

UNIVERSITY OF CALIFORNIA SAN DIEGO

Solving and Dissolving Musical Affection: A Critical Study of Spotify and Automated Music Recommendation in the 21st Century

A dissertation submitted in partial satisfaction of the
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by

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DEDICATION

This dissertation is dedicated to my parents, Alexandra Tracy Maeck and Daniel Chodos.

PREVIEW

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ABSTRACT OF THE DISSERTATION

Solving and Dissolving Musical Affection: A Critical Study of Spotify and Automated Music Recommendation in the 21st Century

by

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Professor Chair David Borgo, Co-Chair

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Music has not been exempt from the so-called “curatorial turn” that is visible in so many parts of our culture – the turn, that is, toward machine learning to help consumers sort through the glut of media with which we are all confronted today. Automated music recommendations, in fact, are probably the single biggest driver of the music industry’s recovery from the crisis it faced at the beginning of the 20th century. Nobody knows what shape the music industry will take if and when this recovery is complete, but it seems certain that automated curation will be at its center. This fact represents a confrontation of the human faculty of aesthetic judgment and machine

learning at a scale the world has never seen. The issue of automated music recommendation raises many of the philosophical problems familiar from the critique of technology in culture. It does so, moreover, in a way that offers new insights into this familiar problem. In spite of this, little critical attention has been paid to music as a subject in the field of critical algorithms studies. In this dissertation, I provide an introduction to thinking critically about this crucial topic in algorithmic culture, taking Spotify as a case study that exemplifies many broader trends. I situate Spotify in the history of American copyright law, I perform a close reading of the Spotify platform, and I conduct quantitative experiments to analyze the large-scale behaviors of Spotify's recommendation engine. Although Spotify has often been seen as a singularly innovative company that somehow managed to "save" the music industry as a whole, this study shows that in many ways Spotify is better understood as an expression of attitudes toward musical meaning and commerce that are quite traditional in the music business.

Introduction

Every day, millions of people turn to Spotify to help them choose their music. This may seem like a simple statement about the company's enormous reach, but it is more than that. The interesting thing about Spotify is not that it has emerged as the world's most visible platform for music streaming, nor even that it signals a broader shift in the music industry away from traditional modes of distribution. Instead, what is interesting about Spotify today is the much more complicated – and much more culturally relevant – fact that the nature of its service is, more than anything else, to provide music recommendations. There was a time, not too long after Napster, when providing access to 30 million tracks was enough to distinguish Spotify from its competition, when having lots of music “at one's fingertips” was a huge draw for music consumers. At that time, Spotify users were still expected to choose for themselves what music to listen to. In fact, it was assumed that they would *want* to do so. But in recent years Spotify, like virtually all its competitors and most tech companies in general, has pivoted toward recommendation, assuming instead a “lean back” posture for its users. Customers today need more than just access; they need help choosing.

The idea that there is a digital “curatorial turn” analogous to the one scholars have spotted in theater and museum studies has, as a result, emerged as a common theme in studies of digital culture.¹ And when it comes to the “curatorial turn,” Spotify is probably the most dramatic example. As of the last 10 years or so, it is not a place to go to listen to music so much as (quoting

1. See e.g. Tom Sellar, “The Curatorial Turn,” *Theater* 44, no. 2 (May 2014): 21–29 and Maria Eriksson et al., *Spotify Teardown: Inside the Black Box of Streaming Music* (The MIT Press, 2019).

Spotify's promotional materials) a place to

Find the right music or podcast for every moment.
Soundtrack your life with Spotify.²

The key to Spotify and the recommendation industry in general, in other words, is personalization; “every pixel,” claims Yves Raimond of Netflix, is personalized.³ And the key to personalization is another technological development currently much in vogue: machine learning. As Tony Jebara, Spotify's current head of machine learning, puts it,

Our algorithms allow us to scale out very personalized, hand-selected experiences that help members feel like they were made just for them. The goal is to deliver an amazing listening experience.⁴

That our lives need soundtracks, and that the primary role of music in general should be to provide them, and that the best way to achieve them is machine learning, are tacit assumptions of much more cultural import than the dazzling size of Spotify's catalogue or the low monthly subscription fee to access it. The real change ushered in by the era of streaming music is not its affordability, ubiquity or ease of access so much as its drift into a position adjunct to the rest of our lives. Market pressures have made personalization necessary; personalization has as its necessary correlate that music serves as part of a broader “listening experience.” Music becomes paired with life, just as wine is paired with food, to cite a comparison that appears at least twice in Spotify's own promotional materials.

It is a general feature of our technologized culture that a rise in algorithmic mediation has been attended by this rise in digital curation. Brute computational tasks like sorting and document classification, traditionally relegated to the dry disciplines of information retrieval and, at their most colorful, library sciences, have assumed an epochal significance that their earliest

2. Accessed at <https://www.spotify.com/us/about-us/contact/>, on 08-08-2019. The addition of “podcasts” is new. Spotify has in recent years made them a bigger part of their strategy.

3. “From Listening to Watching, A Recommender Systems Perspective”, given at ICML June 2019, <https://slideslive.com/38917438/from-listening-to-watching-a-recommender-systems-perspective>, accessed 9-01-2019

4. Accessed at <https://newsroom.spotify.com/2019-10-24/6-questions-and-answers-with-tony-jebara-vp-of-machine-learning/>, 10-15-2019

devotees could never have imagined. When Calvin Mooers heralded the dawn of the discipline of information retrieval in 1950 at a conference at Rutgers University, it was in a rarefied proceedings paper with the uninviting title “The theory of digital handling of non-numerical information and its implications to machine economics.” In it Mooers expressed his frustration with the cumbersome process of finding relevant information at libraries, something his academic colleagues could all relate to. Technological mechanization offered the potential to give researchers easy access to relevant research without having to thumb through reams of irrelevant work. Machines could help researchers get more relevant documents faster; it had nothing titillating about it and certainly contained no special insights for culture at large. It wasn’t particularly prestigious and it bore no conceivable relationship to the arts or consumer culture. Nevertheless it is this same essential project – the science of “machine searching and retrieval of information from storage according to a specification by subject,” as Mooers puts it – that lies at the heart of Spotify and countless other daily features of life on the Internet today.⁵

Make an Amazon purchase and collaborative filtering algorithms will recommend others to you. Click on a news story and an aggregator will find you others like it. Send a Gmail and Google will use the information in it to serve you more “relevant” ads. Commit a crime and the COMPAS system may make a recommendation to a judge about an appropriate punishment.⁶ Depending on where you stand on the social role of technology and the ethics of surveillance, these examples will hold different meanings for you. They might exemplify the inherent justice of dispassionate reason – this, at least, has always been the pitch for criminal recidivism predictions, which have a much longer history than is often acknowledged.⁷ Or they may point to the hegemony of a way of thinking belonging to a small, powerful group of mostly white men; they may be classic examples of the false objectivity and gendered exnomination that, for feminist

5. Mark Sanderson and W. Bruce Croft, “The History of Information Retrieval Research,” *Proceedings of the IEEE*, no. 100 (May 2012).

6. See Keith Kirkpatrick, “It’s Not the Algorithm, It’s the Data,” *Commun. ACM* (New York, NY, USA) 60, no. 2 (January 2017): 21–23

7. See e.g. Don M. Gottfredson, “Prediction and Classification in Criminal Justice Decision Making,” *Crime and Justice* 9 (1987): 1–20, which builds on his “Base Expectation Score” method from the 1960s.

theorists of science like Donna Haraway, this class customarily evinces.⁸ But they are all, at their core, recommendation tasks, the same ones powering Netflix, Tinder, the Facebook news feed, and pretty much everything else we do on the Internet. The ubiquity of these machine recommendations, the way users are kept in ignorance of how they work, and the biases they must inevitably all contain, are issues of inestimable cultural importance. Real world applications of automated recommendation describe a spectrum from the utopian to the apocalyptic. At the core of this dissertation is the question of where on this spectrum we should locate Spotify.

The question is really alluring, especially because it has seldom been addressed from a specifically musical perspective. But it immediately begs another: who are “we?” If the destructive potential of algorithmic curation has received more attention in its non-musical deployments, that may be due as much to the difficulty of this second question as it is to the admittedly higher stakes of the social justice problems. More attention, for example, has been paid to the question of whether automated credit scores will lead to a form of data-driven redlining.⁹ This is perhaps a more urgent question than the musical one, but in a way it is also a more straightforward one. It is almost impossible, in other words, to know what would actually represent a socially deleterious music recommendation system. Incidentally, as I show in this dissertation, it is also almost impossible to measure the successfulness of such a system, at least in any philosophically coherent manner. And the flatness of that argumentative conundrum – can’t say anything certain against music recommendation, but for the same reason can’t say anything for it either – is one of my core findings. Automated music recommendation presents this argumentative double bind from every angle. It is a weird tautology that the designers of Spotify can evade only by virtue of authoring recommendation software rather than music philosophy. But the puzzle is real for them too, or at least it ought to be; the notion of a “good” recommendation cuts in so many different analytic directions at once that critiquing a recommender system is probably as hard as building

8. Donna Haraway, “Situated Knowledges: The Science Question in Feminism and the Privilege of Partial Perspective,” *Feminist Studies* 14, no. 3 (1988): 575–599.

9. Mark Andrejevic, “Big Data, Big Questions— The Big Data Divide,” *International Journal of Communication* 8, no. 0 (2014).

one. Perhaps building one would be the truest mode of critique; in writing this dissertation, I have often wondered whether a random music recommendation system might actually make my point for me. What better way to deflate the illusory notion of “musical meaning” than to pay attention to the “meanings” that inevitably emerge from random random recommendations, and compare them with Spotify’s?

It has always been the nature of aesthetic faculty, contingent and unruly as it is, to lead to this tricky argumentative predicament. Is not Kant’s solution – purposiveness without purpose, the presumption of universal assent that you assume but never actually demand – a classic expression of this same problem? Nevertheless the allure of that first question, whether or not to call Spotify apocalyptic, is strong enough for me to believe that some kind of answer to it is possible. And that is what this dissertation arrives at: a kind of an answer. It is, of course, neither an endorsement nor a condemnation of Spotify and automated recommendation. I do show some small ways in which the system works, providing statistical sketches of its large-scale behaviors and an intimate look at an early version of its recommendation engine. Depending on the reader’s commitments, these findings may motivate real judgments of Spotify’s quality: a system that, say, is on the whole less “confident” in its assessment of “classical” music than “funk” (this is true of Spotify’s; see Appendix 2) may, for some, be a bad one no matter what. But it is not my goal to arrive at this kind of claim. Nor do I claim to have caught Spotify in tacit acts of implicit bias or sinister collusion with its major label partners, even though these are some of the very considerations around which my experiments are structured. Instead, these issues serve as provocations to a long meditation on the effort to automate music recommendation in general, with conclusions that do not always point in the same argumentative direction. Thus my title’s locution: this dissertation is an open essay on the effort to “solve” musical affection, with the ultimate conclusion being that it admits of no solution whatsoever, but instead “dissolves” before our eyes every time we attempt one.

The interesting thing about that is that musical affection doesn’t dissolve like this until we

try to solve it. The importance of musical affection for identity construction or the management of everyday activities (to cite just two of the many theories of “musical meaning” surveyed in the pages to come) testifies to the apparent solidity with which it constantly presents in real life. So, in a way, does the success of Spotify itself; is not the mere survival of Spotify, a considerable achievement in today’s precarious music business, proof that we actually do know what we like, that our affection for music is as real as anything on earth? The answer to this question, I think, is basically yes. As we click around the Spotify app, we *do* know whether or not we like what Spotify suggests to us. The thumbs up/thumbs down adjudication is a case of genuine aesthetic judgment, one where we postulate a universal accord that we will never actually get. But this raises a related but different question: does the impressive survival of Spotify then prove that there are at some level “right” and “wrong” answers to the question “do I like this?” Does it prove, in other words, that there exists such a thing as a “good” recommendation? Countless other recommendation systems, some using real people where Spotify uses machines, have failed where Spotify has succeeded.¹⁰ Does Spotify’s success not, at some level, make the case that “solutions” to the problem of musical affection exist, even granting that Spotify’s might be wrong or partial?

To that second question (are there “good recommendations”?), this dissertation responds in two ways: first, I go to considerable lengths to demonstrate that Spotify’s answer to this question has to be yes. The system is necessarily predicated on a theory of musical meaning that, first, reifies it and, at second, externalizes it; Spotify seems to believe that there are right and wrong musical recommendations, and that those rights and wrongs involve connecting music to things other than itself. Second, I argue that the real answer to that question is no; in the end Spotify doesn’t actually prove anything about anything about where or what “musical meaning” is. Spotify’s continued existence proves only that Spotify exists – and given the “legal prehistory” of Spotify and its consistent operating losses, in a sense it doesn’t even really prove that (see

10. Neil Young’s fledgling service *PonoMusic*, for example, tanked in 2017. Earbits Media never really took off. There are many other examples.

Chapter One).

On a philosophical level, what Spotify offers are not “solutions” to musical affection in the sense that humanistic inquiry into musical meaning has always understood the problem, but what I term “dissolutions:” makeshift slices of data bludgeoned into an almost recognizable simulacrum of the love for music. This sounds like a condemnation but it is not; the whole enterprise of machine learning can be seen, not unflatteringly, as the creative and often useful practice of information bludgeoning. As a useful, or at least marketable act, of data reduction, I make no quarrel whatsoever with Spotify. Instead, I am making the distinction between a “solution” – a model, say, that offers real insight into some feature of how the world is or behaves – and what I term a “dissolution,” a phenomenon wherein the object under scrutiny goes further and further out of focus the harder you look at it. The philosophical content contained in Spotify occupies the latter tier. If the various quantitative experiments undertaken in this dissertation do too (see Chapter Five), more to my point; the critic and the engineer both confront in musical affection the same evanescent substance, so it makes sense that their results might be philosophical mirror images.

Normative Commitments

One of the easiest places to take issue with Spotify and automated recommendation in general is its “audio features” object, which contains the dozen or so ways in which every track in Spotify’s catalogue is measured. This object, and the difference between it and actual human listening, is a central provocation to this dissertation. The “audio features” according to which the Spotify catalogue is rated are dealt with at great length in Chapter Five, but let us examine them here too:

*liveness, valence, energy, danceability, speechiness, instrumentalness, tempo, loudness, duration_ms, acousticness*¹¹

11. There are other measures, but they are ignored for reasons discussed in Chapter Five. See appendix 1 for

Although we can never know exactly *how* these measures are used in Spotify's system, we do know that they exist, and it seems safe to assume that they are used somehow. Indeed, it seems safe to assume that it is these very features that are brought together with "extra-signal" information like web crawls and purchase data to form the model of "musical meaning" at work in Spotify's system. That these assumptions are safe is one of the main arguments made in Chapter Three. But some of these features are musically naive; *valence* in particular – the "good/bad" emotional qualia of a song – although a standard term from music psychology, feels like it does a gross injustice to the nuance and precision of music as art, to say nothing of Adorno's aesthetic "truth content," if we believe in that nebulous quantity.¹² For the many musicians who today carry on with some version of Romantic aesthetics, seeing music as something like a depiction of the Will Itself, or as an "intimation of the absolute," or believing that it does something very serious with vital if ineffable bearing on world affairs, Spotify's features are dreadfully flat footed and trivializing. Whether or not we call ourselves Romantics, the idea that a statistically derived "valence" captures anything musically meaningful will, I think, rub many readers the wrong way. For these readers, then, the demonstration that machine recommendations are in part predicated on such blunt instruments may be all they need to hear; if it's this silly "valence" behind My Discover Weekly, they might say, then it's obviously a silly system. People should know, though, that in dismissing the "two dimensional musical space" of valence and arousal they will be dismissing much of the history of music psychology, the whole subfield of Music Emotion Recognition, and an unknown but substantial measure of how contemporary recommendation services actually work.¹³ It is not the contention of this dissertation that these fields are inherently meaningless, but

Spotify's full definitions of these words – definitions, never explanations or derivations.

12. See Geoffrey L. Collier, "Beyond valence and activity in the emotional connotations of music," *Psychology of Music* 35, no. 1 (2007): 110–131 for an example that problematizes the idea of "valence," and in doing so demonstrates its ubiquity in music psychology.

13. See Huaping Liu, Yong Fang, and Qinghua Huang, "Music Emotion Recognition Using a Variant of Recurrent Neural Network," in *2018 International Conference on Mathematics, Modeling, Simulation and Statistics Application (MMSSA 2018)* (Atlantis Press, 2019) and Verena Haunschmid, Shreyan Chowdhury, and Gerhard Widmer, "Two-level Explanations in Music Emotion Recognition," *CoRR* abs/1905.11760 (2019) for contemporary examples that preserve these emotion categories.

it is important from the outset to note that within the basic building blocks of my experimental program (the audio features object) there are already in place certain problematic assumptions.

If we grant that these categories can say something meaningful at least some of the time, it is hard to imagine them being equally meaningful for all musical genres. They betray, in other words, a bias toward those musical forms for which they do represent meaningful musical categories. There are, of course, many musical traditions in which tempo, mode, etc., are analytically meaningless. Before any experimentation or analysis, then, the audio features object amounts to a *prima facie* case of implicit bias (the greatest sin in machine learning); if I make music that cannot ever be meaningfully plotted along those 10 axes, I might be forgiven for considering the system to be inherently biased against me. How exactly that bias actually operates – whether it would prejudice the system in favor of certain genres, lead to incoherent recommendations, or have some other effect – is anyone’s guess, but that it on some level exists seems straightforwardly true.

So at a minimum we can tentatively say that Spotify has some normative commitments built into its API methods, and that those normative features probably surface somewhere in its recommendations. What about the commitments of this dissertation? This dissertation moves through a number of them, discards most of them, and concludes by tentatively embracing some of them, an embrace which amounts to the thesis about “dissolution” alluded to above. The experiments are in many cases motivated by clear normative ideas, but in most cases this dissertation tends to try them on without necessarily endorsing them. I occasionally assume normative positions, that is, but usually only as a way of getting inside a particular issue related to Spotify and music recommendation. My experiments play with the idea, for example, that aesthetic homogeneity would be an *a priori* evil effect, but on a broader level I accept the idea that sometimes aesthetic homogeneity would be exactly what you might want from a recommendation engine. My experiments and discussions depart from certain positions for the purpose of exploratory data collection. In my concluding chapter, I revisit these findings an

synthesize them into a claim about the whole problem of automating music recommendation, at which point I take positions that are no longer exploratory but genuinely held.

It makes sense, then, to flag these normative commitments ahead of time in this introduction. I mention above the one about aesthetic homogeneity being bad, but there are others. Chapter One, what I call a “legal prehistory of streaming audio,” uses certain normative positions about copyright law in American culture as a way to begin studying the broader debate that has taken place between “copyright optimists” and “copyright pessimists” in the last half century. Without actually taking the position on, the chapter proceeds from the notion that copyright protections should, wherever possible, favor the interests of the public at large in accessing the collective fruits of society’s creativity rather than the interests of copyright holders in profiting from that creativity. From this perspective, copyright should exist for the sole purpose of making more creative work happen; anything else is cynical overreach. This is the clear rhetorical charge of the US Constitution’s copyright clause, and it is the issue around which the copyright wars of the latter half of the 20th century were fought.¹⁴ Related to this commitment is the notion that there are modes of human creativity that are neither effectively incentivized nor eradicated by copyright enforcement, which therefore should be subject to some other regulatory paradigm. These are commitments with rejoinders from the other side, and the history narrated in Chapter One plays out on the intellectual terrain mapped by that opposition. This discussion also departs from a broadly anti-corporate posture, assuming the position (1) that corporate surveillance is bad and (2) that large conglomerates will tend to exploit unincorporated individuals like musicians. On the other hand are the claims of the record labels and free marketeers, who know the enormous costs needed to produce profitable music, and who see cultural production as just another commercial venture. That opposition, whose most famous case by far is the battle between Napster and the major labels at the turn of the century, leads directly to Spotify. The degree to which Spotify inherits from Napster cannot be overstated, a fact that any critique of the former must take into

14. US Constitution, Article 1, section 8, clause 8: copyright exists “to promote the progress of science and useful arts.”

account. Early Spotify adopted Napster's technological design (P2P), appropriated much of its disruptive caché, and ultimately represents the mirror image of its (Napster's) relationship to copyright norms in law and culture. In neither case – the legislative nor the cultural – does the chapter take a side, but instead plays with the normative commitments outlined here in order to explore the legal topography Spotify has navigated since it arrived in the US market.

Perhaps the single biggest question behind all the others this dissertation raises is the same one motivating most work on machine learning in culture generally: the question of whether human experience and behavior is at all amenable to propositional logic and pattern recognition, whether human intelligence is reducible to symbolic logic, brute computational force, and statistical patterning. Or, put another way, it is the question of what exactly machine intelligence is. We may believe, like Roger Schank, that intelligence is as intelligence does, and that an intelligently behaving system is, by definition, so. Or, with Hubert Dreyfus, that human intelligence depends inevitably upon human corporeality and is fundamentally irreducible to the manipulation of logical symbols. Or, with John Searle, that syntax and semantics bear no special relationship to each other and that, lacking the latter, a computer cannot be said to “understand” anything at all. Or, with Noam Chomsky, that the whole question is off-topic, philosophically confused, and scientifically irrelevant. In Chapter Two, I survey these and other authors, always from a perspective that combines Chomsky's (“can machines think?” is not a real question) with the heartfelt intuition of a professional musician (musical meaning can never be reduced to computation). Making music legible to a computer will always involve doing something like equating musical emotion to “valence” or the complex musical property of rhythm to “danceability.” Or, for that matter, doing something like what I do in my experiments, where songs are reduced to 10-d vectors and aesthetic diversity to Euclidean distance measures in 10-d musical space. For many who have devoted their lives to the art of music, these kinds of reduction will probably never be acceptable. This is inevitably one of the central questions of this dissertation; the question of solution and dissolution, like the question of whether Spotify

is musically apocalyptic, points back to the opposition of man and machine, and the question of whether there is a fundamental incommensurability between them (an opposition that one of Spotify's principal scientists has called "stupid"¹⁵). The normative commitment we are concerned with here is that, yes, they are in fact incommensurable, and that, no, human aesthetic behaviors are not fundamentally predictable given enough training data. These assumptions offer a lens through which I read the history of critical writing on technology in culture. Assuming the worst about technology is my way of extracting the best from its apologists.

The question of human programmability leads to fourth commitment, this time in the philosophy of mind: a commitment to Chomsky's "internalist" perspective in favor of behaviorism. The idea, that is, that the language faculty is a biological human endowment not unlike digestion or vision, whose development is regular (and therefore equal) across the species. Language acquisition is not a matter of instruction upon a blank slate, and the everyday creativity of normal language usage is not under any specifiable stimulus control.¹⁶ This insight, and its implications for a theory of meaning, is both taken up directly in the discussion of technology in culture (Chapter Two) and related directly to my discussion of musical meaning (Chapter Three). Whether machines can ever possess intelligence, on the one hand, and whether a pre-theoretical notion of "meaning" exists for which to find a musical correlate are two central questions for this dissertation: taking just a little license in extending him to a musical domain, Chomsky offers a calm "no" to both of them. I read Chomsky to say that Putnam's "meaning" is nothing more than a stipulative, technical definition; if you say meaning is outside the head, we can imagine Chomsky saying, very well, but I fail to see what that tells me about the mind or the how language organ works. In this dissertation, I proceed under a musical translation of Chomsky's position, which is the assumption that musical meaning, like linguistic meaning, is not the *kind of thing*

15. In a Billboard Q&A, since removed from the Billboard site, cited below in this dissertation.

16. See, e.g., Noam Chomsky, "A Review of B. F. Skinner's *Verbal Behavior*," *Language*, no. 1 (1959) for the famous review of *Verbal Behavior*, or Noam Chomsky, *Cartesian Linguistics: A Chapter in the History of Rationalist Thought*, Originally published 1966 (Cambridge University Press, 2009) for a work that situates his thought in the history of rationalist philosophy.