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AN EFFICIENT CONTEXTUAL SERVICE RESOURCE FINDER

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Abstract:

Cloud computing has become the defector norm for businesses across the world. However the clients of a particular mobile service provider do not get all the desired services from the same providers itself. Using the capabilities of clouds to interconnect with each other the clouds interconnect with one another and get services for the clients. It is here recommendation systems come into the picture. So when a client requires a particular service, the recommendation engine searches the services available along with the costs included from the various cloud services providers and lists them. The proposed model lists them very fast and also takes the context into account. By context it gives filtering options to the users of the service in terms of cost, bandwidth, volume, time taken etc. depending upon the service consumed. Thus the proposed Mobi Context is a hybrid cloud-based Bi-Objective Recommendation Framework (BORF) for mobile social networks and is an effective and efficient framework model.

Introduction:

The ongoing rapid expansion of the Internet and easy availability of numerous e-commerce and social networks services, such as Amazon, Foursquare, and Gowalla, have resulted in the sheer volume of data collected by the service providers on daily basis. The continuous accumulation of massive volumes of data has shifted the focus of research community from the basic information retrieval problem to the filtering of pertinent information, thereby making it more relevant and personalized to user's query. Therefore, most research is now directed towards the designing of more intelligent and autonomous information retrieval systems, known as Recommendation Systems. Recommendation systems are increasingly emerging as an integral component of e-business applications. For instance, the integrated recommendation system of Amazon provides customers with personalized recommendations for various items of interest. Recommendation systems utilize various knowledge discovery techniques on a user's historical data and current context to recommend products and services that best match the user's preferences. In recent years, emergence of numerous mobile social networking services, such as, Face book and Google Latitude has significantly gained the attraction of a large number of subscribers. A mobile social networking service allows a user to perform a "check-in" that is a small feedback about the place visited by the user.

Large number of check-ins on daily bases results in the accumulation of massive volumes of data. Based on the data stored by such services, several Venue-based Recommendation Systems (VRS) were developed. Such systems are designed to perform recommendation of venues to users that most closely match with users' preferences. Despite having very promising features, the VRS suffer with numerous limitations and challenges. A major research challenge for such systems is to process data at the real-time and extract preferred venues from a massively huge and diverse dataset of users' historical check-ins. Further complexity to the problem is added by also taking into the account the real time contextual information, such as: (a) venue selection based on user's personal preferences and (b) venue closeness based on geographic information.

CF-based recommendation systems: Cold start. The cold start problem occurs when are commendation system has to suggest venues to the user that is newer to the system. Insufficient check is for the new user results in zero similarity value that degrades the performance of the recommendation system. The only way for the system to provide recommendation in such scenario is to wait for sufficient check-ins by the user at different venues. Data sparseness. Many existing recommendation systems suffer from data sparseness problem that occurs when users have visited only a limited number of venues. This results into a sparsely filled user-to venue check-in matrix. The sparseness of such matrix creates difficulty in finding sufficient reliable similar users to generate good quality recommendation. Scalability. Majority of traditional recommendation systems suffer from scalability issues. The fast and dynamic expansion of number of users causes recommender system to parse millions of check-in records to find the set of similar users. Some of the recommendation systems employ data mining and machine learning techniques to reduce the dataset size. However, there is an inherent tradeoff between reduced dataset size and recommendation quality.

Mobi Context, a hybrid cloud based Bi-Objective Recommendation Framework (BORF) that overcomes the limitations exhibited by traditional CF-based approaches. The Mobi Context framework combines memory-based and model-based approach of CF in a hybrid architecture to generate optimal recommendations for the current user. The memory based CF model utilizes a user's historical data and user to-venue closeness to predict venues for the current user. To address data sparseness caused by zero similarities, we utilize a metric known as confidence measure.

Modules Description:

- ✓ User Registration
- ✓ Service Request
- ✓ Borf Recommendation
- ✓ Results

User Registration: Use non-cryptographic credential OSN provider obtains the assertion veracity score for a user assertion. It can issue a web-based relaxed credential for this assertion. A credential issued by an OSN will include the assertion type and assertion score. The BORF model classifies mines and enriches information embedded in on-line social networks to provide lightweight and flexible digital credentials of the identity assertions The Administrator is treated as a super user in this system. He can have all the privileges to do anything in this system. He is the person who received the Profile of a User registration. He can able to see details of the Registered Member, Uploaded images and maintain history. Authentication is nothing but providing security to the system. Here every must enter into the system throw login page. The login page will restrict the unauthorized users. A user must provide his credential like user Id and password for log into the system. For that the system maintains data for all users. Whenever a user enters his user id and password, it checks in the database for user existence. If the user is exists he can be treated as a valid user. Otherwise the request will be thrown back.

Service Request: This credential, the user must have posted an age assertion on his profile. User sends question request to his experts. Then requested expert sends the confirmation of his assertion before he attempts to access the restricted content. We also assume that a user selects as friends user that will not try to harm him by send his honest assertion as false. The user information is protecting the privacy of their identity and the list of online user that verify its user's credentials. This verification is used to avoid the lower ratings. They able to share answers from experts. But they can create their personal profile information and other details.

Borf Recommendation: The common element among trust inference methods is that trust flows from a few select trust seed users (trusted seeds) and propagates to the other users in the trust graph. A seed is a highly trusted user, e.g., a trusted employee of the camp service provider that also verifies and tags assertions of many of his acquaintances. The specifics of the trust inference method determine how trust propagates in the graph. The trust inference scheme should assign high trust to users that are well-connected with the trusted seeds and vote similarly to them. It should also assign lower trust to dishonest users that happen to be well-connected but vote dissimilarly to the trusted seeds. Finally, it should assign low trust to Sybil users that are often connected only to their dishonest creator users. What renders a trust inference method Sybil-resilient is the bottleneck property, which we define as follows: "the trust that flows to the region of the graph that consists of dishonest users and their Sybils is limited by the edges connecting the dishonest region with the region that consists of trusted seeds and honest users." Thus expert users are rated better than the ones who simply delegate the tasks.

Results: The HA inference model is applied on users' profiles to compute ranking for users and venues. The higher ranked venues and users are known as popular venues and expert users, respectively. The framework maintains region-wise user-to-venue check-in matrix span that is utilized to compute popularity ranking scores for users and venues. Let represent score matrices for a popular venue and an expert user, respectively, for a region R. The following formulas compute the score for popular venues and expert users. The similarity between two experts is calculated only those venues that are visited by both the users. The similarity calculation in (5) results into a very sparse similarity graph because, majority of the venues are not visited by either of the two users. To address the data sparseness problem, we augment the similarity computation with the confidence measure. The confidence measure can be interpreted as a conditional probability that a venue visited by a one user is also visited by the other user in the dataset.

Existing System:

In recent years, recommendation systems have seen significant evolution in the field of knowledge engineering. Most of the existing recommendation systems based their models on collaborative filtering approaches that make them simple to implement. However, performance of most of the existing collaborative filtering-based recommendation system suffers due to the challenges, such as: (a) cold start, (b) data sparseness, and (c) scalability. Moreover, recommendation problem is often characterized by the presence of many conflicting objectives or decision variables, such as users' preferences and venue closeness.

Disadvantages:

- ✓ **Cold Start:** The cold start problem occurs when a recommendation system has to suggest venues to the user that is newer to the system.
- ✓ **Data Sparseness:**_Many existing recommendation systems suffer from data sparseness problem that occurs when users have visited only a limited number of venues.

Proposed System:

We propose a cloud-based framework consisting of bi-objective optimization methods named as CF-BORF and greedy-BORF. The Genetic Algorithm based BORF (GA-

BORF) utilizes Non-dominated Sorting Genetic Algorithm (NSGA-II) to optimize the venue recommendation problem. We introduce a pre-processing phase that performs data refinement using HA.

Advantages:

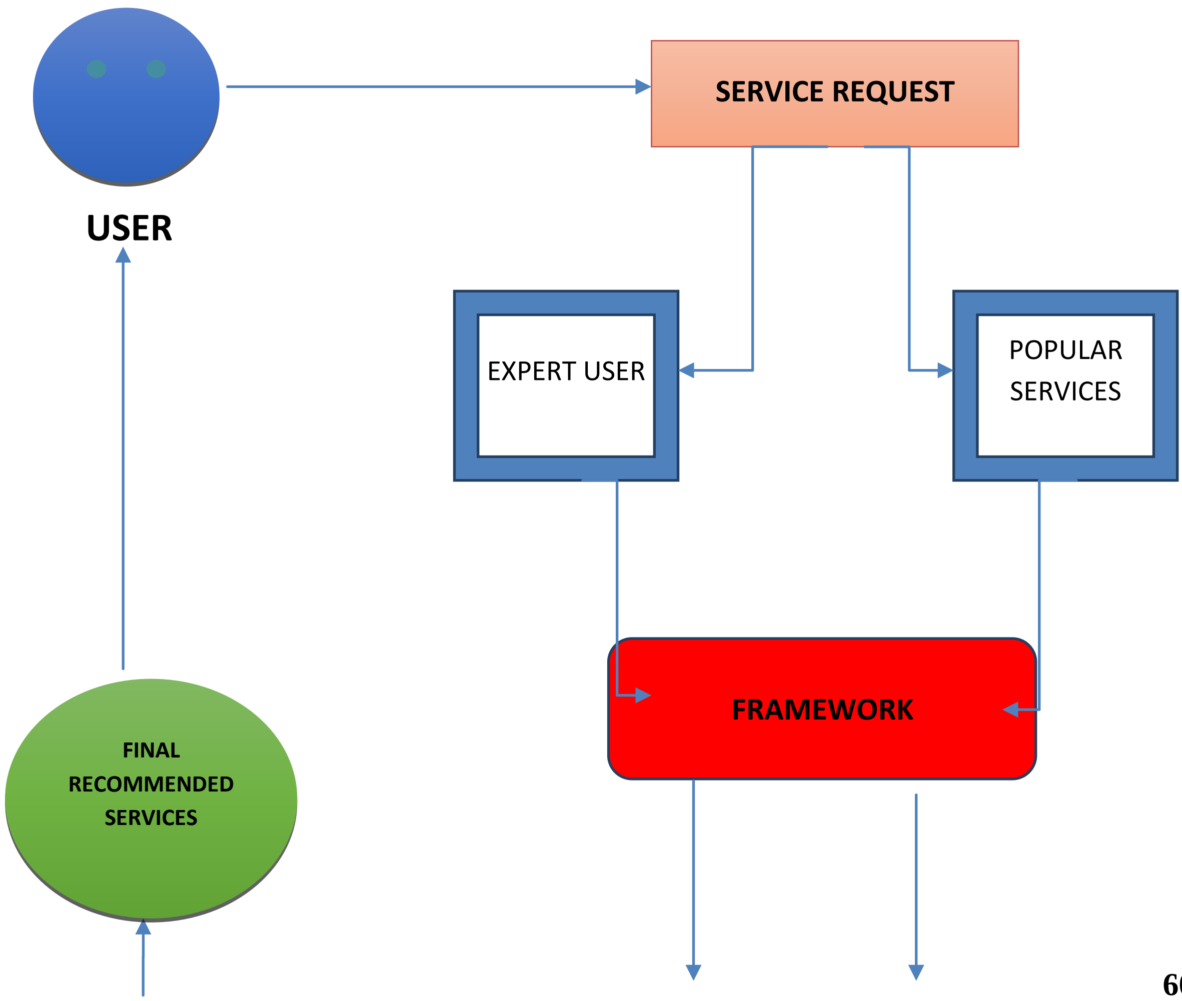
- ✓ Most of the existing recommendation systems utilize centralized architectures that are not scalable enough to process large volume of geographically distributed data.
- ✓ The centralized architecture for venue recommendations must simultaneously consider users' preferences, check-in history, and social context to generate optimal venue recommendations. Therefore, to address the scalability issue, we introduce the decentralized cloud-based Mobi Context BORF approach.
- ✓ Memory Efficiency.

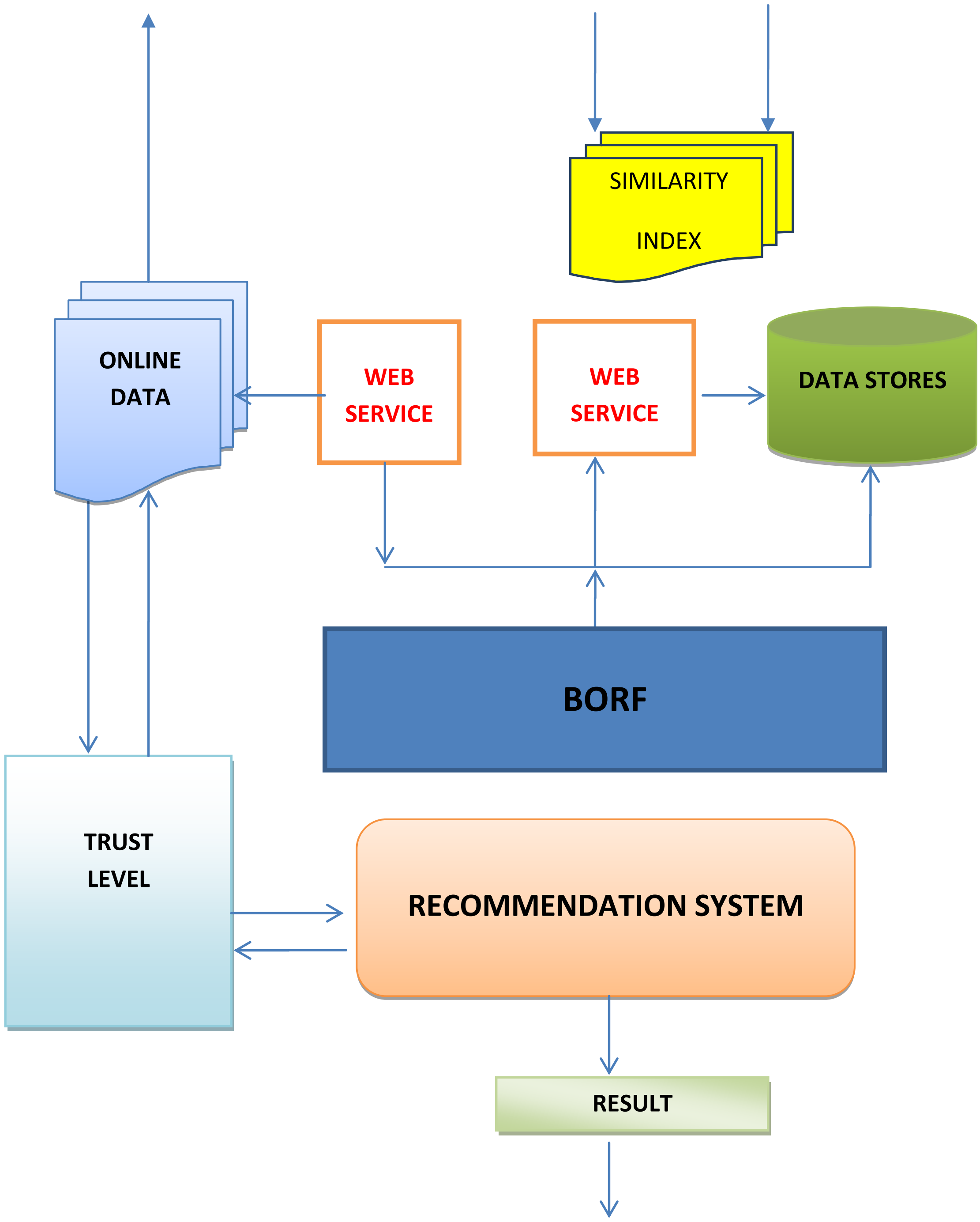
Features:

In the future, we would like to extend our work by incorporating more contextual information in the form of objective functions, such as the check-in time, users' profiles, and interests, in our proposed framework. Moreover, we intend to integrate other approaches, such as machine learning, text mining, and artificial neural networks to refine our existing framework.

System Architecture:

An architecture description is a formal description of a system, organized in a way that supports reasoning about the structural properties of the system. It defines the system components or building blocks and provides plan from which products can be procured, and systems developed, that will work together to implement the overall system.





System Maintenance:

The proposed CF-BORF utilizes a variant of the CF approach and employs the weighted sum method to implement scalar optimization. The function computes the edge weights of the current user c with the expert users by utilizing the similarity. The function indicates the overall aggregate similarity with respect to preferred venues and user to-venue closeness. The user's similarity in terms of preferences is scaled by the average of users' similarity in a specific region denoted by parameterγ The user-to-venue closeness is scaled by the average of user-to-venue closeness, and is indicated by the parameter On completion of the N number of iterations, the algorithm generates the top-N venues for the user by applying the traditional CF-based recommendation greedy approach that generates a set of top N venue recommendations by traversing a graph of the expert users.

The basic motivation is to extract suitable venues from a network of like-minded people who share the similar preferences for various venues they visit in a geographical region. The proposed approach assigns an initial weight on the links among nodes in the graph of expert users. Subsequently, the venues are recommended by those users that are not only the most similar to the current user, but also provide maximum contribution of the venues that needs to be recommended to the current user. In this way, the Greedy-BORF approach finds an optimal path on the graph that carries a collective opinion about venues by a group of expert users. This illustrates the step-by step procedure of the greedy-BORF approach for online recommendations. To compute w(c,e), the edge weights between two nodes in different levels of the graph are multiplied, and then divided by the number of edges between the two nodes. The edge distance of one (δsj = 1)) are assigned according to the non-zero similarity between the current user and the expert users. Only those neighbors of current user are selected from the graph that have non-zero similarity computation with the current user. The current user is stored in the list known as visited list. From here onwards, we interchangeably refer to the expert users as neighbor nodes.

Screen Shots:

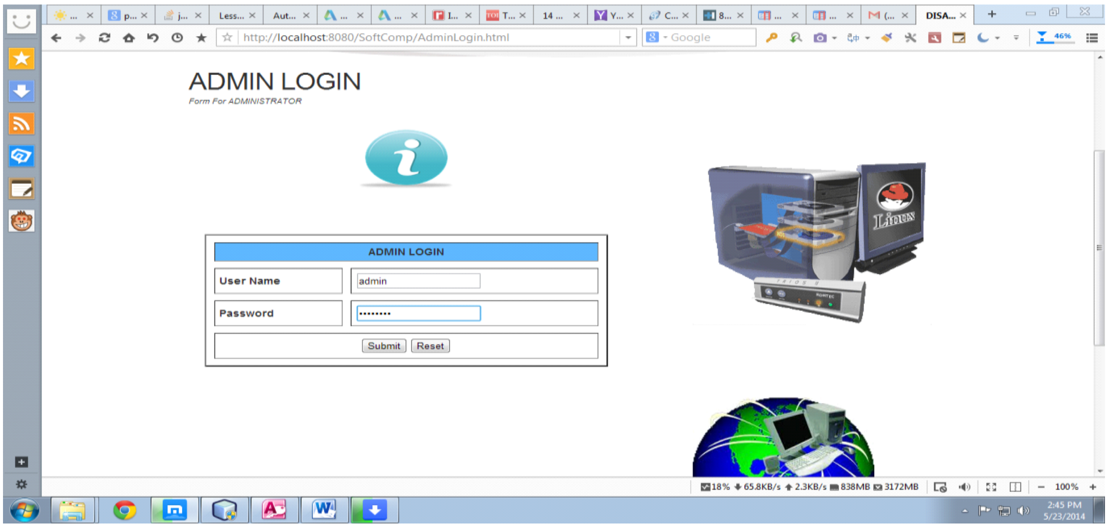


Figure 1: Login

Figure 2: Home Page

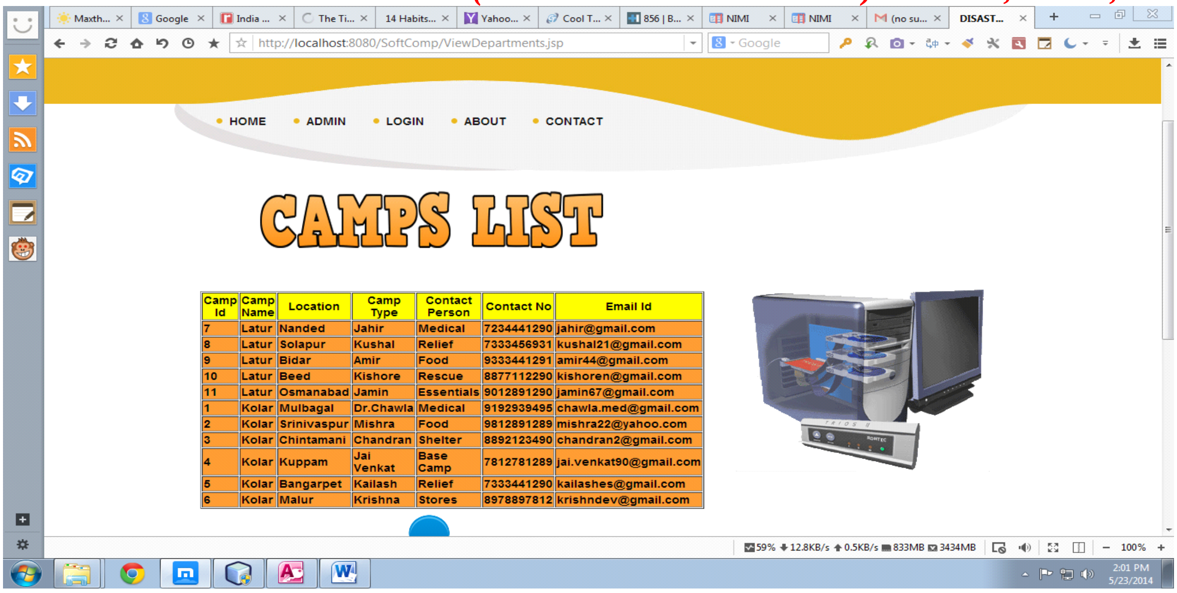


Figure 3: Home Page

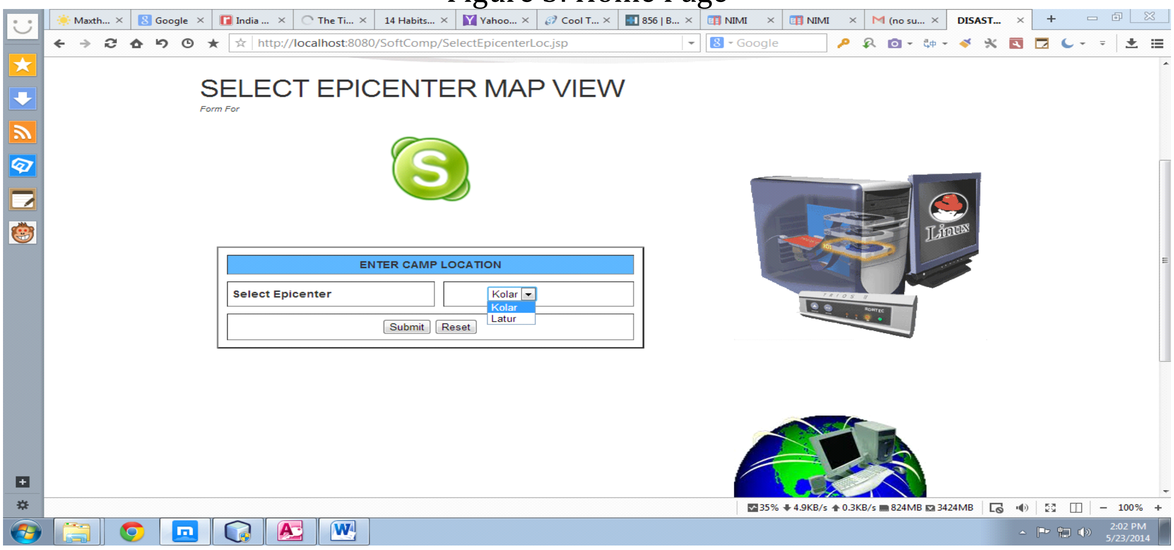


Figure 4

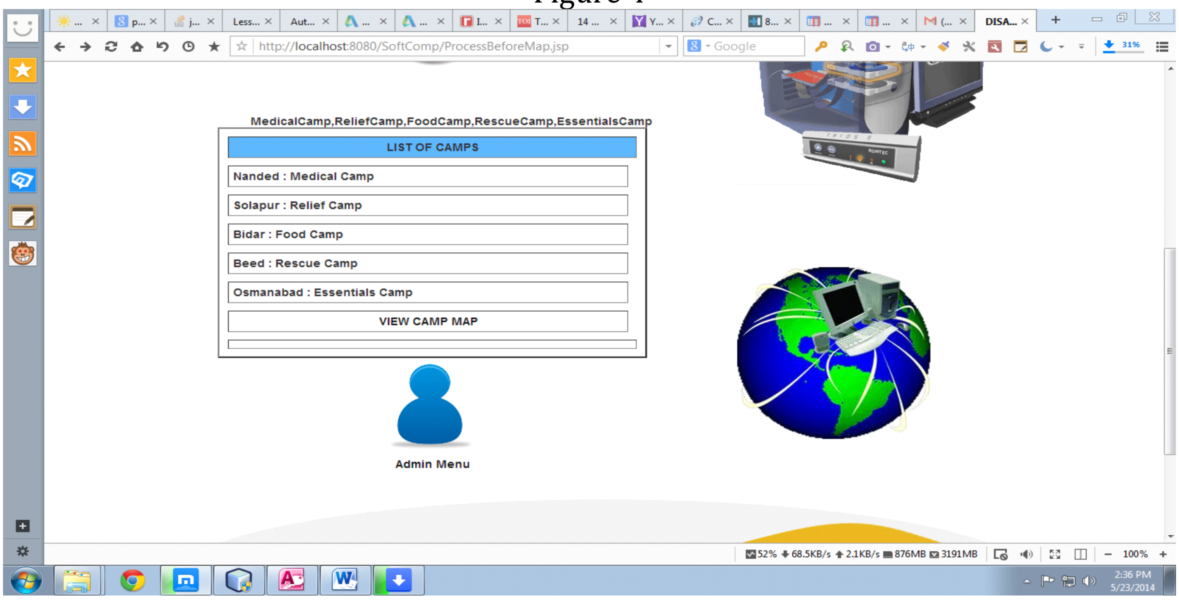


Figure 5: Campus List

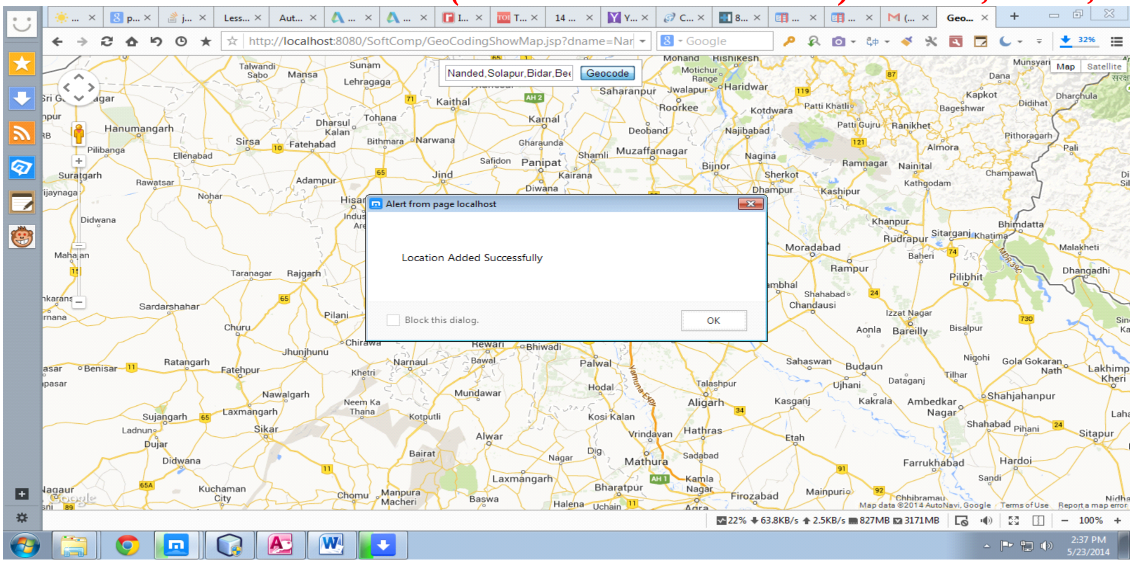


Figure 6: Location Map

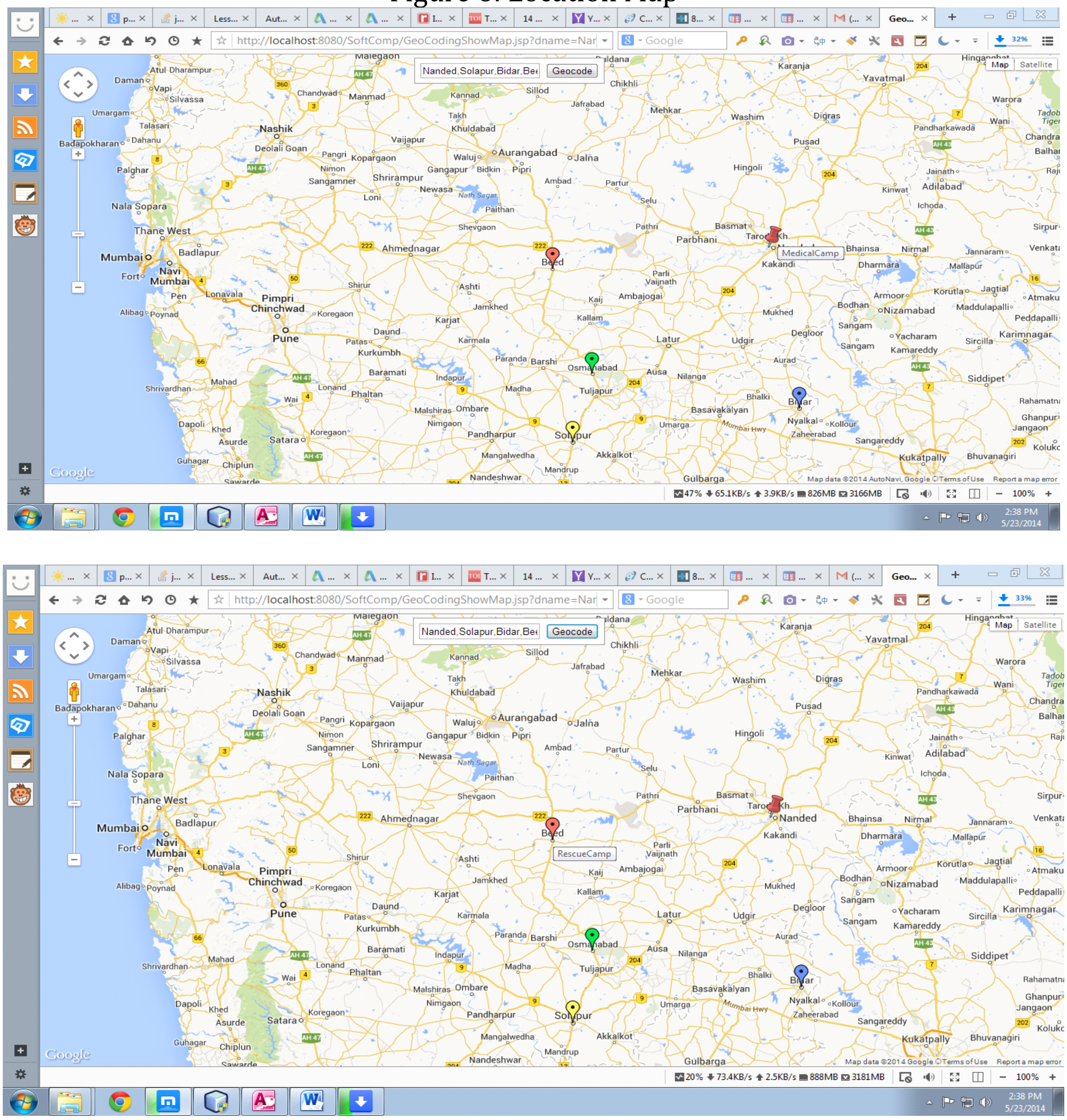


Figure 7: Show the Location

Figure 8: View Rescue

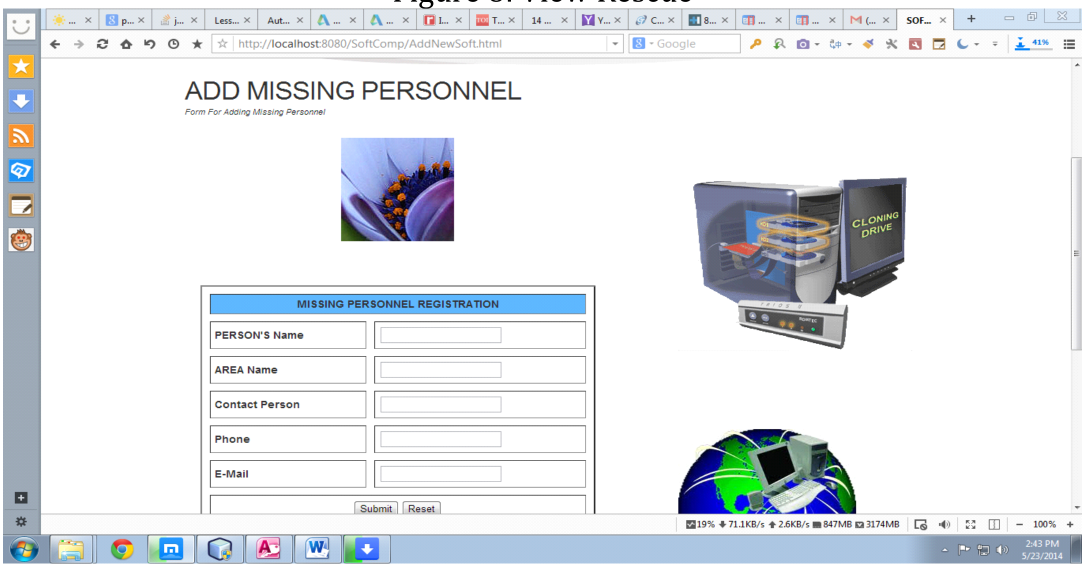


Figure 9: Add Missing Personnel

Figure 10: Missing Person List

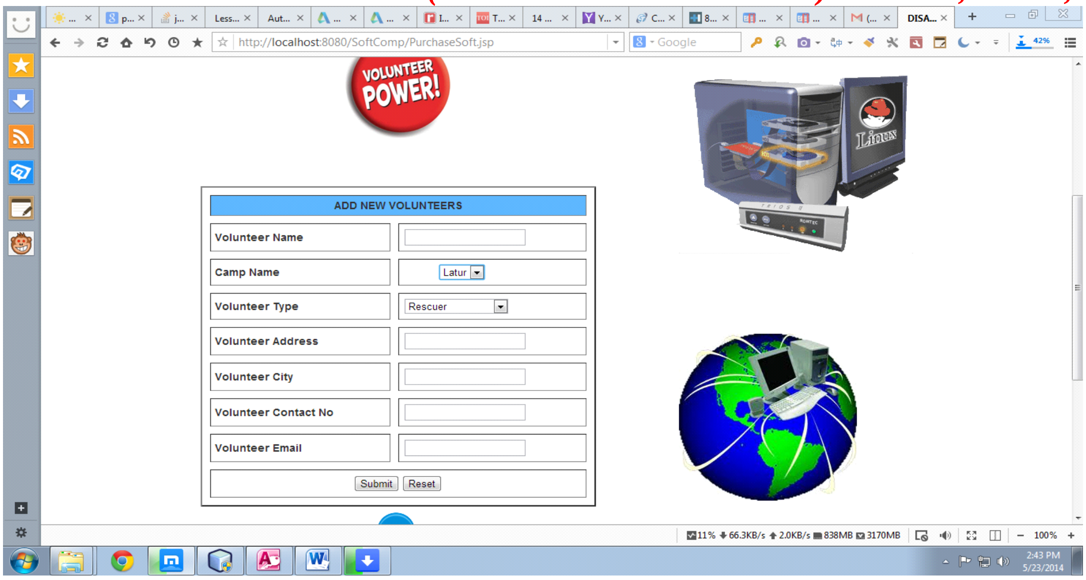


Figure 11: Registration Page

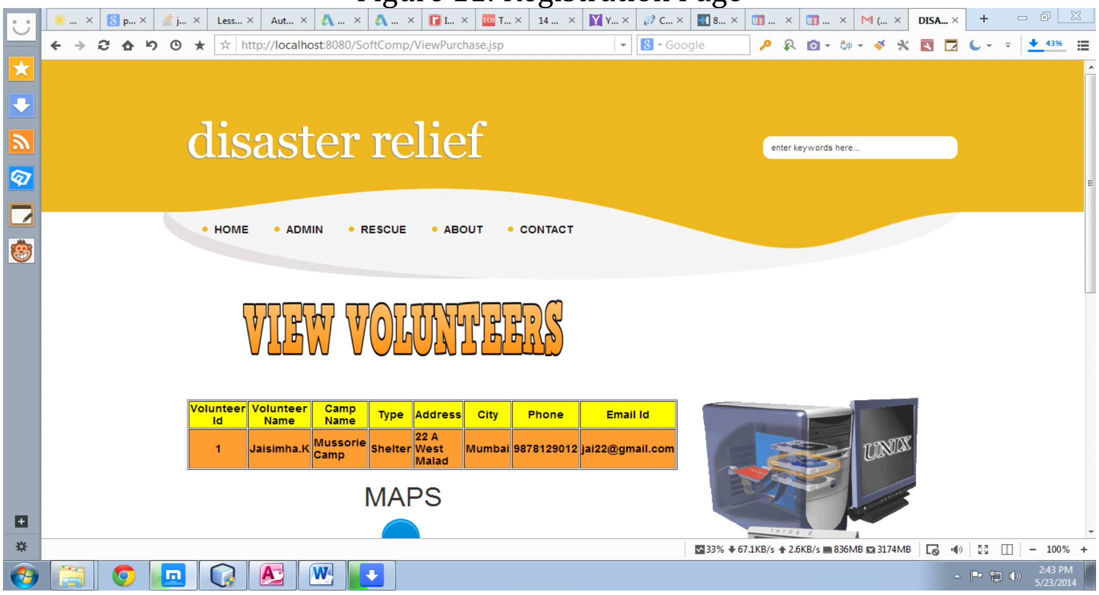


Figure 12: View Volunteers

Figure 13: Sos Message

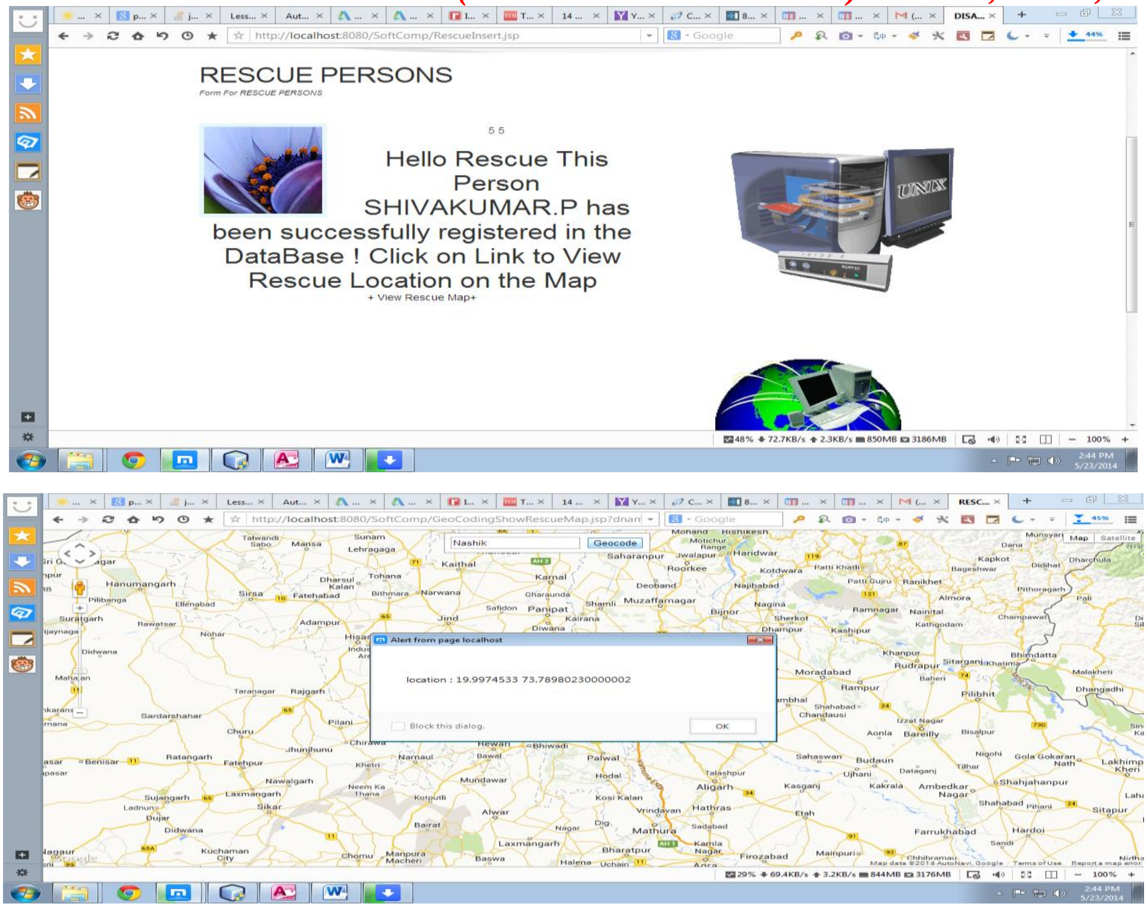


Figure 14: Successfully Registered and Shoe the Location

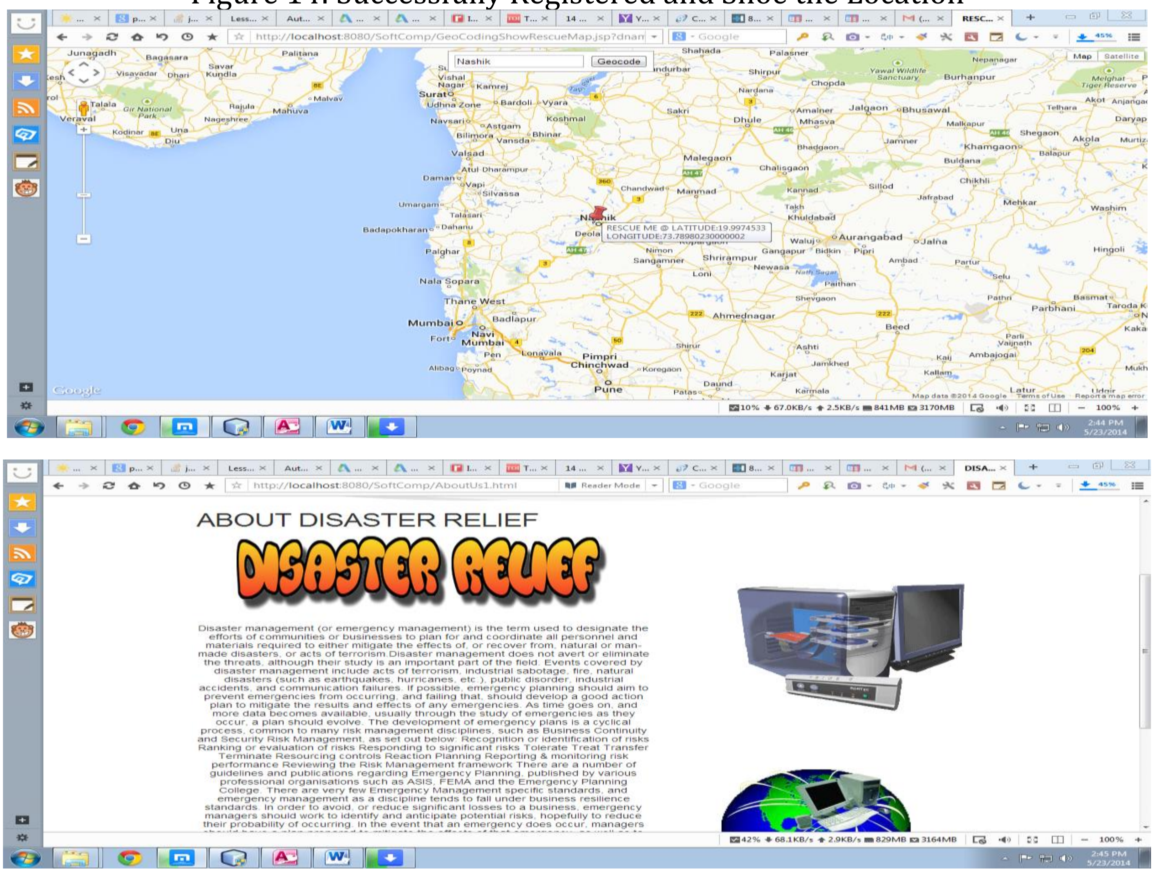


Figure 15: Output

Conclusion:

The proposed Expert BORF model is a system that leverages users and websites to provide lightweight, flexible, relaxed and anonymous credentials. These credentials help users and services to assess the veracity of assertions made by online users. With BORF, the users post identity assertions on their profiles, and their experts explicitly tag these assertions as true or false. An provider analyzes the social graph and the user tags to assess how credible these assertions are, and issues credentials annotated by veracity ranking or rating scores. analysis, real-world deployment and simulation based evaluation, suggest that the model is effective in obtaining. The Trust information is periodically updated to capture dynamically changing interaction preferences and trust relations. We have shown that this can be computed in an online manner, thereby enabling full personalization at runtime The empirical evaluations have shown that proposed model exhibits the desired properties; trust and rating weights influence hub- and authority scores. These properties ensure that our algorithm discovers experts which are well-connected to other experts

Future Enhancements:

In future the web applications may be modified by using web services so that other websites may use the same. In future mobile users downloading applications called apps from the web may also be entitled to such services.

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