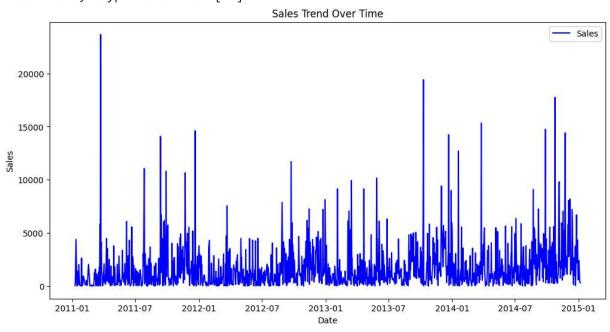
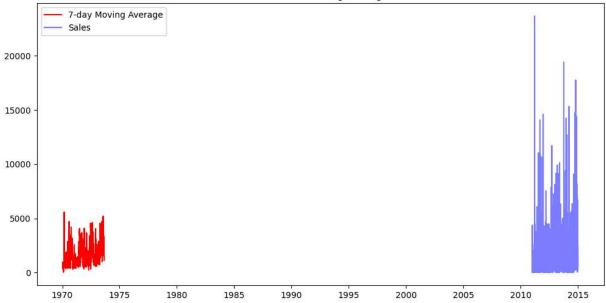
```
In [ ]:
In [1]: import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        from statsmodels.tsa.arima.model import ARIMA
        from sklearn.metrics import mean squared error
        import numpy as np
        # Load dataset with correct encoding
        df = pd.read_excel("Superstore.xlsx", engine="openpyx1")
        # Remove duplicate columns if any
        df = df.loc[:, ~df.columns.duplicated()]
        # Strip extra spaces from column names
        df.rename(columns=lambda x: x.strip(), inplace=True)
        # Ensure the correct column name
        df = df.rename(columns={"Order Date": "Date", "Sales": "Sales"})
        # Check if Date column exists and correctly format it
        if "Date" in df.columns:
            print("Before conversion:")
            print(df["Date"].head(10)) # Check first 10 values
            df["Date"] = pd.to datetime(df["Date"], errors="coerce")
            print("After conversion:")
            print(df["Date"].head(10)) # Verify conversion
        # Drop rows where Date is NaT (invalid dates)
        df = df.dropna(subset=["Date"])
        # Ensure Sales column is numeric
        df["Sales"] = pd.to_numeric(df["Sales"], errors="coerce")
        # Aggregate sales by date
        df = df.groupby("Date")["Sales"].sum().reset_index()
        # Sort values by date
        df = df.sort_values("Date")
        # Visualizing Sales Trend
        plt.figure(figsize=(12, 6))
        plt.plot(df["Date"], df["Sales"], label="Sales", color="blue")
        plt.xlabel("Date")
        plt.ylabel("Sales")
        plt.title("Sales Trend Over Time")
        plt.legend()
        plt.show()
        # Moving Average (7-day) Trend
        plt.figure(figsize=(12, 6))
        df["Sales"].rolling(window=7).mean().plot(label='7-day Moving Average', color='red'
        plt.plot(df["Date"], df["Sales"], label="Sales", color="blue", alpha=0.5)
```

```
plt.legend()
plt.title("Sales with Moving Average")
plt.show()
# ARIMA Model Training
train size = int(len(df) * 0.8)
train, test = df["Sales"][:train_size], df["Sales"][train_size:]
# Fit ARIMA model
model = ARIMA(train, order=(5,1,0)) # (p,d,q) values can be tuned
model_fit = model.fit()
# Forecasting
forecast = model_fit.forecast(steps=len(test))
# Model Evaluation
rmse = np.sqrt(mean_squared_error(test, forecast))
print(f"Root Mean Squared Error (RMSE): {rmse}")
# Plot Forecast vs Actual Sales
plt.figure(figsize=(12, 6))
plt.plot(df["Date"][train_size:], test, label="Actual Sales", color="blue")
plt.plot(df["Date"][train_size:], forecast, label="Forecasted Sales", color="red")
plt.xlabel("Date")
plt.ylabel("Sales")
plt.title("Actual vs Forecasted Sales")
plt.legend()
plt.show()
# Future Forecast for next 30 days
future_forecast = model_fit.forecast(steps=30)
future_dates = pd.date_range(start=df["Date"].max(), periods=31, freq='D')[1:]
# Create Forecasted Table
forecast_df = pd.DataFrame({"Date": future_dates, "Predicted Sales": future_forecas
print(forecast_df)
```

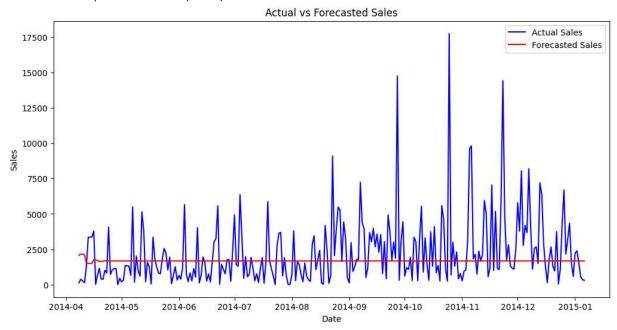
```
Before conversion:
    2013-11-12
1
    2013-11-12
2
    2013-06-17
3
    2012-10-18
4
    2012-10-18
5
    2011-06-14
6
    2011-06-14
7
    2011-06-14
8
    2011-06-14
9
    2011-06-14
Name: Date, dtype: datetime64[ns]
After conversion:
0
    2013-11-12
1
    2013-11-12
2
    2013-06-17
3
    2012-10-18
4
    2012-10-18
5
    2011-06-14
6
    2011-06-14
7
    2011-06-14
8
    2011-06-14
9
    2011-06-14
Name: Date, dtype: datetime64[ns]
```



Sales with Moving Average



Root Mean Squared Error (RMSE): 2475.3345328590963



	Date	Predicted Sales
1067	2015-01-07	2078.413370
1068	2015-01-08	2166.518906
1069	2015-01-09	2122.090293
1070	2015-01-10	1499.859187
1071	2015-01-11	1504.702226
1072	2015-01-12	1496.460961
1073	2015-01-13	1772.057264
1074	2015-01-14	1737.776346
1075	2015-01-15	1718.570607
1076	2015-01-16	1633.062827
1077	2015-01-17	1650.467641
1078	2015-01-18	1656.171167
1079	2015-01-19	1690.753295
1080	2015-01-20	1679.704188
1081	2015-01-21	1676.199516
1082		1665.375896
1083	2015-01-23	1670.089869
1084	2015-01-24	1671.226901
1085	2015-01-25	1675.304507
1086	2015-01-26	1672.989425
1087	2015-01-27	1672.550345
1088	2015-01-28	1671.280400
1089	2015-01-29	1672.213804
1090	2015-01-30	1672.340536
1091	2015-01-31	1672.791358
1092		1672.382724
1093		1672.351228
1094	2015-02-03	1672.212777
1095		1672.372017
1096	2015-02-05	1672.375872