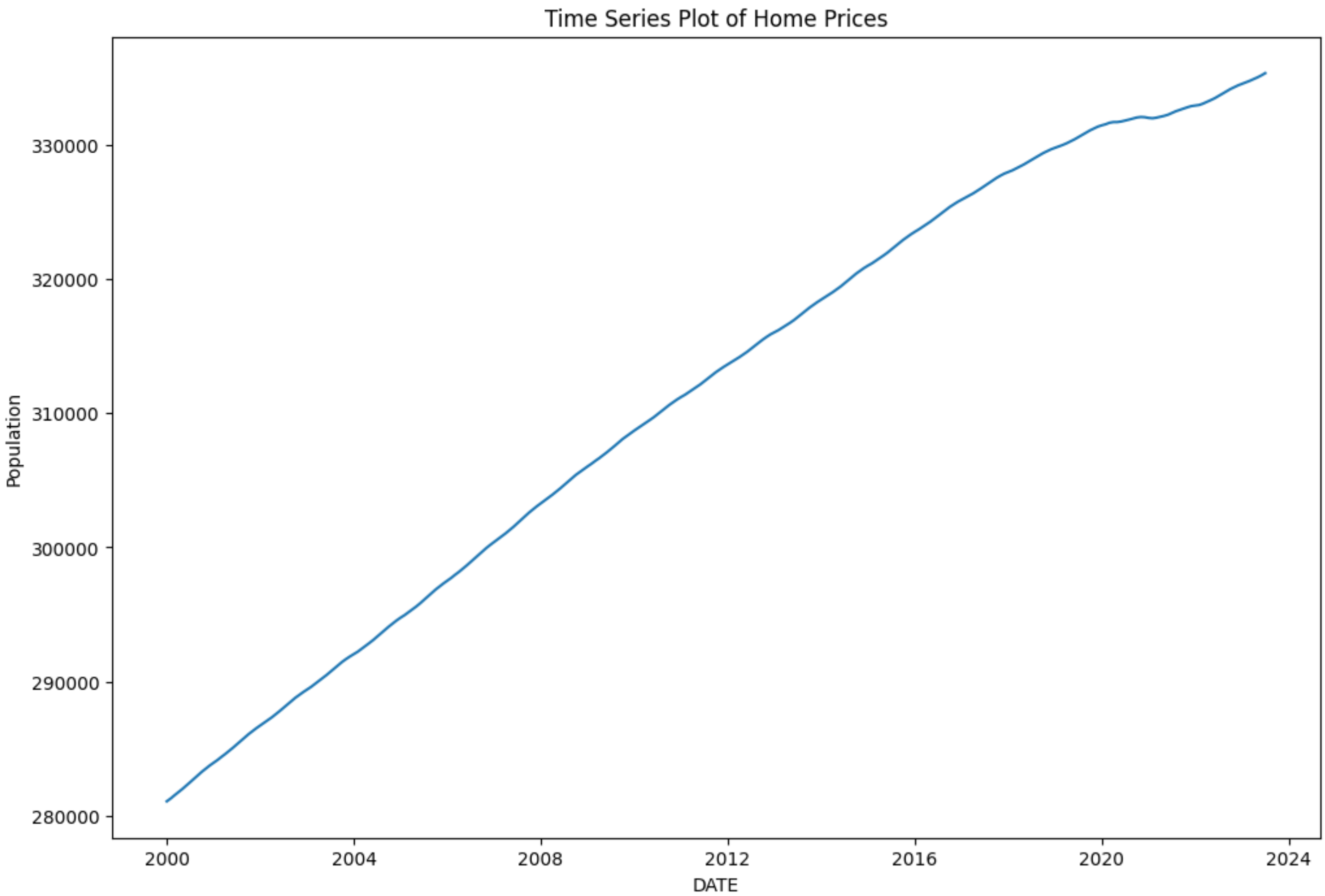

```
<Figure size 600x400 with 0 Axes>
```

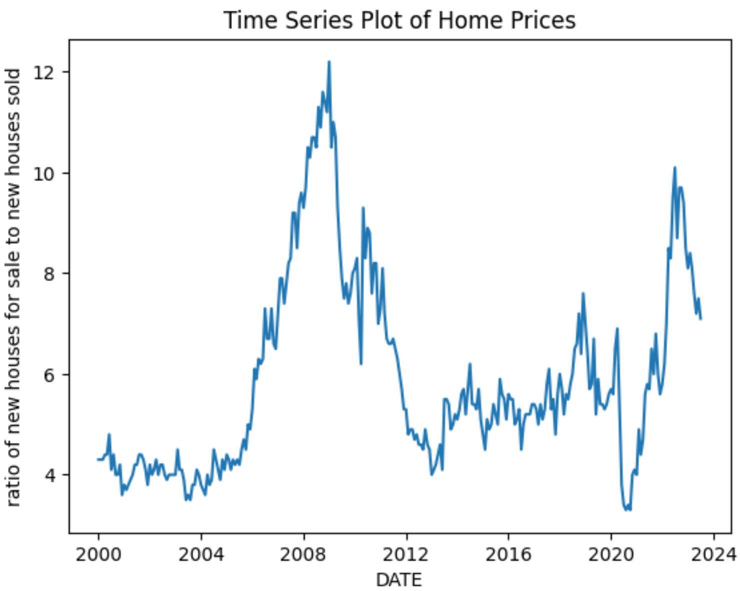


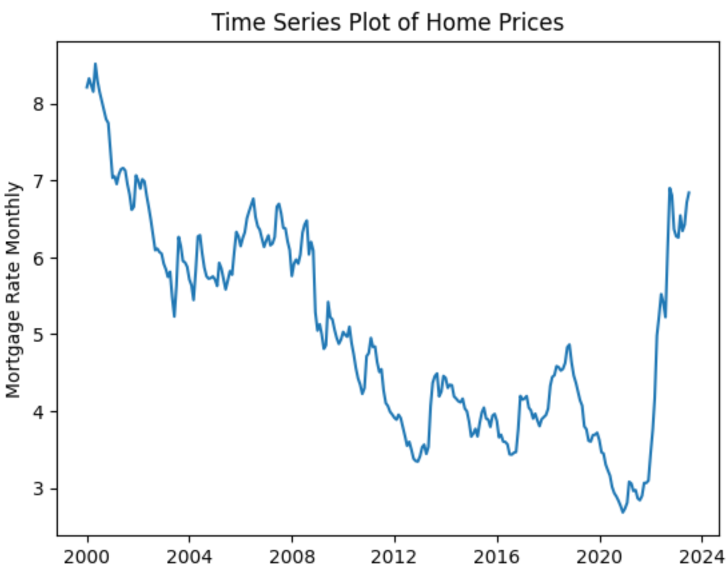

```
<Figure size 600x400 with 0 Axes>
```



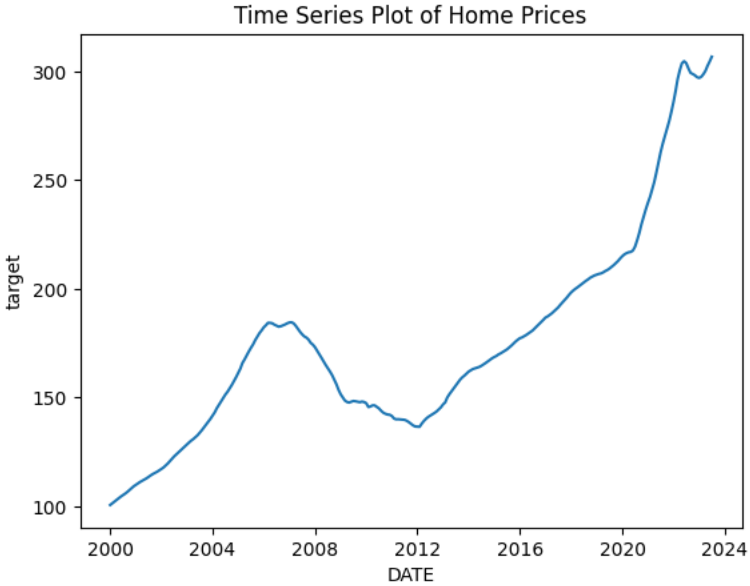

```
# Time series plot
plt.figure(figsize=(12, 8))
for col in final_data.columns.tolist():
  plt.plot(final_data[col])
  plt.ylabel(f"{col}")
  plt.xlabel('DATE')
  plt.title('Time Series Plot of Home Prices')
  plt.show()
```


Time Series Plot of Home Prices
Population
330000
320000
310000
300000
290000
280000
2000
2004
2008
2012
2016
2020
2024
DATE

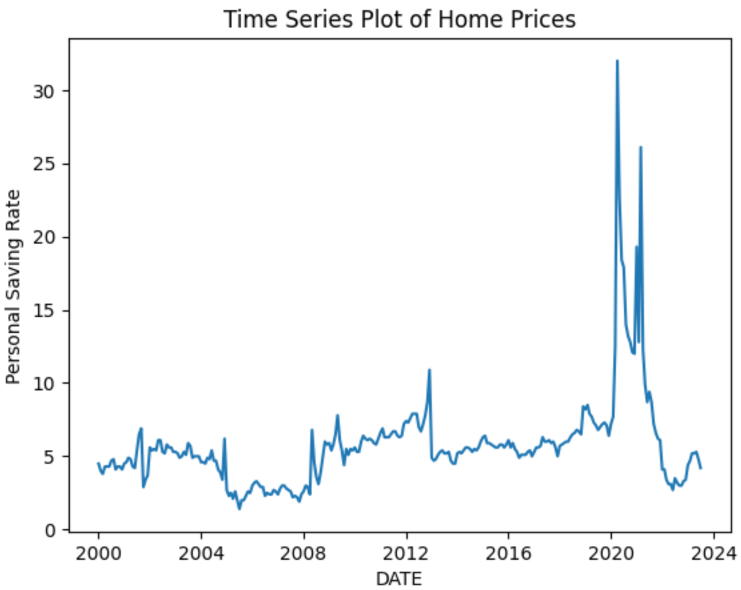

Time Series Plot of Home Prices
ratio of new houses for sale to new houses sold
12
10
8
6
4
2000
2004
2008
2012
2016
2020
2024
DATE

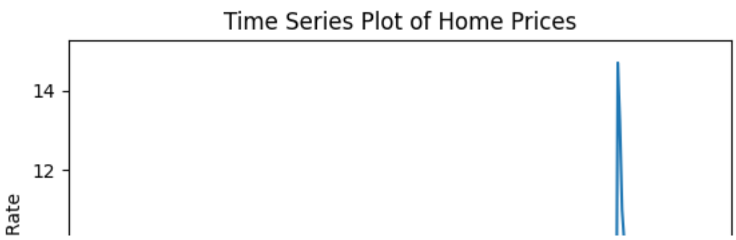

Time Series Plot of Home Prices
Mortgage Rate Monthly
8
7
6
5
4
3
2000
2004
2008
2012
2016
2020
2024

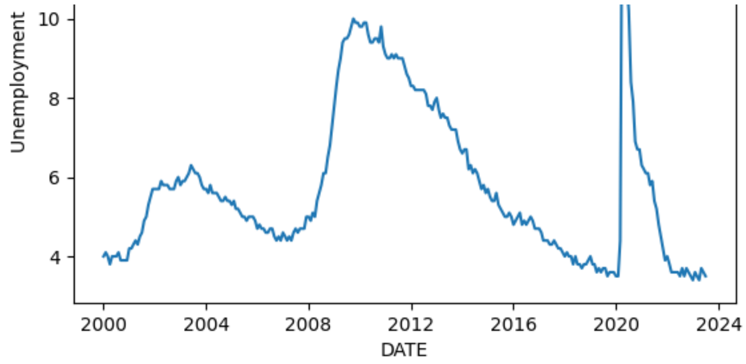
DATE

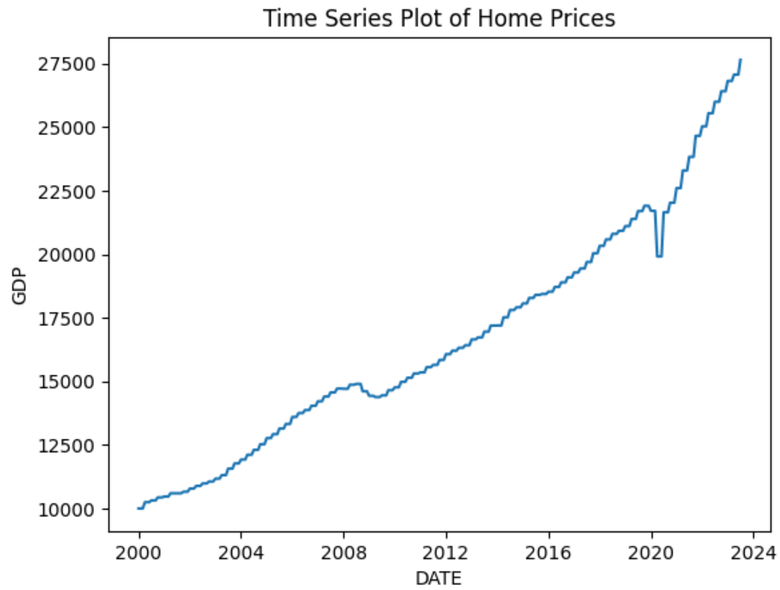

Time Series Plot of Home Prices
target
300
250
200
150
100
2000
2004
2008
2012
2016
2020
2024
DATE

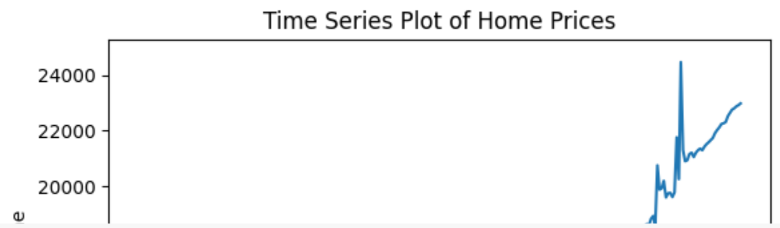

Time Series Plot of Home Prices
Housing unit started
2250
2000
1750
1500
1250
1000
750
500
2000
2004
2008
2012
2016
2020
2024
DATE


Time Series Plot of Home Prices
Personal Saving Rate
30
25
20
15
10
5
0
2000
2004
2008
2012
2016
2020
2024
DATE


Time Series Plot of Home Prices
Rate
14
12

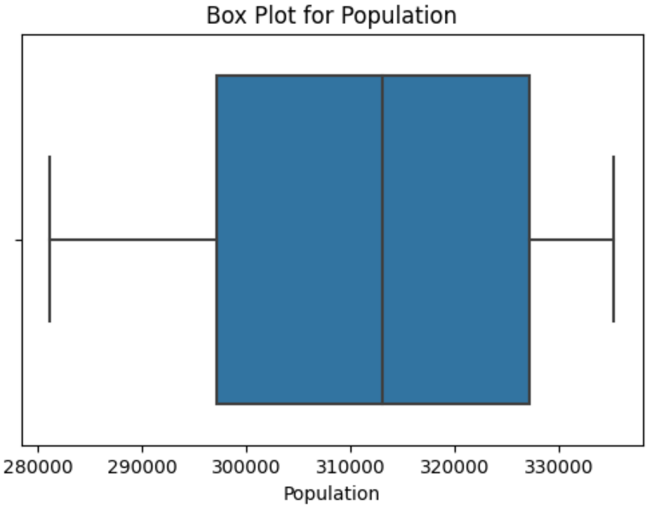


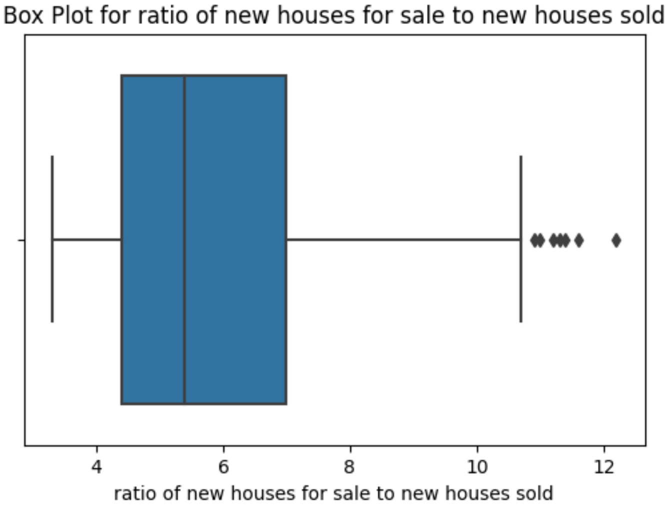


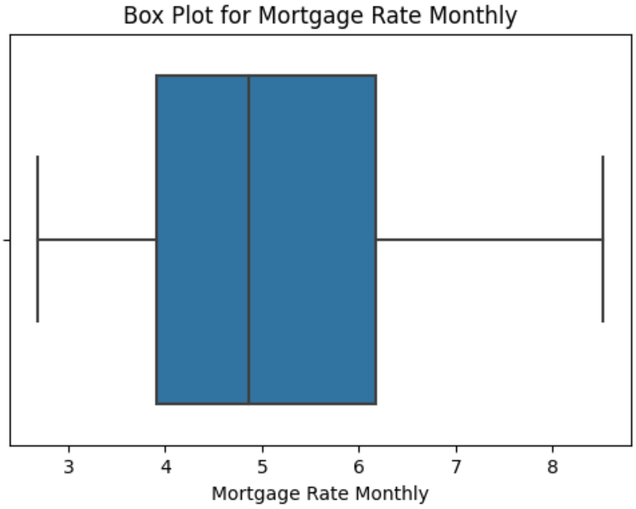


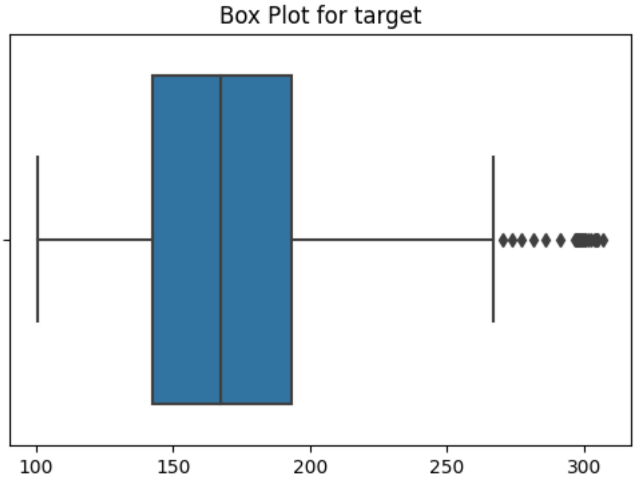

```
# lets plot boxplot for checking outliers in our data
plt.figure(figsize=(12, 6))
for col in final_data.columns.tolist():
    plt.figure(figsize=(6, 4))
    sns.boxplot(data=final_data, x=col)
    plt.xlabel(f"{col}")
    plt.title(f'Box Plot for {col}')
    plt.show()
```

```
<Figure size 1200x600 with 0 Axes>
```

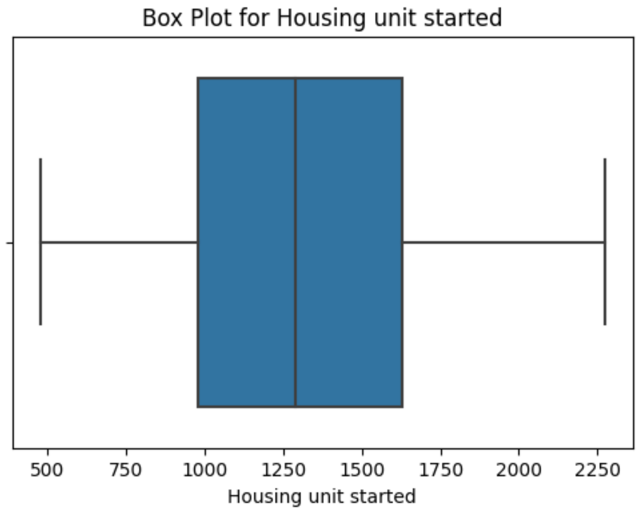


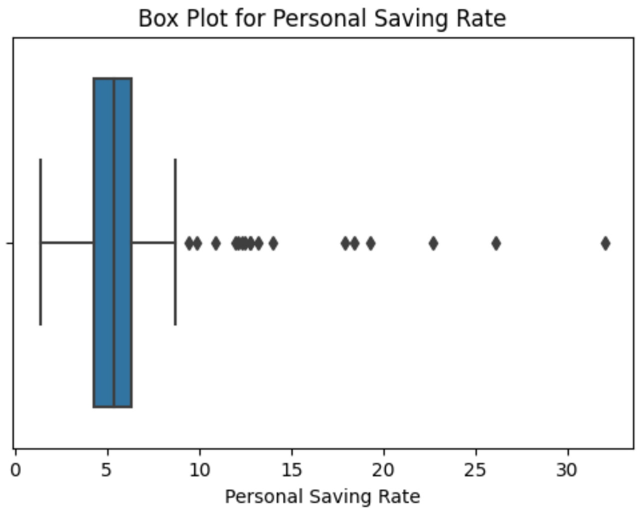


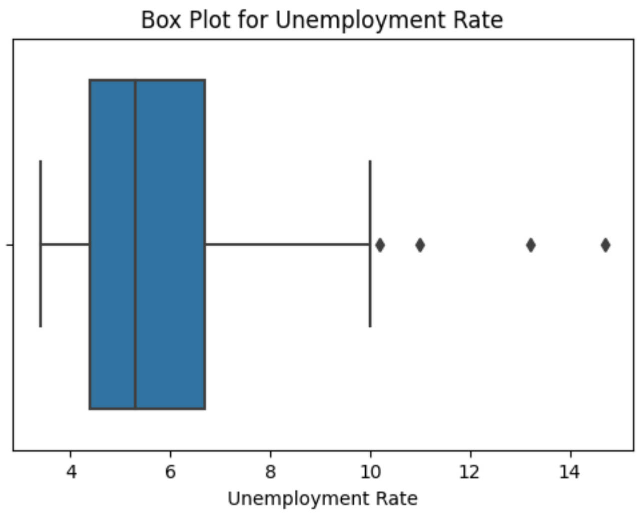


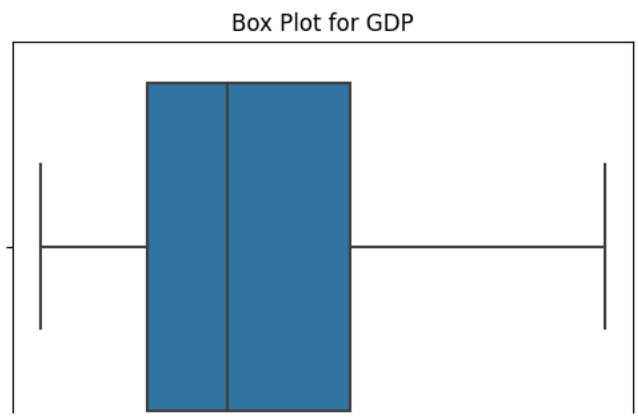


target









As we can see, there are outlier in our data mainly in :

- Unemployment Rate
- Personal Saving Rate
- ratio of new houses for sale to new houses sold

```
# Lets treat skewness and outliers
final_data['Personal Saving Rate'].skew()
```

```
3.881970962649685
```

As we can see, Personal Saving Rate is highly right skewed.

```
from scipy.stats import boxcox
final_data['boxcox_personal_saving_rate'], _ = boxcox(final_data['Personal Saving Rate'])
```

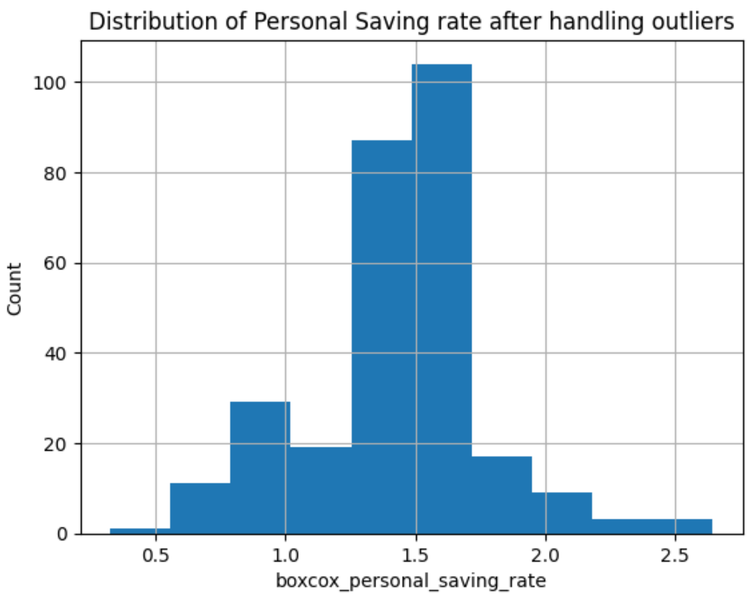
```
final_data['Personal Saving Rate'].skew()
```

```
3.881970962649685
```

```
final_data['boxcox_personal_saving_rate'].skew()
```

```
-0.0359416881912632
```

```
final_data['boxcox_personal_saving_rate'].hist()
plt.title("Distribution of Personal Saving rate after handling outliers")
plt.xlabel("boxcox_personal_saving_rate")
plt.ylabel("Count")
plt.show()
```




```
final_data['Unemployment Rate'].skew()
```

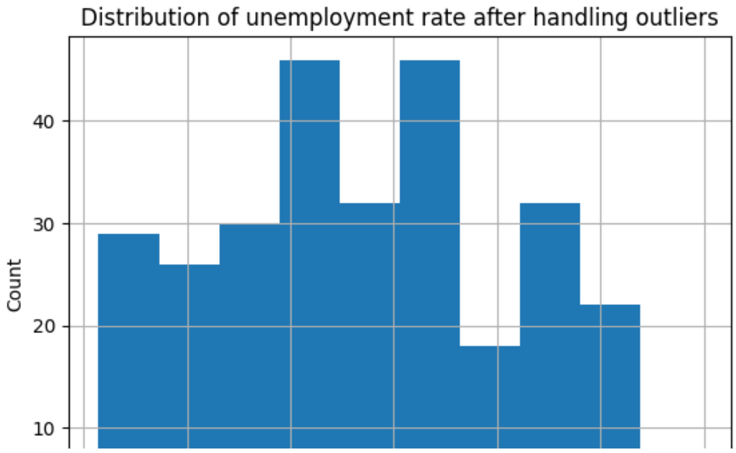
```
1.1831150909985555
```

```
final_data['boxcox_Unemployment Rate'], _ = boxcox(final_data['Unemployment Rate'])
```

```
final_data['boxcox_Unemployment Rate'].skew()
```

```
0.08383545873152397
```

```
final_data['boxcox_Unemployment Rate'].hist()
plt.title("Distribution of unemployment rate after handling outliers")
plt.xlabel("boxcox_unemployment rate")
plt.ylabel("Count")
plt.show()
```



Lets understand the correlation between the data

```
corr_matrix= final_data.corr()
corr_matrix['target'].sort_values(ascending=False)
```

```
target                                          1.000000
GDP                                             0.910526
Personal Income                                 0.897721
Population                                      0.779723
ratio of new houses for sale to new houses sold 0.306087
Personal Saving Rate                            0.174630
Housing unit started                            0.144211
boxcox_personal_saving_rate                     0.067577
Mortgage Rate Monthly                          -0.350813
Unemployment Rate                              -0.352774
boxcox_Unemployment Rate                       -0.469225
Name: target, dtype: float64
```

```
final_data.to_csv("/content/Final Data/final_data.csv")
```

Modeling

Lets start with reading and spliting the data

```
final_data.drop(columns={'Personal Saving Rate', 'Unemployment Rate'}, inplace=True)
```

```
final_data.head(15)
```

DATE	Population	ratio of new houses for sale to new houses sold	Mortgage Rate Monthly	target	Housing unit started	GDP	Personal Income	boxcox_personal_saving_rate	boxcox_Unemployment Rate
2000-01-01	281083.0	4.3	8.2100	100.551	1636.0	10002.179	8348.0	1.332745	0.810307
2000-02-01	281299.0	4.3	8.3250	101.339	1737.0	10002.179	8408.8	1.239841	0.817734

```
from sklearn.model_selection import train_test_split
```

```
X = final_data[['Population', 'ratio of new houses for sale to new houses sold', 'Mortgage Rate Monthly', 'Housing unit sta
y = final_data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
from sklearn.linear_model import LinearRegression

# Initialize the linear regression model
model = LinearRegression()
```

```
model.fit(X_train, y_train) #fitting the model to training data
```

```
▾ LinearRegression
LinearRegression()
```

```
predictions = model.predict(X_test)
```

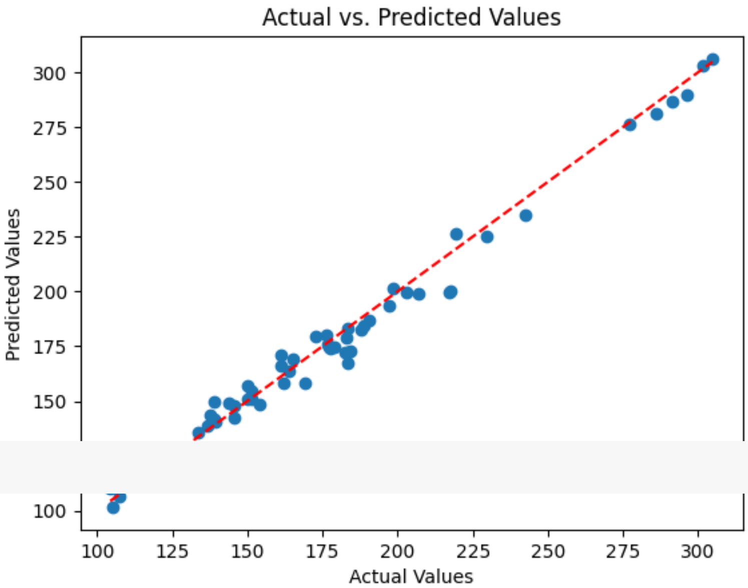
```
# Lets evaluate our model using MSE and R-squared
from sklearn.metrics import mean_squared_error, r2_score

mse = mean_squared_error(y_test, predictions)
r2 = r2_score(y_test, predictions)

print("Mean Squared Error:", mse)
print("R-squared:", r2)
```

```
Mean Squared Error: 43.16023470526665
R-squared: 0.9825452740643759
```

```
# Coefficients and intercept
coefficients = model.coef_
intercept = model.intercept_

print("Coefficients:", coefficients)
print("Intercept:", intercept)
```

```
Coefficients: [-8.14261830e-04  5.43326200e+00 -1.60905934e-01  4.27921037e-02
  9.79650060e-03  4.41873751e-03 -1.93114283e+01  1.09073569e+02]
Intercept: 46.77739455592156
```

```
#Lets visualise our model prediction

plt.scatter(y_test, predictions)
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title("Actual vs. Predicted Values")

x = np.linspace(min(y_test), max(y_test), 100)
plt.plot(x, x, color='red', linestyle='--')
plt.show()
```


Actual vs. Predicted Values
Predicted Values
Actual Values
100
125
150
175
200
225
250
275
300