Facebook Interactions Utilization for Addressing Recommender Systems Cold Start Problem across System Domain

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Abstract

Recommender systems face cold start problem at the time of inception which researchers have addressed by transferring rating knowledge from auxiliary to target domain, hence laying the foundation of cross domain recommender systems (CDRS). Recently social media has been utilized as a potential auxiliary domain for recommender systems because they provide interactions such as *likes, read, download, play, click* etc., for related items. Among existing social media, Facebook provides rich social interactions, broadly grouped as private and public social interactions. Although research exists on private Facebook social interactions, Facebook public social interactions were not explored before. In this paper, we propose Facebook Direct Social Recommendation (Facebook DSR) approach which transforms Facebook's public interactions related to a social page into rating matrix and generate recommendations for provided list of items. Relative ratings obtained from proposed algorithm and random approach were compared with Movielens ratings. It was observed that proposed approach outperformed random approach threefold with respect to mean absolute error (MAE) evaluation and 19.4 % with respect to precision evaluation for new user cold start scenario. Finally, this study highlights future directions.

Keywords: Cross domain recommender systems, Facebook, Social interactions, System domain transfer learning, Cold start problem

1 Introduction

Recommender systems are special softwares designed to recommend items to users based on their observed interest [1]. User's interest with respect to recommended item is stored in form of interaction inside a rating matrix, these interactions can be either explicit e.g. numerical rating or implicit e.g. likes, download etc., as shown in Figure 1. Users, items and rating matrix together create recommender systems ecosystem known as domain [2].

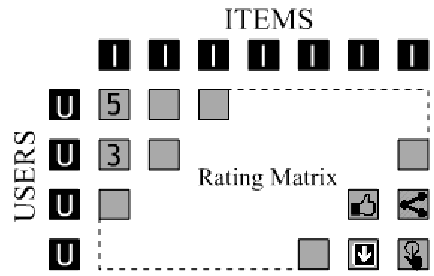

Figure 1. Recommender systems rating matrix

Nowadays recommender systems focus on item recommendation to single domain e.g. AMAZON recommends items for sale to its interested users, Netflix presents its viewers with a list of media content etc. Such recommender systems are increasing rapidly and are found to focus on users having specific interest, rather than relying on the wisdom of crowd i.e. covering a broad range of users [3].

Single domain recommender systems face a variety of problems like cold start, sparsity, new user, items etc. [1]. Recently cold start problem has been described as a problem arising in a recommender system due to insufficient rating inside rating matrix [4]. Although these problems are being researched under single domain perspective. CDRS on the other hand, add a new dimension in solving these problems, by transferring knowledge available from other domains known as auxiliary domain to target domain.

In recent years, CDRS is gaining momentum and researchers have started contributing from diverse viewpoint especially in attempting to resolve cold start problem [30]. Researchers first identify common entities in both domains i.e. users or items and then transfer knowledge with respect to these entities. When items are common in both domains, knowledge is transferred with respect to similar items, for assisting new user cold start problem, and when users are common in both domains, knowledge is transferred

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with respect to similar users for generating recommendation for new items.

Related work of this research is discussed in Section 2. In Section 3, we propose an algorithm for new user cold start problem. Section 4 describes an experimental scenario and obtained results. Finally, Section 5 concludes research with future work.

2 Related Work

This section attempts to gather related research. First conceptual background related to cross domain recommender systems (CDRS) and its building blocks is presented. Second, classification grid is presented for identifying this research with respect to CDRS building blocks. Third, social media involvement in cross domain recommender systems is highlighted. Fourth, compare studies that transform social interactions into rating matrices are presented and finally compared approach is identified and reason of selection is delineated.

2.1 Conceptual Background

Cross domain recommender systems is a new perspective to address recommendation problem, therefore, this section gives a brief overview of cross domain recommender system approach. First, attributes of cross domain recommender systems are described and later classification grid for identification of cross domain scenarios is proposed.

2.1.1 Cross Domain Recommender Systems

Cross domain recommender systems rely on three building blocks i.e. domain, recommendation scenario and recommendation tasks.

Domain. In cross domain recommender systems, domain is an environment identifying and restricting the scope of rating matrix. Although researchers have used domain with a different scope, most widely used domain definitions come from Li [17] and Ivan [3]. Li described *System*, *Data* and *Temporal* domain whereas Ivan domain definitions can be grouped as *Category* domain.

Recommendation scenarios. To assist transfer learning between domains, some relation need to exist between users and items of participating domains. Usually, this relation is formed when users and items are found common in both domains. This relation overlap was highlighted by Cremonesi [2]. He identified four scenarios which were, *no user - no item overlap*, *user - no item overlap*, *no user - item overlap* and *user - item overlap*.

Recommendation tasks. Cross domain recommendation tasks are associated with target user recommendations. Two main factors involved are the scope of recommended items and scope of target users. Recommended items can come from both auxiliary or target domain or either from one of the two domains similarly target users can reside in both or either one of the two domains. This leads to multiple scenarios of recommendation which are multi-domain recommendation [2], single domain recommendation [2] and linked-domain recommendation [3].

2.1.2 Classification Grid

Based on two building blocks i.e. *domain* and *recommendation scenarios*, we propose a classification grid as shown in Figure 2. The objective of this grid is to identify changes between auxiliary and target domain.

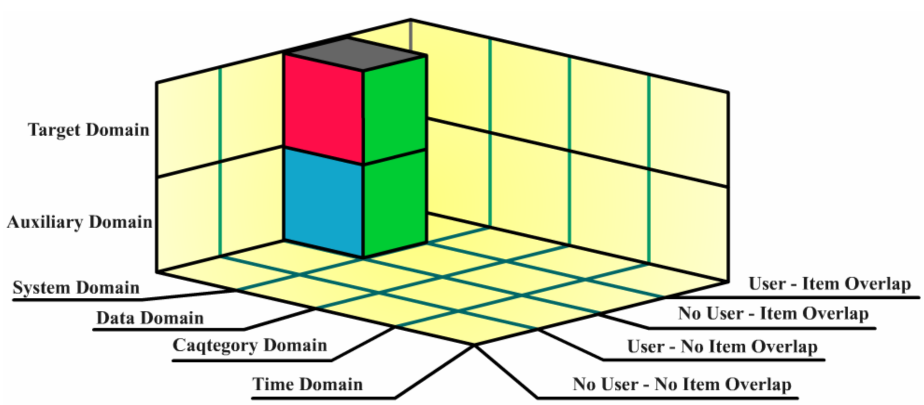

Figure 2. Cross domain recommender system classification grid

A research paper can be represented as two blocks, one existing in auxiliary while other in the target domain. Blocks can have different colors, such as green color represents no change whereas transition from blue to red represents change with the respective axis. For example Figure 2, places this study into classification grid. It shows the transformation of this study from Facebook as source domain to external rating matrix as target domain. As a result system domain changes color from blue to red whereas for transition with respect to recommendation scenarios, color remains same, because both contribute for *No-User, Item overlap.*

2.2 Related Studies

This section is divided into four sub-sections. First section delineates the role of social media in cross domain recommender systems. Second section highlights research related to category domain which helped in identification of research problem. Third section identifies studies that transfer knowledge from one system domain to another. Finally, in section four, compared approach i.e. random approach is explained and reason of selection is outlined.

2.2.1 Social Media in cross Domain Recommender Systems

Social media stands on a balance between user generated content and web 2.0 technologies [21]. Social media emphasizes on hosting, presenting and exchanging user content among connected users, using web 2.0 technologies. [18] identified around 168 social media sited among which some provided an Application Programming Interface (API), to extract data for application development and research purposes.

Researchers also used different social medias as source domain among which Movielens [11], Twitter [12], AMAZON [5], Wikipedia [20], musicload [13] are most prominent. One key feature helping respective sources is that information hosted on these websites is public in nature and is freely available using APIs.

Among existing social medias, Facebook has the largest number of users [10], however, with respect to research, its volume is small [18]. Next section highlights Facebook's research contribution along with problem identification.

2.2.2 Recommendation within a System Domain (Category Domain Recommendation)

While multiple social medias are being used for cross domain recommender systems research, Facebook, in general, has contributed with respect to category domain. Researchers utilized Facebook's social interaction related to movies for improving recommendation related to music and TV shows [6] [19], whereas, [9] used social interactions for posts recommendation. Mentioned researchers addressed recommendation problem inside Facebook, however, they faced privacy concerns. Interactions used by respective researchers were private in nature, therefore, required special permissions from participating users. Also, once user grants permission, researcher's algorithm gain full read, write access to users data. This gives rise to user's concern related to personal information and hinders research participation.

On the other hand, Facebook also hosts public interactions related to specific topics in form of Facebook pages and least user permissions are required to access respective social interactions. Therefore, research problem can be identified as

"How Facebook's public social interactions can be utilized for recommendation generation outside Facebook"

Next section highlights studies that transformed existing social interactions available on some of popular social sites into ratings, used for recommendation generation in the target domain.

2.2.3 Recommendation Outside Facebook

Some studies related to both social media and recommendation across system domain are listed in table 1. These studies transfer knowledge from social media and each of them defines their own transformation criteria. [5] transferred ratings provided to different items on AMAZON to KDD cup dataset [31], [13] first transformed social interactions such as play, download, click etc., available on gameload and musicload website into numeric ratings and later transferred to Netflix dataset. [20] extracted editing information related to different items on Wikipedia and transformed it into numeric ratings for assisting recommendation in target domain whereas [12] crawled twitter for trending tags and keywords in order to assist video recommendation in the target domain. Also twitter was used in creation of movies dataset, known as "MovieTweetings" [16].

Table 1. Similar studies

#	Source	Target	interactions	Transformation method
5	AMAZON	KDD cup	ratings provided by users	Using source ratings for assisting recommendation in target domain
13	Gameload Musicload	Netflix	play, download, click etc.	assigning numeric values to interactions for rating generation
20	Wikipedia	Movielens	Editing pattern	numeric ratings were assigned to number of time a page was edited for creating ratings
12	Twitter	YouTube	trending tags and keywords	Training neural network for prediction

Facebook has different research contributions as compared to mentioned social medias. Mentioned social medias are public in nature, hence anyone can view any tweet, observe item ratings on AMAZON etc., whereas current Facebook research deals with private social interactions for recommendation prediction.

However, Facebook's interactions hosted on pages are public in nature and can be used for recommendation generation outside Facebook.

Next section highlights changes associated with transferring knowledge from Facebook to the external system along with the explanation of compared approach i.e. random approach.

2.2.4 Cross Domain Transfer & Random Approach

In this research, we intend to address pure cold-start problem [27]. This scenario consists of completely empty target rating matrix assisted by source domain. For assist target domain, some similarities needs to exist between both domains, hence for this research, items of both source and target domain are same. Also in the target domain, items and user are new for each other because no previous rating exists for assisting recommendation generation. In conclusion, changes associated with CDRS building blocks of this research are as follow.

Domain. It changes from Facebook to empty target domain hence classifying this study into *system* domain overlap.

Recommendation scenarios. Users of both domains do not overlap whereas items remain same hence classified as *No-User, Item overlap*.

Recommendation tasks. This study is associated with *linked-domain recommendation task*, because source items are recommended to target users based on knowledge learnt from the source domain.

As mentioned earlier, there exist no ratings in the target domain, hence users and items in target domain are new for each other. This scenario resembles partition 4 described in [29] where they labeled it as "hard case". "Random" strategy was recommended by [4] as the only mean of collecting ratings for such scenario. Random approach consists of ratings provided randomly for item existing in rating matrix. This approach was also used by [15, 28-29] where they compared their proposed algorithm with the random approach as a base line.

3 Proposed Approach

This study attempts to address new user cold start problem [27] by exploring and transferring knowledge from Facebook as an auxiliary domain to target domain. Figure 3 shows broad operational workflow of our proposed approach i.e. Facebook Direct Social Recommendation (Facebook DSR).

Facebook DSR has three main components i.e. user-item identification, rating matrix generation and recommendation generation where each component consists of subcomponents explained in respective sections. Once each section is explained, pseudo code is presented.

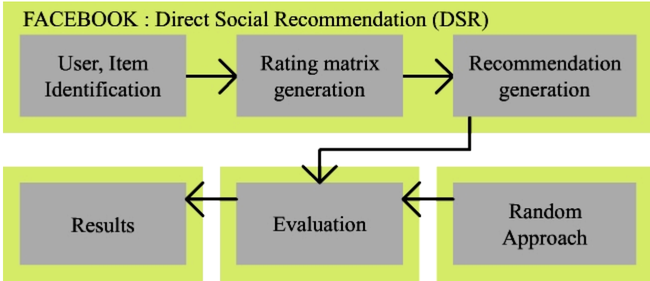

Figure 3. Overview of proposed approach

3.1 User, Item Identification

This component is further divided into sub components which are formulation of Facebook social interactions, common items identification, social interactions extraction and users extraction respectively. Each subcomponent relies on input from the previous component to operate and produce an outcome.

3.1.1 Facebook Social Interactions Formulation

Facebook is world's biggest social media [14] and holds interactions related to an immense number of topics, movies, music, celebrities etc. Although Facebook is a great candidate for recommendation extraction, it limits access to its data based on permissions granted by Facebook users.

Existing research [19-20] related to Facebook recommendation utilized users private social interactions, however, they highlighted privacy issues hindering research. First, permissions granted by Facebook users to generate recommendation could be exploited [19] and second, generated recommendation be presented to Facebook users only [19-20].

To address these issues we focus on Facebook public social interactions which do not require user permissions and can be used for external recommendation. In order to do so, we first identify types of Facebook social interactions included in this research, second we identify Facebook root nodes with least permissions requirement, third, we briefly explain Facebook graph API for social interaction extraction and finally we propose the formulation of respective social interaction.

Facebook's public social interactions. Facebook social interactions are usually represented as likes, comments and shares [22]. Facebook social interactions exist in form of nodes where each node can only be accessed once if appropriate permission is granted by the owner of node. To identify nodes with least permission requirement, Facebook root nodes were analyzed. Facebook root nodes can be queried directly using graph API i.e. a graph exploring tool provided by Facebook.

Facebook root nodes. Facebook handles information in form of nodes, edges and fields [23]. Facebook nodes can be accessed using HTTP request based on an identifier. A total of 48 root nodes have been identified by Facebook [25]. Post is one of the root nodes and it represents message related to the topic of interest for which users can provide likes, comments and shares. Among these nodes, page node requires least permissions and is identified public in nature i.e. any interaction provided on Facebook page → posts will be accessible to all Facebook users and search engines.

Facebook GRAPH API. Facebook graph API provides users with low level HTTP interface to read and write to the Facebook social graph. In order to access page node, an access token with "manage_page" [24] permission is required. This access token can be used with each graph API call to retrieve required page → posts and related social interactions. Graph API only allows access to likes and comments related to page → posts but does not provide access to related shares.

Facebook social interactions formulation. Facebook does not explicitly identify nodes as items, therefore a criteria is required to identify connection from nodes to items. Based on interactions between users and posts, we identify Facebook nodes that represent human users as user nodes, Facebook page and post nodes related to items as item nodes. Hence out of 48 root nodes, we select users, pages and posts nodes, because page → posts are publically accessible using Facebook API [26]. Facebook nodes can be represented as vertices of a graph hence following formulas can be derived.

(1) N = {set of all nodes n on Facebook}

(2) Nu(U) = { n|n $\in$ N ^ n represent user nodes only}

(3) Ni(I) = { n|n $\in$ N ^ n represents page, post nodes only}

Note: For convenience, nodes in (U) are represented as u and nodes in (I) as ipage, ipost similar to [26].

(4) Upage = { u|u $\in$ N ^ u represents user who interact with posts of respective page}

(5) Ipost, page ={ ipost|ipost $\in$ N ^ ipost represents posts belonging to respective page}

(6) R like/comment/share, page = rating matrix i.e. Upage x Ipost, page containing binary representation of social interaction (like or comment) between users and posts of a page.

3.1.2 Common Items Identification

Before transferring knowledge from auxiliary to target domain, it is important to identify the common element of both domains. As a case study, Facebook.com/IMDB is considered as source domain while Movielens is considered as target domain. The only difference in this experiment is that target domain ratings are deleted in order to simulate "pure cold start" scenario in the target domain.

Both Facebook page and Movielens movie list is passed as input to phase 1. As a result, component returns list of shortlisted Facebook posts related to entered movies, shown as connector 1 in Figure 4. For selected case study, 807 movies were found common between both sources whereas, 809 posts were found discussing matched movies. Inputs and outputs of this phase are explained in analysis and results section. The outcome following sections is also discussed in analysis and results section.

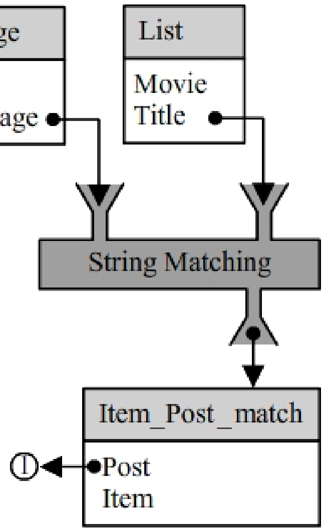

Figure 4. Phase 1 finding common items

3.1.3 Social Interactions Extraction

Once Facebook posts are identified, social interactions i.e. *likes* and *comments* are retrieved using graph API.

Figure 5 shows phase 2: "retrieving social interactions" component, which takes list of posts as input and generates list of user who *liked* and *commented* respective posts. Each list is represented with connector 2 and 3 which are used in next phase.

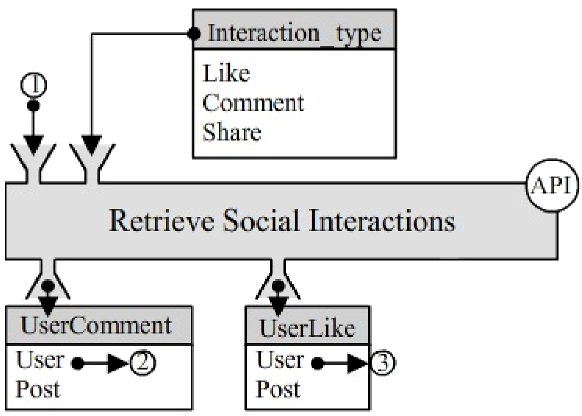

Figure 5. Phase 2 retrieving social interactions

3.1.4 Unique User Extractions

Once lists of users are extracted who *liked* and *commented* on shortlisted posts, unique users from respective lists can be extracted next, as shown in Figure 6.

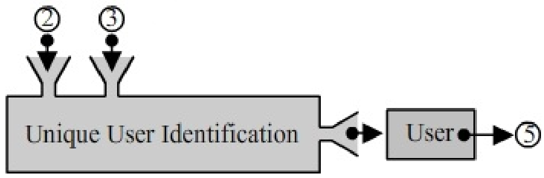

Figure 6. Phase 3 unique users identification

After unique users are identified, rating matrix can be generated between items (movies) and users with respect to *likes* and *comments*.

3.2 Rating Matrix Formation

In order to make Facebook data compatible with recommender systems, it is required to transform social interactions into a rating matrix. In the previous section, users, items and respective social interaction were extracted. This section first proposes generation of interaction matrix which will later be transformed into rating matrix using identified users, items and interactions.

3.2.1 Interaction Matrix Generation

This study focuses on *likes* and *comments* provided by users in order to generate interaction matrix, as shown in Figure 7.

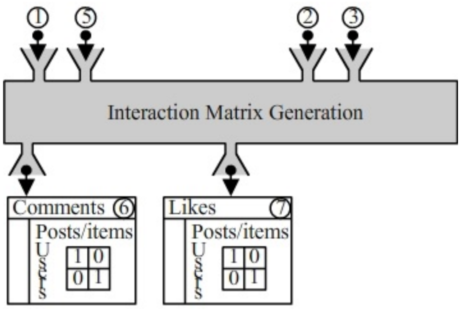

Figure 7. Phase 4 interaction matrix generation

Phase 4 takes posts, users and social interactions as inputs and produce interaction matrix between users and posts, where a corresponding interaction is represented as binary 1.

3.2.2 Rating Matrix Generation

Once interaction matrices are generated, they are merged into a single rating matrix based on appropriate weights assigned to them.

Figure 8 shows phase 5 consists of a component i.e. rating matrix generation that takes two matrices as inputs, assigned weight to each binary interaction and merge into one rating matrix. For *like* interactions, a score of 4.5 was assigned out of 5, whereas for *comment*, sentiment score was calculated using INDICO API [7]. Sentiment score was multiplied with 5, in order to calculate comment rating.

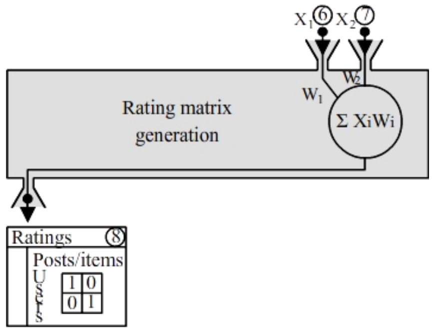

Figure 8. Phase 5 rating matrix generation

3.3 Recommendation Generation (Rank List Generation)

This section consists of a single subcomponent i.e. "recommendation generation component" as shown in figure 9 that takes generated rating matrix as input and outputs a list of movies with calculated ratings.

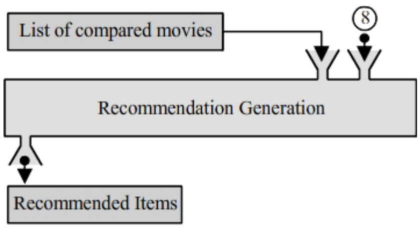

Figure 9. Phase 6 recommendation generation

This component ranks items, with respect to accumulated ratings provided to each item and finally returns the item in descending order, i.e. first item having maximum positive ratings and last item having least.

3.4 Pseudo Code

This section gives an idea of experimental execution of proposed algorithm. Consider each phase represented by a function, having the same name, then pseudo code is written as Algorithm 1.

Algorithm 1: Facebook DSR

```
Prerequisite: case study
FB_Page = "Facebook.com/IMDB";
ItemsList = getItems("Movielens_Dataset");

Phase execution:
FBposts = getTotalPosts(FB_Page);
[Items, Posts] = StringMatching(FBposts,ItemsList);
[ulike, ucomment] = retrieveScoailInteractions( ...
                    posts, ["like", "comment"]);
[users] = uniqueUserIdentification([ulike, ...
          ucomment]);
[l_mat, c_mat] = interactionMatrixGeneration( ...
                 Posts, users, ulike, ucomment);
[R_mat] = ratingMatrixGeneration(l_mat, c_mat...
          l_const, c_const );

Rank list generation:
RankList= rankListGeneration(R_mat);
```

4 Analysis & Results

This section first explains experimental scenario, second, outcome of each phase of proposed approach is described, third, evaluation of experiment is explained and results are discussed.

4.1 Experimental Scenario

Figure 10 shows experimental scenario under consideration. In this study, target recommender system has multiple items in record whereas no user rating is available for recommendation generation. The experiment starts by identifying the list of items in target domain for which ratings are required. This study considers empty Movielens dataset as target domain i.e. movies and users information is present, however, ratings are empty. In beginning, the list of movies is extracted for sharing with DSR and Random approach i.e. step 2 and step 4 respectively. This is done in order to generate relative ratings. Once both approaches return ratings in step 3 and step 5, they are then passed to evaluation section.

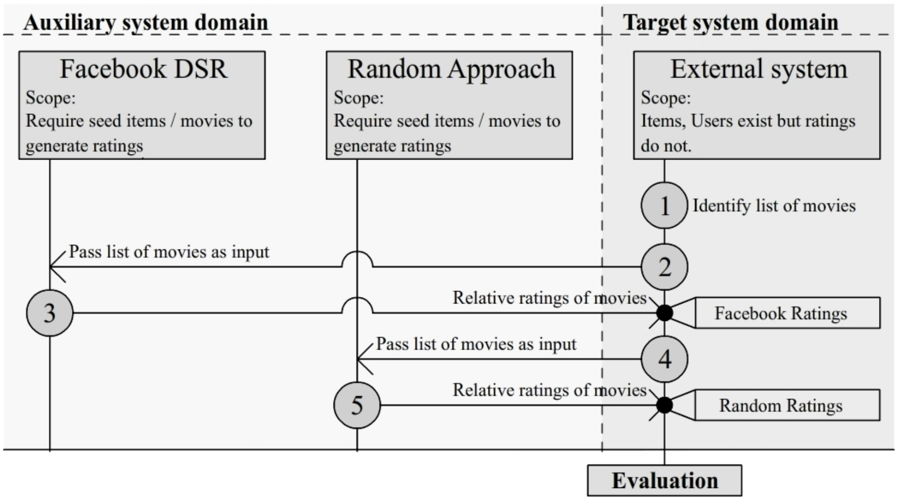

Figure 10. Experimental scenario

4.2 Outcome of Each Phase

Table 2 explains the outcome of each phase of Facebook DSR approach. In phase 1, 807 movies were found common between Facebook IMDB page and Movielens dataset whereas, 809 posts were found related to identified movies. In phase 2, likes and comments related to identified posts were gathered and respective users were identified in phase 3. Interaction matrices were generated in phase 4 which were transferred into rating matrix in phase 5. Finally, in phase 6, items are ranked according to accumulated ratings for recommendation purpose.

Table 2. Facebook DSR description

Phase	Description	Outcome
1	A list of 807 movies was submitted to Facebook DSR algorithm.	807 Movies
1	A total of 809 *posts* were found discussing submitted movies	807 Facebook *posts*
2	Total of 785161 *likes* and 97335 *comments* were retrieved with average of 973 *likes* and 121 *comments* per *post*. Facebook returned shares in an integer rather than providing user id because of user's privacy policy.	785161 *likes* and 97335 *comments*
3	Among all users retrieved from *likes* and *comments*, 432790 user were found unique	432790 unique users identified
4	Using identified users and posts two interaction matrices with dimension of 432790 x 807 was generated	Two 432790 x 807 interaction matrices
5	In order to generate rating matrix from interaction matrix, 4.5 rating was assigned to *likes* whereas comments INDICO [7] sentiment score was multiplied with 5 in order to calculate comment rating.	Single 432790 x 807 rating matrix with 5 as max and 0 as min rating
6	Base on rating matrix, Items were ranked using following equation (i) $ItemScore_i = \sum_{u=1}^{n} Rating_{u,i}$ (ii) $RankedList = \{ItemScore_i \mid ItemScore_i \text{ is stored}\}$ *with respect to score in decending order*	relative ranking of 807 movies

4.3 Evaluation

As an ideal case, Movies were ranked with respect to accumulated ratings provided in Movielens_dataset. These ranked movies were then compared with ranked list generated using Facebook DSR and random approach. For evaluation, precision measure was used to check which source resulted in more accurate prediction, whereas, mean absolute error (MAE) was selected in order to show the amount of error between ideal and compared approach ranked lists. MAPE was not selected because it attempts to provide a percentage of error between forecasted and actual value. Although MAPE can provide a percentage perspective, it fails to produce correct results when forecasted values are too high as compared to actual value. This scenario occurs when predicted rating is greater than 1 and actual rating is less than 1 [8].

MAE. MAE is a measure to observe deviation of a rating from a standard rating, where standard ratings were extracted from Movielens dataset and observed ratings came from Facebook DSR and Random approach. In case of Facebook DSR and random approach, it was observed that random approach had an average MAE of 1.38 whereas Facebook DSR scored 0.42 MAE score.

Figure 11 shows MAE difference between Facebook DSR approach and random approach with respect to chunks having 80 movies each. Lower MAE values of Facebook DSR illustrates closeness to Movielens ratings.

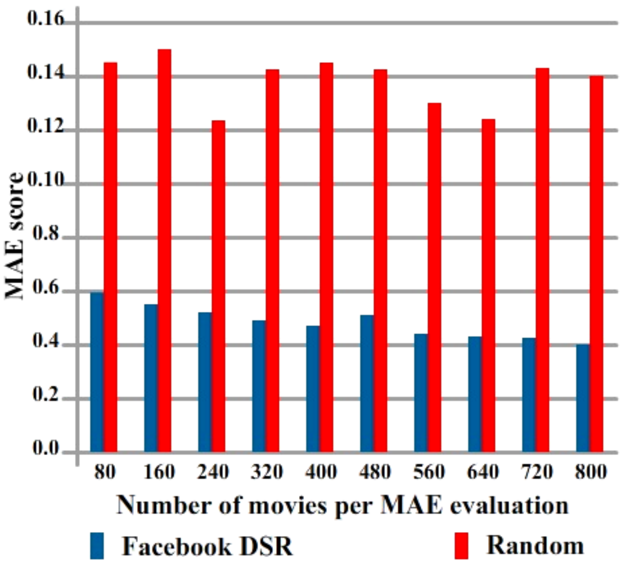

Figure 11. MAE evaluation of compared approaches

Precision. Precision is a measure of correct positive results divided by the sum of predicted positive and negative results [3]. In order to find out precision of compared ratings and Movielens ratings, chunk of movies having a quantity of 50, 100, 150, 200, 250, 300, 350, 400, 450 and 500 were extracted from Movielens dataset, Facebook DSR and random approach. For each chunk movies having ratings more than 2.5 were assigned 1 and less than 2.5 were assigned 0 and keeping Movielens ratings as standard ratings, Facebook DSR and random approach ratings of same movies were compared.

Figure 12 shows precision scores of Facebook DSR and random approach with respect to Movielens dataset. It was observed that Facebook DSR had an average of 19.4% better precision score than random approach while with increasing number of movies, precision score of both approaches improved.

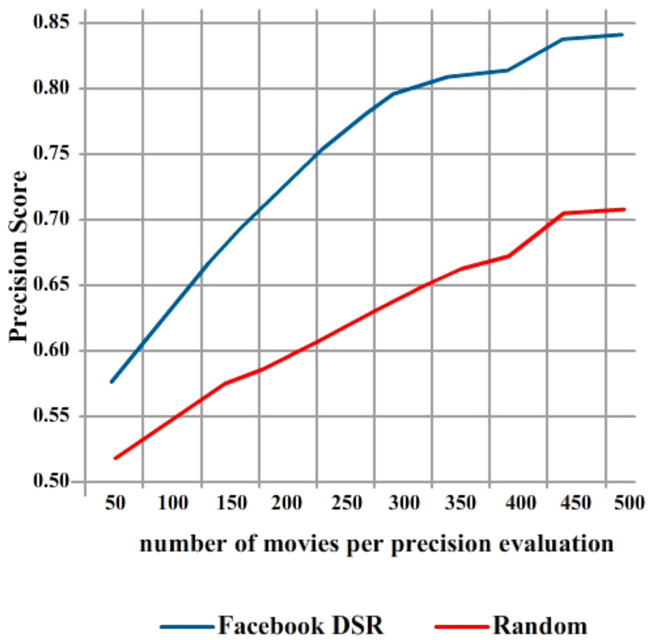

Figure 12. Precision evaluation of compared approaches

5 Conclusion & Future Work

In summary, Facebook DSR approach outperformed random approach threefold with respect to MAE evaluation while 19.4 % improvement was observed with respect to precision evaluation. Therefore this study demonstrates Facebook DSR benefit over random approach for identified experimental scenario where no ratings exist between users and items of the target domain.

In future we want to utilize graph connections between Facebook users, posts in order to compare Facebook DSR approach with KNN [1] and other TAG based approaches such as cross domain folksonomies [32]. Also, Facebook DSR approach can be coupled with existing social media approaches in order to group multiple social medias as source domain for recommendation in target domain such as MovieTweetings [16] (a twitter based movies dataset).

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