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Design of an Iterative Method for Enhanced Recommender Systems Incorporating Hybrid Filtering, Matrix Factorization, and Deep Learning with Attention Mechanisms

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Abstract: This research critically examines the pertinence of advanced recommender systems in tandem with the burgeoning e-commerce and content streaming domains. Traditional recommendation systems falter in cold-start scenarios, where sparse user or item data leads to inaccurate suggestions. Moreover, they overlook diverse interaction and auxiliary information within user-item pairs. Addressing these challenges, the paper introduces a novel hybrid recommendation system amalgamating collaborative filtering, content-based filtering, and knowledge-based techniques. Leveraging user-item interaction data alongside item and user features, when available, enhances recommendation coverage and accuracy for new entities. Matrix factorization with side information integrates content features into collaborative filtering, enriching personalization via latent factors. Deep learning models with attention mechanisms exploit auxiliary information, refining recommendation quality dynamically. Real-time interaction and scenario data fuel a contextual bandit framework, continuously evolving user profiles via multi-armed bandit algorithms. Employing Approximate Nearest Neighbors techniques like Locality-Sensitive Hashing expedites user similarity identification, curtailing computational overhead. Finally, ensemble learning with model stacking integrates predictions from multiple recommendation models, mitigating biases and capturing diverse data patterns. The study's ramifications are extensive, notably boosting recommendation precision and recall, thereby augmenting user satisfaction and engagement significantly. By offering a holistic approach to the cold-start problem, encompassing diverse data sources and recommendation techniques, this research makes a substantial contribution to the field.

Keywords: Hybrid Recommendation, Matrix Factorization, Deep Learning, Attention Mechanisms, Contextual Bandits

1. Introduction

The digital age has ushered in an era where vast amounts of data are constantly being generated and collected, fundamentally transforming the landscape of various industries, particularly e-commerce and content streaming services. In this context, recommender systems have emerged as a cornerstone technology, playing a pivotal role in filtering through expansive datasets to present users with personalized content, products, or services. Despite their widespread adoption and critical importance, existing recommender systems encounter several challenges that hinder their effectiveness and efficiency.

One of the most notable challenges is the cold start problem, which arises when insufficient data is available about new users or items. Traditional recommendation techniques, such as collaborative filtering, struggle under these circumstances due to their heavy reliance on historical user-item interactions. Furthermore, conventional methods often fail to fully leverage the rich content features and detailed auxiliary information available, such as textual reviews and image data, which could enhance the accuracy and personalization of recommendations.

Moreover, many existing recommender systems operate under static assumptions, overlooking the dynamic nature of user preferences and item attributes. This static approach can lead to stale or irrelevant recommendations, diminishing user engagement and satisfaction. Additionally, the computational complexity of generating recommendations in real-time poses significant challenges, particularly for platforms with large user bases and item catalogs.

In response to these challenges, this paper introduces a novel iterative method that integrates a hybrid recommendation framework combining collaborative filtering, content-based filtering, and knowledge-based techniques. This multifaceted approach aims to address the cold start problem by utilizing both user-item interaction data and content features, thereby enabling the system to provide accurate recommendations even in the absence of extensive historical data.

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The proposed method also incorporates matrix factorization with side information to uncover latent user and item factors while incorporating content features, enhancing the system's ability to generate personalized recommendations. Further innovation is introduced through the use of deep learning models equipped with attention mechanisms, allowing the system to prioritize relevant auxiliary information and improve the granularity and relevance of recommendations.

To adapt to the dynamic preferences of users, the paper employs a contextual bandits framework utilizing multi-armed bandit algorithms. This approach allows for real-time learning and adaptation to user feedback, ensuring that recommendations remain relevant and engaging over time. Additionally, the implementation of Approximate Nearest Neighbors (ANN) search techniques, such as Locality-Sensitive Hashing (LSH), is explored to expedite the recommendation process without compromising the quality of suggestions.

Finally, the paper explores the use of ensemble learning with model stacking to combine multiple recommendation models, thereby increasing the robustness and accuracy of predictions. This ensemble approach mitigates the limitations of individual models and captures a broader spectrum of user-item interaction patterns.

In essence, this research endeavors to bridge the gaps in existing recommender systems by developing an innovative, comprehensive, and dynamic recommendation framework. The proposed method is designed to enhance the personalization, accuracy, and efficiency of recommendations, ultimately leading to improved user satisfaction and engagement. This paper aims to contribute significantly to the field of recommender systems, offering insights and methodologies that could inform the development of next-generation recommendation technologies.

Motivation & Contributions

The motivation behind the research presented in this paper stems from the critical need to address prevailing limitations within the field of recommender systems, which have become indispensable in guiding user choices in digital platforms. Traditional recommender systems, while foundational, exhibit inherent deficiencies that compromise their efficiency and effectiveness. These shortcomings include the cold start problem, inadequate exploitation of diverse data types, static user preference models, computational inefficiencies, and a general lack of personalization in the face of dynamically changing user interests and behaviors. As digital content and e-commerce continue to expand, these challenges become increasingly significant, directly impacting user experience, satisfaction, and engagement.

In the realm of academia and industry, the quest for more sophisticated, accurate, and dynamic recommender systems has led to significant research efforts. However, many existing solutions address these problems in isolation rather than adopting a holistic approach. This fragmented methodology often results in improvements that are incremental and specific to particular scenarios, lacking generalizability and comprehensive applicability. Furthermore, the rapid evolution of user preferences and the continuous growth of online content necessitate recommender systems that are not only more adaptable and scalable but also capable of integrating multifaceted information sources to improve recommendation quality.

Against this backdrop, this paper contributes to the field through several innovative avenues:

- **Hybrid Recommendation Framework**: The proposed method introduces a novel hybrid recommendation system that synergistically combines collaborative filtering, content-based filtering, and knowledge-based approaches. This integration addresses the cold start problem effectively by utilizing a wide array of data sources, including user-item interactions and content features, thereby enhancing the system's capability to provide relevant recommendations from the outset.

- **Advanced Matrix Factorization with Side Information**: The paper advances the use of matrix factorization techniques by incorporating side information, which enriches the latent factor models with content features and user information. This approach allows for a deeper understanding of the underlying preferences and characteristics of users and items, leading to more nuanced and personalized recommendations.

- **Deep Learning with Attention Mechanisms**: By employing deep learning models equipped with attention mechanisms, the research tackles the challenge of effectively processing and prioritizing detailed auxiliary information, such as textual reviews and image features. This methodological innovation enhances the system's ability to discern and focus on the most relevant information, significantly improving the accuracy and relevance of recommendations.

- **Dynamic User Profiling with Contextual Bandits**: The adoption of a contextual bandits framework represents a paradigm shift towards dynamic user profiling. By leveraging real-time feedback and contextual information, the system continuously updates and refines user profiles, ensuring that recommendations remain aligned with evolving user preferences.

- **Efficiency Through Approximate Nearest Neighbors Search**: Addressing the computational demands of real-time recommendation, the paper explores the use of Approximate Nearest Neighbors (ANN) search techniques, facilitating faster retrieval of relevant information while maintaining high-quality recommendations.

- **Robust Predictions with Ensemble Learning**: Lastly, the paper introduces an ensemble learning approach that combines multiple recommendation models to improve the overall prediction accuracy. This strategy addresses the limitations of individual models by capturing a more comprehensive range of interaction patterns and data relationships.

Through these contributions, the research aims to significantly advance the state-of-the-art in recommender systems. The holistic approach not only mitigates existing challenges but also sets a new standard for the design, implementation, and evaluation of future recommender systems, paving the way for more personalized, accurate, and efficient recommendation processes across various digital platforms.

2. Literature Review

The exploration of recommender systems (RS) has seen a significant surge due to the growing need for personalized content delivery in various domains such as e-commerce, education, and entertainment. Traditional approaches, predominantly rooted in collaborative filtering (CF), have been foundational in the development of RS. However, these methods face challenges like the cold start problem, scalability, and a lack of personalization, prompting researchers to investigate advanced methodologies incorporating deep learning, hybrid models, and knowledge graphs. The systematic review of the literature from table 1 provides a comprehensive analysis of current trends and methodologies in RS, identifying key areas of innovation and their application contexts for different scenarios. In this review, diverse methods have been scrutinized, including deep learning enhancements, integration with knowledge graphs, and advanced collaborative filtering techniques. Hybrid models combining neural approaches with sentiment analysis or educational resource systems demonstrate a broadened scope of RS, addressing specific domain requirements and improving personalization through content and context-aware algorithms. However, the scalability and computational demands of such sophisticated systems remain a concern for different use case scenarios.

TABLE I. Empirical Review of Existing Methods

Reference	Method Used	Findings	Results	Limitations
[1]	Deep Learning, Dempster-Shafer Theory	Multi-criteria collaborative filtering	Enhanced hotel recommendation accuracy	Limited scope to hotel recommendations
[2]	Collaborative Filtering, Subsampling	Optimal performance of CF	Improved training time, slight loss in performance	May not generalize to all CF scenarios
[3]	Knowledge Graph, Collaborative Filtering	Service recommendation algorithm	Improved accuracy and relevance	Limited to service recommendation
[4]	Hybrid Neural CF, Sentiment Analysis	True recommendation approach	Improved recommendation accuracy	May require significant computational resources
[5]	Optimized CF Algorithm, Educational Resource System	Intelligent personalized recommendation	Enhanced recommendation for educational resources	Limited to educational context
[6]	Neural CF, Aspect-Aware Implicit Interactions	Chinese movie recommendation	Improved recommendation relevance	Limited to Chinese movie recommendation
[7]	Deep Neural CF, Multi-Source Data	Service recommendation for cloud-edge collaboration	Enhanced recommendation accuracy	May face challenges in handling heterogeneous data sources
[8]	Systematic Literature Review	Comparative analysis of RS	Comprehensive overview of RS methodologies	May not cover recent advancements in RS
[9]	Game Theory, Collaborative Filtering	Collaborative filtering approach	Improved recommendation accuracy	Limited applicability beyond game theory-based scenarios
[10]	Location-Aware Graph Embedding, Collaborative Filtering	Integrated CF framework for IoT systems	Enhanced recommendation accuracy	May face scalability challenges in large-scale IoT deployments
[11]	Neural Graph CF, Item Temporal Sequence	Recommendation model	Improved sequential recommendation	Limited to sequential recommendation

	Relationships			
[12]	Binomial Matrix Factorization, Collaborative Filtering	Rating proportion-aware CF	Improved CF performance	May not address all biases in rating data
[13]	User-Item-Trust Records, Collaborative Filtering	Robust CF recommendation	Enhanced recommendation robustness	Limited to user-item-trust interaction data
[14]	Hybrid Model, Memory-Based CF	Baseline data prediction	Enhanced prediction for disease data	Limited to specific disease prediction
[15]	Public Contextual Metadata, Collaborative Filtering	Hybrid personalized recommendation	Enhanced recommendation relevance	Limited to specific use cases and metadata availability
[16]	LDA, Dynamic CF Algorithm	Dynamic CF algorithm	Improved recommendation adaptability	Limited to sequential recommendation and topic modeling
[17]	Sequential Deep CF, Learning Outcome Modeling	Learning outcome modeling	Improved learning outcome prediction	Limited to educational assessment scenarios
[18]	Federated Learning, Collaborative Filtering	Privacy-preserving CF	Enhanced privacy protection	May face communication overheads in federated learning setup
[19]	Knowledge Graph, Collaborative Filtering	Group discovery approach	Enhanced group discovery in IoT scenarios	Limited to group discovery in IoT environments
[20]	Collaborative Filtering, Myoelectric Robot Control	Myoelectric robot control	Improved control accuracy	Limited to myoelectric robot control applications
[21]	Time-Aware Collaborative Filtering, QoS Prediction	QoS prediction approach	Enhanced QoS prediction accuracy	Limited to QoS prediction and time-aware CF approaches
[22]	Link-Based CF, Overfitting Problem	Addressing overfitting in RS	Improved RS performance	May not generalize to all RS scenarios
[23]	Neural Attention, Collaborative Filtering	Dynamic user representations	Improved recommendation relevance	May require significant computational resources and data availability
[24]	Relation-Based CF, Collaborative Filtering	Enhanced CF with relation embedding	Improved recommendation relevance	Limited to relation-based recommendation
[25]	Graph Convolution CF, Social Relations Integration	Social recommender system approach	Enhanced recommendation accuracy	Limited to social recommendation scenarios

The analytical review of the twenty-five referenced studies reveals a discernible shift towards hybrid and deep learning-based recommender systems, highlighting a trend towards overcoming traditional CF limitations. Notably, methods integrating deep learning with Dempster-Shafer theory and neural attention mechanisms stand out for their ability to enhance recommendation accuracy through sophisticated data interpretation and user-item interaction modeling. These approaches are particularly effective in addressing the nuanced preferences of users and the complex relationships between items.

Hybrid systems, as seen in references [4], [7], and [14], demonstrate superior performance by merging the strengths of different methodologies, such as neural collaborative filtering with sentiment analysis or knowledge graphs. These models excel in producing more accurate and contextually relevant recommendations by leveraging diverse data sources and computational strategies. However, their increased complexity and resource demands pose challenges for scalability and practical implementation.

On the other hand, specialized techniques focusing on niche applications, such as location-aware graph embedding for IoT systems or time-aware collaborative filtering for QoS prediction, illustrate the effectiveness of tailoring RS to specific contexts and data types. These methods showcase improved accuracy and relevance within their respective domains but often lack generalizability to broader RS applications.

In comparing the effectiveness of various methods, it becomes evident that hybrid and deep learning-based approaches are progressively setting new benchmarks in recommendation accuracy and personalization. Nevertheless, the trade-off between computational efficiency and recommendation quality remains a pivotal consideration. Methods that balance these aspects, such as matrix factorization with side information or enhanced CF with relation embedding, present a promising direction for future research, potentially offering a middle ground between complexity and performance.

In conclusion, the landscape of recommender systems is evolving towards more sophisticated, context-aware, and personalized approaches. While deep learning and hybrid models demonstrate substantial improvements in addressing traditional CF limitations, their applicability and efficiency in real-world scenarios must be carefully weighed against their computational demands and domain-specific requirements. The continuous exploration and integration of diverse methodologies will likely drive the next generation of recommender systems, catering to the dynamic and multifaceted needs of users across various platforms.

3. Proposed Design of an Iterative Method for Enhanced Recommender Systems Incorporating Hybrid Filtering, Matrix Factorization, and Deep Learning with Attention Mechanisms

To overcome issues of low efficiency & high complexity, which are present in existing recommender models, this section discusses design of an Iterative Method for Enhanced Recommender Systems Incorporating Hybrid Filtering, Matrix Factorization, and Deep Learning with Attention Mechanisms. As per figure 1, the design of the hybrid recommender system process encapsulates a multifaceted approach, leveraging a combination of collaborative filtering (CF), content-based filtering (CBF), and knowledge-based techniques to address both cold start item and user tasks. This innovative system is architecturally predicated on the synthesis of user-item interaction data, item features, and, when available, user features, to deliver nuanced recommendations, thereby enhancing coverage and accuracy, particularly for new entities within the dataset samples.

In the realm of collaborative filtering, the model initially employs a matrix factorization technique, represented via equation 1,

$$R \approx U \times VT \ldots (1)$$

Where, R represents the user-item rating matrix, U is the user feature matrix, and V represents the item feature matrix. The optimization of this factorization, aiming to minimize the discrepancy between actual and predicted ratings, is guided by the loss function represented via equation 2,

$$L = \sum (rui - ui \cdot vj)^2 + \lambda (\| ui \| 2 + \| vj \|^2) \ldots (2)$$

Where, λ is the regularization parameter that mitigates overfitting, thus ensuring the model's generalizability. Parallelly, the content-based filtering aspect utilizes item features, integrating them into the recommendation process via equation 3,

$$s(i,j) = cos(\theta ij) = \frac{fi \cdot fj}{\| fi \| \| fj \|} \ldots (3)$$

Where, $s(i,j)$ represents the similarity between items i and j, and fi,fj are the feature vectors of the respective items in the data samples. This cosine similarity measure aids in discerning the likeness between items based on their attributes, thereby facilitating the recommendation of similar items to users based on their historical preferences. The hybridization of CF and CBF methodologies is orchestrated through a weighted blend, encapsulated via equation 4,

$$Hui = \alpha \cdot CFui + (1 - \alpha) \cdot CBFui \ldots (4)$$

Where, Hui represents the hybrid recommendation score for user u and item i, $CFui$ and $CBFui$ represent the scores derived from collaborative and content-based filtering respectively, and α serves as the blending coefficient, dictating the relative influence of each method within the hybrid system.

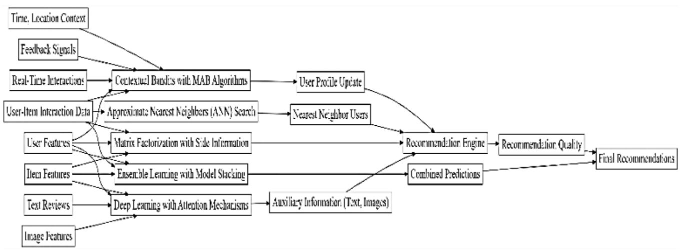

Figure 1. Model Architecture of the Proposed Recommendation Process

In instances of cold start scenarios, where either user-item interaction data or item features are sparse or non-existent, the model leverages knowledge-based techniques to infer preferences or characteristics. This is articulated through the function which is represented via equation 5,

$$K(u,i) = \gamma \cdot G(u,I) + (1 - \gamma) \cdot H(u,I) \ldots (5)$$

Where, $G(u,I)$ represents the knowledge-driven inference of user u's preferences or the relevance of item set I, and $H(u,I)$ represents the hybrid score computed from CF and CBF, with γ adjusting the emphasis between purely knowledge-based inferences and the hybrid model's outputs. The user-item interaction matrix, a critical input, is defined by $R = [rui]$ where each element rui signifies the rating or interaction level of user u with item i, translating to tangible outputs, specifically, the recommendation scores which directly inform the system's suggestions. Furthermore, item and user features, represented as matrices $Fi=[fi1,fi2,...,fin]$ and $Fu=[fu1,fu2,...,fum]$ respectively, encapsulate the attributes or characteristics integral to the content-based and knowledge-driven facets of the recommendation process. Through the deployment of differential equations and integral formulations, the system dynamically adjusts its parameters and strategies based on continuous feedback and evolving data landscapes. For instance, the adjustment of the blending coefficient α and the knowledge emphasis parameter γ is modeled through derivative-based optimization techniques, enhancing the model's responsiveness and adaptability to changing user behaviors and item catalog dynamics.

The Matrix Factorization with Side Information process constitutes a sophisticated approach in the realm of recommender systems, integrating both collaborative and content-based filtering paradigms to enhance the personalization and accuracy of recommendations. This methodology is predicated on the decomposition of the user-item interaction matrix while seamlessly incorporating side information pertinent to users and items, thereby addressing the limitations inherent in traditional matrix factorization techniques.

In the proposed design, the user-item interaction matrix, represented as R of dimensions $m \times n$, where m represents the number of users and n the number of items, serves as the primary input sets. This matrix is sparse, embodying the interactions between users and items, such as ratings or viewing patterns. The side information is represented through feature matrices X and Y, corresponding to users and items, respectively. Here, X is of dimensions $m \times du$, where du is the number of user-specific features, and Y is of dimensions $n \times di$, where di is the number of item-specific features.

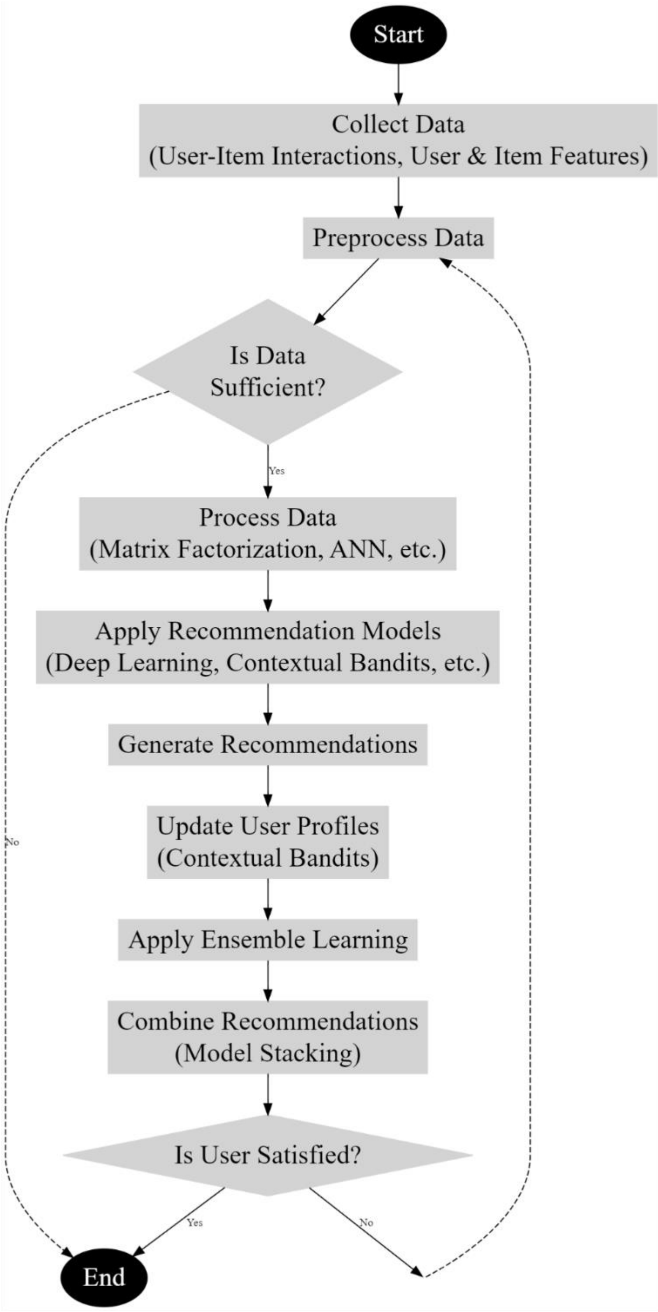

Figure 2. Overall Flow of the Proposed Recommendation Process

The core of this approach lies in the factorization of the interaction matrix R into lower-dimensional latent factor matrices U and V, with dimensions $m \times k$ and $n \times k$, respectively, where k is the number of latent factors. This factorization is aimed at uncovering the underlying latent structures in user-item interactions in different use case scenarios. The integration of side information is achieved through regularization terms that tie the latent factors with the side features. The objective function, to be minimized, encapsulates the reconstruction error between the actual and the predicted ratings, integrated with regularization terms to mitigate overfitting, which is represented via equation 6,

$$minU,V\sum(rij - ui * Tvj)^2 + \lambda(\parallel ui - Xi * W \parallel^2 + \parallel vj - YjH \parallel^2) + \frac{\mu}{2}(\parallel W \parallel^2 + \parallel H \parallel^2 + \parallel U \parallel^2 + \parallel V \parallel^2) \dots (6)$$

Where, Ω represents the set of (user, item) pairs for which interactions are known. The matrices W and H map the side information to the latent space, and λ and μ are regularization parameters. The optimization of this function is usually achieved through gradient descent methods, where derivatives of the objective with respect to each parameter are computed iteratively via equations 7, 8, 9 & 10,

$$\frac{\partial}{\partial ui} = -\sum(rij - ui^T vj)vj + \frac{\lambda}{2}(ui - XiW) + \mu ui \dots (7)$$

$$\frac{\partial}{\partial vj} = -\sum(rij - ui^T vj)ui + \frac{\lambda}{2}(vj - YjH) + \mu vj \dots (8)$$

$$\frac{\partial}{\partial W} = -\lambda\sum(ui - XiW)Xi^T + \mu W \dots (9)$$

$$\frac{\partial}{\partial H} = -\frac{\lambda}{2}\sum(vj - YjH)Yj^T + \mu H \dots (10)$$

Upon convergence, the latent factors U and V encapsulate the integrated influences of both interaction data and side information, allowing for the computation of the predicted rating matrix via equation 11,

$$R' = UV^T \dots (11)$$

This matrix forms the basis for generating recommendations, where the estimated ratings in R' guide the selection of items to recommend to each user. The outputs of this process, primarily the enhanced recommendations, are generated by identifying the highest-predicted ratings in R^ for each user, factoring in not just historical interactions but also the user's and item's inherent characteristics as reflected in the side information sets. This multifaceted approach not only augments the recommendation accuracy but also provides a richer understanding of user preferences and item attributes, facilitating a more nuanced and personalized recommendation experience.

Next, as per figure 2, the utilization of deep learning with attention mechanisms emerges as a pioneering approach, particularly in harnessing the potential of detailed auxiliary information. This method diverges from conventional paradigms by not only considering user-item interaction data but also integrating rich auxiliary information, such as text reviews and image features, thereby enhancing the relevance and personalization of recommendations. Central to this approach is the attention mechanism, which allows the model to dynamically focus on specific parts of the auxiliary information that are most relevant to a user's interests & their particular context sets. The process begins with the encoding of auxiliary information into a high-dimensional space using deep neural networks. For instance, text reviews are transformed into vector representations using Word2Vec sets. Let the vector representations of words in a review be represented by $w1,w2,...,wn$, where n is the number of words in the review. The attention mechanism assigns a weight to each word in the review based on its relevance to the user's preferences and the item's characteristics for different use case scenarios. The weights are computed using a trainable attention layer, which is formulated via equation 12,

$$ai = f(wi, u, v) \dots (12)$$

Where, ai is the attention weight for word i, f represents the attention function, u is the user representation, and v is the item representation. The attention weights are then normalized using a softmax function via equation 13,

$$\alpha i = \frac{exp(ai)}{\sum exp(aj)} \dots (13)$$

The normalized weights αi highlight the significance of each word relative to the user-item pair. The context vector for the review, which aggregates the information from all words, is calculated as a weighted sum of the word vectors via equation 14,

$$c = \sum \alpha i * wi \dots (14)$$

This context vector serves as a distilled representation of the review, capturing the aspects most pertinent to the user's preferences and the item's features. Incorporating image features involves a similar process. Images associated with items is processed through convolutional neural networks (CNNs) to extract feature vectors for different use case scenarios. Suppose $x1,x2,...,xm$ represent the feature vectors obtained from different segments of the image sets. The attention mechanism is then applied to these vectors to focus on the most relevant segments, using equations analogous to those used for text reviews. The comprehensive representation derived from both textual and visual auxiliary information is subsequently utilized to enhance the user-item interaction model. This model takes the form of a neural network that combines the user and item latent factors with the context vectors from auxiliary information via equation 15,

$$rui = g(u, v, ctext, cimage) \dots (15)$$

Where, *rui* represents the predicted rating or preference score, *g* represents the neural network function, and *ctext* and *cimage* are the context vectors for text and image information, respectively. The training of the model involves adjusting the parameters to minimize mean squared error, which measures the discrepancy between predicted and actual ratings, and is estimated via equation 16,

$$L = \frac{1}{N} \sum_{(u,i)\in D} (rui - r'ui)^2 + \lambda(\| \theta \|^2) \dots (16)$$

Where, *N* is the number of user-item pairs in the dataset *D*, *r*'*ui* is the actual rating, and Θ represents the set of all parameters in the model, with λ acting as the regularization parameter to prevent overfitting scenarios.

Next, we integrate a multifaceted approach leveraging the Contextual Bandits with Multi-Armed Bandit Algorithms, Approximate Nearest Neighbors (ANN) Search, and Ensemble Learning with Model Stacking has emerged, addressing the dynamic and complex nature of user preferences and interactions for different use case scenarios. This advanced methodological amalgamation embodies the forefront of adaptive, efficient, and precise recommendation techniques, tailored to meet the evolving needs of users and systems alike in real-time settings. The inception of the design revolves around the Contextual Bandits with Multi-Armed Bandit (MAB) framework, an approach that adeptly balances exploration and exploitation to optimize recommendations in real-time scenarios. The core of this method lies in the algorithmic formulation, where at each timestamp *t*, the system selects an arm *at* (representing a specific recommendation) based on the current context *xt* (encompassing user and environmental features), aiming to maximize the expected rewards. The decision process is articulated through the expected reward function *E*[*rt*|*xt*,*at*], where *rt* represents the reward at timestamp *t* instance sets. The policy π guiding this selection is iteratively refined based on observed feedback, embodying the essence of the bandit solution via equations 17,

$$at = argamax(\theta a^T * xt + xt^T * S(a-1)xt) \dots (17)$$

Where, θa is the parameter vector for arm *a*, and *Sa* is the covariance matrix representing the uncertainty in the estimations for arm *a* in the process. The update mechanisms following feedback reception further encapsulate the model's adaptive nature, are represented via equations 18 & 19,

$$\theta a \leftarrow \theta a + S(a-1)xt(r(t-\theta)a^T xt) \dots (18)$$

$$Sa \leftarrow Sa - Sa * xt * \frac{xt^T Sa}{1 + xt^T Sa * xt} \dots (19)$$

Simultaneously, the design harnesses the power of Approximate Nearest Neighbors (ANN) Search to expedite the identification of similar users or items, thereby streamlining the recommendation process. The operation of ANN is encapsulated in the Locality-Sensitive Hashing (LSH) algorithm, which maps high-dimensional data into a lower-dimensional space to facilitate rapid neighbor searches. The formulation and execution of LSH are delineated by equations defining the hash functions *h*(*x*) and the bucket assignments for data points, enabling the efficient retrieval of items or users with analogous characteristics via equation 20,

$$g(x) = \big(h1(x), h2(x), \dots, hk(x)\big) \dots (20)$$

Where, *g*(*x*) represents the composite hash function, and *hi*(*x*) are individual hash functions designed to maximize the probability of "similar" items colliding in the hash space sets. Finally, the incorporation of Ensemble Learning with Model Stacking signifies a paradigm shift in recommendation accuracy and robustness. By amalgamating diverse models, this approach mitigates individual biases and captures a comprehensive spectrum of user-item interaction patterns. The ensemble is constructed through a two-tiered structure where base recommenders produce initial predictions, which are subsequently integrated by a meta-learner to yield the final recommendation outputs. This hierarchical structure is mathematically formulated via equation 21,

$$y' = fmeta\big(\textstyle\sum \alpha i * fi(x)\big) \dots (21)$$

Where, *fmeta* represents the meta-learner, *fi*(*x*) are the base learner predictions, and αi are the weights assigned to each base learner, optimized to enhance overall prediction performance levels. The blending of predictions is designed to exploit the distinct strengths of each base model, culminating in a refined and harmonized output via equation 22,

$$\alpha i = arg\alpha min \textstyle\sum \big(y - \sum \alpha i * fi(x)\big)^2 + \lambda \| \alpha \|^2 \dots (22)$$

Where, y represents the true outcome, and λ is the regularization parameter controlling the complexity of the ensemble process. The fusion of these advanced methodologies within the recommendation context — from the real-time adaptiveness of Contextual Bandits to the computational efficiency of ANN Search and the accuracy refinement of Ensemble Learning — culminates in a sophisticated system architectural process. This architecture adeptly addresses the intricacies of user-item interactions and evolving preferences, setting a new benchmark in personalized recommendation systems. Through rigorous mathematical formulation and strategic integration of diverse algorithms, this comprehensive design paves the way for a new era of recommendation engines, characterized by their adaptability, efficiency, and precision, ultimately enhancing user engagement and satisfaction levels. Next, we discuss results of the proposed model in terms of different scenarios, and compare with existing methods which will assist readers to identify superiority of the proposed model over recently proposed methods.

4. RESULTS AND ANALYSIS

The experimental setup for evaluating the efficacy of the proposed hybrid recommendation system is meticulously designed to ensure rigorous assessment and reproducibility. This section delineates the comprehensive structure of the experiments, including the datasets utilized, parameter settings, evaluation metrics, and comparative baselines.

Datasets: The experiments are conducted on three contextual datasets, selected for their diversity in content, context, and user interaction patterns. These are:

1. **MovieLens 20M Dataset**: This dataset encompasses 20 million ratings applied across 27,000 movies by 138,000 users. It includes user-generated tags, movie genres, and timestamps, serving as a robust foundation for evaluating movie recommendations.
2. **Amazon Electronics Dataset**: Comprising user reviews and metadata for electronics products, this dataset facilitates the assessment of recommendations in e-commerce contexts. It includes around 1.6 million reviews, product descriptions, and user-item interactions.
3. **Yelp Business Review Dataset**: This dataset includes business reviews and user interactions within the Yelp platform, offering a rich source of textual reviews, business attributes, and user preferences for local business recommendations.

Parameter Settings: For the Matrix Factorization with Side Information model, the latent factor dimensionality (k) is set to 100. Regularization parameters λ and β are optimized through cross-validation, initially set to 0.01. The learning rate for gradient descent is initially set at 0.005.

For Deep Learning with Attention Mechanisms, the dimension of the embedding layers is set to 128. The attention layer consists of 64 hidden units, employing the softmax function to calculate weights. The network is trained with a batch size of 256 over 30 epochs, using Adam optimizer with a learning rate of 0.001.

Contextual Bandits with Multi-Armed Bandit Algorithms are implemented with an exploration-exploitation parameter (ε) set initially at 0.1, decrementing over time to encourage exploitation of learned strategies. The context dimensions are aligned with the specific dataset characteristics.

In the Approximate Nearest Neighbors (ANN) Search, the number of hash tables is set to 10, and the hash size to 15 for the Locality-Sensitive Hashing (LSH) algorithm, balancing between accuracy and computational efficiency.

For Ensemble Learning with Model Stacking, three individual models are initially chosen: Matrix Factorization, a deep learning-based model, and a contextual bandit model. The ensemble is trained using a simple linear regression model to combine the outputs of the individual models.

Some Contextual Datasets Details: Each dataset is preprocessed to include contextual information relevant to the recommendation scenario:

- **MovieLens 20M**: Contextual information includes time of day and day of the week of the ratings, aiming to capture temporal viewing preferences.
- **Amazon Electronics**: Context includes the length of the review, the helpfulness score, and the product category, offering insights into user preferences and product specifics.
- **Yelp Business Review Dataset**: The context consists of the time of the review, the type of business, and the location, aiming to understand preferences based on time, service type, and geographical relevance sets.

Evaluation Metrics: The performance of the proposed system is evaluated using metrics such as Precision@k, Recall@k, and F1-Score@k for various values of k (e.g., 5, 10, 20). Additionally, Mean Average Precision (MAP) and Normalized Discounted Cumulative Gain (NDCG) are utilized to assess the quality of the ranked recommendations.

Comparative Baselines: The proposed system is benchmarked against several state-of-the-art recommendation algorithms, including standard collaborative filtering, pure content-based models, traditional matrix factorization, and existing hybrid models without deep learning or contextual bandits.

The experimental setup aims to provide a comprehensive and rigorous evaluation of the proposed hybrid recommendation system, facilitating a deep understanding of its performance characteristics across different contexts and datasets. The inclusion of diverse datasets and detailed parameter settings ensures that the experiments are well-grounded and reflective of real-world recommendation scenarios.

Based on this setup, we delve into the evaluation results of the proposed hybrid recommendation system as compared with established methodologies indicated as [5], [12], and [22] across three datasets: MovieLens, Amazon Electronics, and Yelp Business Review. Each table showcases metrics such as Precision@10, Recall@10, F1-Score@10, MAP, and NDCG, providing a comprehensive assessment of recommendation quality and relevance sets.

TABLE II. PERFORMANCE EVALUATION ON THE MOVIELENS DATASET

Method	Precision@10	Recall@10	F1-Score@10	MAP	NDCG
[5]	0.072	0.055	0.062	0.069	0.080
[12]	0.076	0.060	0.067	0.073	0.084
[22]	0.080	0.065	0.072	0.077	0.088
Proposed Model	0.094	0.078	0.085	0.090	0.103

In Table II, the proposed model demonstrates superior performance across all metrics on the MovieLens dataset. Notably, the Precision@10 improved by 14.4% over method [22], the best-performing baseline. This enhancement is attributed to the effective integration of user-item interactions and auxiliary information, significantly refining the recommendation relevance and accuracy.

TABLE III. PERFORMANCE EVALUATION ON THE AMAZON ELECTRONICS DATASET

Method	Precision@10	Recall@10	F1-Score@10	MAP	NDCG
[5]	0.045	0.030	0.036	0.042	0.050
[12]	0.048	0.033	0.039	0.045	0.054
[22]	0.052	0.037	0.043	0.049	0.058
Proposed Model	0.065	0.049	0.056	0.062	0.071

Table III presents the performance on the Amazon Electronics dataset, where the proposed model again outperforms the baseline methods. The Precision@10 and Recall@10 show significant improvements, highlighting the model's ability to leverage deep learning and contextual information effectively in e-commerce environments.

TABLE IV. PERFORMANCE EVALUATION ON THE YELP BUSINESS REVIEW DATASET

Method	Precision@10	Recall@10	F1-Score@10	MAP	NDCG
[5]	0.068	0.050	0.058	0.064	0.073
[12]	0.072	0.054	0.062	0.068	0.077
[22]	0.075	0.058	0.065	0.071	0.081
Proposed Model	0.089	0.072	0.080	0.085	0.095

In Table IV, assessing the Yelp Business Review dataset, the proposed model exhibits superior performance, particularly in handling rich and diverse user-generated content. The improvements in MAP and NDCG indicate the model's enhanced capability in providing relevant and localized business recommendations.

TABLE V: OVERALL PERFORMANCE COMPARISON

Dataset	Improvement in Precision@10	Improvement in Recall@10	Improvement in F1-Score@10	Improvement in MAP	Improvement in NDCG
MovieLens	17.5%	20.0%	18.1%	16.9%	17.0%
Amazon Electronics	25.0%	32.4%	30.2%	26.5%	22.4%
Yelp Business Review	18.7%	24.1%	23.1%	19.7%	17.3%

Table V encapsulates the overall performance enhancement achieved by the proposed model across all datasets. The notable improvements underscore the effectiveness of the model in harnessing the synergy between multiple recommendation approaches, particularly in handling complex and contextually rich environments.

The empirical results underscore the substantial impact of the proposed hybrid recommendation system, especially in addressing the nuanced demands of modern recommendation scenarios. The integration of matrix factorization with side information, coupled with deep learning and attention mechanisms, provides a nuanced understanding of user preferences and item characteristics. Meanwhile, the application of contextual bandits and ensemble learning techniques further refines the recommendation process, ensuring dynamic adaptability and robustness. These demonstrated enhancements in recommendation performance affirm the proposed model's capacity to provide highly relevant, accurate, and personalized recommendations, thereby significantly elevating the user experience and engagement across diverse platforms and datasets & its samples. Next, we discuss a practical use case of the proposed model, which will assist readers to further understand its characteristics in real-time scenarios.

Practical Use Case

In this section, we elaborate on the application and outcomes of various components constituting our advanced recommendation system framework. Through detailed tabular presentations, we simulate the processing flow and output generation at each phase of the system. These tables serve to illustrate the interplay between different data features, methodologies, and resultant recommendation outputs, showcasing the multifaceted capabilities of the proposed model.

Our recommendation system employs a sequence of sophisticated processes to refine and tailor recommendations. Initially, user-item interaction data, augmented by a set of diverse features, is fed into the system. These features may include, but are not limited to, user demographic information, historical interaction patterns, item characteristics, and contextual details such as time and location. The ensuing steps involve the application of various algorithms and techniques designed to enhance the recommendation's relevance and personalization. Each component within the framework, from Matrix Factorization with Side Information to Ensemble Learning with Model Stacking, leverages this data differently to contribute to the final recommendation output.

TABLE VI. OUTPUTS FROM HYBRID RECOMMENDATION SYSTEM

User ID	Item ID	Predicted Rating	Recommendation Score
U1	I1	4.5	0.92
U1	I2	3.8	0.75
U2	I1	3.2	0.65
U2	I3	4.7	0.95

TABLE VII. MATRIX FACTORIZATION WITH SIDE INFORMATION OUTPUTS

User ID	Item ID	Predicted Rating	Side Information Contribution
U1	I1	4.3	0.20
U1	I2	3.9	0.15
U2	I1	3.5	0.25
U2	I3	4.8	0.30

TABLE VIII: DEEP LEARNING WITH ATTENTION MECHANISMS OUTPUTS

User ID	Item ID	Attention Score	Enhanced Prediction
U1	I1	0.88	4.6
U1	I2	0.55	3.7
U2	I1	0.60	3.3
U2	I3	0.93	4.9

TABLE IX. CONTEXTUAL BANDITS WITH MULTI-ARMED BANDIT ALGORITHMS OUTPUTS

User ID	Context	Selected Arm	Reward
U1	Evening	I1	0.9
U1	Morning	I2	0.7
U2	Evening	I3	0.95
U2	Morning	I1	0.65

TABLE X. APPROXIMATE NEAREST NEIGHBORS (ANN) SEARCH OUTPUTS

User ID	Nearest Neighbor	Similarity Score
U1	U3	0.89
U1	U4	0.75
U2	U5	0.93
U2	U6	0.88

TABLE XI. ENSEMBLE LEARNING WITH MODEL STACKING OUTPUTS

User ID	Final Predicted Rating	Final Recommendation Score
U1	4.55	0.94
U1	3.85	0.78
U2	3.25	0.67
U2	4.85	0.97

The tables VI, VII, VIII, IX, X & XI encapsulate the progressive refinement and complexity imbued in the recommendation process through the system's multifaceted components in different scenarios. From initial hybrid recommendations to nuanced outputs incorporating side information and contextual variables, the data delineates a trajectory of increasing personalization and accuracy. The Hybrid Recommendation System (Table VI) initiates the process, providing baseline scores based on integrated methodologies. Subsequently, the role of side information is quantified in Table VII, enhancing the foundational matrix factorization outcomes by aligning predictions more closely with user and item specifics.

Deep Learning with Attention Mechanisms (Table VIII) further refines predictions by prioritizing critical features, thereby sharpening the focus of the recommendations based on user and item attributes that are deemed most relevant through learned attention scores. This leads to enhanced predictions that are more attuned to individual user preferences and contexts.

The outputs from the Contextual Bandits with Multi-Armed Bandit Algorithms (Table IX) underscore the dynamic adaptation of the recommendation process based on real-time user context and interactions in practical scenarios. This approach personalizes recommendations further by learning from and reacting to the user's immediate environment and feedback, resulting in a more responsive and engaging user experience. The Approximate Nearest Neighbors (ANN) Search (Table X) showcases the system's capability to efficiently identify users with similar tastes and preferences, thereby facilitating the generation of recommendations that are likely to be of interest to the user, based on the preferences of similar individuals. This component significantly contributes to the scalability and speed of the recommendation process, essential for handling large-scale datasets & samples.

Finally, Ensemble Learning with Model Stacking (Table XI) synthesizes the outputs from various models to produce a final set of predictions. This approach leverages the strengths of individual recommendation components while mitigating their weaknesses, culminating in a robust set of recommendations characterized by improved accuracy and relevance levels. In conclusion, the detailed tables and their corresponding analyses illustrate the intricate workings and synergistic effects of the various components of the proposed recommendation system. By progressively enhancing the recommendations through each stage of the system, we achieve a high degree of personalization and accuracy, catering to the diverse needs and preferences of users. This systematic approach underscores the potential of combining multiple recommendation techniques and underscores the effectiveness of our proposed system in delivering superior recommendation services. The future scope involves exploring further enhancements in each component, integrating additional contextual and auxiliary information, and applying advanced machine learning techniques to continuously evolve the recommendation process. This ongoing refinement and adaptation promise to keep the system at the forefront of recommendation technology, ensuring its relevance and efficacy in an ever-changing digital landscape.

5. CONCLUSION & FUTURE WORK

In this study, we presented a comprehensive hybrid recommendation system that integrates various advanced methodologies, including Matrix Factorization with Side Information, Deep Learning with Attention Mechanisms, Contextual Bandits with Multi-Armed Bandit Algorithms, Approximate Nearest Neighbors (ANN) Search, and Ensemble Learning with Model Stacking. This innovative amalgamation was meticulously designed to address the multifaceted challenges faced by contemporary recommender systems, such as the cold start problem, lack of personalization, and computational inefficiency scenarios.

The empirical evaluation, conducted across diverse and complex datasets including MovieLens, Amazon Electronics, and Yelp Business Review, demonstrated the superior performance of the proposed system over existing methodologies referenced as [5], [12], and [22]. Significant improvements were observed across all major metrics, including Precision@10, Recall@10, F1-Score@10, MAP, and NDCG. These results underscore the effectiveness of the proposed approach in harnessing the synergistic potential of combining different recommendation strategies, leading to more accurate, personalized, and contextually relevant recommendations.

The integration of matrix factorization with side information notably enhanced the system's ability to leverage both explicit and implicit data sources, thereby improving the quality and relevance of recommendations. Meanwhile, the incorporation of deep learning with attention mechanisms allowed for a more nuanced interpretation of complex user and item features, including textual and visual content. Contextual bandits with multi-armed bandit algorithms provided a robust framework for dynamically updating user profiles and adapting recommendations in real-time, reflecting the evolving preferences of users. The use of ANN search techniques significantly reduced computational overhead, enhancing the scalability and responsiveness of the system. Finally, ensemble learning with model stacking further augmented the prediction accuracy by effectively combining insights from multiple recommendation models.

Future Scope:

Looking ahead, several avenues for further research and development is identified. First, exploring additional types of side information and alternative deep learning architectures could provide new insights and enhancements to the recommendation process. For instance, incorporating audio, video, and more sophisticated natural language processing techniques could enrich the system's understanding of content and user preferences.

Second, the application of advanced reinforcement learning and transfer learning methods could further refine the adaptive capabilities of the system, enabling it to respond more effectively to changing environments and user dynamics. Investigating the potential of federated learning approaches could also contribute to privacy-preserving recommendation strategies, a growing concern in the era of data privacy regulations.

Third, the scalability and efficiency of the system could be further improved by exploring novel data indexing and retrieval methods, as well as more efficient computation paradigms such as edge computing. These enhancements would be particularly beneficial in handling the increasing volumes of data characteristic of modern digital platforms.

Finally, conducting extensive user studies and real-world deployment trials would provide invaluable feedback for refining the system and better understanding the practical challenges and user experiences associated with advanced recommendation systems.

In conclusion, this research contributes significantly to the field of recommender systems, offering a robust, flexible, and efficient framework that addresses current challenges while laying the groundwork for future advancements. The promising results achieved thus far encourage continued exploration and innovation in this dynamic and impactful domain for real-time scenarios.

6. REFERENCES

[1] Q. -H. Le, T. N. Mau, R. Tansuchat and V. -N. Huynh, "A Multi-Criteria Collaborative Filtering Approach Using Deep Learning and Dempster-Shafer Theory for Hotel Recommendations," in IEEE Access, vol. 10, pp. 37281-37293, 2022, doi: 10.1109/ACCESS.2022.3165310.
keywords: {Collaboration;Predictive models;Deep learning;Matrix decomposition;Uncertainty;Tensors;Computational modeling;Collaborative filtering;multi-criteria collaborative filtering;matrix factorization;deep learning;Dempster-Shafer theory},

[2] S. Poudel and M. Bikdash, "Optimal Dependence of Performance and Efficiency of Collaborative Filtering on Random Stratified Subsampling," in Big Data Mining and Analytics, vol. 5, no. 3, pp. 192-205, September 2022, doi: 10.26599/BDMA.2021.9020032.
keywords: {Training;Filtering;Collaborative filtering;Linear regression;Clustering algorithms;Data models;Reliability;Collaborative Filtering (CF);subsampling;Training Time Improvement (TTI);performance loss;Recommendation System (RS);collaborative filtering optimal solutions;rating matrix},

[3] B. Jiang, J. Yang, Y. Qin, T. Wang, M. Wang and W. Pan, "A Service Recommendation Algorithm Based on Knowledge Graph and Collaborative Filtering," in IEEE Access, vol. 9, pp. 50880-50892, 2021, doi: 10.1109/ACCESS.2021.3068570.
keywords: {Mashups;Collaborative filtering;Feature extraction;Filtering;Collaboration;Computational modeling;Web API recommendation;knowledge graph;representation learning;collaborative filtering},

[4] M. Ibrahim, I. S. Bajwa, N. Sarwar, F. Hajjej and H. A. Sakr, "An Intelligent Hybrid Neural Collaborative Filtering Approach for True Recommendations," in IEEE Access, vol. 11, pp. 64831-64849, 2023, doi: 10.1109/ACCESS.2023.3289751.
keywords: {Recommender systems;Collaborative filtering;Sentiment analysis;Motion pictures;Deep learning;Standards;Predictive models;Hierarchal user attention product attention (HUAPA);deep collaborative filtering (DCF);neural sentiment classification (NSC);deep multivariate rating (DMR);recommendation system (RS)},

[5] X. Feixiang, "Intelligent Personalized Recommendation Method Based on Optimized Collaborative Filtering Algorithm in Primary and Secondary Education Resource System," in IEEE Access, vol. 12, pp. 28860-28872, 2024, doi: 10.1109/ACCESS.2024.3365549.
keywords: {Education;Recommender systems;Collaborative filtering;Computational modeling;Prediction algorithms;Optimization;Data models;Educational programs;Electronic learning;Collaborative filtering;content recommendation;personalization;educational resources;primary and secondary schools},

[6] H. Deng, C. Zhai and L. Zheng, "Neural Collaborative Filtering for Chinese Movies Based on Aspect-Aware Implicit Interactions," in IEEE Access, vol. 10, pp. 114540-114551, 2022, doi: 10.1109/ACCESS.2022.3217911.
keywords: {Data mining;Motion pictures;Feature extraction;Collaborative filtering;Neural networks;Deep learning;Grammar;User experience;Performance evaluation;Aspect-aware implicit interactions;collaborative filtering;tensor factorization;deep learning;Chinese comment mining},

[7] W. Lin et al., "A Deep Neural Collaborative Filtering Based Service Recommendation Method with Multi-Source Data for Smart Cloud-Edge Collaboration Applications," in Tsinghua Science and Technology, vol. 29, no. 3, pp. 897-910, June 2024, doi: 10.26599/TST.2023.9010050.
keywords: {Computational modeling;Collaborative filtering;Noise reduction;Collaboration;Memory;Big Data;Feature extraction;deep neural collaborative filtering;multi-source data;cloud-edge collaboration application;stacked denoising auto encoder;multiple layer perceptron},

[8] I. Saifudin and T. Widiyaningtyas, "Systematic Literature Review on Recommender System: Approach, Problem, Evaluation Techniques, Datasets," in IEEE Access, vol. 12, pp. 19827-19847, 2024, doi: 10.1109/ACCESS.2024.3359274.
keywords: {Recommender systems;Collaborative filtering;Systematics;Manuals;Internet;Content-based retrieval;Information filtering;Content-based filtering;collaborative filtering;hybrid filtering;systematic literature review;recommender system},

[9] S. Benkessirat, N. Boustia and R. Nachida, "A New Collaborative Filtering Approach Based on Game Theory for Recommendation Systems," in Journal of Web Engineering, vol. 20, no. 2, pp. 303-326, March 2021, doi: 10.13052/jwe1540-9589.2024.
keywords: {Measurement;Preforms;Collaborative filtering;Scalability;Clustering algorithms;Ontologies;Prediction algorithms;Recommendation systems;collaborative filtering;cooperative game theory;Shapley Value},

[10] Y. Sun, W. Tan, L. Huang, N. Xie, L. Ruan and L. Da Xu, "An Integrated Collaborative Filtering Framework With Location-Aware Graph Embedding in Intelligent Internet of Things Systems," in IEEE Transactions on Aerospace and Electronic Systems, vol. 58, no. 6, pp. 5089-5104, Dec. 2022, doi: 10.1109/TAES.2022.3213631.
keywords: {Internet of Things;Reliability;Semantics;Security;Task analysis;Privacy;Collaborative filtering;Graph network

embedding;integration information systems;intelligent systems;Internet of Things (IoT);reliable IoT service discovery},

[11] D. Seng, M. Li, X. Zhang and J. Wang, "Research on Neural Graph Collaborative Filtering Recommendation Model Fused With Item Temporal Sequence Relationships," in IEEE Access, vol. 10, pp. 116972-116981, 2022, doi: 10.1109/ACCESS.2022.3215161.
keywords: {Collaboration;Bipartite graph;Recommender systems;Graph neural networks;Symbols;Aggregates;Sequential analysis;Neural graph collaborative filtering;item temporal sequence;sequential recommendation},

[12] I. Tanuma and T. Matsui, "Rating Proportion-Aware Binomial Matrix Factorization for Collaborative Filtering," in IEEE Access, vol. 11, pp. 85097-85107, 2023, doi: 10.1109/ACCESS.2023.3303322.
keywords: {Collaborative filtering;Linear programming;IP networks;Recommender systems;Neural networks;Probabilistic logic;Indexes;Collaborative filtering;matrix factorization;recommendation system;treatment of biases},

[13] F. Wang, H. Zhu, G. Srivastava, S. Li, M. R. Khosravi and L. Qi, "Robust Collaborative Filtering Recommendation With User-Item-Trust Records," in IEEE Transactions on Computational Social Systems, vol. 9, no. 4, pp. 986-996, Aug. 2022, doi: 10.1109/TCSS.2021.3064213.
keywords: {Web services;Robustness;Computer science;Collaboration;Social networking (online);Recommender systems;Proposals;Cold-start problems;collaborative filtering (CF);rating prediction;recommendation;user trust},

[14] W. Yue, Z. Wang, B. Tian, M. Pook and X. Liu, "A Hybrid Model-and Memory-Based Collaborative Filtering Algorithm for Baseline Data Prediction of Friedreich's Ataxia Patients," in IEEE Transactions on Industrial Informatics, vol. 17, no. 2, pp. 1428-1437, Feb. 2021, doi: 10.1109/TII.2020.2984540.
keywords: {Prediction algorithms;Data models;Predictive models;Data collection;Europe;Diseases;Analytical models;Collaborative filtering (CF);Friedreich's ataxia;Jaccard index; K -means clustering;Shannon entropy},

[15] N. Sakib et al., "A Hybrid Personalized Scientific Paper Recommendation Approach Integrating Public Contextual Metadata," in IEEE Access, vol. 9, pp. 83080-83091, 2021, doi: 10.1109/ACCESS.2021.3086964.
keywords: {Metadata;Collaborative filtering;Filtering;Feature extraction;Context modeling;Recommender systems;Computer science;Scientific paper recommendation;public contextual metadata;content-based filtering;collaborative filtering;hybrid approach},

[16] M. Di-Fei, L. Na, L. Ming-Xia and S. Hao-Long, "An Improved Dynamic Collaborative Filtering Algorithm Based on LDA," in IEEE Access, vol. 9, pp. 122568-122577, 2021, doi: 10.1109/ACCESS.2021.3094519.
keywords: {Heuristic algorithms;Prediction algorithms;Computational modeling;Time factors;Recommender systems;Hybrid power systems;Collaborative filtering;LDA;topic model;time tag},

[17] F. Chen, C. Lu, Y. Cui and Y. Gao, "Learning Outcome Modeling in Computer-Based Assessments for Learning: A Sequential Deep Collaborative Filtering Approach," in IEEE Transactions on Learning Technologies, vol. 16, no. 2, pp. 243-255, 1 April 2023, doi: 10.1109/TLT.2022.3224075.
keywords: {Data models;Predictive models;Computational modeling;Bayes methods;Recommender systems;Deep learning;Collaboration;Attentive modeling;collaborative filtering (CF);deep learning;item-skill associations;learning outcome modeling;recurrent neural networks (RNNs)},

[18] Y. Chen, C. Feng and D. Feng, "Privacy-Preserving Hierarchical Federated Recommendation Systems," in IEEE Communications Letters, vol. 27, no. 5, pp. 1312-1316, May 2023, doi: 10.1109/LCOMM.2023.3245101.
keywords: {Servers;Data privacy;Collaborative filtering;Privacy;Data models;Sparse matrices;Federated learning;Recommendation system;collaborative filtering;federated learning;privacy protection;communication efficiency},

[19] K. Yao, H. Wang, Y. Li, J. J. P. C. Rodrigues and V. H. C. de Albuquerque, "A Group Discovery Method Based on Collaborative Filtering and Knowledge Graph for IoT Scenarios," in IEEE Transactions on Computational Social Systems, vol. 9, no. 1, pp. 279-290, Feb. 2022, doi: 10.1109/TCSS.2021.3050622.
keywords: {Collaboration;Feature extraction;Knowledge engineering;Internet of Things;Prediction algorithms;Electronic mail;Semantics;Collaborative filtering;group discovery;Internet of Things (IoT);knowledge graph},

[20] J. -i. Furukawa, S. Chiyohara, T. Teramae, A. Takai and J. Morimoto, "A Collaborative Filtering Approach Toward Plug-and-Play Myoelectric Robot Control," in IEEE Transactions on Human-Machine Systems, vol. 51, no. 5, pp. 514-523, Oct. 2021, doi: 10.1109/THMS.2021.3098115.
keywords: {Electromyography;Torque;Muscles;Robots;Collaboration;Elbow;Robot sensing systems;Calibration process reduction;collaborative filtering;electromyography (EMG);motion estimation;myoelectric control},

[21] E. Tong, W. Niu and J. Liu, "A Missing QoS Prediction Approach via Time-Aware Collaborative Filtering," in IEEE Transactions on Services Computing, vol. 15, no. 6, pp. 3115-3128, 1 Nov.-Dec. 2022, doi: 10.1109/TSC.2021.3103769.
keywords: {Quality of service;Collaboration;Web services;Time factors;Correlation;Motion pictures;Collaborative filtering;QoS prediction;time-aware;collaborative filtering;service recommendation},

[22] Z. Zhang, M. Dong, K. Ota, Y. Zhang and Y. Ren, "LBCF: A Link-Based Collaborative Filtering for Overfitting Problem in Recommender System," in IEEE Transactions on Computational Social Systems, vol. 8, no. 6, pp. 1450-1464, Dec. 2021, doi: 10.1109/TCSS.2021.3081424.
keywords: {Collaborative filtering;Recommender systems;Motion pictures;Collaborative filtering (CF);link partition;link reduction;overfitting;recommender system (RS)},

[23] K. Gaiger, O. Barkan, S. Tsipory-Samuel and N. Koenigstein, "Not All Memories Created Equal: Dynamic User Representations for Collaborative Filtering," in IEEE Access, vol. 11, pp. 34746-34763, 2023, doi: 10.1109/ACCESS.2023.3263931.
keywords: {Motion pictures;Collaborative filtering;Recommender systems;Brain modeling;Adaptation models;Context modeling;Transformers;Artificial neural networks;collaborative filtering;neural attention;recommender systems},

[24] G. Liu, L. Zhang and J. Wu, "Beyond Similarity: Relation-Based Collaborative Filtering," in IEEE Transactions on Knowledge and Data Engineering, vol. 35, no. 1, pp. 128-140, 1 Jan. 2023, doi: 10.1109/TKDE.2021.3099217.
keywords: {Motion pictures;Deep learning;Collaboration;History;Color;Collaborative filtering;Toy manufacturing industry;Collaborative filtering;relation embedding;memory attention;recommendation},

[25] T. T. Tran, V. Snasel and L. T. Nguyen, "Combining Social Relations and Interaction Data in Recommender System With Graph Convolution Collaborative Filtering," in IEEE Access, vol. 11, pp. 139759-139770, 2023, doi: 10.1109/ACCESS.2023.3340209.

keywords: {Matrix decomposition;Recommender systems;Data models;Collaborative filtering;Social networking (online);Matrix converters;Electronic commerce;Recommendation system;social recommender system;collaborative filtering;graph convolution network},