Stating and discussing challenges of radio recommender systems in contrast to music recommendation

Stefan Hirschmeier, Daniel A. Döppner, and Detlef Schoder

University of Cologne

{lastname}@wim.uni-koeln.de

Keywords: Radio Recommendation, Audio-Text Recommendation, Recommender Systems, Public Radio, Interactive Player design

Abstract. Recommendation for public radio is a challenging area. In contrast to music recommendation, which has been intensively discussed in research as well as in practice, recommendation for radio has some special additional challenges as it mixes diverse formats, such as news, articles, audio dramas, biographies, etc. Focusing on the interaction design of a radio player, we bring up and discuss these special challenges and find that in a radio recommender context, optimal interaction design has conflicting issues with optimal algorithmic design.

1 Motivation and problem

While the entertainment industry has created popular apps, such as Spotify and Netflix, with powerful recommendation systems behind them, public radio has received less attention in recommender systems research. As in a lot of countries, people pay for broadcast receiving licenses in order to finance public radio, and there is always a latent need to come up with appealing solutions that provide value as perceived by the user. Apart from the public value provided by public radio programs, individuals' appreciation of public radio depends on not only the content but also, and perhaps more importantly, the user's interaction with the radio application.

What makes recommendation approaches for public radio so much different from the well-known approaches for music, movies, or TV recommendation, and what implications do these differences have for the design of recommender systems?

Challenge 1. First, from a content perspective, radio is a **mixture of diverse formats**, such as news, articles, audio dramas, biographies, long features, talks, interviews, and—last but not least—music. Additionally, live formats, like dial-in games, are an option as well. A direct implication of these heterogeneous formats is that each format requires its own recommendation algorithms. For instance, as research on recommendation has brought up the discussion of where and whether to draw the border of a filter bubble [1,2], in the context of news, this has to be considered carefully for a radio broadcaster with a public mission. In contrast, recommendation for music is deliberately intended to build a closed world and filter out music that the user dislikes. Even interaction behavior might differ for each format. This mixture of formats makes building a recommender system for radio significantly different from building recommender systems for homogeneous content types like movies, series, or music.

Challenge 2. From an **interaction** perspective, portable radio accompanies the user everywhere while he/she does other things, such as driving or washing dishes. In the core use case of radio listening, there is no choice process as would be the case for a "lean-back experience" (e.g., browsing), a term coined by movie recommender systems. That is, because users do not spend two hours with one choice (as in the case of a movie) but rather get a stream of audio pieces that are a couple of minutes in length each, users are less willing to spend time with their choice. Also, there are no interactive recommendation games like in Netflix. Rather, the interaction with traditional linear radio is reduced to the max: tune in and tune out; listen or ignore. In order to stay with this paradigm, interactive radio must stay as simple as possible. Few interaction possibilities, however, result in few (distinguishable) data.

Challenge 3. One-time consumption. Whereas users do not mind hearing songs they like over and over again, they do not usually feel this way about news. Users might want to repeat news in some cases, but generally not more than one time. Whereas eliminating duplication and not playing the same content again sounds simple, it is not. It is challenging to decide whether a news audio piece provides new details compared to other news that has already been played or whether it is better to skip that particular piece.

Challenge 4. There is a **steady content stream** of new media coming in every day that a radio recommender system has to cope with. Whereas a lot of recommender systems researchers tackle the "cold-start problem" [5,6]—when little is known about the interaction of users of new media—radio recommender systems also face another problem: after four to six weeks, the content disappears from the media library again, reducing the value of past interaction data for, as an example, collaborative filtering.

Challenge 5. Context-Dependency. Radio is highly contextual, depending on the day of the week, the time, user mood, and the things users do while listening. The hypothesis of a context-aware recommendation is that it can significantly improve recommendation accuracy because playlists can be tailored according to the actual condition of the context [9]. Whereas considering contextual information in recommendations is one challenge, getting the contextual information is another. In a mobile radio context, mobile device sensors can determine if the user is moving, relaxing, or playing sports and then incorporate this information into the recommendation playlist [10].

Challenge 6. Program management. Program managers have gained experience over the years regarding which content to play at which time and in which order as well as how to assemble and mix the content so that the program will be entertaining for the user. When assembling radio playlists automatically, this program managing experience has to be reflected in recommender algorithms (sequential recommendation [8]). Interdependencies between audio pieces have to be taken into account in general. There are some well-known examples of misplaced advertisements (e.g., the headline "11-year-old charged with driving drunk" followed by a beer advertisement). The ability to mix content can therefore range from a faux pas to enjoyable radio.

Whereas all these challenges relate to algorithmic design, especially challenges 1, 2, and 3, also have a major impact on interaction design. In the following section, we take a closer look at interaction design challenges for radio recommender systems.

2 Interaction design in radio players

When designed to be interactive, radio necessarily takes the shape of an audio player, typically providing play/pause, previous, and next interaction buttons. Whereas from a user's perspective, it is generally sufficient to have these three buttons, for a recommender system, these are rather inadequate as it is hard to distinguish the intention behind hitting a button (e.g., the next button). In a music context, to understand the preferences of the user, the following questions arise: Why did the user click on the next button? Does he/she generally dislike this kind of music, or does he/she just not want to listen to it right now? This discrimination does not matter to the user in the moment he/she hits the button, but it matters very much to the recommender system. A way to find out the user's preference could be to provide additional like and dislike buttons, so when a user hits a button, it does not need to be interpreted (though there is a trend toward implicit feedback [7]). Following this approach, in some popular music player apps, there are like and dislike buttons in addition to previous and next buttons.

Going back to the radio context again, the situation gets much more complex. In a radio context, when news, radio dramas, and other formats are mixed, the reasons behind users' hitting the next button are much more diverse and are important to understand for a good recommendation: the user may not find the topic to be interesting, he/she may have heard the content before, he/she may find the topic interesting but is uncomfortable with the speaker's voice, the user may find the topic interesting but may not want to hear it right then, etc. If buttons were added for every possible cause (e.g., "I don't like the speaker"), the user interface would inevitably become complex and messy. As a result, we find that in a radio player context, the tasks of designing interactions and designing recommendation algorithms have conflicting objectives.

The concept of traditional radio interactions (i.e., almost no interaction at all) matches the design paradigms of mobile app interaction very well. Mobile apps have made a simple interaction design imperative: "Not only are the apps easy, but so are the processes," (translated from German) said Jens Wehrmann, CEO of Mobile Software AG [3]. Thus, a very reduced interaction design of a player fits well with the radio domain.

In contrast, recommender systems follow a different approach: the more data (in terms of amount as well as diversity), the better. Recommender systems cannot reach their full potential with little data or with data that while available, still needs to be interpreted. Especially in a radio player context, we find a mismatch between optimal interaction design and optimal algorithm design. Hence, a tradeoff has to be made between optimal interaction design and optimal algorithmic design in this context.

3 Further research

The findings herein give rise to research on how users behave when having multiple buttons to express their interests and preferences in a radio player context. Spotify has made interesting contributions with their combination of a like and next button: namely, the ratio of like and dislike does not always correlate with user engagement. In other words, implicit and explicit feedback does not lead to the same results. According to Spotify, "what users say they like is not always what they watch/listen" [4]. This puts the usefulness of additional buttons in question and limits their value. Further research has to show which buttons make sense to include in player design and which buttons eventually produce data that enable recommender systems to give appropriate recommendations.

4 References

1. Pariser, Eli (2001). The Filter Bubble: What The Internet Is Hiding From You, Penguin Books.
2. Nguyen, T. T., Hui, P.-M., Harper, F. M., Terveen, L., and Konstan, J. A. (2014). Exploring the filter bubble: the effect of using recommender systems on content diversity. In: Proceedings of the 23rd international conference on World wide web, pp. 677-686.
3. Wehrmann, Jens (2013). Nicht Apps sind einfach, sondern die Prozesse. In: Mobile Technology Magazin 4/2013, pp. 10-11, Frankfurt.
4. Steck, H., van Zwol, R. and Johnson, C. (2015). Tutorial Interactive Recommender Systems. ACM Recommender Systems, Vienna.
5. Tkalčič, M., Kunaver, M., Košir, A., Tasič, J.F. (2011). Addressing the New User Problem with a Personality Based User Similarity Measure. In: Proceedings of the 2nd Workshop on User Models for Motivational Systems.
6. Schein, A. I., Popescul. A., Lyle H. Ungar, L. H., and Pennock, D. M. (2002). Methods and metrics for cold-start recommendations. In: Proceedings of the 25th ACM SIGIR conference, pp. 253-260.
7. Moling, O, Baltrunas, L., and Ricci, F. (2013). Optimal Radio Channel Recommendations with Explicit and Implicit Feedback, Epilog Conference, Vienna, Technical University of Vienna, June 13, 2013, p. 8.
8. G. Shani, Heckerman, D., and Brafman, R. I. (2005). An mdp-based recommender system. Journal of Machine Learning Research, 6:1265-1295.
9. Hidasi, B. (2015): Context-aware Preference Modeling with Factorization, ACM RecSys 2015, pp. 371-374.
10. Unger, M. (2015). Latent Context-Aware Recommender Systems, ACM RecSys 2015, pp. 383-386.