PRODUCT RECOMMENDATIONS AND MARKET CONCENTRATION

Giacomo Calzolari
with E. Calvano, V. Denicolò, S. Pastorello

Special digital keynotes Zoom session

Suzanne Scotchmer Memorial

Lecture

January 14, 2022

Digital Center
Toulouse School of Economics

Research agenda

- AI (Artificial Intelligence) is already impacting markets
- We are all excited by AI' shining marvels
- But also worried about its consequences

- We want to understand how AI applied to markets works
- This requires bringing Computer Science and Economics closer
- Studying actual AI in realistic economic environments
  as in our papers on *"AI and algorithmic pricing"*

Ocean of products

- Choice set for consumers is becoming immense, mostly unknown, e.g. products, news, movies, songs, assets, posts to read, papers ...
  - products in Amazon Marketplace: 353 mil
  - songs on Spotify: 90 mil
  - movies on (US) Netflix catalog: 6000
  - videos on YouTube: 26 bil
  - ...

Ocean of products-items

- We will never be able to explore this ocean entirely
  - **too many alternatives** and even if we knew they exist...
  - we would **not know our own tastes** for these products

- We need some help!

  What is the new sextant to navigate this ocean?

Recommender Systems

- Def. *Recommender Systems (RS) are software programs providing personalized suggestions to users/consumers about specific items/products.*

- RS designed to predict users' preferences for unknown items, using assessments of other users/items, **collaborative tool**

- RS remarkable and visible market application of AI mediating interactions between (consumers/users)–(RS platform)–(producers/items)

Why do we care?

Recommender Systems (RS) are already shaping users' choices

- Recommended: Netflix movies 75%, Amazon views 35%, Spotify songs 40%, YouTube videos 60%

Worries about algorithmic recommendations

- Heated policy debate, risks for competition and democracy
  (Vestager 17, 20, US congress FTC 20, CMA 21, French-German paper 19)
- Rich-get-richer: RS exasperate popularity
  (Fleder&Hosanagar 09, Adomavicius et al 20, Abdollahpouri al 21)
- This may be caused by AI algos in markets, (re)trained on data which contributed to generate (endogeneity)

"RS reinforce market power amplifying competitive advantage."

We decided to look into it, with our research agenda

Some questions

- RS shape consumers' choices $\rightarrow$ affect competition and market structure

1. RS simply another search-cost reduction (e.g. Internet)?
2. Are recommendations biased?
3. Will dominance of sellers/products be further reinforced?
4. What is RS' impact on competition and market power?

Approaches and Literature

- Theory - stylized
  - Reducing search costs (Brynjolfsson et al. 11, Goldfarb&Tucker 19)
  - Steering (Hagiu&Jullien 11, Drugov&Jeon 17, Calvano&Jullien 18, de Corniere&Taylor 19, Teh&Wright 20, Bourreau&Gaudin 21)
  - Information design (Bergemann&Ozmen 06 Che&Hörner 18, Aridor&Gonçalves 21, Lee 21)

  Useful but stylized and missing collaborative nature of RS

- Empirical on actual algorithms
  - Causal effects (Tucker&Zhang 07, Elberse et al 07, Brynjolfsson et al. 11, Ferreira et a. 16)

  Rare data, difficult identify mechanism and generalize

- Experimental with realistic simulations
  - This research

Research approach

- We operate actual RS in synthetic and controlled environments
  - Synthetic = we generate preferences&products
  - Controlled = we control training data of the algo

- Challenges: (i) Algos must be similar to those used in markets, (ii) Environments must be realistic

Intended Contribution

1. Methodological: bridging ECO–CS
   use sound economic model with realistic AI algorithms
2. Specific: studying the following links

Users/Items $\rightarrow$ Recommendations $\rightarrow$ Product market competition

Conceptual framework for RS

- I users & J items
- Rating matrix R (IxJ)
- Some observed ratings r_{ij}
- R very large and very **sparse** (typically 1-10% non-blanks)

		Items			
		A	B	C	D
Users	1		4.5	2.0	
	2	4.0		3.5	
	3		5.0		2.0
	4		3.5	4.1	1.0

The task is:
predict missing ratings $\rightarrow$ make personalized recommendations

The RS algorithm

State of the art RS algorithm in a nutshell (model-based collaborative-filtering) in industry.

Step 1 RS assumes parsimonious model of ratings with k factors (no semantic meaning):

- user-dimension θ_{ih}: proclivity to factor h of user i
- item-dimension β_{jh}: intensity of factor h in item j

factors combined with simple model $r_{ij} = \sum_{h=1}^{k} \theta_{ih}\beta_{jh}$

Step 2 Estimate $\hat{\theta}, \hat{\beta}$ minimizing accuracy loss on observed ratings

Step 3 Impute all missing entries: $\hat{r}_{iw} = \sum_{h=1}^{k} \hat{\theta}_{ih}\hat{\beta}_{wh}$

Step 4 Recommend user i item(s) highest observed/imputed rating

Model-based collaborative-filtering

- Formally the problem is akin to matrix factorization albeit with an incomplete matrix

Items

Users		A	B	C	D
	1		4.5	2.0	
	2	4.0		3.5	
	3		5.0		2.0
	4		3.5	4.1	1.0

=

User matrix

1	1.2	0.8
2	1.4	0.9
3	1.2	1.0
4	1.4	0.8

$\times$

Item matrix

A	B	C	D
1.5	1.2	1.0	0.8
1.7	0.6	1.6	0.4

- Exploiting user and item correlations, *collaborative* component
- Observation: not just cost-reducing search tool which would only rely on *idiosyncratic personal* tastes

Economic environment

Synthetic Preferences

- We assume exact same model (eliminating uncontrolled biases) $u_{ijt} = \sum_{h=1}^{k} \theta_{ih}\beta_{jh} + \varepsilon_{ijt}$
- Random Utility with Logit errors iid
- Parameters θ_{ih} "handpicked" to achieve specific goals

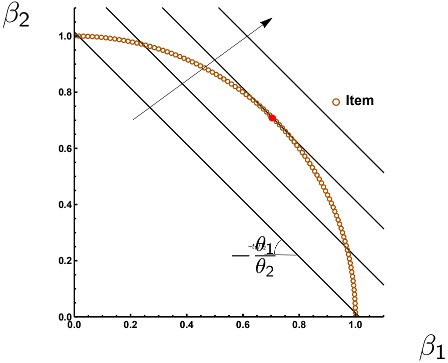
Synthetic Items

- Products are substitutes and β_{jh} handpicked
- Pure horizontal + Pure Vertical + Mixed
- No prices for the moment (firms are passive)

Baseline environment: 100 users, 100 items, k=2

Example: pure horizontal differentiation

Items designed distributed uniformly over circle



- We make sure that for each user there is one preferred item (possibly unknown) and vice-versa

Experimental protocol

Repeated consumption and recommendation: $t = 1, 2, ..., 100$

- At any t:
  1. **Update** R_t: for each user i add rating of one item (which?)
  2. **Estimate**: feed R_t into the algorithm $\rightarrow \hat{R}_t$
  3. **Recommend**: the best single product to each user
- New data updating:
  - *Endogenous data*: add $r_{ijt} = u_{ijt}$ of recommended item
  - *Exogenous data*: add $r_{ijt} = u_{ijt}$ of item at random
- We run this procedure for 1000 sessions and study averages

Note, we need to understand how RS work, hence no biases:

- no steering of recommendations
- users follow recommendations and truthfully report ratings

Benchmark: individual search model

We contrast RS with *individual search*: at any t

- each consumers samples a random item observing u_{ijt}
- perfect recall of past observations
- consumes item with highest observed utility so far

As time passes...

- with individual search, consideration set becomes larger
- with RS, R_t becomes less sparse

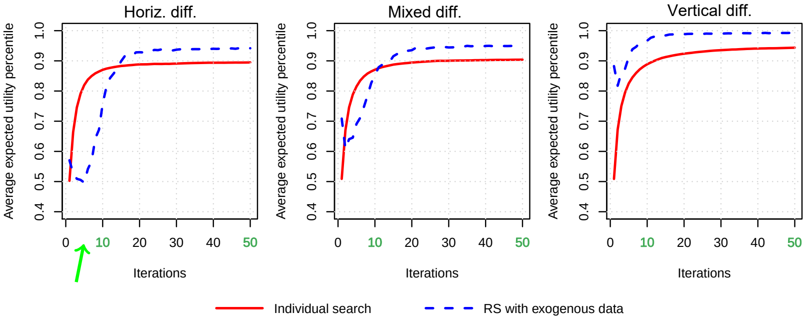
Findings

First with exogenous data

Then with endogenous data

Findings: Quality of recommendations

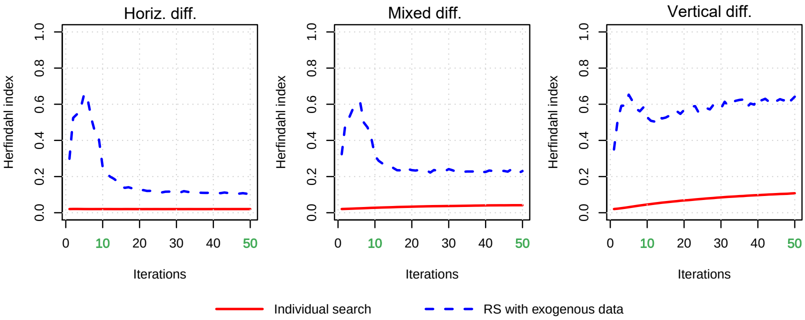
Recommended items utility with exogenous data



- Expected (normalized) utility higher with RS if R_t is not too sparse ("cold-start" problem of RS)
- RS best with vert. diff.: RS exploits consumers' similarities

Findings: Concentration

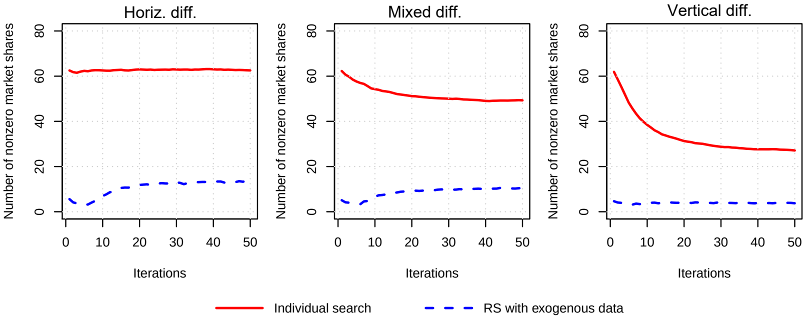
Hirsh-Herfindahl Index induced market-shares



- RS induces substantial concentration

Findings: Concentration

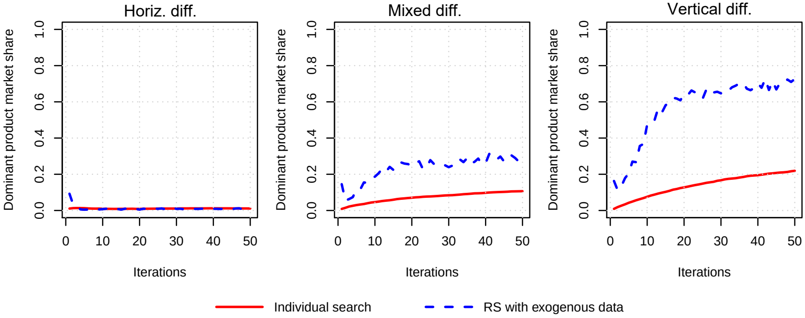
Number of products with non zero-market share



- With RS, fewer items with positive market-share
- With Horiz. diff. (not shown) selling firms change over sessions, but some are favored, and persistence within session

Findings: Dominant's product

Market share of the best product(s)



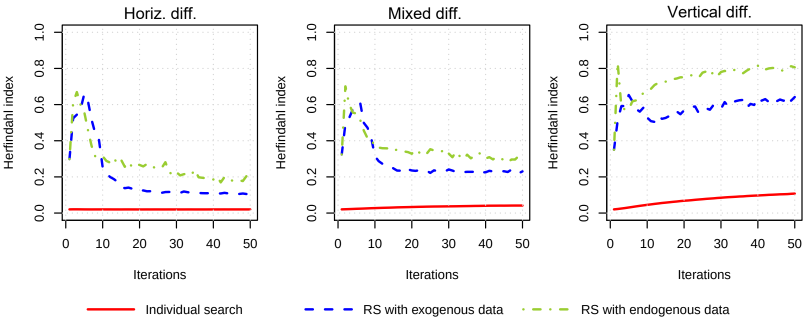
- RS helps identifying superior products when they exist

Richer-get-richer concern

We have seen, RS with exogenous data augment concentration
$\rightarrow$*Bias in the algorithm*

- A concern with RS: recommended items become more popular and thus get recommended more and more... cumulative feedback-loop creating entrenchment
- It could realize because, in reality, *data are endogenous*: AI algorithms retrained on data they contributed to generate
- Do endogenous data produce a degenerate feedback-loop?
  $\rightarrow$*Bias in the data*

Findings: Endogenous data



- Concentration slightly increases with endogenous data ($t = 10$)
- But it is a second order effect w.r.t. bias in the algorithm

Summarizing findings so far

- RS may help consumers, especially when vertical diff. is relevant and the rating matrix not too sparse
- RS significantly increase concentration
- Worries on cumulative feedback-loop not supported

Two more steps to better understand

1. Is concentration induced by the RS an issue?
2. Where does this excessive concentration come from?

Is concentration bias an issue?

- It depends on competition
  - few lucky firms with no merit get market power
  - competitive market selects best firms that become large
- What effect of RS on implied intensity of competition?

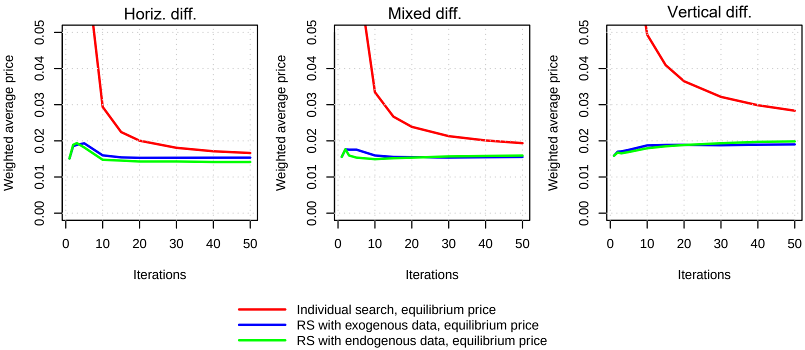
RS and intensity of competition

Measure intensity of competition with implicit Nash equilibrium prices at any t

- Find Nash Equilibrium prices with demand mediated by the RS
- Similarly we do for individual search benchmark

- Static Equ. prices $p^{\star}$, our inverse measure of competition
- Firms not strategic, no forward looking manipulation of RS

Findings: Nash equilibrium prices



- RS intensifies competition: with RS prices significantly lower
- Prices reflect concentration bias
- Rich effect of data on competition (perceived differentiation reduces with high sparsity)
- Endogenous data again not relevant

Driving forces for market concentration

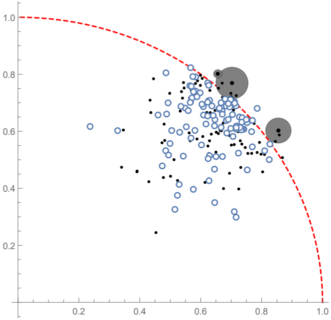
- We observed concentration towards a small subset of items
- Concentration reflects systematic failure to recover the true parameters: *a bias in the algorithm*

Possible causes of algorithmic bias

- failure estimate product characteristics $\hat{\beta}$
- failure to estimate consumer preferences $\hat{\theta}$
- both

Driving forces for market concentration?

Example Horizontal differentiation with exogenous data ($t = 10$)



- Red arc= true item/user β, θ
- Blue disks = estimated users $\hat{\theta}$
- Black dots = estimated items $\hat{\beta}$ (market share)

- We observe three systematic estimation biases
  1. Consumers bunched: reducing heterogeneity (competition $\uparrow$)
  2. Items bunched: reducing heterogeneity (competition $\uparrow$)
  3. Some items with overstated too-high quality (competition $\downarrow$)

Robustness and work in progress

How robust are these results (concentration, prices and biases)?

- "Huge" matrices
- Categorized ratings (e.g. 1-5 stars)
- Role of algo's hyper-parameters and cross-validation
- Mis-specified algos' model (e.g. k different form real)
- Multiple recommendations and users' decisions
- Other market reactions, e.g. entry/exit
- Different amount of ratings per users/items
  (informs debate on data portability across platforms/RS)
- RS with constraints (producers, serendipity, AI Magazine '20)

Conclusion (preliminary)

Takeaways

1. Design of RS algo contains biases: *homogenization* (increases competition), *quality overstatement* (reduces competition)
2. All these biases increase concentration but, overall, they also increase competition
3. Concern for feedback-loop (bias with endogenous data): too much emphasis, second order

So far a positive message:

- There are biases with RS, but they are not due to unavoidable problems (e.g. endogenous data)
- These systematic biases (negatively affecting consumers and some firms) could be eliminated with future better algos

PRODUCT RECOMMENDATIONS AND MARKET CONCENTRATION

Giacomo Calzolari (EUI)
with E. Calvano, V. Denicolò, S. Pastorello

Special Digital Keynotes Zoom Session
Suzanne Scotchmer Memorial Lecture
Jan. 14th, 2022