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ORIGINAL RESEARCH

Using a Recommendation System to Support Problem Solving and Case-Based Reasoning Retrieval

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Abstract In case library learning environments, learners are presented with an array of narratives that can be used to guide their problem solving. However, according to theorists, learners struggle to identify and retrieve the optimal case to solve a new problem. Given the challenges novice face during case retrieval, recommender systems can be embedded in case libraries to support the decision-making process about which case is most relevant to solve new problems. This emerging technology reports how experts' assessment of case relevancy was used to retrieve and suggest the most relevant cases for the learner as they engaged in an inquiry-based learning. Specifically, our case library learning system integrates a content-based filtering, which recommends items similar to those a user has selected based on item descriptions or other user data, and is most widely used in textual domains. Implications for practice are also discussed.

Keywords Recommender systems · Case-based reasoning · Problem solving · Case retrieval

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1 Introduction and Description of the Emerging Technology

1.1 Case-Based Reasoning and Problem Solving

Instructional strategies that employ inquiry-based strategies often pose ill-structured problems to students (Jeong and Hmelo-Silver 2016; Lazonder and Harmsen 2016). In contrast to well-structured problems, which have predefined correct answers, ill-structured problems are often contextualized, require multiple solution paths, and embody many different perspectives (Jonassen 1997; Jonassen and Hung 2008). Theorists have argued that in endeavoring to address these kinds of problems, learners develop higher-order learning skills, such as self-direct learning, hypothesis generation, evidence evaluation, and causal reasoning (Herrington et al. 2014; Ifenthaler et al. 2011; Jonassen 1997; Weinberger and Fischer 2006).

To date, comparison studies have found significant learning gains when properly supported in inquiry based settings (Belland et al. 2016; Lazonder and Harmsen 2016; Leary and Walker 2009). These supports, also known as scaffolds (Vygotsky 1978), are able to bridge the gap between what learners are able to do in isolation and what they are able to accomplish in the presence of a more knowledge peer. Reiser (2004) further argued that scaffolds can be used to structure or problematize information as a way to engender learning gains. When scaffolds are structured, learners are guided through (a) key concepts and (b) planning and/or performance. Alternatively, problematized scaffolds encourage learners to "see something as requiring attention and decision making that they might otherwise overlook" (p. 287). Approaches such as intelligent tutoring systems have also been shown to support learning outcomes (Ma et al. 2014). However, the information presented to learners via these systems is often granular and lacking context (Ma et al. 2014).

One additional way to problematize learning is through the use of case libraries. According to case-based reasoning (CBR) (Schank 1999), leveraging previous experience to solve new problems is an effective way to support problem solving. The theory posits that as learners are presented with complex problems, they can use previous cases to both interpret the new situation and derive solutions. In terms of scaffolding and problematization, a database of cases (also known as a case library) is provided to the learners. Using stories, the cases convey to learners important topics of a problem space and provide models of decision-making processes (Hernandez-Serrano and Jonassen 2003; Jonassen 2011). Based on their constructed meaning, the learners then reflect on how the lessons learned can be used to solve the ill-structured problems presented to them.

In order to bridge the zone of proximal development, an important issue in the problematization of case library learning environments is how learners are able to reuse the cases effectively in solving new problems (Hernandez-Serrano and Jonassen 2003). According to CBR, each case in an individual's memory has associated indices (labels) based on general context (place, individuals), lessons learned, explanations, or other key indicators. The indices, in turn, are used to (a) assess the extent to which cases are similar to the problem and (b) allow the learner to retrieve a case (Kolodner 1991). As part of this retrieval process, the reasoner (learner) must sort through available cases and their accompanying indices in order to identify the case that is most germane to the new problem (Tawfik and Kolodner 2016).

The quality of the retrieval process is mediated by the learner's ability to identify the most important characteristics of the referred case. If the learner is not able to do this, the search in the case library will yield inapplicable cases (Kolodner et al. 2004). Studies find that experts and novices differ in their ability to progress through the case-based reasoning process—specifically, in terms of their ability to fully understand the elements of a case. Experts are able to effectively reference the appropriate cases, draw on information to derive solutions, and apply the lessons learned (Kim and Hannafin 2011; Shokouhi et al. 2014). Alternatively, novices tend to focus on the surface level elements of a case and fail to understand how variables impact one another (Danish 2014; Hmelo-Silver and Pfeffer 2004). This poses a major problem because learners who cannot understand the dynamic concepts depicted in a case are unlikely to retrieve the ideal case and reuse it to solve a new problem.

To overcome the challenges of case reuse associated with novices, researchers have begun to investigate how to optimally design case libraries. For instance, studies have explored how the integration of question scaffolds (Tawfik 2017) and multimedia (Gartmeier et al. 2015; Lajoie et al. 2014) can be used to support case retrieval. Although these systems have been shown to result in learning gains, an issue remains in terms of how experts and novices identify an ideal case and determine its relevancy (Ma et al. 2014). A recommender system is another approach that may support case retrieval. Similar to intelligent tutoring systems, recommender systems tend to supply relevant and targeted information to an individual. When learners lack sufficient knowledge, recommender systems can augment the decision-making process by providing new information about how to solve the problem (Resnick and Varian 1997). Of the approaches to recommendation systems, collaborative filtering (CF) is one of the most widely recognized techniques (Goldberg et al. 1992; Konstan et al. 1997; Schafer et al. 2007). Through this technique, items are recommended based on the recommendations of other similar users (user-based CF) or on similar ratings received by items (item-based CF). CF has the ability to provide recommendations for items that are complex to analyze, and it occasionally provides serendipitous recommendations. This technique has been used in several domains, including recommending movies (Hill et al. 1995), music (Shardanand and Maes 1995), and books (Woodruff et al. 2000). Another commonly used recommendation technique is content-based filtering. Most widely used in textual domains, this technique recommends items similar to those a user has selected based on item descriptions or other user data (Pazzani and Billsus 2007).

Although these technologies offer clear benefits, collaborative filtering suffers from some issues, such as data sparsity or data quality. Many of the implemented case-based reasoning and recommendation systems treat users equally, ignoring differences in the expertise of users. Within the context of learning systems, this could create noise in users' opinions (e.g. careless or malicious ratings), which could affect the performance of the system and the quality of recommendations. Indeed, domain experts have deeper knowledge such that their ratings will be considerably more consistent than those of novice users. Using an expert-based recommendation system of this kind would remove the gaming that could occur in a traditional collaborative system, as the feedback has been validated by "professional" raters.

1.2 Design and Development of Case Library Recommendation System

As noted earlier, learners struggle both to identify and retrieve the optimal cases needed to solev new problems (Tawfik and Kolodner 2016) optimal cases. Thus, given the challenges that novices face in terms of retrieving a relevant case, recommender systems can be embedded in case libraries to support the decision-making process in terms of identifying the case most relevant to any given new problems. The following sections detail the design and development process of how we combined the benefits of case libraries and recommendation systems.

In the previous environment, learners were provided a set of cases as they solved an ill-structured hiring and selection business problem. To support their solution generation, the learners were provided with links to other cases that were germane to the primary problem. For instance, one case (Janice's Story) discussed the relationship between internal hiring and improving employee morale. Another case highlighted the importance of providing clear responsibilities when hiring workers. However, our previous version was designed such that a single subject matter expert (SME) identified the most relevant index to relate to the case. Depending on the primary lesson of the case, the SME identified indices (labels) such as the mix between technical expertise and social skills, job advertisements, related experience, and promotion from within (Fig. 1). The primary indices were then included in the system as interface links that learners could click on as they read the main problem to solve. Once these primary indices were embedded, it was implicitly assumed that students would reflect on the similarities between the primary problem they were to solve and the selected cases. Moreover, it was also assumed that learners could generate and apply additional indices from the case beyond the initial links.

The method depicted above provides an initial cue that points learners toward a relevant case. However, it has two potential flaws. First, it relies on a single SME to determine the relevancy of the case. Second, the hyperlink approach suggests only one index to determine similarities between the problem to solve and a narrative in the case library learning system. In reality, cases have multiple indices embedded in a narrative (Schank 1999). To overcome those challenges, an expert-based recommendation system (Amatriain et al. 2009) solution was identified. In the new iteration of the case library, multiple SMEs were asked to rate the relevancy of a given case using various indices. The resulting recommendation system provides multiple SME assessments on the value of the case and weighs the perceived value of a case as applied to the focal problem (Fig. 2).

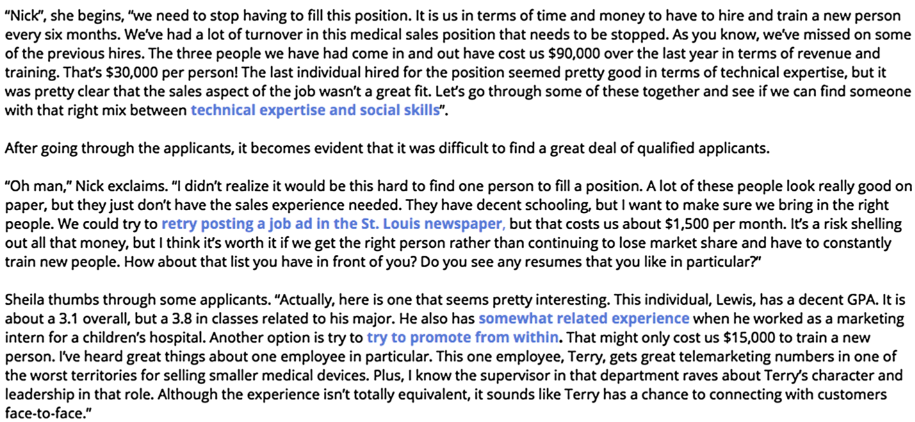

Fig. 1 Hyperlink-based version of case library learning environment

1		Nick's Dilemma	Holly	Jesse	Chris	Janice	Alex
2	recruitment	5	5	5	5	5	5
3	selection	5	5	5	4	5	5
4	aptitude	5	5	5	5	5	4
5	qualifications	5	3	5	5	2	3
6	selection criteria	5	4	5	5	2	2
7	external recruitment/sources	3	0	0	0	0	0
8	internal recruitment/sources	3	0	0	0	0	0
9	sales role	3	3	0	3	4	2
10	interview types	0	0	0	0	0	0
11	application blanks	0	0	0	0	0	0
12	personality tests	0	0	0	0	0	0
13	motivation	3	4	3	4	4	3
14	compensation	3	0	0	0	2	0
15	selling activities	0	0	0	0	4	0
16	customer service	3	0	0	0	4	0
17	relationships	3	0	0	0	4	0
18	relatable skills	3	3	0	4	4	0
19	job analysis	0	0	0	4	3	0
20	job description	0	0	4	0	3	3
21	job responsibilities	0	0	4	0	3	0

Fig. 2 Expert matrix

1.3 Retrieval Algorithm

In order to design the system, we asked experts (N = 5) to first (a) rate the topics on the problem to solve and then (b) rate each of the five narratives in the case library (Fig. 2). In order to return the optimal cases, we had to balance two related issues that impacted retrieval: the indices that are present within each individual case and the relevancy of that case to the main problem to solve. For instance, the index "gender discrimination" is very prominent in a related case (Janice's Story), but is not as foundational for the main problem to solve. However, the indices of "internal advancement" and "employee morale" are highly relevant to the main problem to solve. Thus, although a narrative may have an array of issues within the narrative, the retrieval system must be designed such that it retrieves that indices that best align with the primary problem to solve.

In the older case library, learners were suggested a single index for a case in the form of a hyperlink. In the new system, learners are provided a set of indices from which they can select and search from. However, simply providing a list of other cases in order of score on that index provides little value, as a high score on the index is not necessarily the only reason to consider it important. In order to construct an informed measure of related cases on this index, we instead calculate the similarity of each case in our library. Several ($k = 5$) experts thus scored each index (j), giving us a j-by-k matrix of scores for each case. In each case, we use the arithmetic mean of expert scores to reduce each index to a single value. We denote the main problem to solve—i.e., the case that we comparing with all other cases—as b, and the case we are comparing with as c. We define the similarity between the base case b and any case c for an index j as the difference between the mean expert scores for j for each case, normalized by the range of possible values in the scoring system. Using this method, we calculate the distance on an index from b to each one of the other cases in the library and return them, sorted, to the user. Based on experts' ratings (Fig. 3), the system would be able to retrieve the ideal case based on multiple experts' assessments of the main problem and other relevant cases. In doing so, the search retrieval process essential to CBR is scaffolded using the experts' assessments, which are built into the recommendation system retrieval algorithm (Fig. 4).

The new algorithm also allows learners to search on specific concepts they consider relevant to solving the ill-structured problem (Fig. 5). In the older version, learners could

$$\begin{array}{lcccc} & \text{Expert } 1 & \text{Expert } 2 & \ldots & \text{Expert } k \\ \text{Index } 1 & x_{11} & x_{12} & \ldots & x_{1k} \\ \text{Index } 2 & x_{21} & x_{22} & \ldots & x_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \text{Index } j & x_{j1} & x_{j2} & \ldots & x_{jk} \end{array}$$

Fig. 3 Example case with *j* indexes and *k* experts

Fig. 4 Algorithm retrieval formula

$$1 - \frac{\left| \frac{1}{k} \sum_{i=1}^{k} b_{ji} - \frac{1}{k} \sum_{i=1}^{k} c_{ji} \right|}{score_{max} - score_{min}}$$

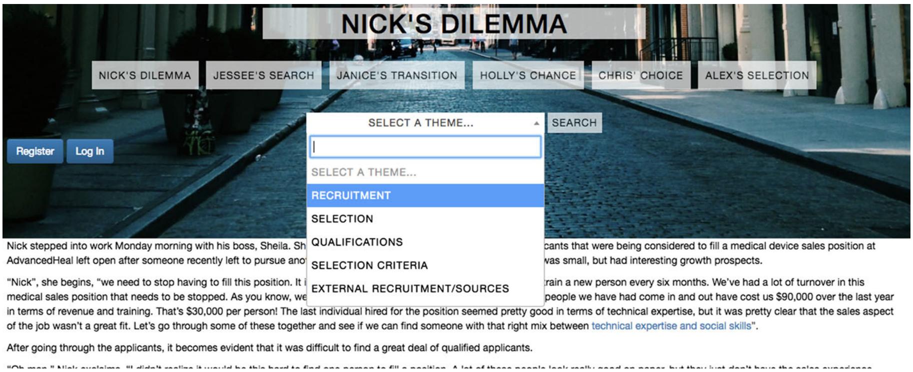

Fig. 5 Recommendation drop down

see an embedded hyperlink (e.g.—“internal recruitment”) that provided a preliminary recommendation index about how the case was related. In the current version, a learner can search for a term (e.g.—“internal recruitment”) and be provided with a list of cases and their expert ranked relevancy scores. By providing a list of indices (Fig. 5) and their retrieved relevancy scores (Fig. 6), learners engage in more directed inquiry and approach the cases with a more targeted similarity assessment of the case library.

2 Relevance for Learning, Instruction, and Assessment

Given that previous experience is of foundational importance to reasoning, theorists have argued that a lack of experience poses problems to novices in problem solving settings (Kirschner et al. 2006; van Merriënboer 2013). Specifically, they argue that a lack of previous experience means that ill-structured problems are often too complex for novices to solve in classroom contexts. As noted earlier, one way to overcome this challenge is by allowing learners to access case libraries, which detail how experts encountered similar experiences. Indeed, some research has shown that the use of case libraries can have a positive effect on a learner’s understanding of a problem (Ertmer and Koehler 2014) and his/her ability to present an argument relating to it (Tawfik and Jonassen 2013).

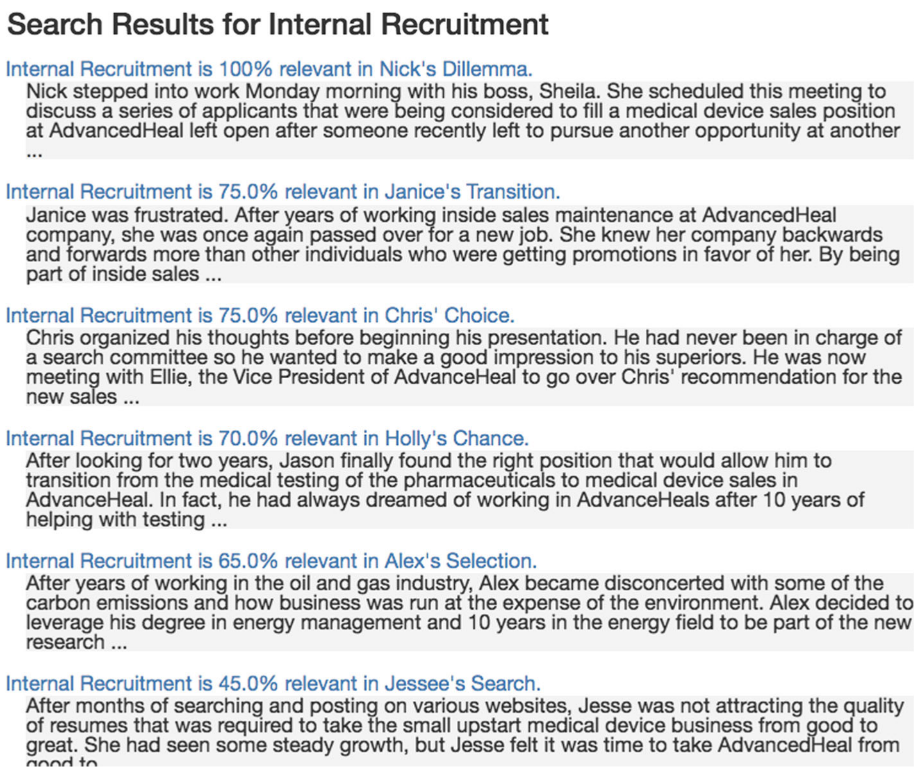

Fig. 6 Recommendation system results

Case-based reasoning argues that the alignment between the new problem and case libraries is a key element in problem-solving. This has many implications for problem-based learning (PBL) and case-based reasoning (CBR) theory. In terms PBL, research shows that how learners retrieve the optimal resources during inquiry constitutes a significant challenge (Jeong and Hmelo-Silver 2010). Although some research on case libraries have shown them to be beneficial, Kolodner (1991) has argued that novices struggle with retrieving cases. In particular, novices fail to effectively retrieve the right cases and apply the lessons learned because they tend retrieve based on surface level features. Novices also struggle to properly define the problem (Schon 1984) and favor simple causality (Jacobson 2001; Loh et al. 2015). Alternatively, studies find that experts are able to focus on the deep, structural issues and use a robust set of causal rules to solve problems (Hmelo-Silver et al. 2007; Hmelo-Silver and Pfeffer 2004). That is, experts perceive the reuse utility of a case differently than novices. This discrepancy is one challenge that may be addressed by using recommender systems to scaffold the case retrieval process for the learner. In other contexts, recommender systems have been especially important in filtering an overwhelming amount of data by using various techniques to alleviate information overload and provide optimal suggestions (Speier et al. 1999). To date, recommendation systems have been used to retrieve information in social networks, academic papers, mind maps, and other contexts.

The differences between experts and novices has implications for the use of recommendation systems. Tawfik and Kolodner (2016) argue that the more “systematic and careful a reasoner is at interpreting a situation and identifying its most relevant characteristics, the more likely s/he is to find relevant knowledge and experience to use in reasoning" (p. 5). From a CBR perspective, if a learner is not able to properly evaluate the indices of the problem, they not be able to retrieve and reuse the appropriate cases. It follows that case library learning systems should help learners identify the key features that allow them to (a) accurately assess the extant problem and (b) understand the elements of a case that might be useful to solve problems. In terms of the latter, systems that support CBR should also encourage the learner to ascertain the seemingly subtle distinctions of a case that learners might miss, such as the assessment of the problem, the connections between indices and the problem, and the rationales that experts make for their decisions. When retrieval is scaffolded for the learner, a more robust set of indices is developed and opportunities for reuse is increased.

Although the current system was designed to scaffold an individual's retrieval and reuse, there are also opportunities to use the retrieval patterns as a form of assessment. In particular, learning analytics can use secondary data, such as inputs from aggregations of data in the form of learner behavior (Ifenthaler 2017; Xing et al. 2015). Specifically, assessment approaches could explore what students search for as they solve problems. Search terms could provide important information about the indices learners assign to the problem and the knowledge deficiencies they hope to address. Furthermore, the sequence of search terms (e.g.—employee morale and compensation strategies) can provide important insight into the iterative causal reasoning that students develop as they interact with the cases over time.

3 Emerging Technology in Practice

The case based recommendation library has been piloted in a variety of contexts. In the first pilot, participants were asked to identify, read, and identify the relevancy of narratives in order to solve the main problem. In this initial study, the ability of novices to understand the narrative descriptions was the primary objective. Interestingly, we found that learners struggled to identify the relevancy of the cases when not provided with recommendations. That is, they struggled to generate the same indices that the experts had identified. The cases were then redesigned to better align with the most important indices of the problem to be solved.

The second pilot was also implemented to assess how a learner perceived relevancy of the case and how a learner might interpret the relevancy score (e.g.—Janice's Story is 75% relevant on employee morale). As in the case with the SMEs, pilot participants were asked to weigh the relevancy of a case on a variety of indices. Results suggest that novices indicated that learners had significantly different weights regarding the importance of various concepts embedded within the case. However, the percentage score encouraged them to reflect further and better reuse the cases.

4 Significant Challenges and Conclusions

Altough the initial results are promising, there are challenges we hope to address as we further improve the system. A challenge is that CF is affected by the cold-start problem (Schein et al. 2002), in which the system cannot produce good recommendations for new users or unrated items. This problem can be remedied to some extent by using a hybrid approach that combines CF and content-based filtering or by using pseudo-users who provide ratings according to the attributes of items or users (Balabanović and Shoham 1997). Other recommenders have used a matrix factorization approach based on the stochastic gradient descent (Bousquet and Bottou 2008), singular value decomposition (Koren et al. 2009), which addresses the issues of sparsity and scalability.

Another challenge pertains to displaying the results. Specifically, we struggled with how to display the results of SME rankings to the user. For instance, if a user searches the term "job advertisement" and a case low on that index is displayed, we could not immediately determine how best to display the result to the user. In our design, it was necessary to show that the index was identified as low for that specific case. However, if a low relevancy score were displayed, the learner might posit that a specific index might not be as relevant to a new problem. Over time, further research is needed about the design and development of case libraries to ensure that students problem solving is best supported. By identifying multiple indices that are germane to a given case, learners can begin to develop the ability to render better similarity assessments, retrieval, and reuse of cases.

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