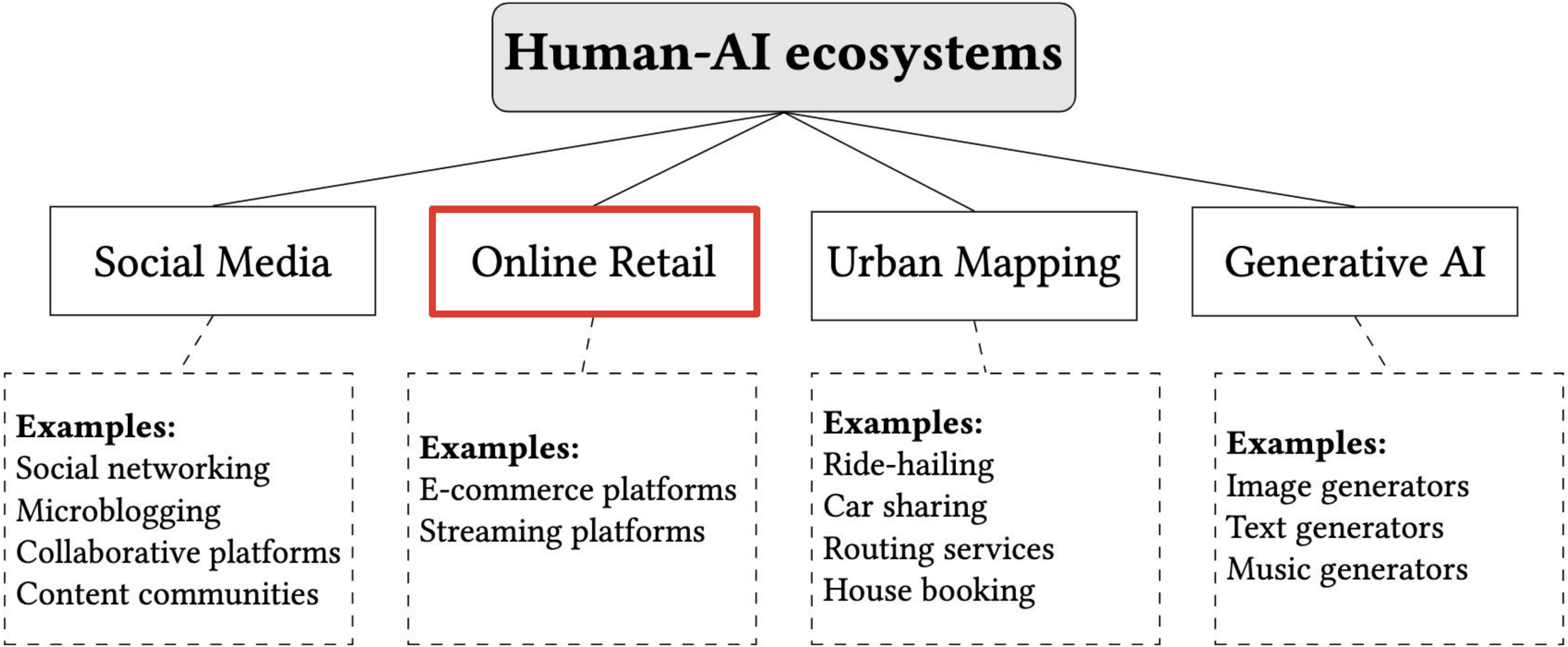

Human-AI ecosystems
Social Media
Online Retail
Urban Mapping
Generative AI
Examples:
Social networking
Microblogging
Collaborative platforms
Content communities
Examples:
E-commerce platforms
Streaming platforms
Examples:
Ride-hailing
Car sharing
Routing services
House booking
Examples:
Image generators
Text generators
Music generators

Designated VLOPs

https://digital-strategy.ec.europa.eu/en/policies/list-designated-vlops-and-vloses#ecl-inpage-Infinite

updated to February 6th, 2025

amazon

AliExpress

SHEIN

TEMU

Google Shopping

zalando

Discussion

What is the business model of online retail platforms? What do they optimise for?

Shopping addiction

E. Marris, The science of shopping addiction: what makes people buy loads of stuff? Nature 639, 26-28 (2025)

- Online retailers are increasingly using *psychological techniques* to keep shoppers spending money
- >1,000 people in Switzerland grouped into categories of shoppers:
  - **3% addicted** to online shopping
  - **11% at risk**
    - "I think about shopping/buying things all the time"
    - "I shop/buy things in order to change my mood"

Augsburger, M. *et al. J. Behav. Addict.* 9, 808–817 (2020).


A
• DATE / TIME
• NOISE REDUCTION ☐ON ☐OFF
B
• DATE / TIME
• NOISE REDUCTION ☐ON ☐OFF
ATTENZIONE: Le cassette con fotocopie non sono
MIXED BY ERRY
LA DIMENSIONE IDEALE PER UN ASCOLTO PULITO
Opening
Moon tears
Sensitive and delicate
Promises of moon love
Sara love
Casa bianca
As we dance
Composition in Venice
Moon-cake la la
Lakes
Joseph is calling
Goodbye song
Closines
Cinema part. II

Proto-Recommenders (80s)

- Enrico Frattasio (**Erry**) created a business based on counterfeit cassette tapes (“pezzotto”)

- A cassette tape contained an album
    - at the end, Erry put songs similar to those in the album

- The first music recommender!

Quiz

Which kind of recommender was Erry’s?

user-based CF

item-based CF ✅

Collaborative Filtering

Item-Based CF:

recommends items that are similar to those a user has interacted with

Two steps:

1) select co-interacted items
2) suggest an item

Example:

If many people who watched *Inception* also watched *Interstellar*:

- the system recommends *Interstellar* to a user who has watched *Inception*

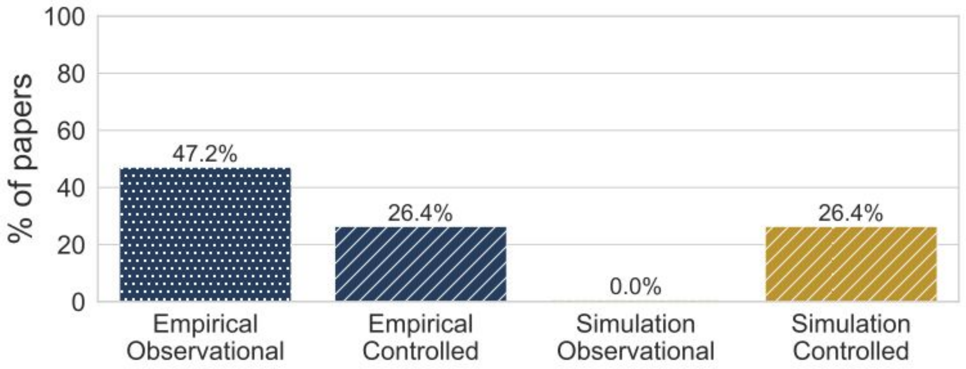
Two hypothesis

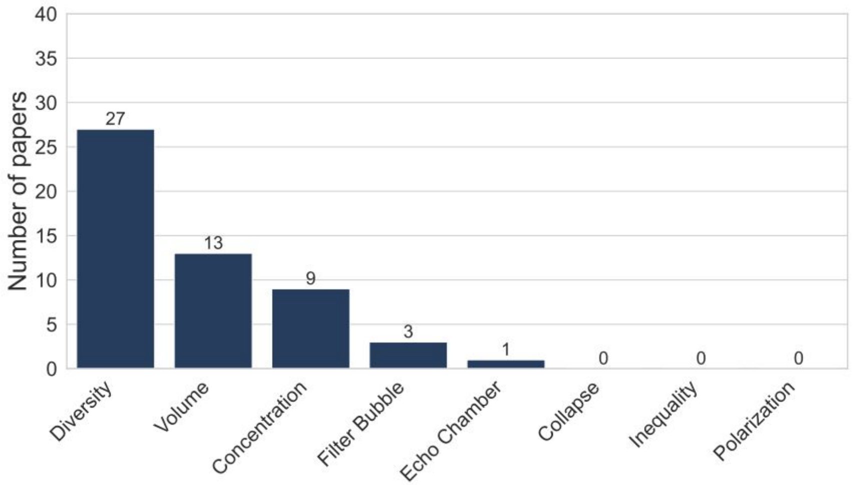
Anderson's hypothesis:
main effect of recommenders will be to help people move from the world of hits to the world of niches

Diversity hypothesis:
recommenders will reinforce the world of hits making niches disappear

Experiments and outcomes

L. Pappalardo et al. A survey on the impact of AI-based recommenders on human behaviours, 2024, https://doi.org/10.48550/arXiv.2407.01630



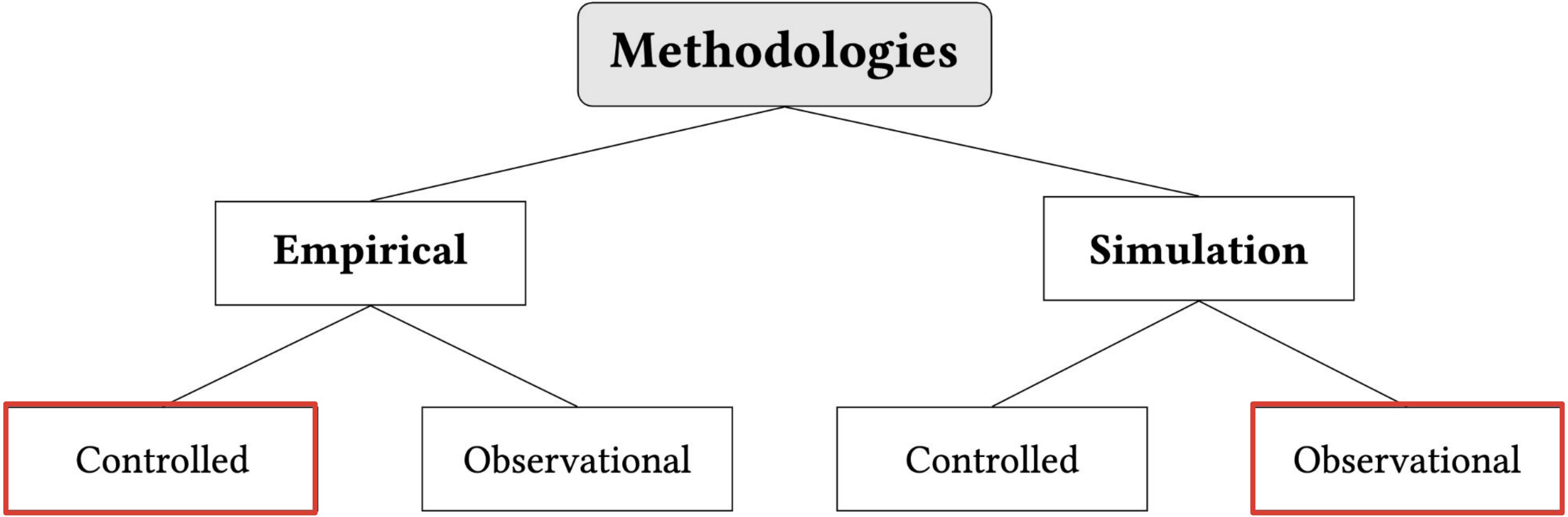


Online Retail		Empirical		Simulation	
		Observational	**Controlled**	**Observational**	**Controlled**
Individual	**Filter Bubble**	[124]	[29]	[125]	
	Radicalization				
Model	**Collapse**				
Systemic	**Concentration**	[58, 78]	[96, 97, 164]	[57, 59, 111, 161]	
	Echo Chamber	[63]			
	Inequality				
	Polarization				
Individual Item Systemic	**Diversity**	individual: [9, 63, 124], systemic: [28, 130]	individual: [8, 77, 96–98, 100, 164], item: [118], systemic: [47, 77, 95, 117, 118, 164]	individual: [10, 57, 59, 125], item: [74], systemic: [10, 26, 74, 111]	
	Volume	individual: [58, 78, 124], item: [28, 44, 130]	individual: [29, 47, 77, 96, 98, 103], item: [95, 97], systemic: [9]		

Selected studies:

- [97] Lee and Hosanagar 2019

Examples on Online Retail



How do recommender systems affect sales diversity? A cross-category investigation via randomized field experiment

Lee and Hosanagar et al., Information Systems Research, 2019

Type:	Empirical controlled
VLOP:	Canadian online retail platform
Outcomes:	diversity paradox

Experimental Setup

Lee and Hosanagar 2019

Consumers on a Canadian online retail website

- **Two weeks**: August 8 to 22, 2013
- **A/B/n testing platform** that tracks users' behaviour during the experiment
- View and purchase logs are collected:
  - views and purchases of 1M users
  - 82K stock-keeping-units (products)
  - 2.8M rows of individual-level data

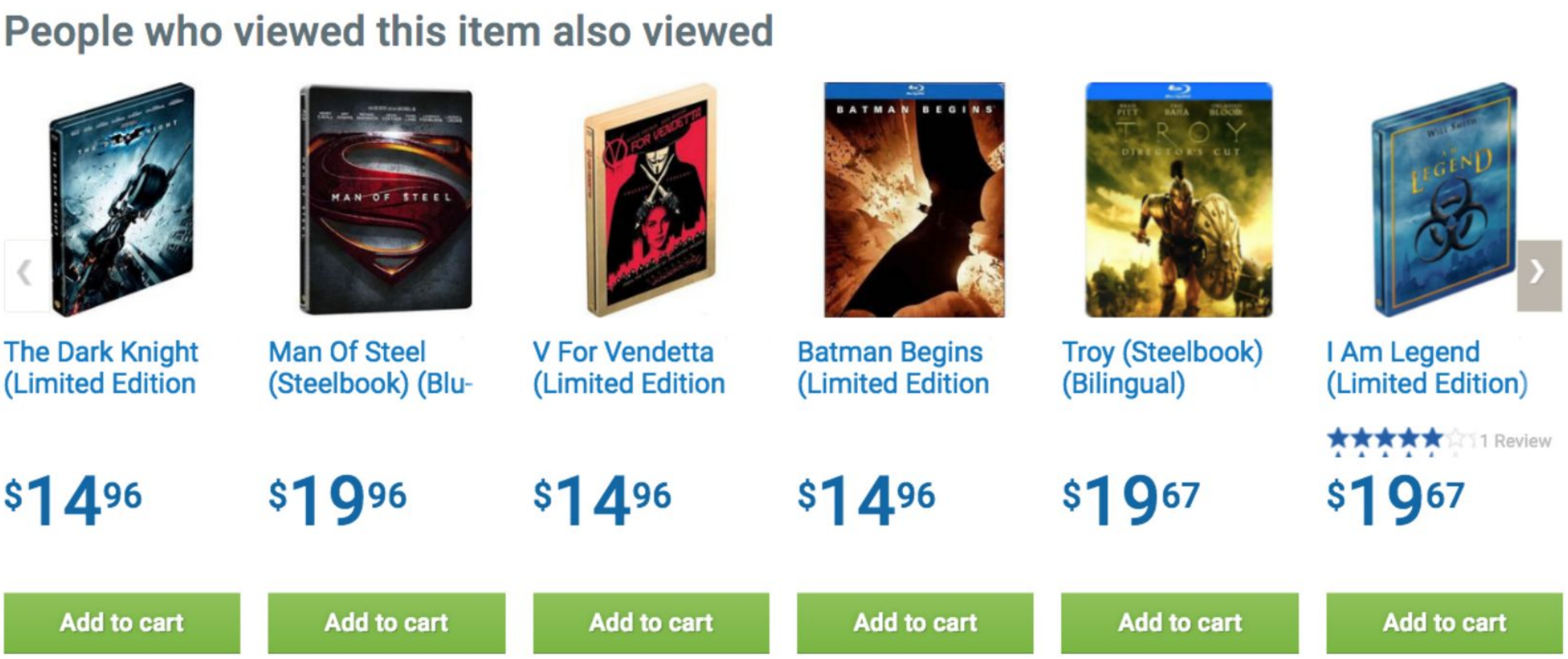
Experimental Setup

Lee and Hosanagar 2019

- **Control group**: no recommendation
- **Treatment** (10% of users):
  - **Treatment group 1**: visualizes recommendations from a view-based collaborative filtering (VBCF)
    - “People who viewed this item also viewed”
  - **Treatment group 2**: visualizes recommendations from a purchase-based collaborative filtering (PBCF)
    - “People who purchased this item also purchased”

Experimental Setup

Lee and Hosanagar 2019



Experimental Setup

The recommender takes as input:

- the **focal item** (the product a user is viewing)
- the user's **past purchases**
    - data about 60 days before the experimentation starts
    - recommender retrained every 3 days

The top N candidate products that are not yet purchased/viewed by the consumer are recommended

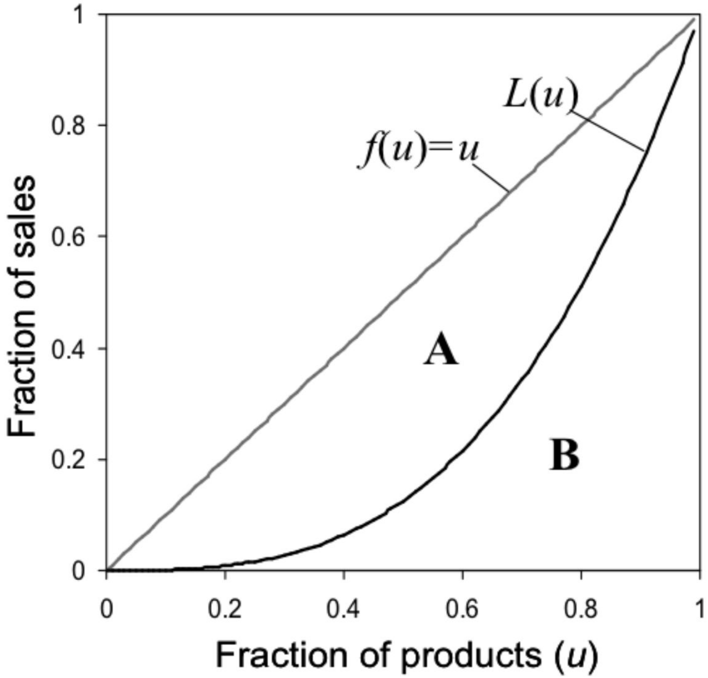
Sales diversity

Lee and Hosanagar 2019

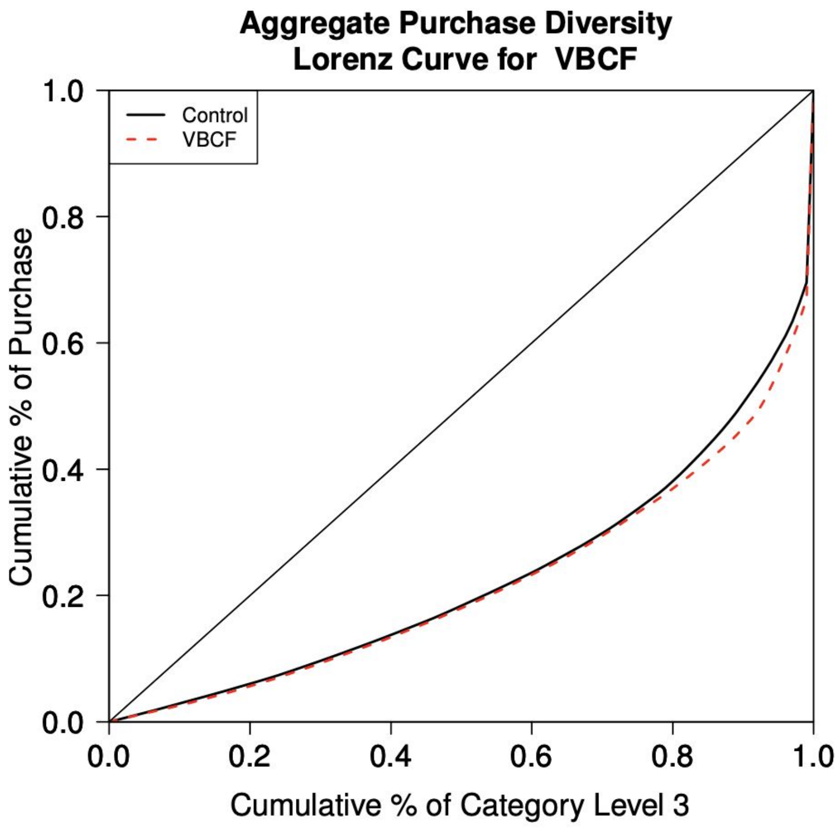
Gini coefficient:

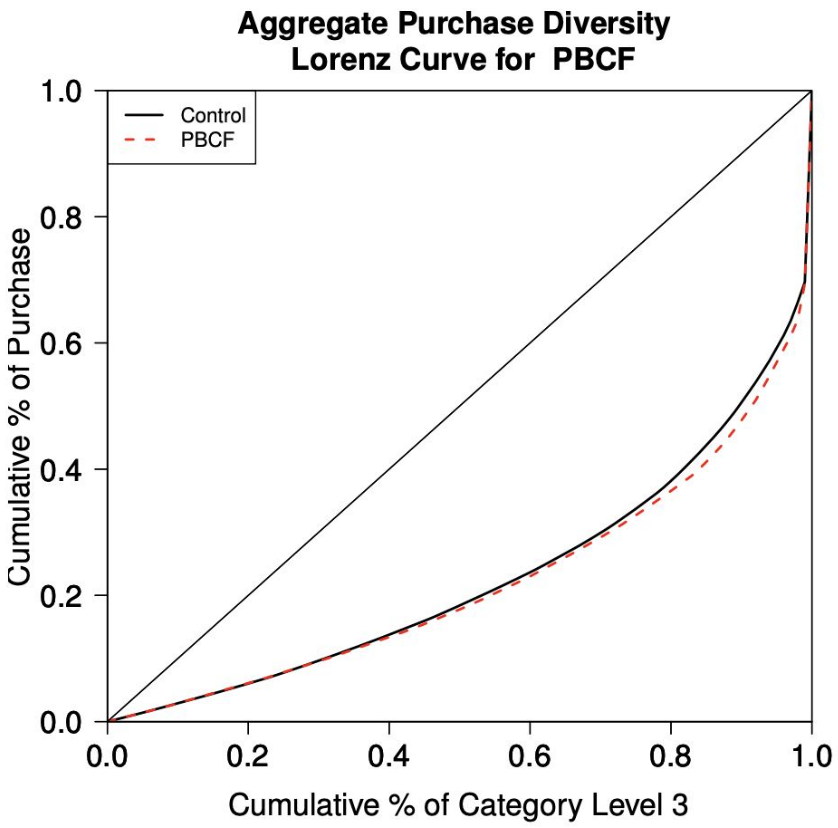
- **0** is the least amount of concentration (**highest diversity**, equal sales)
- **1** represents the highest amount of concentration (**lowest diversity**, a few broad-appeal blockbuster items account for most of the sales)

$$G = \frac{A}{A+B}$$

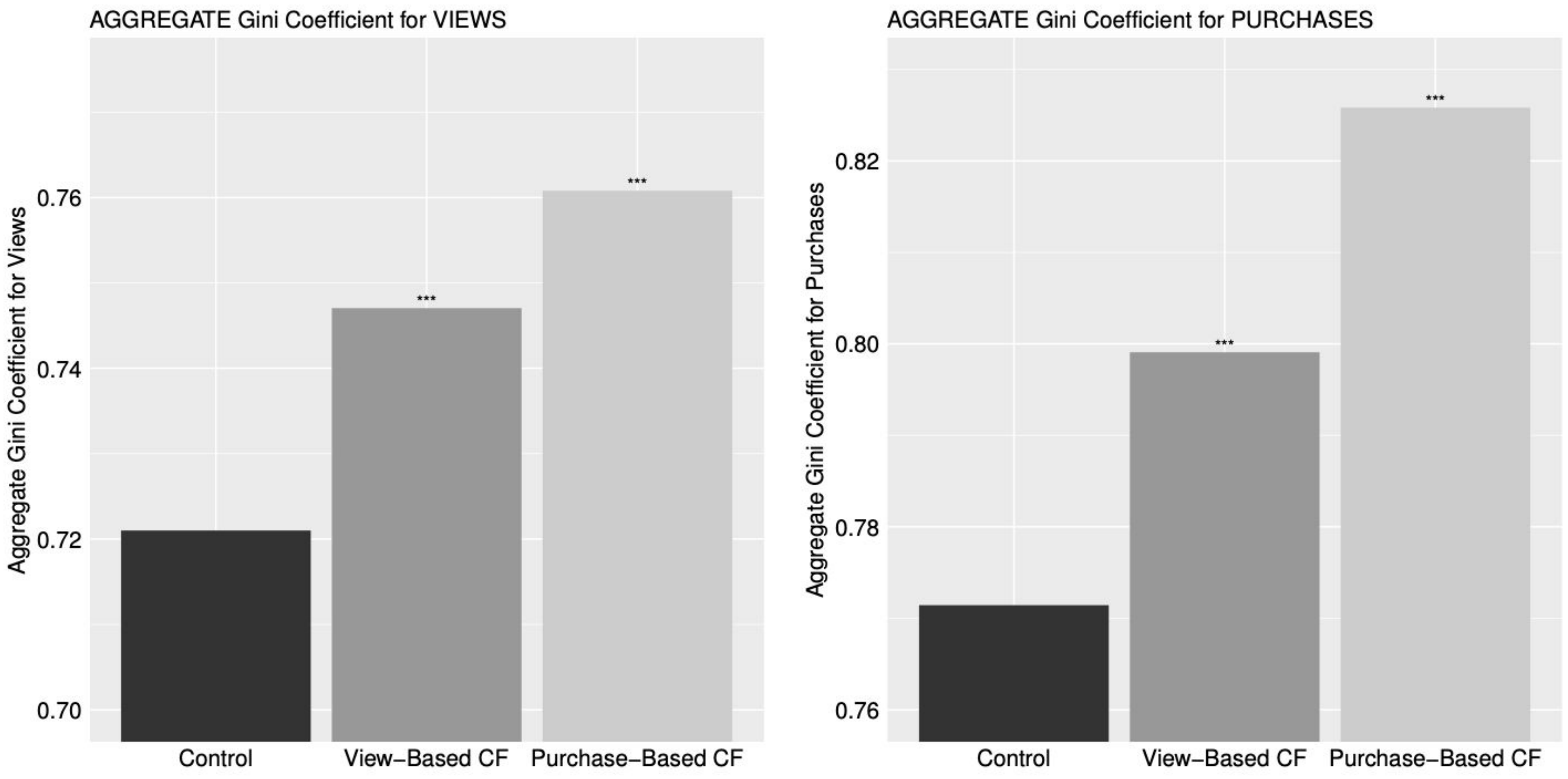


Aggregated diversity

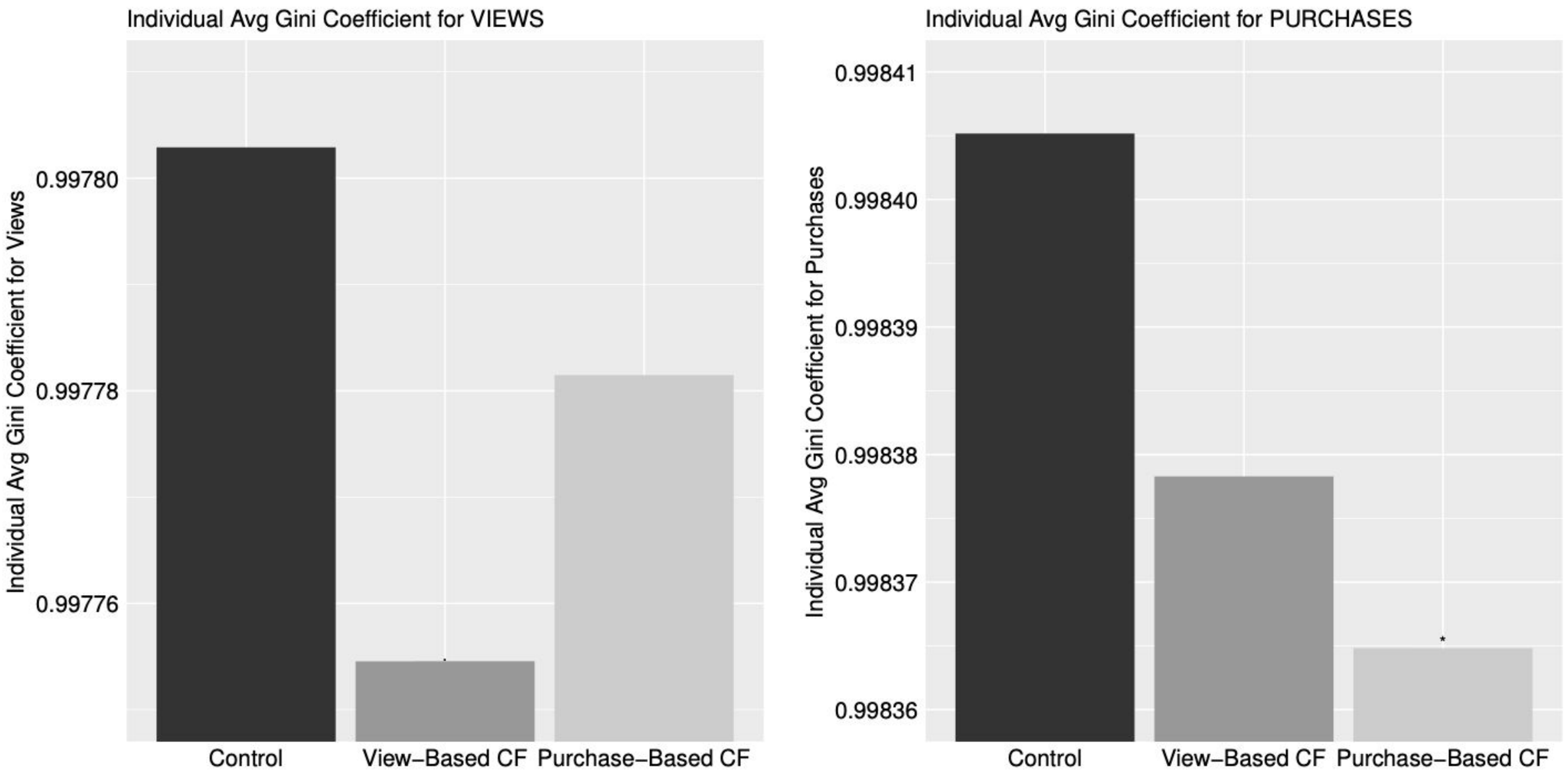




Aggregated diversity



Individual diversity



'•'= p-value <0.1, '*'= p-value <0.05, '**'= p-value <0.01, '***'= p-value <0.001.	Control	VBCF	PBCF
Aggregate View	0.720997	0.747055***	0.760807***
Aggregate Purchase	0.771437	0.799075***	0.825829***
Individual Avg View	0.997803	0.997755•	0.997781
Individual Avg Purchase	0.998405	0.998378	0.998365*

Aggregate PBCF: 0.825829 - 0.771437 = **0.054**

*"Increasing the Gini coefficient of DVD rentals by **0.0029** translates to increasing the market share of the top 1% of DVDs by 1.96% and the market share of the top 10% of DVDs by 0.58%. At the same time, the market share of the bottom 1% of DVDs is reduced by 21.29%, while the market share of the bottom 10% of DVDs is reduced by 5.28%."*

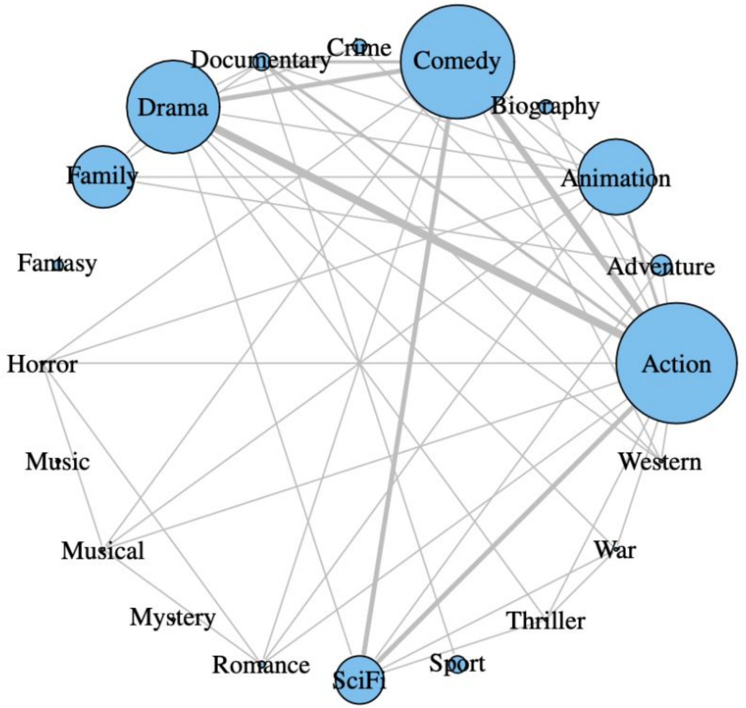
Tan et al., 2017, 'Is Tom Cruise Threatened? An Empirical Study of the Impact of Product Variety on Demand concentration'. Information Systems Research 28(3), 643–660.

Aggregated vs individual

- **at the aggregate level**
  both VBCF and PBCF are causing consumers to view and purchase less variety of products
  - PBCF generates stronger concentration

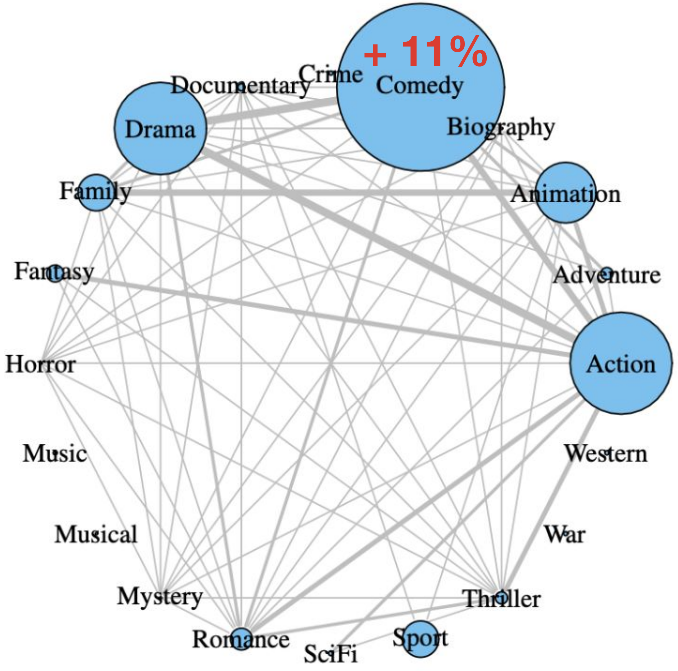
- **at the individual level**
  no concentration bias (Gini is lower for CF but not significantly)

Genre Cross–Pollination Visualization
Control



Edge Thickness: Number of consumers in common
Node Size: Purchase Volume

Genre Cross–Pollination Visualization
Purchase–Based CF



Edge Thickness: Number of consumers in common
Node Size: Purchase Volume

Co-Purchase networks

- Purchases concentrate on a few genres
- The PBCF network is more connected

PBCF **shifts users to buy a few top genres** at the aggregate level while increasing individual diversity through a **cross-buying behaviour** that is aided by a few “pathway” genres.

True for other categories as well:

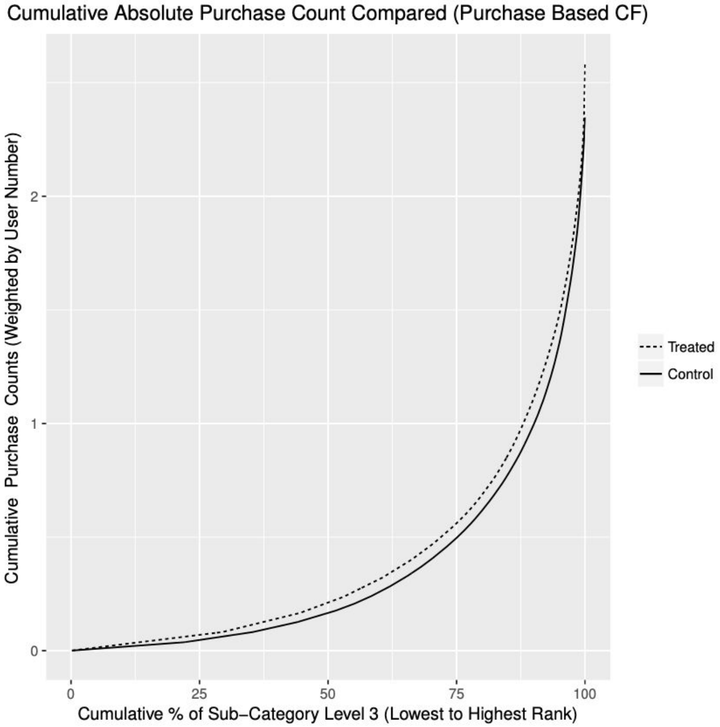
- PBCF increases the concentration bias by increasing market share of the top subcategories

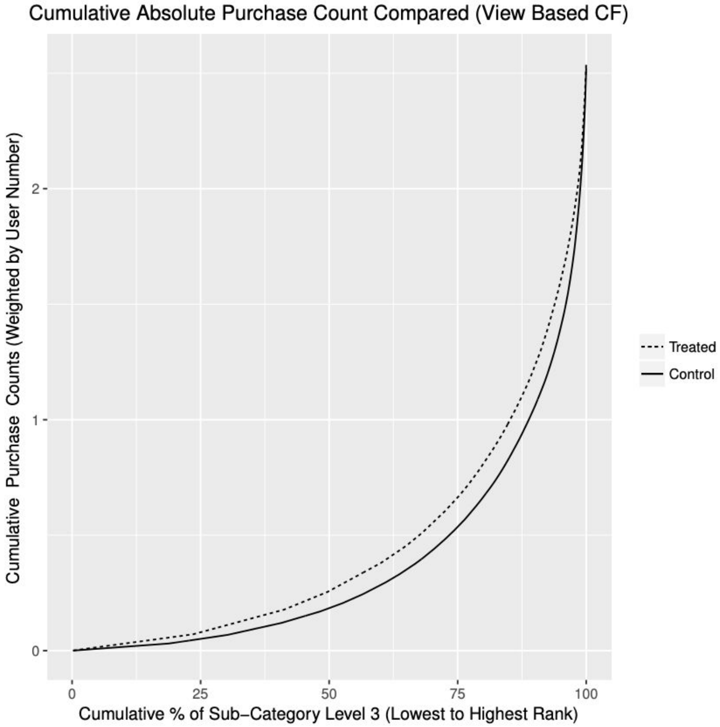
In summary

- Consumers cross-purchase more
- At the same time, their explorations are highly correlated due to the nature of CF

- Therefore, **the market share for the top-selling products keeps increasing**, creating a *rich-get-richer* bias

Niche products





All products are sold more, regardless of their popularity!

In Summary

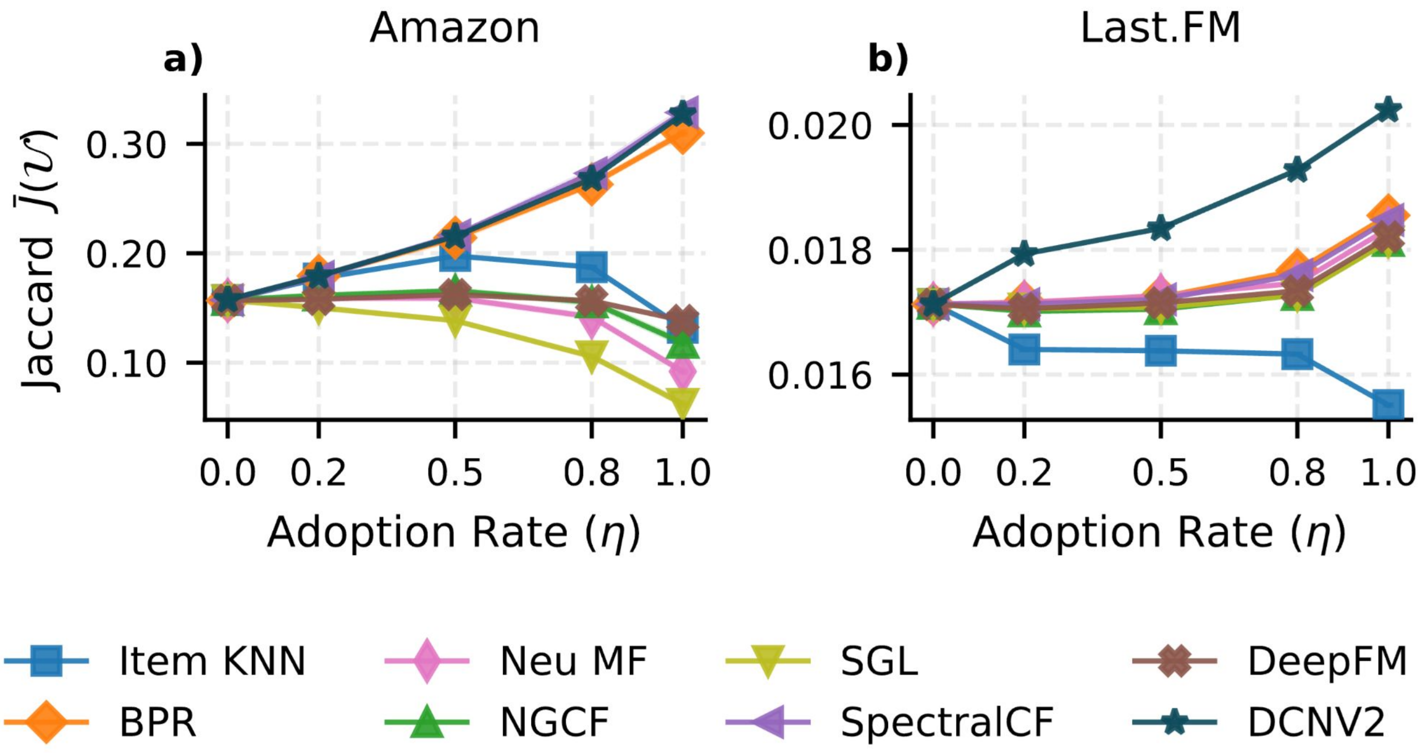
CF **decreases aggregate product view and sales diversity** across categories consistently
CF **does not seem to influence individual view and purchase diversity** consistently across product categories
CF enables greater exploration among individuals via cross-selling products. But the exploration is correlated across individuals
However, **niche items do not necessarily lose because CF increases absolute sales volume** for all type of items.

The Diversity paradox revisited: systemic effects of feedback loops in recommender systems

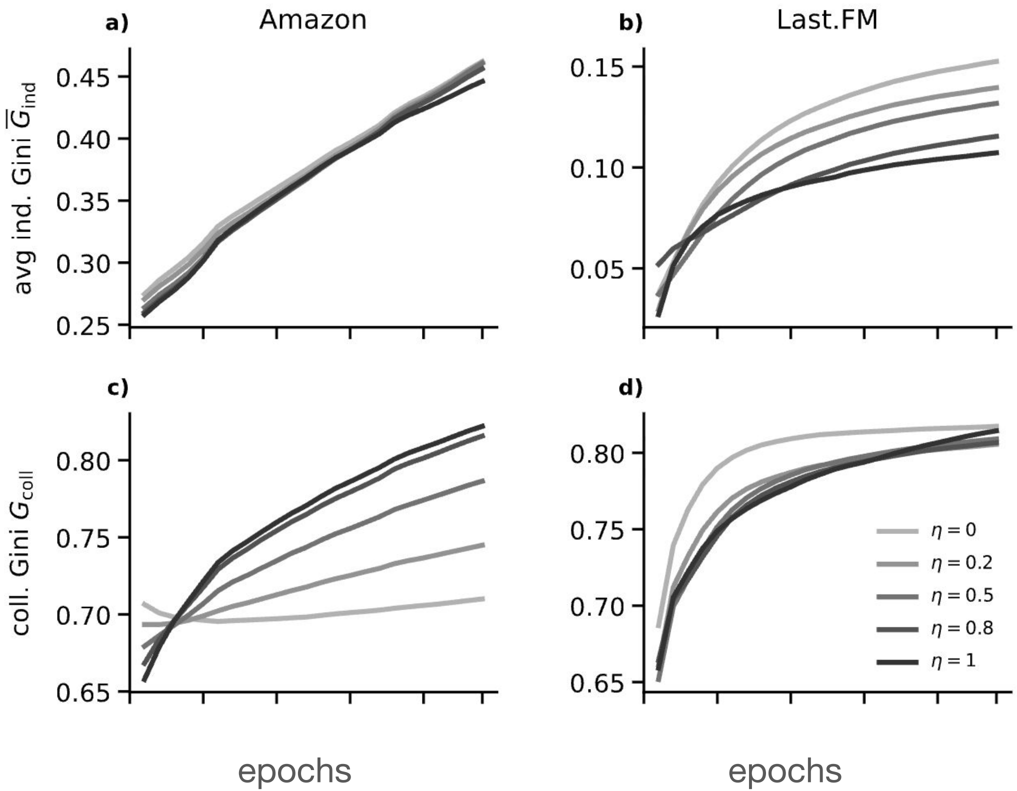
Barlacchi et al., arXiv 2025

Type:	Simulation observational
VLOP:	Any
Outcomes:	diversity paradox

Homogenization



Diversity paradox: revisited



Discussion

How can we make
online retail recommenders fairer?

References

Articles (useful for the project):

- Lee and Hosanagar et al., **How Do Recommender Systems Affect Sales Diversity? A Cross-Category Investigation via Randomized Field Experiment**, Information Systems Research, 2019
- Barlacchi et al., **The Diversity Paradox revisited: Systemic Effects of Feedback Loops in Recommender Systems**, ArXiv, https://arxiv.org/abs/2602.16315, 2026
- L. Pappalardo et al. **A survey on the impact of AI-based recommenders on human behaviours: methodologies, outcomes and future directions**, 2024, https://doi.org/10.48550/arXiv.2407.01630
  - Section 4 Online Retail Ecosystem

Books, articles, podcasts

To learn more:

- The history of Amazon’ s recommendation algorithm
  https://www.amazon.science/the-history-of-amazons-recommendation-algorithm
- E. Marris, The science of shopping addiction: what makes people buy loads of stuff? Nature 639, 26-28 (2025) doi: https://doi.org/10.1038/d41586-025-00615

Intellectually stimulating:

- Chris Anderson, The Long Tail: Why the Future of Business is Selling Less of More, Grand Central Publishing, 2008

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