REVOLUTIONIZING COURSE SELECTION IN HIGHER EDUCATION: A HIDDEN MARKOV CHAIN-BASED RECOMMENDER SYSTEM

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Abstract
Course recommendation systems have a significant role in providing personalized educational suggestions through the analysis of student preferences, course information, and their interactions. This paper presents a sequential course enrollment recommendation system using the Hidden Markov Chain method. The system analyzes students' academic records, including past course selections and grades, to create student-specific recommendations. The recommendation process is framed as a sequential optimization problem in which the system calculates a new list of course preferences based on the student's academic background. The study includes the use of the success rates of the hidden and observed matrices derived from the Hidden Markov Chain to perform prediction tasks. These matrices are created with data based on all targeted transitions from technical courses to elective courses and success rates. Viterbi and entropy concepts are additionally utilized to constitute the Hidden Markov Chain method while considering the students' selection and the outcome, the compatibility of the course contents with each other, and the course preference and success of other students. Experimental results based on multiple experiments and various parameters outperform the traditional Markov Chain implementation by 0.15 on average accuracy. The proposed system has the potential to improve the course selection experience for students, allowing for improved academic outcomes.

Keywords: Course Recommendation, Sequential Recommendation, Markov Chains, Collaborative Filtering, Higher Education, Hidden Markov Chain, Observed Matrix, Hidden Matrix

INTRODUCTION
The rapid progress of the Internet has given rise to the challenge of information overload and creating difficulties in locating desired information. So far, personalized recommendation systems have emerged as the most effective and encouraging approach to tackle the problem of information overload (Zhou & Wenbo, 2019). Recommendation systems are prevalent in effectively all digital platforms and have a significant role on the decisions we make, the products we purchase, and the movies we watch (Warnes and Smirnov, 2020; Shani et al., 2005). Recently, recommender systems have been applied in a wider range of fields, including the education sector, particularly in higher education. Systems that recommend courses are particularly relevant among recommender systems for academic decisions (Campos et al., 2014).
In today's educational landscape, learners face numerous challenges when making the right career choices. One of the primary challenges college students encounter is creating and handling their course schedule for the semester (Bydžovská, 2016). With the availability of online university admissions, students are faced with selecting from a vast array of courses, often without sufficient guidance or support (Chen et al., 2017). In this process, recommender systems can be used to assist students on an individual basis. In this study, a course recommendation system was designed for a student automation application that includes student and course information in the ESOGU course management system.
When dealing with large collections of items, recommender systems (RS) are aimed at helping users in information access and retrieval applications (Campos et al., 2014). There are several techniques to create a well-performing course recommender system (CRS): content-based systems, collaborative-filtering systems, and popularity-based ranking systems (Shen et al., 2013). Collaborative filtering (CF) has recently become increasingly popular and effective. CF can be categorized into memory-based or model-based approaches. Memory-based techniques utilize user-item databases to predict users' item preferences by

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leveraging the preferences of similar users who share common interests within a group (Mlika and Karoui, 2020). This traditional recommendation system provides recommendations based on users' past preferences and similar users' choices. However, this approach is often limited to a fixed and narrow time frame.

In this study, a new recommendation system is designed using the Markov chain method to model users' past preferences and provide a more flexible time framework for future recommendations. The Markov chain models a state sequence that represents the user's past preferences. This model then predicts the user's future preferences based on their past choices.

The main contributions of the paper are summarized below.

• A Markov chain system-based recommendation approach is proposed, along with the consideration of the grades received by students from the courses.

• Labels and weights are applied to the courses and course contents. Thus, a probability-based recommendation system was developed. The weighting of courses and tags provided by a university based on their importance levels enabled us to achieve relative impact in predictions.

• Instead of directly calculating probabilities, the Viterbi concept was employed to evaluate the proximity of each path to the maximum path value within its target group.

The rest of the paper is organized as follows. The next section provides a reference to previous research and draws attention to the methods we utilize. Section 3 presents the material and methods that are realized in our research. Section 4 presents the experimental design for course recommendation, including the recommendation engine and testing criteria. The study is concluded in Section 5, which also discusses potential future research plans.

RELATED WORK

One of the goals that universities aim to accomplish is to provide guidance to students on which courses to enroll in (Bhumichitr et al., 2017). This section examines various methods to help students choose a limited number of courses for enrollment in the upcoming semester.

Recent research in course recommender systems has explored varied approaches. Collaborative filtering leverages user-item interaction data to identify similar users or items and make personalized recommendations, while content-based filtering analyzes the content of courses and recommends similar courses based on relevant features (Nurakhmadyavi and Wahyudi, 2024). The hybrid methodology can combine different techniques (Gulzar et al., 2017).

In a study, a Markov chain model is employed to enhance the performance of recommendation systems by predicting future preferences based on a user's past choices and behaviors. The researchers conducted experimental studies to demonstrate the effectiveness of MCRS in accurately predicting user preferences. This study offers a novel approach to the development of recommendation systems and suggests that Markov chain-based recommendation systems can enhance the user experience (Zhou and Wenbo, 2019). A student program recommendation system was developed by Booker (2009), which takes the keywords of the users' interests and their current GPA scores as input. The system employs a content-based filtering model and unlike the study we conducted does not evaluate information regarding students' grades. Additionally, the presented prototype in the study is designed to provide recommendations about suitable programs for students and support the program selection process (Booker, 2009).

In the literature, there are course recommendation systems carried out with different techniques using the Markov Chain method. Polyzou and colleagues assume that students' choices for the next semester depend on the courses they have taken so far. It establishes a Markov chain through courses for each degree program (Agoritsa et al., 2019). Elham S. Khorasani and colleagues have suggested a Markov Chain Collaborative Filtering approach to make course recommendations based on past academic records, considering the order in which each course was taken (Khorasani et al., 2016). CF methods are based on the principle that individuals who have similar preferences for items in the past are likely to have similar preferences for items in the future (Bakhshinategh et al., 2017). Hana presents a mechanism that utilizes this approach to suggest suitable courses for a student by examining their academic record and comparing it with the records of others to determine similarity (Bydžovská, 2016). A proposed system by Amer Al-Badarenah and Jamal Alsakran recommends elective courses for students by considering both their grades and similarities with other students (Al-Badarenah and Alsakran, 2016). Another study presents research on the design of a personalized recommendation system for learning resources based on collaborative filtering. Conducted by researchers Mingxia Zhong and Rongtao Ding, this study utilizes collaborative filtering method to recommend suitable learning resources to students. The aim of the study is to enhance students' learning experiences and facilitate their access to resources that meet their needs. Collaborative filtering method considers users' personal preferences and interests to provide customized recommendations (Zhong and Ding, 2022). In a different study using the Hidden Markov Model, HMMs are utilized to determine students' academic performance levels. The developed HMMs are employed to classify students' academic performance in a standardized and intuitive manner. This classification aims to represent students' academic performance levels in a more comprehensible way. The use of HMMs provides a tool for understanding students' academic performance trajectories and investigating the relationship between different performance levels and final academic outcomes (Boumi, 2022).

The recommender system discussed in the paper is centered on identifying past course data among students by analyzing their academic records. The grades that the students took from the courses were also added to the Hidden Markov Chain. In addition, the study incorporated the grading system as an essential component for analyzing academic records within the recommender system. This was done to facilitate the identification of similarities among students based on their academic performance.

MATERIALS AND METHODS

This section typically encompasses the origin of the dataset and the modifications made to the data through code-based edits, additions, and deletions prior to its processing. These adjustments have enhanced the data comprehensibility and usability.

Dataset:

The dataset consists of the letter grades and scores of Eskisehir Osmangazi University computer engineering students between 2010-2020. The post-2020 records were not taken into consideration due to the courses mostly being switched to online education and the inconsistency of data during this unusual period. Considering that students choose non-compulsory courses according to their own wishes, operations were carried out using the data of elective courses in the dataset.

Preprocessing:

The dataset contains compulsory and non-compulsory courses. Non-compulsory courses are chosen by students based on their future specializations (Ceyhan et al., 2022). The motivation is that students with the same specialization tend to take similar courses and achieve success in line with their choices. The dataset is structured by classifying the courses according to their contents and qualifications to facilitate its use in the system later. The classified categories include information such as course credits, elective status, and whether the course was offered in the current year. This classification helps separate courses that may lead to misinformation during the process.

Since the online education system and pandemics were new after 2018, the data contains deviations and inconsistencies. In the evaluation of the trained data in the conducted research, the last regular data from the first quarter of 2018 and before the pandemic was used as the test dataset.

Course information in the dataset is listed with course IDs, years of offering, and periods. This allows us to determine which courses the retrospective students took, when they took them, what grade they achieved, and identify relationships based on these key IDs. The student data includes student ID, GPA, and the list of courses taken during semesters. The numerical values corresponding to the letter grades are shown in Figure 1. Grades for courses that students do not take are assigned a value of 0. Courses with 'DZ' letter grades indicate that students do not pass due to absence, and non-credit courses are excluded from the training set (Arık, Okyay, and Adar, 2021). This way, previously taken courses are excluded from suggestions based on the student ID, creating a reliable suggestion environment.

Letter Grade	Numerical
AA	4.0
BA	3.5
BB	3.0
CB	2.5
CC	2.0
FF	0.0

Figure 1. Letter Grades

Chain Implementation:

Markov Model was taken as a basis to obtain the method needed in the estimation process. It is aimed to reveal different probabilistic connections by adding another matrix to the classical Markov chain model with a single matrix.

The Hidden Markov Chain method and two transition matrices used to predict course recom-mendations are shown in Figure 2. The first of these transition matrices is called "Observed Matrix," representing courses in the department, indicating their correlation values between. The second one is called "Hidden Matrix" and represents a more abstract correlation between pre-defined course tags. The Markov model and two transition matrixes are shown in Figure 2.

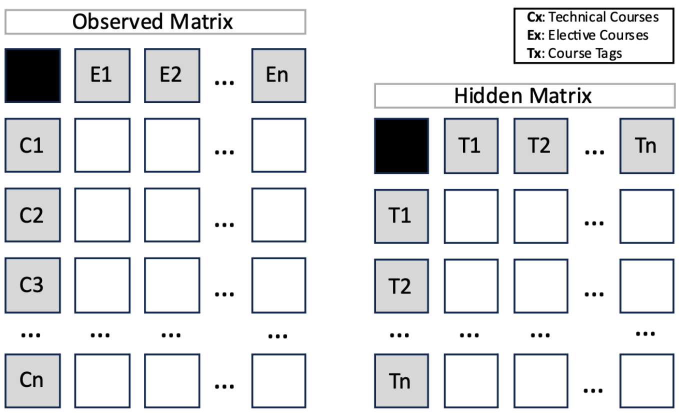

Figure 2. Matrix Representation

For the Observed Matrix, values are determined by the probability of successful course transi-tions. For Hidden Matrix, values determined by the probability of successful transitions between course tags are weighted by course credit.

Elective courses from technical courses in the range of previous semesters are recorded and combined to fill the matrix as success rates. This part of the implementation stands as the foundation of the Markov Model. Onto the basic model, other improvements are implemented and tested to create an optimized predictor.

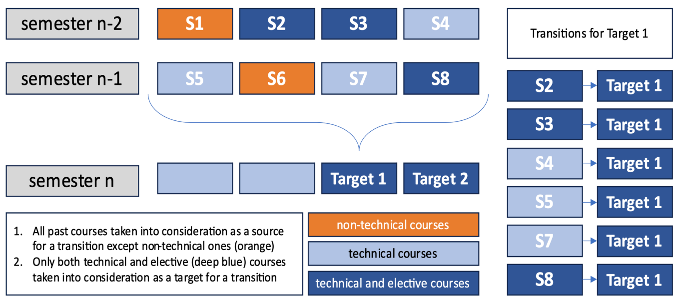

Figure 3. Transition Extraction

Hidden Matrix includes course tags defined in the course script as both rows and columns therefore it is a square matrix. The process of filling the Hidden Matrix is the same as filling the Observed Matrix. The only difference is that in describing a transitions value in terms of numbers, credits of the courses are distributed on lesson labels weights of the courses. The course labels mentioned here are defined by ESOGU. The course labels are used by distributing the course credit amounts to these labels' weights.

	T1	T2	T3	Credit
Course 1	2	3	1	4
Course 2	3	1	1	3

$$\underset{of\ single\ tag}{numerical impact} = \langle tag\ weight \rangle * \frac{Credit}{sum(\langle all\ tag\ weights \rangle)}$$

Figure 4. Weighting for Hidden Matrix

This process is implemented to set a tag weight to every tag in the course to differentiate the significance of the lesson label for the specific course and to set a single course weight among all courses to differentiate course significance. As shown in Figure 4, a matrix has been created to assign a label weight to each label in the course. For each course, the label and credit value have been placed in the matrix, and the specified operation has been applied. As a result, the importance of the label for a particular lesson is determined, and the calculated transition values are used in the Hidden matrix.

Once the matrices are created with training data, a prediction algorithm is needed to run on the matrices to recommend courses. In this study, two methods are combined and implemented onto the classical Markov Chain prediction system. What is called a classical Markov Chain prediction system simply depends on finding path probabilities of states and returning it as the probability of the transition to happen.

In this study, besides the classical estimation technique, the concepts of Viterbi and entropy difference were adapted in the estimation process and added to the study as an additional method. In a single prediction process, for each matrix; algorithm calculates the Viterbi (maximum probability value in the set to transit to target) value of the target state and returns the entropy difference between the Viterbi and transition probability value. It calculates how close the transition probability value is to the Viterbi value, and the calculated value is set as the prediction point of the target course. The aim of this process is to alter the probability of transaction happening to more inter-pretable representation by calculating relative transaction values.

This process is executed for every course possible for students to take in the current semester, and a list is created by combining the final value of each transition calculation. To create a whole recommendation list for a student, algorithm iterates through the student's past course preferences and creates recommendation lists for each course. After the calculation of single courses, results are combined to create a final prediction array. Overall mapping of the system can be seen in Figure 5.

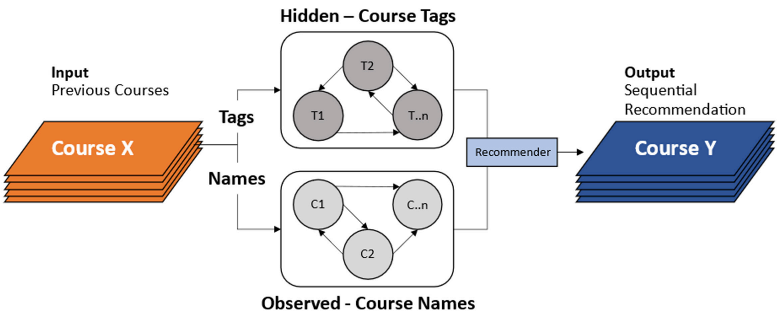

Figure 5. Overall Process

EXPERIMENTAL DESIGN

This section presents the experimental design of our sequential course enrollment recommender system, focusing on different parameters for the succession and cutting of the prediction array. The algorithm was evaluated using various criteria for success, including values of 3.0, 3.5, and different cutoff points, such as the top 3, 4, and 5 predictions. In addition, ESOGU's definition of "Student with a weighted grade point average of at least 2.00 is considered successful" is also included.

The concepts of success criteria implemented in this study are derived from various sources. The 3.0 success point is used (Ceyhan et al., 2021) as the valid succession grade. On the other hand, the method applied by the school to determine if a student failed or passed the course is implemented - This criterion is referenced in Figure 6 and Figure 7 as "Pass." Lastly, the 3.5 success point was added for experimental purposes. At this point, the dimension of the prediction array is an important consideration, determined by the current semester's available courses. Seven elective courses were available during the test phase, which influenced the number of recommendations generated. The change in the number of courses suggested is within the range of 3-5, which is a middle range, far from both ends of the number of courses. This approach aims to maintain data consistency without reaching the limits of the course list.

Furthermore, a classical statistic-based Markov Chain was implemented to compare the results of the optimizations made in this study with the performance of the classical implementation. This action aims to measure the contributions of concepts like course labels, Viterbi, and entropy difference implemented with the Hidden Markov model. By comparing the outcomes of the sequential course enrollment recommender system constructed in this study with the results obtained from the tradi-tional Markov Chain approach, a comprehensive comparison can be made to evaluate the effec-tiveness of the proposed methods of optimizations in this study. The experimental design involved comparing different combinations of success criteria and the number of recommendations to identify the optimal settings for the system. The effects of the parameters were analyzed by evaluating the metrics of the generated recommendations.

In conclusion, the experimental design was designed to assess the performance of the se-quential course enrollment recommender system under various conditions and settings. It provides valuable insights into the effectiveness and performance of the recommender system, offering a comprehensive understanding of its capabilities.

RESULTS AND DISCUSSION

Firstly, comparing the thresholds, it was observed that using a passing point of 3.5 resulted in higher accuracy and sensitivity/recall compared to the passing point of 3.0 and the passing criteria determined by the school. This indicates that setting a higher passing point can improve the system's ability to identify positive instances correctly. However, precision values tended to be higher when the passing point was set to 3.0, suggesting a higher proportion of relevant recommendations.

Optimized Markov Model Result Metrics

		Accuracy	F1 Score	Precision	Recall	Specificity
Cut 3	3.0	0.6752	0.6041	0.6041	0.6041	0.8064
	3.5	0.7264	0.6190	0.6046	0.6341	0.7763
	Pass	0.4358	0.5352	0.6666	0.4470	0.4062
Cut 4	3.0	0.6923	0.7000	0.6461	0.7636	0.6290
	3.5	0.6324	0.5742	0.4833	0.7073	0.5921
	Pass	0.4615	0.5882	0.6617	0.5294	0.2812
Cut 5	3.0	0.6581	0.7014	0.5949	0.8545	0.4838
	3.5	0.5897	0.5789	0.4520	0.8048	0.4736
	Pass	0.5897	0.7176	0.7176	0.7176	0.25

Figure 6. Optimized Markov Model Result Metrics

Secondly, considering the cutoff points, increasing the cutoff point from 3 to 4 led to improved performance in terms of accuracy, precision, sensitivity, and F1 score. This indicates that considering a larger number of top recommendations can enhance the system's ability to make accurate pre-dictions. However, when the cutoff point was set to 5, there was a decrease in performance across most metrics, suggesting that including too many recommendations might introduce noise and lower the system's precision.

Classical Markov Model Result Metrics

		Accuracy	F1 Score	Precision	Recall	Specificity
Cut 3	3.0	0.5384	0.4000	0.3673	0.4390	0.5921
	3.5	0.5555	0.4090	0.3829	0.4390	0.6184
	Pass	0.4529	0.5223	0.7142	0.4117	0.5625
Cut 4	3.0	0.5042	0.4081	0.3508	0.4878	0.5131
	3.5	0.4957	0.3917	0.3392	0.4634	0.5131
	Pass	0.4615	0.5771	0.6718	0.5058	0.3437
Cut 5	3.0	0.4871	0.4642	0.3661	0.6341	0.4078
	3.5	0.4273	0.4273	0.3289	0.6097	0.3289
	Pass	0.5726	0.7058	0.7058	0.7058	0.2187

Figure 7. Classical Markov Model Result Metrics

Comparing the impacts of different parameter combinations, the configuration with a passing point of 3.0 and a cutoff point of 4 emerged as the most favorable. This combination demonstrated high accuracy, precision, sensitivity/recall, specificity, and F1 score, indicating a well-balanced performance in predicting course enrollments. However, it is important to note that the optimal parameter settings may depend on the specific goals and requirements of the course enrollment system.

The comparison between the classical model of Markov Chain and the proposed algorithmic design in this study reveals that, on average, the accuracy of the recommender system improved by 0.15. This improvement indicates that the proposed algorithmic modifications and techniques im-plemented in the proposed design have contributed to a more accurate recommendation process.

Additionally, the comparison underscores that the system's stability becomes more fragile when exposed to varying conditions in the classical Markov Model implementation. The proposed design, with its refined algorithms and techniques, has created a more balanced recommendation process with higher-valued metrics. By fine-tuning the parameters and optimizing the algorithm, the system achieves improved accuracy and a more robust performance.

In summary, adjusting the passing point and cutoff point parameters can significantly influence the performance of the sequential course enrollment recommender system. Higher passing points can improve positive instance identification, while lower passing points tend to result in higher precision. Increasing the cutoff point enhances overall performance, but selecting an excessively large cutoff point may introduce noise. Choosing the most suitable parameter settings requires careful consideration of the desired trade-offs and objectives of the recommender system.

The comparison between the classical model of Markov Chain and the optimized algorithmic design demonstrates that the optimized design outperforms the classical implementation, resulting in higher accuracy and improved system balance.

CONCLUSIONS

In this paper, we proposed a sequential course enrollment recommender system based on the Hidden Markov Chain method to address the challenge of course selection faced by college students. The system utilizes students' academic records, including past course choices and grades, to generate personalized recommendations. By framing the recommendation process as a sequential optimization problem, the system computes a new list of course preferences based on the student's academic history.

Experimental results demonstrated the effectiveness of the proposed system, surpassing traditional Markov chain implementations. Incorporating Hidden and Observed Matrices derived from the Hidden Markov Chain allowed for accurate prediction tasks. The system considered the grades received by students from courses, applying labels and weights to courses and course contents, which resulted in a more precise recommendation system.

The study contributes to the field of course recommendation systems by introducing the use of the Hidden Markov Chain method and incorporating grading systems as an essential component for analyzing academic records. By considering the order in which courses were taken, the system provided more flexible time frames for future recommendations. The personalized recommendations offered by the system have the potential to enhance the course selection experience for students, leading to improved academic outcomes.

Future research can explore further enhancements to the system, such as incorporating ad-ditional factors like students' interests, career goals, and feedback on previous course recom-mendations. Moreover, the system can be extended to handle larger datasets and consider real-time updates in academic records. Evaluating the system's performance across different educational institutions and diverse student populations would also be valuable for its broader applicability. Overall, the presented sequential course enrollment recommender system offers a promising ap-proach to assist college students in making informed course selection decisions. By leveraging the Hidden Markov Chain method and analyzing academic records, the system provides tailored recommendations that align with students' past choices and grades. The system has the potential to contribute to improved academic experiences and outcomes for students in higher education. In addition to the proposed enhancements mentioned in the conclusion, future research in course enrollment recommendation systems should focus on incorporating relative grade values for students based on their personal success and the overall distribution of grades within specific courses. This approach would provide more personalized and accurate recommendations by considering a student's relative performance compared to their peers, as well as accounting for the difficulty of the course and the individual's capabilities. Moreover, analyzing the distribution of grades across all students in a course would refine the recommendation process, helping guide students toward courses that align with their abilities and provide a balanced workload. Additionally, integrating qualitative feedback from students regarding their course experiences and the relevance of rec-ommended courses would allow for continuous improvement and fine-tuning of the recommendation algorithm. These advancements would contribute to a more comprehensive and accurate course recommendation system, ultimately enhancing the academic journey for college students.

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