FORECASTING REAL ESTATE PRICES USING TIME SERIES MODEL

DATA SCIENCE PHASE 4 PROJECT: MORINGA SCHOOL

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INTRODUCTION

Accurately predicting future prices has significant implications for buyers, sellers, and investors alike.This project uses time series analysis, a powerful tool for unraveling trends and patterns within sequential data. We leverage historical real estate price data, and aim to develop a robust forecasting model capable of predicting future values with greater accuracy.

This introduction sets the stage for us to explore the intricacies of data preparation, Exploratory data analysis, model selection, and evaluation, ultimately aiming to illuminate the path towards a more informed and predictable real estate future.

BUSINESS UNDERSTANDING & PROBLEM STATEMENT

The real estate market is complex and influenced by numerous factors, making the identification of prime investment locations a significant challenge. Traditional methods often rely on limited data and subjective expertise, leading to inconsistencies and reduced decision-making power.

This project aims to develop a robust and data-driven model to identify the top 5 best zip codes for real estate investment. The model will leverage advanced analytics and machine learning techniques to analyze historical data on property characteristics, market trends, and economic indicators, providing clear and actionable insights for strategic investment decisions.

OBJECTIVES

1. Provide a valuable and accurate predictive time series model with improved accuracy for stakeholders in the real estate industry.
2. Identify the most significant factors influencing property values in real Eastate.
3. To achieve stationarity in the real estate price data which is crucial for many forecasting models.
4. To identify and account for potential trends in the real estate market:

DATA UNDERSTANDING

This project involves thoroughly understanding the real estate data with 272 columns and 14723 rows. We explored the characteristics of the properties such as the RegionID,RegionName, City, State, Mtero,CountyName, SizeRank and changes in prices with time from the year 1996 to 2018.

DATA PREPARATION

In the data preparation process for real estate dataset, we focused on data cleaning to check and handle missing values and address outliers, we performed exploratory data analysis to understand data distribution and identify relationships and to make it ready for modelling.

MODELLING

We used ARIMA and SARIMA to model our dataset. SARIMA proved to be the best predicting upto XX% of change in price...................

STEP 1: DATA PREPARATION

```
#Importing necessary libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

import seaborn as sns
```

We have imported the libraries that we will need in our noteboook

```
#Loading the dataset, and preview the first five rows
df = pd.read_csv("/Users/andrewbaraka/Downloads/zillow_data.csv")
df.head()
```

```
   RegionID  RegionName      City State              Metro CountyName  \
0     84654       60657   Chicago    IL            Chicago       Cook   
1     90668       75070  McKinney    TX  Dallas-Fort Worth     Collin   
2     91982       77494      Katy    TX            Houston     Harris   
```

```
3     84616       60614   Chicago    IL            Chicago       Cook

4     93144       79936   El Paso    TX            El Paso    El Paso


   SizeRank   1996-04   1996-05   1996-06  ...  2017-07  2017-08
2017-09  \
0         1  334200.0  335400.0  336500.0  ...  1005500  1007500
1007800
1         2  235700.0  236900.0  236700.0  ...   308000   310000
312500
2         3  210400.0  212200.0  212200.0  ...   321000   320600
320200
3         4  498100.0  500900.0  503100.0  ...  1289800  1287700
1287400
4         5   77300.0   77300.0   77300.0  ...   119100   119400
120000

   2017-10  2017-11  2017-12  2018-01  2018-02  2018-03  2018-04
0  1009600  1013300  1018700  1024400  1030700  1033800  1030600
1   314100   315000   316600   318100   319600   321100   321800
2   320400   320800   321200   321200   323000   326900   329900
3  1291500  1296600  1299000  1302700  1306400  1308500  1307000
4   120300   120300   120300   120300   120500   121000   121500

[5 rows x 272 columns]

#Viewing the tail
df.tail(3)

       RegionID  RegionName                 City State      Metro
CountyName  \
14720     75672       40404                Berea    KY   Richmond
Madison
14721     93733       81225  Mount Crested Butte    CO        NaN
Gunnison
14722     95851       89155             Mesquite    NV  Las Vegas
Clark

       SizeRank   1996-04   1996-05   1996-06  ...  2017-07  2017-08
2017-09  \
14720     14721   57100.0   57300.0   57500.0  ...   121800   122800
124600
14721     14722  191100.0  192400.0  193700.0  ...   662800   671200
682400
14722     14723  176400.0  176300.0  176100.0  ...   333800   336400
339700

       2017-10  2017-11  2017-12  2018-01  2018-02  2018-03  2018-04
```

```
14720    126700    128800    130600    131700    132500    133000    133400
14721    695600    695500    694700    706400    705300    681500    664400
14722    343800    346800    348900    350400    353000    356000    357200

[3 rows x 272 columns]
```

We have previewed the first 5 rows and the last 5 row and our data seems okay so far.

```
df.shape
```

```
(14723, 272)
```

Our dataset has 14,723 rows annd 272 columns.

We now preview the columns

```
df.columns
```

```
Index(['RegionID', 'RegionName', 'City', 'State', 'Metro',
'CountyName',
       'SizeRank', '1996-04', '1996-05', '1996-06',
       ...
       '2017-07', '2017-08', '2017-09', '2017-10', '2017-11', '2017-
12',
       '2018-01', '2018-02', '2018-03', '2018-04'],
      dtype='object', length=272)
```

There are too many columns so we melt the dataframe so as to convert the many date columns to one, make sure the date column is in the datetime datatype and set it as index

```
# Melt the DataFrame to convert wide format to long format
date_columns = df.columns[7:]
df_long = pd.melt(df, id_vars=['RegionID', 'RegionName', 'City',
'State', 'Metro', 'CountyName', 'SizeRank'],
                  value_vars=date_columns, var_name='Date',
value_name='price')

# Convert the 'Date' column to datetime
df_long['Date'] = pd.to_datetime(df_long['Date'], format='%Y-%m')

# Set the 'Date' column as the index
df_long.set_index('Date', inplace=True)

# Check the first few rows to ensure the transformation is correct
df_long.head()
```

```
            RegionID  RegionName      City State              Metro  \
Date
1996-04-01     84654       60657   Chicago    IL            Chicago
1996-04-01     90668       75070  McKinney    TX  Dallas-Fort Worth
```

```
1996-04-01     91982       77494      Katy    TX            Houston
1996-04-01     84616       60614   Chicago    IL            Chicago
1996-04-01     93144       79936   El Paso    TX            El Paso

           CountyName  SizeRank     price
Date
1996-04-01       Cook         1  334200.0
1996-04-01     Collin         2  235700.0
1996-04-01     Harris         3  210400.0
1996-04-01       Cook         4  498100.0
1996-04-01    El Paso         5   77300.0
```

```
df_long.tail()
```

```
            RegionID  RegionName                  City State
Metro  \
Date

2018-04-01     58333        1338              Ashfield    MA
Greenfield Town
2018-04-01     59107        3293             Woodstock    NH
Claremont
2018-04-01     75672       40404                 Berea    KY
Richmond
2018-04-01     93733       81225  Mount Crested Butte    CO
NaN
2018-04-01     95851       89155              Mesquite    NV        Las
Vegas

           CountyName  SizeRank     price
Date
2018-04-01   Franklin     14719  209300.0
2018-04-01    Grafton     14720  225800.0
2018-04-01    Madison     14721  133400.0
2018-04-01   Gunnison     14722  664400.0
2018-04-01      Clark     14723  357200.0
```

```
df_long.shape
```

```
(3901595, 8)
```

After melting down our dataset we also set date as datetime datatype. We preview the first and last 5 rows of our data.The data now has 3901595 rows and 8 columns.

```
#Checking the columns and data types
df_long.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 3901595 entries, 1996-04-01 to 2018-04-01
Data columns (total 8 columns):
```

```
 #   Column      Dtype
---  ------      -----
 0   RegionID    int64
 1   RegionName  int64
 2   City        object
 3   State       object
 4   Metro       object
 5   CountyName  object
 6   SizeRank    int64
 7   price       float64
dtypes: float64(1), int64(3), object(4)
memory usage: 267.9+ MB
```

The data types are okay.

Data Cleaning

a). Missing Values

```
#checking for missing values
df_long.isnull().sum()
```

```
RegionID           0
RegionName         0
City               0
State              0
Metro         276395
CountyName         0
SizeRank           0
price         156891
dtype: int64
```

The Metro and Price Columns have missing values and we are going to fill the missing values using the .bfill() method.

```
df = df_long.bfill()
#Confirming the null values were filled
df.isnull().sum()
```

```
RegionID      0
RegionName    0
City          0
State         0
Metro         0
CountyName    0
SizeRank      0
```

```
price         0
dtype: int64
```

We have filled the missing values and confirmed that there are no missing values.

b). Dropping columns

Since we have the RegionName column we shall drop the RegionID column because it is irrelevant.

```
#drop irrelevant columns
data = df.drop(['RegionID'], axis=1)
data.head()

            RegionName      City State              Metro
CountyName  \
Date

1996-04-01       60657   Chicago    IL            Chicago       Cook

1996-04-01       75070  McKinney    TX  Dallas-Fort Worth     Collin

1996-04-01       77494      Katy    TX            Houston     Harris

1996-04-01       60614   Chicago    IL            Chicago       Cook

1996-04-01       79936   El Paso    TX            El Paso    El Paso


            SizeRank     price
Date
1996-04-01         1  334200.0
1996-04-01         2  235700.0
1996-04-01         3  210400.0
1996-04-01         4  498100.0
1996-04-01         5   77300.0

data.columns

Index(['RegionName', 'City', 'State', 'Metro', 'CountyName',
'SizeRank',
       'price'],
      dtype='object')
```

We just confirmed that the column has been dropped.

c). Handling Duplicates

```
data.duplicated().sum()

677191
```

Our dataset has 677191 duplicated rows which we shall drop.

```
#drop the duplicated values
data_1 = data.drop_duplicates()
data_1.duplicated().sum()

0
```

We have confirmed that our dataset does not have any duplicates now.

```
data_1.shape

(3224404, 7)
```

Our data now have 3,224,404 rows after dropping duplicates and 7 columns

d). Checking for Placeholders

We need to check whether there are any placeholders in our data.

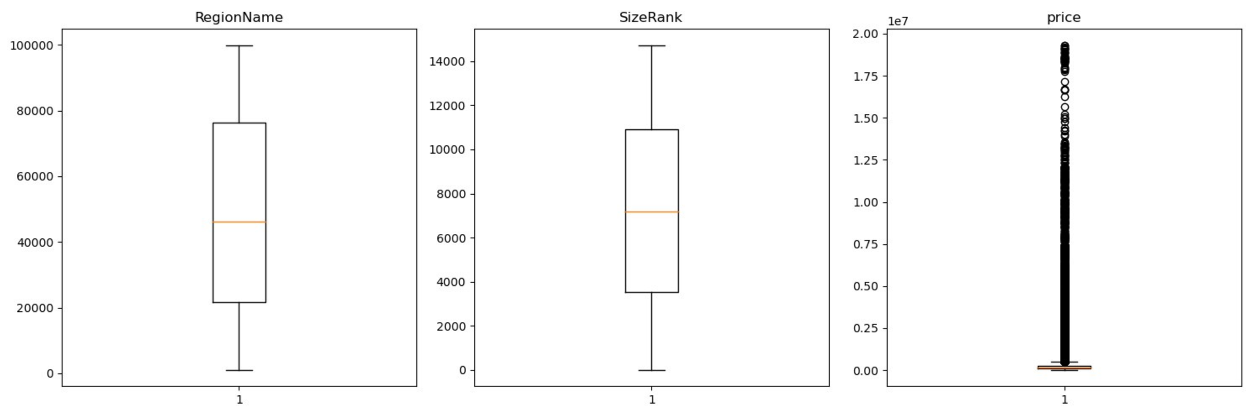
```
#Checking for placeholders
# Define a list of potential placeholder values
common_placeholders = ["", "NA", "N/A", "nan", "none", "null", "?",
"unknown", "missing"]

# Loop through each column and check for potential placeholders
found_placeholder = False
for column in data_1.columns:
    unique_values = data_1[column].unique()
    for value in unique_values:
        if pd.isna(value) or (isinstance(value, str) and
value.strip().lower() in common_placeholders):
            count = (data_1[column] == value).sum()
            print(f"Column '{column}': Found {count} occurrences of
potential placeholder '{value}'")
            found_placeholder = True

if not found_placeholder:
    print("No placeholders found in the DataFrame.")

No placeholders found in the DataFrame.
```

Yeh! Our data does not have any placeholders so we proceed.

e). Handling outliers

```
#Checking for outliers
numeric_columns = data_1.select_dtypes(include=['float64', 'int64',
'int32'])
```

```python
# Plot box plots for each numeric column
num_cols = len(numeric_columns.columns)
cols_per_row = 3
num_rows = (num_cols - 1) // cols_per_row + 1

plt.figure(figsize=(15, 5 * num_rows))
for i, col in enumerate(numeric_columns.columns):
    plt.subplot(num_rows, cols_per_row, i+1)
    plt.boxplot(numeric_columns[col])
    plt.title(col)
plt.tight_layout()
plt.show()
```



The Sales column seems to have an outlier, lets take a look at the values

```python
#Checking for unique values
data_1['price'].unique()
```

```
array([ 334200.,  235700.,  210400., ..., 2458000., 3069100.,
2161900.])
```

```python
#Checking for the maximum sales value
data_1['price'].max()
```

```
19314900.0
```

```python
#Checking for the minimum sales amount
data_1['price'].min()
```

```
11300.0
```

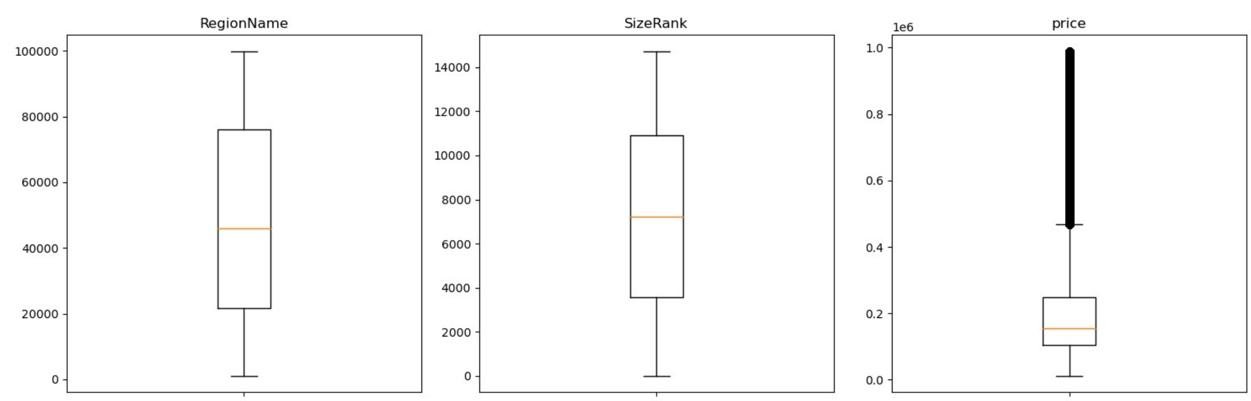
There are outliers in our dataset but since we are doing a timeseries which is greatly affected by outliers we shall drop them.

```python
# Calculate the Z-scores for the 'price' column
data_1['Z-score'] = (data_1['price'] - data_1['price'].mean()) /
data_1['price'].std()
```

```python
# Identify outliers
outliers = data_1[np.abs(data_1['Z-score']) > 3]

# Remove outliers
cleaned_data = data_1[np.abs(data_1['Z-score']) <= 3].copy()

# Drop the 'Z-score' column as it's no longer needed
cleaned_data.drop(columns=['Z-score'], inplace=True)
```

```
/var/folders/zb/8mcvjv4d1gd0k4hjdpzxw6bw0000gn/T/
ipykernel_13978/3916941200.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  data_1['Z-score'] = (data_1['price'] - data_1['price'].mean()) /
data_1['price'].std()
```

```python
#Lets check if we still have outliers
numeric_columns = cleaned_data.select_dtypes(include=['float64',
'int64', 'int32'])

# Plot box plots for each numeric column
num_cols = len(numeric_columns.columns)
cols_per_row = 3
num_rows = (num_cols - 1) // cols_per_row + 1

plt.figure(figsize=(15, 5 * num_rows))
for i, col in enumerate(numeric_columns.columns):
    plt.subplot(num_rows, cols_per_row, i+1)
    plt.boxplot(numeric_columns[col])
    plt.title(col)
plt.tight_layout()
plt.show()
```



FEATURE ENGINEERING

```
#renaming the columns
cleaned_data.rename(columns={
    'RegionName' : 'Region_Name',
    'CountyName' : 'County_Name',
    'SizeRank' : 'Size_Rank'
},inplace = True)

#renaming the columns
#cleaned_data.rename(columns=lambda x: x.replace(' ', '_'),
inplace=True)
cleaned_data.head()
```

```
            Region_Name      City State              Metro County_Name
\
Date

1996-04-01        60657   Chicago    IL            Chicago        Cook

1996-04-01        75070  McKinney    TX  Dallas-Fort Worth      Collin

1996-04-01        77494      Katy    TX            Houston      Harris

1996-04-01        60614   Chicago    IL            Chicago        Cook

1996-04-01        79936   El Paso    TX            El Paso     El Paso


            Size_Rank     price
Date
1996-04-01          1  334200.0
1996-04-01          2  235700.0
1996-04-01          3  210400.0
1996-04-01          4  498100.0
1996-04-01          5   77300.0
```

STEP 2: EXPLORATORY DATA ANALYSIS

```
#Sampling the dataset
df = cleaned_data.sample(n=20000, replace=False)

#view te sampled dataset df
df.head()
```

```
            Region_Name            City State        Metro County_Name
\
Date
```

```
2008-04-01         31765             Meigs     GA  Thomasville       Thomas

1999-02-01          6105          Hartford     CT     Hartford     Hartford

2002-01-01         21678            Worton     MD  Springfield         Kent

2009-05-01         53104           Bristol     WI      Chicago      Kenosha

2016-07-01         29690   Travelers Rest     SC   Greenville   Greenville


            Size_Rank     price
Date
2008-04-01      13233   70700.0
1999-02-01       4011  165300.0
2002-01-01      13162  112300.0
2009-05-01      10188  225100.0
2016-07-01       5044  147000.0
```

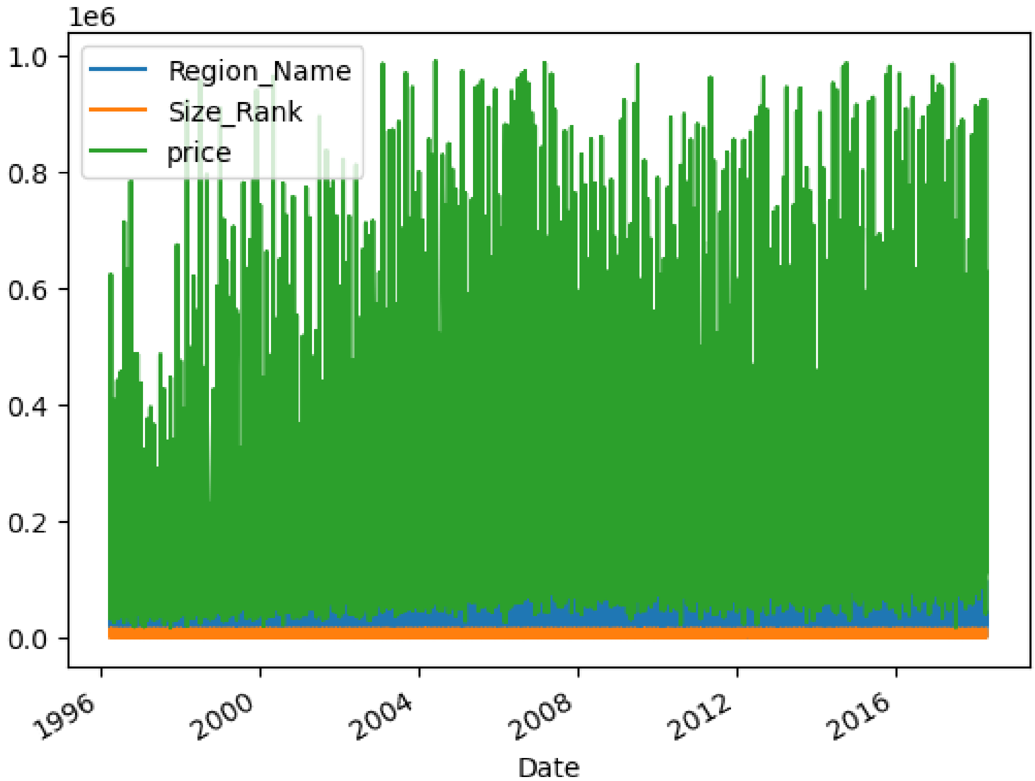
```
df.shape
```

```
(20000, 7)
```

Univariate Analysis

```
df.plot()
```

```
<Axes: xlabel='Date'>
```



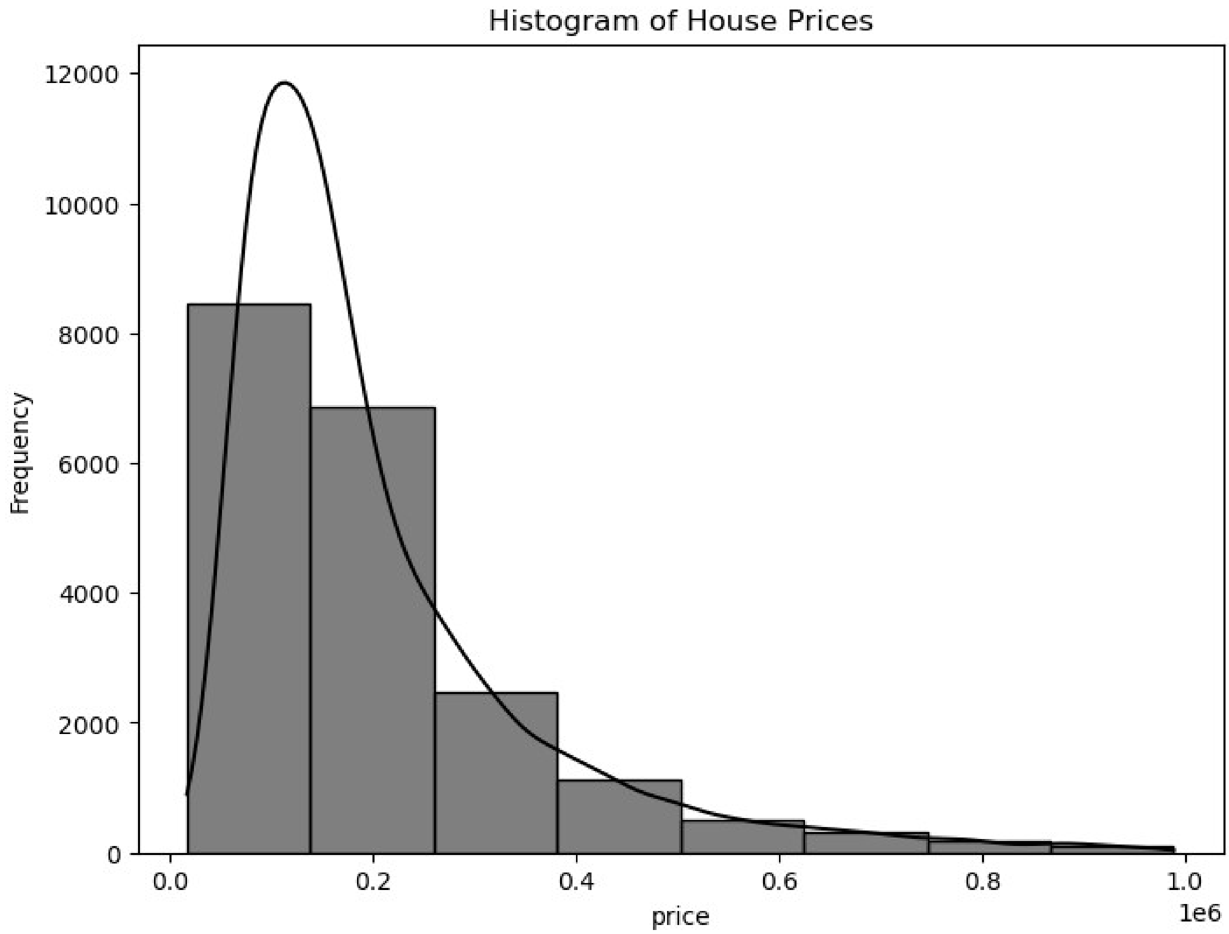
We are checking for the distribution of the prices column

```
#descriptive statistics
df.describe().T
```

```
                count          mean            std      min        25%  \
Region_Name   20000.0   48363.06175   30060.116512   1001.0   21655.00  
Size_Rank     20000.0    7246.35175    4246.814628      1.0    3563.75  
price         20000.0  203836.18000  151363.340080  17300.0  104200.00  


                  50%       75%       max  
Region_Name   46117.5   76152.0   99901.0  
Size_Rank      7197.0   10883.0   14723.0  
price        155950.0  250525.0  988800.0  
```

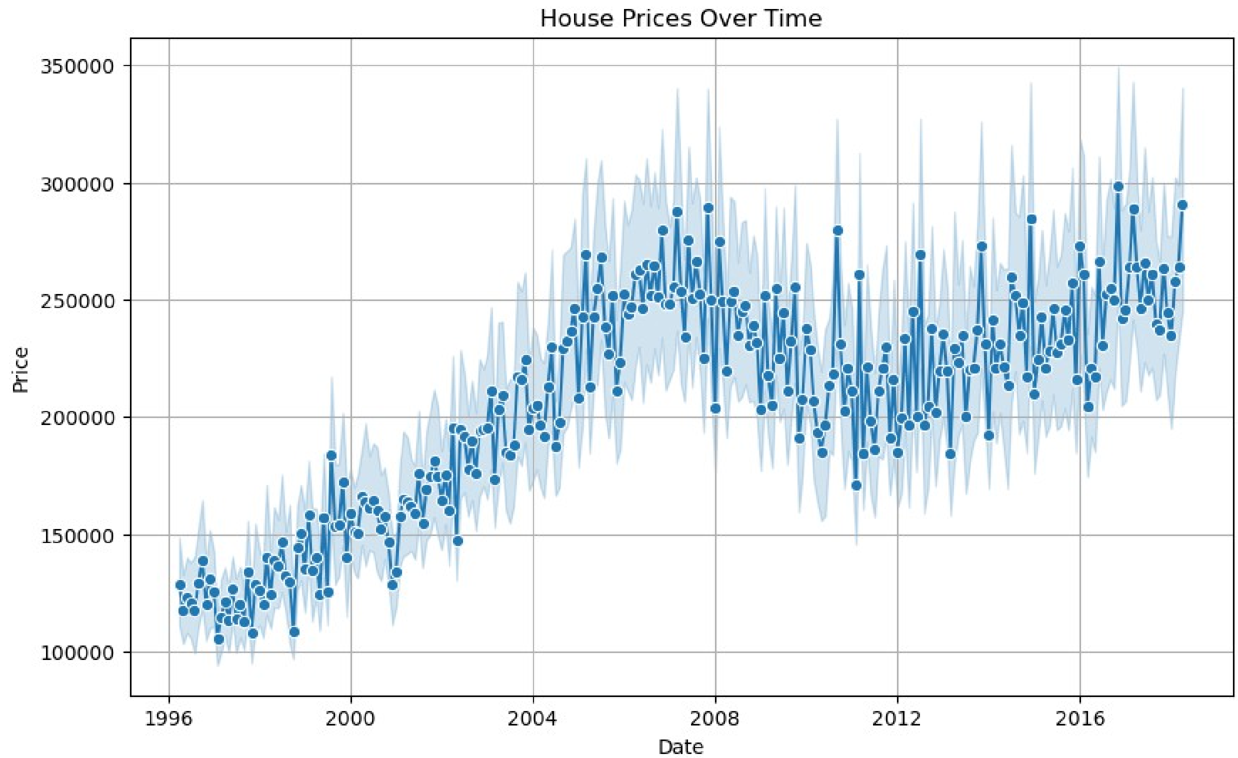
```
# Plot the histogram of house prices
plt.figure(figsize=(8, 6))
sns.histplot(df['price'], bins=8, kde=True, color='black')

# Add titles and labels
plt.title('Histogram of House Prices')
plt.xlabel('price')
```

```
plt.ylabel('Frequency')

# Show the plot
plt.show()
```



The sales prices have a right skew. Majority of the houses were sold at 2.5million to 3million.

```
plt.figure(figsize=(10, 6))
sns.lineplot(x='Date', y='price', data=df, marker='o')

# Add titles and labels
plt.title('House Prices Over Time')
plt.xlabel('Date')
plt.ylabel('Price')
plt.grid(True)

# Show the plot
plt.show()
```

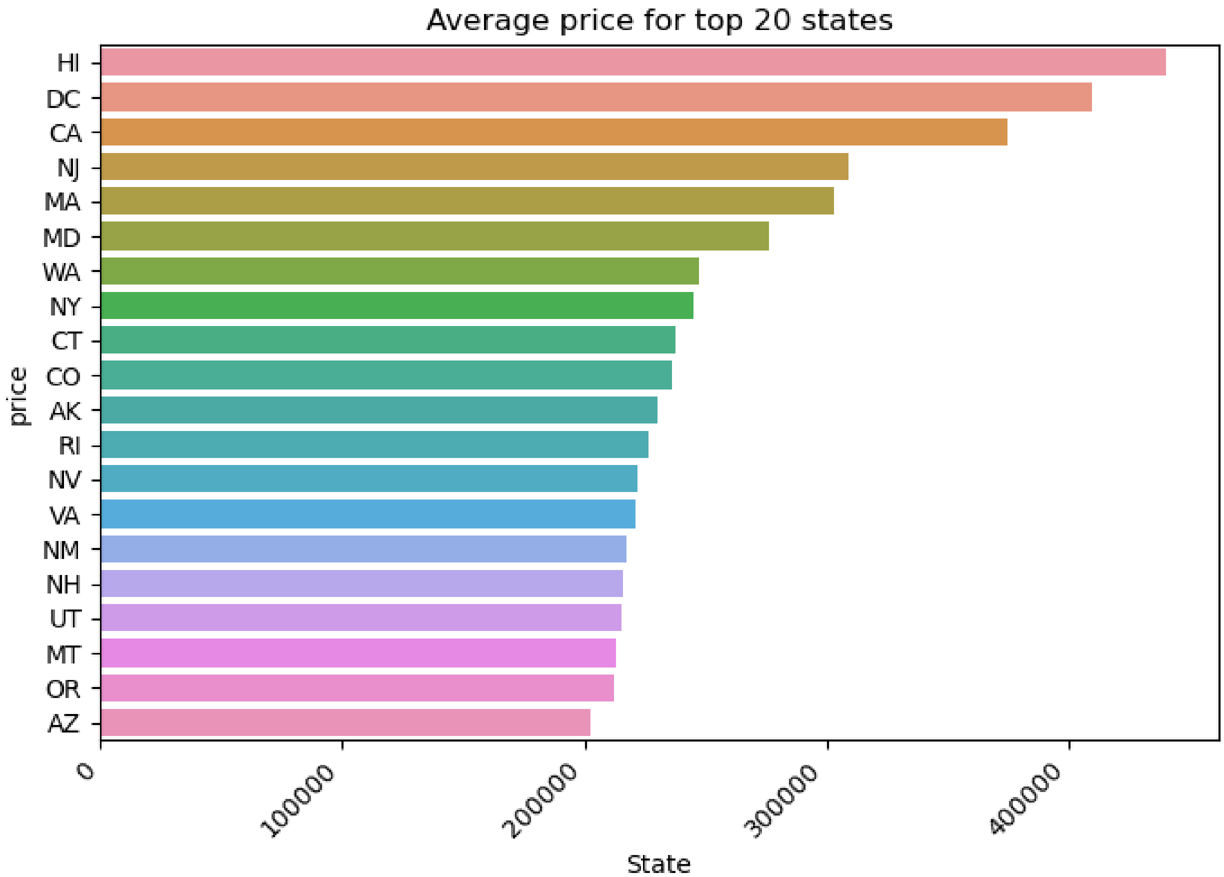


There has been an upward trend in the value of properties over time.

Checking for the relationship between Price and the top 20 states

```
# Aggregate price data by state
state_prices = df.groupby('State')['price'].mean().reset_index()

# Sort by price and get the top 20 state
top_state=state_prices.sort_values(by='price',
ascending=False).head(20)

plt.figure(figsize=(8,5))
ax = sns.barplot(x='price', y='State', data=top_state, ci = None)
plt.xticks(rotation=45, ha ='right')
plt.title('Average price for top 20 states')
plt.xlabel('State')
plt.ylabel('price')
plt.show()
```

```
/var/folders/zb/8mcvjv4d1gd0k4hjdpzxw6bw0000gn/T/
ipykernel_13978/1137472917.py:8: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same
effect.

  ax = sns.barplot(x='price', y='State', data=top_state, ci = None)
```



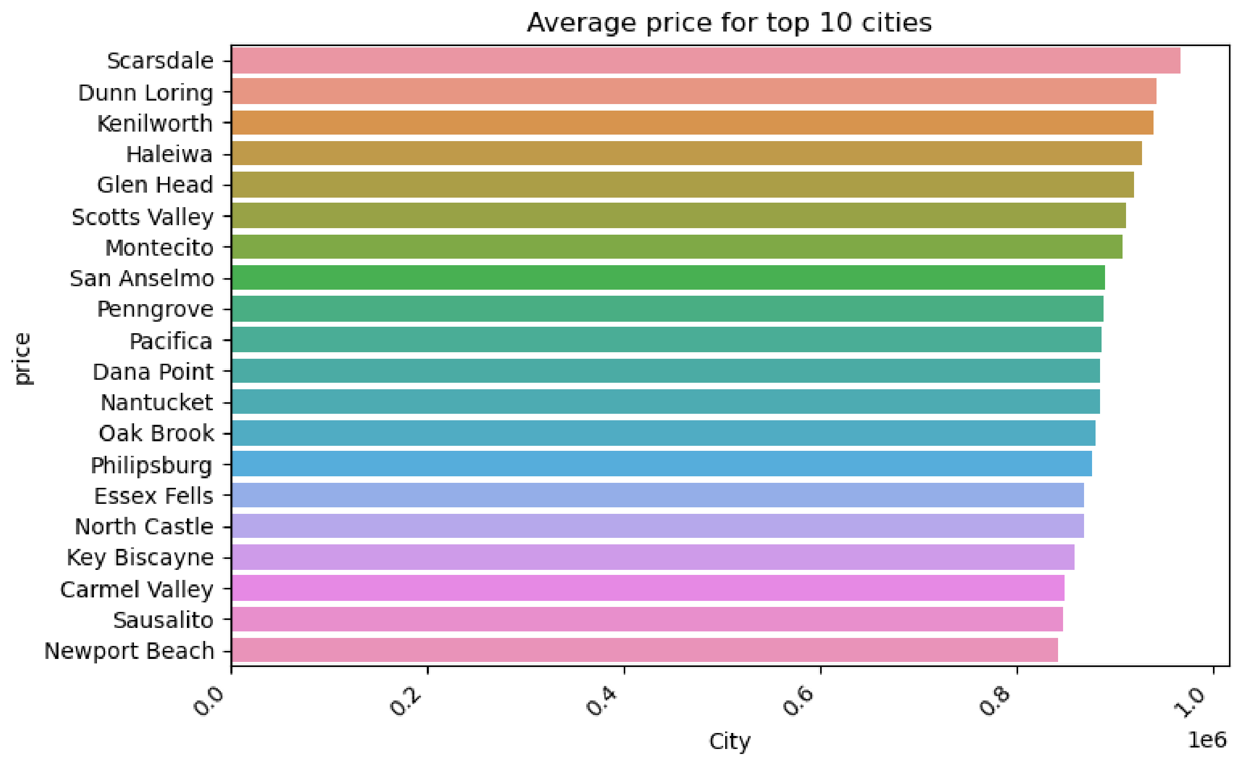
The plots indicate that properties in Washington, D.C. have been consistently purchased at increasingly higher prices over time.

Checking for the relationship between Price and the top 10 cities.

```
# Aggregate price data by city
city_prices = df.groupby('City')['price'].mean().reset_index()

# Sort by price and get the top 10 cities
top_city=city_prices.sort_values(by='price', ascending=False).head(20)

plt.figure(figsize=(8, 5))
ax = sns.barplot(x='price', y='City', data=top_city, ci = None)
plt.xticks(rotation=45, ha ='right')
plt.title('Average price for top 10 cities')
plt.xlabel('City')
plt.ylabel('price')
plt.show()
```

```
/var/folders/zb/8mcvjv4d1gd0k4hjdpzxw6bw0000gn/T/
ipykernel_13978/3410905616.py:8: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same
```

```
effect.

  ax = sns.barplot(x='price', y='City', data=top_city, ci = None)
```

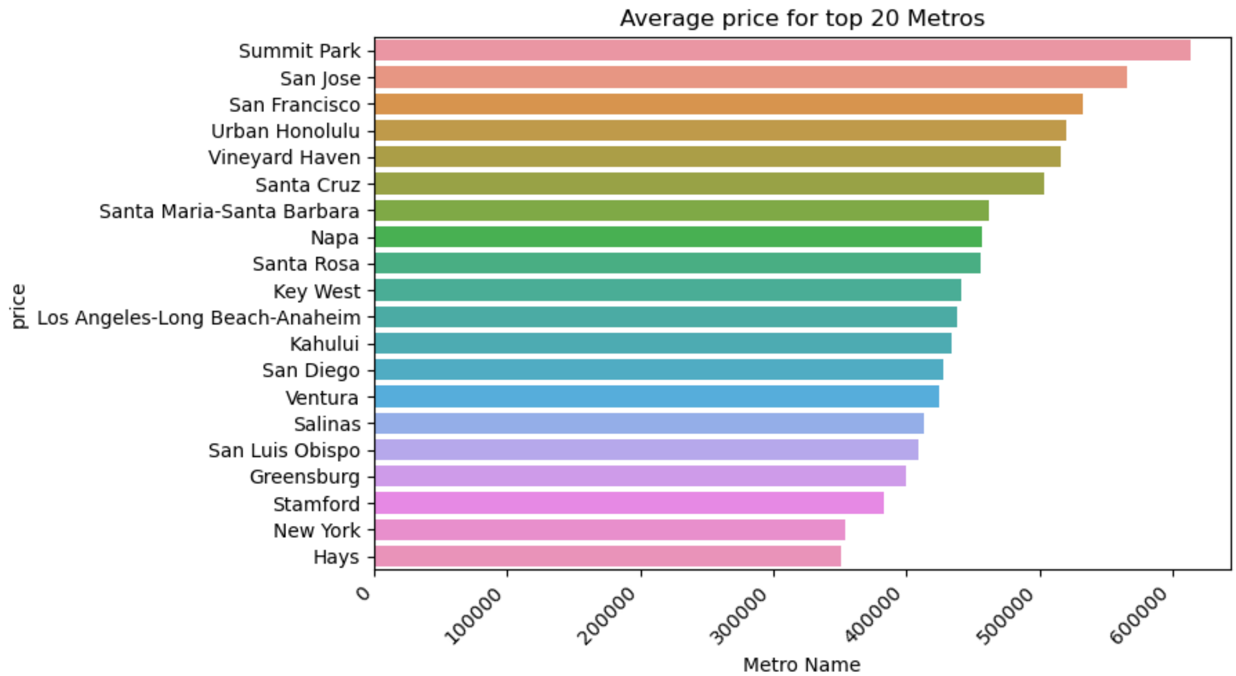


Foster city had the highest price followed by Malibu, Lexington Hills & Newport Beach.

Checking for the relationship between Price and the top 10 Metro.

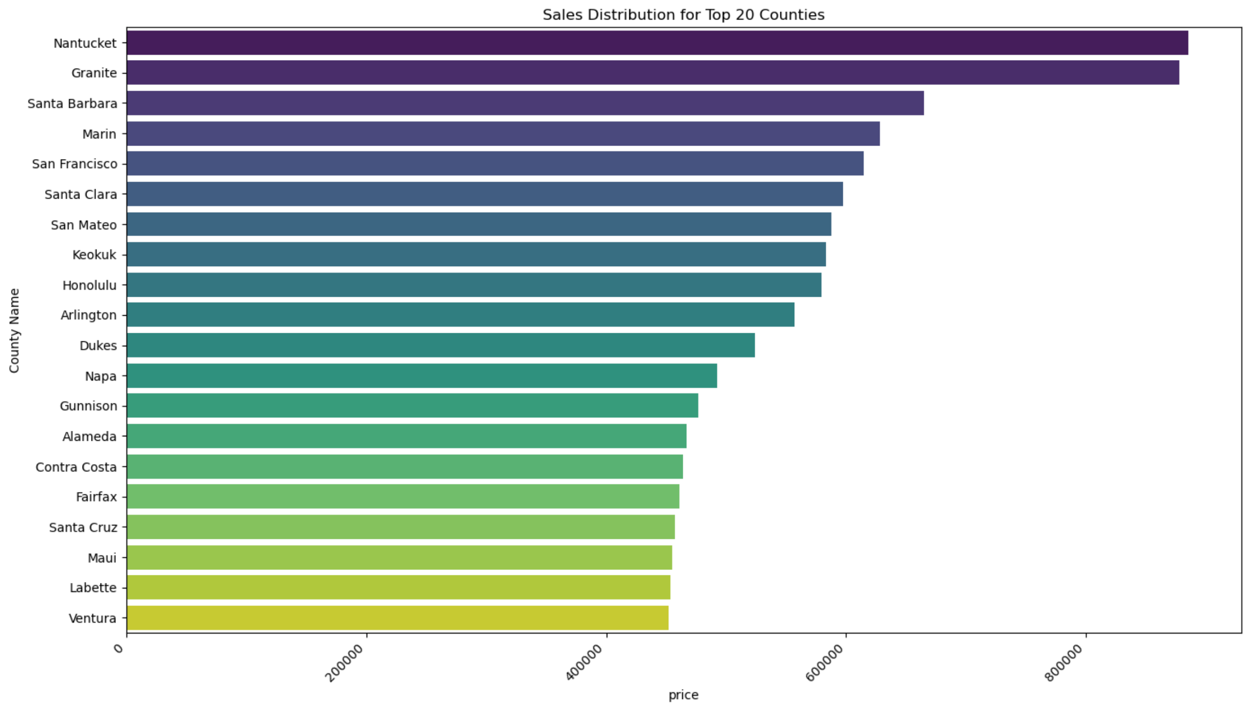
```
metro_prices = cleaned_data.groupby('Metro')
['price'].mean().reset_index()
# Sort by sales and get the top 20 metro areas
top_metro = metro_prices.sort_values(by='price',
ascending=False).head(20)

plt.figure(figsize=(8, 5))
ax = sns.barplot(x='price', y='Metro', data=top_metro, ci = None)
plt.xticks(rotation=45, ha ='right')
plt.title('Average price for top 20 Metros')
plt.xlabel('Metro Name')
plt.ylabel('price')
plt.show()

/var/folders/zb/8mcvjv4d1gd0k4hjdpzxw6bw0000gn/T/
ipykernel_13978/1201039876.py:2: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same
effect.
```

```
ax = sns.barplot(x='price', y='Metro', data=top_metro, ci = None)
```



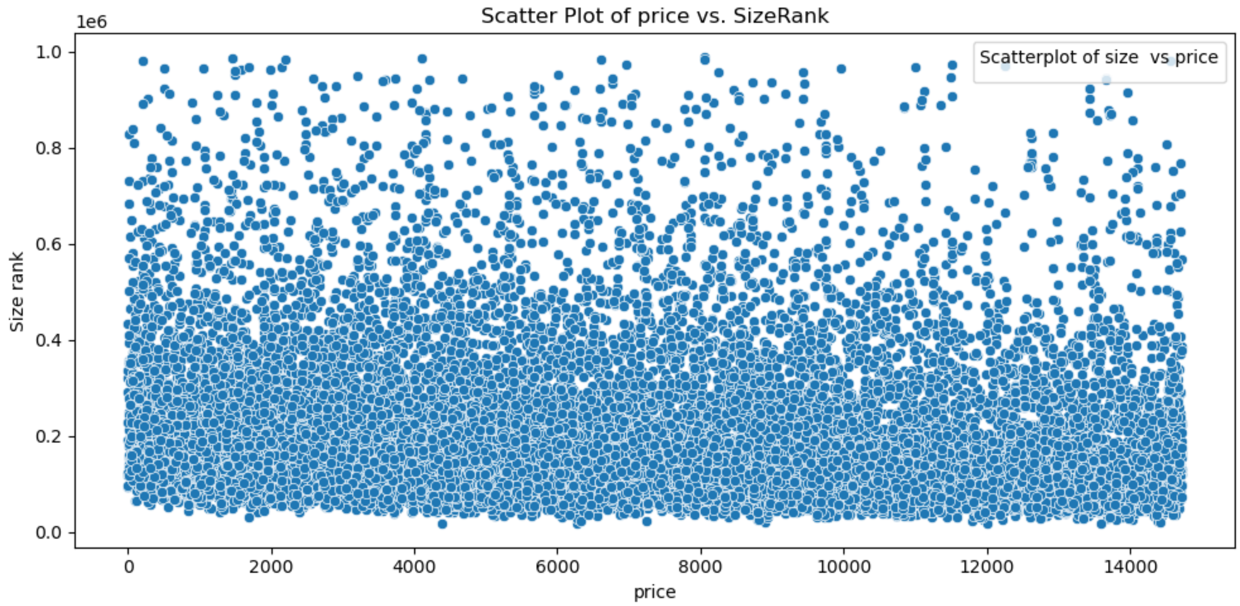
- Checking relationship between country name & price

```
county_price = df.groupby('County_Name')['price'].mean().reset_index()
# Sort by sales and get the top 20 cities
top_counties = county_price.sort_values(by='price',
ascending=False).head(20)

plt.figure(figsize=(14, 8))
sns.barplot(data=top_counties, y='County_Name', x='price',
palette='viridis')
plt.xticks(rotation=45, ha='right')
plt.title('Sales Distribution for Top 20 Counties')
plt.xlabel('price')
plt.ylabel('County Name')
plt.tight_layout()
plt.show()
```



- Checking relationship between siderank & price

```
sizerank_price = df.groupby('State')['Size_Rank'].mean().reset_index()
# Sort by sales and get the top 20 cities
top_rank = sizerank_price.sort_values(by='Size_Rank',
ascending=False).head(20)

plt.figure(figsize=(10, 5))
sns.scatterplot(data=df, x='Size_Rank', y='price', palette='viridis')
plt.title('Scatter Plot of price vs. SizeRank')
plt.xlabel('price')
plt.ylabel('Size rank')
plt.legend(title='Scatterplot of size  vs price')
plt.tight_layout()
plt.show()

/var/folders/zb/8mcvjv4d1gd0k4hjdpzxw6bw0000gn/T/
ipykernel_13978/1487183105.py:2: UserWarning: Ignoring `palette`
because no `hue` variable has been assigned.
  sns.scatterplot(data=df, x='Size_Rank', y='price',
palette='viridis')
No artists with labels found to put in legend.  Note that artists
whose label start with an underscore are ignored when legend() is
called with no argument.
```



STEP 3: Stationarity Check and Transformation

We shall first check for stationarity by using a time series plot.

```
# Plot the entire dataframe
df.plot(figsize=(12, 6))

# Customize the plot (optional)
plt.xlabel("Date Time")
plt.ylabel("Values")
plt.title("Time Series Plot")
plt.grid(True)
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
with dates

# Show the plot
plt.show()
```

Our dataset seems to be stationary but we can double check using the Augmented Dickey-Fuller test.

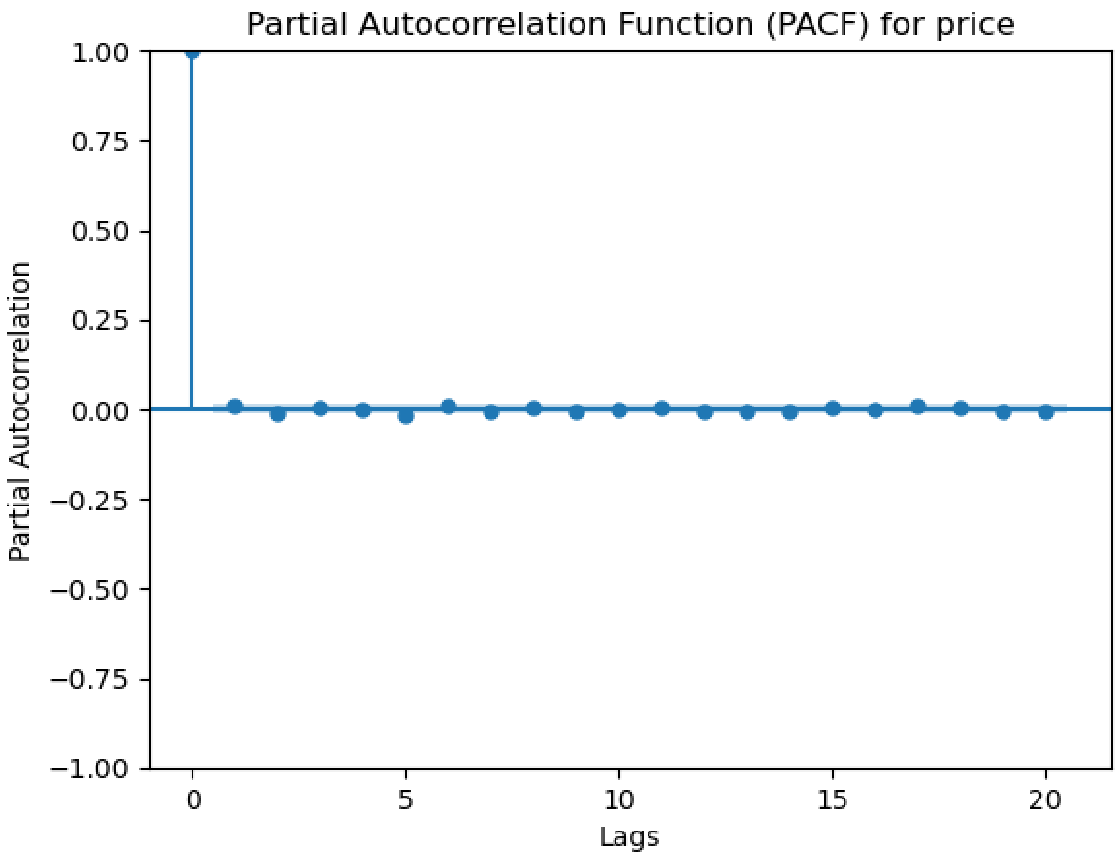
```
#A function to check for stationary
from statsmodels.tsa.stattools import adfuller

def check_stationarity(series):
    result = adfuller(series)
    print("P value:", result[1])

    if result[1]>0.05:
        print("Is non stationary")
    else:
        print("Is stationary")

#Using the function to check for stationarity
check_stationarity(df["price"])

P value: 0.0
Is stationary
```

Our dataset is stationary from the adfuller method.

```
#Getting P,Q,& D
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
#Plot partial autocorrelation (P)
plt.figure(figsize=(15, 5))
plot_pacf(df["price"],lags=20)
plt.xlabel("Lags")
plt.ylabel("Partial Autocorrelation")
```

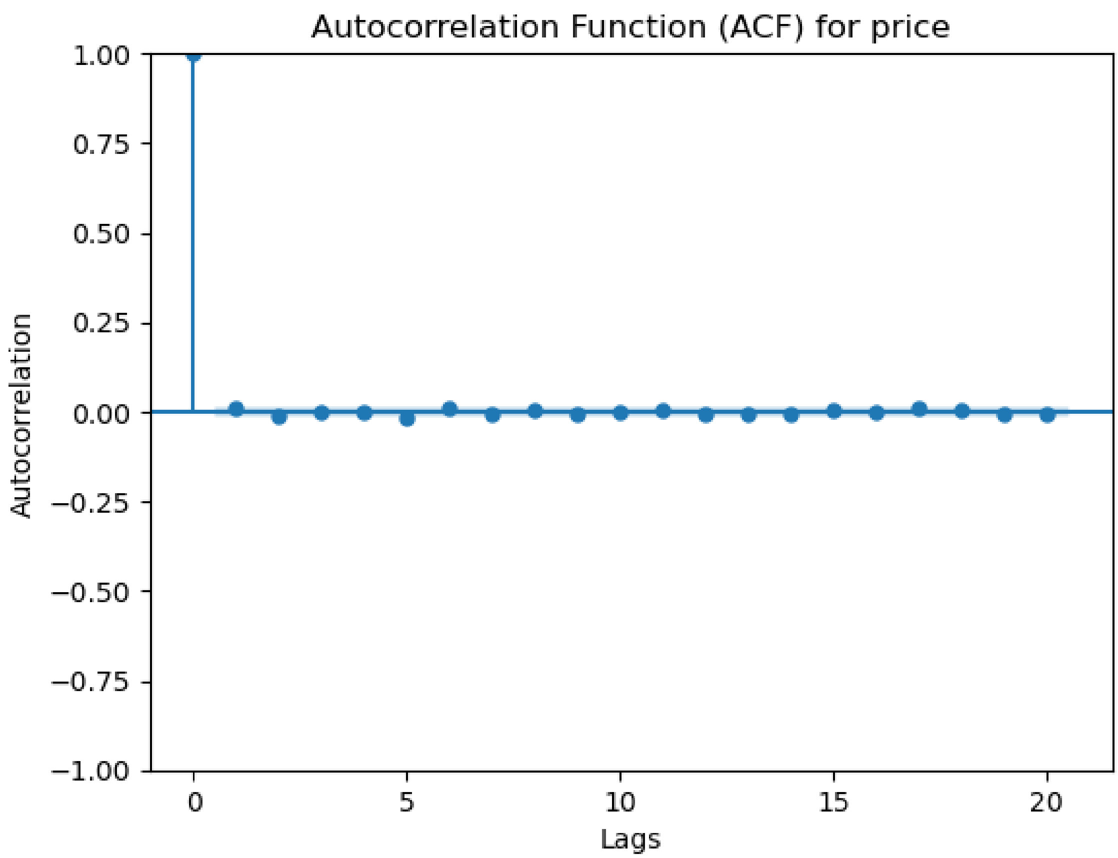
```
plt.title("Partial Autocorrelation Function (PACF) for price")
plt.show()
```

```
<Figure size 1500x500 with 0 Axes>
```




```
#Plot autocorrelation plot(Q)
plt.figure(figsize=(15, 5))
plot_acf(df["price"],lags=20);
plt.xlabel("Lags")
plt.ylabel("Autocorrelation")
plt.title("Autocorrelation Function (ACF) for price")
plt.show()
```

```
<Figure size 1500x500 with 0 Axes>
```



STEP 4: MODELLING

Fitting an ARIMA MODEL

```
p,d,q = (4,1,3)

# Defining the ARIMA parameters
p = 3  # Autoregressive parameter
d = 1  # Differencing parameter
q = 2  # Moving average parameter

from statsmodels.tsa.arima.model import ARIMA

arima = ARIMA(df["price"], order=(4,1,3))
arima_fit = arima.fit()
```

```
/Users/andrewbaraka/anaconda3/lib/python3.11/site-packages/
statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has
been provided, but it has no associated frequency information and so
will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
/Users/andrewbaraka/anaconda3/lib/python3.11/site-packages/statsmodels
/tsa/base/tsa_model.py:473: ValueWarning: A date index has been
```

```
provided, but it is not monotonic and so will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/Users/andrewbaraka/anaconda3/lib/python3.11/site-packages/statsmodels
/tsa/base/tsa_model.py:473: ValueWarning: A date index has been
provided, but it has no associated frequency information and so will
be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
/Users/andrewbaraka/anaconda3/lib/python3.11/site-packages/statsmodels
/tsa/base/tsa_model.py:473: ValueWarning: A date index has been
provided, but it is not monotonic and so will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/Users/andrewbaraka/anaconda3/lib/python3.11/site-packages/statsmodels
/tsa/base/tsa_model.py:473: ValueWarning: A date index has been
provided, but it has no associated frequency information and so will
be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
/Users/andrewbaraka/anaconda3/lib/python3.11/site-packages/statsmodels
/tsa/base/tsa_model.py:473: ValueWarning: A date index has been
provided, but it is not monotonic and so will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
```

```python
# Printing the summary of the ARIMA model
print(arima_fit.summary())
```

```
                               SARIMAX Results

======================================================================
========
Dep. Variable:                  price   No. Observations:
20000
Model:                 ARIMA(4, 1, 3)   Log Likelihood             -
266958.413
Date:                Sat, 29 Jun 2024   AIC
533932.826
Time:                        21:27:46   BIC
533996.053
Sample:                             0   HQIC
533953.512
                              - 20000

Covariance Type:                  opg

======================================================================
========
                 coef    std err          z      P>|z|      [0.025
0.975]
```

```
--------------------------------------------------------------------------------
ar.L1         -1.6988      0.039    -43.502      0.000      -1.775      -1.622
ar.L2         -0.9397      0.040    -23.224      0.000      -1.019      -0.860
ar.L3         -0.0079      0.016     -0.497      0.619      -0.039       0.023
ar.L4         -0.0066      0.009     -0.773      0.439      -0.023       0.010
ma.L1          0.7109      0.038     18.562      0.000       0.636       0.786
ma.L2         -0.7622      0.018    -42.692      0.000      -0.797      -0.727
ma.L3         -0.9476      0.038    -25.161      0.000      -1.021      -0.874
sigma2      2.524e+10   1.24e-13   2.03e+23      0.000    2.52e+10    2.52e+10
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):          31603.95
Prob(Q):                              0.99   Prob(JB):                      0.00
Heteroskedasticity (H):               1.02   Skew:                          2.00
Prob(H) (two-sided):                  0.49   Kurtosis:                      7.69
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 2.69e+39. Standard errors may be unstable.
```

The model seems to capture the autoregressive nature of the differenced data (diff1) with statistically significant coefficients for past values (ar.L1 to ar.L4). However, the moving average terms (ma.L1 to ma.L3) don't appear to have a strong influence. The high variance of the error term (sigma2) suggests there might be room for improvement.

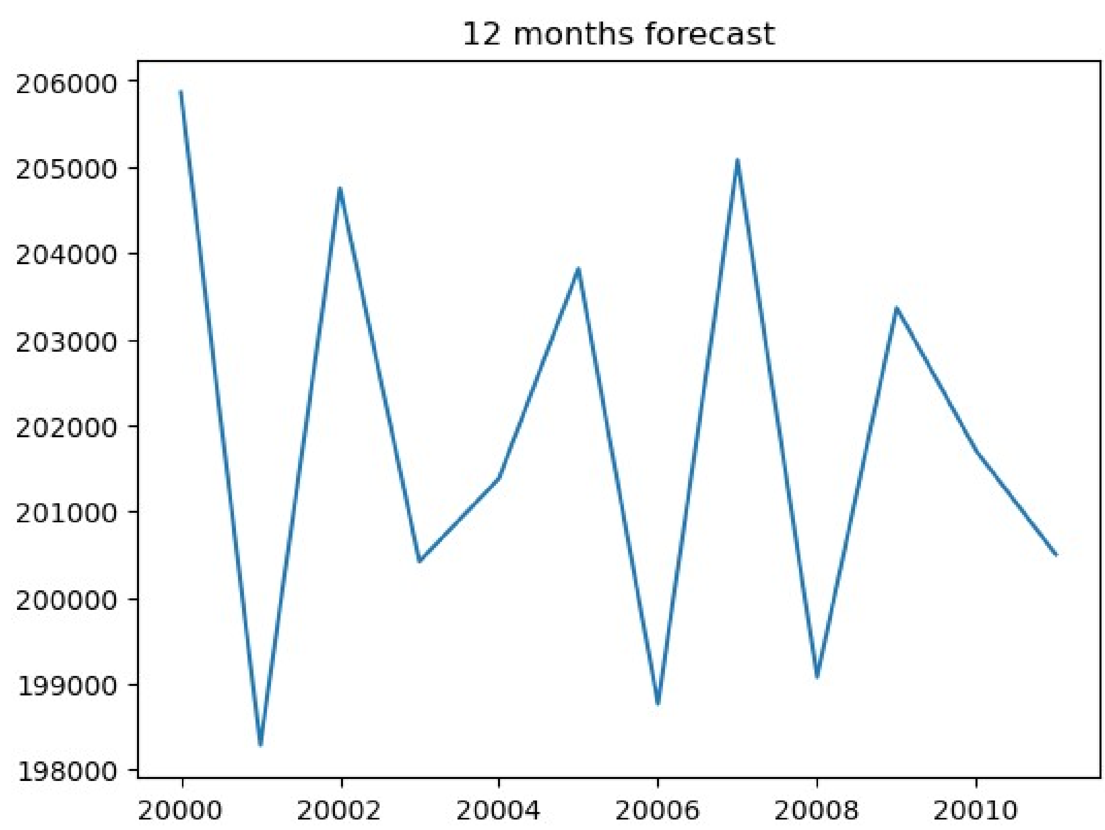
```python
# Calculating AIC value
aic_value = arima_fit.aic
print("AIC value:", aic_value)
```

```
AIC value: 533932.8255195577
```

- The AIC (Akaike Information Criterion) is a measure used to evaluate the goodness of fit of a statistical model. It balances the trade-off between the complexity of the model and its goodness of fit to the data. In the context of time series analysis and the ARIMA model, a lower AIC value indicates a better-fitting model.
- The lower the AIC value, the better the model fits the data

```
#predicting future 12 months
arima_fit.forecast(steps=12).plot()
plt.title('12 months forecast')
```

```
/Users/andrewbaraka/anaconda3/lib/python3.11/site-packages/
statsmodels/tsa/base/tsa_model.py:836: ValueWarning: No supported
index is available. Prediction results will be given with an integer
index beginning at `start`.
  return get_prediction_index(
/Users/andrewbaraka/anaconda3/lib/python3.11/site-packages/statsmodels
/tsa/base/tsa_model.py:836: FutureWarning: No supported index is
available. In the next version, calling this method in a model without
a supported index will result in an exception.
  return get_prediction_index(

Text(0.5, 1.0, '12 months forecast')
```



```python
# from sklearn.metrics import mean_squared_error
# mse = np.sqrt(mean_squared_error(arima_fit, arima_fit.forecast))
# mse

p_values = range(0,5)
d_values = range(0,3)
q_values = range(0,5)

#Getting the optimal params function

import numpy as np
def find_optimal_params(series):
  """
  This function finds the optimal values for p, d, and q parameters
for an ARIMA model.

  Args:
    series: A Pandas Series containing the time series data.

  Returns:
    A tuple containing the optimal values for p, d, and q.
  """

  min_aic = np.inf
  optimal_params = None

  for p in p_values:
    for d in d_values:
      for q in q_values:
        try:
          model = ARIMA(series, order=(p, d, q))
          result = model.fit()
          if result.aic < min_aic:
            min_aic = result.aic
            optimal_params = (p, d, q)
        except:
          continue

  return optimal_params

#show the optimal params

optimal_params = find_optimal_params('diff1')
print("Optimal parameters:", optimal_params)
```

```
Optimal parameters: None
```

Fitting SARIMA Model

```python
# create sarima model
```

```python
from statsmodels.tsa.statespace.sarimax import SARIMAX

# Define the model
sarima_model = SARIMAX(df['price'], order=(4, 1, 2),
seasonal_order=(4, 1, 2, 12))

# Fit the model
sarima_result = sarima_model.fit()
```

```
/Users/andrewbaraka/anaconda3/lib/python3.11/site-packages/
statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has
been provided, but it has no associated frequency information and so
will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
/Users/andrewbaraka/anaconda3/lib/python3.11/site-packages/statsmodels
/tsa/base/tsa_model.py:473: ValueWarning: A date index has been
provided, but it is not monotonic and so will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/Users/andrewbaraka/anaconda3/lib/python3.11/site-packages/statsmodels
/tsa/base/tsa_model.py:473: ValueWarning: A date index has been
provided, but it has no associated frequency information and so will
be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
/Users/andrewbaraka/anaconda3/lib/python3.11/site-packages/statsmodels
/tsa/base/tsa_model.py:473: ValueWarning: A date index has been
provided, but it is not monotonic and so will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)

RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =           13     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  1.35309D+01    |proj g|=  4.92965D-02

 This problem is unconstrained.


At iterate    5    f=  1.34867D+01    |proj g|=  6.04842D-02

At iterate   10    f=  1.34757D+01    |proj g|=  4.97338D-03

At iterate   15    f=  1.34742D+01    |proj g|=  2.06900D-03

At iterate   20    f=  1.34738D+01    |proj g|=  1.11983D-03
```

```
At iterate   25    f=  1.34738D+01    |proj g|=  7.78330D-05

At iterate   30    f=  1.34738D+01    |proj g|=  1.31594D-03

At iterate   35    f=  1.34737D+01    |proj g|=  1.55857D-04

At iterate   40    f=  1.34737D+01    |proj g|=  1.74117D-03

At iterate   45    f=  1.34737D+01    |proj g|=  1.43060D-04

At iterate   50    f=  1.34737D+01    |proj g|=  3.40888D-04

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
   13     50     63      1     0     0   3.409D-04   1.347D+01
  F =   13.473672105000595

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT

/Users/andrewbaraka/anaconda3/lib/python3.11/site-packages/
statsmodels/base/model.py:607: ConvergenceWarning: Maximum Likelihood
optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

```
# Make predictions
sarima_forecast = sarima_result.forecast(steps=12)
```

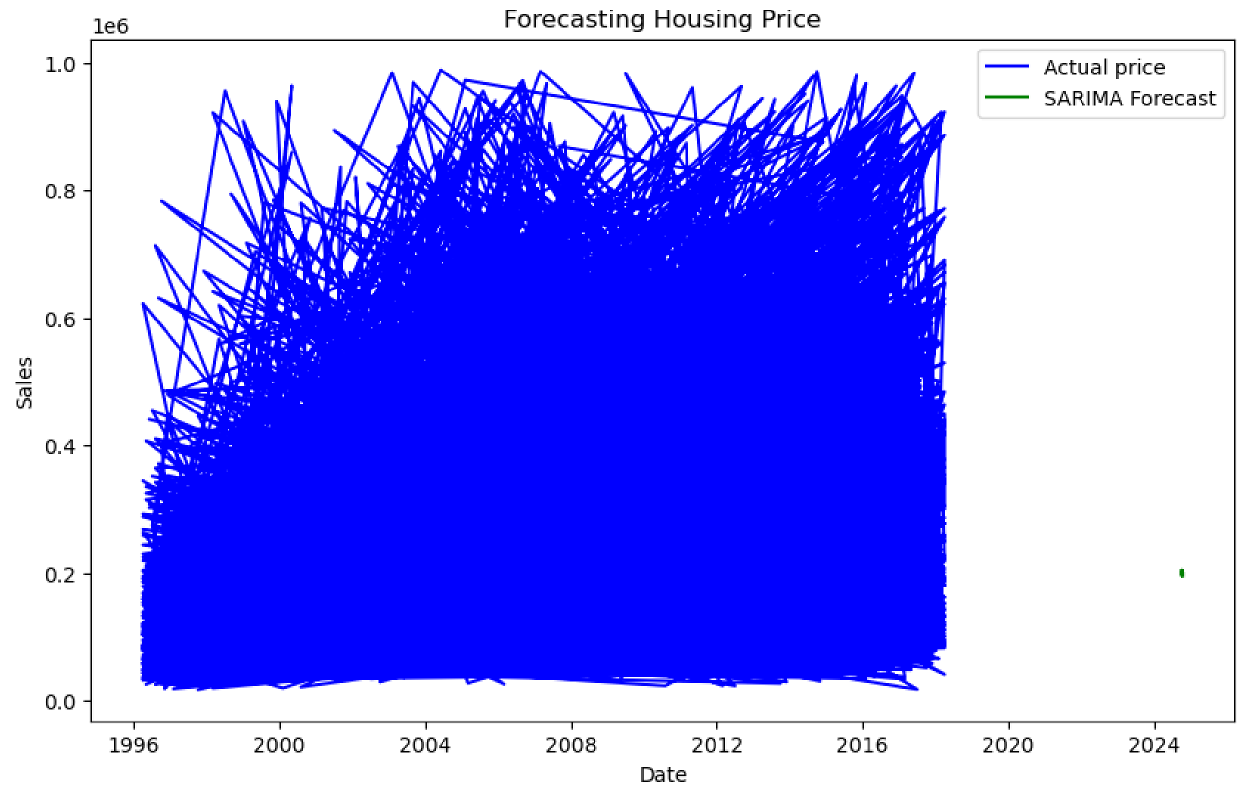
```
/Users/andrewbaraka/anaconda3/lib/python3.11/site-packages/
statsmodels/tsa/base/tsa_model.py:836: ValueWarning: No supported
index is available. Prediction results will be given with an integer
index beginning at `start`.
  return get_prediction_index(
```

```
# Print the forecasted values
print("Forecasted Housing price:")
print(sarima_forecast)
```

```
Forecasted Housing price:
20000    202556.053110
```

```
20001    196049.605732
20002    204828.845832
20003    200995.127188
20004    200911.066002
20005    198972.453787
20006    197848.520859
20007    202971.504796
20008    200579.346374
20009    198805.690570
20010    200700.391353
20011    195901.163480
Name: predicted_mean, dtype: float64
```

```python
#visualize the forecasting
import matplotlib.pyplot as plt

# Plot the actual and forecasted values
plt.figure(figsize=(10, 6))
plt.plot(df["price"], label="Actual price", color="blue")
# plt.plot(arima_fit.forecast, label="ARIMA Forecast", color="red")
plt.plot(sarima_forecast, label="SARIMA Forecast", color="green")
plt.xlabel("Date")
plt.ylabel("Sales")
plt.title("Forecasting Housing Price")
plt.legend()
plt.show()
```



FINDINGS

1. Price Trends: Based on the model's forecasts, stakeholders can gain insights into anticipated price movements in the near future (e.g., next few months or year). This can inform decisions like buying, selling, or holding investment properties.

2. Market Shifts: The analysis might reveal potential turning points in the market, such as a shift from a buyer's to a seller's market. This knowledge allows stakeholders to adjust strategies and potentially gain a competitive edge.

3. Risk Assessment: The model's prediction intervals can indicate the level of uncertainty associated with the forecasts. This information helps stakeholders assess potential risks involved in real estate decisions.

RECOMMENDATIONS

1. Property Valuation: The model can be used to estimate a more data-driven value for specific properties, potentially improving the accuracy of appraisals.

2. Targeted Investments: By identifying factors influencing price fluctuations (e.g., location, property type), stakeholders can make more informed decisions about which properties might offer the best returns.

3. Market Segmentation: The analysis might reveal price variations within different segments of the market (e.g., luxury vs. affordable housing). This knowledge allows stakeholders to tailor their strategies to specific market segments.

4. Continuous Improvement: Recommend regularly updating the model with new data to maintain its accuracy and adapt to evolving market conditions.

CONCLUSION

In conclusion the project's value has reaffirmed how the time series analysis has provided valuable insights into market trends and price as the driver