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Connecting Social Media to E-Commerce Using Cold Start Product Recommendation

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ABSTRACT: Social media is becoming a major and popular technological platform that allows users to express personal opinions toward the subjects with shared interests. Opinions are good for decision making, people would want to know others' opinion before taking a decision, while corporate would like to monitor pulse of people in social media about their products and services and take appropriate actions. This paper reviewed about world and realized that e-commerce is not just buying and selling over Internet, rather it is to improve the efficiency to compete with other giants in the market. Their opinions on specific topic are inevitably dependent on many social effects such as user preference on topics, peer influence, user profile information.

KEYWORDS: E-commerce, Cold start, Product Recommender, Product Demography, Micro-blogs, Data Mining, Recurrent Neural Networks, Information Search.

I. INTRODUCTION

Social media has gotten to be one of the mainstream correspondence stages that permit clients to examine and share points of enthusiasm without essentially having the same geo-area, time, etc. Information can be created and can be overseen by PCs or cell phones by one individual and devoured by numerous others. Distinctive individuals can express diverse assessments on the same theme. Individuals can likewise express their sentiments on different subjects of hobby. A wide mixture of subjects, extending from current occasions and political civil argument, to games and diversion, are in effect effectively talked about on these social discussions, for instance, Face book clients could remark on or “like” campaign posted by an organization. Twitter clients could send tweets with a most extreme length of 140 characters to immediately impart and convey their insights on games, motion pictures, and so forth. Some e-trade stages (1), for example, Amazon.com permit clients to leave their surveys on items. Conclusions are vital in light of the fact that at whatever point we have to settle on a choice, we need to hear others’ sentiments. Worldwide size of sentiment is no more constrained to people in which one's friend network and organizations little scale reviews minor centred gatherings.

II. RELATED WORK

Our work is mainly related to three lines of research: Recommender systems. In recent years, the matrix factorization approach [12], [4] has received much research interests. With the increasing volume of Web data, many studies focus on incorporating auxiliary information [3], [1]into the matrix factorization approach. Two typical frameworks of such studies are the SVD Feature [8] and Factorization Machine [9].There has also been a large body of research work focusing specifically on the cold-start recommendation problem. Seroussi et al. [7] proposed to make use of the information from users’ public profiles and topics extracted from user-generated content into a matrix factorization model for new users’ rating prediction. Zhang et al. [8] proposed a method by combining content and collaborative data under a single probabilistic framework. Lin et al. [10] addressed the cold-start problem for App recommendation by

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using the social information from Twitter. Trevisiol et al. Zhou et al. [6] experimented with eliciting new user preferences using decision trees by querying users' responses progressively through an initial interview process. Moshfeghi et al. [9]proposed a method for combining content features such as semantic and emotion information with ratings information for the recommendation task. Liu etal. [3] identified representative users whose linear combinations of tastes are able to approximate other users.

Cross-domain recommendation – One of the key techniques for cross-domain recommendation is Transfer Learning [3], and the idea is to learn transferable knowledge from the source domain, and further apply it in a target domain. Singh [12] proposed collective matrix factorization to estimate the relations of multiple entities by factorizing several matrices simultaneously while sharing parameters in the latent space. Li [4] attempted to transfer user-item rating patterns from an auxiliary matrix in another domain to the target domain through Codebooks. Hu [11]and Zhao [6] extended transfer learning to triadic factorization and active learning for cross-domain recommendation, respectively.

Social network mining – We follow the early commercial mining studies on social networking web-sites. Hollerit et al. [7] presented the first work on commercial intent detection in Twitter. Zhao et al.[5] first proposed to route products from e-commerce companies to micro blogging users. Our work is also related to studies on automatic user profiling [8] and cross-site linkage inference [9].Our work is built upon these studies, especially in the areas of cross-domain and cold-start recommendation. Though sharing some similarities, we are dealing with a very specific task of highly practical value, cold-start product recommendation to micro blogging users. To the best of our knowledge, it has not been studied on a large data set before. The most relevant studies are from [4], [7] by connecting users across eBay and Facebook. However, they only focus on brand- or category-level purchase preference based on a trained classifier, which cannot be directly applied to our cross-site cold-start product recommendation task. In addition, their features only include gender, age and Facebook likes, as opposed to a wide range of features explored in our approach. Lastly, they do not consider how to transfer heterogeneous information from social media websites into a form that is ready for use on the e-commerce side, which is the key to address the cross-site cold-start recommendation problem.

III. PROPOSED SYSTEM

The boundary between e-commerce and social networking has become blurred. E-commerce websites such as e-Bay has many of the traits of social networks, including real-time updates and interaction between buyers and sellers. Some e-commerce websites also support the mechanism of social login, which allows new users to sign in with their existing login information from social networking. None of the e-commerce systems have adopted the use of micro-blogging and other demographic information for cold start situation where a customer to e-commerce site is offered suggestion of the products. We are focused on the details of the micro-blogs, demo graphic information, location information, user posts, hobbies etc. to address the product recommendation. In this paper, we address the problem of recommending products to users who do not have any purchase records, i.e., in "cold-start" situations. We called it cold-start product recommender.

Fig1. Overview of Project

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Let's see the concept of this project with the help of this diagram. Here the first step is when the customer comes to the E-commerce site.

1) NEED ANALYSIS:- By using customers social information like his/her age,location,education,gender etc we can analyse what user want.
2) BEFORE PURCHASE:- Admin shows product to the customers as per their social information (like if he/she is a sport person then admin will show product related to sports only).
3) DURING PURCHASE:- Admin will shows that product during purchase with detail description that customer can buy.
4) AFTER PURCHASE:- After purchasing the product user can give feedback related to that product, according to users feedback Rating and Ranking is decided by Admin and posted it on social site of user.

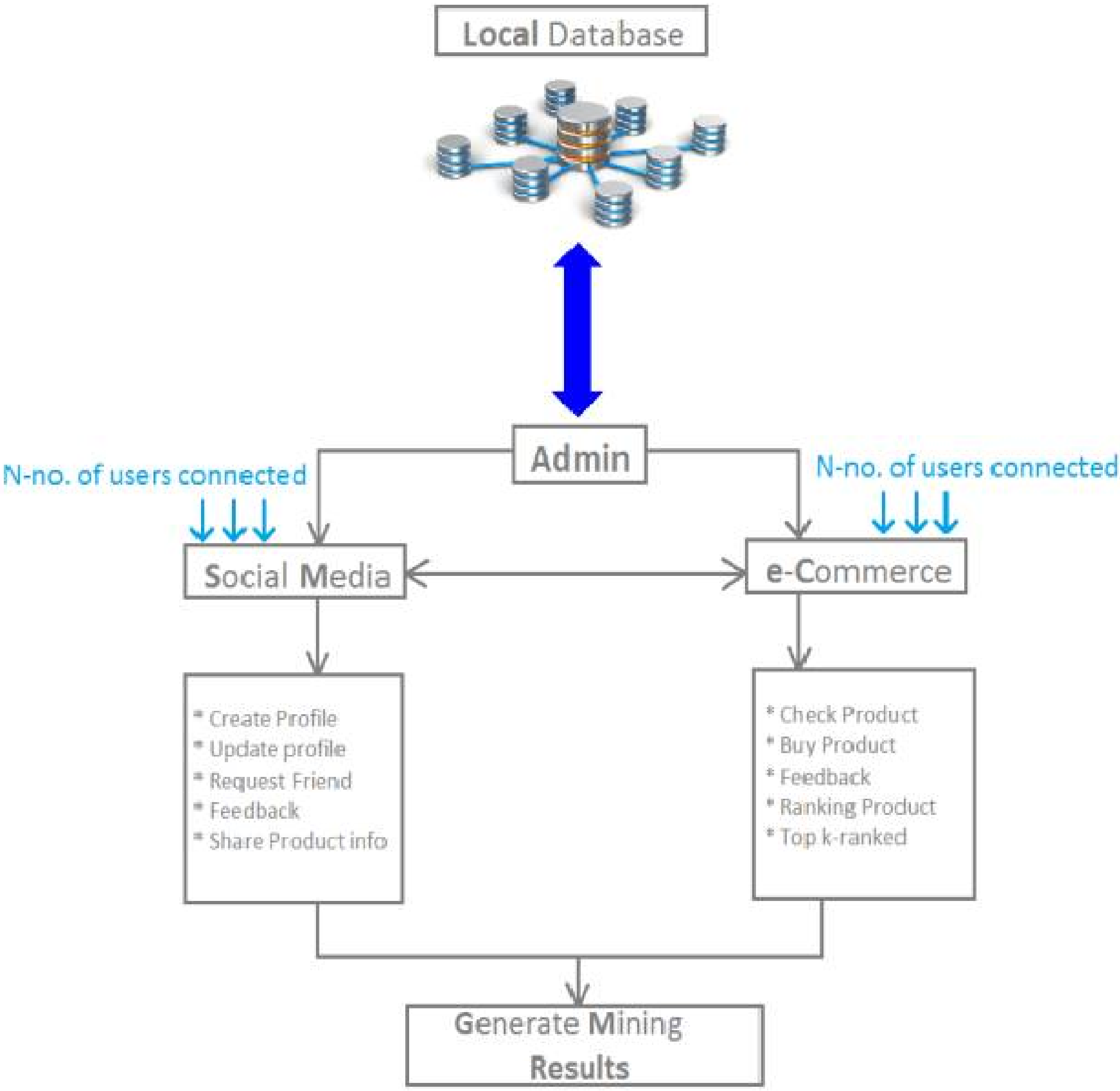

Fig2. System Architecture

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The above is the combination of the socialand e-commerce site. This system gives the more accuracy for analysing both technologies. In this system user can use both websites at same location. If any user purchases any product from e-commerce website, he can send review of the product on his/her social site. Once user sends that review then that post is updated on social site for product recommendation to his/her friends.

In this project, we are going to create two websites namely social site and e-commerce site.
All the users are connected to both sites.

Social site have functions like Create profile, Update profile, Sending friend request, Give feedback,and Share the product information. E-commerce site also has features likeCheck product, Buy product, Feedback, Ranking the product.

Mining the results from both sites user can get to know appropriate product recommendation and sale of e-commerce also get increased by receiving feedback from users.

We used two algorithms to implement project. These are as follows:

1. K-means algorithm
2. Wu-Palmer algorithm

IV.ALGORITHM USED

1. K-means algorithm:

In the clustering problem, we are given a training set x(1),...,x(m), and want to group the data into a few cohesive "clusters". Here, we are given feature vectors for each data point $x(i) \in R^n$as usual; but no labels y(i) (making this an unsupervised learning problem). Our goal is to predict k centroids and a label c(i) for each datapoint. The k-means clustering algorithm is as follows:

1.Initialize **cluster centroids**$\mu_1,\mu_2,....,\mu_k$ € R^n randomly.
2. Repeat until convergence: {
For every i, set

$$C^{(i)} = \arg\min \| x^{(i)} - \mu_j \|^2.$$

For each j, set

$$\mu_j = \frac{\sum_{i=1}^{m} 1\{c^{(i)} = j\}\, x^{(i)}}{\sum_{i=1}^{m} 1\{c^{(i)} = j\}}.$$

}

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2. Wu-Palmer algorithm:

The Wu & Palmer calculates relatedness by considering the depths of the two synsets in the WordNet taxonomies, along with the depth of the LCS (Least Common Subsumer).

The formula is **score = 2 * depth (lcs) / (depth (s1) + depth (s2))**.

This means that 0 < score <= 1. The score can never be zero because the depth of the LCS is never zero (the depth of the root of taxonomy is one). The score is one if the two input concepts are the same.

V. EXPERIMENTAL RESULTS

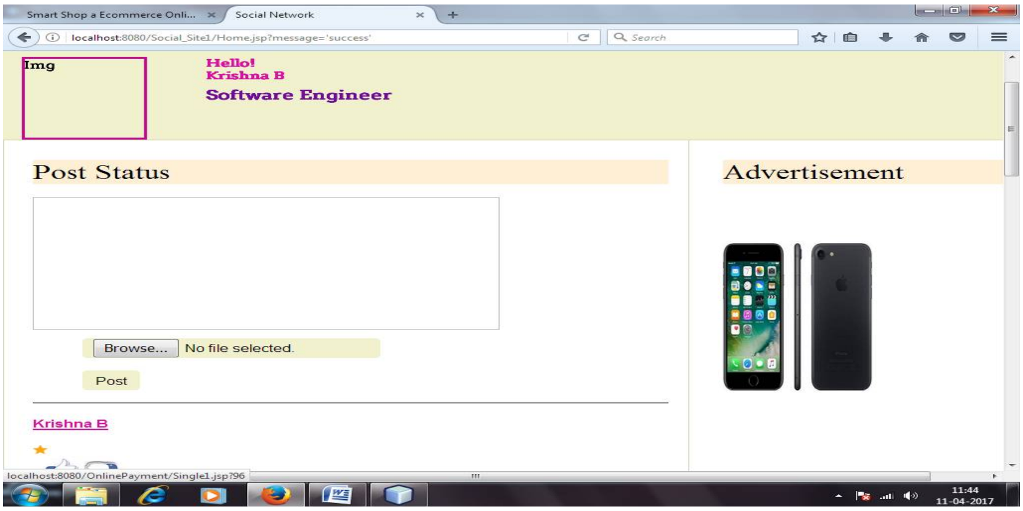

Fig3. Social site.

In this figure show advertise. This figure shows user status and list of products user brought or liked. This will be done by using Wu-palmer and k-means algorithm.

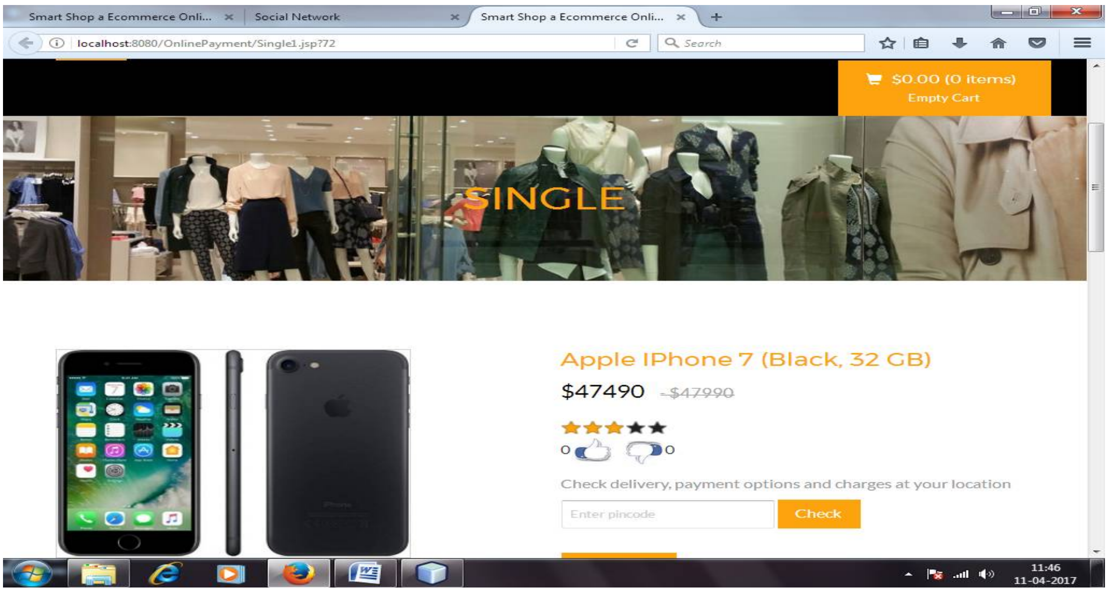

Fig4. E-commerce site.

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In this figure, product which is clicked by user on social site is shown.Detail information about product is present on the e-commerce site.

VI. CONCLUSION

We studythe new problem: how to recommend the right product at the right time?Experimental results on a data collected by a user e-commerce website show that itcan predict a user's follow-up purchase behavior at a particular time with descent accuracy. 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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