Time_Series_Retail_Assignment

June 30, 2025

1 Week 12: Required Assignment 12.1

Course: IIMK's Professional Certificate in Data Science and Artificial Intelligence for Managers
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1.1 1. Influence of Trend, Seasonality, and Cycles on Retail Strategic Decisions

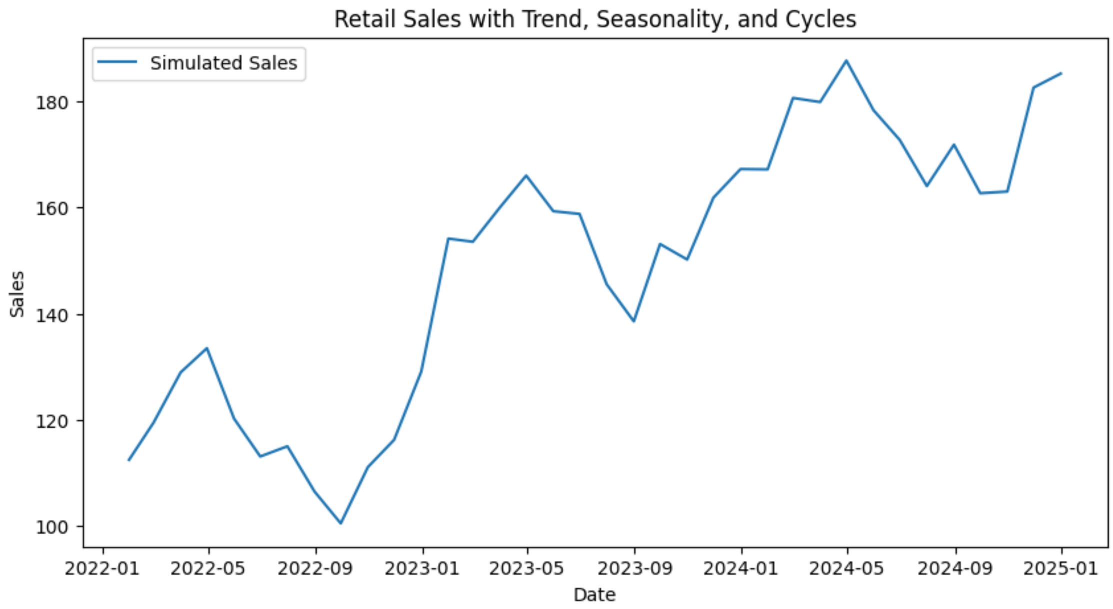
Business Explanation: Trends represent long-term changes, seasonality covers regular periodic effects, and cycles are longer-term economic or industry patterns. Recognizing these helps optimize inventory, marketing, and operations.

[5]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
np.random.seed(42)

# Simulate 3 years of monthly retail sales
months = pd.date_range('2022-01-01', periods=36, freq='ME')
trend = np.linspace(100, 200, 36)
seasonality = 20 * np.sin(2 * np.pi * months.month / 12)
cycle = 10 * np.sin(2 * np.pi * months.year / 3)
noise = np.random.normal(0, 5, 36)
sales = trend + seasonality + cycle + noise
df = pd.DataFrame({'Sales': sales}, index=months)

plt.figure(figsize=(10,5))
plt.plot(df.index, df['Sales'], label='Simulated Sales')
plt.title('Retail Sales with Trend, Seasonality, and Cycles')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.legend()
plt.show()

# The plot shows how trend, seasonality, and cycles combine to shape sales data.
```

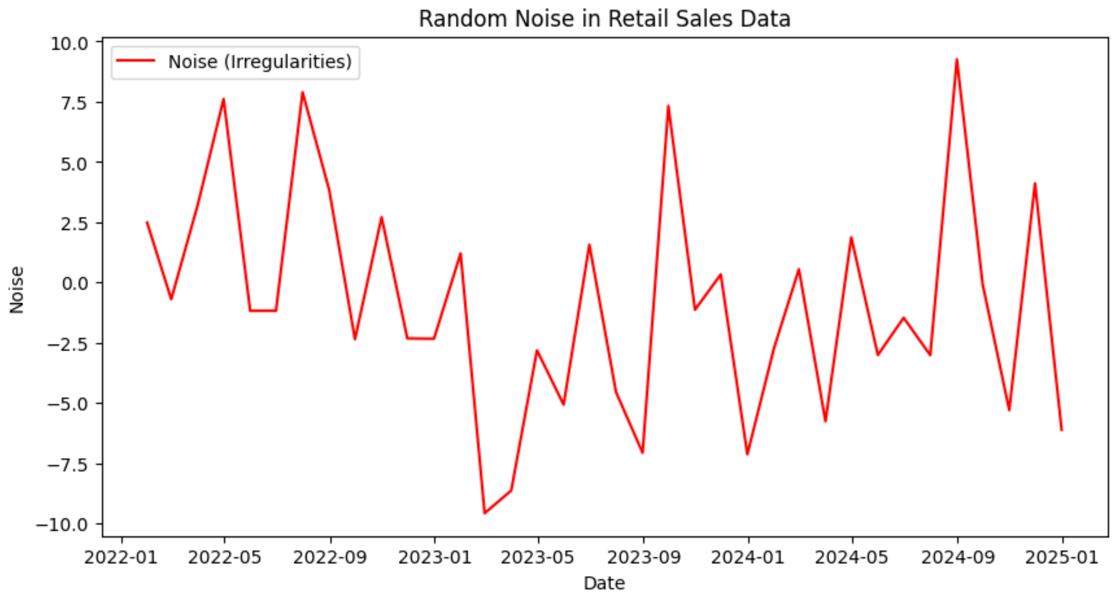


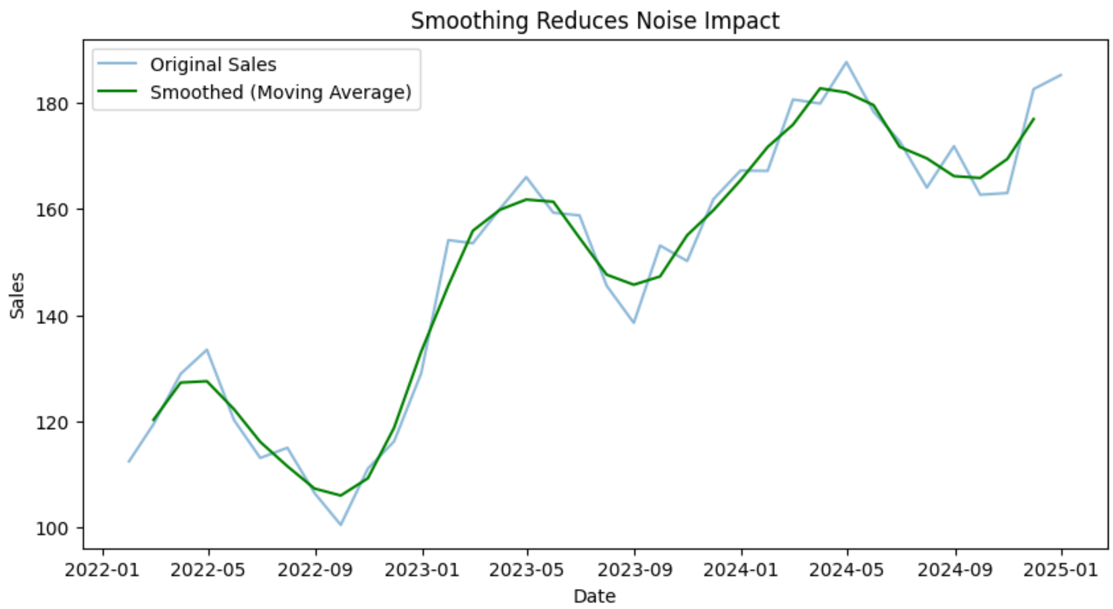
1.2 2. Role and Impact of Irregularities (Noise) in Retail Data

Business Explanation: Noise refers to random, unpredictable fluctuations. If misinterpreted, it can lead to poor decisions, such as overreacting to a one-time sales spike. Smoothing and decomposition help separate noise from real patterns.

[6]:
```
# Highlighting noise
plt.figure(figsize=(10,5))
plt.plot(df.index, noise, label='Noise (Irregularities)', color='red')
plt.title('Random Noise in Retail Sales Data')
plt.xlabel('Date')
plt.ylabel('Noise')
plt.legend()
plt.show()

# Demonstrate effect of smoothing
df['Smoothed'] = df['Sales'].rolling(window=3, center=True).mean()
plt.figure(figsize=(10,5))
plt.plot(df.index, df['Sales'], label='Original Sales', alpha=0.5)
plt.plot(df.index, df['Smoothed'], label='Smoothed (Moving Average)',␣
↪color='green')
plt.title('Smoothing Reduces Noise Impact')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.legend()
plt.show()
```





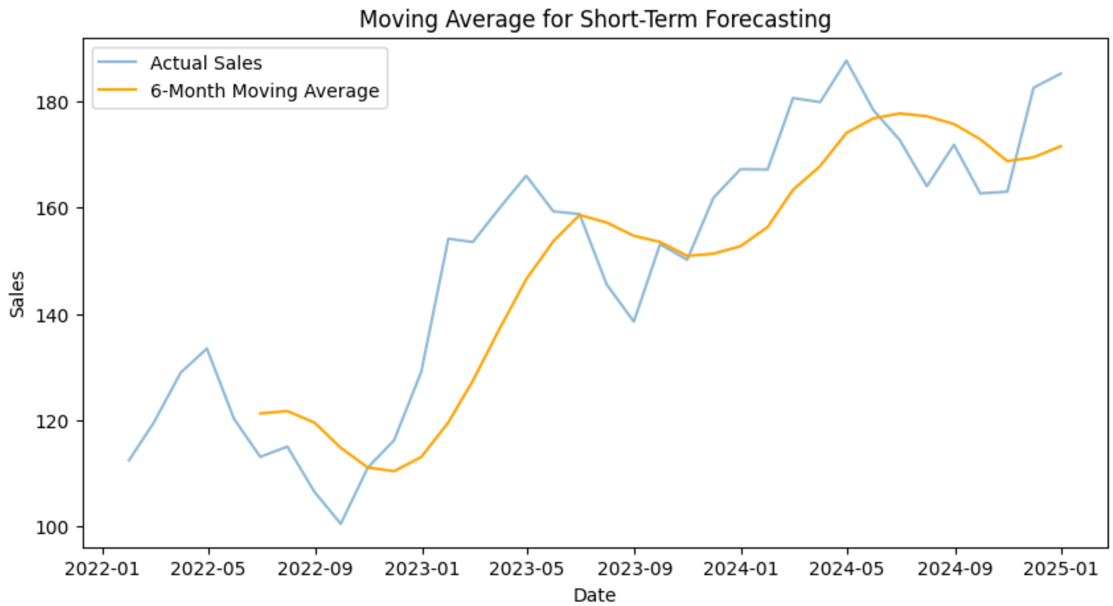
1.3 3. Importance of Moving Average Model for Short-Term Forecasting

Business Explanation: Moving averages smooth out short-term fluctuations, helping retailers identify real sales patterns and plan inventory for seasonal peaks.

[7]:
```
# Moving Average for short-term forecasting
df['MA_6'] = df['Sales'].rolling(window=6).mean()
```

```python
plt.figure(figsize=(10,5))
plt.plot(df.index, df['Sales'], label='Actual Sales', alpha=0.5)
plt.plot(df.index, df['MA_6'], label='6-Month Moving Average', color='orange')
plt.title('Moving Average for Short-Term Forecasting')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.legend()
plt.show()

# The moving average line helps spot underlying sales patterns, especially
 ↪during seasonal peaks.
```



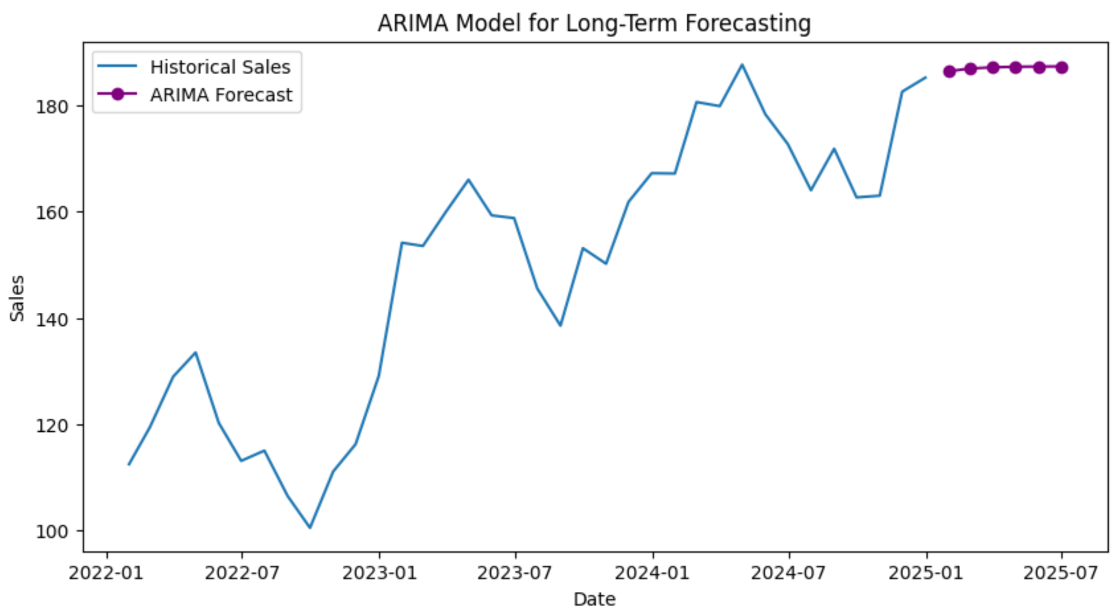
1.4 4. Advantages of ARIMA Models for Long-Term Retail Forecasting

Business Explanation: ARIMA models capture trend and seasonality, supporting long-term planning in inventory, staffing, and resource allocation.

[10]:
```python
import warnings
warnings.filterwarnings("ignore", message="Non-stationary starting
 ↪autoregressive parameters found")
warnings.filterwarnings("ignore", message="Non-invertible starting MA
 ↪parameters found")
from statsmodels.tsa.arima.model import ARIMA
# Fit ARIMA model (simple parameters for illustration)
model = ARIMA(df['Sales'], order=(1,1,1))
model_fit = model.fit()
forecast = model_fit.forecast(steps=6)
```

```
plt.figure(figsize=(10,5))
plt.plot(df.index, df['Sales'], label='Historical Sales')
future_months = pd.date_range(df.index[-1] + pd.offsets.MonthEnd(1), periods=6,␣
 ↪freq='ME')
plt.plot(future_months, forecast, label='ARIMA Forecast', color='purple',␣
 ↪marker='o')
plt.title('ARIMA Model for Long-Term Forecasting')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.legend()
plt.show()

# ARIMA forecast helps plan inventory and workforce for the coming months.
```



Conclusion: A deep understanding of time series components empowers retailers to make data-driven decisions. Moving averages support agile, short-term planning, while ARIMA models provide robust, long-term forecasts essential for sustainable growth.