

# Fairness in Information Retrieval from an Economic Perspective



Half-day tutorial at ECIR&ICMR 2026

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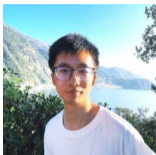
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Website: <https://economic-fairness-ir.github.io/>

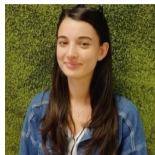
Toolkit: <https://github.com/XuChen0427/FairDiverse>

## Tutors



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Professor



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# Outline

1. Introduction: Fairness in IR (Yuanna, 20 min)
2. An Economic View on Fairness in IR (Marleen, 30 min)
3. Economic-based Fairness Mitigation and Evaluation Strategies I (Chen 30 min)
4. Economic-based Fairness Mitigation and Evaluation Strategies II (Clara, 30 min)
5. Economic-based Fairness Mitigation and Evaluation Strategies III (Yuanna, 30 min)
6. Open Problems, Quick Start for Learning about Fairness, and Conclusions (Clara, 20 min)

# Motivation

## 1. Economics provides good fairness frameworks and tools

- Economists have studied complex fairness problems for centuries. Their theory and methods can help us to structure the IR fairness problems better

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## 2. Leveraging economic thinking for fairness in IR

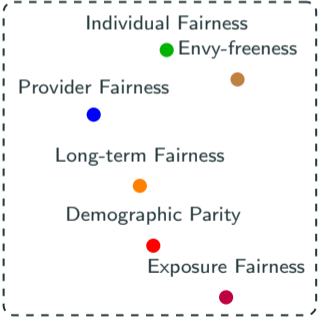
- Economic theory shows that fairness is not just “the right thing to do” but often also the “**profitable choice**”

## 3. Economic perspectives point out future directions

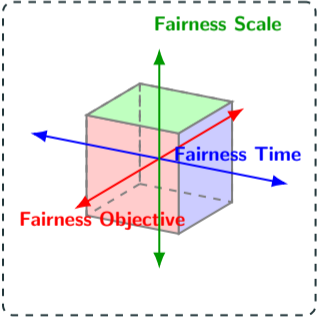
- Economics highlights that we need to consider practical multi-agent scenarios and develop more rigorous, theory-driven fairness mechanisms

# Overall Framework

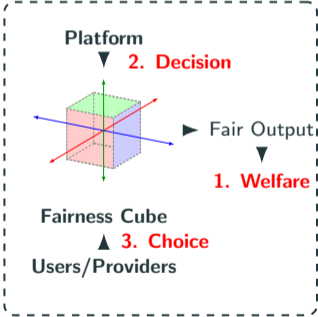
## Existing Fairness Foundations (Part I)



## Economic Perspective on Fairness (Part II)



## Future Fairness Directions (Part III)



# 1. Introduction: Fairness in IR

(Yuanna, 20 min)

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# Information retrieval

# What is information retrieval?

- **Information retrieval (IR)** is the process of getting the right information to the right people in the right way and at the right time
- It focuses on matching user queries with documents or data items
- IR is the core technology behind **search engines** and **recommender systems**



1. **Document/item collection** – Large repository of data (e.g., web pages, products)
2. **Indexing** – Efficient representation for fast search
3. **User intent understanding** – Understanding and interpreting user queries
4. **Retrieval and ranking models** – Scoring documents based on relevance
5. **Evaluation** – Measuring quality

# IR is more than accuracy

- Traditional IR systems aim to maximize **ranking accuracy**



**Traditional: User-centric**

**Now: Ecosystem-centric**

# IR is more than accuracy

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- However, real-world IR systems operate in a complex **ecosystem** involving many stakeholders, such as content creators, advertisers, and even society



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# IR is more than accuracy

- Traditional IR systems aim to maximize **ranking accuracy**
- However, real-world IR systems operate in a complex **ecosystem** involving many stakeholders, such as content creators, advertisers, and even society
- Sustainable and responsible IR must consider all stakeholders and long-term system dynamics



**Traditional: User-centric**

**Now: Ecosystem-centric**

# Key stakeholders in IR

## 1. User

- Seeks relevant, timely, and useful content
- User satisfaction directly impacts system reputation

## 2. Platform

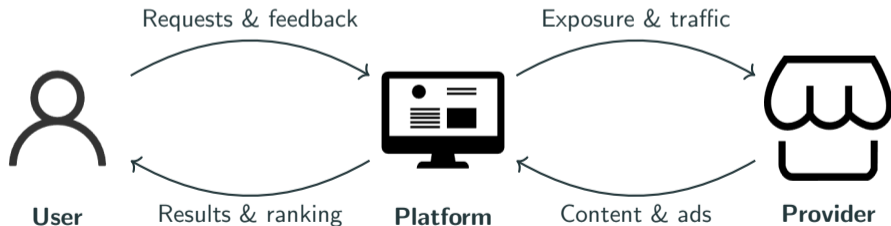
- Operates and optimizes the IR system
- Acts as a mediator between users and providers

## 3. Provider

- Supplies the content or items retrieved by the system (e.g., sellers, content creators)
- Interested in exposure, traffic, and conversions

# Stakeholder interactions in IR

- **User**, **platform**, and **provider** form a dynamic ecosystem [Abdollahpouri and Burke, 2019]
- Each stakeholder has different goals and influences the system
- Balancing the goals of each stakeholder means **fairness**



# Fairness in IR

## What is “beyond accuracy” in IR?

- **Definition:** *Beyond-Accuracy* in IR refers to a class of evaluation and modeling approaches that go beyond traditional relevance-based metrics, aiming to account for broader user and societal values

### Key dimensions beyond accuracy:

- **Fairness:** Ensuring equitable or right outcomes across different groups
- **Diversity:** Promoting varied content to reduce redundancy
- **Novelty:** Encouraging discovery of unexpected but useful items
- **Transparency:** Providing users with understandable reasons behind rankings
- ...

## What is fairness?

**Fairness** refers to the quality of treating **people** equally or in a way that is **right or reasonable** – *Cambridge Dictionary*

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**Fairness** has been defined in **numerous ways** across history and disciplines – from justice in social science and humanities to algorithmic fairness in IR

## 1. Distributive justice [Lamont, 2017]

- Are resources (e.g., income) distributed fairly among individuals or groups?

## 2. Procedural justice [Tyler and Allan Lind, 2002]

- Is the decision-making process transparent, consistent, and unbiased?

## 3. Recognition and inclusion [Eisenstadt, 1973]

- Are marginalized groups fairly represented and respected?

**Unfairness** often leads to **harm** by systematically disadvantaging certain individuals or groups, thereby reinforcing inequality and reducing overall welfare

# Fairness in social science vs. Fairness in machine learning

Fairness in social science	Fairness in IR
<b>Distributive justice</b>	<b>Allocation harms:</b> How to allocate resources (e.g., computational costs, user traffic) fairly for different stakeholders? [Xu et al., 2023a]
<b>Procedural justice</b>	<b>Procedural harms:</b> How can we ensure models do not rely on discriminatory or harmful information when making decisions? [Lee et al., 2019]
<b>Recognition and inclusion</b>	<b>Representation harms:</b> How can we ensure that the model fairly represents different groups in its latent (hidden) space? [Zemel et al., 2013]

## Allocation harms

Individual-  
group fairness  
[Jiang et al., 2021]

User-provider  
fairness  
[Xu et al., 2023a]

Short-long  
term fairness  
[Xu et al., 2023b]

## Procedural harms

Controllable fairness  
[Lee et al., 2019]

Explainable fairness  
[Ge et al., 2022]

Transparent fairness  
[Lee et al., 2019]

## Representational harms

Anti-classification  
[Rus et al.,  
2023, 2024]

Anti-subordination  
[Lahoti et al., 2019]

- **Procedural harms**

- ⇒ Reflect constraints or flaws in the process

- ⇒ But they matter because they are the right properties to address allocation harms

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- **Representational harms**

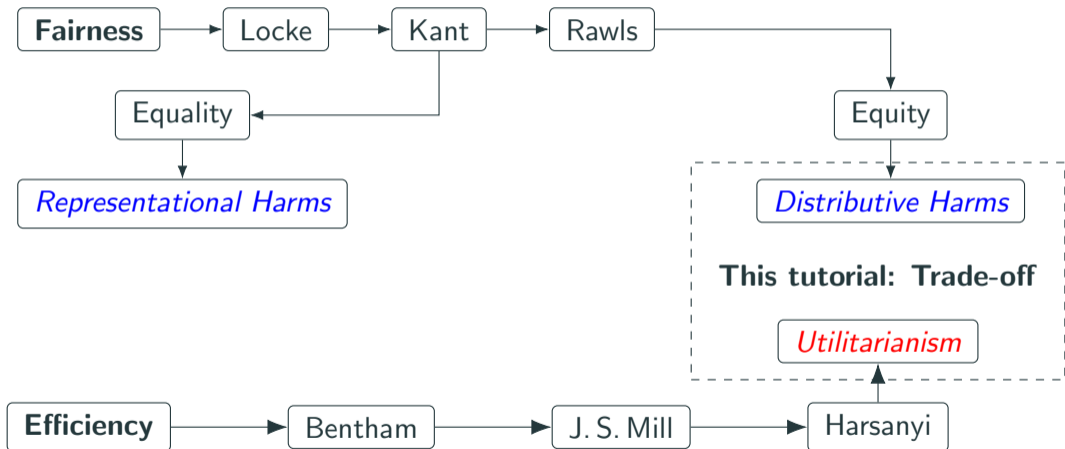
- ⇒ In IR, often act as *means* to an unfair allocation

- ⇒ Not always the final objective

## What do we focus on?

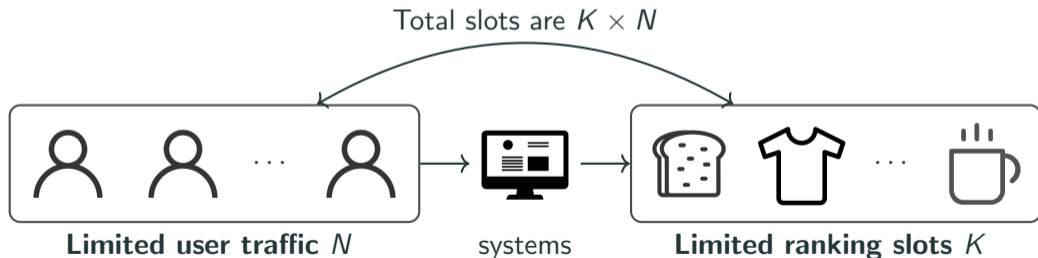
- In IR, we mainly focus on **allocation harms**. This is because:
  - **Allocation harm** is the central concern in IR: *Who gets ranked, recommended, or seen – and how much?*
  - Ranking slots and user traffic are scarce and impactful resources

# Fairness origin and development



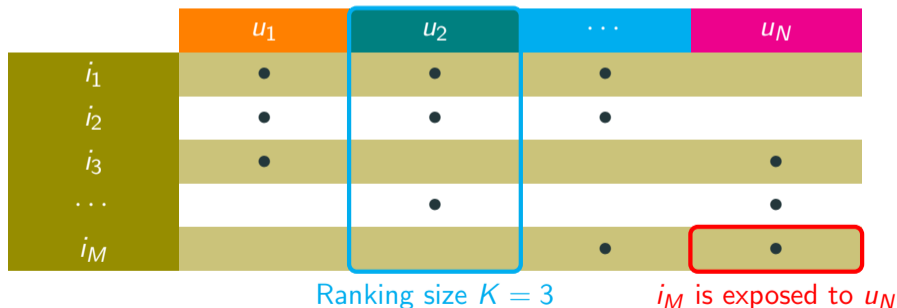
# What are resources in allocation harms?

- The resource allocated in the IR could be
  - The number of item/document exposures [Xu et al., 2023a]
  - The number of item/document clicks [Xu et al., 2024, Baumann et al., 2024]
  - The utilities of user groups [Liu et al., 2024]
- The resources in IR are typically **limited** (limited ranking slots and user traffic)



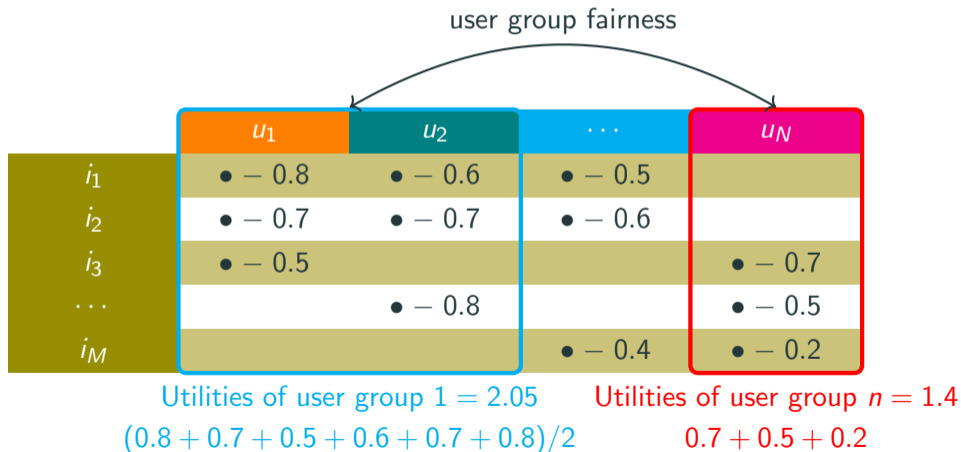
## Allocation harms in IR

- Assuming  $N$  users ( $u_1, u_2, \dots, u_N$ )
- Assuming  $M$  items/documents ( $i_1, i_2, \dots, i_M$ ).
- IR systems can only adjust the **slots allocation matrix**  $X$



## Allocation harms in IR

- Based on the IR resource allocation, we can define the utilities of different stakeholders, such as user groups:



# Allocation harms in IR

- Based on the IR resource allocation, we can define the utilities of different stakeholders, such as providers:

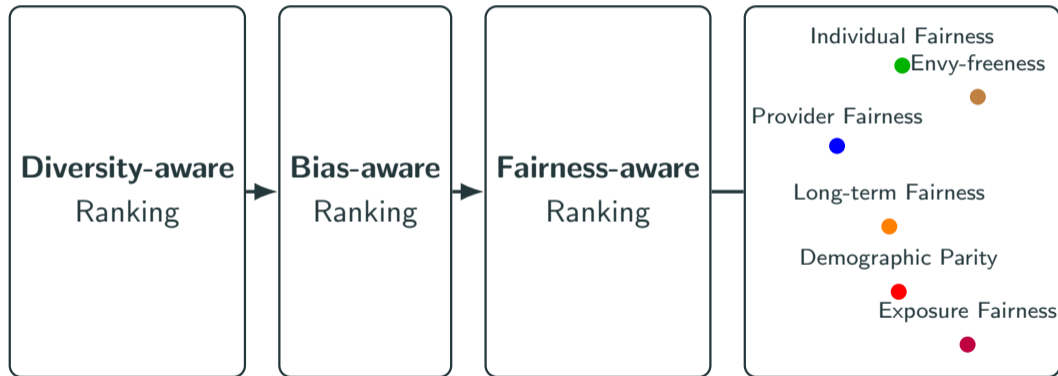
	$u_1$	$u_2$	$\dots$	$u_N$
$i_1$	● - 0.8	● - 0.6	● - 0.5	
$i_2$	● - 0.7	● - 0.7	● - 0.6	
$i_3$	● - 0.5			● - 0.7
$\dots$		● - 0.8		● - 0.5
$i_M$			● - 0.4	● - 0.2

Provider 1 utility = 1.95

Provider  $m$  utility = 0.6

provider fairness

# Evolution of Fairness Algorithms in IR



# Fairness evaluation in IR

## How to measure allocation harms?

- Assuming the utilities (such as exposures) of one stakeholder are

$$\mathbf{v} = [v_1, v_2, \dots, v_g],$$

where  $g$  is the stakeholder internal group number.

- A fairness evaluation function  $f(\mathbf{v})$  is designed to measure the degree of fairness
- An example:

$$\mathbf{v}_1 = [1, 5, 10, 20], \quad \mathbf{v}_2 = [2, 4, 12, 18].$$

**How much less fair** is  $\mathbf{v}_1$  compared to  $\mathbf{v}_2$ ?

## Common evaluation metrics I

- Max-min fairness [Xu et al., 2023a]: ensures worst-off groups get enough utilities

$$f(\mathbf{v}) = \min_i(v_i).$$

- Gini Index [Do et al., 2021]: inequality by quantifying distribution disparity

$$f(\mathbf{v}) = \frac{\sum_{i=1}^n \sum_{j=1}^n |v_i - v_j|}{2n \sum_{i=1}^n v_i}.$$

- Entropy [Jost, 2006]: captures overall diversity or uncertainty in allocation

$$f(\mathbf{v}) = - \sum_{i=1}^g v_i \log(v_i).$$

- Demographic parity [Jiang et al., 2021]: equal outcomes across groups

$$f(\mathbf{v}) = \sum_{i=1}^g |v_i - \sum_{i=1}^g v_i / g|.$$

## Common evaluation metrics II

- Min-max ratio [Jain et al., 1984]: ratio between the best-off and worst-off groups

$$f(\mathbf{v}) = \min_i(v_i) / \max_i(v_i)$$

- $p$ -norm [Bektaş and Letchford, 2020]: penalizing large deviations in utility

$$f(\mathbf{v}) = \left( \sum_{i=1}^g v_i^p \right)^{1/p}$$

- Elastic fairness [Xu et al., 2025c]: a unified fairness evaluation metric

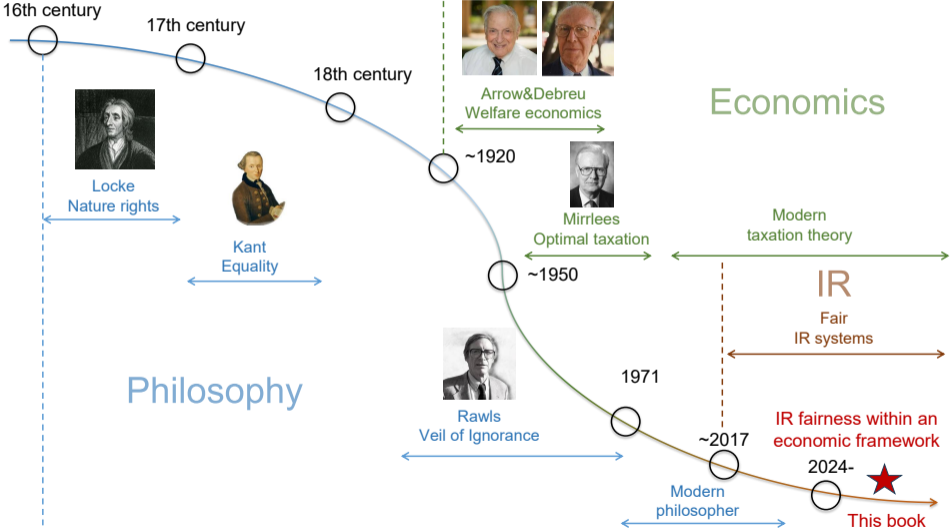
$$f(\mathbf{v}) = \text{sign}(1 - t) \left( \sum_{i=1}^g \bar{v}_i^{1-t} \right)^{(1/t)}$$

The goal is to enforce **fairness** across stakeholders while preserving the **effectiveness** and **relevance** of the information retrieval process

## 2. An Economic View on Fairness in IR (Marleen, 30 min)

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# Fairness concept history



# Motivation for an economic view on fairness in IR

An economic lens does not just add more complexity, more methods, and more theories: it integrates different stakeholders and justifies its relevance

- The current landscape:
  - **Fragmented objectives:** Many well-defined criteria, but no common framework for comparing them
  - **Translation gap:** Hard to quantify what fairness costs and delivers
  - **Limited generalization:** Solutions designed per setting, principles don't always transfer

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  - **Translation gap:** Hard to quantify what fairness costs and delivers
  - **Limited generalization:** Solutions designed per setting, principles don't always transfer
- Without a shared theoretical language:
  - Harder to compare approaches across the literature
  - Harder to justify sustained investment in production
  - Harder to transfer insights across settings

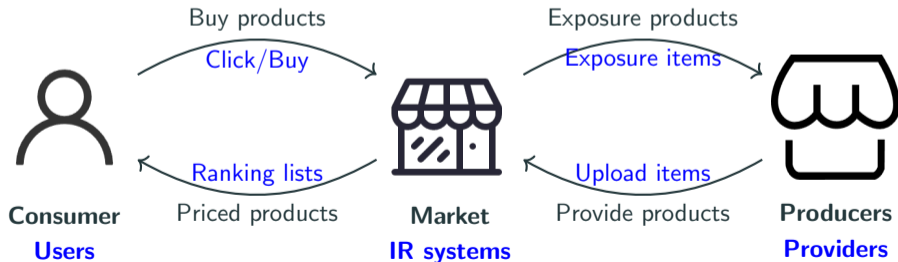
# **An economic view on information retrieval**

## What is a market economy?

*“A market economy is an economic system in which the production and allocation of goods and services is determined by forces of **supply and demand**.”*

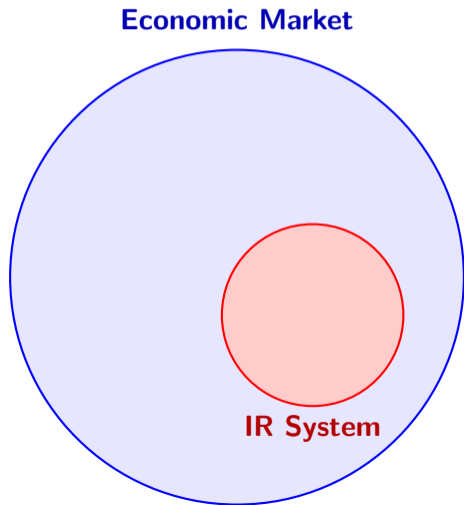
# IR systems and economic markets: A natural analogy

- IR systems do the same:
  - **Users** are the *demand side* – they express preferences through queries, clicks, engagement.
  - **Providers** are the *supply side* – they create content and compete for visibility.
  - The **platform** allocates the scarce resource – *user attention* – guided by relevance scores that function.



## IR system as an economic market

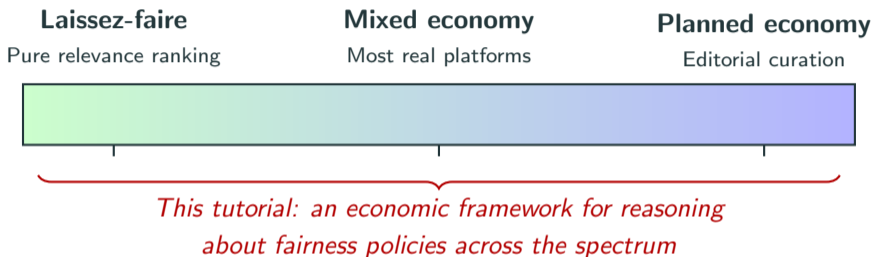
IR system can be considered as a special **multi-sided matching economic market**



## Market mechanisms vs. IR system tasks

Market mechanism	IR system analogy / task
Price mechanism	Ranking signals emerge from competition for scarce user attention [Baeza-Yates et al., 1999].
Incentive design	Stability, advertisement bidding mechanism [Yang et al., 2019], Coupons design [Yang et al., 2019].
Regulation and intervention	Platform policies enforce diversity [Dang and Croft, 2012], reduce bias [Chen et al., 2023], or increase fairness [Li et al., 2023].

# Market economies include regulation by design



- Markets can **fail**: monopolies, externalities, extreme concentration
- When they do, governments intervene with taxes, subsidies, or rules
- IR ranking markets fail in the same way — fairness intervention is the **regulation** that corrects it

# Why model IR as an economic market?

## 1. Import, don't invent

Centuries of theory on competing agents, scarce resources, and mediating mechanisms.

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Taxation → redistribution    |    Auctions → preference elicitation    |    Social choice →  
fairness trade-offs

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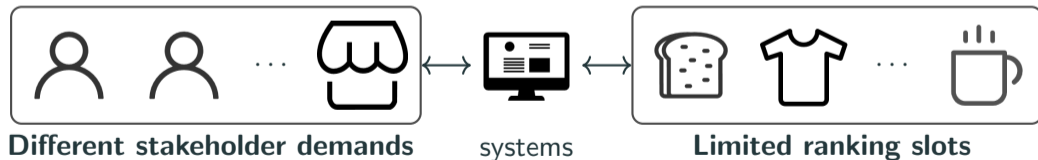
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fairness trade-offs

## 3. It works both ways

IR generates new challenges for economics: attention  $\neq$  money, platforms  $\neq$  governments; agents, feedback loops, and real-time bidding add new dynamics.

## Recall: Fairness in IR

- In IR, we are mainly concerned with **allocation harms**
- **Unlimited** stakeholder demands vs. **limited** ranking resources



## Recall: Fairness in IR

- In IR, we are mainly concerned with **allocation harms**
- **Unlimited** stakeholder demands vs. **limited** ranking resources
- Taxonomy of allocation harms [Li et al., 2021]
  - Allocation **object**: user fairness vs. provider fairness
  - Allocation **time**: short-term fairness vs. long-term fairness
  - Allocation **scale**: individual fairness vs. group fairness



### 1. Objective: supply side vs. demand side (consumer vs. producer)

- **Supply and demand** describe how the availability of goods and the desire to purchase them determine prices and quantities in a market.

### 2. Scale: micro- vs. macro- view

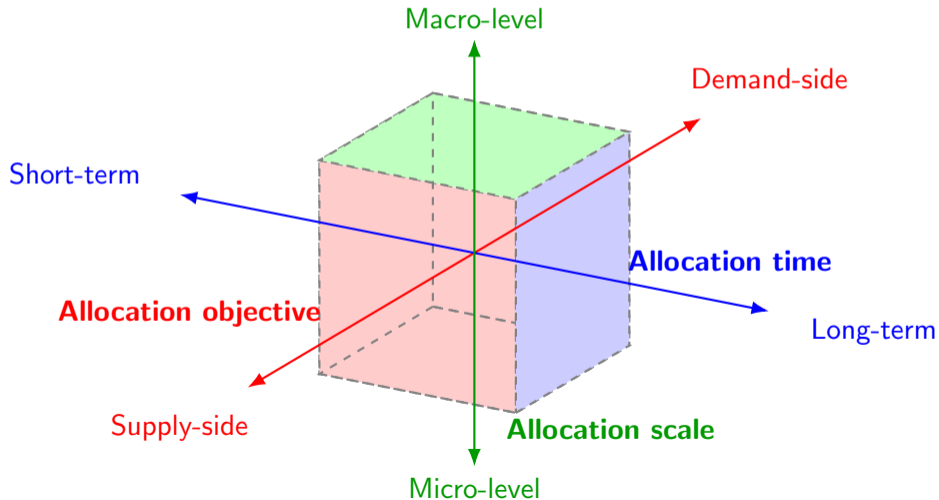
- **Microeconomics** analyzes individual decision-making and market interactions, while **macroeconomics** focuses on economy-wide phenomena like growth, inflation, and unemployment.

### 3. Time: short-term vs. long-term results

- **Short-term shocks** cause immediate fluctuations, while **long-term returns** reflect stable outcomes as markets adjust over time.

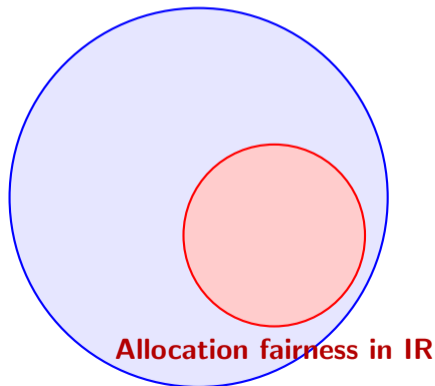
# Taxonomy of fairness in economics

- Allocation in economics: **Allocation objective, scale and time**



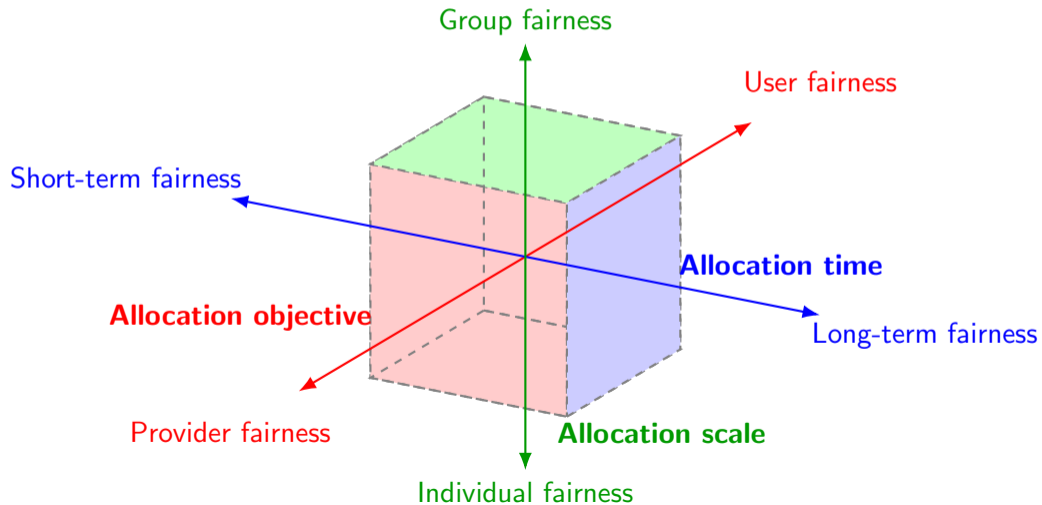
- Governments or authorities may step in to correct market failures (e.g., externalities, inequality, monopolies) through economic tools.

### Fairness in economics

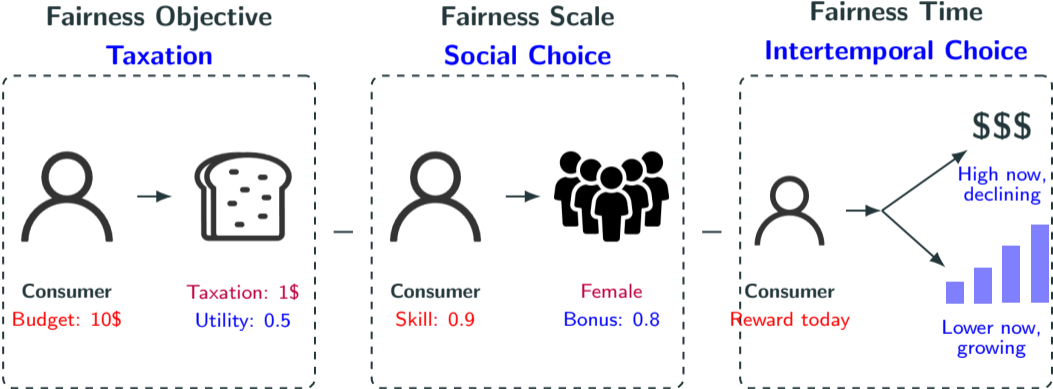


# Taxonomy of fairness in IR: Alignment

- Allocation fairness in IR: **Allocation objective, scale and time**



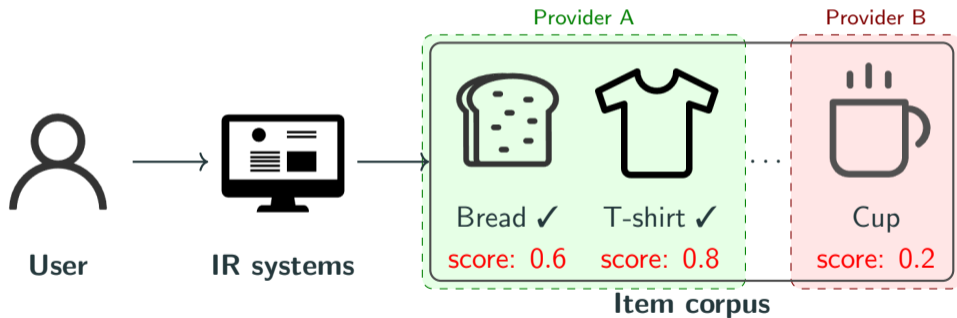
# Economic Tools for Fairness



## **Case 1: An economic view on allocation objective**

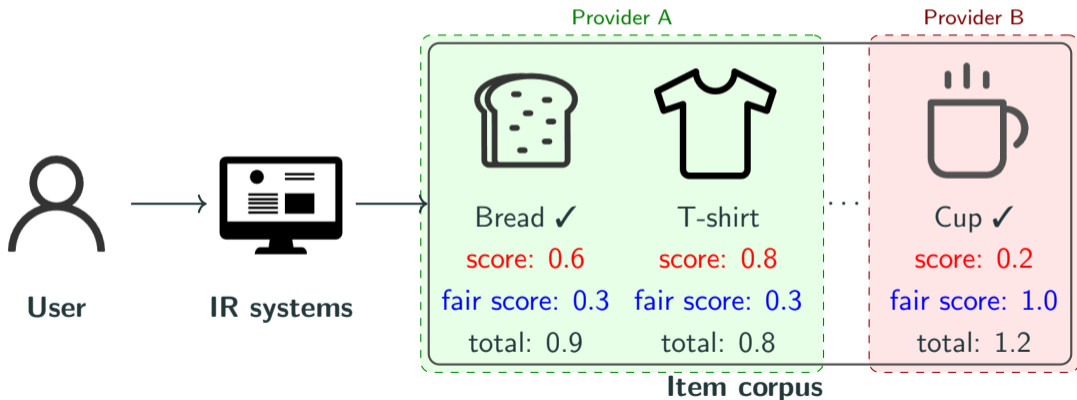
## Example: Provider fairness in IR

Every user will be exposed to  $k = 2$  items that have highest ranking scores:



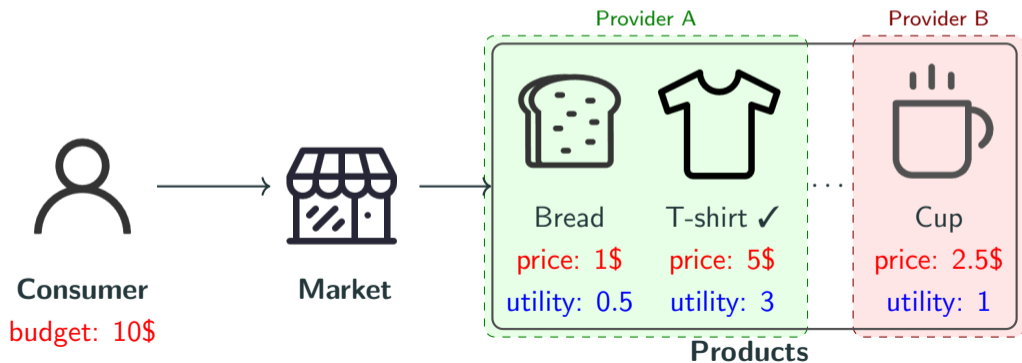
## Example: Provider fairness in IR

We aim to increase the exposure of certain providers: **Through fairness score!**



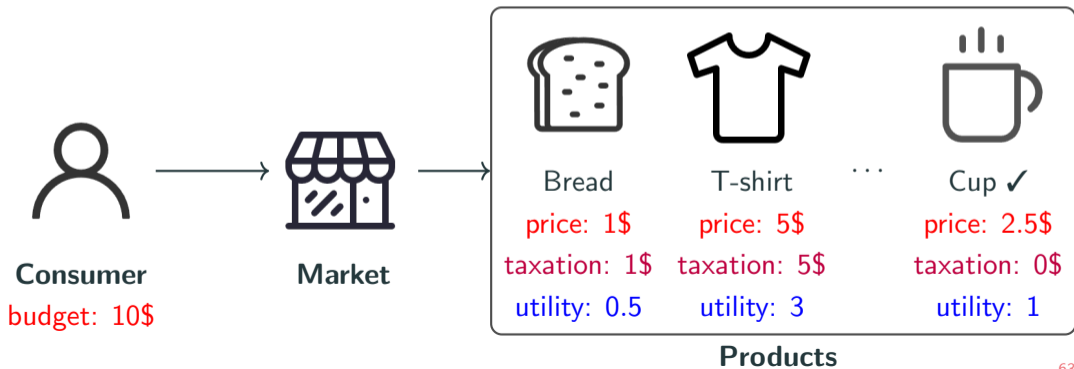
## Examples: Supply-side fairness in economic market

- Users enter the market and purchase products available within it.
  - Bread: buy  $10/1 = 10$  and get  $0.5 \times 10 = 5$  utility
  - **T-shirt: buy  $10/5 = 2$  and get  $3 \times 2 = 6$  utility (win!)**
  - Cup: buy  $10/2.5 = 4$  and get  $1 \times 4 = 4$  utility



## Examples: Supply-side fairness in economic market

- How can we prevent that “*the rich get richer*” **Through taxation!**
  - Bread: buy  $10/2 = 5$  and get  $0.5 \times 5 = 2.5$  utility
  - buy  $10/10 = 1$  and get  $3 \times 1 = 3$  utility
  - Cup: buy  $10/2.5 = 4$  and get  $1 \times 4 = 4$  utility (**win!**)



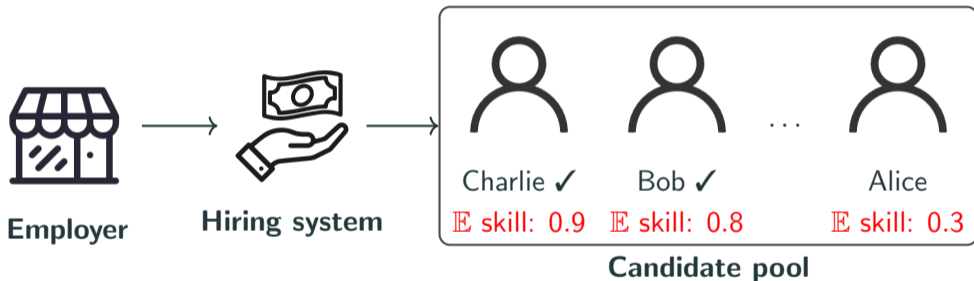
## Supply-side fairness vs. provider fairness

- Supply-side fairness vs. provider fairness [Xu et al., 2024]
- **Same goal:** increasing the exposures of poor providers/demanders
- **Similar tools:** taxation mechanism as learned fairness score

## **Case 2: An economic perspective on allocation scale**

## Example: Individual fairness in employment

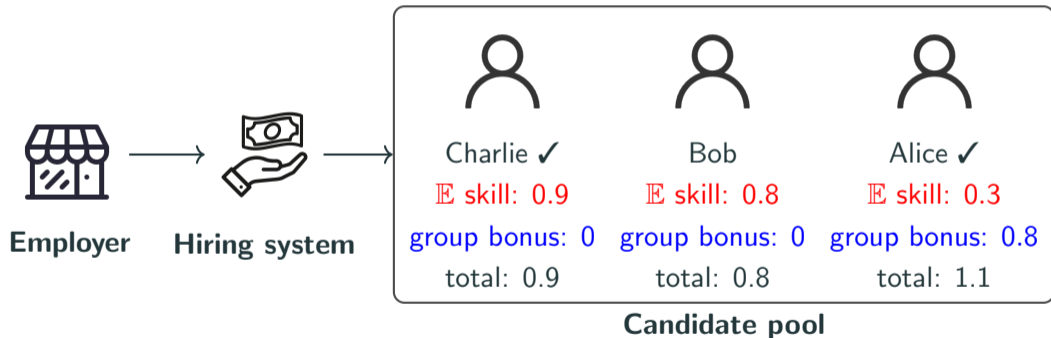
A firm wants to find the best hire, but cannot observe the candidates' *real* abilities



**Microeconomic principle:** Each person is evaluated on their expected marginal productivity; the firm applies statistical screening

## Example: Group Fairness in Employment

Optimality at the firm-level  $\neq$  aggregate optimality. Systemic discrimination means underemployment of the workforce!



**Macroeconomic principle:** System-level outcomes benefit from fairness

# The micro and macro dimensions are complementary

Economics addresses fairness through complementary frameworks:



**Microeconomics**  
Individual merit

+



**Macroeconomics**  
System outcomes

→



**Economic policy**  
Balanced approach

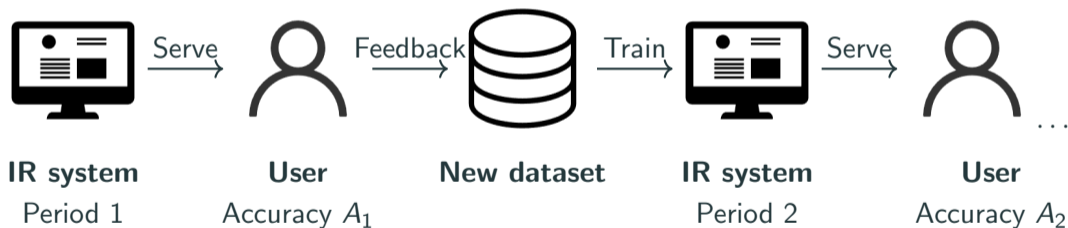
**Key economic frameworks that integrate these dimensions:**

- **Welfare economics:** Balance efficiency and fairness in resource allocation
- **Game theory:** Achieve fair outcomes in strategic interactions
- **Social choice theory:** Aggregate individual preferences into collective decisions

## **Case 3: An economic view on allocation time**

## Examples: Long-term fairness in IR

Multiple interactions between IR and users:



## Examples: Long-term fairness in IR

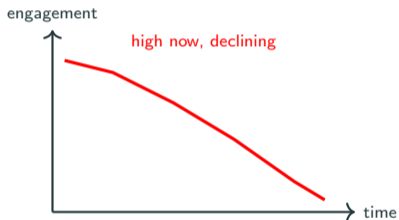
- User  $u$  long-term utility reward:  $R_u = A_1 + \gamma A_2 + \dots + \gamma^n A_n$
- Using reinforcement learning (RL) to balance the long-term user reward [Ge et al., 2021]



# Examples: Long-term fairness in economics

## Short-term focus

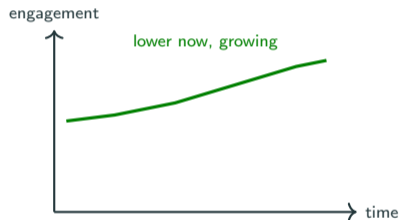
*"Consume now"*



- Maximise immediate clicks
- Providers crowd out
- Catalogue shrinks → fragility

## Long-term focus

*"Invest for the future"*



- Explore and diversify
- Providers stay viable
- Catalogue stays rich → resilience

*The discount rate  $\gamma$  determines where the platform sits between these two extremes.*

## Long-term fairness in economics vs. in IR

- **Same question:** How much do we sacrifice now for a better system later?
- In economics: the **social discount rate** is a policy choice that shapes investment in infrastructure, education, climate
- In IR: the **discount factor**  $\gamma$  is a design choice that shapes whether the platform invests in ecosystem health or optimises for immediate engagement
- **Same insight:** This is not a technical parameter; it is a fairness decision with long-term consequences

*Yuanna will develop the formal tools for this in Section 5 — including how homogeneity creates vulnerability to demand shocks, making fairness a form of risk management.*

## **Conclusion on an economic view on fairness in IR**

- Fairness in IR can be viewed as **how to allocate** limited exposure or relevance to competing stakeholders (users, providers, platforms).
- The **choice of allocation** approach shapes the corresponding fairness goals and techniques.

## 1. Scarcity and trade-offs

There is no free lunch. Every fairness intervention has a cost – the question is not *whether* to trade off, but how to minimise it.

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## 3. Incentive compatibility

The goal is not to enforce fairness top-down, but to design rules where doing the right thing is also the profitable choice. Fairness becomes self-sustaining.

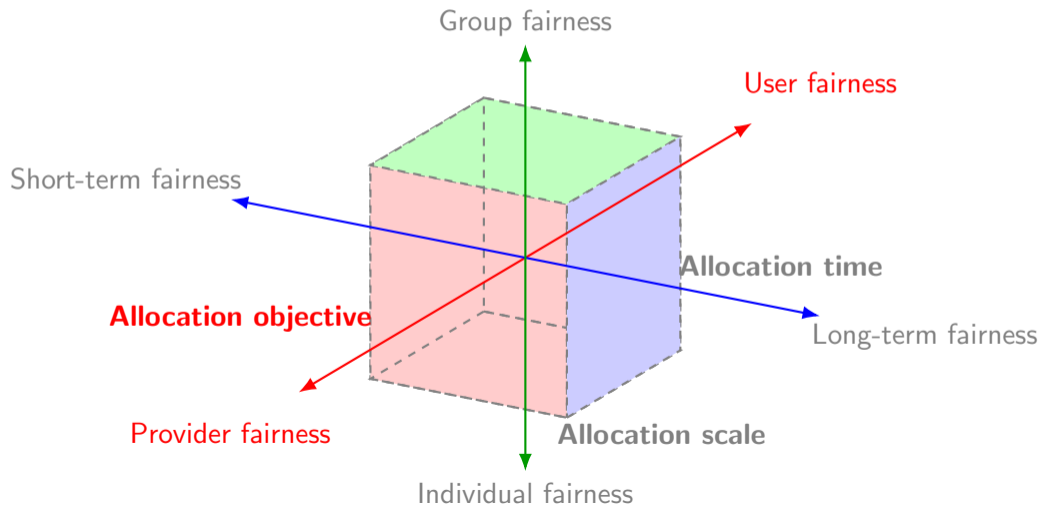
- Allocation **Object**: section 3
  - Economic tool: **Taxation** for provider and user fairness
  - Application used: Next basket recommendation
  - Future and related works to explore
- Allocation **scale**: Section 4
  - Economic tool: **Micro-macro economic theory** for individual and group fairness
  - Application used: Recruitment search systems
  - Future and related works to explore
- Allocation **time**: Section 5
  - Economic tool: **Risk theory** for short-term and long-term fairness
  - Application used: Connection recommendations
  - Future and related works to explore

### **3. Economic-based Fairness Mitigation and Evaluation Strategies I (Chen 30 min)**

---

# Allocation objective

- In this section, we focus on the **allocation objective**:



**Taxation inspired user & provider fairness**

- Assuming there are  $n$  users:  $\mathcal{U} = \{u_1, u_2, \dots, u_n\}$  arriving in IR systems

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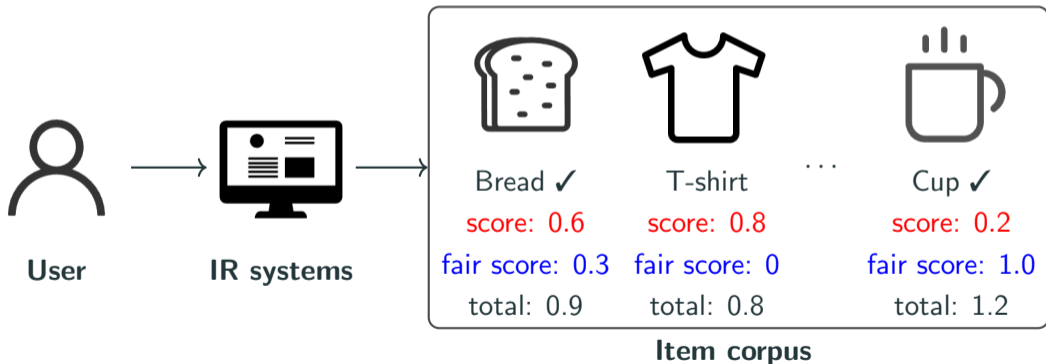
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- At each time  $t$ , the user  $u$  may input a query (search) or their profile (recommendation)  $u_t$  to the IR system.
- Then, the IR system  $f(\cdot)$  will score the item or document  $i \in \mathcal{I}$  according to user's preference:  $s_{u_t, i} = f(u_t, i)$

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- Finally, the system will generate a ranked list of size  $K$  with the highest ranking scores:

$$L_K(u_t) = \underset{S \subset \{1, 2, \dots, |\mathcal{I}|, |S|=K\}}{\operatorname{arg\,max}} \sum_{i \in S} s_{u_t, i}$$

## Recall: Fairness scoring approach

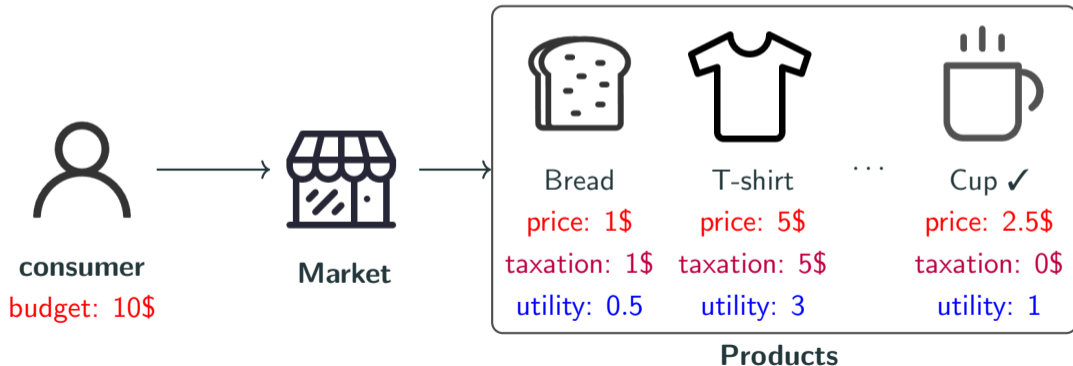
Most fairness-aware IR methods aim to utilize **fairness score**  $w_{u_t,i}$  to adjust the fairness degree of users and providers:  $s_{u_t,i} \rightarrow s_{u_t,i} + w_{u_t,i}$ .



## Taxation inspired fairness scoring

The fairness score  $w_{u_t, i}$  can be viewed as the **taxation value**.

We can analyze the methods according to the taxation perspective.



## Theory: taxation and fair re-ranking are equivalent

**Table 1:** Analogy between the economic market and the fair re-ranking market.

<b>Economic market</b>	<b>Fair re-ranking market</b>
Buying products ( <i>demand</i> )	Consuming attention ( <i>users</i> )
Producing products ( <i>supply</i> )	Producing attention ( <i>providers</i> )
Binding income	Limited attention
Taxation mechanism	Fairness function
Selling price	Re-ranking score
Seeking equilibrium	Optimizing re-ranking

## Theory: taxation and fair re-ranking are equivalent

### Theorem (Walrasian Equilibrium in Re-ranking)

Assuming  $r'(v)$  is convex, we have:

$$\max_{x_{u,i} \in \mathcal{X}} \sum_u w_u - r'(v) \iff \max_{x_{u,i} \in \mathcal{X}} \sum_u \sum_i (s_{u,i} - f_g^*) x_{u,i},$$

where  $\mathcal{X} = \{x_{u,i} \mid \sum_i x_{u,i} \leq K, x_{u,i} \in [0, 1]\}$

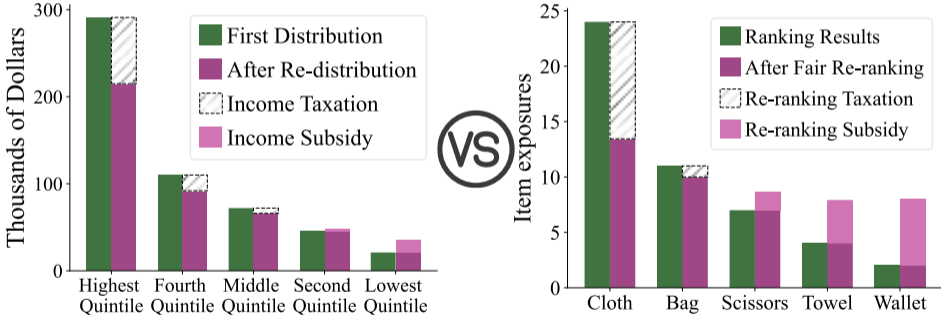
Moreover, assume that the price  $f_g^*$  is such that

$$\sum_g X_g^d(f_g^*) = \sum_g X_g^s(f_g^*) = |\mathcal{U}|K.$$

Then the allocation for demand and supply  $\{X_g^d, X_g^s\}$  is Pareto optimal.

# Taxation inspired fairness

Same goal: Balancing the utilities of providers and users [Xu et al., 2024].



### 1. Taxation provides a unified framework for provider and user fairness

- It helps move beyond piecemeal solutions by providing a coherent framework, making it easier to identify the strengths and limitations of existing methods.

### 2. Taxation inspires us to design better fairness-aware ranking models

- Taxation bridges economic fairness mechanisms with ranking systems, enabling principled, interpretable, and scalable solutions to fairness-aware IR.

# Provider fairness

# 1. Fixed taxation: Max-min fairness

- Aims to maximize the worst-off provider's utility (Minimum wage policy):

$$r(v_g) = \min v_g,$$

where  $v_g$  is the utility of provider  $g$  (provider  $g$  produces items  $i \in I_g$ ).

- Accuracy-Fairness trade-off:

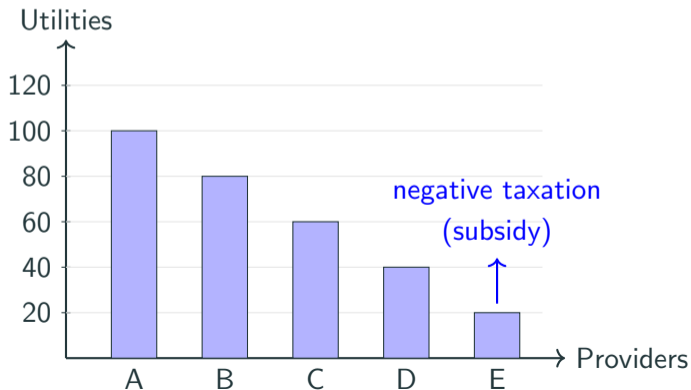
$$\max g(w_u) + \lambda r(v_g),$$

where  $g(w_u)$  is the utility of user-side and  $\lambda$  is the trade-off co-efficient

# 1. Fixed taxation: Max-min fairness

- From an economic perspective, the taxation rate will be:

$$w_{u,i} = \begin{cases} -\lambda, & \text{if } v_g \leq v_{g'}, \forall g' \in G \\ 0, & \text{else} \end{cases} \quad (1)$$



## 1. Fixed taxation: Max-min fairness

- To make such taxation efficient and effective in online scenarios, we design a dual-form gradient descent algorithm:

$$w_{u_t,i} = -\frac{\mathbf{A}^T \boldsymbol{\mu}_t}{s_{u_t,i}}, \text{ where } \boldsymbol{\mu}_t = \arg \min_{\boldsymbol{\mu} \in \mathcal{D}} \left[ \langle \mathbf{g}_t, \boldsymbol{\mu} \rangle + \eta \|\boldsymbol{\mu} - \boldsymbol{\mu}_{t-1}\|_{\gamma^2}^2 \right]$$

# 1. Fixed taxation: Max-min fairness

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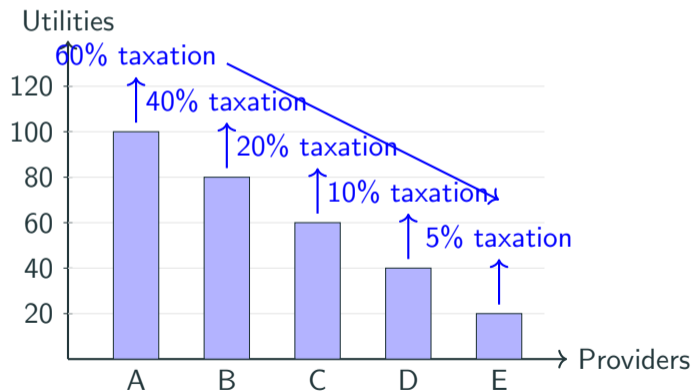
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- Problem 1: Focus only on the worst-performing suppliers, ignoring the long tail of **middle-tier suppliers**
- Problem 2: The tax function is **complex and discontinuous**, making it difficult to choose  $\lambda$

## 2. Progressive taxation: $\alpha$ -fairness

Progressive tax: the more exposure an item receives, the higher the tax rate:

$$w_{u,j} \propto v_g^t. \quad (2)$$



## 2. Progressive taxation: $\alpha$ -fairness

- Optimization problem:

$$\mathbf{x}^*(t) = \arg \max_{\mathbf{x} \in \mathcal{X}_s} f(\mathbf{x}; t) = \begin{cases} \sum_i \gamma_i \mathbf{v}_i^{1-t} / (1-t) & \text{if } t \geq 0, t \neq 1 \\ \sum_i \gamma_i \log(\mathbf{v}_i) & \text{if } t = 1 \end{cases}$$
$$\text{s.t. } \mathbf{v}_i = \sum_{u \in \mathcal{U}} w_{u,i} \mathbf{x}_{u,i}, \quad \forall i \in \mathcal{I}$$

- We utilize the optimal transportation (OT) to solve this:

$$\tilde{\mathbf{x}} = \arg \min_{\mathbf{x} \geq 0} \langle \mathbf{x}, -\mathbf{C} \rangle + \lambda_{ot} H(\mathbf{x}) \quad \text{s.t.} \quad \mathbf{x} \mathbf{1} = K \mathbf{1}, \quad \mathbf{1}^\top \mathbf{x} = \mathbf{e}^*,$$

## 2. Progressive taxation: $\alpha$ -fairness

- Problem 1: Suppliers vary in quality, and providing excessive preferential treatment to lower-quality suppliers may significantly harm user welfare.
- Problem 2: During optimization, the presence of exponentiation means that even very small errors can lead to large differences in the results (i.e., high variance).

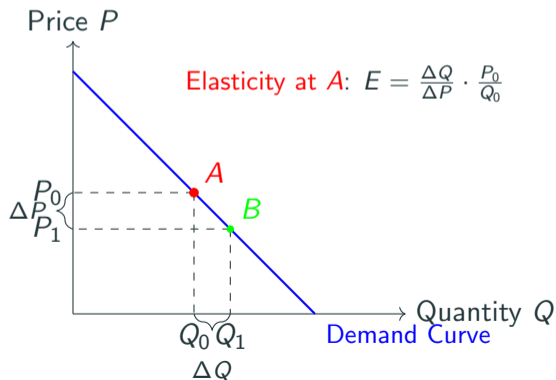
Chen Xu et al. A Taxation Perspective for Fair Re-ranking SIGIR 2024 **Best Paper Honorable Mention**

### 3. Elasticity-aware taxation: Elastic fairness

The taxation is proportional to **Price Elasticity of Demand**:

$$E = \frac{\% \text{ Change in Quantity}}{\% \text{ Change in Price}} = \frac{\partial Q/Q}{\partial P/P},$$

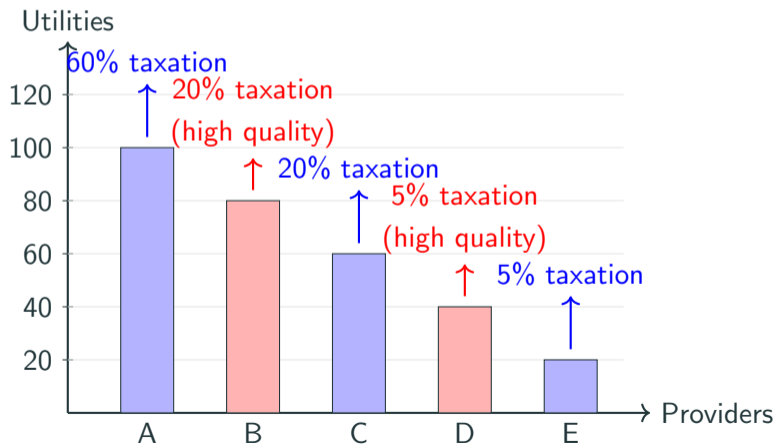
where  $Q$  is the purchase quantity of an item and  $P$  is the item price.



### 3. Elasticity-aware taxation: Elastic fairness

Elasticity tax: the higher the elasticity an item has, the higher the tax rate:

$$w_{u,i} \propto E_{i,*}. \quad (3)$$



### 3. Elasticity-aware taxation: Elastic fairness

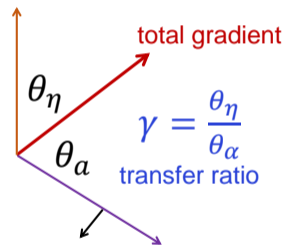
#### Theorem

The transfer ratio between fairness (commodity tax on groups) and accuracy (commodity tax transferred to users) is:

$$\gamma = \frac{\langle \nabla_{\mathbf{v}} L, \eta \rangle}{\langle \nabla_{\mathbf{v}} L, \alpha \rangle} = 1 - \frac{1}{1 + k(E_{r,p})},$$

$$k(E_{r,p}) = \frac{\sum_{p \in \mathcal{G}} \sum_{r \neq p} \mathbf{v}_p^{1-|t|} E_{r,p}}{\sum_{p \in \mathcal{G}} \mathbf{v}_p^{1-|t|}}$$

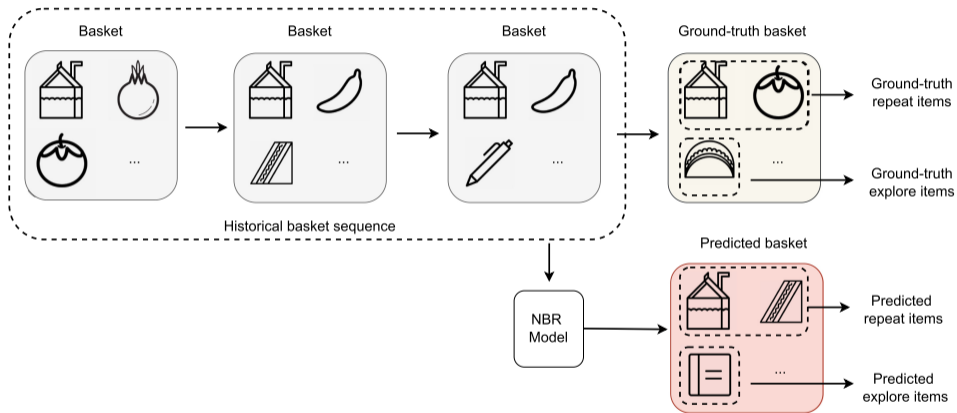
$\eta$ : fair gradient  
(commodity tax on item)



$\alpha$ : accuracy gradient  
(commodity tax on users)

**Application: Next basket recommendation**

# Next basket recommendation



- The predicted basket contains both repeat and explore items.

State-of-the-art NBR methods have heavy repeat bias. [Liu et al., 2025] jointly optimize item fairness and repeat bias via mixed-integer linear programming.

- Repeat-bias-aware item fairness optimization (RAIF):

$$\max \quad f(x) + \alpha g(x) - \lambda \text{RepRatio}(x)$$

## A taxation perspective on RAIF

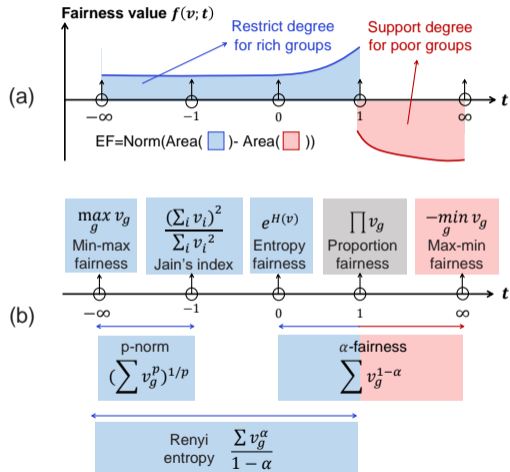
- Higher taxation rate  $\alpha$  on the unprotected group
- Another taxation rate  $\lambda$  on the repeated items

$$\max \quad f(x) + \alpha g(x) - \lambda \text{RepRatio}(x)$$

## Future and related work

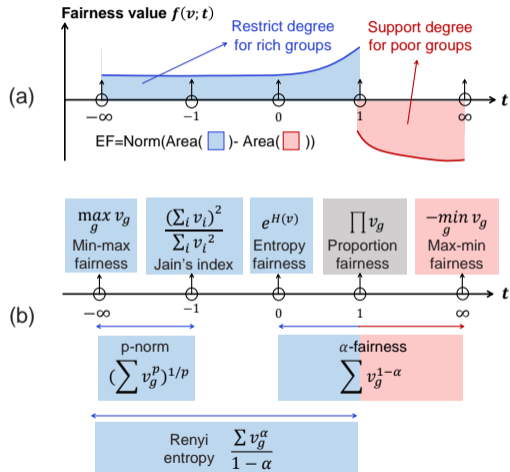
# Carefully choose fairness function

- Different fairness objectives **taxes** on different types of users/providers [Xu et al., 2025b]!



# Carefully choose fairness function

- Different fairness objectives **taxes** on different types of users/providers [Xu et al., 2025b]!
- Different fairness objectives **have** different taxation properties [Xu et al., 2024].



## 1. Evaluation metrics

- To measure algorithm convergence performance, we need to make sure the taxation policy (fairness objective) be same.
- To assess an algorithm's fairness, we should analyze the shifts in utility experienced by every user or provider, rather than only relying on a single overall metric.

## 1. Evaluation metrics

- To measure algorithm convergence performance, we need to make sure the taxation policy (fairness objective) be same.
- To assess an algorithm's fairness, we should analyze the shifts in utility experienced by every user or provider, rather than only relying on a single overall metric.

## 2. Evaluation properties

- Economic principles tell us that, beyond just looking at a single fairness metric, we also need to consider the inherent properties of fairness algorithms, such as continuity.

- Taxation can be regarded as a tool to theoretically analyze the **accuracy-fairness trade-offs** in IR [Xu et al., 2025b].

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- Taxation theory can inform real-world systems, suggesting the need for **mixed taxation policies** tailored to different applications.
- Inspired by taxation mechanisms, IR systems can **adopt diverse taxation strategies**—for instance, taxing user traffic to fund essential infrastructure and other foundational services.

Provider fairness:

- FairRec: Two-Sided Fairness for Personalized Recommendations in Two-Sided Platforms
- FairSync: Ensuring Amortized Group Exposure in Distributed Recommendation Retrieval

User fairness:

- User Fairness in Recommender Systems

Two-sided fairness:

- CPFair: Personalized Consumer and Producer Fairness Re-ranking for Recommender Systems
- Intersectional Two-sided Fairness in Recommendation

# Q&A



Website



Toolkit

Contact information: [chenxu0427ruc@gmail.com](mailto:chenxu0427ruc@gmail.com)

## Break (Coming Section 4-6)

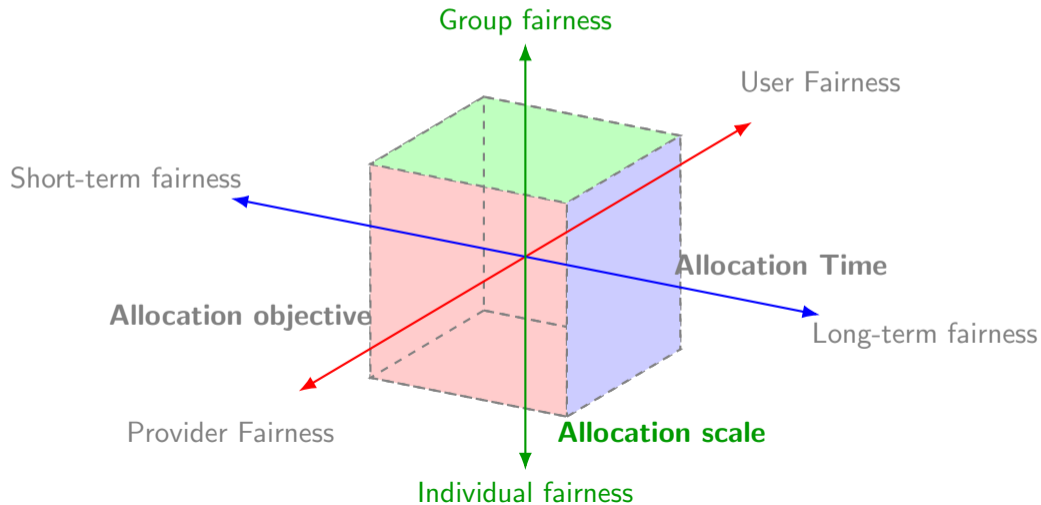
1. Introduction: Fairness in IR (Yuanna, 20 min)
2. An Economic View on Fairness in IR (Marleen, 30 min)
3. Economic-based Fairness Mitigation and Evaluation Strategies I (Chen 30 min)
4. Economic-based Fairness Mitigation and Evaluation Strategies II (Clara, 30 min)
5. Economic-based Fairness Mitigation and Evaluation Strategies III (Yuanna, 30 min)
6. Open Problems, Quick Start for Learning about Fairness, and Conclusions (Clara, 20 min)

**4. Economic-based Fairness  
Mitigation and Evaluation  
Strategies II (Clara, 30 min)**

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# Allocation scale

- In this section, we focus on **Allocation scale**



**Micro-macro economic inspired individual & group fairness**

**Individual fairness:** Individuals who are similar with respect to a particular task should receive similar outcomes [Dwork et al., 2012].

**Group fairness:** Members of different protected groups should be treated the same.

### **Economic parallel: Microeconomics vs. macroeconomics**

Economists have studied a similar dichotomy between local level optimization and aggregate level outcomes using micro- and macroeconomics.

- **Microeconomics** focuses on individual behavior and incentives
  - Individuals, firms, local optimization
  - Key idea: merit-based allocation (e.g. productivity → reward)
- **Macroeconomics** focuses on system-level outcomes
  - Aggregates, growth, stability, equity
  - Key Idea: optimize welfare, diversity

## Microeconomic approach

- **Individual Fairness:** Each person receives treatment based on their specific circumstances
- **Pareto Efficiency:** No individual can be made better off without making another worse off
- **Personalized Allocation:** Resources distributed based on individual merit/need

## Macroeconomic approach

- **Group Fairness:** Focus on aggregate outcomes of the system and across demographic groups
- **Distributional Justice:** Ensuring equal group-level statistical parity
- **Market Equilibrium:** Balancing overall system fairness

## What we gain from this economic lens

Often group and individual fairness are viewed as competing and independent goals.

**Economic view:** Individual decisions and behaviors (micro level) collectively shape system-wide outcomes (macro level), while macro-level conditions (such as inequality, growth, or systemic biases) in turn influence individual opportunities and choices.

**Can help understand the relationship between group and individual fairness.**

## How does this map to IR?

In IR, we have multiple **stakeholders**:

- **Users** - individuals with an information need (e.g. candidates, consumers).
- **Items** - entities being ranked/recommended (e.g. documents, products, **people**).
- **Providers** - parties offering or supplying items (e.g. companies, publishers).

**Individual fairness:** Similar users/items/providers should receive similar outcomes.

**Group fairness:** Groups of users/items/providers should receive proportional or equal outcomes.

## How does this map to IR?

**Individual fairness:** Similar users/items/providers should receive similar outcomes.

**Group fairness:** Groups of users/items/providers should receive proportional or equal outcomes.

- How to define similar outcomes in IR?
- How to define similar individuals? How to divide the groups?
- How to achieve group/individual fairness in IR and how does the economic view help?

Individuals who are similar with respect to a particular task should receive similar outcomes [Dwork et al., 2012].

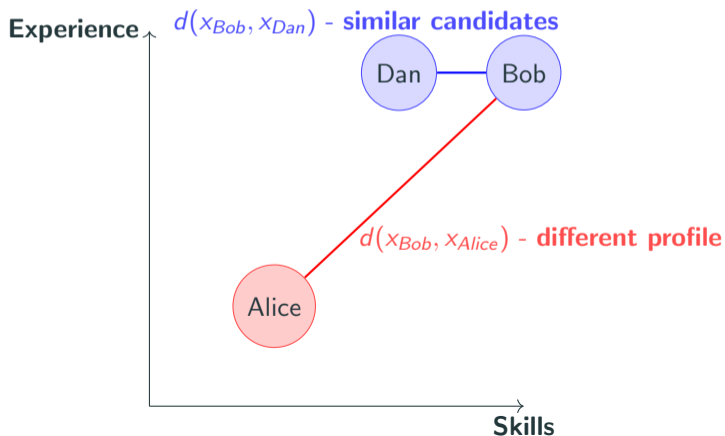
**Individual fairness in IR:** Similar users/items/providers should receive similar outcomes.

How to define similarity among individuals?

# Input Similarity

How to define **similarity** among individuals?

Input similarity is measured as the **distance** between individuals in the feature space.

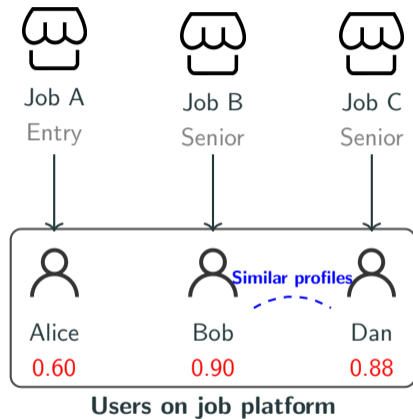


How to define similarity in the outcomes for individuals?

**Output similarity** is defined relative to each stakeholder's need:

- **Items:** similar items should get similar levels of exposure over time [Biega et al., 2018, Lahoti et al., 2019, Rus et al., 2024].
- **Users:** similar users should receive similar recommendations [Chawla and Jagadeesan, 2022].

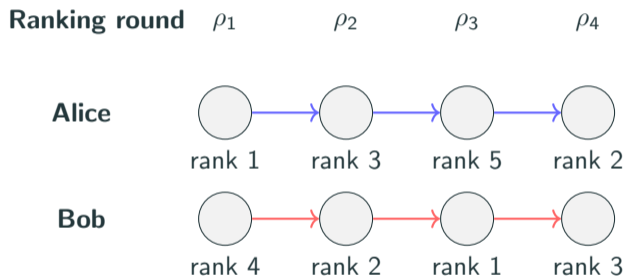
## Individual Fairness and Output Similarity: User



**Individual fairness:** Bob and Dan, with similar skill levels, should receive similarly senior-level job recommendations, unlike Alice.

## Output similarity: Items

Items should receive **similar levels of exposure** across time.



**Cumulative exposure**

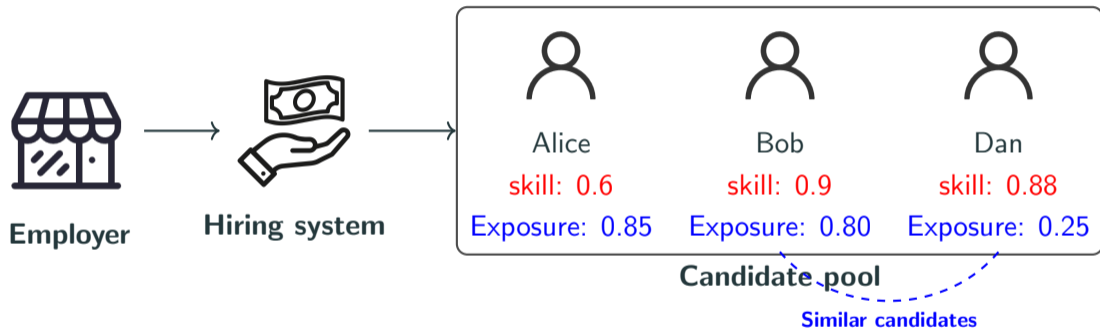
$$\sum_{t=1}^T \frac{1}{\log_2(\text{rank}_t+1)} \approx \text{equal for Alice and Bob}$$

An individually fair ranking system should give similar candidates similar exposure over time [Dwork et al., 2012, Lahoti et al., 2019, Rus et al., 2024].

$$|\text{Cumulative Exposure}(x_i) - \text{Cumulative Exposure}(x_j)| \leq L \cdot d_X(x_i, x_j)$$

- Cumulative Exposure( $x$ ): the attention or visibility individual  $x$  receives across time
- $d_X(x_i, x_j)$ : similarity metric between individuals (e.g., feature distance)
- $L$ : Lipschitz constant - controls how much exposure difference is allowed for a given dissimilarity

## Example: Individual fairness



**Fairness violation:** Bob and Dan have nearly identical skill levels, but Bob receives exposure similar to Alice.

## Achieving individual fairness: Lipschitz fairness constraint

- Define an **input similarity metric**  $d_X$  between individuals.
- Define an **output similarity metric**  $d_Y$  between individuals.
- Optimize the ranking function  $f(x)$  under fairness constraints  $g(x)$ .

$$\begin{aligned} \max \quad & f(x) \\ \text{s.t.} \quad & g(x) \leq c, \end{aligned}$$

where  $g(x)$  is defined as

### Lipschitz fairness constraint

$$d_Y(x_i, x_j) \leq L \cdot d_X(x_i, x_j) \quad \forall (x_i, x_j)$$

### Defining an input similarity function

- Requires a task-specific, ethically-grounded distance metric between individuals.
- In practice, it's difficult to know which features are truly “non-sensitive”.
- **Proxy problem:** Non-sensitive features may still encode sensitive information.
  - Example: years of experience could be a proxy to age or gender

**Consequence:** This definition of **individual fairness** requires strong assumptions and domain knowledge to avoid fairness-washing.

## A different view on individual fairness

**Goal:** Ensure that each individual receives attention proportional to their relevance over time [Biega et al., 2018, Singh and Joachims, 2018, 2019, Heuss et al., 2022].

### Equity of attention [Biega et al., 2018]

For each subject  $i$ , over a sequence of rankings  $\rho_1, \dots, \rho_m$ :

$$\frac{\sum_{\ell=1}^m a_i^\ell}{\sum_{\ell=1}^m r_i^\ell} = \text{constant}, \quad \forall i$$

- $a_i^\ell$ : attention (exposure) in ranking  $\rho_\ell$
- $r_i^\ell$ : relevance score in that round

Use integer linear programming (ILP) to generate a new ranking  $\rho_{\ell^*}$  that:

$$\begin{aligned} \min \quad & \sum_i |A_i - R_i| \\ \text{s.t.} \quad & \text{NDCG@k}(\rho^j, \rho^{j^*}) \geq c, \quad \forall j = 1, \dots, m \end{aligned}$$

where  $A_i$  and  $R_i$  are cumulative attention and relevance over  $m$  rankings ( $\rho$ ) for an individual

$$\text{NDCG@k}(\rho, \rho^*) = \frac{\text{DCG@k}(\rho^*)}{\text{DCG@k}(\rho)}$$

It is crucial to ensure that the utility or relevance function is **objective** and does not reinforce existing biases.

Members of different **protected groups** should be treated the same.

**Group fairness:** Groups of users/items/providers should receive proportional or equal outcomes.

## How to define the groups?

- **Protected attributes:** gender, race, age ...
- **Task-specific attributes:** seniority levels, job types, user tiers ...
- **Popularity:** popular vs niche items
- **Behavioral groups:** active vs. passive users, frequent vs. infrequent buyers ..

- **Multiple** attributes
- **Non-binary** groups
- **Intersectional** groups: Intersectional discrimination arises when an individual faces discrimination due to their **membership in multiple groups** at the same time [Wang et al., 2022, Gohar and Cheng, 2023].

# Intersectionality

Original

$\tau$
d
e
a
c
b
f
g
h
i

$\tau 1'$
d
e
c
h
i

Male White  
Female White  
Male Black  
Female black  
Female Asian

$\tau 1'$  - at least *two* candidates from each gender and *one* of each race group → *returns a candidate from the female, male, white and black group.*

Not all intersectional groups are present in the top  
→ *no representant from the Male Black group.*

Members of different protected groups should be treated the same.

- Demographic parity:

$$P(\hat{Y} = 1 \mid A = a) = P(\hat{Y} = 1 \mid A = b)$$

- Equal opportunity:

$$P(\hat{Y} = 1 \mid Y = 1, A = a) = P(\hat{Y} = 1 \mid Y = 1, A = b)$$

- Equalized odds:

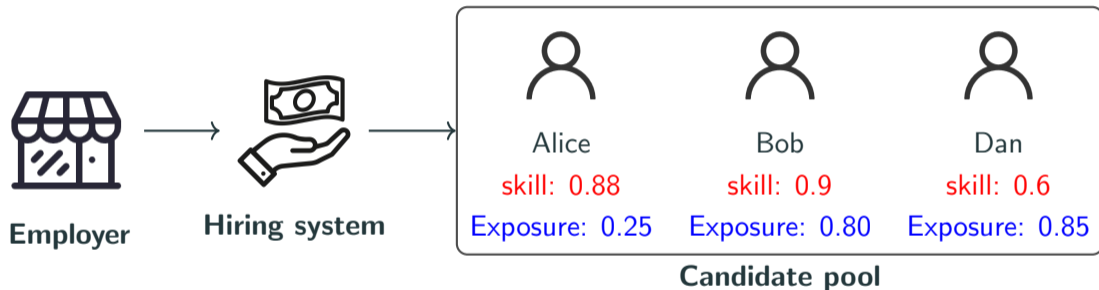
$$P(\hat{Y} = 1 \mid Y = y, A = a) = P(\hat{Y} = 1 \mid Y = y, A = b) \quad \text{for all } y \in \{0, 1\}$$

- **Items:** Groups of items should receive proportional/equal **exposure**.
- **Users:** Groups of users should receive **equal quality** of recommendations, ensuring no group is systematically disadvantaged.

- **Items:** Groups of items should receive proportional/equal **exposure**.
- **Users:** Groups of users should receive **equal quality** of recommendations, ensuring no group is systematically disadvantaged.

In this part we focus on the item side! Check out Economic-based Fairness Mitigation and Evaluation Strategies I (User Fairness)

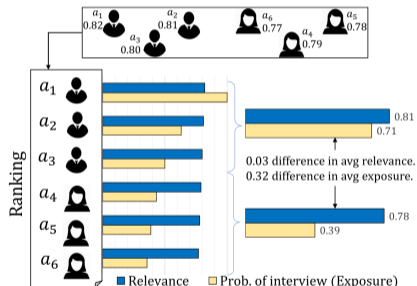
## Example: Group fairness



Even though Alice is more skilled than Dan, she receives lower exposure - ranking favoring one group in the top of the ranking.

## Group fairness in rankings

Small a difference in relevance can lead to a large difference in exposure (an opportunity) for the group of females [Singh and Joachims, 2018].



**Group fairness:** Members of different protected groups should receive similar/proportional exposure.

**Goal:** Generate a ranked list which balances utility and group fairness.

$$\begin{aligned} \max \quad & f(x) \\ \text{s.t.} \quad & g(x) \leq c, \end{aligned}$$

where  $g(x)$  is the fairness constraint and  $f(x)$  is the ranking function.

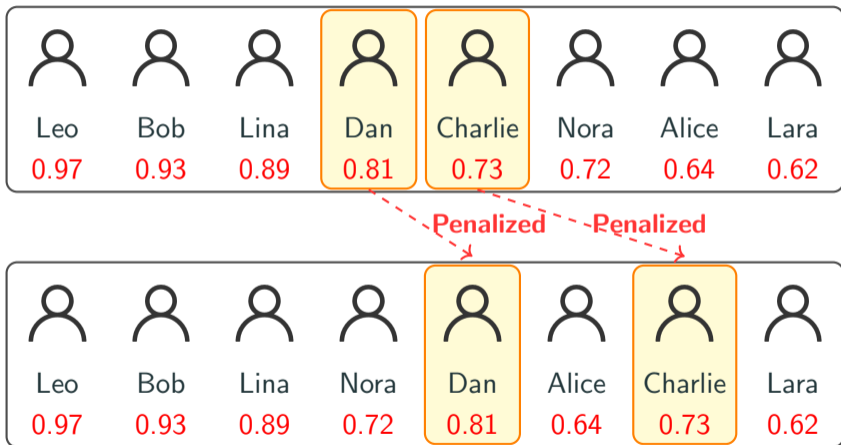
**Fairness constraint:** At each position  $i$  in the top- $k$  list, the number of protected candidates should be at least as high as the expected number in a fair distribution.

### Approach:

- Create a ranked list for each protected and non-protected group.
- At each position  $i$ , if the current ranking has fewer protected candidates than the lower bound  $\Rightarrow$  select next most relevant protected candidate.
- Otherwise, select next most relevant candidate (protected or not).

## Example: Group fairness vs. individuals

### Candidate ranking



Group fair constraint: have at least  $k/2$  individuals of each gender in top- $k$  ( $k \geq 3$ )

**Challenge:** Enforcing group-fairness often hurts high-scoring individuals.

**Goal:** Minimize the amount of individual unfairness when enforcing group fairness [García-Soriano and Bonchi, 2021].

**Approach:** Rawls's theory of justice [John et al., 1971] – arranging social and financial inequalities to the benefit of the worst-of.

$$\begin{aligned} \max_P \quad & \min_{u \in \mathcal{U}} \mathbb{E}_{r \sim P} [V(r, u)] \\ \text{s.t.} \quad & \mathbb{E}_{r \sim P} [g(r)] \leq c \end{aligned}$$

where  $P$  is a probability distribution over rankings.

$V(r, u)$  is the received utility of individual  $u$  in ranking  $r$ ,

and  $g(r)$  is the fairness constraint applied to ranking  $r$ .

## Individual fairness under group-fairness constraint

**Deterministic group fairness ranking:**

$r' = \langle \text{Leo, Bob, Lina, Nora, Dan, Alice, Charlie, Lara} \rangle$

**Worst-off utility:**  $V(r, \text{Charlie}) = -2$

**Probability Distribution over Fair Rankings ( $P$ ):**

$r_1 = \langle \text{Leo, Dan, Lina, Lara, Bob, Nora, Charlie, Alice} \rangle$   $\mathbb{P}(r_1) = \frac{1}{4}$

$r_2 = \langle \text{Bob, Leo, Lina, Nora, Dan, Alice, Lara, Charlie} \rangle$   $\mathbb{P}(r_2) = \frac{1}{2}$

$r_3 = \langle \text{Bob, Leo, Lina, Lara, Charlie, Nora, Dan, Alice} \rangle$   $\mathbb{P}(r_3) = \frac{1}{16}$

$r_4 = \langle \text{Charlie, Leo, Lina, Lara, Bob, Nora, Dan, Alice} \rangle$   $\mathbb{P}(r_4) = \frac{3}{16}$

**Worst-off expected utility:** all users have  $\mathbb{E}[V(r, u)] \geq -0.75$

## Individual fairness (micro view)

- Focus on **pairwise treatment** of individuals.
- Ensures **similar individuals** receive **similar outcomes**.

$$|\text{Exposure}(i) - \text{Exposure}(j)| \cdot \frac{1}{d_X(i,j)} \leq c$$

**Economic view:** Like microeconomics, focusing on individual outcomes.

## Group fairness (macro view)

- Focus on **aggregated outcomes** across groups.
- Ignores within-group differences.

$$\left| \frac{1}{|G_a|} \sum_{i \in G_a} \text{Exposure}(i) - \frac{1}{|G_b|} \sum_{i \in G_b} \text{Exposure}(i) \right|$$

**Economic view:** Like macroeconomics, focusing on group-level outcomes.

## How is this useful?

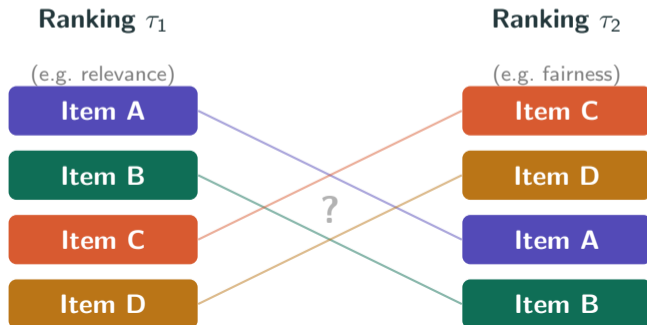
The economic perspective offers new approaches to fairness by drawing connections between individual and group-level concerns.

By adopting this economic view, we can better understand the **trade-offs** between group and individual fairness and design fairness-aware systems that account for both levels simultaneously.

## Social choice for fairness in recommendation

For example, recent work [Aird et al., 2023, 2024a,b, Sonboli et al., 2020] uses **social choice theory**, which formalizes how to aggregate individual preferences into collective decisions.

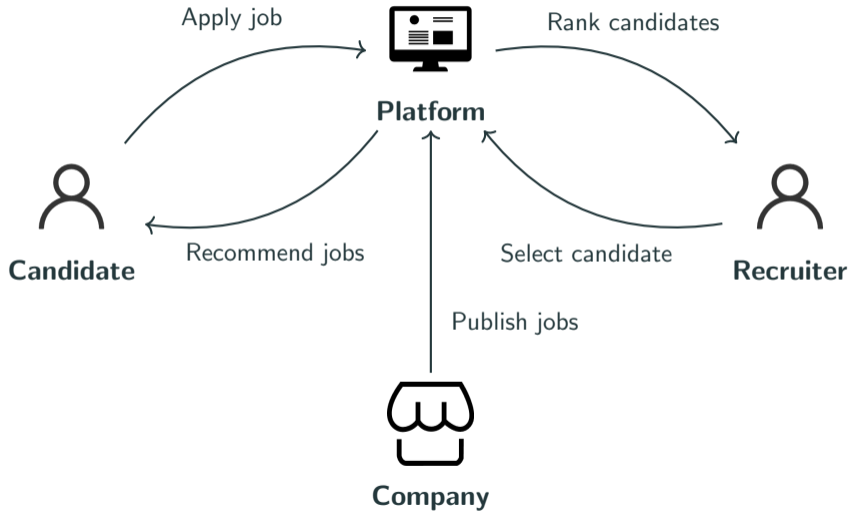
**Approach:** Fairness concerns and individual preferences are represented as agents which interact through social choice.



- The recommendation system is modeled as a **multi-agent system** with two types of agents:
  - **User agents:** Represent individual user preferences.
  - **Fairness agents:** Represent different fairness principles (e.g., exposure parity, diversity) and can evaluate or re-rank recommendations for fairness.
- **Stage 1: Allocation of fairness agent** When a user arrives, a suitable fairness agent (or multiple) is assigned to the user.
- **Stage 2: Aggregation** Lists from user agents and fairness agents are aggregated via a **social choice rule** (e.g., Borda Count).

**Application: Recruitment search systems**

# Recruitment system



- Groups of candidates defined by protected attributes are often subject to discrimination in the interaction with the:
  - **platform**: not being exposed to well-paid jobs [Rus et al., 2022]
  - **recruiter**: not being in the top-k of the list, thus not being selected for an interview

Most existing approaches focus on **group fairness**, often ignoring individual qualifications and needs. This can unintentionally amplify existing stereotypes and biases.

**Economic tools:** Leverage **social choice theory** to incorporate individual qualifications while achieving group-fair outcomes.

## Future and related work

- **Individual fairness** remains under-explored compared to group fairness.
- **Group fairness** approaches typically focus on a single binary protected attribute.
- The relationship and trade-offs between **group fairness** and **individual fairness** need further investigation.
- Adopting an **economic perspective** (e.g., micro- and macroeconomics, social choice theory) can provide new insights and solutions.

### Individual fairness

- [Evaluation Measures of Individual Item Fairness for Recommender Systems: A Critical Study](#)
- [Fair Ranking as Fair Division: Impact-Based Individual Fairness in Ranking](#)
- [Operationalizing Individual Fairness with Pairwise Fair Representations](#)

### Group fairness:

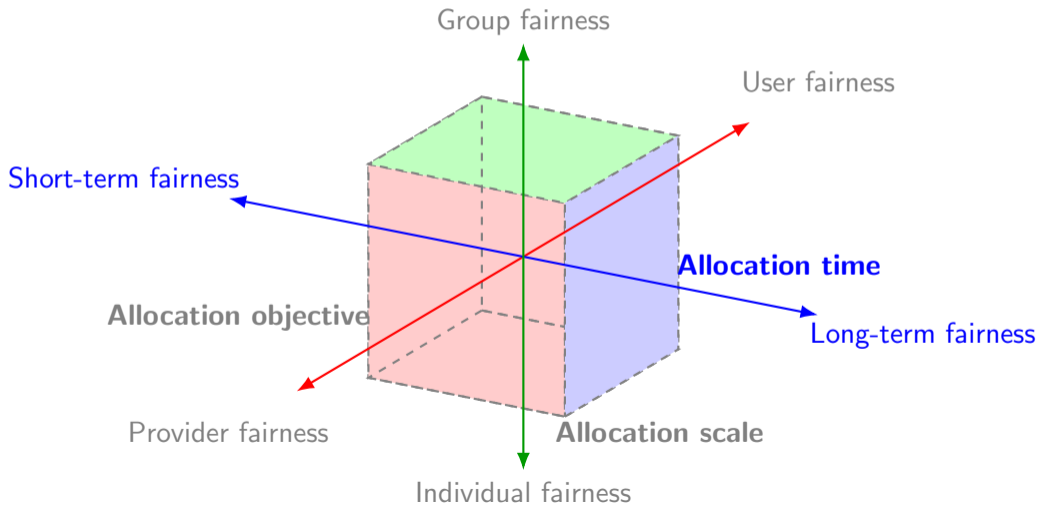
- [Fair Top-k Ranking with multiple protected groups](#)
- [Balanced Ranking with Diversity Constraints](#)
- [Causal Intersectionality for Fair Ranking](#)

**5. Economic-based Fairness  
Mitigation and Evaluation  
Strategies III (Yuanna, 30 min)**

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# Allocation time

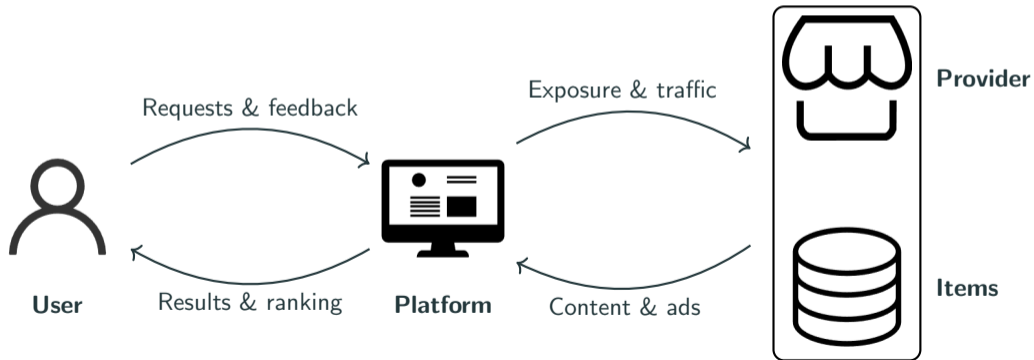
- In this section, we focus on **allocation time**



**Dynamic allocation inspired short & long-term  
fairness**

## Dynamic interactions among stakeholders in IR

- **User, platform, items** and **provider** form a dynamic ecosystem [[Abdollahpouri and Burke, 2019](#)].
- Maintaining fairness for each of the changing stakeholders.



- Short-term fairness (static fairness): most of work are situated in a **static** or one-shot setting, and the model provides a **one-time fairness solution** based on fairness-constrained optimization.

- Short-term fairness (static fairness): most of work are situated in a **static** or one-shot setting, and the model provides a **one-time fairness solution** based on fairness-constrained optimization.
- Long-term fairness (dynamic fairness): due to the dynamic nature of IR systems, **attributes of each stakeholder** will change over time.
  - **Users** & user preference shift
  - **Ranking model** in the feedback loop
  - **Item** popularity, rating, content information, stock availability
  - **Provider** behavior

## Formulation of long-term fairness in IR

Optimize ranking model and maintain the fairness constraint during time period  $t = 1, 2, \dots, T$ .

$$\max \sum_t \gamma_r^t f(x) \rightarrow \text{accumulated reward w/ time discount}$$

$$\text{s.t.} \sum_t \gamma_c^t g(x) \leq c \rightarrow \text{accumulated fairness-related variable w/ time discount}$$

or

$$\max \sum_t (\gamma_r^t f(x) + \lambda (\gamma_c^t g(x))),$$

where  $f(x)$  is the ranking utility function and  $g(x)$  is the fairness-related function;  $\gamma_r^t, \gamma_c^t \in [0, 1]$  are time discount rate.

## Economic Intuition

Platforms must balance **immediate utility** vs. **long-term fairness**

### Short-term Focus:

- Maximize current engagement
- Show popular/relevant items
- High immediate utility

### Long-term Focus:

- Maintain fair exposure
- Include diverse/niche items
- Sustainable ecosystem

## Ranking optimization through economic time discounting

An [economist](#) would see this as a **dynamic optimization problem**:

The platform chooses ranking  $r_t$  at each time  $t$  so that it is maximizing expected utility of the platform's engagement  $E$  over time:

$$\max_{r_t} \mathbb{E} \left[ \int_0^T \underbrace{e^{-\rho t}}_{\text{Discount factor}} u(E_t) dt \right]$$

A higher discount rate  $\rho$  reflects a stronger preference for immediate engagement and utility over long-term outcomes.

## Platform-specific calibration: Tunable Discount Rates

The discount rate  $\rho$  in our optimization framework can be **adjusted based on platform priorities**:

$$\max_{r_t} \mathbb{E} \left[ \int_0^T e^{-\rho t} u(E_t) dt \right]$$

- **High**  $\rho$ : Short-term focused platforms (startups, growth phase)
  - Prioritize immediate engagement and user acquisition
  - Accept higher long-term fairness risks
- **Low**  $\rho$ : Long-term focused platforms (established, regulated)
  - Emphasize sustainable ecosystem health
  - Invest more in fairness and diversity

## Engagement can be modeled as an uncertain time process

The platform's **engagement**  $E_t$  can be modeled as a **dynamic process** dependent on the platform's rankings and fairness.

$$\Delta E_t = f(r_t)\Delta t - \beta g(\mathbf{r})\xi_t\Delta t$$

- $f(r_t)$  is the immediate engagement outcome of ranking  $r_t$
- $g(\mathbf{r})$  is the platform's fairness policy
- $\xi_t$  is a random demand shock that can be positive or negative.

An unfair platform becomes more homogeneous and is therefore more vulnerable to shocks in consumer demand. This threatens *long-term* engagement of the platform.

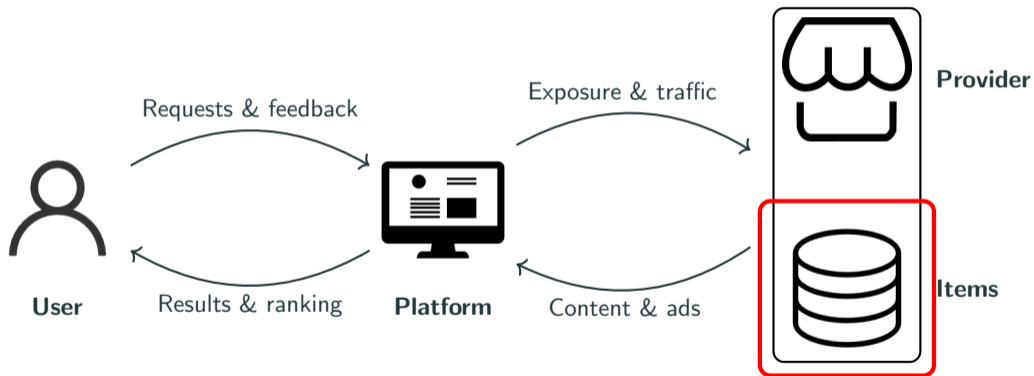
## What we gain from this economic lens:

- The discount rate  $\rho$  reflects the 'impatience' of the platform. A higher  $\rho$  prioritizes immediate utility, while a lower  $\rho$  promotes long-term fairness and sustainability.
- Future engagement depends on both current rankings and long-term fairness, due to vulnerability to demand changes.
- By summing over (discounted) future rewards, resilience of the platform is naturally taken into account.

Long-term fairness methods that specifically model dynamic attributes of each stakeholder:

- **Item** popularity
- Performance disparity between **user** groups
- **Ranking model** in the feedback loop
- **Provider** behavior

## Long-term fairness in IR: Item popularity

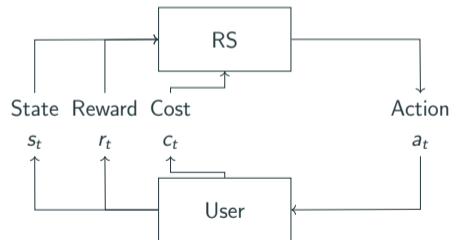


## Long-term fairness in IR: Item popularity

In the dynamic recommender systems, **item popularity** may change over time due to the recommendation policy and user engagement [Ge et al., 2021].

Target: maintain long-term fairness of item exposure with **changing group labels**.

- Problem formulation: Constrained Markov decision process
  - State  $\mathcal{S}$ : user features (e.g., user's recent click history)
  - Action  $\mathcal{A}$ : recommendation list
  - Reward  $\mathcal{R}$ : user feedback, i.e., click, purchase
  - Cost  $\mathcal{C}$ : the number of recommended items that come from popular group
  - Discount rate of reward  $\gamma_r$ ; discount rate of cost  $\gamma_c$ .

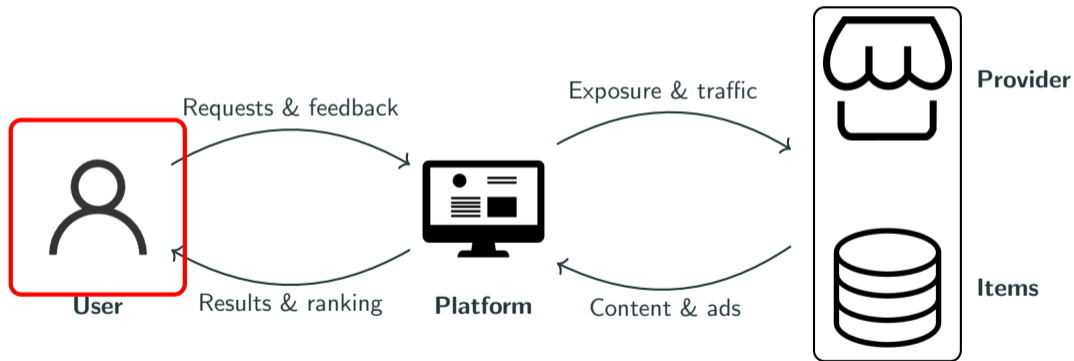


- Fairness constrained policy optimization (FCPO)

$$\begin{aligned} & \max_{\pi} J_R(\pi) \\ & \text{subject to } J_C(\pi) \leq d \end{aligned}$$

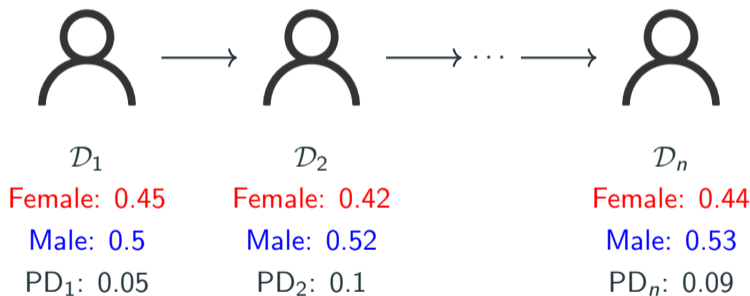
- Cumulative reward  $J_R(\pi)$
- Cumulative cost  $J_C(\pi)$
- Limit  $d$ : the limit is computed by fairness constraints  $\frac{\text{Exposure}_t(G_0)}{\text{Exposure}_t(G_1)} \leq \alpha$
- Aim to learn a policy  $\pi$  that maximizes reward while satisfying the fairness constraint.

# Long-term fairness in IR: User fairness



## Long-term fairness in IR: User fairness

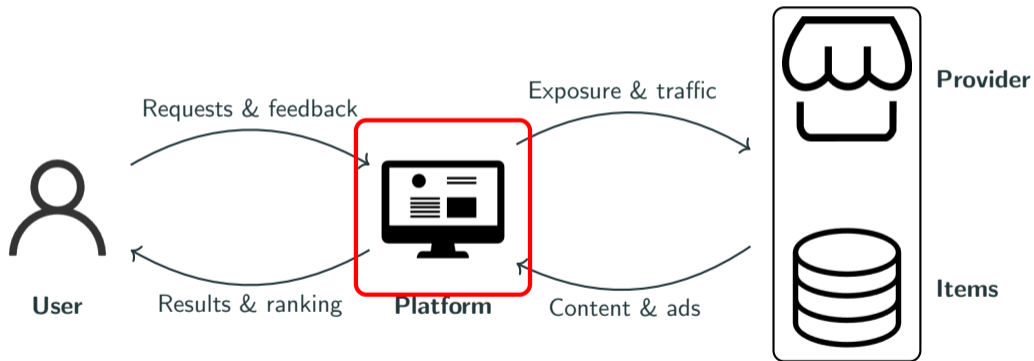
Neglecting user fairness during dynamic adaptation leads to **performance disparity** between user groups persisting or even expanding over time [Yoo et al., 2024].



- Performance disparity:  $PD_t = \text{Perf}(\mathcal{D}_t^{\text{test}}|\text{male}) - \text{Perf}(\mathcal{D}_t^{\text{test}}|\text{female})$

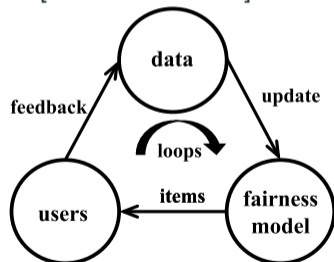
- Problem formulation: incremental fine-tuning
- FAir Dynamic rEcommender (FADE) fine-tunes the model parameters incrementally over time only with the new data  $\mathcal{D}_t$ .
- **Loss:**  $\mathcal{L}^{\mathcal{D}_t} = \mathcal{L}_{\text{rec}}^{\mathcal{D}_t} + \lambda \mathcal{L}_{\text{fair}}^{\mathcal{D}_t}$ 
  - $\mathcal{L}_{\text{rec}}^{\mathcal{D}_t}$  uses BPR loss
  - $\mathcal{L}_{\text{fair}}^{\mathcal{D}_t}$  is computed based on differentiable Hit (DH).
  - Model update:  $\mathcal{W}_t := \mathcal{W}_t - \eta \nabla_{\mathcal{W}_t} (\mathcal{L}_{\text{rec}}^{\mathcal{D}_t} + \lambda \mathcal{L}_{\text{fair}}^{\mathcal{D}_t})$

## Long-term fairness in IR: RS model in feedback loop



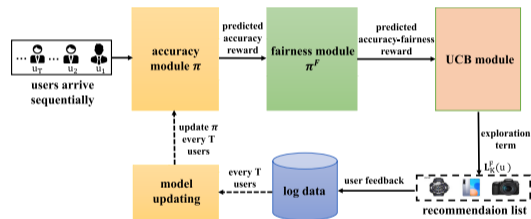
**Recommendation feedback loops** (RFL) will influence the provider Max-Min Fairness in the long term since RS can only receive feedback on exposed items, while **unexposed items** are considered as negative samples [Xu et al., 2023b].

- Problem formulation: Repeated resource allocation problem under batched bandit setting

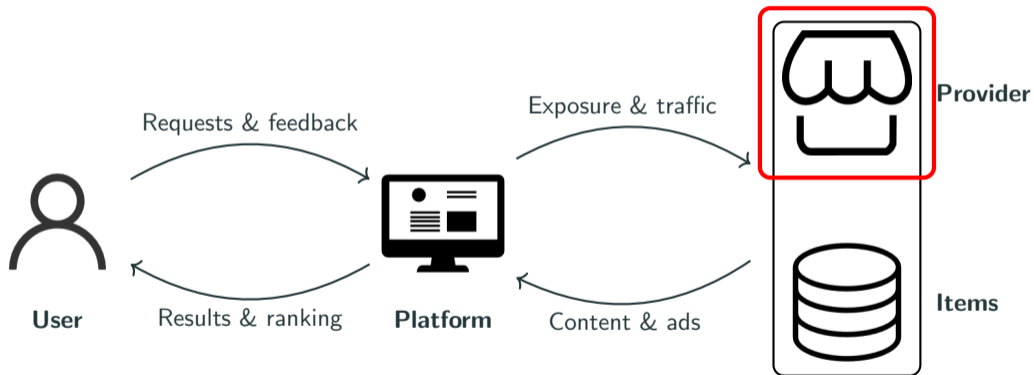


# Long-term fairness in IR: RS model in feedback loop

- LTP-MMF: for a batch of users, **accuracy-fairness-exploration score**:  
 $R = f(x) + \lambda g(x) + e(u, i)$ .  
Then, collect users' feedback to update accuracy module.
- UCB module: explores the feedback of unexposed items.

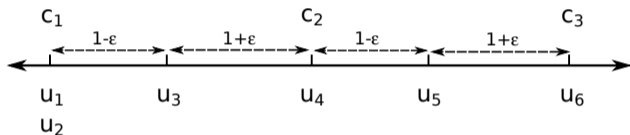


# Long-term fairness in IR: Provider behavior



## Long-term fairness in IR: Provider behavior

Content providers cannot **remain viable** unless they receive a certain level of user engagement. Myopic policies often drive the dynamical system to a poor equilibrium, with low user social welfare and poor provider diversity [Mladenov et al., 2020].



$$\epsilon < 0.5, v_c = 2$$

### Myopic policy

- $C_1$  :  $u_1, u_2, u_3$
- $C_2$  :  $u_4, u_5$
- $C_3$  :  $u_6 \Rightarrow c_3$  quit
- future reward:  $8 + 2\epsilon$

### Long-term policy

- $C_1$  :  $u_1, u_2$
- $C_2$  :  $u_3, u_4$
- $C_3$  :  $u_5, u_6$
- future reward:  $10 - 2\epsilon$

- Problem formulation: epoch-based optimal constrained matching problem

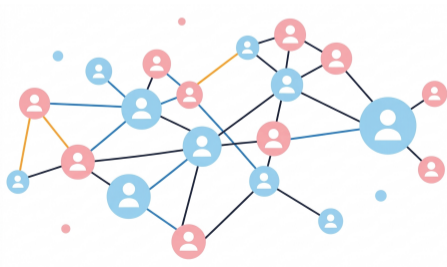
$$\begin{aligned} \max_{\pi} \quad & \sum_{u \in \mathcal{U}} f(u|\pi) \\ \text{s.t.} \quad & g(c) \geq v_c, \forall c \end{aligned}$$

- objective: maximize social welfare (user utility) over the epoch
- constraint: ensure that any matched provider remains viable

## **Application: Connection recommendation**

## People you may know

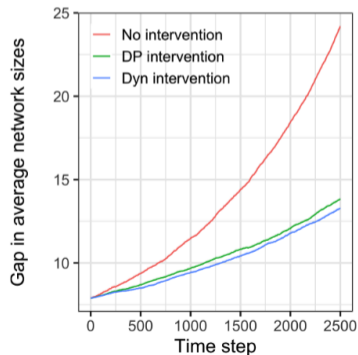
- Real-world connection recommendation systems are dynamic systems with feedback loops. Recommendations alter users' social graphs and influence future recommendation strategies [Akpinar et al., 2022].
- **Questions:**
  - What consequences and side effects can result from ignoring fairness interventions?
  - In the long run, are existing fairness interventions truly effective?



# Rich get richer



- 65% male vs. 35% female
- No intervention
- Destination-side interventions:
  - Demographic parity of exposure (DP)
  - Dynamic parity of utility (Dyn)



- Only applying fairness interventions on the destination side (i.e., list of recommended people) fails to prevent the long-term amplification of inequality.

- Only applying fairness interventions on the destination side (i.e., list of recommended people) fails to prevent the long-term amplification of inequality.
- **Source-side bias:**
  - Initial differences in the distributions of users' similarity and their number of common connections
  - Users with larger networks are served connection recommendations more frequently, and are more likely to form connections

## Future and related work

All these long-term fairness works update RS model and consider the dynamic change of a certain stakeholder.

- Long-term fairness requires additional algorithm designs to maintain the sustainability of the system.
- Long-term fairness algorithms can draw on tools such as **dynamic optimization** in economics.
- How to model/simulate the changes of **multi-stakeholders**?
- How to use **LLM-powered agent** to simulate the long-term behavior of each stakeholder?

RS model in feedback loop:

- [Controlling Fairness and Bias in Dynamic Learning-to-Rank](#)
- [Maximizing Marginal Fairness for Dynamic Learning to Rank](#)

Provider behavior:

- [CreAgent: Towards Long-Term Evaluation of Recommender System under Platform-Creator Information Asymmetry](#)

Survey:

- [Long-Term Fairness Inquiries and Pursuits in Machine Learning: A Survey of Notions, Methods, and Challenges](#)

**6. Open Problems, Quick Start for  
Learning about Fairness, and  
Conclusions (Clara, 20 min)**

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# Open problems

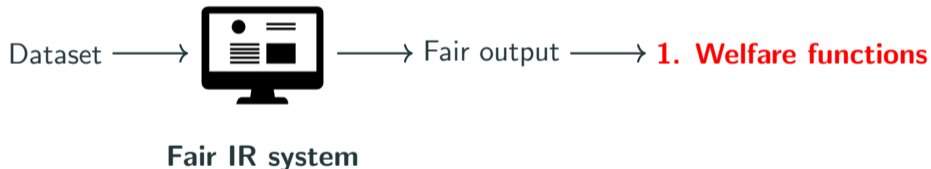
- Economics suggests future directions for fairness-aware IR
- Three levels of fairness [Rosenfeld and Xu, 2025]:
  - **Level-1:** Designing fair welfare functions (most papers)
  - **Level-2:** Incorporating platform Policies (few papers)
  - **Level-3:** Considering user/provider choices (few papers)

Adjust IR systems to meet fairness requirements!



## Level 1: Designing a fair welfare function

- **Level-1:** How to design a better welfare evaluation function?



## Level 1: Designing a fair welfare function

**Objective: Can we design a unified fair welfare function for stakeholders?**

- For **single** stakeholder (user, provider) [Xu et al., 2025b]
- For **multi-sided** stakeholders

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**Scale: Can we design a unified fair aggregation function?**

- **Single** layer aggregation (time, category)
- **Hierarchical** aggregation

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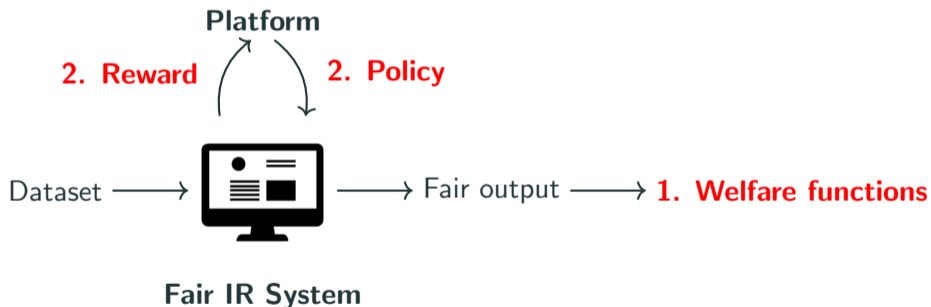
- **Single** layer aggregation (time, category)
- **Hierarchical** aggregation

**Time: Can we design a unified long-term fair function?**

- **Accumulated** fairness constraint

## Level 2: Incorporating platform Policies

- **Level 2:** Incorporating platform policies: from **predictions** to **actions**



**Objective: Platform needs adapt different policy for stakeholders**

- Incorporating platform and user/provider objectives

## Level 2: Incorporating platform policies

**Objective: Platform needs adapt different policy for stakeholders**

- Incorporating platform and user/provider objectives

**Scale: Platform policy influences different scales of stakeholders**

- **Simulating and modeling** different scale of stakeholders

## Level 2: Incorporating platform policies

**Objective: Platform needs adapt different policy for stakeholders**

- Incorporating platform and user/provider objectives

**Scale: Platform policy influences different scales of stakeholders**

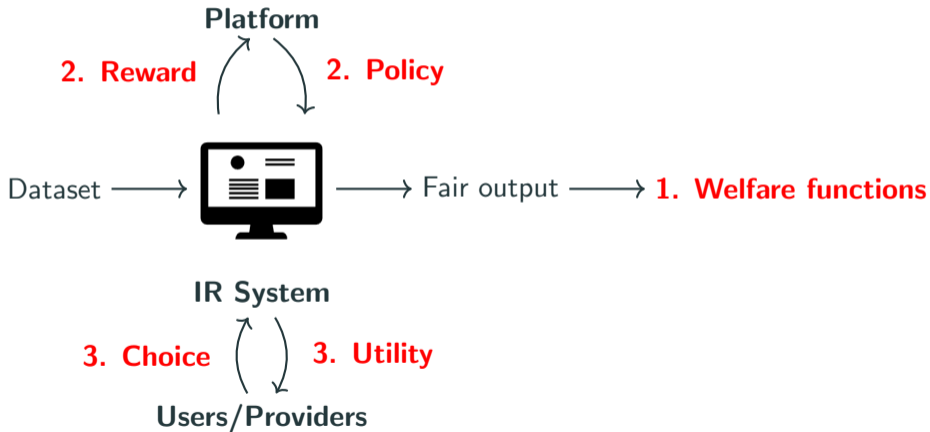
- **Simulating and modeling** different scale of stakeholders

**Time: Platform policy will influence both short and long-term fairness**

- **Simulating and modeling** the change of platform policy

## Level 3: Considering user/provider choices

- **Level 3:** User and provider are rational: change action according to utilities



## Level 3: Considering user/provider choices

### **Objective: Objective needs to consider user/provider's choice**

- Game theory-inspired fairness objective for users/providers

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### **Objective: Objective needs to consider user/provider's choice**

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### **Scale: Different scale stakeholders make different choice**

- **Micro**-individual behavior patterns
- **Macro**-group behavior patterns

## Level 3: Considering user/provider choices

### **Objective: Objective needs to consider user/provider's choice**

- Game theory-inspired fairness objective for users/providers

### **Scale: Different scale stakeholders make different choice**

- **Micro**-individual behavior patterns
- **Macro**-group behavior patterns

### **Time: Choices of users and providers evolve over time**

- Fairness **equilibrium** remains stable and aligned with the predefined objectives

# Quick start for learning about fairness in IR

- We have developed an easily-usable toolkit *FairDiverse* [Xu et al., 2025a] for learning about fairness in IR
- GitHub: <https://github.com/XuChen0427/FairDiverse>

- We have developed an easily-usable toolkit *FairDiverse* [Xu et al., 2025a] for learning about fairness in IR
- GitHub: <https://github.com/XuChen0427/FairDiverse>
- Advantages
  - Contains **29** fairness algorithms across **16** base models for two fundamental IR tasks – search and recommendation
  - Contains **tens of fairness datasets** for fairness tasks
  - Offers **multiple APIs** (such as evaluation metrics) to enable IR researchers to quickly develop their own fairness IR models

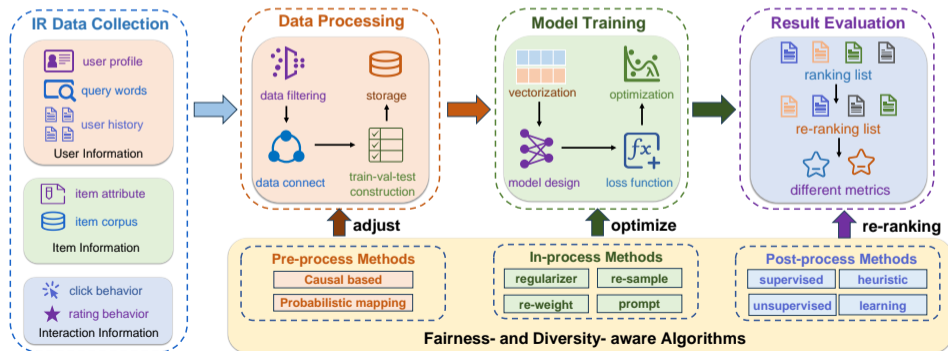
## Existing toolkits

Comparison of **FairDiverse** with existing toolkits:

Features	<i>RecBole</i>	<i>FFB</i>	<i>Fairlearn</i>	<i>AIF360</i>	<i>Aequitas</i>	<b><i>FairDiverse</i></b>
Recommendation	✓	✗	✗	✗	✗	✓
Search	✗	✗	✗	✗	✗	✓
Pre-processing	✗	✗	✓	✓	✓	✓
In-processing	✓	✓	✓	✓	✓	✓
Post-processing	✗	✗	✓	✓	✓	✓
Number of models	4	6	6	15	10	<b>29</b>

# Toolkits: FairDiverse

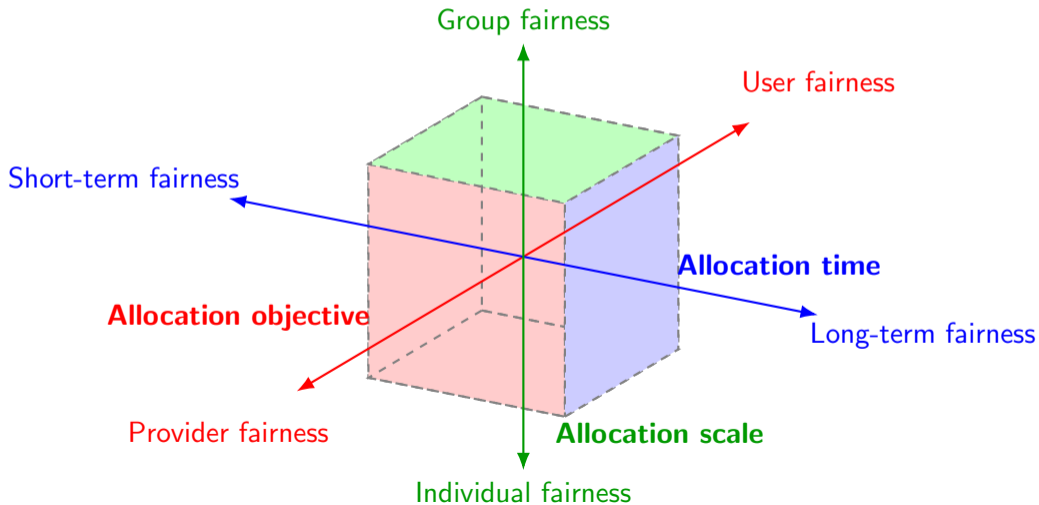
- End-to-end coverage: From **data collection**, **data processing**, and **model training** to **result evaluation**
- Helps researchers understand & apply fairness in **structured, reproducible** way
- Helps researchers develop their **own fairness-aware IR models**



# Conclusions

# Economics provides a helpful framework for understanding fairness in IR

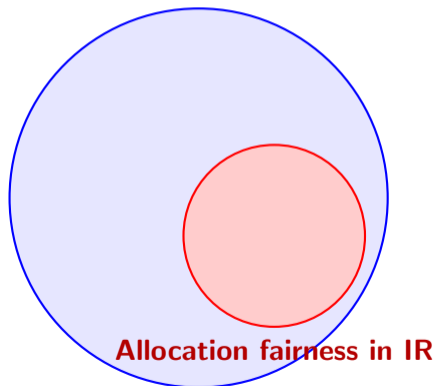
- Allocation objective, scale, and time



## Economics perspective provides new tools

- Taxation, risk-return, game theory, social choice

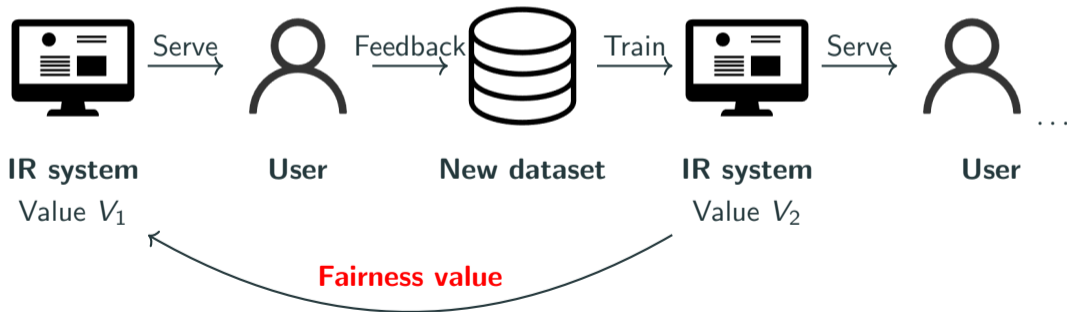
### Fairness in economics





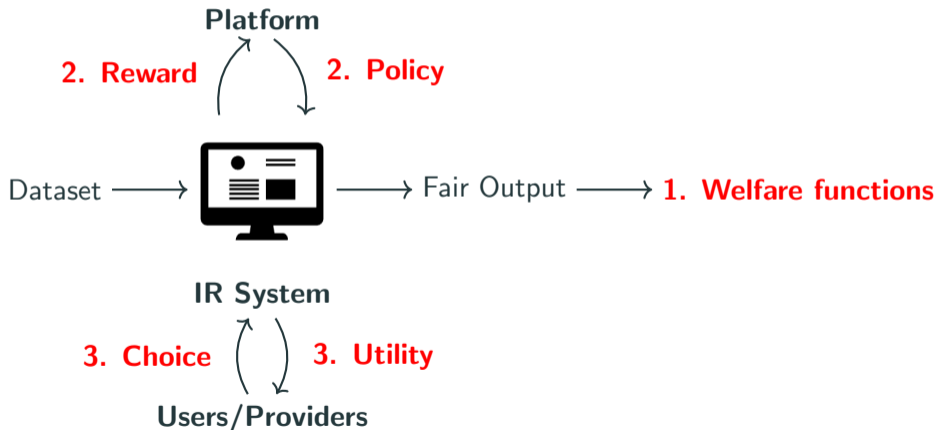
## Using economic thinking for fairness in IR

- Fairness is not just “the right thing” but often also the “**profitable choice**”
- Fairness can be seen as a form of **anticipatory consumption**: it discounts future value to be accounted for in the present



## Economic perspective hints at future firections

- Three levels of fairness problem





- This tutorial is only a first step toward a broader research agenda on economic perspectives on fairness in IR.
- We are currently planning to develop these materials into a book, where we will present more detail.
- The book and related resources will be gradually made available on our website in the future.

More updates will be shared at: <https://economic-fairness-ir.github.io/>

### Surveys:

- [A Survey on the Fairness of Recommender Systems](#)
- [Fairness in Recommendation: Foundations, Methods and Applications](#)
- [Fairness in Ranking: A Survey](#)
- [Bias and Unfairness in Information Retrieval Systems: New Challenges in the LLM Era](#)

### Open toolkit:

- [FairDiverse](#), [RecBole2.0](#)

# Q&A



Website



FairDiverse toolkit

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