Adaptive Radio: Achieving Consensus Using Negative Preferences

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ABSTRACT

We introduce the use of *negative preferences* to produce solutions that are acceptable to a group of users. This technique takes advantage of the fact that discovering what a user does not like can be easier than discovering what the user does like. To illustrate the approach, we implemented Adaptive Radio, a system that selects music to play in a shared environment. Rather than attempting to play the songs that users want to hear, the system avoids playing songs that they do not want to hear. Negative preferences could potentially be applied to information filtering, intelligent environments, and collaborative design.

Categories and Subject Descriptors: H.5.3 [Information interfaces and presentation]: Group and organization interfaces—*collaborative computing, computer-supported cooperative work*

General Terms: Design, Experimentation, Human Factors

Keywords: audio, collaborative systems, shared spaces, ubiquitous computing

1. INTRODUCTION

It can be difficult for groups of people to agree on anything. These decisions can be as mundane as deciding where everyone in your office wants to go for lunch or what movie you and your friends want to see, or they can be as important as finding a single solution that satisfies a group of collaborating designers. A standard approach to this problem would be to have the members of the group express their individual preferences then attempt to find a compromise solution that is the intersection or average of their desires. These intersections can be hard to find, or even non-existent. We propose the use of *negative preferences* to help groups find common ground. If each individual lists the kinds of solutions that he or she *doesn't* want, then the union of the lists defines the set of solutions that are *not* satisfactory to the group. The complement of this set can be considered potentially good solutions that the group can explore. Although using negative preferences is formally equivalent to using positive preferences, they differ in practice. We believe that the use of negative preferences will be beneficial for groups that need to find solutions to satisfy all of their members. To illustrate these principles, we present a new application, Adaptive Radio, which plays music in a shared environment.

2. RELATED WORK

Finding group-approved solutions using negative preferences is distinct from collaborative filtering. Collaborative filtering uses the preferences of others to help an individual make choices [5]. A typical example is a system that recommends items to purchase based on individuals with a similar purchase history. By harnessing the collective preferences of many individuals, such systems can infer similarity between items. This approach is useful when it is difficult to quantify the similarity between items, such as for art or music, and is used by many music sharing applications, such as Last.FM (http://www.last.fm). Unlike collaborative filtering, the negative preferences approach is simply a way for groups of users to consolidate their preferences so that group recommendations can be made. Negative preference applications could potentially incorporate collaborative filtering techniques to determine the similarity between solutions.

A few other systems recommend items to groups instead of individuals. MusicFX [6] selects music stations that are broadcast to a gym. The members of the gym must rate all the stations beforehand, and MusicFX plays one of the stations with the highest average rating. The system thus attempts to maximize the mean happiness of the group. One of its shortcomings is that users need to be able to rate all of the stations for MusicFX to produce good recommendations, making it difficult to scale to a large number of musical choices. GroupCast [7] is a conceptually similar system that selects content for a public display system. In this example, the user profiles needed to be too large for any user to complete. Without extensive profiles it was difficult to find appropriate intersections of user preferences to put on the GroupCast displays. Instead, it displayed content that was interesting to *one* of the users, hoping that by chance others would have similar interests.

PolyLens [9] recommends movies to small groups of people who watch movies together. It applies a standard collaborative filtering algorithm to find recommendations for each

GROUP'05, November 6–9, 2005, Sanibel Island, Florida, USA.

of the group members, and then it combines the results to make a group recommendation. Unlike MusicFX, PolyLens attempts to satisfy all users to some degree, without necessarily maximizing the group average. PolyLens bases its recommendations on the expected happiness of the *least* satisfied group member. Therefore, a movie that is barely acceptable to each of the group members is recommended over one that one person would hate but everyone else would enjoy immensely.

3. NEGATIVE PREFERENCES

A system that uses negative preferences acts like a filter that blocks items that the user does not want and allows everything else to pass through. Such a system can initially assume that all solutions are acceptable and the user must notify it when an undesirable solution is encountered. From then on, the system will censor this undesirable solution for the user. It gradually learns a user's preferences as he or she provides negative feedback over time. Eventually, the information filter will allow only desirable items to reach the user. Users do not need prior knowledge of the solutions—they simply need to know what they don't like. In contrast, a positive preference scheme that keeps track of what the user *wants* usually requires that user preferences be determined beforehand. User profiling is tedious and the resulting profiles are usually incomplete due to the impatience or forgetfulness of the users. Negative preference applications do not require explicit user profiling processes—the users can train it by expressing dissatisfaction with its output.

A negative preference system would not be practical if a user needed to reject every undesirable item explicitly. An essential component is a distance or similarity measure between data items. When a user rejects a candidate, it can be assumed that the user would dislike similar candidates as well. Thus, rejecting one data item effectively censors a set of similar ones. This similarity metric might be difficult to implement in practice, especially when the domain is as subjective as music.

A major benefit of using negative preferences is the ease with which user preferences of multiple individuals can be combined. One simply takes the union of the negative preferences of the individuals to find the group's preferences. This combined preference set will filter out items that are disliked by any of the group members. We call the remaining solutions *consensus solutions* because they have been implicitly approved by everyone. Although this is formally equivalent to finding the intersection of the positive preferences of the same group, it can be more effective in practice. Because knowledge of user preferences, positive or negative, is typically incomplete, a positive preferences scheme is likely to underestimate the number of solutions a user would tolerate while the negative scheme would overestimate this value. Because the intersections of multiple users' preferences can be hard to find, if they exist at all (a problem encountered by GroupCast developers [7]), it is preferable to err on the side of overestimating rather than underestimating the space of acceptable solutions.

Negative preference systems might enhance the influence of group members who hold minority opinions. In group decision making, social influence can pressure people to change their expressed views. These influences can be normative (the desire to conform) or informational (learning from others to inform one's own judgement) [4]. The negative preference approach can reduce the normative processes that suppress minority opinions by requiring that the group reaches consensus, which might alleviate the need for the minority to accept the majority opinion [1], and by making the decision-making process anonymous, which reduces the social pressures exerted by the majority. In addition to enhancing minority opinions, this feature of negative preferences could be applied to other privacy-preserving situations. Negative preference systems implicitly favor informational influences, which can increase the influence of the minority [8]. Experienced group members with the largest negative preference profiles exert the most control over the group decision by censoring more of the decision space. Therefore, knowledgeable members holding a minority opinion have the opportunity to convert members of the majority to their side.

We believe that the use of negative preferences can be extended to other domains [3]. Tasks that require catering to the desires of multiple individuals could benefit from this approach. For example, intelligent environments that dynamically change the contents of displays based on who is observing them could use negative preferences. Negative preference systems could also be used as an aid to creativity. A designer could brainstorm by viewing random design candidates filtered using his or her set of negative preferences [2]. Initially, a large number of unacceptable candidates would be presented, but as the designer trains the system it would present a wide range of acceptable candidates. Collaborating designers could use the same technique by combining their sets of negative preferences. Only solutions that are acceptable to all would be likely to survive the filtering by the designers' preferences.

4. ADAPTIVE RADIO

Adaptive Radio (http://www.cs.unm.edu/∼dlchao/radio) is a music server that broadcasts to a group of people. It chooses its song selections from MP3s contributed by users of the system. Adaptive Radio streams music to users' personal computers using Icecast (http://www.icecast.org), but users must log on if they want their preferences to influence the choice of songs. It has a simple web-based interface (Figure 1). After logging on, the user can indicate that he or she does not like the currently playing song by pushing the "censor" button, which causes the Adaptive Radio server to remember not to play this song or similar ones in this user's presence again. Pressing the "skip" button causes the server to stop playing the current song and to randomly choose another. This function is intended to be used when there is only one listener or when it is obvious that everyone in the room dislikes the song. Having separate censor and skip functions allows users to register dislike for a song without interrupting the flow of music or to quickly survey the musical choices (channel-surf) without registering dislike.

Adaptive Radio constructs musical preference profiles for each person using only the list of songs that are disliked by the users, implicitly assuming that unrated songs are acceptable until proven otherwise. If instead one played songs that users already know that they like, unfamiliar music and music that has recently been added to the system would be unrated, and therefore unused by the system. By including unfamiliar music and songs that are not preferred but still acceptable to users, Adaptive Radio can select from a much larger set of songs. It avoids playing songs similar to those that have been rejected by any of the users who are

Figure 1: The Adaptive Radio user interface.

currently listening, resulting in a song playlist that should please all users. If there is only one listener, the system will play music that this person likes. As more people arrive, the selection of music will narrow to accommodate the listening preferences of the new users. In effect, all users can veto song selections.

Because it is difficult to determine automatically the similarity between songs, Adaptive Radio assumes that only songs on the same album are similar to each other. Therefore, if a user rejects a song, the rest of the album is censored as well. This crude similarity measure seems to work well in practice, but collaborative filtering techniques could be used to create a more accurate metric.

5. EVALUATION AND DISCUSSION

We evaluated Adaptive Radio by making informal observations of its use, examining users' Adaptive Radio music profiles, and giving users a short survey a few months after it was installed in our office. The survey results indicate that users were happy with the performance of Adaptive Radio. Prior to its installation, music was rarely played in the office. This was due in part to the fear of bothering coworkers with one's own music. The participation of all office members in the musical selection alleviated this concern. Users quickly became comfortable with the user interface, which allows them to reject songs with little conscious effort. Registering disapproval became a nearly automatic reaction to undesirable music, as evidenced by the channel-surfing behavior during which a user would quickly reject several consecutive songs without interrupting his or her work. When Adaptive Radio is playing desirable music, the listener does not need to think about the system. When undesirable music intrudes upon a listener's consciousness, he or she can quickly register disapproval. Had our system used positive preferences, it would have required users to provide feedback during desirable songs.

According to our survey, Adaptive Radio introduced some users to music with which they were not previously familiar but now appreciate. Some users who had seemingly different musical tastes discovered that they enjoyed the music of their coworkers. These serendipitous newfound musical connections would be difficult to discover using a positive preference approach like MusicFX's, which preferentially plays what the listeners already know they like. Other users with little obvious overlap in musical tastes have noticed that Adaptive Radio often plays Simon and Garfunkel songs when they are in the room together. We soon realized that fast or loud songs are prone to rejection by people trying to work, which was confirmed in our survey results.

We examined the Adaptive Radio profiles of the four most regular users. Each of these users explicitly rejected between 45 and 117 songs, and their combined profiles censored 1498 out of 1862 songs in the system, or 80%. Most of the albums that were not rejected by anyone were folk (including Simon and Garfunkel) and jazz, while albums from louder and faster genres like funk and electronic dance music were consistently rejected. The survey indicated that people generally agreed on what they did not want to listen to at work (fast or hard music), but they did not agree on the types of music they would like to hear. Therefore, a positive preferences scheme that queries users for their musical preferences would have had found it difficult to find an intersection of all the individual user preferences.

The songs that are least likely to be rejected are slow, quiet, and familiar, and the music tended to be inoffensive and bland, perhaps not much different than the Muzak played in a typical workplace. Our *passive* musical preferences can be quite different from our *active* ones. While we might enjoy dynamic and challenging music in a concert setting, at work we often prefer something less intrusive. Background music that calls attention to itself could be distracting. In a workplace with broadcast music, *everyone* must be accommodated, even if compromising seems unsatisfactory to the majority. Adaptive Radio in the office tends to play bland music, but it tailors its selections to current occupants. The users are likely to appreciate the fact that they have control over the music being broadcast [6]. If they happen to share musical tastes, the variety of acceptable music can be large; if not, the range is likely to be small and possibly unsatisfactory.

We explored the relationship between the number of users present and the number of songs that Adaptive Radio could play to them. As mentioned earlier, when the four most regular users were present, the system would censor 80% of the songs. When only one of these users was present, it would censor between 27% and 52% of songs, depending on the user. For two users, we computed the percentage of songs Adaptive Radio would censor for all possible pairs of these four users and averaged the results, and for three users we did the same for all possible subsets of three users. The results are shown in Figure 2. The percentage of songs censored rises rapidly with the number of users. For one and two users, the number of songs censored is heavily dependent on the particular users involved, as indicated by the large difference between the minimum and maximum values in Figure 2. However, with three users, the minimum and maximum percentages of songs censored converges, indicating that no matter which three users are present, the song selection will be similar. Adding a fourth user does

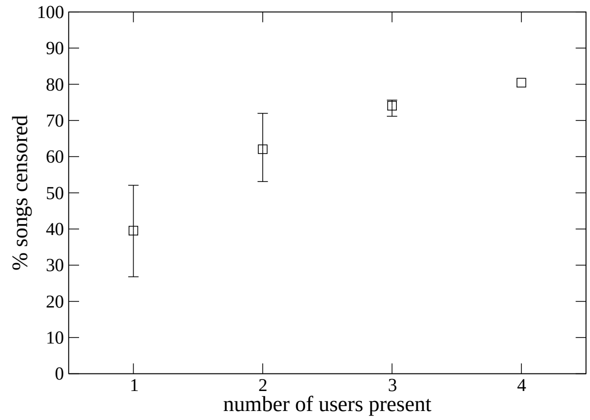

Figure 2: The relationship between the number of users and the percentage of songs Adaptive Radio must censor. The boxes represent the mean percentage of songs that Adaptive Radio censors in the presence of a given number of users, and the bars indicate the minimum and maximum values.

not greatly increase the number of songs censored. In other words, the presence of only three users in our office guarantees a narrow song selection for Adaptive Radio. Although reconciling the musical tastes of even a modest number of random individuals (perhaps as few as three!) can result in "lowest common denominator" music, Adaptive Radio might play a broader range of music in environments where the number of people is small (such as the home or in a car) or where the musical preferences might be broader (e.g., in social settings or retail stores).

Adaptive Radio could also be used to create non-intuitive groupings of individuals who share musical tastes, which would be useful when a limited number of broadcast channels needs to accommodate a large number of listeners. Normally, radio stations specialize in genres of music, and listeners must choose among them based on these predetermined categories of music. If Adaptive Radio were to partition the listeners automatically based on their preferences and cater to each group's collective preferences, it could generate novel playlists that cross established genre boundaries. For example, one could use a greedy algorithm to assign users to groups in such a way that maximizes the overlap of musical dislikes within the groups. The broadcaster could then choose music for each group that would reflect the preferences that the listeners in each have in common.

6. CONCLUSIONS

We introduced the use of negative preferences to help groups find consensus solutions satisfactory to all individuals, and we developed an application, Adaptive Radio, to illustrate their use. Adaptive Radio's use of negative preferences expanded the set of songs that could be played to a group and provided a natural way to combine user preferences. By requiring feedback only when the user is dissatisfied with its performance, using Adaptive Radio does not distract users from their work. Our results suggest that the system will play bland music in the workplace once there are three or more people present, but this may be the inevitable result of consensus and of the nature of the office environment. We believe that in other environments, Adaptive Radio will choose more "interesting" music and could be an effective mediator of differing musical tastes.

The use of negative preferences can easily be applied to other tasks, such as information filtering, intelligent environments, and collaborative design. Group-mediated solutions will become essential as computers migrate from our desktops to our daily lives in the form of intelligent environments and ubiquitous computing applications. Most research in these areas emphasizes the preferences of a single individual, but for many environments it will be important to satisfy multiple occupants simultaneously. Without an intelligent means of reconciling individual preferences, these personalized technologies are likely to follow the path of the Walkman (personalized but antisocial service) or Muzak (impersonal and catering to the lowest common denominator).

7. ACKNOWLEDGMENTS

We thank Allan MacLean and Joe McCarthy for their insightful comments. The authors acknowledge the support of the National Institutes of Health (NIH T32 CA80416, P20 GM066283, and RR-1P20RR18754), the National Science Foundation (ANIR-9986555, CCR-0331580, and CCR-0311686), and the Defense Advanced Research Projects Agency (F30602-02-1-0146).

8. REFERENCES

[1] Beersma, B. and De Dreu, C. K. W. Integrative and distributive negotiation in small groups: Effects of task structure, decision rule, and social motive. *Organizational Behavior and Human Decision Processes*, *87* (2002), 227–252.

[2] Chao, D. L. and Forrest, S. Generating biomorphs with an aesthetic immune system. In R. Standish, M. A. Bedau, and H. A. Abbass, eds., *Artificial Life VIII: Proceedings of the Eighth International Conference on the Simulation and Synthesis of Living Systems*. MIT Press, Cambridge, Massachusetts, 2003, 89–92.

[3] Chao, D. L. and Forrest, S. Information immune systems. *Genetic Programming and Evolvable Machines*, *4*, 4 (2003), 311–331.

[4] Deutsch, M. and Gerard, H. B. A study of normative and informational social influence upon social judgment. *Journal of Abnormal and Social Psychology*, *51* (1965), 629–636.

[5] Goldberg, D., Nichols, D., Oki, B. M., and Terry, D. Using collaborative filtering to weave an information tapestry. *Communications of the ACM*, *35*, 12 (1992), 61–70.

[6] McCarthy, J. F. and Anagnost, T. D. MusicFX: An arbiter of group preferences for computer supported collaborative workouts. In *Proceedings of the ACM 1998 Conference on Computer Supported Cooperative Work*. ACM Press, New York, 1998, 363–372.

[7] McCarthy, J. F., Costa, T. J., and Liongosari, E. S. UniCast, OutCast & GroupCast: An exploration of new interaction paradigms for ubiquitous, peripheral displays. In *Workshop on Distributed and Disappearing User Interfaces in Ubiquitous Computing at the SIGCHI Conference on Human Factors in Computer Systems (CHI 2001)*. ACM Press, New York, 2001.

[8] Moscovici, S. Towards a theory of conversion behavior. In L. Berkowitz, ed., *Advances in experimental social psychology*, Academic Press, London, 1980. 209–239.

[9] O'Connor, M., Cosley, D., Konstan, J. A., and Riedl, J. PolyLens: A recommender system for groups of users. In *Proceedings of the Seventh European Conference on Computer Supported Cooperative Work*. Kluwer Academic, New York, 2001, 199–218.