Relating Personality Types with User Preferences in Multiple Entertainment Domains

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Abstract. We present a preliminary study on the relations between personality types and user preferences in multiple entertainment domains, namely movies, TV shows, music, and books. We 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. As a result of our analysis, we extract personality-based user stereotypes and association rules for some of the considered domain genres, and infer similarities of personality types related to genres in different domains.

Keywords: types of personality, user profiles, personalization, cross domains.

1 Introduction

The majority of services for personalized information access, retrieval, and filtering deals with the exploitation of user preferences – tastes, interests, goals – obtained explicitly (e.g. by means of ratings) or implicitly (e.g. by mining click-through and log data). In addition to these preferences, contextual signals – such as the current time, and the user's location and social companion – are also taken into consideration [1].

Many effective personalization approaches have been proposed in a large number of applications [3]. However, little work has been done on the characterization of user models in personalized services with regard to *affective traits*, such as moods, emotions, and types of personality. Emotions are intense feelings that are directed at someone or something [9]. Moods, in contrast, are feelings that tend to be less intense than emotions, and often – though not always – lack a contextual stimulus [8]. Personality, on the other hand, can be defined as a combination of characteristics or qualities that form an individual's style of thinking, feeling and behaving in different situations [22].

Personality influences how people make their decisions [18]. In fact, it has been proved that people with similar personality characteristics are likely to have similar preferences. In [20] Rentfrow and Gosling show that "reflective" people with *openness to experiences* usually have preferences for jazz, blues and classical music, and "energetic" people with high degree of *extraversion and agreeableness* usually appreciate rap, hip-hop, funk and electronic music. In [5] Chausson presents a preliminary study showing that people *open to experiences* are likely to prefer comedy and fantasy movies, *conscientious* individuals are more inclined to enjoy the action movie genre, and *neurotic* people tend to like romantic movies. Finally, in [15] Kosinski et al. show that there are psychologically meaningful relationships between personality and preferences related to websites and website categories. Traits and types of personality could thus help explain why people prefer one option to other, and could be used to improve personalization services and enhance user experience [12][17].

In psychology the Five Factor model [6] – also known as *the Big Five* model – is a widely accepted theory that establishes five factors to describe the human personality: *openness* to experiences, *conscientiousness*, *extraversion*, *agreeableness* and *neuroticism*. Similarly to user preferences, the personality factors can be inferred explicitly, e.g. by means of personality questionnaires [6], or implicitly, e.g. by analyzing digital footprints [14], linguistic features of user texts [21], and by correlating personality traits with patterns of social network use – such as posting, rating, establishing friendship relations, and participating in user groups [2].

Once extracted, personality factors can be used to build personality-based user profiles that may be exploited by personalized information retrieval and filtering approaches. In [24] Tkalčič et al. apply and evaluate three user similarity metrics for the heuristic-based collaborative filtering strategy: a typical rating-based similarity, a similarity based on the Euclidean distance with the Big Five data, and a similarity based on a weighted Euclidean distance with the Big Five data. The reported results show that approaches using the Big Five data perform statistically equivalent or better than the rating-based approach. Following the findings of Rentfrow and Gosling [20], in [13] Hu and Pu present a collaborative filtering approach based on the correlations between personality types and music preferences, in which the similarity between two users is estimated by means of the Pearson's correlation coefficient on the users' Big Five personality scores. Combining this approach with a rating-based collaborative filtering, the authors show significant improvements over the baseline of considering only ratings data. Finally, in [21] Roshchina presents an approach that extracts Big Five factor-based profiles by analyzing hotel reviews written by users, and incorporates these profiles into a nearest neighbor algorithm to enhance personalized recommendations.

Before developing personality-based recommender systems, we aim to **establish and understand relations existing between personality types and user preferences in multiple entertainment domains**. Rentfrow's work [20] only addresses the music domain, and Chausson's analysis [5] considers a very limited number of movies. In this paper we present a preliminary, but extensive study on the relations between personality types and user preferences in multiple domains, namely movies, TV shows, music, and books. Specifically, we analyze a total of 53,226 Facebook[1] user profiles

[1] Facebook social network, http://www.facebook.com

composed of both Big Five personality scores and explicit interests about 16 genres in each of the above domains. As a result of our analysis, we extract personality-based user stereotypes and association rules for some of the considered domain genres, and infer similarities of personality types related to genres in different domains.

The reminder of the paper is structured as follows. In Section 2 we detail the Five Factor model. In Section 3 we describe the analyzed personality- and preference-based Facebook user profiles. In Sections 4 and 5 we present our analysis on the relations between personality types and user preferences on single and crossed domains respectively. Finally, in Section 6 we conclude with some lines of future work.

2 Personality Traits: The Five Factor Model

In psychology identifying the structure and types of human personality has been a fundamental goal. Researchers have extensively studied known personality traits, and have analyzed a large variety of measures of such traits – on self-report and questionnaire data, and objective measures from experimental settings – in order to find underlying personality factors.

The Five Factor model [6] is a theory that establishes five broad domains or dimensions – called factors – to describe human personality. These factors are commonly known as the *Big Five* personality traits, and can be defined as follows:

- **Openness (OPE)**: from *cautious*/*consistent* to *curious*/*inventive*. This factor reflects a person's tendency to intellectual curiosity, creativity and preference for novelty and variety of experiences. A high score of openness entails strong degrees of imagination, artistic interest, emotionality, adventurousness, intellect and liberalism.
- **Conscientiousness (COS)**: from *careless*/*easy-going* to *organized*/*efficient*. This factor reflects a person's tendency to show self-discipline and aim for personal achievements, and to have an organized (not spontaneous) and dependable behavior. A high score of conscientiousness entails strong degrees of self-efficacy, orderliness, dutifulness, achievement-striving and cautiousness.
- **Extraversion (EXT)**: from *solitary*/*reserved* to *outgoing*/*energetic*. This factor reflects a person's tendency to seek stimulation in the company of others – showing sociability, talkativeness and assertiveness traits –, and to put energy in finding positive emotions, such as happiness, satisfaction and excitation. A high score of extraversion entails strong degrees of friendliness, gregariousness, activity level, excitement-seeking and cheerfulness.
- **Agreeableness (AGR)**: from *cold*/*unkind* to *friendly*/*compassionate*. This factor reflects a person's tendency to be kind, concerned, truthful and cooperative towards others. A high score of agreeableness entails strong degrees of morality, altruism, sympathy, modesty, trust, cooperation and conciliation.
- **Neuroticism (NEU)**: from *secure/calm* to *unconfident*/*nervous*. This factor reflects a person's tendency to experience unpleasant emotions, such as anger, anxiety, depression and vulnerability, and refers to the degree of emotional stability and impulse control. A high score of neuroticism entails strong degrees of hostility, social anxiety, depression, immoderation, vulnerability and impulsivity.

It is important to note that although these factors are statistical aggregates, exceptions may exist on individual personality profiles. In general, people who register high in *openness* are willing to new experiences, receptive to emotions, intellectually curious, and interested in art. A particular individual, however, may have a high overall *openness* score, and may be interested in learning and exploring new cultures, but may have no great interest in art.

Nonetheless, the Big Five factors have been shown to encompass most known personality traits, and are assumed to represent the basic structure behind all personality traits [19]. They thus provide a rich conceptual framework for integrating all the research findings and theories in personality psychology.

Moreover, the Five Factor model is a comprehensive, empirical, data-driven research finding investigated, discovered and defined by distinct groups of researchers. Tupes and Christal presented an initial model of personality factors [25]. Digman [7] proposed a five factor model of personality, which was extended with a high level of organization by Goldberg [10]. Independently, Cattell et al. [4] and Costa and McCrae [16] used different methods with which the five personality factors were found. Hence, each set of five factors found has had different names and definitions. All of them, however, have been proved to be highly inter-correlated and factor-analytically aligned [11].

The measurement of the Big Five factors comprises items that are self-descriptive sentences or adjectives, commonly presented in the form of short tests. In this context, the International Personality Item Pool[2] (IPIP) is a publicly available collection of items for use in psychometric tests, and the 20-100 item IPIP proxy for Costa and McCrae's NEO-PI-R test [6] is one of the most popular and widely accepted questionnaires to measure the Big Five factors in adult (≥18 years old) men and women without overt psychopathology.

3 Personality- and Preference-based User Profiles

myPersonality [23] is a Facebook application with which users take real psychometric tests and receive feedback on their scores. As of May 2013, the tool has let record a database that contains more than 6 million test results and more than 4 million individual Facebook profiles with a variety of personal user information, such a demographic and geo-location data, *likes*, status updates, and friendship relations, among others.

myPersonality project [3] offers large fraction of the data collected from myPersonality users to wide academic community.. For example, the public dataset contains the Big Five personality scores of 3.1 million users, collected using 20 to 336 item IPIP proxy for Costa and McCrae's questionnaires, and from which around 40% of the users took the 100 item version. The users either decided the length of questionnaire they wanted to take in advance, or took extra questions in blocks of 10 until finishing all 100 items. The users filled the questionnaires to get feedback, so they were quite well motivated, which resulted in high accuracy (reliability > 0.8,

[2] International Personality Item Pool (IPIP), http://ipip.ori.org
[3] myPersonality project, http://mypersonality.org

better than in most supervised pen-and-paper applications of the same measure). The public dataset also contains 46 million Facebook *likes* of 220,000 users for 5.5 million items of diverse nature: people (celebrities, politicians, directors, actors, musicians, writers, sportsmen, etc.), objects (movies, TV shows, songs, books, games, etc.), organizations, events, etc.

Due to the size and complexity of the dataset, in this paper we restrict our analysis to a subset of the dataset's items. Specifically, we selected all *like record*s associated to items belonging to one of the following 4 categories: `Movie genre`, `TV genre`, `Musical genre`, and `Book genre`. Thus, for instance, selected items belonging to the `Movie genre` category are movie genres, such as *comedy*, *action*, *adventure*, *drama*, and *science fiction*. Note that we do not take into consideration a large number of potential valuable items, such as particular *movies* preferred by users. In our study, we discarded such items because no domain categories were available for them in the dataset, and acquiring their categories requires complex data acquisition and processing methods: 1) the items have to be found in external knowledge sources – like Wikipedia – with category information, and 2) the items in the dataset are identified by plain text names that do not follow a well-established naming convention: a certain concept (person, object, etc.) may have different names.

Next, we selected those users of the dataset that had *likes* for the considered items. Once the items and users were selected, we conducted text processing operations to consolidate morphological derivations of certain item names (e.g. *science fiction*, *science-fiction*, *sci-fi*, *sf*). Finally, we chose the items (i.e., domain genres) with the highest number of user *likes*. Specifically, we chose the top 16 genres of each of the 4 considered domains: movies, TV shows, music and books. In the end, the dataset used in our study contained **53,226 users** (60.37% female, 39.63% male) and their corresponding Big Five personality scores, 16 x 4 = **64 items**, and **58,576 *like* records** (12,420 in the movie domain, 3,705 in the TV show domain, 32,784 in the music domain, and 9,667 in the book domain).

4 Relations between Personality Types and User Preferences in Individual Domains

We have analyzed the dataset presented in Section 3 aiming to find meaningful relations between personality types and user preferences in each of the 4 considered entertainment domains: movies, TV shows, music and books. In the following we present preliminary results of our study: personality-based *user stereotypes* (Subsection 4.1) and *association rules* (Subsection 4.2) for some of the considered domain genres.

4.1 Domain-specific Personality-based User Stereotypes

Table 1 shows personality-based user stereotypes for the 16 genres selected in each domain, distinguishing female and male users. These stereotypes are vectors of 5 real values in the [1, 5] range that correspond to the average scores of the Big Five personality factors of the dataset users who had *likes* for the corresponding genres.

The colors of the cells are used to facilitate the analysis of differences in the factor scores for distinct stereotypes. In the table the colors are assigned for each column as follows. The highest scores of the column are marked in green, and the lowest ones are marked in red. The color intensities indicate how high/low the scores are. In this section we will refer as “high” scores to those colored with darkest green, and as “low” scores to those colored with darkest red. For the sake of simplicity and due to the preliminary nature of this study, we do not provide results on the statistically significance of all score differences.

It is important to note that for some genres, the number of users whose profiles were used to build the stereotypes is quite small; e.g. in the movie domain, the personality stereotype associated to the *tragedy* genre for male users was built with only 8 profiles. This is taken into consideration in the discussions and conclusions we provide in the reminder of the paper, by discarding the analysis of personality-based stereotypes built with a few (less than 40) users. Moreover, in each domain, the numbers of user profiles are quite different among the genre stereotypes. We could perform the analysis with equally sized groups of profiles. However, we decided to use all the available profiles in order to not lose information. In the following we discuss obtained relations between user personality types and preferences.

In the **movie domain**, users with high degree of *openness* (OPE) tend to like tragedy, neo-noir, independent, cult, and foreign movies, whereas a low degree of this factor corresponds with user preferences for war, romance, action, and comedy movies. For the *conscientiousness* (CON) factor, high scores correspond to independent, adventure, and science fiction movies, whereas low values correspond to cult, animation, and cartoon movies. For the *extraversion* (EXT) factor, drama, romance, comedy, and action movies are linked to high scores, whereas animation, tragedy, neo-noir, and science fiction are associated with lower scores. Adventure, romance, comedy, and drama movies tend to be liked by people with high degree of *agreeableness* (AGR), whereas a low degree of this factor is associated with parody, animation, neo-noir, cult, and horror movies. Finally, users with high degrees of *neuroticism* (NEU) prefer cult, tragedy, and animation movies, while users with low values tend to like adventure, independent, and war movies.

In the **TV show domain**, high scores of OPE implies user preferences for surviving shows, documentaries, and standup comedies, while low score imply user preferences for soap operas, and game and sports shows. Moreover, high values of CON are associated to surviving, talk, and sports shows, whereas low degrees correspond to cartoon and animation genres. People with low degrees of EXT tend to prefer animation and cartoon shows, and people with high values of this factor tend to like sports and reality shows. Game and talk shows are liked by users with high scores of AGR, while surviving and prank shows are generally liked by users with low scores of that factor. Finally, high values of NEU are associated to preferences for cartoon, music videos and soap opera, whereas people with low values prefer sports, prank, and surviving shows.

In the **music domain**, users with high degree of OPE tend to prefer blues, classical and indie music, whereas low values of this factor correspond to user preferences for r&b, rap, pop, and hip hop. For the CON factor, high values correspond to country, jazz, salsa, and r&b, while low values correspond to indie, metal, techno, and rap music. Users with high EXT scores prefer salsa music, but also tend to like hip hop and rap; low scores of that factor refer to user preferences for metal, techno and rock music. With respect to AGR, people with high degree of this factor tend to like country, oldies, dance, and jazz music, while people with lower values prefer metal, rap, and indie genres. Finally, indie, metal, and rock music genres are also usually preferred by users with high degree of NEU, and salsa, jazz, and hip hop are preferred by those users with low values of that factor.

Finally, in the **book domain**, people with a high degree of OPE tend to like poetry and science fiction, whereas those with low degree prefer drama, scary and crime books. Regarding the CON factor, high values are related to educational books, and low values to like comic, fantasy, and poetry genres. Users with a low degree of EXT tend to like fantasy and comic genres, along with science fiction and war books, whereas users with high values of that factor prefer scary and humor books. Drama and educational books are generally preferred by people with high degree of AGR, and war, crime, and comic books are liked by those with a low degree of this factor. Finally, people with a high degree of NEU prefer crime and poetry books, while those with a lower degree prefer educational, thriller, mystery, and non-fiction books.

Some differences between **genders** are worth mentioning. For instance, in the **movie domain** the adventure, animation, and parody genres present significant differences with respect to which personality factors have higher and lower scores depending on the gender. Hence, adventure movies are preferred by female users with high EXT and AGR, whereas low degrees of EXT and neutral of AGR are observed for male users who like the genre. For animation movies, the opposite situation is observed; female users with low degrees of CON, EXT, and AGR tend to like the genre, but male users with high scores of EXT and AGR and neutral of CON are predominant. Similarly, for the parody genre, female users tend to have low degrees of CON and EXT and high degree of NEU, which is completely the opposite situation for male users. In the **TV show domain**, music videos, reality shows, soap operas, standup comedies, and surviving and talk shows present interesting differences between female and male users. On the other hand, in the **music domain** there are less differences, although some distinctions could be observed for jazz, pop, r&b, and salsa genres, where male users show higher degrees of AGR and CON factors. Finally, these differences are more remarkable in **the book domain**, where crime, drama, fiction, humor, mystery, non-fiction, romance, and self-help genres show significant variability in the personality scores for each gender. For instance, male users with high degrees of CON tend to like humor, non-fiction, romance, and self-help books, whereas for female users this factor seems to be neutral.

4.2 Association Rules Relating User Personality Factors and Domain-specific Preferences

In the previous section, relations between personality types and user preferences were derived by analyzing personality-based user stereotypes, and considered individual personality factors. In order to find more complex relations that take various personality factors into account, we applied the well-known Apriori algorithm, which generates association rules based on co-occurrences of attribute values in a set of data patterns.

To apply the Apriori algorithm we processed our dataset with the Weka[4] machine learning toolkit as follows. We transformed the dataset into a set of data patterns, each of them with 5 attributes corresponding to the Big Five personality factors of a particular user, and a discrete class label corresponding to a domain genre liked by such user. Each of the attributes had discrete values associated to 10 ranges of personality factor scores based on the attribute's factor score distribution, and are automatically generated by the Apriori algorithm. Moreover, aiming to generate generic (non overfitted) association rules, for each domain genre, we applied the Apriori algorithm on the 20 patterns most similar (i.e., with smallest Euclidean distance) to the genre's personality-based user stereotype. We ran the Apriori algorithm with other numbers of similar patterns, but here we do not report the rules obtained with them. When using less than 20 similar patterns we obtained a very small number of generic rules relating wide factor score ranges, whereas for more than 20 similar patterns we obtained a very large number of specific rules relating narrow factor score ranges.

The Apriori algorithm derives two strength measures for each rule $X \rightarrow Y$: *confidence* and *support*. The *confidence* represents the conditional probability $\Pr(Y|X)$ and is computed as $(X \cup Y).count/X.count$, and the *support* metric represents the probability $\Pr(X \cup Y)$ and is computed as $(X \cup Y).count/n$, where n is the total number of patterns, and $X.count$ is the number of patterns that contain the set of attribute values X.

Tables 2, 3, 4 and 5 show the generated association rules with highest confidence values. The reported support values give an idea of the "coverage" of the rules, i.e., the percentage of patterns satisfied by the rules.

The rules generated from **movie** preferences relate the OPE and EXT personality factors with different genres, depending on other personality factors. If a user with high OPE and EXT factors has high AGR, then she is likely to prefer comedy movies, but if she has low NEU, she is likely to prefer horror movies. Horror movies are also preferred by people with more complex personalities, such as those with high OPE, EXT, and AGR but low NEU. Additionally, cult movies tend to be liked by people with moderate CON and low AGR.

Regarding **TV show** preferences, only high confidence rules for two genres were generated: news and reality shows. People with high OPE and EXT, and moderately high CON tend to like news, whereas reality shows are liked by people with different types of personality: either high CON and EXT, and low NEU; high CON, EXT and OPE; or low NEU, and high OPE and AGR.

In the **music** domain, we found that people with high scores of OPE and EXT but low scores of NEU tend to like country music, whereas people with moderately low EXT and low NEU tend to like metal music. Jazz is liked by people with high EXT and AGR, and high CON or low NEU, whereas reggae is preferred by people with high OPE and AGR, and salsa is preferred by people with high scores of CON and EXT.

Finally, regarding **book** preferences, the rules indicate that people with high OPE and CON tend to like education books, whereas if CON is lower and OPE and AGR are high, people prefer science fiction books.

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4 Weka machine learning toolkit, http://www.cs.waikato.ac.nz/ml/weka

Taken into account the users' **gender**, it is worth noting that significant differences exist in the support values of the rules generated for female and male users. In the movie, TV show, and music domains, the support of the rules generated for male users was higher than that of the rules generated for female users, which may reflect a higher variability or complexity of the female personality-preference relations. In the **movie** domain, there was an interesting difference in the generation of rules for the animation genre, which is preferred by female users with low EXT and high NEU, and by male users with low CON and (much lower than female) NEU. In the **TV show** domain, news seemed to be preferred by female and male users sharing high OPE and CON and low NEU. In the **music** domain, the rules extracted for country music are very similar for female and male users (moderately high OPE, CON, and AGR). On the other hand, the rules for r&b music show differences: female users with NEU higher than male and high OPE, and male users with a moderately low CON and high EXT. Finally, in the **book** domain, no rules where generated for common genres, since the rules for female users were associated to crime, scary, and poetry books, and rules for male users were associated to humor books.

5 Relations between Personality Types and User Preferences in Crossed Domains

Table 6 shows the similarities between types of personality related to genres across the analyzed domains. In the table the colors of the cells correspond to relative values of the Euclidean distances between the personality-based user stereotypes associated to each pair of genres (maybe in distinct domains). Green cells correspond to high relative similarities (small distances), and red cells correspond to low relative similarities (large distances).

In the **movie domain** users who like action and comedy genres present very similar personality-based profiles. Similarly, people who like romance films show personality traits close to those who like comedy or drama. Users with tastes for cult movies show low similarity with other genres, in particular with those who like adventure movies. We can also observe that people who like foreign movies and people who like TV documentaries have similar personalities. Users that prefer tragic, independent or cult movies are in general dissimilar to people who like any kind of TV shows, especially to users that watch sports shows, a pattern that also appears in the music and book domains. Specifically, salsa and r&b are the farthest music genres, whereas educational, scary and thriller are the least similar book genres.

In the **TV show domain** there is little positive correlation between personality stereotypes of different genres. We can observe for instance differences between users who like sports shows and those who prefer animation and cartoons. We also notice that news, music videos, sitcoms and cooking shows are mostly independent of the user personality. With regard to the music domain there is a high similarity between documentaries and classical music, reality shows and dance music, and news and jazz. We also observe dissimilarity between people who like cartoons and those who enjoy hip hop, jazz or salsa. Regarding books, we see that comics and fantasy are the genres with users with similar personalities who like animation TV shows. On the other hand, people who like cartoons have on average a dissimilar personality to those who prefer educational books, and users who prefer sports shows have low similarity with respect to book preferences in general, specially comic, fantasy, science fiction and poetry.

In the **music domain** we can see that stereotypical users who like indie and metal music are quite dissimilar to those who like country, hip hop, r&b and salsa music. Interestingly, people who enjoy country and dance music show similar personality traits.

Finally, in the **book domain** we see that the genres with the closest associated user personalities are thrillers and mystery, as opposed to educational and war, or science fiction and scary books. Relating domains, we observe that in general, comic, fantasy, science fiction, poetry and war books link to a few personality traits in common with most music genres. Moreover, people who enjoy humor, mystery and romance books, on the other hand, have associated personality-based stereotypes similar to most of the music genre personality-based stereotypes.

6 Future Work

In this paper, we have preliminary analyzed the relations between user personality types and preferences. We have restricted our analysis to explicit preferences for a limited number of genres in the movie, TV, music, and book domains. However, as done by other authors [5], it would also be interesting to analyze those relations for particular items, such as representative or popular movies, TV shows, songs, and books. In our analysis we have focused on the users' gender as a characteristic that may influence the underlying personality-based preferences. In addition to or in combination with it, other user characteristics could be utilized. In this context, we consider interesting to explore the users' age and educational attainment. For instance, we may hypothesize that people with highest levels of education are more open-minded, and have larger and more diverse sets of preferences. Moreover, we have focused on the relations of personality-based stereotypes with preferences for single domains and genres. We plan to extend our analysis by considering relations involving several domains and genres. For instance, we could analyze the number and diversity of user preferences for particular personality-based stereotypes.

In any case, we believe that, although preliminary, the obtained relations between personality types and user preferences can be very valuable to enhance personalization services, not only on single domains, but also in cross-domain scenarios where user preferences on a source domain are used to infer user preferences on a different target domain, which can be a useful approach in e-commerce systems, among others. Hence, for example, we could investigate if a fact like "people with personality type *x* enjoy items *i* and *j*" (*i* and *j* belonging to different domains), could be used to suggest *i*, *j* (and other related items) to a person from whom we only known that has personality type *x*, or could be used to suggest item *j* to a person from whom we only know that has a preference for *i* (of a different domain of *j*). This, together with the investigation of more exhaustive automatic processes to infer and model user personality-preference relations, represents the next steps of our research.

	All users						Female users						Male users					
MOVIE GENRE	**OPE**	**CON**	**EXT**	**AGR**	**NEU**	**#users**	**OPE**	**CON**	**EXT**	**AGR**	**NEU**	**#users**	**OPE**	**CON**	**EXT**	**AGR**	**NEU**	**#users**
action	3.87	3.45	3.57	3.58	2.72	2488	3.89	3.46	3.57	3.61	2.85	1361	3.85	3.44	3.57	3.56	2.57	1127
adventure	3.91	3.56	3.54	3.68	2.61	179	3.88	3.55	3.64	3.77	2.66	104	3.96	3.57	3.39	3.55	2.52	75
animation	4.04	3.22	3.26	3.35	3.02	85	4.02	3.14	3.10	3.22	3.28	56	4.09	3.39	3.55	3.59	2.52	29
cartoon	3.95	3.33	3.49	3.57	2.81	957	3.92	3.32	3.48	3.55	2.88	655	4.03	3.34	3.51	3.61	2.66	302
comedy	3.88	3.44	3.58	3.60	2.75	3969	3.87	3.48	3.61	3.62	2.86	2392	3.89	3.39	3.54	3.56	2.60	1577
cult	4.27	3.10	3.45	3.40	3.16	38	4.21	2.97	3.54	3.27	3.34	22	4.36	3.26	3.33	3.59	2.90	16
drama	3.99	3.43	3.66	3.60	2.86	905	3.96	3.44	3.65	3.63	2.89	668	4.07	3.41	3.67	3.51	2.78	237
foreign	4.15	3.46	3.47	3.54	2.81	112	4.20	3.52	3.53	3.54	2.81	90	3.95	3.22	3.22	3.53	2.84	22
horror	3.90	3.38	3.52	3.47	2.91	2284	3.89	3.38	3.53	3.47	2.98	1614	3.94	3.37	3.49	3.45	2.75	670
independent	4.31	3.59	3.51	3.55	2.69	104	4.27	3.56	3.49	3.53	2.79	65	4.36	3.65	3.56	3.60	2.52	39
neo-noir	4.34	3.35	3.33	3.37	2.97	92	4.39	3.41	3.40	3.39	3.07	46	4.28	3.28	3.25	3.35	2.87	46
parody	4.13	3.36	3.35	3.28	2.73	25	4.18	3.08	2.84	3.22	3.07	10	4.10	3.56	3.68	3.33	2.50	15
romance	3.84	3.48	3.62	3.62	2.85	776	3.83	3.48	3.63	3.62	2.93	610	3.88	3.50	3.59	3.63	2.59	166
science fiction	3.99	3.55	3.33	3.57	2.73	215	3.95	3.59	3.36	3.58	2.84	96	4.02	3.51	3.30	3.57	2.63	119
tragedy	4.40	3.34	3.27	3.52	3.11	26	4.31	3.45	3.37	3.44	3.09	18	4.60	3.07	3.05	3.69	3.15	8
war	3.82	3.51	3.49	3.50	2.71	148	3.99	3.57	3.62	3.56	2.94	44	3.75	3.49	3.44	3.47	2.62	104
	4.05	**3.41**	**3.46**	**3.51**	**2.84**		**4.05**	**3.40**	**3.46**	**3.50**	**2.95**		**4.07**	**3.40**	**3.45**	**3.54**	**2.69**	

	All users						Female users						Male users					
TV GENRE	**OPE**	**CON**	**EXT**	**AGR**	**NEU**	**#users**	**OPE**	**CON**	**EXT**	**AGR**	**NEU**	**#users**	**OPE**	**CON**	**EXT**	**AGR**	**NEU**	**#users**
animation	4.03	3.23	3.25	3.48	2.83	166	4.07	3.22	3.25	3.51	2.96	108	3.96	3.23	3.24	3.43	2.58	58
cartoon	3.77	3.21	3.22	3.48	3.03	64	3.84	3.18	3.27	3.47	3.10	39	3.65	3.26	3.13	3.51	2.91	25
cooking show	3.71	3.54	3.54	3.51	2.76	134	3.68	3.56	3.53	3.53	2.80	108	3.83	3.45	3.59	3.46	2.60	26
documentary	4.12	3.45	3.37	3.53	2.85	722	4.14	3.45	3.41	3.57	2.88	466	4.09	3.46	3.30	3.45	2.79	256
game/quiz show	3.58	3.45	3.30	3.68	2.90	72	3.53	3.55	3.32	3.62	3.09	44	3.65	3.29	3.27	3.78	2.61	28
lgbt show	4.28	3.28	3.54	3.51	2.95	62	4.24	3.31	3.44	3.42	2.98	39	4.35	3.21	3.72	3.66	2.90	23
music video	3.98	3.32	3.56	3.55	3.02	163	3.95	3.30	3.50	3.60	3.13	123	4.09	3.38	3.76	3.39	2.67	40
news	3.97	3.58	3.58	3.54	2.74	676	3.96	3.59	3.65	3.58	2.82	374	3.98	3.56	3.49	3.50	2.63	302
prank show	4.08	3.41	3.51	3.33	2.65	65	4.13	3.40	3.63	3.36	2.78	31	4.04	3.43	3.41	3.31	2.54	34
reality show	3.76	3.56	3.61	3.58	2.75	808	3.73	3.55	3.63	3.58	2.78	623	3.86	3.61	3.56	3.55	2.64	185
sitcom	3.93	3.37	3.22	3.44	2.78	53	3.82	3.26	3.26	3.50	2.98	29	4.06	3.49	3.16	3.36	2.53	24
soap opera	3.57	3.46	3.56	3.42	3.01	151	3.56	3.45	3.51	3.40	3.05	135	3.66	3.52	3.96	3.59	2.67	16
sports show	3.67	3.58	3.67	3.64	2.52	119	3.68	3.73	3.62	3.72	2.74	37	3.66	3.52	3.70	3.60	2.42	82
standup comedy	4.10	3.36	3.53	3.49	2.85	339	4.07	3.43	3.59	3.42	3.06	156	4.12	3.29	3.48	3.55	2.67	183
surviving show	4.11	3.62	3.48	3.26	2.66	43	4.06	3.89	3.66	3.26	2.75	16	4.14	3.46	3.37	3.26	2.60	27
talk show	3.81	3.58	3.58	3.68	2.67	61	3.79	3.71	3.67	3.62	2.50	38	3.86	3.38	3.43	3.77	2.95	23
	3.90	**3.44**	**3.47**	**3.51**	**2.81**		**3.89**	**3.47**	**3.50**	**3.51**	**2.90**		**3.94**	**3.41**	**3.47**	**3.51**	**2.67**	

	All users						Female users						Male users					
MUSIC GENRE	**OPE**	**CON**	**EXT**	**AGR**	**NEU**	**users**	**OPE**	**CON**	**EXT**	**AGR**	**NEU**	**#users**	**OPE**	**CON**	**EXT**	**AGR**	**NEU**	**#users**
blues	4.08	3.48	3.55	3.57	2.71	1054	4.05	3.51	3.57	3.64	2.81	501	4.10	3.46	3.53	3.52	2.62	553
classical	4.10	3.50	3.39	3.54	2.77	2235	4.10	3.55	3.40	3.57	2.87	1231	4.11	3.44	3.37	3.50	2.66	1004
country	3.79	3.55	3.64	3.65	2.78	7475	3.79	3.54	3.65	3.67	2.86	5370	3.79	3.55	3.62	3.58	2.56	2105
dance	3.79	3.50	3.66	3.60	2.79	456	3.74	3.51	3.64	3.61	2.95	275	3.86	3.50	3.69	3.58	2.54	181
hip hop	3.82	3.49	3.75	3.52	2.66	2510	3.81	3.50	3.78	3.52	2.77	1513	3.82	3.46	3.71	3.53	2.49	997
indie	4.06	3.26	3.51	3.49	2.98	476	4.05	3.22	3.45	3.50	3.12	309	4.09	3.35	3.63	3.47	2.73	167
jazz	4.03	3.55	3.61	3.60	2.64	1735	4.02	3.61	3.65	3.63	2.73	944	4.05	3.48	3.57	3.58	2.53	791
metal	3.97	3.30	3.37	3.34	2.87	1273	4.03	3.34	3.35	3.40	3.05	474	3.93	3.27	3.38	3.30	2.76	799
oldies	3.86	3.51	3.57	3.65	2.75	932	3.83	3.53	3.59	3.67	2.81	693	3.93	3.45	3.51	3.59	2.58	239
pop	3.79	3.41	3.55	3.55	2.77	412	3.80	3.39	3.56	3.54	2.86	285	3.79	3.45	3.53	3.58	2.57	127
r&b	3.69	3.54	3.63	3.57	2.71	1367	3.66	3.55	3.63	3.56	2.78	974	3.75	3.54	3.64	3.58	2.52	393
rap	3.74	3.33	3.69	3.43	2.67	323	3.73	3.36	3.66	3.45	2.88	163	3.75	3.30	3.72	3.41	2.45	160
reggae	4.00	3.43	3.66	3.53	2.67	2802	3.98	3.46	3.68	3.52	2.77	1701	4.02	3.37	3.63	3.56	2.53	1101
rock	3.93	3.37	3.48	3.51	2.83	6196	3.95	3.38	3.46	3.50	2.99	3429	3.91	3.35	3.51	3.52	2.64	2767
salsa	3.94	3.55	3.80	3.55	2.62	467	3.93	3.53	3.82	3.56	2.69	334	3.98	3.58	3.77	3.53	2.45	133
techno	4.00	3.32	3.51	3.50	2.81	2481	4.01	3.31	3.51	3.49	2.97	1249	3.99	3.33	3.51	3.51	2.64	1232
	3.91	**3.44**	**3.59**	**3.54**	**2.75**		**3.91**	**3.46**	**3.59**	**3.55**	**2.87**		**3.93**	**3.43**	**3.58**	**3.52**	**2.58**	

	All users						Female users						Male users					
BOOK GENRE	**OPE**	**CON**	**EXT**	**AGR**	**NEU**	**#users**	**OPE**	**CON**	**EXT**	**AGR**	**NEU**	**#users**	**OPE**	**CON**	**EXT**	**AGR**	**NEU**	**#users**
comic	4.06	3.28	3.38	3.47	2.86	1107	4.05	3.24	3.36	3.49	2.98	540	4.08	3.31	3.40	3.45	2.73	567
crime	3.83	3.44	3.43	3.47	2.99	191	3.82	3.46	3.38	3.47	3.06	146	3.88	3.39	3.59	3.46	2.76	45
drama	3.81	3.36	3.53	3.67	2.84	66	3.83	3.38	3.55	3.72	2.95	52	3.75	3.29	3.43	3.51	2.44	14
educational	4.02	3.66	3.57	3.66	2.74	977	3.97	3.71	3.59	3.68	2.82	656	4.12	3.55	3.53	3.62	2.57	321
fantasy	4.04	3.34	3.27	3.54	2.87	994	4.03	3.34	3.29	3.56	2.97	624	4.05	3.35	3.23	3.51	2.70	370
fiction	4.00	3.41	3.42	3.55	2.82	339	3.97	3.43	3.45	3.53	2.90	214	4.04	3.36	3.37	3.60	2.67	125
humor	3.90	3.40	3.62	3.56	2.78	743	3.88	3.36	3.61	3.56	2.94	470	3.93	3.47	3.64	3.56	2.51	273
mystery	3.91	3.53	3.51	3.61	2.76	302	3.93	3.58	3.53	3.63	2.77	219	3.83	3.39	3.43	3.55	2.71	83
non fiction	4.01	3.51	3.43	3.62	2.76	319	4.02	3.51	3.49	3.65	2.87	205	4.00	3.52	3.31	3.57	2.58	114
poetry	4.16	3.34	3.38	3.54	2.94	160	4.11	3.35	3.41	3.59	2.98	108	4.25	3.32	3.33	3.45	2.86	52
romance	3.89	3.52	3.49	3.60	2.85	1132	3.88	3.52	3.49	3.61	2.86	987	3.99	3.52	3.47	3.60	2.80	145
scary	3.81	3.41	3.68	3.55	2.83	1084	3.83	3.43	3.68	3.54	2.89	822	3.75	3.36	3.67	3.55	2.61	262
science fiction	4.13	3.42	3.25	3.51	2.81	1191	4.15	3.44	3.25	3.52	2.95	552	4.12	3.40	3.25	3.50	2.68	639
self help	4.03	3.50	3.42	3.62	2.83	196	4.05	3.49	3.45	3.71	2.98	129	3.98	3.53	3.35	3.45	2.55	67
thriller	3.85	3.54	3.51	3.59	2.76	639	3.86	3.55	3.53	3.61	2.87	410	3.84	3.50	3.47	3.55	2.56	229
war	3.87	3.44	3.33	3.23	2.80	108	4.14	3.45	3.41	3.29	3.05	15	3.83	3.44	3.32	3.22	2.76	93
	3.96	**3.44**	**3.45**	**3.55**	**2.83**		**3.97**	**3.45**	**3.47**	**3.57**	**2.93**		**3.97**	**3.42**	**3.42**	**3.51**	**2.66**	

Table 1. Personality-based user stereotypes in individual domain genres.

MOVIES	**Rule**	**Confidence**	**Support**
All users (support ≤ 20.30 %)	$con \in (3, 3.25] \wedge agr \in [2.55, 2.87] \rightarrow$ cult	67 %	1.87 %
	$ope \in (3.6, 3.80] \wedge ext \in (3.35, 3.62] \wedge agr \in (3.52, 3.85] \rightarrow$ comedy	67 %	1.87 %
	$ope \in (3.8, 4] \wedge con \in (3.25, 3.5] \wedge agr \in (3.2, 3.52] \wedge neu \in (2.85, 3.17] \rightarrow$ horror	67 %	1.87 %
	$ope \in (4.88, 5] \rightarrow$ tragedy	63 %	2.50 %
	$ope \in (4.4, 4.6] \wedge ext \in (3.62, 3.89] \rightarrow$ foreign	63 %	2.50 %
	$ope \in (3.6, 3.8] \wedge ext \in (3.62, 3.89] \wedge agr \in (3.2, 3.52] \rightarrow$ horror	57 %	2.19 %
	$ope \in (3.6, 3.8] \wedge ext \in (3.62, 3.89] \wedge agr \in (3.20, 3.52] \wedge neu \in (2.53, 2.85] \rightarrow$ horror	57 %	2.19 %
	$ope \in (3.6, 3.8] \wedge agr \in (3.2, 3.52] \wedge neu \in (2.53, 2.85] \rightarrow$ horror	50 %	2.50 %
	$ope \in (3.8, 4] \wedge ext \in (3.62, 3.89] \wedge agr \in (3.52, 3.85] \rightarrow$ comedy	50 %	2.81 %
Female users (support ≤ 6.82 %)	$ext \in (2.37, 2.75] \wedge neu \in (3.7, 4.02] \rightarrow$ animation	67 %	1.95 %
	$ope \in (3.8, 4.1] \wedge ext \in (3.5, 3.87] \wedge neu \in (2.4, 2.72] \rightarrow$ cartoon	57 %	2.27 %
	$con \in (3.67, 3.98] \wedge agr \in (3.3, 3.6] \wedge neu \in (2.72, 3.05] \rightarrow$ romance	50 %	2.60 %
Male users (support ≤ 81.61 %)	$ext \in (4.2, 4.6] \wedge neu \in (1.79, 2.1] \rightarrow$ independent	100 %	1.34 %
	$ope \in (4.6, 4.8] \wedge con \in (3.25, 3.6] \rightarrow$ neo-noir	100 %	1.00 %
	$con \in (3.25, 3.6] \wedge neu \in (1.47, 1.79] \rightarrow$ animation	100 %	1.00 %
	$ope \in (4.2, 4.4] \wedge con(3.25, 3.6] \wedge ext \in (3.8, 4.2] \rightarrow$ animation	100 %	1.00 %
	$ope \in (4.2, 4.4] \wedge con(3.6, 3.95] \wedge neu \in (2.74, 3.058] \rightarrow$ drama	80 %	1.67 %
	$con \in (1.85, 2.2] \rightarrow$ cult	75 %	1.34 %
	$ope \in (3.4, 3.6] \wedge ext \in (3.8, 4.2] \rightarrow$ war	75 %	1.34 %
	$con \in (4.65, 5] \wedge \text{agr} \in (3.7, 4.05] \rightarrow$ independent	75 %	1.34 %
	$ext \in (3, 3.4] \wedge neu \in (2.10, 2.42] \rightarrow$ adventure	75 %	1.34 %
	$ope \in (3.8, 4] \wedge ext \in (3, 3.4] \wedge neu \in (2.42, 2.74] \rightarrow$ comedy	75 %	1.34 %
	$ope \in (4.2, 4.4] \wedge agr \in (3.35, 3.7] \wedge neu \in (1.786, 2.104] \rightarrow$ adventure	75 %	1.34 %
	$con \in (3.6, 3.9] \wedge ext \in (3, 3.4] \wedge neu \in (2.74, 3.06] \rightarrow$ drama	75 %	1.34 %
	$ope \in (3.6, 3.8] \wedge ext \in (3.4, 3.8] \wedge agr \in (3.7, 4.05] \wedge neu \in (2.42, 2.74] \rightarrow$ action	75 %	1.34 %

Table 2. Association rules relating user personality factors and movie preferences.

TV	Rule	Confidence	Support
All users (support ≤ 5.93 %)	$ope \in (3.65, 3.87] \wedge con \in (3.18, 3.4] \wedge ext \in (3.47, 3.73] \rightarrow$ news	100 %	1.25 %
	$con \in (3.62, 3.84] \wedge ext \in (3.47, 3.73] \wedge neu \in (2.65, 2.87] \rightarrow$ reality show	100 %	1.25 %
	$ope \in (3.65, 3.87] \wedge agr \in (3.69, 3.87] \wedge neu \in (2.65, 2.87] \rightarrow$ reality show	80 %	1.56 %
	$ope \in (3.65, 3.87] \wedge con \in (3.62, 3.84] \wedge ext \in (3.47, 3.73] \rightarrow$ reality show	67 %	1.87 %
Female users (support ≤ 3.48 %)	$ope \in (4, 4.25] \wedge con \in (3.55, 3.84] \wedge neu \in (2.66, 3.00] \rightarrow$ news	100 %	1.27 %
	$con \in (4.13, 4.42] \rightarrow$ talk show	57 %	2.21 %
Male users (support ≤ 14.58 %)	$con \in (3.78, 4.08] \wedge agr \in (3.2, 3.5] \wedge neu \in (2.08, 2.43] \rightarrow$ sports	100 %	1.27 %
	$ope \in (4.33, 4.67] \wedge con \in (2.86, 3.17] \rightarrow$ lgbt show	57 %	2.22 %
	$ope \in (4.67, 5] \wedge agr \in (2.9, 3.2] \rightarrow$ surviving show	57 %	2.22 %
	$ope \in (3.67, 4] \wedge ext \in (3.47, 3.78] \wedge neu \in (2.77, 3.12] \rightarrow$ news	57 %	2.22 %
	$ope \in (4.33, 4.67] \wedge ext \in (3.47, 3.78] \wedge neu \in (2.43, 2.77] \rightarrow$ standup comedy	57 %	2.22 %
	$agr \in (3.2, 3.5] \wedge neu \in (2.08, 2.43] \rightarrow$ sports	50 %	1.90 %
	$ope \in (4, 4.33] \wedge neu \in (3.12, 3.46] \rightarrow$ music video	50 %	2.53 %

Table 3. Association rules relating user personality factors and TV preferences.

MUSIC	Rule	Confidence	Support
All users (support ≤ 14.35 %)	$con \in (3.64, 3.76] \wedge ext \in (3.635, 3.774] \wedge agr \in (3.598, 3.731] \rightarrow$ jazz	80 %	1.56 %
	$ope \in (3.75, 3.875] \wedge agr \in (3.465, 3.598] \rightarrow$ reggae	67 %	1.87 %
	$con \in (3.64, 3.76] \wedge ext \in (3.913, 4.052] \rightarrow$ salsa	67 %	1.87 %
	$ope \in (3.625, 3.75] \wedge con \in (3.4, 3.52] \wedge ext \in (3.496, 3.635] \rightarrow$ country	67 %	1.87 %
	$ext \in (3.635, 3.774] \wedge agr \in (3.598, 3.731] \wedge neu \in (2.49, 2.61] \rightarrow$ jazz	67 %	1.87 %
	$ext \in (3.218, 3.357] \wedge neu \in (2.97, 3.09] \rightarrow$ metal	57 %	2.19 %
	$ope \in (3.625, 3.75] \wedge ext \in (3.496, 3.635] \wedge neu \in (2.49, 2.61] \rightarrow$ country	50 %	3.12 %
Female users (support ≤ 7.81 %)	$ope \in (4.25, 4.375] \wedge con \in (3.42, 3.57] \rightarrow$ classic	80 %	1.56 %
	$ope \in (3.625, 3.75] \wedge con \in (3.42, 3.57] \wedge ext \in (3.4, 3.55] \rightarrow$ country	80 %	1.56 %
	$ope \in (3.625, 3.75] \wedge con \in (3.42, 3.57] \wedge agr \in (3.652, 3.789] \rightarrow$ country	57 %	2.19 %
	$ope \in (3.375, 3.5] \wedge neu \in (2.91, 3.058] \rightarrow$ r&b	50 %	2.50 %
Male users (support ≤ 12.49 %)	$agr \in [1, 2.915] \rightarrow$ rap	80 %	1.56 %
	$ope \in (3.35, 3.525] \wedge con \in (2.9, 3.05] \rightarrow$ pop	80 %	1.56 %
	$ope \in (3.7, 3.875] \wedge con \in (3.35, 3.5] \wedge agr \in (3.41, 3.575] \rightarrow$ country	80 %	1.56 %
	$con \in (3.2, 3.35] \wedge ext \in (3.47, 3.625] \wedge neu \in (2.618, 2.776] \rightarrow$ r&b	80 %	1.56 %
	$con \in (2.9, 3.05] \wedge agr \in (2.915, 3.08] \rightarrow$ metal	67 %	1.87 %
	$ope \in (3.875, 4.05] \wedge agr \in (2.915, 3.08] \rightarrow$ metal	57 %	2.19 %
	$con \in (3.35, 3.5] \wedge agr \in (3.41, 3.575] \wedge neu \in (2.144, 2.302] \rightarrow$ country	57 %	2.19 %

Table 4. Association rules relating user personality factors and music preferences.

BOOKS	Rule	Confidence	Support
All users (support ≤ 8.74 %)	$ope \in (4.09, 4.28] \wedge con \in (3.9, 4.07] \rightarrow$ education	67 %	1.87 %
	$ope \in (3.91, 4.09] \wedge con \in (3.375, 3.55] \wedge agr \in (3.5, 3.65] \rightarrow$ science fiction	67 %	1.87 %
	$ope \in (1, 3.37] \rightarrow$ drama	57 %	2.19 %
	$ope \in (3.91, 4.09] \wedge agr \in (3.5, 3.65] \rightarrow$ science fiction	56 %	2.81 %
Female users (support ≤ 9.53 %)	$ope \in (3.4, 3.6] \wedge agr \in (3.95, 4.3] \rightarrow$ crime	80 %	1.59 %
	$ope \in (3.8, 4] \wedge ext \in (3.62, 3.9] \wedge neu \in (3, 3.4] \rightarrow$ scary	63 %	2.54 %
	$ext \in (2.52, 2.8] \rightarrow$ poetry	56 %	2.86 %
	$ope \in (4.6, 4.8] \rightarrow$ poetry	50 %	2.54 %
Male users (support ≤ 7.21 %)	$ope \in (3.52, 3.89] \wedge agr \in (3.25, 3.55] \wedge neu \in (2.04, 2.32] \rightarrow$ humor	80 %	1.57 %
	$ext \in (3.86, 4.16] \wedge neu \in (2.04, 2.32] \rightarrow$ humor	57 %	2.19 %
	$ope \in (3.52, 3.89] \wedge neu \in (2.04, 2.32] \rightarrow$ humor	55 %	3.45 %

Table 5. Association rules relating user personality factors and book preferences.

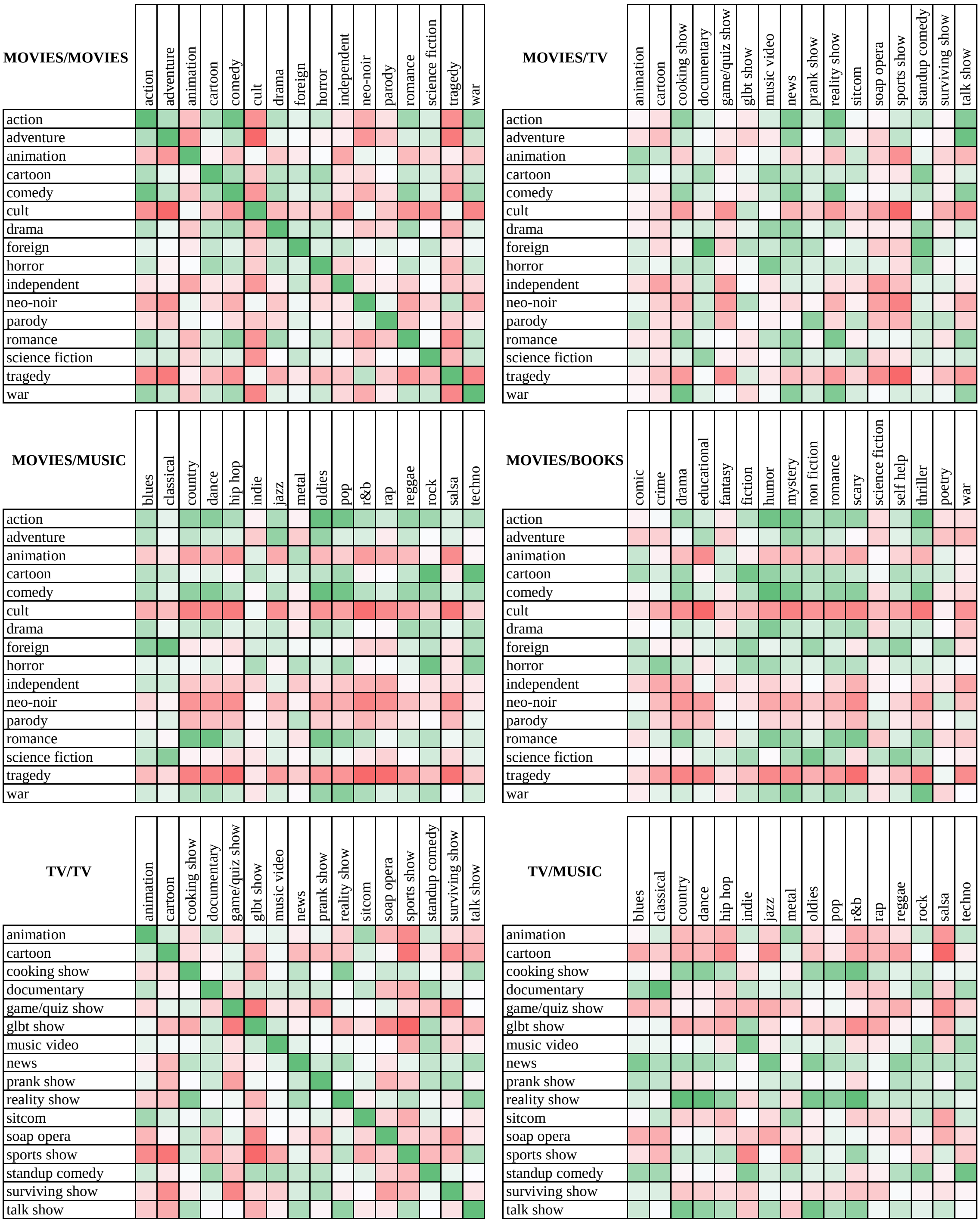
MOVIES/MOVIES
action
adventure
animation
cartoon
comedy
cult
drama
foreign
horror
independent
neo-noir
parody
romance
science fiction
tragedy
war
MOVIES/TV
animation
cartoon
cooking show
documentary
game/quiz show
glbt show
music video
news
prank show
reality show
sitcom
soap opera
sports show
standup comedy
surviving show
talk show
MOVIES/MUSIC
blues
classical
country
dance
hip hop
indie
jazz
metal
oldies
pop
r&b
rap
reggae
rock
salsa
techno
MOVIES/BOOKS
comic
crime
drama
educational
fantasy
fiction
humor
mystery
non fiction
romance
scary
science fiction
self help
thriller
poetry
war
TV/TV
TV/MUSIC

Table 6. Similarities between personality-based user stereotypes for genres in different domains.

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