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Use of Microbloged Information for Recommendation of Cold-Start Product and Acquaintance of Social Media and E-Commerce

[1]Prof. B K Patil, [2]Priyanka Dhongade

[1]Asst Prof., [2]Student ME-II, Department of Computer Science and Engg. EESCOET, Aurangabad, India.

priyankadhongade18@gmail.com

Abstract: **Now a day's use of social media and online shopping is increased. The difference between Online Media and Ecommerce is diminishing. As the smart phones enters in market and it make hike of use of various online application. The ease of its use is also a reason for tremendous new user of social media and online shopping. And now it's impossible to deny the rise of online shopping over the years. 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 use of microblogged information of linked users across social networking sites and 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 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 embedding's. We then develop a feature-based matrix factorization approach which can leverage the learnt user embedding's for cold-.start product recommendation.**

Keywords: *e-commerce, Social Network, product recommender, product demographic, microblogs, recurrent neural networks.*

I. INTRODUCTION

Now days, the difference between Online Media and Ecommerce is diminishing. Almost every single person in a metropolitan daily uses both social media like Facebook, Twitter, and Google+ for networking and uses internet to make huge purchases using ecommerce sites like Amazon, Snap deal, Flipkart, etc. We often login to e-commerce websites using our social accounts like FB, Gmail. We usually share our recent purchase details on the social media using the links to the product pages of e-commerce sites. We are focusing on the product recommendation to the users on e-commerce sites by leveraging the information or knowledge gained from the user's social accounts. This will enable to assess the needs of the user in cold start situations. 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.[1][2][3]

II. RELATED WORK

1. Opportunity Models for E-commerce Recommendation: Right Product, Right Time Author: Jian Wang, Yi Zhang 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[4].
2. Retail Sales Prediction and Item Recommendations Using Customer Demographics at Store Level Author: Michael 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. A recommender system was built based on a fast-online thin Singular Value Decomposition. [5].
3. G. Linden, B. Smith, and J. York, "Amazon.com recommendations Item-to-item collaborative filtering," *IEEE Internet Computing*, vol. 7, no. 1, Jan. 2003: Recommendation algorithms are best known for their use on e-commerce Web sites,1 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 [6].
4. The new demographics and market fragmentation," *Journal of Marketing by* V. A. Zeithaml: The underlying premise of this article is that changing

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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 [7].

5. We Know What You Want to Buy: A Demographic-based System for Product Recommendation On Microblogs Author: Wayne Xin Zhao1, YanweiGuo :In this paper, we develop a novel product recommender system called METIS, a Merchant Intelligence Recommender System, which detects users' purchase intents from their microblogs 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 microblogs and online reviews[7].

III. PROPOSED ARCHITECTURE

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.

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 a bridge 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 cold start product recommendation.

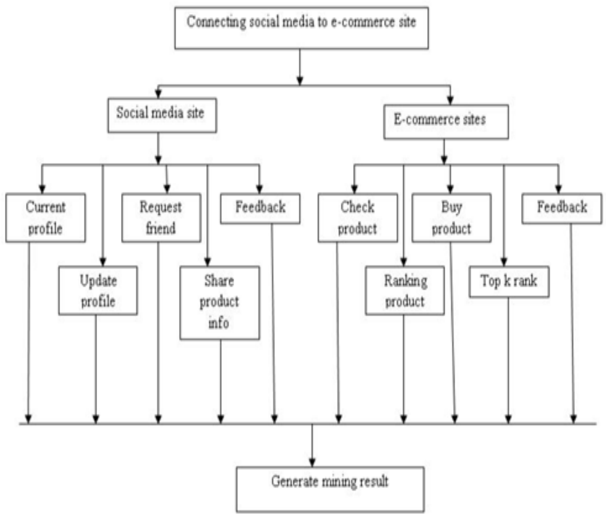

Figure no 1. System Overview of Proposed System

The above fig 1 shows that combining the socio and ecommerce. This system gives the more accuracy for analyzing the both technology. In this system user can user both website same location. If any user can purchase the any product from e-commerce website. But user use that product and he allow to give the review of the product, like how it is, how work functionality etc. so he can send review of the product. Once user send that review then that post is updated on social to recommendation friends.[8]

IV. PROPOSED SYSTEM

We take a look at an thrilling hassle of recommending merchandise from e-commerce websites to users at social networking web sites who do now not have ancient purchase data, i.e., in "cold-start" conditions. We called this hassle move-web site cold-begin. product recommendation. In our hassle putting here, simplest the customers' social networking facts is available and it is a difficult task to transform the social networking statistics into latent person capabilities which can be effectively used for product recommendation.

1. OSN System Construction Module

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

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purchase timestamps. Furthermore, a small subset of users can be linked to their microblogging accounts (or other social network accounts).

2. Microblogging Feature Selection

In this module, we develop the Microblogging Feature Selection. Prepare a list of potentially useful microblogging attributes and construct the microblogging 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 microblogging attribute information au to the distributed feature representations in the second step. It utilizes the feature representation pairs of all the linked users as training data. A 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 personalized 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. Extracting and representing microblogging attributes

Our solution to microblogging feature learning consists of three steps:

1. Microblogging Feature Selection: Prepare a list of potentially useful microblogging attributes and construct the microblogging feature vector *au* for each linked user *u 2 UL*.
2. Distributed Representation Learning With Recurrent Neutral Networks: Generate distributed feature representations *fvugu∈U* using the information from all the users *U* on the e-commerce website through deep learning.
3. Heterogeneous Representation Mapping using Gradient Boosting Regression Trees: Learn the mapping function, *f*(*au*) *!* v*u*, which transforms the microblogging attribute information *au* to the distributed feature representations v*u* in the second step. It utilizes the feature representation pairs *fau; vug* of all the linked users *u 2 UL* as training data.

We have built a single learner for each dimension in the transformed feature representation v*u* using a modified gradient boosting trees model. The reason why we choose MART is that its components are regression trees, and trees are shown to be effective to generate high-order and interpretable knowledge using simple plain features [9], [11], [12]. Note other tree-based ensemble methods can apply here, such as Random Forest (RF)[10]. In our experiments, we have found MART is sightly better than RF, and therefore we adopt MART as the fitting model.

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 time stamped 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. Applying the transformed features to cold-start product recommendation Once the MART learners are built for feature mapping, the original microblogging feature vectors a*u* are mapped onto the user embedding v*u*. In this section, we study how to incorporate *fau; vug* into the feature based matrix factorization technique. In specific, we develop our recommendation method based on the recently proposed SVD Feature . Our idea can also be applied to other feature-based recommendation algorithms, such as Factorization Machines. we do not require users made any purchases before recommending products to them. Thus, our proposed recommendation framework can be applied for cold-start recommendation. These diagrams helped us to understand working of system that we are going to develop using available resistances. This design also helped us to determine problems those may encounter during system construction

Screenshot 1 Register and Login users

This is the login page for users , from which user can register herself as new user. If User is already registered then she can login. Only registered User can get login into the next page.

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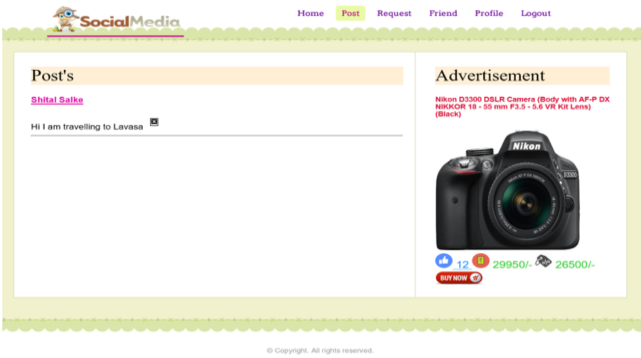
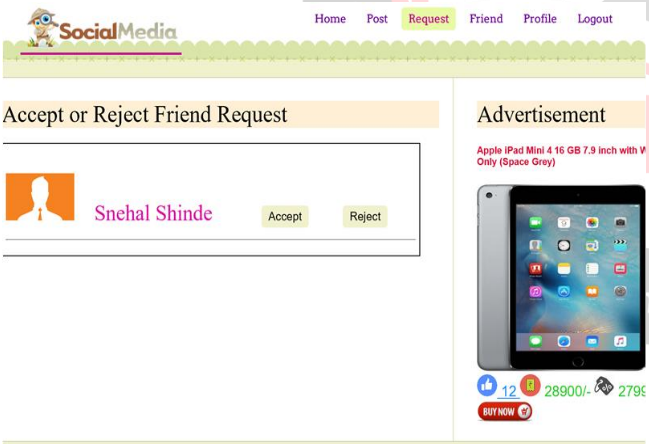
Screenshot 2 User home page

Registered User Can Get Access to the next page as shown above. She can Post her status in post status Block. If user wants to see her older all post she can , by clicking on "Click to view all post" .



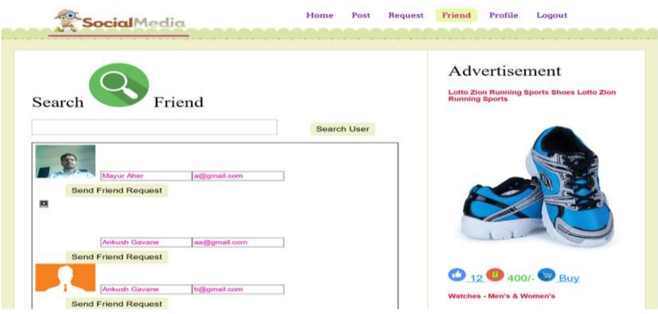
Screenshot 3 User post uploaded

This is the "post " page where the status is shown. And in another partition the Cold Start Product's Advertisement is displays.



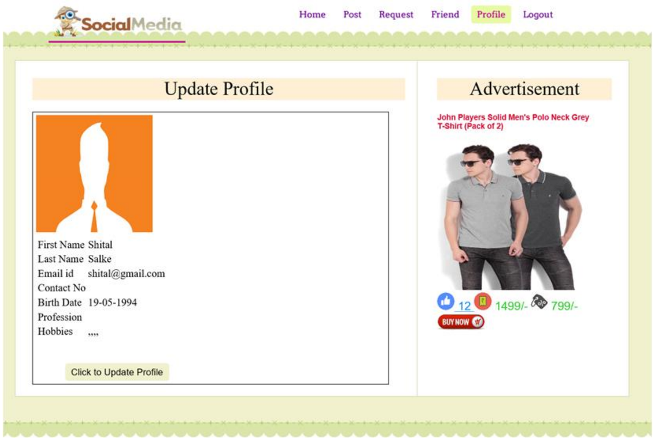
Screenshot 4 User check request

This is The "Request Page ", Where the friend request and can be sent or receive.



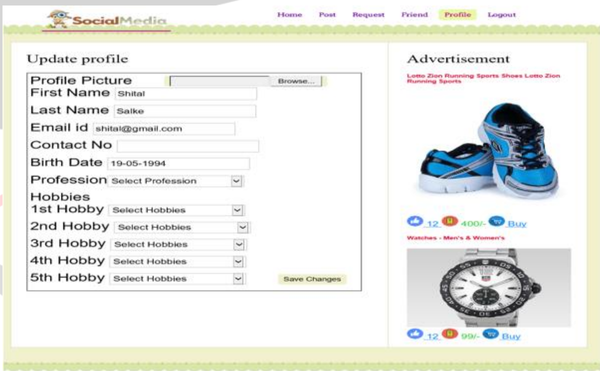
Screenshot 5 User send request

"Friend " Page will Show the all friend's of you with their profile picture.



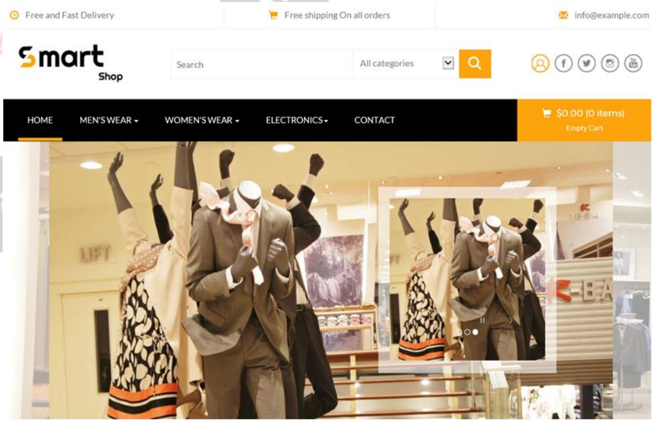
Screenshot 6 User profile

By this page you may update your profile. Profile having Various attribute to update with time or location like E-Mail id, Contact no, Profession.



Screenshot 7 User updates profile

Here we can see the updated Profile Of user. As we mention above the updated field may be again shown in the updated profile.



Screenshot 8 E-commerce site

This is the page of our ecommerce website. As we are merging two site social networking site and e commerce site . until we are seen only social networking related pages . This is the home page of our E-commerce site. From here we can navigate on other pages as we are interested to shop items related to.

Now This Page will Show the product for selling. This page comes after navigating from home page or it can be directly access when the items which occurred on this page

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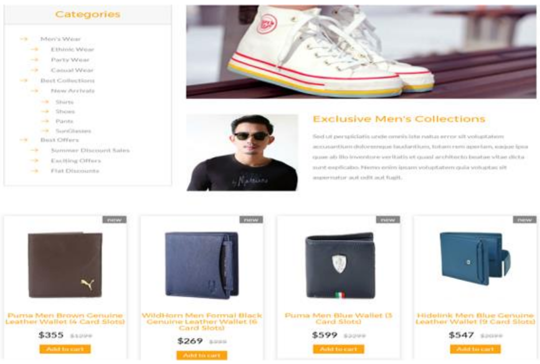
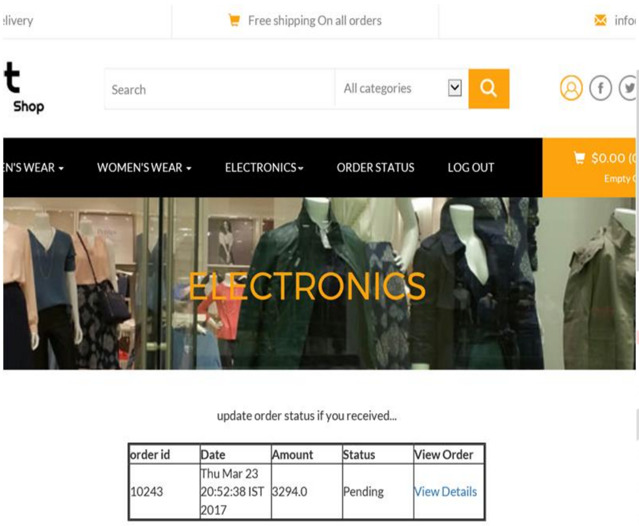
are shown on the social networking site and user click on the product.



Screenshot 9 Show product



Screenshot 10 Show product receiving or not

This is the page displayed when the user purchased any product. the table will show the list of product which is purchased by user. The status of the order is also maintain in the view details block.

V. CONCLUSION

Social networks in a way is changing e-commerce and helping it towards new directions. With its help, e-commerce can conquer some problems facing by e-business enterprises. In this paper, we have studied a novel problem, cross-site cold-start product recommendation, i.e., recommending products from e-commerce websites to microblogging 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 prediction of multiple users.

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