Raise Performance in Mobile Cloud-Based Learning

Ribata Najoua, Aknin Noura, El Kadiri Kamal Eddine

Abstract— This paper will describe the research method used for the design of the Collaborative as a Service (CaaS). Which is to provide a novel approach to raise performance in mobile Cloud-Based Learning, by a constructive approach of task allocation in mobile cloud-based learning, using Kolb's Learning Style (KLS) to accurately allocate responsible tasks to each learner in order to raise collaborative learning performance? We employ a Genetic Algorithm (GA) to facilitate the task allocation.

Index Terms*—Collaborative as a Service, Genetic Algorithm, Kolb's Learning Style, *Mobile Cloud-Based Learning, Task allocation problem.

I. INTODUCTION

A. Cloud Computing

Cloud computing is the fusion of parallel computing, cluster computing, distributed computing, virtualization, etc. It becomes a new trend of the development of information technology nowadays. National Institute of Standards and Technology (NIST) currently describes cloud computing as "a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources (e.g. network, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" [1]. The fundamental principle of cloud computing is that computing is arranged in large distributed systems instead of in local computers or remote servers. Benefitting from the continual improvement of process capabilities of the cloud, the burden of the user terminal is decreased. Ultimately, user terminal will be simplified as an input and output device which can access resources and computing capabilities from the cloud on demand [2]. Generally, cloud computing offers its functions in the shape of services, to the extent that a new viewpoint comes out, which is every IT resource and component can be considered as a service (XaaS). Typically, some researchers indicate that cloud computing has a three-tier up-down nature, differentiated by the types of provided services, where in each tier is a kind of XaaS, namely Software as a Service (SaaS), Platform as a Service (PaaS) and Infrastructure as a Service (IaaS) [3]. The features of these can be argued as follows.

Infrastructure as a Service (IaaS)

IaaS is the most basic cloud service model that delivers the service of offering directly accessible computer infrastructure to consumers through the internet. The service providers have the duty to host and maintain the infrastructures, which are sometimes as physical, but more usually as virtual machines, or other resources, such as servers, storages, network capacities and load balancers.

Manuscript Received on October 2014.
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Some examples of IaaS include Amazon Elastic Cloud Computing (EC2), Microsoft Azure, Eucalyptus, Google Compute Engine and HP cloud.

Platform as a Service (PaaS)

PaaS contributes a new model of delivering services which allows consumers to develop and run their applications without the complexity and cost of purchasing and managing the basic hardware and software. These services include not only the operation systems, web servers or databases, but also other services working as technical supporting, even the development and optimization of applications based on those platforms. At present, the famous PaaS products include Google App Engine, Force.com, Orangescape and so on.

Software as a Service (SaaS)

Actually, the concept of SaaS comes earlier than cloud computing, evolving from the mainframe, the Client/Server (C/S) structure and the Browser/Server (B/S) structure. It is a software distribution model, in which the providers deliver the functions of applications and the associated data through the network, and consumer access those by thin clients or web browsers. Instead of purchasing licences and installing software, consumers usually rent the permissions of applications, by which they are billed depending on their real requirements and using conditions. Meanwhile, the providers take care of all the technical problems and managements, including security, availability, and performance. The marketplace of SaaS is in intense competition, leaded by several IT giants, IBM, Microsoft, Oracle, Google and Apple, and also accelerating booms of several rising IT enterprises, such as Amazon and SalesForce.

B. Mobile Computing

Mobile computing is a new technology that crosses multiple fields and rises popular in recent years, with the technology development of communication, network and mobile processors. Mobile computing becomes a new branch of distributed computing. It is the activity of using mobile devices' computing abilities without pre- defined locations, towards publishing or subscribing information. Accordingly, several mobile operation systems emerge to meet the increasing requirements of running applications, for example, iOS, Android OS and Windows Mobile. However, mobile computing is limited by the memory, battery power and processing speed of mobile devices, and that during the process of mobile computing, the conditions of network connection are usually diverse, possibly in high speed, low speed or disconnected. These may result in discontinuousness of the computing process, and security issues are also brought in because mobile devices are preferred targets of attack [4]. Some literature states that traditional mobile computing is inefficient and unreliable.

C. Mobile Cloud Computing

Defined as an extension of cloud computing, mobile cloud computing (MCC) is the instance that uses the technology of that in mobile environments. Users are able to access resources and services, such as infrastructure, platform, software, over the internet through mobile devices. MCC inherits the features of cloud computing [5]. Cloud is treated as a secure and dependable data storage centre, where millions of computers in cloud form a super-power server, providing the ability of massive data processing. The sharing, searching, management, mining and analysis of data can be executed systematically in the cloud. In addition, the scales of computer clusters in the cloud are changeful depending on different computing amounts, and they can work in parallel to achieve rapid response. The data backup mechanisms are mature in the cloud, similarly disaster recovery mechanisms are also ready to deal with the unexpected data loss. A significant innovation of cloud computing is that it takes the granularities of services into consideration, distinguished by scale [6]. It causes that various kinds of consumers who have separate requirements are totally satisfied after a one-time large-scale deployment of the same cloud-based system, without modifying and resetting the configuration exhaustively. Moreover, from the huge shared pool in the cloud, consumers are free to acquire resources and customize services on demand, which reduces the quantity of waste. MCC holds high Quality of Service (QoS). If there are vast increases of visits to the cloud at the same time, which may result in the congestion and disconnection of network, these kinds of conditions are in good charge of numbers of load balancers.

II. MOBILE CLOUD-BASED LEARNING

A. Mobile Learning

Mobile learning (m-learning) appears as a new trend of e-learning with the evolution of wireless technologies and widespread use of mobile devices [7]. The main difference between e-learning and m-learning is that the first takes place in front of a computer or in internet labs, while the second takes place at any location [8]. For this reason, learners can utilize m-learning wherever they are and whenever they want. Learning activities happening on campus, at home or outside school facilities can be integrated into mobile education environment [9]. In addition, a phenomenon of the use of m-learning is that the learners are using mobile devices and actually in movements while the teachers may use multiple kinds of equipment other than mobile devices and be located in unique places [10]. Koole et al. [11] state that the m-learning promotes the utility of distance learning compared with which it has several additional features that should be considered when preparing how to deliver a quality education experience:

- Accessibility
- Personalization
- Convenience:
- Interactivity

The development of m-learning is neither intended to replace traditional distance learning, nor about to restrain the course into pocket devices, but to enhance it with the value of wireless network, and augment the formal knowledge delivering [12]. Hence, it is believed that some new trends brought by m-learning will arrive in the near future, which can be concluded as:

- More mobile devices are brought into classrooms as the supplements of traditional learning resources.
- More online courses are delivered through the LMSs, giving learners more choices to participate in on demand.
- The e-book gradually replaces the traditional paper-printed textbook, the content of which is easy to update to avoid being outdated [13].
- More multimedia content is blended in teaching materials, which expresses knowledge in creative and vivid ways.
- Learning for multiple times and each time with small quantity becomes common.
- Combining social network with m-learning works to link learners, generate discussions and transmit information
- Online collaborative learning rises popular which leads numbers of learners to join for working towards common goals.
- A great development that emerges in conjunction with m-learning is the cloud computing.

B. Mobile Cloud-based Learning

We expound the disadvantages of traditional m-learning without cloud computing as the following two aspects:

For education providers, administers and teachers, the deployment and management for LMSs supporting m-learning pose difficult problems to them. Because of a variety of user requirements, the m-learning system is obliged to set by user-defined, while how to choose and configure the extended components of LMSs is also not easy so that teachers and administers have to get training otherwise they cannot adapt to the changeability of component configuration which is unique to each component. On the other hand, the traditional LMS is defective in large-scale deployment. In research and utilization of m-learning, deployment from single site to provide overall services is generally centralized in the level of schools. For this reason, once problem happens to the open-source m-learning system, general teachers and administers have difficulty in solving the problem without aid from professional technicians. In the last, the cost is always the unavoidable issue caused by the charges of hardware, software, collocation, network renting and electricity. Nevertheless, all above issues are feasible to be solved along with a new trend, which is embracing mobile learning with MCC. Consequently, with the solutions that either migrating current LMSs to cloud or directly developing them over the cloud, learners can learn through mobile devices [14]. This is a novel way of m-learning, namely mobile cloud-based learning. Leveraging mobile cloud-based learning, the primary advantage which is seen obviously is the lower cost. The requirement of hardware and software is significantly reduced. In particular, since all of the data storage and processing are taking in the cloud side, the limited processor capacity and memory size of mobile devices are no longer bottlenecks for a pleasant m-learning experience, so as the learners can only use mobile devices, which only have to run a browser and connect to the wireless network, for input and output of data. The mobile cloud-based learning catalyses the appearance of diversified virtual learning communities and virtual teams, which are dismissed the restraint of location, nation, culture background of learners and expanded the influence scopes [15]. Therein, learners are free to participate into those kinds

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of personnel structure of learner cohorts to exchange their ideas, discuss their viewpoints, share their experiences and learn from others' strengths to find and improve their weaknesses, where more collaborative learning has a favorable environment to be happened among learners who have similar learning purposes. As a consequence, collaborative learning is a more and more frequent learning activity and important learning approach in the mobile cloud-based learning [16].

III. Collaborative Learning Performance

The issues of collaborative learning performance in traditional learning still exist in the mobile cloud-based learning [17] [18] [19] [20]:

- Learner types of members in one group are different. Each learner has dissimilar abilities to acquire new knowledge, and they may utilize diverse methods to learn optimally.
- Expectations of each learner in one group are different.
- The preferences of each learner may affect their final outcome, which means learners sometimes feel unmotivated while they are facing some bottlenecks in their loath tasks, or striving in their willingness.
- Current criteria used for assessing a student's performance are based on final results of the whole group. It cannot mark each learner depending on their individual contributions.
- The whole group's achievement may be negatively affected by some under- performing learners. Specifically, in some kinds of collaboration, a learner's task should take another learner's work as the premise, while the delay of the latter one may cause the delay of the whole group. For example, if a learner who takes charge of collecting data has not finished his work, another learner with subsequent allocated task cannot start to analyse data, and the harmful delay may be in a chain reaction.

IV. The Kolb's Learning Style (KLS)

Kolb points out that the types of behaviour in the team learning can be represented as concrete experience (feeling), reflective observation (watching), abstract conceptualization (thinking) and active experimentation (doing) [21] [22] [23] [24]. He also explains that an individual learner naturally prefers a certain learning style, combining each two of those four types of learning behaviour. Therefore, four learning styles are demonstrated, namely accommodating, assimilating, converging and diverging. Briefly, the "accommodating" is learning from hands-on practice and intuition rather than logic analysis; the "assimilating" refers to discovering and understanding a wide range of information and then categorizing and conforming them into concise and logical forms; the "converging" is to solve problems into practical uses and find solution using learning experiences; and the "diverging" is more relevant to observation at concrete situations from many different viewpoints. Belbin [25] and Loo [26] mapped these four learning styles to four roles (accommodator, assimilator, converger, and diverger) which are equally important and generally existing in an experienced team. The features of Kolb's learning style (KLS) are shown as Figure 1.

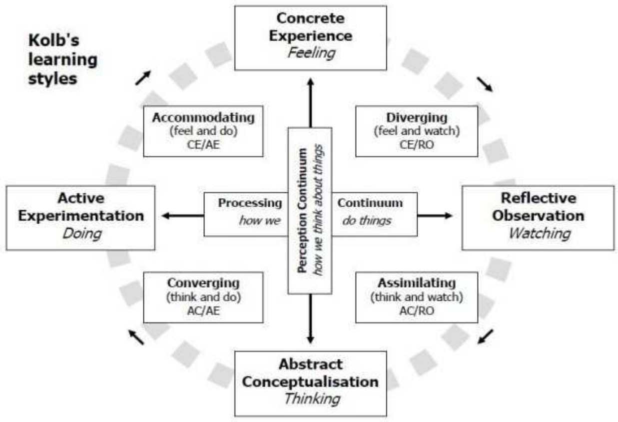

Fig. 1. The Kolb's Learning Style [22]

Some researchers have applied teaching approaches involving identifying learners' KLS into real fields for improving education by recognizing the importance of consideration of individual student needs [27] [28] [29]. Some other authors also note that the concept of KLS can be also utilized to assist structuring virtual learning environment, adapting the design of course of online distance education to accommodate learners' styles [30] [31].

V. Genetic Algorithm For Enhanced Collaborative learning

A. *Overview*

An entire collaborative-enhanced learning flow is realized that learners in virtual groups can participate in its involved activities through mobile devices, where their learning styles in KLS are identified by self-assessment and peer assessment, and a collaborative editing environment is provided for them to clarify task schedules along with evaluating difficulties and preferences. while all ultimate groups are working on their allocated tasks, the Service, which we call Collaborative as a Service (CaaS), allows them to take mutual supervisions in pairs, who are encouraged to finish their subtasks on time for each stage otherwise a penalty mechanism is appointed to deal with their unsatisfactory performance. Learners' total marks for assessing their performance are also processed to be referred by the teacher. As the core of CaaS, the math model and computing procedure for task allocation in the CaaS will be particularly discussed. The core of CaaS is the task allocation, each subtask is assigned to one learner, mean while learners who take subtasks belonged to the same task will be grouped into the same group. In this section we will discuss a constructive approach of task allocation in mobile cloud-based learning, using KLS to accurately allocate responsible tasks to each learner in order to raise collaborative learning performance. We employ a Genetic Algorithm to facilitate the task allocation.

B. *Problem Modeling*

For initialization, the CaaS checks whether the k^{th} learner (L^k) is appropriate to accomplish a $SubTask^{i,j}$ ($SubTask^{i,j}$ represents it is the j^{th} subtask of the i^{th} task) by calculating. Two variables are introduced to describe the deviation of

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subtask versus learner. In the CaaS, L^k's capability will be compiled from questionnaires, from both peer and self-assessment. The results of each question for evaluating L_k will be registered in a matrix, in which each column stands for a question while each row corresponds to a learner who gives the marks. So five matrixes are obtained, they are $\{Acc^k\}$, $\{Ass^k\}$, $\{Cov^k\}$, $\{Div^k\}$ and $\{Comp^k\}$. For example, the capability of accommodating (Acc) of L^k can be stated as:

$$Acc^k = \begin{bmatrix} M_1^1 & \cdots & M_1^n \\ \vdots & \ddots & \vdots \\ M_m^1 & \cdots & M_m^n \end{bmatrix} \quad (1)$$

In this matrix $\{Acc^k\}$, means of each column describe strengths of different types of accommodating, and we use the next equation to calculate the value of accommodating capability of L^k:

$$Acc^k = \frac{\sum_{j=1}^{m}\sum_{i=1}^{n} M_j^i}{nm} \quad (2)$$

M_m^n: An integer between 1 and 10, it represents the mark for the n^{th} question of the accommodating aspect depending on the order of the question title; which is given in the m^{th} assessment in accordance with the sequence of questionnaire submission times. In the same way, the CaaS calculates the values for the other four matrixes, Ass^k, Cov^k, Div_k and $Comp_k$. They represent respectively the capability values of assimilating, converging, diverging and comprehensive teamwork skills. Therein, a 4 Tuple $KLS^k = \{Acc^k, Ass^k, Cov^k, Div^k\}$ denotes the KLS capability values of L^k. The CaaS subtask's difficulty are modeled in a 4 tuple $SubTask^{ij} = \{Acc^{ij}, Ass^{ij}, Cov^{ij}, Div^{ij}\}$, where each value is a real between 1 and 10. The variable $Pref_{ij}^k$ denotes the preference grade of the $SubTask_{i,j}^k$, given by the k^{th} learner. The $Pref_{ij}^k$ is an integer between 1 and 5, the more preferred subtask to do by a learner correspond to the higher the grade.

C. Problem Definition

For a given task allocation, a learner L^k is allocated with a $SubTask^{i,j}$. It is necessary to check whether they are matching and on which level they suit to each other. We initiate two attributes to describe the deviation of that learner versus subtask. The first one is *DeviationPref*, which stands for the preference gap between learner's ideal and reality:

$$DeviationPref_k^{ij} = 5 - Pref_k^{ij} \quad (3)$$

And the second variable *DeviationKLS*, which represents the deviation of learner's KLS capability values versus a subtask's expected- achievable values, where:

$$DeviationKLS_k^{ij} = -\{sgn[\sum(KLS^k - SubT^{ij})]\} \left\| KLS^k - SubT^{ij} \right\| \quad (4)$$

Both of these deviations are the lower the better. The main idea of the task allocation is to assign the appropriate subtasks to the learners. The chosen subtasks may mismatch and cannot compose into full tasks. CaaS working for assisting real mobile-based cloud learning, several situations should be considered realistically. The ultimate purpose of each learner who participates in the cloud-based course is to get a final grade for their group assignment, in order to pass the subject. In the task allocation, learners might have unexpected performance or unsatisfactory capabilities. On the other hand, overflowing subtasks is not allowed. An integrated task should be allocated to a team rather than just part of its subtasks being allocated to several learners.

D. Genetic Algorithm (GA)

The problem of task allocation is concerned in many research areas, and currently their purposes are reached in lots of literature, in which the heuristic algorithms are widely utilized, especially when the problem models are large and complex. The heuristic is a technique designed for solving a problem more quickly when classic methods are too slow, or for finding an approximate solution when classic methods fail to find any exact solution. This is achieved by trading optimality, completeness, accuracy, or precision for speed. For example, Vidyarthi et al. [32] present a study of two task allocation models in distributed computing system based on genetic algorithm (GA), and then these models are upgraded in their further work, GA is also utilized for dynamically mapping tasks to processors in a heterogeneous distributed system [33]; in globally distributed software projects, individual tasks can be allocated to resources across locations using GA [34]. GA is an optimal self-adaptive heuristic algorithm, which simulates the natural biological selection and genetic evolution mechanism. The basic idea of GA is inspired by evolution process in the natural world, to optimize candidate solutions towards better ones [35] [36]. Traditionally, candidate solutions start randomly and change in generations, by selection, crossover and mutation. Every generation is evaluated by a fitness function and the new generation is then used in the next iteration of the algorithm. Once a satisfactory of fitness level has been reached, the iterations terminate and the algorithm outputs the final generation as the optimal solution. To start the GA operation, arrays of k learner/subtask pairs are randomly generated, where k is the number of learners. In each array, the integrities of tasks should be checked. If any overflowing subtask exists, that array will not be adopted as the initial solution. Taking these initial solutions as individuals (chromosomes), we need to encode them into populations (genomes) for creating the first generation. Let the population size is 2k. The pseudo code of GA is shown in figure 2:

```
Input: KLS^k, SubT^ij, Pref^ij, N^i
Output: Sets of L^k/SubT^ij pairs
begin: Calculate DeviationPref, DeviationKLS.
    Randomly generate arrays of k L^k/SubT^ij pairs
    Check the task integrity in each array, give up unmatched ones.
    Take the matched individuals as the initial population. Make the
    population size as 2k.
 for each individual ∈population do
        Evaluate the fitness of each individual.
 end for
while iteration times < max iteration time do
      Select the individuals with lower fitness.
      Use crossover operator to produce offspring.
      Operate offspring through mutation operator.
      Evaluate the fitness of new individuals.
      Take the lower-fitness individuals to replace the old ones.
end while
     Output the task allocation.
End
```

Fig. 2. The Pseudo Code of GA

VI. RESULTS

Firstly, we determine that the GA algorithm make the task allocation possible. The data of learner and task information with all attributes are randomly simulated obeying normal distribution. For GA, The number of learners (k) and subtasks are separately chosen as 80 and 160, the crossover probability is set as 0.9, and the mutation probability is 0.2. Once the terminal condition is met, the algorithm outputs solution, for allocating learners to their most appropriate subtasks. In the first scenario (figure 3), we can find that learners are divided into 20 groups, and the values of total *DeviationPref* and *DeviationKLS* of each group are balanced on almost the same levels.

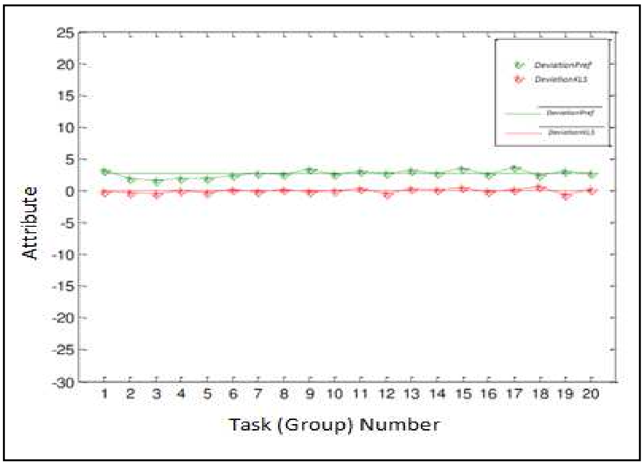

Fig. 3. The First Scenario

That is to say, the three attributes between groups are all in close proximities, which mean that the groups have almost equal capabilities and preferences to achieve goals of their responsible tasks.

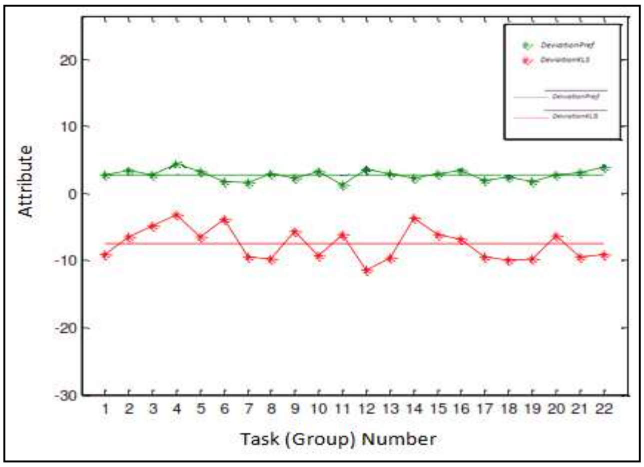

Fig. 4. The Second Scenario

And in the second scenario (figure 4), as the solution would group learners into 22 groups, the *DeviationKLS* attributes of each group are below 0, so that each group is competent to their allocated tasks. The *DeviationPref* level of each group is less than 3. The group size is 3 to 5 persons; then results means the allocated tasks are benefiting high preferences.

VII. CONCLUSION

We have introduced the core of CaaS, the task allocation, which is designed for avoiding the confusion and the misunderstanding in the teamwork process, and letting the learners give full play to their talents. We have described a model of this problem; we combined learners' capabilities and preferences, and tasks' difficulties. We used the genetic algorithm to solve the problem. Experiments prove that the GA algorithm is possible to complete the collaborative task allocation, yielding the results satisfying our design purpose. As perspective, we want to use a second algorithm as a Simulated Annealing algorithm in order to compare the performances of both algorithms in view of deciding which will be implemented in our CaaS.

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