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Research on Sales Forecast of Fresh Produce Considering Weather Factors

(Full Paper)

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ABSTRACT

In order to ensure the freshness of agricultural products and reduce the cost of loss due to product decay, weather factors such as weather conditions, wind level and air quality index are incorporated into the fresh agricultural product sales forecasting model. Then, based on the historical sales data of agricultural products, three machine learning methods of Ridge Regression, Random Forest and Support Vector Machine are used to perform regression prediction. The prediction results show that the fresh agricultural product sales forecasting model considering weather factors can significantly improve the prediction accuracy. The relative reduction rate of the Root Mean Square Error achieved by the three algorithms is 68.90%, 23.66% and 59.52%. And relative reduction rate of the Mean Absolute Percentage Error is 66.2%, 34.99% and 61.13%, respectively.

Keywords: sales forecast, weather factors, machine learning algorithm, fresh produce.

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INTRODUCTION

Fresh agricultural products mainly refer to vegetables, fruits, eggs, aquatic products, meat, dairy products and other necessities. Due to the large population, the production and consumption of fresh agricultural products in China is very large. According to the National Bureau of Statistics (China), the output of fresh agricultural products in China has ranked first in the world for many years. In 2016, the total retail sales of fresh products in China were 324 million tons, and the total retail sales was 4.57 trillion yuan, a year-on-year increase of 9.30%. In 2016, the total retail sales of consumer goods in China amounted to 3.323 billion yuan, and the proportion of fresh retail sales was as high as 13.8%. Besides, the proportion of offline fresh supermarkets has steadily increased in fresh agricultural products retail channels, which makes offline purchase as the main channel for consumers.

However, different from other products, the fresh is perishable and deteriorated, which make it more time-sensitive. In order to ensure the freshness of the products sold in supermarkets, it is required to keep the quantity of purchases and sales as equal as possible. Demand underestimation or overestimation negatively affects the revenues of the retailer. Stock-outs have an undesired impact on consumers while unsold items need to be discarded at the end of the day. Therefore, how to forecast the future sales accurately and quickly has become a key issue in the whole supply chain of fresh agricultural products. In practice, accurate sales forecast results can provide decision support for suppliers in scheduling material, as well as reduce cost due to deteriorated goods. In theory, how to incorporate various proper and significant factors into the fresh agricultural product sales forecasting framework? How to apply advanced and solid model to verify the value of the factors? Our research tries to make some explorations about expanding the application area of feature engineering and machine learning.

At present, scholars at home and aboard have made meaningful explorations on sales forecasts, but most of them focus on the fields of clothing (e.g., Huang *et al.* 2017, Thomassey 2010, Cui *et al.* 2015), cosmetics (e.g., Vahdani *et al.* 2016, Chern *et al.* 2009, Kim *et al.* 2018), electronic products (e.g., Chen and Lu 2017, Lu 2014), vehicles (e.g., Fantazzini 2015) and others, the sales forecast in fresh produce field was less studied. Huber *et al.* (2017) applied multivariate ARIMA models to predict the daily demand for perishable goods. In order to forecast the sales of dairy products, Doganis *et al.* (2006) presented a nonlinear time series sales forecasting model which is a combination of the radial basis function (RBF) neural network architecture and genetic algorithm (GA). Chen *et al.* (2010) proposed the "ordinary day and holiday moving average method" and "back-propagation neural network" to predict the sales of fresh food. Dellino *et al.* (2017) provided a decision support system (DSS) for the supply chain of packaged fresh and highly perishable products. The DSS used ARIMA model and ARIMA-X model that take the price factors of sales forecast into account. In summary, most scholars focused on algorithm integration or method innovation for better forecast accuracy, but fewer pay enough attention to the factors affecting the sales of fresh products.

As an important factor affecting consumers' shopping plans, the weather is bound to have an important impact on the sales of fresh produce, especially offline fresh supermarkets. To our knowledge limited, researches about the effect of weather on production and operations management is relatively scarce. Belasco *et al.* (2015) examined the economic losses to cattle feeding associated with extreme weather. Albers *et al.* (2017) disentangled the relative impacts of inputs and weather on regional yield volatility, and proved that models with only weather variables deliver biased but reasonable approximations for climate impact research. Besides, Craig *et al.* (2018) analyzed the impact of climatic factors and weather conditions on outdoor tourism. Lee (2010) verified the economic value of weather forecasts for decision-making problems in the profit/loss situation.

Due to perishability and vulnerability of fresh agricultural products, it is of great practical significance to accurately predict the sales of such products. However, there is no rigorous evidence regarding the effect of incorporating weather factors within the foresting sales about agricultural fresh goods. This paper constructs two prediction models: baseline prediction model and weather prediction model. Among them, the features of the baseline prediction model are conventional factors that do not include weather factors while the weather prediction model adds weather factors in contrast with the baseline model. As for predictive model, we use three different types of machine learning algorithms, Ridge Regression (RR), Random Forest (RF) and Support Vector Machine (SVM), to perform regression prediction. The value of weather factors for fresh produce sales forecast is verified via different horizons by comparing the results of the predictions of the two models under three algorithms.

NOVEL DATA SOURCES

Sales Data

We select a 64-day sales data from a fresh supermarket in Hangzhou from May 9, 2016 to July 11, 2016 as experimental data, in which we use the sales data from May 9 to July 4 as a training set, and the 7-day data from July 5th to July 11th is used as a test set to verify the accuracy of the sales forecast results. We draw the daily sales data of the fresh produce of the supermarket into a line chart, as shown in Figure 1.

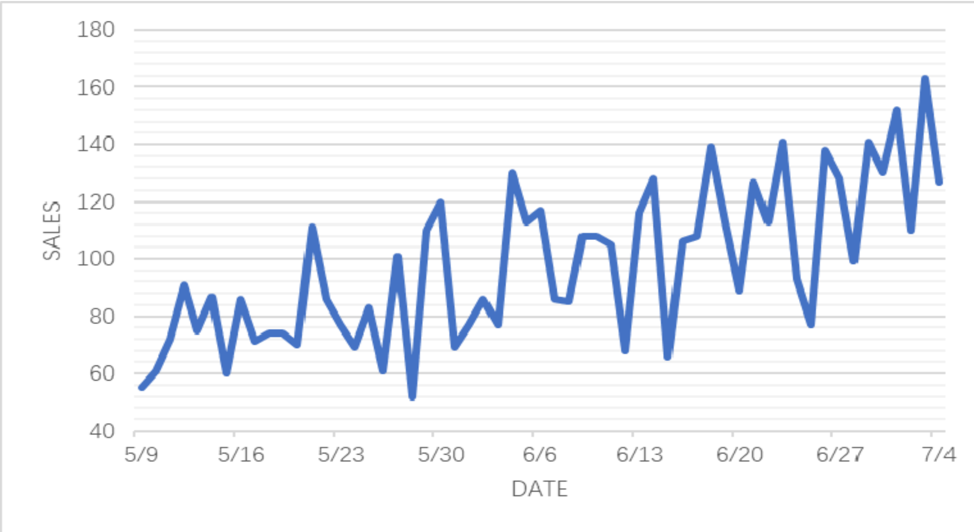

Figure 1: Daily Sales Data of the Fresh Supermarket

Weather Data

This paper selects three weather factors: weather conditions, wind level and air quality index (AQI). Daily weather conditions and wind level information can be obtained from the website: https://www.15tianqi.cn/, and air quality index information can be gained from the following website: https://www.aqistudy.cn/historydata/. All the weather data needed for this article is crawled by Python, and all data is true.

SALES FORECASTING FRAMEWORK AND MACHINE LEARNING ALGORITHMS

Sales Forecast Framework

To prove the value of weather factors in the sales forecast of fresh produce, we construct two prediction models: baseline prediction model and weather prediction model. Among them, the characteristic variables of the baseline prediction model are conventional factors, such as sales, workday or weekends and holidays, without weather factors. The weather prediction model is obtained by adding weather factors (weather conditions, wind level, air quality index) based on the baseline prediction model. Concentrated on historical sales data from fresh supermarkets, we use three different types of machine learning algorithms, Ridge Regression (RR), Random Forest (RF) and Support Vector Machine (SVM), to perform regression prediction for the two predictive models. The value of weather factors for fresh produce sales forecast is verified via different horizons by comparing the results of the predictions of the two models under three algorithms. Figure 2 shows the forecasting framework for fresh agricultural products sales.

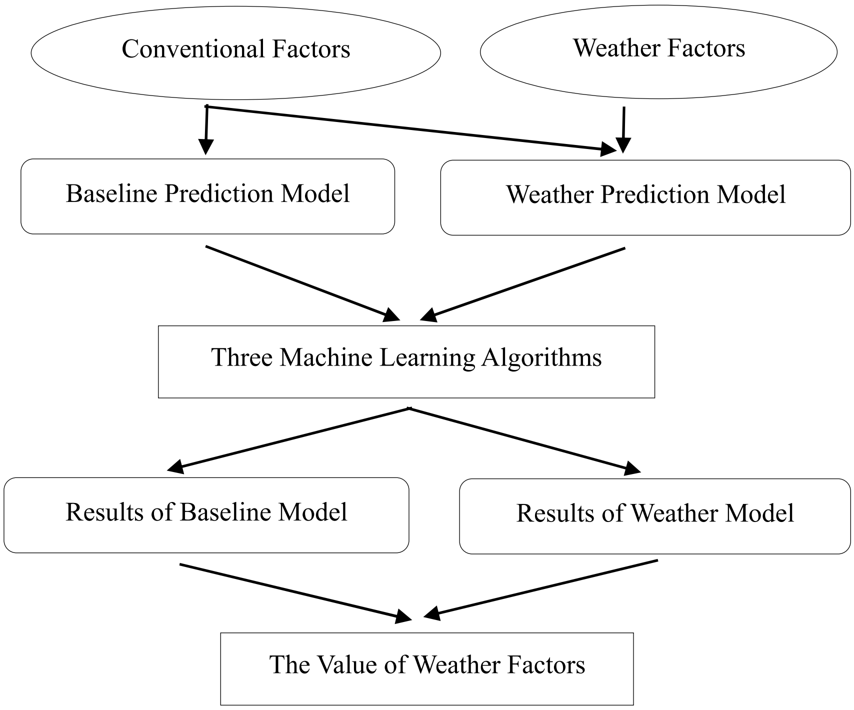

Figure 2: Forecasting Framework

Baseline Prediction Model:
In the baseline prediction model, we assume that the sales on day t is a function of sales in the past week (i.e., past seven days) and the characteristics associated with that t days.

$$S_t = F_1(S_{t-1}, S_{t-2}, S_{t-3}, S_{t-7}, W_t, W_{t-1}, H_t)$$

Where S_t is the output value (predicted value) indicating the sales on the t day. $F_1(S_{t-1}, S_{t-2}, S_{t-3}, S_{t-7}, W_t, W_{t-1}, H_t)$ represents the baseline prediction model function and related features.

The features are explained in Table 1:

Table 1: Features and Explanation of Baseline Prediction Model

Features	Explanation
S_{t-1}	Sales of day t-1(yesterday)
S_{t-2}	Sales of day t-2(the day before yesterday)
S_{t-3}	Sales of day t-3(big day before yesterday)
S_{t-7}	Sales of day t-7(last week)
W_t	A dummy variable equal to 1 if day t is weekend
W_{t-1}	A dummy variable equal to 1 if day t-1 is weekend
H_t	A dummy variable equal to 1 if day t is National statutory holiday

Weather Prediction Model：
In the weather prediction model, we assume that it has the similar structure as the baseline prediction model, the only difference being that the weather factors are added to the model. This facilitates comparisons to show the impact of weather factors on sales forecasts.

$$S_t = F_2(S_{t-1}, S_{t-2}, S_{t-3}, S_{t-7}, W_t, W_{t-1}, H_t, A_t, C_t, P_t)$$

Where $F_2(S_{t-1}, S_{t-2}, S_{t-3}, S_{t-7}, W_t, W_{t-1}, H_t, A_t, C_t, P_t)$ represents the weather prediction model function and related features. The unique factors of the weather forecasting model and the corresponding meanings are illustrated in Table 2. Other features and their meanings are the same as those of the baseline prediction model.

Table 2: Features and Explanation of Weather Prediction Model

Features	Explanation
A_t	Category of weather conditions in day t
C_t	Category of wind level in day t
P_t	Category of air quality index in day t

Machine Learning Model for Sales Forecast of Fresh Agricultural Products

In order to eliminate the influence of accidental random factors and to verify the value of weather factors on the sales forecast more reasonably and effectively, we select three different types of representative algorithms in a variety of machine learning algorithms to predict the sales of fresh produce. These three algorithms are Ridge Regression(RR) based on Linear Regression、Random Forest(RF) based on Tree Model、Support Vector Machines(SVM) based on the Kernel Method.

Ridge Regression

Ridge Regression is a biased estimation regression method dedicated to collinear data analysis. It is essentially an improved Least Squares Estimation Method. Ridge Regression gives up the unbiasedness of the Least Squares Method, and obtains a more realistic and reliable regression coefficient at the cost of losing part of the information and reducing the accuracy. When dealing with ill-conditioned data, the fitting effect of Ridge Regression is much stronger than the Least Squares Method.

Ridge Regression shrinks the coefficient by increasing the penalty of the regular term based on the squared error. The algorithm minimizes the expression as follows:

$$\mathrm{w}^{ridge} = \mathrm{argmin}_w \sum_{i=1}^{n} (y_i - w_0 - \sum_{j=1}^{p} w_j x_{ij})^2 + \alpha \sum_{j=1}^{p} w_j^{\,2} \tag{1}$$

As α increases, the variance of the model decreases and the deviation increases. By determining the value of α, a balance can be achieved between the variance and the deviation. Find the partial derivative for w and let the expression be zero to get the w value:

$$\mathrm{w}^{ridge} = (X^T X + \alpha I)^{-1} X^T Y \tag{2}$$

Random Forest

Random forest is built on regression trees. Regression trees use a tree-like structure to map observations of an item in order to reach conclusions about the item's target value. The random forest model first uses cross-validation to determine the best number of variables, m, to include in a tree. It then draws bootstrap subsamples from the training dataset and grows a regression tree on each of those bootstraps. This is done by bootstrapping variables at each split—randomly selecting m variables at each node and picking the best one as a split-point, which generates a diverse set of trees. In this way, we grow a vast number of trees and average those trees in order to yield a prediction. The biggest advantage of a Random Forest is that it produces highly accurate results, making it one of the most popular statistical learning methods in practice.

Support Vector Machines

Support vector machine is a classical machine learning method based on statistical learning theory which can handle classification and regression. Compared with other machine learning methods, SVM successfully solves the problems of high dimension and local minima. The basic idea of SVM is to design a linear classifier with maximal classification margin, while minimizing the training error. Maximizing the margin plays the role of capacity control so that the learning machine will not only have small empirical risk but also hold good generalization ability. The key to SVM is the kernel function. Low-dimensional space vector sets are often difficult to partition, and the solution is to map them to high-dimensional space. But the difficulty with this approach is the increase in computational complexity, and the kernel function solves this problem subtly. That is, by selecting the appropriate kernel function, the classification function of the high-dimensional space can be obtained. In SVM theory, using different kernel functions will result in different SVM algorithms.

THE VALUE OF WEATHER FACTORES IN THE SALES FOREACST OF FRESH AGRICULTURAL PRODUCTS

Parameter Estimation

In order to make the results of sales forecasting more accurate and compare the performance between the baseline forecasting model and the weather forecasting model, it is necessary to estimate the hyperparameters of the three different algorithms respectively.

To be more specific, we use the 10-fold cross-validation to choose the hyperparameters of our models. The original data set is divided into a training set and a test set, the training set is used for training the model, and the test set is used to verify the accuracy of the results. For the sake of making full use of the training set to select algorithm parameters, the training set is randomly partitioned into 10 equal-size subsets. Of the 10 subsets, a single subset is retained as the validation data for testing the model's performance and the remaining 9 subsets are used as training data. This process is repeated 10 times (the folds), with each of the 10 subsets used exactly once as the validation data. After averaging the performance of model in each of 10 subsets, we have a measure of the performance for each potential value of the hyperparameter. Finally, the value of the hyperparameter that gives the best performance is chosen. Once we set the best value for the hyperparameter, we use the entire training set to estimate the parameters of the model and the features we retain. The cross-validation is shown in Figure 3.

Comparison of Forecasting Results between Baseline Prediction Model and Weather Prediction Model

In this paper, two commonly used indicators, Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), are applied to measure the error between the predicted sales and actual sales of different models. The two error formulas are as follows.

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(\mathrm{real}_t - \mathrm{predicted}_t\right)^2} \tag{3}$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{\mathrm{real}_t - \mathrm{predicted}_t}{\mathrm{real}_t}\right| \times 100\% \tag{4}$$

In addition, the relative reduction rate of the Root Mean Square Error ($\Delta RMSE$) and the relative reduction rate of Mean Absolute Percentage Error ($\Delta MAPE$) are introduced in this paper to more significantly depict the accuracy of the weather prediction model compared to the baseline prediction model. Formulas are as follows.

$$\Delta RMSE = \frac{RMSE_{base} - RMSE_{wea}}{RMSE_{base}} \times 100\% \tag{5}$$

$$\Delta MAPE = \frac{MAPE_{base} - MAPE_{wea}}{MAPE_{base}} \times 100\% \tag{6}$$

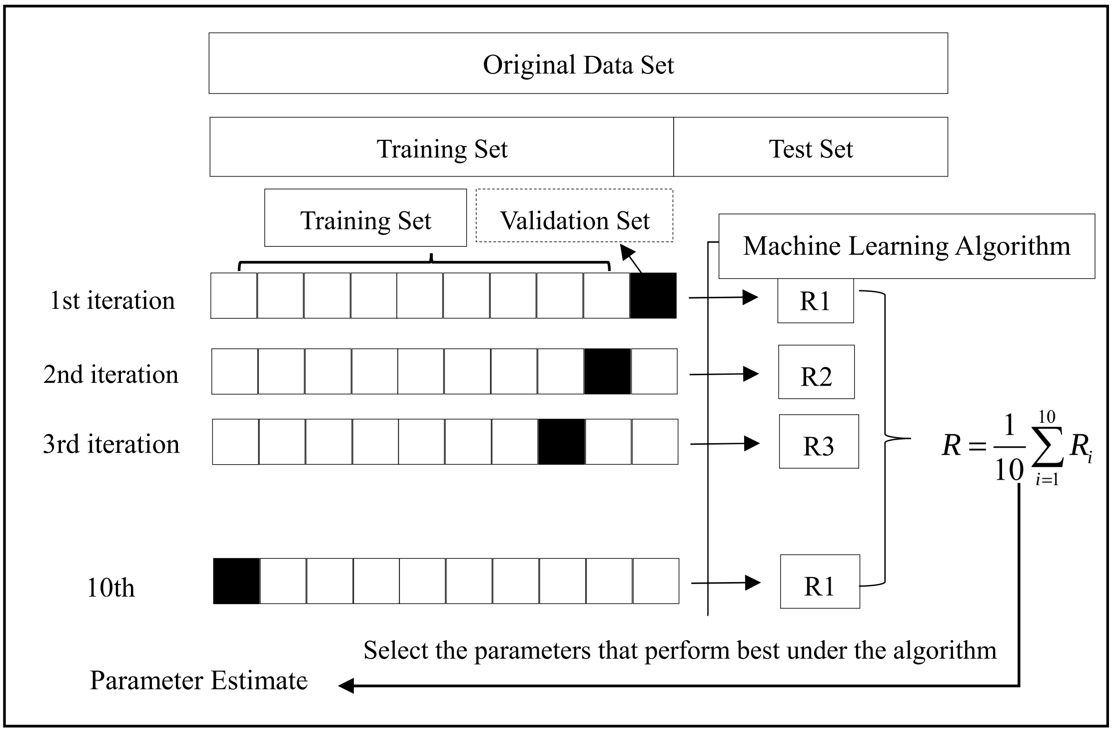

Figure 3: Select Parameters by Cross-validation

According to the historical sales data of a fresh supermarket, three kinds of machine learning methods are used to predict the sales via the baseline prediction model and the weather prediction model respectively. The error statistics between the forecasting sales and the actual sales are shown in Table 3 and Table 4.

Table 3 Comparison of RMSE between Baseline Model and Weather Model

	$RMSE_{baseline}$	$RMSE_{weather}$	ΔRMSE (%)
Ridge Regression	9.69	3.01	68.90
Random Forest	11.21	8.55	23.66
Support Vector Machines	13.75	5.56	59.52

Table 4 Comparison of MAPE between Baseline Model and Weather Model

	$MAPE_{baseline}$ (%)	$MAPE_{weather}$ (%)	ΔMAPE (%)
Ridge Regression	6.01	2.03	66.20
Random Forest	7.46	4.85	34.99
Support Vector Machines	9.33	3.63	61.13

As can be seen from Table 3 and Table 4, the RMSE and MAPE of the weather prediction model under the three algorithms have a significant reduction compared to the baseline prediction model. The relative reduction rate of the Root Mean Square Error achieved by the three algorithms is 68.90%, 23.66%, 59.52%, and relative reduction rate of the Mean Absolute Percentage Error is respectively 66.2%, 34.99%, 61.13%. The performance of the fresh agricultural product sales forecasting model considering weather factors is more prominent, which can greatly reduce the forecasting error. So, the value of weather factors in the sales forecast of fresh agricultural products is verified. Weather factors can greatly reduce the error in the forecast of sales of fresh agricultural products.

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