Solving and Dissolving Musical Affection

Thoughts on Musical Meaning in the Era of Automated Recommendation

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2-9-2020

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

Pony, transcribed

“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.

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

The Paranoid Hypothesis

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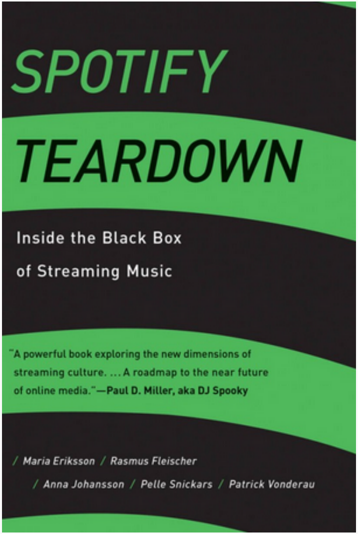
Pelle Snickars:

> *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]

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

The Paranoid Hypothesis



"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."

How does Spotify make its recommendations?

Problems:

- What are recommendations?
- Black Box
- Knowability

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 Unpublished draft available on nickseaver.com.

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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]

[2] Seaver, "Knowing Algorithms".

Likely Strategies

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

[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.

Likely Strategies

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

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Likely Strategies

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

[3] McInerney et al., "Explore, Exploit, and Explain: Personalizing Explainable Recommendations with Bandits".
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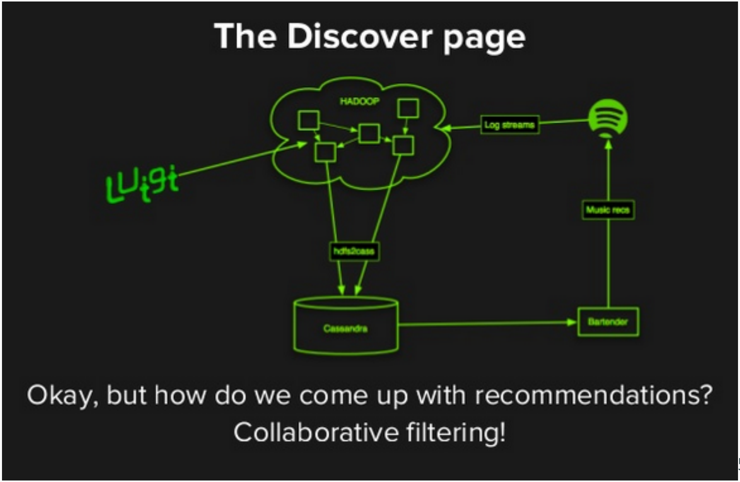
Andy Sloane, describing Spotify's recommendations in 2015



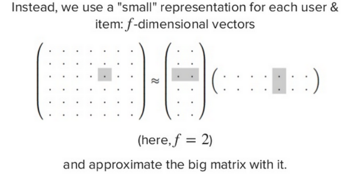
[5]

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

Matrix representing users and ratings

$$
N = \begin{array}{c}
\begin{array}{cccc} & & \text{Andy} & \end{array} \\
\begin{pmatrix}
0 & 7 & 21 & 0 \\
5 & 0 & 0 & 1 \\
4 & 0 & 13 & 9 \\
0 & 0 & 0 & 7 \\
19 & 1 & 0 & 13 \\
0 & 3 & 0 & 0
\end{pmatrix}
\end{array}
\begin{array}{l} \\ \\ \\ \text{Chumbawumba - Tubthumping} \\ \\ \\ \\ \end{array}
$$

Factored into two smaller matrices, with f factors



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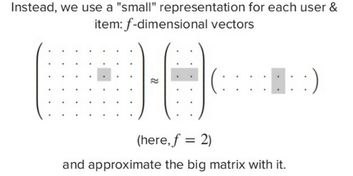

Latent factors

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]

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

Factors

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 – Cambridge Analytica

[7]

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

Return of the paranoid hypothesis

Spotify presumes:

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

[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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1. Good ground truth data – no "algorithmic confounding"[8]
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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Spotify vs. Cambridge Analytica

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

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- Integrate with Facebook.

NY Times, Dec. 18, 2018[9]

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.

[9] "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

Spotify vs. Cambridge Analytica

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- Rely upon extensive surveillance.
- Integrate with Facebook.
- Influence behavior.

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- 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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