Fairness in Information Retrieval from an Economic Perspective

Half-day Tutorial in SIGIR 2025

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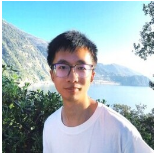
Website: https://economic-fairness-ir.github.io/
Toolkit: https://github.com/XuChen0427/FairDiverse

Tutors



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Outline

Introduction: Fairness in IR (Maarten, 20min)

An Economic View on Fairness in IR (Chen, 30min)

Economic-based Fairness Mitigation and Evaluation Strategies I (Chen 30min)

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

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

Open Problems, Quick Start for Learning Fairness, and Conclusions (Maarten, 20min)

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" but often also the "**profitable choice**".

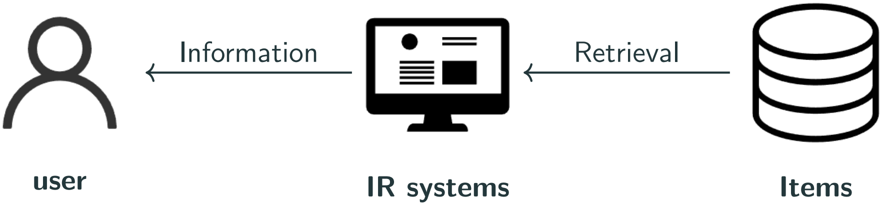
3. **Economic Perspectives Point out Future Directions**
    - Economics highlights that we need to consider practical multi-agent scenarios and develop more rigorous, theory-driven fairness mechanisms.

Introduction: Fairness in IR (Maarten, 20min)

Information Retrieval

What is Information Retrieval?

- **Information Retrieval (IR)** [Manning et al., 2009] is the process of finding relevant information from large collections of data.
- It focuses on matching user queries with documents or data items.
- IR is the core technology behind **search engines** and **recommender systems**.



Core Components

1. **Document/Items 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. **Ranking Model** – 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**

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

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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 and advertisers.
- 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

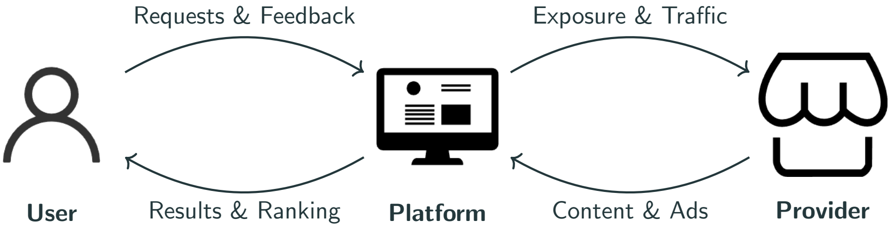
- Operates and optimizes the IR system.
- Acts as a mediator between users and providers.

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 sociology to algorithmic fairness in IR

Taxonomy of Fairness in Sociology

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 as Harms

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

Fairness in Sociology vs. Fairness in Machine Learning

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

Taxonomy of Fairness in IR

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**

  $\Rightarrow$ Reflect constraints or flaws in the process

  $\Rightarrow$ But they matter because they are the good properties for Allocation Harms

Taxonomy of Fairness in IR

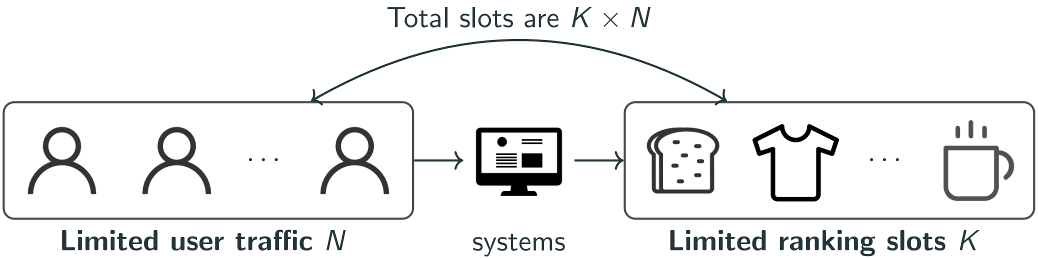
- **Procedural Harms**
  - $\Rightarrow$ Reflect constraints or flaws in the process
  - $\Rightarrow$ But they matter because they are the good properties for Allocation Harms
- **Representational Harms**
  - $\Rightarrow$ In IR, often act as *means* to an unfair allocation
  - $\Rightarrow$ Not always the final objective

What 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

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

	u_1	u_2	$\cdots$	u_N
i_1	●	●	●	
i_2	●	●	●	
i_3	●			●
$\cdots$		●		●
i_M			●	●

Ranking size $K = 3$

i_M is exposed to u_N

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

user group fairness

	u_1	u_2	$\cdots$	u_N
i_1	• – 0.8	• – 0.6	• – 0.5	
i_2	• – 0.7	• – 0.7	• – 0.6	
i_3	• – 0.5			• – 0.7
$\cdots$		• – 0.8		• – 0.5
i_M			• – 0.4	• – 0.2

Utilities of user group $1 = 2.05$

$(0.8 + 0.7 + 0.5 + 0.6 + 0.7 + 0.8)/2$

Utilities of user group $n = 1.4$

$0.7 + 0.5 + 0.2$

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	$\cdots$	u_N
i_1	• − 0.8	• − 0.6	• − 0.5	
i_2	• − 0.7	• − 0.7	• − 0.6	
i_3	• − 0.5			• − 0.7
$\cdots$		• − 0.8		• − 0.5
i_M			• − 0.4	• − 0.2

Provider 1
utility $= 1.95$

provider fairness

Provider m
utility $= 0.6$

Fairness Evaluation in IR

How to Measure Allocation Harms?

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

$$\boldsymbol{v} = [v_1, v_2, \cdots, v_g],$$

where g is the stakeholder internal group number.

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

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

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

Common Evaluation Metrics I

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

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

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

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

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

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

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

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

Common Evaluation Metrics II

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

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

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

$$f(\boldsymbol{v}) = (\sum_{i=1}^{g} v_i^p)^{1/p}.$$

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

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

Goals of Fair-aware IR

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

An Economic View on Fairness in IR (Chen, 30min)

Motivation for an Economic View on Fairness in IR

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

- Currently:
  - **Vague objectives:**"Be more fair to underrepresented items"
  - **No ROI argument**: Hard to justify resource investment
  - **Ad-hoc solutions:** Rules-based, not systematic

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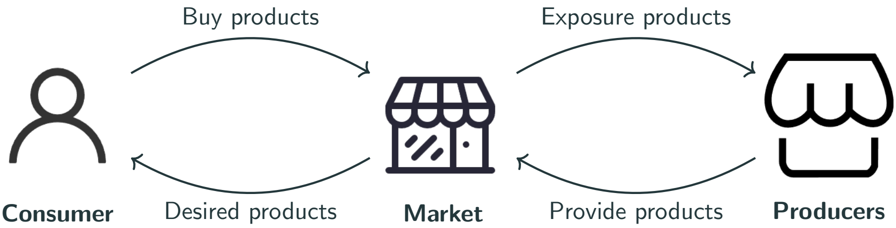
An economic framework does not just add more complexity, more methods, and more theories: it integrates different stakeholders and justifies its relevance

- Currently:
  - **Vague objectives:**"Be more fair to underrepresented items"
  - **No ROI argument**: Hard to justify resource investment
  - **Ad-hoc solutions:** Rules-based, not systematic
- Without proper economic justification, fairness initiatives:
  - Get defunded during budget cuts
  - Lack measurable success criteria
  - Don't scale to real-world systems

An Economic View on Information Retrieval

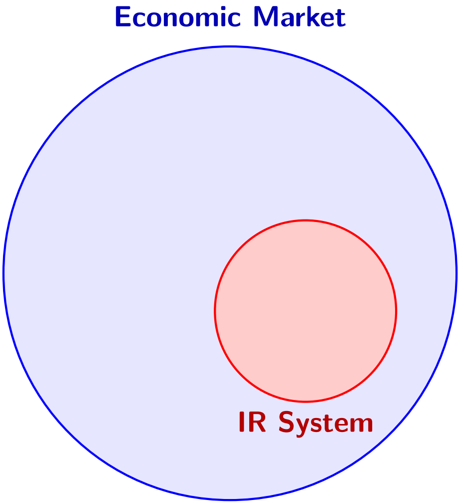
IR Systems and Economic Markets: A Natural Analogy

- Both IR systems and economic markets involve interactions between **demand and supply side**.
  - **Users** in IR systems express *demand side* — similar to *consumers* in a market.
  - **Providers** act as *supply side*, competing for attention — similar to *producers*.
  - **Platform** like a *market mechanism*, making the demand and supply side be balanced.



IR System as An Economic Market

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



Market Mechanisms in Economics

1. **Price Mechanism [Saari and Simon, 1978]**
   - Prices adjust based on supply and demand, signaling scarcity or surplus and guiding resource allocation efficiently.
2. **Incentive Structures [Rainey, 1983]**
   - Markets align incentives (e.g., profit, utility) so that individuals and firms act in ways that contribute to overall efficiency.
3. **Regulation and Intervention [Ramsey, 1927]**
   - Governments or authorities may step in to correct market failures (e.g., externalities, inequality, monopolies) through taxes, subsidies, or rules.

Market Mechanisms vs. IR System Tasks

Market Mechanism	**IR System Analogy / Task**
Price Mechanism	Getting accurate ranking scores, such as retrieval and ranking tasks [Baeza-Yates et al., 1999].
Incentive Design	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].

Why Model IR as Economic Market?

1. **Economics Provide a Better Framework**
   - Economics has studied complex multi-agent ecosystems for centuries. Its mature concepts (e.g., equilibrium, welfare, regulation) help us systematically define and organize IR tasks.

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2. **Economic Theory and Metrics Help IR Tasks**
   - Tools such as auctions, incentive analysis, and resource allocation theory and corresponding objectives are directly applicable to IR problems.

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2. Economic Theory and Metrics Help IR Tasks

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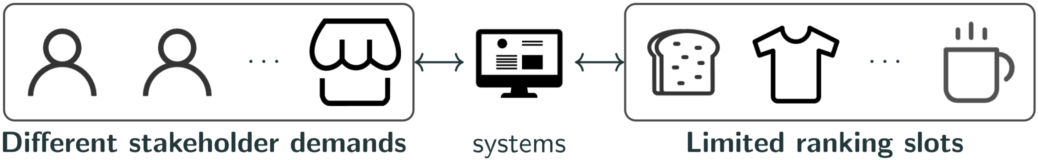
3. Contributes back to Economics

- The scale and algorithmic nature of modern IR systems create new challenges (e.g., dynamic markets, real-time bidding, feedback loops) that push the boundaries of traditional economic theory.

An Economic View on Fairness in IR

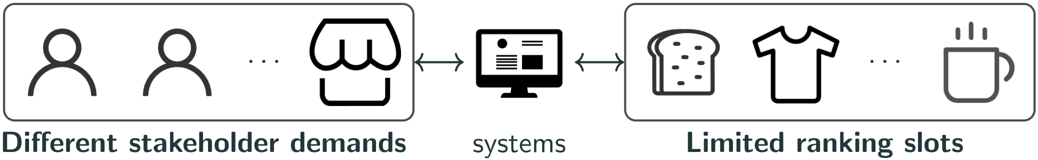
Recall: Fairness in IR

- In IR, we mainly focus on **Allocation Harms**
- **Unlimited** Stakeholder Demands vs. **Limited** Ranking Resources



Recall: Fairness in IR

- In IR, we mainly focus on **Allocation Harms**
- **Unlimited** Stakeholder Demands vs. **Limited** Ranking Resources
- Taxonomy of allocation harms [Li et al., 2021]
  - Allocation **object**: user fairness v.s. provider fairness
  - Allocation **time**: short-term fairness v.s. long-term fairness
  - Allocation **scale**: individual fairness v.s. group fairness



Economic Perspective on Fairness

- Economics: how to allocate **limited** resources to meet **unlimited** human wants

Economic Perspective on Fairness

- Economics: how to allocate **limited** resources to meet **unlimited** human wants
- Long history of fairness in Economics:
  - Welfare Economics [Ng, 1983]: how to evaluate the social merits of resource allocation? Emphasizes a balance between **efficiency and fairness**
  - Game Theory [Owen, 2013]: how to achieve fair results in **strategic interactions**, such as equilibrium strategy fairness
  - Social Choice Theory [Sen, 1986]: explores the fairness issue of how to **aggregate individual preferences** into collective decisions
  - $\cdots$

Economic Concepts [Ng, 1983]

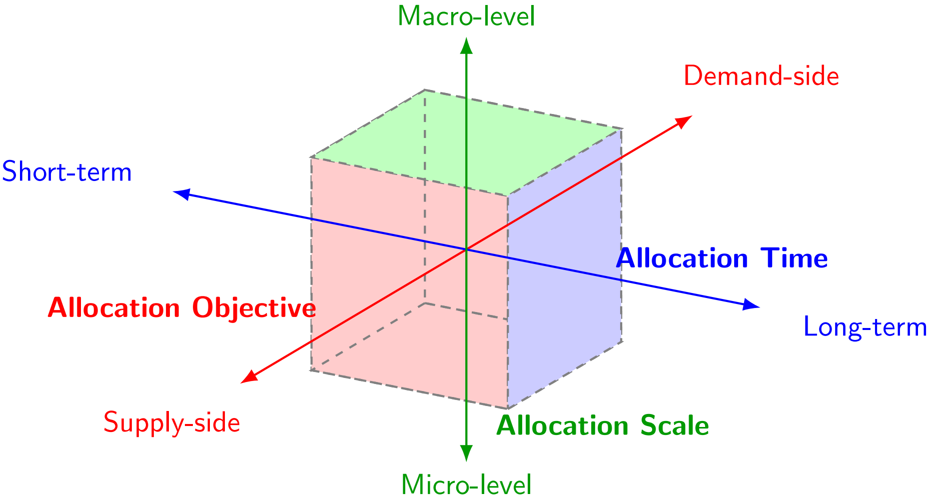
1. **Objective: Supply and Demand**
   - **Supply and demand** describe how the availability of goods and the desire to purchase them determine prices and quantities in a market.

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

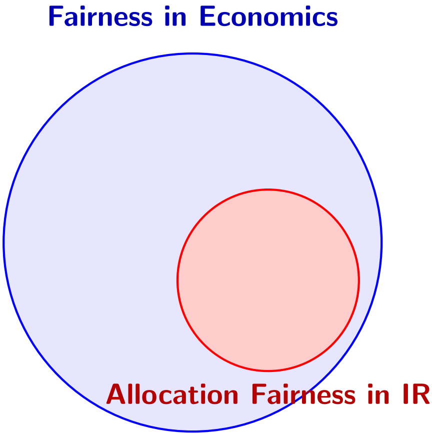
3. **Time: Short-term Shocks and Long-term Returns**
   - **Short-term shocks** cause immediate fluctuations, while **long-term returns** reflect stable outcomes as markets adjust over time.

Taxonomy of Fairness in Economics

- Allocation in Economics: **Allocation Objective, Scale and Time**

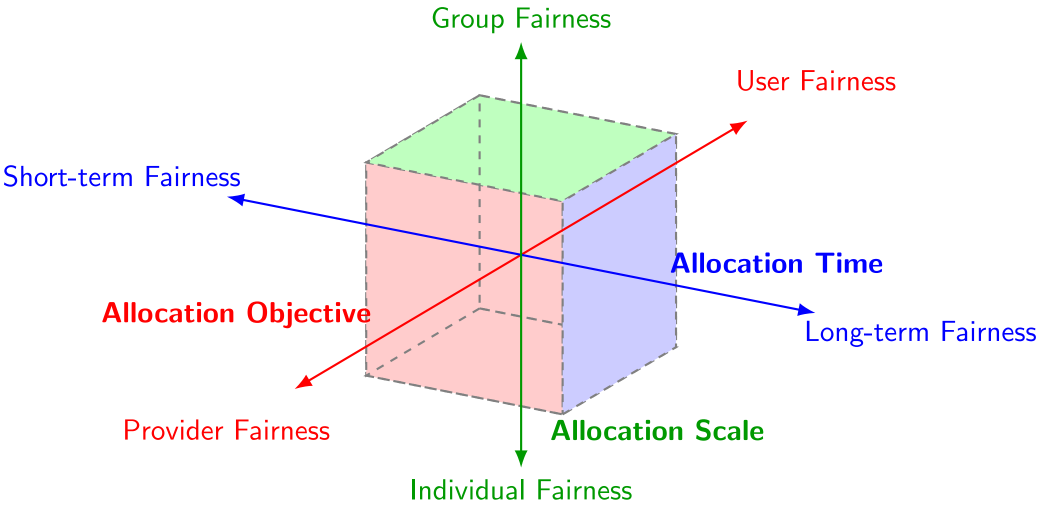


- Governments or authorities may step in to correct market failures (e.g., externalities, inequality, monopolies) through economic tools.



Taxonomy of Fairness in IR: Alignment

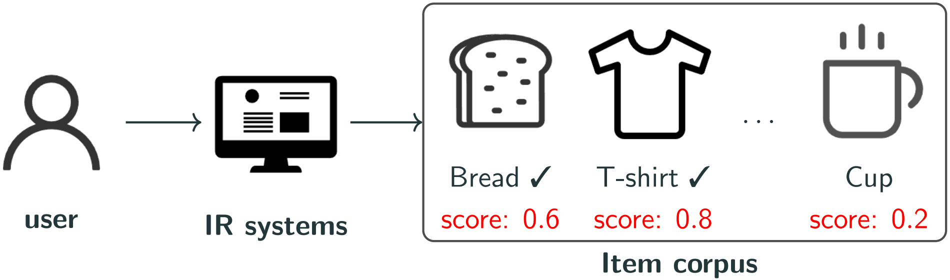
- Allocation Fairness in IR: **Allocation Objective, Scale and Time**



Case 1: Economic View on Allocation Objective

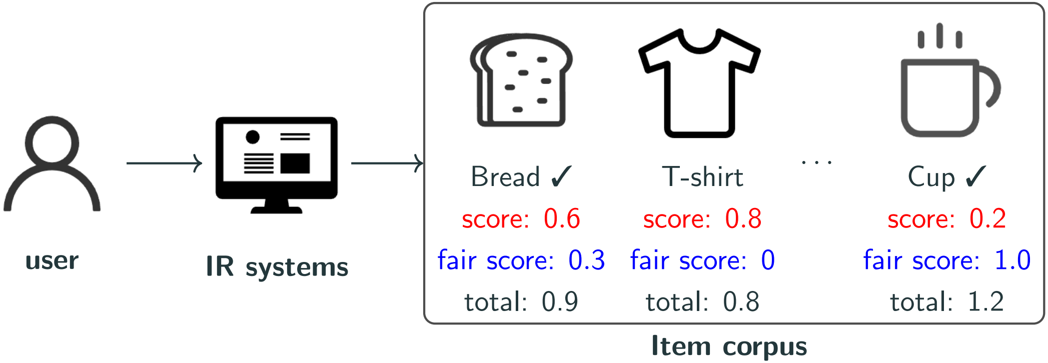
Example: Provider Fairness in IR

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



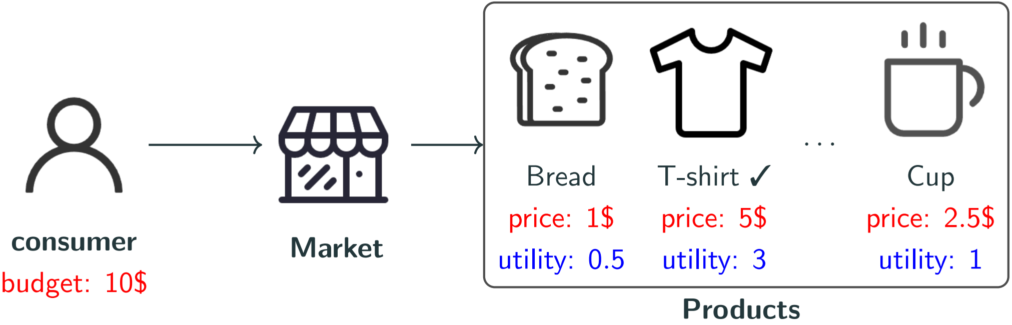
Example: Provider Fairness in IR

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



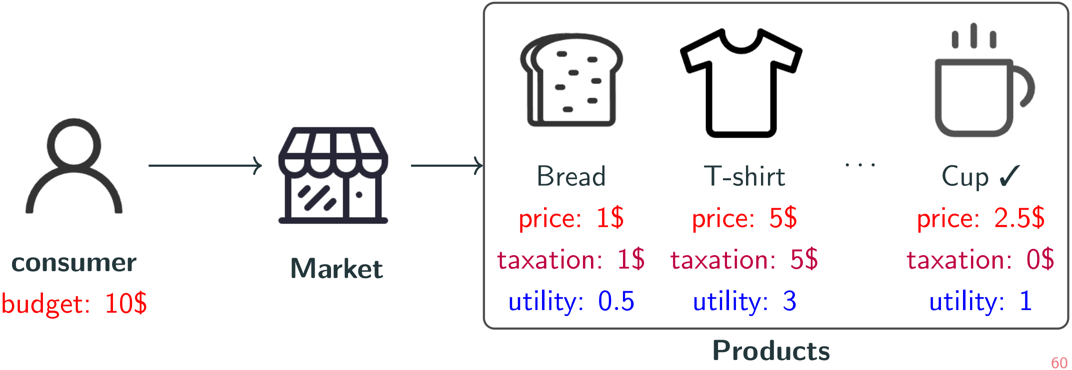
Examples: Demand-side Fairness in Economic Market

- 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 increase the number of cups sold? **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!)**



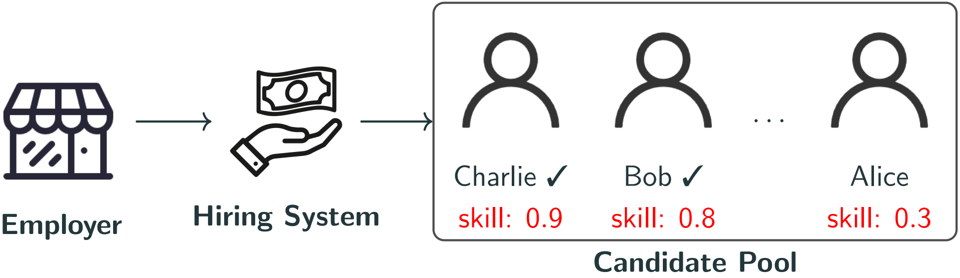
Supply-side Fairness V.S. Provider Fairness

- Supply-side Fairness V.S. 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

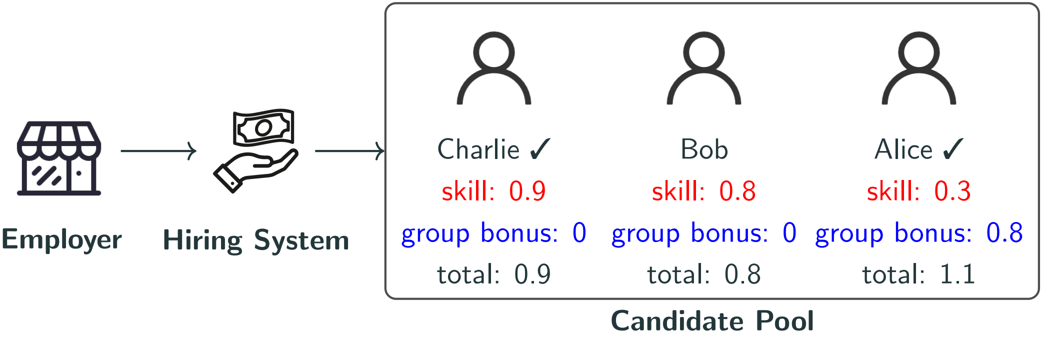
Each worker is evaluated based on individual merit and productivity:



Microeconomic Principle: Hire based on marginal productivity: *you* get the best value for your money and optimal allocation of skills

Example: Group Fairness in Employment

We aim to achieve demographic parity across groups: **Through affirmative action!**



Macroeconomic Principle: Diversified talent allocation maximizes *aggregate* productivity

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:

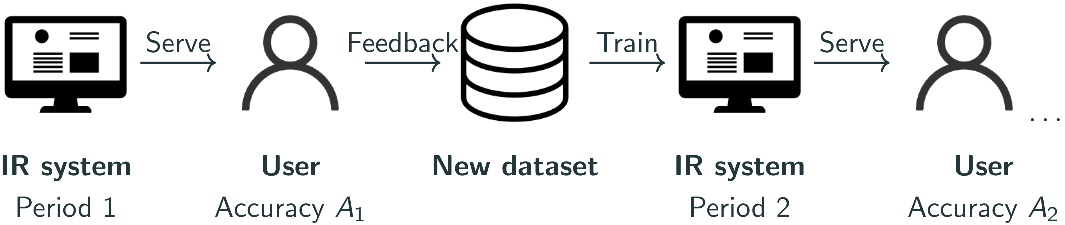
- **Welfare Economics**: Balance efficiency and fairness in resource allocation
- **Game Theory**: Achieve fair outcomes in strategic interactions
- **Social Choice Theory**: Aggregate individual preferences into collective decisions

ML Lesson: Use both individual and group fairness metrics together

Case 3: Economic View on Allocation Time

Examples: Long-term Fairness in IR

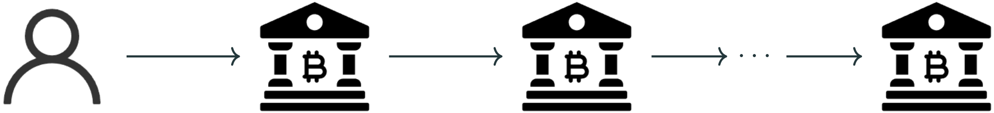
Multiple interactions between IR and users:



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

Examples: Long-term Fairness in Economics

A user enters the bank with saving M, where the interest rate is $r\%$:



consumer
saving: $M\$$

Bank
period 1
$M \times (1 + r\%)$

Bank
period 2
$M \times (1 + r\%)^2$

$\cdots$

Bank
period n
$M \times (1 + r\%)^n$

Examples: Long-term Fairness in Economics

- A social planner wants to balance **current consumption** vs. **future consumption** across different income groups
- **Lower-income** individuals often have **higher** discount rates (need money now), while higher-income individuals can afford to wait

consumer
saving: $M_1\$$

Bank
period n
$M_1 \times (1 + r_1\%)^n$

consumer
saving: $M_2\$$

Bank
period n
$M_2 \times (1 + r_2\%)^n$

Long-term Fairness in Economics V.S. in IR

- **Same goal**: An IR system wants to balance **immediate relevance** vs. **long-term user satisfaction** across different user groups
- Some users (like researchers) may value long-term learning, while others need immediate results
- Similar tools: RL reward vs. Interest rate adjustment

Conclusion on Economic-viewed Fairness in IR

Fairness as Allocation Problem

- 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.

Fairness Insights from Economics

1. Scarcity & Trade-offs

- Any fairness or efficiency goal must be analyzed in the context of "**trade-offs**"
- Algorithm design should clarify the priority and ethical basis of goals

Fairness Insights from Economics

1. **Scarcity & Trade-offs**
   - Any fairness or efficiency goal must be analyzed in the context of "**trade-offs**"
   - Algorithm design should clarify the priority and ethical basis of goals
2. **Emergence**
   - The issue of fairness requires more "**intertemporal thinking**" and takes into account future social costs

Fairness Insights from Economics

1. **Scarcity & Trade-offs**
   - Any fairness or efficiency goal must be analyzed in the context of "**trade-offs**"
   - Algorithm design should clarify the priority and ethical basis of goals
2. **Emergence**
   - The issue of fairness requires more "**intertemporal thinking**" and takes into account future social costs
3. **Incentive Compatibility**
   - The task of fairness is not to enforce, but to design rules so that "doing the right thing" becomes a "**profitable choice**"

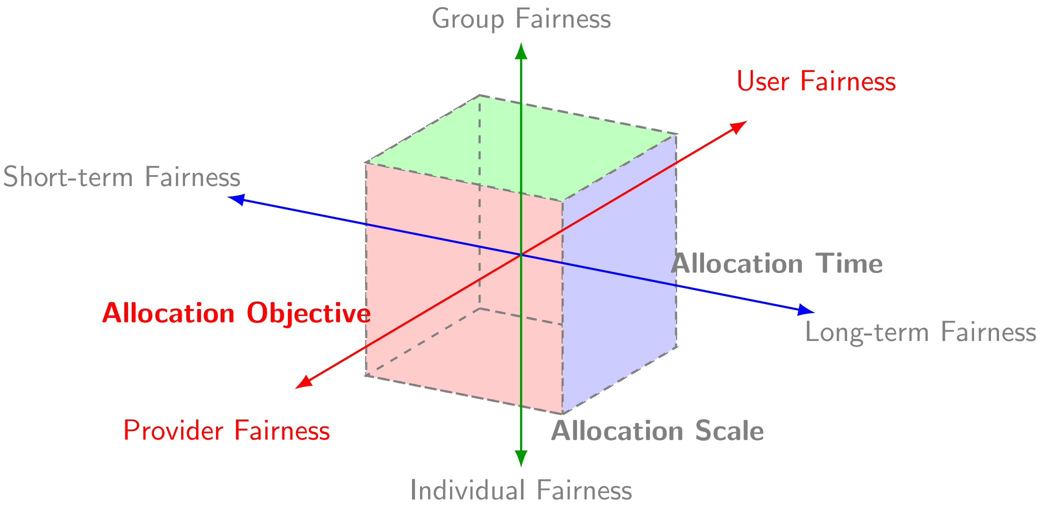
Organization for Next Sections

- Allocation **Object**: Section 3
  - Economic Tool: **Taxation** for provider and user fairness
  - Application applied: 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 applied: 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 applied: Personalized Financial Product Recommendations
  - Future and related works to explore

Economic-based Fairness Mitigation and Evaluation Strategies I (Chen 30min)

Allocation Objective

- In this section, we focus on the **Allocation Objective**:



Taxation Inspired User & Provider Fairness

Formal notations

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

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Formal notations

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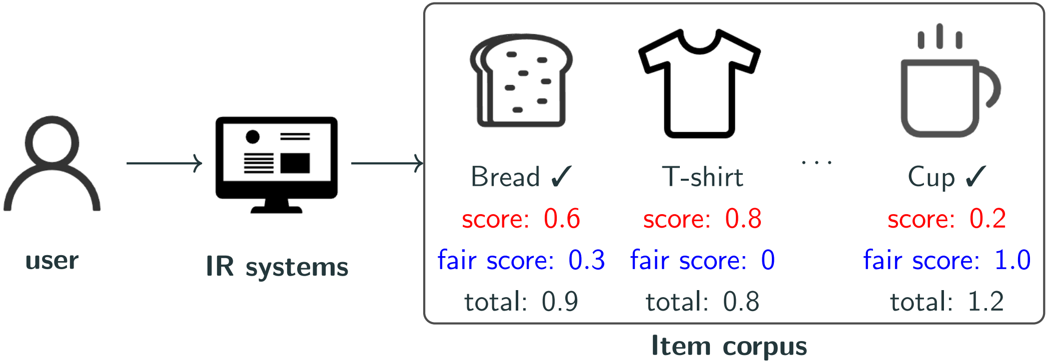
- Then, the IR system $f(\cdot)$ will score the item or document $i \in \mathcal{I}$ according to user's preference: $s_{u_t,i} = f(u_t, i)$
- Finally, the system will generate a ranking list of size K with the highest ranking scores:

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

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: $s_{u_t,i} \rightarrow s_{u_t,i} + w_{u_t,i}$.



Fairness Scoring Approach

Scoring approaches originated from the Lagrange multiplier method [Boț et al., 2008], which is efficient:

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

becomes

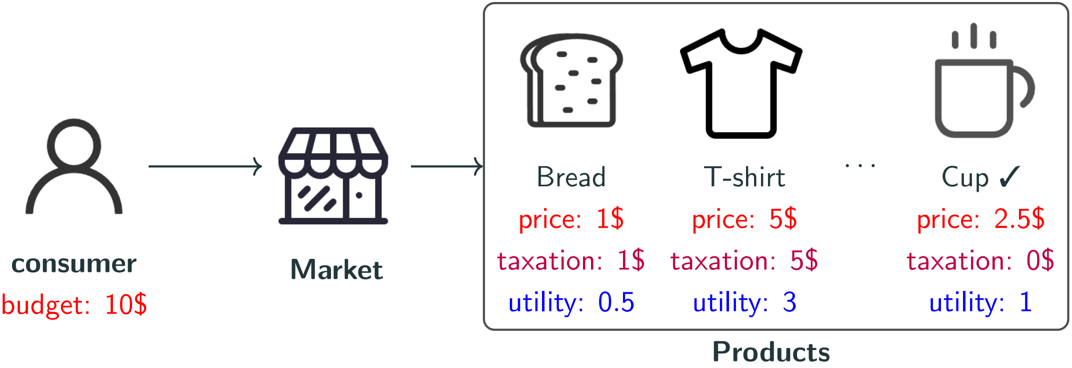
$$\max \quad f(x) + \lambda(g(x) - c),$$

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

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.



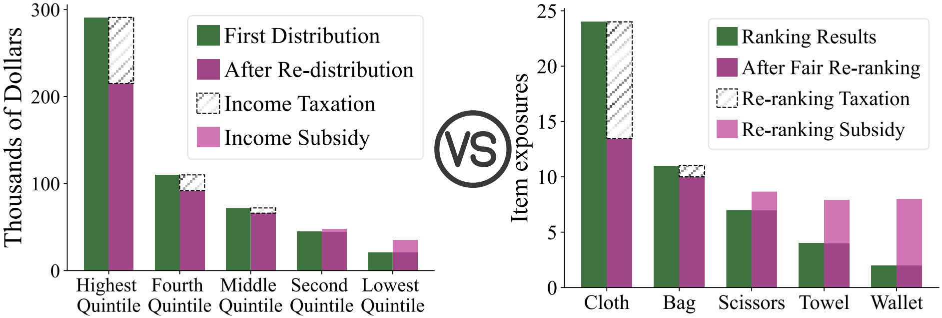
Taxation Aligns with Fairness

Correspondence between taxation elements in economics and fair re-ranking [Xu et al., 2025b]

Economics	**Fair re-ranking**
Consumer (buy product)	Users $\mathcal{U}$ (click items)
Supplier (sell product)	Item groups $\mathcal{G}$ (provide items)
Commodity tax	Fairness constraint
Tax subsidies for the poor	Increase ranking score for the poor
Selling price (tax objective)	Ranking scores (fairness objective)

Taxation Inspired Fairness

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



Advantages of Taxation Inspired Fairness

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

Provider Fairness

Max-min Fairness

P-MMF [Xu et al., 2023a]:

- $\mathbf{e}_p$: exposure of provider p; γ_p: p's weight
  - MMF: $r(\mathbf{e}) = \min_{p\in\mathcal{P}} [\mathbf{e}_p/\gamma_p]$
- Trade-off between ranking accuracy and provider fairness

$$\max_{L_K^F} \quad \frac{1}{T}\sum_{t=1}^{T} f\left(L_K^F(u_t)\right) + \lambda r(\mathbf{e}) \quad , \tag{1}$$
$$\text{s.t.} \quad \mathbf{e} \le \gamma \rightarrow \text{restrict largest exposures}$$

  - $L_K^F(u_t)$: ranking list to user u_t.
  - Accumulated reward over periods from 0 to T(Amortized group fairness)

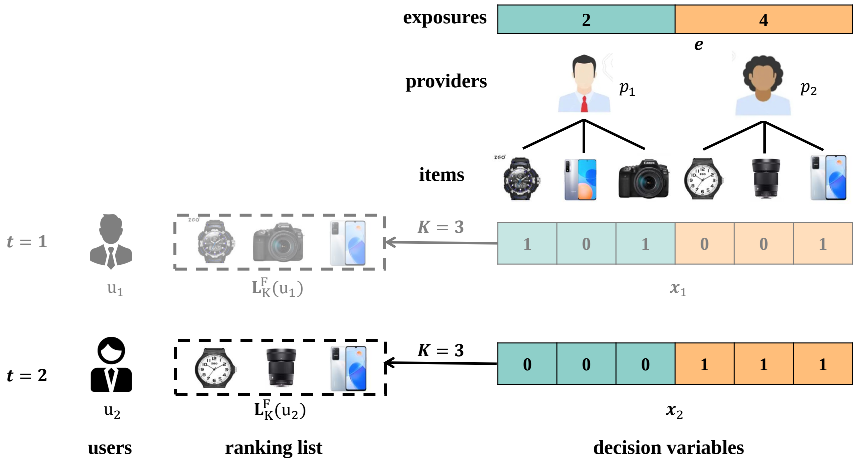
P-MMF: Offline Version

- Optimization goal: trade-off user utilities and provider fairness.
- Can be written as a linear programming:

$$\begin{aligned} \max_{\mathbf{x}_t} \quad & \frac{1}{T}\sum_{t=1}^{T} g(\mathbf{x}_t) + \lambda r(\mathbf{e}) \\ & \sum_{i} \boldsymbol{x}_{t,i} = K, \forall t \end{aligned} \tag{2}$$

A Toy Example for MMF

- Two users, u_1 and u_2, arriving at the system one by one.



Taxation Perspective for MMF

Taxation based on the worst-off provider: We give the worst-off provider a **negative taxation rate** to help them increase their exposures.

The taxation value $w_{u_t,i} = \boldsymbol{A}^T\boldsymbol{\mu}$, where the $\boldsymbol{\mu}$ can be obtained according to the dual form of the max-min fairness.

It is a provider-level constant tax.

Such a taxation policy based on the worst-off provider **violates two important properties** of taxation [Xu et al., 2024]:

- **Continuity**: implying that slight variations in tax rates lead to minor shifts in performance.

Analyzing MMF from Taxation Perspective

Such a taxation policy based on the worst-off provider **violates two important properties** of taxation [Xu et al., 2024]:

- **Continuity**: implying that slight variations in tax rates lead to minor shifts in performance.
- **Controllability over accuracy loss**: ensuring an accurate estimation of accuracy loss caused by a specific tax rate.

Objective of TaxRank [Xu et al., 2024]:

$$\boldsymbol{x}^*(t) = \underset{\boldsymbol{x} \in \mathcal{X}_s}{\arg\max} f(\boldsymbol{x}; t) = \begin{cases} \sum_i \gamma_i \boldsymbol{v}_i^{1-t}/(1-t) & \text{if } t \geq 0, t \neq 1 \\ \sum_i \gamma_i \log(\boldsymbol{v}_i) & \text{if } t = 1 \end{cases}, \tag{3}$$

$$\text{s.t.} \quad \boldsymbol{v}_i = \sum_{u \in \mathcal{U}} w_{u,i} \boldsymbol{x}_{u,i}, \quad \forall i \in \mathcal{I}$$

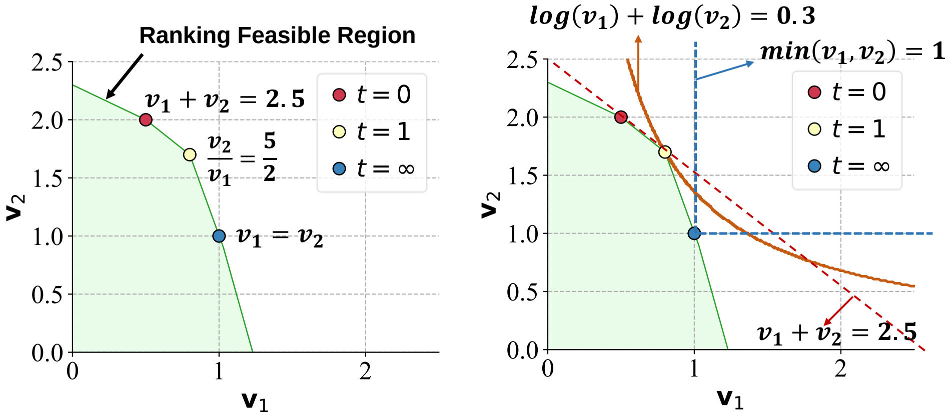
where $\boldsymbol{v}_i$ is typically defined as the accumulated utilities of item i across all ranking lists.

Taxation Perspective on $\alpha-$fairness

- The taxation **subsidy** value depends on the item's utilities: $\boldsymbol{v}_i \rightarrow \boldsymbol{v}_i(\boldsymbol{v}_i^{-t}), t > 0.$
- Taxation rate is $\boldsymbol{v}_i^{-t}$: If an item has higher utility, its fairness score will be lower $\rightarrow$ leading to higher taxation value.
- **It is a progressive tax.**

Geometric Explanation on $\alpha-$fairness

A geometric explanation for our taxation process, which imposes taxes based on between two items.



(a) optimal points

(b) tax process in geometrics

Better Taxation Property

Controllable over the loss:

Theorem

The price of taxation (POT) of Tax-rank is bounded:

$$POT = \frac{\mathbf{Acc}(0) - \mathbf{Acc}(t)}{\mathbf{Acc}(0)} \leq 1 - O(|\mathcal{U}|^{-\frac{t}{1+t}}), \tag{4}$$

where $\mathbf{Acc}(t)$ *denotes the accuracy under Tax-rank tax policy with tax rate* t.

User Fairness

Formulation

Similarly, for user fairness, previous work [Ge et al., 2021, Naghiaei et al., 2022] also formulate the utility of user u as $\mathcal{M}(W_u)$, where $W_{u,i} = 1$ means the item is exposed to user u, otherwise $W_{u,i} = 0$.

($\epsilon-$fairness):

$$UGF(Z_1, Z_2, W) = |\sum_{u \in Z_1} \mathcal{M}(W_u) - \sum_{u \in Z_2} \mathcal{M}(W_u)| \leq \epsilon \tag{5}$$

$$\text{UGF} = |2.05 - 1.4| = 0.65$$

	u_1	u_2	$\cdots$	u_N
i_1	• – 0.8	• – 0.6	• – 0.5	
i_2	• – 0.7	• – 0.7	• – 0.6	
i_3	• – 0.5			• – 0.7
$\cdots$		• – 0.8		• – 0.5
i_M			• – 0.4	• – 0.2

Utilities of user group 1 $= 2.05$ Utilities of user group $n = 1.4$

Optimization Procedure

0–1 integer programming problem [Ge et al., 2021, Naghiaei et al., 2022]:

$$
\begin{aligned}
\max_{W} \quad & \sum_{i=1}^{n} \sum_{j=1}^{N} W_{ij} S_{ij} \\
& UGF(Z_1, Z_2, W) \leq \epsilon \\
& \sum_{j=1}^{N} W_{ij} = K, W_{ij} = \{0, 1\}
\end{aligned}
$$

Optimization Procedure

0–1 integer programming problem [Ge et al., 2021, Naghiaei et al., 2022]:

$$\max_{W} \quad \sum_{i=1}^{n}\sum_{j=1}^{N} W_{ij}S_{ij}$$

$$UGF(Z_1, Z_2, W) \leq \epsilon$$

$$\sum_{j=1}^{N} W_{ij} = K, W_{ij} = \{0, 1\}$$

Greedy Solution for $\epsilon-$fairness [Naghiaei et al., 2022]:

$$S_{ij} \rightarrow S_{ij} + \lambda \times UG_u \times UGF(Z_1, Z_2, W^{i+1}),$$

where $UG_u = 1$ when user u is in the protected group and $UG_u = -1$ otherwise.

Taxation perspective on $\epsilon-$fairness

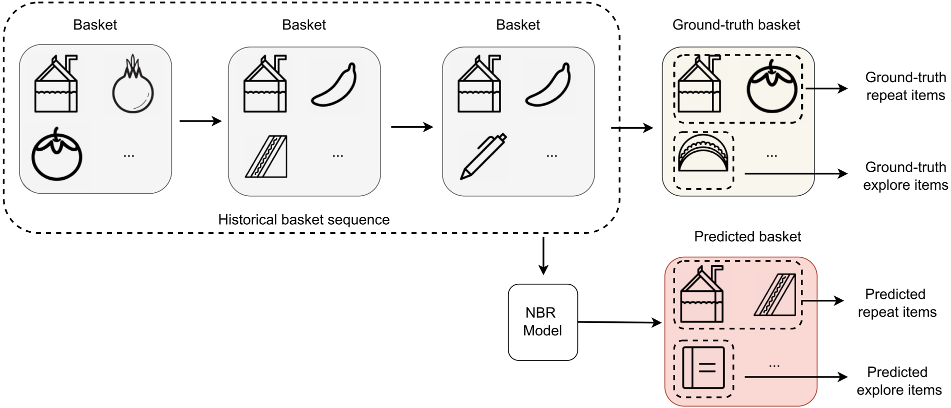
Give a higher ranking score to the protected group and give a lower score to the unprotected group.

Taxation value is

$$w_{u_t,i} = \lambda \times UG_{u_t} \times UGF(Z_1, Z_2, W^{i+1})$$

Application: Next Basket Recommendation

Next Basket Recommendation



- The predicted basket contains both repeat and explore items.

Next Basket Recommendation

SOTA 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):

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

Taxation Perspective for RAIF

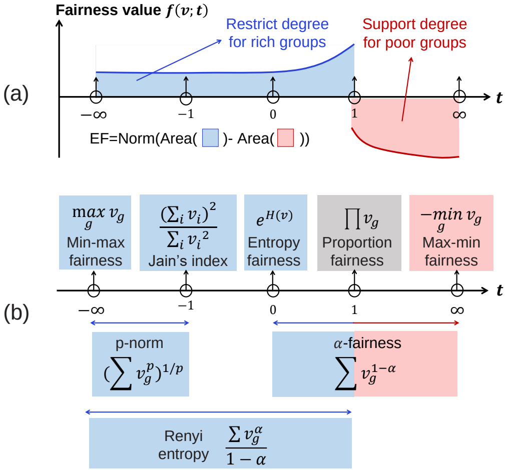
- Higher taxation rate α on the unprotected group
- Another taxation rate λ on the repeated items

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

Future and Related Works

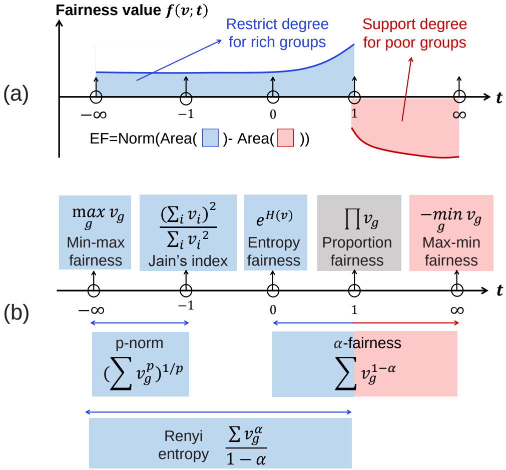
Carefully Choose Fairness Function

- 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].



Evaluation

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.

Evaluation

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.

Better Tools

- 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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Better Tools

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

Fairness in IR on Allocation Objective: Related Work

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

Break (Coming Section 4-6)

Introduction: Fairness in IR (Maarten, 20min)

An Economic View on Fairness in IR (Chen, 30min)

Economic-based Fairness Mitigation and Evaluation Strategies I (Chen 30min)

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

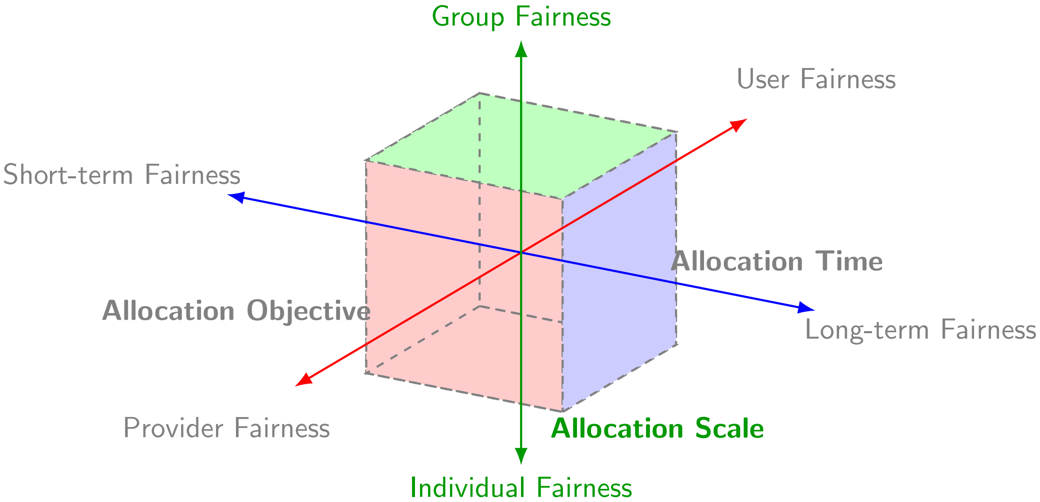
Economic-based Fairness Mitigation and Evaluation Strategies III (Yuanna, 30min)

Open Problems, Quick Start for Learning Fairness, and Conclusions (Maarten, 20min)

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

Allocation Scale

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



Micro-Macro Economic Inspired Individual & Group Fairness

Individual and 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 Lens: Individual vs Group Fairness

Economic Parallel: Microeconomics vs Macroeconomics

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

Micro vs. Macro objectives

- Microeconomics focuses on individual behavior and incentives
  - Individuals, firms, local optimization
  - Key idea: merit-based allocation (e.g. productivity $\rightarrow$ 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 lense:

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?

Individual Fairness

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.

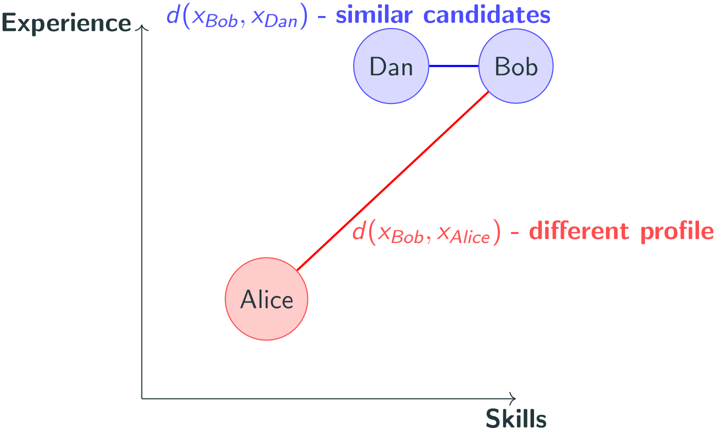
Input Similarity

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.



Output Similarity

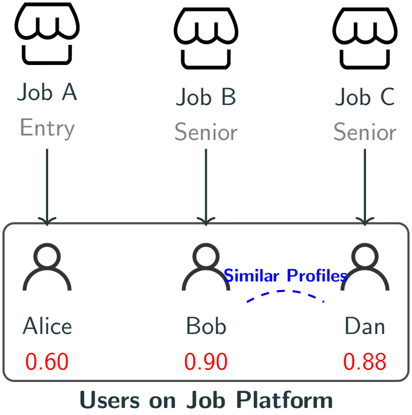
How to define similarity in the outcomes for individuals?

Output Similarity

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].

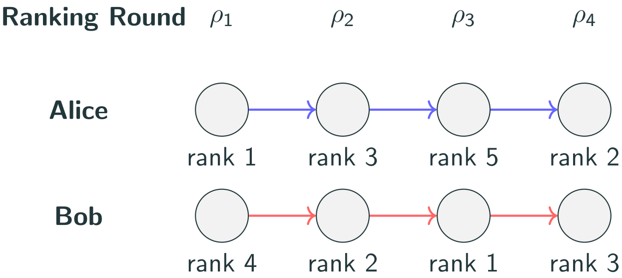
Individual Fairness and Output Similarity: User



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

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

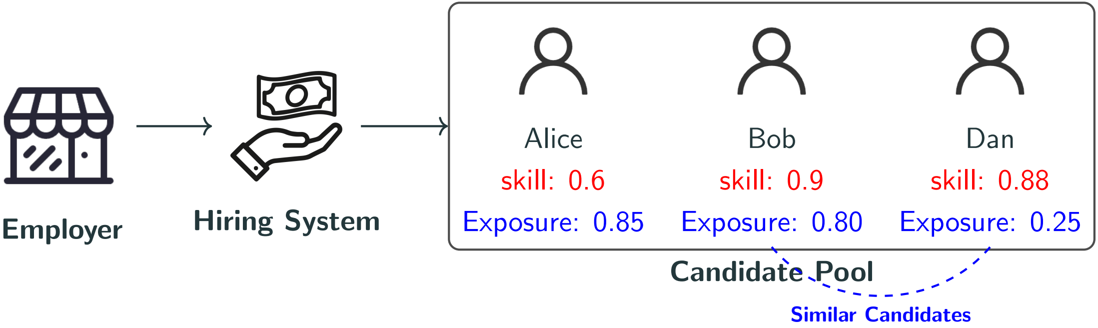
Individual Fairness: Items

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 $g(x)$.

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

where $g(x)$ is defined as

Lipschitz Fairness Constraint

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

Individual Fairness: Challenges

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 $\rho_1, \ldots, \rho_m$:

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

- a_i^ℓ: attention (exposure) in ranking ρ_ℓ
- r_i^ℓ: relevance score in that round

Achieving Individual Fairness: Equity of Attention

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

$$\begin{aligned} \min \quad & g(x) \\ s.t. \quad & f(x) \geq c, \end{aligned}$$

where $g(x)$ is the fairness constraint defined as the deviation between attention and relevance over time for an individual and $f(x)$ is the ranking (utiliy) function.

Achieving Individual Fairness: Equity of Attention

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

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

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

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

Challenges

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

Group Fairness

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 ..

Group Fairness

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:

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

Group Fair Outcomes

- **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.

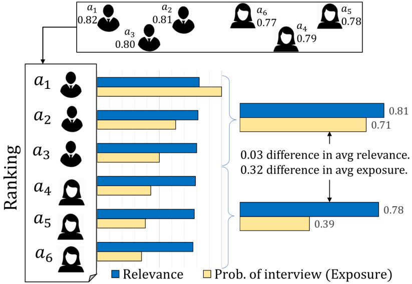
Group Fair Outcomes

- **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)

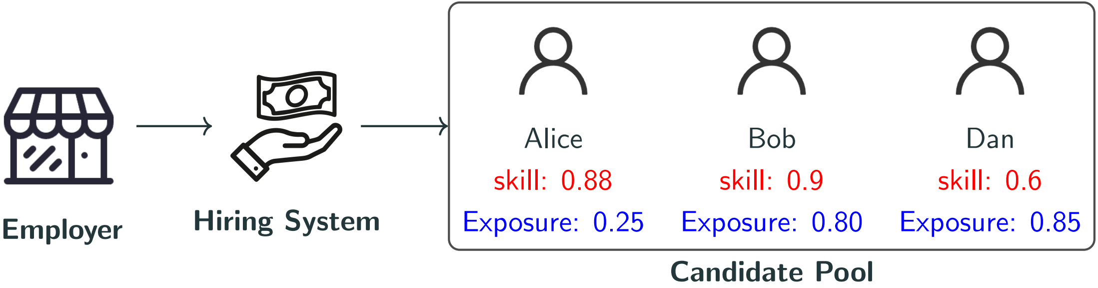
Group Fairness in Rankings

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.

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.

Achieving Group Fairness

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

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

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

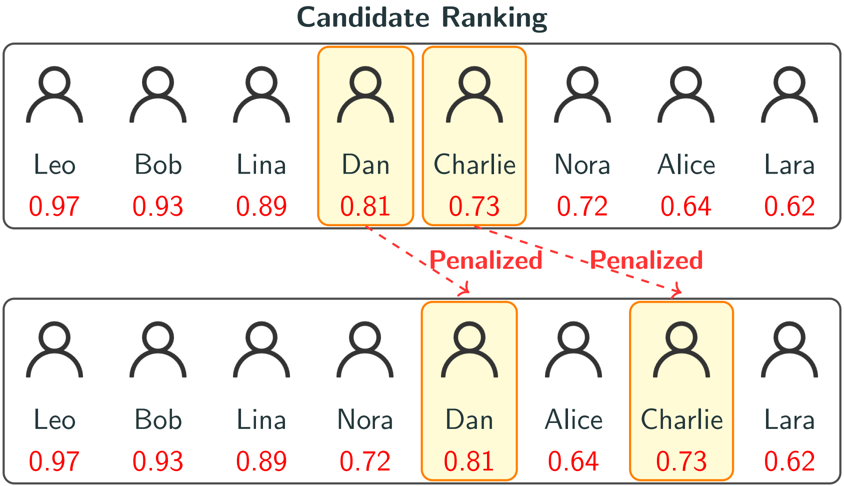
Achieving Group Fairness: FA*IR [Zehlike et al., 2017]

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



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

Individual Fairness under Group-Fairness Constraints

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.

Individual Fairness under Group-Fairness Constraints

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

where P is a probability distribution over rankings.
$V(r, u)$ is the receivedutility 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:

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

Worst-off utility: V(r,Charlie) = -2

Probability Distribution over Fair Rankings (P):

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

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

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

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

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

Economic Perspective in IR

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] leverages **social choice theory**, a branch of economics that formalizes how to aggregate individual preferences into collective decisions.

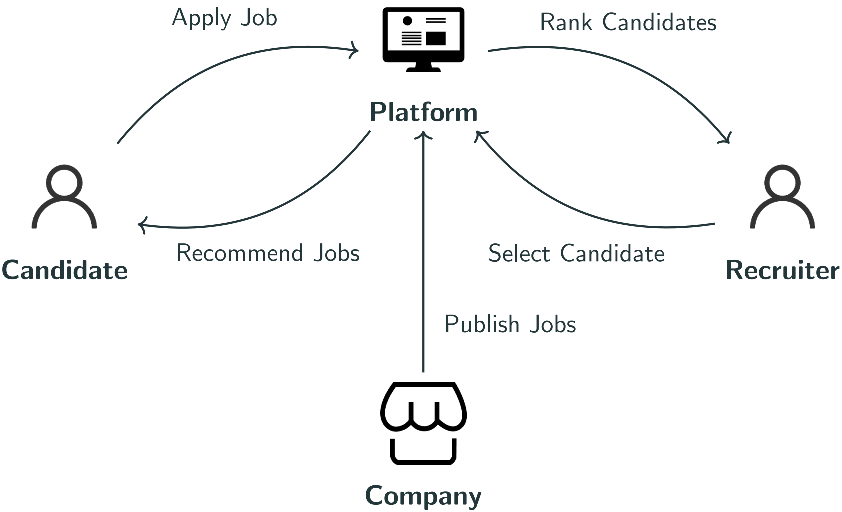
Approach: Fairness concerns are represented as agents and interact through social choice.

Social Choice for Recommendation Fairness: SCRUF-D

- 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



Fairness Concerns

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

Fairness Concerns

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 Works

Future 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.

Related Work

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

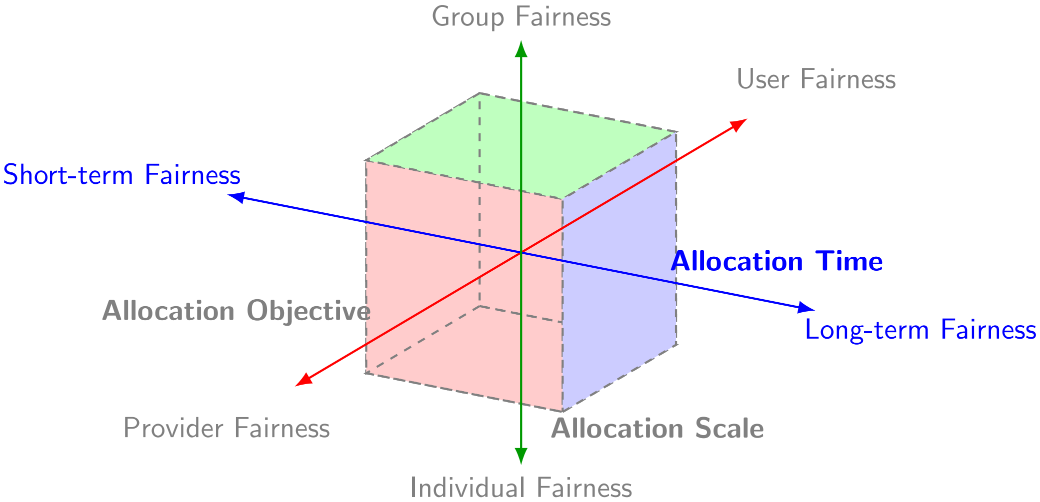
Group Fairness:

- Fair Top-k Ranking with multiple protected groups
- Balanced Ranking with Diversity Constraints

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

Allocation Time

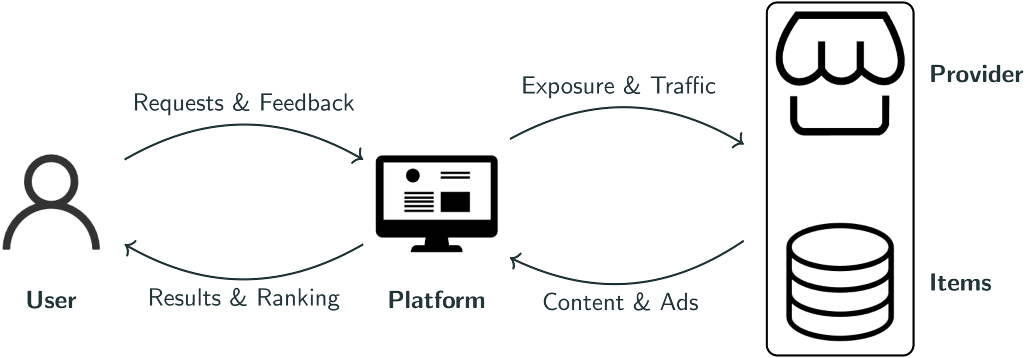
- In this section, we focus on **Allocation Time**



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 & Long-term fairness in IR

- 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 & Long-term fairness in IR

- 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 $t = 1, 2, ..., T$.

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

or

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

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

Economic intuition of IR platform

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 ρ reflects a stronger preference for immediate engagement and exposure over long-term outcomes.

Platform-specific calibration: Tunable Discount Rates

The discount rate ρ 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** ρ: Short-term focused platforms (startups, growth phase)
  - Prioritize immediate engagement and user acquisition
  - Accept higher long-term fairness risks
- **Low** ρ: 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.

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

Where $f(r_t)$ is the immediate engagement outcome of ranking r_t, $g(\boldsymbol{r})$ the platform's fairness and ξ_t 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:

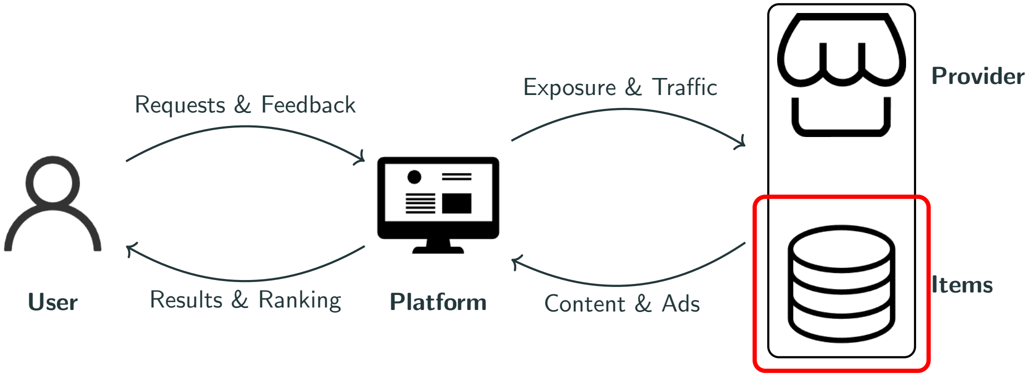
- The discount rate ρ reflects the ‘impatience’ of the platform. A higher ρ prioritizes immediate utility, while a lower ρ promotes long-term fairness and sustainability.
- Future engagement depends on both current rankings and long-term fairness, due to vulnerability to demand changes.
- By summing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

Long-term fairness in IR

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

- **Item** popularity
- **Users** & user preference
- **Ranking model** in the feedback loop
- **Provider** behavior

Long-term fairness in IR: item popularity

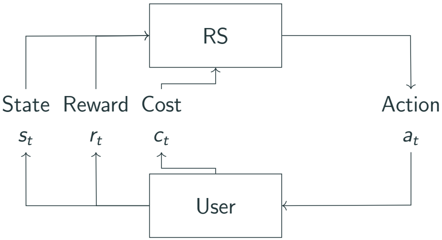


Long-term fairness in IR: item popularity

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 γ_r; discount rate of cost γ_c.



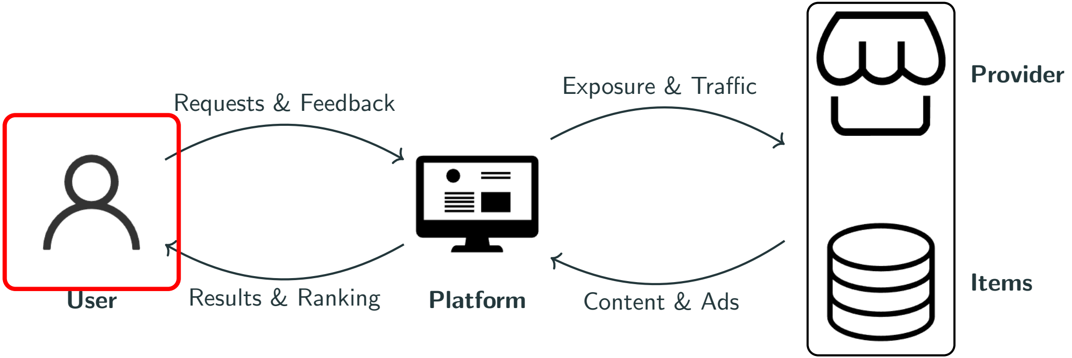
Long-term fairness in IR: item popularity

- Fairness Constrained Policy Optimization (FCPO)

$$\max_{\pi} \quad J_R(\pi)$$
$$\text{subject to} \quad J_C(\pi) \leq d$$

  - 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 π that maximizes reward while satisfying the fairness constraint.

Long-term fairness in IR: user preference



Long-term fairness in IR: user preference

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

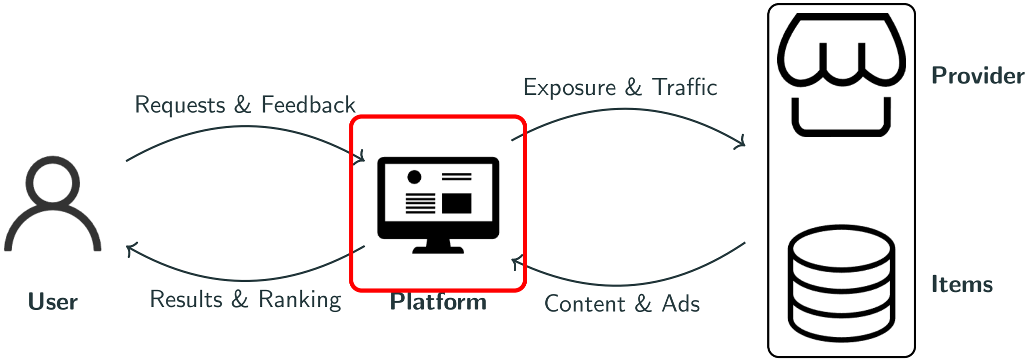
$\mathcal{D}_1$	$\mathcal{D}_2$	$\mathcal{D}_n$
Female: 0.45	Female: 0.42	Female: 0.44
Male: 0.5	Male: 0.52	Male: 0.53
PD_1: 0.05	PD_2: 0.1	PD_n: 0.09

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

Long-term fairness in IR: user preference

- 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: $\mathcal{W}_t := \mathcal{W}_t - \eta \nabla_{\mathcal{W}_t}(\mathcal{L}_{\text{rec}}^{\mathcal{D}_t} + \lambda \mathcal{L}_{\text{fair}}^{\mathcal{D}_t})$

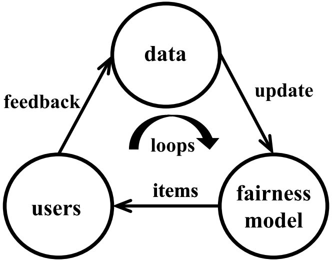
Long-term fairness in IR: RS model in feedback loop



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

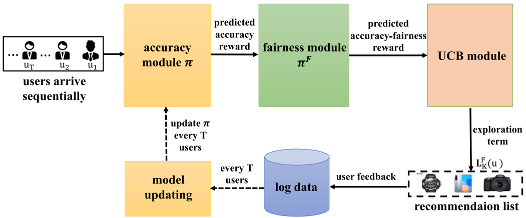
Recommendation feedback loops (RFL) will influence the provider Max-Min Fairness in the long term since RS can only receive feedback on exposed items, while **unexposed items** are considered as negative samples [Xu et al., 2023b].

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

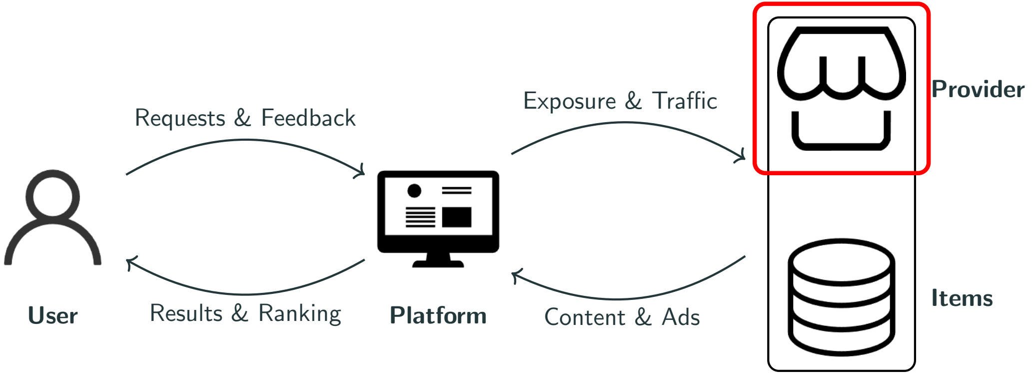


Long-term fairness in IR: RS model in feedback loop

- 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.

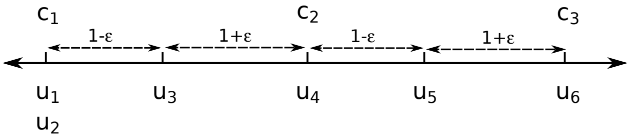


Long-term fairness in IR: provider behavior



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 - 2ϵ

Long-term fairness in IR: provider behavior

- Problem formulation: epoch-based optimal constrained matching problem

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

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

Application: Personalized Financial Recommendation

Personalized Financial Recommendation

- Platforms increasingly adapt financial products - such as loans, credit cards, and insurance plans - based on personal data analysis.
- **Challenge:** Build predictive systems that estimate repayment likelihood while balancing:
  - **Profitability:** Minimize default risk and maximize financial returns.
  - **Access:** Ensure fair and inclusive access to credit across different social and economic groups.

Fairness in Credit Scoring

- Credit scoring and loan underwriting often reflect existing **societal inequalities** along income, education and racial lines
- These biases are reinforced through data-driven models, perpetuating financial exclusion [Hassani, 2021].
- Unfair credit markets are inefficient and can cause financial instability!
- **Fairness methods should account for long-term impacts on financial inclusion and stability.**

Towards Fairness Over Time

- Economic *time discounting* helps balance short- and long-term fairness.
- The platform's utility of recommendations is dependent on both imminent rewards and fairness of the system, which affects future rewards

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

- $u(\boldsymbol{r}, \boldsymbol{f})$: obtained value from recommendations, dependent on both immediate rewards and long-run fairness
- ρ: discount rate controlling short- vs. long-term focus

Future and Related Works

Future 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?

Long-term fairness in IR: related work

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

Open Problems, Quick Start for Learning Fairness, and Conclusions (Maarten, 20min)

Open Problems

Future Direction of Fairness From Economic Perspective

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

Current Fair-aware IR Style

Adjust IR systems to meet fairness requirements!

Dataset ⟶  ⟶ Fair Output

IR System

Level-1: Designing Fair Welfare Function

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

Dataset ⟶  ⟶ Fair Output ⟶ **1. Welfare Functions**

Fair IR System

Level-1: Designing 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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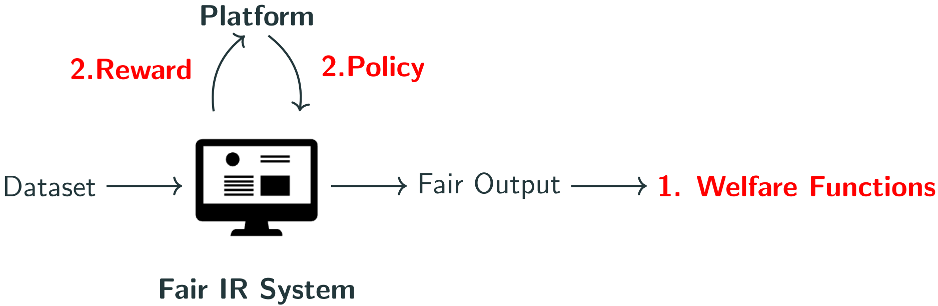
- **Single** layer aggregation (time, category)
- **Hierarchical** aggregation

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

- **Accumulated** fairness constraint

- **Level-2**: Incorporating Platform Decisions: from **predictions** to **actions**



Level-2: Incorporating Platform Decisions

Objective: Platform needs adapt different policy for stakeholders

- Incorporating platform and user/provider objectives

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Scale: Platform Policy Influences Different Scales of Stakeholders

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

Level-2: Incorporating Platform Decisions

Objective: Platform needs adapt different policy for stakeholders

- Incorporating platform and user/provider objectives

Scale: Platform Policy Influences Different Scales of Stakeholders

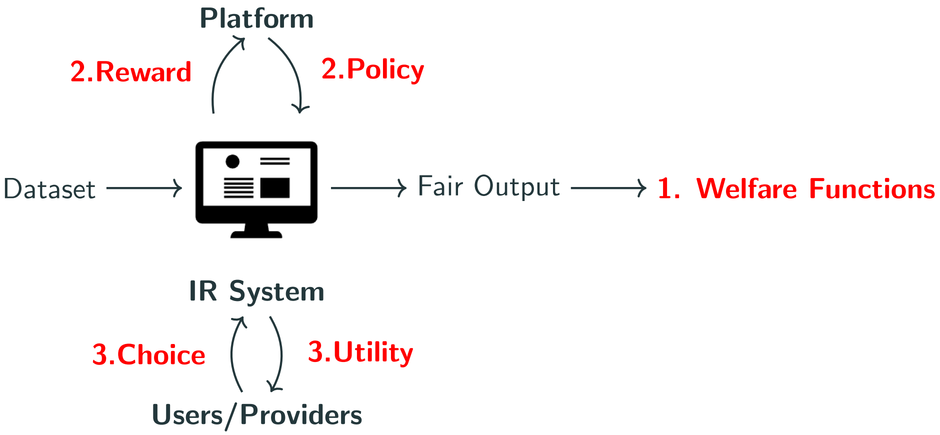
- **Simulating and modeling** different scale of stakeholders

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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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 Fairness in IR

Toolkits: FairDiverse

- We develop an easily-usable toolkit *FairDiverse* [Xu et al., 2025a] for learning fairness in IR
- Github: https://github.com/XuChen0427/FairDiverse

Toolkits: FairDiverse

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

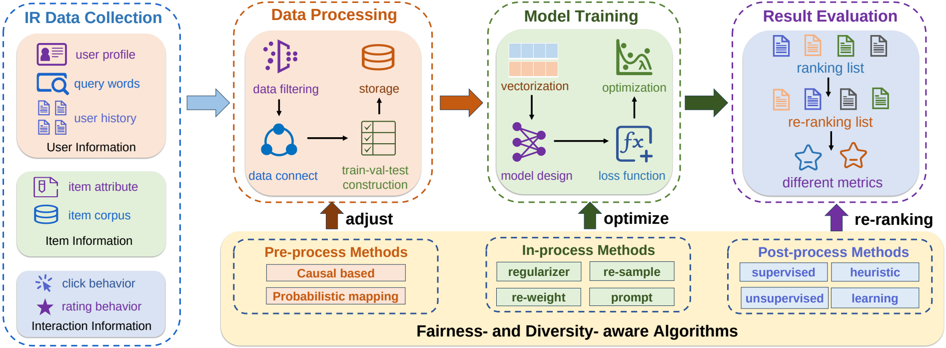
Existing Toolkits

Comparison of **FairDiverse** with existing toolkits:

Features	Recbole	FFB	Fairlearn	AIF360	Aequitas	**FairDiverse**
Recommendation	✓	✗	✗	✗	✗	✓
Search	✗	✗	✗	✗	✗	✓
Pre-processing	✗	✗	✓	✓	✓	✓
In-processing	✓	✓	✓	✓	✓	✓
Post-processing	✗	✗	✓	✓	✓	✓
Number of models	4	6	6	15	10	**29**

Toolkits: FairDiverse

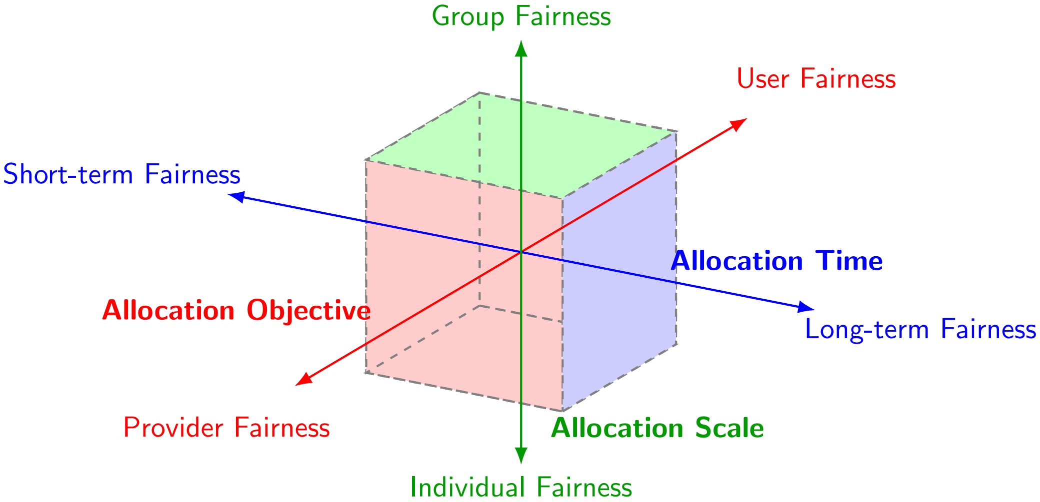
- End-to-End Coverage: From **data collection**, **data processing**, **model training** and **result evaluation**
- Helps users understand and apply fairness in a **structured, reproducible** way
- Helps users develop their **own fair-aware IR models**



Conclusions

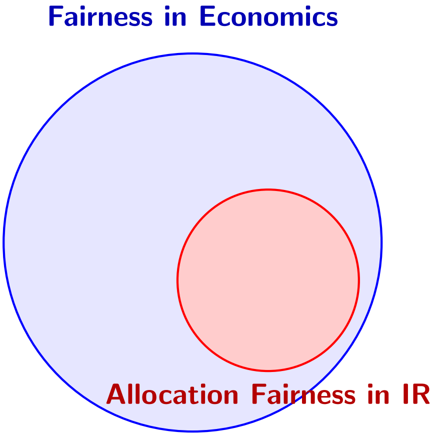
Economic Providers Good Framework for Analyzing Fairness in IR

- Allocation Objective, Scale, and Time



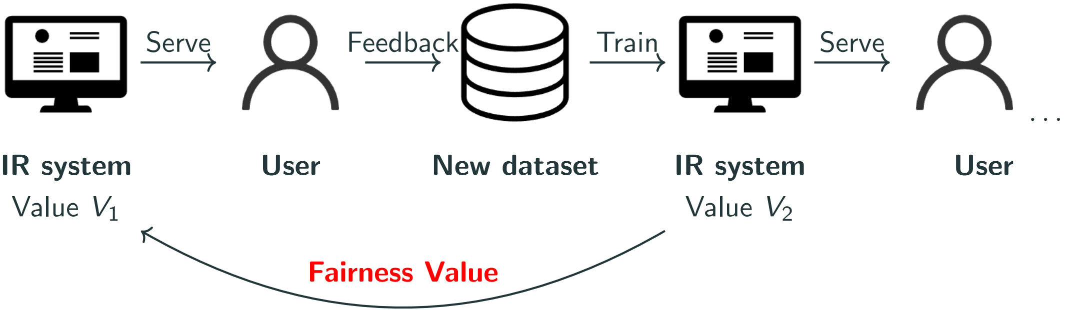
Economic Provides New Tools

- Taxation, Risk-return, Game-theory, Social Choice



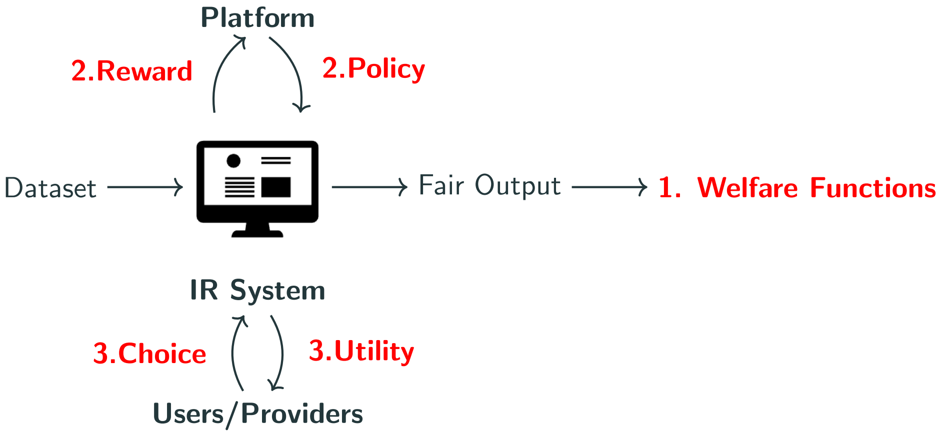
Leveraging Economic Thinking for Fairness in IR

- F airness 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 Points out Future Directions

- Three levels of fairness problems



Related Materials for Exploring Fairness in IR

Survey:

- 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 **Toolkit**

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