Proposal of an e-Learning System with Skill-based Homework Assignments

Tomoko Kashima, Simpei Matsumoto, Tatsuhiko Ihara

***Abstract*— In this paper, we build a learning environment that combines "lectures", "e-Learning", and "push-type homework assignments". We study the feasibility of automatic homework assignments by the degree of comprehension and also quantitatively evaluate the degrees of achievements of each student. Furthermore, we develop a push-type e-Learning system that permits studying with a cellular phone for instantly and automatically receiving assignments by e-mail. Not only active students but also inactive students can get assignments by e-mail. Therefore, we expect that a familiar and easy study situation can be created by developing this e-Learning environment. Our system uses the accumulated learning history and information recommendation processing based on collaborative filtering for making assignments. Thus, presentation of an assignment to each student based on his skill level can be combined with the tendency for covering every topic of study. The result of our research considers the feasibility of content-based filtering by text-mining processing towards homework assignments in future systems.**

***Index Terms*— e-Learning, collaborative filtering, content base filtering, text analysis**

I. Introduction

Recently, the introduction and discussions aiming at next-generation school education have become increasingly active. The feasibility of using digital textbooks and e-Learning systems has steadily improved through the progress in information technology. Additionally, e-Learning is becoming also popular in companies or other educational facilities. However, if a user does not actively request for learning material in conventional e-Learning systems, he usually cannot access it. Therefore, conventional e-Learning has the drawback that it is of limited use to only those students who actively participate in the lectures. Instead, our intention is to build a new environment for e-Learning to support all students.

We think that in conventional e-Learning a major factor is that some time and effort is required for the user to log in to the system. Usually, the user has to actively request the system to use various services and learning materials. Therefore, it is implicitly assumed that the user shows a positive learning attitude and regular schedule in conventional e-Learning. In this research, we develop an e-Learning system for students who cannot use e-Learning continuously. Together with the user's selection, this research also takes the diversification of the study topic into account. Specifically, the novelty of our approach is in offering a custom-made educational style according to each student's skills rather than being instructed in the conventional educational style. In order to solve this problem, we believe to have identified the key point that teaching materials of the same contents are offered to all users. In our view, it is more effective to distribute the assignments according to each student's skills and we therefore propose this push type e-Learning system for assignments.

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II. Background on E-learning

A. Overview of e-Learning Systems

In recent years, introductory examples of e-Learning and their effectiveness have been reported [1]. Construction and application of an e-Learning environment are often based on open source packages, such as Moodle or NetCommons [2-3]. Universities or higher education institutions have started introducing the open source software and practical experiences have been reported by them in various scientific journals. Since e-Learning offers a learning environment which transcends spatial and temporal restrictions, its usage has been continuously increasing every year. According to the official website of Moodle, it is reported that it has been used at 49,659 sites by November 2010. All information systems built for the purpose of educational support are summarized under the term "e-Learning" [4]. Installation and operation of an e-Learning environment are already playing an important role in educational facilities, such as universities [5] and by using commercial software, such as WebCT, Blackboard, or a free open-source alternative, anyone can install an e-Learning system without much effort.

Especially, ubiquitous learning by means of a Personal Digital Assistant (PDA) has also been a subject of great attention recently. For example, a lot of software for study training is sold for the Nintendo DS handheld console and several examples in which Nintendo DS was introduced into the lecture have been reported [6]. Furthermore, if the communication capability of a cellular phone or PDA can be utilized, various enhanced services, such as voice and video delivery through the Internet as well as web-based systems, can be used. First studies on the possibility and effectiveness of the study training using a PDA have been reported in scientific journals [7-8].

B. Function of Moodle

Moodle is a free e-Learning management system and has

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various default functions. Specifically, there are functions, such as an automatic scoring system, lecture material browser, a discussion forum (BBS), and result management. The analysis and judgment of the performance at each problem are displayed automatically within the item analysis function. The report presents data about each question of a quiz in a table form and gives measures that aid in analyzing and judging the performance at each question. This is done for all students in total or a group of students, who took the quiz at the same time. In summary, this report will tell the teacher what percentage of students selected each answer, how the highest scoring quiz takers answered a question compared to the lowest scoring candidates, and other information for statistical assessment. We use the output of this item analysis function in our research as described in the Moodle documentation [9].

Facility Index (% correct) is the overall difficulty of the questions. If questions can be distributed dichotomically into correct/incorrect categories, this parameter coincides with the percentage of users that answer the question correctly. *Standard Deviation* (SD) indicates the range of responses. This parameter measures the spread of answers in the response population. If all users' answers are the same, then SD = 0. SD is calculated as the statistical standard deviation for the sample of fractional scores (achieved/ maximum) at each particular question. *Discrimination Index* (DI) and *Discrimination Coefficient* (DC) are effectiveness measures. Both DC and DI can be used as powerful methods of evaluating the effectiveness of the quiz when assessing differentiation of learners. The advantage of using the Discrimination *Coefficient* as opposed to the *Discrimination Index* is that the former uses information from the whole population of learners, not just the extreme upper and lower thirds. Thus, this parameter may be more sensitive to detect item performance. DI provides a rough indicator of the performance of each item to separate high scores vs. scorers. The DI parameter is calculated by first dividing learners into thirds based on their overall score in the quiz. Then, the average score at the analyzed item is calculated for the groups of top and bottom performers and the average score is subtracted. This parameter can take values between +1 and -1. If the index goes below 0.0, it means that more of the weaker learners got the item right than the stronger learners. Such items should be discarded as worthless since they in fact reduce the accuracy of the overall score for the quiz. DC is a measure of the separating power of the item to distinguish proficient from weak learners.

The discrimination coefficient is a correlation coefficient between scores for an item and the whole quiz. Again, this parameter may take values between +1 and -1. Positive values indicate items that discriminate proficient learners, whereas negative indices mark items that are answered best by those with lowest grades. Items with negative DC are incorrect answers by the seasoned learners and thus they are actually a penalty against the most proficient learners. Those items should also be avoided.

III. Outline of Developed System

We assume a push-type e-Learning system that uses the e-mail service of a cellular phone. The system can distribute the homework exercises automatically to each student's cellular phone. Each student solves the exercise and replies with his solution of the homework. The student can then instantly receive a marked result. Moreover, a dedicated website displays a history of answers, the degree of achievement in each field, and individual weak points. The student can see the status of his own learning progress. The entire distribution of marks or comments is made automatically, and all users' answer history and results are maintained in a database. The database stores the information, including a user's personal data, past exercise data, difficulty, topic, correct answers, comments, etc. The teacher can then monitor each student's degree of comprehension and degree of achievement. Thus, the teacher is assisted in advance planning and individual guidance of a lecture.

The push-type e-Learning system runs as server software developed in the Java programming language. First, the system regularly checks for incoming mails from a mail server. Next, when the Java application marks a mail in the database, it automatically replies to the student. The information about the student's degree of comprehension is forwarded to the teacher. In addition, the teacher sets up mail delivery time and the number of distribution. These functions cooperate with Moodle.

1) Recommendation Algorithm of the Assignment Creation Classified by Tendency

Realization of a recommendation algorithm consists of acquisition of data, prediction, and presentation of the recommendation. It is called O-I-P (Output-Input-Process) recommendation model [10].

2) Step 1: Input

This step consists of the user providing some information to the system. For example, when used in marketing, information such as "*one likes to eat*", "*one wants*", "*one likes*", etc. is input here. There are two methods in gaining this information. One is the *explicit acquisition* (student is asked directly) method and another other is the method of *implicit acquisition* (predicted or inferred from data on the web etc.). In this study we distinguish among the cases where we can use each acquisition method. In the case of explicit acquisition, the student is directly asked about what he likes and dislikes and information is collected by this way. Hereby, the correctness of the data content can be guaranteed. The student himself can be convinced to provide the collected information in many cases. However, answering in detail to a large number of questions may occasionally become troublesome for a student, so it is regarded that large-scale information gathering becomes very difficult. In that case, this research uses the method of implicit acquisition, which can collect a large amount of data. In this research, we use data obtained by building the e-Learning environment of Moodle.

3) Step 2: Ways to Estimate Student's Skills

Student i's strong points of study is guessed and

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recommended from his results and the comparison to other students' result data. The technique of recommendation can be done by two methods. These are *content-based filtering* (using the features of an exercise) and *collaborative filtering* (using others' answer data). Unlike when guessing the preferences for goods, consideration of serendipity is also needed for this research data. Serendipity is a propensity for making fortunate discoveries while looking for something unrelated. So, not only weak subjects, but also exercises with content that the student may have forgotten over time are being recommended. In this case, the method of collaborative filtering is considered beneficial because the method of content-based filtering requires a historical trend analysis of learning. However, when there is only little past learning history available, content-based filtering is better because a prediction by similarity is difficult to achieve with only little data. So, we use a hybrid type where the feature of an exercise is used and a student cluster with the same weak field is created and evaluated.

4) Problem Classification by Content-based Filtering

Here, the exercise of Moodle is classified. The attributes in question are facility, standard deviation, discrimination index, and distinction coefficient. *Cluster analysis* is a class of statistical techniques that can be applied to data that exhibit "natural" groupings by sorting through the raw data and grouping them into clusters. A cluster is a group of relatively homogeneous cases or observations. Objects in a cluster are similar to each other. The joining or tree clustering method uses the dissimilarities (similarities) or distances between objects when forming the clusters.

Similarities are a set of rules that serve as criteria for grouping or separating items. The k-means method is used in this paper. In k-means clustering, one specifies a priori how many clusters to expect. The algorithm attempts to find the best division of objects into the requested number of clusters. Various statistics are provided to aid in the decision, whether an adequate clustering of objects was achieved, i.e., whether the objects within each cluster are indeed more similar to each other than objects in different clusters. The representative point $c_{1,} c_{2,\dots} c_K$ of K clusters is created suitably. The distance of x and c_i is measured for each data x. The cluster c_i with the shortest distance is set as the class of x. The clustering algorithm ends, when the cluster of each data x does not change. When a cluster changes, the center of gravity of each cluster is set as the representative point $c_{1,}$ $c_{2,\dots} c_K$, and is remeasured. A formula is shown below.

$$\sum_i \sum_{x \in Ci} ||x - c||^2 \qquad (1)$$

All exercises are classified into five clusters. Next, a text analysis is conducted for each cluster. We count what kind of language is contained in the exercise of each class. Furthermore, the trend of the whole text is analyzed and frequency analysis from text mining is used as method. For instance, all the exercises on basic inorganic chemistry currently used in Moodle are written in English. A text is standardized in order to facilitate the analysis of an English exercise sentence. The beginning of a sentence is changed from a capital letter into a small letter and a contracted form is developed. A conjugation is transformed into its prototype and a plural form is changed into a singular number. After this reduction, the number of appearances of a word (noun) is counted. Most frequently appearing words are predicted to serve as the classification keyword for the exercise. Moreover, the modification relationships are also analyzed. For example, if modification relationships are extracted by the text "*I eat two apples*", there are "*I* → *eat*", "*apples* → *eat*" and "*two* → *apples*".

The most frequently appearing three words are observed for each class and modification relationships are analyzed for those words. The set which is in agreement with a frequently appearing word w among all the groups of words appearing in a text is set to $W = \{w_i\}$. The number of exercises in which the word appeared is set to $n(w)n(w$.. For two different words w_i and w_j, the number of lines where both words appeared simultaneously is $n(w_i,w_j)$. The lexical co-occurrence relation is extracted according to the following five steps. First, reliability P_{ij} and number ij of lexical co-occurrence relation rules are calculated for all the groups of the word, which appears in an exercise.

$$P_{ij} = n(w_i,w_j)/n(w_i) \qquad (2)$$
$$C_{ij} = n(w_i,w_j) \qquad (3)$$

Here, reliability expresses the probability that the word w_i had appeared in the same line, when a word w_j appears in a certain line. Moreover, w_i is a premise and w_j is a conclusion. The lexical co-occurrence relation rules are the number of lines where a words w_i and w_j appeared simultaneously. Reliability P_{ij} is more than the lower limit $\underline{P}$ among (w_i,w_j) and number C_{ij} of lexical co-occurrence relation rules are above the lower limit $\underline{C}$. The two conditions are fulfilled. Furthermore, at least one side of w_i,w_j is an attention word or, one of w_i,w_j calls a lexical co-occurrence relation rule specially what is contained in the group of being an attention word (w_i,w_j). Within the group which fulfills the conditions that at least one side of w_i,w_j is an attention word (w_i,w_j),, both a premise and a conclusion are T_u about what is contained in set W_N of an attention word. Only a premise is T_{tf} about what is an attention word. Only conclusion w_j is T_{ft} about what is an attention word. It is expressed with T of the following formula.

$$T = T_{tt} \cup T_{tf} \cup T_{ft} \qquad (4)$$

w_i or w_j are contained in the group of being an attention word (w_i,w_j). Within the group which fulfills the condition (w_i,w_j), the word of the side which is not an attention word is made into W_{tf} and W_{ft} about T_{tf} and T_{ft}, respectively.

$$W_{tf} = \{ w_j \mid (w_i,w_j) \in T_{tf} \} \qquad (5)$$
$$W_{ft} = \{ w_i \mid (w_i,w_j) \in T_{ft} \} \qquad (6)$$

Any word W' other than the attention word which appears in the group of (w_i,w_j) containing an attention word is set to $W' = W'_{tf} \cup W'_{ft}$. (w_i,w_j) which fulfills conditions can be expressed with T'.

$$T' = \{ (w_i,w_j) \mid P_{ij} \geq \underline{P}, C_{ij} \geq \underline{C}, w_i \in W', \qquad (7)$$

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$w_j \in W' \}$

$T \cup T'$ is output in the descending order of the reliability as a co-occurrence word pair. In addition to reliability and the number of co-occurrence rules, a result also outputs the value of support S_{ij} which is the rate of a line that a word w_i and w_j appeared simultaneously among all the lines in a text. The number of all questions titles is set to N, and S_{ij} is shown by the following formula.

$$S_{ij} = n(w_i,w_j)/N \tag{8}$$

5) Results Classification by Collaborative Filtering

The exercises registered into Moodle are classified. The correlation of Student i and other students is analyzed and the score of each student's exercise is predicted. Here, Student i's score is predicted from two or more students' learning history data.

In this paper, the correlation coefficient method, which is the typical technique in collaborative filtering, is used [11]. When a student i's degree of comprehension of exercise x is M_{ix}, the correlation coefficient is given by the following formula.

$$M_{ix} = M_i + \sum_j C_{ij} (M_{jx} - M_j) / \sum_j |C_{ij}| \tag{9}$$

Here, all the sums are taken except missing value. M_i is the average about x of M_{ix}. C_{ij} expresses the correlation coefficient between the i-th line and j-th line. In addition, C_{ij} is given by the following formula.

$$C_{ij} = \sum_x (M_{jx} - M_i) (M_{jx} - M_j) \times 1/(\sum_x (M_{jx} - M_i) \sum_x (M_{jx} - M_j)^2)^{1/2} \tag{10}$$

It predicts by a geometric mean using the data of a student with the high degree of similarity.

6) Step 3: Presentation of a Recommendation Exercise

Finally, the obtained recommendation exercise is presented to each student.

IV. Experimental Results from the System

We verify the effectiveness of our e-Learning system with skill-based homework assignments. As exercises we use the homework of the e-learning environment built by Moodle. The subject is basic inorganic chemistry. It is the homework for 7 times and there are 384 exercises. The classification according to the k-means method into 5 classes is shown in Table 1. The facility of classification 3 has the highest value with 73.89. It means that many students understand the exercise of classification 3. Similarly, the value of discrimination index is high for classification 3, which indicates that it was a suitable exercise for students. Furthermore, the students roughly understand the contents of the classification 5. On the other hand, only less than half of the students can answer the classification 1 correctly, showing that the exercises of classification 1 had too difficult contents for the students. Similarly, it turns out that the exercises belonging to classification 2 is also too difficult. The facility and the number of identifiers of the classification 4 were 0 and the distinction coefficient was negative. Such a value represents a completely unsuitable exercise or is the case when nobody can solve the exercise. So, the classification 4 was removed from the analysis.

TABLE 1. CLASSIFICATION BY THE K-MEANS METHOD

Class ID	Size	Average Facility	DI	DC	Residual
1	87	44.37	0.55	0.61	294.84
2	86	28.29	0.33	0.51	451.72
3	104	73.89	0.87	0.62	494.66
4	2	0.01	0.00	-998.69	0.61
5	105	57.58	0.73	0.62	384.11

TABLE 2. THE WORD FREQUENCY FOR CLASSIFICATION 1

1	Electron	16
2	Atom	12
3	Element	12
4	Bond	11
5	Compound	9
6	Octet	9
7	Structure	9
8	Energy	7
9	Lewis	7
10	Pair	7

TABLE 3. THE WORD FREQUENCY FOR CLASSIFICATION 2

1	Atom	18
2	Bond	18
3	Electron	14
4	Compound	12
5	Covalent	12
6	Energy	12
7	Ion	11
8	Lewis	9
9	Structure	9
10	Pair	8

TABLE 4. THE WORD FREQUENCY FOR CLASSIFICATION 3

1	Element	31
2	Electron	19
3	Atom	16
4	Reference	16
5	Configuration	15
6	Color	11
7	Group	11
8	Style	8
9	Consider	8
10	Div	8

TABLE 5. THE WORD FREQUENCY FOR CLASSIFICATION 5

1	Element	21
2	Bond	16
3	Compound	14
4	Electron	14
5	Energy	12
6	Covalent	9
7	Molecule	9
8	Atom	8
9	Ion	7
10	Color	6

This research tries to distribute the exercises to each student for fields they are weak in. Then, it is necessary to show clearly what kind of feature each exercise has. Word frequency was analyzed by the text-mining method described before and the word used as the key of each classification was extracted. The results are shown in Tables 2-5.

It is considered that the word with high frequency is an important keyword in an exercise. Moreover, a word with high frequency, which has not appeared in other classifications, may serve as a key for this exercise. When the meaning of this word is not understood, it is difficult for a student to solve the exercise of this classification. So, a word with high frequency is considered to be an especially important word.

The relation nature of the extracted keywords is checked. Top three frequently appearing words are analyzed whether they have appeared simultaneously with what kind of word. The modification relation is displayed visually in Figures 1-4. The problem of classification 2 is that it is complicated.

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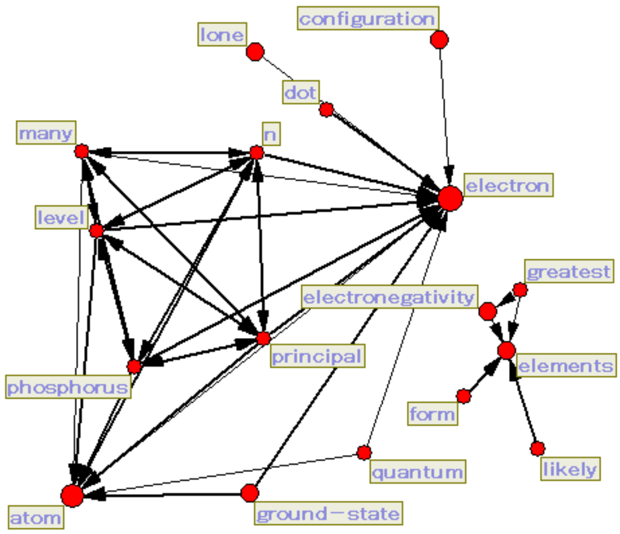

Fig. 1. The word frequency network of classification 1

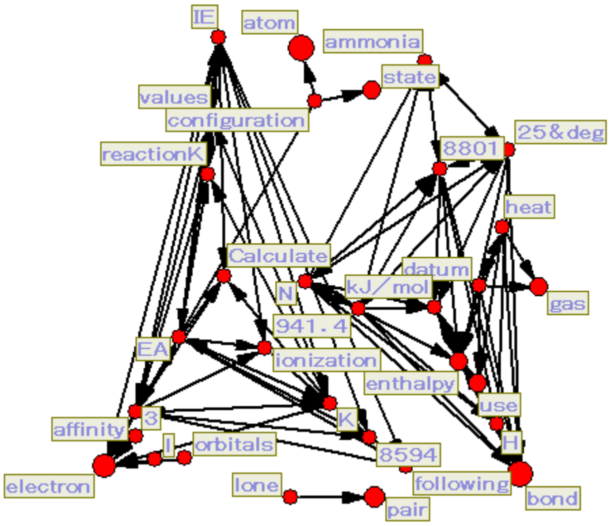

Fig. 2. The word frequency network of classification 2

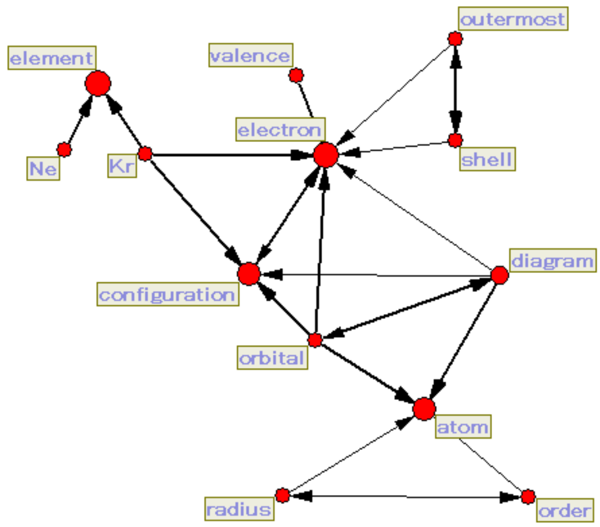

Fig. 3. The word frequency network of classification 3

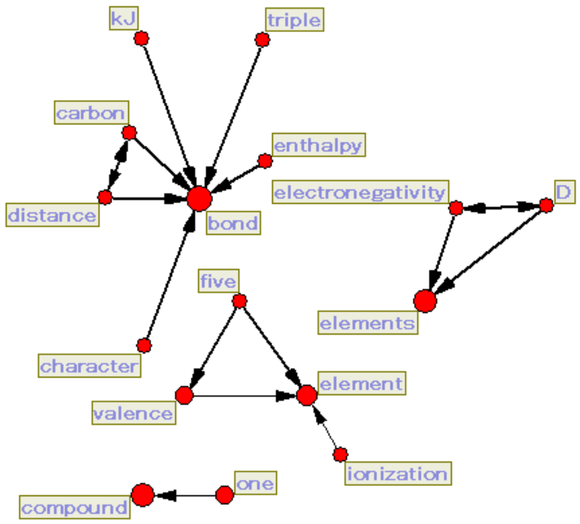

Fig. 4. The word frequency network of classification 5

It can be recognized that many words and much knowledge are needed for an exercises of this classification. On the other hand, classification 3 has a simple relation, thus it can be predicted that an exercise belonging to classification 3 is an easy exercise. So, when there is large vocabulary in an exercise sentence, the difficulty of this exercise goes up.

Next, collaborative filtering analysis is performed using each student's results data. The analysis result is shown in Table 6. This paper shows an exercise recommendation process to a student. First, correlation with each student was analyzed by the following method. When the correlation coefficient was at least 0.8, the value with a high degree of prediction was shown. Then, the analysis used the data of the student whose correlation coefficient is 0.8 or above in the calculation. The target had 26 students and the target student's features were analyzed. The 1st exercise did not receive good marks. However, the scores of the other exercises were good. Many exercises of the classification 2 were set on the 1st exercise problem. So, the target student is poor at the exercises of classification 2 and needs to review the frequently appearing word of classification 2. Moreover, a geometric mean is obtained based on the results data of a strong mutually related student's past.

The prediction score in Table 6 was obtained. A student is expected to be unable to take high mark on the 8th exercise. Student i's 8th exercise actually obtained the result of five points. In the case of the 11th exercise, Student i was predicted to get 3.81 points. However, Student i got 9 points. The histogram of the 11th exercise is shown in Fig. 5. The standard deviation of the 11th exercise is low. Moreover, the average of a mutually related high student was 3.8 points. Therefore, prediction is difficult when an average of a mutually related high student has a difference and the time of the low exercise of standard deviation. When flexibility 5 and a 5% of level-of-significance chi-square test were performed, the chi-square value was 9.42. The chi-square value of 5% of the chi-square distribution upper part of flexibility 5 is 11.07. So, it cannot be said that there is a difference in an actual score and a predicting point.

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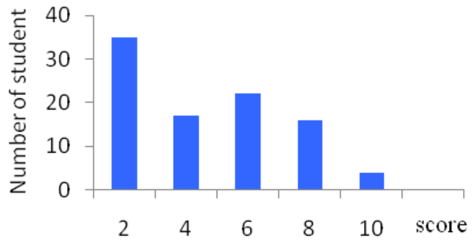

Fig. 5. The histogram of the 11th exercise

TABLE 6. THE PREDICTION MARK OF AN EXERCISE AND AN ACTUALLY RECEIVED SCORE

Number of exercise	6	7	8	9	10	11
Actual getting point	10	9	5	10	10	9
Standard deviation	4.05	2.15	1.99	4.43	4.07	2.96
Prediction	7.02	8.36	5.21	7.86	8.11	3.81

TABLE 7. THE UTILIZATION FACTOR AND NUMBER OF REPLIES

User	A	B	C	D	E	F	G
Empirical value	342	501	207	1879	551	68	373
Number of sending	160	137	122	122	123	122	124
Number of return	133	122	32	62	49	30	46
Probability of return	83%	89%	26%	50%	39%	24%	37%

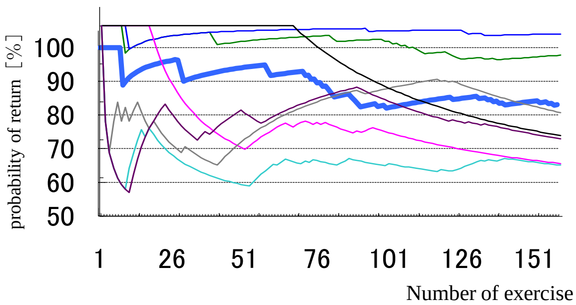

Fig. 6. The transition of reply rate (7users)

We verified the transition of our developed system independent of the utilization factor. Specifically, experiments were conducted by the developers and several cooperators. The system distributed mail of the exercise to the students for about three months. Students' utilization factor and number of replies are shown in Table 7. Transition of reply rate is shown in Fig. 6. It is confirmed that a push type e-Learning system could be used from this result. If a lecture and e-Learning are used together, it will be thought that the system becomes useful.

V. CONCLUSION

In this paper, we proposed an e-Learning system with skill-based homework assignments. The applied method of how to let a lecture, e-Learning, and a push-type system cooperate was described. In order to distribute the exercise in consideration of each achievement, the exercises and the strength of student correlation were classified. It became possible to predict the exercises at which a student performed poorly. Specifically, for students with high correlation of their degree of study training achievements, it was shown that they also had similar degrees of comprehension. Information recommendation processing based on collaborative filtering was applied to offer exercises connected with the skill level and the trend for every field to each student. Moreover, in order to construct an exercise distribution algorithm, content-based filtering with text analysis was used and it became possible to perform clustering of an exercise, classification of difficulty, etc. We implemented the exercise distribution by an e-mail push-type system based on the analysis result of e-Learning, and aim at processing all steps automatically. It is expected that a student's learning effect will increase assisted by a teacher. Simultaneously, it is necessary to repeat further experiments and to verify the learning effect and quantify how much the degree of comprehension improves over a longer time scale.

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