Computers in Human Behavior 27 (2011) 276–284

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Encouraging user participation in a course recommender system: An impact on user behavior

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ARTICLE INFO

Article history:
Available online 16 September 2010

Keywords:
User participation
Incentive mechanism
User study

ABSTRACT

User participation emerged as a critical issue for collaborative and social recommender systems as well as for a range of other systems based on the power of user community. A range of mechanisms to encourage user participation in social systems has been proposed over the last few years; however, the impact of these mechanisms on users behavior in recommender systems has not been studied sufficiently. This paper investigates the impact of encouraging user participation in the context of CourseAgent, a community-based course recommender system. The recommendation power of CourseAgent is based on course ratings provided by a community of students. To increase the number of course ratings, CourseAgent applies an incentive mechanism which turns user feedback into a self-beneficial activity. In this paper, we describe the design and implementation of our course recommendation system and its incentive mechanism. We also report a dual impact of this mechanism on user behavior discovered in two user studies.

1. Introduction

In our information age, everyone is faced with abundance of information while making decisions about almost everything: movies to watch, restaurant to go, or research papers to read. People traditionally turn into others who they trust when overwhelmed with decision making process. They will watch a movie which is recommended by a friend, or go to a busy and popular restaurant. Social web applications such as collaborative recommender systems, social networking sites, and social bookmarking sites capitalize on natural tendency of people to follow each other. They try to bring together the collective wisdom of the community and exploit this wisdom to guide their users.

Collaborative recommender systems could be considered as the most explored kind of community-powered systems. A range of recommendation techniques have been proposed and extensively studies over the last 15 years in order to improve the quality of recommendation (Schafer, Frankowski, Herlocker, & Sen, 2007). However, the last 5 years of research in the area of collaborative recommender systems demonstrated that the amount and the quality of user ratings can be as vital for the success of a recommender system as the quality of its recommendations (Herlocker, Konstan, Terveen, & Riedl, 2004).

The problem of user contribution is not unique for collaborative recommender systems, but shared by all community-based systems including forums, wikis, social bookmarking, and social linking systems. In all these areas the value of the system and the very survival of online communities is highly dependent on user contribution. Naturally, the rise of community-based systems in the age of Web 2.0 lead to an increased interest to the problem of user participation and various incentive mechanisms to encourage participation (Beenen et al., 2004; Cheng & Vassileva, 2005, 2006; Harper, Li, Chen, & Konstan, 2005; Rashid et al., 2006).

This paper explores the effect of incentive mechanism on users' contribution in a specific community-based recommender systems. We attempt to extend existing research in three ways. First, we explore a relatively non-traditional social recommender system driven by the community of users. Second, we evaluate the effectiveness of a new incentive mechanism to encourage user ratings for the recommender system. Finally, we want to assess both positive and negative impacts of the incentive mechanism on user behavior.

The incentive mechanism explored in our studies appeals to user personal needs. The core idea of this approach is turning user contributions into an activity, which can benefit to the users themselves. This approach is specifically useful when the kind of expected contribution has no inherent benefit for the users, while being beneficial to the community as a whole. A good example of this context is provided by social course recommendation system CourseAgent presented in this paper. CourseAgent employs social navigation approach to provide course recommendations based on students' assessment of course relevance to their career goals. In brief, course ratings left by students after completing their

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doi:10.1016/j.chb.2010.08.005

courses are used to guide future students to most relevant courses. While this context looks similar to collaborative recommender systems, CourseAgent is different because the volume and the quality of student ratings does not influence the quality of recommendation given to this student, it only affects the community, i.e., future students of the rated courses. Thus users of CourseAgent have relatively weak motivation to rate courses such as liking the community and affiliation with community. Our experience shows that this is not sufficient to fuel the social recommendation system.

Following the "personal needs" approach, we extended CourseAgent with a career progress feature, which turns user feedback into an activity that is both attractive and meaningful for each student. The career progress feature allowed the students to view the progress towards their career goals. The progress report considers all courses evaluated by a student to calculate their progress. With this feature, course rating becomes meaningful for the students themselves: the more taken courses are rated, the more accurate is the displayed progress report. To investigate the effect of our proposed incentive mechanism on students' rating behavior we run two user studies. This paper presents the results of our studies focusing on both advantages and shortcomings of the incentive mechanism.

This paper is organized as follows: Section 2 reviews the current approaches in encouraging user participation in online communities. Section 3 describes our system, CourseAgent and the design of the incentive mechanism in CourseAgent. Section 4 presents two studies, which evaluated the effectiveness of our approach to motivate users' ratings. Sections 5 and 6 talk about possible drawbacks of different incentive systems and present the evaluation of the potential negative effect of our motivational forces for course ratings. We conclude the paper with the summary of results and some ideas for the future work.

2. Encouraging user participation

It has been recognized that success of all kinds of social software and online communities is highly dependent on participation of their users. This recognition influenced large interest to the problem of user participation and increasing volume of research on this problem. One of the most frequently cited issues in the area of user participation is the under-contribution and inequality of contribution in online communities. In most online communities 1% of users account for 90% of content (Nielsen, 2006). Wikipedia, the web-based collaborative encyclopedia, is one of the most successful example of online communities. As of 2008, the site has 684 million unique visitors; however, only 75,000 (0.01%) of them are active contributors and very small percentage of users account for large amount of data on the site (Wikipedia). While survival of small online communities with small number of users is highly dependent on contribution of majority of the users, bigger communities like Wikipedia with large number of users can survive even with small percentage of users contributing. However, even large community can be affected by the under-contribution problem through participation inequality bias when small percentage of population represent the views of larger population. While it is not possible to encourage all users to contribute, it is important for both small and large online communities to motivate larger percentage of users to contribute.

A substantial amount of research in the field of social sciences have focused on understanding user motivation for participation in communities and group works and different incentive mechanisms. Social exchange theory is a social psychological theory which explains social behavior as a result of an exchange process (Emerson, 1976). The purpose of the exchange is maximizing the benefit and minimizing the cost. According to social exchange theory, users need to be motivated to contribute. As summarized by Lui, Lang, and Kwok (2002), community contribution can be motivated by individual and interpersonal factors. Individual factors include extrinsic motivations, such as rewards and personal need, and intrinsic motivations, such as reputation and altruism. Interpersonal factors are motivations such as liking and affiliation.

2.1. Intrinsic motivation

Intrinsic motivation happens when people engage in activities for the activity itself and without any obvious external incentives such as rewards. Intrinsic motivation can be affected by different factors. According to "social loafing" theory, people are more likely to make less effort when performing a task as part of a group and it tends to be robust and generalized across tasks and populations. Social loafing mainly occurs because uniqueness and effect of individual effort is not clear in a group task. "Collective Effort Model" suggests that social loafing can be decreased by clarifying the importance and uniqueness of individual contributions (Karau & Williams, 1993). Additionally, "goal setting theory" suggests that a challenging, short-term goal, rather than a vague, long-term goal stimulates high performance in users (Locke & Latham, 2002). These ideas have been explored by several projects focusing on increasing user participation.

Beenen et al. studied the application of collective effort and goal setting principles in motivating contribution in online communities. They conducted several experiment in MovieLens, the online movie recommender system (Beenen et al., 2004). They studied the effect of revealing to the user the uniqueness and benefit of their contribution to determine which motivated users to rate more movies. In their analysis, they examined the differences between revealing the benefit to oneself versus the benefit to others. Their result shows that users are more likely to participate when they are reminded about benefit to oneself and the others. Coherent with goal setting theory, their result shows that specific goals resulted in higher number of ratings. Furthermore, they find out that group goals stimulate higher contribution than individual goals.

Application of goal setting theory in online communities can also be observed in social networking sites such as LinkedIn, which provide information about how complete a users profile is.

2.2. Extrinsic motivation

Extrinsic motivation comes from outside. It happens when people engage in activities as a result of an external incentive mechanism such as contingent rewards. In those cases the task is not satisfying enough and the external incentives add into the pleasure and satisfaction of the task. The following subsections discuss some examples of external incentive mechanisms. Each incentive mechanism examined below extends the interface and functionality of a social system in order to increase the volume of user contributions.

2.2.1. Rewards

Researchers in the filed of human–computer interaction have tried to study the effect of rewards on user contribution in online communities. For example, Bretzke and Vassileva have tried several reward mechanisms for encouraging contributions to their resource-sharing system Comtella (Bretzke & Vassileva, 2003). Comtella is a resource-sharing system that allows the members of an online community share web resources amongst each other. The system rewards more cooperative users with incentives such as greater bandwidth for download or higher visibility in the community. A more recent version of Comtella uses an adaptive reward mechanism to influence the quality of participation. This new incentive mechanism only rewards high-quality participation rather than all kinds. This is done by allowing the users to rate the contributions of others. Ratings are averaged and negative ratings serve to decrease the rewards given to low-quality contributions (Cheng & Vassileva, 2005, 2006).

2.2.2. Reputation

As suggested by Kollock (1999), reputation is an important factor affecting motivations for community contribution. Wasko and Faraj (2005) surveyed the users of an electronic network of a professional legal association to study the effect of reputation on users participation. They showed that people are more likely to share their knowledge when it enhances their reputation. At a basic level many social networking site employ reputation-based incentives by displaying the number of connections and friends a user has. Other community-based systems such as Flickr address user reputation by highlighting specific user content, such as Flickrs the most interesting photos. Farzan et al. (2008a) experimented point-based reward and reputation incentives in an enterprize social networking site to motivate employees to add content into the site. Their experiment indicates that employees are motivated by both reward and reputation within their test platform. Furthermore, they found evidence that the increase in contributions to the site inspired other users to visit more and comment more.

2.2.3. Personal needs

A substantial number of works in the field of economic and social psychology have shown that extrinsic motivations such as reward and reputation undermines intrinsic motivations (Deci, Koestner, & Ryan, 1999). In this light, an incentive approach based on addressing user personal needs could be considered as an alternative to the mechanisms discussed above. The idea and the challenge of this approach is to turn user contribution into an activity that is both attractive and meaningful for the user. In some sense, this approach bridges the gap between extrinsic and intrinsic motivations instead of causing a conflict between them. This approach is less explored in the literature. An example of the personal needs approach can be provided by our our earlier work on encouraging students feedback for course related educational materials in the form of annotations (Farzan & Brusilovsky, 2005). Several studies in the field of education has shown that annotations turn passive learning into active learning and can be self-beneficial (Bonifazi, Levialdi, Rizzo, & Trinchese, 2002). On the other hand, students' annotations can serve as an implicit indicator of interest in a resource and importance of this resource. In our system, AnnotatEd, we employ annotation-based social navigation support to guide students into important resources. To increase the volume of student annotations, we engineered an annotation interface, which encourages students to annotate educational content by further increasing the value of annotations for the students themselves.

The work presented in this paper expands our earlier work and explores an incentive mechanism based on personal need in a different context. In Section 3.3 we describe our approach in details.

3. CourseAgent

CourseAgent is a community-based recommender system that provides personalized access to information about courses. CourseAgent was developed for students and instructors in the School of Information Sciences at the University of Pittsburgh. While the current version is based on information about courses offered at the School, the system can easily be adopted for different programs by merely integrating the program-specific course data into the system. The following subsections present both the interface of the system, its social recommendation engine, and the incentive mechanism, which we developed to increase the volume of student course ratings.

3.1. Community-based recommendation in CourseAgent

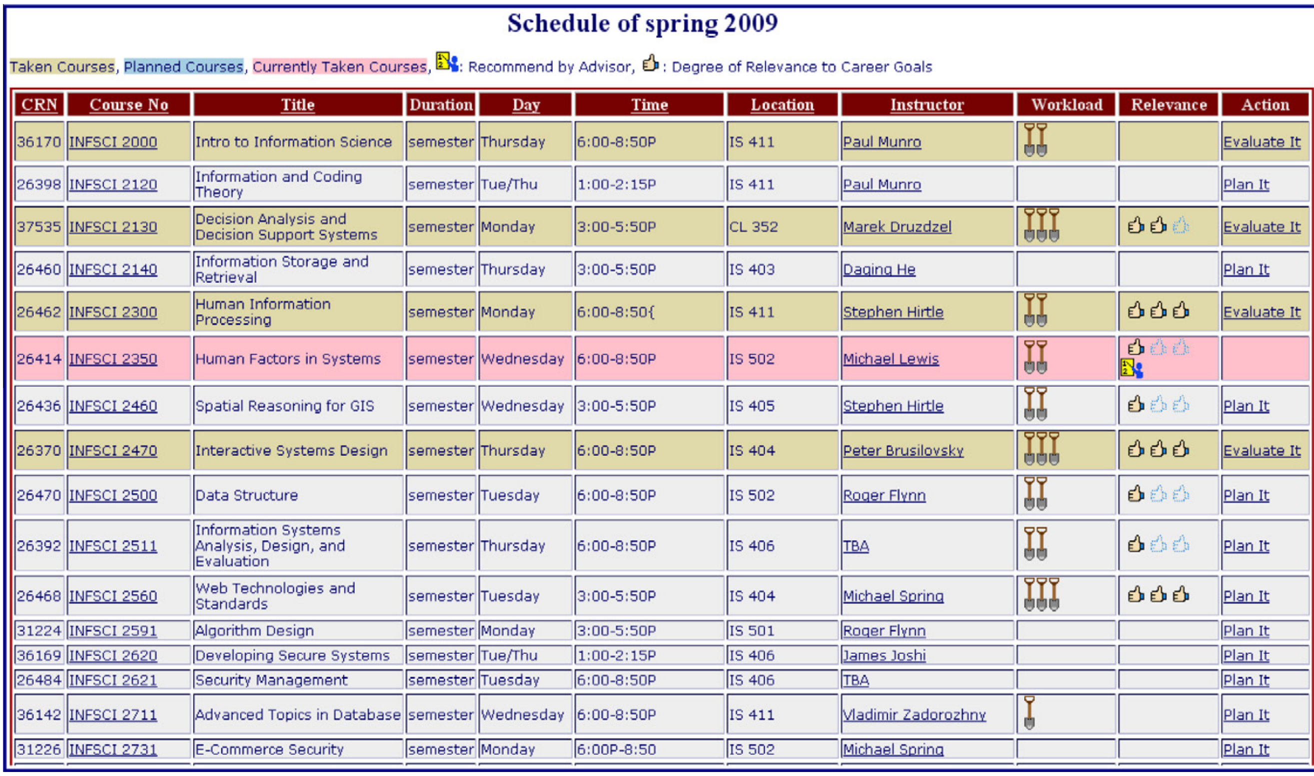
The goal of CourseAgent is to attract user attention to courses, which are most relevant to their career goals motivating their study. The social recommendation engine of CourseAgent attempts to predict how relevant each offered course is to the career goals of each individual student. However, in contrast to traditional recommender system, the recommendation power of CourseAgent is expressed not as a ranked list of courses, but in the form of in-context adaptive annotations. Course information is annotated with adaptive visual cues that help students to select their most appropriate courses. Fig. 1 demonstrates the use of in-context adaptive community-based annotations on the schedule page of CourseAgent. The schedule provides various information about each offered course, such as course number, course title, date, time, location, and information about the instructor. If the student finds a specific course relevant and interesting, they can use a system provided link to register for this course or to plan to pursue this in the future ("Action" column). To help the student with registering and planning decisions, the system augments each link with two kinds of community-based annotation displayed as icons to the left of the links. One icon expresses the expected course workload (one shovel for low, two for average, and three for a high workload). The other icon expresses the expected relevance of the course to the career goals of the given student (from one thumb up for a relevant course to three for a highly relevant course). The estimated workload and relevance of a specific course is calculated using community feedback about past offerings of this course, as taught by the same instructor as indicated in the schedule. In addition, the student's advisor can directly recommend a course as relevant. This information is represented by an "instructor" icon in the relevance column.

Similar community-based recommendations are provided in the Course Catalog section of the system. In Course Catalog, courses are grouped by areas of study defined by the program as shown in Fig. 2. For example, an Information Science degree includes areas such as Cognitive Science, Cognitive Systems, and Mathematical and Formal Foundation. Each course in the catalog is annotated with social recommendation information representing the relevance and workload of the course. Since different instructors might teach the same course, the average relevance and workload of each course is based upon the average score over all instructors who taught the course in the past.

3.2. From community feedback to social recommendations

CourseAgent provides social recommendations by collecting three kinds of information from the community of students: (a) the students self-selected career goals, (b) the students explicit evaluation of course workload, and (c) the students explicit evaluation of relevance of courses taken to their career goals. We have defined an extendable list of 22 career goals that cover different ranges of careers related to the information science field. Students are able to select as many career goals as they want from the list to add to their profile. These goals are communicated to student advisors and also serve as a basis for social recommendations.

The system provides an interface to evaluate courses already taken. Students are asked to evaluate the relevance of each taken course to each of their career goals on a scale of 1–5 and to evaluate the workload of the course on a scale of 1–3. Leaving the feedback is not mandatory in the system. Students are free to leave no feedback for a course taken or to evaluate the course in relation to just one or two of their career goals. Fig. 3 presents the evaluation

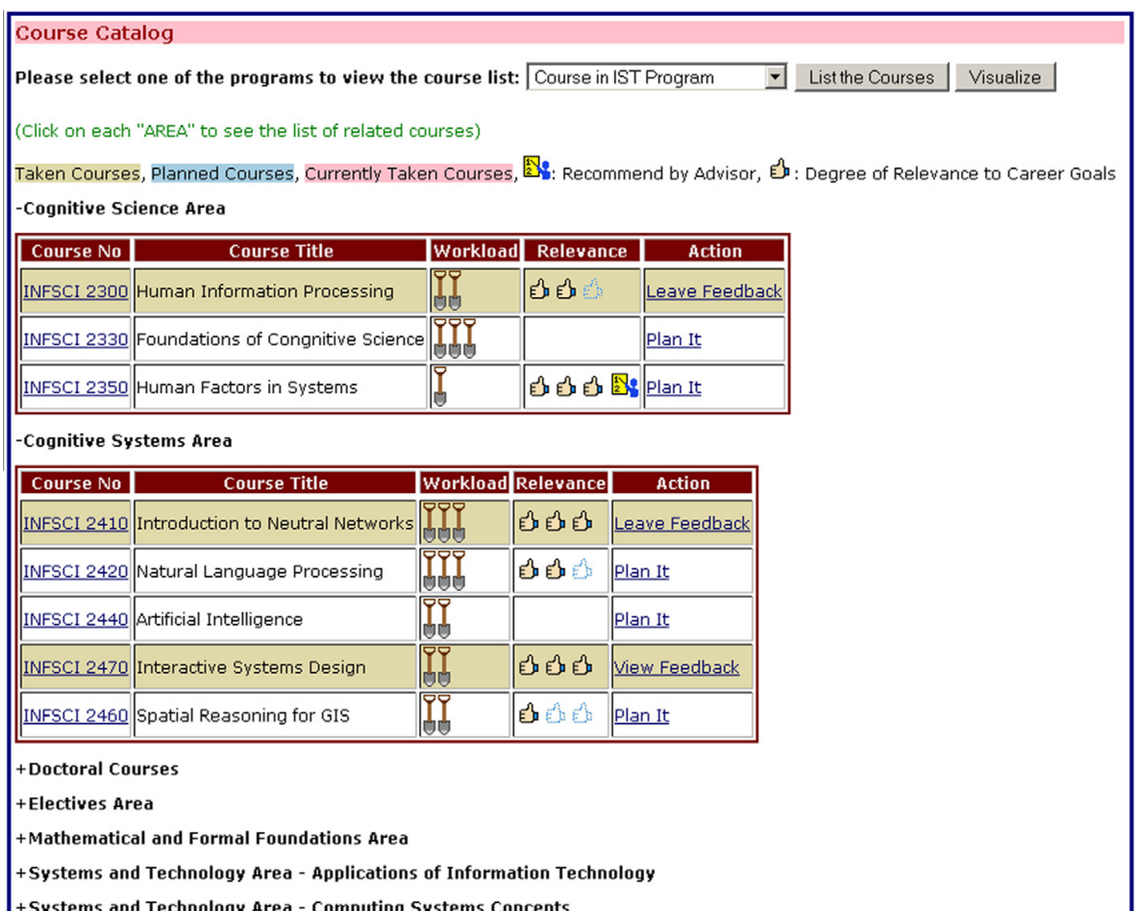


Schedule of spring 2009

Taken Courses, Planned Courses, Currently Taken Courses, : Recommend by Advisor, : Degree of Relevance to Career Goals

CRN	Course No	Title	Duration	Day	Time	Location	Instructor	Workload	Relevance	Action
36170	INFSCI 2000	Intro to Information Science	semester	Thursday	6:00-8:50P	IS 411	Paul Munro			Evaluate It
26398	INFSCI 2120	Information and Coding Theory	semester	Tue/Thu	1:00-2:15P	IS 411	Paul Munro			Plan It
37535	INFSCI 2130	Decision Analysis and Decision Support Systems	semester	Monday	3:00-5:50P	CL 352	Marek Druzdzel			Evaluate It
26460	INFSCI 2140	Information Storage and Retrieval	semester	Thursday	3:00-5:50P	IS 403	Daqing He			Plan It
26462	INFSCI 2300	Human Information Processing	semester	Monday	6:00-8:50{	IS 411	Stephen Hirtle			Evaluate It
26414	INFSCI 2350	Human Factors in Systems	semester	Wednesday	6:00-8:50P	IS 502	Michael Lewis			
26436	INFSCI 2460	Spatial Reasoning for GIS	semester	Wednesday	3:00-5:50P	IS 405	Stephen Hirtle			Plan It
26370	INFSCI 2470	Interactive Systems Design	semester	Thursday	6:00-8:50P	IS 404	Peter Brusilovsky			Evaluate It
26470	INFSCI 2500	Data Structure	semester	Tuesday	6:00-8:50P	IS 502	Roger Flynn			Plan It
26392	INFSCI 2511	Information Systems Analysis, Design, and Evaluation	semester	Thursday	6:00-8:50P	IS 406	TBA			Plan It
26468	INFSCI 2560	Web Technologies and Standards	semester	Tuesday	3:00-5:50P	IS 404	Michael Spring			Plan It
31224	INFSCI 2591	Algorithm Design	semester	Monday	3:00-5:50P	IS 501	Roger Flynn			Plan It
36169	INFSCI 2620	Developing Secure Systems	semester	Tue/Thu	1:00-2:15P	IS 406	James Joshi			Plan It
26484	INFSCI 2621	Security Management	semester	Tuesday	6:00-8:50P	IS 406	TBA			Plan It
36142	INFSCI 2711	Advanced Topics in Database	semester	Wednesday	6:00-8:50P	IS 411	Vladimir Zadorozhny			Plan It
31226	INFSCI 2731	E-Commerce Security	semester	Monday	6:00P-8:50	IS 502	Michael Spring			Plan It

Fig. 1. Community-based recommendations in CourseAgent schedule of courses.



Course Catalog

Please select one of the programs to view the course list: Course in IST Program | List the Courses | Visualize

(Click on each "AREA" to see the list of related courses)

Taken Courses, Planned Courses, Currently Taken Courses, : Recommend by Advisor, : Degree of Relevance to Career Goals

-Cognitive Science Area

Course No	Course Title	Workload	Relevance	Action
INFSCI 2300	Human Information Processing			Leave Feedback
INFSCI 2330	Foundations of Congnitive Science			Plan It
INFSCI 2350	Human Factors in Systems			Plan It

-Cognitive Systems Area

Course No	Course Title	Workload	Relevance	Action
INFSCI 2410	Introduction to Neutral Networks			Leave Feedback
INFSCI 2420	Natural Language Processing			Plan It
INFSCI 2440	Artificial Intelligence			Plan It
INFSCI 2470	Interactive Systems Design			View Feedback
INFSCI 2460	Spatial Reasoning for GIS			Plan It

+Doctoral Courses
+Electives Area
+Mathematical and Formal Foundations Area
+Systems and Technology Area - Applications of Information Technology
+Systems and Technology Area - Computing Systems Concepts

Fig. 2. Community-based recommendations in CourseAgent course catalog.

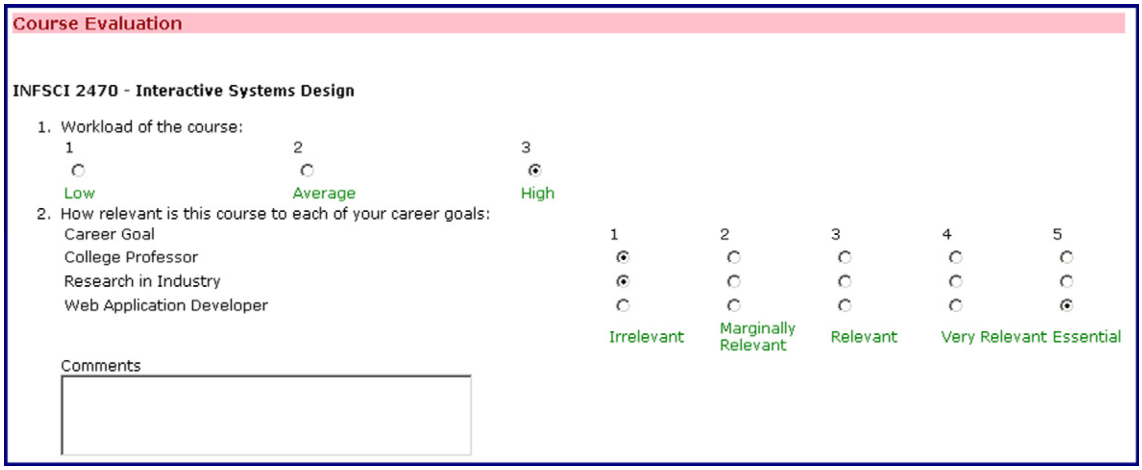


Fig. 3. Evaluation interface in CourseAgent course catalog.

interface. The collected information is used to deliver adaptive annotations presented in the previous section. The overall workload level of the course is computed by simply averaging all ratings provided by the students. The relevance of a course to a student is computed based on the relevance of the course to each of the students career interests. To compute total relevance, we cannot easily average the relevance to all career goals of the student: a worthy course might be irrelevant to most of the students career goals while being critical to only one goal. In this case, a simple average will give it a poor relevance rating, while the student might actually be especially interested in taking the course since it is essentially relevant to one of their career goals. To overcome this, we designed a simple case-based algorithm to compute course relevance. The relevance of a course to each career interest of the student ranges from 1 to 5, where 1 is not relevant and 5 is very relevant. Courses with a relevance level of 3 and above to at least one of the students career goals contribute to the overall relevance of the course to the student. The relevance of the course to the student is visualized with a thumbs-up icon (one icon means reasonable relevance and three means the highest relevance). Table 1 presents part of the cases in our algorithm for computing course relevance. For example, if a course is essentially relevant (relevance level of 5) in two of the students career goals, the course will be considered highly relevant to the student. The complete set of rules consists of 16 cases.

3.3. Adding incentive mechanism in CourseAgent

Similar to any other community-based adaptive system, the success of CourseAgent is highly dependent upon the feedback provided by the community. However, during the first semesters of CourseAgent's use, we observed that few courses were rated by few students. We hypothesized that low level of user participation stems from the nature of social recommendation engine. CourseAgent's engine differs from traditional collaborative recommenders, such as MovieLens (Miller, Albert, Lam, Konstan, & Riedl, 2003) in one important aspect: recommendations that are provided to a specific student do not take into account her own ratings, but only the ratings of students who took potentially interesting courses earlier. As a result, ratings provided by the students in CourseAgent are beneficial solely to the community but not to the author of the ratings. This typical contradictory situation motivated us to try an incentive approach based on personal needs and to find some way to turn rating courses into a self-beneficial activity.

Table 1
Case-based algorithm for computation of course relevance.

Number of career goals with relevance 5	Number of career goals with relevance 4	Number of career goals with relevance 3	Final relevance
⩾2	*	*	3
1	>1	*	3
0	1	0	1
0	0	2	1

* Means the parameter can take any value or zero or more.

Therefore, our challenge has been to design an activity that is both attractive and meaningful for the students and can use course ratings provided by the student for the benefit of the author of the ratings. Since the main goal of students from taking courses is their future career, connecting course rating to their career planning can be an attractive candidate. To integrate career planning with student course evaluation, we developed the Career Progress section of the system. In Career Progress, students can view the progress they have made towards each of their career goals. Courses they have taken and evaluated are used to compute their progress towards the career goals. The more relevant the course to the career goal, the more progress they will make towards the goal. Also, the difficulty level of the course will affect the progress. A low-load course would not necessarily cause the same progress as a high-load course. To calculate the progress, we have assumed that a specific career goal can be "covered" by taking four relevant courses with medium level difficulty. More difficult courses with higher relevance will contribute higher progress. To take into account non-additive knowledge accumulation in courses contributing to the same goal, we used a logarithmic-style contribution function (Fig. 4) instead of a lines one. With this approach, each next course taken towards the same career progress contribute to that career less. The first course adds 40% of progress while the rest of courses add only 25%, 15%, and 10%, respectively, and taking more than four courses does not contribute to career progress.

Fig. 5 shows a screen-shot of the Career Progress section. For each of student's career goals, there is a progress bar that displays the contribution of relevant courses taken and planned towards achieving this goal. As mentioned before, the contribution of taken courses into the progress depends on student's evaluation of relevance and difficulty of the course. A taken, but not evaluated course does not contribute to student progress towards a goal. Since planned courses are not yet taken (and rated) by this student, the total contribution of the students' planned courses is computed from the average relevance and average difficulty level provided by the community of students. To distinguish actual progress from

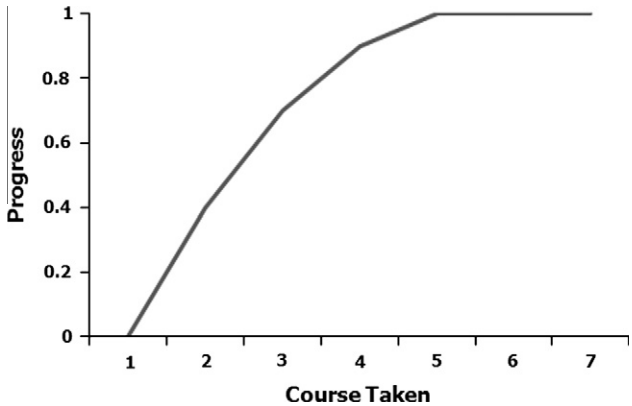


Fig. 4. Contribution of each course taken in calculation of career progress.

planned progress, the contribution of planned courses is shown in the progress bar with a different color (blue[1] for planned courses, and brown for taken courses).

The career progress visualized by the progress bar can be examined in details by expanding a career goal as shown in Fig. 5. An expanded career goal lists three possible groups of courses: taken, planned, and recommended. The students are able to see their own evaluation of taken courses. Taken but not evaluated courses are presented in the Taken Courses table with a lighter background. This prompts the students to evaluate the course (using the link to the right) in order to be count as a part of progress toward the career goal. They are also able to view the community's evaluation of their planned courses, as rated by relevancy to each specific career goal. The list of recommended courses (based on the community's evaluation) is provided for each specific career goal and students are able to plan any of the recommended courses.

4. Evaluation

To study the impact of our incentive mechanism on user contribution in CourseAgent, we conducted two series of evaluations at the School of Information Sciences at the University of Pittsburgh. At the first stage, we conducted a preliminary study to assess the motivating effect of career progress report feature by opening the feature to only half of the students. The preliminary study includes one semester data from 20 graduate students. It compared the behavior of students who had access to this feature with the control group, which had no access to career progress. We hypothesized that the ability to track career progress encourages students to rate more courses. At the second stage, we were interested on evaluating the effect of career scope on long-term usage of the system. On this stage, the career progress feature was available to all students. The longitudinal study includes data from 3 years usage of 171 graduate students. CourseAgent is an opt-in system and the usage of the system was optional throughout both studies.

4.1. Preliminary evaluation

For the preliminary evaluation, the system was advertised to graduate students of the School of Information Sciences 2 weeks prior to registration deadline, when we expected high demand for its services. When a student requested to use the system, they were randomly assigned to either control or experimental group.

Throughout the period of the study, 20 students used the system. Eleven students were assigned to control group and 9 to the experimental group. To compare the contribution of control and experimental group we calculated number of courses taken, courses planned, career goals, and ratings entered into the system by each group. Table 2 shows the result. The result is compatible with our expectation and shows that experimental group contributed more into the system. They added more information about courses taken, and planned, and their career goal and they rated larger number of courses.

While analyzing the data we noticed that some users in the experimental group never clicked on career progress page. The career progress feature was not advertised in any specific way. As a result even though the feature was available to all users, some users apparently have not noticed it since they have not accessed the career progress page even once. To evaluate the real effect of the feature we decided to compare the contribution of users who at least visited career progress once with those who did not use it at all whether in control or experimental group. Table 3 show the result of this comparison. The data shows that the difference of the group is much more visible and it suggests that career progress is successful in encouraging users' contribution.

These result are considered preliminary and due to the small number of subjects, we did not conduct any statistical analysis. As a result, it is difficult to draw any reliable conclusions; nevertheless, the results are very encouraging. This has motivated our longer term evaluation. Since we believe career progress is an important feature of the system, we decided to make it available to all users and in our long term evaluation study the correlation of usage of it and contribution to the site. Section 4.2 presents our long-term evaluation in details.

4.2. Long-term evaluation

Once our preliminary stage evaluation was over, we opened the career progress feature to all students and advertised the usage of the system among all graduate students at the School of Information Sciences at University of Pittsburgh. We were interested in assessing the effect of our incentive mechanism on long-term real usage of the system. The system was advertised before each semester registration. The system has been used for three years. Table 4 shows the general statistics about the usage of the system over three years. We separated data for Masters and Ph.D. students since they have different goals from taking courses. For Masters students courses contribute much stronger into their career goals and they plan their courses according to their career goals while for Ph.D. students research plays the most important role and courses have small contribution towards their career goals. Given the fact that the incentive mechanism of the system relies on relevancy of courses to students' career goal, we focus the rest of evaluation on Masters students.

As it can be seen in Table 4, overall about 23% of students have at least rated one course. While this seems a low number, it is in fact higher than average contribution rate in online communities. So overall the system has achieved less inequality of contribution and higher percentage of users are contributing to the rating of courses.

To analyze the effect of career progress page on students' navigation behavior we looked at the correlation between number of times students have looked at career progress page and number of ratings they have provided. We divided the students into two groups depending on whether they have visited career progress page or not. In the rest of the paper, we call the group who have visited career progress at least once as CP and the group who have not visited career progress page NO-CP. Since rating is only possible after student have entered their courses taken and career goals, in the analysis we have included only those students who have at least one course taken and one career goal selected. That includes 76 students in total, 32 in CP group and 44 in NO-CP group.

[1] For interpretation of the references to color in this figure, the reader is referred to the web version of this article.

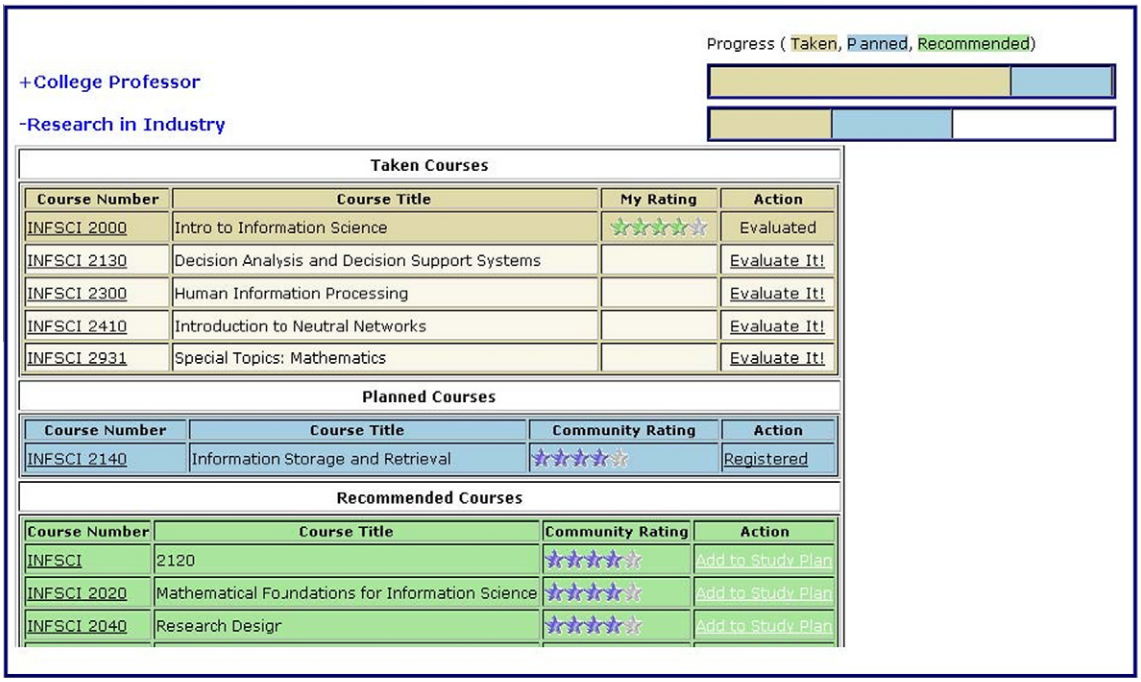


Fig. 5. Career progress interface in CourseAgent.

Table 2
Comparison of contribution of users in control and experimental group.

	Mean course taken	Mean course planned	Mean career goal	Mean of ratings
Control	5	2	0.91	4.55
Experimental	5.89	5	2.2	6.22

Table 3
Comparison of contribution of users using or not using career progress.

	Mean course taken	Mean course planned	Mean career goal	Mean of ratings
Not using career progress	4.27	1.87	1	4.33
Using career progress	8.8	7	3	8.2

Table 4
General statistics of usage of the system.

	Number of students				
	Used the system	Added taken courses	Added planned courses	Added career goals	Added course ratings
MS	143	93 (65%)	105 (73%)	76 (53%)	33 (23%)
Ph.D.	28	25 (89%)	17 (61%)	22 (79%)	15 (54%)

4.2.1. Percentage of students rating

First we compare the percentage of students in each group who rated any courses. Fig. 6 shows that higher percentage of students in CP group rated courses (70% versus 47%). Chi-square test of equality of proportions suggest marginal significant difference of percentage of CP versus NO-CP students who rated courses (Pearson $\chi^2 = 2.71$, df = 1, 2-sided p-value = 0.09).

4.2.2. Correlation of usage of career progress and number of ratings

Next we were interested to evaluate whether there is a correlation between the number of times a student visited career progress page and number of ratings they provided. We expected that the more visit to career progress page correlates with higher number of ratings since career progress encourages rating and is dependent on ratings. Fig. 7 shows the average number of ratings provided by each group. Nonparametric test of correlation of career progress visits and number of ratings shows a significant positive correlation (Spearman's $\rho = .27$, 2-tailed p-value = 0.04).

However, it can be argued that students who visited career progress page are generally active contributors on the site and are generally more active on the site. To verify that we compared their activities in terms of number of course taken, number of course planned, and number of career goals. The result is shown in Fig. 8. Mann–Whitney test shows no significant difference between CP and NO-CP groups ($Z_{taken} = -1.23$ and 2-tailed p-value = .22, $Z_{mhboxplanned} = -.34$ and 2-tailed p-value = .73, $Z_{mhboxcareergoals} = -.49$ and p-value = .62). The result suggests that the general activity of CP and NO-CP groups in CourseAgent is comparable, while the volume of their course rating activity is significantly different.

The result of our analysis suggests that our proposed incentive mechanism is successful in encouraging users to rate more courses. We have observed that extrinsic motivations are activated when personal needs are targeted. Thus we confirmed the ability of yet another incentive mechanism to effectively change users' behavior. However, can we assume that our incentive mechanism affects users' behavior only in positive direction? In the next section we discuss some possible problems of changing users' behavior by incentives and examine possible negative effects of our incentive mechanism on CourseAgent users.

5. Problems and drawbacks of incentive systems

While there has been wide rage of research on encouraging user participation in online communities, little has been done on studying the drawbacks of incentive systems. As mentioned in Section 2.2.3, a possible drawback of extrinsic motivation is reducing internal incentives. Another easily anticipated drawback of incentive systems is gaming. Users are known to game various incentive systems to achieve higher reputation or rewards. Gaming is a serious

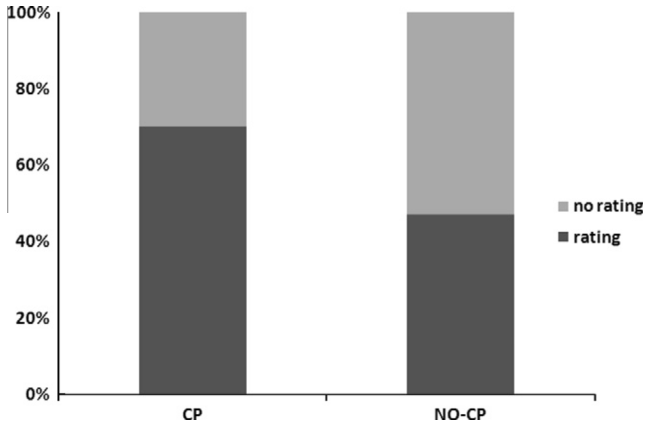


Fig. 6. Percentage of students rating courses.

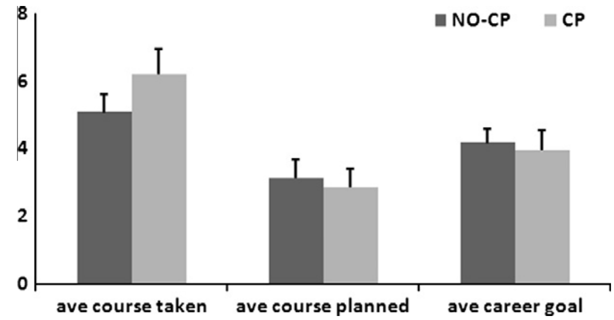


Fig. 8. Average number of courses taken, courses planned, and career gaols provided by students in CP and NO-CP group.

concern for all kinds of social systems since gaming leads to low quality contributions, which in turn can discourage other users from using the system. Cheng and Vassileva observed that enhancing users' status as a response to their contribution could motivate users in adding low-quality resources and inaccurate ratings (Cheng & Vassileva, 2006). They had to adapt their reward mechanism to prevent "gammers". Farzan et al. (2008b) showed that a point-based reward and reputation incentive for encouraging contribution to a social networking site motivated several different gaming behaviors. Some users started gaming the incentive system to criticize the validity of the reward based contributions. Others tried to earn points by adding fake content or automatically generated content. Preventing gaming stays a challenge for incentive systems specially those based on reputation, rewards, and interpersonal motivations (Ellis, Halverson, & Erickson, 2005).

While individual motivations based on personal needs can be immune to direct gaming, they may be subject to another problem: self-deception. Balcetis defines self-deception as "process of ignoring, rationalizing, or manipulating some thought or behavior to create consistency between that thought or behavior and one's sense of self" (Balcetis, 2008). Balcetis discusses that motivations influence cognition in four different ways by biasing perception of information, attention to information, processing of information, and memory retrieval. She suggests that these motivational biases make self-deception successful.

Unlike gaming, the effect of motivations in online communities on self-deception has not been explored. The incentive mechanism in CourseAgent capitalizes on individual motivation and personal needs. We anticipated a potential adverse effect of the incentive on students' rating of courses. Next section describes our exploration of the effect of the incentive mechanism in CourseAgent on students' self-deception.

6. Positive rating bias in CourseAgent

An example of self-deception, which can be provoked by our incentive approach is what we call "positive rating bias". The more relevant a course is rated to student's career goal, the more progress will be contributed towards the goal. With this design, students may have an implicit motivation to rate courses higher in order to attain higher visible progress. The positive rating bias may not be as destructive as gaming, but it is still not harmless. Artificially increase course ratings may affect system's recommendations encouraging students to take courses, which are not as relevant to their goals as shown by the system.

To explore the presence of the positive rating bias in CourseAgent, we analyzed the correlation of average rating value and the number of visits to career progress page. Fig. 9 shows the average value of ratings given by students in CP and No-CP group. The result suggests that CP students are likely to give higher ratings to courses. Nonparametric test of correlation of career progress visits and average ratings shows a significant positive correlation (Spearman's $\rho = .44$, 2-tailed p-value = 0.03).

While these results may not be considered as a definite proof of the positive rating bias, the evidence is strong enough to consider the incentive mechanism based on personal needs, as well as other incentive mechanisms with care, taking into account both positive and negative effects, which it may cause.

7. Discussion and future work

Social recommender systems and other kinds of social software are highly dependent on the users' feedback and participation. The

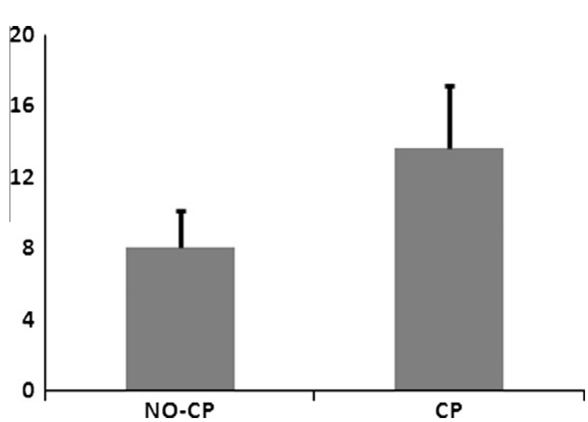


Fig. 7. Average number of ratings provided by students in CP and NO-CP group.

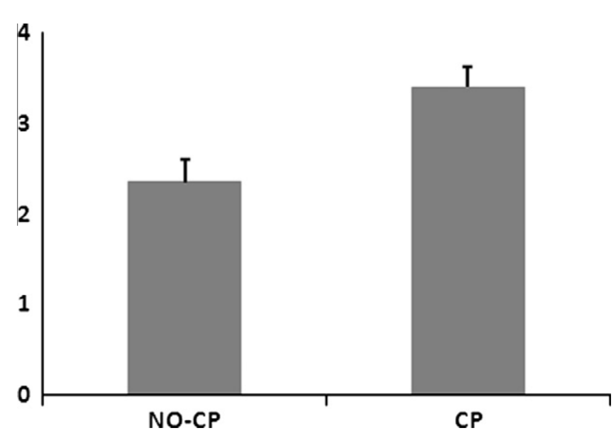


Fig. 9. Average value of ratings given by students in CP and NO-CP group.

need to attract a high quality and volume of participation has been recognized by both researchers and practitioners and caused an increasing interest in both developing various incentive mechanisms and studying the impact of these mechanisms on user behavior. Over the last few years, several incentive mechanisms were explored in the context of different social systems. In our work we explored a new type of incentive mechanism based on users' personal needs to increase the volume of user feedback about taken courses. In CourseAgent, this mechanism was implemented through career goal interface, which turned course rating into a valuable activity for the users by allowing them to better track their progress towards career goals. Our results suggest that this specific incentive mechanism can significantly affect the behavior of CourseAgent users. Users who did not use career progress feature of CourseAgent rated significantly fewer courses even though the average activity of both groups of users was comparable. However, we also observed that an incentive based on personal needs motivates self-deception which causes positive rating bias in this case. Users who used career progress feature more were more likely to rate courses higher. This result along with previous research on gaming incentive systems and effect of extrinsic incentives on intrinsic ones hints that incentive systems should be employed with careful consideration of possible drawbacks. Different incentive mechanisms trigger different side effects and are subject to different problems. Understanding positive and negative influences of these mechanisms on user behavior is important while designing and deploying any incentive mechanism.

We are interested in deeper analysis of the positive rating bias to understand users' behavior better. From our current evaluation, it is not clear whether the impact of our incentive mechanism made ratings artificially higher or whether, instead, it just motivated the users to think more carefully about their ratings. User interviews and questionnaires can help to conduct a more profound analysis. Deeper evaluation will inform us to modify the incentive mechanism in CourseAgent to minimize the positive rating bias. We are also interested on exploring different incentive mechanisms known in the literature and studying their effects on users' behavior. Following collective effort model, we would like to increase user awareness about the importance of their contribution for themselves and for the community and assess its effect on encouraging users contribution and self-deception.

Acknowledgement

This research is partially supported by the National Science Foundation through Grant IIS-0447083 and Graduate Research Fellowship to R. Farzan.

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