

Retraction

Retracted: Adaptive Integration Algorithm of Sports Event Network Marketing Data Based on Big Data

Security and Communication Networks

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Security and Communication Networks has retracted the article titled “Adaptive Integration Algorithm of Sports Event Network Marketing Data Based on Big Data” [1] due to concerns that the peer review process has been compromised.

Following an investigation conducted by the Hindawi Research Integrity team [2], significant concerns were identified with the peer reviewers assigned to this article; the investigation has concluded that the peer review process was compromised. We therefore can no longer trust the peer review process, and the article is being retracted with the agreement of the Chief Editor.

References

- [1] J. Wu, J. Zhang, and J. Qiao, “Adaptive Integration Algorithm of Sports Event Network Marketing Data Based on Big Data,” *Security and Communication Networks*, vol. 2022, Article ID 7660071, 9 pages, 2022.
- [2] L. Ferguson, “Advancing Research Integrity Collaboratively and with Vigour,” 2022, <https://www.hindawi.com/post/advancing-research-integrity-collaboratively-and-vigour/>.

Research Article

Adaptive Integration Algorithm of Sports Event Network Marketing Data Based on Big Data

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To address the issues of low-data integration accuracy and efficiency, as well as a lack of data integration impact, an adaptive data integration algorithm for sports event network marketing data based on big data is presented. The fundamental theory of tensor is researched by examining the notion and features of big data and by using the associated technologies of the big data framework. Collect network-marketing data from a variety of sporting events and feed it to a big data platform. Combined with MapReduce parallelization mode, tensor represents the online marketing data of sports events according to the structured, semistructured, and unstructured characteristics of different big data. Integrate each tensor model based on semitensor product, build a unified data adaptive integration tensor model, and realize the adaptive integration of sports event network marketing data. The experimental results show that the proposed algorithm has a good effect on the adaptive integration of sports event network marketing data and can effectively improve the accuracy and efficiency of data adaptive integration.

1. Introduction

Sports events refer to a special kind of sports competitive activities. Taking sports as the focus of the sports competitive activities belongs to the sports with competitive significance, and it has certain sports rules, and it needs to ensure its high fairness and organization to a certain extent [1]. The core content of sports events is that, at a predetermined time and location, athletes carry out sports competitive activities of a specified scale and social impact in accordance with predetermined sports competitive activity rules, in order to compel people to participate in or watch sports competitive activities [2]. Science and technology are rapidly evolving at the moment, particularly in the Internet and computer industries. The constant advancement of connected technology has aided in the enhancement of people's everyday lives. With the continuous development of the Internet and computer technology, under the influence of this technology, the existing commercial marketing model has been severely impacted, prompting the current sports event

network marketing to accumulate a large amount of data resources. However, the great growth of data leads to the phenomenon of excessive redundancy of data, unable to query data resources, and difficult to make effective decision support for data [3]. Therefore, it is of great significance to study the network marketing data integration of sports events, build an effective marketing data integration model, and accurately integrate the network marketing data of sports events for effectively controlling the data rules and improving the utilization of information resources.

At present, scholars in related fields have studied network data integration and achieved some theoretical results. Reference [4] proposed a general joint matrix decomposition framework for data integration and its system algorithm. Nonnegative matrix decomposition is extended to analyze multiple matrices at the same time by discovering hidden features and part-based patterns from high-dimensional data. This paper introduces the regularization joint matrix decomposition framework of sparse multi-relational data and constructs two models suitable for

pattern recognition and data integration to realize effective data integration. The algorithm is effective in pattern recognition and data mining. Reference [5] proposed a streaming data integration algorithm for the Internet of things from multiple sources. For different format types of data from multiple sources, several data integration mechanisms are designed to deal with most static data. To resolve temporal conflicts between data streams from numerous sources, a formal technique for integrating such IOT stream data sets in real time is used. The window-based ISDI approach is utilized to handle IOT data in a variety of forms, and an algorithm for integrating IOT stream data from numerous sources is devised. The algorithm may be used efficiently to offer people with an integrated picture of their data. However, the aforementioned methodologies continue to suffer from low-data integration accuracy and efficiency, as well as a lack of impact. To solve the above problems, an adaptive integration algorithm of sports event network marketing data based on big data is proposed. The basic theory of tensor is studied by using big data features and framework-related technologies. By collecting different big data structured, semistructured, and unstructured sports event network marketing data, combined with MapReduce parallelization mode, tensor represents sports event network marketing data. Integrate each tensor model based on semitensor product, build a unified data adaptive integration tensor model, and realize the adaptive integration of sports event network marketing data. This method has a good effect of data adaptive integration and can effectively improve the accuracy and efficiency of data adaptive integration.

2. Big Data Technology

2.1. Big Data Concept. Big data technology is actually an information asset. Only through a new processing mode can it strengthen its decision-making ability and greatly improve its insight and process optimization ability [6]. The big data industry with data as the core will eventually display the quantitative information generated by collection, storage, processing, analysis, and application to users. Its data processing is efficient and short cycle. The data processing technology contained in big data makes the effective integration of sports event network marketing data more scientific.

2.2. Big Data Characteristics. The 4V characteristics of big data are mainly manifested in volume, variety, velocity, and value. The 4V characteristics of big data are as Figure 1.

- (1) **Volume:** Voluminousness is one of the basic attributes of big data. At present, Internet technology is widely used and developed, and the number of Internet users has increased sharply to a certain extent, which makes the acquisition and sharing of data information more and more convenient. At present, through a computer or a mobile phone, people can quickly and easily obtain a large amount of information and data. In addition, the interactive behavior of network users on the Internet will generate

a large amount of data through clicking, browsing, and sharing. The data magnitude will gradually increase, and the storage unit will gradually change from the original GB to TB, even Pb and EB. Sports event network marketing data have natural big data attributes, and its huge marketing data are a natural data pool.

- (2) **Variety:** Big data come in a variety of forms and sources. For sports event networks, the standard sports event network database is no longer sufficient to satisfy the marketing requirements for sports event networks. Along with its own audio, live video, and network transaction records for sports events, the sports event network can obtain additional data from sports event websites, GPS global positioning systems, sports event e-commerce transaction records, and a sports event information platform, among other sources. Not only typical relational data types are supported, but also organized unstructured data.
- (3) **Velocity:** Fast generation and updating of data are also an important feature of big data. There is a saying about data processing in the era of big data, which is called the one second law. Taking the online sports event network marketing transaction as an example, on the trading platform, a large amount of sports event network marketing transaction data and logistics transportation data will be generated every second. The data are transmitted at any time, which makes it necessary to quickly generate and update the data.
- (4) **Value:** For the sports event network, how to find useful information from the massive amount of network information is a problem. Because the online marketing data of sports events have strong financial strength, we can seek cooperation with professional data providers. At present, the data providers represented by professional data service providers such as Ninth Power, IBM, and Intel provide online marketing data collection, analysis, and mining services for sports events, and help sports event online marketing mine data value.

2.3. Big Data Framework Related Technologies

2.3.1. Hadoop Distributed Computing Framework. The Hadoop distributed computing framework belongs to the most basic big data processing programming framework. It mainly deals with data-level big data-related information such as PB and EB and can allow the execution of thousands of nodes [7]. Hadoop decomposes a large number of work contents into several smaller work units. In order to achieve the effect of simplification, the overall work is subdivided and calculated by assigning it to different machines. Hadoop is mainly composed of two core modules: HDFS distributed file system and MapReduce big data parallel computing framework. In this case, HDFS can be applied on general-purpose hardware devices, and MapReduce can be applied in

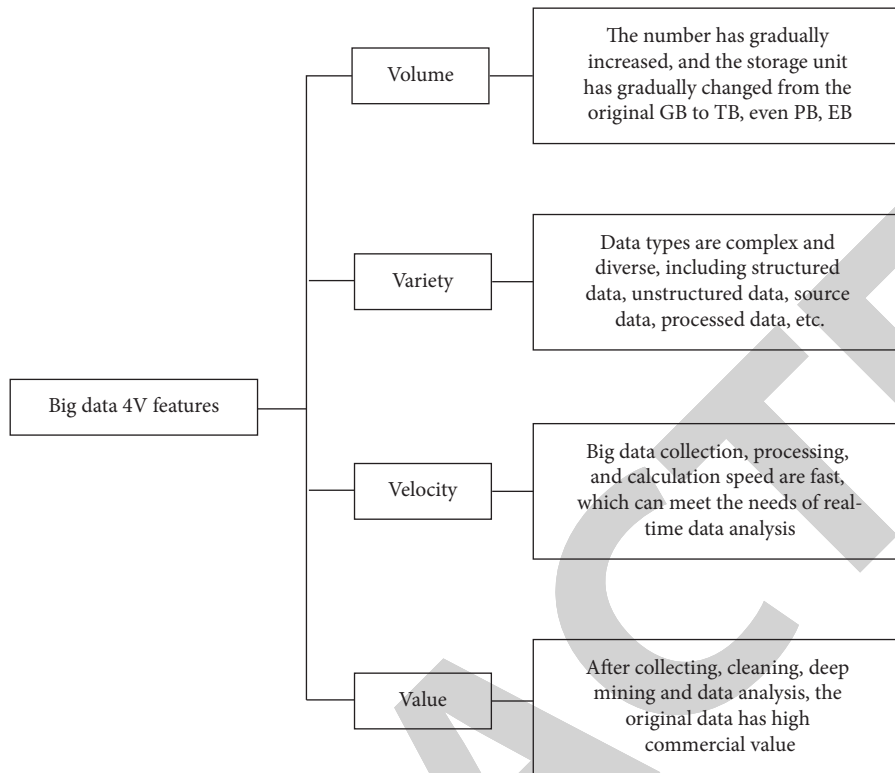


FIGURE 1: 4V characteristics of big data.

the process of distributed parallel computing. HDFS deploys each node in a cluster and allocates storage data to a single node, thereby avoiding reading a single storage when performing work tasks, so that data throughput efficiency is improved. The structure of HDFS distributed file system is as Figure 2.

In Figure 2, the master node Master needs to configure multiple processes such as NameNode, and multiple slave node Slaves need to configure multiple processes such as DataNode so that they can call and process local files. NameNode belongs to the core program in HDFS. It can record file block patterns and data block distribution, thereby centrally managing hard disk and memory resources. The master node Master cannot store and calculate data, thereby ensuring good server performance. The DataNode program can realize the management of multiple slave node slaves that read the content of HDFS data blocks. The NameNode program can monitor the status of HDFS data blocks.

Hadoop’s distributed computing platform is built on the MapReduce paradigm. MapReduce may distribute and execute cluster work tasks over several computers, allowing the cluster to successfully complete the best allocation [8]. As seen in Figure 3, the MapReduce execution architecture.

The specific operation of MapReduce is mainly to input big data and split the big data set, randomly distribute the split multiple subsets and process them through the pre-written Map function. The results obtained after processing are rearranged using the Shuffle stage and then processed by the Reduce function for reduction and saved in HDFS.

The execution process of MapReduce consists of input, Map, Shuffle, Reduce, and output stages. The MapReduce execution process is as Figure 4.

First, divide the data set and save it in each InputSplit and use the MapReduce program to copy the divided data set and place it in the cluster. Then, the master node Master is used to dispatch the Map and Reduce tasks. In this process, the Map function is used to obtain the results. The results are shuffled through the Shuffle stage and passed to the Reduce task node. Finally, the results obtained by scrambling are calculated in parallel, and the final results are output and stored.

2.3.2. Spark Distributed Computing Framework. Spark distributed computing framework belongs to the most basic big data-computing framework. Spark uses memory computing to realize big data processing. So Spark has better computing performance than MapReduce framework. The Spark distributed computing framework is as Figure 5.

The core of Spark distributed computing framework is composed of Spark-SQL, Spark Streaming, MLlib, GraphX, independent scheduler, resource manager, and distributed system kernel [9]. Data analysis and extraction are performed using Spark-SQL. Spark-SQL is used to do data extraction, summarization, and other operations. Spark-Streaming is primarily used to examine and process log files and is often used in combination with open source tools. MLlib mainly mines-related data and implements it in conjunction with related algorithms such as machine

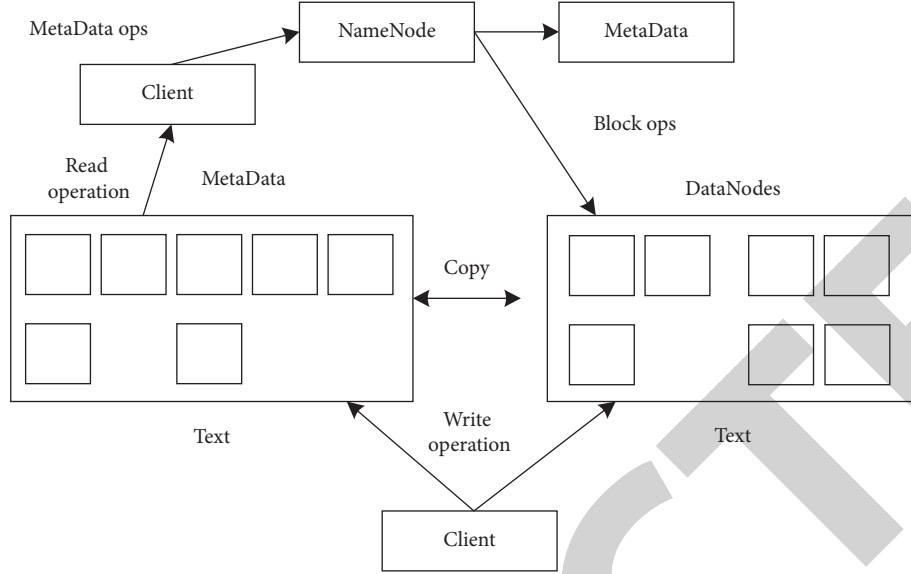


FIGURE 2: HDFS distributed file system structure.

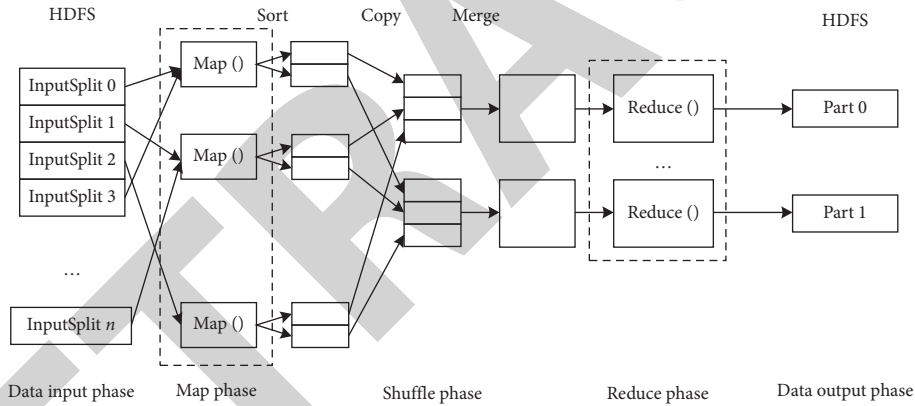


FIGURE 3: MapReduce running framework.

learning. The independent scheduler is mainly used for data resource allocation and scheduling. Mainly to manage persistent data in the Spark distributed computing framework. The kernel of the distributed system is mainly to update the local cache data to complete dynamic routing. The Spark execution process is as Figure 6.

Spark can generally process real-time streaming big data with low latency in high concurrency in practical application scenarios. In addition, Spark can store the iterated data in memory [10, 11]. In Spark, it consists of two main modules, Driver and Worker. The Driver program is mainly responsible for executing application logic, and the Worker is mainly responsible for parallel processing of related data.

2.4. Basic Theory of Tensors. Tensor belongs to one of multilinear mappings and is a kind of high-dimensional data, which is defined by the Cartesian product of some vectors and dual space [12]. If Q is described as a tensor and $Q_p \in R^{W_1 \times W_2 \times \dots \times W_l}$ is described as an p order tensor, then its

expansion matrix is denoted as $Q_{(p)} \in R^{W_p \times (W_{p+1} \times W_{p+2} \times \dots \times W_{p-1})}$. Assuming that $Q_p \in R^{2 \times 2 \times 2}$ is described as a third-order tensor, three expansion matrices can be obtained, and the expansion matrices are denoted as $Q_1 \in R^{2 \times 4}$, $Q_2 \in R^{2 \times 4}$, $Q_3 \in R^{2 \times 4}$, respectively. The second-order tensor model is shown in Figure 7.

It can be obtained by performing 1-modulus expansion on the tensor Q :

$$Q_1 = \begin{bmatrix} 1 & 2 & 11 & 12 \\ 3 & 4 & 13 & 14 \end{bmatrix}. \quad (1)$$

It can be obtained by performing 2-modulus expansion on the tensor Q :

$$Q_2 = \begin{bmatrix} 1 & 3 & 11 & 13 \\ 2 & 4 & 12 & 14 \end{bmatrix}. \quad (2)$$

It can be obtained by performing 3-modulus expansion on the tensor Q :

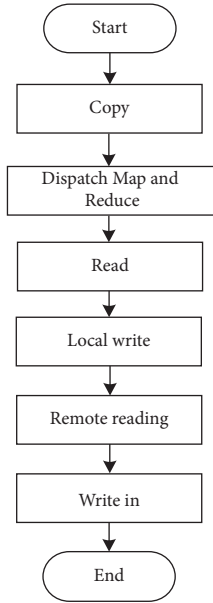


FIGURE 4: MapReduce execution process.

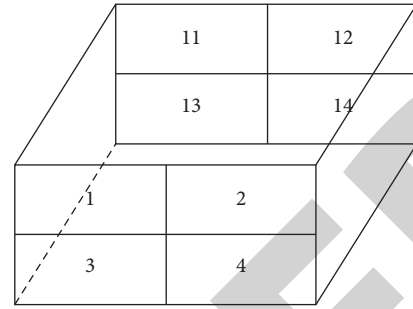


FIGURE 7: Second order tensor model.

$$Q_3 = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 11 & 12 & 13 & 14 \end{bmatrix}. \quad (3)$$

- (1) Multiplication of single-modulus tensor and matrix: The new tensor is mainly obtained by multiplying the p order tensor Q_p by its matrix E , which can be expressed as follows:

$$(Q_p \times E)_{i_1, i_2, \dots, i_p} = \sum_{i_p=1}^{i_p} (e_{i_1, i_2, \dots, i_p} \times \alpha). \quad (4)$$

When decomposing the tensor, the new tensor can effectively reduce the dimensionality of the p order tensor.

- (2) Multiplication of multimodular tensor and tensor: The new tensor is mainly obtained by multiplying the tensor Q by its tensor Q_n of a certain order, which can be expressed as follows:

$$(Q_n \times Q)_{i_1, i_2, \dots, i_n, k_{n+1}, \dots, k_m} = \sum_{k_1, k_2, \dots, k_n} q_{i_1, i_2, \dots, i_n, k_1, k_2, \dots, k_n} q_{k_1, k_2, \dots, k_n, k_{n+1}, \dots, k_m}. \quad (5)$$

In formula (5), the tensor Q and a certain order tensor Q_n are denoted as $Q \in R^{I_1 \times \dots \times I_n \times K_1 \times \dots \times K_m}$ and $Q_n \in R^{K_1 \times \dots \times K_n \times K_m}$, respectively.

- (3) Tensor product: It is also the Kronecker product of the matrix. Describe $Z \in M_{ij}$, $X \in M_{xy}$ as a matrix, then the tensor product of the matrix can be expressed as follows:

$$Z \otimes X = \begin{bmatrix} z_{11}X & z_{12}X & \dots & z_{1j}X \\ z_{21}X & z_{22}X & \dots & z_{2j}X \\ \dots & \dots & \dots & \dots \\ z_{i1}X & z_{i2}X & \dots & z_{ij}X \end{bmatrix}. \quad (6)$$

In formula (6), \otimes is expressed as the Kronecker product of the matrix. Two matrices can be merged effectively through the tensor product of matrices.

- (4) Semitensor product: belongs to the new matrix multiplication. In the case where the number of front arrays and the number of back columns are not equal, general matrix multiplication is promoted to

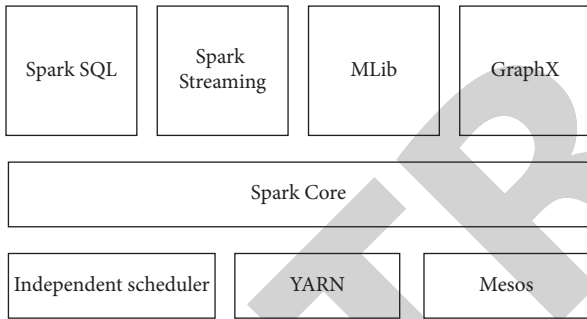


FIGURE 5: Spark distributed computing framework.

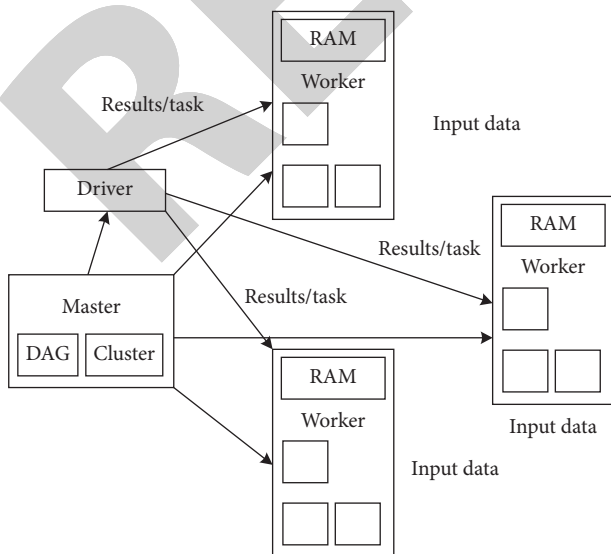


FIGURE 6: Spark execution process.

effectively improve its pseudo-commutability and other characteristics [13].

If $\mathbf{Z} \in M_{i \times j}$, $\mathbf{X} \in M_{x \times y}$ is described as a matrix, then $v = \text{lcm}\{j, x\}$ is defined as the least common multiple of j and x , then the semitensor product of the matrix can be expressed as follows:

$$\mathbf{Z} \ltimes \mathbf{X} = (\mathbf{Z} \otimes L_{v/j})(\mathbf{X} \otimes L_{v/x}). \quad (7)$$

Formula (7) is called the left half tensor product of the matrix. In general, the matrix tensor product referred to is the left half tensor product of the matrix, and in formula (7), when $j = x$ is the ordinary matrix multiplication. It is derived from this that the right half tensor product is expressed as follows:

$$\mathbf{Z} \oslash \mathbf{X} = (L_{v/j} \otimes \mathbf{Z})(L_{v/x} \otimes \mathbf{X}). \quad (8)$$

Based on the above analysis, the mixed tensor product can be expressed as follows:

$$\mathbf{Z} \triangleright \triangleleft \mathbf{X} = (L_{v/j} \otimes \mathbf{Z})(\mathbf{X} \otimes L_{v/x}). \quad (9)$$

or:

$$\mathbf{Z} \triangleright \triangleleft \mathbf{X} = (\mathbf{Z} \otimes L_{v/j})(L_{v/x} \otimes \mathbf{X}). \quad (10)$$

The above is the semitensor product of the matrix and its generalization. The semitensor product of the matrix can effectively guarantee the two front and rear matrices and meaningfully multiply the row numbers of different matrices without destroying the original basic properties of the matrix.

3. Adaptive Integration Algorithm of Sports Event Online Marketing Data

This article discusses an adaptive integration methodology for sports event network marketing data that is based on a semitensor product. To begin, gather structured, semistructured, and unstructured web marketing data on sporting events and upload it to a big data platform. Then, using MapReduce parallelization, tensor depicts sports event network marketing data in terms of its structured, semistructured, and unstructured features. Finally, integrate each tensor model based on semitensor product, so as to build a unified data adaptive integration tensor model to realize the adaptive integration of sports event network marketing data. The adaptive integration algorithm flow of sports event network marketing data based on big data is as Figure 8.

3.1. Collect Network Marketing Data of Sports Events with Different Characteristics. Different data acquisition equipment are used to collect structured, semistructured, and unstructured sports event network marketing data, and classify and process sports event network marketing data with different characteristics. Transfer the collected, classified, and processed structured, semistructured, and unstructured online marketing data of sports events to the big data platform, and ensure that its original data format is

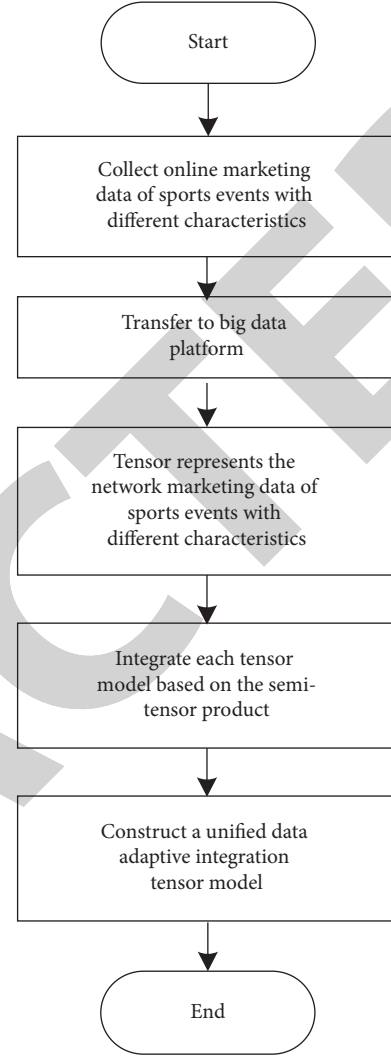


FIGURE 8: Flow chart of the adaptive integration algorithm of sports event online marketing data based on big data.

retained in the process of online marketing data transmission of sports events with different characteristics.

3.2. Tensor Represents the Network Marketing Data of Sports Events with Different Characteristics. Combined with MapReduce parallelization mode [14], according to the structured, semistructured, and unstructured characteristics of different big data, tensor represents the network marketing data of sports events with different characteristics.

- (1) The network marketing data tensor of structured sports events represents:

Structural data is mainly realized through two-dimensional table structure logic, and relational database is used to realize data management and storage [15]. System database is widely used in the management of structured data. In a simple type of database table, a field is often represented by numbers or characters, so it can be represented as a matrix. When complex types of fields are involved,

they can be represented by adding a new tensor order [16].

- (2) The text data tensor of network marketing of semistructured sports events indicates:

Since the semistructured sports event network marketing text data has labels, types, and elements, it is expressed as a third-order tensor:

$$Q_{\text{text}} = R^{I_{bq} \times I_{lx} \times I_{ys}}. \quad (11)$$

In formula (11), I_{bq}, I_{lx}, I_{ys} is, respectively, represented as semistructured sports event network marketing text label, type, and element.

- (3) Unstructured sports event network marketing video data tensor indicates:

Because the unstructured sports event network marketing video data have the characteristics of video frame, picture width, height and color, it is expressed as a fourth-order tensor:

$$Q_{\text{video}} = R^{I_z \times I_k \times I_g \times I_s}. \quad (12)$$

In formula (12), I_z, I_k, I_g, I_s is, respectively, expressed as the width, height, and color of the unstructured sports event network marketing video frame, picture.

3.3. Construct a Unified Adaptive Integration Tensor Model of Sports Event Network Marketing Data. The network marketing data of sports events with different characteristics are represented by tensor, and each tensor model is integrated based on semitensor product, so as to build a unified adaptive integration tensor model of sports event network marketing data, so as to realize the adaptive integration of sports event network marketing data.

When $Z \in R^{I_z \times I_s \times I_u \times I_1}$, $X \in R^{I_t \times I_s \times I_u \times I_2}$, the tensor expansion operator based on the semitensor product is expressed as follows:

$$f = \begin{cases} Z \vec{\times} X \longrightarrow C, C \in R^{I_t \times I_s \times I_u \times I_1 \times I_2}, \\ Z \otimes X = (Z \otimes L_{v/j})(X \otimes L_{v/x}). \end{cases} \quad (13)$$

When $\vec{\times}$ in formula (13) satisfies the associative law, we can get:

$$(Z \vec{\times} X) \vec{\times} C = Z \vec{\times} (X \vec{\times} C). \quad (14)$$

On this basis, the order of tensor can be extended to the existing tensor model in different directions by semitensor product. Structured, semistructured, and unstructured sports event network marketing data can be expressed as low-order tensors. The tensor expansion operator based on semitensor product is fused in the high-order tensor space to realize the unified representation of the adaptive integration tensor model of sports event network marketing data.

If H_j is expressed as structured sports event network marketing data represented by a tensor, H_b is expressed as a semistructured sports event network marketing text data

represented by a tensor, and H_f is expressed as an unstructured sports event network marketing text data represented by a tensor. Then based on the semitensor product integration of each tensor model, the unified tensor model of the self-adaptive integration of sports event network marketing data constructed is expressed as follows:

$$f: (H_j \otimes H_b \otimes H_f) \longrightarrow Q_j \otimes Q_b \otimes Q_f. \quad (15)$$

Through the above steps, the adaptive integration of sports event network marketing data are realized.

4. Experimental Analysis

4.1. Experimental Environment and Data. In order to verify the effectiveness of the adaptive integration algorithm of sports event online marketing data based on big data, the experiment used the Eclipse development environment as the experimental environment, equipped with the Linux operating system, and established the Hadoop 2.2.0 big data platform. Use different data collection equipment to collect structured, semistructured, and unstructured data characteristics of sports event network marketing data, and transfer the collected sports event network marketing data with different characteristics to the big data platform [17]. This study selected 5000 GB of online marketing data of sports events as the experimental sample. Through the above steps, a unified tensor model for adaptive integration of sports event network marketing data is constructed, and JSON is used to describe the tensor model, and JAQL query statements are used to query the model to verify the effectiveness of the algorithm.

4.2. Comparison of Adaptive Integration Accuracy of Sports Event Network Marketing Data. To evaluate the proposed algorithm's data adaptive integration accuracy, the data adaptive integration packet loss rate is used as the evaluation index. The lower the packet loss rate for data adaptive integration, the greater the accuracy of data adaptive integration. Compare the algorithm in reference [4] and the algorithm in reference [5] with the proposed algorithm, respectively, and get the comparison results of data adaptive integration packet loss rate of different methods, as shown in Figure 9.

It can be seen from Figure 9 that under different amount of network marketing data, the average packet loss rate of data adaptive integration of the algorithm in reference [4] is 0.39%, the average packet loss rate of data adaptive integration of the algorithm in reference [5] is 0.51%, while the average packet loss rate of data adaptive integration of the proposed algorithm is only 0.09%. It can be seen that compared with the algorithms in reference [4] and the algorithms in reference [5], the data adaptive integration packet loss rate of the proposed algorithm is low, and the adaptive integration accuracy of sports event network marketing data is high.

4.3. Comparison of Adaptive Integration Effect of Sports Event Network Marketing Data. Further, verify the data adaptive integration effect of the proposed algorithm and take the

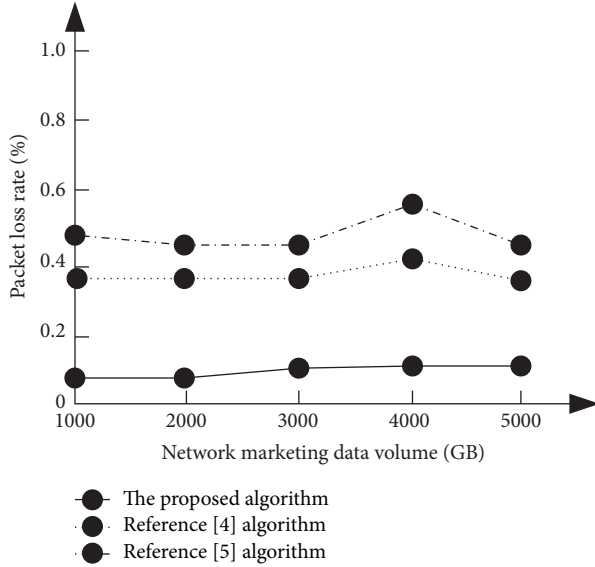


FIGURE 9: Comparison results of data adaptive integration of different methods of packet loss rate.

data adaptive integration coverage as the evaluation index. The higher the data adaptive integration coverage, the better the data adaptive integration effect. By comparing the algorithm in reference [4], the algorithm in reference [5] and the proposed algorithm, the data adaptive integration coverage of different methods is obtained, and the comparison results are as Figure 10.

As can be seen from Figure 10, under different amounts of online marketing data, the average coverage of data adaptive integration of the algorithm in reference [4] is 78%, the average coverage of data adaptive integration of the algorithm in reference [5] is 69%, and the average coverage of data adaptive integration of the proposed algorithm is as high as 92%. It can be seen that compared with the algorithms in reference [4] and the algorithm in reference [5], the proposed algorithm has higher data adaptive integration coverage and better data adaptive integration effect.

4.4. Comparison of Adaptive Integration Efficiency of Sports Event Network Marketing Data. On this premise, the proposed algorithm's data adaptive integration efficiency is further tested, with the execution time of data adaptive integration serving as the evaluation metric. The faster data adaptive integration can be executed, the more efficient it is. The algorithms in reference [4], reference [5] and the proposed algorithms are compared, respectively, to obtain the execution time of data adaptive integration of different methods. The comparison results are as Table 1.

According to the data in Table 1, with the increase of online marketing data of sports events, the execution time of data adaptive integration of different methods increases. When the amount of online marketing data is 5000 GB, the data adaptive integration execution time of the algorithm in reference [4] is 24.6 s, the data adaptive integration execution time of the algorithm in reference [5] is 33.5 s, while the data adaptive integration execution time of the proposed

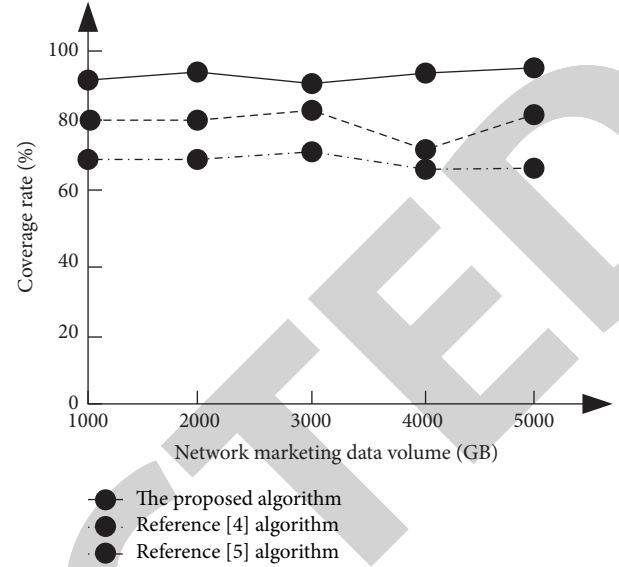


FIGURE 10: Comparison results of data adaptive integration coverage of different methods.

TABLE 1: Comparison results of data adaptive integration execution time of different methods.

Network marketing data volume/GB	The proposed algorithms/s	The algorithms in reference [4]/s	The algorithms in reference [5]/s
1000	3.87	6.64	9.76
2000	5.76	9.98	14.8
3000	9.06	14.5	22.6
4000	13.3	19.8	27.9
5000	15.9	24.6	33.5

algorithm is only 15.9s. Therefore, compared with the algorithm in reference [4] and the algorithm in reference [5], the data adaptive integration execution time of the proposed algorithm is shorter, which can effectively improve the adaptive integration efficiency of sports event network marketing data.

5. Conclusion

This article presents an adaptive integration method for sports event network marketing data that are based on big data and takes full use of the technology's capabilities. The adaptive integration of sports event network marketing data is accomplished using the MapReduce parallelization method in conjunction with tensor theory. Its data adaptive integration for sports event network marketing is very precise and efficient and has a positive influence on data adaptive integration. However, owing to the large and multidimensional nature of sports event network marketing data, this research was unable to effectively mine the tensor model of adaptive data integration. Thus, in the future study, we will need to mine the data adaptive integration tensor model more effectively in order to assess the security of data adaptive integration, thus improving the model and optimizing the integration impact.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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