International Journal of Engineering Research in Computer Science and Engineering (IJERCSE) Vol 3, Issue 4, April 2016

Social Recommendation with Cross-Domain Transferable Knowledge

[1] Ajin Brabasher A, M.E [2] MadhanKumar M [3] VeeraKumar M [4] Krishna Moorthi R
[1] Assistant Professor [2][3][4] UG Student
Department of CSE
Loyola Institute of Technology, Chennai, India.
[1] ajinlitcse@gmail.com [2] kumarmadhan244@gmail.com [3] m.veerakumar5@gmail.com
[4] kmoorthi002@gmail.com

Abstract **Social recommendation forms a specific type of information filtering technique that attempts to suggest information (blog, news, music, travel plans, web pages, images, tags, etc.) that are likely to interest the users.Social recommendation involves the investigation of collective intelligence by using computational techniques such as machine learning, data mining, natural language processing, etc. Social behavior data collected from the blogs, wikis, recommender systems, question & answer communities, query logs, tags, etc. from areas such as social networks, social search, social media, social bookmarks, social news, social knowledge sharing, and social games. In this tutorial, it will introduce collaborative filtering (CF) techniques, social recommendation and hybrid random walk (HRW) method.The social recommendation system is conducted according to the messages and social structure of target users. The similarity of the discovered features of users and products will then be calculated as the essence of the recommendation engine. A case study will be included to present how the recommendation system works based on real data.**

Index Terms**—Social recommendation, transferability, cross-domain, star-structured graph, random walk**

I. INTRODUCTION

A social networking service is a platform on which users can create and adopt different types of items such as web posts (e.g., articles and tweets), user labels, images, and videos. The huge volume of items generates a problem of information overload. Traditional web post recommendation approaches suffer from data sparsity (i.e., limited inter-action between users and web posts) and the issue of cold start (i.e., giving recommendations to new users who have not yet created any web posts).

One common type of approach to recommendations, known as collaborative filtering (CF) techniques. For example, users read web posts created by their community and may adopt similar user labels to their friends. Therefore, an effective social recommendation approach should acknowledge social tie strength (hence-forth, tie strength) between users and different user-item interactions. The multiple item domains reflect users' intrinsic preferences and tend to be tightly connected among a massive number of users. In this paper, it reconsider the representation of social networks and propose a star-structured graph, where the social domain is at the center and is connected to the surrounding item domains, as shown in Fig. 1.The value of the cross-domain link weight represents how often a given user adopts a given item, while the value of the within-domain link weight in the social domain represents the tie strength between users. Users are more likely to have stronger ties if they share similar characteristics. Cross-domain links.

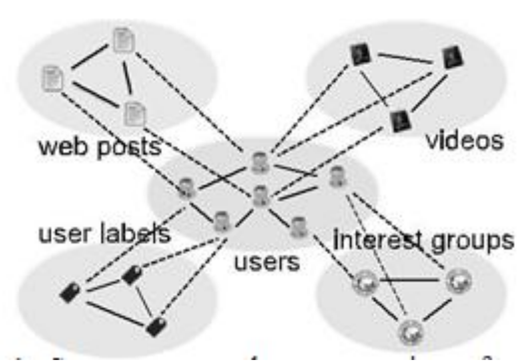


Fig.1. Star - structured representation of a social network connecting multiple item domains and one social domain.

To address the above challenges, it propose an innova-tive hybrid random walk (HRW) method for transferring knowledge from auxiliary item domains according to a star-structured configuration to improve social recommendations in a target domain. HRW estimates weights for (1) links between user nodes within the social domain, and (2) links between user nodes in the social domain and item nodes inthe item domain.

3. The domains are heterogeneous. Heterogeneity is a challenging issue in social recommendation. Within-domain links can be directed ("following" links in the social domain) or undirected (semantic similarity links in the item domains). Cross-domain links can be signed (indicating a positive or negative connotation, such as web-post adoptions and rejections) or unsigned (user-label adoptions). The issue of how to transfer knowledge across heterogeneous domains poses a challenge to method comprehensibility.

Extensive experimentation on a large real social dataset demonstrates that HRW produces signifi-cantly superior recommendations for web posts on social networks. In terms of providing recommenda-tions to cold-start users, only 30 percent of historical data from the web-post domain is necessary to achieve a comparable performance to that of an approach that makes use of user-label data. reflect users' characteristics in different ways.
Cross-domain links are user-item links (item adoptions), i.e., links between the social domain and the item domains.

II. RELATED WORK

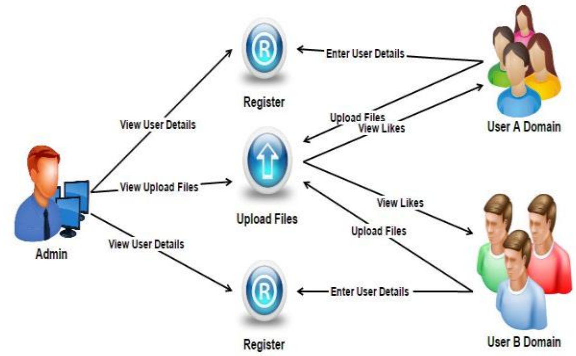
2.1 Cross-Domain Collaborative Filtering

One-Class Collaborative Filtering (OCCF) problems are more problematic than traditional collaborative filtering problems, since OCCF datasets lack counter-examples. Social networks can be used to remedy dataset issues faced by OCCF applications. In this work,it compare social networks belong to specific domains and the ones belong to more generic domains in terms of their usability in OCCF problems. Our experiments show that social networks that belong to a specific domain may better be appropriate for use in OCCF application.

2.2 Hybrid Random walk Algorithm

In this section, this introduce our random walk-based method on social recommendation. Owing to data sparsity in the target domain, traditional bipartite random walk (BRW) algorithms cannot accurately derive user tie strength to predict user behaviors in the target domain. Fortunately, it have auxiliary domains in which user ties are formed for the same reason as in the target domain: homophily, trust, and influence. The key idea is to utilize rich knowledge from the auxiliary domains to better describe user tie strength and then more precisely predict user behaviors. Thus, this derive HRW algorithms on star-structured graphs

2.3 Architectural Diagram



III. MODULES AND NOTATION

3.1 Authentication:

Authentication is a process in which the credentials provided are compared to those on file in a database of authorized users' information on a local operating system or within an authentication server. In this project authentication is done to provide more security for the users to have their own credentials to log in.

3.2. *Cache of the data:*

Cache is in wide use and very stable, but has not changed in years and is no longer actively developed. The Cache is designed to assist a developer in persisting data for a specified period of time. In this project it is used as the collection of data to store which is used for various processing.

3.3. Transferring Resource:

Users Post images, videos, status into their timeline where the data's are stored specifying their domain.In this the data's which is posted by the user are retrieved and visible to the other users.User can like the data's which is been posted by the other user and can also see the likes of the data posted.

3.4. Aspects:

3.4.1 Timeline Aspects:

In this every data posted by the user is present in the Page according to their respective domains.User can like the data's whichever posted on their domain.

3.4.2 Current Domain Aspects:

In this view the most liked data's which are not liked by the current user are recommended to the current user.The current user can like the data's which is been recommended.

3.4.3 Cross Domain Aspects:

In this view the most liked data's of the cross domain are recommended to the current user. The current user can like the data's which is been recommended if the user is already registered.

3.4.4 Collaborative Aspects:

In this view the data's which are liked by their friends are recommended to the current user .The current user can like the data's which is been recommended.

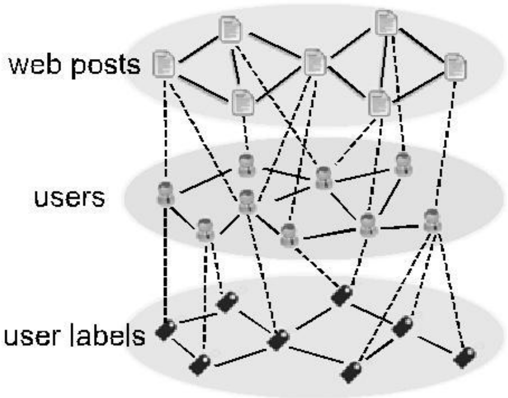


Fig. 3. Our social network data represented by a second-order hybrid star-structured graph, where within-domain links are between users, posts, and labels, and cross-domain links are between user and post, user and label.

popularityðjÞ ¼ ^{X}w^{ðUT}$_{ij}$ ^{Þþ} :
i

1) consistency with users' post contents, i.e., the average similarity of the web posts between a pair of users who have the label j, denoted by

consₚₒₛₜ j ð Þ ¼ P i ... k;wðUT Þþ ;wðUT Þþ ... ;wðUPÞþ ;wðUPÞþ ... ðUT Þþ > 0 ... 1

2) consistency with users' followers, i.e., the similarity of followers between a pair of users, denoted by

cons follower j ð Þ ¼ P ... k;wðUT Þþ ;wðUT Þþ ... kj ... 1

IV.HYBRID RANDOM WALK

In this section, it introduces our random walk-based method on social recommendation. Owing to data sparsity in the target domain, traditional bipartite random walk (BRW) algorithms cannot accurately derive user tie strength to predict user behaviors in the target domain. Fortunately, it have auxiliary domains in which user ties are formed for the same reason as in the target domain: homophily, trust, and influence. The key idea is to utilize rich knowledge from the auxiliary domains to better describe user tie strength and then more precisely predict user behaviors. Thus, this derive HRW algorithms on star-structured graphs

4.1 Collaborative Filter

One-Class Collaborative Filtering (OCCF) problems are more problematic than traditional collaborative filtering problems, since OCCF datasets lack counter-examples. Social networks can be used to remedy dataset issues faced by OCCF applications. In this work, it compare social networks belong to specific domains and the ones belong to more generic domains in terms of their usability in OCCF problems. Our experiments show that social networks that belong to a specific domain may better be appropriate for use in OCCF application. Collaborative filtering methods are based on collecting and analyzing a large amount of information on user behaviors, activity or preference and predicting what users will like based on their similarity to other users. It is based on the assumption that people who agreed in the past will agree in the future and that they liked in the past

4.2 SPARSITY

Sparsity generates code for two operations: a sparse matrix times a dense vector and a sparse matrix times a set of dense vectors. The strategy for choosing register blocks, for example is to use a performance model based on: A matrix-independent, machine-dependent performance profile.

4.3 Generic Random Walk

The plots compare the stationary probability of finding a particle performing a random walk on a 2D square lattice with randomly distributed defects for Generic Random Walk (GRW) and Maximal Entropy Random Walk (MERW). The darker a region, the lower the stationary probability of finding a particle there

consfollowee j P ¼P ¼ Ij kj ... k;wðUT Þþ ;wðUT Þþ > 0 ... Wi;ðUÞ :Wk;ð ...

6

k;wðUT Þþ ;wðUT

i Þþ > 0

PðUÞ ¼ ðDðUÞÞ_1WðUÞ

PðPÞ ¼ ðDðPÞÞ_1WðPÞ

PðT Þ ¼ ðDðT ÞÞ_1WðT Þ;

Where it denote the degree matrices of cross-domain links by DðUPÞþ , DðUPÞ– , and DðUT Þþ .

Algorithm 1. Random Walk over a High-Order Hybrid Star-Structured Graph

Require: 0 _ a; fbig N i¼1; fdig N i¼1; fmig N i¼1; ftig N i¼1 _ 1
1. Construct GðUÞ, fGðDiÞg N i¼1, fGðUDiÞg N i¼1
2. Compute PðUÞ and fPðDiÞg N i¼1
3. Derive RðUÞ and fRðDiÞg N i¼1
4. Initialize fPðUDiÞþ ð0Þg N i¼1 and fPðUDiÞ– ð0Þg N i¼1
5. for t ¼ 1 : T do
6. Compute RðUÞðtÞ, fPðUDiÞþ ðtÞg N i¼1 and fPðUDiÞ– ðtÞg N i¼1
7. end for
8. Output: Final transition probability matrices

RðUÞ, fPðUDiÞþ g N i¼1 and fPðUDiÞ_ g N i¼1

V. CONCLUSION AND FUTURE ENHANCEMENT

In this paper, it addressed the problems of data sparsity and cold start in social recommendation. it reconsidered the problem from the transfer learning perspective and alleviated the data sparsity problem in a target domain by transferring knowledge from other auxiliary social relational domains. By considering the special structures of multiple relational domains in social networks, it proposed an innovative HRW method on a star-structured graph, which is a general method to incorporate complex and heterogeneous link structures.

It conducted extensive experiments on a large realworld social network dataset and showed that the proposed method greatly boosts the social recommendation performance. In particular, it gained improvement in web-post recommendation by transferring knowledge from the userlabel domain for the user tie strength updating process, compared with the recommendation methods, which only use information from the web-post domain. In addition, it demonstrated that, by using only 27.6 percent of the available information in the target domain, our method achieves comparable performance with methods that use all available information in the target domain without transfer learning. The proposed method and insightful experiments indicate a promising and general way tosolve the data sparsity problem.

REFERENCES

[1] Social Recommendation withCross-Domain Transferable Knowledge,vol27,nov 2015.

[2] H. Ma, D. Zhou, C. Liu, M. R. Lyu, and I. King, "Recommender system with social regularization," in Proc. 4th ACM Int. Conf. Web Search Data Mining, 2011, pp. 287–296.

[3] I. Konstas, V. Stathopoulos, and J. M. Jose, "On social networks and collaborative recommendation," in Proc. 32nd Annu. Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval, 2009, pp. 195–202.

[4] J. Wang, H. Zeng, Z. Chen, H. Lu, L. Tao, and W. Ma, "ReCoM: Reinforcement clustering of multi-type interrelated data objects," in Proc. Annu. Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval, 2003, pp. 274–281.

[5] J. Brown, A. J. Broderick, and N. Lee, "Word of mouths communi-cation within online communities: Conceptualizing the online social network," J. Interactive Marketing, vol. 21, pp. 2–20, 2007.

[6] J. Leskovec, A. Singh, and J. Kleinberg, "Patterns of influence in a recommendation network," in Proc. 10th Pacific-Asia Conf. Knowl. Discovery Data Mining, 2006, vol. 3918, pp. 380–389.

[7] X. Yang, H. Steck, and Y. Liu, "Circle-based recommendation in online social networks," in Proc. 18th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, 2012, pp. 1267–1275.

[8] X. Qian, H. Feng, G. Zhao, and T. Mei, "Personalized recommen-dation combining user interest and social circle," IEEE Trans. Knowl. Data Eng., vol. 26, no. 7, pp. 1763–1777, Jul. 2014.

[9] P. Massa and P. Avesani, "Trust-aware recommender systems," in Proc. ACM Conf. Recommender Syst., 2007, pp. 17–24.

pp. M. Jamali and M. Ester, "TrustWalker: A random walk model for combining trust-based and item-based recommendation," in Proc. 15th ACM SIGKDD Int. Conf. Knowl.

[10] N. N. Liu, M. Zhao, and Q. Yang, "Probabilistic latent preference analysis for collaborative filtering," in Proc. 18th ACM Conf. Inf. Knowl. Manage., 2009, pp. 759–766.

[11] M. Harvey, M. J. Carman, I. Ruthven, and F. Crestanig, "Bayesian latent variable models for collaborative item

rating prediction," in

Proc. ACM Conf. Inf. Knowl. Manage., 2011, pp. 699–708.

[12] J. Noel, S. Sanner, K. N. Tran, P. Christen, L. Xie, E. V. Bonilla, E. Abbasnejad, and E. D. Penna, "New objective functions for social collaborative filtering," in Proc. 21st Int. Conf. World Wide Web, 2012, pp. 859–868.

[13] H. Ma, H. Yang, M. R. Lyu, and I. King, "SoRec: Social recommen-dation using probabilistic matrix factorization," in Proc. ACM Conf. Inf. Knowl. Manage., 2008, pp. 931–940.

[14] M. Jiang, P. Cui, R. Liu, F. Wang, W. Zhu, and S. Yang, "Scalable recommendation with social contextual information," IEEE Trans. Knowl. Data Eng., vol. 26, no. 11, pp. 2789–2802, Nov. 2014.

[15] P. Winoto and T. Tang, "If you like the devil wears prada the book, will you also enjoy the devil wears prada the movie? a study of cross-domain recommendations," New Generation Comput., vol. 26, no. 3, pp. 209–225, 2008.

[16] J. Tang, S. Wu, J. Sun, and H. Su, "Cross-domain collaboration rec-ommendation," in Proc. ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, 2012, pp. 1285–1293.

[17] C. Li and S. Lin, "Matching users and items across domains to improve the recommendation quality," in Proc. ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, 2014, pp. 801–810.

[18] Y. Shi, M. Larson, and A. Hanjalic, "Collaborative filtering beyond the user-item matrix: A survey of the state of the art and future challenges," ACM Comput. Surv., vol. 47, no. 1, p. 3, 2014.

[19] S. Berkovsky, T. Kuflik, and F. Ricci, "Cross-domain mediation in collaborative filtering," in Proc. 11th Int. Conf. User Model., 2007, 355–359.

[20] S. Gao, H. Luo, D. Chen, S. Li, P. Gallinari, and J. Guo, "Cross-domain recommendation via cluster-level latent factor model," in Proc. Mach. Learn. Knowl. Discovery Databases, 2013, pp. 161–176.

[21] W. Chen, W. Hsu, and M. L. Lee, "Making recommendations from multiple domains," in Proc. ACM SIGKDD Int. Conf. Knowl. Dis-covery Data Mining, 2013, pp. 892–900.

[22] J. Tang, X. Hu, H. Gao, and H. Liu, "Exploiting local and global social context for recommendation," in Proc. 23rd Int. Joint Conf. Artif. Intell., 2013, pp. 2712–2718.

[23] J. Tang, X. Hu, and H. Liu, "Social recommendation: A review," Soc. Netw. Anal. Mining, vol. 3, no. 4, pp. 1113–1133, 2013.

[24] S. Sedhain, S. Sanner, L. Xie, R. Kidd, K. N. Tran, and P. Christen, "Social affinity filtering: Recommendation through fine-grained analysis of user interactions and activities," in Proc. 1st ACM Conf. Online Soc. Netw., 2013, pp. 51–62.

[25] B. Shapira, L. Rokach, and S. Freilikhman, "Facebook single and cross domain data for recommendation systems," User Model. User-Adapted Interaction, vol. 23, no. 2-3, pp. 211–247, 2013.

[26] S. Sedhain, S. Sanner, D. Braziunas, L. Xie, and J. Christensen, "Social collaborative filtering for cold-start recommendations." in Proc. ACM Conf. Recommender Syst., 2014, pp. 345–348.

[27] Y. Chen, Y. Lin, Y. Shen, and S. Lin, "A modified random walk framework for handling negative ratings and generating explan-ations," ACM Trans. Intell. Syst. Technol., vol. 4, no. 1, p. 12, 2013.

[28] G. Adomavicius and A. Tuzhilin, "Toward the next generation of recommender systems: A survey of the state-of-the-art and possi-ble extensions," IEEE Trans. Knowl. Data Eng., vol. 17, no. 6, 734–749, Jun. 2005.

[29] S. J. Pan and Q. Yang, "A survey on transfer learning," IEEE Trans. Knowl. Data Eng., vol. 22, no. 10, pp. 1345–1359, Oct. 2010.

[30] B. Cao, N. N. Liu, and Q. Yang, "Transfer learning for collective link prediction in multiple heterogeneous domains," in Proc. Int. Conf. Mach. Learn., 2010, pp. 159–166.

[31] Y. Zhu, Y. Chen, Z. Lu, S. J. Pan, G.-R. Xue, Y. Yu, and Q. Yang, "Heterogeneous transfer learning for image classification," in Proc. 25th AAAI Conf. Artif. Intell., 2011, pp. 1–9.

[32] O. Moreno, B. Shapira, L. Rokach, and G. Shani, "Talmud: Trans-fer learning for multiple domains," in Proc. ACM Conf. Inf. Knowl. Manage., 2012, pp. 425–434.

[33] Z. Lu, W. Pan, E. W. Xiang, Q. Yang, L. Zhao, and E. Zhong, "Selective transfer learning for cross domain recommendation," in Proc. 13th SIAM Int. Conf. Data Mining, 2013, pp. 641–649.

[34] B. Tan, E. Zhong, M. K. Ng, and Q. Yang, “Mixed-transfer: Trans-fer learning over mixed graphs,” in Proc. 14th SIAM Int. Conf. Data Mining, 2014, pp. 208–216.

[35] W. Pan, E. W. Xiang, N. N. Liu, and Q. Yang, “Transfer learning in collaborative filtering for sparsity reduction,” in Proc. 25th AAAI Conf. Artif. Intell., 2010, pp. 230–235.

[36] B. Li, Q. Yang, and X. Xue, “Can movies and books collaborate? cross-domain collaborative filtering for sparsity reduction,” in Proc. 21st Int. Jont Conf. Artif. Intell., 2009, vol. 9, pp. 2052–2057.

[37] H. Jing, A.-C. Liang, S.-D. Lin, and Y. Tsao, “A transfer probabilis-tic collective factorization model to handle sparse data in collabo-rative filtering,” in Proc. Int. Conf. Data Mining, 2014, pp. 250–259.

[38] H. Tong, C. Faloutsos, and J. Pan, “Fast random walk with restart and its applications,” in Proc. Int. Conf. Data Mining, 2006, 613–622.

[39] M. Gori and A. Pucci, “ItemRank: A random-walk based scoring algorithm for recommender engines,” in Proc. Int. Jont Conf. Artif. Intell., 2007, pp. 2766–2771.

[40] B. Gao, T. Liu, X. Zheng, Q. Cheng, and W. Ma, “Consistent bipar-tite graph co-partitioning for star-structured high-order heteroge-neous data co-clustering,” in Proc. ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, 2005, pp. 41–50.

[41] B. Gao, T. Liu, and W. Ma, “Star-structured high-order heteroge-neous data co-clustering based on consistent information theory,” in Proc. Int. Conf. Data Mining, 2006, pp. 880–884.

[42] C. Avin and B. Krishnamachari, “The power of choice in random walks: An empirical study,” Comput. Netw., vol. 52, no. 1, pp. 44– 60, 2008.

[43] Safro, P. D. Hovland, J. Shin, and M. M. Strout, “Improving ran-dom walk performance,” in Proc. Int. Conf. Sci. Comput., 2009,