Emotion and Movement with AppIHC: Promoting Interaction and Socialization Among Participants of Scientific Events via Mobile Application

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Abstract. Scientific events bring together a large number of researchers and are composed of different types of sessions, consisting of workshops, mini-courses, full papers, etc., with different topics. The high content diversity may cause an overload of information to attendees, making it difficult to choose between all sessions. This paper describes a mobile application called AppIHC to help attendees access event's schedule and promote users' engagement. Developed for the Android platform, the application has a Recommender System that uses information from the users' profile and their interests to generate recommendation by content, and also produces social recommendations from a pre-existent database of co-authoring from previous event editions. A gamification process was applied to promote engagement between the attendees. The application was used during the event XVI Brazilian Symposium on Human Factors in Computing Systems (IHC 2017) and had 108 registered users, being evaluated through a satisfaction questionnaire and through analysis of activity records. The results indicate the goal of facilitating access to information and improving user participation in the event has been achieved.

Keywords: Application · Scientific event · Recommendation · Social · Gamification

1 Introduction

Scientific/Academic events can be defined as a gathering of people interested in a particular area of knowledge or culture whose propose is to present and discuss ideas on specific topics over a period of time. Event activities (e.g., workshops, lectures, posters, technical sessions) are defined based on the objectives of each event [1] and usually involve the dissemination of research results. Papers may be grouped into

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sessions that will be part of the event schedule. In order to help participants with easy access to this schedule, several scientific events have already made or use mobile applications, such as [2–4].

Existing applications typically offer functionalities such as calendar management, keynote speakers, sessions information, etc. However, the personalization of these applications is still a gap [5]. In many scientific events the schedule allows sessions to occur in parallel [6], which can give the attendee difficulty in choosing which sessions to participate in. Recommender Systems (RS) can help attendees find the sessions best suited to their particular interests because these systems provide personalized recommendations that best fit the tastes and preferences of the attendees [7].

RS are a set of techniques that select items for users of a particular system based on the interaction data and interests of those users. RS may be used in different applications and for different recommendations, such as movies, music, products in virtual stores. The use of RS to recommending sessions in scientific event applications can help attendees in the decision process by which session to participate based on their interests. This paper presents a solution to help participants in scientific events to obtain information about the event's schedule as well as to promote their engagement. This solution was designed through a Mobile Application called AppIHC and applied in the XVI Brazilian Symposium on Human Factors in Computing Systems (IHC 2017). This paper presents its conception, functionalities, experiment and achieved results.

The paper is organized as follows: Sect. 1 presents the Introduction. Section 2 describes the AppIHC, its design, functionalities and architecture. Section 3 details the Recommender System Module. Section 4 presents the evaluation of the AppIHC, how participants interacted with the app, the evaluation process and the achieved results. Section 7 presents the conclusion and future works.

2 AppIHC

The Mobile Application for Scientific Events called AppIHC was developed aiming to facilitate attendees' access to event's information. AppIHC helps participants find information about sessions, through schedule, recommendations, favorite items, and a gamified environment. The application was designed in a generally way, in a manner that it could be used in any scientific event.

The application was developed for the Android OS, for devices with OS version 4.4 (Android Kit-kat) or higher. The choice of this version was motivated by the number of users that the application would achieve, about 95% of Android devices [8]. The target audience of the application is composed of the participants of the event (e.g., lecturers, researchers, students, organizers). The technologies used for development were Java, Android Studio, Firebase and the principles of Material Design.

To represent the target audience, we used the Personas technique. Figure 1 presents a Persona created, named Junior da Silva, his profile, occupation, wishes and needs regarding the use of the application (*in Portuguese*).

As an example for the use of a mobile application in scientific events, a scenario was created with the persona Junior presented in Fig. 1:

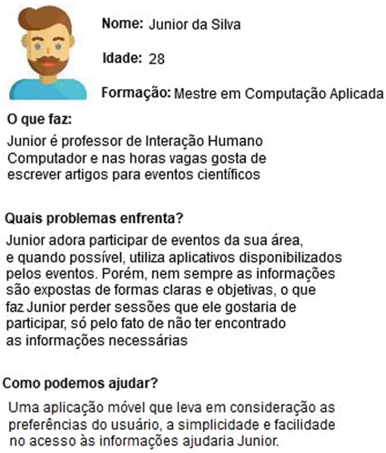

Fig. 1. Junior's Persona

"Junior saw a post about the IHC Symposium on a social network page, stating that registration for the event was open, and as soon as he could, he made his application. On the same page, Junior received information about the AppIHC application for the event, and decided to use it to check some details of the event's schedule. To use the application, Junior registers with his personal information. In the application, Junior can quickly view the information of all sessions, and decides to look for a technical session about accessibility that he knew would occur on the first day and, through the search, Junior finds the desired information about the technical session. To make it even quicker, he adds it to his favorite sessions list. On the second day of the event, Junior has already added several sessions to his favorites list and received his daily recommendations, based on his interests. Arriving at event, he does not remember exactly in which room the session will take place, and to avoid delays he quickly opens the app and checks in his favorites that the session will take place in room "A". Throughout the day of the event, Junior continues to use the application to view information about event programming quickly and easily. He checks the app and prepares to attend the sessions according to his preferences."

To identify the main functionalities that the application needed, brainstorming sessions and workshops with user groups were conducted. At the same time, other event-oriented systems were investigated to observe essential functionalities. The following functionalities were specified after development team meetings:

User Registration: Each user has unique information, such as his/her profile, topics of interest, favorite sessions, recommended items, ranking position of users and responses to the satisfaction questionnaire. During the registration, the user's co-authors are also verified, if they exist. If the user has co-authors in previous event's editions, the schedule shows some implicit co-authoring recommendation.

Profile: It should be possible to change data such as: name, surname, institution, topics of interest.

Schedule: The schedule is divided in tabs, one tab for each day, and each tab is divided into sessions, which usually has different works/papers. Each tab shows a list of event sessions with information such as: session type (e.g., Technical Session, Panels, Posters), session name, time, location. It should be possible to add sessions to the favorites list for easy access. It should be possible to locate information in the schedule list quickly and efficiently by means of a search, which takes into account all the information previously mentioned, allowing the creation of filters according to the desired information. If the user has co-authors in a session, a co-authoring icon is displayed in this session in question and a text field informing the co-authorship. If there are no items to display, a screen should report this.

Favorites: Favorite items in the schedule should be separated into another screen that is similar to the schedule but that only shows the sessions selected by the user. The user can add or remove each item in an easy way.

Recommendations: Based on the user profile, recommendations are generated by an external module, which is also included in the database. Recommendations are daily and for each recommendation users can give their feedback by selecting one of the two feedback buttons ("like" and "dislike"). If there are no items to display, a screen should inform the user.

Login: Authentication is performed via email and password provided by Firebase Authentication. The user must be able to recover the password if needed.

About: Information about the application and of support.

The following shows the application architecture, the gamification system, as well as the content-based and social recommendation modules.

The general architecture is illustrated in Fig. 2. The **user interface** is the communication module with users, in which the users inform their data and topics of interest in the register process. Once the registration is done, interface helps users interact and browse through the system, access to information about event programming, favorite items, select sessions as favorites, receive recommendations and provide explicit feedback to be used to generate the new recommendations, respond to the satisfaction questionnaire, etc.

Figure 2 also shows **the recommender module** (implemented on the server), which uses the content-based approach and generates daily recommendations when the user interacts with the recommended items screen. The "G" that appears next to the database represents the **gamification module**. The "RC" that also appears next to the database represents the **co-authorship recommendation data and the content recommendation data**, stored in the same database.

The gamification is implemented by "Easter Eggs" technique. Through hidden "hashtags" in the event's physical environment, including moving elements like hashtags stuck in people, different keywords were created with topics related to the event. These topics became available in the environment, in different limited time period. Each new word could be inserted into the app through a specific code screen, and so the participants could increase their number of points. Figure 3 shows an example of moving code placed on the back of an event participant.

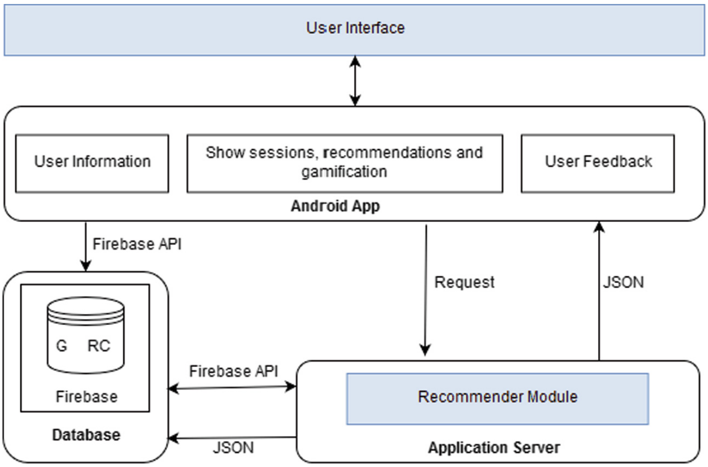

Fig. 2. AppIHC architecture

Fig. 3. A hashtag on the back of an event participant

The final ranking of the event had top five places awarded with prizes. This ranking was visible and public to the users of the application in real time. Gamification was an important part of the participants' engagement. The evaluation section will detail the results achieved.

3 Recommender Module

The recommender module is composed of content and social recommendations.

3.1 Content-Based Recommendation

In the content-based recommendation there are gathered data from users' registration (name, email, topics of interest and institution) and data from explicit feedbacks through the interaction with the system. Topics of interest are presented at the time of registration by means of a list of topics, in which the user can select the ones that correspond to their interests. This list represents the topics of the event IHC 2017, with a total of 42 topics. The selection of topics at the time of registration is not mandatory. In this way, the user who wants to make changes in topics of interest has the option to access his profile and edit it, being able to remove, change or insert topics.

Using the application when the event was occurring, explicit user feedbacks were collected to improve the recommendations. In addition, this feedback helped to generate recommendations for users who did not select topics of interest to complete their profile. Explicit feedback is collected in two ways, analyzing the sessions users put on their favorites list and through positive or negative user feedback for each session that is already recommended. This choice is represented by the "Positive feedback" and "Negative feedback" buttons. Figure 4 shows the Recommendations of one screen. In this screen, user can check the recommended items as well as select the feedback regarding the recommendation received.

Fig. 4. Recommendations screen for an event participant IHC 2017

The recommendations are pre-generated daily, based on the sessions that occur on the day and recalculated each time the user accesses the "Recommended of the Day" menu item, that is, in real time. So, each time user interacts with the system and accesses the "Recommended of the Day" the recommender module will improve the recommendations.

The programming language used for content-based RS development was Python. Profile data and topics of interest are stored in Firebase. All explicit feedback provided by the user while using the system is also stored in Firebase. In addition, information related to the Symposium sessions is also stored. This way, when users access the

"Recommended of the Day" (in Portuguese "Recomendados do Dia") in the AppIHC menu, the Recommender Module requests the user's data and the previously registered sessions and calculates the similarity of each session of the day with the user profile by calculating the Cosseno [10].

To facilitate the understanding of how the user profile is represented, an example is illustrated in Fig. 5, with a limited number of topics. The vectors have size 5 and each letter (A, B, C, D and E) represents a topic of interest addressed. Thus, when the user inserts the topics of interest A and B in his/her profile, the vector of topics of interest receives 1 in the positions referring to topics A and B, remaining 0 in the other positions. When the user favors the X session, the topics covered in that session (A, B, and E) receive 1 in the positions related to them in the subject session vector of favored sessions. For positive feedbacks, when the user positively evaluates the recommended Y session, session related topics (B and E) receive 1 in the positions related to them in the vector with the topics of the positive sessions. In Fig. 5 it is possible to see that when the user provides negative feedback for session Z that addresses topics A, C, and E; topics A and E are not inserted as 1 in the vector with negative session topics. This is because topic A is in the topic vector of user interest, and topic E is in the vector with topics from the favored sessions. Thus, topic C is the only one inserted in the negative topic vector, since it is the only one that is not either in the vector of topics of interest nor in the vector with the topics of the favorite sessions.

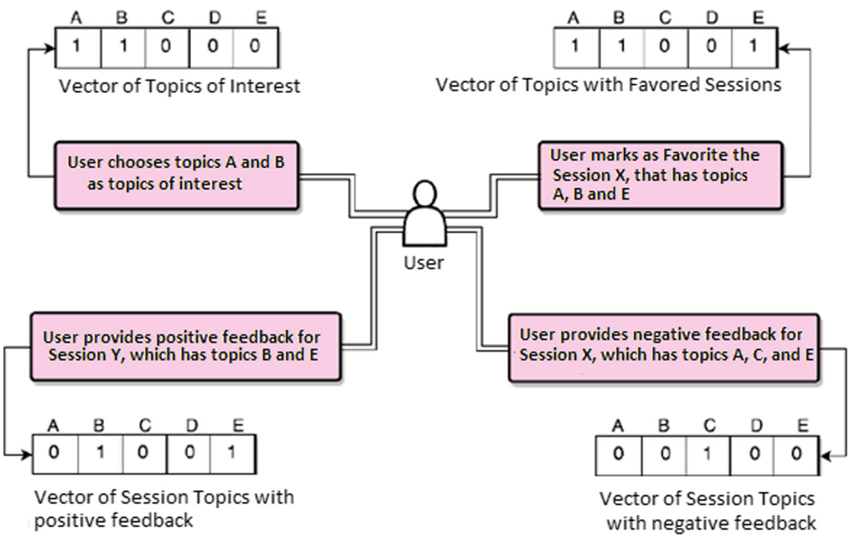

Fig. 5. Representation of user profile vectors

In order to calculate the similarity between the sessions and the user profile, the following formula was used:

$$sim(di, dj) = \frac{\sum_{i=1}^{k} w_{i,c} w_{i,s}}{\sqrt{\sum_{i=1}^{k} w_{i,c}^2}\sqrt{\sum_{i=1}^{k} w_{i,s}^2}} \quad (1)$$

The term $\boldsymbol{w_{i,c}}$ represents the profile of a user as a vector. A user's profile, containing his/her preferences, can be represented as a weight vector (***wc1 … wck***), in which each weight ***wc1*** illustrates the importance of a word (term) ***ki*** for the user ***c*** and can be calculated from individually categorized content vectors using a variety of techniques. The term $\boldsymbol{w_{i,s}}$ represents the contents of a document as a vector. The contents of a document can be represented as a TF-IDF vector of word weights. Finally, k is the total number of terms present in the vectors [11].

The complement of the result is used to calculate the Cosine between the sessions of a certain time and the vector with the topics of the sessions that received negative feedback. This is because the calculation of the Cosine indicates how similar a given session is to a user's profile, where 1 indicates total similarity and 0 indicates dissimilarity. Thus, the greater the similarity between the user vector that contains the threads of the sessions that received negative feedback and a particular session, the lower it indicates to be the user's interest in the session. For the other vectors of the user profile, the calculation of the Cosine is also performed, not undergoing changes. At the end of all calculations, a weighted average is performed with all resulting values. The similarity value between the session and the vector of the topic of interest has the greatest weight, being 40%. The remaining values remain equal weight of 20%. Thus, the similarity value between a session and the user profile remains between 0 and 1. The higher weight is set to vector of topics of interest because the topics of interest are the items provided directly by the user. Therefore, in order to determine which of the sessions is most related to the user profile, the calculation of the Cosine between the sessions and the vectors are performed. Sessions most similar to users' profile are recommended to them.

3.2 Social Recommendation

Interpersonal influence is an important contextual factor, and it follows the idea that a person tends to attend events accompanied by his/her friends. The similarity between friends is also an aspect that contributes to the recommendation process, as well as the frequency of interactions and participation in events, important social characteristics and that contribute greatly to the improvement of the recommendation process. Different approaches can be used to recommend events. One of the most used is the Collaborative Filtering approach. Recently the contextual dimensions is being add in social recommender systems.

Choosing the most relevant lectures/sessions and meeting potential collaborators with similar interests may be a difficult task at large events, especially because parallel sessions occur. Scientific/academic conferences are dynamic, the participants are moving, participating in different presentations in different environments and

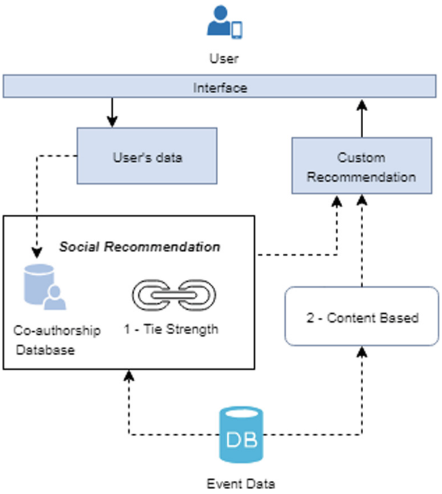

Fig. 6. Social recommendation process

schedules. Considering the mentioned aspects, a social recommender model was developed that considers social relations as co-author relations. Figure 6 shows the basic recommendation procedure.

A social network is created from the co-authorship researcher's history, based on who have already published in the event. Then, the first step is to calculate the tie strength among authors within the network. The calculation is made through the frequency of publications between two authors, inferring that, the greater the number of publications in co-authorship, the stronger the tie between the authors. Thus, the recommendation to the target user is generated based on the interests of the co-author with strong ties, and in publications which the target user is not a co-author. The tiebreaker is held by the most recent co-authorship.

The co-authorship network can be represented as a non-directed graph, with the following representation: the authors are the vertices and the publications are the edges. The objective is to quantify the number of co-authored publications, that is, how many edges each pair has in the network. Thus, according to Fig. 7, the co-authorship relationship between two authors, vertices *u2* and *u3*, is represented by a prominent link, since they have more than one work together.

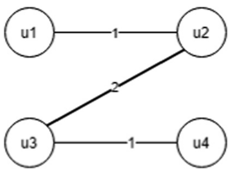

Fig. 7. Representation of the tie strength in the co-authorship network

4 Evaluation

The AppIHC application, its recommendation and gamification systems were evaluated in the IHC 2017 event. The app was available on Google Play and was made available to event participants.

4.1 AppIHC General Usage Data at IHC 2017

The IHC 2017 had a total of 250 participants enrolled and of these, 108 registered in the AppIHC during the event. Application usage data was obtained through Firebase Analytics.

According to Fig. 8, it is possible to verify the engagement of the users with the application, in minutes. Users used the application from October 22 to October 27 (event period). By calculating the average daily engagement, it was found that users spent about 13 min and 45 s using the application every day.

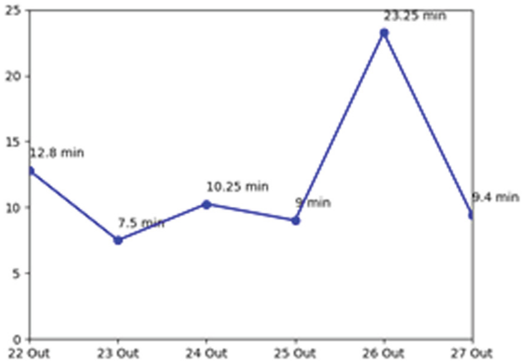

Fig. 8. User engagement

User Registration and Topic of Interest activities had the longest average interaction time (42 s), meaning that users' longest interactions with the application occurred during the registration and insertion of topics of interest. Following this order, the main activity of the application appears in the next position, with an average interaction time of 32 s. The average duration of the interactions of the other activities was 18 s, much smaller than those previously mentioned.

Using the event database in the Firebase Realtime Database, it was found that of the 108 users of the application, 74 users (68%) obtained some content-based recommendation, 66 users (61%) used the feature of adding a session to the favorites list, 47 users (43%) used and evaluated the recommendation system, 56 users (51%) used some printed code to score in the gamification and 55 users (51%) answered the satisfaction questionnaire.

The questionnaire was created based on the Likert scale with three response options, represented by emoticons: I do not agree, neutral and agree. The neutral was created to allow the user not to be forced to make a choice between extremes (no and yes) or if he/she does not want or has no opinion on the issue. The questionnaire was added to AppIHC itself and it was used to get answers about application usage and the content-based recommendation system.

Of the 55 users who answered the questionnaire, 46 users (83.6%) answered that they were assisted in obtaining information faster and 9 users (16.4%) responded in a neutral way. About the functionalities of the application being useful, the data collected showed that 44 of the 55 users (80%) agreed with the statement, 10 users (20%) answered in a neutral way and no users disagreed. Regarding the content displayed on the screens were clear and organized, 43 users (78.2%) agreed with the statement, 8 users (14.5%) answered in a neutral way and 4 users (7.3%) disagreed.

On gamification, Fig. 8 also highlights the increase in user engagement on October 26, the day that hashtags were most heavily included in the event, and users knew that it would be the last day to improve their rankings by entering the codes in the application. A gamification award was given at the end of the day. In addition, the satisfaction questionnaire presented two issues related to gamification.

Regarding the statement “The proposed challenges stimulated my participation in the event”, there were 56 respondents, where 36 (64.28%) agreed, 3 (5.3%) disagreed and 17 (30.35%) were neutral. On the statement “My achievements at the end of the event reflected my participation in the IHC 2017”, 37 (66.97%) agreed with the statement, 7 (12.5%) disagreed and 12 (21.42%) responded in a neutral way. On the statement “Playing made the application more fun” 48 participants (85.71%) answered in the affirmative, 2 (3.5%) negatively and 6 (10.71%) in a neutral way. This issue highlights the importance of gamification to engage participants in the IHC 2017.

5 Recommendation Module

The content-based recommendation was explicitly displayed and the social recommendation was presented implicitly, so the evaluations of the recommendations were performed separately.

The evaluation of the content-based recommendation in AppIHC was performed in two ways: (1) quantitative analysis and (2) satisfaction questionnaire. The first was based on the positive and negative feedbacks given by users with the likes and dislikes buttons to know how many users who received the recommendations considered these recommendations positive or negative. The second was through a questionnaire that allowed to acquire a greater amount of feedback on the recommendations generated, since the questions contained in it were more specific about each detail of the recommendations.

For the users who used the recommendations, of 108 AppIHC users, 73 (around 67.6%) used the recommendations at least one day during the IHC 2017. In order to know who used the recommendations, it was verified within the profile of each user in the database, since this field is only created if the user has accessed the “Recommended of the Day” at least once during the event week.

For the 73 users who used the AppIHC recommendations, a total of 537 sessions were recommended during the event IHC 2017. Of this total of recommended sessions, 180 (33.5%) received evaluations of 47 users. The users provided positive feedbacks for the total of 156 recommended sessions (86.66% of the evaluations) and negative feedback for 24 sessions (13.33% of the evaluations). It was possible to notice that most of the recommended sessions that received evaluations were evaluated positively, indicating that the recommendations were satisfactory for the majority of users.

The social recommendation by co-authoring was added implicitly in order to not conflict with the content recommendation. When using AppIHC, the user receives recommendations through text and icon in the event schedule, presented per day according to Fig. 9.

Fig. 9. Social icon and social recommendation.

From the 108 users enrolled in the application, the social recommender system identified 35 event participants who are co-authors, but only 14 of them used the AppIHC application. A questionnaire was sent after the event to these 14 participants, but only 8 users answered the following questions on Table 1:

Table 1. Closed questions about social recommendation

Questions	Yes	No answer	No
Q1. Did you notice the indication that your co-author(s) are in a given session?	5	2	1
Q2. This information influenced your decision-making about which sessions to attend?	1	2	5
Q3. Do you find useful indicate co-authoring to recommend sessions?	5	2	1

Although the participants affirmed that they were not influenced by the coauthoring recommendation, we could see in the database that they mark some of the sessions recommended as favorite. This could indicate that although the user considers not to have been influenced, he/she liked the recommended session.

The other questions were open and aimed to identify suggestions for improvements to the recommendation process, with and without the use of social elements. These suggestions made it possible to obtain requirements for the improvement of the recommendation module and the application.

In terms of social issues, users suggested: allowing the selection and visualization of co-authors' interests; create a network of friends by adding people from the academic community, not necessarily co-authors; share preferences, interests and works to be presented, with due consent; recommend and receive recommendations from other users. The evaluation provided the improvement of the social recommendation model that were applied it in the event 2018 edition.

6 Discussion

Choosing the most relevant lectures/sessions and meeting potential contributors/partners with similar interests can be a tedious task at large events, especially because parallel sessions occur. Academic conferences are dynamic, participants are moving, participating in different presentations in different environments and at different times.

AppIHC is a mobile application for scientific/academic events that helps users to find sessions. The application was developed to support participants attending the event to find sessions according to their interests and collaborations/co-authors/partners.

The main problems found in recommending sessions are scarcity of evaluations and cold start. The scarcity of evaluations occurs when the number of items evaluated is much smaller than that of items available in the system, making it difficult to obtain similarities between people. The cold start problem occurs when a new user or item is entered into the system because there are no evaluations of the item or no items evaluated by the user, so it is not possible to recommend items or find similar users. In the case of the recommender systems for events, the above problems are aggravated due to the short period of time that an event exists and the lack of history of participations and evaluations.

To make recommendations through the use of the content-based approach, it is necessary to know only the target user of the recommendation and to compare the content similarity of the works to be presented with the user's tastes. A good point that helps to solve the mentioned problems, since evaluations are not necessary to initiate the recommendations by content, in this case they are used to improve the recommendations every user interaction with the AppIHC.

However, interpersonal influence is an important contextual factor. The similarity between friends can be an aspect that contributes to the recommendation process, as well as the frequency of interactions and participation in events, important social characteristics that contribute greatly to the improvement of the recommendation process. For this reason, the social recommendation by co-authoring has the objective of helping the participants to find their coauthors in the sessions of the scientific event.

This way, the recommender system present in AppIHC reduces the users' attention overload when navigating the event schedule by searching for sessions of their interest.

7 Considerations

This applied research aimed to describe, discuss and evaluate a mobile application to facilitate the participants' access to the event's programming and to promote their engagement. This application was used and evaluated during and after the IHC 2017 event. AppIHC includes a recommender system that uses information from the user profile and his/her interest to generate recommendation by content, and generates social recommendation through the co-authoring IHC network.

As future work new social elements, in addition to co-authorship relationships, are being added to the social recommendation model. In addition, the application is also being improved and developed for other platforms and is being used in different scientific events.

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