Research on Key Technologies of Data Service Based on Adaptive Deep Learning

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Abstract: With the widespread adoption of big data technology, the diversity of data sources is continuously evolving. Data service technology is a technology derived from providing effective data interfaces for data applications. Based on the adaptive deep learning algorithm, this study proposes an improved service plan. First, the problem of randomly selecting the sending location of the data packet in the asynchronous random service scheme was analyzed, which leads to the waste of channel resources. Then, combined with the adaptive deep learning algorithm, an adaptive service scheme is specified. For the problem of large delay, the data frame is divided into multiple uniform position intervals. Therefore, the user learns the position interval until the user tends to select a position within the fixed position interval to send the data packet. Furthermore, in the algorithm's iterative process, adaptive deep learning was used based on the ability of the algorithm to perform intensive learning. A detailed analysis of the various scenarios, the essential mode of the technology, and the computer simulation of the throughput and packet loss rate indicators of the proposed scheme in the three environments are provided to demonstrate the superiority of the proposed scheme.

Key words: Adaptive deep learning, data service, particle weights, asynchronous random.

1. Introduction

Data governance service is a data application process in which a data governance platform provides access to data. Based on the definition of data governance service, it is possible to analyze and study methods of providing data, data transmission methods, and the service of providing data to the destination. The source side has no control over how the target side loads because the data loading process is not captured. The data governance service provider first provides a detailed description of the data resources that need to be serviced and then registers them with the registry. The data resource requester uses certain addressing method to find the data resource service that meets the demand according to the demand information. In this process, the modeling and representation of data resource services is the most important part of the computing model of data resource services.

This study examined the key techniques of data resource service patterns and time-aware adaptive deep learning algorithms. Based on the deep learning algorithm, an improved model of data resource service is presented. First, this study reviewed the random location of packets in the asynchronous random service

schemes, which leads to the waste of channel resources. Then, combined with the time-aware adaptive deep learning algorithm, an adaptive service scheme is proposed. The data frame is divided into multiple uniform position intervals to solve the large time delay problem. The user learns the position interval until the user tends to choose a fixed position interval location to send packets. In the process of iteration algorithm, the right of using particle reconstruction strategy makes populations evolution ability weaker capability of particles to the evolution of particle.

2. Related Work

Data management service combination has been extensively studied in computing [1], [2], for resource-intensive data services, which involves mass data resources and update operations. There are challenges in implementing methods for providing resource-intensive data services; therefore, service composition methods for resource-intensive data services have also been widely studied [3]–[5].

Presently, many researchers have proposed modeling methods for various data governance service resource patterns. The event-condition-action-based data governance service business process pattern method has been used in the data in the business process. This data governance service process modeling method supports the dynamic modification of the data governance service pattern, making the model flexible [6]–[8]. However, this model only considers the service's preconditions and does not form a complete data governance service model. In [9]–[11], they proposed a modeling method based on the data management service process instance. They changed the data management service mode driver from traditional ways like change the way of data management service resources, the data management service resources control flow driver change for the data management service resources data driven [13]. Literature [14]–[16] proposed a document-driven data governance service pattern, which does not show control flow but adopts a document-driven approach to complete the flow of data governance services. This method is helpful for data governance service personnel to discover data dependency in the process. In [17]–[19], a data-driven service model was proposed, and the data management service mode based on the dynamic changes of the data management service mode was presented. In this model, data management services and data resources are combined via a loose coupling relationship. Modeling service patterns using this method can reduce the difficulty in processing large-scale data management service process modeling. BPEL(Business Process Execution Language) is proposed extension-based data management service composition method [20]-[22]. This method can be explicitly described in the service data flow and integrated with some special data management service agreement to improve data governance, which provides data using the execution speed of the service resources. However, this method does not take into account the data resources and data dependencies between governance service. Literature [23]–[25] proposed an automatic integration method of service data based on arbitration ontology, which modeled the data in the service as an RDF(Resource Description Framework)-based view and designed the corresponding service composition algorithm based on query rewrite technology [26]. The data governance service composition algorithm achieved the automatic combination of data-intensive services by classifying and merging data governance services. The experiment shows that the algorithm can improve the execution speed of services [27], [28].

3. Hierarchical Stochastic Petri Nets for Data Governance Services

In the data governance service mode, the time of providing service to users is delayed because of network and other reasons, so the service time is random. Similarly, the time users access the data governance service is also random. Assuming that the implementation time t is a random variable conforming to distribution, the probability density function of T is

$$f(t)=\int_{-\infty}^{t} fx(t)dt=\{\ \frac{\beta^{\alpha}t^{\alpha-1}/\tau(\alpha)\sin^{-1}\theta.....t>0}{0\qquad\qquad\qquad t<=0} \tag{1}$$

where $\alpha > 0$ and $\beta > 0$ are all constants, $\Gamma(\alpha)=\int_0^{+\infty} t^{\alpha-1}e^{-t}dt$

$$\Gamma(\frac{1}{2})=\sqrt{\pi}\ ,\quad \Gamma(1)=1\ ,\quad \Gamma(\alpha+1)=\alpha\Gamma(\alpha) \tag{2}$$

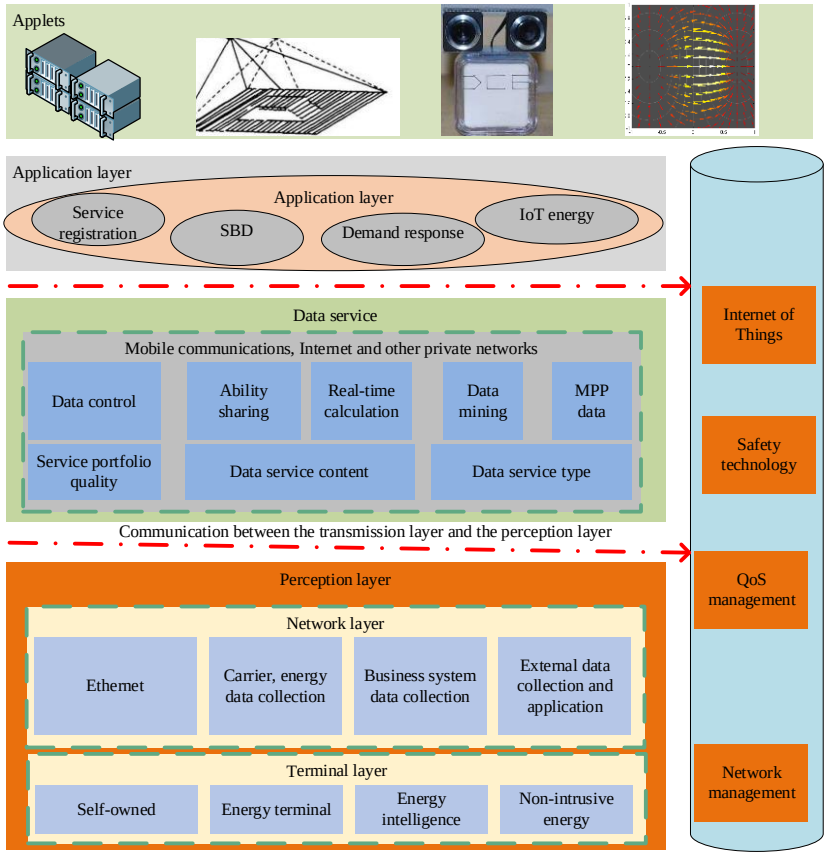


Fig. 1. Basic framework for data resource services.

Then, the hierarchical stochastic Petri net model of the data governance service resource service model is defined as

Definition 1: SPN = (P, T, D, A, M0, c1, α, β)

1) SPN (P, T, D, A, M0, $c1$, α, β) is a random Petri net.

2) P is the set of a non-empty finite library of control and data token, and it is the buffer where data governance service nodes and data governance service application parameters are stored.

3) T is the transition state finite set, T = {$T1$, $T2$, ..., Tn} is a finite transition set, $n > 0$, and $T = Tt\ U\ Ts$, where Tt is a finite set of time transition, Ts is a finite set of instantaneous transition, the average transition implementation rate set associated with hierarchical randomness λ = {$\lambda1$, $\lambda2$, ..., λk}, and k is the number of time transition.

4) D = (P ∩ T) U (T ∩ P) is the flow relation (that is, directed arc set), P ∩ T = ϕ, P U T! = ϕ. In D, forbidden arc h is allowed and h ∈ (P × T).

5) M0 represents the initial node of the finite set of all data governance service resources in the library,

namely, the initial node of data governance service.

6) $c1$: $t->[0,1]$ represents the mapping of the time cost of each transformation arc to the probability of [0,1].

7) α : p- > [0,1] represents the mapping of each library to the probability of [0,1].

8)β: the mapping function of p- > D library to server resources, where the transformation path is determined by the selection of routing topology algorithm of time-aware adaptive deep learning algorithm.

A data governance service is a data-centric service that requires continuous acquisition, storage, and updating of large-scale data resources during execution. To model and represent data resource services, an adaptive deep learning algorithm based on time perception was proposed. This method mainly includes service ID and service behavior description. The service ID assigns a globally unique name to the data governance service, whereas the service behavior description describes the data resource service semantically from the aspects of topology location, service function, and other features of the data governance service. The basic framework is shown in Fig. 1.

4. Data Governance Services for Time-Aware Adaptive Deep Learning Algorithms

4.1. Intensive Deep Learning Algorithm

According to the data governance service model, enhanced deep learning algorithms can be divided into two categories: first, the data governance service-based model, which models the data governance service environment and then learns continuously from the established data governance service environment model to deduce the optimal strategy, and second, the data governance service resource model that does not require data governance service resource modeling. However, it directly conducts adaptive deep learning to obtain the optimal strategy. Common reinforcement deep learning algorithms are as follows:

1) Time series difference algorithm, combined with Monte Carlo's dynamic programming algorithm, can learn directly without knowing the dynamic model parameters of the data governance service environment. According to the appropriate step size, a sequential difference algorithm can be expressed as $TD(\lambda)$, among which the simplest is the one-step algorithm, namely, TD(0) algorithm. After the one-step TD algorithm obtains the instantaneous reward value, it needs to go back one step and modify the estimated value of adjacent states. It can be expressed by the following formula:

$$V(S_t) = V(S_t) + \alpha(R_{t+1} + \gamma V(S_{t+1})) \tag{3}$$

2) The deep learning algorithm learns the unknown data governance service environment through unsupervised learning. The basic formula is as follows:

$$P_m(i) = P_m(i) + \beta(r - P_m(i)) \tag{4}$$

where $P_m(i)$ represents the evaluation value of adaptive deep learning in this state, β represents the learning rate, and R represents the reward factor. Furthermore, adaptive deep learning needs to adopt a greedy strategy to conduct deep learning.

4.2. Data Governance Service Based on a Time-Aware Adaptive Deep Learning Algorithm

Consider the random service model of data governance services, as shown in Fig. 2. There are many user terminal nodes for random data governance services, and the sending end users send packets to random locations within the frame. A data governance service solution based on adaptive deep learning is shown in Fig. 2.

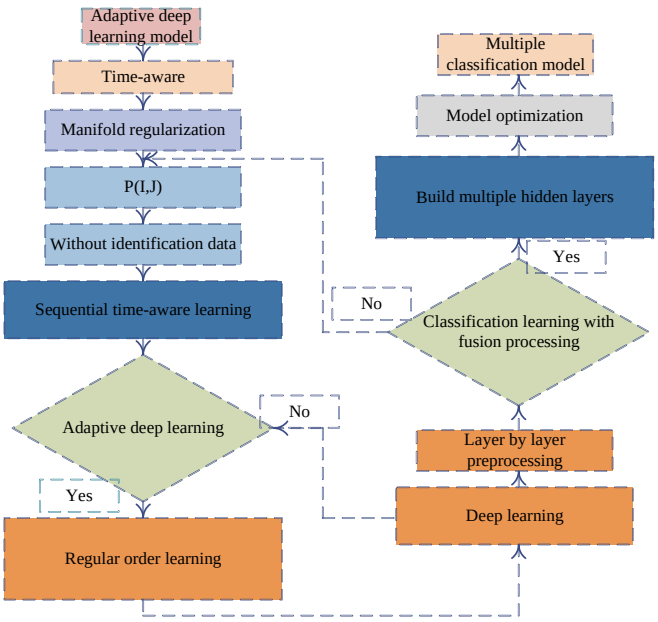


Fig. 2. A schematic diagram of data governance services based on time-aware adaptive deep learning.

We calculate the location interval for each user to evaluate all data management services on the current data frame, and use P(I, J) to apply for the i-th data management service resource from the user. In the first J position interval evaluation value, the position with the larger evaluation value is the higher probability of the user in the data management service position. Therefore, each time the user selects the location of the data management service evaluation value, the two maximum intervals of data management are sent. In the initial sending stage, the application user does not know the environment information of other applications, so the time-aware adaptive deep learning algorithm evaluation table is initialized to a complete zero matrix. The update algorithm of adaptive deep learning is as follows:

$$P(i, j) = P(i, j) + \beta(r - P(i, j)) \,. \tag{5}$$

Simultaneously, because of the problem of large delay in the data governance service channel, the feedback signal of the data governance service package cannot be timely fed back to update the evaluation value. The user sending end of the current data governance service frame cannot get the feedback of the transmission of the data governance service packet of the previous frame promptly, but the delay from the signal sent by the user to the feedback signal received generally does not exceed one frame of transmission time. We propose a scheme in which the sending end of data governance service adopts frame alternations; namely, the data governance service frame is divided into the first half and the second half, respectively, using adaptive deep learning access. The data governance service location interval assessment values in the first half and the second half are independent, and the feedback in the first half is fed back in the transmission delay of the frame, that is, the next half receives feedback from the previous half to update the assessment value, as well as the second half. This is equivalent for conducting two independent and unrelated adaptive deep learning processes simultaneously in the first half and the second half. Finally, when the adaptive deep learning process in the current part and the latter part reaches convergence, the whole data governance service system is considered to reach a stable state of convergence.

The steps of time-aware adaptive deep learning algorithm are shown in Table 1.

Table 1. Time-Aware Adaptive Deep Learning Algorithm

1. In the first half, the initial evaluation value is 0, the maximum number of learning frames T = 60, the learning rate is A, the number of activated users is N_{users}, and the number of position interval k = 100.
2. for episode = 1 to T do
3. for episode2 = 1 to N_{users} do

4. Select the two data governance service location interval Numbers P and Q with the highest evaluation value. If there are multiple identical and maximum values, then randomly select two-location intervals from the multiple maximum values, and then randomly select one location from the two-location intervals P and Q.
5. end for
6. Send the data according to the selected data governance service resource location and receive feedback before the next half arrives
7. In the first layer of the ResNet network, OpenCV is used to obtain HOG feature, and SENet network is used to obtain the adaptive weight of feature T_l;
8. The convolution computation of the first convolutional layer of ResNet intensified and pooled to extract the convolution feature T_l of the original image. The network was used to calculate the convolution feature adaptive weight P_λ, and the new convolution feature was $T_l P_\lambda$.
9. For the state S of any given hidden layer neural unit, the activation probability of neurons is:

$$\gamma(m_i = 1) = \lambda\left(d_j + \sum_{j=1}^{l} h_j \omega_{ji}\right)$$

10. For the state S of any given hidden layer neural unit, the activation probability of neurons is:

$$\Delta\omega_{ij} = \delta\left(\omega_i h_j\right)_{data}$$

11. For the state S of any given hidden layer neural unit, the activation probability of neurons is:

$$E_i^l(t) = h_j(l - h_j)\sum_{j=1}^{n} \omega_j^l E_i^{l+1}(t)$$

return
12. if return = ACK then
13. r = 1
14. else if return == NACK then
15. r = −1
16. end if
17. Update the evaluation value of each user

The framework diagram of time-aware adaptive deep learning algorithm is shown in Fig. 3.

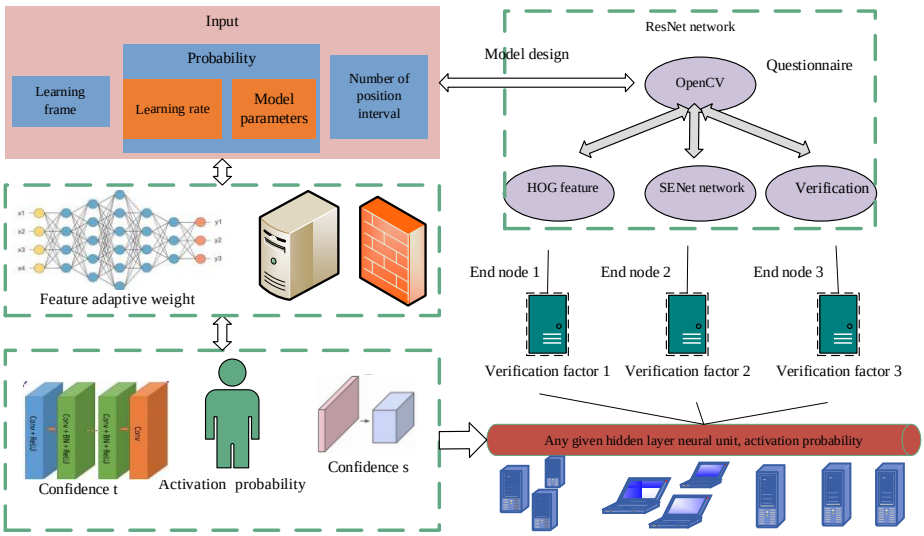


Fig. 3. Time-aware adaptive deep learning algorithm framework diagram.

The system uses time-aware adaptive deep learning algorithms to implement data governance services as follows:

1) Divide the data frame into the first half and the second half.

Broadcast frame data management service information to each requesting user. Each data frame is divided into k data management service location intervals. The length of the location interval is the same as the length of the user data packet. When the user sends the data packet, the first part of the data packet is in

the corresponding data governance service location range.

2) At the initial moment, the user sends a data management service package.

The user selects the first or second half of the data management service according to the broadcast information received in Step 1. When sending a data packet for the first time, all users sequentially generate source signals, modulate to generate transmission data, and then randomly select a random location in the interval of two different data management service locations within the frame to send, and the two copies sent have the same power.

3) The user updates the time-aware adaptive deep learning evaluation value of each location interval according to the detection result.

After the user receives the detection information of the data management service, the evaluation value of each location interval will be updated according to the detection result.

4) All users select the two-position intervals with the largest adaptive deep learning evaluation value to continue sending data packets.

After the user has updated the adaptive deep learning evaluation value, in the next transmission, the two-location intervals with the largest adaptive deep learning evaluation value will be selected to send a copy of the data packet. If there are multiple location intervals with the largest evaluation value, the user will randomly select two locations. If the sequence number of the previous frame and the current frame in the location interval of the data packet copy is the same, then the user keeps the location of the previous frame and continues to send the copy; if it is different, the copy is in the selected data management. Randomly select a location within the service location range to send.

4.3. Theoretical Analysis of Innovation

In this section, we theoretically analyze the time-aware adaptive deep learning prediction algorithm. Given there are n services managed and invoked by M users, in the proposed method, we first construct a pair of data frames to obtain local ordering. In this data governance service model, since every two services need to be compared according to time perception, each pair of services is predicted by time series analysis. Therefore, for a single data governance service user, the time complexity of the algorithm is $O(T_j^2)$, where T_j^2 is the number of services managed by user J. For all users who apply for data governance service, the time complexity of the algorithm is $O_{\max_j}(T_j^2)$. Assuming that the algorithm can achieve the final convergence in one step and get the evaluation value of time-aware adaptive deep learning, the time complexity of the algorithm is $O(\ln^2)$. Subsequently, we need to sort the computed adaptive deep learning evaluation values to get the final global ranking of data governance services. The time complexity of the sorting algorithm is $O(n\log n)$.

The complexity of the proposed time-aware adaptive deep learning algorithm is $O(n^2)$. Compared with the traditional data governance service methods, the algorithm complexity is $O(mn)$ because the traditional method needs to evaluate all services at each client. The time-aware adaptive deep learning algorithm in this study only costs n/m extra time. In the method proposed in this chapter, a client only needs to manage part of the data governance services, which reduces the load of the client. Therefore, this method is very beneficial to data-intensive services.

5. Simulation Verification

To verify the performance of the time-aware adaptive deep learning data governance service scheme proposed in this section, the computer simulation of the physical layer combined with MAC(Media Access

Control) layer is conducted using MATLAB, assuming that the arrival rate of user access request in the system follows the Poisson distribution. Suppose that there are two copies of the user's data packet; the packet length is 200 bits, and the data frame length is 20000 bits. From the point of view of the physical layer, high-SNR(Signal Noise Ratio) and low-SNR environments are considered. The specific simulation parameters are shown in Table 2.

Table 2. Simulation Parameters of Data Governance Service

Parameter	Value
Packet length (bits)	200
Frame length (bit)	20000
Simulation times	6000
Number of packet copies	2
FEC coding	Turbo coding, 1/2 bit rate
Learning rate	0.1
Learning frames	50
SNR (DB)	4,20

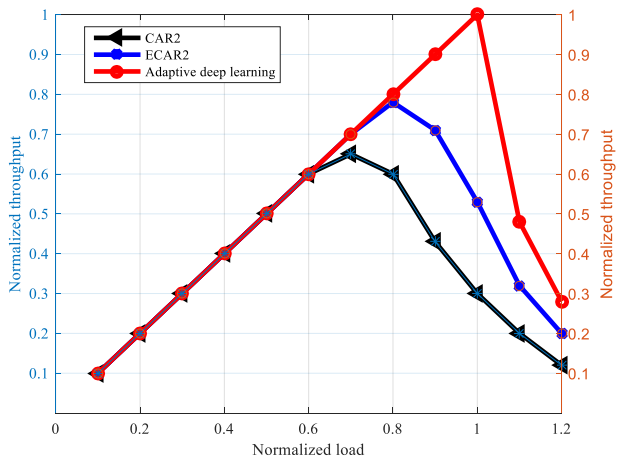


Fig. 4. Data governance service throughput curve with FEC and SNR = 10 dB.

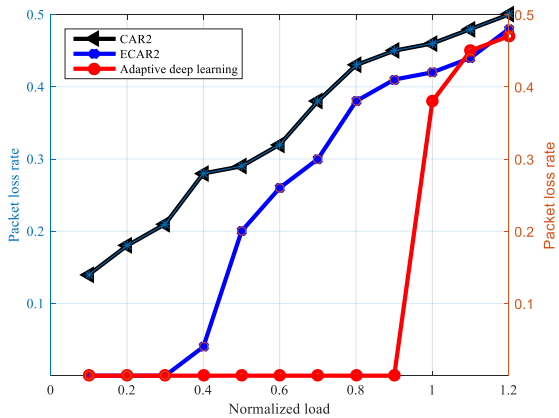


Fig. 5. Packet loss rate curve of data governance service with FEC and SNR = 10 dB.

The throughput performance and packet loss rate (PLR) of CRA, ECRA, and the proposed QECRA data governance service mode in the simulation environment with two packet copies are compared in Figures 4 and 5. The system performance of the proposed QECRA-2 data governance service mode with FEC(Fabulous Excellent Customer) in the physical layer is better than without FEC, as shown in Figure 4. When the system

load does not exceed 1 bit per symbol and the Q-learning algorithm makes the system reach convergence state, the system load and throughput of QECRA-2 have a linear relationship, whereas CRA-2 and ECRA-2 can only reach 0.5 and 0.6, respectively. As can be seen from Figure 5, although the PLR of CRA-2 and ECRA-2 protocols is relatively low, it still increases rapidly with the increase of system load. The proposed QECRA-2 data governance service mode is 0 when the system load is less than 1; that is, all users in the data frame are correctly connected.

Table 3. Through Wilcoxon's test results

D	p-value	+	=	-	β=0.05
20	0.005063	15	0	0	Yes
	0.005064	10	1	0	Yes
	0.007676	15	1	0	Yes
	0.005072	15	0	0	Yes
30	0.005042	15	1	0	Yes
	0.005052	15	1	0	Yes
	0.005022	15	0	0	Yes
	0.005066	15	1	0	Yes
60	0.005066	15	0	0	Yes
	0.005066	15	1	0	Yes
	0.005066	15	0	0	Yes
	0.005066	15	1	0	Yes

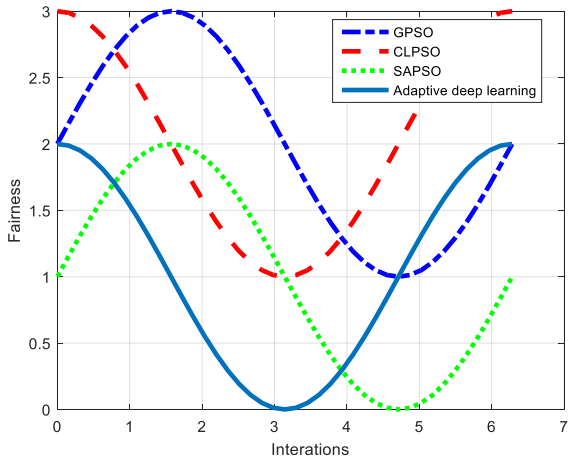


Fig. 6. Convergence curve of function f (d = 30).

According to the results in Table 3, when a = 0.05, the time-aware adaptive deep learning algorithm has obvious advantages over the comparative algorithm in test function. Compared with other algorithms, time-aware adaptive deep learning algorithm has outstanding advantages in solving high-dimensional problems. Furthermore, the convergence of the algorithm on some functions is shown in Figs. 6 and 7. It can be clearly observed that the time-aware adaptive deep learning algorithm has significant advantages in convergence speed and convergence accuracy. Although the time-aware adaptive deep learning algorithm itself has its own shortcomings, when the dimension increases, the stability of the algorithm is slightly insufficient compared with those of other algorithms, but generally, the time-aware adaptive deep learning algorithm has greatly improved the optimization results compared with other algorithms.

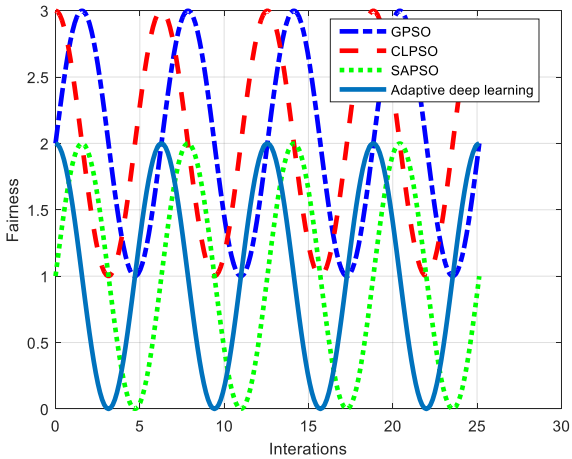


Fig. 7. Convergence curve of function f (d = 60).

To demonstrate the time-aware adaptive deep learning algorithm's optimization speed, run the algorithm independently for 20 times in the same experimental environment with particle number of 40. If the required accuracy is not reached after 200000 iterations, it is represented by "one," as shown in Table 4. Under the same experimental environment, when the time-aware adaptive deep learning algorithm reached the specified accuracy requirements, the running time is smaller than that of the standard particle swarm optimization (PSO((Particle Swarm Optimization)) algorithm, as shown in Table 4.

Table 4. Running Time of Algorithm Reaching Specified Precision

Function	CLPSO	SRPSO	Adaptive deep learning
F0	1.04E+00	4.94E-01	5.73E-02
F1	1.02E+00	8.17E-01	9.43E-01
F2	1.23 E+00	5.22E-01	1.58E-02
F3	1.16E+00	5.36E-01	1.46E-02
F4	1.23E+00	5.92E-01	1.42E-02
F5	1.04E+00	-	4.60E-02
F6	-	-	4.70E-02
F7	-	-	3.77E-01
F8	-	-	9.25E-O1
F9	-	-	-

To compare the effectiveness and accuracy of the methods proposed in this section, we conduct multiple comparative experiments. We select some data governance services randomly from the data set of real data governance services to conduct experiments. We change the proportion of services selected from each data governance service client as the data set changes. The proportion varies from 10% to 60%, and the change step size is 10%. Therefore, the ability of time-aware adaptive deep learning data governance service method to handle data sets with varying density matrix is compared. For example, 10% means that each client applying for data governance services randomly selected 10% of services to predict the global ranking of adaptive deep learning evaluation values of all data governance services. As mentioned above, we conducted 20 groups of experiments and computed the accuracy of ranking the evaluation values of adaptive deep learning according to the two evaluation criteria mentioned above. Furthermore, we compared the response time of the traditional method with the method in this section to further demonstrate the adaptability of the proposed method for different types of data governance services.

The introduction of the adaptive deep learning algorithm and time-aware mining technology significantly

improved the adaptability of the data governance service model. Furthermore, it made the data governance service evaluation system become self-learning and adaptive intelligent system. Each algorithm has its advantages and disadvantages when constructing the data governance service evaluation model. The above comparative analysis can be analyzed the effectiveness of various classification algorithms. The comparison between various data governance service evaluation models and traditional fuzzy comprehensive evaluation methods is summarized in Table 5.

Table 5. Comparison of Data Governance Service Models

Model	Construction complexity	Self-study	Adaptability	Astringency	Accuracy	Effectiveness
Fuzzy comprehensive evaluation model	Simple	No self-learning	No adaptability	---	Rely on knowledge and experience	---
Particle swarm optimization	Simple	Self-study	Adaptability	Easily limited to local optimum	Sample dependent	Few invalid rules
Adaptive particle swarm optimization	Simple	Self-study	Certain adaptability	Local optimization is not easily limited	Sample dependent	Few invalid rules
Time-aware adaptive deep learning	Simple	Self-study	Adaptability	Good convergence	Depending on the sample, the accuracy is high	Few invalid rules

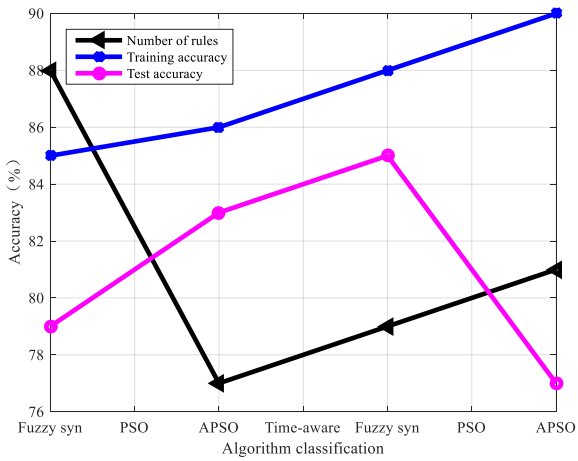


Fig. 8. Comparison of algorithm accuracy and classification rules.

The training accuracy of the fuzzy comprehensive evaluation is adequate, as shown in Fig. 8. However, its test accuracy is not adequate, and the number of classification rules extracted is more precise. Although the PSO algorithm's training and test accuracy can be improved, the number of level rules extracted is small.. The time-aware adaptive deep learning algorithm achieved the highest accuracy of 87%. Furthermore, it can classify and learn the continuous input attributes, and the test accuracy was 84%. The time-aware adaptive deep learning algorithm's performance shows that it can learn various types of data governance services.

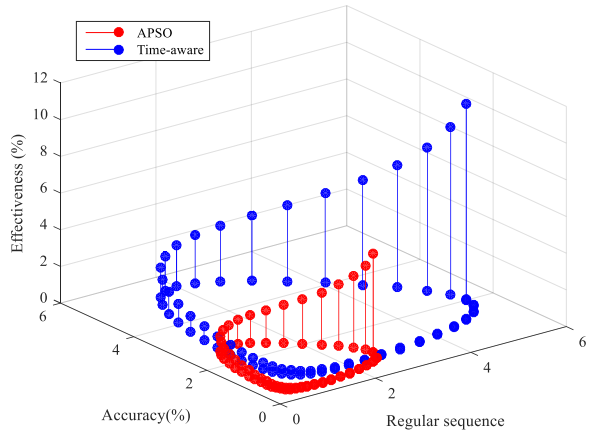
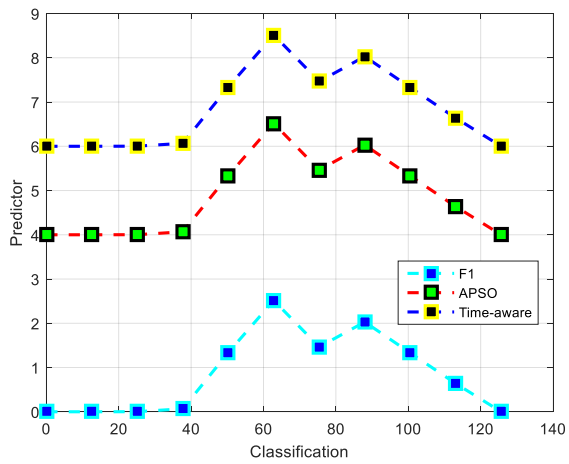
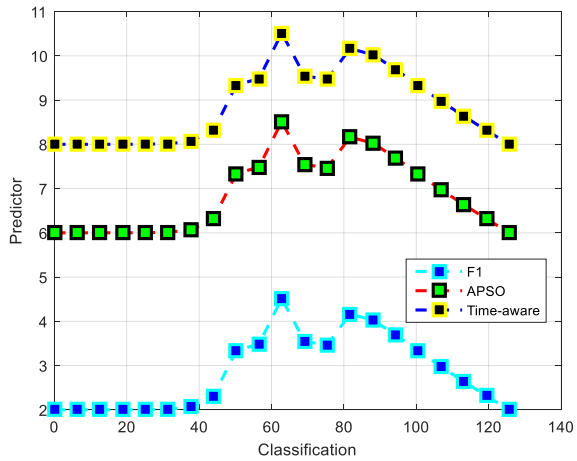


Fig. 9. Comparison of rules and accuracy effectiveness.



(a) 5-SWD



(b) MUSK

Fig. 10. Classification performance of adaptive deep learning algorithm based on time perception.

The time-aware adaptive deep learning algorithm for classification has high accuracy and transparent rules and is easy to understand, as shown in Fig. 9. Analyzing each rule and computing its effectiveness reveal that the average effectiveness of all six rules is 0.01. Moreover, the time-aware adaptive deep learning algorithm's data governance service eliminates invalid and inefficient rules; therefore, there are fewer

invalid rules in the ruleset, and the average effectiveness of all six rules is 0.02.

Figure 10 shows the classification performance of adaptive deep learning algorithms based on time perception. These features are based on the effectiveness of data governance services. It can be seen from Figure 10 that the curves of all predictors increase with an increase in the number of features and rise sharply in the early stage and then flatten or slightly decrease. This shows that the use of some of these functions can achieve the same or similar classification effect as the use of all functions, which once again proves that the time-aware adaptive deep learning algorithm proposed in this article is more suitable for the effectiveness of data governance services.

6. Conclusion

This study proposed an adaptive deep learning-based data governance service scheme based on the existing asynchronous random data governance service protocol of the Internet of things. The data frame is divided into the first and second half frames considering the large communication delay problem. Moreover, the data frame is divided into several uniform position intervals, and the infinite sending positions in the data frame are converted into limited position intervals. The adaptive deep learning algorithm based on time perception is used to connect the positions of the data governance service packets sent by users in the first and second half frames. Each user sending the data governance service package in the frame learning solves the randomness of the user's packet sending location, which leads to the low utilization of channel resources. However, it leads to the problems of low throughput and a high PLR. The adaptive deep learning-based data governance service scheme was simulated in three simulation environments based on the assumption that sending user's data packets follow the Poisson distribution. The experimental results show that the adaptive deep learning-based data governance service scheme based on time perception can significantly improve the system performance by increasing throughput and reducing PLR. The convergence speed and accuracy of the algorithm make it useful in solving high-dimensional complex problems. In some test functions, the adaptive deep learning-based data governance service scheme's stability needs to be improved, and the algorithm should be verified in practical application. We plan to focus on the above problems in future work. Adaptive deep learning data governance service technology is based on time perception; however, when the amount of data increases, this method does not completely solve the space explosion problem. We will conduct further research on this issue in the future. Moreover, we will formally verify the consistency, completeness, or accessibility of the data-aware business process model to verify the effectiveness of the data-aware modeling method from a theoretical perspective.

Conflict of Interest

The authors declare no conflict of interest

Author Contributions

Zhigang Zhao conducted the research; Xinju Zhang conducted the research, analyzed the data and wrote the paper.

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