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Food Enterprises' Profit Growth Rate Prediction Based on LSTM from the Perspective of the Supply Chain

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Abstract. Food is the fundamental guarantee of people's lives, and the food industry has always occupied an essential position in the national economy. Profit growth rate, as a measure of an enterprise's development ability, can intuitively reflect the change in operating profit for food enterprises. The accurate prediction of profit growth rate can provide a decision-making reference for enterprises in planning business objectives in the next stage. However, many factors affect the profit variation of a company, and it is hard to make accurate predictions using traditional statistical economics forecasting methods. Since the Long-Short Term Memory (LSTM) model can capture nonlinear relationships in time series analysis, we propose an LSTM-based model to predict the profit growth rate of enterprises by using the operational data of four seasons ahead. Moreover, due to the COVID-19 pandemic, the impact of supply chain integrity on enterprise operations is increasing. We introduce the information of the supply chain owned by the enterprise to predict the profit growth rate of the enterprise. The result of our model exhibits high prediction accuracy, which indicates that our model could provide practical guidance for companies' production and operation activities.

Keywords. Profit growth rate; LSTM model; Food supply chain

1. Introduction

The profit growth rate is crucial in providing a decision-making reference for enterprises in planning business objectives in the next stage. The prediction of profit growth rate can assess the company's operating results for the planning period. Accurate forecasting of profit growth rate can provide adequate guidance for the production and operation activities of the company and maximize the output of the company's inputs in the next phase.

Normally, the prediction of profit growth rate can be achieved by modeling previous enterprise operation information as time series and then capturing the pattern of profit growth rate. However, the profit growth rate is affected by many factors, and accurate forecasting is challenging. Traditional methods usually use linear modeling to obtain the characteristics of time series, such as the Auto-Regressive and Moving Average (ARMA) model and multiple linear regression forecasting[1]. Artificial neural networks'

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nonlinear information processing ability makes it successfully applied in the field of prediction, where the nonlinear relationship is a common characteristic in many prediction issues. The Long-Short Term Memory (LSTM) model is an artificial neural network capable of processing and predicting events with relatively long intervals and delays in time series. LSTM model also has the advantage that traditional methods cannot compare in dealing with incomplete or irregular data.

Therefore, in this paper, we propose an LSTM-based model to predict the profit growth rate of 41 food enterprises by using the operational data of four seasons ahead. Moreover, considering that the COVID-19 epidemic has a significant impact on the food supply chain and affects enterprises' profits, we introduce the factor of the supply chain into the prediction of profit growth rate. The 41 food enterprises are classified according to the integrity of the supply chain they own, and the classification information is employed in the LSTM model, which could enhance the learning of the profit growth rate pattern. The experiment results show that the LSTM prediction model exhibits high accuracy in predicting the profit growth rate, which indicates that the model can provide a decision-making basis for the operation of food enterprises.

2. Methodology

2.1. Dataset and Index

The data required for this study were collected from China Stock Market & Accounting Research Database (CSMAR). CSMAR database is a research-based database in the economic and financial fields, containing listed companies' financial data.

Table 1. Financial Index

Primary Index	Secondary Index
Income	Operating income Operating profit Net profit Cash received from sales of goods or rending of services Other cash received relating to operating activities Net cash flows from operating activities Net amount of other receivables Retained earnings
Costs	Total operating costs Business taxes and surcharges Selling expenses Financial expenses Cash paid for goods and services Taxes paid
Administration	General and administrative expenses Cash paid to and on behalf of employees Other cash paid relating to operating activities Cash paid to acquire fixed assets, intangible assets and other long-term assets Net cash flows from investing activities Cash Net value of fixed assets Other payables Total liabilities Total shareholder's equity

The financial data of listed food enterprises is served quarterly, mainly from March 2016 to March 2021. We choose 24 secondary indexes from the financial dataset, which can be classified into three dimensions, income, costs, and administration. The income dimension contains 8 secondary indexes: operating income, operating profit, net profit, etc. The costs dimension contains 6 secondary indexes: total operating costs, financial expenses, taxes paid, etc. The administration dimension contains 10 secondary indexes: general and administrative expenses, net value of fixed assets, total liabilities, etc. The index framework shows in table 1.

We construct these data into a time series, where each sample is combined with four-time steps and one output. We calculate the profit growth rate of each sample in the fifth quarter to get y and normalize it. The calculation formula of profit growth rate is constructed as follows:

$$R = (V_{n+1} - V_n)/|V_n| \times 100\% \quad (1)$$

Where R denotes the profit growth rate, V denotes the operating profit, and n+1 means the data belongs to the fifth quarter.

2.2. *Food Enterprises Classification based on Supply Chain Perspective*

From the food supply chain perspective, some large food enterprises are running under the whole industry chain mode, which integrates production, supply and marketing. This mode is usually more stable because it contains every link from planting and procurement, breeding and slaughtering, food raw materials and processing, distribution and logistics, and brand promotion to food sales. The other food enterprise mode only owns the production and processing supply chain. These enterprises are mainly responsible for raw material procurement and processing of food products, supplying or distributing to some large companies that lack direct distribution channels to consumers. We select 41 listed food enterprises in this paper, of which 9 are production and processing type, and 32 are the integration of production, supply and marketing type. The selected enterprises are shown in table 2

Table 2. Classification of food enterprises

Division Basis	Type	Food Enterprises
Type of supply chain	Production and processing	New Hope Liuhe, Tech-Bank Food, Fujian Sunner Development, Shandong Delisi Food, Jinzi Ham, Cheng De Lolo, Chenguang Biotech Group, Shandong Homey Aquatic Development, Shanghai Kaichuang Marine International
	Integration of production, supply and marketing	Jiangsu Provincial Agricultural Reclamation And Development, Henan Shuanghui Investment & Development, Shandong Xiantan, Inner Mongolia Yili Industrial Group, Beijing Yanjing Brewery, Wuliangye Yibin, China Quanjude(Group), Sanquan Food, Maiquer Group, Lanzhou Zhuangyuan Pasture, Yanker Shop Food, Anji Food Group, Qianhe Condiment And Food, Jiangsu Hengshun Vinegar-industry, Jiangxi Huangshanghuang Group Food, Royal Group, Guangdong Yantang Dairy, Foshan Haitian Flavouring and Food Company, Beingmate, Shanghai Maling Aquarius, Shandong Huifa Foodstuff, Shandong Longda Meishi, Nanfang Black Sesame Group, Lontrue, Chongqing Fuling Zhacai Group, Cofco Sugar Holding, Nanning Sugar Industry, Yantai Shuangta Food, Hai Nan Yedao (Group), Shanghai Bairun Investment Holding Group, Joyvio Food, Guangdong Jialong Food

2.3. LSTM Model

LSTM introduces internal LSTM cellular loops, i.e., self-loops, in recurrent networks, with gates controlling their weights, enabling it to learn and remember long-term dependencies[2]. The LSTM model consists of a chain of repetitive memory units. Each unit contains three gates: input gate, forget gate, and output gate(figure 1). With these three gates, the LSTM network can remove or add information to the cell state and control the effect of transferring unit states, which helps the LSTM keep track of information over time.[3]

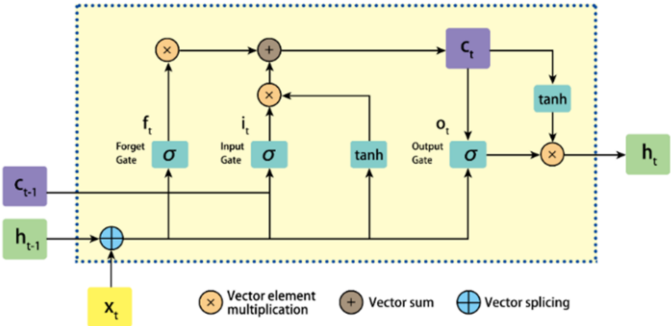

Figure 1. A memory unit of LSTM

The gates operate according to the current input and the previous hidden state. In the unit of the t^th word of the input sequence, for any representation vector w_t, the representing state of each gate and the hidden state is calculated using the following composite functions. Where the activation function σ denotes the logistic sigmoid function, c refers to the cell, and tanh stands for the hyperbolic tangent function:

The f_t denotes the forget gate:

$$f_t = \sigma(\lambda_{xf}x_t + \lambda_{hf}h_{t-1} + \lambda_{cf}c_{t-1} + b_f) \tag{2}$$

The i_t denotes the input gate:

$$i_t = \sigma(\lambda_{xi}x_t + \lambda_{hi}h_{t-1} + \lambda_{ci}c_{t-1} + b_i) \tag{3}$$

$$\widetilde{c_t} = tanh\ (\lambda_{xc}x_t + \lambda_{hc}h_{t-1} + b_c) \tag{4}$$

$$c_t = i_t * \widetilde{c_t} + f_t * c_{t-1} \tag{5}$$

The o_t denotes the output gate:

$$o_t = \sigma(\lambda_{xo}x_t + \lambda_{ho}h_{t-1} + \lambda_{co}c_t + b_o) \tag{6}$$

The h_t denotes the hidden layer state at time t:

$$h_t = o_t\, tanh(c_t) \tag{7}$$

In the above functions, the $\widetilde{c_t}$ denotes the state of the candidate memory unit in the current time step, and c_t stands for the state value in the memory cell at the current time. The meaning of the subscripts in the weight matrix is as the name suggests.

The model uses only the 'above' information in a one-way recurrent neural network. The Bi-LSTM combines the information of the input sequence in both forward and backward directions based on the LSTM. [4]We calculate the output of the backward and the hidden unit at time t as follows:

$$\vec{h}_t = H(x_t, \vec{h}_{t-1}, c_{t-1}) \tag{8}$$

$$\overleftarrow{h}_t = H(x_t, \overleftarrow{h}_{t+1}, c_{t+1}) \tag{9}$$

Where H denotes the hidden layer operation, $\overrightarrow{h_t}$ denotes the output of the forward hidden unit, $\overleftarrow{h_t}$ denotes the output of the backward hidden unit, and the link between $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ is to obtain the feature expression.

2.4. Model Construction

We apply an LSTM model with 4 layers of Bi-LSTM , and each one contains 32 units and a ReLU activation function. Each input contains a 4-time step. Add 2 fully connected layers after the Bi-LSTM layers. One fully connected layer with 32 neurons and one with 16 neurons. The model structure is shown in figure 2. The fully connected layer can convert the output of LSTM into the prediction. We can calculate the loss by comparing the prediction with actual data.

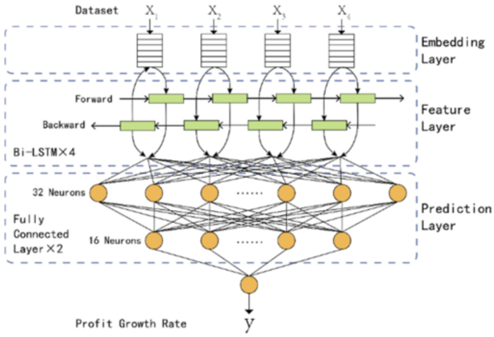

Figure 2. Model construction

3. Training Process

We collect 192 samples in total for this experiment. Each data sample includes the enterprise's financial data for four quarters; each input contains a 4-time step. Each time step has 24 financial indexes and one enterprise-type index, so each step has 25 attributes. We use the 4-fold cross-validation method to perform the dataset's training, which divides the dataset into four parts on average. For each training, 3 part is treated as training data and 1 part is treated as testing data. There are 4 training in total, and each one uses a different training dataset and testing data. The input shape is (4,25), and then the model is trained. The specific training parameters are listed in table 3.

Table 3. Training hyperparameters setting

Model	Construction and output shape	Training Hyperparameters
Bi-LSTM	Input Bi-LSTM layer × 4 Fully connected layer×2 RELU	Batch size 6, 8,12 Learning rate 0.01,0. 001, 0.0001 Epochs 500, 800, 1000 Loss function: Mean Absolute Error Update strategy: Adam

*The BOLD labels indicate the final chosen parameters.

4. Results

The result of 4-fold absolute error and relative error shows in Table 4. It shows that the average absolute error in the 4-fold training set is 0.065 and 0.130 in the 4-fold test set. We can see that the difference between the predicted and actual value is very small, as the model's output is the profit growth rate. It indicates that the LSTM prediction model achieves high accuracy in predicting profit growth rate.

Table 4. LSTM training and test error

Fold Number	Training error		Test error	
	Absolute error	Relative error	Absolute error	Relative error
1-fold	0.059	9.62%	0.173	14.56%
2-fold	0.078	6.50%	0.117	13.21%
3-fold	0.053	8.79%	0.138	10.99%
4-fold	0.067	6.16%	0.091	10.67%
Average	0.065	7.77%	0.130	12.36%

The change of the loss value as the epoch increases during the training process shows in figure3. We can find that the loss value of the training set and test set both decreases during the training process in figure3. Finally, it stabilizes around 0.06 and 0.13, respectively. It indicates that the training of this study is effective.

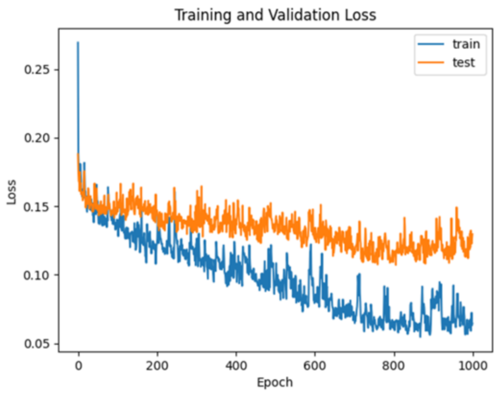

Figure 3. Variation of loss value

5. Conclusion

This paper uses enterprises' operation data to predict the profit growth rate, and introduces the Bi-LSTM model to train the financial data of listed food enterprises. Considering the type of supply chain owned by enterprises under the background of the COVID-19 pandemic, we divide enterprises into production and processing type and integration of production, supply and marketing type. We select 41 food enterprises and collect 192 samples including 25 features for this study. A prediction model of profit growth rate integrating various factors is obtained. The result of our study indicates that the Bi-LSTM model performs better than the traditional prediction methods and enhances the guiding role for enterprise management.

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