

CHAPTER 15 – SOCIAL NAVIGATION FOR SELF-IMPROVING INTELLIGENT EDUCATIONAL SYSTEMS

Peter Brusilovsky¹, Vasile Rus²

University of Pittsburgh¹, Georgia Institute of Technology²

Introduction

The idea of self-improving intelligent educational systems is almost as old as the field of intelligent educational systems itself. The origin of this research stream could be traced to the paper of Tim O’Shea “A self-improving quadratic tutor” (O’Shea, 1982), which was published 40 years ago in the famous special issue of *International Journal on the Man-Machine Studies*. This special issue later re-published in a separate book (Sleeman & Brown, 1982), which arguably launched the very field of intelligent tutoring systems (ITS) and defined its research agenda for years ahead. O’Shea’s paper was somewhat different from the rest of the papers in the special issue. Unlike the majority of researchers who believed that intelligent educational systems should be created by domain experts through knowledge elicitation and engineering, O’Shea argued that an intelligent system should be able to improve itself not just by constant engagement of experts but by using data collected in the process of its practical application. While his self-improving tutor started with an expert-engineered teaching strategy in the form of production rules and assertions, the system also included a pro-active self improvement cycle. The idea of this cycle was to select an educational objective, make an experimental change in teaching strategy, statistically evaluate the resulting performance over time, and make necessary update if the change is successful.

While the idea of self-improving ITS and the original paper produced a stream of follow-up work, for many years this stream was really small and not easily visible in a large body of work on intelligent educational systems. The main obstacle was a rather low level of practical use of these systems. Without a large number or real users working with an intelligent system year by year the idea of automatic experimentation and constant improvement was hard to implement. The situation, however, gradually changed over the years. As the field of ITS became more mature, some systems, like the famous Algebra Tutor, got exposed to hundreds and thousands of real users year by year (Koedinger, Anderson, Hadley, & Mark, 1997) and the need to constantly improve the knowledge representation and algorithms behind these systems was brought back to the agenda of ITS researchers. Several research teams demonstrated that learning data routinely collected by ITS could offer valuable insights on how the systems could be improved and suggested specific approaches to data-driven improvement of ITS (Martin, Mitrovic, Koedinger, & Mathan, 2011; Pavlik, Cen, Wu, & Koedinger, 2008).

Following these pioneer work, the use of learner data to improve the performance of ITS and other educational systems (i.e., MOOCs) gradually emerged as one of the most popular topics of research in several research communities including Artificial Intelligence in Education (AI-Ed), Educational Data Mining (EDM), and Learning Analytics and Knowledge (LAK) with dozens papers published every year. Yet, the absolute majority of research on this topic focus on just one way of using this data. Whether the learner data is used to improve domain models or to adjust parameters of student modeling and personalization approaches, the focus is on enhancing the “machine” intelligence side of ITS. Yet, every intelligent system could be improved in two different ways. One way, indeed, is to enhance the internal intelligence of the system. The other way, however, is to empower the intelligence of the system user through more advanced and intelligent interfaces. While developers of intelligent systems frequently over-focus on enhancing the

internal functionality of the systems, the research in the area of intelligent user interfaces demonstrate that augmenting human intelligence through a more powerful, AI-driven interface could remarkably improve the overall efficiency of an intelligent system. In other words, best results could be achieved when human and artificial intelligence work together, not when when all efforts are spent on improving the AI and the power of human intelligence is wasted due to a primitive interface. Getting back to the problem of improving ITS using data of past learners, an interesting challenge is how this data could be used to advance the interface side of ITS so that it could empower human learners, better engage them into interacting with the system, and improve the overall performance. In this chapter, we review one of the approaches, which could efficiently use data of past learners to offer a more efficient interface for future learning: social navigation. In the following sections we introduce the idea of social navigation (Farzan & Brusilovsky, 2018) and review several studies exploring social navigation in different contexts.

Social Navigation

Social navigation is a group of approaches belonging to a broader field of *social information access* (Brusilovsky & He, 2018). Social information access can be formally defined as a stream of research that explores methods for organizing users' past interaction with an information in order to provide better access to information to the future users. Various information traces left by past users of interactive systems form highly valuable "community wisdom", which could be harnessed to support various kinds of information access such as search, browsing, and recommendations. Within this stream of research, social navigation approaches (Farzan & Brusilovsky, 2018) focus on using "community wisdom" to assist their users in the process of browsing and navigation, i.e., selecting the most relevant information item or link among many possible options.

The ideas of social navigation are frequently traced back to the pioneer Read Wear and Edit Wear system (Hill, Hollan, Wroblewski, & McCandless, 1992). This system visualized the history of authors' and readers' interactions with a document enabling new users to quickly locate the most viewed or edited parts of the document. Social navigation in information space as well as the term social navigation was introduced two years later by Dourish and Chalmers as "moving towards cluster of people" or "selecting subjects because others have examined them" (Dourish & Chalmers, 1994). The pioneer systems Juggler (Andreas Dieberger, 1997) and Footprints (Wexelblat & Mayes, 1999) used the ideas of social navigation to help users navigate in two kinds of information spaces – a Web site and a text-based virtual environment (known as MUDs and MOOs). Both systems attempted to visualize "wear" traces left by the system users in order to guide future users. In addition to this indirect social navigation, Juggler also implemented several types of direct social navigation (for example, allowing users to guide each other directly through chat). This allowed Dieberger (1997) to start the process of generalizing the ideas of social navigation. Further generalization of the field of social navigation was propelled by several workshops, which gathered like-minded researchers, and publications, which streamed from these workshops (A. Dieberger, Dourish, Höök, Resnick, & Wexelblat, 2000; Höök, Benyon, & Munro, 2003; Munro, Höök, & Benyon, 1999). As a result of this active ideas exchange, the understanding of what forms the "community wisdom" in social navigation systems was considerably expended to include a variety of options – from past user "clicks" to rich explicit feedback and resource annotations.

In the context of learning and education, the ideas of social navigation have been introduced in the context of research on Web-based education. Early generation of Web-based education systems (Khan, 1997) supported the learning process by providing learners with access to a variety of educational resources. In this context, it was natural to explore the technology of social navigation, which was known to help users in accessing most appropriate information. First attempts to introduce social navigation in Web-based education has been made by Dron, Boyne, Mitchell, and Siviter (2000) and Kurhila, Miettinen, Nokelainen, and

Tirri (2002). The EDUCO system built by Kurhila and his colleagues (Kurhila et al., 2002) could be considered as a classic example of exploring the ideas of social navigation in the education context. EDUCO was a collaborative learning environment which implemented social navigation support to enrich learners' experiences in Web-based learning. EDUCO supported synchronous social navigation by visualizing the presence of others in the learning environment. As users of the system were accessing the educational Web documents, others can view their presence as dots next to the documents in a visualized document space (Figure 1). The color of the documents represented the popularity of the document among the users based on how many times they have been clicked. Furthermore, users can leave comments associated with documents that are visible to others navigating to the document.

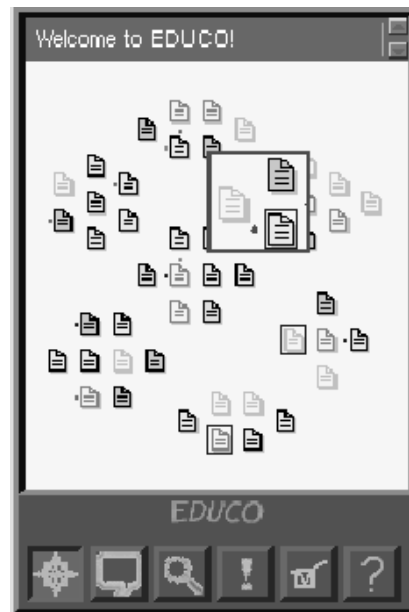


Figure 1. Representation of documents and users within EDUCO learning environment

The early examples of educational social navigation and the increased popularity of research on “collective wisdom” and social information access helped to engage several other research teams working on similar topics. In just a few years, the number and the diversity of explored social navigation approaches in educational context increased remarkably (Brusilovsky, Chavan, & Farzan, 2004; Hübscher & Puntambekar, 2004; Mitsuhashi, Kanenishi, & Yano, 2004; Tattersall et al., 2004; Vassileva, 2004). Since that time, both the variety and the complexity of research on this topic has been gradually increasing. However, due to the practical focus of this paper, we do not intend to provide a comprehensive overview of this research stream. Instead, we focus on three well-explored and extensively used systems, which applied different kinds of social navigation to educational processes. We believe that a review of these systems can provide both, a list of useful social navigation techniques and a demonstration how the research on social navigation in educational context has gradually advanced from simple ideas explored in proof-of-concept systems to more complex designs validated by large-scale field studies.

Knowledge Sea II

Knowledge Sea II (Brusilovsky et al., 2004), originally developed in 2003-2005, provides a good example of how early ideas of “traffic-based” social navigation explored in the pioneer systems Juggler (Andreas Dieberger, 1997) and Footprints (Wexelblat & Mayes, 1999) could be applied in the educational context. Knowledge Sea II uses ideas of social navigation to support both browsing and visualization access to

information. The visualization-based access is provided through an 8 by 8 cell-based map of the information space. This map is assembled using Kohonen's Self-Organized Map (SOM) technology (Kohonen, 1995) from about 25,000 Web pages devoted to C programming language. Every cell on a resulting map provides access to a subset of these pages. By clicking on a cell, the user can open it and get access to the set of pages located in this cell (Figure 2). An interesting property of SOM technology is that it places similar pages into the same or adjacent cells on the map, so the result presents a reasonably good semantic map of the information space. The cells of the map are marked by keywords, which are most frequently found in the corresponding pages of each cell and by landmark resources located in the cell. The map itself was re-used from the earlier version of the system, Knowledge Sea (Brusilovsky & Rizzo, 2002). In the Knowledge Sea II project, we added a layer of social navigation on top of the map.

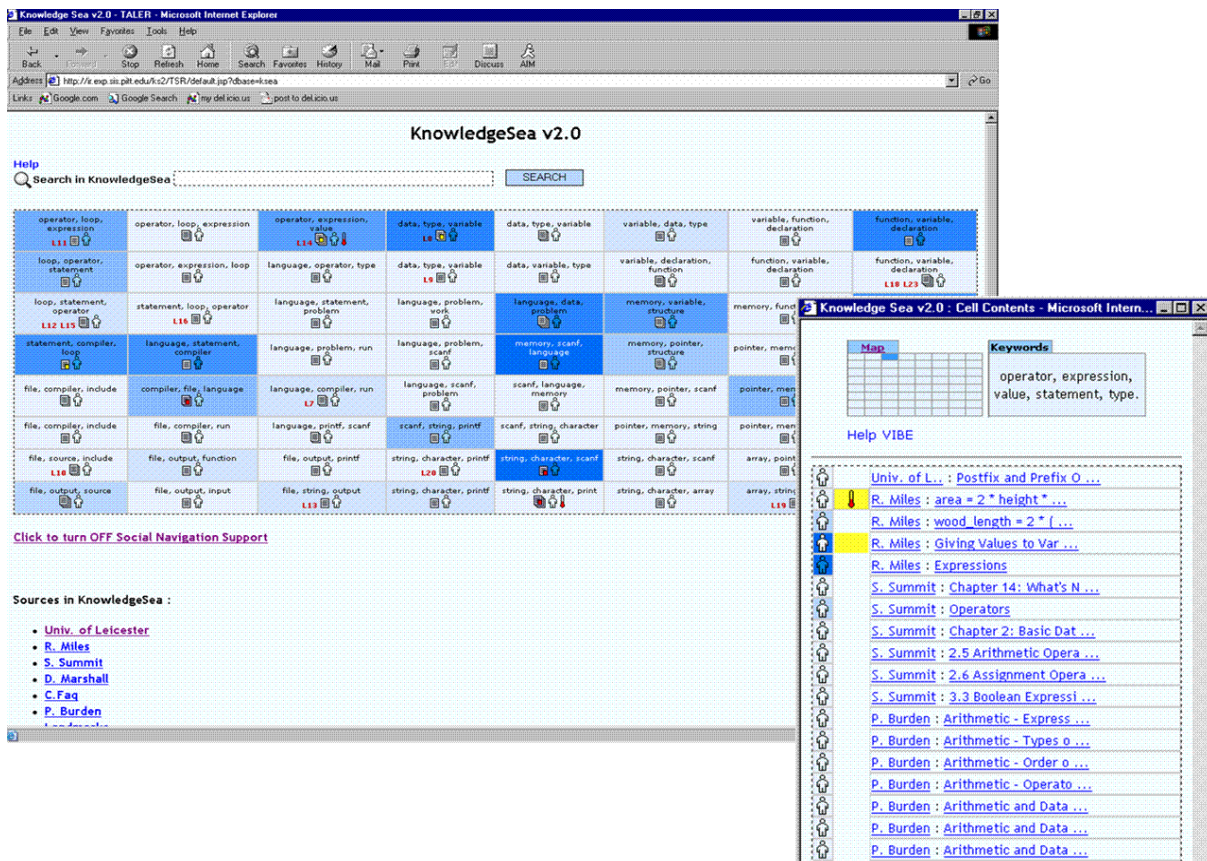


Figure 2. Social navigation support in the Knowledge Sea II system. The knowledge map is shown on the top left and an opened cell is shown on the right. The list of links to the tutorial roots is shown on the bottom left. A darker blue background indicates documents and map cells that have received more attention from users within the same group. Human icons with darker colors indicate documents and cells that have received more attention from the user herself.

The browsing-based access is provided through the hierarchical structure of the C programming tutorials assembled by the system. Each tutorial site is organized as a tree with table of contents, sections, and subsections. The home page of Knowledge Sea II provides access to the root pages of all these tutorials. Starting from that, users can navigate down to the sections or subsections of interest assisted by social navigation visual cues (Figure 3).

The community wisdom in Knowledge Sea II is collected by tracking two kinds of page-centric user information: timed page visits (traffic) and page annotations. This information is used to generate a history-enriched environment with two types of visual cues, which change the appearance of links on the pages and map cells presented to the user (Figure 2). These cues are based on the two kinds of tracked information and are known respectively as traffic- and annotation-based social navigation support. The system generates appropriate cues individually for each user by analyzing past individual activities of the user and other users belonging to the same group.

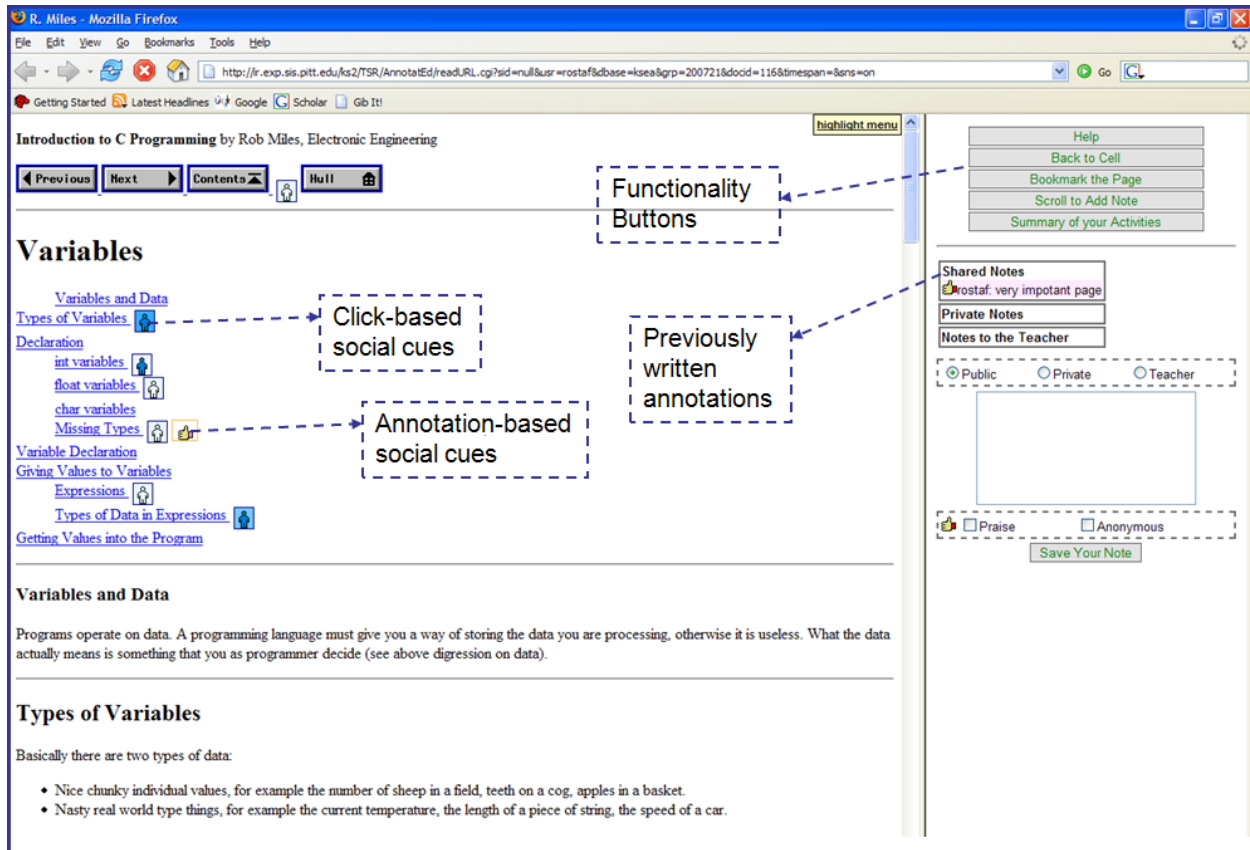


Figure 3. Social navigation in C-programming tutorial pages, from (Farzan & Brusilovsky, 2008)

Traffic-based navigation support attempts to express how much attention the user herself and other users from the same group paid to each of the 25,000 pages that the system monitors. The level of attention for a page is computed by considering both number of visits and time spent on the page and is displayed to the user through an icon that shows a human figure on a blue background. The color saturation of the figure expresses the level of the user's own attention while the background color expresses the average level of group attention. The higher the level of attention is, the darker the color appears to the user. The contrast between colors allows the user to compare her navigation history with the navigation of the entire group. For example, a light figure on a dark background indicates a page that is popular among group members but remains under-explored by the user. The color of the map cell and the human figure shown in the cell is computed by integrating attention parameters of all pages belonging to that cell.

Annotation-based navigation support uses a similar approach to represent the number of page annotations made by the users from the same group. Users can annotate each page in the system. Users can also indicate

that a note is praise (i.e., the page is good in some aspect). While users make annotations mainly for themselves, Knowledge Sea II allows all users of the same group to benefit from collective annotation behavior. The yellow annotation icon shown next to the blue traffic icon shows the density and the “praise temperature” of annotations for each page. The more annotations a page has, the darker the yellow background color appears to the user. The temperature shown on a thermometer icon indicates the percentage of praise annotations.

Both types of social visual cues were provided to guide users to most relevant and useful pages as implicitly indicated by the past users’ activity. Traffic-based social navigation was provided in the very first version of Knowledge Sea II (Brusilovsky et al., 2004) and could be considered as a direct application of the early ideas of social navigation in education contexts. Annotation-based social navigation was added in the second version (Farzan & Brusilovsky, 2005b). This feature was motivated by our experience with the first version. As we found during first classroom studies, despite its overall effectiveness, traffic-based social navigation was subject to the *avalanche effect*, which has not been well-studied at that time. User clicks and page visits were an important, but not reliable signs of user attention and page importance. Frequently, users clicked on a less relevant page by mistake, attracted by a seemingly relevant title. After landing on the page and realizing that it is not helpful, the first visitor backed away. Yet, with traffic-based navigation, every visit left a visible trace: the page link annotation became darker, further increasing a chance to be visited by future users. As we discovered, simple version of traffic-based social navigation lead to creating some “tar pits”, low-value pages with attractive titles, which were falsely indicated as important by social navigation. The addition of more reliable annotation-based social navigation and developing a smarter time-based approach to score user page visits (Farzan & Brusilovsky, 2005a) resolved this problem.

The advanced version of Knowledge Sea II with dual sources of social navigation support has been explored in many classroom studies. In these studies, we were able to discover and confirm several effects of social navigation. We found that a community of students was remarkably good in co-discovering most important and valuable pages in the context of the course. Note that only a part of the 25,000 pages extracted from multiple tutorials were relevant and useful for our specific C programming course. Even in the classes that started with an empty map, we were able to observe most relevant pages and their clusters to be discovered relatively fast creating a class-adapted map to guide future users. Moreover, the ability to annotate pages and the visualization of annotations through visual cues could considerably increase a chance for an important page to be noticed. We also found that social visual cues highly influence user navigation behavior. Pages which attracted past attention of the users – as revealed by visual cues – have a significantly higher chance to be re-visited by users who already explored them and visited by new users. In fact, very popular pages visualized by the displayed density of visits and annotations, were more attractive for the users than top results in a ranked search list. As we found in a study of social search in Knowledge Sea II, adding social visual cues to the ranked list of search results shifts user’s attention from top-3 results in the list to most popular pages in this list. We also found that the presence of annotation-based cues doubled an user’s chance to follow a specific link. It was clear that the users considered annotation-based as more indicative and reliable in finding useful pages. Following our success in using social navigation in Knowledge Sea II, we re-used both explored social navigation approaches in another project (Farzan, Coyle, Freyne, Brusilovsky, & Smyth, 2007.) An extensive report of our findings in both projects is available in (Farzan & Brusilovsky, 2008).

Progressor

Our experience with social navigation in Knowledge Sea II project, revealed the importance of the reliability of “social wisdom”. Comparing traffic-based traces with annotation-based traces of past behavior, we discovered that actions that require higher-level commitments from the past users are both more reliable in

discovering important pages and more influential for the future users. In the Progressor project (Hsiao, Bakalov, Brusilovsky, & König-Ries, 2013), we explored another high-commitment traces of behavior: the problem-solving traces of students taking the same course. The work on Progressor followed our past attempts to combine open student modeling (Bull & Kay, 2007) and adaptive navigation support (Brusilovsky, 2007) to help user in accessing most relevant problems in a programming course. In our first attempts, we explored traditional knowledge-driven adaptive navigation support where personalized guidance decisions were made on the basis of manually engineered domain models and personalization algorithms (Hsiao, Sosnovsky, & Brusilovsky, 2010). While we found it highly efficient and engaging (Sosnovsky & Brusilovsky, 2015), our concern was that the knowledge-based approach required a considerable engagement of domain experts. By replacing traditional knowledge-based navigation support with social navigation support, we hoped that the “community wisdom” could provide an alternative source of knowledge for efficient navigation. On the way to find the most appropriate way to process and visualize past problem solving behavior in such a way that it could provide efficient help for future users, we explored a sequence of design options (Brusilovsky, Hsiao, & Folajimi, 2011; Hsiao, Bakalov, Brusilovsky, & König-Ries, 2011; Hsiao et al., 2013). The Progressor system reviewed in this section was the last and the most efficient design in this sequence.

The design of Progressor was motivated by the ideas of Open Social Student modeling and the theories of Social Comparison and Self-Regulated learning. Open Social Student Modeling (OSSM) can be considered a social extension of open student modeling. Open student modeling has been suggested as a way to externalize student models, the key component of any personalized learning systems. While in a traditional personalized learning system this model is usually hidden from the student and only used by the personalization engine to provide adaptation effects, systems with an open student model expose this model to the learner and provide an interface for its exploration and possible editing. Open student modeling is known for a number of positive effects. It increases the transparency of personalization, helps raise the students’ awareness of their learning performances, and supports meta-cognitive processes (Bull & Kay, 2013). In combination with adaptive navigation support, it can also efficiently guide students to the appropriate content (Sosnovsky & Brusilovsky, 2015). In this context, the idea of Open Social Student Modeling is simply to make the content of individual and student models accessible not only to the target student herself, but to a broader group of students, for example, students in the same class. The most natural way to do it is through social visualization that can visually present the content of multiple student models to the target student in a form that enables comparison of her own knowledge to the knowledge of her peers and the class as a whole.

Research in self-regulated learning examines students’ metacognitive strategies for planning, monitoring, and modifying their management and control of their effort on classroom academic tasks (Pintrich & De Groot, 1990). Self-regulated learning involves self-monitoring to optimally interpret feedback from their academic learning process and environment (Zimmerman, 1990). Our work aimed to leverage awareness, motivation, and content organization through social visualizations in the hopes of promoting students’ self-regulated learning behavior. Research in social comparison (Festinger, 1954) has demonstrated that people often determine appropriate behavior for themselves by examining the behavior of others, especially similar others (Buunk & Gibbons, 2007). Consequently, it has been shown that individuals tend to behave similarly to their friends and peers (Cialdini, Wosinska, Barrett, Butner, & Gornik-Durose, 1999). Researchers and designers of online systems have used the insights from social comparison research in the study of online social behavior. In the educational domain, the positive impact of social comparison on student performance has been reported in several papers (Light, Littleton, Bale, Joiner, & Messer, 2000). However, the value of social comparison in the context of personalized learning and navigation support has not been studied. Based on the past studies, we hoped that social navigation design that directly engages social comparison could increase its impact and positive value.

Figure 4 shows the Progressor interface. The visualization consists of two panes: the left pane displays the student's own progress and the right one displays the progress of any class peer or the whole class, whichever is selected from a dropdown menu. Each pane visualizes the respective student's progress as a pie chart. The pie chart representation visually conveys the chronological order of lectures while the size of a sector represents the number of problems for each lecture. A lecture may consist of one or several topics, which are represented as angular segments placed within the circular sector of the corresponding lecture. This representation allows the student to easily estimate the amount of work on each individual topic or lecture, while an apparent topical sequence provides a good picture of progress through the course. In addition to that, the ability to view someone else's progress allows the student to quickly find the peers who can help with a difficult topic or quiz. Finally, the ability to view the average progress of the entire class allows the student to relate her progress to that of the whole class and estimate whether she is ahead or behind of the class. In addition to serving as OSSM, the Progressor interface provided direct access to learning content. Clicking on any topic on the student's own model (Figure 4, left) or on a peer or class model (Figure 4, right) opened a list of practice problems available for this topic. Links to problems have been also socially annotated using the same color-coding scheme.



Figure 4. Peers model comparison and social navigation support interface in Progressor. The color of course topics indicate students own progress with the topic knowledge (left) and class or peer progress (right). A click on a specific topic on either side opens a list of practice problems for the topic.

From a semester-long study cross-compared with previous attempts to organize access to Java problems, we learned that the new design of the OSSM interface was very engaging. Students used Progressor extensively. On average, it achieved the highest system usage across all OSSM interface designs surpassing even the former champion, JavaGuide (Hsiao et al., 2010). Progressor also engaged students to explore more topics and to work on more distinct questions. In addition, the amount of time spent on the system (in terms of the sessions) was doubled. To check whether the boost of usage could be credited to the new design, we examined student interaction with the peer side of the Progressor interface such as re-sorting, scrolling, and accessing the peer list. As before, we found that students interacted with the peer side quite considerably,

comparing their progress with the progress of peers and accessing a considerable volume of content from the peer side. Moreover, the more students engaged in interacting with the social features of Progressor, the more likely they were to achieve a higher success rate in answering the self-assessment questions. The findings were consistent with the subjective evaluation outcome, which demonstrated high satisfaction with Progressor (Hsiao et al., 2013).

Mastery Grids

Following the success of Progressor and the discovered value of combining social navigation, open learner modeling, and social comparison ideas within the same design, we attempted to expand these ideas to a more realistic online learning context. One serious limitation of Progressor was its focus on one type of learning content, which in our past studies was one type of programming problems. In a more typical online learning situation, the student has access to multiple types of learning content: readings, worked examples, questions, problems, etc. The first attempt to expand the ideas of Progressor to multiple types of content was done in the Progressor+ system (Hsiao & Brusilovsky, 2017). Following the encouraging results of its evaluation, we developed Mastery Grids, an open-source domain-independent framework for open social student modeling and social navigation (Loboda, Guerra, Hosseini, & Brusilovsky, 2014).

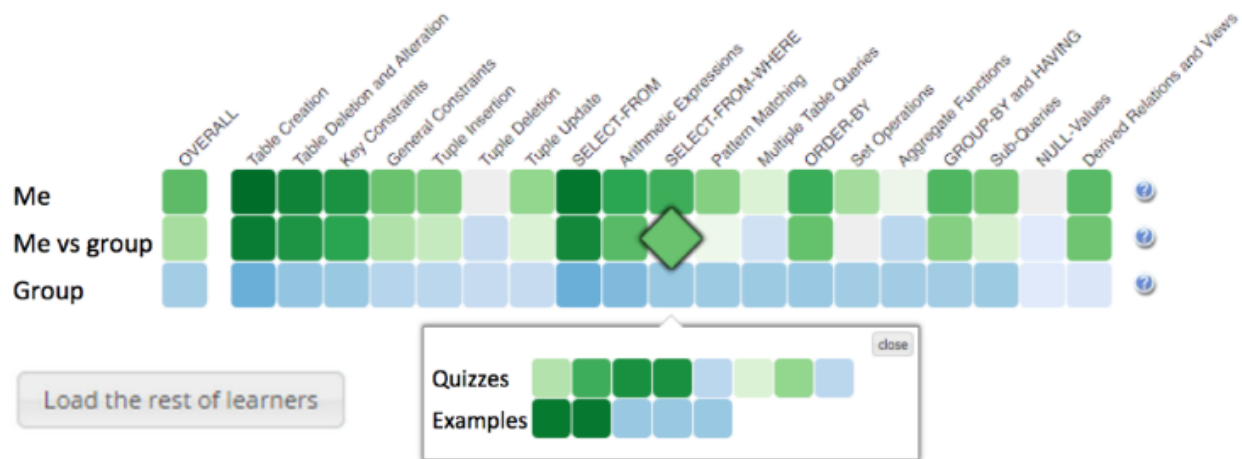


Figure 5. MasteryGrid interface for a Database course

MasteryGrids uses a grid-based social visualization approach pioneered in Progressor+, which allows easy comparison of the progress of the student against peer students or against the aggregated progress of all students of the class. MasteryGrids uses cells of different color saturation to show knowledge progress of the target student, her reference group, and other students over multiple kinds of educational content organized by topics. Figure 5 shows the “collapsed” version of MasteryGrids’ interface for a database management course. Left to right, the first column of the grid (“OVERALL”) shows student average progress, and the remaining columns show student knowledge progress topic by topic starting from the first topic of the database course: “Table Creation”. The collapsed version of OSSM grid includes 3 rows. The first row of the grid (Me) presents the topic-by-topic knowledge progress of the *current student* and uses green colors of different saturation to represent the level of progress (the darker is the color, the higher the progress). The third row (Group) shows the aggregated topic-by-topic progress of the reference group (in this case, the whole class) using blue colors of different saturation. The second row (Me vs. Group) presents a topic-by-topic difference between the student progress and the class progress. The cells in the second row are

green if the student knowledge progress is higher than the class, blue if the class is ahead, and gray when both the student and the rest of the class have the same progress. Higher color saturation indicates a larger difference. MasteryGrids can be configured to disable the OSSM features turning it into a standard Open Student model (OSM), as it can be seen in Figure 5. In the OSM version only the first row with the progress of the current student is shown.

By clicking on any topic cell, the student can access learning content associated with the topic. For example, in Figure 5, the student has clicked in a cell of the topic SELECT-FROM-WHERE and the system displays two kinds of learning content available for this topic (quizzes and examples) in two rows of content items represented as colored cells. By clicking in the content cells, the content (problem or example) will be loaded in an overlaid window. The student can access the content by clicking on any of the three rows of the topic (i.e., Me, Me vs. group, or Group). The row clicked defines whether the colors of content cells (Quizzes/Examples) will represent individual progress, comparison between the individual and the group, or the group progress. For example, in Figure 5, the student clicked in the second, differential progress row. Thus, the colors of the content cells also show differential progress (resulting in both green and blue cells.)

The “collapsed” version of the interface is the simplest one available for students. In addition to displaying the overall class progress, MasteryGrids can display and compare progress for each or all types of content. For example, Figure 6 shows an expanded comparison interface for a Java programming course. Here the upper grid (green) shows students own knowledge progress within each type of content, the bottom (blue) grid shows class progress, and the middle grid allows detailed comparison for each combination of topic and content. The full interface of Mastery Grids allowed the students to choose which resources are visualized and which peer group is used for social comparison. For example, in Figure 6, the student selected “class average” as a basis for comparison, but there are many other options, like top 10 students, upper part of the class, lower part of the class, etc. The interface also provides an option to show the full anonymized ranked grid of individual students with their progress over the course topics. The position of the current student in the list is highlighted to make the overall class standing more clear.

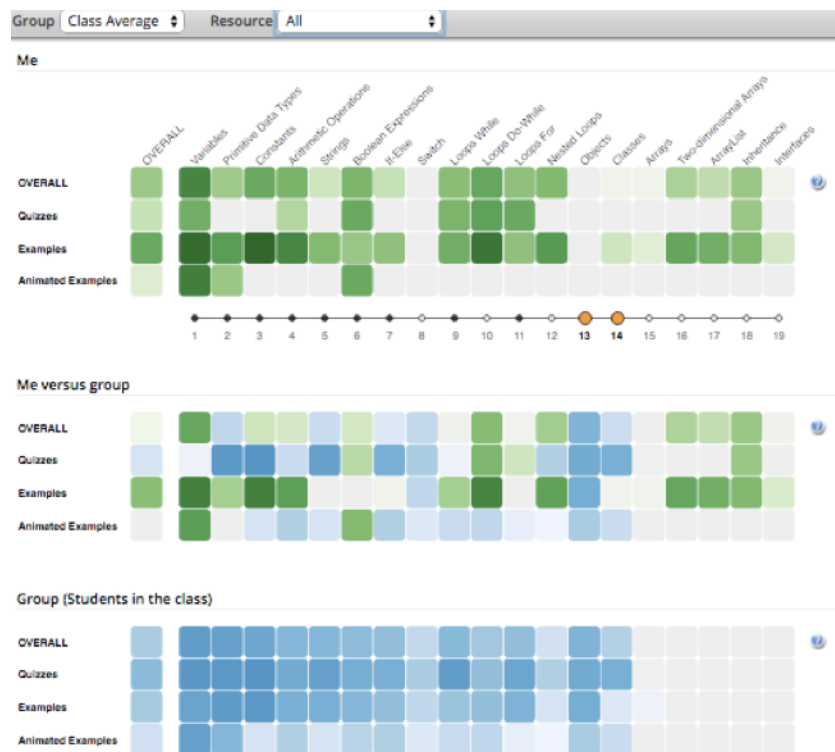


Figure 6. An expanded version of Mastery Grids interface for a Java programming course displaying and comparing progress over different types of content.

Mastery grids interface has been developed for Java (Guerra, Hosseini, Somyurek, & Brusilovsky, 2016), Database (Brusilovsky et al., 2016), and Python (Brusilovsky et al., 2018) courses and extensively studied in these contexts in many classroom studies. To date, the most extensive study has been done in a database course with over a hundred students (Brusilovsky et al., 2016) where the version of Mastery Grids shown in Figure 5 was offered as a non-mandatory practice system to be used during students' study time. Our most valuable discovery from this study is a remarkable ability of the social navigation and comparison interface to engage and retain students, as compared with a more traditional open student model (OSM) interface without the social component. OSSM motivated students to perform significantly more work with non-mandatory learning content. In addition, social visualization enabled students in the OSSM group to work more efficiently, which could be attributed to the social navigation aspect of our OSSM implementation. Working with OSSM also positively impacted student learning, significantly improving the learning gain of weaker students. This could be attributed to the increased work with the content (as shown by the correlation between the amount of work and exam grade). While it is hardly surprising that more work with learning content resulted in better learning, it is impressive that we were able to achieve this effect with non-mandatory educational content, which the students explore at their own will.

Social Navigation in Dialogue-based Intelligent Tutoring Systems

While the majority of work on social navigation (including the examples reviewed above) focused on social navigation via link augmentation in virtual environments, such as hypertext, MUDs, and WWW, the early promoters of social navigation pointed out that social navigation in real word frequently happening in the context of a natural language dialogue (Andreas Dieberger, 1997; A. Dieberger et al., 2000). While the research on dialogue-based social navigation received very little attention since the early days (Farrell, Rajput, Das, Danis, & Dhanesha, 2010), it could very relevant for the area of Intelligent Tutoring Systems due to the increasing popularity of conversational ITS. Intelligent Tutoring Systems with conversational dialogue form a special category of educational technologies (Rus, D'Mello, & Graesser, 2013). These conversational ITSs are based on explanation-based constructivist theories of learning and the collaborative constructive activities that occur during human tutoring. Conversational ITSs have several advantages over other types of ITSs. They encourage deep learning as students are required to explain their reasoning and reflect on their basic approach to solving a problem. Conceptual reasoning is more challenging and beneficial than mechanical application of mathematical formulas. Furthermore, conversational ITSs have the potential of giving students the opportunity to learn the language of scientists, an important goal in science literacy. A student associated with a more shallow understanding of a science topic uses more informal language as opposed to more scientific accounts (Mohan, Chen, & Anderson, 2009). The impact of conversational ITSs allegedly can be augmented by the use of social elements such as the OSSM as well as dialogue-based social navigation components. For instance, we conjecture that student engagement will increase in conversational ITSs if open learner model and open social student models will be added. We are currently working on an NSF-sponsored project that will study the impact of adding open learner models and social navigation elements to the DeepTutor conversational ITS.

Summary, Recommendations, and Future Research

In this chapter, we introduced the social navigation technology in the context of online education systems. Social navigation offers an alternative approach for using large volume of past learners' data for developing self-improving intelligent learning systems. While the majority of work on self-improving ITS focus on improving components or the whole system, here we argued that improvements may come from exploiting

the “user community wisdom” which results in improved domain models, student modeling, and personalization algorithms. Indeed, the social navigation approach provides an example of using the “wisdom of the crowds” for empowering humans’ own intelligence through a more powerful and intelligent interface. A specific goal of social navigation among other interface-focused intelligent interfaces is to help users in finding most appropriate learning content among multiple options usually available in an online learning system. As the data of our studies shows, the presence of social navigation considerably influences students’ navigation behavior successfully guiding them to most useful content. In turn, it positively affects student learning performance. By integrating social navigation with open social student modeling, the value of social interface could be further expanded. As the studies show, most important impact of the OSSM interface with social comparison is an impressive increase of student engagement and retention, which makes OSSM very attractive for contexts where motivation and retention are critical, such as modern MOOCs. The literature on self-regulated learning indicates that the individual and social student models could have an even more significant positive impact on student learning in self-regulated context. Exploring this direction, we already demonstrated that OSSM interface considerably improves student ability to assess their performance in both absolute and relative sense (Somyurek & Brusilovsky, 2015). However, more extensive longer-term studies are required to assess these effects.

Taken together, our experience and findings provide important insights on the impact of social navigation and open social student modeling. The positive nature of the observed changes and the magnitude of this impact demonstrated in several studies encourages us to recommend social navigation in general and a MasteryGrids-style integration of social navigation and social comparison interfaces to the developers of various kinds of educational systems, especially those focused on more mature learners, self-regulated learning context, and non-mandatory practice learning content. Specifically, focusing on Intelligent Tutoring Systems, we recommend replacing a “hard sequencing” interface in this category of systems, which dictates which problems should be practiced at any moment, with an opportunity to choose the most relevant problem guided by both knowledge-driven intelligent guidance (adapted to students’ own knowledge level) and social navigation guidance (adapted to a community of comparable peer learners). This interface will engage both artificial intelligence of the ITS and the natural intelligence of its human users. Multiple studies demonstrated that this kind of navigation support is more efficient and more attractive for mature learners than traditional “sequencing”. Moreover, when student engagement or support for self-regulated learning are important, we recommend to use an interface, which integrates social navigation, open student models, and social comparison – as suggested in the Progressor and Mastery Grids interfaces. As our studies show, it could result in a considerable increase of student engagement and better support of self-regulated learning.

In our current and future studies, we plan to further explore the value of social navigation and open student models in different learning contexts. One direction of our research is focused on exploring a value of granularity in OSM and OSSM models. While the projects reviewed in this paper use relatively coarse-grain “topic-level” student models, we are now running a sequence of studies to explore the value of fine-grain “concept-level” models (Barria-Pineda, Guerra-Hollstein, & Brusilovsky, 2018). We also continue a stream of research, which explores the value of these technologies in contexts where learning content is specifically structured in a non-linear form, such as in hierarchical textbooks (Guerra, Parra, & Brusilovsky, 2013). We hope that our future work will bring more insights on the value of “social wisdom” for improving online learning and help in developing more efficient systems.

We also plan to explore the content dynamics in online learning systems with social navigation capabilities and investigate how content dynamics (adding new learning objects, deleting some, modifying some) impacts its performance. For instance, when you add a new problem, i.e., learning object, it will might take a while for students to explore it and therefore accumulate sufficient “community wisdom”. In extreme cases, when you add a new item to an established pool of items in a system with social navigation, the new item will likely to be obscured by the previous successful items. In other words, unless the platform pushes students somehow to work with new items, the new item will never have a chance to compete with existing,

items which by default might be recommended to the users. It is a typical characteristic of social network to make “the rich richer”, i.e., a socially “rich” learning object will get “richer” by the very nature of the social navigation mechanism. The system should have ways to balance exploitation versus exploration of new, recently added objects and give the chance of “newcomers” to become visible in case they are truly valuable for, in this case, learning.

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