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Collaborative Filtering Based Sequential Modelling of User Interest for Hotel Industries

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Abstract: Nowadays, implemented different software applications, increasing user engagement. Social influence plays an important role in product marketing. Our Social Media creates an online user group and shares their experiences, interests and views with each other. To provide better service to users and grow a business, there is a need to analyze user interest, need, preferences, and habits. The social circle and influence of people in contact also matters to the user's purchase. Sequential actions of friends and temporal autocorrelation influences user point of interest. Design and development of proposed work includes recommendation generation based on deep learning. Recommender systems which can utilize information in social media, newspaper, TVs, internet, including user preferences, item's general acceptance, and influence from social friends. This paper includes the study of various sequential modelling techniques. Based on the study of existing system, a new system is proposed for sequential modelling.

Keywords: Recommender Systems, Social Media, Machine Learning.

I. INTRODUCTION

In today's world customers have diver's needs for products and services. Recommendation systems help customers to choose & purchase according to their needs & help businesses and their customers while attracting new ones. Recommendation system overcomes the limitations of e-commerce services & utilizes customer behavior & product information to identify customer preferences. Recommendation systems can offer products based on the customer's needs. They can also help the decision-making process by filleting out unnecessary information .In order to overcome information overload, recommender systems have become a key for providing users with personalized recommendations on items such as movies, music, books, Shopping Sites, restaurants, news, and web pages. Some of them have been commercialized by online lenders such as Amazon.com, Netflix.com, and IMDb.com. These systems predict user preferences (often represented as Star ratings) for new items based on the user's past ratings on other items. In our research, we collect data from social media, shopping sites in recommender systems, such as how user preferences or ratings are correlated with those of friends to design a better recommender system. We design an algorithm framework which makes recommendations based on the user's own preferences, the general acceptance of the target item, and the opinions from social media friends. We crawl social media from Yelp.com, and perform extensive analysis on this dataset. Some of the questions, such as whether or not friends tend to select the same item or product, and whether or not friends tend to give similar ratings, have been studied in this dataset. We also use this dataset to evaluate the performance of our proposed system. They direct users towards those items that meet their needs by reducing unwanted information spaces. Here, efforts are made to review and discover the techniques to investigate the proper usage of recommender systems in e-commerce applications.

A SOCIAL AWARE RECOMMENDER SYSTEM

For ex. Meena wants to watch and have dinner on a weekend. Her favorite restaurants are with Chinese cuisine. From the Internet, she finds two restaurants particularly interesting, "THE CONTINENT" and "Friendship Restaurant" These two restaurants are all highly rated in the message board at Google restaurants. Because she cannot decide in which restaurants to eat, she calls her best friend Rani whom she often hangs out with. Rani has not viewed these two restaurants either, but she knew that one of her office mates had just taken a brunch at "THE CONTINENT" and highly recommended it. So Rani suggests "Why don't we go to watch THE CONTINENT together?" Meena takes Rani's recommendation. If we review this scenario, we can see at least three factors that really contribute to the Meena's final decision. The first phase is Meena's own preference for Chinese cuisine. If Meena did not like Chinese cuisine, she would be less likely to pick something like "THE CONTINENT" to begin with. The second Phase is the public reviews on these two restaurants. If these restaurants received terrible reviews, Meena would most likely lose interest and stop any further investigation. Finally, it is the recommendation from Meena's friend, Rani, that makes Meena finally choose "THE CONTINENT." Interestingly, Rani's opinion is also influenced by her officemate. If we recall the decisions that we make in our daily life, such as finding restaurants, buying a house, and looking for jobs, many of them are actually influenced by these three factors.

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II. RELATED WORK

Following researchers previously worked on modeling of user interest for various industries which is discussed below.

S. Isaacman, R. Becker, R. Caceres, proposes a technique to identify important locations in a user's life like home, working place, etc. the technique is based on clustering and regression. It analyses cellular network data. This is a static scenario. It does not focus on users interest or temporal autocorrelation. It do not uses sequential modeling of data.[1]
A new recommender system is proposed by P. Matuszyk, J. Vinagre.Marko Balabanovic .”An adaptive recommendation service for collection and selection of web pages”The system uses incremental matrix factorization. This technique keeps data up to date by forgetting the old outdated data. The current preferences of users are preserved by eliminating old data. Five new data forgetting techniques are proposed in this system.[2]
J. Wang, A. P. de Vries, and M. J. T. Reinders, “Unified relevance models for rating prediction in collaborative filtering,” ACM Transactions on Information Systems, vol. 26, no. 3, pp. 1–42, June 2008.It is a probabilistic item-to-user relevance framework which uses the Parzen-window method for density estimation. This approach reduces data sparsity problem[3]
Yi Zhang , Jonathan Koren Proposes a faster technique to gather a huge number of individual user profiles even if feedbacks available are less. It uses various parameters of BHM for optimization of joint data likelihood.[4]
Norma Saiph Savage,Maciej Baranski,Norma Elva Chavez,Tobias Höllerer.Improved version of a location recommender system by implementing Decision Tree (DT) along with discrete Hidden Markov Model (HMM).Together HMM and DT differentiate between transport modes and reduce noise.[5]
Prem Melville, Raymond J. Mooney, Ramadass Nagarajan. It gives an approach to combine content and collaboration to enhance existing user data and to give better performance than a pure content based predictor.[6]
Marwa Hussien Mohamed, Mohamed Helmy Khafagy and Mohamed Hasan Ibrahim introduces survey about recommendation systems, techniques, challenges the face recommender systems and list some research papers solve these challenges.[7]
Madhuri Kommineni; P. Alekhya; T. Mohana Vyshnavi; V. Aparna; K Swetha; V Mounik introduces survey about recommendation systems, techniques, challenges the face recommender systems and list some research papers solve these challenges[8]
G. Adomavicius, and A. Tuzhilin presents an overview of the field of recommender systems and describes the current generation of recommendation methods that are usually classified into the following three main categories: content-based, collaborative, and hybrid recommendation approaches.[9]
C. Basu, H. Hirsh, and W. Cohen presents an inductive learning approach to recommendation that is able to use both ratings information and other forms of information about each artifact in predicting user preference.[10]
D. Billsus and M. Pazzani. propose a representation for collaborative filtering tasks that allows the application of virtually any machine learning algorithm. [11]
P. Bonhard’s and M. A. Sasse’s research on recommender systems has focused on improving the matching algorithms. The research presented in this paper takes a user-centred approach. [12]
J. S. Breese, D. Heckerman, and C. Kadie compare the predictive accuracy of the various methods in a set of representative problem domains.[13]
According to the above discussion, every researcher worked on one type of filtering & results of algorithms are not compared. The main goal of our personalized recommender system is to provide useful recommendations on various items to the users using various filtering & algorithm comparisons.

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III. SYSTEM ARCHITECTURE

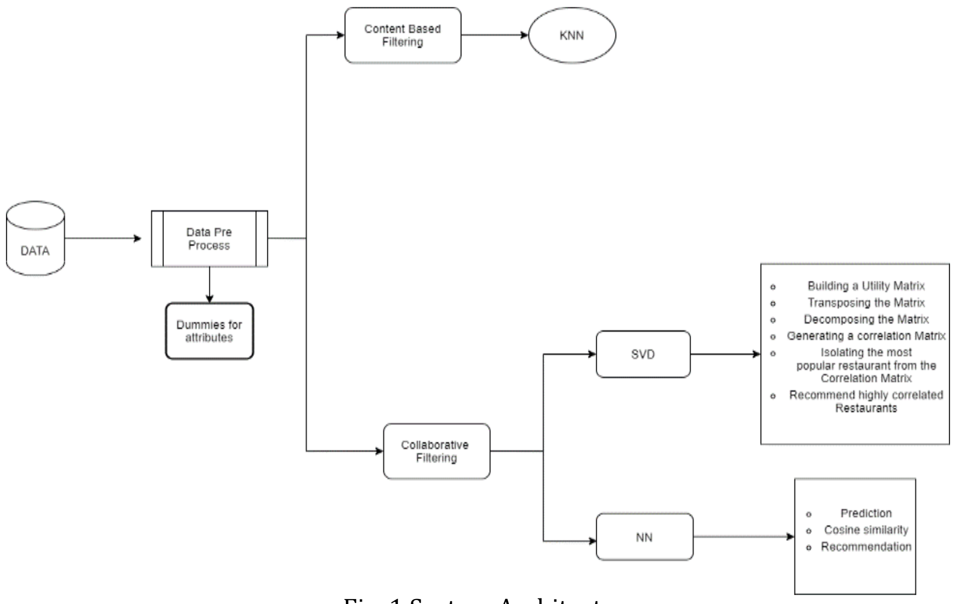

Fig. 1 System Architecture

Here we are merging both categories of recommendation systems, based on previous papers by adding collaborative as well as content based filtering, to give more relevance to users.

IV. METHODOLOGY

Step 1: Introduction & Problem defining
To recommend restaurants in specific cities from the Yelp dataset.
Step 2: Data Over Viewing
To explore the dataset and use a subset of each table to reduce the chunk of data size.
Step 3: Preprocessing Data
Filtering the dataset by removing outliers, replacing missing values and doing other preprocessing to get a clean numeric data.
Step 4: Content Based Filtering
Recognizing the similarity based on specific features to recommend restaurants.
Step 5: Collaborative Filtering
Recognizing the similarity based on user similarity taste to recommend restaurants.
Step 6: Neural Network
Recommending restaurants from NN with sense of collaborative filtering approach
Algorithm and concept used:
KNN
SVD
Correlation
NN
Cosine Similarity
1. Exploration
1.1 Keywords
1.2 Filling factor: missing values
2. Cleaning
2.1 Missing values
2.2 Column Selection
3. Recommendation Engine
3.1
3.1.1 Similarity
3.1.2 Popularity
3.2 Making meaningful recommendations

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KNN:

KNN Algorithm is based on **feature similarity**: How closely out-of-sample features resemble our training set determines how we classify a given data point: KNN can be used for **classification** — the output is a class membership (predicts a class — a discrete value). An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors. It can also be used for **regression** — output is the value for the object (predicts continuous values). This value is the average (or median) of the values of its k nearest neighbours.

V. RESULT ANALYSIS

Result has been Shown :

```
# the most POPULAR restaurants by stars.
combined_business_data.groupby('business_id')['stars'].count().sort_values(ascending=False).hea
d()
```

```
business_id
bZiIIUcpgxh8mpKMDhdqbA    4818
YZs1gNSh_sN8JmN_nrpxeA    3603
jREzLrIEkc4jQKLfYMJ0gg    2576
v1UzkU8lEWdjxq8byWFOKg    2532
4sfF1paqVfXvzAIdzs6MQg    1838
Name: stars, dtype: int64
```

```
# see the NAME of the most popular restaurant
Filter = combined_business_data['business_id'] == 'bZiIIUcpgxh8mpKMDhdqbA'
print("Name: ", combined_business_data[Filter]['name'].unique())
print("Address:", combined_business_data[Filter]['address'].unique())
```

```
Name:  ['Hopdoddy Burger Bar']
Address: ['1400 S Congress Ave, Ste A190']
```

Fig. 2 Result

VI. CONCLUSION

The main goal of a personalized recommender system is to provide useful recommendations on various items to the users. Social media provides an important source of information regarding users and their friends. This is valuable to recommender systems. Here, we presented a social aware recommender system which makes recommendations on the basis of content as well as collaboration, considering a user's own preference, an item's general acceptance and influence from friends. In addition, we have collected data from social media. The analysis on this database collected from friends has a tendency to review the same restaurants and give similar ratings. This is being accepted by many platforms, to be in more context with users.

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