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Christine Bauer
Johannes Kepler University of Linz, christine.bauer@jku.at

Marta Kholodylo
University of Vienna, a1048685@unet.univie.ac.at

Christine Strauss
University of Vienna, christine.strauss@univie.ac.at

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A. Pucihar, M. Kljajić Borštnar, C. Kittl, P. Ravesteijn, R. Clarke & R. Bons

Music Recommender Systems Challenges and Opportunities for Non-Superstar Artists

CHRISTINE BAUER, MARTA KHOLODYLO & CHRISTINE STRAUSS

Abstract Music Recommender Systems (MRS) are important drivers in music industry and are widely adopted by music platforms. Other than most MRS research exploring MRS from a technical or from a consumers' perspective, this work focuses on the impact, value generation, challenges and opportunities for those, who contribute the core value, i.e. the artists. We outline the non-superstar artist's perspective on MRS, and explore the question if and how non-superstar artists may benefit from MRS to foster their professional advancement. Thereby, we explain several techniques how MRS generate recommendations and discuss their impact on non-superstar artists.

Keywords: • Music Recommender Systems • Non-superstar artists • Popularity bias • Online Business •

CORRESPONDENCE ADDRESS: Christine Bauer, Johannes Kepler University Linz, Altenbergerstraße 69, 4040 Linz, Austria, e-mail: christine.bauer@jku.at. Marta Kholodylo, University of Vienna, Universitätsring 1, 1010 Wien, Austria, e-mail: a1048685@unet.univie.ac.at. Christine Strauss, University of Vienna, Universitätsring 1, 1010 Wien, Austria, e-mail: christine.strauss@univie.ac.at.

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1 Introduction

In the era of digitalisation, music has become easier to create, distribute, and access than ever. Music recommender systems (MRS) are meant to assist listeners in navigating through the myriad of available musical works and provide them with suggestions that would fit their preferences and needs. This paper aims to present the most common techniques in music recommendation and how these affect the positions of non-superstar artists. While previous research on MRS typically takes a technical perspective or focusses on the consumers, the artists' perspective has yet largely been neglected. "The phenomenon of Superstars, wherein relatively small numbers of people earn enormous amounts of money and dominate the activities in which they engage, seems to be increasingly important in the modern world" (Rosen, 2004, p. 215). Still, the impact of MRS on non-superstar artists is particularly important as (i) the vast majority of artists are non-superstar artists (Anderson, 2004; Mulligan, 2013), (ii) the economic situation of non-superstar artists is usually precarious (Bauer & Strauss, 2015), and (iii) the technological and managerial skills required to manage and promote one's own business as an artist are usually not part of the typical educational paths of aspiring artists (Bauer, 2012; Bauer, Viola, & Strauss, 2011).

The importance of non-superstar artists is further underpinned by the "long tail" concept introduced by Anderson (2004, 2006), a model that is specifically applicable to the music industry. This model describes the economic tendency, when there is a concentration of sales on the most popular items ("hits"), which form the head, and then a long tail of less popular items that may fulfil niche demands of potential customers. This model is considered the opposite of the "hit model" (or "short tail") in industries where an item either becomes a "hit" or does not make any profit at all. The implication is that it is more profitable to sell small amounts of the long tail of less popular items than large amounts of a small number of hits. Later, empirical findings (e.g., Brynjolfsson, Hu, & Simester, 2007) confirm this idea, provided there are effective search and recommender systems available that enable users to access these long-tail items easily. At the same time, MRS is an enabler to introduce niche items to a consumer who usually follows hits only in such a sophisticated (preference-matching) manner, so that this hit-affine user may start consuming long-tail products (Goel et al., 2010). As a result, the employment of recommender systems in the long-tailed online music market enables users to discover and access the work of non-superstar artists.

The paper is structured as follows: Section 2 provides a structured overview MRS and their functionality. In Section 3 we explore the influence of MRS on non-superstar artists by explaining the phenomenon of popularity bias, the cold start problem, and superstar economy. Section 4 provides details and results of a semi-structured interview with an artist, followed by the last section containing concluding remarks.

7 Music Recommender Systems

This section provides an overview of the structure of MRS, its components and functionality, and the most common techniques used.

Typically, recommender systems consist of three key components: users, items, and user-item-matching processes. This general structure also applies for MRS, where users are the listeners and items are the music items (music works). The system collects relevant data about its users and applies mathematical models and diverse techniques to find and propose items, which might be of interest for the listener. To recommend items that most likely fit the listeners preferences the system needs to manage data about listeners and music items, the system generates profiles for each of them and determines "good" matches by comparing these profiles (Song, Dixon, & Pearce, 2012). In the following, we discuss in detail the data and approaches associated with the three key components, i.e., user, item and matching.

7.1 User Data

In order to be able to make valid recommendations, an MRS requires data about its users' needs. However, getting such exact data is a costly process (Turnbull, Barrington, & Lanckriet, 2008). Thus, MRS rely on user modeling. The system analyses its users' data and generates profiles based on their differences to model music preferences and thus determine which music items might be of interest for the individuals. Typically, the user modeling process consists of two sub-processes: (i) user profile modeling and (ii) user experience modeling. User profile modeling is generally used to determine the "position" of the listener in comparison to others based on their features. One of the approaches suggests dividing user profiles based on three major categories: demographic, geographic, and psychographic (Celma, 2008). Further, a number of attributes can be assigned to each category, such as age, gender, country, interests, etc. (Song, Dixon, & Pearce, 2012). Whereas, user experience modeling is meant to approach the users with consideration of their music expertise level, which further can be used to determine some of their expectations towards the MRS (Jennings, 2007; Song, Dixon, & Pearce, 2012; Uitdenbogerd & Van Shyndel, 2002). Combining both approaches, it is possible to predict some of the users' demands and desires regarding music; for instance, it is possible to predict a user's preferred ratio of new, previously unknown vs. popular, already known music items she would like to listen to when engaging with a music platform (Anderson, 2006). Some data can be obtained through observing listeners in their actions on the music platform, such as listening patterns (Shao et al., 2009; Song, Dixon, & Pearce, 2012), other data may be retrieved through input inquiries, e.g., surveys to retrieve profile information (Song, Dixon, & Pearce, 2012).

7.2 Music Item Data

Item profiles are based on the metadata of music works. Such item metadata typically differentiates three types: editorial, cultural, and acoustic (Pachet, 2011; Song, Dixon, & Pearce, 2012). Editorial metadata is the type of data provided by music editors, such as name of the artists, name of the composer, title of the musical work ('track title'), music genre, etc. Such editorial metadata is usually provided by those who submit the music item to the system. Cultural metadata is the result of analysis of data connected to the music item over the Internet. It discovers the associations, emerging patterns, similarities to other musical works based on the data from public sources. Acoustic metadata describes the musical work itself, including its qualities, such as beat, instruments involved, tempo, pitch, mood, etc. It does not require any other data than those related to the musical work itself (Song, Dixon, & Pearce, 2012).

7.3 User-Item Matching

Music recommendations rely on mechanisms, matching users and music items. To provide understanding of such matching mechanisms, we present an overview of the most popular techniques employed.

Metadata retrieval methods are used to retrieve music items that match input from the user, such as artist's name, title of a musical work, etc. This technique implies that the users already know data about the musical work they would like to listen to (Song, Dixon, & Pearce, 2012).

Collaborative filtering (CF) offers listeners new music (in the sense of "previously unknown to the listener") based on the listeners' past evaluations (Uitdenbogerd & Van Shyndel, 2002). There are three approaches: (i) CF determines the "nearest neighbour" user group that share similar tastes. The MRS then suggests items that are typical for this group (memory-based CF); or (ii) the MRS applies a mathematical procedure to suggest – based on the user's previous ratings to music items – new music items, previously unknown to the respective user (model-based CF) (Adomavicius & Tuzhilin, 2005); or (iii) the MRS combines both approaches to a so-called "hybrid CF" (Song, Dixon, & Pearce, 2012; Wang, de Vries, & Reinders, 2006).

Content-based filtering uses characteristics of a musical work (in the machine learning domain also referred to as "features") to determine similarities between items and derives predictions thereupon (Aucouturier & Pachet, 2002; Li et al., 2004). This way an MRS suggests music items to a user that are similar to those he or she has already listened to (Song, Dixon, & Pearce, 2012; Uitdenbogerd & Van Shyndel, 2002). Since the analysis is based on the qualities of music itself, content-based filtering does not require human input to operate.

Demographic filtering techniques create music suggestions based on a user's personal data (e.g., gender, age). Such filtering techniques divide users into groups based on their personal data and provide music items that match a "typical" user of the respective group (Celma, 2008). This technique usually supplements other filtering techniques such as collaborative or content filtering (Song, Dixon, & Pearce, 2012; Uitdenbogerd & Van Shyndel, 2002).

Context-based modeling uses context (e.g., cultural metadata) of music items to come up with suggestions for its MRS' users. This technique uses open data available on the Internet, such as music reviews, comments, ratings, friends' lists, etc. (Lamere, 2004). Note, while the terms "context" and "cultural data" are established within a specific meaning in the MRS community (e.g., Schedl, 2013), these terms may be misleading as related communities use these terms with distinct meanings (e.g., for "context" in the context-aware computing community see Bauer & Novotny, 2017, to appear; Dey & Abowd, 2000).

Emotion-based modeling creates music recommendations on the basis of the emotions the music item is associated with (Yang & Chen, 2011). This modeling technique provides an emotional grid where users may define a mood and the MRS suggests corresponding music items. Advanced systems analyse musical features of the musical work and associate them with particular emotions.

Finally, hybrid methods are the combination of two or more techniques. The goal is to create better predictions than any technique would supply on its own, while avoiding their limitations and problems (Celma, 2008).

8 Impact of Music Recommender Systems on Non-Superstar Artists

This section focuses on the position of non-superstar artists in MRS. The information analysed provides both theoretical hypothesis and empirical research on the topic. We tried to estimate the effect that the techniques employed in the user-item matching process (cf. Section 2) have on non-superstar artists; our discussion focusses on the techniques that actually do have an impact on them.

Overall, current MRS have some deficiencies that affect the position of non-superstar artists in a negative way. While some problems originate from flaws in system design, sometimes the reasons for these problems are of different nature, mostly inherent to the employed techniques in the user-item matching process (Levy & Bosteels, 2010; Song, Dixon, & Pearce, 2012) (cf. Section 3.1.) In Section 3.2, we outline the positive effects of MRS for the position of non-superstar artists.

8.1 Popularity Bias

One of the most problematic issues that affect the position of non-superstar artists is the so-called popularity bias. In general, the popularity bias phenomenon suggests that over time the most popular music items tend to get more and more attention, while music items in the long tail get less and less attention. In particular, popularity bias is a significant problem when employing CF or context-based filtering due to the nature of the integrated algorithms (Levy & Bosteels, 2010; Song, Dixon, & Pearce, 2012). As concerns MRS, this phenomenon manifests in several ways.

For instance, CF uses listeners' ratings to create recommendations. This implies that popular music items receive generally more ratings than items of the long tail. This, in turn, entails that an MRS recommends popular items (that have more ratings) more frequently than less frequently rated items. This, however, reinforces the popularity of popular items and, thus, also increases their suggestion rates. As a result, items in the long tail receive less and less ratings, and so the system recommends them less frequently (Song, Dixon, & Pearce, 2012). For example, Fleder and Hosanagar (2007) could show this effect in a simulation study. They simulated an MRS based on CF, where music items were recommended based on the results of previous recommendations. Across several different user groups, the overall diversity of consumption by the end of the simulation was decreasing. In other words, the MRS was giving preference to more popular items over time.

In a similar way, context-based filtering uses data available about a musical works to derive recommendations. Since popular items are generally better promoted on media and are mentioned in more online sources, overall more information is available about those items compared to items of non-superstar artists (Song, Dixon, & Pearce, 2012). As a result, an MRS employing context-based filtering suggests popular and widely discussed items more frequently than items with less popularity; and this gap grows over time.

8.2 The Cold Start Problem

Closely related to the popularity bias is the so-called cold start problem, which refers to the difficulty to get recognition in an early stage when a new user or new item enters a MRS – due to the lack of data related to the user or item (Song, Dixon, & Pearce, 2012). When a listener just starts to use an MRS and has not (yet) submitted much information about herself or her preferences, etc. (e.g., ratings, clicks, etc.), the MRS will only provide her with general recommendations (Celma, 2008). Similarly, when new music items are introduced to a system, they do not make it into the recommendation results because there is not enough data available about these items (cold start), which would trigger the MRS suggestion (Celma, 2008; Song, Dixon, & Pearce, 2012; Uitdenbogerd & Van Shyndel, 2002). In addition, artists new to the market do not only have merely new music items in their portfolio, there is also not much data available about them as artists, entailed with less frequent discussion, promotion, etc. As a result, the chance that new artists' items are recommended by an MRS are even less likely than that for new items of established artists (Celma, 2008; Song, Dixon, & Pearce, 2012).

8.3 Superstar Economy Speculations

In addition to research on the effects of and consequences inherent in the techniques an MRS employs, some sources assume that MRS are biased towards popular tracks not only due to their design and the algorithms employed, but on purpose as hit items generate larger profits than items of non-superstars (due to, e.g., economies of scale).

For instance, a marketing report by Media Insights & Decisions in Action Consulting (Mulligan, 2013) concludes that the recording music industry is not at all oriented at long-tail items; according to this source, one of the main reasons for it is that MRS do not only offer popularity-biased recommendations, but also that music platforms get polluted with musical works that are created in "bad" quality (not so pleasant to the listener) on purpose, with the aim to enhance the positions of the already popular music items (hits). Such "bad" musical works sound similar to the bestselling songs, but in comparison the listener would still prefer the more popular, "better" song (Mulligan, 2013). As a result, the sum of sales for hit songs is higher than that for non-hits, so music platforms are more motivated to sell more of popular music items (Guadamuz, 2015). This opinion is supported by findings of research investigating users' music preferences (e.g., Farrahi et al. (2014) show that users who prefer mainstream music are in general easier to satisfy with an MRS).

In contrast, for instance, Levy and Bosteels (2010) investigated whether the MRS employed by the Last.fm platform is indeed biased towards more popular items, as suggested in earlier literature. They compared three different data sets: (i) the one of Last.fm Recommendation Radio, which recommends specific music to specific users based on their (user) data, (ii) the Last.fm Radio data set, which plays music recommended to Last.fm users in general, and (iii) and a data set of the Last.fm music streaming services as a whole, which summarizes the information about what users are listening to while using Last.fm. The findings suggest that Last.fm, as one of the largest worldwide MRS, is biased towards non-hits rather than towards hits in comparison to overall user listening experience, and this bias is stronger for Last.fm Recommendation Radio. Based on these results, the authors conclude that real-world data can significantly differ from simulations and also state that not all MRS seem to be biased towards more popular artists.

8.4 Impacts of Music Recommender Systems

While the topic of popularity bias and the recommender system inadequacies seems to be one of the most broadly studied topics with regard to MRS research, it seems that research has been limited on the existence and the reasons of these phenomena. Yet, exploring the impact of these phenomena on different artist groups (e.g., superstars versus non-superstars) or differentiating in more detail within an artist group (e.g., artists from different genres, countries, age groups, etc.) has not (yet) been investigated.

For instance, as mentioned in a Billboard article (Maddux, 2014), researchers and media tend to focus on disadvantages and flaws of MRS' performances, while neglecting the fact that the existence of the discussed phenomena may be a big advantage for a privileged group of artists. For example, in the "old" music business, when music was either distributed on physical media (e.g., vinyl, CDs) and/or promoted through live shows, it was tremendously challenging for newcomers to the industry to get recognition, if their music did not "score" to become an immediate hit (Anderson, 2004). Now, newcomers ("no names") have the chance to slowly make their way up in industry by experimenting with the recommendation mechanisms and promoting their works accordingly (Maddux, 2014). The shift from the short-tail to the long-tail model might not be as significant as in other entertainment industries such as films as books, but it is still present and it continues growing (Guadamuz, 2015). This view is supported by the case we investigated and is presented in the following Section 4.

9 Insights from a Real-world Case

To gain some insights on how MRS impact non-superstar artists from their point of view, we drew from the experience of an aspiring, non-superstar music band using the Internet as the main tool to promote their music.

9.1 Approach

Several criteria motivated the selection of an interviewee to gain hands-on insights on challenges and opportunities for non-superstar artists: recent release of an album, experience with MRS, use of Internet as a main promotion tool, newcomer on the market, limited information about the artists (yet) available on the Internet, and professional attitude and aspiration (no "just for hobby" band).

Based on these criteria, we selected a Ukrainian oriental metal band, founded in July 2011 under the name "Parallax", renamed in 2015 to "IGNEA". Their first work "Alga" was released in 2015, whereas they released their first full-length album "The Sign of Faith" in 2017 (cf. http://ignea.band).

This band was selected to provide insights on the topic of MRS from the artists' point of view because since their debut in 2011 they mostly use Internet to promote their work and have experience with MRS as a non-superstar artist. It matches the definitions of the long-tail artist in music industry, since it works in a highly specific, niche genre, which is very different from popular music. As one of the founders of the band, vocalist and songwriter, Olga was a highly suitable candidate to provide information regarding IGNEA's activities.

We conducted the interview via Skype using a semi-structured approach (i.e., relevant questions prepared beforehand, but preserving the flexibility to stray away from the intended plan, if the artist provided interesting thoughts on the topic). The interview took 17 minutes (full audio recording is available). We applied content analysis (Krippendorff, 2013) for text reduction, analysis, and interpretation.

9.2 Findings

According to the interview, the band promotes their music on the majority of well-known music platforms, such as Spotify, YouTube, iTunes, and others. The music items are submitted to the platforms through a third-party aggregator. Using such a service, the artist may – aside from the name of the artist and the titles of the music items – provide several tags associated with their music items (typically up to three), such as genre, beat, and other similar characteristics describing the music items. The strategic steps on the artist's side usually consist of the timing for the releases and coming up with tags that would attract the attention of their potential audience.

The interview indicates that the band's overall experience with them as a non-superstar artists is very positive. For instances, about 80% of their listeners and purchasers discovered the band through MRS recommendations. Furthermore, achieving success on the platforms (through MRS) has led to mentions on the media. Overall, our interviewee pointed out that MRS combined with the power of Internet had helped the band to generate international audience instead of regional listeners; currently the majority of their listeners is located in the United States.

The interviewee expressed her opinion that she thinks many artists fail on platforms with MRS due to the lack of knowledge and/or effort that the artists put into managing their activities on such platforms, trying to exploit MRS for their own ends. She emphasized the importance of studying and understanding how such systems work, and pointed out the lack of knowledge that artists seem to have about the tools available. She said that those might not be aware of the tools and possibilities and do not sufficiently search for their opportunities. The observation of the lack of managerial skills is backed up by research findings (e.g., Bauer & Strauss, 2015; Bauer, Viola, & Strauss, 2011)). Behaviour on the market, partly resulting from such an educational deficit, may lead to (self-)destruction of the economical basis of aspiring artists (Bauer & Strauss, 2017, to appear). She believes that a good artist can reach success with the help of MRS. She stated that her band will continue using MRS to promote their music in the future.

Among the disadvantages, she complained of the lack of flexibility for submitting information that artists could easily provide to specify and characterise their own music, such as the limited amount of tags they can include when submitting a music item. Another drawback is that most platforms keep confidential what kind of data is used in the employed MRS, and in what way it is used by their algorithms. Furthermore, the artists get access to only very general and aggregated information such as number of plays/purchases and country of origin of the users; accordingly, it is difficult to adjust their strategies efficiently to use the MRS for their own benefit.

10 Conclusion

This paper provides insights into mechanisms of current MRS and explored the challenges and benefits that non-superstar artists are confronted with on platforms employing MRS. While research on MRS tends to focus on technical issues and/or explores the field from a rather technical perspective, this work dedicates to the impact on and value generation for the group of artists that provide the vast majority of music items available on platforms using MRS (i.e., non-superstar artists) – a topic that had been neglected so far. We outline several techniques how MRS generate recommendations and discuss their pros and cons. We elaborate the non-superstar artist's perspective on MRS and present considerations from the point of view of a non-superstar artist. In particular, we explored the question how the professional advancement of non-superstar artists is affected by MRS.

It may be concluded from literature that some techniques of MRS do have a negative impact for non-superstar artists as these are biased towards more popular music and fall short in overcoming the cold start problem; yet, some MRS do support the aspiring non-superstar artist. Based on literature and our case elaboration it may further be concluded that MRS provide opportunities for aspiring artists to exploit MRS for their own benefits, as MRS provide a comparatively inexpensive tool for artists to strategically promote their music in a self-determined manner. Further research on the impact of Internet technologies on non-superstar artists may compare the influence, value, and impact of MRS with other means available to this artist group to promote their music. Future work could focus on MRS from the artists' perspective; with regard to the findings from the interview in Section 4, we believe that the results of such studies could reveal interesting insights and may constitute a valuable contribution to MRS research.

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