# Exploration and Explanation: An Interactive Course Recommendation System for University Environments

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**Abstract**
The abundance of courses available in university and the highly personalized curriculum is often overwhelming for students who must select courses relevant to their academic interests. A large body of research in course recommendation systems focuses on optimizing prediction and improving accuracy. However, those systems usually afford little or no user interaction, and little is known about the influence of user-perceived aspects for course recommendations, such as transparency, controllability, and user satisfaction. In this paper, we argue that involving students in the course recommendation process is important, and we present an interactive course recommendation system that provides explanations and allows students to explore courses in a personalized way. A within-subject user study was conducted to evaluate our system and the results show a significant improvement in many user-centric metrics.

**Keywords**
Course Recommendation, Visualization, Exploration, Explanation

## 1. Introduction

A course recommendation system suggests a student decide what they should study as per their requirements, which can solve the increasingly severe problem of information overload of course selection. Different from the traditional movie recommendation domain or music recommendation domain, the interaction factor is essential for course recommendations in universities.

Course recommendations in universities particularly suffer from the cold start problem. Every year, there are freshmen enroll in, who have difficulty navigating their new academic and environment. It is difficult for a traditional course recommendation system to make successful suggestions for those new students without enough available information. Moreover, the necessary information is often too small to generate precise recommendations even for senior students. One common practice is using popular courses regardless of students' interests when the system is short of students' information and behavior. However, a promising alternative is to capture their preferences interactively. That is, if we could involve students in the recommendation process, we may get better results.

Many researchers have focused on recommending courses that align with students' interests extracted from their historical data, but students may not choose courses based purely on their interests. For instance, many students have no idea what they want to study, and their choice of courses is aimless [1]. Besides, student interests and goals can change as they explore and learn new things, their preferences extracted from historical data may differ from their current interests. So, involving the student in the recommendation process becomes more significant than in other domains.

Also, the cost to students of making an inappropriate decision is much higher than investing two hours watching a movie they don't like or listening to a song they are not interested. In a domain such as a course recommendation and learning goal discovery in universities, course selection is a low-frequency behavior. Students only need to make decisions every new semester for four academic years. However, it can have a long-lasting effect on the student as improperly selecting courses would seriously affect their course achievements, even leads students to drop out.

Recently, a large body of research focuses on developing course recommendation systems. However, those systems afford little user interaction and lack options to control how recommendations are produced. To address these challenges which have not been well explored in the research community, this work presents an interactive course recommendation system by combining visualization techniques with recommendation techniques to support the diverse information needs of students. The interactive feature stresses user involvement with the system, allows users to flexibly explore large-item spaces while providing a high level of user control and transparency [2]. Also, our proposed approach could increase

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the usability of the course recommendation system compared to previous works that only focus on improving accuracy.

# 2. Related work

## 2.1. Interactive recommendation system

Current recommendation systems often produce recommendations that fit well the user's requirements automatically, trying to reduce the user's interaction effort and cognitive load [3]. However, such recommendation systems generally do not allow the user to influence or control the recommendation process, which may lead to filter bubble effects. Also, users may feel too much dominated by the system because it difficult for them to give feedback [4]. More recently, the potential of interactive recommendation approaches has been highlighted to solve these problems.

Several researchers have proposed interactive visualizations to support interaction with recommendation systems [5, 6, 7, 8]. Visual representation of information can strongly influence users' understanding of complex data and help reduce cognitive efforts. Several interactive recommendation systems focus on allowing users to control the recommendation process [9, 10]. Those applications let users have a more active role to iteratively refine the result set towards their requirements. Their results show that the recommendations are more likely to be accepted by users if the system offers a higher level of user control. It has also been shown that interactive recommendation systems have the potential to support better exploration [11, 12], and increase the diversity of content [13].

Findings from previous works suggest a great benefit of interactive recommendation. However, those works are limited to traditional recommendations such as movie or music, which may significantly differ from the course recommendation in education field.

## 2.2. Course recommendation system

Course selection is a critical activity for students in higher education contexts. Various methods have been used in applications for course recommendation systems by learning from historical enrollment data.

A related body of work focus on recommending courses to students that will match their interests [14, 15]. Another set of recommendation method involves mining relationships and discovering sequences from historical data [16, 17]. Recently, representation learning uses neural network architecture has been used in this domain [18, 19]. However, those systems suffer from several disadvantages: First, those systems offer little user interaction and do not permit students to change their interests. Second, those systems do not support exploration, which is particularly important in the context where students go through a broad exploratory phase before specializing. Finally, those systems often behave like a "black box" and do not give explanations that would allow students to reflect on their course selection.

In contrast to the approaches that consider more about the accuracy of predicted results, in this work, we build an interactive course recommendation system, which allows students to interactively improve the recommendations and bring their own preferences to the system. Also, it has the benefit of allowing better exploration, as well as the increased explanatory value of the recommendation algorithm.

# 3. The CourseQ system

In this section, we present CourseQ, a web-based interactive course recommendation system to help students with different information needs to find suitable courses. We first propose a visualization based on a topic model in Section 3.1. Then we describe how we incorporate it as an interactive course recommendation interface in Section 3.2.

## 3.1. Visualization

To understand the relationships of each course and display them in the latent space, we collected data for 380 courses from the syllabus of our university. First, we extracted the text content of collected course data after filtering irrelevant content such as instructor's name. Then we used the Latent Dirichlet Allocation (LDA) generative probabilistic model [20] to fit a topic model to the course data collected to give a latent representation for each course. After employing the topic model, we got a k-dimensional vector representation for each course where k is the topic number. The latent representation of course content provides us a convenient way to show the relationships among courses which is an important measurement in our recommendation system. Finally, Linear Discriminant Analysis (LDA) and T-Distributed Stochastic Neighbor Embedding (T-SNE) were used to reduce the dimensionality of these vectors to the 2D layout. The visualization affects the way the system processes the information by displaying the course relevance in two dimensions layout. It helps the student to understand the course content according to its topic distribution. Based on the topic model, the interface presents each item (a course) as a circle node on the canvas in a 2D layout (Figure 1f). We colored each course node according to the topics for a visual explanation. Our interface support zooming and panning the visualization, the layout also could be shifted by the slider (Figure 1g). Recommenda-

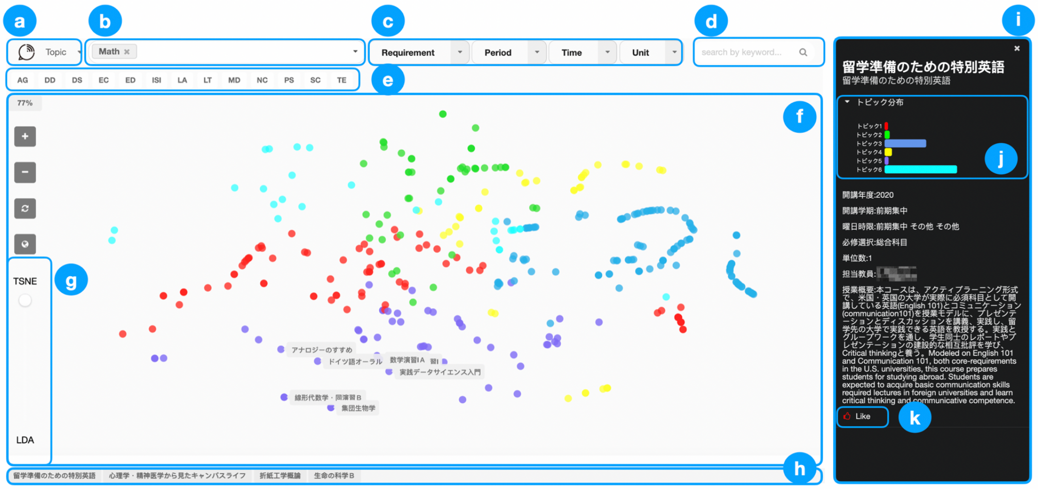


**Figure 1:** The screenshot of the CourseQ. The interface supports the exploration of recommended courses in left and detail inspection in right. (Some text is in Japanese, and the instructor's name has been pixelated for privacy protection).

tions are displayed as the corresponding course nodes and their labels are highlighted within the visualization. We hope that the ability of interactive visualization could explain the recommendation results and help students to explore more within the latent space. In terms of topic number, we find that too many topics may hard to visualize and colorize while too few may cause poor performance, as a result, we set 6 as a practical number in our follow-up experiments. It means that a course will be represented by a vector with 6 dimensions.

## 3.2. Interface design

Figure 1 illustrates the design of the interface. Different functions that help students interact with the system to find suitable courses are demonstrated at the top of the interface. Students can see all topics and related keywords determined by the topic model respectively in Figure 1a, and construct their interest by selecting keywords via a drop-down list (Figure 1b). The keywords that the student selects will be used as a seed for recommendations. Besides, they could filter the results based on their own needs (e.g., the requirement of the degree program, course period, time slot, unit) as shown in Figure 1c. For example, a student dislike waking up in the early morning so he/she would like to filter morning classes out when exploring the system. On the upper right side, Figure 1d, students can use a search box with auto-completion to find courses. This is suitable for situations when a clear search goal has been formed. Moreover, we have the department information extracted from historic enrollment data in the system (Figure 1e). Upon clicking on one of the buttons that represent different departments, popular courses within this department will be shown. Students can explore popular courses for convenience's sake and it is helpful to figure out the similarity or differences among departments, comprehend the course selection pattern, and build their learning path.

Based on the student's interest topics associated with selected keywords, the system recommends courses for students and shows them in the latent topic space. Recommendations are displayed as the corresponding course nodes and their labels are highlighted within the visualization. Upon clicking on the node of the recommended course, various information about this course are shown in the right-sidebar (Figure1i), students can explore official information provided by the university such as course period, instructor, date, time, location, and course descriptions. To explain why a course is recommended, we used a grouped bar chart, as seen in Figure 1j, which shows the topic distribution of the selected course. The colors of the bars match those of the circle nodes from the visualization to show their relations. With the bar charts, students can compare the topic distributions among different courses to help their decision-making process. Finally, the student can click on the button to like a course or cancel it as seen in Figure 1k. On the bottom of the interface, Figure 1h, students can see the list of courses they liked. In this part of the interface, they can also click the course to check the detailed information or edit their list to generate personalized results. Every time the student liked a course while browsing the recommendation result or exploring with the visualization, it will be added into the like list automatically to calculate the student interest together with the selected keywords. Also, students could edit their like list conveniently, which allows them to

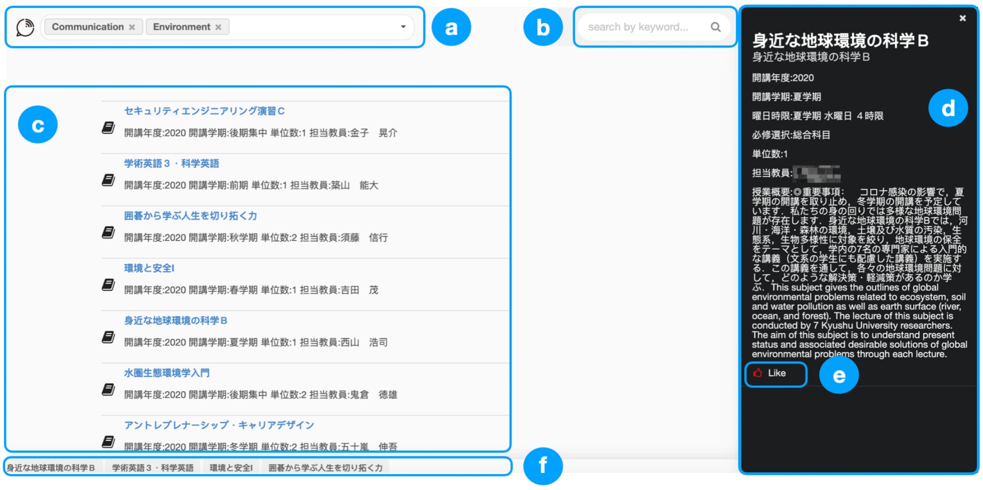


**Figure 2:** The screenshot of the baseline application. The interface shows recommended courses in left and detail inspection in right. a) Keyword input, b) Search bar, c) Ranked list, d) Information sidebar, e) Like button, f) Like list.

provide immediate feedback and control the system to generate a more personalized result.

### 3.3. Generating recommendations

Our system recommends courses based on the student interest corresponding to topic distribution. The student interest is extracted from the keywords that he/she selected and courses he/she liked while exploring the system. To calculate convenience, the vector of courses and keywords, based on course content and topic distribution, is stored in two separate data structures. The recommended courses are ranked based on their similarity to the student interest. To this end, we computed the Euclidean distance between the vector of student interest and the vector of each course. The student's 'like' list is also important information for the system to give more personalized results. Every time the student 'liked' a course while browsing the recommendation result or exploring the visualization, it will be added to the 'like' list automatically to calculate the student's interest together with the selected keywords. Also, students could edit their 'like' lists conveniently, which allows them to provide immediate feedback and control the system to generate a more personalized result.

## 4. Evaluation

To evaluate the system in terms of subjective effectiveness and quality, we developed a baseline system as a comparison that uses the same algorithm, values, and dataset as CourseQ. Figure 2 illustrates the design of the baseline interface. Considering the fairness of the comparison, we implemented all features as same as CourseQ. Students can search for courses of interest, get recommendations by select keywords, click the recommended course to check details with the information sidebar, and click the button to like and save a course he/she is interested in. However, to have a better understanding of user-perceived transparency and experience of exploration, the visualization and filter component are removed from the baseline interface. The topic distribution component which acts as an explanation for users is not provided in this interface either. Instead, a ranked list was selected as a traditional way of presenting recommendation results.

### 4.1. Participants

We recruited 32 participants (22 male, 10 female) for the user study. The participants are all students who came from different departments of our university, their ages ranged from 19 to 28 (M=25.5, SE=0.39). The study was conducted fully online because of the Covid-19 situation of this year.

### 4.2. Experimental setup and data collection

We used online meeting software (Zoom) to communicate with our participants and asked them to access our interfaces by a web browser. The two different interfaces were tested in a within-subject design to avoid the influence in the first trial for the second. The first half of the participants will use the CourseQ interface and then use the baseline interface. The other half uses the baseline

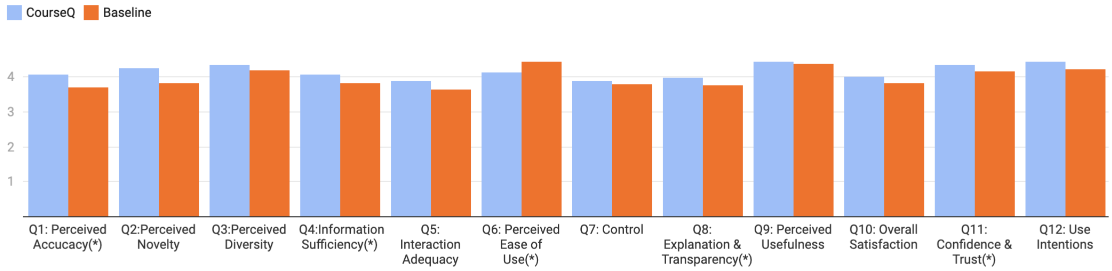


**Figure 3:** User feedback analysis results. (Significance level: (*) p < 0.05).

interface first, and then CourseQ. We asked participants to fill in a questionnaire to collect their demographic and personal characteristics data. Then we show the introduction of the experiment and the video tutorial of two interfaces. After that, they were asked to freely interact with the interface to find relevant courses (at least five) matching their interests. They could use all features of the respective interface and were not restricted in time. After performing the tasks, participants filled in a questionnaire (5-point Likert scale, 1-completely disagree, 5-completely agree), that measured different aspects of the recommendation system using the ResQue framework [21]. We also collected and analyzed logging data to capture user interactions with the various elements of the interface during the experiment. Finally, we conducted a qualitative interview to ask their opinions about two different systems.

# 5. Preliminary results

## 5.1. User Feedback

To compare user feedback, we analyzed the results of post-stage questions using paired sample t-tests. Figure 3 presents the different aspects of subjective feedback from the participants. CourseQ received a significantly higher rating for four aspects: Perceived Accuracy(Q1), Information Sufficiency(Q4), Explanation & Transparency(Q8), and Confidence & Trust(Q11). The baseline scored higher than CourseQ in Perceived Ease of Use(Q6), which is not strange because the richer functionality in CourseQ might cost more effort for participants to use. In other questions, although not significantly, CourseQ scored higher than the baseline.

## 5.2. Interaction patterns

To better understand the use of the system, we logged the clicks of participants as well as the time they consumed through the task. Table 1 shows the user interaction statistics for two interfaces. Overall, the click frequency presented a significant difference between the two interfaces. The participants tended to interact more with the visualization in CourseQ (M=65.34) than the ranked list in the baseline interface (M=12.13). This finding is not surprising because the baseline interface lacks the visualization information that pushes the participant to click more to explore within the item space. Moreover, the participants tended to interact more with the Information sidebar in CourseQ (M=23.2) than the baseline interface (M=7.8). Also, there is a significant difference in the time spent on the task between CourseQ (M=542.28) and the baseline interface (M=290.31). This hints that CouresQ could serve as an interactive exploration interface that delivered more interesting information to engage.

# 6. CONCLUSION

In this paper, we presented CourseQ, a course recommendation system by combining visualization technique with recommendation technique to help the exploration and explanation of the recommendation process through an interactive interface.

An online within-subject user study (N=32) was presented to evaluate the interaction and recommendation concept of CourseQ, compared with a baseline system. Our preliminary results show that CourseQ is potentially useful to the students. Also, most participants indicated that they feel confident and trust using CourseQ and will use it again.

There are some limitations to this work that needs to be articulated. The scale of reported user studies is relatively small, and the current gender distribution of participants (more males) may have a gender bias.

For future work, we will analyze user behaviors and feedback for a comprehensive understanding. Moreover, we aim to investigate more sophisticated visualizations to show structure-related topics, for example, show the prerequisite courses.

**Table 1**
User interaction statistics (Significance level: (*) p < 0.05)

| | CourseQ | Baseline | |
|---|---|---|---|
| Component - Behavior | M(SE) | M(SE) | P-Value |
| Ranked List - Total Clicks | - | 12.13(6.76) | |
| Scatter Plot - Total Clicks | 65.34(13.55) | - | |
| Navigation and Keywords Input - Total Clicks | 11.81(2.29) | 12.29(3.42) | |
| Search and Filter - Total Clicks | 25.22(5.26) | 2.9(3.72) | * |
| Department Feature - Total Clicks | 7.81(1.71) | - | |
| Information and Explanation - Total Clicks | 23.22(5.59) | 7.8(4.2) | * |
| 'Like' list - Total Clicks | 1.63(0.85) | 3.2(1.1) | |
| Time Spent - Second | 542.28(105.38) | 290.31(56.89) | * |

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