OSN BASED APPLICATION FOR COMPLAINING LOCALITY ISSUES

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Abstract

We propose a project that mainly focuses on sanitation and development of a municipal corporation. In earlier existing systems, one must visit the office and complaints are given through written statement. Based on the priority, the complaint can be submitted in drop box or directly to the commissioner or the concerned department, which may take physical effort and time consuming task. In this paper, the people belonging to the municipal corporation are provided with an opportunity of raising a complaint regarding any issue that take place in their locality. The issues are garbage management, water supply, electricity management, road repairs or layering of roads and threatening of animals. To raise the complaints through Social network for Municipal Corporation regarding the above categories, a simplified solution is designed where the different type of complaints made by people are integrated. The issues are verified with the help of user ratings. The complaints will be isolated based on the feedback given by the locality user. If the rating exceeds more than a particular value then E-mail will be sent automatically to authorities (Low, Medium, High).This project involves major problem solving modules where these acts as best solution for incoming bulk complaints. For every submission of complaint, the user gets complaint acknowledgement. All these type of acknowledgement is generated by the system; the solution of time may differ from the type of the complaint and category.

Keywords —K-Means Clustering algorithm, 3-tier concept, Reviews, User Rating, Mail notification

I. INTRODUCTION

Data mining is the computational process of discovering patterns in large data sets involving methods at the intersection of artificial intelligence, machine learning, statistics and database systems.The overall process of the data mining is to extractinformation from a data set and transform it into an understandable structure.It allows users to analyze data from many different dimensions or angles, categorize it and summarize the relationships identified. Technically, data mining is the process of finding correlations or patterns among dozens of fields in large relational databases. Store and manage the data in a multidimensional database system. Provide data access to business analysts and computer professionals

Clustering can be considered the most important unsupervised learning problem; so, as every other problem of this kind, it deals with finding a structure in a collection of unlabeled data.A cluster is a subset of similar objects. The clustering isthe process of organizing objects into groups whose members are similar in some way. A clusteris therefore a collection of objects which are “similar” between them and are “dissimilar” to the objects belonging to other clusters. The goal of clustering is to determine the intrinsic grouping in a set of unlabeled data.

A.*K-means clustering*

K-means clustering is a type of unsupervised learning, which is used when you have unlabeled data (i.e., data without defined categories or groups). The goal of this algorithm is to find groups in the data, with the number of groups represented by the variable *K*. There are

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multiple ways to cluster the data but K-Means algorithm is the most used algorithm, Which tries to improve the inter group similarity while keeping the groups as far as possible from each other.The algorithm works iteratively to assign each data point to one of *K* groups based on the features that are provided. Data points are clustered based on feature similarity.

The *K*-means clustering algorithm is used to find groups which have not been explicitly labeled in the data.The algorithm uses iterative refinement to produce a final result. The inputs are the number of clusters *K* and the data set. The dataset is a collection of features for each data point.The algorithm starts with initial estimates for the *K* centroids, which can either be randomly generated or randomly selected from the data set. K-means clustering is a method of vector quantization, originally from signal processing. K-means clusteringaims to partition n observations into k clusters in each observation.

II. RELATED WORKS

There are several techniques used for rating and reviews. The content based and collaborative filtering [1] are used for finding similarities between user groups. This paper also describes various limitations of current recommendation methods and discusses possible extensions that can improve recommendation capabilities and make recommender system applicable to an even broader range of applications. The trust based predictions uses collaborative filtering [2] to find the recommendations. The recommendations with social trust information using matrix factorization technique [3] to find the social connections. Using the FilmTrust system as a foundation [4], we show that these recommendations are more accurate than other techniques when the user's opinions about a film are divergent from the average. Another technique was ranking from implicit feedback[5] uses k-nearest-neighbor(kNN). The results show that the prediction quality does not depend only on the model but also largely on the optimization criterion.Social recommendation using low-rank semidefinite program[6]. The algorithm used was quasi-Newton algorithm. The empirical evaluation on a large scale dataset of high sparsity, the promising experimental results shows that this method is very effective and efficient for the social recommendation task.

Collaborative filtering is a widely accepted technique to provide recommendations based on ratings of similar users[9]. Another method combines collaborative filtering and matrix factorization. A novel social recommendation framework fusing a user-item rating matrix with the user's social network using probabilistic matrix factorization [10].Recommender systems with social regularization [11] .The technique used was matrix factorization and social regularization. The method is quite general, which can be easily extended to incorporate other contextual information like social tags. In this paper, we only constrain user feature vectors while ignoring the item side. Social MF deals better with cold start users than existing methods. There is no method to handle negative trust relations [12].

III. EXISTING WORK

Recommender systems have been widely used to provideusers with high-quality personalized recommendations from a large volume of choices. Robust and accurate recommendations are important in e-commerce operations (e.g., navigating product offerings, personalization,improving customer satisfaction), and in marketing (e.g.,tailored advertising, segmentation, cross selling).Collaborative filtering (CF) is one of the most popular techniques to implement a recommender system. The idea of CF is that users with similar preferences in the past are likely to favor the same items (e.g., movies, music, books, etc.) in the future. CF has also been applied to tasks besides itemrecommendation in domains such as image processing and bioinformatics .However, CF suffers from two well known issues: data sparsity and cold start . The formerissue refers to the fact that users usually rate only a smallportion of items while the latter indicates that new usersonly give a few ratings (a.k.a. cold-start users). Both issuesseverely degrade the efficiency of a recommender systemin modeling user preferences and thus the accuracy ofpredicting a user's rating for an unknown item. One possible explanation is that these trust-based models focus too much on the utility of user trust but ignore the influence of item ratings themselves. To investigate this phenomenon, we conduct an empirical trust analysis based on four real-word data sets (FilmTrust, Epinions, Flixster and Ciao) through which three important observations are concluded.

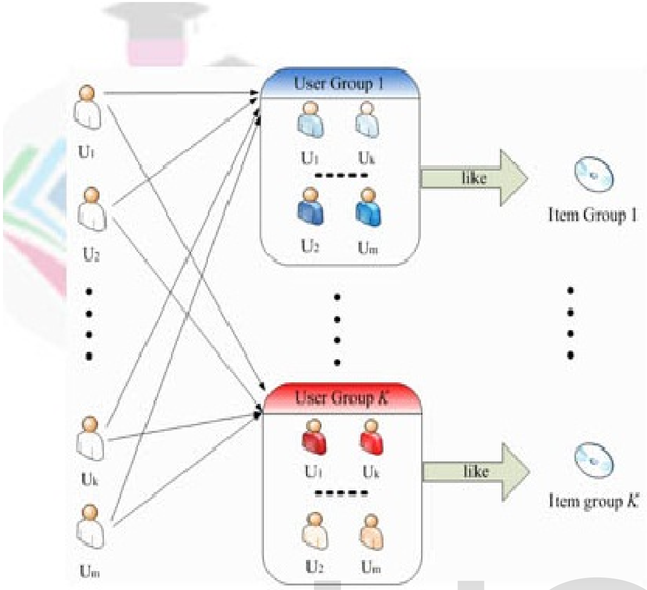


Fig 1. Architecture of novel recommendation model regularized with user trust and item ratings.

IV.PROPOSED WORK

The main purpose of the project is to help the public who are facing different problems in the localities by this online application. This project is having that potential to reduce the gap between people and Govt. It can control unethical work of bribe and even it can reduce the processing time.Theidentification and solutions for thecomplaints given by the people, rectifying them within the system generated time limit through online application.If it is not solved, then the report is automatically forwarded to the higher authorities so that it maintains an effective problem solving solution.In this existing system, one cannot get any acknowledgement that the complaint has been received. Guarantee for problem solution is given through verbal communication. Hence, it is not meant for problem solution

V. MODULE DESCRIPTION

A. Admin Module
B. User Module

A. Admin Module:

I. Login:
In this module consist for admin login, admin name and password will stored in database. If admin entered incorrect name and password means error message will display in that page.

II. View Register User Details:
In this module Admin can we all the Registered User details.

III. Add category :
In this module admin can add category like Irrigation Water supply department and EB department, sewage water control Board, etc

IV. Add Area:
In this module admin can add Area details.

V. Add authority:
In this module admin can add authorities for corresponding categories. And also in this session had authorities Name, mail id, mobile number etc.

B.User Module:

I. Register:
In this page user can add their personal details like full name, name, and gender, and password, mobile, email and user can add their area and location according to admin registered area and location only, Can't be add their personal wish.

II. Login
In this page user can login with registered name and password if user entered wrong name and password mans login session won't work

III. Forget Password
In this Module used to user can change password with help of JAVA OBJECT API. User should enter registered mobile number and he/she will get Reset code for changing their Password. If user enter

wrong code error message display in that page

IV. Profile

In this page user can see their personal details.

V. Update Profile

In this page user update their personal details.

VI. Share Post

In this module have tweet box, photo uploading optionCategory, area, location and so user can text municipal related problem in that tweet box and corresponding photo, area and location so user can share their post in this page. This post will Shown same area mats only.

VII. View Post

In this module have user posts with information. User can rating for posts if rate score above 3 mail will forward for corresponding authorities with help of **JavaMail API**

K-means clustering algorithm

k-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed apriori. The main idea is to define k centers, one for each cluster. These centers should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest center. When no point is pending, the first step is completed and an early group age is done. At this point we need to re-calculate k new centroids as barycenter of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new center. A loop has been generated. As a result of this loop we may notice that the k centers change their location step by step until no more changes are done or in other words centers do not move any more. Finally, this algorithm aims at minimizing an objective function know as squared error function given by:

$$J(v)=\sum_{i=1}^{c}\sum_{j=1}^{ci}(||xi - vj||)2$$

where,

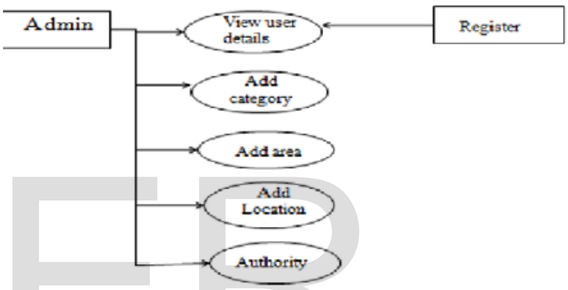
'$||x_i - v_j||$' is the Euclidean distance between x_i and v_j.

'c_i' is the number of data points in i^{th} cluster.

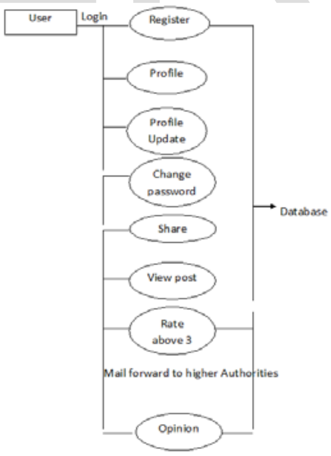
'c' is the number of cluster centers.

C.IMPLEMENTATION MODULES

A. ADMIN MODULE



B. USER MODULE



VI. CONCLUSION AND FUTURE WORK

An effective online based application for the process of complaining is designed that will efficiently make easy the process of complaint reporting with very simplified and effective way.

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This project involves major problem solving modules where these acts as best solution for incoming bulk complaints. For every submission of complaint, the user gets complaint acknowledgement. To make any complaint, it is made mandatory for the user to mention his contact details; so that it does not receive any anonymous complaint detailsThe system is efficient comparing to the earlier systems. There is no complaint acknowledgement for the users in previous systems, Which is used for future references.

If the system is extended for videos instead of photos it will be more efficient and it also enables people to give their suggestions during the video recording and alternate application for non social media users is also applicable. The implementation can be done in the future work.

VII. RESULTS

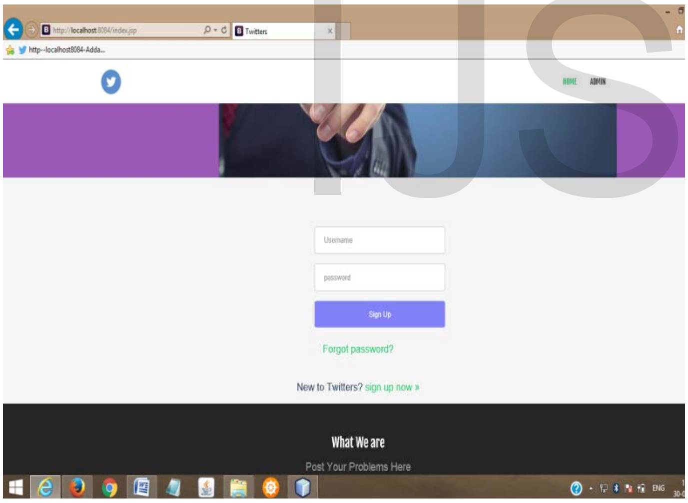

Fig A.Login page

The registered users can login with user id and password. The new users can sign up.

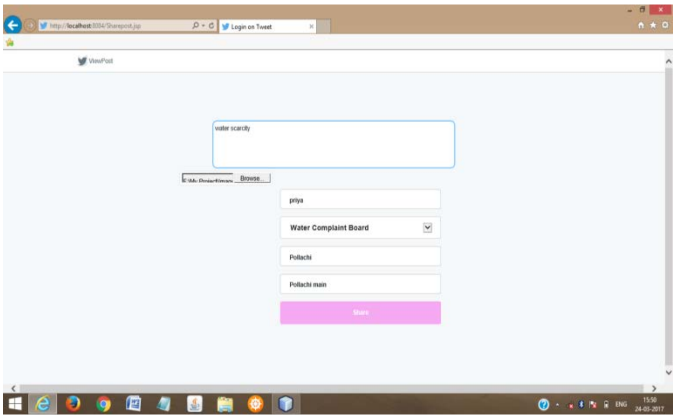

Fig.B. Uploading the complaints

The user can upload the complaints with the images and write the detailed complaint in the what's happening dialogue box

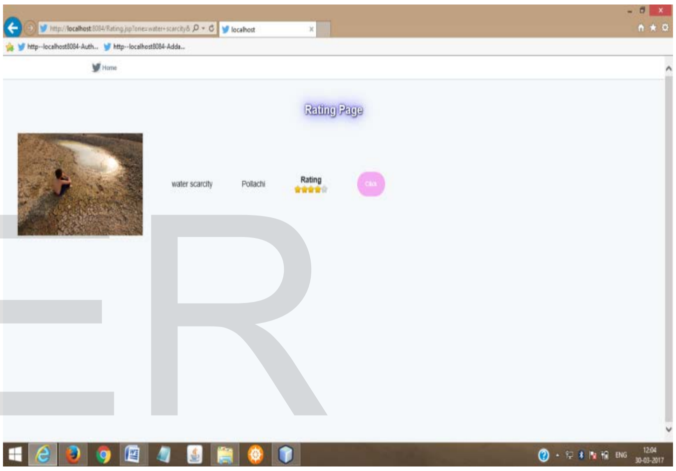

Fig C.Rating the complaint

The people who belong to the same area and location can rate the complaint with the stars

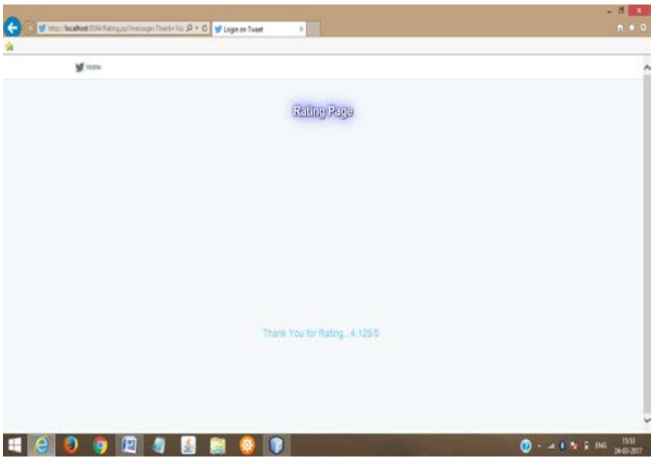

Fig.D. Rating page

The average of the rating will be calculated. If the rating exceeds more than 3 then E-Mail will be sent automatically to authorities.

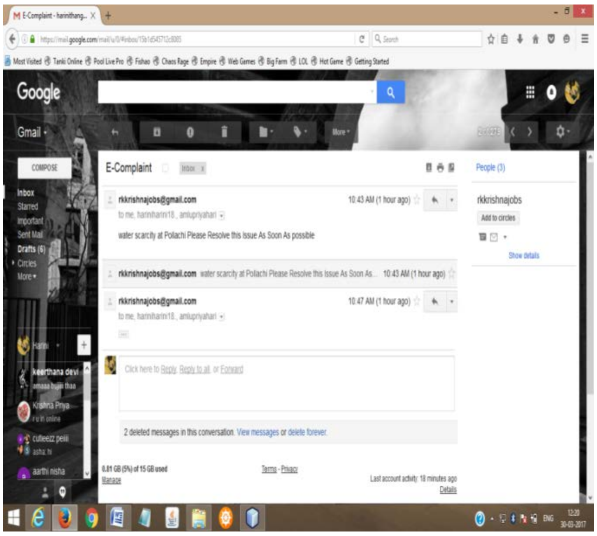

Fig.E.E-mail complaint to authorities

The E-mail notification sent to the authorities (Low,Medium,High) along with the complaint.

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