Social Traits Identification System using LD Algorithm

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Abstract:- **The existing social networking websites caters friend proposition to users based on pre-existing user relationships or that determined by the geographical distances. The results obtained from the system, may not be the most efficient to reflect users preferences in picking friends. As a substitute, certain mechanisms which make recommendations based on Lifestyles and Interests can be used. Where the lifestyles refer to activities accomplished by an individual on a daily basis.Buddy-Finder, is a recommendation system, which recommends friends to users based on their interests and social traits. The Smart phones such as iPhone or Android –based phones are equipped with a rich set of embedded sensors, which serves as an ideal platform for sensing daily routines from which people's lifestyles could be discovered. The user's interests are collected from the web portal and the users lifestyles are extracted using LDA algorithm from the activities captured from the smart phones. Upon receiving a request, Buddy-Finder returns a list of people with highest similarity scores.**

Keywords:
- ***Friend recommendation***
- ***Mobile sensing***
- ***Social networks***
- ***Life style***

INTRODUCTION

For the natural and social interaction it is necessary to understand human behavior. Personality is one of the fundamental aspects, by which we can understand behavioral dispositions. It is evident that there is a strong correlation between users' personality and the way they behave on online social network (e.g., Facebook). This paper presents automatic recognition of Big-5 personality traits on social network (Facebook) using users' status text. For the automatic recognition we studied different classification methods such as SMO (Sequential Minimal Optimization for Support Vector Machine), Bayesian Logistic Regression (BLR) and Multinomial Naïve Bayes (MNB) sparse modeling. Performance of the systems had been measured using

macro-averaged precision, recall and F1; weighted average accuracy (WA) and un-weighted average accuracy (UA). Our comparative study shows that MNB performs better than BLR and SMO for personality traits recognition on the social network data.

For the social communication, we interact with unknown individuals, even with machines that exhibit human-like features and behaviors such as robots, embodied virtual agents and animated characters (Nass et al., 2005). To make these automated systems more human-like, we need to understand human behavior and how it is affected by personality traits. Personality is the most complex of all the human attributes and it also characterizes the uniqueness of a person. It has been a long-term goal for psychologists to understand human personality and its impact on human behavior. Behavior involves an interaction between a person's underlying personality traits and situational variables. The situation, that a person finds himself or herself in, plays a major role on his or her reaction. However, in most of the cases, people respond with respect to their underlying personality traits.

EXISTING SYSTEM:

In the present days we are making friends with persons that you know or the persons that you are suggested in suggested list. It makes the people to communicate with the people that who we know and the friend that our friends know possible. so the system makes friends only by the know friends on certain regions. Here the system help to make friends on the basis of the our friends list.

PROPOSED SYSTEM:

When people with similar interests are recommended as friends, then user interest in activities enhances she can keep into ouch with interested friends and share Knowledge also community building can been handed with this new approach offrendship recommendation . It is easy for people to get friends for jogging, shopping etc in their close quarters. People with similar interests can establish a virtual community and share knowledge using the social network platform with our approach.

ADVANTAGES:

- This system helps to find the friends based on the our personal interests
- It helps to improve the intelligence through communicating with other superiors
- It helps to provide the services better through the help of the other persons that who are in the same field

RESULT ANALYSIS:

1. Computation of centroid values to be given to Client:

a. A huge dataset, consisting of raw sensor values in the form (acc_x ,acc_y, acc_z, gyr_x, gyr_y, gyr_z) are given to server.

b. The raw data are further filtered using median filtering for outlier removal.

c. K Means algorithm is applied on the filtered data with pre defined value of K as 10, where K represents K activities(clusters).

d. Centroid values obtained from K-means clustering, for K clusters are stored in a file.

e. The resulting file with centroid values are distributed to all the users, who are registered with the application.

2. FRIEND COMPUTATION:

a. The user has to configure the server by providing server IP address.

b. The user has to next register with the app. After which the user can start using the buddy-finder service.

c. Instead of raw data the activity sequence are sent to the server. Thus reducing the overhead of pre-processing computation at the server end.

CONCLUSION:

Unlike the current friend recommendation schemes, which depend on the preexisting social relationships and geographical information, "Lifestyle based friend recommendation system" is a scheme where the friend suggestions are provided based on users daily activities. The Buddy Finder mobile application captures the user's daily activities from their smart phones and suggests friends to users if they share identical lifestyles. The proposed scheme is implemented as a mobile App on the android devices. And small scale experiments are performed to evaluate the system performance. This report provides a detailed description of the design, implementation and analysis of the results obtained by the experiments conducted on the system.

FUTURE ACHIEVEMENTS:

Beyond the present model, the future work can be a three fold. First, the Buddy Finder application can be integrated in to current real social networking services suchas Facebook, twitter and soon. Second to conduct largescaleexperimentsandevaluatethesystemtobescalabletolargesystems.Thesimilaritythresholdusedintheexperimentisfixed. Experimentscouldbeconductedwithvaryingthresholdandacomparisonontheresultsobtainedwithvaryingthresholdcouldbe computed. Third, moresen sorscould beincorporatedonmobilephones,intothesystemsandalsomakeuseofwearablesensors,sothatthesystemcouldusemoreinformationforlifestyleextraction,whichwouldimprovetherecommendationaccuracy.

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