A Personalized “Course Navigator” Based on Students’ Goal Orientation

Prateek Basavaraj
University of Central Florida
Orlando, Florida 32826
Prateek.basavaraj@ucf.edu

Ivan Garibay
University of Central Florida
Orlando, Florida 32826
Ivan.garibay@ucf.edu

Abstract
Higher education institutions must understand students' mastery and performance goals in order to guide them in selecting suitable courses to take, so that they are successful. We propose a personalized recommendation system called “Course Navigator” for guiding undergraduate Information Technology (IT) students in selecting course curriculum based on their self-reported goal orientation and past course performance. We analyzed data from 2500 IT students at University of Central Florida (UCF) to create course recommendations. Our preliminary results show that the course recommendations for students with different goal orientations differ and may help students customize their course selections based on their goals.

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CCS CONCEPTS
• Social and professional topics~Information technology education

Introduction
Increasingly, higher education institutions are using data to improve student success through improved academic advising [1]. One way of improved academic advising is by providing personalized course recommendations to students. In this research, we developed a personalized course recommendation system called ‘Course Navigator’ that takes into account: (i) course performance data, (ii) program curriculum requirements and (iii) student-based surveys that take into account their (a) goal orientation and (b) program interests. The main goals of Course Navigator are: (i) to ease students’ burden while making course decisions and (ii) to reduce students’ cognitive load by providing suitable recommendations

based on their academic background and goal orientations.

Related Work

Recommendation Systems for Personalized Learning

There are different artificial intelligence methodologies used for personalized and adaptive learning educational systems [3]. The focus of some of these educational systems has been to generate learner profiles by examining students' characteristics [3,5]. Chen [2] considered course difficulty levels and proposed a genetic-algorithm-based personalized e-learning system, which provides individualized learning paths based on the learner's incorrect testing responses. Lin et al. [4] developed a system using a decision tree approach to provide learning paths for learners. Some of the important variables analyzed by Lin in his study were creativity levels, gender and self-perception of creativity. Hill et al. [8] designed a recommendation system that uses Human-Computer Interaction, Artificial Intelligence and Big Data methods to help academic researchers, students to collaborate. Akbas et al. [1] designed a personalized course recommendation system with the application of historical data for the benefit of students and decision makers in higher educational and training institutions.

Student Goal Orientations

Goal orientation refers to the type of goal a student is working towards, which has been shown to have a significant impact on learning [6]. Based on the achievement goal orientation theory, there are two types of students: 1) *Mastery-Goal-Oriented (MGO)* and 2) *Performance-Goal-Oriented (PGO)* students [6]. MGO students work very hard, persist in the face of difficulty, try new things to challenge themselves, so that they can master the tasks they have undertaken. In contrast, PGO students prefer to undertake tasks that they are already good at and consider making mistakes a lack of competence; therefore, they avoid taking risks where they might fail [7]. Students with performance avoidance goal orientation are negatively related to their academic standing [7]. Students who are in academic probation often adopt performance avoidance goals than those in good academic standing [7]. We considered these characteristics of students with PGO and MGO in the design of our personalized recommendation system.

A Personalized "Course Navigator"

To the best of our knowledge, the personalized recommendation system proposed in this paper is the only course recommendation system that leverages students' goal orientations, course relative importance in combination with past course performance data. The course navigator is intended to serve as a collaborative system between advisors and students. Academic advisors can use course navigator to customize students' plan of study based on their needs. Based on a recent survey of students 49% reported that the departmental curriculum provides little or no flexibility in choosing courses. The goal of course navigator is to provide more flexibility and improve student advising.

Student Survey Data

First, we inferred each student's program interests (Information Technology, Computer Science, Computer Engineering) and goal orientation (MGO, PGO) based on the student-based survey data. For this paper, we only analyzed data for the IT program.

Term-1	Term-2	Term-3	Term-4
COP3223	COP3502	COP3330	CGS3269
MAC1105	ECO2013	PHY2053	STA2023
	PSY2012	CGS2545	CIS3003
	MAC1114	MAD2140	
Term-5	Term-6	Term-7	Term-8
CAP4104	CIS4524	CNT4703	COP4910
PHY2054	PHI3626	CIS4004	CNT4714
CNT3004	CGS3763	CNT4603	
CIS3360			

Table 1: UCF IT Program Catalog Recommendations

IT Program Curricula

Next, we conceptualized the IT curriculum in the form of a directed graph by considering course prerequisite requirements. With the application of network science parameters such as betweenness centrality and path length, we calculated the cruciality value for all courses by multiplying betweenness centrality and path length of courses [5]. In general, this value helps identify the relative importance of a course in the curriculum. The cruciality values of IT courses are shown in **Figure 1**.

Student Course Performance Data

Finally, we considered student performance. We analyzed student performance data (grades) and the degree status (number of courses completed or failed). Our personalized recommendation system takes into account individual students versus their relative performance to other students in a course. Therefore, the personalized recommendations are based on both the student's GPA and average grade for each course.

Preliminary Results

Descriptive Statistics

We analyzed student survey responses of 510 IT majors. Based on the questions related to satisfaction and pleasure in learning new skills, we found that approximately 46% and 24% of students exhibit one or more characteristics of MGO and PGO, respectively. Whereas rest 30% answered neutral (0) to these questions. The IT program course catalog at UCF suggests students take courses in order as shown in Table 1.

MGO Student Recommendations

For MGO students, our system recommends courses with low or average grades (i.e. challenging) in the beginning terms. Based on the number of courses a student is willing to take in the first term, the personalized system checks the courses with no prerequisites and their cruciality values. For example, if a student wishes to enroll in four courses and his initial goal orientation is MGO then the recommendation system checks the cruciality values of courses with no prerequisites. Then the Course Navigator checks the average grades of these courses. Since student's initial goal orientation is MGO, the system recommends difficult course (MAC1114) in addition to COP3223, MAC1105 and CGS2545. The personalized recommendations for MGO's is shown in Table 2.

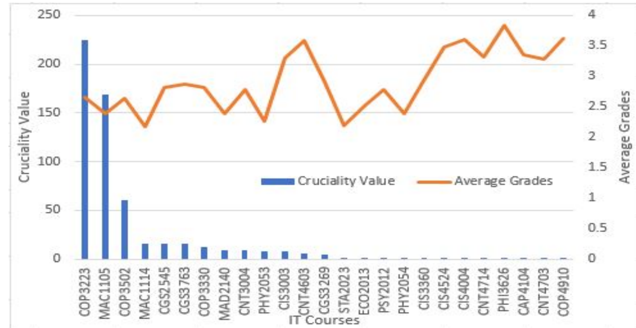

Figure 1: Representation of Cruciality values and Average Grades of IT Courses

PGO Student Recommendations

For PGO students, our system recommends courses with high average grade (i.e. easy) in the beginning terms. The reason behind recommending easy courses was PGO students are low risk takers. For PGO, the system recommends CGS2545, CGS3763 which are easy courses in addition to MAC1105 and COP3223. The recommendations for PGO student profiles for IT program are shown in Table 3. Based on these results,

Term-1	Term-2	Term-3	Term-4
N=4	N=4	N=2	N=4
COP3223	PHY2053	MAD2140	CNT4603
MAC1114	COP3502	CIS3003	CGS3269
MAC1105	CGS3763		STA2023
CGS2545	COP3330		ECO2013

Term-5	Term-6	Term-7	Term-8
N=4	N=2	N=4	N=4
PSY2012	CNT3004	CIS4524	COP4910
PHY2054	CAP4104	CIS4004	
CIS3360		PHI3626	
CNT4714		CNT4703	

Table 2: Course Recommendations for MGO IT Students

Term-1	Term-2	Term-3	Term-4
N=4	N=4	N=2	N=4
CGS2545	MAD2140	PHY2053	PHI3626
CGS3763	CIS3003	COP3502	CAP4104
MAC1105	COP3330		CIS4524
COP3223	MAC1114		CNT4603

Term-5	Term-6	Term-7	Term-8
N=4	N=2	N=4	N=4
PHY2054	CNT4714	STA2023	COP4910
CIS3360	CNT3004	ECO2013	
CGS3269		CIS4004	
PSY2012		CNT4703	

Table 3: Course Recommendations for PGO IT Students

the recommendations differed significantly for MGO versus PGO students'. These recommendations may help both MGO and PGO students plan and successfully complete courses each term.

CONCLUSION

In this paper, we proposed a personalized course recommendation system to assist students. Our proposed approach determines students' goal orientations and analyzes the program curriculum, and course performance data. The preliminary results suggest that this proposed system helps in course selection based on their initial goal orientation. In the near future, we will study the effectiveness of our recommendation system on student success by measuring the course completion and success rates of students who followed our recommendations with those who followed program specified catalog recommendations.

Our initial work has focused on better understanding the differing self-reported goal orientation of students to identify the type of tasks that course navigator can support. The next step is to determine whether these personalized course recommendations are perceived by students and advisors as an improvement to the static course guidelines from the university catalog. Additionally, it will be important to conduct a longitudinal study on whether students who elect to adopt an MGO or PGO plan of study experience better or different learning outcomes.

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