Eng Int Syst (2018) 2-3: 83–89

Engineering
Intelligent Systems

Modeling of intelligent decision-making based on cognitive learning and context-aware data

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At present, big data has some applications in discovering the laws of things and analyzing problems. However, there are still some deficiencies in smart decision-making. The paper proposes a cognitive computing model, and then studies the data processing techniques that may be used in the model and the task scheduling algorithm in a distributed environment. Through the model analysis, an effective analysis of context-aware data is implemented and the model is simulated. By comparing the initial model of traditional data with the model proposed in this study, the compared results are presented in the form of statistical charts. The comparative study shows that the model of this study has better results in processing data and intelligent decision-making and can provide a theoretical reference for subsequent related research.

Keywords: machine learning; big data; decision; prediction

1. INTRODUCTION

At present, from the perspective of the application and research projects at home and abroad, the research on the items related to machine learning technology has now developed into a research hotspot in the field of cognition and computational science. As early as 2002, the National Science Foundation (NSF) of the United States and the U.S. Department of Commerce jointly funded and jointly sponsored a plan for machine learning. The aim of the plan is to "aggregate four scientific technologies and improve human performance." The project argues that the four key technologies in the 21st century, include nanotechnology, biological science, information technology, and cognitive science and technology which should be given priority in the development of cognitive science and technology. Cognitive science has also received considerable attention in Europe (Poleto, 2015). The Georgia Institute of Computing Technology has set up a machine learning laboratory the main research direction of which is machine learning-related technical problems i.e. machine learning systems that solve problems in the real world and its main research directions include the following themes: the first is the neural network-based agent in games and the second is Web proxy technology with decision support capabilities.(Almeida, 2016). IBM and the Swiss government worked together to launch a research project named the Blue

Brain Project. The project's research goal is to develop a system similar to human cortical tissue to aid human cognitive task. Lockheed Martin Space Systems Company's Advanced Technology Lab is also engaged in machine learning-related project research. At present, they are designing a militarized system that can work automatically. This system can realize the continuous learning of knowledge and the accumulation of experience, and can automatically conduct knowledge learning and logical reasoning. The company's advanced technology laboratory developed a system called ontology driven interpretive system and cognitive processing. The key technologies of this system include: ontology interpretation protocols and empirically accumulated ontology protocols for class logic reasoning and various forms of cognitive structures (Vera-Baquero, 2015). The Information Processing Technology Center of the US Department of Defense Advanced Research Projects Agency began funding a machine learning technology-related project in 2003 and its research goal is to finally develop a machine learning machine system that has the following capabilities: (a) It is able to sense the environment and goals and think in conjunction with its own abilities; (b) it has a certain level of learning ability; (c) It is able to interact with the user and able to explain its reasoning process; (d) It has the ability to deal effectively with emergencies (Santos, 2017).

From the above discussion, we can see that there is much research work on machine learning at the present, but there is little research on applying it to decision support models. Based on this, our present study based on machine learning conducts machine learning on the basis of big data processing, and carries out cognitive learning to achieve intelligent decision-making, so that information technology can be better applied to various decisions.

2. RESEARCH METHODS

2.1 Task scheduling system model

When dealing with very large data usage scenarios, we often use distributed processing methods. Distributed computing environments are often characterized by large scale and dynamics, and computing and data resources are not evenly distributed. In such an environment, it is necessary to properly schedule and allocate computing tasks and computing resources in order to achieve the best results.

Based on the strategy of task scheduling which utilizes accurate classification of resource queues, this study adopts the task scheduling model and scheduling strategy, that is implemented by queue matching. First, the resources are clustered, and then the tasks are clustered according to the clustered resources and this is utilized for Scheduling.

The system model structure is shown in Figure 1. In the task scheduling system shown in this figure, the task queue is on the left, the resource queue is on the right, and a central server is in the middle, which is responsible for the task and resource matching operations (Jin, 2015).

As shown, its task can be represented as a set Q, the task queue stores arrival tasks that are waiting for the system to allocate. There are N tasks to represent the task queue, and these can be expressed as formula (1)

$$Q = \{Q_1, Q_2, \ldots, Q_N\} \tag{1}$$

In this model, $A_n(t)$ represents the number of tasks belonging to category n in the new task that arrived at the system at time t. According to this concept, the arrival task vector can be defined (Vardarlier, 2016) and can be expressed as formula (2)

$$A(t) = \{A_1 t, A_2 t, \ldots, A_N t\} Q \tag{2}$$

In many systems, the arrival task may not be able to be processed under certain circumstances, such as when the server is busy. This situation is also modeled. $R_n(t)$ represents the number of new tasks that arrive at the system at time t when they belong to the n-th task and the server can handle them. It is called real arrival task at time t. $Q_N(t)$ represents the number of tasks of the corresponding class stored at time t, and the stored task queue vector is expressed as Equation (3). The resource queue is used to represent and allocate system resources. Assuming that there are M system resources (when clustering, the value of K is set to M), the resource queue is expressed as formula (4)

$$Q(t) = \{Q_1(t), Q_2(t), \ldots, Q_N(t)\} \tag{3}$$

$$H = \{H_1, H_2, \ldots, H_M\} \tag{4}$$

The assignable class j-th resource owned by the system at time t is denoted by $H_n(t)$ and the resource queue vector at time t is expressed as formula (5). Assuming that the system is not time-varying, such system conditions are called system states and are expressed using a random state variable $\omega(t)$ and defined as in Equation (6). Among them, $z(t)$ accords with the independent and identical distribution system. At time t, the system operator determines the amount of resources allocated to each queue. The above decision is expressed using a matching matrix formula (7). Among them, $b_{mn}(t, m, n)$ represents that the resource of the category m is assigned to the queue n. Therefore, at any time t, the result shown in expression (8) holds (Yang, 2015).

$$H(t) = \{H_1(t), H_2(t), \ldots, H_n(t)\} \tag{5}$$

$$z(t) = (A(t), e(t), \omega(t)) \tag{6}$$

$$b(t) = (b_{mn}(t, m, n)) \tag{7}$$

$$\sum_n b_{mn}(t, m, n) \leq H_{mn}(t, m, n) \tag{8}$$

Because a task cannot consume more resources than all possible values, according to system status and resource allocation, each task queue has a service rate, which can be expressed as Equation (9). Furthermore, the rule as shown in expression (10) must hold. When the left side of equation (10) is greater than or equal to the right side, expression (11) can be obtained. In addition, if there are two vectors b and b', if b' is obtained by setting b_{mn} in b to 0, then expression (12) can be obtained. The constraints are simple, requiring only non-zero resources to obtain a positive service rate. According to the above discussion, the derivation formulas of the task queue and the resource queue are as shown in formula (13)

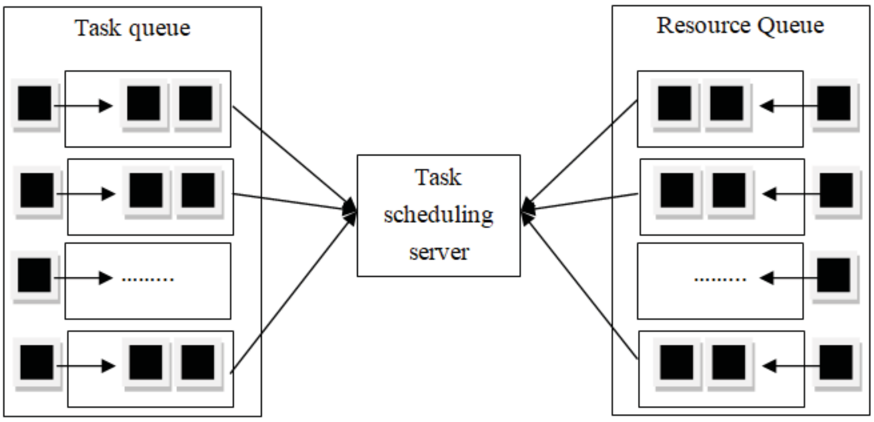

Figure 1 Task scheduling system model.

and formula (14) (Phillips, 2014):

$$u_n(t) \triangleq u_n(z(t), b) \tag{9}$$
$$u_n(z(t), b) > 0 \tag{10}$$
$$u_n(z(t), b) \geq \beta'_u \min(b_{mn}) \tag{11}$$
$$u_n(z(t), b) \leq u_n(z(t), b') + \beta'_u b_{mn} \tag{12}$$
$$Q_n(t+1) = \max Q_n(t) - u_n(t), 0 + R_n(t) \tag{13}$$
$$H_m(t+1) = H_m(t) - \sum_n b_{mn}(t) + h_m(t) \tag{14}$$

The performance of the system is mainly determined by the average queue income. r_n is defined as Equation (15), The revenue of a single classification in the system can be expressed as $\bar{r}$, then the total system revenue is the sum of all the benefits and the formula for system revenue is given as Equation (16). The maximum value of the difference between the system revenue and system cost is used as the basis for system optimization. This difference is represented by f_{av}. The difference between the benefit of the whole system and the cost equation of the system, and the system's cost equation can be expressed as c_{total} and it can be expressed as shown in formula (17).

$$r_n \triangleq \lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} r_n(\tau) \tag{15}$$
$$U_{\text{total}}(\bar{r}) \triangleq \sum_n U_n(\bar{r}_n) \tag{16}$$
$$f_{av} = U_{\text{total}}(\bar{r}) - C_{\text{total}} \tag{17}$$

The stability of the system is to prevent tasks and resources from waiting in the queue for a long time without being processed or used. This is important in many situations. For example, in energy collection network, it is very important to guarantee the timely delivery of the package; in a crowdsourcing system, it is also important to keep the processor waiting time to be as short as possible (Syeda, 2018).

The selection of the center point is completed in two steps. The first step is to divide the resource data set into several small clusters. In the second step, these small clusters are further gathered into groups according to distances. The final cluster center is obtained from these clusters. The first step is actually an incremental processing algorithm. Therefore, the data set is traversed first, and each small cluster is initialized with only one data point, which is recorded as a small cluster head. Then the incremental update operation is performed.

The incremental update method is as follows: For any data point in the data set, if the distance of the resource data point from a small cluster head is less than or equal to a set threshold, the data point is assigned to this small cluster. If no small cluster head satisfies the condition that the distance to the data point is less than the set threshold, the data point is classified into the small cluster head that is traversed first (for the efficiency of the algorithm operation).

In addition, each small cluster also has a counter to record the number of data points currently belonging to the small cluster. Finally, the average of all the data points in a small cluster is calculated as the new center point of the small cluster head. All the data points whose distance from the center point is smaller than the set small cluster radius are assigned to this small cluster. After the first step, a small cluster centered on the center point of a small cluster is obtained. The distance from the center of all data points within a small cluster is less than or equal to the set threshold. The small cluster is a data point surrounded by a circle whose center point is a center and whose radius is a set threshold distance. At the same time, all the small clusters obtained in the first step will be combined into their own cluster groups.

The combined method will calculate the distance and the number of nodes in each cluster. In addition, the center point of the newly formed cluster group will be used as the cluster initial center point of the K-means clustering algorithm. If the distance between two data points of any two small clusters is greater than the set threshold distance, all the small clusters become a cluster group; if the number of cluster groups is larger than the value of K specified by the K-means algorithm, the clusters are combined into K-sized cluster groups; If the number of cluster groups is smaller than the value of K specified by the K-means algorithm, the cluster with the largest number of data points in a small cluster is divided into two, so that the K number of clusters specified by the K-means algorithm is consistent with the number of clusters. The center of the adjusted cluster group is used as the initial cluster center of the K-means algorithm.

Figure 2 shows a schematic diagram of the cluster formation process of small clusters. The figure shows the process of a cluster. Small clusters where the distance between all center points is smaller than the set value will collectively form a cluster group (Boulila, 2017).

3. EXPERIMENTAL RESULTS

The selection of the test system is mainly to ensure the stability of the experimental results and the subsequent practicality of the test. Distributed environments are used for algorithm simulation. In the experiment, to improve system stability, the experimental environment used was an 8-node cluster and the system was Ubuntu 13.04's 64-bit operating system. The computer used is the Lenovo 710s series. The actual allocated memory size for each node is 2G, the distributed file storage system is HDFS, and the Map Reduce framework design is used. The cluster contains a main section, and the rest are slave nodes.

The performance of the improved resource clustering algorithm and the K-means algorithm provided by Mahout are compared in terms of clustering accuracy. The performance in terms of accuracy for each category of a data set with 20 categories was measured and the cluster was set to use 8 nodes. The 20 data categories are numbered 1 to number 20, respectively, and the resulting accuracy of each category is shown in Figure 3.

The performance of the improved resource clustering algorithm and the K-means algorithm provided by Mahout in terms of the time spent in clustering are compared. Other parameters are fixed, the number of nodes from 2 to 8 clusters is changed, and then the clustering algorithm execution time corresponding to the number of each node is recorded. The experimental results obtained are shown in Figure 4.

The number of task categories in the system is set to 5, and the number of resource categories is set to 5. At the same time $r_{\max} = 5$, $\mu_{\max} = 5$, $b_{\max} = 5$, $h_{\max} = 5$ is set. After the parameters are set, the control parameter V is first changed according to 10, 20, 50, 80, 100 (V is a parameter of the balance relationship between the control system gain and the system delay), and the task scheduling algorithm based on the improved queue matching and the task delay performance analysis of the RAM are compared. Task delay performance is represented by the total number of tasks in the task queue. The results obtained are shown in Figure 5.

Next, the performance of the SMQ and RAM in terms of resource allocation efficiency is compared. This performance is determined based on the number of unallocated resources included in the resource queue in the task schedule. The greater the unallocated amount, the lower the resource allocation efficiency. Similarly, the parameters V are controlled to change in order of 10, 20, 50, 80, and 100. The experimental results obtained are shown in Figure 6.

4. ANALYSIS AND DISCUSSION

As can be seen from Figure 3, the clustering algorithm has better performance than the K-means clustering algorithm provided by Mahout in accuracy and stability. The reason for this result is mainly that the initialization operation of the cluster center point has been improved, the accuracy of the classification has been improved, and the selection of the center point is more regular, and the result of each clustering is stable. Therefore, the stability of each clustering result is also greatly improved.

From the result of Figure 4, we can see that the improved resource clustering algorithm performs better than the K-means algorithm provided by Mahout in the execution time. The main reason is the optimization strategy of the initialization of the center point of the clustering algorithm, which effectively reduces the number of iterations of the clustering algorithm, thereby greatly Improving the time consumption of the clustering algorithm .

From Figure 5, it can be seen that the total amount of tasks accumulated in the task queue of the TSMQ algorithm is less than the RAM algorithm, which means that it has better performance than the RAM. From Figure 6, it can be seen that TSMQ has better performance in terms of resource allocation efficiency than RAM.

In order to realize the analysis of large-scale data and the automatic extraction of valuable information, it is necessary to find a new data interaction processing method, which is machine learning technology. Machine learning is a kind of data analysis that can continuously learn knowledge and improve cognitive ability in the interactive way with the continuous change of data. It is designed to make computers, liking humans, to learn knowledge, analyze problems and make appropriate decisions based on experience and data. At the same time, it should be recognized that machine learning does not want computers to replace human thinking, but to become an effective auxiliary tool for people to recognize and process large-scale data. This tool has the ability to help people solve some problems and filter out invalid interference information.

Based on the above analysis, The paper proposes a cognitive computing model, and then studies the data processing techniques that may be used in the model and the task scheduling algorithm in a distributed environment. Based on this goal, this paper addresses the following three aspects :

1. Due to the use of Internet applications, a large amount of perceptual data and context-aware data flows are generated. This kind of data stream has characteristics such as fast transmission speed, large flow, unclear degree of correlation, arrival in disorder, etc. It is very difficult to extract the desired data from it and understand its meaning. In response to this problem, this paper studies a machine learning model based on context-aware data flow to achieve effective analysis of context-aware data and to derive effective cognitive results. In addition, this paper proposes a data flow-oriented decision tree algorithm to optimize the data flow for data stream classification and processing.

2. In today's ever-expanding data scale, it is difficult for people to find information that they are interested in or to analyse for themselves the vast amounts of data. For this background, how to more effectively use the computer's high-efficiency computing capability and use machine learning and other related technologies to achieve human-like cognition and judgment, so as to make accurate decision results has very important practical significance. Based on this, this paper presents a cog-

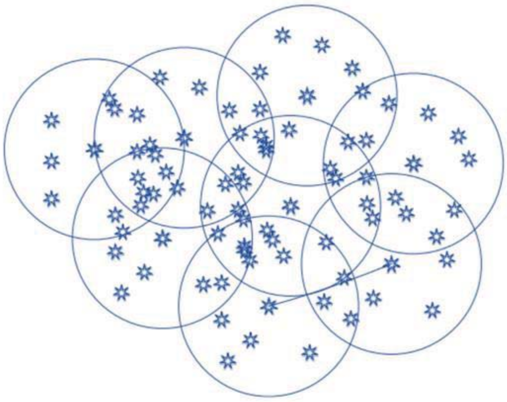

Figure 2 A cluster group consisting of multiple small clusters.

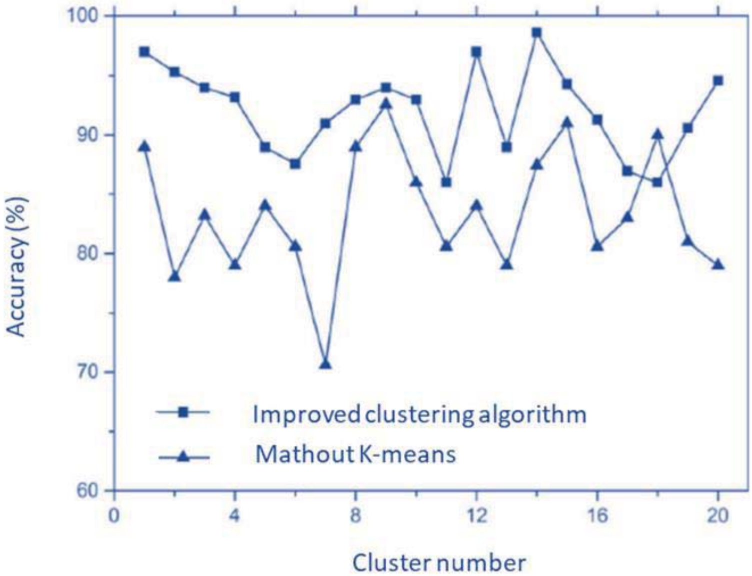

Figure 3 Comparison of the accuracy of improved resource clustering algorithm and Mahout K-means algorithm.

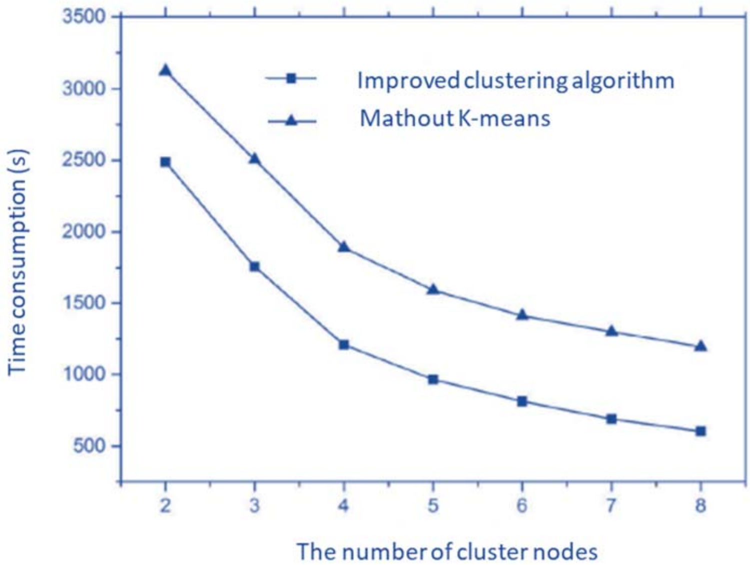

Figure 4 Comparison of the speed of improved resource clustering algorithm and Mahout K-means algorithm.

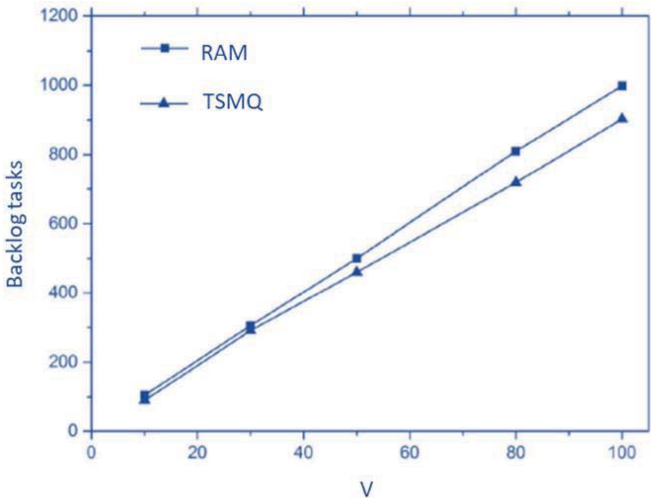

Figure 5 Comparison of task delay performance.

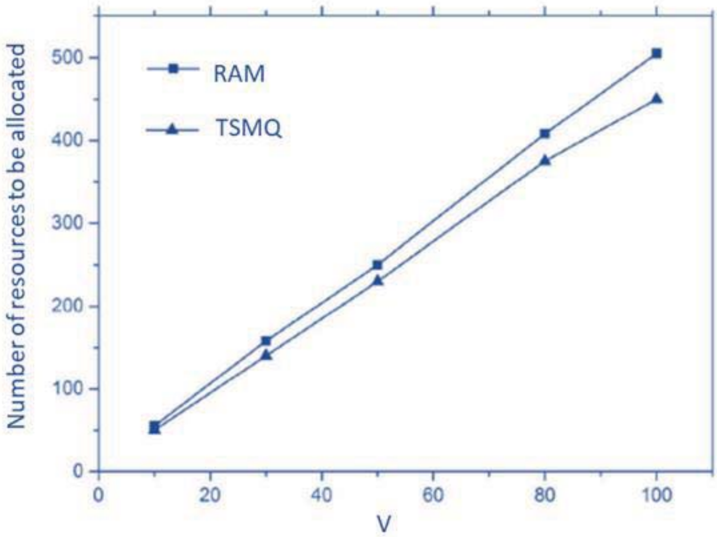

Figure 6 Comparison of resource allocation efficiency.

nitive decision-making algorithm based on deep belief networks and linear sensors. Based on the deep belief network, it implements a cognitive decision model with error control function, comprehensively considers the information itself and context information, and finally procides the decision result as to whether the information is valid or not.

3. In a very large data usage scenario, distributed processing methods are often used in actual applications. Distributed computing environments often have scaling up capability, dynamic features, and computing and data resources are not necessarily evenly distributed. Under such a usage scenario, it is necessary to perform reasonable scheduling and allocation of computing tasks and computing resources so that optimal resource utilization and data processing can be achieved. Therefore, this paper proposes a task scheduling algorithm based on improved queue matching to solve the task scheduling problem in distributed computing environments. First, the resources are clustered, and then the tasks are scheduled according to the clustered resource clusters, so that the system can achieve higher computing efficiency and resource utilization.

5. CONCLUSION

The task scheduling algorithm based on improved queue matching proposed by the research is based on resource and task size. The resources are clustered first, and then the resource queues are generated according to the clustered resource clusters for task scheduling and resource allocation. It can be seen from the simulation results that the first clustering strategy in the article has better performance than the direct scheduling method. The clustering algorithm has better performance than the K-means clustering algorithm provided by Mahout in accuracy and stability. This is due mainly to the fact that the initialization operation of the cluster center point has been improved, the accuracy of the classification has been improved, the selection of the center point is more regular, and the result of each clustering is stable. The improved resource clustering algorithm performs better than the K-means algorithm provided by Mahout in the execution time. The main reason is the optimization strategy of the initialization of the center point of the clustering algorithm, which effectively reduces the number of iterations of the clustering algorithm, thereby greatly improving the time consumption of the clustering algorithm. The total number of tasks accumulated in the task queue of the TSMQ algorithm is less than the RAM algorithm, which means that it has better performance than the RAM. From Figure 6, it can be seen that TSMQ has better performance in terms of resource allocation efficiency than RAM. Thus the big data decision support technology based on this study and its learning has a certain effect, and it can be applied to the actual decision model to improve the accuracy of the decision.

Acknowledgement

This work is supported by Projects of the China Postdoctoral Science Foundation (No. 2018M643214).

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