식품 소매 수요 예측에 관한 연구: 전통 시계열 모델과 딥러닝 모델 간 비교 분석

An Empirical Study on Food-Retail Demand Forecasting: A Comparative Analysis of Traditional Time Series and Deep Learning Models

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Abstract

Accuracy demand forecasting in the food-retail industry is an important task since it can reduce costs caused by shortage and overflow of food ingredients. In this paper, we conduct a comparative study on food-retail demand forecasting using two traditional time series models and one deep learning model. Using a café point-of-sale (POS) dataset exhibiting event-driven daily changes and predictable sale shocks on holidays, we analyze which model is superior in terms of prediction error according to some circumstances.

Ⅰ. Introduction

Precisely forecasting food-retail demands is crucial since food is sensitive to the expiry date. Due to the fact that demands in retails often have seasonal variations [1], many time series models have been developed to date. In this paper, we aim to perform food-retail demand forecasting by comparing the performance of traditional time series models and a deep learning model. We empirically validate which model is superior in terms of prediction error using a café point-of-sale (POS) dataset exhibiting event-driven daily changes (e.g., COVID-19) and sale shocks on holidays.

Ⅱ. Model and Dataset Description

We use the following two time series models: seasonal autoregressive integrated moving average (SARIMA) and Prophet [2]. In SARIMA, it follows that $Y_t = T_t + S_t + \epsilon_t$, where Y_t, T_t, S_t, ϵ_t are the sales, trend, seasonality, and error, respectively, at time t. In Prophet, it follows that $Y_t = T_t + S_t + H_t + \epsilon_t$ with an extra term H_t for the holiday effect. As a deep learning model, we adopt long short-term memory (LSTM). In addition to the short term memory, LSTM also keeps long time dependencies such as yearly patterns.

We use the "Christmas Bean" POS dataset collected from August 3, 2016 to March 31, 2021. In the dataset, we select the following three menus for demand forecasting: Hot-ChristmasBean Royal Americano having a small sample size (Menu #1), Hot-Americano having a strongly decreasing tendency from the 40^{th} week (Menu #2), and Ice-Americano having three extreme peaks in the training set and a peak in the test set (Menu #3). In SARIMA and LSTM models, we convert the existing daily data into the weekly one by summing up weekday sales records. In Prophet, we train on daily data to include event dates and then convert daily predictions in weekly scale. We split the dataset in chronological order into training/test sets with a ratio of 80/20%.

Ⅲ. Experimental Results

To empirically evaluate the performance of our models, we use the root mean squared error (RMSE) as a metric. Table 1 show the RMSE of three models for three menus. Our findings include that 1) the LSTM model almost consistently outperforms others in terms of prediction error, 2) In Menu #1 with a small sample size, the performance of SARIMA is slightly superior to that of LSTM, and 3) In Menu #3 with several peaks driven by events, Prophet shows not only remarkable gains over SARIMA but also marginal gains over LSTM.

Menu	SARIMA	Prophet	LSTM
Menu #1	8.71	12.94	9.04
Menu #2	48.38	44.24	19.35
Menu #3	64.37	42.94	46.15

Table 1. Performance comparison of three demand forecasting models

ACKNOWLEDGMENT

This research was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2021R1A2C3004345), by the Republic of Korea's MSIT (Ministry of Science and ICT), under the High-Potential Individuals Global Training Program (No. 2020-0-01463) supervised by the IITP (Institute of Information and Communications Technology Planning Evaluation), and by the Yonsei University, Republic of Korea Research Fund of 2021 (2021-22-0083).

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