Recommending Music to Groups in Fitness Classes

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ABSTRACT

Research in the fitness domain proves that music has an important motivating effect on the athletes' performance. This effect is even stronger when music is used in sport synchronously like, for instance, in fitness classes. Indoor cycling is one of these activities in which music is a key issue of success during the lesson, providing a high motivational mean for the instructor towards the classroom. In this paper we present the result of a study in which we tested a group recommender system aiming at supporting the instructor music choice when preparing the lesson. This is done aggregating data present in the individual profiles of each user in the class that are built by combining explicit and implicit gathering of information about their music tastes. In order to refine the profiling process, users may express their feedback on the proposed music tracks after the workout, thus improving the quality of the future music recommendations.

1. INTRODUCTION

The positive effects of music on sport performance and in exercise contexts are well-known. Research in the field of sport psychology suggests that the effects of music in stimulating athletic performance has scientific bases [6]. Some studies proved that selecting the most appropriate music may improve the athlete performance up to 20%.

In particular, many research works, which investigate the relation between music and sport performance, outline that several factors determine the motivational power of a music track. For instance, factors are related to perceptual features, such as rhythm and musicality, to the cultural impact or even to the association with a certain feeling or a situation (for example "Chariots of Fire by Vangelis is often associated with Olympic glory" [7]). In addition, there are other personal factors related to the exerciser (gender, age, personality, commitment to exercise, fitness level, etc.) and the context (exercise environment and specifics of exercise regimens). There are different ways in which music aids athletic performance. According to [6,7], music can distract the mind from sensations of fatigue (dissociation), music can be used to regulate arousal during exercise and a consequence of using the correct music can be the attainment of flow, a state of complete optimal functioning of body and mind on auto-pilot with minimal conscious effort [8].

Therefore, these considerations suggest that selecting the right music can be crucial for improving performance especially in activities that use music synchronously (i.e. aerobic, step, indoor cycling classes). Research work in this domain addresses issues of personalization and tailoring of playlists to single users. In this paper we address the issue of tailoring the music selection to a group of people in order to motivate the entire class to workout. To this aim, we looked at several disciplines that could benefit of this service and we selected indoor cycling. It is a form of high-intensity exercise that uses a stationary exercise bicycle in a classroom setting. A typical class involves a single instructor who leads the participants through the lesson, which is designed to simulate situations similar to riding a bike outdoors. A well-trained instructor uses music as a motivational means to lead participants through a ride that best suits their fitness level and goals. Then, music is a key issue of success during the lesson since: i) its rhythm and beats per minute (bpm) have an effect on the cadence and the difficulty of pedalling and ii) it represents a high motivational means for the instructor towards the classroom.

In this paper we present how XMusic, a group recommender system for music, has been applied and tested in the context of indoor cycling. The system aims at supporting the instructor music choice when preparing the lesson with suggestions about the music tracks to include in the playlist that suits both the preferences of the group and the motivational goals.

The system is composed of a module for profiling individual members, a group profiling module and a music recommender module for creating the playlists. As described later in the paper, the group profile is built by aggregating information about music tastes of individual users. Individual users' profiles are built by gathering information about music preferences both explicitly (questionnaires about motivating music tracks) and implicitly (mining Facebook profiles). The group modelling strategy used by the system is a variation of the average that takes into account the rates of the majority of the group members. However contextual factors such as guests and events (e.g. birthdays) may be taken into account by using the most respected person strategy to give priority to a particular user. According to the resulting music profile for the class, the instructor receives recommendations about music that is appropriate for a given class. In order to refine the profiling process, users in the class may express their feedback on the proposed playlist after the workout, thus improving the quality of future music recommendations.

The paper is organized as follows. Related work is described in Section 2. In Section 3, we describe the XMusic system. An evaluation of our approach is presented in Section 4. Conclusions and future research directions are discussed in Section 5.

2. RELATED WORK

Group profiling has become increasingly important especially in the context of recommender systems in which suggestions and recommendations are addressed to a group of people instead of an individual. These applications may have different purposes as, for instance, providing information and news on public displays [5] or a music playlist in an ambient in which a group of people is located [10,4].

The majority of systems that adapt their behaviour to groups of users employ two main approaches. The former combines individual recommendations to generate a list of group recommendations, while the latter computes group recommendations using a group profile derived from individual profiles (e.g. [10,11]). Strategies to aggregate individuals' preferences are various (see [9,2] for details from the perspective of group recommendation). These strategies try to maximize group satisfaction and/or to avoid un-satisfaction of some members in the group or to privilege a particular member. In [12] a novel group recommendation solution is proposed, which incorporates both social and content interests of group members. They propose a group consensus function that captures the social, expertise, and interest dissimilarity among group members.

In all cases, when developing a group recommender system, there is a need to know as much as possible of each user for generating the most relevant and appropriate set of recommendations [1]. Sometimes this is not possible and some authors integrate missing information with a demographic statistical approach [5].

There exist many group recommender systems in literature, the most popular of which have been applied in the field of music, movies and TV programs recommendations.

For instance, one of the first group recommender systems for movies is PolyLens [11], a component of MovieLens. This system models intentional groups, explicitly selected for a particular reason: watching a movie together. Polylens uses an algorithm that merges users' recommendation lists, and sorts the merged list according to the principle of Least Misery. Then selected movies are ordered in a decreasing degree of preference, by taking into account the minimum score given to every item in the list. In this way, less favourable users may exert a big influence on the final result. This strategy seems appropriate for MovieLens since it suggests movies that part of the group really wants to see.

Another interesting application field of group recommenders is music. Systems like MusicFx [10], Flytrap [4], AdaptiveRadio [3] and PartyVote [14] aim at selecting music that is most appropriate to the tastes of a group. In particular, MusicFx is a system employed in fitness centres to choose music according to the preferences of the groups of users present in different rooms. The strategy used by MusicFx is the Average without Misery, which is based on the sum of normalized scores of every item in the list of preferences. Since this strategy allows fixing a threshold (a minimum predefined value under which that alternative is cancelled from the final sequence of interests), it ensures a minimum degree of satisfaction for every item in the final list of music songs. For this reason, the less favourable user can eliminate from the list the pieces he hates, by giving them an evaluation score equal to zero. This, however, may represent a problem since, if several users give a zero score to several items, the system will not be able to create a list because all the preferences will be equal to zero. Flytrap is a system that constructs a playlist that tries to please everyone in an active environment. Users' musical tastes are automatically derived by information about the music that people listen to on their computers. As in MusicFX users are recognized by their active ID badges that let the system know when they are nearby. The system, using the preference information it has gathered from watching its users, and knowledge of how music genres interrelate, how artists have influenced each other, and what kinds of transitions between songs people tend to make, finds a compromise and chooses a song. Once it has chosen a song, music is automatically broadcast and played.

Adaptive Radio is 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 can potentially be applied to other domains, such as information filtering, intelligent environments, and collaborative design. PartyVote is a system that provides established groups with a simple democratic mechanism for selecting and playing music at social events. Finally, GroupFun [13] is designed to help a group of friends to reach a common music playlist starting from their distinct tastes and applying a voting strategy.

3. THE XMUSIC SYSTEM

XMusic is an application that, using a group profiling strategy, aims at supporting the instructor's music choice, when preparing the lesson, with recommendations about the best tracks that suit the music preferences of the group. The group profile can be created according to preferred genres, artists or songs and XMusic may recommend tracks to include in the playlist according to these features. In the current version of the system the creation of the group profiling is guided by genres. The architecture of the system is realized by a number of distributed components, implemented as software agents written in Java (see Figure 1). In particular, the process of creating a playlist matching the tastes of a group of users is divided in three main phases.

The *first phase* aims at profiling the users that will attend to the indoor cycling class to create the class group profile. The *User Agent*, which represents the user in this process, is responsible for the acquisition of music preferences. This task is performed using a questionnaire about motivational music preferences in combination with data obtained by crawling Facebook profiles. We chose Facebook because of its popularity among our users, yet similar information can be gathered from mining microblogs in Twitter [14] or from downloading user listening history in LastFm [15]. We assume equal interest to all artists and genres in the case a user did not have a profile on a social network, although in our experiments all the users had a Facebook profile.

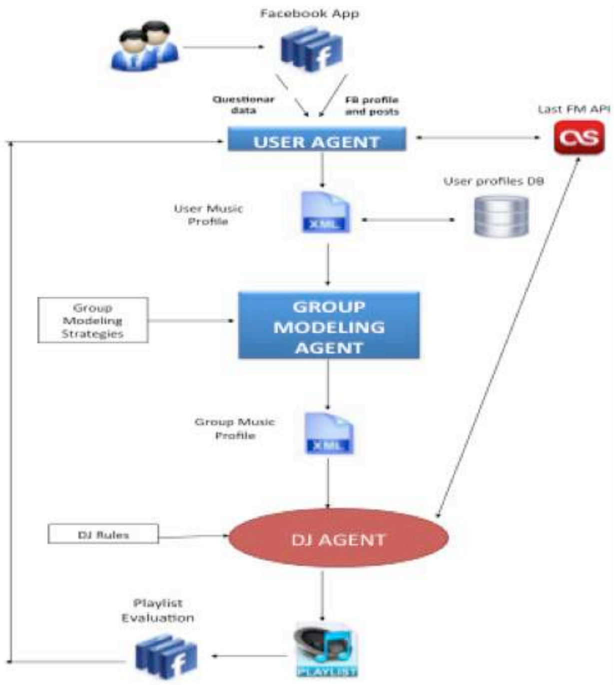

Figure 1. The Architecture of the XMUSIC System

This is done using the Facebook and YouTube APIs in combination with Last.fm and Echonest APIs. Last.fm provides a number of Web services providing access to information such as the genre tags attached to a song, artist-to-artist similarity, the list of the top 100 tags for each artist and statistics on the most popular artists on the site. Echonest is a service purely created for the music domain. Among its various functions, it is able to identify the artist name (single or group) from a textual paragraph that mentions him/her and provide additional information about the artist, such as the related musical genres.

The *second phase* concerns the group profiling task. In case the User Agent cannot gather any information about the associated user, we set the initial profile to the demographic one that is built from the questionnaire results. Starting from the user profiles, the Group Modelling Agent (GMA) computes a ranked list of music genres and one of the most popular artists and, from these lists creates the group profile. At the moment the GMA generates the profile according to the most appropriate music genres for the group.

Analysing the most commonly used strategies and their effect on the resulting group profile we decided to adopt a variation of the *average without misery* (whose definition and strengths have been discussed in Section 2). The agent may use different grouping strategies according to some parameters that can be set by the instructor. For instance the “most respected person” [9] can be used in case there is a guest or a person that is participating to the class for the first time.

In the *third phase*, starting from the group music profile the DJ Agent composes and proposes to the instructor a set of playlists ordered according to how much they match the music preferences in the group profile. To this aim, the DJ Agent accesses to a repository containing the musical tracks. The instructor may accept one of the proposed playlists and, eventually, modify it according to his training goals. The system will provide suggestions about music of the same genres, similar authors or songs, using the Last.fm APIs.

The *fourth phase* concerns the evaluation and the refinement of the user profiles of the group members. This evaluation is performed by users that participated to the class, by expressing a rating about the playlist songs. Besides this, we performed an experiment for evaluating the group satisfaction. In this experiment, besides collecting data with a questionnaire, we asked the instructor to report the training data of each user during the workout.

3.1 Gathering Music Preferences

The characterization of the user’s musical tastes in XMusic is derived both from a survey and from the analysis of music preferences expressed on the various social media used by the user. In particular, from the analysis of Facebook profiles in which many people post music video or likes musical pages.

In XMusic we have developed an agent that acquires information about the music a user is currently interested in. First the user is invited to fill a questionnaire about motivational music (derived by the BMRI questionnaire [7]) developed under Facebook, whose aim is twofold: gathering explicit user data concerning his music tastes and get the consent to access to his Facebook profile in order to get the music video posted by the user, fan pages and to analyse them.

The questionnaire aims at assessing which are the preferred music genres of the user during the workout. Besides personal information such as gender, age and type of physical activity that is usually performed by the user, questions concern the user’s preferred genres when training, the preferred radio station, the list of top ten songs listened by the user during the workout, and the motivations for listening at those songs.

In this survey study we collected 250 questionnaires. The average age of people participating at the study was 38; 40% of them declared to workout 3 days/week, 30% 5 days/week, 20% every day and the rest occasionally. The performed activities varied among: indoor cycling 19%, running 37%, fitness 33%, cycling 9%, other 2%. Most of them (75%) used music regularly when training. From the analysis of preferred genres and songs the most frequent ones were the following: rock 39%, pop 23%, dance 31%, soul 6%, soundtrack 1%.

Besides collecting information about motivational music tastes, the User Agent integrates this information with data present in the user Facebook profile (Fan pages) and with the analysis of musical video posted by the user. In order to analyse this data we used the Last.fm and Echonest APIs that allow to extract the artist name, the title of the song and the most relevant tags used to indicate the genre of that song.

Let's consider for instance "user#8", who filled the questionnaire and indicated rock and pop as his preferred motivational genres during workout. As shown Figure 2, from the analysis of the video posted on his Facebook wall the application found 12 music videos and for each song the two main genre tags for that song are extracted.

Title	Artist	Genre
Wuthering Heights	Kate Bush	pop female vocalist
Born Alone	Wilco	rock indie rock
Set Fire to the Rain	Adele	soul pop
Someone Like You	Adele	soul adele
Howlin' for You	The Black Keys	indie rock blues rock
Days Are Forgotten	Kasabian	indie indie rock
My Baby Just Cares for Me	Nina Simone	jazz female vocalist
Give a Little More	Maroon 5	pop maroon 5
Sunday Morning	Maroon 5	rock pop
L'Uomo Che Amava le Donne	Nina Zilli	italian pop

Figure 2. An example of data collected from the Facebook profile

The additional information, derived from posted music, is used to enrich the User Music Profile that is structured in order to include information about preferred genres and artists. In computing the weight to give to a genre in the profile, it is necessary to combine information derived by the questionnaire and posted music. According to the purpose of XMUSIC we decided to give the same weight to the information taken from the two knowledge sources.

Then, denoting with u_i a user, with g_j a genre, with a_k an artist and with s_l a song, the rate at time t0 is calculated as follows:

$$\mathbf{rate_{t0}(g_j,u_i)= (testrate(u_i,g_j)+FBrate_{t0}(u_i,g_j))/2}$$

where:

- $testrate(u_i,g_j)=((x+nr(ans(u_i),g_j)/nr(qst))/2)$ is calculated considering: a) x=1, if the genre g_j is indicated as one of the preferred genres in the questionnaire, x=0 otherwise, b) the number of the user's answers $ans(u_i)$ characterising a genre g_j in the questionnaire and c) nr(qst) being the number of the tracks indicated by the user in the questionnaire.
- $FBrate_{t0}(u_i,g_j)=((nr(s_l,g_j)/nr(s_l)+nr(fan,g_j)/nr(fan))/2$ is the average of the percentage of songs present in the Facebook profile belonging to a genre g_j with the percentage of fan pages for the same genre.

In order to evaluate the popularity of an artist a_k it is possible to consider an absolute preference list relative to the posted songs or one for each genre. In the latter case, the popularity of an artist a_k for a user u_i is calculated for each of the genres to which the artist belongs. Then, for each genre and artist, the list of songs, ordered according to their popularity among the group members, is inserted in the database that will be used for the recommendation.

In particular it is computed as follows:

$\forall$ g_j: genre(a_k,g_j) where this predicate indicates the genre of the considered artist:

$$\mathbf{popularity_{t0}(a_k,g_j)=nr(s_l,a_k)/nr(s_l,g_j) + fan(a_k)}$$

where fan(a_k) may be 1 if the user likes that artist or 0 otherwise.

Consider again user#8, who indicated rock as his main motivational genre for workout and indicated as examples of motivational music three rock tracks. In a five-points Likert scale, from *none* (1) to *very much* (5), user#8 indicated that he liked two of those *very much* (5) and one *quite a bit* (4); moreover he indicated that he liked one indie *very much* (5) and one dance song *quite a bit* (4) on a total of five songs. Figure 2 shows the list of songs present on his Facebook profile and he likes Adele and the Rolling Stones.

Then, at the first interaction the rates for the genres in the profile will be:

$rate_{t0}$(rock,user#8) = 0.70
$rate_{t0}$(indie,user#8) = 0.13
$rate_{t0}$ (pop,user#8) = 0.17
$rate_{t0}$(swing_jazz, user#8) = 0.08
$rate_{t0}$(soul, user#8) = 0.08
$rate_{t0}$(dance, user#8) = 0.005
the other genres rates are equal to 0.

Then, the User Agent computes the list of artists according to their popularity. For instance, for user#8:

$popularity_{t0}$(Maroon5,rock,user#8) = 1
$popularity_{t0}$(Maroon5,pop,user#8) = 2
$popularity_{t0}$(Adele,pop,user#8) = 2
$popularity_{t0}$(Adele,soul,user#8) = 3
and so on.

In this way the User Agent will build the User Music Profile (UMP) that will be represented as a XML document. In particular, in order to distinguish between songs that were tagged as motivational in the questionnaire and songs that the user liked in different contexts, we included the attribute motivate in the profile with the score given by the user.

As described later, the UMP is updated according to modification in the FBrate (new music is posted or shared) and from the evaluation of the proposed music after the indoor cycling class.

3.2 Creating the Group Profile

In building the Group Music Profile (GMP) the Group Modelling Agent (GMA) combines information about music preference of people participating to the class.

As a first step, the GMA consults each User Agent representing the group members to get information about the preferred genres, artists and songs. In case no information is available about a user, his profile will be set equal to the demographic one that has been built from the questionnaire.

At this stage of development of the system, the GMA generates the profile according to the most appropriate music genres for the group. Analysing the most commonly used strategies and their effect on the resulting group profile we decided to adopt a variation of the average without misery by computing the average of the individual preferences only for those items for which the majority of the group members has a rating above a certain threshold (say 0.2). Moreover, in case the instructor needs to privilege a particular user, the most respected person strategy is employed. Let's suppose that the instructor decides to create the GMP for a class of 10 people and that for two of them we do not know any information about music preferences. The situation will be the one illustrated in Table 1.

	Soul	Pop	Indie	Rock	Dance	Jazz
U1	0	0.17	0.13	0.7	0	0
U2	0.2	0.13	0	0.4	0.17	0
U3	0.49	0.2	0	0.11	0.1	0.1
U4	0.3	0.4	0	0	0.3	0
U5	0	0.39	0.17	0.17	0.19	0.08
U6	0.7	0.4	0.11	0.19	0	0.1
U7	0.2	0.55	0.05	0.21	0	0
U8	0	0.35	0.05	0.1	0.2	0
U9 -DP	0.06	0.3	0	0.39	0.3	0
U10 - DP	0.06	0.3	0	0.39	0.3	0
Average without misery	0.2	0.32	-	0.27	-	-

Table 1. GMP according to genre preferences.

Therefore the following genres will be initially included in the group profile: pop with a rate of 0.32, rock with a rate of 0.27 and soul with a rate of 0.2. The Dance genre, that has a good rate in the demographic profile, does not have enough popularity in the group for which the playlist is generated and its rate does not pass the 0.2 threshold.

Differently from the genre, the matrix illustrating preferences about artists for each group member is very sparse. For this reason, at this stage of the project, we just compute the artists and songs lists according to their popularity among group members and we indicate which are the songs that were considered motivational by the user, in case this information is known.

3.3 Selecting the Group Adapted Music Tracks

The DJ Agent suggests tracks to include in the playlists according to the content of the GMP. Let's suppose that the instructor wants to create a playlist of *n* tracks using the strategy shown before according to genre preferences of the group. Then, the percentage of songs p_songs to include in the playlist of the genre g_k is calculated by dividing the genre rate by the total of the rating values for all the genres promoted in the GMP. This is necessary since the use of the threshold excludes some genres.

The number of songs for each genre to include in a playlist *p* is calculated as:

$$\mathbf{nr\_songs(g_k)=round(p\_songs(g_k)*n)}$$

for k=1 to j-1, for the last genre $nr\_songs(g_j)=n-\Sigma_{k=1, j-1} nr\_songs(g_k)$.

Then, in this example, let's suppose to recommend 10 tracks for the playlist, it will contain 4 pop, 4 rock and 2 soul tracks (see Figure 3).

Figure 3. An example of generated playlist and the interface used for its evaluation.

The successive step consists in selecting the tracks for each genre to include in the playlist. As said in the introduction, familiarity is considered an important factor in using music for motivating people during workout. On the other hand listening every time to the same music may result boring. Therefore it is necessary to introduce a certain level of serendipity that can be given by selecting a certain number of tracks similar to the favourite ones for working out or songs of artists similar to the most popular ones.

To this aim the DJ agent first considers the set of artists(g_k) for a genre g_k ordered according to their popularity in the group profile. Then, for each artist a_j we consider the most popular songs and we select for each artist a number of songs that is proportional to his popularity in the genre list. This is done using Last.fm API. 50% of the tracks is selected from this ordered list, the other half is selected as follows:

- 20% of the set is selected by songs similar to the most motivational and popular ones.
- 20% with songs of artists similar to the most popular ones.
- 10% with new hits for that genre.

At the moment the DJ Agent does not follows complex rules in deciding how to schedule the tracks in the playlist. It simply avoids putting two tracks by the same artist in a row and in order to avoid playing the same songs in temporally near workouts (2 weeks), all tracks have a flag (played) that is reset every 2 weeks. The rules and tracks order can be changed by the instructor in the application.

3.4 Taking Feedback into Account

People participating in the indoor cycling class may express their feedback about the playlist used for the workout by expressing their approval about the music choice by pressing the like button aside the song link (Figure 3).

The user's evaluation is sent to the system and used to refine the user's music profile. In fact, positive feedbacks are used to improve the rating of the genre, the artist and also of the specific song. The genre and artist rates are computed again by considering the positively evaluated songs in the same way as the posted ones. If a user does not provide any feedback, then his profile is updated only on the basis of new acquisition of information on his Facebook profile. Moreover, from the evaluations made be the group members, it is possible to compute the group rating of the proposed playlist. This rating is used to refine the demographic music profile.

4. EVALUATION

We evaluated the current version of the system prototype in a Fitness centre. The evaluation study involved 30 users that were randomly divided into 6 groups of 10 persons each attending to two different indoor cycling classes. The week before the experiment we asked each user to fill the motivational music questionnaire and then we built his music profile according to the procedure explained in the previous section.

For each group the instructor ran a "baseline" workout in which the music was selected randomly from a list of tracks. During the workout the instructor monitored the bpm of each user and annotated the training zone of the user as: lower, right, higher. After the workout, we asked members attending each class to answer a questionnaire aiming at collecting an overall evaluation of the music used for the workout and to provide a feedback for each song as explained before.

Group	Baseline – Random Music	Adapted music
G1	30% lower, 55% right, 15 % higher	23% lower, 56% right, 21 % higher
G2	40% lower, 48% right, 12% higher	13% lower, 62% right, 25 % higher
G3	20% lower, 50% right, 30% higher	15% lower, 55% right, 30% higher
G4	45% lower, 35% right, 20% higher	15% lower, 45% right, 40% higher
G5	15% lower, 65% right, 20% higher	12% lower, 65% right, 23% higher
G6	55% lower, 40% right, 5% higher	30% lower, 55% right, 15% higher

Table 2. Workout performance results in the two conditions.

Then in order to test the proposed approach we performed the same test by using XMusic and selecting tracks according to the preferred genres and music of the group. Results of the workout performance are listed in Table 2, while results of the questionnaire are shown in Table 3. Table 2 shows that on average most of the groups had a better performance in the second condition, when music was adapted to the group.

Besides the questionnaire results shown in Table 3, that confirmed our hypothesis that the group appreciated the fact that the playlist included some of their favourite genres, artists and songs, we evaluated the feedback expressed by each participant. For the first and the last questions reported in Table 3, we carried out a Student's t-test to verify the statistical significance of the differences between the average scores (baseline and adapted). In both cases the could conclude that the difference was significant. Moreover, we compared the prevision of the system for a group with the evaluation provided by each group after the workout using the MAE (Mean Average Error) obtaining a value of 0.12.

Question	Answers	Baseline average	Adapted average
How much did you like the music today?	5-points: from *very dissatisfied* to *very satisfied*	2.4	3.6
Did the playlist included some of your favourite artists?	yes/no	30% yes	80% yes
Did the playlist included some of your favourite songs?	yes/no	20% yes	70% yes
How much energy the music gave to you?	5-points: from *none* to *very much*	2.6	3.8

Table 3. Post-Workout Questionnaire results.

5. CONCLUSIONS AND FUTURE WORK

We presented the design and prototype implementation of a system that recommends tracks for a playlist for indoor cycling classes. This application has been selected as a good domain for testing group profiling strategies. In order to create the group profile the system starts from information about individuals that are collected by combining their answers to a questionnaire and the music they share on their Facebook profile. The performance of the system has been evaluated and results show that the groups involved in the experiment appreciated and found motivating the music proposed by the system.

At present, we are running a longer experiment in terms of time, since the system is currently used in a fitness centre where we are collecting data for a period of 6 months. This is important in order to test whether the quality of the recommendations improve. This is the first prototype of XMusic and after this first evaluation study we plan to tackle some of its weakness.

First of all we plan to improve the approach adopted for generating the rates of artist and songs. A solution may consists in reducing the sparsity of data using a collaborative approach. On the other side we would like to improve the similarity function that, at present, is based on Last.fm API. In order to develop such a function we are currently collecting a dataset (see Music4Fitness under Facebook) of songs tagged by users in terms of impact of the music to fitness-related parameters (i.e. energy, emotion, etc.). Starting from this dataset we will build a classification model that will be used to find tracks similar to the one considered as motivational by the user in order to improve serendipity. Then we plan to study how theories of social influence and personality-based approaches can be used to improve the group modelling. Resolving such issues is a challenge that would require careful investigation.

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