Personality-Based User Modeling for Music Recommender Systems

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Abstract. Applications are getting increasingly interconnected. Al-though the interconnectedness provide new ways to gather information about the user, not all user information is ready to be directly implemented in order to provide a personalized experience to the user. Therefore, a general model is needed to which users' behavior, preferences, and needs can be connected to. In this paper we present our works on a personality-based music recommender system in which we use users' personality traits as a general model. We identified relationships between users' personality and their behavior, preferences, and needs, and also investigated different ways to infer users' personality traits from user-generated data of social networking sites (i.e., Facebook, Twitter, and Instagram). Our work contributes to new ways to mine and infer personality-based user models, and show how these models can be implemented in a music recommender system to positively contribute to the user experience.

Keywords: Personalization · Music recommender systems

1 Introduction

An abundance of information about users is getting available with the increased interconnectedness of applications, which provide new ways to tackle problems that systems, such as recommender systems are facing (e.g., lacking behavioral data to infer preferences, such as with the "cold-start problem").[1] For example, the implementation of single sign-on (SSO) mechanisms[2] allow users to easily login and register to the application, but also let applications import user information from the connected application, which could be used for personalization.

Although with the interconnectedness of applications new information sources become available, not all the new information is directly applicable to

[1] The cold-start problem is most prevalent in recommender systems and occurs with new users of the application. It refers to that (almost) no information exists yet about the user to make inferences from.

[2] Buttons that allow users to register or login with accounts of other applications. For example, social networking services: "Login with your Facebook account."

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create personalized experiences with. Therefore, a general user model is needed to which users' behavior, preferences, and needs can be connected to in order to create personalized experiences for users. This allows the creation of only one user model that can be used across applications without the need of information that is directly related to a specific behavior, preference, or need of the user [1].

We model users based on their personality to make inferences about their behavior, preferences, and needs. Personality has shown to be a stable and enduring factor, which influences an individual's behavior, interest, and taste. As personality plays such a prominent role in shaping human preferences, one can expect similar patterns (i.e., behavior, interest, and taste) to emerge for people with similar personality traits, which makes it suitable for user modeling. In our works, we rely on the widely used five-factor model (FFM), which categorizes personality into five traits: openness to experience (O), conscientiousness (C), extraversion (E), agreeableness (A), and neuroticism (N) [10].

In the next sections we provide an overview of our works on user modeling, which comes in twofold: (1) understanding the relationship between personality traits of users and their behavior, preferences, and needs, and (2): implicit acquisition of users' personality traits from social media.

2 Understanding the User

In order to create personality-based recommender systems, the relationship with their behavior, preferences, and needs need to be identified first. We conducted several user studies on different aspects of the user experience in music recommender systems in order to identify relationships with users' personality.

Listening needs. In [4] we aimed to understand the music listening needs of users in order to provide better personalized recommendations. We investigated the relationship between personality traits and the preference for different kinds of music, and how these preferences change depending on users' emotional state. Our findings show that, in general, users like to listen to music in line with their emotional state. However, individual differences based on personality occur; especially in a negative emotional state (e.g., sadness). We found that when in a negative emotional state, those who scored high on openness to experience, extraversion, and agreeableness tend to cheer themselves up with happy music, while those who scored high on neuroticism tend to prefer to dwell a bit longer in this negative state by listening to sad music. This has important implications for playlist generation. By inferring users' emotional state (e.g., mining user-generated content), the next song can be better targeted toward their needs.

Meta information. In [14] we investigated the amount of meta information a user would want about the music pieces that is listened to. The results showed that the following personality traits tend to have a higher preference for more meta information: openness to experience, agreeableness, conscientiousness, and extraversion. This provides implications about the amount of meta information a system should present to the user without them experiencing information overload, which in turn, negatively affects the user experience of the user.

User interface. In [8] we simulated an online music streaming service to identify the relationship between personality traits and the way users browse for music. By exploring the most frequently used taxonomies to categorize music (i.e., by genre, activity, mood), we were able to identify distinct music browsing behavior based on users' personality, which could be used to create adaptive user interfaces. For example, findings indicate that those scoring high on openness to experience show a high preference for browsing for music by mood, while conscientious users show a preference for browsing by activity.

3 Acquisition of Users' Personality Traits

Besides identifying relationships between personality traits and users' behavior, preferences, and needs, we also looked into the implicit personality acquisition of users. We specifically focused on personality acquisition from social networking sites (SNSs: e.g., Facebook, Twitter, Instagram), as they are getting increasingly interconnected through SSO buttons. Besides accessing users' basic profile information, applications often ask for additional permissions to access other parts of the users profile [2]. By granting access, applications are able to unobtrusively infer users' personality traits. We report the RMSE on personality trait prediction (i.e., O, C, E, A, N) for each of our work below ($r \epsilon$ [1,5]).

Several works exist that show that it is possible to infer personality traits from user-generated data of SNSs (e.g., Facebook [11], and Twitter [9,12]). In [5,7] we add to the work on SNS analyses by inferring personality traits from users' Instagram picture features. We showed that personality traits are related to the way Instagram users modify their pictures with filters, and a reliable personality predictor can be created based on that ($RMSE$: $O = .68$, $C = .66$, $E = .90$, $A = .69$, $N = .95$). For example, open users tend to apply filters to their pictures in order to make them look more greenish. In [13] we tried to increase the prediction accuracy by fusing information from different SNSs (i.e., Instagram and Twitter). We show a significant improvement of the prediction accuracy when combining different sources ($RMSE$: $O = .51$, $C = .67$, $E = .71$, $A = .50$, $N = .73$).

One problem with the implicit acquisition of personality is that when users are not sharing information, the acquisition fails. We investigated this problem from two different directions: (1) understanding the underlying mechanisms of sharing information, (2) personality acquisition with limited user information.

In [3] we found that the lack of sharing and posting comes from the uncertainty of approval of the users viewing the posts. We were able to increasing sharing and posting by analyzing the user's social network and create proxy measures about how the shared or posted content would be received.

In [6] we looked at whether or not disclosing Facebook profile information reveals personality as well. By solely analyzing whether profile sections were disclosed or not (e.g., occupation, education), disregarding their actual content, we were able to create a personality predictor that is able to approximate the prediction accuracy of methods extensively analyzing content ($RMSE$: $O = .73$,

$C = .73$, $E = .99$, $A = .73$, $N = .83$). This provide opportunities to still being able to infer users' personality even when they are not disclosing information.

4 Conclusion

This paper gave an overview of our work on creating personalized experiences in music recommender systems. We revealed relationships between personality traits and different user behavior, needs, and preferences to improve the user experience, and showed how personality can be mined and inferred using the increased connectedness between applications and SNSs.

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