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Enhanced Collaborative Filtering Algorithm for Movies Recommendation using Big Five Personality Traits

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Abstract: Recommender System suffers from data sparsity and cold start problems which arises when there is no sufficient rating history for user who has recently log into the system and no proper recommendations can be made. This paper develops an Enhanced collaborative filtering algorithm for Movie recommender system Using genre and Big five Personality traits (EMUBP) as system's input. The experimental result shows that the EMUBP system improved recommendation quality and accuracy by 8.33% compared with the existing state-of-the-art using precision, recall and MAE.

Keywords: Recommender System, Collaborative Filtering, Cold Start Problem, Big Five Personality Traits, Genre, K Nearest Neighbor.

1. INTRODUCTION

The massive increase in the volume of available digital information and the number of visitors to the web has created potential challenge of information overload which hinders timely access to items of interest on the internet. The increasing growth of web information makes it difficult for web users to locate relevant information, products or services according to their needs and preferences. Recommender System (RS) come on board to address the problem of information overload by assisting web users in finding the most related information, products or services in diverse application domains such as e-learning, e-commerce, e-tourism and social media. The RS is a personalized decision support tools employed to exploit the user's explicit and implicit preferences to recommend the most relevant information, product or services. RS help users search large amounts of digital contents and identify more items that are likely to be more useful or attractive. RS is further divided into three namely: Content Based Filtering (CBF), Collaborative Filtering (CF) and

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Hybrid Filtering (HF) [12]. Cold start problem is a situation where the system cannot accurately identify recommendation for new users because the new user does not have any rating history or new movies that are not rated by any user[6],[8]. With Cold Start problem, there will be no accurate recommendation for new user. This prompted many research to mitigate the cold start problem [1], [2], [6]. For example [1], combined personality traits and demographic attributes in a user based recommender system to solve cold start but people living in same demographic area have different inferences, interest and personality therefore, their choices on item is quite different. [2], proposes an approach that apply the relationship of user feature scores derived from user item interaction via ratings to optimize the prediction algorithms. The approach uses genre as feature to determine user's interaction, their approach is accurate and effective when the user has past record and refused to acknowledge users with no past record.

To address the above mentioned problems, in this paper, an Enhanced collaborative filtering algorithm for Movie recommender system Using Big five Personality traits (EMUBP). It is based on the assumption that people having same personality tend to have same interest and inferences in movies. The system prompts to the user an interface which ask users personality questions using International Personality Item Pool (IPIP) [11], [13] questionnaire and the user provide answers to the personality questions, the system generate a score for each trait and generate a matrix of size N x 5, each element of the matrix is a personality score. N is number of users. The system subtract genre preference away from the acquired personality traits throughout the entire genre and add together to obtain the active user matrix score. However, the system selects all the active users K Nearest Neighbor (KNN) who share the same personality with the active user to determine recommendation of movies to the target user based on their tastes and preferences. The EMUBP describes in details in section three.

The paper is organized as follows: section two describes literature review, section three describes the notation, some basic definitions and the proposed system (EMUBP), section four describes the experiment, dataset, performance evaluation, result, discussion, section five presents the conclusion. Ease of Use.

Related Works

In this section, several collaborative filtering systems were reviewed by highlighting the contributions, strength and weaknesses of each research work as follows:

[1] Proposes Solving Cold Start Problem by Combining Personality Traits and Demographic Attributes in a User Based Recommender System. The system fails to examine that people living in same demographic area tend to have different inferences, interest and personality therefore, their choices on item is quite different.

[13] Proposed a short five factor personality inventory developed from the International Personality Item Pool (IPIP) implemented as an online questionnaire and completed by 2,448 participants. Following factor analyses, a revised version was created with acceptable reliability and factor univocal scales. As preliminary evidence of construct validity, support was found for 25 hypothesized links with self-reports of relevant behaviors and demographic variables, In a replication using a different recruiting strategy to test for differences due to

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motivational factors, similar results were obtained. This set of scales appears to provide acceptable measures of the Five Factor Model for use in internet mediated research.
[6] Use alleviating the new user problem in collaborative filtering by exploiting personality information. The work does not consider the actual acquisition of user personality information and always assumed that it was already available this makes recommendation ineffective and items were recommended with high rate of error, recommending items that are not interested by the active user.
[14] Uses Cross domain user preferences and personality traits in collaborative filtering to improve the accuracy of recommender system, the work incorporate additional ratings from source domains. The work focuses on preferences for item genres and also uses small volume of dataset.
[2] Uses user profile feature based approach to address the cold start problem in CF for personalized movie recommendation, application of the relationship of user features scores derived from user item interaction using ratings. This approach is only effective when there exist interaction between user and movie and ignores to consider new users who have not rated any movie which shows that the method is still not effective as it did not addresses the cold start problem.
[9] Presents a preliminary study on the relations between personality types and user preferences in multiple entertainment domains, namely movies, TV shows, music, and books. The work analyze a total of 53,226 Facebook user profiles composed of both personality scores (openness, conscientiousness, extraversion, agreeableness, neuroticism) from the Five Factor model, and explicit interests about 16 genres in each of the above domains.
Several studies have been conducted to enhance CF but effectiveness and accuracy of the recommender system remains the major setback [6]. There has been increased in the demand for the best recommender system more than ever before and movie play a prominent role in our daily life.

Proposed EMUBP System

This section presents the proposed system (EMUBP) that is used to recommend movies to new users based on genre and their Big Five Personality Traits (BFPT). Before describing the system, firstly the definition of BFPT would help us in understanding the rest of the paper. Therefore, this section is divided into three sub sections as follows:

A. Definition of some Basic Terms

According to [15] BFPT can be define as a theory that establishes five broad domains or dimensions called factors that describes human personality. These factors are commonly known as the BFPT and they are as follows: [10],[11],[13], [15],[17]

1. Openness to Experience (OPE): Openness is a general appreciation of art, curiosity, adventure, emotion, unusual ideas, imagination, and variety of experience. They are likely to hold unconventional believes, they tend to be more creative and more aware of their feelings.

2. Conscientiousness (CON): Conscientiousness is a tendency to display self-discipline, act dutifully and strive for achievement against measures or outside expectations. It is related to

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the way in which people regulate, control and direct their impulse. The level of conscientiousness rises among young adults and then declines among older adults.

3. Extraversion (EXT): Extraversion is characterized by breadth of activities, assurgent from external activity/situations and energy creation from external means. Extraverts enjoy interacting with people and are often perceived as full of energy. They tend to be enthusiastic, action oriented individuals. They possess high group visibility, like to talk and assert themselves.

4. Agreeableness (AGR): The agreeableness trait reflects individual differences in general concern for social harmony. They are generally considerate, kind, generous, trusting and trustworthy, helpful and willing to compromise their interests with others. They also have optimistic view of human nature.

5. Neuroticism (NEU): Neuroticism is the tendency to experience negative emotions, such as anger, anxiety or depression.

B. EMUBP System Architecture

Figure 1 Personality Based Approach for New User

This section presents the EMUBP architecture/algorithm which consists of the following modules:

1. New User: This is the registration interface which allows new users to log into the system and enters some basic personal information such as name, age, address, email.

2. Personality Score Acquisition: Having known the user through the new user interface, next the system provides personality questionnaire in the form of interface to the active user to acquire his BFPT in the form of 1-5 scale for onward processing. The output of five sample new users of this step is in Table 1.

Table 1: Users personality scores of five sample users

	OPE	**CON**	**EXT**	**AGR**	**NEU**
USER 1	3.82	3.45	4.7	3.53	2.60
USER 2	3.87	3.56	3.53	4.7	2.89
USER 3	3.90	4.40	3.33	3.28	3.10
USER 4	4.34	3.10	3.57	3.60	4.20
USER 5	4.40	3.44	3.51	4.50	2.97

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Table 1 contains the acquired personality score (OPE, CON, EXT, AGR, NEU) of five users that are used as sample throughout the system development evaluation and experiment. The work uses the score to determine individual personality on the entire genre so that the system can be more accurate and efficient for recommendation.

3. Subtraction of Genre from Personality Score: Here the correlation between genre and BFPT obtained from [9] and represented in Table 2 are subtracted from users personality acquisition scores in Table 1. For example User 1, Table 3 is generated where the last column represents the personality score of 16 genres.
The same procedure was repeated to generate scores for U_{II}, U_{III} and U_{IV} and U_5. After which Table 4 was generated titled users genre preference or personality matrix.

4. Personality Matrix: The personality scores are obtained after performing the last section in which the scores are extracted to form Table 4 The values are used to build our EMUBP system.

5. Similarity Measure: This step is a similarity matrix formation; it is a method use to calculate the scores that express similarities between the users who share common personality this step enable the system to determine K-Nearest Neighbor (KNN). The scores obtained are use as the basic building block of user-user or movie-movie recommendation. Table 5 contains similarity between five sampled users and it is obtain using Equation 1.1.

6. Combination of Personality with KNN: As the user continue to interact with the system, the system implicitly pick up the neighbors of the active user who share the same personality as illustrated in Table 5 and recommend movie to the active user, it is believed that users with same personality tend to have same preferences.

7. Recommendation to New User: The system recommends movies based on the personality of the active user considering nearest users who share common personality with the active user.

Table 2: Correlation between genre and BFPT adopted from Ivan C. etal (2013)

Movie genre	**OPE**	**CON**	**EXT**	**AGR**	**NEU**
Action	3.87	3.45	3.57	3.58	2.72
Adventure	3.91	3.56	3.54	3.68	2.61
Animation	4.04	3.22	3.26	3.35	3.02
Cartoon	3.95	3.33	3.49	3.57	2.81
Comedy	3.88	3.44	3.58	3.60	2.75
Cult	4.27	3.10	3.45	3.40	3.16
Drama	3.99	3.43	3.66	3.60	2.86
Foreign	4.15	3.46	3.47	3.54	2.81
Horror	3.90	3.38	3.52	3.47	2.91
Independent	4.31	3.59	3.51	3.55	2.69
Neo-noir	4.34	3.35	3.33	3.37	2.97

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Parody	4.13	3.36	3.35	3.28	2.73
Romance	3.84	3.48	3.62	3.62	2.85
Science fiction	3.99	3.55	3.33	3.57	2.73
Tragedy	4.40	3.34	3.27	3.52	3.11
War	3.82	3.51	3.49	3.50	2.71

Table 2 contains correlation between genre and big five personality traits that shows personality based on user stereotypes for the genres selected in movie domain. The stereotypes are vectors of 5 real values in the 1-5 scale that correspond to the average scores of the Big Five personality factors[9].

Table 3: User I Personality Score

Movie genre	OPE	CON	EXT	AGR	NEU	PER. SCORE
Action	0.05	0	1.13	0.05	0.12	0.91
Adventure	0.09	0.11	1.16	0.15	0.01	0.8
Animation	0.22	0.23	1.44	0.18	0.42	1.21
Cartoon	0.13	0.12	1.21	0.04	0.21	0.95
Comedy	0.06	0.01	1.12	0.07	0.15	0.85
Cult	0.45	0.35	1.25	0.13	0.56	0.72
Drama	0.17	0.02	1.04	0.07	0.26	0.56
Foreign	0.33	0.01	1.23	0.01	0.21	0.67
Horror	0.08	0.07	1.18	0.06	0.31	0.92
Independent	0.49	0.14	1.19	0.02	0.09	0.45
Neo-noir	0.52	0.1	1.37	0.16	0.37	0.74
Parody	0.31	0.09	1.35	0.25	0.13	1.25
Romance	0.02	0.03	1.08	0.09	0.25	0.69
Science fiction	0.17	0.1	1.37	0.04	0.13	0.93
Tragedy	0.58	0.11	1.43	0.01	0.51	0.46
War	0	0.06	1.21	0.03	0.11	1.07

Table 3 was generated after we subtract each correlation between genre of table 2 and big five personality traits of table 1, personality acquisition score of user 1 was obtained as the absolute user's personality score which would be use throughout the system development. However, this step is repeated for all the other users of U2-U5, the smaller the score obtain the more likely the user like the genre.

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Table 4 Users Genre Preference (Personality Matrix)

Movie Genre	**User I**	**User II**	**User III**	**User IV**	**User V**
Action	0.91	1.36	0.82	1.62	1.63
Adventure	0.83	1.25	0.71	1.51	1.48
Animation	1.21	1.69	1.12	1.92	1.93
Cartoon	1.37	1.4	0.86	1.66	1.67
Comedy	0.83	1.3	0.76	1.56	1.57
Cult	0.72	1.14	0.63	1.43	1.44
Drama	0.56	1.01	0.45	1.27	1.28
Foreign	0.67	1.12	0.58	1.38	1.39
Horror	0.92	1.39	0.83	1.63	1.64
Independent	0.45	0.9	0.36	1.16	1.17
Neo-Noir	0.74	1.17	0.65	1.45	1.46
Parody	1.25	1.7	1.16	1.96	1.97
Romance	0.69	1.14	0.60	1.40	1.41
Science Fiction	0.93	1.38	0.84	1.64	1.65
Tragedy	0.46	0.93	0.37	1.13	1.18
War	1.07	1.52	0.98	1.78	1.79
Movie Genre	User I	User II	User III	User IV	User V
Action	0.91	1.36	0.82	1.62	1.63
Adventure	0.83	1.25	0.71	1.51	1.48
Animation	1.21	1.69	1.12	1.92	1.93
Cartoon	1.37	1.4	0.86	1.66	1.67
Comedy	0.83	1.3	0.76	1.56	1.57
Cult	0.72	1.14	0.63	1.43	1.44
Drama	0.56	1.01	0.45	1.27	1.28
Foreign	0.67	1.12	0.58	1.38	1.39
Horror	0.92	1.39	0.83	1.63	1.64
Independent	0.45	0.9	0.36	1.16	1.17
Neo-Noir	0.74	1.17	0.65	1.45	1.46
Parody	1.25	1.7	1.16	1.96	1.97
Romance	0.69	1.14	0.60	1.40	1.41
Science Fiction	0.93	1.38	0.84	1.64	1.65
Tragedy	0.46	0.93	0.37	1.13	1.18
War	1.07	1.52	0.98	1.78	1.79

Table 4 contains the user's Genre Preferences, it is the absolute score obtained after subtracting the user acquired personality score and the score was use in the development of our system. The user genre preference score enable the system to work more effectively and accurately the lesser the personality scores the more the user prefers the genre.

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C. Similarity Score

Similarities between two users U_1 and U_2 are computed using Pearson Correlation Coefficient of their preferences using Equation 1.

$$\text{simp}\ (u_1, u_2) = \frac{\sum_k (Pu_1 - \overline{Pu_1})(Pu_2 - \overline{Pu_2})}{\sqrt{\sum_k (P_{u1} - \overline{P_{u1}})^2}\ \sqrt{\sum_k (P_{u2} - \overline{P_{u2}})^2}} \qquad 1$$

Where simp (u_1, u_2) is the similarity based on personality of the user's Pu_1 and Pu_2 and $\overline{Pu_1}$ and $\overline{Pu_2}$ are the average personality of the users u_1 and u_2.

Table 5: Relationship Matrix between Users

	U2	**U3**	**U4**	**U5**
U1	0.913876	0.991396	0.998915	0.998254
U2		0.991396	0.991124	0.986242
U3			0.998915	0.998841
U4				0.998254

Table 5 uses Pearson correlation coefficient to describe the relationship matrix between five users. However, 1 show that users are strongly correlated and -1 indicate that users are not related.

Experiment

The computer system use during the research is omatek window 10pro operating system, processor intel(R) Celeron(R) cpu B830 @ 1.80 GHz 1.80 GHz. Installed ram 2.0GB (1.89GB usable). System type 64-bit operating system, x64-based processor, no pen or touch input available.

Proposed Algorithm

// Implements new user recommender system using personality
// Input: Matrix A[1..n, 1…n] and column-vector b[1..n]
// Output: An equivalent matrix in place of A and the corresponding right-hand side values in place of the (n+1)st column
n ←1000 //assume we have 700 users and 1700 movies
m ←n/2 //middle value
For i ←1 to n **do**
b[i] ←**INPUT**() //Input values to column-vector
end
For i ←1 to n **do**
For c ←1 to n **do**
A[i, c] ←**INPUT**() //Input values to matrix A
end
end

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Dataset

To evaluate this method, we use experimental dataset from Movie Lens dataset. The dataset consists of 100,000 ratings (1-5) from 1000 users on 1,700 movies[16]. Each user has rated at least 20 movies. Here users were asked to answer personality questions based on the BFPTs to build users profile. Personality is seen as composition of human behavior or qualities that describes an individual's style of reasoning, feeling and behaving in different situations. Personality influences how people make their decisions. In fact, it has been proved that people with similar personality characteristics are likely to have similar preferences [4].

Performance Evaluation

To evaluate the performance of EMUBP system on the cold start problem, a simulation of five sample users at different scenarios was conducted. After performing the experimental settings based on the selected dataset, the results obtained from evaluating the accuracy of the EMUBP system compared with the rest of the methods on the benchmark using precision, recall and MAE.

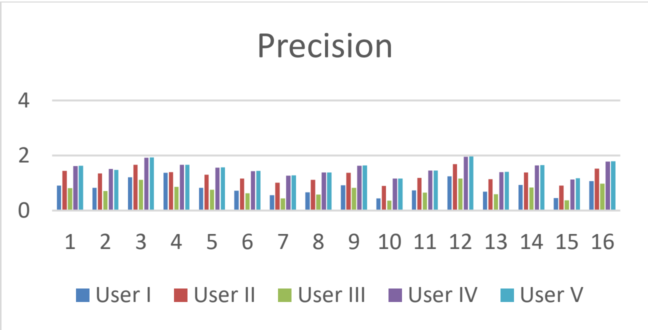

Figure 3: Precision

The figure 3 describes the positive predictions of the system where the proposed design determines relevant movies retrieved out of all movies across all the sixteen genre.

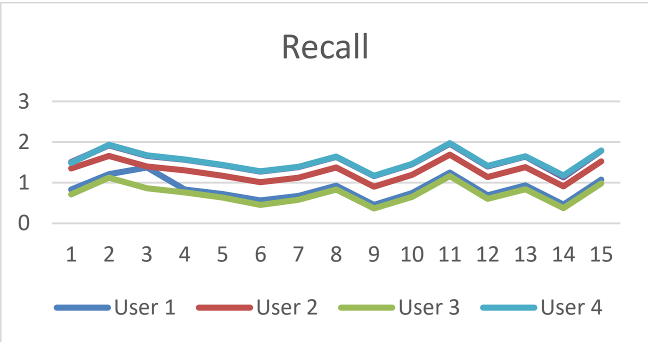

Figure 4: Recall

Figure 4 describes the relevant movies retrieved out of the all-relevant movies across the genre.

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The significant differences of Mean Absolute Error (MAE) clearly expresses the enhanced CF system outperform the existing system more accurately and high quality prediction and recommendation. The quality of a recommender system is dependent on the result of evaluation also the type of metrics used depends on the type of CF applications. The Mean Absolute Error (MAE) as the measure for performance evaluation, measures the differences of the absolute error between the prediction of the algorithm and the real rating.

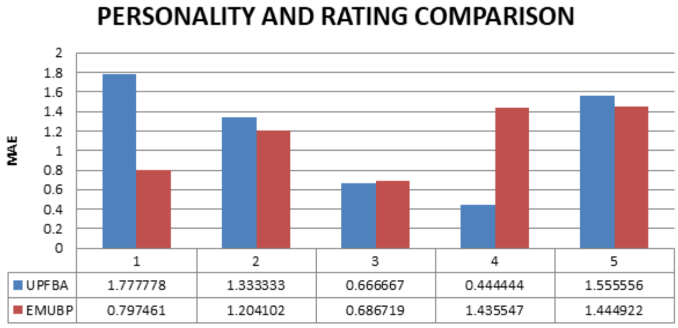

Figure 5: Personality and rating comparison

Figure 5 describes the impact made using personality in movies recommendation. The MAE shows that the target user/new user can get accurate recommendation even without rating when compared with the state of the art.

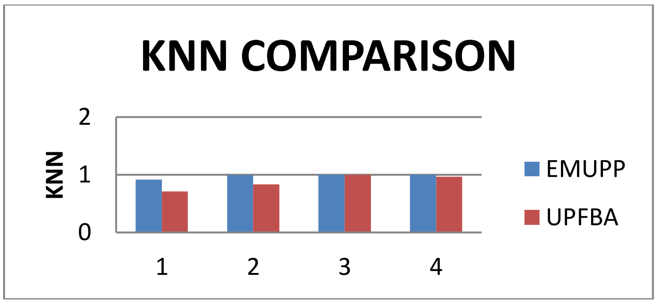

Figure 6: KNN between EMUBP and UPFBA

Figure 2**:** describes the EMUPP which easily recognize and identify KNN based on the BFPT when compared with UPFBA as illustrated in the figure.

2. RESULTS AND DISCUSSION

The result of the work shows that using precision and recall, we set 1.0 as the threshold value to determine genres that are relevant and non relevant to the new user.
The result shows that the user like genres independent, tragedy, drama, foreign, romance, cult, neo-noir, adventure, comedy, action, science fiction and horror, and for any genre that score <=1.0 the genre is relevant to the user. In our system we have 12/16= 0.75 =75%.
When comparing the system with the existing UPFBA system that score 66.67% we can deduce that the system recommend more relevant and more accurate movies by 8.33% with

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minimum errors using MAE this shows reasonable improvement in RS. We assessed that the performance of the EMUBP personality based CF method outperform the existing system on cold start issue. The result have positively support that using user personality into the CF framework indeed effectively addresses cold start problem because new user with no rating history can get accurate recommendation.

3. CONCLUSION

The development of society had led to the bombardment of information on the internet every second therefore, recommendation systems are exponentially being used widely to mitigate the bombardment by allocating resources to the actual user. Using the traditional collaborative filtering alone which is based on only users rating cannot calculate the similarity of new users because the new users do not have rating history so cold start problem exist. The main goal of this paper is to overcome cold start problem, the work presented a unique filtering approach that uses ideas from existing algorithms and combines them with BFPT and genre preferences to improve user based collaborative filtering. The evaluation result showed that the system outperform the existing system better since the EMUBP system uses personality traits instead of rating to recommend movies to the new user since the user has no rating history and it is proved and justified by 8.33% accuracy.

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