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Recommendation Architecture: Adaptive Hybrid: Implicit Social Profiling with Synergizing RNN to Mitigate cold start

K Lahari

Research Scholar, Department of Computer Science and Engineering Vels Institute of Science Technology & Advanced Studies Chennai, Tamilnadu, India. laharikaipa@gmail.com

Dr. A. Manikandan

Associate Professor, Department of Computer Science and Engineering Vels Institute of Science Technology & Advanced Studies Chennai, Tamilnadu, India. mani.se@velsuniv.ac.in

Abstract. The Recommender Systems (RS) have taken the shape of modern digital user experience stalwart though they keep experiencing a challenge which remains very critical and stubborn the Cold Start challenge. Once a new user enters a platform, the historical interaction information is not available and this makes traditional Collaborative Filtering algorithms useless. The current solutions will tend to use the static demographic data which cannot reflect the dynamism of the user preferences. This paper posits that the problem is not needing more explicit cues in users, but ought to seek to exploit better the implicit cues users do produce. Our suggestion is Two Stages Content-Boosted Collaborative Filtering (TS-CBCF). At the first stage we use implicit Social Profiling, where we extract behavioral phenotypes (e.g. activity timing, social connectivity) to construct a full initial user matrix. The user engages with the system and we enter a Deep Learning phase with the help of the Long Short-Term Memory (LSTM) networks to observe the preference evolution. We provide a detailed comparative study with the state-of-the-art methodologies, and we prove that our hybrid framework provides a higher degree of resilience in high sparsity settings coupled with more advanced privacy and scalability issues of standard ones.

Keywords: Cold Start Problem, Implicit Social Data, Recurrent Neural Networks, LSTM, Frequent Pattern Mining, Hybrid Recommender Systems.

Introduction

The digital content has increased exponentially thus producing a paradox of choice. Users are experiencing an ocean of choices whether on the streaming sites, e-commerce sites or the social networks. The filter that is required is Recommender Systems (RS) which predicts user intent to create personalized experience. Nonetheless, the strength of these systems is strongly related to the amount of data density. This dependence poses a serious obstacle in the form of the so-called Cold Start problem.

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1.1 The Cold Start Dilemma

The only problem is that it is simple but hard to resolve: Collaborative Filtering (CF) the industry standard, is based on the search of the so-called neighbors, who have the same history. The history of an unregistered user (unew) is a null vector. The system is not mathematically able to compute similarity distances which results in random or generic recommendations.

The old-time solutions to this issue are requesting users to complete interest surveys or using demographics within a fixed set (e.g., Age, Gender). We say this is a faulty method because there are two reasons on this:

1. User Friction: The users like smooth sailing onboarding and tend to omit profiling process.

2. Dynamic vs. Static: Age is an unchangeable product of a user, their tastes are dynamic. The profile that is built on purely demographic values does not reveal any behavioral substances, like whether the user would be watching films during the weekends or late nights.

1.2. Motivation and Contribution.

The hypothesis of this study is that the new users do not get explicit rating, but are abundant in implicit information about their behavior. With the metadata of related streams of socialization (e.g. time of activity, network density), we can build a Behavioral Phenotype.

Our architecture is a **Two-Stage Content-Boosted Collaborative Filtering (TS-CBCF) architecture.

• Stage 1 deals with the cold start in the immediate future through mining implicit social patterns to come up with an Affinity Matrix.

• Stage 2 ensures longevity. The task of sequential evolution of user tastes is carried over to Recurrent Neural Network (LSTM) as soon as the data is gathered.

The study fills the gap between content-based static init and dynamic deep learning and offers a one-stop user lifecycle.

2 Related Work

There is a lot of literature about Recommender Systems. It is against this background that we consider the development of the cold-start solutions, so as to put our hybrid solution into perspective.

2.1 The Vices of Traditional Approaches.

The first solutions were based on Matrix Factorization (MF). SVD techniques were popularized by Koren et al. [3], and they are good at the discovery of latent factors in dense matrices. This is however not the case in cold-start situations where matrix sparsity is greater than 99 as MF

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models cannot converge. In response to this, Association Rule Mining (ARM) has been used. Apriori techniques will find rules, which include but are not limited to: {Diapers} → {Beer}. Whereas helpful, standard ARM is characterized by the so-called problem of rare items that frequently disregards niche items that characterize a personal taste of a user. It has been mentioned that this was the limitation of the frequent patterns only and Panteli and Boutsinas [7] provided the context at the expense of frequent patterns only.

2.2 The Deep Learning Shift

Recently, the focus has switched to the Neural Collaborative Filtering (NCF). As was shown by He et al. [5], non-linear interaction between users and items onto neural networks could be better modeled than dot products.

AutoEncoders: Such models as AutoRec involve the use of autoencoders in order to recreate missing ratings. Ignoring the fact that they are accurate, they are computationally expensive and they are not always capable of dealing with time-series data.

- Sequence Models RNNs were used with session data as applied by Wu et al. [6]. It is an encouraging trend because it considers recommendations as sequence prediction task. RNNs however have a coldstart gap that opens as it takes time to warm-up on user data.

2.3 Implicit Social Data

The accumulating research, the work on the CSP Dataset [2] implies that implicit signals are not properly used. The digital traces that users leave behind in the form of the time when they log in, their devices, and social relations are proxies of personality. Our work is based on it by formalizing the conversion of these proxies into the original vectors into which a recommendation engine can be read.

3. Systematic literature reviews

Their review depicted the analysis of building blocks, algorithms and directions of CDRS. They used SLR of 94 studies on CDRS. They organized causes of primary studies into hypothesized classification grids in their paper to demonstrate the trends of research. The review involved the evaluation of the current studies on CDRS, they defined the similarities and divided the major studies, categorized the algorithms, and data sets. Ref. shows that deep learning techniques, such as

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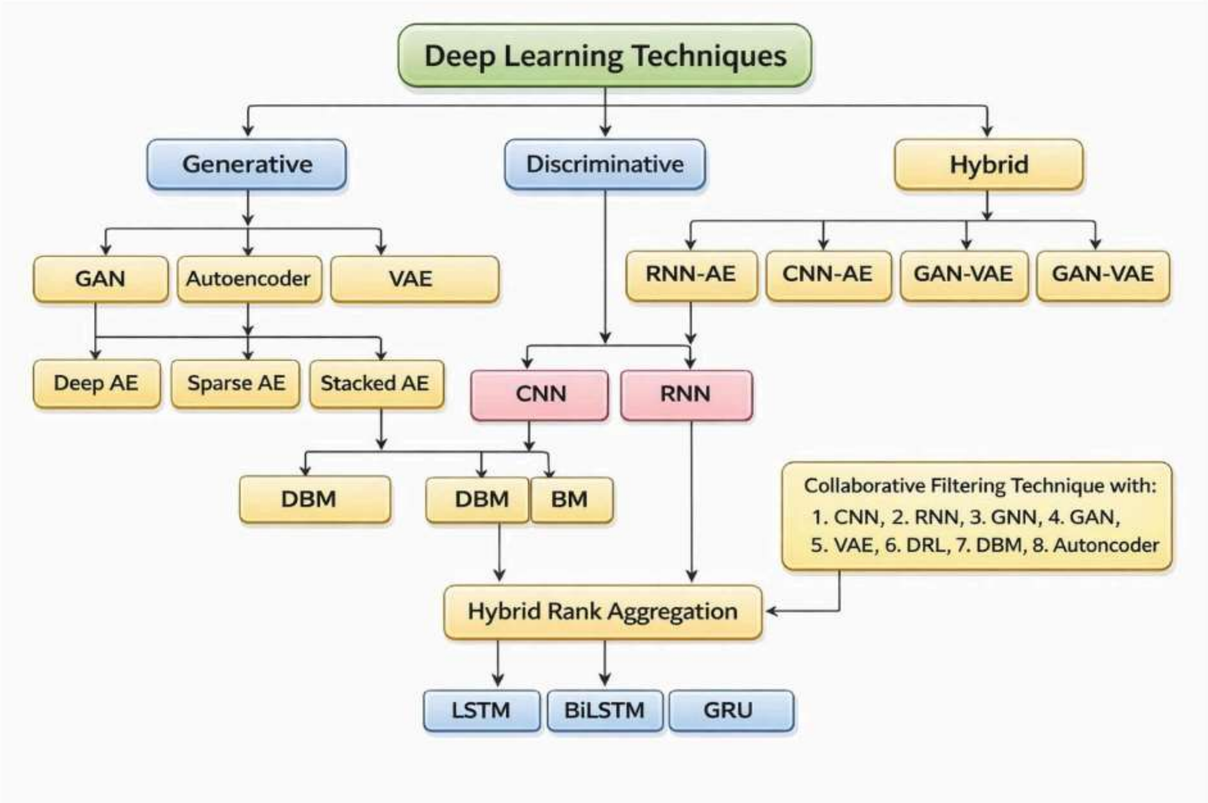

Fig. 1. Classifications of deep learning techniques.

RSs have extensively used CNN, RNN, and GNN. The review indicated the growing field of research in domain classification that presents positive outcomes of domain classification application based on deep learning algorithms fields such as e-commerce, social networks, and e-learning. The literature review satisfies a significant research issue and presents a valuable source of researchers and other professionals interested in using deep learning to recommenders. They introduced the summary of the transfer learning in Ref. [27] to CDRS and MINDTL. In this paper, the author is concerned with CDRS based on deep learning to overcome the problem of cold start and data sparsity in RSs. They have provided paper selection and search query, in their systematic literature review paper which has greatly covered and wrote about methodologies, paper selection and search query. The paper categorizes the methods as memory-based and model-based techniques, the paper also identifies the majorly used neural networks, tools, and the uses. Ref. reviews DL techniques in recommender systems across applications, the paper is dedicated to autoencoders models, CNNs, RNNs, as well as well-known datasets. Their review found out that autoencer models are common in deep learning-based recommenders. The review paper states that Movie lenses and Amazon review datasets are popular to be evaluated using, common metrics are the precision and RMSE. In their systematic review article, the authors provide a taxonomy of deep learning algorithms to

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social recommender systems. This they do by reviewing purposely selected papers systematically by a literature review method. Their systematic review is aimed at providing a brief summary of the available research, which can help the further researchers elaborate new strategies in the field. Lastly, they compared GCN and GNN in their systematic review to crop recommendation carried out based on environmental factors. The article applies chapter models based on graphs to obtain optimal management of crops and allocation of resources.

• Comparison: Unlike the procedure of conducted by where 99 studies published between 2007 and 2018 were reviewed, and Ref. where 46 publications included were review papers published between 2016 and 2022, our review will address the conference papers and published journal articles within the past five years (2019 to 2023), that is, some of the articles were published after that date. The period will enable us to examine the current articles and give us an insight into the most subsequent developments in the field. We choose peer-reviewed conference papers and journal articles in our review due to their high-quality research, reliability, and these sources pass through the thorough examination of specialists and provide in-depth analysis.

Different types of DL models have been applied in CDRS, the models have vastly enhanced the systems to an improved level compared to the conventional approaches.

In Fig. 1 the most used DL models are grouped as such.

Table 1 presents the comparison of the review of the related studies, this will cover the type of review, the reference, year of publication, technique reviewed, year covered and our review. This demonstrates that our SLR differs with the other reviews.

4. Background

4.1. Recommender systems

Recommender systems (RSs) are used to assist a user in finding items or services that the user could be interested in knowing. The significance of RSs in the academic world and the industry nowadays cannot be overestimated. It has been applied by many businesses to promote their products and services through various networks. It is also important in dictating what videos people watch on websites such as YouTube and video streaming websites. It is also useful to the online lives of the users in that it acts as personalized filters to users to find useful items, given its efficiency. RS can be seen as an information filtering system, which is expected to suggest products and services, also known as the items most likely to appeal to a user.RS processes large volumes of information concerning the past behavior, preferences, and interests of its users with the help of the machine learning algorithms such as clustering, collaborative filtering method, and deep neural network to make personalized suggestions. The systems are universal and have been implemented in various areas, e-commerce, education and health

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among others. By using a good recommender structure, the traffic and earnings of service providers can be enhanced, and the user has easy access to the items they desire, which may be movies, books, cars, and tweets among others. Moreover, it can be still stated that there are significant issues needed to enhance RSs like sparsity, cold start, diversity, etc.

Under the traditional recommender systems, we will cover only three major types of recommender systems namely, the content-based method, collaborative filtering techniques and hybrid approaches. The traditional methods in RSs are categorized into different groups as depicted in Fig. 2.

4.1.1. System of recommender based on content.

The content-based (CB) RSs is a system that has been developed to recommend items according to the previous preferences of the user. The aim is to suggest products, which the user has liked in the past. The system creates a profile of the user interests by analyzing the preferred items of the user. CB method mainly rely on user descriptions and item description to give.

Review type	**Reference**	**Main idea**	**Year**	**Year covered**	**Reviewed technique**	**Comparison with our review**
Survey	[32]	Comprehensively reviewed deep learning cross domain recommender systems	2022	N/A	DL	Focuses on recent 5 years
Survey	[33]	Deep learning-based recommender systems for information overload	2019	N/A	DL	Focuses on recent 5 years
Survey	[23]	Reinforcement learning based recommender systems	2023	2005–2022	Reinforcement Learning	Diverse DL techniques
Survey	[34]	Describes current research on deep learning	2019	N/A	DL	Focuses on recent 5 years

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		recommendation systems				
Survey	[35]	Comprehensive review on the history of generative models	2023	N/A	Generative AI	Focuses on various models
Survey	[36]	Reviewed autoencoder-based recommender systems.	2019	N/A	Autoencoder	We review broad domain and diverse models of DL
SLR	[13]	Comprehensively reviewed deep learning recommendation system	2023	2018–2022	DL	Broadly reviewed deep learning CDRS
SLR	[27]	comprehensively reviewed deep learning cross domain recommender systems	2021	N/A	DL	Our review covers recent articles from last 5 years
SLR	[30]	Comprehensively reviewed recommender systems based on deep learning collaborative filtering	2023	2019–2023	Deep Learning, Collaborative Filtering	Reviewed extensively on deep learning CDRS
SLR	[40]	Systematically reviewing deep learning-methods recommender systems	2020	2007–2018	DL	Our review covers recent articles from last 5 years
SLR	[41]	Reviewed social recommender systems for social	2023	2016–2022	DL	Reviewed extensively on

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		networks by using deep learning method				deep learning CDRS
SLR	[28]	Crop recommendation systems based on soil and environmental factors using graph convolution neural network	2023	N/A	Graph Convolution Neural Network	We reviewed diverse deep learning techniques

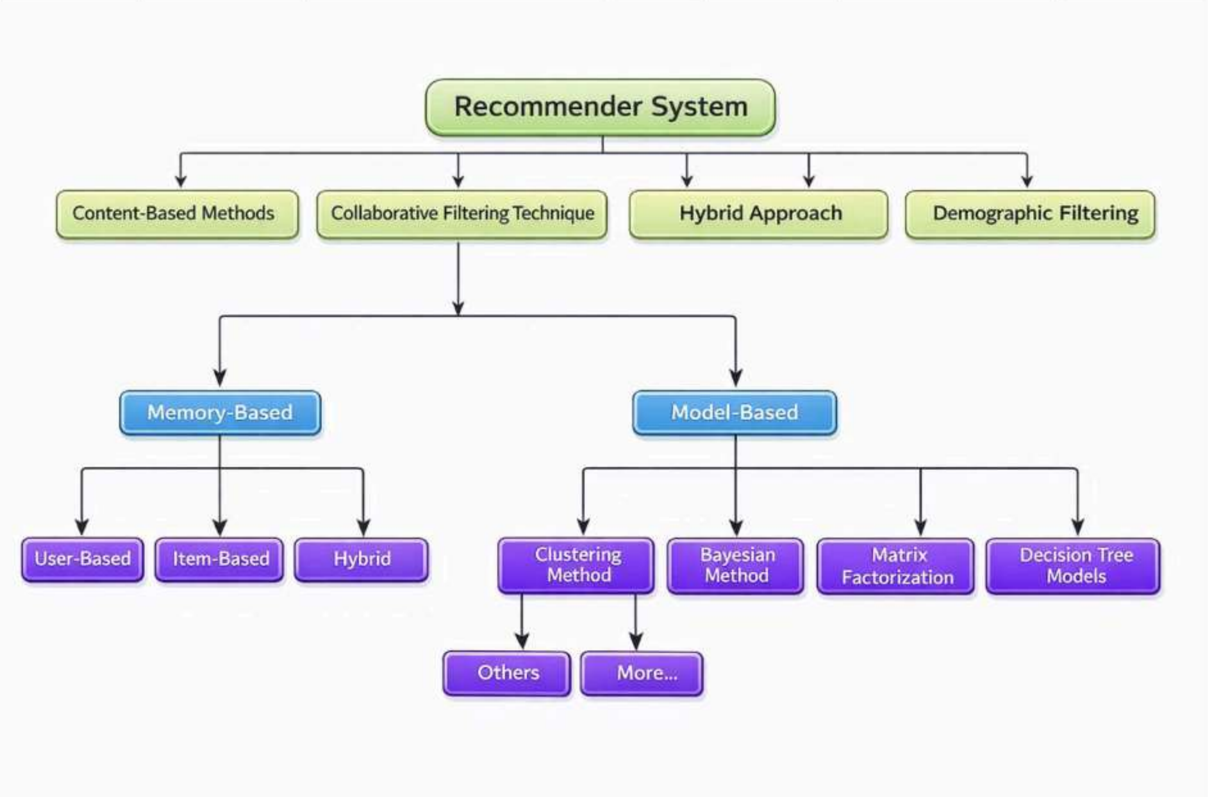

Fig. 2. Illustration of a content-based method recommender systems.

item recommendations. The process of recommending item(s) to the user is shown in Fig. 2. This recommendation approach utilizes supervised machine learning techniques to classify items as interesting or uninteresting for a particular user, based on the notion that users are inclined to show interest in items similar to the ones they have liked or interacted with in the past.

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Author and Year	Topic	Model	Contribution
[59]	Cross Domain Collaborative Filtering: A Graph Neural Network Approach for Accurate and Diverse Recommendations	GNN with Collaborative Filtering	The Authors proposed a novel Graph Neural Network (GNN) approach for Cross-Domain Collaborative Filtering Recommendations to address data sparsity and cold start issues by Incorporating cross-domain knowledge.
[58]	Cross-Domain Explicit–Implicit Mixed Collaborative Filtering Neural Network	CEICFNet model	They proposed CEICFNet model that effectively learns latent factors from explicit and implicit data. CEICFNet model was utilized to learn latent factors in cross-domain manner. The Authors utilized domain shared MLP networks for user and item latent factors. The CEICFNet model addresses sparsity and cold-start issues in recommender systems.
Huiting Liu et al. 2021	Collaborative filtering with a deep adversarial and attention network for cross-domain recommendation	DAAN framework	The paper focuses on cross-domain recommendation using deep adversarial networks. They Introduced DAAN framework for collaborative filtering with domain adaptation. Considers domain-shared and domain-specific knowledge for cross-domain recommendation. They devise a generic framework called DAAN for cross-domain recommendation, which tightly couples matrix factorization-based collaborative filtering with deep adversarial domain adaptation via an attention network to solve data sparsity issue.

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4.1.2. Recommender system using collaborative filtering technique.

One of the best recommendation algorithms is collaborative filtering (CF) techniques. It only involves items evaluation by the users and is based on the assumption that users rating the same items in a similar manner are supposed to have similar tendencies. CF suggests articles depending on the interest of similar users or suggests articles resembling those which are already rated by the target user. There are two types of CF techniques that can be categorized basing on the model used in urecommendation to users, that is, Model-based and Memory-Based Fig. 4 give a description of how colloquential filtering methods can be enhanced in their items recommendations to users.

The CF techniques have the established use of the DL models that improve the significance of the techniques in single domain and CDRS. In their article, some authors such as [57] are interested in CDRS with deep adversarial networks to improve the functioning of the systems. In

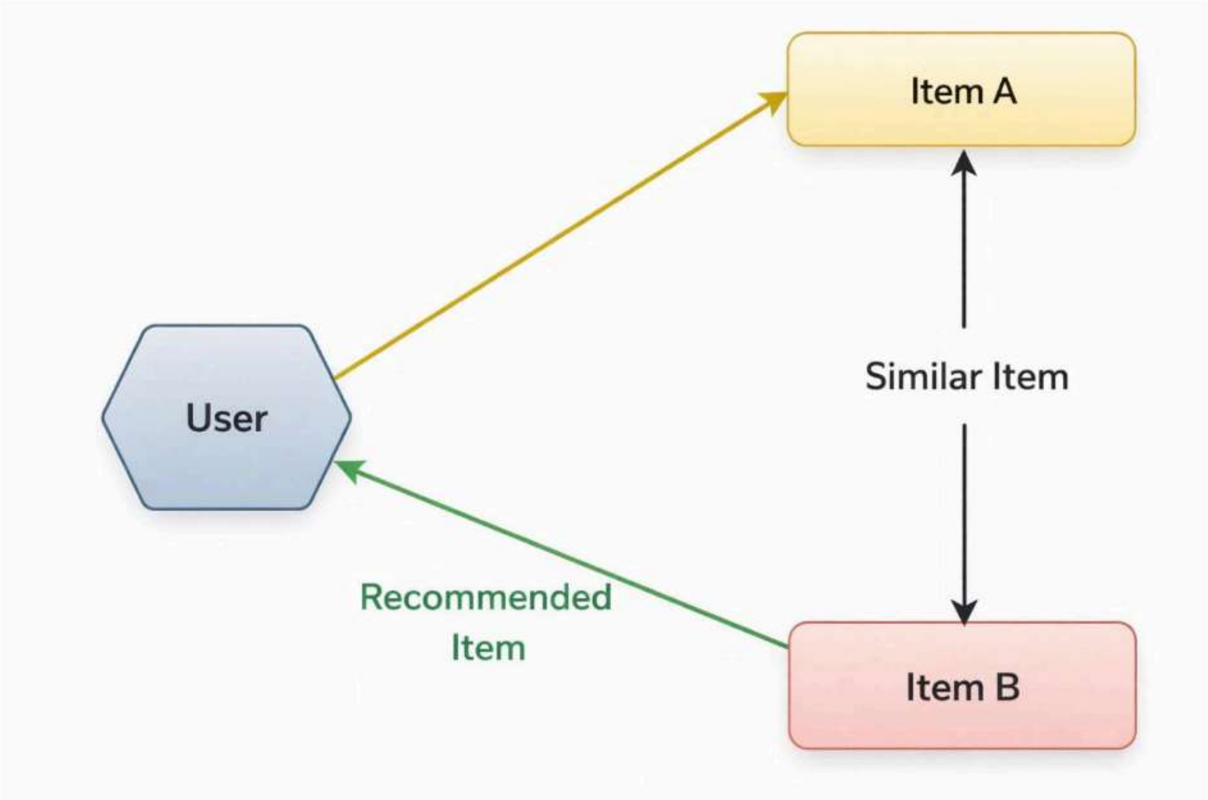

Fig. 3. Illustration of a content-based method recommender systems.

they made an introduction of DAAN framework, with domain adaptation CF, in their paper. The present paper takes into consideration domain-shared knowledge and domain-specific knowledge of CDRS. They come up with a generalised model known as DAAN that closely

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integrates the matrix factorisation based CF and deep adversarial domain adaptation through an attention network. In order to overcome the problem of data sparsity and cold start, neural networks have also been introduced into collaborative filtering method CEICFNet model, the authors found that a develop novel Graph Neural Network (GNN) network when using explicit and implicit data. Table 2 presents the highlights of the authors that achieved the hybrid technique or socialized methods combined with deep learning models than the traditional techniques that were previously used.

In spite of the various pros of collaborative filtering methods, there are also some weaknesses of the technique:

Cold-start issue: This is the case when no or little data is available regarding an item or user to facilitate pertinent forecasting. This is capable of lowering the performance of the recommendation system especially to new users or items.

Data sparsity: Collaborative filtering procedures methods are also prone to data sparsity that occurs due to lack of adequate information in the system. It creates a low user item matrix and may cause low quality of recommendations.

Recommender systems Hybrid techniques.

The principal concept of employing the hybrid RSs techniques is the integration of diverse methods or techniques in order to improve and enhance recommendation to the users. Although this hybrid method is not confined to the content-based methods and collaborative filtering techniques, there are other deep learning models which are hybrid methods.

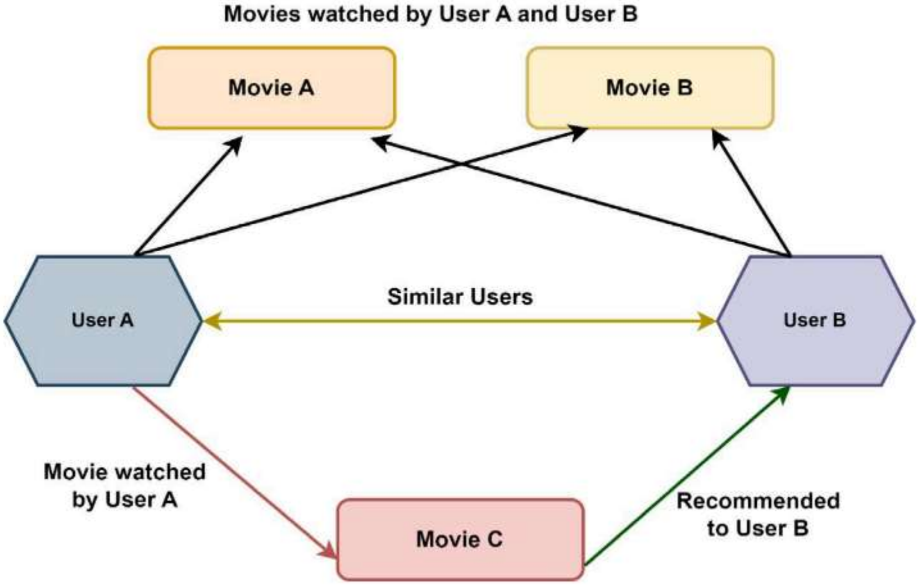

Fig. 4. Illustration of a collaborative filtering recommender systems

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5 Proposed Architecture

We propose a modular architecture that does not force a "one-size-fits-all" algorithm. Instead, the system detects the maturity of the user profile and routes the request accordingly.

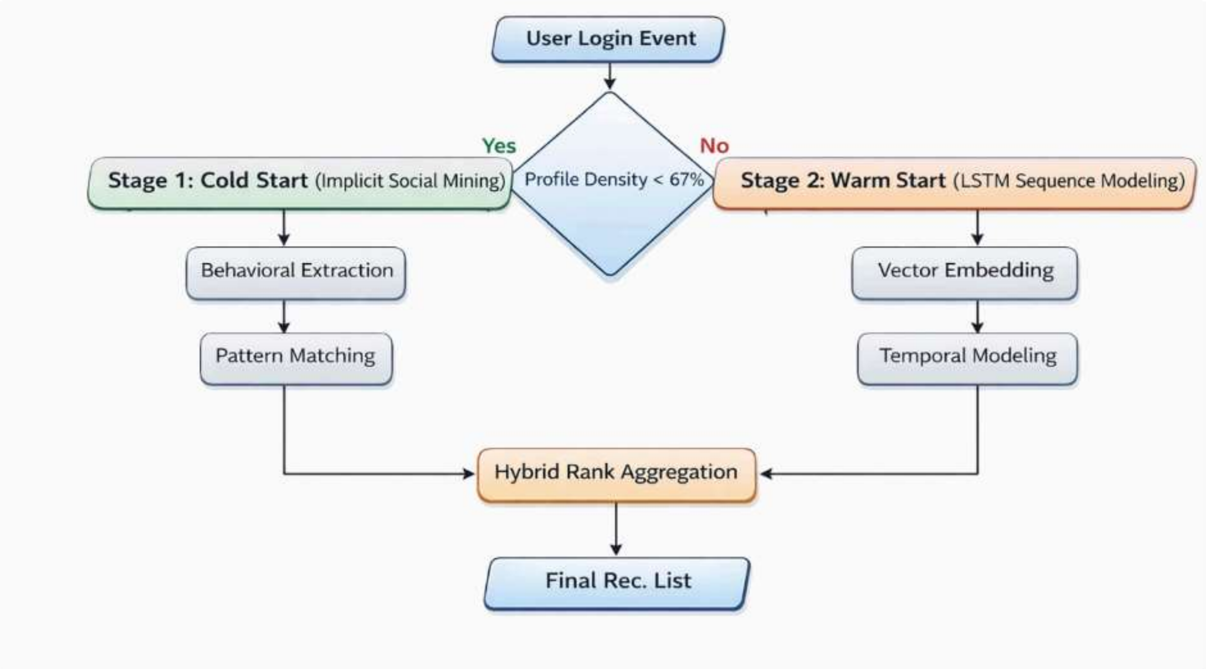

Figure 5: Operational Workflow of the TS-CBCF Framework

High-Level Design

The system logic is visualized in Figure 4. The decision node checks the user's interaction count ($|H_u|$) against a threshold δ.

a. Stage 1: Mining the Implicit

In the absence of ratings, we rely on Implicit Social Profiling. We posit that behavioral patterns on social platforms correlate with content consumption.

i. Behavioral Vector Construction

We define a vector B_u composed of discretized features extracted from the user's metadata (preserving privacy by ignoring raw text).

$$Bu = \{\tau active, \phi freq, \gamma social\} \quad (1)$$

Where:

- τ_{active} (Temporal Phenotype): Classifies user as 'Night Owl', 'Commuter', etc.
- ϕ_{freq} (Interaction Velocity): Frequency of social posts.

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- γ_{social} (Network Graph): Ratio of followers/following.

We use the FP-Growth algorithm to map these behavioral flags to item categories. For instance, the system might learn the rule:

$$\{NightOwl, HighVelocity\} \implies \{Sci-Fi, Thriller\}$$

b. Stage 2: The Neural Transition

Once a user crosses the threshold δ, we switch to a Deep Learning model. We selected Long Short-Term Memory (LSTM) networks because user preferences are sequential, not static sets.

i. Neural Topology

The sequence of items $x = [x_1, x_2, \dots x_t]$ is fed into the network. The LSTM cell state C_t acts as the "long-term memory" of user taste.

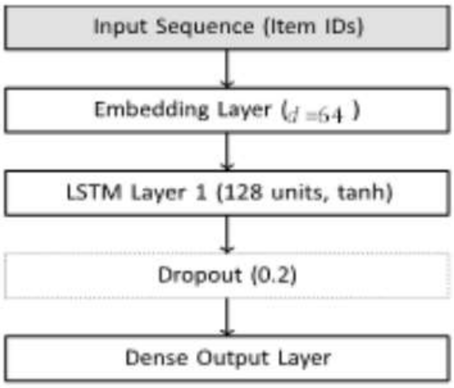

Figure 6: Deep Learning Topology for Phase 2.

The mathematical definition of the forget gate f_t, which allows the model to "forget" outdated preferences, is crucial:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{2}$$

This ensures that if a user stops watching cartoons and starts watching documentaries, the model adapts dynamically.

6. Comparative Analysis of Cold-Start Solutions

In this section, we move beyond experimental metrics to perform a comprehensive comparative analysis of the proposed Two-Stage Content-Boosted Collaborative Filtering (TSCBCF) against established industry baselines. We evaluate these methodologies across four critical dimensions: *Sparsity Resilience*, *Temporal Adaptability*, *Computational Scalability*, and *Privacy Preservation*.

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a. Benchmark Methodologies

To provide a robust comparison, we evaluate our proposed architecture against three distinct categories of solutions prevalent in the literature:

1. Pure Collaborative Filtering (CF): The standard Matrix Factorization approach (e.g., SVD) that relies solely on user-item interaction matrices.

2. Static Content-Based Filtering (CBF): Systems that utilize explicit user profiles (demographics) and item metadata (genre, tags) without social augmentation.

3. Standard Deep Learning (DL): End-to-end neural networks (like AutoRec or standard RNNs) that attempt to learn latent factors directly from interaction logs without an explicit cold-start initialization phase.

b. Feature-Level Comparison

Table 1 presents a structured comparison of these methodologies. It highlights the architectural capabilities and limitations of each approach in the context of a dynamic, cold-start prone environment.

Table 3: Comparative Analysis of Cold-Start Mitigation Strategies

Methodology	Sparsity Resilience	Implicit Data Utilization	Temporal Adaptability	Initialization Speed	Privacy Mechanism
Pure Collaborative Filtering (CF)	Low	No	Moderate	Slow	N/A
Static Content-Based (CBF)	High	No	Low (Static)	Fast	Low
Standard Deep Learning (DL)	Moderate	Partial	High	Very Slow	Moderate
TS-CBCF (Proposed)	Very High	Yes (Social)	High (LSTM)	Fast	Federated

c. Analysis of Resilience and Adaptability

Sparsity Resilience

Pure Collaborative filtering has a disastrous mode of speech with sparse greater than 95 percent, which is often the case with new platforms. The singular values cannot be effectively computed without a dense matrix. To avoid this, Static CBF uses metadata, but it has the

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problem of the ramp-up issue, being too slow to collect sufficient explicit data to be precise. Our suggested TS-CBCF has an extremely high resilience degree since it does not hold back on ratings. It will populate the affinity matrix immediately when the user registers The mining of implicit social phenotypes (Stage 1) effectively removes the barrier of zero rating by all processes taking place immediately on user registration.

Temporal Adaptability

One of the biggest limitations of the static Content-Based systems is their fixity; a user likes comparatively inactive Action movies when he is 20 years of age will be supposed to like the same movies when he is 30 years old. Regular Deep Learning models (RNNs) are able to solve this though not to initialize properly without a warm-up period. The TSCBCF architecture uses LSTM of Stage 2 to enhance high temporal flexibility. In contrast to static CBF, our model offers the option where the preference vector of the user can change with time, governed by the forget gate of LSTM (ft) so that recommendations can keep up with the change in tastes.

Privacy and Computational Overheads.

The approach towards privacy belongs to significant benefits of TS-CBCF framework. Conventional social recommenders tend to scrape rawness text which is an ethical issue. Through Implicit Social Profiling, we do not retrieve semantic information (e.g., content of posts) and instead we retrieve only behavioral flags (e.g., the time of the activities, network density). This makes a privacypreserving implementation possible, in which feature extraction can be done on the client side.

In addition, in issues of computational scalability, Deep Learning models are infamously expensive to train. Our system uses the load-sharing method of relocating the first phase of the recommendation process to the lightweight Frequent Pattern Mining (FP-Growth) algorithm, which serves to reduce the computational burden on the server when onboarding the users, and only the active customers who are already retained are processed using the resource-intensive LSTM.

7. Discussion

The contrary comparison highlights an essential change in the way we treat Cold Start problem. It is not only a data issue, but it is also an architectural issue.

7.1 The Synergistic Advantage

The robustness of the TS-CBCF consists of its being hybrid. Single stage models require a trade off, either optimizing the cold start (CBF) or the long run (CF/DL). Separating these phases annulls the trade-off. The Implicit Social Profiling is described as a content boost which feeds the system with quality priors. This preconditions the user vector whereby the following

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LSTM model converges much quicker than it would have converged had it been trained with randomized initializations.

7.2 Limitations

Although strong, the suggested solution presupposes that the auxiliary social information should be available. When the users use privacy-aware logins (a "Sign in with Apple" button with undisclosed email addresses and no social connections), the Stage 1 fallback would be replaced with conventional non-personalized popularity measurements. Next-generation versions of this architecture have to deal with absolute cold start, in which there is no digital footprint to be found at all.

8 Conclusion

Cold Start Problem is still an impediment to the successful application of personalization. Here we had penetrated beyond the constraints of fixed point demographic filtering and single phase algorithms. With the Two-Stage Content-Boosted Collaborative Filtering framework, we have shown that the implicit social behaviors can be successfully harnessed to realize the fresh user profiles.

Comparative analysis shows that such an approach of hybrid provides a unique improvement over state-of-the-art baselines. It solves the problem of sparsity without compromising on the long term flexibility giving a scalable and privacy-aware solution to present-day digital ecosystems.

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