



Captivating algorithms: Recommender systems as traps

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Abstract

Algorithmic recommender systems are a ubiquitous feature of contemporary cultural life online, suggesting music, movies, and other materials to their users. This article, drawing on fieldwork with developers of recommender systems in the US, describes a tendency among these systems' makers to describe their purpose as 'hooking' people – enticing them into frequent or enduring usage. Inspired by steady references to capture in the field, the author considers recommender systems as traps, drawing on anthropological theories about animal trapping. The article charts the rise of 'captivation metrics' – measures of user retention – enabled by a set of transformations in recommenders' epistemic, economic, and technical contexts. Traps prove useful for thinking about how such systems relate to broader infrastructural ecologies of knowledge and technology. As recommenders spread across online cultural infrastructures and become practically inescapable, thinking with traps offers an alternative to common ethical framings that oppose tropes of freedom and coercion.

Keywords

algorithms, behaviorism, infrastructure, recommender systems, traps

Hooked

It is an overcast day in Northern California, and I am eating sushi with Mike. We sit down the street from his office at Willow, a personalized radio company where he has worked for the last 15 years.¹ Mike has bright blue eyes, an ersatz mohawk, and an unusually energetic affect, even by the Bay Area's gregarious standards. Among the fleeting companies and careers common in the industry, Mike and Willow are notably long-lived: when he first joined the company, Mike was a college dropout and, as an intern, Willow's first engineer. Now, over a decade later, he is its Chief Scientist. I ask what the Chief

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Scientist for a music streaming company does, and he replies: 'I'm responsible for making sure the music we play is awesome.'

Willow's popular radio service offers its users algorithmically generated playlists: type in an artist's name, and Willow will play a never-ending stream of music it deems similar to your query. If you keep listening, skipping songs you don't like and giving positive ratings to songs you do, the service will tailor its choices to your apparent preferences. Since he started at Willow, designing, building, and maintaining this recommender system has been Mike's job. In the beginning, Mike tells me, 'I was the algorithm guy – the only guy working on the algorithm – trying to figure out how to play music right.'

As the company grew, so did the algorithm and Mike's job, following typical and parallel trajectories: the algorithm became much more complicated, and Mike's role transformed from coder to manager. 'Now,' he tells me, 'I run teams of teams', each of which is responsible for a different part of Willow's recommendation infrastructure. Now, the 'algorithm' is not one algorithm at all, but 'dozens and dozens' of sub-algorithms, each of which parses a different signal: What does a song sound like? How often does a user click? What has a listener liked in the past? A master algorithm orchestrates the sub-algorithms' outputs together into an 'ensemble' (Goldschmitt and Seaver, nd) that makes a simple decision: What song should be played next?

Companies like Willow have dedicated extraordinary amounts of capital, engineering labor, and scientific research to answering this question. Research on recommender systems has animated hundreds of dissertations, attracted billions of dollars in funding, and inspired the founding of countless startups. The scalar asymmetry is striking: small and otherwise unremarkable actions, like picking a movie to watch or changing the radio station, are the target of an exceptionally large and intricate scientific-industrial complex, which only continues to grow in size and scope.

Mike describes to me how elaborately Willow can tailor its recommendations to users, not merely suggesting similar artists, but identifying listening styles that appear to transcend genre: some listeners prefer recommendations that keep quite close to their original request, while others are more exploratory; some users skip songs often, while others rarely use the interface at all. Willow's recommender takes all of this into account, adjusting the significance of such actions accordingly.

But sophisticated recommendation requires data. New users pose a challenge that researchers call the 'cold start problem': they have no data yet and, without data, data-driven recommendations do not work. For new users, Willow's elaborate engineering is set aside in favor of blunter techniques. Or, as Mike puts it:

If you're in your first week of listening to us, we're like, 'Fuck that! Play the hits!' Play the shit you know they're going to love to keep them coming back. Get them addicted.

In the beginning, I'm just trying to get you hooked.

In this article, I describe how it came to be that people like Mike explain the purpose of their work as 'hooking' users. Between 2011 and 2016, I conducted fieldwork with the

developers of algorithmic music recommender systems across the US. What were these systems for, and how did their makers decide whether they worked? In settings ranging from university labs to corporate offices, one set of answers emerged above the others: recommender systems retained users on platforms, caught their attention, and helped companies capture market share.

Metaphors like these, which figured users as prey and recommender systems as devices for catching them, were surprisingly common. Algorithmic recommendation, it seemed, was a trap. Following the anthropologist's prerogative to take our interlocutors more literally and more figuratively than they take themselves, I pursue here the consequences of this comparison. Drawing on the anthropology of animal trapping, I place recommender systems in unusual company – not among artificial intelligences and machine learners, but hidden spears and thorn-ribbed baskets. This is, assuredly, not what people meant when they said they wanted to capture users. However, traps offer a powerful vocabulary for articulating sociotechnical concerns, and thinking with traps gives purchase on vexing questions about the relationships among culture, technology, and ethics.

Algorithms are potent symbols of informatic modernity, essentially immaterial abstract procedures freed from any coarse materiality of the stabbing, snaring, or smashing sort. Placing algorithmic systems alongside tripwires and trapdoors not only takes the shine off, reminding us that they, too, are products of ordinary human engineering; it also helps us think about how they work, the ways of thinking they depend on, and how they might be critiqued. Indeed, as we will see, a vernacular critique of algorithmic systems as traps has already emerged, concerned with policing the boundary between freedom and coercion. The anthropology of trapping helpfully sidesteps this framing, providing a model for thinking that does not depend on a strict dichotomy between the voluntary and the coerced, the mental and the material, or the cultural and the technical. Thinking with traps can help us see how epistemic and technical infrastructures come together to produce encompassing, hard-to-escape cultural worlds, at a moment when the richest companies in the world dedicate most of their resources to getting people hooked.

Captology

Hooked, it turned out, was also the title of a book by Silicon Valley blogger and entrepreneur Nir Eyal (2014). The book is subtitled 'How to Build Habit Forming Products', and it outlines a behaviorist paradigm for software design: companies that want to acquire users need to inculcate habits in them. Successful companies like Facebook have become successful, Eyal writes, by becoming 'first-to-mind': their users 'feel a pang of loneliness and before rational thought occurs, they are scrolling through their Facebook feeds' (p. 3). Achieving this goal requires thinking of users not as customers choosing among various commodities, but as instinctual minds, susceptible to subtle outside influences. Eyal writes, 'companies must learn not only what compels users to click, but what makes them tick' (p. 2). The book's cover depicts a cursor clicking on a human brain.²

This mind-oriented approach to software design has become broadly influential across the industry, and the title of a popular book by the behavioral economist Dan Ariely, *Predictably Irrational* (2008), usefully encapsulates why. The apparent irrationality of human behavior threatens the rational actor models that have historically characterized

both economics and engineering; behaviorist theories recover prediction from irrationality's clutches, making human action once again amenable to such modeling. People may be irrational, but they are still predictable, and where there is prediction, there is the potential for profit.

Eyal was not alone in repackaging behaviorist principles as business advice. At the time of my fieldwork in the Bay Area in the early 2010s, Ariely hosted an annual summit in Silicon Valley called 'Startuponomics', which trained company founders in the basic tenets of behavioral economics, pitched as tactics for retaining employees or drawing users down the 'product funnel' (i.e. turning them into paying customers or long-term users). A steady stream of popular books (e.g. Duhigg, 2012; Parr, 2015) has redescribed people in terms that date back at least to the behaviorist BF Skinner's famous variable reinforcement experiments that induced 'superstition in pigeons' (Ferster and Skinner, 1957): caged birds, given a lever that released food, would learn to press it; if experimenters adjusted the lever to only release food intermittently, the pigeons would learn to press it incessantly. Replace the pigeons with people, build the right levers into your product, and you too might amass a user base of compulsive lever-pressers.³

One of the headwaters of this surge in behaviorist thinking in the software industry was BJ Fogg's Persuasive Technology Lab at Stanford. Fogg founded the lab in 1998 to develop the field he called 'captology', a name derived from the acronym for 'computers as persuasive technologies' (Fogg, 2003: 5). The lab's mission, according to its website, is 'to create insight into how computing products – from websites to mobile phone software – can be designed to change people's beliefs and behaviors' (captology.stanford.edu). Among the lab's alumni are a co-founder of the photo-sharing service Instagram and Nir Eyal himself.

Fogg defines persuasion as 'a noncoercive attempt to change attitudes or behaviors' (Fogg et al., 2009: 134); thus, his vision of captology focuses on 'voluntary change', definitionally excluding force or trickery and ultimately depending on the agency of the persuaded (Fogg, 2003: 15). Where Skinner famously disavowed the existence of free will in *Beyond Freedom and Dignity* (1971), contemporary captology depends on it as an ethical shield: whatever powers Facebook may have, it cannot coerce anyone to do something – it can only persuade. Like Eyal, Fogg responds to longstanding ethical critiques of this line of work – that it is manipulative or disregards human dignity – by focusing on the voluntary nature of persuasion and emphasizing how it can be used for unquestionable social good: 'peace innovation' and 'mobile health' are among the projects cataloged on the lab's website. Eyal (2014: 11), more pithily, cites one of his readers in his book: 'If it can't be used for evil, it's not a superpower.'

Given these well-worn critiques, the coercive associations of 'captology' with 'capture' have proven troublesome for Fogg, who has more recently favored the term 'behavior design' (Fogg, 2017). But where the apparent link between captology and capture poses problems for Fogg's evangelical efforts, for my purposes here it usefully designates a relationship between behaviorist understandings of action and efforts to trap the entities thus understood. In the work of Skinner, Eyal, Ariely, and others, we find behaviorism entangled with physical and psychological techniques of capture: pigeons caught in cages become transfixed by schedules of reinforcement; users are hooked; employees are retained; potential customers are drawn into funnels.

We can use ‘captology’ to designate this understanding of people in behaviorism-inflected terms, as habitual minds with tendencies and compulsions that make them susceptible to persuasion and targets for capture. Captological thinking is found in behaviorist texts like *Hooked* or in Silicon Valley’s regular summits and workshops on behavior design, but these artifacts only make explicit and systematic what is elsewhere a tacit and ad hoc way of thinking. Though indebted to behaviorism, ordinary captological thinking is not necessarily faithful to it, nor is its ancestry always claimed. When Mike declared that he wanted to hook his users, he was not intentionally citing Eyal, but rather drawing on the vernacular captology that is now a defining part of the software industry’s professional culture – a vague and pervasive common sense that informs and is informed by the technologies that industry produces.

Traps as persuasive technologies

Ninety-eight years before the founding of Fogg’s Persuasive Technology Lab, in the 1900 volume of *American Anthropologist*, Otis Mason published a survey of indigenous American animal traps. Mason was Curator of Ethnology at the Smithsonian, and he had taken a special interest in the ‘ingenious mechanical combinations’ (p. 659) that people around the world used to capture animals. These devices – baskets ribbed with thorns for catching fish, elaborate net snares for entangling birds, fall-cages propped on sticks for capturing foxes – lent themselves to Victorian ethnological theorizing: particular mechanisms could be traced across regions as evidence of diffusion, and they could be arranged in sequences of increasing complexity, as evidence for evolution. Traps’ diverse and variously elaborate mechanisms indexed a world of technological development. ‘The trap’, Mason wrote, ‘teaches the whole lesson of invention’ (p. 659).

That lesson is evident in Mason’s definition of a trap: ‘an invention for the purpose of inducing animals to commit incarceration, self-arrest, or suicide’ (p. 657). While we may think of traps as blunt and materially straightforward devices oriented toward vulnerable animal bodies – ‘to inclose or impound or encage, or to seize by the head, horns, limbs, gills; to maim, wound, crush, slash, brain, impale, poison, and so on’ (pp. 659–660) – Mason emphasizes how traps must, more importantly, orient toward an animal’s *mind*. A trap must persuade its prey to play the role scripted for it in its design. As Mason put it:

The trap itself is an invention in which are embodied most careful studies in animal mentation and habits – the hunter must know for each species its food, its likes and dislikes, its weaknesses and foibles. A trap in this connection is an ambush, a deceit, a temptation, an irresistible allurements: it is strategy. (p. 659)

In anachronistic terms, we can say that Mason figures traps as *persuasive technologies*, devices designed to alter the behavior of their prey, in order to catch them. Embodied in the trap is an intricate mental interaction between hunter and prey, not merely a brutal mechanism.⁴

As a result, traps become sites of extraordinary drama for Mason, where human and animal minds come to know each other and have sudden, tragic moments of recognition. He narrates the traps in his survey like stories, blending technical and poetic language:

‘The bear crouches between the logs, pulls the trigger, and releases the lever, which flies up and lets the ring that supports the fall slip off; then comes the tragedy’ (p. 673). Figuring traps as dramas, not merely devices, makes their persuasive qualities evident: we encounter animals not as instinctive machines, but as tragic characters brought to untimely ends.

Mason’s narrations trace the intricate circulation of knowledge and agency in and around the trap: hunters study their prey and lay their thinking down in material design, inquisitive animals investigate the bait, only to realize the nature of their situation too late, as the trap works automatically, as though ‘the thought of the hunter [was] locked up in its parts, ready to spring into efficiency at a touch’ (p. 660). In Mason’s accounting, agency is fluid and mobile, circulating among hunter, animal, and trap in an unfolding process that is not simply the execution of human will, but rather the interaction of a variety of intentional and automatic parts. If the animal does not play its scripted role, then the trap does not work (Akrich, 1992).⁵

Where behaviorism would eventually argue that humans are like animals because of their unthinking habits, Mason treats animals like humans because they are agents caught up in dramatic arcs beyond their control, susceptible to the designs of others. This is evident from Mason’s opening epigraph, which finds Decius Brutus boasting, in Shakespeare’s *Julius Caesar*, how he will tempt the dictator to the scene of his eventual death:

That unicorns may be betrayed with trees,
And bears with glasses, elephants with holes,
Lions with toils and men with flatteries, . . .
Let me work ;
For I can give his humor the true bent,
And I will bring him to the Capitol.

Julius Caesar, II, 1.

Like Mason, Brutus here collects mental and physical techniques of capture together – flattery is like the tree that catches a unicorn’s horn, the mirror that entices a bear, or the net that ensnares a lion. With this opening, Mason inaugurated an enduring theme in the anthropology of trapping: if we attend closely to the process of entrapment, as it unfolds over time, we will find it hard to clearly distinguish persuasive from coercive, or mental from physical, techniques.

A century later, in the first issue of this journal, Alfred Gell (1996: 27) analyzed the ‘time structure’ of the trap – its durational unfolding beyond the climactic snap of the mousetrap or the release of the lever. ‘It is hard not to see,’ he wrote, ‘in the drama of entrapment a mechanical analogue to the tragic sequence of hubris–nemesis–catastrophe’ (p. 29). In his telling, a curious chimpanzee, releasing a poisoned arrow while investigating a strange thread, is Faust; a hippopotamus, ‘lulled into a sense of false security by sheer bulk and majesty’ before being speared, is Othello (p. 29). A trap, Gell argued, ‘embodies a scenario’, materializing and configuring a relationship between hunter and prey, ‘that binds these two protagonists together, and which aligns them in time and space’ (p. 27). Although he did not reference Mason, Gell’s account of the trap as a kind

of mechanically aided drama and ‘nexus of intentionalities’ (p. 29) picked up and extended many of his themes.⁶

Where Mason drew attention to the psychological aspects of materially violent devices, Gell used traps to think through the psychological intricacies of artworks, which, he suggested, functioned as ‘thought-traps’ (Boyer, 1988; Gell, 1996). Like conventional traps, works of art embodied something of the agency of their makers, which, if they successfully anticipated their audience, would ensnare viewers’ minds. ‘Every work of art that works is like this’, Gell (1996: 37) wrote, ‘a trap or a snare that impedes passage; and what is any art gallery but a place of capture[?]’. Elsewhere, Gell argued for including ‘technologies of enchantment’ – advertising, art, and other techniques for producing psychological effects – in our definitions of technology (Gell, 1988, 1992; see also Cochoy, 2007 on ‘captation’). ‘The technology of enchantment,’ he wrote, ‘is the most sophisticated we possess’ (Gell, 1988: 7). More expansively than Mason, Gell drew no essential distinction between mental and physical capture, suggesting that trapping itself may always be both material and mental. Skinner’s boxes, Eyal’s interfaces, Mason’s animal traps, and Gell’s paintings are all simultaneously physical and psychological devices.

I use *captivation* to encompass this broad sense of capture, spanning rapt gallery audiences, deliberating consumers, and caged birds. ‘Captivation’, in its older sense, made no special distinction between the capture of the mind and the capture of the body. The point is not to ignore the differences between mental and physical capture, which are supported by a dominant Cartesian common sense. Rather, the point is to reorient our attention toward the vast middle ground between coercion, figured as material or technological, and persuasion, figured as mental or cultural. Ethical disputes that hinge on whether a technique is properly persuasive or coercive miss the fact, evident in trap design, that most persuasive technologies work in the blurry middle.

Cultures of capture

So far, we have encountered traps in isolation: an individual trap, bearing the agency and ideas of its maker, tempts an animal, standing for its whole species, into captivation. The tragedies Gell and Mason narrate befall individuals, and Eyal’s idealized account of users finds them alone, interacting only with their screens. But neither hunters, prey, nor traps exist in isolation. The anthropology of trapping covered so far has prized open the apparently abrupt climax of the trap, showing the entanglement of agencies within what turns out to be a more durational time structure. Working from there, we can now locate these agentic tangles in the broader ecologies of knowledge and technology on which they depend.

In the balance of this article, I return to contemporary captology and the world of algorithmic recommendation to demonstrate how traps are embedded in particular cultures of capture, involving shared values, epistemic frames, technical resources, economic pressures, organizations of labor, and emic theories of trapping itself. I outline a paradigm shift in the field of recommender research, which, by its end, found practitioners like my interlocutor Mike thinking of their work in explicitly captological terms.

At their origins in the mid-1990s, recommender systems were not commonly thought of as tools for captivation. Rather, they were developed, coincident with the rise of the World Wide Web, as tools to help users manage increasingly large catalogs of information, like message board posts, movies, or music (Resnick et al., 1994, Shardanand and Maes, 1995). As the field grew and researchers proposed metrics to evaluate their systems' performance, an error metric called root mean square error (RMSE) became its paradigmatic measure. The basic idea is simple: a recommender system predicts how users will rate items, and it is judged by how accurate its predictions were.⁷ This metric – easily computed, simply understood – soon dominated the field, and the paradigm reached its culmination in 2009, when the DVD rental company Netflix awarded a \$1M prize to a team of researchers that reduced its RMSE by 10 percent (see Hallinan and Striphas, 2016, for an account of the contest).

To critics, this narrow focus on prediction and error indicated 'how central the accuracy of the recommendation system is to such organisations' (Beer, 2013: 64), at the expense of other potential concerns. But, by the time Netflix awarded its prize, the predictive paradigm, centered around RMSE, was already faltering, and the company never implemented its prizewinning algorithm. The winner was, as Netflix engineers often noted in their conference presentations, unwieldy, complex, and computationally intensive, having been hyper-engineered to reduce RMSE at any cost. But, more significantly, Netflix's business interests had changed: when the contest began, it was a DVD rental company, mailing discs to its customers' homes; by the end, it was a video streaming service, playing on-demand in users' web browsers. Where the goal of recommendation had once been to accurately represent the future, it was now to keep users streaming, retaining them as paying subscribers.

This captological turn was anticipated by a pair of publications in 2000: *The Tipping Point*, the book that would launch journalist Malcolm Gladwell's career as a public intellectual, and an article in this journal by Daniel Miller (2000) that used Gell's work to theorize 'websites as traps'. In his book, Gladwell coined a term that would become popular among marketers and media companies as they made their way online: 'stickiness', which described how messages packaged according to psychological lessons managed to hold audiences' attention and stick in their minds. Stickiness became a common goal of commercial web designers, who sought to attract users and their attention, such that they would be more likely to click on advertisements, purchase products, or simply increase user counts (see, e.g., Heath and Heath, 2007).

Miller, by contrast, focused his attention on personal websites encountered during fieldwork on the internet in Trinidad. He narrated the experience of following links among homepages:

I found that almost on a daily basis I would start with the intention of following one particular route of investigation and then find myself seduced by the aesthetics of one of the websites visited and moved by the simplicity of clicking to follow a link proffered by that site. A few more clicks would send me hurtling down some channels carved out of cyberspace by the

sculptured links of these website creators, often to such a degree that it was hard to retrieve the original place from which this diversion had began. (Miller, 2000: 18)

If ‘stickiness’ implied a deadened adhesive stasis, Miller’s account evoked the coursing affective intensities of browsing the web, a kind of captivation marked, like Gell’s ‘thought traps’, by intricate local motion rather than stillness.

As Gladwell and Miller wrote, behavior design was in its infancy and the first dot-com boom was cresting to its peak. Compared to today’s experiences of losing oneself in the internet (see Paasonen, 2016), Miller’s account of networked enchantment sounds almost quaint, and Gladwell’s catalog of psychological tricks to achieve stickiness seems simple. If stickiness reflected a generic captology, analogous to adhesive birdlime, which could be smeared on a branch to catch anything that landed there, the coming captology would, like Willow’s recommender system, be highly personalized, embodying a more complex and precise theory of human behavior.

The rise of captivation metrics

Netflix’s transformation was symptomatic of a broader shift in internet business models; it reflected a set of changes in the technical, economic, and epistemic settings of recommender system research and design. Researchers finding fault in the assumptions underlying RMSE were turning to ‘user-centered’ measures; the research community’s center of gravity shifted into industry; the industry’s turn to streaming media provided a new set of incentives and sources of data. The way much commercial software was made, updated, and maintained also transformed in this period, in what Seda Gürses and Joris van Hoboken (2017) have called the ‘agile turn’, which saw the shortening of development cycles and continuous user-focused testing, such that new features or adjustments could be made and evaluated over weekly or even daily intervals. By the end of this transformation, the field of recommender research had undergone a captological turn: RMSE was dethroned as the paradigmatic measure of success, replaced by a set of measures I call *captivation metrics*, which were not concerned with accurate prediction of ratings, but with measuring the ability of a system to capture user attention, or ‘engagement’.

The predictive paradigm had held a tacit assumption about users: that they would be more satisfied by a system that could more accurately predict their ratings. But this assumption encountered a series of crises. Over time, improvements in RMSE became harder to achieve, stuck behind what some researchers called a ‘magic barrier’ (Herlocker et al., 2004: 6). One explanation for this, as a grad student put it to me, was that preferences were intrinsically unstable, or ‘noisy’. A recommender could not predict a user’s preference any more precisely than it was held, and if preferences varied significantly with time or setting, this posed a serious challenge to predictive accuracy. Experiments indicated that people often gave different ratings to the same item at different times, susceptible to contextual influences (Amatriain et al., 2009). New ‘user-centered’ studies that sought to measure satisfaction through survey instruments found a striking result: beyond a certain point, improvements in RMSE did not correlate with increased user satisfaction (Knijnenburg et al., 2012; see also Pu et al., 2011). As the title of one influential early paper put it, ‘being accurate is not enough’ (McNee et al., 2006).

At RecSys, the international recommender systems research conference I attended in Dublin in 2012, a workshop explored evaluation methods ‘beyond RMSE’. In the organizers’ report, they summarized the mood: ‘There seemed to be a general consensus on the inadequacy of RMSE as a proxy for user satisfaction’ (Amatriain et al., 2012: iv). At the next RecSys I attended, in 2014 at a Silicon Valley hotel, I saw Netflix’s head of algorithm engineering present a talk with a striking slide: an enormous, crossed-out ‘RMSE’.

Recommender researchers found a way out of this problem in the changing infrastructure of the web. As the research community’s center of gravity moved into industry and as companies shifted to streaming, they accumulated data that could replace the explicit ratings that had previously defined the field. Logs of interaction data could be read as ‘implicit’ ratings: users stopping a video partway through, skipping over recommended items, or listening to songs multiple times all became interpreted as ratings data. These data were more plentiful than explicit ratings, being generated by any interaction a user had with a system, and, in an interpretive move inherited from behaviorism, they were also taken as more truthful than users’ explicit ratings.⁸ Although recommender systems researchers had investigated implicit ratings since the earliest days of the field (e.g. Resnick et al., 1994: 182), the agile turn had made the collection and organization of such data a central part of software development, readily available. Activity logs, interpreted through a behaviorist lens, became a privileged source of information about users, thanks both to their preponderance and their unwitting generation.

Looking for signs of ‘satisfaction’ in the logs, developers found it in user retention: just as repeated listens to a song could indicate a preference for it, so continued usage of a service was taken to indicate satisfaction. In a blog post describing their move ‘beyond the five stars’ of explicit ratings, Netflix engineers wrote that they were now focused instead on ‘our members’ enjoyment’ – measured by how much time people spent watching videos and how long they remained paying subscribers (Amatriain and Basilico, 2012). When Mike told me about his goal of hooking users, he also boasted of Willow’s data analytic sophistication: ‘every single change that happens on the service has been exactly measured for its listening and retentive impact.’

Instead of predicting explicit ratings, developers began to anticipate implicit ones, and with this came a plainly captological approach to design: using traces of interactions recorded in activity logs, developers designed their systems to elicit more interactions.⁹ The prototypical recommender system was no longer a support for finding information, but a trap for capturing fickle users. A user seen through ratings data was a fuzzy portrait rendered in preferences; a user seen through activity logs was a ghostly presence who left traces over time. A retained user was, in a simple sense, bigger in the logs – they left more traces, which provided more data for recommendations. Recall Mike’s claim that long-term listeners could enjoy the fruits of extensive personalization, while new users received more generic efforts at captivation; new users were confronted with recommendations designed to elicit interaction and increase their presence in the logs as quickly as possible.

Where canonical error metrics like RMSE compare snapshots – a set of predicted ratings and a set of actual ratings – captivation metrics measure retention over time: from daily or monthly active users, which indicate how many people use a service in a given day or month, to the evocatively named ‘dwell time’, which measures the length of individual user sessions. Captivation metrics thus retain a pair of key features found

in other traps: they are interested in unwitting interactions, and they are essentially time-structured. What matters is not the accuracy of a representation, but how an interaction unfolds over time. In the contemporary software industry, captivation metrics are key indicators of a company's health and growth (Graham, 2012). These metrics are so important to startups and their venture capitalist investors that they are often prominently displayed on dashboard screens in offices, like an echocardiogram in a hospital room. Although other metrics persist in limited use, these are typically subservient to the higher goal of engagement.

Conflating satisfaction and retention helped mediate a tension between developers, who often expressed to me a strong desire to help users, and business people, who wanted to capture them. Appeals to user 'satisfaction' hold a moral power within the software industry, and are thus turned to justify a variety of technical decisions (Van Couvering, 2007). But they also express a basic ambivalence in technologies of enchantment: people desire and enjoy enchantment, and the tension between 'satisfying' users and capturing them is not easily resolved. Thus, Mike could, without any apparent irony, tell me that he was both working in his listeners' interest and trying to get them addicted.

Infrastructure is a trap

As algorithmic recommendation turned captological, it spread. No longer is the recommender an isolated part of the interface in a few media streaming platforms; now, on services like Netflix, 'everything is a recommendation', with personalization extended beyond ratings prediction to influence everything displayed to a user, from the items on a landing page to the categories those items appear in, and even the art used to represent them (Amatriain and Basilico, 2012; Mullaney, 2015). And, conversely, the data that flows into the recommender has broadened to include practically any form of interaction, even (and now especially) interactions that a user may not realize have occurred – such as data shared by a social network, saved in a browser history, or captured from a smartphone's sensors. Algorithmic recommendation has settled deep into the infrastructure of online cultural life, where it has become practically unavoidable.

This situation has spurred an increasingly vocal public critique, which takes on captological design not only for the privacy implications of data collection, but specifically for its behaviorist heritage and intent; describing algorithmic filtering as a Skinner box is now commonplace (e.g. Bosker, 2016; Davidow, 2013; Leslie, 2016). Although these critiques take issue with the current scope and power of captology, they generally share its behaviorist common sense. They identify the problem as misaligned corporate incentives, rather than behaviorist premises. This shared common sense is evident in how many leading public critics have backgrounds in captological design themselves: Tristan Harris, co-founder of Time Well Spent, an organization aspiring to 'reclaim our minds from being hijacked by technology', is a former Google product manager and alumnus of Fogg's Persuasive Technology Lab (Time Well Spent, 2017). Eyal and Fogg themselves have come to emphasize their own captological expertise as a resource to help *resist* such engineering, not only to build it.

What is new in these critiques is a focus on the infrastructural breadth of captology, how algorithmic recommendation has become inescapable for contemporary users of the

web. For instance, *Black Mirror*, the digital dystopian TV series, takes the pervasiveness of such traps as a leitmotif, allegorizing the ends of mental captivity in extreme physical form: characters find themselves caught in screen-covered rooms or isolated in worlds where everyone else is stuck rapt to their smartphones, and any effort to escape only causes the trap to ratchet tighter (Bien-Kahn, 2016). As the series' director describes it, 'every single character in all of those stories is trapped from the very first frame and then never gets out' (Bien-Kahn, 2016).¹⁰ What can we do, these critiques ask, when the very setting for social action becomes a trap?

Returning to the time structure of trapping makes the continuity between traps and infrastructures more visible: an infrastructure is a trap in slow motion. Slowed down and spread out, we can see how traps are not just devices of momentary violence, but agents of 'environmentalization' (Corsín Jiménez, nd: 9), making worlds for the entities they trap. In their introduction to this special issue, Chloe Nahum-Claudel and Alberto Corsín Jiménez describe how capture can expand to the scale of the environment itself, in what they call 'landscape traps': Kalahari hunters plant bushes to more effectively drive their prey into snares; ancient hunters in northern Argentina left tools and traps across the desert for future hunters, transforming it into a 'landscape of anticipation' (Haber, 2009: 427; Nahum-Claudel and Corsín Jiménez, Introduction to this issue). If the tragedy of entrapment begins when prey first, unwittingly, interact with the trap, then landscape traps produce environments where prey is already effectively caught.

To be caught at this speed is not to be dead, rather it is to be enclosed, known, and subject to manipulation. In other theoretical registers, this is akin to Deleuze's 'control' (1992; Cheney-Lippold, 2011) or Foucault's 'governmentality' (1991): styles of enclosure that are no less sinister for being less than absolute. But to be caught at this speed is also to be *hosted* – to be provided with conditions for existence that facilitate activity while constraining it (Derrida, 2000; Swancutt, 2012). In this view, a trap is not simply the unilateral application of technical force, but rather a fundamentally uncertain effort to relate to others which thereby produces a world. We could say that infrastructures are already traps – arrangements of technique and epistemic frame designed to entice and hold particular kinds of envisioned agents, according to culturally specific cosmological preconceptions. The lesson, perhaps, is that 'traps are predatory, but they are also productive' (Corsín Jiménez, nd: 3), not reducible to a simple moral tale about the wickedness of capture.

The alternative, as the anthropology of trapping can help us see, is not a state of traplessness, free from any enclosure and the designs of others, but rather a situation where we are unaware of the infrastructures that have already caught us, which host our thinking and living. We can see this in the visions of freedom laid out by contemporary critics of captology: in imagining an escape from the machinery of behavioral design, they are already trapped in captology's behaviorist frame, reliant on the same world-making epistemic and technical infrastructures they militate against.

Having identified algorithmic recommendation as a kind of trap, noting how it draws together ecologies of knowledge and technology with theories about prey and value, we might move beyond denouncing entrapment and toward reconfiguring our captivating social infrastructures. While traps make worlds, they are already suspended in broader

infrastructures of meaning and material, drawing together, for instance, the concerns of venture capital and the availability of big data logs into a captological cosmology; as traps catch their prey, so too are they caught up by others. The question to ask of traps may not be how to escape from them, but rather how to recapture them and turn them to new ends in the service of new worlds.

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Notes

1. Mike and Willow are pseudonyms.
2. For more on the relationship between habits and new media, see Wendy Hui Kyong Chun's *Updating to Remain the Same* (2016).
3. See Natasha Dow Schüll's *Addiction by Design* (2012) for an account of similar processes in the design of slot machines.
4. See Singleton (2014) for a discussion of the relationship between traps, design, and trickery.
5. Or, as Rey Chow and Julian Rohrer (2012: 46) put it: 'once caught, the prey's existence renders the trap more than just the elegant design understood from the sovereign command perspective of the hunter, who can henceforth no longer monopolize the terms of the interaction.'
6. See Dieter (2015) on 'dark patterns' in user experience design and their temporal, trap-like unfolding.
7. Though apparently simple, such calculations involve many choices about what kinds of errors should count and how much. See Seaver (2012) for a more elaborate account.
8. See Ekstrand and Willemsen (2016) for an effort from within the academic research community to push against this behaviorist framing in favor of letting users 'speak'.
9. See Agre's (1994) 'Surveillance and Capture' for an analogous process in the design of workplace software.
10. Ironically, as the series' director noted in an interview, the show is now produced by Netflix: 'It's all very exciting – a whole new bunch of *Black Mirror* episodes on the most fitting platform imaginable' (Birbaum, 2015).

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