Wheaton College
Department of
Mathematics and
Computer Science

Forecasting FMCG Demand Using Generalized Additive Models

Carson Slater

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Abstract

AwanTunai provides supply chain business solutions with embedded financing to suppliers and merchants in Indonesia. Here we compare different forecasting methods against white-noise FMCG time series. We examine exponential smoothing, ARIMA, and generalized additive regressions as potential model options. We observe that the generalized additive models were the most accurate models for the FMCG time series we examined.

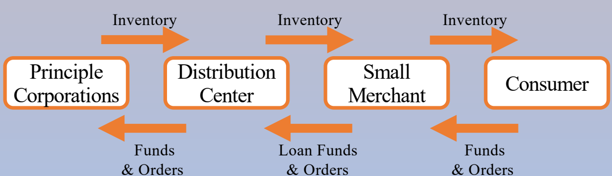
Background

Introduction

Consumer staples in Indonesia flow from principle corporations, to distributors, to merchants, and finally to the consumer. What is atypical about Indonesia is over 50% of FMCG sales come from small, single store merchants, as opposed to large retail outlets (1). Around 80% of the Indonesian population purchases goods from these smaller merchants.

Problem Statement

Many of these small merchants have very tight profit margins, making it difficult to restock goods to grow their customer base. AwanTunai offers cloud-based solutions for small merchants to restock their inventories with options to finance their orders. This enables them to keep up with demand, attract new customers, and pay for the goods when they turn a larger profit. AwanTunai's services provide a financial buffer for the "mom and pop" shops during market shocks. We hope to forecast the quantity demanded for the most popular SKU's, to optimize efficiency and mitigate sunk costs for distribution centers and merchants by building suitable forecasting models.



The Data

These raw data feature three different products aggregated by daily volumes being sold from the distribution center. This project assumes that the products are shipped on the same day on which they are ordered. Each of the three time-series contains 338 daily observations.

Preprocessing Step

Daily volumes that were more than two standard deviations away from the mean were removed and imputed with the mean daily volume training data.

Acknowledgements

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Scan to go to the Github Repository:

Adviser: Dr. Ying Li

Methods

The Models

We explored four types of time series models. We utilized OLS Regression as a the baseline model for the whole experiment, and then considered three types of exponential smoothing, Hyndman's ARIMA models, and finally basic and tuned generalized additive models (GAMs). To generate the forecasts at scale, the `fable` package in R was used (2), and to generate the GAMs, Facebook's `Prophet` was used. The generalized form of the GAM found in the paper by Taylor and Letham (3) can be represented as such:

$$\max\{0, y(t)\} = \beta_0 + g(t) + s(t) + h(t) + \varepsilon,$$

where $g(t)$ represents the linear trend with specified changepoints $a(t)^{\mathrm{T}}$,

$$g(t) = \left(k + a(t)^{\mathrm{T}}\delta\right)t + \left(m + a(t)^{\mathrm{T}}\gamma\right),$$

$s(t)$ is the term computing the periodic seasonality for period of length P, written as,

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

and $h(t)$ is the holiday component of the time series. Letting D be the set of all holidays in the past and future for the time series, we have that

$$Z(t) = [1(t \in D_1), \ldots, 1(t \in D_L)],$$

giving the holidays a corresponding coefficient $\mathcal{K}_i$ such that

$$h(t) = Z(t)\mathcal{K}.$$

This generalized form of the GAMs contains many hyperparameters to tune, such as the changepoint trend shifts δ, the weights on seasonality trends, a_n and b_n, and holiday coefficients $\mathcal{K}_i$. In our experiment we trained two GAMs for each time series, one of which enabled `Prophet` tofind optimal hyperparameters and additionally a manually tuned one, where some parameters were specified using domain knowledge.

Experiments

To evaluate the accuracy of these models, we took the last eight weeks, or 56 observations, as the evaluation criterion. We trained the model on the first 282 daily observations of total daily volumes. We then had the models produce forecasts for those eight weeks, comparing the predicted results with the real observations. The GAMs were trained as a naïve model and also a tuned model, which was given holidays, changepoints, and trend sensitivity specifications. The naïve model did not have any of this information.

Results

The GAMs had the lowest error rates for the eight-week forecasts, which is to be expected given the algorithm takes advantage of more information. Looking at the table, the error rates for all seven models are listed. Simple exponential smoothing and the ARIMA models performed the best of the older methods, but were always substantially more erroneous than the GAMs. Even for an erratic time series, such as time series 2 (see Figures 3 and 4), Prophet was able to keep MAPE to under 32%.

Discussion

These time series were fairly stationary, so future research might suggest comparing these models with a control time series that possesses different trends. Generally speaking, forecasting methods like exponential smoothing and ARIMA models perform better on differenced time-series, whereas `Prophet` demonstrates flexibility in determining the trend at a given t.

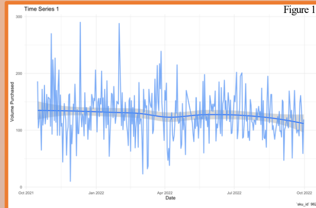

Figure 1

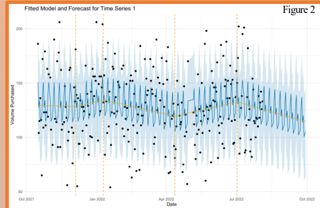

Figure 2

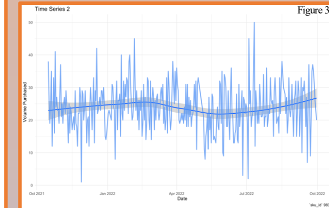

Figure 3

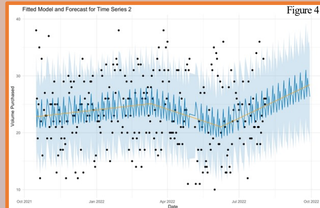

Figure 4

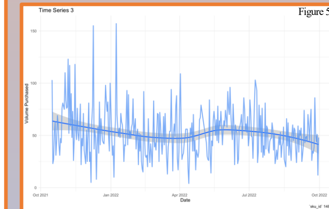

Figure 5

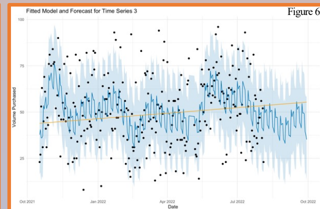

Figure 6

Model	RMSE (Series 1)	MAPE (Series 1)	RMSE (Series 2)	MAPE (Series 2)	RMSE (Series 3)	MAPE (Series 3)
Ordinary Least Squares	47.9	36.5	10.2	42.6	21.8	63.6
Simple Exponential Smoothing	39.3	33.3	7.39	38.7	17.8	52.1
Holt's Method	69.7	41.4	11.1	43.3	38.2	72.5
Holt's Method (damped)	54.9	37.6	7.61	38.1	24.1	55.5
Stepwise ARIMA	39.2	33.2	7.38	39.1	22.3	50.7
Naïve GAM (Prophet)	35.4	29.6	7.27	**28.3**	**14.6**	**32.8**
Tuned GAM (Prophet)	**30.8**	**24.9**	**7.09**	31.9	15.5	37.0

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