Rethinking Online Content Ecosystems through the Lens of Computational Economics

A Tutorial Talk at Sigecom Winter 25 Meeting

Haifeng Xu

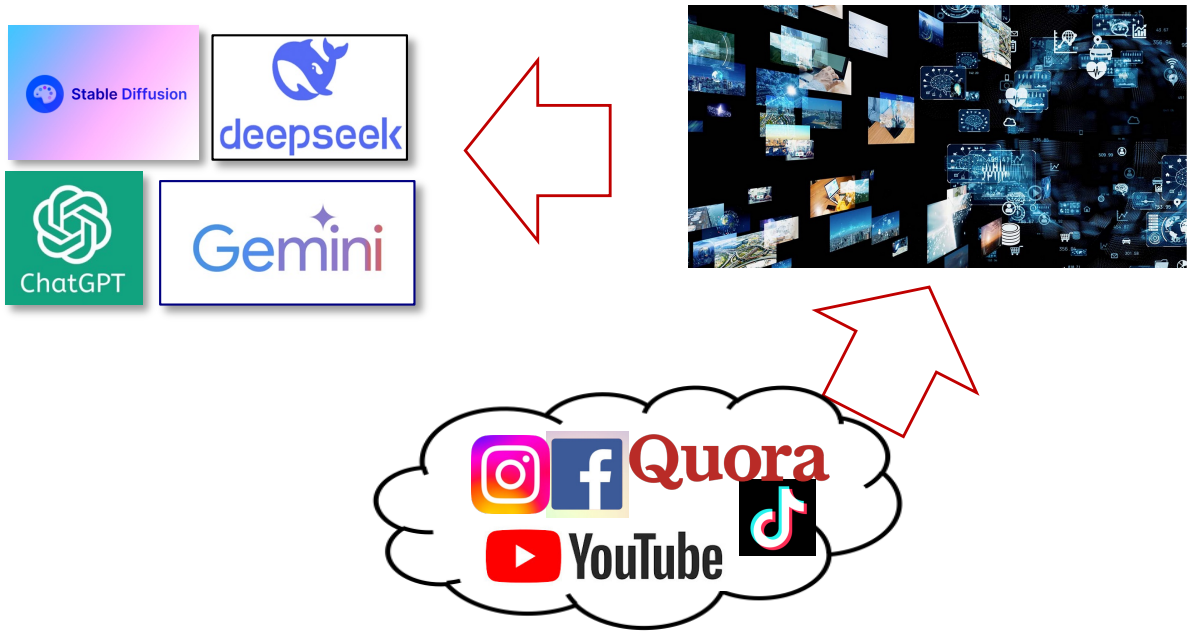
Department of Computer Science
and Data Science Institute

University of Chicago

SIGMA LAB
Strategic IntelliGence in Machine Agents

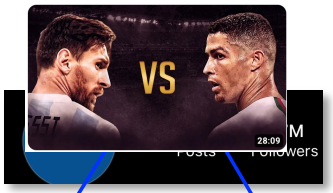
Content Recommendation System (RS)

- An indispensable component of our life
- Crucial to success of generative AIs (GenAIs)



Classic Research Paradigm in RSs

System learning/optimization
in
static environments



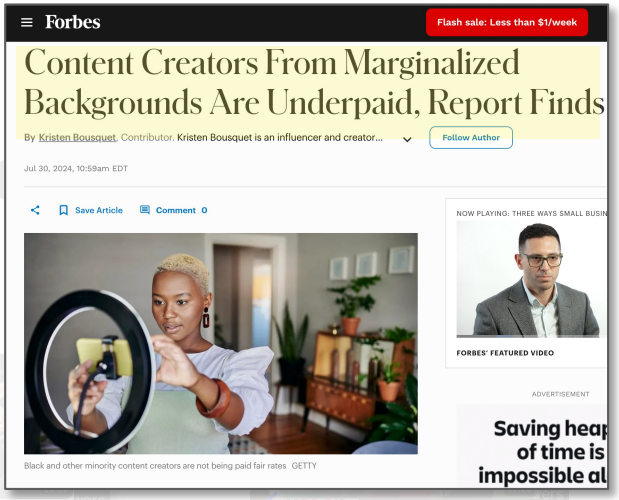
Static

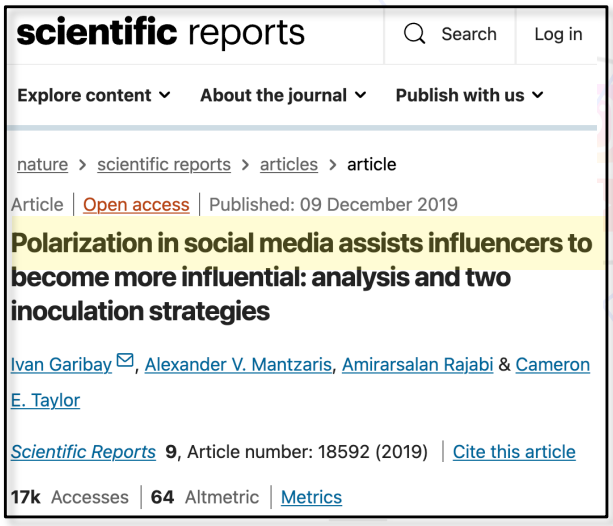
- ✓ Extensively studied in information retrieval
- ✓ Technology for learning to rank or match preferences is pretty mature (also affirmed by personal experience)

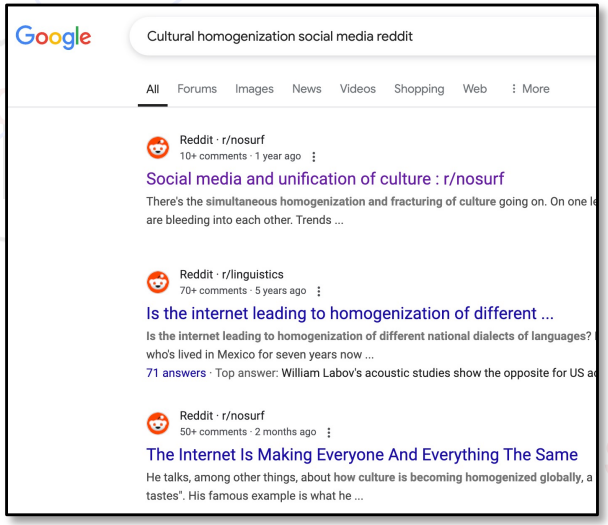
The only
“active” party

Static

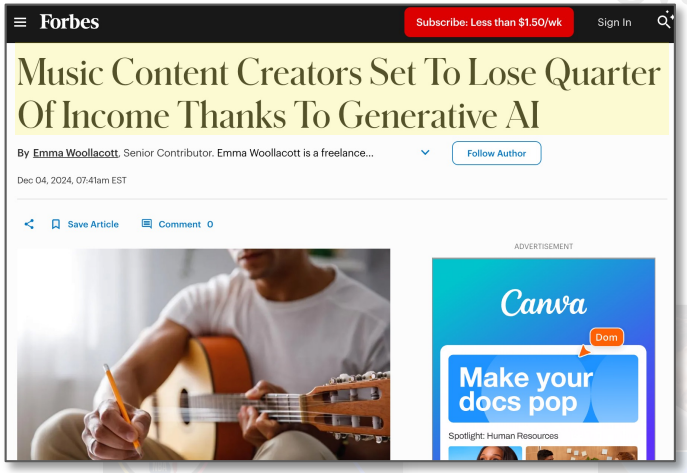
But… Still Many Pressing Issues

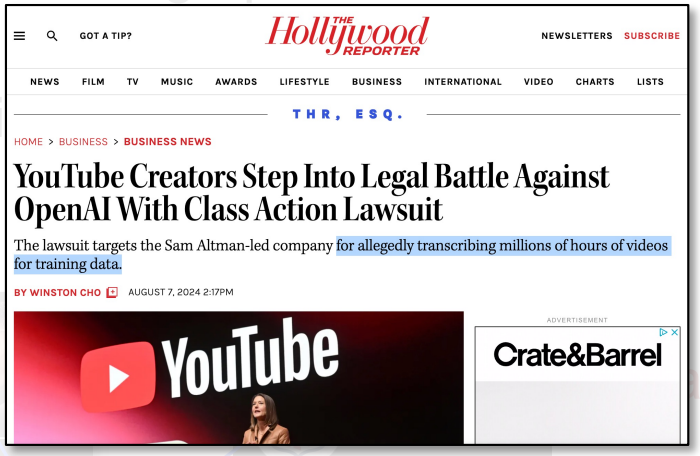


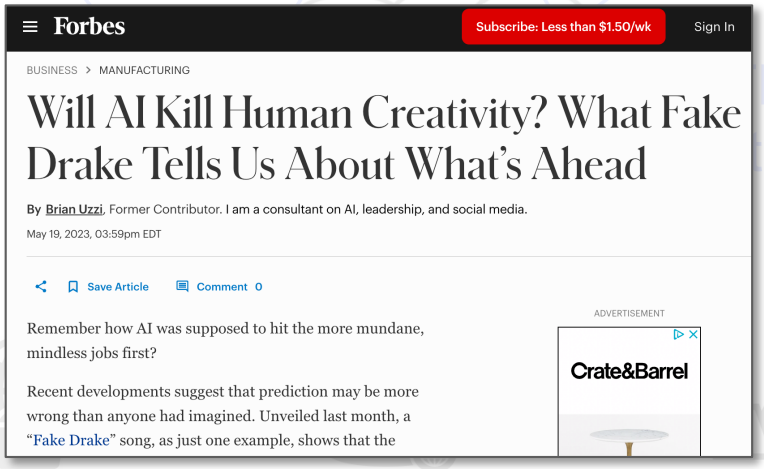




More Issues Arise with AI-Generated Content (AIGC)



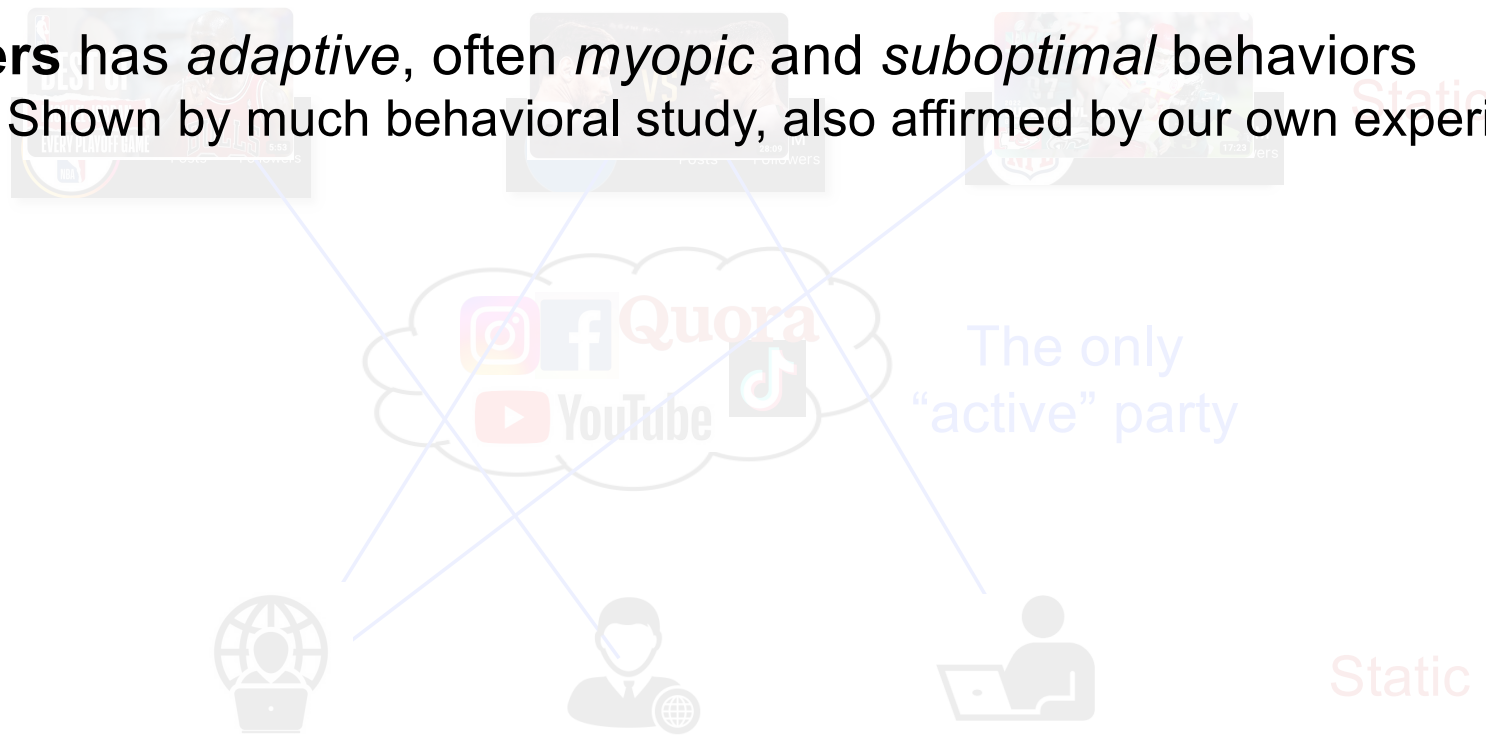




Why?

Pure Learning Overlooks Creators' and Users' Autonomy

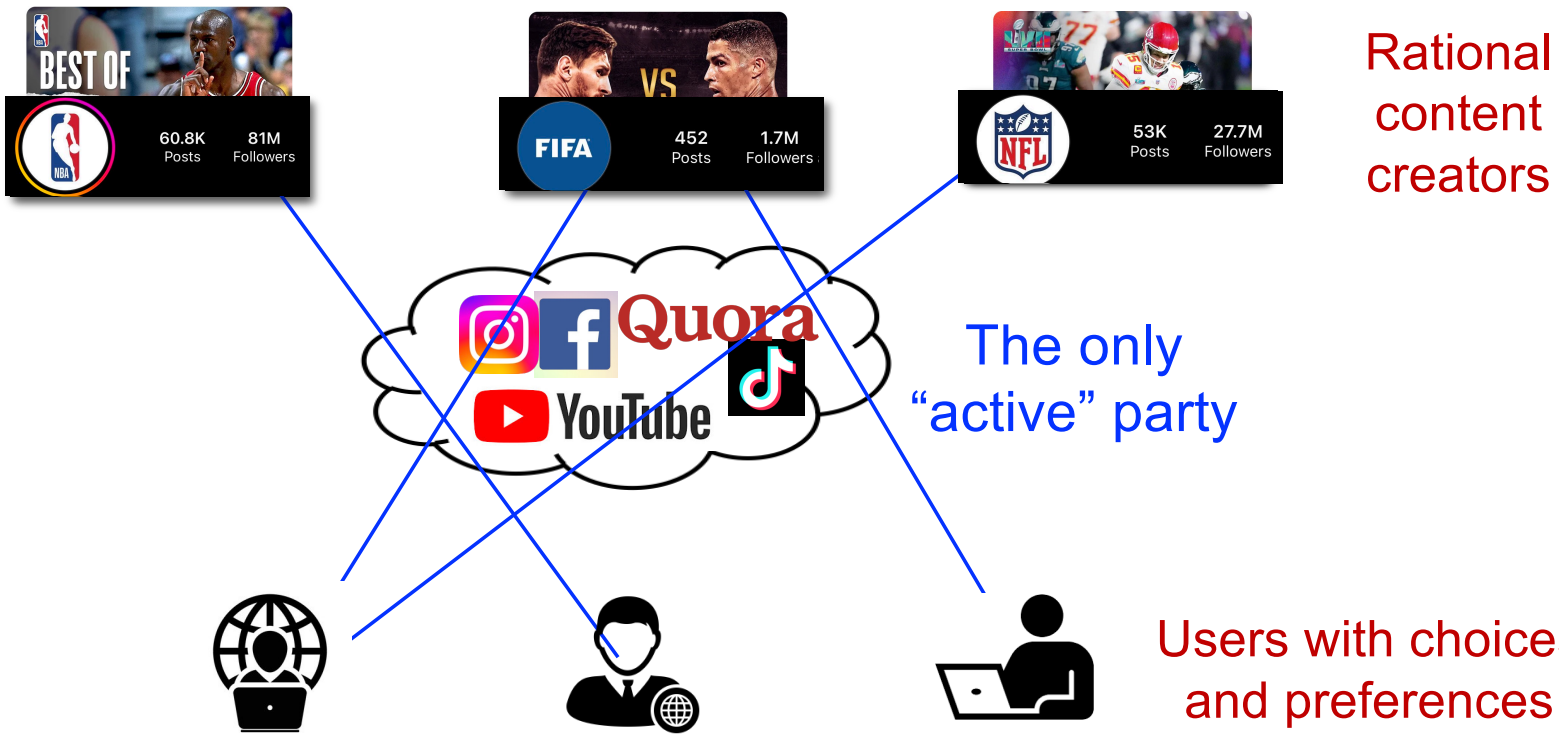
- **Creators** respond to incentives
  - E.g., Youtubers create longer videos when they are rewarded by view duration [MC'23])
  - AIGC significantly reshapes creators' incentives
- **Users** has *adaptive*, often *myopic* and *suboptimal* behaviors
  - Shown by much behavioral study, also affirmed by our own experience



How the YouTube Algorithm Works in 2023: The Complete Guide. Stacey McLachlan, Paige Cooper (2023)

Rethinking classic RS paradigm….

System optimization
in
static environments



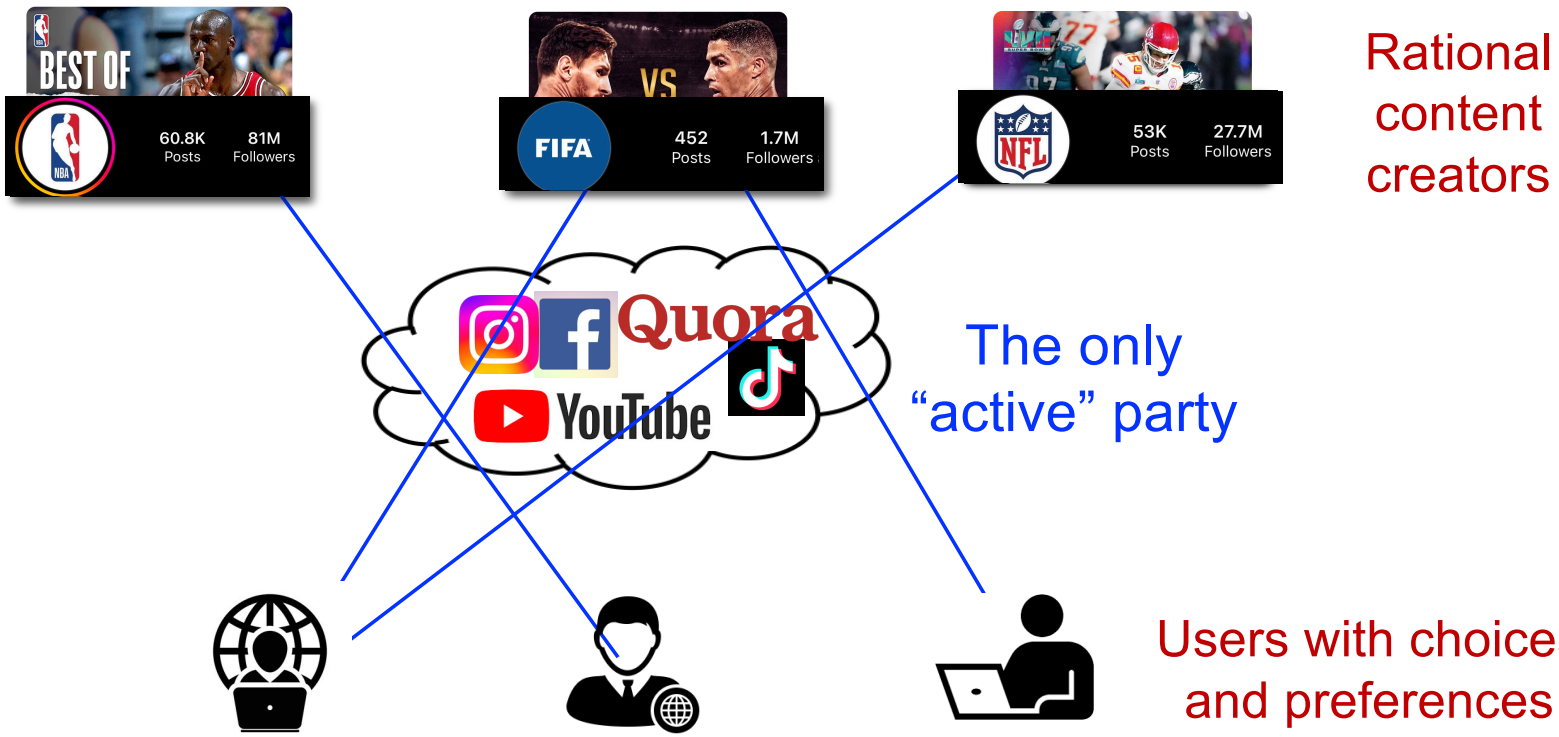
Rational
content
creators

The only
“active” party

Users with choices
and preferences

Rethinking classic RS paradigm….

~~System optimization~~ Multi-agent interactions in changing ~~static~~ environments

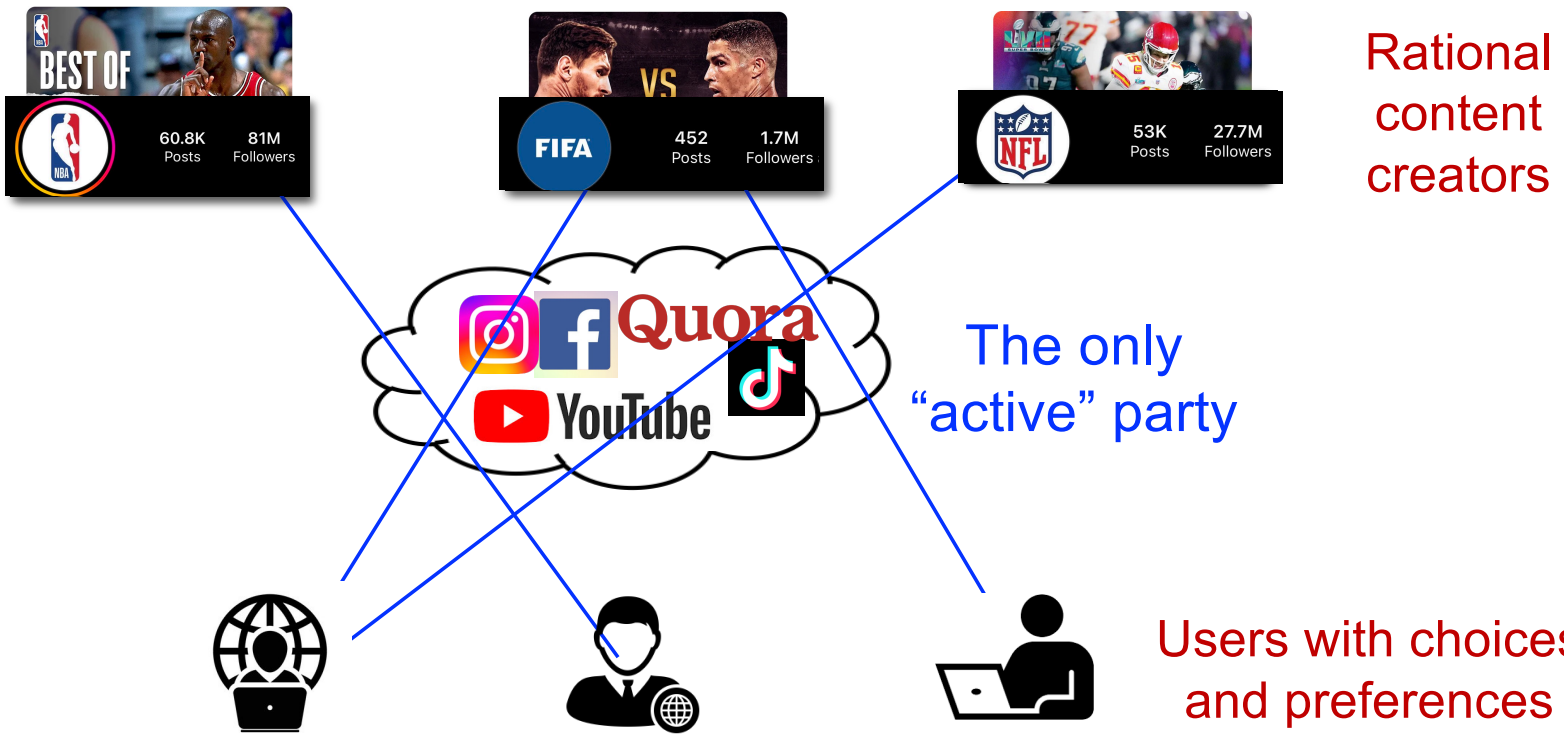


Remainder of this talk will survey recent works that

- Model incentives and agency in content ecosystems
- Study equilibria, incentive mechanisms, and impact of AIGC

Rethinking classic RS paradigm….

Multi-agent interactions ~~System optimization~~ in changing ~~static~~ environments

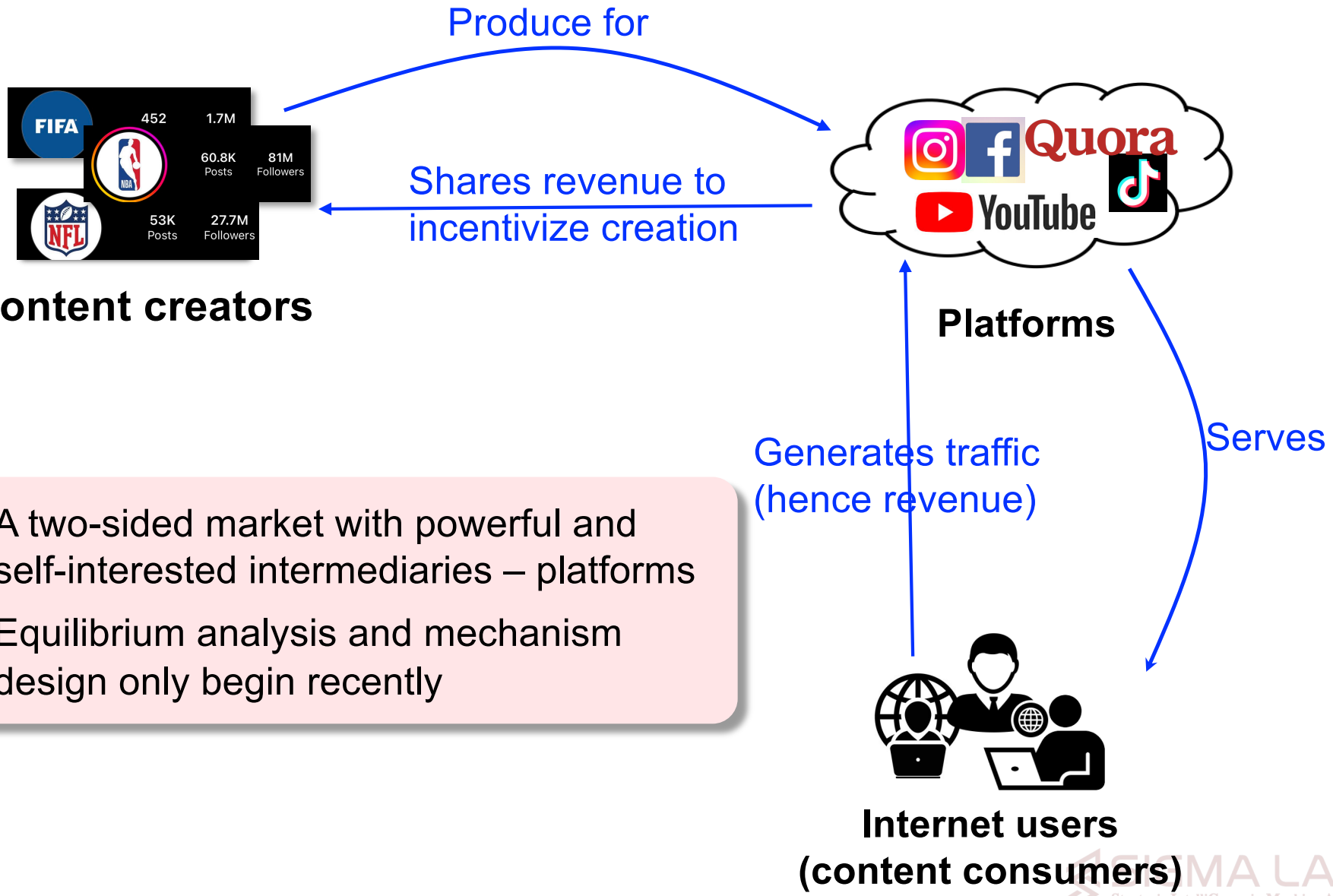


Outline

- **Part I:** Diagnosing and Optimizing Existing Content Ecosystems

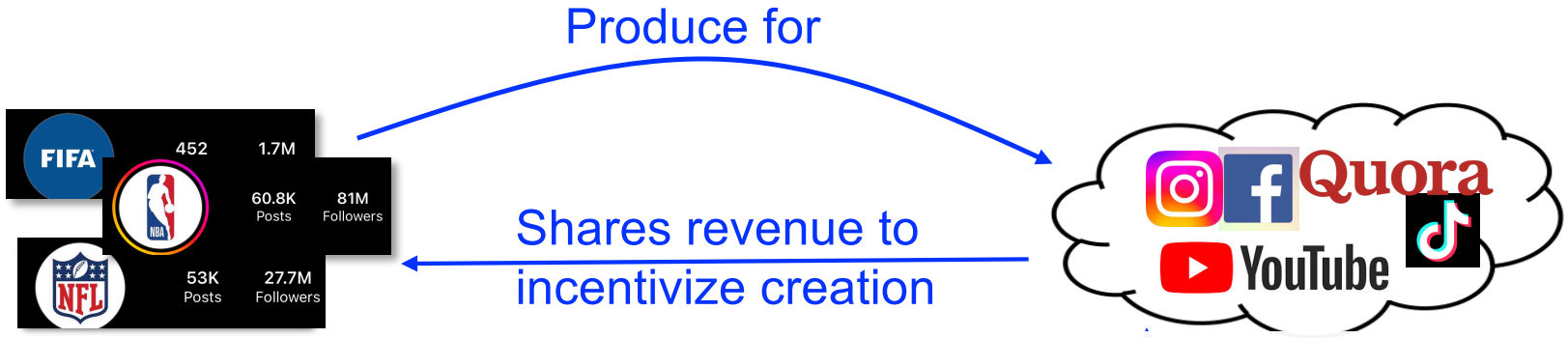
- **Part II:** How Does AIGC Transform Future Content Ecosystems

A Game with Three Types of Players



- A two-sided market with powerful and self-interested intermediaries – platforms
- Equilibrium analysis and mechanism design only begin recently

Recent Advances: Supply Side



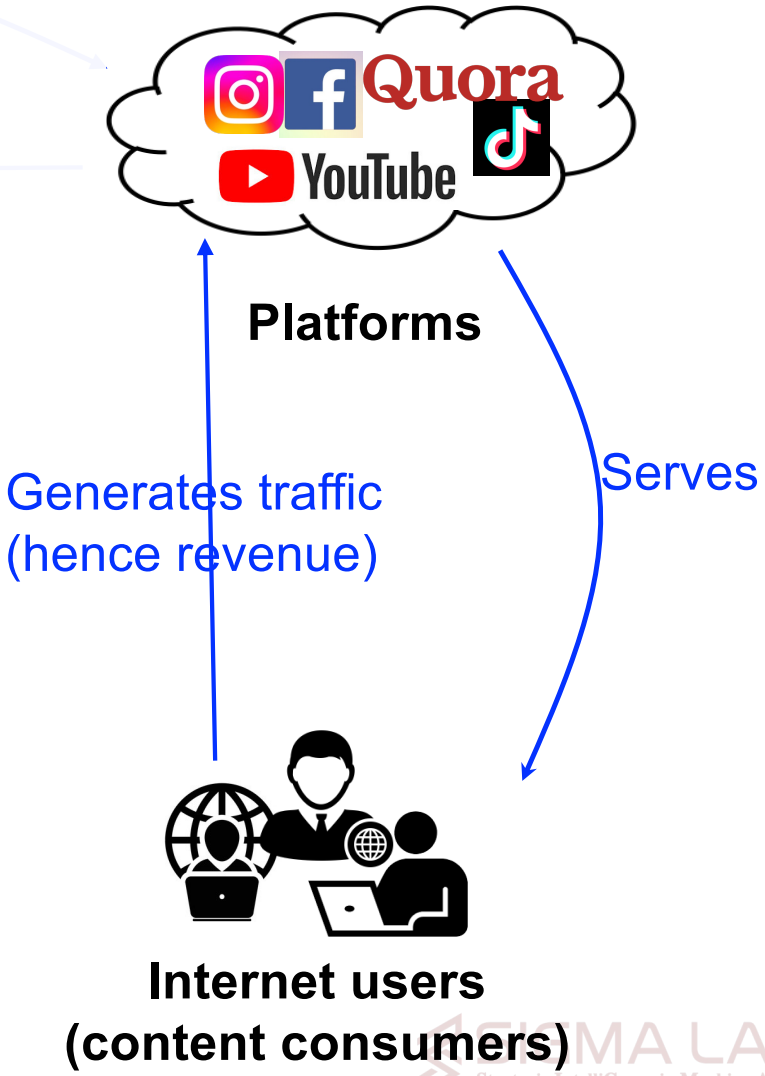
Content creators

- [Ben-Porat and Tennenholtz, NeurIPS'18] and [Ben-Porat et al., NeurIPS'20] are the first to consider creator competition and platform mediation
- [Mladenov et al. ICML'20] studies system's matching mechanism, accounting for creator incentives
- [Jagadeesan et al, NeurIPS'23] characterizes content distributions at equilibrium

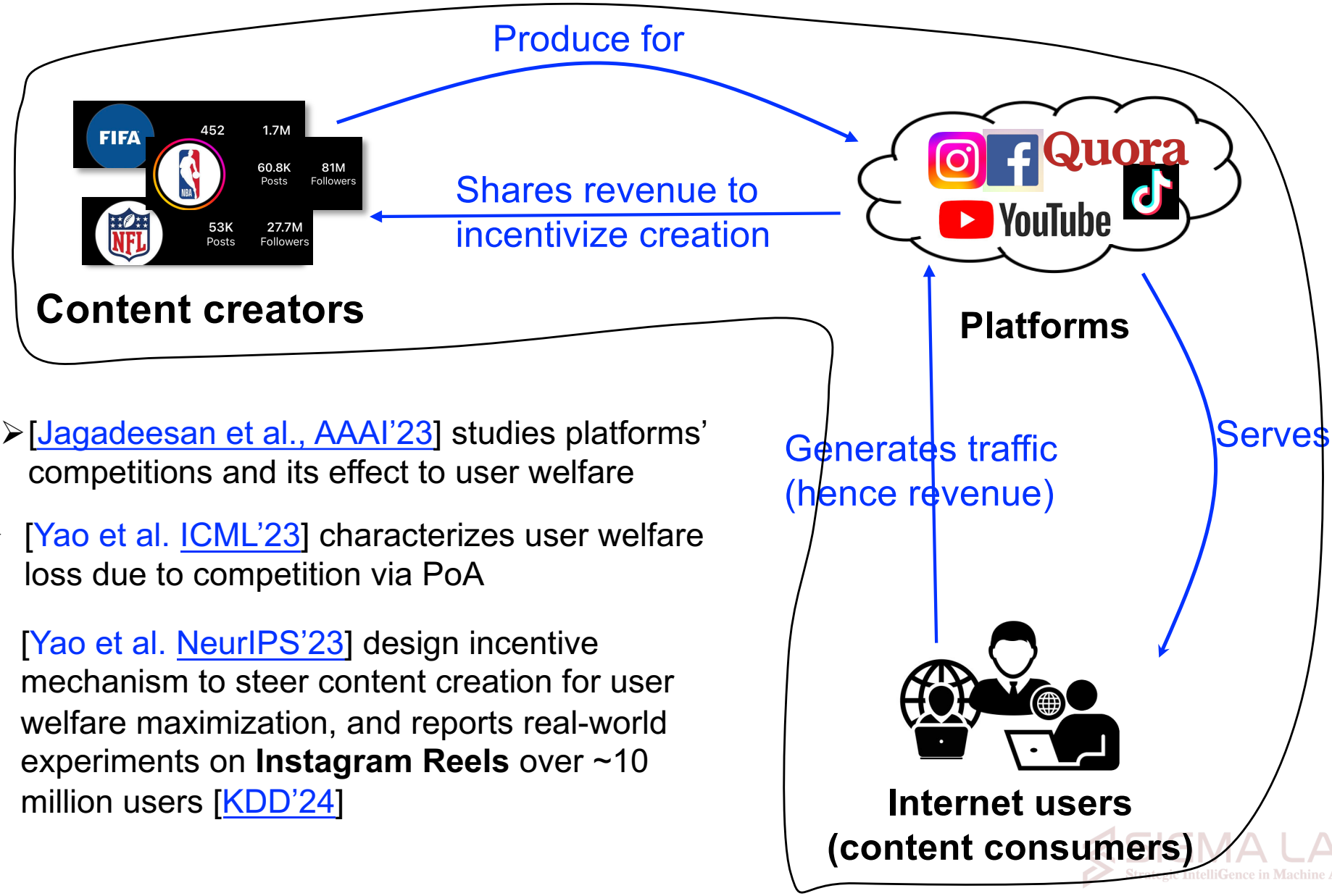
Recent Advances: Consumption Side

Less studied; research mostly focuses on improving recommendation efficiency via "behavior-aware" system learning

- [Kleinberg et al., MS'23] considers platform's learning of user preferences and argues that sub-optimality comes from human's irrational behaviors
- [Yao et al., ICML'22] designs platform's algorithms to learn from explorative users

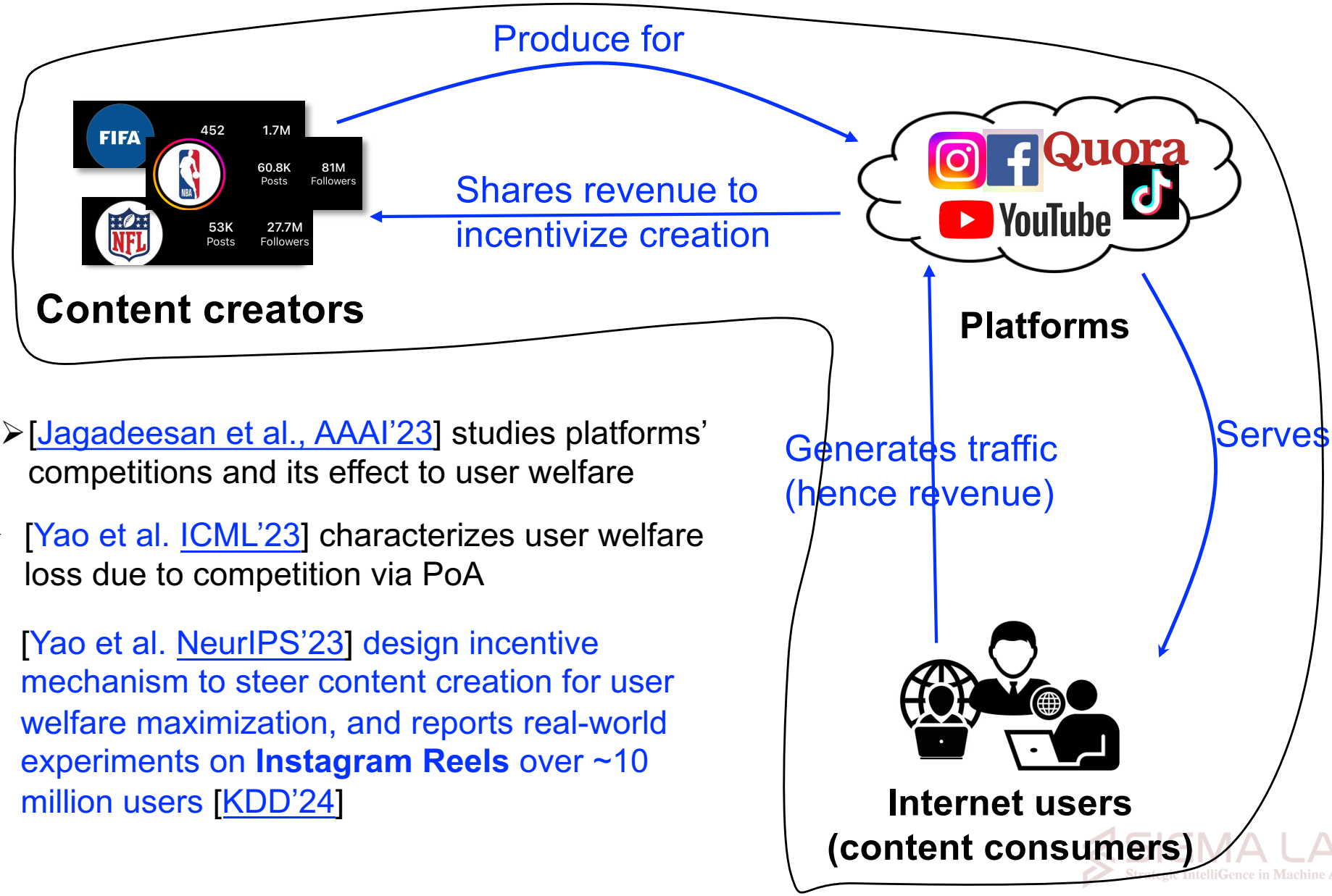


Recent Advances: Ecosystem Perspective



- [Jagadeesan et al., AAAI'23] studies platforms' competitions and its effect to user welfare
- [Yao et al. ICML'23] characterizes user welfare loss due to competition via PoA
- [Yao et al. NeurIPS'23] design incentive mechanism to steer content creation for user welfare maximization, and reports real-world experiments on **Instagram Reels** over ~10 million users [KDD'24]

Recent Advances: Ecosystem Perspective



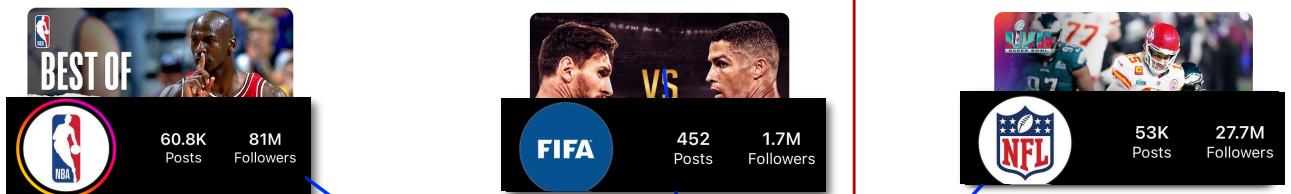
- [Jagadeesan et al., AAAI'23] studies platforms' competitions and its effect to user welfare
- [Yao et al. ICML'23] characterizes user welfare loss due to competition via PoA
- [Yao et al. NeurIPS'23] design incentive mechanism to steer content creation for user welfare maximization, and reports real-world experiments on **Instagram Reels** over ~10 million users [KDD'24]

Modeling the Content Creation Competition (C3)

Top 2 Choices

Contents (actions)

$s_1 \in S_1$ $s_2 \in S_2$ $s_3 \in S_3$



Estimated user utility: $\sigma(s_1, x)$ $\sigma(s_2, x)$ $\sigma(s_3, x)$

True user utility $\sigma(s_1, x) + \epsilon_1 \; (<) \; \sigma(s_2, x) + \epsilon_2$

- i.i.d Gumbel noise (a.k.a random utility model [Manski'77])
- Correspond to softmax choice

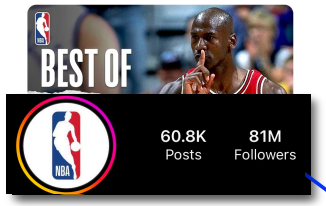
User x

drawn from population/distribution F

Modeling the Content Creation Competition (C3)

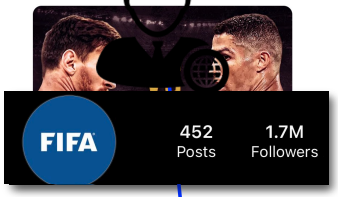
Contents (actions)

$s_1 \in S_1$



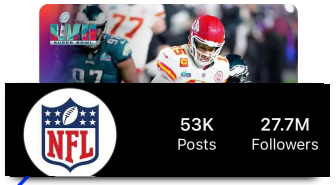
$\sigma(s_2, x) + \epsilon_2$

$s_2 \in S_2$



=Creator 2's utility (= welfare)

$s_3 \in S_3$



Estimated user utility: $\sigma(s_1, x)$ $\sigma(s_2, x)$ $\sigma(s_3, x)$

True user utility $\sigma(s_1, x) + \epsilon_1$ $(<)$

drawn from population/distribution F

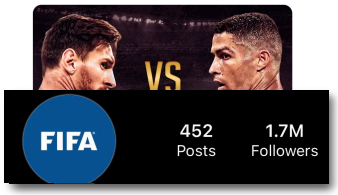
Modeling the Content Creation Competition (C3)

- Content creator's objective: (1) maximize traffic (i.e., attracted users), minus producing cost

$$\mathbb{E}_{x\sim F}\left[\mathbb{I}(x \text{ visits creator 2})\right] - c_2(s_2)$$

$\sigma(s_2, x) + \epsilon_2$ =Creator 2's utility (= welfare)

$s_2 \in S_2$



$\sigma(s_2, x)$

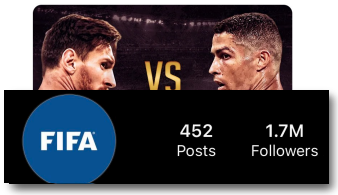
Modeling the Content Creation Competition (C3)

- Content creator's objective: (1) maximize traffic (i.e., attracted users), minus producing cost or (2) maximize welfare/happiness of their traffic

$$\frac{\mathbb{E}_{x\sim F}\left[\mathbb{I}(x \text{ visits creator 2}) \cdot (\sigma(s_2, x) + \epsilon_2)\right]}{\text{Rewards from platform}} - c_2(s_2)$$

$\sigma(s_2, x) + \epsilon_2$ =Creator 2's utility (= welfare)

$s_2 \in S_2$



$\sigma(s_2, x)$

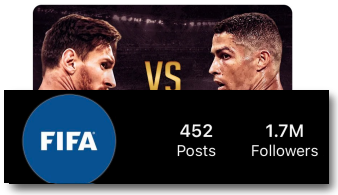
Modeling the Content Creation Competition (C3)

- Content creator's objective: (1) maximize traffic (i.e., attracted users), minus producing cost or (2) maximize welfare/happiness of their traffic

$$\frac{\mathbb{E}_{x\sim F}\left[\mathbb{I}(x \text{ visits creator 2}) \cdot (\sigma(s_2, x) + \epsilon_2)\right]}{\text{Rewards from platform}} - c_2(s_2)$$

$\sigma(s_2, x) + \epsilon_2$ =Creator 2's utility (= welfare)

$s_2 \in S_2$



$\sigma(s_2, x)$

- Platform cares about system efficiency – i.e. total welfare

$$\sum_i U(\text{creator } i) + \sum_x [\, U(\text{user } x)\,]$$

This modeling structure is the backbone of many previously mentioned works, though details could be different

The Inefficiency of Rewarding Only Traffic or Welfare

Content creator's objective: (1) maximize traffic (i.e., attracted users), minus producing cost or (2) maximize welfare/happiness of their traffic

$$\mathbb{E}_{x\sim F}\left[\mathbb{I}(x \text{ visits creator 2}) \cdot (\sigma(s_2, x) + \epsilon_2)\right] - c_2(s_2)$$

- Can have large price of anarchy (though often smaller than 2) [Yao at el., ICML'23]

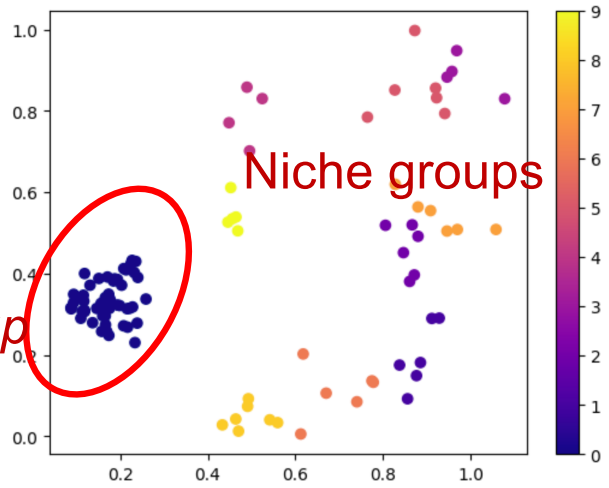
The Inefficiency of Rewarding Only Traffic or Welfare

Content creator's objective: (1) maximize traffic (i.e., attracted users), minus producing cost or (2) maximize welfare/happiness of their traffic

$$\mathbb{E}_{x\sim F}\left[\mathbb{I}(x \text{ visits creator 2}) \cdot (\sigma(s_2, x) + \epsilon_2)\right] - c_2(s_2)$$

- Can have large price of anarchy (though often smaller than 2) [Yao at el., ICML'23]

Inefficiency is due to "tragedy of commons" type of phenomenon



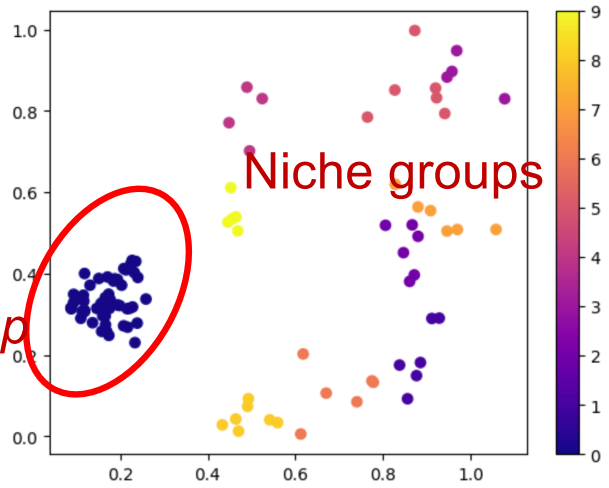
The Inefficiency of Rewarding Only Traffic or Welfare

Content creator's objective: (1) maximize traffic (i.e., attracted users), minus producing cost or (2) maximize welfare/happiness of their traffic

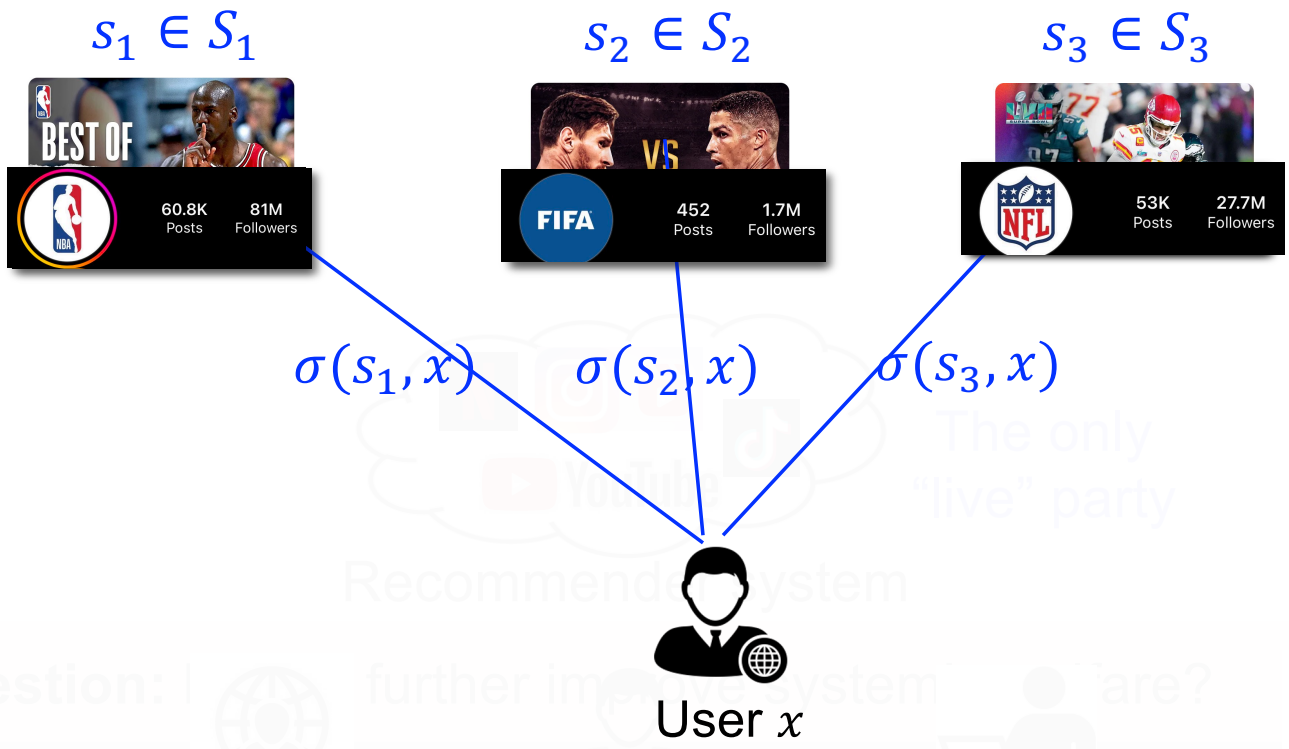
$$\mathbb{E}_{x\sim F}\left[\mathbb{I}(x \text{ visits creator 2}) \cdot (\sigma(s_2, x) + \epsilon_2)\right] - c_2(s_2)$$

- Can have large price of anarchy (though often smaller than 2) [Yao at el., ICML'23]
- In fact, if creator reward mechanism satisfies certain monotone properties, it can never be welfare-maximizing [Yao at el., NeurIPS'23]

Inefficiency is due to "tragedy of commons" type of phenomenon



Mechanism Design to Incentivize Content Creation



Mechanism Design to Incentivize Content Creation

Contents (actions)

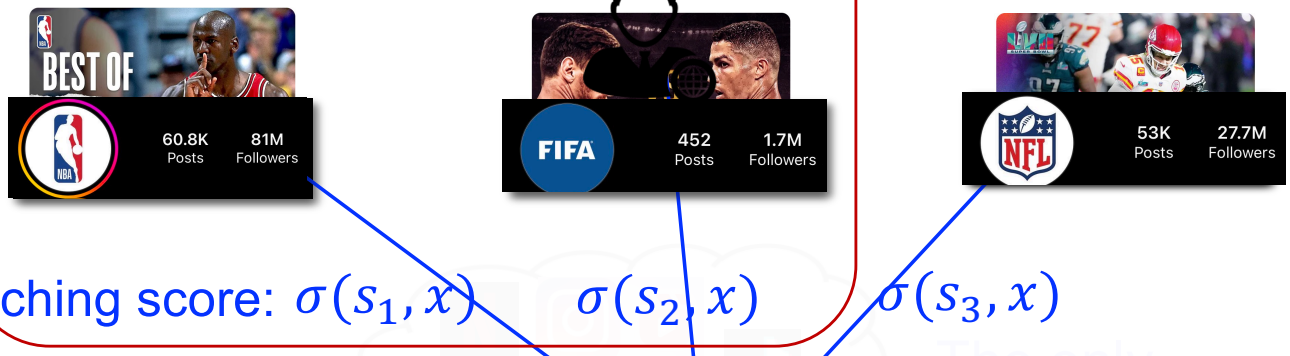
$s_1 \in S_1$

$\sigma(s_2, x) + \epsilon_2$

$s_2 \in S_2$

$s_3 \in S_3$

=Creator 2's utility (= welfare)

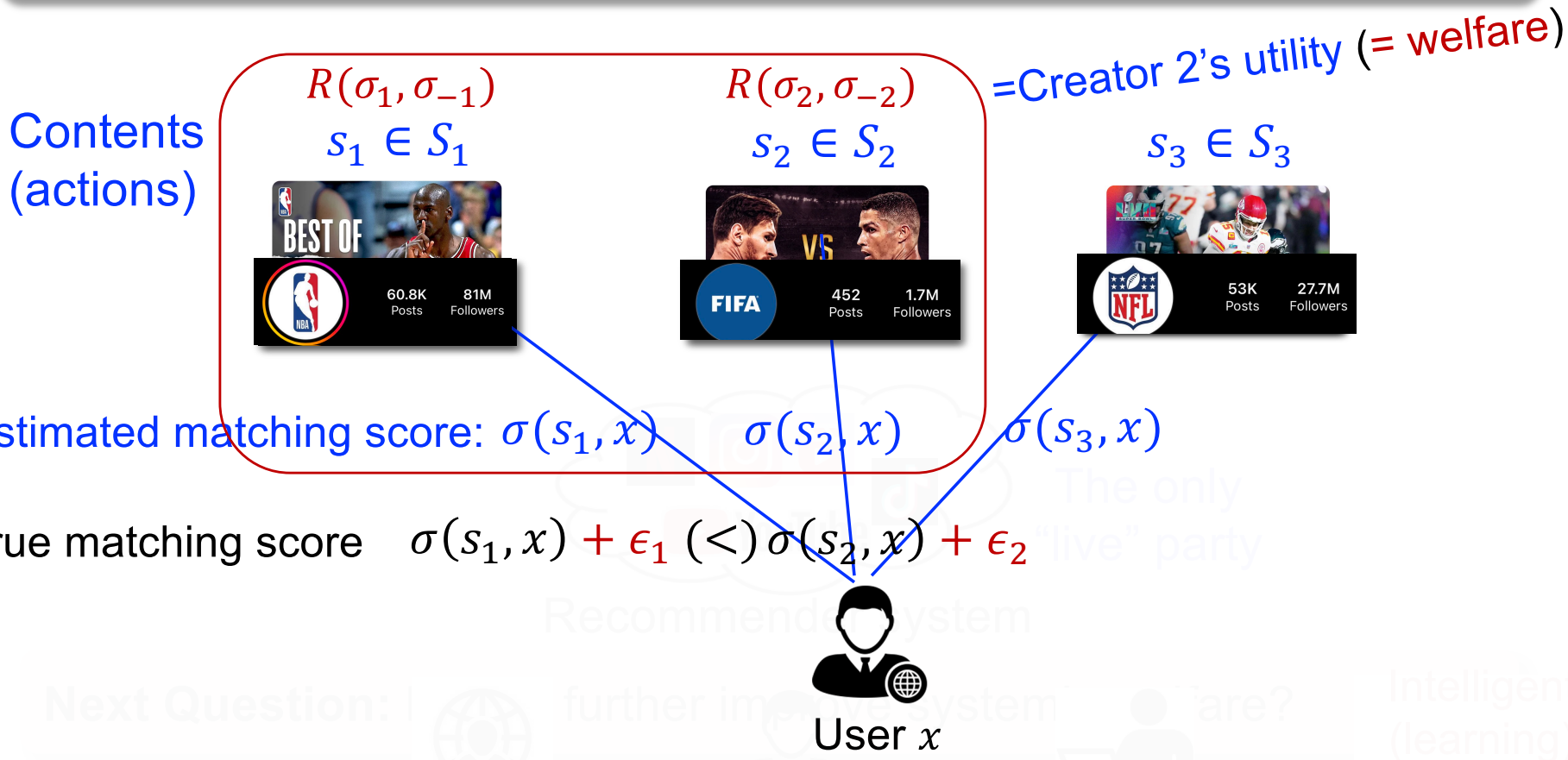


Estimated matching score: $\sigma(s_1, x)$ $\sigma(s_2, x)$ $\sigma(s_3, x)$

True matching score $\sigma(s_1, x) + \epsilon_1$ (<)

Mechanism Design to Incentivize Content Creation

Q: Can we design/optimize the reward values R to "steer"/incentivize creators' collective behaviors towards better total welfare?

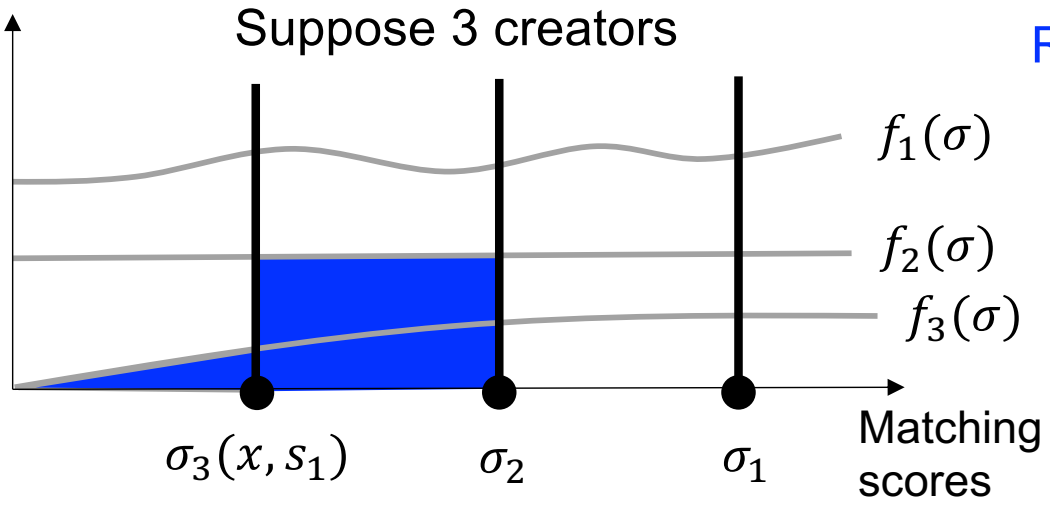


Mechanism Design to Incentivize Content Creation

[Yao et al.'23] develops a new mechanism that introduces more competition for congested topics, and achieves optimal welfare at equilibrium

Core idea: reward based on how much a creator is better than the next

- Mechanism is fully described by these functions
- Reward = area of 

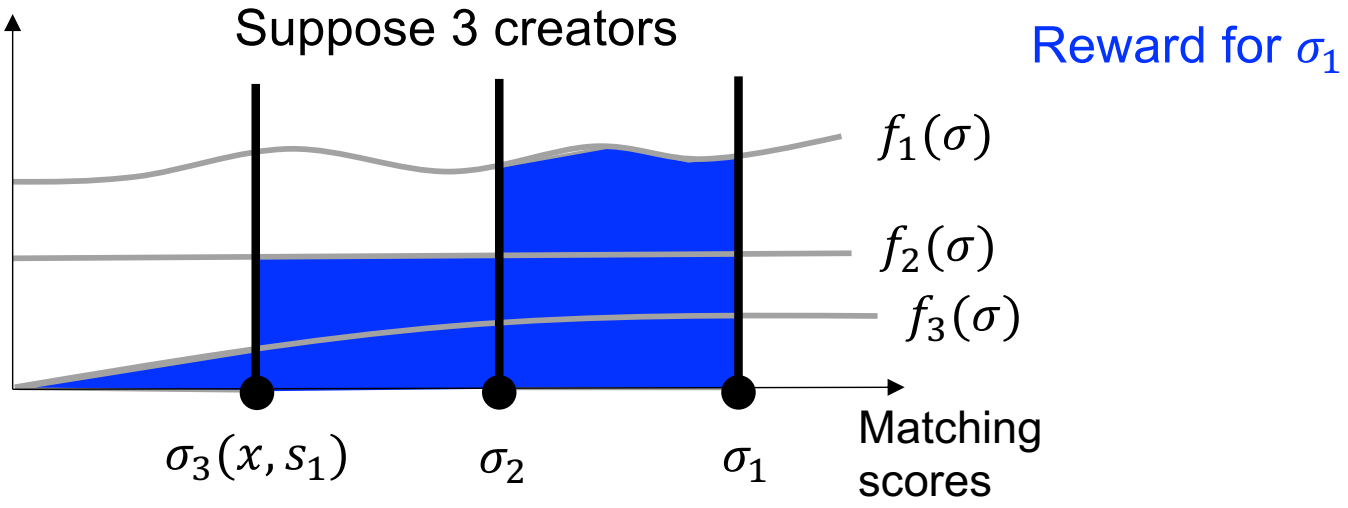


Mechanism Design to Incentivize Content Creation

[Yao et al.'23] develops a new mechanism that introduces more competition for congested topics, and achieves optimal welfare at equilibrium

Core idea: reward based on how much a creator is better than the next

- Mechanism is fully described by these functions
- Reward = area of 



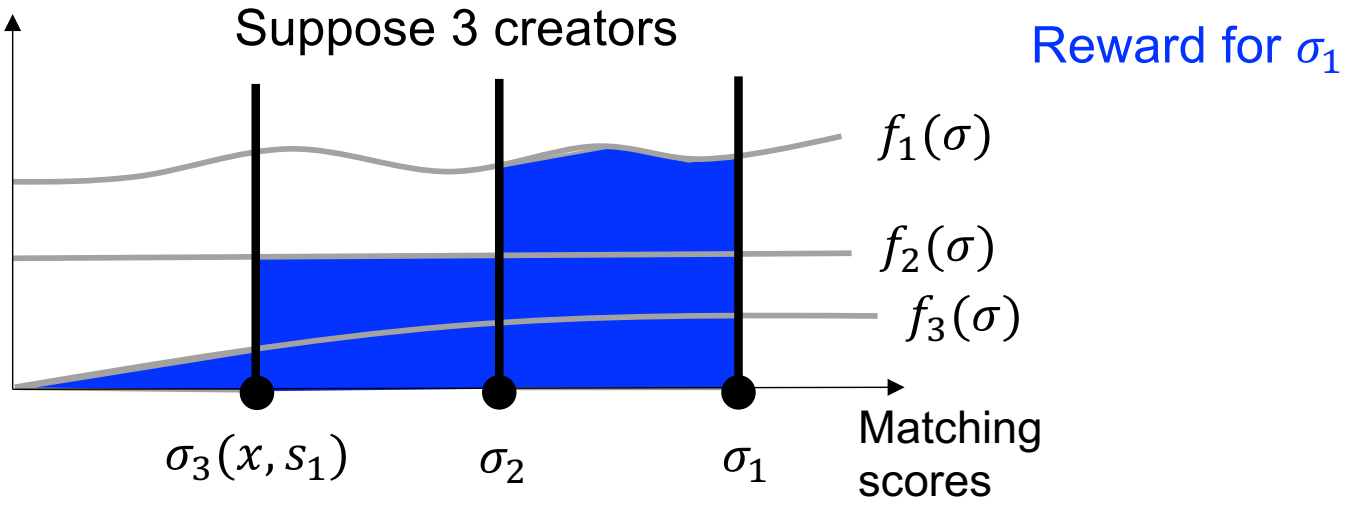
Mechanism Design to Incentivize Content Creation

[Yao et al.'23] develops a new mechanism that introduces more competition for congested topics, and achieves optimal welfare at equilibrium

Core idea: reward based on how much a creator is better than the next

Advantages

✓ σ_1's reward decreases when σ_2 becomes better (i.e., competition reduces rewards)



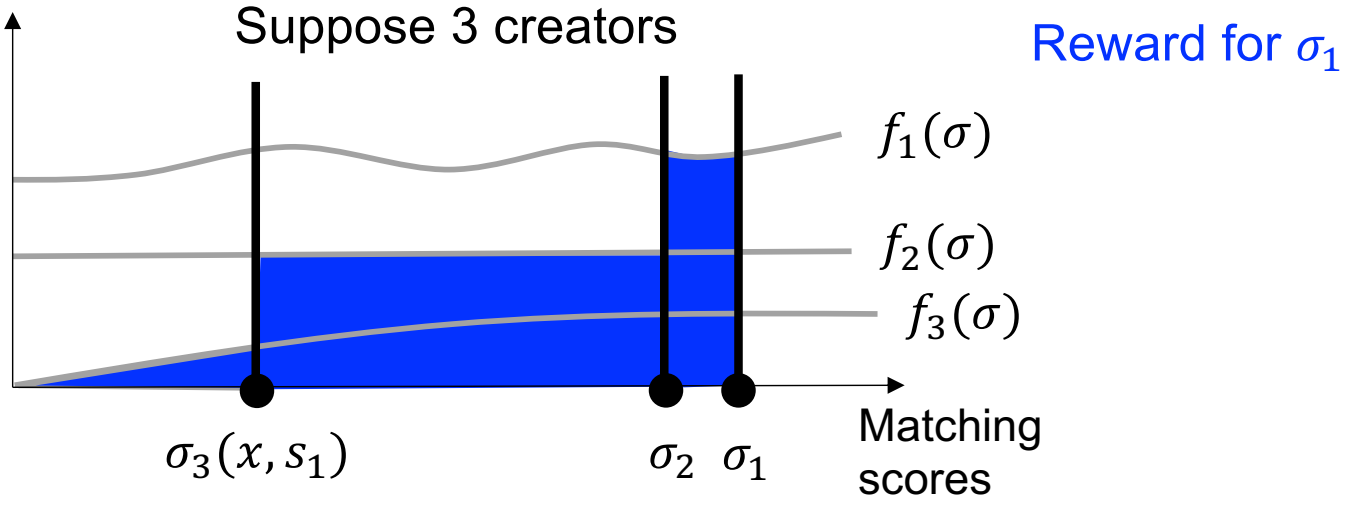
Mechanism Design to Incentivize Content Creation

[Yao et al.'23] develops a new mechanism that introduces more competition for congested topics, and achieves optimal welfare at equilibrium

Core idea: reward based on how much a creator is better than the next

Advantages

✓ σ_1's reward decreases when σ_2 becomes better (i.e., competition reduces rewards)



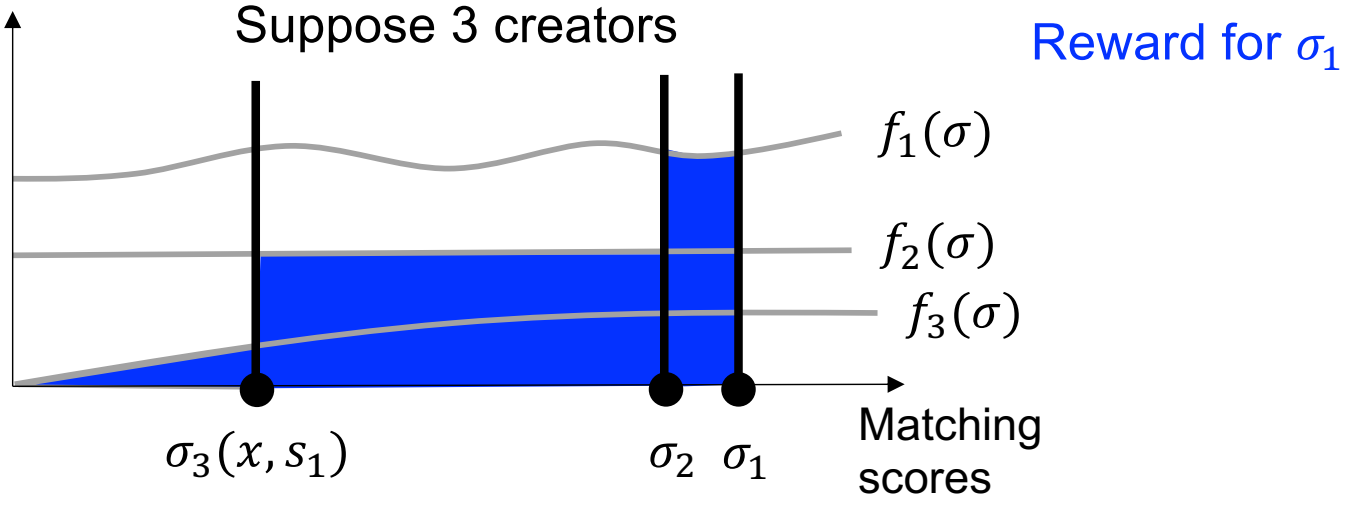
Mechanism Design to Incentivize Content Creation

[Yao et al.'23] develops a new mechanism that introduces more competition for congested topics, and achieves optimal welfare at equilibrium

Core idea: reward based on how much a creator is better than the next

Advantages

- ✓ σ_1's reward decreases when σ_2 becomes better (i.e., competition reduces rewards)
- ✓ Naturally handles top-K selection by setting $f_{K+1} = \cdots = f_n = 0$



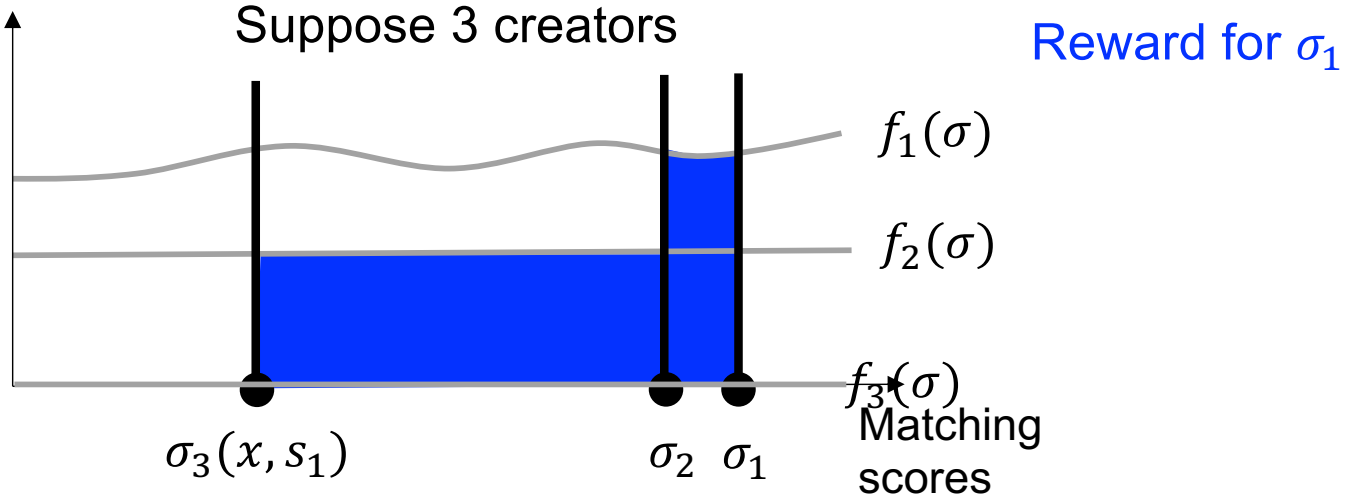
Mechanism Design to Incentivize Content Creation

[Yao et al.'23] develops a new mechanism that introduces more competition for congested topics, and achieves optimal welfare at equilibrium

Core idea: reward based on how much a creator is better than the next

Advantages

- ✓ σ_1's reward decreases when σ_2 becomes better (i.e., competition reduces rewards)
- ✓ Naturally handles top-K selection by setting $f_{K+1} = \cdots = f_n = 0$



Mechanism Design to Incentivize Content Creation

[Yao et al.'23] develops a new mechanism that introduces more competition for congested topics, and achieves optimal welfare at equilibrium

Theorem (informal).

1. Previous mechanism always induces a *potential game* among creators;
2. There is a choice of $f_1, f_2, \ldots f_n$ that make the potential function precisely the system's welfare function ($\Rightarrow$ welfare is maximized at a pure Nash)

- A variant of this mechanism was tested on Instagram Reels, with results reported in [Yao et al, KDD'24]
  - A "separated world" with ~10 millions users/creators
  - A/B testing for 8 weeks

Real-world Experimental Results from A/B Test

User Groups	1-5	6-20	21-74	75+	TOTAL
Like-Through-Rate	+0.43%	+1.40%	+0.75%	+1.36%	**+1.13%**
Impression	+2.64%	+0.62%	+1.42%	+0.11%	**+0.76%**

Nice side effects

- ✓ 3.7% increase in diversity of user impression
- ✓ Increased diversity of user consumption
  - 0.71 increase on average number of consumed topic per user

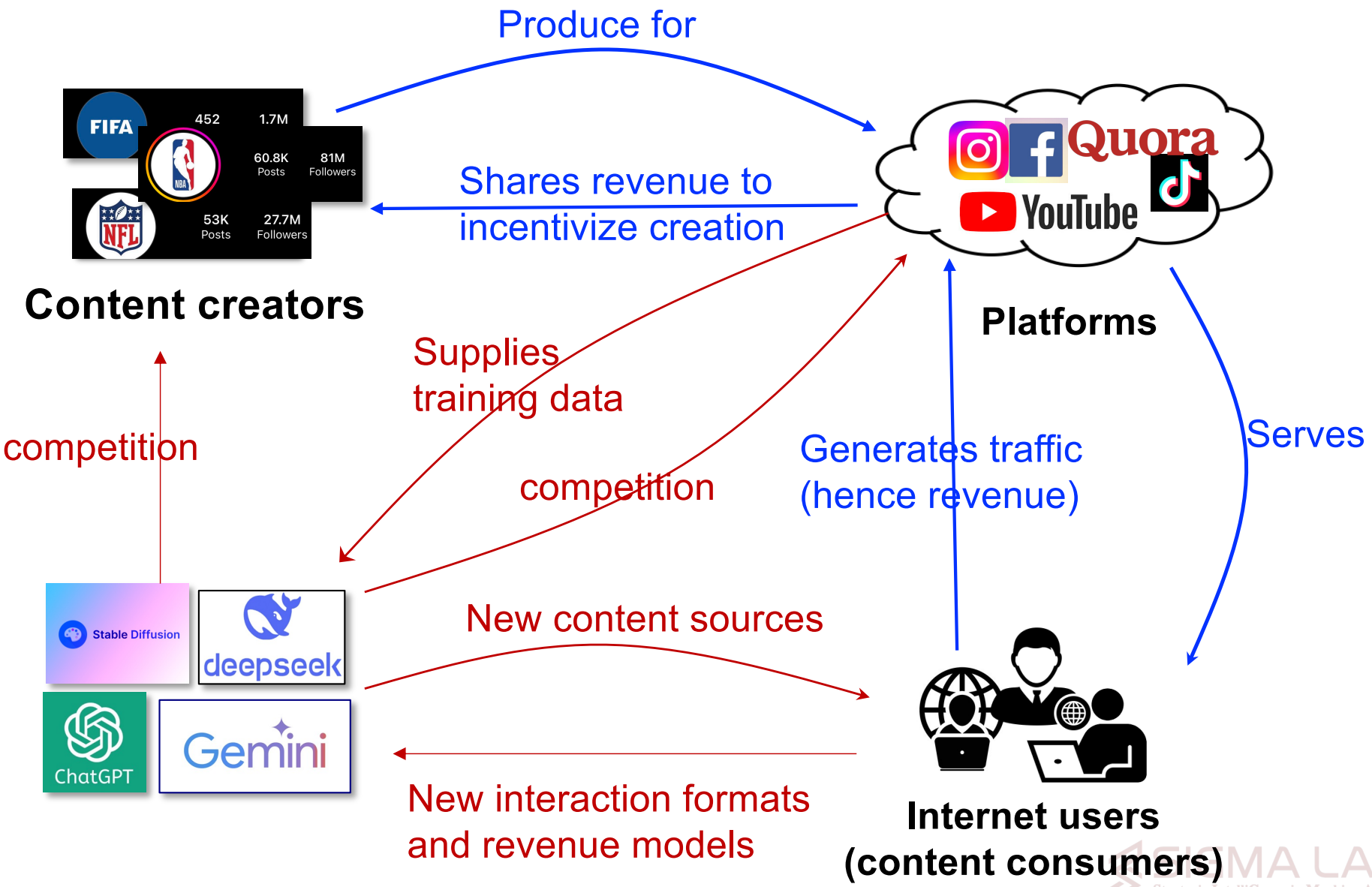
These improvements are significant even compared to launched methods

Outline

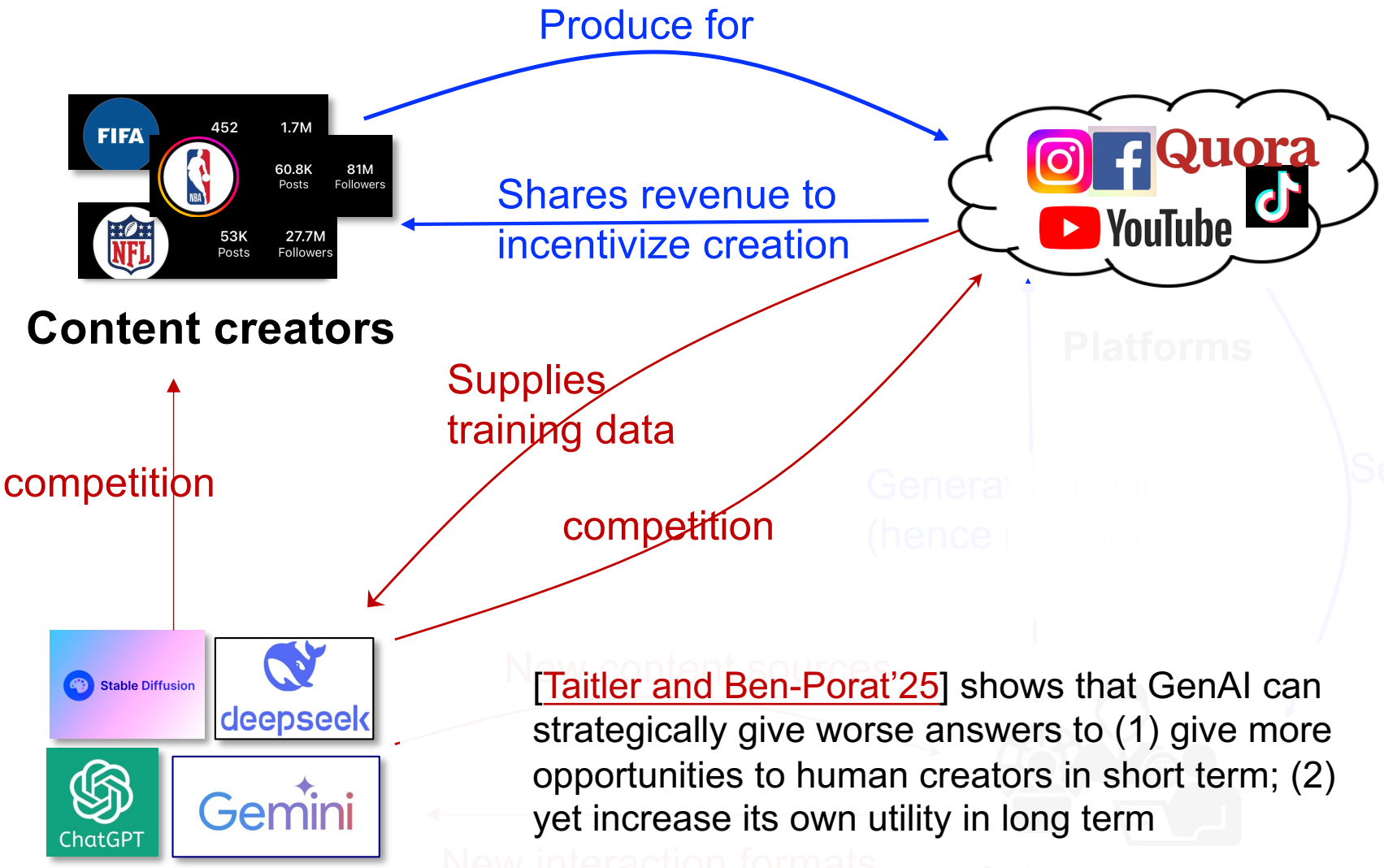
- **Part I:** Diagnosing and Optimizing Existing Content Ecosystems

- **Part II:** How Does AIGC Transform Future Content Ecosystems

Generative AI as a Forth Player Type



Interesting Recent Works; Huge Amount of Future Directions



[Taitler and Ben-Porat'25] shows that GenAI can strategically give worse answers to (1) give more opportunities to human creators in short term; (2) yet increase its own utility in long term

Interesting Recent Works; Huge Amount of Future Directions

Content creators

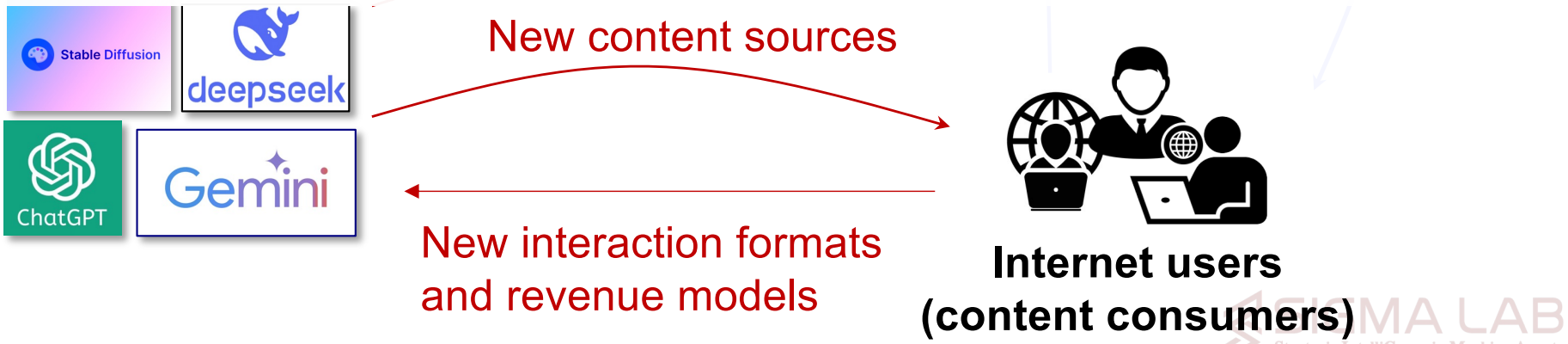
competition

[Yao et al. ICML'24] and [Esmaeili et al.'24] worried about distorted incentives in GenAI-vs-human content creation competition

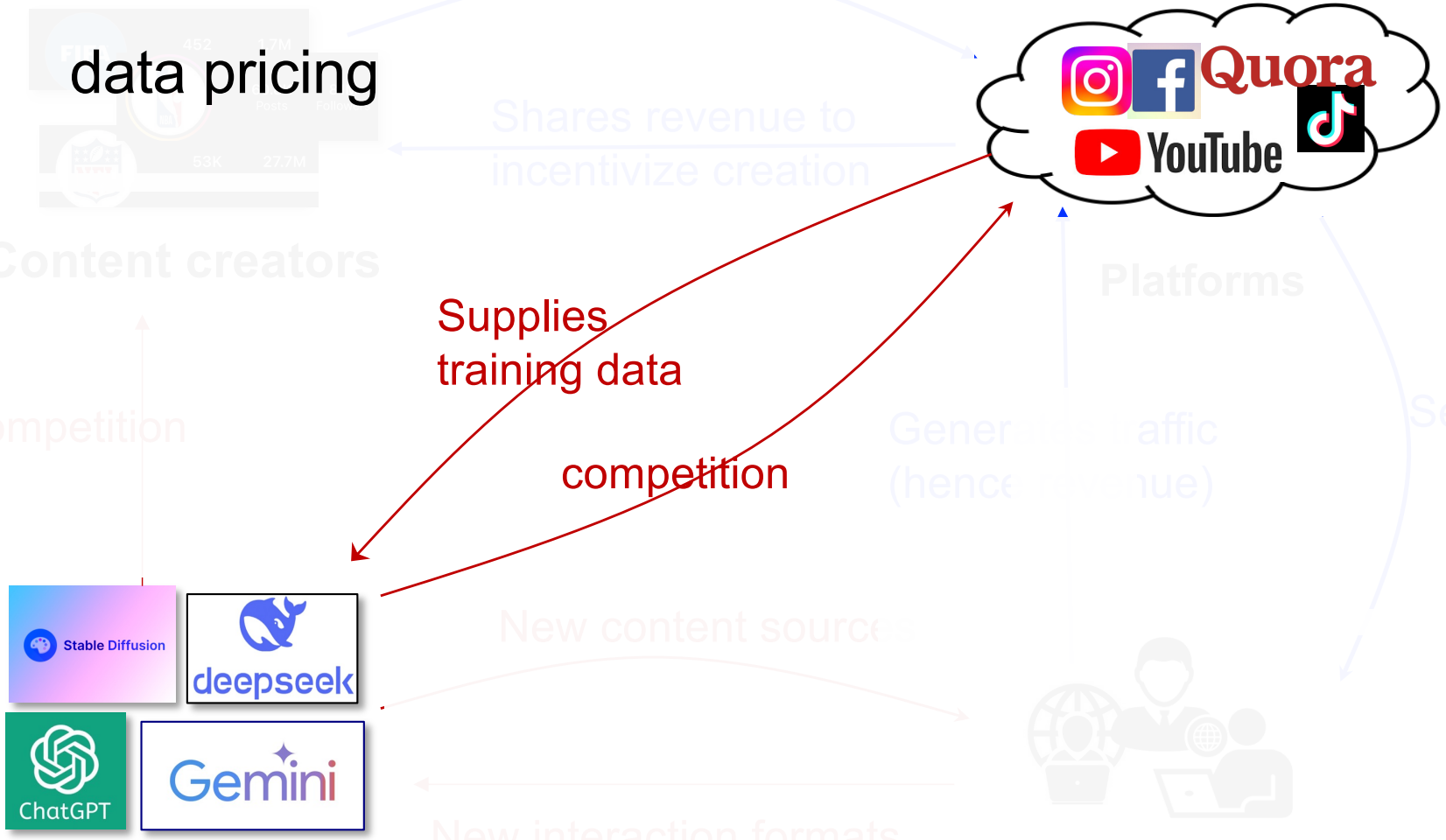
[Taitler and Ben-Porat AAAI'25] illustrates a Braess's paradox phenomenon after introducing GenAI for content creation

Interesting Recent Works; Huge Amount of Future Directions

[Raghavan, 24] studies how use of GenAI for content creation may reduce content diversities and whether competing GenAI platforms help



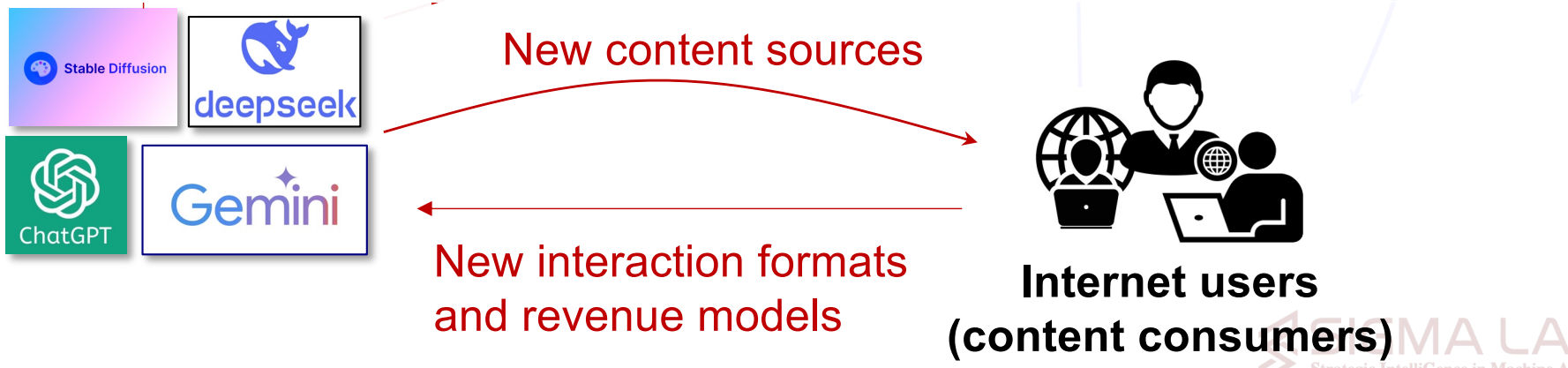
Natural and Important Mechanism Design Questions



Natural and Important Mechanism Design Questions

Preference aligned generation and new monetarization mechanisms

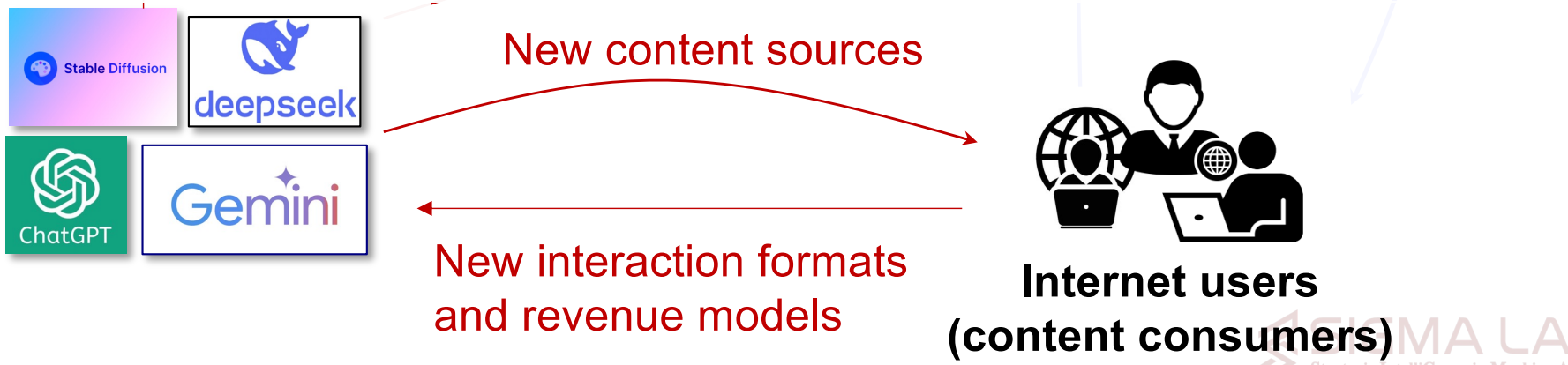
- [Duetting et al., WWW'24] studies how to generate texts that aligned with a group of users' preferences, with advertising as one motivation
  - Follow-up refinements and variants [Dubey et al. KDD'24, Soumalia et al'24] and position papers [Feizi et al 2023]



Natural and Important Mechanism Design Questions

Preference aligned generation and new monetarization mechanisms

- [Duetting et al., WWW'24] studies how to generate texts that aligned with a group of users' preferences, with advertising as one motivation
  - Follow-up refinements and variants [Dubey et al. KDD'24, Soumalia et al'24] and position papers [Feizi et al 2023]



Mechanism Design for LLMs

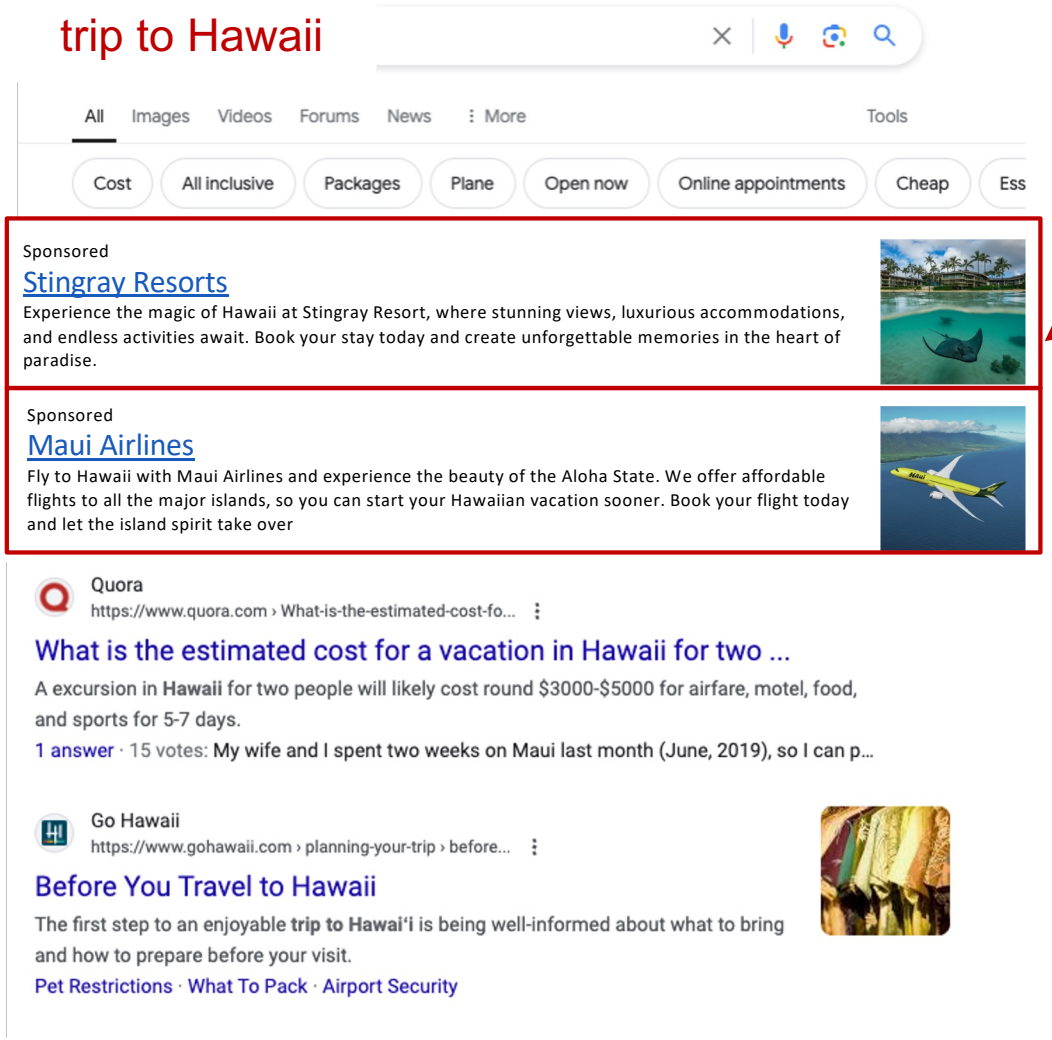
Motivations

In many applications, different parties prefer different generations

Research Question:

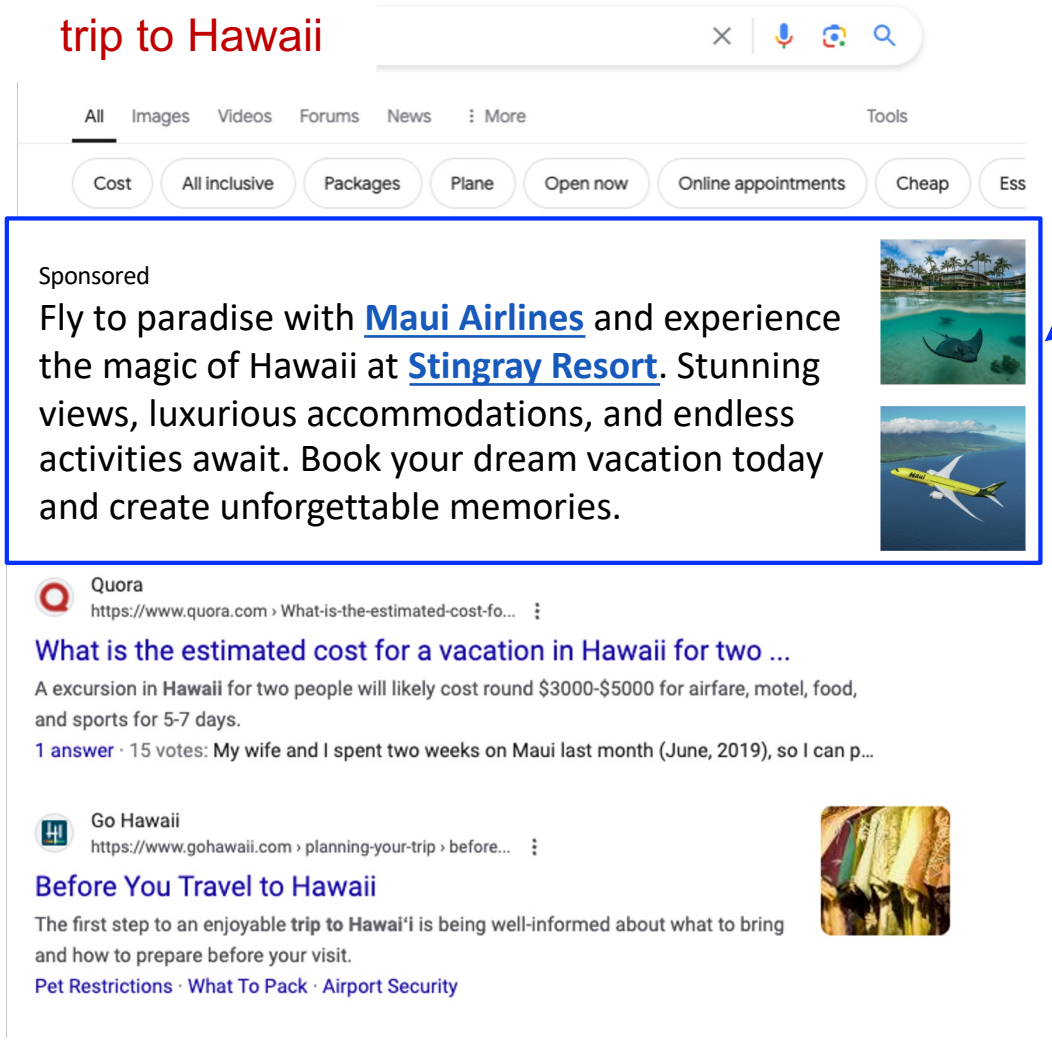
How to allow different parties to influence an LLM's generation by incentivizing them to express preferences "truthfully"?

Application 1: Internet Advertising



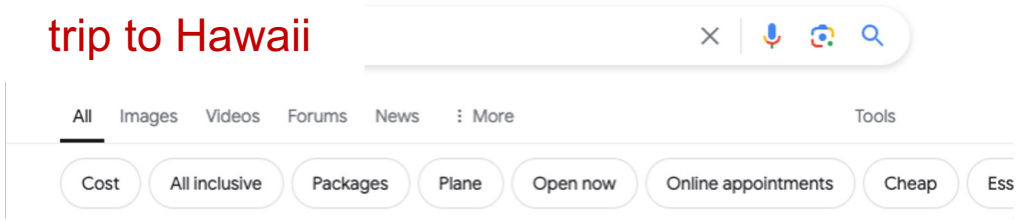
Currently, advertisers bid to have fixed ad creatives placed in certain slots in the page.

Application 1: Internet Advertising



In the future, it could be a creative co-branding ads!

Application 1: Internet Advertising

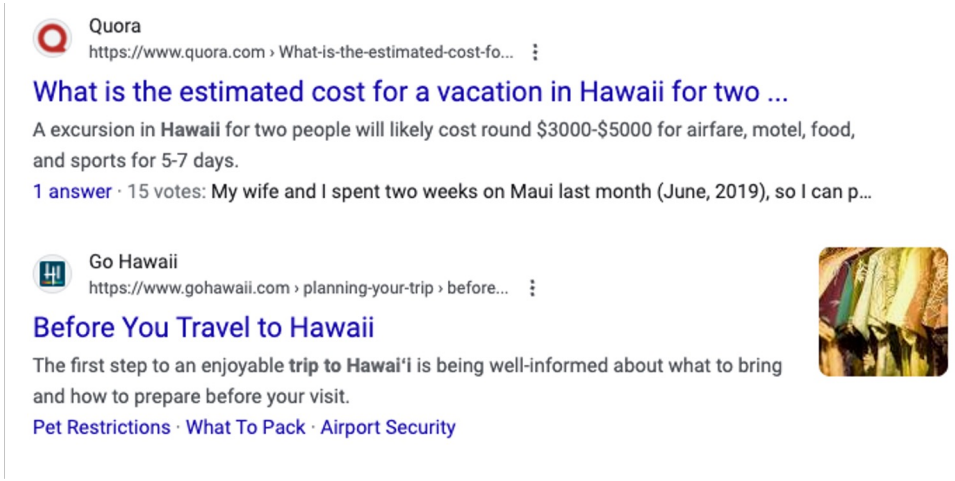


Sponsored

Fly to paradise with **Maui Airlines** and experience the magic of Hawaii at **Stingray Resort**. Stunning views, luxurious accommodations, and endless activities await. Book your dream vacation today and create unforgettable memories.

In the future, it could be a creative co-branding ads!

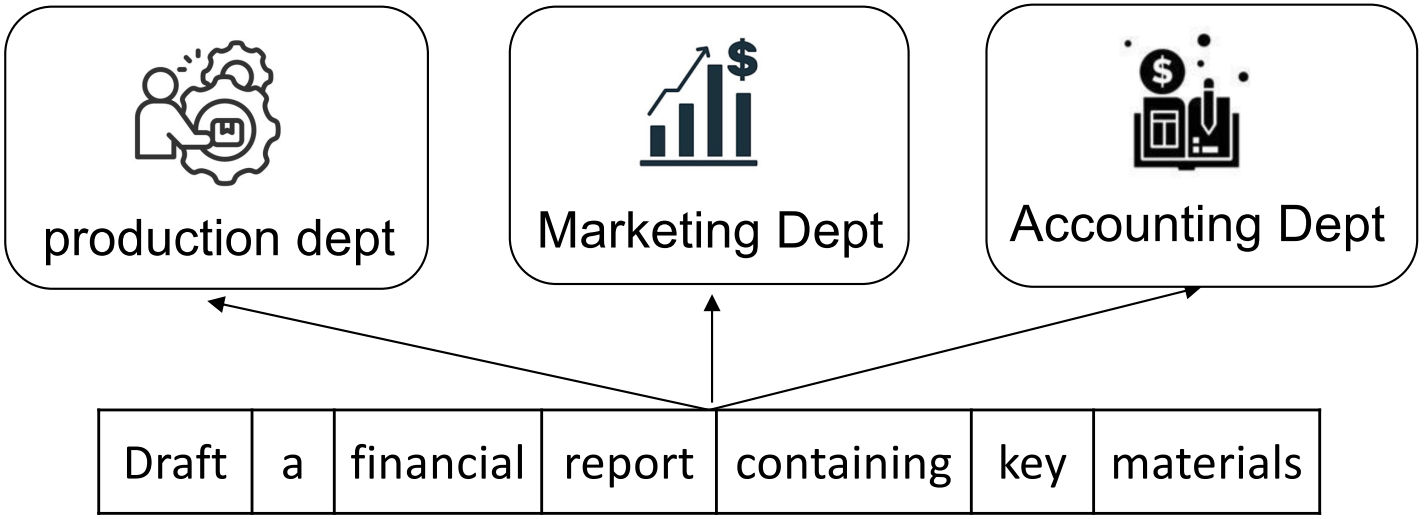
Even co-branding pictures!



The wish:

A way to auto-generate ad creative, which allows advertisers to express preferences and influence results via bids

Application 2: Enterprise LLMs



How to incentivize them to honestly express their preferences to be aggregated into final output?

Desired Properties We Want

1. Avoid asking each agent (e.g., an advertiser) to report their value function or preferences over language outputs → unrealistic
   - ✓ Use LLMs to encode each agent's preferences

2. Each agent should still be able to influence the output
   - ✓ Allow each agent use a single bid to influence outcome (bid captures their intent strength)

3. Randomized token sampling → crucial for LLMs [Holtzman et al., 2019]
   - ✓ True by design

4. Efficiency → cannot call LLMs too many times
   - ✓ Each agent's LLM is called once

5. Technological compatibility → easy integration into current systems
   - ✓ Our design is a lightweight layer over existing LLMs

A proposal:

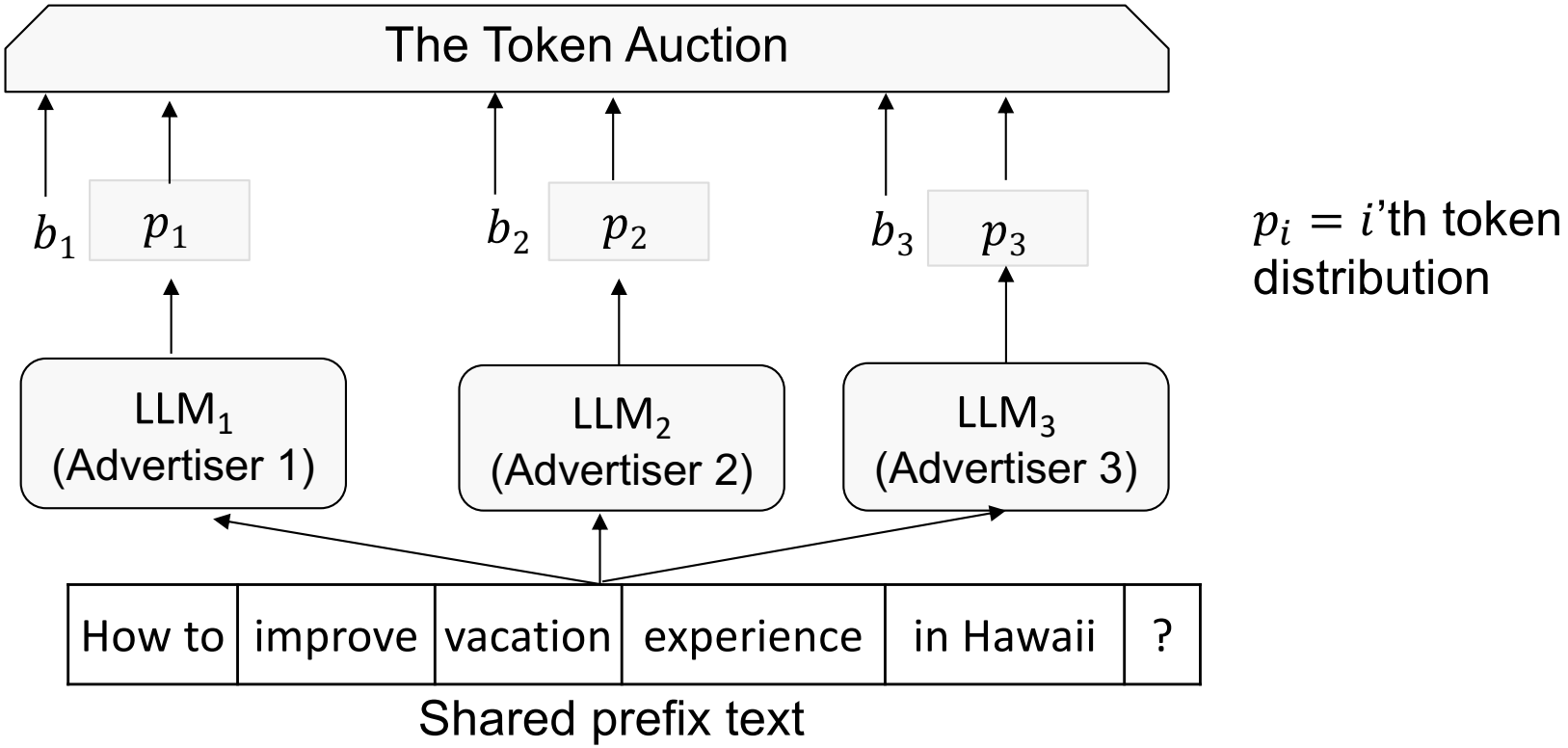
The Token Auction Model

The Token Auction

- Each advertiser's preference over outputs is encoded by an LLM
  - These LLMs are assumed publicly known (e.g., obtained via fine-tuning)

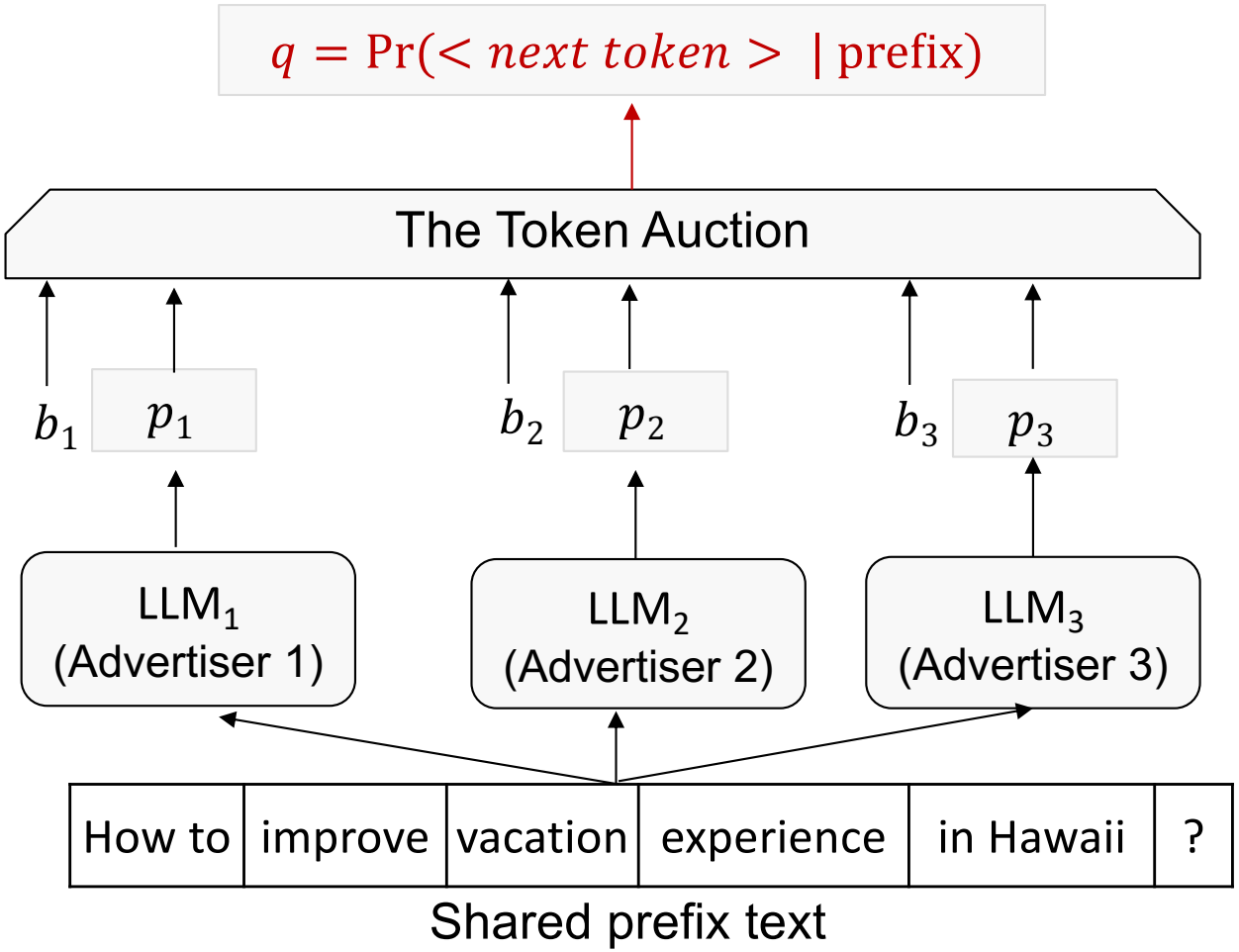
The Token Auction

- Auction runs when a prompt arrives
- Each advertiser can influence output via a bid
  - One of the LLMs can be the organic output with a default bid



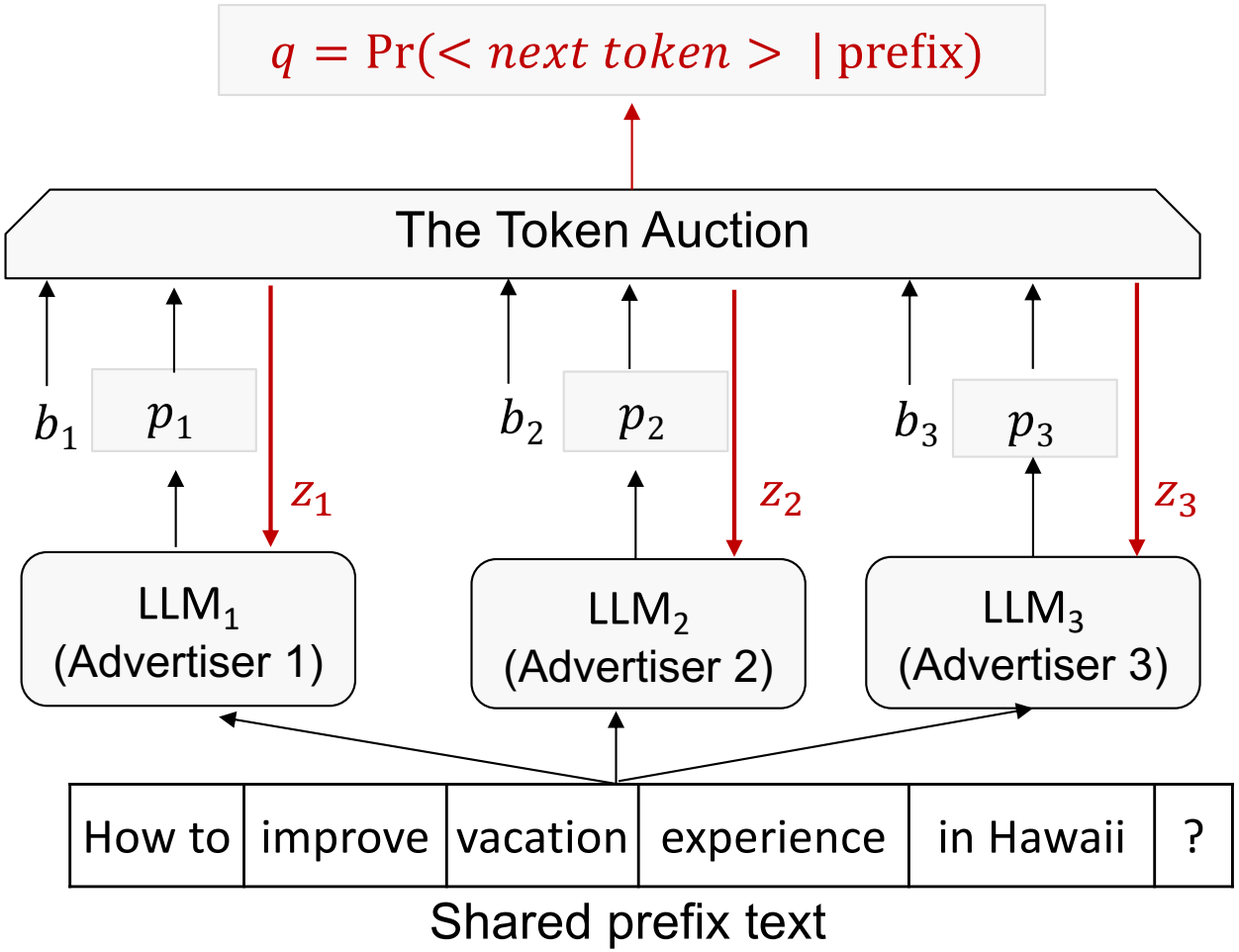
The Token Auction

- Auction determines aggregated distribution $q(\boldsymbol{b}; \boldsymbol{p})$



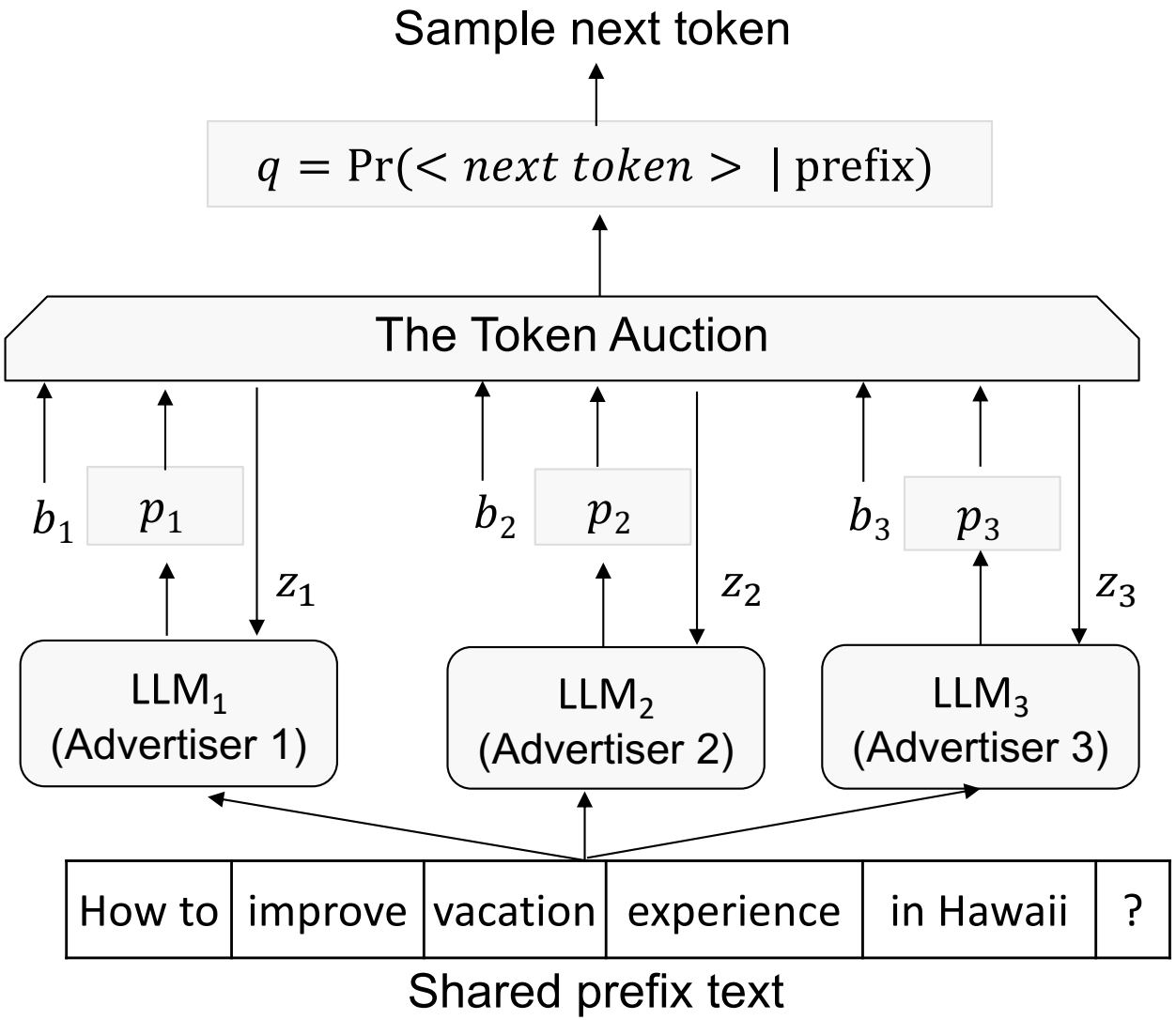
The Token Auction

- Auction determines aggregated distribution $q(\boldsymbol{b};\boldsymbol{p})$ and payment $z_i(\boldsymbol{b};\boldsymbol{p};)$



The Token Auction

Repeat this process with the same bids but updated prefix



Core Designs under the Auction Protocol

Aggregated function $q(\boldsymbol{b};\boldsymbol{p})$ **+** payment $z_i(\boldsymbol{b};\boldsymbol{p};)$ for each i

Why not VCG?

- The auction did not elicit value functions from bidders
- We employ *indirect* mechanism design, with *robust* consideration of agent preferences

Incentive Design in Our Indirect Mechanisms

Reduce incentive design to aggregation design

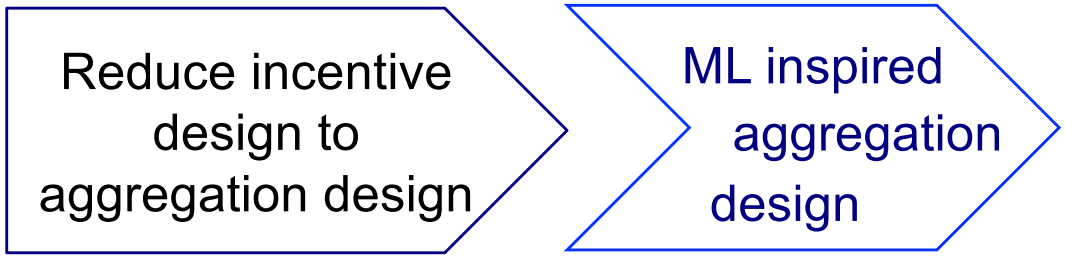
Desired incentive properties

1. Higher pay → robustly better distribution
2. Hold irrespective of others' bids

→ Aggregation function $q(\boldsymbol{b}; \boldsymbol{p})$ must be "monotone"

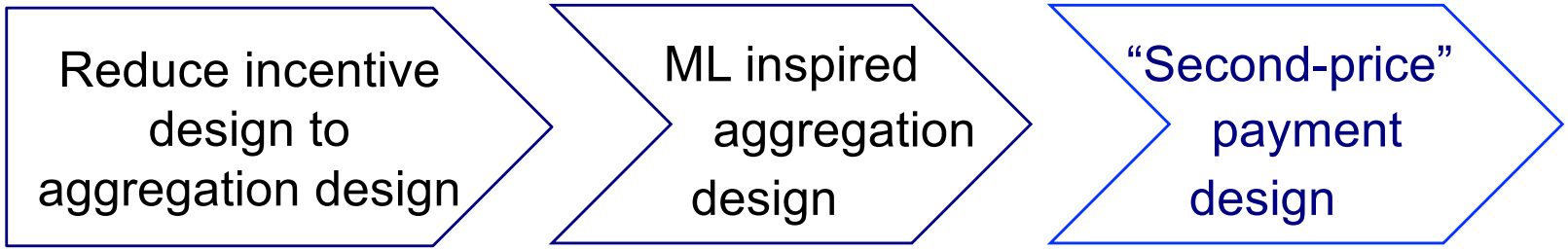
Proof employs Debreu's representation theorem

Incentive Design in Our Indirect Mechanisms



1. Training LLM based on combined data and KL-divergence loss → Linear aggregation (monotone)
2. RLHF based on combined agent preferences → Log-linear aggregation (not monotone)

Incentive Design in Our Indirect Mechanisms



A novel token sampling technique for monotone aggregation function that leads to natural “second-price” payment rule

Demonstration on Google's Bard LLM

- Two advertisers
- Create their LLMs via prompting

You are an expert of writing texts that naturally combines two ads together. Your choice of words and sentences is full of artistic flair.

Write a one-sentence ad for _____.

- Agent A use: a flight to Hawaii using [Alpha Airlines].
- Agent B use: a vacation in Hawaii at the [Beta Resort].

Bard-Generated Texts ($\lambda = \frac{b_1}{b_1 + b_2}$)

λ	Linear aggregation function q_{KL}	Log-linear aggregation function $\bar{q}_{\mathrm{KL}}$
1	**Alpha Airlines**: Your ticket to paradise.	
0.75	**Alpha Airlines**: Fly to Hawaii and experience the beauty of the islands with aloha. **Beta Resorts**: Stay at our resorts and enjoy the best of Hawaii.	Feel the magic of Hawaii with a flight on **Alpha Airlines**, now offering 20% off all flights when you book with us today!
0.6	**Alpha Airlines** flies you to Hawaii, where you can enjoy a week-long stay at the **Beta resort** for just $1000.	Experience the magic of Hawaii with a flight on **Alpha Airlines**, now offering 20% off all flights when you book with us today!
0.55	**Alpha Airlines** flies you to Hawaii, where you can enjoy a week-long stay at the **Beta resort**.	Escape to the tropical paradise of Hawaii with [**Alpha Airlines**]!
0.5	**Alpha Airlines** flies you to Hawaii, where you can enjoy a beautiful sunset on the beach. Stay 3 nights and get the 4th free at the **Beta Resort**.	Experience the magic of Hawaii with a stay at the luxurious [**Beta Resort**] and a refreshing flight on [**Alpha Airlines**].
0.45	Fly **Alpha Airlines** to sunny Hawaii and enjoy the secluded beaches and private lagoons of the Royal Hawaiian **Beta Resort**.	Experience the magic of Hawaii with a stay at the luxurious [**Beta Resort**] and a special flight offer from [**Alpha Airlines**].
0.4	Fly **Alpha Airlines** to sunny Hawaii and enjoy the first-class treatment that awaits you at **Beta Resort**, all for one low price.	Experience the magic of Hawaii at the [**Beta Resort**], where you'll feel like you're in a tropical paradise.
0.25	Experience the magic of Hawaii at the **Beta Resort**, where the sun shines brighter and the waves crash louder — book your stay today with our exclusive 20% off discount!	Experience the magic of Hawaii at the **Beta Resort**, where you'll be pampered like royalty and surrounded by breathtaking beauty.
0	Hawaii's **Beta Resort**: a paradise where the sun shines brighter, the waves sing sweeter, and the sand feels softer.	

- Linear aggregation function (monotone) does appear to more smoothly transit from favoring agent A to favoring agent B
- Log-linear aggregation tends to say less and repeat more

Other Works in EconCS Space

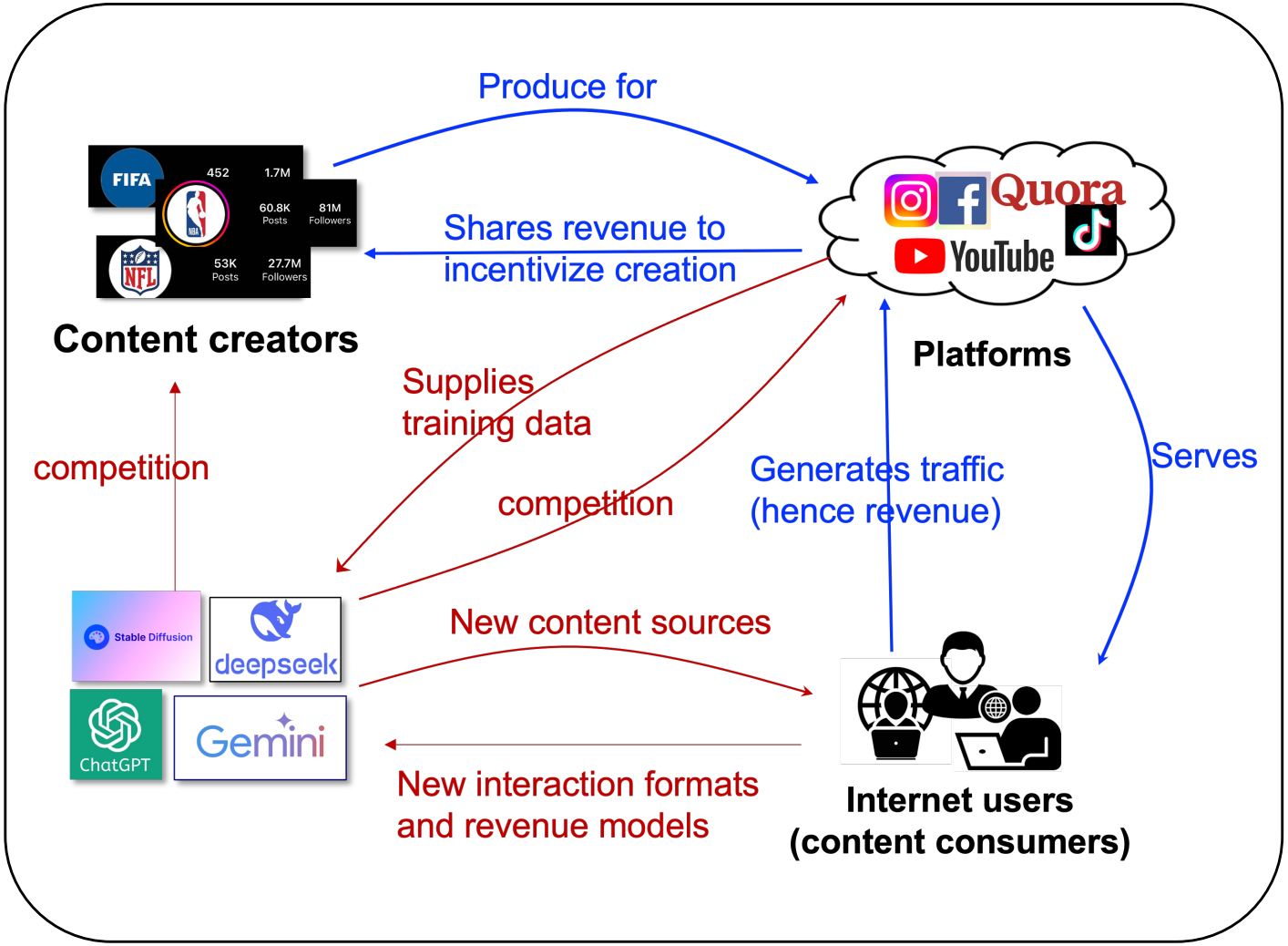
- This talk is biased towards algorithmic studies of non-cooperative competitions and mechanism design
  - Many recent works from economic/operational perspective
  - GenAI for social choice [Fish et al., EC'24] and preference alignment [Conitzer et al. ICML'24]
  - GenAI for peer prediction [Lu et al., EC'24]

Many Questions Remain to Be Understood/Solved

- Better and sustainable monetization of GenAI technology
- Fair and more equitable creator compensations
- Escape echo chamber
- Preserve/increase content diversity
- Sustainable human-GenAI co-evolution
- …

Incentives and agency are crucial to both learning algorithms and market mechanisms for resolving these pressing issues

Summary



Thank You

Questions?

haifengxu@uchicago.edu

National Science Foundation
SCHMIDT SCIENCE
Office of Naval Research Science & Technology
ARL Army Research Lab
Google Research

SIGMA LAB
Strategic IntelliGence in Machine Agents