University of Zurich[UZH]

NCCR Automation

Strategic Interactions among Social Media Content Creators

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University of Zürich

Workshop on "Games on Networks":
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STORY-TELLING

Emily is a young and passionate travel blogger with a keen eye for photography. She loves exploring new places and documenting her experiences through her camera lens.

STORY-TELLING

When Emily first started her travel blog, she struggled to gain traction. She had a few followers, but her content wasn't reaching a wider audience.

That's when she decided to try a new approach.

STORY-TELLING

Emily began to connect with other travel bloggers and photographers on social media, commenting on their posts and sharing their content with her own followers. Through these interactions, Emily was able to build relationships with other bloggers and photographers, and soon she was collaborating on joint projects and cross-promotions.

Motivation

- Social media platforms are increasingly being leveraged as a means of making a living.

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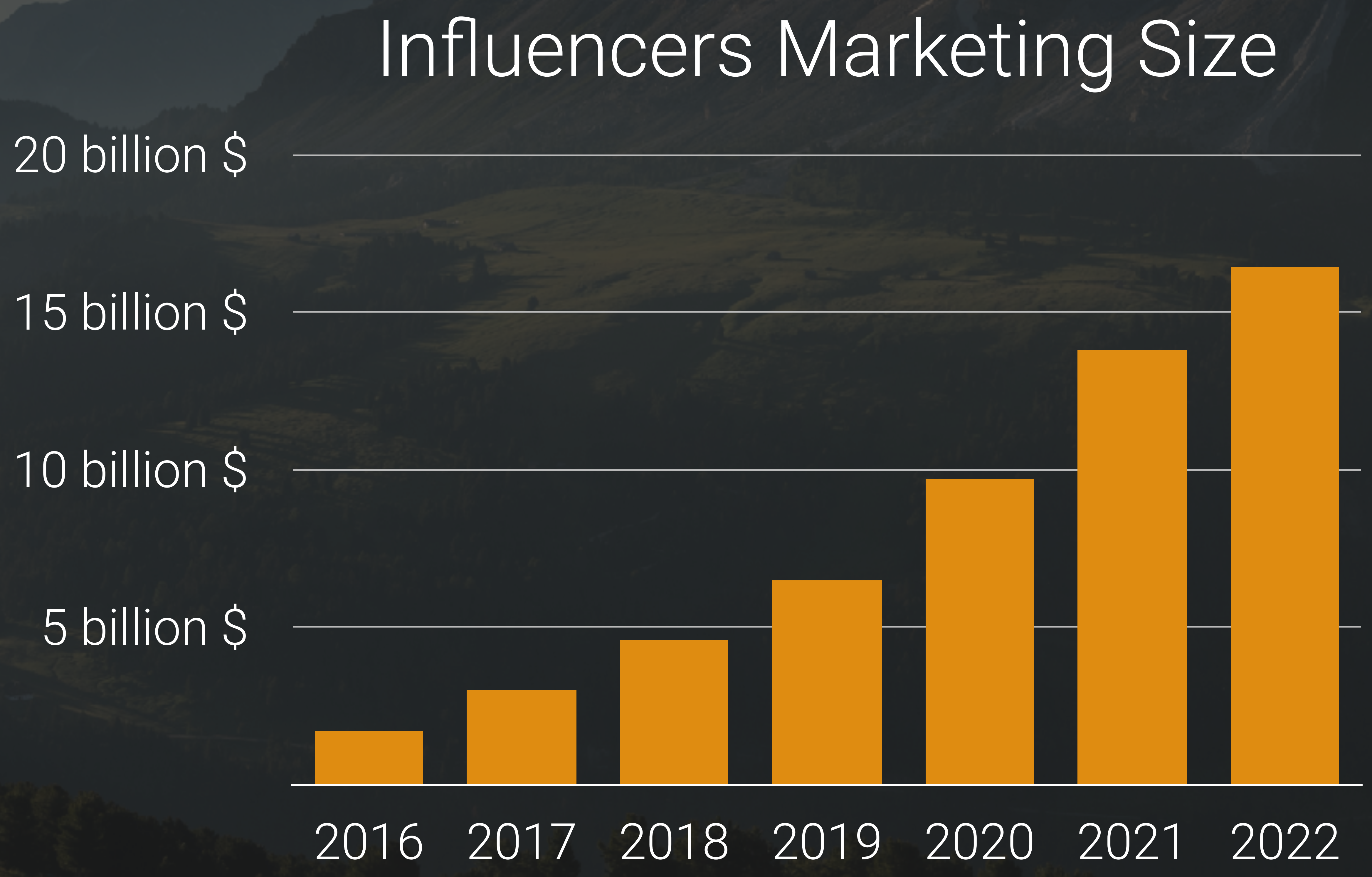
- The Creator Economy has seen tremendous growth over the past decade with more than 50 million content creators



Source: Influencer Marketing Hub

Motivation

- Social media platforms are increasingly being leveraged as a means of making a living.
- The Creator Economy has seen tremendous growth over the past decade with more than 50 million content creators
- However, social media platforms do not always provide FAIR OPPORTUNITIES and COMPENSATION for these creators.
  For example: there exists 30% gender earning gap, and a 35% racial earning gap [1-3].

[1] IZEA. 2022. The State of Influencer Equality: 2022 Report. https://izea.com/resources/insights/2022-state-of-influencer-equality/
[2] MSL. 2021. MSL Study Reveals Racial Pay Gap in Influencer Marketing https://www.mslgroup.com/whats-new-at-msl/msl-study-reveals-racial-pay-gap-influencer-marketing
[3] Amy Pei, Yakov Bart, Koen Pauwels, and Kwong Chan. 2022. Racial Pay Gap in Influencer Marketing. Available at SSRN 4156872 (2022)

Research Questions

1. Do Social media platforms offer a FAIR place, meaning that they reward Content Creators proportionally to their efforts?

2. What is the role of the RECOMMENDATION SYSTEMS in allocating fair outcomes?

3. Which STRATEGIES can Content Creators apply to improve their outcome?

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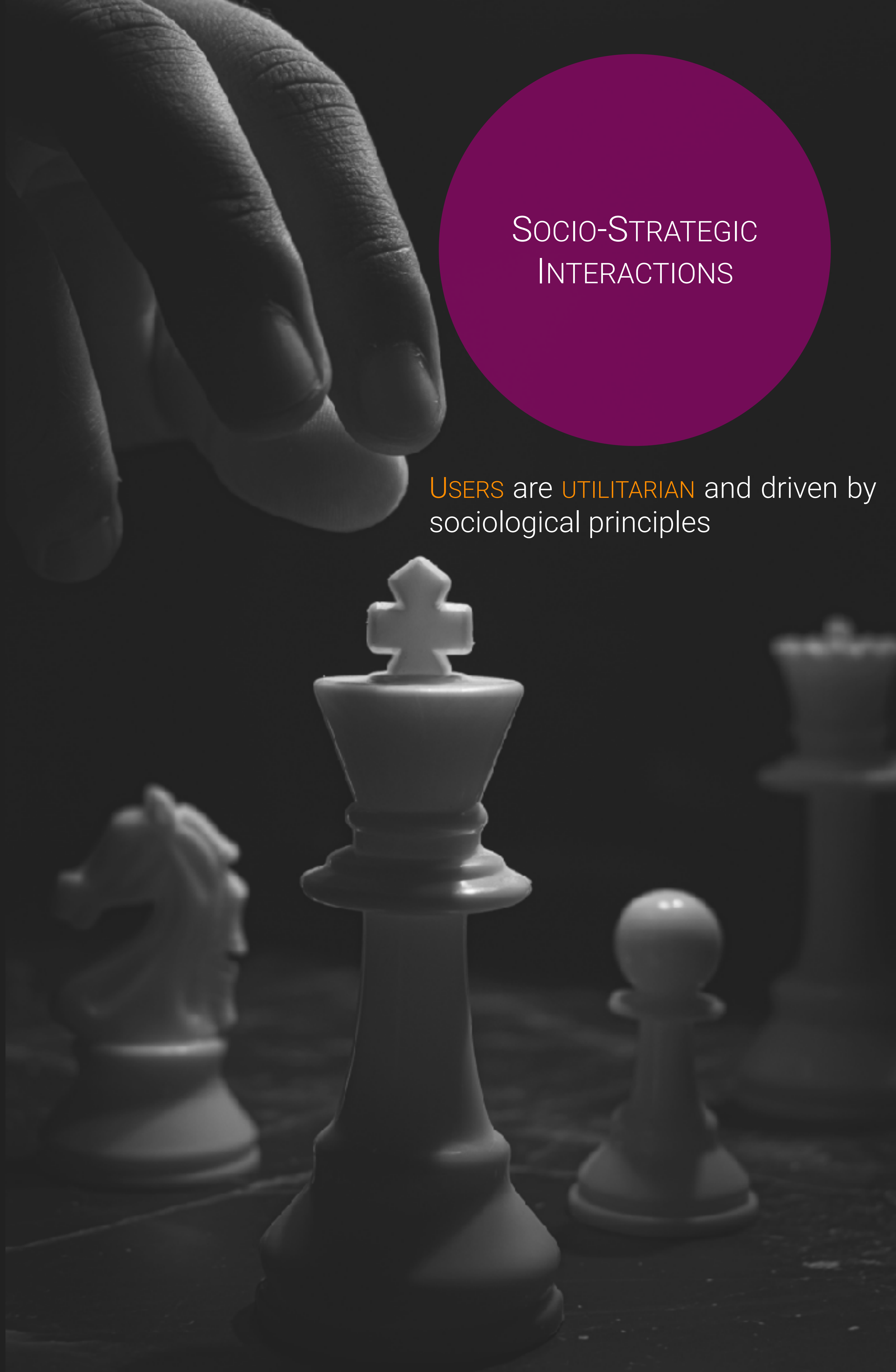
Network Formation models In the Literature



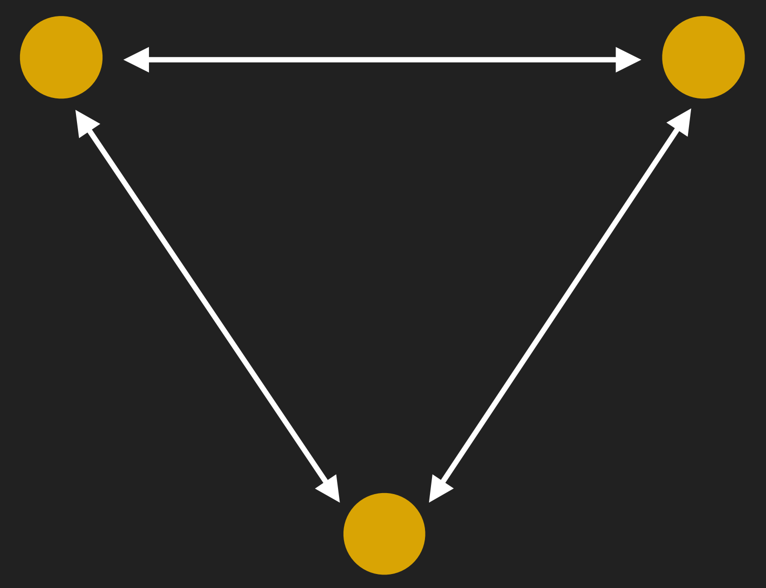
Socio-Strategic Interactions

Users are utilitarian and driven by sociological principles

Probabilistic Interactions

Users are not utilitarian and follow statistical Recommendations

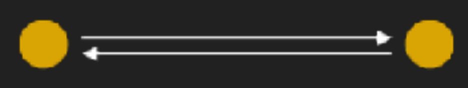
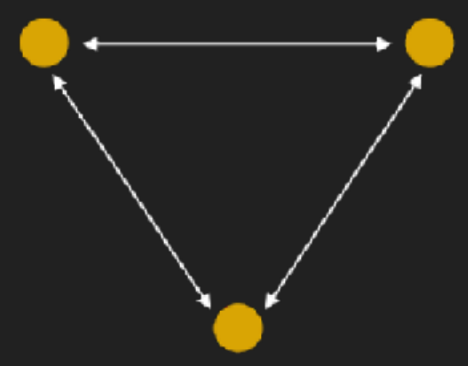
Real-world social connections tend to be RECIPROCATED and in TRIADIC STRUCTURES



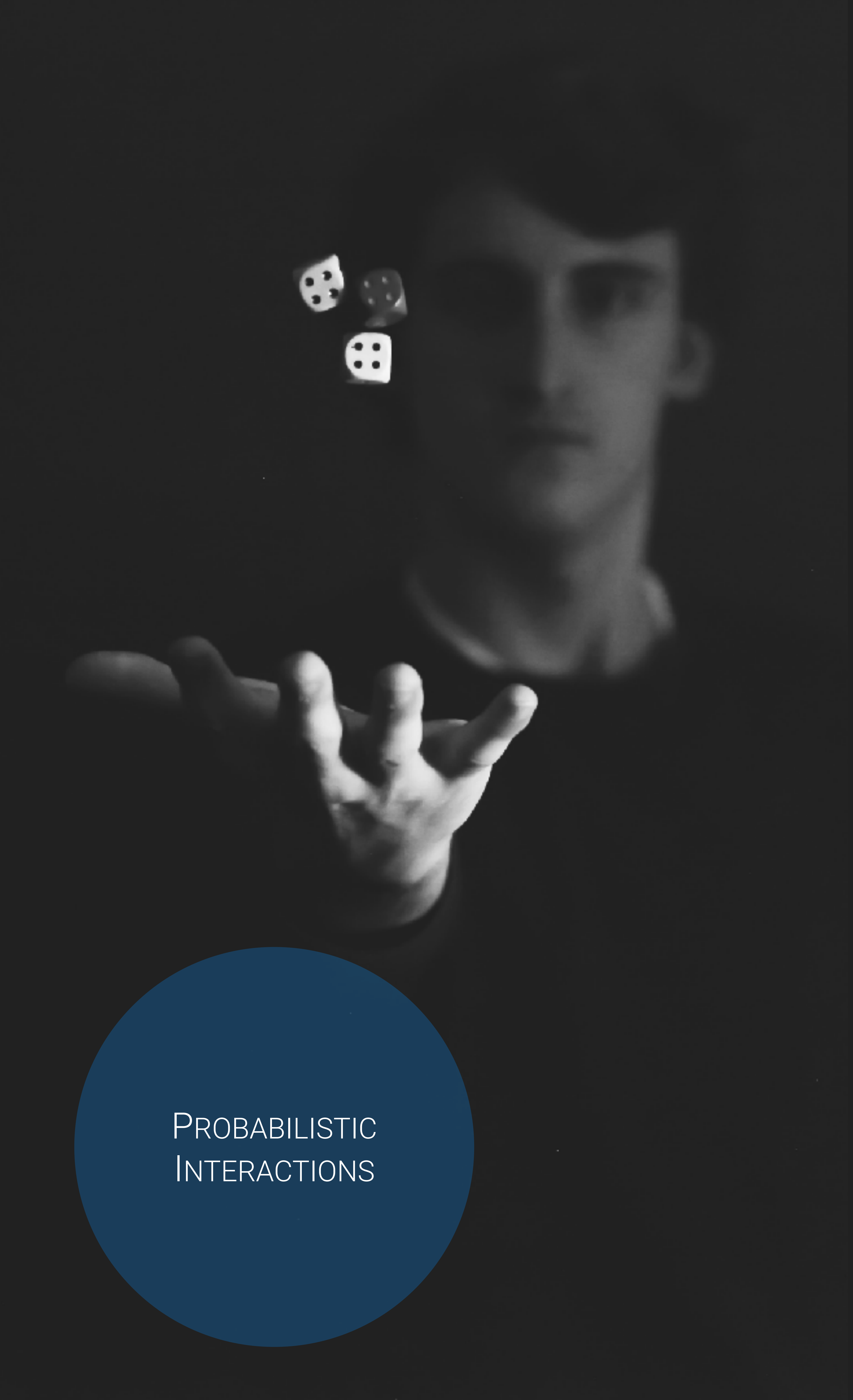
Pagan, N. and Dörfler, F., 2019. Game theoretical inference of human behavior in social networks. **Nature communications**, *10*(1), p.5507.

Socio-Strategic Interactions

These motifs are NOT significantly present on DIRECTED SOCIAL NETWORKS because people can follow STRANGERS

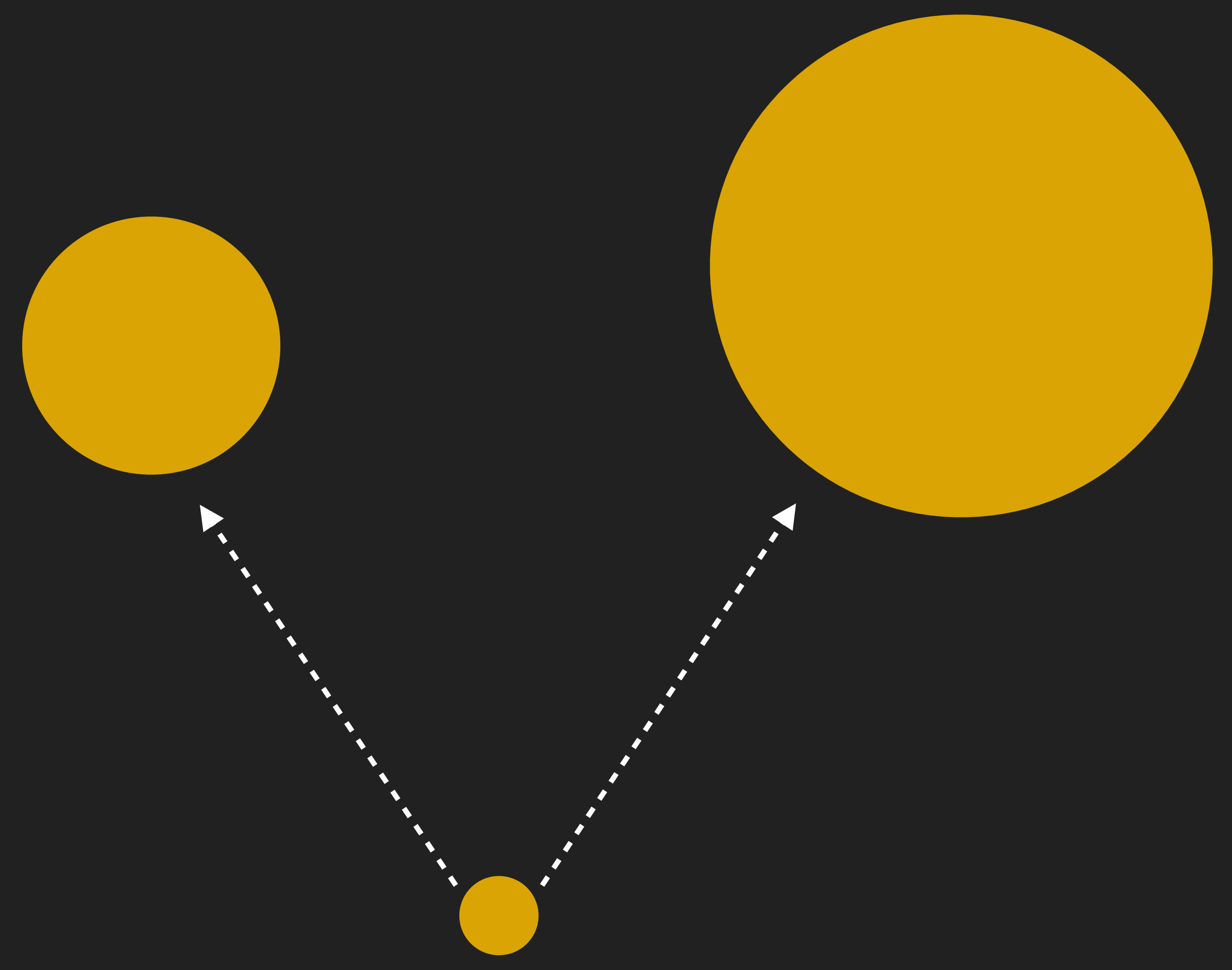
	100%	22%	14%
	40%	23%	8%

Pagan, N. and Dörfler, F., 2019. Game theoretical inference of human behavior in social networks. **Nature communications**, *10*(1), p.5507.

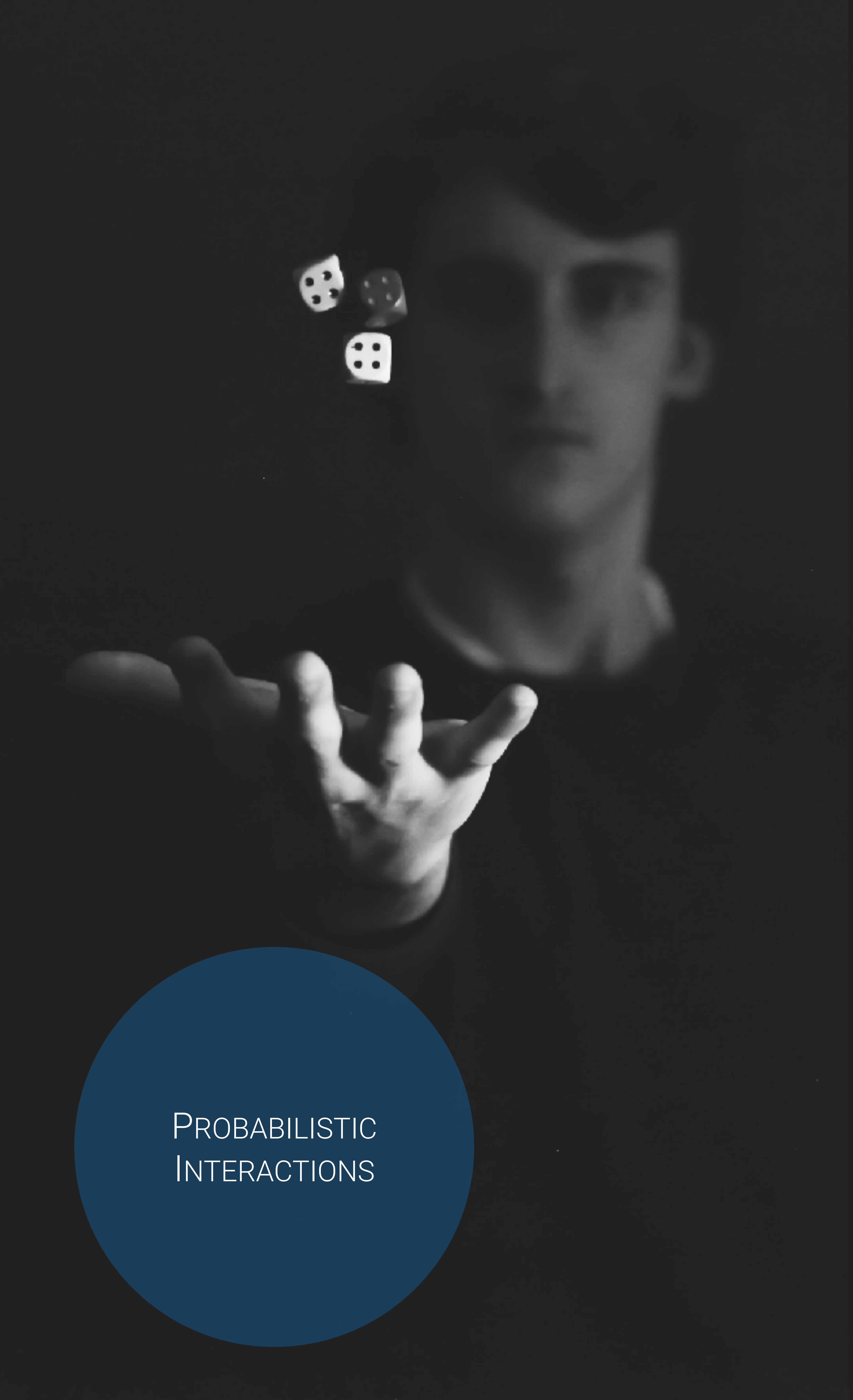


Probabilistic Interactions

Preferential attachment model:
The probability of following an other user is proportional to their number of followers



Barabási, A.L. and Albert, R., 1999. Emergence of scaling in random networks. **Science**, *286*(5439), pp.509-512



Probabilistic Interactions

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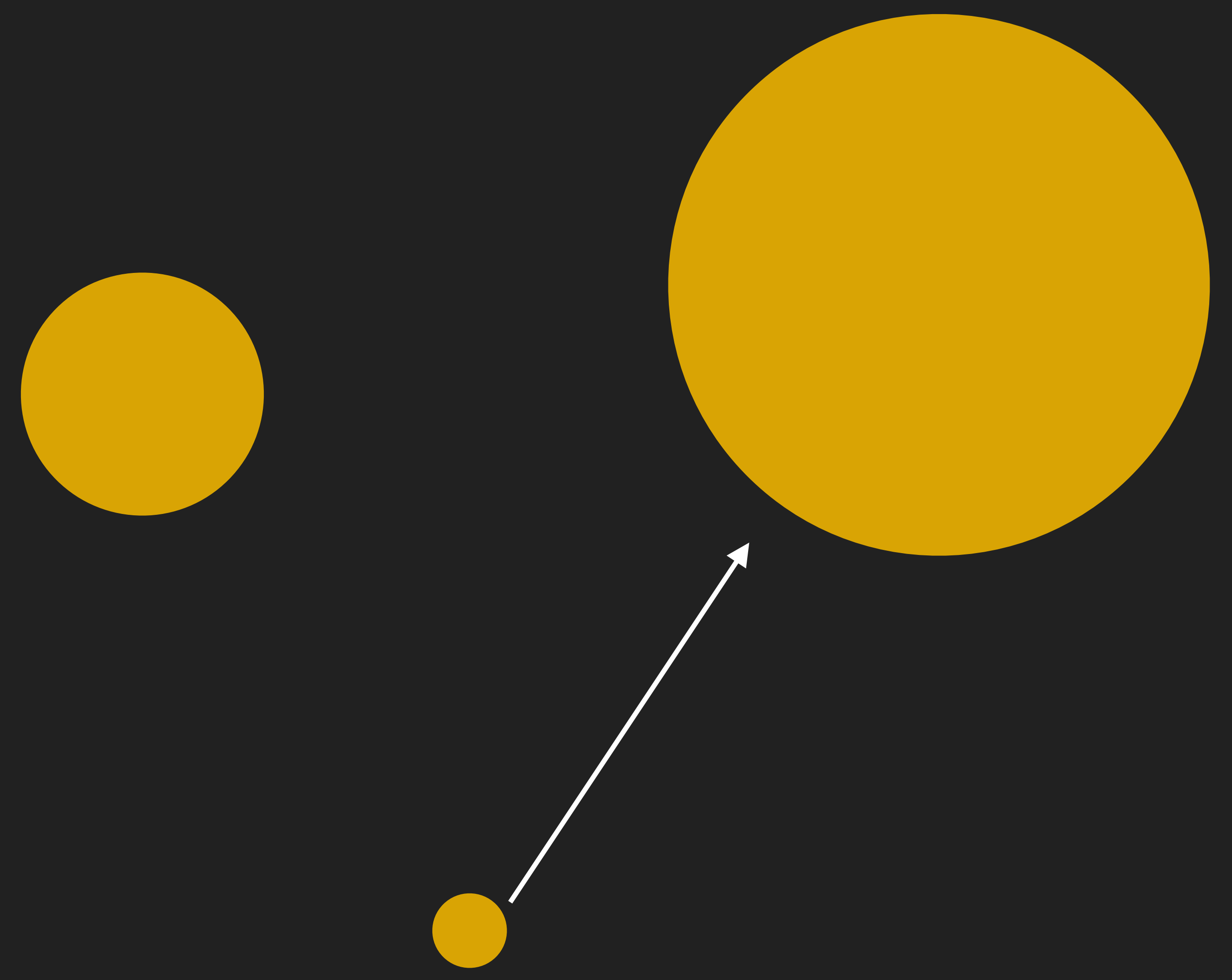


Leads to the "rich-get-richer" effect
but leaves no space to individual Decision-Making

Barabási, A.L. and Albert, R., 1999. Emergence of scaling in random networks. **Science**, *286*(5439), pp.509-512

Network Formation models In the Literature

Socio-Strategic Interactions

Users are utilitarian and driven by sociological principles

Both Approaches are not suitable to model Today's Online Social Networks:

Seekers Vs Content Creators

Link Directionality

Recommendation Systems

Probabilistic Interactions

Users are not utilitarian and follow statistical recommendations

Network Formation models In the Literature

Socio-Strategic Interactions

Users are utilitarian and driven by sociological principles

We Need a Different Model that considers the Quality dimension

Probabilistic Interactions

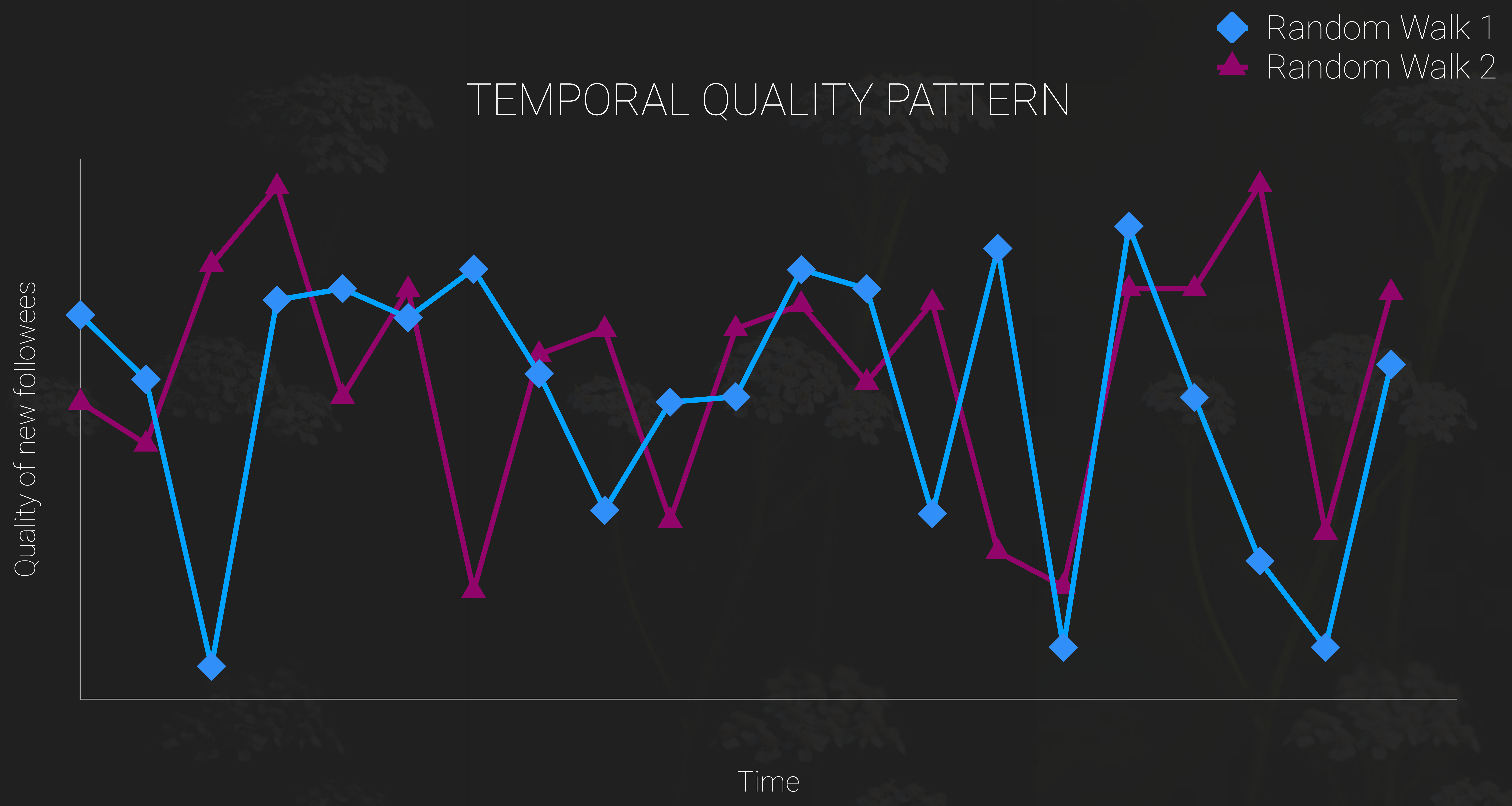
Users are not utilitarian and follow statistical recommendations

SEEKERS maximise the "QUALITY" of the content they want to receive

QUALITY-BASED INTERACTIONS

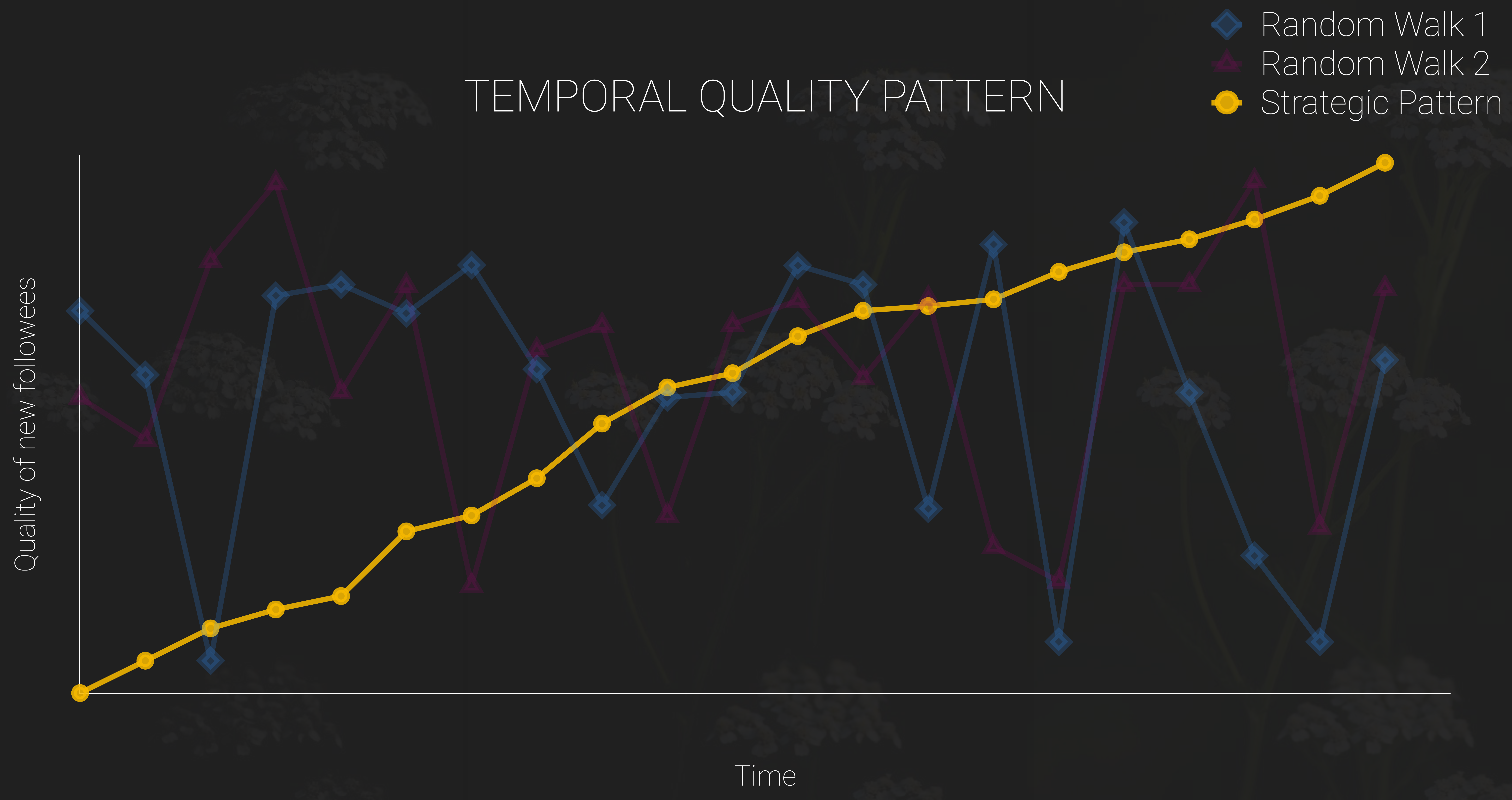
The RECOMMENDATION SYSTEM governs the "VISIBILITY" of the CONTENT CREATORS

DO USERS TRY TO OPTIMISE QUALITY RECEIVED OVER TIME?

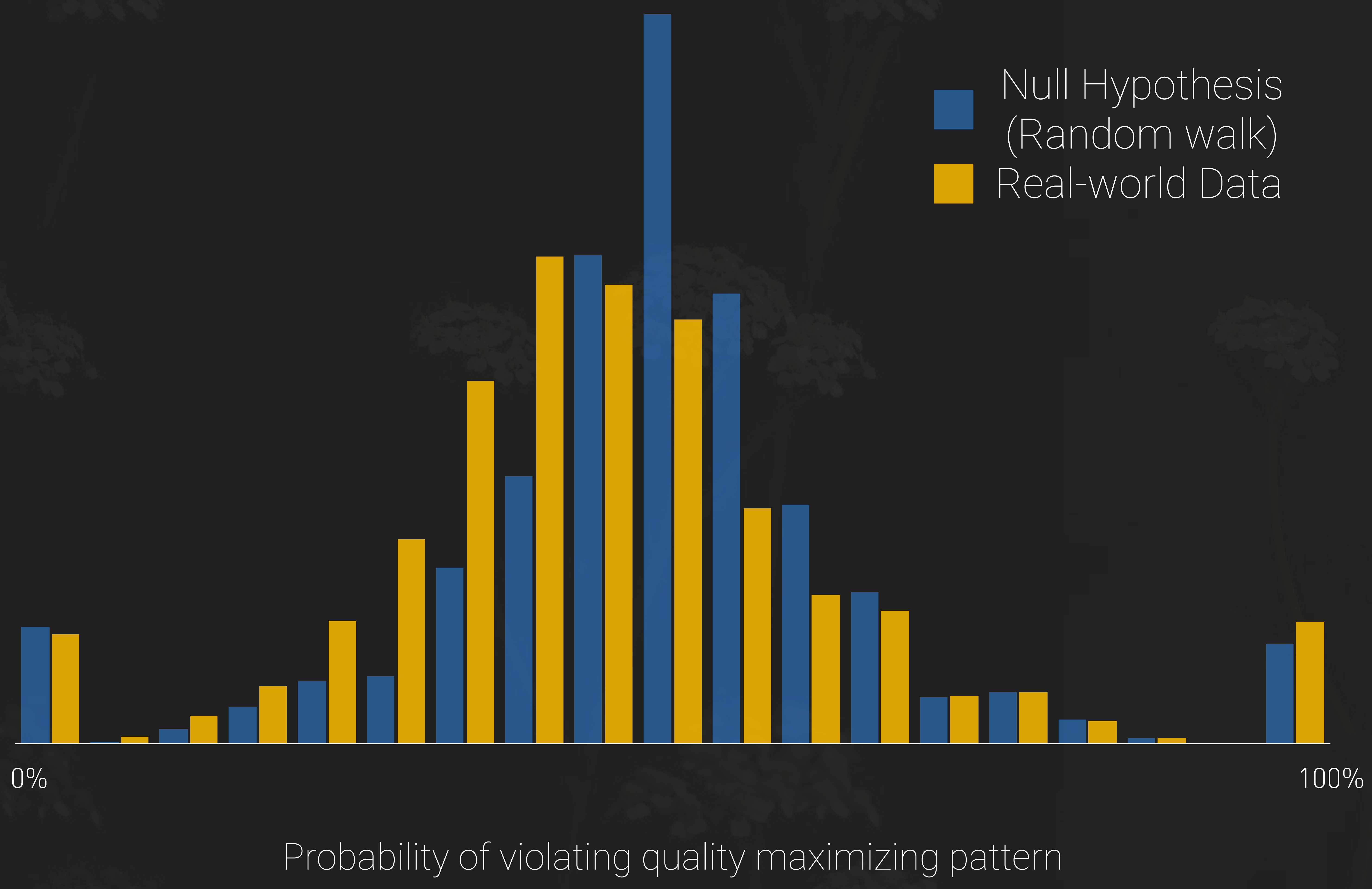


Random Walk 1
Random Walk 2
TEMPORAL QUALITY PATTERN
Quality of new followees
Time

TEMPORAL QUALITY PATTERN



TWITTER DATA-SET ON NETWORK SCIENTISTS



[**Pagan, N**., Mei, W., Li, C. and Dörfler, F., 2021. A meritocratic network formation model for the rise of social media influencers. **Nature communications**, 12(1), p.6865.


DO USERS TRY TO OPTIMISE THE
QUALITY RECEIVED OVER TIME?
YES, USERS TEND TO FOLLOW
OTHER USERS ACCORDING TO
INCREASING LEVELS OF
USER GENERATED CONTENT
(UGC)-QUALITY

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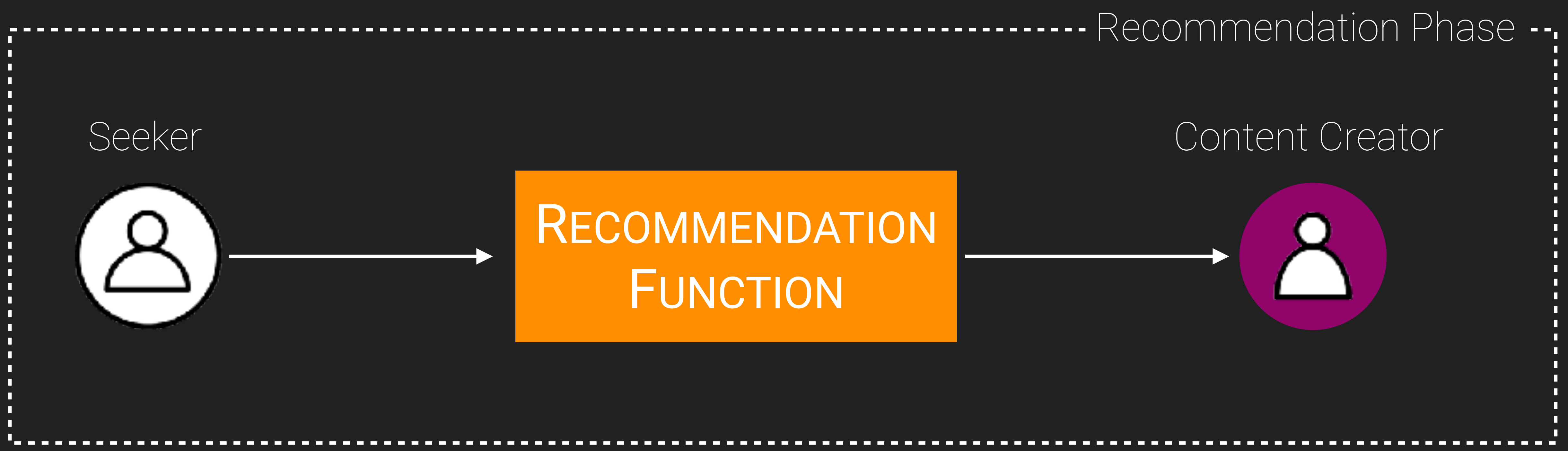
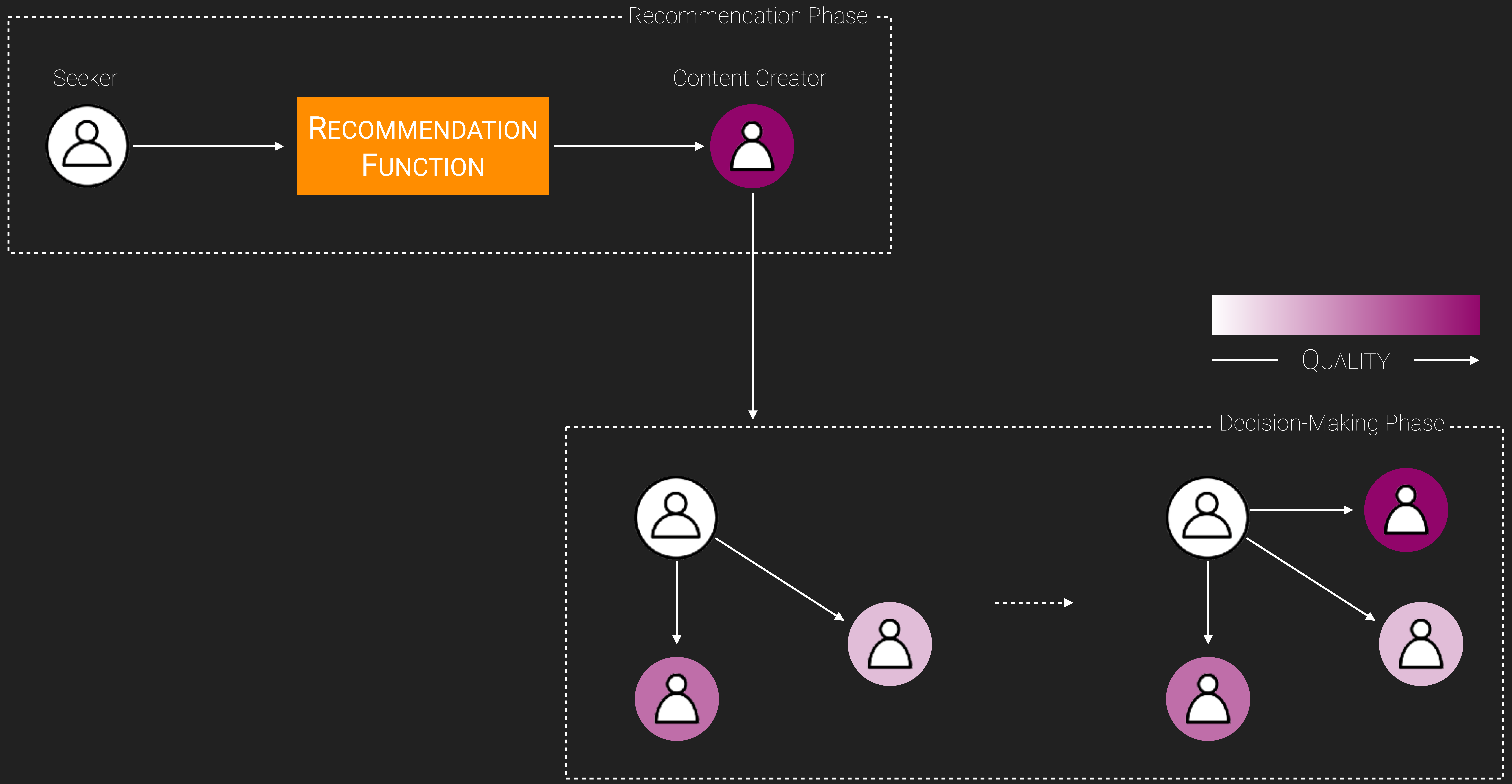
The Quality-Based Network Formation Model

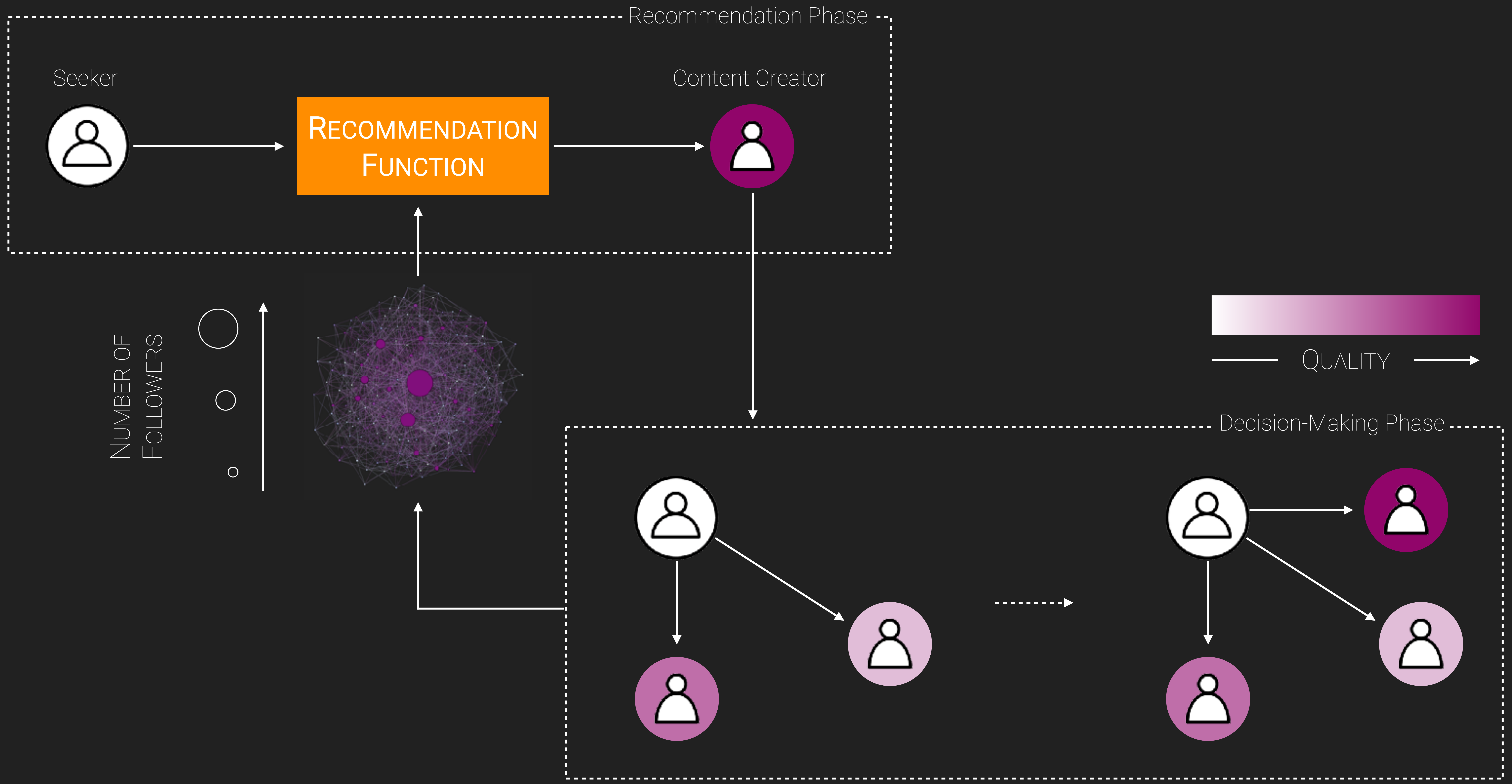
The Quality-Based Network Formation Model



The Quality-Based Network Formation Model

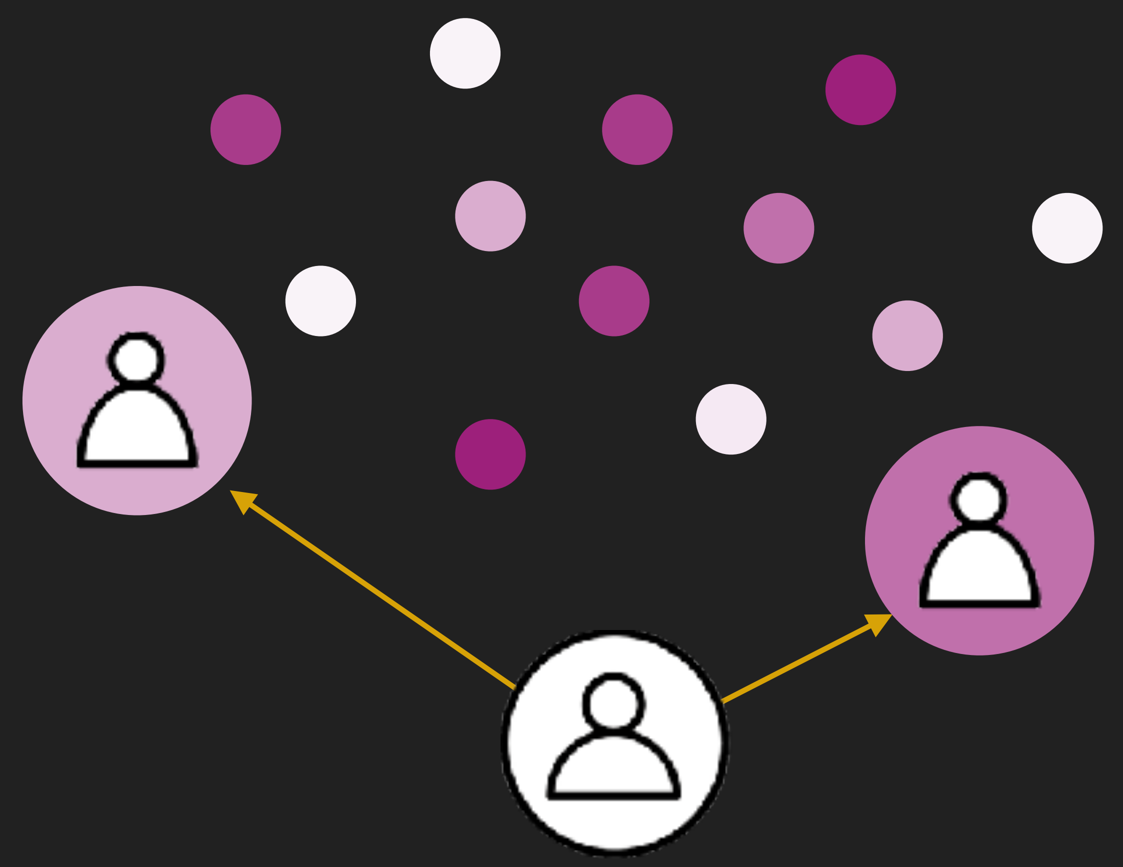


THE QUALITY-BASED NETWORK FORMATION MODEL

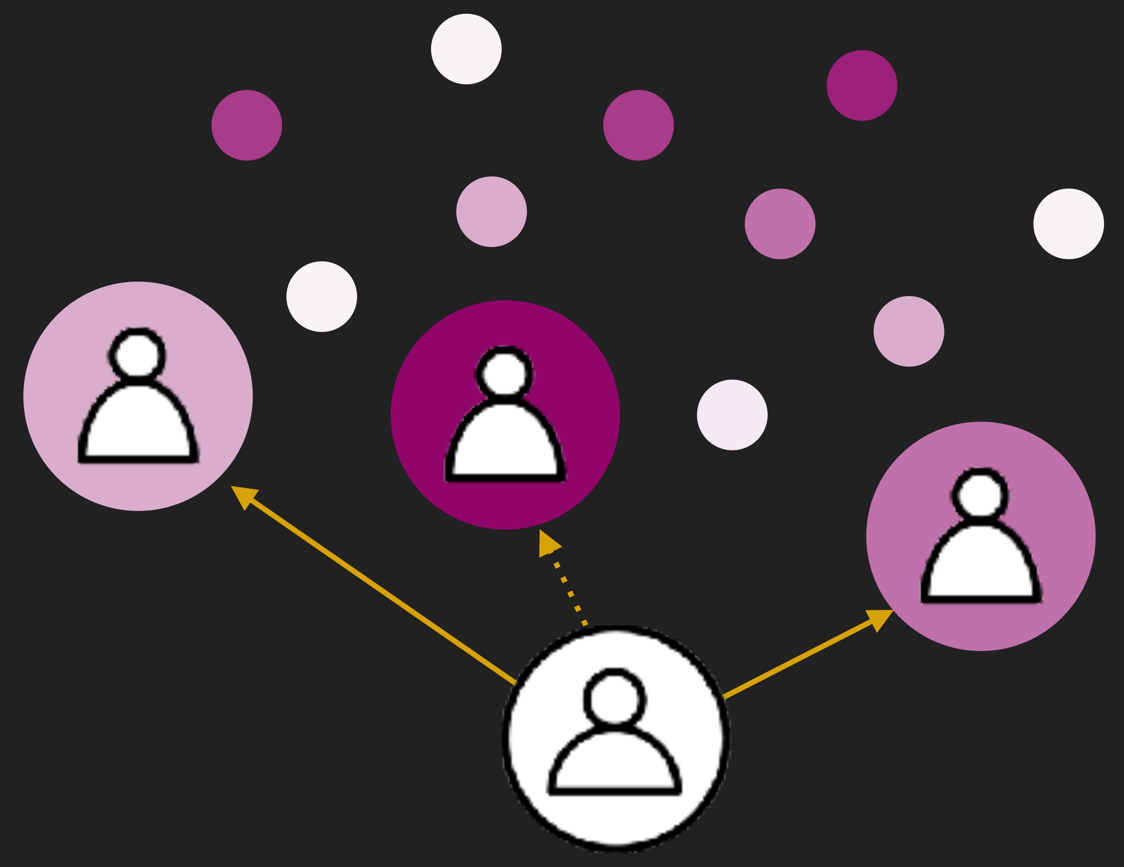


Step 1: Recommendation Functions

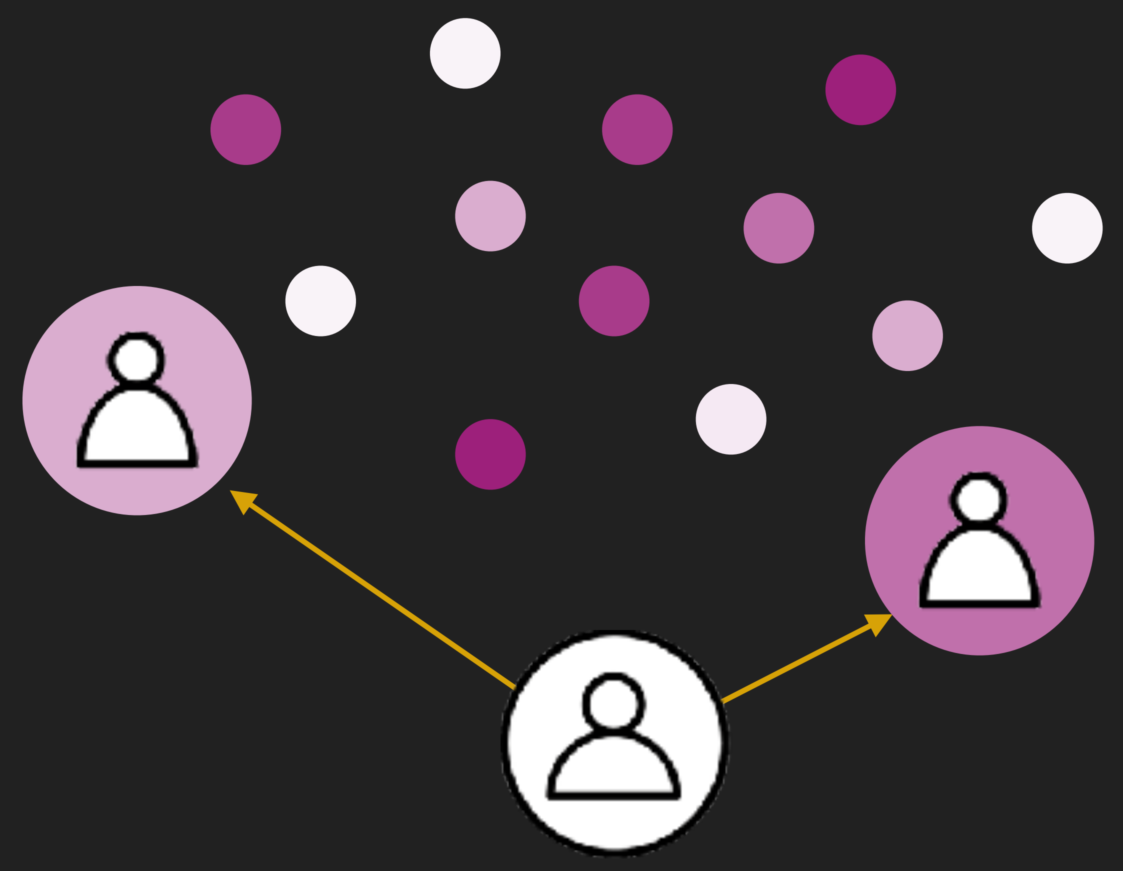
Step 2: Strategic Decision



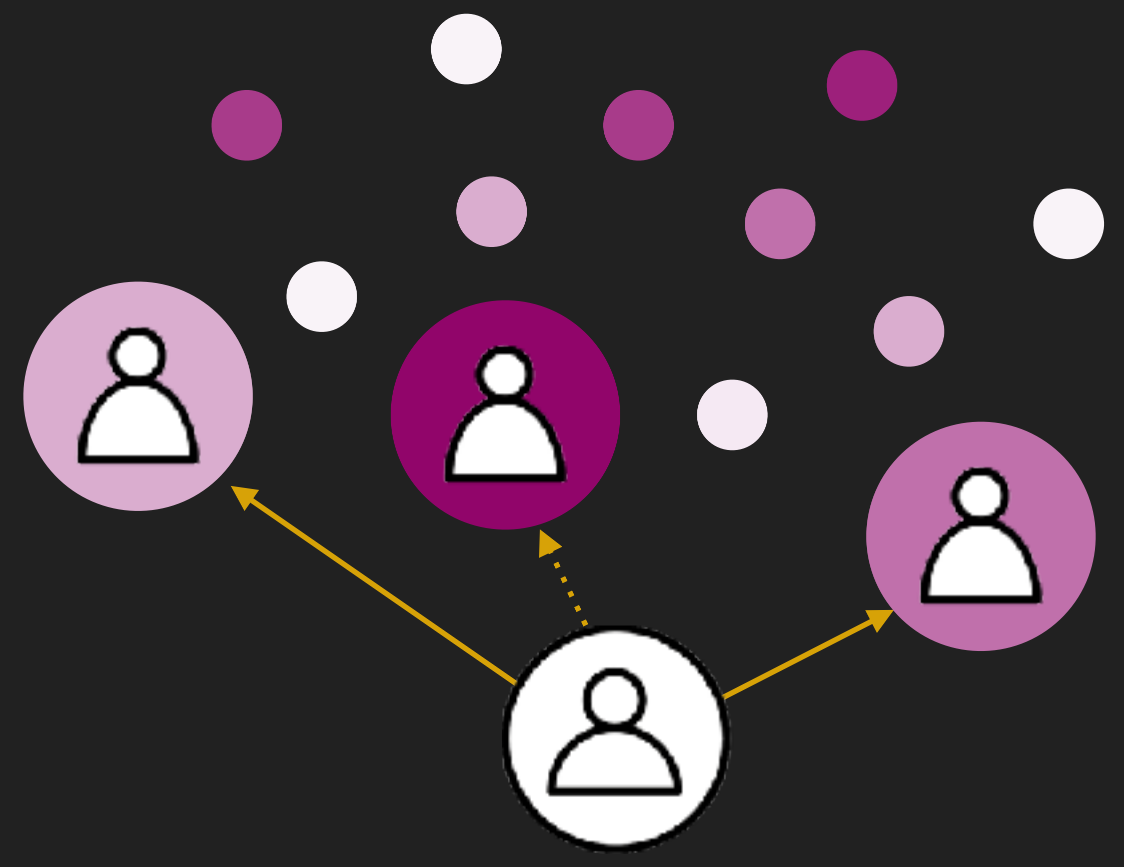
Step 2: Strategic Decision



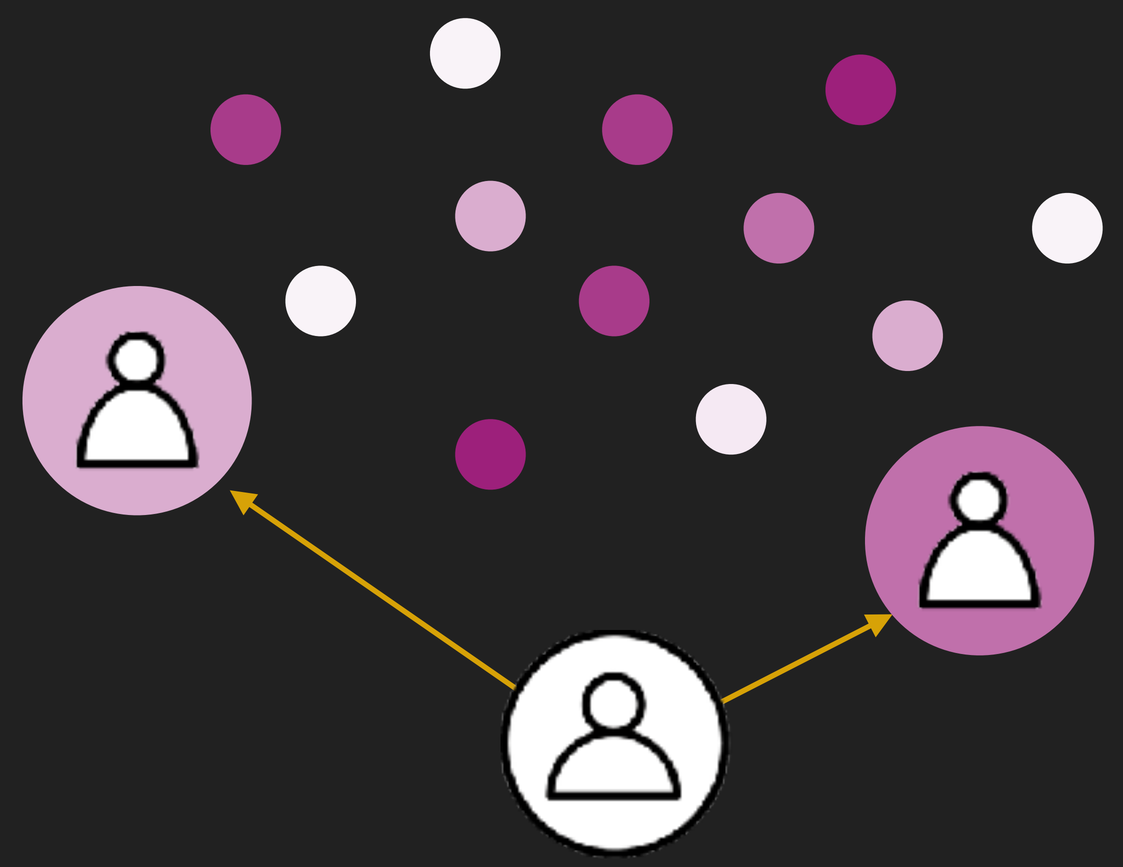
Phase 1
(Recommendation)



Step 2: Strategic Decision

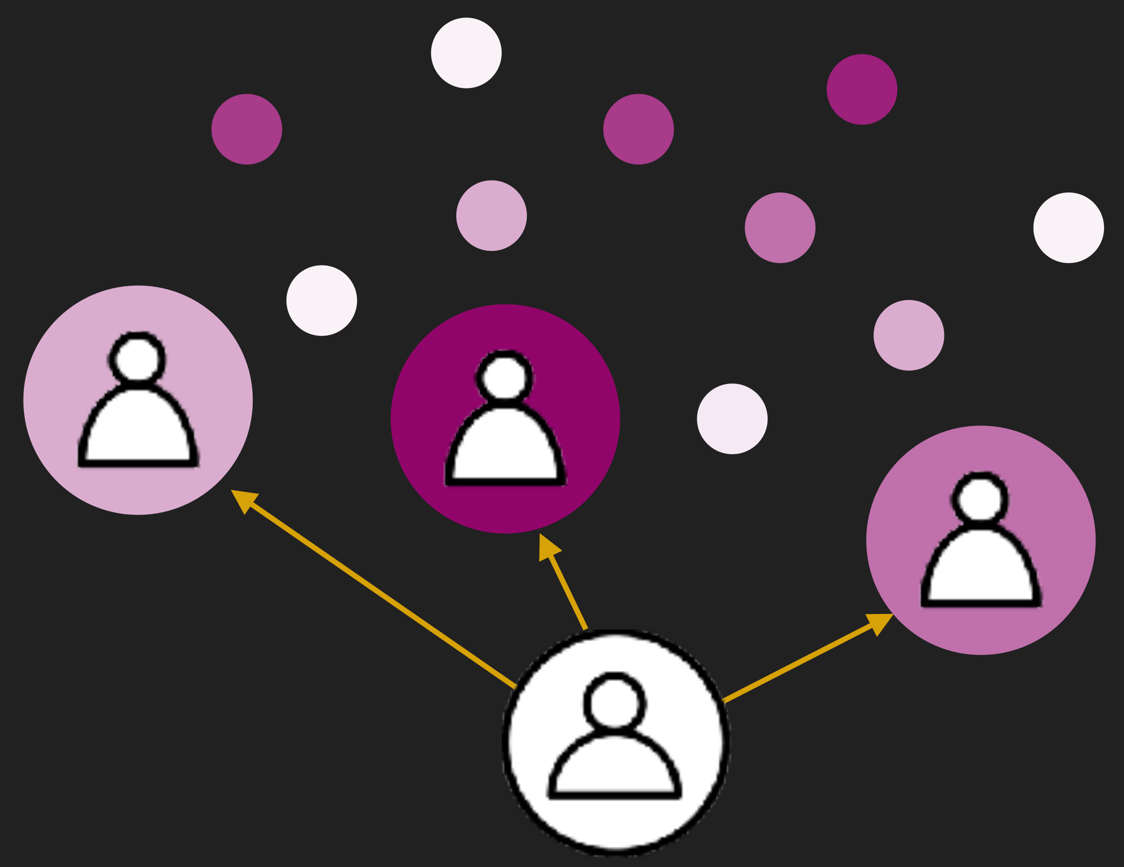


Phase 1
(Recommendation)



Phase 2
(Decision)

ACCEPTED

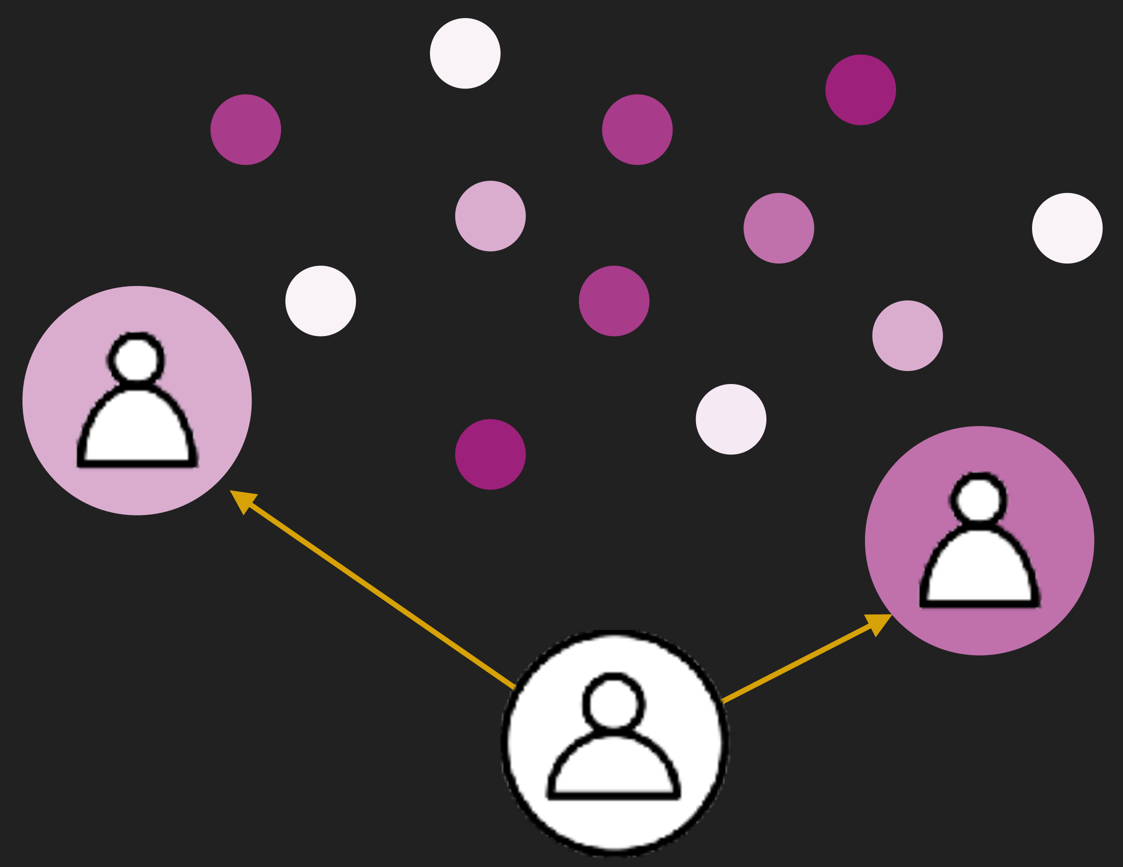


THE SEEKER **ACCEPTS TO FOLLOW** THE NEW RECOMMENDATION **ONLY IF ITS QUALITY IS HIGHER THAN THAT OF ALL CURRENT FOLLOWEES**

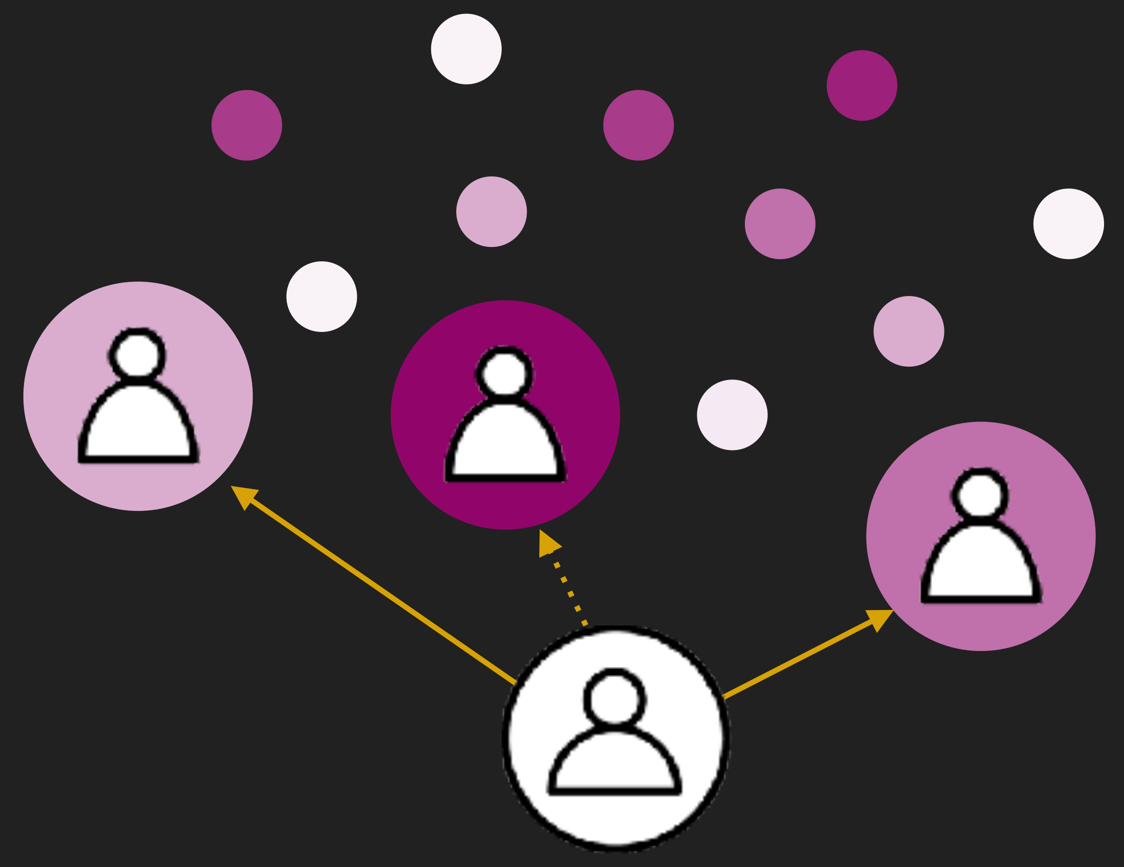
Quality

Step 2: Strategic Decision

Phase 1
(Recommendation)

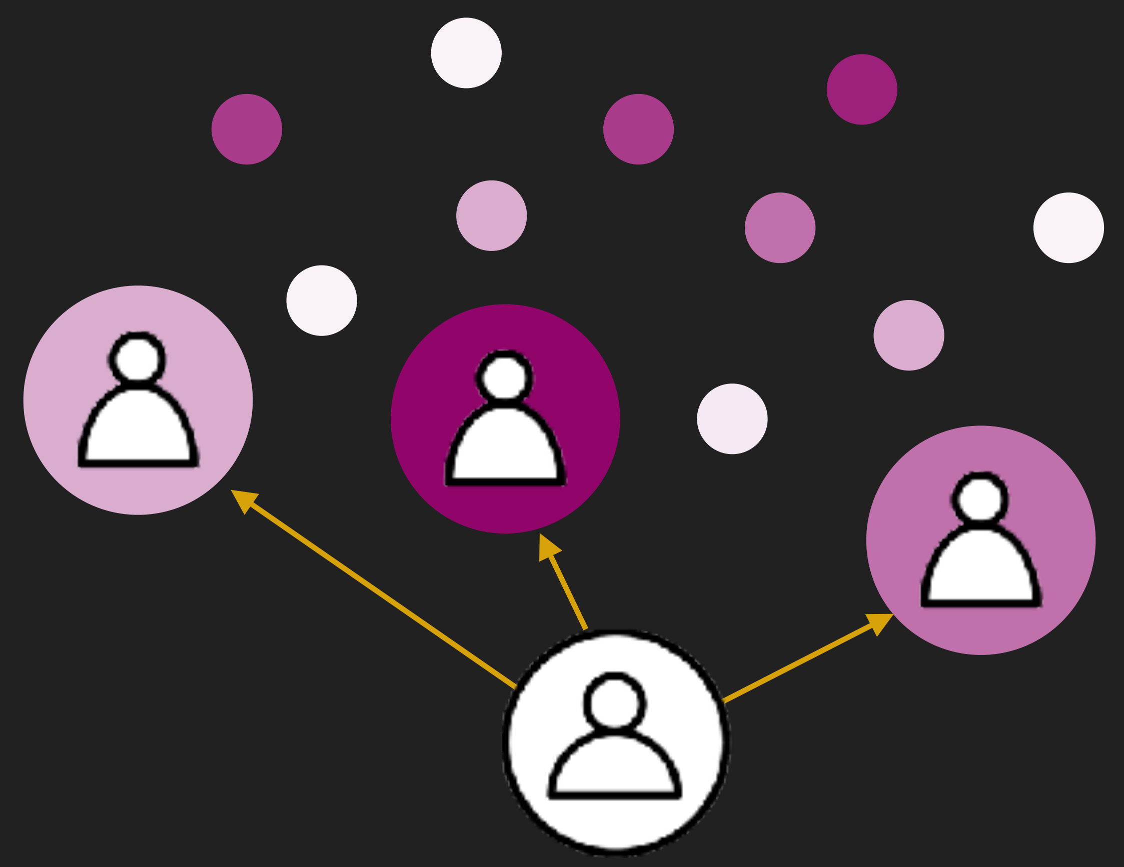


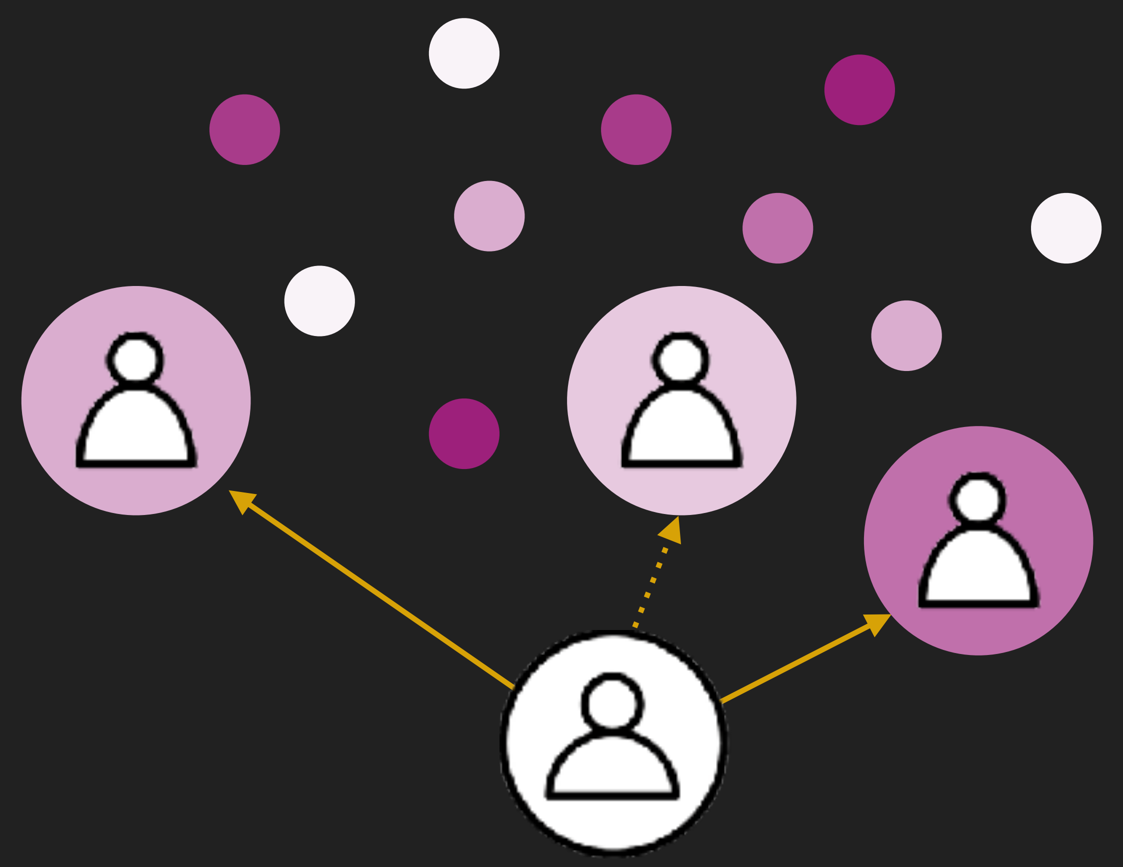
Phase 1
(Recommendation)



Phase 2
(Decision)

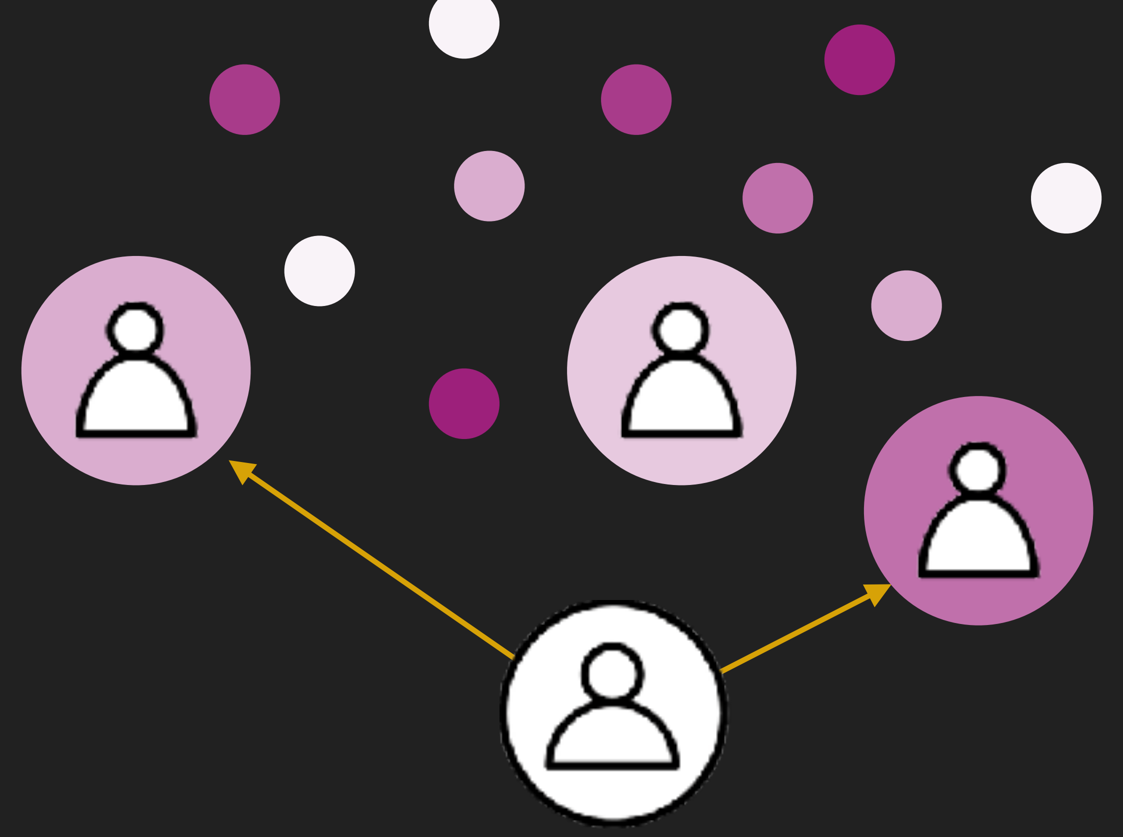
Accepted





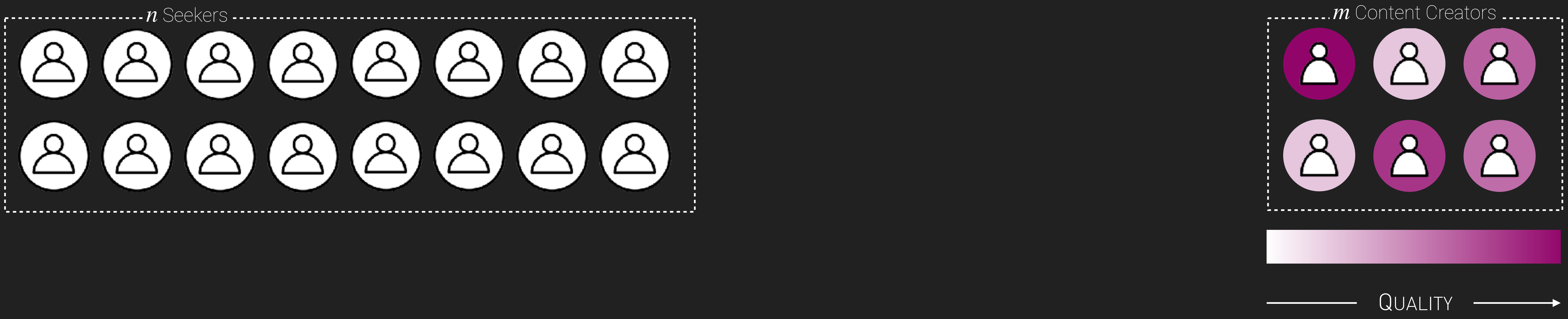
Phase 2
(Decision)

Not accepted

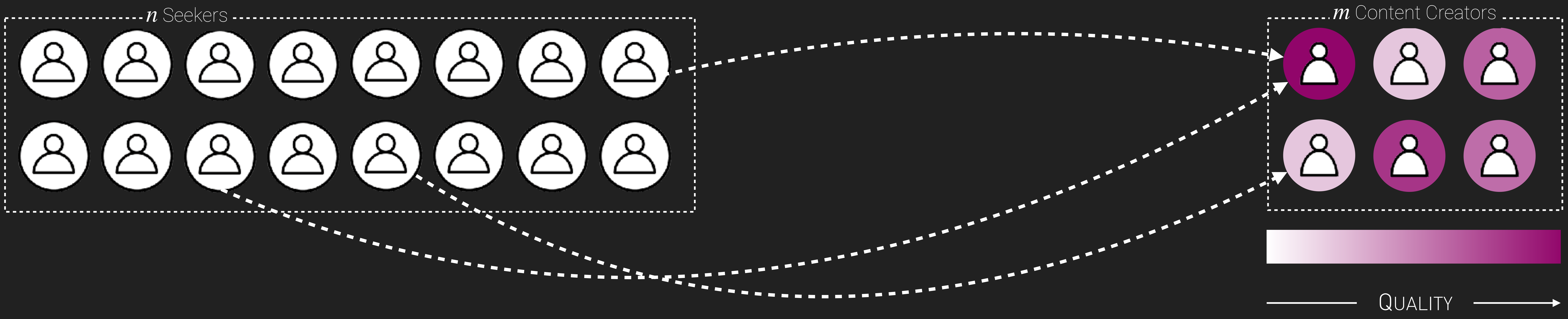


The seeker **accepts to follow** the new recommendation **only if its quality is higher than that of all current followees**

Quality



Initial empty network
$(a_{ij} = 0, \forall i \in \{1, \ldots, n\}, \forall j \in \{1, \ldots, m\})$

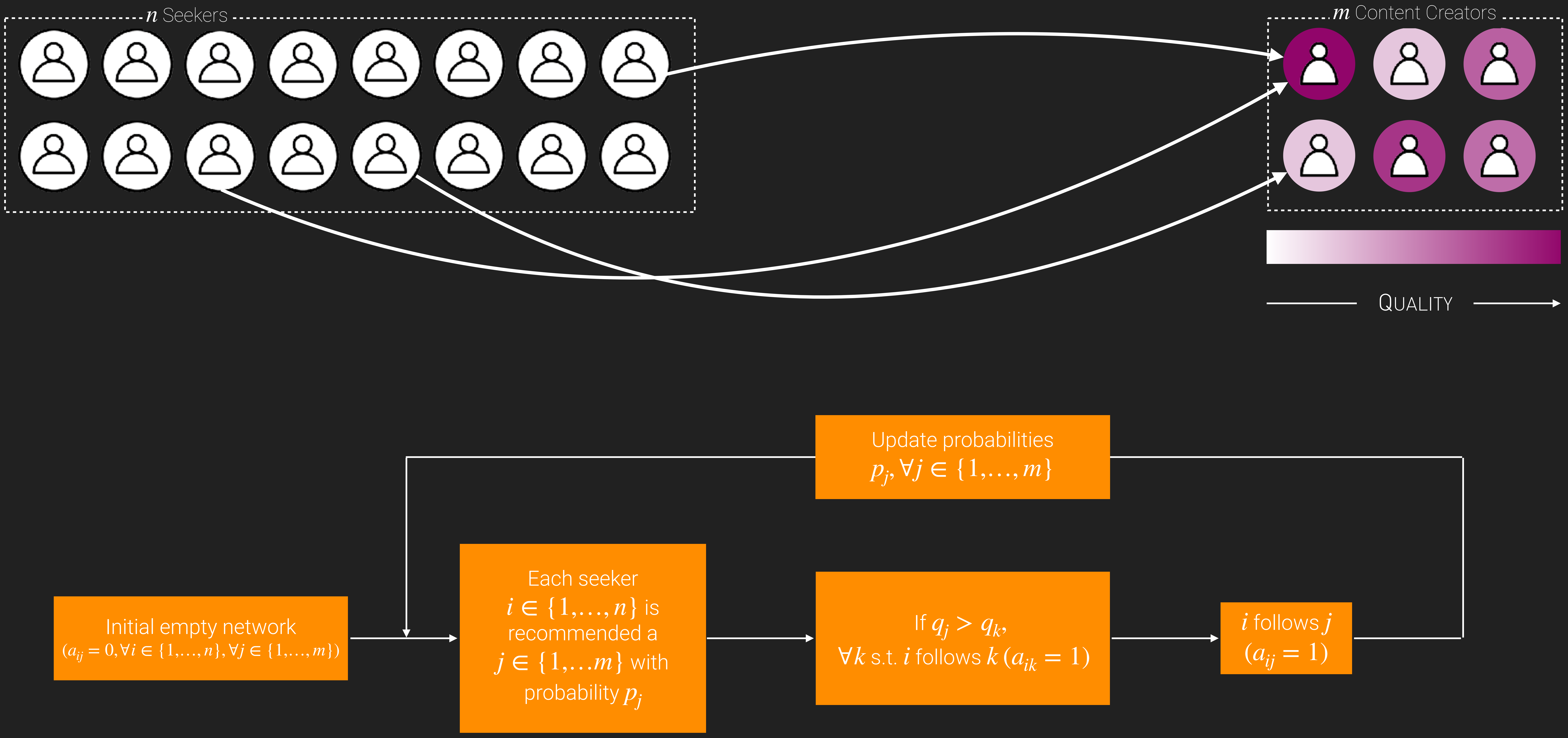


Initial empty network
$(a_{ij} = 0, \forall i \in \{1,\ldots,n\}, \forall j \in \{1,\ldots,m\})$

→

Each seeker $i \in \{1,\ldots,n\}$ is recommended a $j \in \{1,\ldots m\}$ with probability p_j

Initial empty network $(a_{ij} = 0, \forall i \in \{1,\ldots,n\}, \forall j \in \{1,\ldots,m\})$ → Each seeker $i \in \{1,\ldots,n\}$ is recommended a $j \in \{1,\ldots m\}$ with probability p_j → If $q_j > q_k$, $\forall k$ s.t. i follows k $(a_{ik} = 1)$ → i follows j $(a_{ij} = 1)$



n Seekers
m Content Creators
QUALITY
Update probabilities $p_j, \forall j \in \{1,\dots,m\}$
Initial empty network $(a_{ij} = 0, \forall i \in \{1,\dots,n\}, \forall j \in \{1,\dots,m\})$
Each seeker $i \in \{1,\dots,n\}$ is recommended a $j \in \{1,\dots m\}$ with probability p_j
If $q_j > q_k$, $\forall k$ s.t. i follows k $(a_{ik} = 1)$
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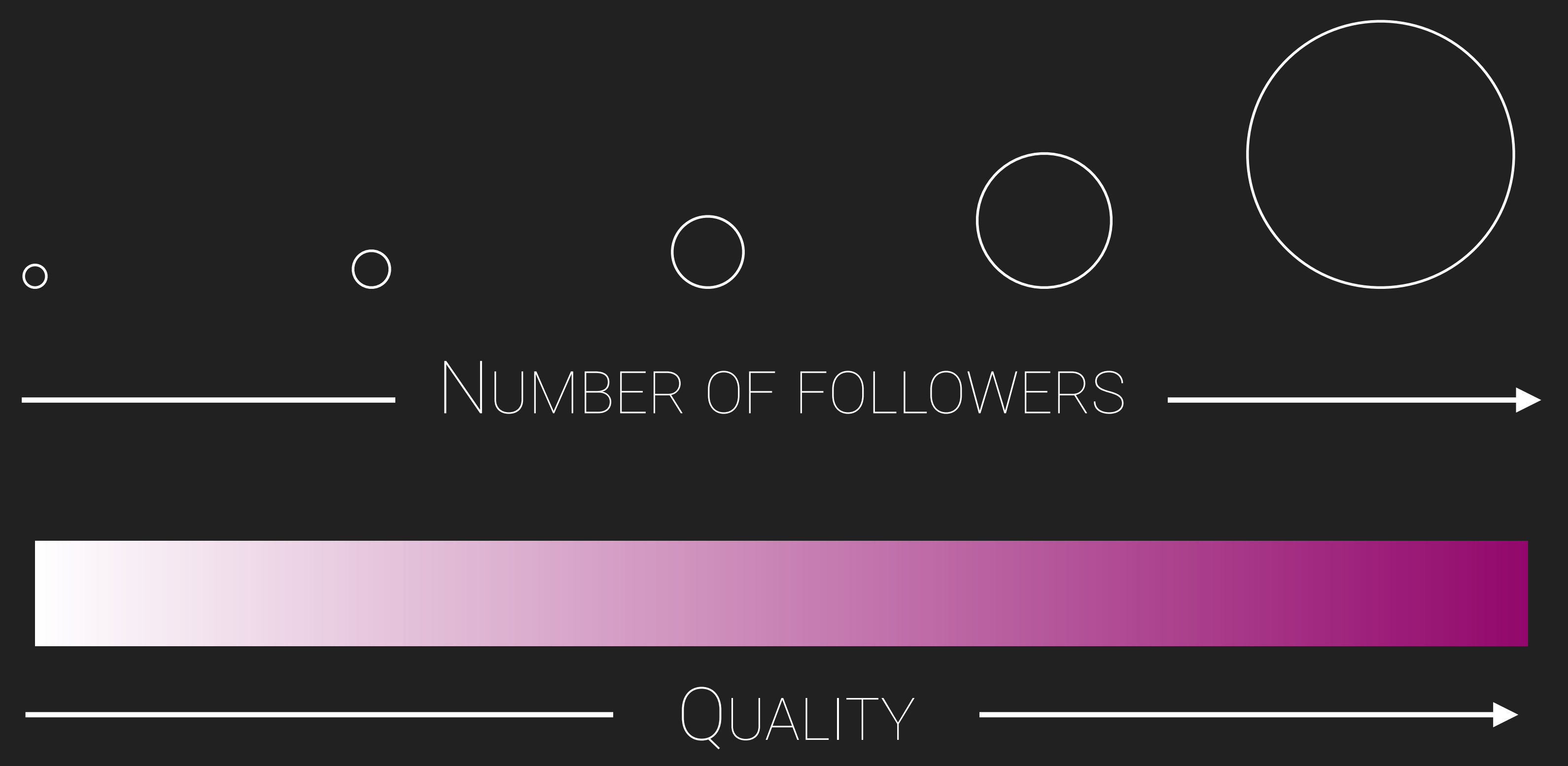

MERITOCRACY: IS THE NUMBER OF FOLLOWERS CORRELATED WITH THE QUALITY?

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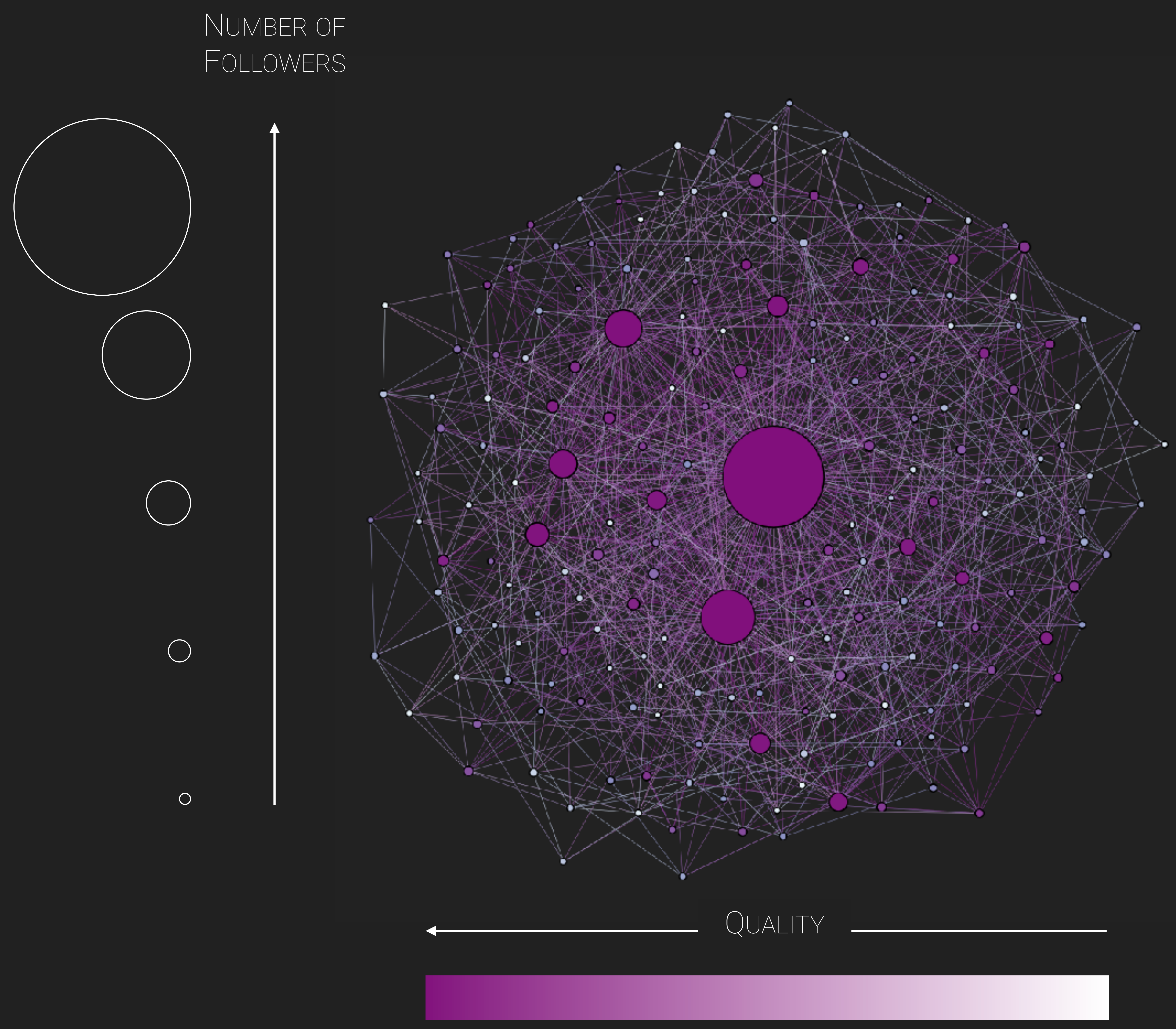
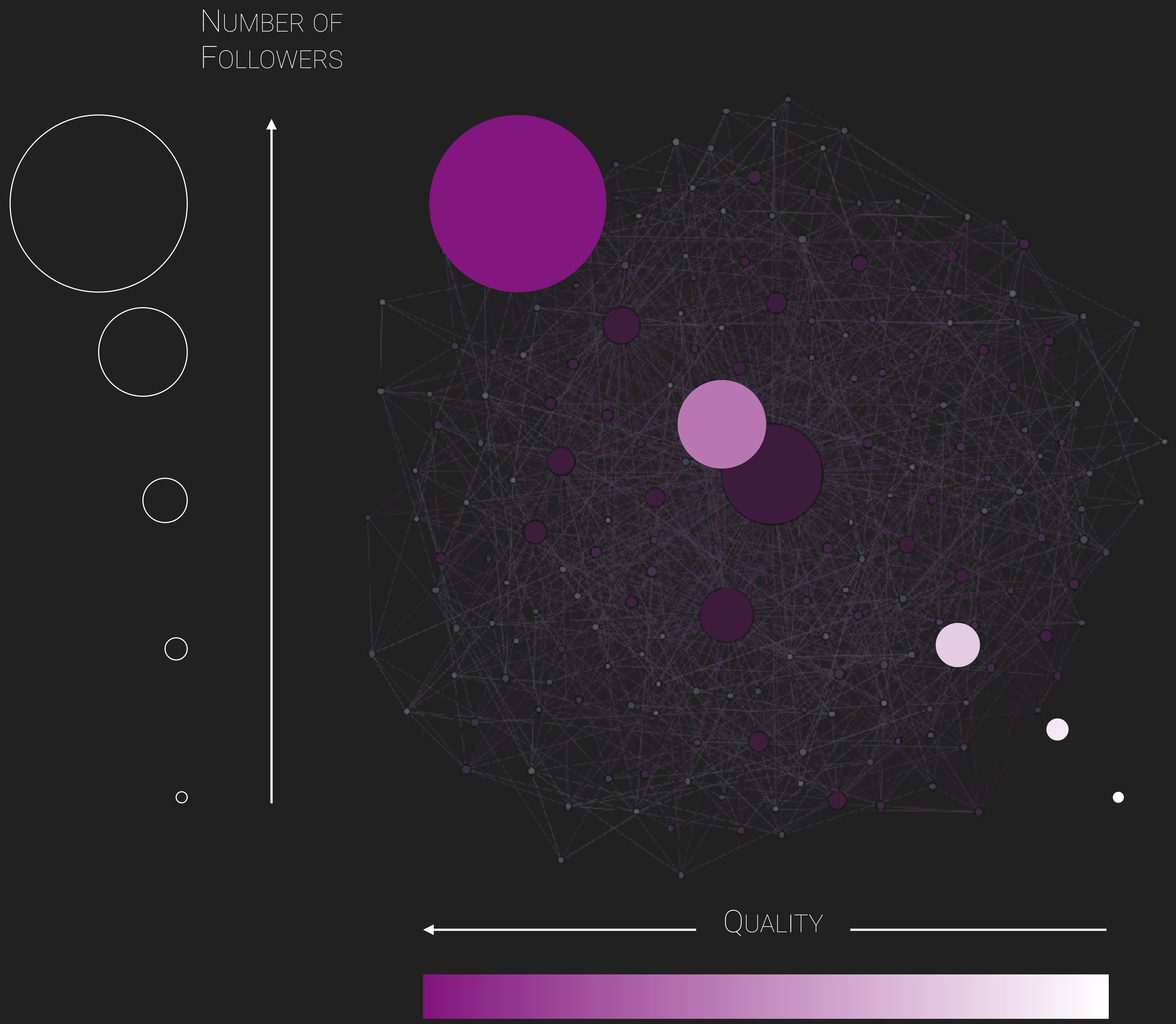
Convergence Results

THEOREM.

For any quality vector $\mathbf{q} = [q_1, \dots, q_m]$, the network reaches an equilibrium almost surely.
At equilibrium, every seeker follows the best Content Creator.

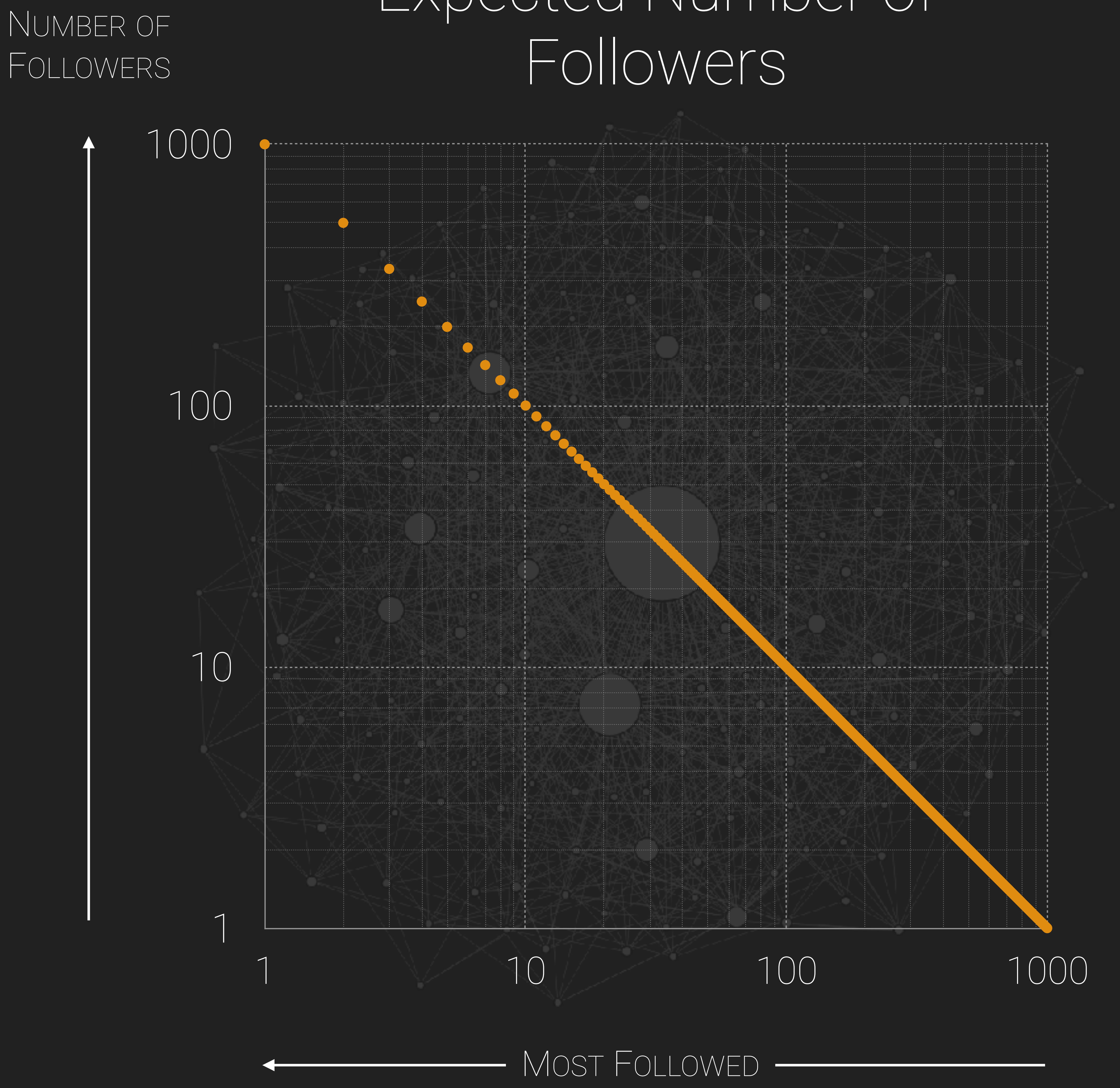

Number of
Followers
Quality



Number of Followers correlates with UGC-quality:

The highest the Quality, the Highest the number of followers.

Expected Number of Followers

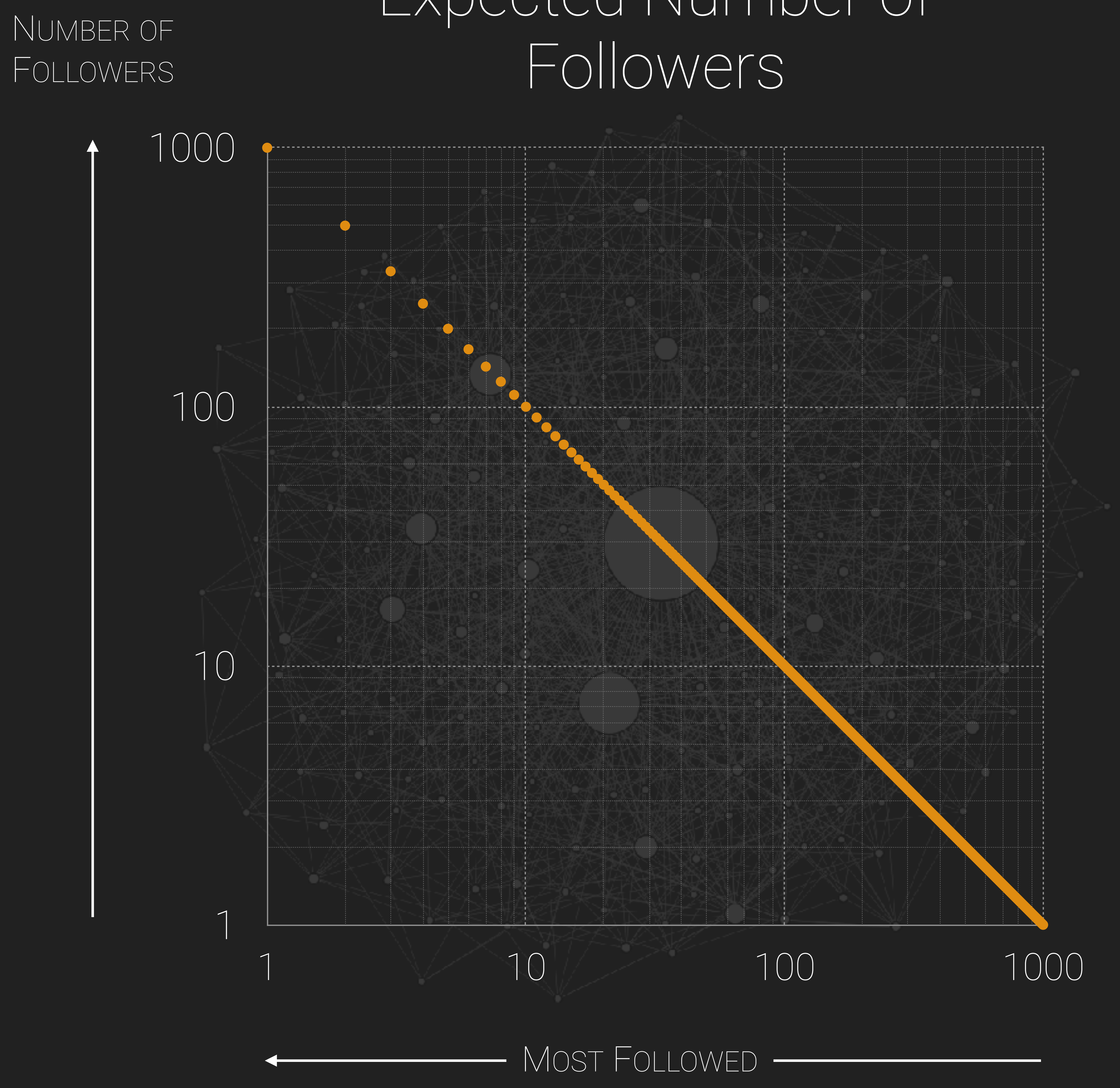


1ST MOST FOLLOWED USER HAS:

- 2 TIMES AS MANY FOLLOWERS AS THE 2ND
- 3 TIMES AS MANY FOLLOWERS AS THE 3RD
- 4 TIMES AS MANY FOLLOWERS AS THE 4TH
- …

[1] Pagan, N., Mei, W., Li, C. and Dörfler, F., 2021. A meritocratic network formation model for the rise of social media influencers. **Nature communications**, 12(1), p.6865.

Expected Number of Followers



Intuitively...

Model Validity

In [1], we fully validated the model by studying:

- Indegree distribution
- Outdegree distribution
- Overlap Index (similarities between followers' lists)

Furthermore, we collected and analysed several data-sets on Twitch.

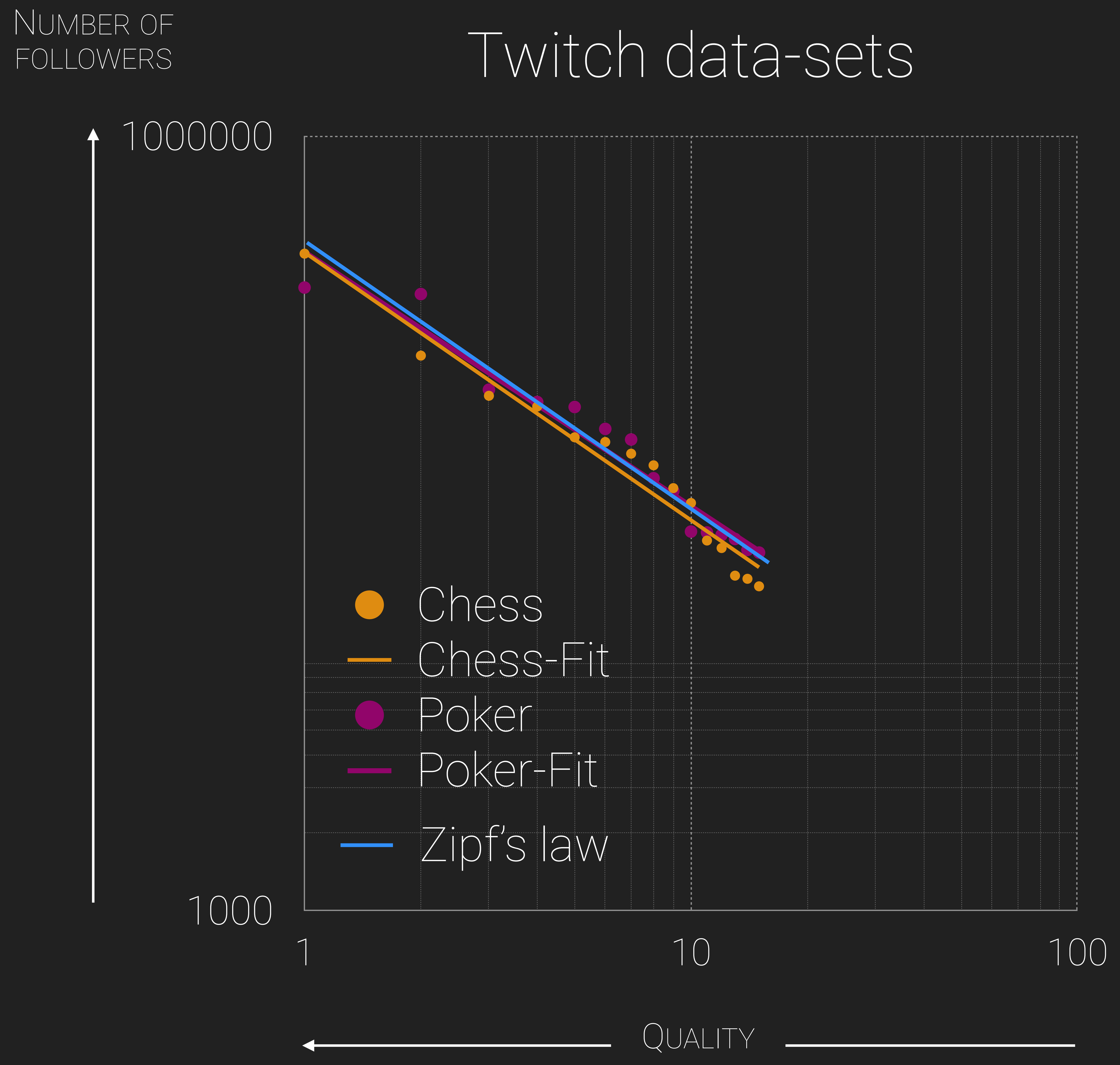
Theorem.

At equilibrium, the CC's expected indegree (when indexed by decreasing quality) follows a Zipf's law:
$\mathbb{E}(d_i^{in,\star}) = \frac{n}{i}$

Theorem.

The seekers' expected outdegree is equals to the harmonic number m:

$$\mathbb{E}[d_N^{out,\star}] = \sum_{k=1}^{N-1} \frac{1}{k}.$$



[1] **Pagan, N.**, Mei, W., Li, C. and Dörfler, F., 2021. A meritocratic network formation model for the rise of social media influencers. **Nature communications**, 12(1), p.6865.

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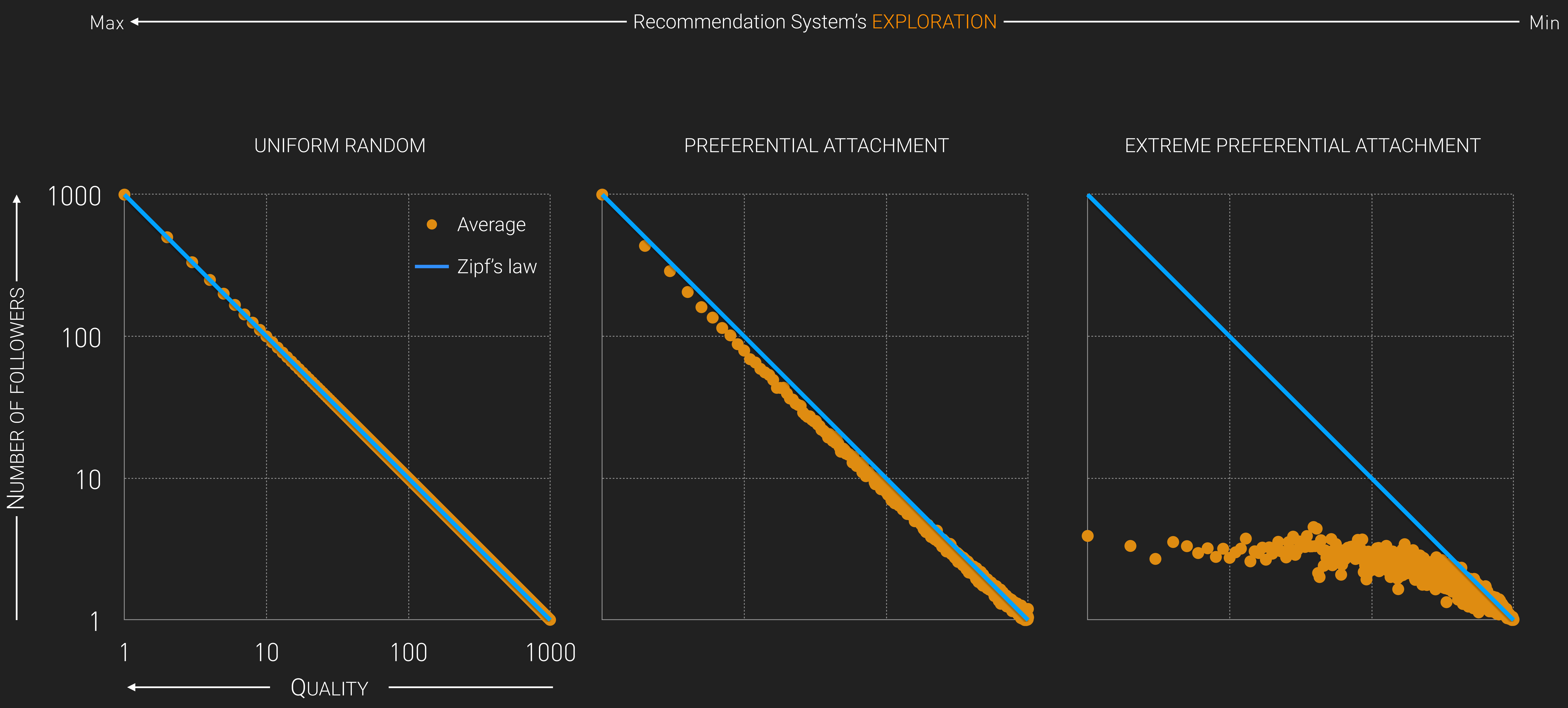
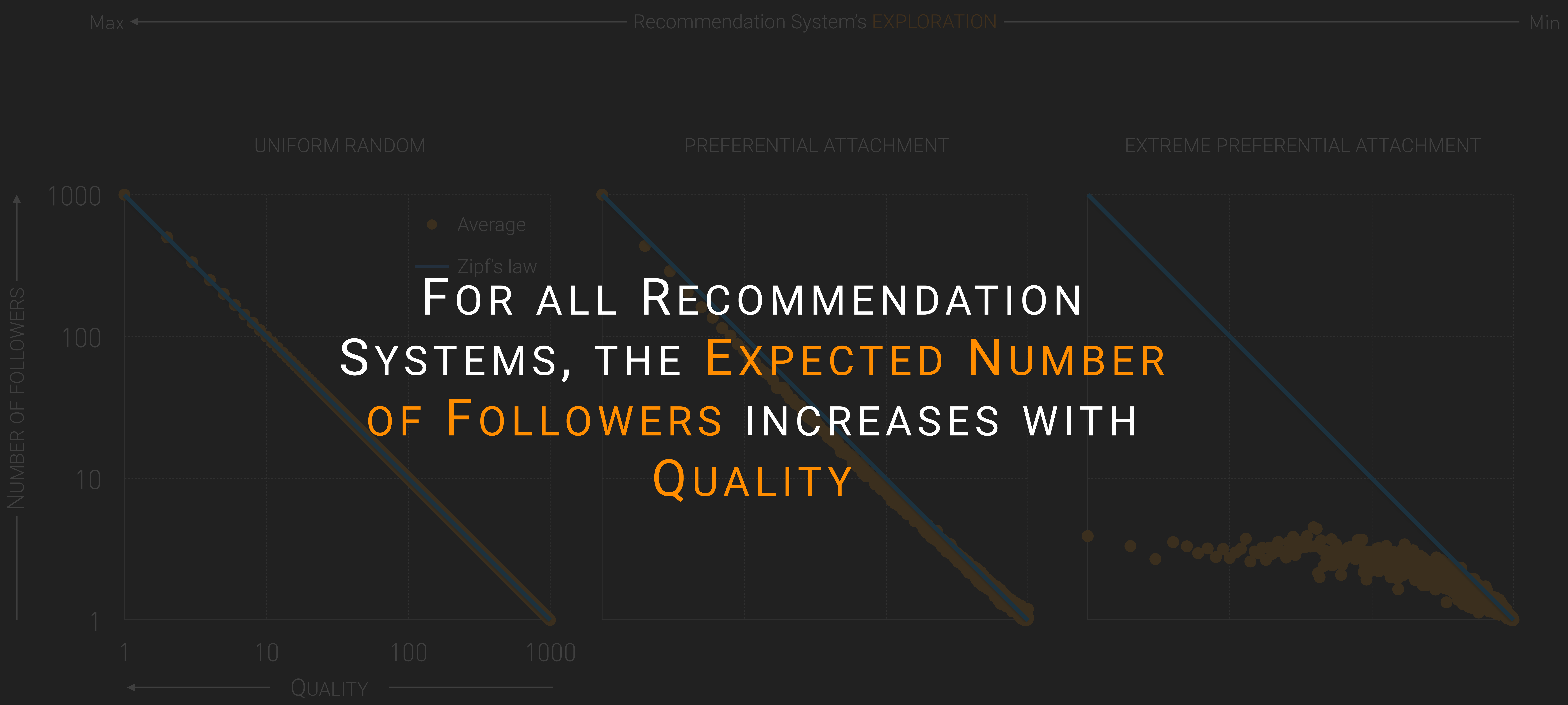
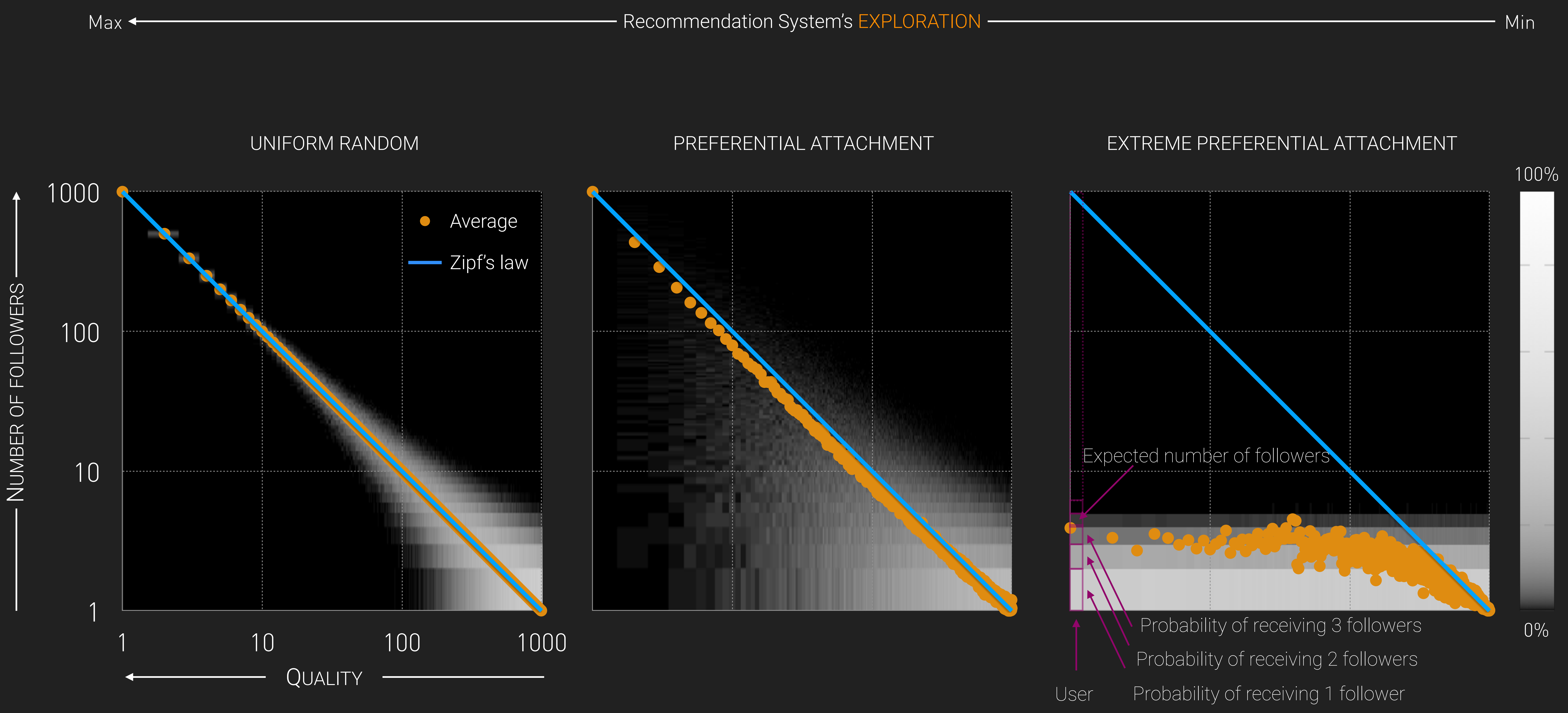
Max
Recommendation System's EXPLORATION
Min
UNIFORM RANDOM
PREFERENTIAL ATTACHMENT
EXTREME PREFERENTIAL ATTACHMENT
NUMBER OF FOLLOWERS
QUALITY



Max
Recommendation System's EXPLORATION
Min
UNIFORM RANDOM
PREFERENTIAL ATTACHMENT
EXTREME PREFERENTIAL ATTACHMENT
Average
Zipf's law
NUMBER OF FOLLOWERS
1000
100
10
1
1
10
100
1000
QUALITY



FOR ALL RECOMMENDATION SYSTEMS, THE EXPECTED NUMBER OF FOLLOWERS INCREASES WITH QUALITY



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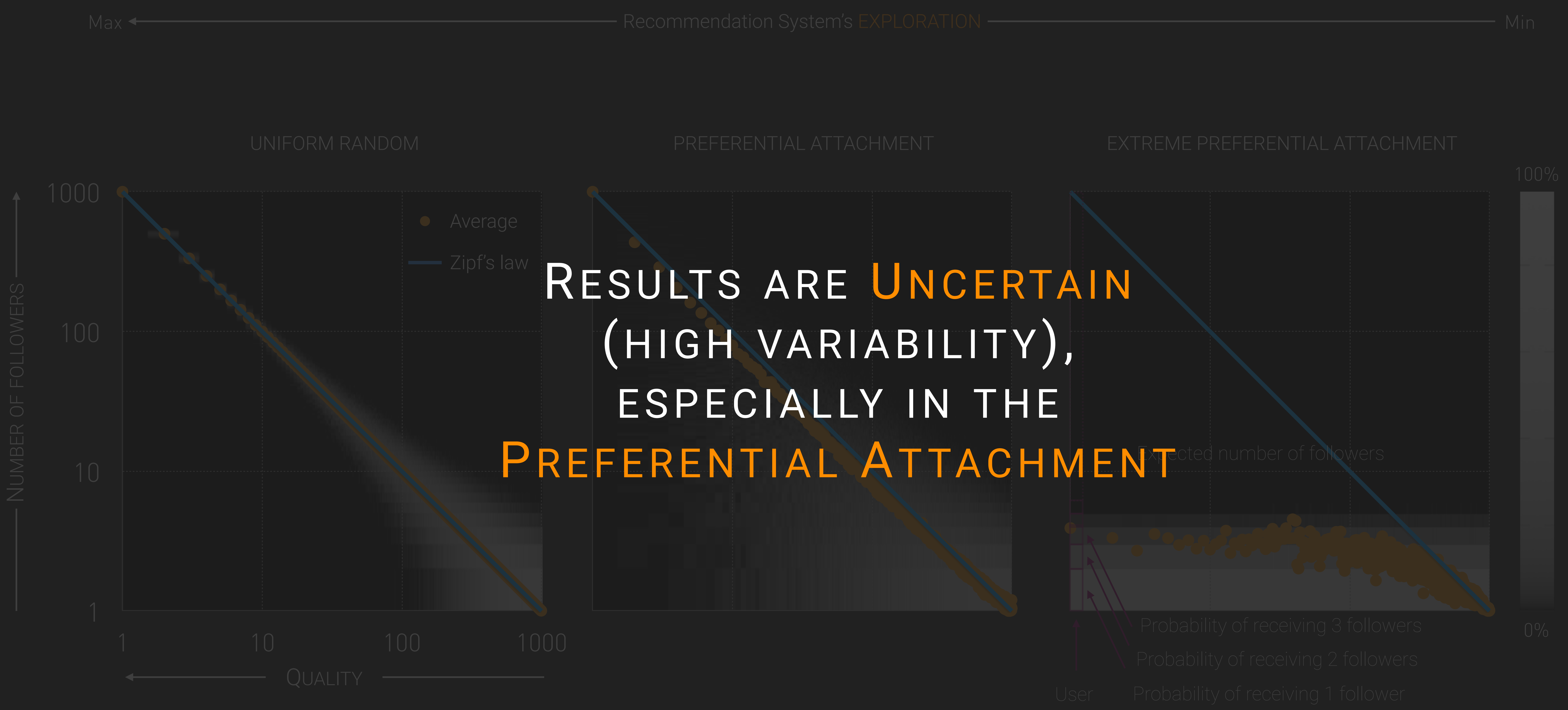
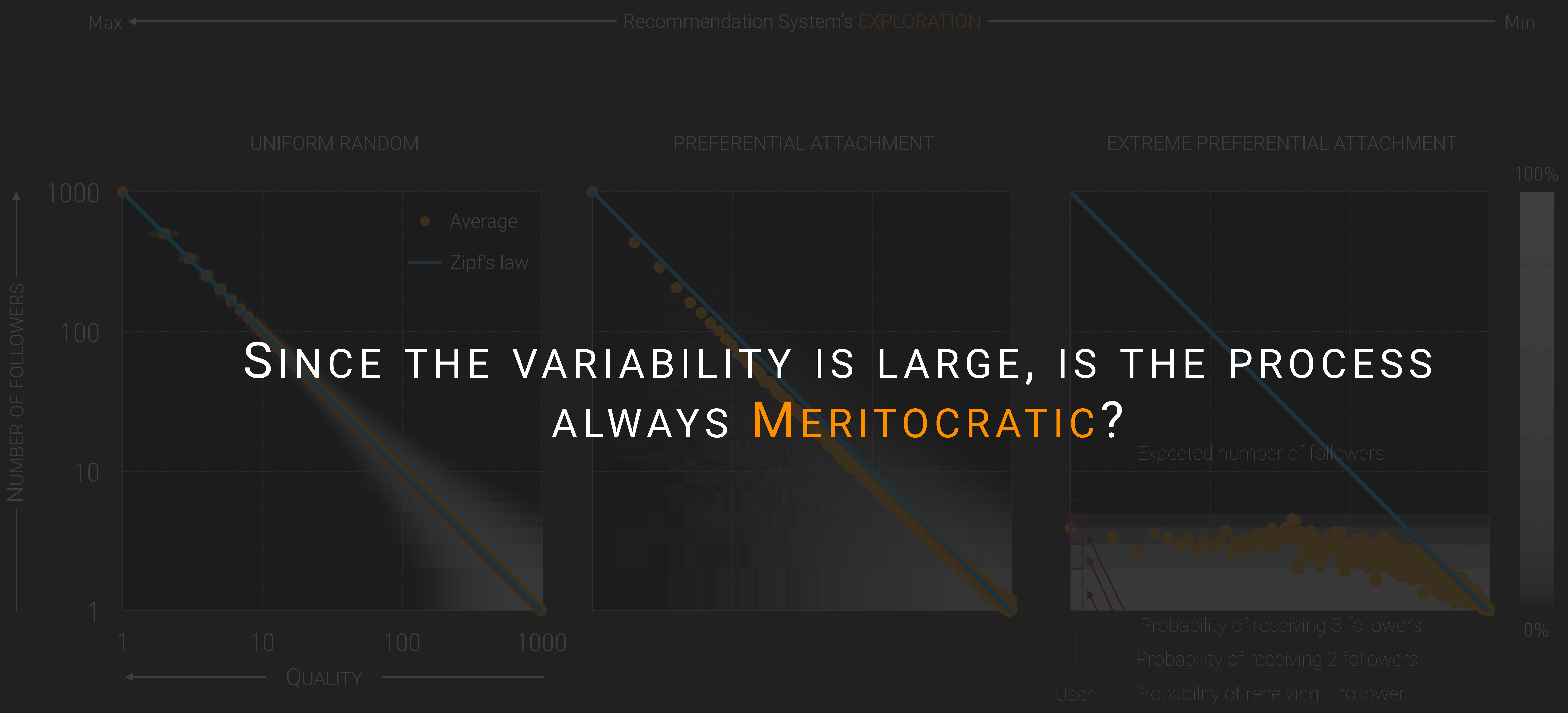
Ionescu, S., **Pagan, N.** and Hannák, A., 2023, January. Individual Fairness for Social Media Influencers. In **Complex Networks and Their Applications XI**.



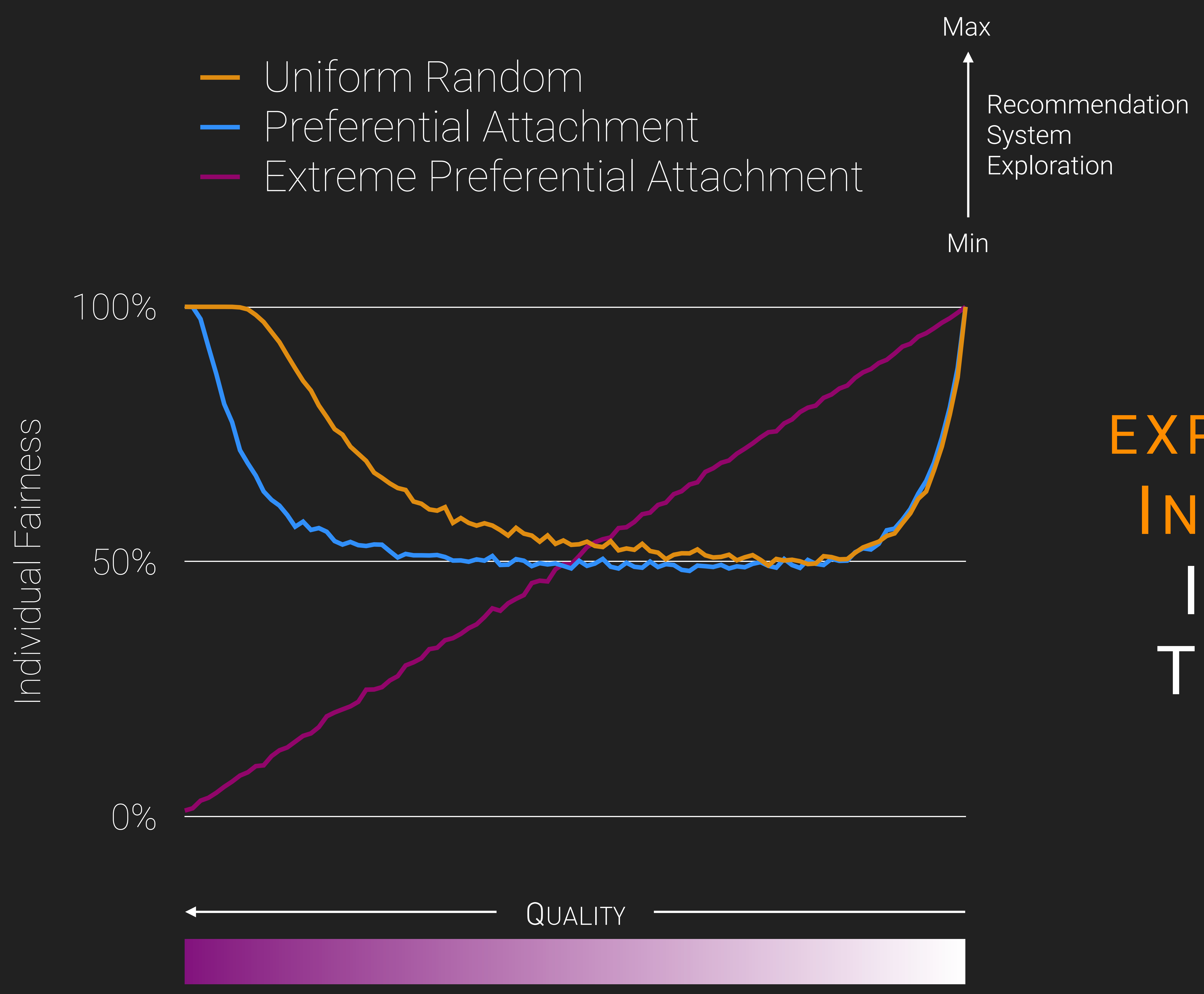
RESULTS ARE UNCERTAIN (HIGH VARIABILITY), ESPECIALLY IN THE PREFERENTIAL ATTACHMENT

Since the variability is large, is the process always Meritocratic?



Individual Fairness:

What is the probability that the Nth quality-ranked individual is in the top-N most followed ones?



EXPLORATION IMPROVES INDIVIDUAL FAIRNESS, IN PARTICULAR FOR TOP-QUALITY NODES

Ionescu, S., Pagan, N. and Hannák, A., 2023, January. Individual Fairness for Social Media Influencers. In Complex Networks and Their Applications XI.

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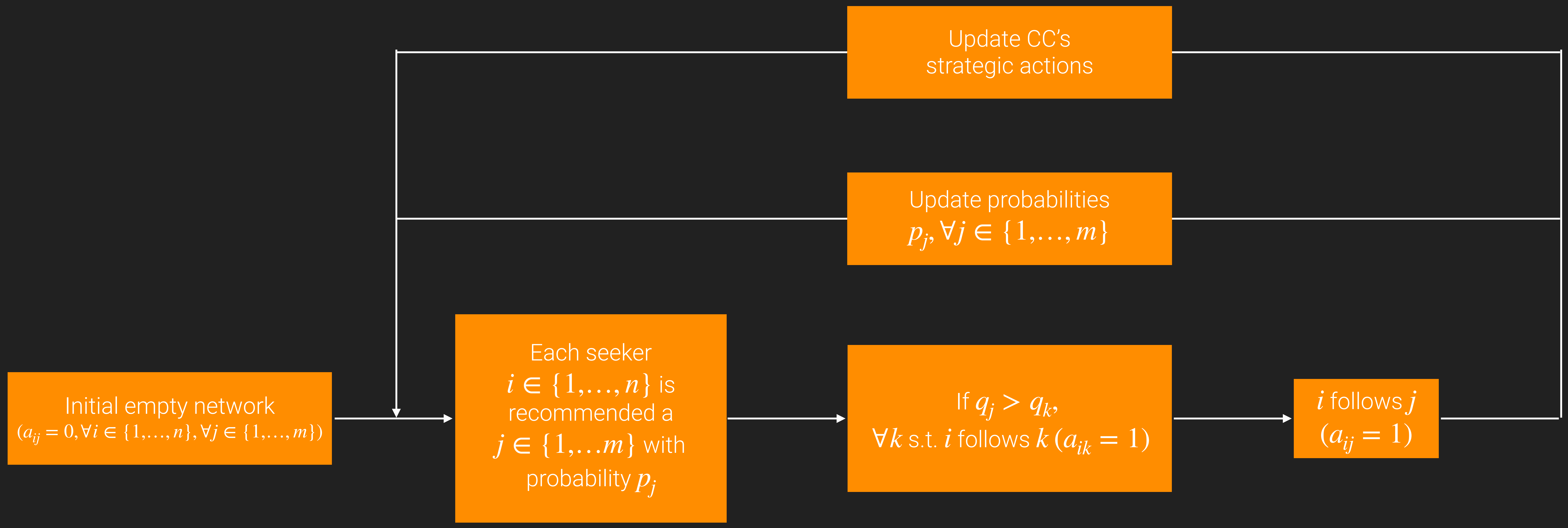
Update CC's strategic actions
Update probabilities $p_j, \forall j \in \{1, \ldots, m\}$
Initial empty network $(a_{ij} = 0, \forall i \in \{1, \ldots, n\}, \forall j \in \{1, \ldots, m\})$
Each seeker $i \in \{1, \ldots, n\}$ is recommended a $j \in \{1, \ldots m\}$ with probability p_j
If $q_j > q_k$, $\forall k$ s.t. i follows k $(a_{ik} = 1)$
i follows j $(a_{ij} = 1)$

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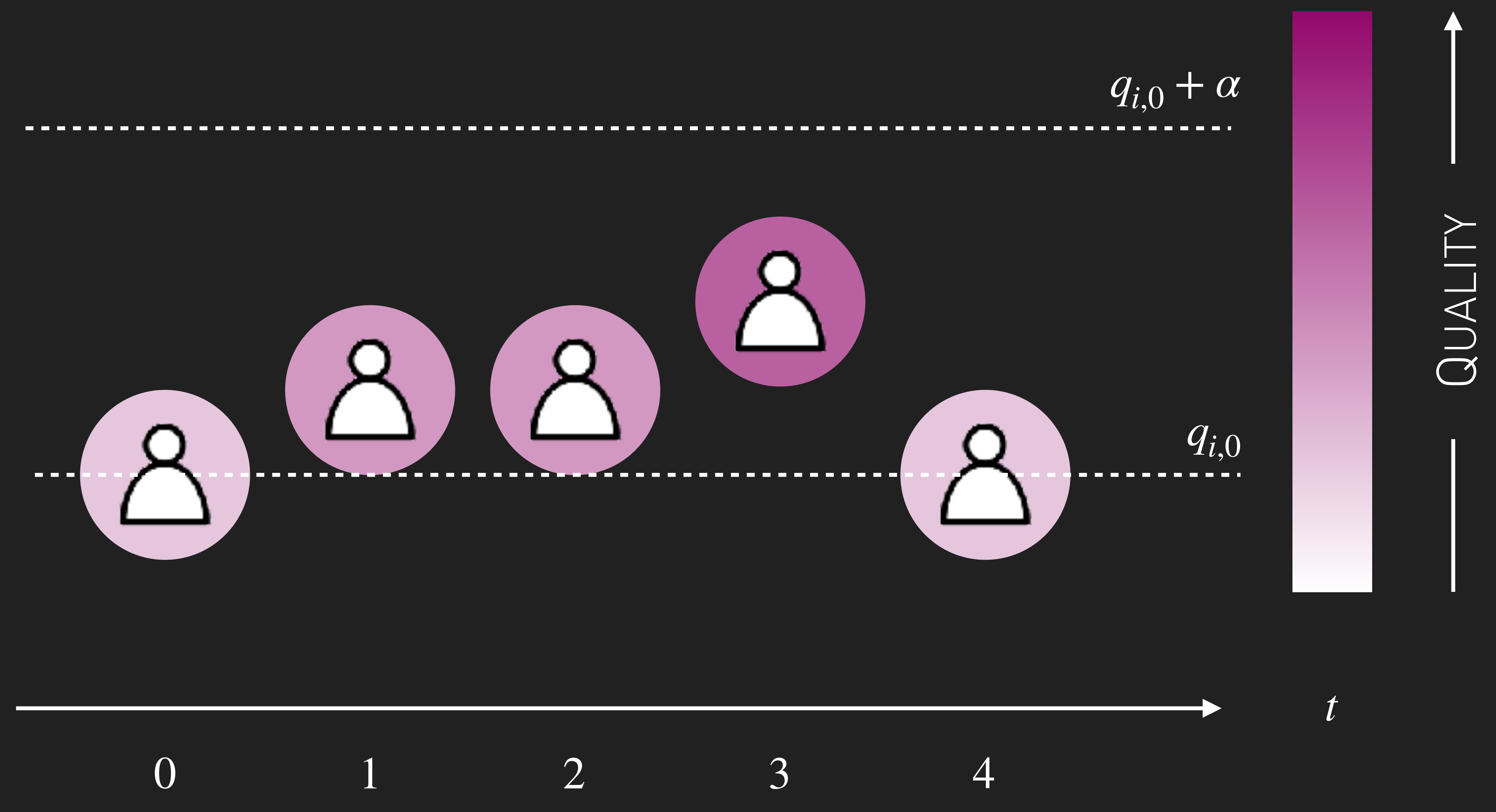
Quality Game

Content Creators can purposefully change the QUALITY of their content by choosing:

- An action (quality) $q_i(t) \in [q_{1,0}, q_{i,0} + \alpha]^{\star}$, where α is now the maximum deviation from the INTRINSIC QUALITY.



* : Again, we force $q_i(t) \in [0,1]$, as it is intended to be the probability a seeker will like the content.

Quality Game

Content Creators can purposefully change the QUALITY of their content by choosing:

- An action (quality) $q_i(t) \in [q_{1,0}, q_{i,0} + \alpha]^\star$, where α is now the maximum deviation from the INTRINSIC QUALITY.
- They aim at maximising their utility function , given the current state of the network, i.e.,

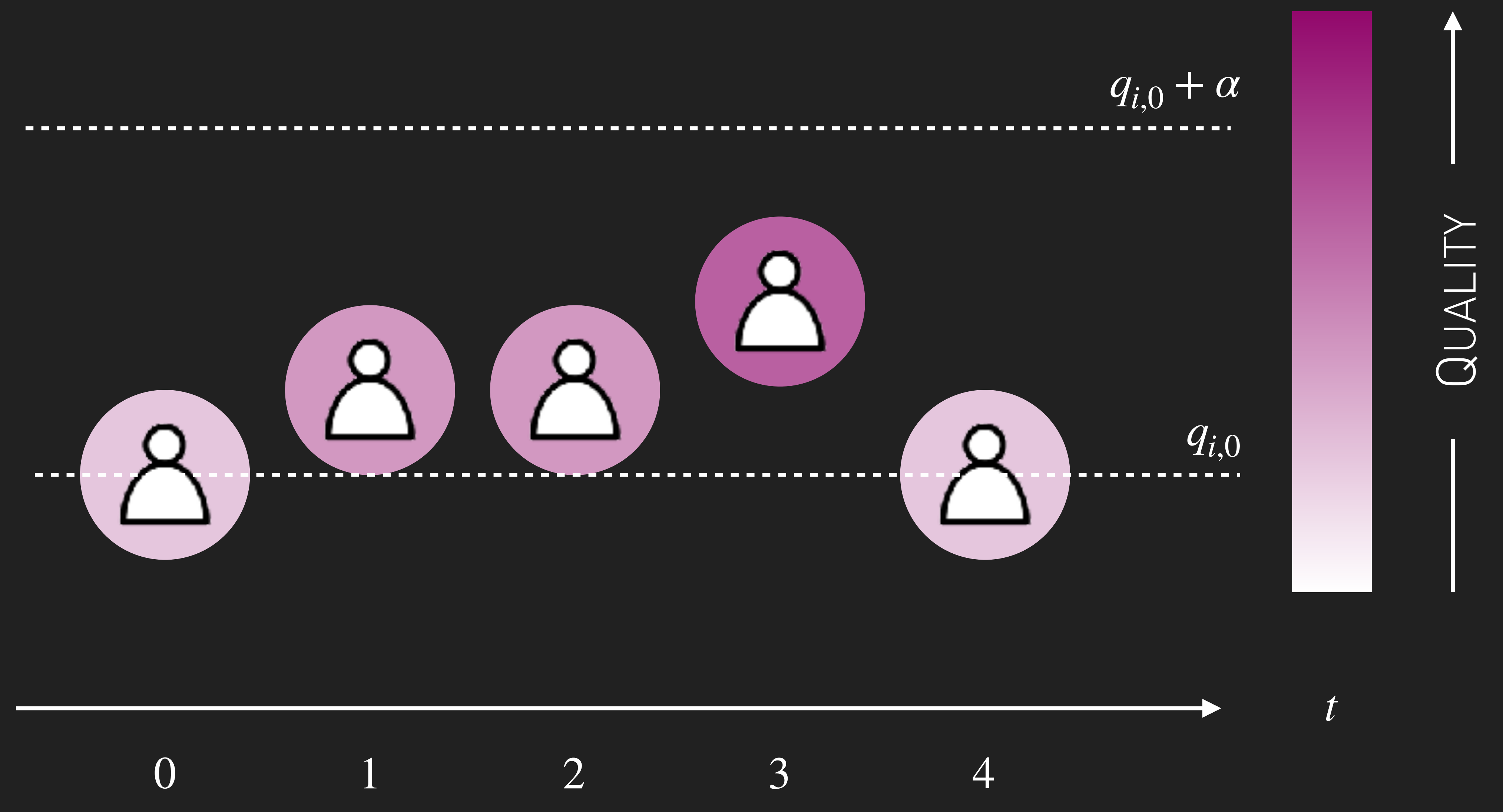
  $q_i^\star(t) := \arg\max_{q_i \in Q_i} \left\{ U_i\left(q_i, q_{-i}(t-1), A(t-1)\right) \right\}$, where

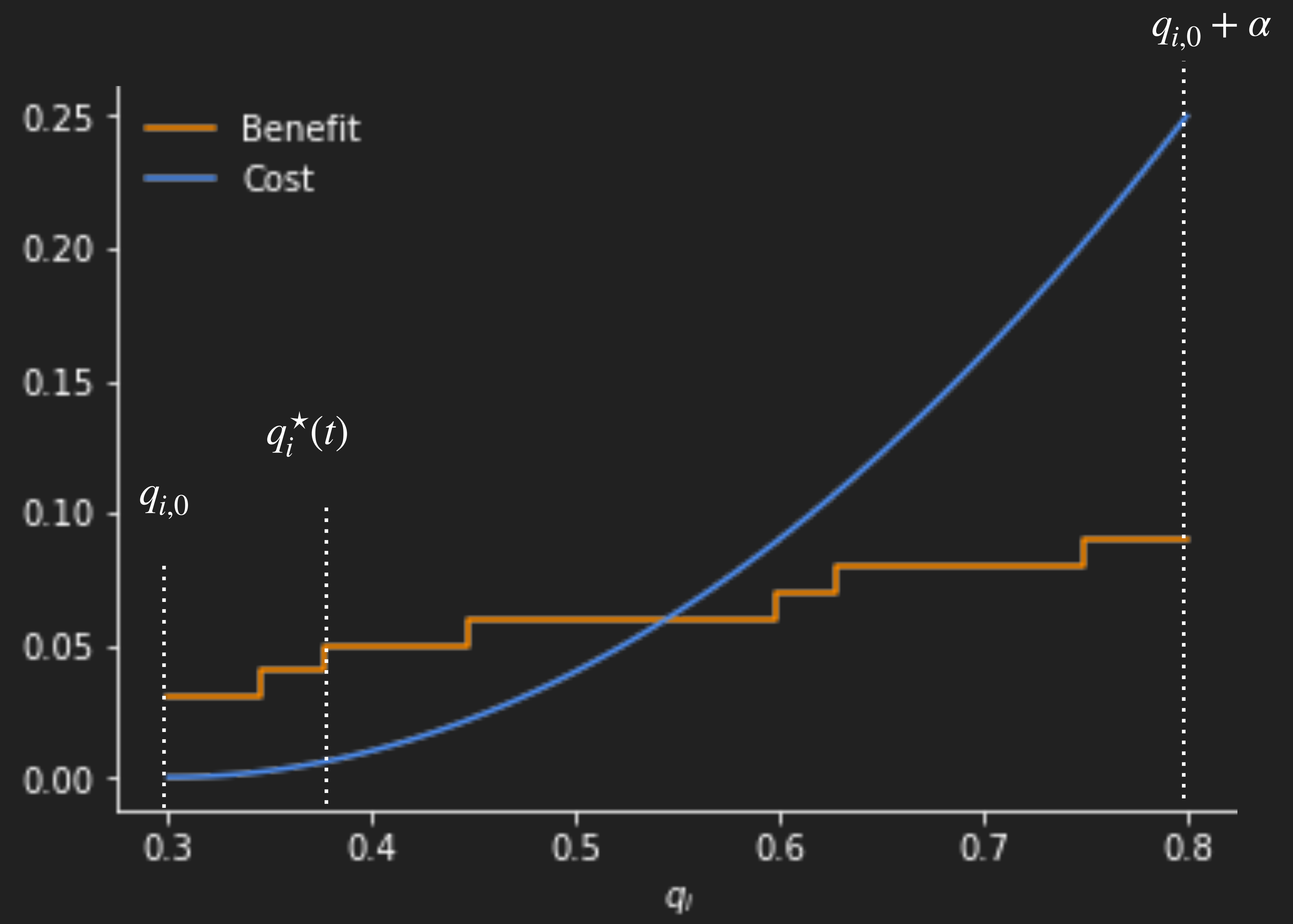
  $U_i\left(q_i, q_{-i}(t-1), A(t-1)\right) = b_i\left(q_i, q_{-i}(t-1), A(t-1)\right) - c_i(q_i)$, and

  $b_i(\cdot) := \frac{1}{n} \left| \{ j \in \{1,\ldots,n\} \text{ s.t. } j \text{ does not follow } i, \text{ and } \forall k \text{ s.t. } j \text{ follows CC } k, q_k(t-1) < q_i \} \right|$

  measures the ratio of potential new followers,

  and $c_i(q_i) := (q_i - q_{i,0})^2$, models the cost of increasing the quality from the baseline INTRINSIC QUALITY.



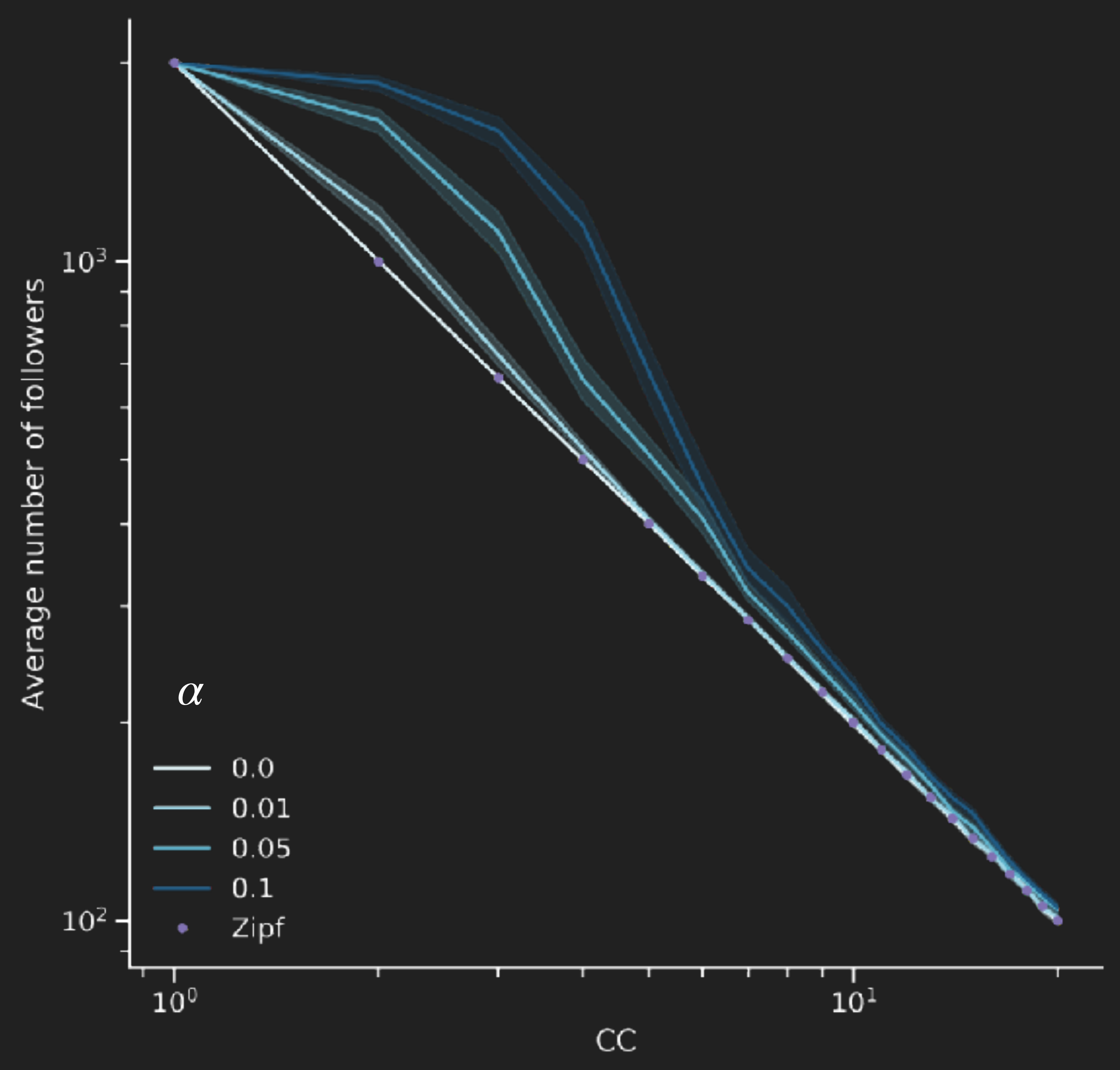


* : We also force $q_i(t) \in [0,1]$, as it is intended to be the probability a seeker will like the content.

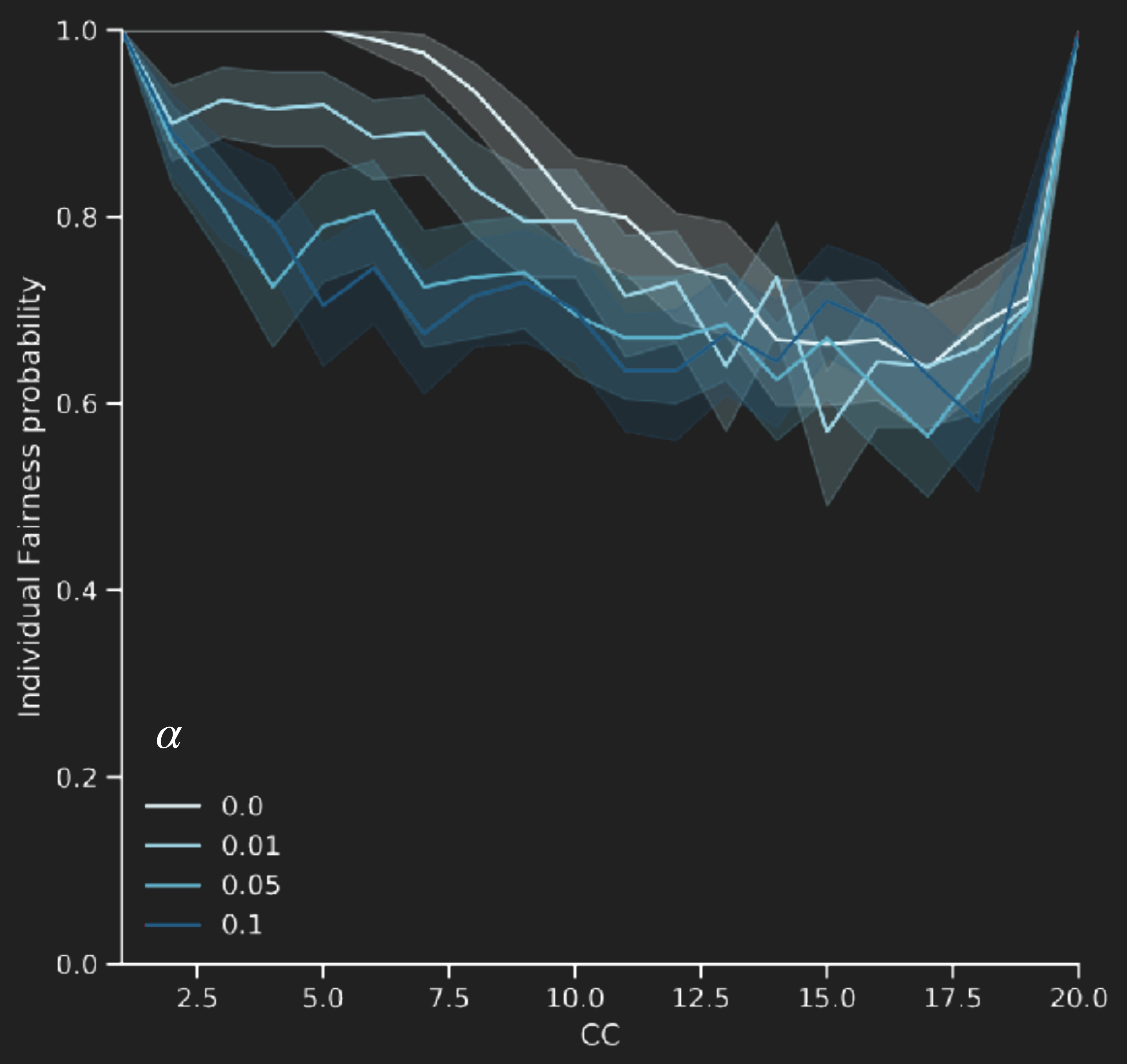
Quality-Game Results

Fixed: Uniform Random Recommendation

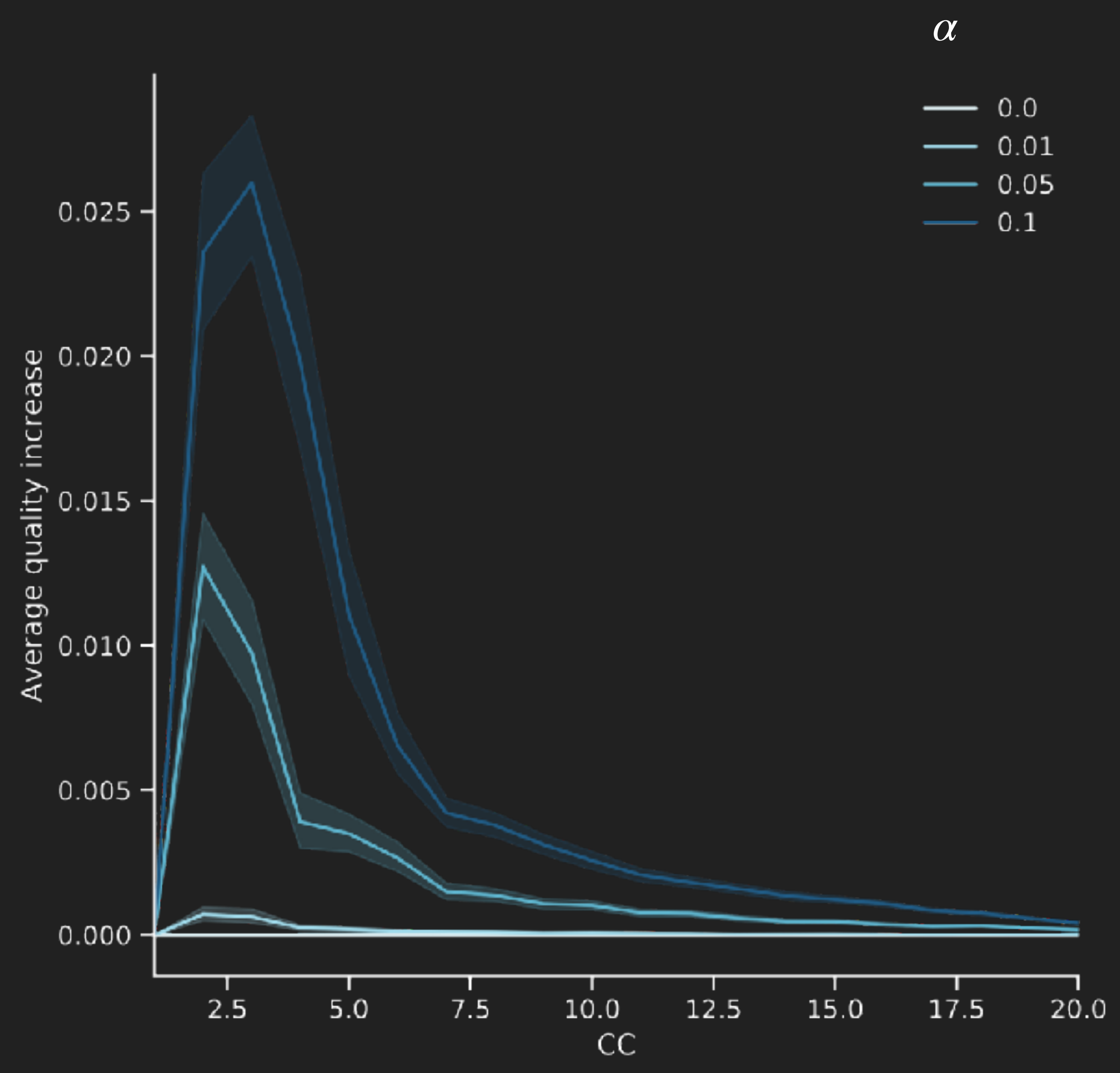
Number of Followers



Individual Fairness



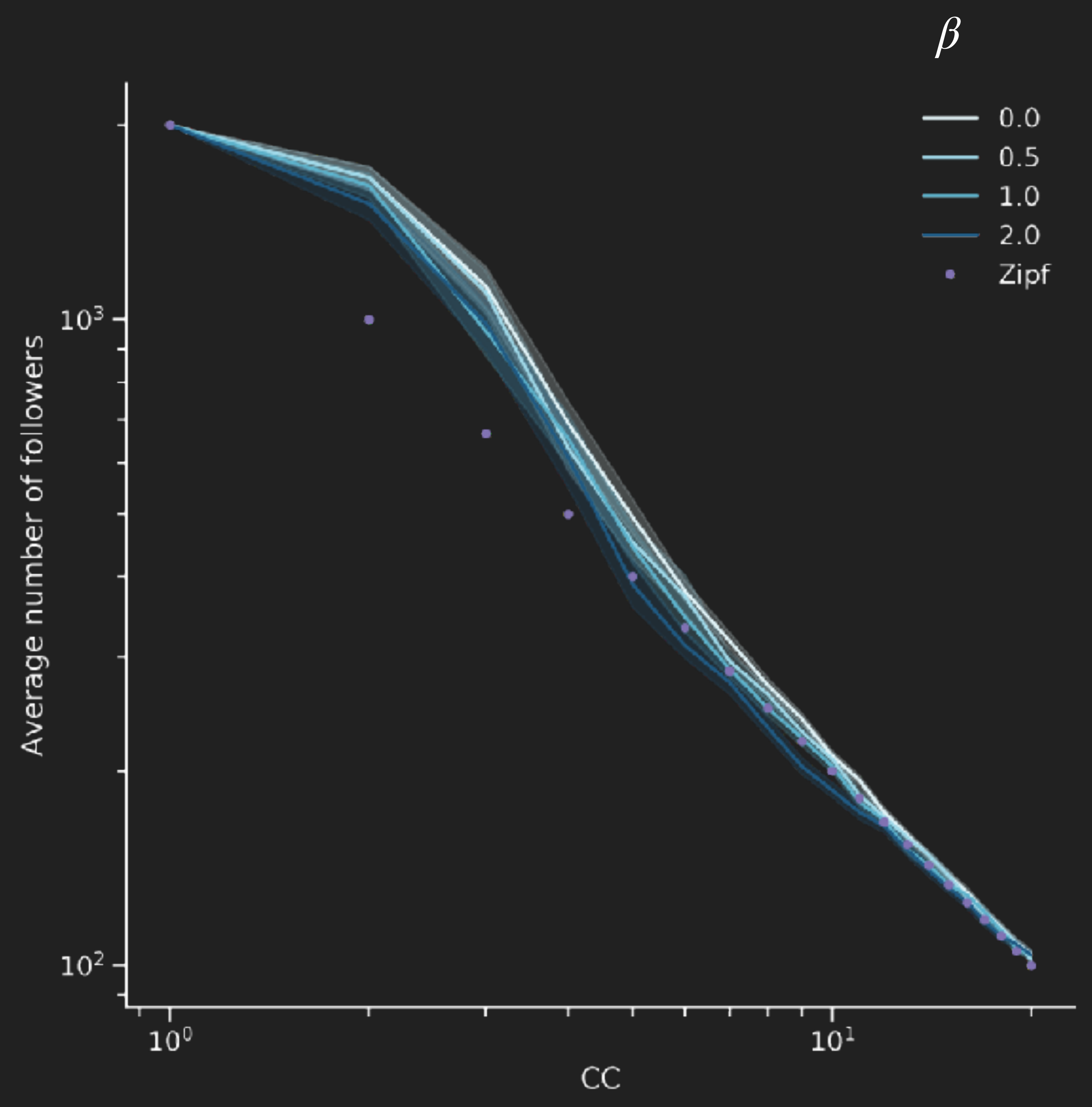
Quality Increase



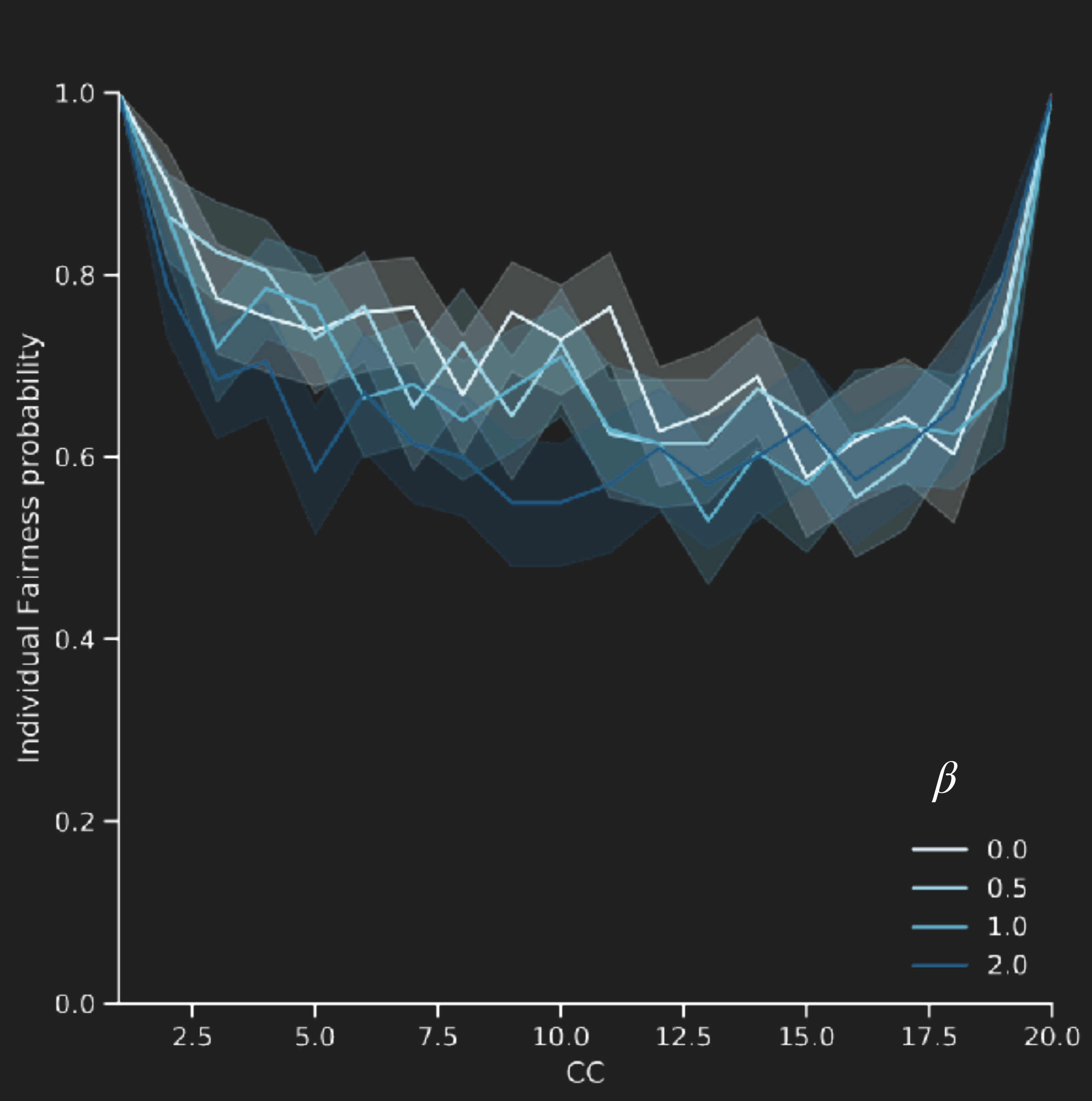
Quality-Game Results

Fixed: $\alpha = 0.05$

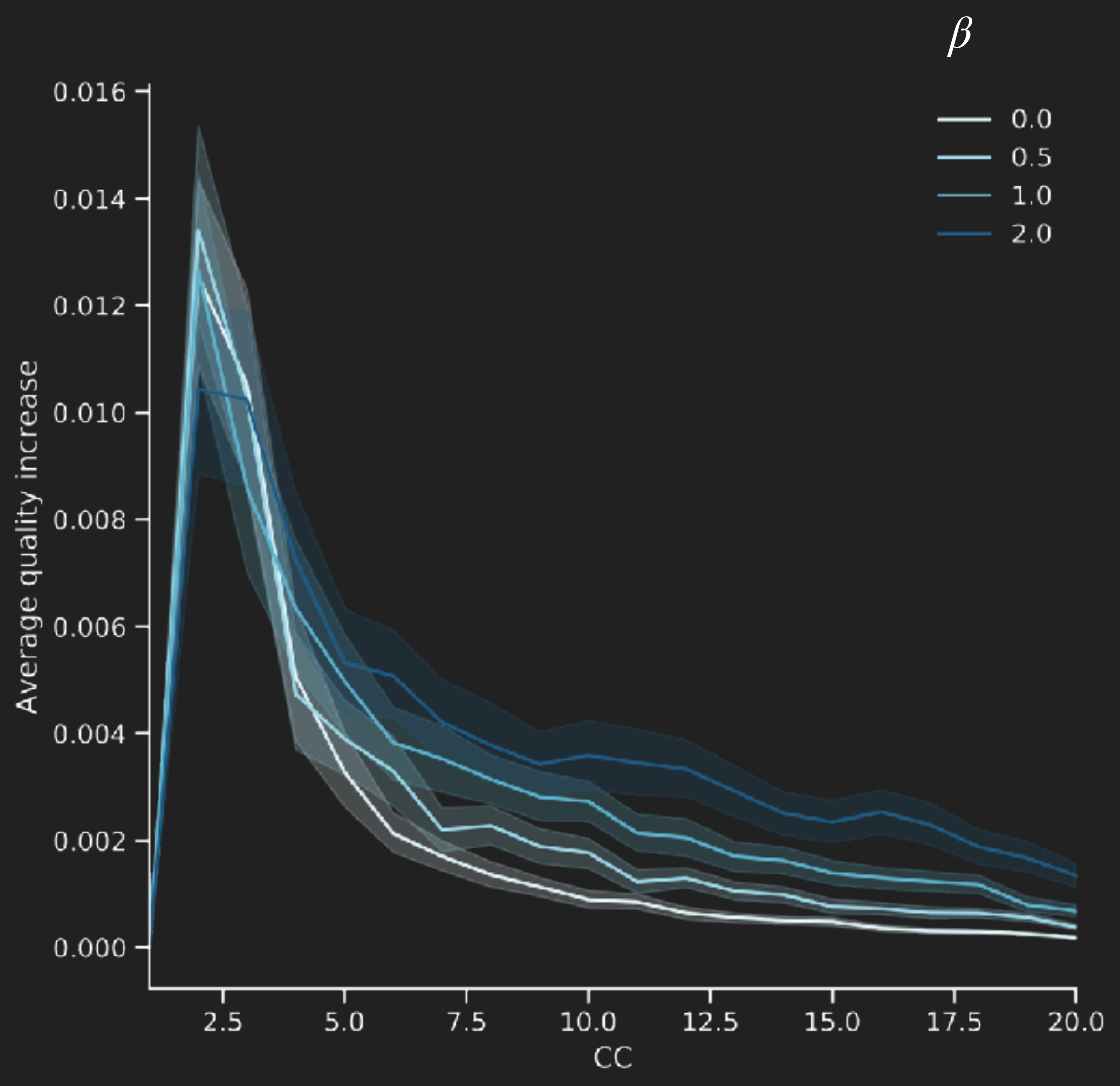
Number of Followers



Individual Fairness

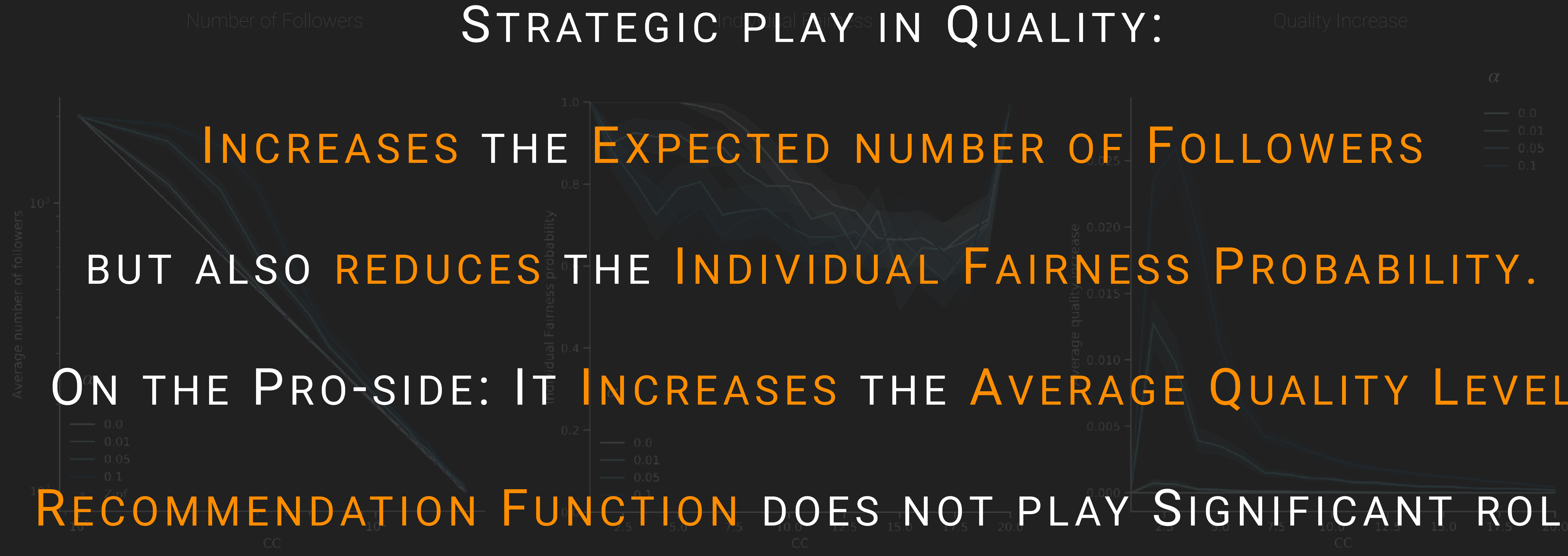


Quality Increase



$$\mathbb{P}\left(i \text{ is recommended}\right) = \frac{\left(d_{in}^{i}\right)^{\beta} + 1}{\sum_{j=1}^{m}\left(\left(d_{in}^{j}\right)^{\beta} + 1\right)}$$

Quality-Game Results



Strategic play in Quality:

Increases the Expected number of Followers

but also reduces the Individual Fairness Probability.

On the Pro-side: It Increases the Average Quality Level

Recommendation Function does not play Significant role

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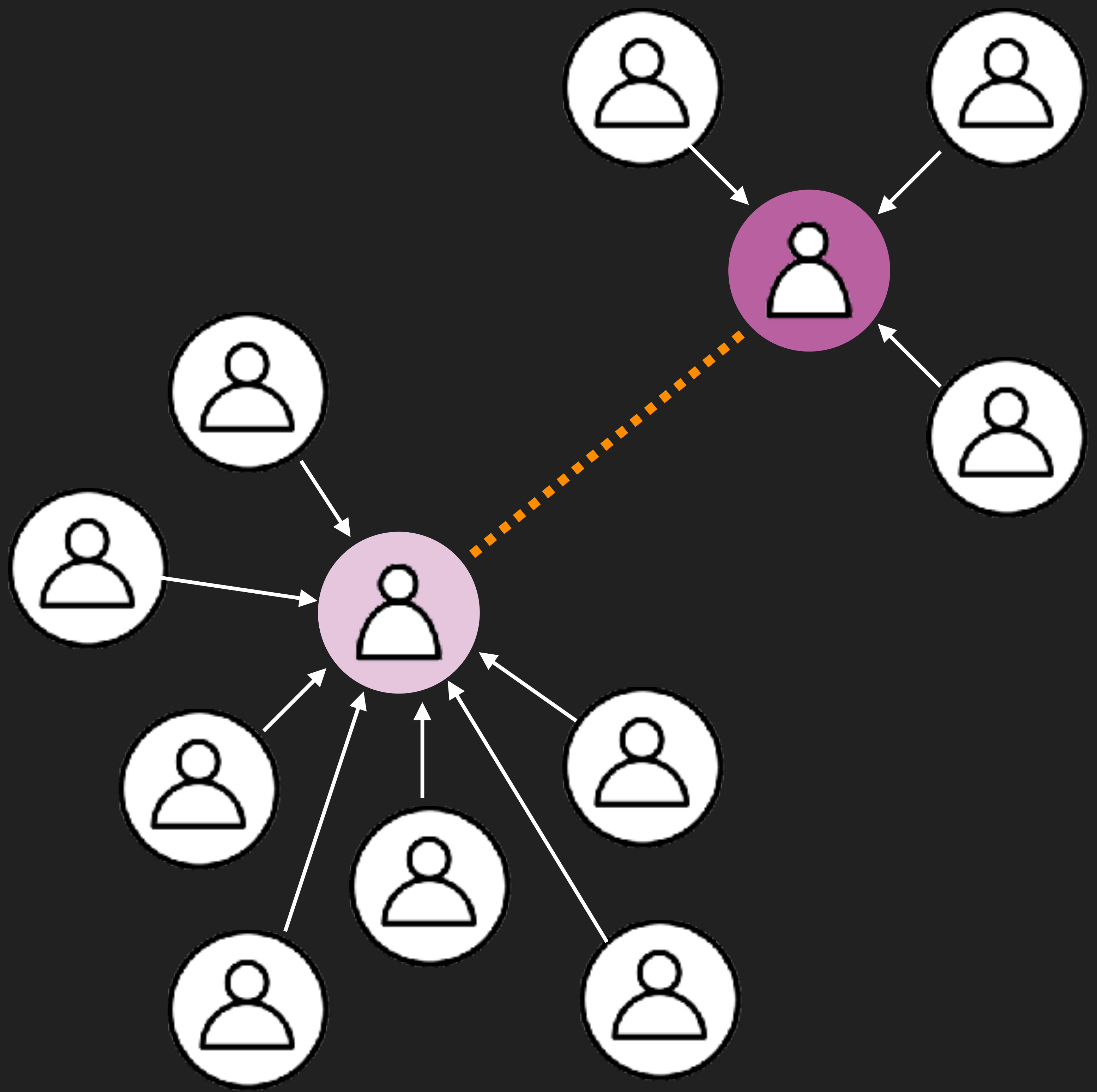
Coalition Game

Content Creators can purposefully create coalition with one another by choosing:

- Another content creator $j \in \{1, \ldots, m\}^{\star}$,



*: $j = i$ means that the CC does not form a coalition.

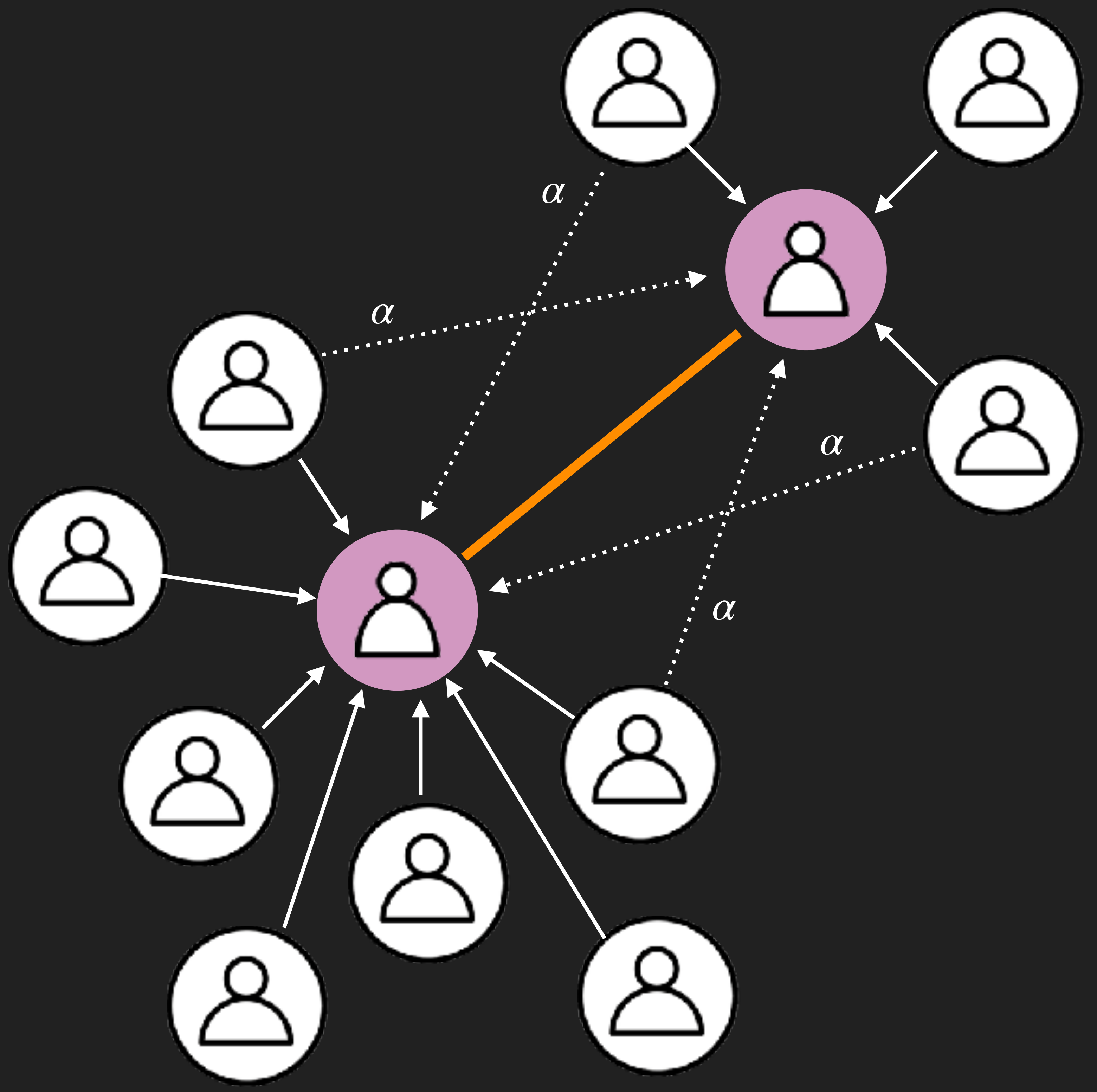
Coalition Game

Content Creators can purposefully create coalition with one another by choosing:

- Another content creator $j \in \{1, \ldots, m\}^{\star}$, such that:

$$q_i(t) = \frac{1}{2}\left(q_{i,0} + q_{j,0}\right).$$

Whenever such a COALITION is in place, with probability α (strategic level), a follower of i (respectively, j) will be recommended j (respectively, i).



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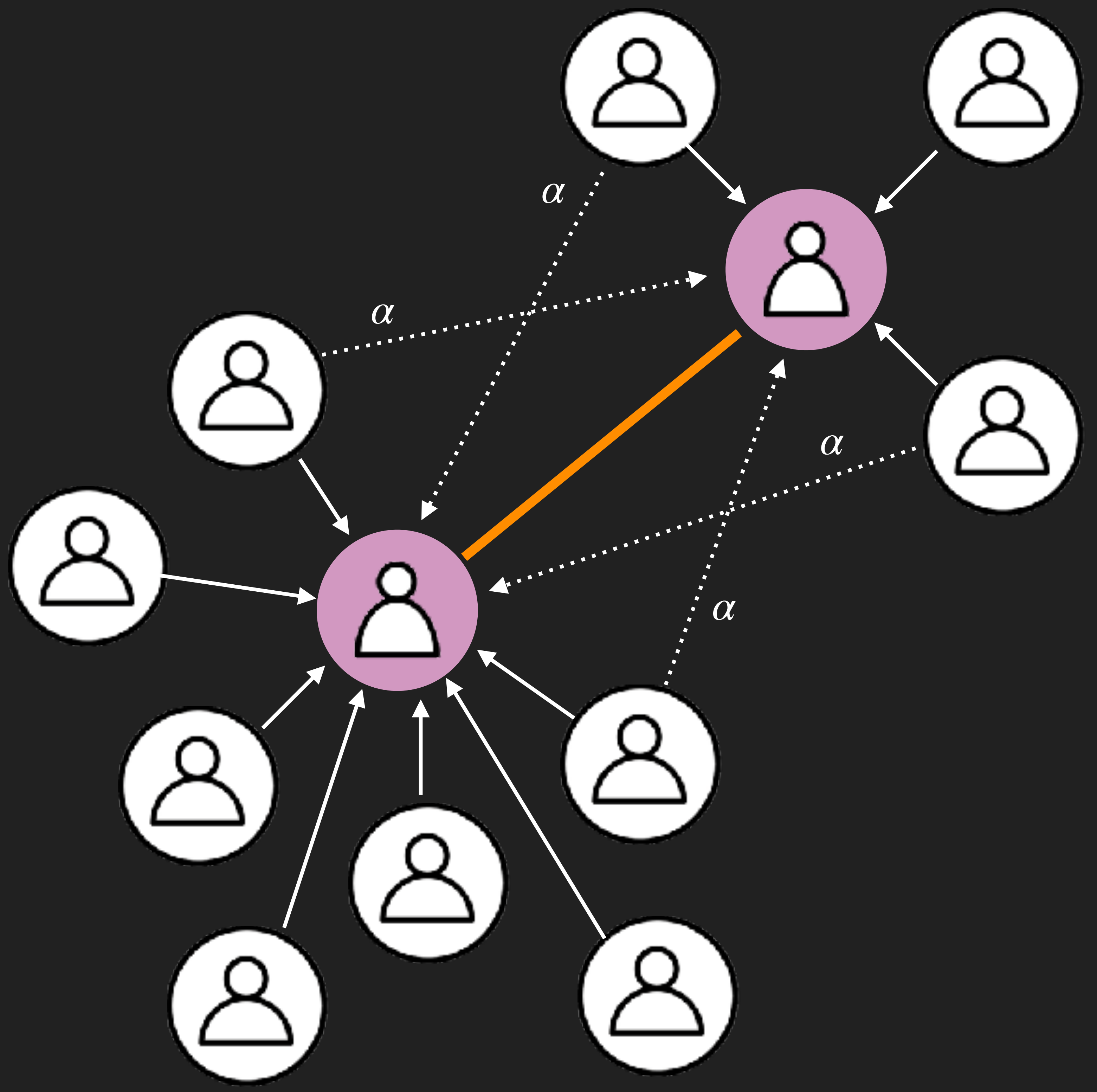
Coalition Game



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- At each time-step, Content Creators are selected in random order, and they propose a coalition to their best match:

  $$j^{\star} \in \arg \max_{\{i, \ldots, m\}, j \neq i} U_i\left(j, A(t-1)\right), \text{ where}$$

  $$U_i\left(j, A(t-1)\right) := (1-\alpha)\left|\left\{k \in \{1, \ldots, n\} \text{ s.t. } k \text{ does not follow } i, \text{ and } \forall l \text{ s.t. } k \text{ follows CC } l, q_l < \frac{1}{2}\left(q_{i,0} + q_{j,0}\right)\right\}\right| + \alpha \left|\left\{k \text{ follows } j \text{ but not } i\right\}\right|^{\star\star}$$

  measures the number of potentially available followers also thanks to a direct recommendation from the coalized CC.

* : $j = i$ means that the CC does not form a coalition.
** : if $j \neq i$, otherwise, the second term does not appear.

Coalition Game

Content Creators can purposefully create coalition with one another by choosing:

- Another content creator $j \in \{1,\ldots,m\}^\star$, such that:

  $$q_i(t) = \frac{1}{2}\left(q_{i,0} + q_{j,0}\right).$$

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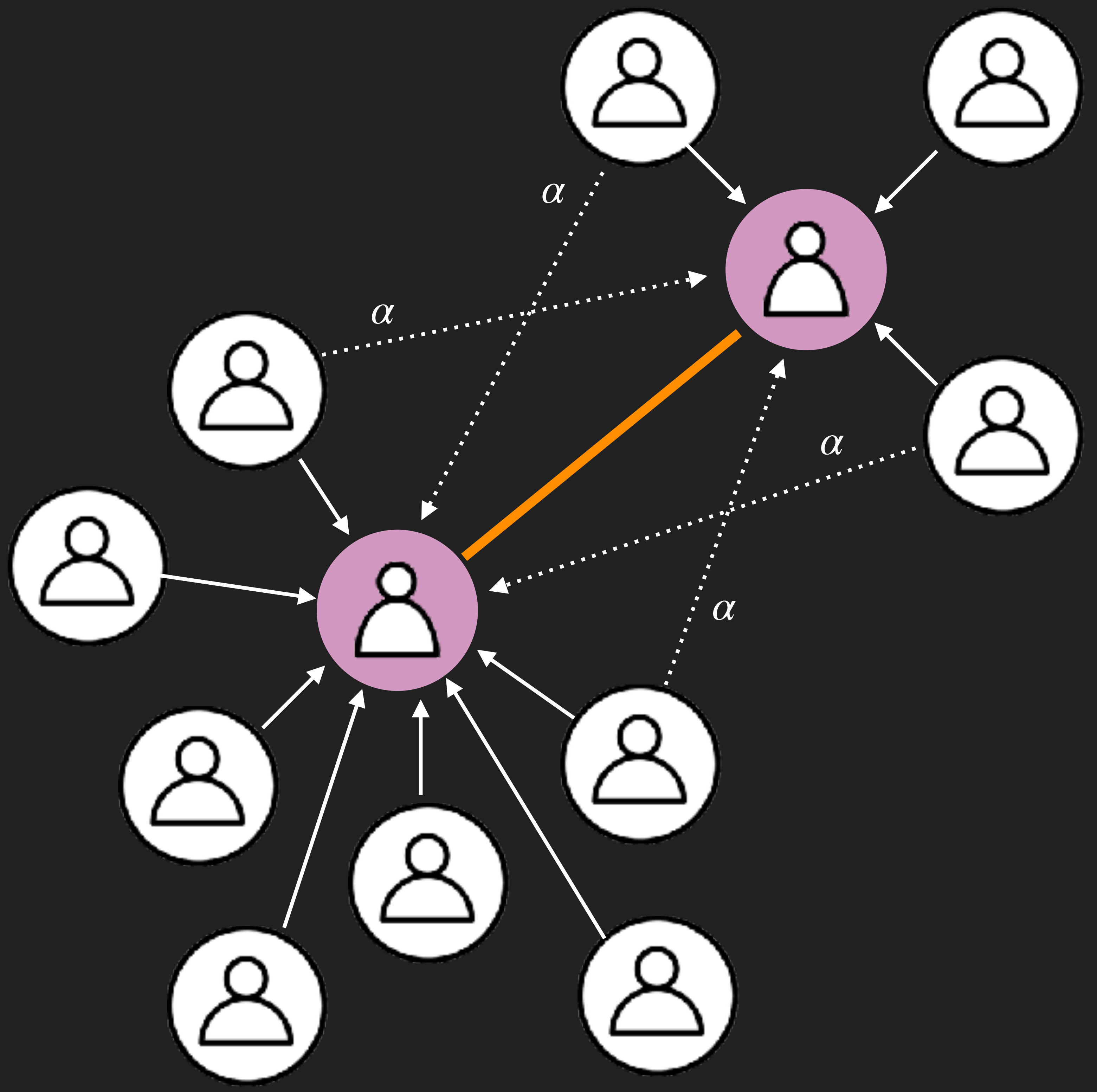
  measures the number of potentially available followers also thanks to a direct recommendation from the coalized CC.

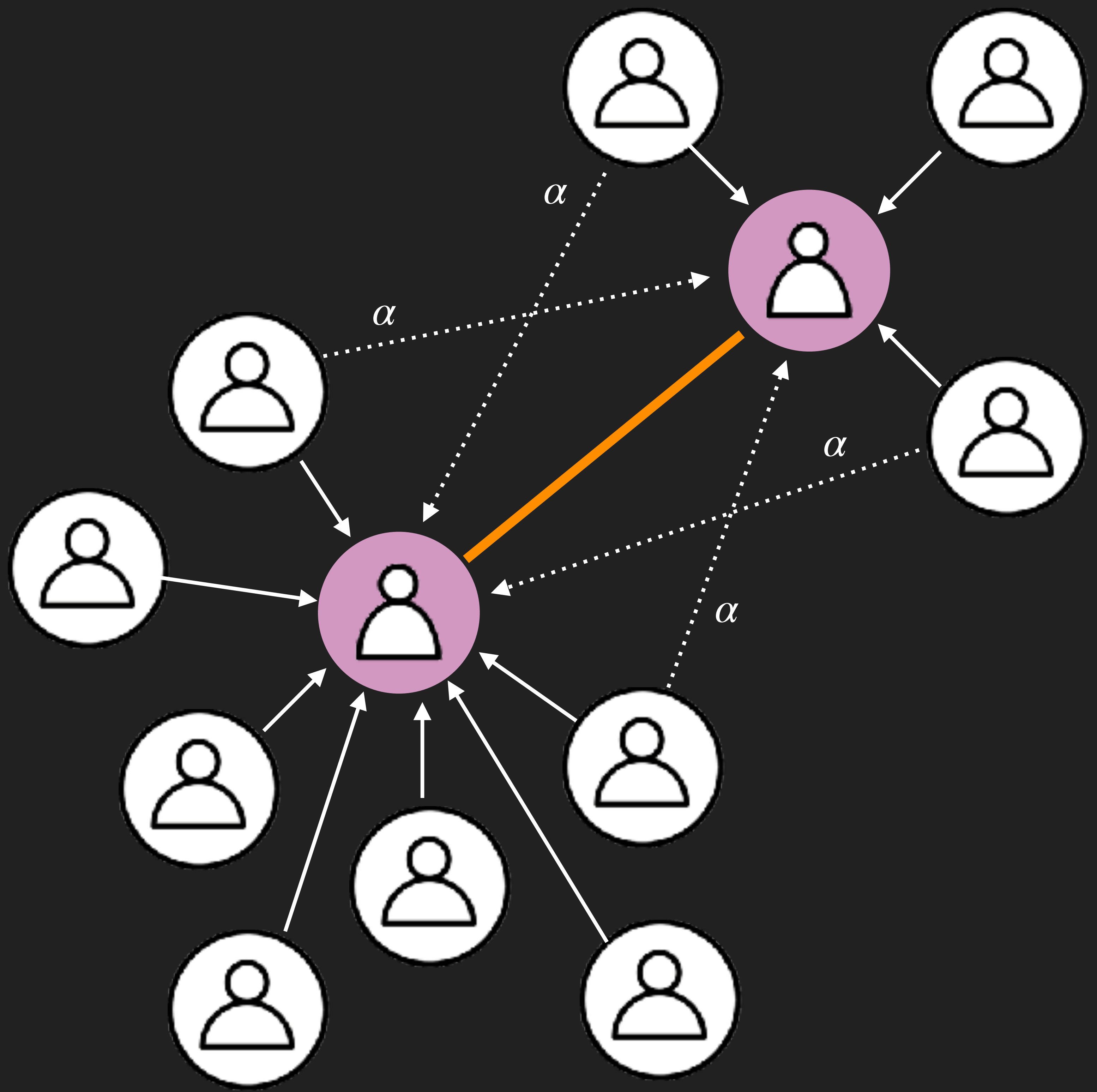
- Then, $j^\star$ can decide (based on a similar utility function) whether to form a coalition with i, or keep its current status.



Coalition Game

- Connecting to a higher-quality Content Creators is always beneficial (compared to no coalition).

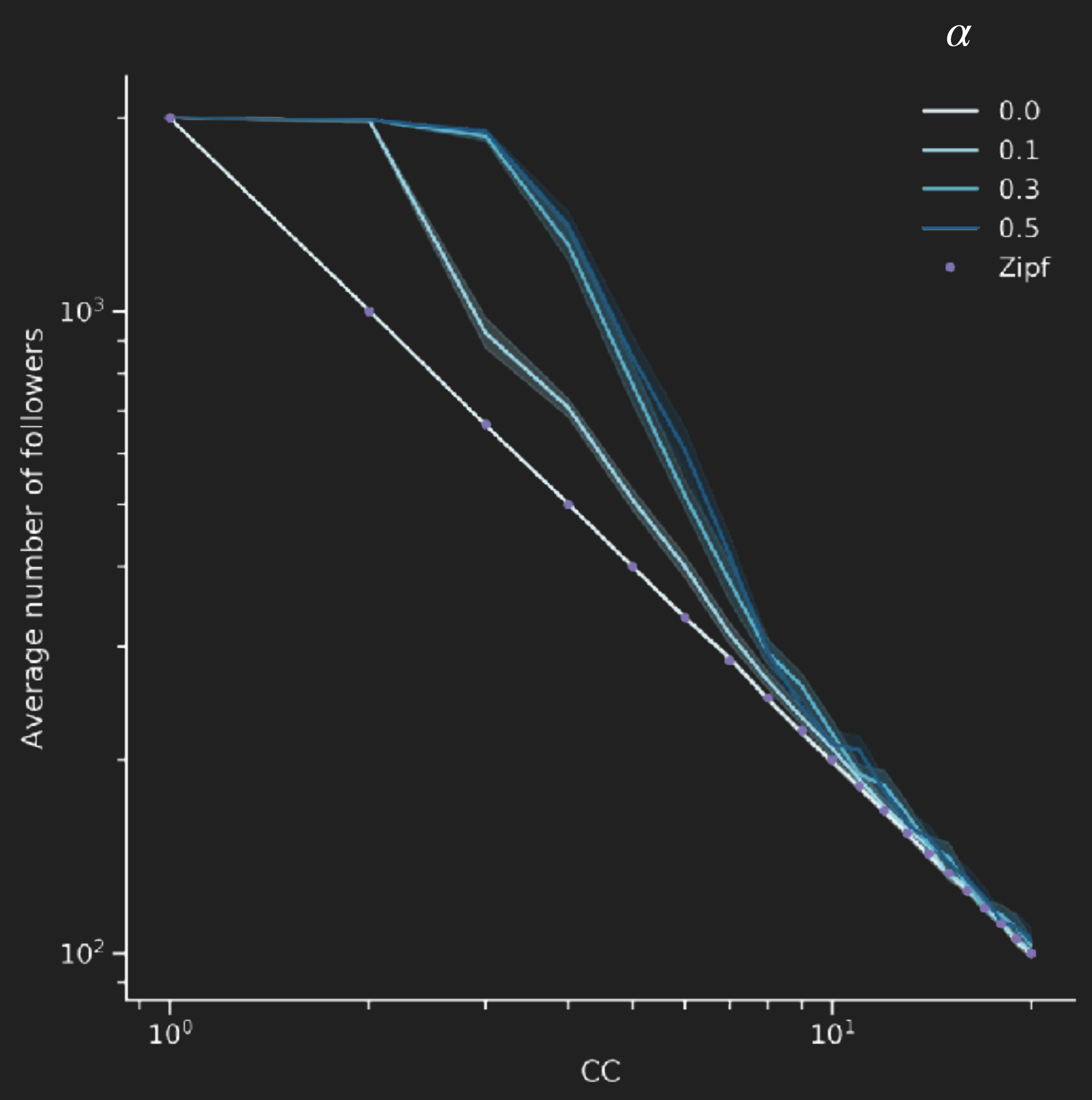
- Connecting to lower-quality Content Creators can be beneficial, provided that they have a large number of (non-overlapping) followers (as in the example on the right).



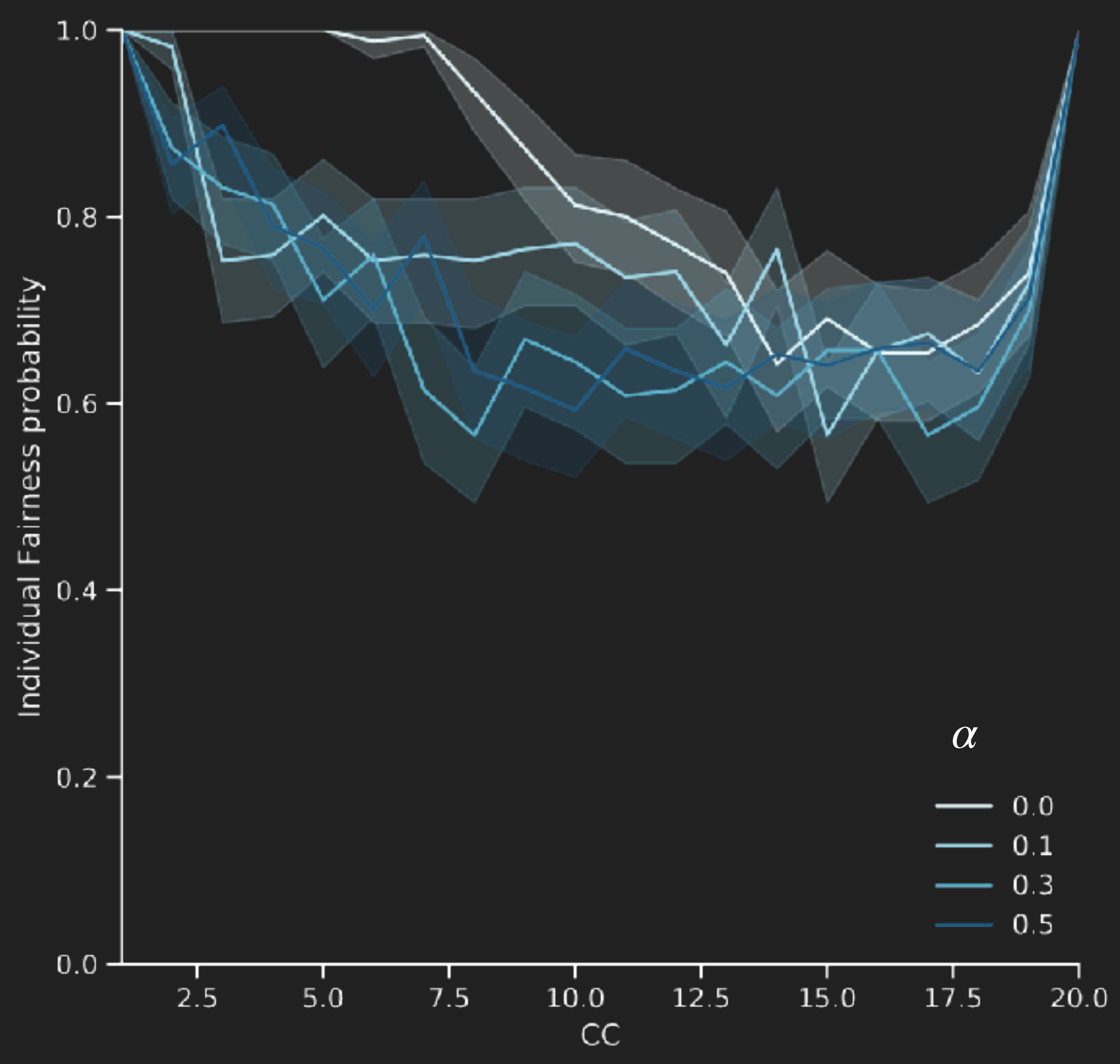
Coalition-Game Results

Fixed: Uniform Random Recommendation

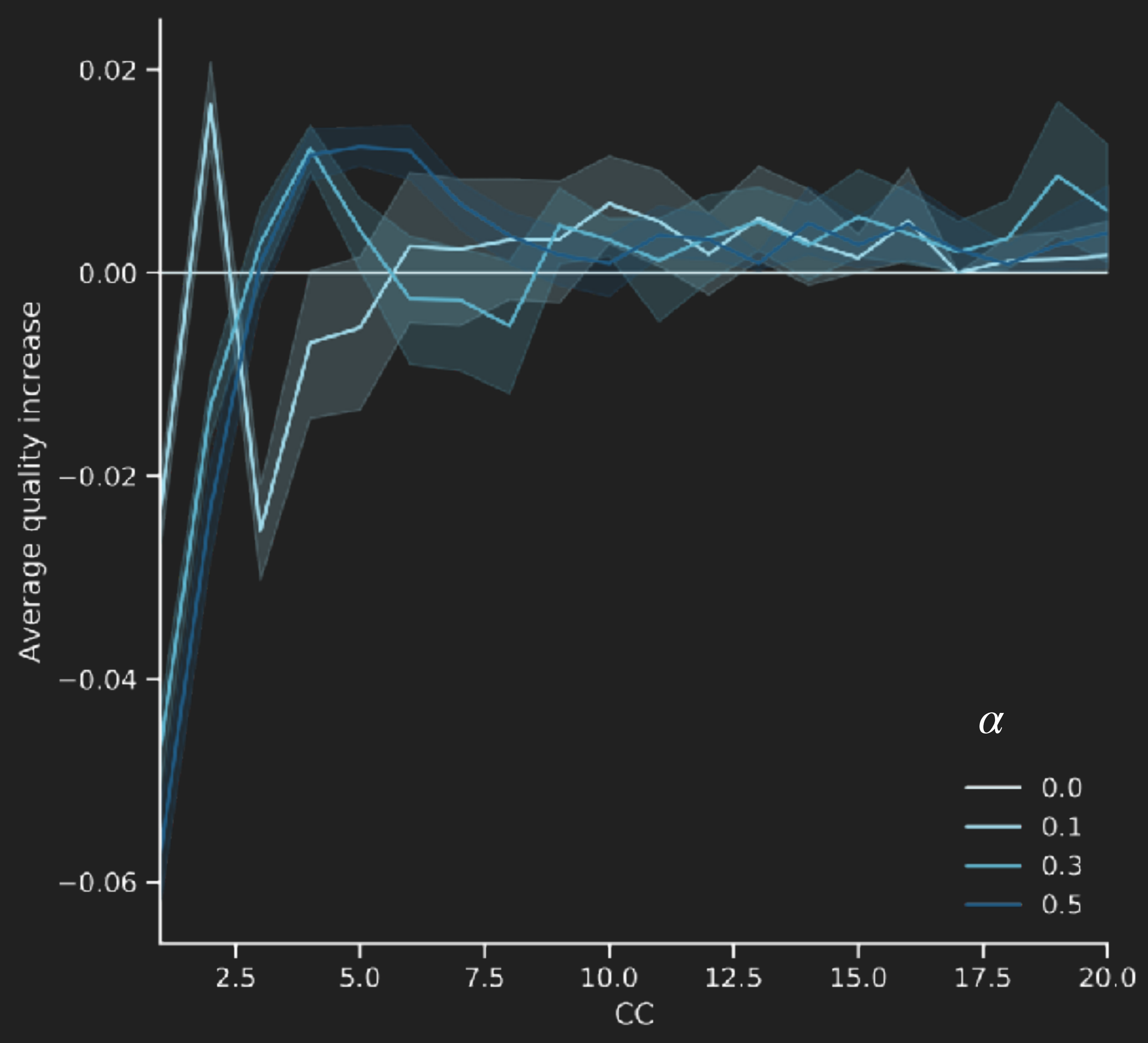
Number of Followers



Individual Fairness



Quality Increase



Coalition-Game Results

Coalition-Game Results

Similar to previous analysis, strategic Coalitions:

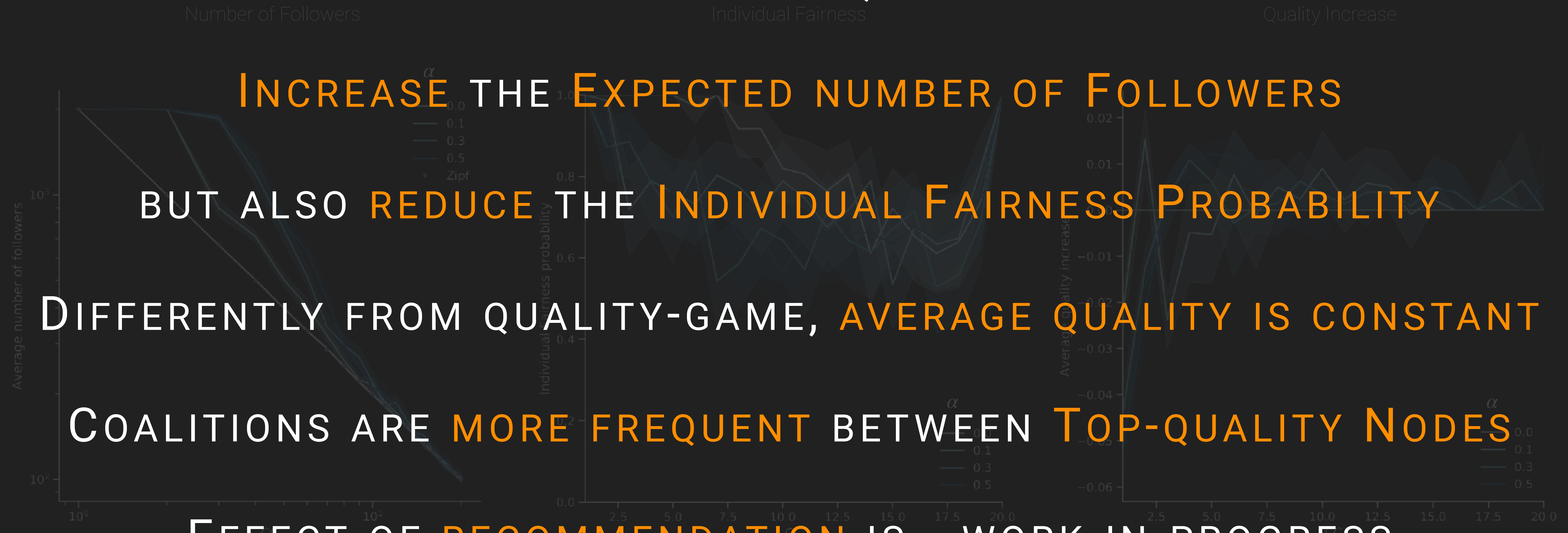
Increase the Expected number of Followers

but also reduce the Individual Fairness Probability

Differently from quality-game, average quality is constant

Coalitions are more frequent between Top-quality Nodes

Effect of recommendation is… work-in-progress



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SUMMARY

- Social Media Platforms are COMPETITIVE environments
- RECOMMENDATION SYSTEMS play a key role in distributing INDIVIDUAL FAIRNESS to Content Creators
- STRATEGIC QUALITY PLAY decreases the probability of achieving individual fairness (while increasing the average engagement). However, it increases the average quality on the platform
- STRATEGIC COALITIONS, instead, do not improve the average quality on the platform (which is necessarily conserved). Similar to the other scenario, they decrease the probability of achieving individual fairness (while increasing the average engagement)

Outlook

- Explore the COUPLED EFFECT of Recommender Systems and CC strategic play.
- Study the effect on individual fairness when only a LIMITED AMOUNT of players act strategically
- Starting from the simulation results, set up a rigorous game-theoretical framework to derive THEORETICAL INSIGHTS.
- Add to the strategic play techniques the case of CONTENT AGGREGATORS (users that mainly re-post others' content)
- Perform a similar analysis when individuals are partitioned into different (ADVANTAGED/DISADVANTAGED) groups.

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NCCR Automation

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