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Qiongwei Ye
Yunnan University of Finance and Economics, Kunming, China, yeqiongwei@163.com

Qiang Yuan
Yunnan University of Finance and Economics, Kunming, China, yq704553253@163.com

Dan Ding
Southwestern University of Finance and Economics, Chengdu, China, dingd@swufe.edu.cn

Qichen Liao
Beijing Foreign Studies University, Beijing, China, lqc_cara@163.com

Yiu Ching Chan
Au Bet Company, Ke Chuan Holding Co. Ltd, ycchan@tech-trans.com

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Qiongwei Ye [1]
Qiang Yuan [2]
Dan Ding [3,*]
Qichen Liao [4,*]
Yiu Ching Chan [5]

*Corresponding author
[1] Yunnan University of Finance and Economics, Kunming, China, Professor, yeqiongwei@163.com
[2] Yunnan University of Finance and Economics, Kunming, China, yq704553253@163.com
[3] Southwestern University of Finance and Economics, Chengdu, China, Associate Professor, dingd@swufe.edu.cn
[4] Beijing Foreign Studies University, Beijing, China, lqc_cara@163.com
[5] Au Bet Company, Ke Chuan Holding Co. Ltd, ycchan@tech-trans.com

ABSTRACT

To improve the forecast accuracy of the sales of stores in shopping malls, this paper proposes a prediction method based on deep learning that comprehensively considers the external data, such as online review data of shopping mall stores, weather data, weekday/weekend data, and historical transaction data of the stores. To begin with, the online review data of the stores are pre-trained with BERT (Bidirectional Encoder Representations from Transformers) to complete the multi-label sentiment classification and obtain the intensity index of perceived sentiment of reviews. The index, together with other external data, such as online ratings, weather, weekday/weekend differences, and historical transactions of the stores, is pre-processed. At last, the Long Short-Term Memory (LSTM) and the Attention models are used to predict the sales volume of stores in a certain shopping mall. The results show that the addition of external data – weather, weekday/weekend, online ratings and intensity index of sentiment of reviews – to the historical sales data-based model can effectively improve the forecast accuracy of store sales.

Keywords: BERT pre-training; LSTM Network; sales forecasting; online reviews

INTRODUCTION

A shopping mall is the space that provides more than three forms of services and businesses, such as supermarkets, department stores, professional stores and exclusive shops, and meanwhile includes more than three combinations of commerce, such as entertainment, catering, offices and residence. These internal components form a collaborative relationship characterized by interconnection and mutual promotion. As China's urbanization rate keeps growing in recent years and urban areas continue to see their land expand and populations grow, shopping malls have become an inseparable part of the urban economy and urban life.

Shopping malls have played an active role in mitigating the negative economic impacts of COVID-19, including stimulating domestic demand, expanding consumption and improving the real economy. However, partly because of the global and domestic economic growth deceleration and the decline in urbanization rate and demographic dividend in recent years, and partly because of the increasing development of online shopping, subsequently, the expansion of bricks-and-mortar shopping malls is slowing down. In first-tier cities in China, the market for shopping malls has reached saturation point. According to Huaon Industry Research Institute (as shown in Figure 1), the average year-on-year growth rate of stock of shopping malls featuring over 30,000 square meters in first- to sixth-tier cities was 28.8% between 2008-2017. In 2018 this figure fell below 20% for the first time, and in 2020 it slid to below 15%. Although their year-on-year growth rate trended upwards in 2021, shopping malls still face the risk of overstocking and need to seek out new prospects for their businesses.

The sign of decline in brick-and-mortar retail is not unique to China. Since 2015, the United States has seen closures of a large number of retail stores. As McArthur *et al.* (2016) and others have wisely proposed, it is important that we try to understand the significant structural differences in the retail sector from the consumer's perspective and make changes accordingly. In this connection, Helm *et al.* (2020) have developed a conceptual framework for retail transformation that, though incomplete, could prepare retailers and public policymakers for changes in the retail environment.

With rapid advancements of technologies, artificial intelligence (AI), big data, cloud computing, etc., have been widely used in the real world and become hot topics in retailing research. For example, Fuentes *et al.* (2017) introduced the AI-enabled interaction into physical retail stores to modify the shopping settings and environment, such as rearranging the location of products displays in the store according to consumers' habits. In terms of the application of big data, the portraits of social network users (Pan *et al*., 2019) can be used for precision marketing and product optimization to offer targeted advertisements and recommend products to customers. It not only reduces advertising costs but also expands the scope of business. It can be seen that the use of deep learning technology can be used to predict sales.

Source: Huaon Industry Research Institute (2022).
Figure 1: Number and growth rate of shopping centers in China from 2011 to 2021

Using deep learning for sales forecasting has significant implications for managers in developing business strategies, rationalizing purchases, and controlling operational costs (Singh *et al*., 2020). Stores are profit-oriented and the sales are the prerequisite for proper operation. When there is excess supply of products, it will lead to excess inventory and slow down the capital flow, which will affect the revenue earned by stores. When the products are in short supply, it can cause negative customer experience and even customer loss, which also affects the revenue. Therefore, sales forecasting is very important to solve these problems and increase sales and drive rapid growth.

This paper comprehensively uses the internal and external data of the stores and the online data from the perspective of consumers, pre-trains the reviews through BERT, and inputs the pre-trained data into the time series models, i.e., LSTM and Attention models, to forecast sales, which provides a reasonable explanation for the results of physical retail sales from multiple perspectives. The empirical study on bricks-and-mortar stores in shopping malls draws a clear conclusion: synthesizing the stores' internal and external data and the online data from the consumers' perspective can yield more accurate results when predicting store sales. These predictions can guide the stores in developing better inventory plans and sales strategies, reduce inventory costs, improve operational efficiency, and seize market opportunities.

In the following section, we review and discuss related works on: (1) sales prediction; (2) the relationship between online reviews and offline sales; and (3) recent technologies that are adopted in this study, i.e., Long Short-Term Memory (LSTM), Attention and BERT. After this, we introduce our data context and propose research methodology. Based on the proposed research framework, we conduct data experiments and provide the results. Finally, we conclude our findings and discuss potentials for future research.

LITERRATURE REVIEW

Sales Forecasting

Sales forecasting is of great importance for both business and academic research. A large amount of academic literature has studied the causes that affect sales from different perspectives, and the overall research focus can be divided into two categories: internal and external factors (Tartaglione *et al.*, 2019), and online consumer factors (Martínez-de-Albéniz & Belkaid, 2021). The external factors include weather, weekday/weekend, geographic location, etc. The online consumer perspective includes into online ratings and online reviews.

Impact of Internal and External Factors on Sales Forecasts

Taghizadeh *et al.* (2017) developed robust demand prediction methods for weather sensitive products in retail stores. Their methodology provided the cumulative annual contributions of weather on sales and allowed for deriving the maximum potential annual impact of adverse weather. Using the non-alcoholic beverages as an example, Štulec *et al.* (2019) proposed a design of customized weather derivatives as tools for offsetting failed sales due to adverse weather. Badorf and Hoberg (2020) examined the influence of weather on daily sales in brick-and-mortar retailing using empirical data of 673 stores. Tian *et al.* (2021) analyzed over 6 million transactions made by more than 1.62 million unique consumers at 146 convenience stores in a convenience store chain in China. Their results show that different weather changed the propensity to visit the point of sales because travel cost was affected by weather conditions. In addition, they had different influences on different product categories, because the reference utility in the mind of the consumer was affected by current weather. Martínez-de-Albéniz and Belkaid (2021) studied the two impact dimensions at a large fashion apparel retailer. Oh *et al.* (2022) examined research directions on the integration of clothing and weather and how weather information was utilized in the clothing industry.

From the above research, it can be seen that the external factors can influence shopping mall store sales. However, it is also obvious that existing literature often focuses on single aspect of the issue and uses relatively traditional methods, leaving the research gaps in retail sales prediction, which this paper intends to address.

The Impact of Online Consumer Perspective on Sales

In the past two decades, online reviews have played an increasingly important role in consumptions. Eslami *et al.* (2018) demonstrated the unique importance of online review positiveness and review score inconsistency in increasing product sales which varied for low and high involvement products. Hu *et al.* (2018) proposed either the impact of reviews had been incorporated into sales or reviews were less truth worthy due to potential review manipulation. As for the design/methodology/approach, Lee *et al.* (2018) used publicly available data from www.naver.com to build a sample of online review data concerning box office. Numerous surveys suggest that consumers often conduct pre-purchase searches not only on the retailer-hosted websites but also on third-party review sites (Wu *et al.* 2018). Ai *et al.* (2019) examined the impacts of online review features on hotel online room sales for various types of hotel segments utilizing a dataset that included 227,378 post-purchase customer review comments for 1,092 hotels. Based on the two-step flow theory, Su *et al.* (2021) explored the impact of online review valence, review volume, and their interactions on online sales. In particular, they focused on the factors that influenced customer purchase decisions and the moderating effect of popular reviews on review valence. From 28 studies focusing on online reviews and sales, Li *et al.* (2020) performed a meta-analysis on the true impacts of six review-related factors, namely, the number of reviews, star ratings, standard deviation of ratings, helpfulness, review length and sentiment, as well as two motivating factors (i.e., price discounts and special shipping) on product sales. In a two-step approach, a measurement model was estimated and a structural model analyzed to test the proposed hypotheses (Ruiz-Mafe *et al.* 2020). Alzate *et al.* (2021) incorporated the notion of review visibility to study the relationship between online reviews and product sales, which was proxied by sales rank information, studying three different cases: (1) when every online review was assumed to have the same probability of being viewed; (2) when Alzate *et al.*(2021) assumed that consumers sorted online reviews by the most helpful mechanism; and (3) when Alzate *et al.* (2021) assumed that consumers sorted online reviews by the most recent mechanism. Yin *et al.* (2021) investigated the impact of online review richness (i.e., reviews containing videos or follow-on reviews) on sales.

In summary, the existing literature on the impact of online rating and review data on sales volume shows that online data have a great impact on product sales. However, most of the existing literature focuses on the impact of online data to online sales, and little uses online data as the basis for studying retail sales of offline physical stores. In particular, there has been no research that combines online rating, sentiment intensity of reviews with the external data of stores. To address these gaps, this paper integrates the data on weather, weekday/weekend differences, and online multi-dimensional sentiment of reviews, to build sales forecast models for offline physical stores. The results show that the gradual addition of weather, weekday/weekend and online multi-dimensional review data can effectively improve the accuracy of offline sales forecast. Meanwhile, making full use of multi-dimensional online data will significantly help improve the accuracy of prediction.

Technological Developments

BERT (Bidirectional Encoder Representations from Transformers) is a pre-training technique used for natural language processing. It contains a two-layer bidirectional Transformer model, unsupervised language representation, and only uses a plain text corpus. BERT solves the problem of massive amounts of data required by NLP models (Devlin *et al.*, 2018). Researchers have developed techniques to train universal language models that use enormous amounts of unannotated text from the Internet as data sources (called “pre-training”). These universal pre-training models can be fine-tuned on smaller task-specific datasets, which can greatly improve the accuracy compared with training on smaller task-specific datasets from scratch.

LSTM is a type of Recurrent Neural Network (RNN). Compared with traditional backpropagation, although standard RNN can utilize time series information, it is prone to the vanishing gradient and the exploding gradient problems during long-distance transmission, which leads to the inability of neural network to train weights in the process of backpropagation, and makes it difficult for RNN to learn long-distance information. To tackle this problem, Hochreiter and Schmidhuber (1997) introduced the Long Short-Term Memory (LSTM) method, which controls the flow of information and avoids long-term dependency problems by adding the cell and three gates: the input gate, the forget gate, and the output gate. The forget gate decides if we want to dispose of a piece of information, the input gate decides the update of information, and the output gate decides what output to generate from the current cell state. The gate structures are used for storing important information and forgetting unnecessary information to improve memory for long time sequences.

Pan *et al.* (2018) proposed a LSTM-based model to cope with airlines’ needs for daily demand forecasting. Helmini *et al.* (2019) showed that deep learning models (e.g. recurrent neural networks) could provide higher accuracy in predictions compared to machine learning models due to their ability to persist information and identify temporal relationships. Shih *et al.* (2019) proposed a model to forecast short-term goods demand in e-commerce context. Weng *et al.* (2019) designed a model that could accurately forecast the supply chain sales. Goel *et al.* (2020) used different noise distributions, such as normalized, uniform, and logistic distributions to prove that sales forecasting research had very important value for strategic decisions and improvement measures made by enterprises. Pliszczuk *et al.* (2021) developed an algorithm for forecasting sales in the supply chain based on the LSTM network using historical sales data of a furniture industry company. They also found that the main challenges of the forecasting task were the high-dimensional influence variables with noise and the complex time series relationships. Zhao *et al*. (2021) proposed a DAE-LSTM algorithm combined with denoising autoencoder (DAE) and long short-term memory (LSTM) to deal with this problem. Based on real sales data, Li *et al.* (2022) constructed LGBM and LSTM sales prediction models to compare and verify the performance of the proposed models. Other influential work includes Han's (2020).

In 2014, a research team from Google proposed the Attention mechanism (Mnih *et al*. 2014) that is better at capturing the internal correlation of data or features. It changes the traditional encoder-decoder structure. The traditional decoder gives the same weight to each input, but in reality different inputs often have different importance. During the process of decoding, Attention uses the scoring function to calculate the influence of different inputs on the predicted value and gives them different weights to solve this problem. In essence, the Attention model calculates the difference between the current input sequence and the output vectors, and the smaller the difference is, the higher weight Attention should assign here.

In summary, the existing studies mainly focus on the impact of internal and external factors on bricks-and-mortar store sales and the impact of online review data on online stores. Gaps remain in terms of sales forecasting of physical stores in shopping malls. This paper comprehensively considers the weather, weekday/weekend, online ratings and sentiment intensity of reviews, using BERT, LSTM and Attention, to improve the forecast accuracy of the sales of stores.

DATA SOURCES AND METHODOLOGY

Data Sources

Stores data

A total of 45,692,624 data from physical stores in a certain shopping mall from January 2017 to March 2019 are selected for this research. Bound by the relevant cooperation agreement that the disclosures of data on store names and sales volume shall not be allowed, the actual store names are replaced by Store A and Store B. In this conference paper, we select two representative brick-and-mortar stores in City A to conduct the sales forecasting study.

Weather data

The weather data selected in this paper are weather conditions withdrawn from the website https://www.lishi.tianqi.com/ by using a Python web crawler. The Historical Weather Channel (https://www.lishi.tianqi.com) provides historical weather forecasts for 2290 areas belonging to 34 provinces and cities across China, with data from the China Meteorological Administration for the day in which the city is located. To make the sales forecasting results more accurate, over ten weather conditions are divided into four major categories: sunny, cloudy, rainy and snowy. The number of days for the above four weather conditions is counted.

Online rating and review data

The online rating and review data in this paper are extracted from the shopping mall stores registered in Dianping, China's leading local lifestyle information and trading platform, using a Python web crawler. In line with the rating scale used in Dianping, the online rating data are divided into four categories: overall rating, food rating, environment rating, and service rating. Online reviews are divided into seven categories according to the importance of the reviews: location, attitude in customer service, store environment, price level, taste, overall evaluation, and customer flow.

Pre-processing of data

In terms of the internal data of the shopping mall, the historical transaction data of the shopping mall are first pre-processed. Since the raw dataset is messy and contains outliers and missing values, we first Extract, transform, and load (ETL) the data so as to obtain a complete and correctly sorted dataset. In terms of the external dataset, we collect the daily weather conditions corresponding to the daily sales of the shopping mall, and after counting the days of different weather conditions, we have the historical weather dataset. Finally, after indexing and saving the time, location and internal data, we attain the complete input data for the LSTM model, and the structure of their features are shown in Table 1.

Table 1: Structure of the features of input data

Symbol	Meaning	Measurement
X_1	Sales hours	Daily sales hours
X_2	Weekend	Dummy: no: 0, yes: 1
X_3	Weekday	Dummy: no: 0, yes: 1
X_4	Sunny	Dummy: no: 0, yes: 1
X_5	Cloudy	Dummy: no: 0, yes: 1
X_6	Rainy	Dummy: no: 0, yes: 1
X_7	Snowy	Dummy: no: 0, yes: 1

X_8	Overall rating	Rating scale: 1-5 (1 for the lowest rating, 5 for the highest rating)
X_9	Environment rating	Rating scale: 1-5 (1 for the lowest rating, 5 for the highest rating)
X_{10}	Food rating	Rating scale: 1-5 (1 for the lowest rating, 5 for the highest rating)
X_{11}	Service rating	Rating scale: 1-5 (1 for the lowest rating, 5 for the highest rating)
X_{12}	Location	Rating scale: 1-5 (1 for the lowest rating, 5 for the highest rating)
X_{13}	Attitude in customer service	Sentiment intensity: 1-3 (1 for negative, 2 for neutral, 3 for positive)
X_{14}	Store environment	Sentiment intensity: 1-3 (1 for negative, 2 for neutral, 3 for positive)
X_{15}	Price level	Sentiment intensity: 1-3 (1 for negative, 2 for neutral, 3 for positive)
X_{16}	Taste	Sentiment intensity: 1-3 (1 for negative, 2 for neutral, 3 for positive)
X_{17}	Overall evaluation	Sentiment intensity: 1-3 (1 for negative, 2 for neutral, 3 for positive)
X_{18}	Customer flow	Sentiment intensity: 1-3 (1 for negative, 2 for neutral, 3 for positive)
X_{19}	Service rating	Sentiment intensity: 1-3 (1 for negative, 2 for neutral, 3 for positive)
X_{20}	Sales volume	Daily sales, by yuan

Methodology

BERT

Sentiment Analysis (SA), also known as opinion mining and viewpoint mining, is the use of information extraction, text mining, machine learning, natural language processing, and other text processing technologies to analyze, process and summarize subjective texts. It involves text classification, viewpoint analysis, tendency analysis, and many other methods, and is used to analyze people's opinions, feelings, evaluations, attitudes, and emotions regarding entities and their attributes. The sentiment analysis that uses Word2Vec ignores the context of words when calculating their similarity, while the BERT model displays outstanding accuracy when conducting sentiment analysis of the reviews. Therefore, currently, BERT is often used for classification in sentiment analysis.

The BERT model first obtains the word vectors containing the context and semantics information by pre-training, and introduces the Attention mechanism to extract text information, assign weights, and highlight the key information for text sentiment classification. The ternary sentiment classification of the reviews includes negative, neutral, and positive. The processes of sentiment analysis with the BERT model include:
1) Loading the pre-trained BERT model;
2) Input of features to the BERT model.

Attention-LSTM

We input the historical time series data (X_1 , X_2 , … , X_n) to learn the features, and fit the highest daily sales on day n+k. Figure 2 shows the overall structure of the AM-LSTM model for sales prediction, including four parts: data pre-processing, the LSTM layer, the Attention layer, and the fully connected layer.
1) Data pre-processing, i.e., all input data are processed into the structure as shown in Table I, and normalized;
2) The LSTM layer uses the deep features of the input time series data after pre-processing, to learn the long-term dependencies of the time series data;
3) The Attention layer first encodes the data through the Encoder, then calculates the corresponding weights for the encoded vectors by Attention. The calculated weights are used to weight the encoded vectors and as the input to the Decoder, and finally gets the output through the Decoder;
4) The fully connected layer calculates the input to this layer and gets the sales forecast result. The predicted sales are subtracted from the real sales to return the loss function, and the weights and forecast result are continuously modified by backpropagation of the loss function.

Framework of Sales Forecasting of Stores in the Shopping Mall based on External Data and Transaction Data

Figure 2 illustrates the framework of sales forecasting of stores in the shopping mall based on external data and transaction data. The framework includes processing of sentiment intensity of reviews, input data processing, the LSTM model, the Attention layer, and specific applications of the fully connected layer, and finally obtains sales forecasts.

1) Crawl the review data of physical stores from online, and load the review contents to the pre-trained BERT model, and input the BERT model features;
2) Crawl the rating scores of physical stores from online, pre-process the data on weather, weekday/weekend, store sales, and the already processed sentiment intensity of reviews, meanwhile fill in the missing values and conduct other necessary operations. All the final features are shown in Table 1;
3) Input the historical time series data (X_1 , X_2 , … , X_n) into the LSTM model to learn the features. Through the training in the LSTM layer, the long-term relationship of time series data can be learned more fully;
4) The output of the LSTM layer is used as the input to the Attention layer, which is first encoded by the Encoder, and the corresponding weights of the encoded vectors are calculated by Attention. The calculated weights are then used to weight the encoded vectors, which will be the input to the Decoder, and finally the output is obtained by the Decoder. Through continuous learning, the corresponding weights are optimized, the key information in the input features is highlighted, the nonlinear characteristics between variables are further explored in depth. The higher the score, the higher the attention, and the Attention mechanism will assign more weight to it;
5) The output of the Attention layer is used as the input to the fully connected layer. The fully connected layer calculates the input to obtain the sales forecast result. The predicted sales are subtracted from the real sales to return the loss function, and the weights and prediction results are continuously modified by backpropagation of the loss function.

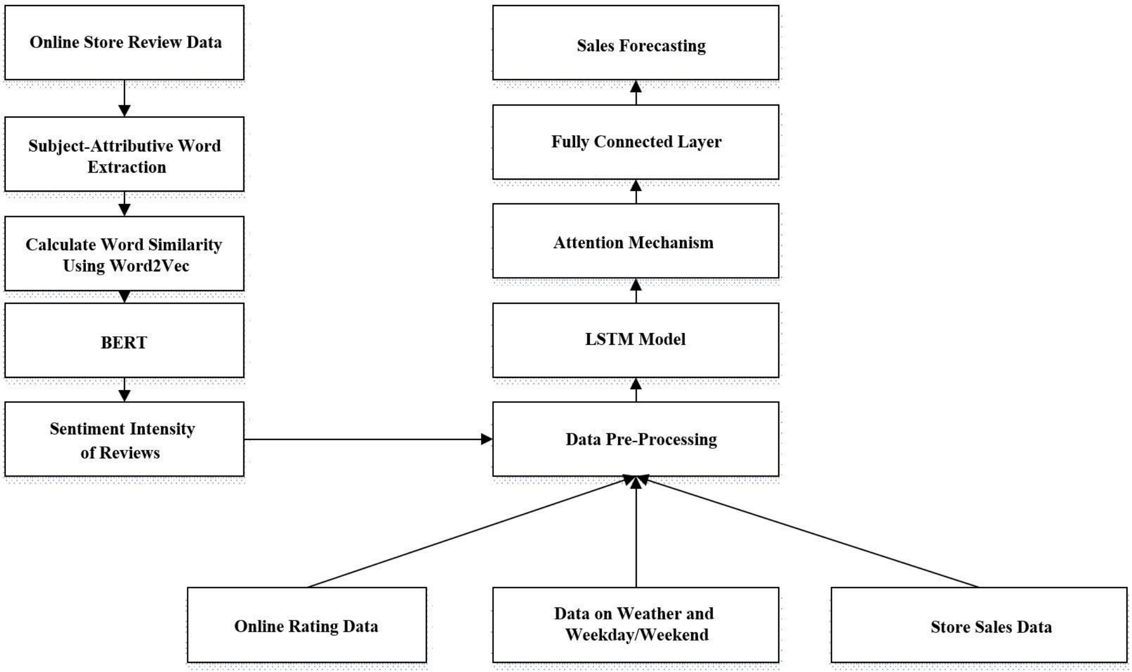


Figure 2: Framework of Sales Forecasting of Stores in the Shopping Mall based on External Data and Transaction Data

EXPERIENTS AND RESULTS

Performance Metrics

This paper uses the Root Mean Square Error (RMSE), as in equation (12), and the Mean Absolute Percentage Error (MAPE), as in equation (13), which are commonly used in time series forecasting, as the metrics for the model. They are used to measure the difference between the predicted value and the actual value. The lower the RMSE and MAPE, the closer the predicted value is to the actual value, and the better the model is. RMSE and MAPE are calculated as:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t' - y_t)^2} \quad (12)$$

$$MAPE = \frac{100\%}{T}\sum_{t=1}^{T}\left|\frac{y_t' - y_t}{y_t}\right| \quad (13)$$

Where y_t' represents the predicted value on day t, and y_t represents the actual value on day t.

Case Verification

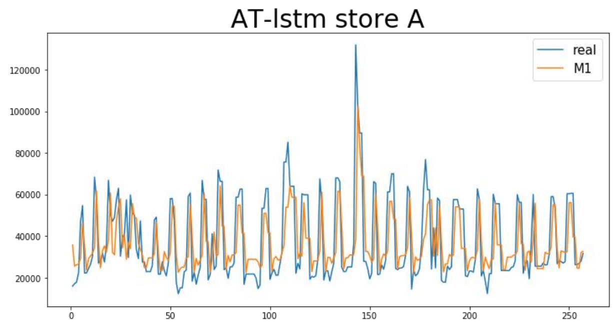
To verify that the addition of each metric improves the forecast accuracy of the model, this paper constructs four models for comparative analysis: (1) Model 1 (M1) that only has sales hours and weekday/weekend as metrics; (2) Model 2 (M2) with sales hours, weekday/weekend and weather; (3) Model 3 (M3) with sales hours, weekday/weekend, weather and ratings; and (4)

Model 4 with sales hours, weekday/weekend, weather, ratings and perceived sentiment of reviews. The forecasting results for the 2 brick-and-mortar stores are shown in Table 2. Compared with M1 that only considers the historical weekday/weekend sales, the MAPE and RMSE for the 2 stores' sales forecasts are significantly lower in M2 with the addition of the weather variable. Similarly, compared to M1, M3 with the addition of the online ratings variable demonstrates improved forecast accuracy. The forecast accuracy of M4 is further enhanced with the addition of online ratings and perceived sentiment of reviews. Also, compared with M1, the MAPE of Store A, which has the best forecast result, decreases from 32% to 23%, and the RMSE decreases from 15305.9 to 13019.5. The MAPE of Store B also declines by about 8% and RMSE by about 2,000.

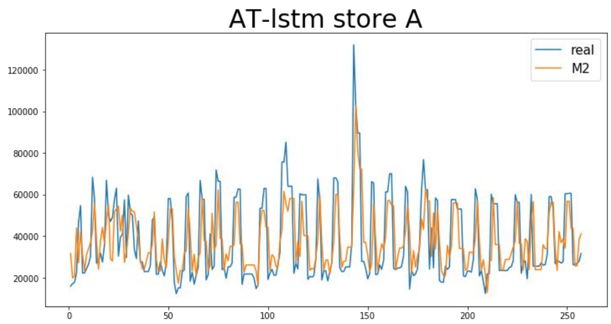
Table 2: Model evaluation results of Store A and Store B

Model	Metrics	Store A		Store B	
		MAPE	RMSE	MAPE	RMSE
M1	Sales hours and weekday/weekend	32	15305.9	42	15083.4
M2	Sales hours, weekday/weekend and weather	28	14497.5	39	14629.1
M3	Sales hours, weekday/weekend, weather and ratings	27	14265.3	37	13937.9
M4	Sales hours, weekday/weekend, weather, ratings and perceived sentiment of reviews	23	13019.5	34	13038.2

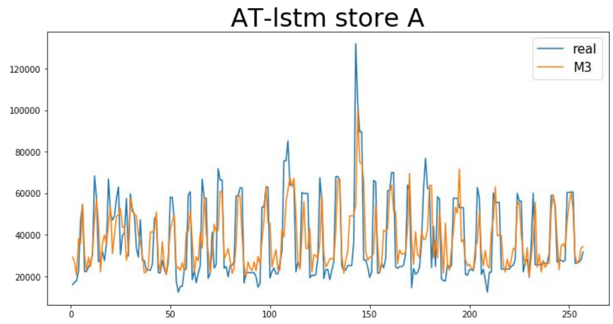
Figure 3: Comparison of the model evaluation results



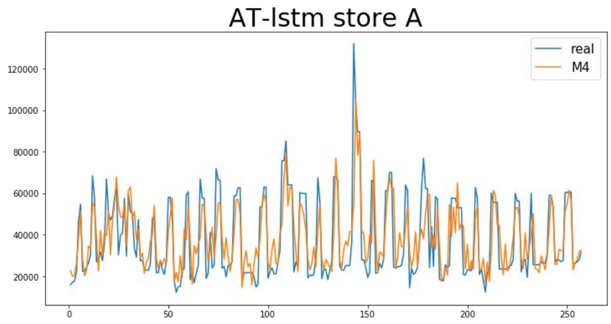
(a) Store A M1



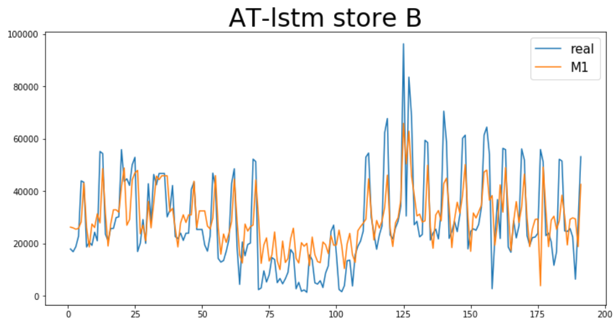
(b) Store A M2



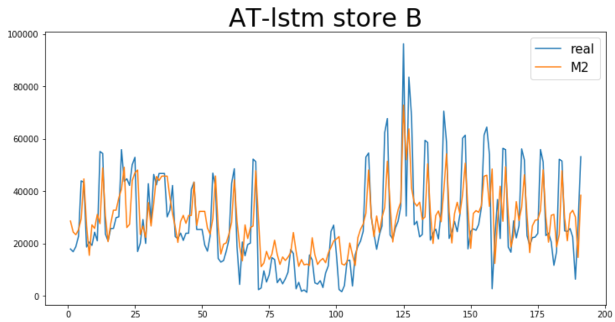
(c) Store A M3



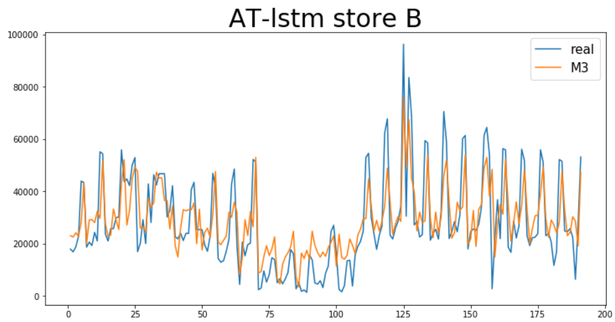
(d) Store A M4



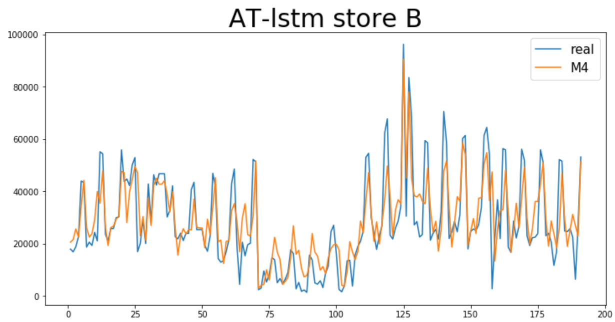
(a) Store B M1



(b) Store B M2



(c) Store B M3



(d) Store B M4

With the above results, we find that simultaneously using multi-dimensional inputs, such as sales hours, weekday/weekend, weather, online ratings and perceived sentiment of reviews, can substantially improve the accuracy of sales forecasting of bricks-and-mortar stores. The reason is that the integration of the consumers' perspective can reflect the overall store sales more accurately. The features of the consumers' reviews often contain the attendant's attitude, the overall environment of the store, and the customer flow on that day, all of which can improve the accuracy of the forecast. Store managers can also take these perspectives to improve the store's service and environment to enhance competitiveness and increase customer stickiness.

CONCLUSION

In the post-pandemic era where online shopping is surging, bricks-and-mortar stores in shopping malls seem to be lacking momentum. For these offline stores, it is of far-reaching significance to improve sales forecasting accuracy from multiple perspectives, thereby enhancing operational efficiency, increasing revenue and competitiveness. In this paper, we consider multiple data such as weather, weekday/weekend, online ratings and reviews and sentiment intensity to improve sales forecasting accuracy for physical stores. For stores, the improved sales forecasts can help them develop reasonable business strategies and purchasing arrangements, improve operational efficiency while avoiding the risk of overstocking, optimize services and increase profits. For consumers, online reviews can help them form a more comprehensive understanding of the products and make better-informed purchasing decisions, meanwhile, the improved customer service can bring them better in-store shopping experience. For online platforms, the findings can facilitate the use of the platform and contribute to a better platform experience. Specifically, this study has the following theoretical and managerial implications

Theoretical Implications

Unlike existing sales forecasting studies that focus on the impact of online reviews on online store sales (Eslami et al., 2018), this paper integrates the impact of weather, weekday/weekend, online ratings and reviews on bricks-and-mortar stores, which provides new insights into the sales forecasting of stores. The methodological innovation of this paper is that it considers multiple data — online and offline, such as online reviews and offline sales, and internal and external, such as historical transactions and weather — when trying to improve the accuracy of the sales forecasts. In addition, by mining text reviews with the BERT model, the reviewer's (consumer's) sentiment towards products is extracted, and the impact of reviews on sales is examined. The innovative evaluation of the role of different review information in increasing sales will be useful for targeted marketing campaigns, user-centered product design, and effective customer service in the future. What's more, this paper uses the Attention mechanism and LSTM model (Hochreiter & Schmidhuber, 1997) based algorithms to deep learn the features of the data from the stores in a certain shopping mall, optimizes and configures the model parameters, and conducts simulation experiments with the models. The simulation results show that the predicted sales of the stores using the deep learning Attention mechanism and LSTM only have very small errors, indicating that the model can be used to predict the sales of the shopping mall stores. And it presents a strong validation and solution idea for subsequent theoretical research on multi-perspective shop sales forecasting.

Managerial Implications

Since both the weather and weekday/weekend differences have an impact on sales, stores should be circumspect when making business plans, and maintain a good indoor environment to attract potential customers even during adverse weather. When the weather is good, and customer flow increases on weekends, stores should try to maintain a good attitude in service and improve efficiency to reduce customer waiting time and provide courteous and attentive service. When the research framework and forecasting project goes live it will solve the problem of high cost of goods inventory that exists in the business, the overall number of days of goods turnover in shops will drop, and the cost of warehouse and space will be greatly reduced

From the perspective of online reviews and rating data, both variables have a significant positive impact on customers' purchase decisions. Potential customers consider the overall rating score of a store and the textual information of the reviews to decide they want to choose that store for their purchases. Therefore, merchants and brand owners should continue to optimize the quality of their products and services, including improving the service provided by attendants. They should also pay attention to online reviews and make improvements to address the issues and complaints raised by customers. Further, the stores can encourage customers to give real and objective comments on the food, services, environment, pricing, for the stores to improve management. Finally, to adapt to the needs of consumers of various income classes, the stores may consider lowering the price or increasing the portion size as appropriate to provide cost-effective products.

Limitations

Since only two stores are selected for sales forecasting in this paper, the data are insufficient compared to the massive amounts of data nationwide. Follow-up research can consider increasing the sales data of bricks-and-mortar stores for forecasting experiments. In addition, the stores data in the current study are all from the restaurant industry, which is limited for comparative studies. Future research can consider adding other types of physical stores, such as clothing and outdoor gears stores, and changing the corresponding evaluation metrics in the reviews data BERT pre-training, it is possible to extend the research framework to other categories in other offline retail sectors.to enrich the research landscape of sales forecasting of stores in shopping malls.

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