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Proposing an ESL recommender teaching and learning system

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Abstract

This paper proposes an ESL recommender teaching and learning system capable of generating for ESL instructors practical information on problems and questions of grammar their students encounter. Not only does the system assist teachers to identify students' specific difficulties and weaknesses in learning, it can also provide data of recommendation that helps the student to find out his or her weak points in learning and offers improvement recommendations.

In general, instructors can easily find out the number of students who have failed their exams, but have trouble identifying their real difficulties in learning. Based on the students' testing records, the system works to identify and find those problems, and then comes up with its suggestions for designing new teaching strategies. Besides, the information so produced can also be helpful for the students themselves to improve their grammar.

The experiment in this study is based on real students' testing data, and a detail processing is developed that incorporates the advantages of the clustering technology. The system as here proposed has proved to be impressively effective, its performance having been tracked for one year.

Keywords: Online learning; Learning system; ESL; Clustering; Remedial teaching; Recommender system

1. Introduction

Because learning-based, individualized online lessons allow learners to plan their lesson process according to their own schedules, demands, interests, and capabilities, the benefits from such lessons are self-evident and can be enormous. In recent years, therefore, a major concern for open educators has been to make individualized e-learning more effective, convenient, and easily accessible.

Of all individualized education theories, the most classic is Keller's "personalized system of instruction" (1968). According to Keller, The teaching material can be divided into many units, each of which has self-learning guidelines as well as assessment tests designed to achieve 90–100% proficiency. Using this material as the major teaching resource, the teacher, however, plays an assisting role only. The student, who shall prepare for the class, studying the assigned unit in advance, can determine his or her own learning process according to individual ability and time spent. The student is expected to go to the next step only after having demonstrated proficiency on the assessment tests; he or she is asked to re-learn the unit if found below the required level of proficiency.

How to use education strategies to improve education has always been a major concern of education scholars (Airasian & Walsh, 1997; Lawson, 1996; Shymansky, 1992). This also suggests that for teachers to design appropriate teaching activities for different levels of learners has always been a worthy task to do. However, such a task has largely remained a harder goal to attain in the case of large classes, say, 50 or more students. To help resolve this issue and bridge the gap between grammar teaching and learning, this paper has developed an ESL recommender teaching and learning system, using a methodology that integrates the advantages of detail processing and clustering.

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Lampert and Clark (1990, p. 21) have noted, "Teaching is a complex act requiring the moment-by-moment adjustments of plans to fit continually changing and uncertain conditions". By the same token, it is essential for individualized lesson plans to fit respective students' requirements; this is especially true when remediation, or additional instruction, is provided for students with low-achievement levels.

Slavin, Karweit, and Madden (1989) define specific qualifications for students' at-risk status: *remediation*, *retention*, *dropping out*, and *substandard basic skills*. *Remediation* refers to the additional instruction provided for students who do not demonstrate competency in basic skill in reading, writing, and mathematics at an expected rate. The practice of having a student repeat a grade level because of low academic performance is referred to as *retention*. Students who do not complete high school are *dropouts*. *Substandard basic skills* are performance levels in reading, writing, and computing, that are below those regarded as necessary for working in high-performance workplaces (Thornburg, Hoffman, & Remeika, 1991).

Remedial teaching activities are targeted at students with low achievement. Low-achievement students are defined as those who perform below average in academic achievement. Ideally, after a certain period of remediation, underachieving students are expected to have kept up with the learning pace of their class, but in most cases that is only achieved – if indeed achieved – with great difficulty.

The question of remedial teaching must necessarily follow when it comes to personalized learning. Remedial teaching is a type of cycling process of "assessment–education–reassessment". Ideally, low-achievement students are expected to keep up with the learning pace of his class after a period of remedial teaching activity. In the early period, the students who need remedial teaching were defined as those of normal intelligence but with lower achievement levels than normal. Recently, such students have been defined as those who fail to pass achievement assessment, being much inferior to other average students (McLaughlin & Vacha, 1992).

Numerous studies have indicated that using CAI technologies can effectively help low-achievement students in learning, particularly because appropriate technology kits will inspire an aggressive, positive attitude that helps the students build self-confidence and interest in learning. Hancock (1992), for example, has shown that the application of computer and latest technology can trigger the motives of students who need remedial teaching to do their homework assignments.

In recent years, particularly in the information technology field, the recommender system has attracted a growing amount of attention because of its success in many applications (Wang, Chuang, Hsu, & Keh, 2004). A recommender system is a system that recommends useful information or suggests strategies users might apply to achieve their goals. A recommendation may come up based on a given event, such as an error, or on the observation of a user's overall behavior. A simple example is a research engine that, when no results are found for a query, suggests alternate keywords or queries that may achieve better results (Diamond Bullet, 2004). Many successful recommender systems have been used in the fields of E-commence, movies, music, books, and Web pages. Ma, Liu, Wong, Yu, and Lee (2000) target the right students using data mining. Chang (2000) discover learning patterns from Web logs by concept transformation analysis.

Table 1
Testing results

Student ID	Questions				
	Q1	Q2	Q3	Q4	Q5
920001	X	O	O	O	X
920002	O	X	X	X	O
920003	O	X	X	X	O
920004	O	X	X	X	O
920005	X	O	O	O	X
920006	X	O	O	O	X

When there is a failed remediation, the problem often lies not so much in the teaching or learning itself as in failure to identify, in the first place, the specific learning weaknesses and difficulties of the targeted student and then to provide effective remedies accordingly. For example, a set of students' test records are shown in Table 1. The letter "O" represents correct answers; "X" represents wrong answers.

As the table shows, to Question 1 (Q1) three students give correct answers and the other three give wrong answers. The same results occur for questions Q2 through Q5. The data also shows that students 92001, 92005, and 92006 give wrong answers to Q1 and Q5, and students 92002, 92003, and 92004 give wrong answers to Q2, Q3, and Q4. An analysis of statistics as such, however, can not identify the specific problems or difficulties that the students encounter in learning.

To provide a solution to that problem, this paper borrowed the concept of recommender devises an ESL recommender teaching and learning system capable of generating for ESL instructors practical information on problems and questions of grammar their students encounter. Not only does the system assist teachers to identify students' specific difficulties and weaknesses in learning, it can also provide data of recommendation that helps the student to find out his or her weak points in learning and offers improvement recommendations.

2. Preliminary

2.1. Grouping and clustering

Teachers often resort to grouping by ability because of "an inescapable fact of life: students differ dramatically from one another". (Berliner & Casanova, 1993, p. 6).

Homogeneous or same-ability grouping is the practice of putting students at approximately the same achievement level together for instruction. Although research on the effectiveness of homogeneous grouping was inconsistent, early reviewer of such literature generally recognized the positive impact of homogeneous grouping, particularly for student with learning difficulties (Miller & Otto, 1930; Whipple, 1936).

During the 1950s, the practice of within-class same-ability grouping for reading and mathematics began to take hold in elementary classes (Harris & Sipay, 1980). *Within-class same-ability grouping* occurs when students in a single classroom are placed with other students of similar abilities for an entire school year. The goal of same-ability small groups is to reduce the range of abilities among group members so that the teacher can instruct students who are functioning at approximately the same level (Barr, 1995).

The main concept of clustering is that a set of data is divided into several groups so that all of the data in same cluster has a closer similarity. The clustering algorithms can be roughly classified into the partitioned and the hierarchical (Jain & Dubes, 1988).

The *partitional* clustering algorithm divides the data set into k clusters. MacQueen's algorithm is the first and most commonly used (1967). With this algorithm, the upper k data of the data set is used as the center points for k clusters. In this paper, since some of the data is ranked and some not ranked, the k center point or points are randomly sampled. Then every record is allocated to the center closest to the cluster using the Euclidean distance.

The data so obtained is then assigned to the closest cluster, the distance between it and the center of each cluster having been considered. In this way, the data is divided into k clusters and the positions of all the points in each cluster are averaged to obtain a new center. Each data cluster is then reallocated until the stop conditions are satisfied, meaning that all data points do not change the clusters to which they belong two consecutive times.

The hierarchical clustering algorithm takes the original data clusters and changes them into a multilayer hierarchical structure. An algorithm for hierarchical clustering starts with disjointed sets of clusters and places each input data point in an individual cluster. Pairs of items or clusters are then successively merged and reduced. At each step, the pair of clusters merged are the ones between which the distance is the minimum.

2.2. Recommender systems

The idea of recommender systems comes from personalized information delivery. In "Personalized Information delivery: An analysis of Information Filtering methods", Foltz and Dumais (1992) present results of an experiment aimed at determining the effectiveness of four information-filtering methods in the domain of technical reports. Goldberg, Nichols, Oki, and Terry (1992) use collaborative filtering to weave an information tapestry. They describe an experimental system that manages an incoming stream of electronic documents, including Netnews, e-mails, newswire stories and Netnews articles. Resnick and Varian (1997) propose the idea of using content-based and collaborative filtering methods in developing recommender systems. A simple example is a search engine that, when no results are found for a query, suggests alternate keywords or queries that may achieve better results (Diamond Bullet, 2004).

Sarwar, Kerypis, Konstan, and Riedl (2001) state that recommender systems apply knowledge discovery techniques to the problem of making product recommendations during a live customer interaction, and that one successful recommender system technology is collaborative filtering, which works by matching customer preferences to those of other customers in making recommendations. In the collaborative filtering approach, one identifies users whose tastes are similar to those of the given user and recommends items they have liked. Given a set of items, users can express their ratings of items they have tried before. The recommender can then compare the user's ratings to those of other users to find the "most similar" users based on some criteria of similarity and recommend items that similar users have liked in the past. Scores for unseen items are predicted based on a combination of the scores known from the nearest neighbors. The other techniques of recommender system is the content-based approach, to recommend objects to users. Wang et al. (2004) state that with the content-based approach, one tries to recommend items similar to those a given user has liked in the past. It is based on a comparison between their content and a user profile.

Today recommender systems are widely used in many different domains. Schafer, Konstan, and Riedl (1999) stress that recommender systems are achieving widespread success in e-commerce, especially with the advent of the Internet. The Group Lens recommender system helps users wade through articles in Usenet news (Konstan et al., 1997; Resnick, Iacovou, Suchak, Bergstrom, & Riedl, 1994). Ringo, a Net-based music recommendation service, allows users to get music recommendations online and connect with other music fans (Shardanand & Maes, 1995). Gauch, Gauch, Bouix, and Zhu (1999) propose a real-time video scene detection and classification. Cheng and Yang (1999) advocates the idea of a new content-based access method for video databases. Mooney and Roy (2000) bring up a content-based book recommending the use of learning for text categorization. Kim and Choi (2002) pointed out a content-based video transcording in the compressed domain. Fleischman and Hovy (2003) suggests a natural language processing approach for recommendation without user preferences. Carenini, Smith, and Poole (2003) finds a set of techniques to intelligently select what information to elicit from the user.

In fact, numerous other recommender systems are successfully applied by online food stores (Svensson, Laaksolahti, Höök, & Waern, 2000), music suggestion services (Chen & Chen, 2001), and on-line bookstores, of which the most notable is Amazon.com (Linden, Smith, & York, 2003).

3. Proposing an ESL recommender teaching and learning system

Based on the cycling process of ''assessment–education–reassessment'', this paper has designed an ESL recommender teaching and learning system that follows the cycle as illustrated in Fig. 1. The basic concept is for the system to analyze automatically the result of a carefully designed grammar test that the student has done and to make immediate suggestions for improved ability in areas where the student is found to be weak. Then, having studied to improve his weaknesses, the student takes another similar test, and the analysis and recommendation process automatically repeats itself. The simplified architecture of the system is given in Fig. 2.

3.1. Preclassified test bank

The test questions are preclassified into twenty kinds (see Table 2), and each question is labeled (*Ai, Bi*), with *Ai*meaning the question number and *Bi* the question kind it belongs to. For example, when a student's wrong answers are denoted as (1, 1), (3, 2), (5, 1), it means that the student has given wrong answers to Q1, Q3 and Q5, and that Q1 belongs to question kind 1, Q3 to question kind 2, and Q5 to question kind 1.

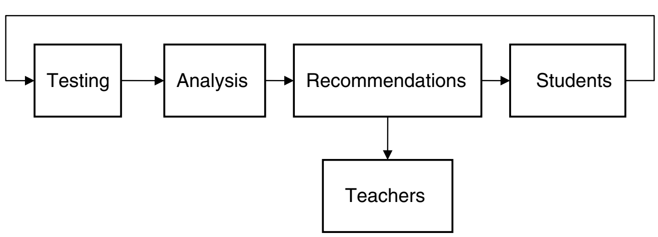

Fig. 1. The teaching and learning recommendation cycle.

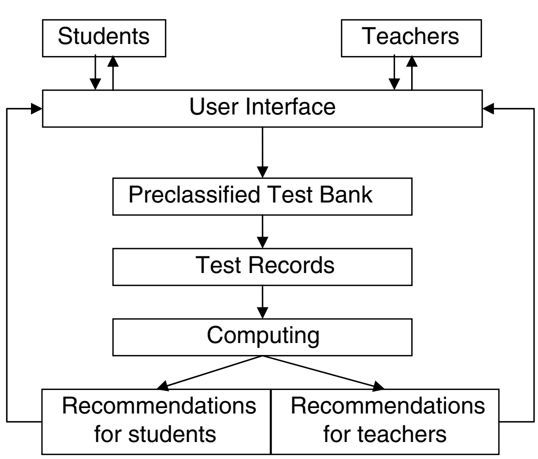

Fig. 2. The simplified architecture of the system.

Table 2
The 20 kinds of questions

Kind	Description
1	Transitive and intransitive verbs
2	Phrasal verbs
3	Auxiliaries
4	Tenses
5	Subjunctive mood
6	Passive voice
7	Subject–verb agreement
8	Direct and indirect speech
9	Prepositions
10	Coordinate conjunctions
11	Nouns
12	Pronouns
13	Adjectives
14	Adverbs
15	Noun clauses
16	Noun phrases
17	Adjective clauses
18	Adjective phrases
19	Adverbial clauses
20	Adverbial phrases

3.2. Computing

For every student, the system creates a right/wrong answer statistical table, with the numbers in the far left column indicating question numbers and those in the first row representing question kinds. Employing bit summary concept, a wrong answer is represented by 1 and a right answer by 0 (see Table 3).

The right/wrong answer statistical tables for respective students are integrated and compiled in a summary table of students' wrong answers (see Table 4), and the sum values in the table are then ranked in descending order so as to show the descending degrees of weaknesses the students have collectively (see Table 5). Based on the weaknesses so found, the system is therefore able to make accurate teaching recommendations. For example, as Table 5 shows, 19 times are wrong on question kind 3; 12 on question kind 1; and 5 on question kind 2. Thus the system comes up with its suggestion that the teacher, in planning remedial strategies, take into consideration the following

Table 3
A right/wrong answer statistical table

Questions	Kind			
	1	2	3	...
1		1		...
2	1			...
3		1		...
4			0	...
5		1		...
.	1			...
.			1	...
.	0			
Sum	2	3	1	...

Table 4
A summary table of students' wrong answers in order of question numbers

Question kind	1	2	3	...
Sum	12	5	19	...

Table 5
A summary table of students' wrong answers in descending order of sum values

Question kind	3	1	2	...
Sum	19	12	5	...

grammar areas in descending order of priorities: tenses, transitive and intransitive verbs, and auxiliaries.

Hierarchical clustering algorithm is then applied to data collected from Tables 2–5 to segment the students into a certain number of clusters, or categories, each of which includes students sharing the same or similar characteristics (see Table 6). The students that belong to category 1, for example, have shown common weaknesses in tenses and the subjunctive mood. Based on such information, the teacher will be able to better understand and help the students.

3.3. Recommendations for teachers

For every student, the system creates a right/wrong answer statistical table (see Table 3). For example, the Table 7 is summary all students' right/wrong answer statistical tables. Each value in the sum row is the number of students who give a wrong answer.

A clustering analysis is made of the data in Table 7, hierarchical clustering algorithm. It is evident that the students whose numbers are enclosed in the following separate parentheses belong to different clusters respectively: (9, 15, 6, 17, 13, 19, 14, 5); (22, 23, 4, 3, 21, 11, 24, 20, 7, 1); (12, 18, 2, 8, 25, 10, 16).

Table 6
χ Clusters of students

Cluster	Students number
1	93002
	93011
	93025
	93034
	93045
2	93003
	93007
	93010
	93023
	93033
	93035
	93029
3	93006
	93012
	93018
:	:
:	
:	93009

Table 7
All students' wrong answers

Student no.	Kind																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	7	18	19
1	1	0	2	2	2	2	1	1	1	1	1	2	1	1	2	1	3	2	2
2	2	1	2	2	3	1	2	2	1	1	2	3	2	1	1	1	1	1	1
3	1	2	3	2	2	2	2	2	2	3	1	2	3	1	3	1	2	1	2
4	2	2	2	2	2	1	2	1	3	2	1	2	2	2	2	1	2	0	1
5	1	3	3	0	2	2	2	2	1	2	1	2	2	2	1	1	1	1	1
6	1	2	2	2	1	1	3	3	1	2	1	1	2	2	1	1	1	1	2
7	2	0	2	2	2	3	2	2	2	2	2	2	0	0	2	1	1	1	2
8	1	2	3	2	2	1	2	2	1	0	2	2	1	2	1	2	1	2	2
9	1	2	2	2	2	1	2	3	3	2	2	2	1	0	2	1	1	1	1
10	2	1	1	3	2	2	3	2	1	2	2	2	1	3	1	3	2	1	1
11	1	1	1	2	2	3	2	2	1	2	1	1	2	1	3	2	2	1	1
12	2	0	3	3	2	0	1	2	2	2	2	2	1	2	1	1	2	1	1
13	1	2	2	2	1	1	1	2	1	2	1	2	1	1	2	3	1	2	2
14	1	3	2	0	1	2	2	2	1	1	0	1	1	2	2	3	1	1	3
15	1	3	2	2	2	1	2	3	2	2	2	2	2	0	1	1	1	2	1
16	0	1	1	1	1	1	1	1	3	2	2	3	1	0	2	2	1	2	2
17	1	2	1	2	2	1	2	2	2	3	1	1	2	2	2	2	0	0	1
18	2	1	2	2	0	1	2	2	2	2	1	2	0	2	1	2	1	0	1
19	1	2	2	1	1	2	2	1	1	3	1	1	1	2	2	2	2	2	1
20	1	2	2	2	2	2	1	2	2	2	3	2	1	2	2	1	2	1	1
21	1	1	3	2	2	2	2	2	2	1	2	1	3	1	2	1	3	2	1
22	3	2	1	2	1	2	1	0	2	2	2	2	3	2	2	1	1	2	0
23	2	2	2	2	1	2	1	1	2	2	2	2	2	2	2	1	1	1	1
24	2	1	2	2	2	3	2	2	2	2	2	1	1	1	2	2	2	1	1
25	2	1	1	2	2	0	3	2	1	1	1	1	1	1	1	2	2	2	1
Sum	36	39	48	44	41	40	45	46	43	45	41	43	35	38	42	36	37	31	32

Table 8
The cluster of (9, 15, 6, 17, 13, 19, 14, 5)

Student ID	Kind																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
5	1	3	3	0	2	2	2	2	1	2	1	2	2	2	1	1	1	1	1
6	1	2	2	2	1	1	3	3	1	2	1	1	2	2	1	1	1	1	2
9	1	2	2	2	2	1	2	3	3	2	2	2	1	0	2	1	1	1	1
13	1	2	2	2	1	1	1	2	1	2	1	2	1	1	2	3	1	2	2
14	1	3	2	0	1	2	2	2	1	1	0	1	1	2	2	3	1	1	3
15	1	3	2	2	2	1	2	3	2	2	2	2	2	0	1	1	1	2	1
17	1	2	1	2	2	1	2	2	2	3	1	1	2	2	2	2	0	0	1
19	1	2	2	1	1	2	2	1	1	3	1	1	1	2	2	2	2	2	1
Sum	8	19	16	11	12	11	16	18	12	17	9	12	12	11	13	14	8	10	12
Recommendation:	Kind 2 > Kind 8 < Kind 10 > Kind 3 = Kind 7...																		

Table 9
The cluster of (22, 23, 4, 3, 21, 11, 24, 20, 7, 1)

Student ID	Kind																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	1	0	2	2	2	2	1	1	1	1	1	2	1	1	2	1	3	2	2
3	1	2	3	2	2	2	2	2	2	3	1	2	3	1	3	1	2	1	2
4	2	2	2	2	2	1	2	1	3	2	1	2	2	2	2	1	2	0	1
7	2	0	2	2	2	3	2	2	2	2	2	2	0	0	2	1	1	1	2
11	1	1	1	2	2	3	2	2	1	2	1	1	2	1	3	2	2	1	1
20	1	2	2	2	2	2	1	2	2	2	3	2	1	2	2	1	2	1	1
21	1	1	3	2	2	2	2	2	2	1	2	1	3	1	2	1	3	2	1
22	3	2	1	2	1	2	1	0	2	2	2	2	3	2	2	1	1	2	0
23	2	2	2	2	1	2	1	1	2	2	2	2	2	2	2	1	1	1	1
24	2	1	2	2	2	3	2	2	2	2	2	1	1	1	2	2	2	1	1
Sum	16	13	20	20	18	22	16	15	19	19	17	17	18	13	22	12	19	12	12
Recommendation:	Kind 6 = Kind 15 > Kind 3 = Kind 4 > Kind 9 = Kind 10 = Kind 17...																		

The sum values in Table 7 shows a result: Kind 8 > Kind 7 = Kind 10. This demonstrates that the 25 students are weakest on questions of Kind 8, Kind 7, and Kind 10, in descending order. Thus the system recommends that grammar areas related to those kinds be given priority treatments in recommender teaching. Also, the same analysis is also made of the different clusters of students, and the respective results with recommendations are given in Tables 8–10.

3.4. Recommendations for students

Refer to Table 3, the system knows from the table that the student has given two wrong answers to question kind 1 (transitive and intransitive verbs), three wrong answers to question kind 2 (phrasal verbs), and one wrong answer to question kind 3 (auxiliaries). Then the system turns out a test score report with recommendations for improvement given in order of descending priority in the bottom row (see Table 11).

The student can thereafter follow the recommendations offered him and study for improvement either at our free online learning center or in other ways that may suit his learning needs. He or she will then return for another test at our online testing center, and the system will automatically repeat the same process of assessment and recommendation.

4. Experimental result

The test to be given in the experiment is a GEPT elementary-level simulation test. There are 30 tests in the test bank, each containing a total of 65 questions on 20 different areas of grammar (see Table 2). GEPT, or General English Proficiency Test, is administered by the Language Training and Testing Center on behalf of Taiwan's Ministry of Education. The GEPT elementary-level is equivalent to level A2, or *Waystage*, in the Common European Framework of Reference for Language Learning, Teaching and Assessment.

4.1. From teachers' view

The subjects of experiment are 50 ESL students of low English proficiency who have failed an elementary grammar test given by the system. Of these 50 students, 25 are the experimental group and the other 25 the control group. The experimental group is taught according to the recommender plan and method provided by the system, while the control group is taught in normal ways.

Table 10
The cluster of (1, 25, 19, 8, 13)

Student ID	Kind																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
2	2	1	2	2	3	1	2	2	1	1	2	3	2	1	1	1	1	1	1
8	1	2	3	2	2	1	2	2	1	0	2	2	1	2	1	2	1	2	2
10	2	1	1	3	2	2	3	2	1	2	2	2	1	3	1	3	2	1	1
12	2	0	3	3	2	0	1	2	2	2	2	2	1	2	1	1	2	1	1
16	0	1	1	1	1	1	1	1	3	2	2	3	1	0	2	2	1	2	2
18	2	1	2	2	0	1	2	2	2	2	1	2	0	2	1	2	1	0	1
25	2	1	1	2	2	0	3	2	1	1	1	1	1	1	1	2	2	2	1
Sum	11	7	13	15	12	6	14	13	11	10	12	15	7	11	8	13	10	9	9
Recommendation:	Kind 12 = Kind 4 > Kind 7 > Kind 3 = Kind 8 = Kind 16...																		

Table 11
A test score report with recommendations for improvement

Question type		Right answers/total questions	Score
Part 1	Q&A on pictures	5/10	20
Part 2	Q&A on short sentences	4/10	16
Part 3	Environment dialogs	4/10	16
Part 4	Vocabulary/sentence patterns	10/15	30
Part 5	Cloze	7/10	28
Part 6	Reading comprehension	5/10	25
Total			135
Rank			1033/21712
Total average			151.13
Recommendations for improvement in order of descending priority: (1) phrasal verbs; (2) transitive and intransitive verbs; and (3) auxiliaries			

After three months of remedial teaching, the same 50 students take another elementary-level grammar test, and the test results show that the experimental group students have a substantially high level of improvement. These students have an average score of 104 on the first test (see Fig. 3), but an average score of 124 on the second test (Fig. 4), taken three months after the first. There is a significant increase in score of 20. By contrast, the control group students have an average score of 111 on both the first and the second test (Figs. 5 and 6), making no progress.

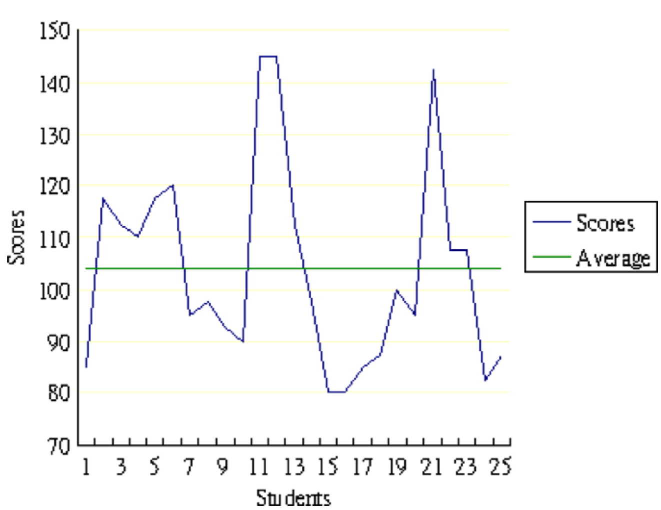

Fig. 3. The 1st test results of the experimental group.

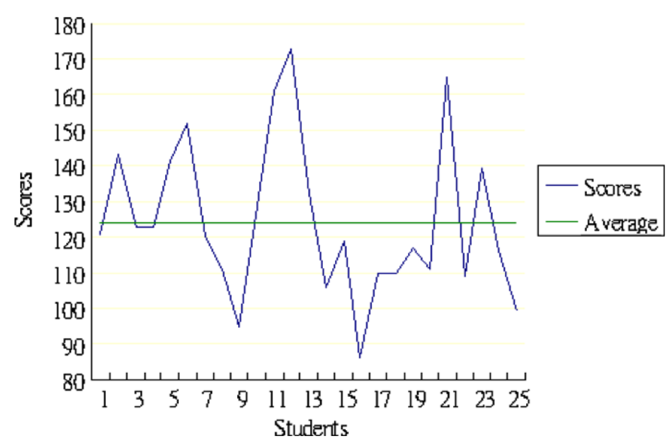

Fig. 4. The test results of the experimental group after three months.

4.2. From students' view

The subjects of experiment are 100 ESL students of low English proficiency, of which 50 students are the experimental group and the other 50 the contrast group. All the students are asked to take the said simulation test at the system's online testing center. However, after the test, only the students of the experimental group are offered system recommendations for improvement as well as well-designed learning activities, while those of the contrast group, receiving no suggestions for improvement, continue their own learning activities.

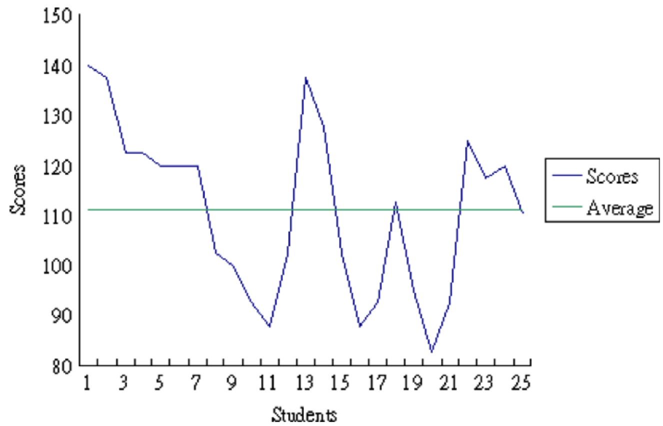

Fig. 5. The 1st test results of the control group.

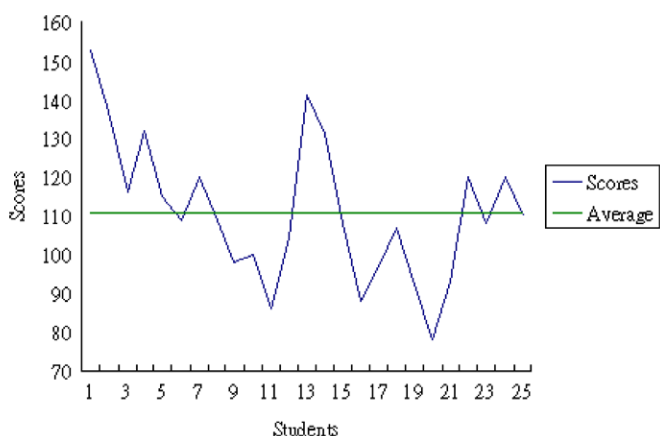

Fig. 6. The test results of the control group after three months.

Three months after that test, the same 100 students are asked to take a second GEPT elementary-level simulation test. As a result, the students receiving system recommendations record higher improvement. Fig. 7 shows the first test results of the experimental group, with an average score of 133. Fig. 8 shows the second test results of this group, with an average score of 143 – a significant increase of 10 points, or 7.5%, compared to the group's first test

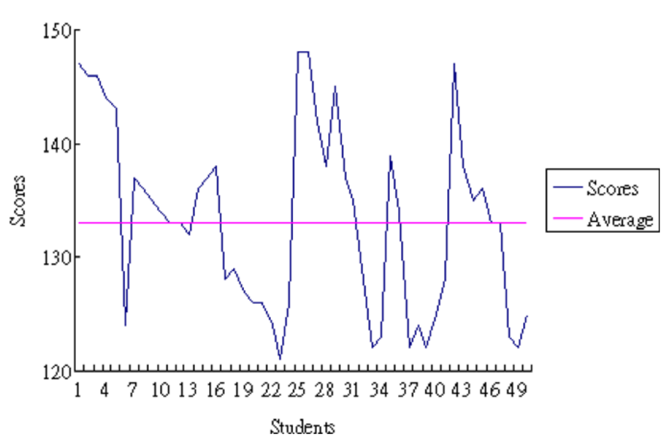

Fig. 7. The first test results of the experimental group.

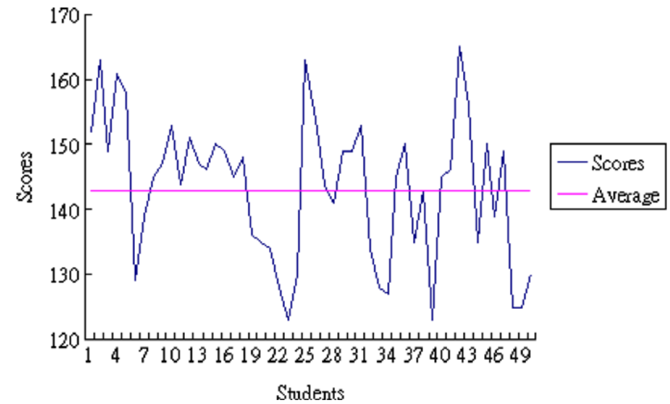

Fig. 8. The second test results of the experimental group (after three months).

results. In contrast, a comparison of the first with the second test results of the contrast group indicates no progress in performance, with an average score of 135 on the first test (Fig. 9) and 134 on the second (Fig. 10).

4.3. Discussion

The experimental results show that the students under our recommendation system have made impressive progress in performance after remedial teaching and learning

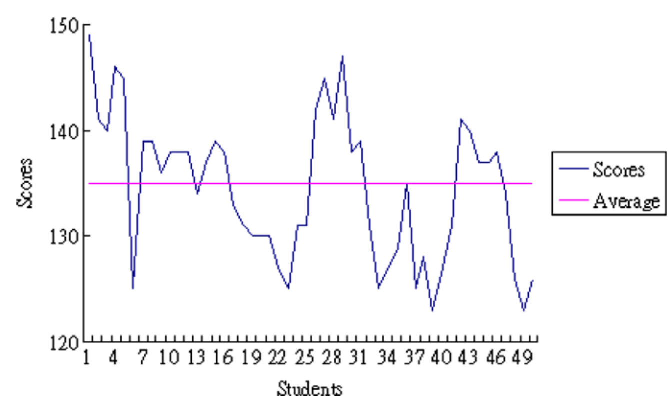

Fig. 9. The first test results of the contrary group.

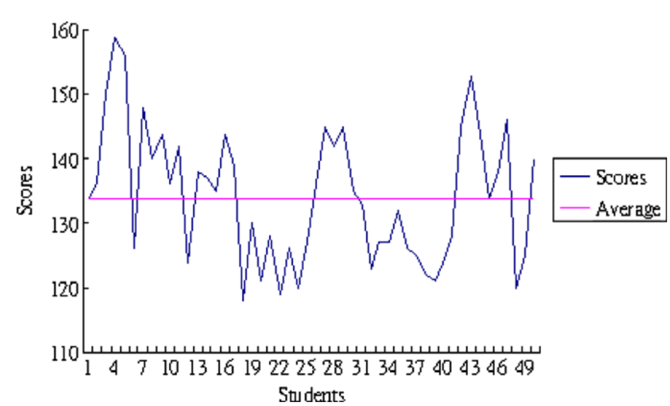

Fig. 10. The second test results of the contrary group (after three months).

that followed the system's suggestions. In contrast, those outside the system have made limited or no progress. The recommendation system, therefore, has proved a very useful tool to assist teaching and learning of English grammar.

5. Conclusion

The test results of the experimental and control groups demonstrate that remedial teaching following the system's recommendations can greatly help the students improve their grammar ability. Not only the System helps identify and find students problems and weaknesses in learning, and with its recommendations, the teacher can plan remedial strategies accordingly and effectively but also help students who need remedial teaching to identify their strengths and especially weakness in language learning, it can offer practical suggestions for remedial improvement. While the sampling scale is slightly small, the system as a whole as well as the methodology used has proved impressively useful. Therefore, in case of a larger population, the results would also be similar. The ideas of this recommender system should be worth applying to other areas of remedial education.

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