



# Time Series Analysis and Forecasting

Chapter 9: Prophet and TBATS



Daniel Traian PELE

Bucharest University of Economic Studies

IDA Institute Digital Assets

Blockchain Research Center

AI4EFIN Artificial Intelligence for Energy Finance

Romanian Academy, Institute for Economic Forecasting

MSCA Digital Finance

## Learning Objectives

By the end of this chapter, you will be able to:

- Handle time series with multiple seasonal patterns
- Use Facebook Prophet for flexible forecasting with holidays
- Apply TBATS models for complex seasonality
- Compare and select between modern forecasting methods



## Outline

Multiple Seasonalities

TBATS Model

Facebook Prophet

Comparison and Guidelines

Case Study

Quiz

Summary



## The Problem: Complex Seasonal Patterns

### Real-World Examples

- **Hourly electricity demand:** Daily + Weekly + Annual patterns
- **Website traffic:** Daily + Weekly + Holiday effects
- **Retail sales:** Weekly + Monthly + Annual + Holiday effects
- **Call center volume:**
  - ▶ Hourly + Daily + Weekly patterns

### SARIMA Limitation

Standard SARIMA( $p, d, q$ )( $P, D, Q$ ) $_s$  handles only **one** seasonal period  $s$ .

For hourly data with daily AND weekly patterns, we need  $s_1 = 24$  and  $s_2 = 168$ .



## Solutions for Multiple Seasonalities

### Traditional Approaches

- **Fourier terms:** Add sin/cos regressors
- **Dummy variables:** Many parameters
- **Nested models:** Complex specification

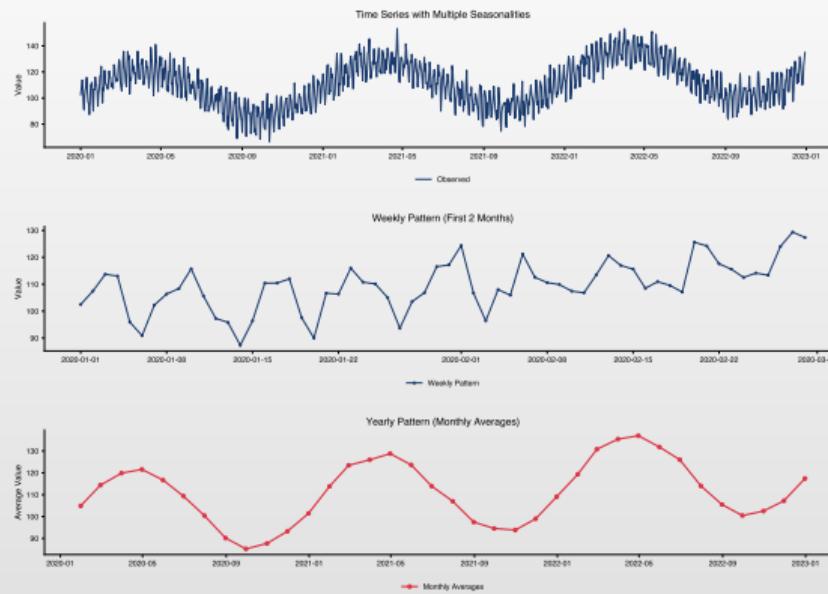
### Modern Approaches

- **TBATS:** Automatic, handles many periods
- **Prophet:** Flexible, interpretable
- **Neural methods:**
  - ▶ Deep learning

Method	Max Seasonalities	Interpretable
SARIMA	1	Yes
Fourier + ARIMA	Multiple	Moderate
TBATS	Multiple	Moderate
Prophet	Multiple	Yes



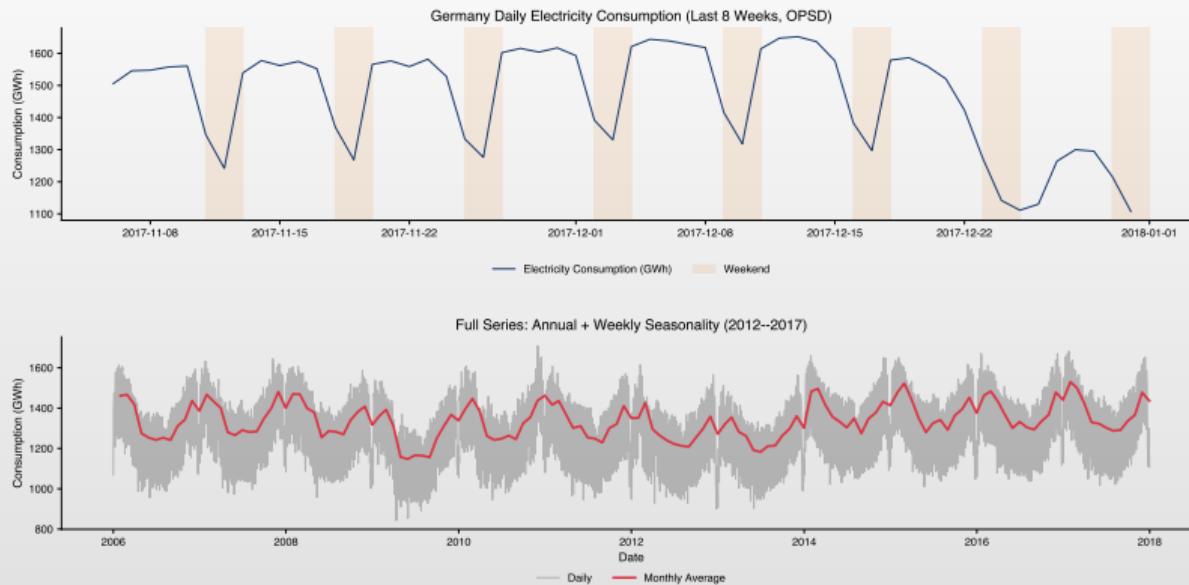
## Example: Hourly Data with Multiple Seasonalities



Q TSA\_ch9\_multiple\_seasonality



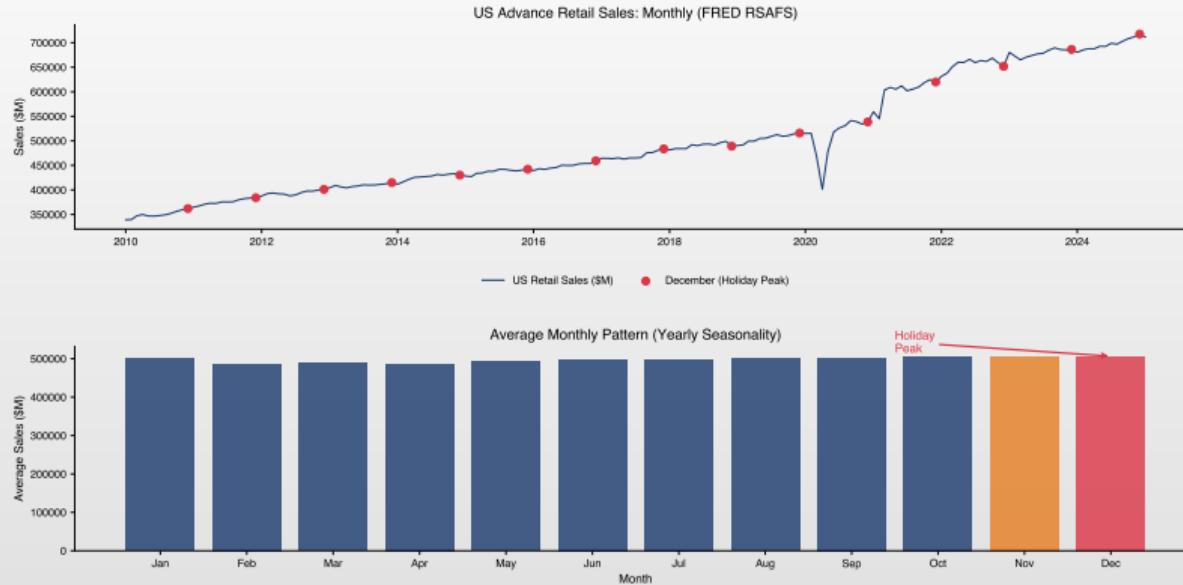
## Real Example: Electricity Demand



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## Real Example: Retail Sales with Holidays



Q TSA\_ch9\_retail\_sales



## TBATS: What Does It Stand For?

### TBATS Components

- T Trigonometric seasonality using Fourier terms
- B Box-Cox transformation for variance stabilization
- A ARMA errors for remaining autocorrelation
- T Trend component (possibly damped)
- S Seasonal components (multiple allowed)

### Key Innovation: Trigonometric Seasonality

$$s_t^{(i)} = \sum_{j=1}^{k_i} \left[ s_j^{(i)} \cos\left(\frac{2\pi j t}{m_i}\right) + s_j^{*(i)} \sin\left(\frac{2\pi j t}{m_i}\right) \right]$$

$m_i$  = seasonal period,  $k_i$  = number of harmonics



## Box-Cox Transformation

### Definition 1 (Box-Cox Transformation)

The Box-Cox transformation with parameter  $\omega$  is defined as:

$$y_t^{(\omega)} = \begin{cases} \frac{y_t^\omega - 1}{\omega} & \text{if } \omega \neq 0 \\ \ln(y_t) & \text{if } \omega = 0 \end{cases}$$

### Purpose

- Variance stabilization:** Makes variance constant over time
- Normalization:** Reduces skewness in the data
- Common values:  $\omega = 0$  (log),  $\omega = 0.5$  (square root),  $\omega = 1$  (no transform)



## TBATS Model Structure

### State Space Representation

$$y_t^{(\omega)} = \ell_{t-1} + \phi b_{t-1} + \sum_{i=1}^T s_{t-m_i}^{(i)} + d_t \quad (1)$$

$$\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha d_t, \quad b_t = \phi b_{t-1} + \beta d_t \quad (2)$$

- $y_t^{(\omega)}$ : Box-Cox transformed observation
- $\ell_t$ : local level (smoothed mean)
- $b_t$ : trend with damping  $\phi \in (0, 1)$
- $s_t^{(i)}$ :  $i$ -th seasonal component
- $d_t$ : ARMA( $p, q$ ) error process
- $\alpha, \beta$ : smoothing parameters



## TBATS: Trigonometric Seasonality State Evolution

### Definition 2 (Trigonometric State-Space Recursion)

For each seasonal component with period  $m_i$  and  $k_i$  harmonics, define states:

$$\begin{pmatrix} s_{j,t}^{(i)} \\ s_{j,t}^{*(i)} \end{pmatrix} = \begin{pmatrix} \cos(\lambda_j) & \sin(\lambda_j) \\ -\sin(\lambda_j) & \cos(\lambda_j) \end{pmatrix} \begin{pmatrix} s_{j,t-1}^{(i)} \\ s_{j,t-1}^{*(i)} \end{pmatrix} + \begin{pmatrix} \gamma_1^{(i)} \\ \gamma_2^{(i)} \end{pmatrix} d_t$$

where  $\lambda_j = \frac{2\pi j}{m_i}$  is the  $j$ -th harmonic frequency.

### Interpretation

- The rotation matrix preserves the periodic structure
- Total seasonal:  $s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)}$
- Parameters:  $2k_i$  states per seasonal period



## TBATS: Choosing the Number of Harmonics

### Why Fourier/Trigonometric Terms?

1. **Parsimonious:**  $2k$  parameters vs  $m$  dummy variables
2. **Smooth:** Captures smooth seasonal patterns naturally
3. **Flexible:** Number of harmonics  $k$  controls complexity
4. **Non-integer periods:** Can handle  $s = 365.25$  for daily data

#### Low $k$ (few harmonics)

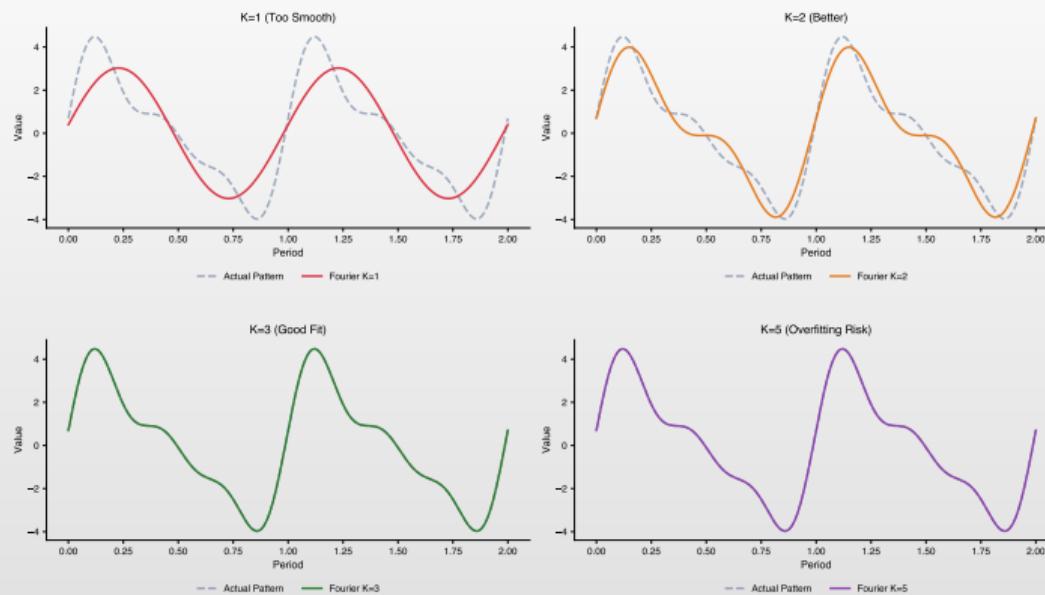
- Smooth pattern
- Fewer parameters
- May miss sharp peaks

#### High $k$ (many harmonics)

- Can capture any pattern
- More parameters ( $2k$  total)
- Maximum useful:  $k \leq \lfloor m/2 \rfloor$



## Fourier Approximation of Seasonality



Q TSA\_ch9\_fourier\_approximation



## TBATS: Key Features

### Automatic Model Selection

TBATS automatically determines:

- Box-Cox parameter  $\omega$  for variance stabilization
- Number of harmonics  $k_i$  for each seasonal period
- ARMA orders  $(p, q)$  for residual autocorrelation
- Damped vs non-damped trend specification

### BATS vs TBATS

- BATS**: Traditional seasonal states (dummy variables)
- TBATS**: Trigonometric (Fourier) seasonal representation
- TBATS more parsimonious for long seasonal periods



## TBATS: Advantages and Limitations

### Advantages

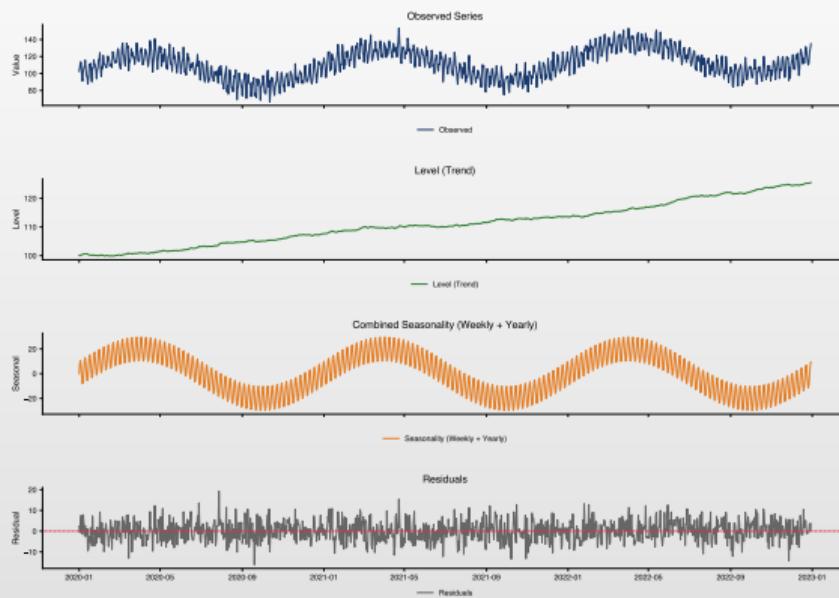
- Handles **multiple** seasonal periods
- **Automatic** model selection
- Handles **non-integer** periods (365.25)
- **Box-Cox** for heteroskedasticity
- Good for **high-frequency** data

### Limitations

- **Computationally intensive**
- No external regressors
- Less **interpretable** than Prophet
- Can be **slow** for very long series
- Requires **sufficient data** per season



## TBATS Decomposition Example



 TSA\_ch9\_tbats\_decomposition



## Prophet: Overview

### What is Prophet?

Forecasting procedure developed by Facebook (Meta) in 2017 for **business time series**:

- Strong seasonal effects (daily, weekly, yearly)
- Holiday effects and trend changes (changepoints)
- Handles missing data and outliers

### Key Philosophy: “Analyst-in-the-loop”

Designed for analysts with domain knowledge but without time series expertise.



## Prophet Model Structure

### Decomposition Approach

Prophet uses an **additive decomposition**:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t$$

#### $g(t)$ : Trend

- Linear or logistic
- Automatic changepoints
- Growth saturation

#### $s(t)$ : Seasonality

- Fourier series
- Multiple periods
- Custom seasonality

#### $h(t)$ : Holidays

- Country holidays
- Custom events
- Window effects



## Prophet: Trend Component

### Linear Trend with Changepoints

$$g(t) = (k + \mathbf{a}(t)^T \boldsymbol{\delta}) \cdot t + (m + \mathbf{a}(t)^T \boldsymbol{\gamma})$$

- $k$ : base growth rate (slope)
- $\boldsymbol{\delta} = (\delta_1, \dots, \delta_S)$ : slope changes at  $S$  changepoints
- $\mathbf{a}(t) \in \{0, 1\}^S$ : indicator if changepoint  $s$  is active at time  $t$

### Logistic Growth

For saturating trends:

$$g(t) = \frac{C(t)}{1 + e^{-(k + \mathbf{a}(t)^T \boldsymbol{\delta})(t - m - \mathbf{a}(t)^T \boldsymbol{\gamma})}}$$

$C(t)$  = time-varying carrying capacity

### Continuity Constraint

The offset  $\gamma_j = -s_j \cdot \delta_j$  ensures  $g(t)$  is continuous at each changepoint  $s_j$ .



## Prophet: Seasonality Component

### Fourier Series Representation

$$s(t) = \sum_{n=1}^N \left[ a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right) \right]$$

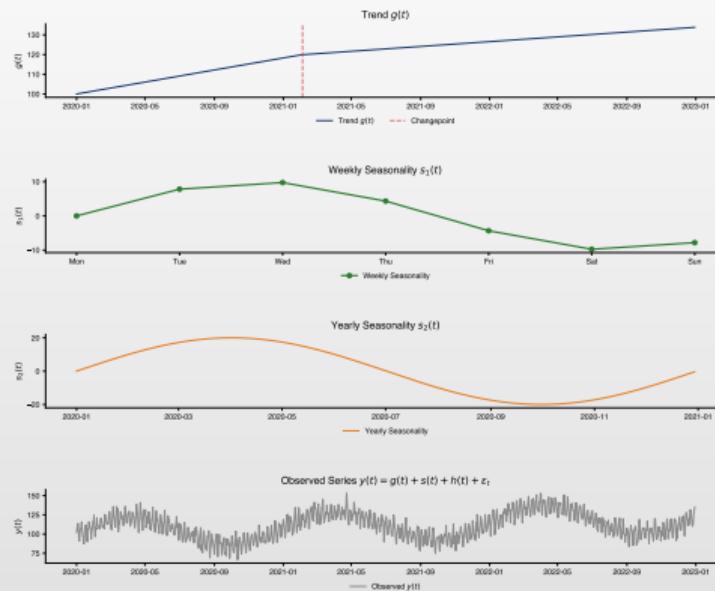
### Default Settings

Seasonality	Period	Fourier Order
Yearly	365.25 days	10
Weekly	7 days	3
Daily	1 day	4

Higher  $N$  = more flexibility but risk of overfitting



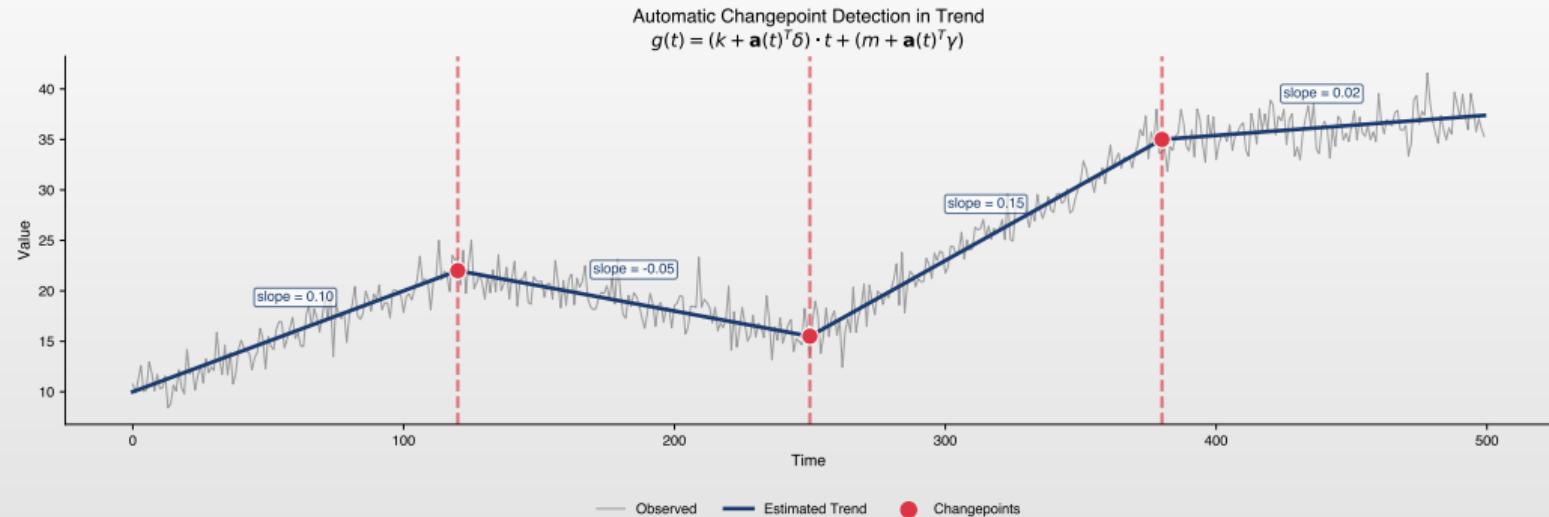
## Prophet Component Decomposition



**TSA\_ch9\_prophet\_components**



## Trend Changepoint Detection



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## Prophet: Holiday Effects

### Holiday Model

$$h(t) = Z(t) \cdot \kappa$$

where  $Z(t)$  is an indicator matrix for holidays and  $\kappa$  are holiday effects.

### Built-in Features

- 60+ countries supported
- Custom holiday definitions
- Window effects (before/after)

### Holiday Types

- National holidays
- Religious observances
- Business events



## Prophet: Customization Options

### Seasonality Customization

- Add custom seasonal periods (monthly, quarterly)
- Control Fourier order for each seasonality
- Enable/disable default seasonalities

### External Regressors

Prophet supports adding external variables:

- Weather data, promotions, special events
- Binary or continuous regressors
- Automatic regularization



## Prophet: Uncertainty Quantification

### Bayesian Framework

Prophet uses a **Laplace prior** on changepoint magnitudes:

$$\delta_j \sim \text{Laplace}(0, \tau), \quad \tau = \text{changepoint\_prior\_scale}$$

Smaller  $\tau$  = sparser, smaller changepoints (more regularization).

### Sources of Uncertainty

1. **Trend:** Future changepoints
2. **Seasonality:** Coefficient variance
3. **Observation:** Residual noise  $\sigma^2$

### Prediction Intervals

- MAP estimation for point forecasts
- Monte Carlo sampling for intervals
- Default: 80% credible interval



## Prophet: Tuning Parameters

### Key Parameters

Parameter	Effect
changepoint_prior_scale	Trend flexibility (default: 0.05)
seasonality_prior_scale	Seasonality flexibility (default: 10)
holidays_prior_scale	Holiday effect size (default: 10)
seasonality_mode	'additive' or 'multiplicative'
changepoint_range	Portion of history for changepoints

### Practical Tips

- ☐ Overfitting trend? Decrease `changepoint_prior_scale`
- ☐ Underfitting seasonality? Increase `seasonality_prior_scale`
- ☐ Seasonal amplitude varies? Use `seasonality_mode='multiplicative'`



## Prophet: Advantages and Limitations

### Advantages

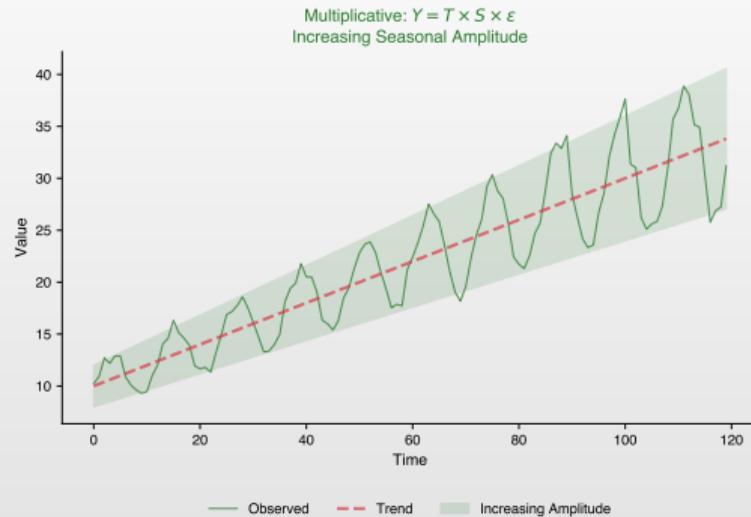
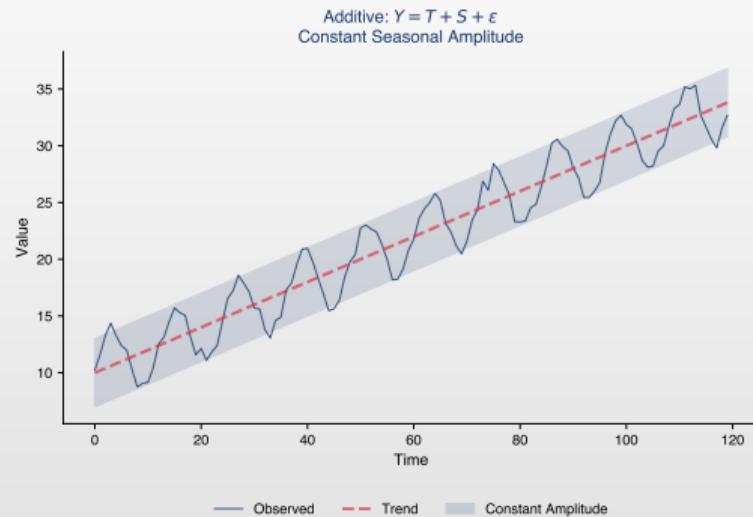
- **Easy to use:** Minimal tuning needed
- **Interpretable:** Clear decomposition
- **Handles missing data well**
- **Holiday effects built-in**
- **Multiple seasonalities**
- **External regressors supported**
- **Fast fitting**

### Limitations

- **Not ARIMA-based:** No autocorrelation modeling
- **Daily data focus:** Less suited for very high frequency
- **Trend assumptions:** Linear/logistic may not fit
- **No built-in CV:** Must implement manually
- **Overfitting risk** with many seasonalities



## Additive vs Multiplicative Seasonality



Q TSA\_ch9\_additive\_vs\_multiplicative



## TBATS vs Prophet: Head-to-Head

Feature	TBATS	Prophet
Multiple seasonalities	Yes (automatic)	Yes (manual or auto)
Holiday effects	No	Yes (built-in)
External regressors	No	Yes
Trend changepoints	No (smooth)	Yes (automatic)
Missing data	Interpolation needed	Handles natively
Interpretability	Moderate	High
Computation speed	Slow	Fast
High-frequency data	Good	Moderate
Non-integer periods	Yes (e.g., 365.25)	Yes
Uncertainty intervals	Yes	Yes



## When to Use Each Model

### Use TBATS when:

- High-frequency data
- Multiple seasonal periods
- No external regressors
- Automatic selection preferred

### Use Prophet when:

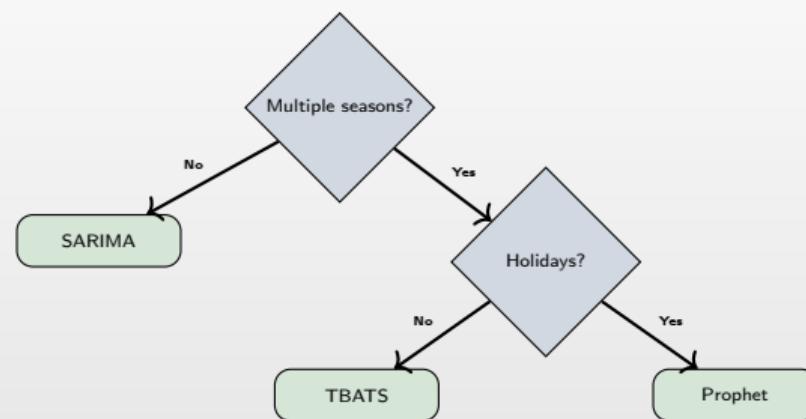
- Business forecasting
- Holiday effects important
- Trend has changepoints
- External regressors available

### General Guideline

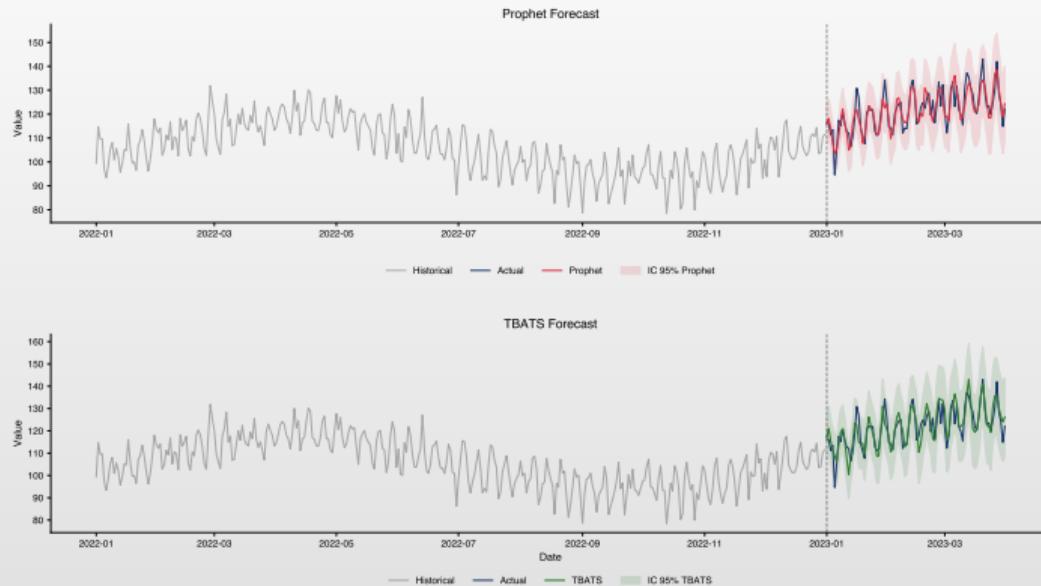
Prophet: business applications with daily data  
TBATS: technical applications with high-frequency data



## Decision Flowchart



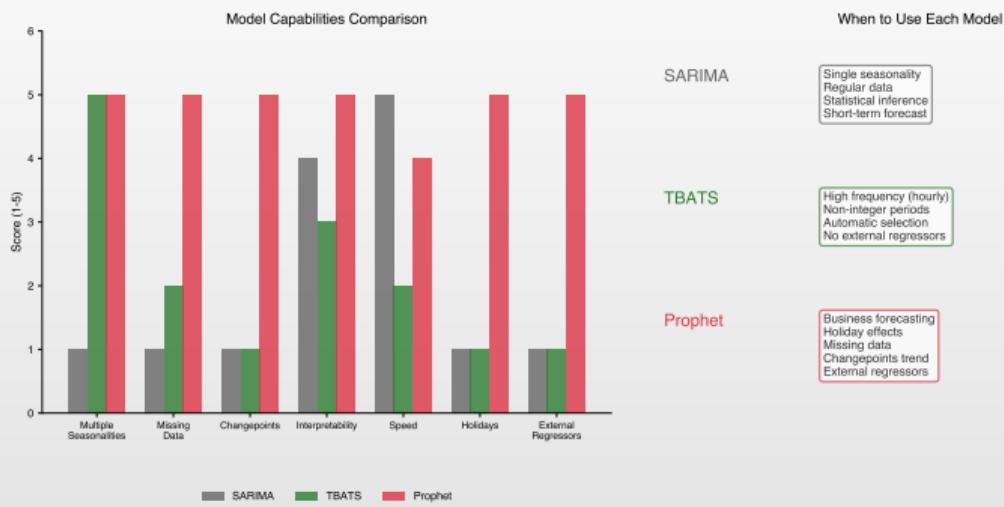
## Prophet vs TBATS: Forecast Comparison



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## Model Selection Guide



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## Evaluation Metrics

### Definition 3 (Forecast Accuracy Metrics)

Let  $y_t$  denote actual values,  $\hat{y}_t$  forecasts, and  $n$  the forecast horizon:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2} \quad (\text{penalizes large errors})$$

$$\text{MAE} = \frac{1}{n} \sum_{t=1}^n |y_t - \hat{y}_t| \quad (\text{robust to outliers})$$

$$\text{MAPE} = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right| \quad (\text{scale-free})$$

### Coverage

For prediction intervals  $[\hat{y}_t^L, \hat{y}_t^U]$ , coverage rate is the proportion of actual values falling within the interval.  
Target: match the nominal level (e.g., 80%).



## Case Study: Energy Demand Forecasting

### Problem

Forecast hourly electricity demand with:

- Daily pattern:** Peak at noon and evening
- Weekly pattern:** Lower on weekends
- Annual pattern:** Higher in summer (AC) and winter (heating)
- Holiday effects:** Lower demand on holidays

### Approach

1. Try TBATS with periods [24, 168, 8766]
2. Try Prophet with daily, weekly, yearly seasonality + holidays
3. Compare using cross-validation



## Case Study: Results

### Model Comparison

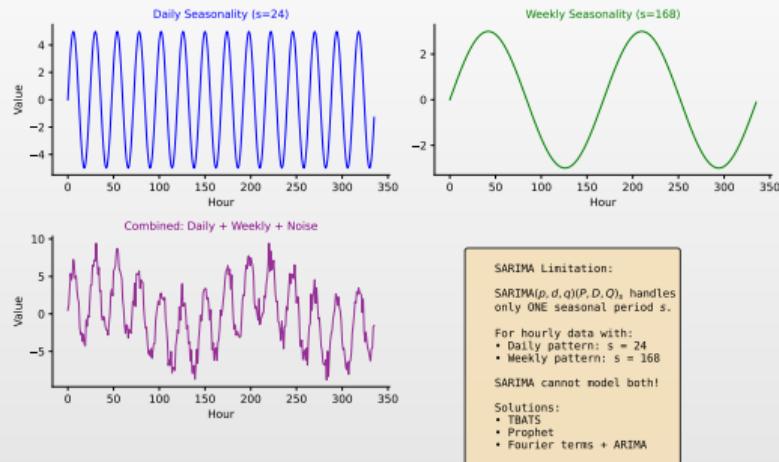
Model	MAPE	RMSE	Coverage
SARIMA (daily only)	8.5%	450 MW	75%
TBATS	4.2%	220 MW	82%
Prophet	4.8%	250 MW	85%
Prophet + holidays	3.9%	200 MW	88%

### Key Finding

Multiple seasonality models significantly outperform single-seasonality SARIMA.



## Quiz 1: Multiple Seasonality



**Question:** Why can't standard SARIMA( $p, d, q$ )( $P, D, Q$ )<sub>s</sub> model hourly electricity data with both daily and weekly patterns?

**Answer:** SARIMA handles only **one** seasonal period  $s$ . Cannot set  $s = 24$  and  $s = 168$  simultaneously.



## Quiz 2: TBATS Components

### TBATS: What Does It Stand For?

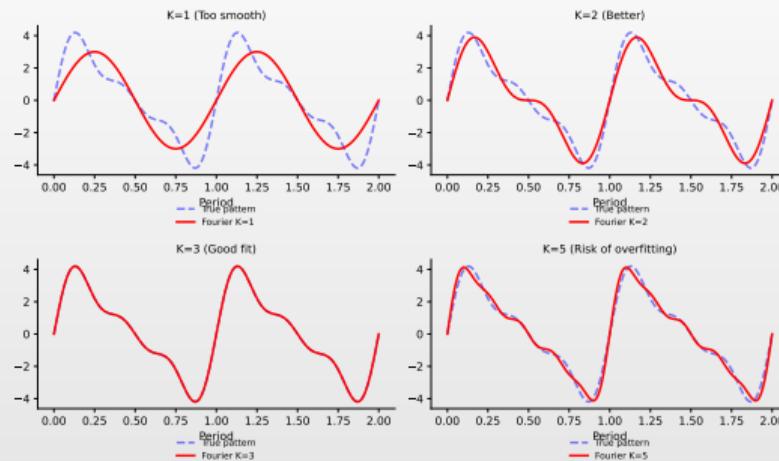
<b>T</b>	<b>Trigonometric</b>	Fourier terms for seasonality $\sum [a_n \cos(\frac{2\pi n t}{m}) + b_n \sin(\frac{2\pi n t}{m})]$
<b>B</b>	<b>Box-Cox</b>	Variance stabilization $y^{(b)} = (y^b - 1)/\omega$
<b>A</b>	<b>ARMA</b>	Error autocorrelation $\phi(L)d_t = \theta(L)\epsilon_t$
<b>T</b>	<b>Trend</b>	Level + slope (possibly damped) $t_t = t_{t-1} + \phi t_{t-1}$
<b>S</b>	<b>Seasonal</b>	Multiple seasonal periods $m_1, m_2, \dots, m_T$

**Question:** What does each letter in TBATS represent?

**Answer:** Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend, Seasonal components.



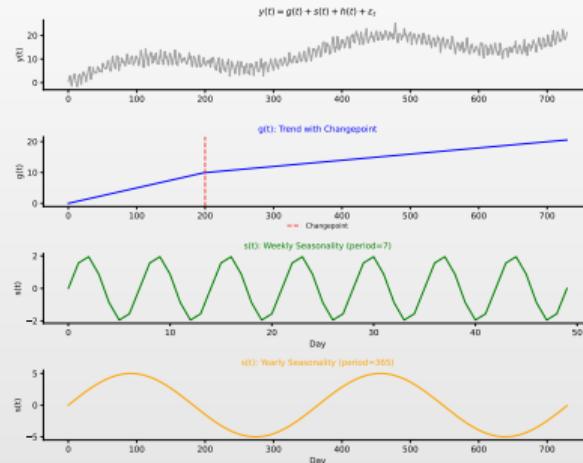
## Quiz 3: Fourier Harmonics



**Question:** What happens when we increase the number of Fourier harmonics  $K$ ?

**Answer:** Higher  $K$  captures more complex patterns but increases overfitting risk.

## Quiz 4: Prophet Decomposition



**Question:** What are the main components in Prophet's model  $y(t) = g(t) + s(t) + h(t) + \varepsilon_t$ ?

**Answer:**  $g(t)$  = trend with changepoints,  $s(t)$  = seasonality,  $h(t)$  = holiday effects.



## Quiz 5: Model Comparison

**TBATS vs Prophet: Head-to-Head Comparison**

Feature	TBATS	Prophet
Multiple seasonalities	Yes (automatic)	Yes (manual/auto)
Holiday effects	No	Yes (built-in)
External regressors	No	Yes
Trend changepoints	No (smooth)	Yes (automatic)
Missing data	Needs interpolation	Handles natively
Interpretability	Moderate	High
Computation speed	Slow	Fast
High-frequency data	Good	Moderate
Non-integer periods	Yes (e.g., 365.25)	Yes
Best for	Technical/high-freq	Business/daily

**Question:** What key features does Prophet have that TBATS lacks?

**Answer:** Holiday effects, external regressors, trend changepoints, native missing data handling.



## Key Takeaways

### What We Learned

- ☐ TBATS handles multiple seasonalities with Fourier terms and Box-Cox transformation
- ☐ Prophet provides interpretable decomposition with trend changepoints and holiday effects
- ☐ Both methods scale better than SARIMA for high-frequency and complex seasonal data

### Important

Choose Prophet for business forecasting with holidays and interpretability needs. Use TBATS for automatic modeling of high-frequency data. Always validate with time series cross-validation—never standard k-fold!



## Questions?

Questions?

### Next Steps:

- Practice with the Jupyter notebook
- Try Prophet on your own data
- Explore NeuralProphet for deep learning extension



## Online Resources and Code

- **Quantlet:** <https://quantlet.com> → Code repository for statistics
- **Quantinar:** <https://quantinar.com> → Learning platform for quantitative methods
- **GitHub TSA\_ch9:** [https://github.com/QuantLet/TSA/tree/main/TSA\\_ch9](https://github.com/QuantLet/TSA/tree/main/TSA_ch9)



# Thank You!

Questions?

Course materials available at: <https://danpele.github.io/Time-Series-Analysis/>

