Importing Necessary Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.stattools import acf, pacf
from statsmodels.stats.diagnostic import het_arch
from statsmodels.tsa.stattools import adfuller
import pickle
import warnings
warnings.filterwarnings("ignore")
pd.options.display.float_format = '{:,.4f}'.format
from sklearn.preprocessing import LabelEncoder
```

Loading Dataset

```
train_data = pd.read_csv(r"C:\Users\asus\Downloads\train (1).csv")
oil_data = pd.read_csv(r"C:\Users\asus\Downloads\data\oil.csv")
```

Convert into Date-Time Format

```
train_data['date'] = pd.to_datetime(train_data['date'])
oil_data['date'] = pd.to_datetime(oil_data['date'])
```

Filling Missing Values

```
oil_data['dcoilwtico'] = oil_data['dcoilwtico'].fillna(method='bfill')
oil_data['dcoilwtico'] = oil_data['dcoilwtico'].fillna(method='ffill')
oil_data
```

	date	dcoilwtico
0	2020-01-01	93.1400
1	2020-01-02	93.1400
2	2020-01-03	92.9700
3	2020-01-04	93.1200
4	2020-01-07	93.2000
...	...	...
1049	2024-01-09	51.9500
1050	2024-01-10	50.8200
1051	2024-01-11	52.1900
1052	2024-01-12	53.0100
1053	2024-01-13	52.3600

[1054 rows x 2 columns]

Merge Train Data with Oil Data

```
merged_data = pd.merge(train_data, oil_data, on='date', how='left')
merged_data['family'] = merged_data['family'].replace('BREAD/BAKERY',
'BREAD_BAKERY')
merged_data['dcoilwtico'] =
merged_data['dcoilwtico'].fillna(method='bfill')
merged_data['dcoilwtico'] =
merged_data['dcoilwtico'].fillna(method='ffill')
merged_data
```

```
              id       date  store_nbr                      family
sales  \
0              0 2020-01-01          1                  AUTOMOTIVE
0.0000
1              1 2020-01-01          1                   BABY CARE
0.0000
2              2 2020-01-01          1                      BEAUTY
0.0000
3              3 2020-01-01          1                   BEVERAGES
0.0000
4              4 2020-01-01          1                       BOOKS
0.0000
...          ...        ...        ...                         ...
...
2596369  2596369 2023-12-31          9                     POULTRY
687.8530
2596370  2596370 2023-12-31          9              PREPARED FOODS
100.4050
2596371  2596371 2023-12-31          9                     PRODUCE
3,091.3560
2596372  2596372 2023-12-31          9  SCHOOL AND OFFICE SUPPLIES
2.0000
2596373  2596373 2023-12-31          9                     SEAFOOD
13.0000

         onpromotion  dcoilwtico
0                  0     93.1400
1                  0     93.1400
2                  0     93.1400
3                  0     93.1400
4                  0     93.1400
...              ...         ...
2596369            1     53.7500
2596370            1     53.7500
2596371            3     53.7500
2596372            0     53.7500
2596373            2     53.7500

[2596374 rows x 7 columns]
```

Exploratory Data Analysis

Checking Missing Values

```
merged_data.isnull().sum()
```

```
id             0
date           0
store_nbr      0
family         0
sales          0
onpromotion    0
dcoilwtico     0
dtype: int64
```

```
merged_data.drop(columns = ["id", "onpromotion"], inplace = True)
merged_data
```

```
              date  store_nbr                      family
sales  \
0       2020-01-01          1                  AUTOMOTIVE     0.0000

1       2020-01-01          1                   BABY CARE     0.0000

2       2020-01-01          1                      BEAUTY     0.0000

3       2020-01-01          1                   BEVERAGES     0.0000

4       2020-01-01          1                       BOOKS     0.0000

...            ...        ...                         ...        ...

2596369 2023-12-31          9                     POULTRY   687.8530

2596370 2023-12-31          9              PREPARED FOODS   100.4050

2596371 2023-12-31          9                     PRODUCE 3,091.3560

2596372 2023-12-31          9  SCHOOL AND OFFICE SUPPLIES     2.0000

2596373 2023-12-31          9                     SEAFOOD    13.0000


         dcoilwtico
0           93.1400
1           93.1400
2           93.1400
3           93.1400
4           93.1400
...             ...
2596369     53.7500
```

```
2596370     53.7500
2596371     53.7500
2596372     53.7500
2596373     53.7500

[2596374 rows x 5 columns]
```

```
print(merged_data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2596374 entries, 0 to 2596373
Data columns (total 5 columns):
 #   Column      Dtype
---  ------      -----
 0   date        datetime64[ns]
 1   store_nbr   int64
 2   family      object
 3   sales       float64
 4   dcoilwtico  float64
dtypes: datetime64[ns](1), float64(2), int64(1), object(1)
memory usage: 99.0+ MB
None
```

```
print(merged_data.describe())
```

```
                                date      store_nbr           sales  \
count                        2596374 2,596,374.0000 2,596,374.0000
mean   2021-12-31 06:24:27.673301248        27.5000        338.7139
min              2020-01-01 00:00:00         1.0000          0.0000
25%              2021-01-01 00:00:00        14.0000          0.0000
50%              2022-01-01 00:00:00        27.5000          9.0000
75%              2023-01-01 00:00:00        41.0000        184.0608
max              2023-12-31 00:00:00        54.0000    124,717.0000
std                              NaN        15.5858      1,055.8287

          dcoilwtico
count 2,596,374.0000
mean         70.7374
min          26.1900
25%          46.2100
50%          60.0100
75%          97.0000
max         110.6200
std          26.4728
```

```
print(merged_data['family'].nunique(), "unique product families")
```

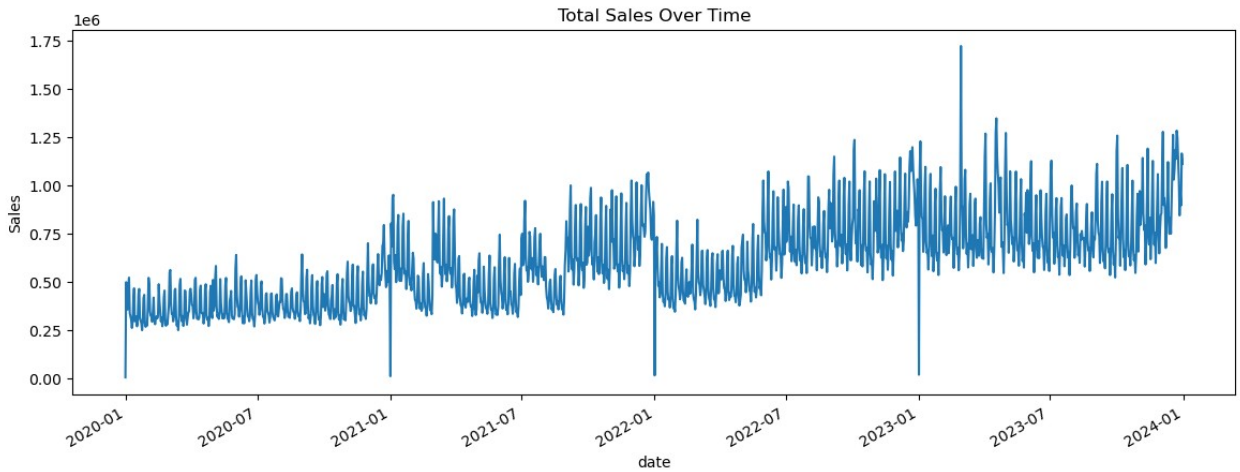
```
33 unique product families
```

```
print(merged_data['store_nbr'].nunique(), "unique stores")
```

```
54 unique stores
```

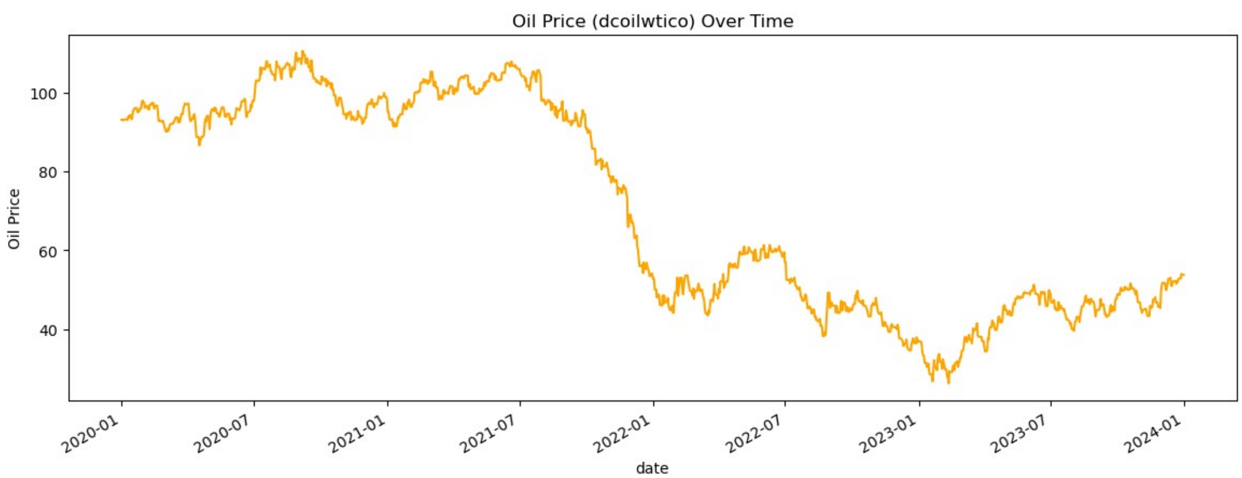
Sales Over Time (Total)

```
merged_data.groupby('date')['sales'].sum().plot(figsize=(14, 5))
plt.title("Total Sales Over Time")
plt.ylabel("Sales")
plt.show()
```



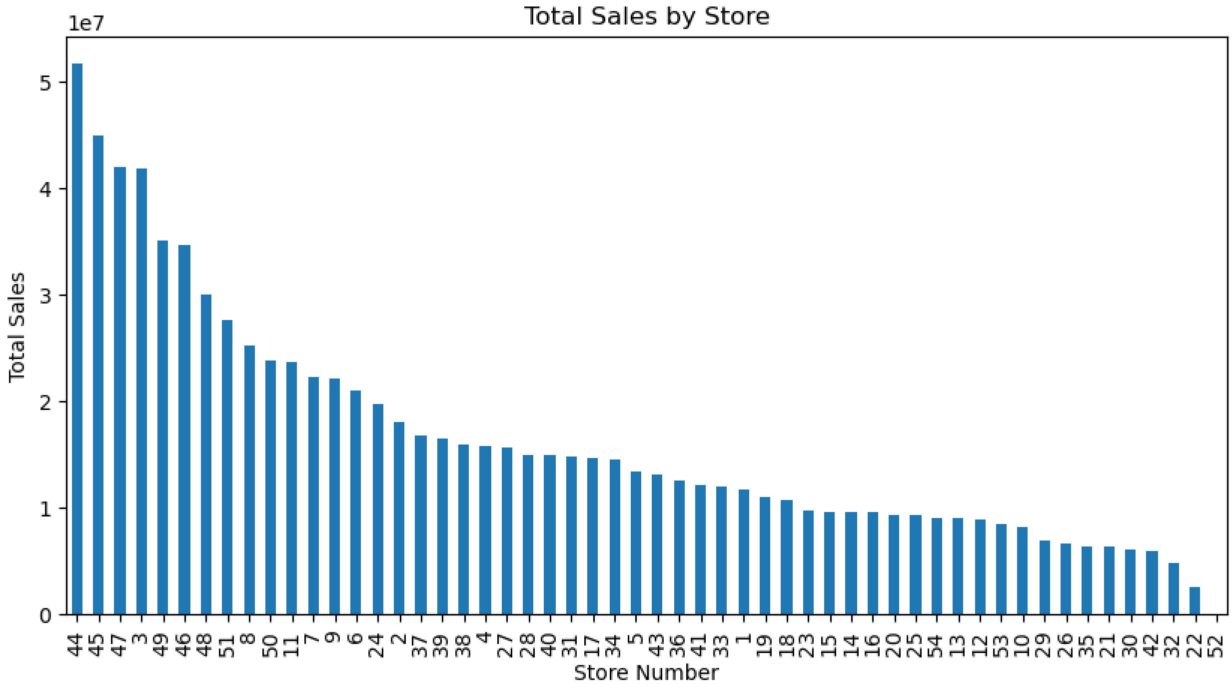
Oil Price Over Time

```
merged_data.groupby('date')['dcoilwtico'].mean().plot(figsize=(14, 5),
color='orange')
plt.title("Oil Price (dcoilwtico) Over Time")
plt.ylabel("Oil Price")
plt.show()
```



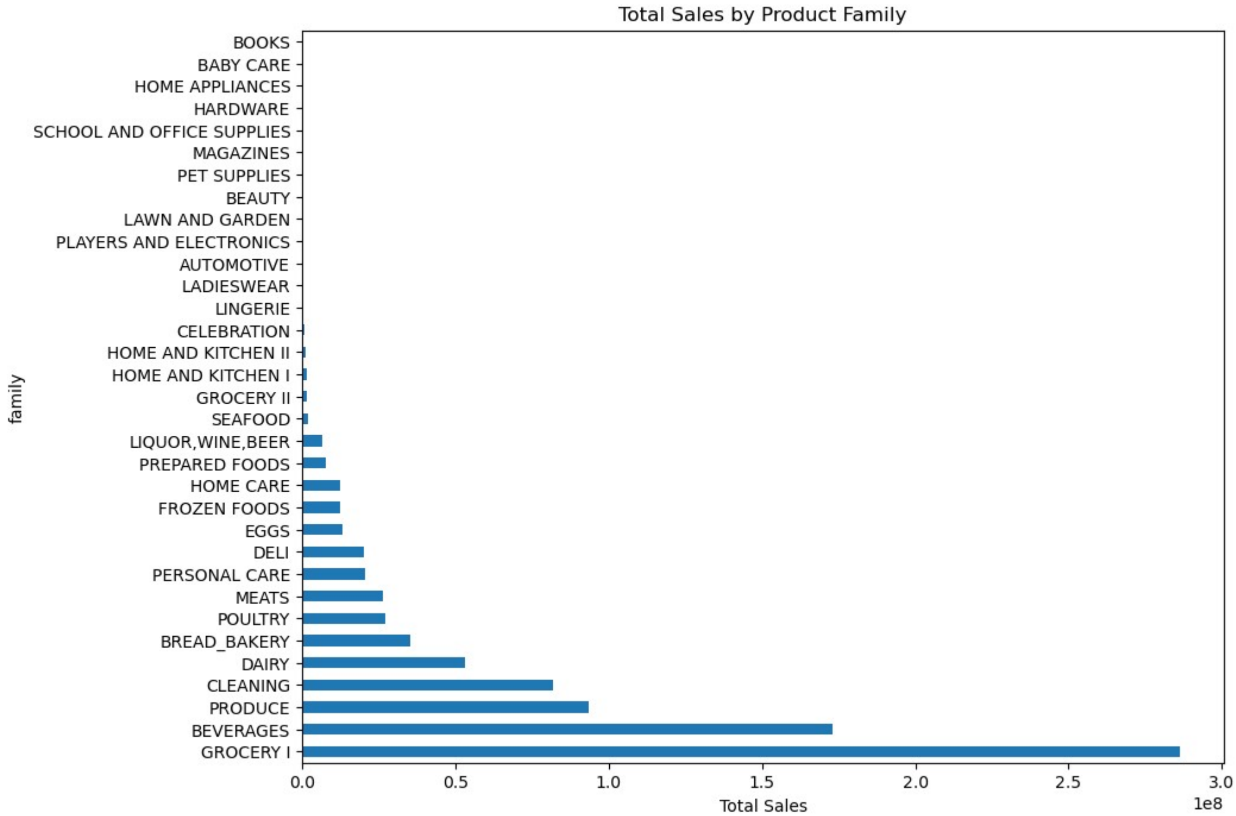
Sales by Store

```
store_sales = merged_data.groupby('store_nbr')
['sales'].sum().sort_values(ascending=False)
store_sales.plot(kind='bar', figsize=(10,5))
plt.title("Total Sales by Store")
plt.xlabel("Store Number")
plt.ylabel("Total Sales")
plt.show()
```



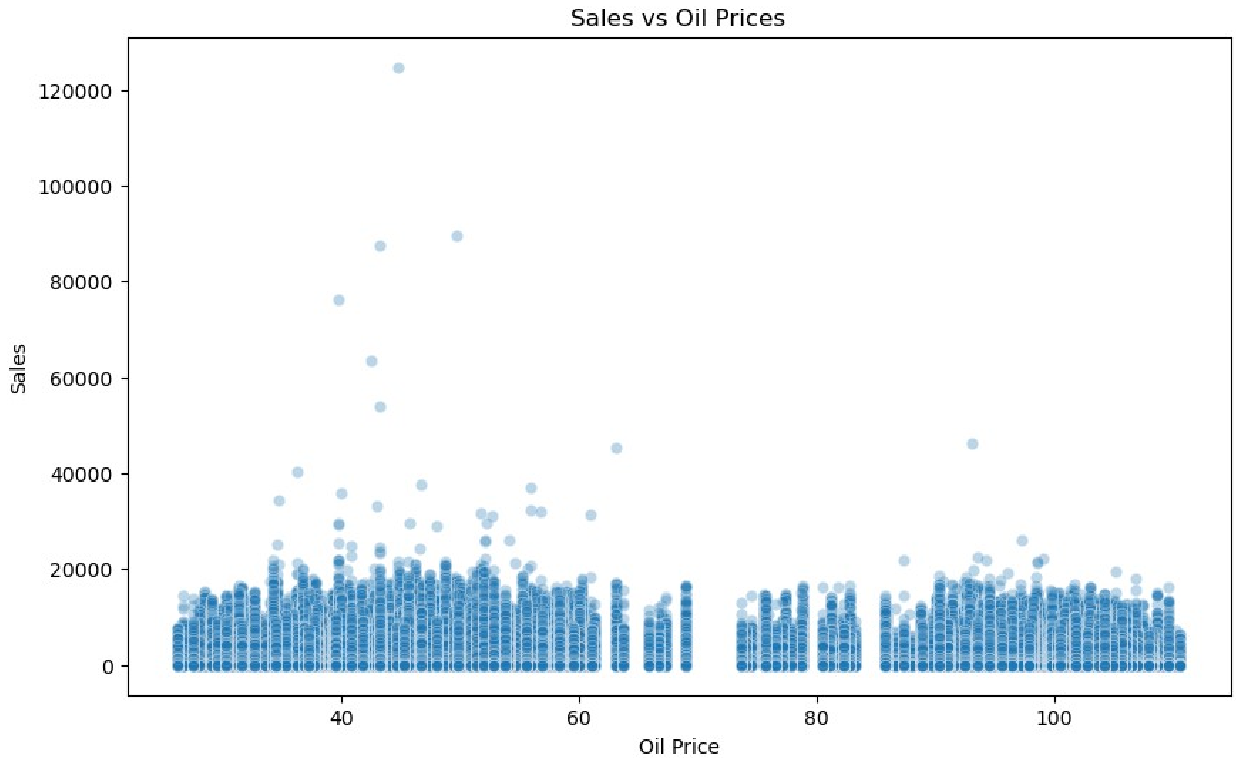
Sales by Product Family

```
family_sales = merged_data.groupby('family')
['sales'].sum().sort_values(ascending=False)
family_sales.plot(kind='barh', figsize=(10, 8))
plt.title("Total Sales by Product Family")
plt.xlabel("Total Sales")
plt.show()
```



Relationship Between Sales & Oil Prices

```
plt.figure(figsize=(10,6))
sns.scatterplot(data=merged_data, x='dcoilwtico', y='sales',
alpha=0.3)
plt.title("Sales vs Oil Prices")
plt.xlabel("Oil Price")
plt.ylabel("Sales")
plt.show()
```



Correlation Matrix

```
merged_data[['sales', 'dcoilwtico']].corr()
```

	sales	dcoilwtico
sales	1.0000	-0.0733
dcoilwtico	-0.0733	1.0000

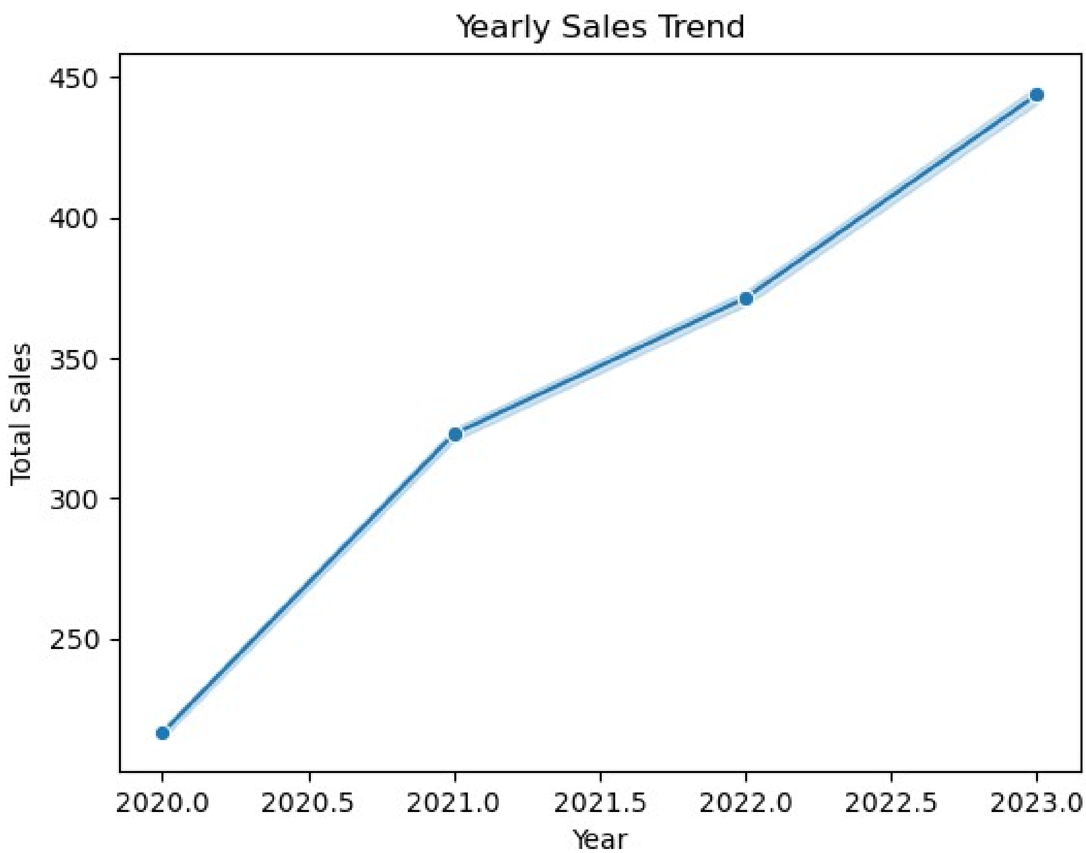
Splitting Date Yearly, Monthly, and Quarterly

```
merged_data["Year"] = merged_data["date"].dt.year
merged_data["Month"] = merged_data["date"].dt.month
merged_data["Quarter"] = merged_data["date"].dt.quarter
merged_data
```

```
              date  store_nbr                      family
sales  \
0       2020-01-01          1                  AUTOMOTIVE     0.0000

1       2020-01-01          1                   BABY CARE     0.0000

2       2020-01-01          1                      BEAUTY     0.0000

3       2020-01-01          1                   BEVERAGES     0.0000

4       2020-01-01          1                       BOOKS     0.0000
```

```
...             ...        ...                           ...        ...

2596369 2023-12-31          9                        POULTRY   687.8530

2596370 2023-12-31          9                  PREPARED FOODS   100.4050

2596371 2023-12-31          9                        PRODUCE 3,091.3560

2596372 2023-12-31          9  SCHOOL AND OFFICE SUPPLIES     2.0000

2596373 2023-12-31          9                        SEAFOOD    13.0000


         dcoilwtico  Year  Month  Quarter
0           93.1400  2020      1        1
1           93.1400  2020      1        1
2           93.1400  2020      1        1
3           93.1400  2020      1        1
4           93.1400  2020      1        1
...             ...   ...    ...      ...
2596369     53.7500  2023     12        4
2596370     53.7500  2023     12        4
2596371     53.7500  2023     12        4
2596372     53.7500  2023     12        4
2596373     53.7500  2023     12        4

[2596374 rows x 8 columns]
```

```python
sns.lineplot(data=merged_data, x='Year', y='sales', marker='o')
plt.title("Yearly Sales Trend")
plt.xlabel("Year")
plt.ylabel("Total Sales")
plt.show()
```

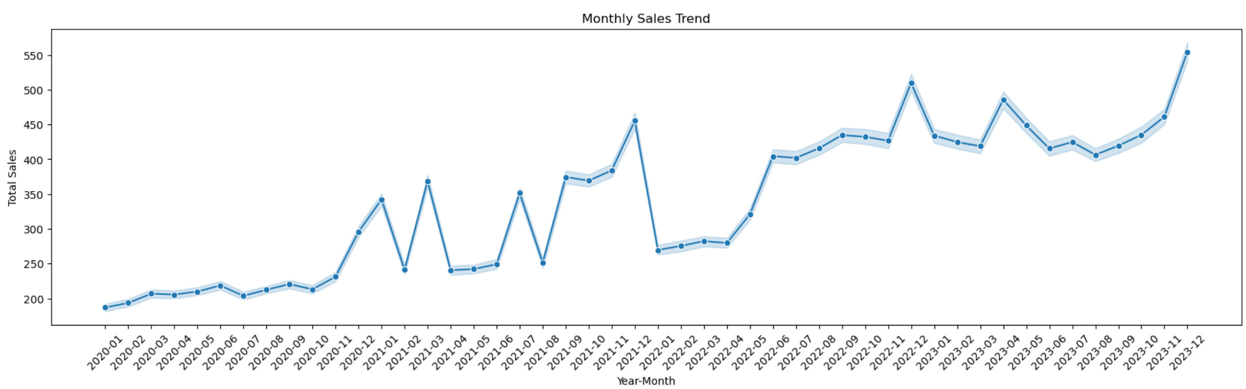


Monthly Sales

```
merged_data["Year-Month"] = merged_data["Year"].astype(str) + "-" +
merged_data["Month"].astype(str).str.zfill(2)
merged_data

              date  store_nbr                        family
sales  \
0       2020-01-01          1                    AUTOMOTIVE      0.0000

1       2020-01-01          1                     BABY CARE      0.0000

2       2020-01-01          1                        BEAUTY      0.0000

3       2020-01-01          1                     BEVERAGES      0.0000

4       2020-01-01          1                         BOOKS      0.0000

...            ...        ...                           ...         ...

2596369 2023-12-31          9                       POULTRY    687.8530

2596370 2023-12-31          9                PREPARED FOODS    100.4050
```

```
2596371 2023-12-31          9                       PRODUCE 3,091.3560

2596372 2023-12-31          9  SCHOOL AND OFFICE SUPPLIES      2.0000

2596373 2023-12-31          9                       SEAFOOD    13.0000


         dcoilwtico  Year  Month  Quarter Year-Month
0           93.1400  2020      1        1    2020-01
1           93.1400  2020      1        1    2020-01
2           93.1400  2020      1        1    2020-01
3           93.1400  2020      1        1    2020-01
4           93.1400  2020      1        1    2020-01
...             ...   ...    ...      ...        ...
2596369     53.7500  2023     12        4    2023-12
2596370     53.7500  2023     12        4    2023-12
2596371     53.7500  2023     12        4    2023-12
2596372     53.7500  2023     12        4    2023-12
2596373     53.7500  2023     12        4    2023-12

[2596374 rows x 9 columns]
```

```python
plt.figure(figsize = (20,5))
sns.lineplot(data=merged_data, x='Year-Month', y='sales', marker='o')
plt.title("Monthly Sales Trend")
plt.xlabel("Year-Month")
plt.ylabel("Total Sales")
plt.xticks(rotation=45)
plt.show()
```



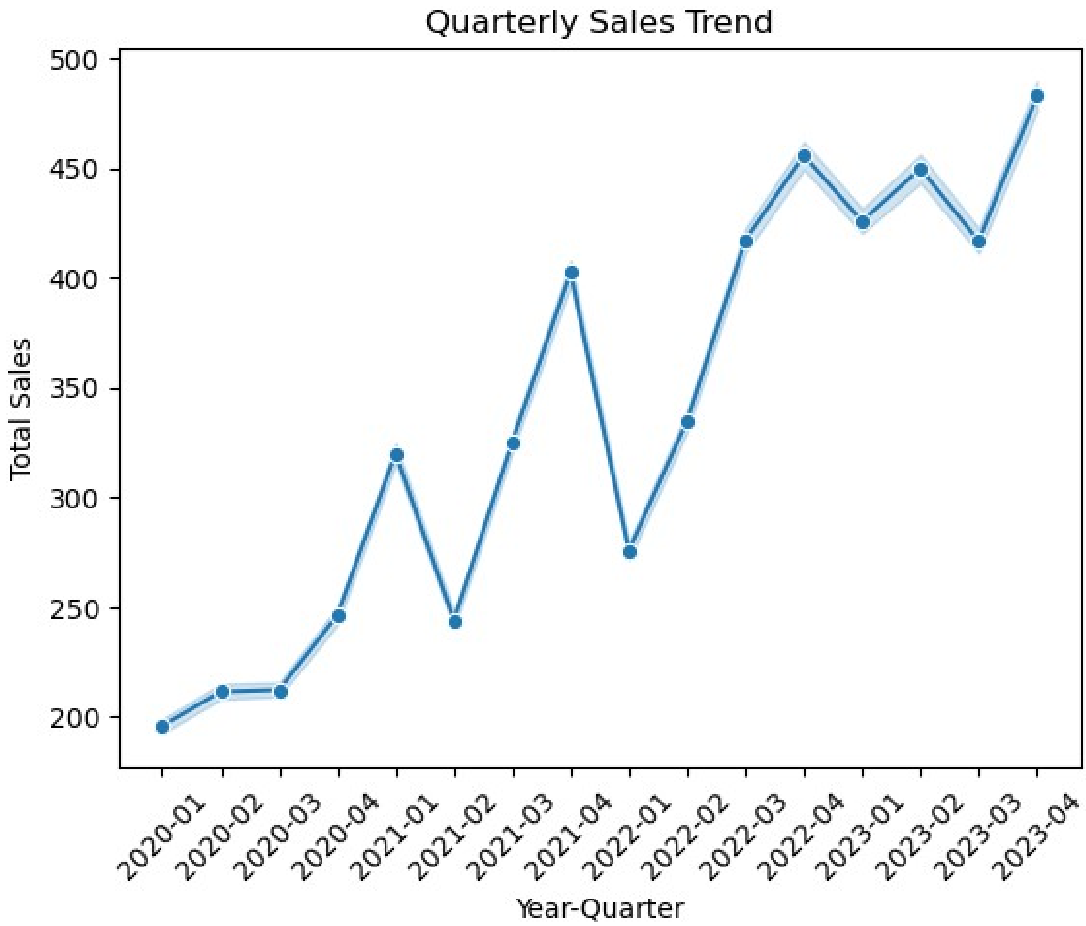
Quarterly Sales

```python
merged_data["Year-Quarter"] = merged_data["Year"].astype(str) + "-" +
merged_data["Quarter"].astype(str).str.zfill(2)
merged_data
```

```
              date  store_nbr                      family
sales  \
```

```
0       2020-01-01          1                         AUTOMOTIVE     0.0000
1       2020-01-01          1                          BABY CARE     0.0000
2       2020-01-01          1                             BEAUTY     0.0000
3       2020-01-01          1                          BEVERAGES     0.0000
4       2020-01-01          1                              BOOKS     0.0000
...            ...        ...                                ...        ...
2596369 2023-12-31          9                            POULTRY   687.8530
2596370 2023-12-31          9                     PREPARED FOODS   100.4050
2596371 2023-12-31          9                            PRODUCE 3,091.3560
2596372 2023-12-31          9  SCHOOL AND OFFICE SUPPLIES     2.0000
2596373 2023-12-31          9                            SEAFOOD    13.0000

         dcoilwtico  Year  Month  Quarter Year-Month Year-Quarter
0           93.1400  2020      1        1    2020-01      2020-01
1           93.1400  2020      1        1    2020-01      2020-01
2           93.1400  2020      1        1    2020-01      2020-01
3           93.1400  2020      1        1    2020-01      2020-01
4           93.1400  2020      1        1    2020-01      2020-01
...             ...   ...    ...      ...        ...          ...
2596369     53.7500  2023     12        4    2023-12      2023-04
2596370     53.7500  2023     12        4    2023-12      2023-04
2596371     53.7500  2023     12        4    2023-12      2023-04
2596372     53.7500  2023     12        4    2023-12      2023-04
2596373     53.7500  2023     12        4    2023-12      2023-04

[2596374 rows x 10 columns]
```

```
sns.lineplot(data=merged_data, x='Year-Quarter', y='sales',
marker='o')
plt.title("Quarterly Sales Trend")
plt.xlabel("Year-Quarter")
plt.ylabel("Total Sales")
plt.xticks(rotation=45)
plt.show()
```



Group By:

```
df = merged_data.groupby(["Year", "Quarter", "family"], as_index =
False).agg({"sales" : "sum","dcoilwtico" : "mean" })
df

     Year  Quarter                      family           sales
dcoilwtico
0    2020        1                  AUTOMOTIVE     21,412.0000
94.4666
1    2020        1                   BABY CARE          0.0000
94.4666
2    2020        1                      BEAUTY     11,667.0000
94.4666
3    2020        1                   BEVERAGES  5,001,127.0000
94.4666
4    2020        1                       BOOKS          0.0000
94.4666
..    ...      ...                         ...             ...
...
523  2023        4                     POULTRY  1,966,067.5634
```

```
49.1047
524  2023        4               PREPARED FOODS    516,604.2458
49.1047
525  2023        4                      PRODUCE 11,354,309.3796
49.1047
526  2023        4  SCHOOL AND OFFICE SUPPLIES      7,721.0000
49.1047
527  2023        4                      SEAFOOD    107,702.5450
49.1047

[528 rows x 5 columns]
```

Sort Index Quarterly

```
df['quarter_start'] = pd.PeriodIndex(year=df['Year'],
quarter=df['Quarter'], freq='Q').start_time

df.set_index('quarter_start', inplace=True)

df.sort_index(inplace=True)
df

               Year  Quarter                      family
sales  \
quarter_start

2020-01-01     2020        1                  AUTOMOTIVE
21,412.0000
2020-01-01     2020        1                   BABY CARE
0.0000
2020-01-01     2020        1                      BEAUTY
11,667.0000
2020-01-01     2020        1                   BEVERAGES
5,001,127.0000
2020-01-01     2020        1                       BOOKS
0.0000
...             ...      ...                         ...                .
..
2023-10-01     2023        4                     POULTRY
1,966,067.5634
2023-10-01     2023        4              PREPARED FOODS
516,604.2458
2023-10-01     2023        4                     PRODUCE
11,354,309.3796
2023-10-01     2023        4  SCHOOL AND OFFICE SUPPLIES
7,721.0000
2023-10-01     2023        4                     SEAFOOD
107,702.5450

               dcoilwtico
```

```
quarter_start
2020-01-01        94.4666
2020-01-01        94.4666
2020-01-01        94.4666
2020-01-01        94.4666
2020-01-01        94.4666
...                   ...
2023-10-01        49.1047
2023-10-01        49.1047
2023-10-01        49.1047
2023-10-01        49.1047
2023-10-01        49.1047

[528 rows x 5 columns]
```

```python
# Initialize LabelEncoder
le = LabelEncoder()

# Fit and transform the 'family' column
df['family_encoded'] = le.fit_transform(df['family'])

# Create a mapping dictionary
family_mapping = dict(zip(le.classes_, le.transform(le.classes_)))

# Display the mapping
print("Category to Label Mapping:")
for category, label in family_mapping.items():
    print(f"{category}: {label}")

df
```

```
Category to Label Mapping:
AUTOMOTIVE: 0
BABY CARE: 1
BEAUTY: 2
BEVERAGES: 3
BOOKS: 4
BREAD_BAKERY: 5
CELEBRATION: 6
CLEANING: 7
DAIRY: 8
DELI: 9
EGGS: 10
FROZEN FOODS: 11
GROCERY I: 12
GROCERY II: 13
HARDWARE: 14
HOME AND KITCHEN I: 15
HOME AND KITCHEN II: 16
HOME APPLIANCES: 17
```

```
HOME CARE: 18
LADIESWEAR: 19
LAWN AND GARDEN: 20
LINGERIE: 21
LIQUOR,WINE,BEER: 22
MAGAZINES: 23
MEATS: 24
PERSONAL CARE: 25
PET SUPPLIES: 26
PLAYERS AND ELECTRONICS: 27
POULTRY: 28
PREPARED FOODS: 29
PRODUCE: 30
SCHOOL AND OFFICE SUPPLIES: 31
SEAFOOD: 32

               Year  Quarter                      family
sales  \
quarter_start

2020-01-01     2020        1                  AUTOMOTIVE
21,412.0000
2020-01-01     2020        1                   BABY CARE
0.0000
2020-01-01     2020        1                      BEAUTY
11,667.0000
2020-01-01     2020        1                   BEVERAGES
5,001,127.0000
2020-01-01     2020        1                       BOOKS
0.0000
...             ...      ...                         ...              .
..
2023-10-01     2023        4                     POULTRY
1,966,067.5634
2023-10-01     2023        4              PREPARED FOODS
516,604.2458
2023-10-01     2023        4                     PRODUCE
11,354,309.3796
2023-10-01     2023        4  SCHOOL AND OFFICE SUPPLIES
7,721.0000
2023-10-01     2023        4                     SEAFOOD
107,702.5450

               dcoilwtico  family_encoded
quarter_start
2020-01-01        94.4666               0
2020-01-01        94.4666               1
2020-01-01        94.4666               2
2020-01-01        94.4666               3
2020-01-01        94.4666               4
```

```
...                      ...              ...
2023-10-01        49.1047                28
2023-10-01        49.1047                29
2023-10-01        49.1047                30
2023-10-01        49.1047                31
2023-10-01        49.1047                32

[528 rows x 6 columns]
```

```
df.drop("family", axis = 1, inplace = True)
df

df.to_csv("Cleaned_Data.csv")
```

Differencing Data Quarterly

```
df["sales_lag"] = df["sales"].diff(33)
df
```

```
               Year  Quarter           sales  dcoilwtico
family_encoded  \
quarter_start

2020-01-01     2020        1      21,412.0000     94.4666
0
2020-01-01     2020        1           0.0000     94.4666
1
2020-01-01     2020        1      11,667.0000     94.4666
2
2020-01-01     2020        1   5,001,127.0000     94.4666
3
2020-01-01     2020        1           0.0000     94.4666
4
...             ...      ...             ...         ...              .
..
2023-10-01     2023        4   1,966,067.5634     49.1047
28
2023-10-01     2023        4     516,604.2458     49.1047
29
2023-10-01     2023        4  11,354,309.3796     49.1047
30
2023-10-01     2023        4       7,721.0000     49.1047
31
2023-10-01     2023        4     107,702.5450     49.1047
32

                 sales_lag
quarter_start
2020-01-01             NaN
2020-01-01             NaN
```

```
2020-01-01              NaN
2020-01-01              NaN
2020-01-01              NaN
...                     ...
2023-10-01    143,668.9392
2023-10-01      7,664.2459
2023-10-01    827,308.8577
2023-10-01    -34,795.0000
2023-10-01    -10,243.9800

[528 rows x 6 columns]
```

Dropping Null Values

```
df.dropna(inplace = True)
df

               Year  Quarter           sales  dcoilwtico
family_encoded  \
quarter_start

2020-04-01     2020        2     24,830.0000     94.1429
0
2020-04-01     2020        2          0.0000     94.1429
1
2020-04-01     2020        2     11,228.0000     94.1429
2
2020-04-01     2020        2  5,396,350.0000     94.1429
3
2020-04-01     2020        2          0.0000     94.1429
4
...             ...      ...             ...         ...              .
..
2023-10-01     2023        4  1,966,067.5634     49.1047
28
2023-10-01     2023        4    516,604.2458     49.1047
29
2023-10-01     2023        4 11,354,309.3796     49.1047
30
2023-10-01     2023        4      7,721.0000     49.1047
31
2023-10-01     2023        4    107,702.5450     49.1047
32

                   sales_lag
quarter_start
2020-04-01      3,418.0000
2020-04-01          0.0000
2020-04-01       -439.0000
2020-04-01    395,223.0000
```

```
2020-04-01          0.0000
...                    ...
2023-10-01    143,668.9392
2023-10-01      7,664.2459
2023-10-01    827,308.8577
2023-10-01    -34,795.0000
2023-10-01    -10,243.9800

[495 rows x 6 columns]
```

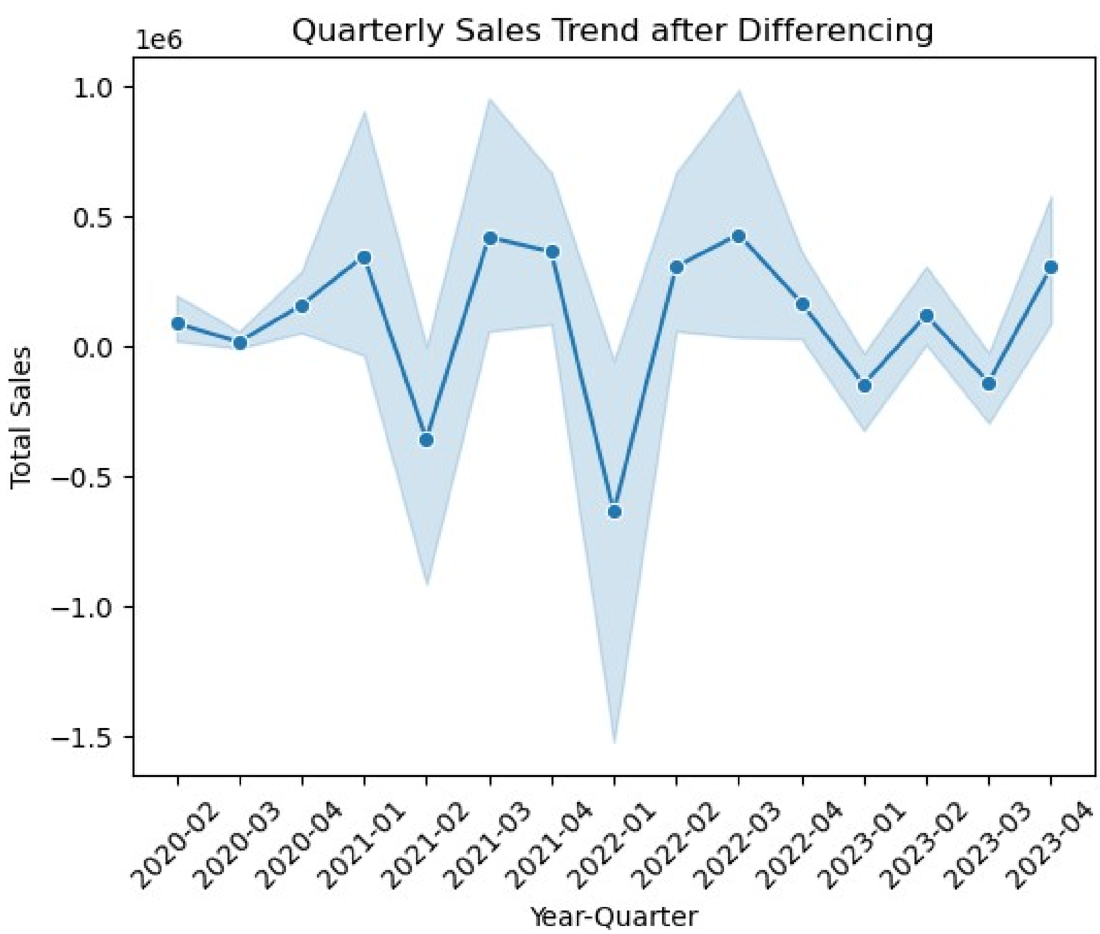
```
df["Year-Quarter"] = df["Year"].astype(str) + "-" +
df["Quarter"].astype(str).str.zfill(2)
df
```

```
               Year  Quarter           sales  dcoilwtico
family_encoded  \
quarter_start

2020-04-01     2020        2     24,830.0000     94.1429
0
2020-04-01     2020        2          0.0000     94.1429
1
2020-04-01     2020        2     11,228.0000     94.1429
2
2020-04-01     2020        2  5,396,350.0000     94.1429
3
2020-04-01     2020        2          0.0000     94.1429
4
...             ...      ...             ...         ...              .
..
2023-10-01     2023        4  1,966,067.5634     49.1047
28
2023-10-01     2023        4    516,604.2458     49.1047
29
2023-10-01     2023        4 11,354,309.3796     49.1047
30
2023-10-01     2023        4      7,721.0000     49.1047
31
2023-10-01     2023        4    107,702.5450     49.1047
32

                 sales_lag Year-Quarter
quarter_start
2020-04-01      3,418.0000      2020-02
2020-04-01          0.0000      2020-02
2020-04-01       -439.0000      2020-02
2020-04-01    395,223.0000      2020-02
2020-04-01          0.0000      2020-02
...                    ...          ...
2023-10-01    143,668.9392      2023-04
```

```
2023-10-01      7,664.2459      2023-04
2023-10-01    827,308.8577      2023-04
2023-10-01    -34,795.0000      2023-04
2023-10-01    -10,243.9800      2023-04

[495 rows x 7 columns]
```

Checking Seasonality After Differencing

```
sns.lineplot(data=df, x='Year-Quarter', y='sales_lag', marker='o')
plt.title("Quarterly Sales Trend after Differencing")
plt.xlabel("Year-Quarter")
plt.ylabel("Total Sales")
plt.xticks(rotation=45)
plt.show()
```




```
df.to_csv("Differencing_1.csv")
```

Checking Stationarity using Augmented Dickey-Fuller Test

```
def check_stationarity(timeseries):
    result = adfuller(timeseries)
    print("ADF Statistic:", result[0])
    print("p-value:", result[1])
    print("Critical Values:", result[4])

    if result[1] < 0.05:
        print("The time series is stationary.")
    else:
        print("The time series is non-stationary.")

# Example usage
check_stationarity(df['sales_lag'])
```

```
ADF Statistic: -9.966937012191245
p-value: 2.2937883409570914e-17
Critical Values: {'1%': -3.4437936797256317, '5%': -2.867468682890213,
'10%': -2.5699277594606915}
The time series is stationary.
```

Checking Homoscedasticity using ARCH

```
# Perform the ARCH test
arch_test = het_arch(df['sales_lag'])

print("ARCH Test Statistic:", arch_test[0])
print("p-value:", arch_test[1])

# Interpretation
if arch_test[1] < 0.05:
    print("Heteroscedasticity detected")
else:
    print("Homoscedasticity detected")
```

```
ARCH Test Statistic: 13.987843793358284
p-value: 0.17354681263428837
Homoscedasticity detected
```

Dropping rows containing INF and NaN Values

```
df.replace([np.inf, -np.inf], np.nan, inplace=True)
df.dropna(inplace=True)
df.isnull().sum()
```

```
Year                 0
Quarter              0
sales                0
dcoilwtico           0
```

```
family_encoded    0
sales_lag         0
Year-Quarter      0
dtype: int64
```

```
df.shape
```

```
(495, 7)
```

```
df.drop(columns = ["sales", "Year-Quarter"], inplace = True)
df
```

quarter_start	Year	Quarter	dcoilwtico	family_encoded	sales_lag
2020-04-01	2020	2	94.1429	0	3,418.0000
2020-04-01	2020	2	94.1429	1	0.0000
2020-04-01	2020	2	94.1429	2	-439.0000
2020-04-01	2020	2	94.1429	3	395,223.0000
2020-04-01	2020	2	94.1429	4	0.0000
...	...	...	...	...	...
2023-10-01	2023	4	49.1047	28	143,668.9392
2023-10-01	2023	4	49.1047	29	7,664.2459
2023-10-01	2023	4	49.1047	30	827,308.8577
2023-10-01	2023	4	49.1047	31	-34,795.0000
2023-10-01	2023	4	49.1047	32	-10,243.9800

```
[495 rows x 5 columns]
```

Splitting Data for Training and Testing

```
train_size = int(0.8*len(df))
X_train = df.iloc[:train_size].copy()
Y_train = X_train.pop("sales_lag")

X_test = df.iloc[train_size:].copy()
Y_test = X_test.pop("sales_lag")
```

```
X_train.shape
```

```
(396, 4)
```

```
X_test.shape
```

```
(99, 4)
```

Getting ACF and PACF values

```
target = df['sales_lag']

max_lag = 33
```

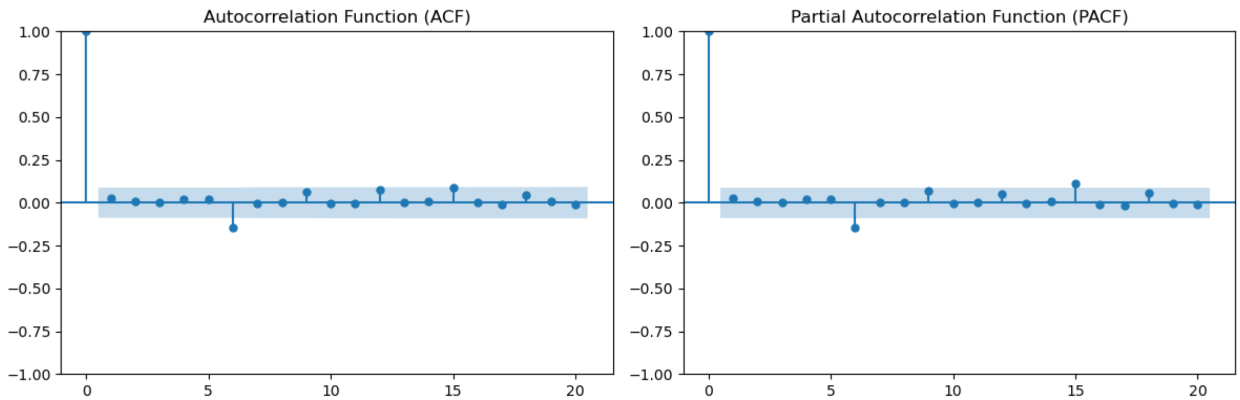
```
acf_vals = acf(target, nlags=max_lag)
pacf_vals = pacf(target, nlags=max_lag)

lags = np.arange(max_lag + 1)
acf_pacf_temp_monthly = pd.DataFrame({'Lag': lags, 'ACF': acf_vals,
'PACF': pacf_vals})

print(acf_pacf_temp_monthly)
```

	Lag	ACF	PACF
0	0	1.0000	1.0000
1	1	0.0252	0.0252
2	2	0.0096	0.0090
3	3	0.0041	0.0037
4	4	0.0231	0.0230
5	5	0.0212	0.0203
6	6	-0.1451	-0.1485
7	7	-0.0030	0.0042
8	8	-0.0002	0.0023
9	9	0.0655	0.0682
10	10	-0.0038	-0.0013
11	11	-0.0033	0.0018
12	12	0.0730	0.0534
13	13	-0.0001	-0.0068
14	14	0.0107	0.0071
15	15	0.0894	0.1138
16	16	-0.0010	-0.0109
17	17	-0.0084	-0.0147
18	18	0.0428	0.0601
19	19	0.0053	-0.0027
20	20	-0.0080	-0.0121
21	21	-0.0433	-0.0244
22	22	0.0097	0.0109
23	23	0.0101	0.0043
24	24	-0.0258	-0.0331
25	25	0.0046	0.0122
26	26	-0.0052	-0.0056
27	27	0.3929	0.4024
28	28	-0.0069	-0.0329
29	29	-0.0165	-0.0269
30	30	-0.0093	-0.0403
31	31	-0.0055	-0.0219
32	32	-0.0186	-0.0433
33	33	-0.3609	-0.3397

Plotting ACF and PACF

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 4))
plot_acf(df['sales_lag'], ax=axes[0], lags=20)
```

```
axes[0].set_title('Autocorrelation Function (ACF)')


plot_pacf(df['sales_lag'], ax=axes[1], lags=20)
axes[1].set_title('Partial Autocorrelation Function (PACF)')


plt.tight_layout()
plt.show()
```




```
df['sales_lag'].describe()
```

```
count              495.0000
mean            94,743.9112
std          1,045,943.2266
min        -10,250,091.0875
25%             -1,827.5000
50%              1,244.0000
75%             39,661.5496
max          7,207,902.7638
Name: sales_lag, dtype: float64
```

Applying SARIMAX

```
model = SARIMAX(Y_train, exog=X_train, order=(6, 0, 6))  # adjust
(p,d,q) based on AIC/BIC/grid search
model_fit = model.fit(disp=False)

# Forecast
pred = model_fit.predict(start=len(Y_train), end=len(Y_train)
+len(Y_test)-1, exog=X_test)

# Optional: evaluate model
from sklearn.metrics import mean_squared_error
import numpy as np
```

```
rmse = np.sqrt(mean_squared_error(Y_test, pred))
print("RMSE:", rmse)
```

```
RMSE: 639050.4538762666
```

Applying SARIMAX by Product Family

```
rms = {}
error = []
adequacy = {}
adequacy["Max"] = []
adequacy["Min"] = []
adequacy["RMSE"] = []
adequacy["RMSE_Ratio"] = []


for family in df['family_encoded'].unique():

    try:
        temp_df = df[df["family_encoded"] == family]
        train_value = int(0.8*len(temp_df))
        X_train = temp_df.iloc[:train_value].copy()
        Y_train = X_train.pop("sales_lag")

        model = SARIMAX(Y_train, exog=X_train, order=(6, 1, 6),
enforce_stationarity=False)  # adjust (p,d,q) based on AIC/BIC/grid
search
        model_fit = model.fit()

        X_test = temp_df.iloc[train_value:].copy()
        Y_test = X_test.pop("sales_lag")


        Y_pred = model_fit.predict(start=len(Y_train),
end=len(Y_train)+len(Y_test)-1, exog=X_test)



        rmse = np.sqrt(mean_squared_error(Y_pred, Y_test))

        mean_sales = temp_df['sales_lag'].mean()
        rmse_ratio = rmse / mean_sales
        adequacy["RMSE_Ratio"].append(rmse_ratio)
        adequacy["Max"].append(temp_df['sales_lag'].max())
        adequacy["Min"].append(temp_df['sales_lag'].min())


        print(f"{family}done...")
        adequacy["RMSE"].append(rmse)
```

```
    except:
        error.append(family)
        pass
```

```
0done...
1done...
2done...
3done...
4done...
5done...
6done...
7done...
8done...
9done...
10done...
11done...
12done...
13done...
14done...
15done...
16done...
17done...
18done...
19done...
20done...
21done...
22done...
23done...
24done...
25done...
26done...
27done...
28done...
29done...
30done...
31done...
32done...
```

Checking Model Adequacy

```
data_frame = pd.DataFrame(adequacy)
data_frame
```

	Max	Min	RMSE	RMSE_Ratio
0	6,517.0000	-2,956.0000	2,831.3890	3.3879
1	926.0000	-832.0000	521.3647	5.5347
2	5,901.0000	-3,937.0000	4,222.7258	3.5445
3	4,543,100.0000	-6,784,893.0000	4,387,117.5931	5.5506
4	4,119.0000	0.0000	2,378.1058	8.6603

5	430,127.1401	-150,807.3087	123,876.6208	1.9591
6	48,801.0000	-61,302.0000	34,977.4479	7.0603
7	565,941.0000	-362,573.0000	615,558.6632	5.3067
8	895,388.0000	-217,301.0000	284,961.2107	1.4804
9	155,230.6540	-131,518.0310	203,463.7953	4.8286
10	127,991.0000	-40,371.0000	94,355.2366	3.5901
11	1,057,098.4722	-1,004,931.3481	584,755.5863	7.0356
12	3,870,652.8930	-2,444,630.5180	2,953,465.1745	3.9334
13	40,358.0000	-28,619.0000	23,102.2714	8.4178
14	1,410.0000	-1,902.0000	672.5326	6.5210
15	81,798.0000	-70,797.0000	18,982.3664	1.6737
16	55,888.0000	-45,509.0000	189,965.9074	21.1559
17	1,680.0000	-1,195.0000	1,794.8607	-47.7357
18	869,724.0000	-1,286,497.0000	1,063,601.7754	10.8655
19	41,950.0000	-64,004.0000	55,798.7126	15.0938
20	17,138.0000	-1,380.0000	9,543.4334	4.5416
21	7,735.0000	-8,956.0000	2,503.9843	-2.3149
22	152,267.0000	-135,817.0000	75,990.2606	3.7127
23	24,726.0000	-6,735.0000	16,921.0241	7.5435
24	115,918.1619	-156,887.7559	72,864.1260	3.4364
25	161,177.0000	-208,309.0000	168,399.3446	3.8279
26	15,513.0000	-27,036.0000	20,379.6217	8.1174
27	38,800.0000	-47,347.0000	22,074.4415	5.4822
28	612,834.3281	-133,655.1271	240,732.5353	3.4110
29	50,420.7129	-15,584.4129	4,490.5033	0.6620
30	7,207,902.7638	-10,250,091.0875	9,091,844.1498	12.0154
31	31,418.0000	-34,795.0000	27,636.4915	53.6909
32	26,342.4306	-12,322.4981	4,674.9120	-113.7439

Predicting Sales by Product Family

```
predictions = []  # to store results

for family in df['family_encoded'].unique():
    try:
        temp_df = df[df["family_encoded"] == family]
        train_value = int(0.8 * len(temp_df))
        X_train = temp_df.iloc[:train_value].copy()
        Y_train = X_train.pop("sales_lag")

        model = SARIMAX(Y_train, exog=X_train, order=(6, 1, 6), 
enforce_stationarity=False)
        model_fit = model.fit(disp=False)

        X_test = temp_df.iloc[train_value:].copy()
        Y_test = X_test.pop("sales_lag")

        Y_pred = model_fit.predict(
            start=len(Y_train),
```

```
            end=len(Y_train) + len(Y_test) - 1,
            exog=X_test
        )

        # Extract corresponding date info from X_test
        test_dates = X_test.index

        for date, pred in zip(test_dates, Y_pred):
            year = pd.to_datetime(date).year
            quarter = pd.to_datetime(date).quarter
            predictions.append({
                'family': family,
                'year': year,
                'quarter': quarter,
                'prediction': pred
            })

        print(f"{family} done...")

    except Exception as e:
        error.append(family)
        print(f"Error in {family}: {e}")
        pass
```

```
0 done...
1 done...
2 done...
3 done...
4 done...
5 done...
6 done...
7 done...
8 done...
9 done...
10 done...
11 done...
12 done...
13 done...
14 done...
15 done...
16 done...
17 done...
18 done...
19 done...
20 done...
21 done...
22 done...
23 done...
24 done...
25 done...
```

```
26 done...
27 done...
28 done...
29 done...
30 done...
31 done...
32 done...
```

Creating Data Frame for Predicted Sales

```
pred_df = pd.DataFrame(predictions)
pred_df
```

```
    family  year  quarter  prediction
0        0  2023        2   -803.5572
1        0  2023        3   -755.9646
2        0  2023        4 -1,676.1854
3        1  2023        2    708.8533
4        1  2023        3    591.0062
..     ...   ...      ...         ...
94      31  2023        3 17,939.5781
95      31  2023        4 12,829.6736
96      32  2023        2 -2,223.7848
97      32  2023        3 -5,462.5529
98      32  2023        4 -7,847.4777

[99 rows x 4 columns]
```

Sorting Predicted Sales Quarterly

```
# Step 1: Keep only the required columns
df_filtered = pred_df[['year', 'quarter', 'prediction',
'family']].copy()

# Step 2: Create quarter_start as a datetime index
df_filtered['quarter_start'] = pd.to_datetime(
    df_filtered['year'].astype(str) + 'Q' +
df_filtered['quarter'].astype(str)
).dt.to_period('Q').dt.start_time

# Step 3: Sort by Quarter (2, then 3, then 4), then by Family
quarter_order = [2, 3, 4]
df_filtered['quarter'] = pd.Categorical(df_filtered['quarter'],
categories=quarter_order, ordered=True)
df_sorted = df_filtered.sort_values(by=['quarter', 'family'])

# Step 4: Set quarter_start as index and keep only the desired columns
df_final = df_sorted.set_index('quarter_start')[['year', 'quarter',
'family', 'prediction']]
```

```python
df_final.columns = ['Year', 'Quarter', 'family', 'Prediction']

df_final
```

```
               Year Quarter  family      Prediction
quarter_start
2023-04-01     2023       2       0       -803.5572
2023-04-01     2023       2       1        708.8533
2023-04-01     2023       2       2      5,080.0664
2023-04-01     2023       2       3  3,263,638.9535
2023-04-01     2023       2       4          0.0000
...             ...     ...     ...             ...
2023-10-01     2023       4      28   -155,025.3304
2023-10-01     2023       4      29      3,438.8906
2023-10-01     2023       4      30 11,804,841.5150
2023-10-01     2023       4      31     12,829.6736
2023-10-01     2023       4      32     -7,847.4777

[99 rows x 4 columns]
```

```python
df["Year-Quarter"] = df["Year"].astype(str) + "-" +
df["Quarter"].astype(str).str.zfill(2)
df
```

```
               Year  Quarter  dcoilwtico  family_encoded    sales_lag
\
quarter_start

2020-04-01     2020        2     94.1429               0   3,418.0000

2020-04-01     2020        2     94.1429               1       0.0000

2020-04-01     2020        2     94.1429               2    -439.0000

2020-04-01     2020        2     94.1429               3 395,223.0000

2020-04-01     2020        2     94.1429               4       0.0000

...             ...      ...         ...             ...          ...

2023-10-01     2023        4     49.1047              28 143,668.9392

2023-10-01     2023        4     49.1047              29   7,664.2459

2023-10-01     2023        4     49.1047              30 827,308.8577

2023-10-01     2023        4     49.1047              31 -34,795.0000

2023-10-01     2023        4     49.1047              32 -10,243.9800
```

```
                 Year-Quarter
quarter_start
2020-04-01            2020-02
2020-04-01            2020-02
2020-04-01            2020-02
2020-04-01            2020-02
2020-04-01            2020-02
...                       ...
2023-10-01            2023-04
2023-10-01            2023-04
2023-10-01            2023-04
2023-10-01            2023-04
2023-10-01            2023-04

[495 rows x 6 columns]
```

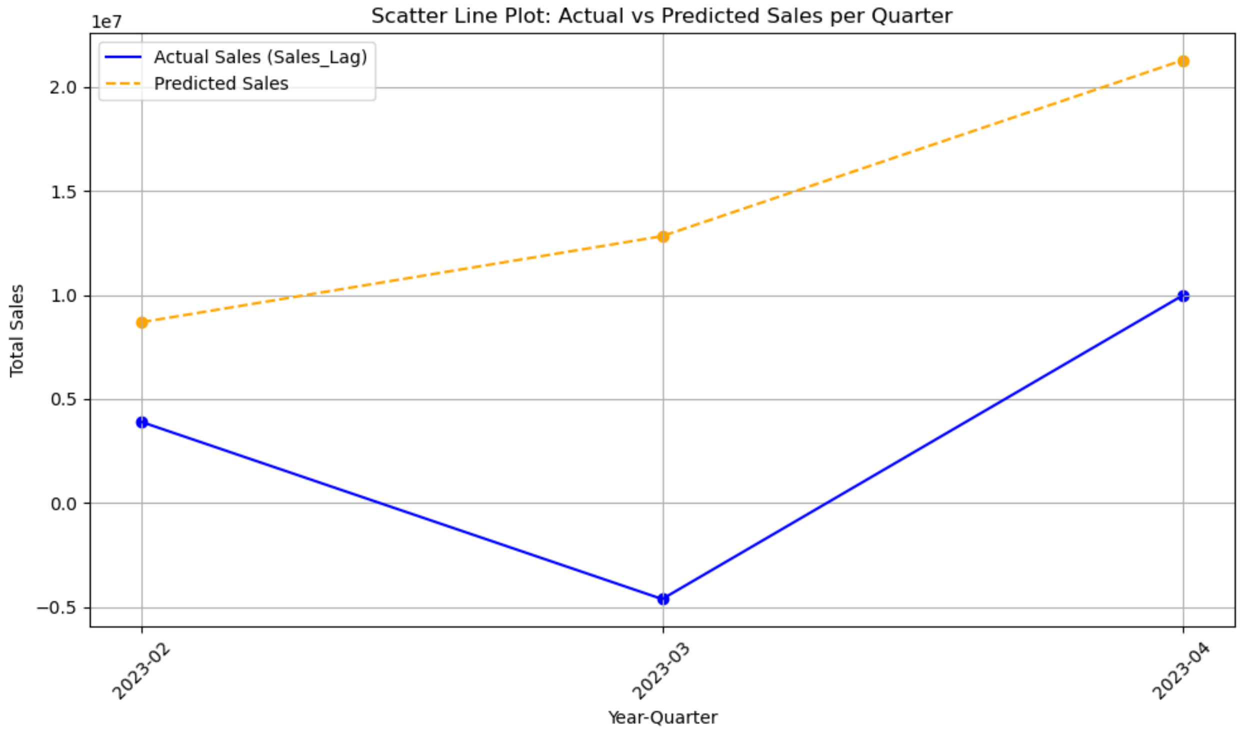
```
df_final["Year-Quarter"] = df_final["Year"].astype(str) + "-" +
df_final["Quarter"].astype(str).str.zfill(2)
df_final
```

```
                  Year Quarter  family      Prediction Year-Quarter
quarter_start
2023-04-01        2023       2       0       -803.5572      2023-02
2023-04-01        2023       2       1        708.8533      2023-02
2023-04-01        2023       2       2      5,080.0664      2023-02
2023-04-01        2023       2       3  3,263,638.9535      2023-02
2023-04-01        2023       2       4          0.0000      2023-02
...                ...     ...     ...             ...          ...
2023-10-01        2023       4      28   -155,025.3304      2023-04
2023-10-01        2023       4      29      3,438.8906      2023-04
2023-10-01        2023       4      30 11,804,841.5150      2023-04
2023-10-01        2023       4      31     12,829.6736      2023-04
2023-10-01        2023       4      32     -7,847.4777      2023-04

[99 rows x 5 columns]
```

Comparing Predicted Sales with Actual Sales

```
df = df.rename(columns={'family_encoded': 'family', 'sales_lag':
'Sales_Lag'})
df_final = df_final.rename(columns={'Prediction': 'Predicted_Sales'})

# Reset index to work with 'quarter_start'
df_reset = df.reset_index()
df_final_reset = df_final.reset_index()

# Group and sum sales by Year-Quarter
df_grouped = df_reset.groupby('Year-Quarter')
['Sales_Lag'].sum().reset_index()
df_final_grouped = df_final_reset.groupby('Year-Quarter')
```

```python
['Predicted_Sales'].sum().reset_index()

# Merge on Year-Quarter
merged = pd.merge(df_grouped, df_final_grouped, on='Year-Quarter')

# Sort for plotting
merged = merged.sort_values('Year-Quarter')

# Plotting: scatter + line plot
plt.figure(figsize=(10, 6))

# Actual Sales
plt.plot(merged['Year-Quarter'], merged['Sales_Lag'], linestyle='-',
color='blue', label='Actual Sales (Sales_Lag)')
plt.scatter(merged['Year-Quarter'], merged['Sales_Lag'], color='blue')

# Predicted Sales
plt.plot(merged['Year-Quarter'], merged['Predicted_Sales'],
linestyle='--', color='orange', label='Predicted Sales')
plt.scatter(merged['Year-Quarter'], merged['Predicted_Sales'],
color='orange')

# Decorations
plt.title("Scatter Line Plot: Actual vs Predicted Sales per Quarter")
plt.xlabel("Year-Quarter")
plt.ylabel("Total Sales")
plt.xticks(rotation=45)
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



Calculating Actual Predicted Sales

```
# Ensure df_final is sorted correctly
df_final = df_final.sort_values(['family', 'Quarter'])

# Strip any spaces from column names (if there are any)
df_final.columns = df_final.columns.str.strip()

# Pivot the predictions: rows = family, columns = Quarter
pivot = df_final.pivot(index='family', columns='Quarter',
values='Predicted_Sales')

# Apply your logic:
# Quarter 2 final prediction = prediction Q2 + prediction Q4
pivot['final_Q2'] = pivot[2] + pivot[4]
# Quarter 3 final prediction = previous + prediction Q3
pivot['final_Q3'] = pivot['final_Q2'] + pivot[3]
# Quarter 4 final prediction = previous + prediction Q4
pivot['final_Q4'] = pivot['final_Q3'] + pivot[4]

# Convert back to long format
final_df = pivot[['final_Q2', 'final_Q3', 'final_Q4']].reset_index()
final_df = final_df.melt(id_vars='family',
                         value_vars=['final_Q2', 'final_Q3',
'final_Q4'],
                         var_name='Quarter',
                         value_name='Final_Prediction')
```

```
# Extract quarter number from column names
final_df['Quarter'] = final_df['Quarter'].str.extract(r'final_Q(\
d)').astype(int)

# Add constant year and quarter_start based on your original structure
final_df['Year'] = 2023
quarter_start_map = {2: '2023-04-01', 3: '2023-07-01', 4: '2023-10-
01'}
final_df['quarter_start'] = final_df['Quarter'].map(quarter_start_map)

# Reorder columns to match your original df_final structure
final_df = final_df[['quarter_start', 'Year', 'Quarter', 'family',
'Final_Prediction']]

final_df
```

```
   quarter_start  Year  Quarter  family  Final_Prediction
0     2023-04-01  2023        2       0        -2,479.7427
1     2023-04-01  2023        2       1         1,189.3288
2     2023-04-01  2023        2       2        14,124.9114
3     2023-04-01  2023        2       3    10,209,675.3711
4     2023-04-01  2023        2       4             0.0000
..           ...   ...      ...     ...                ...
94    2023-10-01  2023        4      28      -768,937.0525
95    2023-10-01  2023        4      29          -558.4717
96    2023-10-01  2023        4      30    38,668,590.2551
97    2023-10-01  2023        4      31        60,260.5812
98    2023-10-01  2023        4      32       -23,381.2932

[99 rows x 5 columns]
```

Replacing Negative Sales from 0

```
# Replace negative Final_Prediction values with 0
final_df.loc[final_df['Final_Prediction'] < 0, 'Final_Prediction'] = 0
final_df
```

```
   quarter_start  Year  Quarter  family  Final_Prediction
0     2023-04-01  2023        2       0             0.0000
1     2023-04-01  2023        2       1         1,189.3288
2     2023-04-01  2023        2       2        14,124.9114
3     2023-04-01  2023        2       3    10,209,675.3711
4     2023-04-01  2023        2       4             0.0000
..           ...   ...      ...     ...                ...
94    2023-10-01  2023        4      28             0.0000
95    2023-10-01  2023        4      29             0.0000
96    2023-10-01  2023        4      30    38,668,590.2551
97    2023-10-01  2023        4      31        60,260.5812
98    2023-10-01  2023        4      32             0.0000
```

```
[99 rows x 5 columns]
```