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Chapter 8
The Behavioral Code: Recommender Systems and the Technical Code of Behaviorism

Marit de Jong and Robert Prey

Abstract Our lives are increasingly mediated, regulated and produced by algorithmically-driven software; often invisible to the people whose lives it affects. Online, much of the content that we consume is delivered to us through algorithmic recommender systems ("recommenders"). Although the techniques of such recommenders and the specific algorithms that underlie them differ, they share one basic assumption: that individuals are "users" whose preferences can be predicted through past actions and behaviors. While based on a set of assumptions that may be largely unconscious and even uncontroversial, we draw upon Andrew Feenberg's work to demonstrate that recommenders embody a "formal bias" that has social implications. We argue that this bias stems from the "technical code" of recommenders – which we identify as a form of behaviorism. Studying the assumptions and worldviews that recommenders put forth tells us something about how human beings are understood in a time where algorithmic systems are ubiquitous. Behaviorism, we argue, forms the *episteme* that grounds the development of recommenders. What we refer to as the "behavioral code" of recommenders promotes an impoverished view of what it means to be human. Leaving this technical code unchallenged prevents us from exploring alternative, perhaps more inclusive and expansive, pathways for understanding individuals and their desires. Furthermore, by problematizing formations that have successfully rooted themselves in technical codes, this chapter extends Feenberg's critical theory of technology into a domain that is both ubiquitous and undertheorized.

Keywords Technical code · Behaviorism · Recommender systems · Formal bias · Andrew Feenberg · B.F. Skinner · Algorithms · Data

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8.1 Introduction

Our lives are increasingly mediated, regulated and produced by algorithmically-driven software that are often invisible to the people whose lives it affects. Online, much of the content that we consume is delivered to us through algorithmic recommender systems (hereafter "recommenders"). Recommenders, as a popular textbook explains, "are software tools and techniques that provide suggestions for items that are most likely of interest to a particular user" (Ricci et al., 2011, p. 1). Although the techniques of such recommenders and the specific algorithms that underlie them differ, they share one basic assumption: that individuals are "users" whose preferences can be predicted through past actions and behaviors. Developers of these systems believe that the collection and analysis of such interactional data provides a representation of individuals that is far less susceptible to the prejudices that plague media and market research predicated on demographic profiling. In forwarding an explicitly "post-demographic" agenda, these systems and their developers promote an anti-essentialist ethos that is dictated by "preferences, not stereotypes" (Riedl & Konstan, 2002, p. 113).

Nevertheless, while based on a set of assumptions that may be largely unconscious and even uncontroversial, in this chapter we demonstrate that recommenders embody a "formal bias" (Feenberg, 2017) that has social implications. We argue that this bias stems from the "technical code" (ibid.) of recommenders – which we identify as a form of behaviorism. In line with behaviorism, recommenders work with a definition of preferences that frames them as behavioral dispositions rather than inner states (such as emotions, meaning or values).

Apps and online platforms have sometimes been accused by critics of employing behaviorist tactics to "hook" users and "nudge" behavior (e.g. Zuboff, 2019). Such critics charge that "surveillance capitalism" manipulates users by adopting the practices of operant conditioning, made famous by the behaviorist B. F. Skinner. Our focus here is somewhat different: We are interested in the *episteme* that grounds the development of recommenders. Studying the assumptions and worldviews that recommenders put forth tells us something about how human beings are understood in a time where algorithmic systems are ubiquitous (Cheney-Lippold, 2011). As we increasingly turn to computational tools to organize much of the information and content we create and consume, we subject our discourse and knowledge to the logics undergirding computation. This means that the presumptions of a small subset of the world's population decides on the logic that significantly shapes our understanding of ourselves and the world around us (Gillespie, 2014, p. 168).

What we refer to as the "behavioral code" of recommenders, we argue, promotes an impoverished view of what it means to be human. Leaving this technical code unchallenged prevents us from exploring alternative – perhaps more inclusive and expansive – pathways for understanding individuals and their desires. By problematizing "formations that have successfully rooted themselves in technical codes" (Feenberg, 2008, p. 52), this chapter extends Feenberg's critical theory of technology into a domain that is both ubiquitous and undertheorized.

8.2 The History and Study of Recommenders

Many early Internet users were affected by a paralysing condition known to psychologists as "overchoice" as a seemingly infinite supply of information, products, and services greeted them in their first forays online. Recommenders soon came to the rescue, bringing a degree of order to the chaos of digital information. The foremost technique used in early recommenders was collaborative filtering. Collaborative filtering is a widely used method to filter information by grouping together users deemed to have similar tastes or preferences. Developed as a research project at Xerox PARC in 1992, "Tapestry" is widely considered to be the first algorithmic recommender to use the term "collaborative filtering" (Goldberg et al., 1992). By the mid-1990s, a team from the University of Minnesota employed the same method for a Usenet news recommender called GroupLens. This team later created MovieLens, which asked users to rate movies on a five-star scale and then recommended movies seen by other users who had provided similar ratings. Soon after, MIT's Media Lab released "Ringo" (later Firefly), which used collaborative filtering to automate music recommendations (Riedl & Konstan, 2002). As e-commerce websites began to proliferate in the 1990s, recommenders fulfilled a need by business to help customers sort through products and make choices. In the March 1997 issue of the *Communications of the ACM*, the guest editors marvelled at how "a flurry of commercial ventures have recently introduced recommender systems for products ranging from Web URLs to music, videos, and books" (Resnick & Varian, 1997, p. 58).

Today, we encounter recommenders seemingly everywhere online: They filter books and other products on Amazon, television shows and films on Netflix, and news and social media posts on Facebook. Indeed, much of the online content that we consume is delivered to us through algorithmic recommenders. While collaborative filtering remains the archetypal recommender, a wide array of different filtering systems, such as content-based and context-based recommenders, have been developed over the years. Most recommenders now use an ensemble or hybrid approach, combining two or more filtering methods. While the information that drives these filtering systems can include explicit signals, such as product ratings, there has been a marked trend in recent years towards favoring implicit feedback, such as clicks or other trackable user interactions (Ekstrand & Willemsen, 2016).

The majority of research on recommenders (cf. Adomavicius & Tuzhilin, 2005; Bobadilla et al., 2013; Lops et al., 2011; Pazzani & Billsus, 2007; Ricci et al., 2011), is focused on explaining or comparing the strengths and weaknesses of different approaches, or offering suggestions on how to improve recommendations (cf. Burke, 2007; Linden et al., 2003; Salter & Antonopoulos, 2006; Tkalčič et al., 2010). More recently, humanities and social science scholars have begun to shine a critical light on recommenders to explore how they produce, reproduce and manage consumer desire (Drott, 2018) and individual subjects (Prey, 2018). Other critical research is concerned with privacy issues that surround recommenders (Perik et al., 2004) and with how such systems exercise influence over the culture we consume

(Beer, 2009, 2013; Morris, 2015; Seaver, 2012). For example, the specific techniques Netflix utilizes to understand its users' tastes and to recommend content could impact the type of television programs and films that get produced (Hallinan & Striphas, 2016). Importantly, scholars have pointed out how algorithms and the recommenders they power are always sociotechnical ensembles that extend and magnify "the all-too-human biases, worldviews, and blind spots of the people who designed, built, and maintained them" (Seaver, 2021). One such bias or worldview, we argue, is the assumption that individual preferences can best be defined as behavioral dispositions and predicted through past action and implicit behavior. Before we develop this argument, we will briefly review Feenberg's concept of "formal bias" and how such a bias emerges out of specific "technical codes."

8.3 Technical Code and Formal Bias

Technology, Feenberg writes, is technically underdetermined (e.g., 1992 p. 305; 2008 p. 51). In designing any technological object, one cannot work solely from the principles of technical logic. This manifests itself first in the availability of a surplus of workable solutions to any problem that a technology is supposed to solve. The social actors involved in the design process make the final choice between (technically) equally viable options. They thus need to motivate their choice by something other than technical criteria. The second manifestation of underdetermination can be found in the many ways in which a problem is chosen and defined. What is perceived as a need or problem arises from the viewpoint of the individual. As Feenberg (2017 p. 6) explains: "people who must commute to work acquire an interest in good roads, while those whose homes are polluted by the cars exhaust acquire an interest in better pollution controls, and so on." Neither the subject of technology nor its approach to this subject can thus be fully determined by technical criteria. Technical development does not follow a definitive path towards advancement since there are multiple branches possible and "the final determination of the "right" branch is not within the competence of engineering, because it is simply not inscribed in the nature of the technology" (Feenberg, 1992, p. 308). Other choices are always possible in terms of what to make and how to make it.

Since technology is underdetermined by purely rational considerations, developers must turn to social judgment in order to select between alternative feasible technical designs. In making decisions, developers rank "items as ethically permitted or forbidden, or aesthetically better or worse, or more or less socially desirable" (Feenberg, 2008, p. 52). Consequently, Feenberg argues that what guides the selection process is the "political-cultural horizon" (e.g. Feenberg, 1999, p. 87) of our society. This term refers to society's broad assumptions about social values. The realization of such social values in the form of technological specification is what he calls the "technical code" (Feenberg, 1999, p. 87–9). Once these values are materialized in technologies, they work to validate the cultural horizon that they stem from. As such, technologies perform a "formal bias" (e.g., Feenberg, 2017):

Seemingly neutral, they actually offer a material affirmation of – and thus a bias towards – the ruling social values. This does not mean that they lose their claim to being rational, as for Feenberg rationality is relative to social context. He makes this clear in his example of "rational" machine design in the era of child labour. As Feenberg writes in this volume:

> [W]hen the socially accepted definition of the labor force included children, features of the technology such as the placement of controls were designed for small workers. This was technically rational under the given conditions although today we might consider the whole business of child labor a scandal.

Technology can as such be simultaneously technically rational *and* formally biased. In the design of recommenders, as we shall subsequently argue, a certain underlying technical code can be identified; one that may be "rational" yet manifests in these systems' formal bias. In order to analyze recommenders in terms of their technical code and formal bias, we first turn to the workings of these systems.

8.4 Inside Recommenders

Since the algorithms that drive recommenders are largely kept a secret (they are, after all, what determines the success of a digital platform), another approach is needed to study them. We choose to study recommenders from the outside and fill in the gaps by reading texts from within the field of recommender systems. We performed a close reading of educational textbooks (e.g., Aggarwal, 2016; Falk, 2019) and papers from the annual ACM Conference on Recommender Systems (e.g., Ekstrand & Willemsen, 2016; Wan & McAuley, 2018): "the premier international forum for the presentation of new research results, systems and techniques in the broad field of recommenders" (RecSys, n.d.). In what follows we provide an overview of the core techniques and data primarily utilized in the development of contemporary recommender systems.

8.4.1 Behavioral and Environmental Data

Demographic markers for identity, such as age and gender, have long been used by media and market research as a proxy for preference. Algorithmic recommenders instigated a break with this method by claiming to circumvent the need for proxies altogether. "Treat customers as individuals, not demographics," two pioneers of collaborative filtering advised their readers: "Let their preferences, not stereotypes, dictate which products and messages you present to them" (Riedl & Konstan, 2002).

Indeed, contemporary recommenders could be described as "post-demographic machines" (Rogers, 2009). As the vice-president of Netflix's Original Series remarked: "We found that demographics are not a good indicator of what people like to watch" (Lynch, 2018). Rather than eliminating proxies for preference altogether however, demographics have been replaced with real-time behavioral data. More specifically, users are typically reduced to (1) *measurable*, (2) *implicit*, (3) *past,* and, increasingly, (4) *contextualized* behavior.

Recommenders only allow for input that can be processed by algorithms. Consequently, they work with a certain type of behavior: the kind that can be digitally observed, or "datafied" (Fisher & Mehozay, 2019 p. 10). In other words, their input is *measurable behavior*. What cannot be directly observed by recommenders, however, are inner states such as thoughts, feelings, motives, and preferences. In other words, recommenders cannot immediately observe the very thing that they are after. One way to get around this difficulty is to directly ask users to communicate their inner states. Indeed, coaxing users to provide explicit feedback, such as ratings and reviews, to express their preferences used to be a common approach.

Over time, however, a different method began to be given primacy: tracking *implicit behavior,* like clicks or other trackable user interactions (Ekstrand & Willemsen, 2016; Seaver, 2019, p. 430). This shift resulted from the discovery that explicit user-data – such as ratings – poses a threat to prediction. It turns out that explicit ratings vary significantly depending on time and setting: a user could give a movie three stars one day and five the next one. In addition, explicit data is relatively scarce as it requires users to take time to express preferences. On the other hand, implicit behavioral data, or interaction data such as clicking and scrolling, is demonstrably good at predicting future user behavior, and is also readily available and thus easier to collect (Ekstrand & Willemsen, 2016). Consequently, explicit ratings have been widely replaced with implicit behavioral data (Seaver, 2019).

Explicit data based on users' subjective interpretation is now often perceived as a hindrance to actually understanding the user. In a recent paper, Nick Seaver (2021, p. 15) describes a conversation he had with "Tom," a product manager for "audience understanding" at a music recommendation company anonymized as "Whisper":

> '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.

Netflix developers likewise explain that their platform tracks activity such as "the time elapsed since viewing, the point of abandonment (mid-program vs. beginning or end), whether different titles have been viewed since, and the devices used" (Gomez-Uribe & Hunt, 2015, p. 4). Listening or viewing logs are considered a more legitimate and reliable form of knowledge that better represents how users "*actually* behaved" (Seaver, 2021, p. 15), rather than what they might claim to have consumed if asked explicitly.

Finally, it follows that recommenders work with *past behavior*. As an influential early book in the field announced: "In order to know what someone wants, what you really need to know is what they've wanted" (Riedl & Konstan, 2002, para. 13). This is typical for algorithmic systems: Existing data is used to predict some future state of affairs. For instance, the music you listened to last week will be used as input by the recommender to make predictions about your future listening behavior.

With collaborative filtering the basic premise is that "people who agreed in their subjective evaluation of past [items] are likely to agree again in the future" (Resnick et al., 1994 p. 176).

However, this premise assumes that taste is static, with many users complaining about being "haunted" by their past preferences. In reaction, the field of recommender systems research has recently taken a "contextual turn" (Pagano et al., 2016). As one paper explains:

> [...] a context-driven recommender system, 'personalizes' to users' context states. In this way, it introduces a disassociation between users and their historical behavior, giving users room to develop beyond their past needs and preferences. Instead, users receive recommendations based on what is going on around them in the moment (situation) and on what they are trying to accomplish (intent). (*ibid*. p. 249)

Developers thus began incorporating contextual factors into recommenders to reflect the recognition that users interact with a system from within a particular context. Here "context" is defined as "a set of conditions under which an activity occurs" (Adomavicius et al., 2011, p. 68). In addition to factors that can be immediately known such as day and time, context-aware recommenders can also infer contextual information from behavioral data gathered from smartphone sensors:

> [I]f a user is listening to music on a smartphone, the system might try to deduce whether the device is moving or not. If it is moving, the person might be exercising or they might be driving or cycling. If the device is stationary, the consumer may be sitting on a sofa at home and the appropriate music might be different. (Falk, 2019, p. 17)

The input that recommenders work with is thus composed of *measurable*, *implicit*, and *past* behavioral data (hereafter "behavioral data"), in combination with data about the *context* (hereafter "contextual data") in which the behavior takes place. In the next section we build from here to identify the underlying technical code of recommender systems.

8.5 The Technical Code of Recommenders

Technologies offer a material affirmation of, and a bias towards, particular values and worldviews. More specifically, Feenberg argues that modern technology is biased by contingent social factors specific to capitalism (Kirkpatrick, 2020). Developers of recommenders, like technologists more generally, do not typically aim at specific social benefits or prejudicial outcomes. Instead, they focus on efficiency gains that are to result from the technology that is developed. Over time, the technologies as well as the systems of thought that underlie them become seemingly uncontroversial. As Bernhard Rieder (2020, p. 253) puts it when describing the history of how observed market behaviour came to stand for consumer preference in economics, "[w]hat users do is what they want and what they want is what they shall receive. How could it be otherwise?" It is precisely the apparent incontestability of this "technical code" that renders recommenders "formally biased."

The highly technical perspective involved in the creation of recommenders makes them vulnerable to the influence of existing systems of thought that are likewise disinterested in values or meanings (Kirkpatrick, 2020). In the case of recommenders, we argue that they work according to the objectivist principles of *behaviorism*. As such they embody what we term a "behavioral code." In this section we therefore provide a brief overview of the core ideas of behaviorism and show how they are reflected in recommenders. In the subsequent section we discuss several existing critiques of behaviorism as a way of proving the formal bias of recommenders while also opening up pathways for imagining alternative directions for recommender systems.

8.5.1 Behaviorism: The Core Principles

Since John B. Watson coined the term in 1913, behaviorism grew into a highly influential school of thought that covers multiple scientific fields. For B. F. Skinner (1904–1990), perhaps the most well-known and influential behaviorist, to know a person means to know "what he does, has done, or will do" in certain contexts (Skinner, 1974, p. 176). According to Skinner, "[a] self or personality is at best a repertoire of behavior imparted by an organized set of contingencies" (1974 p. 149). Contingencies refer to the relationship between three things: events that occur immediately before a behavior (antecedents), behavioral responses, and consequences that take place immediately after the response. Certain behavior can be "reinforced" (e.g., Skinner, 1974 p. 42) when its consequences are positive, or weakened if the consequences are negative. Thus, the self, for behaviorists, is "at best" a set of likely behaviors under certain circumstances. As a result, the ingredients necessary to know someone are their overt behavior and the environment in which this takes place.

The emphasis on overt behavior does not mean that behaviorists deny the existence of inner states such as feelings, thoughts, and preferences. Instead, feelings and thoughts are reduced to bodily states and processes. In other words, inner states are seen as a type of behavior, just as overt actions are.[1] However, behaviorists do object to assigning inner states causal power and, as such, explanatory power. Skinner, for example, argued that inner states are by-products. The following passage from his book *On Behaviorism* (1974) sheds more light on this position:

> When a person has been subjected to mildly punishing consequences in walking on a slippery surface, he may walk in a manner we describe as cautious. It is then easy to say that he walks with caution or that he shows caution. There is no harm in this until we begin to say that he walks carefully because of his caution (p. 161).

What Skinner objects to, then, is the role of inner states as the subject of scientific study. "The objection to inner states," Skinner wrote, "is not that they do not exist,

[1] As such, behaviorists deny the Cartesian mind-body dualism.

but that they are not relevant in a functional analysis" (Skinner, 1953, p. 35). Instead, he argues, we should shift our focus from the inside to the outside – to overt behavior and the environment in which people act. For Skinner and his followers, only behavior provides publicly observable data upon which to construct rigorous and scientifically-sound models of how and why people do what they do (Moore, 1999). What is more, behaviorists believe that to understand behavior means to be able to both predict and control behavior. In other words, it is about being able to anticipate what people will do *and* being able to steer this behavior through reinforcement and punishment.

8.5.2 The Behavioral Code

Contemporary recommenders posit the internet user in much the same way as Skinner and other behaviorists posited their test subjects. Behaviorists broadly work with two variables: overt behavior and environmental factors. Regarding the latter, recall the turn towards "context-aware" recommenders. Like behaviorists, such systems emphasize the importance of environmental factors in understanding a person's behavior. If you listen to classical music almost every night before you go to bed, Spotify will very likely recommend playlists of this genre to you around this time.

With regard to the first variable, the primary input of recommenders consists of behavioral data. The idea that past behavior lends itself for predicting the probability of future behavior endorses the behaviorist doctrine. As Skinner wrote: "The probability of behavior depends upon the kind of frequency of reinforcement in similar situations in the past" (1974, p. 69). In addition, by focusing on overt and implicit behavior, recommenders meet the behaviorist "rule" of shifting one's attention from inner states to overt behavior. Recommenders focus their attention on what can be "objectively" and consistently measured. While explicit behavioral data used to be collected by recommenders, as pointed out above, subjective interpretations of inner states are now largely dismissed due to their inconsistency and scarcity. For example, in recommending music, Spotify is not that interested in how users self-identify as music fans, or even in demographic markers that traditionally acted as a proxy for music preferences. Instead, a "taste profile" – a dynamic record of one's musical identity – is constructed for each user. This profile is generated primarily through implicit behavioral feedback that is generated every time you search for an artist, listen to a track, add songs to a playlist, or skip a song.

Combining behavioral data and context, recommenders aim to understand the user by identifying patterns of behavior. In Fisher and Mehozay's (2019, p. 10) formulation of the "algorithmic episteme": "To *know* someone does not mean to analytically and empirically understand the reasons for her behavior, but simply to be able to recognize patterns of behavior." This appears to follow the behaviorist doctrine – that to know someone is to know what someone has done, is doing, and will do in the future.

Nevertheless, recommender systems appear to contradict the principles of radical behaviorists by assigning causal power to inner states. As was mentioned earlier, a popular textbook defines recommenders as "software tools and techniques that provide suggestions for items that are most likely of *interest* to a particular user" (Ricci et al., 2011, p. 1, italics added). Similar explanations of recommenders can be found throughout the literature. Lu, Dong and Smyth (2018, p. 4, italics added) write: "Recommender systems learn to predict the degree to which a user will *like* an item." This could merely be a rhetorical device. Considerable research has been conducted in making recommenders more "persuasive" (e.g., Yoo & Gretzel, 2011) and it appears that we are more comfortable following recommendations from a source that claims to understand our inner preferences than from a system that monitors our behavior. Regardless, while recommenders may use mental concepts to present themselves to end users, this does not take away from the fact that they work according to an objectivist, behaviorist interpretation of such concepts.[2]

8.6 The Formal Bias of Recommenders: Critiques of Behaviorism

Recommender systems, we argue, embody behaviorist assumptions. To make this claim is not to suggest that developers are behaviorists who consciously create recommenders according to Skinnerian principles. To restate what was argued earlier: The technical perspective that focuses on efficiency gains makes recommenders vulnerable to influences by systems of thought that are likewise indifferent to meaning and values.[3] As has already become clear from the brief discussion of behaviorism's core ideas, it is the influence of this particular objectivist system of thought that recommenders are vulnerable to.

The materialization of behaviorist ideas in recommenders has closed off alternative pathways for understanding individuals and their desires. While other directions for the development of recommenders were – and always are – possible, now that the behavioral code is materialized it works to affirm itself and obscure its

[2] Skinner preferred to avoid mental concepts, but the underlying idea of (analytical or logical) behaviorism is that a mental state or condition is the idea of a behavioral disposition or family of behavioral tendencies (Graham, 2019). This means that a behaviorist can in principle continue to use mental concepts, but they would refer to a certain behavioral disposition rather than inner states.

[3] Even though developers and behaviorists work with different motivations – developers work according to a commercial incentive while behaviorists are motivated by a certain ideal of "real" science – they eventually both aim for the prediction and control of human behavior. These goals have proven to be greatly compatible; the founder of behaviorism, John B. Watson, joined an advertising agency after he left academia and became highly successful in that field (Baars, 1986; Waldrop, 2001). In addition, Skinner's analysis has been called the psychological equivalent of wage-labor capitalism (Baars, 1986), as the prediction and control of human behavior in order to increase productivity has been a central focus of managerial practices; from "scientific management" to "nudge management" more recently (Ebert & Freibichler, 2017).

contingent nature. As such, recommenders perform a formal bias: Seemingly neutral they offer a material affirmation of the ideas that underlie them. Since recommenders reintroduce a behaviorist understanding of humans, a critical analysis of these systems should draw upon criticism of, and alternatives to, behaviorism. This therefore forms one of our aims for this chapter; to reopen the debate around behaviorism. These critiques not only provide alternative stipulations but also allow us to see how the behavioral code that currently underlies recommenders results in a formal bias with social implications – specifically an impoverished view of what it means to be human.

8.6.1 Existing Critiques of Behaviorism

Between approximately 1920 and the mid-1950s (e.g., Baars, 1986; Chung & Hyland, 2012; Miller, 2003; Reisberg, 2016), the majority of psychologists in the United States were behaviorists. By the mid-1950s, however, the popularity of behaviorism went into fast decline as it was critiqued from several angles. In psychology, behaviorism was largely obliterated by the "cognitive revolution" (e.g., Miller, 2003; Reisberg, 2016; Waldrop, 2001). Psychologists grew convinced that a subject's behavior was guided by how the subject understood or interpreted a situation – not by the objective situation itself. By focusing merely on the objective situation, we misunderstand the motivations people have for their actions and subsequently make mistakes in predicting future behavior. In other words, it became clear that psychologists needed to study mental states after all.

From a philosophical perspective, critical theorists contrasted Skinner's "science of behaviour" with what they viewed as the much richer Marxist concept of "praxis."[4] Praxis, according to one critic of Skinner, "refers to man as an active agent in the world, a world that he constructs and transforms, on which he confers meaning, and to which he responds" (Mishler, 1976, p. 25). In other words, from the perspective of praxis the human subject is an interpretive being engaged in meaningful action. One does not simply run, for example, but rather one runs *because* of a reason – a reason that emerges out of the subjective interpretation of an event. The meaning of the behavior is what defines the behavior; which could be as varied as running from something that scares you or going for a run to clear your head.

[4] Apart from the praxis critique, there are roughly three main reasons for the rejection of behaviorism within philosophy (Graham, 2019). First of all, many people were, and still are, sceptical about behaviorism's commitment to the thesis that behavior can be understood without referring to mental processes. A second reason for the dismissal of behaviorism is the existence of "qualia" (e.g., Place, 2000): behaviorism cannot account for the qualitatively distinctive experience underlying overt behavior. Yet another critique came from Noam Chomsky (1967 [1959]). According to Chomsky, behaviorism cannot account for the fact that language does not seem to be learned through explicit teaching. He pointed out that linguistic performance outstripped individual reinforcement histories.

Behaviorists, however, reject a focus on meaning not because they deny subjective or inner states, but because they see them as functionally useless for predicting rates of response. There is an analogous focus on "rating prediction accuracy" in recommender system design. Both can be seen as expressions of what Habermas (1970, p. 105–7) called "technocratic consciousness":

> It is a singular achievement of this (technocratic) ideology to detach society's self-understanding from the frame of reference of communicative action and from the concepts of symbolic interaction and replace it with a scientific mode. . . . This is paralleled subjectively by the disappearance of the difference between purposive-rational action and interaction from the consciousness not only of the sciences of man, but of men themselves. The concealment of this difference proves the ideological power of the technocratic consciousness.

For critical theorists, behaviorism represented the further colonization of the life-world by positivist scientism. As one trenchant critique put it, behaviorism circumvents the necessity of interpretation "by defining a single scalar index as the "behaviour" of interest, and by coding many different types of behaviour in this one category while ignoring other features of the behaviour" (Mishler, 1976, p. 32). It conveniently ignores *why* the human subject gently pushes the lever or smashes it. "Instead of a science constructed so as to be appropriate to its phenomena of study, the phenomena are transformed so as to be appropriate to a particular methodology" (ibid., p. 33).[5]

The principal takeaway here is that the model of human action and motivation becomes defined through the lens that it is perceived through. Like the example earlier of the product manager at a music recommendation company that equated "audience understanding" with aggregated listening data, behaviorism distinguished itself from alternative methods of human understanding by claiming the mantle of "real science." In doing so, it defined the world in its image and allowed for certain questions while ignoring others. Another vision of science – one that sees human beings as meaning constructors and symbols users – would result in an alternative definition of the world.

What made behaviorism especially dangerous was not that it did not work, but rather that it pretended to be the only scientific approach to the study and understanding of humans. As Baars (1986, p. 51–52) put it: "Behaviorism was viewed as the one right way to do psychological science; every alternative was unscientific." As we have shown, however, behaviorists actually worked with a very limited understanding of the meaning and purpose of science and of human-beings. While behaviorists could lay claim to an undoubted objectivity in their observations, they had to pay a very high price for it. They had rejected too many things: "[...] in hot pursuit of scientism, psychology had lost psychology" (Baars, 1986, p. 69). In other words, and to return to Feenberg, even though behaviorism might have been rational, it was also formally biased. As Mishler (1976, p. 29) puts it: "More is at stake than whether information about "inner states" helps to "predict" a discrete and

[5] Notice here that behaviorism is a presupposed framework rather than a scientific theory, meaning that it cannot be falsified by any experimental results (Baars, 1986).

meaningless response. Rather, these states are central topics of interest in and of themselves, as are their complex relationships to behaviour and the rules governing the stability and change of these relationships." Behaviorism could have been *a* way of doing experimental psychology to be complemented by other forms of study that focus on meaning and understanding. That way, behaviorists would at least have recognized and respected the formal bias that was integrated into their program. Yet this is exactly what they did not allow for.

Like behaviorism, recommenders get the job done. And like behaviorism, this does not mean that they are not formally biased. Recommenders also embody the same impoverished view of what it means to be human. Interestingly, their developers show a similar attitude toward their method as behaviorists did. Recall "Whisper," the music recommendation company studied by Seaver (2021). This company believed to have overcome the "challenging alterity of their users by appealing to "data," which was taken to provide a putatively objective position beyond individual perspectives" (p. 14). Note the further similarity with behaviorism when the employee says: "We think we have real science here" (ibid.).

While the developers of recommenders, unlike behaviorists, may not explicitly claim that their account of humans is *the* way to view them, the materialization of behaviorist assumptions in these omnipresent recommenders does create a formal bias that reinforces a behaviorist understanding of humans. As such, they might even cause users to see *themselves* through a behaviorist lens. After all, recommenders are said to "personalize" content, which critics have argued "imbues the system with the power to co-constitute users' experience, identity and selfhood in a performative sense (Kant, 2020, p. 12). There is however another concern, namely that "[i]t is the programmers themselves who are more likely to suffer these consequences. It is the objectification of others that is dehumanizing, and this is integral to the behaviourist approach" (Mishler, 1976, p. 34).

To summarize, recommenders embody a behavioral code and are as such biased towards the beliefs and values that underlie behaviorism. This formal bias promotes an impoverished view of what it means to be human – among users as well as developers. As such, the formal bias of recommenders should be of public concern.

8.7 Conclusion

Over a decade ago, Google's former CEO Eric Schmidt pointed out how ubiquitous recommendation was (Jenkins Jr., 2010). Today, on platforms like Netflix, "everything is a recommendation": Not only are the films personalized to fit viewing behavior, but so is the cover art (Mullaney, 2015; Yu, 2019). At the same time, data is drawn from an ever-widening and growing array of interactions. As Nick Seaver (2019, p. 11) writes, "algorithmic recommendation has settled deep into the infrastructure of online cultural life, where it has become practically unavoidable."

If recommenders exert such a ubiquitous and powerful influence on our lives, then – as Feenberg asks of technology in general – "why don't we apply the same democratic standards to it as we apply to other political institutions" (Feenberg, 1999, p. 131). In *Questioning Technology,* Andrew Feenberg outlines three forms of democratic intervention in technology: controversy, innovative dialogue and creative appropriation (Feenberg, 1999, p. 120–9). The potential solutions to the problem of the "behavioral code" in recommender design will rely on both the creative appropriation by users of these technologies, as well as innovative dialogue between users and developers.[6] However, what is first required is that the assumptions inscribed in recommenders be made a controversy; an issue of public concern. That is what this chapter has attempted to do.

As we have demonstrated, recommender systems generally share a basic assumption – that individuals are "users" whose preferences can be understood as behavioral dispositions and whose behavior can therefore be predicted through (past) implicit behavior and contextual cues. Extending Feenberg's critical theory of technology into the domain of recommenders, we call this the "behavioral code" of recommenders – a particular technical code that exerts a "formal bias" with social implications. Other choices are always possible in terms of what to make and how to make it. The way in which recommenders currently work is thus not set in stone. The task that remains is to explore other "branches" of development, which perhaps provide a more expansive way in which to understand individuals and their desires.

[6] While the purpose of this chapter is not to explore solutions, there are several interesting proposals and projects underway. For example, academics and developers have called for and experimented with more user-centric recommenders that allow users some degree of control over how they are profiled. One example of user-centric design is *gobo.social*, a social media news aggregator designed by the MIT Media Lab. This tool offers sliders that users control in order to filter information: The user can explore a range of political perspectives on a continuum from left to right, or "the extent of seriousness, rudeness, gender, and other parameters" (Reviglio & Agosti, 2020, p. 6). In another example, Harambam et al. (2018) provide an interesting proposal to grant users greater "voice" in our algorithmically-driven media ecosystem. The authors propose the creation of *algorithmic recommender personae* to "allow people instead to demand from [recommenders] to behave in ways that align with their own specific... interests at each single moment" (ibid. p. 4). It is also possible to involve users in the earliest stages of the design and development of recommender algorithms. The benefits of participatory design are not only in creating more user-friendly technologies, but also in making "explicit the critical, and inevitable, presence of values in the system design process" (Suchman, 1993, p. viii). As Feenberg convincingly argues in *Questioning Technology*, by widening opportunities to intervene, user participation in design serves to limit "the operational autonomy of technical personnel" (Feenberg, 1999, p. 135) who are socialized into the technical codes of the profession (ibid, p. 142).

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