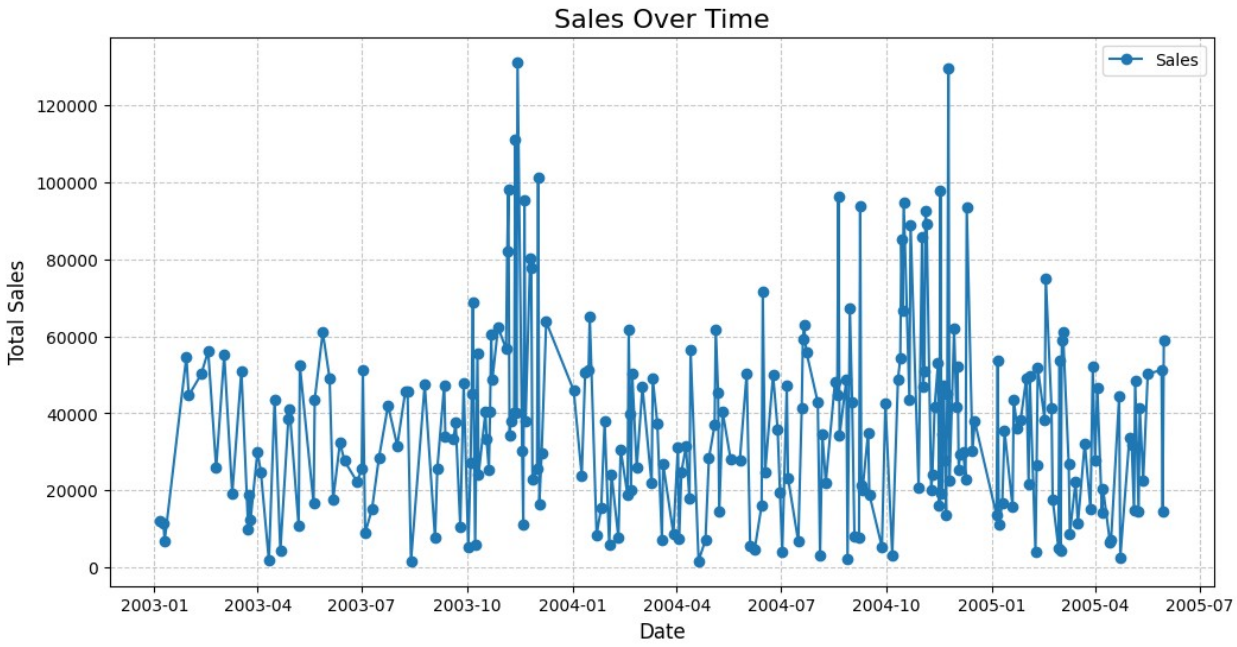
```
import pandas as pd
file_path = r'C:\Files\Developer\Sales_Time_Series\sample-sales-data\
sales_data_sample.csv'

sales_data = pd.read_csv(file_path, encoding='latin1')
print(sales_data.head())
```

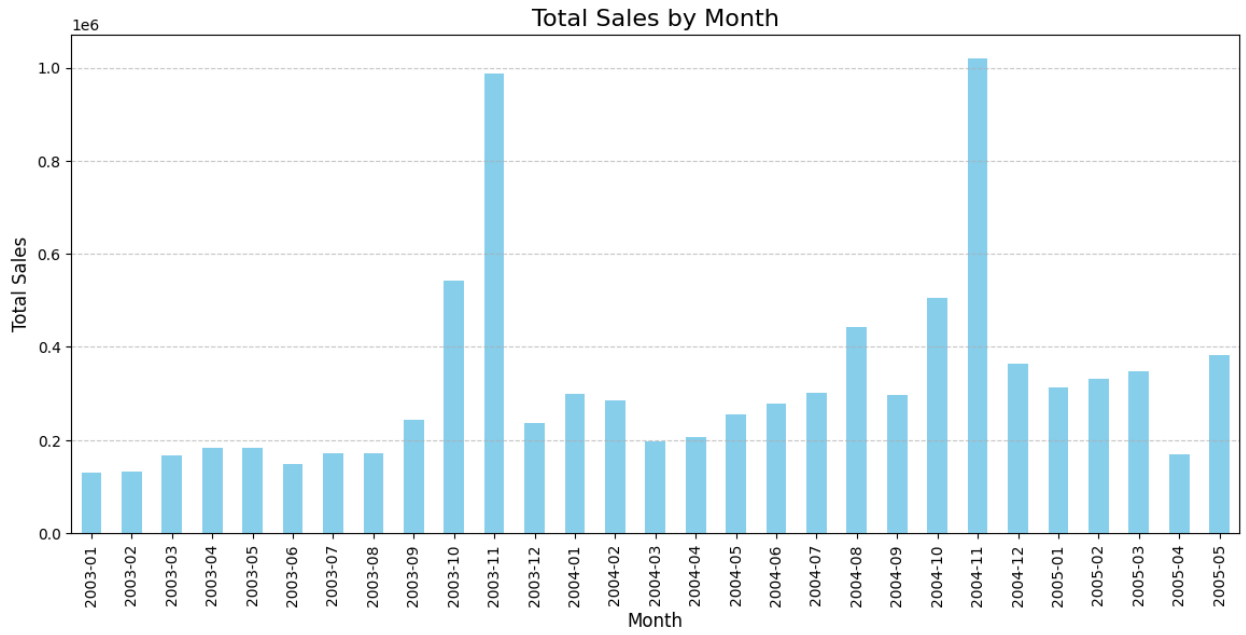
```
   ORDERNUMBER  QUANTITYORDERED  PRICEEACH  ORDERLINENUMBER
SALES  \
0        10107               30      95.70                2  2871.00

1        10121               34      81.35                5  2765.90

2        10134               41      94.74                2  3884.34

3        10145               45      83.26                6  3746.70

4        10159               49     100.00               14  5205.27


         ORDERDATE   STATUS  QTR_ID  MONTH_ID  YEAR_ID  ...  \
0   2/24/2003 0:00  Shipped       1         2     2003  ...
1    5/7/2003 0:00  Shipped       2         5     2003  ...
2    7/1/2003 0:00  Shipped       3         7     2003  ...
3   8/25/2003 0:00  Shipped       3         8     2003  ...
4  10/10/2003 0:00  Shipped       4        10     2003  ...

                     ADDRESSLINE1  ADDRESSLINE2           CITY STATE  \
0        897 Long Airport Avenue           NaN            NYC    NY
1             59 rue de l'Abbaye           NaN          Reims   NaN
2  27 rue du Colonel Pierre Avia           NaN          Paris   NaN
3             78934 Hillside Dr.           NaN       Pasadena    CA
4                7734 Strong St.           NaN  San Francisco    CA

  POSTALCODE COUNTRY TERRITORY CONTACTLASTNAME CONTACTFIRSTNAME
DEALSIZE
0      10022     USA       NaN              Yu              Kwai
Small
1      51100  France      EMEA         Henriot              Paul
Small
2      75508  France      EMEA        Da Cunha            Daniel
Medium
3      90003     USA       NaN           Young             Julie
Medium
4        NaN     USA       NaN           Brown             Julie
Medium

[5 rows x 25 columns]
```

```
import matplotlib.pyplot as plt
```

```
sales_data['ORDERDATE'] = pd.to_datetime(sales_data['ORDERDATE'],
errors='coerce')

cleaned_data = sales_data[['ORDERDATE', 'SALES']].copy()

#Calculate IQR
Q1 = cleaned_data['SALES'].quantile(0.25)
Q3 = cleaned_data['SALES'].quantile(0.75)
IQR = Q3 - Q1

#Define bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

#Remove outliers
filtered_data = cleaned_data[(cleaned_data['SALES'] >= lower_bound) &
(cleaned_data['SALES'] <= upper_bound)]

time_series_data = filtered_data.groupby('ORDERDATE',
as_index=False).sum()

plt.figure(figsize=(12, 6))
plt.plot(time_series_data['ORDERDATE'], time_series_data['SALES'],
marker='o', linestyle='-', label='Sales')
plt.title('Sales Over Time', fontsize=16)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Total Sales', fontsize=12)
plt.grid(True, linestyle='--', alpha=0.7)
plt.legend()
plt.show()
```



```
time_series_data['Month'] =
time_series_data['ORDERDATE'].dt.to_period('M')
monthly_sales = time_series_data.groupby('Month')['SALES'].sum()

plt.figure(figsize=(14, 6))
monthly_sales.plot(kind='bar', color='skyblue')
plt.title('Total Sales by Month', fontsize=16)
plt.xlabel('Month', fontsize=12)
plt.ylabel('Total Sales', fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```

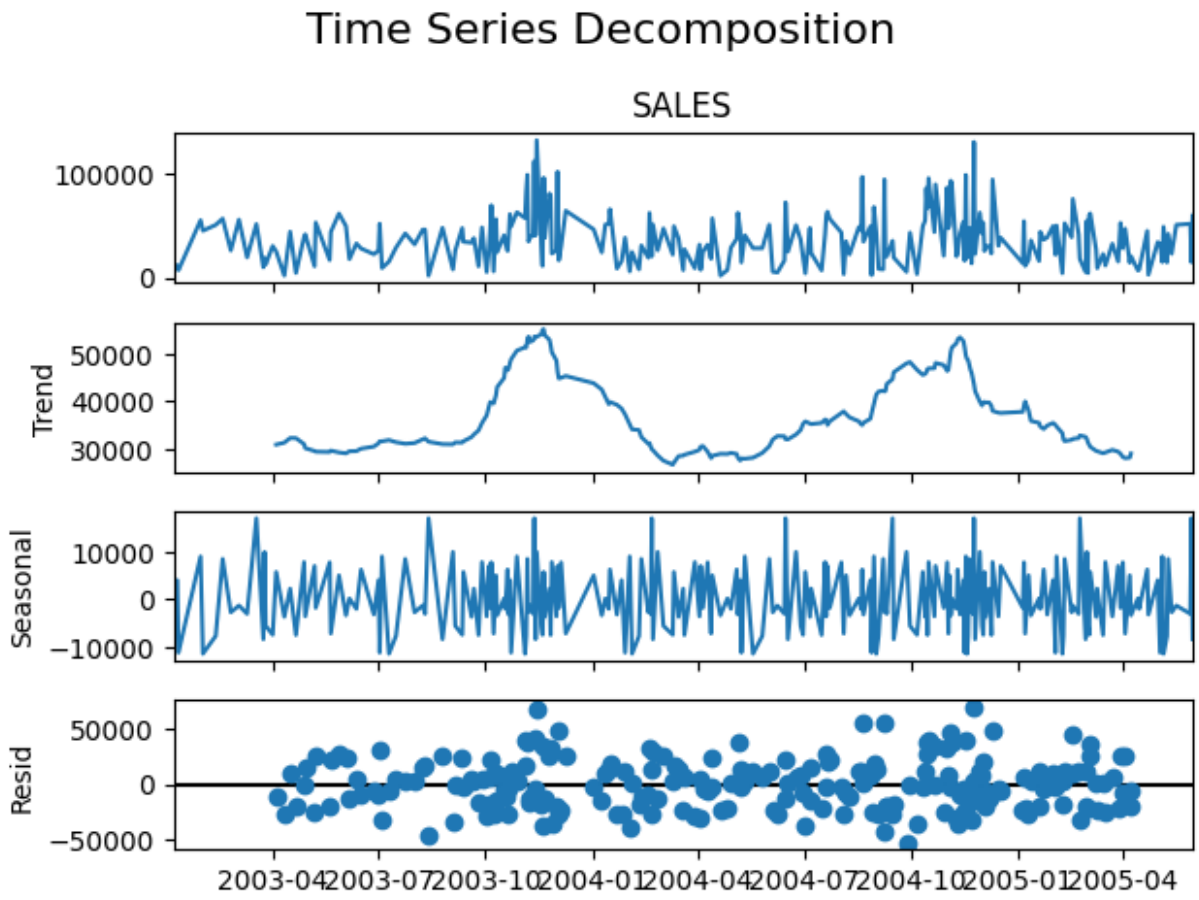



```
time_series_data['SALES'].describe()
```

```
count       252.000000
mean      36863.811786
std       24433.565922
min        1637.200000
25%       18928.992500
50%       34228.410000
75%       49686.012500
max      131236.000000
Name: SALES, dtype: float64
```

```
from statsmodels.tsa.seasonal import seasonal_decompose

time_series_data = time_series_data.set_index('ORDERDATE')

result = seasonal_decompose(time_series_data['SALES'],
model='additive', period=30)  # Assuming ~30 days in a month
```

```
#Plotting the decomposed components
result.plot()
plt.suptitle('Time Series Decomposition', fontsize=16)
plt.tight_layout()
plt.show()
```




```
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_absolute_error
import numpy as np

#Split point
split_point = int(len(time_series_data) * 0.8)

#Data split
train = time_series_data[:split_point]
test = time_series_data[split_point:]

#Daily frequency
time_series_data = time_series_data.asfreq('D')

import warnings
warnings.filterwarnings("ignore")
```

```python
#Fitting the ARIMA model
model = ARIMA(train['SALES'], order=(2, 1, 2))
fitted_model = model.fit()

print(fitted_model.summary())
```

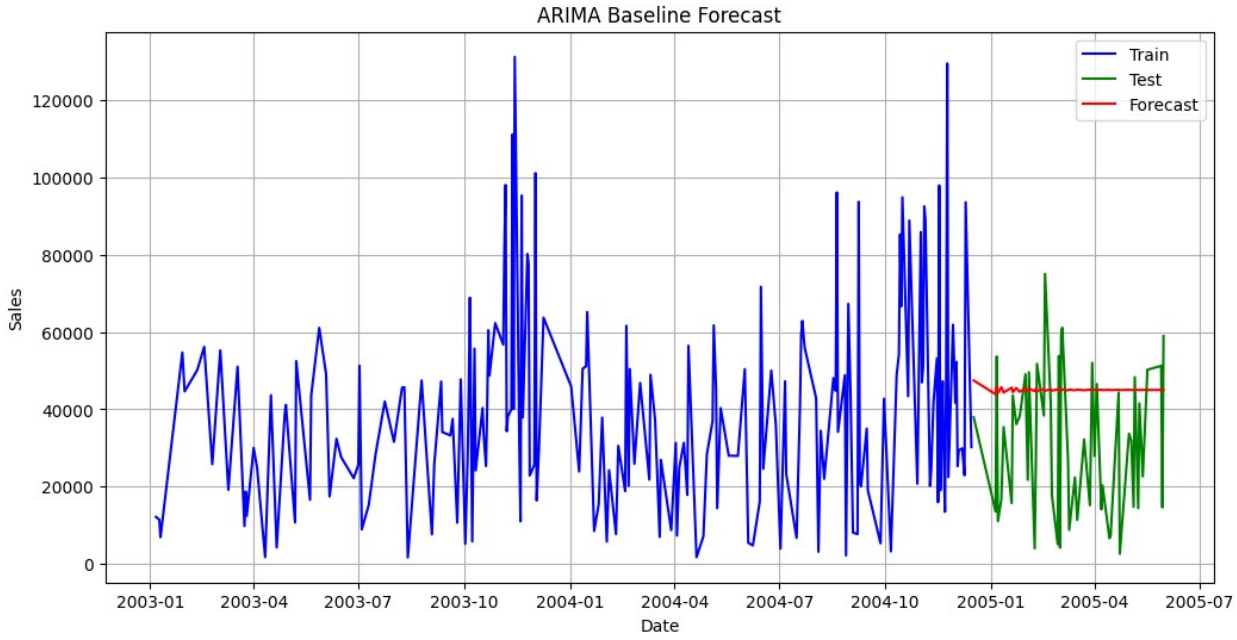
```
                               SARIMAX Results
==============================================================================
Dep. Variable:                  SALES   No. Observations:
201
Model:                 ARIMA(2, 1, 2)   Log Likelihood                -
2309.764
Date:                Mon, 27 Jan 2025   AIC
4629.529
Time:                        12:47:37   BIC
4646.020
Sample:                             0   HQIC
4636.203
                                - 201

Covariance Type:                  opg

==============================================================================
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
ar.L1         -1.0180      0.282     -3.610      0.000      -1.571
-0.465
ar.L2         -0.0950      0.100     -0.945      0.345      -0.292
0.102
ma.L1          0.0178      0.278      0.064      0.949      -0.527
0.563
ma.L2         -0.7784      0.228     -3.414      0.001      -1.225
-0.331
sigma2      6.389e+08   9.28e-10   6.88e+17      0.000    6.39e+08
6.39e+08
==============================================================================
=============
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):
10.72
Prob(Q):                              0.98   Prob(JB):
0.00
Heteroskedasticity (H):               2.09   Skew:
0.56
Prob(H) (two-sided):                  0.00   Kurtosis:
```

```
3.21
==============================================================================
=============

Warnings:
[1] Covariance matrix calculated using the outer product of gradients
(complex-step).
[2] Covariance matrix is singular or near-singular, with condition
number 6.61e+33. Standard errors may be unstable.
```

```
#Forecasting sales
forecast = fitted_model.forecast(steps=len(test))

# Evaluating the model using Mean Absolute Error
mae = mean_absolute_error(test['SALES'], forecast)
print(f"Mean Absolute Error: {mae}")
```

```
Mean Absolute Error: 19134.15196767558
```

```
#Plot actual vs predicted sales
plt.figure(figsize=(12, 6))
plt.plot(train.index, train['SALES'], label='Train', color='blue')
plt.plot(test.index, test['SALES'], label='Test', color='green')
plt.plot(test.index, forecast, label='Forecast', color='red')
plt.title('ARIMA Baseline Forecast')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.legend()
plt.grid()
plt.show()
```



```python
from itertools import product

#Define the range of parameters to search
p = range(0, 4)  # Test p from 0 to 3
d = range(0, 2)  # Test d as 0 or 1
q = range(0, 4)  # Test q from 0 to 3

#Create a grid of all combinations of p, d, q
pdq_combinations = list(product(p, d, q))

#Initialize variables to track the best model
best_aic = float("inf")
best_order = None
best_model = None

#Loop through all combinations and evaluate ARIMA models
for order in pdq_combinations:
    try:
        model = ARIMA(train['SALES'], order=order)
        fitted = model.fit()
        if fitted.aic < best_aic:  # Select the model with the lowest
AIC
            best_aic = fitted.aic
            best_order = order
            best_model = fitted
    except Exception as e:
        continue  # Skip combinations that fail to converge

print(f"Best ARIMA order: {best_order} with AIC: {best_aic}")
```

```
Best ARIMA order: (2, 1, 3) with AIC: 4624.763054033143
```

```python
#Fitting the optimized ARIMA model
optimized_model = ARIMA(train['SALES'], order=(2, 1, 3))
optimized_fitted = optimized_model.fit()

print(optimized_fitted.summary())
```

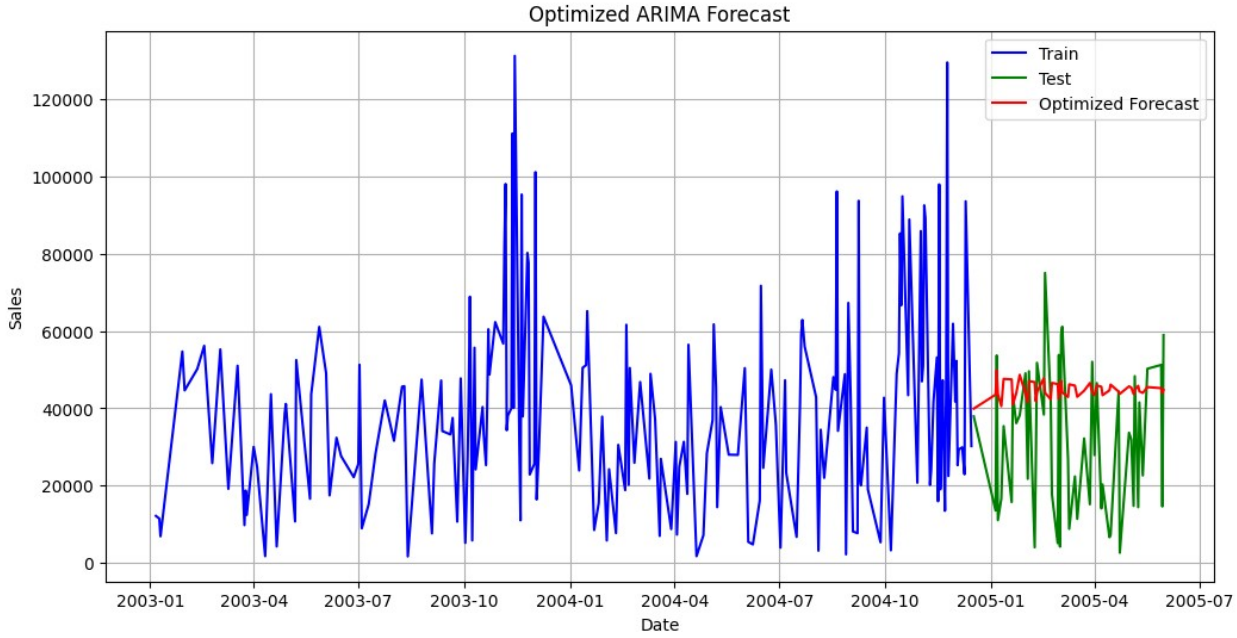
```
                               SARIMAX Results

==============================================================================
========
Dep. Variable:                   SALES   No. Observations:
201
Model:                 ARIMA(2, 1, 3)   Log Likelihood                -
2306.382
Date:                Mon, 27 Jan 2025   AIC
4624.763
Time:                        12:48:55   BIC
4644.553
Sample:                             0   HQIC
```

```
4632.772
                                  - 201

Covariance Type:                    opg

==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.4365      0.044    -10.020      0.000      -0.522      -0.351
ar.L2         -0.9280      0.041    -22.622      0.000      -1.008      -0.848
ma.L1         -0.5266      0.043    -12.213      0.000      -0.611      -0.442
ma.L2          0.6375      0.035     18.277      0.000       0.569       0.706
ma.L3         -0.8763      0.040    -21.976      0.000      -0.954      -0.798
sigma2      6.371e+08   1.49e-11   4.26e+19      0.000    6.37e+08    6.37e+08
===================================================================================
Ljung-Box (L1) (Q):                   0.23   Jarque-Bera (JB):                12.49
Prob(Q):                              0.63   Prob(JB):                         0.00
Heteroskedasticity (H):               2.09   Skew:                             0.60
Prob(H) (two-sided):                  0.00   Kurtosis:                         3.22
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.47e+35. Standard errors may be unstable.
```

```python
#Forecasting sales of optimized model
optimized_forecast = optimized_fitted.forecast(steps=len(test))

#Evaluating the optimized model using MAE
optimized_mae = mean_absolute_error(test['SALES'], optimized_forecast)
print(f"Optimized Model MAE: {optimized_mae}")
```

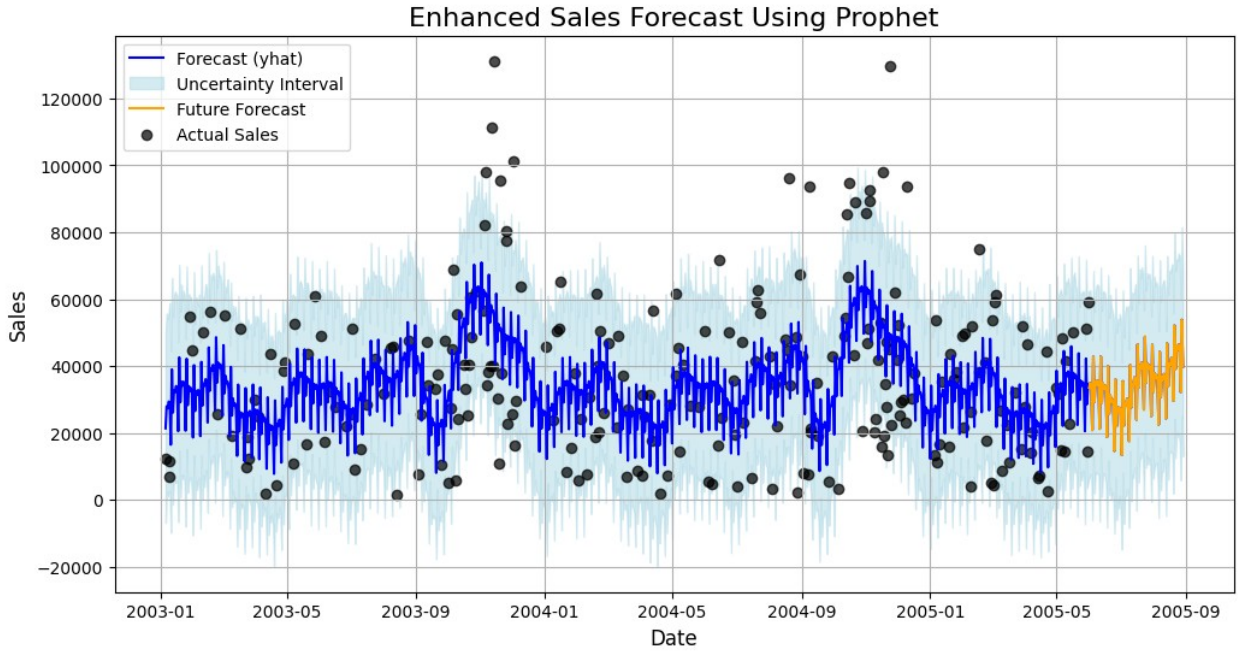
```
Optimized Model MAE: 18825.484862841993
```

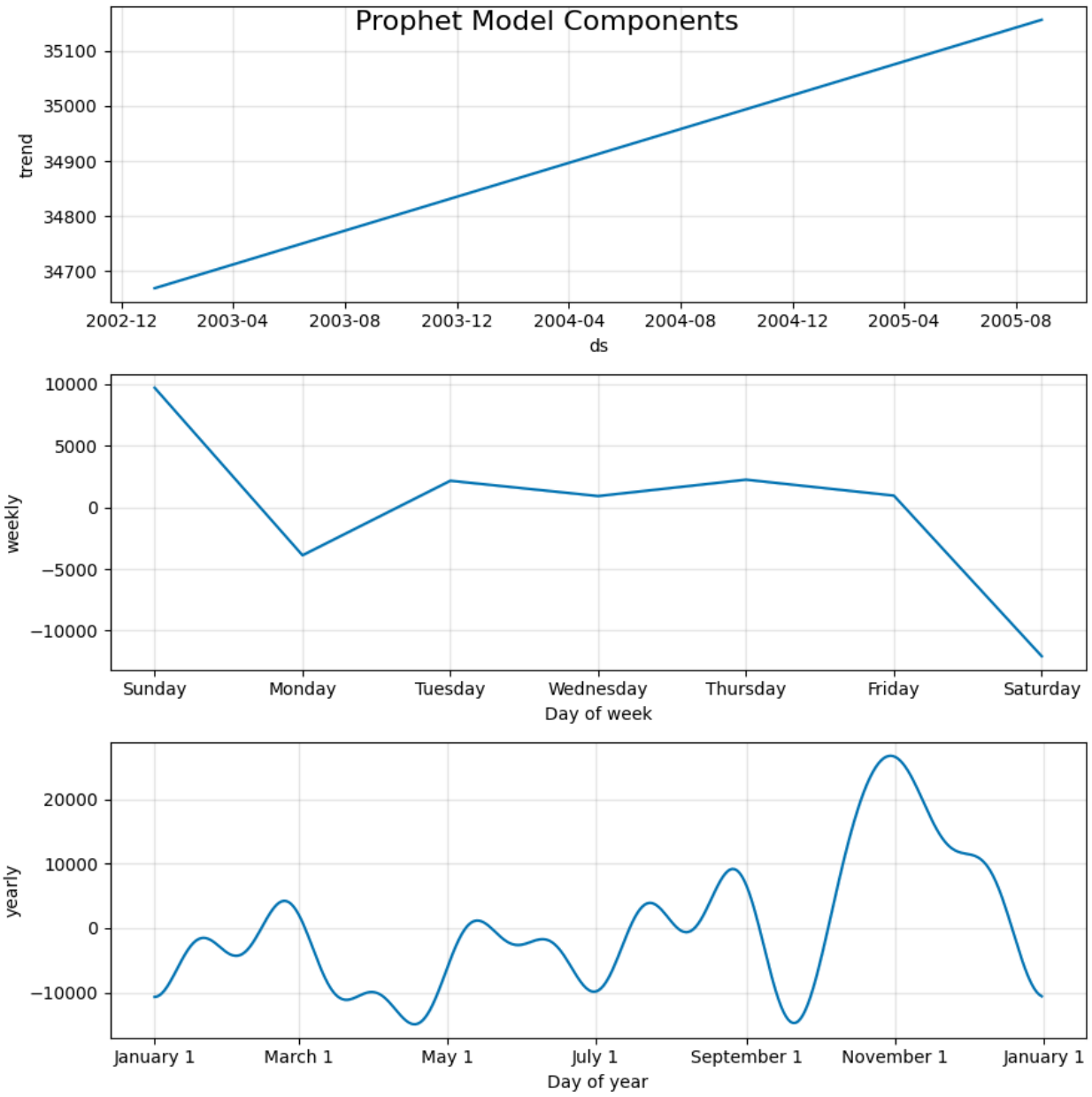
```
#Plot actual vs optimized forecast
plt.figure(figsize=(12, 6))
plt.plot(train.index, train['SALES'], label='Train', color='blue')
plt.plot(test.index, test['SALES'], label='Test', color='green')
plt.plot(test.index, optimized_forecast, label='Optimized Forecast',
color='red')
plt.title('Optimized ARIMA Forecast')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.legend()
plt.grid()
plt.show()
```




```
from prophet import Prophet

prophet_data = time_series_data.reset_index()[['ORDERDATE',
'SALES']].rename(columns={
    'ORDERDATE': 'ds',
    'SALES': 'y'
})

model = Prophet()

#Fitting the model
model.fit(prophet_data)

12:49:10 - cmdstanpy - INFO - Chain [1] start processing
12:49:10 - cmdstanpy - INFO - Chain [1] done processing

<prophet.forecaster.Prophet at 0x16cff550590>
```

```
#Creating a DataFrame for 90 days in future
future = model.make_future_dataframe(periods=90)

#Forecasting sales
prophet_forecast = model.predict(future)

#Plotting the forecast
fig, ax = plt.subplots(figsize=(12, 6))
ax.plot(prophet_forecast['ds'], prophet_forecast['yhat'],
label='Forecast (yhat)', color='blue')
ax.fill_between(
    prophet_forecast['ds'],
    prophet_forecast['yhat_lower'],
    prophet_forecast['yhat_upper'],
    color='lightblue',
    alpha=0.5,
    label='Uncertainty Interval'
)
forecast_part = prophet_forecast[prophet_forecast['ds'] >
prophet_data['ds'].max()]
ax.plot(forecast_part['ds'], forecast_part['yhat'], label='Future
Forecast', color='orange')
ax.scatter(prophet_data['ds'], prophet_data['y'], label='Actual
Sales', color='black', alpha=0.7)
ax.set_title('Enhanced Sales Forecast Using Prophet', fontsize=16)
ax.set_xlabel('Date', fontsize=12)
ax.set_ylabel('Sales', fontsize=12)
ax.legend(loc='upper left', fontsize=10)
ax.grid(True)
plt.show()

#Components
fig_components = model.plot_components(prophet_forecast)
plt.suptitle('Prophet Model Components', fontsize=16)
plt.show()
```


Enhanced Sales Forecast Using Prophet
Forecast (yhat)
Uncertainty Interval
Future Forecast
Actual Sales
Sales
Date
120000
100000
80000
60000
40000
20000
0
−20000
2003-01
2003-05
2003-09
2004-01
2004-05
2004-09
2005-01
2005-05
2005-09




```
#Extracting the forecasted values for the test period
forecast_test =
prophet_forecast[prophet_forecast['ds'].isin(test.index)][['ds',
'yhat']]
forecast_test = forecast_test.set_index('ds')

#MAE Calculation
prophet_mae = mean_absolute_error(test['SALES'],
forecast_test['yhat'])
print(f"Prophet Model MAE: {prophet_mae}")

Prophet Model MAE: 13720.40093438655
```

```
# Debugging: Verify prophet_forecast is a Series
print("Prophet forecast preview:")
print(prophet_forecast.head())  # Ensure it contains the forecast
values

# Align Prophet forecast with test set
prophet_forecast = prophet_forecast.iloc[:len(test)]  # Truncate to
match test length
prophet_forecast.index = test.index  # Align with test index

# Debugging: Check lengths and structure
print(f"Length of test['SALES']: {len(test['SALES'])}")
print(f"Length of forecast (ARIMA): {len(forecast)}")
print(f"Length of optimized_forecast (Optimized ARIMA):
{len(optimized_forecast)}")
print(f"Length of prophet_forecast: {len(prophet_forecast)}")

# Create the forecasted DataFrame
forecasted_df = pd.DataFrame({
    'Date': test.index,
    'Actual_Sales': test['SALES'].values,
    'ARIMA_Forecast': forecast,
    'Optimized_ARIMA_Forecast': optimized_forecast,
    'Prophet_Forecast': prophet_forecast.values,  # Use .values to
ensure clean array
    'ARIMA_Residuals': test['SALES'].values - forecast,
    'Optimized_ARIMA_Residuals': test['SALES'].values -
optimized_forecast,
    'Prophet_Residuals': test['SALES'].values -
prophet_forecast.values
})

# Preview the DataFrame
print(forecasted_df.head())
```

```
Prophet forecast preview:
ORDERDATE
2004-12-17    21352.124811
2005-01-05    27960.412306
2005-01-06    27347.197112
2005-01-07    29356.586587
2005-01-10    28775.529501
dtype: float64
Length of test['SALES']: 51
Length of forecast (ARIMA): 51
Length of optimized_forecast (Optimized ARIMA): 51
Length of prophet_forecast: 51
          Date  Actual_Sales  ARIMA_Forecast  Optimized_ARIMA_Forecast
\
201 2004-12-17      37905.15    47462.752223              39898.976600
```

```
202 2005-01-05      13529.57    43901.598582                43531.886385

203 2005-01-06      53690.93    45888.591502                49840.935635

204 2005-01-07      11021.30    44204.087743                43715.995128

205 2005-01-10      16628.16    45730.172436                40534.558441


     Prophet_Forecast  ARIMA_Residuals  Optimized_ARIMA_Residuals  \
201      21352.124811     -9557.602223               -1993.826600
202      27960.412306    -30372.028582              -30002.316385
203      27347.197112      7802.338498                3849.994365
204      29356.586587    -33182.787743              -32694.695128
205      28775.529501    -29102.012436              -23906.398441

     Prophet_Residuals
201       16553.025189
202      -14430.842306
203       26343.732888
204      -18335.286587
205      -12147.369501
```

```
import sqlite3

# Connect to SQLite database
conn = sqlite3.connect('sales_forecasting.db')

# Reset the index to move ORDERDATE into the columns
time_series_data = time_series_data.reset_index()

# Convert ORDERDATE to datetime (if needed)
time_series_data['ORDERDATE'] =
pd.to_datetime(time_series_data['ORDERDATE'], errors='coerce')

# Check and convert the 'Month' column if it is of type Period
if 'Month' in time_series_data.columns and
isinstance(time_series_data['Month'].iloc[0], pd.Period):
    time_series_data['Month'] = time_series_data['Month'].astype(str)

# Save to SQLite
time_series_data.to_sql('sales_data', conn, if_exists='replace',
index=False)

# Verify the table creation
cursor = conn.cursor()
cursor.execute("SELECT name FROM sqlite_master WHERE type='table';")
print(cursor.fetchall())
```

```
[('sales_data',)]
```

```
#Aggregate sales by date
query = """
SELECT
    ORDERDATE,
    SUM(SALES) AS total_sales
FROM
    sales_data
WHERE
    SALES IS NOT NULL AND SALES > 0
GROUP BY
    ORDERDATE
ORDER BY
    ORDERDATE;
"""

cleaned_data_sql = pd.read_sql_query(query, conn)

print(cleaned_data_sql.head())
```

```
             ORDERDATE  total_sales
0  2003-01-06 00:00:00     12133.25
1  2003-01-09 00:00:00     11432.34
2  2003-01-10 00:00:00      6864.05
3  2003-01-29 00:00:00     54702.00
4  2003-01-31 00:00:00     44621.96
```

```
cleaned_data_sql.to_csv('cleaned_sales_data.csv', index=False)
print("Cleaned data exported to 'cleaned_sales_data.csv'")
```

```
Cleaned data exported to 'cleaned_sales_data.csv'
```

```
#Monthly data
monthly_query = """
SELECT
    strftime('%Y-%m', ORDERDATE) AS month,
    SUM(SALES) AS total_sales
FROM
    sales_data
WHERE
    SALES IS NOT NULL AND SALES > 0
GROUP BY
    month
ORDER BY
    month;
"""
monthly_data_sql = pd.read_sql_query(monthly_query, conn)

monthly_data_sql.to_csv('monthly_sales_data.csv', index=False)
print("Monthly data exported to 'monthly_sales_data.csv'")
```

```
Monthly data exported to 'monthly_sales_data.csv'
```

```
forecasted_df.to_sql('forecasted_sales', conn, if_exists='replace',
index=False)
forecasted_df.to_csv('forecasted_sales.csv', index=False)

conn.close()
```