

Semantic Aware Multistage Hybrid Framework For Personalised Book Recommendation

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Abstract

Digitalisation has encouraged online reading to a great extent. Variety of books are available online on diverse platforms. It creates the challenges like data overload due to which users often get confused about the selection of choices. This challenge can be addressed through the data filtering tool known as Recommendation system (RS). RS available for book domain often relies on traditional methods like Content based filtering and Collaborative filtering which are unable to capture the semantic relevance and hidden contextual features. Thus, this paper proposes a semantic aware multistage Book Recommendation framework for personalised book recommendation. The framework processes through graph modelling layer and discover structural relevance then it goes through semantic intelligence layer to get the semantic similarity score between books and finally heuristic relevance layers further adds various scores to enhance the alignment , relevance and diversity of recommendation. All these scores are aggregated to generate Final Recommendation score. Based on this score books are ranked in descending order and personalised Recommendations are provided for intended users. It is evaluated using User wise Holdout Strategy for accuracy , precision , recall , F1 score and have achieved promising results. These findings indicates that combination of structural , semantic and heuristic information together significantly improve recommendation relevance and personalisation .

Keywords: Book Recommendation system , Semantic intelligence , Heuristic scoring , performance evaluation.

1 Introduction

The rapid development in the online reading platform and digital libraries has significantly increased the volume of books across diverse genres and domains on the internet[1]. Although such an abundance of information provides users a lot of choices, it also creates the hazardous problem of information overload at the same time[2]. This information overload has made it difficult for the users to find the books of their individual choice and preferences[3]. Personalised book recommendation systems are the potential solution for such situations[[4],[5]]. These RS are one of a kind that emerged in digital book domain platforms for assisting users in exploring large collection of online books while assuring efficient access to relevant and personalised content of their individual preferences[[4]]. It works by analysing user preferences, behavioural patterns, book features and various other factors affecting the candidate choice[[4],[5]]. It then customises the tailored recommendations for the intended users[[4],[5]].

The effectiveness of a Personalised Recommendation Systems lies in their own ability to accurately and thoroughly understand the needs and preferences of a user while matching them with the most suitable data available [6]. Specifically for personalised book recommendation, users' choices like their reading taste, themes, writing styles, genre preferences, reading history, contents preferred etc. play a very crucial role[5]. These could be understood through their own written reviews, contents they liked and so on. Thus, for customising personalised book recommendation system, it is very important to understand and identify the meaningful relationship between user preferences and book features. An effective personalised recommendation framework should not only capture explicit user preferences but also understand the implicit semantic understanding lies behind user preferences so that it can provide recommendations that are closely related to individual user's reading preferences[[5],[7]].

For generating personalised recommendations, various recommendation paradigms have been explored in the existing literature. They are content based filtering, collaborative filtering and other hybrid approaches[[8]-[10]]. Content based recommenders work on the principle of content similarity. It recommends the items by analysing the characteristics and contents of a book previously preferred by users to that of all the candidate books. If similarity in their content is found, it gets recommended to the intended users[10]. While collaborative filtering provides recommendations are provided on the principle of similar users get the similar recommendations. In collaborative filtering, any two users proffering similar contents are marked as similar users[10]. Later the choices of one is the recommendation for another. Similarly, Hybrid recommenders combine multiple approaches at once in order to provide personalised recommendations to the intended user, they may combine content based and collaborative filtering together or these techniques may further be combined with some other

existing techniques present in the literature with the intent of providing the most accurate and personalised recommendations to the intended users[11].

Despite the effectiveness and popularity of existing recommendation approaches there exists so many limitations and challenges that exist along. For example content based recommenders often suffers with over specialisation, user cold start and other limitations[[11],[13]]. Content based recommender techniques primarily relies on explicit item attributes and keyword matching through term frequency (TF-IDF) for content similarity and thus it only do the surface level task and fails to capture the deeper semantic relationship between user preferences and book contents[[12],[13]]. Similarly , collaborative filtering techniques are highly dependent on historical preferences of users and thus it often suffers from cold start issues , sparse data problem , handling multidimensional data etc when adequate prior information is unavailable[[12],[13]]. Hybrid approaches combine multiple techniques and thus, benefit from one may cause challenge for another. Similarly , many existing conventional recommenders generate recommendations that solely relies on similarity score , interaction patterns which is inadequate to tailor personalised recommendations as they do not model underlying relationship between users and books[[13], [14],14]. As a result , recommendations lack contextual understanding , personalisation , interpretability etc making it difficult to explain why a particular book is recommended to an intended user[14]. These limitations highlights the need for recommenders that are capable of integrating semantic intelligence , relational interaction modelling and explainable ranking mechanism that can improve the effectiveness and quality of recommendations while achieving a good user satisfaction at the same time.

To address these challenges , This paper proposes a personalised Hybrid book recommendation system (PHBRS) that integrates the semantic intelligence , graph based relationship and heuristic ranking strategies to enhance the quality of recommendations and personalisation. The proposed model uses Sentence-BERT (SBERT) ,an NLP based transformer to generate semantic embeddings from user reviews and book description that enable the system to understand the contextual meaning of book description and user reviews beyond the conventional keyword matching techniques. Through these semantic embeddings , semantic user profile and book feature profiles are created in order to capture meaningful semantic matching between the readers and books . Further , a heterogenous multi di graph based interaction network is incorporated to model the complexities present within the user - book relationship and interaction patterns . This graph is able to capture structural dependencies among users and books in the recommendation environment. To further enhance the interpretability and making recommendation ranking more effective , we introduced three heuristic features such as Attraction degree (AD), Rating Degree(RD) and Novelty Degree (ND) that collectively contribute to the generation of personalised and interpretable book recommendations. By leveraging the combined potencies of semantic understanding , graph based relational intelligence and heuristic scoring in a single recommendation framework , our proposed model aims to achieve an interpretable , context aware , accurate and personalised recommendations for intended users.

The primary contributions of this research are as follows

1. This paper proposes a Multistage Hybrid book recommendation framework to generate Personalised Book Recommendations.
2. Transformer based Semantic Intelligence is introduced to discover contextual features and semantic similarity rather than relying on traditional key word matching .
3. A heuristic scoring layer is proposed to incorporate measures like attraction degree, rating degree and novelty degree to obtain user interest alignment , book popularity and recommendation novelty for improving recommendation relevance , personalisation and diversity.
4. A combined recommendation scoring and raking mechanism is proposed to generate the aggregated recommendation score for generating Top 5 personalised book recommendation which is further evaluated through user based holdout evaluation strategy on various evaluation metrics.

2 Literature Survey

Currently , Book recommendation system have attracted a significant research attention due to the increased Online book reading and increased volume of book availability on internet. Over the years , researches have designed the techniques for book recommendations by exploiting the datasets on the basis of various data filtering techniques. The proposed approaches have given promising results yet they have various limitations and challenges like lack of recommendation diversity , cold start issue , sparsity etc. Therefore this sections examines the existing literatures for their strengths and research gaps. The presented LR presents a comprehensive analysis of recent studies and highlights the motivation behind the proposed model.

There are only few evidences of pure content based book recommendation systems . Generally the book recommenders are designed as a combination of content based and collaborative approaches . Focusing on content based recommenders includes methods like [15] proposes a mechanism which emphasises on finding the relevant features of an item to be recommended and for this they employed Principal Component Analysis (PCA) and Support Vector Machines (SVM).but their study is limited unto here.While [[16]] suggested finding the candidate books for personalised recommendation to children . For that , they have used vector space model and naive Bayes model along with matrix factorisation techniques on book crossing dataset. Their model is based on similarity of content but still they lack in finding the semantic similarity which could have contributed in better understanding of the content and enhanced recommendations. More examples includes [17] a pattern based hybrid recommendation framework by integrating content based and collaborative filtering based semantic patterns extraction framework for book recommendation and [18] proposed pattern based hybrid book recommendation system that combines content based and collaborative filtering along with semantic relation discovery. The model is based on clustering of users and books by using semantic semantic patterns to improve recommendation accuracy and deal with sparsity issues. Model achieves promising results on accuracy , precision , recall and F1 score compared to existing methods but the limitation of model is that its depends on clustering techniques which fails to capture deeper semantic semantic features and structural modelling.

[19] proposed a book recommendation system (BRS) by exploiting the content and emotional aspect of user reviews. They used the tweets and book reviews for extracting the sentiment of users and the content present in the book. Finally the similarity between the respective computed to analyse whether it matches or not. If similarity is found, the book is recommended to the user else ignored. Experimental results demonstrated the effectiveness of incorporating emotional information with the content for providing recommendations. Yet the model lacks advanced semantic representation learning and understanding the user book relationship.

Collaborative filtering is a popular algorithm in designing recommendation systems as well as book recommendation system in particular. As the paper focuses on book recommendation thus, we will discuss about the book recommenders that are based on collaborative filtering. Examples include [20], proposed a collaborative filtering based BRS for digital library. The framework was proposed using matrix factorisation techniques like singular value decomposition (SVD) to exploit user item interactions and generate recommendations. They also shown the effectiveness of SVD over neighbourhood based approaches like K- nearest neighbours (KNN). Although the method was effective as a collaborative filtering mechanism yet, it is highly dependent of historical ratings and informations which may arise challenges like cold start and sparse data. Similarly [21] also proposed a book recommender for digital library that is based on tag mining. It integrates collaborative filtering, user reviews, user generated tags, book borrowing records and content similarity together to generate effective and personalised book recommendation. The method highly relied on manually generated tags and content similarity measures which may not adequately captures latent semantic relationship and complex user book interactions. Similar to this [22] also emphasised on the importance of integrating multiple aspects together for generating book recommendations. They combined user profile components with that of borrowing histories and content of the target book within the digital library recommendation system. The model successfully combined content based and collaborative approaches together to generate recommendations effectively. They have showed that combined approaches enhance recommendation qualities. Yet the model is limited towards proving diverse and novel recommendations even after the application of such complex framework.

[23] proposed book recommender system by discovering the latent factors using matrix factorisation techniques. Again this paper is limited to exploiting the dataset into user item matrix construction and similarity computations while ignoring the concept of context rich and userspecific recommendations. Similarly, [24] proposed book recommendation based on collaborative filtering algorithm focused on user item similarity ignoring the actual content similarity score generation. Collaborative filtering alone isn't sufficient to achieve rich and relevant recommendations.[25] yet again exploits the user based collaborative filtering and item based collaborative filtering through Singular value decomposition (SVD) and similarity is finally computed using KNN (K-nearest neighbours) technique. They have also compared these techniques among themselves for accuracy and testing time and obtained the results. But they also focused on same technique of exploiting the dates for user and item similarity through traditional algorithms only. [26] proposed the recommendation system by combining content based filtering and collaborative filtering through a unified deep

learning architecture to provide book recommendations on some movies dataset. They are also focusing on generating a book recommendation that relies on traditional filtering techniques and not discovering any intelligence embedding or vectors as such to make the recommendations more relevant.

Overall, while searching for the literature's on book recommendations system we have found that researchers are still focusing on designing the book recommendation by exploiting the same traditional matrix factorisation techniques or the traditional filtering techniques. Moreover hybrid systems also focus on integrating the same traditional methods along with some deep learning techniques but nobody is focusing on discovering important factors. Focusing on these factors we are proposing recommendation system that is semantically rich and can provide more relevant book recommendations.

3 Proposed Framework and Methodology

3.1 Overview of Proposed Framework

The proposed framework is a multistage filtering based technique for BR in which Amazon book reviews dataset is incrementally passed through dedicated layers for generating book recommendations. The data is preprocessed and passed through multiple layers. The very first layer is Graph relational modelling in which the whole dataset is converted into multi di graph to discover how users have interacted with the available books. The resultant graph establishes the relationship between the users and books. The user relevant books are selected and rest are ignored. We named these books as candidate books. This layer is crucial because it filters the relevant books for further layer which reduces the unnecessary overhead of comparing all the books of the dataset with user preference.

The candidate books generated in the relational modelling layer are passed through semantic intelligence layer to generate the semantic embeddings to make the candidate book so obtained for understanding the meaningful interaction. This layer discovers USTP and finds the semantic similarity between them. The similarity score isn't alone sufficient because the recommendation may be semantically relevant but it is necessary to verify if they are also novel, popular and relevant as per the user preferences.

Thus, To ensure the novelty, diversity and relevancy the semantic similarity score so obtained is further aggregated with heuristic scores like AD, RD AND ND in heuristic scoring layer. Finally, the aggregated score is normalised using sigmoid function to generate the final recommendations score. The same process is iterated for every user present in the dataset to generate the relevant recommendation score. These scores so obtained are ranked in descending order and top 5 ranked recommendations gets recommended to each intended user. The proposed model could be depicted using fig. 01. Further model is discussed in detail in upcoming sections of the paper.

3.2 Data Acquisition and Pre processing Layer

The dataset Amazon book reviews is downloaded from Kaggle. It contains book ratings, reviews, descriptions and other book meta data. To ensure data quality and improve

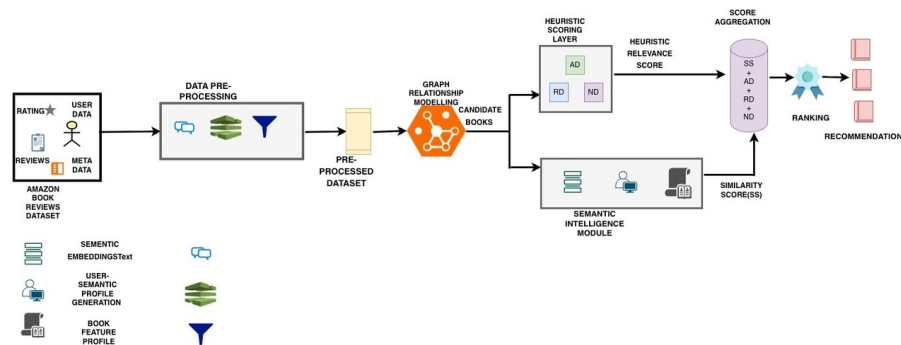


Fig. 1 Overview of Proposed Model

the effectiveness of recommendation framework, several preprocessing operations were performed in a sequential manner.

First of all the dataset is loaded. For preprocessing steps, first of all the number of reviews per books were calculated and stored for imposing the popularity factor. Only books that have received at least 300 reviews were retained and rest were discarded. This step has reduced a large amount of data sparsity and retained most important books in the dataset. We have to follow preprocessing steps to make data fit to feed into recommendation framework as well as we have hardware limitation too.

Further, so many columns were not necessary and relevant for recommendation process and thus, we dropped them. From the dataset, columns named price, profile name, review time, info link, preview link, published date and review summary were dropped for the reason they were redundant and were not directly useful for either of the layer we applied in our framework. Only reviews that were considered helpful by users are kept rest are discarded. For that, review helpfulness score was there and the review helpfulness score of 1 was retained and rest were discarded. To obtain rich semantic information the reviews should be of standard size. Very short or very very long reviews may fail to obtain the actual meaning thus, reviews having minimum 250 words have kept and reviews with less than this count is discarded to make it more suitable for semantic analysis using sentence BERT. After completing all the preprocessing steps final dataset for designing our framework is obtained.

3.3 Graph Modelling Layer

This layer is dedicated to filter the user relevant books by analysing the interaction relationship between the users and books metadata for reducing the recommendation search space. This search space needs to be reduced because the direct comparison of user choices with all the books available in the dataset may increase the computational complexity and can create noise during the recommendation process. To design this layer, A Heterogeneous multi directed graph is constructed, where V represents the set of nodes and E represents the set of directed edges. The set of nodes consist

of while the set of edges constitutes . The graph is constructed by iteratively processing the dataset row wise . For each row , users , books and corresponding book meta data is fetched and nodes of the graph is constructed from these entities. Further , The relationship between these entities are established by analysing the corresponding interactions through directed edges. For example, if a user has interacted with any book then an edge is constructed between between that user and corresponding book. Similarly multiple directed edges are constructed for relationships like written by author , published by publisher etc if the relationship exists. The process is repeated for each user present in the dataset until the complete relationship network is established. Based on the obtained graph, relationships are analysed . Books that have meaningful interactions with the user's interest are identified and kept in relevant book set (RBS) while the unrelated books are filtered out.

This layer filters out the books that are unrelated to user and keeps only the books that are relevant and interacted by users. It ensures relevant recommendations while reducing the noise in the recommendation generation process. Keeping only the books that matches user preferences reduces the search space and make the recommendation process more suitable , personalised and efficient. The generated relevant book set also called as candidate book set, is further passed to semantic intelligence layer for semantic similarity computation.

3.4 Semantic Intelligence Layer

The candidate books obtained from graph modelling layer (GML) is fed as an input in this layer. GML is responsible to discover the interaction patterns and the existing structural relationship among the entities like users, books , category , authors and publishers. This helps us to discover contextual relationship among the entities. These entity relationship modelling alone aren't sufficient to provide personalised recommendation for a user. These relationships or the interaction patterns are one of the aspect of understanding the user preference at an initial level. To further enhance this process , this layer introduces Text based contextual semantic understanding to further enhance the personalisation.

Traditional recommenders used keyword matching techniques like TF-IDF which measures the similarity by looking at the exact matching word or we can say that the keyword overlap and not the actual meaning of the words present in the document[29]. This technique is based on lexical similarity of keyword occurrence. This is insufficient to capture the contextual meaning of the textual data. Multiple texts can have similar words conversing different meaning while they may also contain dissimilar words with same meanings and thus they can appear unrelated to each other and this can convey totally wrong information and the recommendations generated can horribly go wrong. Thus, to overcome this limitation , semantic intelligence layer is introduced. This layer transforms the textual reviews and book description into dense semantic representations to capture the contextual meaning and conceptual relations between the textual words. Thus, semantically similar reviews and book description can also be captured if vocabularies are different. By integrating semantic similarity along with structural relevance obtained from previous layer, our proposed model will be able to discover deep conceptual similarity and thus , it will be able to generate

more relevant and personalised book recommendation while improving overall recommendation relevance and effectiveness. The layer processes from collecting the reviews and descriptions and finally computing the semantic similarity through dense vectors in an incremental way.

First of all , the review texts written by users and the candidate book descriptions are collected. These textual information are passed through pre trained Sentence Bert (SBERT) [28]all-MiniLM-L6-v2 model to generate semantic embeddings . For a review , the semantic representation is generated as equation (1)

$$RE_i = SBERT(R_i) \quad (1)$$

Where , RE_i denotes the semantic embeddings of the i^{th} review and $RE_i \in \mathbb{R}^{384}$. A user may have given more than one review and thus it is important to collect the overall preferences of a user . Thus, the individual review embeddings are aggregated using the mean pooling to get the aggregated semantic representation of the user. It is shown as (2)

$$UR_u = \frac{1}{n} \sum_{i=1}^n RE_i \quad (2)$$

Where , UR_u represent the semantic representation of user u , and n denotes the total no of reviews written by user. Also $UR_u \in \mathbb{R}^{384}$. The vector so obtained contains the overall semantic interest of user expressed in all the reviews collectively.

To further enhance the user representation , category preferences are also extracted from the heterogeneous knowledge graph plotted earlier to get the frequencies of category preferences. The categories that appears frequently indicates stronger user interests. The category preference vector is represented as

$$CP_u = [cp_1, cp_2, \dots, cp_C] \quad (3)$$

$$cp_k = \frac{f_k}{\sum_{j=1}^C f_j} \quad (4)$$

Here, f_k denotes the frequency of category k . C denotes the total no of unique book categories in the dataset and $CP_u \in \mathbb{R}^C$, . The semantic representation and category preference vector are combined together through vector concatenation for generating the final user taste profile. It is denotes as (5)

$$UP_u = UR_u \oplus CP_u \quad (5)$$

Where, $\oplus$ denotes the concatenation operation and $UP_u \in \mathbb{R}^{(384+C)}$

Similarly, semantic representations of book descriptions are also generated. The textual description of each book is passed through the same SBERT model to generate the respective semantic embeddings. It is denoted as (6)

$$BD_b = SBERT(D_b) \quad (6)$$

Here, D_b denotes the description of book b . BD_b denotes the semantic embeddings and $BD_b \in \mathbb{R}^{384}$. Along with these embeddings each books is also represented by a semantic vector shown in equation (7).

$$BC_b = [bc_1, bc_2, \dots, bc_C] \quad (7)$$

Here,

$$bc_k = \begin{cases} 1, & \text{if book } b \text{ belongs to category } k \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

Also, $BC_b \in \mathbb{R}^C$. The semantic description embeddings and category representations are concatenated together to generate the final book profile. The concatenation can be shown in equation (8).

$$BP_b = BD_b \oplus BC_b \quad (9)$$

Where,

$$BP_b \in \mathbb{R}^{(384+C)}$$

Finally, Semantic similarity matching is performed between the generated users profiles and the book profiles. To find this semantic similarity score, dot product similarity is used to compute the relevance between user preference and the candidate book.

$$SS(u, b) = UP_u \cdot BP_b \quad (10)$$

This can further be expanded as

$$SS(u, b) = \sum_{i=1}^{384+C} UP_{u,i} \times BP_{b,i} \quad (11)$$

Here , $SS(u, b)$ is the similarity score obtained that denotes the degree of similarity between user u and the candidate book b . Based on this similarity score , relevance between the user and book is considered or known. A higher similarity score value indicates stronger similarity alignment between the user preference and candidate book. The resulting semantic score so obtained is further concatenated with the heuristic scores obtained in the further layer.

4 Heuristic Relevance Estimation Layer

The previous layer finds the semantic similarity between user preferences and relevant book set. Semantic similarity plays a crucial role in identifying most relevant books for user by understanding the meaning of reviews and description. But, to make recommendations even more relevant and personalised this layer incorporates some additional factors. These factors include Attraction Degree (AD) , Rating Degree (RD) , and novelty Degree (ND). These measures introduce better preference alignment , popularity and recommendation diversity.

Given the heuristic features , AD is computed to measure the degree of alignment between the features of user preferred book and the candidate books .it is calculated because , it may happen that the books might be semantically relevant ie they are having the same meaning but it may not belong to the preferred category of the user then such recommendations will become irrelevant for the user. Higher value of AD indicates stronger category alignment between the books . It is computed using the eq (12) below

$$AD(b) = \sum B_c \frac{U_c}{B_c} \quad (12)$$

Where,

U_c = user category preference vector

B_c = candidate book category vector

Sigma B_c = total categories associated with candidate books

After computing AD, Rating degree (RD) is computed to introduce popularity of the candidate book into recommendation. User preference alignment alone may not be sufficient for generating relevant recommendation because it may happen that some of the candidate books may be more accepted by readers than the other ones. Thus, RD is computed on the basis of popularity of the candidate book. This popularity can be judged by using the rating count value. Books having received more user interactions are given higher RD values and vice versa. It is computed using the equation (13)

$$RD(b) = \frac{P_b}{P_{\max}} \quad (13)$$

Where, P_b = rating count / popularity value of book b

$P_{\max}$ = maximum rating value in the dataset

Similarly, recommendations should not only restricted to popular items only. Thus, to encourage diversity among recommendations, Novelty Degree (ND) is incorporated too. A book to be recommended is considered as novel if the features of its category exhibits a very low or no overlap with the characteristics of the books that user have preferred as per the interaction history. Degree of novelty is computed as equation (14)

$$ND(b) = \begin{cases} 1, & \text{if } U_c \cdot B_c = 0 \\ \text{otherwise} & \end{cases} \quad (14)$$

As per the formula mentioned , book that belong to previously unexplored categories will receive higher novelty and vice versa.

The computed values of AD ,RD and ND will collectively ensure the user preference alignment , popularity based relevance and novelty of the book recommendations.these scores along with semantic similarity scores are forward to scoring and ranking layer to generate the final recommendation score

5 Recommendation Scoring And Ranking Layer

This layer finally aggregates all the scores computed in the previous layers to rank the books and provide relevant recommendations. The semantic similarity score obtained

from semantic intelligences layer while attraction degree , Novelty degree and Rating degrees are aggregated to provide semantic relevance , popularity , novelty and recommendation relevance. The final recommendation relevance score is computed by using the formula in equation(15)

$$S(u, b) = Sim(u, b) + AD(b) + RD(b) + ND(b) \quad (15)$$

Where, $Sim(u, b)$ represents the similarity relevance score, while $AD(b)$, $RD(b)$ and $ND(b)$ are attraction degree, rating degree and novelty degree respectively of the books to be recommended. The aggregation of all the scores together for final recommendation ensures the recommendation is a amalgamation of variety of scores at a time.

Since, the values of these scores may vary to some extent as there are so many candidate books available, thus, sigmoid normalisation is applied to transform these values into a single scale. The normalisation formula is shown in eq (16)

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (16)$$

Finally , the books that were found relevant will be ranked in the descending order of their normalised score. Books with highest scores are considered most relevant to the user preferences and there fore are ranked higher. Finally top 5 highest ranked books are recommended to the users.

This layer serves as a final recommendation stage where semantic relevance , heuristic modelling , and all the respective informations are combined to generate final recommendation.

6 Experimental Setup

For the sake of reproducibility important description about how the experimental is carried out is mentioned in this section. The proposed model is implemented in Python programming language by using the google colab environment. The Amazon book reviews dataset is downloaded from Kaggle website and pre processed as per the requirements to remove noise and various other discrepancies. The dataset consists of the values like user interaction, ratings, reviews, category information , book meta data and descriptions. Data Preprocessing was done by using the dedicated python libraries like Numpy and Pandas. User-Book interaction graph was created using NetwrokX-MultiDiGraph. The semantic representations were obtained through all-MiniLM-L6-v2 model of Sentence BERT by using dedicated Sentence transformer library. For semantic similarity computation and accelerating the embeddings operations PyTorch library and CUDA enabled GPU was used by checking if they are available. Finally to perform the evaluation of proposed model user wise hold out strategy was employed. As per this method two interaction per candidate user were randomly reserved for testing by using $random_state = 42$. In this way the model is evaluated for Accuracy , Precision , Recall and F1 -score metrics on Top-5 recommendations.

7 Evaluation

The proposed model was evaluated using user wise hold out evaluation strategy. In this method a subset of interactions are made reserved for each user while remaining interactions are utilised for generating the recommendation. The method requires more than two interactions per users for successful evaluation. Further, at least 2 two interactions are selected randomly and held outs test set. While remaining interactions are used for user profile creation and recommendation generations. The evaluation strategy ensures that the proposed model predicts the real recommendations by predicting the user preferences based on the historical interaction.

During evaluation, the books that were held out (hidden) from each user interaction history are treated as test set. The model now works in the designed algorithmic way and generates the recommendations. The recommendation so obtained is compared with the books that were kept hidden , if the recommendations include the hidden books that means framework is able to recommend correct items successfully and vice versa. Based on this comparison, True Positive (TP) ,False Positive (FP) , False negatives and True negatives were obtained. These values are further used to compute the Accuracy , Precision , Recall and F1 score.

Accuracy indicates the overall correctness of the recommendations generated and is computed using the formula (17)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (17)$$

Precision is the indicator of actually relevant recommendations for the intended user. It is computed from the equation (18)

$$Precision = \frac{TP}{TP + FP} \quad (18)$$

Recall is the ability of the RS to retrieve the relevant books from the candidate book. Its is calculated using the formula (19) below

$$Recall = \frac{TP}{TP + FN} \quad (19)$$

F1 scores measures the balance between precision and recall and is measured using the formula(20)

$$F1-Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (20)$$

The results so obtained are reported in the result and discussion section further.

8 Results And Discussion

The performance of proposed model was evaluated on the basis of accuracy , precision , recall and F1 score. It has obtained the accuracy of 0.98 , precision of 1 , recall of 0.98 and 0.99 of F1 score.

The accuracy achieved by the model indicates that it identifies the relevant recommendations for the target users. Higher value of precision demonstrates that all the

recommended values were relevant as per the intended user. Similarly the value indicator of recall highlights that the model successfully fetched the correct books from the dataset to recommend and 99 percent of F1 score suggests that the model perfectly balances precision and recall which is also an indicator of consistency of the proposed model.

Overall, the results confirm that the integration of semantic intelligence along with the relational modelling and heuristic measures such as attraction degree, rating degree and novelty degree contributes significantly to achieve better recommendation quality. The metrics indicate that the proposed model is generating highly accurate, relevant and personalised recommendations to the intended users.

We have also compared our model with various existing models and discovered that it performs better than some of the existing models to a great extent. We have compared our model in terms of precision, recall and F1 score as the models with which we have compared have not calculated the recommendation Accuracy. We have evaluated our model for accuracy too and thus, we have included that metric too. The proposed model is our results. Comparison results can be depicted from fig (2) and table 1. below.

Table 1 Comparison with existing methods

MODEL	PRECISION	RECALL	F1 SCORE	ACCURACY
NOVA[27]	0.63	0.40	0.52	-
Semantic Hybrid[17]	0.59	0.53	0.55	-
Hybrid DL+ CF[18]	0.89	0.59	0.71	-
Proposed	1	0.98	0.99	0.98

9 Conclusion And Future Work

Thus, This paper proposes a semantic aware multistage hybrid framework for book recommendation. It combines three layers dedicated to specific tasks. First layers discover the structural relationships while the semantic layer is dedicated to find out the semantic similarity score by discovering the user and book semantic features. Finally heuristic scoring features add relevance, accuracy and diversity in recommendation. In this way the framework is designed to explore personalised book recommendation domain. The model is evaluated using user wise hold out strategy to check the accuracy of recommendation. Thus, we can say that the framework designed along with the obtained experimental results demonstrated the effectiveness of the framework and enhances recommendation relevance, personalisation and provides robust solutions for personalised book recommendation.

Through the proposed framework gives the promising results yet it can further be enhanced. Future work may focus on incorporating graph neural nets (GNN) to learn more complex relationships. Semantic modelling could be further enhanced with LLMs to obtain rich contextual understanding. Additionally, temporal reading preference

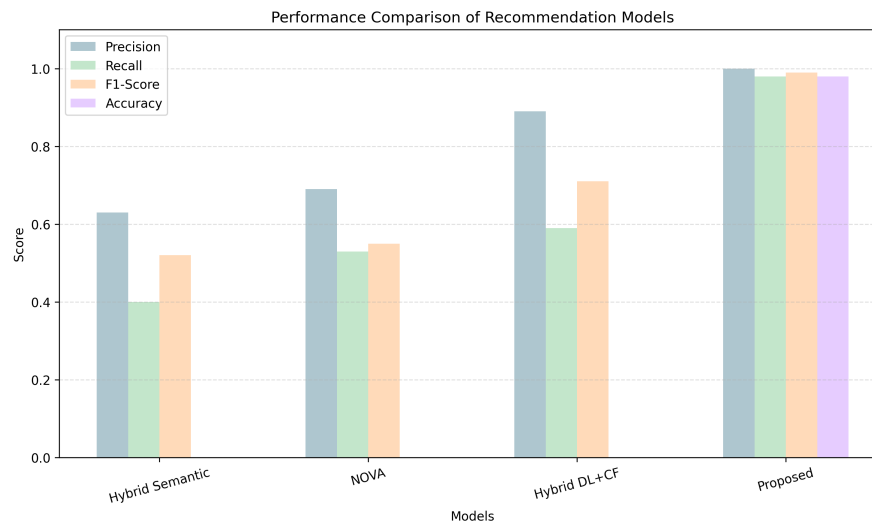


Fig. 2 Performance Comparison of Recommendation Models

may provide more dynamic Recommendation. the model can also be trained on large datasets. As we have trained our model on a set of amazon book reviews dataset after pre processing.

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