Courselect: Motivation-Centric Course Recommendation for University Students

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Abstract University students enrolled in academic programs across the globe face a common problem at the onset of each semester - figuring out which courses to register for. This paper presents qualitative interviews to identify the motivations of university students underlying course selection. The paper then proposes an algorithm for a course recommendation system 'Courselect' which helps students select courses based on their motivations. We also present a prototype web interface of the proposed system. The proposed algorithm models each agent in the university system as a node and provides course recommendations by minimizing the distance between relevant nodes. The web interface facilitates the course selection decision without undermining students' freedom of choice. This paper argues that Courselect can be calibrated for any university-level academic model or e-learning application to improve the student experience of the academic system.

Keywords: course recommendation, academic motivation, qualitative interviews

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1 Introduction

University education is an important predictor of economic success [1]. A major part of university education is the educational curriculum, consisting of formal courses operating on a credit system. While universities spend significant resources on designing course curriculums, similar attention is not paid to matching students with relevant courses. As a result, even if universities are able to design an excellent cohort of courses, students are not able to discover them for right reasons at the right time. There is a need to design a system that can match students with appropriate courses relevant to their goals and interests. This system would require an understanding of the motivations of university students underlying course selection.

The aim of this paper is to design a course selection system which can help university students discover academic courses based on their motivations. Towards this aim, we conducted qualitative interviews with university students to identify their motivations underlying course selection. This was followed by the development of a course recommendation system 'Courselect'. In this paper, we present the results of the motivational analysis from qualitative interviews. This is followed by the proposal of an algorithm for Courselect for course recommendation, and a prototype web interface that can facilitate students' academic decision making.

2 Background

There is a significant body of research on the psychological aspects of course selection in an academic setting. Students register for courses based on their potential learning and occupational gains, the course's prospective intellectual level, expected quality of teaching, but also, comfortable grading, ease of completion and time of day the course is offered [2, 3]. Students prefer courses taught by effective instructors [4] and instructors who give higher grades are better liked by students [5]. Students tend to enroll in courses taught by lenient instructors [6]. Course and instructor evaluations by past students also influence course selection [7]. Courses that receive lowest ratings by students are either too difficult or too elementary and higher rated courses are ones which are in between the two extremes [8].

There have been previous advances in the development of course recommendation systems. A self-help method for comparison of (up to 7) courses is presented in [9]. A recurrent neural network and skip-gram model based course recommendation system is presented in [10] which displays course suggestions based on the course history of the student and their major, on the top of which explicit personalization filters can be added by the student. A social navigation system called CourseAgent adaptively annotates courses with respect to their difficulty level and based on students' assessment of course relevance to their career goals [11]. Stanford University's CourseRank provides students with detailed course descriptions, tag based searching, a course planner, and recommended courses based on explicit parameters entered by the student [12]. UC Berkeley's Berkeleytime provides data regarding grade distributions and enrollment rates in courses [13].

Despite the pragmatic research in this field recently, there is a research gap for a holistic recommendation system that takes into account the students' (intrinsic and extrinsic) motivations to select their courses. Existing research focuses well on certain aspects of course recommendation like user participation and feedback in CourseAgent [11] or data presentation and filtering in CourseRank [12]. But to the best of the authors' knowledge, no reported recommendation systems exist to suggest a personalized list of courses to university students based on their interests and motivations. The role of interface design in facilitating this course selection has also not received sufficient attention. To address this gap, this paper proposes a course recommendation system under the label 'Courselect'. The proposed algorithm of Courselect accounts for students' individual preferences and motivations identified from qualitative interviews. The prototype web interface is designed to facilitate student decision making without undermining their freedom of choice.

3 Research Methodology: Identification of Student Motivations

To identify student motivations underlying course selection, in-depth interviews were conducted with 25 participants (16 males, 9 females). The participants were enrolled in a four-year undergraduate program majoring in various branches of science and technology at a publicly funded university. At this university, Year I students were only required to complete compulsory foundation courses. Therefore, we recruited our participants from years II, III and IV (5, 7, and 13 students respectively), who had a choice to pick elective courses. Deep qualitative semi-structured interviews for about 35 to 45 minutes per participant were conducted to understand the students' motivations underlying course selection for elective courses.

3.1 Analysis

The interviews were transcribed and open coded, with codes identifying the factors which influence the decision of course selection. Then, we conducted an inductive thematic analysis on these codes, creating categories for similar motivations and identifying within them the contributing factors which influence students' decision making. A rating score (S) was developed based on the frequency of occurrence of each factor in the interview data according to the Eq. 1. The rating score is indicative of the weight of each factor in the decision process.

$$f = \frac{\sum_1^N Rj}{N} \qquad Score\ (S) = \frac{\mathrm{f}}{\max value(\mathrm{f})} \qquad \text{(Eq. 1)}$$

where Rj represents the number of times the jth factor was mentioned in the interviews and N is the total number of interviews.

4 Findings

Table 1 shows the identified motivations and their respective contributing factors for course selection against their rating scores (S).

The findings from Table 1 suggest that some factors were more prevalent than others, and hence potentially carried a higher weight in the students' decision making. Within the interviews, each student also displayed individual preferences like quality of course content, ease of the course policies, slots in which courses are offered, and preferences regarding the peer group in the course. The process of course selection may be visualized as a complex interdependent checklist which is used by the student to select their courses at the beginning of every semester, even though each student may assign a different weight or importance to each factor.

During the interviews, almost all participants shared that the existing course registration portal of the institute did not facilitate their way of selecting courses. The portal only provided basic information like the course names, the instructor names, and the time slot allotted for classes. To gather information about other aspects of course, they had to rely on approaching seniors and/or friends. Many students expressed frustration regarding several pieces of information, which were felt important (like how manageable a course would be, grading patterns followed by the professor, whether friends are registered in the course etc.) but were not directly available. This lack of this information increased the time and effort needed to gather this information and became a hurdle for the student in this process. Hence, we argue that there is an opportunity to aid students in course selection based on their personal motivations behind taking a course. However, any such recommendation system should only facilitate decision making, and not compromise students' freedom of choice to make this important decision for their academic life [14].

Table 1. Motivations for Course Selection and their Rating Scores (S)

Motivation	Contributing Factor	Rating Score (S)
Get maximum grade	To fulfill job/ internship requirements	0.717
	To become eligible for higher studies (Masters/ PhD)	0.435
	Self-efficacy	0.326
	To gain respect of others	0.174
Get a 'good' professor	Teacher is passionate/ puts in effort/ is involved in class	0.695
	Oration & handwriting	0.326
	Easy resolution of doubts/ approachable	0.304

	Good knowledge of the subject	0.435
	Famous/ higher H-index	0.478
	Personality/ likeability	0.217
	Reputation of being a good/easy grader	0.652
Suitable course policies	Attendance policy	0.435
	Weightage of exams or assignments/ marks distribution	0.369
	Exam policy, quiz policy	0.326
	Type of assignments (group/ individual)	0.261
	Amount of self-study required	0.217
Desired academic content	Ease of completion of course	1.000
	Interesting content	0.870
	Will help in personal/knowledge development	0.391
	In demand topics from job perspective	0.630
	Related to my topic of research interest	0.217
	Foundational knowledge for job	0.739
	Prerequisite skills (math, drawing, writing, software)	0.196
	Breadth of topics in course	0.217
	Depth of topics in course	0.152
	Is a prerequisite for a desired future course	0.109
Preferred time slots	Morning slot	0.652
	Evening slot	0.304
Peers and cohort	Friends are in the course	0.739
	People I know (whom I can contact if I need help/ need assignment partners) are in the course	0.435
	Small class (<20 students)	0.369
	Larger class (>100 students)	0.261
	Want to do course with new/ unknown cohort (for minimizing disturbance/ exclusive experience)	0.043

5 Courselect: Proposal of a Course Recommendation System

This section describes the design of ‘Courselect’, a course recommendation system that helps students in course selection. In Section 4.1, we describe the proposed algorithm for the system. In Section 4.2, we describe the prototype web interface of the system. The aim of ‘Courselect’ is to facilitate decision making for students, rather than make a decision for them. An AI algorithm is used to determine the suggested course selection for the student personalized to the student’s needs and motivations. Nevertheless, the onus of the final selection is placed on the student by presenting information in a way that helps them make this decision.

5.1 Proposed Algorithm

A schematic diagram of Courselect is presented in Fig. 1. The recommendation system takes in data from students, professors and the university's databases through its 'Input Mechanisms'. Then it uses an AI algorithm to suggest a recommended list of courses (for the next semester) personalized for each student in the 'Suggestion Phase'. Finally, it provides an engaging web interface for students to view information about courses and make a final selection in the 'Selection Phase'.

Within the *'Input Mechanisms'*, Courselect requires certain input parameters from the student and the university database for its functioning. The selection of input parameters was based on the motivations identified from Table 1. These input parameters, which are relevant to students' course selection, are sourced from relevant sources such as the university database, course feedback, professor feedback, etc., and are fed into the suggestion phase. The input mechanisms are as follows:

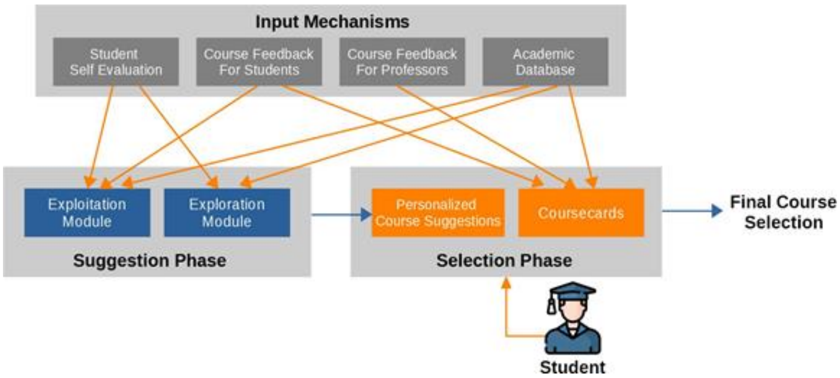


Fig. 1 Schematic Diagram of Proposed Courselect Algorithm

- *Student Self-Evaluation:* The student self-evaluation assesses each student on the spectrum of motivations identified in Table 1. The student self-evaluation is conducted through a self-assessment questionnaire to gauge (i) interest of the student towards certain fields of study and (ii) student's personal preferences (course content, policies, slots, and cohort preferences). Based on the responses, which are collected on a 5-point Likert scale (1 - Not a priority; 2 - Low priority; 3 - Medium priority; 4 - High priority; 5 - Essential), relative weights are assigned for each student for each contributing factor from Table 1.
- *Course Feedback by Students*: Collection of course feedback from students at the end of each semester is a common practice in universities. Since this feedback process is already in place, the feedback forms can be designed to contain questions assessing the course and the instructor on the factors identified in Table 1. Responses to the course feedback questionnaire are also collected on a 5-point Likert scale, with questions relating to course policies, academic content of the

course, the professor's pedagogical style, and general questions like how fun the course was. This data will also be used to recommend courses to future students.

- *Course Feedback by Professors:* This a compulsory feedback to be provided by course instructors at the time of the course being made available to students. This feedback collects course information from Table 1 which can be most accurately provided by the instructors such as the content covered, grading curves, course policies, evaluation, attendance and other statistics.
- *Academic Database:* Data like student registration, course content and policies for past iterations of courses is collected from the university databases (or crawling web pages for older courses). This data is used to match course contents with student's interests by the algorithm. Data of students enrolled in past iterations of the course will also be collected from the academic database.

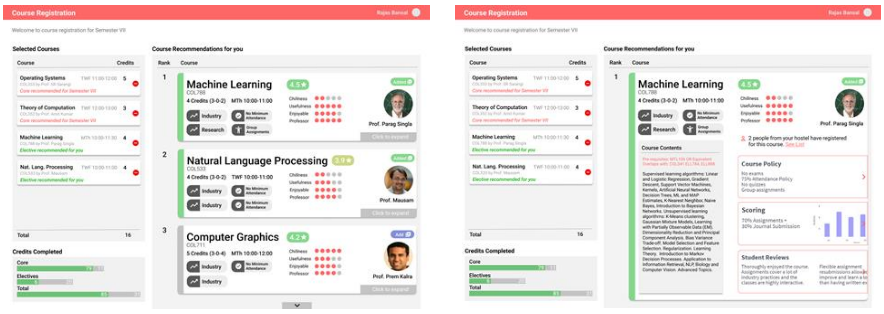
Within the *'Suggestion Phase'* in Fig. 1, the data collected from 'Input Mechanisms' is used to predict suitable courses for the student. Based on the input parameters, the algorithm identifies the interests and preferences of each student. These are then used to create 'nodes' used in the nearest neighbor classifier algorithm. The algorithm works in two modules:

- *Exploitation Module:* The purpose of this module is to find relevant courses for the student based on the student's individual preferences that have been elicited in the student self-evaluation. The students and courses are modelled as nodes, and the algorithm matches the students to courses based on 'interest tags' and 'preference tags' by a node matching algorithm. Firstly, a 'Student Node' is constructed for each student modelled by their academic interests and stored along with their associated weights. Then, nodes for individual courses are constructed which are called 'Course x Professor Nodes'. An important factor identified from the interviews was that a particular course is characterized by its professor. Hence, we typify a course with the corresponding professor. This means that if the same course is taught by two different professors, they would have two different course nodes corresponding to each professor. An instance of this node encapsulates the areas of study covered by the contents, administrative policies, list of prerequisite courses, and other details about the pedagogy of the course. Finally, a 'Student Node' is matched with relevant 'Course x Professor Nodes'. The nearest neighbor classifier algorithm is used to calculate distances between the student and different course nodes. This algorithm returns courses (in increasing order of distance) from the student node. This order is used as the order of suggestion to the student for enrollment in the semester. The course with the least distance satisfies the student's preferences best and hence, is suggested first.
- *Exploration Module:* The purpose of this module is to find new courses for the student in addition to the top-ranked suggestions from the exploitation module. The inspiration for this module to be incorporated in our proposed model comes from students' interviews. Students heavily rely on trusted seniors who they believe to be similar to themselves to take advice about which courses to choose. This module algorithmically incorporates course suggestions based on courses

done by seniors who bear a ‘similar’ profile to that of the student. This path towards course suggestion may broaden the suggestions for each student by recommending unexplored courses that still have a chance of being found relevant. These courses may not have been discovered by the exploitation module because it recommends courses based on data provided by the students themselves.

5.2 Prototype Interface

The *‘Selection Phase’* of Courselect (Fig. 1) comprises of its proposed web interface. The aim of this web interface is to facilitate the choice of elective courses for a student, without undermining their freedom of choice of opting for any course. In this web interface, we propose that the student see a list of recommended courses, with the top courses selected by default (Fig. 2a). However, we also propose that the default selection should have a prominent ‘remove’ or a ‘delete’ button, to minimize default effects. The relevant information about each course can be seen by the student in the form of a ‘course card’ by clicking on any course (Fig. 2b). The information contained in the course cards is based on the motivations identified in Table 1. Course cards for different elective courses are designed to help students make an informed choice, as well as satiate the need to spend time on the course selection decision to take ownership of the subsequent choice made.



(a) (b)

Fig. 2 Prototype Interface (a) Recommendation Screen (b) Course Card

6 Discussion

In this paper, we proposed a course recommendation system ‘Courselect’ to facilitate students’ decision making concerning course selection in university settings. Through in-depth qualitative interviews, we identified the motivations of students underlying the process of course selection. We modelled these motivations as input parameters within a nearest neighbor classifier algorithm that can be used to suggest relevant courses to students based on their individual preferences. The parameters of the different modules of the proposed algorithm can be configured according to requirements of the educational institution, and hence it has wide ranging applications within any university-level academic model (or e-learning applications).

To the best of our knowledge, the proposed course recommendation system is novel in terms of its incorporation of students' self-endorsed motivations within the recommendation algorithm. While there are several resources documenting research on course recommender systems [9-13], the steps taken in this paper to model the different agents (students, courses, professors) as nodes is a novel concept. Our model also accounts for the fact that course information is heavily dependent on the instructor conducting the course, which may change over time. Therefore, the courses in our algorithm are modelled as 'Course x Professor' nodes.

The proposed system acknowledges the role of interface in determining the user experience of the system. We have designed the web interface to preserve the students' experience of nuanced and thoughtful decision making, preserving their freedom of choice to discard the recommendations if they so choose. The information contained within the course cards is aimed at facilitating this decision making, by including the information found relevant from the interviews. Course cards for different courses are also separated for different instructors, as several relevant characteristics of the same course are instructor dependent.

This paper also contributes to user research in the form of motivational analysis of 25 university students. This qualitative research surfaced empirical evidence that aligned with prior research that has been conducted in the domain of student psychology [2-8]. From our motivational analysis, we observed that university students have a wide range of motivations underlying the course selection decision, and we have segregated these motivations into six categories. We observed that some motivations could be classified as intrinsic, such as interesting content, passionate instructor, etc., and others could be classified as extrinsic, such as easy grading, no attendance policies, etc. Student motivations may also evolve with time and maturity. Our system gives students the opportunity to choose the motivations that they value and endorse and provide recommendations based on those. Systems which solely rely on students' own or even seniors' past selection of courses may end up recommending courses which satisfy students' extrinsic motivations, instead of the intrinsic motivations they want to endorse consciously.

7 Conclusion

We now discuss the limitations of the paper and opportunities for future research. The current work only presents an academic model, and a full-scale backend for Courselect was not developed for the purpose of this research. Therefore, the model has not currently been tested and evaluated with users. Another limitation is that the motivational analysis presented in the paper has been conducted on science and technology students. As this is a convenience sampling approach, we suspect that the pool of motivations identified is not exhaustive, and further research is required to identify motivations of students from diverse educational backgrounds. However, as the system already takes into account that students of different backgrounds might place different weights on individual motivations, expanding its user base does not affect the proposed algorithm. Within this paper, we have also not explored the pros and cons of using different algorithms to calculate node distances, and that remains an avenue for future research in the AI aspect of this paper.

While recommender systems are becoming commonplace in various domains of information seeking, commercially driven recommendation algorithms have come under scrutiny for exploiting lower order motivations of the user, instead of supporting their consciously chosen higher order motivations. Therefore, recommendation systems pose the threat of producing choices biased towards lower order motivations (such as choosing easy courses over interesting ones). In our proposed model, we have explicitly attempted to address this limitation of recommendation algorithms. We believe that the incorporation of students' self-endorsed motivations and the preservation of their freedom of choice is critical to create a holistic system for course recommendations.

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