Department of Computer Science and Engineering

SOUTHEAST UNIVERSITY

CSE459: Research Methodology

Research Report On

Solving Cold Start Problem of Course Recommendation System for Students Using K-means Clustering and Recommendation System

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LETTER OF TRANSMITTAL

November, 2024

The Chairman,
Department of Computer Science & Engineering,
Southeast University,
Tejgaon, Dhaka.

Through: Supervisor, Md. Mijanur Rahman

Subject: Submission of Research Report

Dear Sir,

It is a great satisfaction to submit our research report on "**Solving Cold Start Problem of Course Recommendation System for Students Using K-means Clustering and Recommendation System**" under the course Research Methodology. This manuscript presents a comprehensive literature review on the recent advancements in recommender systems, with a particular focus on personalized course recommendation techniques and the challenges posed by the cold-start problem.

We have prepared this report with absolute sincerity and effort. We request your approval of this research report in partial fulfillment of our degree requirement.

Thank You.

Sincerely Yours,

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CERTIFICATE

This is to certify that the research report on "**Solving Cold Start Problem of Course Recommendation System for Students Using K-means Clustering and Recommendation System**" has been submitted to the respected member of the board of examiner of the School of Science and Engineering in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science & Engineering by the following students and has been accepted as satisfactory.

This Paper has been carried out under my guidance.

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ACKNOWLEDGEMENT

Foremost, thanks to almighty Allah for whose given strength makes us able to complete our research successfully.

After that, we would like to thank our honorable supervisor, **Md. Mijanur Rahman**, Assistant Professor, Department of Computer Science and Engineering at Southeast University. This research would not have been possible without the exceptional support of our supervisor. His enthusiasm, knowledge, and exacting attention to detail have been an inspiration and kept us on track from our first encounter with machine learning to the final draft of this paper.

We would also like to thank **Shahriar Manzoor**, Associate Professor & Chairman, Department of Computer Science and Engineering, Southeast University, for making Md. Mijanur Rahman, our supervisor.

We also want to thank the whole faculties of the Department of Computer Science and Engineering, Southeast University, for their encouragement and motivation. Finally, with pleasure and appreciation, we acknowledge our contributions and day-after-day hard work with proper responsibility.

In addition, we owe a sincere debt of gratitude to every one of our great group members for their thought-provoking debates, unwavering commitment, and endless sleepless hours spent together, which were essential to finishing this project ahead of schedule. Thanks to their unflagging encouragement and assistance, we finished this report within the allotted time.

Finally, we want to say that all of those kindnesses were indispensable to complete our research.

ABSTRACT

This study aims to address and solve the difficulties that face students during their undergraduate periods while selecting courses. Choosing courses during the undergraduate period has a great impact on a student's results and career. University students with an open credit system often face difficulties while choosing their courses during their undergraduate study period. For the undergraduate degree generally, every university offers various courses for the degree. Educational institutions offer several courses for undergraduate degrees, but students have to choose courses that maintain the prerequisites and sequence. As they do not have proper knowledge about the courses and curriculum, they often make mistakes in choosing courses or are misguided by seniors. This influences breaking the sequence of taking courses and selecting the wrong courses in the wrong semester. Thus, by selecting inappropriate courses, they face difficulties in learning, do not get proper outcomes, and suffer from dissatisfaction. That's why course recommendations on the open credit system are very essential for undergraduate students to select proper courses according to their semester. This paper introduces a machine-learning-based method designed to assist undergraduate students with an open credit system to recommend relevant courses based on the popularity of courses for particular semesters. The k-means clustering algorithm has been used to visualize students' most popular courses based on the course count for each semester. After that, connections between courses will be established via the graph-based recommendation system. After that, content-based recommendations will examine various course characteristics and suggest them to students. Lastly, based on the course count, the popularity-based recommendation system will suggest courses to new students. The dataset belongs to a real educational institute that follows an open credit system in its undergraduate program. The proposed method has been evaluated by the dataset, and it performs better than the traditional course recommendation system.

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CHAPTER 1

INTRODUCTION

The recommendation system has proven to be immensely helpful in everyday situations. Recommendations from various sources, including individuals, online platforms, reviews, and articles, influence us in making decisions. The main objective of a recommender system is to offer suggestions that users will assess positively and embrace [1]. Recommender systems have emerged as a significant field of application, attracting considerable attention from both academic and commercial sectors in recent years [2]. Today, recommender systems span diverse domains, enhancing individuals' daily lives. In modern times, we use recommendations for buying products, selecting movies and music, choosing tourist places, booking hotels, selecting books, and many more [1]. Among these established domains, course recommendation stands out as a challenging area that remains largely unexplored [1]. However, in the case of types of recommendation, there are three different kinds of recommendation: Content-based recommendation, Collaborative filtering, and Hybrid recommendation. Though many suitable modes are available, a large number of problems remain unsolved. The "Cold Start" is one of the unsolved problems in the recommendation system [3]. In the beginning, a new user will be advised by various non-personalized recommendations because of insufficient information [4]. Some other reasons behind this problem are data sparsity [5], the grey-sheep problem [6], and scalability [7], which are some major problems researchers have yet to solve. Though the recommendation system is used widely over the world, course recommendation is still a challenging field that remains largely unexplored [1].

A course recommendation system assists students in identifying suitable courses from a plethora of options. At the college or university level, students have several courses to choose from one's major as well as elective courses. In the case of an open credit system, there is a problem as to what course one would want to take. Maintaining the sequence of courses according to the particular semesters is also a challenge for the students. A course may or may not have related prerequisites that are to be cleared in order to pursue the desired course. Generally, the enrolment system of today does not permit students to form preferences of courses that would fulfill their particular niche interests [8]. In that case, students make their choices by asking their seniors, friends, or advisors. In order to address these concerns, university students can utilize a course recommendation system that helps them identify appropriate courses and reduces the time spent searching for them. The goal of the course recommendation system is to match students with relevant courses based on their preferences, thereby reducing the time spent on research of selecting courses.

Numerous methods and approaches have been employed in this field. Some of them are k-means clustering and FP growth [8], Singular Value Decomposition (SVD) [9], collaborative filtering [10], hybrid recommendation [4], K-Nearest Neighbor (KNN), and Collaborative filtering [10]. Educational resources are growing massively, and different techniques are used to build recommendation systems for course recommendations. However, existing systems mostly rely on only students' course selection history and past performance and mapping similarities between students based on their history [10] [11] [12]. Essentially, by ignoring which courses are in demand and which are not, many studies view course grades as a crucial factor [13]. However, students may have very different circumstances and motivations for receiving the same mark in the same course. Another problem is that students must enroll in a variety of courses, which leaves them perplexed. It not only costs students a great deal of time, but it may also influence them to select a subject that is not relevant to them. Because suggested courses are either in demand by students or not, it is crucial to recommend a pertinent course, and the recommendation process should be quick and effective.

The main objective of our research is to generate the most demanded courses among students and recommend them. Every semester, a large number of courses are offered, making it difficult for students to select the best ones for them. Our suggested work focuses on a recommender system that is based on the course that students want to take the most. The K-means clustering algorithm and various recommendation (graph-based, content-based, and popularity-based) algorithms have been used to develop a course recommendation system using real data records of undergraduate students. First, our approach uses K-means to cluster the most popular courses according to how many times students take them over several semesters. A recommendation system was used to recommend the most appropriate course to students that helped students find the most appropriate course. We think that this method offers students relevant recommendations for selecting the most popular course in a given semester that best fits their course selection for grade as well as career.

The format of this document is as follows: The background research of course recommendation systems is explained in Section 2. The suggested methodology is provided in Section 3. The study's findings are examined in Section 4. The study's findings are provided in Section 5, and Section 6 offers the findings and recommendations for further research.

CHAPTER 2

RELATED WORK

One of the most important problems facing university students is the recommendation of courses. Commonly employed techniques are determined by the grade of the course.

In this study, M. M. Rahman [3] worked on the cold start problem in recommendation systems, which occurs when there is not enough user data for precise recommendations. It highlights how well hybrid strategies work to improve performance by combining different recommendation techniques, like weighted and mixed methods. In their discussion of various data collection methods, the authors find that mixed methods are the most widely used. The report is a useful tool for scholars and practitioners in the field because it also emphasizes the necessity of further research to create better solutions for the cold start problem.

In the other study, M. M. Rahman [8] proposed a recommendation system for undergraduate students, focusing on challenges in course selection that affect academic performance and satisfaction. The system uses machine learning techniques, specifically K-means clustering, to classify courses based on course count to find the most and least demanded course and FP-growth to generate personalized recommendations. This system used 78,859 historical records from Southeast University's Department of Computer Science & Engineering. The system achieved more relevant and efficient recommendations than existing methods.

To suggest elective courses, M. M. Rahman [9] developed a collaborative filtering strategy that looks at students' prior coursework and GPAs to identify patterns among former students. The objective was to provide precise suggestions for electives by utilizing the Singular Value Decomposition (SVD) algorithm, which they assessed using RMSE and MAE metrics. By accurately predicting the top Top-N elective courses, those results assist students in making well-informed decisions and advancing the field of recommender systems.

Dr. D. V. Divakara Rao [10] focuses on a hybrid course recommendation system based on three main components and algorithms: collaborative filtering, content-based filtering, and the K-Nearest Neighbor (KNN) algorithms. The objective of the system is to assist students in choosing courses based on their individual preferences and career objectives. The system also discerns trends and recommends courses to users based on their data profile collected through an Excel dataset of ratings, likes, and enrolments.

A course recommendation system based on grades [14] demonstrated how to create a grade-based course recommendation system that analyzes students' academic records and learning preferences to offer them tailored course recommendations. They employed online testing to evaluate adaptation, frequent pattern mining to analyze patterns, collaborative filtering to provide suggestions, K-means clustering to classify, and association rule mining to provide tailored recommendations.

The majority of approaches employed grades as a primary metric and concentrated on students' academic performance and background. By calculating the frequency with which different students in different semesters took each course, our method focuses on the most popular and sought-after courses.

CHAPTER 3

METHODOLOGY

Our study evaluates student preferences and explores courses that would be more suitable for them according to their choice. A detailed description of the methodology and suggested approaches is provided through a diagram. Lastly, the approach for evaluation was also implemented. The suggested system for recommending courses is depicted in Figure 1.

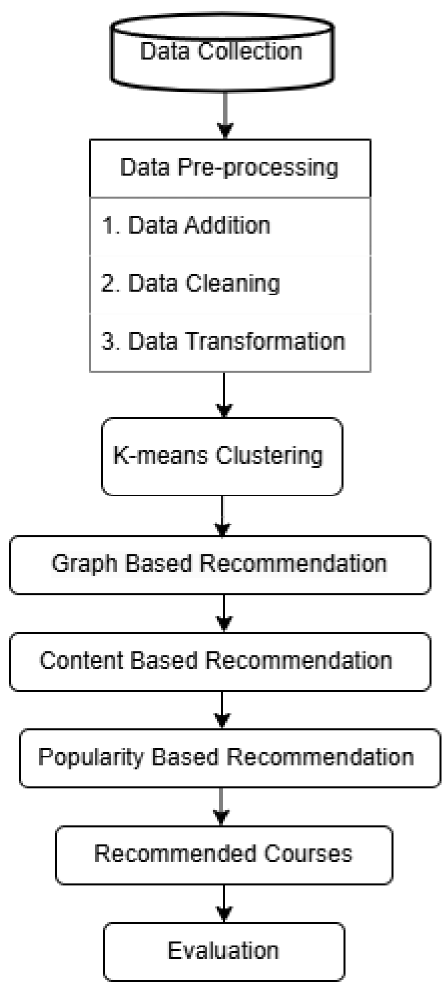

Figure 1: Research Framework.

Data Collection: The academic data of the undergraduate students is represented in the dataset. It was collected from Southeast University's Department of Computer Science & Engineering in Dhaka. A total of 1275 data records from 2019 to 2024 were included in the dataset. The dataset consists of name, batch, semester, course name, result, pre-requisite1& pre-requisite2.

Data Pre-processing: Data preprocessing is a systematic process of transforming rows and columns, including adding some relevant information and cleaning unnecessary data for better accuracy and performance of the model.

K-Means Clustering: K-means clustering is known as the best clustering technique for grouping datasets. The data is grouped using K-means based on commonalities. One group has similar data, whereas another group contains different data. The distances between each center and each data point are determined by the K-Means technique by calculating the distance between data points. The computational cost of this approach is relatively high for large datasets. The key component of the technique is identifying the most accurate cluster set. Typically, the elbow approach is employed to determine the ideal K value. Consequently, we determine the proper cluster number using the Elbow method. The K-Means technique is used because it is easy to understand, quick to implement, adaptable to rare data, fast to converge, and scalable [8].

In this paper, we are implementing K-means clustering to create groups based on course count according to the different semesters. Through K-means, we can identify the different clusters with higher and lower course counts. The cluster with a lower course count will be removed as we consider that the lower course count courses are not popular for the particular semester among the students, and we consider it an inappropriate cluster to recommend. Our system focuses on recommending popular courses for a particular semester. To construct the ideal number of clusters, we use the Elbow method, which sets K=6 according to our data set. A convenient method to calculate the distance between two numeric values is the Euclidean distance measurement [8]. If (x_n,x_1) and (y_n,y_1) consider two points in two-dimensional data, then we can calculate Euclidean distance by the following formula:

Euclidean Distance $d = \sqrt{(x_n - x_1)^2 + (y_n - y_1)^2}$

Using the elbow approach, our dataset yields six clusters, where (k=6). The Euclidean distance is then used to determine each data point's distance from the centroids and assign it to the nearest cluster.

Graph-Based Recommendation: In our approach, we use a unique Knowledge Graph-based Recommendation system that focuses on the recommendation of course progressions with respect to their prerequisites. This recommendation system is structured as follows:

Knowledge Representation: Courses are nodes in a directed graph, and directed edges represent prerequisite relations. It suffices to say that a node represents a distinct course, while an edge represents a prerequisite relationship, thus encoding course knowledge in a hierarchy. Such a configuration is consistent with knowledge graph constructs in such a way that relationships between the entities (courses) expose key dependencies that need to be followed by the students in order to complete their coursework in the right sequence.

Prerequisite-Based Course Recommendations: Through the use of a directed graph representing paths and connections on the knowledge graph, it is possible to suggest other courses that a given student may take in relation to his/her current coursework. It makes it possible for the system to recommend courses that a student can take based on the courses that have been offered and passed as prerequisites. It therefore helps in the order of selection of courses in a more logical manner as the interdependence of courses is exploited.

Content-Based Recommendation: The content-based recommendation system utilizes user-specific attributes and course characteristics to suggest relevant courses. The system efficiently suggests new courses that match the user's interests and previous choices by analyzing the characteristics of completed courses and calculating similarity scores of courses. In our system, content-based recommendations suggest courses to users based on the attributes of courses they have previously selected. This method applies the characteristics of courses, such as prerequisites, subject matter, and popularity, to generate recommendations among students.

Popularity-Based Recommendation: The popularity-based recommendation suggests courses based on their overall popularity among all students. It doesn't require personalized data to recommend; that's why this approach is particularly effective in addressing the cold start problem. This method recommends courses based on the popularity of courses, and it doesn't require any interaction history of new users.

The cold start problem arises when a new user or item does not have sufficient interaction history for personalized recommendations. Popularity-based recommendations solve this issue by providing recommendations based on the popularity score, and it allows new users to discover mostly selected and trending courses on the system. The popularity score can be dynamically updated based on user interactions over time.

We implemented the k-means clustering initially to get some set of the most popular courses, then we used graph-based recommendation to find out the similar courses. The content-based recommendation in our system helped students choose courses according to their interests. The popularity-based recommendation utilizes the most popular courses based on course count. Through this recommendation technique, we are able to recommend courses to new students who do not have any previous history in our system.

CHAPTER 4

RESULTS AND DISCUSSION

The data was collected from the Department of Computer Science and Engineering, Southeast University, Dhaka. To commit this study, we collected university data with 45560 data records of 14 different batches. This study used 1275 records among them in one batch. The university data has attributes for name, batch, semester, course, and grade. This data will be analyzed to generate course recommendations, aiding students in selecting courses that are most relevant and popular for their academic needs. Table 1 shows the dataset of university students.

Table 1: Raw data collected from Southeast University

1	name	Batch	Semester	Course	Grade
2	OMXEOEFNTOFFF	HT	Fall 2017	CSE1013	B-
3	OMXEOEFNTOFFF	HT	Fall 2017	ENG1001	B
4	OMXEOEFNTOFFF	HT	Fall 2017	MATH1034	R
5	OMXEOEFNTOFFF	HT	Fall 2017	PHY1021	R
6	OMXEOEFNTOFFF	HT	Spring 2018	CSE1011	C
7	OMXEOEFNTOFFF	HT	Spring 2018	CSE1012	C+
8	OMXEOEFNTOFFF	HT	Spring 2018	ENG1002	B
9	OMXEOEFNTOFFF	HT	Spring 2018	MATH1024	R
10	OMXEOEFNTOFFF	HT	Spring 2018	PHY1021	D
11	OMXEOEFNTOFFF	HT	Summer 2018	CSE1021	R
12	OMXEOEFNTOFFF	HT	Summer 2018	EEE1021	C
13	OMXEOEFNTOFFF	HT	Summer 2018	EEE1022	C+
14	OMXEOEFNTOFFF	HT	Summer 2018	MATH1024	B
15	OMXEOEFNTOFFF	HT	Summer 2018	MGT2011	R

To recommend courses among students, we required the addition of pre-requisite courses. Following the course curriculum of Southeast University, we added two additional columns named pre-requisite1 and pre-requisite2 to the dataset using the Pandas library.

Table 2: Dataset after pre-processing

1	Name	Batch	Semester	Course	Pre-requisite1	Pre-requisite2	Grade
50	OMXEOEFNTOFFF	HT	Fall 2020	CSE2031			B
51	OMXEOEFNTOFFF	HT	Fall 2020	CSE3014	CSE1011	CSE2013	B-
52	OMXEOEFNTOFFF	HT	Fall 2020	CSE3031	CSE2013		R
53	OMXEOEFNTOFFF	HT	Fall 2020	CSE4053	CSE2021		B
54	OMXEOEFNTOFFF	HT	Fall 2020	ETE2023	EEE2011	MATH2014	C
55	OMXEOEFNTOFFF	HT	Spring 2021	CSE3031	CSE2013		B-
56	OMXEOEFNTOFFF	HT	Spring 2021	CSE3035	CSE2016	CSE2015	B
57	OMXEOEFNTOFFF	HT	Spring 2021	CSE4013	CSE2015	MATH2015	C+
58	OMXEOEFNTOFFF	HT	Spring 2021	SOC2031			B+
59	OMXEOEFNTOFFF	HT	Summer 2021	CSE2032	CSE1026	CSE1021	B
60	OMXEOEFNTOFFF	HT	Summer 2021	CSE3027	CSE2013		C+
61	OMXEOEFNTOFFF	HT	Summer 2021	CSE3032	CSE3014	CSE2013	B
62	OMXEOEFNTOFFF	HT	Summer 2021	CSE3036	CSE2016	CSE2015	A-
63	OMXEOEFNTOFFF	HT	Summer 2021	CSE4011	ETE2023		B-
64	OMXEOEFNTOFFF	HT	Summer 2021	CSE4014	CSE2016	CSE2015	B

There are some null values, and some columns had to be added following the university course curriculum; some columns are not significant for this process. In the beginning, we remove data columns that are not in use for this system, erase null data, and change some column names using Pandas. After completing the pre-processing stage, we have 1275 data records of the HT batch. Table 3 shows the new dataset.

Table 3: Dataset for course recommendation system

Batch	Semester	Course	Pre-requisite1	Pre-requisite2
HT	Spring 2020	CSE3025	CSE2021	
HT	Summer 2020	CSE3011	CSE1033	CSE2015
HT	Summer 2020	CSE3012	CSE1034	CSE2015
HT	Summer 2020	CSE4041	CSE2021	
HT	Summer 2020	ENG1021	ENG1002	
HT	Summer 2020	MATH2014	MATH1034	
HT	Fall 2020	CSE2031		
HT	Fall 2020	CSE3014	CSE1011	CSE2013
HT	Fall 2020	CSE3031	CSE2013	
HT	Fall 2020	CSE4053	CSE2021	
HT	Fall 2020	ETE2023	EEE2011	MATH2014
HT	Spring 2021	CSE3031	CSE2013	
HT	Spring 2021	CSE3035	CSE2016	CSE2015
HT	Spring 2021	CSE4013	CSE2015	MATH2015

To perform K-means clustering, we had to find out the ideal value of K (clusters) that were used to create groups. We used the elbow method to determine the ideal value of K. By using the Elbow method, we plotted the value of K to visualize and used the Within-Cluster Sum of Squares (WCSS) in a graph.

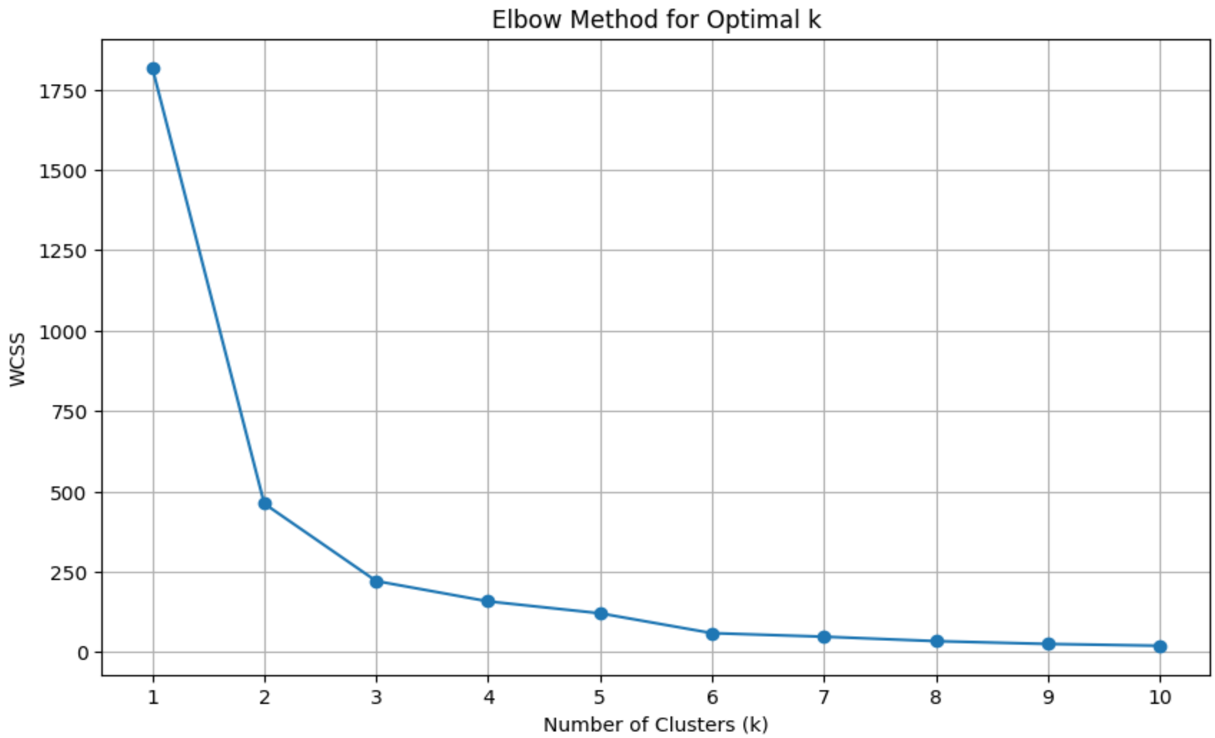

Figure 2: Elbow method for the optimal value of K

In the graph, it can be seen that the ideal elbow is 6. So, we selected the ideal number of clusters as K = 6. Based on the elbow value, the preprocessed data is now separated into six clusters. Courses were categorized using only one variable, course count. We will remove the cluster with the fewest courses taken after clustering. This course, which is taken by different students in different semesters, is said to be the least popular.

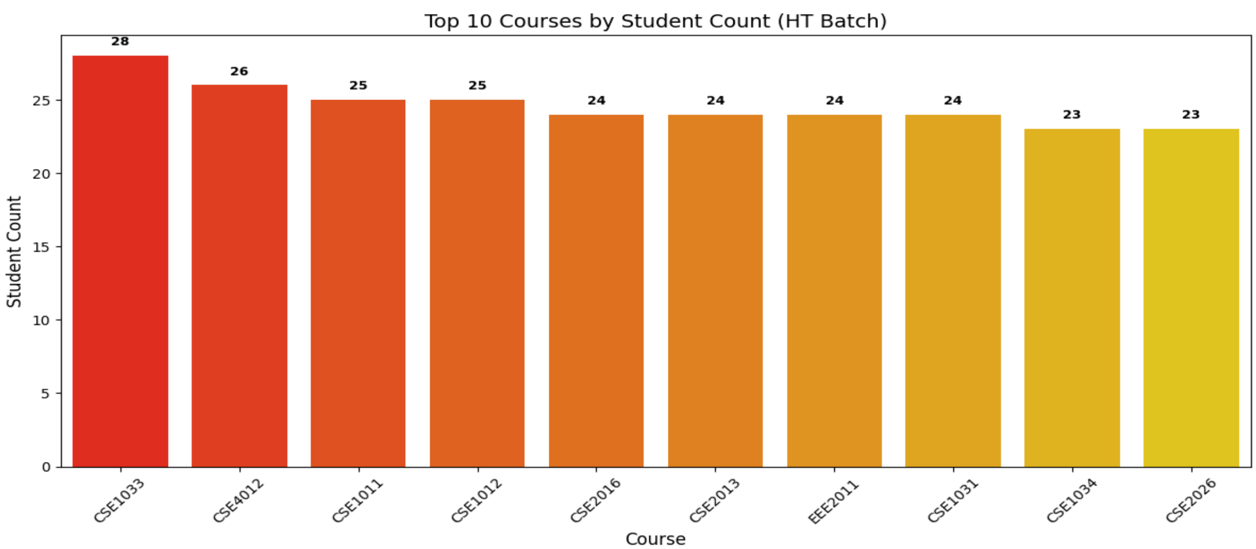

Figure 3: Top 10 courses of HT batch

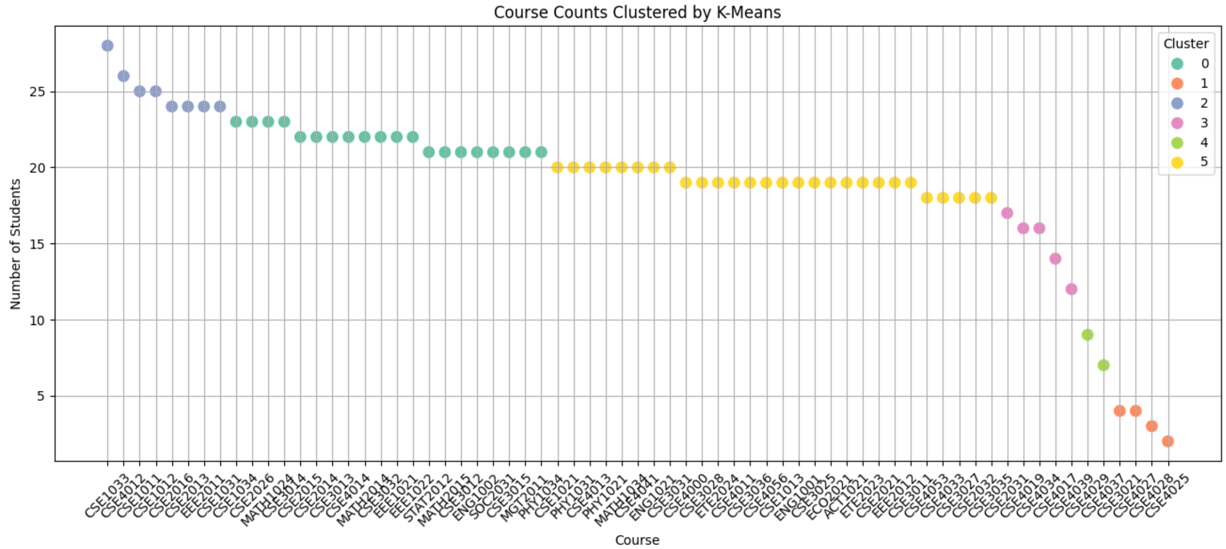

Figure 4: Result before removing clustering

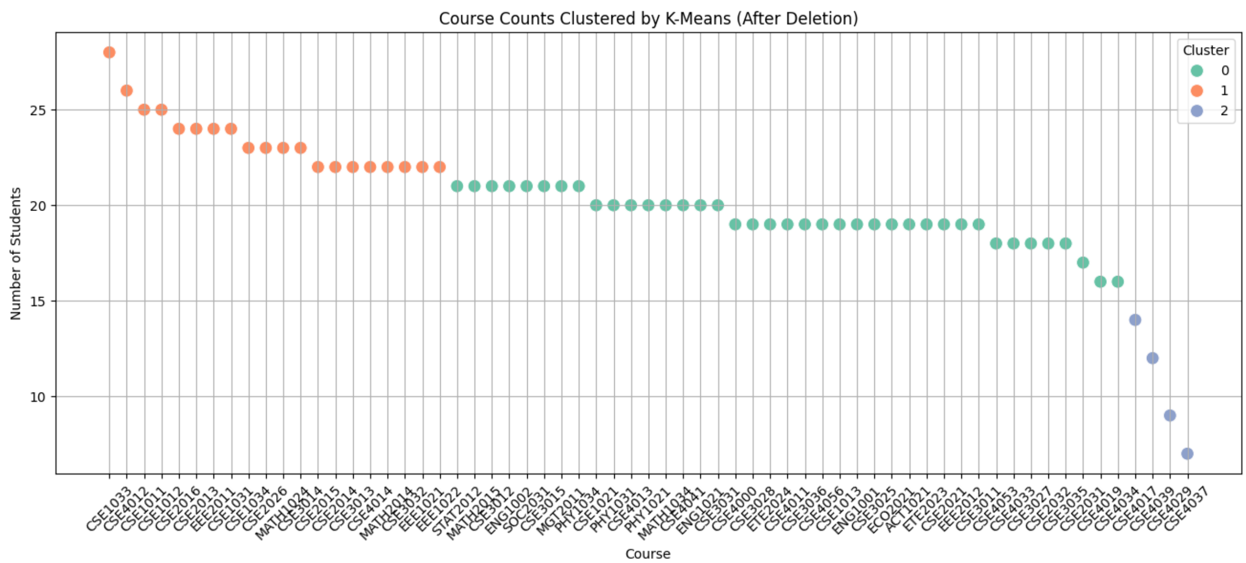

Figure 5: Result after removing clustering

The value of course count for each of the six clusters is shown in Graph 3. Cluster 1 has a minimum course count taken by various students. Since our system is built on suggesting only popular courses which students have taken frequently, we will remove cluster 1 from the recommendation.

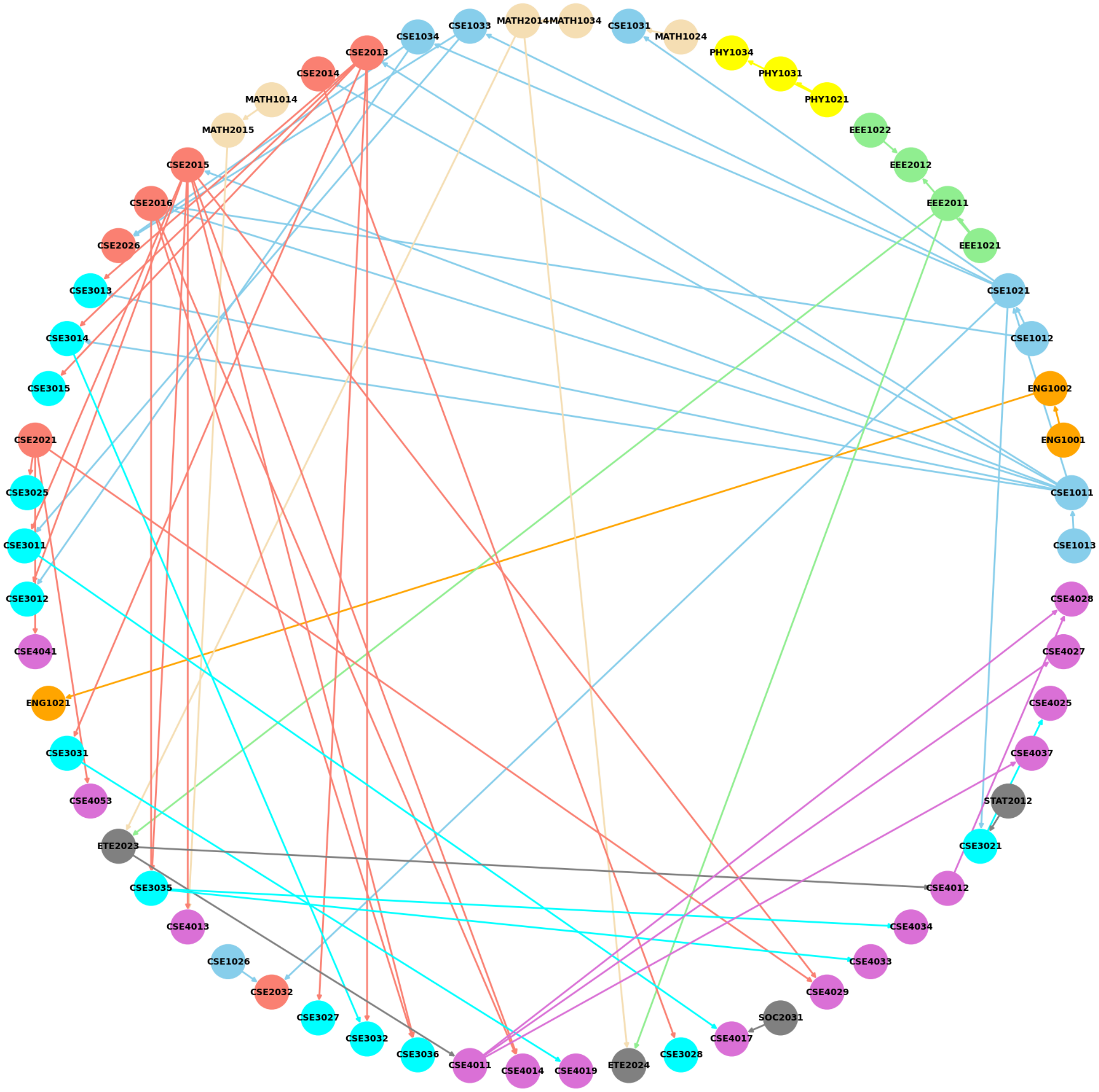

Figure 6: Graph-based recommendation

To follow the structured learning paths, where certain courses are required before moving on to others, this method uses the Graph-Based Recommendation to capture the prerequisite relationships between courses. The recommendation system represents requirements as directed edges and courses as nodes in a graph; it also ensures logical academic progression by recommending courses based on direct successors. For instance, under this approach, students must finish ENG1002 and ENG1001 before they can take ENG1021.

To make recommendations more personalized, we employed content-based recommendations to make sure that courses are relevant to students' previously finished courses. By following the course prerequisite, the algorithm suggests courses that are logically similar to what the user has already finished. This results in tailored recommendations that meet with students' academic experiences, increasing the probability of their success in the next courses.

```
Enter the list of completed courses separated by commas (e.g., CSE1011, CSE1013): ENG1001,CSE1011,MAT2011
Enter clusters of interest for cold start (comma separated, e.g., 1, 2, 3), or leave empty for no profile: 1

Recommended Courses:
     Course  Count  Cluster
4   CSE2016     24        2
5   CSE2013     24        2
11  CSE3014     23        0
12  CSE2015     22        0
13  CSE2014     22        0
14  CSE3013     22        0
23  ENG1002     21        0
28  CSE1021     20        5
```

Figure 7: Recommended courses

Popularity-based recommendations have been used for new users or those who have a limited course history. It is known as the "cold start" problem. Popular courses on clusters represent common user interests and are recommended based on enrollment frequency. This system assumes that highly enrolled courses may be of general interest. This strategy offers relevant suggestions even for users without a strong course history and helps in overcoming the cold start problem effectively.

CHAPTER 5

CONCLUSION AND FUTURE WORK

This study provides a technique for recommending courses to students by examining the most popular, in-demand, and out-of-demand courses. K-means clustering, graph-based recommendation, content-based recommendation, and popularity-based recommendation are the algorithms it uses. We used K-means clustering to group courses according to how many times students have chosen them. Based on prerequisites, the graph-based recommendation system then analyzes relationships between each course. By examining the characteristics of completed courses and calculating course similarity scores, the content-based recommendation system recommends new courses that match the student's interests and previous choices. Finally, the popularity-based recommendation is used to recommend courses for those who do not have any previous record, which also solves the ‘cold start’ problem by suggesting the most popular courses among students. We have evaluated the performance of our system. Results show that the presented course suggestion approach is more appropriate, effective, and supportive for students than other approaches.

The recommendation system was tested to see how well it suggested the right courses to different types of users. For students following a structured path, the graph-based approach worked well by recommending necessary prerequisite courses, helping students move forward smoothly. Content-based recommendations provided courses similar to what students had already completed, making the suggestions feel relevant and useful. For new users without much course history, the popularity-based method suggested commonly taken courses, offering a helpful starting point. Together, these methods achieved good accuracy, showing that the system can meet different user needs and make course recommendations that feel personalized and helpful.

In the near future, we will be adding user reviews and continuously updating course popularity. We will be upgrading the statistics. We would have expected that our system would operate more effectively with a dataset that is more relevant.

CHAPTER 6

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