USING SOCIAL MEDIA BACKGROUND TO IMPROVE COLD-START RECOMMENDATION DEEP MODELS

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ABSTRACT

In recent years, the boundaries between e-commerce and social networking became a lot of blurs. Many e-commerce websites support the mechanism of social login where users can check in the websites mistreatment their social network identities like their Face book or Twitter accounts. Users can also post their freshly purchased product on micro blogs with links to the e-commerce product websites. Throughout this paper, we have a bent to propose a novel resolution for the cross-site cold-start product recommendation that aims to advocate product from e-commerce websites to users at social networking sites in "cold- start" things, a haul that has rarely been explored before. a significant challenge may be thanks to leverage information extracted from social networking sites for a cross-site cold- start product recommendation. We have a bent to propose to use the joined users across social networking sites and e-commerce websites (users administrative unit have social networking accounts and have created purchases on e-commerce websites) as a bridge to map users' social networking choices to a special feature illustration for a product recommendation. In specific, we have a bent to propose learning every users' and products' feature representations (called user embeddings and product embeddings, respectively) from data collected from e-commerce websites mistreatment recurrent neural networks so apply a modified gradient boosting trees technique to remodel users' social networking choices into user embeddings. we have a bent to then develop a feature-based matrix resolution approach which could leverage the learned user embeddings for the cold-start product recommendation. Experimental results on an associate degree outsize dataset created from the foremost vital Chinese micro blogging service SINA WEIBO and so the biggest Chinese B2C e-commerce website JINGDONG have shown the effectiveness of our planned framework.

I. INTRODUCTION

In recent years, the boundaries between e-commerce and social networking have become increasingly blurred. Ecommerce websites such as eBay features many of the characteristics of social networks, including real-time status updates and interactions between its buyers and sellers. Some e-commerce websites also support the mechanism of social login, which allows new users to sign in with their existing login information from social networking services such as Face book, Twitter or Google+. Both Face book and Twitter have introduced a new feature last year that allow users to buy products directly from their websites by clicking a "buy" button to purchase items in adverts or other posts. In China, the e-commerce company ALIBABA has made a strategic investment in SINA WEIBO1 where ALIBABA product adverts can be directly delivered to SINA WEIBO users. With the new trend of conducting e-commerce activities on social networking sites, it is important to leverage knowledge extracted from social networking sites for the development of product recommender systems.

1.1 Problem Statement

1. Recommender systems help people find products, movies, or friends based on their interests. But they have a problem called the cold-start issue, which happens when a new user or item has no past data, making recommendations less useful.
2. A good way to fix this is by using

social media data. If a new user joins a shopping website, their likes, comments, and follows from social media can help predict what they might like.

3. This method makes recommendations more accurate and helpful from the start, improving the user's experience

4. Connecting social media with shopping websites creates a smarter system that helps users find what they need while also benefiting businesses.

1.2 Scope and Objective

Scope:

This document is the only one that describes the requirements of the system. It is meant for the use by the developers, and will also by the basis for validating the final deliver system. Any changes made to the requirements in the future will have to go through a formal change approval process. The developer is responsible for asking for clarifications, where necessary, and will not make any alternations without the permission of the client.

Objective

1. Input Design is the process of converting a user-oriented description of the input into a computer-based system. This design is important to avoid errors in the data input process and show the correct direction to the management for getting correct information from the computerized system.

2. It is achieved by creating user-friendly screens for the data entry to handle large volume of data. The goal of designing input is to make data entry easier and to be free from errors. The data entry screen is designed in such a way that all the data manipulates can be performed. It also provides record viewing facilities.

3. When the data is entered it will check for its validity. Data can be entered with the help of screens. Appropriate messages are provided as when needed so that the user will not be in maize of instant. Thus the objective of input design is to create an input layout that is easy to follow

II. LITERATURE SURVEY

Likelihood model for E-commerce recommendation: Right product; right time

AUTHORS: J. Wang and Y. Zhang. Year: 2013

Most of existing e-commerce mastermind systems aim to advocate the correct product to a user, supported whether or not the user is maybe about to get or sort of a product. On the opposite hand, the effectiveness of recommendations place along depends on the time of the advice. Permit U.S.A. to need a user coalition agency just purchased a notebook computer as honor example. She could purchase a replacement battery for a pair of years (assuming that the pc laptop personal computer laptop computer notebook computer's original battery usually fails to figure around that time) and notice a replacement portable computer in another a pair of years. throughout this case, it is not Associate in Nursing honest arrange to advocate a replacement notebook computer or a replacement battery right once the user purchased the new notebook computer. It ought to hurt the user's satisfaction of the recommender system if she receives a presumably right product recommendation at the incorrect time. We have a bent to argue that a system shouldn't solely advocate the foremost relevant item, however, place along advocate at the correct time.

This paper studies the new problem: the best thanks to advocating the correct product at the correct time? we have a bent to adopt the proportional hazards modeling approach in survival associate degree analysis to the advice Analysis field Associate in Nursing propose a replacement likelihood model to expressly incorporate time in an e-commerce recommender system. The new model estimates the prospect of a user creating a follow- up purchase of a particular product at a particular time. This joint purchase likelihood is that that generally leveraged by recommender systems in varied eventualities, still thanks to the zero-query pull-based recommendation state of affairs.

Retail sales prediction and item recommendations exploitation client

demographics at store level
AUTHORS: M. Giering Year: 2008

This paper outlines a retail sales prediction and merchandise recommendation system that was enforced for a series of retail stores. The relative importance of client demographic characteristics for accurately modeling the sales of every client kind unit derived and enforced among the model. Data consisted of daily sales info for 600 merchandise at the planning level, broken out by a bunch of non-overlapping client varieties. A recommender system was designed supported a quick online skinny Singular Value Decomposition. it's shown that modeling data at a finer level of detail by agglomeration across client varieties and demographics yields improved performance compared to a minimum of one combination model designed for the whole dataset. Details of the system implementation unit represented and wise problems that arise in such real-world applications unit mentioned. Preliminary results from check stores over Associate in nursing annual amount indicate that the system resulted in considerably hyperbolic sales and improved efficiencies. a quick definition of however the first ways that within which mentioned here was extended to the best method larger data set is given to substantiate and illustrate the standard of this approach.

Amazon.com recommendations: Item-to-item cooperative filtering AUTHORS: G. Linden, B. Smith, and J. York.
Year: 2003

Recommendation algorithms unit best well-known for his or her use on e-commerce websites, wherever they use to input some of the customer's interests to come up with an inventory of steered things. Several applications use solely the things that customers purchase and expressly rate to represent their interests, however, they'll place along use totally different attributes, still as things viewed, demographic data, subject interests, and favorite artists. At Amazon.com, we have a bent to use recommendation algorithms to individualize cyber web store for every client. The planning radically changes supported client interests, showing programming titles to Associate in Nursing human and baby toys to a replacement mother. There unit 3 common approaches to break down the advice problem: ancient cooperative filtering, cluster models, and search-based ways that within which. Here, we have a bent to envision these ways that within which with our formula, that we have a bent to decision item-to-item cooperative filtering. In distinction to ancient cooperative filtering, our algorithm's on-line computation scales severally of vary the amount the quantity} of shoppers and range of things among the merchandise catalog. Our formula produces recommendations in Associate in nursing excessive quantity of some time, scales to huge data sets, and generates prime of the various recommendations.

The new demographics and market fragmentation AUTHORS: V. A. Zeithaml.
Year: 1985

The underlying premise of this text is that dynamic demographics may end up during a break of the mass markets for grocery merchandise and supermarkets. A field study investigated the relationships between five demographic factors-sex, female in operation standing, age, income, and legal status status- and a decent variety of variables associated with preparation for and execution of grocery looking out. Results indicate that the demographic groups dissent in necessary ways in which from the conventional grocery shopper. Discussion centers on the ways in which during which dynamic demographics and family roles might need an impact on retailers and manufacturers of grocery merchandise.

We tend to all understand what you want to buy: A demographic- based system for product recommendation on micro blogs
AUTHORS: W. X. Zhao, Y. Guo, Y. He, H. Jiang, Y. Wu.
Year: 2014

Product recommender systems unit usually deployed by e-commerce websites to boost user experience and increase sales. However, the advice is restricted by the merchandise data hosted on those e-commerce sites and is simply triggered once users unit liberal arts e-commerce activities. throughout this paper, we have got a bent to develop a novel product recommender system observed as bread, a bourgeois Intelligence recommender System, that detects users' purchase intents from their micro blogs in near amount of your time and makes product recommendation supported matching the users' demographic data extracted from their public profiles with product demographics learned from micro blogs and online reviews. Breed distinguishes itself from ancient product recommender systems inside the subsequent aspects: 1) breed was developed supported a micro blogging service platform. As such, it is not restricted by the info gettable in any specific e-commerce information processing system. to boot, the breed is prepared to trace users' purchase intents in near amount of your time and build recommendations consequently. 2) Inbreed, product recommendation is framed as a learning to rank disadvantage. Users' characteristics extracted from their public profiles in micro blogs and products' demographics learned from every online product reviews and micro blogs unit fed into learning to rank algorithms for a product recommendation. we have got evaluated our system in a huge dataset crawled from Sina Weibo. The experimental results have verified the practicability and effectiveness of our system. we have got put together created a demo version of our system publicly gettable and have implemented a live system that allows registered users to receive recommendations in realty.

EXISTING SYSTEM:

Most studies solely concentrate on constructing solutions among sure e-commerce websites and mainly utilize users' historical dealings records. To the foremost effective of our knowledge, cross-site cold-start product recommendation has been seldom studied before.

There has additionally been Associate within the Nursing oversized body of analysis work focusing specifically on the cold-start recommendation downside.

Seroussi et al. projected to create use of the data from users' public profiles and topics extracted from user-generated content into a matrix resolution model for complete clean users' rating prediction.

Zhang et al. propose a semi-supervised ensemble learning the rule.

Schein projected away by combining content and cooperative data to a lower place one probabilistic framework.

Lin et al. addressed the cold-start downside for App recommendation by victimization the social knowledge.

DISADVANTAGES:

They solely concentrate on the complete or category-level purchase preference supported a trained classifier, that can't be directly applied to our cross-site cold begin product recommendation task.

Their selections solely embrace gender, age, and Facebook likes, as opposition a good style of selections explored in our approach.

They are doing not suppose the thanks to transferring heterogeneous knowledge from social media websites into a sort that's able to be employed on the e-commerce side, that is what the key to handling the cross-site cold-start recommendation downside.

PROPOSED SYSTEM:

During this paper, we have a bent to review a noteworthy downside of recommending a product from e-commerce websites to users at social networking sites World Health Organization haven't got historical purchase records, i.e., in "cold-start" things. we have a bent to note as this downside cross-site cold-start product recommendation. In our downside setting here, solely the users' social networking knowledge is gettable and it's a troublesome task to rework the social networking knowledge into latent user selections which might be effectively used for a product recommendation. to handle this challenge, we have a bent to propose to use the joined users across social networking sites and e- commerce websites (users World Health Organization have social networking accounts and have created purchases on e-commerce websites) as a bridge to map users' social networking selections to latent selections for a product recommendation.

In specific, we have a bent to propose learning each users' and productss' feature representations (called user embeddings and product embeddings, respectively) from data collected from e-commerce websites victimization continual neural networks then apply a changed gradient boosting trees methodology to rework users' social networking selections into user embeddings.

We have a bent to then develop a feature-based matrix resolution approach which might leverage the learned user embeddings for cold begin product recommendation.

ADVANTAGES

- Our projected framework is so effective in addressing the cross-site cold-start product recommendation downside.
- We have a bent to believe that our study can have a profound impact on each analysis and trade communities.
- We have a bent to formulate a completely unique downside of recommending the merchandise from the associate e-commerce informatics system to social networking users in "cold-start" things.
- To the foremost effective of our knowledge, it's been seldom studied before. We propose to use the continual neural networks for learning to correlate feature representations for each user's associated product from data collected from Associate within the Nursing e-commerce computing device.
- We have a bent to propose a changed gradient boosting trees methodology to rework users' micro blogging attributes to latent feature illustration which might be just incorporated for a product recommendation.
- We have a bent to propose and instantiate a feature-based matrix resolution approach by incorporating user and merchandise selections for a cold-start product recommendation.

III. MODULE DESCRIPTION

OSN System Construction Module

In the 1st module, we tend to develop the web Social Networking (OSN) system module. We tend to build up the system with the feature of online Social Networking. wherever this module is employed for brand new user registrations and once registrations the users will log in with their authentication.

Where once the present users will send messages to in camera and publically, choices square measure designed. Users also can share the post with others. The user will able to search the opposite user profiles and public posts. during this module, users also can settle for and send friend requests.

With all the fundamental feature of online Social Networking System, modules are build up within the initial module, to prove and judge our system options.

Given associate e-commerce website, with a group of its users, a group of product and get record matrix, every entry of that may be a binary price indicating whether or not has purchased product. Every user is related to a group of purchased product with the acquisition timestamps. Moreover, a little set of users will be joined to their micro blogging accounts (or alternative social network accounts).

Micro blogging Feature choice

In this module, we tend to develop the Micro blogging Feature choice. Prepare an inventory of probably helpful micro blogging attributes and construct the micro blogging feature vector for every joined user. Generate distributed feature representations mistreatment the data from all the users on the e-commerce website through deep learning. Learn the mapping performs, that transforms the micro blogging attribute info automotive vehicle the distributed feature representations within the second step. It utilizes the feature illustration pairs of all the joined users as coaching information.

A demographic profile (often shortened as “a demographic”) of a user like sex, age and education will be utilized by e-commerce corporations to supply better-personalized services. we tend to extract users’ demographic attributes from their public profiles. Demographic attributes are shown to be important in promoting.

Learning Product Embeddings

In the previous module, we tend to develop the featured choice, however, it's not simple to ascertain connections between users and product. Intuitively, users and product ought to be painted in the same feature house so a user is nearer to the product that he/she has purchased compared to those he/she has not. Galvanized by the recently planned strategies in learning word embeddings, we tend to propose to be told user embeddings or distributed illustration of a user in a very similar method.

Given a group of image sequences, a fixed-length vector illustration for every image will be learned in a very latent house by exploiting the context info among symbols, during which “similar” symbols are mapped to near positions. If we tend to treat every product ID as a word token and convert the historical purchase records of a user into a time stamped sequence, we are able to then use identical strategies to be told product embeddings. in contrast to matrix resolution, the order of historical purchases from a user will be naturally captured.

Cold-Start Product Recommendation

We used a local host-based e-commerce dataset, which contains some user group action records. Every group action record consists of a user ID, a product ID, and therefore the purchase timestamp. We tend to 1st cluster group action records by user IDs and so get an inventory of purchased product for every user.

For our strategies, a vital part is that the embedding models, which might be set to 2 straightforward architectures, particularly CBOW and Skip-gram.

IV. SYSTEM DESIGN

SYSTEM ARCHITECTURE

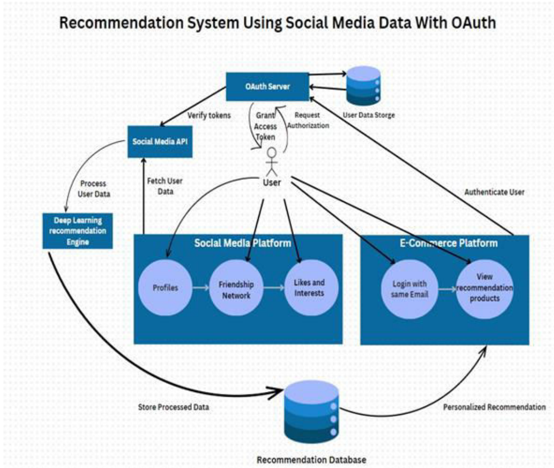

Fig. System Architecture

V. OUTPUT SCREENS

USER REGISTRATION ON SOCIAL MEDIA ACCOUNT

User will register on the social media account with their details, by entering the details the user will move on to login page.

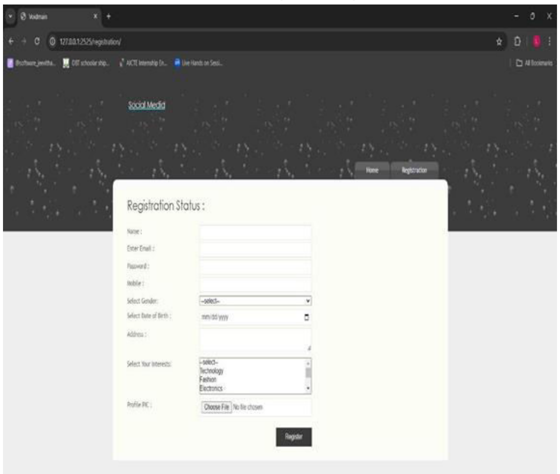

Fig No: 8.1 Registration page

USER LOGIN ON SOCIAL MEDIA

User will login with their username as email id and with password then the user will move on to interface page of social media.

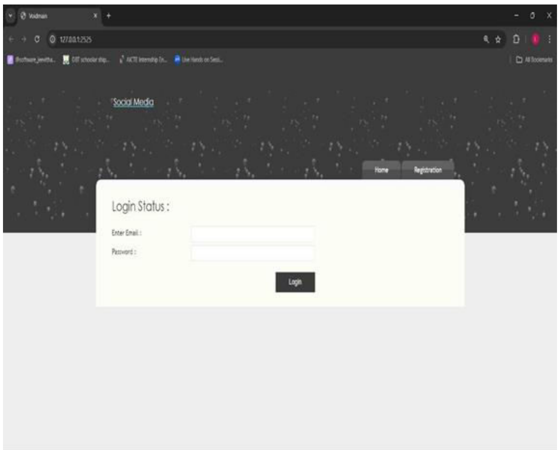

Fig: Login page

SOCIAL MEDIA INTERFACE

When user login with their details the user can access social media account and the user will see the options are post, friends, profile, logout

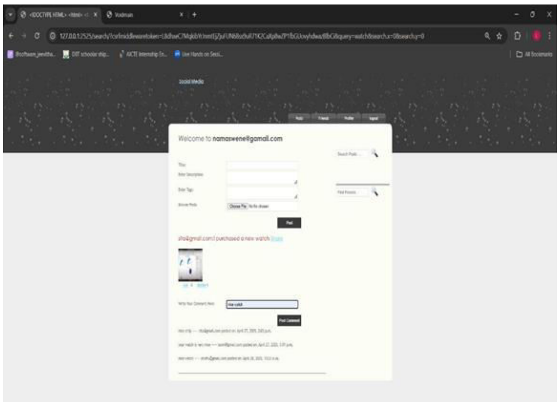

Fig: Interface of Social Media

SENDING FRIEND REQUEST TO FRIENDS

The user will build a network through sending friend requests to their respective friends, through their requests

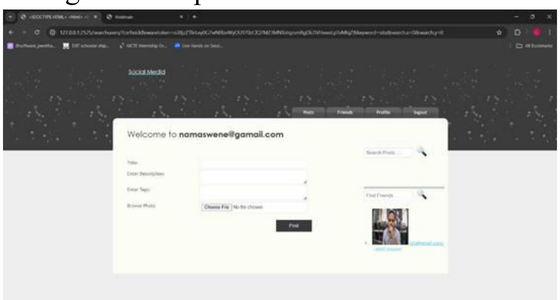

Fig: Sending Friend Request

ACCEPTING FRIEND REQUEST ON FRIEND ACCOUNT

Before accepting the friend request of the user by their friend they can't build any social network.

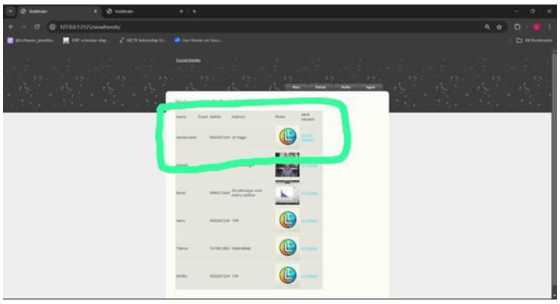

Fig: Accepting Friend request

FRIEND REQUEST ACCEPTED SUCCESSFULLY

The friend request of the user is accepted by their friend and they can share post and comment to the post other to build a network.

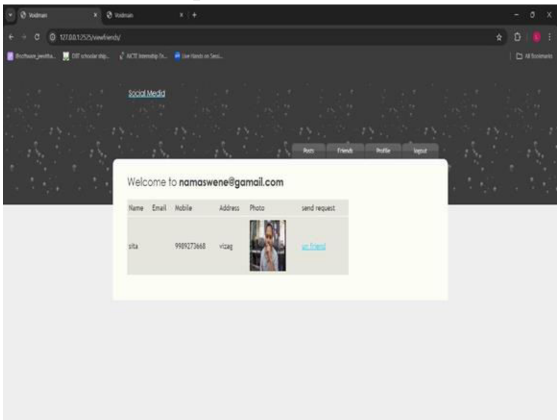

Fig: Request accepted successfully

VI. CONCLUSION

In this paper, we've studied a unique drawback, cross-site cold-start product recommendation, i.e., recommending a product from e-commerce websites to micro blogging users while not historical purchase records. Our main plan is that on the e-commerce websites, users and product will be diagrammatical within the same latent feature house through feature learning with the continual neural networks. employing a set of coupled users across each e-commerce websites and social networking sites as a bridge, we are able to learn feature mapping functions employing a changed gradient boosting trees methodology, that maps users' attributes extracted from social networking sites onto feature representations learned from e-commerce websites. The mapped user options will be effectively incorporated into a feature-based matrix resolving approach for a cold-start product recommendation. We've created an outsized dataset from WEIBO and JINGDONG. The results show that our planned framework is so effective in addressing the cross-site cold-start product recommendation drawback. We have a tendency to believe that our study can have a profound impact on each analysis and trade communities. Currently, solely an easy neutral spec has been utilized for the user and products embeddings learning. Within the future, a lot of advanced deep learning models like Convolutional Neural Networks13 will be explored for feature learning. We'll conjointly think about up the present feature mapping methodology through concepts in transferring learning.

REFERENCE

[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.

[20] S. Rendle, “Social network and Click-through prediction with factorization machines,” in Proc. KDDCup Workshop, 2012.

[21] B Kundan, Sangaralingam P. Combining Machine Learning and Deep Learning in the Retinopathy Diagnostic Algorithm for Enhanced Detection of DR and DME. J Neonatal Surg [Internet]. 2025Apr.2 [cited 2025Apr.9];14(5):128-40. Available from: https://www.jneonatalsurg.com/index.php/jns/article/view/2914