Research & Analysis / Trend Analysis

Extract underlying trend from seasonal patterns and irregular noise.

Difficulty: Advanced

Model: GPT-4 / Claude / Gemini

Use Case: Retail Planning, Web Analytics, Financial Forecasting

Updated: May 2026

Why This Prompt Exists

December sales always look amazing — but is it growth or just Christmas?

You get:

- comparing December to November and panicking about the “surge” (it’s seasonal)
- comparing January to December and panicking about the “crash” (it’s seasonal)
- making year-over-year comparisons without adjusting for different holiday dates
- missing real growth because it’s hidden inside seasonal peaks
- forecasting that fails because it doesn’t account for repeating patterns

But time series have components:

- trend: long-term direction (up, down, flat)
- seasonal: repeating pattern (weekly, monthly, quarterly, yearly)
- cyclical: multi-year waves (economic cycles)
- irregular: random noise (can’t be predicted)
- calendar effects: holidays, leap years, trading days

Without decomposition, you mistake seasonality for trend.

This prompt separates what’s real growth from what’s just the time of year.

The Prompt

Assume the role of a time-series economist who decomposes seasonal patterns.

Your task is to separate a metric into trend, seasonal, and noise components.

Generate:

1. SEASONAL PATTERN IDENTIFICATION
   - Does seasonality exist? (Yes/No — confidence)
   - Period length (weekly, monthly, quarterly, annual)
   - Typical high periods (e.g., "December is 30% above average")
   - Typical low periods (e.g., "January is 20% below average")

2. TREND COMPONENT (seasonally adjusted)
   - Underlying direction (up / down / flat)
   - Rate of change (per period, after removing seasonality)
   - Is the trend statistically significant?

3. SEASONAL ADJUSTMENT
   - Raw value for most recent period: [value]
   - Seasonal adjustment factor: [multiplier]
   - Seasonally adjusted value: [value]
   - Plain-English: "After removing seasonal effects, the real change is X%"

4. CALENDAR EFFECTS (if applicable)
   - Holiday shifts (Easter, Black Friday)

   - Trading day differences
   - Leap year effects

5. WHAT THIS MEANS FOR DECISIONS
   - Compare performance to same period last year (not previous period)
   - Use seasonally adjusted numbers for trend analysis
   - Plan inventory/staffing around seasonal peaks

INPUTS:

Time-series data (at least 2 years recommended):
[PASTE MONTHLY OR WEEKLY VALUES]

Metric name:
[E.G., "E-commerce revenue"]

Business context:
[E.G., "Retail, heavy holiday season"]

Known seasonal factors (if any):
[E.G., "December is typically 2x normal"]

RULES:
- Require at least 1.5 cycles of data to identify seasonality (18 months for annual pattern)
- Flag when seasonality is changing over time (evolving pattern)
- Note that seasonally adjusted numbers can still be noisy
- Distinguish between calendar seasonality (e.g., weather) and

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business-driven patterns (e.g., back-to-school)
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How To Use It

- Use at least 2 years of data — 1 year can't distinguish seasonality from trend.
- Always compare to same period last year, not previous period, for seasonal metrics.
- Calculate seasonally adjusted metrics for internal performance tracking.
- For retail, account for holiday calendar shifts (e.g., Thanksgiving is different dates).
- Present both raw and seasonally adjusted numbers to stakeholders — explain the difference.

Example Input

Time-series data:
"Monthly revenue ($M): Jan 24: 8.2, Feb: 7.9, Mar: 8.5, Apr: 8.1, May: 8.4, Jun: 8.3, Jul: 8.6, Aug: 8.7, Sep: 8.9, Oct: 9.2, Nov: 12.5, Dec: 18.2, Jan 25: 8.5, Feb: 8.1, Mar: 8.8"

Metric name:
E-commerce revenue

Business context:
Retail with strong holiday season (Nov-Dec)

Why It Works
Most business metrics are compared to last month — which is almost always wrong for seasonal businesses.

This framework improves outcomes by forcing:

- seasonal pattern identification (know your rhythm)
- trend extraction (what's actually changing)
- seasonal adjustment (apples-to-apples comparison)
- calendar effect detection (holidays move)

- decision implications (how to act on decomposed data)

Great seasonality decomposition doesn't remove the pattern — it helps you see through it.

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