Good and Similar Learners' Recommendation in Adaptive Learning Systems

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Abstract: Classic challenges in adaptive learning systems are about performing adaptive navigation that recommends a topic or concept to be learned next and learning materials relevant to the topic. Both recommendations have to meet active learners' needs. As adaptive navigation problems have been solved using artificial intelligence techniques, learning material recommendation problems can be solved using recommender techniques that have been successfully applied to other problems. Until recently there have been a number of techniques that come with certain advantages and disadvantages. This paper proposes a new technique for recommending learning materials that combine content-based filtering and collaborative filtering based on the similarity between learners and learners' competence. It aims to diminish the drawback of classic collaborative filtering, which is based on the similarities between learners and does not consider learners' competence. It also diminishes problems arising from collaborative filtering based on good learners' competence, which potentially produces recommended objects that do not meet the learners' condition. The results of a recent experiment show that the proposed technique performs well, as indicated by the MAE score of 0.96 for a rating scale of 1 to 10.

1 INTRODUCTION

Adaptive learning technologies aim to individualise learning by taking into account the learner's needs, learning styles, preferences, competence, and learning goals in tailoring content and teaching strategies. The adaptation is delivered in various types of adaptive techniques, including adaptive navigation that selects and recommends concepts to be learned next by the active learner. The recommended concepts are the most appropriate concepts for the learner regarding their characteristics. A challenge emerges when adaptive learning systems use existing online materials. The challenge deals with how to find appropriate learning materials for the recommended concept. Challenges occur in matching multi-dimensional learner models and a large number of learning materials with various formats (Knutov et al., 2009). Previous studies have implied that an individual user model should find appropriate learning objects (Sicilia et al., 2010; Wang et al., 2007).

As learning tends to be a social process, other learners' experiences become important and act as references. According to social learning theories, a learner learns better when accompanied by experienced learners (McLeod, 2007; Vygotsky, 1978). Furthermore, learners learn by observing the behaviour of others and the outcomes, and they most likely copy the behaviour if the outcome is positive. This is supported by another study which reports that learners can build their knowledge from the help and support they receive from peers who perform well; these are called peer helpers (Topping, 2005).

The principles of social learning have been implemented in recommender systems with collaborative filtering approaches. A recommendation for a learner is performed based on recommendations from peers who share certain similarities with the learner (Indrayadi and Nurjanah, 2015; Lops et al., 2011; Wang et al., 2007). This approach is considered to produce appropriate recommendations since similar learners will like similar objects. However, in the context of learning, the recommended objects are probably not the objects needed to boost the learner's performance. Hence, other approaches that consider recommendations from good learners will be more useful. Learning material recommendation systems based on good learners' recommendations have been studied before

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(Ghauth and Abdullah, 2011). According to precision and recall scores, it has been proved that recommendation results are better than recommendations based on similarities between learners.

The inclusion of good learners in learning the process is not a new concept. Topping's theory on peer learning spots the importance of peer helpers in learning (Topping, 2005). Peer helpers are chosen out of the best learners and they have superior mastery in a small part of the curriculum. In terms of the recommender systems of learning materials, Topping's theory is implemented by including good learners' experiences in the recommendation. It is different from conventional collaborative filtering, which considers the similarity between learners in rating learning materials without considering how good the peer learners are.

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In this study, we combine collaborative tagging and filtering and introduce a new approach to collaborative filtering by applying good learners' recommendations combined with similar learners' recommendations. By considering good learners' recommendations, the recommender will produce learning materials that meet the learners' needs. On the other hand, the conventional method produces recommendations appropriate to the learners' characteristics in that learners like the recommended objects. Hence, we argue that a combination of the two methods will improve the quality and the suitability of the recommendations for learners.

The remaining part of this paper is organised as follows. Section two, on related work, discusses current studies on recommender systems. Section three, on recommenders of learning materials, discusses our proposed framework for recommending learning materials based on recommendations from good learners who have been rated as similar to the active learner. Section four discusses the experiments and the results. It is followed by section five, which includes the conclusion and discusses future work.

2 RELATED WORK

The process of recommending learning objects can refer to previous studies on recommendation systems for various objects, such as movies, learning materials, books, goods, et cetera. A recommender system is a tool that identifies items that are similar to the active user's interests. Recommendation systems help users to choose objects they might find in their interests or that are useful. The main purpose of recommendation systems is to choose certain objects that meet the users' requirements. The quality of the recommendation depends on the experience of the active user in rating the objects and the rating patterns the objects have received.

There are two main approaches in recommender systems: content-based and user-based approaches. The first approach recommends objects that share similarities with other objects liked by the active user in the past (Lops et al., 2011). The key to this approach is that the objects that might interest the user must be similar to the objects he or she has liked previously. Content-based approaches identify new, interesting items based on the similarities between the features of the items. Hence, new items share similarities with the items that the user has previously viewed. It treats the recommendation problem as a search for related objects. When a user rates an item, the algorithm constructs a search query to find other items with similar keywords or subjects that have been given similar ratings. Information about objects is stored and considered in the recommendation process. In previous studies, content-based approaches have been combined with the user's preferences. In learning material recommender systems, for example, the preferences could be media, language, or the topic being learned by the user (Wang et al., 2007).

On the other hand, user-based approaches or collaborative filtering make recommendations based on similarities between the active user and other users (Sicilia et al., 2010). The principle is that users with similar profiles will like similar objects. The similarities could be measured according to users' competence (Cazella et al., 2010), preferences and rating pattern (Indrayadi and Nurjanah, 2015; Wang et al., 2007), or other parameters (Verbert et al., 2012). In terms of the use of rating in collaborative filtering, users are required to express their preferences by rating items.

There have been many previous studies on recommender types of learning systems (Chen et al., 2005; Lu, 2004; Verbert et al., 2012) proposed a framework for a recommender system that helped learners to find learning materials that meet their needs based on the learners' abilities. Another study implementing collaborative filtering for recommending learning materials was carried out by (Soonthornphisaj et al., 2006). This research also proposed a mash-up technique to aggregate recommended materials from several websites.

A combination of content-based filtering and collaborative filtering can be found in (Liang et al., 2012) who applied knowledge discovery techniques to perform personalised recommendations for a courseware selection module. On the other hand, to compute relevant links for active users (Khribi et al., 2008) used web mining to process the recent navigation histories of learners combined with the similarities and dissimilarities between user preferences and the learning resources.

A further study exploiting collaborative filtering and learners' preferences was proposed by (Wang et al., 2007). They suggested a personalised recommendation mechanism based on content and user similarity to choose learning materials out of a large number of materials available on the web. They combined two algorithms, a preference-based algorithm and a correlation-based algorithm, to rank the recommended results to advise a learner about the most suitable learning objects. This model uses a specific ontology of a certain course to infer objects required for a learner. The inference is based on his or her past studying history, which is recorded as the learner's personal preference pattern. Another consideration in selecting learning objects is to refer to the experiences of similar learners. The similarities between learners can be inferred from similar values for certain parameters.

Until recently, improvements for recommender systems for learning materials have been made by taking into account learners' competence. In a previous study (Tai et al., 2008), learners' competence was used to retrieve relevant learning materials from the web. A combination of collaborative filtering and learners' competence was proposed by (Cazella et al., 2010). A learner's competence is relative to other learners' competence as it is assessed by comparing it to the average of all the learners' competence. On the other hand, Ghaut in (Ghauth and Abdullah, 2011) proposed a collaborative filtering method based on good learners' recommendations, rather than similar learners' recommendations.

3 THE FRAMEWORK

The method we propose is for learning material recommendations. The recommender is part of the adaptation engine in our proposed adaptive learning architecture, as described in Figure 1. The difference between such architecture and the conventional adaptive learning systems lies in the existence of an adaptation engine that produces recommendations for topics or concepts to be learned next and relevant learning materials.

There are two modules in the adaptation engine:

1. An adaptive navigation engine that decides which topic or concept the learner will learn next. This module applies the Bayesian network, but this is not discussed in this paper.
2. A recommender system for learning materials. Once the adaptive navigation engine recommends a concept, the recommender starts working to choose learning materials relevant to the concept and the learner. The proposed collaborative filtering technique is applied in this module.

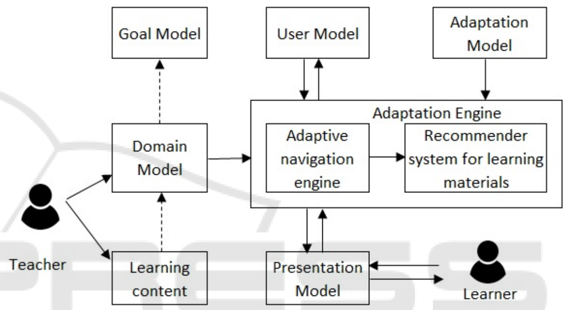

Figure 1: Architecture of an adaptive learning system.

A domain model is important for the recommender system as it contains learning concepts, learning content (materials), tags, and ratings. The concepts and learning content are designed by teachers, while the tags and ratings are given by teachers and learners. In Figure 2, tags are described as hubs that link learning materials to concepts.

Before the recommendation begins, the teacher has developed learning concepts and uploaded learning materials in the domain model. Afterwards, learners tag and rate the learning materials. All the tags and rates are recorded in the domain model and will be used for the recommendation process.

Once the active learner receives the next concept to be learned, the recommender will run content-based filtering to find all the learning materials tagged with the concept. Furthermore, the recommender will calculate its ratings by good learners and the similarity between good learners and the active learner. When a good learner has not rated a learning material, the recommender will predict the rating based on the similarity between the material and other materials that have been rated by the good learner.

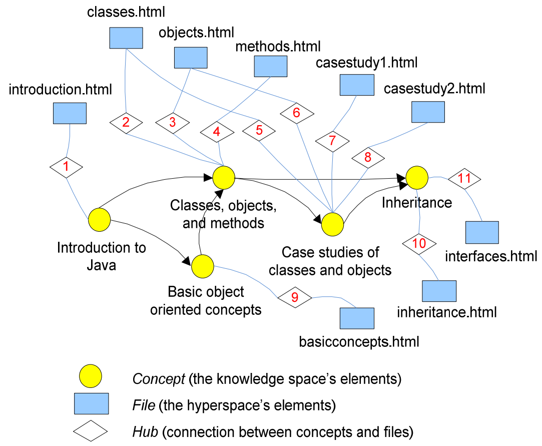

Figure 2: Domain model.

We define good learners as those who show good track records in all topics they have learned in the course and they have mastered a given concept, that is the concept being learned by the active learning. The processes to measure and maintain learners' achievements are parts of student modelling in the adaptive learning system in which the recommender resides.

The framework of the proposed recommendation strategy is described in Figure 3. To conclude, the better a good learner in mastering a concept and the more similar she/he is with the active learner in rating learning materials, the more contribution she/he has in the recommendation process.

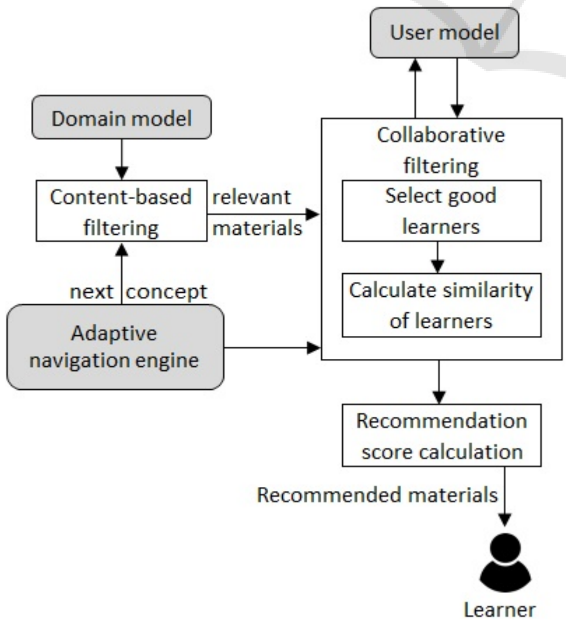

Figure 3: Recommender framework for learning materials based on similar-good learners' recommendations.

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4 THE RECOMMENDATION MODEL

The proposed technique consists of three steps: content-based filtering, collaborative filtering, and recommendation score calculation. The proposed technique.

4.1 Content-based Filtering

Content-based filtering is aimed at selecting learning materials that meet the concept being learned by the active learner. One concept can relate to a number of learning materials and vice versa, as shown in Figure 2. The hub is created through collaborative tagging by learners. In the first step, the weight of each tag in the learning materials is calculated using the following formula:

$$w_{i,lm} = \frac{|C_{i,lm}|}{Max|C_{lm}|} \, x \, \frac{|C_{i,lm}|}{Max|C_i|} \tag{1}$$

where $|C_{i,lm}|$ is the frequency of tag C_i on material lm, which is similar to the number of learners tagging lm with C, Max$|C_{lm}|$ is the maximum frequency among the tags given to material lm, while Max$|C_i|$ is the maximum frequency of concept C_i put as a tag on all the materials. The first step produces weights for all the tags in all the learning material and it would be normalised by comparing $w_{i,lm}$ to the maximum of the weights.

In the second step, the relevance scores (*RS*) of learning materials are calculated. The higher the RS is, the more relevant the learning material to the concept being learned. The relevance of learning material *lm* is calculated according to the following formula:

$$RS_{lm} = \frac{Wu.Wlm}{|Wu||Wlm|} \tag{2}$$

Variable w_u is a weight vector of learner u's competence. It is a dynamic vector of the learner model, which is dynamically updated in adaptive learning systems. Since this paper focuses on the recommender, we do not discuss when and how the vector is updated. Another vector counted in the relevance score is w_{lm}, a weight vector of tags given to learning material *lm*. The second step produces *L*, a set of materials that have the highest RS. At the end of this process, a set of learning materials relevant to the concept being learned by the active learner has been defined. The kinds and number of tags are the only parameters to determine the relevance or irrelevance.

4.2 Collaborative Filtering based on Recommendation from Similar Good Learners

This part is the heart of the proposed collaborative filtering technique. It aims to select good learners and calculate the similarity scores between good learners and the active learner based on ratings they have given to learning materials. Good learners are those who have mastered the concept being learned by the active learner and consistently achieve well in all the concepts they have learned so far. From the previous parts, we have *M*, a set of learning materials with the current learning context. We define *G*, a set of good learners selected based on their overall competence and their competence on the current topic being learned by the active learner, *al*.

Once *G* has been defined, the similarity score between the active learner and good learners will be calculated. The similarity between learners is identified from the ratings they have given to learning materials. The similarity between the active learner, *al*, and a good learner, *gl*, is calculated using the following formula:

$$sim(al,g1) = \frac{\sum_{m_i=1 \in M}^{|M|}(r_{al,m_i} - \overline{r_{al}})(r_{g1,m_i} - \overline{r_{g1}})}{\sqrt{\sum_{m_i=1 \in M}^{|M|}(r_{al,m_i} - \overline{r_{al}})^2 (r_{g1,m_i} - \overline{r_{g1}})^2}} \quad (3)$$

where $r_{al,mi}$ is the rating of material *mi* given by active learner, *al*. Furthermore, $r_{gl,mi}$ is the rating of material *mi* given by good learner, *g1*. The formula also applies the average of the ratings given by active learner, *al*, $\overline{r_{al}}$, and the average of the ratings given by active learner, *g1*, $\overline{r_{g1}}$. At the end of this module, the similarity scores between the active learner and each good learner will have been defined.

4.3 Recommendation Score Calculation

The final stage of the recommendation process is the calculation of the recommendation scores. The recommendation score of learning material *lm* is calculated by considering the similarity between good learners and active learners, and the ratings given by good learners for *lm*. The formula is described as follows:

$$R_{lm} = \frac{\sum_{i=1}^{|G|} sim(al,g_i) * rating_{g_i.lm}}{\sum_{i=1}^{|G|} sim(al,g_i)} \quad (4)$$

where $sim(al,g_i)$ is the similarity score between the active learner, *al*, and good learner, g_i. On the other hand, $rating_{gi,lm}$ is the rating for the learning material *lm* given by the good learner, g_i (equation 5). The value of $sim(al,g_i)$ is set at 1 when the active learner has not rated any learning material. In case a good learner *g* has not rated learning material *lm*, then a rating prediction will be calculated (equation 6).

$$R_{lm} = \frac{\sum_{i=1}^{|G|} rating_{g_i.lm}}{|G|} \quad (5)$$

$$P_{g,lm} = \frac{\sum_{i=1}^{|M|} sim(lm,m_i) * rating_{g,mi}}{\sum_{i=1}^{|N|} sim(lm,m_i)} \quad (6)$$

where $rating_{gi,mi}$ is the rating of learning material *mi* given by good learner g_i and $sim(lm,m_i)$ is the similarity score of the learning material *lm* and m_i, which is given by:

$$sim(lm,m_i) = \frac{W_{lm}.W_{mi}}{|W_{lm}||W_{mi}|} \quad (7)$$

At the end of this stage, a set of learning materials with their recommendation scores has been defined.

5 IMPLEMENTATION AND TESTING

To test the proposed method, an experiment is designed. For this experiment, we design 100 documents for 10 topics in a programming course, including variables and data types, expressions and assignments, case analysis, functions, recursion, loops, array, searching, sorting, and a matrix in the forms of slides or short articles. Teachers have given some tags to the learning materials and afterwards the participants have been invited to tag and give ratings.

We invite 171 undergraduate students to participate in the experiment. They are students who are registering on the programming course or have completed the course. The experiment consists of various steps. Firstly, we need to recognise which are the good learners among them. As we have discussed previously, good or other types of learners are recognised in adaptive learning systems by processing learner models. However, as this research is focused on the recommender system itself, we conducted a pre-test covering the aforementioned 10 programming topics, two problems for each topic. At the end of this activity, each participant has a competence model that records his or her competence with respect to the 10 topics examined. The status for each topic consists of good mastering or 1 if they could correctly solve both given problems, half mastering or 0.5 if they correctly solve one of the given problems, and need to learn, or 0 if none of the given problems can be solved. Good learners are those who pass a threshold, for example 0.75, for the mean score of mastered and half-mastered topics.

Secondly, 51 of the participants are invited to participate in testing the recommender. They are requested to rate and tag learning materials for topics they have mastered or half-mastered. Then, the recommender testing is carried out for a topic they have not yet mastered. As we have previously discussed, the recommender of learning materials, as part of adaptive learning systems, should receive input from the adaptive navigation engine in the form of a topic where the active learner can go next. As we focus on the recommender, we simulate the input process with a query asking for a topic input from the active learner. Then the recommender suggests learning materials discussing the topic and they have not been rated by the learner, along with the predictive scores. The participants are requested to input ratings for the recommended materials on rating scale up to 10.

We use the *mean absolute error (MAE)*. MAE represents the deviation between the predicted ratings and the user-given ratings.

$$MAE = \sum_{i=1}^{N} \frac{|pi - ri|}{N} \tag{8}$$

The recent experiment produces an MAE score of 0.96 for the rating scale up to 10, which means that the predicted and user-given ratings are not significantly different. Compared to the standard for the MAE score concluded from previous studies, which is 0.73 for a rating scale up to 5, the proposed algorithm shows better performance. The MAE score will possibly change since more students will participate in the experiment.

6 CONCLUSIONS

In this paper we have discussed our proposed recommendation technique, which combines content-based filtering and collaborative filtering, which considers learners' competence and similarities in rating learning materials. The consideration of good learners' recommendations is inspired by the existence of helpers in peer learning. The technique aims to improve the suitability of the recommendations with respect to learners' needs. The recent experiment to test the proposed technique results in a low MAE score, 0.96 on rating scale up to 10. In comparison with the standard MAE score from previous studies, which is 0.73 on a rating scale up to 5, the MAE score of the proposed method is relatively low. The experiment is now still running so that more participants can be invited to participate.

Following the results presented in this paper, there is some work to carry out in the near future. Firstly, since this recommender is part of adaptive learning systems, this recommendation technique can be improved by enhancing the method for identifying good learners. This could be achieved by enhancing the number of problems that learners have to solve in each topic or using different types of problems, whereby good learners can be more precisely identified.

Secondly, the collaborative filtering can be extended by considering the similarities between learners' characteristics, for instance learners' competence, in addition to similarities between rating learning materials. By considering the learning method, and various dimensions of learners' characteristics, the recommendations are expected to more precisely meet learners' needs.

REFERENCES

Cazella, S. C., Reategui, E. B. & Behar, P., 2010. Recommendation of Learning Objects Applying Collaborative Filtering and Competencies. In the proceeding of *IFIP Advances in Information and Communication Technology*, pp. 35-43. Springer.

Chen, C. M., Lee, H. M. & Chen, Y. H., 2005. Personalized E-Learning System Using Item Repository Theory. *Computers and Education*, vol. 44, pp. 237-255.

Ghauth, K. I. & Abdullah, N. A., 2011. The Effect of Incorporating Good Learners' Ratings in e-Learning Recommender System. *Educational Society and Technology*, vol. 14, pp. 248-257.

Indrayadi, F. & Nurjanah, D., 2015. Combining Learner's Preference and Similar Peers' Experience in Adaptive Learning. In the proceeding of *The 7th International Conference on Computer-Supported Education*, pp. 486-493. ScitePress.

Khribi, M. K., Jemni, M. & Nasraoui, O., 2008. Automatic Recommendations for E-Learning Personalization Based on Web Usage Mining Techniques and Information Retrieval. In the proceeding of *Advanced Learning Technologies, 2008. ICALT '08. Eighth IEEE International Conference on*, pp. 241-245.

Knutov, E., Bra, P. D. & Pechenizkiy, M., 2009. AH 12 Years Later: A Comprehensive Survey of Adaptive Hypermedia Methods and Techniques. *New Review of Hypermedia and Multimedia* vol. 15, pp. 5-38.

Liang, M., Guerra, J. & Brusilovsky, P., 2012. Building multi-layer social knowledge maps with Google Maps API. In the proceeding of *Workshop on Semantic and Adaptive Social Web (SASWeb 2012)*.

Lops, P., Gemmis, M. D. & Semerano, G., 2011. Content-Based Recommender Systems: State of the Art and Trends. In *Recommender Systems Handbook*, pp. 73-105. Springer.

Lu, J., 2004. A Personalized E-Learning Material Recommender System. In the proceeding of *The 2nd International Conference on Information Technology for Application (ICITA 2004)*, pp. 374-379.

Mcleod, S., 2007. *Vygotsky*. From http://www.simplypsychology.org/vygotsky.html. Accessed on 16 June, 2012.

Sicilia, M. A., Garcia-Barriocanal, E., Salvador Sanchez Alonso & Cechinel, C., 2010. Exploring User-Based Recommender Results in Large Learning Object Repositories: The Case of MERLOT. In the proceeding of *1st Workshop on Recommender Systems for Technology Enhanced Learning (RecSysTEL 2010)*, pp. 2859–2864.

Soonthornphisaj, N., Rojsattarat, E. & Yim-Ngam, S., 2006. Smart e-learning using recommender system. In the proceeding of *The 2006 international conference on Intelligent computing: Part II*, pp. 518-523. Springer-Verlag.

Tai, D. W. S., Wu, H. J. & Li, P. H., 2008. Effective e□learning recommendation system based on self□organizing maps and association mining. *The Electronic Library*, vol. 26, pp. 329-344.

Topping, K. J., 2005. Trends in Peer Learning. *Educational Psychology*, vol. 25, pp. 631-645.

Verbert, K., Manouselis, N., Ochoa, X., Wolpers, M., Drachsler, H., Bosnic, I. & Duval, E., 2012. Context-Aware Recommender Systems for Learning: A Survey and Future Challenges. *IEEE Transaction on Learning Technology*, vol. 5, pp. 318-335.

Vygotsky, L., 1978. *Mind in Society.* 1st edition. USA: Harvard University Press. As cited by Mcleod, S. (2007). *Vygotsky*. http://www.simplypsychology.org/vygotsky.html. Accessed on June 16, 2012.

Wang, T. I., Tsai, K. H., Lee, M. C. & Chiu, T. K., 2007. Personalized Learning Objects Recommendation Based on the Semantic-Aware Discovery and the Learner Preference Pattern. *Educational Technology and Society*, vol. 10, pp. 84-105.

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