## Follow the guides to the filter niches

Disentangling human and algorithmic curation in online music consumption


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## Three types of affordances



## Filter bubbles?

## State of the art: not very bubbly...

youtube
Zhou, Khemmarat,
Goo, 2010
"The impact of YouTube recommendation system on video views"
movielens

Nguyen, Hui, Harper, Terveen, Konstan, 2014
"Exploring the filter bubble: the effect of using recommender systems on content diversity"
facebook
Bokshy, Messing, Adamic, 2015
"Exposure to ideologically diverse news and opinion on Facebook"
tumblr
Aiello, Barbieri, 2017
"Evolution of egonetworks in socia media with link recommendations"
spotify
Datio, Knox, Bronnenberg, 2018
"Changing Their Tune: How Consumers' Adoption of Online Streaming Affects Music Consumption and Discovery"
google news
Hoim, Groefe, Brosius, 2018
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except (admittedly...) in the case of explicit preferences

Thurman,
Schifferes, 2012
"The Future of Personalization at News

Websites"

## Zuiderveen Borgesius, Trilling, Möller, Bodó, de Vreese, Helberger, 2016

Dylko, Dolgov, Hoffman, Eckhort, Molina, Auziz, 2017
"The dark side of technology: An experimental investigation of the influence of customizability technology on online

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except (admittedly...) in the case of explicit preferences
...and some cases

## Thurman, <br> Schifferes, 2012

"The Future of Personalization at News

Websites"


## Dylko, Dolgov, Hoffman, Eckhart, Molina, Auziz, 2017

"The dark side of technology: An experimental investigation of the influence of customizability technology on online political selective exposure"
youtube

## Roth, Mazières, Menezes, 2020

"Tubes and bubbles: topological confinement of YouTube recommendations"
spotify
Anderson, Maysire, Anderson,
Mehroitra, Lolmas, 2020
"Algorithmic effects on the diversity of consumption on spotify"

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Figure 1: Use profiles and classes, where each dot on the ternary plot corresponds to a user of barycentric coordinates $\left(p_{a}, p_{e}, p_{o}\right)$, and each color refers to one of the four categories a (blue), e (red), $\mathbf{o}$ (green), $\mathbf{0}+$ (yellow).

```
8639 users in total, of which:
-989 a
-655 e
-1614 o
-5381 o+
```


## Two dimensions of diversity

## Dispersion, i.e. S/P



Fig. 3. Breakdown of dispersion values for each user class and for each access mode. Histograms are further binned by deciles of increasing $S / P$ values (from 0 to 1 from left to right) and indicate how many users of each class (a, e, o and $\mathbf{o}+$ ) exhibit which dispersion value for a certain access mode (algorithmic, editorial or organic). Average activity values for users of each decile bar are further indicated by a grayscale, where darkest shades correspond to highest $P$ values.

- Dispersion generally lower as a function of activity
- Dispersion lower for the main access mode, especially as activity increases
- Generally lower for organic access, especially for o+ users
- o users still appear to have lower dispersion in the algorithmic access mode


## Two dimensions of diversity

## Artist popularity

| bin | \# artists | access mode |  |  |  |
| :---: | ---: | :---: | :---: | :---: | :---: |
|  |  | algorithmic | editorial | organic |  |
| $\nu_{1}$ | 73 | $9 \%$ | $\mathbf{8 \%}$ | $\mathbf{8 3 \%}$ | $100 \%$ |
| $\nu_{2}$ | 319 | $16 \%$ | $\mathbf{8 \%}$ | $76 \%$ | $100 \%$ |
| $\nu_{3}$ | 1462 | $\mathbf{1 8 \%}$ | $5 \%$ | $77 \%$ | $100 \%$ |
| $\nu_{4}$ | 166869 | $15 \%$ | $5 \%$ | $80 \%$ | $100 \%$ |
| all | 164955 | $14 \%$ | $7 \%$ | $79 \%$ | $100 \%$ |

Table 1: Proportion of access modes for each nicheness bin (preferred bins for each access mode are marked in bold).

- algorithmic: less popular
- editorial: more popular
- organic: U-curve


## Two dimensions of diversity

## Artist popularity and dispersion

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## Two dimensions of diversity

## Artist popularity and access modes



Fig. 5. Relative consumption of content from each popularity bin, average log-ratio with respect to a uniformly random baseline for each bin ( 0 corresponds to no deviation, the $x$-axis is ordered from $v_{1}$ to $v_{4}$ i.e., for musical content from more to less popular artists). Top: average over all plays. Bottom: breakdown by access mode.

## Two dimensions of diversity

## Artist popularity and access modes




$\circ$




- algorithmic: towards niche, except for e users
- editorial: monotonous
- organic: it depends

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- Organic users focus most on less popular content - yet, these users precisely exhibit a relatively balanced diet of platform affordances,
- hypothesis: these are the most "expert" users who best exploit platform affordances
- Editorial access, by contrast, even more so for editorial users, fulfills a role traditionally ascribed to radios in terms of mainstream exploration, yet with more exploration / higher dispersion



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thanks!

