A recommender system using novel deep network collaborative filtering

Shruthi Nagaraj, Blessed Prince Palayyan
Department of Computer Science and Engineering, Presidency University, Bangalore, India

ABSTRACT
The recommendation model aims to predict the user’s preferred items among million through analyzing the user-item relations; furthermore, Collaborative Filtering has been utilized as one of the successful recommendation approaches in last few years; however, it has the issue of sparsity. This research work develops a deep network collaborative filtering (DeepNCF), which incorporates graph neural network (GNN), and novel network collaborative filtering (NCF) for performance enhancement. At first user-item dual network is constructed, thereafter custom weighted dual mode modularity is developed for edge clustering. Furthermore, GNN is utilized for capturing the complex relation between user and item. DeepNCF is evaluated considering the two distinctive. The experimental analysis is carried out on two datasets for Amazon and movielens dataset for recall@20 and recall@50 and the normalized discounted cumulative gain (NDCG) metric is evaluated for Amazon Dataset for NDCG@20 and NDCG@50. The proposed method outperforms the most relevant research and is accurate enough to give personalized recommendations and diversity.

This is an open access article under the CC BY-SA license.

Keywords: Deep network collaborative filtering, Dual network, Graph neural network, Network collaborative filtering, Recommender system

1. INTRODUCTION
Nowadays, it is customary to make purchases online. Consumers sometimes find it difficult to select the most interesting product from among the various ones offered by E-platforms. A substantial amount of internet information may now be available rapidly with advances in recent technological developments and the popularity of online services. For a diversity of online services and goods, users can leave reviews, comments, and ratings. Because of recent advancements in global computing, the problem of online data overload has arisen. Finding meaningful and helpful information online is becoming more and more challenging because of the data flood. Yet, several contemporary approaches with reduced computing demands may now more effectively and efficiently direct users to the relevant material. As a result, generating recommender systems has gained a lot of traction lately. Generally considering, recommender systems serve as information filtration tools, providing customers with pertinent and practical information [1]–[3]. For each page of the website, we are on, a recommendation algorithm is used. For instance, e-commerce companies typically provide "guess your favorite" on the front page. There are many more websites, including those for movies, videos, news, books, restaurants, maps, and other content, that have built-in recommendation engines, amongst which a few of the ones are already in use.

Collaborative, content-based, and hybrid systems are the three primary categories of recommender systems (RSs). Without taking into account any information about other users, content-based filtering (CBF)
predicts a user's preferences based on his or her information (gender, age and activities on social media). Given that it employs several strategies to provide the user with the information they need, CBF might be seen as an information-filtering task. Instead of looking for particular data within an incoming stream, filtering is frequently considered of as the removal of undesirable data (viewed as noise) from that stream. The most often used strategy is based on the semantic content of an item. In this scenario, a number of the guiding principles from the information retrieval discipline, upon which it is built, are applied: products are suggested based on comparisons between their content and the user profile. This profile is shown as a table with the user-specific key elements and weights. This method of information retrieval is straightforward, quick, and effective [4]–[7]. The majority of current research has been on recommendation systems based on deep learning. Deep learning model topologies may be easily changed to accommodate different recommendation situations and specific application conditions. By mining feature combinations and fitting data patterns, deep learning recommendation models outperform traditional recommendation algorithms. Yet, the majority of these current recommendation algorithms ignore the potential worth of supplementary data, user ratings, and user reviews. Auxiliary information, a type of implicit feedback, contains user characteristics and item characteristics. Hence, it is possible to mine auxiliary data for implicit attributes of objects. Yet, it is important to remember that different users may have different rating habits. Ratings from users may seem to indicate a user's preference for a certain item. As an illustration, some people constantly offer great ratings, whilst others may have high expectations and frequently offer negative ones. In this situation, it is challenging to evaluate an item's quality just based on customer reviews. In addition, just because two people give a product a high rating does not always mean that they have the same opinion on it. Because of his rating habits, one individual could just give everything that is not invasive, a good review while the other might truly appreciate the product. We will incorporate user feedback into the recommendation system to address these issues efficiently. Both user ratings and reviews are explicit observations, but since reviews are more customized than ratings, they are more likely to represent people's emotional tendencies [8]–[11].

The internet, books, e-learning, travel, movies, music, e-commerce, news, specialized research resources and television shows, are just a few of the applications in a variety of recommender systems. To offer its customers personalized recommendations across a range of applications, it is critical to create better and more efficient recommender systems. For a wider range of applications, the current generation of recommender systems must be improved to offer better useful and suitable recommendations. It is necessary to conduct further research on recent studies on recommender systems that focus on different applications. Further, research contribution is given as follows,

- Deep network collaborative filtering (DeepNCF) comprises a novel network collaborative filtering and graph neural network (GNN) for performance enhancement; user-item based dual mode network is constructed through rating matrix; later custom weighted dual mode modularity is developed for edge clustering.
- GNN is adopted for optimization of edge clustering and understand the more complex relationship between user as well as item. Integrated approach of network collaborative filtering (NCF) and GNN. Furthermore, Edge reduction approach is used for selection of non-redundant edges.
- DeepNCF is evaluated considering the two distinctive dataset of Amazon Books and MovieLens considering the metrics normalized discounted cumulative gain (NDCG) and recall with different variants.

This Particular research is organized as follows: First section of the research work starts with the background of recommendation system, importance of collaborative filtering and integration of deep learning towards recommendation system. Second section discusses the existing work for recommendation system. DeepNCF is designed and develop in third section along with mathematical modelling and architecture; DeepNCF is evaluated considering the different dataset along with comparative analysis.

2. RELATED WORK

Graph neural network (GNN) has been one of the key research areas in recommendation system since development of earlier one; this section discuss little recent existing mechanism that adopted GNN for exploiting the optimal relationship among user and items. To develop precise session embedding and train item representations from session graphs, gated graph neural networks were employed [12]. Identified the local and long-range interdependence of session-based recommendations using GNN and self-attention approaches [13]. To locate and create item and user choice embedding, several weighted graph attention networks were used [14]. Removed nonlinear activations and feature transformations from the network architecture to address graph convolutional networks [15]. They uses GNN to handle a variety of characteristics and created a component to look at the relationship between potential neighbor nodes [16].

A recommender system-using novel deep network collaborative filtering (Shruthi Nagaraj)
Object interactions were captured in using a self-attentive graph neural network and a soft attention method [17]. Yet, statistics on user-item interaction are frequently scarce. By including item attribute data in interaction characteristics, some researchers have started to combine multimodal data to alleviate the data shortage. To find user and object embedding for the goal of making recommendations, consider persons and objects as knowledge networks, including their traits and interactions; Proposes linking user-item interaction graphs with user-user social networks to improve social recommendation [18], [19]. A technique for capturing the intricate relationship between explicit user decisions and edge data was developed by Inx [20].

To get over these limitations and provide more precise item recommendations, the review text and node attributes for graph neural network recommendation (RTN-GNNR) model combines the review text and node attributes for graph neural network recommendation. There are four parts to the RTN-GNNR. A bidirectional, gated network is suggested by the module for obtaining review text attributes. Bidirectional encoder representation from transformers (BERT) and an attention mechanism are used in the recurrent unit (Bi-GRU) text analysis method to assist the model choose the most important reviews [21], [22]. Construct a context-aware recency-based attention network (CARAN) that uses the attention mechanism to give recent visitation spots the highest priority based on the temporal and spatial context and the weather. Using linear interpolation and spatiotemporal matrices to characterize spatial distance smoothly, enables interaction between non-adjacent check-ins.

3. PROPOSED METHODOLOGY

This research develops DeepNCF, which integrates the graph neural network (GNN) and network collaborative filtering for performance enhancement in terms of diversity and recommendation accuracy. Figure 1 shows the DeepNCF workflow; at first novel dual mode graph is designed, later novel NCF with edge clustering and edge reduction is carried out; further we adopt GNN architecture and design Deep NCF train DeepNCF to make the recommendation. Figure 2 shows the proposed workflow. The first step here is to develop a bipartite graph, which performs link segmentation that generates a dual mode graph community. On this basis, a link segmentation algorithm divides the so that it has a robust structure. The second step is the execution of a deep reinforcement learning (DRL) into a specific single community such as the neighborhood chosen among the group that generates a varied type of recommendations. The in-depth discussion of the proposed model is discussed here.

![Figure 1. DeepNCF workflow](image1)

![Figure 2. Proposed workflow](image2)

3.1. Problem statement

The main goal of this work is to draw attention to the problem of recommendation overfitting while ensuring recommendation accuracy and maintaining variation without the need for additional data. The
traditional user-based collaborative filtering method wherein a neighborhood consists of the user’s relevant ratings that focus on specific items. This will allow the users that are present in the neighborhood to retain the similarity with the target user, which consists of various choices. Because the links here are connected to various items that do not efficiently reflect a user’s choice. Upon considering an example of users rating to meet the personalized requirements, henceforth ensuring that the candidate neighbor ensures the same rating features irrespective of the correlated dense items with the target user. To enhance the recommendation system, the users recommend a specific category of items. The existing techniques are based on the mechanism of user-based collaborative filtering which enhances the performance of the recommendation system recently. Solving the overfitting in user-based collaborative filtering is further applicable to various techniques used in recent Recommendation systems. The proposed system (PS) approach is shown below.

3.2. Edge clustering

Simultaneously, the dual mode network has gained widespread use for various events such as customer-item relationships. Here there exist two categories of the non-overlapping category of nodes for uppermost and bottommost nodes. A specific single link here collaborates with a set of nodes that belongs to various categories. The two-mode graph is an essential measure to enhance the community structure of the two-mode graph. To attain an effective community identification model that proposes a dual mode graph which states that there exists top k top nodes and e below nodes in the dual mode graph. Henceforth the two-mode graph here is considered as $k * e$ incidence matrix $B$ that focuses on the communication among the top and bottom nodes whereas $B_{m,n} = 1$ if there exists a link between uppermost node $m$ and bottommost node $n$ and $B_{m,n} = 0$. Hence $C_{m,n}$ shows the probabilities associated with any random model through a link that is present between the uppermost node $m$ and bottommost node $n$. Accordingly, to the connection matrix $B$ and $C$, for the two-mode graph, $D$ is shown as,

$$D = \sum_{m=1}^{k} \sum_{n=1}^{e} \left( \frac{B_{m,n}}{K} - C_{m,n} \right) \varphi(H(m),H(n))$$

$$= \frac{1}{K} \sum_{m=1}^{k} \sum_{n=1}^{e} \left( \frac{B_{m,n}}{K} \right) \varphi(H(m),H(n))$$

(1)

Here $K$ denotes the number of links in $B$. $H(m)$ in addition, $H(n)$ denotes the degree of nodes $m$ and $n$ irrespective. The $\varphi$ function here shows the $\varphi(H(m),H(n))$ to equalize the nodes $m$ and $n$ are segmented into a similar community else 0. The RS consists of customer-item relation; it shows the dual mode graph. An RS is transformed into IBG = $H(T, J, S)$, which shows the $|T|$ denotes the user nodes, $|J|$ consists of item nodes and $|S|$ denotes the number of links. $S_{t,j}$ shows that a customer $t$ has rated an item $j$. Henceforth IBG is denoted as $|T|*|J|$ adjacent matrix $B$. The adjacency matrix $B$ in (3) shows the correlation degree between the node $t$ and item $j$, which consists of two links that accommodate the transformation. The links consisting of degree $\alpha$, $g_{i,j} \leq 1$ are denoted as strong links and $0 \leq g_{i,j} \leq \alpha$ are denoted as weak links.

$$G^v_{t,j} = s(t,j) = 0 \text{ else } \frac{c_{t,j}}{\max_{j \in |J|}} \, \, \, 0 < c_{t,j} < \mu \, \, \, \mu \leq c_{t,j} \leq 1$$

(3)

Here each link denotes the parameter for each community, to analyze a co-efficient $Probl_{l_f} | S_{t,j}$ that denotes the link $S_{t,j}$ that denotes the community $l_f$. In this step, each link is associated with many communities at a specific time and the main advantage levied on the dual mode graph is weighted by the co-efficient. The dual mode graph is reformed upon substitution by $\varphi(S(t), S(j))$ with different parameters as $\psi_{t,j,f}$ and $\omega_{t,j,f}$ respectively.

$$X^v = \frac{1}{|S|} \sum_{t=1}^{|T|} \sum_{j=1}^{|J|} \left( \psi_{t,j,f} \cdot G^v_{t,j} - \omega_{t,j,f} \frac{P(O|P(J))}{|S|} \right)$$

$$\psi_{t,j,f} = pred(S_f | S_{t,j})$$

(4)

The two co-efficient $\psi_{t,j,f}$ and $\omega_{t,j,f}$ are constructed. For $\psi_{t,j,f}$ the probability that is associated with $S_{t,j}$ to the model belonging to a community $S_f$. $\psi_{t,j,f}$ is equivalent to 1 if the customer node $t$ and item node $j$ are segmented into similar community $S_f$ if $S(T) = S(J) = S_f$ this is equivalent to 0. Henceforth the probability of two nodes associated with a similar community is high in comparison if the nodes considered are neighbours. We can state that, 

$$\omega_{t,j,f} = pred^l(S_f | S_{t,j})pred^T(S_f | S_{t,j})$$

A recommender system using novel deep network collaborative filtering (Shruthi Nagaraj)
\[
\text{pred}^l(S_{t_j}) = \frac{\sum_{j \in l} \text{pred}(S_f|S_{t_j})}{|l|} \quad (7)
\]
\[
\text{pred}^T(S_{t_j}) = \frac{\sum_{E \in l} \text{pred}(S_f|S_{t_j})}{|T|} \quad (8)
\]

Accordingly, to (4) - (8) a dual mode weighted graph is,
\[
X^V = \frac{1}{|S|} \sum_{f=1}^{|F|} \sum_{t=1}^{|T|} \sum_{j=1}^{|l|} \left( \text{pred}(S_f|S_{t_j})G^v_{t_j} - \text{pred}^l(S_{t_j})\text{pred}^T(S_{t_j}) \right) \frac{p(t)p(j)}{|S|} \quad (9)
\]

A high-end value \(X^V\) denotes a robust community structure for , the \(X^V\) shows the difference amidst a dual mode graph after the community is identified and an unstructured network doesn’t contain a community structure. The wider the change the clearer the community structure is Assumption \(X^V = 0\) then all the links belong to a similar community, if so then \(F = 1\) we get, \(\forall f \in F, t \in T \text{ pred}(S_{t_j}) = 1\). Simultaneous to (7) and (8) we can find the equation,
\[
\text{pred}^l(S_{t_j}) = \frac{\sum_{j \in l} \text{pred}(S_f|S_{t_j})}{|l|} = \frac{|l|}{|l|} = 1 \quad (10)
\]
\[
\text{pred}^T(S_{t_j}) = \frac{\sum_{E \in l} \text{pred}(S_f|S_{t_j})}{|T|} = \frac{|T|}{|T|} = 1 \quad (11)
\]

The \(9-th\) equation is simply reduced to,
\[
X^V = \frac{1}{|S|} \sum_{f=1}^{|F|} \sum_{t=1}^{|T|} \sum_{j=1}^{|l|} \left( \text{pred}(S_f|S_{t_j})G^v_{t_j} - \text{pred}^l(S_{t_j})\text{pred}^T(S_{t_j}) \right) \frac{p(t)p(j)}{|S|} \quad (12)
\]
\[
= \frac{1}{|S|} \sum_{f=1}^{|F|} \sum_{t=1}^{|T|} \sum_{j=1}^{|l|} \left( G^v_{t_j} - \frac{p(t)p(j)}{|S|} \right) \quad (13)
\]

Henceforth if all inks are focused on the same community, then we have \(X^V = 0\). The \(X^V\) uses local data the details of the link associated with each community. Community identification comes under the category of minima or maxima. A global value is introduced here as \(X^V\), the \(\text{Max}_d\) is related to global data, and integrate \(\text{Max}_d\) into \(X^V\). The \(\text{Max}_d\) is denoted as,
\[
\text{Max}_d = \frac{1}{|S|} \frac{1}{|l|} \sum_{t=1}^{|T|} \sum_{j=1}^{|l|} \left( \text{pred}(S_f|S_{t_j}) \right) \quad (13)
\]

Here the dual mode graph is denoted by,
\[
X^v_{\text{globloc}} = \frac{2\text{Max}_d + X^V}{3} \quad (14)
\]

Consequently, by (14) we can show that \(X^v_{\text{globloc}}\) that focuses on local as well as global information whereas the variation exists in the \([0, 1]\) range. Increasing the value \(X^v_{\text{globloc}}\) the effective result is generated in terms of community detection. Parallely, a novel algorithm is developed for a dual mode weighted graph for each link here \(S_{t_j}\) the initialization is done as \(\text{pred}(S_f|S_{t_j})\) for \(\sum_{f=1}^{|F|} \text{pred}(S_f|S_{t_j}) = 1\).
\[
\text{pred}(S_{t_j}) = \frac{\text{pred}(S_f|S_{t_j})}{\sum_{f=1}^{|F|} \text{pred}(S_f|S_{t_j})} \quad (15)
\]

Here \(\tau\) and \(\theta\) are considered as the hyper-parameter so that the denominator is not 0. Based on the values of \(\text{pred}(S_f|S_{t_j})\) shown by (16) we try to compute the equation \(\text{pred}(S_f|t)\) and \(\text{pred}(S_f|j)\).
\[
\text{pred}(t) = \frac{\sum_{f \in t} \text{pred}(S_f|S_{t_j})}{\sum_{f \in T} \text{pred}(S_f|S_{t_j})} \quad (16)
\]
\[
\text{pred}(j) = \frac{\sum_{E \in l} \text{pred}(S_f|S_{t_j})}{\sum_{E \in l} \text{pred}(S_f|S_{t_j})} \quad (17)
\]
Based on the results considered $\text{pred}(t)$ and $\text{pred}(t)$ the value of $\text{pred}(S_t|S_{t,j})$ is re-evaluated by (15). The evaluation is carried out above until the $\text{pred}(S_t|S_{t,j})$ that reaches the community to achieve the large value for $\text{pred}(S_t|S_{t,j})$ as the final community that links the $S_{t,j}$. The custom dual mode weighted graph $X_{\text{globloc}}^v$ is evaluated at each level from $F_{\text{min}}$ to $F_{\text{max}}$. The higher the value for $X_{\text{globloc}}^v$, the robust the community is, the maximum value obtained by $X_{\text{globloc}}^v$ by considering an optimal number of $F$ communities. The value $F_{\text{min}}$ is estimated to be 2, whereas the $F_{\text{max}}$ value is given by $F_{\text{max}} = (|T| + |J|)^{0.5}$. Edge clustering algorithm as shown in Algorithm 1.

Algorithm 1. Edge clustering algorithm

Input: Dual Mode Network $IBG = (H, T, J, S)$, the number of communities $F$.

Step 1: Partition the $H(T, J, L)$ into $F$-number of communities $\{l_1, l_2, ..., l_f\}$.
Step 2: for each link $S_{t,j}$ do
Step 3: Initialize probability $\text{Prob}(l_f|S_{t,j})$, for $\sum_{f=1}^{F} \text{Prob}(S_{t,j}) = 1$
Step 4: end for
Step 5: for each link $S_{t,j}$ do
Step 6: repeat
Step 7: Evaluate $\text{Prob}(l_f|t)$ and $\text{Prob}(l_f|j)$
Step 8: Use the values of $\text{Prob}(l_f|t)$ and $\text{Prob}(l_f|j)$ to evaluate $\text{Prob}(S_{t,j})$ accordingly.
Step 9: Till it converges $\text{Prob}(S_{t,j})$
Step 10: Choose a community that has the largest $\text{Prob}(S_{t,j})$ that is the final community that connects $S_{t,j}$
Step 11: Update the value in $\{l_1, l_2, ..., l_f\}$
Step 12: end for
Step 13: Return $k$ number of communities $\{l_1, l_2, ..., l_f\}$

output: $F$ number of communities $\{l_1, l_2, ..., l_f\}$

3.3. Edge reduction

Once the edge clustering is done there exist many redundant links that may reduce the performance of the system with the $IBG$ denotes as redundant links. Consider customers $c_1$, $c_2$ and $c_3$ generate comparisons by considering the items $l_1$, $l_2$, $l_3$, $l_4$, $l_5$ and $l_6$ is reduced into a similar community. Additionally, $c_1$, $c_2$ and $c_3$ generate comparisons with a target customer $t_c$ and the comparisons denoted as ranks are depicted in the table. It is essential to ensure that the community includes this customer, hence $c_1$ and $c_2$ is selected. In the next phase, the information of customer $c_3$. Via Figure 3 to evaluate a $S(c_3) = \{s_1, s_2, s_3\}$, $S(c_2) = \{s_2, s_2, s_2, s_3, s_3, s_3\}$ and $S(c_1) = \{s_1, s_2, s_3, s_3, s_3, s_3\}$. The links are connected to a similar item that is equal $s_1$ to $s_2$ upon computation with $c_4$ that has additional links $\{s_2, s_2, s_2\}$ in comparison with $c_1$, indicates $c_7$ that recommends items $IM_1$ and $IM_3$ additionally along with $c_1$. Edge reduction as shown in Algorithm 2.

The suggestions from the united $c_1$ and $c_2$ communities will be identical to those from $c_5$ alone. Thus, establishing connections with $c_1$ is irrational. Used to foster community The connections to $IM_1$, $IM_2$, and $IM_3$ are the same for $c_2$ and $c_5$ but $c_3$ also has a connection to $IM_3$. This suggests that while $c_1$ cannot approve $IM_6$, $c_3$ can. Therefore, to assess similarity links leading to $c_3$ must be preserved. So, $c_2$, $c_3$, rather than $c_3$, $c_2$, will be a superior decision if we chose the top two users as neighbours. As $c_3$'s link set includes $c_1$, it is a stronger contender for acceptance into the community than $c_1$. Duplicate $IBG$ connections are covered in this section. Let $c_a$ stand in for a single user node, and let $C$ represent the group of user nodes in the $IBG$. Connections in $S(c_a)$ are evaluated if another user node already exists such that $S(c_a)$. The remaining linkages in a $IBG$ are known as nonredundant links once all redundant connections have been eliminated, at which point the $IBG$ ceases to be reducible. Duplicate links in the user’s link list will be removed. Duplicate links prevent the algorithm from determining how similar a user is to a target user. As a result, this user is removed from the target user’s list of prospective neighbors. In this study, we postulate that removing redundant connections produced by user nodes like $c_1$ may broaden the variety of ideas. Comprehensive edge reduction, data are provided by the second technique. It is essential to stress that we conduct edge reduction in each local community rather than the entire $IBG$ for two reasons.

a) It is possible to lessen the computational difficulty of edge reduction.

b) Any number of unnecessary links may be deleted.

First, following edge clustering, each community’s size is significantly reduced to the size of the $IBG$ as a whole, representing the edge reduction that is performed in a lesser region. In addition, edge reduction is performed concurrently in many communities, hence decreasing computing time by a factor of $T$ compared to processing the whole $IBG$. The second argument is because it is simple to derive that redundant
Algorithm 2. Edge reduction
Input  G community \( l_f \)
Step 1  Fix the value \( l_f^c = l_f \)
Step 2  for \( a = 1 \) to \(|T(l_f)|\) do
Step 3   for \( b = 1 \) to \(|T(l_f)|\) do
Step 4   if \( S(l_a) \subseteq S(l_b) \) then
Step 5     \( l_f^c = l_f^c - S(l_a) \)
Step 6   end if
Step 7   end if
Step 8   end for
Step 9   end for
Step 10  return G community to \( l_f^c \)
Output G community to \( l_f^c \)

Algorithm 3. Novel NCF algorithm
Input  Item matrix \( IM \) and a target customer \( tc \), \( K \) recommendations for the target customer \( tc \)
\( K \): the total items recommended to the target customer \( tc \)
\( X_{globloc}^v \): the custom dual mode model
\( f_{tc} \): The item set which the target customer has not rated yet.
\( pred_{tc,i} \): predicted target score for the target customer \( tc \) for item \( i \)
Step 1  Map a IM to an item Dual Mode graph \( IBG = H(T,J,S) \)
Step 2  \( X_{globloc}^v = 0; F = 0 \)
Step 3  for \( F = f_{min} \) to \( f_{max} \) do
Step 4  Use edge clustering algorithm (alg 1) to get the communities \( \{l_1,l_2,...,l_f\} = ps(H(T,J,S),F) \).
Step 5  Evaluate the \( X_{globloc}^v \) value for \( \{l_1,l_2,...,l_f\} \)
Step 6  if \( X_{globloc}^v \leq X_{globloc}^v_{\text{ref}} \), then
Step 7   \( H(T,J,S) \) is clustering into \( \{l_1,l_2,...,l_f\} \)
Step 8  end if
Step 9  end for
Step 10  Compute \( H(T,J,S) \) with community \( F \) and peak \( X_{globloc}^v \)
Step 11  for \( f = 1 \) to \( F \) do
Step 12  Utilize (alg 2) to remove redundant links in \( l_f \), such that \( l_f^c = ps(l_f) \)
Step 13  end for
Step 14  Fetch a set of communities \( \{l_f^c,l_f^c_2,...,l_f^c\} \)
Step 15  for each item \( j \in f_{tc} \) do
Step 16  Extract the community \( l_f^c \) that consists of the target customer \( tc \) and item \( j \)
Step 17  Evaluate the similarity between the target customer \( tc \) for each customer \( c \in l_f^c \)
Step 18  Choose customers in \( l_f^c \) having maximum similarity for the neighbourhood \( N_{tc} \) of the target customer \( tc \)
Step 19  Predicting the score \( pred_{tc,i} \) for item \( j \) for \( N_{tc} \)
Step 20  end for
Step 21  The \( K \) items with \( pred_{tc,i} \) recommended to the target customer \( tc \)
Step 22  \( K \) recommendations for the target customer \( tc \), \( X_{globloc}^v, f_{tc}^c, pred_{tc,i} \)
Output \( K \) recommendations for the target customer \( tc \), \( X_{globloc}^v, f_{tc}^c, pred_{tc,i} \)
4. RESULT SECTION

In this section, we compare the effectiveness and robustness of the proposed PS approach comparison with the existing state-of-art methods on two datasets i.e. Amazon Dataset and MovieLens Dataset, which are the benchmark datasets. We evaluate recall for Amazon dataset and MovieLens dataset for recall @20 and recall @ 50, whereas the NDCG metric is evaluated for the amazon database for metrics NDCG@20 and NDCG@50. The various state-of-art techniques used for comparison are MostPopular, YouTube DNN, GRU4Rec, MIND, ComiRec-DR, ComiRec-SA and Fat technique.

4.1. Methods considered for evaluation

The methods considered for evaluations are: i) MostPopular is a traditional recommendation method, which will recommend the most popular items to users, ii) YouTube DNN [23] is one of the most successful deep learning models of industry recommender system, iii) GRU4Rec [24] is the first time to use a gated recurrent neural network to model the sequence relationship between items in the sequence, iv) MIND [25] is a recommendation model of multi-interest extraction using a capsule network, v) ComiRec-DR [26] is the capsule network model based on the original dynamic routing method that has better performance than MIND, vi) ComiRec-SA [26] is a multi-interest extraction model based on self-attention, vii) Future aware diverse trends (FAT) [27] is a recent state-of-the-art model, which takes into consideration of users’ feature sequence. FAT uses ComiRec-DR methods to get the future sequence multi-interest, and it computes correlations among different users by using a collaborative filtering method.

Moreover, the above all method has been compared in the existing model [28], thus proposed DeepNCF is compared with existing model.

4.1.1. Dataset details

The dataset details are: i) Amazon Dataset: This consists of product reviews and metadata from Amazon. In our experimental analysis, we use the book category of the Amazon dataset. The length of each training sample is truncated to 20, and ii) MovieLens Dataset: The benchmark data set in the field of recommendations is the MovieLens dataset. These facts consist of user demographics (age, gender), movie ratings, and movie information (style kind, age and employment). In this case, we use the Movielens-1M dataset, which contains 1 million score records, to examine how the PS framework works.

4.2. Recall

We use the better interpretable average per user rather than the global average. The recall is evaluated here for two databases, one is amazon Dataset and the other is the MovieLens dataset. For both of these datasets, the recall is evaluated at metrics@20 and metrics@50.

\[
\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}
\]

- Recall@20 for Amazon dataset

In Figure 3 and Table 1 we can see that the recall@20 is evaluated for Amazon Dataset, the method MostPopular method gives a value of 1.368 which is the least value, whereas we can see that ComiRec –SA denotes an average value of 5.103 and FAT technique shows a value of 5.177. However, the existing approach EA attains a value of 6.761, means–ends analysis (MEA) technique denotes a higher value than the existing system as 7.084 and in comparison, with the existing techniques, and our proposed model ensures better performance and gives a value of 13.89.

- Recall@50 for Amazon dataset

In Figure 4 and Table 2 the recall@20 is evaluated for Amazon Dataset, the method MostPopular method gives a 1.368 recall value, which is the least value; whereas the method self efficacy academic (SEA) method generates an average recall value of 8.172 and future aware diverse trends (FAT) technique gives a value of 8.161. However, the existing approach existing approach (EA) attains a value of 10.625, gives a higher value than the existing system as 11.054, in comparison with the existing techniques our proposed model ensures better performance and gives a value of 13.58.

- Recall@50 for MovieLens Dataset

In Figure 5 and Table 3 we can see that the recall@20 is evaluated for the MovieLens dataset, the method MostPopular method gives a value of 4.636, which is the least value, whereas the ComiRec -SA denotes an average value of 11.205 and the MIND technique shows a value of 11.155. However, the existing approach (EA) attains a value of 10.958, YouTube-DNN technique denotes a higher value than the existing system as 13.58, in comparison with the existing techniques our proposed model ensures better performance and gives a value of 20.41.
In Figure 6 and Table 4 we can see that the recall@50 is evaluated for MovieLens Dataset, the method MostPopular method gives a value of 10.829 which is the least value, whereas we can see that MIND denotes an average value of 23.889 and the SEA technique shows a value of 24.325. However, the existing approach EA attains a value of 23.478, YouTube-DNN technique denotes a higher value than the existing system as 26.596 and in comparison, with the existing techniques, and our proposed model ensures better performance and gives a value of 47.05.

Table 1. Comparison recalls@20 for various technique

<table>
<thead>
<tr>
<th>Method</th>
<th>Recall@20</th>
<th>Method</th>
<th>Recall@20</th>
</tr>
</thead>
<tbody>
<tr>
<td>MostPopular</td>
<td>1.368</td>
<td>FAT</td>
<td>5.177</td>
</tr>
<tr>
<td>GRU4Rec</td>
<td>4.057</td>
<td>MIND</td>
<td>5.576</td>
</tr>
<tr>
<td>MIND</td>
<td>4.035</td>
<td>EA</td>
<td>6.761</td>
</tr>
<tr>
<td>ComiRec-DR</td>
<td>4.299</td>
<td>MEA</td>
<td>7.084</td>
</tr>
<tr>
<td>YouTube DNN</td>
<td>4.573</td>
<td>PS</td>
<td>13.89</td>
</tr>
<tr>
<td>ComiRec-SA</td>
<td>5.103</td>
<td>YouTube DNN</td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Comparison of recall@50 for various techniques

<table>
<thead>
<tr>
<th>Method</th>
<th>Recall@50</th>
<th>Method</th>
<th>Recall@50</th>
</tr>
</thead>
<tbody>
<tr>
<td>MostPopular</td>
<td>2.4</td>
<td>FAT</td>
<td>8.161</td>
</tr>
<tr>
<td>GRU4Rec</td>
<td>6.510</td>
<td>SEA</td>
<td>8.172</td>
</tr>
<tr>
<td>YouTube DNN</td>
<td>6.544</td>
<td>EA</td>
<td>10.625</td>
</tr>
<tr>
<td>ComiRec-DR</td>
<td>6.957</td>
<td>MIND</td>
<td>11.054</td>
</tr>
<tr>
<td>ComiRec-SA</td>
<td>7.458</td>
<td>EA</td>
<td>10.625</td>
</tr>
<tr>
<td>YouTube DNN</td>
<td>7.638</td>
<td>MEA</td>
<td>11.054</td>
</tr>
</tbody>
</table>

Table 3. Comparison of recall@20 for MovieLens dataset

<table>
<thead>
<tr>
<th>Method</th>
<th>Recall@20</th>
<th>Method</th>
<th>Recall@20</th>
</tr>
</thead>
<tbody>
<tr>
<td>MostPopular</td>
<td>4.636</td>
<td>ComiRec-DR</td>
<td>11.205</td>
</tr>
<tr>
<td>ComiRec-SA</td>
<td>10.834</td>
<td>MIND</td>
<td>11.366</td>
</tr>
<tr>
<td>FAT</td>
<td>10.892</td>
<td>MIND</td>
<td>11.645</td>
</tr>
<tr>
<td>EA</td>
<td>10.985</td>
<td>YouTube DNN</td>
<td>13.558</td>
</tr>
<tr>
<td>MIND</td>
<td>11.115</td>
<td>PS</td>
<td>20.41</td>
</tr>
</tbody>
</table>

Table 4. Comparison of recall@50 for MovieLens dataset

<table>
<thead>
<tr>
<th>Method</th>
<th>Recall@50</th>
<th>Method</th>
<th>Recall@50</th>
</tr>
</thead>
<tbody>
<tr>
<td>MostPopular</td>
<td>10.829</td>
<td>MIND</td>
<td>23.962</td>
</tr>
<tr>
<td>ComiRec-DR</td>
<td>22.391</td>
<td>MIND</td>
<td>24.325</td>
</tr>
<tr>
<td>ComiRec-SA</td>
<td>23.137</td>
<td>GRU4Rec</td>
<td>29.467</td>
</tr>
<tr>
<td>YouTube DNN</td>
<td>23.364</td>
<td>YouTube DNN</td>
<td>26.596</td>
</tr>
<tr>
<td>EA</td>
<td>23.478</td>
<td>PS</td>
<td>47.05</td>
</tr>
<tr>
<td>MIND</td>
<td>23.889</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.3. NDCG

Normalized Discounted Cumulative Gain (NDCG) considers the location of the correct project. In Figure 7 and Table 5 the NDCG@20 is evaluated for Amazon Dataset, the method MostPopular method...
gives a value of 2.259, which is the least value, whereas we can see that ComiRec-DR gives an average value of 4.508. The FAT technique shows a value of 4.07, however, the existing approach EA attains a value of 5.613, MIND technique denotes a higher value than the existing system as 7.933, in comparison with the existing techniques our proposed model ensures better performance and gives a value of 7.95.

In Figure 8 and Table 6 the NDCG@50 is evaluated for Amazon dataset, the method MostPopular method gives a value of 3.936, which is the least value, whereas YouTube DNN denotes an average value of 5.039 and ComiRec-DR technique shows a value of 5.591. However, the existing approach EA attains a value of 7.184, MIND technique denotes a higher value than the existing system as 7.238, in comparison with the existing techniques our proposed model ensures better performance and gives a value of 10.02.

![Figure 7. Comparison of NDCG@20 for MovieLens dataset](image1)

![Figure 8. Comparison of NDCG@50 for MovieLens dataset](image2)

Table 5. Comparison of NDCG@20 for MovieLens dataset

<table>
<thead>
<tr>
<th>Method</th>
<th>NDCG@20</th>
<th>Method</th>
<th>NDCG@20</th>
<th>Method</th>
<th>NDCG@20</th>
</tr>
</thead>
<tbody>
<tr>
<td>MostPopular</td>
<td>2.259</td>
<td>YouTube DNN</td>
<td>4.675</td>
<td>ComiRec-SA</td>
<td>3.807</td>
</tr>
<tr>
<td>ComiRec-SA</td>
<td>3.807</td>
<td>EA</td>
<td>5.613</td>
<td>FAT</td>
<td>4.07</td>
</tr>
<tr>
<td>SEA</td>
<td>3.99</td>
<td>MEA</td>
<td>5.816</td>
<td>GRU4Rec</td>
<td>4.163</td>
</tr>
<tr>
<td>FAT</td>
<td>4.07</td>
<td>MIND</td>
<td>7.933</td>
<td>PS</td>
<td>7.95</td>
</tr>
<tr>
<td>ComiRec-DR</td>
<td>4.508</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6. Comparison of NDCG@50 for MovieLens dataset

<table>
<thead>
<tr>
<th>Method</th>
<th>NDCG@50</th>
<th>Method</th>
<th>NDCG@50</th>
<th>Method</th>
<th>NDCG@50</th>
</tr>
</thead>
<tbody>
<tr>
<td>MostPopular</td>
<td>3.936</td>
<td>ComiRec-DR</td>
<td>5.591</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ComiRec-SA</td>
<td>4.41</td>
<td>GRU4Rec</td>
<td>5.678</td>
<td>FAT</td>
<td>4.824</td>
</tr>
<tr>
<td>SEA</td>
<td>5.231</td>
<td></td>
<td></td>
<td>MIND</td>
<td>4.907</td>
</tr>
<tr>
<td>FAT</td>
<td>4.824</td>
<td>EA</td>
<td>7.184</td>
<td>YouTube DNN</td>
<td>5.039</td>
</tr>
<tr>
<td>MIND</td>
<td>4.907</td>
<td>MEA</td>
<td>7.238</td>
<td>PS</td>
<td>10.02</td>
</tr>
</tbody>
</table>

4.4. Comparative analysis

The comparative analysis carried out here by the proposed system with the existing system, for Amazon Dataset the metric Recall@20 the existing system gives a value of 6.761. Table 7 shows the comparative analysis. Our proposed model denotes a value of 13.89 the improvisation done is 69.0427%, for Recall@50 the existing system gives a value of 10.625 and our proposed model denotes a value of 21.48 the improvisation done is 67.62%. For MovieLens Dataset the metric Recall@20 the existing system gives a value of 10.895 and our proposed model gives a value of 20.41 the improvisation done is 60.0414%, MovieLens Dataset the metric Recall@50 the existing system gives a value of 23.478 and our proposed model denotes a value of 47.05 the improvisation done is 66.8444%. , Amazon Dataset the metric NDCG@20 the existing system gives a value of 5.613 and our proposed model denotes a value of 7.95 the improvisation done is 34.4614%., Amazon Dataset the metric NDCG@50 the existing system gives a value of 7.184 and our proposed model denotes a value of 10.02 the improvisation done is 32.9691%, upon the comparative analysis of the proposed system with the existing system it can be concluded that our proposed model outperforms the existing model.

Table 7. Comparative analysis

<table>
<thead>
<tr>
<th>Dataset Details</th>
<th>ES</th>
<th>DeepNCF</th>
<th>Improvisation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon Dataset Recall@20</td>
<td>6.761</td>
<td>13.89</td>
<td>69.0427%</td>
</tr>
<tr>
<td>Amazon Dataset Recall@50</td>
<td>10.625</td>
<td>21.48</td>
<td>67.62%</td>
</tr>
<tr>
<td>MovieLens Dataset Recall@20</td>
<td>10.985</td>
<td>20.41</td>
<td>60.0414%</td>
</tr>
<tr>
<td>MovieLens Dataset Recall@50</td>
<td>23.478</td>
<td>47.05</td>
<td>66.8444%</td>
</tr>
<tr>
<td>Amazon Dataset NDCG@20</td>
<td>5.613</td>
<td>7.95</td>
<td>34.4614%</td>
</tr>
<tr>
<td>Amazon Dataset NDCG@50</td>
<td>7.184</td>
<td>10.02</td>
<td>32.9691%</td>
</tr>
</tbody>
</table>

A recommender system using novel deep network collaborative filtering (Shruthi Nagaraj)
5. CONCLUSION

In this paper, a DeepNCF model is developed that addresses the several issues such as overfitting, sparsity and performance metrics; DeepNCF incorporated the dual mode network into the collaborative filtering; DeepNCF designs user-item dual mode network from rating matrix; further considering the edges in network, it carries out edge clustering through custom weighted dual model modularity for higher densing. Furthermore, GNN is utilized for learning the complex relation among the user and items. The performance is better of the DeepNCF model in comparison with other existing approaches on two datasets. The edge-clustering algorithm is applicable here for developing a dual mode graph and implementing a edge reduction algorithm for every single community. The DeepNCF attains higher metrics in comparison with the existing methods in aspects of recommendation accuracy and variation in attaining the item from the customer for rating data and discarding irrelevant information.

REFERENCES


BIOGRAPHIES OF AUTHOR

Shruthi Nagaraj is a Research Scholar in the school of Computer Science and engineering at Presidency University, Bengaluru. She has a Bachelor's degree in Computer Science Engineering from VTU, Master's degree in Software Engineering from Ramaiah Institute of Technology, VTU. She has two years of experience working in the IT industry in Communication and Network Security. Her area of interests in research are Recommendation Systems, Deep Learning and Machine Learning Technologies, Artificial Intelligence and Intelligent Information Retrieval. She can be contacted at: shru.nag95@gmail.com.

Blessed Prince Palayyan is an Associate Professor with the school of computer science and engineering at Presidency University. He has served in the education sector for more than 17 years at college level and among the top university in India and has served with university abroad. He has received his bachelor’s degree from Manonmaniam Sundaranar University, Master’s degree from Annamalai University and Doctorate from Anna University, Chennai. His research interest includes major areas of computer science, particularly security in computing, Recommendation System, Image Processing, Artificial Intelligence, Robotics and IoT. He can be contacted at this email: blessedprince@presidencyuniversity.in.

A recommender system using novel deep network collaborative filtering (Shruthi Nagaraj)