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Cold Start Problem Alleviation in a Research Paper Recommendation System Using the Random Walk Approach on a Heterogeneous User-Paper Graph

Manju G., SRM Institute of Science and Technology, India
Abhinaya P., Anna University, India
Hemalatha M.R., Anna University, India
Manju Ganesh G., Anna University, India
Manju G.G., Anna University, India

ABSTRACT

Recommendation approaches generally fail to recommend newly-published papers as relevant, owing to the lack of prior information about the said papers and, more particularly, problems associated with cold starts. It would appear, to all intents and purposes, that researchers currently interact more on social networks than they normally would in academic circles, and relationships of a purely academic nature have witnessed a paradigm shift, in keeping with this new trend. In existing paper recommendation methods, the social interaction factor has yet to play a pivotal role. The authors propose a social network-based research paper recommendation method, that alleviates cold start problems by incorporating users' social interaction, as well as topical relevancy, among assorted papers in the Mendeley academic social network using a novel approach, random walk Ergodic Markov Chain. The system yields improved results after cold start alleviation, compared with the existing system.

KEYWORDS

Belief Propagation, Cold Start Problem Alleviation, Ergodic Markov Chain, Label Propagation, Paper Recommendation, Random Walk, Trust Score

1. INTRODUCTION

In recent years, recommender systems have become increasingly familiar and changed the way people find products, information, and even other people. Recommender systems are being used in different kinds of recommendation tasks, including movies, music, news, books, research publications, and so on. Recommender systems investigate behavioral patterns to analyse preferences in terms of things especially actions, activities or thoughts not as yet experienced by the users in question. A recommender system is implemented under three major approaches: content-based, collaborative filtering, and hybrid. In a content-based approach (Ricci et al., 2011), profiles are built for both users and items

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and recommendations made by matching profiles: that of users with items. In a collaborative filtering approach (Adomavicius and Tuzhilin, 2005; Ricci et al., 2011) user or item behaviors and preferences are analyzed and, based on their past activity, users are recommended new items or users. A hybrid approach (Ricci et al., 2011) combines both content and collaborative approaches. New users offer very few ratings where items are concerned. As a result, it is difficult to find similar neighbors for new users, leading to the elimination of all new users during recommendations, thereby setting in motion cold start user problems.

In current scenario, world's knowledge is captured and archived within a digital library system. However, these new trends imposes information overload, where users retrieve enormous number of publications that match their search queries but are largely irrelevant to their needs. Hence as a solution to ease the work of the researchers, most relevant papers are retrieved and recommended to the researchers using the research paper recommendation system (Sugiyama et al., 2010).

Nevertheless, most systems cannot guarantee user-specific data derived according to users' interest domains and work areas. Social networking-based recommendation systems can provide personalized recommendations adapted to user interests and needs. Consequently, a social network-based research paper recommendation is essential. In this work, we have combined collaborative and content-based approaches and proposed a social network-based research paper recommendation, built on the Mendeley social network.

A user's social activity helps to determine the much larger number of similar users based on social relations and this can help exponentially increase the number of users in researcher communities. In turn, this takes into consideration research papers published by users (regardless of the publication year) brought together on the basis of social interaction. Furthermore, indirectly this provides an initial trust regarding the newly collected papers. It follows, then, that along with topic relevance, users' social interaction can be combined to retrieve more research papers that are relevant, and so eliminate cold start problems. Therefore, in our work we build a social interaction-based user graph in the Mendeley social network, and a topical relevance-based paper graph established on the topical relevance between papers in the Mendeley network. To efficaciously handle cold start problems during the process of paper graph construction, our work attempts to determine belief in the trustworthiness of newly-published papers and further consider the papers with better trust for recommendation. The trust score based on topical relevance is determined using a novel approach termed label propagation-based belief propagation. We aim to reduce the number of neighbors considered for message computation by selecting neighbors with label propagation rather than considering information from all of a node's neighbors. Nodes are selected using the label propagation algorithm to reduce the computation time incurred in the belief propagation algorithm's message computation. We build a heterogeneous graph by linking the papers of the paper graph with their corresponding authors in the user graph. Henceforth, a random walk on the heterogeneous graph using ergodic Markov chain traverses through the papers of both the users (authors) and their socially related neighbors based on the trust information given by both the user and the paper graph.

2. RELATED WORK

This section discusses the existing literature in research paper recommendation and the different kinds of solutions provided by miscellaneous studies for cold start problems.

2.1. Cold Start Problems

Cold start problems are handled using different approaches, such as the statistical model-based approach (Lam et al., 2008), average approach (Guo, 2008) and mode approach. In the statistical approach, depending on the user, probability statistics are determined and rates initialized. Based on the score, items with high probability are prioritized and recommended to the user. In the average approach, the average of all item ratings before collaborative filtering is computed and filled as an original rating matrix. In the mode approach, the frequent score found as the ratings of users is given as users predict results.

The existing research has used one of the following techniques to deal with new user cold-start problems: (i) using additional data sources like a user's profile, opinions, social tags, and so on for selecting the the new user's best neighbors, (ii) determining the best method to identify similar groups of users, and (iii) using hybrid methods to calculate similarities between analogous users and prediction ratings.

As a mode of improving the quality of recommendations made, multiple solutions have been provided to manage cold start problems, a primitive solution being collaborative filtering (Saini and Binda, 2012) using the tagging method. (Chen et al., 2013) built a user model based on trust and distrust networks to determine trustworthy users, and proposed a cold start recommendation method to provide new users recommendations that integrate a user model with trust and distrust networks to identify trustworthy users, aggregated thereafter to provide new users useful recommendations. A user similarity model, NHSM, was proposed (Liu et al., 2014) that considers both the local context information of user ratings as well as user behaviors in terms of global preferences. Ji et al. (2015) proposed a scalable recommendation method to alleviate cold start problems by considering content-based information comprising user tags and item keywords. Zhang et al. (2015) proposed a dual discriminative selection (DualDS) framework to elicit valuable user ratings by incorporating category labels that indicate user preferences and item attributes and so resolve cold start recommendation problems. Lika et al. (2014) considered a user's information in terms of age, gender and occupation to determine similar users and recommend them to new users.

Researchers have, in recent times, introduced two kinds of cold starts namely absolute and partial to enhance recommendation performance. A novel approach for alleviating both absolute and partial cold starts was introduced (Ocepek et al., 2015) by assigning missing values to the input matrix.

Furthermore, attempts were made to incorporate social network information into recommendation systems. A regularization-based method was introduced (Sun et al., 2015) in which user friendships and the correlation between items and users were fused into the matrix factorization objective function. Another approach to alleviate cold start problems in product recommendation was carried out (Lie at al., 2015) incorporating the textual data of social networks.

As a solution to cold start problem, hybrid approaches were proposed. HI-FCF++, a hybrid approach that integrates the advantages of several methods has been proposed (Son et al., 2015). In one of the hybrid approaches, two probabilistic aspect models were used (Lam et al., 2008), combining user information along with pure collaborative filtering to build aspect models. The other hybrid approach, (Park and Chu, 2009), utilized user and item features, apart from user ratings, and built a predictive regression framework.

Ongoing research to resolve cold start problems involves the use of filterbots. A filterbot is a surrogate user (an automated agent) that helps to rate items using collaborative techniques. An analysis with different types of personal filterbots (Good et al., 1999) has been made to resolve cold start problems found in collaborative filtering. Enhancements using filterbots have been carried out by employing global filterbots rather than personal ones (Park et al., 2006). Further, the approach has been applied to item-based collaborative filtering instead of a user-based technique. Profiling new users has been affected to eliminate cold start problems, with new users' preferences obtained by interviewing users and creating profiles. A recommendation algorithm was proposed (Sun et al., 2013) that interviews new users using a decision tree, and uses the answers so obtained to build new users' profiles.

Sahebi and Cohen (2011) used the concept of homophily in social networks as a solution to cold start problems. The authors extracted communities possessing similarity relations - such as friendship, ratings, and interests and used the determined similarities for solving cold start problems in recommendation systems. Several recommendation algorithms aim to improve the recommendation process to do away with cold start problems while choosing to ignore the social aspects of the users involved.

2.2. Paper Recommendation

In academic circles, professors, students, and researchers constantly search for relevant domain-related papers, paving the way for miscellaneous research paper recommendation systems that ease the work of the research community. Techlens (Torres et al., 2004) was one of the foremost research paper recommendation systems based on collaborative filtering and content-based approaches. Later, other recommendation systems like CiteULike (Bogers and Bosch, 2008), Claper (Wang et al., 2010), SCuBA (Agarwal et al., 2006), a system-improving serendipity of recommender systems (Miao et al., 2014), paper recommendation using the decision theory (Matsatsinis et al., 2007), and paper recommendation using citation and reference information (Sugiyama and Kan, 2010) were introduced. But the drawback in the systems cited above is that they depend only on document text and disregard users' intentions or interests.

A content-based recommendation system (Beel et al., 2014) for a smaller network has been proposed. The system, however, focused only on user profiles and bypassed concentrating on user interactions. Pan and Wenxin (2010) made an attempt to alleviate cold start problems in item-based research paper recommendations by carrying out topic analyses on papers and introducing thematic similarities. The problem with the system, however, is that user preferences have not been considered and citation analyses not performed.

Collaborative filtering approaches have been modified to incorporate serendipity in recommendation tasks. A few attempts have been made to develop recommender systems with the inclusion of users' social interactions. Chiu et al. (2011) employed the social network's user interaction history in recommendation tasks. Furthermore, social interaction and trust scores between users have been used in recommendations (Mican et al., 2012). Asabere et al. (2014) proposed a scholarly paper recommendation method SARSP that computes the social ties between the types of participants and use them to suggest papers. These recommendation approaches considered users' social interaction alone. Moreover, in paper recommendation tasks, users' social interaction and trust have not been considered so far. Further, recommendations based on trust between users and research papers have yet to be addressed. All kinds of recommendation approaches, however, do face problems in terms of data sparsity, addressed by a few studies (Yuan et al., 2014; Adomavicius and Tuzhilin, 2005; Liu et al., 2009) that have sought to mitigate them.

Cold start problems are noticed in paper recommendation tasks as well. (Ha et al., 2014) proposed a paper recommendation method emphasizing the recommendation of recently-published articles using a probabilistic inference belief propagation algorithm. However, the approach does not consider users' (researchers) social interactions and trust scores between users for generating recommendation results. An approach (Chang et al, 2014) incorporating social distance for estimating trust has been proposed, but the approach does not focus on recommendation tasks.

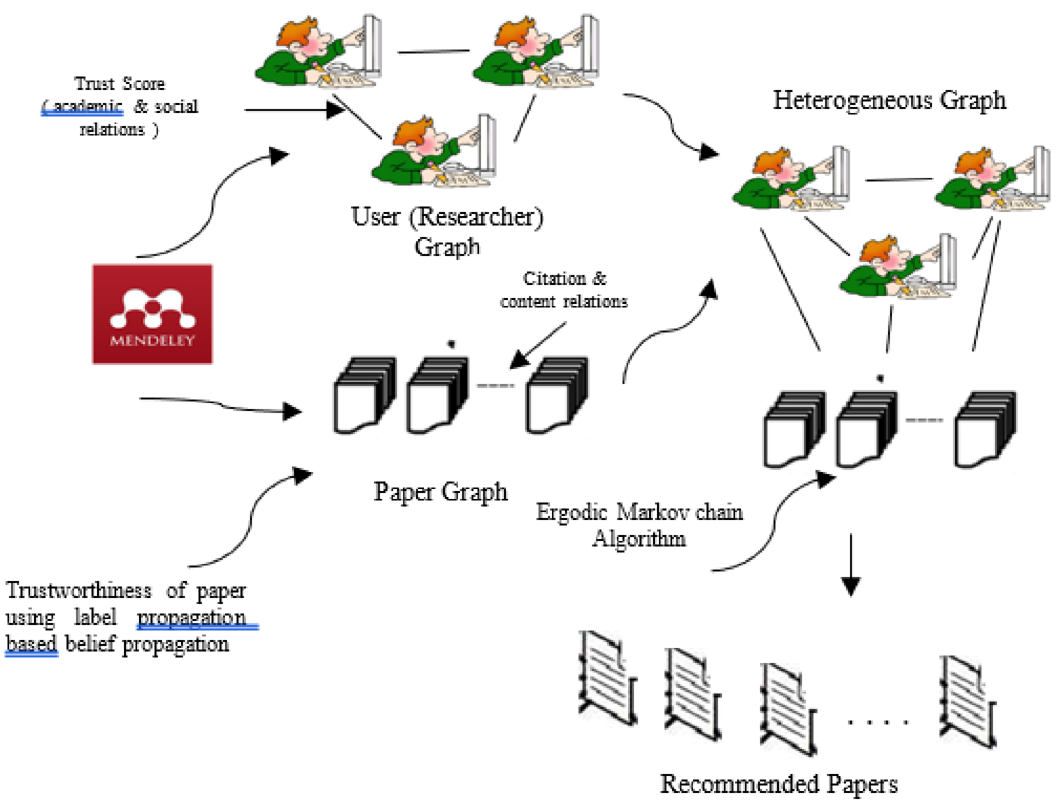
Generally, in a social network, users tend to follow others based on some similarity between them. In a researcher social network, a particular researcher will be followed by other researchers owing to similar research interest, organizational relationship, co-author relationship etc. Hence, considering follower relationship between the researchers in a social network paves way to include the papers published by the researchers irrespective of their year of publication. In the existing approaches to research paper recommendation discussed above, an attempt to include the users'/researchers' activity in the social network is missing. Trust scores between users have not been considered for paper recommendation, either. In these approaches, the following topical relevance, the researchers' publications or citation information has been considered for paper recommendation, leading to chances of newly-published papers being ignored during recommendation, a cold start problem. We attempt to alleviate the said problem by considering users' social interaction as well for recommending newly-published papers.

3. METHODOLOGY

The objective of our work is to recommend relevant research papers for a given research paper, taking into consideration the alleviation of cold start problems. The proposed recommendation method depends on the user's social network interaction and the relevancy of the topic, among the very many papers available in the said network. Existing paper recommendation approaches consider either paper graph or user graph as feature for paper recommendation task. In user graph-based approaches, only the authorship details are considered that results in neglecting their influence which will give deeper level information about their published paper. At the same time, information about the published papers alone are considered in the paper-based approaches thereby ignoring the social interaction between the authors, which is helpful in finding the past history of the paper. Hence, in order to analyze about both the author and paper with a deeper insight, this proposed work construct a user graph and paper graph and links them to form a heterogeneous graph. A recommendation algorithm is introduced to jump through the nodes of the heterogeneous graph considering the trust provided by both the paper and user graphs to mitigate the cold start problem and recommend most relevant papers as output. The details involved in building the user graph, paper graph and the heterogeneous graph have been explained in the subsections 3.1, 3.2 and 3.3 respectively.

Figure 1 shows an overview of our proposed approach. We first construct a user graph Gu from the Mendeley social network S based on academic and social relations. We then construct a paper graph G_p based on citation and content relations. We combine the two graphs and apply the ergodic Markov chain algorithm on the heterogeneous graph to probabilistically recommend papers.

Figure 1. System overview



Definition 1 (Paper Recommendation): For a particular paper P of a user U, the most relevant papers are recommended. The aim of a recommender system, in this context, is to compute a meaningful score $s\left(p_i\right)$ for every $p_i \in S$ such that the higher the score of paper p_i, the higher its relevance with respect to the topic of paper p.

3.1. User Graph Construction

Author profile-based approaches (Pan and Wenxin, 2010; Beel et al., 2014) took into consideration a plethora of information about authors, including the said authors' roles, research interests, affiliations, and disciplines, all considered as features. If affiliation is considered, the approach discusses only the level of organization, in terms of work, that authors finds themselves ranked on, and does not dwell on their research. Similarly, while considering the role of authors, information pertaining to authorship and or co-authorship is disseminated without clearly establishing the link between authors and papers. The research restricts itself to providing information only on the major topic of the paper and does not digress into offering exhaustive information on topics more relevant to the title given. Therefore, the features discussed above are scarcely sufficient to retrieve the kind of relevant information appropriate to the title of the given paper. Moreover, it makes light of their influence and the kind of insights offered in their published paper. Hence, we consider the social interaction (following relation) of the researchers in addition to the features described in the author based approaches. The follower of a particular user in the social network might have published the new paper. In this scenario additional information about the newly published paper can be inferred through social interaction. In turn this provides chance to accommodate the published papers of the socially related (follower) researchers regardless of the year of publication. Henceforth, we build the user graph that helps to consider the newly published paper as a candidate for recommendation and thereby gives solution to the cold start alleviation.

Given the Mendeley social network S, with nodes $n_1, n_2, n_3, \ldots n_m$ and the subset:

$$followers\left(n_i\right) = \left\{n_j \in S \middle|\ 1 < j < \mathrm{x},\ \forall n_j \in S, there \text{ exists } n_j \leftrightarrow n_i\right\}$$

construct a user graph $Gu \subset S$ with nodes as users $u_1, u_2, u_3, \ldots, u_n$ and edge pairs as $\left(u_i, u_j\right)$ with the edge weight as the aggregated trust score calculated between the users. Edges are formally denoted as $\left(u_i, u_j\right), \left(u_j, u_i\right) \in Edge\left(G_u\right)$.

From the social network, user profile information that decides the reputation of the researchers is extracted and utilized to determine the edge weight, denoted as:

$$w^u_{u_i,u_j} = \sum\left(d_{i\leftrightarrow j} + s_{i\leftrightarrow j} + r_{i\leftrightarrow j} + a\_p_{i\leftrightarrow j} + t_{i\leftrightarrow j} + profile\_date_{i\leftrightarrow j}\right) \tag{1}$$

where:

- $d_{i\leftrightarrow j}$ represents discipline. If two users belong to the same discipline, for example in computer science, they are considered similar users with a score '1';
- $s_{i\leftrightarrow j}$ represents subdiscipline. If two users belong to the same subdiscipline, for e.g., artificial intelligence, they are considered similar users with a score '1';
- $r_{i\leftrightarrow j}$ represents research interest. The percentage overlap of research interest between two users is computed;

- $a\_p_{i \leftrightarrow j}$ represents academic status, with each academic status assigned a priority. For example, professor is a higher rank and graduate a lower one. Based on academic status, the similarity between two users 'A' and 'B' is calculated as:

$$val = \left(diff + 1\right) * 10, \quad if\left(ac\left(A\right) \geq ac\left(B\right)\right) \tag{2}$$

where *diff* is based on ranking.

- $t_{i \leftrightarrow j}$ represents the title/institution where the researcher is working, which is compared with premier institutions elsewhere;
- $profile\_date_{i \leftrightarrow j}$ represents the date of profile creation.

In order to determine the profile creation date of Mendeley users, the following formula is used:

$$profile\_date_{i \leftrightarrow j} = \frac{present\,date - joined\,date}{present \quad date\text{-}\ mendeley\,release\,date} \tag{3}$$

Our objective is to recommend relevant papers while considering the cold start alleviation as well. The first level retrieval of users and their papers are scarce for paper recommendation as there is a chance of ignoring many published papers, which might include newly published papers. In a social network, generally speaking, people tend to follow others who, like themselves, share similar ideas, beliefs or interests. In order to expand the number of users in the user graph, we used the following relation that exists between researchers in a social network, and thereby including their respective papers for paper recommendation task. Among the followers of a particular user, few users will only possess strong academic profile and reasonable publications. In order to avoid the inclusion of non-reputable followers into the user graph, a strategy has to be followed. The trust score determines whether a particular user and his academic profile are worthy enough to consider as a candidate for paper recommendation task. Hence, we have used trust score as deciding criteria to include the socially related neighbors (followers) of the users into the user graph. The followers of each user $followers\left(u_i\right)$ are identified from social network S and connected with their respective user in the user graph based on the trust score as shown below:

$$u_j \in Gu, \mathrm{edge}\left(u_i, u_j\right) \in Gu$$

such that there exists a pair:

$$\left(u_{i,} u_j\right) \in S \quad \text{and} \quad u_j \in followers\left(u_i\right)$$

At the second level of user graph expansion, we considered followers with a degree as 3, and determined trust scores between those followers and their followers. The determined trust scores were ranked and the second level of followers with top scores included in the user graph.

3.2. Paper Graph Construction

The motive behind our work is to recommend research papers for a given paper title. Hence, a network of research paper is essential to search the relevant paper for the given input. In the existing paper profile-based approaches (Bogers & Bosch 2008; Wang et al., 2010; Agarwal et al., 2006; Miao et al., 2014), the paper relevant information like the publication details of the paper, citation information, author of the paper, paper title was considered. However, the information regarding the social linking (follower relation) of the authors' researcher profile with the other researchers' profile has been ignored in the existing approaches which is especially useful in increasing the research paper population as well. Henceforth, in addition to the features discussed above we consider the feature associated with the social linking of the authors and construct a paper graph and use them for research paper recommendation.

Given the Mendeley social network S with nodes $n_1, n_2, n_3, \ldots n_m$, construct a paper graph $Gp \subset S$ with nodes as papers $p_1, p_2, p_3, \ldots, p_n$ and the set of authors associated with the set of papers as $a_1, a_2, a_3, \ldots, a_n$ edge pairs as $\left(p_i, p_j\right)$ with the edge weight as the aggregated trust score between the papers:

$$\left(p_i, p_j\right), \left(p_j, p_i\right) \in Edge\left(G_p\right)$$

From the social network, paper-related information is extracted and used to determine the edge weight, denoted as:

$$w_{p_i \leftrightarrow p_j}{}^{p} = \sum \begin{pmatrix} title_{i\leftrightarrow j} + key_{i\leftrightarrow j} + author_{i\leftrightarrow j} + type_{i\leftrightarrow j} + \\ year_{i\leftrightarrow j} + source_{i\leftrightarrow j} + last\_access_{i\leftrightarrow j} + read\_stat_{i\leftrightarrow j} \end{pmatrix} \tag{4}$$

where $title_{i\leftrightarrow j}$ similarity between the papers is computed, based on pattern matching between the titles of papers. If similar, the edge score is assigned '1':

- $key_{i\leftrightarrow j}$ represents the percentage overlap among the keywords extracted from the paper;
- $author_{i\leftrightarrow j}$ represents the weight between the authors of papers. Papers with common authors are given a higher weight;
- $type_{i\leftrightarrow j}$ is the type of the paper that is compared. For example, paper type can be one at a journal or conference;
- $year_{i\leftrightarrow j}$ represents the year of publication:

$source_{i\leftrightarrow j}$

The source of the paper is compared:

$last\_access_{i\leftrightarrow j}$ is computed as $last\_access_{i\leftrightarrow j} \dfrac{\left(present\, date - publication\, year\right)}{\left(present\, date - last\, accessed\right)}$ (5)

- $read\_stat_{i \leftrightarrow j}$ represents the paper's readership statistics.

Our aim is to recommend relevant research papers alleviating cold start problems. As far as publication networks are concerned, newly-published papers are generally not recommended owing to a lack of information on their history (citation). Consequently, cold start problems occur during the recommendation of relevant papers. Our proposed work handles this issue by computing the belief score of each paper node to determine the paper's worthiness for recommendation, irrespective of the year of publication, paving the way for the consideration of newly-published papers as well for recommendation. Belief score computation is carried out using label propagation-based belief propagation.

3.2.1. Modified Belief Propagation for Neighbor Selection During Message Passing

The belief propagation (BP) algorithm is generally used to probabilistically reason out the state of a particular node (Chau et al., 2011; Felzenszwalb & Huttenlocher, 2006). Belief propagation works through message passing between nodes in a network. A message in belief propagation is defined as the belief provided about the state of a particular node by the target node. Messages sent from one node to another are represented as message vectors. The possible states of the nodes concerned are represented as the elements of message vectors. A message m_{ij} is passed from node 'n_i' to node 'n_j'. Message 'm_{ij}' denotes the belief of the node 'n_i' about the node 'n_j' in a particular state. The message is computed as:

$$m_{ij}\left(x_c\right) = \sum_{x_d \in X} \varphi_i\left(x_d\right) \psi_{ij}\left(x_d, x_c\right) \prod_{k \in N(i) \setminus j} m_{ki}\left(x_d\right) \quad (6)$$

where:

- 'v_i' denotes the probability of node 'n_j' being in state 'x_c'. Messages from node n_i to node 'n_j' are the product of messages from all neighboring nodes of 'n_i' except 'n_j';
- $\varphi_i\left(x_d\right)$ denotes node potential and the probability of node 'n_i' being in state 'x_d';
- $\psi_{ij}\left(x_d, x_c\right)$ denotes the probability of node 'n_j' being in state 'x_c' when its neighboring node 'n_i' is in state 'x_d' and is defined by the propagation matrix.

Cold start problems occur owing to the lack of information on a paper's history. Hence, apart from information on history – such as citation - an additional score is required to bring in papers that lack such history as candidate papers for recommendation. We aim to provide, as additional information, the trust state of published papers in the paper graph. As belief propagation helps to determine the state of a node, we use this probabilistic algorithm to determine the trust state of the paper. In belief propagation, the possible states of the node have initially to be fixed. Based on our work, we consider the possible state of the paper as 'trustworthy' or 'not trustworthy'. The state of the paper node is determined probabilistically by the message computation step of the belief propagation.

During message computation, the product of the messages (probabilistic belief) from all neighboring paper nodes, except the original paper node, is considered. The messages given by neighboring nodes might be similar or dissimilar, i.e., one or more neighbors might assign similar beliefs to a particular node while a few neighbors might assign totally dissimilar beliefs. Rather than considering the states provided by all neighboring nodes, similar beliefs assigned by a larger number of neighbors are alone considered, like the concept of homophily (people with similar characteristics tending to associate with one another). This technique will help reduce the message computation time of belief propagation as well as discard insignificant beliefs. Appropriate neighbors have to be selected so as to consider the state provided by the maximum number of neighbors. Label propagation, a semi-supervised algorithm proposed by Raghavan et al. (2007), assigns labels to a particular node based on the labels possessed by the maximum number of its neighboring nodes. For example, node 'n_i' has 'v' neighbors. Among these 'v' neighbors, if the maximum number of neighbors have similar labels, i.e., for instance, 'label a', node 'n_j' acquires label 'a', according to the label propagation algorithm. We aim to consider belief states provided by similar neighbors for message computation. Hence we incorporate label propagation to select neighbors with similar states as significant neighbors and their probabilistic beliefs as significant beliefs, and ignore suggestions provided by the remaining neighbor nodes. Moreover, neighbor selection of this sort is based on the edge weight and similarity between one neighbor and another. As per our approach, edge weight is calculated based on document-specific features associated with the paper, and similarity is based on the similarity in authorship between papers. Hence, trust information provided by this modified approach is based on the most relevant node and a valid opinion suggested.

Message passing is iteratively carried out until convergence, and the message passing score aggregated as belief scores. The state of a particular node is determined by its aggregated belief score. The belief score of a node 'n_i' being in state 'x_c' is computed as:

$$b_i\left(x_c\right) = \delta \prod_{j \in N\left(i\right)} m_{ji}\left(x_c\right) \tag{7}$$

where δ is the normalization factor.

Based on the belief score of a paper node, the trustworthiness of the research paper is determined and additional value provided to it.

3.3. Heterogeneous Graph Construction

The trustworthiness given by the paper graph and the user graph has to be used efficiently for yielding a better recommended output. Hence the proposed work combines the user graph and paper graph constructed by establishing links between the authors of the paper graph and the users (authors) of the user graph.

Given a user graph G_u and a paper graph G_p, construct a heterogeneous graph H such that:

$$H = \left\{\left(G_u U G_p\right) \mid u_i \in G_u = a_i\left(p_i\right), p_i \in G_p\right\} \subset S$$

with the edge weight as:

$$w^h_{i \leftrightarrow j} = topical\_relevance + \frac{\left(Y_{current} - Y_{authorship}\right)}{\min\left(Y_{current} - Y_{authorship}\right)} \tag{8}$$

Definition 2 (The Cold Start Problem Alleviation during Paper recommendation): Given a set of papers A, a set of papers O that a researcher r_i published in the past (O ⊂ A), and a set of newly-published papers N (A∩N = ∅), retrieve the top-k published papers $K\left(\subseteq O \cup N\right)$ that are most relevant to target paper A_j of a researcher r_i, from the graph H such that every researcher r_u of user graph G_u is similar to researcher r_p of the paper graph Gp.

For example, a researcher has published papers in the year 2019 and as well as in the past years on various topics. Our approach aims to retrieve the top 'K' papers of that researcher in the area "Cloud Computing" by considering the papers published by him in the year 2019 also (cold start problem alleviation), which is generally not carried out in the traditional recommendation approaches.

3.4. Heterogeneous Random Walk Based on Ergodic Markov Chain

Our framework includes three random walks on graph namely G_r, G_p, G_h. A random walk on graph is a Markov chain, where the states are the vertices of the graph. It is represented by a $n \times n$ matrix M, where n is the number of vertices in the graph. M represents the transition probabilities, where $0 \le p(i,j) = M_{i,j} \le 1$ is the conditional probability such that the next state will be vertex j, given that the current state is vertex i. If there is no edge, between vertex i and j, then $M_{i,j} = 0$, indicating that there are no outgoing edges from vertex i. In that case, we consider $M_{i,j} = 1 / n$ for all vertices j. M is a stochastic matrix, where its entries are non-negative and every row adds up to one. All Markov chains are ergodic (irreducible and aperiodic).

As mentioned above, we have three random walks where the random walk on G_r is described by a matrix R' and random walk on G_p is described by a matrix P'. R' and P' are called as intra-class random walks, because the random walk occurs within the researcher or the paper network. The other random walk on G_h is called the inter-class random walk, which is described by a $n_r \times n_p$ matrix R and $n_p \times n_r$ matrix P, since G_h is bipartite.

In our work, we consider a jump probability α, in the intra-class random walk and α has the similar role like the damping factor used in page rank algorithm. The coupling of the random walk is controlled by λ, which represents the extent to which the researchers and papers are dependent on each other.

3.5. Intra-Class Random Walk on Researcher Graph

Let R be the transition matrix that represents the intra-class random walk on the researcher network G_r. The transition probability:

$$P(j \mid i) = R_{i,j} = \frac{K_{i,j}}{\sum_j K_{i,j}} \tag{9}$$

$K_{i,j}$ is the cumulative matrix that represents the profile similarity between the researchers. Now the graph G_r is viewed as a weighted graph with $K_{i,j}$ being the edge weight between i and j.

In the existing approaches, the researchers were connected based on certain features like collaboration on a paper, participation in similar events. However, in a novel way we consider multiple factors to link the researchers. Moreover, we bring in the social relation (follower) to create a researcher graph. This helped us to carry out the random walk on a researcher graph that possess strong profile-based and social-based links paving way to retrieve more relevant papers associated with the researchers, irrespective of the year of publication.

3.6. Intra-Class Random Walk on Paper Graph

The transition probability of the intra-class random walk on graph G_p is:

$$P\left(j \mid i\right) = P_{i,j} = \frac{P_{i,j}}{\sum_{i=1\ldots k} P_i} \tag{10}$$

where $P_{i,j}$ is the edge weight between the papers P_i and P_j and $\sum_{i=1\ldots k} P_i$ represents the sum of edge weight computed between paper i and all of its neighbouring papers ranging from $1 \ldots k$.

In the existing approaches, transition probabilities were computed based on the citation relationship alone. However, in our work we considered multiple attributes of the paper to determine the transition probabilities, since they provide valuable information to decide the potential of the particular paper.

3.7. Inter-Class Random Walks on Heterogeneous Graph

The intra-class random walks G_r and G_p are coupled into a single-inter-class random walk G_h. The coupling is parameterized by four parameters m, n, k and λ.

In the combined random walk, the traversal can be an intra-class step or inter-class step. For example, if the current state is in researcher graph, then the next step would be an intra-class step in researcher graph or inter-class step to the inter-class random walk. The similar case is followed if the current state is in paper graph.

The combined random walk is defined as:

1. If the current state of a recommender system is a researcher $r \in G_r$, then with probability λ take $2k+1$ inter-class steps, whereas with probabilities $1-\lambda$, takes m intra-class steps on G_r;
2. If the current state of a recommender system is a researcher $p \in G_p$, then with probability λ take $2k+1$ inter-class steps, whereas with probabilities $1-\lambda$, takes n intra-class steps on G_p.

We used the parameter settings as specified in the existing work (Zhou et al.2007) as $m = 2, n = 2, k = 1, \alpha = 0.1$ and $\lambda = 0.2$.

Based on the traversal in the heterogeneous graph, the neighbour nodes and the corresponding traversal probabilities of the paper nodes $M_{i,j}$ are inserted into the priority queue.

In the stochastic matrix M, the combined random walk is parameterized as:

$$M = \begin{vmatrix} \left(1-\lambda\right)\left(R'^{T}\right)^{m} & \lambda \mathrm{PR}^{T}\left(RP^{T}PR^{T}\right)^{k} \\ \lambda \mathrm{RP}^{T}\left(PR^{T}RP^{T}\right)^{k} & \left(1-\lambda\right)\left(P'^{T}\right)^{m} \end{vmatrix}$$

Based on the ranking scores in the matrix *M*, for the paper graph the papers are recommended.

4. EVALUATION

The objective of the work is to recommend research papers considering users' activity in the social network, research paper history information like citation, year of publication, keywords, and so on. This section engages in detail on the experimental setup, results and discussions related to our proposed work.

4.1. Experimental Setup

We have used the Mendeley academic social network for our proposed work. When a user logs into the network and uploads a paper's title, the system retrieves a set of papers relevant to the particular user. We have used Neo4j as our graph database. Graphs are ideal technical representations of a social network comprised of people, and relationships between people. Neo4j's graph data model, in tandem with Neo's Cypher query language, helps easily build fast social data applications. The user graph and paper graph constructed by our system are stored in the Neo4j database.

The chief contributions in the proposed work are:

- User graphs and paper graphs;
- A belief state computation using the modified belief propagation algorithm;
- Heterogeneous graphs;
- Cold start alleviation; and
- A novel recommendation algorithm – the random walk using the ergodic Markov chain.

We assessed the performance of our approach with respect to the above contributions. In our approach, we have considered heterogeneous graph (user graph and paper graph combination) as the features. The effectiveness of features plays a major role in recommending appropriate research papers. Hence, we evaluated the effectiveness of our features by comparing it with the baseline method using the evaluation measure P@k. For alleviating the cold start problem, as a first step, we determined the trust score of the paper using modified label propagation algorithm. We have evaluated the modified label propagation algorithm by comparing it with the label propagation algorithm in terms of execution time. Further, we evaluated the effectiveness of cold start alleviation by comparing with different methods based on two parameters totNP_EU and avgNP_EU and the accuracy of the recommendation using NDCG, quality of the recommendation using Fallout, and MRR. In addition, we have carried out the Statistical test using Annova for measuring the performance of recommendation algorithm.

4.2. Feature Evaluation

In our work, information related to users' activity is accessed from the Mendeley network and a user graph is constructed. Similarly, a paper graph is constructed based on information available in the network. The user graph and paper graph are considered as features of the system and their effectiveness is evaluated.

4.2.1. User Graph Evaluation

Randomly we gathered the researchers and initially we obtained the user graph with node size as 76 and determined the corresponding metric values for this graph size. Later we increased the user graph size gradually to 43,124 by including the followers of the researchers as described in Section 3.1. The user graph, comprising nodes representing users and edge weights representing the trust score between users, is evaluated using the following evaluation metrics:

- Number of communities - User graphs are evaluated using the Louvain method (Blondel et al., 2008), a community detection algorithm which determines community structures with high modularity in a short span of time. This process naturally leads to a hierarchical decomposition of the network and the social network analysis tool, Gephi, is used for the purpose;
- Size of the biggest community;
- Number of strongly-connected components;
- Modularity score – a score to determine whether the nodes in a community are strongly connected.

The result statistics of varying graph size and their corresponding metric values are shown in Table 1.

The results in Table 1 illustrates that, as the size of the user graph increases, the corresponding values of Modularity score, number of communities, size of the biggest community increases. The inclusion of user activity information in constructing the user graph and the rules followed in the trust score calculation leads to the formation of strongly connected communities irrespective of the user graph size. It is evident that, if the community has stronger relation then trustable users exist in the community and if their corresponding papers (recent or old papers) are trustable, they find a place in the heterogeneous graph. Hence, during paper recommendation such papers will be considered thereby alleviating the cold start problem as well.

4.2.2. Paper Graph Evaluation

In our experiment, we started with paper graph size as 200 and further increased the graph size to around 24310 by including the papers of the followers (two level of followers) of the user graph. In the paper graph, research papers are considered as nodes and the edge score based on different parameters were used to link papers. In order to evaluate the paper graph, it is clustered using the Lingo (Osinski et al., 2004) clustering algorithm as the first step. This algorithm, based on the singular value decomposition method, determines cluster labels and using them determines the actual content of the cluster. The clusters determined using the Lingo algorithm are evaluated using a parameter, the cluster ratio, computed as:

$$\text{Cluster ratio} = \frac{\text{Number of papers in the clusters of input paper}}{\text{Total number of papers in paper graph}} \tag{11}$$

Table 2 shows the statistics of the sample paper graph size and the corresponding cluster ratio. The observed results in Table 2 shows that as the paper graph size increases the cluster ratio also increases. The reason behind the linear increase in cluster ratio with respect to paper graph size illustrates that a better cluster of papers related to the input paper is formed. In turn, this helps to consider more relevant papers for recommendation. Moreover, the determination of the trustworthiness of the newly published papers using modified belief propagation helps to consider recent paper as a relevant paper for the input paper.

Table 1. User graph statistics

User Graph Size	Modularity Score	Number of Communities	Size of the Biggest Community
76	0.63	5	36
1957	0.71	76	475
2016	0.794	92	1158

Table 2. Paper graph statistics

Paper Graph Size	Cluster Ratio
200	0.53
432	0.65
500	0.72

4.2.3. Heterogeneous Graph Evaluation

We evaluated the effectiveness of using Heterogeneous graph (paper graph and user graph) for research paper recommendation using the evaluation metric Precision@k (Kavitha et al,2014) which is calculated using the formula:

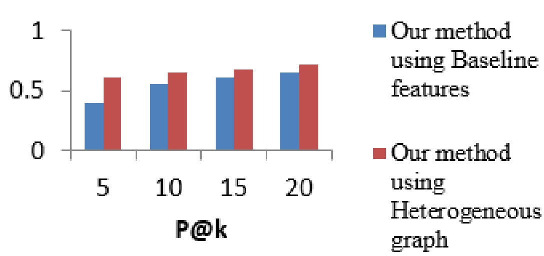
$$P@k = \frac{r\left(k\right)}{k} \tag{12}$$

where $r\left(k\right)$ is the number of relevant papers retrieved in the top 'k' positions. In the baseline approach, an undirected graph has been built with paper as node and citation as the linking information for paper recommendation. In order to illustrate the effectiveness of our features in recommending papers, we tested our method by incorporating the baseline features [Ha et al.]. Figure 2 shows that we achieved an improvement in the precision while incorporating our features (Heterogeneous graph) in our method when compared to the other scenario where the baseline features are incorporated in our method. The reason behind the improvement is, baseline approach considers only the citation information of the research papers. But in our approach, we consider the combination of researchers (academic and social) information and paper information in the form of a heterogeneous graph. Moreover, in addition to the paper graph the social activity information (followers) available in the user graph provides additional information to infer the state of the newly published paper. For example, when we gave the input of the paper title as "A model of a trust-based recommendation system on a social network", we obtained one of the recommended papers as "A social trust aware recommender for teachers." On analysis, we found that the paper was a recent paper and has been recommended because the author of the paper is a follower (identified as described in Section 3.1) of the author of the input paper. Moreover, the author of this particular paper has obtained a better trust score. Furthermore, this paper provides relevant information regarding trust aware recommendation in spite of the context for which it is used. This case is impossible with the baseline features, as it lags the user related information. Hence it is evident that, along with the trust score of the paper, trust score of the user is also required to recommend newly published paper.

4.3. Methodology Evaluation

We evaluated our proposed method by comparing it against the existing method (Ha et al., 2014) that used the belief propagation algorithm to recommend newly-published papers. In our work, we have modified the belief propagation algorithm by incorporating label propagation to reduce computation costs incurred during message passing. This, in turn, reduces the number of iterations required for convergence. To illustrate the effectiveness of the proposed algorithm, a comparison is made in terms of execution time between the belief propagation algorithm and the label propagation-based belief

Figure 2. Comparison of precision values between baseline features and our features in our method



propagation algorithm. Figure 3 shows the number of iterations involved in the convergence of the algorithm for the recommendation task. The graph depicts that the LPA-based belief propagation converges faster with fewer iterations than the traditional belief propagation.

4.4. Effectiveness of Recommendations

We conducted experiments for nearly 12 weeks from March 2015 to May 2015 and applied four different algorithms – the LRMF collaborative filtering (Shi et al., 2010), content-based (BPR) (Rendle et al., 2009) approach, baseline approach (Ha et al., 2014) and our own approach to recommend papers to Mendeley users. Initially, the collaborative filtering algorithm was applied for nearly three weeks and, subsequently, other algorithms were applied sequentially for the next three weeks and their performances in terms of yielding the recommended results were compared. To the best of our knowledge, we found that the available recent methods are for cold start alleviations of product recommendations. But the features used for product recommendations are not suitable for research paper recommendations. Hence, our research paper recommendation approach cannot be compared with such methods. Moreover, we did not find any recent approach for research paper recommendation (with or without cold start alleviation). Hence, we have carried out the experiment with another baseline method Scholarly paper recommendation method (Asabere et al.2014) and compared the recommended results with them. The experimental results were analysed with two aspects in view: that of resolving cold start problems, and ascertaining the effectiveness of prediction accuracy.

4.4.1. Cold Start Problem Alleviation

In a scenario where new items or users are involved, collaborative and content-based methods suffer from cold start problems (Shani and Gunawardana, 2010). Our approach mitigated this issue using social network features and the random walk ergodic Markov chain algorithm. In this context, detailed statistics are shown in Table 3. The series of data gathered is shown in the second column of this table and to this gathered data, five recommender algorithms (collaborative filtering, content-based, baseline approaches-Ha et al.2014 and Asabere et al.2014 and our approach) were applied. The next two columns (new items and existing users) show the updated results obtained based on the number of existing users and items. Finally, the last two columns represent the values of parameters used to measure the cold start problem. We used two parameters (Rohani et al., 2014), defined as follows, for evaluating the performance of recommender algorithms in solving cold start problems:

- **totNP_EU:** Total number of new papers recommended to existing users with a prediction value > 1;

Figure 3. Comparison of number of iterations required for convergence between BP and LPA based BP method

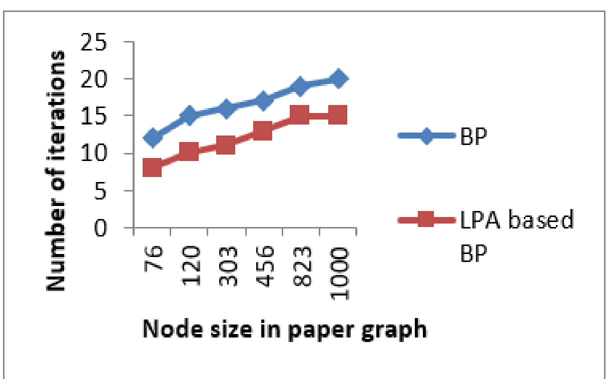


Table 3. Cold start item results

Algorithms	Data Series Number	Cold Start Parameters			
		New Items	Existing Users	totNRP_EU	avgNRP_EU
Collaborative Filtering (LRMF)	LRMF_series1	200	1034	0	0
	LRMF_series2	176	1200	0	0
	LRMF_series3	169	999	0	0
Content-based (BPR)	BPR_series1	180	1115	2950	2.95
	BPR_series2	146	1099	2912	2.912
	BPR_series3	192	997	2876	2.876
Baseline approach 1 (Ha et al., 2014)	Baseline_series1	185	1000	3603	3.603
	Baseline_series2	195	1109	3814	3.439
	Baseline_series3	200	1090	3980	3.651
Baseline approach 2 (Asabere et al., 2014)	SARSP_series1	101	980	3080	3.143
	SARSP _series2	112	1010	3520	3.485
	SARSP _series3	116	965	3660	3.792
Our approach	Ergodic_series1	177	1099	4556	4.146
	Ergodic_series2	200	1199	4407	3.676
	Ergodic_series3	189	1067	4334	4.062

- **avgNP_EU:** Average number of new papers recommended to existing users with a prediction value > 1.

We illustrate how many new papers are recommended to the user by different recommendation methods using the totNP_EU under multiple trials. The average values of totNP_EU show the extent to which the recommendation algorithm achieves success in resolving cold start problems in case of new paper recommendation.

Table 3 shows that the average number of new papers recommended by the collaborative recommender algorithm is nil, implying that the algorithm presents cold start problems while recommending papers. The average number of new papers recommended by the content-based algorithm is around 3. Generally, the content-based approach has major problems with cold start users rather than with cold start items. Our work concentrates on the alleviation of cold start problems in item (paper) recommendation alone and, consequently, we have not evaluated cold start user problems. The baseline approach1 and baseline approach 2 produced avgNP_EU value as 3.5 and 3.4 respectively. On an average, our ergodic approach produced an avgNP_EU of 4. This illustrates that our method improved results by 36%, 11% and 17% respectively, compared with the content-based algorithm and baseline method 1 and baseline method 2 that handles cold start problems. The reason behind the improvement lies in determining the trust score of the paper using the modified belief propagation algorithm. Further, the ergodic Markov chain algorithm applied on the heterogeneous graph helps to recommend newly published papers based on the current state. A researcher in the Mendeley social network has lots of followers. As user's social interaction is included as a key feature, new papers written by a particular researcher's followers yield better impact irrespective of their publication year, leading to the alleviation of cold start problems in paper recommendation.

4.4.2. Accuracy of Recommendation Problems

The results provided by recommendations are required to be relevant and possess quality. Hence we evaluate the performance of the recommendation algorithms using the NDCG measure (Järvelin and Kekäläinen, 2000), Fallout (Shani and Gunawardana, 2010), and the Mean Reciprocal Rank (MRR) (Sugiyama and Kan, 2010), based on the online experiments we carried out for nearly 12 weeks among 4200 members of the Mendeley academic social network.

4.5. Normalized Discounted Cumulative Gain (NDCG)

The discounted cumulative gain (DCG) is used to measure the quality of ranking and the usefulness (gain) of an item based on its relevance and position in a ranked list. This measure includes different relevance levels, such as relevant or irrelevant, based on the gain values:

$$DCG\left(i\right)=\begin{cases}G\left(1\right) & \text{if i} = 1\\ DCG\left(i-1\right)+\dfrac{G\left(i\right)}{\log i} & \text{otherwise}\end{cases} \tag{11}$$

where 'i' denotes the i^{th} ranked position.

Since the recommended result is concerned with relevant or irrelevant outputs, we consider $G\left(i\right)=1$ for relevant outputs and $G\left(i\right)=0$ for irrelevant outputs. Among the ranked results of the recommendation algorithm, we are concerned about the quality and usefulness of the top K results of the recommendation algorithm. Hence, we use the NDCG@N (N=10) for evaluating the results of different recommendation algorithms, where N is the number of top-N recommended papers. Normally NDCG varies from 0.0 to 1.0.

Table 4 shows the NDCG@10 values obtained through different recommendation algorithms during different runs. The graph shows that our approach produced better NDCG values when compared with other recommendation algorithms. Specifically, the NDCG@10 value of our approach is higher than that of the baseline methods (Ha et al., 2014; Asabere et al., 2014). This illustrates that taking both socially and topically relevant features into consideration has led to improved accuracy in our approach. As discussed in Section 3, our ergodic recommender algorithm uses trust scores as a key factor to determine the eligibility of papers for recommendation. This in turn improves the relevancy of the considered papers in terms of the target output.

4.6. Fallout

Fallout is the proportion of irrelevant items recommended out of the total of all irrelevant items. It is the probability that an irrelevant item is recommended to a user:

Table 4. Comparison of NDCG@10 between different methods

Trials	Collaborative	Content	Baseline Approach 1 (Ha et al.2014)	Baseline Approach 2 (Asabere et al.2014)	Our Approach
Round 1	0.3	0.4	0.5	0.394	0.6
Round 2	0.5	0.43	0.45	0.423	0.526
Round 3	0.5	0.46	0.56	0.44	0.64

$$Fallout = \frac{irrelevant\,items \cap retrieved\ \text{items}}{irrelevant\,items} \tag{13}$$

The recommendation algorithm performs better if the fallout rate is low. Figure 3 illustrates the fallout values of different recommendation algorithms obtained during different trials. The average fallout value of our proposed approach is 0.068, a lower value compared to baseline approaches and collaborative filtering, but, fallout is slightly higher than content based approach, the approach that poses major problem on cold start users rather than cold start items (Rohani et al., 2014). Our aim is to overcome the problem in cold start items. Hence, the increase in fallout value of our method when compared to content-based approach can be ignored. The lower fallout value shows that the prediction accuracy of our recommendation approach is better than baseline approaches that focus largely towards research paper recommendation.

4.7. Mean Reciprocal Rank (MRR)

The mean reciprocal rank (MRR) is a statistical measure for evaluating processes that produce a possible set of outcomes for sample queries. The reciprocal rank is the multiplicative inverse of the rank of the correct answer in a specific outcome. The mean reciprocal rank is the average of all the reciprocal ranks of the responses obtained for a sample set of queries:

$$MRR = \frac{1}{\left|Q\right|}\sum_{i=1}^{|Q|}\frac{1}{rank_i} \tag{14}$$

where $rank_i$ refers to the rank position of the first relevant item of the i^{th} query.

This metric varies from 0.0 to 1.0. We evaluated our system to show how a combination of user and paper graphs contribute in retrieving the first relevant paper with a higher rank using the MRR. To highlight the effectiveness of user and paper graph features, we tested our system using different feature combinations including:

- Paper graphs (PG);
- User graphs with academic features (UG_A);
- User graphs with academic and social features (UG_A+S); and
- Paper graphs and user graphs with academic and social features (PG+UG_A+S).

Table 5 shows the MRR results of our recommendation algorithms under multiple trials with different feature combinations. Our approach produced considerably improved MRR values when

Table 5. Comparison of MRR based on different combination of features

MRR (With Different Combination of Features)	Trial 1	Trial 2	Trial 3
PG	0.441	0.439	0.44
UG_A	0.453	0.446	0.456
UG_A+S	0.462	0.455	0.466
PG+UG_A+S	0.58	0.6	0.62

both the user graph and paper graph are considered for paper recommendation, compared with other kinds of features. and helps in determining the rank of first relevant correct paper and in cases where MRR is equal to '1', it illustrates that we have retrieved the most correct (perfect relevant) paper. Among the relevant papers recommended, on an average we obtain the MRR values as 0.6. This shows that our method was able to retrieve the nearing correct paper. The results demonstrate that the algorithm is robust enough to retrieve the first relevant papers with a higher rank for a sample set of target papers. Our recommendation performs a random walk on the heterogeneous graph based on the jump probability and trust scores. The papers in the paper graph are connected, based on content similarity. In turn, the researchers in the user graph are connected based on academic and social network relations. This helps to obtain a deeper acuteness and retrieve the relevant paper with a higher rank.

4.8. Statistical Significance Test Using One-Way Anova

We tested the performance of our recommendation algorithm statistically using the one-way Anova [45], a statistically significant test in terms of NDCG@10. We compared our approach with other recommendation algorithms to test our approach statistically. We considered the null hypothesis as the mean of all algorithms of NDCG@10 as equal and used the mean of NDCG@10 values obtained through three trial runs. Table 6 shows the analysis of the variance obtained. The last column in the table (Pr>F) illustrates that the null hypothesis is rejected with a risk of 0.01%, implying that all the recommender algorithms considered are statistically different and the improved results produced by our recommendation algorithm are statistically significant.

The analysis above of the variance test shows whether or not the means of the NDCG@10 have statistically significant differences but does not quantify the difference in means. Therefore, we use the Fischer test to quantify the difference between the means. In Table 7, the statistical difference between the means is shown in the column labeled 'Difference.' The statistical difference between the ergodic and collaborative is high because the former considers better features for recommendation. Further, the last column of Table 7 shows that all the methods are statistically significant. The test also shows that even the baseline is better than the collaborative method, but the difference mean for the baseline is larger than that of other mean values.

Table 8 shows group formation between different methods based on the NDCG@10. Group formation takes place based on the similarity between NDCG@10 values. The results in Table 8 demonstrate that four groups are formed and each of the recommender algorithms considered forms a standalone group, implying that statistically significant differences exist between the recommender algorithms. From the statistical test, we can conclude that the proposed method is statistically different and shows improved performance compared to other methods.

5. CONCLUSION

In this paper, we proposed a social network-based research paper recommendation system that considers both researchers' social interaction (user graph) and topical relevance between papers (paper graph) for recommendation. Our paper recommendation system aims to reduce cold start problems by determining beliefs about the trustworthiness of published articles using the LPA-

Table 6. Analysis of variance

Source	DF	Sum of Squares	Mean Squares	F	Pr > F
Model	3	0.117	0.039	3073.670	< 0.0001
Error Corrected	16	0.000	0.000		
Total	19	0.117			

Table 7. X1 / Fisher (LSD) / Analysis of the differences between the categories with a confidence interval of 95%

Contrast	Difference	Standardized Difference	Critical Value	Pr > Diff	Significant
Ergodic vs Collaborative	0.198	87.873	2.120	< 0.0001	Yes
Ergodic vs Content	0.171	75.808	2.120	< 0.0001	Yes
Ergodic vs baseline 1	0.101	44.729	2.120	< 0.0001	Yes
Ergodic vs baseline 2	0.134	47.789	2.120	< 0.0001	Yes
Baseline1 vs Collaborative	0.097	43.143	2.120	< 0.0001	Yes
LSD-value:			0.005		

Table 8. Group formation

Category	LS Means	Standard Error	Lower Bound (95%)	Upper Bound (95%)	Groups			
Ergodic	0.603	0.002	0.600	0.607	A			
Baseline 1	0.503	0.002	0.499	0.506		B		
Baseline 2	0.467	0.002	0.45	0.475		B		
Content	0.433	0.002	0.430	0.436			C	
Collaborative	0.406	0.002	0.402	0.409				D

based belief propagation algorithm. We proposed a modified belief propagation algorithm that helps reduce the computation time involved in message computation during message passing by selecting nodes using the LPA. Furthermore, we proposed a recommendation algorithm that uses ergodic Markov chain (recommendation based on current state) concept on the heterogeneous graph and traverse through the nodes randomly to alleviate the cold start problem encountered in research paper recommendation. We evaluated the recommendation algorithm using NDCG@10 and assessed the performance of the algorithm by comparing with different approaches. The system gives more relevant results when compared to the baseline method. The results illustrate that the user community with more kind of social interactions can produce more resourceful set of personalized recommendations. The system can be enhanced to improve the quality of the recommendation algorithm. Further study could be made to implement and test the above algorithm to alleviate the cold start problem in researcher recommendation.

REFERENCES

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering*, *17*(6), 734–749. doi:10.1109/TKDE.2005.99

Agarwal, N., Haque, E., Liu, H., & Parsons, L. (2006). A subspace clustering framework for research group collaboration. *International Journal of Information Technology and Web Engineering*, *1*(1), 35–58. doi:10.4018/jitwe.2006010102

Ahn, H. J. (2008). A new similarity measure for collaborative filtering to alleviate the new user cold-starting problem. *Information Sciences*, *178*(1), 37–51. doi:10.1016/j.ins.2007.07.024

Beel, J., Langer, S., Gipp, B., & Nürnberger, A. (2014). The Architecture and Datasets of Docear's Research Paper Recommender System. *D-Lib Magazine*, *20*(11/12).

Blei, D. M. (2012). Probabilistic Topic Models. *Communications of the ACM*, *55*(4), 77–84.

Blondel, V. D., Jean-Loup, G., Renaud, L., & Etienne, L. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics*, *2008*(10), P10008. doi:10.1088/1742-5468/2008/10/P10008

Bogers, T. & Van den Bosch, A. (2008). Recommending scientific articles using citeulike. *Proceedings of the 2008 ACM conference on Recommender systems* (pp. 287–290). ACM. doi:10.1145/1454008.1454053

Chang, W. L., Diaz, A. N., & Hung, P. C. (2014). Estimating trust value: A social network perspective. *Information Systems Frontiers*, 1–20.

Chen, C. C., Wan, Y. H., Chung, M. C., & Sun, Y. C. (2013). An effective recommendation method for cold start new users using trust and distrust networks. *Information Sciences*, *224*, 19–36. doi:10.1016/j.ins.2012.10.037

Chiu, Y. S., Lin, K. H., & Chen, J. S. (2011). A social network-based serendipity recommender system. In *Proceedings of the International symposium on intelligent signal processing and communications systems ISPACS*. Academic Press.

Good, N., Schafer, J. B., Konstan, J. A., Borchers, A., Sarwar, B., Herlocker, J., & Riedl, J. (1999). Combining collaborative filtering with personal agents for better recommendations. In AAAI (pp. 439–446). IAAI.

Feller, W. (1971). Introduction to Probability Theory and Its Applications, Vol II (2nd edition),Wiley. pages 9 and 20).

Felzenszwalb, P., & Huttenlocher, D. (2006). Efficient belief propagation for early vision. *IJCV*, *70*(1), 41–54. doi:10.1007/s11263-006-7899-4

Frank, E., Paynter, G. W., Witten, I. H., Gutwin, C., & Nevill-Manning, C. G. (1999). Domain specific keyphrase extraction. In *Proceedings of the 16th International Joint Conference on Artificial Intelligence*. Academic Press.

Gori, M., & Pucci, A. (2006). Research paper recommender systems: A random-walk based approach. In *Proceedings of the IEEE/WIC/ACM WI* (pp. 778–781). Academic Press.

Gunawardana, A., & Shani, G. (2009). A survey of accuracy evaluation metrics of recommendation tasks. *Journal of Machine Learning Research*, *10*, 2935–2962.

Guo, Y. H. (2008). *On Collaborative Filtering Algorithm and Applications of Recommender Systems*. Dalian University of Technology.

Hoang, L. (2015). HU-FCF++: A novel hybrid method for the new user cold-start problem in recommender systems. *Engineering Applications of Artificial Intelligence*, *41*, 207–222.

Järvelin, K., & Kekäläinen, J. (2000).IR Evaluation Methods for Retrieving Highly Relevant Documents. In *Proc. of the 22nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2000)* (pp. 41–48). ACM.

Ji, K., & Shen, H. (2014). Addressing cold-start: Scalable recommendation with tags and keywords. *Knowledge-Based Systems*, *83*, 42–50. doi:10.1016/j.knosys.2015.03.008

Jiwoon, H., Soon-Hyoung, K., Sang-Wook, K., & Dongwon, L. (2014). Recommendation of newly published research papers using belief propagation. In *Proceedings of the 2014 Conference on Research in Adaptive and Convergent Systems* (pp. 77-81). Academic Press.

Kavitha, V., Manju, G., & Geetha, T. V. (2014). Learning to Rank Experts using combination of Multiple Features of Expertise. In Proceedings of *ICACCI* (pp. 1053–1058).

Kim, H. N., El-Saddik, A., & Jo, G. S. (2011). Collaborative error- reflected models for cold-start recommender systems. *Decision Support Systems*, *51*(3), 519–531. doi:10.1016/j.dss.2011.02.015

Lam, X. N., Vu, T., Le, T. D., & Duong, A. D. (2008). Addressing Cold-Start Problem in Recommendation Systems. In *Proceedings of the 2nd International Conference on Ubiquitous Information Management and Communication (ICUIMC'08)* (pp. 208-211). Academic Press.

Li, C., Wang, F., Yang, Y., Li, Z., & Zhang, X. (2015). Exploring Social Network Information for Solving Cold Start in Product Recommendation. In *Web Information Systems Engineering – WISE 2015* (pp. 276–283). Springer. doi:10.1007/978-3-319-26187-4_24

Liang, Y., Li, Q., & Qian, T. (2011). Finding relevant papers based on citation relations, In *Proceedings of the 12th international conference on Web-age information management* (pp. 403–414). Academic Press. doi:10.1007/978-3-642-23535-1_35

Lika, B., Kolomvatsos, K., & Hadjiefthymiades, S. (2014). Facing the cold start problem in recommender systems. *Expert Systems with Applications*, *41*(4, Part 2), 2065–2073. doi:10.1016/j.eswa.2013.09.005

Liu, H., Hu, Z., Mian, A., Tian, H., & Zhu, X. (2014). A new user similarity model to improve the accuracy of collaborative filtering. *Knowledge-Based Systems*, *56*, 156–166. doi:10.1016/j.knosys.2013.11.006

Liu, J. G., Zhou, T., & Wang, B. H. (2009). Research progress in personalized recommendation system. *Progress in Natural Science*, *19*, 1–15.

Matsatsinis, N. F., Lakiotaki, K., & Delias, P. (2007). A system based on multiple criteria analysis for scientific paper recommendation. In *Proceedings of the 11th Panhellenic Conference on Informatics*. Academic Press.

McNee, S. M., Albert, I., Cosley, D., Gopalkrishnan, P., Lam, S. K., Rashid, A. M., & Riedl, J. et al. (2002, November). On the recommending of citations for research papers. In *Proceedings of the 2002 ACM conference on Computer supported cooperative work* (pp. 116-125). ACM.

Miao, E., Xiao, Z., Che, F., & Lu, M. (2014). Increasing serendipity of recommender system with ranking topic model. Applied Mathematics Information System - an International Journal, 2041-2053.

Mican, D., Mocean, L., & Tomai, N. (2012). Building a social recommender system by harvesting social relationships and trust scores between users. In W. Abramowicz, J. Domingue, & K. Wecel (Eds.), *Business Information Systems Workshops, Lecture Notes in Business Information Processing* (pp. 1–12). Springer. doi:10.1007/978-3-642-34228-8_1

Nachenberg, C., Wilhelm, J., Wright, A., & Faloutsos, C. (2010). *Polonium: Tera-scale graph mining for malware detection*. ACM KDD.

Ocepek, U., Rugelj, J., & Bosnić, Z. (2015). Improving matrix factorization recommendations for examples in cold start. *Expert Systems with Applications*, *42*(19), 6784–6794.

One Way ANOVA - University of Wisconsin - Stevens Point. Retrieved from http://www.uwsp.edu/psych/stat/12/anova-1w.ht

Osinski, S., Stefanowski, J., & Weiss, D. (2004). Lingo: Search results clustering algorithm based on singular value decomposition. In *Proceedings of the IIS: IIPWM'04 Conference*. Academic Press. doi:10.1007/978-3-540-39985-8_37

Pan, C., & Li, W. (2010). Research paper recommendation with topic analysis. In *Proceedings of the International Conference on Computer Design and Applications (ICCDA)* (Vol. 4, pp. 264-268). Academic Press.

Park, S. T., & Chu, W. (2009).Pairwise preference regression for cold-start recommendation. In *Proceedings of the 3rd ACM Conference on Recommender Systems* (pp. 21–28). Silicon Valley, CA: Association for Computing Machinery.

Park, S. T., Pennock, D. M., Madani, O., Good, N., & DeCoste, D. (2006). Naive filterbots for robust cold-start recommendations. In *Proceedings of the 12th ACM SIGKDD International Conference on Knowledge Discovery and Data mining*. ACM. doi:10.1145/1150402.1150490

Raghavan, U. N., Albert, R., & Kumara, S. (2007). Near linear time algorithm to detect community structures in large-scale networks. Phys. Rev. E, 76(3), 036106.

Rendle, S., Freudenthaler, C., Gantner, Z., & Schmidt-Thieme, L. (2009). *BPR: Bayesain Personalised Ranking from Implicit Feedback*. In *Proceedings of the twenty-fifth conference on uncertainty in artificial intelligence* (pp. 452-461). AUAI Press.

Rey Bellet, L. (2003). Ergodic properties of Markov processes. In *Lecture Notes of the 2003*. Grenoble Summer School on Open Quantum Systems.

Ricci, F., Rokach, L., Shapira, B., & Kantor, P. B. (2011). *Recommender Systems Handbook*. New York: Springer. doi:10.1007/978-0-387-85820-3

Rohani, V. A., Kasirun, Z. M., Kumar, S., & Shamshirband, S. (2014). An effective recommender algorithm for cold-start problem in academic social networks. *Mathematical Problems in Engineering*. doi:10.1155/2014/123726

Rohani, V. A., Kasirun, Z. M., Kumar, S., & Shamshirband, S. (2014). An effective recommender algorithm for cold-start problem in academic social networks. *Mathematical Problems in Engineering*, *2014*, 1–11. doi:10.1155/2014/123726

Sahebi, S., & Cohen, W. W. (2011). Community-based recommendations: a solution to the cold start problem. In *Proceedings of the Workshop on Recommender Systems and the Social Web (RSWEB'11)*. Academic Press.

Saini, S., & Banda, L. (2012). Improving scalability issues using gim in collaborative filtering based on tagging. *International Journal of Advances in Engineering and Technology*, *4*(1), 600–610.

Schein, A., Popescul, I. A., Ungar, L. H., & Pennock, D. M. (2002). Methods and metrics for cold-start recommendations. In *Proceedings of the 25th Annual International ACM Conference on Research and Development in Information Retrieval (SIGIR'02)* (pp. 253–260). ACM.

Shani, G., & Gunawardana, A. (2010). Evaluating recommendation systems. In F. Ricci, L. Rokach, B. Shapira, & P. B. Kantor (Eds.), *Recommender Systems Handbook* (pp. 257–297). Springer.

Shi, Y., Larson, M., & Hanjalic, A. (2010, September). List-wise learning to rank with matrix factorization for collaborative filtering. In Proceedings of the fourth ACM conference on Recommender systems (pp. 269-272). ACM. doi:10.1145/1864708.1864764

Sugiyama, K., & Kan, M. Y. (2010). Scholarly paper recommendation via user's recent research interests. In *Proceedings of the 10th annual joint conference on Digital libraries JCDL '10* (pp. 29–38). New York: ACM.

Sun, M., Li, F., Lee, J., Zhou, K., Lebanon, G., & Zha, H. (2013). Learning multiple-question decision trees for cold-start recommendation. In *Proceedings of the 6th ACM International Conference on Web Search and Data Mining* (pp. 445–454). Association for Computing Machinery. doi:10.1145/2433396.2433451

Sun, Z., Han, L., Huang, W., Wang, X., Zeng, X., Wang, M., & Yan, H. (2015). Recommender systems based on social networks. *Journal of Systems and Software*, *99*, 109–119. doi:10.1016/j.jss.2014.09.019

Torres, R., McNee, S. M., Abel, M., Konstan, J. A., & Riedl, J. (2004). Enhancing Digital Libraries with Techlens. In *Proceedings of the 4th ACM/IEEE-CS Joint Conference on Digital Libraries* (pp. 228–236). Academic Press.

Wang, Y., Zhai, E., Hu, J., & Chen, Z. (2010). Claper: Recommend classical papers to beginners. *Seventh International Conference on Fuzzy Systems and Knowledge Discovery*, 2777–2781. doi:10.1109/FSKD.2010.5569227

Yuan, J., & Li, L. (2014). Recommendation based on trust diffusion model. *The Scientific World Journal*. doi:10.1155/2014/159594

Manju G. is currently working as Assistant Professor in SRM Institute of Science and Technology. The research interests of the authors include: machine learning, text mining, social network analysis and the recommender system.

Abhinaya P. is a software professional working in at a product-based company. They are a tech enthusiast, blogger and mainly interested in machine learning applications. He graduated with a bachelor's degree in computer science and Engineering from the College of Engineering, Guindy, Anna University.