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# Product Recommendation Using Social Media to E-Commerce with MicroBlogging: Cold Start

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**Abstract**—In recent years, the boundaries between e-commerce and social networking have become increasingly blurred. Manye-commerce websites support the mechanism of social login where users can sign on the websites using their social networkidentities such as their Facebook or Twitter accounts. Users can also post their newly purchased products on microblogs with linksto the e-commerce product web pages. In this paper we propose a novel solution forcross-site cold-start product recommendation which aims to recommend products from e-commerce websites to users at social networking sites in "cold-start" situations, aproblem which has rarely been explored before. A major challenge is how to leverage knowledge extracted from social networkingsites 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 toanother feature representation for product recommendation. In specific, we propose learning both users' and products' featurerepresentations (called user embeddings and product embeddings, respectively) from data collected from e-commerce websitesusing recurrent neural networks and then apply a modified gradient boosting trees method to transform users' social networkingfeatures into user embeddings. We then develop a feature-based matrix factorization approach which

can leverage the learntuser embeddings for cold-start product recommendation. Experimental results on a large dataset constructed from the largestChinese microblogging service SINAWEIBOand the largest Chinese B2C e-commerce website JINGDONGhave shown theeffectiveness of our proposed framework.

**II.LITRATURESURVEY**

1] **Opportunity model for e-commerce recommendation: Right product right timeAuthor:**-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 effectiveness 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 anexample. 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 online skinnySingular 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 modeldesigned for the complete dataset. Details of the system implementation square

measure represented and sensible problems that arise in such realworld applications square measure mentioned.

**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 favouriteartists. 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 searchbased strategies. Here, we tend to compare these strategies with our algorithmic program, that we tend to decision itemtoitem 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 fivedemographic factorssex, feminine operating standing, age, income, and matrimonial statusand a large vary of variables related to preparation for and execution of food market looking. Results 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 userinformation from microblogs to constructaufor amicroblogging 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 canbe used by e-commerce companies to provide betterpersonalised services. We extract users' demographicattributes from their public profiles on SINAWEIBO. Demographic attributes have been shown to be veryimportant 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 andinterests.To quantitatively measure these attributes,we have further discretized them into different binsfollowing our previously proposed method describedin [5].

**Text Attributes**

Recent studies have revealed that microblogs containrich commercial intents of users [5], [6]. Also, users'microblogs often reflect their opinions and intereststowards certain topics. As such, we expect a potentialcorrelation between text attributes and users' pur-chase preferences. We perform Chinese word segmentation and stopword removal before extracting twotypes of text attributes below.

**Topic distributions**

Proposedto extract topics from user-generated text using theLatent 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 topicdistributions for each user. The benefits of topicsdistributions over keywords are two fold. First, thenumber of topics is usually set to50~200in practice,which largely reduces

the number of dimensions towork with. Second, topic models generate condenseand meaningful semantic units, which are easier tointerpret and understand than keywords.Word embeddings. Standard topic models assumeindividual words are exchangeable, which is essentially the same as thebag-of-wordsmodel assumption.Word representations or embeddings learned usingneural language models help addressing the problem of traditional bag-of-word approaches which failto capture words' contextual semantics . Inword embeddings, each dimension represents a latentfeature of the word and semantically similar wordsare close in the latent space. We employ the Skip-gram model implemented by the toolword2vec4tolearn distributed representations of words. Finally, weaverage the word vectors of all the tokens in a user'spublished document as the user's embedding vector.

**Network Attributes**

In the online social media space, it is often observedthat users connected with each other (e.g., throughfollowing links) are likely to share similar interests.As such, we can parse out latent user groups by theusers' following patterns assuming that users in thesame group share similar purchase preferences.Latent group preference. Since it is infeasible toconsider all users on WEIBOand only keeping thetop users with the most followers would potentiallymiss interesting information, we propose to use topicmodels to learn latent groups of followings as in [10].We treat a following user as a token and aggregate allthe followings of a user as an individual document.In this way, we can extract latent user groups sharingsimilar interests (called "following topics"), and werepresent each user as a preference distribution overthese latent groups.

## 4 Evaluation on Cold-Start Product Recommendation

For cold-start product recommendation, we aim torecommend products to microblog users without theknowledge of their historical purchase records.Construction of the Evaluation SetThe evaluation set splits users into training set andtest set. For the training set, we sample negative products with a ratio of 1:1 for each user, i.e., we have thesame number of negative and positive products. Forthe test set, we randomly sample negative productswith a ratio of 1:50 for each user, i.e., each positive product would involve 50 negative products. Allnegative products are sampled from the same product category as the corresponding positive one. Forexample, for "iPhone 6",

we can sample "SamsungGalaxy S5" from the "Mobile Phones" category as anegative product.Given a user, we can generate a listof candidate products consisting of both positive andnegative products. On average, a user has about 52positive products and 2,600 negative products in ourexperimental dataset, which is indeed a challengingtask. Similar to the evaluation scenario in InformationRetrieval, we would like to examine the performancethat a system ranks positive products over negativeproducts.Methods to CompareWe consider the following methods for performancecomparison:

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

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

(1) the popularity scoreS1;

(2) the cosine similarityS2between product description and user textinformation, including profile, tweets and tags.The two scores are combined bylog(1 +S1)×log(1 +S2).

•Embedding Similarities (ES): Similarity scores$\hat{v}$>u·vpbetween a user embedding$\hat{v}$uand a

list of product embeddingsvpare used to rankproducts.

•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 lossfunction to train the model.

•FM without User Interactions (FMUI): Rendleapplied the Factorization Machines (FM) for

"follow" recommendation in KDDCup 2012. Ithas been found that similar performance was

obtained with or without the interactions of userfeatures. FM without user feature interactions isequivalent 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.

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 featurebased matrix resolving approach by incorporating user and merchandise options for coldstart 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 samelatent feature space through feature learning withthe recurrent neural networks. Using a set of linkedusers across both e-commerce websites and social networking sites as a bridge, we can learn feature mapping functions using a modified gradient boostingtrees method, which maps users' attributes extractedfrom social networking sites onto feature representations learned from e-commerce websites. The mappeduser features can be effectively incorporated into afeature-based matrix factorisation approach for cold-start product recommendation. We have constructed alarge dataset from WEIBOand JINGDONG. The resultsshow that our proposed framework is indeed effectivein addressing thecross-site cold-start product recommendationproblem. We believe that our study willhave profound impact on both research and industrycommunities.Currently, only a simple neutral network architecture has been employed for user and product embeddings learning. In the future, more advanced deeplearning models such as Convolutional Neural Networkscan be explored for feature learning. We willalso consider improving the current feature mappingmethod through ideas in transferring learning

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