INTRODUCTION

With more than 3 billion active users around the globe, social networking sites (SNSs) have become the main method of making new friends. It had been proven that friendship in SNS can better describe self-report friendship compared to friendship created by frequent physical encounters. Each one of these social networks relies on a friend recommendation system (FRS) that is used to detect common features between two people and, consequently connect them to each other. Many FRS have been proposed in the past few years, but most of the systems will recommend people that have a common feature with you as friends. Homophily based FRS is adequate when the common feature is a physical or social feature, such as age, race, location, job, or lifestyle. However, when it comes to personality types, things are different. Personality-based FRS brings up a very old psychological debate about the personality similarities between friends. While most of the mainstream researchers argue that there is no similarity in personality between friends. Recent researchers have suggested that friends and couples indeed are similar in their personality. In addition to that, a major challenge for FRS is known as the cold-start problem, where the recommendation system does not have enough information about the new user, and the missing information is crucial in the recommendation process. In this case, personality information can help to alleviate the cold-start problem. For the above-mentioned reasons, in this paper, we have evaluated an FRS based on the big-five personality traits model and hybrid filtering, in which the friend recommendation process is based on personality traits and users' harmony rating. To validate the proposed system's accuracy, a personality-based social network site that uses the proposed FRS named PersoNet is implemented. The proposed system not only enhances the prediction accuracy of recommendation systems but also alleviates the cold-start problem of the legacy collaborative filtering (CF) systems. To compare PersoNet with the legacy FRSs, we have implemented three recommendation systems and compared them based on their precision and recall values:

1) FRS based only on personality matching;

2) FRS based only on CF

3) the proposed system PersoNet, which is based on personality traits and hybrid filtering.

LITERATURE SURVEY

Social networking sites are getting more benefits from recommender system that's why in these days recommender system is the more popular tool among online user.

We have done the literature survey through various papers that got published in line with this subject. This section gives the works related to recommendation system through social networking. The Literature study enlightens the study done by some authors on existing system, and respective pros and cons.

Following are the few papers studied.

- Probabilistic mining of socio geographic routines from mobile phone data :

  Authors: K. Farrahi and D. Gatica-Perez

  In this paper, they suggest that human interaction data, or human proximity, obtained by mobile phone Bluetooth sensor data, can be integrated with human location data, obtained by mobile cell tower connections, to mine meaningful details about human activities from large and noisy datasets. We propose a model, called bag of multimodal behavior that integrates the modeling of variations of location over multiple time-scales, and the modeling of interaction types from proximity. Our representation is simple yet robust to characterize real-life human behavior sensed from mobile phones, which are devices capable of capturing large-scale data known to be noisy and incomplete. We use an unsupervised approach, based on probabilistic topic models, to discover latent human activities in terms of the joint interaction and location behaviors. Our methodology also finds dominant work patterns occurring on other days of the week. We further demonstrate the feasibility of the topic modeling framework for human routine discovery by predicting missing multimodal phone data at specific times of the day.

- Collaborative and structural recommendation of friends using weblog-based social network analysis

  Authors: W. H. Hsu, A. King, M. Paradesi, T. Pydimarri, and T. Weninger

  In this paper, they address the problem of link recommendation in weblogs and similar social networks. First, they present an approach based on collaborative recommendation using the link structure of a social network and content-based recommendation using mutual declared interests. Next, they describe the application of this approach to a small the user/community network of the blog service Live Journal. They then discuss the ground features available in Live Journal's public user information pages and describe some graph algorithms for analysis of the social network. These are used to identify candidates, provide ground truth for recommendations, and construct features for learning the concept of a recommended link. Finally, they compare the performance of this machine learning approach to that of the rudimentary recommender system provided by Live Journal.

- Reality Mining: Sensing Complex Social Systems

  Authors: N. Eagle and A. S. Pentland

  These authors introduce a system for sensing complex social systems with data collected from 100 mobile phones over the course of 9 months. They demonstrate the ability to use standard Bluetooth-enabled mobile telephones to measure information access and use in different contexts, recognize social patterns in daily user activity, infer relationships, identify socially significant locations, and model organizational rhythms.

- **Information Retrieval (cs.IR)**; Computers and Society (cs.CY); Machine Learning (cs.LG)

  Author: Erion Çano, Maurizio Morisio

  Recommender systems are software tools used to generate and provide suggestions for items and other entities to the users by exploiting various strategies. Hybrid recommender systems combine two or more recommendation strategies in different ways to benefit from their complementary advantages. This systematic literature review presents the state of the art in hybrid recommender systems of the last decade. It is the first quantitative review work completely focused in hybrid recommenders. We address the most relevant problems considered and present the associated data mining and recommendation techniques used to overcome them. We also explore the hybridization classes each hybrid recommender belongs to, the application domains, the evaluation process and proposed future research directions. Based on our findings, most of the studies combine collaborative filtering with another technique often in a weighted way. Also cold-start and data sparsity are the two traditional and top problems being addressed in 23 and 22 studies each, while movies and movie datasets are still widely used by most of the authors. As most of the studies are evaluated by comparisons with similar methods using accuracy metrics, providing more credible and user oriented evaluations remains a typical challenge. Besides this, newer challenges were also identified such as responding to the variation of user context, evolving user tastes or providing cross-domain recommendations. Being a hot topic, hybrid recommenders represent a good basis with which to respond accordingly by exploring newer opportunities such as contextualizing recommendations, involving parallel hybrid algorithms, processing larger datasets, etc.

PROBLEM FORMULATION

There is a need for Recommendation Systems that can suggest items from multiple domains with high recommendation accuracy. Most research in the area of recommender systems focuses on making single-domain recommendations, while recommendations from multiple domains are not yet widely explored. Our research addresses the question of whether or not using personality information in making cross-domain recommendations can provide high recommendation accuracy. In this work, we capture the personality traits of fans of a product and use them to create the representation of that product. Then, we find items with a similar representation to recommend them to those fans. The user is the common element in all products a user purchases. Therefore, we think that a system which utilizes users' personality information would be useful for cross domain recommendations.

Most of the friend suggestions mechanism relies on pre-existing user relationships to pick friend candidates. For example, Facebook relies on a social link analysis among those who already share common friends and recommends symmetrical users as potential friends. The rules to group people together include:

1. Habits or life style

2. Attitudes

3. Tastes

4. Moral standards

5. Economic level

6. People they already know.

Apparently, rule #3 and rule #6 are the mainstream factors considered by existing recommendation systems.

Users' rating results show that PersoNet performs better than the other FRS in terms of precision and recall. The contributions can be summarized as follows.

1) Propose a personality-based FRS based on big-five personality traits and hybrid filtering.

2) Implement the proposed system in a social network site.

3) Conduct an online experiment using the implemented site to validate the robustness of PersoNet.

ABOUT THE SEMINAR

1. APPROACH

The system design of the proposed system is presented in Fig. 1. After joining the network, the user must answer a personality measurement questionnaire. As the user has no preferences at this moment (cold start), to overcome this situation, the initial recommendation is based on personality similarity between the user and his neighbors (users with similar personality traits). In other words, the system recommends users that have identified as harmonic friends with neighbors of the new user. When the user passes the cold-start period, the recommendation will be gradually enhanced by incorporating the user's harmony rating preferences. As shown in Fig. 2, at the second stage, the recommendation is based on personality similarity and hybrid filtering approach (CF in terms of rating similarity with neighbors, and content filtering in terms of personality trait similarity between the previously rate friends and the potential friends).

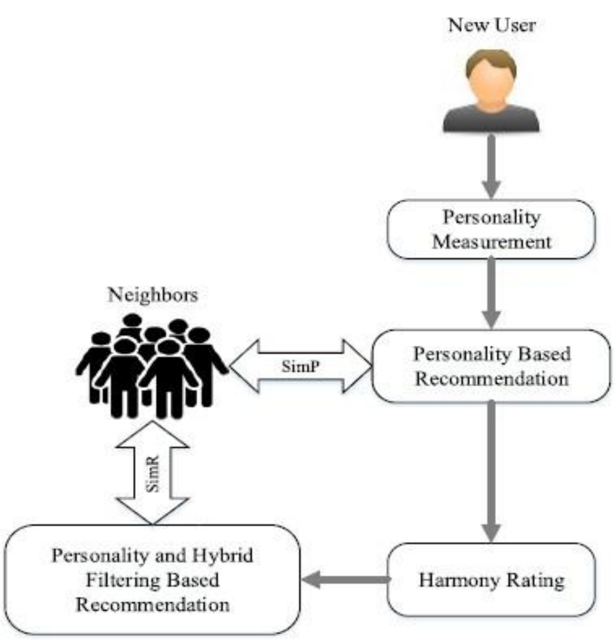

FIG 1: Personet's System Design

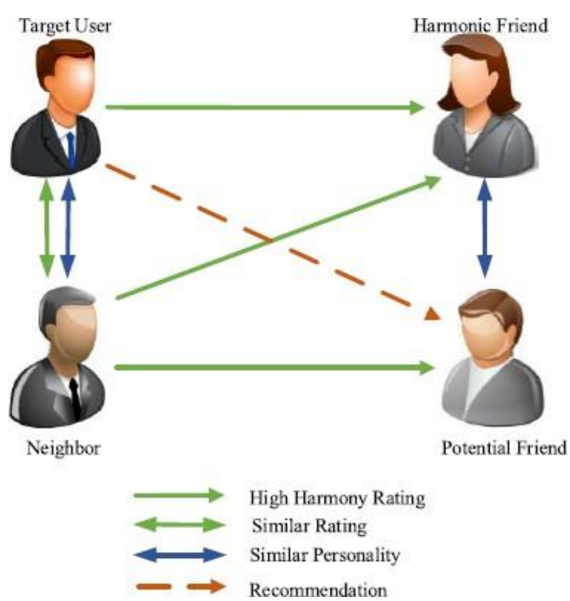

FIG 2: Personality traits and hybrid filtering-based recommendations

1.1 Similarity Measure

Similarity measure is the main component of any recommendation system and is used to measure the similarity between two entities (e.g., users and items) based on a similarity factor (e.g., product ratings, browsing history, product category, and so on), in the context of recommendation systems, a precise similarity measurement enables the system to predict the future behaviors of the targeted entity based on the behaviors of its similar entities (neighbors).

In this paper, they have used the Pearson correlation coefficient, as it is one of the most commonly used similarity measures. In this paper, we are interested in two kinds of similarity between the users as follows.

1) *Personality Traits Similarity* (SimP)*:* In this, we will measure the similarity between two users based on their personality trait (similarity factor). SimP is computed using the

$$\mathrm{SimP}(u_x,\ u_y) = \frac{\sum_i (p_x^i - \overline{p_x})(p_y^i - \overline{p_y})}{\sqrt{\sum_i (p_x^i - \overline{p_x})^2 (p_y^i - \overline{p_y})^2}}$$

Pearson correlation coefficient as shown in (1)

where *px* and *py* are the average value of the personality traits vector for user *ux* and *uy*, respectively, and *pi x* is the *i* th trait in the personality traits vector.

2) *Harmony Rating Similarity* (SimR)*:* In this, we will measure the similarity between two users based on their harmony rating to other users. SimR is computed using Pearson

$$\mathrm{SimR}(u_x,\ u_y) = \frac{\sum_{i\in R_x \cap R_y} (r_{x,i} - \overline{r_x})(r_{y,i} - \overline{r_y})}{\sqrt{\sum_{i\in R_x \cap R_y} (r_{x,i} - \overline{r_x})^2 (r_{y,i} - \overline{r_y})^2}}$$

correlation coefficient as shown in the following equation:

where *rx,i* and *ry,i* are the harmony rating given by *ux* and *uy* to *ui* , respectively, and *rx* and *ry* are their mean harmony rating.

A. Human Personality

There is no general theory that defines the human personality. Nevertheless, many theories have elaborated the concept of human personality from different perspectives, including the cognitive perspective, biological perspective, learning perspective, humanistic perspective, psychodynamic perspective, and trait perspective. Trait theory (also known as dispositional theory) is the most adapted personality theory. The trait theory suggests that human personality can be identified by the measurement of personality traits. Trait theorists define personality traits as habitual patterns of behaviors, thoughts, and emotions. Personality traits are relatively stable over time, differ across individuals, relatively consistent over situations, and they influence human behaviors. There are two major methods used in trait theory to measure personality traits, Eysenck Personality Questionnaire (EPQ) also known as the three-factor model and big-five personality traits also known as the five-factor model (FFM). The big-five traits are based on common language description of personality, which make trait theory an ideal model for computing technologies, such as natural language processing, machine learning, and semantic technologies. FFM is widely used for various purposes, such as job recruitment or mental disorders diagnosis. The model defines the five factors as openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism, often represented by the acronyms OCEAN or CANOE, in Table I, the five factors along some of the associated characters are presented.

BIG-FIVE TRAITS AND ASSOCIATED CHARACTERS

Personality Trait	Related Characters
Openness to Experience	Artistic, Curious, Imaginative, Insightful, Original, Wide interests
Agreeableness	Trusting, Generous, Appreciative, Kind, Sympathetic, Forgiving
Conscientiousness	Efficient, Organized, Planful, Reliable, Responsible, Thorough
Extraversion	Energetic, Outgoing, Active, Assertive, Talkative
Neuroticism	Anxious, Unstable , Tense, Touchy, Worrying, Self-pitying

TABLE I

B. Recommendation Systems

A recommendation system is an information filtering system that is used to match a subject (e.g., user) with the best items (e.g., product and friend) that is suitable for its “needs” and/or “preferences.” An FRS is a special case of recommendation system where the items are a set of users (potential friends).

There are three main recommendation approaches as follows.

1) Content filtering [Fig. 3(a)] recommends items that are similar to those that a user (liked/bought/viewed) in the past (or is examining in the present). Particularly, various candidate items are compared with items previously (liked/bought/viewed) by the user and the best-matching items are recommended.

2) CF [Fig. 3(b)] is based on the hypothesis that people who agreed in the past will agree in the future, and that

they will (like/buy/view) be the same (or similar) items as they have (liked/bought/viewed) the same (or similar)

items in the past.

3) Hybrid filtering is a combination of content filtering and CF.

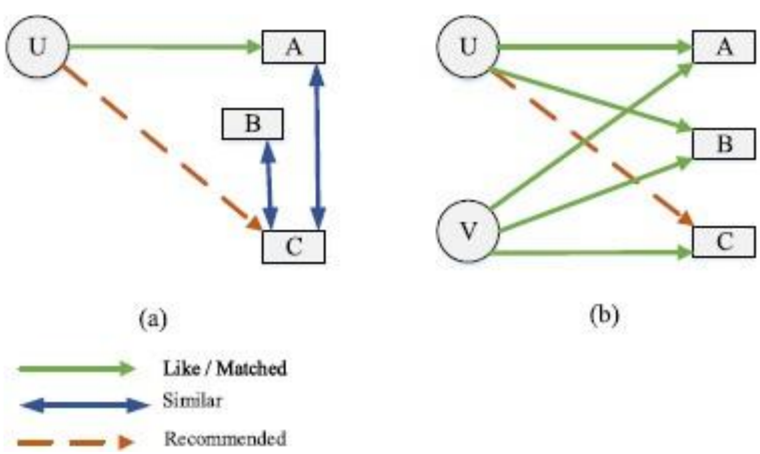

Fig 3(a): content filtering Fig 3(b): CF

3) PersoNet: In PersoNet, the recommendations are computed based on many factors.

- The personality traits similarity between the user and his neighbors.
- The personality traits similarity between the potential friend and the previously rated users (content filtering).
- The rating similarity between the user and his neighbors (CF).

1.2 EXPERIMENT DETAILS

The main phases of the experiment are presented in Fig. 4.

A. Data

To validate the proposed system's accuracy, we have conducted an online experiment, in which we have created an SNS named PersoNet.1 The participants have used the site for a period of 3 months. The experiment duration is divided into two phases. The first is the data collection phase, and it lasted for 2 months, in which each participant was befriended with a set of friends that have different personality traits. The recommendation at this stage was based only on neighbors' personality traits. At the end of this phase, participants were asked to rate the harmony level with their friends. The second phase is the testing phase, and it had lasted for 1 month, in which the participants were giving a chance to communicate with the recommended friends. To measure the recommendation system's accuracy, at the end of the experiment, given the list of friends that were recommended by the system, the participants were asked to rate the correctness of these recommendations.

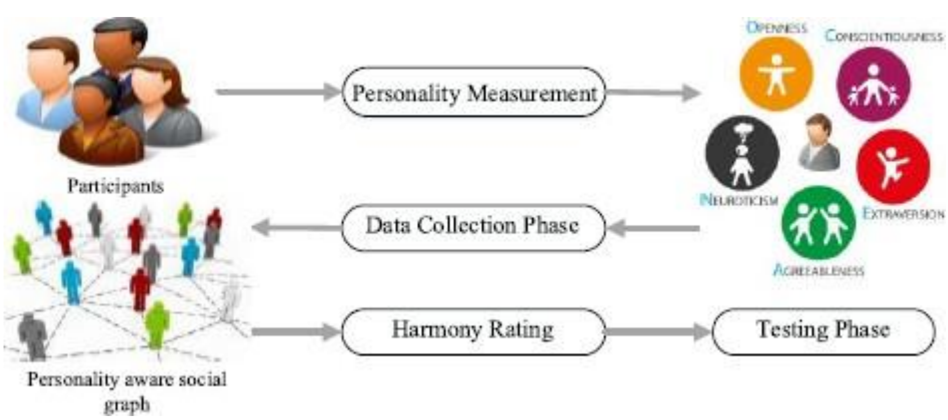

Fig 4: Evaluation Phases

B. Participants

To conduct the experiment, a total of 149 participants were solicited, most of them were undergraduate/graduate international students from different Chinese universities, and the other few were Chinese students. The benefit of using international students for this study is to conduct a holocultural study, as the participants were of different countries and even from different continents with different languages and cultural backgrounds. However, we have ensured that all participants can speak English fluently. In addition, the participants were of different ages and genders. Table III details the participants' demographics. The participants were volunteers and no compensation was made. From a total of 149 participants, only 123 active participants were considered in the later steps of the experiment, as the other 26 participants did not meet the minimum requirement of the experiment, because they did not use the system regularly, including such inactive users in neighbor formation process would negatively affect the accuracy of the recommendation.

TABLE III
PARTICIPANTS' DEMOGRAPHICS

Parameter	Value
Number of volunteers	149
Number of active participants	123
Countries	12
Male	91 (61%)
Female	58 (39%)
Average age	23 years

C. Personality Measurement

After registering on the site, the users were asked to take (International Personality Item Pool Representation of the
NEO PI-R)-60 personality questionnaire, and their big-five traits scores were recorded. The IPIP-NEO-60 is ideal for our situation. First, because it is open access, and second, because we did not want the volunteers to feel bored by answering a long questionnaire such as NEO-PI-R. Although they are easier to fill, their measurements are usually inaccurate, simply because the taker may underestimate the answer of one of the ten questions.

D. Data Collection Phase

In the data collection phase, during 2 months, the participants were befriended with 30 people with different dominant traits, 6 people from each trait. The participants were encouraged to chat with their default friends as much as possible; the chat was done via PersoNet's integrated messaging system. To ensure that the participants' harmony rating is based on personality traits and to reduce the influence of homophily, the participants were asked not to reveal their real identities or any other information that would influence their rating later on, such as location, religion, age, sex, and political views. However, the participants were strongly recommended to discuss their views about other topics.

E. Harmony Rating

After 2 months of the data collection phase, the participants were asked to rate the harmony level of their friends. Each participant was asked, based on his knowledge of a given friend, whether their personality types are matched and his desire to see people like him in his recommendations. The harmony rating was scaled as Likert scale [40]. These ratings were used to determine the user's neighbors.

F. Friend Recommendations

After all participants finished the harmony rating of their friends, all participants' usernames were changed, and each participant is friended with 30 friends, the top five most recommended users by BOF, CF, and PersoNet (a friend might be recommended by more than one system), in addition to these recommendations, each participant is also friended with the top five least recommended users.

G. Testing Phase

The second phase is the testing phase, and it lasts for 1 month, in which the participants were giving the chance to communicate with the recommended friends. To measure the robustness of the three recommendation systems, at the end of the experiment, the participants were asked to rate the correctness of the recommendations. The participants did not know any details about the used recommendation systems. Based on the recommendation correctness ratings that were given by the participants, PersoNet, BOF, and CF systems were evaluated.

1.3 PERFORMANCE EVALUATION

In this section, we present the evaluation that we conducted to validate the proposed system.

A. Implementation

To validate the proposed system's accuracy, a personality based SNS that uses the proposed FRS named PersoNet was implemented, in which the online experiment was conducted to study users' satisfaction about the site's recommendation system. PersoNet was implemented using PHP, and the database management using MySQL, and the front-end interface using the bootstrap framework, see Fig. 5.

Fig 5: Personet Social Network

B. Evaluation Metrics

Recommendation systems are evaluated based on their ability to identify the relevant items for a given user from all available items. Four groups of decisions are yielded from the confusion matrix that lists the correct and incorrect recommendations:

1) true positives (TPs): the recommended friends that were rated as successful recommendations;

2) true negatives (TNs): the least recommended friends that were rated as unsuccessful recommendations;

3) false positives (FPs): the most recommended friends that were rated as unsuccessful recommendations; and

4) false negatives (FNs): the least recommended friends that were rated as successful recommendations.

We have evaluated the three systems based on the following metrics.

1) Precision (P): It is the fraction of confirmed recommendations among the total recommended users by the recommendation system and is computed using the following equation:

2) Recall (R): It is the fraction of confirmed recommendations over the total confirmed recommendations by all systems and is computed using the following equation:

3) F-Measure: A combination of precision and recall in a single numerical value, it is also known as F-score and is computed using the following equation:

4) Result Discussion: The mean values of precision, recall, and F-measure of the three systems are presented in Fig. 6. As we can see, BOF has the worst performance in terms of precision (0.55) and recall (0.58), as it considers only personality trait similarity measurement and ignores the user's previous harmony ratings, while CF scores are much better than BOF with precision (0.78) and recall (0.79). However, PersoNet has the highest precision and recall values among the three systems, with precision (0.81) and recall (0.82), that is, because it incorporates personality traits in similarity measurement without neglecting the user's preferences. While harmony rating can be a strong indicator of how the friends are matched. However, to further validate the proposed system, we have analyzed the text exchanges between friends regarding their personalities. In this regard, we have computed the neighbor set based on the exchanged messaged between the participants rather than the harmony rating that was given
by the users.

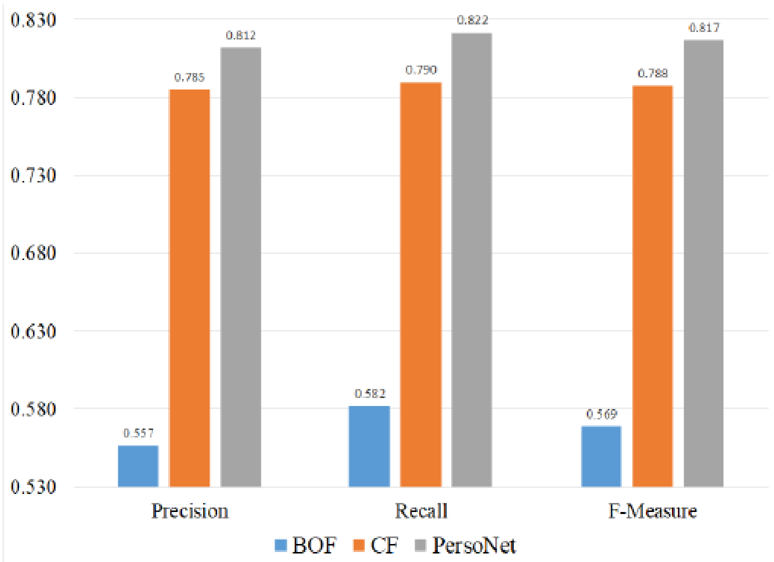

Fig 6: Systems evaluation with rating-based similarity

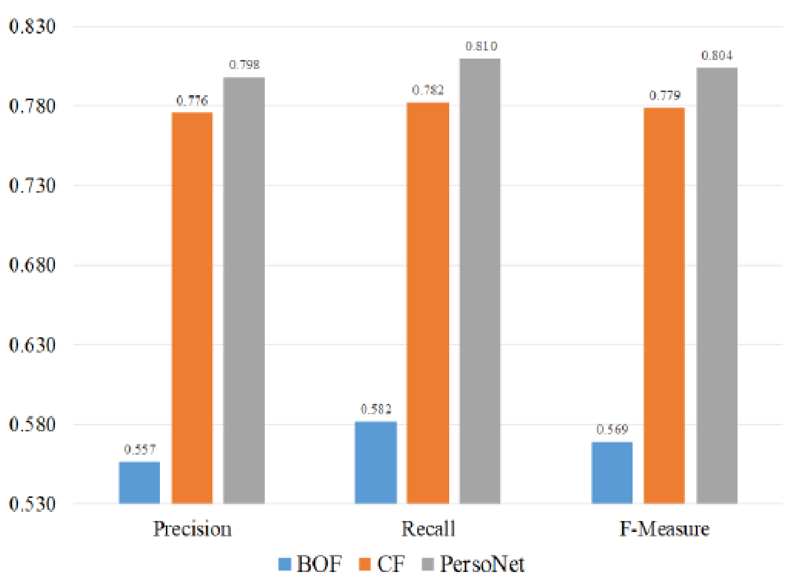

Fig 7: Systems evaluation with message-exchange-based similarity.

The precision, recall, and F-measure of the three systems when similarity computed based on exchanged messages are presented in Fig. 7. As we can observe, BOFs precision (0.557) and recall (0.582) are the same as harmony rating-based similarity, that is, because BOF depends only on personality similarity between the potential friend and previous friends (content filtering). Although CF performs better than BOF in terms of precision (0.776) and recall (0.782), however, PersoNet still has the upper hand with precision (0.798) and recall (0.810).

Present Approaches And Methods Used in RS

A. Context – Aware Recommender System

Context has many definitions and is a multidimensional concept that has been studied across different research disciplines including Computer Science, Cognitive Science, linguistic, philosophy, psychology and organizational context. Since context has been studied in multiple disciplines, each of them view the context in their own way and are different from each other. We will try to understand the term context specifically in the domain of RS. Traditional recommender systems usually compute the similarity using two-dimensional user-item matrix. They did not take into consideration contextual information which affects and influence the decisions. The contextual information are time, location, companions, weather, and so on. Considering context information as one system design factor is necessary for producing more accurate recommendations. Adomavicius and Tuzhilin proposed a multidimensional approach to incorporate contextual information into the design of recommender systems Adomavicius et al. (2005). They also proposed a multidimensional rating estimation method based on the reduction based approach, and tested their methods on a movie recommendation application that took time, place, and companion contextual information into consideration. Here, recommendations are generated using only the ratings made in the same context of the target prediction. However, in fact, it is rarely the same context occurs in the future but instead the similar context. The disadvantage of that method is the increase of data sparsity. Yap et al. (2007) exploit a different way of incorporating contextual information and tries to improve prediction accuracy using a Content Based (CB) approach. The authors model the context as additional descriptive features of the user and build a Bayesian Network to make a prediction. They increase the accuracy even with noisy and incomplete contextual information. Umberto and Michele have analyzed post filtering, pre filtering and contextual modeling for context-aware recommender system. There is research done on selecting relevant context features, relevant contexts increases the accuracy of recommender system while the irrelevant ones actually degrades the performance both in terms of output accuracy and computational load. Ante Odic et al. in, describes different methods for elicitation of relevant context selection.

B. Hybrid Methods in Recommender System:

Hybrid recommender systems combine two or more recommendation techniques to gain better performance with fewer of the drawbacks of any individual one. Most commonly, collaborative filtering is combined with some other technique in an attempt to avoid the ramp-up problem. Hybrid methods are:

C. Content Boosted Collaborative Filtering

Hybrid Method	Description
Weighted	The scores of several recommendation techniques are combined together to produce a single recommendation.
Switching	The system switches between recommendation techniques depending on the situation. The issue of this hybrid is selecting one recommender among candidates. This selection is made according to the situation it is experiencing. The criterion for the selection like confidence value or external criteria should exist and the components might have different performance with different situations
Mixed	Each component of this hybrid should be able to produce recommendation lists with ranks and the core algorithm of mixed hybrid merges them into a single ranked list. The challenge here is how the new rank scores should be produced.
Feature combination	Features from different recommendation data sources are thrown together into a single recommendation algorithm
Cascade	One recommender refines the recommendations given by another.
Feature augmentation	Output from one technique is used as an input feature to another
Meta-level	The model learned by one recommender is used as input to another.

ADVANTAGES

Recommender systems have become an important research area because they have been a kind of Web intelligence techniques to search through the enormous volume of information available on the Internet. Collaborative filtering and content-based methods are two most commonly used approaches in most recommender systems. Although each of them has both advantages and disadvantages in providing high quality recommendations, a hybrid recommendation mechanism incorporating components from both of the methods would yield satisfactory results in many situations. In this paper, we present an elegant and effective framework for combining content and collaboration. Our approach uses a content-based predictor to enhance existing user data and item data, and then provides personalized suggestions through user-based collaborative filtering and item-based collaborative filtering. The proposed system clusters on content-based approach and collaborative approach then it contributes to the improvement of prediction quality of a hybrid recommender system.

Recommendation algorithms mainly follow collaborative filtering, content-based filtering, demographics-based filtering and hybrid approaches. Collaborative filtering:-It recommends items based on the similarity measures between users and items. The system recommends those items that are preferred by similar category of users.

Collaborative filtering has many advantages:

1. It is content-independent

2. In CF people makes explicit ratings so real quality assessment of items is done.

3. It provides effective recommendations because it is based on user's similarity rather than item's similarity.

- Content based filtering:-It is based on profile of the user's preference and the item's description. In CBF, to describe items we use keywords apart from user's profile to indicate users preferred likes or dislikes. In other words, CBF algorithm recommend items or similar to those items that were liked in past. It examines previously rated items and recommends best matching item.

- Demographic: It provides recommendation based on the demographic (like age, profession) profile of the user. Recommended products can be produced for different demographic niches, by combining ratings of users in those niches. Knowledge-based: It suggests products based on inferences about user's needs and preferences, item selection and its basis for recommendation.
- Hybrid recommender: Hybrid recommender system is the one that combines multiple recommendation techniques together to produce the output. If one compares hybrid recommender systems with collaborative or content-based systems, the recommendation accuracy is usually higher in hybrid systems. The reason is the lack of information about the domain dependencies in collaborative filtering, and about the people's preferences in content-based system. The combination of both leads to common knowledge increase, which contributes to better recommendations. The knowledge increase makes it especially promising to explore new ways to extend underlying collaborative filtering algorithms with content data and content-based algorithms with the user behaviour data.

NEED FOR HYBRID CLUSTERING AND CLASSIFICATION ALGO

- Accuracy-search results must be accurate.
- Fast retrieval-Data retrieval time must be fast.
- Entropy reduction-Dispersion in the retrieved data leads to unreliability.
- Outlier Detection-Detection of irrelevant or exceptional data.

We believe relying on personality allows our system to provide users with recommendations that are diverse, noble and serendipitous; the authors identified these as factors of a successful RS. In general, most cross-domain RSs need to provide these factors; however, we believe our system surpasses the other approaches in accomplishing this. For example, a CF system could recommend an e-book to someone who bought an e-book reader, or a laptop cover to a user who purchased a laptop. Although these suggestions are from multiple domains they are not serendipitous, as the user would expect them. With cross-domain CB systems, a user who likes romance movies would not be surprised to receive a romantic song or book. However, our system could suggest a laptop cover to a user based on a song they liked, because both items were mostly liked by extroverts.

It employs an unusual and original method of recommendation that users might find interesting. If users favor and reuse personality-based RSs more frequently than traditional rating based RSs.

FUTURE SCOPE

Future Trends in Recommender System Recommender system has been an active area of research for a decade or so and continues to be an interesting research domain. Although recommender systems have witnessed unprecedented improvements starting from very primitive content based and collaborative filtering methods, a lot of research is going on to further enhance the output accuracy and improvements in all dimensions of recommender system. The search is focused on various areas to make the RS more and more useable and practical in real life scenarios. The following are some of the areas of RS where there are intense research going on and these efforts are surely shaping the future of recommender systems.

A. Privacy :

Privacy preserving RS is one of the major challenges towards developing a practical RS. There are various real life situations where getting input data is not easy and at times extremely difficult for the recommender system to make a reliable recommendation. There are various reasons for that. In the case of systems like medical recommendation system, availability of input data is in sparse as medical history is often treated as personal, confidential information. As a result of these, developing a reliable medical recommender system or any such system which requires data that is considered to be private and confidential is extremely difficult. In [26], an approach towards privacy preserving RS is detailed that makes use of Homomorphic cryptography to achieve the same.

B. Recommendation List Diversity:

Most research into recommending items has been towards the accuracy of predicted ratings. There are also other factors those have been identified as important to users. One such factor is the diversity of items in the recommendation list. In a user survey aimed at evaluating the effect of diversification on user satisfaction, it is found that it had a positive effect on overall satisfaction even though accuracy of the recommendations was affected adversely. There is a great need for a shift in focus that is related to the functionality offered by recommender systems that can exploit directly the usage data, and add more value to the user.

C. Dynamics in User Interest:

Human beings have varied interest and most importantly this interest is dynamic. Recommender system needs to adapt to this dynamism. Most personalization systems tend to use a static profile of the user. However, user interests are not static, changing with time and context. Few systems have attempted to handle the dynamics within the user profile. The behavior of users varies over time and it should affect the construction of models. A Recommender system should be able to adapt to the user’s behavior, when this changes.

D. Data Sparseness & Cold start:

In many of the practical dataset, it has been found that data sparseness is a major issue, many of the recommender algorithms makes this issue worse and cold start problem is becoming a deterrent for the RS usage. There are many research initiatives towards eliminating data sparseness using singular value decomposition.

E. Adaptive and Scalable:

RS Although the accuracy of RS is being enhanced, the computing requirements are also becoming more and more complex. Scalable RS has become an impending need towards practical use-case scenarios and indeed an area of focused research. F. Collaborative RS Recommender systems need to collaborate among themselves in order to increase the accuracy of RS and also increase the scope of RS. These collaborative RSs would be linked to each other over a simplified but standard interface and would be complementary to each other.

CONCLUSIONS

In this paper, a novel FRS based on the big-five personality traits model and hybrid filtering was presented and evaluated, in which the friend recommended process is based on personality traits and users' harmony rating. To validate the proposed system's accuracy, a personality-based social network site that uses the proposed system named PersoNet was implemented.

The experimental results have proved that PersoNet performs better than the legacy CF-based system in terms of precision and recall. However, many aspects that could improve the effectiveness of Personet have not been discussed in this paper, such as follows.

1) In this paper, the subjects' personality traits measurement was done through questionnaires. However, PersoNet could be further improved by implementing automatic personality recognition scheme, which measures the user's personality traits based on its posted content, without the need for personality test.

2) The effectiveness of PersoNet was evaluated based on the recommendations accuracy that was validated by the users' rating. Extending the experiment by comparing PersoNet's recommendations accuracy to other schemes, such as graph-based and semantic-based recommendations, is our future direction.

3) The proposed recommendation system is based on the big-five personality traits model. Extending the model to incorporate other personality traits models such as Myers–Briggs type indicator is one of the future works.

4) The population of the experiment is relatively small (n = 126). Conducting the experiment on a large size population (n > 1000) from all ages is a future direction.

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