An Algorithm of Employment Resource Allocation for College Students Based on Social Network Mining

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Abstract. Aiming at the current uneven distribution of employment resources and poor accuracy of college students, social network mining is applied to the design of college students' employment resource allocation algorithm, and a college student employment resource allocation algorithm based on social network mining is proposed. First, build an LTE (Long Term Evolution) system. LTE interference suppression is performed through inter-cell interference randomization technology, inter-cell interference cancellation technology, and inter-cell interference coordination technology. Construct a resource allocation model based on the constructed LTE system, and the constructed resource allocation model is a continuous decision model. In terms of resource allocation, virtual machines can be simulated and placed through the established energy consumption model and performance loss model, so the state value can be obtained through the Monte Carlo method. Based on social network mining, according to the constructed resource allocation model and the obtained state value, the employment resource allocation algorithm for college students is realized. Experiments verify that this method has short task scheduling time, better resource allocation accuracy and efficiency, and it can optimize the allocation of employment resources for college students to a certain extent.

Keywords: Allocation algorithm · College students · Employment resource · Social network mining

1 Introduction

Since the expansion of college enrollment, the number of college students graduating each year has been increasing, but the number of employers has not increased rapidly, resulting in an imbalance in market supply and demand, and the employment situation for college students is very severe. This problem has become one of the key issues of concern to the whole society [1]. In order to alleviate the employment difficulties of college students, the state has issued a series of related policies, such as encouraging graduates to work at the grassroots level in urban and rural areas, central and western regions, and small and medium-sized enterprises, encouraging graduates to enlist in

S. Liu and X. Ma (Eds.): ADHIP 2021, LNICST 416, pp. 254–265, 2022.
https://doi.org/10.1007/978-3-030-94551-0_21

the army, and encouraging graduates to start their own businesses. Self-employment of graduates has been the focus of work in recent years. However, these policies cannot completely solve the problem of employment difficulties for college students [2]. Since China has been a "relationship" society since ancient times, many college students will try their best to use family or personal social capital in order to find an ideal job. The phenomenon of using social capital for employment is very common in China. It can allow job seekers to obtain more comprehensive employment information, increase employment opportunities, and reduce employment pressure. At the same time, it can also cause unfairness and affect social order. It can be said that social capital will have a great impact on the employment rate and employment quality of college students [3].

However, too much social capital will also have a negative impact on college students and society as a whole. Therefore, the government must regulate the employment order, create a relatively fair employment environment, and allocate employment resources for college students. In this context, an algorithm for the allocation of employment resources for college students based on social network mining is proposed. At present, relevant scholars have done research on the allocation algorithm of college students' employment resources. Literature [4] proposes to give priority to the allocation of medical care and employment resources during the period of new coronary pneumonia. Designed an online survey on how much priority should be given to the elderly in healthcare-related scenarios and three related employment scenarios. The results show that benevolent age discrimination predicts that older people will have higher priority for access to healthcare (classification, COVID-19 vaccine, COVID-19 testing) and employment resources (reserving jobs, working from home), and more recognition of hostile age discrimination Significantly predicts a lower priority rating. Literature [5] proposes employment resources for patients with Parkinson's disease: resource review and needs assessment. Parkinson's disease patients (PwP) exit the labor market five years earlier than non-Parkinson's patients due to motor, cognitive, communication, and emotional symptoms. The reduction in employment will result in huge personal and social costs. The purpose of this research is to determine the advantages and disadvantages of employment resources, and to evaluate the needs of consumers and clinical stakeholders to improve job retention. The research uses a qualitative content analysis and quasi-needs assessment framework. Sixteen PwP and 10 clinician stakeholders participated in two rounds of stakeholder discussion groups.

Interference suppression by LTE is to use inter-cell interference randomization technology to construct a resource allocation model based on the constructed LTE system, and the constructed resource allocation model is a continuous decision model. In resource allocation, the virtual machine can be simulated and placed through the established energy consumption model and performance loss model, so that the state value can be obtained through the Monte Carlo method. On the basis of social network mining, according to the constructed resource allocation model and the obtained state value, the employment resource allocation algorithm for college students is realized.

2 The Algorithm Design of Employment Resource Allocation for College Students Based on Social Network Mining

2.1 Building an LTE System

The LTE system is different from the previous wireless communication system. It mainly supports packet switching services by establishing a seamless mobile IP connection between the user terminal and the packet data network. First, the LTE system is constructed [6]. The constructed LTE network consists of two parts: a core network and an access network. The core network is composed of many logical nodes, and the access network basically has only one node, which is an evolution type, and all network elements are connected to each other through interfaces. The main function of the core network is to establish relevant bearer and control user terminals. The main logical nodes of EPC (Electronic Product Code) mainly include the following three parts: PDN (Public Data Network) gateway, service gateway, mobility management entity, in addition to some registers such as home location register, etc. [7].

Among them, P-GW is responsible for user IP address allocation and QoS guarantee, and performs traffic-based charging according to PCRF rules. The S-GW is responsible for sending user IP data packets. The MME is responsible for handling the control of the signaling interaction between the UE and the core network.

E-UTRAN is composed of eNodeB networks, which are connected to each other through interface X2 and to MME through interface S1. The main functions of the access network include: wireless resource management, IP header compression, and security assurance. The main functions of radio resource management include: radio access control, radio bearer control, dynamic resource allocation, UE uplink and downlink scheduling, etc. Security is mainly reflected in the need to encrypt all data packets sent through the wireless interface. The access network is also responsible for the MME signaling and the establishment of the bearer path to the S-GW. LTE not only cancels the radio network controller node, but also adopts the all-IP network architecture, and at the same time improves the air interface physical layer technology, so that it can support wider system bandwidth and shorter transmission delay, and in terms of spectrum utilization Three to five times the previous standard. The system not only optimizes the traditional UMTS network architecture, but also supports both FDD and TDD duplex modes.

2.2 LTE Interference Suppression

In the LTE system, there are the following three technologies according to different interference processing methods: inter-cell interference randomization technology, inter-cell interference cancellation technology, and inter-cell interference coordination technology. These three technologies can suppress inter-cell interference [8].

Inter-cell interference randomization techniques include scrambling and interleaving. Scrambling is performed by using different pseudo-random codes for the signals of each cell. Interleaving is to use different interleaving patterns for channel interleaving to obtain interference whitening effects.

Inter-cell interference cancellation technology includes spatial interference suppression technology based on multi-antenna receiving end and interference cancellation technology based on interference reconstruction. The principles of these two methods are to demodulate or even decode the interference signal of the interfering cell to a certain extent, and then use the processing gain of the receiver to eliminate the interference signal component from the received signal.

Inter-cell interference coordination techniques include soft frequency reuse and partial power control. The principle of soft frequency reuse is to allow cell center users to freely use all frequency band resources, while cell edge users can only use a certain part of the frequency band resources.

2.3 Building a Resource Allocation Model

According to the constructed LTE system, the resource allocation model is constructed. The constructed resource allocation model is a continuous decision-making model. The goal of the model is to minimize the energy consumption and performance loss of cloud computing. The resource allocation model is constructed by the cloud computing simulation tool CloudSim. CloudSim is written in java language, so it can run normally on different systems. The simulation tool provides a power component, which includes the placement strategy class of the virtual machine, the energy consumption model class of the virtual machine, and the dynamic migration selection strategy class of the virtual machine. By inheriting or modifying existing classes, users can implement their own virtual machine placement strategies and simulate them on the platform. The constructed resource allocation model consists of the following parts: Energy consumption evaluation model: This model performs energy consumption evaluation after simulation placement based on the possible relationship between the energy consumption of cloud computing and the resource occupancy ratio, which makes the obtained solution close to the optimal solution. An indispensable model. Resource allocation model: This model is mainly used to model and constrain resources in cloud computing. The constraint conditions are generally that a virtual machine can only be placed on one physical machine, and the required memory of the placed virtual machine should not exceed the physical machine's Available memory, etc.

2.4 Evaluation of State Value

In resource allocation, the virtual machine can be simulated and placed through the established energy consumption model and performance loss model, so the state value can be obtained by Monte Carlo method.

In a standard Monte Carlo process, a lot of random simulations are run, in this case, start with the board position where you want to find the best move position. Every possible move from this starting state retains statistical information, and then returns the move with the best overall result. However, the disadvantage of this method is that for any given branch in the simulation, there may be many possible moves, but only one or two moves are good. If a move is randomly selected for each round, the simulation is unlikely to find the best path forward. Therefore, the UCB1 strategy is used to enhance the selection. The strategy of UCB1 is different from random simulation, but the branch child nodes are selected according to the current number of games and the total number of wins of the node each time [9].

The Monte Carlo tree search is divided into four stages in total:

(1) The first stage: selection, when you use statistical data to deal with each position you reach, it is like a multi-gambling machine problem. Then, the move used will be obtained by the UCB1 strategy instead of randomly selected, and applied to obtain the next position to be considered. Then make a selection until you reach a sub-location that is not recorded with statistical information. The specific operation of selection is shown in Fig. 1. The number on the left of the figure represents the number of times the node is finally won, the number on the right of the figure represents the total number of times the node is selected, and the left and right sides of the top number represent respectively The total number of matches won and the total number of matches [10].

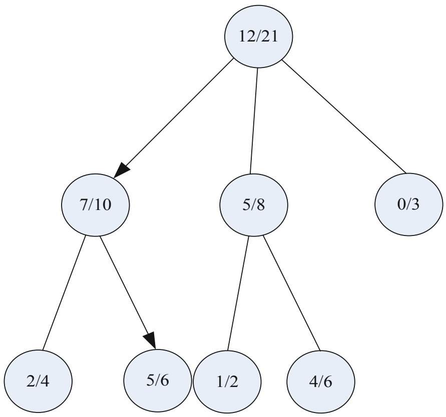

Fig. 1. Selection flow chart

(2) The second stage, expansion, occurs when the UCB1 strategy can no longer be used for selection [11]. Randomly select an unvisited sub-location, and add a new record node to the statistics tree. The specific operation of the extension is shown in Fig. 2. Compared with Fig. 1, the new node is explored, and the attribute of the new node is 0/0.

(3) The third stage, simulation. This is a typical Monte Carlo simulation. It is either purely random or some simple weighted heuristic algorithm. If it is a lightweight match, choose a random simulation. If it is a non-lightweight match, use the more computationally expensive one. Weighted heuristic algorithm for simulation. For games with fewer branches in each branch node, using random simulation can produce better results. Simulation is a complete process. From selection, exploration

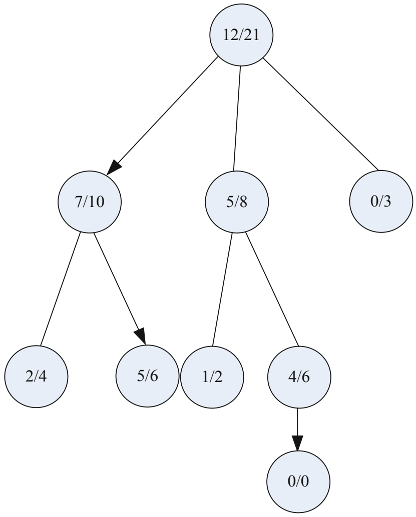

Fig. 2. Extended flowchart

and finally to the victory or defeat, the simulation operation is shown in Fig. 3. After the expansion, continue to select the child nodes, and finally get the game result 0 (negative) or 1 (win).

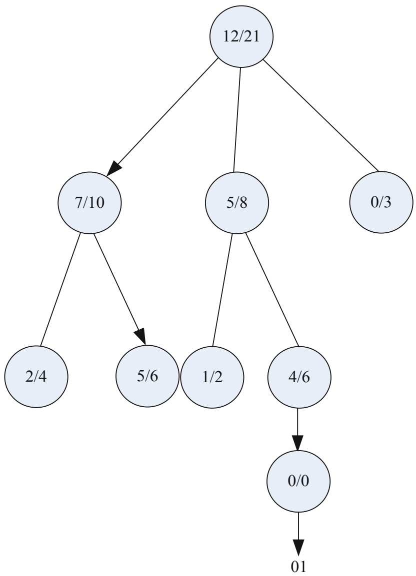

Fig. 3. Simulation flow chart

(4) Finally, the fourth stage is the update or back propagation stage. This happens at the end of a simulation. The number of visits to all locations visited during this simulation will increase, and if a player in that location wins the game, the number of wins will also increase. The update operation is shown in Fig. 4, which is based on the update operation after the final simulation result in Fig. 3 is victory. That is, the number of visits and the number of wins of all nodes traversed in the last simulation is increased by 1.

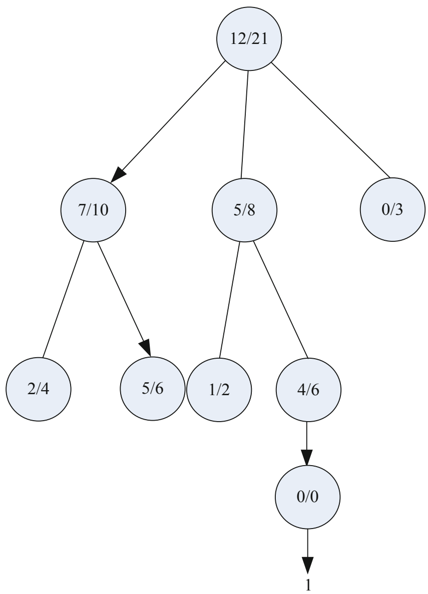

Fig. 4. Backpropagation flowchart

2.5 Allocation Algorithm of Employment Resources for College Students

Based on social network mining, according to the constructed resource allocation model and the obtained state value, the employment resource allocation algorithm for college students is implemented [12–14].

The basic description of the allocation algorithm of employment resources for college students is as follows:

(1) Enter the virtual machine list, physical machine list, and historical information list of college students' employment resources, and create a matrix Y of the advantage value of college students' employment resources.

(2) Based on social network mining, traverse the virtual machine list of college students' employment resources, and calculate the advantage value Yij for each virtual machine according to the state value and frequency matrix and the advantage frequency matrix [15].
(3) According to the advantage value Yij, the virtual machine placement of the employment resource agent of college students is carried out, and the placement strategy is as follows:

When another agent does not place the placement, select the physical machine with the largest current placement times and meet the constraints between the virtual machine and the physical machine according to the placement matrix information for placement, and update the times matrix after placement. If another agent has already placed the selected virtual machine, according to the frequency matrix, select the physical machine with the frequency matrix value of 0, and then select the following from the selected physical machines: perform another based on the historical placement optimal information The agent's placement simulation predicts to obtain an energy consumption value and based on the historical placement information, the current agent is divided by the current virtual machine placement prediction to be placed (after the prediction, only the current virtual machine has not been placed) and an energy consumption value is obtained. Select the physical machine that can win the remaining part of the agent after the placement is completed and save it into a list.
(4) After traversing and selecting the physical machine of employment resources for college students, perform the following operations:

Determine whether the list is empty. If it is empty, perform unfavorable expansion, that is, select the physical machine that satisfies the constraint condition and minimizes the additional energy consumption after placement from the physical machines with the value of 0 in the order matrix. If the list is not empty, traverse the virtual machines in the list, and find out the physical machine that minimizes energy consumption after placement.
(5) Return to the selected college student employment resource allocation physical machine.

The specific description of the allocation algorithm of college students' employment resources is shown in Fig. 5.

```
Input:              VMS,PMS,discount               factor
y,listl,list2,list3,C(S),U(S),Q(S),VMi
Output:Selected PM
create matrix Yu ,pm=null,listpm,count=O,double min=999
    for VMi in VMS do:
By C(S),U(S) use equal (5-4):
by ,u ,Q(S) use equal (5-9)
    end for
    get E2 by list2
    get E1 by listl
     for PMj in PMS do:
        e= getE(PMj,VMi)
         if E l+e<E2:
add PMj into listpm
                  count++
endfor
     if count==0:
      pm=getSuit(PMS,VMi)
     else:
      for PMk in listpm do:
         if min>getE(PMk,VMi):
            min=getE(PMk,VMi)
            pm=PMk
endfor
  return pm
```

Fig. 5. Detailed description of the allocation algorithm of employment resources for college students

3 Experimental Test

3.1 Experimental Environment

The experiment used four types of virtual machines and two types of physical machines. The parameter configurations of the physical machine and virtual machine are shown in Table 1 and Table 2 respectively.

Table 1. Virtual machine parameter configuration

Type	VM1	VM2	VM3	VM4
MIPS	2500	2000	1000	500
PES	1	1	1	1
RAM/M	870	1740	1740	613
BW/Ms	100000	100000	100000	100000
SIZE/M	2500	2500	2500	2500

Table 2. Physical machine parameter configuration

Type	HPProLiant ML110 G4	HPProLiant ML110G5
MIPS	1860	2660
PES	2	2
RAM/M	4096	4096
BW/Ms	1000000	1000000
STORAGE	1000000	1000000

Build an experimental platform under the configuration of Table 1 and Table 2, set environment variables as required. The specific settings are shown in Table 3.

Table 3. Environment variable settings

Serial number	Path	Environment variable settings
1	ClassPath	D:\Program Files (x86)\Java\jdk1.6.0_12\lib;
2	Path	D:\Program Files (x86)\Java\jdk1.6.0_12\bin;

In the experiment, the computing power of each virtual machine ranges from 100-1000MIPS, and the task length ranges from 10000-100000MI.

The network topology built in the experiment is shown in Fig. 6.

3.2 Simulation Experiment Process

When starting the simulation, you first need to create a data center, then create virtual machines and cloud tasks in the data center, select appropriate scheduling strategies and set resource parameters, etc., and finally register resource information with the agent center so that users can use it The resources of the data center are simulated. In the simulation experiment, the task scheduling time data of the employment resource allocation algorithm based on social network mining is obtained as the experimental data.

3.3 Analysis of Experimental Results

The experimental data of the task scheduling time of the employment resource allocation algorithm based on social network mining is shown in Table 4.

According to the experimental data of task scheduling time in Table 4, the task scheduling time of the employment resource allocation algorithm for college students based on social network mining is shorter. This method uses LTE interference suppression technology to construct a resource allocation model, and the constructed resource allocation model is a continuous decision model. Through the established energy consumption model and performance loss model to simulate and place the virtual machine,

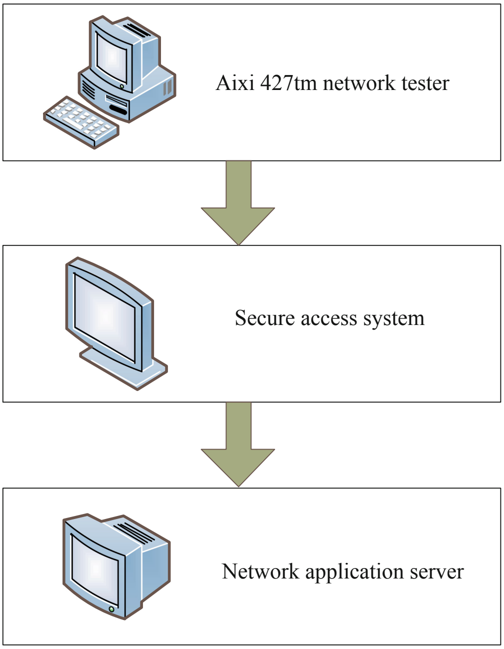

Fig. 6. Network topology built in the experiment

Table 4. Experimental data of task scheduling time

Serial number	Number of tasks	Task scheduling time(ms)
1	50	742.25
2	100	1183.16
3	150	2032.38
4	200	3206.24
5	300	4559.25
6	400	5324.57
7	500	5484.34

the state value can be obtained by the Monte Carlo method. It saves a lot of calculation steps and improves the efficiency of resource allocation.

4 Concluding Remarks

The employment resource allocation algorithm for college students based on social network mining realizes the improvement of task scheduling performance, effectively improves the accuracy and efficiency of college students' employment resource allocation, and has a certain significance for improving the employment prospects of college students.

In future research, the employment problems of college students of different majors should be classified, so as to improve the distribution of employment resources of college students in a more targeted manner.

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