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Connecting Social Media to E-Commerce site using Cold-Start Product Recommendation

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Abstract*: Many e-commerce web sites help the mechanism of social login where customers can sign up the web sites using their social community identities which include their Facebook or Twitter debts. Users can also submit their newly purchased merchandise on microblogs with links to the e-commerce product net pages. In recent years, the bounds between e-commerce and social networking have turn out to be increasingly blurred. Proposed a novel answer for cross-web site cold-begin product recommendation, which pursuits to advise products from e-commerce websites to users at social networking websites in "coldstart" conditions the usage of demographic attributes, a trouble which has hardly ever been explored earlier than. A major project is the way to leverage know-how extracted from social networking websites for move-site bloodless-start product recommendation. Proposed to use the linked customers across social networking websites and e-commerce websites, as a bridge to map users' social networking functions to some other characteristic representation for product advice.
***Keywords*: E-commerce, microblogs, coldstart, cross-site, demographic attributes.**

I. INTRODUCTION

A. Social media
Websites and applications that enable users to create and share content or to participate in social networking.

B. Social networking
The use of dedicated websites and applications to interact with other users, or to find people with similar interests to one's own.

C. E-commerce
E-commerce is a transaction of buying or selling online.

D. Microblogging
Microblogging is a broadcast medium that exists in the form of blogging. Microblogs "allow users to exchange small elements of content such as short sentences, individual images, or video links", which may be the major reason for their popularity. These small messages are sometimes called microposts.

E. Cold start
Cold start is a potential problem in computer based information systems which involve a degree of automated data modelling. Specifically, it worries the difficulty that the gadget cannot draw any inferences for users or objects about which it has not yet amassed sufficient statistics.

F. Data Mining
Generally, data mining (sometimes called data or knowledge discovery) is the process of analyzing data from different perspectives and summarizing it into useful information - information that can be used to increase revenue, cuts costs, orboth. Technically, data mining is the process of finding correlations or patterns among dozens of fields in large relational databases.

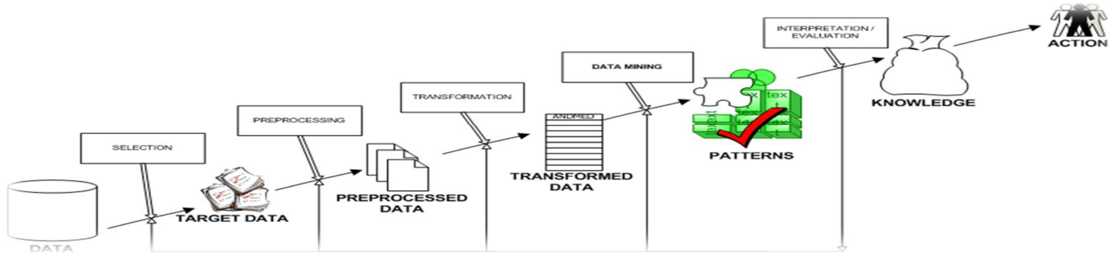

Fig.1 Structure of Data Mining[11].

Data mining software is one of a number of analytical tools for analyzing data. It allows users to analyze data from many different dimensions or angles, categorize it, and summarize the relationships identified.

II. IMPLEMENTATION

A. Modules

OSN System Construction Module
Microblogging Feature Selection
Learning Product Embeddings
Cold-Start Product Recommendation

B. Modules description

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

C. 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 utilises the feature representation pairs of all the linked users as training data.Ademographic profile (often shortened as “a demographic”) of a user such as sex, age and education can be used by ecommerce companies to provide better personalised 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

D. Learning Product Embedding

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 timestamped 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.

E. Cold-Start Product Recommendation

We used a local host based e-commerce dataset, which contains some user transaction records. Each transaction record consists of a user ID, a product ID and the purchase timestamp. We first group transaction records by user IDs and then obtain a list of purchased products for each user. For our methods, an important component is the embedding models, which can be set to two simple architectures, namely CBOW and Skip-gram. We empirically compare the results of our method ColdE using these two architectures, and find that the performance of using Skip-gram is slightly worse than that of using CBOW.

III. SYSTEM ARCHITECTURE

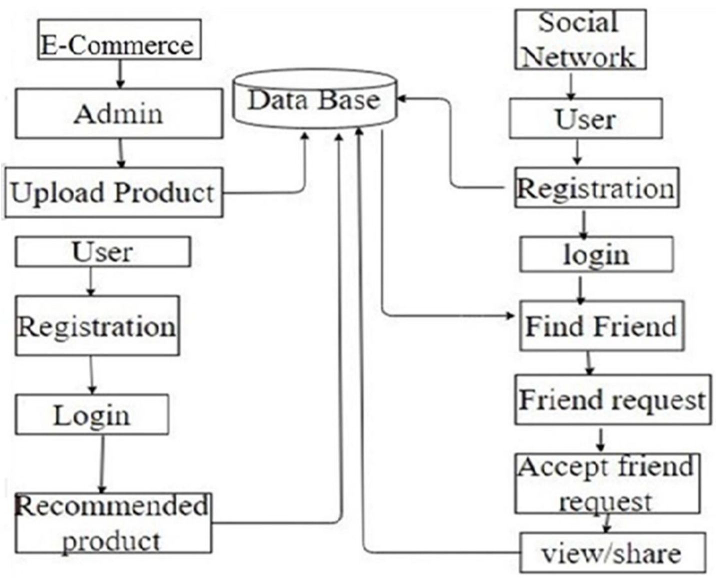

Fig.2 System Architecture

Product recommendation was done based on data collected from the social networking site. E-commerce login add the products to the database. Using the demographic attributes such as gender, interests, age related product was selected automatically from the database.

IV. SYSTEM ANALYSIS

A. *Existing System*

Most research handiest consciousness on constructing solutions inside sure e-commerce web sites and specifically utilise users' ancient transaction data. To the satisfactory of our expertise, pass-site cold-begin product advice has been rarely studied before.There has also been a huge body of research paintings focusing mainly at the cold-begin advice hassle.Seroussi et al. Proposed to make use of the data from customers' public profiles and subjects extracted from user generated content material right into a matrix factorization model for new users' rating prediction. Zhang et al. Recommend a semi-supervised ensemble getting to know algorithm. Schein proposed a method by way of combining content and collaborative records beneath a unmarried probabilistic framework. Lin et al. Addressed the bloodless-begin problem for App advice .

B. *Disadvantages of Existing System*

They only awareness on emblem or class-degree purchase desire based on a skilled classifier, which can not be at once carried out to our go-website online bloodless begin product advice assignment. Their features only consist of gender, age and Facebook likes, as opposed to a extensive range of capabilities explored in our approach. They do now not don't forget how to transfer heterogeneous statistics from social media web sites into a form that is prepared for use on the e-trade facet, that is the key to address the cross-web page bloodless-begin recommendation problem.

C. *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. To deal with this venture, we advise to use the linked customers across social networking sites and e-commerce web sites (users who've social networking accounts and have made purchases on e-commerce web sites) as a bridge to map users' social networking capabilities to latent functions for product recommendation. In particular, we endorse studying each users' and merchandise' function representations (called user embeddings and product embeddings, respectively) from records collected from e-commerce web sites the use of recurrent neural networks and then observe a modified gradient boosting bushes approach to transform customers' social networking functions into consumer embeddings. We then increase a characteristic-based matrix factorization approach which can leverage the learnt user embeddings for bloodless begin product recommendation.

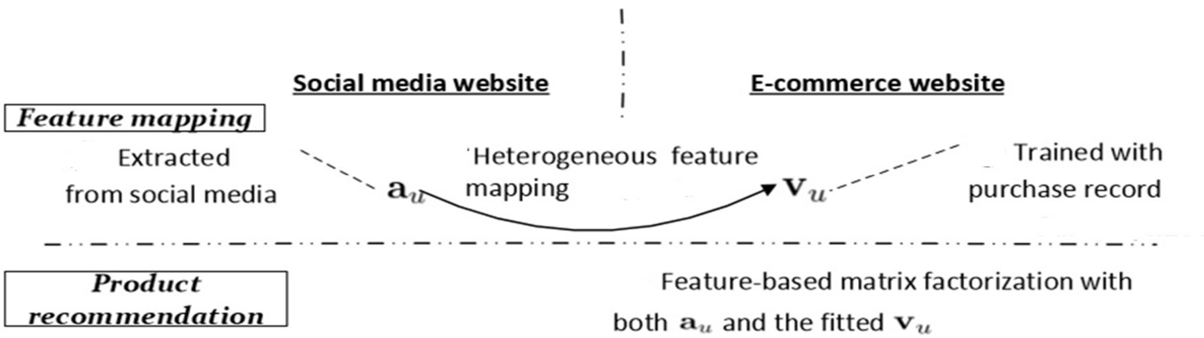

Fig.3 Workflow diagram

D. Advantages of proposed system

Our proposed framework is certainly powerful in addressing the move-website online cold-begin product advice trouble. We agree with that our look at can have profound effect on both studies and industry groups.We formulate a unique trouble of recommending merchandise from an e-commerce website to social networking users in "cold-begin" conditions. To the quality of our understanding, it's been hardly ever studied earlier than. We advocate to use the recurrent neural networks for getting to know correlated feature representations for each customers and products from data collected from an e-trade website.We advise a modified gradient boosting timber approach to transform users' microblogging attributes to latent characteristic illustration which may be easily included for product advice.We advise and instantiate a function-primarily based matrix factorization technique via incorporating consumer and product capabilities for cold-start productadvic

V. LITERATURE SURVEY

A. Opportunity model for E-commerce recommendation

Right product; right time: Most of existing e-commerce recommender systems aim to recommend the right product to a user, based on whether the user is likely to purchase or like a product. On the other hand, the effectiveness of recommendations also depends on the time of the recommendation. Let us take a user who just purchased a laptop as an example. She may purchase a replacement battery in 2 years (assuming that the laptop's original battery often fails to work around that time) and purchase a new laptop in another 2 years. In this case, it is not a good idea to recommend a new laptop or a replacement battery right after the user purchased the new laptop. It could hurt the user's satisfaction of the recommender system if she receives a potentially right product recommendation at the wrong time. We argue that a system should not only recommend the most relevant item, but also recommend at the right time[1].

B. Retail sales prediction and item recommendations using customer demographics at store level:

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. Data consisted of daily sales information for 600 products at the store level, broken out over a set of non-overlapping customer types. A recommender system was built based on a fast online thin Singular Value Decomposition. It is shown that modeling data at a finer level of detail by clustering across customer types and demographics yields improved performance compared to a single aggregate model built for the entire dataset. Details of the system implementation are described and practical issues that arise in such real-world applications are discussed. Preliminary results from test stores over a one-year period indicate that the system resulted in significantly increased sales and improved efficiencies. A brief overview of how the primary methods discussed here were extended to a much larger data set is given to confirm and illustrate the scalability of this approach [2].

C. Amazon.com recommendations

Item-to-item collaborative filtering: Recommendation algorithms are best known for their use on e-commerce Web sites, 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. The store radically changes based on customer interests, showing programming titles to a software engineer and baby toys to a new mother. There are three common approaches to solving the recommendation problem: traditional collaborative filtering, cluster models, and search-based methods. Here, we compare these methods with our algorithm, which we call item-to-item collaborative filtering. Unlike traditional collaborative filtering, our algorithm's online computation scales independently of the number of customers and number of items in the product catalog. Our algorithm produces recommendations in real-time, scales to massive data sets, and generates high quality recommendations [3].

D. The new demographics and market fragmentation

The underlying premise of this article is that changing 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 [4].

E. We know what you want to buy: A demographic-based system for product recommendation on microblogs:

Product recommender systems are often deployed by e-commerce websites to improve user experience and increase sales. However, recommendation is limited by the product information hosted in those e-commerce sites and is only triggered when users are performing e-commerce activities. 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[5].

VI. CONCLUSION

In this paper, we've got studied a unique hassle, cross site cold-start product advice, i.e., recommending products from e-commerce websites to microblogging customers with out historical buy facts. Our essential idea is that at the e-trade websites, users and merchandise may be represented inside the identical latent characteristic area via characteristic getting to know with the recurrent neural networks. Using a set of connected users throughout both e-commerce websites and social networking websites as a bridge, we can study characteristic mapping capabilities using a modified gradient boosting bushes technique, which maps customers' attributes extracted from social networking websites onto characteristic representations discovered from e-commerce web sites. The mapped consumer functions can be effectively integrated into a chilly-start product recommendation. The effects display that our proposed framework is certainly effective in addressing the go-web site cold-start product recommendation trouble. We agree with that our observe can have profound impact on each research and industry groups.

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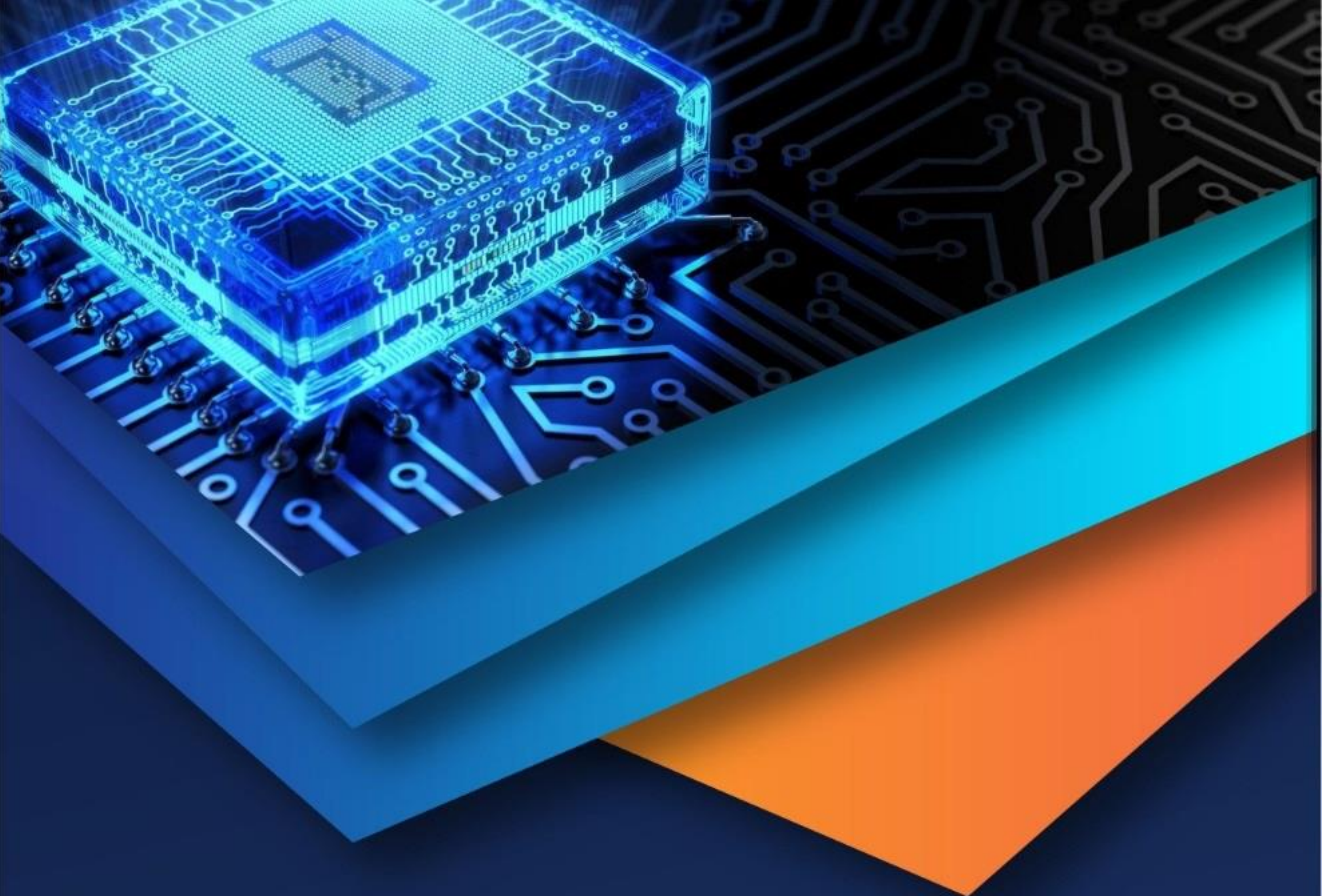

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