Research Trend in Personality-based Recommender System

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Abstract- At the beginning of its appearance, recommender system made use of content-based filtering method where recommendation was based on similarity between keywords in item description and in user profile. The unability to differentiate item quality in this method was overcome by collaborative filtering method by facilitating users to rate items they consumed. However, this rating-based collaborative filtering suffered from cold-start problem. This problem was in turn solved by the use of personality traits due to its advantages. Initially, personality was predicted explicitly by means of questionnaire. Since this technique was regarded burdensome and time consuming, this led to the application of implicit personality elicitation technique. The commonly used techniques is Personality Elicitation from Text (PET) which predicts personality from what someone write in his/her social media account. When applied to a personality-based recommender system, the obligation to have social media account and to write status with certain length are the weaknesses of PET. In order to cope with such drawbacks, personality prediction based on demographic data is proposed.

Index Terms- Personality-based Recommender System, Content-based Filtering, Collaborative Filtering, Personality Elicitation from Text, Demographic Data.

I. Introduction

The drawbacks in content-based filtering and rating-based collaborative filtering methods and also the advantages of personality traits led the emergence of researches in personality-based recommender system. Personality is individual differences in characteristic patterns of thinking, feeling and behaving [1], [2] therefore it can distinguish one from another. Beside that it is known to have correlation with one's preference. These two are important reasons why personality is used besides its advantages. In order to predict personality, questionnaire is used. The commonly used personality questionnaires are the ones based on Five Factor Model (FFM) also known as Big Five. Big Five itself consists of five factors, namely: extraversion, agreeableness, conscientiousness, neuroticism, and openness.

Extraversion is related to the degree of desire to connect to the outside world. High scorer (extrovert) is energetic and outgoing, while low scorer (introvert) is reserved and solitary. Agreeableness is related to empathy to others. Someone with high agreeableness score is altruistic, friendly and compassionate. Meanwhile someone with low agreeableness score is selfish, cold or unkind. Conscientiousness has to do with organizing and controlling behavior or desires. Organized and efficient are characteristics of high conscientiousness person. Whereas, careless and easy-going are the characteristics of low conscientious person. Neuroticism is a measure of emotional stability. High score neuroticism person is characterized by unconfident and nervous. The one with low score is characterized by secure and calm. Openness is related to how someone interprets new situations. High openness scorers like new thing, therefore they are curious and inventive. In the opposite, low scorers like familiar things. They are also cautious and consistent [3], [4], [5].

This paper discusses about research trend in personality-based recommender system and is structured as follows: section 2 talks about content-based filtering. Section 3 discusses about rating-based collaborative filtering. Personality-based collaborative filtering is presented in sections 4, 5, and 6 where section 4 explains personality-based recommender system in general, section 5 contains description on implicit personality elicitation using Personality Elicitation from Text (PET), and section 6 talks about the proposed method, implicit personality elicitation using demographic data. Conclusion is presented in section 7.

II. Content-based Filtering

Content-based filtering is a recommendation technique that is based on correlation between item content and user preference [6]. One attribute on item description is keywords. The same attribute is also used in user profile. A user is regarded has a preference on an item if his user profile stores the same keywords as on item description. Similarity between these keywords is the basis of recommendation in content-based recommendation filtering [7]. The mostly used method to create item keywords is by counting the words that appear frequently on a document or TF-IDF. The keywords selected as keywords are the ones having the best TF-IDF values [8], [9], [10], [11]. Although the TF-IDF used by [11] is the improved one.

In order to group items, similarity value must be calculated. Reference [7] used Hamming distance and K-Means clustering to group films into several genres. Meanwhile [8], [11], and [10] applied cosine similarity to calculate similarity between two documents. For similarity or distance between to web pages, minimum number of steps to go from one page to another was used by [9]. Reference [12] used a tool called Lemur to calculate distance between items.

Several examples of recommender systems applying content-based filtering are Pandora Radio which is a recommender system for music, Rotten Tomatoes and Internet Movie Database which recommend movies. However, content-based filtering has several weaknesses, namely [6]:

1. There are two ways to provide description on items: (1) if the data is of type text, the description can be obtained by parsing the text. (2) the description is inputted manually if the data is in the form of voice, photo, or video. However, it is a difficult task to input data manually or even impossible if the data is not available.

2. This technique does not have a way to recommend serendipitous items because it only recommends items based on only what have already been consumed by users. This problem is called serendipity problem [13].

3. Since content-based filtering recommends items based on similarity between keywords on item description and on user profile, this technique cannot differentiate the quality or the contents of the items. This is because high and low quality items use the same keywords.

III. Collaborative Filtering

The weaknesses in content-based filtering led researchers to find alternative method. In 1990, Jussi Karlgren proposed new method in recommending items to users [14]. Although he did not use term collaborative filtering, the method he was proposing already provided solution on one of problems on content-based filtering that was on item quality. He did that by asking users to answer a questions: How good was this document? The users were asked to answer the question by giving a grade. This was similar to the current collaborative filtering method that uses rating to grade item quality [12]. In order to predict ratings of the recommended items, the current collaborative filtering applies matrices. The matrices contain users rating data on all items they have consumed [12], [15]. From this matrices, a recommender system applying collaborative filtering will calculate rating of all new items [15], select top N items with the best rating values then recommend those items along with their rating predictions [12]. These was already conducted by Jussi Karlgren using grading data provided by the users to predict document grading to be recommended to those users.

Reference [16] and followed by [17] started to use the term collaborative filtering when they discussed their system called GroupLens. GroupLens recommended articles to its users based on what have been consumed by other users. After reading an article, users could rate the article. As already discussed above, this rating data was used to predict article rating to be recommended to other users.

References [6] and [18] proposed a variant of collaborative filtering called social information filtering. This method can be classified into collaborative filtering since it still uses information from other users to recommend items. Reference [6] applied this method to a recommender system called Ringo which was a recommender system for music and artist. Meanwhile [18] applied the method in a recommender system for video.

A recommender system applying collaborative filtering recommends items to an active user based on profile similarity to his/her nearest neighbors. The nearest neighbors are users with similar rating behaviors as the active user. Similar rating behavior means that they give similar rating to similar items. In such system, before recommending items to a user, the system will first search the nearest neighbors who have consumed similar items and given similar rating [15]. Since the data being used here is user profile containing list of items already consumed together with their ratings, collaborative filtering assumes that user preference does not change. If he liked item A, then he is now still like A. If he did not like item B, then he still does not like item B.

In order to search for nearest neighbors, similarity between the active user and all of his/her neighbors must be calculated. Several methods have been applied, among others are: Pearson correlation coefficient [19], [15]; Cosine similarity [12]; Naive Bayes [20], [21]; and Rule-based [21].

The famous example of recommender systems applying collaborative filtering is Amazon.com. It applies what so called item-to-item collaborative filtering. Other examples include Last.fm and Readgeek. Last.fm is a recommender system for music which recommends music by comparing music preference of a user to preferences of other users. Meanwhile Readgeek is recommender system for book.

In practice, rating-based collaborative filtering has some drawbacks, one of them is called cold-start problem also known as new-user problem [22]. This is a problem of a recommender system when it cannot give accurate recommendation to a new user. This is because the new user has not consumed any item therefore his/her user profile is empty. In other words, there is no consumption and rating history. Previously, this problem was overcome by applying hybrid recommender system that made use of combination of content-based filtering and collaborative filtering methods. Another way to overcome this problem was by recommending popular items [23].

IV. Personality-based Recommender System

In order to solve cold-start problem, user profile must be available soon after he/she registers to be a member of a recommender system. One way to do this is by obliging new users to fill certain data on registration step. One kind of data that can be used here is personality data. By using this personality data, the system can then recommend items based on user's personality. The advantages of the use of personality data are:

1. The system can recommend accurate items to new users as soon as they register [24].
2. Similarity between users does not need to always be calculated after a user rates an item [25]. This is because personality-based user profile never change and is not influenced by rating data.
3. For cross-domain system, it can use the same personality data to recommend items from different domains. This is because personality is not attached to certain domain [5].

Another advantage of personality over rating is found by [26]. From his research, he found that 53% of all users liked personality quiz-based system and only 13% liked rating-based system. Besides that, users also wanted to use personality quiz-based system again and introduced it to their friends.

In calculating similarity, [24] found that personality-based similarity calculation performed better than rating-based. This is similar to experiment results obtained by [25]. In their experiment, they compared three similarity measure methods: rating-based, Euclidean distance with Big Five, and weighted Euclidean distance with Big Five. Experiment results revealed that the performance of personality-based similarity methods are the same or even better than rating-based method.

In practice, personality data can be obtained in two ways: explicitly and implicitly. Explicit personality elicitation requires users to answer personality questionnaire to predict their personality traits. As already mentioned above, the commonly used personality questionnaires nowadays are the ones based on Big Five. The longest Big Five-based questionnaire contains 504 questions and the shortest contains only 10 questions [27], [28].

Several researchers predicted personality explicitly using Big Five-based questionnaires. In her two experiments, [29] employed two kinds of questionnaires. In the first experiment, she utilized NEO-IPIP questionnaire containing 300 questions. And in the second experiment, she made use of Ten-Item Personality Inventory (TIPI) with only 10 questions. IPIP50 questionnaire consisting of 50 questions was used by [25]. Reference [30] employed 44 questions Big Five Inventory (BFI) questionnaire. Meanwhile, [24] and [31] also used TIPI questionnaire.

In searching nearest neighbors, [29] tried two techniques, they were k-NN and Naive Bayes where she found that k-NN performed better than Naive Bayes. Reference [24] used Pearson Correlation Coefficient. Meanwhile, [32] compared three methods, namely Linear Regression, k-NN, and K-Means Clustering where they obtained that Linear Regression outperformed the other two methods. K-NN method was also employed by [25] where they used Euclidean formula to calculate distance.

When a recommender system applies explicit personality elicitation method to collect personality data, then users must answer personality questionnaire before being registered to be a member of such recommender system. Although, this method can indeed predict personality accurately, it is burdensome and time consuming. Therefore, this explicit method suits only on laboratory study [5].

V. Implicit Personality Elicitation

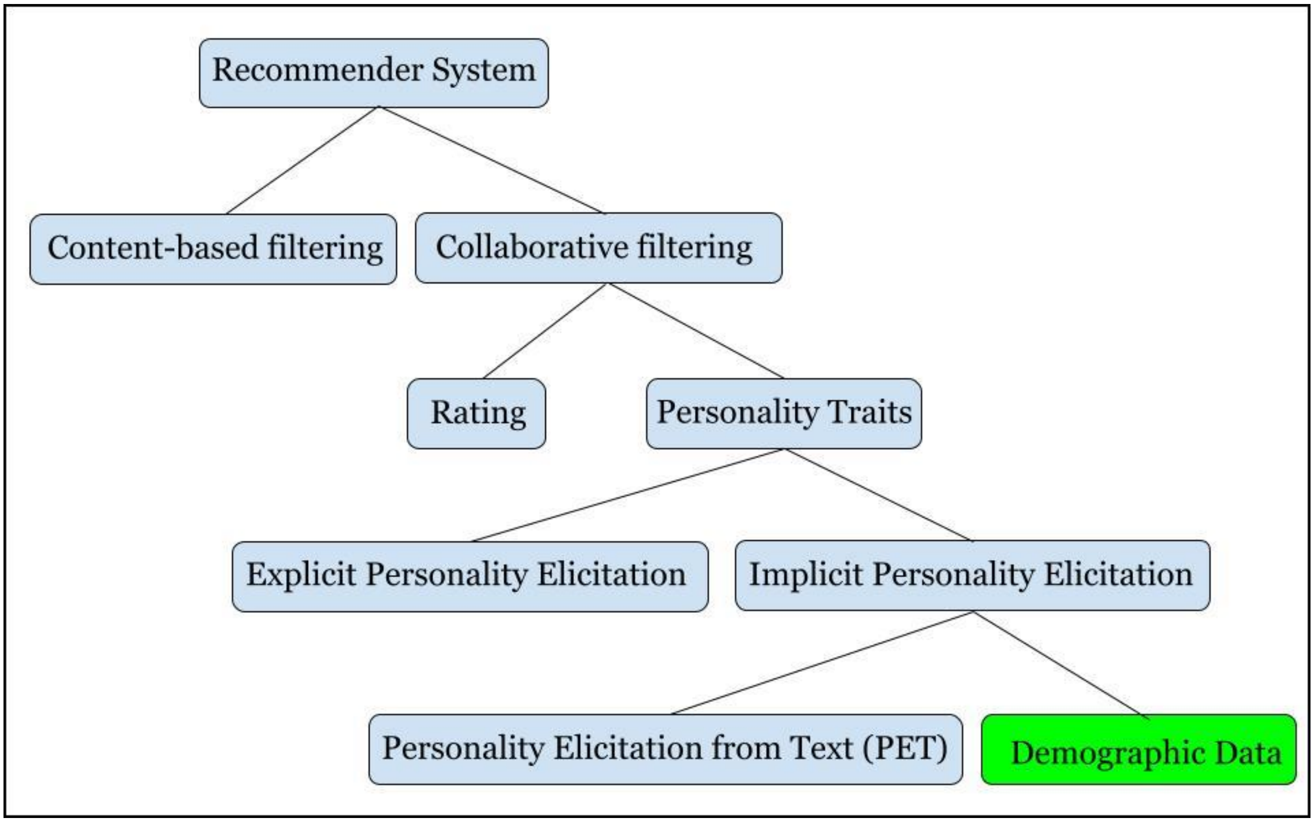
To resolve drawbacks on explicit personality elicitation, researchers make use of implicit personality elicitation. In this method, users' personalities are predicted implicitly. The commonly used implicit technique is Personality Elicitation from Text (PET). This technique predicts users' personality from the text they write in their social media accounts. PET has been applied to predict personality by extracting statuses of social media users such as Facebook [33], TripAdvisor [34], [35], Twitter [36], [37], Friendfeed [38], and Weblog [39].

The most important thing in implicit personality elicitation method is database. This database will be used to predict users' personality. Reference [38] collected data for his database from 748 FriendFeed users with 1065 posts. Meanwhile, weblog database were collected by [39] from 71 respondents (47 women and 24 men) by asking them to write about their studies in their own blogs. They were also requested to answer IPIP50 personality questionnaire.

The most common components in a recommender system applying PET are explained below.

1. Text Collector. This component collects text from what social media users write. This can be done by asking users to input usernames they use in one of their social media accounts. The system then crawls to retrieve the text they have written in their accounts. In order to be processed further, the text must exceed minimum length. For instance, [33] used average 42.6 words.
2. Text Processor. The task of this component is to extract linguistic cues. Linguistic cues is the words commonly used by a user. The steps to process collected text are [35], [37]: conversion of text to lowercase, tokenization, removal of stop words, stem- ming, text tagging, and short post removal. The processed text is then sent to text analysis tool like LIWC tool [34], [33] to get linguistic cues.
3. Personality Recognizer.This component predicts user's personality. There are two kinds of prediction results: score [34], [33] or text [35]. The user's personality is obtained by comparing linguistic cues and a table containing correlation between personality and linguistic cues (Table 1).
4. Similarity Estimator. This component searches for user's nearest neighbors. Reference [40] applied K-Means clustering method, k-NN method was used by [33]. Meanwhile [39] compared two methods namely Naive Bayes and SVM. In their study they obtained that Naive Bayes performed better than SVM. In calculating distance, [34] made use of Euclidean distance.

As already explained above, in order to predict user's personality by means of PET, This method obliges users to have at least one social media account and write at least one status with certain length. With this obligation, when this method is applied to a recommender system, such system can only be accessed by users having social media account. Not to mention, users must also write statuses in their accounts with certain length. Users having no such prerequisites cannot access such system.



Picture 1. Research trend in personality-based recommender system.

Table 1. Research trend in personality-based recommender system

No.	Papers	Methods	Recommendation	Similarity	Distance	Traits Prediction	Drawbacks
1	Van Meteren and van Someren (2000), Bogers and van den Bosch (2009), Li et al. (2012), Manjula and Chilambuchelvan (2016), Ke Ma (2016), Glauber and Loula (2019)	Content-based filtering	Keywords similarity	Number of steps, K-Means, Cosine similarity	Hamming distance		Difficult to input item description manually, Serendipity problem, Cannot differentiate item quality
2	Karlgren (1990), Resnick et al (1994), Shardanand and Paes (1995), Hill et al (1995), Breese et al. (1998), Gutta et al. (2000), Pronk et al (2007), Bogers and van den Bosch (2009), Burke et al. (2011), Rubbens et al. (2015)	Collaborative filtering	Rating history similarity	Pearson, Cosine similarity, NB, Rule-based			Cold-start problem
3	Hu and Pu (2011), Tkalcic et al. (2009), Nunes (2008), Ferwerda et al. (2016), Lu and Tintarev (2018), Ariely et al. (2004)	Collaborative filtering	Personality traits similarity	k-NN, NB, Pearson, Liner Regression, K-Means	Euclidean	Explicit personality elicitation (Questionnaire)	Burdensome, Time consuming, Suit only on laboratory study
4	Golbeck et al. (2011a), Roshchina et al. (2011), Roshchina et al. (2015), Di Rienzo and Neishabouri (2016), Golbeck et al (2011b), Carducci et al. (2018), Celli (2012), Oberlander and Nowson (2006)	Collaborative filtering	Personality traits similarity	K-Means, k-NN, NB, SVM	Euclidean	Implicit personality elicitation (Personality Elicitation from Text-PET)	Obligation to have social media account, Obligation to write status with certain length
5	Paryudi, Ashari, Tjoa (2019), Paryudi and Nursari (2020)	Collaborative filtering	Personality traits similarity	k-NN	Simple matching coefficient	Implicit personality elicitation (Demographic data)	

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VI. Implicit Personality Elicitation Based on Demographic Data

Reference [27] and [28] proposed novel approach to predict personality implicitly where the prediction is based on demographic data.

So far, demographic data have been applied directly to a recommendation system hence it is called Demographic Recommender System. The demographic data in such recommender system is used by classifiers to find correlation between certain demographic data and rating or propensity to buy something [41]. One example of such system is Grundy. It is a recommender system recommending books based on user's characteristics. These characteristics are collected by means of a dialog. Basically, Grundy works like a librarian. With familiar customer, the system recommends books right away, no dialogue needed. However, with new unfamiliar customer, the system will have a dialogue first to collect his/her characteristics [42].

Demographic data is also used in a recommender system called Waldo the Web Wizard that recommends websites. The demographic data being used are American citizens data grouped into 62 demographic clusters. Each cluster has its own characteristics. When a user uses such system, it will ask questions. From the answers, the system will group that user into one of those clusters hence the system can predict user's characteristics [43]. Demographic data being used include age, gender, education [44].

Many researches have been carried out to find correlation between demographic data and preferences. In their study, [45] found that older users were more attentive than younger users. For instance, click-through rates (CTR) of younger users of ages from 20 to 24 years old was only 2.73%. A higher CTR, 9.26%, was obtained from older users of ages between 50 and 54 years old. Age and education also influence movie preference. Young people and/or low educated people were found to prefer across genre movies [46]. Similar to the above, preference of television programs were also influenced by age and education. Compared to younger people and/or lower educated people, older people and/or higher educated people preferred more on cultural and information programs than soap and erotic programs [47]. Beside age and education, gender also influences preference on television programs. Women prefer more on cultural and soap programs than erotic programs compared to men. In relation to movie preference, [48] found that women prefer romantic movies and men prefer action movies.

Summary of research trend on recommender system can be seen in table 2 dan figure 1.

VII. Conclusion

One of the Weaknesses on content-based filtering was inability to differentiate item quality. This problem was solved by collaborative filtering that enabled users to rate items they consumed. With this rating data on each item, users were informed on each item's quality. However, rating-based collaborative filtering was unable to give accurate recommendation to new users. This problem is called cold-start problem also known as new-user problem. Personality traits were used to overcome this problem. The advantages of using personality traits in a recommender system are: (1) accurate items can be recommended soon after users join the system, (2) no obligation to always calculate similarity, (3) can use the same personality for different domains. Initially, personality is predicted explicitly using questionnaire. However, this technique is burdensome and time consuming. To cope with this problem, implicit personality elicitation was used. Nowadays, the commonly used implicit personality elicitation was the one based on what someone write in social media. Hence, it was called Personality Elicitation from Text (PET). The obligation to have at least one social media account and write at least one status with certain length made a recommender system applying PET could only be accessed by certain users. To solve this problem, implicit personality elicitation using demographic data was proposed. Demographic data such as age, gender, and education could be used to predict personality.

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