Research on the Application of Multi-Objective Algorithm Based on Tag Eigenvalues in e-Commerce Supply Chain Forecasting

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***Abstract*—With the continuous development of Internet technology, the scale of Internet data is increasing day by day, and business forecasting has become more and more important in corporate business decision-making. Therefore, to improve the accuracy of Multi Target Regression in the actual e-commerce supply chain forecasting, research through the method of constructing the labeling feature for each target is optimized, the Multi-Target Regression via Sparse Integration and Label-Specific Features algorithm is obtained, and the experimental analysis is carried out on the performance of the algorithm and the application effect in the actual e-commerce supply chain. The experimental results show that the average of Relative Root Mean Square Error value of the research algorithm and is the lowest in most datasets, with a minimum of 0.058 in the effect experiments of prediction and label-specific features; in the effect and flexibility experiments of sparse sets, the lowest average of Relative Root Mean Square Error value of the research algorithm was 0.058, and the average rank value was the smallest. In addition, the average of Relative Root Mean Square Error value of the research algorithm is the smallest under the target variable of Y2 in the Enb data, and its value is 0.075. In the actual e-commerce supply chain forecast, the research algorithm has the highest score of 0.097 points. Overall, research algorithm has a better forecasting effect and higher performance, and has better practicality in practice, and can play a better effect in actual e-commerce supply chain forecasting.**

Keywords*—Label features; multi-objective algorithm; sparse set; e-commerce supply chain; multi target regression

I. Introduction

In the business decision-making of enterprises, planning and control are very critical, and forecasting is the basis for the control planning and forecasting of future trends, and forecasting is also important to avoid one-sided decision-making and mistakes [1]. In traditional regression analysis, the marker and target variables are often single, but a single object variable cannot accurately describe the complex information contained. Therefore, the single target regression analysis method has been unable to predict objective problems well and accurately, and Multi-Target Learning (MT) came into being [2]. At the same time, MT-based multi-target regression (Multi Target Regression, MTR) has also been gradually paid attention to, which refers to the use of a common set of input variables to predict multiple continuous variables. In this regard, a large number of domestic and foreign scholars have carried out a lot of research. Based on MTR, Nabati et al. proposed a Gaussian regression-related algorithm to avoid the fitting problem in training [3]. Based on multi-objective regression, Osojnik et al. proposed a contour tree to improve the prediction effect of multi-label classification [4]. Syed et al. conducted research on semi-supervised techniques based on multi-objective regression by analyzing limited instances, thereby achieving efficient prediction of new objects [5]. However, current multi-objective regression methods mainly focus on mining the correlation between targets and handling the complex relationship between input and output, and most methods learn models from the same feature space, resulting in insufficient flexibility and low prediction performance. At the same time, there is not much research on its application in e-commerce supply chain prediction. Based on this, the study obtained a multi-objective regression via Sparse integration and Label Specific Features (SI-LSF) algorithm by improving MTR, aiming to effectively improve the flexibility of processing multi-objective datasets and thereby enhance the accuracy of the algorithm in e-commerce supply chain prediction.

The research is divided into six sections. Section I is the Introduction of the study. The Section II is a summary and discussion of the current research on multi-objective optimization methods. Section III is the study of the SL-LSF algorithm in e-commerce supply chain prediction, including the definition and related methods of multi-objective regression, and the optimization of the SI-LSF algorithm for multi-objective regression problems. Section IV analyzes the performance and practical application of the SL-LSF algorithm. Section V presents the discussion and last Section VI is a summary of the entire article.

II. Related Work

With the rapid development of information technology, the amount of data on the network is increasing day by day, and the expression of data is also changing rapidly, which makes the ability of data analysis and data mining more and more important. At the same time, the ability to predict data is required. It is also becoming more and more important, and MT has gradually gained attention as a method that is more in line with the laws and characteristics of objective things. Based on this, scholars at home and abroad have carried out research on it. By using multi-objective optimization, Das et al. proposed a fast and accurate meta-model to accurately calculate the effective degree of losses and oil spills, reducing the risk at sea [6]. Dong performed multi-objective optimization of hybrid composites based on multi-objective

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regression to verify the effectiveness of the positive hybrid effect in improving the flexural strength of materials [7]. Irodov et al. solved the multi-objective optimization problem of pellet burners by performing a multi-objective regression optimization analysis on the work of tubular gas burners [8]. Wang et al. solved the multi-objective constrained optimization problem of variables by introducing random forests and other methods to continuously approach the objective and constraint functions [9]. Based on the tripartite competition mechanism, Han et al. proposed an improved multi-objective particle swarm optimization algorithm to effectively solve the problems of multi-objective diversity and poor convergence performance [10]. Pereira et al. developed a numerical model of complex structures by proposing equi-grid multi-objective optimization with six objectives, thereby reducing the instability of such grid tubes [11]. Based on reinforcement learning, Dang et al. proposed a multi-objective optimized resource allocation model to achieve a better-distributed search [12]. Ullah et al. achieved multi-objective optimization of motor switching by proposing a new permanent magnet forward pole with flux bridges etc [13].

In addition, Grover et al. comprehensively study e-commerce and supply chain management, to purchase raw materials according to demand forecast, which greatly facilitates supply chain management [14]. Li et al. established a digital model based on signal game theory to obtain revenue forecast information, and then proposed the optimal information acquisition strategy in the supply chain [15]. Yang et al. identified the importance of forecast updates in supply chains by studying the pricing problem in a two-tier fashion supply chain [16]. Shen et al. determined the driving effect of shared information on supply chain management by comprehensively analyzing the problem of forecasting information sharing in supply chain management so that it can better match supply chain demand [17]. Li et al. built an effective forecasting model to reasonably control the multi-item inventory in the supply chain [18]. Chaudhuri et al. integrated extreme learning machines to propose an optimized forecasting model, thereby realizing real-time accurate forecasting of products in supply chain management [19]. Wan realizes the risk prediction of the supply chain by proposing a risk prediction model related to the manufacturing industry and ensures the healthy development of enterprises [20]. Proposing a combined model, Jaipuria et al. constructed a hybrid forecasting technology for supply chain demand, thereby ensuring inventory safety and sufficient order quantity in the replenishment cycle of goods [21].

Through the research of domestic and foreign scholars, it can be found that the multi-objective method can predict the future based on summarizing the laws of objective things, and predictive analysis is very important in the e-commerce supply chain. Therefore, it is expected that the proposed SI-LSF algorithm will be helpful in the actual prediction of the e-commerce supply chain.

III. Research on e-Commerce Supply Chain Forecasting based on the SL-LSF Algorithm

A. Analysis of Correlation Methods based on Multi-Objective Regression

To improve the breadth and accuracy of the MTR method in e-commerce supply chain forecasting, the research proposes SI-LSF and analyzes its performance and application in actual forecasting by creating a special marker feature for each target. MTR refers to the existence of multiple dependent variables in a model, which takes into account the mapping between multiple output objects. These mapping relationships can be linear or nonlinear. In addition, for the MTR problem, a class of samples contains multiple different output variables, and there are often different semantic relationships between them [22]. By mining the correlation of each output object, the comprehensive prediction effect of multiple indicators can be effectively improved. It is assumed here that X represents the input feature space, Y stands for the output target space, and the membership formulas of the two are shown in Eq. (1) and (2).

$$\begin{cases} X \subset R^m \\ X = (X_1, X_2, \cdots, X_m) \end{cases} \tag{1}$$

In Eq. (1), R represents the datasets and m represents the number of feature vectors.

$$\begin{cases} Y \subset R^d \\ Y = (Y_1, Y_2, \cdots, Y_d) \end{cases} \tag{2}$$

In Eq. (2), d represents the number of target variables. Therefore, the input vector and the output vector can be given in the MTR problem, and the related equations are shown in Eq. (3).

$$\begin{cases} x^{(l)} = (x_1{}^{(l)}, \cdots, x_m{}^{(l)}) \\ y^{(l)} = (y_1{}^{(l)}, \cdots, y_d{}^{(l)}) \end{cases} \tag{3}$$

In Eq. (3), $x^{(l)}$ and $y^{(l)}$ represents a sample, which l represents the target variable, and its number range is between [1, n], which n represents the number of samples. On this basis, the relevant equation of the training set can be given as Eq. (4) shown.

$$D = \left\{ \left(x^{(l)}, y^{(l)} \right), \cdots, x^{(n)}, y^{(n)} \right\} \tag{4}$$

In Eq. (4), D represents the training set. Therefore, it can be determined that the task of MTR is to learn a mapping function, so that for any uncertain vector, all output variables can be obtained at the same time through $\hat{y} = h(x)$. The multi-objective regression problem and the multi-label problem are similar in that the output variable of the multi-objective regression problem is continuous, while the classification problem is discrete, so it can be divided into two types, namely problem transformation method and algorithm adaptation method, the contents of which are shown in Fig. 1.

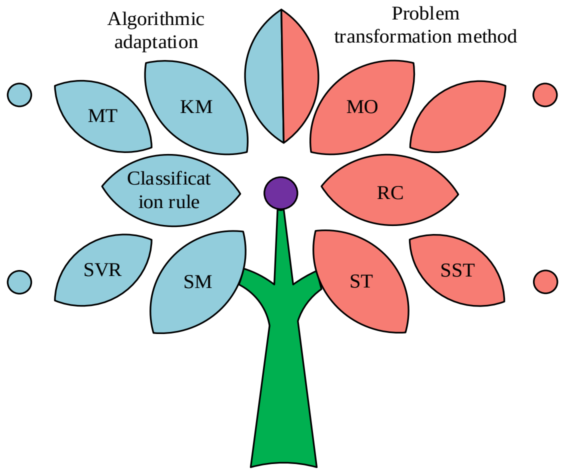


Fig. 1. Specific classification of multi-objective regression methods.

It can be seen in Fig. 1, the problem transformation method mainly includes Single-Target Method (ST), Stacked Single-Target (SST), Regressor Chains (RC), and multi-target support vector regression (Multi-Output Support Vector Regression, MO), algorithm adaptation methods include statistical methods (Statistical Methods, SM), support vector machines (Support Vector Regression, SVR), kernel methods (Kernel Methods, KM), regression tree (Multi-Target) Regression Trees, MT) and classification rules. The ST problem is often used to deal with the MTR problem, so ST is used for learning prediction. The least squares criterion is used to solve it, and its formula is shown in Eq. (5).

$$\left\{\hat{a}_{ij}\right\}^{m}{}_{j=1} = \arg\min_{\left\{\hat{a}_{j}\right\}^{m}{}_{j=1}} \left\{ \sum_{l=1}^{N}\left(y_i^{(l)} - \sum_{j=1}^{m} a_j x_j^{(l)} \right)^2 \right\} + \lambda_i \sum_{j=1}^{m} a_j^2 \tag{5}$$

In Eq. (5), $\hat{a}_{ij}$ represents the regression coefficient, i represents the target variable, j represents the feature vector, and $\lambda_i > 0$ represents the ridge parameter. In the MO problem, multiple virtual samples can be constructed by virtualizing the eigenvectors, and the objective function definition formula is shown in Eq. (6).

$$\begin{cases} f = \dfrac{1}{2}\|w\|^2 + \displaystyle\sum_{l=1}^{N}\frac{1}{c}\sum_{i=1}^{d} e_i{}^{(l)^2} \\ s.t. y_i{}^{(l)} = w^T\phi(I_i, x^{(l)}) + I_i b + e_i{}^{(l)} \end{cases} \tag{6}$$

In Eq. (6), f represents the objective function, w represents the weight vector, w represents the trade-off factor between dimension and loss, $e_i{}^{(l)}$ represents the fitting error, $\phi(.)$ represents the nonlinear transformation of the feature space, b represents the deviation vector, I represents the virtual sample, T represents the transpose.

The algorithm adaptation method uses a single model to predict all the targets at one time, so that the correlation and internal connection between the target and the input features can be captured, which has the advantages of more interpretability and better prediction performance. In the adaptation method, the most important are SM and SVR. SM is believed to treat the first attempt as predicting multiple targets at the same time, and its purpose is to improve the prediction accuracy by using the correlation between target variables, while SVR is usually used to deal with single-target regression problems. It reflects the relationship between input variables and output variables on a certain datasets, and the operation formula is shown in Eq. (7).

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N} L\left(y^{(l)} - \left(\phi\left(x^{(l)}\right)^T w + b\right)\right) \tag{7}$$

In Eq. (7), w represents the regressor, C represents the user-selected parameters, and b represents the bias. In addition, the MT method in the algorithm adaptation method can predict multiple continuous targets when dealing with multi-objective problems. It has two advantages, that is, the scale of a single multi-objective regression tree model is often smaller than that of a single multivariate model. The multi-target regression tree can better distinguish the correlation of multiple target variables; the KM method is an index kernel with a coupled regularization function; the classification rule is to convert the regression tree set into a rule set, to select the best subset of rules to improve prediction accuracy.

B. Research on SI-LSF Algorithm Optimized for Multi-Objective Regression Problem

MTR types are mainly problem transformation methods and algorithm adaptation methods, and their basic functions have been widely used in computer vision and medical image analysis. However, current MTR is mainly studied for linear models but lacks a method capable of simultaneously handling the nonlinear relationship of multiple objects with the input space [23]. Therefore, the research optimizes the existing problems of MTR and proposes the SI-LSF algorithm. The SI-LSF algorithm is based on the superposition of a single target, adopts the method of boosting learning, and studies the specific characteristics of the markers to explore multiple targets. Inter relationships between variables. Second, a sparse ensemble-based model is built using the sparse ensemble method. Finally, combining sparse integration with target features can simultaneously address two challenges of MTR within a single framework, namely establishing the fundamental relationship between input features and output objects and exploring their inter-correlation to improve prediction performance. The stacking of a single target is also called Stacked Single Target (SST) [24]. Its training and prediction framework is shown in Fig 2.

It can be seen in Fig. 2, its frame structure is divided into two stages of training and two stages of prediction. In the training phase, the first is to train the model for each target through the training set, to obtain the predicted value, and then enter the second phase of training, that is, to establish the second phase of training and then output the final training model. In the prediction stage, for an unknown sample, first pass the model in the first stage to obtain the prediction vector, then extend the prediction vector into the feature vector, and then set the result as the new input predicted by the model in the second stage value, and finally use the second-stage model to obtain the final prediction result. The core idea of SST is to use the predictions of the remaining targets in the first stage as additional input variables. Although the real value of the target can be obtained in the training set, there is no real target in the prediction set. Therefore, in the prediction process, the SST must depend on the estimation of the target based on the prediction results of the single-target regression. However, such an approach violates a central assumption of supervised learning theory: training and trial data must be consistent and independent of each other [25].

In the second stage, due to the introduction of additional input variables, the noise of the prediction is caused, which leads to the estimation error of the model. Therefore, to solve this problem, it is necessary to improve the training and prediction of the target variable. The numerical value used in the prediction compatibility. Label-Specific Features (LSF) is another important element in SI-LSF, and its framework is shown in Fig.3.

It can be seen in Fig. 3, before each object is marked for recognition, it is first preprocessed and extended as an additional feature. The training set transformed by the instruction is $D' = \left\{ \left(x^{(j)} \cup \hat{y}^{(j)}, y^{(j)} \right) \middle| 1 \le j \le n \right\}$, which $x^{(j)}$ represents the initial feature vector and $y^{(j)}$ is the target real value vector. In the learning process of LSF, the first step is to find the relevant features for each target, to improve its learning accuracy. The formulas are shown in Eq. (8), (9), and (10).

$$R_1(\gamma, s) = \left\{ X_i \middle| x_{i\gamma} \le s \right\}, R_2(\gamma, s) = \left\{ X_i \middle| x_{i\gamma} > s \right\} \quad (8)$$

In Eq. (8), it x_i represents a certain column attribute, s represents x_i a certain value in it, which is represented as the corresponding split point, R_1 and R_2 represents s the two parts of the attribute using the division, and the value in the γ representation X represents a feature.

$$\hat{c}_t = \frac{\sum_{X_i \in R1(\gamma, s)} y_{ij}}{|R_t|} \quad (9)$$

In Eq. (9), it $\hat{c}$ represents the corresponding target mean value, t which is a determined value, which is 1 or 2.

$$\min_{\gamma, s} \left(\min \sum_{X_i \in R1(\gamma, s)} \left(y_{ij} - \hat{c}_1 \right)^2 \right) + \min_{\gamma, s} \left(\min \sum_{X_i \in R1(\gamma, s)} \left(y_{ij} - \hat{c}_2 \right)^2 \right) \quad (10)$$

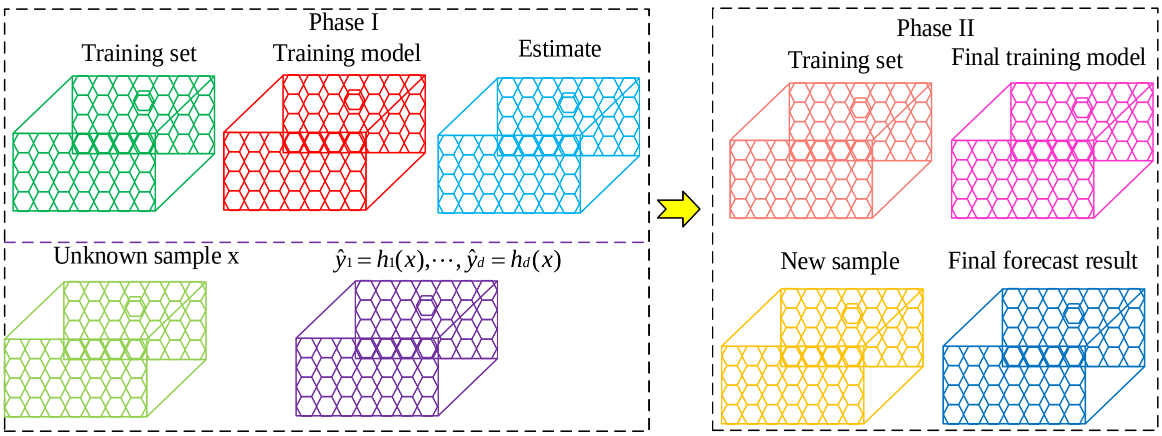


Fig. 2. SST training and testing framework diagram.

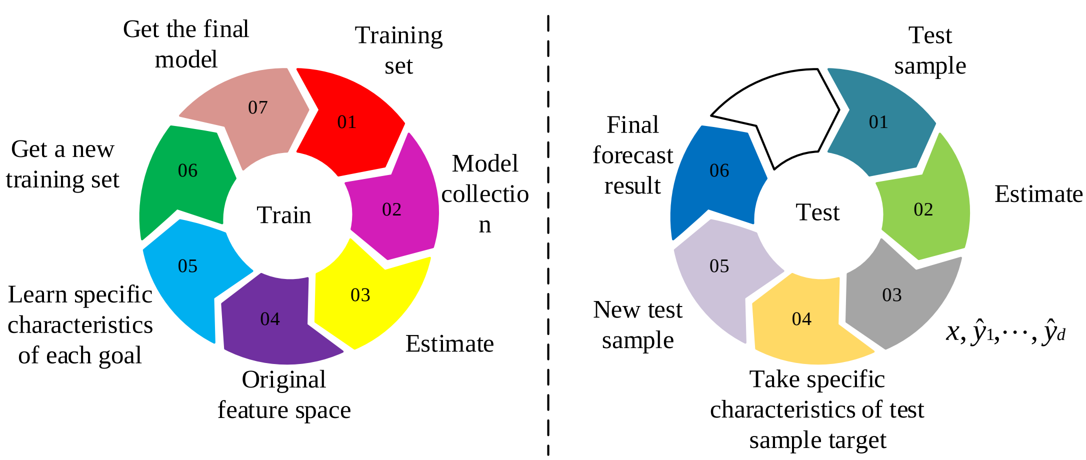


Fig. 3. LSF frame structure diagram.

According to the minimized square error in Eq. (10), the best division feature and split point can be found, to determine the relevant feature set of the target and delete redundant features. It is worth noting that these features are only a subset of features in the training set, and there is not enough diversity in the feature space to represent objects well. To improve the difference of the feature space, the target correlation method is used to construct the marker-specific feature, and the residual of each repetition is used to describe the local feature, and it is used as an additional feature to reflect the local information of the feature space. Perform direct modeling to improve the expressiveness of the model. The relevant calculation formulas are shown in Eq. (11), (12), and (13).

$$g_0\left(X'_{TR}\right)=f_q\left(\left(X'_{TR}\right);Y_j\right) \quad (11)$$

Set the initial value represented by Eq. (11). Among them, g represents the predicted value, X'_{TR} represents the output space, f_q represents the basic learner, and Y_j represents the target.

$$r_t^{(j)}=-\left[\frac{\delta l\left(Y_j,g_{t-1}\left(X'_{TR}\right)\right)}{\delta g_{t-1}\left(X'_{TR}\right)}\right] \quad (12)$$

Eq. (12) means to find the negative value of the current mode and treat it as a residual. Among them, r represents the relevant features and l represents the squared error loss function.

$$g_t\left(X'_{TR}\right)=g_{t-1}\left(X'_{TR}\right)+f_q\left(X'_{TR};r_t^{(j)}\right) \quad (13)$$

Equation (13) is to set the target as the residual estimation in Eq. (12), to use the negative gradient value to update the model, and use it as the target of the next iteration. In addition, after the introduction of marker features, LSF still selects a single-target regression analysis method, which will cause the complex input and output relationship models in the first and second stages to be unable to be established. Therefore, the proposal of SI-LSF is exactly to flexibly handle these complex relationships. SI-LSF is a sparse ensemble algorithm, which will be applied to ensemble learning. Therefore, the research proposes a corresponding aggregation function to deal with the complex problem of ensemble learning calculation, and its calculation formula is shown in Eq. (14) and (15).

$$w_j^*=\min_{w_j}\frac{1}{2}\sum_{i=1}^{N}\left(w_j^T\hat{y}_i-y_{ij}\right)^2+\lambda\left\|w_j\right\|_1 \quad (14)$$

In Eq. (14), w_j represents the weight vector and $\lambda\left\|w_j\right\|_1$ represents the regular term. It means that by introducing a regular term, the weight of the base model becomes 0, which realizes the sparseness of the data and automatically selects a regression method suitable for learning, which improves the flexibility of the algorithm. And reduce the time and space complexity and enhance the prediction effect.

$$h_j=\sum_{i=1}^{k}w_{ij}^*f_i \quad (15)$$

In Eq. (15), h represents the final prediction result, f represents the regression method, and w_{ij} represents the distribution weight. Based on this, the frame structure of SI-LSF can be given, as shown in Fig. 4.

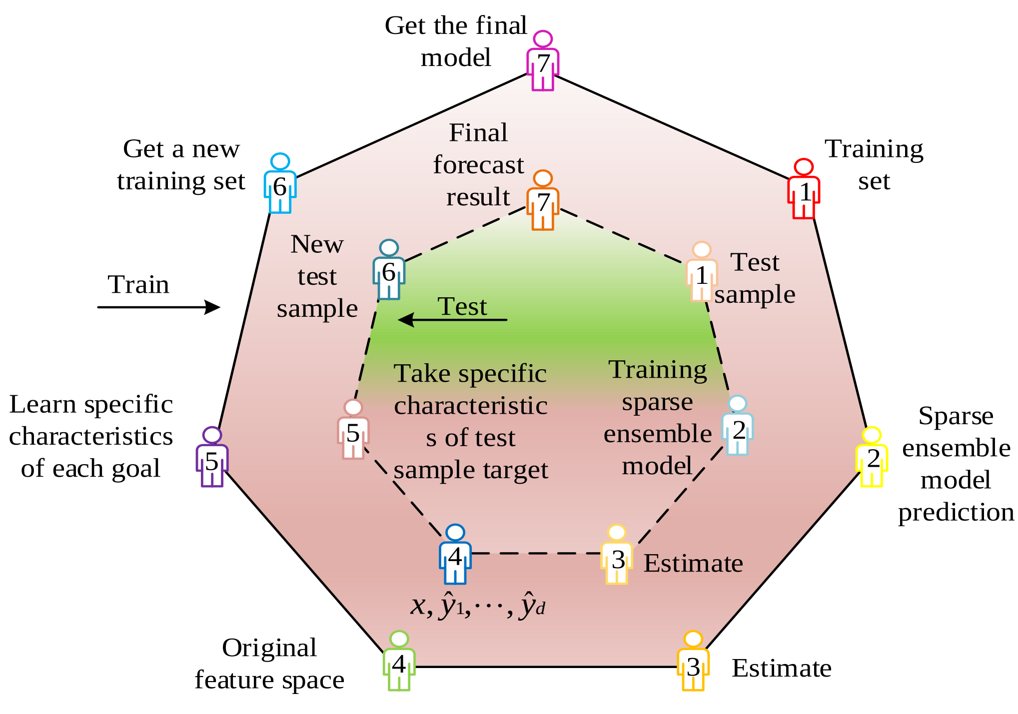


Fig. 4. SI-LSF frame structure diagram.

It can be seen in Fig. 4, unlike most existing methods that integrate the prediction results into the final stage, the SI-LSF algorithm integrates the prediction results of each model, and its advantage is that it can accurately determine the first, the second stage marks, the eigenvalues and selects the most important mode by weighting, thereby reducing the interference of the system and improving the accuracy of the system. Therefore, the framework structure of the SI-LSF algorithm utilizes a sparse ensemble to generate a sparse ensemble model and perform relevant training predictions on it to obtain the specific characteristics of the sample target. Add the target and specific features to form a new training set and test set to get the final model and prediction results.

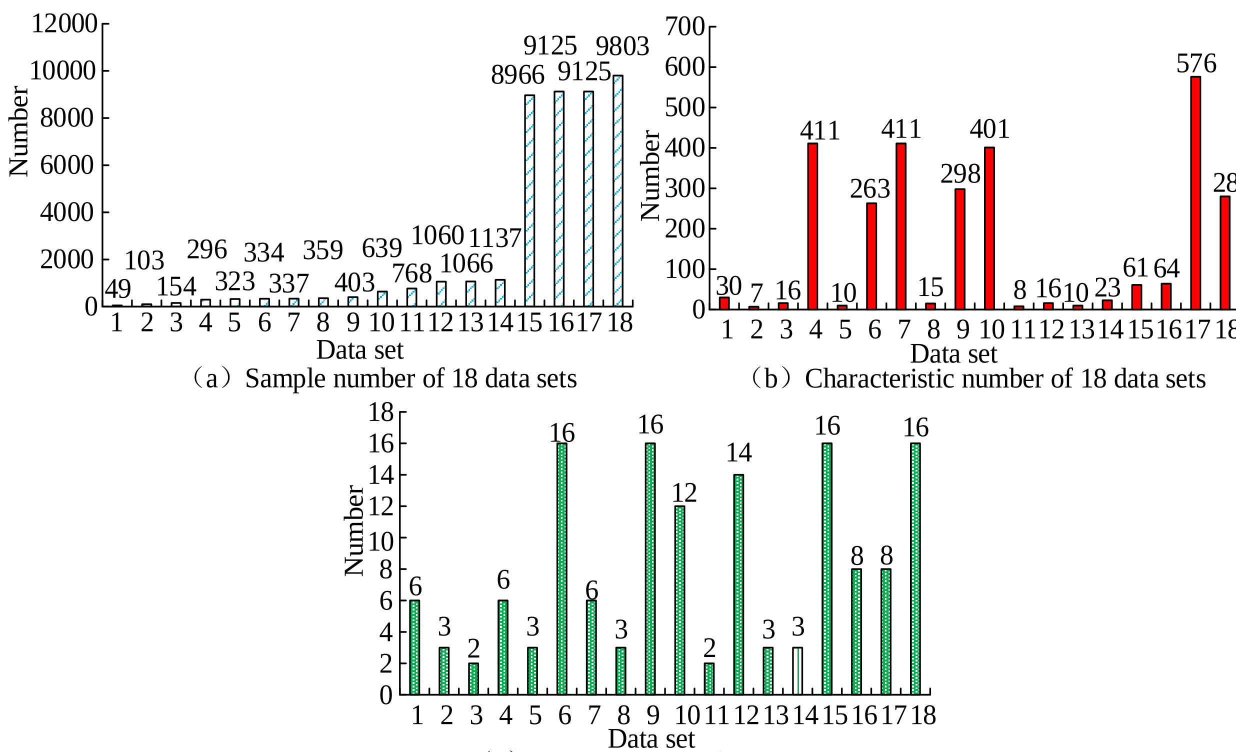
IV. SI-LSF Algorithm Performance and Practical Application Analysis

To test the performance of the SI-LSF algorithm, related experiments were carried out. Before the experiment, the study collected related datasets. Since there are relatively few related public datasets, the study selected 18 commonly used datasets for the experiment. The dataset information is shown in Fig. 5.

In Fig. 5, the horizontal axis 1-18 represent 18 data sets, namely Aandro (prediction of future values of water quality variables), Slump (concrete slump), Edm (electronic discharge machining), Atp7d (airline ticket prices), Sfl (solar flares), Oes97 (occupational employment survey), Atpld, Jura (determination of 359 seven heavy metals in soils in the Swiss Jura region), Oes10, Osales ("online product sales") preprocessed version in competition), Enb (energy building), Wq (14 target attributes of water quality), Sf2, Scpf (preprocessed version of the dataset used in a competition) , S cm20d (supply chain management)) , R f1 (river flow) , R f2, and S cmls. In addition, the three sub-graphs represent the number of samples, the number of features, and the number of targets in the dataset, respectively.

Among them, these datasets are predictions for the future or related content, which can effectively improve the actual response speed of the research algorithm, which is more in line with the overall research. They contain different target attributes in different fields, so they have high effectiveness and practicality in promoting intelligent analysis and improving actual work efficiency. Therefore, this study selected these 18 publicly available multi-objective regression datasets to validate the research algorithm.

On this basis, the research uses the average relative root mean square error (aRRMSE) measure as the evaluation index, and the smaller the value, the better the performance. And introduce the integrated regression chain (Ensemble of Regression Chains, ERC), support vector regression chain (SVR-correlation Chains, SVRCC) and multi-layer multi-target regression (Multi-layer Multi-target Regression, MMR) and SST algorithm, it is combined with the performance comparison of SI-LSF algorithm mainly includes three aspects: prediction effect, the effectiveness of label-specific features, and effectiveness of sparse ensemble. The first is to compare the prediction effects of the experiments. The prediction effects of several algorithms under different datasets are shown in Fig. 6.



(c) Target number of 18 data sets

Fig. 5. Relevant information of 18 datasets.

It can be seen in Fig. 6, the SI-LSF algorithm has the lowest aRRMSE values in all 16 datasets, and only the second lowest aRRMSE values in two datasets, roughly between 0 and 0.9. Among them, the SI-LSF algorithm has the smallest Rf2 in the datasets, which is 0.058, and the overall average value is 0.477. In addition, in the average ranking of the five algorithms, SI-LSF also has the lowest aRRMSE value of 1.111. The experimental results show that the prediction effect of the SI-LSF algorithm is the best among the five algorithms, and the performance is also the best. The second goal is to verify the validity of the specific features of the SI-LSF labels. Based on this, the research sets the control scalar as the label-specific feature, compares the SI-LSF algorithm with the sparse integration (Sparse Integration, SI) algorithm, and also compares the aRRMSE values of the two. The results are shown in Fig. 7.

It can be seen in Fig. 7 that the aRRMSE value of the SI-LSF algorithm is smaller than that of the SI algorithm on the 16 datasets, greater than that of the SI algorithm on the Rf1 dataset, and equal to the SI algorithm on the Oes97 dataset. In addition, the aRRMSE value of SI-LSF is generally between 0 and 0.9, and its minimum value appears on the Enb dataset at 0.070. On the whole, the prediction performance of SI-LSF on most datasets has the rain SI algorithm. Through the verification of the specific characteristics of the label, it is proved that it can further improve the SI-LSF algorithm and significantly improve it. The prediction accuracy of the SI-LSF algorithm, so label-specific features are effective for the SI-LSF algorithm to improve. Finally, to verify the effectiveness of the sparse ensemble, the study introduced Support Vector Regression and Label-Specific Features (SVR-LSF), Linear regression (Linear regression and Label-Specific Features, Linear-LSF), and random forest (The three basic regression models of Random Forest and Label-Specific Features, RF-LSF) are compared with the SI-LSF algorithm. It is worth noting that the SI in the SI-LSF algorithm is used to solve the complex relationship between the input characteristics and the output objects, so it is necessary to use the SI as a control variable to conduct experiments, and the results are shown in Fig. 8.

It can be seen in Fig. 8, in the 15 datasets, the aRRMSE value of SI-LSF is lower than that of the other three algorithms. It is the same as the RF-LSF algorithm in the Atp7d and Wq datasets, which is 0.428. -LSF is the same, which is 0.796; the lowest value of the SI-LSF algorithm appears in the datasets Rf2, which is 0.058, and its average value is 0.477, which is lower than 0.615 of SVR-LSF, 0.695 of Linear-LSF and 0.542 of RF-LSF, its average rank value is one, which is much lower than the other three algorithms. On the whole, the prediction effect of the SI-LSF algorithm is better, and it has the best performance among the four algorithms, which shows that the sparse ensemble is effective in improving the performance of the SI-LSF algorithm. In three aspects, namely the prediction effect, the effectiveness of label-specific features, and the effectiveness of sparse ensemble, it is proved that the SI-LSF algorithm has better performance. In the complex relationship between objects, the study selected seven datasets from 18 datasets and compared the value of aRRMSE for each object, and the results are shown in Table I.

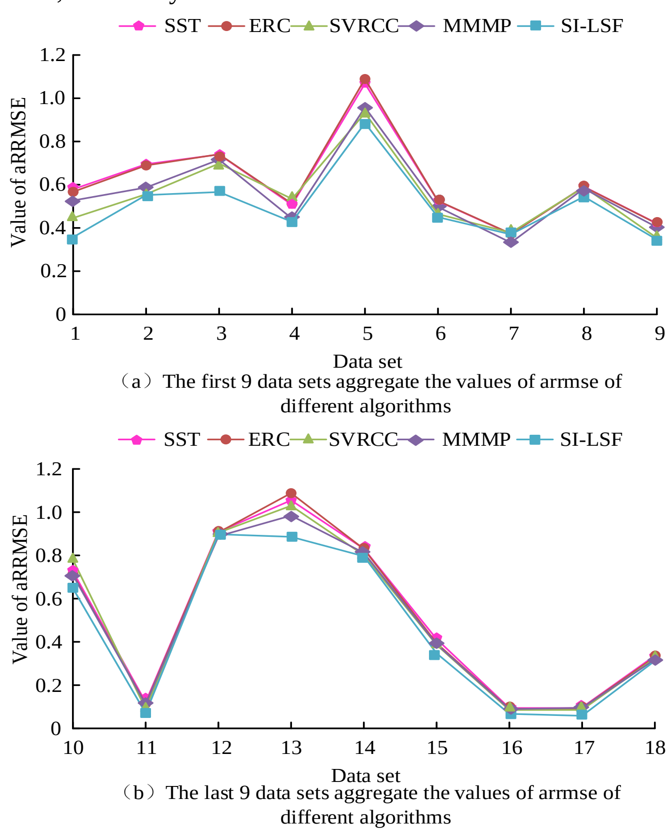
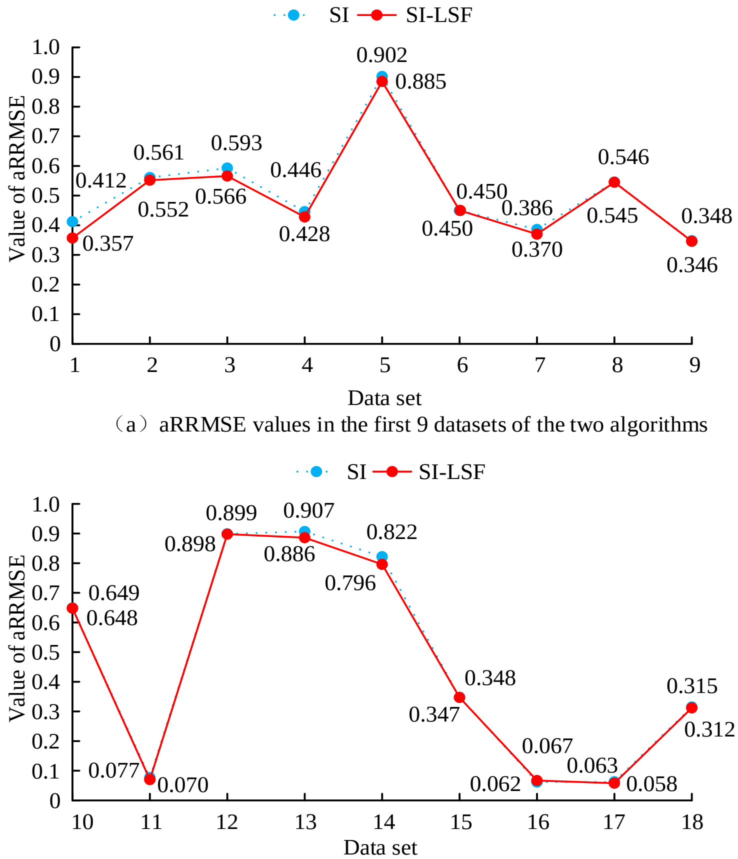


Fig. 6. aRRMSE values of several algorithms under different datasets.



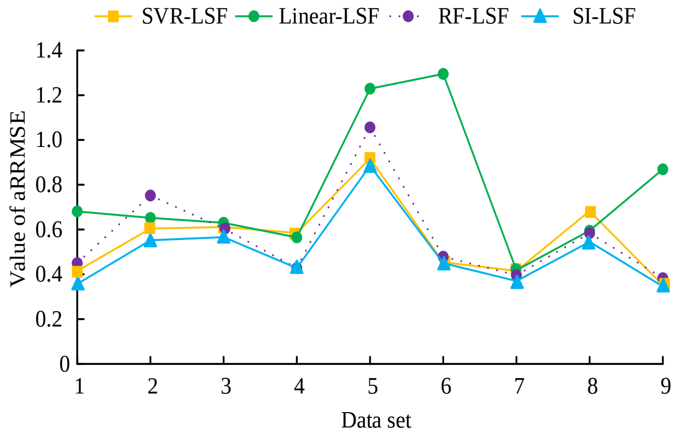
（a）aRRMSE values in the first 9 datasets of the two algorithms

（b）aRRMSE values in 9 data sets after two algorithms

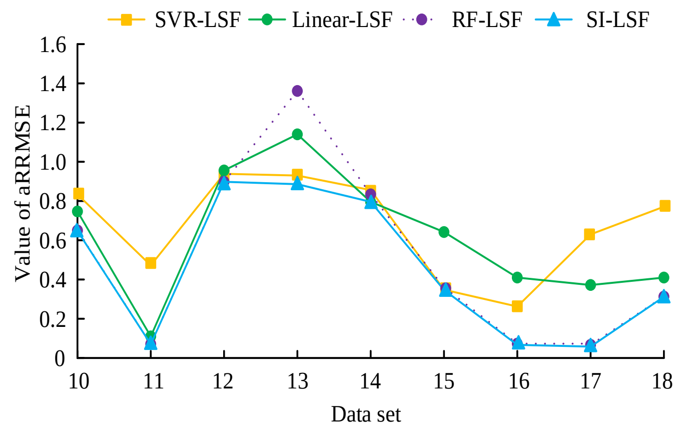
Fig. 7. aRRMSE values in different datasets of the two algorithms.

TABLE I. A RRMSE VALUES OF DIFFERENT TARGET VARIABLES OF FOUR ALGORITHMS IN SEVEN DATASETS

Datasets	Target variable name	SVR-LSF	Linear-LSF	RF-LSF	SI-LSF
S lump	C_S_Mpa	0.155	0.391	0.628	0.155
	FLOW_cm	0.821	0.755	0.756	0.755
	SLUMP_cm	0.822	0.789	0.789	0.781
E dm	DFlow	0.497	0.568	0.557	0.497
	DGap	0.721	0.668	0.642	0.629
S fl	c-class	0.951	0.951	0.951	0.951
	m-class	1.011	0.915	0.873	0.873
	x-class	0.781	1.752	1.215	0.779
Jura _	Cd	0.675	0.700	0.701	0.661
	Co	0.617	0.599	0.538	0.498
	Cu	0.764	0.500	0.541	0.481
Enb _	Y1	0.524	0.075	0.069	0.069
	Y2	0.412	1.213	0.075	0.075
S f2	c-class	1.101	0.955	0.955	0.955
	m-class	0.991	1.101	0.99 0	0.99 0
	x-class	0.751	1.415	2.102	0.751
S cpf	comments	1.044	0.892	0.895	0.887
	views	0.845	0.762	0.775	0.761
	votes	0.789	0.775	0.979	0.732

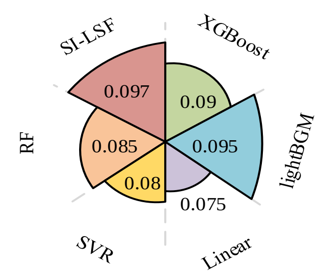


（a）aRRMSE values of the four algorithms in the first nine datasets

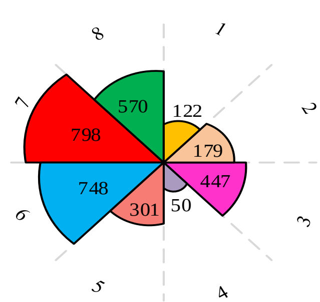


（b）aRRMSE values of the four algorithms in the last nine datasets

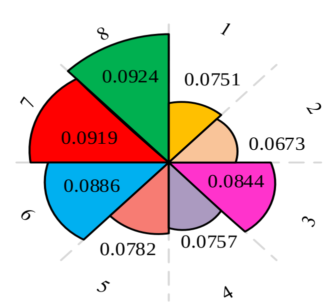
Fig. 8. aRRMSE values of four algorithms in different datasets.



（a）Score value of several algorithms in supply chain demand forecasting



（b）Feature dimension of si-lsf algorithm under different feature groups



（c）Score of si-lsf algorithm under different feature groups

Fig. 9. Comparison score results of several algorithms and score results of SI-LSF.

It can be seen from Table I that the aRRMSE value of SI-LSF on most datasets is the smallest, and in the Enb data, the Y2 target variable is at the smallest value, which is 0.075. In general, in each dataset, there is a complex relationship between the input target and the output feature. At the same time, the SI-LSF algorithm has a sparse integration, so its prediction performance is significantly better than other algorithms, which also proves that the SI-LSF algorithm is effective in processing. It has strong flexibility in multi-objective problems. To further verify the effectiveness of the SI-LSF algorithm in practical applications, the research applies it to the field of the e-commerce supply chains to predict multi-objective tasks for supply chain demand, and it mainly conducts comparative experiments under different feature groups. Here again, two regression models are introduced, namely extreme gradient boosting (eXtreme Gradient Boosting, XGBoost) and distributed gradient boosting framework (light Gradient Boosting Machine, lightGBM). The experimental results are shown in Fig. 9.

In Fig. 9, numbers 1-8 represent feature groups, representing basic statistical features, discrete features, time-series-related features, optimal combination features, basic statistical features + discrete features, basic statistical features + discrete features + time-series-related features, and basic statistics Features + discrete features + time series related features + optimal combination features and feature selection. It can be seen in Fig. 9(a), the scores of several algorithms are roughly between 0.08 and 0.09, of which the score of the SI-LSF algorithm is 0.097, which is the highest among several algorithms, showing that the SI-LSF algorithm is used in the supply chain. The forecasting performance in demand is the highest and has strong applicability. It can be seen in Fig. 9(b) and 9(c), the SI-LSF algorithm has the highest score when the number of feature dimensions is 570, that is, 0.0924. Therefore, it can be determined that the SI-LSF algorithm has the highest score after data preprocessing and feature selection. It can achieve a good forecast in supply chain demand and has strong practicability.

V. Discussion

The SI-LSF algorithm has the lowest aRRMSE value in all 16 datasets, with only the second lowest aRRMSE value in both datasets, roughly between 0 and 0.9. Among them, the SI-LSF algorithm is the smallest in the dataset Rf2, with a value of 0.058 and an overall average of 0.477. In addition, among the average rankings of the five algorithms, the aRRMSE value of SI-LSF is also the lowest, at 1.111. In addition, the overall aRRMSE value of SI-LSF is between 0 and 0.9, with its minimum value appearing on the Enb dataset at 0.070. When comparing with other algorithms, the aRRMSE value of SI-LSF is lower than that of the other three algorithms. In the Atp7d and Wq datasets, it is the same as the RF-LSF algorithm with a value of 0.428, while in the Scpf dataset, it is the same as the Linear-LSF algorithm with a value of 0.796. This result is superior to the results of Wang et al [26]. In practical applications, the SI-LSF algorithm has a score of 0.097, which is the highest among several algorithms. This indicates that the SI-LSF algorithm has the highest predictive performance in supply chain demand and has strong applicability. This result is basically consistent with the results of Moghadam et al [27]. Overall, the SI-LSF algorithm can achieve good prediction in supply chain demand after data preprocessing and feature selection, and has strong practicality.

VI. Conclusion

The advent of the big data era requires enterprises to improve their data mining capabilities, and at the same time requires enterprises to make effective predictions based on these data. Therefore, the research proposes the SI-LSF algorithm by creating special marking characteristics for each target and conducts experimental analysis on its performance and practical application, so as to improve the accuracy of MTR in e-commerce supply chain prediction. The experimental results show that in the prediction effect experiment, the aRRMSE value of the SI-LSF algorithm is the lowest in most datasets, with a minimum of 0.058 and an average of 0.477; in the validity experiment of label-specific features, the aRRMSE value of the SI-LSF algorithm is lower than that of the SI algorithm, and its lowest value is 0.070; in the effectiveness experiment of sparse integration, the aRRMSE value of the SI-LSF algorithm is lower than the other three algorithms in most datasets, and the lowest value is 0.058, and its average ranking value is 1, which is also the lowest; in the flexibility experiment of the SI-LSF algorithm, it is found that the aRRMSE value of the SI-LSF algorithm in most datasets is the smallest, and it is the smallest value in the Y2 target variable in the Enb data, which is 0.075. In addition, in the actual e-commerce supply chain prediction experiment, it is found that the SI-LSF algorithm has the highest score of 0.097. Under different feature groups, the SI-LSF algorithm has the highest score when the feature dimension is 570, with a score of 0.0924. In this case, better results can be obtained. In general, compared with other algorithms, SI-LSF has the best prediction effect and the best performance, and its prediction results are more effective. In practical applications, the SI-LSF algorithm has higher applicability with greater practicality. However, the selection of label-specific features does not take into account the shared information among variables, so it needs to be optimized for this aspect in the follow-up. At the same time, multi-objective regression algorithms have high applicability to practical application scenarios, so future research will consider applying the SI-LSF algorithm to practical problems in more fields, such as big data analysis, artificial intelligence, etc.

Acknowledgment

The research is supported by The first batch of construction projects of Applied Technology Collaborative Innovation Center of Fujian Higher Vocational Colleges (Min Jiao Ke [2016] No. 71 document);" Fujian Special Agricultural Products E-commerce Logistics Application Technology Collaborative Innovation Center" The science and technology plan projects of Fujian Provincial Department of science and technology (2022J01132808) "Construction of carbon footprint traceability and carbon label evaluation system of fresh agricultural products supply chain based on the blockchain technology". The science and technology plan projects of Fujian Provincial Department of science and technology (2023J011153) "Study on spatial and temporal

differentiation and development path of digital economy industrial structure in Fujian Province".

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