



## Online Resource Recommendation System

---

Gunasekhar Vemula, Mehar Swaraj Valpishetty,  
Brahmananda Reddy Yama, Sai Srujan Macharla, Hemlata Patel  
and Komal Bonde

EasyChair preprints are intended for rapid dissemination of research results and are integrated with the rest of EasyChair.

March 28, 2024

# ONLINE RESOURCE RECOMMENDATION SYSTEM

An Online Resource Recommendation System using ML

Gunasekhar Vemula  
*Computer Science & Engineering*  
Parul University  
Vadodara, India  
gunasekharvemula@gmail.com

Valpishetty Mehar Swaraj  
*Computer Science & Engineering*  
Parul University  
Vadodara, India  
Meharswarajvalpishetty@gmail.com

Yama Brahmananda Reddy  
*Computer Science & Engineering*  
Parul University  
Vadodara, India  
brahmamyama@gmail.com

Macharla Sai Srujan  
*Computer Science & Engineering*  
Parul University  
Vadodara, India  
saisrujanmacharla@gmail.com

Dr. Hemlata Patel  
*Computer Science & Engineering*  
Parul University  
Vadodara, India  
hemlata.patel29913@paruluniversity.ac.in

Prof. Komal Bonde  
*Computer Science & Engineering*  
Parul University  
Vadodara, India  
komal.bonde32617@paruluniversity.ac.in

**Abstract**— In recent years, the use of online resources for learning has increased significantly due to their convenience and accessibility. However, with the vast amount of resources available online, it can be challenging for users to identify and access the most relevant and valuable resources. This has led to the development of recommendation systems that can generate personalized recommendations based on user preferences and behavior. This project aims to develop an online resource recommendation system using content-based filtering, which is a widely used method for generating personalized recommendations based on user behavior and preferences. content-based filtering, works by identifying users who have similar interests and behavior and recommending resources that these similar users have found valuable. The proposed system will also use item-based content-based filtering to recommend resources that are similar to those that the user has already interacted with. The system will be developed using Python programming language and will use the open-source library for content-based filtering algorithm implementation. The system will also incorporate features such as resource ratings to enhance the quality and relevance of the recommendations generated. The success of the proposed system will be measured by the extent to which it can enhance the quality of online learning experiences by providing users with personalized and relevant recommendations. The proposed system has the potential to promote engagement and motivation among users and can serve as a valuable tool for lifelong learning. **Keywords:** online learning, recommendation systems, content-based filtering, personalized recommendations, user preferences, resource ratings, online learning experiences.

## I. INTRODUCTION

The rise of online resources has brought about significant shifts in the way we acquire knowledge, carry out our professional tasks, and interact with one another. In a digital landscape teeming with millions of information sources, the task of sifting through this vast ocean of data to pinpoint the most pertinent and valuable resources can be quite daunting for users. As a response to this challenge, recommendation systems have emerged as a practical solution, harnessing the power of user preferences and behavior to offer tailored suggestions [1]. In today's digital era, individuals often find themselves inundated with an overwhelming surplus of

online information and assets. Consequently, numerous websites and applications have embraced the implementation of recommendation systems to facilitate the discovery of new and contextually pertinent content, which might otherwise remain hidden [2]. These resource recommendation systems represent a profound application of artificial intelligence, adept at delivering individualized recommendations by analyzing users' historical interactions, inclinations, and interests [3]. Their versatility extends across a spectrum of domains, including education, entertainment, and e-commerce. By gauging user ratings or course preferences, these recommendation systems proficiently winnow the array of available information, striving to serve products and content that best align with the user's unique needs and desires.[4] The three primary components of a comprehensive recommendation system are user resources, course resource and algorithm for recommendations. The course recommendation system will help students make informed decisions about their course selection, which can result in higher engagement, improved academic performance, and increased graduation rates [5]. The system can also help academic advisors and administrators by reducing the workload associated with course selection and counselling. By providing personalized and relevant recommendations, the system can improve overall student satisfaction and retention rates, leading to a more successful and fulfilling academic experience.[6]

### A. Problem Statement

Conventional resource search methods suffer from inherent flaws, including their propensity to consume an excessive amount of time, generate a sense of overwhelming information overload, and frequently yield subpar recommendations. The expanse and diversity of Resource 7's data pose a formidable challenge, as manually sifting through this vast trove in pursuit of the precise resource can be an intimidating and arduous endeavor. [7]. Therefore, there is a need for an efficient and accurate resource recommendation system that can provide personalized recommendations to job seekers or those seeking resources.[8] The overwhelming amount of information and resources available to users online,

which can make it difficult for users to discover new and relevant content.[9] Numerous students face the challenge of selecting courses that harmonize with their academic passions and future career aspirations. This predicament often leads to diminished engagement, subpar academic achievements, and a drop in graduation rates.[10]. Existing course recommendation systems often provide generic recommendations that do not take into account the specific needs and preferences of each student, resulting in low satisfaction and adoption rates.[11]

### B. Objectives

The Goal is to develop a course recommendation system that carefully considers the individual requirements and preferences of each student, offering tailored and pertinent course suggestions. This, in turn, is aimed at enhancing academic performance, boosting graduation rates, and elevating overall satisfaction with the academic program.[12] To achieve this objective, the project team will explore various content-based filtering techniques and algorithms to identify the most effective approach for generating personalized recommendations.[13] The Course recommendations customized by the system will empower students to make well-informed choices regarding their course selections. This, in turn, is expected to result in heightened engagement, enhanced academic performance, and elevated graduation rates.[14] The system can also help academic advisors and administrators by reducing their workload associated with course selection and counselling.[15] The Main aim of a content-based filtering-based resource recommendation system is to furnish users with individualized suggestions that align with their specific interests and requirements.[16] Therefore, the first objective of the project would be to develop a content-based filtering algorithm that can effectively analyze user preferences and behavior to generate accurate recommendations.[17] The algorithm should possess the capability to discern patterns and affinities among users and resources, utilizing this insight to propose resources that are probable to pique the interest of each individual user.[18] To improve the accuracy and relevance of recommendations, it is important to collect ratings from users about their experiences with recommended resources. Therefore, the project should include a user interface that allows users to rate.[19] For the recommendation system to effectively manage substantial data volumes and accommodate a high influx of user traffic, it is vital to design and execute it with scalability as a fundamental consideration. This may involve using distributed computing frameworks, optimizing data storage and retrieval, and implementing caching strategies to reduce latency.[20]

## II. MOTIVATION

The motivation for our research arises from the challenges faced by modern learners in navigating the vast array of online resources, leading to information overload. Conventional search methods often fail to provide personalized recommendations tailored to individual preferences and learning goals. Our aim is to leverage advanced recommendation algorithms, particularly content-based filtering, to alleviate these challenges and empower users with curated and contextually relevant content. This research is driven by a desire to revolutionize the online learning

experience, enhance engagement, and contribute to improved learning outcomes

. Furthermore, the broader motivation extends to the impact on educational institutions and stakeholders. Implementing a robust recommendation system can optimize resource utilization, support academic advisors, and enhance overall student satisfaction and success. Our research strives to uphold academic integrity and originality while leveraging data-driven insights and user-centric design principles to pave the way for recommendation systems that anticipate and adapt to evolving learner needs.

## III. LITERATURE REVIEW

In this chapter, we have given our critical evaluation summary of all research papers that we read related to our project. After reading many reference papers covering the topics related to Online Course Recommendation system, Image-Based Service Recommendation System, Autonomous Permission Recommendation, etc. We studied the latest existing model and found some flaws. All those details are given below.

## IV. METHODOLOGY

### A. Data Preprocessing and Feature Engineering

This phase involved cleansing the dataset and selecting relevant features to construct the Tags column, incorporating course attributes like title, difficulty level, description, and skills.

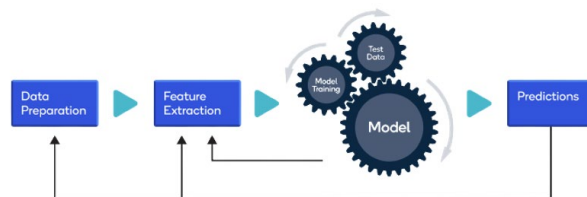


Figure 1 Data Preprocessing

### B. Natural Language Processing (NLP) Analysis

NLP techniques, including Count Vectorizer, were applied to the Tags column to tokenize and statistically analyze the text data, extracting meaningful insights and patterns.

Table 1 Count vectorization

Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9
0	1	1	1	0	0	1	0	1
0	2	0	1	0	1	1	0	1
1	0	0	1	1	0	1	1	1
0	1	1	1	0	0	1	0	1

### C. Cosine Similarity for Course Recommendation

The Cosine Similarity algorithm was implemented to compute similarity scores between courses based on their attributes and Tags, enabling the generation of personalized recommendations.

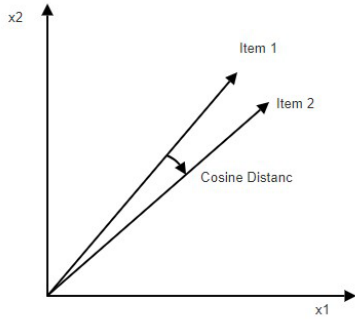


Figure 2 Cosine Similarity

## V. IMPLEMENTATION

Developing an effective recommendation system requires a systematic and comprehensive approach that encompasses data preprocessing, algorithm development, user interface design, and rigorous testing. In this section, we delve into the technical intricacies of bringing our recommendation system to life, detailing each step from data preparation to system deployment.

### A. Data Preprocessing and Feature Engineering:

The implementation phase commenced with meticulous data preprocessing aimed at ensuring data quality and consistency. This involved handling missing values, removing duplicates, and standardizing formats to prepare the dataset for analysis. Feature engineering techniques were then applied to extract relevant attributes such as course titles, descriptions, difficulty levels, and skills. These attributes were instrumental in creating the Tags column, a pivotal component that encapsulated key course characteristics for subsequent analysis and recommendation generation.

```
data['Course Name'] = data['Course Name'].str.replace(' ', '')
data['Course Name'] = data['Course Name'].str.replace(' ', '')
data['Course Name'] = data['Course Name'].str.replace(' ', '')
data['Course Description'] = data['Course Description'].str.replace(' ', '')
data['Course Description'] = data['Course Description'].str.replace(' ', '')
data['Course Description'] = data['Course Description'].str.replace(' ', '')
data['Course Description'] = data['Course Description'].str.replace(' ', '')
data['Course Description'] = data['Course Description'].str.replace(' ', '')
data['Course Description'] = data['Course Description'].str.replace(' ', '')

#removing parenthesis from skills column
data['Skills'] = data['Skills'].str.replace('(', '')
data['Skills'] = data['Skills'].str.replace('(', '')
```

Figure 3 Data Processing and Feature Engineering

### B. Natural Language Processing (NLP) Analysis:

Leveraging Natural Language Processing (NLP) techniques played a critical role in our implementation strategy. The Tags column underwent tokenization using the Count Vectorizer method, converting textual data into a structured format suitable for statistical analysis. NLP analysis provided valuable insights into keyword frequency, semantic relationships, and patterns within course attributes, facilitating the identification of relevant features for recommendation generation.

```
from sklearn.feature_extraction.text import CountVectorizer
cv = CountVectorizer(max_features=1000, stop_words='english')
vectors = cv.fit_transform(new_df['tags']).toarray()

import nltk
from nltk.stem.porter import PorterStemmer
```

Figure 4 Natural Language Processing

### C. Recommendation Algorithm and Model Development:

Leveraging Natural Language Processing (NLP) techniques played a critical role in our implementation strategy. The Tags column underwent tokenization using the Count Vectorizer method, converting textual data into a structured format suitable for statistical analysis. NLP analysis provided valuable insights into keyword frequency, semantic relationships, and patterns within course attributes, facilitating the identification of relevant features for recommendation generation..

```
from sklearn.metrics.pairwise import cosine_similarity
similarity = cosine_similarity(vectors)

def recommend(course):
    course_index = new_df[new_df['course_name'] == course].index[0]
    distances = similarity[course_index]
    course_list = sorted(list(enumerate(distances)), reverse=True, key=lambda x:x[1])[1:7]
    for i in course_list:
        print(new_df.iloc[i][0].course_name)
```

Figure 5 Cosine Similarity Function

#### D. User Interface and Interaction Design::

An intuitive and user-friendly interface was crafted to facilitate seamless interaction with the recommendation system. Upon receiving user input or preferences, the system dynamically generated personalized course suggestions using the computed similarity scores. Integration of user interaction elements, including feedback mechanisms and user profiles, further enhanced recommendation quality by refining suggestions based on user feedback and historical interactions.

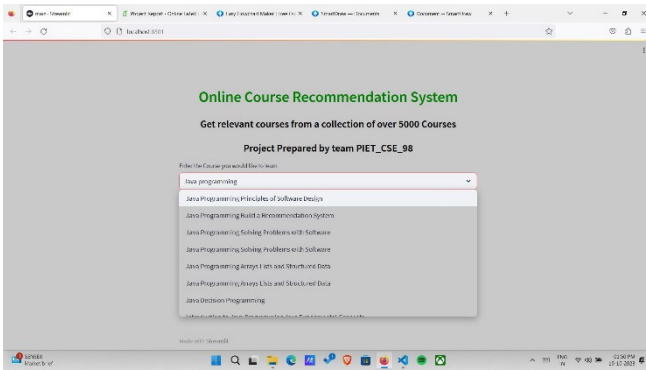


Figure 6 Webpage

#### VI. CONCLUSION

A well-designed recommendation system for courses can enhance the learning experience for students and improve the effectiveness of educational institutions. However, it is important to ensure that any such system is effective in providing recommendations. By considering the key factors and selecting the appropriate algorithm, a recommendation system for courses can provide students with personalized and relevant course recommendations, ultimately improving their learning outcomes. In this project, we have effectively implemented a content-based recommendation system, primarily harnessing the capabilities of the Cosine Similarity algorithm. Our approach revolves around examining course attributes and aligning them with the preferences and behaviors of the target user. Through the application of the Cosine Similarity algorithm, we have achieved the precise measurement of course similarity based on content attributes and their alignment with user preferences. Our system has demonstrated its proficiency in delivering personalized course recommendations that are finely tuned to each user's distinct interests and previous interactions. The use of the Cosine Similarity algorithm ensures that our system suggests courses that closely match the user's profile, leading to an enriched user experience and heightened satisfaction. As we look ahead, we anticipate that content-based recommendation systems, particularly those incorporating the Cosine Similarity algorithm, will continue to hold a prominent role

in the advancement of personalized course recommendation systems. This method is poised to provide increasingly precise and tailored recommendations, offering significant benefits to both users and educational institutions.

#### VII. FUTURE ENHANCEMENT

The future scope for our Online Resource recommendation system project will be to increase the model's accuracy in recommending relevant courses to learners who are looking for online resources to upskill themselves. This objective can be achieved by continuously updating our Data Set with more and more latest and relevant course materials that are being generated at a rapid pace. We can acquire the latest data of online courses by collaborating with Educational institutions and Online Content Providers. This updation of our Dataset Can be done in a periodic manner which will ensure that we can keep our system up to date with the Current and Rapidly Changing Landscape of Online Education.

#### REFERENCES

- [1] Ibrahim, Mohammed Yang, Yanyan Ndzi, David Yang, Guangguang. (2018). OntologyBased Personalized Course Recommendation Framework. IEEE Access. 7. 5180 5199. 10.1109/ACCESS.2018.2889635.
- [2] Khalid, Asra Lundqvist, Karsten Yates, Anne. (2020). Recommender Systems for MOOCs: A Systematic Literature Survey (January 1, 2012– July 12, 2019). The International Review of Research in Open and Distributed Learning. 21. 255-291. 10.19173/irrodl.v21i4.4643.
- [3] Kulkarni, Pradnya Rai, Sunil Kale, Rohini. (2020). Recommender System in eLearning: A Survey. 10.1007/978-981-15-0790-8-13.
- [4] Maphosa, Mfowabo Doorsamy, Wesley Paul, Babu. (2020). A Review of Recommender Systems for Choosing Elective Courses. International Journal of Advanced Computer Science and Applications. 11. 10.14569/IJACSA.2020.0110933.
- [5] Nnadozie, JohnBordrick. (2021). Collaborative Filtering Algorithm for Recommender Systems.
- [6] T B, Lalitha P S, SREEJA. (2020). Personalised Self-Directed Learning Recommendation System. Procedia Computer Science. 171. 10.1016/j.procs.2020.04.063.
- [7] Kanwal, Safia Nawaz, Sidra Malik, Muhammad Nawaz, Zubair. (2021). A Review of TextBased Recommendation Systems. 10.1109/ACCESS.2021.3059312.
- [8] Gao, Ming Luo, Yonghan Hu, Xiaonan. (2022). Online Course Recommendation Using Deep Convolutional Neural Network with Negative Sequence Mining. Wireless Communications and Mobile Computing. 2022. 1-7. 10.1155/2022/9054149.
- [9] Gulzar, Zameer Leema, Anny Deepak, Gerard. (2018). PCRS: Personalized Course Recommender System Based on Hybrid Approach. Procedia Computer Science. 125. 518 524. 10.1016/j.procs.2017.12.067.
- [10] Lynn, Ninyikiriza Emanuel, Andi. (2021). A review on Recommender Systems for course selection in higher education. IOP Conference Series: Materials Science and Engineering. 1098. 032039. 10.1088/1757-899X/1098/3/032039.