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Explainable English Material Recommendation Using an Information Retrieval Technique for EFL Learning

Kensuke TAKII[a*], Brendan FLANAGAN[b], Huiyong LI[b], Yuanyuan YANG[a] & Hiroaki OGATA[b]

[a]*Graduate School of Informatics, Kyoto University, Japan*
[b]*Academic Center for Computing and Media Studies, Kyoto University, Japan*
*kensuke.takii96@gmail.com

Abstract: Learning material recommendation has been a common field in the recommendation in e-learning due to the difficulty the learners experience in choosing appropriate learning materials among many resources. However, few traditional recommendation methods can be applied to e-learning as they are because they do not consider the learners' characteristics. Such methods may not be persuasive enough for the learners and make them less motivated. In this study, we propose an explainable English material recommendation that can adapt to the changes of learners' learning state and can explain the basis of the recommendation by using an information retrieval technique. This aims to address learners' trust and motivation issues. The algorithm estimates the difficulty of materials and learners' English skills and makes material recommendations that fit their skill levels. A case study in the setting of extensive reading is also described. Lastly, this paper introduces plans for implementation using an e-learning system with this recommendation. In the future, we will conduct an experiment and improve the recommendation algorithms.

Keywords: e-learning, learning material recommendation, English as a foreign language, system transparency

1. Introduction

These days, as learning resources available online are exponentially increasing, learners are having difficulty in choosing appropriate learning materials due to information overload. This is a partial reason why learning material recommendation is one of the most common fields in the recommendation in e-learning (Tarus, Niu & Mustafa, 2018). Although various traditional recommendation methods have been proposed in the field of information retrieval in the past (e.g., collaborative filtering, and content-based filtering), they cannot be applied to e-learning material recommendation as they are because they do not take into account the chronological change of learners' cognitive states and learning contents (George & Lal, 2019). In addition, black-box recommendation, which has no transparency in its mechanism, may not be trusted by the users, especially when they cannot agree with the recommendations (Herlocker, Konstan & Riedl, 2000; Abdi, Khosravi, Sadiq & Gasevic, 2020). According to previous work, intelligent tutoring systems with prompt and feedback mechanisms can improve students' motivation in self-regulated learning and lead them to higher achievement (Duffy & Azevedo, 2015). Thus, if learning material recommendation is not persuasive enough and not trusted by the learners, it may make them less motivated and not be effective in their learning. To address these problems, we argue that the recommendation mechanisms in education should entail the explanation of the rationale behind the recommendation to foster learners' trust and motivation for learning.

In this study, targeting English as a Foreign Language (EFL) learning, we propose an explainable English learning material recommendation that takes into consideration learners' characteristics changing over time and makes explanations of its recommendation for the purpose of being persuasive for learners. This recommendation involves an e-book reader system and a vocabulary profile. It processes learners' reading logs and the difficulty of vocabulary with an information retrieval technique to estimate learners' English skills and the difficulty of materials. Using the estimated skills and difficulties, the mechanism makes material recommendations so that the materials which have the closest difficulty to the learners' skills will be recommended. This mechanism can adapt to the chronological change of the learners' English skills by processing learners' learning logs with the materials in real-time. Besides, this recommendation can generate explanations about its basis according to the proximity between the difficulty of recommended materials and the learners' skills. This can contribute to improving learners' trust and motivation.

In addition, this paper proposes an implementation plan for evaluating the effect of the recommendation on learners' learning and motivation. This recommendation will be implemented in an existing e-learning platform including an e-book reader. Lastly, future work for the improvement of the recommendation will be described.

2. Related Work

2.1 Recommender System in E-learning

Many previous studies have stressed the importance of personalized systems in e-learning. Shishehchi, Banihashem, Zin & Noah (2011) stated that personalized environments in e-learning are very important since learning is a cognitive activity that differs from learner to learner. Many e-learning systems developed in the past provide a personalized learning experience based on the individual learner's needs, prior knowledge, preferences, and/or learning styles, and are more effective than non-personalized systems (Zou & Xie, 2018).

To provide personalized recommendation in e-learning systems, learners' knowledge and learning materials knowledge are necessary (Shishehchi, Banihashem, Zin & Noah, 2011). Most of these systems use learners' preferences (Hsu, 2008; Bourkoukou & Bachari, 2018), learning styles (Truong, 2016; Klašnja-Milićević, Vesin, Ivanović & Budimac, 2011), and knowledge levels (Bobadilla, Serradilla & Hernando, 2009). As a technique for generating recommendations, data mining is used these days to learn about students' behaviors in educational systems (Aher & Lobo, 2013). This is because a huge amount of educational data has been available. For example, Hsu (2008)'s English learning recommender system for English as a Second Language (ESL) students recommends reading lessons that suit their interests by using content-based analysis, collaborative filtering, and data mining techniques.

2.2 Generation of Explanations for Recommendations in E-learning

Explanations of the rationale behind the recommendations can be considered important for learners. Abdi, Khosravi, Sadiq & Gasevic (2020) mentioned the potential of a transparent educational recommender system, and these days this has been proven positively. Ooge, Kato & Verbert (2022)'s investigation on explaining exercise recommendations showed that explanations significantly increased initial trust for the recommendation when the trust was measured as a multidimensional construct. Flanagan and his colleagues proposed a system called EXAIT (Educational eXplainable AI Tools) (Flanagan, Takami, Takii, Dai, Majumdar & Ogata, 2021), which aims to tackle learners' trust and motivation issues behind recommendations made by e-learning systems. Their recent studies developed explainable math exercise recommenders with the Bayesian Knowledge Tracing algorithm (Takami, Dai, Flanagan & Ogata, 2022) and knowledge concepts extracted from textbooks (Dai, Flanagan, Takami & Ogata, 2022).

3. Recommendation Platform

3.1 Recommender Overview

The overview of the recommendation platform is shown in Figure 1.

First, a learner uses learning materials with an e-book reader system. This system is designed to convert the reading logs of the materials to the form of an Experience Application Programming Interface (xAPI) (Advanced Distributed Learning Initiative, 2013), and send them to a Learning Record Store (LRS) (xAPI.com, 2011), a general repository for learning/education records. The reading logs stored in LRS are used together with information on the difficulty of each material to estimate the learner's English proficiency. The difficulty levels of the materials are calculated in advance from the information on the difficulty of vocabulary in the wordlist. Then, the recommender generates material recommendations with explanations about why the recommendations were made to the learner. These explanations contain recommendation weights (how highly the materials are recommended), and explanatory sentences that explain the basis of the recommendations. Lastly, the generated recommendations are shown to the learner through a recommendation UI.

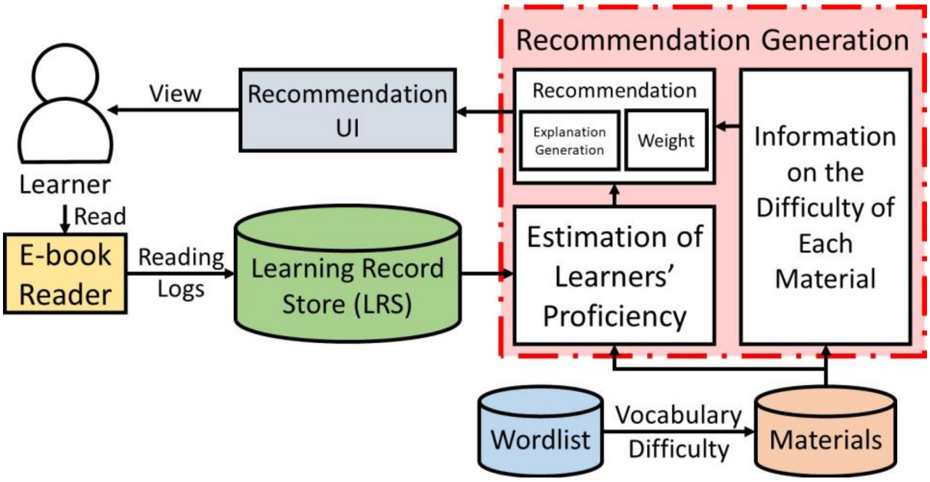

Figure 1. An overview of the recommendation platform.

3.2 Platform Components

3.2.1 GOAL – Recommendation User Interface

The user interface for the recommendation is implemented on the GOAL (Goal Oriented Active Learner) system (Majumdar, Yang, Li, Akçapınar, Flanagan & Ogata, 2018; Li, Majumdar, Chen & Ogata, 2021). The GOAL system is a platform to support students' development of data-informed self-directed learning (SDL) ability. SDL scaffoldings are implemented and provided to students in GOAL using the DAPER (Data collection – Analysis – Planning – Execution monitoring – Reflection) model. The DAPER model-based implementations systematically assist learners in taking initiatives to identify their status in contextual activities, set SMART goals, monitor their progress, and reflect their strategies. The self-directed activity context can be a set of learning activities where learners' learning trace data can be synchronized through learning behavior sensors. In this study it is the extensive reading activity. The SMART goals mean Specific, Measurable, Attainable, Relevant and Time-related goals.

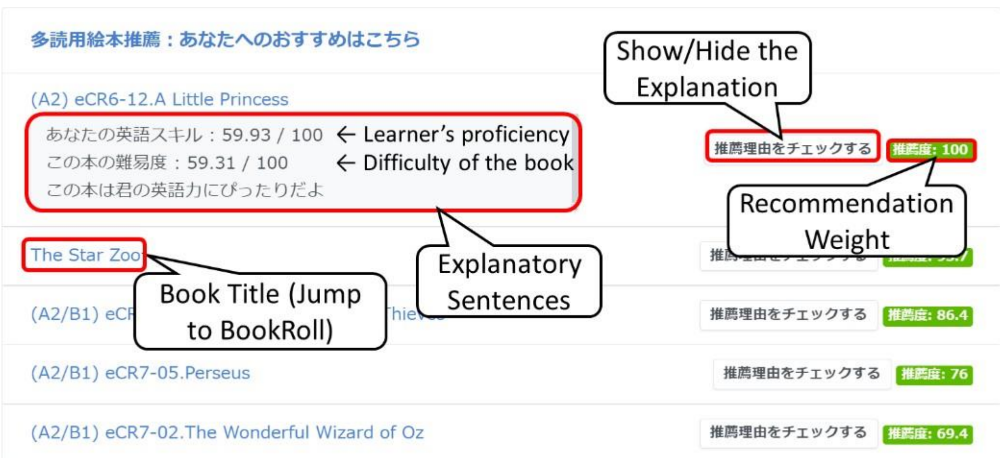

Figure 2. UI of the picture book recommender system implemented in GOAL system

The interface shown in Figure 2 provides at most 5 recommended learning materials. Users can jump directly to the BookRoll, an e-book reader, by clicking the title, and read the recommended material. Each of the recommended materials is followed by the recommendation weight and explanatory sentences that provide the reason why the recommendation was made to the learner. The provided explanation can be shown/hidden when users click a button next to the explanation.

3.2.2 BookRoll – An E-book Reader System

BookRoll, developed by Flanagan & Ogata (2018) is an e-book reader system linked to Moodle (Moodle.org, 2017). Figure 3 shows a user interface of BookRoll.

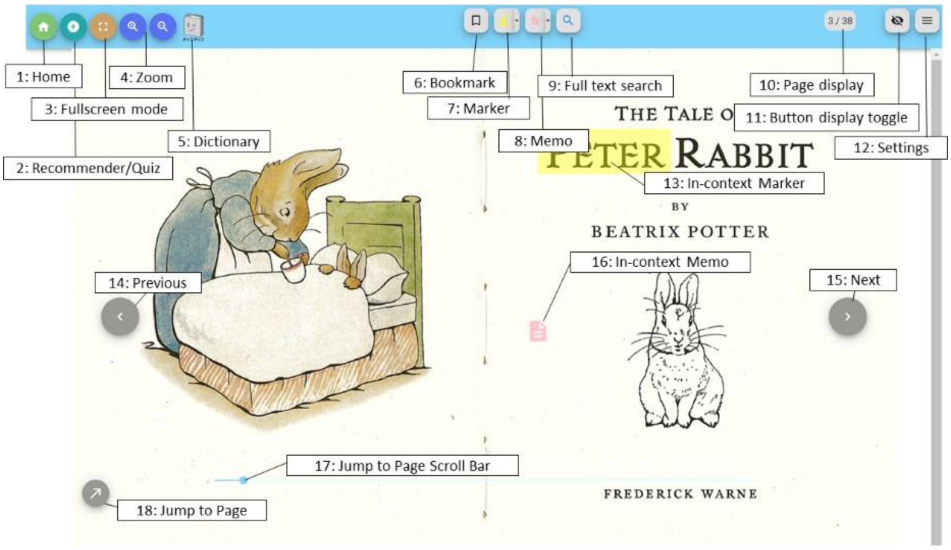

Figure 3. UI and functions of BookRoll

BookRoll provides an e-book page display and many additional functions including bookmark (6 in the figure), text highlighting (7), notes taking (8), text search (9), and recommendation/quiz function (2). When users raise events on BookRoll, such as moving pages, highlighting text, answering quizzes, etc., the detailed information on these events (e.g., the date and the page on which they occurred) is stored as reading logs in a Learning Record Store (LRS). From these features, BookRoll is suitable to gather English learners' learning logs. Thus, we will adopt it as an interface for reading e-books: that is, the whole reading activity in this study will be done through BookRoll and only reading logs performed through BookRoll will be recorded.

4. Recommendation Mechanism

4.1 Material Difficulty Evaluation

4.1.1 Difficulty of Vocabulary

The difficulty of materials should be determined by the difficulty of words consisting of them and their significance in the materials. A material which includes many difficult words is naturally difficult, but if they are not significant in the material, learners can ignore them and understand the content sufficiently. To estimate the difficulty of materials, we used a vocabulary profile and a ranking function in information retrieval.

In this study, the difficulty of vocabulary is used as a rationale for the difficulty of materials. We used "CEFR-J Wordlist Version 1.6" (Yukio Tono Lab., 2020) as a reference for the difficulty of vocabulary. This vocabulary list was constructed for English education in Japan by extracting common vocabulary used in CEFR level texts in each country/region based on corpora generated from English textbooks used in China, Taiwan, and Korea. The list contains 6868 headwords, each of which has 4 CEFR levels of difficulty, A1, A2, B1, and B2.

The difficulty of each word is converted to a numerical value, such as A1 to 1, A2 to 2, B1 to 3, and B2 to 4. Several words have multiple levels according to their multiple meanings, whose difficulties are set as the average of these multiple ones. Besides, identical words with different spellings are considered different words. Therefore, the difficulty of the word t, represented as $D(t)$, should be expressed as $D(t) \in [1, 4]$.

4.1.2 Difficulty of Materials

We computed the difficulty of materials by using the difficulty of each word introduced above, its TF-IDF score (Rajaraman & Ullman, 2011) in each material, and the length of each material. TF-IDF is a ranking function in information retrieval to estimate the relevance of documents to a query, and its score means how relevant the query is to the document. In this study, we assume that every word in the "CEFR-J Wordlist Version 1.6" is used as the query word and interpret the score of the document as the importance of the word in the document.

In this study, we deal with each material as a bag-of-words consisting of the words in the vocabulary list. Namely, when a set of all words in the vocabulary list is represented as Σ, the material d is expressed as $d' \cap \Sigma$, where d' is a bag-of-words of the material corresponding to d.

The difficulty of a material d is expressed as the following equation:

$$D(d) = f\left(c_1 \sum_{t \in d} D(t) \cdot \mathrm{TFIDF}(d, t) + c_2 \frac{|d|}{\max_{d' \in L} |d'|}\right) \quad (f(x) = \log_{10}(1 + x))$$

where the $\mathrm{TFIDF}(d, t)$ is the TF-IDF score of material d given a word t as a query, c_1 and c_2 are constants, and L is a set of all the materials. $|d|$ represents the length of the material d. This formula can be interpreted that the difficulty of each word and its significance in a certain document contributes to the overall difficulty of the document. Besides, since the length of materials is considered to affect its difficulty, the value obtained by normalizing it is also used. Thus, the difficulty of the document will be computed as a total of products of the difficulty of the word and its significance.

To make sure that this equation works, we measured the difficulty of English picture books prepared for extensive reading. These books have metadata about these difficulties. First, the books are classified into 8 groups by these difficulty levels. Each group was labeled in order from A1 to B2/C1 in advance, and the books in the group become more difficult in this order. These levels are according to CEFR levels (Council of Europe, 2001), which shows the achievement of foreign language learners mainly across Europe. Then, we computed the difficulty of each book with the equation above and found the average of the difficulty in each group. At this time, the constants c_1 and c_2 were respectively set as 0.1 and 1. Table 1 shows how many books there are and the average of the estimated difficulty in each group. The results show that as the difficulty level in the metadata increases, the estimated difficulty also increases. To verify that the estimated rank of difficulty matches the rank of difficulty in the metadata, we also computed Kendall's rank correlation coefficient between them, which was a statistically significant value of 0.9820 (p<0.001). We concluded that the equation above could calculate the difficulty of materials correctly from these features.

Table 1. *Results of an evaluation of an equation that computes the difficulty of books*

Difficulty	# of books	Average of estimated difficulty
A1	193	0.857
A1/A2	10	1.196
A2	70	1.210
A2/B1	92	1.210
B1	10	1.743
B1/B2	10	1.807
B2	10	1.908
B2/C1	10	1.995

1.1 Learner's Proficiency Estimation

In general, learners use English materials whose difficulty levels fit their English proficiency levels. According to previous work, there is a linear relationship between the degree of reading comprehension and the percentage of vocabulary in an English material known by the reader (Schmitt, Jiang & Grabe, 2011). This implies that the difficulty of materials the learner is using is a good indicator of the learner's English proficiency. In this study, we adopted the materials used by the learner as input information for estimating the learner's English proficiency level.

According to the difficulty of materials mentioned above, we extract the top 5 most difficult materials from the ones read by the learner. We consider that the difficulties of these 5 materials will best reflect the learner's English ability since learners are considered to change materials to use as their English skills improve. Then, the average difficulty of these 5 materials is computed as the learner's English proficiency. From now on, the learner s's estimated English proficiency will be denoted as $P(s)$.

1.2 Recommendation Generation

1.2.1 Recommendation Weight

The difficulty-based material recommendation is designed to recommend materials whose difficulties are the closest to the learner's estimated English proficiency. The recommended materials should not be too easy or difficult since such materials will have a bad influence on the learning effect. In this study, we introduce the material d's recommendation weight (denoted as $R(s,d)$), i.e., a value that shows how highly the material d is recommended to the learner s. This value should take a large value when the difficulty of the material is close to the learner's English proficiency level. Thus, we define this value as follows:

$$R(s,d) = \log_{10}\left|\frac{1}{P(s) - D(d)}\right|.$$

This equation takes a large value when the difficulty of the material d (i.e., $D(d)$) is close to the learner s's English proficiency (i.e., $P(s)$), and takes a small value when it is not. If the recommendation weight $R(s,d)$ takes a larger value, the material d is more highly recommended to the learner s. In the implementation, the value $P(s) - D(d)$ is adjusted so that it does not take a value of 0.

1.2.2 Explanation for the Recommendation

The recommendation algorithm we propose is designed to provide feedback about recommended materials and reasons why these materials were recommended to the learner. This is to make the recommendation persuasive for the learners so that they can agree with the recommendation and learn with self-motivation. This supplementary information includes the learner's estimated English proficiency, the recommendation weights of the recommended materials, and sentences that explain why these recommendations were suitable for the learner.

The recommended weights provided are normalized so that the minimum value is 0.0 and the maximum value is 100.0, to make them easier to understand. The learner's proficiency and the difficulty level of materials are similarly normalized, but the minimum and maximum difficulties of the materials are used at that time.

We prepared 5 types of sentences that explain the reasons why the materials were recommended to the learner. According to the theory of region of proximal learning, when learners make a decision of whether to study, they depend on their belief whether they already know the items: that is, they will choose to not study if they believe they know the item already, and vice versa (Metcalfe & Kornell, 2005). Thus, the explanatory sentences should lead the learners to select the recommended materials to use. The sentences depend on the difference between the difficulty of the recommended material and the learner's English proficiency, i.e., the value of $D(d) - P(s)$. This takes a value close to 0 when the difficulty of the recommended material d (i.e., $D(d)$) is close to the learner s's English proficiency. When the value is smaller than 0, it means that the recommended material is easy for the learner, and when it is larger than 0, the material is difficult. The recommender provides different sentences according to the difficulty of recommended materials for the learner, as shown in Table 2.

Table 2. *Sentences that explain why the materials were recommended. They depend on the difference between the difficulty of the material and the learner's English proficiency.*

$D(d) - P(s)$	Explanatory Sentence
~ -0.3 (easy)	"This book is easy, but you can learn basic vocabulary with fun from this."
-0.3 ~ -0.1 (a little easy)	"This book is a little easy, but you can learn important vocabulary with this book."
-0.1 ~ 0.1 (average)	"This book is perfect for your English skills!"
0.1 ~ 0.25 (a little difficult)	"This book is a little difficult, but worth trying!"
0.25 ~ (difficult)	"This book is very difficult. Let's challenge!"

These sentences were written to motivate learners to use the recommended materials. The materials whose difficulty is close to the learner's proficiency are explained so that they perfectly fit the learner's level. Besides, even if the materials too easy or difficult are recommended, the recommender explains that they are worth reading.

2. Implementation and Case Study

2.1 Materials

As an example of actual implementations, we first suppose that this recommendation is used for an extensive reading (ER) program, and are going to use English picture books as the learning materials. As of May 2022, 534 English picture books for an ER program are stored at our e-book library, and they are classified into several categories by their difficulties according to the metadata based on the levels of CEFR. The numbers of books are shown in Table 3.

Table 3. *The numbers of picture books classified by CEFR levels*

Difficulty	# of books
pre-A1	27
A1 or A1+	205
A1/A2	10
A2 or A2+	75
A2/B1	126
B1 or B1+	37
B1/B2	27
B2	12
B2/C1	10
N/A	5
Total	534

The books which have difficulty level A1 or A1+ are the most common of all (for beginners, 205 books), and the books which have difficulty level A2/B1 are the second most common (for elementary-intermediate learners, 126 books). The 5 N/A level books did not have information about the level.

2.2 Case Study

Using the picture books introduced above, we generated material recommendations with the proposed mechanism. We set 2 conditions, "easy" and "difficult", and compared the recommendation result in each one. In the "easy" condition, a virtual reader was supposed to have read 9 easy books, and 9 difficult books in the "difficult" condition. The difficulty of the picture books read by the virtual reader was according to the metadata of the books. Then, material recommendations for the reader were generated in both conditions. The reader's English skill level was also estimated.

Table 4. *The estimated English skill levels and the recommendation results*

Condition	Read books and its difficulty	Estimated English skill level	Average difficulty of recommended books
Easy	9 books with A1	42.69 / 100	42.702 / 100
Difficult	3 books with B2 & 6 books with B2/C1	81.11 / 100	81.222 / 100

Table 4 shows the reader's estimated English skill level and average difficulty of the recommended picture books. In the "easy" condition, the reader's estimated skill level was lower than that in the "difficult" condition. This shows that an English skill level of a reader who has read easy books was estimated to be low, and the opposite was true for difficult books. The same can be said about the difficulty of recommended books: that is, easy books were recommended in the "easy" condition, and difficult ones were in the "difficult" condition. The average difficulty of the recommended books was very close to the reader's estimated skill level in both conditions. From this result, we can say that the proposed recommendation mechanism could recommend picture books whose difficulties were close to the reader's English skills.

3. Discussion

This recommendation mechanism depends on 3 sources: difficulty of vocabulary, difficulty of materials, and learners' learning logs. We consider that a source which is the most important for making the recommendations persuasive for learners, that is, for recommending materials whose difficulties are closest to the learners' skills, is the learners' learning logs. This mechanism estimates the learners' skill levels from materials they have used before, but we admit there is still room for improvement on the algorithm. Learners' personality including their skill levels is not so simple that this recommendation should take into account more detailed information about this. Besides, even if this exploitation of the further information is implemented, the estimated learners' skills might conflict with their actual levels. The system then should allow the learners to modify their knowledge states so that the estimated skills correctly reflect it.

Moreover, the proposed recommendation can make one-way recommendations from the system to learners, but we should also consider introducing an interactive recommendation mechanism. This recommendation is designed to recommend materials that have moderate difficulty levels for each learner. However, sometimes it might be not enough for learners who are willing to improve their skills actively or relearn what they have learned before. In the current implementation, the difficulties of the recommended materials will be close to the learners' skills. Therefore, the algorithm should allow the learners to adjust the difficulty levels of recommended materials according to the learners' learning objectives.

The implementation and the experiment will be conducted in the setting of an ER program, but we believe that this recommendation will be effective even with more general English materials.

4. Conclusion and Future Work

In this paper, we proposed an English learning material recommendation that takes into account learners' English skills changing over time and generates its explanations to make it persuasive. In this algorithm, we adopted TF-IDF, one of the information retrieval techniques, to realize these features of the recommendation. We also described the implementation of this recommendation and verified its learning and motivating effect.

The overall system using the proposed recommendation is made of multiple components. As all the components including front-end and back-end are fully implemented, conducting an experiment in an actual educational environment is our urgent task. We also have to prepare the plan for the evaluation of the experimental results, for instance, measuring learners' reading speed and comprehension and comparing the results before and after the experiment. The learners' system usage will be an important index for measuring the effect on their motivation.

For future work, we set two goals for the purpose of the improvement of the recommendation: 1) refinement of the algorithm and 2) utilizing more detailed information on learners. First, we recognize that there is still room for improvement in the estimation of the difficulty of learning materials. The estimation in the current implementation only depends on the vocabulary included in the materials and their length. The difficulty of the materials should be measured from more viewpoints, such as the complexity of grammar and how much expert knowledge will be needed to understand the material. We may be able to use a grammar profile to extract grammar items from English sentences in the materials.

Second, we may be able to combine the proposed recommendation with learner models. Learner models can manage learners' various characteristics including learning styles, preferences, and personality as well as learning skills. For example, the difficulty of one material may be different from learner to learner because of their background knowledge or preferences. By introducing the recommendation to a system using open learner models (Bull & Kay, 2010), the recommendation will be more persuasive for learners because it can utilize their learning states and provide them as more detailed explanations of the recommendation to the learners. This will improve learners' trust for the system and their motivation for learning. Moreover, by letting the learners check their learning states and the suitable levels of materials, the system can assist in improving learners' meta-cognition.

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