Follow the guides to the filter niches

Quentin Villermet, Jérémie Poiroux, Manuel Moussallam, Thomas Louail, Camille Roth

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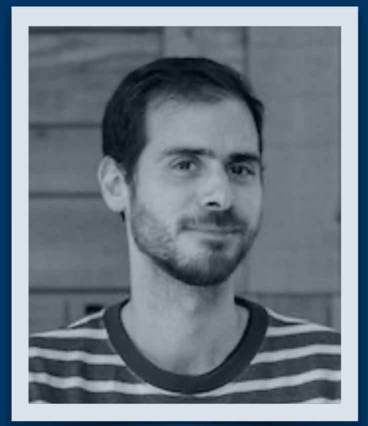
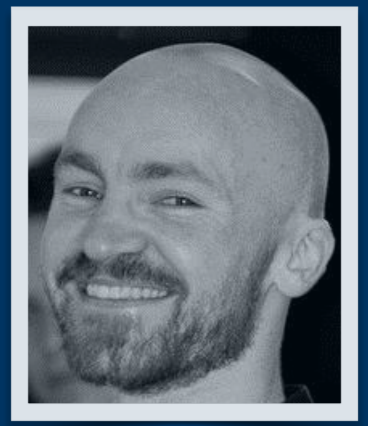
Disentangling human and algorithmic curation in online music consumption

Quentin **Villermet**

Jérémie **Poiroux**



Manuel **Moussallam**



Thomas **Louail**

Camille **Roth**

RECORDS
pRatiques dEs publiCs des platefORmes De Streaming musical

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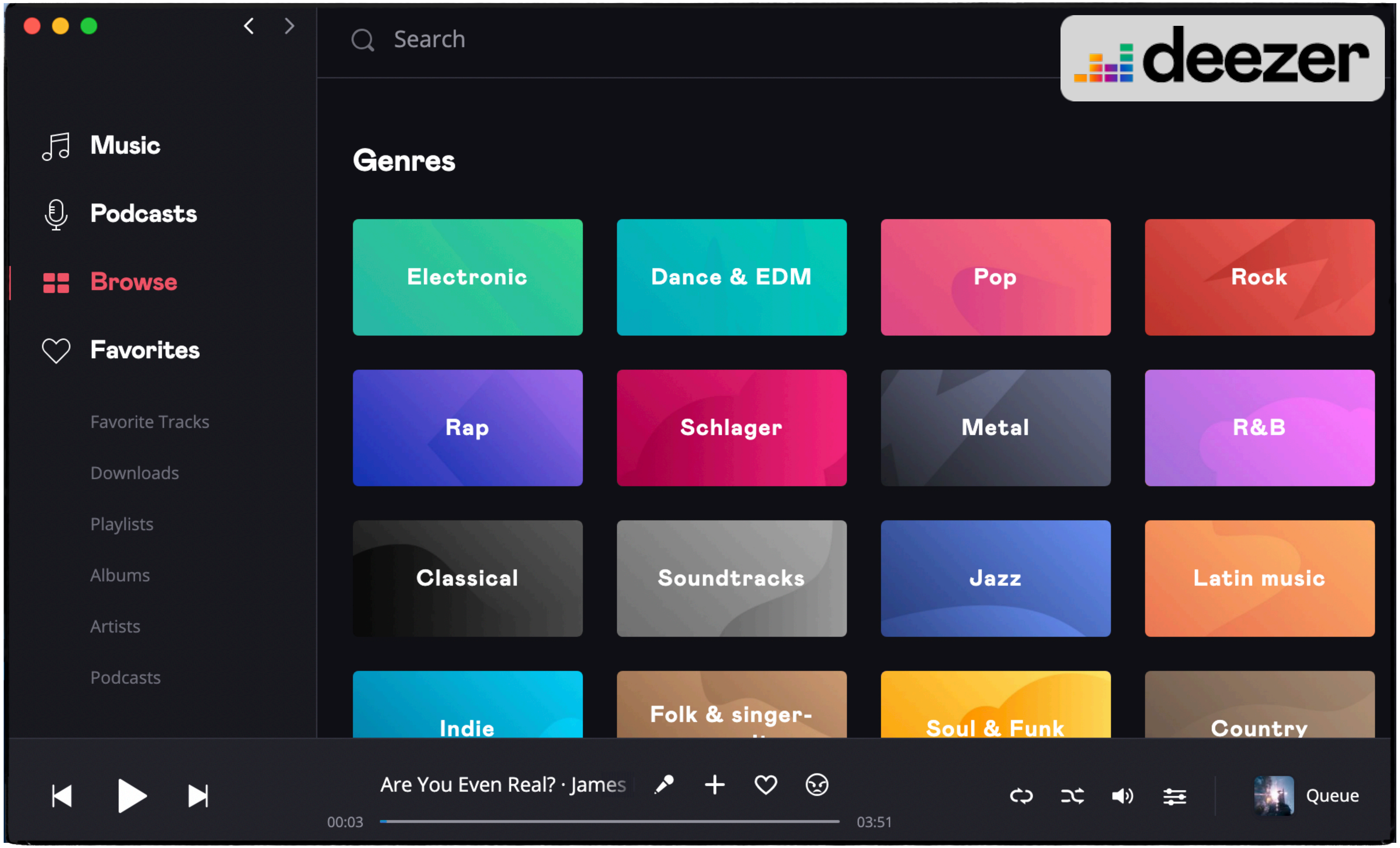
Centre Zentrum Marc Bloch
Computational Social Science Team

Three types of affordances



Filter bubbles ?

State of the art: not very bubbly...

illustration courtesy of DuckDuckGo

youtube	movielens	facebook	tumblr	spotify	google news
Zhou, Khemmarat, Gao, 2010	Nguyen, Hui, Harper, Terveen, Konstan, 2014	Bakshy, Messing, Adamic, 2015	Aiello, Barbieri, 2017	Datta, Knox, Bronnenberg, 2018	Haim, Graefe, Brosius, 2018
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except (admittedly...) in the case of explicit preferences

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

...and some cases

youtube

Roth, Mazières, Menezes, 2020

"Tubes and bubbles: topological confinement of YouTube recommendations"

spotify

Anderson, Maystre, Anderson, Mehrotra, Lalmas, 2020

"Algorithmic effects on the diversity of consumption on spotify"

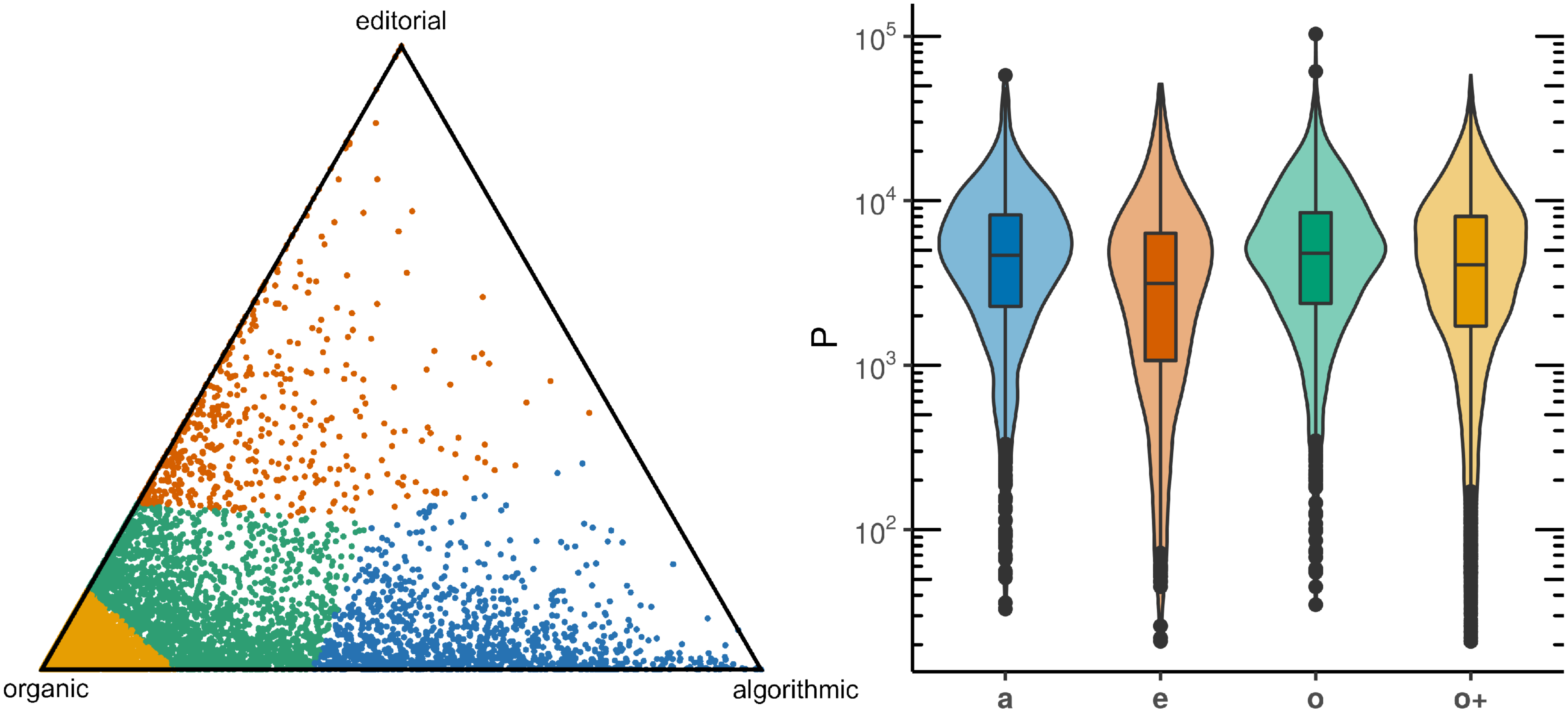

Figure 1: Use profiles and classes, where each dot on the ternary plot corresponds to a user of barycentric coordinates (p_a, p_e, p_o), and each color refers to one of the four categories **a** (blue), **e** (red), **o** (green), **o+** (yellow).

8639 users in total, of which:

- 989 **a**
- 655 **e**
- 1614 **o**
- 5381 **o+**

Two dimensions of diversity

Dispersion, i.e. S/P

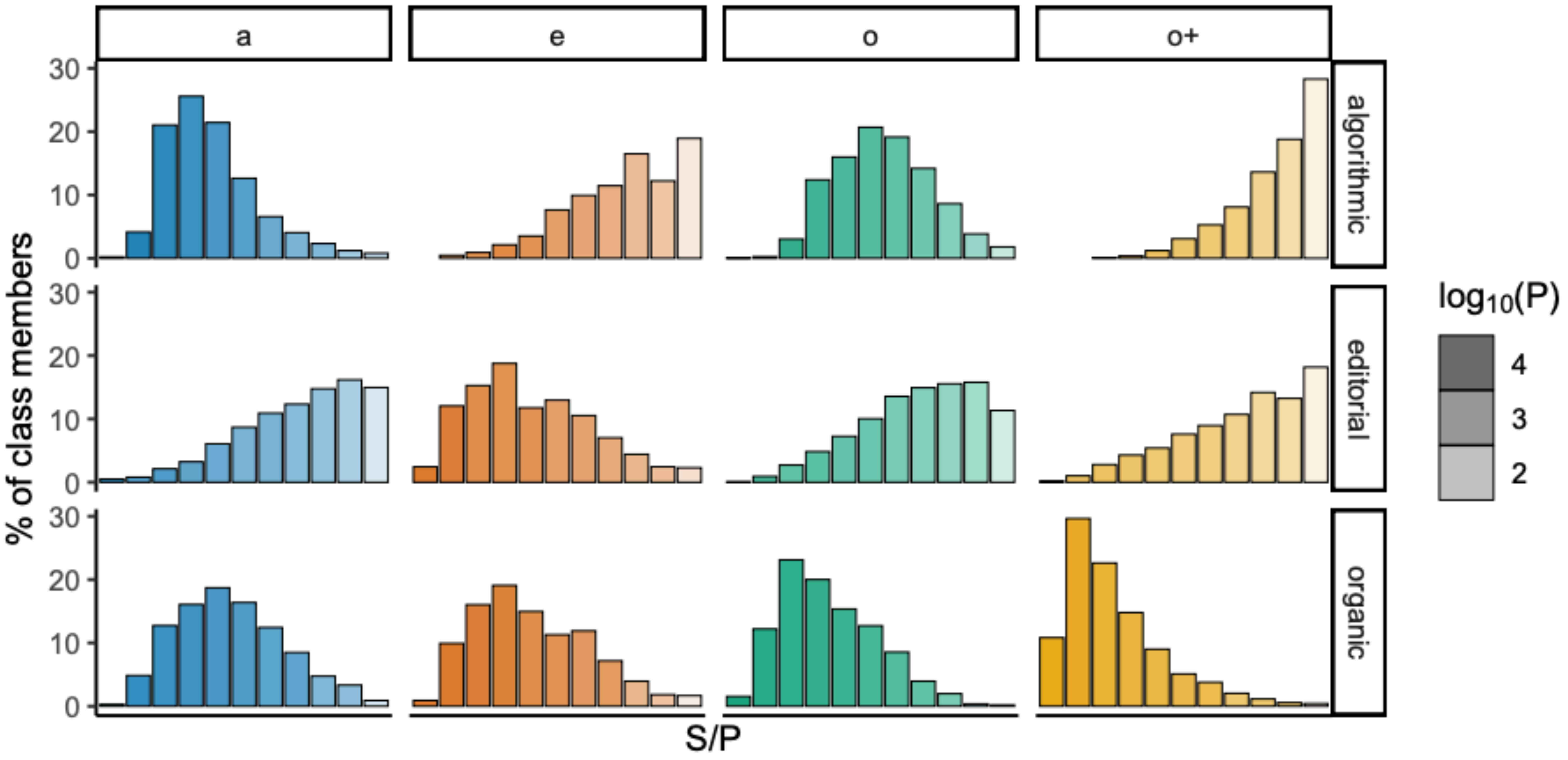

Fig. 3. Breakdown of dispersion values for each user class and for each access mode. Histograms are further binned by deciles of increasing S/P values (from 0 to 1 from left to right) and indicate how many users of each class (**a**, **e**, **o** and **o+**) exhibit which dispersion value for a certain 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	
ν_1	73	9%	**8%**	**83%**	100%
ν_2	319	16%	**8%**	76%	100%
ν_3	1462	**18%**	5%	77%	100%
ν_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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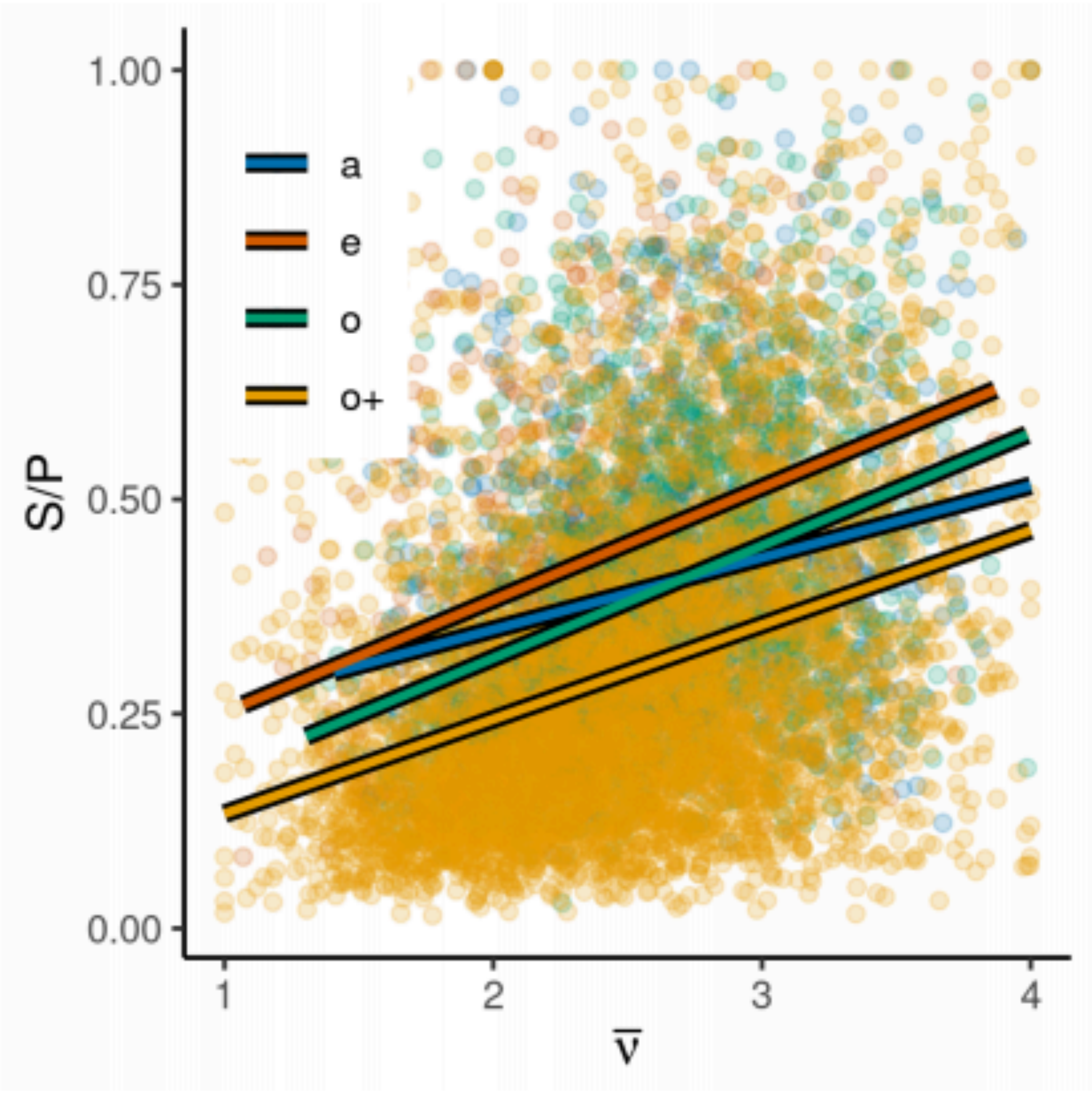
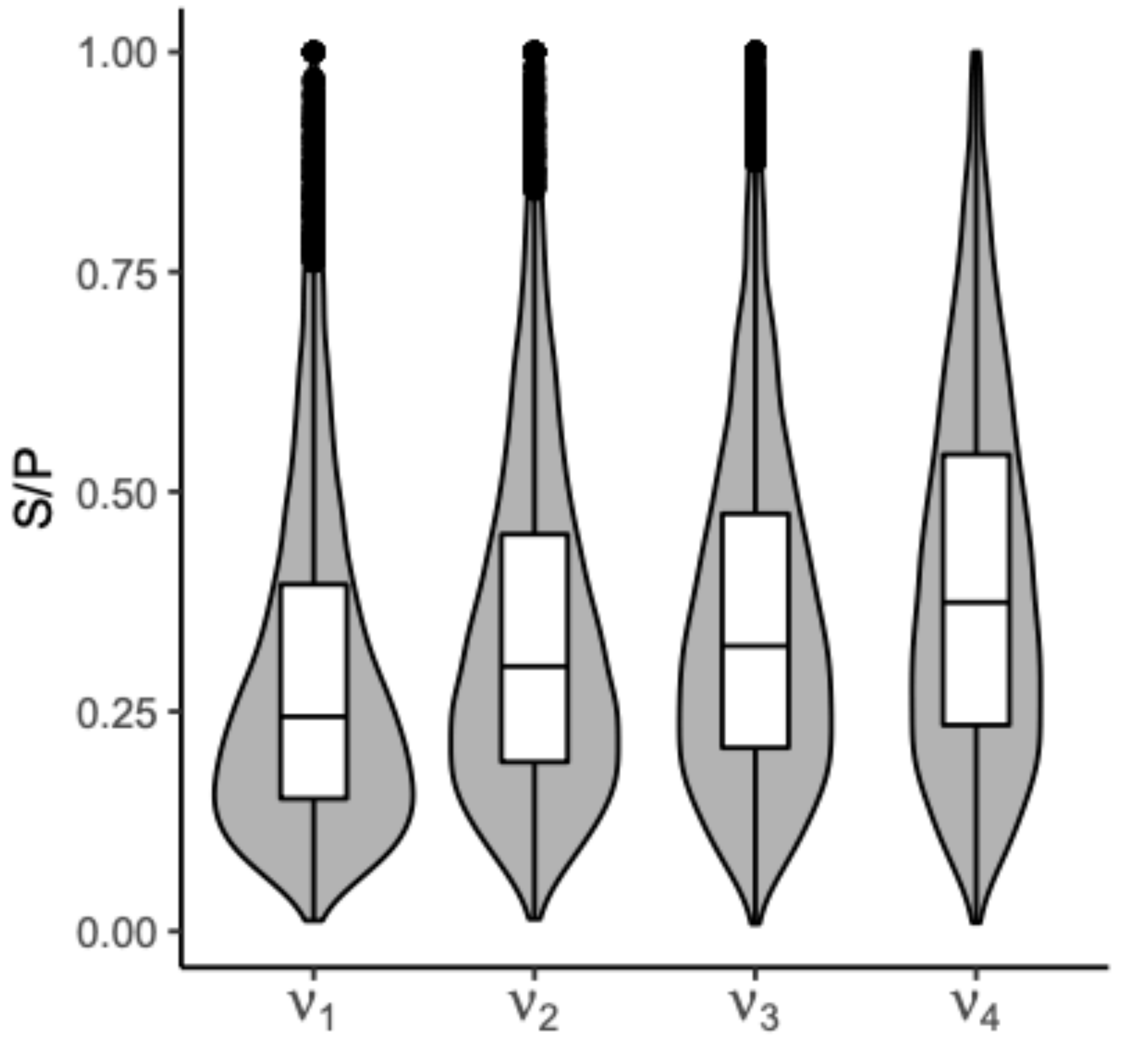
- dispersion increases with less popular content on average, for all user types





Two dimensions of diversity

Artist popularity and access modes

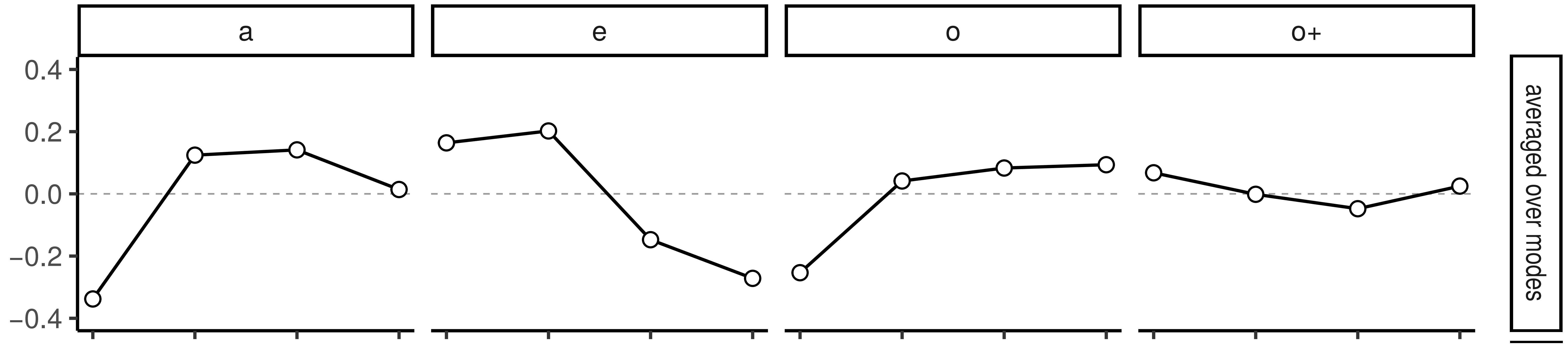
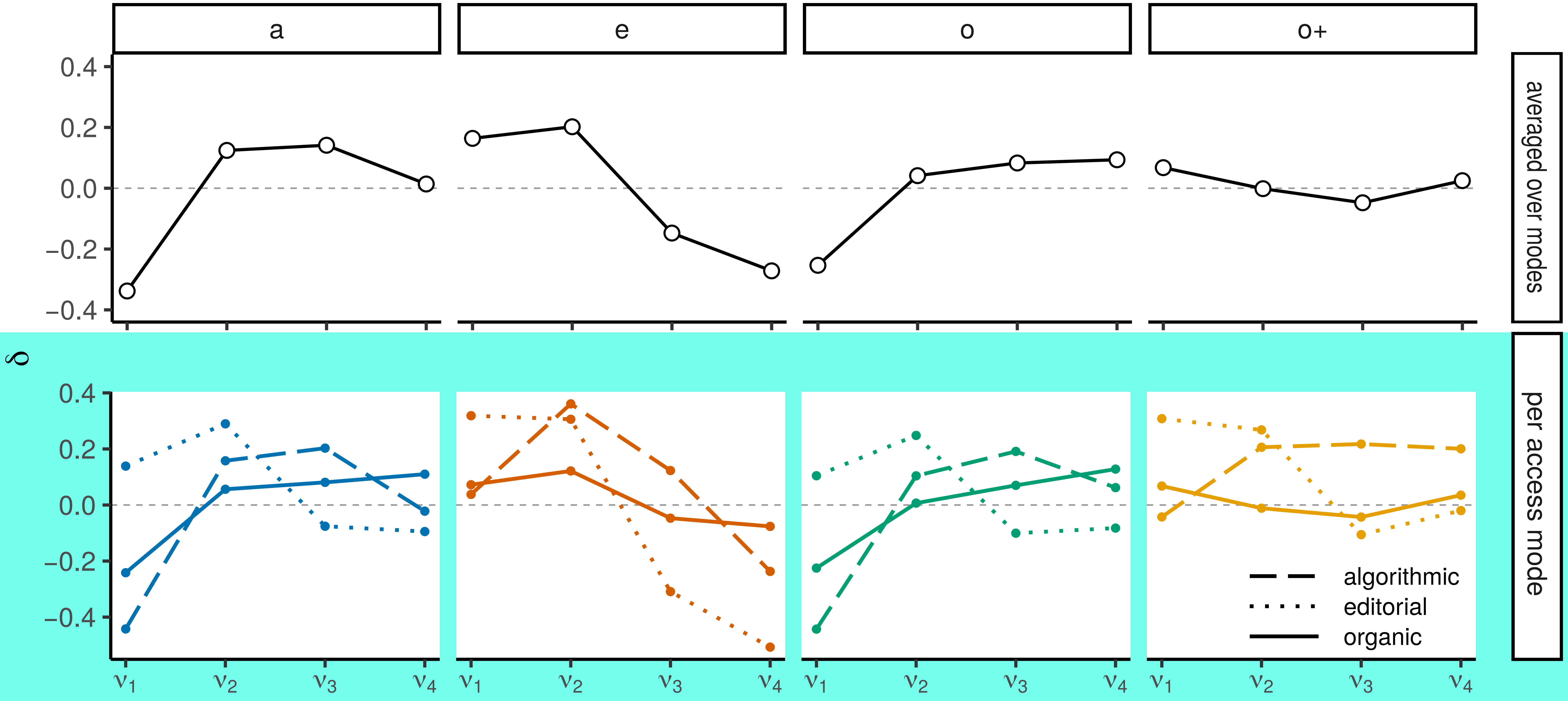


Fig. 5. Relative consumption of content from each popularity bin, average log-ratio with respect to a uniformly random baseline for each bin (0 corresponds to no deviation, the x-axis is ordered from ν_1 to ν_4 i.e., for musical content from more to less popular artists). *Top:* average over all plays. *Bottom:* breakdown by access mode.

Two dimensions of diversity

Artist popularity and access modes



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

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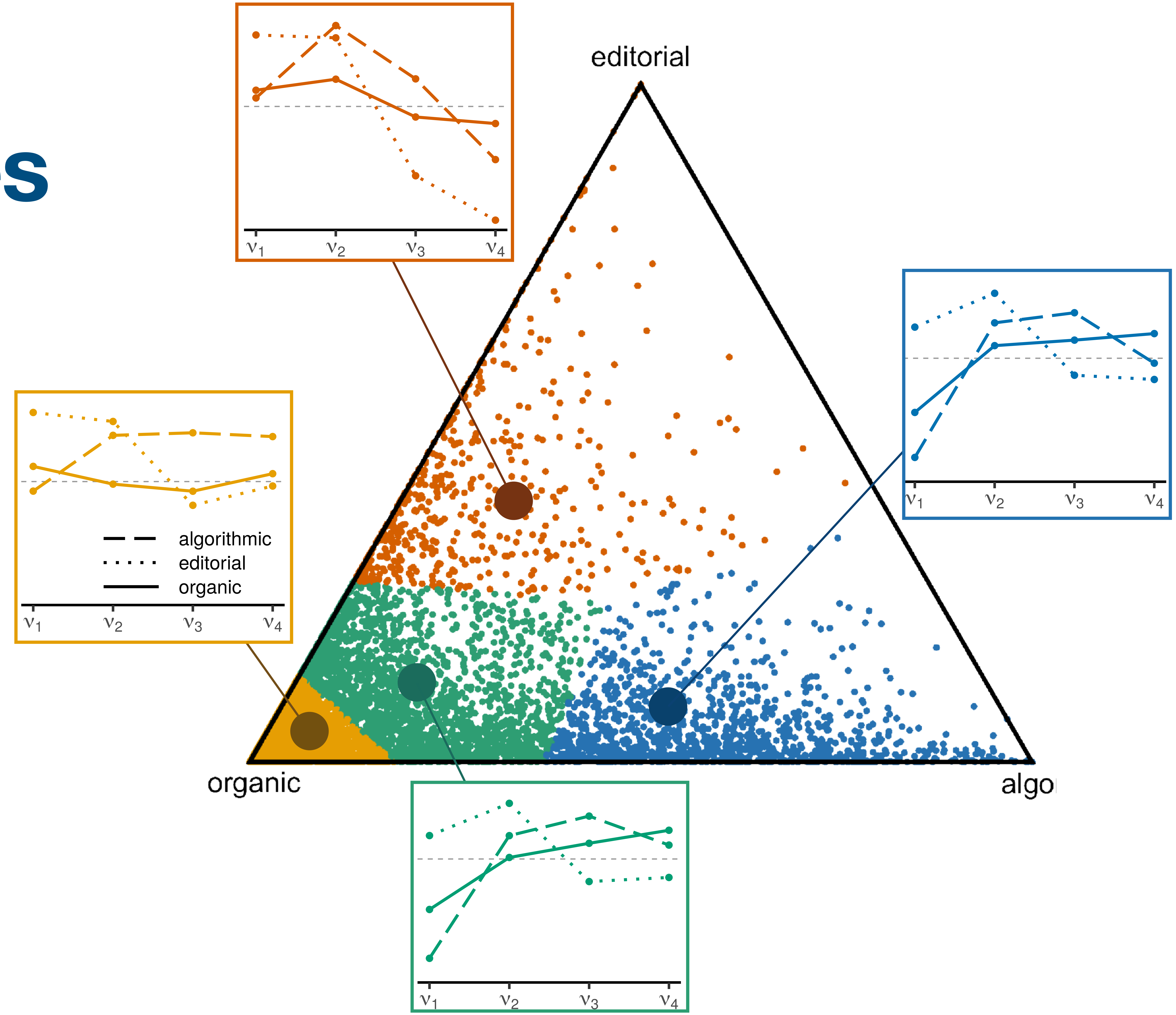
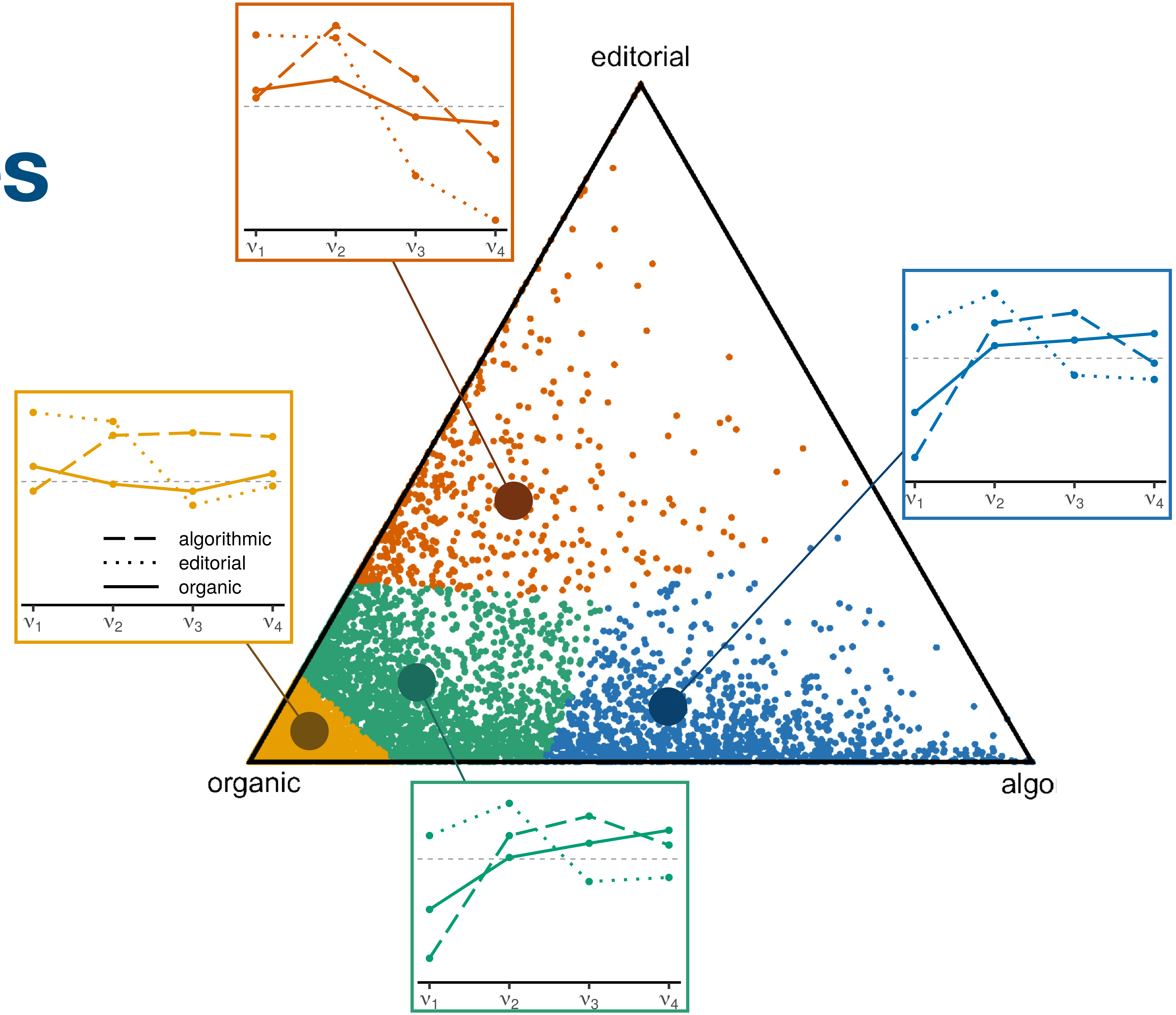
Filter niches rather than bubbles



Filter niches rather than bubbles

- **Radio playlists** generally **less dispersed than user types** (more exploitation)**,** while they are wide variations in terms of **artist popularity**



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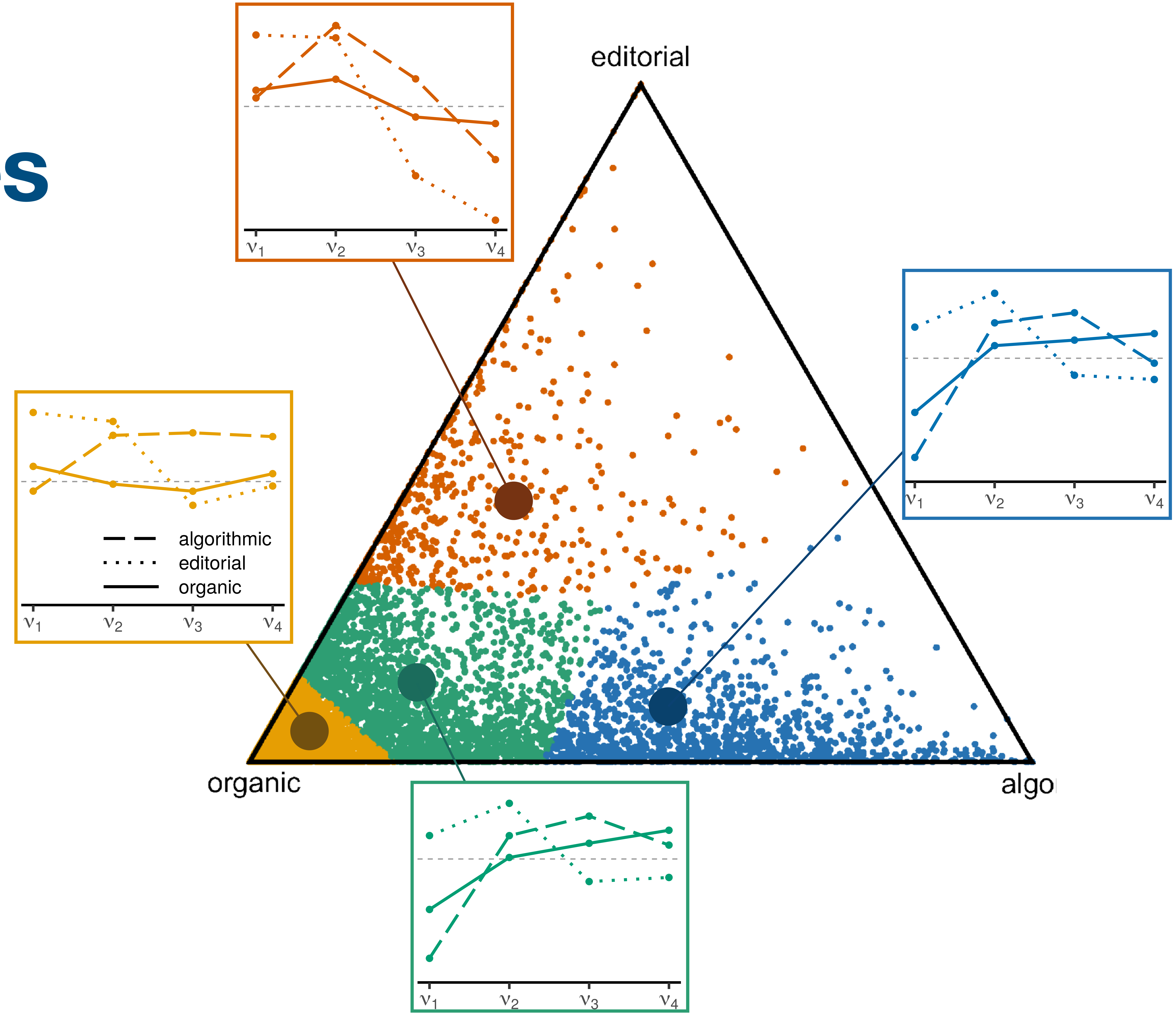

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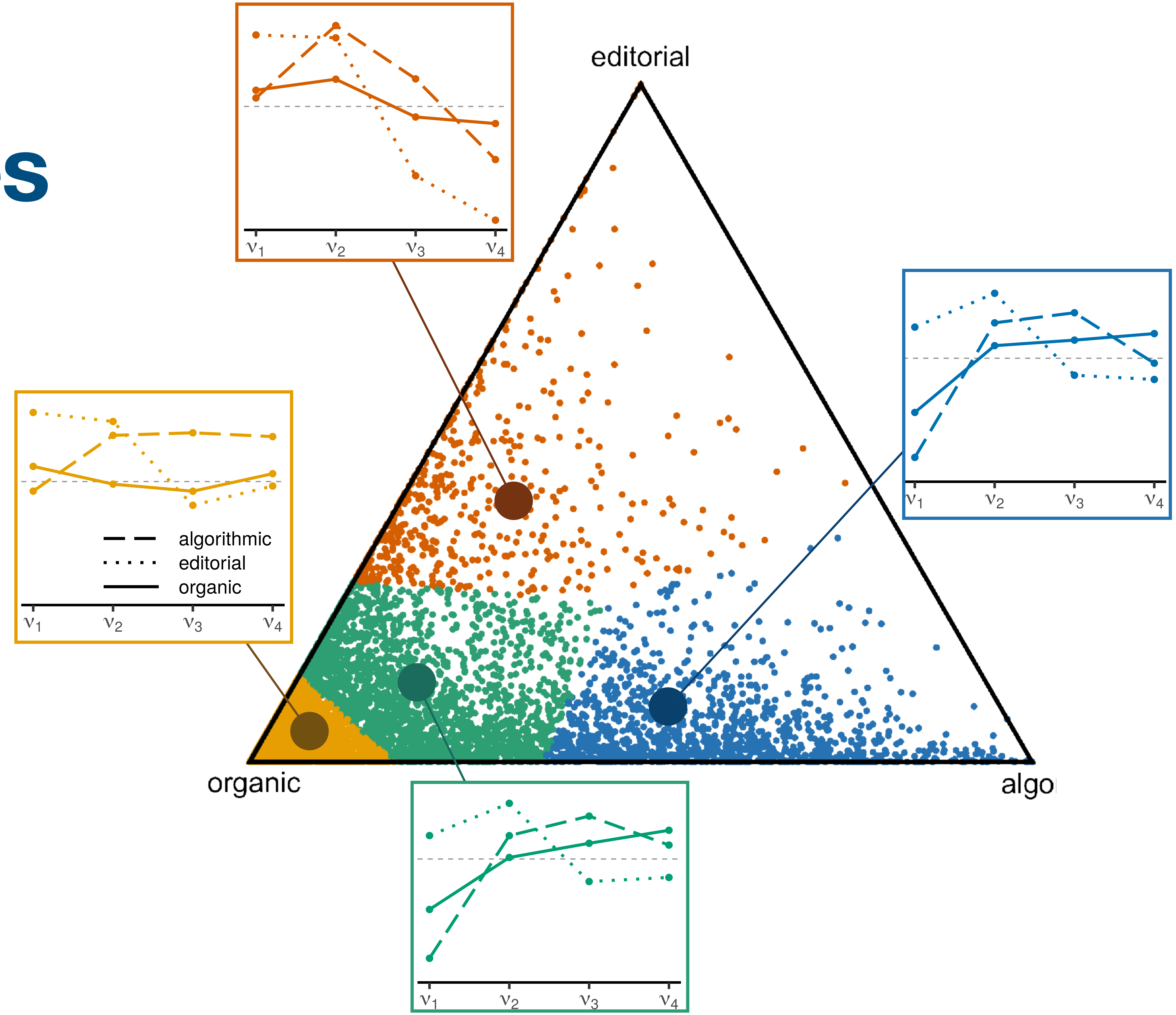
- **Organic users** focus most on **less popular content** — yet, these users precisely exhibit a relatively balanced diet of platform affordances,
    - *hypothesis*: these are the most "expert" users who best exploit platform affordances



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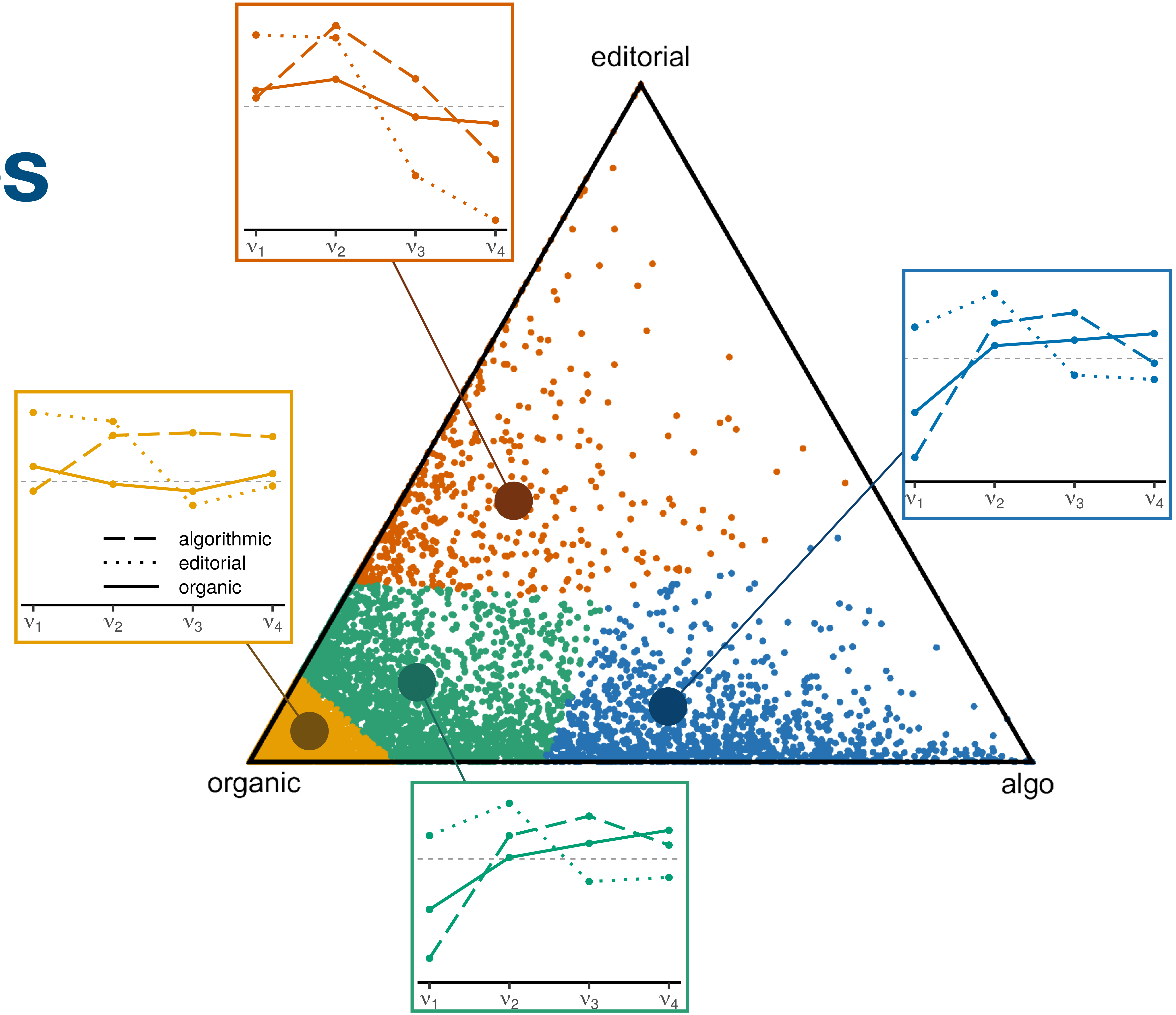
- **Editorial access**, by contrast, even more so for **editorial users**, fulfills a role traditionally ascribed to radios in terms of mainstream exploration, yet with more exploration / higher dispersion



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thanks!