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Connecting Social Media to E-Commerce Cold-Start Product Recommendation Using Micro Blogging Information

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Abstract:-

In recent years, the boundaries between e-commerce and social networking have become increasingly blurred. Many e-commerce websites support the mechanism of social login where users can sign on the websites using their social network identities such as their Facebook or Twitter accounts. Users can also post their newly purchased products on microblogs with links to the e-commerce product web pages. In this paper, we propose a novel solution for cross-site cold-start product recommendation, which aims to recommend products from e-commerce websites to users at social networking sites in "cold-start" situations, a problem which has rarely been explored before. A major challenge is how to leverage knowledge extracted from social networking sites for cross-site cold-start product recommendation. We propose to use 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 to map users' social networking features to another feature representation for product recommendation. In specific, we propose learning both users' and products' feature representations (called user embeddings and product embeddings, respectively) from data collected from e-commerce websites using recurrent neural networks and then apply a modified gradient boosting trees method to transform users' social networking features into user embeddings. We then develop a feature-based matrix factorization approach which can leverage the learnt user embeddings for cold-start product recommendation. Experimental results on a large dataset constructed from the largest Chinese microblogging service SINA WEIBO and the largest Chinese B2C e-commerce website JINGDONG have shown the effectiveness of our proposed framework.

Keywords— Neural networks, Feature-based matrix factorization approach, Face book, Twitter

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 Facebook, Twitter or Google+. Both Facebook 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 hasmade a strategic investment in SINA WEIBO 1 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.

In this paper, we study an interesting problem of recommending products from e-commerce websites to users at social networking sites who do not have historical purchase records, i.e., in "cold-start" situations. We called this problem cross-site cold-start product recommendation. Although online product recommendation has been extensively studied before [1], [2], [3], most studies only focus on constructing solutions within certain e-commerce websites and mainly utilise users' historical transaction records.

To the best of our knowledge, cross-site cold-start product recommendation has been rarely studied before. In our problem setting here, only the users' social networking information is available and it is a challenging task to transform the social networking information into latent user features which can be effectively used for product recommendation. To address this challenge, we propose to use 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 abridge to map users' social networking features to latent features for product recommendation. In specific, we propose learning both users' and products' feature representations (called user embeddings and product embeddings, respectively) from data collected from e-commerce websites using recurrent neural networks and then apply a modified gradient boosting trees method to transform users' social networking features into user embeddings. We then develop a feature-based matrix factorization approach which can leverage the learnt user embeddings for coldstart product recommendation.

We built our dataset from the largest Chinese microblogging service SINA WEIBO 2 and the largest Chinese B2C e-commerce website JINGDONG,3 containing a total of 20,638 linked users. The experimental results on the dataset have shown the feasibility and the effectiveness of our proposed framework.

Our major contributions are summarised below:

We formulate a novel problem of recommending products from an e-commerce website to social networking users in "cold-start" situations. To the best of our knowledge, it has been rarely studied before.

We propose to apply the recurrent neural networks for learning correlated feature representations for both users and products from data collected from an e-commerce website.

We propose a modified gradient boosting trees method to transform users' microblogging attributes to latent feature representation which can be easily incorporated for product recommendation.

We propose and instantiate a feature-based matrix factorization approach by incorporating user and product features for cold-start product recommendation.

LITERARY WORKS 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. We 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?

We 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). We 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.

4) The new demographics and market fragmentation

AUTHORS: V. A. Zeithaml

The underlying premise of this article is that changing demographics will lead to a splintering of the mass markets for grocery products and supermarkets. A field study investigated the relationships between five demographic factors-sex, female working status, age, income, and marital status-and a wide range of variables associated with preparation for and execution of supermarket shopping. Results indicate that the demographic groups differ in significant ways from the traditional supermarket shopper. Discussion centers on the ways that changing demographics and family roles may affect retailers and manufacturers of grocery products.

5) We know 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, and X. Li

Product recommender systems are often deployed by e-commerce websites to improve user experience and increase sales. However, recommendation is limited by the product information hosted in those e-commerce sites and is only triggered when users are performing e-commerce activities. In this paper, we develop a novel product recommender system called METIS, a MErchanT Intelligence recommender System, which detects users' purchase intents from their micro blogs in near real-time and makes product recommendation based on matching the users' demographic information extracted from their public profiles with product demographics learned from micro blogs and online reviews. METIS distinguishes itself from traditional product recommender systems in the following aspects: 1) METIS was developed based on a micro blogging service platform. As such, it is not limited by the information available in any specific e-commerce website. In addition, METIS is able to track users' purchase intents in near real-time and make recommendations accordingly. 2) In METIS, product recommendation is framed as a learning to rank problem. Users' characteristics extracted from their public profiles in microblogs and products' demographics learned from both online product reviews and microblogs are fed into learning to rank algorithms for product recommendation. We have evaluated our system in a large dataset crawled from Sina Weibo. The experimental results have verified the feasibility and effectiveness of our system. We have also made a demo version of our system publicly available and have implemented a live system which allows registered users to receive recommendations in real time.

IMPLEMENTATION

MODULES:

[1] OSN System Construction Module
[2] Micro blogging Feature Selection
[3] Learning Product Embeddings
[4] Cold-Start Product Recommendation

MODULES DESCSRIPTION:

[1] 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 micro blogging accounts (or other social networkaccounts).

[2] Micro blogging Feature Selection:

- In this module, we develop the Micro blogging Feature Selection. Prepare a list of potentially useful micro blogging attributes and construct the micro blogging 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 micro blogging 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.
- Demographic 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

[3] 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.

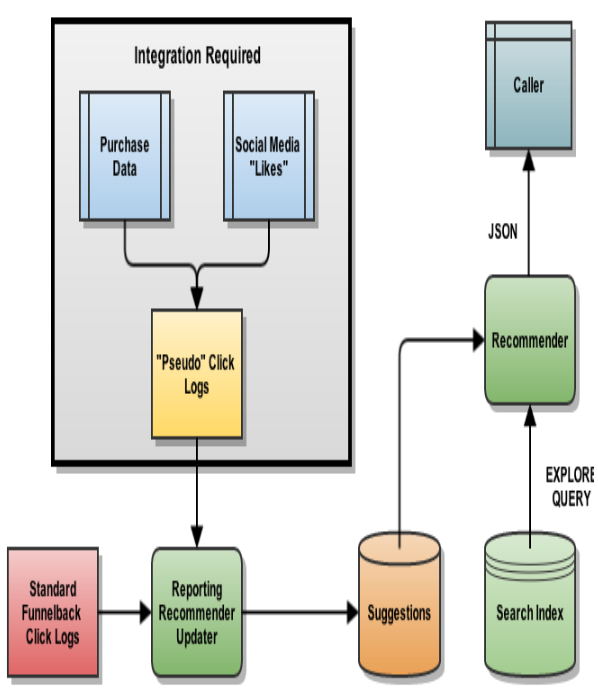
[4] Cold-Start Product Recommendation:

- 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.

SYSTEM DESIGN

SYSTEM ARCHITECTURE:



CONCLUSION

In this paper, we have studied a novel problem, cross-site cold-start product recommendation, i.e., recommending products from e-commerce websites to micro blogging users without historical purchase records. Our main idea is that on the e-commerce websites, users and products can be represented the same latent feature space through feature learning with the recurrent neural networks. Using a set of linked users across both e-commerce websites and social networking sites as a bridge, 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. The mapped user features can be effectively incorporated into a feature-based matrix factorization approach for cold-start product recommendation. We have constructed a large dataset from WEIBO and JINGDONG. There sites show that our proposed framework is indeed effective in addressing the cross-site cold-start product recommendation problem. We believe that our study will have profound impact on both research and industry communities. Currently, only a simple neutral network architecture has been employed for user and product embeddings learning .In the future, more advanced deep learning models such as CNN13 can be explored for feature learning. We will also consider improving the current feature mapping method through ideas in transferring learning.

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