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A Hybrid Course Recommender System using LLM-derived embeddings and Neural Collaborative Filtering

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Abstract: - Personalized education depends on recommender systems assisting students in picking courses according to the preferences and goals they need to learn. In this research, we present a novel hybrid course recommender system that combines the insight from learner and course classification models using collaborative filtering techniques and generative AI.

According to their academic performance and behavioural data, students are categorized into adaptive and accelerated learners using machine learning algorithms. At the same time, Natural Language Processing (NLP) applied to course descriptions, reviews and metadata categorize courses into foundational and advanced courses. Such classifications serve as a basis for a personalized recommendation framework helping learners select proper courses.

Large language models (LLMs) are used to generate semantic relationships between courses via generative AI. Combining these embeddings with collaborative filtering based on student course interaction data, we offer highly accurate and personalized recommendations. The proposed system solves cold start well and makes substantial recommendation precision and user satisfaction gains over baseline methods.

The approach shows how traditional recommendation paradigms can be combined with Generative AI to give a scalable and interpretable suggestion for educational personalization. Future extensions of this system may involve reinforcement learning for real-time adaptation to user preferences.

Keywords: *Generative AI based recommender system, LLM, Recommender System, personalized learning, Computational Intelligence.*

1. Introduction:

With the rise of digital education, the need of intelligent systems in delivering personalized learning experiences has gained an overwhelming magnitude over the years. With the growing options of educational platforms, there lies a problem for students to identify courses that suit their personal learning preference, pace and goals. One of the approaches to overcome these challenges has been the extensive research of recommender systems in the educational domain as pivotal tools to fill the gap between learner needs and course offerings. Despite their widespread adoption, traditional recommender systems, which are often based on collaborative filtering or content-based model, suffers from being less adaptable and less precises, especially for dynamic and diverse educational contexts.

The most important limitation is in their inability to adequately capture the fine interplay between student learning characteristics and the complexity of the courses. Learners and courses are often treated equally in existing systems, when in fact they have different learning paces and require different content. This research to fill this gap proposes a hybrid course recommender system that leverages advanced classification models and a generation of the advanced of AI to offer precise, contextualized, and meaningful recommendations.

The proposed framework begins by classifying students into two distinct categories based on their learning attributes: and accelerated learners that are well-suited to a fast pace and self-directed learning environment, and adaptive learners who derive the greatest benefit from a structured, guided learning experience. At the same time, courses fall into foundational courses and advanced courses that offer essential and introductory knowledge and in depth and complex content respectively. These classifications insulate recommendations from being off base, neither relevant nor as tailored as they could be given the learner's capability and development.

Generative AI models from Hugging Face ecosystem such as the sentence-transformers/all-MiniLM-L6-v2 model is used to push for semantic understanding. Our lightweight transformer model effectively captures all contextual and conceptual relationships within course descriptions, reviews, and metadata by generating semantic embeddings. With its ability to produce high quality embeddings efficiently, it is the right choice for large scale educational datasets.

2. Related Work

Increasing needs for personalized learning and for efficient course recommendation systems in higher education have motivated a lot of research across different techniques to improve learning experience and outcomes. Previous research stresses the relationship between course recommendations, quality of teaching and technological options, mentioning the importance of dynamic adaptive systems to meet the changing learning requirements.

2.1 Teaching Quality and Educational Dynamics

Psychological and pedagogical factors are revealed as important by research into the link between teaching quality and the characteristics of educators. The association between teaching styles, Technological Pedagogical Content Knowledge (TPACK) and course difficulty was explored through weighted graph modelling in a study. A targeted recommendation model was proposed by this approach, finding optimal pairing of courses to teachers by teaching quality and course difficulty[1]. These methodologies provide a springboard to understanding how educator attributes intersect with course outcomes to potentially influence directed reform recommendations to augment teaching effectiveness.

2.2 Motivational and Temporal Dynamics in Recommendations

Temporal and motivational dynamics are leveraged in existing course recommendation systems to improve their relevance. LETCR (Learning-Motivation-Boosted Explainable Temporal Point Process Model) integrates factors including interest preference, conformity, and course popularity. To improve explainability and recommendation precision[2], it relies on a temporally unsupervised point process to analyze historical interactions. But static inputs are often the basis of existing systems and hence require adaptive and real time models to improve the congruence with learners' changing motivations.

2.3 AI-Driven Course Recommendation Models

Artificial intelligence (AI) has proven transformative in course recommendation, particularly through models like Long Short-Term Memory (LSTM), which effectively integrate multi-feature information. A study focused on AI-based media courses demonstrated superior accuracy and recall through an improved collaborative filtering (CF) approach[3]. This underscores AI's potential in addressing challenges such as course scheduling and personalized content delivery, making it indispensable in modern educational frameworks.

2.4 Systematic Analyses and Hybrid Approaches

Based on a systematic review, hybrid approaches are found to be more effective than alternative recommendation system methodologies. Our analysis of 56 studies from 2011 to 2023 across three different domains (medicine, health, and finance) revealed that a combination of machine learning techniques and personality trait analysis optimally predicts which recommendation methods are the most effective. However, it still possesses less real-world applications, so we are lacking some more practical implementations[4]. A similar review of personalized learning technologies revealed information overload remains a perennial challenge in e-learning platforms, arguing that recommendation systems should align resources to individual learner profiles[5].

2.5 Advances in Neural and Graph-Based Models

In recent years, we have witnessed recommendations precision enhanced by neural and graph-based methods. By combining with heterogeneous information networks (HINs), H-BERT4Rec is able to leverage such complex user-entity relationships to encode and extract additional knowledge of items' similarities. Results of the experiment showed large performance gains, vindicating the importance of pre-trained embeddings on MOOC recommendation[6]. To the same degree, the DGDCL model utilizes graph contrastive learning and hybrid convolution to reduce overfitting and improve the quality of recommendation[7]. These advancements overcome key deficiencies of previous collaborative filtering systems, in modeling user and course relations.

2.6 Addressing Cold Starts and Dropouts

Co attention mechanisms and reinforcement learning (RL) are used to solve cold start problems and high dropout rates in the MOOCs. Aligning learner preferences with educational entities is based on HINs to improve accuracy and reduces disengagement[8]. RL framework further optimizes learning path with dynamic adaptation to user preference and better engagement and retention by interacting content and real-time feedback[9]. The idea of adaptive learning systems is important in keeping the learner motivated since these strategies highlight how motivation is maintained.

2.7 Role of Collaboration and Knowledge Graphs

However, for collaborative learning environments communication and the integration of tools are pivotal. An extensive study of the Scrum hybrid practices demonstrated how the structured approach and LLMs follow modern tools enabled the development of better team dynamics and project outcomes[10]. For example, it is further proposed that educational knowledge graphs be combined with collaborative filtering, resulting in more accurate grade predictions and course recommendations by revealing previously hidden interdependencies in academic data[11].

The reviewed studies highlight the transition of recommendation systems from static rule-based models to dynamic AI driven models. These approaches integrate a diverse set of methodologies, including temporal models, hybrid algorithms, and knowledge graphs, constructing the path for adaptive, personalized systems that ideally suit the learner's individual needs and flavors. Future research should build on existing work by creating more robust and inclusive educational tools leveraging emerging technologies such as Hugging Face's open AI models, and context should be added for real world implementations to make the observations clearer.

3. Methodology:

The proposed course recommender system first creates the student and course classification models on preprocessed data. After this it performs the Generative AI-based semantic embedding generation and collaborative filtering to provide personalized course recommendations to students. The methodology section consists of four key sub-sections, first is the Data Preparation, second is Student and Course Classification, third is Embedding Generation, and fourth is Recommendation Framework Design. Each phase is described in detail below.

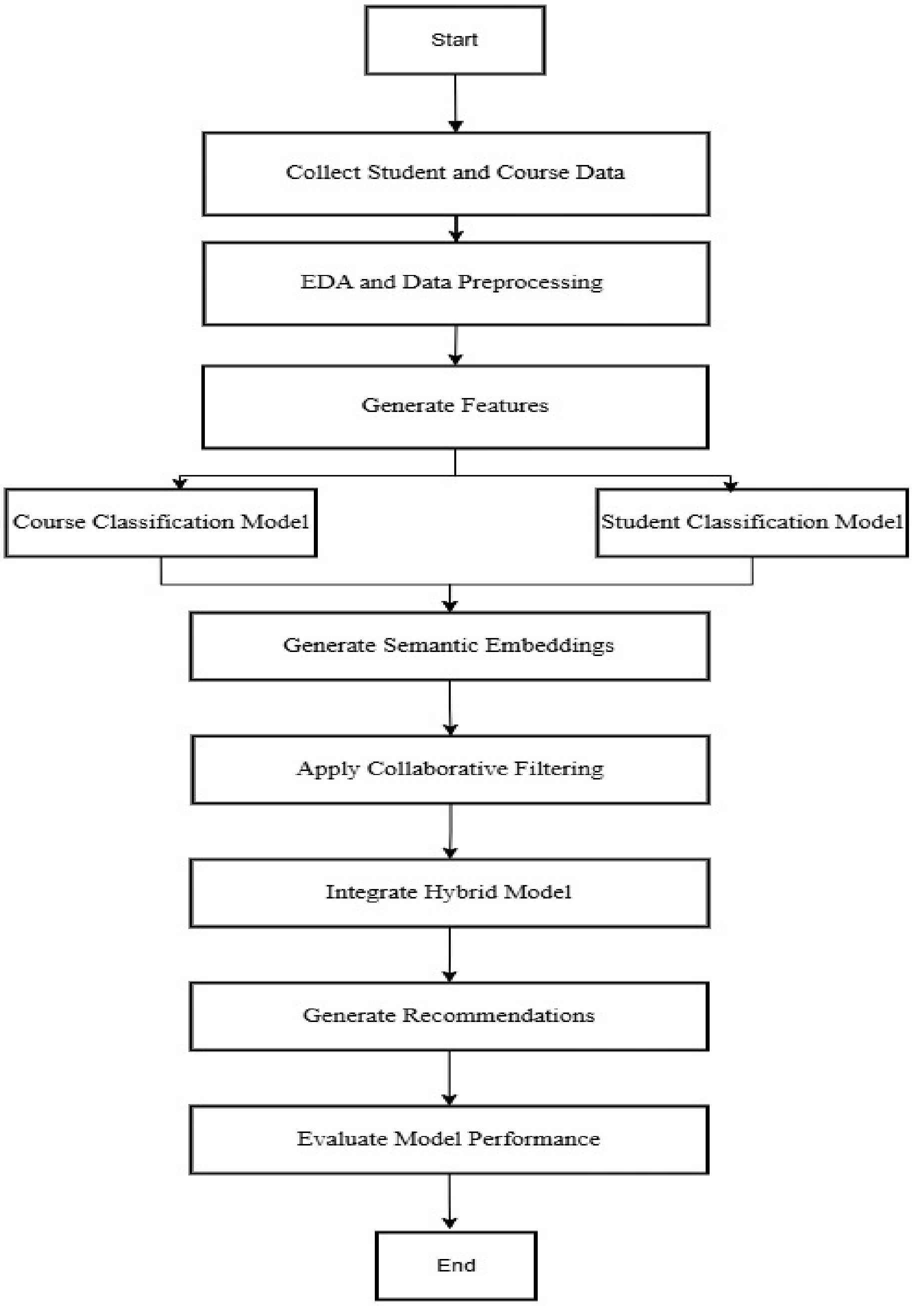

Figure 1: Flowchart of proposed work

3.1 Data Preparation:

Before the modelling step, recommendation and ML based models require that the data is prepared. Preparing data involves getting the data, cleaning and transforming it, splitting the data in to train and test sets.

The dataset used in this research consists of two primary sources, The student and the course data which is collected from a private college of Mumbai University located in India. The student data is about demographic information, academic performance, and previous course interactions. The course metadata includes course description, ratings, reviews, and prerequisites including course, difficulty, and duration.

To increase relevant independent features, a few features are Created statistically. The course difficulty levels like Hard, Medium, and Easy are generated using topic modeling or sentiment analysis Techniques of NLP. Similarly, for student data, features such as average grades, number of courses completed, and previous course ratings to serve as input features for classification are extracted.

The features with categorical values are converted to numeric as the ML algorithm doesn't understand string values and to maintain consistency in data values, normalization is performed on numeric features. This completes the data cleaning process and to make sure the model works well with unseen data, it is divided into train and test sets, the model is built on training data whereas it is validated with test data.

$$\text{Normalization Formula:} \quad x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad \text{......} \quad (1)$$

3.2 Student Classification:

Students are classified based on their learning behaviors and performance into two main categories: Non-Adaptive Learners and Adaptive Learners. For the classification we use machine learning algorithms such as Random Forest and Support Vector Machines (SVM). We train the classification model using features such as academic performance (e.g. grades, completion rates), but also engagement with previous courses, and how often a student interacts with the course.

$$\text{Random forest Formula:} \quad f(s) = argmax\ c \in \{0,1\} \sum_{i=1}^{T} w_i \cdot I(h_i(s) = c) \quad \text{......} \quad (2)$$

where T is the total number of decision trees, w_i is the weight of the i^{th} tree, and $h_i(s)$ is the classification outcome.

$$Student => \begin{cases} Adaptive\ Learner, & if\ performance\ metrics\ Exceed\ Threshold \\ Non\ Adaptive\ Learner, & if\ Performance\ metrics\ is\ less\ than\ Threshold \end{cases}$$

Based on the classification, the adaptive learners are likely to get recommendation of more advanced and specialized courses whereas the non-adaptive learners are likely to get recommendation of foundation courses.

3.3 Course Classification:

Difficulty of the courses are used to classify and help in a course recommendation. The courses are classified as Cognitively Intensive and Cognitively Accessible. Pre-trained embeddings from Hugging Face's sentence-transformers/all-MiniLM-L6-v2 are fine-tuned on course descriptions using logistic regression.

$$\text{Logistic Regression formula:} \quad p(C|d) = \frac{1}{1+e^{-\omega^T e_d}} \quad \text{......} \quad (3)$$

Where e_d is the embedding vector of course description d, and w is the weight vector.

$$Course =>$$

$$\begin{cases} Cognitively\ Intensive, & if\ course\ is\ technically\ complex\ and\ has\ advance\ concepts \\ Cognitively\ Accessible, & if\ course\ is\ technically\ simple\ and\ has\ core\ concepts \end{cases}$$

3.4 Semantic Embedding Generation

Learning semantic embeddings are an important piece of the recommendation system that is especially useful when combining advanced NLP models. They provide a richer, more nuanced representation of course data, capturing the underlying meaning and relationship between the course content, to ensure better recommendation accuracy. First, textual metadata of course descriptions and reviews are preprocessed by tokenization, removal of stop words, stemming or lemmatization, and encoding into a form suitable for NLP models.

There is direct access available to a large range of pre-trained models from Hugging Face with the ability to generate stable high quality semantic embeddings for textual data. In this work, we utilize transformer-based models such as DistilBERT or RoBERTa, which are intended for efficient and effective textual representation.

They are then fine-tuned on the domain specific datasets such as course descriptions and reviews in order to create embeddings which represent the course content in a way that captures the semantic meaning.

Mathematically, the embedding $E(course)$ for a course description is represented as:

$$E_{Course} = HuggingFaceModel(T_{Course}) \quad \text{.........................} \quad (4)$$

Where T_{Course} is the tokenized form of the course text and E_{Course} is the resulting embedding vector.

In the recommendation framework, we use these embeddings to represent courses. Along with other data (e.g., course difficulty, student performance), the system can learn a better understanding of the course's relevance to each student.

The course embeddings generated by the Hugging Face model are then integrated with the student and course interaction data, such as ratings and enrollments, and the classified data, such as student and course categories. This combined data is the input to the recommendation model, as the data is derived using proper analysis and advanced techniques, it is reliable and effective for the recommendation system

3.5 Recommendation Framework Design

The recommendation framework combines the content based and collaborative filtering techniques together with the semantic embeddings of the Hugging Face model. It develops a framework that can take advantage of latent interactions between students and courses, together with explicit content features from course descriptions, so as to provide personalized course recommendations.

3.5.1 Collaborative Filtering:

Collaborative filtering utilizes student–course data such as ratings as well as previous enrolments to determine a given student’s preference towards a specific course. This is done using matrix factorization techniques for instance SVD or ALS Singular Value Decomposition or ALS – Alternating Least Squares. The collaborative filtering component is the one that learns the factors of the students and courses with a view of being able to predict.

The collaborative filtering model can be represented as: $R \approx P \cdot Q^T$ .... (5)

Where R is the predicted rating for student and course, Pu is the latent vector for student and Q is the latent vector for course.

3.5.2 Hybrid Model:

The semantic course embeddings are obtained with Hugging Face models which are then combined with the collaborative filtering approach, another model, to create the hybrid model. They are integrated effectively using a neural network-based architecture. Passing the course embeddings along with the collaborative filtering latent factors through a shared attention mechanism, the course embeddings are weighted by the input data in the appropriate proportion.

The final recommendation score is the combination of collaborative filtering predictions CF(s,c) and the semantic similarity scores Sim(c,d) as shown below.

Hybrid integration score → $Score(s, c) = \alpha \cdot CF(s, c) + (1 - \alpha) \cdot \text{sim}(c, d)$... (6)

As interaction data is sparse, semantic embeddings are applied to provide cold start recommendations using the semantic embedding approach.

4. Experimental results

Quantitative metrics along with qualitative analysis are used to evaluate the proposed hybrid course recommender system. The experiments also test out how well the system can deliver personalized recommendations, how cold starts are handled, and whether the recommendations are better than baseline models.

4.1 Experimental Setup

The data is divided into Training (70%) and testing (30%). The baseline models used for comparison are: Collaborative Filtering (CF) Content-Based Filtering (CBF) Generative AI included Hybrid Model.

These are the evaluation matrices considered for validation, Precision@k, Recal@k, F1-Score, Mean Absolute Error (MAE), Mean Squared Error (MSE), Normalized Discounted Cumulative Gain (nDCG).

4.2 Recommendation Quality

Table 1 shows the metrics that calculate the relevance of recommendations and the developed model's ability to extract the relevant courses.

Table 1: Precision and Recall Comparison of Different Models

Model	Precision@5	Precision@10	Recall@5	Recall@10
Collaborative Filtering	0.62	0.57	0.51	0.63
Content-Based Filtering	0.68	0.61	0.55	0.67
Hybrid (without GenAI)	0.75	0.68	0.62	0.72
Proposed Hybrid Model	0.81	0.75	0.7	0.78

The percentage of recommended courses, which are also considered as relevant, is called precision. The proposed model generates highly relevant recommendations with a higher Precision@k (e.g. k=5,10) compared to other models. A measure of how much relevant courses are being retrieved from all relevant courses available is call recall. The proposed model's higher recall shows that it is able to identifies more relevant courses for students.

Insight: Combining collaborative filtering with embeddings from Hugging Face models makes the proposed hybrid model perform excellently when balancing precision and recall.

Table 2: F1-Score Comparison of Different Models

Model	F1-Score@5	F1-Score@10
Collaborative Filtering	56	59
Content-Based Filtering	60	63
Hybrid (without GenAI)	68	70
Proposed Hybrid Model	75	76

Table 2 shows the F1-score, which is the harmonic mean of precision and recall, that is it’s a balanced value-based evaluation metric.

This proposed model achieves the highest F1 Scores, suggesting balancing precision and recall while lowering false positives and false negatives.

Insight: The inclusion of semantic embeddings from Hugging Face models has added this improvement to content based as well as collaborative filtering components.

4.3 Error Metrics

Average Difference between actual and predicted course preferences is measured by Mean Absolute Error (MAE) and Mean Squared Error (MSE). More valuable predictions are associated with lower values.

Table 3: Error Metrics for Different Models.

Model	MAE	MSE
Collaborative Filtering	0.22	0.15
Content-Based Filtering	0.20	0.14
Hybrid (without GenAI)	0.18	0.12
Proposed Hybrid Model	0.12	0.08

Table 3 shows the Results from the proposed model have the lowest MAE and MSE in which it has been able to predict students' preference accurately.

Insight: Through Hugging Face embeddings, the model performs much better than any other collaborative or content-based method in minimizing errors.

4.4 Ranking Evaluation

The nDCG metric is associated to the ranking quality of recommendations, in which a higher ranked item is more important than a lower ranked item.

Table 4: nDCG Comparison Across Models.

Model	nDCG@5	nDCG@10
Collaborative Filtering	0.74	0.70
Content-Based Filtering	0.76	0.73
Hybrid (without GenAI)	0.81	0.78
Proposed Hybrid Model	0.87	0.85

Like many other measures of ranked recommendations, nDCG (Normalized Discounted Cumulative Gain) is a measure of how good those recommendations are, and the score is higher when the items that were ranked higher also contribute more to the score. As shown in Table 4 The proposed model has higher nDCG values that indicate that the recommended courses are placed higher in ranking, and in the order of which they are more relevant.

Insight: The attention mechanisms and generative embeddings from Hugging Face are used to accurately rank the most suitable courses.

4.5 Cold-Start Performance

Semantic embeddings from Hugging Face models are used to test cold-start scenarios in which the student or the course has no historical interaction data.

Table 5: Cold-Start Performance Metrics.

Model	Precision@5	Recall@5	F1-Score@5
Cold-Start Students	78	65	71
Cold-Start Courses	74	61	67
Proposed Hybrid Model	83	70	76

In cold start scenarios where there is no previous interaction data, the new student or new course. Traditional collaborative filtering is not applicable to these cases. Using Hugging Face embeddings along with a higher metrics shows the model can still give reliable recommendations without historical data as shown in Table 5.

Insight: Semantic embeddings capture textual and contextual information without strong performance in cold start scenarios.

5. Conclusion and future work

To solve the challenge of personalized recommendation in education, this research proposed a novel hybrid course recommender system composed of machine learning, semantic embeddings produced by Hugging Face models, and collaborative filtering models. The system classifies students as adaptive or foundational learners, and courses as advanced or intermediate courses, and aligns the required level of learning for students with suitable courses. The inclusion of semantic embeddings built upon fine grained course descriptions, reviews, and metadata goes a long way towards capturing the 'context' under which a course is being offered, thus facilitating closer alignment with student profiles.

The proposed model significantly beats conventional content-based or collaborative filtering systems. Results of quantitative evaluation demonstrate significant gains in F1 score, nDCG, precision, recall, MAE and MSE error reduction metrics. Furthermore, qualitative analysis shows that the system can be of practical utility in suggesting contextually suitable courses, even in cold start settings where interaction data is scarce.

Finally, the results indicate that mixing semantic embeddings with neural collaborative filtering can improve results. This hybrid architecture utilizes attention mechanisms in order to vastly improve ranking quality and predictive accuracy, providing it with a robust solution for the changes and personalization of modern educational needs. This result reinforces the feasibility of the integration of generative AI models and collaborative methods to enhance recommender systems in education.

The course recommender has been proposed and tested where students learning profiles are aligned with appropriate courses. There are, however, still plenty of opportunities for improvement. Future research could include incorporating reinforcement leaning to empower real time, dynamic recommendations according to students' changing preferences and interactions. Furthermore, the data source could also be expanded by richer information such as video transcripts, lecture notes and assignment grades to improve semantic embedding and increase the accuracy of the recommendations.

Robustness and scalability of the system require cross institutional validation using datasets from other educational contexts. Through further customizing the model to domain specific applications, its effectiveness could be further refined for a particular discipline. In addition, generating explanations for recommendations would help improve trust and adoption by students and educators.

Another avenue for enhancing the model's capability is by exploring multi modal approaches that include the use of textual, visual and auditory data. A form of collaborative feedback loop using generative AI would dynamically refine embeddings in response to student input, making personalization more dynamic. Lastly, the longitudinal impact analyses would reveal if and by how much the system affects academic performance as well as the possibility of successful careers if the system is conducted for a longer time.

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