A System for Recommending Products with Personality Based on Metapath Discovery and Interest Mining of Users

MS. ANURADHA ANUMOLU1, MR. CHALAPATI KESAVARAO2

#1 Associate professor in the Department of IT at DVR & DR. HS MIC College of Technology (Autonomous), Kanchikacherla, NTR District.

#2 MCA student in the Department of Computer Applications (DCA) at DVR & DR. HS MIC COLLEGE OF TECHNOLOGY, Kanchikacherla, NTR District

ABSTRACT_ A recommendation system is a basic component of any contemporary social networking or e-commerce site. One such example of a legacy recommendation system is the product recommendation system, which has two main problems: recommendations that are redundant and unpredictable when it comes to new products (cold start). These restrictions result from the fact that older recommendation algorithms only suggest new products based on a user's past purchasing patterns.

We suggest mapping users' social networking features to another feature representation for product suggestion by using the linked users across social networking sites and e-commerce websites (users who have social networking accounts and have made purchases on e-commerce websites) as a bridge. Specifically, we suggest using recurrent neural networks to learn feature representations of both users and products (referred to as user embeddings and product embeddings, respectively) from data gathered from e-commerce websites. Users' social networking features are then converted into user embeddings via a modified gradient boosting trees method. After that, we create a feature-based matrix factorization strategy that makes use of the user embeddings that have been learned for cold-start product recommendation.

1.INTRODUCTION

Means to prescribe items from online business sites to clients at person to person communication destinations in "cool beginning" circumstances, an issue which has seldom been investigated previously. A significant test is the means by which to use information separated from interpersonal interaction destinations for cross-site cold-start item suggestion. We propose mapping users' social networking features to another feature representation for product recommendation using the linked users across social networking sites and e-commerce websites (users who have social networking accounts and have made purchases on e-commerce websites). In unambiguous, we propose learning the two clients' and items' component portrayals (called client implanting and item inserting, separately) from information gathered from online business sites utilizing repetitive brain organizations and afterward apply a changed slope supporting trees technique to change clients' person to person communication highlights into client inserting. We then foster a component based framework factorization approach which can use the learnt client implanting for cold-start item suggestion. Trial results on a huge dataset built from the biggest Chinese microblogging administration SINA WEIBO and the biggest Chinese B2C internet business site JINGDONG have shown the viability of our proposed structure

2.LITERATURE SURVEY

1) Opportunity model for E-commerce recommendation: Right product; right time

AUTHORS: J. Wang and Y. Zhang

Most of existing e-commerce recommender systems aim to recommend the right product to a user, based on whether the user is likely to purchase or like a product. On the other hand, the effectiveness of recommendations also depends on the time of the recommendation. Let us take a user who just purchased a laptop as an example. She may purchase a replacement battery in 2 years (assuming that the laptop's original battery often fails to work around that time) and purchase a new laptop in another 2 years. In this case, it is not a good idea to recommend a new laptop or a replacement battery right after the user purchased the new laptop. It could hurt the user's satisfaction of the recommender system if she receives a potentially right product recommendation at the wrong time. I argue that a system should not only recommend the most relevant item, but also recommend at the right time.

This paper studies the new problem: how to recommend the right product at the right time? I adapt the proportional hazards modeling approach in survival analysis to the recommendation research field and propose a new *opportunity model* to explicitly incorporate time in an e-commerce recommender system. The new model estimates the joint probability of a user making a follow-up purchase of a particular product at a particular time. This joint purchase probability can be leveraged by recommender systems in various scenarios, including the zero-query pull-based recommendation scenario (e.g. recommendation on an e-commerce web site) and a proactive push-based promotion scenario (e.g. email or text message based marketing). I evaluate the opportunity modeling approach with multiple metrics. Experimental results on a data collected by a real-world e-commerce website (shop.com) show that it can predict a user's follow-up purchase behavior at a particular time with descent accuracy. In addition, the opportunity model significantly improves the conversion rate in pull-based systems and the user satisfaction/utility in push-based systems.

2) Retail sales prediction and item recommendations using customer demographics at store level

AUTHORS: M. Giering

This paper outlines a retail sales prediction and product recommendation system that was implemented for a chain of retail stores. The relative importance of consumer demographic characteristics for accurately modeling the sales of each customer type are derived and implemented in the model. Data consisted of daily sales information for 600 products at the store level, broken out over a set of non-overlapping customer types. A recommender system was built based on a fast online thin Singular Value Decomposition.

It is shown that modeling data at a finer level of detail by clustering across customer types and demographics yields improved performance compared to a single aggregate model built for the entire dataset. Details of the system implementation are described and practical issues that arise in such real-world applications are discussed. Preliminary results from test stores over a one-year period indicate that the system resulted in significantly increased sales and improved efficiencies. A brief overview of how the primary methods discussed here were extended to a much larger data set is given to confirm and illustrate the scalability of this approach.

3) Amazon.com recommendations: Item-to-item collaborative filtering

AUTHORS: G. Linden, B. Smith, and J. York

Recommendation algorithms are best known for their use on e-commerce Web sites, where they use input about a customer's interests to generate a list of recommended items. Many applications use only the items that customers purchase and explicitly rate to represent their interests, but they can also use other attributes, including items viewed, demographic data, subject interests, and favorite artists. At Amazon.com, we use recommendation algorithms to personalize the online store for each customer.

The store radically changes based on customer interests, showing programming titles to a software engineer and baby toys to a new mother. There are three common approaches to solving the recommendation problem: traditional collaborative filtering, cluster models, and search-based methods. Here, we compare these methods with our algorithm, which we call item-to-item collaborative filtering. Unlike traditional collaborative filtering, our algorithm's online computation scales independently of the number of customers and number of items in the product catalog. Our algorithm produces recommendations in real-time, scales to massive data sets, and generates high quality recommendations.

3.PROPOSED SYSTEM

In this paper, we concentrate on a fascinating issue of prescribing items from web based business sites to clients at person to person communication locales who don't have authentic buy records, i.e., in "cool beginning" circumstances. We called this issue cross-site cold-start item proposal.

Since only the social networking information of the users is available in our problem setting, it is difficult to convert this information into latent user features that can be used to recommend products. To address this test, we propose to utilize the connected clients across informal communication destinations and web based business sites (clients who have interpersonal interaction accounts and have made buys on web based business sites) as a scaffold to plan clients' person to person communication highlights to dormant elements for item suggestion.

In unambiguous, I propose learning the two clients' and items' component portrayals (called client inserting and item implanting, separately) from information gathered from web based business sites utilizing repetitive brain organizations and afterward apply a changed slope supporting trees strategy to change clients' person to person communication highlights into client implanting.I then, at that point, foster an element based network factorization approach which can use the learnt client implanting for cold beginning item proposal

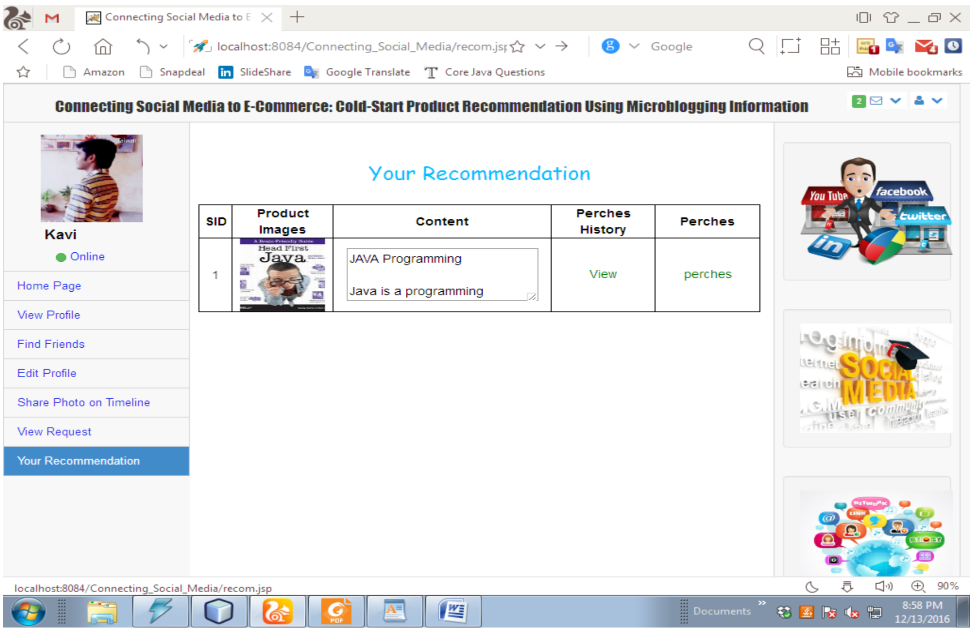
3.1 IMPLEMENTATION

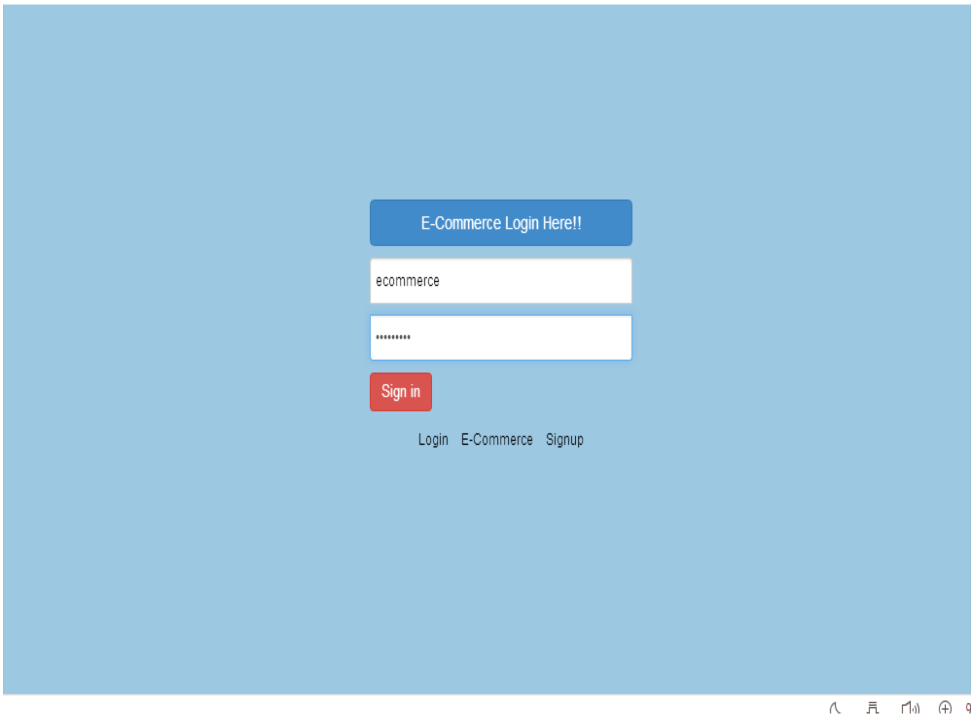
- **OSN System Construction Module**
- In the first module, we develop the Online Social Networking (OSN) system module. We build up the system with the feature of Online Social Networking. Where, this module is used for new user registrations and after registrations the users can login with their authentication.
- Where after the existing users can send messages to privately and publicly, options are built. Users can also share post with others. The user can able to search the other user profiles and public posts. In this module users can also accept and send friend requests.
- With all the basic feature of Online Social Networking System modules is build up in the initial module, to prove and evaluate our system features.
- Given an e-commerce website, with a set of its users, a set of products and purchase record matrix, each entry of which is a binary value indicating whether has purchased product. Each user is associated with a set of purchased products with the purchase timestamps. Furthermore, a small subset of users can be linked to their microblogging accounts (or other social network accounts).
- **Microblogging Feature Selection**
- In this module, we develop the Microblogging Feature Selection. Prepare a list of potentially useful microblogging attributes and construct the microblogging feature vector for each linked user. Generate distributed feature representations using the information from all the users on the ecommerce website through deep learning. Learn the mapping function, which transforms the microblogging attribute information au to the distributed feature representations in the second step. It utilises the feature representation pairs of all the linked users as training data.
- Ademographic profile (often shortened as "a demographic") of a user such as sex, age and education can be used by ecommerce companies to provide better personalised services. We extract users' demographic attributes from their public profiles. Demographic attributes have been shown to be very important in marketing, especially in product adoption for consumers
- **Learning Product Embeddings**
- In the previous module, we develop the feature selection, but it is not straightforward to establish connections between users and products. Intuitively, users and products should be represented in the same feature space so that a user is closer to the products that he/she has purchased compared to those he/she has not. Inspired by the recently proposed methods in learning word embeddings, we

propose to learn user embeddings or distributed representation of user in a similar way.

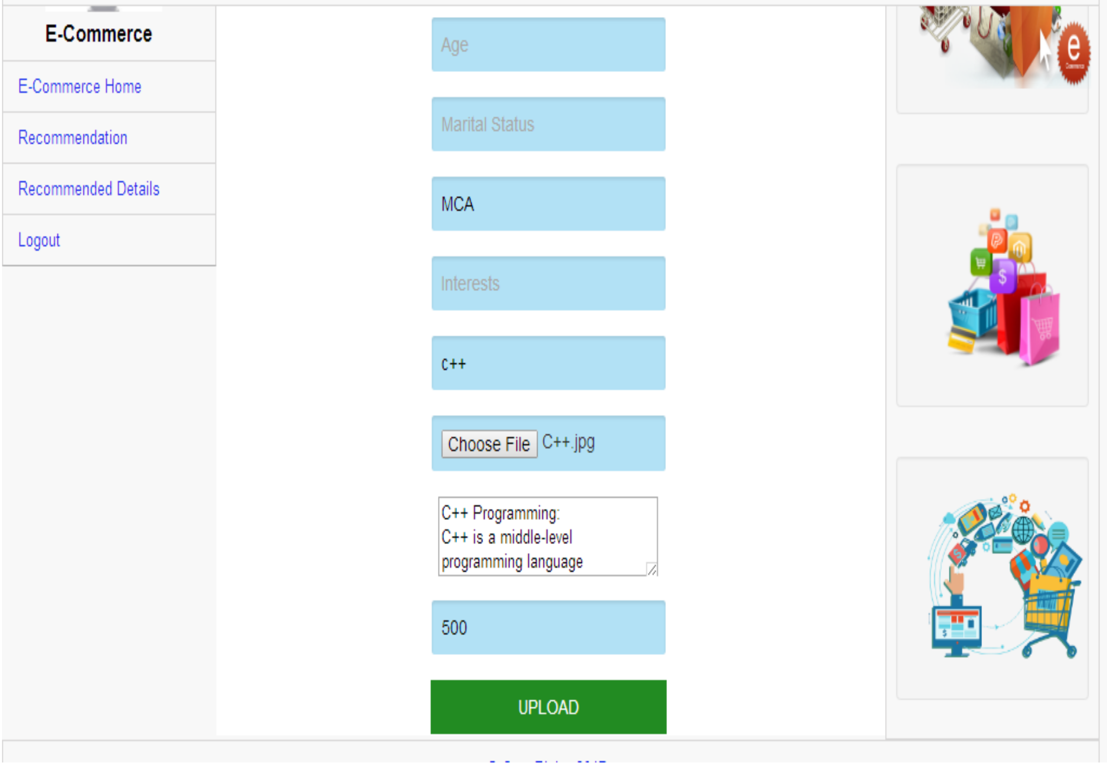
- Given a set of symbol sequences, a fixed-length vector representation for each symbol can be learned in a latent space by exploiting the context information among symbols, in which “similar” symbols will be mapped to nearby positions. If we treat each product ID as a word token, and convert the historical purchase records of a user into a timestamped sequence, we can then use the same methods to learn product embeddings. Unlike matrix factorization, the order of historical purchases from a user can be naturally captured.
- **Cold-Start Product Recommendation**
- We used a local host based e-commerce dataset, which contains some user transaction records. Each transaction record consists of a user ID, a product ID and the purchase timestamp. We first group transaction records by user IDs and then obtain a list of purchased products for each user.
- For our methods, an important component is the embedding models, which can be set to two simple architectures, namely CBOW and Skip-gram. We empirically compare the results of our method ColdE using these two architectures, and find that the performance of using Skip-gram is slightly worse than that of using CBOW.

4.RESULTS AND DISCUSSION




E-Commerce Login Here!!
ecommerce
Sign in
Login E-Commerce Signup


E-Commerce
E-Commerce Home
Recommendation
Recommended Details
Logout
Add to Cart
1 Cart Contents
2 Shipping Address
3 Billing Address
4 Checkout Confirmation
Name: Shop Online
Password: ************



5.CONCLUSION

In this work, we have investigated a new problem: cross-site cold-start product suggestion, which is the task of suggesting e-commerce products to microbloggers who have no past purchase history. Our core hypothesis is that, by using recurrent neural networks for feature learning, customers and items can be represented in the same latent feature space on e-commerce platforms. We can learn feature mapping functions using a modified gradient boosting trees method, which maps users' attributes extracted from social networking sites onto feature representations learned from e-commerce websites, by using a set of linked users across both e-commerce websites and social networking sites as a bridge.

REFERENCES

[1] J. Wang and Y. Zhang, “Opportunity model for E-commerce recommendation: Right product; right time,” in Proc. 36th Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval, 2013, pp. 303–312.

[2] M. Giering, “Retail sales prediction and item recommendations using customer demographics at store level,” SIGKDD Explor. Newsl., vol. 10, no. 2, pp. 84-89, Dec. 2008.

[3] G. Linden, B. Smith, and J. York, “Amazon.com recommendations: Item-to-item collaborative filtering,” IEEE Internet Comput., vol. 7, no. 1, pp. 76–80, Jan./Feb. 2003.

[4] V. A. Zeithaml, "The new demographics and market fragmentation," J. Marketing, vol. 49, pp. 64–75, 1985.

[5] W. X. Zhao, Y. Guo, Y. He, H. Jiang, Y. Wu, and X. Li, "We know what you want to buy: A demographic-based system for product recommendation on microblogs," in Proc. 20th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, 2014, pp. 1935–1944.

[6] J. Wang, W. X. Zhao, Y. He, and X. Li, "Leveraging product adopter information from online reviews for product recommendation," in Proc. 9th Int. AAAI Conf. Web Social Media, 2015, pp. 464–472.

[7] Y. Seroussi, F. Bohnert, and I. Zukerman, "Personalised rating prediction for new users using latent factor models," in Proc. 22nd ACM Conf. Hypertext Hypermedia, 2011, pp. 47–56.

[8] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, "Distributed representations of words and phrases and their compositionality," in Proc. Adv. Neural Inf. Process. Syst., 2013, pp. 3111–3119.

[9] Q. V. Le and T. Mikolov, "Distributed representations of sentences and documents," CoRR, vol. abs/1405.4053, 2014.

[10] J. Lin, K. Sugiyama, M. Kan, and T. Chua, "Addressing cold-start in app recommendation: Latent user models constructed from twitter followers," in Proc. 36th Annu. Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval, 2013, pp. 283–292.

[11] T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," CoRR, vol. abs/ 1301.3781, 2013.

[12] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," Computer, vol. 42, no. 8, pp. 30– 37, Aug. 2009.

[13] J. H. Friedman, "Greedy function approximation: A gradient boosting machine," Ann. Statist., vol. 29, pp. 1189–1232, 2000.

[14] L. Breiman, J. Friedman, R. Olshen, and C. Stone, Classification and Regression Trees. Monterey, CA, USA: Wadsworth & Brooks, 1984.

[15] L. Breiman, "Random forests," Mach. Learn., vol. 45, no. 1, pp. 5–32, Oct. 2001.

[16] K. Zhou, S. Yang, and H. Zha, "Functional matrix factorizations for Cold-start recommendation," in Proc. 34th Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval, 2011, pp. 315–324.

[17] T. Chen, H. Li, Q. Yang, and Y. Yu, "General functional matrix factorization using gradient boosting," in Proc. Int. Conf. Mach. Learn., 2013, pp. 436–444.

[18] T. Chen, W. Zhang, Q. Lu, K. Chen, Z. Zheng, and Y. Yu, "SVDFeature: A toolkit for feature-based collaborative filtering," J. Mach. Learn. Res., vol. 13, pp. 3619–3622, 2012.

[19] S. Rendle, "Factorization machines with libFM," ACM Trans. Intell. Syst. Technol., vol. 3, no. 3, May 2012.

AUTHOR PROFILE

Mrs Anuradha Anumolu completed her M.Tech (CSE) from Acharya Nagarjuna University. She has published more than10 papers in indexing Journals, currently working as an Associate Professor and Head in the department of IT at DVR & Dr HS MIC College of Technology (Autonomous), Kanchikacherla, NTR District. Her areas of interest are Data Structures, Data Mining, Cloud Computing, Artificial Intelligence.

Mr. CHALAPATI KESAVARAO as MCA student in the department of DCA at DVR & DR. HS MIC COLLEGE OF TECHNOLOGY, Kanchikacherla, NTR (DT). He has completed B.Sc (MPCS) in Maruthi Degree College From KRISHNA UNIVERSITY.

His areas of interests are Python and java.