```
In [1]: import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from prophet import Prophet

from sklearn.metrics import mean_absolute_error, mean_squared_error
```

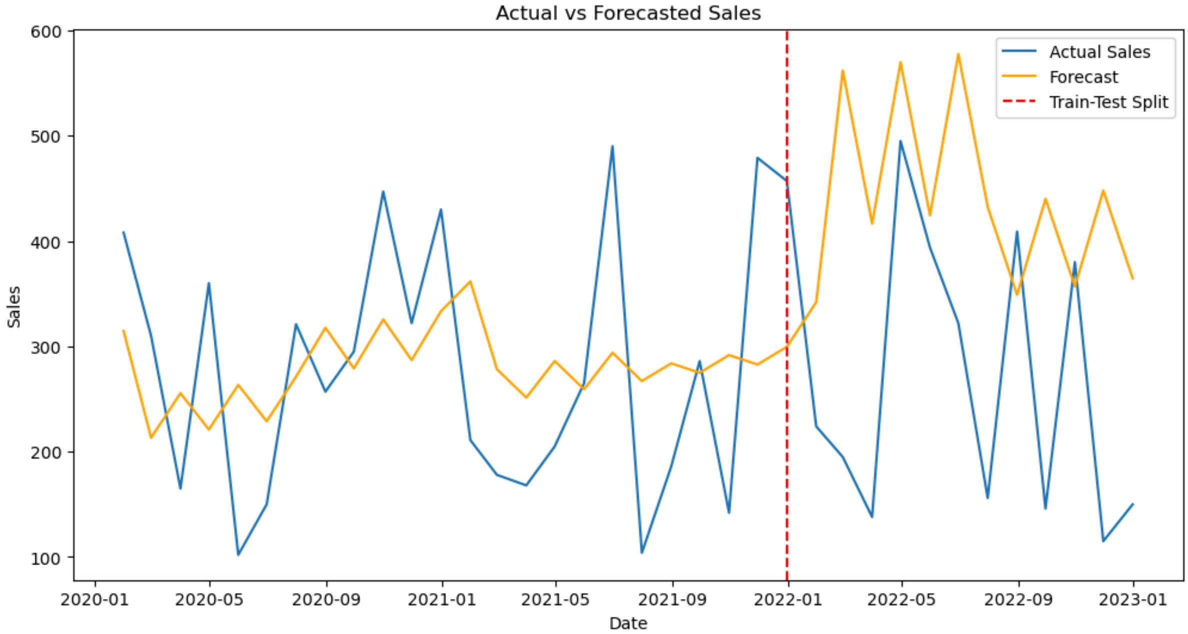
Random data

No pattern, difficult to predict.

```
In [7]: from prophet import Prophet
import pandas as pd
import numpy as np
from sklearn.metrics import mean_absolute_error, mean_squared_error
import matplotlib.pyplot as plt

# Sample sales data
data = {
    'ds': pd.date_range(start='2020-01-01', periods=36, freq='M'), # 36 periods, each peric
    'y': np.random.randint(100, 500, size=36)
}
sales_data = pd.DataFrame(data)

# Split data into train and test
train = sales_data.iloc[:-12]  # Use all except the last 12 months as training
test = sales_data.iloc[-12:]   # Use the last 12 months as testing

# Initialize and fit Prophet model
model = Prophet()
model.add_seasonality(name='monthly', period=30.5, fourier_order=3)  # smaller fourier mean
model.fit(train)

# Make future dataframe for forecast
future = model.make_future_dataframe(periods=12, freq='M')  # Predict 12 months ahead
forecast = model.predict(future)

# Evaluation metrics on test set
test_forecast = forecast.iloc[-12:][['ds', 'yhat']].set_index('ds')  # the date column is m
actual_vs_forecast = test.set_index('ds').join(test_forecast)

mae = mean_absolute_error(actual_vs_forecast['y'], actual_vs_forecast['yhat'])
rmse = mean_squared_error(actual_vs_forecast['y'], actual_vs_forecast['yhat'], squared=Fals

print(f"Mean Absolute Error (MAE): {mae}")
print(f"Root Mean Squared Error (RMSE): {rmse}")

# Plot actual vs forecasted values
plt.figure(figsize=(12, 6))
plt.plot(sales_data['ds'], sales_data['y'], label='Actual Sales')
plt.plot(forecast['ds'], forecast['yhat'], label='Forecast', color='orange')
plt.axvline(x=train['ds'].iloc[-1], color='red', linestyle='--', label='Train-Test Split')
plt.legend()
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Actual vs Forecasted Sales')
plt.show()
```

```
19:37:51 - cmdstanpy - INFO - Chain [1] start processing
19:37:51 - cmdstanpy - INFO - Chain [1] done processing
```

```
Mean Absolute Error (MAE): 193.77739923038735
Root Mean Squared Error (RMSE): 227.638886637485
```



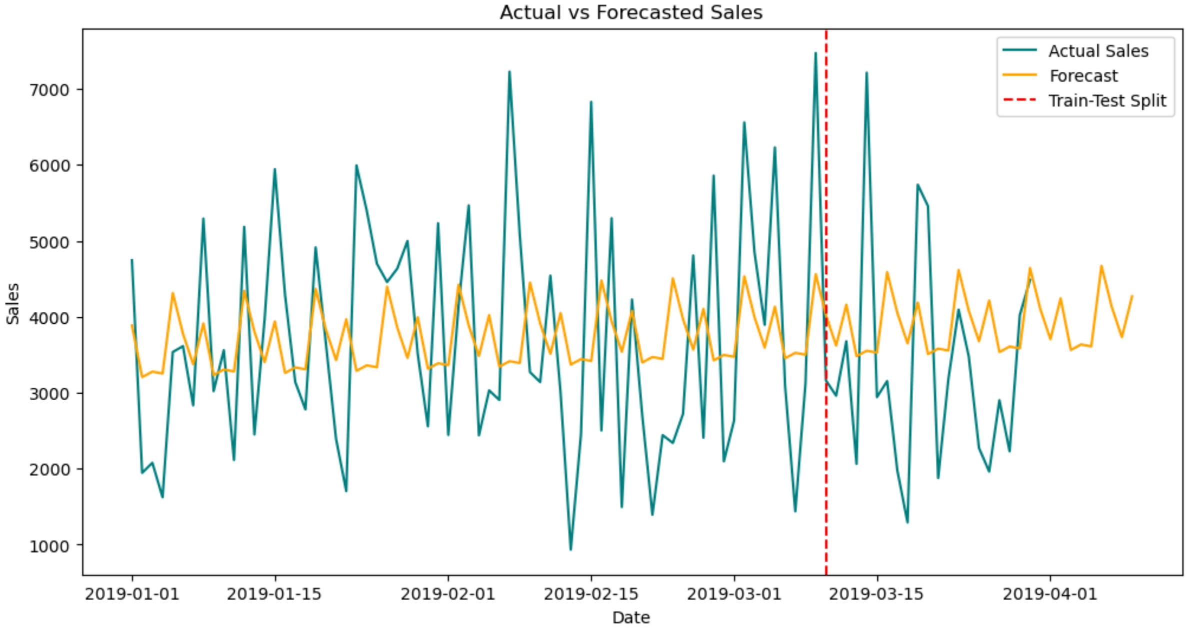
Grocery sales (from Kaggle)

In [8]:

```python
from prophet import Prophet
import pandas as pd
import numpy as np
from sklearn.metrics import mean_absolute_error, mean_squared_error
import matplotlib.pyplot as plt

# Load and preprocess the dataset
data = pd.read_csv('supermarket_sales.csv')
data['Date'] = pd.to_datetime(data['Date'])
data = data[['Date', 'Total']]
data = data.groupby('Date').sum().reset_index()

unique_days = data['Date'].nunique()
print(f"Number of unique days in dataset: {unique_days}")

# Prepare data for Prophet which needs columns to be called ds and y
data = data.rename(columns={'Date': 'ds', 'Total': 'y'})

# Split data into train and test
train = data.iloc[:-20]  # Use all except the last 30 days as training
test = data.iloc[-20:]   # Use the last 30 days as testing

# Initialize and fit Prophet model
model = Prophet(weekly_seasonality=True, changepoint_prior_scale=0.05) # Frequency with whi
model.fit(train)

# Make future dataframe for forecast
future = model.make_future_dataframe(periods=30, freq='D')  # Predict 30 days ahead
forecast = model.predict(future)

# Evaluation metrics on test set
test_forecast = forecast[forecast['ds'].isin(test['ds'])][['ds', 'yhat']].set_index('ds')
actual_vs_forecast = test.set_index('ds').join(test_forecast)

mae = mean_absolute_error(actual_vs_forecast['y'], actual_vs_forecast['yhat'])
rmse = mean_squared_error(actual_vs_forecast['y'], actual_vs_forecast['yhat'], squared=Fals

print(f"Mean Absolute Error (MAE): {mae}")
print(f"Root Mean Squared Error (RMSE): {rmse}")
```

```python
# Plot actual vs forecasted values
plt.figure(figsize=(12, 6))
plt.plot(data['ds'], data['y'], label='Actual Sales', color='teal')
plt.plot(forecast['ds'], forecast['yhat'], label='Forecast', color='orange')
plt.axvline(x=train['ds'].iloc[-1], color='red', linestyle='--', label='Train-Test Split')
plt.legend()
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Actual vs Forecasted Sales')
plt.show()
```

```
19:40:20 - cmdstanpy - INFO - Chain [1] start processing
Number of unique days in dataset: 89
19:40:20 - cmdstanpy - INFO - Chain [1] done processing
Mean Absolute Error (MAE): 1282.5552990873432
Root Mean Squared Error (RMSE): 1546.1473157325272
```



Retail sales

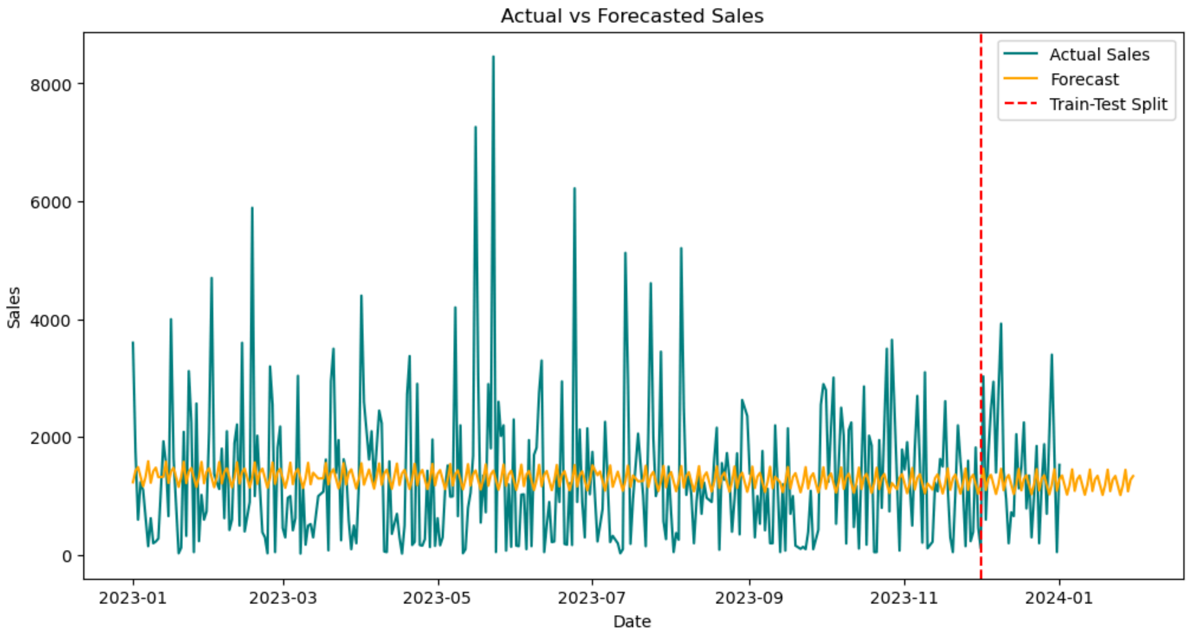
In [10]:
```python
# Load and preprocess the dataset
data = pd.read_csv('retail_sales.csv')
data['Date'] = pd.to_datetime(data['Date'])
data = data[['Date', 'Total']]

unique_days = data['Date'].nunique()
print(f"Number of unique days in dataset: {unique_days}")
```

```
Number of unique days in dataset: 345
```

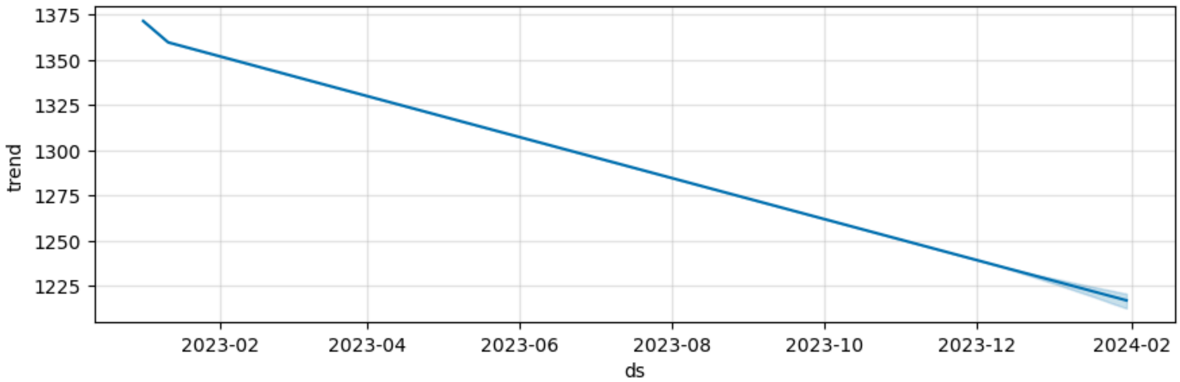
In [11]:
```python
# Aggregate total sales by date
daily_sales = data.groupby('Date')['Total'].sum().reset_index()
daily_sales.head()

# Rename columns to fit Prophet's requirements
daily_sales = daily_sales.rename(columns={'Date': 'ds', 'Total': 'y'})
daily_sales.head()

# Split data into train and test
train = daily_sales.iloc[:-30]  # Use all except the last 30 days as training
test = daily_sales.iloc[-30:]   # Use the last 30 days as testing

# Initialize and fit Prophet model
model = Prophet(weekly_seasonality=True, changepoint_prior_scale=0.1)
```

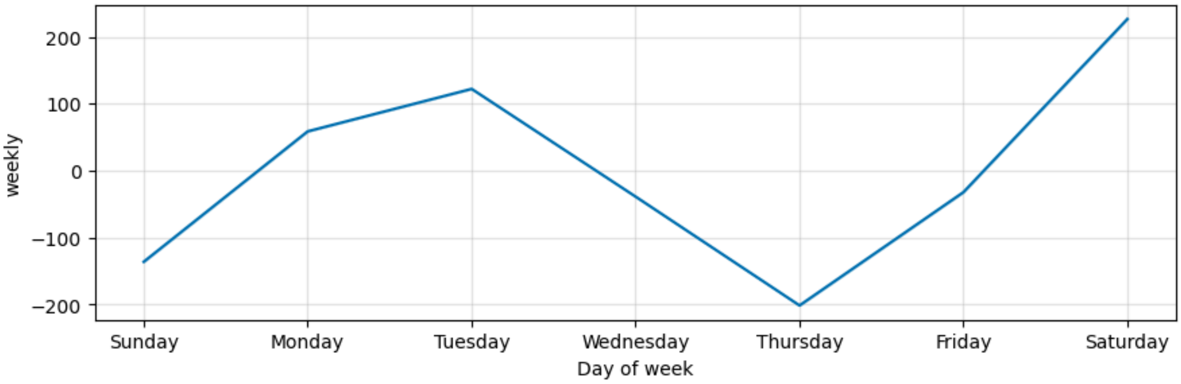
```python
# model.add_seasonality(name='monthly', period=30.5, fourier_order=5)
model.fit(train)

# Make future dataframe for forecast
future = model.make_future_dataframe(periods=60, freq='D')  # Predict 30 days ahead
forecast = model.predict(future)


# Evaluation metrics on test set
test_forecast = forecast[forecast['ds'].isin(test['ds'])][['ds', 'yhat']].set_index('ds')
# The actual values (test['y']) are joined with the predicted values (test_forecast['yhat']
actual_vs_forecast = test.set_index('ds').join(test_forecast)

# Drop rows with NaN values
actual_vs_forecast = actual_vs_forecast.dropna()

mae = mean_absolute_error(actual_vs_forecast['y'], actual_vs_forecast['yhat'])
rmse = mean_squared_error(actual_vs_forecast['y'], actual_vs_forecast['yhat'], squared=Fals
print(f"Mean Absolute Error (MAE): {mae}")
print(f"Root Mean Squared Error (RMSE): {rmse}")

# Plot actual vs forecasted values
plt.figure(figsize=(12, 6))
plt.plot(daily_sales['ds'], daily_sales['y'], label='Actual Sales', color='teal')
plt.plot(forecast['ds'], forecast['yhat'], label='Forecast', color='orange')
plt.axvline(x=train['ds'].iloc[-1], color='red', linestyle='--', label='Train-Test Split')
plt.legend()
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Actual vs Forecasted Sales')
plt.show()
```

```
19:44:34 - cmdstanpy - INFO - Chain [1] start processing
19:44:34 - cmdstanpy - INFO - Chain [1] done processing
Mean Absolute Error (MAE): 785.480746159135
Root Mean Squared Error (RMSE): 986.9846523439865
```



In [5]:
```python
# Plot the forecast components: trend, weekly seasonality, and monthly seasonality
fig = model.plot_components(forecast)
plt.show()
```



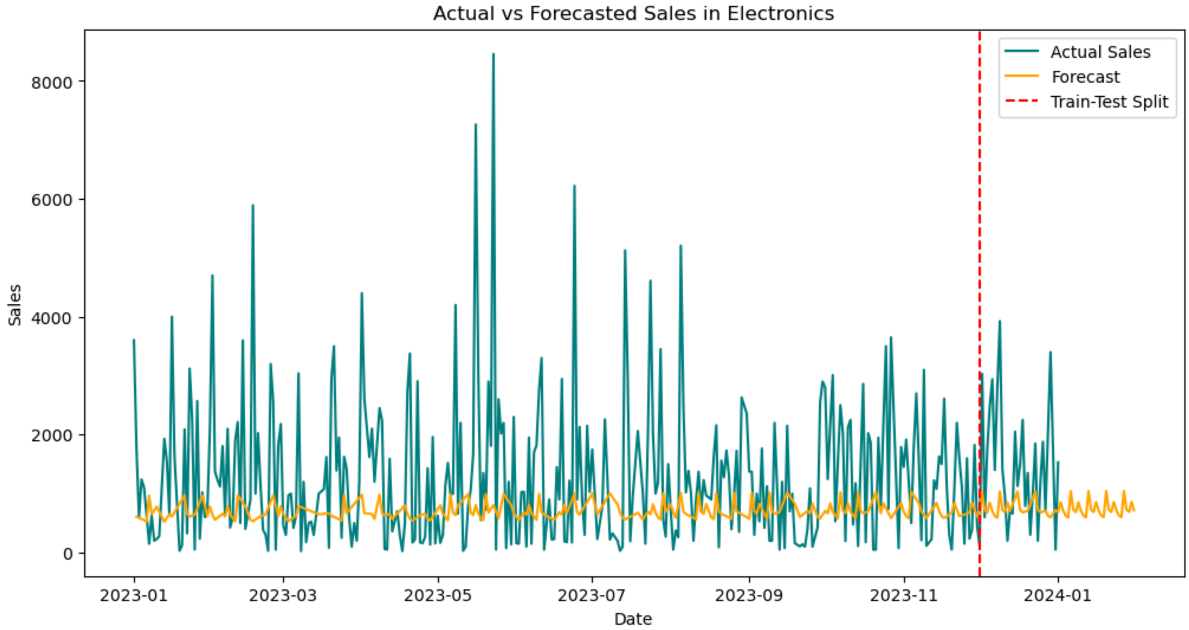


In [6]:

```
# Load and preprocess the dataset
data = pd.read_csv('retail_sales.csv')
data['Date'] = pd.to_datetime(data['Date'])

# Forecast sales for each product category
categories = data['Product Category'].unique()

for category in categories:
    category_data = data[
      data['Product Category'] == category].groupby('Date')[
      'Total'].sum().reset_index()
    category_data = category_data.rename(
      columns={'Date': 'ds', 'Total': 'y'})

print(category_data)

model = Prophet()
model.fit(category_data)

future = model.make_future_dataframe(periods=30, freq='D')
forecast = model.predict(future)

    # Plot actual vs forecasted values
plt.figure(figsize=(12, 6))
plt.plot(daily_sales['ds'], daily_sales['y'], label='Actual Sales', color='teal')
plt.plot(forecast['ds'], forecast['yhat'], label='Forecast', color='orange')
plt.axvline(x=train['ds'].iloc[-1], color='red', linestyle='--', label='Train-Test Split')
plt.legend()
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title(f'Actual vs Forecasted Sales in {category}')
plt.show()
```

```
19:36:37 - cmdstanpy - INFO - Chain [1] start processing
```

```
            ds     y
0   2023-01-02    90
1   2023-01-05  1050
2   2023-01-06   120
3   2023-01-07    75
4   2023-01-08    25
..         ...   ...
214 2023-12-27   600
215 2023-12-28    75
216 2023-12-29   100
217 2023-12-31    50
218 2024-01-01    30

[219 rows x 2 columns]
19:36:37 - cmdstanpy - INFO - Chain [1] done processing
```



Train-Test Split (Red Dashed Line) marks the division between the training and test datasets. Prophet was trained on the data to the left of the line and tested (validated) on the data to the right, plus additional forecast for some future days.

Key Observations:

The forecast (yellow line) seems to underrepresent the peaks and valleys of the actual sales. This is typical for Prophet, as it focuses on capturing trends and seasonality rather than extreme fluctuations. If the forecast aligns reasonably well with the actual sales in the test set (to the right of the red line), it indicates the model has performed adequately. However, the smoothness of forecast line might suggest the need for fine-tuning.