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Research Article

Visual Aggregation of Spatial Recognition Scientific Computations in the Financial Service Sector Based on the Random Forest Graph Model

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In view of the current problems in the visual aggregation of the financial service industry, the random forest graph model is applied to the spatial recognition of the financial service industry's scientific calculation visual aggregation in this paper. Based on the detailed analysis of the characteristics of the financial service industry in the past, combined with the characteristics of finance, this method is used to construct a random forest graph model, which mainly optimizes parameters from different aspects such as model structure, data characteristics, and dynamic changes of the model to obtain optimal parameter values of the random forest graph model. Finally, through the analysis of the experimental results, it can be seen that, according to the spatial state of the financial service industry, the method proposed in this paper can be used for visual aggregation analysis. This method can effectively improve the timeliness of the scientific calculation of spatial recognition in the financial service industry.

1. Introduction

As the level of Internet technology continues to improve, various financial service industries based on the Internet have begun to emerge. Domestic scholars have focused on the scientific computation of spatial recognition and its recognition since it is one of the popular visual aggregation types in the financial service sector [1–3]. However, it is highly tricky to acquire details from raw data of the financial service sector for scientific computation of spatial recognition as financial contents are not clearly defined and signal of the financial service sector is based on a time-sequencing method. The random forest graph model can be used according to its concealment. So far, the features of the financial service sector obtained are not accurate due to the relatively simple classification methods.

The financial service sector has gradually become a brand new engine and driving force for the economic growth and development of various countries. In the face of the complicated and grim economic situation in the world, the global economies have accelerated the development of a new generation of information and communication technologies and sped up the transformation and upgrading of the traditional industries in the direction towards more convenient financial services based on the network and intelligent technologies so as to seize the high ground in the development of financial services and gain a head start in the economic growth and competition across the globe. China is vigorously developing the financial service sector, facilitating the integration of the financial service sector with the real economy, accelerating the continuous transformation of old and new growth drivers, and promoting changes in quality, efficiency, and power for economic growth, thereby creating new drive for the modernization and high-quality growth of the economy [4, 5]. As a more advanced and sustainable economic form, the financial service sector is a vial driving force to promote industrial restructuring and achieve sustainable and high-quality growth of the economy. With the

features of game-changing technology innovation, network based platform, and high penetration, it can stimulate the emergence of new industries and promote the transformation and upgrading of the traditional ones through the industrialization of the financial service sector, thereby further driving the optimization and upgrading of the industrial structure. Among them, the industrialization of the financial service sector represented by the Internet of Things (IoT), e-commerce, artificial intelligence (AI), 5G commercialization, and so on has provided new services, new models, and new business modes for the economic growth [6, 7]. The Internet, IoV, big data, AI, and other emerging technologies are actively promoting the upgrading of the traditional industries to improve their production efficiency. The comprehensive index system for the growth in the financial service sector is established and the intermediary effect model. The impact mechanism and threshold of financial service sector on regional total production are analyzed based on the panel threshold model, which has provided theoretical support and empirical basis for implementing the industrial structure transformation and driving the high-quality economic growth [8–10].

In this paper, the spatial recognition scientific computation in the financial service sector is performed based on the random forest graph model. This method can be applied to the spatial recognition scientific computations of financial service sector as current prior knowledge of the financial service sector according to the spatial features of the financial service sector. The financial features in the financial service sector are extracted by information gain. It uses the random forest graph model to constrain the spatial weight, merges financial content information, integrates the spaces with high similarity, and constructs the spatial recognition scientific computations model in the financial service sector. The proposed system of random forest spectral model can enhance the effectiveness and efficiency of parallelization substantially.

2. Methods and Models

The visual aggregation effect in the development of the financial service sector is analyzed in conjunction with the random forest mapping model. The nonlinear time series set is taken as the spatial recognition parameter for the scientific computing of the financial service sector to establish a high-dimensional space with the distribution of spatially identified visual aggregation parameters in the scientific computing of the financial service sector, as described in the following:

$$x_n = x(t_0 + n\Delta t) = h[z(t_0 + n\Delta t)] + \omega_n. \tag{1}$$

In the above equation: $h(.)$ stands for the multivariate value function of the financial services development analysis; ω_n is the function to measure the assessment error. In the high-dimensional feature distribution space, the feature training subset S_i $(i = 1, 2, \ldots, L)$ to analyze and assess the growth can be obtained through the solution vector by analyzing and assessing the full visualization effect of growth

aggregation in the financial service sector, and the following conditions are met.

(1) $\Sigma = \text{diag}(\delta_1, \delta_2, \ldots, \delta_r), \delta_i = \sqrt{\lambda_i}, \forall i \neq j$.

(2) $oobF_1(k)$.

It is assumed that $X = \{x_1, x_2, \ldots, x_n\}$ is a spatial recognition scientific computation for the visual aggregation of statistical information in the financial service sector, which complies with the decomposition condition $x_k = \{x_{k1}, x_{k2}, \ldots, x_{kp}\}, x_{kj} = [a_{kj}, b_{kj}], 1 \leq k \leq n, 1 \leq j \leq p$ for initial value feature, where $U = \{u_{ik}\}, (i = 1, 2, \ldots, c; k = 1, 2, \ldots, n)$. With regard to the multivariate group, the development class analysis of the financial service sector assesses the sequence x (n) for statistical feature distribution. In the scientific computation for the visual aggregation of the spatial recognition in the financial service sector, the data flow is established according to statistical measure in the previous section:

$$c_{1x} = E\{x(n)\} = 0, c_{2x} = E\{x(n)x(n + \tau)\} = r(\tau),$$

$$\psi_x(\omega) = \ln \psi_x(\omega) = -\frac{1}{2}\omega^2 \sigma^2. \tag{2}$$

It is assumed that the data on the visual aggregation effect for the growth of the financial services is u_{ik}. According to the predicted visual aggregation effect in the growth of financial service sector, the initial feature value is fixed to obtain the estimated probabilistic density generalized function as follows:

$$u_c(t) = Kx_c(t), \tag{3}$$

$$\begin{cases} \sum_{i=1}^{c} u_{ik} = 1, & \forall k \\ 0 \leq u_{ik} \leq 1, & \forall k, i \end{cases} \text{ is continuous model function, and } k \geq 1$$

after $k - 1$ iterations; gray order sequence of the spatial recognition in the financial service sector for scientific computation of visual aggregation meets $N(k) < L$. The output index for the full visualized aggregation effect is obtained based on random forest mapping model in the analysis and evaluation of the growth of the financial service sector [11, 12], which is taken as the value of K neighboring samples of the information flow in the distributed big data:

$$P_{1J} = \sum_{d_i \in KNN} \text{Sim}(x, d_i) y(d_i, C_j). \tag{4}$$

The feature value of the main component is established through big data analysis to assess the full visualized aggregation effect in the growth of the financial service sector, and the similarity in the resource distribution of the financial service sector development is resolved by the ambiguous dense joint filling method, as described in the following:

$$\text{Sim}_1(d_i, d_{1j}) = \frac{\sum_{k=1}^{M} W_{ik} \times W_{1jk}}{\sqrt{\sum_{k=1}^{M} W_{ik}^2} \cdot \sqrt{\sum_{k=1}^{M} W_{1jk}^2}}. \tag{5}$$

In the above equation: g_i stands for the a priori distribution feature vector of the spatial recognition science of

financial service sector to calculate visual aggregation; and $g_i = (g_{i1}, g_{i2}, \ldots, g_{ip})$, $g_{ij} - [\alpha_{ij}, \beta_{ij}]$, $1 \le i \le c$, $1 \le j \le p$ stands for the vector of K-mean clustering center in layer 1 of big data.

The integration of the full visualized aggregation effect assessment in the growth of the financial service sector is implemented in combination with the fusion method for the linear correlation features [13], and the output fusion equation for the resource information in the growth of the financial service sector is described as follows:

$$P(w|x) = \frac{P(x|w)}{P(x)}. \tag{6}$$

It is assumed that the quantitative recursive feature is $\lambda_k^m = (\lambda_{k1}^m, \lambda_{k2}^m, \ldots, \lambda_{kp}^m)$; the feature of probability density in resource distribution of full visualized aggregation effect is $W = \sum_{i=1}^{c} \sum_{i=1}^{n} (u_{ik})^2 \Phi(x_k, g_i) = \sum_{i=1}^{c} \sum_{i=1}^{n} (u_{ik})^2 \sum_{j=1}^{p} [\lambda_k^m (a_{kj} + b_{kj}/2 - \alpha_{kj} + \beta_{kj}/2)^2]$. Thus, X (i) stream of big data in the scientific computing visualized aggregation for the spatial recognition of the financial service sector includes p (i) submatrices $\begin{cases} \lambda_{ij}^m \ge 0 \\ \prod_{j=1}^{p} \lambda_{ij}^m = 1 \end{cases}$ with the size of $\alpha_{ij} = \sum_{i=1}^{n} (u_{ik})^2 a_{kj} / \sum_{i=1}^{n} (u_{ik})^2$, $\beta_{ij} = \sum_{i=1}^{n} (u_{ik})^2 b_{kj} / \sum_{i=1}^{n} (u_{ik})^2$. Index parameters are clustered and integrated to develop a resource distribution plan for the full visualized aggregation effect. In this way, the optimization of the spatial recognition for the scientific computing visualized aggregation of the financial service sector can be implemented.

In general, firms are aggregated in a vertical chain of industrial connections. The manufacturing sector links upstream to downstream firms, which are in cooperative/competitive relationships. It is assumed that the X set of n samples has been processed by SDA.

$$X = \{x_1, x_2, \ldots, x_n\}. \tag{7}$$

With p as the index, fuzzy clustering is conducted by category:

$$x_k = \{x_{k1}, x_{k2}, \ldots, x_{kp}\}, \\ x_{kj} = [a_{kj}, b_{kj}], \quad 1 \le k \le n, 1 \le j \le p. \tag{8}$$

U is the relative membership of model matrix:

$$U = \{u_{ik}\}, \quad (i = 1, 2, \ldots, c; k = 1, 2, \ldots, n), \tag{9}$$

u_{ik} is the membership of sample k in the i category, which complies with

$$\left\{ \sum_{i=1}^{c} u_{ik} = 1, \forall k 0 \le u_{ik} \le 1, \forall k, i, \right. \tag{10}$$

g_i indicates the cluster center in category i:

$$g_i = (g_{i1}, g_{i2}, \ldots, g_{ip}), g_{ij} - [\alpha_{ij}, \beta_{ij}], 1 \le i \le c, 1 \le j \le p. \tag{11}$$

Adaptive parameter λ is introduced to obtain cluster weight:

$$\lambda_k^m = (\lambda_{k1}^m, \lambda_{k2}^m, \ldots, \lambda_{kp}^m). \tag{12}$$

Comprehensive weight is expressed as

$$W = \sum_{i=1}^{c} \sum_{i=1}^{n} (u_{ik})^2 \Phi(x_k, g_i),$$
$$= \sum_{i=1}^{c} \sum_{i=1}^{n} (u_{ik})^2 \sum_{j=1}^{p} \left[\lambda_k^m \left(\frac{a_{kj} + b_{kj}}{2} - \frac{\alpha_{kj} + \beta_{kj}}{2} \right)^2 \right], \tag{13}$$

where it satisfies

$$\begin{cases} \lambda_{ij}^m \ge 0, \\ \prod_{j=1}^{p} \lambda_{ij}^m = 1. \end{cases} \tag{14}$$

Using the Lagrangian method to derive the aggregation function is as follows:

$$\alpha_{ij} = \frac{\sum_{i=1}^{n} (u_{ik})^2 a_{kj}}{\sum_{i=1}^{n} (u_{ik})^2}, \beta_{ij} = \frac{\sum_{i=1}^{n} (u_{ik})^2 b_{kj}}{\sum_{i=1}^{n} (u_{ik})^2},$$
$$\lambda_{ij}^m = \frac{\prod_{h=1}^{p} \left[\sum_{k=1}^{n} (u_{ik})^2 \left(((a_{kh} + b_{kh})/2) - ((\alpha_{ih} + \beta_{ih})/2) \right)^2 \right]^{1/p}}{\sum_{k=1}^{n} (u_{ik})^2 \left(a_{kj} + b_{kj}/2 - \alpha_{ij} + \beta_{ij}/2 \right)^2},$$
$$u_{ik} = \left[\sum_{h=1}^{c} \frac{\sum_{j=1}^{p} \left[\lambda_{ij}^m \left(((a_{kh} + b_{kh})/2) - ((\alpha_{ih} + \beta_{ih})/2) \right)^2 \right]}{\sum_{j=1}^{p} \left[\lambda_{hj}^m \left(a_{kh} + b_{kh}/2 + \alpha_{ih} + \beta_{ih}/2 \right)^2 \right]} \right]. \tag{15}$$

In general, the concentration of firms is subject to natural resources, geographical environment, process technologies, etc. The cooperation of various firms in production and operation is mainly reflected by preliminary integration. Geographical location of firms is integrated through competitive/cooperative relationship. Internal resources of firms are integrated based on the matching degree of the cluster, which has minimized trade costs and maximized profits.

The random forest spectrum model can construct the model in the time series with the highest serialized feature for extensive application during scientific computation of spatial recognition in the financial service sector [14, 15]. In the model, N states are $S = \{S_1, S_2, \ldots, S_n\}$, and the state at t time t is q_t. It is assumed that $A = \{a_{ij}\}$ is established matrix of transition between states; then

$$\alpha_{ij}(k) = P[q_{t+1} = S_j | q_t = S_i], \quad 1 \le i, j \le N. \tag{16}$$

Any state in some RFAMs can be converted to other states in one transition, while other RFAMs allow transitions between specific states only; i.e., $a_{ij} > 0$ for some i and j.

Unlike that in the random forest graph chain, external values can only be observed for each state in the RFAM. The observation vector obtained is discretely or continuously related to the system state.

However, the probability distribution of vectors observed in j state under continuous observation is

$$b_j(v_t) = P[v_t | q_t = S_j], \quad 1 \le j \le N. \tag{17}$$

The probability distribution is generally used as mixed Gaussian distribution:

$$b_j(v_t) = \sum_{m=1}^{M} \omega_{j,m} N(o_t, \mu_{j,m}, \Sigma_{j,m}), \tag{18}$$

where M is the distribution count of mixture Gaussian, ω_m is positive mixture weight, and $N(o_t, \mu_{j,m}, \Sigma_j, m)$ is n-dimensional Gaussian distribution.

$$\pi_i = P[q_1 = S_i], \quad 1 \le i \le N. \tag{19}$$

Thus, RFAM is divided into three groups $\lambda = (A, B, \pi)$. Thus, the sequence observed based on the model is $O = o_1 o_2 \cdots o_T$, where o_t is the vector observed at t time, and T is the total length observed.

The time complexity and space complexity in the spatial recognition scientific computation of the financial service sector are subject to the impact of the dimension of feature vector in the financial service sector. The dimensionality reduction in the financial service sector is processed by extracting model space to make the assessment based on the model more accurate. The mean volume of data in the model is calculated based on information gain algorithm:

$$G(w) = -\sum_{k=1}^{N} P(c^k) \log_2 P(c^k) + p(\overline{w}) \sum_{k=1}^{N} p(c^k | \overline{w}) \log_2 p(c^k | \overline{w}), \tag{20}$$

where $\overline{w}$ is the complementary set of w; $\overline{w}$ is the space count; T is the mean number of words in the financial service sector in the training set. In the preprocessing stage, word2 vec used in the preprocessed financial service sector is taken as a vector, and the word count is recorded in combination with highly similar word vectors. In the selection of space, the meaning of spatial aggregation vector is taken into account in this paper.

The financial service sector automatically consists of several columns of vocabulary. In the specific financial service sector, various vocabulary will automatically be different. Hence, the establishment of the random forest spectrum model is based on the space itself and the space frequency, but in the space extraction process, the meaning information is merged into the space. The random forest spectrum model is established based on the category space set with the word vector as the hidden state and the corresponding word count as the state sequence observed.

For the constructed random forest graph model the state transition period is a process of space traversal. The spatial output sequence is defined by k, which is the spatial sum in line with similarity threshold. Based on the model, the intermediate state (s_i) is obtained, and the distribution observed in c^k class is

$$v_{c_k}^i(w_{c_i}) = p\{k | s_i = w_{c_i}\}. \tag{21}$$

Taking full account of the constraints on the distribution of $b_{c_k}^i$ and spatial frequencies, a greater spatial distance

during processing indicates smaller aggregate in different financial service industries.

$$b_{c_k}^i(w_{c_i}) = IFIDF(i) = \frac{D_c k(i) + 1}{\sum_c k D_c k(i) + |C|} \times \frac{N_c k(i) + 1}{\sum_c k N_c k(i) + |C|}, \tag{22}$$

where $D_c^k(i)$ is business item in the financial service sector (w_{c_i}) of c_k; $N_c^k(i)$ is the occurrences of w_{c_i} in c_k class. Thus, a regularizing effect can be observed in the occurrences of the same class.

The matrix of state transition in state 1 is converted to state 2 until the end position as the random forest graph model (c_k) is classified in the category of financial service sector [16, 17], with A_c^k state transition matrix:

$$a_{ij} = \begin{cases} 1, & j = i + 1, \\ 0, & j \ne i + 1. \end{cases} \tag{23}$$

The probability $\pi = \{1, 0, \ldots\}$ in s_0 initial state is defined, with the random forest graph model in c_k category:

$$\lambda_k = \{\Pi, A_{c^k}, B_{c^k}\}. \tag{24}$$

With regard to the case where the classification is not precise in the evaluation and computation of the scientific computation visualized aggregation for the spatial recognition in the traditional financial service sector, the random forest mapping model is used in this paper for the evaluation and computation of the spatial recognition scientific computation visualized aggregation in the financial service sector. The performance of the established data model is evaluated by quantitative recursive method to obtain its control features and classify the index parameters for visualized aggregation of spatial recognition in the scientific computation of the financial service sector.

Through the use of this computation method, the assessment of scientific computation visualized aggregation for the spatial recognition of the financial service sector can be carried out effectively. Due to the high capacity in comprehensive analysis of data, it can make the evaluation of full visualized aggregation much more accurate and improve the efficiency of resource utilization in the financial service sector.

A visual aggregation method for the spatial recognition of the financial service sector based on the random forest mapping model is put forward. The random forest mapping model is used to analyze the information related to the assessment of the scientific computational visualized aggregation for the spatial recognition in the financial service sector. Through the experiment, it is verified that the information combination analysis capacity of the proposed method is high, which can greatly increase the evaluation accuracy for the aggregation effect of full visualization and application efficiency of resources to boost the development in the financial service sector by evaluating the visualized aggregation effect in the scientific computation of spatial recognition.

The random forest mapping model was used to analyze the information related to the assessment of spatially identified scientific computational visualized aggregation in the financial service sector.

The experiments verify that scientific computational visualized aggregation of financial service sector spatially identified can be evaluated by the computation method, with a high comprehensive information analysis capacity, substantially increased evaluation accuracy of full visualized aggregation effect, and efficient utilization of financial service sector development resources.

RFM parameters should be initialized before computation based on Baum-Welch algorithm. The results obtained based on aggregation algorithm for scientific computation visualization with initial parameters are highly correlated. Whether the transition matrix or iterative operation is 0 is determined by initializing the transformation matrix, and observation sequence is defined as $O = o_1 o_2 \cdots o_T$:

$$P(O|\lambda_k) \geq P(O|\lambda), \tag{25}$$

$P(O|\lambda)$ is calculated based on forward-backward algorithm. Probability $\alpha_t(i)$ is defined using RFAM parameter λ and state i:

$$\alpha_t(i) = P(o_1 o_2 \cdots o_T, q_t = i|\lambda). \tag{26}$$

Namely, $\alpha_t(i)$ is the probability of sequence $(o_1 o_2 \cdots o_t)$ under parameter A in o_t state at t time.

Based on forward algorithm, $P(O|\lambda)$ can be calculated as follows:

(1) Initialization

$$\alpha_1(j) =_j b_j(o_1), \quad 1 \leq j \leq N. \tag{27}$$

(2) Recursion

$$\alpha_t(i) = b_i(o_t) \left[\sum_{j=1}^{N} \alpha_{t-1}(j) \alpha_{ji} \right], \quad 1 \leq t \leq T, 1 \leq i \leq N. \tag{28}$$

(3) Termination

$$P(O|\lambda) = \sum_{j=1}^{N} \alpha T(j), \tag{29}$$

$\beta_t(i)$ and $\xi_t(i,j)$ are defined as

$$\beta_t(i) = P(o_{t+1} o_{t+2} \cdots o_T, |q_t = i, \lambda),$$
$$\xi t(i,j) = P(qt = 1, qt + 1 = j|O, \lambda), \tag{30}$$

$\xi_t(i,j)$ can be expressed by forward-backward computation method:

$$\xi t(i,j) = \frac{P(q_t = i, q_{t+1} = j|O, \lambda)}{P(O|\lambda)}$$

$$= \frac{\alpha_t(i) \alpha_{ij} b_j(o_t + 1) \beta_{t+1}(j)}{P(O|\lambda)} \tag{31}$$

$$= \frac{\alpha_t(i) \alpha_{ij} b_j(o_{t+1}) \beta_{t+1}(j)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_t(i) \alpha_{ij} b_j(o_{t+1}) \beta_{t+1}(j)},$$

where the system is in the m component of i state at t time; the probability $\gamma_t(i, m)$ is

$$\gamma_t(i,m) = \left[\frac{\alpha_t(i) \beta_t(i)}{\sum_{i=1}^{N} \alpha_t(i) \beta_t(i)} \right] \left[\frac{\mu_{j,m} N(o_t, \mu_{j,m}, \sum j, m)}{\sum_{m=1}^{M} \omega_{j,m} N(o_t, \mu_{j,m}, \sum j, m)} \right]. \tag{32}$$

Various types of RFAM are first trained by using the labeled training set. Let the scientific computation for spatial recognition be $k = \{1, 2, \ldots, K\}$ and the parameter of each type corresponding to the model be λ_k. Given Bayes formula, the posterior probability is maximized based on maximum likelihood criteria

$$\overline{k} = \arg \max_{1 \leq k \leq K} P(O|\lambda_k) = \arg \max_{1 \leq k \leq K} \frac{P(O|\lambda_k) P(\lambda_k)}{P(O)}. \tag{33}$$

Provided that each type has the same prior probability $P(\lambda_k)$, since P(O) is independent of k, the determination can be ignored.

$$\overline{k} = \arg \max_{1 \leq k \leq K} P(O|\lambda_k). \tag{34}$$

Due to the maximum value $P(O|\lambda_k)$ and the occurrence of underflow at float point during computation, logarithmic values are taken in general. Each equation is weighted if there are several sequences observed.

The random forest graph model cited in this article uses small samples for multiple sampling. Through the random forest graph model, a scientific and reasonable visual aggregation center can be obtained, so as to reduce the unreasonable phenomenon of scientific computing and visual aggregation in the initialization stage and effectively improve the random forest. Performance and accuracy of graph models: The model is based on the MapReduce model for random forest graph model analysis. The operational framework of the random forest graph model is shown in Figure 1.

In the current space identification sector of the financial service sector, the requirements of individual firms should be timely responded to satisfy their different demands. The financial service sector includes two main subsectors: development and design. In the emerging financial service sector, customized services are offered to firms during development and design cycles after comprehensive analysis of market demand variation, along with individualized design based on the actual demand of firms. Though their objectives differ from the primary missions, they are inherently connected. Modularization and standardization are designed in the process of spatial recognition of the financial service sector as the basis of the process of spatial recognition of the financial service sector. The nonsegmented pieces attached to the process of spatial recognition of the financial service sector is converted to a virtual reality (VR) model, which should also has the supporting information on the growth of the emerging sector and firm design based on their needs. The VR-based random forest graph model is established, where virtual objects, scenes, or systems generated by
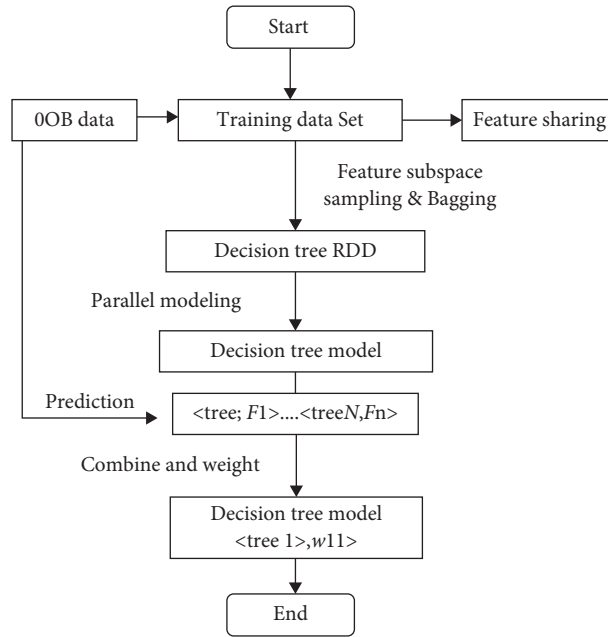
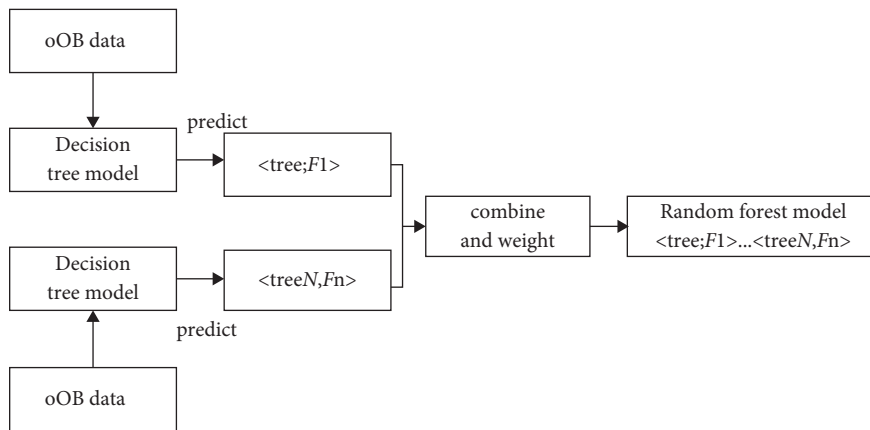FIGURE 1: Computing framework of the random forest graph.

FIGURE 2: Weighting process.

computer are superimposed to "enhance" the prompt on real-world scenes.

Based on the random forest graph model, virtual objects are introduced to real-world context, and their position and posture consistent with real-world scenes are displayed dynamically. In this way, environment roaming can be observed based on random forest graph model so as to ensure more natural interactions. Additionally, the output is more realistic based on random forest graph model.

Based on the random forest graph model, the actual situation can be photographed with a camera. Each frame in the video is processed by tracking to calculate the coordinates and states of virtual objects corresponding to those in the real world based on geometric computation and construct a virtual scene on this basis. The virtual scenes are combined with real-world streams, and the merged results are timely transmitted and displayed. Computation is performed based on the weight corresponding to each tree

according to formula, and the weighted random forest corresponding to these decision trees is combined. Figure 2 is a flowchart of weighting processing.

In the case of the random forest graph model system, the real-time addition of virtual objects to real-world scenes and correct alignment with real-world objects is crucial. Every tree in a random forest requires voting and statistics. In this case, when the number of decision trees is large, the voting process of the entire random forest model is parallelized. Figure 3 is a flowchart of parallelized voting by weighted random forest.

Refer to the design drawings of the financial service sector to zoom in and out of the system at a certain ratio. During the implementation of the financial service sector's exterior wall, consistent specifications are ensured in the solution. The scale issue of all lines in the financial service sector is addressed by the department according to the length and width of a line.
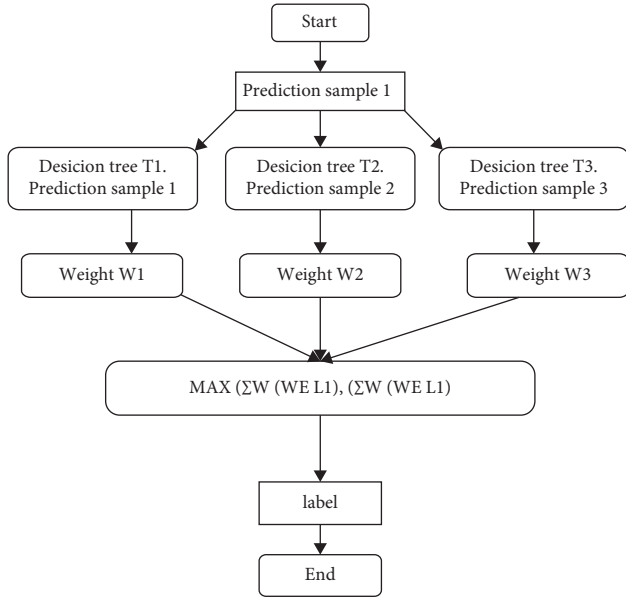
FIGURE 3: Parallel voting flowchart of weighted random forest.

After establishing the coordinate system in scale, each line in the financial service sector is represented by a geometric entity in the virtual sector through a series of computations.

3. Experiment and Result Analysis

In the cluster based on random forest graph model, the parallel frame is established each in the test for storage by Hadoop, and relevant data are calculated according to the model. Let

$$ITUs_{ijkt} = \alpha + \beta_1 \text{fincol}_{ijkt} + \beta_2 X_{ijkt} + \vartheta_i + \tau_j + \varphi_t + \varepsilon_{ijkt}, \quad (35)$$

where k, i, j, and t are company, sector, region, and year, respectively; $ITUs_{ijkt}$ is the conversion result of the manufacturer; fincol_{ijkt} is the distribution of spatial coordination between the financial service and manufacturing sectors; X_{ijkt} is control variable; α is constant term; ε_{ijkt} is random disturbance item. Further, the fixed effects of sector (ϑ_i), region (τ_j), and time (φ_t) are introduced into the model.

3.1. Variables Are Explained. Variable interpretation: manufacturing model transformation. Based on the viewpoint of the industrial value chain, the conversion and upgrading of manufacturers are mainly manifested in moving towards the high end of the global value chain. On this basis, the upstream degree of each subsector is obtained in the input-output table. Furthermore, the firm-product-grade import and export data is used; the formula for calculating the upstream degree of firm-level import and export is

$$UX_{ft} = \sum_{i=1}^{N} U_i \frac{X_{if}}{X_f},$$

$$UM_{ft} = \sum_{i=1}^{N} U_i \frac{M_{if}}{M_f}. \quad (36)$$

Two differences define the upstream degree of pure exports or the conversion and upgrade effects of manufacturing (ITU):

$$ITU = UM_{ft} - UX_{ft}. \quad (37)$$

Firstly, market needs are analyzed to facilitate the subsequent financial services for new commodities. In this way, firms can understand the market situation comprehensively to meet the demand of customers better. Secondly, the fashion trend is predicted to guide the firms correctly. Fashion trends refer to designs, colors, fabrics with higher quality, and patterns that are popular. Further, the design of new clothes requires designers to have both inspiration and creativity [15]. During the process of spatial recognition of the financial service sector, the knowledge base should be combined with market demand and fashion trend at present. The information on market demand and fashion trend should also be used as the source of design inspiration for spatial identifiers in the financial service sector. According to design patterns, the relevant style is identified, combined with inspiration, and stored in the knowledge base. After spatial recognition of the financial service sector is completed, the financial service sector spatial recognition of new products will be converted into the design knowledge of the individual needs of the financial service sector customers.

3.2. Core Explanatory Variable. The spatial coordination distribution of financial services and manufacturing: In the research to date, the deposit amount of local financial institutions in most regions accounts for the ratio of GDP. Or use the location entropy method to measure the scale of industrial integration and the degree of integration of local finance, but it cannot describe the codistribution features of the financial service sector and the manufacturing sector.

$$\text{cluster}_{ij} = \frac{L_{ij}/L_j}{L_i/L}, \quad (38)$$

where cluster_{ij} represents the location entropy index of sector i (i = mcluster, fcluster) in city j in the country; L_{ij} represents the number of employees in sector i in j city; L_j represents personnel count in manufacturing and financial service industries in city j, ($j = 1, 2, 3, \ldots, N$); L_i represents personnel count in i sector nationwide; L represents the number of employees in the manufacturing and financial services industries across the country.
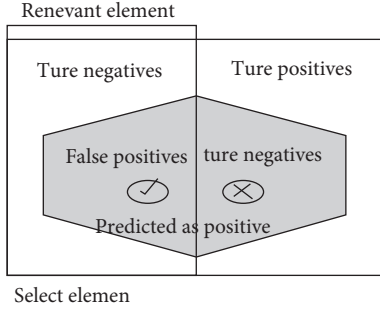
FIGURE 4: Schematic diagram of classification results.

TABLE 1: Confusion matrix.

	Positive	Negative
T	TP	TN
F	FP	FN

$$\text{fincol} = \left(1 - \frac{|m\text{cluster} - f\text{cluster}|}{m\text{cluster} + f\text{cluster}} \right) + |m\text{cluster} + f\text{cluster}|. \tag{39}$$

In Figure 4, the attributes obtained based on the classification model are verified in combination with their mathematical relationship, and the performance of the model is assessed by confusion matrix indices. The confusion matrix is shown in Table 1, where T indicates True, F indicates False, TP indicates True Positive, FP indicates False Positive, TN indicates True Negative, and FN indicates False Negative.

The evaluation indices of the confusion matrix are divided into precision and recall.

Veracity:

$$\text{precision} = \frac{TP}{TP + FP}. \tag{40}$$

Recall rate:

$$\text{recall} = \frac{TP}{TP + FN}. \tag{41}$$

Further to this, there is F_1 value, which is a blending value of veracity and recall rate. The F_1 value is defined as

$$F_1 = \frac{2TP}{2TP + FP + FN}. \tag{42}$$

In the process of constructing the model, the scientific computation visualized aggregation method was used. The prediction of small loans is divided into two types: on-time repayment and overdue. The corresponding values of the type are "0" and "1", respectively, so the value of Class-Number is set as 2. Set the four parameters according to the greedy algorithm; select the value F_1

$$\begin{cases} \max \text{Boxes} = 130 \\ \max \text{Depth} = 6 \\ \text{number Decision Trees} = 240 \\ \text{characteristic Number Strategy} = ''\text{sqrt}'' \end{cases} \tag{43}$$

According to equation, the tree weight is proportional to the value on the out-off-bag data, and 200 weight values for decision tree can be selected to verify the rationality of the tree weight. Figure 5 is the weight map.

For the purpose of testing the recognition capacity of the model put forward in this paper and at the same time comparing with the curve profile offset recognition model, the recognition threshold value based on the random forest mapping model is used as the difference value in the spatial recognition rate for the financial service sector in the experimental samples. In other words, the deviation of the joints in the three consecutive business types will be considered as the business type that can be used to identify the joints when the deviation between the slopes of the fixed points is completed. The financial services are identified based on the curve profile offset identification model and the random forest mapping model in turn. After different experimental threshold values are set, the financial service space is identified accordingly, and the information data on the financial service space are detected in turn. In accordance with Table 2 below, the experimental results suggest that the traditional model can lead to an increase in the recognition volume as the recognition threshold value of the financial service space increases, and the similarity of recognition will also be affected to some extent. Hence, the random forest mapping model is mainly implemented based on the rotation operation so that better recognition capacity can be obtained. Table 3 is shown below.

The proposed method is used in the random forest mapping model for the detection of the financial services space identification, and the detection objects are identified patterns that may be subject to various attacks, as well as the unidentified patterns. The ideal detection model should be able to detect the maximum similarity with the part corresponding to the completely original recognition. It can be observed through the probabilistic theoretical analysis that the algorithm adopted above needs to be associated with the presence of a sequence in the identification of the financial services space. Table 2 below shows the corresponding size of the ms for the different values selected.

In fact, the length of the recognition information is not very small, and the recognition pattern subjected to the ablation attack has no practical application value if the number of valid bits is relatively small. Hence, the minimum value and the maximum length of the identification information bits extracted based on the considered design are set between 25 and 1000. After the above data are interpolated a threshold curve can be plotted based on the similarity threshold value corresponding to each recognition length, as
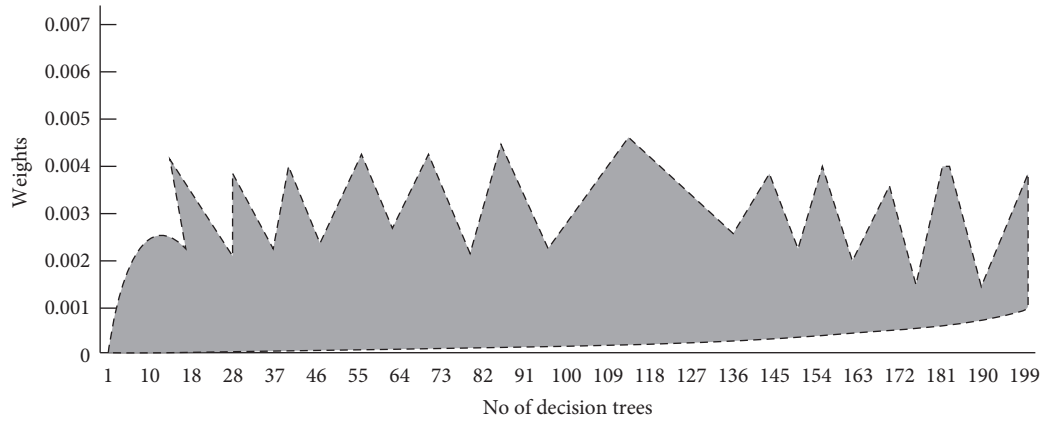
FIGURE 5: Decision tree weight diagram of weighted random forest.

TABLE 2: Maximum similarity of the identification with different lengths and 999 random identifications.

L	25	50	100	200	400	800	1000
Ms	0.5	0.499	0.39	0.28	0.23	0.21	0.198

TABLE 3: Comparison of the recognition capacity of the curve profile offset recognition model and the random forest mapping model.

	Similarity of recognition	
Threshold	Curve profile offset recognition model	Random forest mapping model
0.03	0.45647	0.72135
0.05	0.29183	0.71093
0.09	0.16688	0.68315
0.17	0.09175	0.66406
0.21	0.0748	0.66232
0.31	0.0544	0.6467

shown in Figure 5 above, which can be further used as a reference for the similarity threshold of the recognition information with different lengths during the recognition detection.

4. Conclusion

Various types of data in the traditional financial sector are rich and contain great value. How to effectively use these data and extract useful information to help users make decisions is a major problem faced by people in the financial sector. The random forest map model is used for the scientific computation of spatial recognition of the financial service sector. The random forest map model is used to assess the data model capacity and control the featured resources acquired. The accuracy of scientific computation of spatial recognition is improved by using optimal parameter values based on RFAM, and the spatial recognition and industrial agglomeration analysis of the financial service sector are completed. Finally, the results of example analysis show that accurate and fast spatial recognition scientific

computation can be achieved by introducing the model of random forest graph into independent scientific computation of spatial recognition in the financial service sector. At the same time, combined with the rhythm features of the financial service sector, the spatial recognition scientific computation accuracy of the RFAM model of the financial service sector is improved to 67.9%. The visual analysis of scientific computation of spatial recognition of financial service sector based on random forest graph model is realized.

Data Availability

The supporting data can be obtained from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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