Chapter 9
Personality, Emotions, and Group Dynamics

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Abstract The methods and techniques introduced in the previous chapters provide a basic means to aggregate the preferences of individual group members and to determine recommendations suitable for the whole group. However, preference aggregation can go beyond the integration of the preferences of individual group members. In this chapter, we show how to take into account the aspects of *personality*, *emotions*, and *group dynamics* when determining item predictions for groups. We summarize research related to the integration of these aspects into recommender systems, and provide some selected examples.

9.1 Personality and Emotions

Research has already demonstrated that various properties of recommender systems (e.g., prediction quality) can be improved by taking into account the aspects of personality [9] and emotions [22, 37]. In this chapter, we show how these aspects can be considered in group recommendation scenarios. In contrast to single user recommenders [8], group dynamics [11], i.e., the way group members interact (e.g., in terms of communicating opinions) have to be taken into account [22, 30].

Personality

According to McCrae and John [24], personality reflects *individual differences in emotional, interpersonal, experiential, attitudinal, and motivational styles*. An overview of different models of personality especially in the context of offering personalized services is given by Matz et al. [23, 38]. The traditional approach to the *acquisition of personality information* are (obtrusive) questionnaires [17, 18] which should not be the first choice when following the objective of integrating personality aspects into recommender systems. Such questionnaires are often employed in the context of user studies – see, for example, Quijano-Sanchez et al. [31]. As an alternative, there are a couple of methods for estimating personality in an un-

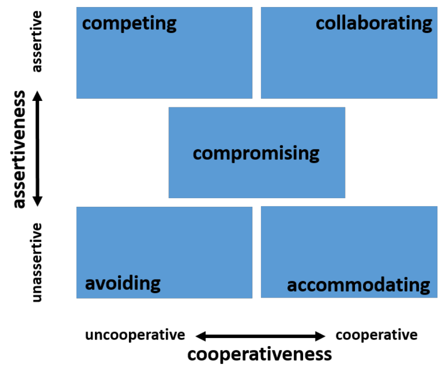

Fig. 9.1: *Thomas-Kilmann* (*TKI*) model of conflict resolution styles [18].

obtrusive fashion. For example, on the basis of social media features such as the number of *Twitter* followers and followees [28] (e.g., an above average number of followers and followees is correlated with *extraversion*), FACEBOOK likes [13, 19] (e.g., music from Leonard Cohen is correlated with *openness*), and color-based, low-level features from INSTAGRAM pictures [36] (e.g., *extroverted people* like a lot of green color). Related work is presented in Neidhardt et al. [26] who show how to elicit travel-related personality information in single user recommender systems. Users had to select pictures which were used to infer tourism-related personality factors such as *sun and chill-out*, *action and fun*, *nature and recreation*, etc. *Unobtrusive methods* come along with a trade-off in terms of lower algorithm accuracy, however, recent research has shown that using a combination of sensors and social media traces with advanced machine learning can yield acceptable predictive quality [10, 35]. Importantly, off-the-shelf solutions such as WATSON PERSONALITY INSIGHTS (e.g., personality prediction through written texts) are available.

In this chapter, we will use the *Thomas-Kilmann Conflict Style Model* (*TKI model*) [18] of personality as a basis for our working examples (see Figure 9.1). In contrast to other models that primarily take into account characteristics of individual users, the advantage of this model is that it focuses on the interaction between group members. In this context, it serves as a basis for the provision of conflict resolution styles applicable in specific group settings. The TKI model differentiates between the two aspects of *cooperation* (*low* .. *high*) and *assertion* (*low* .. *high*). Combinations of these two aspects lead to different personality types which are *competing* (assertive and uncooperative, own concerns are pursued at the expense of other group members), *collaborating* (cooperative and assertive, the goal is to find a solution that satisfies the concerns of all group members), *compromising* (moderate in cooperativeness and assertiveness, focus on finding trade-offs/solutions acceptable for all group members), *avoiding* (not assertive and not cooperative, no concerns are pursued), and *accommodating* (cooperative and not assertive, focus is on primarily satisfying concerns of other group members).

Emotions

Emotions can be regarded as *base affective occurrences that are usually triggered by a stimulus*, for example, if one wins a race (s)he usually gets happy. There are different models of emotion which will not be discussed in this chapter – for a related overview we refer to D'Errico and Poggi [7]. Typical dimensions covered by base models of emotions are *anger*, *disgust*, *fear*, *happiness*, *sadness*, and *surprise*. Due to their direct measurability, *valence* and *arousal* are often used to infer emotional categories [1, 25]. For example, *anger* is related to a high arousal and low valence. Similar to personality, emotions can also be measured on the basis of self-assessment questionnaires. Also, off-the-shelf tools (e.g., AFFECTIVA) support the automated detection of emotions from facial expressions, skin conductance, EEG (electroencephalography) signals, etc. A survey of existing techniques in automated emotion detection is given by Schuller [35]. Ho et al. [16] introduce a single user movie recommender system that takes into account the emotional states of users. Emotional states are determined with regard to colors that have to be chosen by users. Depending on this feedback, an emotional state can be determined and recommendations can be made based on items consumed by users in a similar emotional state (e.g., on the basis of collaborative filtering). Thus, emotions can be interpreted as a contextual dimension. Emotions in contextual recommender systems have also been analyzed by Zheng et al. [39]. The outcome of their study was that emotions can help to improve the predictive performance of recommendation algorithms.

9.2 Group Dynamics

Group dynamics account for processes and outcomes that occur in group settings [4, 11]. Social sciences research has shown that group decisions are not always rational and cannot always be deduced from (explained solely by) the preferences of individual group members. Consequently, supporting group decision processes on the basis of group recommendation technologies also requires knowledge of group dynamics. In the following, we discuss the aspects of *emotional contagion* and *conformity* which are the major influential aspects to be taken into account when analyzing group decision processes. We discuss these aspects in the light of existing research in group recommender systems.

Emotional Contagion. Emotional contagion (see Chapter 8) reflects processes where the emotional state of one group member influences the emotional state of other group members [2, 15]. In this context, emotions can (1) be transferred 'as-is' (e.g., the happiness of one group member makes other group members happy as well) or (2) trigger a *counter-contagion* (e.g., due to competitive situations among group members). In this case, the happiness of one person makes another person annoyed. Usually, this effect occurs automatically, unintentionally, and uncontrollably. Emotional contagion also occurs in online groups where it has been shown that, for example, FACEBOOK users confronted with positively formulated posts also generated more positive ones and vice-versa [20].

Emotional contagion has also been taken into account in the context of group recommendation scenarios [22]. If, for example, one group member is dissatisfied with a recommendation, it can be expected that her disappointment has a negative influence on the other group members. This in turn decreases the overall group satisfaction even though other group members would have enjoyed a given recommendation. In the work of Masthoff and Gatt [22], group recommendations are determined for item sequences (TV programs). In such a context, the satisfaction of an individual is not only a function of the currently-recommended item, but also a function of the items presented earlier. Recommendations of sequences to groups is outside the scope of this chapter – for an in-depth discussion of how to integrate the concept of emotional contagion on an algorithmic level, we refer to Masthoff and Gatt [22].

Conformity. Conformity can be interpreted as a change in opinion, judgement, or action to match the opinions, judgements, or actions of other group members or to match the group's normative standards [11]. In the context of group recommender systems, conformity knowledge can be used to better predict the preparedness of individual group members to adapt their initial evaluations. In Masthoff and Gatt [22], a function to estimate the degree of conformity of a specific group member is based on factors such as *size of the subgroup with a different opinion*, *number of persons outside that subgroup* and *difference between the individual's opinion and the opinion of the subgroup*. Berkovsky and Freyne [3] introduced a model of *influence* of specific group members that is based on rating counts. For example, the higher the share of ratings of one family member in relation to the number of ratings of all family members, the higher his/her influence. In this context, it is assumed that the lower the influence, the higher the preparedness of persons to adapt their evaluations (and the higher the conformity level). Quintarelli et al. [32] introduce a measure of influence that is based on the idea that the more often the individual preference of a group member appears as result in the final group choice, the higher the influence of this group member. Finally, Nguyen and Ricci [27] analyze three conformity types within the scope of an empirical study: (1) group members do not change their preferences (*independence*), (2) preferences of group members tend to become similar (*conversion*), and (3) preferences become more divergent (*anti-conformity*).

An approach to combine *personality* information with *conformity* in the context of group recommendations has been introduced by Quijano-Sanchez et al. [31]. The presented approach is able to estimate the extent of conformity susceptibility (on the basis of a trust measure) of a specific user and to take this information into account when generating group recommendations. The personality model used in [31] is based on the aforementioned *TKI model* [18]. In the following section, we provide an example of the group recommendation approach presented by Quijano-Sanchez et al. [31]. For an in-depth discussion of the integration of emotional contagion into group recommendation processes we refer to Masthoff and Gatt [22].

9.3 Example: Taking into Account Personality and Conformity

In order to show how to integrate aspects of *group dynamics* into group recommendation processes, we give an example that is based on the approach presented in [31]. The ratings shown in Table 9.1 have to be considered as the user-specific item rating predictions determined by the underlying recommender system.

user	t_1	t_2	t_3	t_4	t_5
u_1	2	4	5	1	3
u_2	3	2	3	4	5
u_3	1	3	5	2	1

Table 9.1: Example predictions of user $\times$ item ratings.

Quijano-Sanchez et al. [31] used a *TKI test* consisting of 30 questions [18] to categorize the personality of individual group members. Depending on the determined scores (categorized as *low* or *high*), corresponding *assertiveness* and *cooperativeness* values can be determined. For example, high estimates for competing and collaborating modes result in high assertiveness values (see Table 9.2).

TKI mode	assertiveness		cooperativeness	
	high	low	high	low
competing	0.375	-0.075	-0.15	0
collaborating	0.375	-0.075	0.375	-0.075
compromising	0	0	0	0
avoiding	-0.375	0.075	-0.375	0.075
accommodating	-0.15	0	0.375	-0.075

Table 9.2: Coefficients for determining assertiveness and cooperativeness [33].

User-specific assertiveness and cooperativeness evaluations can be represented as the sum of the five personality modes [31, 33]. After completion of the questionnaire, the degree of cooperativeness and assertiveness can be determined for each user. For the approach used to determine the high/low categories shown in Table 9.3, we refer to [31, 33]. Combining the information contained in Tables 9.2 and 9.3 results in the estimates of *assertiveness* and *cooperativeness* depicted in Table 9.4. For example, group member u_1 is highly assertive whereas u_3 is highly cooperative.

The group recommendation approach then is based on the idea of encapsulating *assertiveness* (selfishness) and *cooperativeness* estimates of group members into the determination of rating predictions. The first step in this context is to determine the *conflict mode weight* (*cmw*) (see Formula 9.1) which represents the predominant behavior of a group member (on a scale -1 .. +1). The underlying assumption is that the higher the *cmw* value, the stronger the influence of that group member (higher

user	competing	collaborating	compromising	avoiding	accommodat-ing
u_1	high	high	low	low	low
u_2	high	low	low	low	low
u_3	low	high	high	low	high

Table 9.3: Personality scores of example users u_i with regard to (*TKI* conflict resolution types [18]).

user	assertiveness	cooperativeness	cmw(u_i)
u_1	.375+.375+0+.075+0=0.825	-.15+.375+0+.075-.075=.225	0.8
u_2	.375-.075+0+.075+0=0.375	-.15-.075+0+.075-.075=-.225	0.8
u_3	-.075+.375+0+.075-.15=0.225	0+.375+0+.075+.375=.825	0.2

Table 9.4: User-specific estimates of *assertiveness* and *cooperativeness* and corresponding *conflict mode weight* (*cmw*) – see Formula 9.1.

assertiveness and lower cooperativeness). The *cmw* values determined for the group members in our example setting are depicted in Table 9.4.

$$cmw(u) = \frac{1 + assertiveness(u) - cooperativeness(u)}{2} \tag{9.1}$$

Personality-enhanced Rating Prediction. Using the *cmw* value, we are able to determine a personality-enhanced item rating prediction for each group member u ($p_{pers}(u,i)$). This rating serves as an input for determining the item rating prediction for the whole group ($g_{pers}(G,i)$) – see Formulae 9.2 and 9.3. In this context, $p(u_a,i)$ denotes the item-i rating predicted for user u_a determined by a recommendation algorithm. The underlying idea is that the original item ratings are adapted depending on the *cmw* value, i.e., users assumed to not be prepared to downgrade their ratings receive a corresponding positive adaptation.

$$g_{pers}(G,i) = \frac{\Sigma_{u \in G} p_{pers}(u,i)}{|G|} \tag{9.2}$$

$$p_{pers}(u_a,i) = \frac{\Sigma_{u \in G(u \neq u_a)} p(u_a,i) + (cmw(u_a) - cmw(u))}{|G| - 1} \tag{9.3}$$

Applying Formulae 9.2 and 9.3 results in the adapted item rating predictions depicted in Table 9.5. For example, group member u_3 has a low *cmw* value compared to group members u_1 and u_2 (see Table 9.4). As a consequence, the rating predictions for u_3 are downgraded whereas those of u_1 and u_2 get increased.

Influence-based Rating Prediction. The idea of influence-based rating prediction [29], i.e., rating prediction based on social influence, is to take into account both the *personality* of group members and *trust* relationships between group members. In this context, trust between two users ($t(u_1,u_2)$) is defined as the weighted sum

	p(u,i)					p_{pers}(u,i)				
user	t_1	t_2	t_3	t_4	t_5	t_1	t_2	t_3	t_4	t_5
u_1	2	4	5	1	3	2.3	4.3	5.0	1.3	3.3
u_2	3	2	3	4	5	3.3	2.3	3.3	4.3	5.0
u_3	1	3	5	2	1	0.4	2.4	4.4	1.4	0.4
AVG	2	3	4.3	2.3	3	2	3	4.2	2.3	2.9

Table 9.5: Example *personality-based rating predictions* (ratings in 0..5). 5.0 is assumed to be the ceiling, i.e., a potential 5.3 rating is downgraded to 5.0. Predictions are determined on the basis of Formula 9.3.

over a set of n factors f_i that are selected to act as indicators of trust relationships between group members (u_1 and u_2 in Formula 9.4).

$$t(u_1,u_2) = \Sigma_{i=1}^{n} w_i \times f_i(u_1,u_2) \tag{9.4}$$

Examples of such factors are *distance in a social network* (e.g., if two users are friends in a social network or have friends in common), *intensity of the relationship* (e.g., how often a user name appears on the wall of the other user), and *duration* (how long have two users known each other).[1]

user	u_1	u_2	u_3
u_1	1.0	0.5	0.6
u_2	0.5	1.0	0.2
u_3	0.6	0.2	1.0

Table 9.6: Example trust relationships among group members $u_i \in G$. For simplicity we assume symmetry, i.e., $trust(u_i,u_j) = trust(u_j,u_i)$.

On the basis of the identified trust level (Formula 9.4), influence-based rating prediction can be performed [29]. In this context, it is assumed that group members may adapt their ratings depending on the ratings of their friends. A rating prediction that integrates both, the level of *trust* and the *personality* of individual group members is defined by Formula 9.5. The positive or negative adaptation of a group member's u_a original rating is defined by the average positive or negative difference between the rating of u_a on those of the other group members. This difference is weighted by (1) the level of trust between u_a and other group members ($t(u,u_a)$) and (2) the *cmw* factor representing a user's preparedness to adapt his/her rating [29].

$$p_{pers}(u_a,i) = p(u_a,i) + (1 - cmw(u_a)) \times \frac{\Sigma_{u \in G(u \neq u_a)} t(u,u_a) \times (p(u,i) - p(u_a,i))}{|G| - 1} \tag{9.5}$$

Applying Formulae 9.4 and 9.5 results in the rating predictions in Table 9.7.

[1] For a detailed discussion of these factors we refer to [29].

	p(u,item)					p_{pers}(u,item)				
user	t_1	t_2	t_3	t_4	t_5	t_1	t_2	t_3	t_4	t_5
u_1	2	4	5	1	3	1.99	3.84	4.9	1.21	2.98
u_2	3	2	3	4	5	2.91	2.12	3.14	3.81	4.82
u_3	1	3	5	2	1	1.40	3.16	4.84	1.92	1.8
AVG	2	3	4.3	2.3	3	2.1	3.04	4.29	2.31	3.2

Table 9.7: Example *influence-based rating predictions* (ratings in 0..5). Predictions are determined on the basis of Formula 9.5.

As mentioned, different approaches exist to integrate the aspects of personality, emotion, and group dynamics into the determination of recommenders. In order to sketch how these aspects can be integrated on the algorithmic level, we demonstrated one possible approach [29] on the basis of a working example. Related open issues for future research will be discussed in the following.

9.4 Conclusions and Research Issues

Existing group recommendation techniques usually assume preference independence (the preferences of one group member do not have an impact on the preferences of the other group members) and thus do not take into account social interactions and relationships among the group members. It is assumed that $rating(user, item) = rating(user, item, group)$ which is not the case, i.e., group members are influenced in their evaluations by the composition of the group and the interaction between and social relationships among group members [12, 14, 22, 31]. Groups can significantly differ in terms of, for example, the *number of group members*, the *roles of persons within a group*, the *social dynamics within a group*, the *underlying goal of the group decision process*, the *status of group members*, the *age of the group members*, the *history of past group decisions and the related sentiments of group members*, and the *implicit decision policies defined within the group* [34]. These examples and many more have to be analyzed in more detail to better understand how to best support group decision making on the basis of recommendation technologies. A first approach to take into account the social dynamics of groups in the context of group recommendation is presented in [5], where social networks are analyzed with regard to aspects such as *relationships between group members*, *social similarity*, and *social centrality*. Related contributions are also provided by Masthoff [21] who shows how to take into account the concept of emotional contagion, and Quijano-Sanchez et al. [31] who also show how to integrate *personality*-related information into group recommendation approaches. The role of group dynamics and decision making in recommender systems has also been analyzed in Delic et al. [6], where a user study is presented that focuses on measuring and observing the evolution of user preferences in travel decision making scenarios - more precisely, selecting a destination to visit. To some extent, not every group member is equally susceptible to emotional contagion and certain differences exist that depend on the personality of group members. A more in-depth investigation on how to best combine personality information with the concepts of emotional contagion is an important issue for future research. For example, a group recommender system could tailor recommendations more to those group members with a higher ability to transfer emotions to others.

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