market-price-prediction

May 30, 2024

[34]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

#displayed directly within the notebook
%matplotlib inline
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelEncoder
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error
```

[35]:
```
# Load the dataset
file_path = 'MarketPricePrediction.csv'
data = pd.read_csv(file_path)

# Display the first few rows
print(data.head())
```

```
       market    month  year  quantity  priceMin  priceMax  priceMod state  \
0  ABOHAR(PB)  January  2005      2350       404       493       446    PB
1  ABOHAR(PB)  January  2006       900       487       638       563    PB
2  ABOHAR(PB)  January  2010       790      1283      1592      1460    PB
3  ABOHAR(PB)  January  2011       245      3067      3750      3433    PB
4  ABOHAR(PB)  January  2012      1035       523       686       605    PB

     city          date
0  ABOHAR  January-2005
1  ABOHAR  January-2006
2  ABOHAR  January-2010
3  ABOHAR  January-2011
4  ABOHAR  January-2012
```

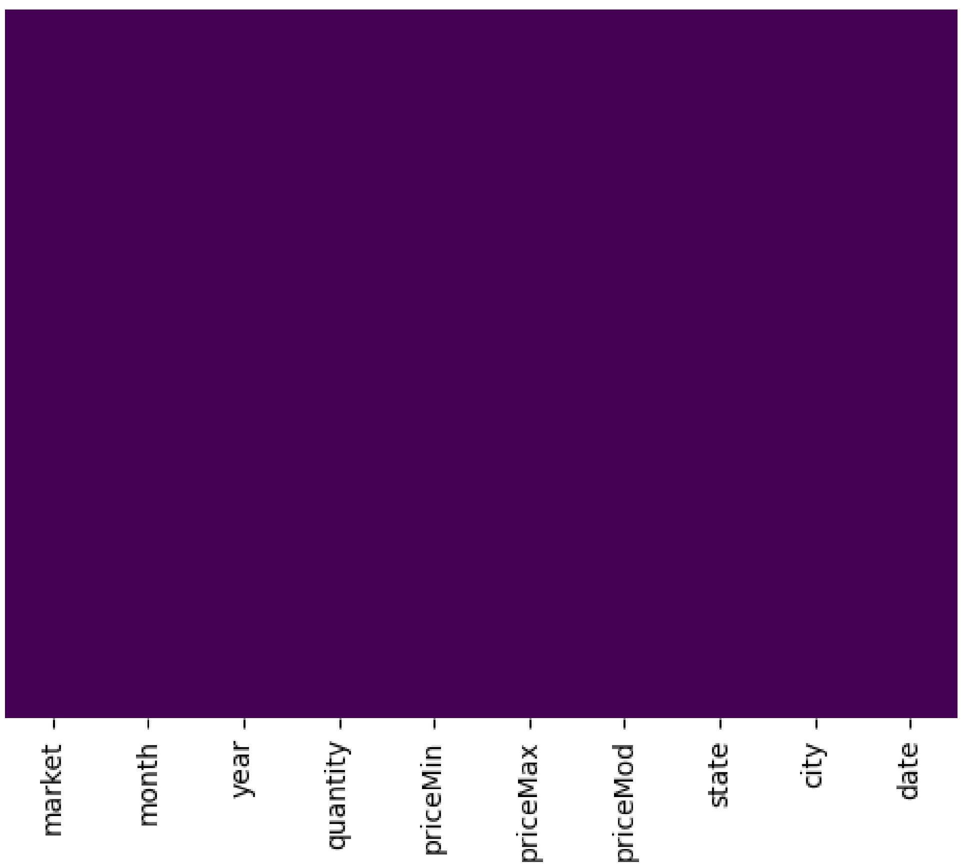
Data Preprocessing

[36]:
```
# Check for missing values
print(data.isnull().sum())
```

```
market      0
month       0
year        0
quantity    0
priceMin    0
priceMax    0
priceMod    0
state       0
city        0
date        0
dtype: int64
```

[37]:
```
#heatmap to see te null values
sns.heatmap(data.isnull(),yticklabels= False, cbar=False,cmap='viridis')
```

[37]: `<Axes: >`



[38]:
```
# Checking duplicate values
data.duplicated().sum()
```

[38]: 0

[39]:
```
# Inspect a few date to determine the format
print(data['date'].head())
```

```
0    January-2005
1    January-2006
2    January-2010
3    January-2011
4    January-2012
Name: date, dtype: object
```

[40]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10227 entries, 0 to 10226
Data columns (total 10 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   market    10227 non-null  object
 1   month     10227 non-null  object
 2   year      10227 non-null  int64
 3   quantity  10227 non-null  int64
 4   priceMin  10227 non-null  int64
 5   priceMax  10227 non-null  int64
 6   priceMod  10227 non-null  int64
 7   state     10227 non-null  object
 8   city      10227 non-null  object
 9   date      10227 non-null  object
dtypes: int64(5), object(5)
memory usage: 799.1+ KB
```

[41]:
```
# Convert the date column to datetime with the correct format
data['date'] = pd.to_datetime(data['date'], format='%B-%Y')

# Set the date column as the index
data.set_index('date', inplace=True)
```

[42]:
```
data
```

[42]:
```
                 market    month  year  quantity  priceMin  priceMax  \
date
2005-01-01  ABOHAR(PB)  January  2005      2350       404       493
2006-01-01  ABOHAR(PB)  January  2006       900       487       638
2010-01-01  ABOHAR(PB)  January  2010       790      1283      1592
2011-01-01  ABOHAR(PB)  January  2011       245      3067      3750
2012-01-01  ABOHAR(PB)  January  2012      1035       523       686
```

```
…                 …         …    …        …         …         …
2011-12-01   YEOLA(MS)  December  2011    131326       282        612
2012-12-01   YEOLA(MS)  December  2012    207066       485       1327
2013-12-01   YEOLA(MS)  December  2013    215883       472       1427
2014-12-01   YEOLA(MS)  December  2014    201077       446       1654
2015-12-01   YEOLA(MS)  December  2015    223315       609       1446

            priceMod state    city
date
2005-01-01       446    PB  ABOHAR
2006-01-01       563    PB  ABOHAR
2010-01-01      1460    PB  ABOHAR
2011-01-01      3433    PB  ABOHAR
2012-01-01       605    PB  ABOHAR
…                 …    …       …
2011-12-01       526    MS   YEOLA
2012-12-01      1136    MS   YEOLA
2013-12-01      1177    MS   YEOLA
2014-12-01      1456    MS   YEOLA
2015-12-01      1126    MS   YEOLA

[10227 rows x 9 columns]
```

[43]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 10227 entries, 2005-01-01 to 2015-12-01
Data columns (total 9 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   market    10227 non-null  object
 1   month     10227 non-null  object
 2   year      10227 non-null  int64
 3   quantity  10227 non-null  int64
 4   priceMin  10227 non-null  int64
 5   priceMax  10227 non-null  int64
 6   priceMod  10227 non-null  int64
 7   state     10227 non-null  object
 8   city      10227 non-null  object
dtypes: int64(5), object(4)
memory usage: 799.0+ KB
```

[44]:
```python
from sklearn.preprocessing import OneHotEncoder

# Define categorical features
categorical_features = ['market', 'state', 'city']
```

```python
# Instantiate OneHotEncoder
one_hot_encoder = OneHotEncoder(sparse_output=False, handle_unknown='ignore')

# Fit and transform the categorical features
encoded_features = one_hot_encoder.fit_transform(data[categorical_features])

# Convert the encoded features into a DataFrame
encoded_df = pd.DataFrame(encoded_features, columns=one_hot_encoder.
 ↪get_feature_names_out(categorical_features), index=data.index)

# Concatenate the encoded DataFrame with the original DataFrame
data_encoded = pd.concat([data.reset_index(drop=True), encoded_df.
 ↪reset_index(drop=True)], axis=1)

# Drop the original categorical features
data_encoded.drop(categorical_features, axis=1, inplace=True)
```

[45]:

```python
data
```

[45]:

```
                market     month  year  quantity  priceMin  priceMax  \
date
2005-01-01  ABOHAR(PB)   January  2005      2350       404       493
2006-01-01  ABOHAR(PB)   January  2006       900       487       638
2010-01-01  ABOHAR(PB)   January  2010       790      1283      1592
2011-01-01  ABOHAR(PB)   January  2011       245      3067      3750
2012-01-01  ABOHAR(PB)   January  2012      1035       523       686
…                    …         …    …         …         …       …
2011-12-01   YEOLA(MS)  December  2011    131326       282       612
2012-12-01   YEOLA(MS)  December  2012    207066       485      1327
2013-12-01   YEOLA(MS)  December  2013    215883       472      1427
2014-12-01   YEOLA(MS)  December  2014    201077       446      1654
2015-12-01   YEOLA(MS)  December  2015    223315       609      1446

            priceMod state    city
date
2005-01-01       446    PB  ABOHAR
2006-01-01       563    PB  ABOHAR
2010-01-01      1460    PB  ABOHAR
2011-01-01      3433    PB  ABOHAR
2012-01-01       605    PB  ABOHAR
…                  …     …       …
2011-12-01       526    MS   YEOLA
2012-12-01      1136    MS   YEOLA
2013-12-01      1177    MS   YEOLA
2014-12-01      1456    MS   YEOLA
2015-12-01      1126    MS   YEOLA
```

```
[10227 rows x 9 columns]
```

[46]:

```
data_encoded
```

[46]:

```
          month  year  quantity  priceMin  priceMax  priceMod  \
0       January  2005      2350       404       493       446
1       January  2006       900       487       638       563
2       January  2010       790      1283      1592      1460
3       January  2011       245      3067      3750      3433
4       January  2012      1035       523       686       605
…           …    …        …        …         …        …
10222  December  2011    131326       282       612       526
10223  December  2012    207066       485      1327      1136
10224  December  2013    215883       472      1427      1177
10225  December  2014    201077       446      1654      1456
10226  December  2015    223315       609      1446      1126

       market_ABOHAR(PB)  market_AGRA(UP)  market_AHMEDABAD(GUJ)  \
0                    1.0              0.0                    0.0
1                    1.0              0.0                    0.0
2                    1.0              0.0                    0.0
3                    1.0              0.0                    0.0
4                    1.0              0.0                    0.0
…                  …                …                    …
10222                0.0              0.0                    0.0
10223                0.0              0.0                    0.0
10224                0.0              0.0                    0.0
10225                0.0              0.0                    0.0
10226                0.0              0.0                    0.0

       market_AHMEDNAGAR(MS)  …  city_SRIGANGANAGAR  city_SRINAGAR  \
0                        0.0  …                 0.0            0.0
1                        0.0  …                 0.0            0.0
2                        0.0  …                 0.0            0.0
3                        0.0  …                 0.0            0.0
4                        0.0  …                 0.0            0.0
…                      …  …                 …              …
10222                    0.0  …                 0.0            0.0
10223                    0.0  …                 0.0            0.0
10224                    0.0  …                 0.0            0.0
10225                    0.0  …                 0.0            0.0
10226                    0.0  …                 0.0            0.0

       city_SRIRAMPUR  city_SURAT  city_TRIVENDRUM  city_UDAIPUR  city_UJJAIN  \
0                 0.0         0.0              0.0           0.0          0.0
1                 0.0         0.0              0.0           0.0          0.0
2                 0.0         0.0              0.0           0.0          0.0
```

```
3                 0.0         0.0               0.0          0.0          0.0
4                 0.0         0.0               0.0          0.0          0.0
…               …         …               …          …          …
10222             0.0         0.0               0.0          0.0          0.0
10223             0.0         0.0               0.0          0.0          0.0
10224             0.0         0.0               0.0          0.0          0.0
10225             0.0         0.0               0.0          0.0          0.0
10226             0.0         0.0               0.0          0.0          0.0

       city_VANI  city_VARANASI  city_YEOLA
0            0.0            0.0         0.0
1            0.0            0.0         0.0
2            0.0            0.0         0.0
3            0.0            0.0         0.0
4            0.0            0.0         0.0
…          …            …         …
10222        0.0            0.0         1.0
10223        0.0            0.0         1.0
10224        0.0            0.0         1.0
10225        0.0            0.0         1.0
10226        0.0            0.0         1.0

[10227 rows x 264 columns]
```

[47]:

```
# Extract the 'date' column from the original data DataFrame
date_column = data.index

# Convert the 'date' column to a DataFrame
date_df = pd.DataFrame(date_column, columns=['date'])

# Add the 'date' column to the data_encoded DataFrame
data_encoded['date'] = date_df.values

# Set the 'date' column as the index
data_encoded.set_index('date', inplace=True)

# Display the updated data_encoded DataFrame
print(data_encoded.head())
```

```
              month  year  quantity  priceMin  priceMax  priceMod  \
date
2005-01-01  January  2005      2350       404       493       446
2006-01-01  January  2006       900       487       638       563
2010-01-01  January  2010       790      1283      1592      1460
2011-01-01  January  2011       245      3067      3750      3433
2012-01-01  January  2012      1035       523       686       605
```

```
            market_ABOHAR(PB)  market_AGRA(UP)  market_AHMEDABAD(GUJ)  \
date
2005-01-01                1.0              0.0                    0.0
2006-01-01                1.0              0.0                    0.0
2010-01-01                1.0              0.0                    0.0
2011-01-01                1.0              0.0                    0.0
2012-01-01                1.0              0.0                    0.0

            market_AHMEDNAGAR(MS)  …  city_SRIGANGANAGAR  city_SRINAGAR  \
date                               …
2005-01-01                    0.0  …                 0.0            0.0
2006-01-01                    0.0  …                 0.0            0.0
2010-01-01                    0.0  …                 0.0            0.0
2011-01-01                    0.0  …                 0.0            0.0
2012-01-01                    0.0  …                 0.0            0.0

            city_SRIRAMPUR  city_SURAT  city_TRIVENDRUM  city_UDAIPUR  \
date
2005-01-01             0.0         0.0              0.0           0.0
2006-01-01             0.0         0.0              0.0           0.0
2010-01-01             0.0         0.0              0.0           0.0
2011-01-01             0.0         0.0              0.0           0.0
2012-01-01             0.0         0.0              0.0           0.0

            city_UJJAIN  city_VANI  city_VARANASI  city_YEOLA
date
2005-01-01          0.0        0.0            0.0         0.0
2006-01-01          0.0        0.0            0.0         0.0
2010-01-01          0.0        0.0            0.0         0.0
2011-01-01          0.0        0.0            0.0         0.0
2012-01-01          0.0        0.0            0.0         0.0

[5 rows x 264 columns]
```

[48]:
```
data_encoded
```

[48]:
```
               month  year  quantity  priceMin  priceMax  priceMod  \
date
2005-01-01   January  2005      2350       404       493       446
2006-01-01   January  2006       900       487       638       563
2010-01-01   January  2010       790      1283      1592      1460
2011-01-01   January  2011       245      3067      3750      3433
2012-01-01   January  2012      1035       523       686       605
…                  …     …         …         …         …
2011-12-01  December  2011    131326       282       612       526
2012-12-01  December  2012    207066       485      1327      1136
2013-12-01  December  2013    215883       472      1427      1177
```

```
2014-12-01  December  2014    201077      446      1654      1456
2015-12-01  December  2015    223315      609      1446      1126

            market_ABOHAR(PB)  market_AGRA(UP)  market_AHMEDABAD(GUJ)  \
date
2005-01-01                1.0              0.0                    0.0
2006-01-01                1.0              0.0                    0.0
2010-01-01                1.0              0.0                    0.0
2011-01-01                1.0              0.0                    0.0
2012-01-01                1.0              0.0                    0.0
…                       …              …                    …
2011-12-01                0.0              0.0                    0.0
2012-12-01                0.0              0.0                    0.0
2013-12-01                0.0              0.0                    0.0
2014-12-01                0.0              0.0                    0.0
2015-12-01                0.0              0.0                    0.0

            market_AHMEDNAGAR(MS)  …  city_SRIGANGANAGAR  city_SRINAGAR  \
date                               …
2005-01-01                    0.0  …                 0.0            0.0
2006-01-01                    0.0  …                 0.0            0.0
2010-01-01                    0.0  …                 0.0            0.0
2011-01-01                    0.0  …                 0.0            0.0
2012-01-01                    0.0  …                 0.0            0.0
…                           …  …               …            …
2011-12-01                    0.0  …                 0.0            0.0
2012-12-01                    0.0  …                 0.0            0.0
2013-12-01                    0.0  …                 0.0            0.0
2014-12-01                    0.0  …                 0.0            0.0
2015-12-01                    0.0  …                 0.0            0.0

            city_SRIRAMPUR  city_SURAT  city_TRIVENDRUM  city_UDAIPUR  \
date
2005-01-01             0.0         0.0              0.0           0.0
2006-01-01             0.0         0.0              0.0           0.0
2010-01-01             0.0         0.0              0.0           0.0
2011-01-01             0.0         0.0              0.0           0.0
2012-01-01             0.0         0.0              0.0           0.0
…                    …         …              …           …
2011-12-01             0.0         0.0              0.0           0.0
2012-12-01             0.0         0.0              0.0           0.0
2013-12-01             0.0         0.0              0.0           0.0
2014-12-01             0.0         0.0              0.0           0.0
2015-12-01             0.0         0.0              0.0           0.0

            city_UJJAIN  city_VANI  city_VARANASI  city_YEOLA
date
```

```
2005-01-01           0.0        0.0            0.0         0.0
2006-01-01           0.0        0.0            0.0         0.0
2010-01-01           0.0        0.0            0.0         0.0
2011-01-01           0.0        0.0            0.0         0.0
2012-01-01           0.0        0.0            0.0         0.0
…                    …          …              …           …
2011-12-01           0.0        0.0            0.0         1.0
2012-12-01           0.0        0.0            0.0         1.0
2013-12-01           0.0        0.0            0.0         1.0
2014-12-01           0.0        0.0            0.0         1.0
2015-12-01           0.0        0.0            0.0         1.0

[10227 rows x 264 columns]
```

Exploratory Data Analysis (EDA)

To perform Exploratory Data Analysis (EDA) on your dataset, particularly focusing on temporal patterns, seasonality, trends, and anomalies, we can use various visualization techniques. Here are the steps we can follow:

Line Plot of Prices Over Time: Visualize the trend of minimum, maximum, and modal prices over time.

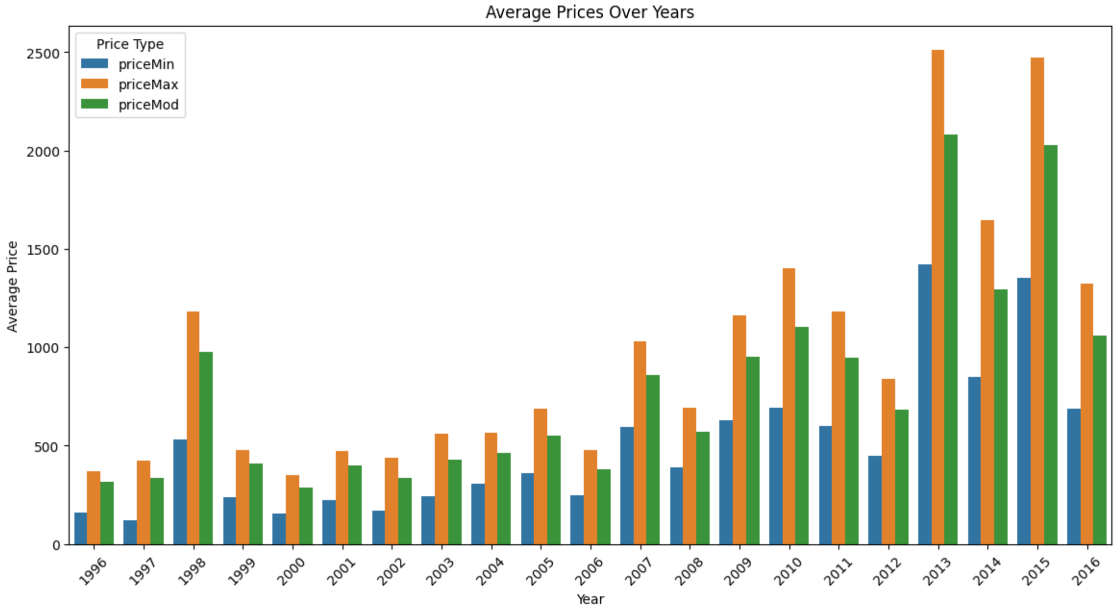
Seasonality Analysis: Analyze how prices vary by month to identify any seasonal patterns.

Trend Analysis: Use rolling means to visualize long-term trends.

Anomaly Detection: Identify any outliers or anomalies in the prices.

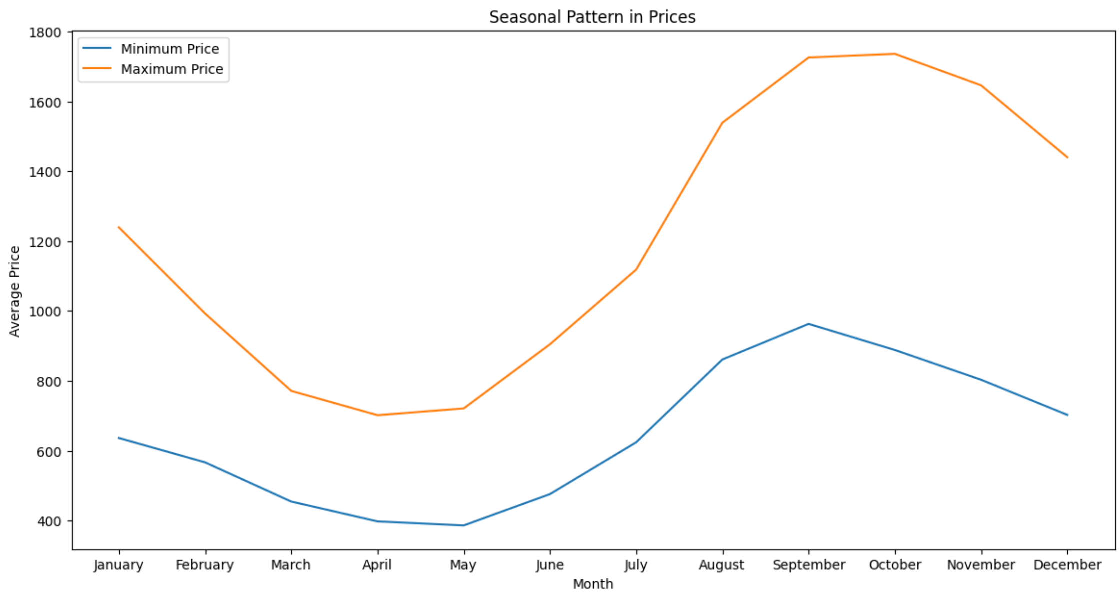
Let's start with these analyses.

[49]:
```
# Bar Plot
yearly_avg = data.groupby('year')[['priceMin', 'priceMax', 'priceMod']].mean().
 ↪reset_index()

plt.figure(figsize=(14, 7))
sns.barplot(x='year', y='value', hue='variable', data=yearly_avg.
 ↪melt(id_vars='year'))
plt.title('Average Prices Over Years')
plt.xlabel('Year')
plt.ylabel('Average Price')
plt.legend(title='Price Type')
plt.xticks(rotation=45)
plt.show()
```



Average prices for each month to see if there's a seasonal pattern.

[50]:
```
data_encoded['month'] = data_encoded.index.month

# Group by month and calculate the average prices
monthly_avg = data_encoded.groupby('month')[['priceMin', 'priceMax']].mean()

# Convert index to datetime object
monthly_avg.index = pd.to_datetime(monthly_avg.index, format='%m')

# Extract month names from the datetime index
monthly_avg.index = monthly_avg.index.strftime('%B')

# Plotting the seasonal pattern
plt.figure(figsize=(14, 7))
plt.plot(monthly_avg.index, monthly_avg['priceMin'], label='Minimum Price')
plt.plot(monthly_avg.index, monthly_avg['priceMax'], label='Maximum Price')

plt.xlabel('Month')
plt.ylabel('Average Price')
plt.title('Seasonal Pattern in Prices')
plt.legend()
plt.show()
```

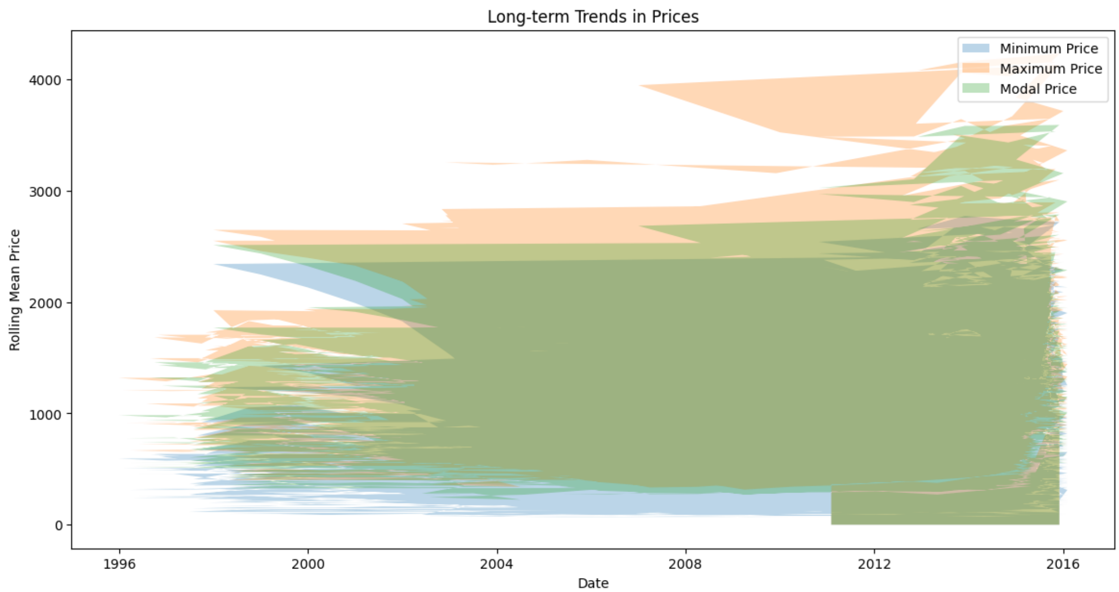


Trend Analysis

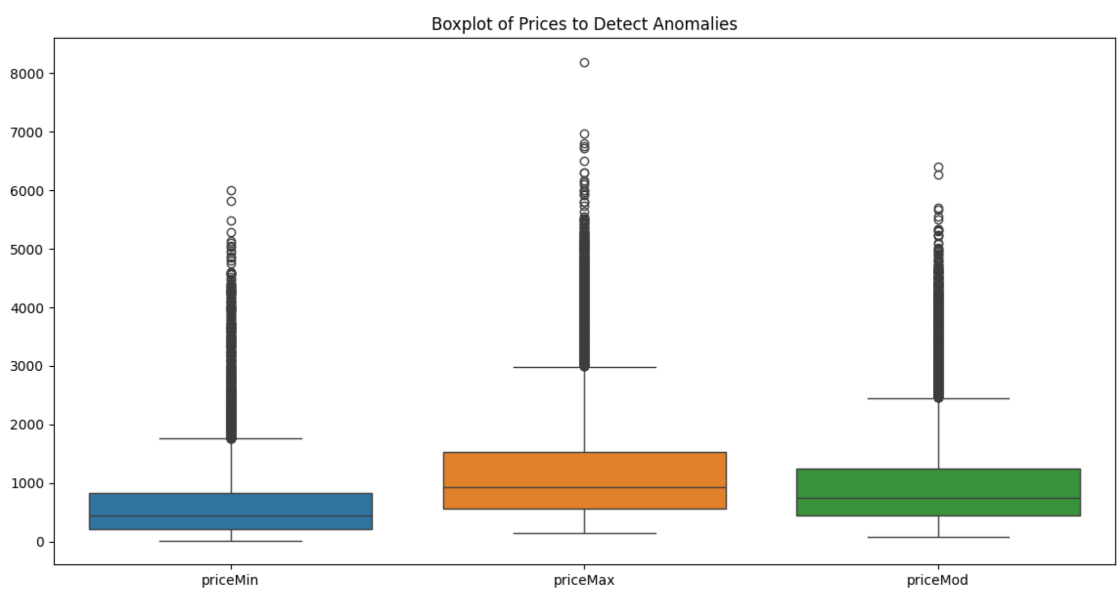
I will use rolling means to smooth the time series data and visualize long-term trends.

[51]:
```
# Calculate rolling means
data_encoded['priceMin_roll'] = data_encoded['priceMin'].rolling(window=12).
    ↪mean()
data_encoded['priceMax_roll'] = data_encoded['priceMax'].rolling(window=12).
    ↪mean()
data_encoded['priceMod_roll'] = data_encoded['priceMod'].rolling(window=12).
    ↪mean()

# Plotting the rolling means using an area plot
plt.figure(figsize=(14, 7))

# Plotting the area for the rolling mean of Minimum Price
plt.fill_between(data_encoded.index, data_encoded['priceMin_roll'],␣
    ↪label='Minimum Price', alpha=0.3)

# Plotting the area for the rolling mean of Maximum Price
plt.fill_between(data_encoded.index, data_encoded['priceMax_roll'],␣
    ↪label='Maximum Price', alpha=0.3)

# Plotting the area for the rolling mean of Modal Price
plt.fill_between(data_encoded.index, data_encoded['priceMod_roll'],␣
    ↪label='Modal Price', alpha=0.3)

plt.xlabel('Date')
```

```
plt.ylabel('Rolling Mean Price')
plt.title('Long-term Trends in Prices')
plt.legend()
plt.show()
```



[52]:
```
# Boxplot to identify anomalies
plt.figure(figsize=(14, 7))
sns.boxplot(data=data_encoded[['priceMin', 'priceMax', 'priceMod']])
plt.title('Boxplot of Prices to Detect Anomalies')
plt.show()
```

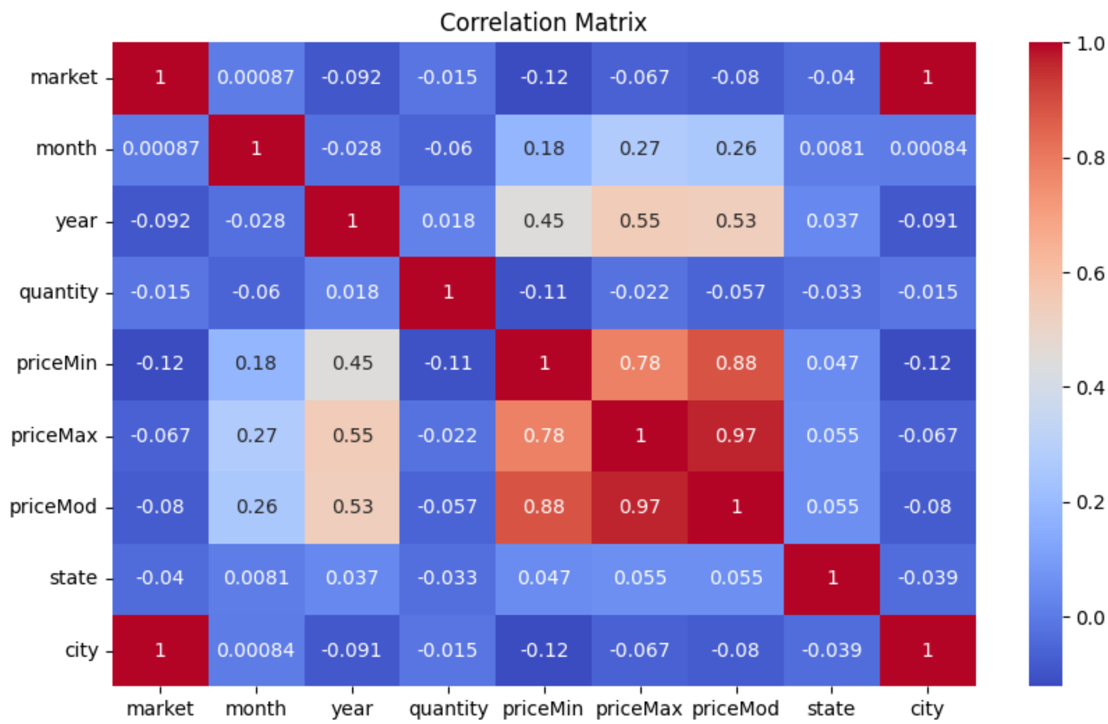


[53]:
```python
data
```

[53]:
```
                  market     month  year  quantity  priceMin  priceMax  \
date
2005-01-01  ABOHAR(PB)   January  2005      2350       404       493
2006-01-01  ABOHAR(PB)   January  2006       900       487       638
2010-01-01  ABOHAR(PB)   January  2010       790      1283      1592
2011-01-01  ABOHAR(PB)   January  2011       245      3067      3750
2012-01-01  ABOHAR(PB)   January  2012      1035       523       686
…                  …         …   …        …         …        …
2011-12-01   YEOLA(MS)  December  2011    131326       282       612
2012-12-01   YEOLA(MS)  December  2012    207066       485      1327
2013-12-01   YEOLA(MS)  December  2013    215883       472      1427
2014-12-01   YEOLA(MS)  December  2014    201077       446      1654
2015-12-01   YEOLA(MS)  December  2015    223315       609      1446

            priceMod state    city
date
2005-01-01       446    PB  ABOHAR
2006-01-01       563    PB  ABOHAR
2010-01-01      1460    PB  ABOHAR
2011-01-01      3433    PB  ABOHAR
2012-01-01       605    PB  ABOHAR
…                …   …     …
2011-12-01       526    MS   YEOLA
2012-12-01      1136    MS   YEOLA
2013-12-01      1177    MS   YEOLA
2014-12-01      1456    MS   YEOLA
2015-12-01      1126    MS   YEOLA

[10227 rows x 9 columns]
```

[54]:
```python
# Encode categorical variables
le_market = LabelEncoder()
data['market'] = le_market.fit_transform(data['market'])
le_state = LabelEncoder()
data['state'] = le_state.fit_transform(data['state'])
le_city = LabelEncoder()
data['city'] = le_city.fit_transform(data['city'])

# Convert month column to numeric
months = ['January', 'February', 'March', 'April', 'May', 'June', 'July',
 ↪'August', 'September', 'October', 'November', 'December']
data['month'] = data['month'].apply(lambda x: months.index(x) + 1)
```

```
# Convert year column to numeric if it's not already
data['year'] = pd.to_numeric(data['year'])

# Plotting the correlation matrix
plt.figure(figsize=(10, 6))
sns.heatmap(data.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



Feature Engineering

[79]:
```
# Lagged Variables
data['priceMin_lagged'] = data['priceMin'].shift(1)
data['priceMax_lagged'] = data['priceMax'].shift(1)

# Rolling Statistics
data['priceMin_roll_mean'] = data['priceMin'].rolling(window=7).mean()
data['priceMax_roll_mean'] = data['priceMax'].rolling(window=7).mean()

# Seasonal Indicators
data['day_of_week'] = data.index.dayofweek

# Drop rows with NaN values resulting from lagged variables and rolling␣
↪statistics
```

```
data.dropna(inplace=True)

# Split the data into train and test sets
train_size = int(len(data) * 0.8)
train_data, test_data = data.iloc[:train_size], data.iloc[train_size:]

# Define the exogenous variables
exog_train = train_data[['priceMin_lagged', 'priceMax_lagged',␣
↪'priceMin_roll_mean', 'priceMax_roll_mean', 'day_of_week']]
exog_test = test_data[['priceMin_lagged', 'priceMax_lagged',␣
↪'priceMin_roll_mean', 'priceMax_roll_mean', 'day_of_week']]

# Display the first few rows of train_data to verify the inclusion of new␣
↪columns
print(train_data.head())
```

```
            market  month  year  quantity  priceMin  priceMax  priceMod  \
date
2012-02-01       0      2  2012       675       510       650       570
2013-02-01       0      2  2013       845      1400      1843      1629
2014-02-01       0      2  2014      1115       831      1163       983
2015-02-01       0      2  2015      1115      1200      1946      1688
2005-03-01       0      3  2005       900       281       357       322

            state  city  priceMin_lagged  priceMax_lagged  priceMin_roll_mean  \
date
2012-02-01     16     0            950.0           1400.0          795.142857
2013-02-01     16     0            510.0            650.0          848.714286
2014-02-01     16     0           1400.0           1843.0          780.428571
2015-02-01     16     0            831.0           1163.0          911.000000
2005-03-01     16     0           1200.0           1946.0          902.142857

            priceMax_roll_mean  day_of_week
date
2012-02-01         1089.285714            2
2013-02-01         1141.000000            4
2014-02-01         1041.714286            5
2015-02-01         1267.571429            6
2005-03-01         1259.857143            1
```

[57]:
```
total_data_points = data_encoded.shape[0]
print("Total data points in the data_encoded DataFrame:", total_data_points)
```

```
Total data points in the data_encoded DataFrame: 10227
```

[77]:
```
# Print the columns of the train_data DataFrame
print(train_data.columns)
```

```
Index(['month', 'year', 'quantity', 'priceMin', 'priceMax', 'priceMod',
       'market_ABOHAR(PB)', 'market_AGRA(UP)', 'market_AHMEDABAD(GUJ)',
       'market_AHMEDNAGAR(MS)',
       …
       'city_SURAT', 'city_TRIVENDRUM', 'city_UDAIPUR', 'city_UJJAIN',
       'city_VANI', 'city_VARANASI', 'city_YEOLA', 'priceMin_roll',
       'priceMax_roll', 'priceMod_roll'],
      dtype='object', length=267)
```

[80]:

```python
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error

# Define exogenous variables
exog_train = train_data[['priceMin_lagged', 'priceMax_lagged',␣
 ↪'priceMin_roll_mean', 'priceMax_roll_mean', 'day_of_week']]
exog_test = test_data[['priceMin_lagged', 'priceMax_lagged',␣
 ↪'priceMin_roll_mean', 'priceMax_roll_mean', 'day_of_week']]

# Define the order and seasonal_order parameters for ARIMA and SARIMA models
order = (5, 1, 0)  # (p, d, q)
seasonal_order = (1, 1, 1, 12)  # (P, D, Q, S)

# Fit ARIMA model
arima_model = ARIMA(train_data['quantity'], exog=exog_train, order=order)
arima_result = arima_model.fit()

# Fit SARIMA model
sarima_model = SARIMAX(train_data['quantity'], exog=exog_train, order=order,␣
 ↪seasonal_order=seasonal_order)
sarima_result = sarima_model.fit()

# Forecast with ARIMA
arima_forecast = arima_result.forecast(steps=len(test_data), exog=exog_test)

# Forecast with SARIMA
sarima_forecast = sarima_result.forecast(steps=len(test_data), exog=exog_test)

# Evaluate performance
arima_mse = mean_squared_error(test_data['quantity'], arima_forecast)
sarima_mse = mean_squared_error(test_data['quantity'], sarima_forecast)

print("ARIMA MSE:", arima_mse)
print("SARIMA MSE:", sarima_mse)

# Choose the best model based on MSE
best_model = "ARIMA" if arima_mse < sarima_mse else "SARIMA"
```

```python
print("Best Model:", best_model)
```

```
C:\Users\acer\AppData\Roaming\Python\Python39\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)
C:\Users\acer\AppData\Roaming\Python\Python39\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)
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been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
```

```
C:\Users\acer\AppData\Roaming\Python\Python39\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)
C:\Users\acer\AppData\Roaming\Python\Python39\site-
packages\statsmodels\base\model.py:607: ConvergenceWarning: Maximum Likelihood
optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
C:\Users\acer\AppData\Roaming\Python\Python39\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(
C:\Users\acer\AppData\Roaming\Python\Python39\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(
C:\Users\acer\AppData\Roaming\Python\Python39\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(
```

```
ARIMA MSE: 7669771056.990435
SARIMA MSE: 20924619524.770756
Best Model: ARIMA
```