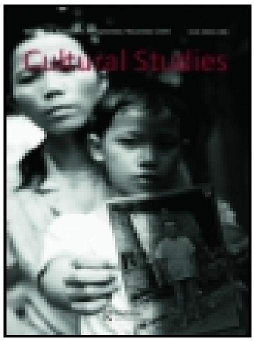

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Seeing like an infrastructure: avidity and difference in algorithmic recommendation

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ABSTRACT
As the influence of algorithmic systems has grown, critics have come to appreciate that algorithms are not autonomous technical forces, but rather heterogeneous sociotechnical systems. The people who build and maintain these infrastructures play integral roles in their functioning: in the tight and continuous cycles of contemporary software development, the thinking of developers shapes how data drives 'data-driven' organizations. This article contributes to contemporary debates on infrastructural politics by describing how the vernacular social theorizing of one group of developers tangles with their technical work. Drawing on ethnographic fieldwork with developers of music recommender systems in the US, I examine how they understand the variability of music listeners. I find that the dominant frame for making sense of listener variation is *avidity*: a level of enthusiasm for music, which manifests as a willingness to expend effort in finding listening material. For people working in this industry, avidity displaces other ways of understanding human variety – particularly demography. While the technical communities behind these systems were predominantly white and male, they understood the difference that set them apart from most users to be their enthusiasm for music. Centreing avidity provided a way to claim elite cultural status and to avoid talking about demographic diversity. It also reflects the infrastructures through which recommender system developers know and intervene upon their users: avidity is what users look like when seen through interaction logs. Less avid users leave fewer traces, and the goal of the recommender system is to encourage them to leave more. As a result, the figure of the less avid listener serves to justify increasingly rapacious data collection practices.

KEYWORDS Recommender systems; avidity; algorithms; infrastructure; music

The numbers

In May 2014, after years of pressure, Google finally released the numbers. The search conglomerate had long declined to report statistics on the demographics of its employees, and when the company finally did, the numbers explained why: they were 'not good' (Bock 2014, Jacobson 2014), showing a workforce that was overwhelmingly white and male. Among 'technical'

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employees – the engineers and scientists who wrote and designed the company's software – demographic diversity was even lower, confirming the suspicions of those who had pressed for the numbers' release: these lucrative, prestigious, and increasingly powerful jobs were going to a very narrow segment of the population (Chou 2013). Over the following months in Silicon Valley, many other companies followed suit, with similar results, and 'the numbers' became practically synonymous with demographic statistics.

The problem the numbers represented was essentially comparative. They were 'bad' when the inside of a company failed to match the outside. Setting the terms of this comparison was thus a key concern for corporations and their critics: What counted as 'inside' or 'outside'? When companies presented their numbers, they often foregrounded the overall diversity of their employees, obscuring the fact that feminized and racialized 'soft' jobs were offsetting the demographic homogeneity of their technical teams. That lack of diversity in technical teams was customarily explained as a 'pipeline problem': the pool of well-trained candidates that a company might hire from was already homogeneous, they argued. Conveniently for tech companies, this framing located the problem of diversity outside their walls, and it motivated a host of publicly funded programming education initiatives, which promised to provide them with more ready labour (Miltner 2019.).

While these concerns about workplace diversity focused on the fairness of the labour market, another line of critique was growing among those concerned with the algorithmic systems that most of these companies produced. The demographic homogeneity of technical teams was not only a problem of access to good jobs; it was also a source of potentially disastrous broader consequences. In the popular press, critics attributed a series of high-profile algorithmic failures to the lack of diversity on development teams. When Microsoft launched a chatbot with the avatar of a teenage girl that 'learned' from social media interactions, women could have predicted that coordinated abuse would turn the bot into an amplifier of violent, misogynist invective (Alexander 2016). When Google Photos automatically tagged a photo of a pair of Black friends as containing 'gorillas', a team with more Black developers might have caught the problem before it reached the public (Lee 2015). As algorithmic infrastructures spread into more and more areas of everyday life, the limited worldviews of homogeneous teams posed a growing threat to people affected by these systems.[1]

Where earlier critiques of algorithms had pointed to their inhumanity as a problem, this new wave of critique was predicated on the idea that algorithms were in fact sociotechnical systems, in which human agents played crucial roles. The most well-known algorithmic systems are under continuous revision, constantly being remade not only as machine learning 'learns' from new data, but as teams of developers respond to various metrics and organizational demands. As a result, we can think of developers themselves as part of these algorithmic infrastructures: their mental models, backgrounds, team dynamics, and organizational imperatives play key roles in how 'algorithms' take shape, respond to the world, and change over time (Seaver 2017, 2018b). The 'black box' is full of people who design, build, and maintain it; algorithmic systems can extend and scale up their all-too-human biases and worldviews (Gillespie 2014, O'Neil 2016, Noble 2018).

The composition of development teams – and the differences between them and those 'outside' of them – has thus become a key concern for the contemporary politics of algorithmic infrastructures. These people, and the way they make sense of the world, play an important role in determining what consequences algorithms have in broader social contexts. If we want to understand how algorithmic infrastructures take shape, then we must attend to the vernacular social theorizing of developers, which informs and is informed by their technical work.

In this article, I examine how people working within algorithmic infrastructures make sense of these concerns: How do they think about the composition of their teams, the differences between themselves and their users, and the resulting technical consequences? I suggest that their vernacular social theorizing is entangled with the infrastructures that they build. As they think about what sets them apart from their users, and how that difference might be ameliorated, they find answers in the infrastructure.

My argument draws on several years of multi-sited ethnographic fieldwork with developers of music recommender systems based in the US, which took place during this dramatic shift in the popular perception of algorithms. These systems provide a useful case for thinking through sociocultural concerns both because they are plainly cultural and because recommender systems have long been figured as 'post-demographic' technologies, which promise to obviate traditional marketing categories of race, gender, and age. People who work on these systems are generally reluctant to recognize demographic categories as technically salient. Instead, I suggest, they have come to understand the difference between themselves and their users primarily in terms of musical enthusiasm, or *avidity*.

Avidity manifests as an interest in musical exploration or a willingness to expend effort in pursuit of new music. In the logs of interactional data on which recommender systems rely, it is apparent in the quantity of users' interactions with a system. The embrace of avidity and rejection of demography shapes how recommender systems function, how developers understand their social position, and how 'insiders' come to know things about 'outsiders'. It is a social theory that makes sense from the perspective of an infrastructure that measures and works to increase the quantity of user interaction. In other words, as they think about what distinguishes themselves from their users, developers come to identify with the object of their labour – they try to 'see like an infrastructure'.

Several months after Google released their numbers, in October 2014, I was sitting in an unremarkable conference hotel in Foster City, California – a precisely planned suburb built into the western marshland of the San Francisco Bay, mid-way between literal Silicon Valley in the south and its metonymic extension to San Francisco in the north. I was attending RecSys, the annual conference for researchers who design and build algorithmic recommender systems, and Foster City was slowly sinking into the bay (Shirzaei and Bürgmann 2018).

RecSys had, since its founding in 2007, been a research community where industry and academia met; it was not uncommon for graduate students to present research conducted as interns for the tech companies that would eventually hire them, or for professors to leave their academic positions for well-funded research jobs at companies like Google, Facebook, or Netflix. This year, thanks to its Silicon Valley location, the conference had sold out; according to the organizers, half of the 500 attendees were employed in industry. Although the conference did not collect demographic data, the attendees seemed to match the diversity of the industry surrounding us, with women perhaps even less well represented. All of the conference's keynote speakers were men, and among the panels dedicated to industry, only 2 of 11 speakers were women.

Recognizing the growing public critique of tech companies in general and recommender systems in particular, the last of these industry panels was dedicated to 'controversial issues', and the panelists debated questions like whether algorithms could be 'evil', if it was ethical to run experiments on users, and whether 'filter bubbles' were a real threat to the diversity of cultural materials that recommender systems might recommend. At this point, one of the audience members stood up and asked the panelists when their employers intended to release their diversity numbers.

While the question had been posed as a hard one, occasioning nervous laughter from the audience, the panelists answered with ease: by now, many months into the ongoing release of numbers, their employers had already put out diversity reports or were on the verge of doing so. Workplace diversity was an important issue, the four male panelists averred, but it was not particularly relevant to recommender systems. A moderator requested that the audience keep their questions related to recommendation, to modest laughter from the room.

Surprised by this response, I raised my hand to ask a follow-up question: While the panelists might be committed to workplace diversity for its own sake, did they think that diversifying their teams would have any effect on how their products actually *worked*?

'I hope we're not injecting DNA into our code', one of the panelists responded, using the idiom of biological essentialism to support an argument for technological essentialism: the basic stuff of diversity was quite distinct from the basic stuff of software.[2] If a diverse workplace was desirable, in his eyes, it was not because it changed the work. Following the political theorist Cristina Beltrán (2014), we can say that this common understanding rendered diversity an *aesthetic* problem: it might be important for a company to appear diverse, but this was a representational concern, divorced from the 'real' work of the firm. In the end, the panelist suggested, the technical functioning of recommendation 'really comes down to the data, and the feedback, and how you process that information to make your product better'. Those features of recommender system development, he suggested, had nothing to do with the backgrounds of the people involved.

Later on, I brought this answer up with Bruno, the research director at a company I call Willow, a personalized radio service.[3] He strongly disagreed with the panelist, who had worked in recommendation, but not on music. Of course the diversity of teams mattered to the quality of their work, Bruno told me: for instance, he was from Germany, while his colleagues came from many other countries; because they were all big music fans, this meant that they could readily assess whether their system was making reasonable recommendations for music from their countries of origin. Their diverse cultural backgrounds were an asset for the 'sniff tests' engineers frequently performed while coding: running quick sample queries to confirm that the system was working as intended. Diversity mattered to the functionality of music recommenders because that function was explicitly cultural. But the diversity Bruno endorsed was not framed in terms of race or gender, but rather national origin. If diversity mattered, it was important to specify what kind, and why.

The magic

Modern algorithmic recommendation was invented, by most accounts, in the mid-1990s with the advent of a technique called 'collaborative filtering' (Goldberg *et al.* 1992, Resnick *et al.* 1994, Shardanand and Maes 1995). To this day, collaborative filters remain the archetypal recommender system: students learn to build them in machine learning classes, papers at RecSys present improvements in the same basic paradigm, and corporations still use collaborative filtering, with some augmentation, as the heart of their recommendation infrastructures.

The basic premise of collaborative filtering is simple: people who liked the same things in the past will probably like the same things in the future. Collaborative filters analyze interactional data, like ratings given to movies or the time spent listening to a particular musical artist, and find patterns in it. When users share much of their listening history, their inferred preferences can be used to make recommendations to each other.

I often heard collaborative filtering described as 'magic'. This magic consisted in its ability to transform 'thin' interactional data – like playcounts or time spent listening – into recommendations that seemed to be informed by cultural details the system knew nothing about. A collaborative filter with no knowledge of musical genre, for instance, could use patterns in listening histories to recommend heavy metal to heavy metal fans; with no demographic data about users, a collaborative filter for online shopping might recommend the same products to people who all turn out to be pregnant women.

These 'aha' moments, where legible cultural clusters emerge from analytic systems, are common features of data science rhetoric. But while apparently demographic outputs might indicate that a system is working correctly, demographic information is generally rejected as an input for recommender systems. Since their origins, recommender systems have been presented as a way to transcend demographic classification. As two of the originators of collaborative filtering wrote, 'simple demographics don't begin to tell the story of individuals' (Riedl and Konstan 2002, p. 109). Given the availability of online interactional data, demographic profiling was not only less accurate, but also irresponsible; it was described as akin to racial profiling in policing, springing from 'the same lazy, prejudiced philosophy' (Riedl and Konstan 2002, p. 112).

Growing alongside the World Wide Web, collaborative filtering shared its post-demographic framing: the idea that virtual communities of anonymous users would obviate demography, allowing individuals to pursue their own distinctive interests, 'free' of qualities like race or gender that were figured as burdens carried by people who were not white or not men (Nakamura 2000). This tendency was not new with the internet; although the early papers on collaborative filtering betrayed no knowledge of this, the post-demographic, fine-grained modelling they espoused fit well within long-standing trends in market research (Arvidsson 2002).[4] This rejection of demography persists today; for instance, in a recent press tour, Netflix executives described how the service orients itself toward a set of roughly 2,000 data-derived 'taste communities' because 'demographics are not a good indicator of what people like to watch' (Lynch 2018). Researchers often remark that incorporating demographic data does not improve the function of a recommender; to the extent that demographics matter, they should already be reflected in behavioural data. They are thus figured as either redundant or a source of error predicated on an unseemly demographic essentialism. As Alondra Nelson wrote in 2002: according to the dominant ideology of digital technology, 'race is a liability […] either negligible or evidence of negligence' (p. 1).

Of course, the fact that most recommender systems do not use explicit demographic data does not mean that they are uninfluenced by race, gender, or other dominant social categories. As scholars have argued about 'post-identity' claims in many domains, powerful social categories often re-emerge from systems premised on their unimportance, in modulated or hard-to-contest forms (McRobbie 2004, Daniels 2015, Cheney-Lippold 2017, Cohn 2019). Not only is the ability to be 'post-identity' marked as white and male (cf. James 2017), but in a social setting where these categories have broad influence, *all* data about people and their behaviours is 'demographic' to a certain extent (Barocas and Selbst 2016, Benjamin 2019). A user's listening history may not explicitly include data about their race, for instance, but the music they listen to is shaped by the social fact of race – in the structure of the music industry and in broader patterns of taste.

As a result, the fact that a recommender system could recognize a cluster of listening behaviours that corresponded to 'hip hop' – a racially marked genre – would be taken as evidence of the system's functional 'magic'. But my interlocutors – who reflected the broader industry in that they were overwhelmingly white and male – were extremely wary of making any intentional effort to either collect and incorporate data about their users' race or to infer their race from the data they already had. 'Racial profiling' served as a shorthand concept for a racial awareness that was, in the context of technological development, to be avoided.

The fact that racialized or gendered listening patterns exist and are thus identified by collaborative filters is not in itself necessarily a problem. As Oscar Gandy has argued, 'not all efforts at segmentation and targeting are associated with commercial exploitation, marketplace discrimination and cumulative disadvantage' (2011, p. 133). In other applications of related technologies – like predictive policing, for instance – the dynamics of biased data collection, extreme power differentials, and self-reinforcing feedback call for much stronger critique (cf. Brayne 2020). Nevertheless, recent critics of algorithmic recommendation have argued that these systems' committed demographic agnosticism may be obscuring the role they play in mainstreaming vicious identifications of racial or gender difference: for instance, by making white supremacist content easier to find or encouraging users to segregate and pursue more extreme racist or misogynist materials (e.g. Chun 2018, Tufekci 2018).

The pyramid

Although demography had nominally been pushed to the side, recommender system developers were still concerned with how their users collectively varied.

In 2011, I interviewed Peter, a senior engineer at the music recommendation company I call Whisper. Sitting in one of the start-up's brick-walled meeting rooms, he told me that the biggest challenge for recommender system design at the time was the fact that listeners were not all alike. Not only did people have preferences for different styles of music, but they had different styles of musical preference.

'There's a pyramid of listeners', Peter told me (see Figure 1). At the base of the pyramid – the largest group – were people he called 'musically indifferent': they did not particularly care for music, and they wouldn't mind just not listening to anything. Moving up through the pyramid, he passed through 'casual' and 'engaged' listeners, before arriving at the smallest group, at the top: 'musical savants'. The name indicated the status ascribed to these listeners, who were extremely avid and knowledgeable – whose 'whole identity is wrapped up in music', as Peter put it. Savants were cool, enthusiastic, and knowledgeable.

The challenge, Peter explained, was that all of these kinds of listeners wanted different things out of a recommender system. 'Savants' might be interested in something to aid their browsing, to introduce them to more obscure music; 'casuals' might just want some music to play inoffensively in the background, without much effort. 'In any of these four sectors', Peter told me, 'it's a different ballgame in how you want to engage them'. What worked for one group might fail for another.

When we spoke in 2011, Peter couldn't remember where he had first seen the pyramid. But over the next few years, I kept encountering it, casually mentioned by PhD students in interviews or shown on the slides of conference presentations. I eventually traced it to a book, titled *Net, Blogs, and Rock 'n' Roll*, published by music industry consultant David Jennings in 2007. Jennings had taken the data for the pyramid from a 2003/2005 market research study called 'Project Phoenix', conducted by UK media conglomerate Emap. Project Phoenix, as the name suggests, had been intended to help revitalize an apparently dying music industry, gathering data about the changing listening habits of people in the UK.

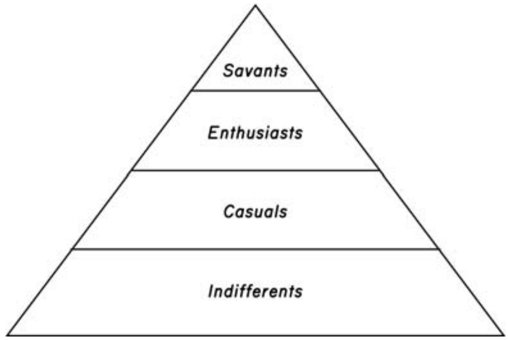

Figure 1. The avidity pyramid, redrawn from Jennings (2007, p. 46).

In his 2007 book, Jennings was circumspect about the generalizability of the Project Phoenix categories: 'They represent a snapshot in a particular country – the UK – at a particular time. Such categories are always evolving' (p. 31). However, he continued, 'Whether or not the subgroups are empirically watertight does not matter […] the main point here is simply the *existence* of different groups' (Jennings 2007, p. 32). The takeaway, for Jennings, was not that listeners could be distinguished in precisely these ways, but rather that they could be distinguished at all: 'Music listeners are not an undifferentiated mass' (2007, p. 32). But as the pyramid travelled, people like Peter used it to think with, reconciling it with their own intuitions about music listening. Jennings' qualifications fell away, and the pyramid became re-shaped into a commonsense fact about musical audiences. While people like Peter might be able to point to the fact that the pyramid originated from a study, they were not concerned with assessing that study's validity or methodology; the pyramid travelled thanks to its intuitive appeal, not as a result of its scientific standing.

I use the term *avidity* to capture the set of loosely related ideas about musical enthusiasm, cultural status, and knowledge represented by the pyramid. Avidity did not necessarily correspond to any particular genres or artists – in theory one could be an avid fan of any sort of music. In this, it was roughly analogous to 'omnivorousness' in the sociology of taste (Peterson and Kern 1996): listeners distinguished themselves not by their favourite genres, but by their attitudes to the cultural field itself. And in practice, avidity often functioned as a vernacular equivalent to omnivorousness: 'savant' listeners were generally considered to be more exploratory and diverse in their listening than their less avid counterparts.[5]

Although avidity was abstracted away from the details of musical genre or listener demography, it often absorbed and came to stand for other kinds of difference. This was most obvious in the production of exemplary listener types: Mike, the long-time head of engineering at Willow, explained to me that teenage girls who wanted to hear the same pop music on repeat needed a different style of recommendation than the erudite jazz listener (here he shifted to masculine pronouns) who was more likely to be open to exploration. The underlying recommender infrastructure might have no data about a user's gender, and if a gender were imputed to a user, it was likely to be used for selling advertisements, not recommending music; however, in conversations among the people working on these systems, user gender (and gendered understandings of musical genres, like pop; see, e.g. Cook 2001, James 2013) often stood in for the more abstract category of avidity.

In practice, the four levels of the pyramid often collapsed into a binary distinction: avid listeners were 'lean-forward', fiddling with settings, actively engaging with the interface, browsing, and skipping songs, while less avid listeners were ‘lean-back’, looking to start the music and then leave it alone. These ideal types were commonly used to describe the ethos of an entire music listening platform: the algorithmic radio streams produced by a company like Pandora Radio were essentially lean-back, while the links cataloged by MP3 blog aggregator The Hype Machine were lean-forward, encouraging enthusiasts to browse in pursuit of obscure new music (cf. Prey 2017). On-demand streaming services like Spotify or Rdio, with their large catalogs, boasted features aimed at both kinds of use: listeners could start algorithmic radio stations and lean back, or they could lean forward and browse through the catalog, guided by algorithmically selected ‘related artists’ and other such features.

As Peter explained it to me, lean-back listeners represented the bulk of the potential market for music recommendation, in spite of their relatively low status in the pyramid: there were more of them, they were more in need of the kind of assistance recommenders could offer, and successfully capturing them could make ‘the big bucks’ for a company. This posed another problem: those target listeners were quite unlike the people who built music recommender systems, who almost universally identified as passionate about music and thus, in the framework of the pyramid, as ‘savants’. As one infomediary company named itself, these people were ‘Music and Data Geeks’. Avidity was thus a frame not only for understanding listener variation, but also for thinking about the cultural differences between the people who used recommender systems and the people who made them.

The culture

On the last day of RecSys 2014, I was drinking in the hotel bar with a few of my long-time contacts in the field. Some of them had recently made the transition from academia to industry, and this was their first year representing commercial employers at the conference. They were arguing about the differences between themselves and their users. Oliver, a PhD computer scientist who now described himself as a ‘data plumber’ for a major music streaming service I call Wavelet, claimed that engineers generally had obscure taste in music. This made it hard for them to evaluate the experience of an average user, who was more likely to want popular music. Thus, while he would complain about the quality of Wavelet’s recommendations for himself, his complaints might in fact indicate that Wavelet worked well – for the typical user. ‘It’s hard to recommend shitty music to people who want shitty music’, he said, expressing the burden of a music recommendation developer caught between two competing evaluative schemes: his own idea about what made music ‘good’ and what he recognized as the proper criteria for evaluating a recommender system. This was a common cause for complaint and source of humour among engineers: when told that Whisper’s algorithmic radio station based on the popular artist Taylor Swift was bad, Michael, one of Whisper's radio developers, declaimed, 'Well, with a seed artist like that, what do you expect?!'

Across the table in the hotel bar, Seth, a research scientist at Willow, described the obligations of a music recommender in terms that were common across the industry: 'We're not tastemakers', he said. A recommender system should give people what they want, even if it offends its developers' sensibilities. While Seth understood the cultural intermediaries of the traditional music industry – the DJs, booking agents, record store clerks, and so on – as actively shaping the flow of music (cf. Bourdieu 1984, Negus 1995, Powers 2012), he felt an obligation to get out of the way. This idea is conventional across the 'platforms' of Silicon Valley, which present themselves as neutral conduits and supports for information, even when they shape its flow through algorithmic filtering (Gillespie 2010).

In spite of that commitment to neutrality, Seth attributed the success of his new employer to the savant status of the company culture: 'everyone in the company is really fucking cool', he said. Within a longer history of knowledge work in Silicon Valley, such claims are not at all unusual (Neff *et al*. 2005). As Alan Liu wrote in *The Laws of Cool*, referring to the ubiquity of 'coolness' as a corporate descriptor during the first dot-com boom: 'Cool is an attitude or pose from within the belly of the beast, an effort to make one's very mode of inhabiting a cubicle express what in the 1960s would have been an "alternative lifestyle"' (2004, pp. 77–78).

In addition to the kind of 'cool' typical to knowledge work, the employees of music streaming services are also 'cool' in their adjacency to the music industry: popular artists may drop by the office and perform at lunch, and knowledge of obscure or marginalized genres is prized. During my fieldwork I met DJs, noise artists, experimental composers, and tabla players who had all ended up working as software engineers. As in the more conventional music industries, a 'passion for music' is essentially obligatory for employees of music streaming companies, regardless of whether a given role is considered 'creative' (Bennett 2018a). The acquisition of cultural capital avidity represents is crucial to getting the job (cf. Koppman 2016).

In my interviews with technical employees of these companies, most recounted a longstanding and avid interest in music – as fans or performers – and many could not imagine moving on to jobs in other domains. After years of making software for insurance companies or banks, they saw working on music as the best possible occupation. Music streaming services often present the musical enthusiasm of their employees as evidence that they properly care for music – that they are not outside interlopers from 'tech', but rather legitimate and passionate cultural stewards.[6] On rare occasions, my interviewees might confide in me that they were less into music than their co-workers, suggesting that this set them apart from the overall company 'culture', which presumed musical avidity as a unifying characteristic. Such people usually worked in roles that were already marginalized within office hierarchies: system administrators who maintained a company's local computers or office managers who were responsible for the logistics of space and scheduling (cf. Bennett 2018b). These employees were not indifferent to music, and by ordinary standards were probably quite avid listeners. Only within the context of company culture, with regular live performances, employee bands, and constant discussion of new genres and obscure musical edge cases did they seem less than enthusiastic.

By 2014, the idea that software companies depended on their internal 'culture' for success had become commonplace in Silicon Valley (Chesky 2014). Such invocations of 'culture' were characteristically vague, referring to something like a shared ethos or a set of values when they did not refer to the material amenities like foosball tables or free snacks that made offices 'fun' (English-Lueck and Avery 2017, Chen 2019). The notion of 'culture fit' – the idea that employees should be hired not only for their relevant skills but for their more subjective compatibility with a corporate disposition – had become an object of critique within broader arguments about workplace diversity (e.g. Tiku 2013). Culture fit was a homogenizing force: workplaces that hired people who were like the people already there tended to hire more young, white men (Noble and Roberts 2019).

For companies building music recommenders, the defining feature of corporate cultural fit was musical avidity. As Seth put it, it was crucial that his co-workers were cool: 'you can't risk polluting the culture'. The boundary between the interior of the company and the people outside of it had to be carefully managed, to ensure that employees were avid enough to do their jobs well. This, too, perpetuated demographic homogeneity – not under the more common Silicon Valley cover of technical expertise and meritocracy, but in relation to musical enthusiasm. Although the people employed by these companies, particularly in technical roles, were predominantly white, English-speaking men between 25 and 40, they cast the key difference between themselves and outsiders – between engineers and users – in terms of avidity, not demography.

The logs

For developers and their critics alike, the difference between insiders and outsiders of software companies posed a knowledge problem. If engineers and users were different kinds of people, how could the people making software know what to make? Answers to this question, and their consequences, depended on how the insider/outsider distinction was imagined.

Many critiques of Silicon Valley suggest that software companies avoid thinking about difference by simply making products for themselves. As one author put it in *The New Yorker*: 'the hottest tech start-ups are solving all the problems of being twenty years old, with cash on hand, because that's who thinks them up' (Packer 2013). When that software is not something like a laundry pick-up service, but rather comes to be pervasive social infrastructure, like a search engine or social networking site, the problem manifests as unanticipated consequences visited upon already marginalized users. Thus, companies implement 'real name' policies that put victims of stalking or abuse at risk (boyd 2012), persistent social network profiles that stymie those making gender or other transitions (Haimson *et al.* 2015), facial recognition systems that cannot see non-white faces (Phillips *et al.* 2011), or speech recognition systems that cannot hear women's voices (Margolis and Fisher 2002). These are some of the problems that can emerge from a combination of demographic homogeneity and what scholars in science and technology studies have called the 'I-methodology' (Oudshoorn *et al.* 2004), whereby developers simply imagine users as themselves. A commonly suggested solution to such problems, as I described at the start of this article, is to diversify these teams, so that they are more likely to anticipate more potential problems, understood here as disparate impacts on marginalized demographic groups.

In practice, of course, there are more ways for people working in companies to learn about their users than the introspective thought experiments of I-methodology. A vast literature in human–computer interaction and design has sought to develop methods for more adequately representing and involving the people affected by technologies in their creation; many companies employ user researchers tasked with precisely this responsibility. However, for my interlocutors, who predominantly worked in 'technical' engineering or research teams, such methods and research agendas were surprisingly remote from their own work. Recommender systems occupied a strange niche in the world of computer science, being obviously user-oriented in a way that other subfields were not, but generally avoiding 'soft' forms of qualitative user research. As one of the organizers of RecSys 2014 noted in an introductory presentation, most of the papers presented that year were oriented toward technical methods, with 'surprisingly few papers addressing issues of user experience'. In industry settings during the period of my research, some companies employed no dedicated user researchers at all, while in others the people working on recommender systems considered user research to be primarily concerned with the visual design of interfaces.[7] This warrants a deeper discussion of how knowledge about users is produced and how the authority to produce such knowledge is claimed within organizations.

In his now-classic ethnographic study of user research, Steve Woolgar (1990) described how legitimate knowledge about users was distributed across a computer company in the late 1980s. Engineers were then (as they are now) chastised for speculating about user behaviour; dedicated user researchers were authorized to represent users and to rein in engineers' speculations (and derisive comments).

> When someone in User Products says that Engineering have no notion what the user expects, the achieved distinction between the monolithic entity – the user – and the monolithic entity – the engineer – makes a political point about the inadequacies of all members of Engineering. (Woolgar 1990, p. 73)

This process, Woolgar suggested, was a form of 'boundary work' (1990, p. 89, Gieryn 1983), which not only established the legitimacy of user researchers in the firm, but also served to reinforce the boundary separating people inside the company from users outside of it. The only legitimate channel for knowledge about users to enter the company was through these user researchers – certainly not through the speculative introspection of engineers.

For my interlocutors, the hazards of speculative projection were also common sense. While I-methodology undoubtedly persisted in the ad hoc pragmatics of making software – in the countless informal evaluations of functionality that mark a programmer's working day (Seaver 2018b) – engineers frequently reminded me and each other that, as passionate about music, they could not simply imagine themselves in users' shoes or pretend that their desires for features were widely shared. With their critics, engineers shared what Kwame Anthony Appiah has described as the key 'insight' of postmodernism: 'the first and last mistake is to judge the Other on one's own terms' (1991, p. 339). Rather than imagining oneself as the user, one had to imagine the user as someone unlike the self. While this relativism may sound appealing in the abstract, Appiah's critique of postmodernism in academia also applies here: this relativism is not empowering to its objects, who have its terms imposed on them from the outside.

Unlike the engineers in Woolgar's study, my interlocutors had another channel for acquiring legitimated knowledge about the outside world. They sought to overcome the challenging alterity of their users by appealing to 'data', which was taken to provide a putatively objective position beyond individual perspectives. On a cross-country video conference in summer 2013, I heard Tom, a product manager for 'audience understanding' at Whisper, describe his employer's data collection efforts. 'We don't interview users', he told me. Instead, audience understanding depended on the same aggregated listening data that powered Whisper's recommendations.

'We think we have real science here', Tom said. The logs of listening data accumulating on their servers were privileged sources of information, granting 'technical' employees the power to explain and interpret how users behaved and what they wanted, without having to rely on dedicated user researchers. Not only was this a legitimated source of knowledge about users directly under engineers' control – it was also figured as more reliable than the kind of knowledge that might be gained through other means. This data, Tom suggested, reflected how people *actually* behaved, unlike what they might tell an interviewer.

This reliance on the logs reinforced the centrality of avidity in the imagination of user/engineer difference. Represented as aggregations of listening events, the first striking feature of users was their varying bulk. Knowing users through interactional data and understanding them in terms of avidity went hand-in-hand: avid listeners interacted more, generating more data, while indifferents scarcely registered. Tom referred to these collections of data as users' 'musical identities', reflecting who they were in terms of what they listened to. To be a listener in this paradigm was to be a collection of listening events. One's 'identity' was constituted narrowly by traces of interaction with an interface. This is not to say that people like Tom were unaware that their users had lives extending beyond their platform; rather, for the purposes of recommendation, those lives were only relevant to the extent that they manifested as detectable patterns in interaction. If the goal of the recommender was to encourage listeners to stay listening, its success could be measured by how much these profiles grew over time (Seaver 2018a).

The infrastructural point of view

I began this essay by suggesting that developers could be considered parts of the algorithmic infrastructures they produce and maintain. As I've described here, many who work in music recommendation broadly agree with me: because the shape of software depends on the intuitions, choices, and assessments of the people who make it, 'good' music recommendation requires developers with cultural sensitivity. This is particularly true in contemporary 'agile' development practices, which place software under continuous revision. These revisions keep human interpretation central to the evolution of algorithmic infrastructures, and they also can give 'technical' employees greater discretion in the overall design of the systems they build.

When they displace demography with avidity, developers are not only claiming elite cultural status for themselves – figuring themselves as 'cool' cultural intermediaries, unlike the prototypical user. These infrastructural agents also use avidity in an effort to occupy an *infrastructural point of view*. Caught in a double bind – they should not think like themselves, but they cannot think like their users – developers are pressed to find a way out. The infrastructure of data collection offers an ostensibly outside position; it facilitates the feeling of objectivity that Tom called 'science', whereby avid music fans might come to understand indifferent listeners.

Following James Scott (1998) and a host of others, we might call this practice 'seeing like an infrastructure'.[8] Avidity is what listeners look like when seen through system logs. In these particular infrastructures, interactional quantity is the first, most visible quality of a user. Increasing that quantity of data is now essentially obligatory for many contemporary corporations, which operate under what the sociologists Marion Fourcade and Kieran Healy call a 'data imperative': 'professionals recommend, the institutional environment demands, and technology enables organizations to sweep up as much individual data as possible' (2017, p. 13). This speculation on the value of data leads to a situation that Fourcade and Healy call 'seeing like a market' – the valorization of data as a new form of capital (cf. Sadowski 2019).

That form of algorithmic infrastructural politics is entangled with the economics of data and investment – how companies seek funding and speculate on the value of data, accumulating it without end. But the data imperative works at an institutional level. It does not explain how people working within these organizations make sense of the world, nor how they justify their decisions. There, we find another form of infrastructural politics, 'inside' the infrastructure, so to speak, as the people working in and on these systems go about their work.

Avidity bridges the economic demands of the data imperative, the 'postdemographic' ideology of algorithmic recommendation, and developers' own experiences of cultural expertise. It feats neatly into existing infrastructures of data collection, being readily measurable through interactional data. But this infrastructure is not neutral. Shaped by the history of personalization and recommendation technologies, it renders users in a particular form, making them legible as collections of interactional traces – entities intentionally lacking demographic qualities and the life experiences that come with them.

Many of my interlocutors were personally opposed to the expansion of surveillant technologies, or at the very least concerned to avoid appearing 'creepy'. These developers justify their data collection with reference to vernacular social theories that make it necessary. But these social theories are already entwined with the infrastructures to which developers turn for 'objective' knowledge, beyond the limits of their own subject positions. For music recommendation, these moves reinforce the centrality of avidity: it is at once a widely shared social theory, aligned with the cultural expertise they seek to cultivate, and an approach to classifying listeners that is reinforced by the structure of technologies designed for increasing engagement.

In Woolgar's account of late-1980s computer design, he described how company insiders came to identify with the physical interior of the computer itself – the casing of the machine stood for the corporate boundary (1990, p. 77). Here, even though the infrastructures in question are distributed and hard to see, we still find 'insiders' identifying with the object of their technical labour, working to see like an infrastructure. Outsiders like users only enter this space as data, formatted by the accreted historical decisions that constitute software.

Recommender systems are not only tools for capturing or aiding users; they are epistemic interfaces, through which developers come to know things about the world. As my panelist respondent at RecSys suggested, the functioning of a recommender system 'really comes down to the data, and the feedback, and how you process that information'. But where he suggested that this made the cultural background of engineers irrelevant, we can understand all of these things as the results of decisions made by people who work in and on algorithmic infrastructures. To see like an infrastructure means seeing like the people who built it, not through the pseudo-objectivity of 'data', but through a cultural theory, congealed in code.

Notes

1. See (O'Brien *et al*. 2017) for a review and critique of this argument in the context of the culture industries.
2. This was ironic, given the historical entwining of understandings of genetic 'codes' and software (e.g. Kay 1997).
3. To protect the anonymity of my ethnographic sources, some names and identifying details have been altered. In this article, people referred to by first name alone are pseudonymous, as are organizations that begin with the letter W.
4. When I interviewed one of the authors of an early collaborative filtering paper in 2012, he told me that they had worked 'quite in ignorance of marketing', discovering its parallel evolution only when he and his colleagues created a company to try and sell their systems.
5. Peter, who was an enthusiastic listener of decidedly 'uncool' genres of music, was described to me by a colleague as a 'trans-savant' – someone who had essentially passed beyond the top of the pyramid, returning to the styles of music listened to by those at the bottom.
6. Thus occasioning media coverage with titles like 'How Spotify's Music-Obsessed Culture Keeps Employees Hooked' (Titlow 2014). Critics often engage with music streaming services in these terms too: see *Spotify Teardown*, which draws the musical enthusiasm of that company's founders into question (Eriksson *et al*. 2018, p. 41).
7. As the industry has changed during the years since the bulk of this fieldwork was completed, there are signs that user researchers are gaining more influence at music streaming services such as Spotify (e.g. Garcia-Gathright *et al*. 2018).
8. On a related point, see (Dourish 2007) on 'seeing like an interface'.

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