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Reconstructing Learning Resource with Collective Knowledge

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Abstract: There currently exist a lot of Web resources, which are useful for learning. However, it is hard for learners to learn these learning resources since the hyperspace is not always well-structured. Our approach to this issue is to mine collective knowledge from a group of learners who learned these resources to reconstruct the hyperspace, which consists of useful pages and links to be learned. This paper proposes a collective knowledge mining method that can extract these useful pages and links from learning histories gathered from the group of learners. The results of the analysis with case data indicate the possibility that this method extracts valid pages and links as collective knowledge.

Keywords: Collective Knowledge, Mining, Hyperspace, Learning Resource Reconstruction

Introduction

There currently exist a lot of hypermedia/hypertext-based resources on the Web, which are useful for learning. Such learning resources generally provide learners with hyperspace, which consists of Web pages and their links. In the hyperspace, the learners can navigate the pages in a self-directed way [1][7]. Such self-directed navigation involves constructing knowledge, in which the learners would integrate the contents learned at the navigated pages [7].

However, there are the following problems with regard to self-directed learning in the hyperspace provided by a Web resource. First, it might become difficult for learners to learn according to their learning goal since the hyperspace could be navigated/learned in multiple goals. The hyperspace is also too huge to learn, and is not always well-structured.

Our approach to these problems is to reconstruct the hyperspace so that the learners can readily navigate and learn the pages to achieve their learning goal. This paper proposes a method of mining collective knowledge from a group of learners who have learned the same learning resource with the same goal to reconstruct the hyperspace [6]. In order to obtain such collective knowledge, this paper demonstrates a learning history mining, which can extract pages and links, which could be useful for learning, from learning histories that could be gathered from the group of learners.

On the other hand, it is difficult to identify these useful pages and links from navigation histories generated by Web browser since they do not make clear which pages have been really learned and do not imply how pages learned have been integrated in knowledge construction. The history mining method accordingly requires learning histories that could represent the knowledge construction processes as properly as possible. We have already developed an Interactive History system (IH for short), which allows learners to annotate their navigation history with knowledge construction process [5]. The proposed history mining method uses learning histories generated from learners who use IH to identify useful pages and links.

This paper also describes an analysis of the learning history mining with case data. The results indicate the possibility that the mining method extracts valid pages and links as collective knowledge.

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1. Navigational Learning with Web resources

Let us first consider self-directed learning with Web resources. In hyperspace provided by Web resources, learners can navigate the Web pages in a self-directed way. The self-directed navigation involves making a sequence of the Web pages, which is called navigation path [5]. It also involves constructing knowledge, in which the learners would make semantic relationships among the contents learned at the navigated pages. The navigation path often includes the pages belonging to different Web sites. The constructed knowledge is also composed of diverse ideas/contents since each Web site is designed by its own author. The learners can accordingly learn more widely in an individualized way [5]. In this paper, such navigation with knowledge construction is called navigational learning.

The hyperspace provided by Web resources, however, is not always well-structured. There are often no links between relative Web pages. It could be also used in multiple learning goals. It is accordingly difficult for learners to learn in such hyperspace.

Our approach to reducing such difficulty is to reconstruct Web resources so that the hyperspace could be appropriate for learners to learn with their learning goals. The types of resource reconstruction operations are classified into the following: (a) revising and refining page contents, (b) extracting part of the hyperspace, and (c) reconstructing the hyperspace including deletion, addition, and change of links. In this work, we focus on extracting part of the hyperspace and reconstructing the hyperspace as resource reconstruction.

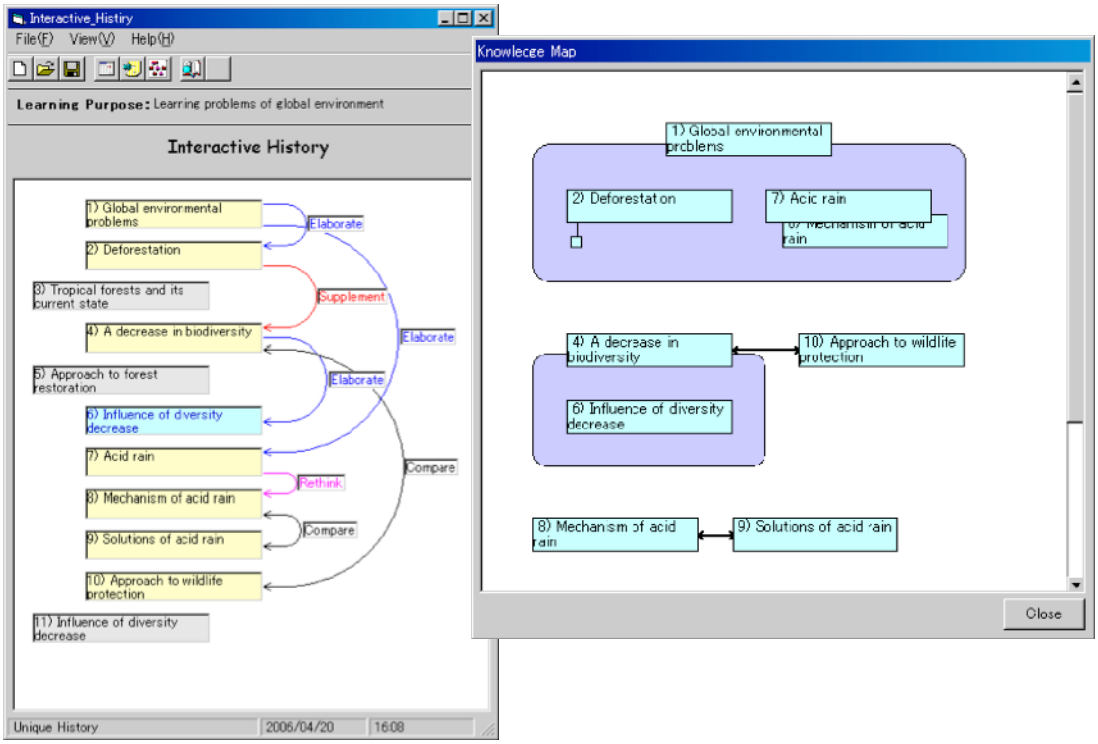
2. Framework for Learning Resource Reconstruction

Let us here propose a framework for reconstructing a Web resource, which uses learning history mining. The learning history mining method can extract the Web pages and links useful for learning from histories that could be gathered from a group of learners who learned the same Web resource with the same learning goal. Such useful pages and links can be viewed as collective knowledge from the group of learners, which could be instructive for other learners to learn the resource with the goal. The framework uses learning histories generated with IH to identify the useful pages and links, which compose a partial hyperspace of the Web resource as reconstructed resource.

The reconstructed resource is represented as highlighted hyperspace map where the useful pages and links are highlighted on the map of the original hyperspace. Such representation is informative for learners to achieve the learning goal.

In the following, let us demonstrate IH and learning history mining.

2.1 Interactive History



(a) Annotated Navigation History (b) Knowledge Map

Figure 1.Example of Annotated Navigation History and Knowledge Map.

In IH, the knowledge construction process is modeled as follows. Learners generally start navigating the pages for achieving a learning goal. The movement between the various pages is often driven by a local goal called navigation goal to search for the page that fulfills it. Such navigation goal is also regarded as a sub goal of the learning goal. The navigational learning process includes producing and achieving a number of navigation goals. We currently classify navigation goals into six: Supplement, Elaborate, Compare, Justify, Rethink, and Apply. We refer to the process of fulfilling a navigation goal as primary navigation process (PNP for short) [3]. PNP is represented as a link from the starting page where the navigation goal arises to the terminal page where it is fulfilled.

The knowledge construction process can be modeled as a number of PNPs [5]. In each PNP, learners would integrate the contents learned at the starting and terminal pages. For instance, a learner may search for the meaning of an unknown term to supplement what he/she has learned at the current page or look for elaboration of the description given at the current page. Carrying out several PNPs, learners would construct knowledge from the contents they have integrated in each PNP.

IH allows the learners to annotate a navigation history, which includes the pages sequenced in order of time they have visited, with their PNPs. Figure 1(a) shows an example of annotated navigation history.

IH monitors learners' navigation in the Web browser to generate the navigation history in the *Annotated Navigation History* window. Each node corresponds to the page visited. The learners can make annotations of the PNPs, which they have carried out, by means of the *Navigation Goal Input* window. (See [4] in more detail.)

Step 1. Generate a set of the first degree PNP from the focused set.
Step 2. Calculate the support value of each PNP.
Step 3. Exclude the PNP which value is less than Sth.
Step 4. Generate a set of (K+1) degree PNPs from a set of K degree PNPs.(Initial value:K=1)
If a set of (K+1) degree PNPs is not generated, go to *Step 7*.
Step 5. Calculate the support values of the(K+1) degree PNPs to be extracted from the set.
Step 6. Exclude the (K+1) degree PNPs which values are less than Sth.
Add one to the value of K, go to *Step 4*.
Step 7. Output the set of K degree PNPs.

Figure 2. Mining Algorithm.

In addition, IH can generate a knowledge map from an annotated navigation history automatically. Figure 1(b) shows a knowledge map generated from Figure 1(a). The knowledge map generally consists of several islands including some PNPs. We call them knowledge islands (KI). We define the number of PNPs included in KI as a degree of KI.

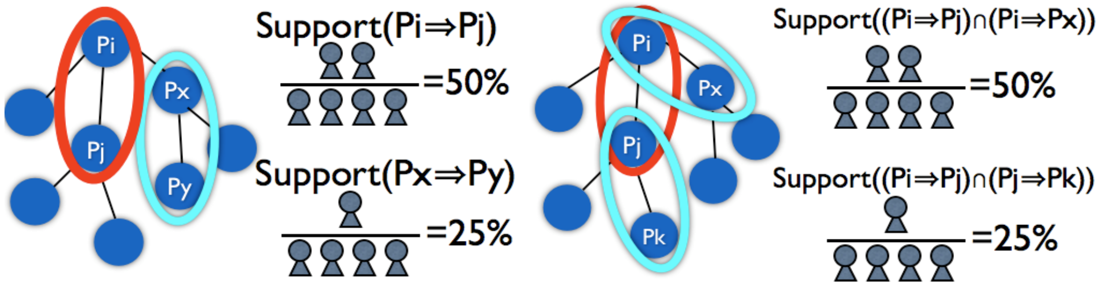
2.2 Learning History Mining

In order to reconstruct a Web resource, our framework prepares a repository that accumulates annotated navigation histories learners generated with IH, and that classifies them according to Web resources they learned and to learning goals they had. It generates a set of annotated navigation histories called *focused set* from the repository, which have been generated from the same Web resource as a learner uses and the same learning goal as he/she has. The focused set is inputted into learning history mining.

Each PNP in the focused set is regarded as association rule *Ps->Pt* that represents an association between two learning events in the starting and terminal pages. It means that learning event in the starting page *Ps* is concurrent with learning event in the terminal page *Pt*. In order to extract useful PNPs from the focused set, we introduce the minimum support (*Sth*) as thresholds.

Each annotated navigation history generated from each learner in the focused set is called transaction. The number of the learners in the set becomes the number of transactions. The support value is then calculated as follows:

Support (*Pi->Pj*) = the number of transactions including (*Pi->Pj*)
/ the number of transactions



(a)Case of the first degree PNP (b)Case of the second degree PNPs

Figure 3.Examples of Support Value Calculation.

The higher support value means that more learners carry out the PNP. The learning history mining method outputs the PNPs whose support values are higher than *Sth*.

Figure 2 shows the procedure of learning history mining. First, a set of the first degree PNP is generated from the focused set, which includes all the PNPs in the set. The support value of each PNP is then calculated. If the value is less than *Sth*, the PNP is excluded. A set of the second degree PNPs is then generated. The second degree PNPs mean the two PNPs connecting via the starting or terminal pages. The support values of the second degree PNPs to be extracted from the set are calculated, and are excluded if the values are less than *Sth*. In the same way, a set of (K+1) degree PNPs is generated from a set of K degree PNPs. When the set of (K+1) degree PNPs is not generated, the history mining outputs the set of K degree PNPs as useful pages and links composing a part of the hyperspace.

Figure 3(a) shows an example of calculating the support value of the first degree PNP. Figure 3(b) also shows an example of calculating the support value of the second degree PNPs. In these examples, the number of transactions included in the focused set is four. *Sth* is 30 %. In Figure 3(a), the value of Support (*Pi->Pj*) is 50 % because there are two learners who execute the PNP. The value of Support (*Px->Py*), on the other hand, is 25 % because there is only one learner who executes the PNP. In this case, the PNP (*Px->Py*) is excluded since the support value is less than *Sth*.

A set of the second degree PNPs is then generated, and the support value of each of the second degree PNPs is calculated. As shown in Figure 3(b), there are two learners who execute the PNPs (Pi->Pj) and (Pi->Px). The support value of the second degree PNPs is 50 %. There is one learner who executes the second degree PNPs (Pi->Pj) and (Pj->Pk) whose support value is 25 %. In this case, the second degree PNPs (Pi->Pj) and (Pj->Pk) is excluded.

2.3 Hyperspace Reconstruction

Figure 4 shows a hyperspace map of the reconstructed Web resource, which was obtained from the focused set that included learning histories generated by 16 graduate and undergraduate students who learned the Web resource about stock investment with the goal of learning the basics about the stock investment. Sth was 25%. The total number of the pages included in the resource was 85, and the average number of links per page was 5.84. It had a quite complex hyperspace. The number of the navigation histories in the focused set was 16. The largest degree of KI was 11 in those histories.

The highlighted part of the hyperspace map in Figure 4 shows the sixth degree PNPs (including pages and links) output by the learning history mining, which is represented in detail as shown in Figure 5. Such reconstructed hyperspace could facilitate navigational learning process with the same learning goal.

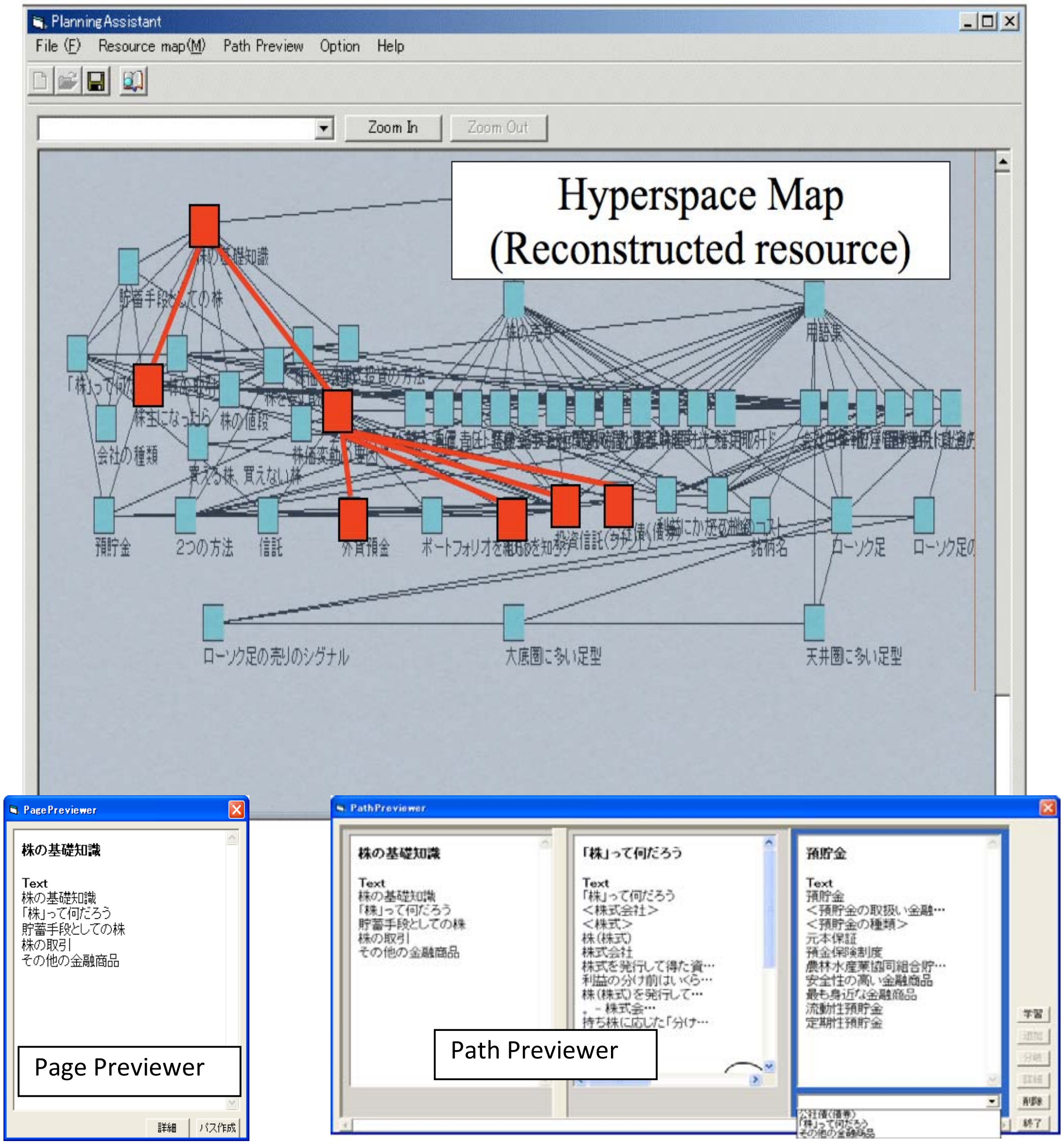


Figure 4. A Hyperspace Map Representing Reconstructed Resource.

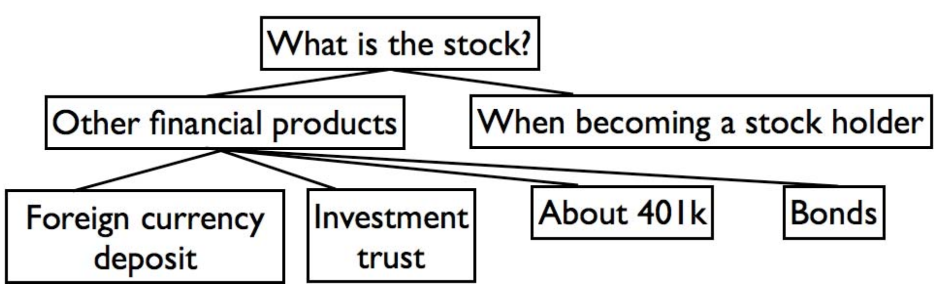


Figure 5. Details of Reconstructed Hyperspace.

In order to help learners follow the reconstructed hyperspace, our system provides them with page previewer, and path previewer in addition to hyperspace map of reconstructed Web resource as shown in Figure 4. Double-clicking any highlighted node in the hyperspace map, the learners can have an overview of the Web page corresponding to the clicked node, which is generated by the page previewer. The page previewer helps the learners to decide from which page they start navigation. When they decide the starting point of the navigation path, they can start the path previewer. The path preview window has a link list, which includes anchors of the links the current page contains. Selecting any one from the list, they can have an overview of the page, to which the selected link points. They can then put the page previewed into the sequence, making a navigation path. The learners are next expected to follow the navigation path to navigate and learn the Web pages with Web browser [2].

2.4 Analysis

We have conducted the analysis of the reconstructed hyperspace shown in Figure 4. The purpose of the analysis is to investigate whether the learning history mining is suitable for constructing the Web resource. In this analyasis, we used the following data: (i) PNPs or pages that were output by the learning history mining (such as Fig.5), and (ii) maximum degree of KI included in learning histories used for the mining. The maximum degree of KI in the navigation history can be viewed as a core of the knowledge structure constructed in hyperspace. We have accordingly checked whether and how much the PNPs or pages output by the mining were included in the maximum KI.

As for 4 subjects among 16 subjects, all the PNPs output were included in their maximum KIs. As for the remaining 12 subjects, Table 1 shows the analysis summary. Since it seems the subjects whose learning histories did not include KIs more than the fifth degree were not good at knowledge construction, we excluded those subjects (6 subjects) to analyze. As for the subjects (B), (E), and (F), more than 50 % of the PNPs or pages output were included in the maximum KIs. Totally, there were the 7 subjects among 16 subjects whose core structure

Table 1. Analysis Summary.

	Maximum degree of KI		The ratio of PNPs and pages(output by the mining) included in the KI	
	Degree	Number of pages included	PNPs included	Pages included
Subject(A)	4	5	2/6(33%)	3/7(43%)
Subject(B)	7	8	5/6(83%)	6/7(86%)
Subject(C)	3	5	0/6	0/7
Subject(D)	1	2	0/6	0/7
Subject(E)	8	9	4/6(67%)	6/7(86%)
Subject(F)	7	8	1/6(17%)	4/7(57%)
Subject(G)	3	5	0/6	0/7
Subject(H)	11	14	0/6	0/7
Subject(I)	6	7	2/6(33%)	3/7(43%)
Subject(J)	11	13	0/6	0/7
Subject(K)	2	3	0/6	0/7
Subject(L)	1	2	0/6	0/7

in their knowledge construction process included more than 50% of the sixth degree PNPs shown in Figure 5.

2.5 Effects Expected

Let us here consider effects obtained from the learning resource reconstruction. We expect two effects from viewpoints of resource author/provider and learners. First, it is time-consuming for the resource author/provider to reconstruct the hyperspace suitable for individual learners. It is also quite difficult for them to decide how the hyperspace should be reconstructed in advance. The learning history mining enables the author/provider to reconstruct it by means of collective knowledge automatically extracted.

Second, the reconstructed hyperspace allows the learners to reduce their cognitive efforts for navigating hyperspace and integrating the contents learned at navigated pages. The learners are then expected to more readily construct their knowledge from the reconstructed hyperspace for achieving the learning goal.

3. Conclusion

This paper has proposed a method of reconstructing Web resources with learning history mining. The important point of this method is to extract useful pages and links from learning histories gathered from a group of learners who learned the same learning resource with the same learning goal, which can be viewed as collective knowledge.

This paper has also analyzed the validity of this mining method with case data. The results suggest that it could extract pages and links useful for self-directed learning in the hyperspace as collective knowledge. We believe such learning resource reconstruction contributes to not only learners but also resource author/provider.

In future, we would like to evaluate the effectiveness of the resource reconstruction method in more detail.

Acknowledgments

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References

[1] Hammond, N. (1993) Learning with Hypertext: Problems, Principles and Prospects. In McKnight, C., Dillon, A., and Richardson, J. (eds): *HYPERTEXT A Psychological Perspective*, 51-69.

[2] Kashihara, A., Hasegawa, S., and Toyoda, J. (2002) How to Facilitate Navigation Planning in Self-directed Learning on the Web. Proc. of the AH2002 Workshop on Adaptive Systems for Web-based Education, 117-124.

[3] Kashihara, A., and Hasegawa, S., (2003) LearningBench: A Self-Directed Learning Environment on the Web. Proc. of ED-MEDIA2003, 1032-1039.

[4] Kashihara, A., and Hasegawa, S. (2004) Meta-Learning on the Web. Proc. of ICCE2004, 1963-1972.

[5] Kashihara, A., and Hasegawa, S. (2005) A Model of Meta-Learning for Web-based Navigational Learning. International Journal of Advanced Technology for Learning, 2, 4, ACTA Press, 198-206.

[6] Powers, J.:The Wisdom of Crowds : Why the Many Are Smarter Than the Few and How Collective Wisdom Shapes Business, Economies, Societies and Nations, 2004

[7] Thuering, M., Hannemann, J., and Haake, J. M., (1995) Hypermedia and cognition: Designing for comprehension. Communication of the ACM, 38, 8, 57-66.