

科技部補助專題研究計畫成果報告 期末報告

植基於羣衆智慧並運用雲端技術提升電腦科學領域數學學習成效

計畫類別：個別型計畫
計畫編號：MOST 104-2511-S-343-003-
執行期間：104年11月01日至105年11月30日
執行單位：南華大學資訊管理學系

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報告附件：出席國際學術會議心得報告

中華民國 105 年 12 月 30 日

中文摘要：對於主修資訊科學的學生，通常需要學習微積分。然而，我們的實證觀察表明，大多數學生不能滿足微積分課程的要求。此外，他們中的許多人完全失去了對微積分的信心和興趣。其中一個可能的原因是他們的數學背景太過發散。由於這些學生不是數學專業，期望他們有統一和穩固的數學背景是不實際的。我們的微積分課程通常是一份教材適用所有學生，難以適應不同的學習狀況。在這項研究中，研究人員有一些假設：第一，具有不同特徵的學生在微積分學習中會有不同的表現；第二，一些具有某些情緒特徵的學生將在微積分課中的一些特定章節中會表現得更好。為了在學習期間捕捉對學生的情緒特徵，將採用一些多媒體工具以及概念圖和基於群體的方法來驗證假設。

中文關鍵詞：行為分析 學習成效 情感學習

英文摘要：For students majoring in computer science, learning calculus well is usually required. However, our empirical observation shows that most students fail to meet the requirements of calculus courses. Furthermore, many of them simply lose the confidence and interests in calculus. Perhaps a possible reason is the diversities in the mathematics capabilities. Since these students do not major in mathematics, expecting them to have uniform and solid mathematics background is not practical. A problem is, similar to other mathematics courses, our calculus courses are often designed uniformly for all participating students with no per-student customization. In this research, the researchers have some assumptions: first, students demonstrating different characteristics will have different performance in calculus classes; and second, some students with some characteristics will perform better in some specific chapters in a calculus class. To capture the emotional feelings to students during calculus learning, some multimedia tools will be adopted along with concept map and crowd-sourcing based methodologies to verify the assumptions.

英文關鍵詞：BehaviorAnalysis LearningPerformance AffectiveLearning

科技部補助專題研究計畫成果報告

(期中進度報告/期末報告)

植基於群眾智慧並運用雲端技術提升電腦科學領域數學學習成效

計畫類別：個別型計畫 整合型計畫

計畫編號：MOST 104-2511-S-343-003

執行期間： 2015/11/01 ~ 2016/11/30

執行機構及系所：南華大學資訊管理系

計畫主持人：曾俊雄

共同主持人：劉吉軒 陳永輝

計畫參與人員：江晏如 林嘉柔

本計畫除繳交成果報告外，另含下列出國報告，共 1 份：

執行國際合作與移地研究心得報告

出席國際學術會議心得報告

出國參訪及考察心得報告

Cloud and Crowd Supported Mathematics Learning in Computer Science

Background

For students majoring in computer science, learning calculus well is usually required. However, our empirical observation shows that most students fail to meet the requirements of calculus courses. Furthermore, many of them simply lose the confidence and interests in calculus. Perhaps a possible reason is the diversities in the

mathematics capabilities. Since these students do not major in mathematics, expecting them to have uniform and solid mathematics background is not practical. A problem is, similar to other mathematics courses, our calculus courses are often designed uniformly for all participating students with no per-student customization. In this research, the researchers have some assumptions: first, students demonstrating different characteristics will have different performance in calculus classes; and second, some students with some characteristics will perform better in some specific chapters in a calculus class. To capture the emotional feelings to students during calculus learning, some multimedia tools will be adopted along with concept map and crowd-sourcing based methodologies to verify the assumptions.

Motivation

Surprisingly, many students majoring in computer science have difficulties in learning mathematics¹. A possible reason is the diversities in the mathematics backgrounds of computer science students. However, some mathematics are required for computer science students. Generally speaking, the mathematics courses scheduled in computer science departments are simpler than those scheduled in mathematics departments, so this should not be a problem that can not be solved. Today, there are several new pedagogies such as flipped classroom² and problem based learning³ and many of them have been proven as effective. Perhaps we should simply adopt different teaching methods for students struggling in mathematics learning. Nevertheless, before utilizing a new pedagogy, a more effective method to evaluate the result will be needed so how the new method performs can be captured.

How do teachers evaluate students' mathematics learning performance today? In most cases, the results from homework, quizzes and exams are utilized, especially the written-based ones. Despite of their popularity, they do not always provide correct evaluation of students' knowledge when it comes to theoretical subjects [5]. Furthermore, homework, quizzes, and exams are post tests, which means they can only be used for assessing students' learning performance after a period of time since they attended the classes. How many homeworks/quizzes/exams can be scheduled in a semester? Too few of them, e.g. 5-7 homeworks/quizzes/exams in a semester, is not sufficient to reflect the learning progress of students. However, if a large amount of homeworks/quizzes/exams is arranged, the teaching load of teachers will become an issue, which will still decrease students' learning performance. According to the research of Petty, the negative results of teaching load on teaching quality is significant [12]. By the name, the scores obtained from homeworks/quizzes/exams may not truly reflect students' learning performance. As stated by O'Malley, children's scores don't match the grades they've earned for their work in school [10]. Therefore, homeworks/quizzes/exams alone does not appear sufficient for evaluating students' learning performance. Note that this should be a general case, i.e. not limited to mathematics learning. But, since it is common for computer science students to have difficulties in learning mathematics and different courses may present different characteristics, the researchers focus on mathematics learning and use the calculus course as a case study in this research.

¹

<https://www.quora.com/Why-do-so-many-college-students-struggle-so-much-to-learn-math-at-the-undergrad-level-even-if-they-did-well-in-math-in-high-school>

² https://en.wikipedia.org/wiki/Flipped_classroom

³ https://en.wikipedia.org/wiki/Problem-based_learning

The challenge is, in addition to homeworks/quizzes/exams, is there another efficient approach to assess students' learning performance and will not incur too many additional teaching load for teachers? Today, most students are very active on social networks. The survey made by Pempek, Yermolayeva, and Calvert on 2009 found that the mean amount of Facebook use during weekdays was 27.93 minutes per day (SD = 19.43; Median= 25.00) and weekend days was 28.44 minutes per day (SD = 23.69; Median= 20.00) [11]. Perhaps the characteristics can be utilized to help evaluate their learning results. For example, one may post several messages on social networks in one day. By analyzing the contents of her/his posts, the clue of her/his current learning status can be captured. If students are directed to learning-related social networks, the accuracy of such evaluation will be even higher. The question is, on social network sites, students tend to express more about their feelings than about their learning status. Hence, the problem to solve will be whether students' emotional feelings reflect their learning status or not. Furthermore, it will be good to understand the relationships between types of emotional feelings and students' learning status. For instance, if students express positive emotions about a mathematics topic, does that guarantees good learning performance? If yes, to what degree? Another challenge is, students use natural language on social networks, which means ambiguities can not be avoid. How to extract adequate features that reflects students' feelings about their learning status and can in turn be used for inferring their learning performance? These challenges are practical and interesting and thus motivate this research.

The goal of this research is to investigate the relationship between students' feelings and their learning performance. Several sub goals have been set:

1. identify important keywords that reflects students' feelings about calculus classes
2. discover the distribution of the selected keywords
3. use the selected keywords to build a model that can be used to predict students' learning performance
4. verify the correctness and significance of the model

Literature Review

Many students today are struggling in learning mathematics, researchers find that the situation may be owed to the inability of the traditional way of teaching to attract the attention of the students to learn mathematics and hence a need for non-traditional and attractive way is needed [1]. Figuring out the way to enhance students' learning motivation and performance has long been a challenging research topic. The research of Nicolete et al. shows it is important to understand the use of technology and media knowledge, helping the teaching practice, motivating the process of learning can transform education [9]. This system proposed by Al-Ajmi provided a suitable environment for e-contents to be utilized easily by the students, their parents and their teachers under the administrative control and with the help of mentors [1]. The work of Hallstrom et al. pointed out that it is possible to excite students about learning the mathematical principles that underlie high-quality software [7]. The research results of Krumm et al. showed the promise in using online learning system data to develop practical measures of productive persistence [8]. The work of Charoenying, T., Gaysinsky, A., and Ryokai proposed the conceptualizing instructional practice in terms of coordinating between the evocation of prior-knowledge, and the construction of new schemes vis-à-vis the enactment of specific situations may provide designers and researchers alike with a useful shared vernacular that bridges

the worlds of cognition, learning, and design [3]. It has been proven that analyzing the emotional feelings of students when they attending mathematics classes will help enhance their learning performance [2]. The research of Girard and Johnson presented a model of emotions developed with teachers as participatory-design partners [6]. Chen et al. proposed a method to improve the accuracy and effectiveness of emotion classification [4].

Research Method

Keyword Collection and Clustering

One's frequently used words reflect the feelings in her/his mind to a certain degree. However, the diversities of human languages make it difficult to infer the correct meanings of these words. An efficient approach to reduce the complexity is to restrict the domains of both the considered words and the feelings. In this research, the domain is limited to calculus learning related. To further reduce the diversities and ambiguities, a keyword collection process is executed in advance. Students of sophomore degree from two classes in the department of information management in Nanhua university in Taiwan are invited to participate in the keyword collection process. These students have joined the calculus course in their last semester. They were instructed to write down five positive and five negative keywords of their feelings about the calculus course. After that, the distribution of the obtained keywords were performed. Totally, there were 31 students participated, and 266 keywords were collected. Among them, there were 130 positive keywords and 136 negative keywords. On average, a positive keyword was used 3.82 times and a negative keyword was used 3.79 times. Since a keyword can only be used once by one student, the result showed that a positive keyword was used by 3.82 students and a negative keyword was used by 3.79 students. The standard deviation of the two group of keywords were 6.03 and 5.41, respectively. The results are summarized in the table below:

Table 1. the distribution of keywords

	Min	Mean	Max	Median	SD
Positive	1	3.82	43	1	6.03
Negative	1	3.79	33	1	5.41

According to the result, it can be concluded that the distribution is very unbalanced. To reduce noises, the keywords with usage frequency lower than the average were dropped. After the process, totally 30 keywords were obtained.

After the keyword collection process, a simple Web site was developed to collect the relationships between these keywords and students' learning results. Another set of students (who already joined calculus courses) were invited to enter their feelings about the calculus course they joined and the scores they obtained. A part of the Web site (developed using google forms) is shown below:

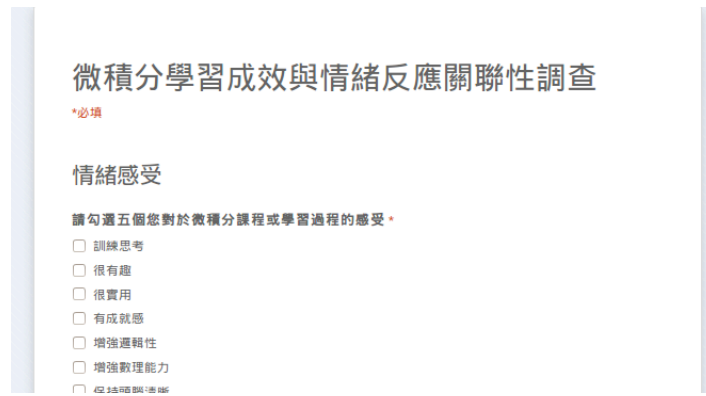


Figure 1. the Web site to collect feelings and scores

In addition to keywords and scores, participants were requested to enter their school year, their class numbers, and their departments. Totally, there were 176 participants from 4 schools in the investigation and each participant was asked to select five keywords that match her/his feelings most. Since participants were from different classes and even different schools, we had to normalize their scores to prevent unfairness. The table below summarizes the values of keywords and scores:

Table 2. values of keywords and normalized scores

Variable	N	Mean	Std Dev	Minimum	Maximum
k1	176	0.38	0.49	0	1
k2	176	0.4	0.49	0	1
k3	176	0.09	0.29	0	1
k4	176	0.34	0.47	0	1
k5	176	0.09	0.29	0	1
k6	176	0.14	0.35	0	1
k7	176	0.16	0.37	0	1
k8	176	0.42	0.5	0	1
k9	176	0.3	0.46	0	1

k10	176	0.02	0.13	0	1
k11	176	0.11	0.32	0	1
k12	176	0.13	0.33	0	1
k13	176	0.09	0.28	0	1
k14	176	0.19	0.4	0	1
k15	176	0.37	0.48	0	1
k16	176	0.16	0.37	0	1
k17	176	0.19	0.39	0	1
k18	176	0.12	0.33	0	1
k19	176	0.14	0.35	0	1
k20	176	0.17	0.38	0	1
k21	176	0.06	0.23	0	1
k22	176	0.06	0.24	0	1
k23	176	0.14	0.35	0	1
k24	176	0.33	0.47	0	1
k25	176	0.05	0.21	0	1
k26	176	0.02	0.15	0	1
k27	176	0.18	0.38	0	1
k28	176	0.09	0.29	0	1
k29	176	0.06	0.23	0	1
k30	176	0.02	0.13	0	1
score	176	0.01	1	-3.7	2.04

As shown in the table above, the adoption frequency of keywords varies from 2% to 42%. Definitely, some keywords will co-occur with high chances. The figure below shows the co-occurrence table:

	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10	K11	K12	K13	K14	K15	K16	K17	K18	K19	K20	K21	K22	K23	K24	K25	K26	K27	K28	K29	K30	
K1	1.0	0.5	0.2	0.2	0.0	0.3	0.3	0.4	0.3	0.0	0.0	0.0	0.0	0.0	0.6	0.2	0.1	0.0	0.0	0.0	0.1	0.1	0.2	0.1	0.1	0.0	0.1	0.0	0.0	0.0	
K2	0.5	1.0	0.1	0.2	0.0	0.2	0.2	0.5	0.3	0.0	0.0	0.0	0.0	0.1	0.6	0.3	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.2	0.1	0.0	0.1	0.0	0.1	0.0	
K3	0.7	0.6	1.0	0.0	0.1	0.0	0.1	0.3	0.4	0.0	0.0	0.0	0.1	0.1	0.5	0.1	0.0	0.1	0.1	0.0	0.1	0.3	0.3	0.1	0.0	0.0	0.1	0.0	0.2	0.0	
K4	0.2	0.3	0.0	1.0	0.1	0.1	0.0	0.4	0.2	0.0	0.2	0.1	0.1	0.3	0.2	0.1	0.3	0.1	0.2	0.2	0.0	0.0	0.1	0.5	0.0	0.0	0.3	0.1	0.1	0.0	
K5	0.1	0.1	0.1	0.2	1.0	0.1	0.0	0.4	0.1	0.0	0.4	0.2	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.4	0.4	0.0	0.0	0.2	0.4	0.0	0.0	0.1	0.1	0.0	
K6	0.8	0.5	0.0	0.1	0.0	1.0	0.5	0.2	0.4	0.0	0.0	0.0	0.0	0.0	0.7	0.2	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.2	0.1	0.0	0.0	0.0	0.0	
K7	0.7	0.5	0.1	0.0	0.0	0.4	1.0	0.5	0.4	0.0	0.0	0.0	0.0	0.0	0.6	0.1	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.0	0.0	
K8	0.4	0.5	0.1	0.3	0.1	0.1	0.2	1.0	0.4	0.0	0.1	0.1	0.1	0.1	0.4	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.2	0.3	0.0	0.0	0.1	0.0	0.1	0.0
K9	0.4	0.4	0.1	0.3	0.0	0.2	0.2	0.5	1.0	0.0	0.0	0.0	0.1	0.1	0.3	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.3	0.1	0.0	0.2	0.0	0.0	0.0	
K10	0.3	0.3	0.0	0.3	0.0	0.3	0.3	0.0	0.3	1.0	0.0	0.3	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.0	0.3	0.0	0.0	0.3	0.0	0.0	0.3	0.0	
K11	0.0	0.1	0.0	0.6	0.4	0.0	0.0	0.3	0.1	0.0	1.0	0.3	0.0	0.1	0.1	0.1	0.0	0.2	0.5	0.7	0.0	0.0	0.1	0.6	0.0	0.0	0.1	0.2	0.0	0.0	
K12	0.1	0.1	0.0	0.3	0.1	0.0	0.0	0.2	0.0	0.0	0.2	1.0	0.1	0.4	0.0	0.1	0.3	0.1	0.2	0.5	0.0	0.0	0.2	0.4	0.0	0.0	0.2	0.2	0.1	0.0	
K13	0.1	0.1	0.1	0.3	0.1	0.0	0.0	0.3	0.3	0.0	0.0	0.1	1.0	0.5	0.0	0.0	0.5	0.3	0.1	0.1	0.0	0.1	0.3	0.0	0.0	0.2	0.5	0.0	0.0	0.0	
K14	0.1	0.1	0.0	0.5	0.0	0.0	0.0	0.2	0.1	0.0	0.1	0.3	0.2	1.0	0.1	0.0	0.6	0.3	0.1	0.2	0.0	0.0	0.1	0.4	0.0	0.0	0.2	0.3	0.0	0.0	
K15	0.6	0.7	0.1	0.2	0.0	0.3	0.3	0.4	0.2	0.0	0.0	0.0	0.0	0.1	1.0	0.3	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.2	0.0	0.0	0.1	0.0	0.0	0.0	
K16	0.5	0.7	0.1	0.1	0.0	0.2	0.1	0.5	0.3	0.0	0.0	0.1	0.0	0.0	0.6	1.0	0.1	0.0	0.0	0.0	0.1	0.1	0.0	0.1	0.1	0.0	0.1	0.0	0.1	0.0	
K17	0.1	0.1	0.0	0.6	0.0	0.0	0.0	0.2	0.2	0.0	0.0	0.2	0.2	0.6	0.1	0.1	1.0	0.2	0.2	0.2	0.0	0.0	0.1	0.5	0.0	0.0	0.2	0.2	0.0	0.0	
K18	0.0	0.1	0.0	0.4	0.1	0.0	0.1	0.3	0.2	0.0	0.2	0.1	0.2	0.5	0.0	0.0	0.4	1.0	0.0	0.1	0.0	0.0	0.0	0.4	0.0	0.0	0.4	0.3	0.0	0.0	
K19	0.1	0.0	0.1	0.4	0.2	0.0	0.0	0.3	0.2	0.0	0.4	0.2	0.1	0.2	0.0	0.0	0.3	0.0	1.0	0.5	0.0	0.0	0.1	0.6	0.0	0.0	0.2	0.0	0.0	0.0	
K20	0.1	0.0	0.0	0.3	0.2	0.0	0.0	0.3	0.1	0.0	0.5	0.4	0.1	0.3	0.1	0.0	0.2	0.1	0.4	1.0	0.0	0.0	0.2	0.3	0.0	0.0	0.1	0.3	0.0	0.0	
K21	0.6	0.6	0.1	0.1	0.0	0.5	0.4	0.2	0.1	0.0	0.0	0.0	0.0	0.0	0.8	0.2	0.0	0.0	0.0	0.0	1.0	0.2	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	
K22	0.5	0.6	0.4	0.0	0.0	0.0	0.0	0.5	0.2	0.0	0.0	0.0	0.1	0.0	0.5	0.2	0.0	0.0	0.1	0.1	0.2	1.0	0.3	0.2	0.0	0.0	0.0	0.0	0.1	0.0	
K23	0.4	0.4	0.2	0.1	0.1	0.0	0.0	0.6	0.3	0.0	0.0	0.2	0.0	0.1	0.4	0.0	0.1	0.0	0.1	0.2	0.0	0.1	1.0	0.2	0.0	0.0	0.2	0.0	0.0	0.0	
K24	0.2	0.2	0.0	0.6	0.1	0.0	0.0	0.4	0.2	0.0	0.2	0.2	0.1	0.2	0.2	0.1	0.3	0.1	0.3	0.2	0.0	0.0	0.1	1.0	0.0	0.0	0.3	0.0	0.0	0.0	
K25	0.6	0.6	0.0	0.1	0.0	0.6	0.3	0.3	0.4	0.0	0.0	0.0	0.0	0.0	0.3	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	1.0	0.3	0.0	0.1	0.0	0.1	
K26	0.5	0.3	0.0	0.3	0.0	0.5	0.8	0.0	0.5	0.3	0.0	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	1.0	0.0	0.0	0.3	0.0	
K27	0.2	0.2	0.1	0.5	0.1	0.0	0.1	0.3	0.4	0.0	0.1	0.1	0.1	0.2	0.1	0.1	0.2	0.3	0.1	0.1	0.0	0.0	0.1	0.5	0.0	0.0	1.0	0.1	0.1	0.0	
K28	0.0	0.1	0.0	0.3	0.1	0.0	0.0	0.1	0.0	0.0	0.2	0.3	0.4	0.7	0.0	0.1	0.5	0.4	0.0	0.5	0.0	0.0	0.1	0.1	0.0	0.2	1.0	0.0	0.1	0.0	
K29	0.3	0.5	0.3	0.4	0.1	0.0	0.0	0.5	0.2	0.1	0.0	0.2	0.0	0.0	0.2	0.2	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.2	0.0	0.1	0.2	0.0	1.0	0.0	
K30	0.3	0.3	0.0	0.3	0.0	0.0	0.0	0.3	0.7	0.0	0.0	0.0	0.0	0.3	0.3	0.3	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.0	0.3	0.0	1.0	

Figure 2. the co-occurrence table of keywords

The figure above summarizes the conditional probability of the occurrence of keywords when other keywords are observed. For example, when the keyword k7 is used, the probability that the user also selects the keyword k1 is 70%.

At first, a naive idea is to simply use the keywords chosen per user as features to construct the mathematical model. Considering the high variation of keyword adoption frequency and co-occurrence rate, the resulting model can hardly be effective. A possible solution is to figure out the relationship between keywords and use grouped keywords instead of standalone keywords as model features. To keep the most amount of information, we have to group similar keywords together and hence a mechanism to evaluate the similarity of keywords is required. In this experiment, the meanings of keywords are not assumed, so semantic similarity is not available. For each participant, keyword adoption can be viewed as an ordered list $K=(k_1, k_2, \dots, k_n)$ in which $n=1\sim 30$. Piling up lists from all participants results in a matrix M in which $M(i, j)$ contains the value of the j^{th} keyword for the i^{th} participant. By transposing M into M^T , a new matrix in which $M^T(i, j)$ represents whether the j^{th} adopts the i^{th} keyword is obtained. For keyword i , we then define its feature vector as an ordered list $L=(M^T(i, 1), M^T(i, 2), \dots, M^T(i, m))$ in which m is the total number of participants. Based on the definition, we then use the euclidean distance to evaluate the similarity of two keywords. For simplicity, k-means algorithm was utilized to classify the keywords. The following clustering result is obtained:

Table 3. the clustering result

Keyword	Class
k1	1
k2	1
k8	1
k9	1
k15	1

k3	2
k6	2
k7	2
k10	2
k16	2
k21	2
k22	2
k23	2
k25	2
k26	2
k29	2
k30	2
k4	3
k5	3
k11	3
k12	3
k13	3
k14	3
k17	3
k18	3
k19	3
k20	3
k24	3
k27	3
k28	3

As shown above, there are totally three classes. Due to the nature of k-means, it is difficult to determine the number of classes in advance. As a result, a certain threshold to stop the clustering process is needed. For any k-means clustering result, there are two types of distance defined: between-cluster distance and in-cluster distance. The former represents the distance between cluster centers while the later refers to distance between nodes and their cluster centers. In this experiment, we use the equation below to calculate the threshold:

$$D = \frac{1}{n} \sum_{i=1}^n \frac{d_i}{d_{max}}$$

Figure 3. the equation for cluster quality

Theoretically, large D number means clear boundaries between clusters. However, large D number may occur with very small clusters (i.e., clusters with only few nodes in it), so we have to balance between D value and number of keywords in each cluster. With 3 clusters, the resulting D value is around 0.5, which should be

acceptable. Investigating the clustering results also demonstrates reasonable semantic meanings. Cluster 1 includes keywords such as *require_practice* and *enhance_logic_reasoning_ability*. Cluster 2 includes keywords including *funny* and *easy_to_understand*. Cluster 3 contains keywords like *difficult* and *boring*. Roughly speaking, cluster 1 contains positive and aggressive keywords. Cluster 2 contains positive but not aggressive keywords. Cluster 3 contains negative keywords.

Model Construction

The frequency distribution of the three resulting clusters is very different. The figures below shows the histogram diagram of the frequency distribution of the three clusters:

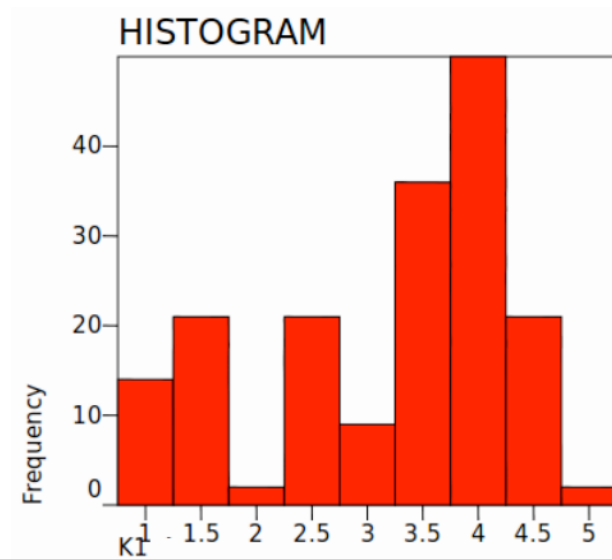


Figure 4. the histogram of frequency distribution of cluster 1

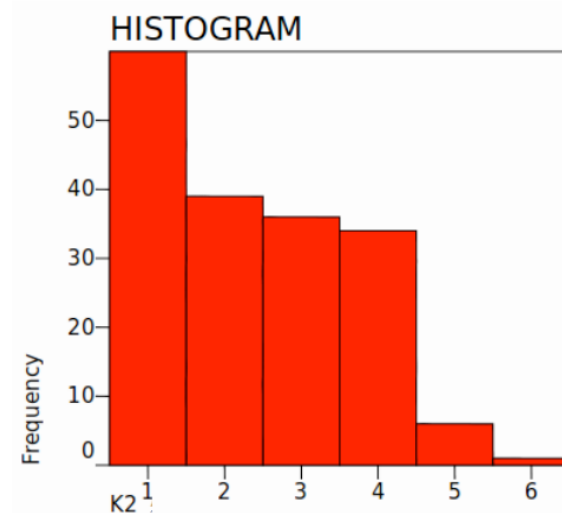


Figure 5. the histogram of frequency distribution of cluster 2

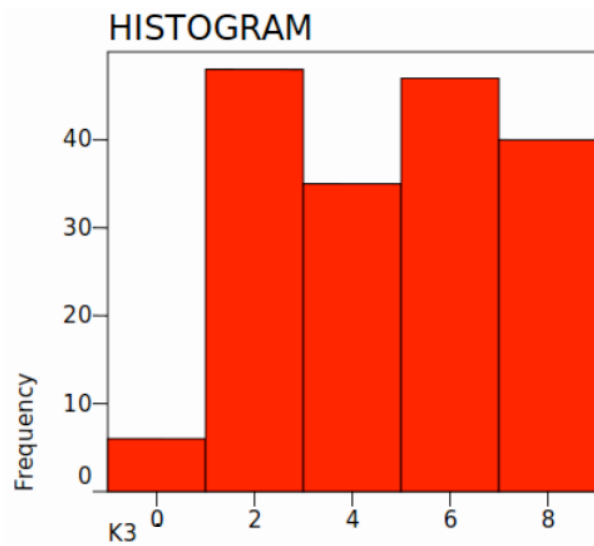


Figure 6. the histogram of frequency distribution of cluster 3

As shown above, the frequency distribution of the adopting number of keywords in cluster 1 is pretty balanced. The frequency distribution of cluster 2 is skewed to the left end, which means few participants use these keywords. The frequency distribution of cluster is skewed to the right end. The characteristic is good for model training. At first, we classified participants' normalized scores into several categories. The distribution of normalized scores is shown below:

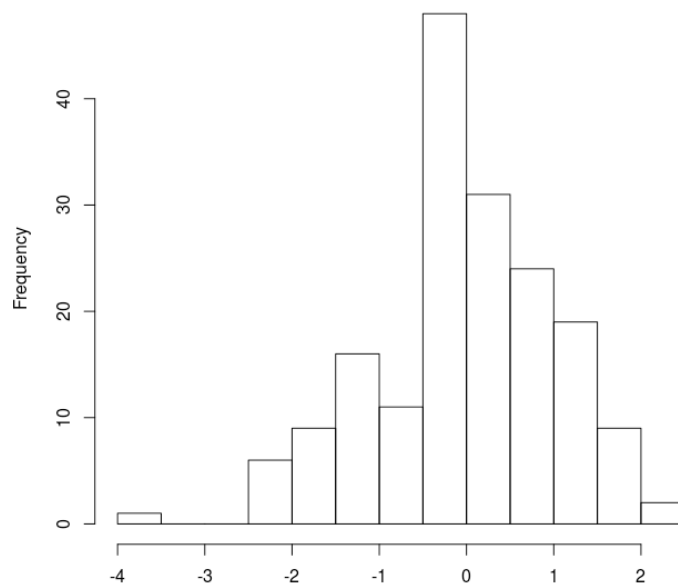


Figure 7. the histogram of the normalized score

Investigating the cumulative distribution, we used 0.24 and -0.14 as cut points to split the score values into three categories: low(-1), medium(0), and high(1). The cumulative distribution is shown in the following figure:

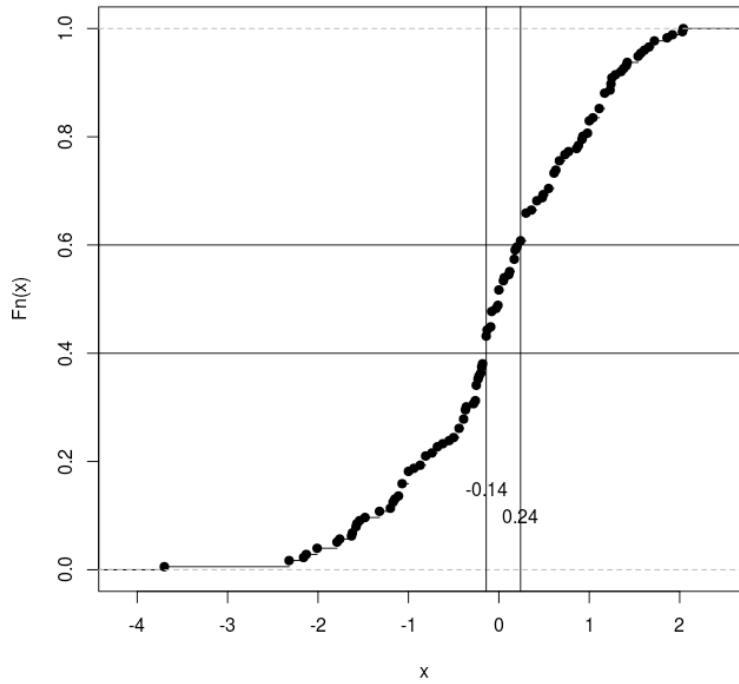


Figure 8. the cumulative distribution of score and the cut points

As shown in the figure above, score values less than -0.14 were labeled as -1, score values between -0.14 and 0.24 were labeled as 0, and score values larger than 0.24 were labeled as 1. Then, a decision tree was created based on the rpart function of R language. The resulting decision tree is shown below:

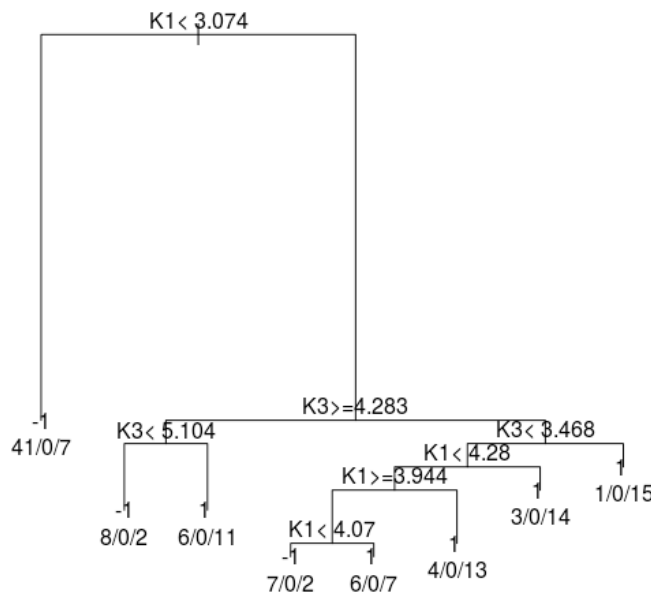


Figure 9. the resulting decision tree(class 0 is omitted)

In the figure above, K1 means the sum of values of keywords in the first cluster while K3 means the sum of values of keywords in the third cluster. With 10-fold cross validation, 16 participants were selected as test

cases, and the prediction result shows 4 wrongly predicted cases and 12 correctly predicted cases, which demonstrates 75% correct rate.

System Implementation

The current implementation of the proposed system integrates the olat platform and augments it by adding four functions including: learning feeling selection, learning performance evaluation, related course materials gathering, and automatic course generation. Learning feeling selection records users' current learning feeling during the process of learning. Learning performance evaluation lets users know whether their performance in the current chapter is good or need more hard work. Related course materials gathering shows the link to related documents. Automatic course generation tells user how to arrange the courses when they archive all files in a file and upload it. The screen capture of the current implementation is shown in the figure below:



Figure 10. the screen capture of the current implementation (the performance assessment feature)

Results and Discussions

In this project, we developed a method to predict students' learning performance based on their demonstrated feelings about the topic they are working on. On 2016/7/20, we did an experiment by organizing 41 students from Lunghwa University of Science and Technology and Oriental Institute of Science and Technology to test our system. The table below records their test result:

Table 4. the results of the 2016/7/20 experiment

	K1n	K2n	K3n	level	total
1	0.045454545	0.090909091	0.863636364	-1	0

2	0.264705882	0.441176471	0.294117647	-1	0.333333333
3	0.210526316	0.210526316	0.578947368	-1	0.5
4	0.5	0.375	0.125	-1	1
5	0.148148148	0.703703704	0.148148148	-1	1
6	0.12	0.4	0.48	-1	1
7	0.125	0.03125	0.84375	-1	1
8	0.176470588	0.647058824	0.176470588	-1	1.5
9	0.0625	0.5	0.4375	-1	1.666666667
10	0.222222222	0.185185185	0.592592593	-1	2
11	0.833333333	0.166666667	0	-1	2.266666667
12	0	1	0	0	2.5
13	0.304347826	0.608695652	0.086956522	0	2.5
14	0.290909091	0.054545455	0.654545455	0	2.5
15	0.181818182	0.03030303	0.787878788	0	2.5
16	0.909090909	0.090909091	0	0	2.75
17	0	1	0	0	3
18	0.016528926	0.958677686	0.024793388	0	3
19	0.071428571	0.357142857	0.571428571	0	3
20	0	0.384615385	0.615384615	0	3
21	0	0	1	0	3
22	0.285714286	0	0.714285714	0	3.5
23	0	0	1	0	3.5
24	0.6	0.2	0.2	1	3.6
25	0.142857143	0.642857143	0.214285714	1	3.666666667
26	0.25	0.166666667	0.583333333	1	3.666666667
27	0.543478261	0.315217391	0.141304348	1	4
28	0.785714286	0	0.214285714	1	4
29	0.196721311	0.229508197	0.573770492	1	4
30	0.142857143	0	0.857142857	1	4
31	0.090909091	0.045454545	0.863636364	1	4
32	0.032258065	0.064516129	0.903225806	1	4
33	0.079365079	0	0.920634921	1	4
34	0	0	1	1	4
35	0.25	0.75	0	1	4.5
36	0.272727273	0.681818182	0.045454545	1	4.5
37	0.066666667	0.4	0.533333333	1	4.5
38	0.116071429	0.339285714	0.544642857	1	4.5

39	0.5	0	0.5	1	4.666666667
40	0.571428571	0.142857143	0.285714286	1	5
41	0.083333333	0	0.916666667	1	5

To test the effectiveness of our method, we applied the resulting model to assess students' learning performance based on the value of K1, K2, and K3. Our model is insensitive for students of average learning performance level, so we kept only students with learning performance level equals to -1 (bad) or 1 (good). There were totally 16 students in the two groups. The table below shows their final test results via the predicted results:

Table 5. the comparison of the result test results and the predicted results

	K1n	K2n	K3n	level	total	p
1	0.045454545	0.090909091	0.863636364	-1	0	-1
2	0.264705882	0.441176471	0.294117647	-1	0.333333333	1
3	0.210526316	0.210526316	0.578947368	-1	0.5	-1
4	0.5	0.375	0.125	-1	1	1
5	0.148148148	0.703703704	0.148148148	-1	1	-1
6	0.12	0.4	0.48	-1	1	-1
7	0.125	0.03125	0.84375	-1	1	-1
8	0.176470588	0.647058824	0.176470588	-1	1.5	-1
9	0.0625	0.5	0.4375	-1	1.666666667	-1
10	0.25	0.75	0	1	4.5	1
11	0.272727273	0.681818182	0.045454545	1	4.5	1
12	0.066666667	0.4	0.533333333	1	4.5	-1
13	0.116071429	0.339285714	0.544642857	1	4.5	-1
14	0.5	0	0.5	1	4.666666667	1
15	0.571428571	0.142857143	0.285714286	1	5	1
16	0.083333333	0	0.916666667	1	5	-1

Column level records the real test results while column p records the predicted results. As shown in the table, in 16 observations, we successfully predicted the final results of 11 participants, which demonstrated $11/16=68.8\%$ accuracy.

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中 華 民 國 年 月 日

技部補助專題研究計畫出席國際學術會議心得

報告

日期： 年 月 日

計畫編號	MOST 104-2511-S-343-003		
計畫名稱	植基於群眾智慧並運用雲端技術提升電腦科學領域數學學習成效		
出國人員姓名	曾俊雄	服務機構及職稱	南華大學資訊管理系
會議時間	2016年7月13日至 2016年7月15日	會議地點	日本東京
會議名稱	(中文) (英文)Frontier Computing Theory, Technologies and Applications FC 2016		
發表題目	(中文) (英文) The Requirement Analysis and Initial Design of a Cloud and Crowd Supported Mathematics Learning Environment for Computer Science Students		

一、參加會議經過

本次會議地點在東京，因此報告者前一天即先行前往，由於經費有限，因此本次報告者沒有直接居住於會場，而是尋找成本較低的旅社，但東京交通便利，因此還算順利。因為不是居住在會場，所以會議當天提早前往，擔心路程不熟悉，而提早出發，結果反而成了最早到的報告者之一，到達會場時，多數工作人員甚至尚未到達。

報告過程，由於報告者自身的論文安排在較後的場次，因此

先聆聽他人的報告，會議中碰到幾位同樣是國內的學者，因此很愉快的交換了意見，也代替共同主持人與會議的主辦人做了簡短的問候。

事實上，該研討會的主題並非以數位學習為主，因此報告者本身的主題成了少數的主題。但由於報告了自身在教學現場面對的經驗，因此還是有獲得共鳴，報告完後，也與與會者進行了簡單的心得交換。

二、 與會心得

FC2016 是一個多主題的研討會，在會場似乎沒有刻意的將相近的主題集中，因此，剛好可以讓研究者進行跨領域的交流，個人感到獲益良多。

三、 發表論文全文或摘要

Math learning has never been easy and math learning in computer science is not an exception. However, the important of math can never be underestimated. In computer science, it was found that students learning performance in math is strongly connected with the development of the following capabilities: problem solving, programming, computer hardware and architecture design, computer science theory understanding, and software engineering and system analysis. The goal of this research is to develop a method based on cloud technologies and crowd intelligence to enhance students learning performance of math in computer science.

Mathematics plays an important role in many learning and research fields, and computer science is not an exception. Several mathematics topics are considered required for students who choose computer science as their major. For example, most students have to pass the training of basic statistics and calculus. Additionally, as shown in several surveys, how university students performed in mathematics classes also affects their working performance. For those who want to be good programmers after being graduated, a solid mathematics background is usually needed for writing error-proof programs. For those who want to participate in research jobs in computer science, the importance of good mathematics background is even higher. Some hot research topics, such as big data,

put high demand on mathematics capabilities. However, teaching and learning mathematics are never easy tasks. The situation motivates this research.

According to the survey made by Bravaco et al. at 2009, there are several reasons about why students majoring in computer science do not perform well in mathematics [10]:

1. students have wide range of mathematical abilities, so course design is difficult
 2. some students do not see the importance of the linkage between mathematics and their major
 3. it is difficult to get students to take their courses in the best order
- To deal with the challenges shown above, the researchers believe that several

information technologies can help. To ease the design difficulties of course materials due to students wide range of mathematical abilities, e-learning technologies can be adopted. A possible solution is to augment the traditional computer supported collaborative learning (CSCL [1]) methods with crowd technologies. In such a way, we can incorporate the advantages of computer supported collaborative personalized learning methods into CSCL by organizing collaborative groups dynamically according to students abilities. Then, the more flexible CSCL groups become stronger supports for students with different mathematics backgrounds. Furthermore, to help students realize the importance of linkages between mathematics and their major, we have to give them more practical materials. For instance, to have students understand the importance and use cases of linear regression, including real data prediction cases in class materials will be helpful.

2 Related Works

For students majoring in computer science, mathematics is a very important course. The survey made by Konvalina et al. showed that mathematical reasoning ability and mathematical background has very important effect for the

potential success in computer science [2]. The work of Henderson et al. showed a similar result and stated that mathematics is an important tool for problem-solving and conceptual understanding in computing [4]. The work of Beaubouef summarized several fields in computer science in which mathematics is essential [5]. However, learning mathematics has never been an easy task. Fleming wrote an article on about.com, which said The thing that makes mathematics difficult for many students is that it takes patience and persistence. For many students, mathematics is not something that comes intuitively or automatically - it takes plenty of effort. It is a subject that sometimes requires students to devote lots and lots of time and energy. Shermans article summarized several factors about why students struggle in mathematics [16]. These factors included: instruction, curricular materials, the gap between learner and subject, locus of control, memory ability, attention span, and mathematics language understanding. Although former studies draw to different conclusions about why learning

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mathematics is difficult, the importance and difficulties of mathematics learning was stated clearly. Focusing on mathematics classes in computer science, the work of Bravaco et al. listed the difficulties encountered in teaching [10]. Many pioneering researchers have devoted their works to make learning and teaching mathematics easier. Some researchers focused on game-based learning. For example, Zanchi et al. described a Next Generation Preschool Mathematics project in which researchers and media developers joined their works to develop mathematics curriculum supplement that supports young childrens learning of subitizing and equipartitioning [15]. Kes study indicated that gaming goal structures, beyond the games themselves, yield significant effects on participants mathematics learning attitudes [7]. Kes another work argued that using computer-based educational game as a motivational tool for cooperative learning is more convincing than using it as a cognitive or metacognitive one [8]. In addition to game-related methods, researchers developed various ways of benefiting from computer technologies to aid learning mathematics. Niess highlighted that Mathematics teachers are challenged to think about scaffolding

students learning about spreadsheets while they are also learning mathematics [6]. Stahl found that mathematics can be accomplished collaboratively, even by small groups of novice mathematics students helping each other, building sequentially on each others moves and exploring together, even across session, and proposed a concept named as virtual mathematics teams [11]. Although not specifically targeted at mathematics learning, Lambropoulos, N. and Romero considered the personalised information retrieval in a CSCL task through the use of a Group-Awareness widget and achieved excellent results [13]. The work of Edrees proposed e-Learning 2.0, which integrated web 2.0 technologies and tools into educational and institutional practice [14]. In this research, in addition to CSCL-based technologies, the researchers would like to benefit from the intelligence of the crowd. The concept is similar with crowd sourcing, and its importance was pointed out by Greengard in his research work [12].

3 Cloud and Crowd Supported Mathematics Learning

In this research, the researchers propose a cloud and crowd supported mathematics learning method which focuses on mathematics classes in computer science. As stated in previous section, since computer science students are usually familiar and feel at ease with information technologies, the researchers will design an e-learning system to facilitate the adoption of the proposed method. The system will utilize crowd intelligence to augment the traditional CSCL method to help students with various mathematics abilities benefit from group learning. The system will also utilize crowd intelligence for the construction of scaffoldings of topic flows and course contents. Furthermore, the system will utilize information extraction technologies to obtain real world supplementary materials from the cloud.

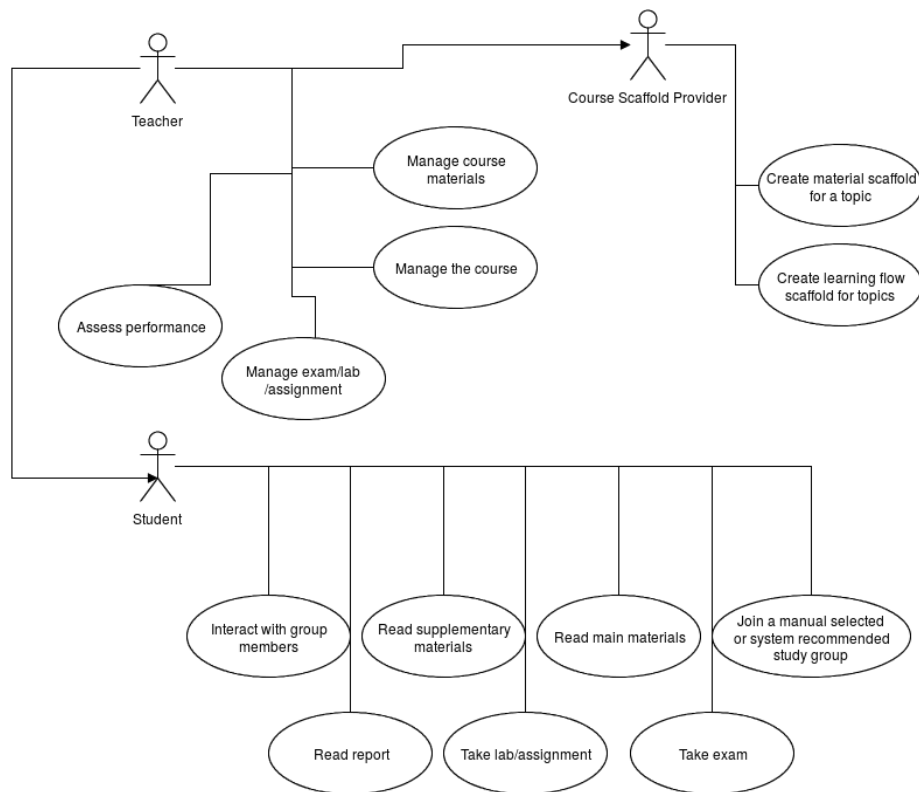
There are three types of users involved in the proposed system: teachers, students, and course scaffold providers. Teachers are the main mediators of a

course and are responsible for the preparation of course materials, the management of courses, and assessments. On the other hand, students are main players in a course. In most cases, students follow the flow designed by teachers. To benefit from group learning, the system includes various group interaction utilities. Furthermore, in addition to main materials, students can read supplementary materials that either contributed by teachers or automatically collected by the system. Course scaffold providers are responsible for designing scaffolds for course materials or flows of topics. The designed scaffolds can be used by teachers to aid the design of the course. Note that teachers can also play the role as students or course scaffold providers. Figure 1 shows the complete use case diagram.

Fig. 1. Figure 1. the usecase diagram

There are 13 use cases included in the design:

1. Create material scaffold for a topic: a material scaffold defines what should be include in a class, e.g. exams, main materials, and the criteria of supple-



mentary materials; additionally, a material scaffold can also include preferred assessment method for this class

2. Create learning flow scaffold for topics: a flow scaffold defines the flow between several topics for a class
3. Read main materials: students can read the main materials of a class
4. Read supplementary materials: students can read the supplementary materials of a class; supplementary materials can be provided by teachers or automatically collected by the system
5. Take exam: students can take exams provided by the teacher; note that if collaboration is allowed and needed, students should execute the interact with group members use case
6. Take lab/assignment: students can take labs or assignments provided by the teacher; note that if collaboration is allowed and needed, students should execute the interact with group members use case
7. Join a manual selected or system recommended study group: classes adopting CSCL benefit from interaction among group members; however, how well a learning group is formed will definitely affect the learning performance; by including a learning group recommendation module, the proposed system can automatically recommend suitable groups for students
8. Interact with group members: after joining a learning group, students can interact with group members; applications such as discussion rooms and collaboration environments will be provided
9. Read report: students can read their assessment reports of the learning performance for their participated classes

10. Manage course materials: teachers can manage both main and supplementary materials for a course; note that for automatically extracting supplementary from the Web, teachers have to specify proper information sources and extraction rules; when managing course materials, teachers can use existing material scaffolds as templates
11. Manage courses: teachers create, update, modify, and delete courses with this functionality; when managing courses, teachers can use existing flow scaffolds as basis to design the learning flow among topics; besides, logs of the courses are also available
12. Manage exams/labs/assignments: exams, labs, and assignments are important for students to practice concepts learned from classes and for teachers to evaluate the learning performance of students; in this use case, teachers will create, update, modify, and delete exams, labs, and assignments; also, teachers can correct exams, labs, and assignments completed by students; note that in some cases, collaboration may be allowed and required to complete exams, labs, and assignments; in such cases, students should execute the interact with group members use case
13. Assess performance: in this use case, teachers will assess students learning performance; four types of assessment are available: exam/lab/assignment assessment, manual assessment, group interaction assessment, and activity assessment; exam/lab/assignment assessments are based on students performance on exam/lab/assignment; manual assessments allow teachers to assess

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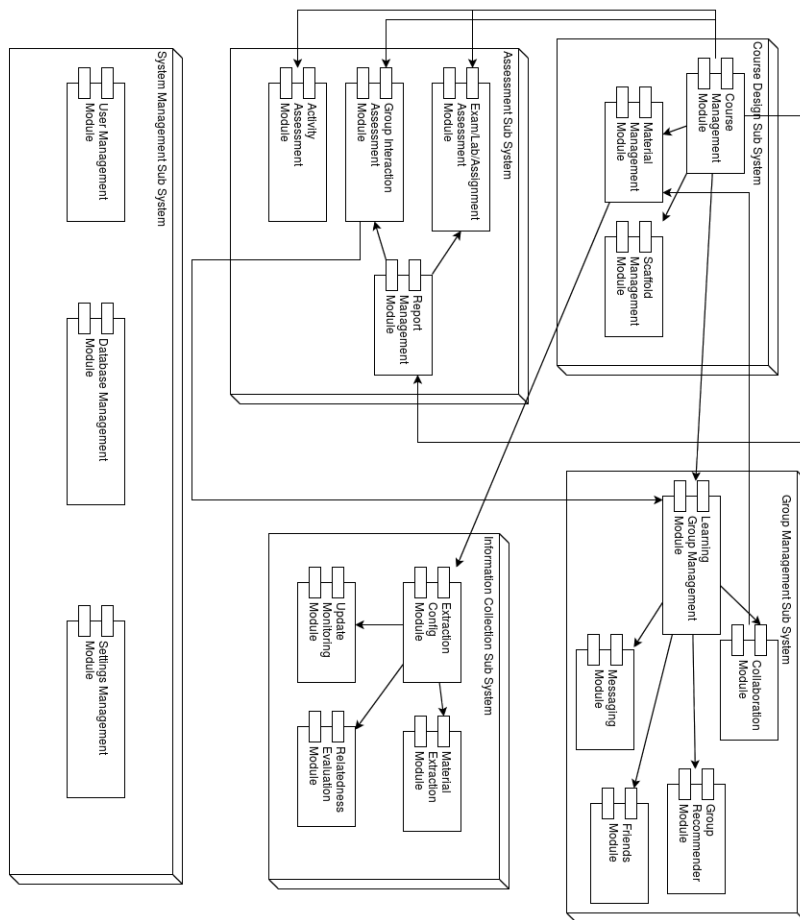
To implement these use cases, figure 2 illustrates the design and relationships of system components. Five sub systems are included: the System Management

Fig. 2. Figure 2. the design of system components

Sub System, the Course Design Sub System, the Group Management Sub System, the Assessment Sub System, and the Information Collection Sub System. These sub systems are described below:

1. System Management Sub System: handle the underlying functionalities of the whole system

students performance according to their empirical impression; group interaction assessments are based on students involvement in group activities; activity assessments come from analyzing students overall activities such as how many times students read course materials, etc.



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2. Course Design Sub System: for teachers to design courses

3. Group Management Sub System: for teachers to design and manage learning groups

4. Information Collection Sub System: for collecting information from the cloud

5. Assessment Sub System: for assessing students learning performance; each individual assessment sub modules assess a certain type of performance and teachers can specify the weight

4 Conclusions and Future Work

In this manuscript, we propose the initial design of a cloud and crowd based mathematics learning environment targeting the students majoring in computer science. To teach computer science students mathematics is challenging since they have diverse mathematics backgrounds. In this research, we listed 13 use cases along with three system components. In the future, we have the following goals:

1. complete the listed sub systems
2. integrate the sub systems with an existing e-learning system
3. incorporate affective learning concepts into the learning groups

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四、建議

國際研討會可以相當程度的促進國際交流，如有可能，希望能有更多的機會讓國內的學者能辦理國際研討會，以增進交流的廣度。

五、攜回資料名稱及內容

本次會議的論文集以隨身碟的方式提供。

六、其他

科技部補助計畫衍生研發成果推廣資料表

日期:2016/12/29

科技部補助計畫	計畫名稱: 植基於羣衆智慧並運用雲端技術提升電腦科學領域數學學習成效
	計畫主持人: 曾俊雄
	計畫編號: 104-2511-S-343-003- 學門領域: 數學教育
無研發成果推廣資料	

104年度專題研究計畫成果彙整表

計畫主持人：曾俊雄			計畫編號：104-2511-S-343-003-				
計畫名稱：植基於羣衆智慧並運用雲端技術提升電腦科學領域數學學習成效							
成果項目			量化	單位	質化 (說明：各成果項目請附佐證資料或細項說明，如期刊名稱、年份、卷期、起訖頁數、證號...等)		
國內	學術性論文	期刊論文		0	篇		
		研討會論文		0			
		專書		0	本		
		專書論文		0	章		
		技術報告		0	篇		
		其他		0	篇		
	智慧財產權及成果	專利權	發明專利	申請中	0	件	
				已獲得	0		
			新型/設計專利		0		
		商標權		0			
		營業秘密		0			
		積體電路電路布局權		0			
		著作權		0			
		品種權		0			
		其他		0			
	技術移轉	件數		0	件		
		收入		0	千元		
	國外	學術性論文	期刊論文		0	篇	
			研討會論文		2		<p>Chun-Hsiung Tseng, Jyi-Shane Liu, Yung-Hui Chen, Lin Hui, Yan-Ru Jiang, and Jia-Rou Lin: The Requirement Analysis and Initial Design of a Cloud and Crowd Supported Mathematics Learning Environment for Computer Science Students. FC2016</p> <p>Chun-Hsiung Tseng, Yung-Hui Chen, Yan-Ru Jiang1, Jia-Rou Lin, "Investigating the Relationship between Students' Feelings and Their Learning Performance: A Case Study on Calculus with Multimedia Support", IMET12016</p>
			專書		0		本
專書論文		0	章				

		技術報告		0	篇	
		其他		0	篇	
智慧財產權 及成果	專利權	發明專利	申請中	0	件	
			已獲得	0		
		新型/設計專利	0			
		商標權	0			
		營業秘密	0			
		積體電路電路布局權	0			
		著作權	0			
		品種權	0			
		其他	0			
	技術移轉	件數	0	件		
收入		0	千元			
參與計畫人力	本國籍	大專生	2	人次		
		碩士生	0			
		博士生	0			
		博士後研究員	0			
		專任助理	0			
	非本國籍	大專生	0			
		碩士生	0			
		博士生	0			
		博士後研究員	0			
		專任助理	0			
其他成果 (無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。)			1. 已投稿 journal of multimedia tools and applications (SCI) 2. 研究成果將與師大附中中國中部合作進行先期推展			
	成果項目	量化	名稱或內容性質簡述			
科教國 合同計 畫加填 項目	測驗工具(含質性與量性)	1	自動根據學習情緒判斷學習成效的運算模型			
	課程/模組	0				
	電腦及網路系統或工具	1	實作運算模型的 google chrome 套件			
	教材	0				
	舉辦之活動/競賽	0				
	研討會/工作坊	3	參與 FC2016 研討會 參與 IMETI2016 研討會，擔任 session organizer & chair 參與科教數學教育學門成果發表會			
	電子報、網站	0				

計畫成果推廣之參與（閱聽）人數	0	150
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科技部補助專題研究計畫成果自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現（簡要敘述成果是否具有政策應用參考價值及具影響公共利益之重大發現）或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估

達成目標

未達成目標（請說明，以100字為限）

實驗失敗

因故實驗中斷

其他原因

說明：

2. 研究成果在學術期刊發表或申請專利等情形（請於其他欄註明專利及技轉之證號、合約、申請及洽談等詳細資訊）

論文： 已發表 未發表之文稿 撰寫中 無

專利： 已獲得 申請中 無

技轉： 已技轉 洽談中 無

其他：（以200字為限）

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性，以500字為限）

在本計劃中，我們針對微積分，提出了一個以學習情緒來判定當下學習成效的模型。我們將該模型實作成一個 google chrome 的套件，並且與一個數位學習系統 olat 做了整合，我們在亞東技術學院及龍華科技大學進行了短期的實驗，獲得大約68%的準確率。目前已經跟師大附中國中部談妥合作，於下一期計劃進行實驗，將試着將模型推展到國中數學。

4. 主要發現

本研究具有政策應用參考價值： 否 是，建議提供機關教育部
（勾選「是」者，請列舉建議可提供施政參考之業務主管機關）

本研究具影響公共利益之重大發現： 否 是

說明：（以150字為限）

方法可以協助教師提早發現學生的學習困難，有助於在學生失去學習興趣前予以輔導改善，或可改善國內學生的數學學習意願（在PISA表現，意願不佳）。