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

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Abstract

Accurate demand forecasting in the food-retail industry is a very important task since it can reduce the cost caused by either shortage or overflow of food materials. In this paper, we show a comparative analysis on food-retail demand forecasting using the following two time series deep learning models: long short-term memory (LSTM) and convolutional neural network (CNN)-LSTM models. Using a café point-of-sale (POS) dataset, it is demonstrated that the CNN-LSTM model has a marginal gain over the LSTM model in terms of prediction error.

Ⅰ. Introduction

In the food-retail industry, demand forecasting is crucial since accurate forecasting can significantly reduce wasted materials and prevent shortage of ingredients [1]. In this paper, we aim to perform food-retail demand forecasting by comparing the performance of two time series deep learning models. More specifically, using a café point-of-sale (POS) dataset, we analyze how much the convolutional neural network (CNN)-long short-term memory (LSTM) model performs better than the LSTM model in terms of prediction error.

Ⅱ. Dataset and Model Description

We use the "Christmas Bean" POS dataset collected from August 3, 2016 to March 31, 2021. In the dataset, we select the following three most popular menus for demand forecasting: Ice-Americano (Dataset #1), Hot-Americano (Dataset #2), and Hot-Caffelatte (Dataset #3). In order to reduce the noise such as daily variances driven by potential events in the prediction, we convert the existing daily data into the weekly one by summing up weekday sales records. Training is carried out by using the weekly sales sequence of the previous 8weeks as the input and the sales volume of the next 1 week as the label. We split the dataset in chronological order into training/test sets with a ratio of 70/30%.

Next, we describe our adopted deep learning models. We design the CNN-LSTM model using 1-dimensional (1D) convolutional layer that is suitable for analyzing time series data. This model extracts features while reflecting the location information of each sales volume from the entire time series data at the first 1D convolutional layer. Then, the data embedded with the number of filters are sequentially fed into the LSTM layer. Here, the convolution filter can reflect the context of the entire sequence by extracting various features from the sequence and feeding them into the LSTM layer [2], which differs from the single LSTM model that sequentially accepts only the previous week sales data.

Ⅲ. Experimental results

To empirically evaluate the performance of our models, we use the root mean squared error (RMSE) as a metric, which is defined as $\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t-\hat{y}_t)^2}$. Here, y_t and $\hat{y}_t$ are the actual and predicted values, respectively, at time t. Table 1 shows the RMSE of two models for three datasets. The results reveal that the CNN-LSTM model is consistently superior to the LSTM model regardless of datasets even if the gain is marginal.

Dataset	RMSE	
	LSTM	CNN-LSTM
Dataset #1	48.24	47.79
Dataset #2	24.10	19.88
Dataset #3	18.23	18.03

Table 1. Performance comparison of LSTM and CNN-LSTM models

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