Online Platforms and the Fair Exposure Problem under Homophily

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INFORMS 2023 MD18 Fairness in Platforms and Recommendations

* denotes equal contribution; listed in reverse alphabetical order

A brief introduction

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Algorithmic decision-making

Design of optimization problems

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E.g., How to design convex loss functions for top-k prediction?

Design of optimization problems

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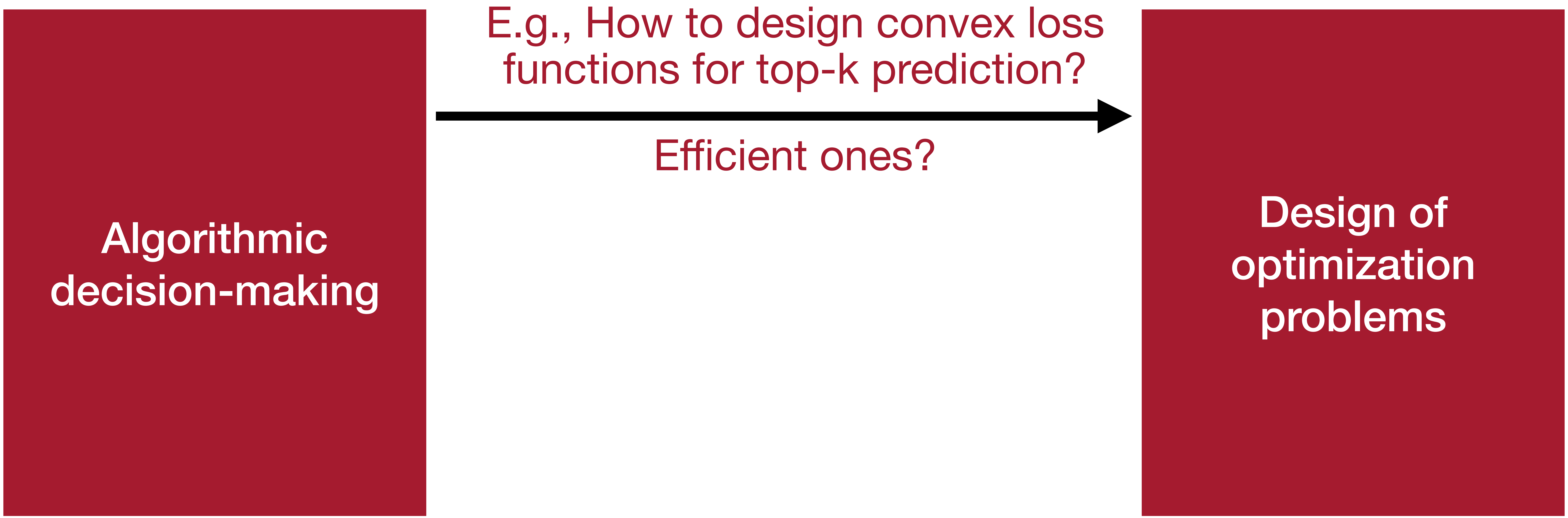

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Efficient ones?

NeurIPS 18, 19, 21, ICML 22, COLT 20, 22

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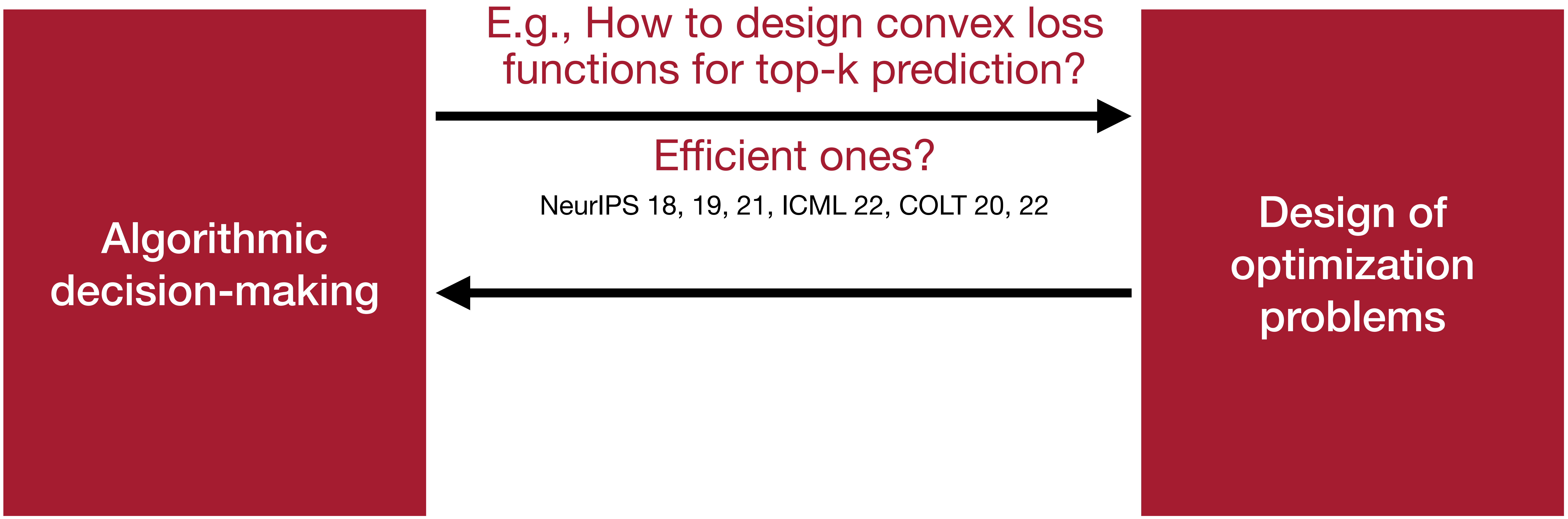

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Today: in online platforms (AAAI 23)

Increasing polarization in online platforms

Moran Yarchi, Christian Baden, and Neta Kligler-Vilenchik. "Political polarization on the digital sphere: A cross-platform, over-time analysis of interactional, positional, and affective polarization on social media." *Political Communication* (2021).

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Yarchi et al. (2021) discuss three types of polarization on social media

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"Interactional polarization aggravates positional polarization"

Promote informational diversity to mitigate positional polarization

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A historical attempt to promote informational diversity

FCC Fairness Doctrine (1949)

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FCC fairness doctrine asked broadcasters…

- Provide adequate coverage of public issues
- Ensure coverage fairly represented opposing views

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FCC fairness doctrine asked broadcasters…

Provide adequate coverage of public issues

Ensure coverage fairly represented opposing views

Informational diversity: Could something in this spirit translate to online platforms?

The fair exposure problem

The fair exposure problem:
Given limited intervention power of a platform, add constraints to enforce a balance in the exposure of content (e.g., impressions of news articles) among groups of users

Broader contexts

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How polarization arises (advertisers' strategy)

Hązła et al. 2023, Gaitonde et al. 2021

How user opinions change

Dean et al. 2022

How users enter/leave platform

Full computational resources: Celis et al. 2019

Limited intervention capacity: Ali et al. 2019, Fish et al. 2019, Stoica et al. 2020

Empirical examinations of polarization

Bakshy et al. 2015, Garimella et al. 2017, Yarchi et al. 2021

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We look at how policy constraints change *platform* behavior with limited intervention capacity

Model participants

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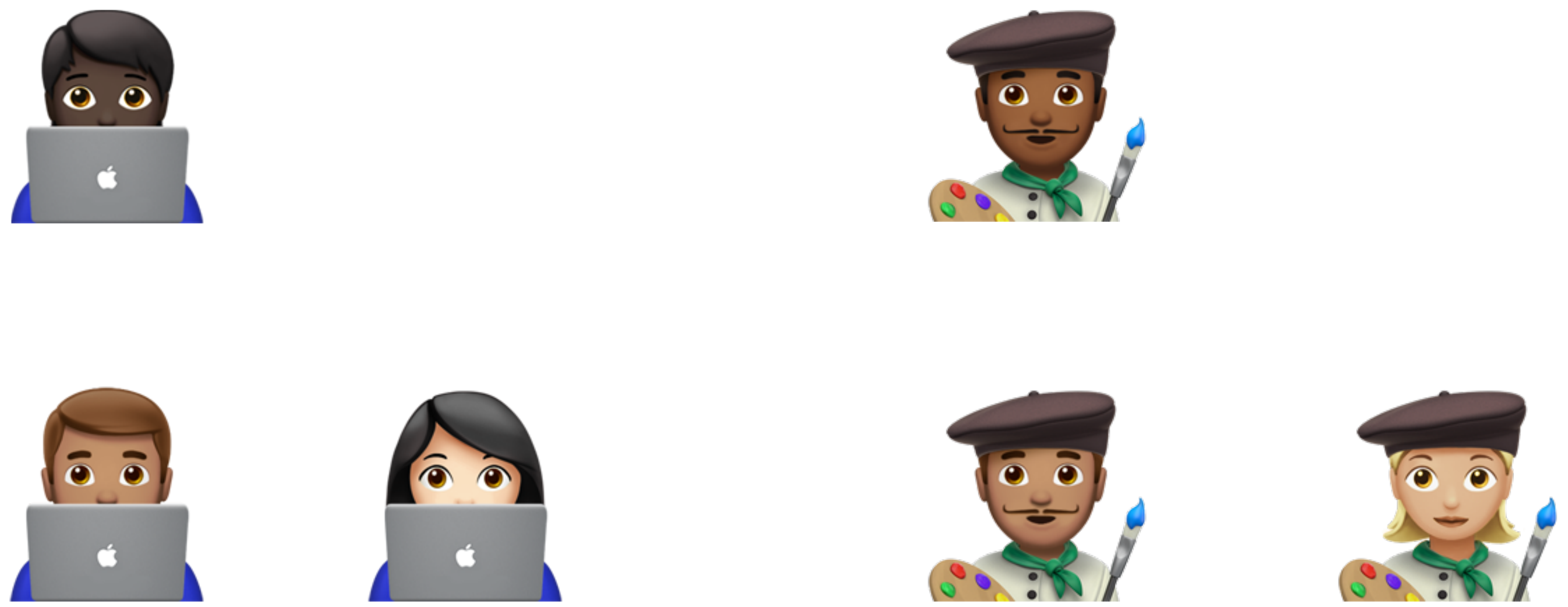
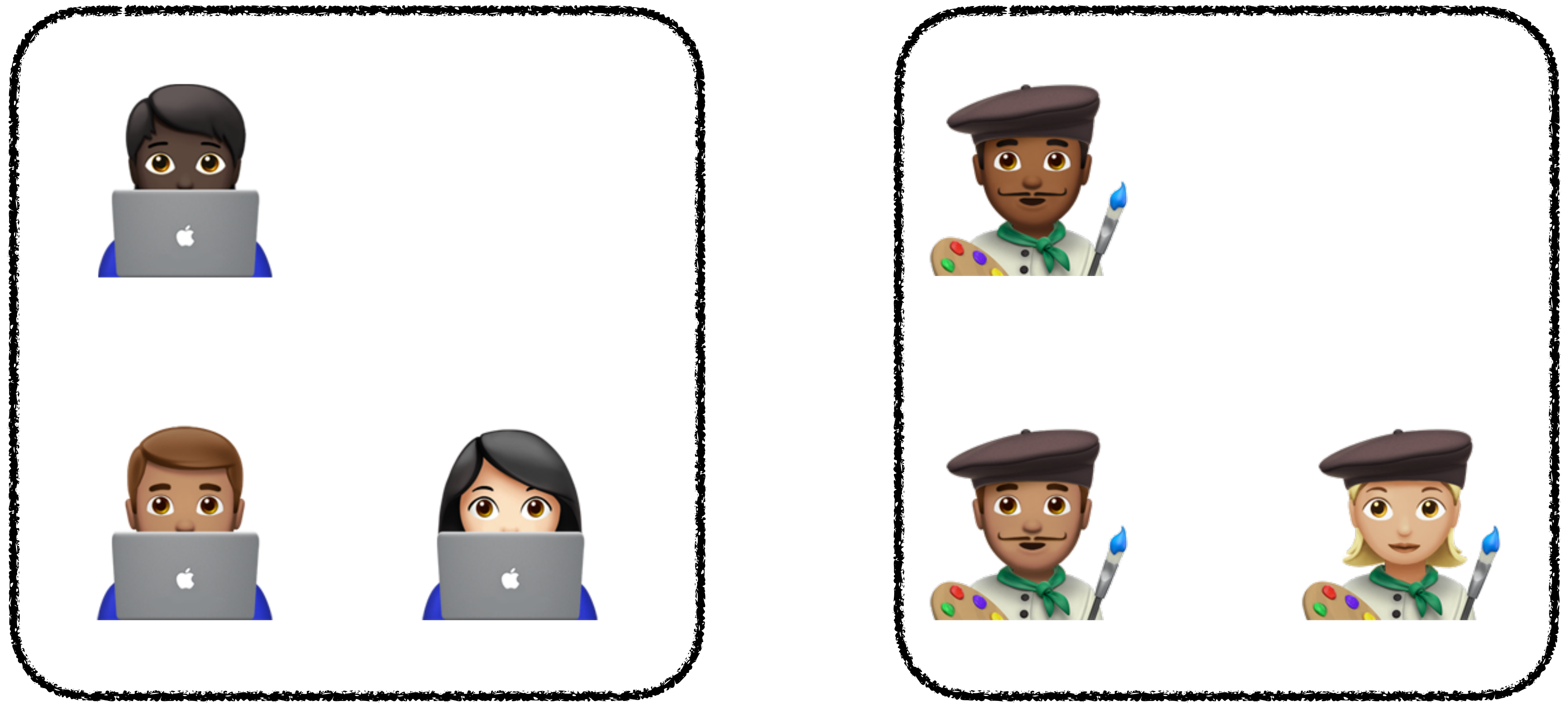


Model participants

$g =$ engineers $\quad$ $g =$ artists



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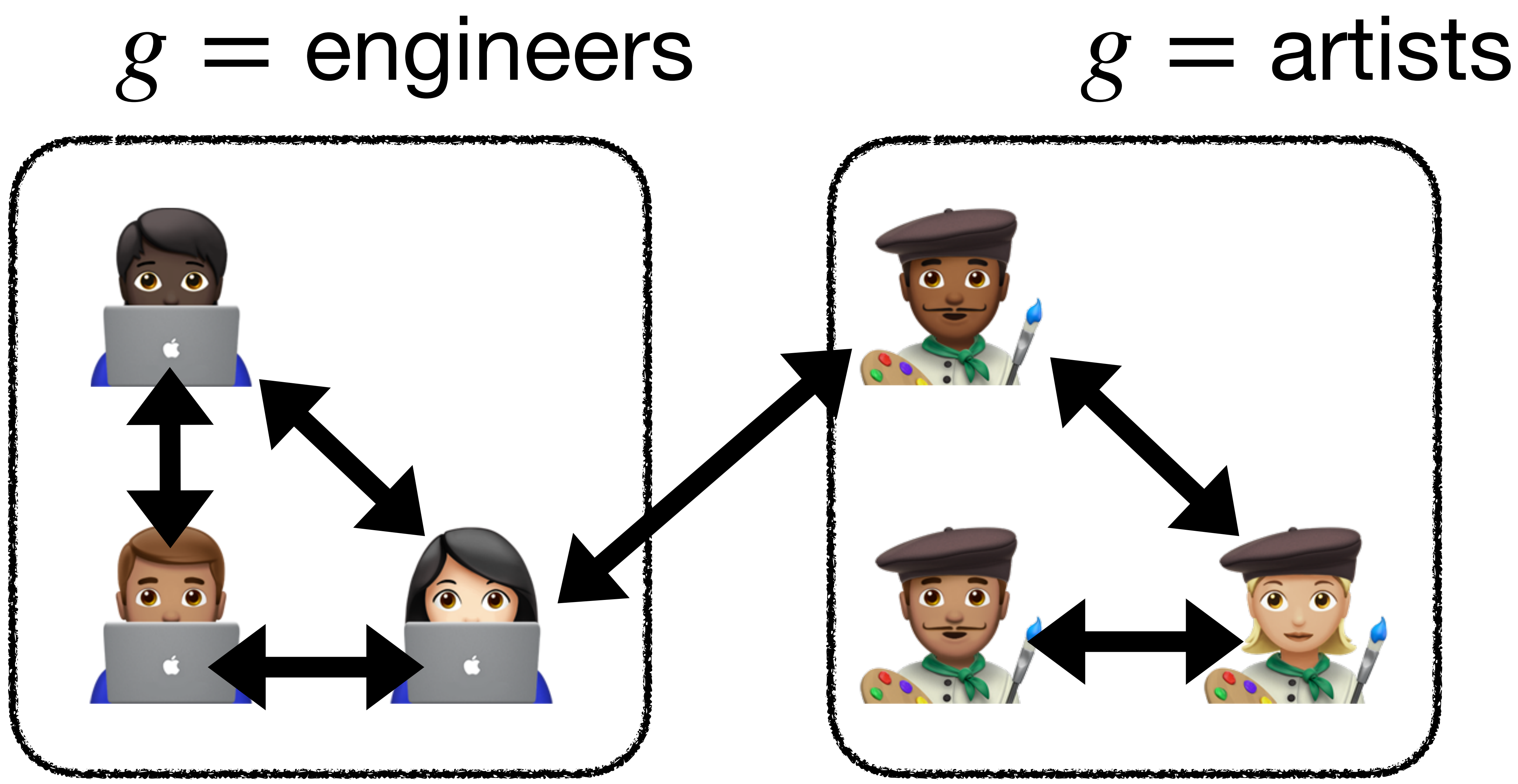

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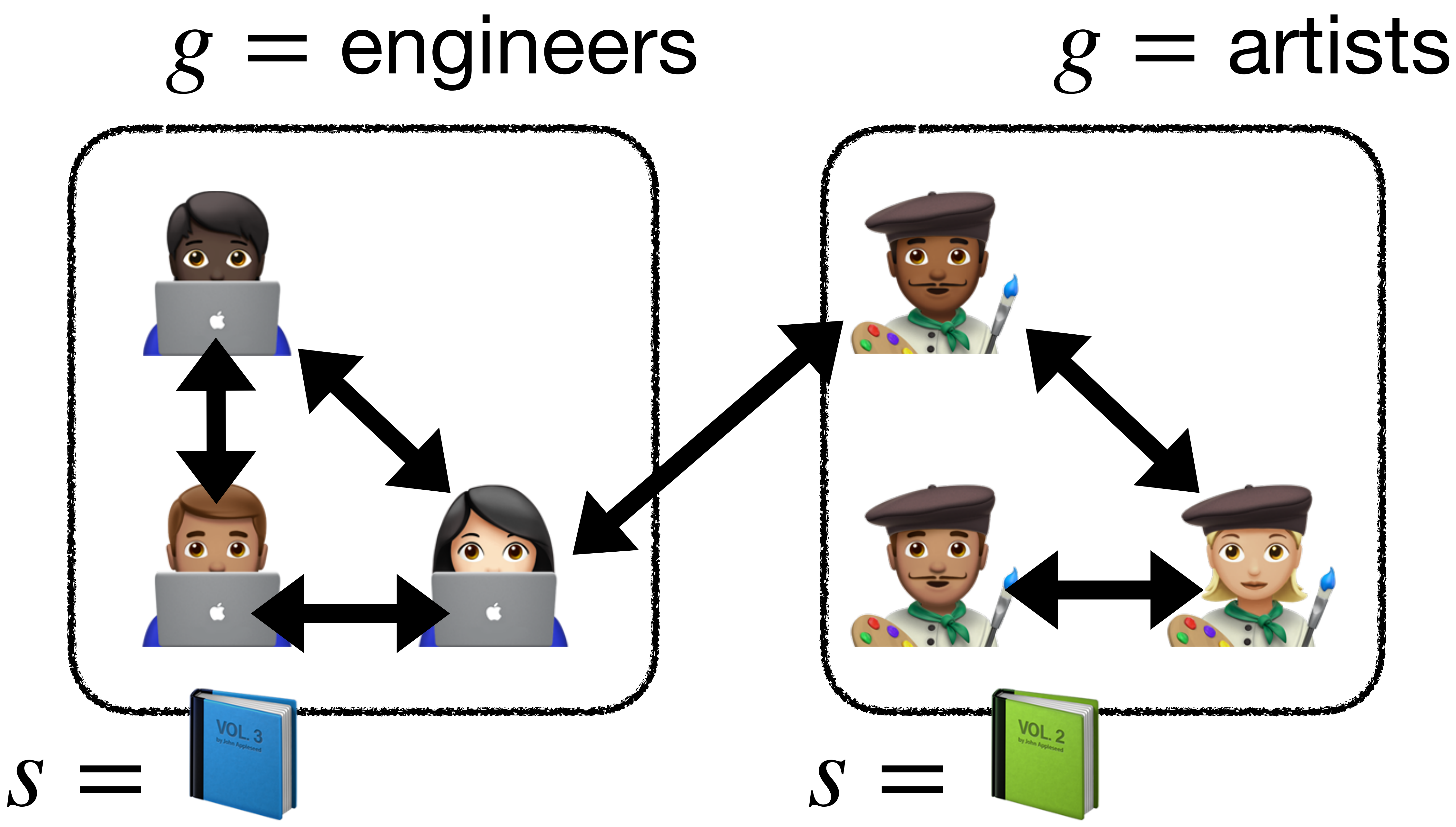

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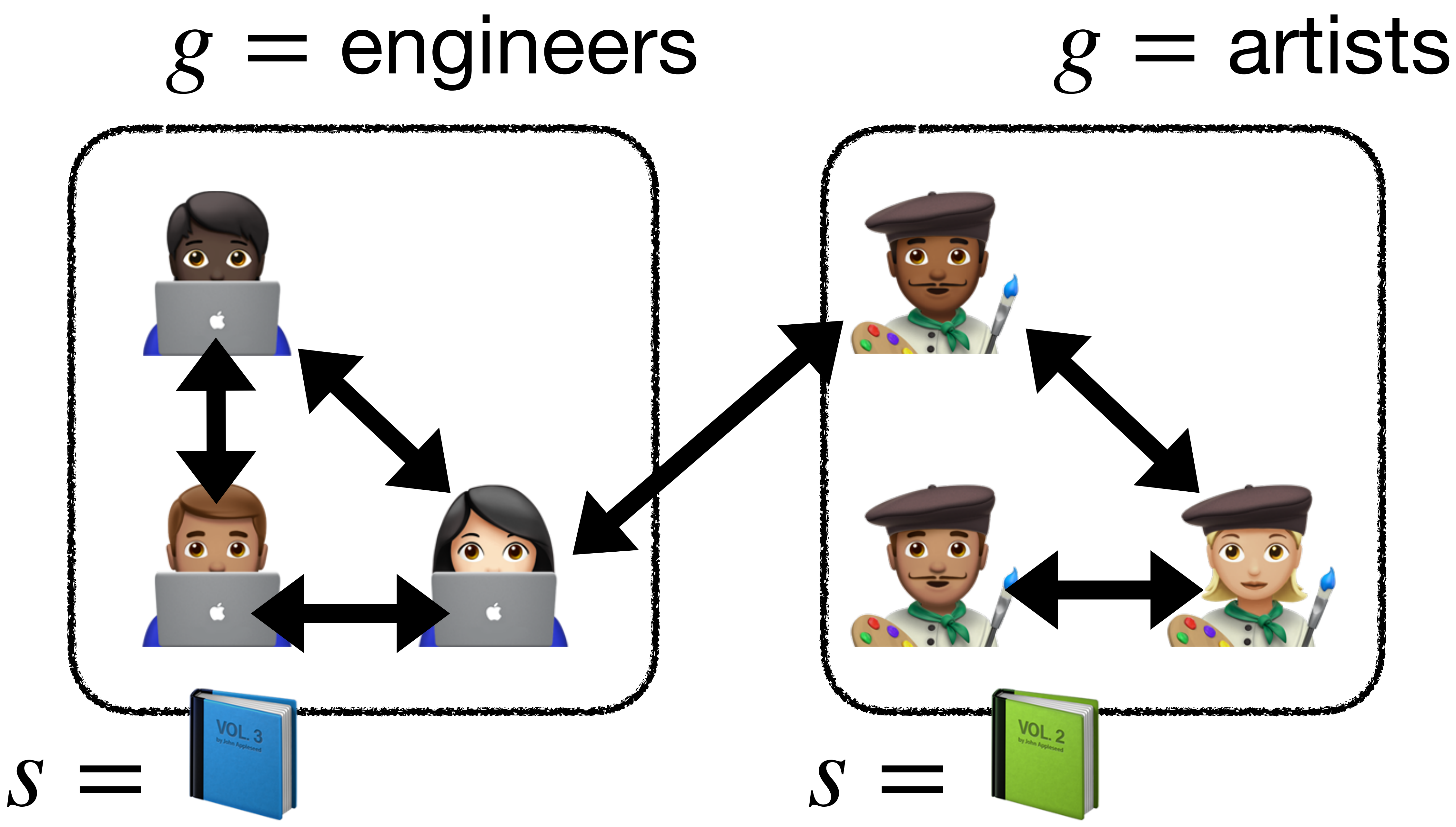

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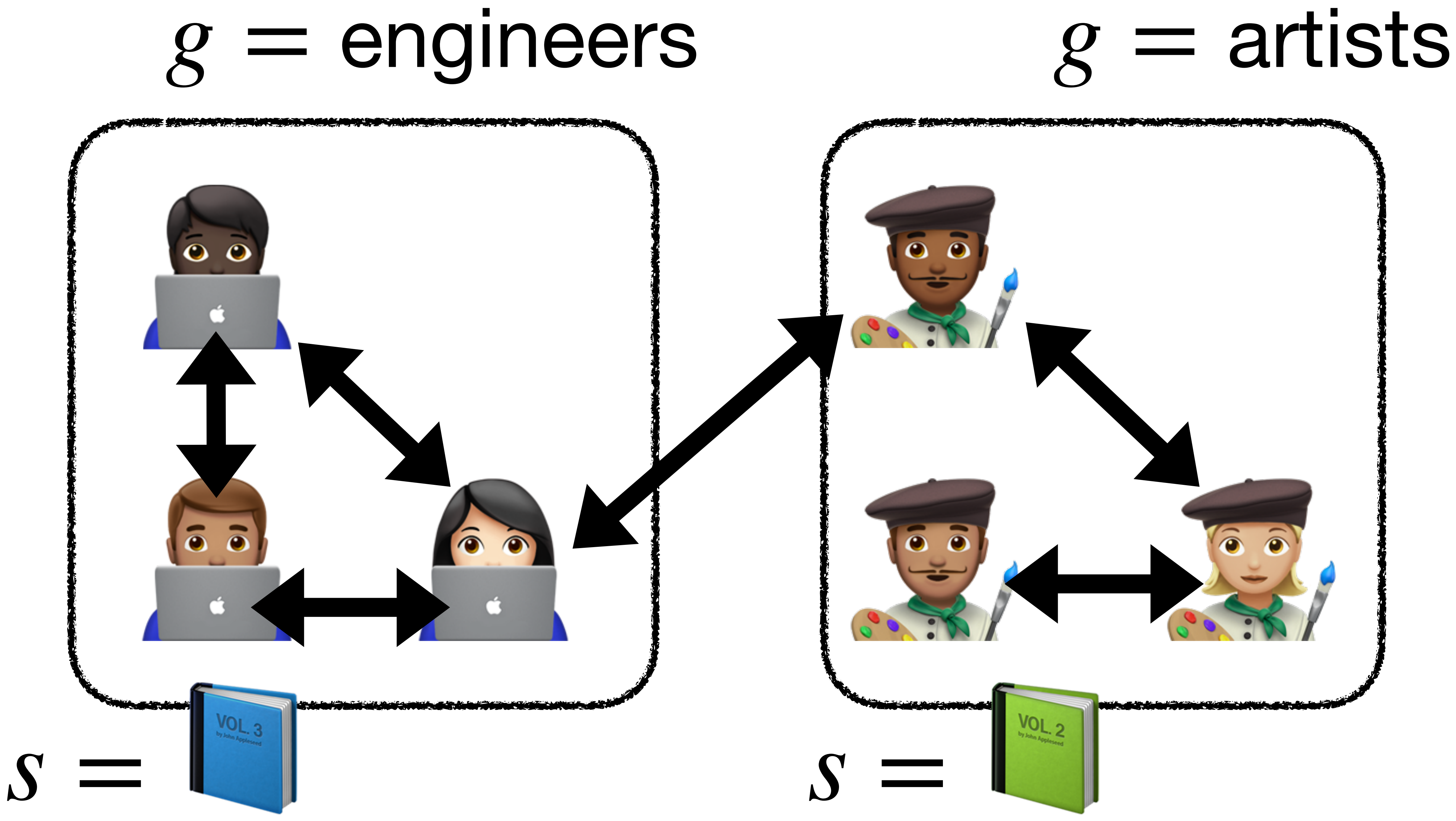

$\Theta_{g,s} = \Pr[\text{platform shows content } s \text{ to user in group } g]$

$$\Theta = (\Theta_{a,A}, \Theta_{a,B}, \Theta_{b,A}, \Theta_{b,B})$$

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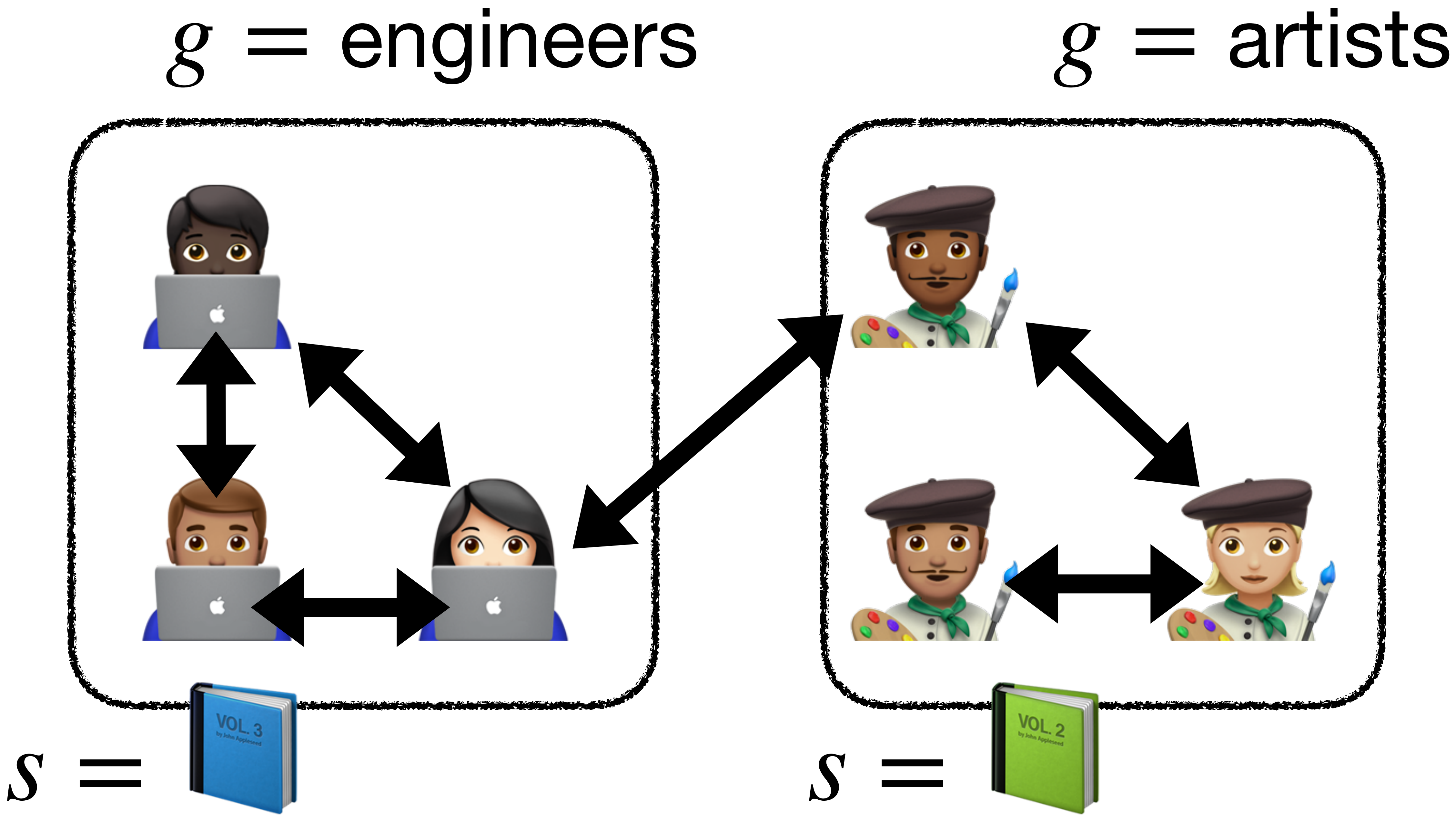

$\Theta_{g,s} = \Pr[$platform shows content s to user in group $g]$

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$\Theta_{b,B} = 1 \implies$ Artist gets shown green content with probability 1.

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Model dynamics

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Model dynamics

$t = 1$

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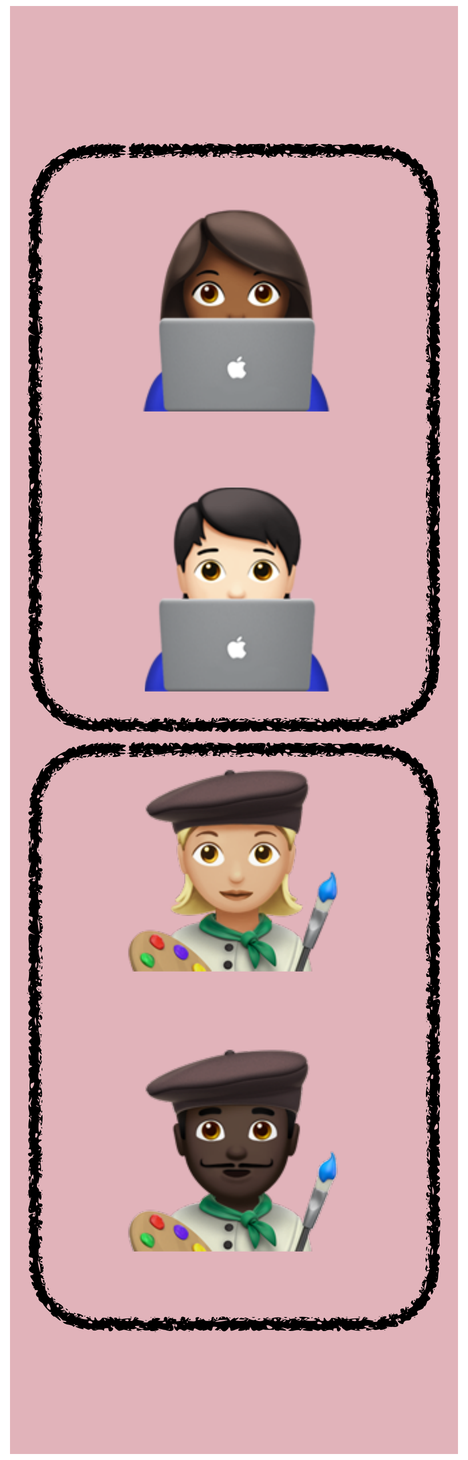
Model dynamics

$t = 1$

$t = \{2, 3, \ldots, T\}$

Model dynamics

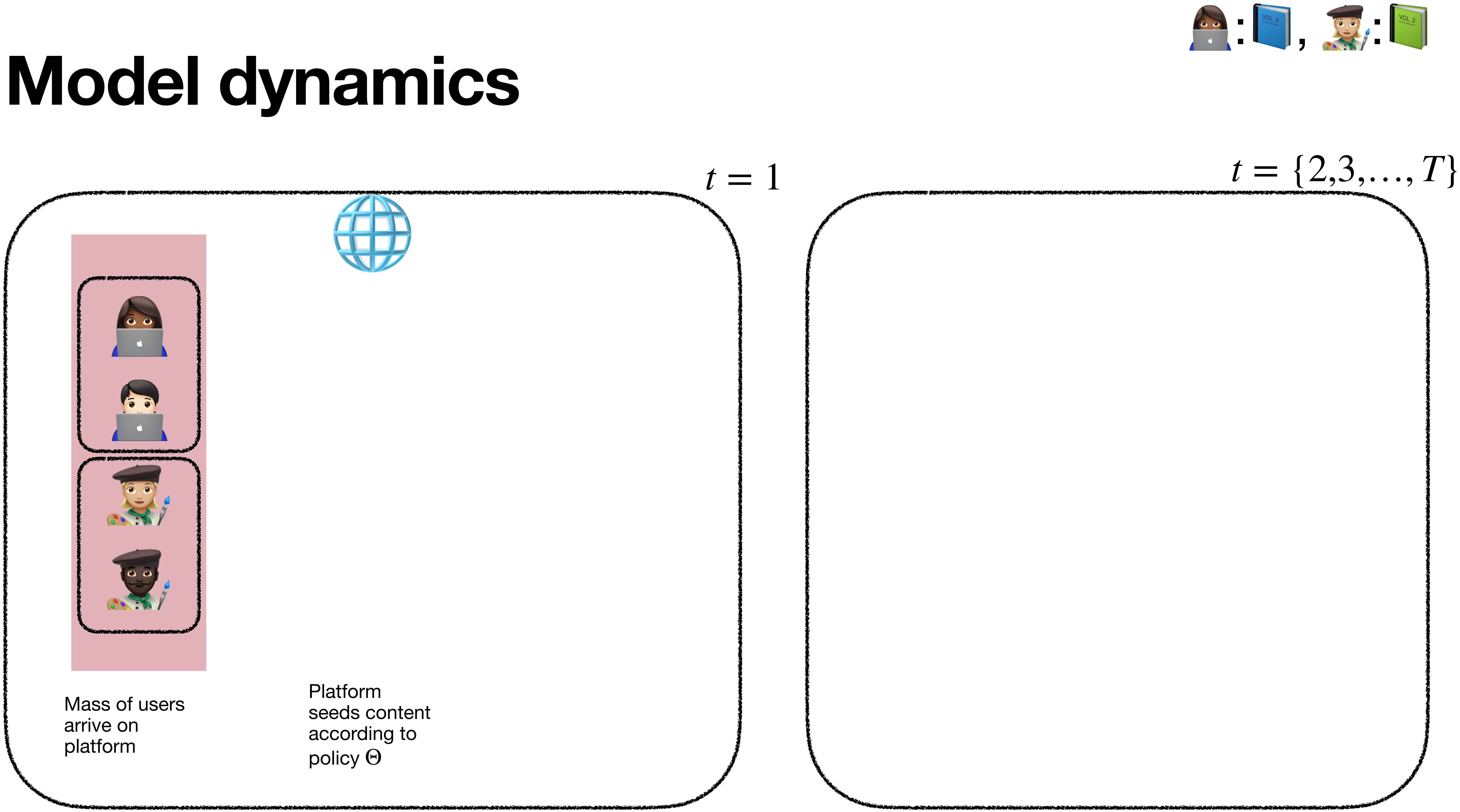
$t = 1$



Mass of users
arrive on
platform

$t = \{2,3,\ldots,T\}$

Model dynamics



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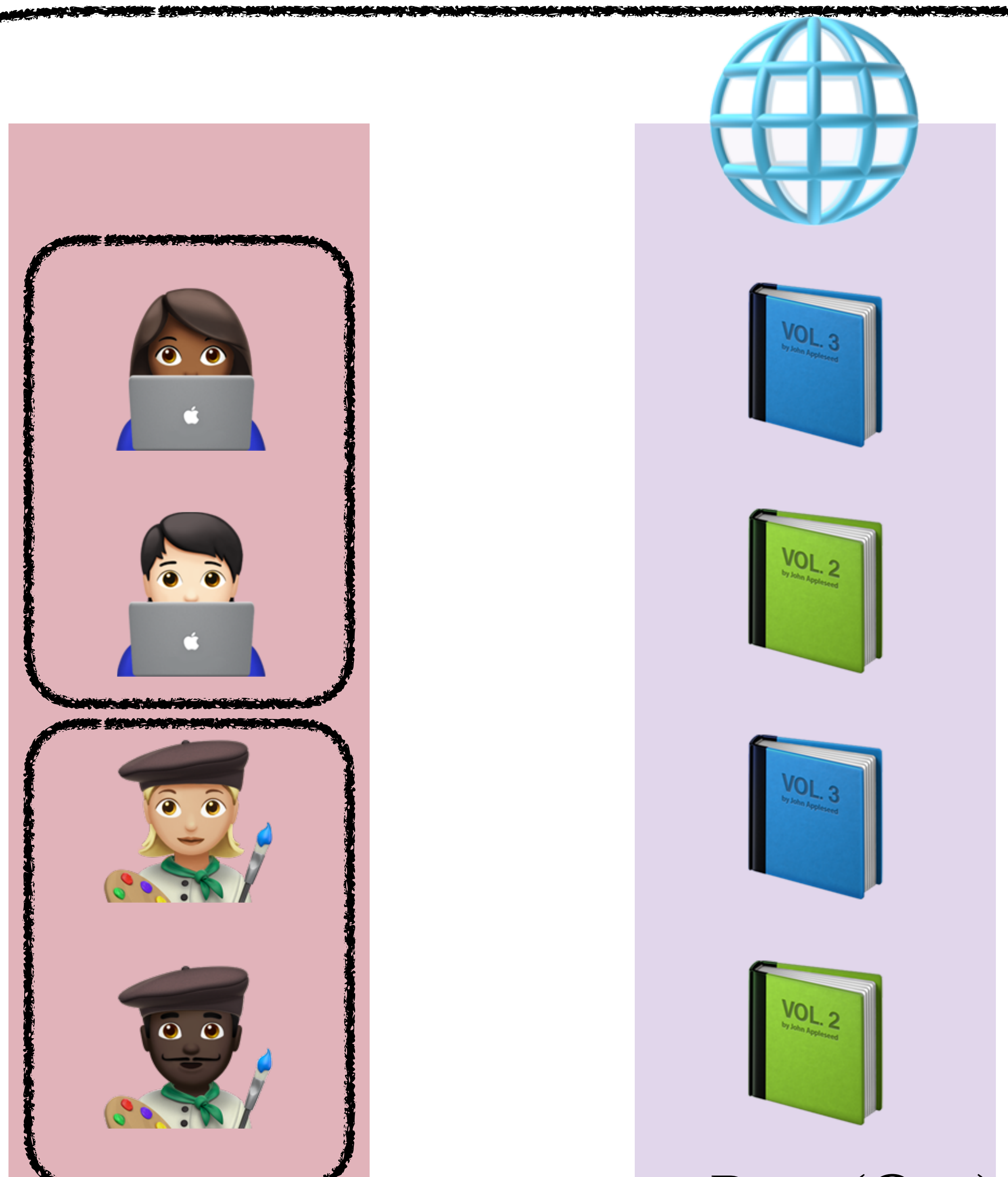

$\sim Bern(\Theta_{g,s})$

Mass of users arrive on platform

Platform seeds content according to policy Θ

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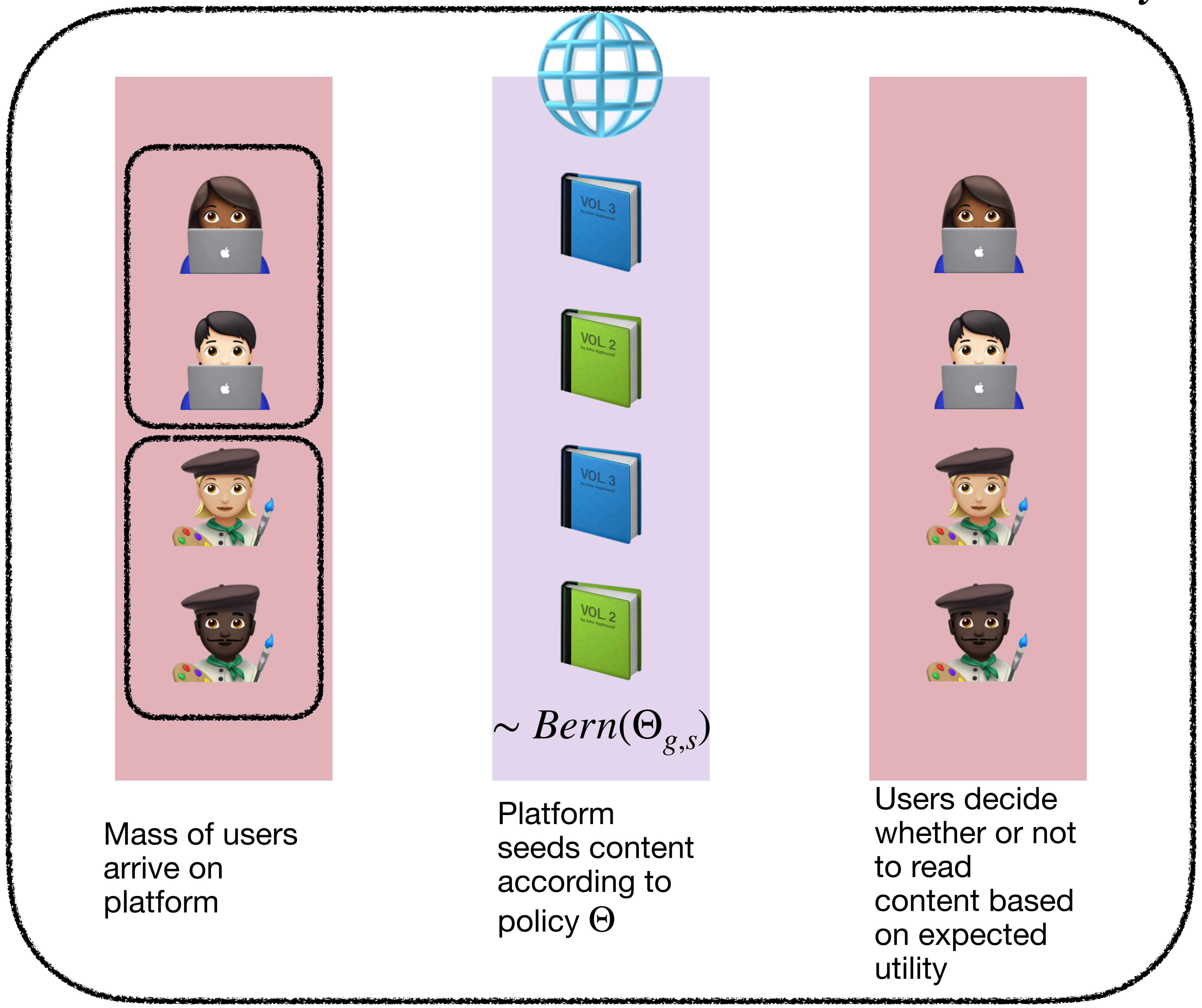

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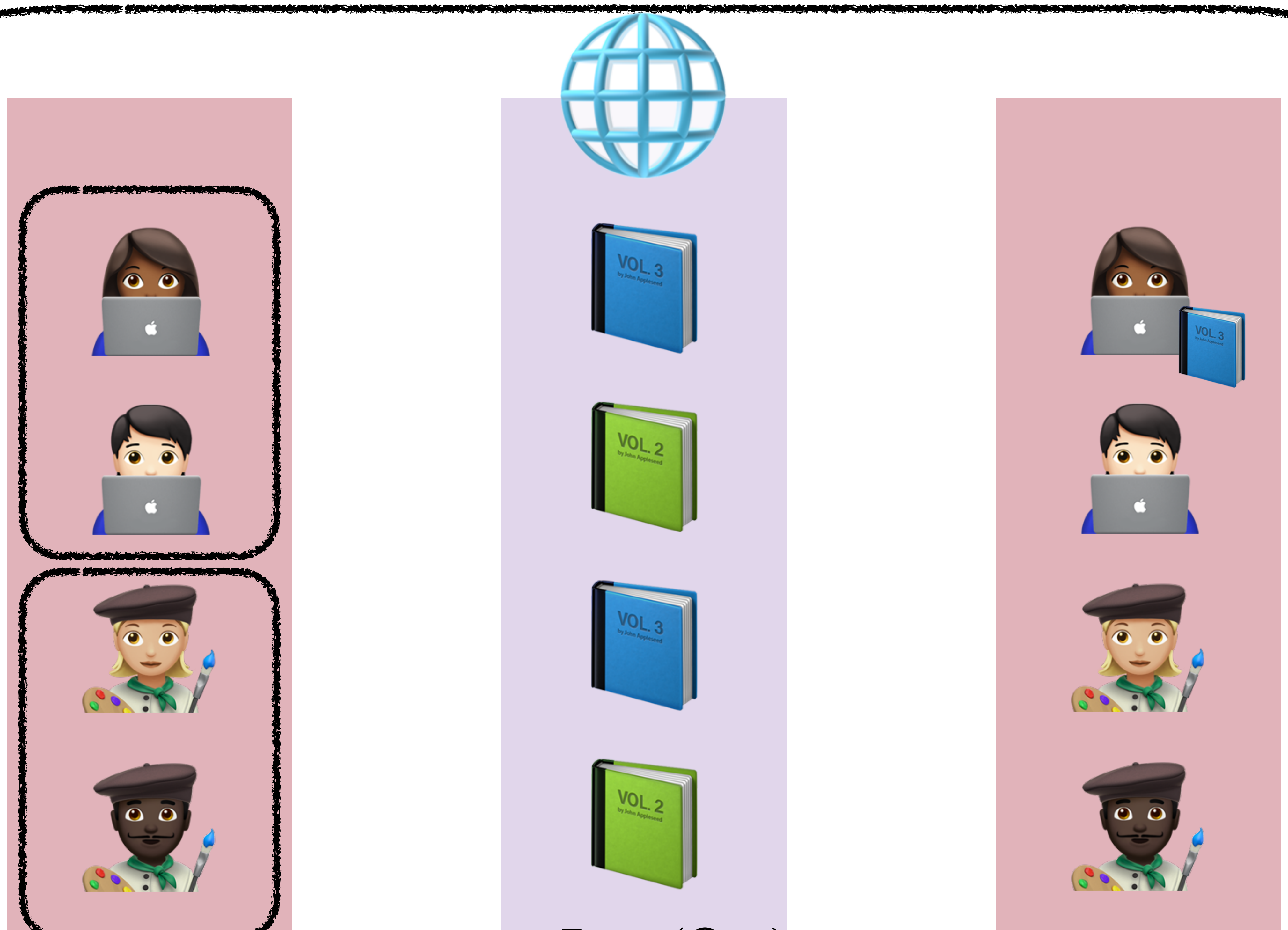

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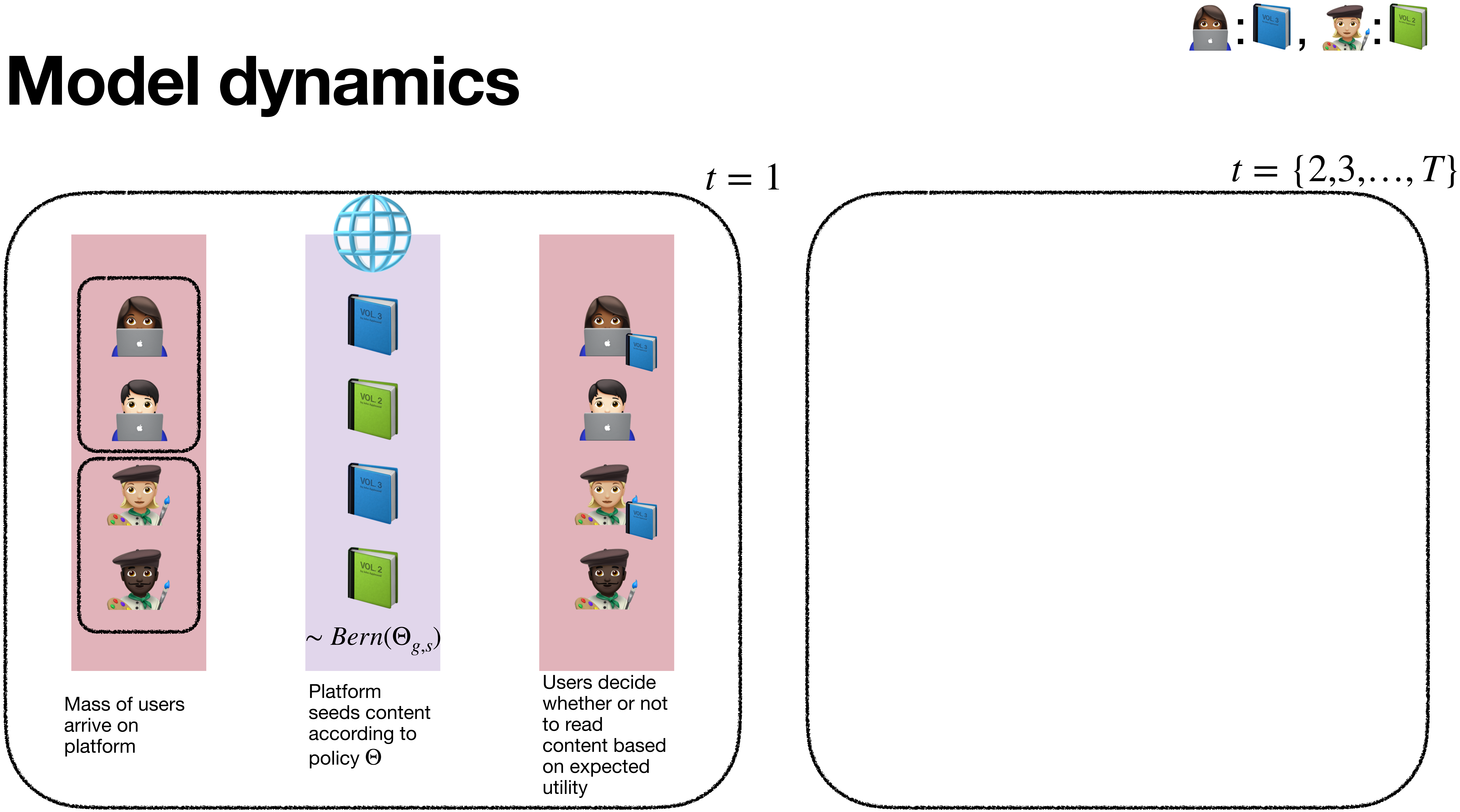

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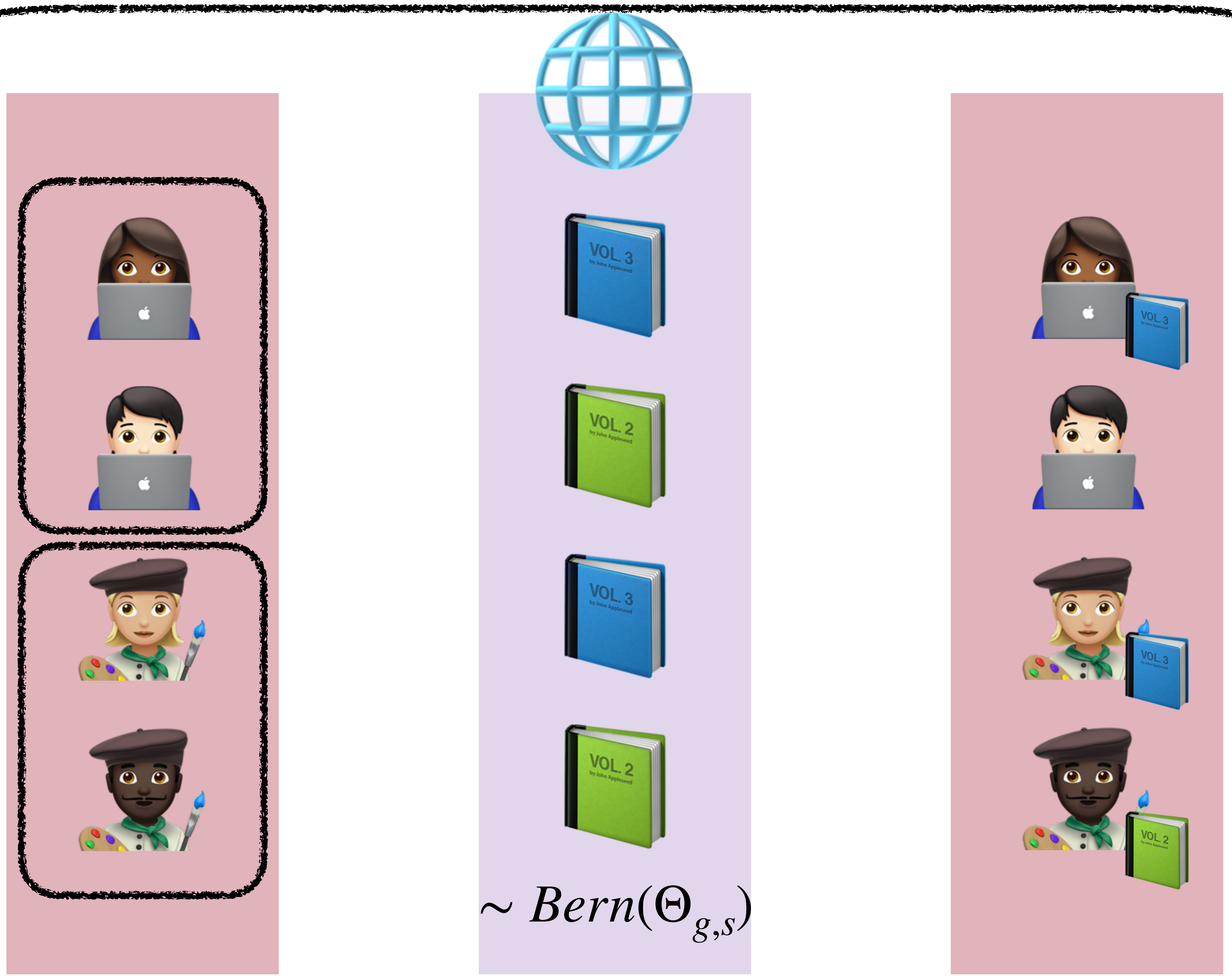

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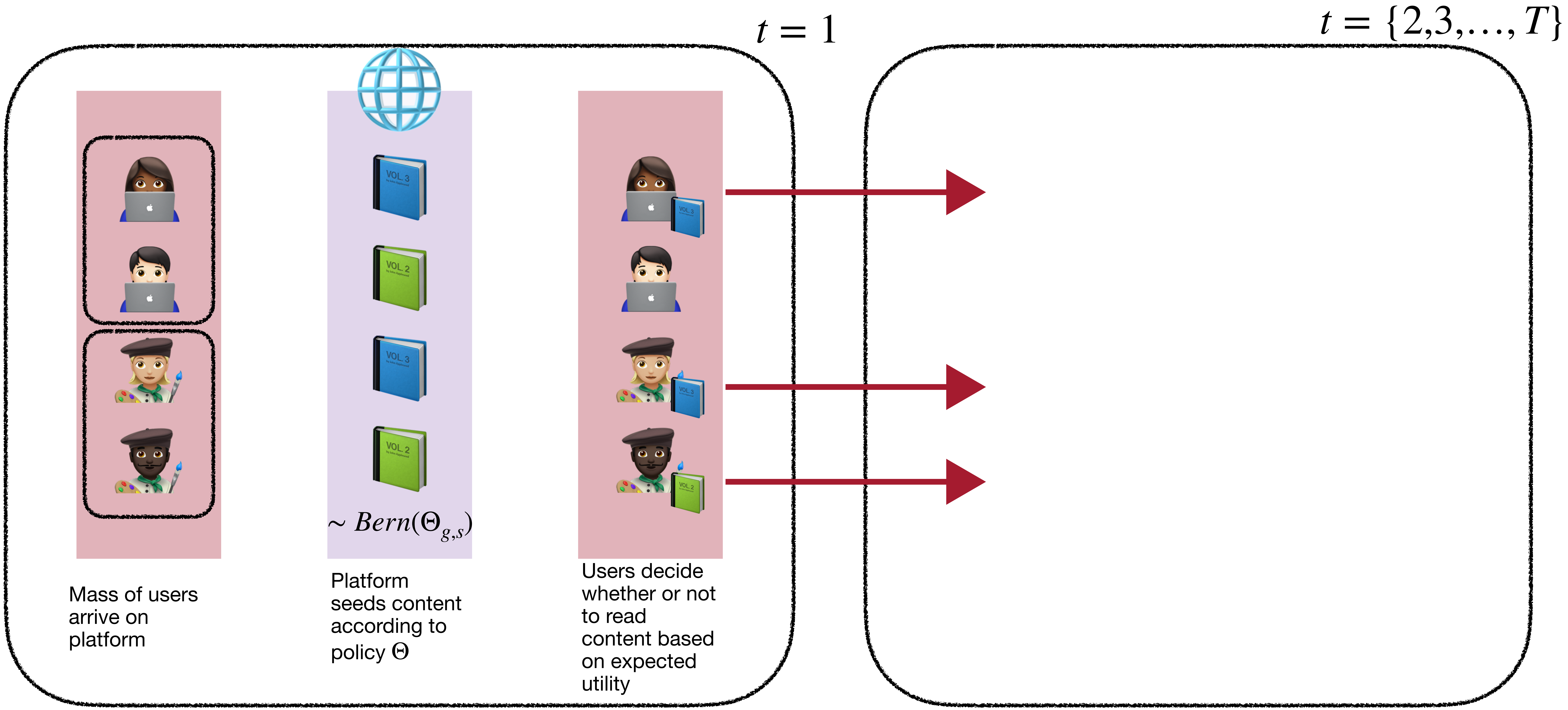

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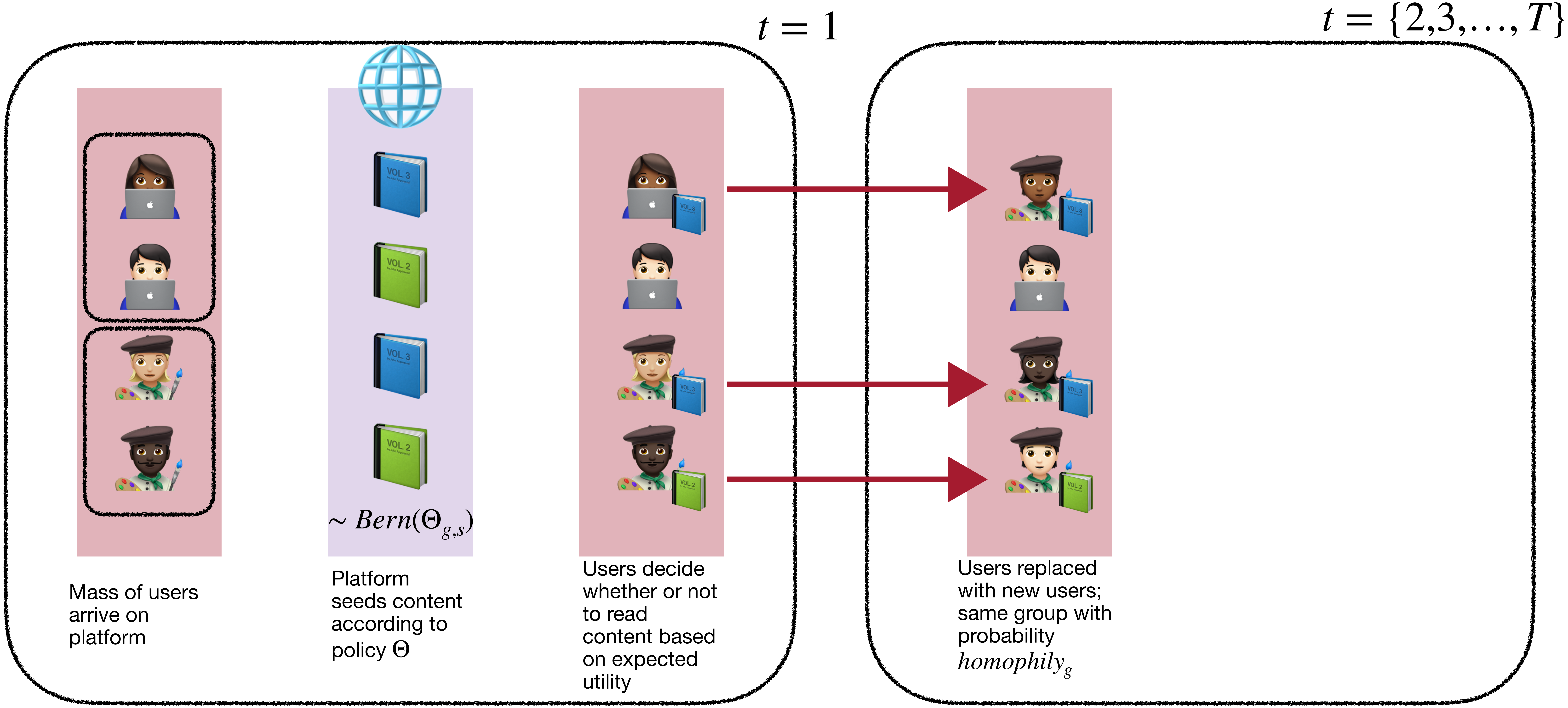

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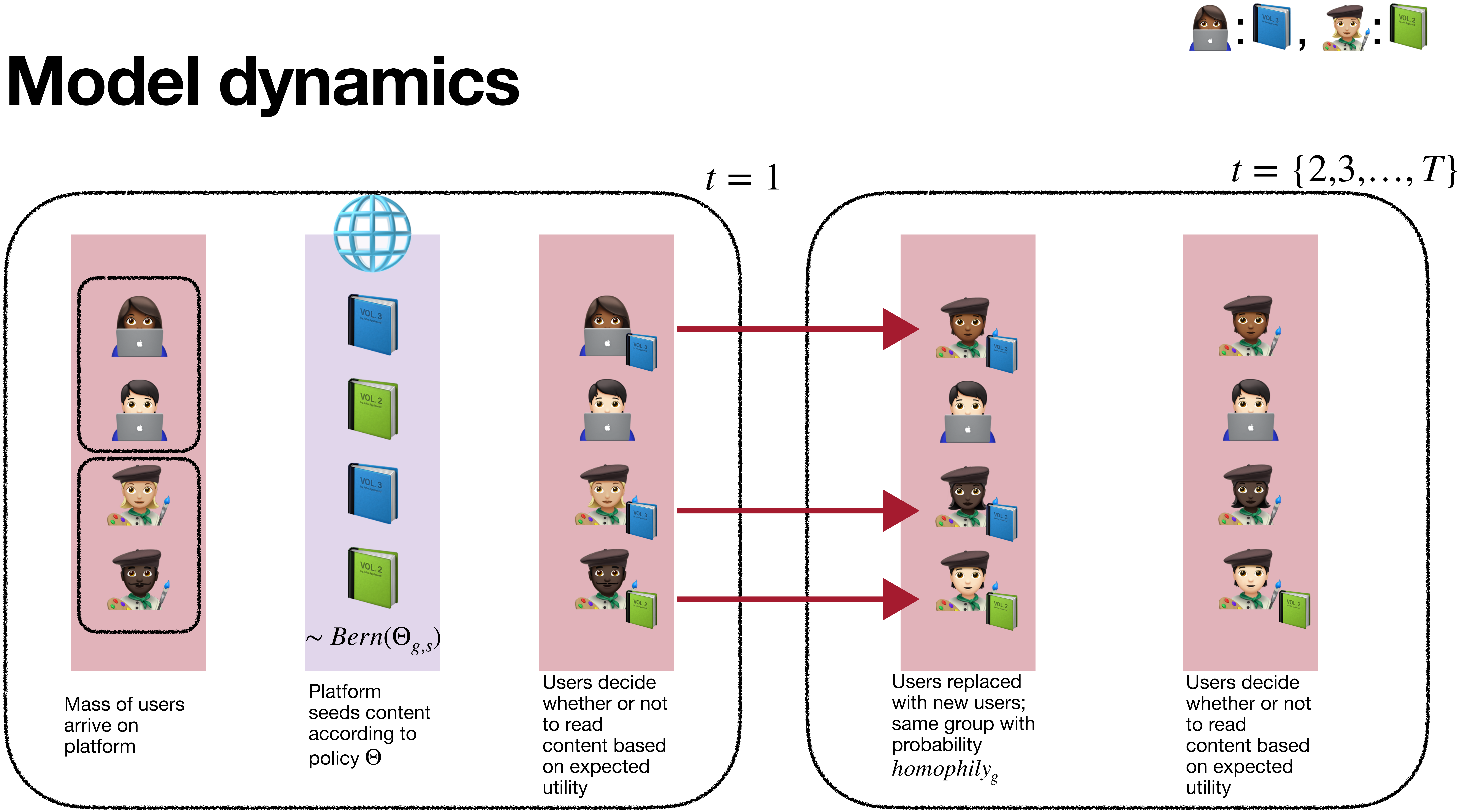

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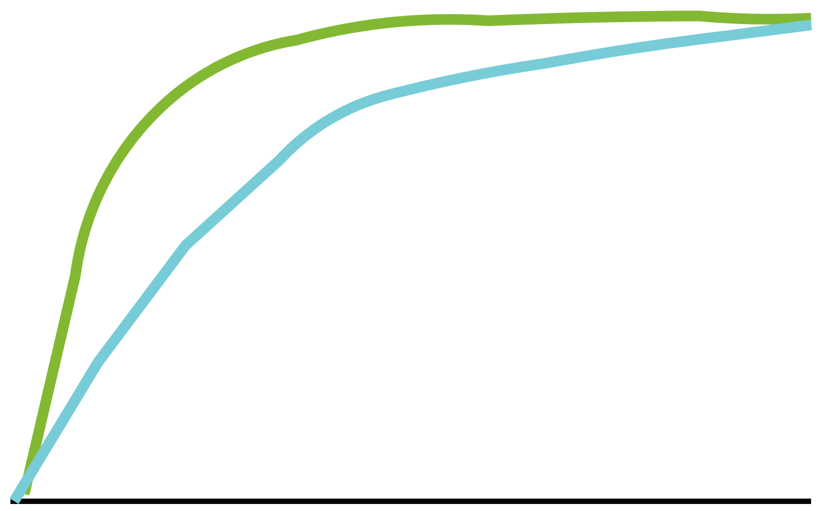
Player's decision process

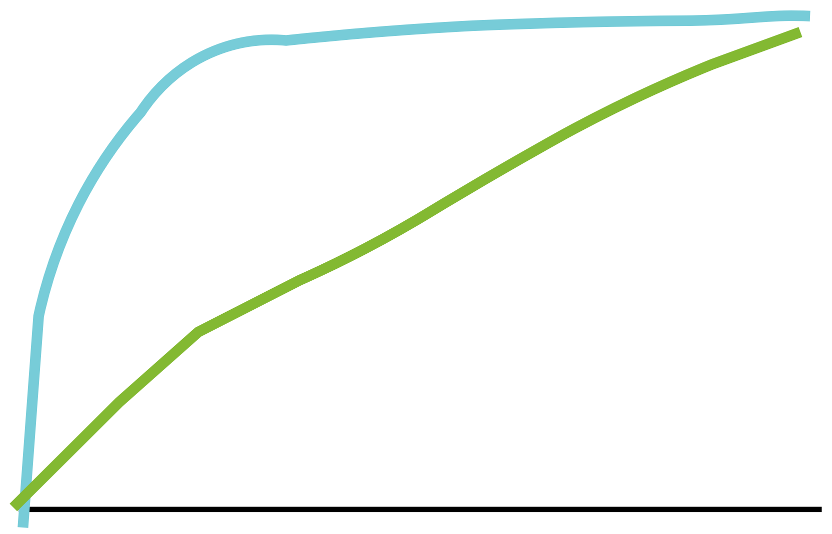
Player’s decision process

CDF[probability liking|engineer] $F_{eng,s}$



$p_{eng,s} \sim F_{eng,s}$

CDF[probability liking|artist] $F_{art,s}$



$p_{art,s} \sim F_{art,s}$

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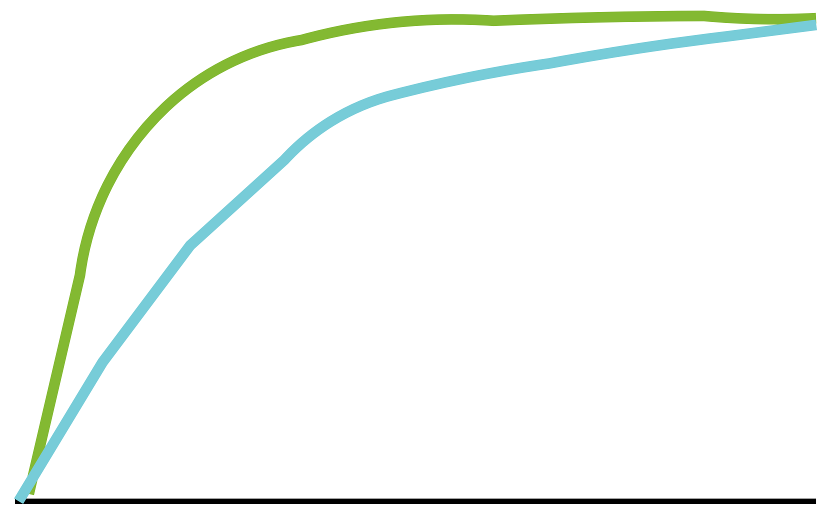

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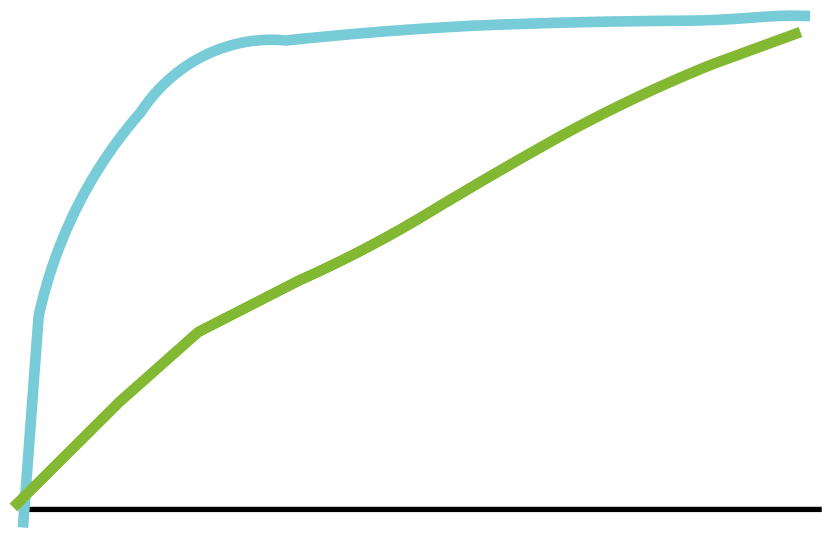

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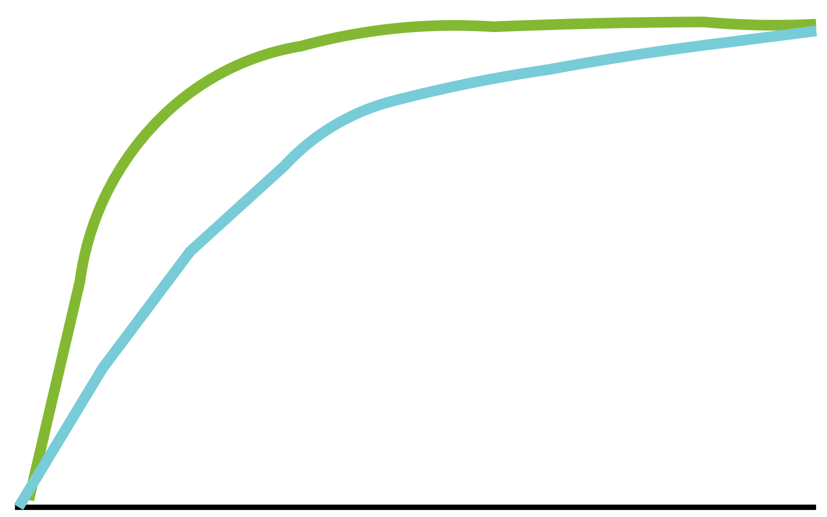

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$$p = \frac{2}{3}$$

$$p = \frac{1}{2}$$

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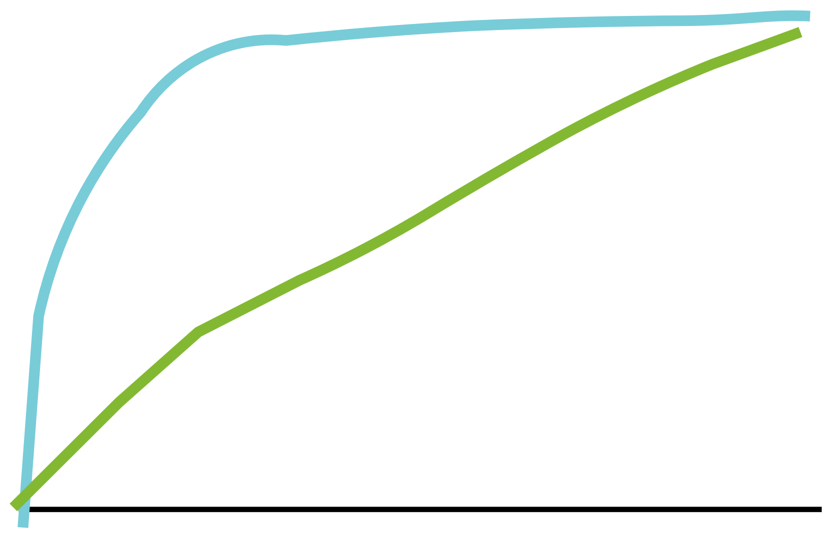

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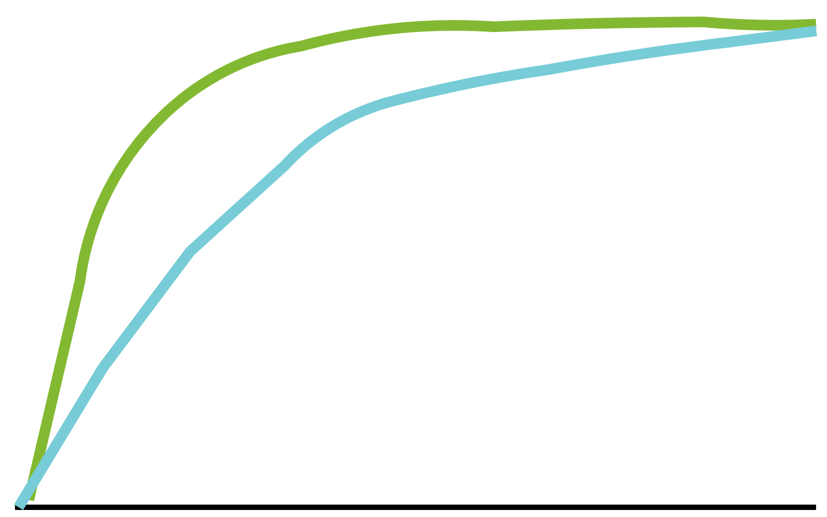

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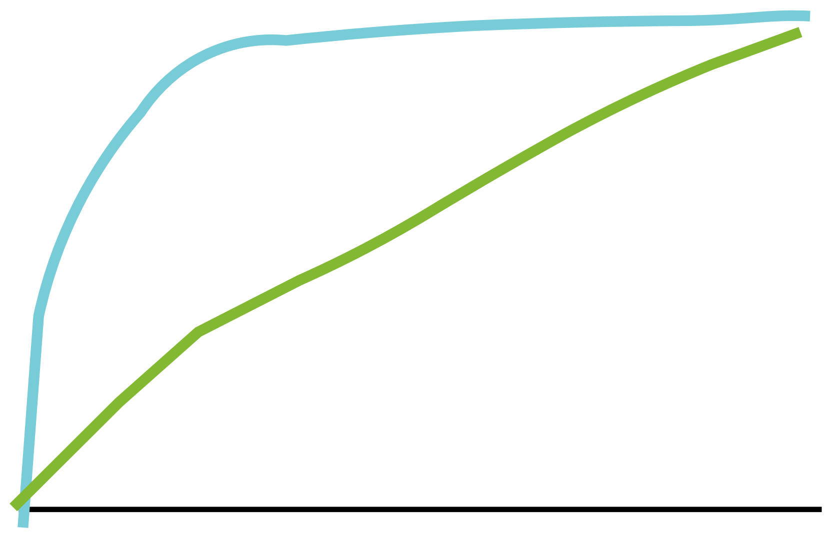

$p_{art,s} \sim F_{art,s}$

🧑🏿‍💻

	Value	Cost
$p_{\text{📘}} = \frac{2}{3}$	$v_{\text{📘}} = \frac{1}{10}$	$c_{\text{📘}} = \frac{1}{20}$
$p_{\text{📗}} = \frac{1}{2}$	$v_{\text{📗}} = \frac{1}{10}$	$c_{\text{📗}} = \frac{1}{10}$

👩🏾‍💻:📘, 👩🏼‍🎨:📗

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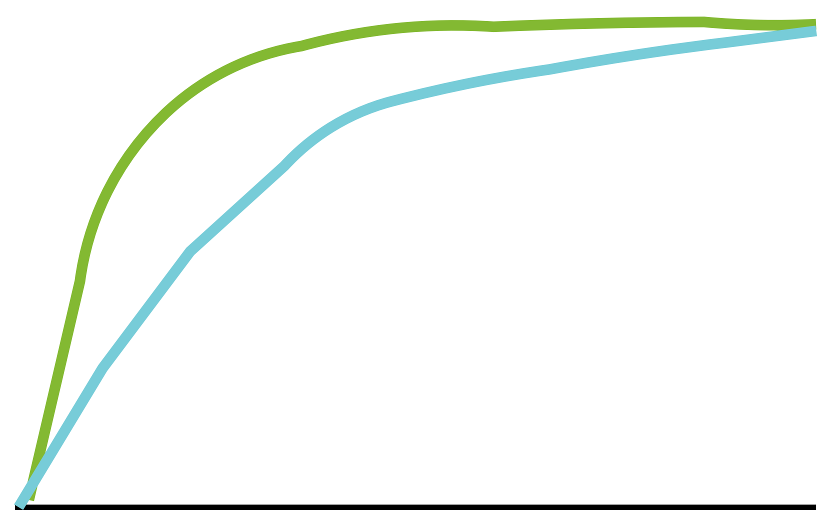

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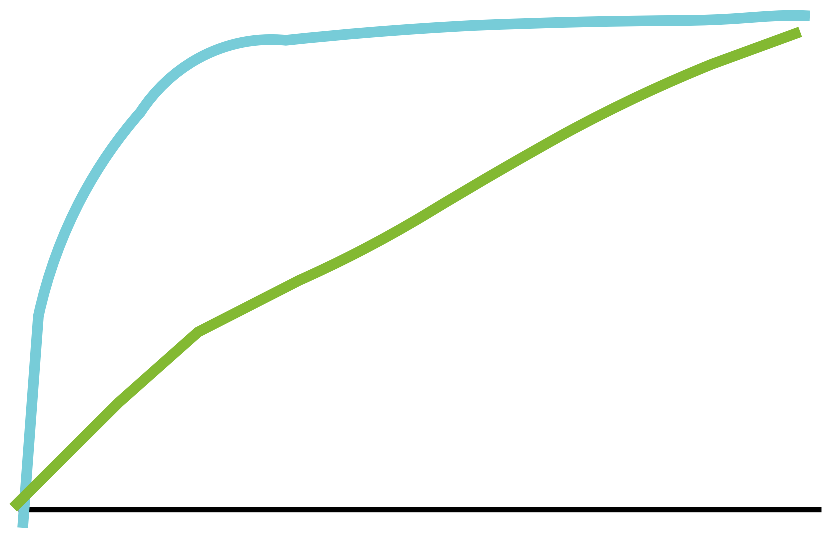

$p_{art,s} \sim F_{art,s}$

🧑🏿‍💻

	Value	Cost	Expected utility
$p_{\text{📘}} = \frac{2}{3}$	$v_{\text{📘}} = \frac{1}{10}$	$c_{\text{📘}} = \frac{1}{20}$	
$p_{\text{📗}} = \frac{1}{2}$	$v_{\text{📗}} = \frac{1}{10}$	$c_{\text{📗}} = \frac{1}{10}$	

👩🏾‍💻:📘, 🧑🏼‍🎨:📗

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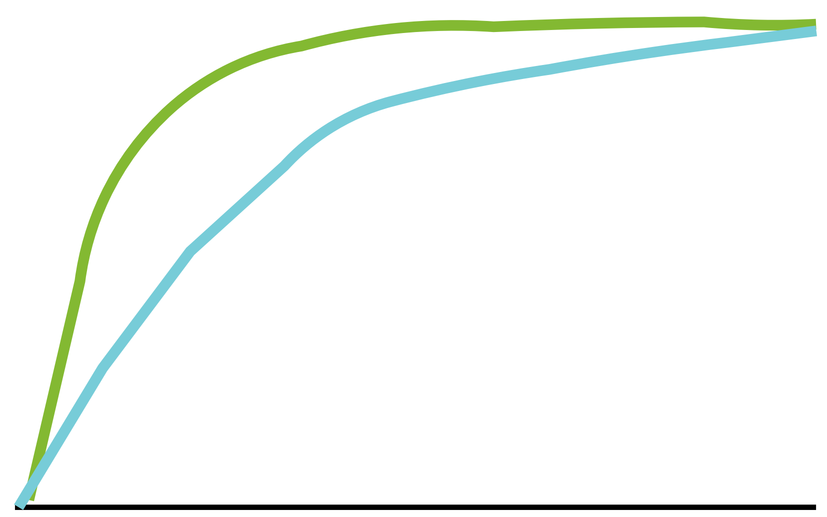

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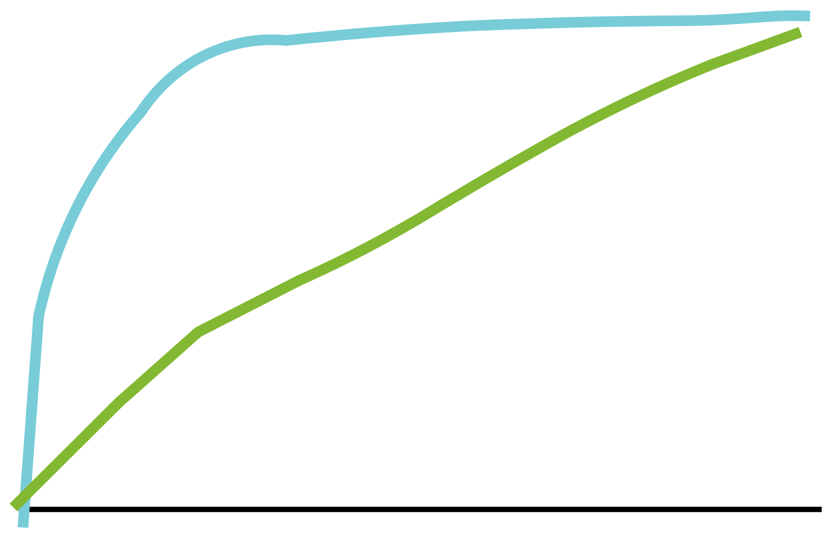

$p_{art,s} \sim F_{art,s}$

🧑🏿‍💻

	Value	Cost	Expected utility
$p_{📘} = \frac{2}{3}$	$v_{📘} = \frac{1}{10}$	$c_{📘} = \frac{1}{20}$	$\frac{1}{60}$
$p_{📗} = \frac{1}{2}$	$v_{📗} = \frac{1}{10}$	$c_{📗} = \frac{1}{10}$	$-\frac{1}{20}$

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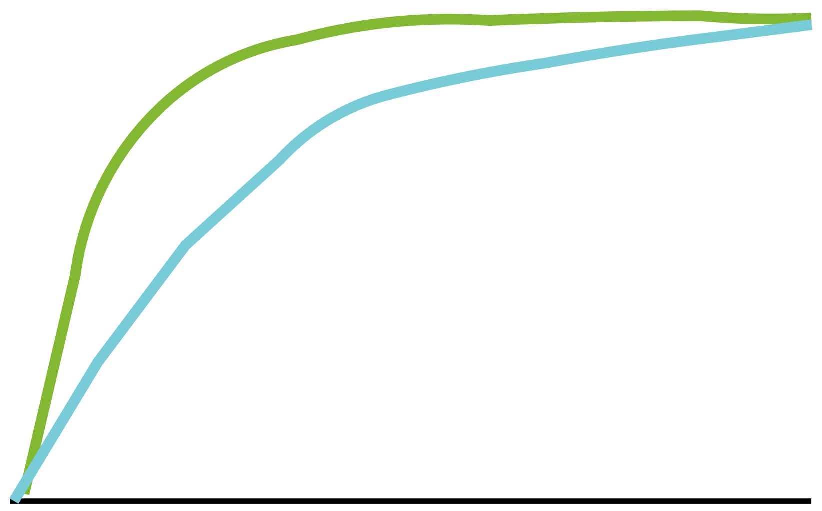

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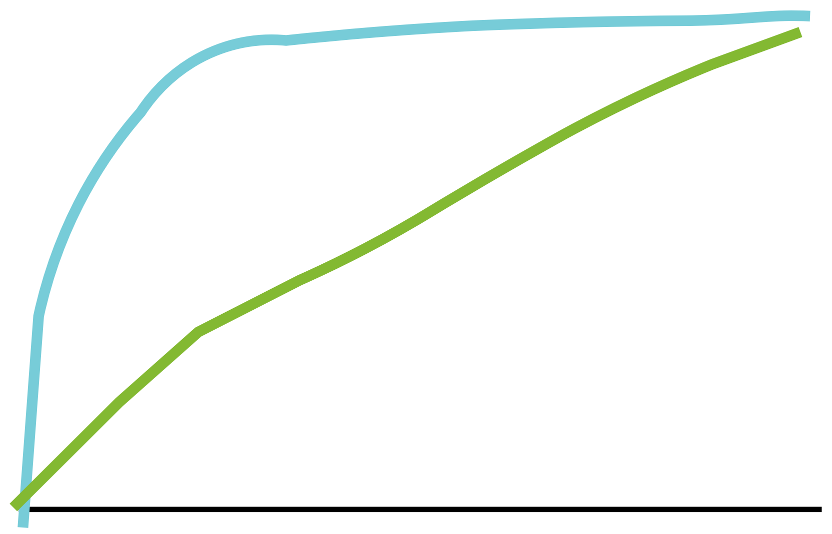

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🧑🏿‍💻

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$p_{📗} = \frac{1}{2}$	$v_{📗} = \frac{1}{10}$	$c_{📗} = \frac{1}{10}$	$-\frac{1}{20}$	

👩🏾‍💻:📘, 👩🏼‍🎨:📗

Player's decision process

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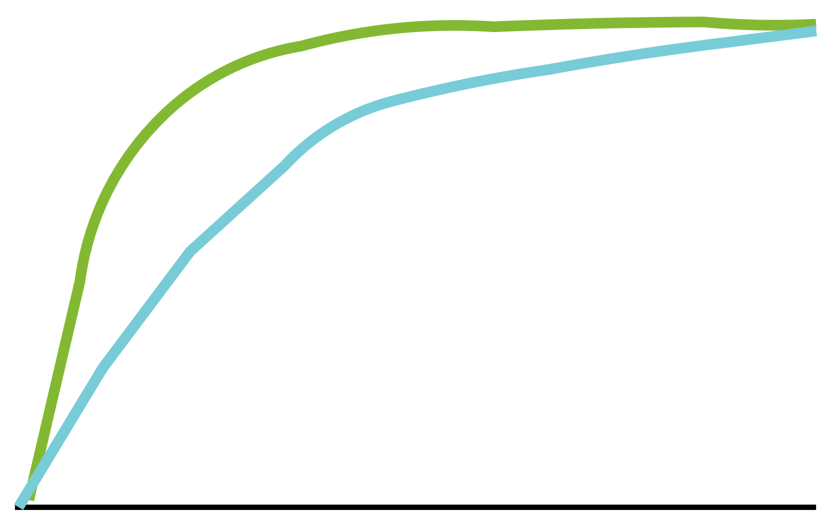

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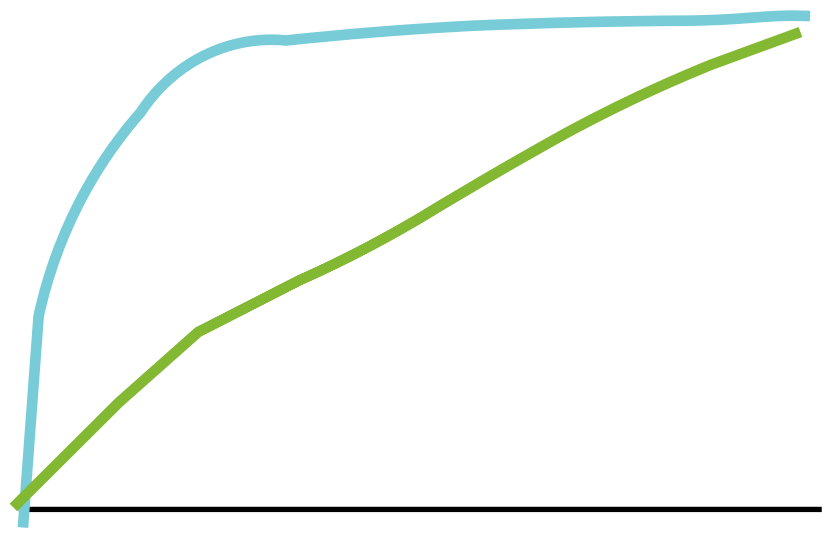

$p_{art,s} \sim F_{art,s}$

		Value	Cost	Expected utility	
🧑🏿‍💻	$p_{\text{📘}} = \frac{2}{3}$	$v_{\text{📘}} = \frac{1}{10}$	$c_{\text{📘}} = \frac{1}{20}$	$\frac{1}{60}$	✅
	$p_{\text{📗}} = \frac{1}{2}$	$v_{\text{📗}} = \frac{1}{10}$	$c_{\text{📗}} = \frac{1}{10}$	$-\frac{1}{20}$	❌

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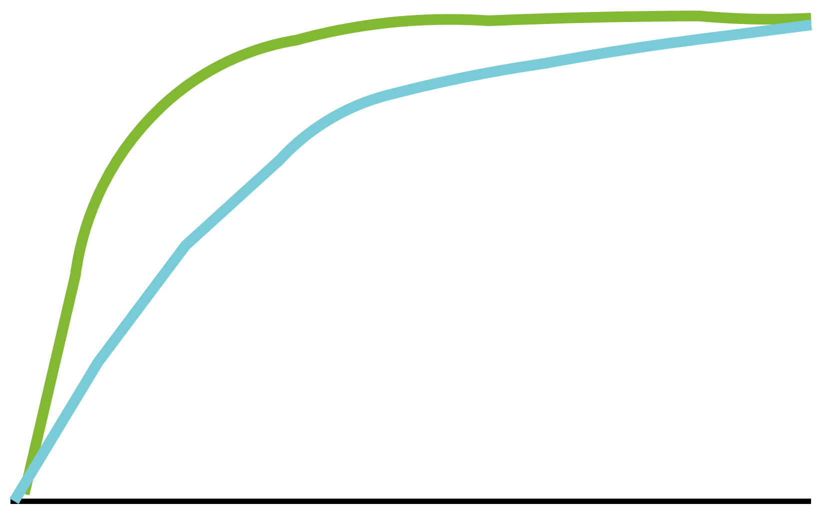

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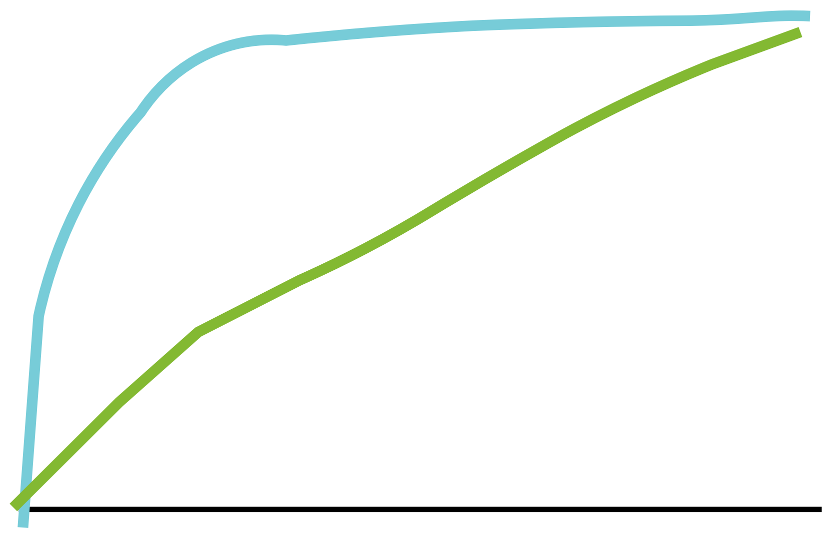

$p_{art,s} \sim F_{art,s}$

		Value	Cost	Expected utility	
🧑🏿‍💻	$p_{📘} = \frac{2}{3}$	$v_{📘} = \frac{1}{10}$	$c_{📘} = \frac{1}{20}$	$\frac{1}{60}$	✅
	$p_{📗} = \frac{1}{2}$	$v_{📗} = \frac{1}{10}$	$c_{📗} = \frac{1}{10}$	$-\frac{1}{20}$	❌
👩🏻‍💻	$p_{📘} = \frac{3}{4}$	$v_{📘} = \frac{1}{10}$	$c_{📘} = \frac{1}{20}$	$\frac{1}{40}$	✅
	$p_{📗} = \frac{1}{3}$	$v_{📗} = \frac{1}{10}$	$c_{📗} = \frac{1}{10}$	$-\frac{1}{15}$	❌
👨🏾‍🎨	$p_{📘} = \frac{2}{3}$	$v_{📘} = \frac{1}{10}$	$c_{📘} = \frac{1}{20}$	$\frac{1}{60}$	✅
	$p_{📗} = \frac{3}{4}$	$v_{📗} = \frac{1}{3}$	$c_{📗} = \frac{1}{40}$	$\frac{9}{40}$	✅
👨🏽‍🎨	$p_{📘} = \frac{1}{4}$	$v_{📘} = \frac{1}{10}$	$c_{📘} = \frac{1}{20}$	$-\frac{1}{40}$	❌
	$p_{📗} = \frac{5}{6}$	$v_{📗} = \frac{1}{3}$	$c_{📗} = \frac{1}{40}$	$\frac{91}{360}$	✅

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Maximize expected number of clicks at time t

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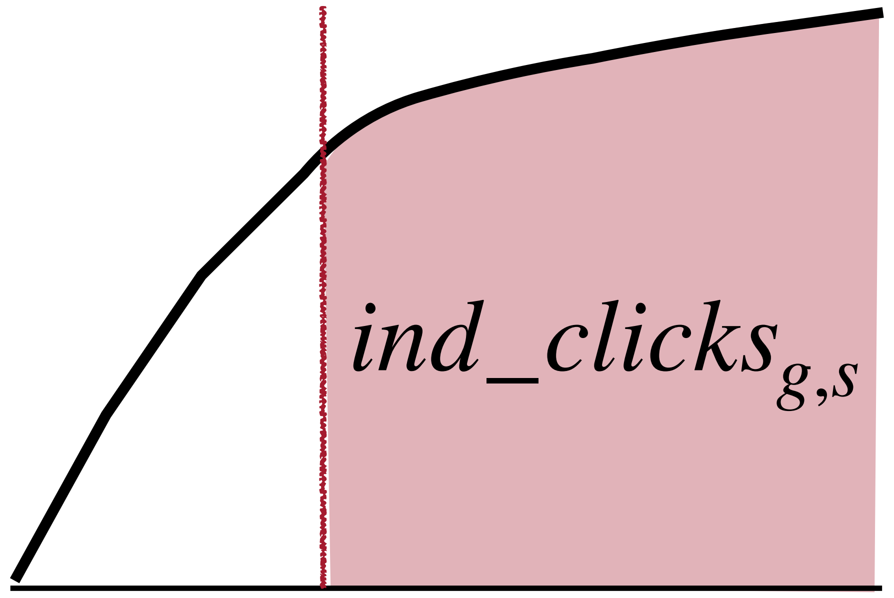

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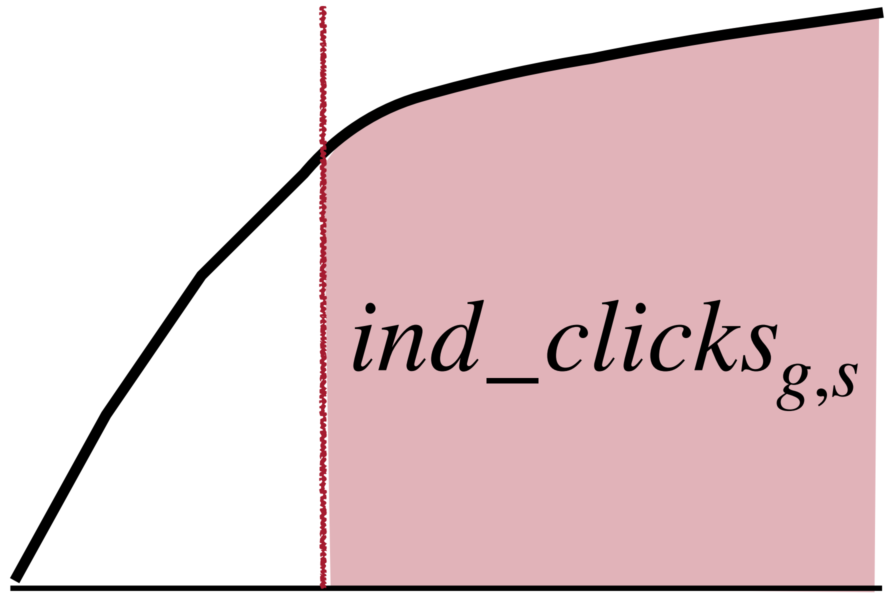

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Proposition (informal): The exclusion of any fairness constraints in the platform's optimization problem ➡️ group homogeneous targeting

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1. Introducing fairness constraints does not necessarily imply that the outcome is truly fair or balanced
2. Constraints forbid group homogeneous targeting for both groups, but there exist optimal solutions that target members of one group deterministically

“Lowering one group to the other” in practice

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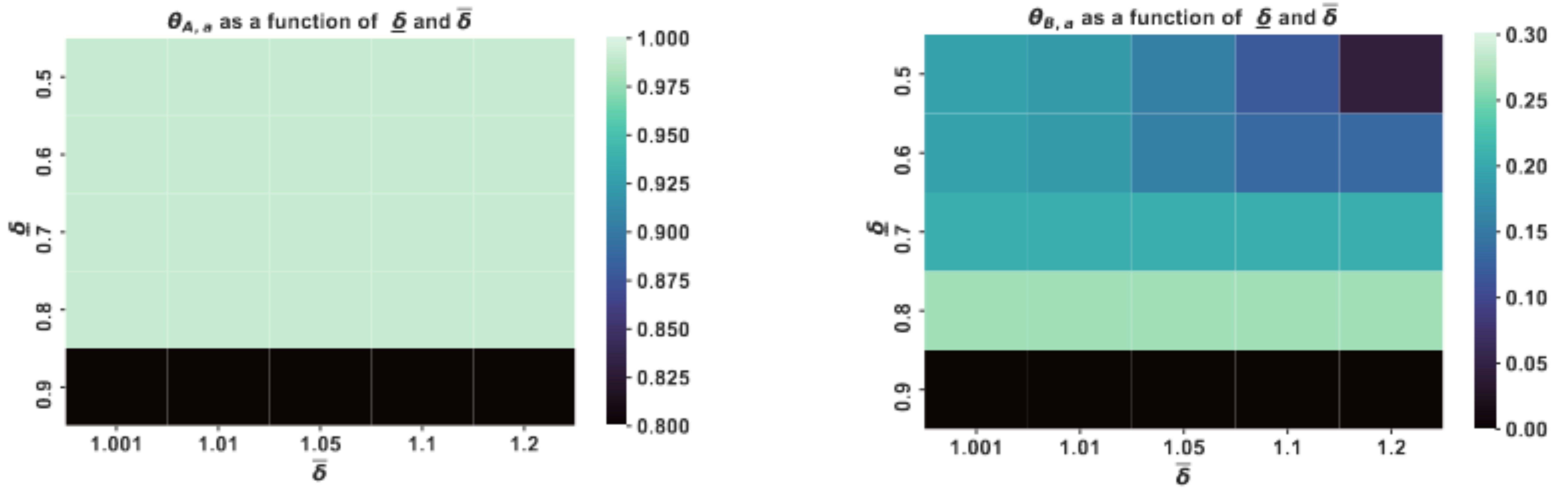

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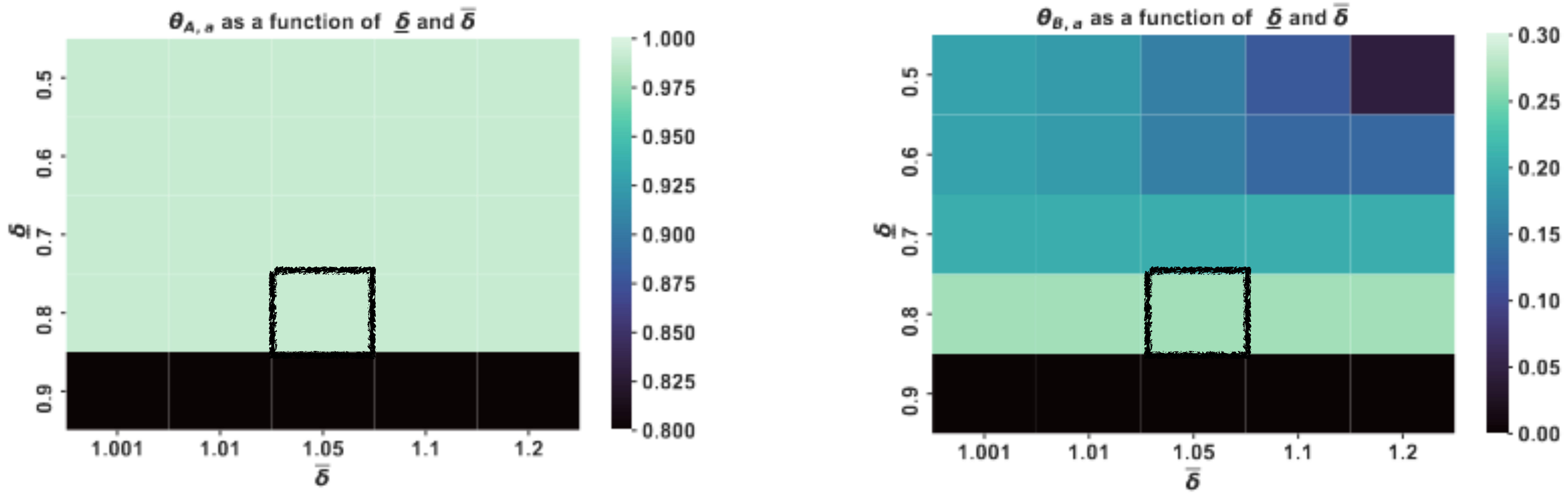

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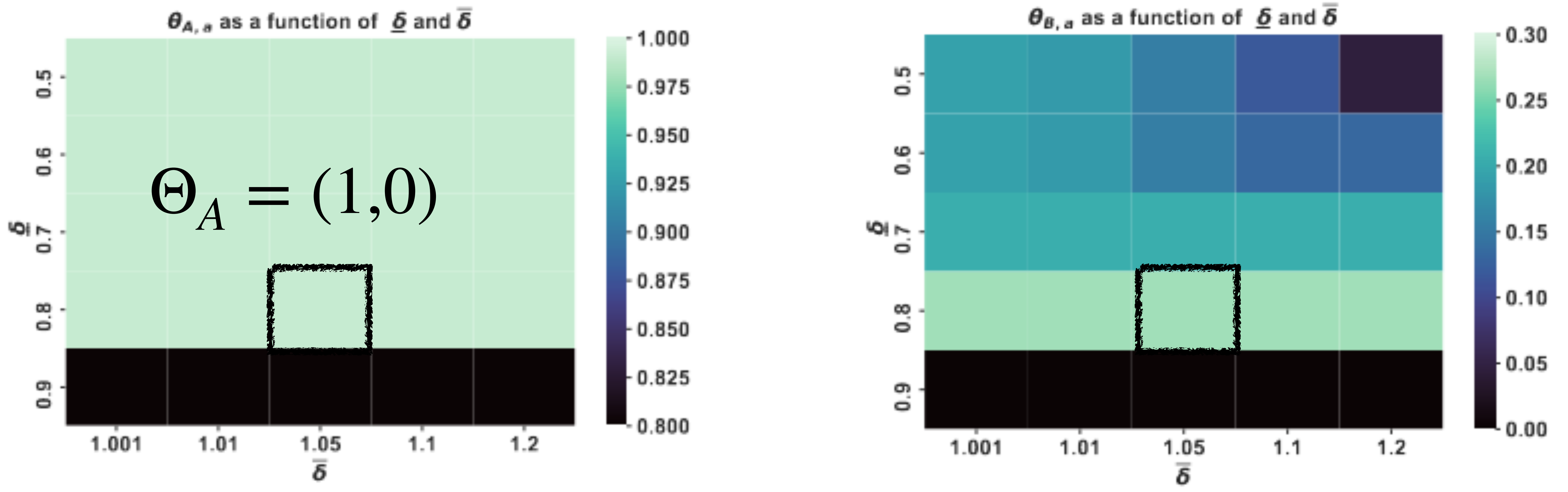

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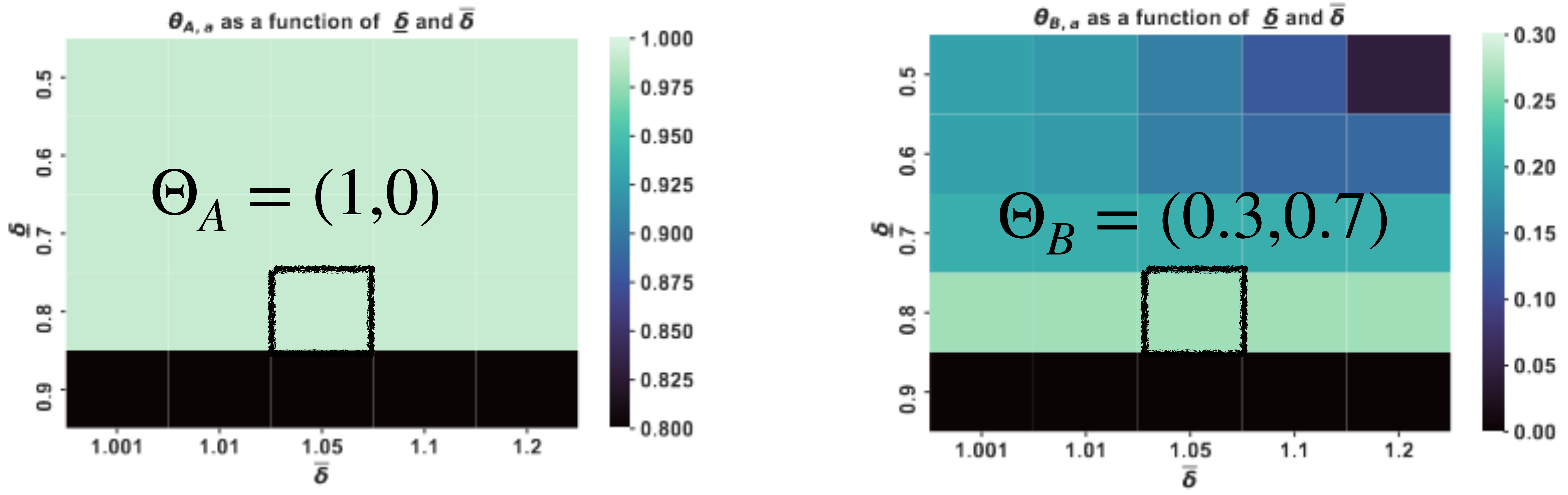

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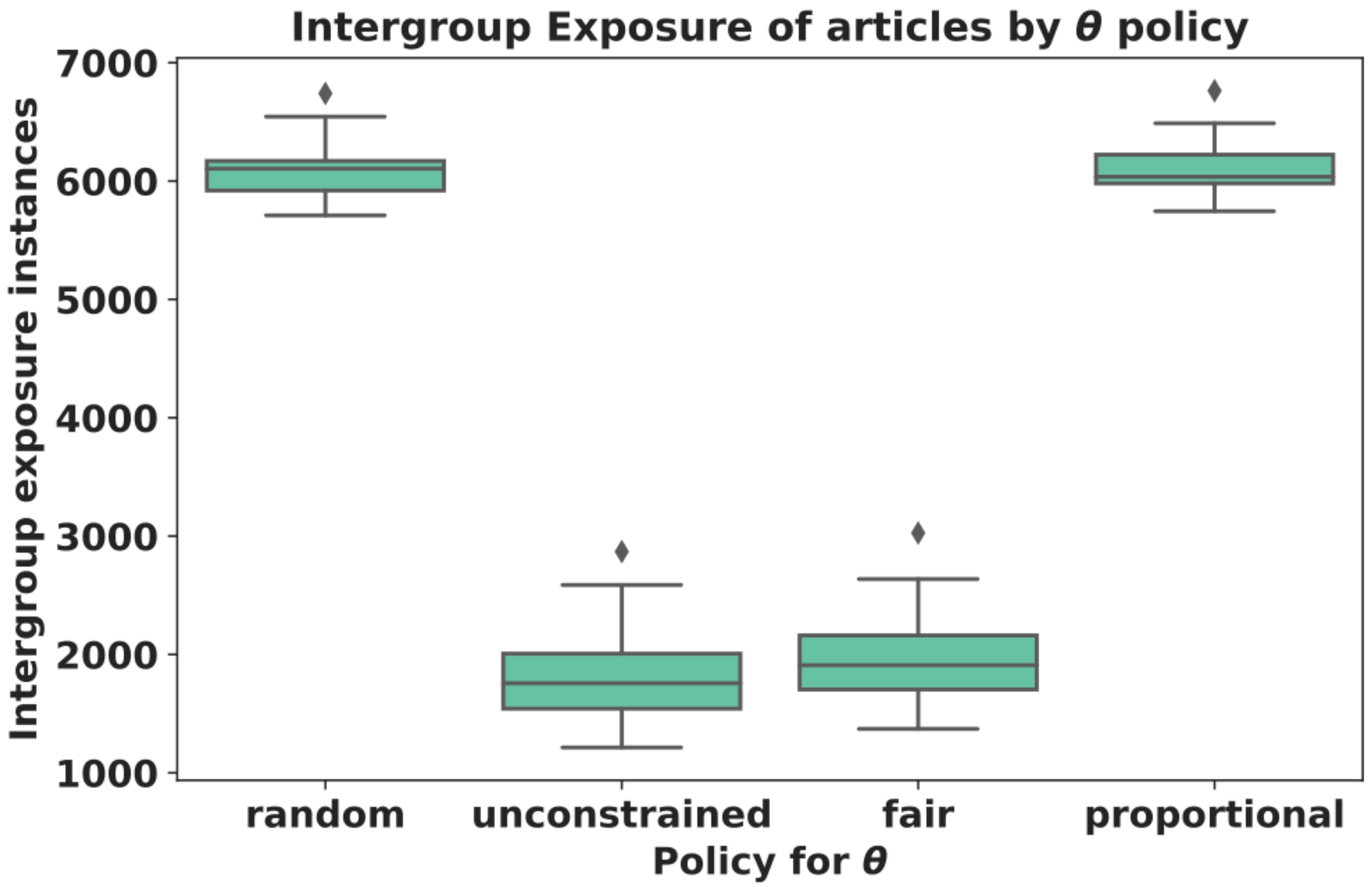

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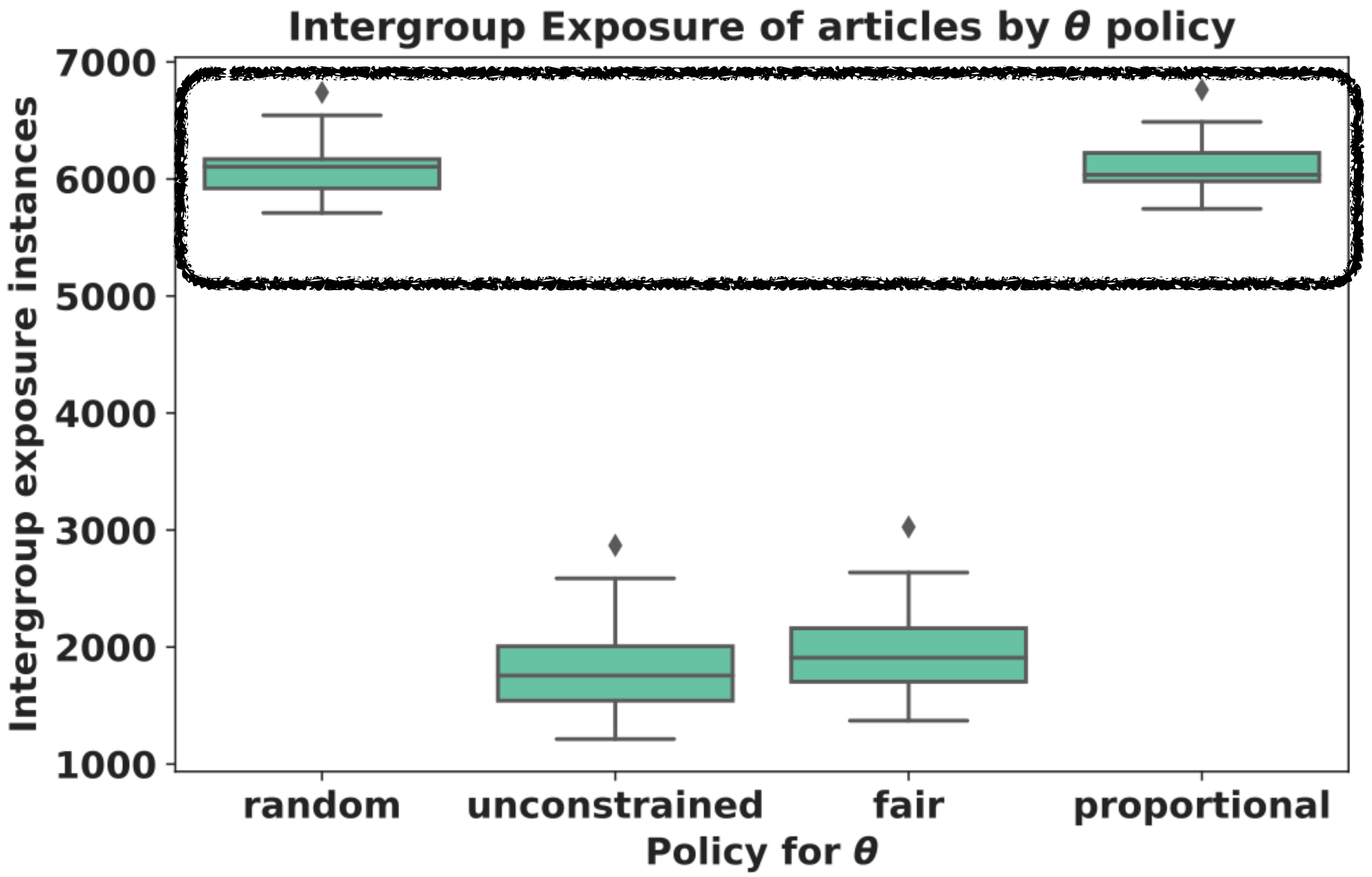

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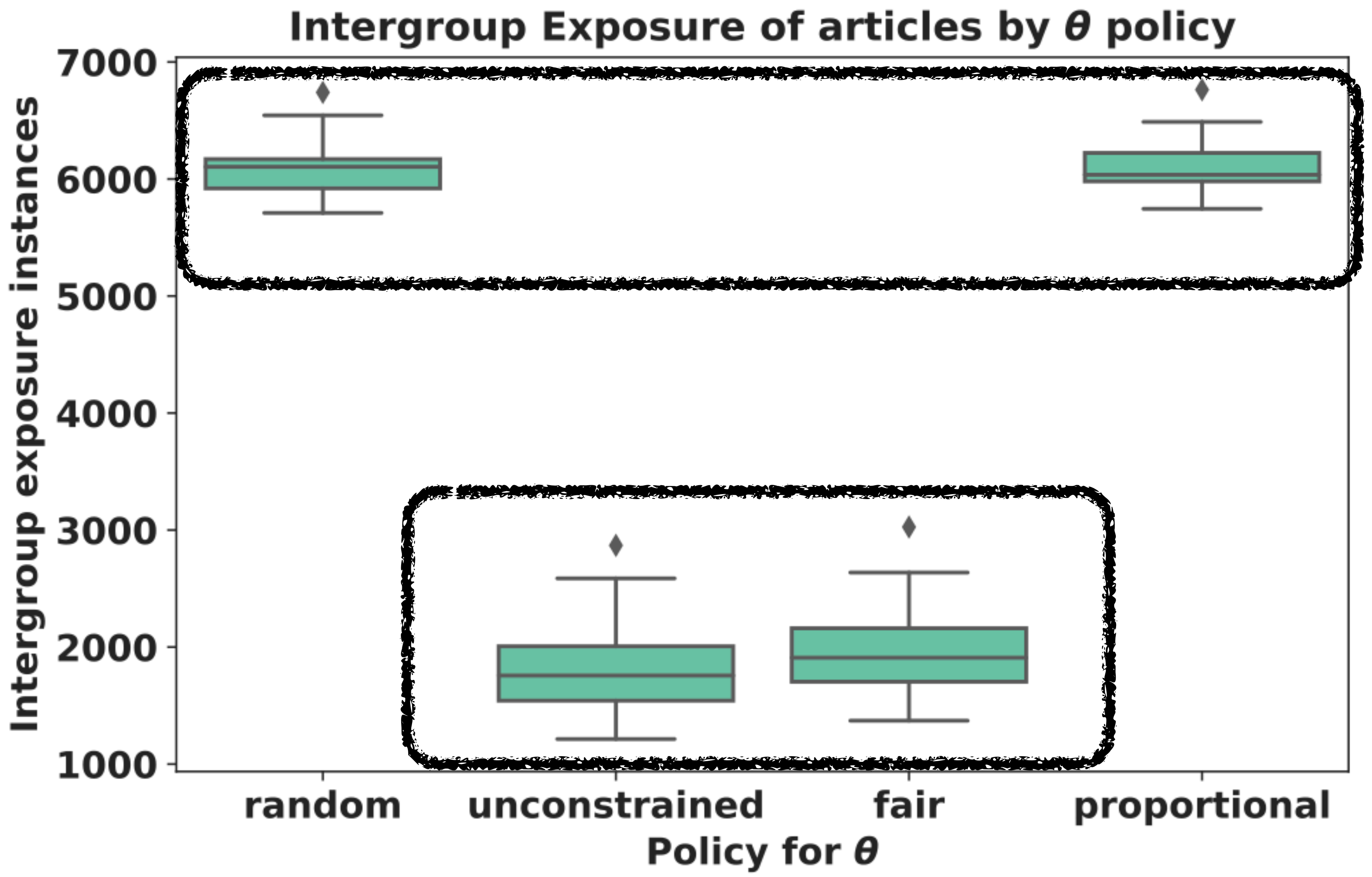

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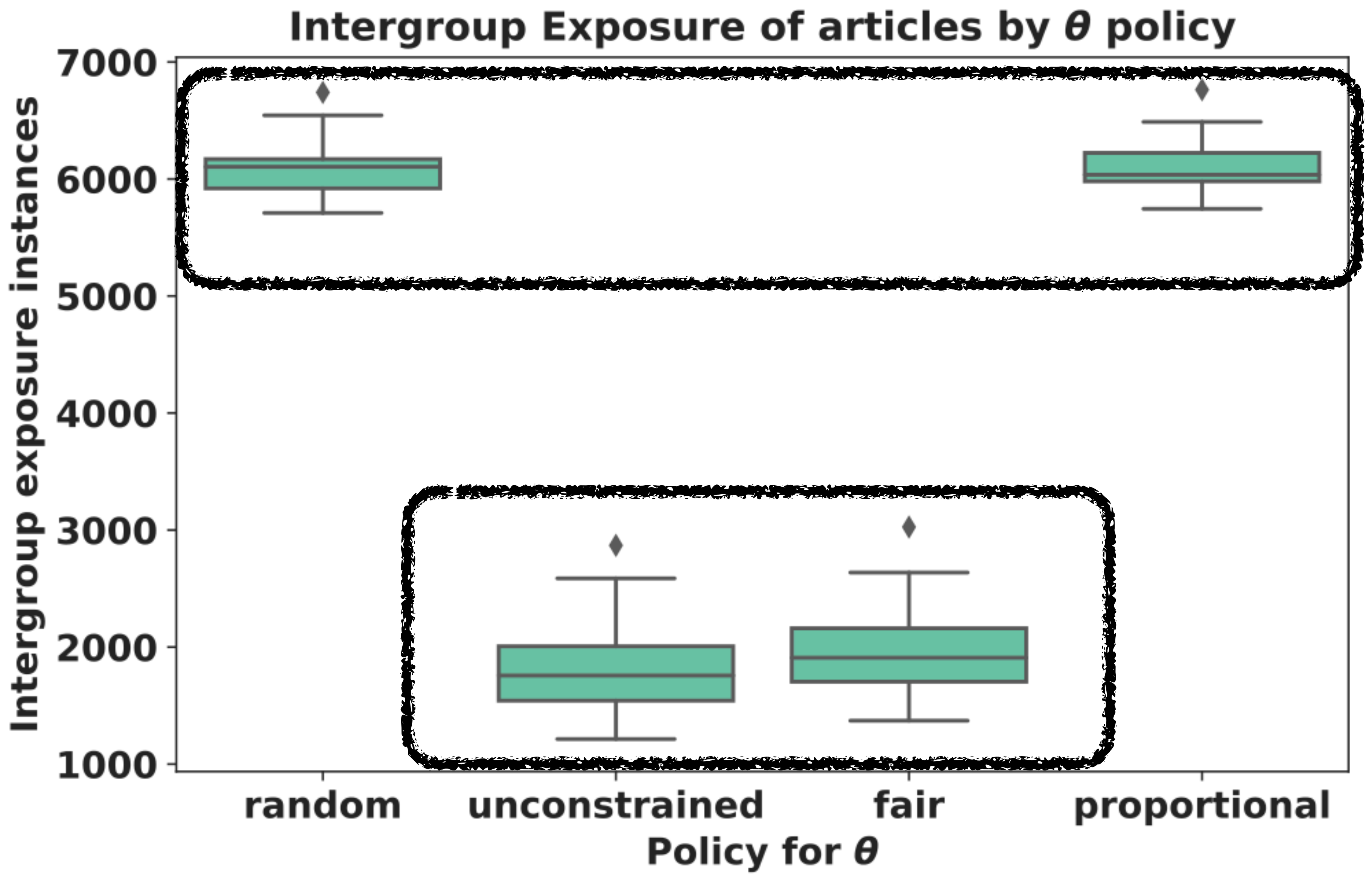

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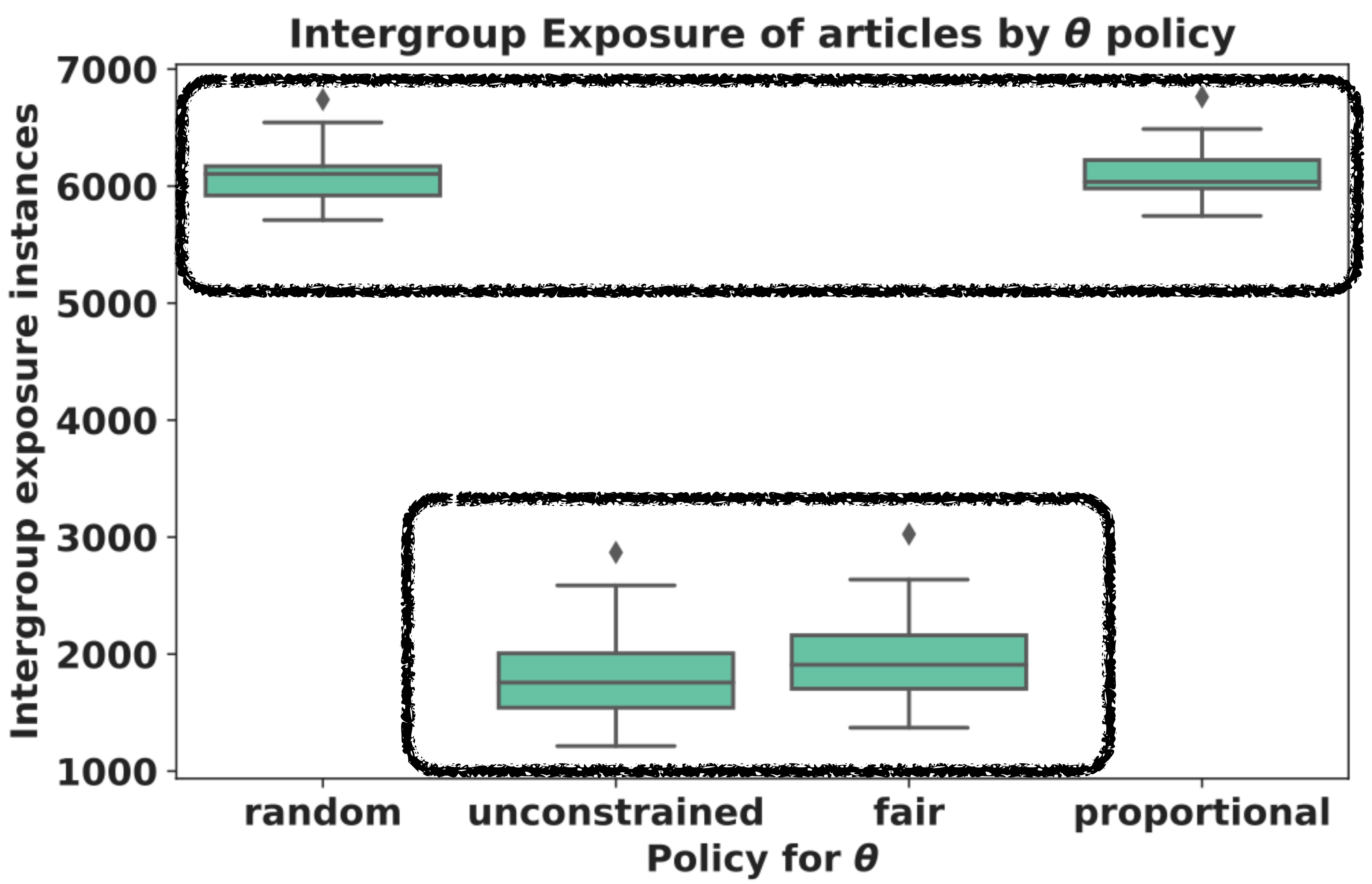

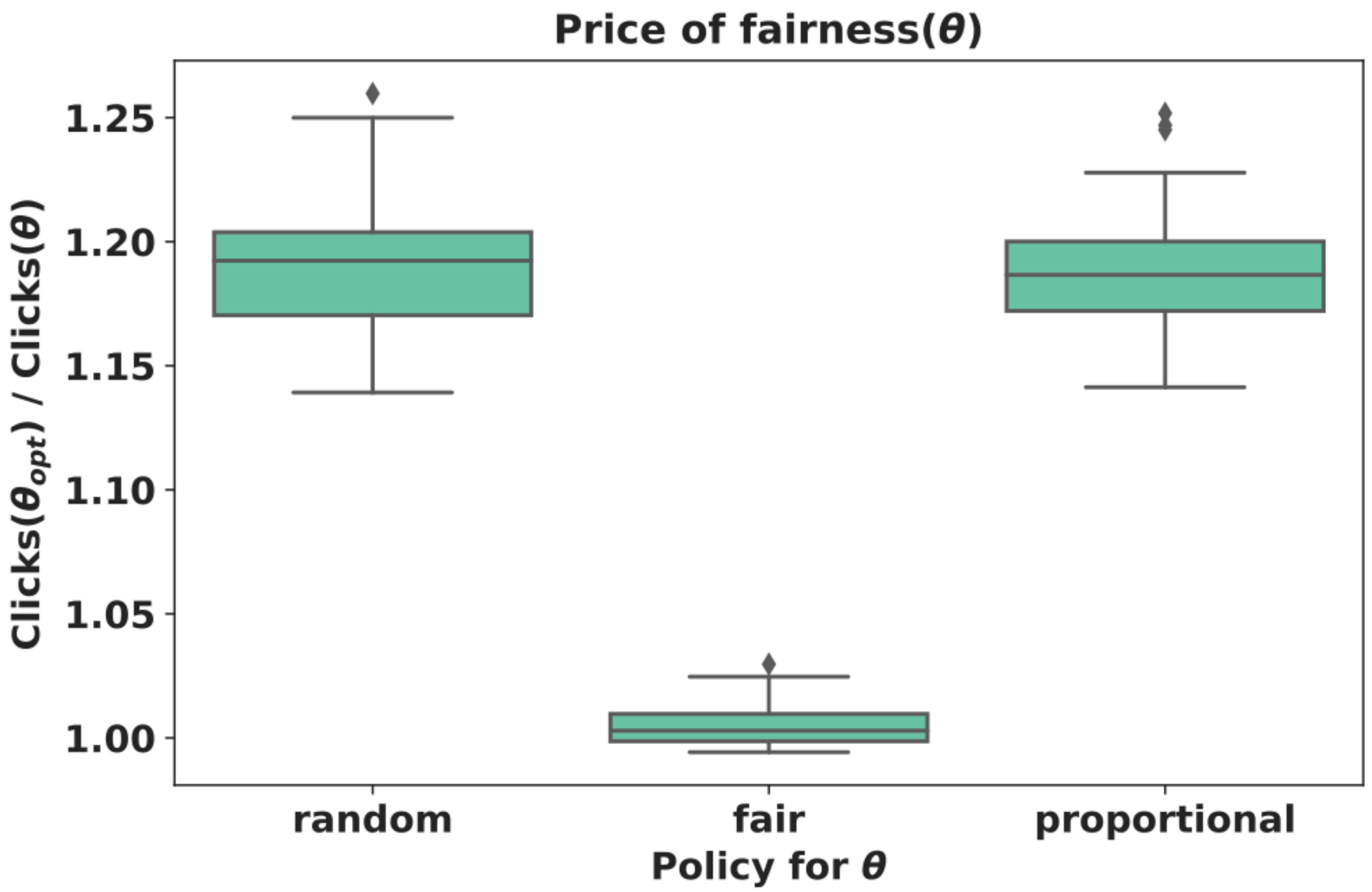

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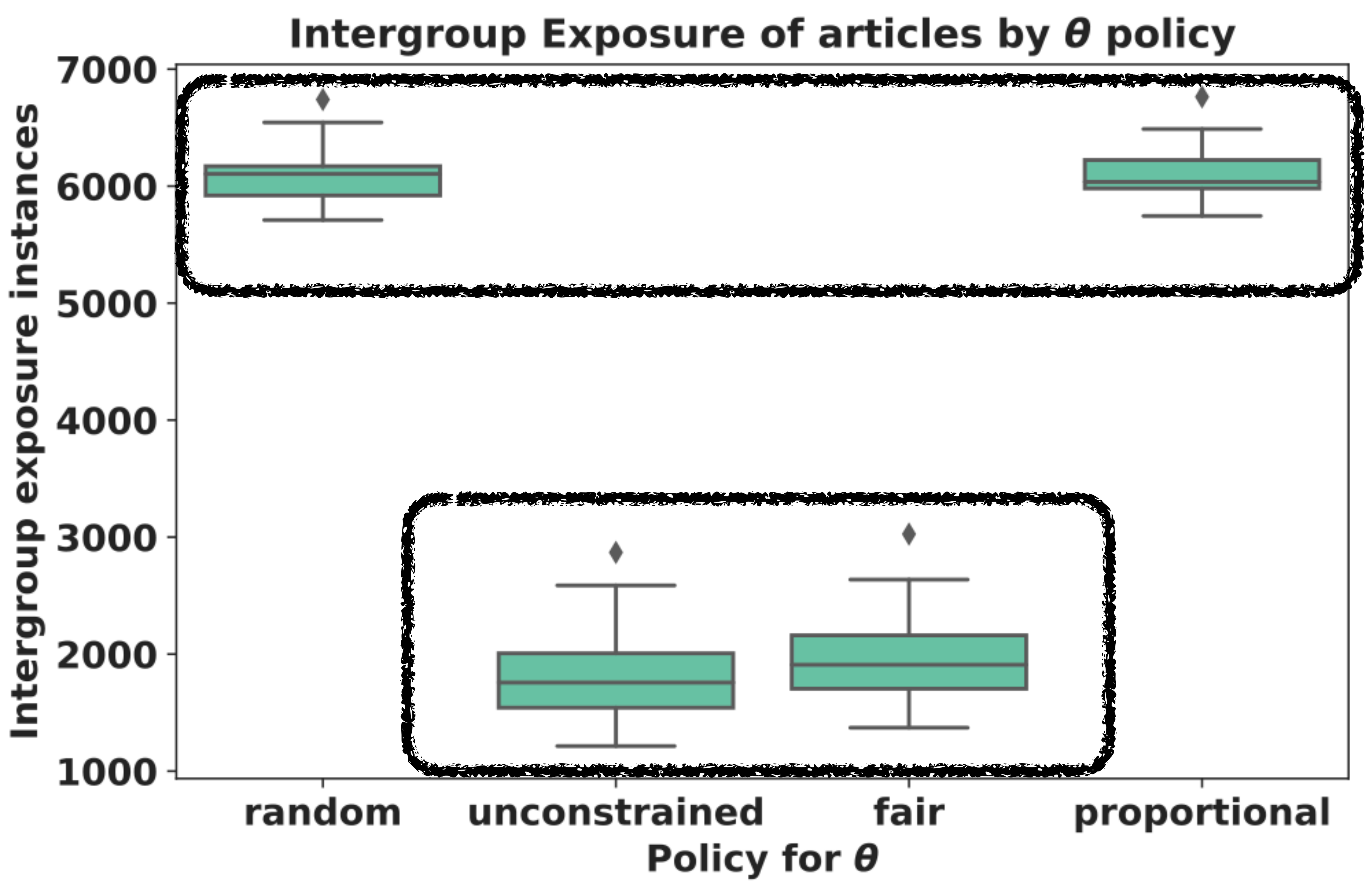

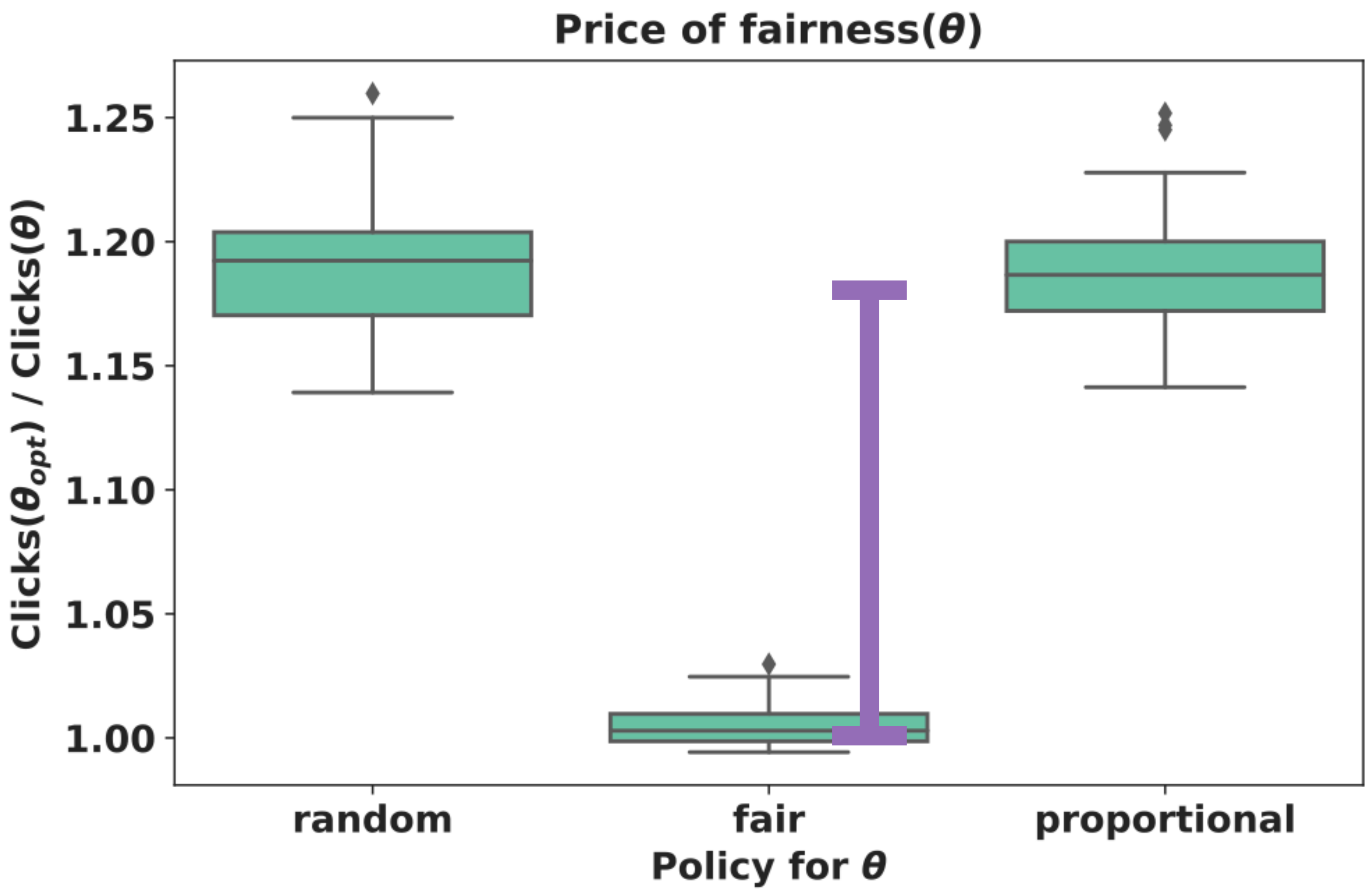

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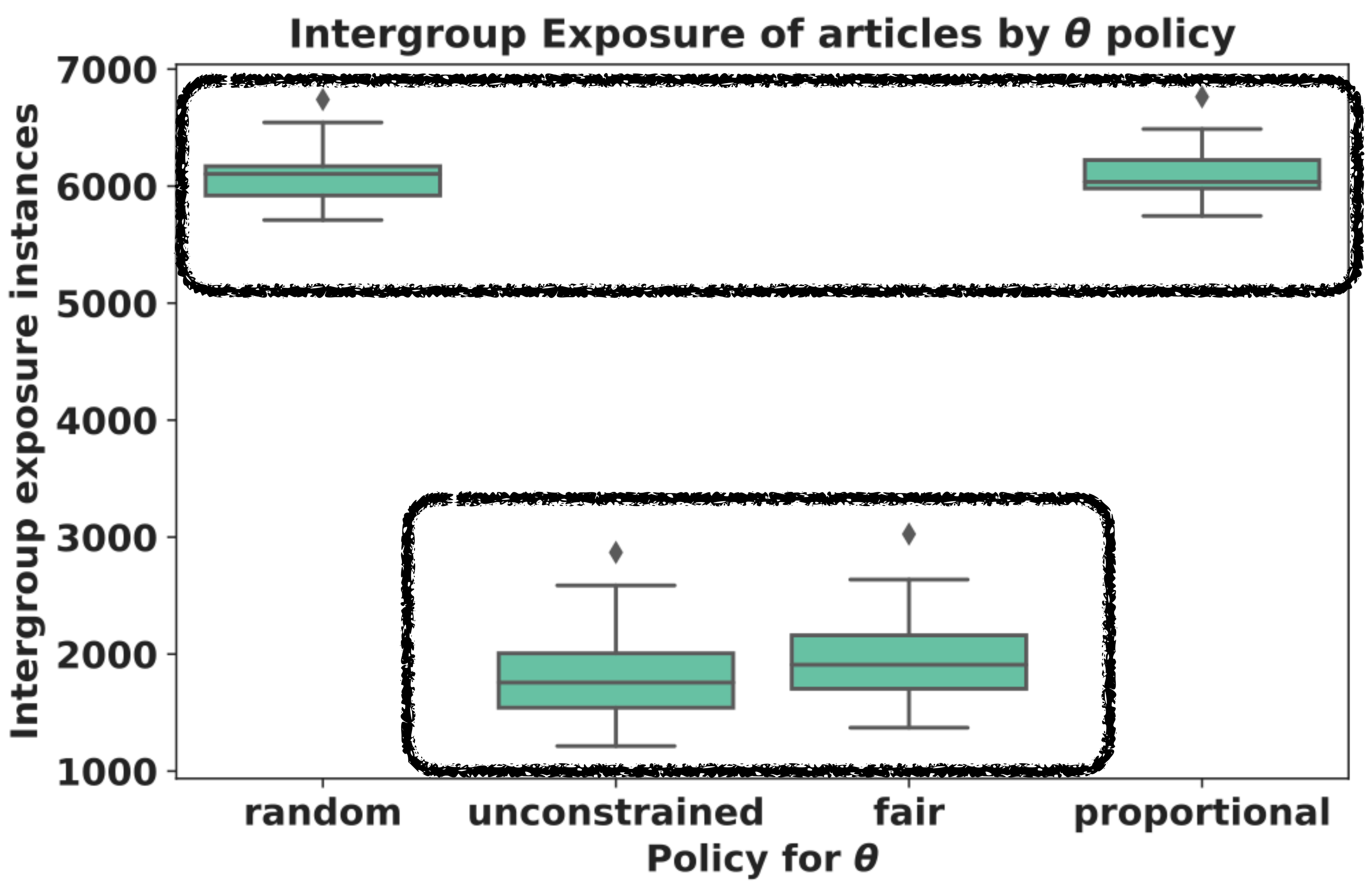

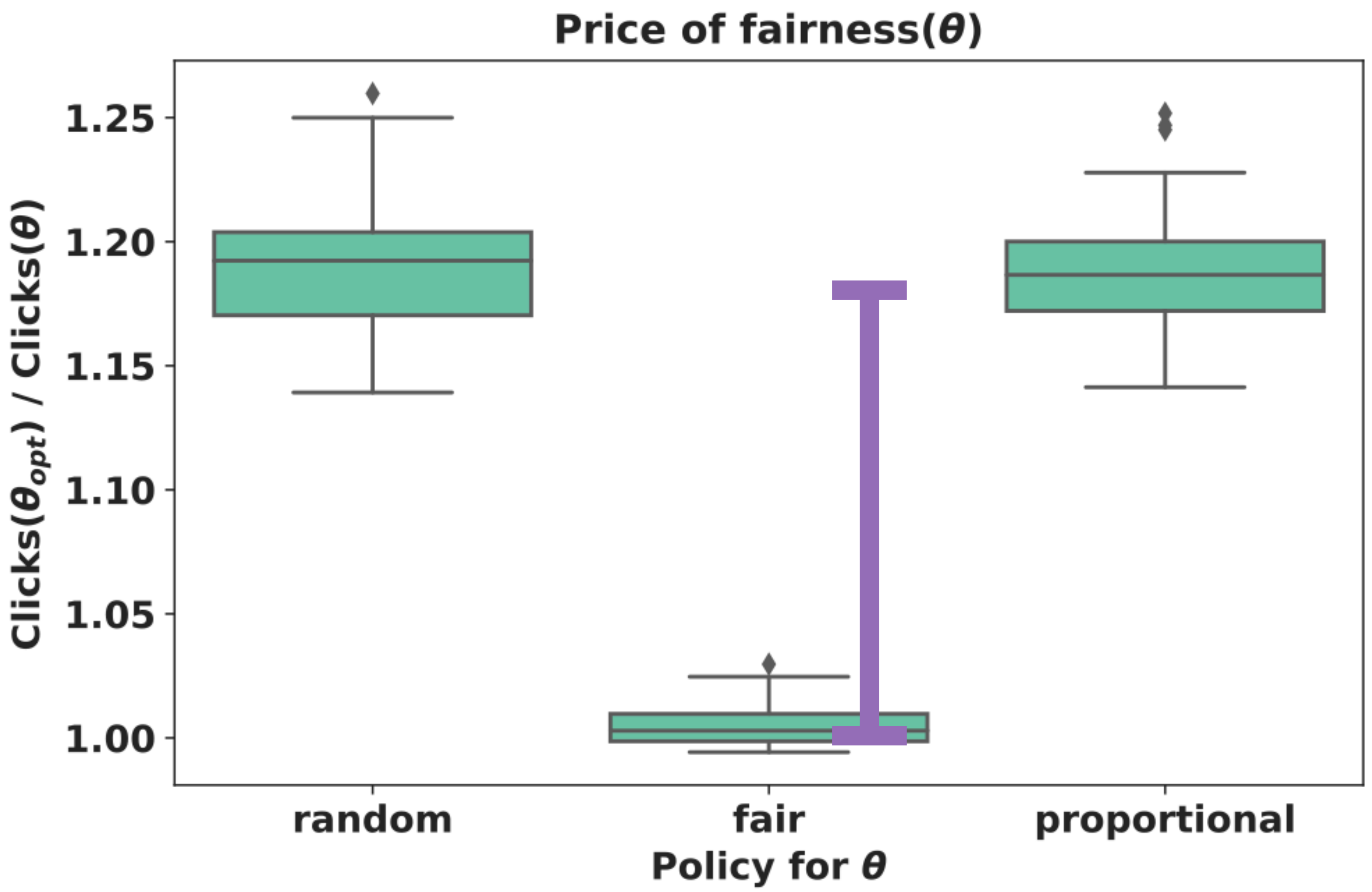

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1. Modest improvements to intergroup exposures with fairness constraints, but significantly reduced from “naive” baseline policies
2. High benefit in clicks to optimize policy, fair exposure constraints come at marginal cost

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Approaches to mitigating interactional polarization may be more effective.

Thank you!

arXiv

Questions? jessie@seas.harvard.edu





SIMONS INSTITUTE for the Theory of Computing

MD4SG Mechanism Design for Social Good

Omitted citations

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