

Impact of Ranking & Personalized Recommendations in Marketplaces



Omar Besbes

Yash Kanoria

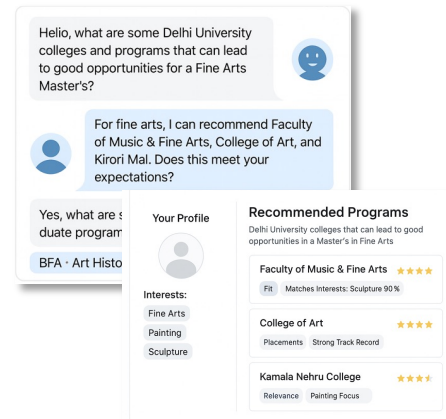
Akshit Kumar

Columbia Business School

Yale CADMY

A Tale of Two Info Provisioning Tools

Personalized Recos



A Tale of Two Info Provisioning Tools

Public Rankings

Top 10 Non IIMs NIRF RANKING 2024			
College	Rank	Fees	Avg. CTC
1. IIT Delhi	4	9.6 L	24.45 LPA
2. XLRI	9	27.4 L	
3. IIT Bombay	10	14.08 L	
4. MDI Gurgaon	11	24.99 L	
5. SBM, Pune	13	28 L	
6. IIT Delhi	15	21.77 L	
7. IIT Madras	16	12.87 L	
8. IIT Roorkee	18	9.68 L	
9. IIT Kharagpur	19	11.0 L	
10. SPJIMR	20	23.50 L	

NIRF India Ranking 2020	
Overall Category	Colleges Category
• IIT Madras	• Miranda House DU
• IISc Bangalore	• SRM for Women DU
• IIT Delhi	• Hindu College DU
University Category	Medical Discipline
• IISc Bangalore	• AIIMS, New Delhi
• JNU New Delhi	• PGIMER Chandigarh
• BMS Varanasi	• Christian Medical College, Bangalore
Engineering Category	Law Discipline
• IIT Madras	• National Law School of India University, Bangalore
• IIT Delhi	• NLU New Delhi
• IIT Bombay	• Noida University of Law, Hyderabad
Management Category	Architecture Discipline
• IIM Ahmedabad	• IIT Kharagpur
• IIM Bangalore	• IIT Roorkee
• IIM Calcutta	• NIT Calicut
Pharmacy Discipline	Dental College
• Jamia Hamdard University	• Madrasa Azad Institute of Dental Science
• Datta University	• Manipal College of Dental Science
• Institute of Medical Education Research Mohali	• Dr DY Patil Vidyapeeth Pune

Personalized Recos

Helio, what are some Delhi University colleges and programs that can lead to good opportunities for a Fine Arts Master's?

For fine arts, I can recommend Faculty of Music & Fine Arts, College of Art, and Kirori Mal. Does this meet your expectations?

Yes, what are the graduate programs

BFA - Art History

Your Profile



Interests:
Fine Arts
Painting
Sculpture

Recommended Programs

Delhi University colleges that can lead to good opportunities in a Master's in Fine Arts

Faculty of Music & Fine Arts ★★★★★

Fit Matches Interests: Sculpture 90%

College of Art ★★★★★

Placements Strong Track Record

Kamala Nehru College ★★★★★

Relevance Painting Focus

A Tale of Two Info Provisioning Tools

What is the added value of personalization?

Public Rankings

Personalized Recos



The image shows two NIRF ranking documents. The top one is 'Top 10 Non IIMs NIRF RANKING 2024' and the bottom one is 'NIRF India Ranking 2020'. Both documents list various colleges and their rankings, fees, and average CTCs. The NIRF logo is prominently displayed at the bottom of the 2020 ranking document.

College	Rank	Fees	Avg. CTC
IT, Delhi	4	9.6 L	24.45 LPA
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A user interface for personalized recommendations. It starts with a query: 'Hello, what are some Delhi University colleges and programs that can lead to good opportunities for a Fine Arts Master's?'. The system responds: 'For fine arts, I can recommend Faculty of Music & Fine Arts, College of Art, and Kirori Mal. Does this meet your expectations?'. Below, a 'Your Profile' section shows interests in Fine Arts, Painting, and Sculpture. A 'Recommended Programs' section lists 'Faculty of Music & Fine Arts' and 'College of Art' with high relevance scores.



A screenshot of the Netflix homepage showing personalized recommendations. It features sections like 'Because you watched Stranger Things', 'Because you watched The Crown', and 'Because you watched American Crime Story'. The interface displays movie and TV show thumbnails with their titles and genres.

A Tale of Two Info Provisioning Tools

What is the added value of personalization?

Public Rankings

Personalized Recos

Limited Supply



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Overall Category	Colleges Category
IFT Madras, IISc Bangalore, IIT Delhi	Miranda House DU, SRM for Women DU, Hindu College DU
University Discipline	Medical Discipline
IISc Bangalore, JNU New Delhi, IIM Bangalore	AIIMS, New Delhi, PGIMER Chandigarh, Christian Medical College, Bangalore
Engineering Category	Law Discipline
IFT Madras, IIT Delhi, IIT Bombay	National Law School of India University, Bangalore, NLU New Delhi, Noida University of Law, Hyderabad
Management Category	Architecture Discipline
IIM Ahmedabad, IIM Bangalore, IIM Calcutta	IFT Khargpur, IIT Roorkee, IIT Bombay
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Jaipur National University, Datta University, Institute of Medical Education Research Mohali	Maulana Azad Institute of Dental Sciences, Manipal College of Dental Science, Dr DY Patil Vidyapeeth Pune

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Yes, what are some other programs?

BFA - Art History

Your Profile



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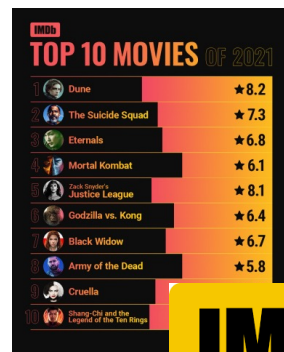
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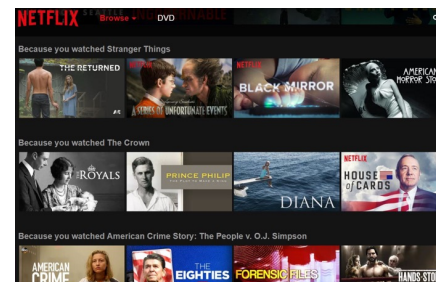
Relevance Painting Focus

Unlimited Supply



Dune	★8.2
The Suicide Squad	★7.3
Eternals	★6.8
Mortal Kombat	★6.1
Jack Ryan's Justice League	★8.1
Godzilla vs. Kong	★6.4
Black Widow	★6.7
Army of the Dead	★5.8
Cruella	
Shang-Chi and the Legend of the Ten Rings	

IMDb



NETFLIX

A Tale of Two Info Provisioning Tools

What is the added value of personalization?

Public Rankings

Personalized Recos

What is the role of capacity constraints?

Limited Supply

Unlimited Supply

Top 10 Non IIMs
NIRF RANKING 2024

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NIRF India Ranking 2020

Category	College	Rank
College Category	Miranda House DU	1
	St. Xavier's College Palayamkottai	2
	Hindu College DU	3
University Category	SRMIST, New Delhi	1
	POMER Chandigarh	2
	Christian Medical College, Bangalore	3
Engineering Category	IIIT Hyderabad	1
	IIIT Delhi	2
	IFT Bhopal	3
Management Category	IIIT Delhi	1
	IIIT Hyderabad	2
	IFT Bhopal	3
Law Category	National Law School of India University, Bangalore	1
	NU New Delhi	2
	Tatler University of Law, Hyderabad	3
Architecture Category	IT Khargpur	1
	IT Bhopal	2
	IT Bhopal	3
Dental Category	Madhwa Road Institute of Dental Sciences	1
	Mangal College of Dental Sciences	2
	Dr DY Patil Vidyapeeth Pune	3

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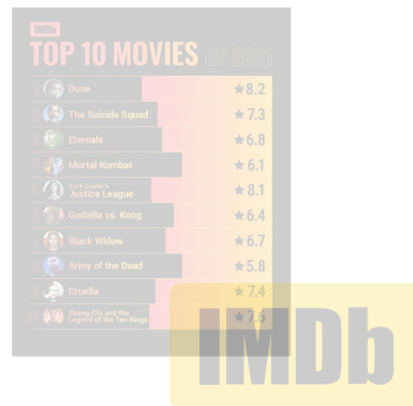
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Kamala Nehru College



NETFLIX

Because you watched Stranger Things

THE RETURNED

BLACK MIRROR

AMERICAN CRIME STORY

Because you watched The Crown

ROYALS

HOUSE OF CARDS

DIANA

Because you watched American Crime Story: The People v. O.J. Simpson

AMERICAN CRIME

THE EIGHTIES

FORENSIC THOUGHTS

HANDS STONE

NETFLIX

Research Problem

How much value do different information provisioning tools – public rankings & personalized recommendations - provide **with** & **without** supply side constraints?

In a Nutshell

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- Study the impact of two information provisioning tools
 - Public Rankings: Provide an overall assessment of the options
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- Study the impact of two information provisioning tools
 - Public Rankings: Provide an overall assessment of the options
 - Personalized Recommendations: Help discover agent-item specific adjustments
- Analyze a stylized model to isolate the impact of these tools

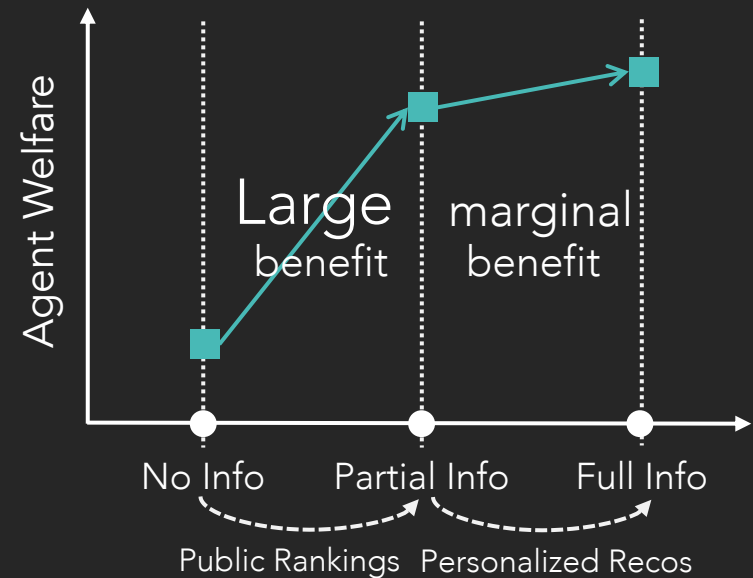
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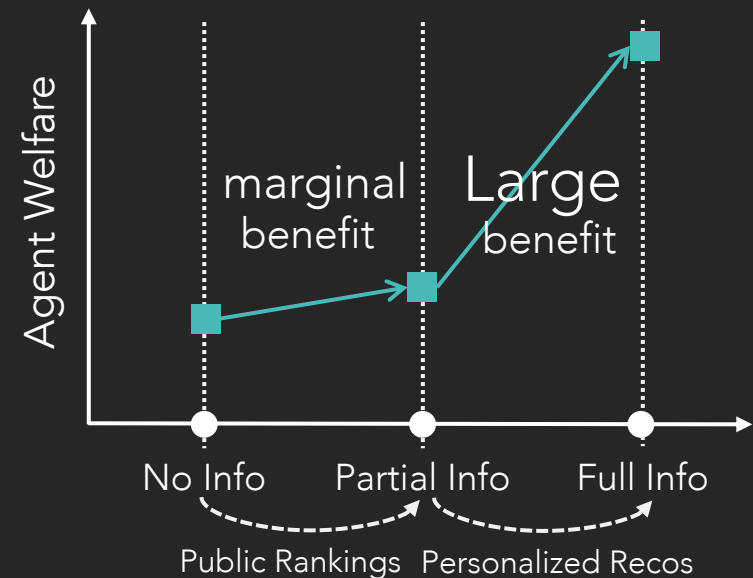
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Without Supply Constraints



Low level of heterogeneity

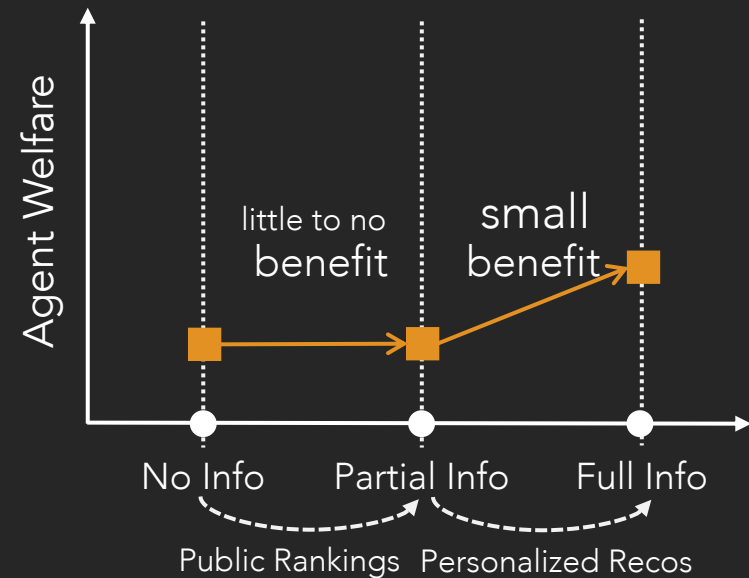


High level of heterogeneity

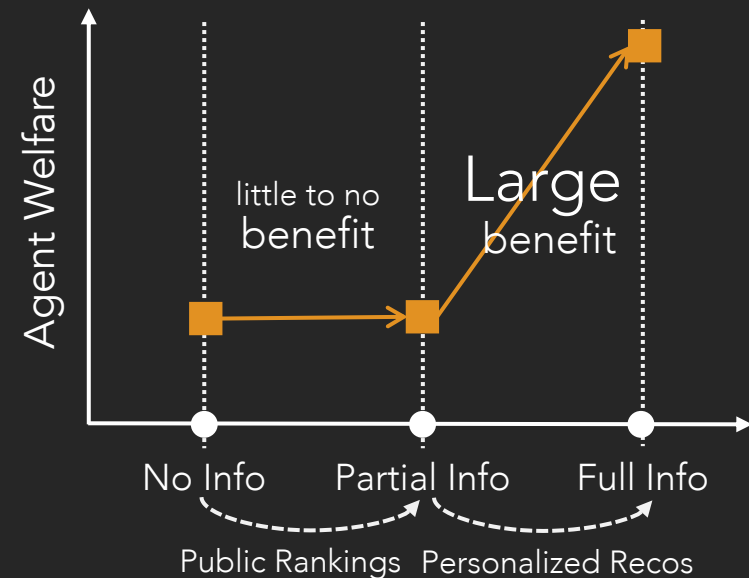
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With Supply Constraints



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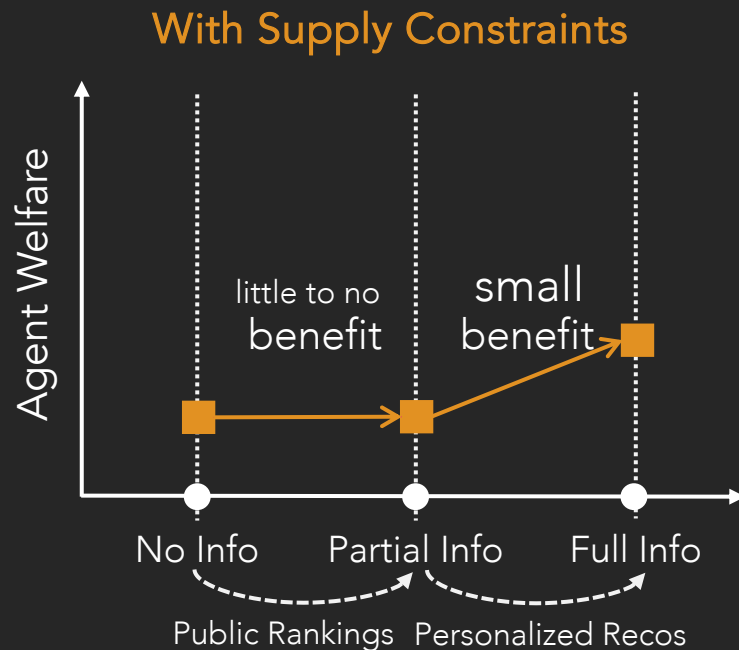
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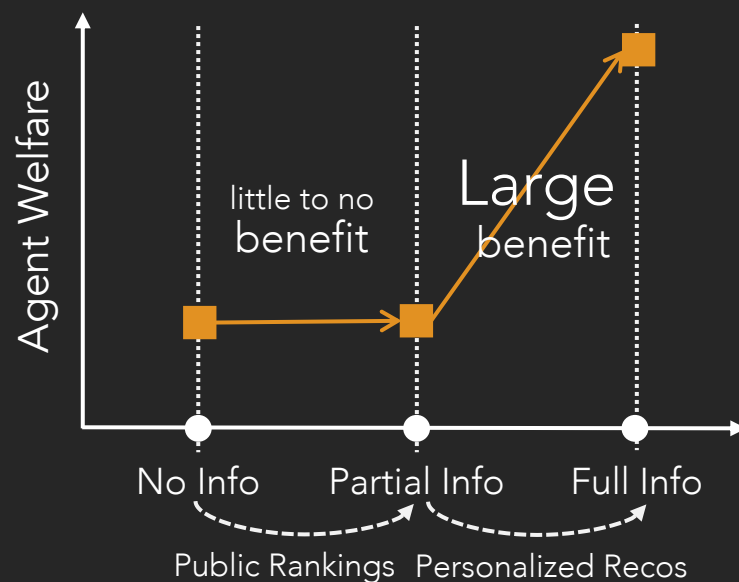
Leveling the Playing Field for High School Choice: Results from a Field Experiment of Informational Interventions

Sean P. Corcoran, Jennifer L. Jennings, Sarah R. Cohodes & Carolyn Sattin-Bajaj

“.... Our findings also suggest that informational interventions *may not* reduce inequality, since *both* disadvantaged and comparatively advantaged students used our materials”



Low level of heterogeneity



High level of heterogeneity

Model

Model

- n agents and n items



agents

items

Model

- n agents and n items
- Agent Utility
 - $U(a, i) = (1 - \rho) \cdot q(i) + \rho \cdot \varphi(a, i)$



agents

items

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 - $U(a, i) = (1 - \rho) \cdot q(i) + \rho \cdot \varphi(a, i)$
 - $q(i)$: Common term depends only on the item



$q(1)$



$q(2)$



$q(3)$



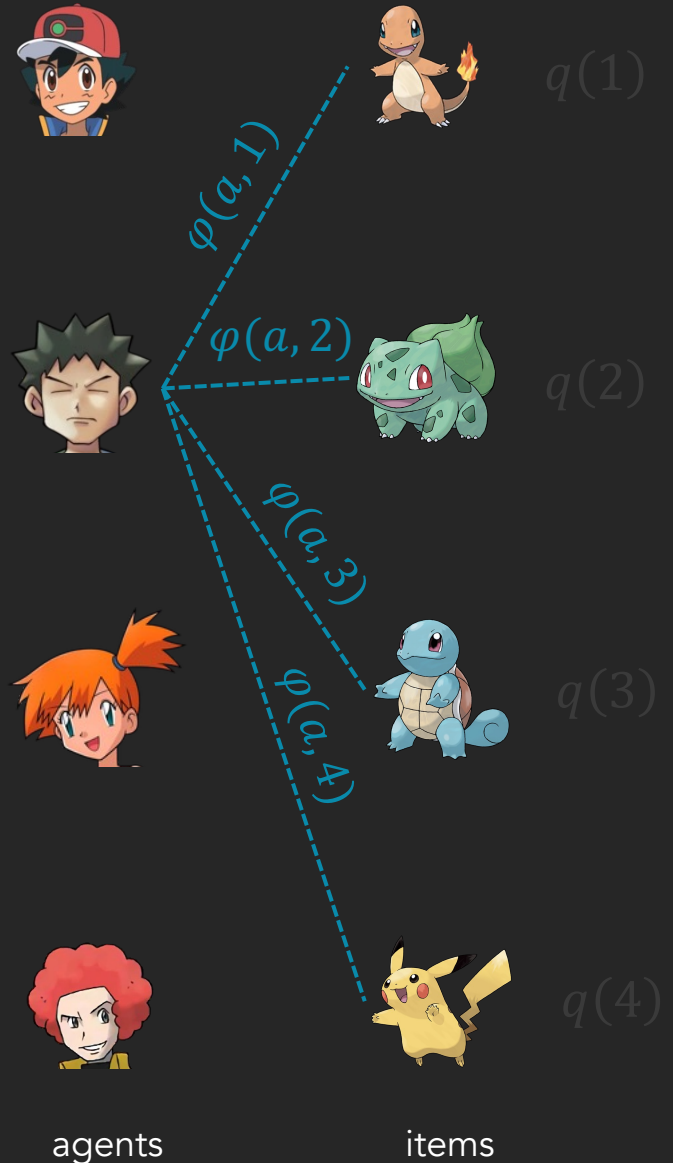
$q(4)$

agents

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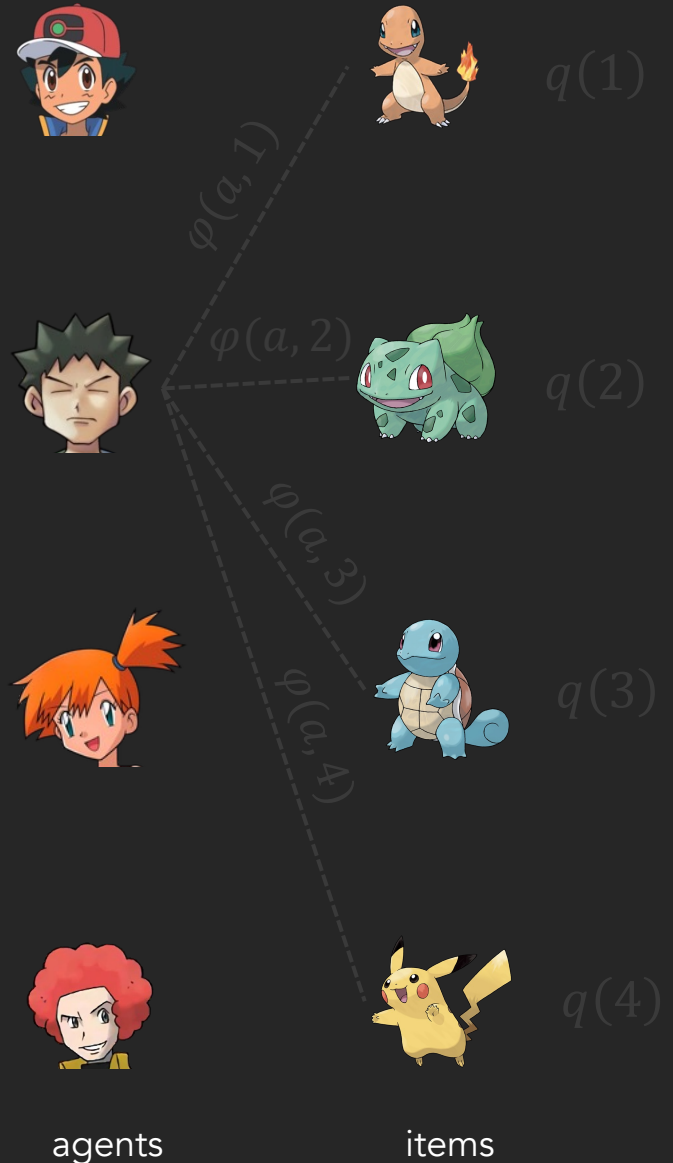
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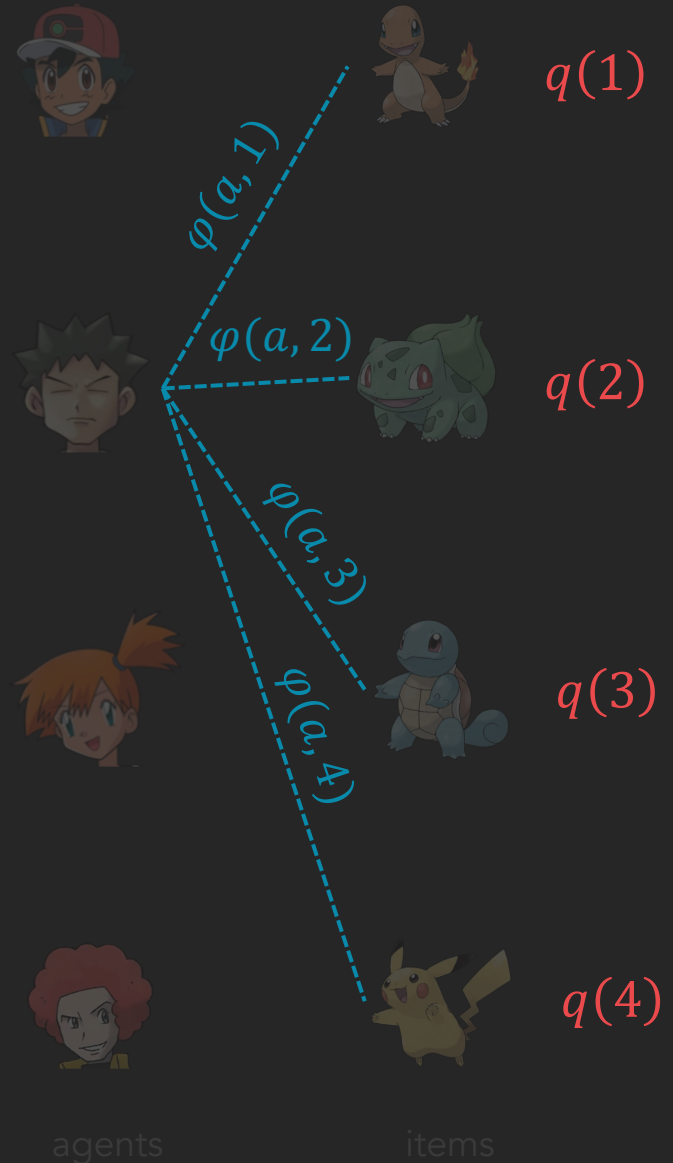
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 - $q(i)$: Common term depends only on the item
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 - ρ : level of heterogeneity in utility
- Assumptions
 - q and φ are independent of each other
 - $q(i)$ drawn i.i.d from P_q
 - $\varphi(a, i)$ drawn i.i.d from P_φ



Model

- Sequential selection of items
 - Agents are **ordered** according to some priority score and have **unit demand**
 - Agents arrive sequentially and select their preferred item from **remaining set of items**

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- **Capacitated Supply Setting**
 - Each item has unit capacity
 - One-to-one match between agents & items

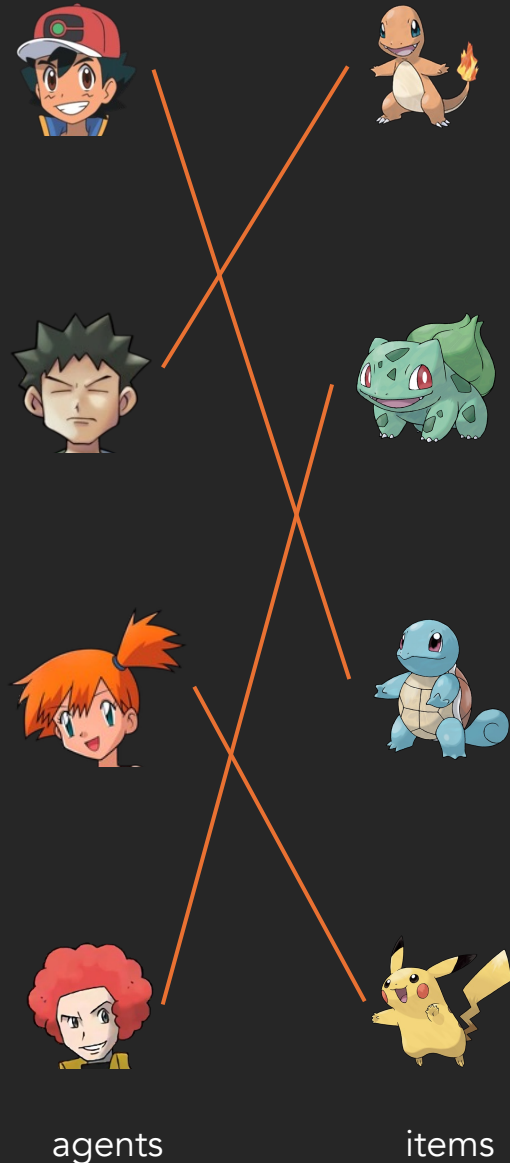


agents

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- **Uncapacitated Supply Setting**
 - Each item has infinite capacity
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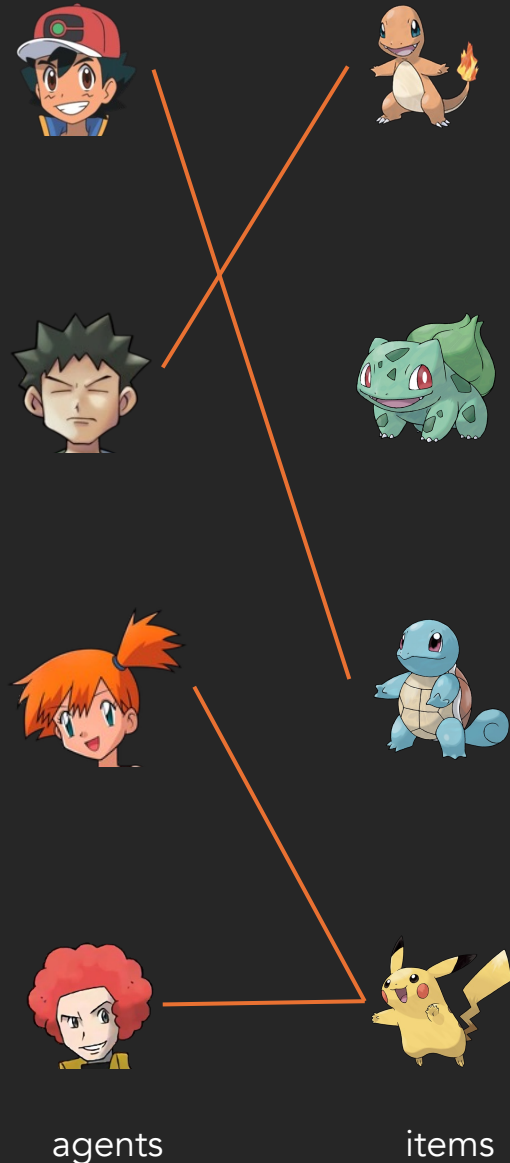


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- Key Measure of Interest
 - **Agent Welfare**: Expected average utility across agents

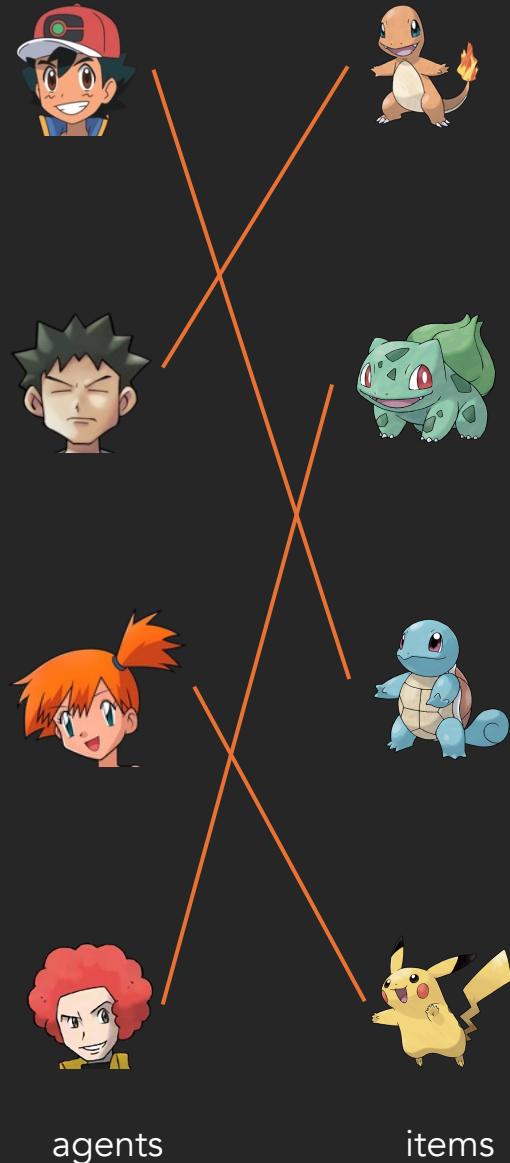


agents

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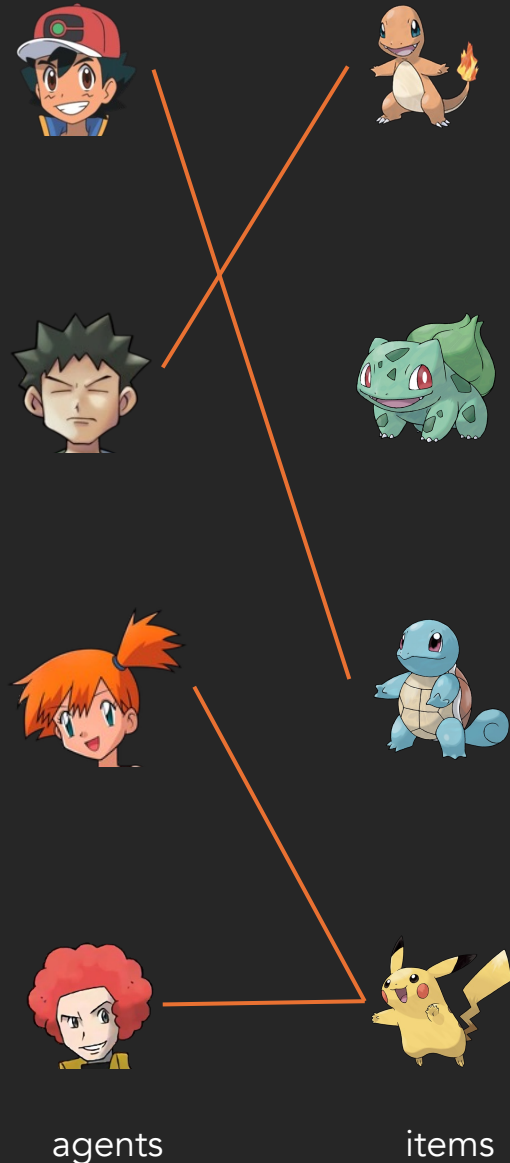
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Information Regimes

Information Regimes



No
Information

$$U = (1 - \rho) \cdot q(i) + \rho \cdot \varphi(a, i)$$

Information Regimes

Agents choose
items randomly

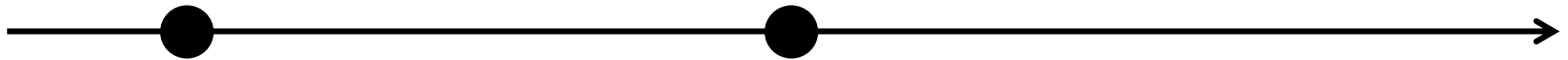


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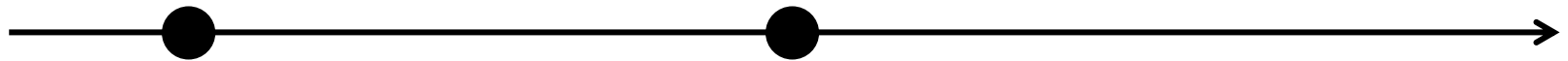
No
Information

Partial
Information

$$U = (1 - \rho) \cdot q(i) + \rho \cdot \varphi(a, i) \quad U = (1 - \rho) \cdot \textcolor{red}{q}(\textcolor{red}{i}) + \rho \cdot \varphi(a, i)$$

Information Regimes

Agents choose
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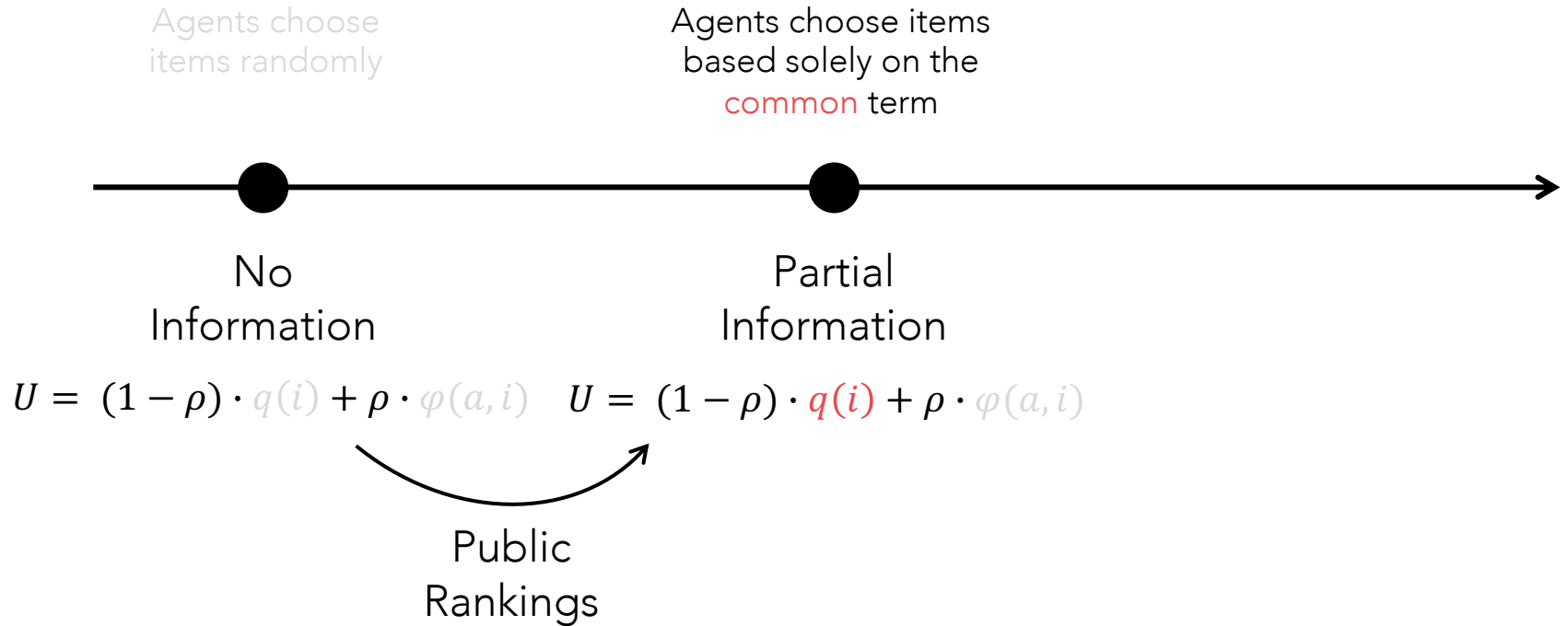
No
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Partial
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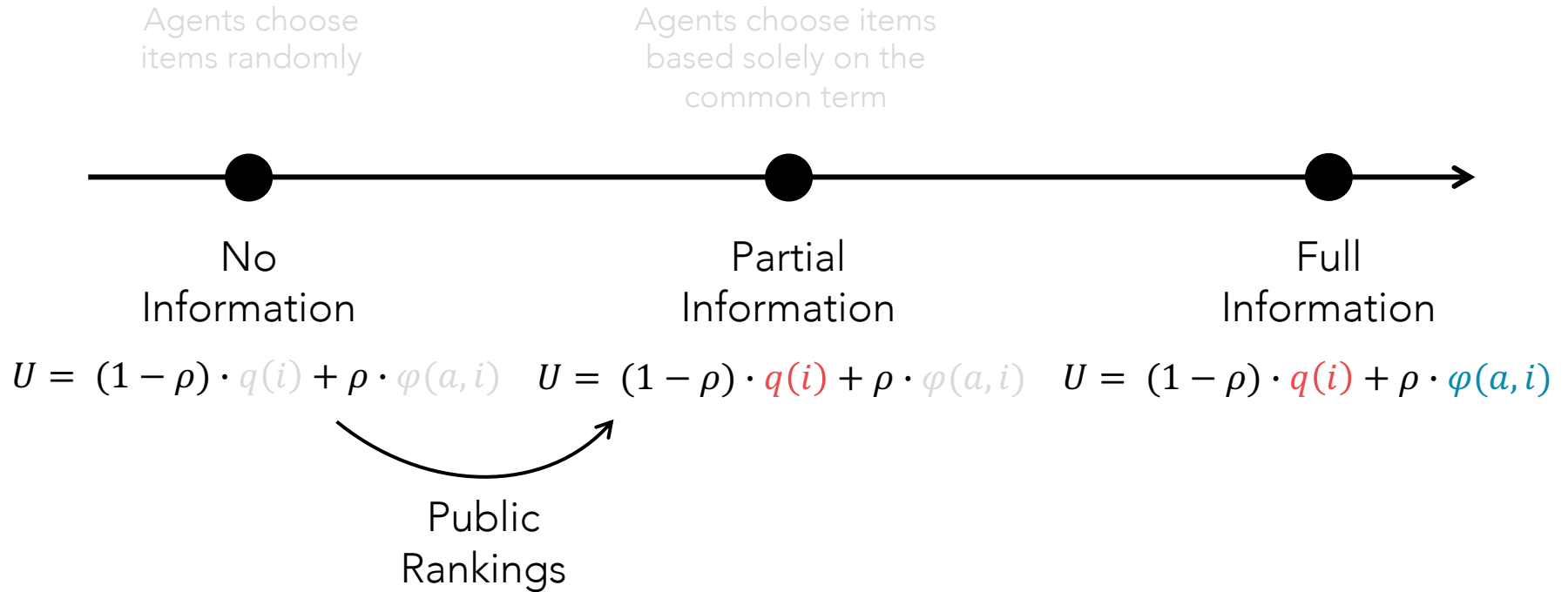
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Public
Rankings

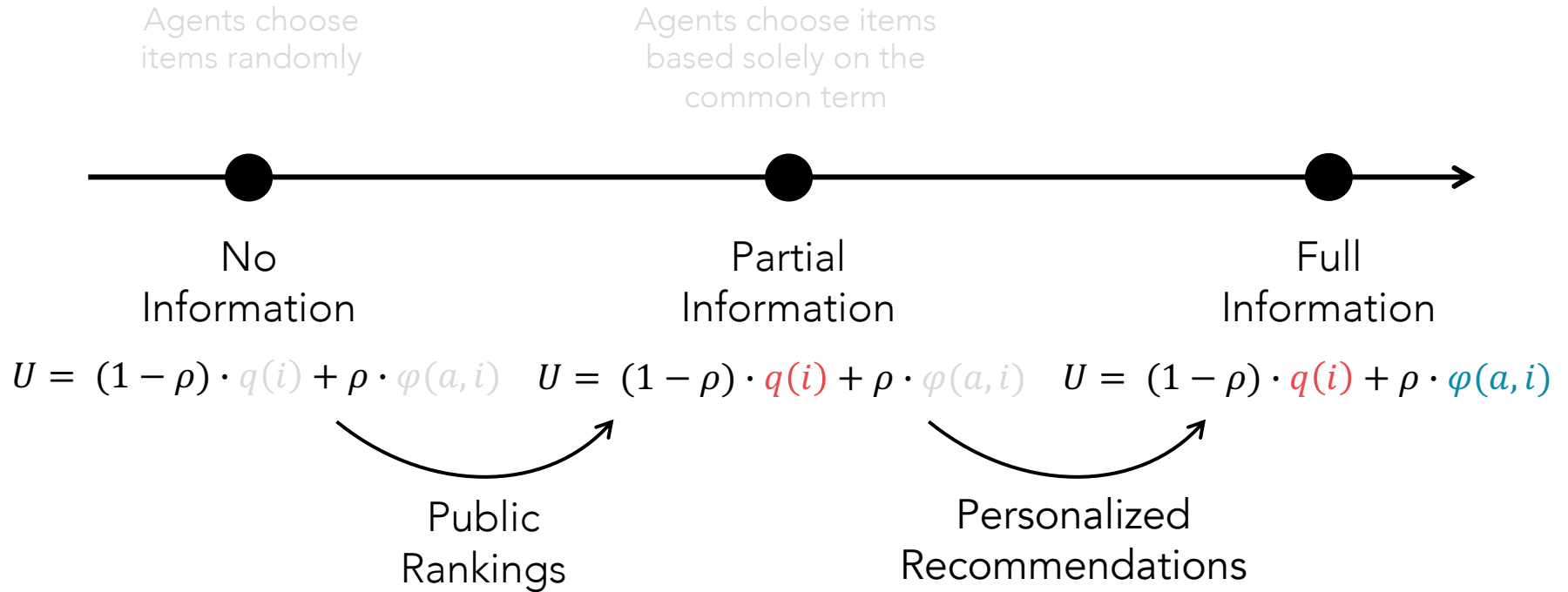
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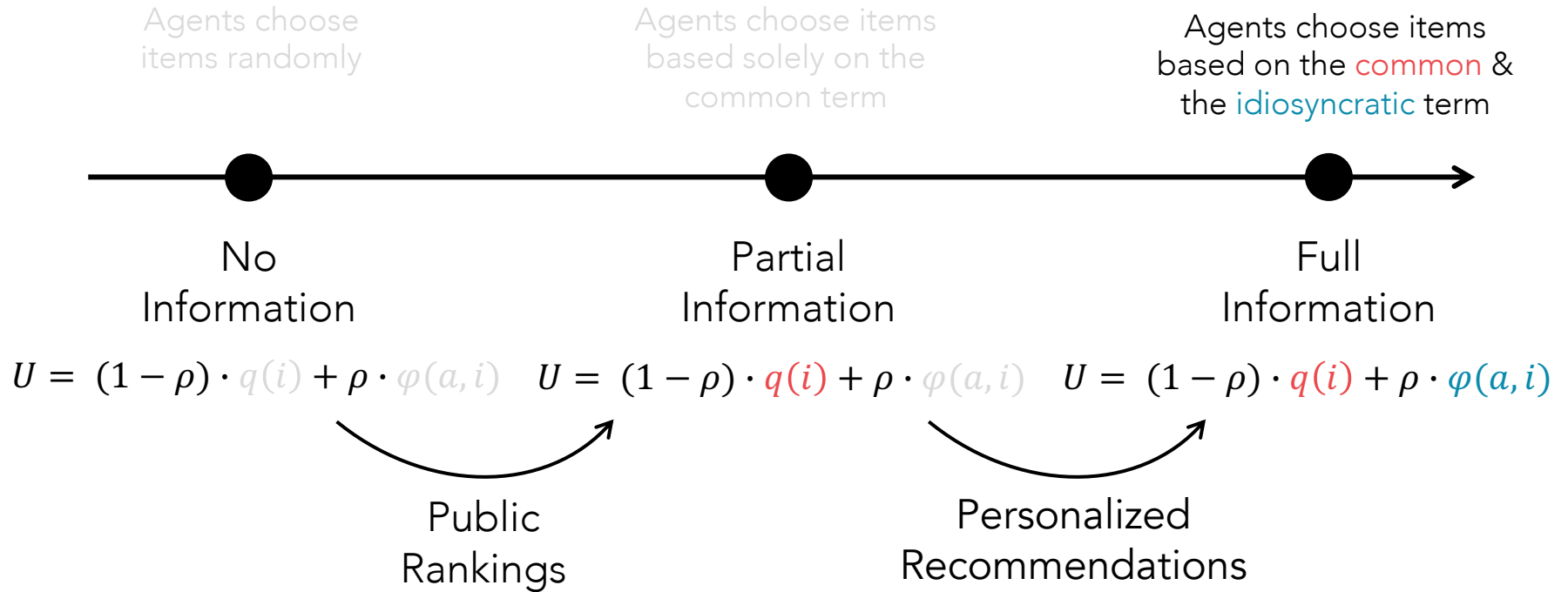
Information Regimes



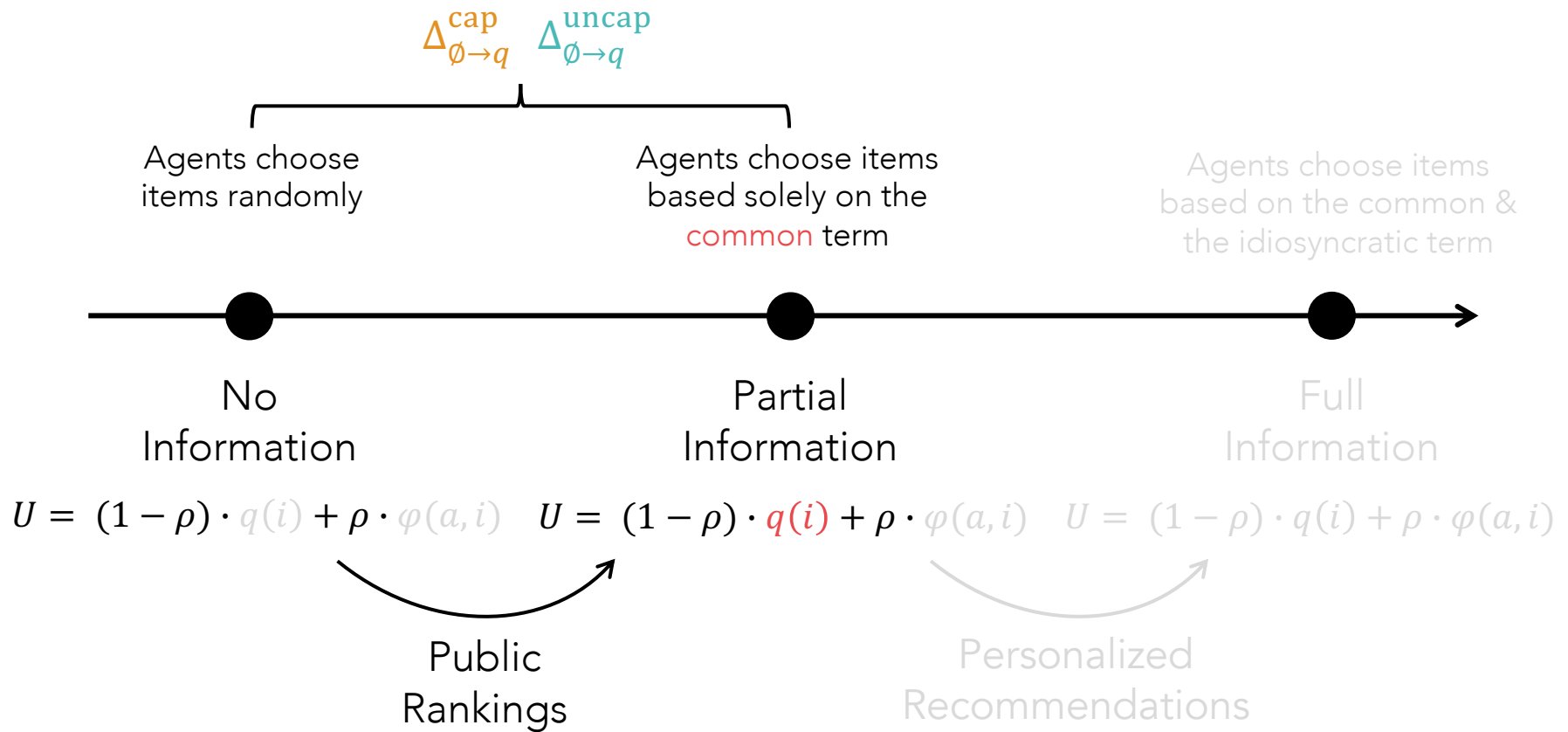
Information Regimes



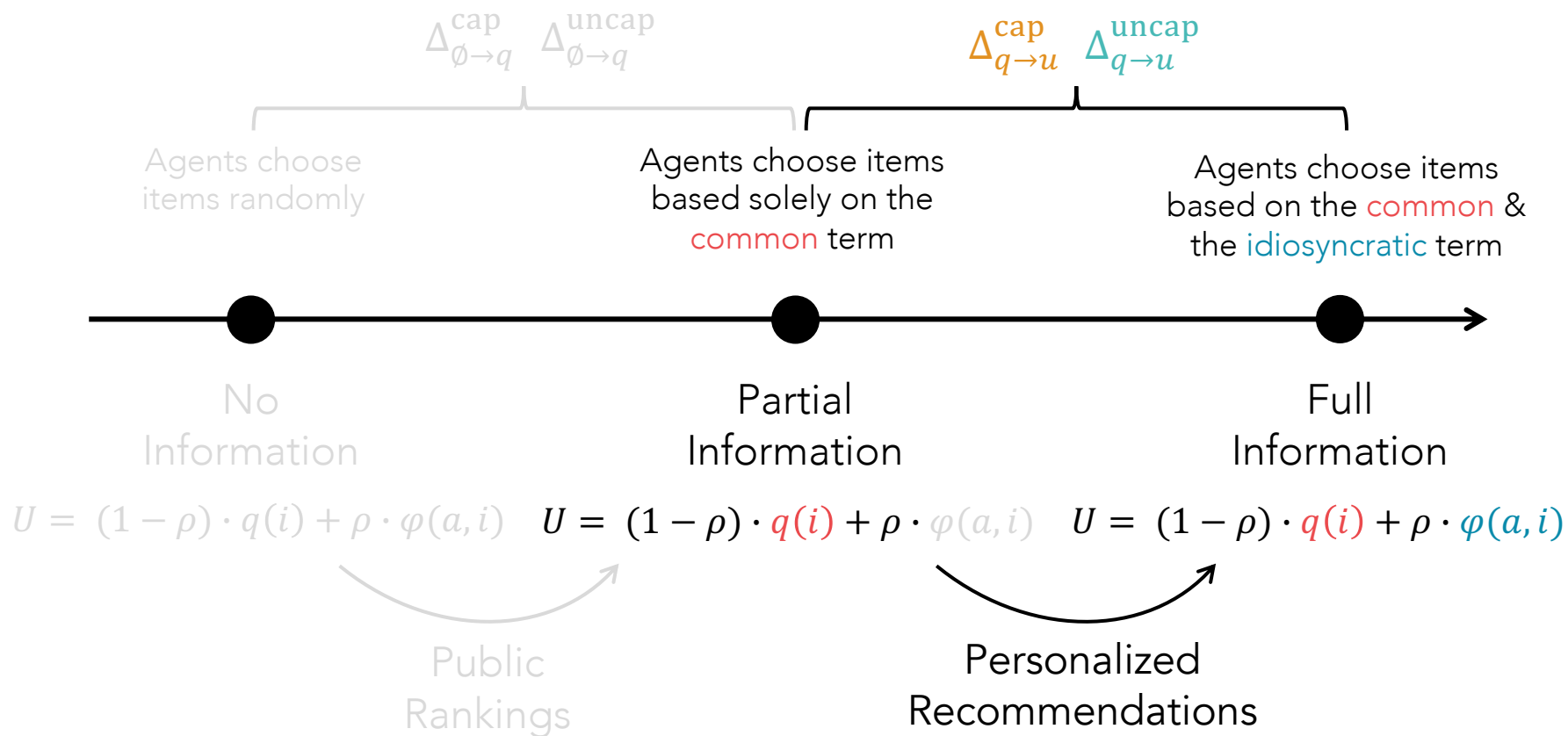
Information Regimes



Information Regimes



Information Regimes



Main Result (Pareto Tail)

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A distribution F is said to have a Pareto tail with parameter (κ, α) if $\lim_{x \rightarrow \infty} \bar{F}(x)/(\kappa/x)^\alpha = 1$.

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We have n agents and n items. Assume that common term distribution F_q and the idiosyncratic term distribution F_φ have Pareto tail with parameters (κ, α) . Then we have that

Capacitated Supply Setting

Uncapacitated Supply Setting

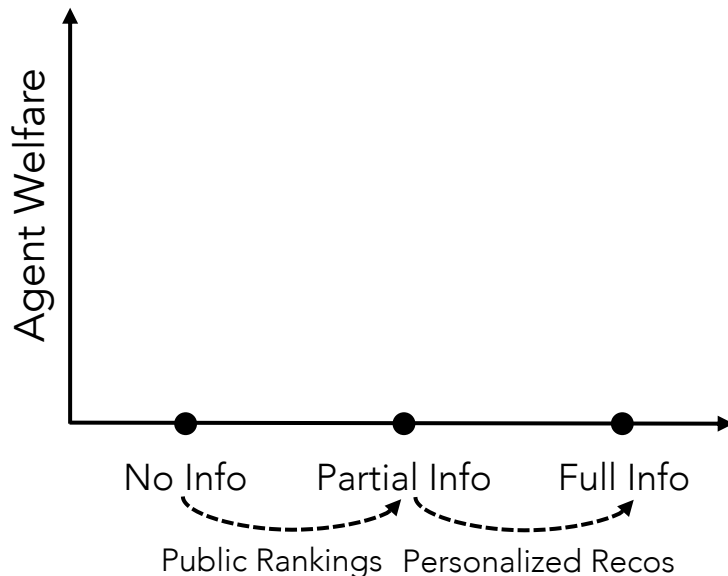
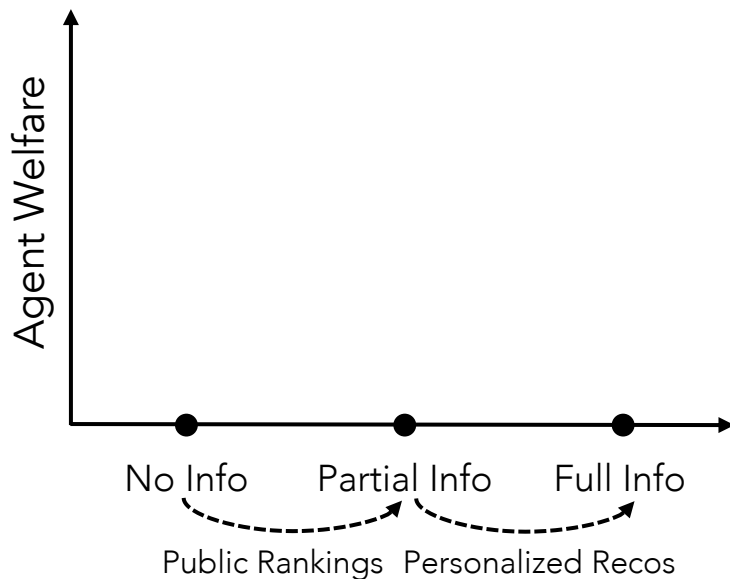
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Main Result (Pareto Tail)

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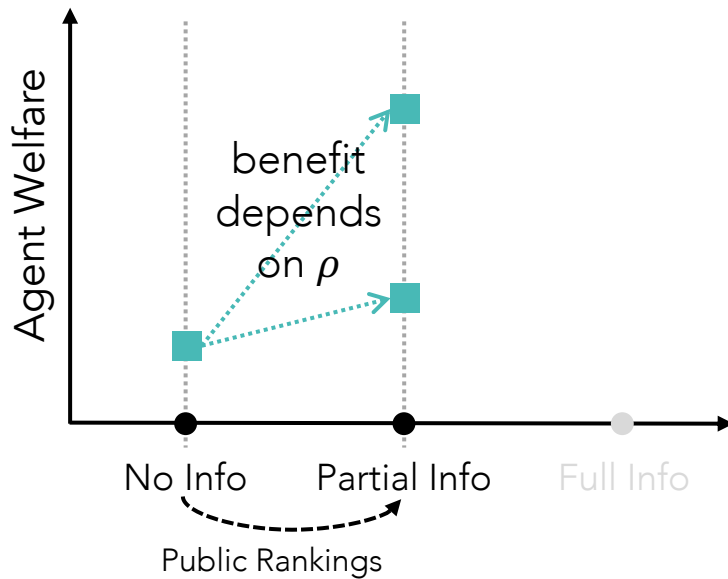
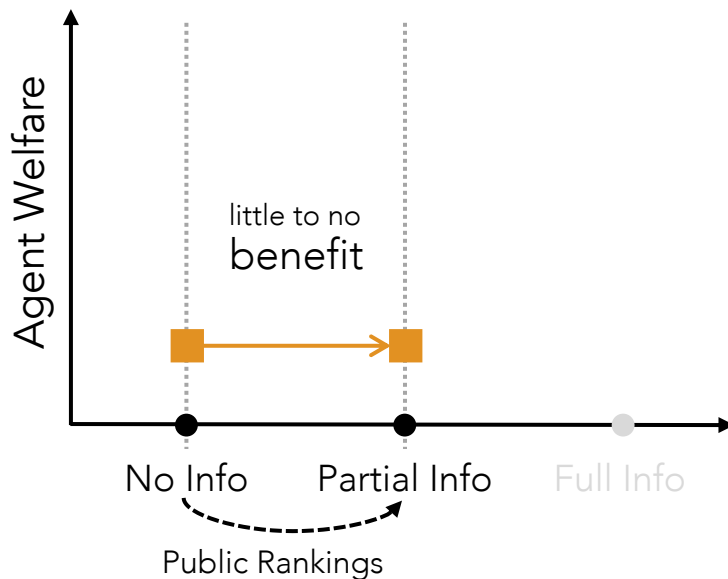
We have n agents and n items. Assume that common term distribution F_q and the idiosyncratic term distribution F_φ have Pareto tail with parameters (κ, α) . Then we have that

Capacitated Supply Setting

- $\Delta_{\emptyset \rightarrow q}^{\text{cap}} = 0$
- $\Delta_{q \rightarrow u}^{\text{cap}} \simeq c\rho \cdot n^{1/\alpha}$

Uncapacitated Supply Setting

- $\Delta_{\emptyset \rightarrow q}^{\text{uncap}} \simeq c(1 - \rho) \cdot n^{1/\alpha}$
- $\Delta_{q \rightarrow u}^{\text{uncap}} \simeq c((1 - \rho)^\alpha + \rho^\alpha)^{\frac{1}{\alpha}} - (1 - \rho) \cdot n^{1/\alpha}$



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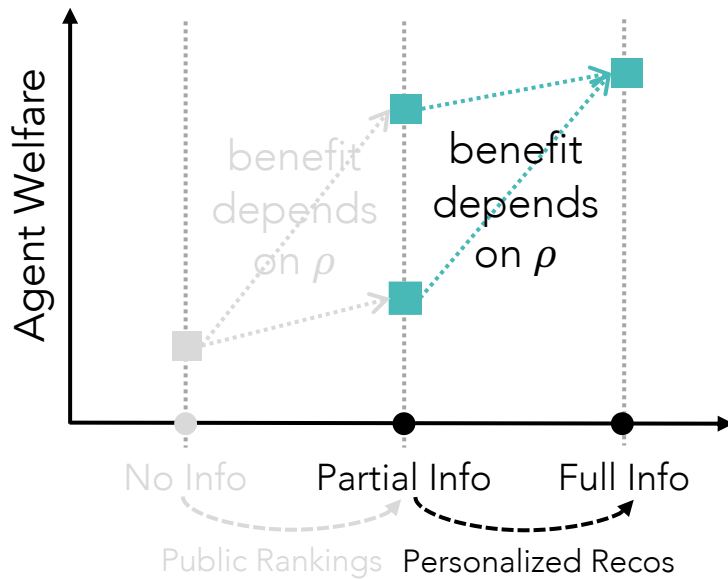
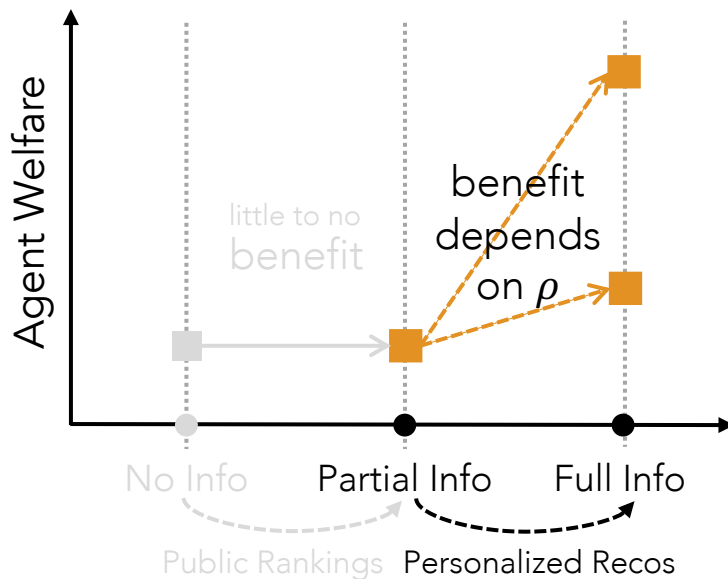
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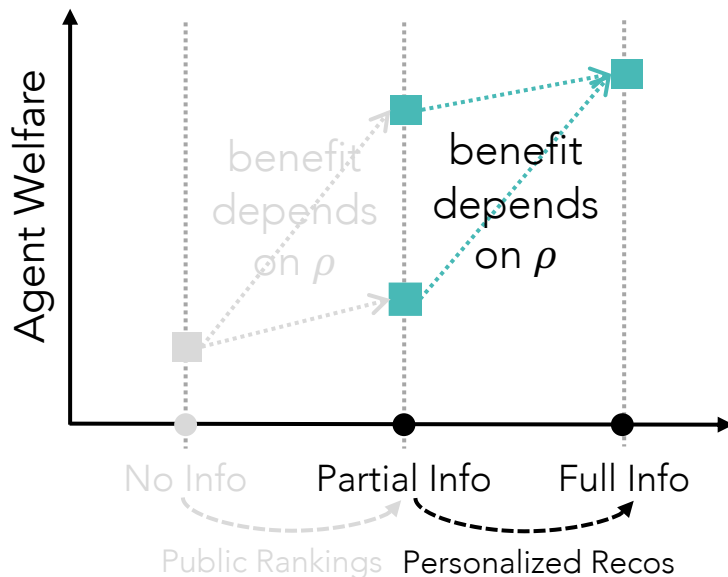
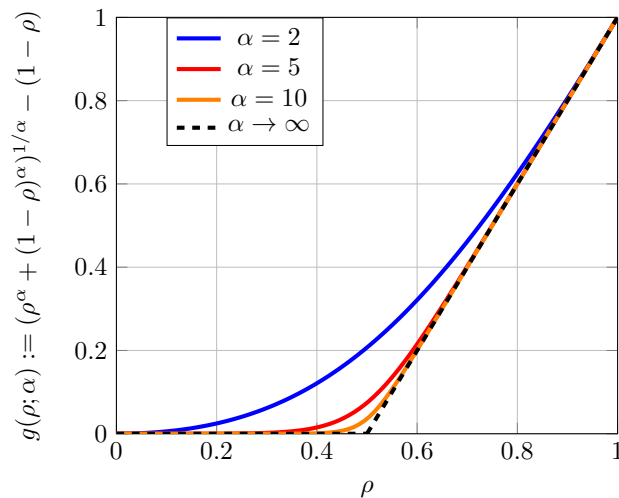
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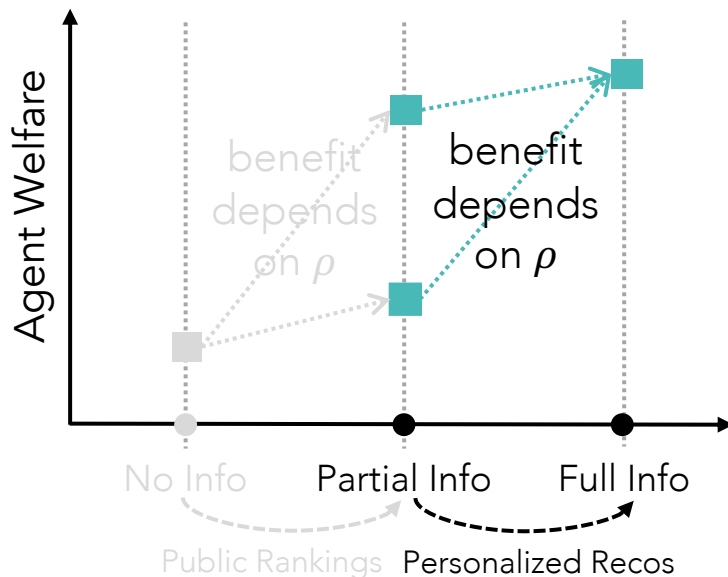
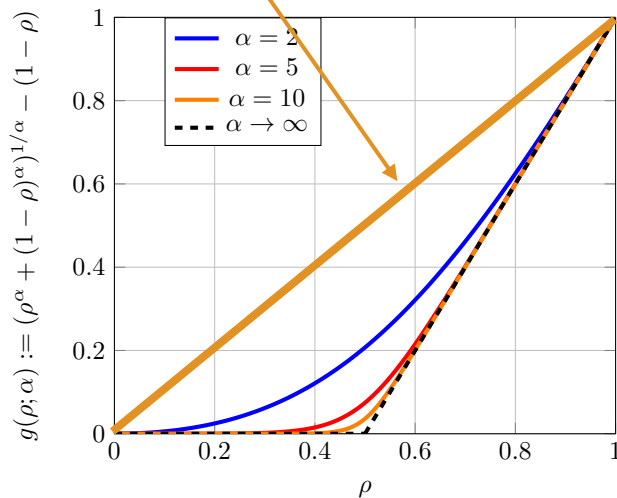
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Take-aways

- A stylized model to isolate the impact of rankings and personalized recommendations
- Fundamental interplay between the impact of different information provisioning tools and supply side capacity
 - **Uncapacitated Settings:** Level of heterogeneity determines the impact of public rankings and personalized recommendations
 - **Capacitated Settings:** Most of the value lies in matching agents to items that they idiosyncratically value highly.

A close-up, artistic photograph of a person's face, focusing on the nose and eyes. The person is wearing dark-rimmed glasses. The lenses of the glasses reflect a scene featuring Keanu Reeves. In the reflection, he is wearing a black shirt and holding a small, glowing red object in his right hand. The background of the reflection appears to be a dimly lit room with some furniture. The overall image has a grainy, high-contrast aesthetic.

Building (possibly
noisy) tools which
inform of idiosyncratic
preferences

v/s

Building a more
accurate public
ranking tool

Thanks

