Decision-Aware Stochastic Consumption Forecasting Under Covariate Scarcity

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***Abstract*—High-stakes materials environments require short-horizon consumption forecasts under extreme data limitations. We present a stochastic decision-aware framework for inventory forecasting using Poisson–Gamma conjugacy with exposure normalization, paired with a waste-constrained restocking policy. Empirical evaluation on masked inventory logs reveals significant nonstationarity and structural complexity, highlighting the limits of automated forecasting and the necessity of expert oversight.**

I. Problem Context

In biotech and regulated manufacturing settings, reagent consumption must be forecasted from sparse operational logs containing only weekly usage counts and the number of days since last inventory. No covariates such as production schedules or experiment metadata are available. Forecasts must support operational restocking decisions under asymmetric cost tradeoffs between stockouts and waste.

II. Probabilistic Model

Let y_t denote weekly units consumed and n_t the exposure in days. We assume

$$y_t \mid \lambda \sim \text{Poisson}(\lambda n_t), \tag{1}$$

where λ is a per-day usage rate. A Gamma(shape–rate) prior is placed on λ,

$$\lambda \sim \text{Gamma}(a_0, b_0), \tag{2}$$

yielding the posterior

$$\lambda \mid \text{data} \sim \text{Gamma}\left(a_0 + \sum_t y_t,\ b_0 + \sum_t n_t\right). \tag{3}$$

III. Posterior Predictive Forecasting

For a future horizon of H days, the posterior predictive distribution of total usage is:

$$Y_{\text{future}} \sim \text{NegBin}\left(\text{size} = a,\ \text{prob} = \frac{b}{b+H}\right), \tag{4}$$

where a, b are posterior parameters. Monte Carlo samples $\{y^{(i)}\}$ from this distribution approximate predictive uncertainty.

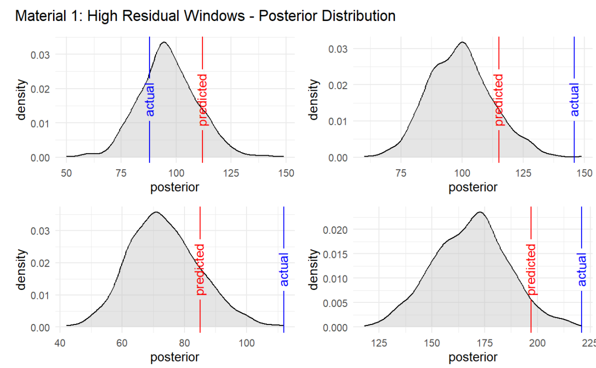

Fig. 1. Posterior predictive vs. actual demand (Material 1).

Algorithm 1 Single-Horizon Stochastic Forecast and Waste-Constrained Reorder

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Require: Data $\mathcal{D} = \{(y_t, n_t)\}_{t=1}^{W}$, horizon H, MC samples N, waste limit α, grid $\mathcal{Q}$
Ensure: Reorder quantity $\widehat{Q}$
Set prior (a_0, b_0)
$a \leftarrow a_0 + \sum_{t=1}^{W} y_t, \quad b \leftarrow b_0 + \sum_{t=1}^{W} n_t$
Sample $Y^{(i)} \sim \text{NegBin}(a, b/(b+H)), \quad i = 1, \ldots, N$
for all $Q \in \mathcal{Q}$ **do**
  $w(Q) \leftarrow \frac{1}{QN} \sum_{i=1}^{N} \max(Q - Y^{(i)}, 0)$
end for
$\widehat{Q} \leftarrow \max\{Q \in \mathcal{Q} : w(Q) \le \alpha\}$
return $\widehat{Q}$

IV. Decision Rule for Restocking

Predictive samples are converted into a reorder quantity Q via a waste-constrained policy. For candidate Q values, the expected waste fraction is computed:

$$\frac{\mathbb{E}[\max(Q - Y, 0)]}{Q} \le \alpha, \tag{5}$$

where α is the maximum acceptable waste fraction (e.g., 0.15). The selected Q is the largest grid value satisfying this constraint.

V. Rolling Evaluation

A rolling-origin validation scheme mimics deployment by sliding a fixed training window across time, forecasting the next H days, and comparing predicted usage to realized consumption. Diagnostics include residuals, variance-to-mean ratios, and posterior calibration behavior.

VI. Results

Empirical results show high residual variance and pronounced nonstationarity. Posterior predictive distributions frequently place realized demand in the tails, and forecast quality deteriorates during regime shifts.

VII. Takeaways

Uncertainty modeling revealed the extent of complexity in the consumption process. Assumptions about the stochastic process and decision rule were insufficient to consistently provide decision-grade forecasts. This process is more appropriately managed through expert oversight and timely communication than fully automated inventory control.

VIII. Reproducibility

Full reproducible analysis and code are available at: https://github.com/TheFifthPostulate/Stochastic-Consumption-Forecasting/. The InventoryProject.Rmd notebook contains narrative, figures, and diagnostics, while utils.R defines forecasting and decision logic functions.