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# Hybrid recommendation systems for online courses

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## ABSTRACT

There is a constant growth in online learning platforms across the internet. It becomes extremely difficult for one to choose a specific online course or learning material from such a huge data pool. Hence, Recommendation system plays a vital role in e-learning platforms. A well-built recommendation system provides personalized online learning resources to users. Numerous approaches and algorithms are out there for recommendation system like Content-based filtering technique and Collaborative-filtering technique. This paper aims to present a technical approach we used for building a Recommendation Systems along with their challenges and algorithms used. A hybrid approach refers to combination of Content-based and Collaborative-filtering. By combining these two techniques accurate results can be observed in the system. Since we wanted to develop a hybrid course recommendation system, we had to implement both content based and collaborative filtering approach. Out of all the approaches we have decided to use one algorithm or model for each approach which are NLTK porter stemmer and TFRS (Tensor Flow Recommenders) along with successful deployment of the models on website using Flask and Material UI

Keywords: Content-based filtering, Collaborative filtering, Hybrid recommendation system, NLTK porter stemmer, TFRS

## 1. Introduction

Ecommerce, Social media platforms, retail sites all of these businesses boost their economy by targeting users with advertisement and personalized cookies. This user centric mechanism used solely relies on recommendation/ recommender system.

Recommendation system is an application of machine learning which predicts the users' preferences/ likes and dislikes. This is achieved by gathering huge amount of data related to user activities and classify those activities into negative and positive experiences. Social media sites and streaming platforms like YouTube, Instagram, Netflix increase their audience by suggesting content the user prefers. But not only social media, recommendation systems also play a significant role in e-learning/ online courses platforms. Today, the main issue learners face is that they are not provided tailored access to information. To overcome this issue recommendation systems are used to provides well curated choices to learners from substantial data. The rapid growth of online education platforms has necessitated the development of effective course recommendation systems to assist learners in finding relevant and personalized learning opportunities. The main advantage of recommendation system for online courses is that it reduces the time and efforts of students/learners in finding the courses they'll benefit from.

A recommendation system is an information filtering technology that suggests items or content to users based on their preferences, interests, and historical behavior. These systems are widely used in various domains such as e-commerce, entertainment, social media, and education. Some common types of recommendation systems:

- Collaborative Filtering: Collaborative filtering recommends items based on the preferences and behaviors of similar users. It identifies users
  with similar tastes and suggests items that those similar users have liked or interacted with. Collaborative filtering can be further categorized
  into two types:
  - a. User-based: This approach recommends items to a target user based on the preferences of users who have similar tastes.
  - b. Item-based: This approach recommends items to a target user based on the similarity between items they have interacted with and items that other users have interacted with.
- Content-Based Filtering: Content-based filtering recommends items to users based on the similarity between the content or attributes of items. It analyzes the features or characteristics of items and recommends similar items based on user preferences. For example, in a course recommendation system, content-based filtering might recommend courses to users based on their interests, the course descriptions, or the topics covered.
- Hybrid Recommendation Systems: Hybrid recommendation systems combine multiple approaches, such as collaborative filtering and contentbased filtering, to provide more accurate and diverse recommendations. By leveraging the strengths of different techniques, hybrid systems aim to overcome the limitations of individual approaches and offer more personalized recommendations.



Fig. 1 - Classification of recommendation system

#### 1.1. Literature review

Nowadays several research have been done in the field of RS. Different approaches have been implemented to make RS more and more accurate. RS has become an essential feature as the information over the internet increases ever second. Users are bombarded with by choices and need help to find what they are looking for and RS helps tremendously in choosing items from such a huge data pool. First, we understood the basic mechanism of RS which starts with understanding the user-product, product-product and user-user relationship [1]. The data provided to RS also determines its working and accuracy Yuri Stekh, Mykhoylo Lobur [3] reviewed different methods and tool for building RS. The paper analyzes a collaborative filtering and talks about fuzzy model for recommendation. A paper by Sneha Khatwani and Dr. M.B. Chandak [7] presents both personalized and non-personalized RS. It heavily talks about CB, CF and Clustering. They build a recommendation model using KNN for user-based CF. Although the dataset used was a movie dataset, it can be used as reference to build course recommendation. The distance functions used for recommending nearest items was Cosine similarity and Pearson Correlation Coefficient. For Non-Personalized top N movies were recommended using a package called recommenderlab. After building the entire model, it was evaluated using Mean absolute error (MAE), Mean Squared error (MSE) and Root Mean Squared error (RMSE) metric.

Marwa Hussien Mohamed, Mohamed Helmy Khafagy and Mohamed Hasan Ibrahim [2] present challenges and solutions while building RS. It describes approaches such as CB, CF, Demographic and Hybrid in detail. The paper compared advantages and disadvantages of all the approaches mentioned above. It also describes different data mining methods with recommender systems like KNN, Decision Tree, Bayesian Network, SVM, ANN (Classification techniques) and K-means, Density, Message Passing, Hierarchical (Clustering techniques).

The challenges highlighted were Cold start problem which arises when a new user logs-on to the platform and doesn't have enough data to recommend items to that user, usually the problem is reflected in CF. Next was the sparsity problem, this occurs when user does not usually rate the items they bought/preferred. This reduces the data in user-item matrix. Scalability issue occurs when number of users increase. There should not be any change in accuracy of recommendation system even after number of users increases rapidly. Over specialization problem happens when recommendations are too well curated and does not recommend any new item to the user [15].

The user does not discover any new items and gets recommended the items that matches his/her profile. Privacy is important in RS since we do not want to breach user's privacy in order to obtain data for RS. Shilling attacks happens if bots or unauthorized users starts giving high ratings to particular items to give that certain item popularity. Gray sheep problem mainly occurs in CF when ratings/reviews if a single user does not agree with a larger group. Shuai Zhang, studied different algorithms and approaches for Deep learning based RS [20]. Faizan Ahemad comes up with a really interesting approach in graph based RS when he uses WAM to increase efficiency [17]. Rianne van den Berg, Thomas N. Kipf, Max Welling also use graph based method along with convolution to form GCMC [21].

#### 2. Block diagram and flowchart

The final recommendation system has several features which allows us to create a learner's profile for accurate recommendation. The user will be asked to login or signup based on new or old user. For new user some questions and preferences will be asked to avoid cold start problem. The user preference will create a user profile which with the course details can be used for recommendation purpose. The user is asked for feedback and ratings on the courses which the user has interacted with and is used to update the user profile to provide better recommendations.



#### Fig. 2 - Course recommender flowchart

#### 2.1. Database schema

The database used has for tables namely Course Details, Course Tags, User, User Tags. The figure 2.3 shows database schema and its relation.

- Course Details It has all the course meta data such as its title, description, rating, platform etc. This is the main table of the database.
- Course Tags It contains the tags made by combining the relevant columns of course details table.
- User This table contains all the data of the ratings and reviews users has left on the coursers they've interacted with.
- User Tags It is similar to course tags. This table contains the tags for user to describe the user profile.





#### 2.2. Content based filtering flowchart

This flowchart shows the approach and method behind the content-based filtering recommendation we used for out CRS.



Fig. 4 - CB approach flowchart

#### 2.3. Collaborative filtering flowchart

This flowchart shows the approach and method behind the collaborative filtering recommendation we used for out CRS. It shows the user and item embeddings created to train the model. Embeddings are low-dimensional vector representations that capture the latent features or characteristics of users and items in a recommendation system.



#### Fig. 5 - User and course embeddings

Deep Learning Integration: TFRS seamlessly integrates with TensorFlow, allowing users to leverage the power of deep learning for recommendation tasks. It supports the creation of neural network architectures using TensorFlow's high-level APIs, such as Keras, and provides compatibility with various neural network layers and activation functions.

# 3. Implementation

Since we wanted to develop a hybrid course recommendation system, we had to implement both content based and collaborative filtering approach. Out of all the algorithms tried and tested we decided for one algorithm or model each for both approaches.

#### 3.1. Database

The database was created by us with the help of web-scrapping in python. We used beautiful soup to write a script to get data from different elearning platforms. The platforms we chose were – Udemy, Coursera, Swayam, EdX, YouTube, LinkedIn Learning.

	Title	Rating	Rating_Count	University	Provider	Description	Instructor	Platform	Access	Language	Certification	Duration	Schedule	Level	Subtitles		Image_U	IRL Subject	Course_URL
J	ava Tutorial or Complete Beginners	4.5	97922	NaN	NaN	Learn to program using the Java programming la	John Purcell	Udemy	Free Online Course	English	NaN	16 hours worth of material	On- Demand	Beginner	English, Dutch, Bulgarian, Czech, Greek, Finni	https://d3f1iyfx	xz8i1e.cloudfront.net/courses	Programming,Programming J Languages,Java	https://www.udemy.com/course/java-tutorial/
E fro t	Microsoft xcel - Excel m Beginner o Advanced	4.7	367673	NaN	NaN	Excel with this A-Z Microsoft Excel Course. Mi	Kyle Pew and Office Newb LLC	Udemy	Paid Course	English	Certificate Available	21 hours worth of material	On- Demand	Beginner	German, English, Spanish, French, Indonesian,	https://d3f1iyfc	xz8i1e.cloudfront.net/courses	Business, Business J Software, Microsoft Office 36	https://www.udemy.com/course/microsoft-excel-2
Pr	utomate the Boring Stuff with Python rogramming	4.7	106541	NaN	NaN	A practical programming course for office work	Al Sweigart	Udemy	Paid Course	English	Certificate Available	10 hours worth of material	On- Demand	Beginner	German, English, Spanish, French, Indonesian,	https://d3f1iyfx	xz8i1e.cloudfront.net/courses	/ Programming,Programming / Languages,Python	https://www.udemy.com/course/automate/
Th D	e Complete 2023 Web evelopment Bootcamp	4.7	275844	NaN	NaN	Become a Full-Stack Web Developer with just ON	Dr. Angela Yu	Udemy	Paid Course	English	Certificate Available	66 hours worth of material	On- Demand	Beginner	German, English, Spanish, French, Indonesian,	https://d3f1iyfc	xz8i1e.cloudfront.net/courses	I Programming, Web	https://www.udemy.com/course/the-complete- web
P	Machine Learning A- Z™: Al, ython & R + ChatGP	4.5	167795	NaN	NaN	Learn to create Machine Learning Algorithms in	Kirill Eremenko, Hadelin de Ponteves, SuperDat	Udemy	Paid Course	English	Certificate Available	43 hours worth of material	On- Demand	Beginner	German, English, Spanish, French, Indonesian,	https://d3f1iyfc	xz8i1e.cloudfront.net/courses	Computer Science,Machine Learning	https://www.udemy.com/course/machinelearning/
					Title					Cours	e_URL	ı	Jserna	ne		Rating	Date		Review
0	Java	Tutoria	I for Com	plete Bec	ainners	https://w	ww.uden	v.com/	course	e/iava-tu	utorial/	At	hanasi	os Ra	atina: 5.0	out of 5	a week ago	Jon has done an e	cellent job explaining Java
1	Java	Tutoria	I for Com	nlete Ber	ninners	https://w	ww.uden	v com/	course	viava-ti	itorial/		Robert	I R	ating: 3.5	out of 5	3 weeks ado	Good course for b	eginners, some things didn't
2	lava 1	Tutoria	I for Com	nlete Rer	ninnere	https://w	MW uden	v com/	course	/iava-ti	itorial/ Fe	derico	Daniel	G R	ating: 5.0	out of 5	a month ago	Better than many na	id courses, very good evola
2	Java 1	Tutorio	I for Com	plata De <u>r</u>	ainnera	https://w		y.com/	000130	viouo t	iterial/	Acrico	bhinou	о. М п. п.	ating: 4.5	out of 5	2 months ago	It's a yory good o	veuroe te start learning, leve
2	Java	rutona	i lor Com	piete Beğ	ginners	nups.//w	ww.uden	iy.com/	course	ะ/java-แ	itoriai/	A	uninay	R. Ri	aung. 4.5	001 01 5	5 monuts ago	its a very good o	ourse to start learning Java
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Fig. 6 - Database details

#### 3.2. Content based filtering approach

Content-based filtering is a recommendation technique employed by recommendation systems to suggest items to users based on the characteristics and attributes of those items. In the context of online courses, content-based filtering focuses on the features of the courses themselves to generate personalized course recommendations [4]. The underlying principle of content-based filtering is to analyze the content, metadata, or other descriptive information associated with each item (in this case, courses) and match them to the user's preferences.[5]

After doing some preprocessing on the tags column we used Stemming to reduce all the words in tag column to its root word.

Here we used NLTK Porter Stemmer ,refer Figure 1 to understand the process of stemming. After the stemming we used Count Vectorizer From sklearn or scikit-learn. This converts all the tags into a text vector. This way we got our text vector. The text vectors are used to construct a similarity matrix. We used cosine similarity measure for similarity matrix construction.



Fig. 7 - NLTK Porter stemmer

```
similarity_matrix = cosine_similarity(text_vectors)
  similarity_matrix
                  , 0.08067103, 0.42527867, ..., 0.01768596, 0.10497158,
array([[1.
       0.02531939],
                               , 0.21671732, ..., 0.00843904, 0.03415111,
       [0.08067103, 1.
        0.07248848],
       [0.42527867, 0.21671732, 1.
                                           , ..., 0.01015032, 0.07667579,
       0.072656481,
       . . .
       [0.01768596, 0.00843904, 0.01015032, ..., 1.
                                                            , 0.07037911,
       0.1037398 ],
       [0.10497158, 0.03415111, 0.07667579, ..., 0.07037911, 1.
       0.06717026],
       [0.02531939, 0.07248848, 0.07265648, ..., 0.1037398 , 0.06717026,
       1.
                  11)
```

#### Fig. 8 - Similarity Matrix

t	estRecommender	('Java T	utorial fo	r Complete Beginne	ns")												
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0	The Self-Taug Programm	ht 4 er 4	5	4173	The Definitive Guide to Programming Profession	Cory Althoff	Udemy	Paid Course	English	Certificate Available	6 hours worth of material		Beginner	English	https://d3f1lyfocz8i1e.cloudfront.net/courses/	Programming, Programming Languages, Python	https://www.udemy.com/course/self- taught-progr
1	Proje Developme Using JAVA f Beginners -	ct nt 4 pr 4	4	2380	Learn Java from scratch and become Software En	Hemanth Kumar	Udemy	Paid Course	English	Certificate Available	45 hours worth of material	On- Demand	Beginner	English	https://d3f1iyforz8i1e.cloudfront.net/courses/	Programming, Programming Languages, Java	https://www.udemy.com/course/project- developme
2	CS106 Programmin Abstraction in C-	B, 19 -+			Learn about programming abstractions in C++ in	Lecture Archive	YouTube	Free Online Course	English		22 hours worth of material	On- Demand			https://ccweb.imgix.net/https%3A%2F%2Fing.yout	Programming, Programming Languages, C++	https://www.youtube.com/playlist? list=PLoCMsyE
3	C Programmin For Beginners Master the Lan	19 - 4	.4	29703	C Programming will increase career options. Be	Tim Buchalka's Learn Programming Academy and J	Udemy	Paid Course	English	Certificate Available	23 hours worth of material		Beginner	Italian, German, Portuguese, English, Spanish,	https://d3f1lyfioiz8i1e.cloudfront.net/courses/	Programming, Programming Languages, C Programming	https://www.udemy.com/course/c- programming-for
4	A Crash Course	in C			In this crash course, you will learn about the	Northwestern Robotics	YouTube	Free Online Course	English		1-2 hours worth of material	On- Demand			https://ccweb.imgix.net/https%3A%2F%2Fimg.yout	Programming, Programming Languages, C Programming	https://www.youtube.com/playlist? list=PLggLP4f

Fig. 9 - Top recommendations

6	6	Λ	2
υ	υ	-	-

Table 1 - Recommendation for course "Java Tutorial for Complete Beginners".

Title	Rating	Platform
The Self-Taught Programmer	4.5	Udemy
Project Development Using JAVA for Beginners	4.4	Udemy
CS106B, Programming Abstraction in C++	-	YouTube
C Programming For Beginners – Master the C Lan	4.4	Udemy
A Crash Course in C	-	YouTube

#### 3.3. Collaborative filtering approach

Collaborative filtering is a popular recommendation technique used by recommendation systems to suggest items to users based on the preferences and behaviors of similar users. It relies on the idea that users with similar tastes and preferences in the past are likely to have similar preferences in the future. In the context of online courses, collaborative filtering analyzes the historical interactions and feedback of users to identify patterns and make recommendations [2]. We used our user reviews along with the course details to create user and item embeddings. Embeddings are low-dimensional vector representations that capture the latent features or characteristics of users and items in a recommendation system. These embeddings are learned during the training process and are used to represent users and items in a continuous vector space. For this approach we used TFRS which creates the embeddings easily using the user and course inputs.TensorFlow Recommenders (TFRS) is an open-source library built on top of TensorFlow that provides a flexible and efficient framework for building recommendation systems. It offers a range of tools and components to simplify the development and training of recommendation models using deep learning techniques. TFRS provides a convenient way to define and incorporate user and item embeddings in recommendation models using the tfrs.layers.Embedding layer. This layer takes as input the unique identifiers for users and items and maps them to dense vector representations (embeddings) of a specified dimensionality.



Fig. 10 - TensorFlow recommenders

userId = 123 N = 5 predict\_course(userId, N)

Top 5 recommendations for user 123:

1. Become a Fiverr Level one seller in Two Weeks - Secret Gig

- Ziołolecznictwo
- 3. Masterclass Collection: Post di una fotografia di Ritratto
- 4. Informática para Concursos da PCDF, PF e PRF
- 5. Application Development Process : PMI CAPM Exam

Predict rating for a course (not-enrolled) for a specific user

Fig. 11 - Top recommendations using collaborative filtering

# predict\_rating(userId,courseTitle) Predicted rating for : 4.356666564941406 Examine the User from historical data

Fig. 12 - Predicting user ratings

## 3.4. Website

We have used ReactJS to deploy the website. ReactJS's primary goal is to create User Interfaces (UI) that increase the speed of apps. It makes use of virtual DOM (JavaScript object), which enhances the app's speed. Faster than the standard DOM is the JavaScript virtual DOM. ReactJS integrates with different frameworks and may be used on the client and server sides. It makes use of component and data patterns to make bigger program mes more readable and maintainable. Material UI is one of the popular UI framework which we have successfully utilized.Moreover, we have sed Flask API. Python is used to create the Flask web application framework. A Python package called Flask serves as a web framework that makes it simple to create web apps. Its core is compact and simple to extend; it's a microframework without an object relationship manager or similar capabilities.

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Fig. 13 – Predictions provided by API

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Fig. 14 - Website implementation

#### 4. Conclusion

The creation of a course recommender system that offers students customize recommendations is the main objective of this project. In this project, we've looked into three popular strategies for creating recommender systems (Content-based, Collaborative Filtering, and Hybrid Method) and used them to implement the course recommender system. The training data for this system includes details on the e-learning programs offered by well-known e-learning providers like Coursera, Nptel, Udemy, Edx, etc. We use two types of collaborative filtering and Content based filtering to create the course recommender system (UBCRS and IBDCRS). Due to the sparseness of the data, Cosine similarity is used for both models to determine how similar the patients are to one another. Three measurements—Recall, Precision, and F1—as well as self-designed tests are used to compare the two models results. The findings demonstrate that IBWCRS outperforms UBCRS across all test situations and categories. We decide to use IBWCRS as our course recommender system's final model as a result. After all, the course recommendation system only makes tailored suggestions; it does not choose the courses for the students. We believe that this CRS is successful as long as the students believe the recommendations are relevant to them and useful.

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