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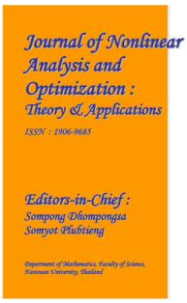

EXPLOITING THE DYNAMIC MUTUAL INFLUENCE FOR PREDICTING SOCIAL EVENT PARTICIPATION

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ABSTRACT

It is commonly seen that social events are organized through online social network services (SNSs), and thus there are vested interests in studying event-oriented social gathering through SNSs. The focus of existing studies has been put on the analysis of event profiles or individual participation records. While there is significant dynamic mutual influence among target users through their social connections, the impact of dynamic mutual influence on the people's social gathering remains unknown. To that end, in this paper, we develop a discriminant framework, which allows integrating the dynamic mutual dependence of potential event participants into the discrimination process. Specifically, we formulate the group-oriented event participation problem as a two-stage variant discriminant framework to capture the users' profiles as well as their latent social connections. The validation on real-world data sets show that our method can effectively predict the event participation with a significant margin compared with several state-of-the-art baselines. This validates the hypothesis that dynamic mutual influence could play an important role in the decision-making process of social event participation. Moreover, we propose the network pruning method to further improve the efficiency of our technical framework. Finally, we provide a case study to illustrate the application of our framework for event plan design task.

1 INTRODUCTION

The newly emerged event-driven social network services target at providing the opportunities for online people to gather together in offline events, which has become popular and attractive for millions of users all around the world. For instance, at Meetup.com, more than 10,000 events are organized every day, and RSVPs may even exceed 100 times per minute. This new business model imposes new challenges on social event analysis with considering social effects, and raises the difficulties for the event organizers to draw the event plan and predict the attendance.

Indeed, the “word-of-mouth” effects can strongly affect the social event participation. For instance, prior study has revealed that 10%-30% of human movement could be explained by social factors, even more evident on longranged travels [3] which indicate casual social gathering rather than periodical commutes. Since face-to-face communication is inevitable for offline social gatherings, people usually tend to stay with the familiars, which leads to more cohesive communities for event-driven social networks than the ordinary ones [20]. Definitely, these results will help to better understand the features of social events. However, statistical analysis may only result in rough estimation of global trend, but may not lead to accurate personalized profiling and prediction, and then fail to support the eventoriented applications. Thus, comprehensive modeling on social effects is still required for the social event analysis.

Literature Survey

Friendship and mobility: user movement in location-based social network

Even though human movement and mobility patterns have a high degree of freedom and variation, they also exhibit structural patterns due to geographic and social constraints. Using cell phone location data, as well as data from two online location-based social networks, we aim to understand what basic laws govern human motion and dynamics. We find that humans experience a combination of periodic movement that is geographically limited and seemingly random jumps correlated with their social networks. Short-ranged travel is periodic both spatially and temporally and not affected by the social network structure, while long-distance travel is more influenced by social network ties. We show that social relationships can explain about 10% to 30% of all human movement, while periodic behavior explains 50% to 70%. Based on our findings, we develop a model of human mobility that combines periodic short range movements with travel due to the social network structure. We show that our model reliably predicts the locations and dynamics of future human movement and gives an order of magnitude better performance than present models of human mobility

3 IMPLEMENTATION STUDY

EXISTING SYSTEM:

For the past several years, some researchers have considered the social effects as features or constraints in their studies, which can effectively improve the prediction results. For instance, treated the static social connections as constraint in PMF, and further proposed the two way constraints between social connection and production adoption.

Disadvantages:

- These researches are intuitive with following the basic idea of, i.e., users tend to befriend those who hold similar preference, and friends tend to act similarly due to similar preference. This phenomenon might be reasonable as long-term interactions gradually affect preference. However, in event-oriented social network, cyber strangers are connected only via short-term social events, and these connections evolve frequently, thus influence might not be persistent enough.
- To be specific, the effects of social interactions on individuals, as well as corresponding feedbacks are totally ignored. Thus, user behavior modeling based on dynamic mutual influence has not been fully exploited in the above studies.

Proposed System & alogirtham

The decision-making analysis of individual participation. Traditionally, social factors will be neglected, or at most treated as **static** constraint or feature, thus users could be analyzed individually. On the contrary

4.1 Advantages:

We can model the group-oriented decision-making process to capture users' preferences as well as their latent social connections. To the best of our knowledge, we are among the first ones to investigate the impact of dynamic mutual influence on social event participation.

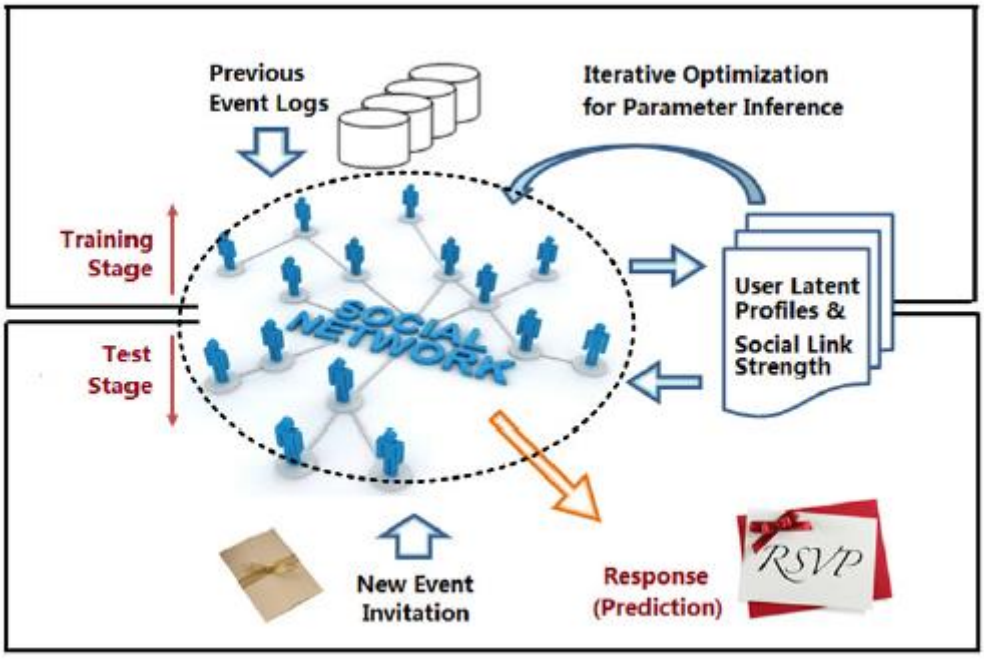


Fig:3.1 System Architecture

IMPLEMENTATION

Introduction of Technologies Used

Initially Java language was called as “oak” but it was renamed as “java” in 1995.The primary motivation of this language was the need for a platform-independent i.e. architecture neutral language that could be used to create software to be embedded in various consumer electronic devices.

Applications and applets

An application is a program that runs on our Computer under the operating system of that computer. It is more or less like one creating using C or C++ .Java’s ability to create Applets makes it important. An Applet I san application, designed to be transmitted over the Internet and executed by a Java-compatible web browser. An applet I actually a tiny Java program, dynamically downloaded across the network, just like an image. But the difference is, it is an intelligent program, not just a media file. It can be react to the user input and dynamically change.

5 RESULTS AND DISCUSSION

Home:

Fig: 9.1

Admin login:

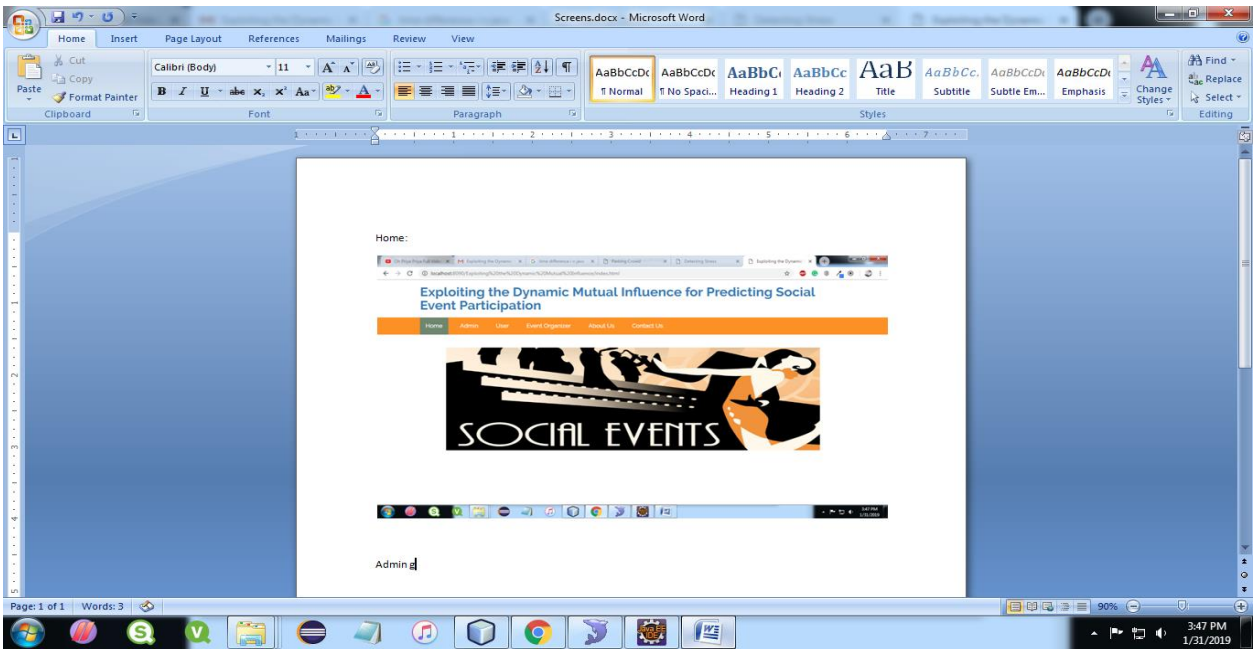


Fig: 9.2

Admin home:

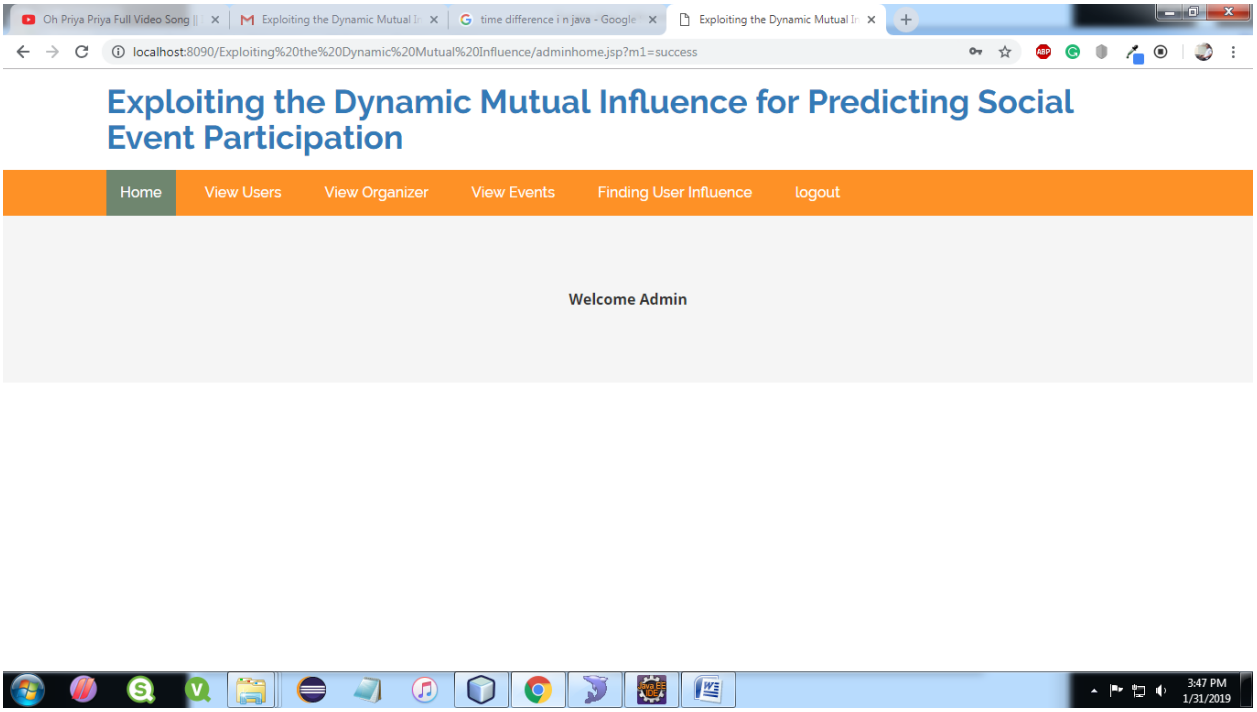


Fig: 9.3

View users:

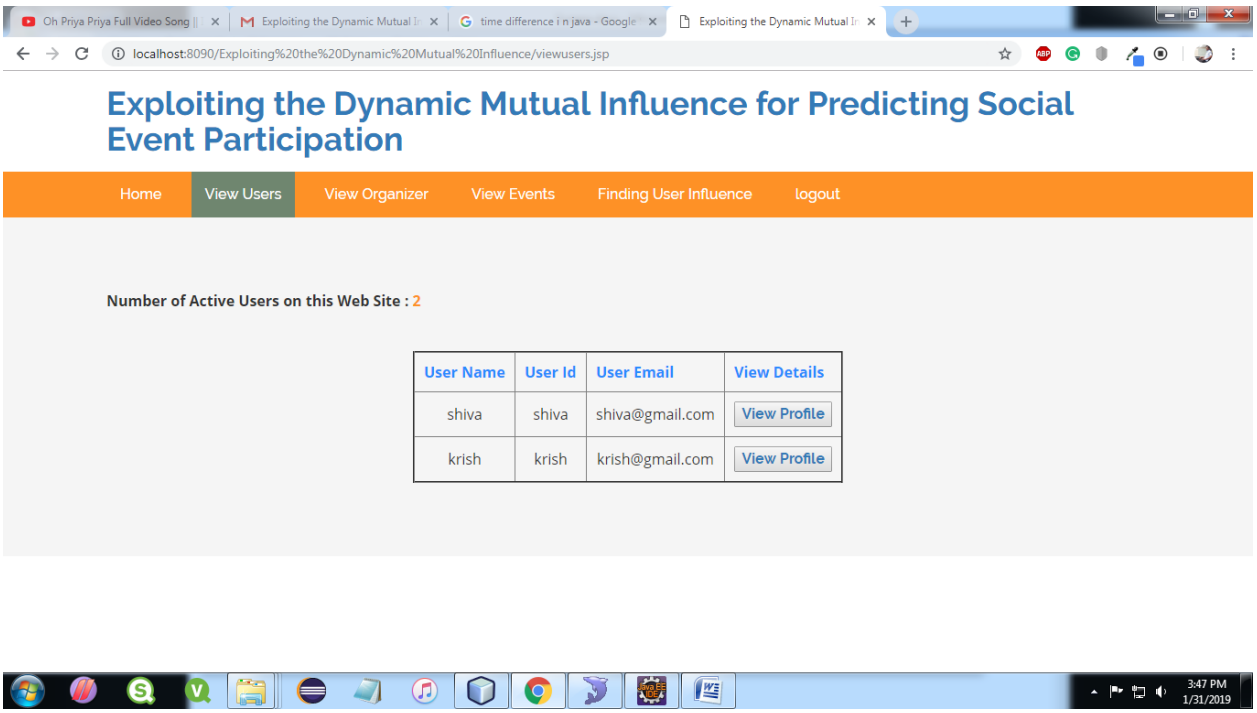


Fig: 9.4

View organizers:

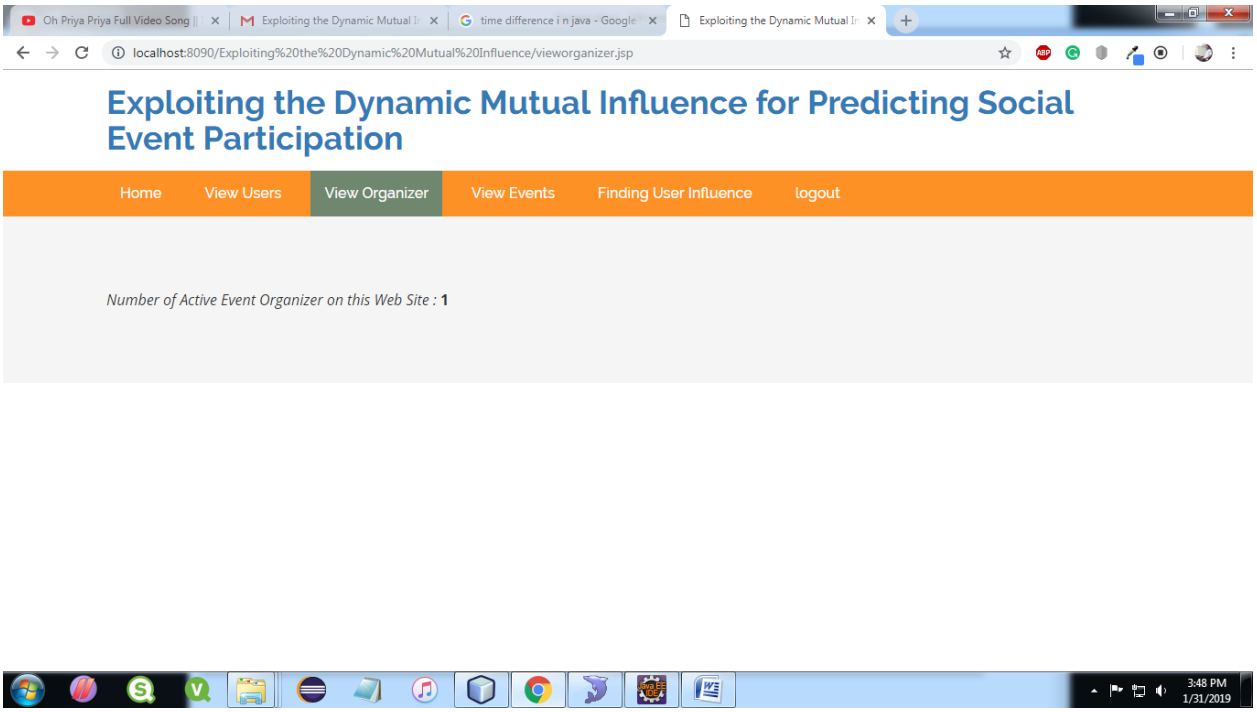


Fig: 9.5

View events:

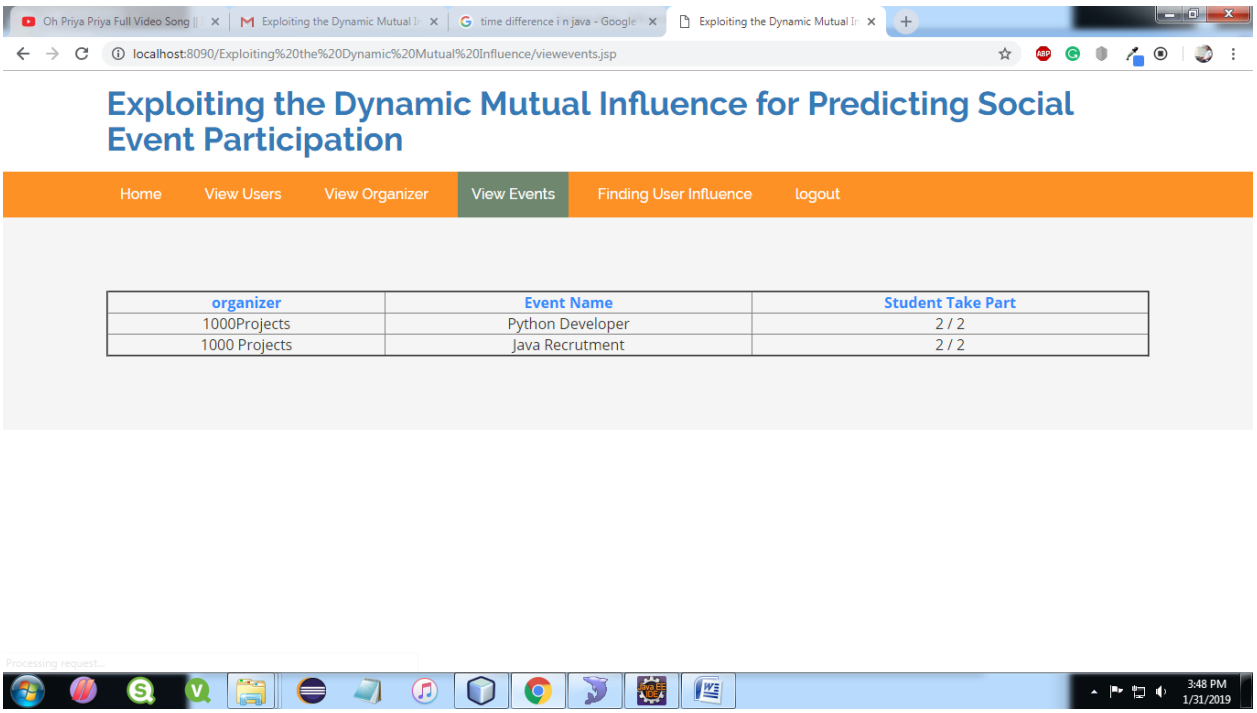
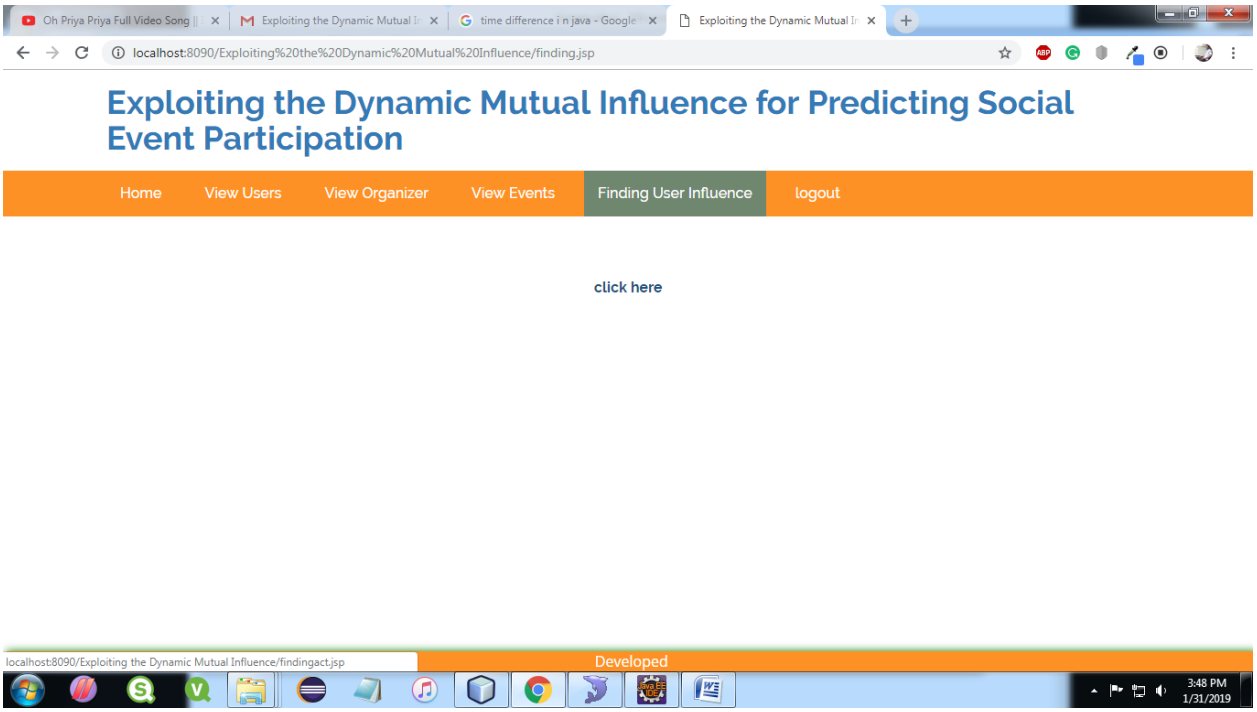


Fig: 9.6

Finding influence:



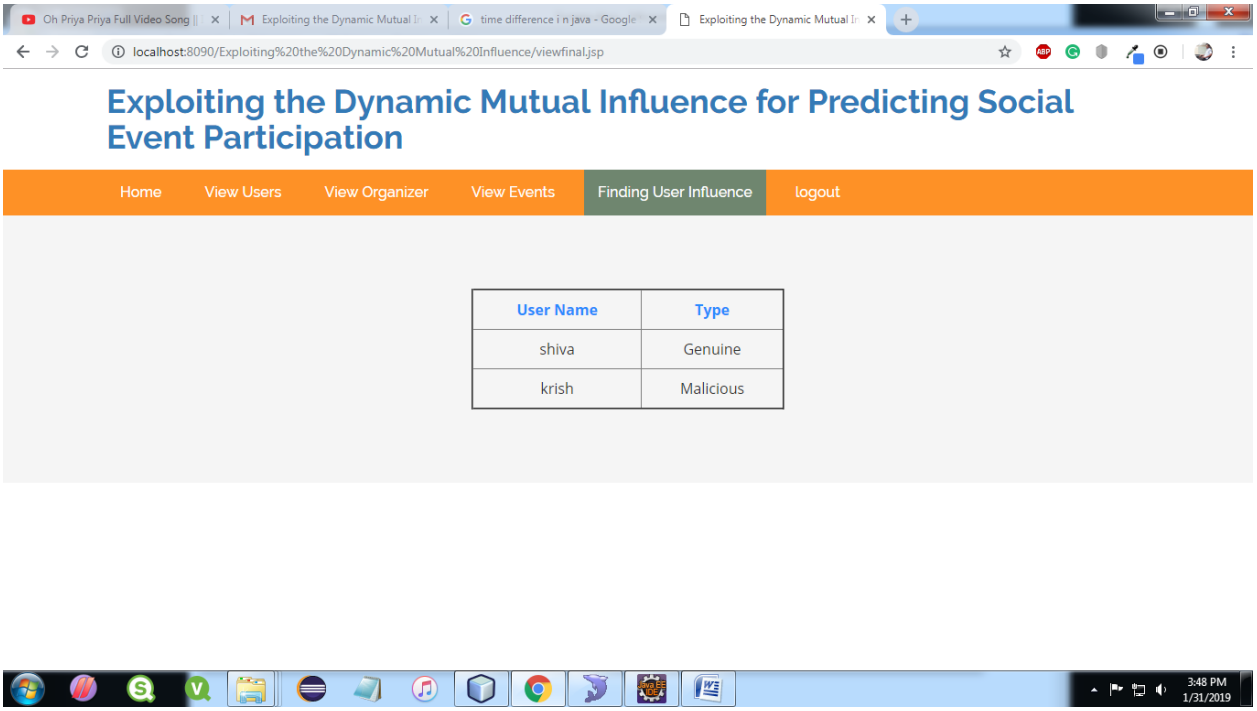


Fig: 9.7

User registration:

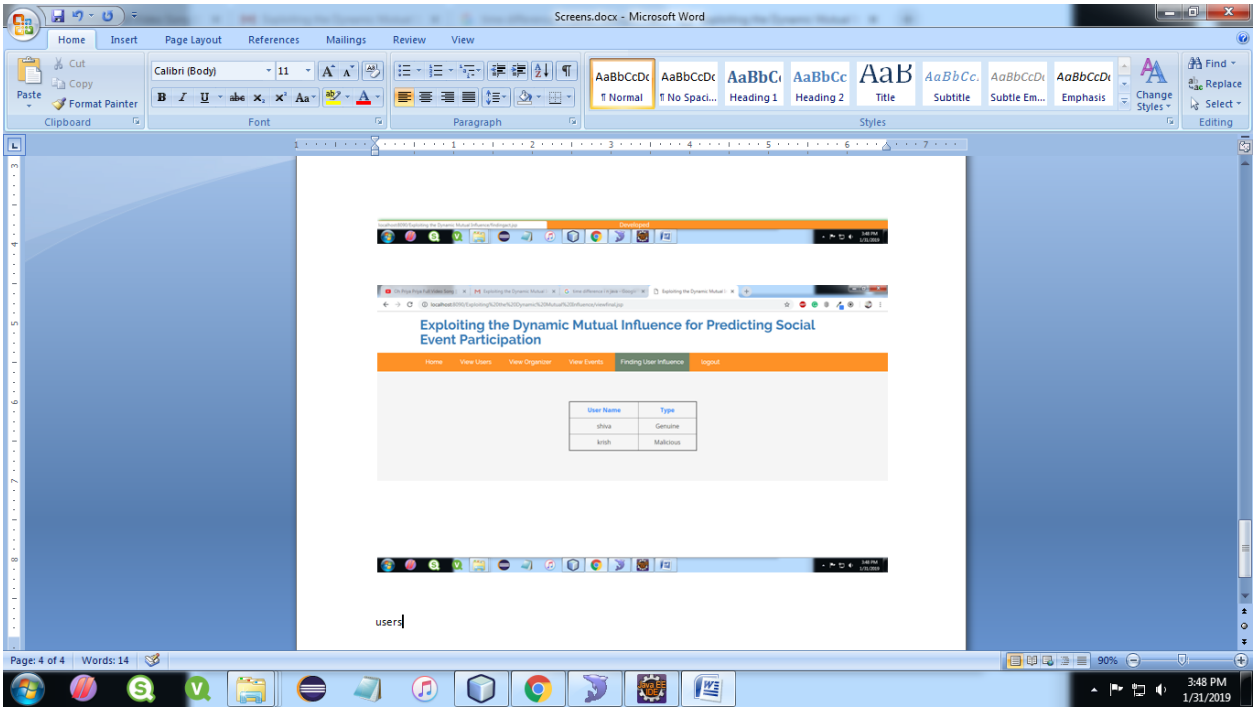


Fig: 9.8

User login:

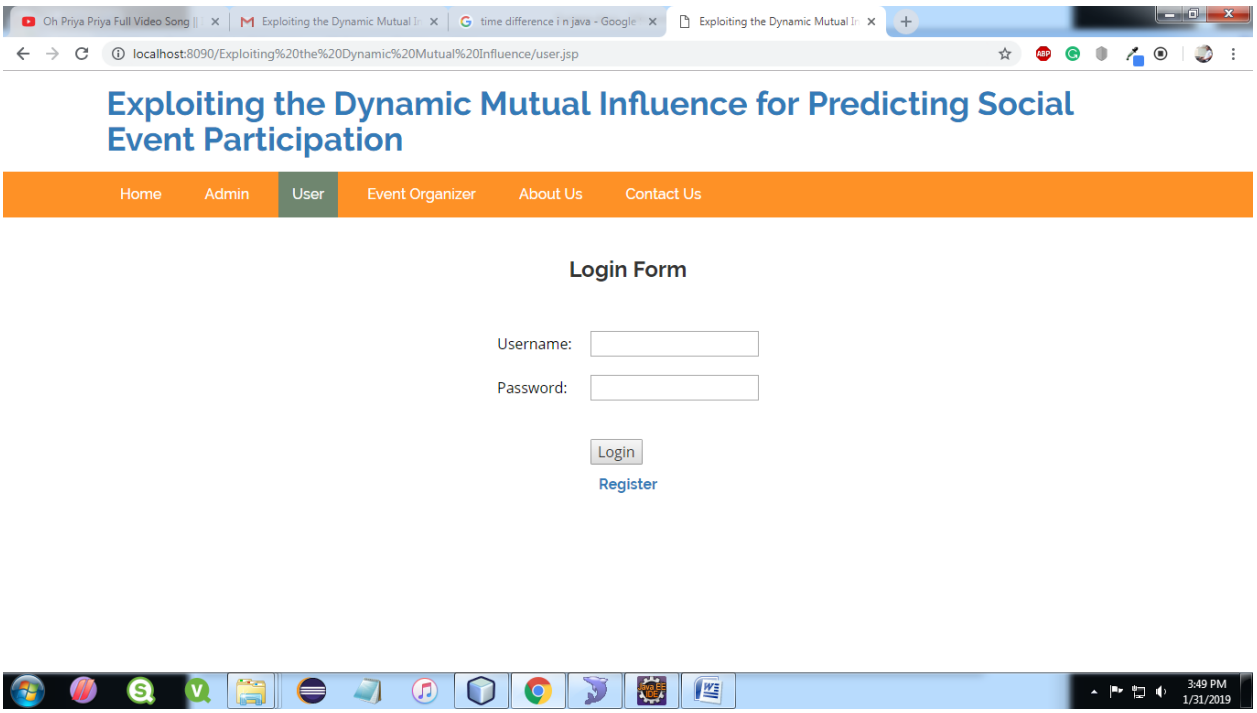


Fig: 9.9

User home:

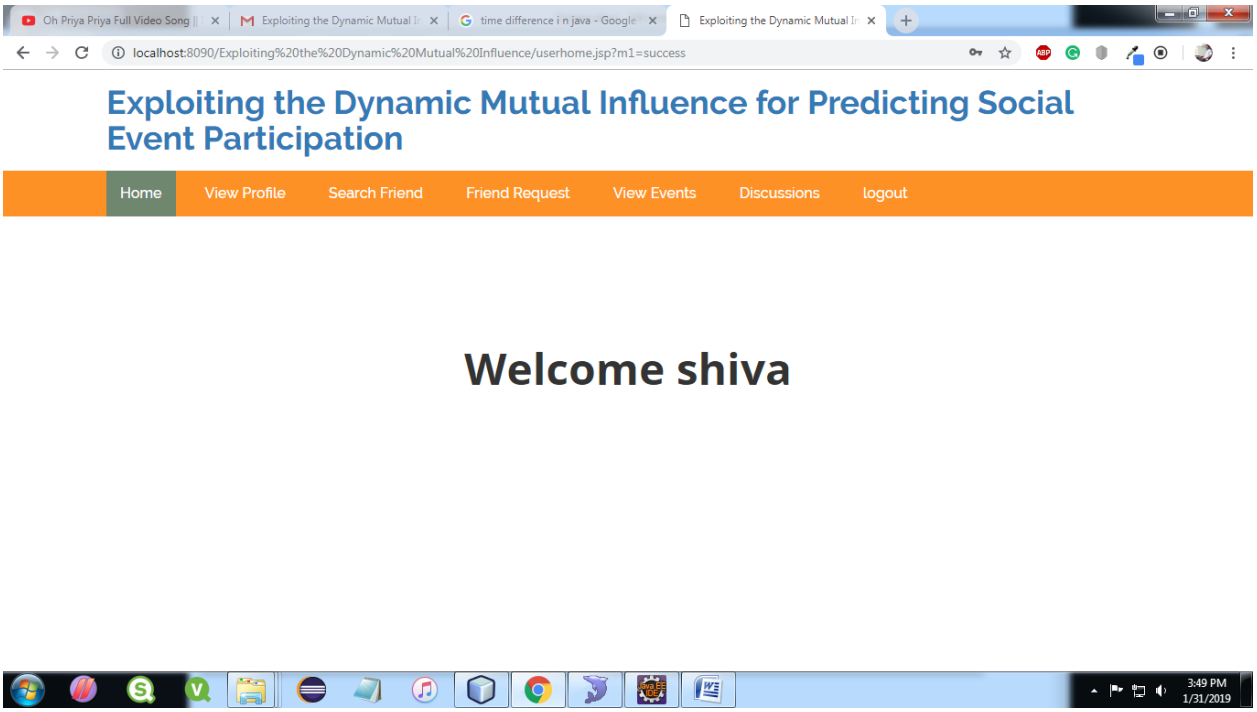


Fig: 9.10

View profile:

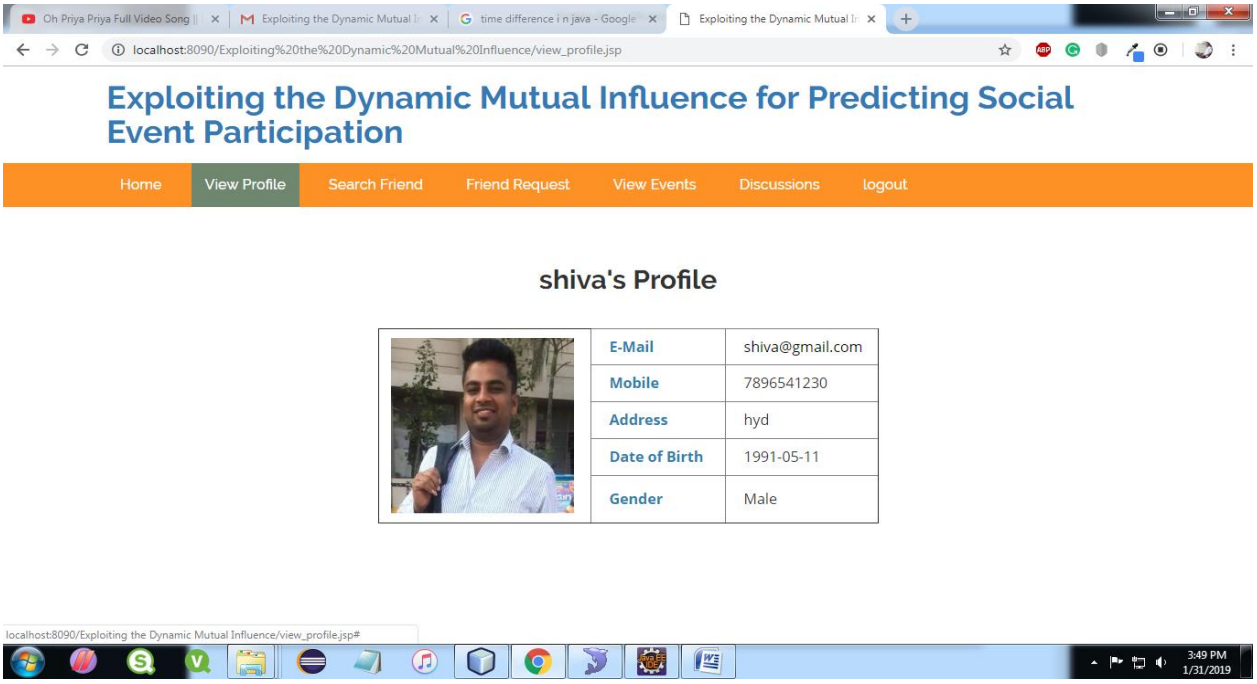
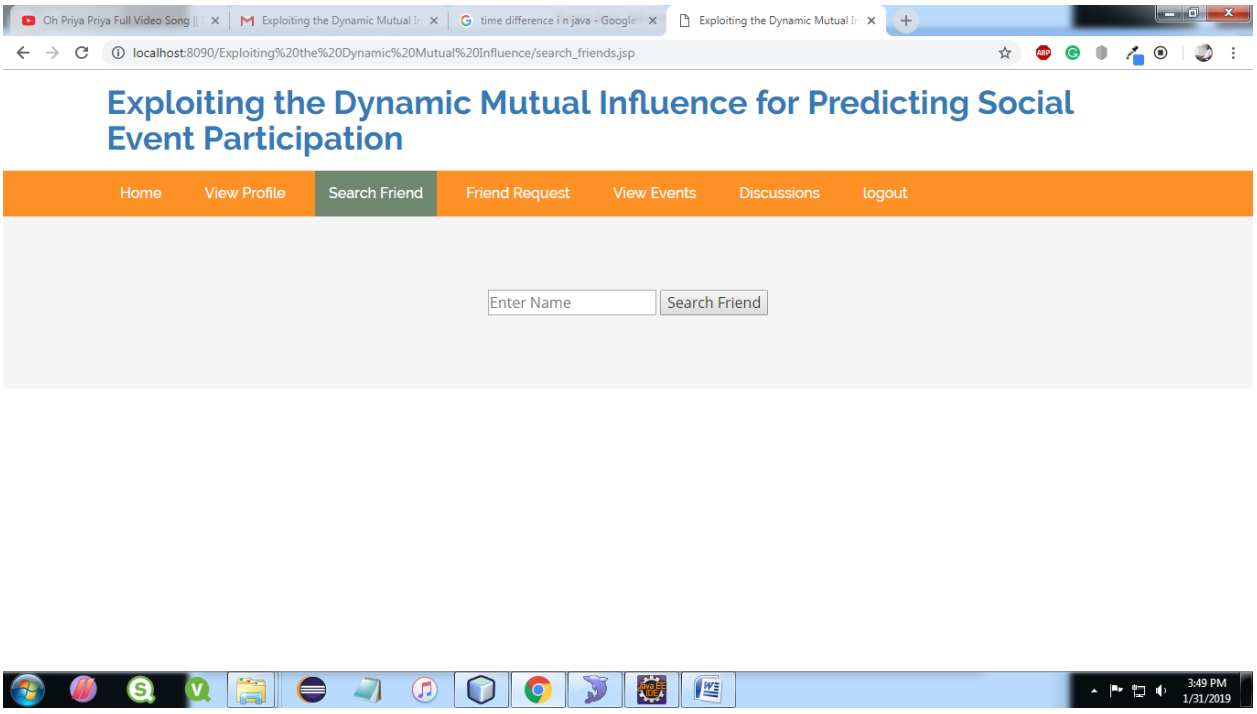


Fig: 9.11

Search friend:



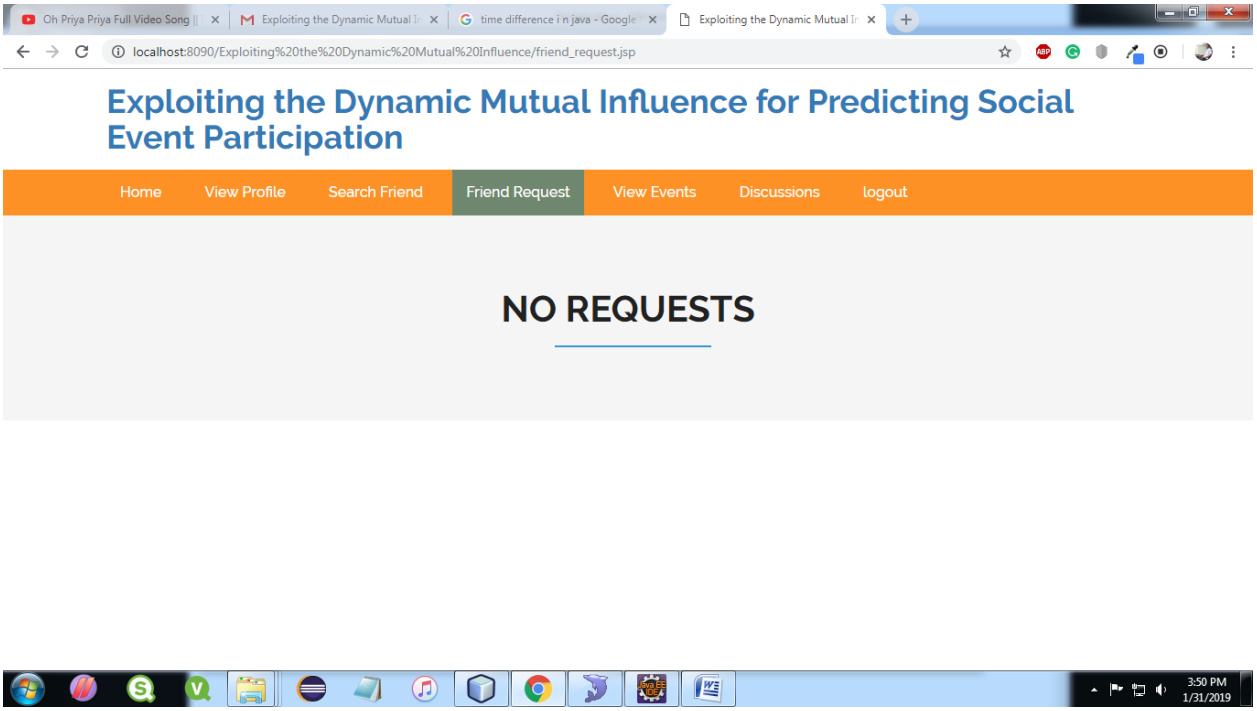


Fig: 9.12

View events:

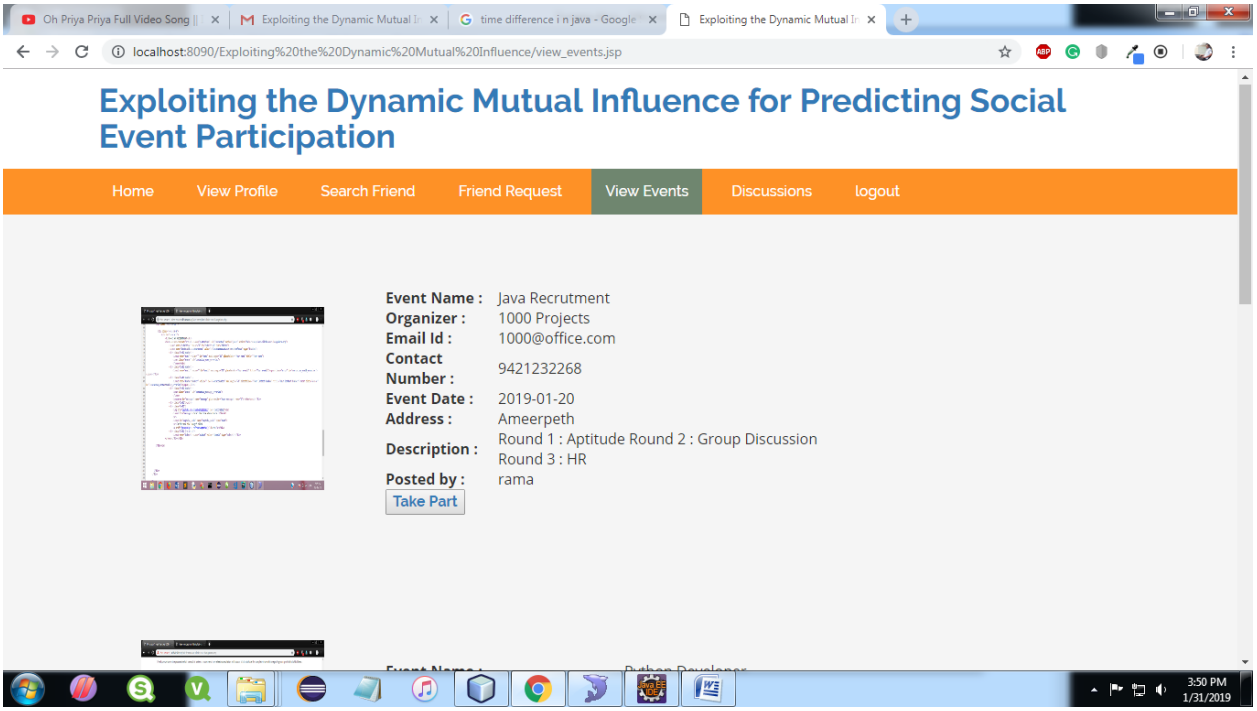


Fig: 9.13

Discussions:

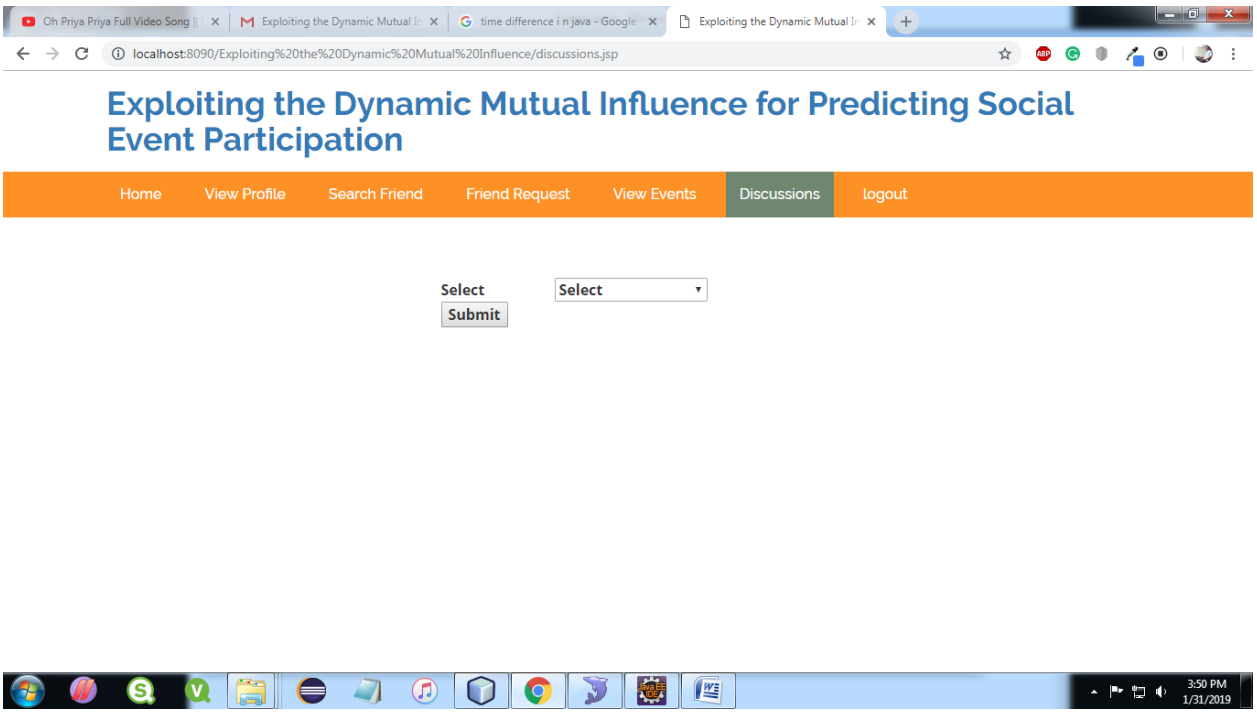


Fig: 9.14

Organizer registration:

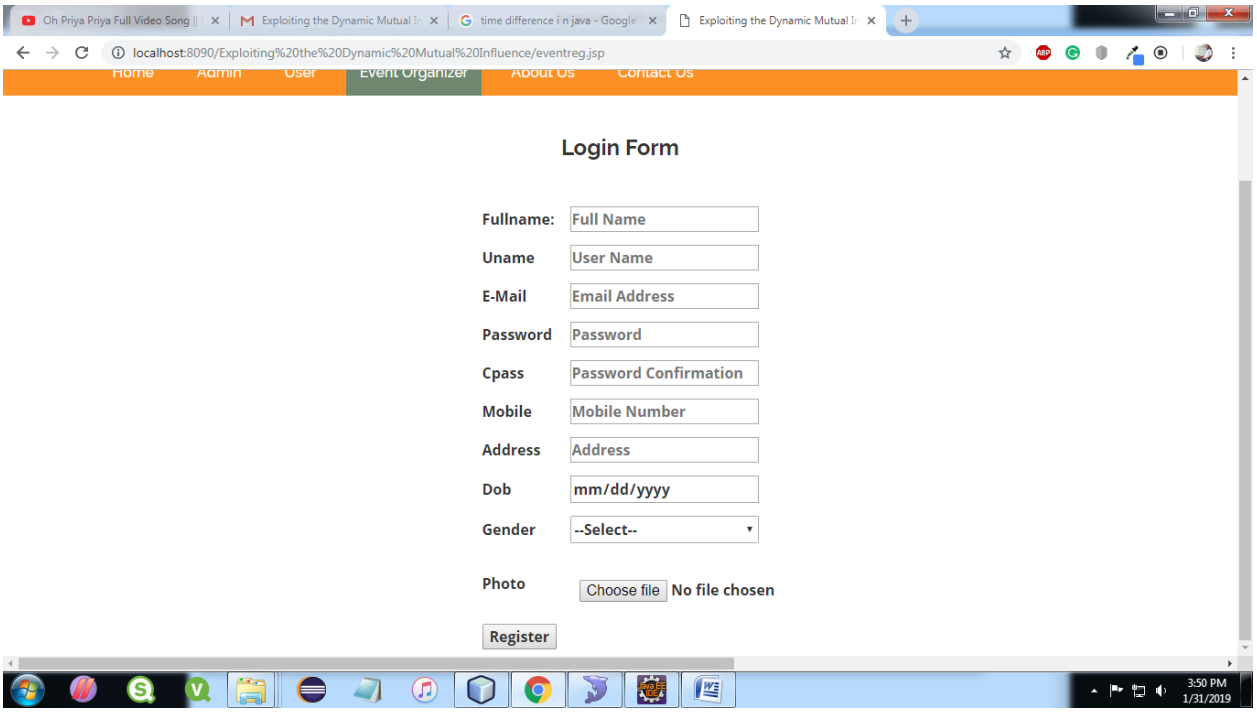


Fig: 9.15

Organizer login:

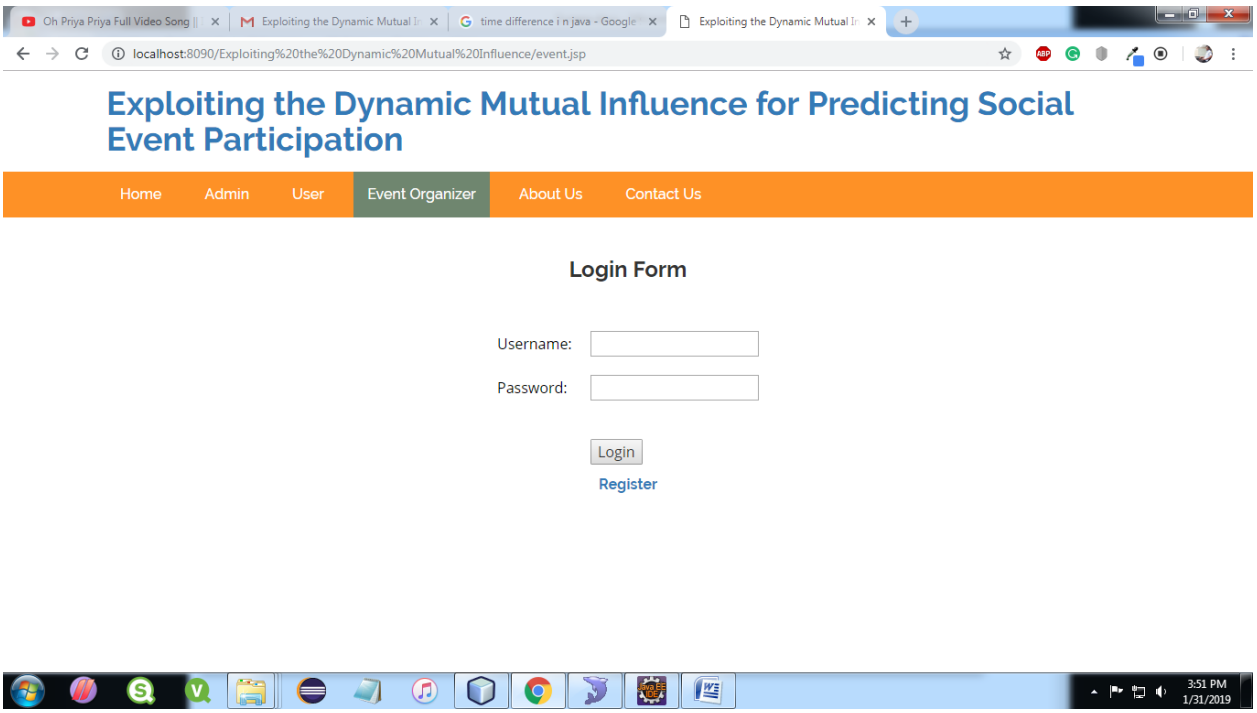


Fig: 9.16

Organizer home:

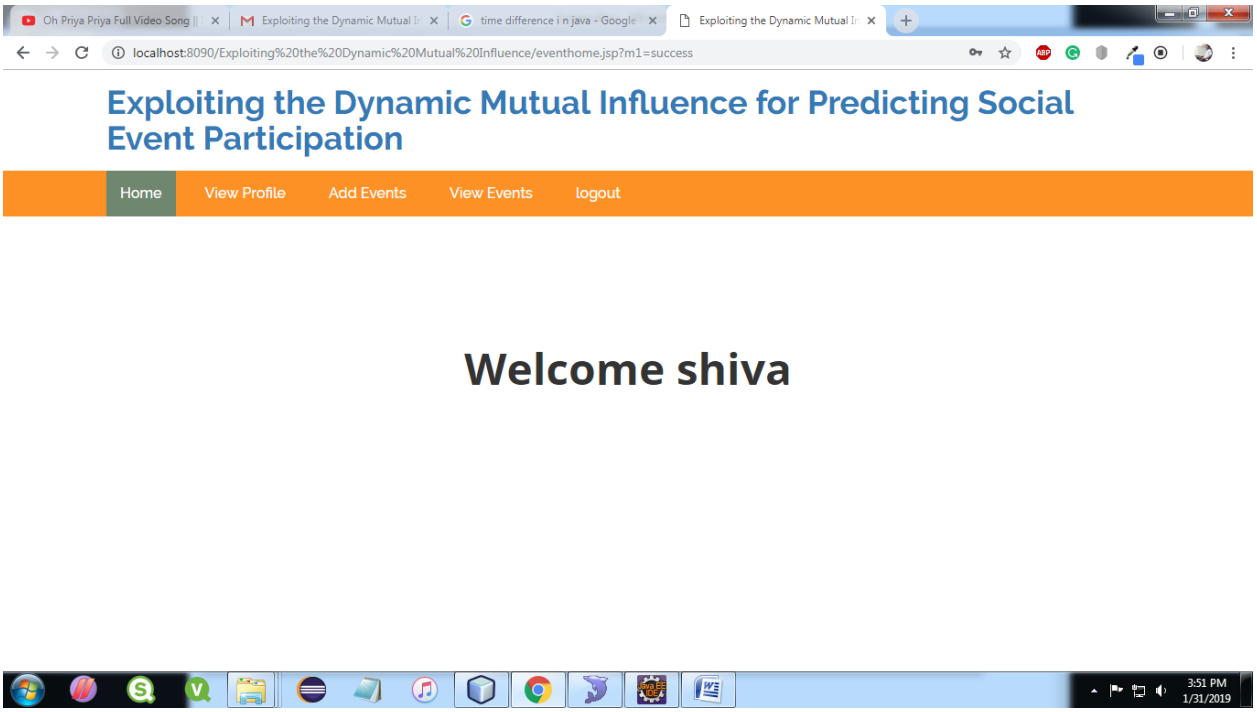


Fig: 9.17

View profile:

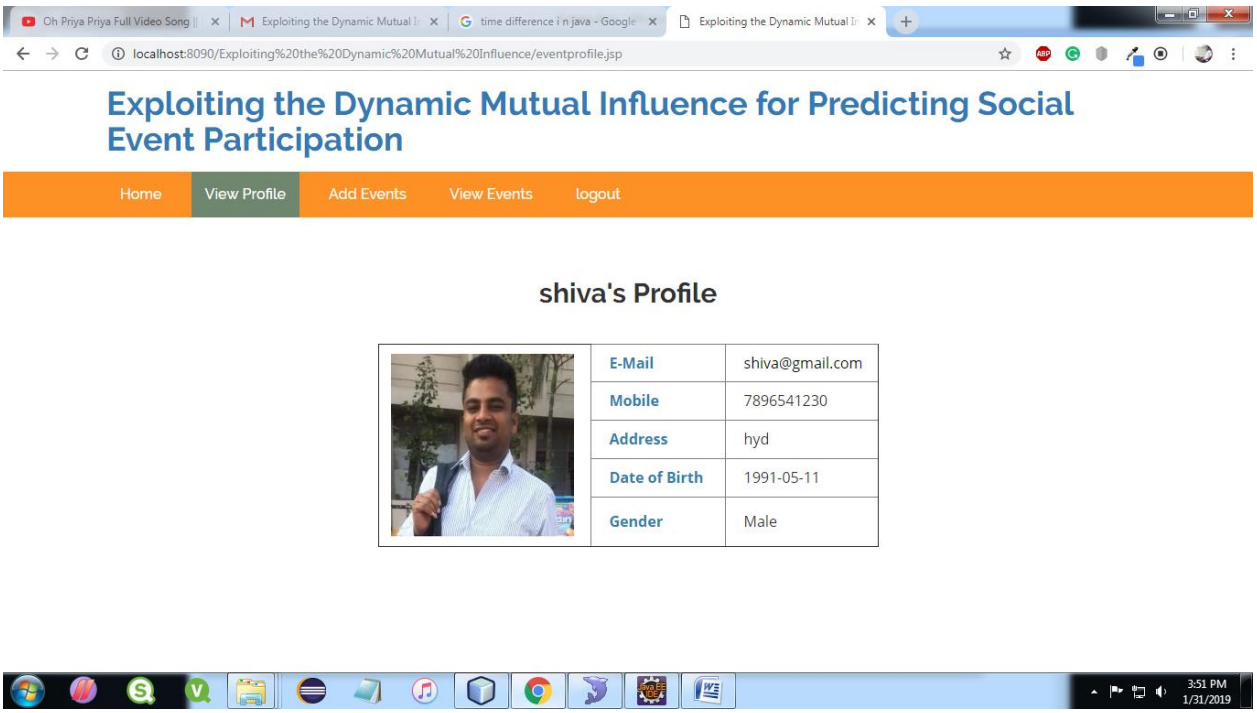


Fig: 9.18

Add events:

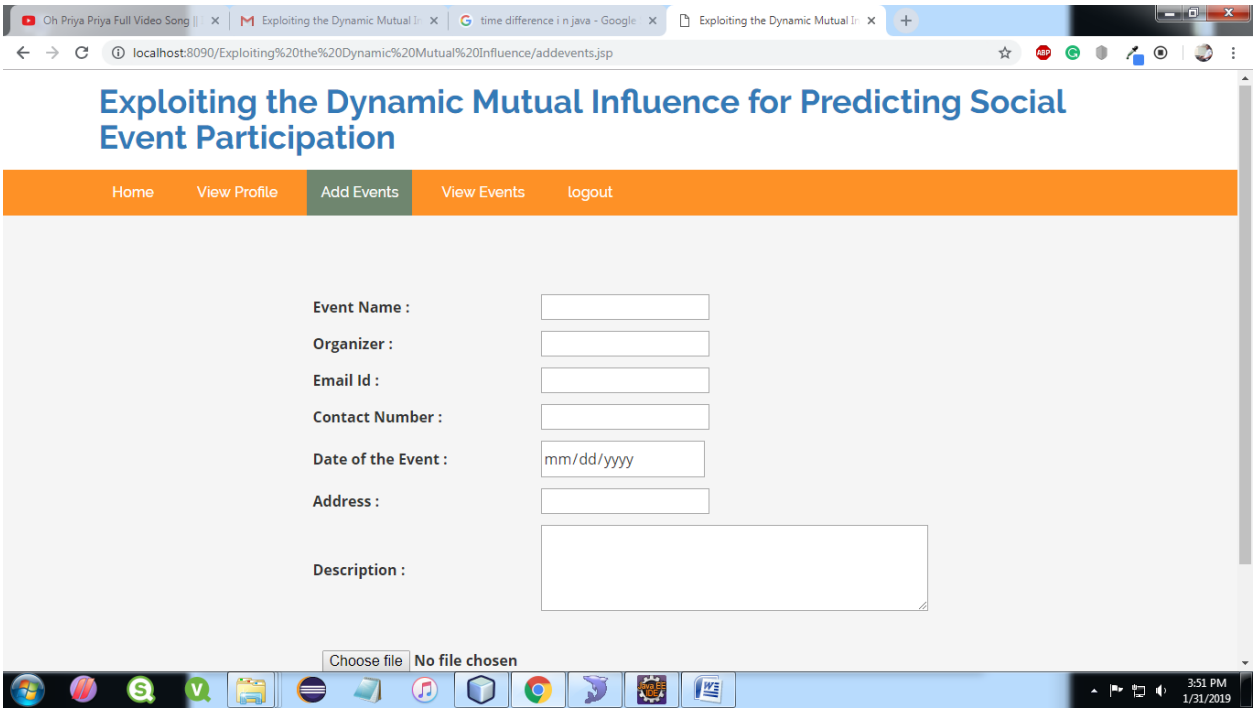


Fig: 9.19

View events:

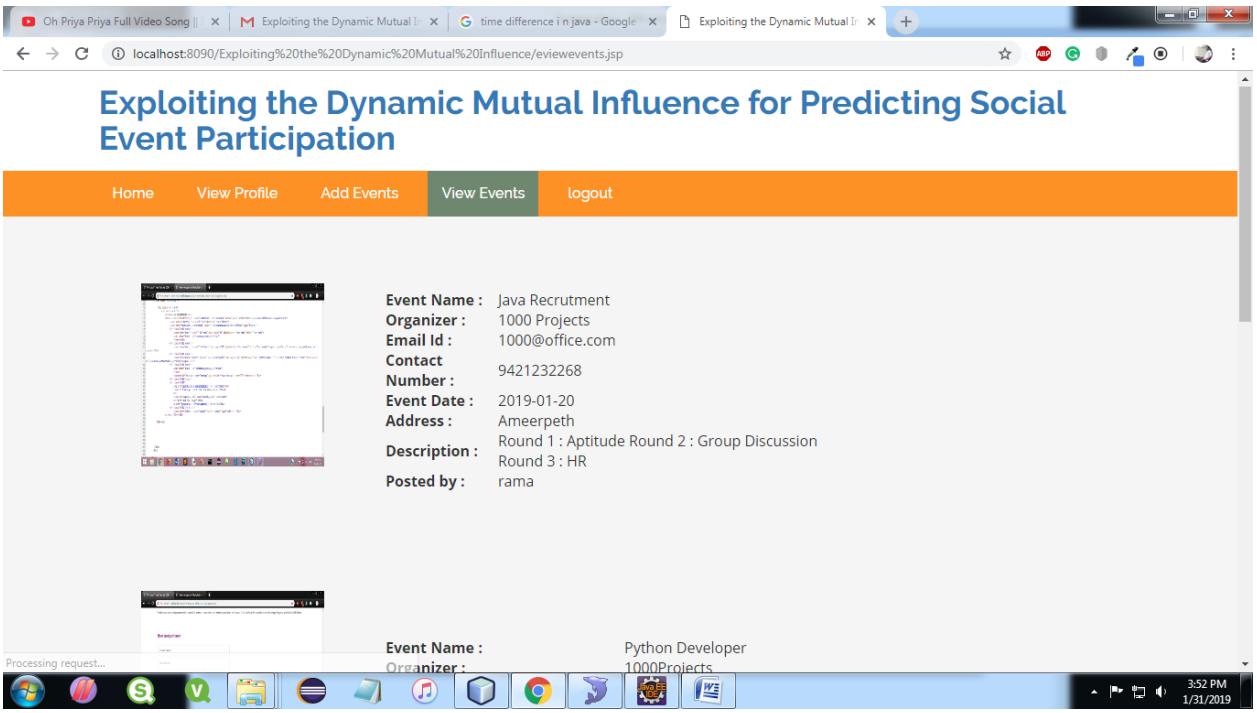


Fig: 9.20

6. CONCLUSION AND FUTURE WORK

CONCLUSION

In this paper, we investigated how to exploit the dynamic mutual influence for enhancing the prediction of social event participation. A unique characteristic of our method is that the social influence is integrated into the threshold calculation for the discriminant function, which reflects the dynamic mutual dependence within friends for event participation. Specifically, we designed a variant two-stage discriminant framework to capture both users' preferences and their latent social connections. General validations on the real-world offline event logs showed that our method could effectively predict the participation with a significant margin compared with several state-of-the-art baselines. Furthermore, validations on efficiency improvement with network pruning, as well as event design applications have been conducted. These results prove the importance of dynamic mutual influence which not only affects the user preferences, but also directly affects the decision-making process of event participation.

7. REFRENCES

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