A Novel Recommendation System for Social Networks in Cold Start Situations

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Abstract— In the context of recommender systems, major work focused on the single domain recommender systems in which the items are utilized to train and examine the data sets belonging to the similar domain. In the case of multi-domain platform, Cross-site domains or item recommendations are available in Amazon that is the incorporation of two or more than two domains. The research work on cross-site recommendation systems is done partially. These Cross-site recommendation systems build the relation between any two items sets belonging to distinct domains. They will give additional details of target domain's users and on this basis the recommendations are done. In our paper work we considered cross-site recommendation model on the cold start situation, in which there will be no past purchasing history of a user is available. Cold-start is the most considerable issue in recommender systems domain. It majorly influences the recommendations in collaborative filtering strategies. In our work, we proposed a novel suggestion for product recommendation through websites. The noticeable issue here is how to attain knowledge through social media when no past purchasing history of a user is available particularly in cold-start systems. Specifically we introduced a solution to cold-start recommendation by connecting the users through the social websites and also via e-commerce websites. Here we are enabling to learn through recurrent neural networks both the user's features representations and product's features representations known as user's embedding and product's embedding by gathered data from the e-commerce website and later apply updated method of gradient boosting trees from transforming the user's social networking features to user's embedding. Practical outputs are showing that our approach will effectively functions and provide best results in the cold-start situations.

Keywords— *Cold-start problems, Micro blogging websites, and multi-domain recommendations.*

1. Introduction

Most of the research work in Recommender Systems (RS) is focused on the single domain recommender systems in which the items are utilized to train and examine the data sets belonging to the similar domain. In the case of multi-domain platform, Cross-site domains or item recommendations are available in Amazon that is the incorporation of two or more than two domains. The research work on cross-site recommendation systems is done partially. These Cross-site recommendation systems build the relation between any two items sets belonging to distinct domains. They will give additional details of target domain's users and on this basis the recommendations are done. In our paper work we considered cross-site recommendation model on the cold start situation, in which there will be no past purchasing history of a user is available. Cold-start is the most considerable issue in recommender systems domain. It majorly influences the recommendations in collaborative filtering strategies.

RS's are the programming tools and techniques helps in giving the recommendations regarding the products to the users [1]. These recommendations are used to find and help during the process of decision making like what to buy, which news to read and so on. At present there exist various application fields that are using the approaches of the recommender systems. Considering those particular fields, we defined many basic domain classes to the recommender system. We can afford many services like recommending the services for travelling, doctor's consultation, and house recommendations and so on [2, 3]. For recommending such kinds of services the RS systemswill mainly considers three different methods namely based filtering, collaborative filtering and hybrid based filtering.

Now a days the microblogging websites are getting huge popularity based on the spending time to post the tweets, sharing images, videos etc. It is good idea to recommend the products in the social websites to recommending the products instead of recommending the products in e-commerce website, where the user's spending less time to purchase the products. We have listed the top-5 micro blogging websites based on Alexa and PR in Table 1. In the context of analytics, the products recommendation through e-commerce is a common issue. The noticeable thing here is that the product recommendation is only to users who are not having the past history of purchasing the products. This scenario is known as cold-start.

S.no	Micro Blogging sites	PR	Alexa	PA
1	Twitter.com	10	10	96.95
2	Tumblr.com	8	31	93.85
3	Posterous.com	8	1528	88.3
4	Friendfeed.com	8	1644	90.24

Table 1: List of Top 5 Microblogging websites

In this paper work, we focused on challenging issue of product recommendation via e-commerce sites to the customers to those who will have no past purchasing history of a user is available known cross-site cold-start product recommendation [4, 5, 6]. For such type of issue, we set only user's details in social media available and this is challenging activity to transform the data of social media in to latent user features that will effectively useful in the product recommendation. To overcome this issue, we suggest using the linked users in the both social media sites and e-commerce websites as a bridge in mapping the user's social media features to the latent features to recommend the products. By using recurrent neural networks we can study both the user's features representations and product's feature representations and later apply gradient boosting tree approach to transform user's social networking features in to user embedding's. Finally we generate a feature based matrix factorization strategy. Practical outputs are showing that our approach will effectively functions and provide best results in the cold-start situations.

We organized our paper as follows: we described the formulation of proposed issue and general framework of our work under section 2. Related works and recommendation issues are depicted under section 3. Extraction and representation of micro blogging attributes and ways to apply the converted features in to cold-start product recommendation is explained under section 4. Experimental outputs and analysis are represented under section 5 whereas conclusion is drawn under section 6.

2. Formulating the Problem

Consider a web related site like e-commerce. Assume U represents group of users, P refers a products set, R is purchased file matrix i.e. |U| x| P|. Every entry in record matrix $R_{u.p}$ represents binary value stating whether user u purchased a product p or not. Every user u belongs to U is related with a purchased products set along with the purchase timestamps. Besides, a small subset of users in U can be mapped to their micro blogging accounts (or any other social networking accounts), and is referred as U^L. Consider 'A' that denotes the group of micro blogging attributes, every user of micro blogging has a |A|-dimensional micro blogging feature vector a_s where every $a_{u,i}$is an attribute value of i^{th} micro blogging attribute feature. Considering the above notation, we are now able to state our problem with recommendation and is as follows: We suggest the notion of cross-site cold start recommendation issue like: user of micro blogging does not belongs to U', $u^{|} \notin U^{L}$ (since $U^L \subset U$). We suggest creating a personal ranking to recommend the products to users 'u' on the basis of micro blogging attributes $a_{u'}$. The major steps include:

1. Extracting the micro blogging attributes of social media.
2. Train the purchase record with the paragraph2vect approach.
3. Applying heterogeneous mapping by the help of MART.

Eventually apply the feature based matrix factorization with both a_u and v_u.

The summary of our entire work is here. The primary issue we consider here is that product recommendation via e-commerce sites to the users in social media under cold-start circumstances. Initially we have applied the recurrent neural networks to study both the features representation of user's and product's from the gathered data from the e-commerce site. Next we have applied the updated approach known as gradient boosting tree for transforming micro blogging attributes in to latent feature representation. Finally we applied an approach known as feature based matrix factorization through incorporation of user and also the product features to cold-start product recommendation.

3. Related Works

There is having many studies regarding the products recommendation in the context of commercial based systems and also proposed many techniques to improve the ways for effective recommendations. Wang and Y. Zhang [10], studied about the similar issue: how to do recommend the precise product at right time? The novel model predicts the together probability of user doing follow-up purchase of specific item at specific time period. Examine the way of ability modeling with distinct metrics. Additionally this model primarily improves the rate of transformation in regardance to pull-based systems and the user satisfaction/utility in push based systems.

Greg Linden, Brent Smith, and Jeremy York [11] explored on the algorithms of recommendations to separate the online store to every user. The store primarily updates on the basis of user's interests, displaying coding titles to software techies and baby dolls to mothers. The two key measures of Web-affiliated and email advertising efficiency are click-through and conversion rates and widely improved.

K. Zhou, S. Yang, and H. Zha [12] was introduced FMF (Functional Matrix Factorization), a way of cold-start recommendation that overcomes the problem of first interview model internally to the context of analyzing the user's and product's details. Particularly, FMF builds an option tree to that first interview with the help of each and every node and is raising a query.

Mi Zhang, Jie Tang, Xuchen Zhang, XiangyangXue [13], "Addressing Cold Start in Recommender Systems". In this paper work, the problem with the cold-start is cleared by introducing a context-aware semi-supervised co-training approach. It has many benefits with the standardized recommendation mechanisms in order to clear the problem of cold-start. Initially it defines a fine-grained context which is highly precise to model the user-item preference. Next the approach will support the supervised learning and semi-supervised learning that gives a better way to incorporate the data that is unlabeled.

Kazunari Sugiyama, Jovian Lin, Tat-Seng Chua, Min-Yen Kan [14], "Addressing Cold-Start in App Recommendation: Latent User Models Constructed from Twitter Followers": Millions of mobile apps are available, but the users are facing the difficulties in finding relevant apps as per their requests. Recent recommender model relies on past ratings of users (that is collaborative filtering or CF) and this overcomes the issue for the apps with enough ratings by the past users. But for the recently released apps, the CF does not contain any ratings from users that lead to occurrence of cold-start problem.

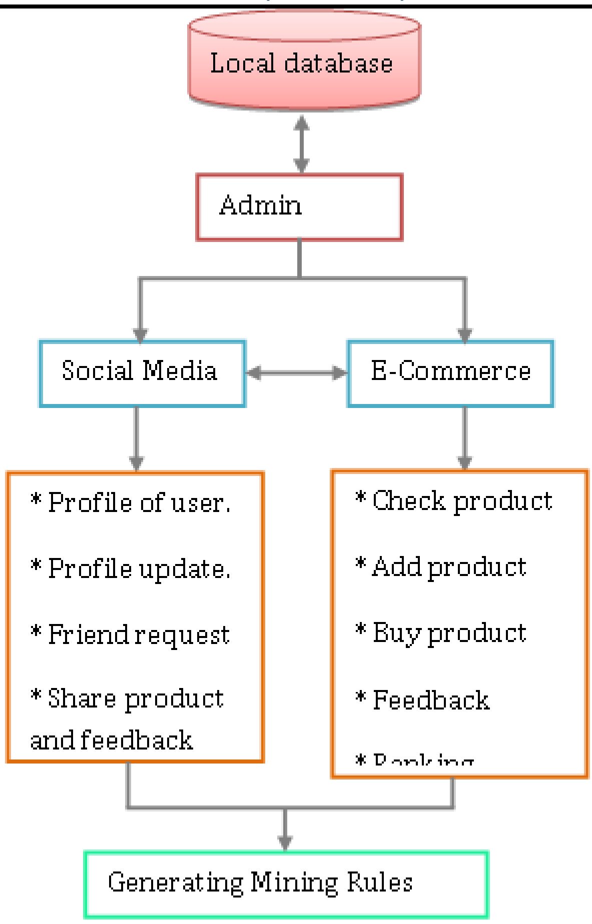

Figure 1: System Architecture

4. Proposed Work

4.1 System Architecture

The below is the system architecture that represents the relationships between the applications of social media and e-commerce. This model yields more accuracy during the analysis of the both. Here, a user can mention both website and location. Through e-commerce website any user can buy anything. Users have an access in giving review about the thing he purchased such as its purpose, price and performance and so on. Once the user sent review about the product it is uploaded in social media to let know this by massive users and also virtually recommending buying a specific product.

If we want to suggest the products through Cold start situations, initially we must retrieve the attributes related to micro blogging websites and later we transform those attributes as feature map representation so that we can recommend the products.

4.2 Extracting and Representing Microblogging attributes

The process is done as in the following 3 steps.

1. Gather the list of usable micro blogging attributes and build a micro blogging feature vector a_u for every connected user u ∈ U^L. In u ∈ U^L, U is using the details from all the users U in e-commerce website.
2. Through deep learning, a distributed feature representation $\{V_u\}$ is generated.
3. Analyze mapping function $f(a_u) \rightarrow v_u$ that transforms the attribute details of micro blogging to a distributed feature representation (i.e. $\{V_u\}$). It utilizes a pair of feature representations $\{a_u, v_u\}$ of every connected users in U_L and this is treated as training data.

4.3 Microblogging Feature Selection

Specifically a micro blogging user a_u we will check the way to retrieve data from micro blogging site. Up to our awareness, the attributes of micro blogging are classified into 4 types. Those are demographic attributes, text attributes, network attributes and temporal attributes [7, 8]. We have sorted out the attributes under every type and are represented in Table 2. Demographic details of a user like gender, hobbies short term goals and so on and this information helps the e-commerce enterprises in giving best personalized services. During the extraction of text attributes of topic distributions, word embedding approaches are helpful. Network attributes are also helpful in recommending a product since the users are connected with the links. Temporal attributes like every day and weekly distributions of user can enable the users with much interest and are useful in recommending a product.

Table 2: Categorization of Microblogging attributes.

Type of Attribute	Features
Demographic Attributes	Gender Age Marital Status Education Career Interests
Text Attributes	Topic Distributions Word Embedding
Network Attributes	Latent Group preferences
Temporal Attributes	Daily activity distribution Weekly activity distribution

4.4 Distributed Representation Learning

The connection establishment between a_u and products is not an easy thing based on the above mentioned 3 steps. Users and products must be placed in similar feature space so that user can find what he purchased and what not he. We are able to learn user embedding or the distributed representation of user V_u by the recently recommended technique known as recurrent neural networks. We must be aware of product embedding before being aware of user embedding. There exists 2 recurrent neural architectures [9] namely CBOW (Continuous Bag-Of-Words) model and Skip-gram models to describe the product embedding. The key contrast between those dual architectures is that CBOW guesses the new product considering the neighboring context and on the other hand, Skip-gram detects the neighboring context of the basis of present product. The probability of conditional prediction is represented by soft max function and is shown in equation (1)

$$P_r(p_t|\ \text{context}) = \frac{exp(v^T{}_{pt} \cdot v_{context})}{\sum p\ exp(v^T{}_{pt} \cdot v_{context})} \frac{exp(v^T{}_{pt} \cdot v_{context})}{\sum p\ exp(v^T{}_{pt} \cdot v_{context})} \quad (1)$$

After trained about product embedding likewise we can also get trained about user embedding by using Paragraph Vector (para2vec) method [9], which enables us to learn about feature representation from variable-length text segments and also includes with sentences, passages and files. For sentence level we have used simplified model of para2vec. As a "sentence" we assumed the history of purchase done by user. It comprises of ID's of products and also word tokens. ID of user is kept at sentence starting whereas the ID's of user and ID's of products are considered as work tokens in vocabulary during the process of learning. User ID is always related with set of purchase files because the dataset while training every sentence, the sliding context window will every time adds the initial word which is user ID in sentence. We also apply the similar learning process in the word2vector to compute $P_r($ context$|$ $p_t)$and $P_r(p_t|$context$)$. Then after we filter user embedding's from product embedding's and also use v_u and $v_p$to represent the already learned K-dimensional embedding for user u and product p respectively.

4.5 Applying the Transformed Features to Cold-Start Product Recommendation

MART is the extensively used gradient tree boosting mechanism in predictive data mining likewise in regression and in classification. In order to find the features we have used this paradigm. When MART learners are being built to map the features, the actual micro blogging feature vectors auis mapped to vu which is user embedding. In this paper, we analyze the incorporation of {au, vu} to feature on the basis of matrix factorization mechanism. Specifically we enhanced our recommended approach on the basis of newly introduced SVD feature [10]. Our thought is also applied on rest of the feature-based recommendation paradigms like Factorization Machines [11]. With the conventional matrix factorization strategy this SVD feature is created. Matrix factorization strategy is considered fewer than three aspects. Those are dynamic/global features, user features and item features. It helps in the task of recommending a product and is as follows:

$$r_{u,p}(\alpha^{(u)} ,\beta^{(p)} ,\lambda^{(u,p)}) \qquad (2)$$

From the above $\alpha^{(u)} \in R^{N} \alpha$, $\beta^{(p)} \in R^{N} \beta$, $\lambda^{(u,p)} \in R^{N} \lambda$ are input vectors comprising of user u features, product p features and global features for a pair (u,p) with N_{α} , N_{β} and N_{λ} lengths. The pair of (u, v) corresponds with feature vector separated by the dynamic features and user features. The major benefit with this strategy is to assist the users who are unaware about e-commerce website. We can suggest the products to such users and can improve the e-commerce business. Contrary, with the model that is derived already, we can do the product recommendation via this e-commerce business on online social media like FB, Twitter and so on. By using MART we may derive the relevant user embedding's. For this the user's purchase history is not essential for recommending the products. Therefore the proposed strategy can recommend the products in the cold-start situations.

5. Results and Discussion

5.1 Mathematical Terminology

Input:

Consider S as the Whole System comprising 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

Procedure:

Step 1: The products details are uploaded in e-commerce website by user.

Step 2: That uploaded details will be displayed over social media where user can like, share and comment on that specific product.

Step 3: Entire reviews are seen in the e-commerce website where user can login to this site.

Output:

The user will be recommended a product via e-commerce site.

5.2 Breakdown Structure of the proposed work

The summary of our work is depicted in three stages. In initial stage, a user is able to create an account in any kind of social media. User can perform all the tasks like tweeting the tweets, sharing message, audio and video so on. Admin will gather the user's micro blogging attributes and he can do mapping of attributes on their requirements basis. In contrast (stage 2) we gathered few of the items from e-commerce sites. Admin is the responsible in maintaining all the details and have complete access on this e-commerce.

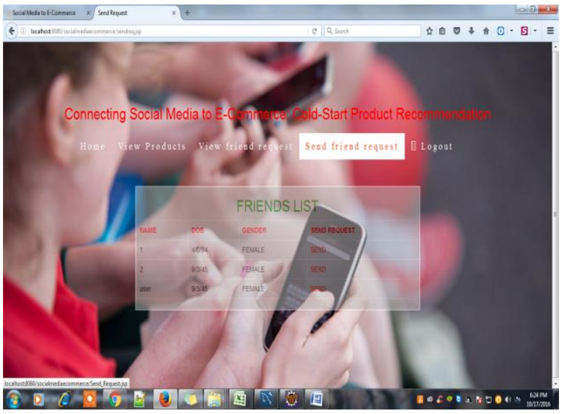

Figure 2: Sending Request to the Friends

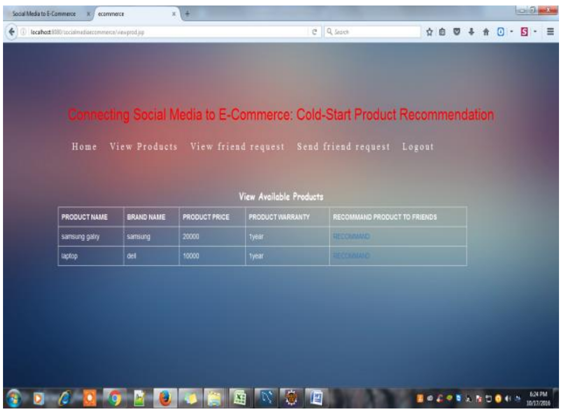

Figure 3: Viewing the product details.

Considering the gathered features from micro blogging site, the admin will recommend the users in social media regarding products. In final stage, we maintain a relation between social media and e-commerce sites. Our proposed work will recommend the products to those who don't have past history of purchases through e-commerce websites by taking micro blogging attributes into consideration. It efficiently works and yields best output in recommendation when compared with the available approaches. The sample screenshots of results are shown in figure 2 and figure 3. It depicts how the requests can be send to friends in social media sites and also how to view the products that are available in the system including the details.

6. Conclusion

A novel concept known as cross-site cold-start recommendation problem in which the problem arises regarding the product recommendation via e-commerce and social media sites and is considered as our paper work here. In the users whoever not having any past purchasing history of products will be recommended. Our idea is to place the users and the products in the similar latent feature space via feature learning with recurrent neural networks. By using the connected users over the e-commerce sites and social media sites as a base, we can analyze the functions of feature mapping using the current approach known as gradient boosting trees. This approach will connect the user's attributes which are gathered from social media site to feature representation analyzed from the e-commerce sites. The user features that are mapped are integrated into feature-based matrix factorization process for cold-start product recommendation. We believe that our review will give better impact over research and also on industries. For now we implemented only a direct neural network model to user and product embedding's. Then after many propelled approaches of deep learning like CNN's are examined for the feature learning. In similar way we consider improving the current feature mapping approach by the transferring learning.

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