# A GENERAL FRAMEWORK FOR IMPLICIT AND EXPLICIT SOCIAL RECOMMENDATION

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**ABSTRACT**

Research of social recommendation aims at exploiting social information to improve the quality of a recommender system. It can be further divided into two classes. Explicit social recommendation assumes the existence of not only the users' ratings on items, but also the explicit social connections between users. Implicit social recommendation assumes the availability of only the ratings but not the social connections between users, and attempts to infer implicit social connections between users with the goal to boost recommendation accuracy. This paper proposes a unified framework that is applicable to both explicit and implicit social recommendation. We propose an optimization framework to learn the degree of social correlation and rating prediction jointly, so these two tasks can mutually boost the performance of each other. Furthermore, a well-known challenge for implicit social recommendation is that it takes quadratic time to learn the strength of pairwise connections. This paper further proposes several practical tricks to reduce the complexity of our model to be linear to the observed ratings. The experiments show that the proposed model, with only two parameters, can significantly outperform the state-of-the-art solutions for both explicit and implicit social recommender systems.

## 1 INTRODUCTION

Social recommendation, a study aiming at incorporating social information of users into a recommender system, has attracted decent attention in recent years. It can further be divided into two tracks: explicit social recommendation and implicit social recommendation. In explicit social recommendation, a variety of models have been developed to exploit the existing social network information to enhance the performance of a recommender system. A common and arguably most successful strategy is to integrate the social information, such as trust or friendship, into a collaborative filtering model in a certain way. Figure 1 describes an explicit social recommendation system given edge strength information is available, while Figure 2 shows another kind of explicit social recommender system where only binary relationship information (e.g., whether two people are friends) is available. Suppose there is a rating dataset including some ratings of four users fU1;U2;U3;U4g to four items fV1; V2; V3; V4g. Such data can be denoted by a matrix where the”?” entries represent unknown ratings. A social-based recommender system reads the matrix together with a given or inferred user social network as the training examples, and then predicts the unknown ratings.

## 2 RELEATED WORK

### A Probabilistic Model for Using Social Networks in Personalized Item Recommendation

Preference-based recommendation systems have transformed how we consume media. By analyzing usage data, these methods uncover our latent preferences for items (such as articles or movies) and form recommendations based on the behavior of others with similar tastes. But traditional preference-based recommendations do not account for the social aspect of consumption, where a trusted friend might point us to an interesting item that does not match our typical preferences. In this work, we aim to bridge the gap between preference- and social-based recommendations. We develop social Poisson factorization (SPF), a probabilistic model that incorporates social network information into a traditional factorization method; SPF introduces the social aspect to algorithmic recommendation. We develop a scalable algorithm for analyzing data with SPF, and demonstrate that it outperforms competing methods on six real-world datasets; data sources include a social reader and Etsy.

## 3 implementation study

### Existing System:

The quality of the given social information is sometimes questionable. Since most of the social data are collected from the web or social network services, inevitably they contain noises. For example, past empirical studies have shown that the auxiliary of friendship links is less useful than trust links in boosting the recommendation performance. Furthermore, although it is generally believed trust or friendship are positively correlated with the level of common-taste of people, this study has shown that two users may not have similar rating tastes even they strongly trust each other. Thus, directly utilizing any given social connection may harm the recommendation performance.

**Disadvantages:**

- Active user's rate many items do not really possess similar rating patterns with their friends since active users does not necessary make friends based on interest sharing. It violates a common assumption in existing social recommendation works that friends share similar preferences. Consequently, this work concludes that explicit social networks are not always beneficial for recommendation

**Proposed System & alogirtham**

- We propose a general social recommender model applicable to the scenarios with or without an explicit social network, as shown in Figure Given an explicit binary social network, our model learns the strength of links from rating data to boost the quality of rating prediction. When the explicit social network is missing, our model learns jointly the existence and strength of social relationships from ratings. Different from most of the previous solutions for implicit social network that treats the learning of the social network and recommendation as two sequential but independent tasks, we propose a Variational Expectation Maximization (VEM) based solution that conducts the learning of social structure and rating prediction together.

**4.1 Advantages:**

- As will be shown in our experiments later on, efforts spent to determine a common parameter that can be effective in inferring implicit social networks across different datasets are usually futile, thus hinders the effectiveness of such models.
- Experiments show that the proposed solution outperforms the state-of-the-art models in both explicit and implicit scenarios.

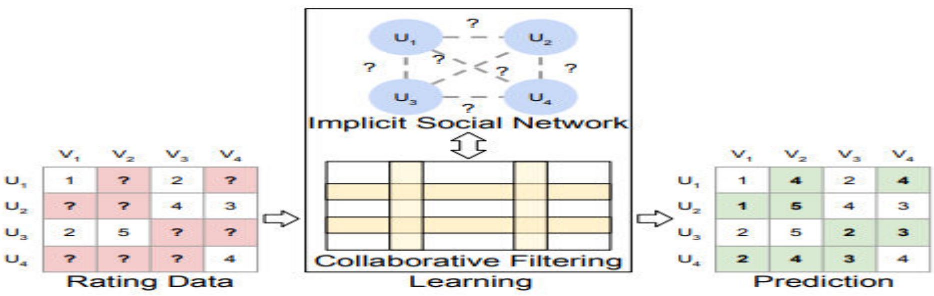



Fig1: SYSTEM ARCHITECTURE

## IMPLEMENTATION

We have implemented a prototype of AdSherlock. The offline pattern extractor is implemented in Python and runs on Ubuntu 14.04 equipped with a 3.30GHz quad-core CPU and 12GB memory. The online fraud detector is implemented within a simple Android application, targeting Android API level 19 and running on a Nexus 5 device equipped with 2.26 GHz quad-core and 2GB memory.

click frauds.

### 4.1 MODULES:

**Admin:**

Admin is main module of application that will check all registered user details of e commerce and OSN users and add products to online shopping site and check product purchase details and recommendation details.

**Online Social Network User:**

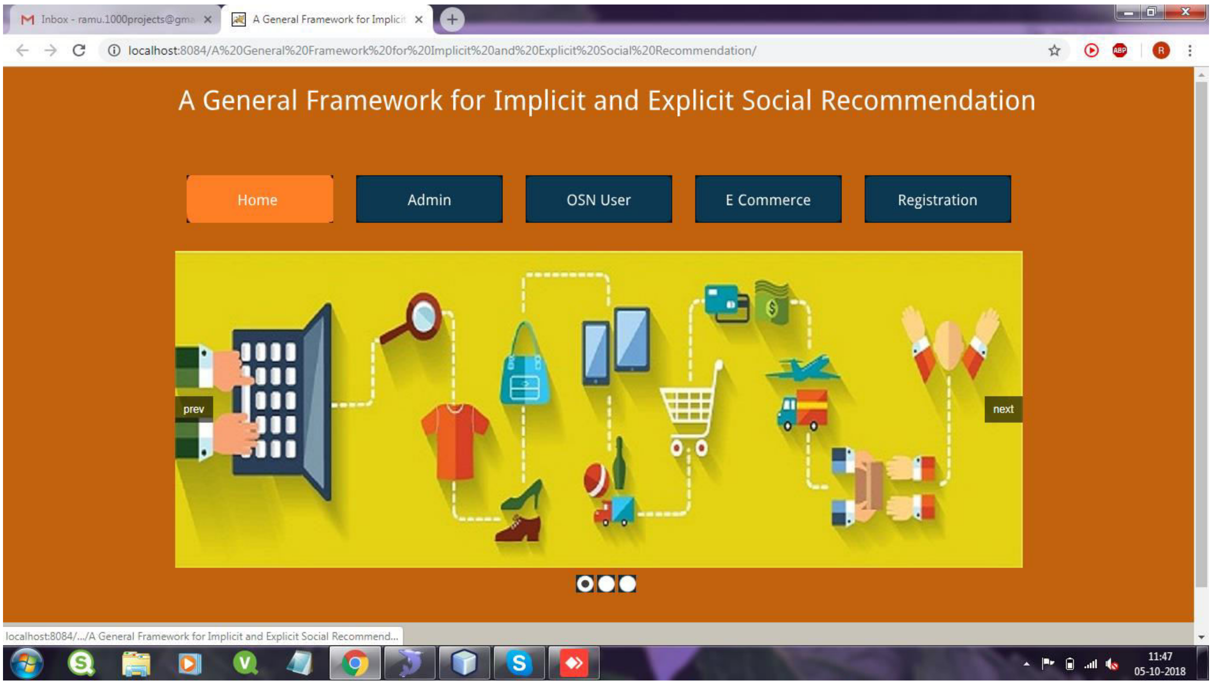
**OSN System Construction Module**

- 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.

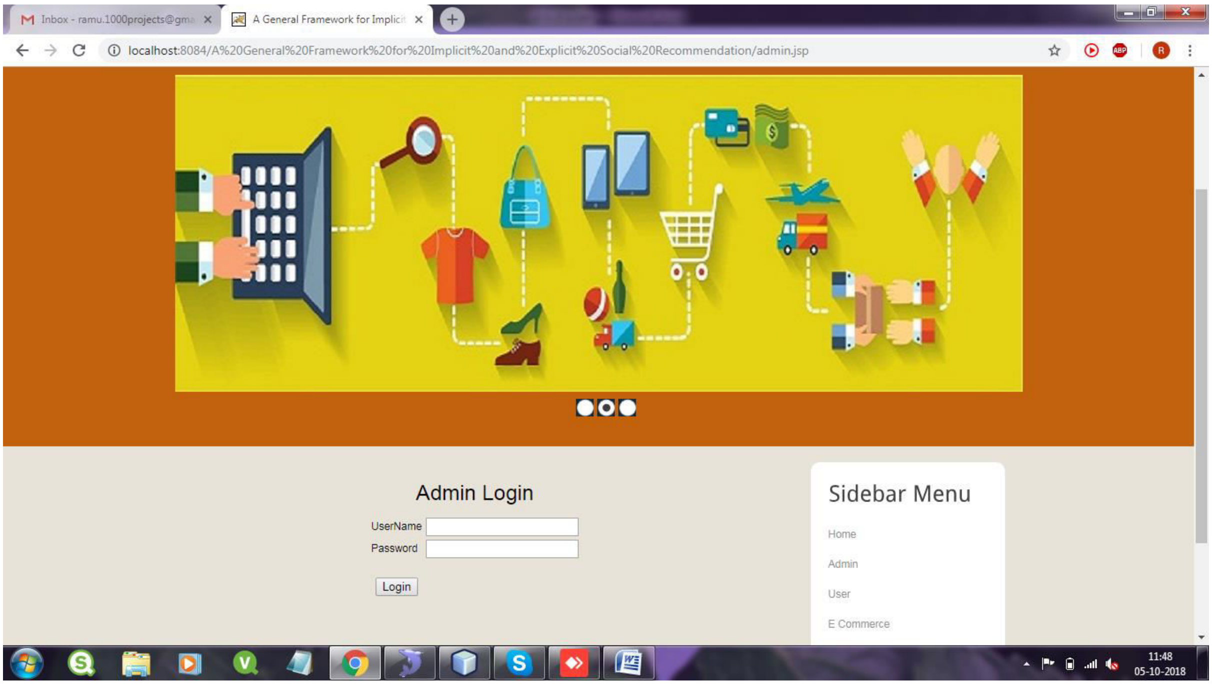
## 5 RESULTS AND DISCUSSION

## SCREENS SHOTS

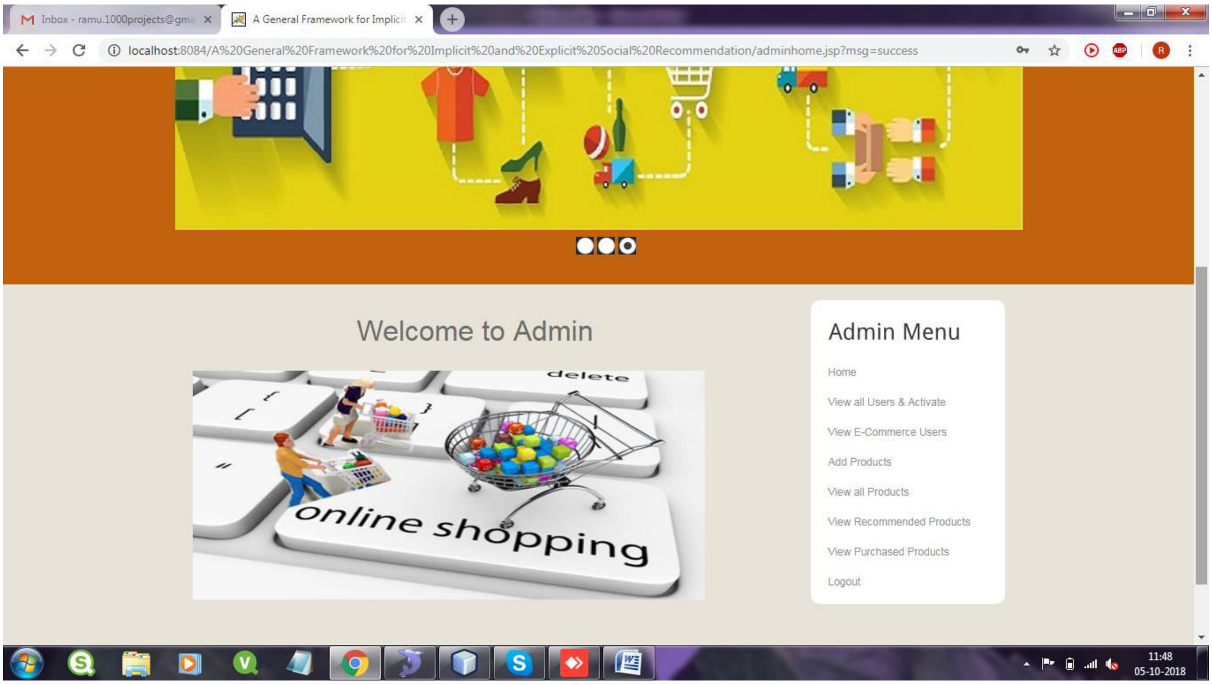
Home:



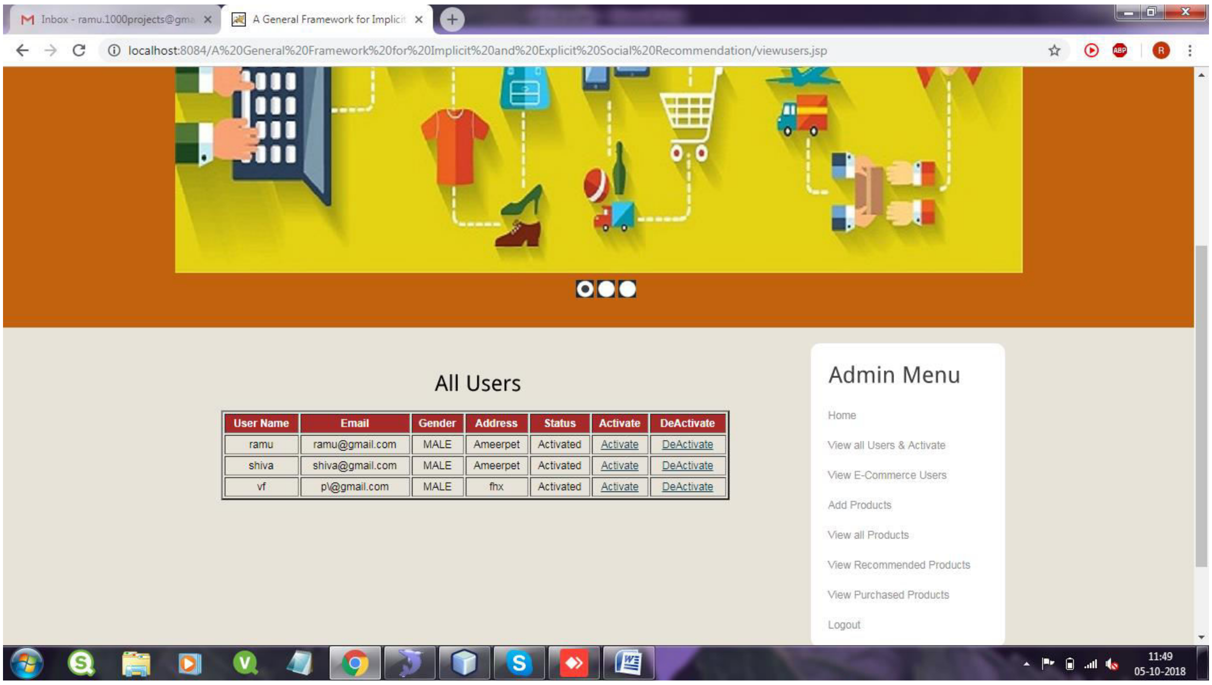

Admin Login:



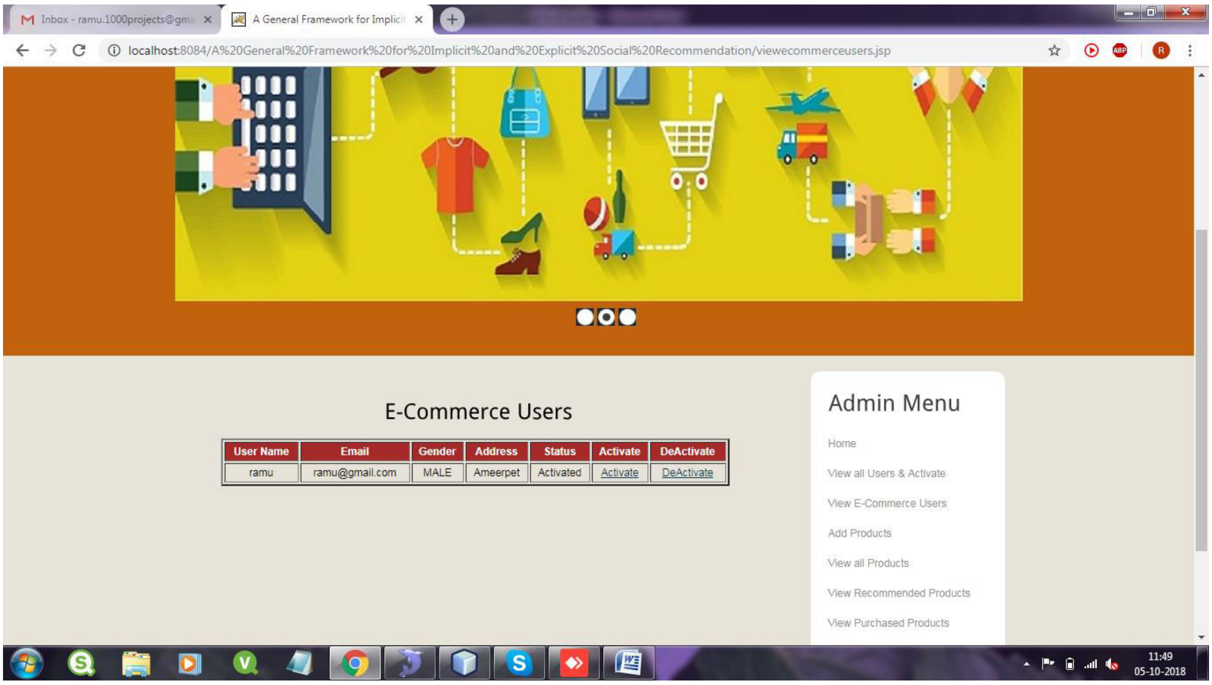

Admin Home:



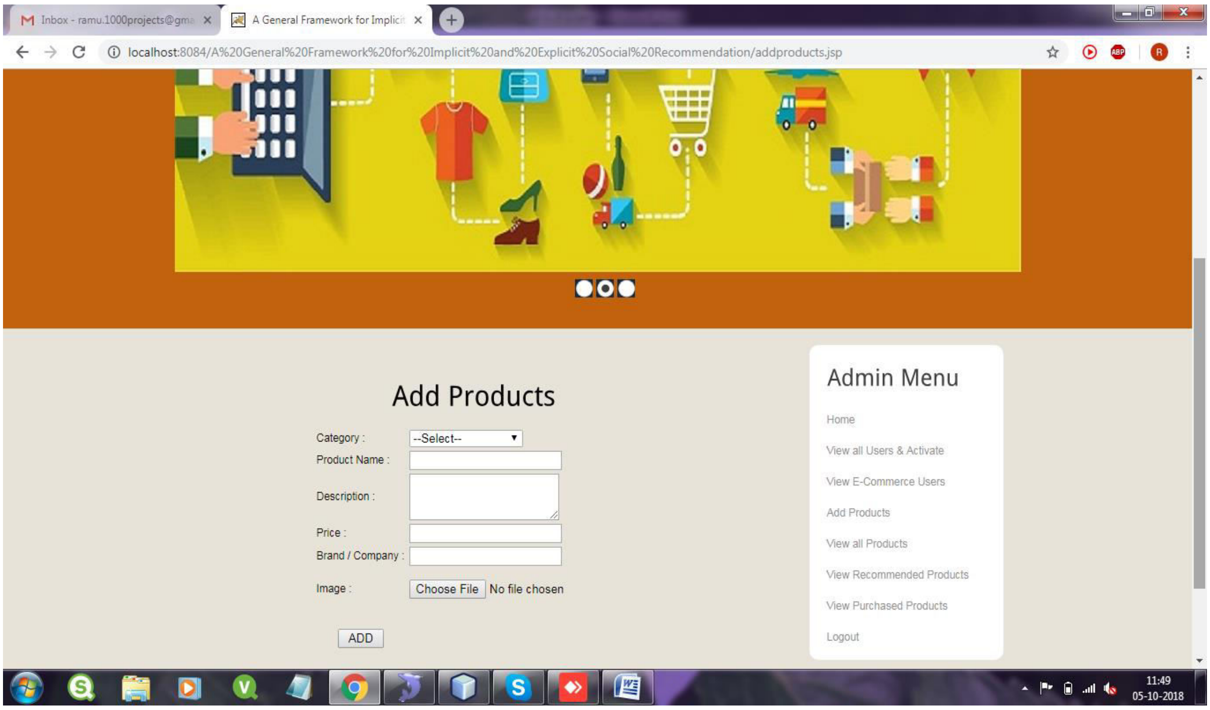

View Users:



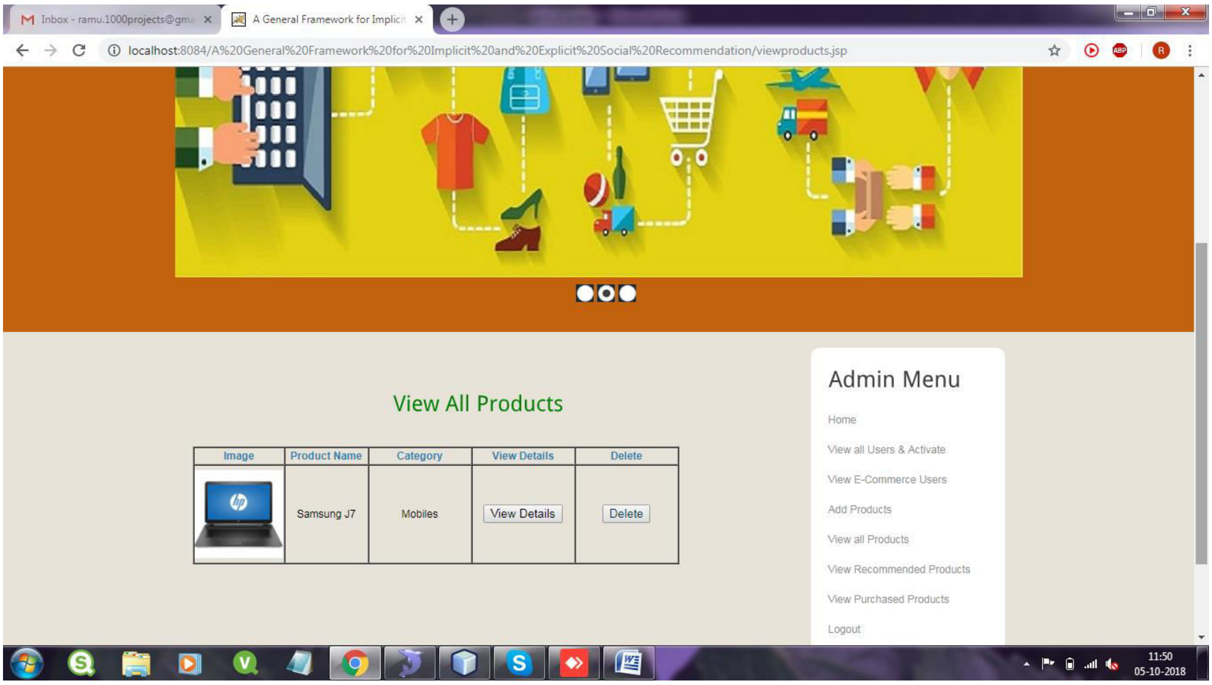

View Ecommerce Users:



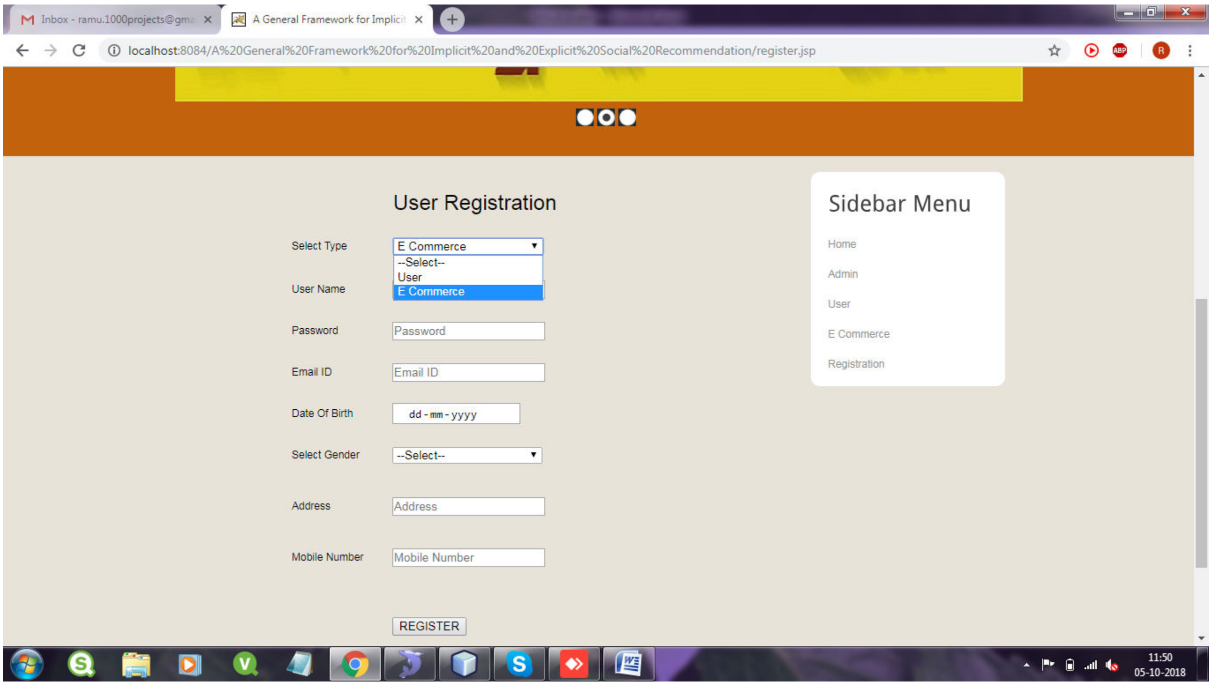

Add Products




View Products:




User Registration:



## CONCLUSION

Probabilistic matrix factorization has been a successful machine learning model toward recommender systems. Based on the social correlation intuition, we propose a new approach to incorporate social network information into probabilistic matrix factorization. We list our contributions again:

**Contribution 1**: In terms of effectiveness, we successfully build a joint model simultaneously to learn factorized matrices and social network structures. Experiments support that our new approach outperforms previous works that either focus on explicit social recommendation or implement implicit social recommendation in two separate stages.

**Contribution 2**: Distinct from learning a shared social strength, our work allows learning an individual social strength for each latent factor. We believe that the multi dimensional social strength learning can benefit the overall recommendation quality.

**Contribution 3**: In terms of efficiency, to address the scalability problem resulting from fully connected implicit social networks, we propose several practical tricks during the learning process so the complexity can be reduced from quadratic to linear.

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