Probabilistic Methods in Time Series Analysis: A Case Study

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Introduction

Modeling real-world time series data poses unique challenges such as:

- Infrequent Reporting
- Data Inconsistences
- Nonlinear Behavior

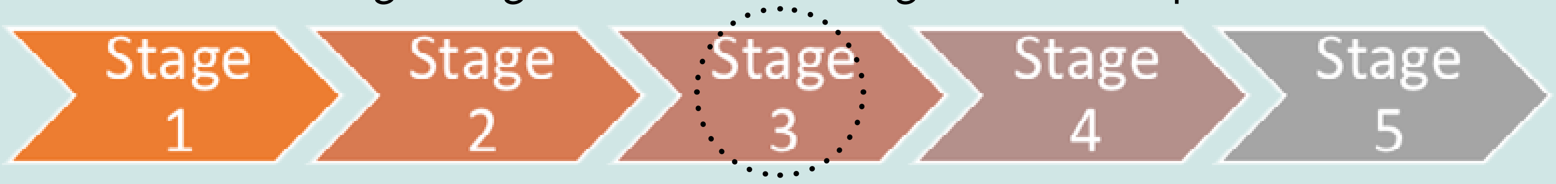
A probabilistic approach helps circumvent these issues by natively handling missing, noisy data while providing a result with measurable uncertainty.

Statement of Purpose

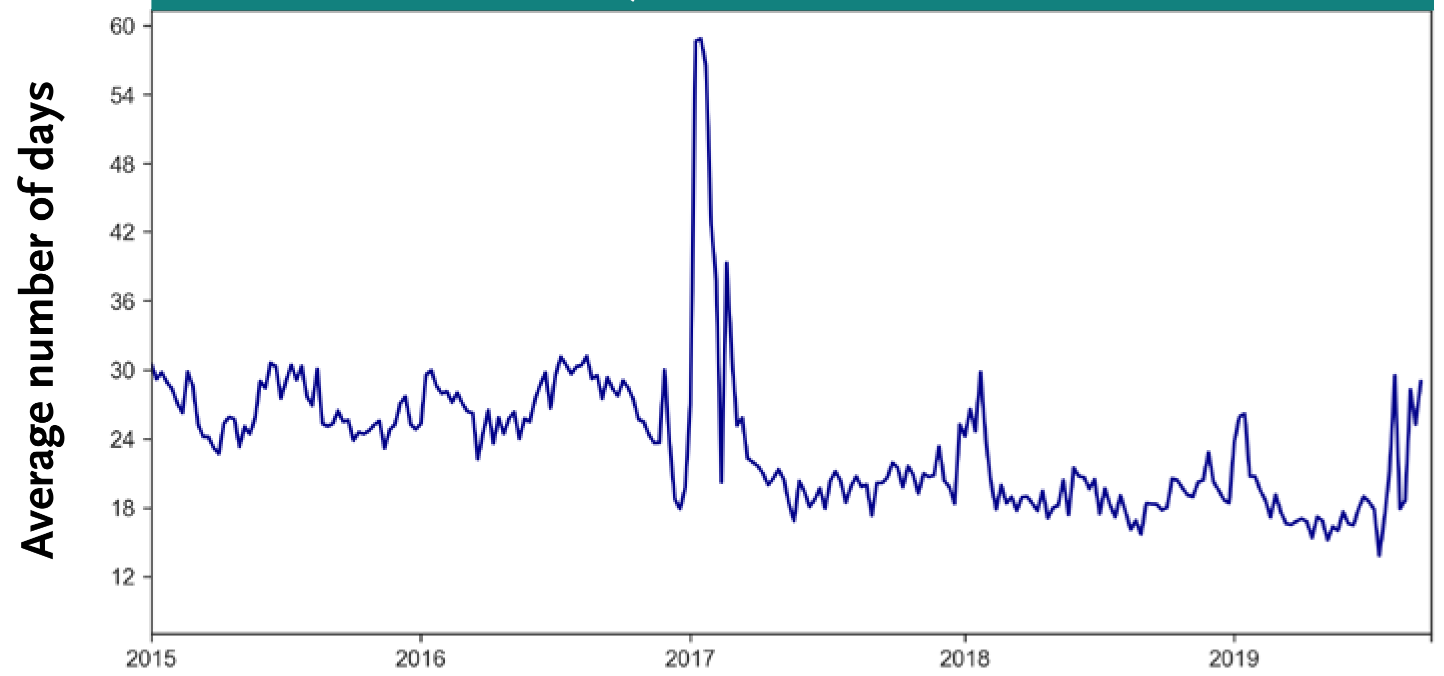
Utilize quantitative methods to enable data-driven policy decisions

Dataset

Analyzed **timeliness**: the number of days spent in a single stage within a multistage evaluation process



Weekly Process Timeliness



Weekly aggregation revealed a seasonal pattern and was the basis for all analysis

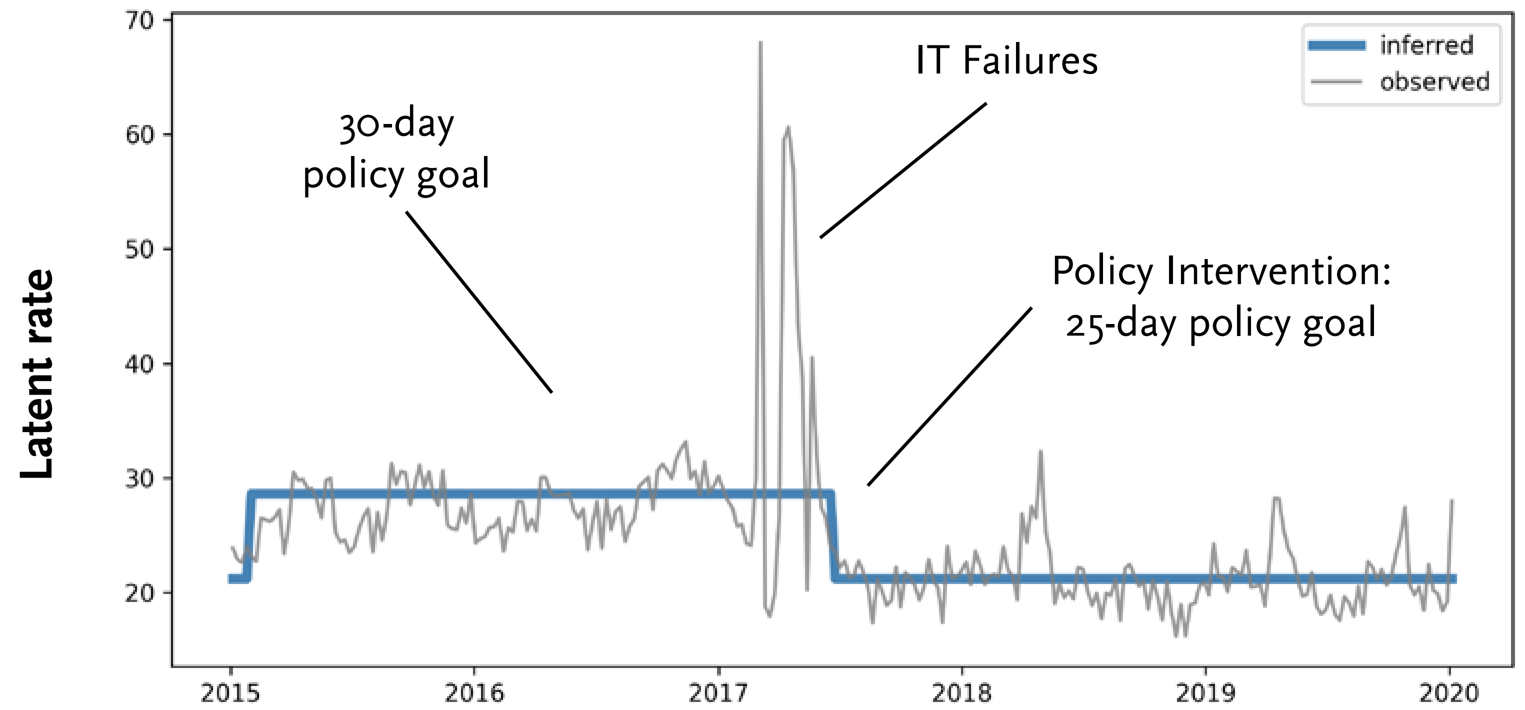
Objectives

1. Forecast future timeliness
2. Derive a data-driven timeliness policy goal
3. Characterize process behavior
4. Detect performance outliers

Model Technique 1: Change Point Analysis

Change Point Analysis was used to determine the effect of policy change on process and stage timeliness.

Change Point Analysis uses **Hidden Markov Model (HMM)** to detect structural changes in behavior. HMM uses hidden layers to detect the change points in the data and an observed layer for the time series.



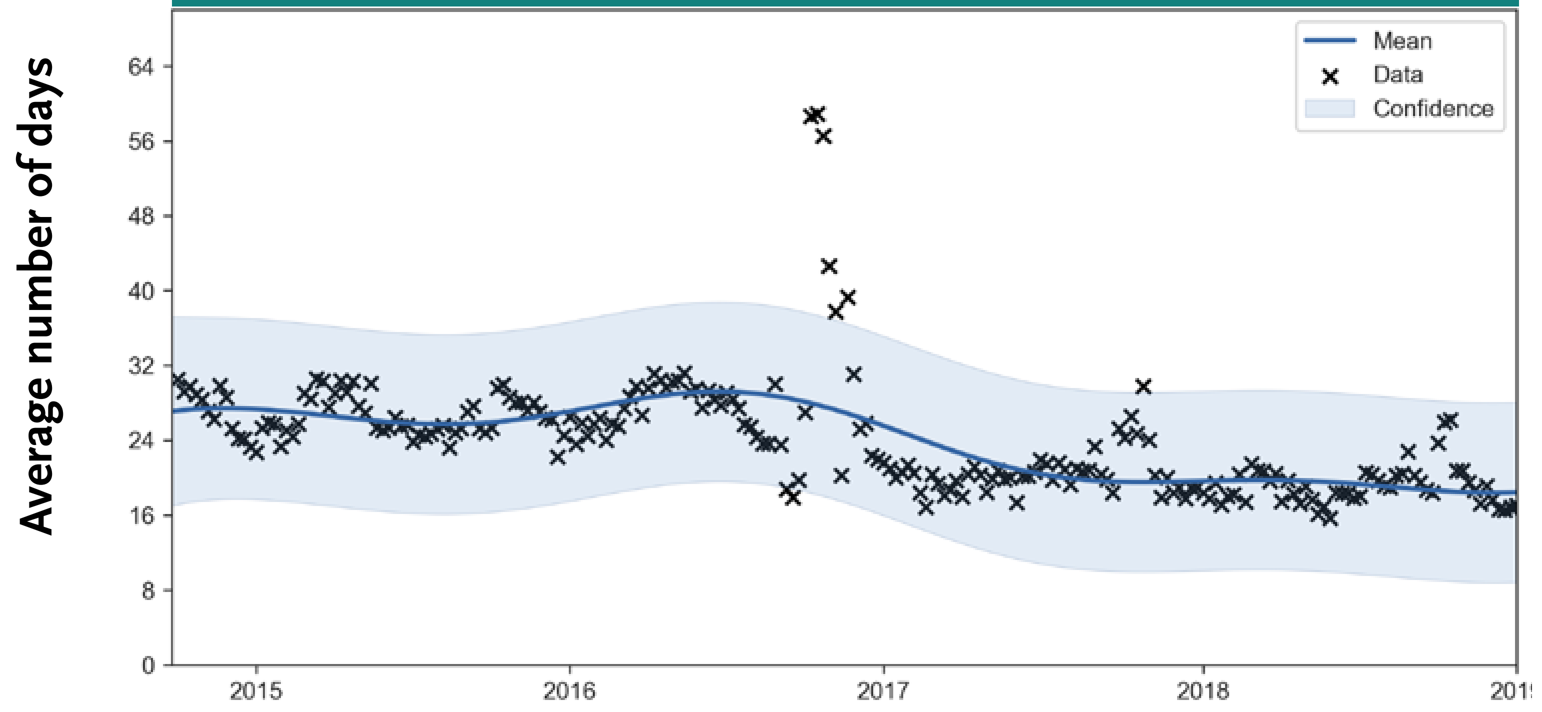
Conclusion: A noticeable shift in timeliness behavior was noticed after a policy change that was enacted in 2017.

Model Technique 2: Gaussian Process Regression

Gaussian Process Regression was used to characterize process behavior and identify performance outliers.

Gaussian Process Regression (GPR) is a Bayesian regression technique that flexibly adapts to the data, assumes noisy data and finds a distribution that best characterizes the data.

Timeliness Regression



Conclusion: Based on the overall characterization of timeliness behavior, a data- driven policy goal of 25 days was derived.

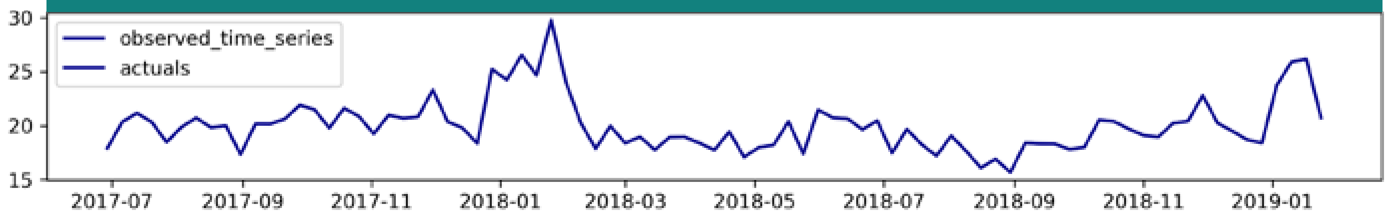
Model Technique 3: Structural Time Series

Structural Time Series was used to forecast timeliness behavior and anticipate backlog.

Structural Time Series (STS) expresses a time series as a *sum* of individual effects, including seasonality, autoregressive, local linear trends, and external influencers.

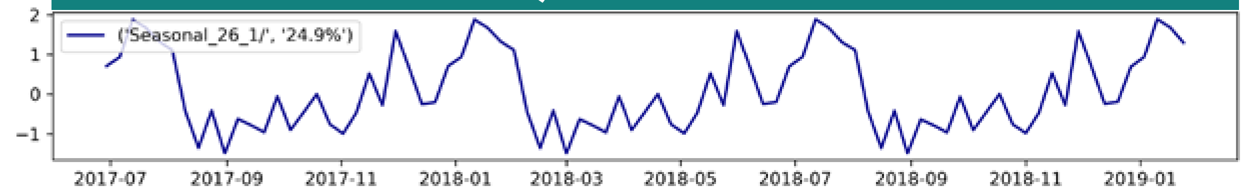
$$f(t) = f_1(t) + f_2(t) + \cdots + f_n(t) + \varepsilon;\ \varepsilon \sim \mathcal{N}(0, \sigma^2)$$

Time Series

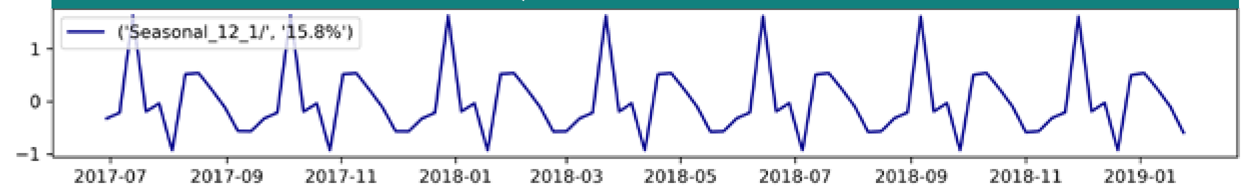


Component Decomposition

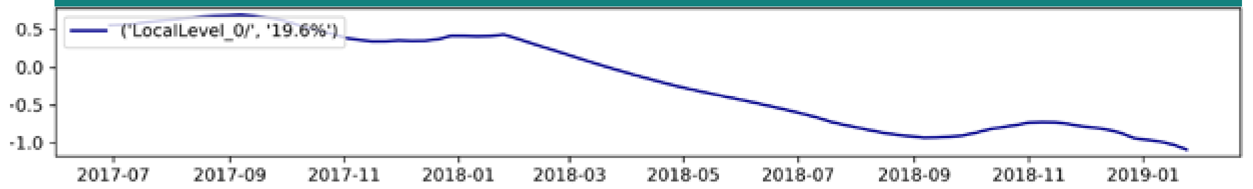
Weekly Seasonal Effect



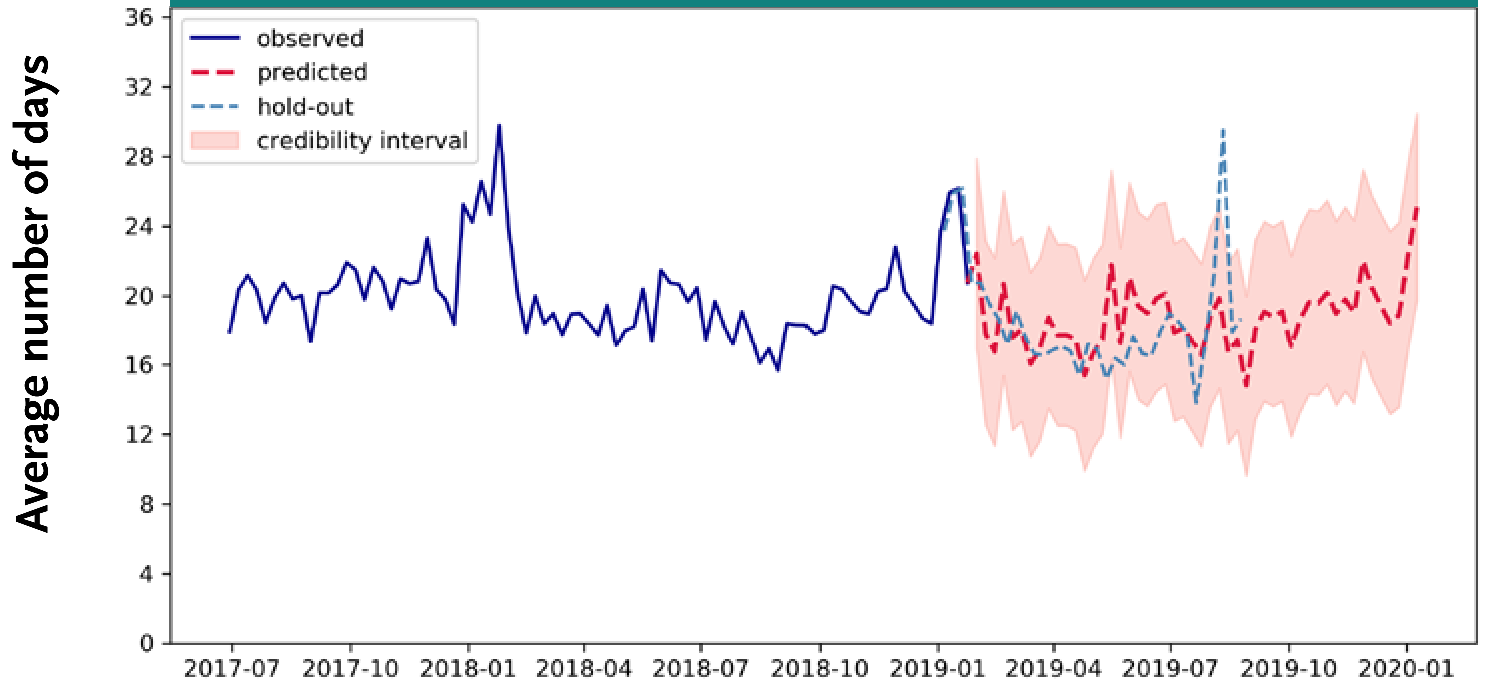
Daily Seasonal Effect



Local Linear Effect



Weekly Timeliness Forecast



Conclusion: By incorporating relevant time series components, timeliness was forecasted with narrow confidence.

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