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Original Article

Smart Recommendation for Unanimous People

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Abstract - *Creativity has become one of the optimal technologies to solve human life problems, and technology is used for facilitating human needs. People always seek and be more comfortable based on a similar mindset. Which in return helps them to build new ideas and thoughts. With the popularity of social networks and social media, many users like to share their reviews, ratings, experiences, and images. The factors that are most considered by social media platforms, like influence, search content and interest based on friends, bring connectivity for smart recommendation systems to establish the relation between the users with the help of the data collected from the users. Social factors like interpersonal interest similarity, interpersonal influence, and personal interest these factors are taken into consideration before recommending friends to users. This smart recommendation model, which we have used, is based on Latent Dirichlet Allocation (LDA) algorithm. The category of personal interest will help the users to club together and can recommend people to the user based on individualities. The interpersonal influence helps users to connect based on their interest towards learning and innovation; they can connect and discuss regarding their common interests.*

Keywords - *Interpersonal interest similarity, Interpersonal influence, Smart recommendation, Personal interest.*

1. Introduction

The idea behind this project is to facilitate meaningful interactions among people based on their personal interests, interpersonal interest similarity, and interpersonal influence. The system utilizes content-based recommendation, primarily relying on similarity among user searches, considered metadata. This metadata is then used to personalize recommendations and create unique connections between users, leading to better interactions based on smart recommendations.

To optimize the process, the metadata is pre-processed to remove irrelevant information and focus on the required data for the system. While many websites use this data for marketing and advertising purposes, this project aims to use it to connect individuals with similar interests and mindsets.

Users can select their personal interests and provide the necessary details to the system. The primary objective is to connect people based on their personal and interpersonal interests, enabling users to interact with like-minded individuals. The application features a search engine that considers keywords in the search string and the website the user opens.

Keyword count is calculated using a hash map function, and redundant data is summarized. User search data is considered before recommending a person, and these data are stored in individual user databases. Based on the collected data, friends are recommended to users. The system contains pre-loaded sets of data that represent different lifestyle categories. Each user is mapped to one or more lifestyle categories based on their searches.

The admin uses this mapping to suggest connections between users with similar interests and users who have interpersonal influence on each other. Additionally, users can be connected based on shared posts in specific categories. The application automatically suggests users with similar interests in the posting category.

The primary objective of this project is to connect people globally based on their interpersonal interests. Unlike other social media platforms, this application offers friend recommendations based on user searches and interests. Users receive smart recommendations without the need to search for like-minded individuals actively. The app suggests connections based on searches and shared data within categories. Some examples of categorized user lifestyles include computer language, sports, animals, and travel.

Overall, this approach helps categorize users and promotes meaningful interactions among individuals with shared interests.

2. Literature Survey

In these applications, the focus is on recommending relevant content from billions of choices in real time. The research has led to the development of optimal recommendation system algorithms, which vary based on specific tasks. These algorithms effectively identify longterm interests and up-to-date content for users. A domain-specific language called IGQL is introduced, simplifying complex recommendation systems by building nested trees and combining rules. IGQL primarily emphasizes machine learning and business logic, contrasting it with logistics, which focuses on the right quantity of candidates for any queries [1].

Social networking heavily relies on rating or feedback-driven recommendation systems. These systems cater to various user activities and introduce a new feature called "Circle of Friends," benefiting from domain-specified "Circle of Trusted People." The main focus is inferring social trust-based circles using categorical specified data ratings in the social network. Users place trust in a subset of friends regarding a particular domain. However, most existing multi-category rating datasets mix connections between social users from different categories. The circle-based recommendation system addresses this issue, considering waiting for friends and circles based on their expertise levels. Experiments on public data demonstrate that this model can be used as a user's social trust information, leading to improved accuracy in recommendations [2].

Social media significantly impacts social activities by influencing people's behavior. The traditional recommendation algorithm gathers information and introduces a new set of measures based on rating information. An optimal linear relation is proposed to quantify the importance of social influence, which varies with the data. This algorithm outperforms traditional methods in terms of accuracy and stability. It also focuses on personalized recommendations on media platforms, utilizing information obtained from social media to examine trust and user influence in social relationships and rating information [3].

The increasing amount of information on the internet has led to the utilization of recommender systems across various fields to manage information overload efficiently. The healthcare field has seen significant growth in the application of recommendation systems. These systems offer proper recommendations, enabling individuals to make informed decisions related to their health. Reviewing recommendation techniques and applications in the healthcare field includes content-based, collaborative filtering, and hybrid methods. Five applications of health recommendation systems are detailed [2].

Personalized recommendation systems play a crucial role in online services such as advertising companies and e-commerce websites. They enable users to see relevant items based on their personalized interests among many choices. This involves information representation across various channels, including online and offline behaviors, to provide better recommendations. The recommendation system considers the user's preference towards specific items, and socially oriented channels are incorporated for the cross-domain recommendation. The system explores features that focus on user and item-centric channels to improve the quality of recommendations [5].

For the analysis of the Netflix prize dataset, various collaborative filtering algorithms, including SVD and neighborhood-based approaches, are blended to enhance system accuracy. The system uses user-item events such as purchases, ratings, bookmarks, and carts to predict future ratings. The K-nearest neighbor algorithm is utilized for prediction, where ratings based on different circles can be predicted. Additionally, algorithms like matrix factorization and restricted Boltzmann machines are blended to create a friend circle in the recommendation system, leading to more accurate recommendations [6].

A Bayesian Inference-based recommendation system is proposed, where users share their content ratings with their friends. The similarity of ratings between friends' circles is calculated, and conditional probabilities are measured from the rating of both users. Based on these responses, a Bayesian network is built to infer the user's rating. The algorithm is evaluated against two different online rating methods, and the base and inference recommendation outperform trust-based recommendation systems and is comparable with the CF recommendation algorithm. The system allows a trade-off between the quality and quantity of recommendations and provides an informative prior distribution to overcome rating sparseness [7].

The exponential growth of information and the features of social networks influence recommendation systems to deliver accurate results. Traditional techniques often overlook relational data in social media. Existing recommendation systems incorporate social network structure but fail to address contextual factors derived from users' behavior, which is crucial for social recommendations. A novel Probabilistic Matrix Factorization is proposed to fuse latent spaces and considers data from Facebook and Twitter social network datasets in China [8].

3. Existing Methods

Smart Recommendation System has been effectively utilized to resolve the excess data information. In E-Commerce websites like Flipkart, Amazon etc., it is very necessary to manipulate a large amount of data, such as recommendations of the products and items the existing user prefers. The survey conducted by Amazon shows that more than 20 percent of the turnover has been obtained from the Smart Recommendation System. The collective filtering algorithms are viewed as the initial generation of the recommendation system to anticipate user interest. Although, with the fast growth in the number of registered customers and numerous products, the difficulty for new users into the recommended system with the traditional actions and the insufficiency of the datasets have been progressively interactable. The emergence of Web 2.0 considerably refines the user's action on the internet, leading to the size of social media like Twitter, Facebook, YouTube etc. The interpersonal connection between the friend's social media circle will make it possible to clear up the above problem. Many social networking sites based on the prototype have been suggested to enhance the accomplishment of the recommendation system. The concept of an 'inferred trust circle' has been put forward on the domain manifest group of like-minded people on social networks to suggest the customer choice of products. This proposal, besides clarifying the interpersonal faith in the compound networks, nevertheless minimizes the huge datasets.

4. Proposed Methods

The three social components, namely, Personal Interest, Interpersonal Influence and Interpersonal Interest Similarity, such components are combined in the form of an integrated smart recommendation prototype built on the Latent Dirichlet Allocation (LDA) algorithm. The personality of the user is denoted by the input that has been entered and the data that has been shared by the user with the ratings. To incorporate the result of the individual user's personality, the data that has been shared is based on the categorizing tags. Accordingly, each data item is represented by a category distribution vector, which reviews the categories of the rated data set. Additionally, our project uses the rating practices of user activity and interest. It also allocated the result of individual users' personalities in the Smart Recommendation model corresponding to their proficiency levels. Furthermore, the user-to-user interests and correlation of the social networks consist of Interpersonal Interest Similarity and Interpersonal Influence. The Interpersonal Interest Similarity in the project assumes the interest group to increase the symbiotic relationship of the user hidden attribute.

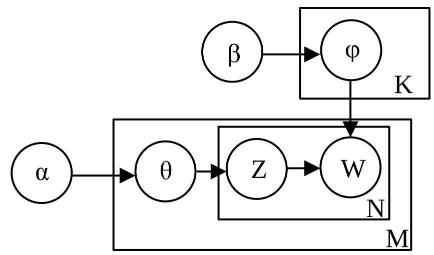

Fig. 1 LDA diagram

LDA Algorithm is a statistical generator approach that gives a set of observations to the given observed groups that explain that some parts of the data are similar to that. LDA algorithm is used to represent the Probabilistic Graphical Methods [9]. Give the dependency of the variables among them which are captured properly. In the given figure, Fig-1 boxes represent repeated entities, and the outer box document and wall represent the repeated words in the document. The variable names are: M is number of documents, N is the number of words in a document, Is the parameter of per document topic, and isthe parameter of a per-topic word.

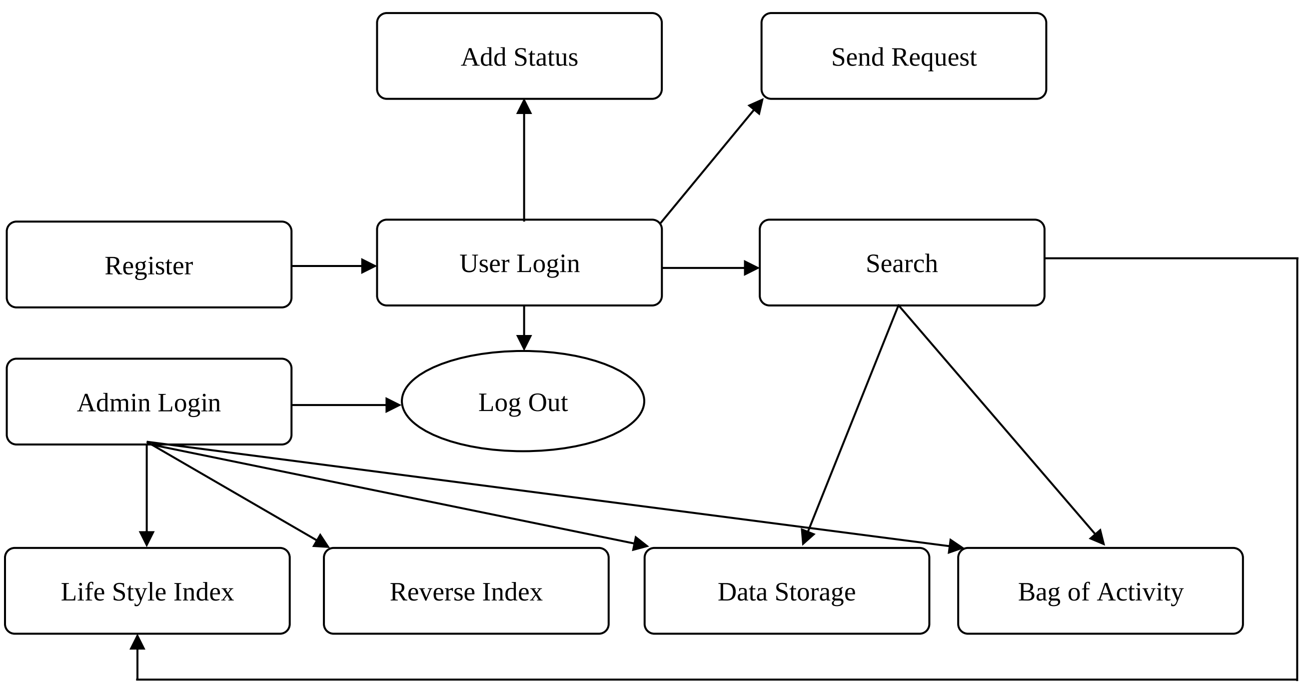

Fig. 2 High-Level diagram

4.1. Algorithms Used

For user queries, user data will calculate ratings based on user relations and user ratings. The data is sorted for the top k list based on the rating.

Input: Query q, User u, relation R, relation size Rs, data d
Output: data d1, k list.

```
for each data d
    Dif uR
        if u(R)R
            Rs =R * Rs
            rating t=t +
            Rs;
        else if
           rating t=t
        +1;end if
    while(d D)
        sort
        ratings D
        d1= k list
        (D);
    end
whileend
for return
k(d1);
```

4.2. Mathematical Model

Let D is the data, (x,y) the data coordinates of data, u(x,y) the data coordinates of the user, RT rating data, UR user rating schema, RD user relation size, K top k list, O is output.

D=U, (x,y), u(x,y), RT[],
UR[]UR= RT[], RD[]
O=RD[], D, K

LDA uses the document as a bag of activities or words in the form of unsupervised learning. It makes our assumption by picking a set of topics and each topic by picking a setof words [4]. These sets of words can be sorted using the respective probability score based on the occurrence of the words. As shown in Fig-2, the words in the lifestyle index are categorized on the reverse indexing is done, where the indexed data storing and mapping from the content is done. It is like a HashMap that directs a word document or a webpage from the given word.

5. Conclusion

In this project, a Smart Recommendation System perspective was intended by incorporating the social networking components such as Personal Interest, Interpersonal Influence, and Interpersonal Interest Similarity. Specifically, the users individually rating the shared data items denotes personal interest, especially for the proficient users. All these components are integrated together to enhance the exactness and appropriateness of the smart recommendation system. Currently, our smart recommendation system model will suggest friends based on the search results that the other user searched, which are categorized under the lifestyle index, taking the categorized interests and Interpersonal correlation of the social networks that are taken into consideration.

Conflicts of Interest

Conflict of interest could arise in the following areas:

Research Bias

The article discusses various recommendation system algorithms and their effectiveness in different fields. However, if the article is sponsored or written by individuals or organizations that have a vested interest in promoting a specific algorithm or technology, there could be research bias or a conflict of interest.

Promotion of Specific Applications

The article highlights several applications of recommendation systems in different domains. If the article promotes or endorses specific products, services, or platforms, there may be a conflict of interest if the authors or publishers have affiliations with those entities.

Health Care Recommendations

The article discusses the application of recommendation systems in healthcare. If the authors or entities involved in the research have affiliations with healthcare companies or pharmaceutical industries, there could be a potential conflict of interest that might affect the impartiality of the recommendations.

Social Media Platform Data

The article mentions the use of data from social media platforms like Facebook and Twitter. If the researchers or authors are associated with these platforms, it may influence the interpretation or presentation of the results.

It is important to consider that the potential conflicts of interest mentioned above are speculative and based solely on the content provided. To verify any conflicts of interest, it would be necessary to examine the specific affiliations, funding sources, and intentions of the authors or entities involved in the research and publication of the article.

Future Work

In the future, the project can be developed in the cloud, which has huge accessibility and high security. The functions and code can be migrated to AWS Cloud and deployed using lambda function and API. This also helps users to access the web application fast by using CloudFront as we need not maintain the servers. Other websites can also integrate with our application and can be used for marketing and advertising based on the lifestyle index. The database can be mainly migrated to the cloud as the accessibility of data will be easier, and there will not be any delay in accessing data. The personalized lifestyle category in which the users are mapped can mainly be used for advertising, so there will be a win-win situation for both the website and the company advertising.

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