



## Social Networking Sites for Cross-Site Cold-Start Product Recommendation

Ankita Kashid<sup>1</sup>, Shubhangi Khedkar<sup>2</sup>, Pooja Limbhore<sup>3</sup>, Archana Shinde<sup>4</sup>, Pragati Mahale<sup>5</sup>,

<sup>1</sup>Department of Information Technology Engineering, Institute of Information Technology, Pune

<sup>2</sup>Department of Information Technology Engineering, Institute of Information Technology, Pune

<sup>3</sup>Department of Information Technology Engineering, Institute of Information Technology, Pune

<sup>4</sup>Department of Information Technology Engineering, Institute of Information Technology, Pune

<sup>5</sup>Associate Professor, Department of Information Technology Engineering, Institute of Information Technology, Pune

**Abstract** — In recent years, the boundaries between e-commerce and social networking became more and more blurred. several e-commerce websites support the mechanism of social login wherever users will register the websites victimization their social network identities like their Facebook or Twitter accounts. Users also can post their recent purchased product on microblogs with links to the e-commerce product websites. throughout this paper we've associate degree inclination to propose a singular account cross-site cold-start product recommendation, that aims to advocate product from e-commerce websites to users at social networking sites in "coldstart" things, a tangle that has seldom been explored before. an important challenge is that the due to leverage info extracted from social networking sites for cross-site cold-start product recommendation. we've a bent to propose to use the coupled users across social networking sites and e-commerce websites (users global organization agency have social networking accounts and have created purchases on e-commerce websites) as a bridge to map users' social networking decisions to a special feature illustration for product recommendation. In specific, we've associate degree inclination to propose learning each users' and merchandises' feature representations (called user embeddings and merchandise embeddings, respectively) from information collected from e-commerce websites victimization continual neural networks therefore apply a changed gradient boosting trees methodology to remodel users' social networking decisions into user embeddings. we've associate degree inclination to then develop a feature-based matrix resolution approach that may leverage the learnt user embeddings for cold-start product recommendation. Experimental results on associate oversized dataset product of necessary|the biggest} Chinese microblogging service SINA WEIBO and to boot the foremost important Chinese B2C e-commerce computing device JINGDONG have shown the effectiveness of our planned framework.

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

### I. INTRODUCTION

Nowadays, Recommender Systems, aiming at serving to users perceive relevant and attention-grabbing things from the information era, unit of measurement wide studied and applied in varied fields starting from e-commerce to medication prediction. Besides the infinite studies on rising the advice performance the because of appropriately justify there commendation results Associate in Nursingd ultimately persuade users to simply accept them is additionally a powerful challenge in each analysis and engineering fields. though several novel algorithms have tested that they need achieved sensible, even extraordinary performance in varied matrices on offline datasets, feedbacks from on-line applications show that users wouldn't invariably trust and follow the machine-produced results, that in additional hinders its wider development in real society Recently, the acquisition intention of users has attracted abundant attention from scientific community. totally wholly totally different from ancient recommender systems, they target finding the factors that might verify one's temperament to buy for merchandise on-line. In fact, the \$64000 on-line things one can face would be far more delicate. Suppose one user arrives at a shirt channel, in spite of what she has purchased any merchandise, whether or not or not or not she is intensively impelled to shop for for one issue this point will very have an impression on the \$64000 recommendation result. Below this circumstance, the user's temperament, notably her purchase intention would play associate primarily necessary role in decisive her judgement to simply accept the counseled things or not. throughout this paper, we've got an inclination to tend to propose a scenario-based approach to see the results of users' purchase intention on a true recommender system, Tmall.com. Firstly, we've got an inclination to tend to statistically analyze the dependence of nineteen representative users' decisions on their on-line activity sequence. Secondly, we've got an inclination to tend to propose a scenario based approach to severally distinguish users into 2 groups: one with obvious purchase intention, and another whereas not such motivation.

## **II. LITERATURE REVIEW**

### **1. Opportunity model for e-commerce recommendation: Right product; right time**

**Author:-** J. Wang and Y. Zhang

Most of existing e-commerce advocate systems aim to recommend the correct 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 United Nations agency simply purchased a portable computer as AN example. She might purchase a replacement battery in two years (assuming that the portable computer's original battery typically fails to figure around that time) and get a brand new laptop in another two years. during this case, it's not a decent plan to advocate a brand new portable computer or a replacement battery right once the user purchased the new portable computer. It may hurt the user's satisfaction of the recommender system if she receives a probably right product recommendation at the incorrect time. we tend to argue that a system mustn't solely advocate the foremost relevant item, however conjointly advocate at the correct time.

### **2. Retail sales prediction and item recommendations using customer demographics at store level**

**Author:-** M. Giering

This paper outlines a retail sales prediction and products recommendation system that was enforced for a series of retail stores. The relative importance of shopper demographic characteristics for accurately modeling the sales of every client kind are derived and enforced within the model. Knowledge consisted of daily sales data for 600 product at the shop level, broken out over a group 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 agglomeration across client varieties and demographics yields improved performance compared to one combination model designed for the complete dataset. Details of the system implementation are delineate and sensible problems that arise in such real-world applications are mentioned.

### **3. Amazon.com recommendations: Item-to-item collaborative filtering.**

**Author:-** G. Linden, B. Smith, and J. York

Recommendation algorithms square measure 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 a listing of counseled things. several applications use solely the things that customers purchase and expressly rate to represent their interests, however they'll conjointly use different attributes, as well as things viewed, demographic knowledge, subject interests, and favorite artists. At Amazon.com, we tend to use recommendation algorithms to individualise the net store for every client. the shop radically changes supported client interests, showing programming titles to a computer user and baby toys to a replacement mother. There square measure 3 common approaches to determination the advice problem: ancient cooperative filtering, cluster models, and search-based ways. Here, we tend to compare these ways with our formula, that we tend to decision item-to-item cooperative filtering.

### **4. The new demographics and market fragmentation**

**Author:-** V. A. Zeithaml

The underlying premise of this text is that ever-changing demographics can result in a breaking of the mass markets for grocery product and supermarkets. A field study investigated the relationships between 5 demographic factors-sex, feminine operating standing, age, income, and married status-and a large vary of variables related to preparation for and execution of grocery store looking. Results indicate that the demographic teams disagree in important ways in which from the normal grocery store shopper. Discussion centers on the ways in which ever-changing demographics and family roles might have an effect on retailers and makers of grocery product.

### **5. We know what you want to buy: a demographic-based system for product recommendation on microblogs**

**Author:-** W. X. Zhao, Y. Guo, Y. He, H. Jiang, Y. Wu, and X. Li

Product recommender systems area unit usually deployed by e-commerce websites to boost user expertise and increase sales. However, recommendation is restricted by the merchandise data hosted in those e-commerce sites and is barely triggered once users area unit activity e-commerce activities. during this paper, we tend to develop a unique product recommender system referred to as breed, a businessperson Intelligence recommender System, that detects users' purchase intents from their microblogs in close to period of time and makes product recommendation supported matching the users' demographic data extracted from their public profiles with product demographics learned from microblogs and on-line reviews. breed distinguishes itself from ancient product recommender systems within the following aspects: 1) breed was developed supported a microblogging service platform. As such, it's not restricted by the data offered in any

specific e-commerce web site. additionally, breed is ready to trace users' purchase intents in close to period of time and create recommendations consequently. 2) In breed, product recommendation is framed as a learning to rank downside. Users' characteristics extracted from their public profiles in microblogs and products' demographics learned from each on-line product reviews and microblogs area unit fed into learning to rank algorithms for product recommendation.

### III. ALGORITHM

It involves fitting the requisite count variables, arbitrarily initializing them, and so running a loop over the specified range of iterations wherever on every loop a subject is sampled for every word instance within the corpus. We used LDA, Clustering and Extraction algorithmic rule in proposed system.

**Input:** words  $w \in$  documents  $d$

Where,

- $w$  be the corpus of words.
- $d$  is the set of documents.
- $n$  be the number of words.
- $k$  be the number of words in the document.
- $\alpha$  and  $\beta$  are LDA constants.

**Output:** topic assignments  $z$  and counts  $n_{d,k}$ ,  $n_{k,w}$  and  $n_k$

Where,

- $n_{d,k}$  the number of words assigned to topic  $k$  in document  $d$ .
- $n_{k,w}$  the number of times word  $w$  is assigned to topic  $k$ .

**Procedure:**

1. randomly initialize  $z$  and increment counter
2. for each iteration do
3. **for**  $i = 0 \rightarrow N-1$  do

word  $\leftarrow w[i]$

topic  $\leftarrow z[i]$

$n_{d,topic} - = 1$  ;  $n_{word,topic} - = 1$  ;  $n_{topic} - = 1$

**for**  $k = 0 \rightarrow K - 1$  do

$$p(z = k | \cdot) = (n_{d,k} + \alpha_k) \frac{n_{k,w} + \beta_w}{n_k + \beta \times W}$$

**end**

4. Topic  $\leftarrow$  sample from  $p(z | \cdot)$
5.  $z[i] \leftarrow$  topic.
6.  $n_{k,topic} + = 1$  ;  $n_{word,topic} + = 1$  ;  $n_{topic} + = 1$  \
7. **end**
8. **end**
9. return  $z$ ,  $n_{d,k}$ ,  $n_{k,w}$ ,  $n_k$
10. **end**

### IV. PROPOSED SYSTEM

We propose to use the coupled users across social networking sites and e-commerce websites (users international organisation agency have social networking accounts and have created purchases on e-commerce websites) as a bridge to map users' social networking decisions to latent decisions for product recommendation. In specific, we have got a bent to propose learning each users' and merchandisess' feature representations (called user embeddings and product embeddings, respectively) from info collected from ecommerce websites exploitation continual neural networks then

apply a changed gradient boosting trees methodology to remodel users' social networking decisions into user embeddings. we have got a bent to then develop a feature based matrix resolution approach that may leverage the learnt user embeddings for cold-start product recommendation.

It target text attribute, network attribute and temporal attribute

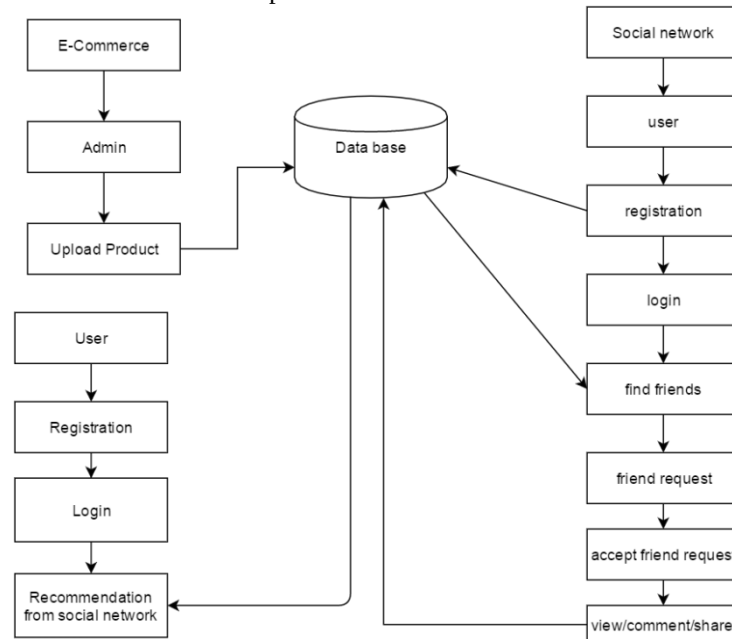


Figure: Proposed system architecture

### **Advantages of projected System:**

1. We've a bent to propose a changed gradient boosting trees methodology to remodel users' microblogging attributes to latent feature illustration which might be just incorporated for product recommendation.
2. We've a bent to propose and instantiate a feature-based matrix resolution approach by incorporating user and merchandise decisions for cold-start product recommendation.
3. The results show that our projected framework is therefore effective in addressing the cross-site cold-start product recommendation disadvantage.

## **V. MATHEMATICAL MODEL**

### **INPUT:-**

Let S is the Whole System Consist of

$$S = \{I, P, O\}$$

I = Input.

$$I = \{U, Q, D\}$$

U = User

$$U = \{u_1, u_2, \dots, u_n\}$$

Q = Query Entered by user

$$Q = \{q_1, q_2, q_3, \dots, q_n\}$$

D = Dataset

P = Process:

Step1: Admin will upload the product in E-commerce site.

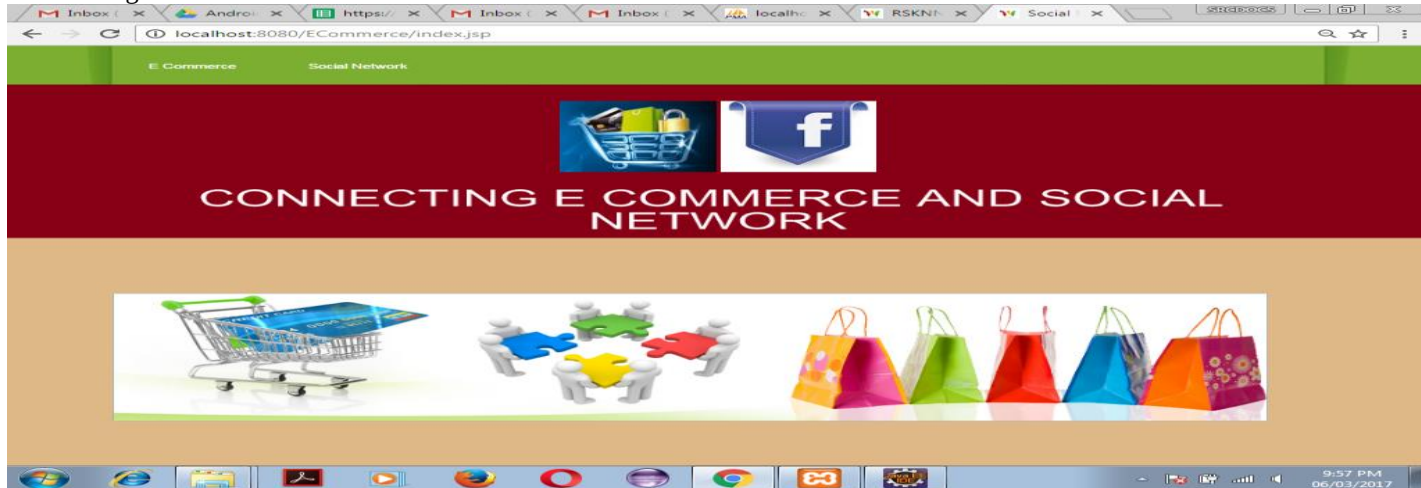
Step2: That uploaded product will be seen on Social sites where user can view, share and give comments on that product. User can send and receive friend request.

Step3: All the reviews should be seen in E-commerce site when user login to E-commerce site.

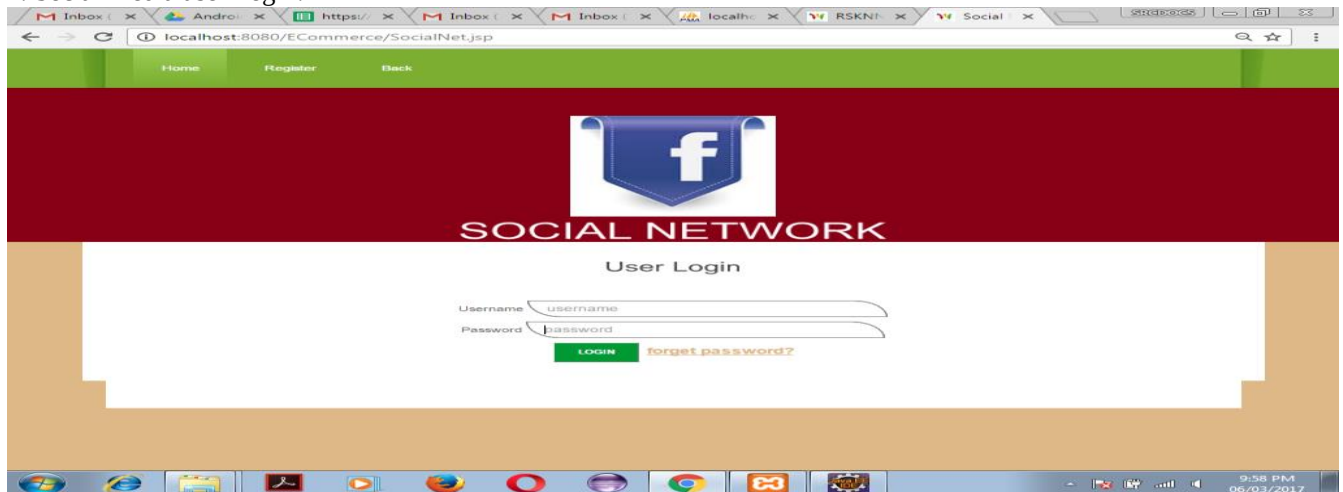
**Output:** User will get recommendation regarding of that product on ecommerce website.

## V. RESULT AND DISCUSSION

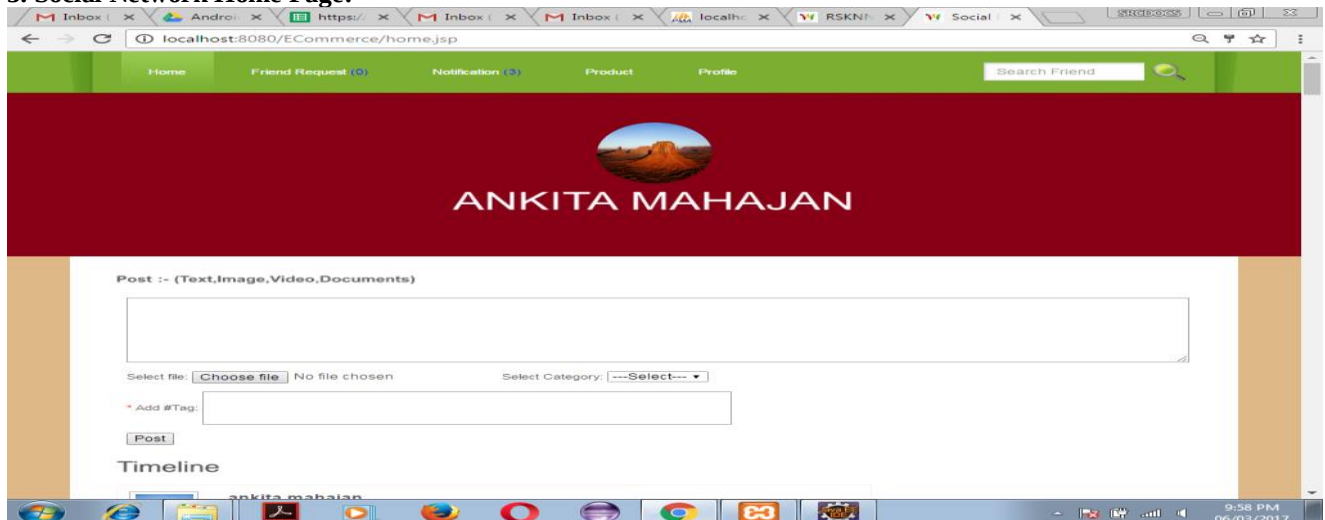
### 1.Home Page:



### 2. Social Media user Login:

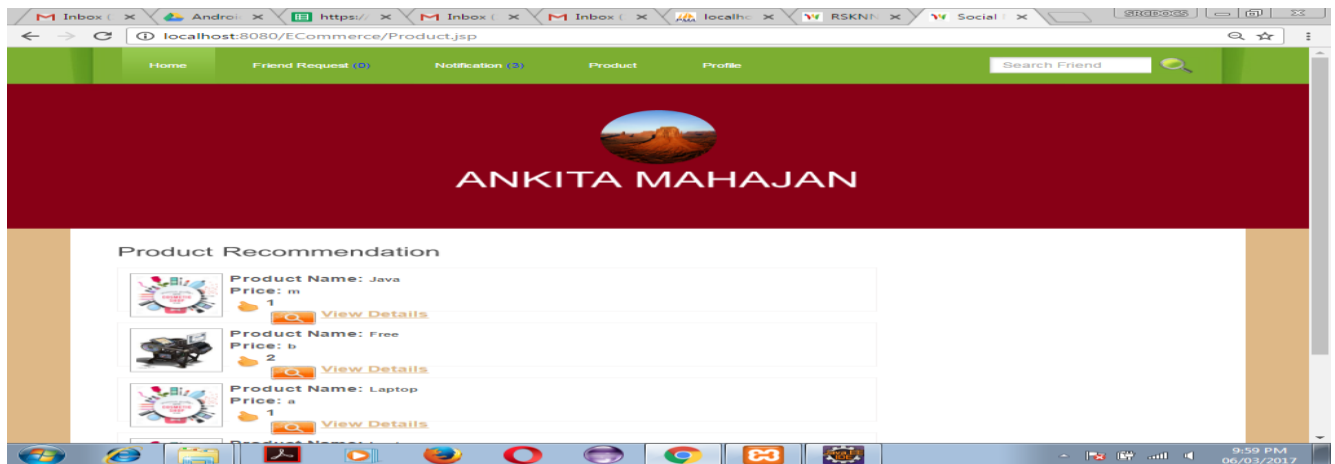


### 3. Social Network Home Page:

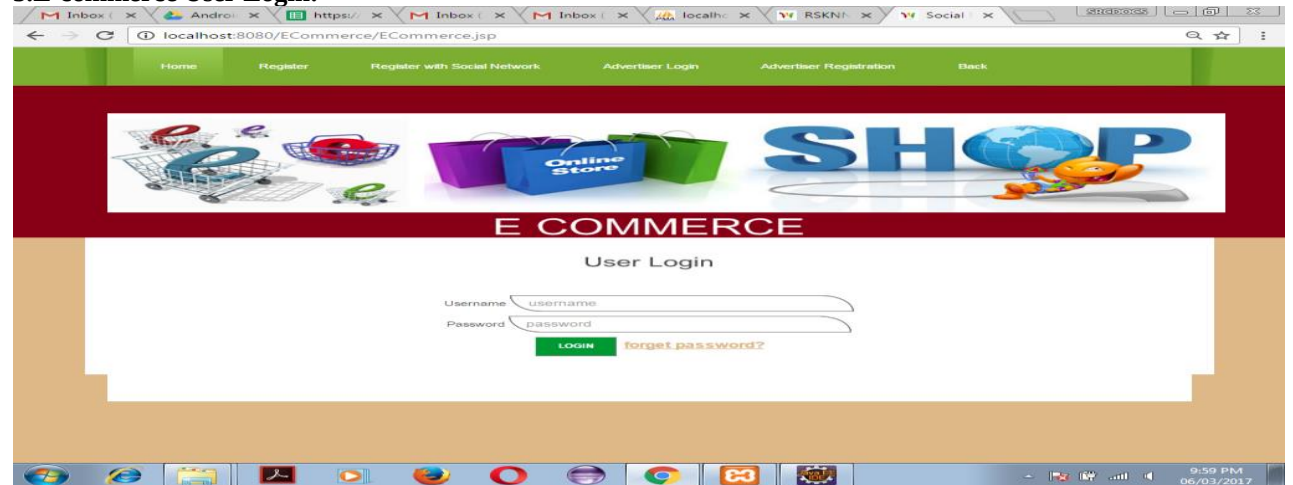


### 4. Social Networking Product Recommendation system:

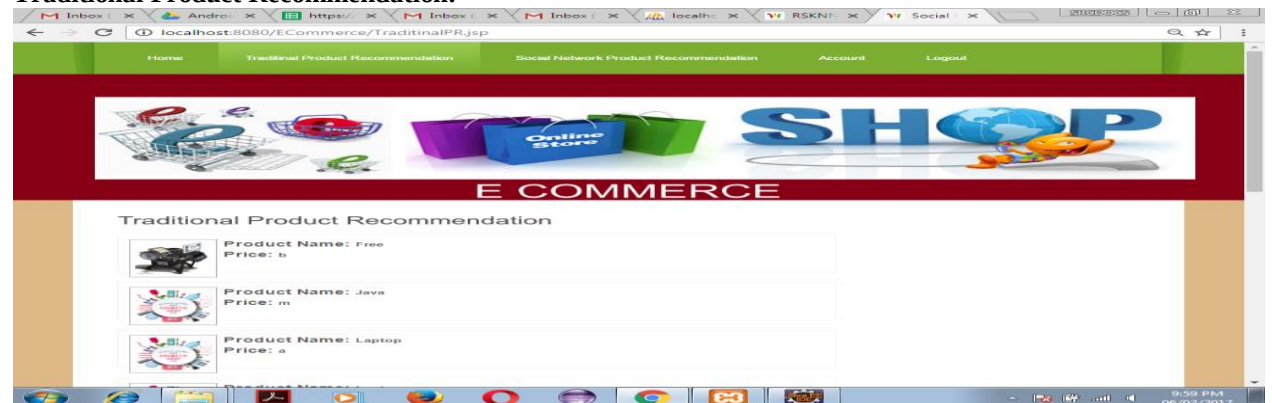




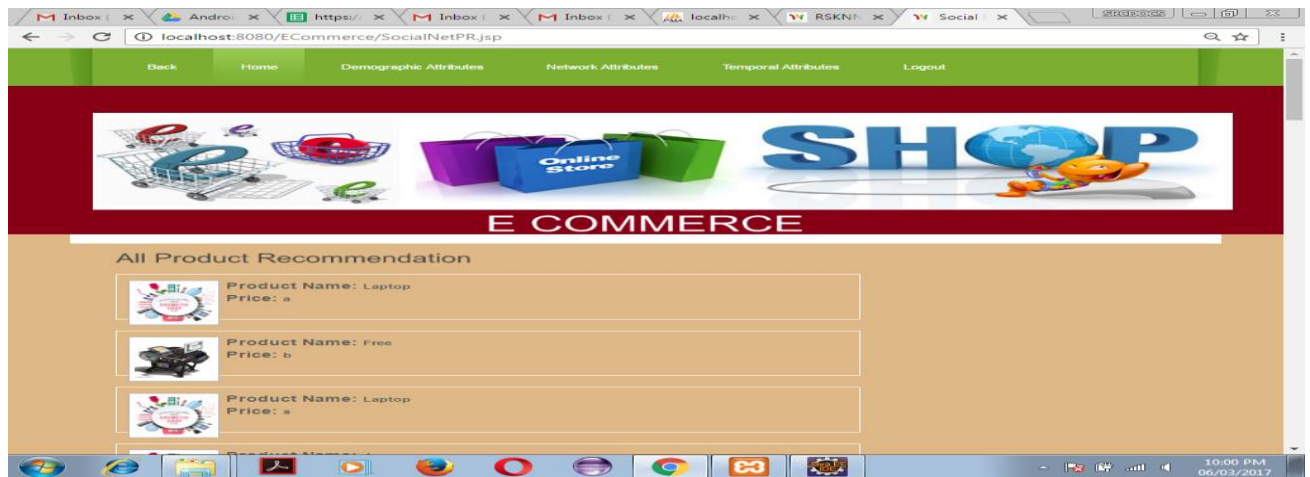
#### 5.E-commerce User Login:



#### 6. Traditional Product Recommendation:



#### 7. Product recommended from social network on e-Commerce:



## VI. CONCLUSION

In this paper, we have got targeted on a totally distinctive issue, cross-site cool begin item suggestion, i.e., prescribing things from e-trade sites to micro-blogging shoppers whereas not authentic get records. Our primary thought is that on the e-trade sites, shoppers and things is spoken to at intervals identical dormant element space through element learning with the repetitive neural systems. Utilizing a meeting of connected shoppers crosswise over every e-trade sites AND long vary social communication destinations as Associate in Nursing extension, we'll learn embrace mapping capacities utilizing a changed angle boosting trees technique, that maps clients' qualities disentangled from long vary informal communication locales onto highlight representations gained from e-business sites. The mapped shopper parts is satisfactorily joined into a embrace primarily based network partitioning approach for cold begin item proposal. we have got built a vast dataset from WEIBO and JINGDONG. The outcomes demonstrate that our projected system is whereas not a doubt compelling in tending to the cross-site icy begin item suggestion issue. we have a tendency to tend to trust that our study will have very important impact on every analysis and trade groups.

## ACKNOWLEDGMENT

Authors want to acknowledge Principal, Head of department and guide of their project for all the support and help rendered. To express profound feeling of appreciation to their regarded guardians for giving the motivation required to the finishing of paper.

## REFERENCES

- 1] F. Cheng, C. Liu, J. Jiang, W. Lu, W. Li, G. Liu, W. Zhou, J. Huang, and Y. Tang. Prediction of drug-target interactions and drug repositioning via network-based inference. *PLoS Computational Biology*, 8:e1002503, 2012.
- 2] E. Constantinides. Influencing the online consumer's behavior: the web experience. *Internet research*, 14:111–126, 2004.
- 3] J. L. Herlocker, J. A. Konstan, and J. Riedl. Explaining collaborative filtering recommendations. In *Proceedings of the 2000 ACM conference on Computer supported cooperative work*, pages 241–250. ACM, 2000.
- 4] C. Jayawardhena, L. T. Wright, and C. Dennis. Consumers online: intentions, orientations and segmentation. *International Journal of Retail & Distribution Management*, 35:515–526, 2007.
- 5] A. Karatzoglou. Collaborative temporal order modeling. In *Proceedings of the 4th ACM conference on Recommender systems*, pages 313–316, 2011.
- 6] I. Konstas, V. Stathopoulos, and J. Jose. On social networks and collaborative recommendation. In *Proceedings of the 32nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 195–202. ACM, 2009.
- 7] A. Liaw and M. Wiener. Classification and regression by randomforest. *R news*, 2:18–22, 2002.

- 8] C.-H. Park and Y.-G. Kim. Identifying key factors affecting consumer purchase behavior in an online shopping context. *International Journal of Retail & Distribution Management*, 31:16–29, 2003.
- 9] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom, and J. Riedl. Grouplens: an open architecture for collaborative filtering of netnews. In *Proceedings of the 1994 ACM Conference on Computer Supported Cooperative Work*, pages 175–186. ACM, 1994.
- 10] B. Sarwar, G. Karypis, J. Konstan, and J. Reidl. Item-based collaborative filtering recommendation algorithms. In *Proceedings of the 10<sup>th</sup> International Conference on World Wide Web*, pages 285–295. ACM, 2001.
- 11] Analytics: An Intelligent Approach in Clinical Trail Management Ankit Lodha\* Analytics Operations Lead, Amgen, Thousand Oaks, California, USA.
- 12] Agile: Open Innovation to Revolutionize Pharmaceutical Strategy Ankit Lodha University of Redlands, 333 N Glenoaks Blvd #630, Burbank, CA 91502.
- 13] Clinical Analytics – Transforming Clinical Development through Big Data Ankit Lodha University of Redlands, 333 N Glenoaks Blvd #630, Burbank, CA 91502.
-