Towards a Character-based Meta Recommender for Movies

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Abstract. Improving user experience through personalization is one of the current research trends in HCI. This includes recommendations that suit the preferences of all users (not only the majority) as dictated by their character, i.e. all aspects that influence human behaviors; including personality traits, affective states, socio-cultural embeddings and individual beliefs to name but a few. The aim of this paper is developing a recommender system for movies , that is adaptive in the way it recommends selections on the basis of the user's character. We present an architecture for a generic module-based recommendation platform that uses the user's character to choose a recommendation algorithm for each user. We deployed a movie recommendation application to determine the relation between recommender algorithm preference and (1) the user's personality, (2) background and (3) gender. Based on the data collected from 84 participants, high correlation between the user's personality (Openness, Extraversion and Conscientiousness) and gender and the recommender algorithm that they prefer.

1 Introduction

With the emergence of the fields of Ubiquitous Computing, Big Data and Affective Computing, the abundance of data available has opened up new approaches on how to personalize and thus enhance the user experience. A perfect example of an application that can take advantage of this opportunity is recommender systems. Recommender systems are utilized in many different areas of our daily lives, ranging from which ads or notifications to display for the user to where to go on vacation; or which movie to watch. Recent work in Personality Computing [27, 26] such as [23], tested the hypothesis that incorporating user personality into recommendation systems can improve the recommendations quality. Most users favored personality-based recommender systems over state of the art counterparts. This highlights that recommendations cannot follow one approach for all users. All previously proposed solutions tackled this by including the personality traits in the recommendation process itself. Not only the recommendations should be based on the user personality, but the algorithm should differ from one user to the other. In this work, we propose the recommender for recommenders concept which chooses one recommender algorithm from a pool of algorithms,

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based on the current user. By giving each user an algorithm tailored to their own preference mechanism dictated by their character, the user experience and recommendation accuracy is bound to increase. Based on Personality and Affective Computing human-centric algorithms started taking human personality or affect into consideration. Character Computing [9, 11, 8, 12, 18] expands this further to include the whole character. The user's character represents all the defining features of an individual; including the appearance, stable *personality* traits, variable *affective*, cognitive and motivational states as well as history, morals, beliefs, skills and socio-cultural embeddings, to name a few. For the purpose of this work, we consider a subset of character components (personality traits, gender and background) to investigate whether it affects the preference of recommendation styles. As a proof of concept, we chose movies as our medium for recommendation for its accessibility. Based on the results we suggest a generic module-based architecture for a recommender for recommenders. Section 2 will represent the related work. Section 3 will give an overview of the architecture of the followed approach. Section 4 will present the conducted study and its results and their evaluations in **Sections 5** and **6**, respectively. The conclusion and possible future plans will be given in Section 7.

2 Related Work

In this section, we give a brief overview of the related work focusing on personalization in recommendation algorithms. Wu *et al.*[29] provides an extensive review of recommendation techniques with their strengths and weaknesses. Most used techniques can be clustered into 1) collaborative filtering algorithm based on item or user similarity, 2)back to higher recommendation, 3) hot recommendation and 4) fresh recommendation, concluding that algorithm preference varies from one person to the other, which further motivates our work. When talking about personality and personalization, the majority of the existing work relies on the five-factor model (FFM) of personality [2] (also known as OCEAN and the big five), which classifies personality into five traits: openness to experience (O), conscientiousness (C), extraversion (E), agreeableness (A), and neuroticism (N). These traits can either be acquired implicitly (through questionnaires e.g. [14] and expert interviews) or explicitly (through different techniques e.g. social media [15], ubiquitous computing and sensors [10] or behavior analysis [30, 1]) (see [27]). Ferwerda *et al.* [13] showed a relation between music listening behaviors and preference and inferred personality traits from social media. Nalmpantis *et al.* [23] combined personality traits with movie genre preference for movie recommendations. Results from previous work on genre preference according to personality were used. New recommendations were made based on the user's value for genre preference and the predicted movie rating using a k-NN algorithm, favoring the expected preferred genre. Their results showed an improvement in user experience to state of the art algorithms. Hu *et al.* [20] investigate the acceptance of using personality traits when recommending something from the perspective of the user. Hu [19] also tackled the idea of how to link the user personality with the characteristics of the item being recommended. Hauger *et al.* [17] discussed the two main shortcomings of collaborative filtering algorithms: 1) the cold start predictions problem and 2) the user-bias problem. The proposed solutions were based on using the user profiles. It was concluded that users with similar mindsets are more likely to like the same items. Potash *et al.* [24] implemented a recommender system that incorporated NLP-based inferred user personality into the recommendations. While most work relies only on the personality, it is clear that other components need to be included. Although it has been inferred in some papers, only one work [23] investigated including the user's personality on the meta-level to help in choosing the recommendation style itself.

3 Recommender for Recommenders

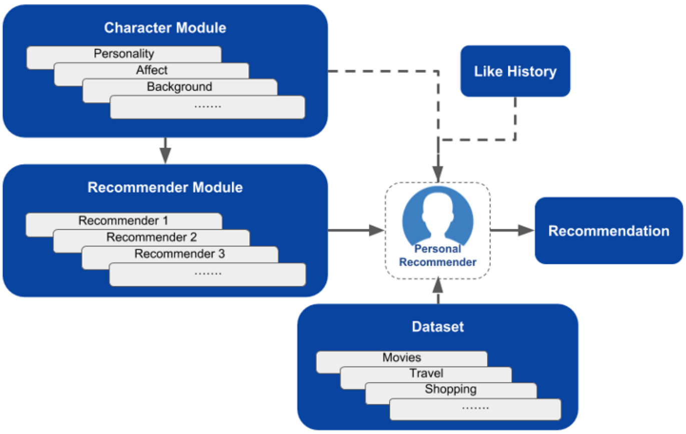


Fig. 1. Modules of the generic meta recommender platform.

The recommendation algorithm liked by the majority is not necessarily the one that suits everyone (as will be shown from Fig. 3a). The focus of most recent research is to improve the user experience, which means every user and not only the majority. That is why personalization plays an integral role in trending research as investigated by Affective, Personality and character Computing. Building on the results shown by our pilot study we present an architecture for a generic recommender system that suits the preferences of all users not only the majority, by including the recommendation algorithms themselves in the personalization process. The idea of creating a recommender system for choosing the recommender algorithm based on character, benefits from being a generic one as it can be applied on many different fields. In this section the architecture of the main character-based recommender systems platform is described. When using the platform each user is presented with the recommendations resulting from the recommendation algorithm most suitable to the user's character. We propose a module-based model that can be described as plug and play, as it can be used in any field that uses recommender systems. For example, if we changed movies to music this meta level recommender will still work. This can be done by exchanging or extending any of the modules. Fig. 1 illustrates the architecture of the recommender for recommenders platform. The Character Module is used to calculate the values for the relevant components of the user's character. In the implemented web application presented in Chapter 4 for example, this module contained a short version of the big five personality test to calculate the personality as well as a short questionnaire to collect background information. The Recommender Dataset can contain any number of recommender algorithms depending on the developed preference and the recommendation domain. As proof of concept we used three simple variations of collaborative filtering as our recommendation algorithms in the implemented web application. The Character Module uses the output of the Character Profile to decide which recommender algorithm to choose from the Recommender Dataset. The Character Module needs to first be trained using labeled data of user preferences to be able to select the most fitting recommendation technique. Alternately, its preferences can be set or verified by personality psychology experts. After a recommender X is chosen, the remainder of the platform proceeds similar to any other recommender system, with the difference being able to include the user's character in the final recommendation process as well, as shown in as shown in [20, **?**]. The chosen dataset from the Dataset Module is then used as input for the chosen recommender X, alongside the current user's liking history. The dataset used in the implemented web application was the MovieLens one (movies and their rating) thus resulting in a movie recommendation application. This dataset can be interchanged with any other one, depending on the recommendation domain. Based on this information the recommender algorithm presents the user with a new recommendation. Upon the user's evaluation of the recommendation it is either added to the "Like History" of the user or discarded and marked to be devalued the next time the algorithm runs. In the future, the recommender algorithm itself can utilise the user's character. This architecture allows for our approach to be universal as none of the modules depend on one specific application domain, character component, assessment method or recommendation algorithm.

4 Experiment: Character Components and Recommendation Preference

To answer research question of the ability to predict the preferred recommendation style based on character, we developed a web application for movie recommendation based on different recommender algorithms (for an overview see Fig 2). The aim of deployed version of the recommender was two-fold: (1) test the hypothesis whether there is a correlation between recommendation technique preferences and character and (2) collect a dataset of user character and recommender preference. 84 users (46 males and 38 females, age: $MEAN = 22$ and $SD = 2.9$) participated in our study, after giving a written informed consent. With the help of the web application we recorded a subset of user character profiles (big five personality, background info and gender), preferred movies per user and score of each recommender per user. All data was fully anonymized. The web platform recorded 812 instances of users liking a recommender over a period of one month. We collected a dataset containing all the required parameters to train our model. Although giving consent prior to participating, the main purpose behind the collected data was reported after the study to avoid affecting their preferences while using the application.

Fig. 2. Overview of the flow of the data collection process resulting from the user's interaction with the movie recommender application.

4.1 Movie Recommender Web Application

To investigate the correlation between user personality traits and different recommender algorithms, movies were chosen as the recommendation medium for its ease of use. To the users, the implemented movie recommendation web application is like any other; requiring the user to sign up, select initial preferences and then ask for movie recommendations which he/she can then evaluate. We made use of the MovieLens [16] dataset which contains 100,000 ratings on 9,000 movies by 700 users. Three different recommendation algorithms were implemented and integrated in the web platform so participants can get recommendations from all three of them without knowing the source algorithm of the recommendations or that there are even different recommendation techniques involved. To sign up to the application participants were asked to sign a consent form, fill in their demographic information (gender, nationality, age, occupation and relationship status) as well as the percentages of their five personality traits [3]. The platform then displayed three recommended movies, each resulted from one of the algorithms in the recommender dataset. The participants were asked to choose the movie they like the most without knowing that each recommendation resulted from a different algorithm. To avoid any biases the results of the three recommenders were randomly shuffled and thus displayed in a different location each

[3] http://www.personalityassessor.com/bigfive/

time. The chosen movies are automatically added to the list of the participant's favorite movies.

4.2 Recommender Algorithms

The deployed data collection application recommended movies using three different variants of the collaborative filtering algorithm using K-nearest neighbor (k-NN) (for a comprehensive survey see [25]). The k-NN algorithm we used took into consideration the z-score normalization for each user. The *first recommender* relies on a most recently liked algorithm. It calculates the nearest neighbor to the movie the user liked last. The recommendation is done using the k-NN algorithm on that movie and then the recommendation is presented to the user. This algorithm has a volatile memory as it only keeps track of the most recent movie the user liked. The *second recommender* obtains the movie closest the last ten movies the user watched using k-NN. This was followed by doing an intersection between the lists and presenting the movie nearest to the ten movies to the user. The *third recommender* (Algorithm 1) starts by getting the genre of movies the user prefers from their list of liked movies before applying collaborative filtering using k-NN to the movies of the user by this genre(similar to [23]).

Algorithm 1 Recommender Three.

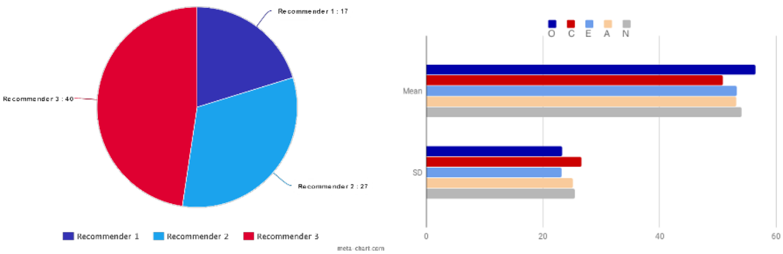
procedure RECOMMENDER3($User$)
 $Movies \leftarrow MoviesLikedByUser(User)$
 $Genre \leftarrow MostCommonGenre(Movies)$
 FilterMoviesByGenre ($Movies, Genre$)
 $k \leftarrow 1$
 for each $m \in Movies$ **do**
  $Recommendations \leftarrow kNN(m, k)$
 end for
 FilterMoviesByGenre ($Recommendations, Genre$)
 $r \leftarrow getItemRandom(Recommendations)$
 return r
end procedure

4.3 Recommender Scoring System

To distinguish between the preferences of each individual participant, a scoring system to rate the recommender algorithms for each participant was implemented. The scoring system was not visible to the participants and only served to further annotate the collected dataset to be able to later train the model for the recommender for recommenders. As mentioned above, after the user is presented with the three recommendations they are prompted to choose which movie they liked the most. This translates that on this occasion this specific user preferred the recommender that recommended the movie they favored. The movie recommendations are all presented to the user together in a single page but the position of the three recommendations are randomized each time as to remove any bias or behavior that might influence the user's choice. The system then records specific user points for this recommender based on a streak system. This means if the user preferred the same recommender more than once consecutively the recommender gets more points. The effect of by chance decisions and false positives is initially not considered as it was manually controlled by monitoring the participants though feedback interviews. In the future, we need to introduce measures to control for false positive, for base rate and for by chance decisions.

5 Results

The aim of the experiment was to collect a dataset from the usage of our test platform including the three recommenders, to analyze it and answer our research question. Fig. 3a shows the distribution of the recommender preference among the users of the web application. Of the 84 users 17 preferred the first algorithm, 27 preferred the second and the remaining 40 chose the third. While these numbers might show that the third algorithm was the best, the 17 or 27 preferring the other algorithms should also be taken into consideration, as together they make up more than half the participants. This fact highlights the motivation for our research, where recommendation should suit the preferences of all users not only the majority. Upon filtering the users by gender, the recommender preferences gain a clear pattern. We found a statistically significant difference at $p < 0.05$ (2-tailed $p = 0.019$ and $t = -2.4$) between females and males with respect to recommender preference. For females the preference is distributed equally among the three recommenders. The majority of males prefer the third recommender with a count of 26 followed by the second recommender while less than a handful of men prefer the first one.



(a) *Distribution of the recommender preferences among the participants.*

(b) *Distribution of the big five personality traits (OCEAN) over the participants, represented by mean and standard deviation.*

Fig. 3. A figure representing the recommender preference and personality distributions.

The five personality traits are normally distributed for the participants. Fig. 3b shows the means and standard deviations of each trait. We can assume no bias introduced by the personality distributions. We applied logistic regression on the collected dataset to train a model to predict recommender preference based on each personality trait. The prediction accuracy for each different parameter (with and without gender) is shown in Table 1. When considering each trait on its own, Conscientiousness yielded the highest accuracy, which is still low.

Table 1. Accuracy of predicting recommender preferences using logistic regression using different parameters.

	trait only	**trait + female**	**trait + male**
Openness	57.1	62.5	75
Conscientiousness	61.9	12.5	83.3
Extraversion	47.6	37.5	75
Agreeableness	52.4	50	75
Neuroticism	52.5	25	58.3

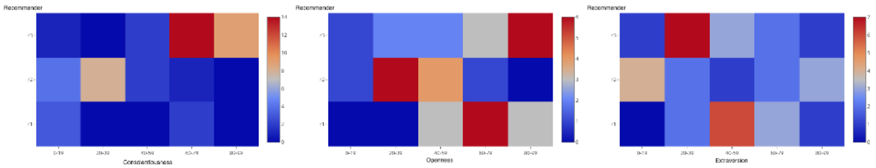
Accuracy %	**O**	**E**	**A**	**C**	**N**
Openness	62.5	80	60	40	70
Conscientiousness	40	20	40	12.5	30
Extraversion	80	37.5	40	20	30
Agreeableness	60	40	50	40	40
Neuroticism	70	30	40	30	25

Table 2. Accuracy of intersecting trait pairs for female participants.

Accuracy %	**O**	**E**	**A**	**C**	**N**
Openness	75	75	75	40	70
Conscientiousness	40	20	40	83.3	30
Extraversion	75	75	40	20	30
Agreeableness	75	40	75	40	40
Neuroticism	70	30	40	30	58.3

Table 3. Accuracy of intersecting trait pairs for male participants.

Openness to experience gave 57.14% accuracy, while Extraversion gave 47.61% . Agreeableness and Neuroticism each produced a slightly higher accuracy of 52.38%. Conscientiousness on the other hand gave the highest score with 61.90%. Adding gender as a parameter improved some of the results, such as Openness, while worsening others, such as Extraversion, Conscientiousness and Neuroticism (see Fig. 4a). When training the models using trait pairs for females, the most accurate model obtained was that of combining Openness with Extraversion which gave a considerable increase to 80%. The rest of the results are shown below in Fig. 2. The heat-maps showing Pearson's correlation coefficient between Recommender liking and Openness and Extraversion in females are shown in Fig. 4b and 4c, respectively. The same was done for the male participants but yielded no improvement. Combining Conscientiousness with any of the other traits produced the highest accuracy of 83.33%, which is identical to the accuracy obtained from Conscientiousness alone. The rest of the results can be found in Table 3. Upon adding more than two traits no increase in accuracy was observed.



(a) *Conscientiousness in males.* (b) *Openness in females.* (c) *Extraversion in females.*

Fig. 4. Heat maps representing the interesting Pearson correlations between gender and some of the big five traits. The x-axis represents the percentile range of the personality trait, the y-axis represents the recommender and the z-axis represents the user count at each intersection.

6 Discussion

The obtained results show that incorporating certain character components in the recommendation process is promising. A difference between the genders and the recommender preferences (see [28]) was found, which aligns with the gender stereotypes related to movie preferences, explaining the bias of males to the third recommender. As the dataset contains 1545 movies that are listed with the genre romance, which is stereotyped as a genre that females like, 924 of these movies are also labeled as drama, however a total of 4365 movies in our dataset are likewise labeled as drama as the most prominent genre. This means if a female user likes the romance genre the algorithm might have a high chance of marking this user's favorite genre as drama which can then recommend an action/drama movie which the user will not like. This can be solved in the future by using a more discriminating database or integrating a confidence scoring system for genres in the recommendation algorithm. The other interesting finding is the varying correlation between the personality traits and recommender preference. From the heat-map in Fig. 4a we can clearly see the clustering of male users across the values of Conscientiousness, users with high Conscientiousness chose *Recommender 3*, while users with low Conscientiousness went for *Recommender 2*. Heat-maps that present the correlations for females in Fig. 4b and 4c, show that female participants preferring *Recommender 1* have moderately high Openness and relatively high Extraversion [4]. For *Recommender 2* the users had low values in both openness to experience and Extraversion, while *Recommender*

[4] Most female participants had relatively lower Extraversion values than males.

3 had very high values in openness to experience and in Extraversion it was relatively in between. Openness to experience trait is linked to unusual ideas, curiosity, and variety of experience [3], explaining why such open individuals preferred a recommender with volatile memory while the others were biased towards *Recommender 2*. Users with high Conscientious prefer adventure, and science fiction movies [6, 28] causing them to prefer *Recommender 3*. The results show that Extraversion, Openness and Conscientious are the traits most contributing to recommendation preferences. This can be explained by considering the personality style graphs resulting from the NEO-PI five factor personality questionnaire [22]. These traits contribute to interest, activity and learning styles.

7 Conclusions and Future Work

In this paper, we showed how certain character components can be used to improve the recommendation process by personalizing the recommender style not only the recommendation itself. As proof of concept, we tested this by deploying a movie recommendation web application running on three different recommendation algorithms. The application was used to collect the necessary data and find correlations between preferred recommendation algorithms and character (personality, gender and background for starters). A difference in recommender algorithm preference related to personality and gender was found. Accordingly, we proposed a generic module-based recommendation framework for enhancing the user experience and increasing the prediction accuracy. The recommendation platform chooses recommendation algorithms compatible with the user's character components to generate domain specific recommendations.

In the future, we will include more character components in the recommender recommendation process, such as affect [4] and socio-cultural [5]. We are also implementing multiple recommendation applications in different domains with different recommendation algorithms to gather the big dataset needed for the generic platform. The applications should be tested on a larger scale and for an extended period of time. A large scale usability and user preference study is to be conducted. The platform will also be tested for more diverse state of the art recommendation algorithms depending on the application domains. Another important investigation is also how to include other factors from the Character Module in the recommender selection process as well as the recommendation process [21]. This can be done in a variety of ways as being investigated in both Personality and Character Computing. Popular approaches include using social network profiles to build a character model and mining behaviour and usage patters from the phone [10, 31, 7].

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