

Notebook 5.1 - Time Series Forecasting

Management Science - Predicting Bean Counter's Future

Introduction

Welcome back, CEO! After successfully using Monte Carlo simulation to plan Bean Counter's expansion, you now face a new challenge: predicting future demand for your seasonal products.

The Seasonal Challenge: Bean Counter has expanded beyond regular coffee into seasonal drinks:

- Iced Coffee (summer favorite)
- Pumpkin Spice Latte (fall special)
- Peppermint Hot Chocolate (winter warmer)

You have 2 years of daily sales data. The board wants accurate forecasts for next month to optimize inventory. Overstock means waste (drinks expire), understock means lost sales and unhappy customers!

How to Use This Tutorial

Cells marked with “YOUR CODE BELOW” expect you to write code. Test your solutions with the provided assertions. Work through the sections in order - each builds on previous concepts!

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from datetime import datetime, timedelta

# Set random seed for reproducibility
np.random.seed(2025)
print("Libraries loaded! Time to predict Bean Counter's future.")
```

Libraries loaded! Time to predict Bean Counter's future.

Section 1 - Working with Time Series Data

Before we can forecast, we need to understand how to work with dates and time-based data in pandas.

Understanding Date Conversion

```
# Example: Converting strings to dates
date_strings = ['2024-01-15', '2024-02-20', '2024-03-10']
dates = pd.to_datetime(date_strings)
print("Original strings:", date_strings)
print("\nConverted to datetime:", dates)
print("\nExtract components:")
print(f" Months: {dates.month.tolist()}")
print(f" Day of week: {dates.day_name().tolist()}")
```

```
Original strings: ['2024-01-15', '2024-02-20', '2024-03-10']

Converted to datetime: DatetimeIndex(['2024-01-15', '2024-02-20',
'2024-03-10'], dtype='datetime64[ns]', freq=None)

Extract components:
Months: [1, 2, 3]
Day of week: ['Monday', 'Tuesday', 'Sunday']
```

💡 Tip

Use `.dt` accessor to extract date parts:

- `.dt.month` - Month (1-12)
- `.dt.day_of_week` - Day (0=Monday, 6=Sunday)
- `.dt.quarter` - Quarter (1-4)
- `.dt.is_month_end` - Boolean for month end

💡 Tip

To access specific elements, e.g. the third month of a year from a DataFrame, you can use `df['date'].dt.month.iloc[2]`. Step by step this happens:

1. You access the `date` column using `df['date']`.
2. You use the `.dt` accessor to extract the month part.
3. You use `.iloc[2]` to select the third element.

Exercise 1.1 - Load and Prepare Sales Data

Create a DataFrame with Bean Counter's sales data and convert the date column properly.

```
# DON'T CHANGE ANYTHING BELOW!
# Creates sample sales data for Bean Counter (3 years for enough seasonal
cycles)
dates = pd.date_range(start='2022-01-01', end='2024-12-31', freq='D')

# Generate sales with trend and seasonality
base_sales = 100
```

```

trend = np.linspace(0, 60, len(dates)) # Growing trend over 3 years
# Summer peaks for iced coffee! (high in June-Aug, low in Dec-Feb)
seasonal = 45 * np.sin(2 * np.pi * (np.arange(len(dates)) - 80) / 365.25)
# Yearly pattern, peaks in summer
weekly = 15 * np.sin(2 * np.pi * np.arange(len(dates)) / 7) # Weekend
# peaks
noise = np.random.normal(0, 20, len(dates)) # Controlled noise
sales = base_sales + trend + seasonal + weekly + noise
# DON'T CHANGE ANYTHING ABOVE!

```

i Creating DataFrames and Working with Dates

```

# Create DataFrame from dictionary
df = pd.DataFrame({'col1': values1, 'col2': values2})

# Access datetime attributes with .dt
df['date'].dt.month # Extract month (1-12)
df['date'].dt.year # Extract year
df['date'].dt.day # Extract day

# Get first/last element
df['column'].iloc[0] # First element
df['column'].iloc[-1] # Last element

```

YOUR CODE BELOW

```

# Create DataFrame with date and sales columns
df = # Create the DataFrame with 'date' and 'sales' columns

# Extract month from the date column
# Hint: Use .dt.month to get month, then .iloc[0] or .iloc[-1]
first_month = # Get the month of the first date
last_month = # Get the month of the last date

```

```

# Don't modify below - these test your solution
assert 'date' in df.columns, "DataFrame should have a 'date' column"
assert 'sales' in df.columns, "DataFrame should have a 'sales' column"
assert first_month == 1, f"First month should be January (1), got {first_month}"
assert last_month == 12, f"Last month should be December (12), got {last_month}"
print("Great! Sales data loaded and dates properly formatted!")

# Quick visualization of your loaded data
plt.figure(figsize=(12, 8))
plt.plot(df['date'], df['sales'], linewidth=1, alpha=0.7, color="#537E8F")
plt.xlabel('Date')
plt.ylabel('Sales (drinks)')
plt.title('Bean Counter Sales - Your Loaded Data')

```

```
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()
```

Exercise 1.2 - Analyze Sales Patterns

Calculate key statistics about Bean Counter's sales to understand the data.

💡 Tip

You can use methods like `mean()`, `max()`, and `min()` to calculate basic statistics with DataFrames. You just need to call these methods on the ‘sales’ column of the DataFrame.

```
# YOUR CODE BELOW
# Calculate basic statistics
mean_sales = # Average daily sales
max_sales = # Highest sales day
min_sales = # Lowest sales day
```

```
# Don't modify below
assert 115 < mean_sales < 135, f"Mean sales should be ~125, got {mean_sales:.1f}"
assert max_sales > 180, f"Max sales should be >180, got {max_sales:.1f}"
assert min_sales < 70, f"Min sales should be <70, got {min_sales:.1f}"
print(f"Excellent! Analysis complete!")
print(f"Daily average: {mean_sales:.0f} drinks")
```

Section 2 - Moving Averages: Smoothing the Noise

Daily sales are noisy. Moving averages help us see the underlying patterns by averaging nearby data points.

Understanding Moving Averages

The Concept: A moving average smooths data by calculating the average of a “window” of recent values. As we move forward in time, the window slides along the data.

Example: For a 3-day moving average:

- Day 3 average: $(\text{Day1} + \text{Day2} + \text{Day3}) / 3$
- Day 4 average: $(\text{Day2} + \text{Day3} + \text{Day4}) / 3$
- Day 5 average: $(\text{Day3} + \text{Day4} + \text{Day5}) / 3$

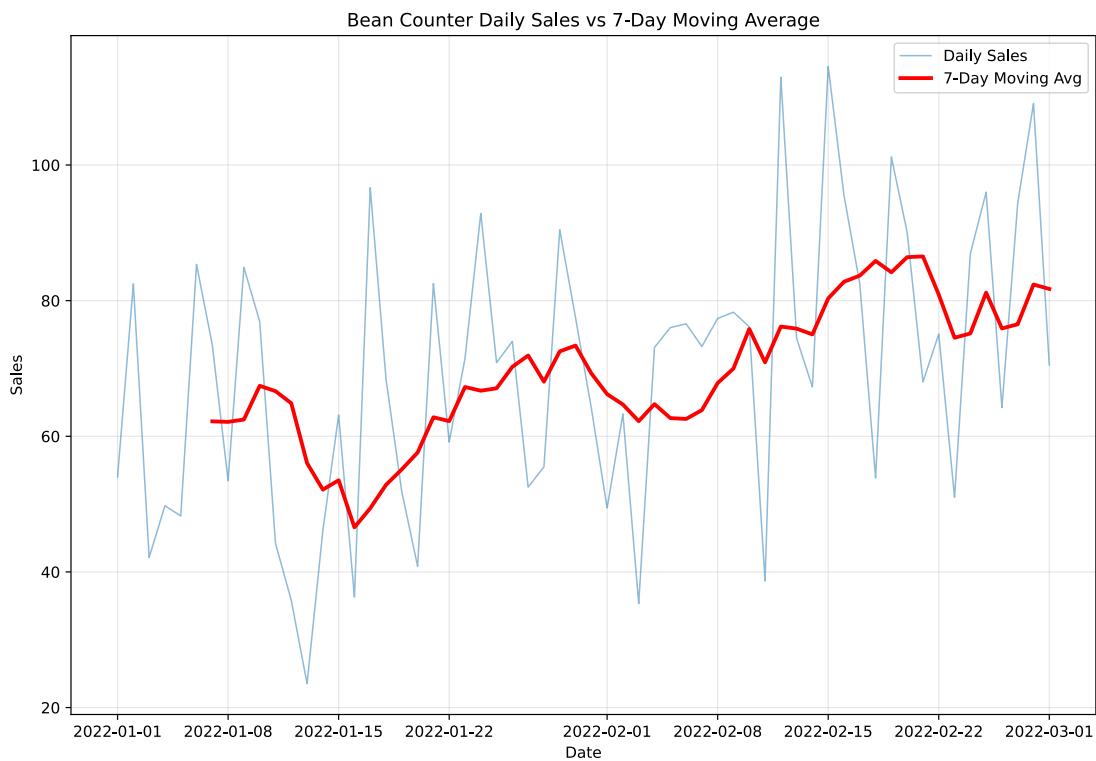
```
# Example: 7-day moving average
df['MA7'] = df['sales'].rolling(window=7).mean()

# Plot comparison (first 60 days)
plt.figure(figsize=(12, 8))
```

```

plt.plot(df['date'][:60], df['sales'][:60], alpha=0.5, label='Daily Sales',
linewidth=1)
plt.plot(df['date'][:60], df['MA7'][:60], linewidth=2.5, label='7-Day
Moving Avg', color='red')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('Bean Counter Daily Sales vs 7-Day Moving Average')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()

```



⚠️ NaN Values in Moving Averages

The first (window-1) values will be NaN because there aren't enough previous values to calculate the average! For a 7-day MA, the first 6 values are NaN. To find the number of NaN values in a moving average, you can use the `isna()` method to check for NaN values and then count them using the `sum()` method, e.g., `df['MA7'].isna().sum()`.

Exercise 2.1 - Create Multiple Moving Averages

Calculate different window sizes to see their smoothing effects.

i Rolling Windows and NaN Values

```
# Create rolling window and calculate mean
df['MA7'] = df['sales'].rolling(window=7).mean()

# Count missing (NaN) values
na_count = df['MA7'].isna().sum()

# Why NaN? First 6 rows have no 7-day window yet!
# Window of 7 → first 6 values are NaN
```

```
# YOUR CODE BELOW
# Calculate moving averages with different windows
df['MA3'] = # 3-day moving average
df['MA14'] = # 14-day (2 week) moving average
df['MA30'] = # 30-day (monthly) moving average

# Count NaN values in each
# Hint: Use .isna().sum()
na_count_3 = # Number of NaN values in MA3
na_count_14 = # Number of NaN values in MA14
na_count_30 = # Number of NaN values in MA30

# Don't modify below
assert na_count_3 == 2, f"MA3 should have 2 NaN values, got {na_count_3}"
assert na_count_14 == 13, f"MA14 should have 13 NaN values, got {na_count_14}"
assert na_count_30 == 29, f"MA30 should have 29 NaN values, got {na_count_30}"
assert df['MA30'].std() < df['MA3'].std(), "MA30 should be smoother (lower std) than MA3"
print("Perfect! Moving averages calculated correctly!")
print(f" MA30 is {df['MA3'].std() / df['MA30'].std():.1f}x smoother than MA3")

# Visualize the smoothing effect
plt.figure(figsize=(12, 8))
plt.plot(df['date'], df['sales'], linewidth=1, alpha=0.2, color='gray',
label='Daily Sales')
plt.plot(df['date'], df['MA3'], linewidth=2, alpha=0.3, color='#DB6B6B',
label='MA3 (noisy)')
plt.plot(df['date'], df['MA14'], linewidth=2, alpha=0.6, color="#537E8F",
label='MA14 (balanced)')
plt.plot(df['date'], df['MA30'], linewidth=2.5, alpha=0.9, color="#F6B265",
label='MA30 (smooth)')
plt.xlabel('Date')
plt.ylabel('Sales (drinks)')
plt.title('Comparing Moving Average Windows - Notice How MA30 is Smoothest')
plt.legend(loc='best')
```

```
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()
```

Exercise 2.2 - Weighted Moving Average

Recent data often matters more! A weighted moving average assigns higher weights to recent observations.

The Idea: Instead of equal weights [1/7, 1/7, 1/7, 1/7, 1/7, 1/7, 1/7], we use custom weights like [0.05, 0.05, 0.10, 0.15, 0.20, 0.20, 0.25] where recent days get more importance.

i NumPy Array Operations

```
# Element-wise multiplication
sales = np.array([100, 105, 110])
weights = np.array([0.2, 0.3, 0.5])
weighted_sales = sales * weights # [20, 31.5, 55]

# Sum all elements
total = np.sum(weighted_sales) # 106.5

# Or combine: weighted average
weighted_avg = np.sum(sales * weights)
```

```
# YOUR CODE BELOW
# Create weighted moving average (last 7 days)
# Weights: [0.05, 0.05, 0.10, 0.15, 0.20, 0.20, 0.25] (sum = 1.0)
weights = np.array([0.05, 0.05, 0.10, 0.15, 0.20, 0.20, 0.25])

# Calculate WMA for day 30 (using days 24-30)
sales_window = df['sales'].iloc[24:31].values # Days 24-30 (7 days)
wma_day30 = # Calculate weighted average: np.sum(sales * weights)

# Compare to simple average for same window
sma_day30 = # Simple average: np.mean(sales_window)
```

```
# Don't modify below
assert 50 < wma_day30 < 150, f"WMA should be between 50-150, got {wma_day30:.1f}"
assert abs(wma_day30 - sma_day30) < 20, "WMA and SMA shouldn't differ by more than 20"
assert len(weights) == 7, "Should have 7 weights"
assert abs(sum(weights) - 1.0) < 0.01, "Weights should sum to 1.0"
print(f"\u2708 Excellent! Weighted MA: {wma_day30:.1f}, Simple MA: {sma_day30:.1f}")
```

Section 3 - Simple Forecasting Methods

Now let's build actual forecasting functions! We'll start with simple methods before moving to more advanced techniques.

Building Basic Forecast Functions

```
def naive_forecast(data, periods=1):
    """Naive forecast: tomorrow = today (simplest baseline)"""
    return [data.iloc[-1]] * periods

def moving_average_forecast(data, window=7, periods=1):
    """Forecast using moving average of last 'window' days"""
    ma = data.iloc[-window:].mean()
    return [ma] * periods

# Example usage
print(f"Last value: {df['sales'].iloc[-1]:.1f}")
print(f"Naive forecast (next 3 days): {naive_forecast(df['sales'], 3)}")
print(f"MA forecast (next 3 days): {moving_average_forecast(df['sales'], 7, 3)}")
```

```
Last value: 110.3
Naive forecast (next 3 days): [np.float64(110.26466239914413),
np.float64(110.26466239914413), np.float64(110.26466239914413)]
MA forecast (next 3 days): [np.float64(117.69909865143963),
np.float64(117.69909865143963), np.float64(117.69909865143963)]
```

Understanding Exponential Smoothing

The Problem with Simple MA: All days in the window are treated equally. The sale from 7 days ago has the same importance as yesterday.

Exponential Smoothing Solution: Weight recent observations more heavily, and the weight decreases exponentially as you go back in time.

The Formula:

$$\text{Forecast}_{t+1} = \alpha \times \text{Actual}_t + (1 - \alpha) \times \text{Forecast}_t$$

Where α (alpha) is between 0 and 1:

- $\alpha = 0.9$: Very responsive (trust recent data heavily)
- $\alpha = 0.3$: Balanced (typical default)
- $\alpha = 0.1$: Very stable (smooth out noise)

Tip

You can also forecast multiple periods at once. The result is then just the last value of the forecast for all future periods.

Exercise 3.1 - Implement Exponential Smoothing

Create an exponential smoothing forecast function.

💡 Exponential Smoothing Formula

Core idea: New forecast = mix of (actual data) and (old forecast)

Formula: `forecast_new = alpha * actual_current + (1-alpha) * forecast_old`

- $\alpha = 0.3 \rightarrow 30\% \text{ actual}, 70\% \text{ old forecast (smooth)}$
- $\alpha = 0.7 \rightarrow 70\% \text{ actual}, 30\% \text{ old forecast (reactive)}$

ℹ️ List Operations You'll Need

```
# Access last element
last_value = my_list[-1]

# Multiply a list (creates repeated elements)
future = [100] * 3 # [100, 100, 100]

# In a loop, use data.iloc[i] to get value at index i
for i in range(1, len(data)):
    current_value = data.iloc[i]
```

```
# YOUR CODE BELOW
def exponential_smoothing_forecast(data, alpha=0.3, periods=1):
    """
    Exponential smoothing forecast
    Formula: forecast = alpha * latest_value + (1-alpha) * previous_forecast
    For first forecast, use the first actual value
    """
    forecasts = [data.iloc[0]] # Start with first value

    # Calculate smoothed values for historical data
    for i in range(1, len(data)):
        # Apply exponential smoothing formula
        # Hint: data.iloc[i] is current actual, forecasts[-1] is previous
        forecast = # alpha * current_actual + (1-alpha) *
        previous_forecast
        forecasts.append(forecast)

    # Use last smoothed value for future periods
    last_forecast = forecasts[-1]
    future = # Return list: [last_forecast] * periods

    return future
```

```
# Test your function
test_data = pd.Series([100, 105, 98, 103, 107])
result = exponential_smoothing_forecast(test_data, alpha=0.3, periods=2)
```

```
# Don't modify below
assert len(result) == 2, "Should return 2 forecasts"
assert 100 < result[0] < 105, f"Forecast should be between 100-105, got {result[0]:.1f}"
assert result[0] == result[1], "All future periods should have same forecast"
print(f"\nGreat! Exponential smoothing implemented correctly!")
print(f" Forecast: {result[0]:.1f} for next 2 periods")
```

Section 4 - Advanced Methods: Holt's Method

The Problem: Simple exponential smoothing assumes data is flat (no trend). But Bean Counter is growing! Sales are trending upward.

Holt's Method Solution: Track TWO things separately:

1. Level - Where are we right now?
2. Trend - How fast are we growing per period?

Understanding Time Series Aggregation

Before applying Holt's method, we need to learn how to convert daily data to weekly data using `resample()`.

The `resample()` Function:

```
df.set_index('date').resample('W')['sales'].mean()
```

Breaking it down:

1. `set_index('date')` - Makes the date column the index (required for resample)
2. `resample('W')` - Groups data by week ('W' = week, 'M' = month, 'D' = day)
3. `['sales']` - Selects the sales column
4. `.mean()` - Calculates the average for each week

Example:

```
# Convert daily Bean Counter sales to weekly averages
weekly_sales = df.set_index('date').resample('W')['sales'].mean()
print(f"Daily data: {len(df)} observations")
print(f"Weekly data: {len(weekly_sales)} observations")
print(f"\nFirst 3 weeks:")
print(weekly_sales.head(3))

# Visualize the difference between daily and weekly data
fig, axes = plt.subplots(2, 1, figsize=(14, 8))
```

```

# Top: Daily data (noisy)
axes[0].plot(df['date'], df['sales'], linewidth=0.8, alpha=0.7,
color='#A7C7C6')
axes[0].set_ylabel('Sales (drinks)', fontsize=11)
axes[0].set_title('Daily Data - Noisy with lots of variation', fontsize=12,
fontweight='bold')
axes[0].grid(True, alpha=0.3)

# Bottom: Weekly data (smooth)
axes[1].plot(weekly_sales.index, weekly_sales.values, 'o-', linewidth=2,
markersize=4,
alpha=0.8, color='#537E8F')
axes[1].set_xlabel('Date', fontsize=11)
axes[1].set_ylabel('Avg Sales (drinks/day)', fontsize=11)
axes[1].set_title('Weekly Aggregated Data - Cleaner, easier to see
patterns', fontsize=12, fontweight='bold')
axes[1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

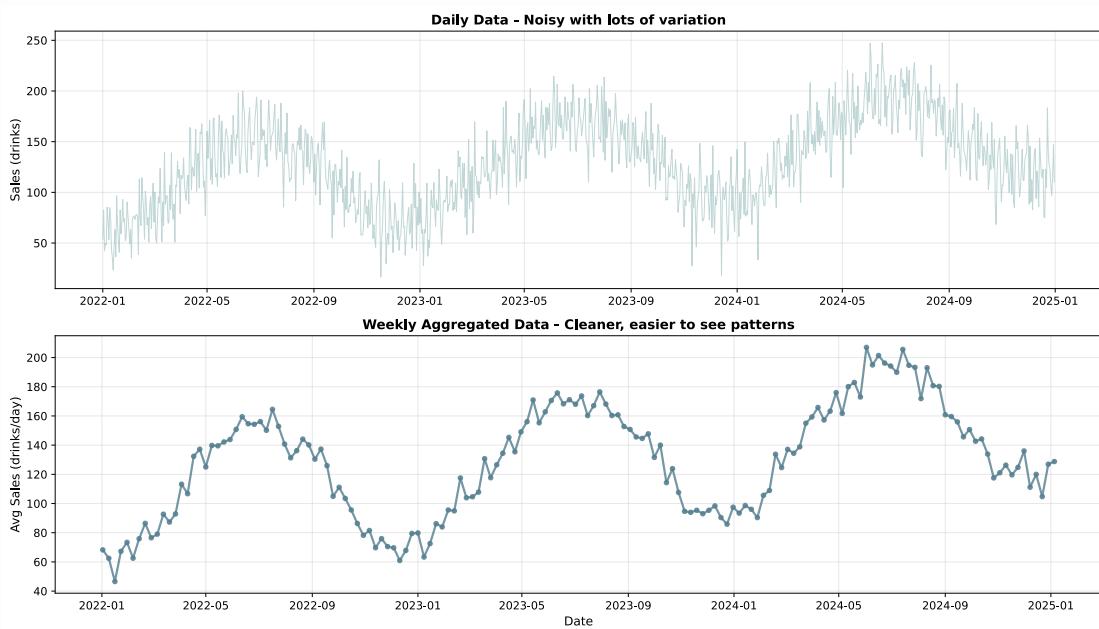
```

Daily data: 1096 observations
Weekly data: 158 observations

First 3 weeks:

date	sales
2022-01-02	68.237589
2022-01-09	62.470797
2022-01-16	46.571824

Freq: W-SUN, Name: sales, dtype: float64



💡 Tip

Aggregating to weekly data reduces noise and makes trends easier to see! Notice how the weekly plot makes the trend much clearer.

Understanding Holt's Method

The Math (simplified):

- Level: $L_t = \alpha \times Y_t + (1 - \alpha) \times (L_{t-1} + b_{t-1})$
- Trend: $b_t = \beta \times (L_t - L_{t-1}) + (1 - \beta) \times b_{t-1}$
- Forecast: $\hat{Y}_{t+h} = L_t + h \times b_t$

In plain English:

- Level smooths the current position
- Trend smooths the growth rate
- Forecast = Current level + (periods ahead × trend)

Let's see Holt's method in action using Python's `statsmodels` library:

```
from statsmodels.tsa.holtwinters import ExponentialSmoothing

# Create sample trending data
weeks = pd.date_range('2024-01-01', periods=20, freq='W')
trending_sales = 100 + 3*np.arange(20) + np.random.normal(0, 5, 20)
ts_trending = pd.Series(trending_sales, index=weeks)

# Fit Holt's model (trend, but no seasonality)
model_holt = ExponentialSmoothing(ts_trending, trend='add', seasonal=None)
fitted_holt = model_holt.fit(smoothing_level=0.3, smoothing_trend=0.2)

# Forecast next 4 periods
forecast_holt = fitted_holt.forecast(steps=4)

print("Last 3 actual values:")
print(ts_trending.tail(3))
print(f"\nNext 4 week forecast with Holt's method:")
print(forecast_holt)
print("\nNotice: Forecasts increase each week (captures trend!)")
```

```
Last 3 actual values:
2024-05-05    147.700470
2024-05-12    156.602208
2024-05-19    165.404895
Freq: W-SUN, dtype: float64
```

```
Next 4 week forecast with Holt's method:
2024-05-26    161.150728
2024-06-02    164.553567
2024-06-09    167.956406
```

```
2024-06-16    171.359244
Freq: W-SUN, dtype: float64
```

```
Notice: Forecasts increase each week (captures trend!)
```

Exercise 4.1 - Apply Holt's Method to Bean Counter

Bean Counter's sales are growing. Use Holt's method to capture this trend.

```
# Prepare weekly data (aggregate daily to weekly to reduce noise)
df_weekly = df.set_index('date').resample('W')['sales'].mean()

# YOUR CODE BELOW
# Split: first 90 weeks for training, last 14 for testing
train_weekly = # First 90 weeks
test_weekly = # Last 14 weeks

# Fit Holt's model
model_holt = # ExponentialSmoothing with trend='add', seasonal=None
fitted_holt = # Fit the model
holt_forecast = # Forecast 14 weeks
```

```
# Don't modify below
assert len(holt_forecast) == 14, "Should forecast 14 weeks"
assert holt_forecast.iloc[0] > holt_forecast.iloc[-1], "Holt's forecast
should decrease (season!)"
print(f"Excellent! Holt's method applied successfully!")
print(f"Holt's captures negative trend: {holt_forecast.iloc[0]:.1f} →
{holt_forecast.iloc[-1]:.1f}")

# Create comparison forecast with simple exponential smoothing
simple_forecast_weekly = exponential_smoothing_forecast(train_weekly,
alpha=0.3, periods=14)

# Visualize comparison
plt.figure(figsize=(12, 8))

# Plot historical training data (last 30 weeks for context)
plt.plot(train_weekly.index[-90:], train_weekly.values[-90:], 'o-',
color='#537E8F',
linewidth=1.5, markersize=2, alpha=0.5, label='Historical (last 30
weeks)')

# Plot actual test data
plt.plot(test_weekly.index[:14], test_weekly.values[:14], 'o',
color='black',
markersize=2, alpha=0.9, label='Actual', zorder=5)

# Plot both forecasts
plt.plot(test_weekly.index[:14], simple_forecast_weekly, 's--',
color='#A7C7C6',
linewidth=2, markersize=3, label='Simple ES (flat)', alpha=0.8)
```

```

plt.plot(test_weekly.index[:14], holt_forecast, 'd-', color="#F6B265",
         linewidth=2.5, markersize=3, label="Holt's Method (with trend)")

plt.xlabel('Week', fontsize=12)
plt.ylabel('Average Daily Sales', fontsize=12)
plt.legend(loc='best', fontsize=10)
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

```

Section 5 - Most Advanced: Holt-Winters Method

The Challenge: Bean Counter has BOTH trend (growing) AND seasonality (summer peaks for iced coffee).

Holt-Winters Solution: Track THREE things:

1. Level - Current baseline demand
2. Trend - Growth rate
3. Seasonal Pattern - Repeating cycle (e.g., summer highs)

Understanding Holt-Winters

When to use:

- Data has trend AND seasonality
- You have ideally 2 full seasonal cycles (e.g., 2 years for yearly patterns)

Let's demonstrate with monthly data:

```

# Create data with trend AND seasonality
months = pd.date_range('2022-01-01', periods=24, freq='M')
trend_comp = np.linspace(100, 150, 24)
seasonal_comp = 30 * np.sin(2 * np.pi * np.arange(24) / 12)
monthly_sales = trend_comp + seasonal_comp + np.random.normal(0, 5, 24)
ts_seasonal = pd.Series(monthly_sales, index=months)

# Fit Holt-Winters model
model_hw = ExponentialSmoothing(
    ts_seasonal,
    trend='add',           # Additive trend
    seasonal='add',        # Additive seasonality
    seasonal_periods=12    # 12 months = 1 year
)
fitted_hw = model_hw.fit()

# Forecast next 6 months
forecast_hw = fitted_hw.forecast(steps=6)

print("Last 3 months actual:")
print(ts_seasonal.tail(3))
print(f"\nNext 6 months forecast:")
print(forecast_hw)

```

```
print("\nNotice: Seasonal pattern continues (Jan is low, summer will be high)")
```

```
Last 3 months actual:  
2023-10-31    121.824928  
2023-11-30    121.818264  
2023-12-31    134.481744  
Freq: ME, dtype: float64
```

```
Next 6 months forecast:  
2024-01-31    157.483905  
2024-02-29    175.816373  
2024-03-31    184.848236  
2024-04-30    187.735748  
2024-05-31    181.651676  
2024-06-30    183.597933  
Freq: ME, dtype: float64
```

```
Notice: Seasonal pattern continues (Jan is low, summer will be high)
```

```
/var/folders/_5/jkkjxxdd5f1955l380dky7n80000gn/T/  
ipykernel_96580/3645223708.py:2: FutureWarning: 'M' is deprecated and will  
be removed in a future version, please use 'ME' instead.  
months = pd.date_range('2022-01-01', periods=24, freq='M')
```

Exercise 5.1 - Apply Holt-Winters

Now use Holt-Winters to capture both trend and seasonality in Bean Counter's weekly sales.

Note: For weekly data with yearly seasonality, we need 2+ years (104+ weeks). We'll use quarterly seasonality (13 weeks) since we have 104 weeks total.

```
# YOUR CODE BELOW  
# Use the weekly data we created earlier  
# Split: first 150 weeks training, last 8 weeks testing  
train_hw = df_weekly.iloc[:150]  
test_hw = df_weekly.iloc[150:158] # Exactly 8 weeks for testing (all  
remaining data)  
  
# Fit Holt-Winters with yearly seasonality (52 weeks = 1 year)  
model_hw = # ExponentialSmoothing with trend='add', seasonal='add',  
seasonal_periods=52  
fitted_hw = # Fit the model  
hw_forecast = # Forecast 8 weeks  
  
# Compare all three methods on same test period  
simple_forecast = exponential_smoothing_forecast(train_hw, alpha=0.3,  
periods=8)  
holt_forecast_test = ExponentialSmoothing(train_hw, trend='add',  
seasonal=None).fit().forecast(8)
```

```

# Don't modify below
assert len(hw_forecast) == 8, "Should forecast 8 weeks"
# Holt-Winters should vary (seasonality), simple ES should be flat
hw_variation = hw_forecast.std()
simple_variation = np.std(simple_forecast)
assert hw_variation > simple_variation, "Holt-Winters should show more variation (seasonality)"
print(f"Fantastic! Holt-Winters applied successfully!")
print(f"Holt-Winters range: {hw_forecast.min():.1f} to {hw_forecast.max():.1f}")
print(f"Simple ES (flat): {simple_forecast[0]:.1f}")

```

Section 6 - Measuring Forecast Accuracy

How good are our forecasts? Let's measure and compare!

Forecast Error Metrics

```

def calculate_mae(actual, forecast):
    """Mean Absolute Error - average size of errors"""
    errors = np.abs(actual - forecast)
    return np.mean(errors)

def calculate_rmse(actual, forecast):
    """Root Mean Squared Error - penalizes large errors more"""
    errors = (actual - forecast) ** 2
    return np.sqrt(np.mean(errors))

# Example
actual = np.array([100, 105, 98, 103])
forecast = np.array([102, 103, 100, 101])
print(f"MAE: {calculate_mae(actual, forecast):.1f} (average error)")
print(f"RMSE: {calculate_rmse(actual, forecast):.1f} (penalizes big errors)")

```

MAE: 2.0 (average error)
RMSE: 2.0 (penalizes big errors)

💡 MAE vs RMSE

- MAE: Average error size (easier to interpret, in same units as data)
- RMSE: Penalizes large errors more heavily (sensitive to outliers)
- In business: MAE often preferred for its simplicity and interpretability

Exercise 6.1 - Compare All Methods

Let's have a forecasting comparison! Which method works best for Bean Counter?

```

# YOUR CODE BELOW
# Calculate MAE for all methods on the test period (last 8 weeks)
test_actual = test_hw.values

# Convert forecasts to numpy arrays for comparison
simple_array = np.array(simple_forecast)
holt_array = holt_forecast_test.values
hw_array = hw_forecast.values

# Calculate MAE for each method
mae_simple = # MAE for simple exponential smoothing
mae_holt = # MAE for Holt's method
mae_hw = # MAE for Holt-Winters

# Find the winner (lowest MAE)
mae_values = [mae_simple, mae_holt, mae_hw]
best_method_index = np.argmin(mae_values) # Index of best method

```

```

# Don't modify below
methods = ['Simple ES', "Holt's Method", 'Holt-Winters']
print("Forecast accuracy comparison complete!")
print(f"\nWinner: {methods[best_method_index]}")

# Visualize the comparison
plt.figure(figsize=(12, 8))

# Plot historical training data
plt.plot(train_hw.index[-30:], train_hw.values[-30:], 'o-',
         color='#537E8F',
         linewidth=1.5, markersize=3, alpha=0.5, label='Historical (last 30
weeks)')

# Plot actual test data
plt.plot(test_hw.index, test_hw.values, 'o', color='black',
         markersize=10, alpha=0.9, label='Actual (Test)', zorder=5)

# Plot all three forecasts
plt.plot(test_hw.index, simple_array, 's--', color='#A7C7C6',
         linewidth=2, markersize=3, label=f'Simple ES (MAE:
{mae_simple:.1f})')
plt.plot(test_hw.index, holt_array, '^--', color="#F6B265",
         linewidth=2, markersize=3, label=f"Holt's (MAE: {mae_holt:.1f})")
plt.plot(test_hw.index, hw_array, 'd--', color="#DB6B6B",
         linewidth=2.5, markersize=3, label=f'Holt-Winters (MAE:
{mae_hw:.1f})')

plt.xlabel('Week', fontsize=12)
plt.ylabel('Average Daily Sales', fontsize=12)
plt.title('Method Comparison: Which Captures Trend + Seasonality Best?',
          fontsize=14, fontweight='bold')
plt.legend(loc='best', fontsize=10)
plt.grid(True, alpha=0.3)

```

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

Conclusion

Outstanding work! You've mastered time series forecasting for Bean Counter! You're now fully prepared for MegaMart's Christmas Challenge!

Tips for Competition

Before You Start:

1. Plot first - Visualize all three products
2. Check for patterns - Trend? Seasonality? Both?
3. Note the lead times - Affects which weeks you forecast

During Analysis:

4. Start simple - Moving average is a great baseline
5. Use Holt's for trends - If sales are growing/declining
6. Use Holt-Winters for seasonality - If you see repeating patterns

Validation:

7. Backtest first - Test your method on last 4 weeks before the test period
8. Calculate MAE - Measure accuracy objectively

Good luck with the MegaMart Christmas Inventory Challenge!

Bibliography