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An Efficient Cross-Domain Recommendation Technique in Cold-Start Situations

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Abstract :- Most of the recent studies on recommender systems are focused on single domain recommendation systems. In the single domain recommendation systems, the items that are used for training and test data set are belongs to within the same domain. Cross-site domains or item recommendations in multi-domain environment are available in Amazon i.e. it incorporate two or more domains. Few research studies are done on the cross-site recommendation systems. Cross-site recommendations provide the relationship between the two sets of items from various domains. They can provide the extra information about the users of a target domain and recommendations will be done based on that. In this paper, we will study cross-site recommendation model on the cold start situation, where the purchase history is not available for the new user. Cold-start is the well-known issue in the area of recommendation systems. It seriously affect the recommendations in the collaborative filtering approaches. In this paper, we propose a new solution to recommend products from e-commerce websites to users at social networking sites. a noteworthy issue is how to leverage knowledge from social networking websites when there is no purchase history for a customer especially in cold start situations.in particular we proposed the solution for cold start recommendation by linking the users across social networking sites and e-commerce websites i.e. customers who have social network identities and have purchased on e-commerce websites as a bridge to map user's social networking features in to another feature representation which can be easier for product recommendation. Here we propose to learn by using recurrent neural networks both user's and product's feature representations called user embedding and product embedding from the data collected from e-commerce website and then apply a modified gradient boosting trees method to transform user's social networking features in to user embedding. Once found, then develop a feature-based matrix factorization approach which can leverage the learnt user embedding for the cold-start product recommendation. Experimental results shows that our approach effectively works and gives the best recommended results in cold start situations.

Keywords *–Cold-start problems,Microblogging websites, and multi-domain recommendations.*

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1. INTRODUCTION

Most of the recent studies on recommender systems are focused on single domain recommendation systems. In the single domain recommendation systems the items that are used for training and test data set are belongs to within the same domain. Cross-site domains or item recommendations in multi-domain environment are available in Amazon i.e. it incorporate two or more domains. Few research studies are done on the cross-site recommendation systems. Cross-site recommendations provide the relationship between the two sets of items from various domains. They can provide the extra information about the users of a target domain and recommendations will be done based on that. In this paper, we will study cross-site recommendation model on the cold start situation, where the purchase history is not available for the new user. Cold-start is the well-known issue in the area of recommendation systems. It seriously affect the recommendations in the collaborative filtering approaches.

Recommender Systems (RS) are programming tools and methods giving recommendations for items to be useful to a user [1]. The recommendations identify and helpful in decision-making processes, such as what products to buy, what music to listen to, or what online news to read. Currently, there are different application domains utilizing the methods of recommender systems. Based on these specific application domains, we define more general classes of domains for the recommender systems. In Entertainment we can recommend the movies, music to the users, to recommend e-papers, magazines, recommendations for documents, recommending web page or websites. In E-commerce we can recommend the products such as books, mobiles or other computer accessories. We can provide several services such as recommending travel services, expert doctor consultations, recommendation houses to rent or purchase, recommending the job portals etc. [2, 3]. To recommending these types of services RS systems can use mainly there kinds of methods such as content based filtering, collaborative filtering, hybrid based filtering.

Recommending products in e-commerce web sites is a common challenge in analytics. An interesting issue here is that recommending products for the customers who don't have any historical records for him. This situation is called cold-start situation. In this paper, we concentrate an intriguing issue of recommending products from e-commerce websites to users at social networking websites who don't have any historical purchased records called cross-site cold-start product recommendation [4, 5, 6].Though we have extensively studied some product recommendation techniques, those studies are related to recommending the products and mostly constructing solution inside the e-commerce system mainly utilizing their user's historical transactions. To best of our insight, cross-site cold start product recommendation has examined sometimes recently. In this kind of problem setting here, only the users social networking information is available and it is challenging task to covert the social networking information in to latent user features which can be effectively used for product recommendation.

To address this challenge, we proposed to utilize the connected users in both social networking sites and e-commerce websites (those who have social networking accounts and have purchased on e-commerce websites) as a bridge to map user's social networking features to latent features for recommending the products. With the help of recurrent neural networks we can learn both users and products feature representations and then apply a gradient boosting tree technique to convert user's social networking features in to user embedding's. At last we develop a feature based matrix factorization approach which can leverage the learnt user embedding for cold start recommendation. Experimental results of our work shows that it works effectively works for cross site cold start recommendation.

The structure of the paper is as follows: Section 2 describes formulation of proposed problem and basic frame work of our work. In Section 3 we described the related works and the issues of recommendations. In Section 4, we described to extracting and representing micro blogging attributes and how to applying the transformed features to cold-start product recommendation; Section 5 lists our experimental results and analysis. Conclusions are drawn in Section 6.

2. FORMULTING THE PROBLEM

Given a web based e-commerce website. Let U denotes a set of users, P denotes a set of products and R denotes a purchase record matrix such that |U| x| P|. Each entry in the record matrix $r_{u.p}$ indicates a binary value indicating whether the user u has purchased the product p or not. Each user $u \in U$ is associated with a set of purchased products with the purchase timestamps. Furthermore, a small subset of users in U can be linked to their micro blogging accounts (or any other social networking accounts), denoted as $U^{L.}$. It means that each user $u \in U^L$ is also associated with their respective microblog information. Let 'A' denote the set of microblogging features, each micro blogging user has a |A|-dimensional micro blogging feature vector a_s in which each $a_{u,i}$is the attribute value for the i^{th} micro blogging attribute feature. From the notations introduced above, we can define our recommendation problem as follows. We proposed the idea of cross-site cold start recommendation problem as: a micro blogging user $\notin$U' whois new to the e-commerce website and has no historical purchase records. $u^| \notin U^L$ since $U^L \subset$ U. we proposed to generate a personalized ranking of recommended products for u' based on micro blogging attributes $a_{u'.}$ The entire work follow of our solution is shown in Figure 1. It consists of four major steps. First we extract the microblogging attributes from the social media, second train the purchase record with paragraph2vect method, and third apply the heterogeneous mapping using MART. Finally apply the feature based matrix factorization with both a_u and v_u

The complete work has done in this paper is summarized here. The main problem we have taken here is that recommending the products from e-commerce website to social network users in cold-start circumstances. First, we applied recurrent neural networks for learning both user and product feature representations from data collected through e-commerce website. Secondly, applying the modified gradient boosting tree technique to transform the user's social networking attributes i.e. micro blogging attributes to latent feature representation, which can be helpful for the product recommendation. Third, we applied feature based matrix factorization approach by incorporating user and product features for the cold-start product recommendation.

3. LITERATURE WORK

There exists various studies on the recommendations of the items in the commercial systems and proposed various methods to increase the chances of the recommendations effectively. Wang and Y. Zhang [10], this kind of paper studies the new problem: how to recommend the right product at the right time? Modify the proportional hazards recreating approach in survival examination to the recommendation research field and propose a new opportunity model to explicitly incorporate the amount of time in an e-commerce recommender system. The new model estimates the joint probability of a customer making a follow-up purchase of a certain product at a particular time. This kind of joint purchase probability can be leveraged by recommender systems in various cases, including the zero-query pull-based recommendation scenario (e. g. recommendation on an e-commerce web site) and a proactive push-based promotion circumstance (e. g. email or text message based marketing). Evaluate the ability modeling way with multiple metrics. Trial and error results on a data collected by an actual e-commerce website (shop. com) show that this can predict a user's follow-up purchase tendencies at a particular time with descent accuracy. In addition, {the ability} model significantly increases the conversion rate in pull-based systems and the user satisfaction/utility in push based systems.

Greg Linden, Brent Smith, and Jeremy York [11] Work with recommendation algorithms to individualize the online store for each and every customer. The store significantly changes based upon customer hobbies, showing programming titles to a software engineer and baby toys to a fresh mother. The

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click-through and conversion rates -- two important measures of Web-affiliated and email advertising efficiency vastly exceed those of untargeted content such as banner advertisements and top-seller lists.

K. Zhou, S. Yang, and H. Zha [12] proposed, Functional Matrix Factorization (FMF), a singular cold-start recommendation way in which solves the issue of initial interview construction inside the context of learning user and item profiles. Specifically, FMF constructs a choice tree for that initial interview with every node becoming an interview question, enabling the recommender to question a person adaptively based her prior responses. More to the point associate latent profiles for every node from the effect restricting the latent profiles to become a purpose of possible solutions to the interview questions which allowing the profiles to become gradually refined with the interview procedure according to user responses.

Mi Zhang, Jie Tang, Xuchen Zhang, XiangyangXue[13], "Addressing Cold Start in Recommender Systems", In this paper, the cold-start problem is addressed by proposing a context-aware semi-supervised co-training method. The method has several unique advantages over the standard recommendation techniques for addressing the cold-start problem. First, it defines a fine-grained context that is more accurate for modeling the user-item preference. Second, the method can naturally support supervised learning and semi-supervised learning, which provides a flexible way to incorporate the unlabeled data.

Jovian Lin, Kazunari Sugiyama, Min-Yen Kan, Tat-Seng Chua[14], "Addressing Cold-Start in App Recommendation: Latent User Models Constructed from Twitter Followers", Millions of mobile applications (apps) are available, but users have difficulty in identifying apps that are relevant to their interests. Earlier recommender method that depends on previous user ratings (i.e., collaborative filtering, or CF) can address this problem for apps that have sufficient ratings from past users. But for newly released apps, CF does not have any user ratings to base recommendations on, which leads to the cold-start problem. In this paper, a new method which uses Twitter followers as a base for app recommendation is used which can address the cold start situations

4. PROPOSED WORK

4.1 System Architecture

The above Figure 1 shows that connection between social media and e-commerce applications. This system gives the more accuracy for analyzing the both technology. In this system, a user can user both website same location. If any user can purchase any product from an e-commerce website. But user uses that product and he allows to give the review of the product, like how it is, how work functionality etc. so he can send the review of the product. Once user sends that review then that post is updated on social to recommendation friends.

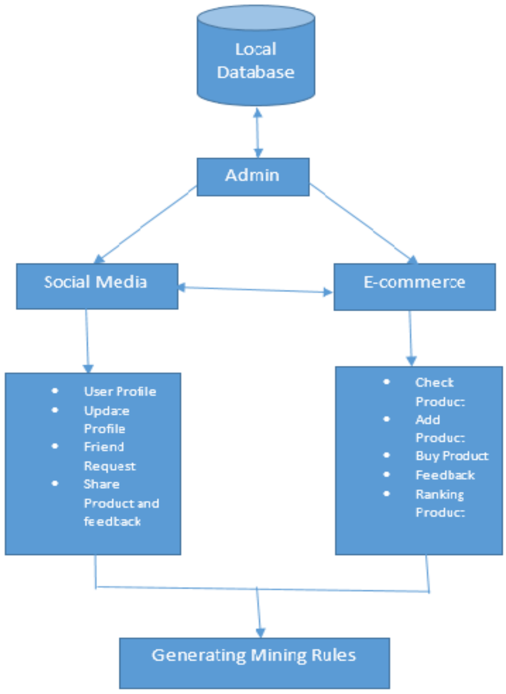

Figure 1: System Architecture

In order to recommend the products in the cold start situations, first, we have to extract the attributes from the microblogging websites and transform them into feature map representation to recommend the products. The process is explained step by step.

4.2 Extracting and Representing Microblogging attributes

We can learn microblogging attributes in three stages

1. Collect a list of useful microblogging attributes and construct a microblogging feature vector a_u for each linked user $\mathbf{u} \in \mathbf{U}^{L.}$
2. With the help of deep learning generate a distributed feature representation $\{V_u\}$ in u belongs to U using the information from all users U on the e-commerce site.
3. Learn the mapping function $f(a_u) \rightarrow v_u$ which converts the microblogging attribute information into a distributed feature representation which is in the second step. It uses the pair of feature representations $\{a_u, v_u\}$ of all the linked users in $U_{L.}$ This is considered to be as training data.

4.3 Microblogging Feature Selection

For a particular microblogging user $a_{u,,}$now we will see how to extract information from the microblogging website. According to our knowledge, the microblogging attributes are divided into four categories. They are demographic attributes, text attributes, and network attributes, temporal

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attributes [7, 8]. We have listed the attributes comes under each category in Table 2. A demographic profile of the user such as gender, marital status, career interests etc. can be used by the e-commerce companies to provide better personalized services. To extract the text attributes topic distributions, word embedding techniques can be useful. It is clear that users connected together with some links, hence extracting network attributes also used for product recommendations. The temporal attributes such daily activity and weekly activity distributions of a user can give the interests of the user, which can be helpful in the product recommendation.

4.4 Distributed Representation Learning

We cannot directly establish a connection between a_u and products with the earlier steps. Intuitively, users and products should be represented in the same feature space so that user is closer to the products that she has purchased compared to those she has not purchased. With the help of recently proposed approach recurrent neural networks, we can learn user embeddings or the distributed representation of user V_u. Before learning to user embedding it is good to learn the product embedding. There are two recurrent neural architectures [9] to train the product embeddings. They are CBOW (Continuous Bag-Of-Words) model and Skip-gram model. The main difference between these two models is that CBOW predicts the current product with the surrounding context whereas Skip-gram will find the surrounding context based on the current product. The conditional prediction probability is characterized by the soft max function shown below:

$$P_r\,(p_t|\text{ context}) = \frac{\exp(V^{T}{pt}\ .\ V_{context}\ )}{\sum_p \exp(V^{T}{pt}\ .\ V_{context}\ )}$$

After learning the product embedding's similarly we can learn the user embedding's with the help of Paragraph Vector (para2vec) method [9], which learns the feature representation from variable-length pieces of text, including sentences, paragraphs, and documents. We implemented the simplified version of para2vec at a sentence level. Here we considered the purchase history of the user and can be considered as a "sentence", it consists of product IDs and word tokens. A user ID is placed at the beginning of the sentence and both user IDs and product IDs are treated as word tokens in a vocabulary in the learning process. When Training the dataset, for each sentence, the sliding context window will always include the first word i.e. user ID in the sentence. Due to this reason, a user ID is always associated with a set of purchase records. We can use the same learning procedure in word2vector for computing the P_r(context| p_t)and $P_r(p_t|\text{context})$. Later, we separate the user embedding's from product embedding's and use v_u and $v_p$to denote the learnt K-dimensional embedding for user u and product p respectively.

4.5 Applying the Transformed Features to Cold-Start Product Recommendation

MART is one of the most widely used gradient tree boosting methods for predictive data mining such as in regression and classification. We applied this algorithm for finding the features. Once the MART learners are built for feature mapping, the original microblogging feature vectors au are mapped onto the user embedding vu. In this section, we study how to incorporate {au, vu} into the feature based matrix factorization technique. In specific, we develop our recommendation method based on the recently proposed SVDFeature [10]. Our idea can also be applied to other feature-based recommendation algorithms, such as Factorization Machines [11]. SVDFeature is built with the help of traditional matrix factorization approach. It considers the matrix factorization approach in three aspects. They are dynamic features (global features), user features and item features.

It can be recommended for the task of product recommendation as follows:

$$r_{u,p}(\ \alpha^{(u)}\ ,\beta^{(p)}\ ,\lambda^{(u,p)})$$

Where $\alpha^{(u)}$ belongs to $R^{N}\ \alpha$, $\beta^{(p)}$ belongs to $R^{N}\ \beta$, $\lambda^{(u,p)}$ belongs to $R^{N}\ \lambda$ are the input vectors consisting of the features of user u, the features of product p and the global features for the pair (u,p) with the lengths of N_{α} , N_{β}, N_{λ} . User- Product pair corresponds to a feature vector concatenated by global features, suer features. The response value to be fitted indicates whether the user has purchased the product or not.

The main advantage of this approach is to recommend the users who are new to the e-commerce website. We can recommend the products to those users and increase the business of e-commerce organizations. In other words, with the derived model, we can recommend the products from e-commerce websites to users in online social networks such as Facebook, Twitter etc. For this kind of recommendation, the only information that existing for us are microblogging attributes. Using MART we can derive the fitted user embedding's. In other terms, we should not require any purchase history of the users to recommend products. Thus the proposed approach can recommend the products in cold-start situations.

5. RESULTS

5.1 MATHEMATICAL TERMINOLOGY

Input:

Let S is the Whole System Consist of

S= {I, P, O}

I = Input.

I = {U, Q, D}

U = User

U = {u1, u2….un}

Q = Query Entered by user

Q = {q1, q2, q3…qn}

D = Dataset

P = Process:

Step1: Admin will upload the product in E-commerce site.
Step2: That uploaded product will be seen on Social sites where a user can view, share and give comments on that product. The user can send and receive the friend request.
Step3: All the reviews should be seen in E-commerce site when user login to E- commerce site.

Output:

The user will get recommendation regarding of that product on e-commerce website.

5.2 Breakdown Structure of the proposed work

The complete work is divided into three stages. In the first stage, the user can create the account in any of the social networks. The user can do all the activities such as he can tweet the messages, share the text, audio, video etc. the admin will collect the microblogging attributes of the user and he can map the attributes based on their interests. On the other hand, we collected some items from the e-commerce websites. The admin here is responsible for maintaining the details and he has all the permissions on the e-commerce website. Based the features collected from the microblogging website the admin can recommend the products to the users who are working on social network websites. Third, we are maintaining a link between the e-commerce website and social networking website. As of our knowledge, there are many algorithms for recommending the product, but very less work has done on a cross-site recommendation in cold start situations. Our work will recommend the products who don't have the previous purchase history in e-commerce website by considering the microblogging attributes. This method works effectively and giving the best recommendation compared to the existing methods. We have shown the sample screens of output how to send the request to the friends and how to view the available products in the system with details in Figure 2 and Figure 3.

Figure 2: Sending Request to the Friends

Figure 3: Viewing the product details.

6. CONCLUSION

In this paper, we have concentrated a novel issue, cross-site cold-start recommendation problem; recommending the product items from online e-commerce websites to social network users without having any previous history of records of that users. Our primary thought is the e-commerce websites, users and items are represented in the same latent feature space through the feature learning with the recurrent neural networks. By utilizing the linked users across the e-commerce websites and social networking websites as a bridge, we can learn the feature mapping functions suing the recent method called gradient boosting trees. This method will map the user's attributes i.e. collected from social networking site to feature representation learned from e-commerce sites.

The mapped user features can be successfully consolidated into a feature-based matrix factorization approach for the cold-start product recommendation. We trust that our review will have the significant effect on both research and industry groups.at present we have implemented just a straightforward neural network architecture for the user and product embedding's. Later on, more propelled deep learning methods such as convolutional neural networks can be investigated for feature learning. We will likewise consider enhancing the present feature mapping method through thoughts in transferring learning. [12].

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