Partner Social Media to E-Commerce:Cold Start Product Recommendation using Microblogging 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-

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commerce website JINGDONG have shown the effectiveness of our proposed framework.

II.LITRATURE SURVEY

1] **Opportunity model for e-commerce recommendation: Right product right time Author:-**J. Wang and Y. Zhang

Description: Most of existing e -commerce suggester systems aim to recommend the proper product to a user, supported whether or not the user is probably going to buy or sort of a product. On the opposite hand, the eff ectiveness of recommendations conjointly depends on the time of the advice. Allow us to take a user World Health Organization simply purchased a laptop computer as an example. She might purchase a replacement battery in a pair of years (assuming that the laptop computer's original battery typically fails to figure around that time) and get a brand new laptop in another a pair of years. During this case, it's not a decent plan to suggest a brand new laptop computer or a replacement battery right when the user purchased the new laptop computer. It may hurt the user's satisfaction of the recommender system if she receives a doubtless right product recommendation at the incorrect time. We have a tendency to argue that a system mustn't solely suggest the foremost relevant item, however conjointly suggest at the proper time.

2] **Retail sales prediction and item recommendations using customer demographics at store level Author:-M. Giering**

Description: This paper outlines a retail sales prediction and products recommendation system that was enforced for a sequence of retail stores. The relative importance of client demographic characteristics for accurately modeling the sales of every client kind square measure derived and enforced within the model. Knowledge consisted of daily sales data for 600 product at the shop level, broken out over a collection of non-overlapping client varieties. A recommender system was designed supported a quick on line skinny Singular worth Decomposition. It's shown that modeling knowledge at a finer level of detail by clump across client varieties and demographics yields improved performance compared to one mixture model designed for the complete dataset. Details of the system implementation square measure represented and sensible problems that arise in such real world applications square measure mentioned.

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3] Amazon.com recommendations: Item-to -item collaborative filtering Author:- G. Linden, B. Smith, and J. York

Description: Recommendation algorithms area unit best glorious for his or her use on e- commerce internet sites, wherever they use input a couple of customer's interests to come up with an inventory of suggested things. Several applications use solely the things that customers purchase and expressly rate to represent their interests, however they'll additionally use alternative attributes, together with things viewed, demographic information, subject interests, and favourite artists. At Amazon.com, we tend to use recommendation algorithms to change the web store for every client. the shop radically changes supported client interests, showing programming titles to a engineer and baby toys to a replacement mother. There area unit 3 common approaches to resolution the advice problem: ancient cooperative filtering, cluster models, and search based strategies. Here, we tend to compare these strategies with our algorithmic program, that we tend to decision item to item cooperative filtering.

4] The new demographics and market fragmentation Author:V. A. Zeithaml

Description:

The underlying premise of this text is that dynamic demographics can result in a breakage of the mass markets for grocery product and supermarkets. A field study investing ated the relationships between five demographic factors sex, feminine operating standing, age, income, and matrimonial status and a large vary of variables related to preparation for and execution of food market looking. Re sults indicate that the demographic teams dissent in important ways that from the standard food market shopper. Discussion centers on the ways in which dynamic demographics and family roles might have an effect on retailers and makers of grocery product.

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 user can view, share and give comments on that product. User can send and receive friend request.

Step3:

All the reviews should be seen in E - commerce site when user login to E-commerce site.

Output:

User will get recommendation regarding of that product on ecommerce website.

3. Microblogging Feature Selection

In this section, we study how to extract rich user information from microblogs to construct au for a microblogging user. We consider three groups of attributes.

Demographic Attributes

A demographic profile (often shortened as "a demo-graphic") of a user such as sex, age and education can be used by e-commerce companies to provide better personalised services. We extract users' demographic attributes from their public profiles on SINAWEIBO. Demographic attributes have been shown to be very important in marketing, especially in product adoption for consumers [4]. Following our previous study[5], we identify six major demographic attributes: gender, age, marital status, education, career and interests.To quantitatively measure these attributes, we have further discretized them into different bins following our previously proposed method described in [5].

Text Attributes

Recent studies have revealed that microblogs contain rich commercial intents of users [5], [6]. Also, users' microblogs often reflect their opinions and interests towards certain topics. As such, we expect a potential correlation between text attributes and users' pur- chase preferences. We perform Chinese word segmentation and stopword removal before extracting two types of text attributes below.

Topic distributions

Proposed to extract topics from user-generated text using the Latent Dirichlet Allocation (LDA) model for recom-mendation tasks. Follow the same idea, we first aggregate all the microblogs by a user into a document, and then run the standard LDA to obtain the topic distributions for each user. The benefits of topics distributions over keywords are two fold. First, the number of topics is usually set to 50 ~ 200 in practice, which largely reduces the number of dimensions to work with. Second, topic models generate condense and meaningful semantic units, which are easier to interpret and understand than keywords. Word embeddings . Standard topic models assume individual words are exchangeable, which is essentially the same as the bag-of-words model assumption. Word representations or embeddings learned using neural language models help addressing the problem of traditional bag-of-word approaches which failto capture words' contextual semantics . In word embeddings, each dimension represents a latent feature of the word and semantically similar words are close in the latent space. We employ the Skip- gram model implemented by the tool word2vec4 to learn distributed representations of words. Finally, we average the word vectors of all the tokens in a user's published document as the user's embedding vector.

Network Attributes

In the online social media space, it is often observed that users connected with each other (e.g., through following links) are likely to share similar interests. As such, we can parse out latent user groups by the users' following patterns assuming that users in the same group share similar purchase preferences. Latent group preference . Since it is infeasible to consider all users on WEIBO and only keeping the top users with the most followers would potentially miss interesting information, we propose to use topic models to learn latent groups of followings as in [10]. We treat a following user as a token and aggregate all the followings of a user as an individual document. In this way, we can extract latent user groups sharing similar interests (called "following topics"), and we represent each user as a preference distribution over these latent groups.

4 Evaluation on Cold-Start Product Recommendation

For cold-start product recommendation, we aim to recommend products to microblog users without the knowledge of their historical purchase records. Construction of the Evaluation Set The evaluation set splits users into training set and test set. For the training set, we sample negative products with a ratio of 1:1 for each user, i.e., we have the same number of negative and positive products. For the test set, we randomly sample negative products with a ratio of 1:50 for each user, i.e., each positive product would involve 50 negative products. All negative products are sampled from the

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same prod uct category as the corresponding positive one. For example, for "iPhone 6", we can sample "Samsung Galaxy S5" from the "Mobile Phones" category as a negative product.Given a user, we can generate a list of candidate products consisting of both positive and negative products. On average, a user has about 52 positive products and 2,600 negative products in our experimental dataset, which is indeed a challenging task. Similar to the evaluation scenario in Information Retrieval, we would like to examine the performance that a system ranks positive products over negative products. Methods to Compare We consider the following methods for performance comparison:

•Popularity (Pop): products are ranked by their historical sale volumes.

•Popularity with Semantic Similarity (Pop++) the ranking score is a combination of two scores:

(1) the popularity score S1;

(2) the cosine similarityS2 between product description and user text information, including profile, tweets and tags.The two scores are combined by log(1 + S1)×log(1 +S2).

•Embedding Similarities (ES): Similarity scoresˆv>u·vp between a user embedding ˆv u and a
list of product embeddings v p are used to rank products.

•MF with user attributes (MFUA): User attributes (including user profile and topic distributions)
are incorporated into the basic matrix factorisation algorithm for product rating prediction
[7]. For fairness, we also use the pairwise loss function to train the model.

• FM without User Interactions (FMUI): Rendle applied the Factorization Machines (FM) for
"follow" recommendation in KDDCup 2012. It has been found that similar performance was
obtained with or without the interactions of user features. FM without user feature interactions is equivalent to SVDFeature. We reimplement this

V. SCOPE OF PROJECT

1)Easy to advertise product exploitation social networking web site.

2)Increase the interaction between user and social networking website.

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3)We believe that our study can have profound impact on each analysis and business communities.

4)We propose a changed gradient boosting trees technique to rework users' microblogging attributes to latent feature illustration which may be simply incorporated for product recommendation.

5) We tend to propose and instantiate a feature based matrix resolving approach by incorporating user and merchandise options for cold start product recommendation.

VI CONCLUSIONS

In this paper, we have studied a novel problem, cross-site cold-start product recommendation , i.e., recommending products from e-commerce websites to mi-croblogging users without historical purchase records. Our main idea is that on the e-commerce websites, users and products can be represented in 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 factorisation approach for cold- start product recommendation. We have constructed a large dataset from WEIBO and JINGDONG. The resultsshow 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 Convolutional Neural Networks 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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