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The butterfly effect in the price of agricultural products: A multidimensional spatial-temporal association mining

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Abstract: With the advent of the era of big data, data mining methods show their powerful information mining ability in various fields, seeking the association information hidden in the data, which is convenient for people to make scientific decisions. This paper analyses the butterfly effect in the agricultural product industry chain from the perspective of producer and consumer by using multidimensional time and space theory and proposes a new price forecasting method. We consider that the price change of agricultural products is not only affected by the balance of market supply and demand but also by the factors of time and space. Taking the pig industry chain of Sichuan Province as an example, this paper explores and excavates the data from 2010 to 2020 in the time dimension. Interestingly, we found that the price changes in pork in the market are generally highly correlated with the prices of slaughtered pigs, piglets a few weeks ago and the prices of multiple feed a few months ago. Based on the precise time-space factors, we improved the price forecasting model, greatly improved the accuracy of price prediction, and proved the effectiveness of multidimensional spatiotemporal association mining. The research in this paper is helpful to establish a brand-new agricultural product price prediction theory, which is of great significance to the development of the agricultural economy and global poverty alleviation.

Keywords: agricultural economics; data mining; industrial chain; machine learning; price forecast

Price is an important element in market elements and a barometer of market information. It is the core index of market economy operation and an important lever of national macro-control. The price of agricultural products is not only related to the development of agriculture itself but also related to the change in the overall price level. Its stability is an important prerequisite to ensure social stability and people's normal life, as well as is crucial to the orderly development of economic society. Therefore, it is of great theoretical and practical significance to research the price prediction of agricultural products to promote the stability of agricultural production, increase farmers' income and guarantee the effective supply of agricultural products market.

The butterfly effect can be traced back to 1963. The widely spread interpretation is that a butterfly flapping its wings in Brazil can cause a tornado in Texas a month later (Lorenz 1963; Damle and Yalcin 2007).

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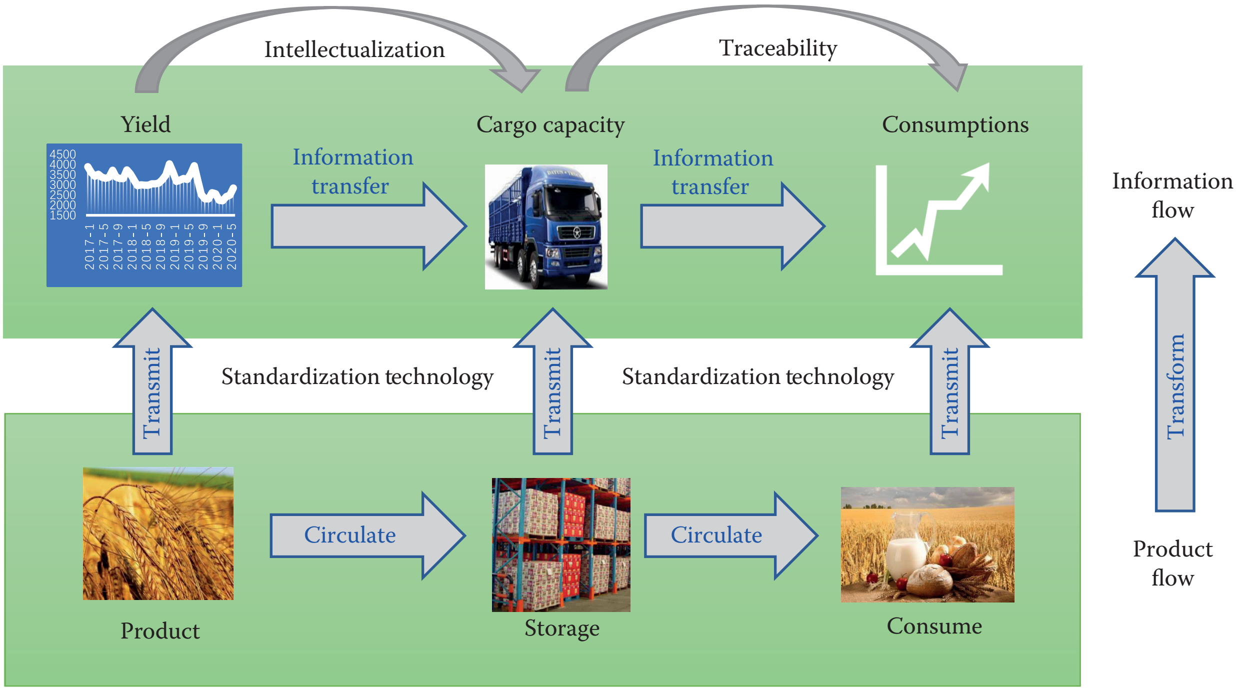

Figure 1. The complexity of the agricultural product industry chain brings challenges to price forecasting

Source: Authors' own processing

Is there a similar butterfly effect in the dynamic system of agricultural product prices? The answer is yes. Studies have shown that the information transmitted by the mass media may affect the amount of pork purchased by consumers (Ryu et al. 2020). And can the weak fluctuation of wheat bran price lead to the sharp fluctuation of pork price after six months? In previous studies (Živkov et al. 2019; Borawski et al. 2020), we found that the price of agricultural products is affected by many factors, such as raw materials, output, transportation, storage, weather, breeding cycle, market supply and demand, the price of substitute products, as shown in Figure 1.

In 2020, affected by the spread of disease, the price of agricultural products fluctuated greatly, causing widespread concern in the society (Abdallah et al. 2020; Wang et al. 2020). According to the data obtained from China's agricultural big data website (AGDATA 2020), the price of corn fluctuated from EUR 0.2527 per kg in January to EUR 0.3110 per kg in August. The price of fish meal fluctuated from EUR 1.1664 per kg in January to EUR 1.5552 per kg in March, and then to EUR 1.2312 per kg in September. Scientific prediction of agricultural product prices is conducive to the government to take timely measures to ensure the stable development of the economy and society. The research goal of this paper is to explore the butterfly effect in the price of agricultural products, that is, a variety of related factors that affect the future price changes, so as to improve the accuracy of the price forecast of agricultural products. This paper takes the pig industry chain in Sichuan Province, China, as an example, analyses the butterfly effect in the price of agricultural products, and explores the time and space influencing factors that affect prices. On the basis of spatiotemporal factor mining, we adjust the input parameters of the prediction model in order to improve the prediction accuracy.

LITERATURE REVIEW

This section analyses the related research of the price of agricultural products and the association rule algorithm. First, the price is affected by many factors. According to the input parameters of previous forecasting models, combined with the unique characteristics of agricultural products, the influencing factors of the price are sought. Secondly, we sort out some research of association rules, which lays a theoretical foundation for the multidimensional spatiotemporal association rules.

Agricultural product prices. The price of agricultural products has an interaction with other fields, and its price stability can promote the development of society. In 2015, Bellemare (2015) studied whether

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there was a link between food prices and social unrest from 1990 to 2011. In 2017, Xie and Wang (2017) found that the price of agricultural products has a lag effect on grain production through agricultural production data from 1970 to 2015. In 2019, Taghizadeh-Hesary et al. (2019) studied the relationship between energy prices and agricultural prices from 2000 to 2016, and the results showed the importance of agricultural price stability. The market of agricultural products has also been valued in other countries in the world. The agricultural sector of the European Union also attaches great importance to the stability of agricultural product prices. Spasojević et al. (2018) have shown in their research that relevant government support measures have played a role in stabilizing agricultural product prices, proving that these measures are positively correlated.

In order to stabilize the prices of agricultural products, many researchers have devoted themselves to using prediction models in agriculture and other fields in recent years and have made some contributions to stabilizing the prices of agricultural products. Drachal et al. (2019) predicted the prices of three kinds of agricultural products with the new Bayesian combination scheme by assigning corresponding weights to the variables. With the development of machine learning and neural network models, many researchers have done some researches on these models, such as the eXtreme Gradient Boosting (XGBoost) model (Elavarasan and Vincent 2020), Random Forest Regression (RFR) model (Maimaitijiang et al. 2020), K-Nearest Neighbor (KNN) model (Gou et al. 2019), Gated Recurrent Unit (GRU) neural network (Jin et al.2020; Liu and Shen 2020), Long Short-Term Memory (LSTM) recurrent neural network (Shin et al. 2018; Haider et al. 2019) and Back Propagation (BP) neural network (Panda et al. 2010). In addition, some researchers combine a variety of models and make a comparison. The experimental results show that for different types of agricultural data, the best prediction model and parameters are not the same (Ribeiro and dos Santos Coelho 2020; Guo et al. 2021).

Association rule mining. Association rules (Agrawal et al. 1993), as a simple and practical rule in data, it is used to mine the relationship between different items in the transaction database. With the advent of the era of multi-source heterogeneous big data, the traditional association rule extraction algorithm is facing new challenges. Zhang et al. (2014) proposed a new tree mining algorithm based on the traditional Apriori algorithm and proved its effectiveness. Mining frequent itemsets from uncertain databases will degrade the performance of the algorithm as the number of data increases. Shah and Halim (2019) proposed an algorithm for mining frequent itemsets to solve this problem.

In the traditional Apriori algorithm, the data in the transaction database has the same importance. However, in the actual data, each project and transaction often have different importance. Sun et al. (2020) established a 0-1 matrix as well as weighted them according to the importance of projects and transactions and then extracted the hidden value data. Considering the importance of features in data, Shao et al. (2020) proposed a prediction model of a mining algorithm based on correlation weighting.

In practical application, some data are composed of numerical values, and traditional association rule mining algorithms cannot work on such data sets. Altay and Alatas (2020) compared the performance of eight intelligent optimization algorithms in 11 data sets, reducing the process of data preprocessing. In the research of requirements engineering, Muhairat et al. (2020) compared two methods of association rule mining and optimized them to reduce the execution time and improve accuracy. Sakai et al. (2020) proposed a mining algorithm on structured query language (SQL) data sets and generated a new tripartite decision framework according to the obtained rules. Bashir (2020) proposed a fault-tolerant frequent itemsets mining method, which greatly reduces the candidate itemsets and does not need to scan the original database multiple times. With the continuous development of the fuzzy set theory, Wu et al. (2020) proposed a mining method of fuzzy frequent itemsets, which is better than the traditional Apriori algorithm in execution time.

MATERIAL AND METHODS

Methodological framework. The traditional association rules mining (ARM) algorithm is mainly 'market basket analysis' to find out the association between various items as well as make decisions on the placement of goods on the shelf (Ünvan 2021). Because of the multiple types of data, it cannot be processed by the traditional data association algorithm. To mine numerical continuous data, this article has made some improvements to the association rule mining algorithm.

Firstly, according to the data characteristics of different prices of agricultural products, the time dimension is extended. Secondly, through scanning the database, the price data of numerical types are transformed by giving certain coefficients according to different numerical attributes. Next, the ARM algorithm is used to find the

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influencing factors of the target price change according to the project support degree, confidence degree and promotion degree. Finally, the regression neural network (RNN) model is established, as well as the linear regression function of the sklearn library is used for training (Wei and Molin 2020). The minimum error is obtained by the gradient descent method as well as the evaluation index is the root mean squared error (RMSE).

The price forecasting model framework based on ARM-RNN is shown in Figure 2, which mainly includes the following two steps: association rule mining and RNN prediction. In the ARM, we first extended the time dimension of the price data in order to find the butterfly effect in the price of agricultural products. Next, the price data is converted to determine whether the price rises, falls or remains unchanged. Finally, according to the association rules, the temporal and spatial factors of price change are found. In the RNN, the spatiotemporal factors affecting the target price are taken as the input parameters of the model, the model is trained, and the RMSE is taken as the evaluation index to output the optimal prediction model.

In the association rule mining of this paper, the occurrence frequency of the target item set in the agricultural product price change database is recorded as the change support degree. For the target item set X in the agricultural product price change database D, its change support degree is defined as the ratio of transaction

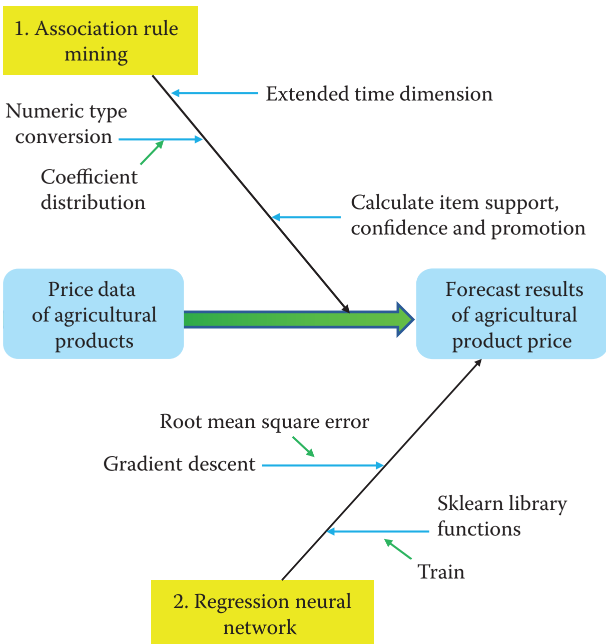

Figure 2. Methodological framework

Source: Authors' own processing

number T containing target item set X to all transactions t in the agricultural product price change database:

$$\mathrm{supp}(X) = \frac{\left|\{t \in T; X \subseteq t\}\right|}{|T|} \quad (1)$$

where: X – target item set; t – all transactions; T – transaction number.

The credibility of the rules to measure price changes is expressed by factor confidence. For a rule $X \Rightarrow Y$, the factor confidence is defined as the ratio between the number of transactions containing X and Y as well as the number of transactions containing X in the database of agricultural product price change:

$$\mathrm{conf}(X \Rightarrow Y) = \frac{\mathrm{supp}(X \cup Y)}{\mathrm{supp}(X)} \quad (2)$$

where: Y – another target item set in the agricultural product price change database D.

The target price is denoted as y and the related factor variable is denoted as x, namely:

$$\begin{cases} y = \beta_0 + \beta_1 x_1 + \ldots + \beta_m x_m + \varepsilon \\ \varepsilon \sim N(0, \sigma^2) \end{cases} \quad (3)$$

where: $x_1, \ldots, x_m$ – various factors of agricultural product price change; y – target price variable; $\beta_0, \ldots, \beta_m, \sigma^2$ – unknown parameters independent of $x_1, \ldots, x_m$; m – number of x parameters; ε – random error term.

In the multiple linear regression prediction model of this paper, it is necessary to observe the target price y and various factors x for n times, get n sets of price observations (y_i, x_{i1}, …, x_{im}), i = 1, 2, …, n, $n > m$, the following equation is satisfied:

$$\begin{cases} y_i = \beta_0 + \beta_1 x_{i1} + \ldots + \beta_m x_{im} + \varepsilon_i \\ \varepsilon_i \sim N(0, \sigma^2), i = 1, \ldots, n \end{cases} \quad (4)$$

where: i – i^{th} observation value.

In Formula (3), the parameter $\beta_0, \beta_1 \ldots, \beta_m$ is estimated by the least square method.

$$Q = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} \left(y_i - \beta_0 - \beta_1 x_{i1} - \ldots - \beta_m x_{im}\right)^2 \quad (5)$$

where: Q – sum of squares of errors.

To minimize Q, let $\frac{\partial Q}{\partial \beta_j} = 0$, $j = 0, 1, 2, \ldots, n$.

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$$\begin{cases} \dfrac{\partial Q}{\partial \beta_0} = -2\sum_{i=1}^{n}\left(y_i - \beta_0 - \beta_1 x_{i1} - \ldots - \beta_m x_{im}\right) = 0 \\ \dfrac{\partial Q}{\partial \beta_j} = -2\sum_{i=1}^{n}\left(y_i - \beta_0 - \beta_1 x_{i1} - \ldots - \beta_m x_{im}\right) x_{ij} = 0,\ j = 1, 2, \ldots, m \end{cases} \tag{6}$$

It is reduced to the following normal equations:

$$\begin{cases} \beta_0 n + \beta_1 \sum_{i=1}^{n} x_{i1} + \beta_2 \sum_{i=1}^{n} x_{i2} + \ldots + \beta_m \sum_{i=1}^{n} x_{im} = \sum_{i=1}^{n} y_i \\ \beta_0 \sum_{i=1}^{n} x_{i1} + \beta_1 \sum_{i=1}^{n} x_{i1}^2 + \beta_2 \sum_{i=1}^{n} x_{i1} x_{i2} + \ldots + \beta_m \sum_{i=1}^{n} x_{i1} x_{im} = \sum_{i=1}^{n} x_{i1} y_i \\ \beta_0 \sum_{i=1}^{n} x_{im} + \beta_1 \sum_{i=1}^{n} x_{im} x_{i1} + \beta_2 \sum_{i=1}^{n} x_{im} x_{i2} + \ldots + \beta_m \sum_{i=1}^{n} x_{im}^2 = \sum_{i=1}^{n} x_{im} y_i \end{cases} \tag{7}$$

Data. The data used in this paper comes from the cooperation project of the Sichuan Provincial Department of Agriculture and Rural Areas (SCPDARA 2020). It includes the weekly report data of average price of slaughter pig, the average price of piglet, the average price of the sow, the average price of pork, the average price of corn, the average price of wheat bran, and the average price of mixed feed for finishing pigs. These factors affect the changes in pork prices in the market, as shown in Figure 3.

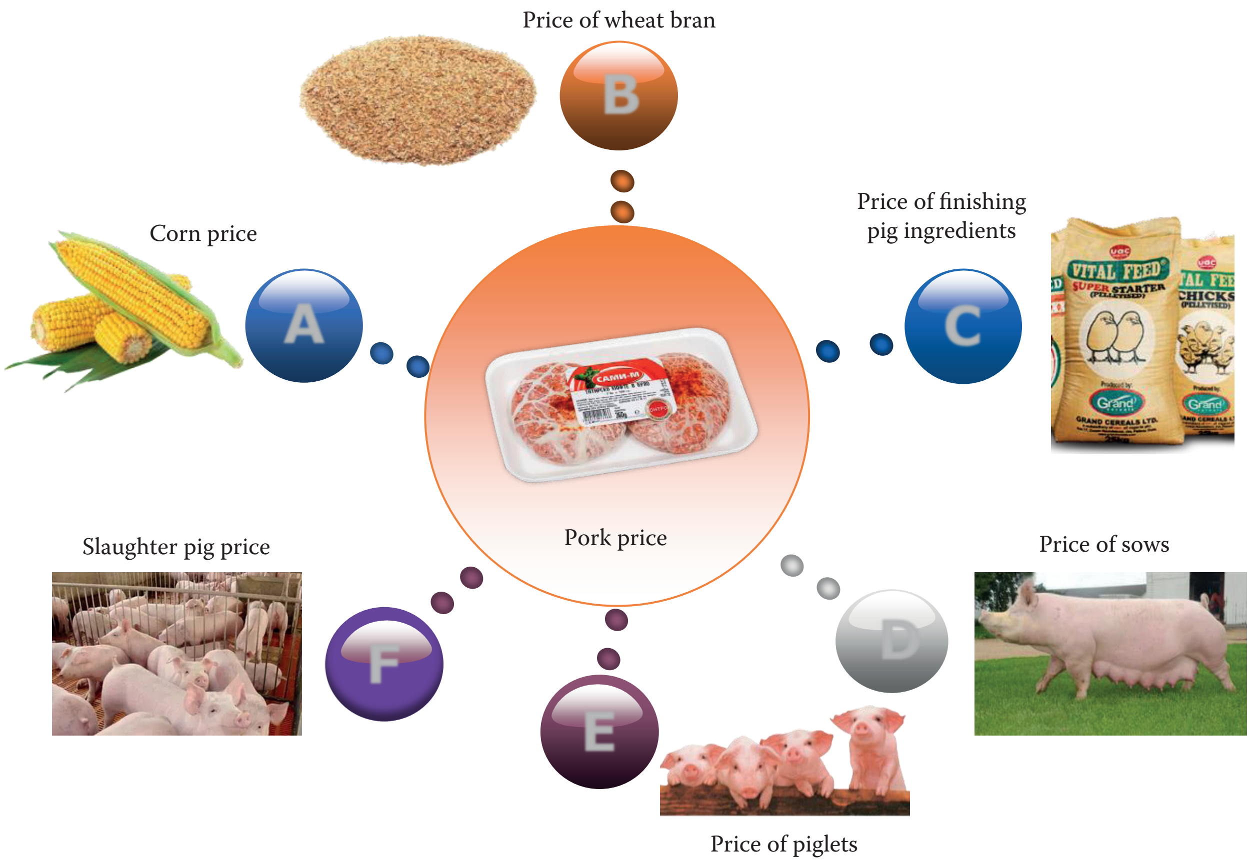

Figure 3. Description of pork price data

Source: Authors' own processing

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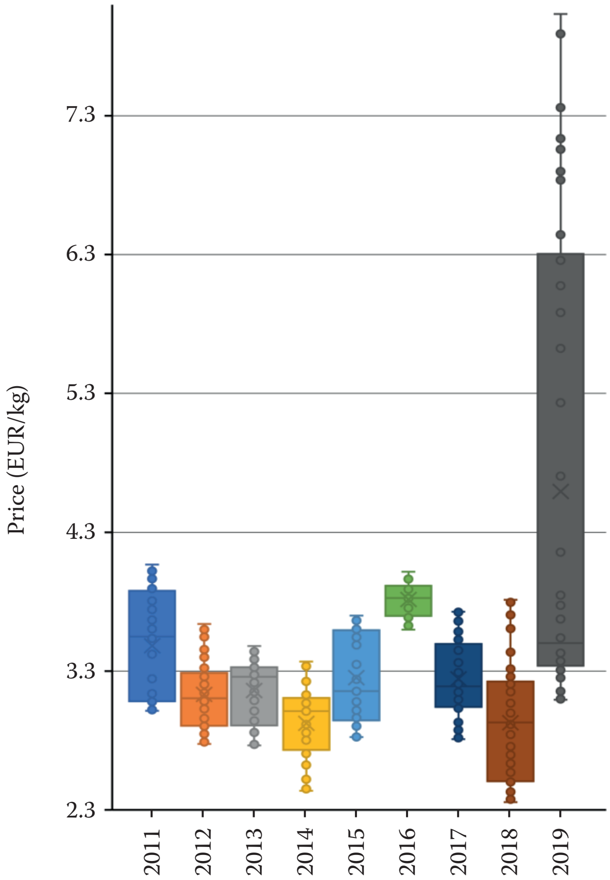

Figure 4. Pork price distribution

Source: Authors' own calculation from AGDATA (2020)

We use a box-plot to analyse pork price data over the past ten years, as shown in Figure 4. The price-scatter chart of slaughter pigs, piglets and pork is shown in Figure 5. As can be seen from Figures 4–5, since 2019, the fluctuation of pork price has become larger, which will bring challenges to price forecast.

Since 2019, the prices of the three pork products have fluctuated greatly, which has brought challenges to price prediction methods. In the experimental phase, the data is expanded in the time dimension, and different periods are expanded according to the attributes of agricultural products. The change decision coefficient is used to determine whether the price of a certain type of agricultural product is going up or down. It will be set dynamically according to the product price attribute. The specific parameter settings are shown in Table 1. According to historical experience, the price of pork in the past few weeks will have a greater impact on the price change next week, so nine-time dimensions are expanded. Because of the difference in the price change range of different commodities, different conversion coefficients are set to determine whether the price rises, falls or remains unchanged in a certain period.

Through the literature review, many researchers use a neural network, machine learning, linear regression as well as other traditional models for price forecasting. However, due to the large range of price changes

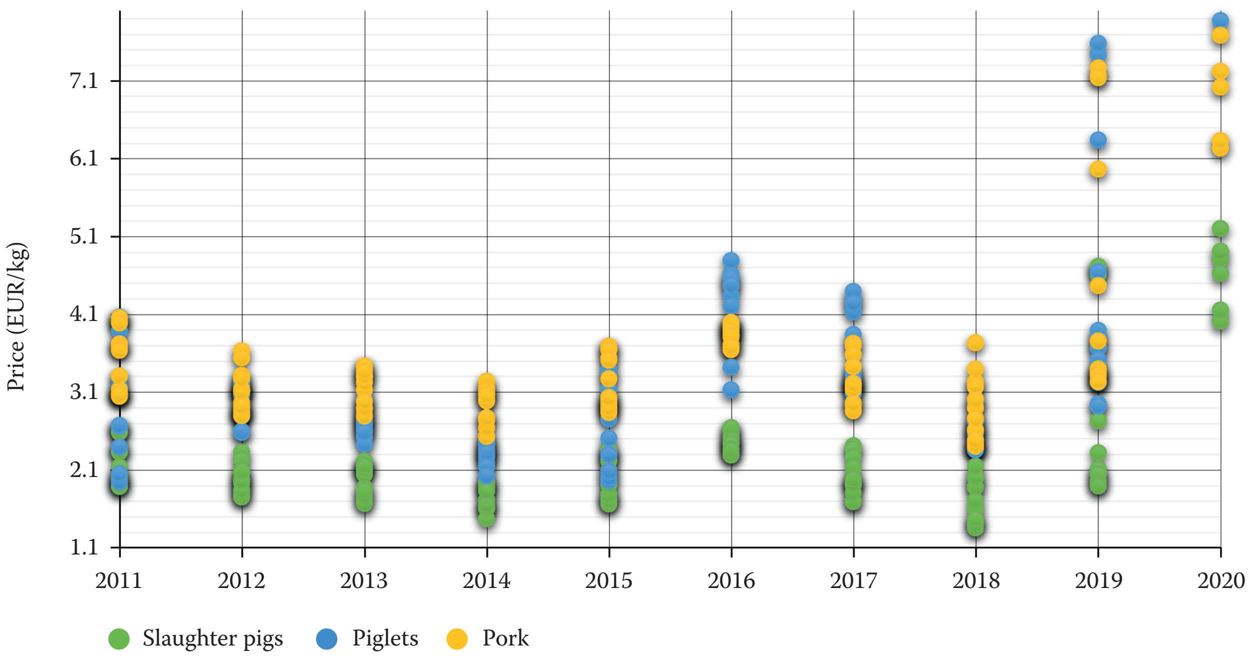

Figure 5. Price scatter distribution

Source: Authors' own calculation from AGDATA (2020)

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Table 1. Parameter setting of association rule mining

Variable name	Expanding dimensions	Determination coefficient	Number of increases	Number of steadiness	Number of decline
Slaughter pig price	5	0.0015	209	66	206
Piglets price	6	0.0013	207	97	177
Sow price	6	0.0020	158	214	109
Corn price	8	0.0010	137	207	137
Price of wheat bran	8	0.0010	141	202	138
Price of mixed feed for finishing pigs	8	0.0010	152	205	124
Pork price	9	0.0012	204	65	212

Source: Authors' own calculation based on SCPDARA (2020)

Table 2. RNN model parameter setting

Parameter name	Parameter setting
Fit intercept	boolean, optional, default True
Normalize	boolean, optional, default False
Copy_X	boolean, optional, default True
N_jobs	int, optional, default 1 int
Element number	34
Number of training sets	378
Number of test sets	95

RNN – regression neural network
Source: Authors' own calculation based on SCPDARA (2020)

in recent years, the effect of previous forecasting methods is not satisfactory. After extending the time dimension of the data, this paper finds out the most direct characteristics that affect the target price change after the association rule mining algorithm. Then the traditional price forecasting model is used to predict the target price, and mean squared error (MSE) is used as the evaluation index to seek the optimal prediction model method. MSE is the square of the difference between the real value and the predicted value, and then the sum is averaged; the formula is as follows:

$$MSE = \frac{1}{M}\sum_{m=1}^{M}\left(y_m - \hat{y}_m\right)^2 \qquad (8)$$

where: MSE – mean squared error; M – total number of test samples; $\hat{y}_m$ – m^{th} predicted value.

In the RNN, the gradient descent algorithm is used, as well as RMSE as the evaluation criteria. The specific parameter settings are shown in Table 2. There are 378 training sets and 95 test sets.

RESULTS AND DISCUSSION

In this part, we show the feature results of association rule mining and the prediction results of predictive models such as multiple linear regression, neural network, and machine learning.

Multidimensional spatiotemporal mining results. Firstly, the data of Sichuan pigs are expanded in the time dimension to dig out the influencing factors of price change. After setting the support and confidence of multiple groups of rules, 34 features with the highest frequency are selected, as shown in Figure 6. It can be seen from Figure 6 that the butterfly effect of pork price changes has initially appeared after eight-time units had been expanded. The time node when the green switch is turned on in Figure 6 indicates that it will have an impact on the pork price in the next week. When setting the parameters of the prediction model, we need to pay special attention to the time nodes of these 34 commodities, which can be used as the input parameters of the prediction model to improve the price prediction accuracy.

According to the experimental results of ARM, the pork price changes in the next week are highly correlated with the historical prices of the slaughter pigs, piglets, and pork, which the selection of feature tags in the next experiment.

Forecast results. The above 34 price attributes are selected as the characteristics of the price forecasting model. The validation set data results of machine learning [XGBoost, KNN, Adaptive Boosting (AdaBoost), RFR], neural network (BP, GRU, LSTM, RNN) used in this study are shown in Figure 7. The abscissa is the observed price, that is, the real price, and the ordinate is the forecast price. According to these scatter diagrams, a curve is fitted, that is, the dotted line on the diagram.

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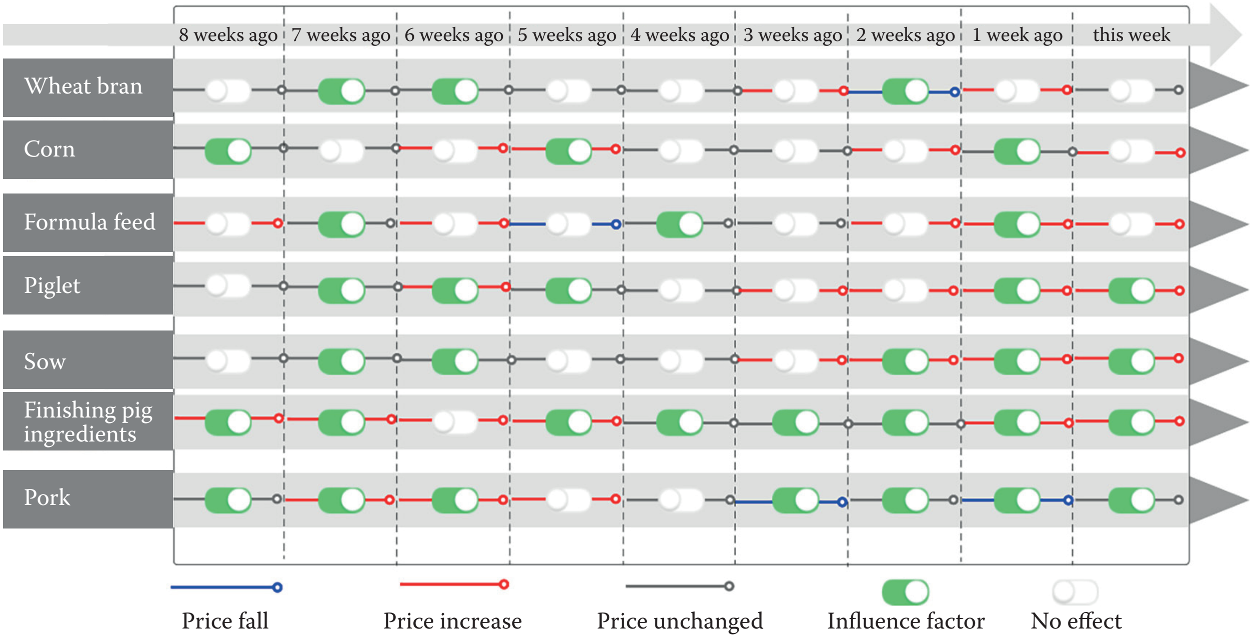

Figure 6. Feature selection details

Source: Authors' own calculation from AGDATA (2020) and SCPDARA (2020)

Table 3. Model prediction effect index

Model name	Reference	SSE	Adjusted R-square	MSE
XGBoost	(Elavarasan and Vincent 2020)	82.69	0.9893	0.955500
RFR	(Maimaitijiang et al. 2020)	118.10	0.9847	1.307279
KNN	(Gou et al. 2019)	128.70	0.9833	1.398200
AdaBoost	(Guo et al. 2021)	153.90	0.9800	1.672500
GRU	(Liu and Shen 2020)	237.20	0.9692	0.490000
LSTM	(Haider et al. 2019)	1 369.00	0.8225	14.425600
BP	(Panda et al. 2010)	89.10	0.9879	1.224031
RNN	–	30.77	0.9960	0.323900

XGBoost – eXtreme Gradient Boosting; RFR – Random Forest Regression; KNN – K-Nearest Neighbor; AdaBoost – Adaptive Boosting; GRU – Gated Recurrent Unit; LSTM – Long Short-Term Memory; BP – Back Propagation neural network; RNN – regression neural network; SSE – sum of squares due to error; MSE – mean square error

Source: Authors' own calculation based on SCPDARA (2020)

Compared with the straight line $y = x$, the closer the fitting line is, the more accurate the prediction result is.

According to the ARM-RNN model proposed in this paper, the predicted average pork price in the next five weeks is predicted to be EUR 3.6083 per kg, EUR 3.6462 per kg, EUR 3.6853 per kg, EUR 3.7245 per kg and EUR 3.7636 per kg.

Results analysis and discussion. The experimental results of mining multidimensional spatio-temporal association rules show that the butterfly effect does exist in the prices of agricultural products. The small changes in the prices of various commodities will have a certain impact on the prices of other commodities in a certain week in the future. For example, in this data example, the price change of corn two months ago, as time goes by, indirectly affects the price of pork two months later.

In the comparative experiment of prediction models, this study compares the above models from three evaluation indexes: sum of squares due to error (SSE), degree-of-freedom adjusted coefficient of determination (adjusted R-square) and MSE, as shown in Table 3. In terms of MSE, the MSE of the RNN model is 0.3239, and the prediction accuracy is the highest. The traditional price forecasting model generally inputs all the data into the model for training, and the prediction results have certain limitations. The hybrid model

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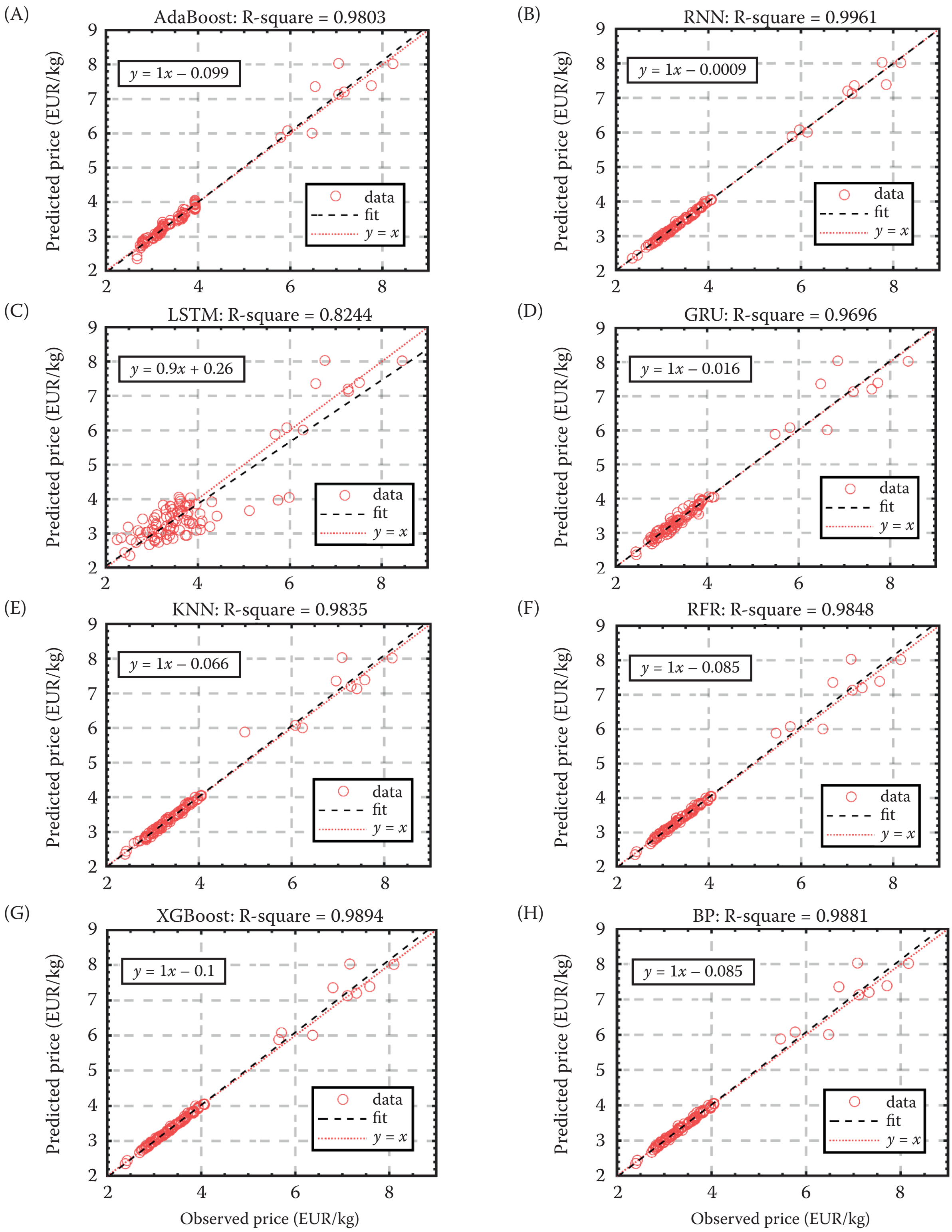

Figure 7. Validation set results under different models (A) AdaBoost, (B) RNN, (C) LSTM, (D) GRU, (E) KNN, (F) RFR, (G) XGBoost and (H) BP

AdaBoost – Adaptive Boosting; RNN – regression neural network; LSTM – Long Short-Term Memory; GRU – Gated Recurrent Unit; KNN – K-Nearest Neighbor; RFR – Random Forest Regression; XGBoost – eXtreme Gradient Boosting; BP – Back Propagation neural network

Source: Authors' own calculation from AGDATA (2020) and SCPDARA (2020)

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method proposed in this paper first uses the ARM algorithm in data mining theory to mine and analyse the influencing factors of target price in multiple time dimensions and then transfers the results to the prediction model for training, which improves the accuracy of the prediction results.

CONCLUSION

In recent years, the price fluctuation of agricultural products has been too large, which brings trouble to the personnel engaged in agricultural products, and is not conducive to the development of poverty alleviation projects. Inspired by the theory of the butterfly effect, this paper seeks whether there is a similar theory of butterfly effect in the price of agricultural products, that is, whether there are temporal and spatial factors affecting the future price trend of agricultural products. In order to solve these problems, this article uses multidimensional spatial-temporal association rule mining to verify the existence of the butterfly effect in the price system of agricultural products, carries out many experiments with different hybrid models, as well as finally proposes a price prediction model that combines data mining theory with RNN algorithms. The model can not only analyse the complex agricultural data but also accurately predict the price of agricultural products. For the government, the macro and micro regulatory policies of the market should be allocated ahead of time according to the forecast results of agricultural products prices. For the people, the healthy development of the agricultural products market can make people live and work in peace and contentment, improve the quality of life as well as stabilize the harmonious development of the whole society. Therefore, this study enriches the existing price forecasting model theory as well as is helpful to predict the prices of various products. At the same time, based on the prediction results of this model, it has an important and positive effect on the coordinated development of relevant government departments, producers, consumers, as well as the related upstream and downstream whole industry chain.

In the later work, we will add other agricultural product price data into the model as well as introduce feedback mechanism and disturbance factor so as to further improve the accuracy of target agricultural product price prediction. In addition, it can also improve the robustness and practicability of the model. On the basis of the above improvements, we believe that the method proposed in this paper can be better promoted and applied, which is of great significance to agricultural economic development and global poverty alleviation.

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