Organizing music, organizing gender: algorithmic culture and Spotify recommendations

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ABSTRACT

Spotify is self-reporting to have 232 million monthly active users in July 2019, including 108 million paying subscribers. Often naturalized by listeners as a mere window into great collections of music, Spotify is an intricate network of music recommendations governed by algorithms, displayed as a visual interface of photos, text, clickable links, and graphics. With the aim to analyze how three Spotify functions, related artists, discover, and browse, organize and represent gender while organizing and representing music Spotify is here investigated through empirical material collected in qualitative online ethnographic studies during 2013–2015. The article problematizes how music is organized in algorithmic culture and uncovers gendering that can ensue as a result of the service’s recommendation algorithms: creating closer circles for music consumption, and organizing music by similarities in genre and gender.

Finding new music and listening to music is a mediated process, whether we hear music on our stereo at home, in the supermarket, watch it on YouTube or in a live performance. Since media and media technology is indispensable in music listening it is constantly co-creating the experience of music (Taylor, 2001; Warner, 2003). While not always recognized as important for music listening, software is playing a central part of any computerized type of media output since web 2.0 (Chun, 2011). Scholars have labeled the marketing of cultural commodity like films, books, and music governed by software recommendations “algorithmic culture” (Galloway, 2006). Companies recommending books, like Amazon, films etcetera, like Netflix, or just any cultural commodity, like Google, are increasingly important in creating ideas about what cultural content is valuable and meaningful. Striphas (2015) has argued that value ascribed to culture is today determined by code hidden from us, owned by private companies. Music streaming services, like Spotify, are heavily relying on software algorithms protected by property rights to order and display its content. In this article, the software of Spotify is investigated through its effects, that is how content is organized to meet the listener by the functions related artists, discover and browse.1 The Irish folk-rock artist Damien Rice serves as an example to enter the recommendation system of Spotify’s algorithms.

Since software is integral for music listening today, one may wonder how software shapes the presentation of music in terms of power dimensions such as gender, sexuality, race/ethnicity, class, and nationality. Braidotti (2003, p. 61) argues that gender is a material

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experience and a symbolic construct. Gender organizes social and cultural life and is both felt and represented symbolically. According to her, the separation of the material from the symbolic and identity from society is false. Thus, feeling like a woman is not separable from ideas about femininity circulating at a certain time and place. Collins (1998, p. 63) has argued that gender is not distinct from other systems of oppression, like race and class. In fact, these systems articulate each other. When investigating the organization and representation of music as gendered it is therefore important to observe how gender intersects with, for example, race. Observing difference and same-ness is intrinsic to analyzing gendered culture. Braidotti (2003, p. 44) argues that ideas about difference within and between subjects are at the core of “gender” in culture and society. When difference is constituted between feminine and masculine so is similarity (between masculine and masculine). Gender as binary is central for meaning-making, according to Braidotti, even though binaries always are contested (Braidotti, 2003, p. 44).

Regarding material and symbolic dimensions of gender, feminist scholars in science and technology studies have studied how technologies are gendered. Technology intersects with the social and cultural formations of gender, in everyday use of technologies as well as processes of technological education and development of new technology (Wajcman, 2010, p. 144). Wajcman writes that in such processes “(n)either gender or technology are pre-existing” (Wajcman, 2010, p. 144). Here, the relationship between technology and gender as meaningful, and co-constituting is understood as involving multiple axes of power. Software, as a technology, is being co-constituted with gender, race, etcetera. Within a similar theoretical framework, McNeil (2007, p. 127) has argued that the masculinization of technology is an idea and practice not only evident in machines and institutions but also in symbols, language, and identity practices surrounding socio-technological relations. While McNeil, like Collins and Wajcman, does not see gender as an isolated power dimension she argues that the way technology is repeatedly masculinized is shaping technology as strongly gendered.

More specifically working on streaming software Eriksson and Johansson (2017, p. 177) has concluded that Spotify recommendations are dominated by artists labeled male in all genres and hereby furthers male-as-norm in the music industry. Their study shows that software is shaping socio-technological relations of gender for their users, making music streaming services worth discussing as technologies of difference in music today.

The aim of this article is to analyze how three Spotify functions, related artists, discover, and browse, organize and represent gender while organizing and representing music. Thus, how the software technology of the service genders the interface of music consumption. When the material for this article was collected related artists, discover, and browse were three prominent functions (Johansson, Werner, Åker, & Goldenzwaig, 2017). Drawing on a material of screenshots of particular pages and artists, and field notes taken while listening to Spotify on a daily basis, the article discusses how Spotify genders music. And how it builds on ideas of difference already existing in genre and artist representations of pre-streaming popular music culture.

These aspects are studied along three lines of inquiry: First the methodology, larger study, and context are presented. Then, critical analysis of music streaming and algorithms as well as current feminist studies of online media software are discussed as two research contexts shaping the analysis at hand. Next, the analysis is divided into three sections drawing on three Spotify functions, each deepening the understanding of how
gendered software recommendations structure the interface on Spotify. And finally, two concluding sections focus on gendered music streaming as part of algorithmic culture.

**Material and method**

The material analyzed here is part of a larger study aiming to understand music use online. The material consisted of focus groups with 80 young adults in Moscow and Stockholm, and material from their favorite platforms. The platforms studied were Spotify, YouTube, and VKontakte. The focus groups were conducted in 2012 and 2013, while material was collected online between February 2013 and March 2015 in order to map the networks and the possibilities provided for online music (Johansson et al., 2017). The contexts of this study were two cities and digitalization of music culture. The study found that streaming has become an increasingly popular way to listen to, and discover music, especially in Stockholm but also in Moscow. In Sweden, Spotify was found to dominate music listening among the participants of the focus groups, while in Moscow VKontakte was the most popular site for music listening.

In this article, analysis begins by focusing on how Spotify software organizes a particular artist’s network. This artist, Damien Rice, was discussed in some Stockholm focus groups as a good artist. Since Spotify adapts to the user by storing previous choices and basing suggestions on them it is hard to know what parts of the service are core-features, presented to all users, and what parts are individually adapted or location specific. To an unknown extent, recommendations discussed here have been adapted for me, based on my previous listening habits on Spotify. I joined Spotify as a paying subscriber in 2012 for research purposes but had been a nonpaying listener since 2009. Besides entry values such as where I live and my gender, what friends I had (Spotify was connected to Facebook in 2012), Spotify already had data about my listening habits. Research with bots (Eriksson & Johansson, 2017) has shown that Spotify recommendations tend to take on a gendered pattern for the listener independent of the given gender of the account holder but that genre listening shapes recommendations. Spotify is personalized and the organization of recommendations and relations between artists are based on accumulated choices of other users, thus, trying to find a “true” Spotify structure is impossible.

Mapping the logics of web sites through screenshots has been discussed as fruitful for digital methods by Moore (2014, p. 142) who argues that screenshots can be important analytical entities. Screenshots would not have been possible to analyze without the context of continuous use of Spotify over a period of time. The researchers’ experiences were documented in field notes, common in online ethnography (Hine, 2015, p. 89; Werner, 2015). This article relies on these two groups of materials together with findings in the focus groups. The analysis is situated in contemporary studies of algorithms and software.

**Algorithmic culture**

Investigating software for music streaming Morris (2015a, p. 178) has argued that the business model of music streaming services relies on libraries of music being nontransferable to other platforms, effectively making one’s record collection owned and organized by a commercial company. This, he claims, presents a game-changer for music culture. Software applications for music streaming change the ownership and durability of music
listening, now highly vulnerable to the companies’ policy development and commercial success. Further, he argues, recommendation systems give companies the power to determine the value of music as the new intermediaries of music (Morris, 2015b), gatekeepers of taste. Streaming services are central players in algorithmic culture, where cultural value is determined by processes partly human, partly machine. Mackenzie (2017, p. 8) argues that critical investigation of what commercial algorithms do has become a new strand of cultural theory devoted to machine learners. In an era where software is learning from experience, constructing complex systems functioning like black boxes (Mackenzie, 2017; Parisi, 2013) the logic behind recommendations on Spotify is difficult to fully know. Digital media is providing cultural content for streaming – for example watching and listening – but discoverability of content is heavily reliant on recommendations and search engines. These organize the large amount of content on Amazon, Netflix, and Spotify. Algorithmic forms of ordering cultural content has been labeled algorithmic culture, when algorithms decide ordering, visibility, and value ascribed to cultural commodity (Galloway, 2006; Hallinan & Striphas, 2016). Striphas (2015, p. 407) concludes that algorithmic culture presents itself as the effect of democratic processes, as if it is promoting culture consumed by many. While it is really private forces – companies – that are deciding the value of culture through software processes that remain hidden to us. Thus, algorithmic culture reduces decisions on taste to a few actors defining what is good and for whom, constructing social groups and cultural value in the process.

In studies of algorithms, it is relevant to ask: what combinations of software, hardware, and actors are encouraged and what does it mean? Someone accessing a website or service from a Swedish IP address is automatically assumed to understand Swedish and be interested in things Swedish, enforcing ideas on Swedish-ness in the process. Big data is not meaningful without the uses of it, as Brayne (2017) shows in her analysis of how police use big data in surveillance. She argues that the preexisting ideas that form what data is collected, for example who is considered a “risk individual” (Brayne, 2017, p. 986), are integrated into the effects of the data: who is surveilled and who is not. Assumptions about risk or more mundane things like national identity, language, and taste are not the only ideas algorithms speak to (and build on): through data mining users are mapped and approached accordingly in content as well as advertisement. The role of gendering in these processes has been studied but deserves more attention.

**Feminist studies of software and social media**

Linking software to power dimensions, Chun (2011, p. 2) has argued that software is omnipresent in new media but also impossible to map since software processes are infinite, and difficult to conceive, because of their invisibility to the user. Softwares are understood by Chun as mediums of power since they provide one way to navigate a complex machine world. The navigation software provides is not self-evident or neutral but based on choices.

One way that software helps the user navigate is by ordering identities in systems of gender and race. Nakamura (2002) argues that online gendered and raced identities often are presented as “menus” to choose from. At the time of her research, such choices were often visible in the interface in games or chatrooms and after the user made their choices the software used them to present the user with some options and not others. Nakamura concludes that identities are perceived as clear-cut choices in this type of software, man/
woman, white/black/Asian, making it impossible to represent the fluidity of everyday identity, identifying for example as both Asian and black, or neither man or woman. Identity consisting of one gender, one race, one hometown, is what the software built on to understand users. Software’s way of coding identity selections was integral in the shaping of web 2.0 (Nakamura, 2002). These choices have stayed on in the development of social media even though they may be less visible. McNicol (2013, p. 205) states that gendered choices are inscribed differently in social media systems, choices are more or less required by different services and the options are formulated differently on social media like Facebook, Twitter, and Diaspora. Therefore, the effects of gendering on social media can also be different. Bivens (2015) has investigated Facebook software paying interest to how Facebook is organized as gender binary. She has argued that one effect of the algorithm people you may know on Facebook is that it puts survivors of sexual harassment and violence in contact with their perpetrators, possibly prolonging the trauma. Paying attention to gendering effects of software in social media Bivens (2015, p. 715) argues that social media software is ripe for feminist analysis, and that social media software is deeper manifestations of power than the surface content. In her research on Facebook Bivens (2015, 2017) investigates how software enacts normalizing logics, for example by offering several choices for gender identity while still hiding a binary division of users in terms of gender in the original code.

The secrecy may also be analyzed as part of the meaning of software (Chun, 2011, p. 5). The interface is presented as neutral, normal, when in fact it is the result of a series of choices made with purposes that are hidden and assuming difference in terms of identity. Bishop (2018, p. 81) has argued that the algorithm of YouTube rewards normative white femininity in beauty vloggers by recommending it more often, in line with desires of brands and advertisers who deem this femininity as more marketable. It does so by the choices made by the algorithms, notably what videos are suggested to viewers watching beauty vloggers.

Three functions

On Spotify, music listeners can make playlists, save favorite artists, and albums in their archive called my music and listen to radio channels, or playlists put together by themselves, other listeners, or by Spotify. In order to discuss how recommendations are structured as socio-technological, and as such building on and furthering some ideas of gender intersecting with race and nationality, I will address three functions on Spotify. The functions are: related artists that lists artists understood as similar to the one you are already listening to, discover that suggests personalized music based on previous listening and what Spotify deems similar to that listening, and the first page called browse that assembles Spotify’s most important features.2 This selective method of approaching Spotify through functions was motivated by the central place of these functions at the time of the study and how they were discussed in focus groups.

Who is kin? The related artists function

On Spotify, at the time of the study, the related artists function suggested artists presented as similar to the one you were currently listening to. While all three functions analyzed in this article were modified during 2013–2015 the main principle of them remained intact.
In some ways, they stay important for Spotify in 2019 even though they are labeled differently (related artists is now called fans also like) and their placement in the interface differs (browse has been moved, discover is now discover weekly). The idea that music is connected to other music is the core of Spotify’s ordering of music through recommendations in related artists and discover. In the first year of material collection, I listened to Irish folk-rock singer Damien Rice – because he was popular among the participants in the Stockholm focus groups. When I first opened Damien Rice’s profile I noticed that all the artists presented by related artists were white-ish men – not a noteworthy or unusual observation in itself. Feminist music scholars have concluded that the genre rock is masculinized, white washed, and also dominant on the western popular music market and in music journalism (Coates, 1998; Leonard, 2007). The most popular rock artists are often presented as white men, solo artists or in groups, even though the type of masculinity they feature varies in different types of rock, from metal to folk. Artists identified as women, often but not always representing femininity, are also present, but often marginal in rock. Music genres interpreted as masculine, like rock, have often been considered of higher value and more authentic than feminized popular music genres like pop (Biddle & Jarman-Ivens, 2007, p. 3).

The idea that some artists were related intrigued me, the word “related” implies kinship, kinship in turn is often imagined in terms of gender, nation, and race. And while white rock music seldom is described as white, it can be labeled as national, like for example British rock and pop music (Stratton, 2010, p. 27, see also Zuberi, 2001). Stratton (2010) argues that when calling music “British” there is an underlying assumption that British means white – if a group or artist is not white this has to be pointed out. Ascribing music to a certain nation also usually takes the sounds of that music into account. Music may be perceived as sounding British, like brit pop, or not, like bhangra, both genres are produced in the UK but understood differently in terms of nation and race. Artists that are seen as related by Spotify may therefore be so – in terms of sharing group identities based on gender, nation, class, and race. The white folk-rock men connected to Damien Rice by Spotify caught my interest and I started keeping track of the network of artists unfolding with Damien Rice as starting point. He will be used as an example to discuss the related artists function.

I concluded that Damien Rice was presented as male by Spotify because he was referred to as a he, and so were most artists suggested by related artists on his page. Artists not referred to as he or she are uncommon on Spotify, still, in cases such as popular transgender artists like Antony Hegarty (of Antony and the Johnsons) Spotify refers to Antony by name, not using any pronoun in the text describing them. Spotify operates with a binary idea of gender while recognizing some openings for alternatives outside the binary, without naming them. Race was not explicitly addressed in the descriptions of the majority of artists related to Damien Rice. And since they appeared white in their photos not addressing whiteness reinforces white as an invisible norm, reinforcing the idea that white people are “outside” of race, and race belongs to the other. Sometimes nationality was used to describe artists, “Irish”, or “Czech” (while Tracy Chapman was “African-American”, a racial signifier), and their nationality could, as Stratton (2010) argues, be seen to contain a racial presentation, Irish implies white and Irish unless some other feature is presented. Sometimes class was mentioned in terms of background, when artists were described as having a “working class background”.
In the first months of 2013, I followed Damien Rice’s related artists around by mapping their (in turn) relations in three steps and observing genre affiliations as well as representations of gender, race, and nationality in their pictures, names, and biographies. I also listened to their music, even though this article does not focus on the in-music qualities of sounds and lyrics. My mapping showed that predominantly male artists, predominantly white artists, predominantly singer-songwriter and folk-rock artists and predominantly solo artists were related to Damien Rice within three steps of recommendations. Musically a slow tempo folk-rock featuring acoustic elements and emotional lyrics (often about romantic love and loss) in the English language dominated. The style of most popular songs of these artists contributed to presenting a brooding, emotional, and sensitive yet strong masculinity easily recognizable from singer-songwriter and folk-rock genre tradition. The nationalities of the artists related to Damien Rice were mainly European or North American. The age and generation of the artists varied: older artists not actively writing music anymore like Bob Dylan and Nick Drake appeared, so did Glen Hansard, The Frames and David Gray and even though there was an Irish white dominance a Swedish artist with parents from Argentina, José Gonzales, and a female African-American artist, Tracy Chapman could both be found in the network (they were presented in this way).

Later on in the study, in March 2015, there was one female white solo artist in the top four related artists to Damien Rice: Lisa Hannigan who is Damien Rice’s ex-girlfriend. In February 2013, there was one artist presented as female in the top five related artists to Damien Rice: Marketa Irglova (one half of The Swell Season, a group also within the network). Marketa Irglova performed alongside Glen Hansard in the popular Irish movie Once: portraying love and Irish folk-rock music. Apart from these two women, Tracy Chapman, and some Irish folk-rock bands with male and female members, very few female artists appeared within three steps of Damien Rice during the years of study, even fewer black or brown artists appeared (only the two artists already mentioned). The related artists function is according to an interview with Spotify founder Daniel Ek (Gelin, 2012) based on accumulation of choices that is fed back to listeners. This is a common practice in algorithmic culture, and his explanation does not give away what choices the algorithms are making. The software appears neutral, and is unknown, but based on multiple choices fed into preexisting number of programming presumptions. As Striphas (2015) has argued the recommendations do not only mirror accumulation of choices, it builds on the companies definitions of commodities, social groups, and categorizations of both, genre being important on Spotify.

In the focus group, study participants described the related artists function as a good way to discover new music. Finding new good things to listen to is every music lover’s dream: therefore, the related artists function as such shapes the use of Spotify. In the case of Damien Rice, the function promoted choices that were similar to Damien Rice in terms of how genre, gender, and race were presented. The latter two categories take shape through the genre category. Genre rules associate the style of folk-rock Damien Rice performs with Irish, British, and North American nationality, whiteness, and masculinity. But there are many more female (mostly white) folk-rock singer songwriters that do not appear around Damien Rice, thus genre as explanation does not fully hold up. As Striphas (2015) has argued algorithmic culture hides an elite system of unknown choices made by
algorithms behind the presumption that the “users” are in charge of culture through the accumulation of choices. The presentation of recommendations and top choices in cultural consumption presents ideas about cultural value, as well as of social groups (Strifhas, 2015, p. 406). In related artists, cultural value around Damien Rice is white and male, with few exceptions. And the female artists often suggested by related artists (Lisa Hannigan and Marketa Irglova) are also presented as romantic partners to Damien Rice in real life and Glen Hansard on screen, rather than successful on their own terms.

**Who are you? The discover function**

The discover function presented a list of personalized suggestions, you could at the time of study find it on the browse page, click on it and enter personalized suggestions. It recommended artists and songs to listen to, based on previous account activity, the collected habits of all listeners and constructed ideas about music similar to the one you liked (thus seemed to build on related artists). As discover is personalized – adapted to previous patterns on the account – and related artists seem to be based on national user habits (Gelin, 2012), my use of Spotify at the time was providing a unique interface. In short, based on my listening habits, nobody else would get the exact same suggestion pattern as I did. On the other hand, the pattern displays the network of artists and genres that Spotify recommendations build on and some of the re-occurring principles of the algorithms. Thus, while geographical points of reference and my already existing choices are particular the logics of discover display algorithms all listeners meet.

Discover implies, by name alone, that there is a possibility for the listener to discover new music. But the suggestions made to me during the period of the study were rarely artists that were unknown to me. Suggestions like “You listened to Beyoncé maybe you would like Brandy” can almost seem to mock the listener, and discover rarely led me to discover artists I did not know. In order to experiment with the discover function, I listed to Spotify every day, according to my own taste in periods and to particular artists and genres I would not normally listen to in other periods. During the autumn of 2014, I listened to a large amount of K-pop, mostly groups with several female members. Within a day discover suggested young South Korean female pop artists back to me, and a few young men. The artists Spotify recommended to me were popular chart successes in South Korea, but not all of the songs were recent releases, this can be understood as a result of my national position, I might have gotten more up-to-date suggestions had I been on a South-Korean IP address since national listening patterns are used in the recommendation algorithms. Accordingly, when I stopped listening to K-pop the suggestions in discover changed. Thus, discover was in 2014 a very temporally sensitive function picking up on recent listening habits. Earlier on in 2013 discover would sometimes suggest music that I had not listened to in a long time, also telling me so “you have not listened to x in a while”. This highlights that Spotify had been tuning the algorithm during the period: experimenting to find the now-ness of recommendations. Being able to use surveillance knowledge in real-time is a consequence of big data (Brayne, 2017, p. 991). It is easy to monitor a certain period, and the present is often seen as more relevant than the past. While related artists was a function producing patterns that did not change that much over time (around Damien Rice) discover was time sensitive and picked up on recent habits of the individual listener. While this distinguished discover from related artists similarity in genre, gender, and race was recommended by both functions.
We are Spotify. The browse function

The first page of Spotify was called browse and contained a banner with announcements on top, and then content consisting of an overview of popular playlists, new releases, news, top lists, genres, moods, and the discover function. Browse promoted the main guiding functions, highlighting some playlists, new releases, and genres. Opposed to early YouTube’s centrality of the search function, Spotify aimed to help the listener by arranging the music like in a record store (but Spotify has a search function too). Forefronting some genres and new releases remediated the organization of a physical record store. The playlist was inspired by early iTunes, and the discover function can be seen as being based on Pandora’s business idea created in 2000, aiming to find the next similar (but not too similar) song. Avdeeff (2012) concludes that personalized music consumption has grown with digital music use. Her research shows the ease with which a listener can personalize one’s listening, picking the next artist or song on the go, the listener understands this as an advantage of digital music use: having a record collection to choose from in one’s pocket. Browse was a function that aimed to present and organize this collection of music for the listener.

Browse was clearly shaped by the day and time one entered it: by advertising playlists like “Morning commute” in the morning and “New music Friday” on Fridays, and by the news (Avicii releases a new single on so-and-so date). The top advertisement banner took up a lot of space in browse and often presented a new album or playlist. All of these ways of guiding the user can be read as aiming to create an experience of time. Browse presented Spotify as a place within time. It strived to be part of the listeners’ everyday rhythm and up-to-date (see Johansson et al., 2017, chapter 2). While browse differed between countries, by presenting popularity of songs divided by countries under top lists, it seemed to appear the same for all users in one country (except in discover). Browse did not order suggestions by similarity. It presented a variety of artists and genres, while at the same time still portraying ideas of genre, gender, and race. For example: the genre soul was during the study represented by a logo shaped as a woman’s head – with afro hairstyle and hoop earrings implying a black woman – while rock was represented by an amplifier. Music genres are established by rules that are based on social understandings (Fabbri, 1981), and as such not given by musical sound or style only. Still, stylistic components in the music do play a part in genre classification. Genre groupings also often hinge on for example nation, race, class, gender, and sexuality (Brackett, 2016, pp.3–4). To illustrate playlists found under the link to the genres soul and rock photos were used. The top playlists under the genre soul were illustrated with African-American artists, often men and women smiling, while the top playlists under the genre rock were illustrated with guitars, empty houses, and white men. Ordering and representation were significant for how Spotify portrayed music for the listener entering through browse, even though browse displayed different routes available. The routes the listener could take were often illustrated visually through ideas about different social groups representing different music genres. Further, most choices Spotify’s software made when targeting the Swedish audience on browse through news promoted Swedish artists and artists from the English-speaking world. National diversity was not promoted by browse. There was a mainstream dominance promoting pop, rock, and EDM but the artists recommended were not necessarily only mega stars of chart pop. The promotions can be assumed to mirror expectations of the Swedish Spotify listeners’ habits by A & R and record companies. Without being sure about how the software selects, and in what pool of different choices the selections are made, browse built an idea of Swedish taste and created patterns of listening, by urging listeners
to notice for example Avicii’s new single. Both the invisible algorithmic choices, and the visible interface design and its portrayal of music and artists nudged the listener in different directions according to taste and identity. Still, the logic of browse was more diversified than the two functions previously discussed and it seemed that browse aimed to speak to multiple (Swedish) audiences at the same time.

**Gendered music streaming**

The functions related artists, discover, and browse, as has been shown, strengthen ideas about genre affiliations of artists and songs. They render presumptions about taste in your nation of IP origin important but invisible. They do this by feeding back other listeners’ choices, algorithmic choices and choices made on your account as recommendations of new music. These recommendations are ordered in terms of similarity, this similarity is musical but also include similar representations of gender and race. What possible music listening does this create? One answer is that the functions result in a feedback loop: following related artists from Damien Rice led me back to Damien Rice every step of the way. The use of genre and previous choices as cornerstones in Spotify’s construction of similarity are here found to reinforce connections between artists similar in terms of gender and race. The recommendation functions on Spotify make similarity central and in that process they emphasize difference. When Tracy Chapman appears as related to Damien Rice she really stands out as a black woman. While genres can be broad, related artists creates networks where most artists are very similar to the first artist of choice. For example: Rihanna leads you to the top-related artist Beyoncé, who leads you to Destiny’s child, bringing you to Kelly Rowland who leads to Ciara and Ciara leads you back to Kelly Rowland. No male artist, white artist, and no artist from another generation, nation, or genre are included in this circle of recommendations.

The recommendations of Spotify reflect patterns already known, premieres very famous artists and rarely gives surprising advice. Also, since the recommendation system is accumulated over time few debuting artists will appear though related artists or discover, and neither will old forgotten artists. Rose (1994) has argued, in relation to hip hop, that musical genres can be racialized in a politically progressive way, fighting racism, and simultaneously contain sexist messages fixing gendered racial stereotypes. Hence, gendering and racialization of genres may have progressive potential and essentializing dangers at the same time. What can be observed in Spotify’s functions is that genres become narrowly gendered through related artists and discover. In a record store Beyoncé or Ciara might be placed next to a male artist within mainstream R&B, or a not so popular artist – they would still likely be categorized as part of an African-American popular music tradition – but on Spotify related artists lists them next to young African-American top-selling females. Participants in focus groups argued that they could find immense amounts of music through the Internet, and researchers have pointed out a heightened possibility for musical eclecticism supported by digital music formats (Avdeeff, 2012). But, it seems doubtful that the software of contemporary streaming services supports these practices. While listeners may perceive Spotify as liberating, and use it in such ways, the functions analyzed here limit listening patterns by building gendered and racialized connections between artists and genres. Users of Spotify may still listen to a variety of music that they find out about for example through other media, through advice from friends or by going to live performances. Also, they may actively use the search function to find artists or explore different genres starting through browse. But this is not what Spotify invites them to do.
Conclusion

The business idea of companies selling streamed music has been scrutinized for its capitalist logics (Morris, 2015a, 2015b). Claims are that algorithmic culture hides how companies shape cultural value and social groups through the algorithms while presenting them as “choices” of audiences (Striphas, 2015). By promoting similarity, emphasizing what is popular right now and building on the genre system, Spotify’s network of music aims to simplify listening. At the same time, Spotify organizes gender, nationality, and race in music culture. This is done materially by connections in the interface, and discursively by representations of artists and genres. While harmless on the surface, when considered more closely Spotify’s functions for recommendations help reconstruct dominating genres like rock as male-focused, masculine, and white. This gendering of rock has material implications in listening experiences and further a masculine rock discourse. While the aim of Spotify may be to personalize listening and guide their users to music they will love, the result is enhancing the already existing gendering of popular music genres. Acknowledging that popular music genres are shaped by nation, race, gender, etcetera (Brackett, 2016), they also articulate historical injustices such as colonialism, slavery, sexism and oppression of women, and violence against transgender persons. The organizing and representation of musical taste and social groups on Spotify are thus not coincidental, or innocent, but reinforcing patterns of power.

Notes

1. Empirical material discussed here was collected within the research project “Music use in the online media age,” 2012–2015, funded by Riksbankens Jubileumsfond, and conducted with Sofia Johansson, Patrik Åker and Gregory Goldenzwaig. The project conducted focus groups and online ethnography (on VKontakte, Spotify, and YouTube) mapping the meaning of music online. The main results are discussed in Streaming Music (Johansson et al., 2017).
2. The functions described here mirrors Spotify in 2014–2015 as it looks in a computer interface for paying subscribers. The material about the related artists function was collected over a longer period of time, starting in February 2013.
3. Male artists dominate popular music (Smith et al., 2019) and most studies put women/others at around 20% among performing artists. The argument here is not that algorithmic culture distorts reality (or not). How algorithmic culture is gendered and what is presented as recommended music is in focus.
4. Debuting artists may appear on browse.

Disclosure statement

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Notes on contributor

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