Solving and Dissolving Musical Affection

Thoughts on Musical Meaning in the Era of Automated Recommendation

Asher Tobin Chodos

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Cultured Data Symposium

Spotify "Audio Features"

Ginuwine, "Pony" (1996)

```
{
    "danceability": 0.749,
    "energy": 0.605,
    "key": 8,
    "loudness": -9.359,
    "mode": 0,
    "speechiness": 0.086,
    "acousticness": 0.00186,
    "instrumentalness": 0.0381,
    "liveness": 0.115,
    "valence": 0.966,
    "tempo": 142.024,
    "type": "audio_features",
    "id": "6mz1fBdKATx6qP4oP1I65G",
    "uri": "spotify:track:6mz1fBdKATx6qP4oP1I65G",
    "track_href": "https://api.spotify.com/v1/tracks/6mz1fBdKATx6qP4oP1I65G",
    "analysis_url": "https://api.spotify.com/v1/audio-analysis/6mz1fBdKATx6qP4oP1I65G",
    "duration_ms": 251733,
    "time_signature": 4
}
```

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Machine listening: Ab minor, 142 bpm

"True" Key: D-flat..."minor", tempo = ca. 70 bpm

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Many other critiques are easy to make:

- "Valence" is too simple
- Does music even always "have" emotions?
- What about genres for which these audio features have no meaning?

The Paranoid Hypothesis

Hypothesis: Automated music recommendation will tend to homogenize music listening and consumption.

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[1]Pelle Snickars. "More of the Same–On Spotify Radio". In: *Culture Unbound* 9.2 (2017).

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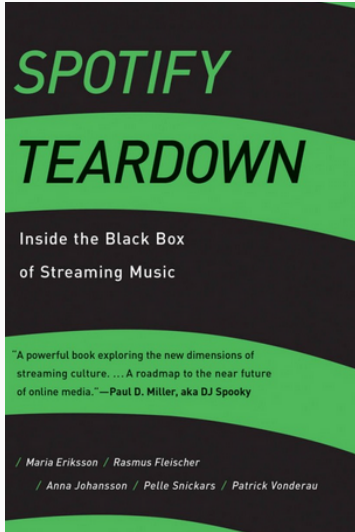
Pelle Snickars:

> *This article concludes that the various forms of public critiques of the inadequate functionality of Spotify Radio are (and were) spot on.* *In short, it is a service that has not functioned particularly well, at least not as a music recommendation system.* *By and large, however, Spotify seems to have been aware of its malfunctioning radio service and continued to neglect the issue (for different reasons).*[1]

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[1] Snickars, "More of the Same–On Spotify Radio".

SPOTIFY TEARDOWN

Inside the Black Box
of Streaming Music

"A powerful book exploring the new dimensions of
streaming culture. ... A roadmap to the near future
of online media."—Paul D. Miller, aka DJ Spooky

/ Maria Eriksson / Rasmus Fleischer
/ Anna Johansson / Pelle Snickars / Patrick Vonderau

"Spotify has been really successful in branding themselves as the friendly company that delivers music that everybody really loves. That is in contrast to Facebook, for example. But both are about the same kind of thing: getting data, working with data, knowing everything about your users. So one should also pose more critical questions."

Problems:

- What are recommendations?
- Black Box
- Knowability

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[2]Nick Seaver. "Knowing Algorithms". In: (2013). Unpublished draft available on nickseaver.com.

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- What are recommendations?
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Nick Seaver:

> *There is not one playlisting algorithm, but five, and depending on how a user interacts with the system, her radio station is assigned to one of the five master algorithms, each of which uses a different logic to select music.*[2]

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[2]Seaver, "Knowing Algorithms".

1. "Exploit, Explore, Explain" – "recsplanations"[3]

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[3]James McInerney et al. "Explore, Exploit, and Explain: Personalizing Explainable Recommendations with Bandits". In: *Proceedings of the 12th ACM Conference on Recommender Systems.* RecSys '18. Vancouver, British Columbia, Canada: Association for Computing Machinery, 2018, pp. 31–39. DOI: *10.1145/3240323.3240354*.
[4]Brian Whitman. "Learning the Meaning of Music". PhD thesis. Massachussets Institute of Technology, 2005.

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2. Machine Listening / ML approaches that combine audio content with "cultural metadata" (The Echo Nest)[4]

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1. "Exploit, Explore, Explain" – "recsplanations"[3]
2. Machine Listening / ML approaches that combine audio content with "cultural metadata" (The Echo Nest)[4]
3. Collaborative Filtering (Matrix Factorization)

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[4]Whitman, "Learning the Meaning of Music".

The Discover page
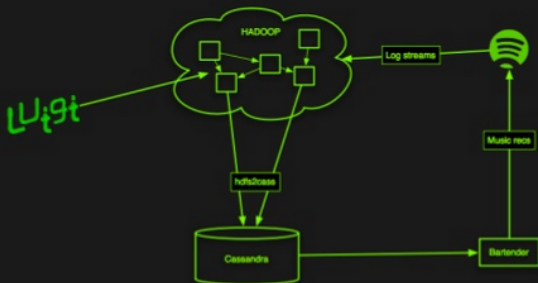
Okay, but how do we come up with recommendations?
Collaborative filtering!

[5] "Machine learning @ Spotify - Madison Big Data Meetup" (2015), published to
Slideshare.com, accessed 02-03-2020

Matrix representing users and ratings

Factored into two smaller matrices, with f factors

Instead, we use a "small" representation for each user & item: f-dimensional vectors

(here, $f = 2$)

and approximate the big matrix with it.

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Latent factors

Factors

Factor < *facere*, to make

Charles Spearman, 1904

- "The proof and measurement of association between two things"
- "'General Intelligence' Objectively Determined and Measured. "

Two factors in test performance, one of which is *g*, "mental energy."

Spearman on the ontology of *g*:

> *Our true correlation in no way deserves the reproach of being a theoretical abstraction, for it only represents the limit to which the observed correlation itself will continually approach.*[6]

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[6]C. Spearman. ""General Intelligence," Objectively Determined and Measured". In: *The American Journal of Psychology* 15.2 (1904), pp. 201–292.

L.L. Thurstone, *The Vectors of Mind* (1935), *The Isolation of Seven Primary Abilities* (1936)

- Seven intelligence abilities
- Five personality factors

Eventually, the "Five Factor" model of personality, or, the "Big Five"

OCEAN and the Big Five

We use the established scientific OCEAN scale of personality traits to understand what people care about, why they behave the way they do, and what really drives their decision making.

O — OPENNESS — Do they enjoy new experiences?

C — CONSCIENTIOUSNESS — Do they prefer plans and order?

E — EXTRAVERSION — Do they like spending time with others?

A — AGREEABLENESS — Do they put people's needs before theirs?

N — NEUROTICISM — Do they tend to worry a lot?

[7] Accessed via the Internet Archive Wayback machine, on 2-03-2020, https://web.archive.org/web/20160216023554/https://cambridgeanalytica.org/about

Spotify presumes:

1. Good ground truth data – no "algorithmic confounding"[8]

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[8]Allison JB Chaney, Brandon M Stewart, and Barbara E Engelhardt. "How algorithmic confounding in recommendation systems increases homogeneity and decreases utility". In: *Proceedings of the 12th ACM Conference on Recommender Systems.* 2018, pp. 224–232.

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3. It's OK to make predictions without being epistemologically specific.

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"Minimal epistemic realism"

"it is, in principle, possible to justify hypotheses that posit unobservable entities"

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[9] S. Brian Hood. "Psychological Measurement and Methodological Realism". In: *Erkenntnis (1975-)* 78.4 (2013), pp. 739–761.

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"Ontological Realism"

Commitment to the existence of some specified entity.[9]

Prediction performance does not require ontological realism.

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Commitment to the existence of some specified entity.[9]

Prediction performance does not require ontological realism. Estimating ability requires both (OR and MER). Where is Spotify?

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[9]Hood, "Psychological Measurement and Methodological Realism".

Return of the paranoid hypothesis

Spotify presumes:

1. Good ground truth data – no "algorithmic confounding"[10]
2. Non-difference of aesthetic experience from other kinds of consumption.
3. It's OK to make predictions without being epistemologically specific.
4. There is such a thing as a "good recommendation." And that RMSE and, above all, user retention, are good proxies for that.

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[10] Chaney, Stewart, and Engelhardt, "How algorithmic confounding in recommendation systems increases homogeneity and decreases utility".

- Rely upon latent factor model without quibbling much about ontology or epistemology.

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- Integrate with Facebook.

Facebook also allowed Spotify, Netflix and the Royal Bank of Canada to read, write and delete users' private messages, and to see all participants on a thread — privileges that appeared to go beyond what the companies needed to integrate Facebook into their systems, the records show. Facebook acknowledged that it did not consider any of those three companies to be service providers. Spokespeople for Spotify and Netflix said those companies were unaware of the broad powers Facebook had granted them. A spokesman for Netflix said Wednesday that it had used the access only to enable customers to recommend TV shows and movies to their friends.

[11]"As Facebook Raised a Privacy Wall, It Carved an Opening for Tech Giants," by Gabriel J.X. Dance, Michael LaForgia and Nicholas Confessore, NY Times, Dec 18 2018

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- Influence behavior.

Spotify vs. Cambridge Analytica

- Rely upon latent factor model without quibbling much about ontology or epistemology.

- Rely upon extensive surveillance.

- Integrate with Facebook.

- Influence behavior.

- Make money.

Thank you!

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