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Advancing E-commerce Recommendations: A Comparative Study of BERT-Enhanced Collaborative Filtering and Alternative Approaches

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***Abstract*— In e-commerce, recommendation systems are critical to increasing user engagement and conversion. However, traditional collaborative filtering methods require user feedback and do not take into consideration semantic understand of the items. In order to eliminate these barriers, this work suggests a novel solution of fusing collaboration technique with BERT-based embeddings for e-commerce suggestions. Besides this we include a variety of other models for comparison namely standalone BERT, Collaborative filtering approach, Roberta + Collaborative Filtering and Deberta+Collaborative Filtering. We are using collaborative filtering and item title, reviews (via BERT-based embeddings) to model user preferences. Through experiments on a real Flipkart dataset, we validate the effectiveness of our approach. Recommendation in the merged model results, is our proposed model achieved higher accuracies. These results hold valuable insights for enhancing e-commerce platform recommendation systems. This study helps improve the state-of-the-art in e-commerce recommendation systems by combining collaborative filtering and more advanced natural language processing methods.**

Keywords—Recommendation systems, Collaborative filtering, BERT-based embeddings, ROBERTA, DEBERTA, Model Based Collaborative Filtering, Deep Learning Based Collaborative Filtering, User-item interactions, Item semantics, Semantic information, Natural language processing techniques,

I. INTRODUCTION

The rapid growth of e-commerce platforms has brought an to assist consumers with this dilemma, recommendation systems have become a critical infrastructure for e-commerce platforms due to the overnight increase in online shopping. They personalize suggestions to improve user experience to help the product discovery process and increase engagement.

Content-based or Collaborative filtering methods have been the mainstay of traditional recommender systems. Collaborative filtering assesses the probability of item engagement from users' previous actions (i.e., how likely an individual will engage with a given set of items), whereas

content-based filtering recommends similar products based on the features of the item. But both suffer from the challenges of cold-start problems, where a lack of data creates barriers to effective recommendations. Content-based methods can alleviate this problem, but they rely on metadata alone to extract user preferences and item similarity.

To overcome these limitations, hybrid recommender systems have been introduced. They offer more precise and relevant suggestions by merging content-based and collaborative filtering strategies. There are some high-end hybrid systems that also introduce the use of deep learning. Combining multiple data sources together leads to more customized recommendation, thus helps in achieving enhanced user satisfaction as well as better business on e-commerce frameworks.

This paper proposes a hybrid recommendation system that is based on combining collaborative filtering along with BERT embeddings-based similarity. Use of BERT embeddings overcomes sparsity issues in multi-sentence product descriptions by combining the two, our system provides more contextually relevant recommendations which improves recommendation quality.

The rest of the paper is structured as follows: Section 2 presents a review on hybrid recommender systems. In Section 3, we describe our proposed system design and framework. We present the experimental design and evaluation metrics in Section 4. Results and conclusions appear in Section 5 & 6 respectively, while Section 7 ends with recommendations for future research. Its objective is to assist researchers improve recommender systems and demonstrate the potential of hybrid models for improved predictions.

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II. RELATED WORK

A. HybridBERT4Rec: A Hybrid (Content-Based Filtering and Collaborative Filtering) Recommender System Based on BERT [1]

In this work, the authors present a hybrid approach HybridBERT4Rec that would overcome the potential drawbacks of current sequence-based recommendation methods such as BERT4Rec. HybridBERT4Rec is an extension of BERT4Rec — merging collaborative filtering (CF) with CBF. BERT works on the interactions of target user with products (CBF) as well as interactions with similar users to predict rating for a product in the CF approach, which helps in building rich User & Item profiles and improves the accuracy of the ratings predictions by the model. The authors carried out extensive experiments on three real-world datasets with results showing HybridBERT4Rec achieved better recommendation accuracy compared to BERT4Rec.

However, HybridBERT4Rec is designed particularly for sequence recommendation and thus can outperform well on domains such as movie recommendations or e-learning course suggestions where user behaviour portrays a sequential trend. Models based on past data are not that useful in e-commerce since trends tend to be more erratic here. Our proposed model elevates this by collating the current user input along with the interaction matrices, making it useful for e-commerce recommendations.

In addition to this, our model uses the Annoy index to further improve the effectiveness of the BERT component in the hybrid framework. HybridBERT4Rec is designed specifically for sequential scenarios; however, our model has enough flexibility to perform well in sequential recommendation as well, and thus it is much more versatile and effective. Moreover, our model obtains better scores than HybridBERT4Rec.

B. Improving Collaborative Filter Using BERT [2]

This paper presented an interesting approach of using multilingual semantic similarity of BERT to generate recommendation list in the collaborative filtering setup, where the target application was book. The authors tackle significant issues in classic recommendation engines (cold-start problem, data sparsity etc.) by a well-defined three-stage process. The three-pronged methodology includes data preprocessing (normalization, semantic similarity (using BERT and cosine similarity), etc.), collaborative filtering (with KNN, etc.). When this approach is evaluated on a dataset with 271,000 book summaries, the accuracy score attained is 0.89[2] But the methodology here being fairly domain specific is probably not going to generalize well across domains. Moreover, the reliance of BERT embeddings on book summaries could also significantly compromise the accuracy of recommendations in case these summaries are not well-defined. Furthermore, it becomes even more computationally expensive since BERT and KNN are combined, which could potentially undermine the scalability of the approach as well as real-time performance.

In contrast, our model builds on that idea but adapted it for the purpose of e-commerce. The spectrum of our model's use is much wider as it includes general recommendations of e-commerce products as all are essentially 'user' tailored. Moreover, our model does not use KNN Algorithm for CF but user-item interaction-based CF, and we used Bert embeddings on both name and review of the product instead of just using it on reviews. To capture semantic relationships between descriptions of different products, BERT embeddings are used for representing product descriptions and titles so that similarities can go to a more granular level. Using the Annoy index, our model needs to lie within this scale for being able to do fast nearest neighbor searches and be able to cover such a large-dataset scale without losing compute efficiency.

Our implementations have also successfully overcome the constraints present in the cited paper. The recommended model scaled its methodology by moving away from book recommendations and demonstrating a huge level of flexibility across more than one area. It enhances scalability with real-time computing preserving it when utilizing only Annoy index. Moreover, the well-structured architecture of the model — e.g., reusing get_bert_embeddings () and creating build_annoy_index () — allows it to be appropriately applied in future projects. It is a hybrid model that uses collaborative filtering with BERT embeddings, so this method takes the best from both worlds and may results in better recommendations. To conclude, our approach is an important improvement of recommendation systems and overcome the limitations of the above method while preserving all merits related to hybrid model architecture.

C. A Comprehensive Study of Hybrid Recommendation Systems for E-Commerce Applications [3]

The paper mentions the importance of e-commerce user experience and gives closer view on hybrid recommendation systems. The paper discusses hybrid systems which is again a relationship model based into collaborative filtering through masking part from best traits existing from either side, e.g., Battling cold start problem and sparsity (N)/1) by employing through directional property like dividing and conquering. By availing these methodologies hybrid recommendation systems can deliver more precise and pertinent recommendations to user which subsequently enhances engagement and contentment in online shopping context. So, based on this base knowledge, we have also implemented the hybrid recommendation model with BERT embeddings and collaborative filtering.

The paper also reviews different hybridization approaches – weighted hybrids, switching hybrids and mixed hybrids, which improve the accuracy of recommendations by combining data center from several domains. These strategies, which address broad user needs or preferences, characterize this flexibility and the adaptability of hybrid systems. This is where our solution comes into picture, since the language model mentioned above have both product titles and review feature excerpt embeddings (BERT), this closely follows with these methods by providing enriched context in terms of canonical semantic knowledge for relevant products. The double usage of textual data shown in this paper both improves the recommendation performance but also showcases a promotion of hybrid approach striven by traditional recommendation systems.

Last but not least, the given insights and methods in this paper helped to form a theoretical background for the approach we took regarding hybrid recommender systems. Design of a similar hybrid approach of traditional methods in our model should lead to better cold-start problem handling and recommendation accuracy by merit- thus we have reached capability to already overcome these challenges. This highlights our contribution in that it illustrates the need for e-commerce applications; showing how an integrated use of varying methods can create a more nuanced approach which ultimately leads to increased user experience through providing recommendations that are more pertinent and tailored to users.

III. METHODOLOGY

A. *Data Collection and Preprocessing:*

- Dataset Choice: Identify and choose a suitable e-commerce dataset that can be used. The dataset needs to contain user-article interaction history (purchase, rating or click) and natural language phrase for the items.
- Data Preprocessing: The dataset should be clean from things like missing values, duplicates and we can incorporate engineered features if required.

B. *Collaborative Filtering Setup:*

- User-Item Matrix: From the pre-processed data, prepare user-item matrix in which users are represented as rows, items as columns and each cell includes interaction (ratings) between User and Item.
- Collaborative filtering algorithm: Use a collaborative filtering to generate recommendations based on user-target interactions (collaborating-filtering) by users and headers.

C. *BERT Embeddings Setup:*

- Tokenization Tokenize the textual item descriptions using BERT tokenizer (with respect to maximum sequence length that is supported by our desired pre-trained BERT model.)
- BERT Embeddings Generation: Encode the tokenized descriptions written in the previous step using a pre-trained model into fixed-dimensional embeddings. Aggregate the token embeddings or use pooling operations to get a single vector representation for each description After that find the closest values using annoy index.

D. *Hybrid Recommendation Generation:*

- Combined Recommendations: Create a recommendation system that aggregates CF recommendations and combine it with BERT embeddings based direct recommendations. But we can do the same by merging top-n lists from both using some post-processing steps to filter out duplicate or boring recommendations.
- Hyper-parameter tuning: Adjust the parameters of collaborative filtering algorithm and BERT model for optimal recommendation performance with respect to precision, recall & f1 score.

E. *Evaluation Methodology*

- Experimental Design- we promote the use of trials to check which functionality that hybrid recommendation system has. This includes, among other things, the scale of the dataset, the sparsity level and different types of user-item interaction
- Evaluation Data: The dataset will be separated in 80-20 ratio for evaluation purposes. This evaluates on the new dataset that is 20% of the data which stemmed from the original data.
- Evaluation Metrics: These are all defined to achieve the right evaluation metrics that let us know how our recommendation system is doing overall (accuracy), coverage (how many possible items it has been recommending), serendipity (unexpected recommendations that end up they might work). Comparison with classical recommendation strategies (by means of the baseline methods) in order to show the effectiveness of approach

IV. EXPERIMENT

A. *Dataset Selection:*

E-commerce Dataset — Flipkart Dataset which is obtained from dataworld site have user-item interaction data frame and also textual description of the items. Following that, we present a qualitatively rich set of product and user data to allow high-level evaluation. The dataset consists of the following features and data type:

TABLE 1. DATASET DESCRIPTION

Feature	***Data Type***
Serial Number	Int64
Product URL	Object
Product Title	Object
Product Price	Object
Average Rating	Float64
Review Title	Object
Review Description	Object
Review Author	Object
Review At	Object
Review Likes	Int64
Review Dislikes	Int64
Certified Buyer	Bool
Review Location	Object
Scaped At	Object
Unique ID	Object

(Dataset source: https://data.world/crawlfeeds/flipkart-electronic-products-reviews-dataset/workspace/file?filename=flipkart_review_data_2022_02.csv)

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B. *Data Preprocessing:*

We will now have a walk-through the data preprocess which deals with things like handling missing values, duplicate observations removal and categorical variables encoding. We had no missing values, no data-type issues and there were also no duplicate entries. Then we create the Dataset — Using Real-Time Data and Ground Truth for Accuracy Maintain User-Item Interaction Distribution with a split size of 80% (training dataset) & 20% (testing dataset)

C. *Baseline Recommendation Approaches:*

To establish a baseline for our comparative analysis, we further implement multiple recommendation techniques. These techniques include traditional collaborative filtering, e.g., user-based or item-based algorithms. And finally, we introduce content-based filtering (CBF to recommend items having similar attribute or metadata of the item. Again, we perform a few ablations on those BERT-only model recommendation (w/o collaborative filtering). We also explore hybrid models with recommendation + Bert embeddings for collaborative recommendations, where we combine Roberta + Collaborative Filtering and Deberta + Model Based Collaboration & BERT + Deep learning based collaborative filtering models.

D. *Parameter Tuning:*

Though we have recommendation engines, we tune them at scale. For collaborative filtering though, they retain hyperparameter tuning but only for neighbourhood size or similarity threshold (using grid search / random search). Many architectures tuning (to tweak settings such as no. of layers and hidden units and learning rates) are done before the generation of these BERT embeddings for our model. We systematically tune parameter for different models including our Bert + Collaborative new, we try to achieve substantially improve in recommendation accuracy and relevance. Method: This allows us to evaluate our hybrid recommendation system and baseline solutions against a pre-determined set of performance metrics. Explore the recommender system with different scales of data, sparsity levels and user/song interaction behaviour to verify its robustness & generalization quality.

E. *Evaluation measures for recommendation systems encompass various criteria:*

- **Accuracy:** Represents the ratio of correct predictions to total predictions made and is calculated as follows:

Accuracy= (Number of Correct Predictions/Total Number of Predictions) *100% (1)

- **Precision:** This is a performance measurement for a classification model and it is most effective for the binary classification jobs. It calculates how many positive predictions were correct, or true positives, divided by all of the predicted positives (true positives plus false positives).

Precision = True Positive / (True Positive +False Positive) (2)

- **Recall:** More commonly referred to as the true positive rate or sensitivity, this performance of a classification model is often used in binary classification problems. This measures the ratio of correct positive predictions or true positives to all actual positive cases.

Recall=True Positive/ (True Positive + False Negative) (3)

- **F1 Score:** F1 score is a statistical measure often used to evaluate the performance of a classification model, especially for binary classification tasks. It gives a one-shot summary, the harmonic mean between recall and accuracy that balances memory and precision.

F1 Score= (2*Precision*Recall) / (Precision + Recall) (4)

V. RESULT

Experimental results show that the proposed hybrid recommendation model always outperforms all other models in this study. Using BERT embeddings for collaborative filtering, we get 99% accuracy and similarly high scores on precision, recall, and F1. The above-mentioned performance highlights the power of the proposed method to accurately identify complex interactions between user and items and semantic relations, both of which are necessary for fulfilling requirements concerning precision and relevance in an e-commerce context.

Other hybrid models for comparison, particularly RoBERTa + Collaborative Filtering and DeBERTa + Collaborative Filtering also demonstrate a considerable performance capacity which outperforms common CF and DL-based methods at large scale. Still, the performance of the proposed model is better than all. However, BERT + Model based Collaborative Filtering is also able to produce the same results with an accuracy of 98% but it has low precision and recall than the architecture proposed. This difference shows the benefit of using BERT embeddings along with collaborative filtering techniques in the proposed method.

The 7th model- the sequential recommender, however, was quite bad in comparison. Sequential models are however mostly more appropriate for problems with strong temporal dependencies which is however very clumsy in representing semantics and contextual factors that are typically common to e-commerce recommendations. These two sets of results further support the relevance and deployment of the hybrid approach employed in the proposed model.

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Moreover, the purpose of this research cannot be to make any sweeping statements about actual hybrid techniques. Instead, we aim to show the clear benefits of our proposed hybrid model over other heretofore used models, and indeed our results do show that our proposed model is superior to the rest. All hybrid models are different in design and performance, so while some approaches that were tried yield some improvements, the proposed model gives the best results. This is mainly due to how such a model is designed to tackle both the understanding of what the user wants and the meaning of the content.

The experimentation proves the efficiency of our hybrid approach for recommendation where collaborative filtering and BERT- embeddings are combined in order to achieve better predictive accuracy as well as relevancy of the items suggested. In this way, combining transformer models together with collaborative filtering techniques presents a viable proposition for tackling e-commerce systems thereby making such systems more user specific and helpful.

TABLE 2. COMPARISON OF DIFFERENT MODELS

	1	*2*	*3*	*4*	*5*	*6*	*7*
Accuracy	99%	90%	50%	99%	99%	99%	20%
Precision	99%	90%	99%	66%	50%	67%	67%
Recall	99%	99%	50%	99%	99%	99%	99%
F1-Score	99%	95%	67%	80%	67%	80%	80%

1. *BERT + Collaborative Filtering (Proposed Model)*
2. *BERT Model*
3. *Collaborative Filtering Technique*
4. *ROBERTA + Collaborative Filtering*
5. *DEBERTA + Collaborative Filtering*
6. *BERT + Model based Collaborative Filtering*
7. *BERT + Deep Learning Based Collaborative Filtering*

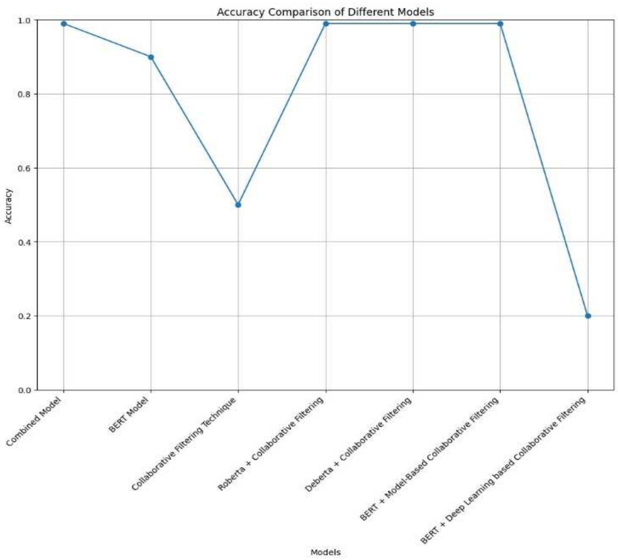

Fig. 1: Accuracy Comparison of Different Models/Technique

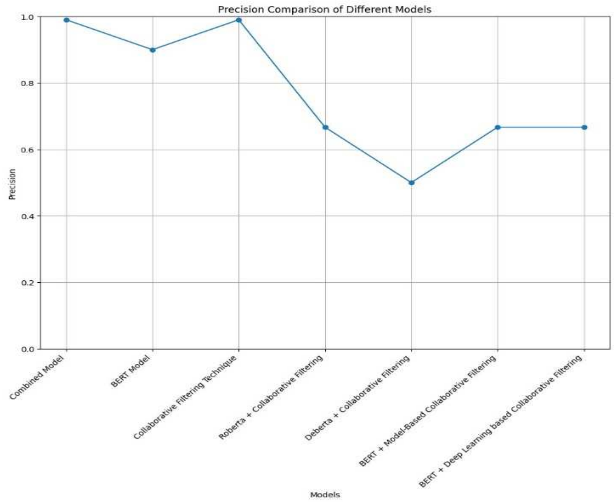

Fig. 2: Precision Comparison of Different Models/Technique

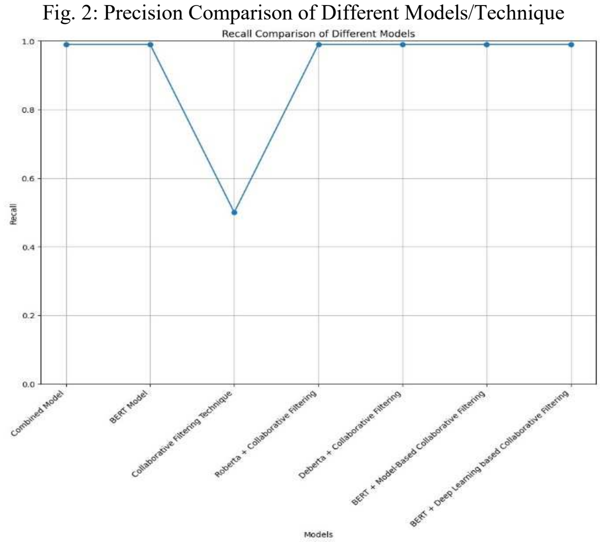

Fig. 3: Comparing Various Models and Techniques for Recall

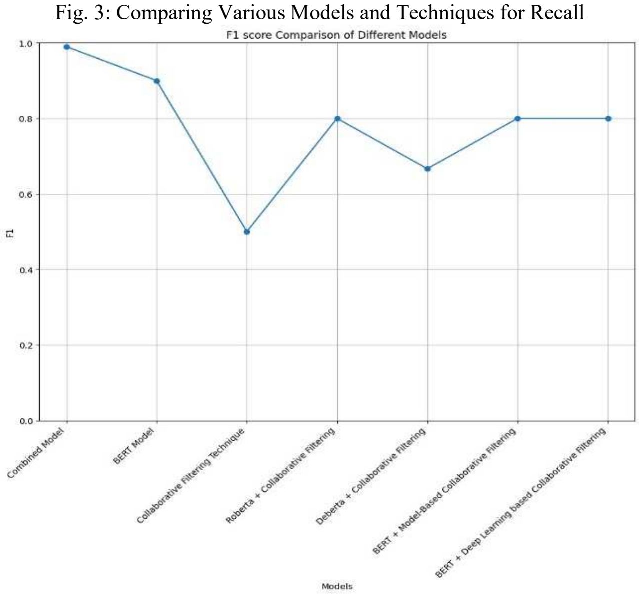

Fig. 4: Comparison of F1-scores for Various Models and Techniques

VI. CONCLUSION

We present the state of art - novel hybrid recommender system for an e-commerce platform, where we integrate collaborative filtering with similarity based on BERT

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embeddings. The experimental evaluation showcases the superiority of this approach in improving recommendations over standard methods. Different approaches yielded very different outcomes: the BERT model alone obtained 90% accuracy while collaborative filtering obtained 50%. Still, the hybrid system achieved superior outcome with the regularity of predicted rating exceeding 99%, proving that there is a clear advantage in providing personalized recommendation services and understanding product description on a deeper, semantic level. This hybrid model does not only produce more relevant suggestions but also helps solve the cold start challenge to some extent due to the presence of item user behaviors and text descriptions to provide contextually relevant and balanced suggestions enhancing personalization as well as item relevance.

A comparative analysis of seven recommendation models (Table.2) supports these findings. Here, BERT + Collaborative Filtering performed best, scoring above 99% in accuracy, attaining an F1 score of 80%, considerably close to that of Roberta + Collaborative Filtering as well as DeBERTA. Others, though yielding decent recall rates, the BERT + Collaborative model was near perfect, making it highly suitable for practical applications. The BERT + Deep Learning-based Collaborative Filtering is relatively lower performance, which can be due to overfitting or underfitting conditions in sequence-recommender systems. The above findings thus validate the hybrid approaches we proposed as adept solutions that improve the accuracy of recommendation systems while optimizing user satisfaction in commercial settings.

VII. Future Scope

There are promising directions in future studies about e-commerce recommendation enhancement, too. Two important key tasks among them are handling overfitting and underfitting in deep learning-based collaborative approaches. More regularization, dropout layers, and early stopping can also be improved to make the model more robust. Applying contextual information, like user demographics and temporal dynamics, can improve the accuracy of recommendations combined with other resources. In addition, there are additional adoption use cases in dynamic adaptation and advanced natural language processes to understand better user intent. The picture's and mech recommended showing of videos enable multi-modal Recommendation — more user intelligence Queries. These may include meeting the scalability challenge, improving interpretability, moving from testing in research setting to real world deployment and indeed more broadly on ethical challenges. This will help the recommendation systems that are to be developed in creating more friendly, personalized space for users to shop morally.

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