



A MERITOCRATIC NETWORK FORMATION MODEL

WORKSHOP ON DYNAMICS IN SOCIAL AND
ECONOMICS NETWORKS,
59TH IEEE CONFERENCE ON DECISION AND CONTROL

DECEMBER 12-13, 2020

NICOLÒ PAGAN

INSTITUT
FÜR
AUTOMATIK **ifa**

ETH zürich

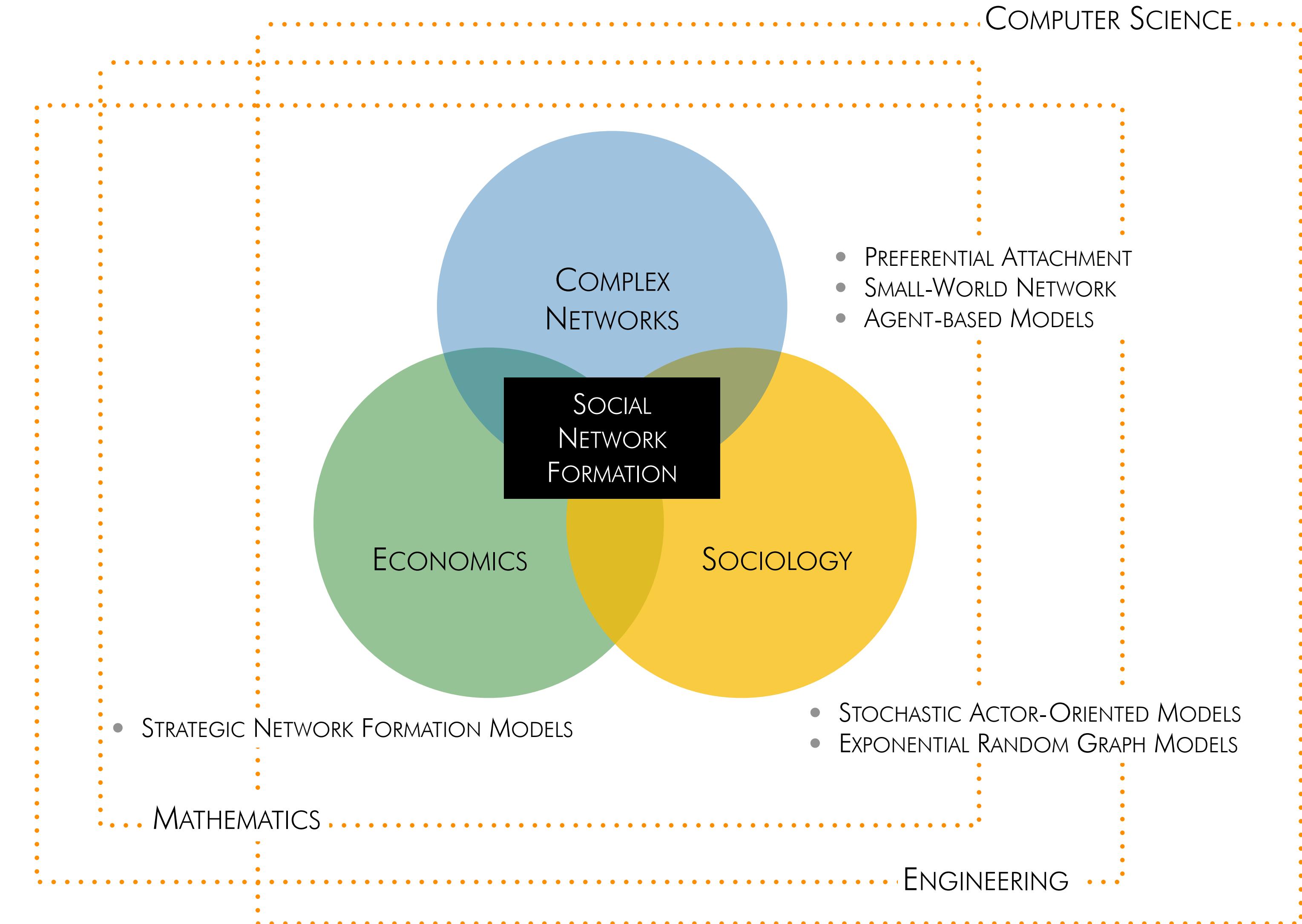
MOTIVATION

- Online Social Networks are ubiquitous.



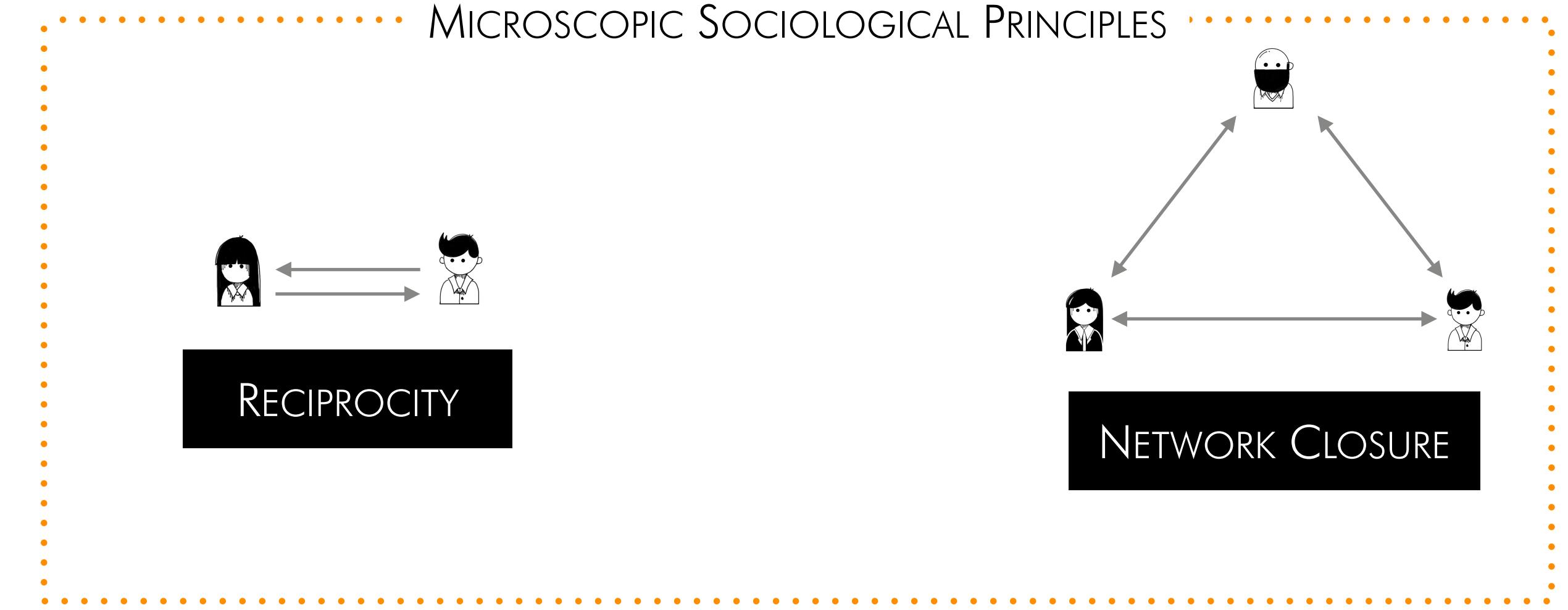
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- Online Social Networks are ubiquitous.
- Researchers from different communities have started considering the problem of *Social Network Formation*.



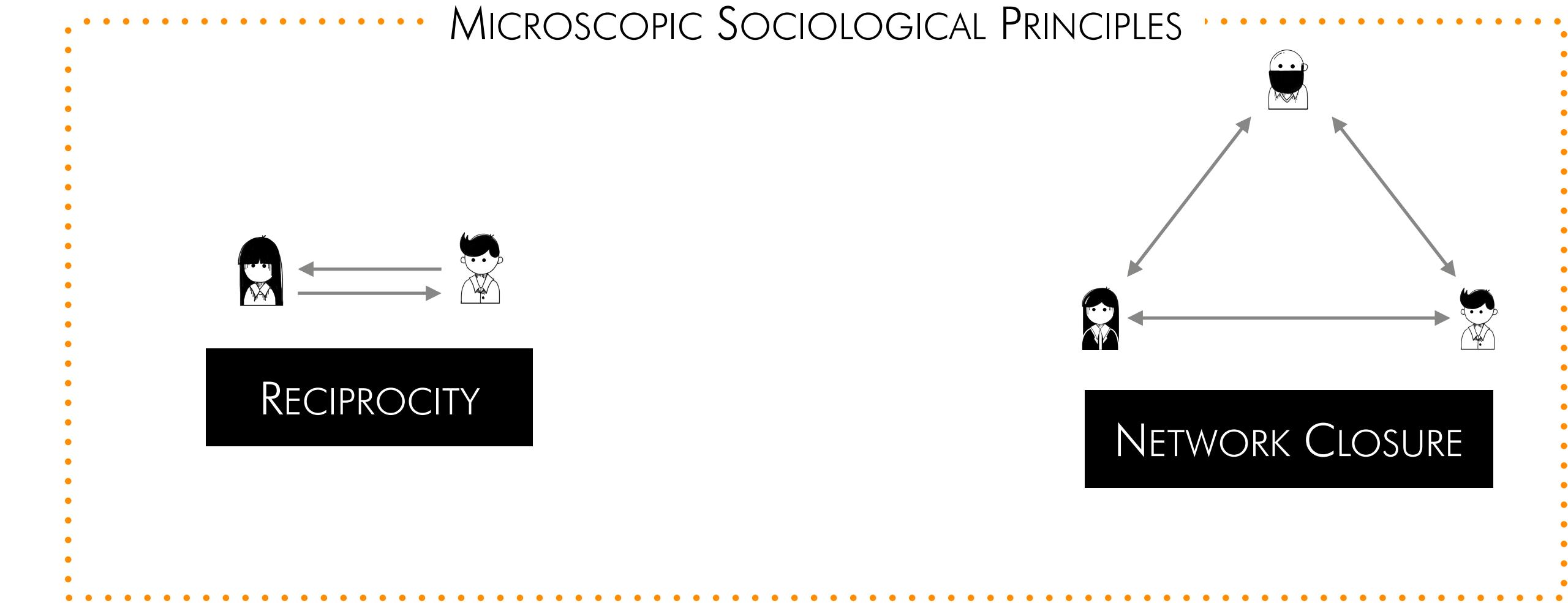
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- Sociologists found that actors' decision on "Offline" Social Networks are driven by sociological principles.



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- Researchers from different communities have started considering the problem of **Social Network Formation**.
- Sociologists found that actors' decision on "Offline" Social Networks are driven by sociological principles.
- "Old-generation" Online Social Networks try to mimic "offline" Social Networks.

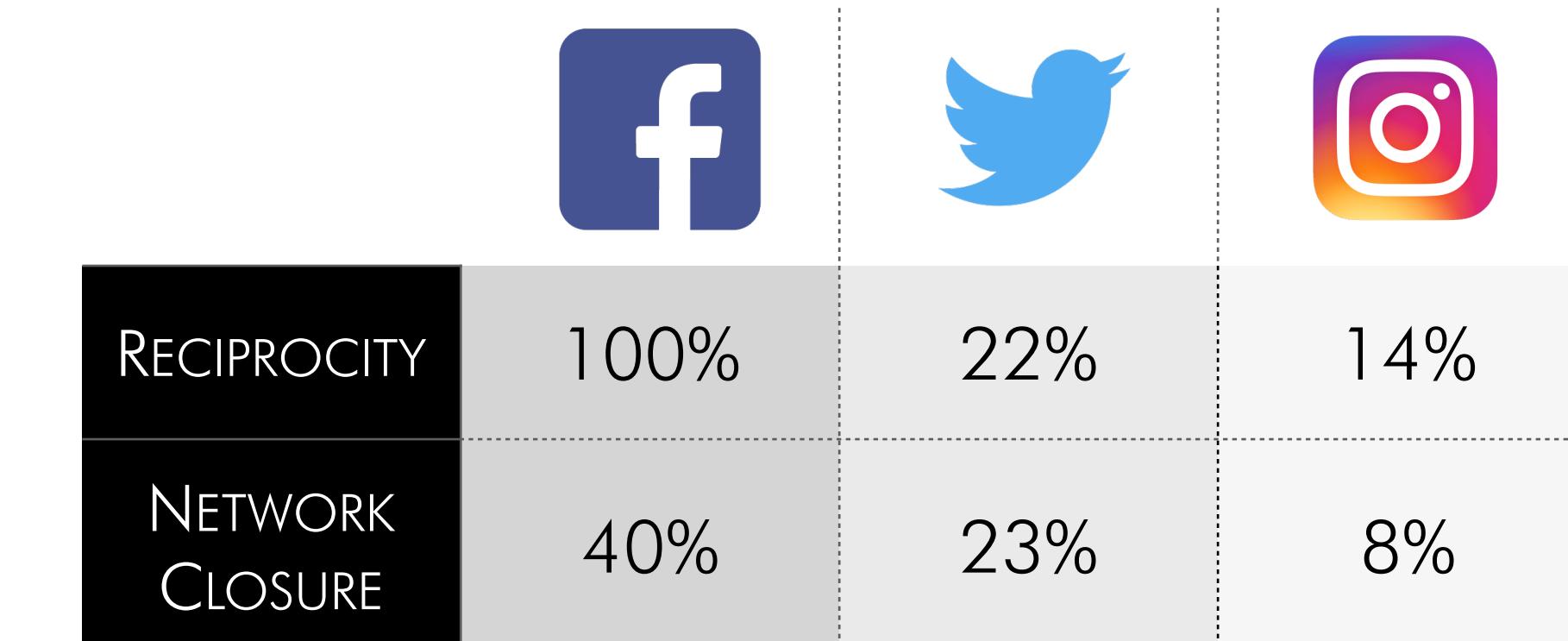
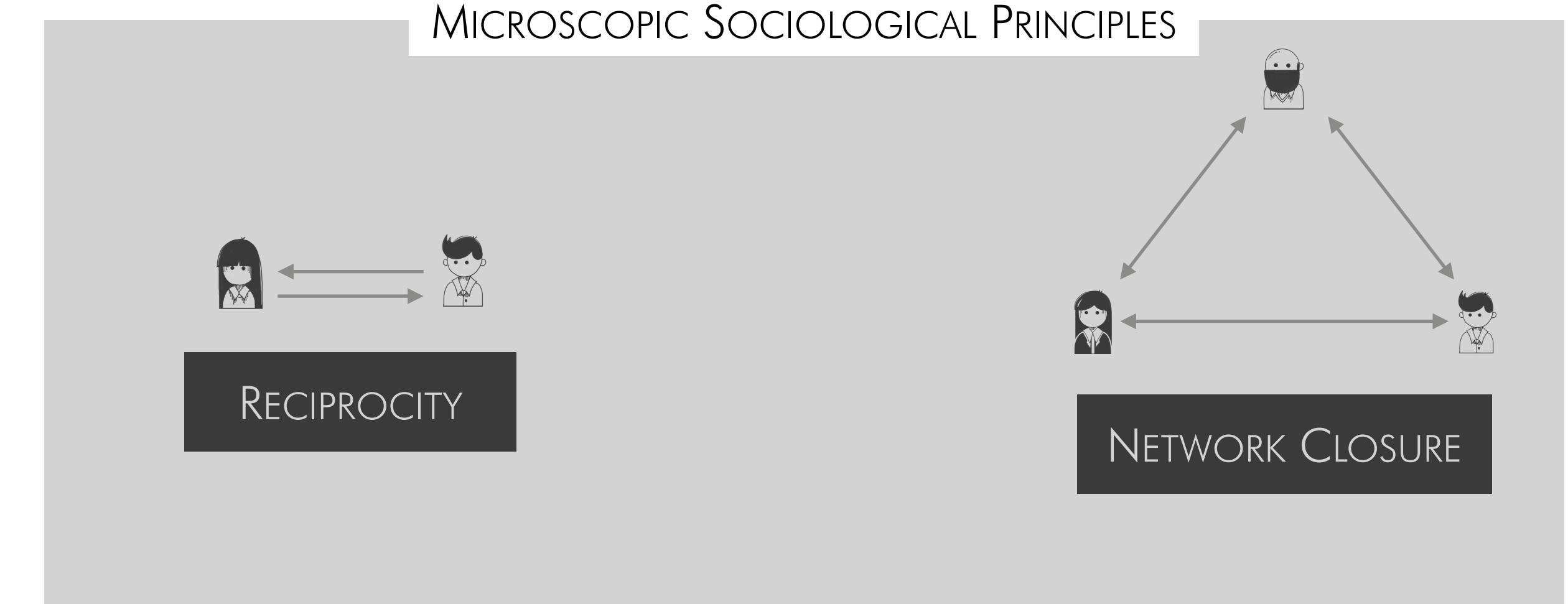


RECIPROCITY	100%
NETWORK CLOSURE	40%

S. Teng, M. Yeh and K. Chuang, "Toward understanding the mobile social properties: An analysis on instagram photo-sharing network". 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining.

MOTIVATION

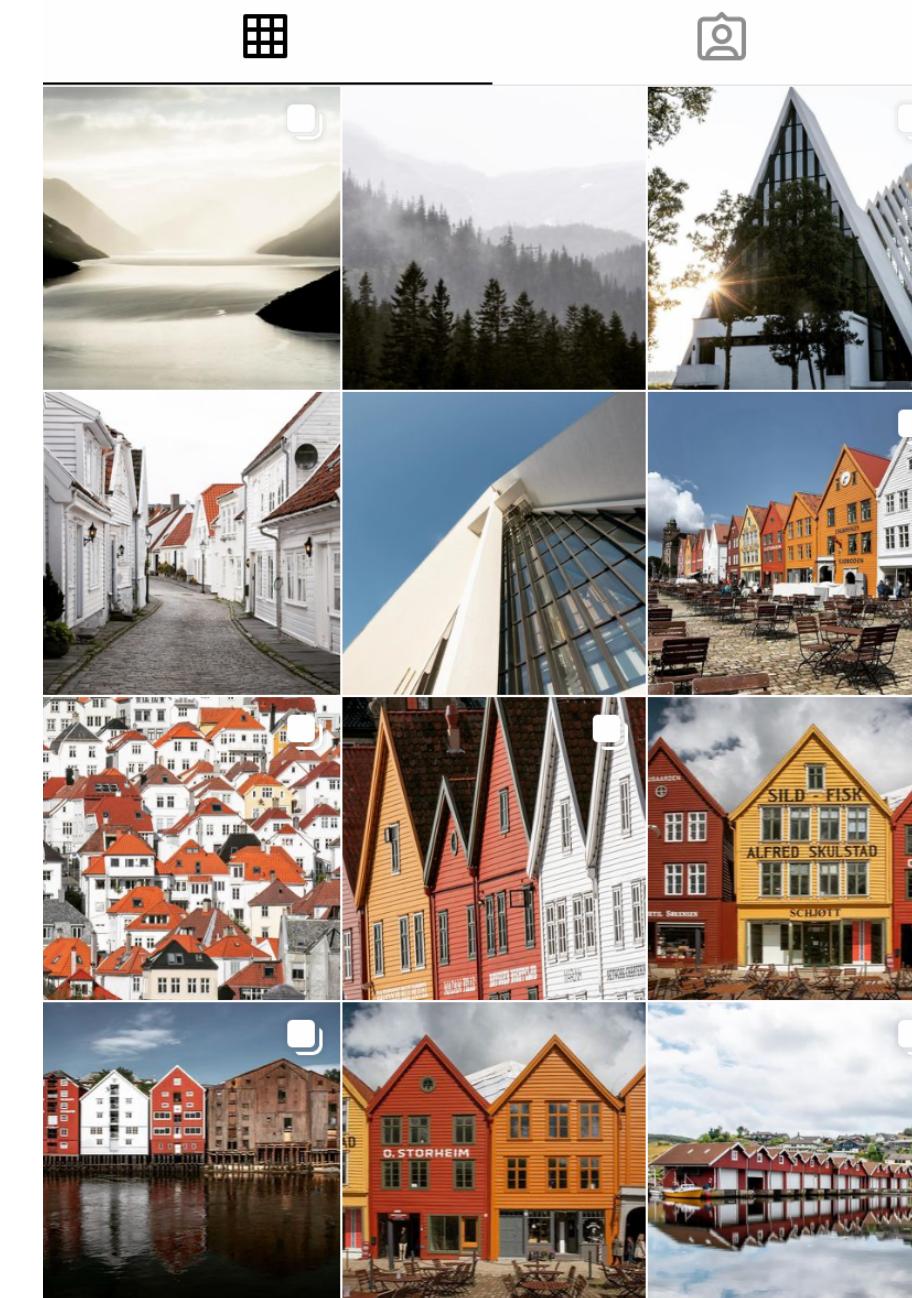
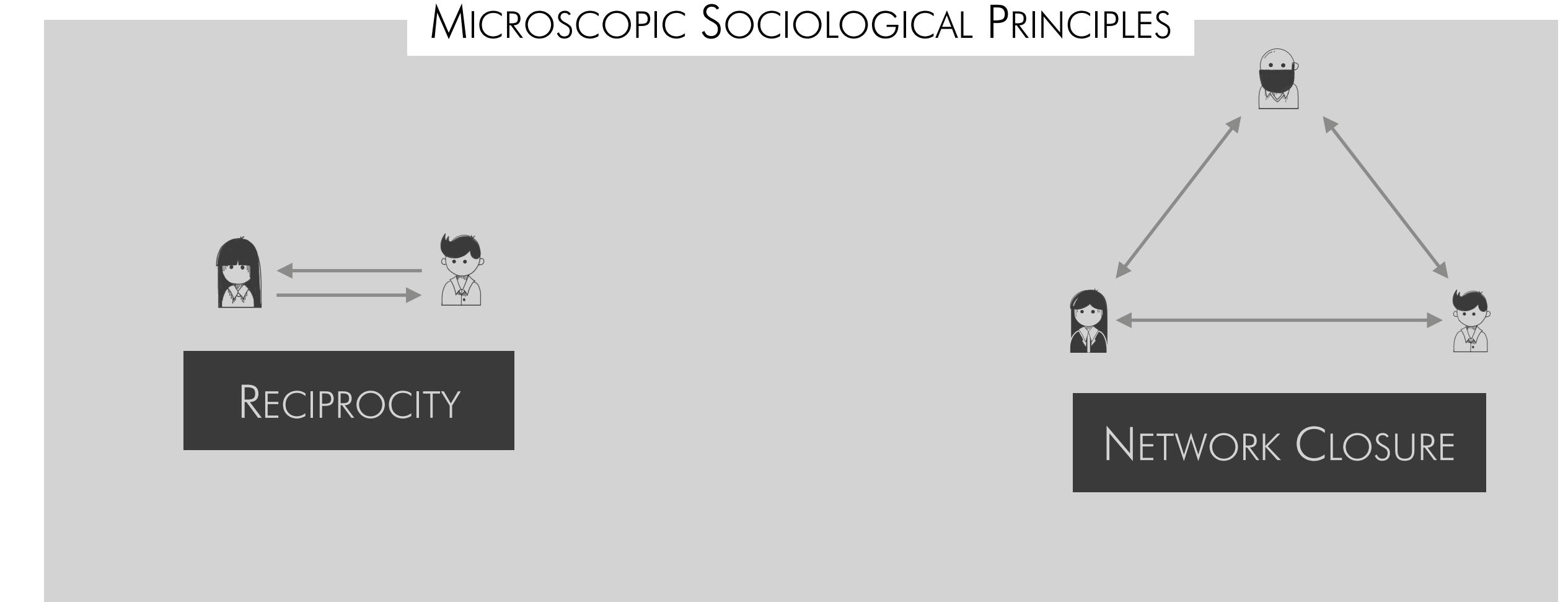
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- Today's most successful Online Social Networks show *limited reciprocity* and *network closure*.



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- Online Social Networks are ubiquitous.
- Researchers from different communities have started considering the problem of **Social Network Formation**.
- Today's most successful Online Social Networks show **limited reciprocity** and **network closure**.
- Rather, they are based on **User-Generated Content** (typically, images or videos), which is widely unexplored in the literature.



UGC-BASED PLATFORMS

- They have a huge impact in our daily lives, e.g.:
 - Activism;
 - Travel planning;
 - Food trends;
 - Social Media Marketing;
 - Spreading of (mis)information;
 - ...



justinbieber I am a white Canadian and I will never know what it feels like to be an African American but what I do know is I am willing to stand up and use my voice to shine light on racism, because it's a real thing and it's more prevalent now than I have ever seen in my lifetime.. we are all Gods children and we are ALL EQUAL.

Load more comments

luhbaby688 @sarahlids04 You're white obviously you're gonna say "All lives matter" Dang don't try to steal our shine we are the most hated race and strongest based on what we been throug unlike WHITE

sarahlids04 @luhbaby688 it's not because I'm white I would say the same if I was Hispanic,Chinese,Japanese etc. we all matter. Jesus loves us all the same no matter what color we are. We're all the same on the inside.

1,725,372 likes

SEPTEMBER 23, 2017

Log in to like or comment. ...

QUALITY-BASED
NETWORK FORMATION
MODEL

OBSERVATIONS

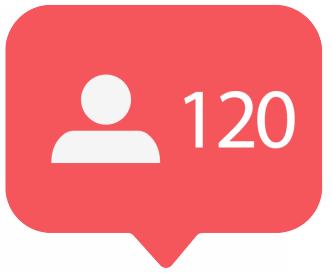
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- Actors have different interests, e.g, travelling, food, politics, ...

OBSERVATIONS

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- Actors provide **User-Generated Content** (of potentially different quality).



ubiquitous.travels



OBSERVATIONS

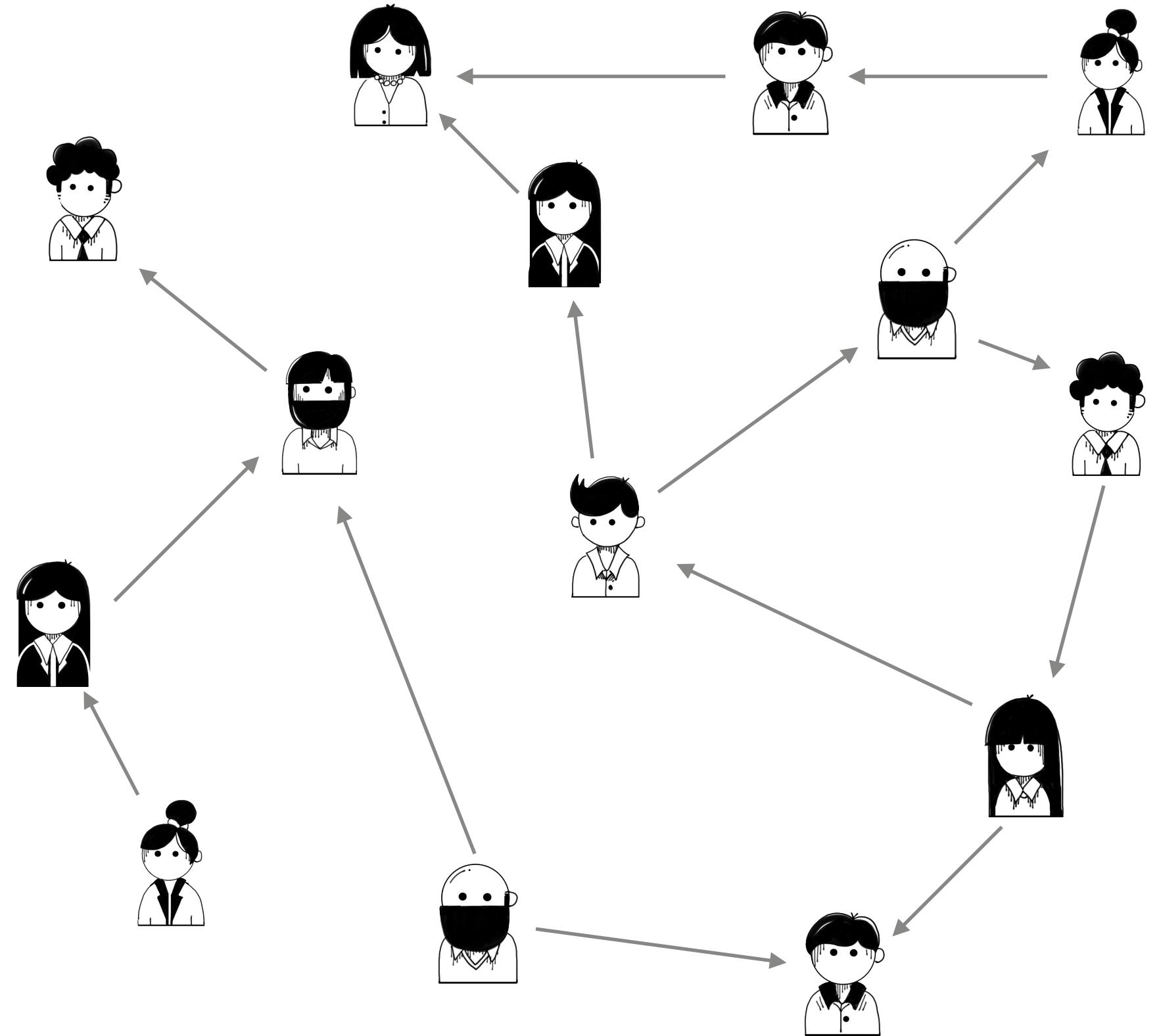
- Actors have different interests, e.g., travelling, food, politics, ...
- Actors provide **User-Generated Content** (of potentially different quality).
- Actors decide whom they want to follow.

Directionality: followees \neq followers



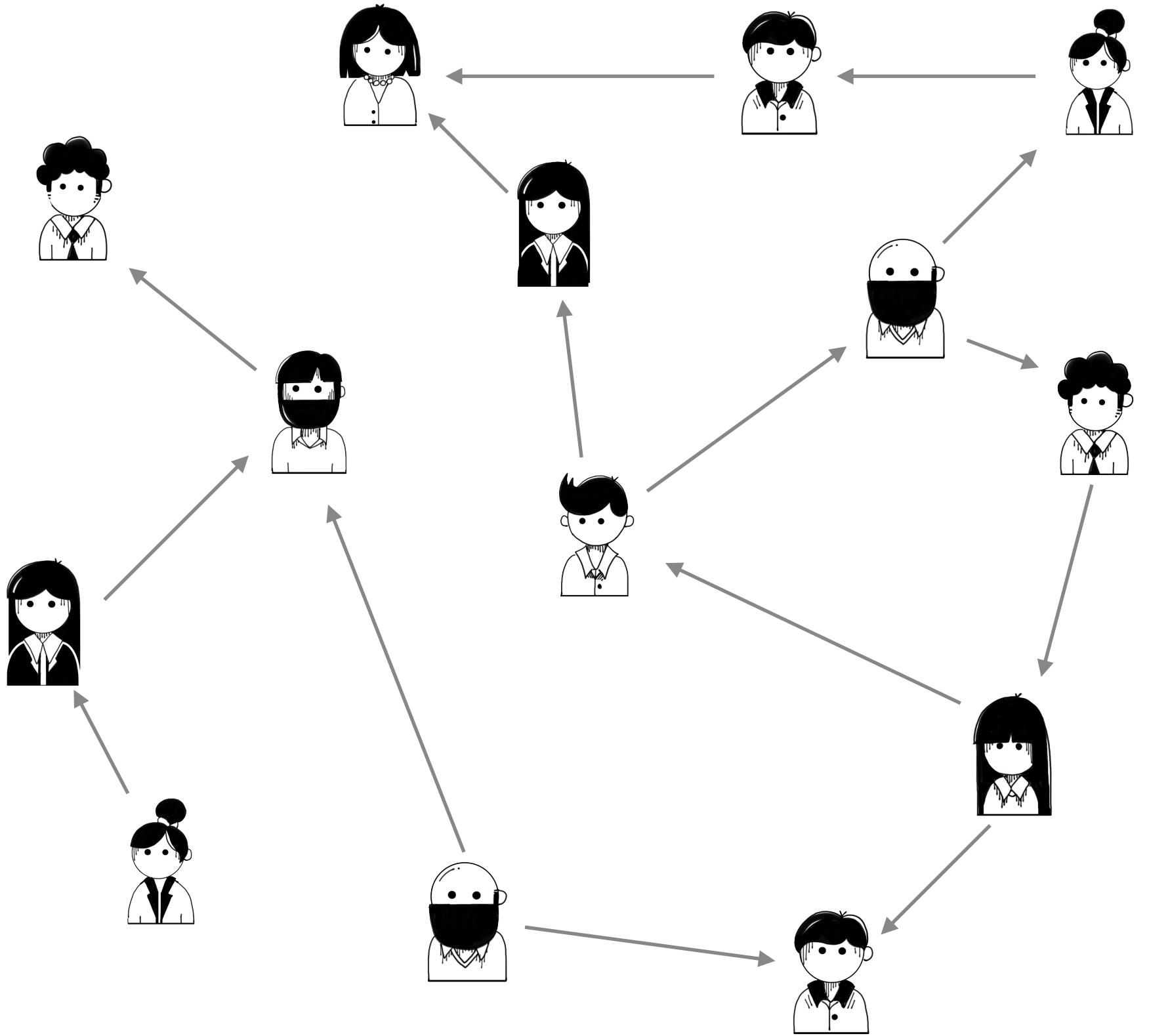
QUALITY-BASED NETWORK FORMATION MODEL

- **Directed Unweighted** network \mathcal{G} with $\mathcal{N} = \{1, \dots, N\}$ agents.
 $a_{ij} \in \{0,1\}$ means i follows (or not) j .



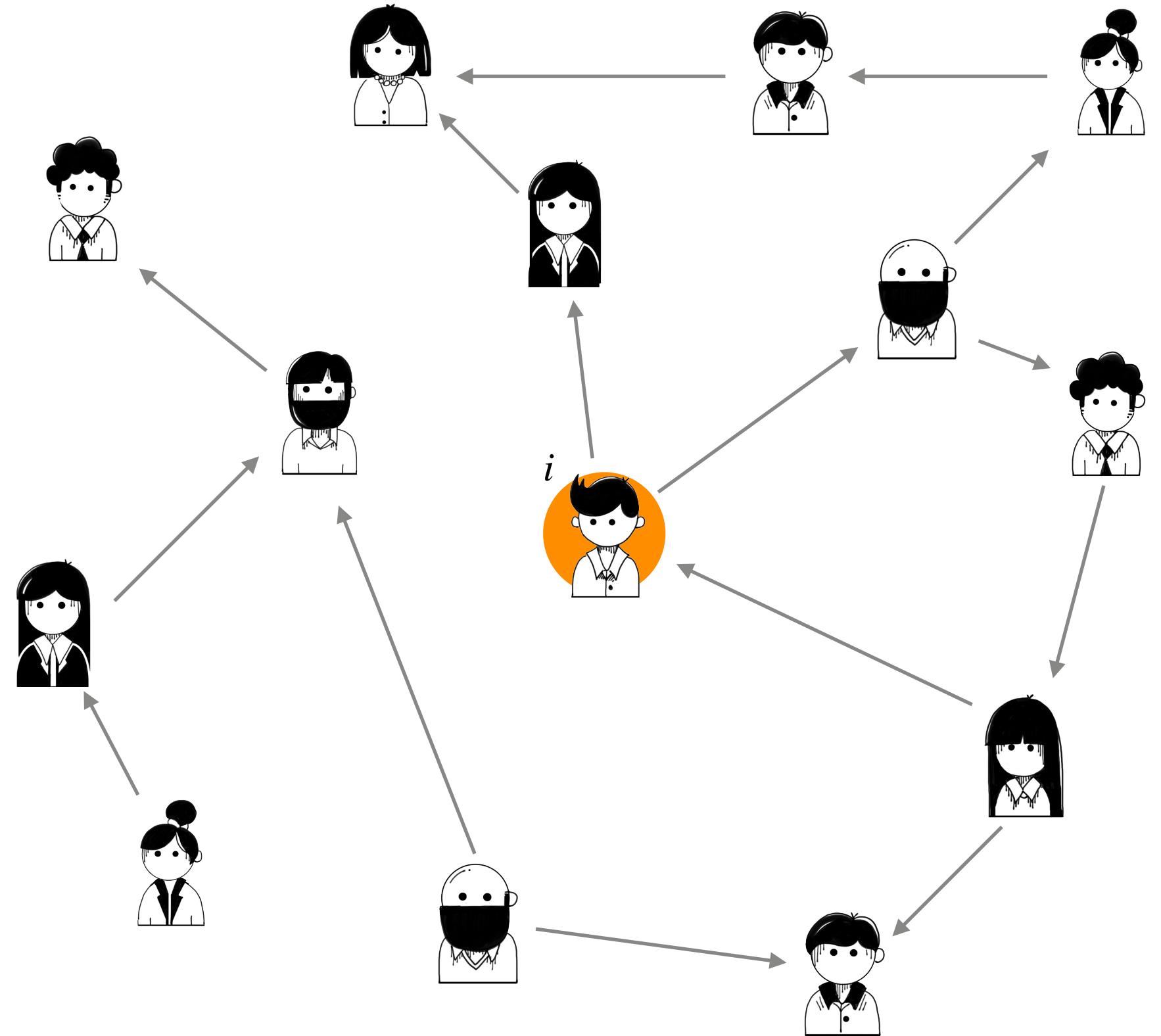
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- All the agents share a common interest for a specific topic.
- Each agent i is attributed with a **quality parameter** $q_i \in [0,1]$ describing the likelihood her content will be liked by others.
Wlog, we assume $q_1 > q_2 > \dots > q_N$.

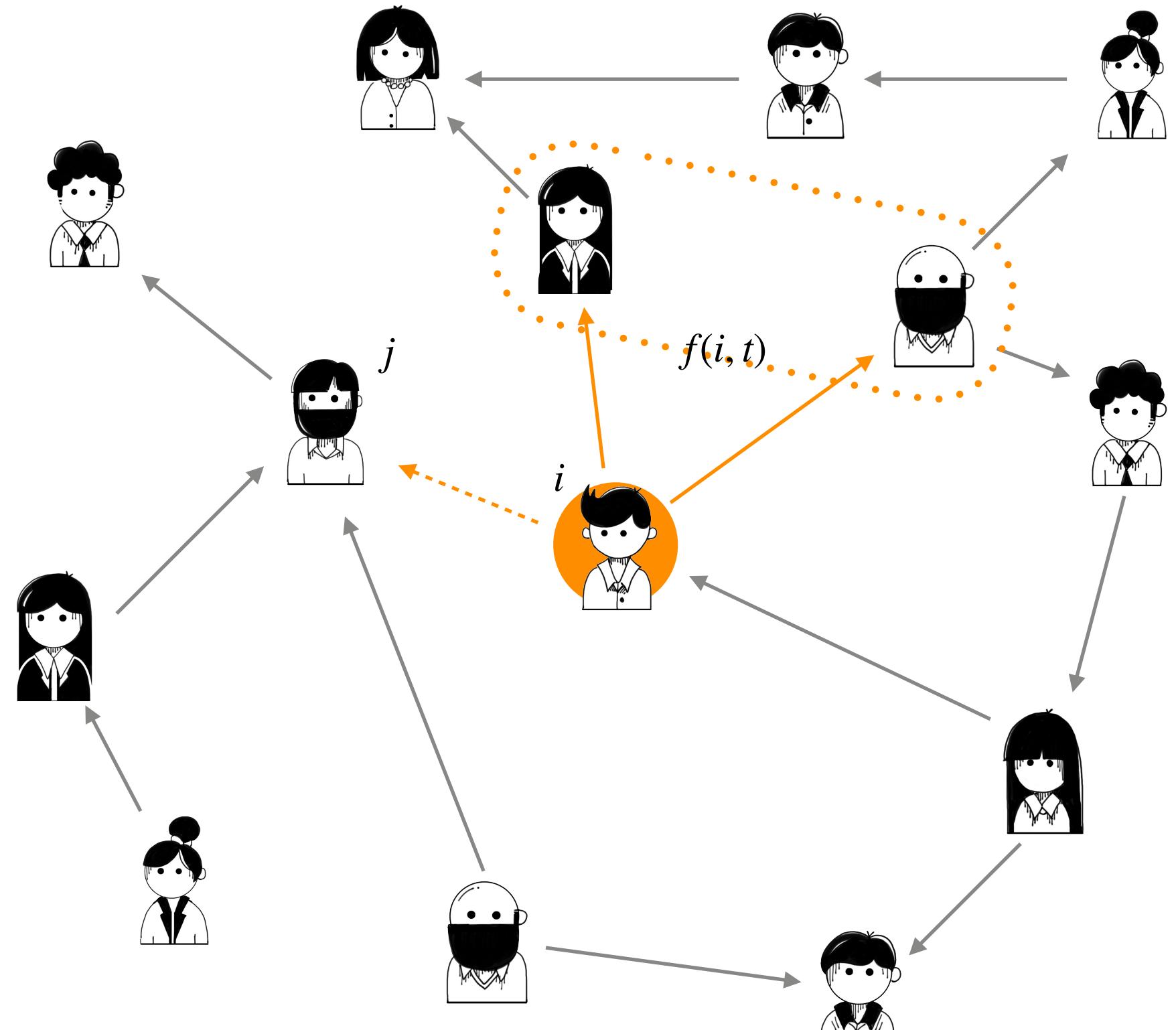


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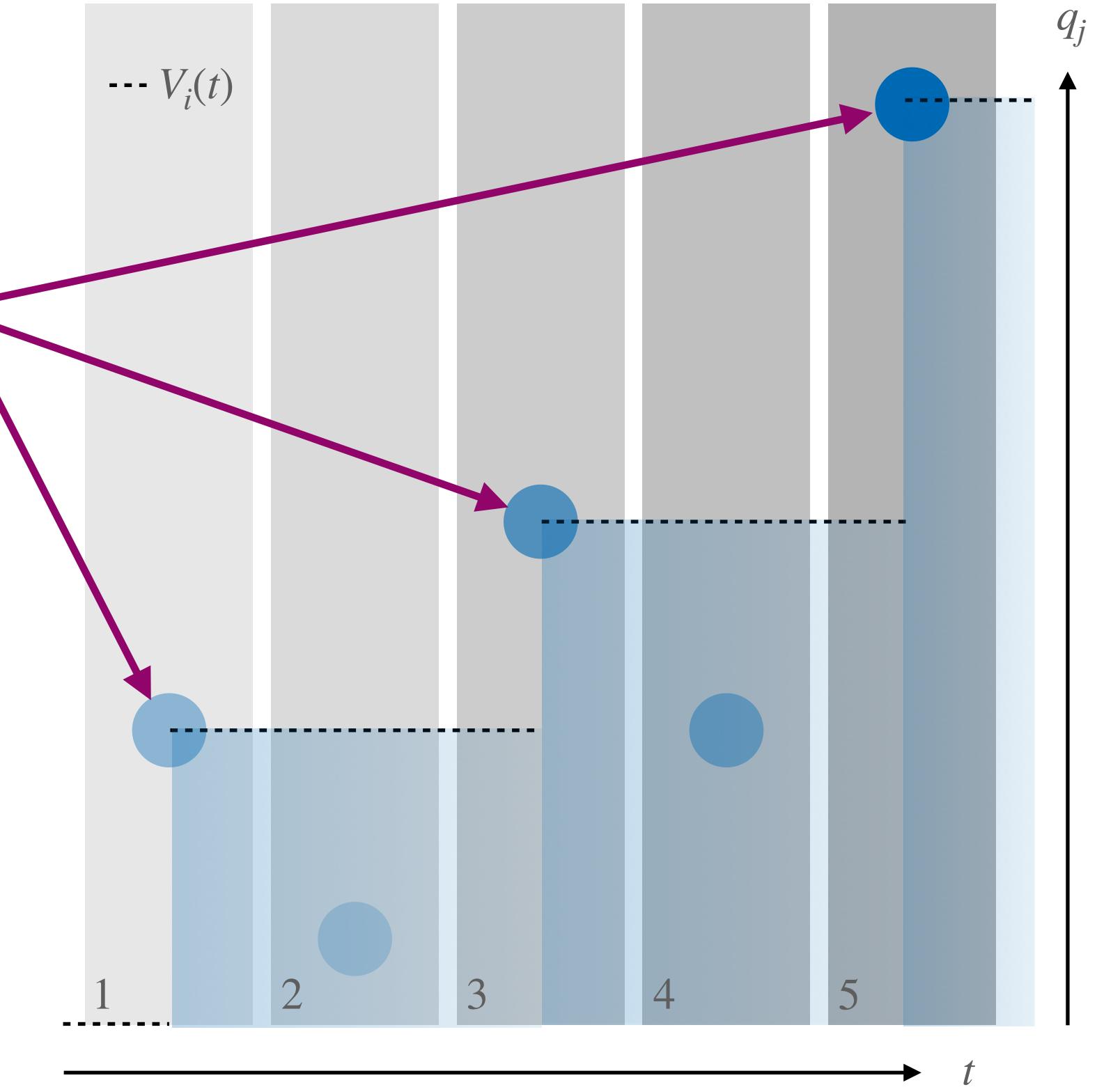
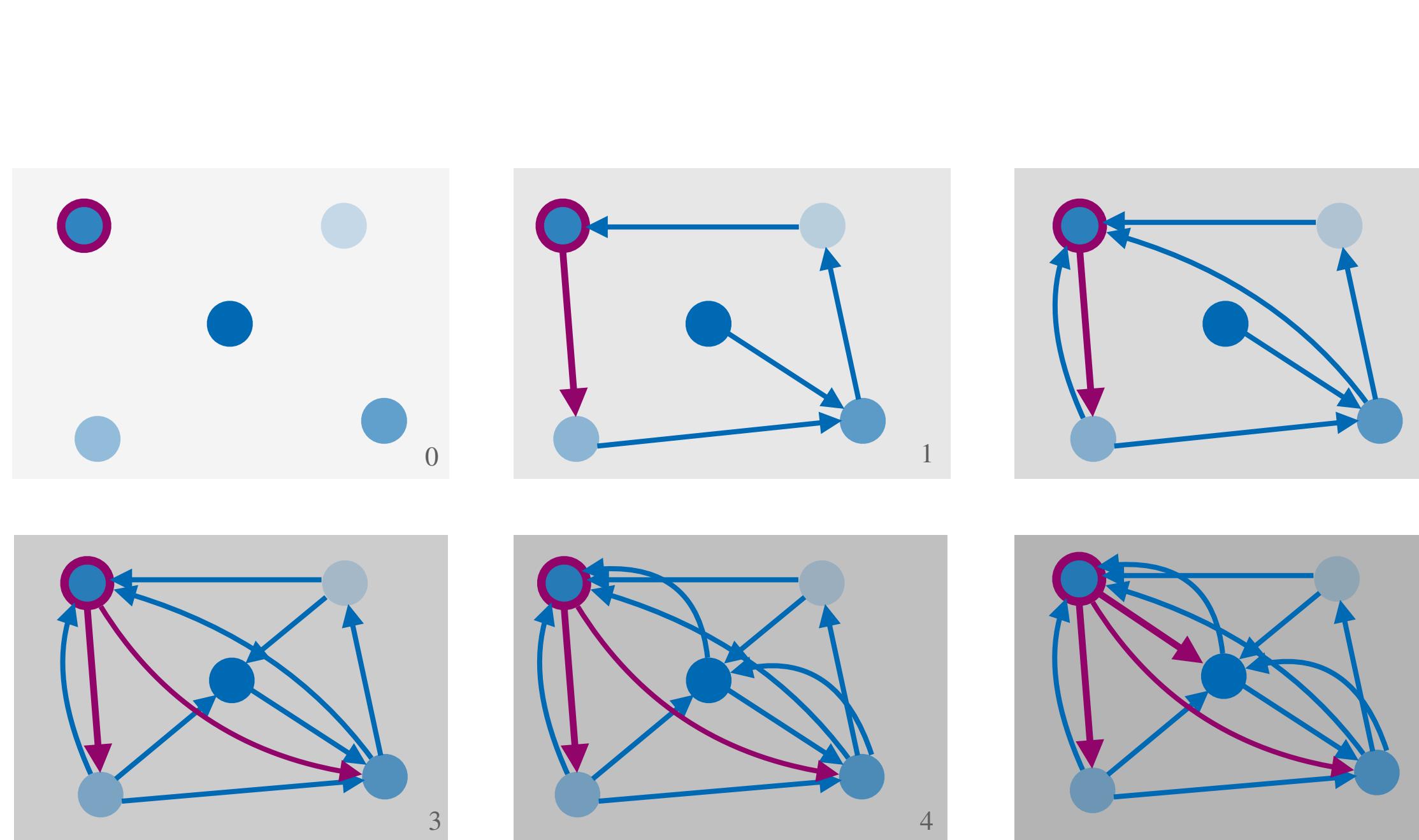
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- Each agent i is attributed with a **quality parameter** $q_i \in [0,1]$ describing the likelihood her content will be liked by others.
Wlog, we assume $q_1 > q_2 > \dots > q_N$.
- Each agent i sequentially meets another distinct agent j (**uniformly at random**) and decides whether to start following j or not according to:

$$a_{ij}(t+1) = \begin{cases} 1, & \text{if } q_j > V_i(t) := \max_{j \in f(i,t)} q_j, \\ a_{ij}(t), & \text{otherwise,} \end{cases}$$

where $f(i,t) = \{j, \text{ s.t. } a_{ij}(t) = 1\}$ denotes the set of i 's followees.



QUALITY-BASED NETWORK FORMATION MODEL



RESULTS

CONVERGENCE

THEOREM.

For any quality vector $\mathbf{q} = [q_1, \dots, q_N]$, the network reaches an equilibrium almost surely.

At equilibrium, every node except node 1, follows node 1.

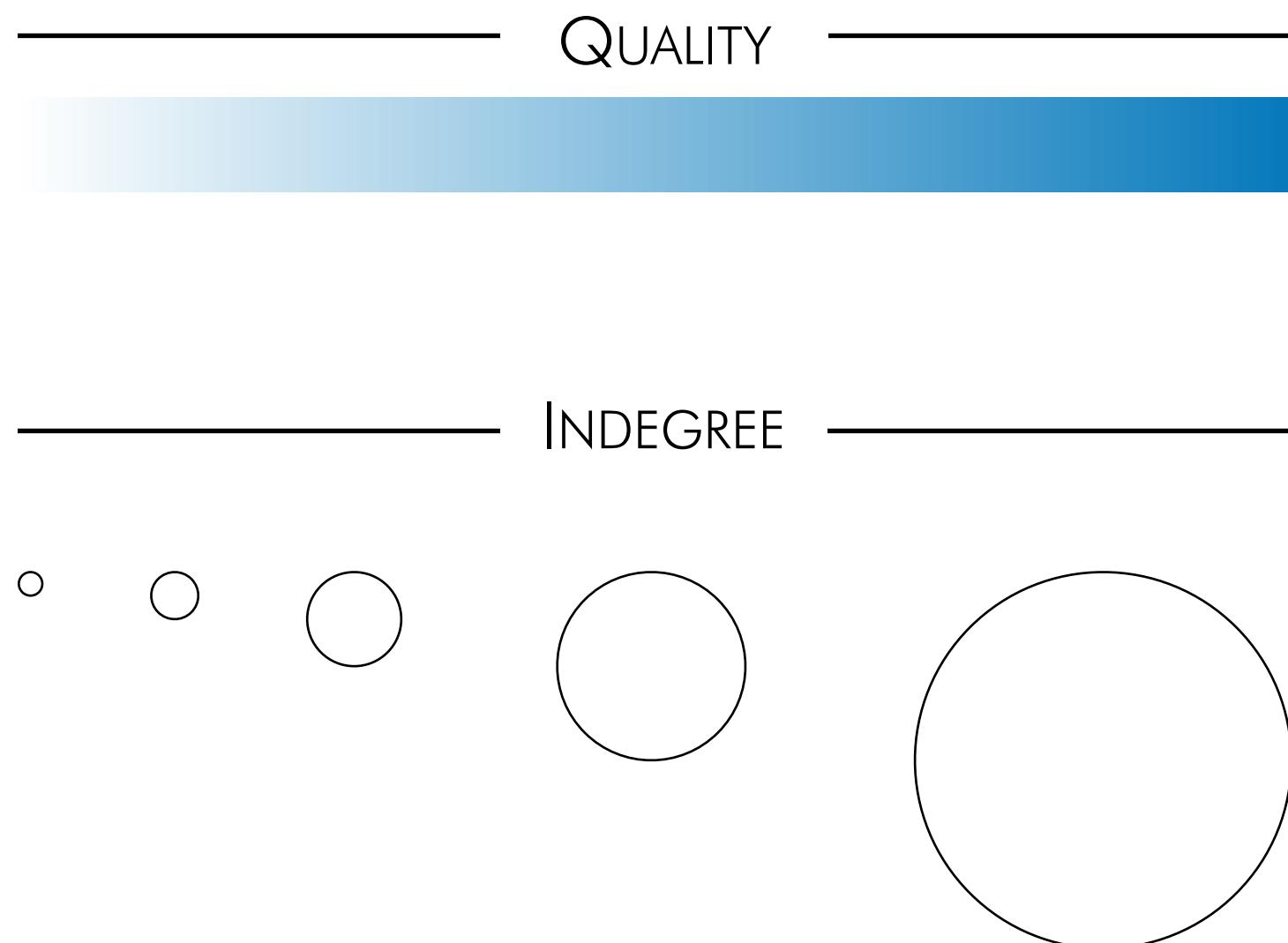
NUMERICAL SIMULATION

THEOREM.

For any quality vector $\mathbf{q} = [q_1, \dots, q_N]$, the network reaches an equilibrium almost surely.

At equilibrium, every node except node 1, follows node 1.

- A **meritocratic** network formation process.



RESULTS

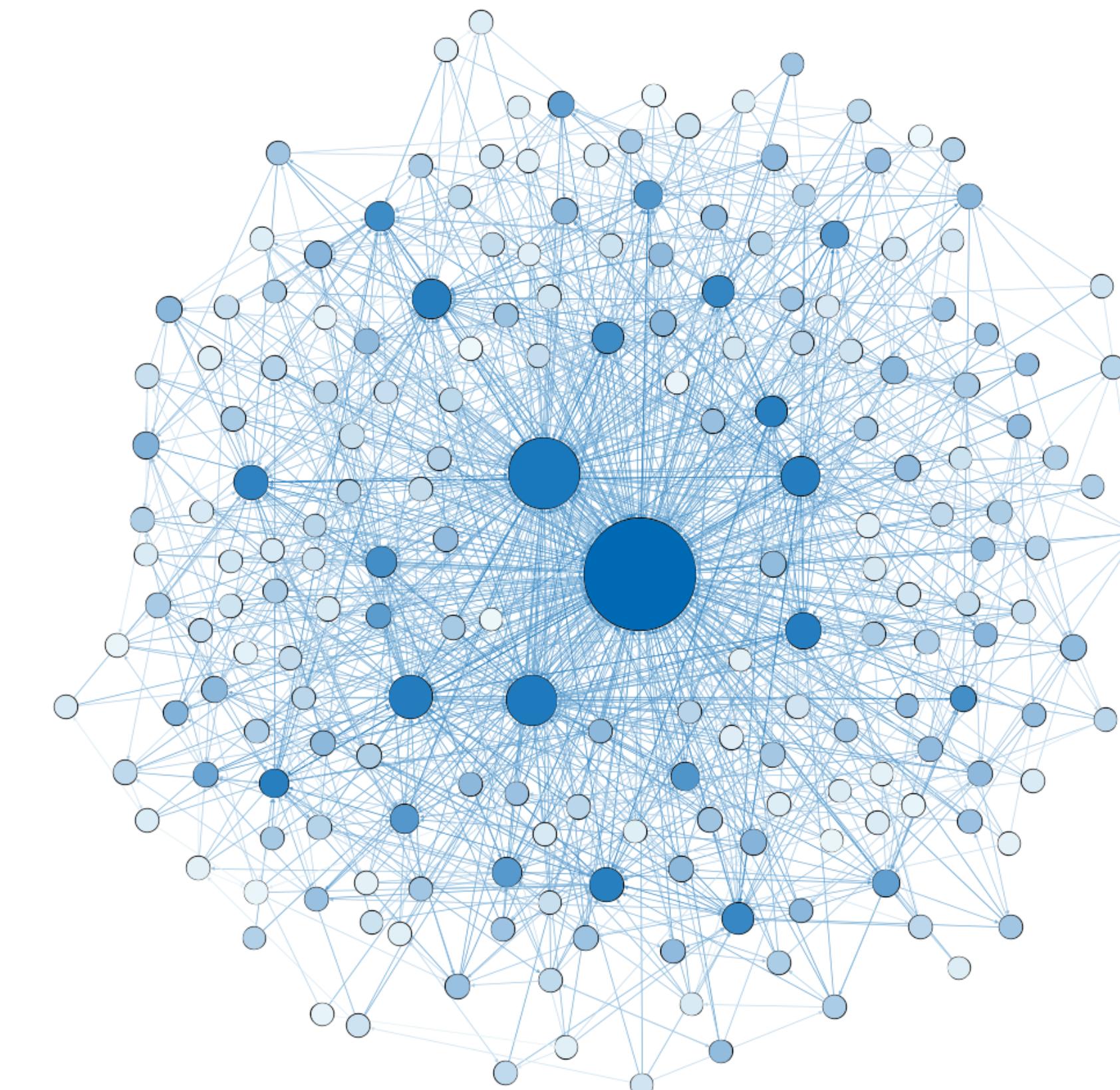


Fig. **Numerical** simulation with 200 agents. Colors are associated with quality, node's dimension is proportional to the indegree.

INDEGREE DISTRIBUTION

THEOREM.

At equilibrium, the expected indegree follows a Zipf's law:

$$\mathbb{E}(d_i^{in,\star}) = \begin{cases} N-1, & \text{if } i=1, \\ \frac{N}{i}, & \text{otherwise.} \end{cases}$$

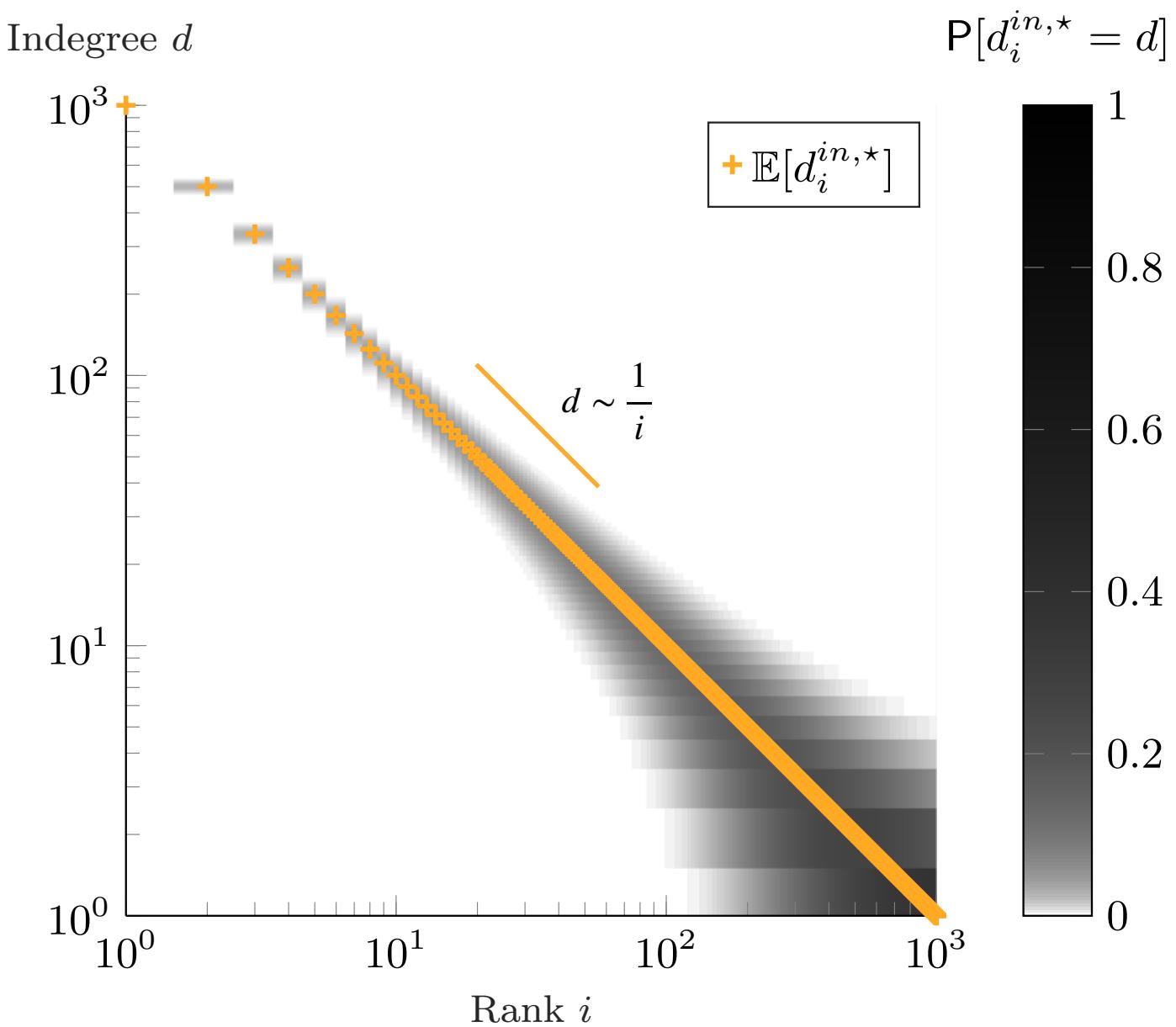


Fig. **Theoretical** probability density function of the nodes' indegree in a network of $N=1000$ agents.

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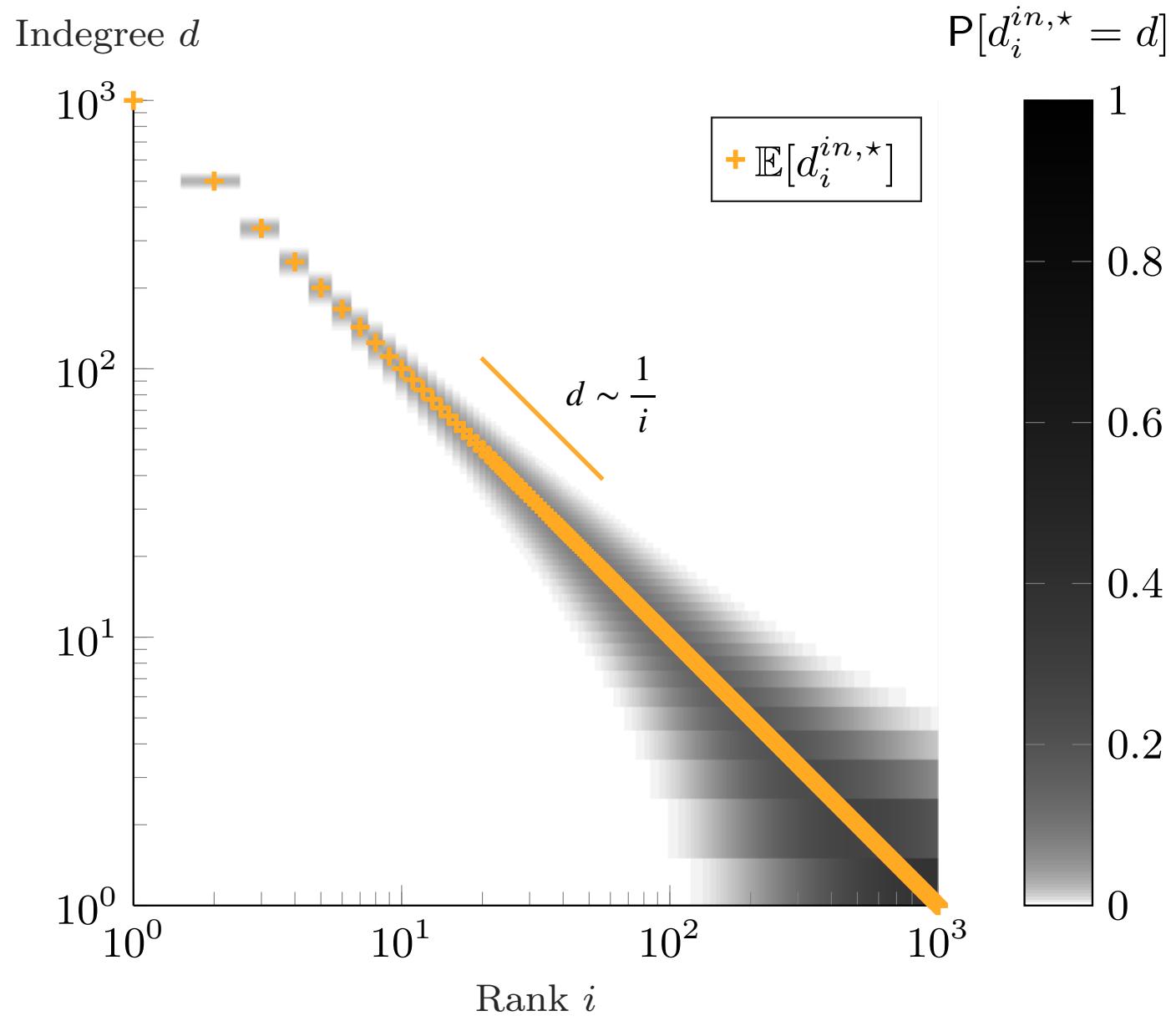


Fig. Theoretical probability density function of the nodes' indegree in a network of $N=1000$ agents.

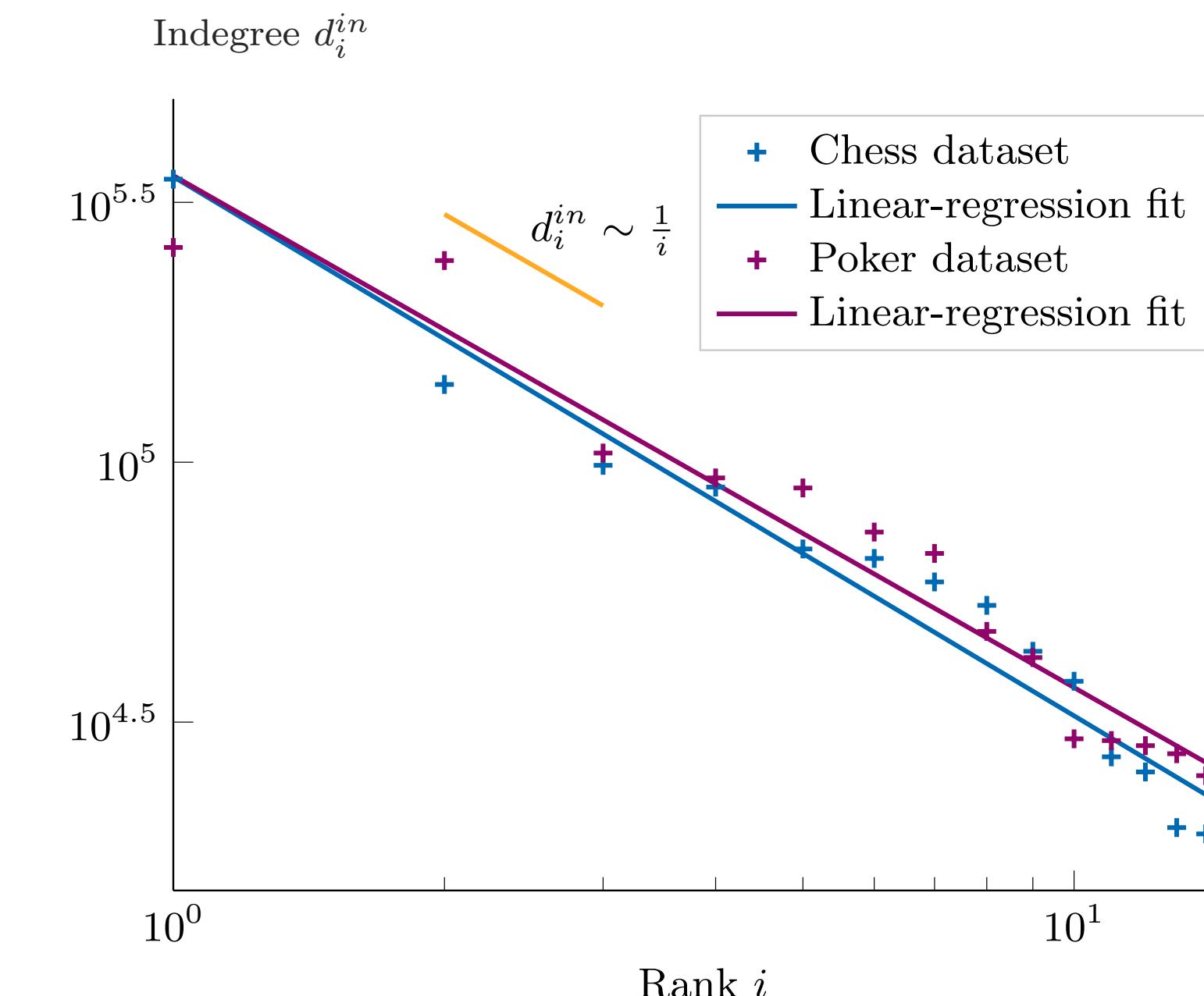


Fig. The empirical results from our collected Twitch data-sets are aligned with the theoretical prediction.

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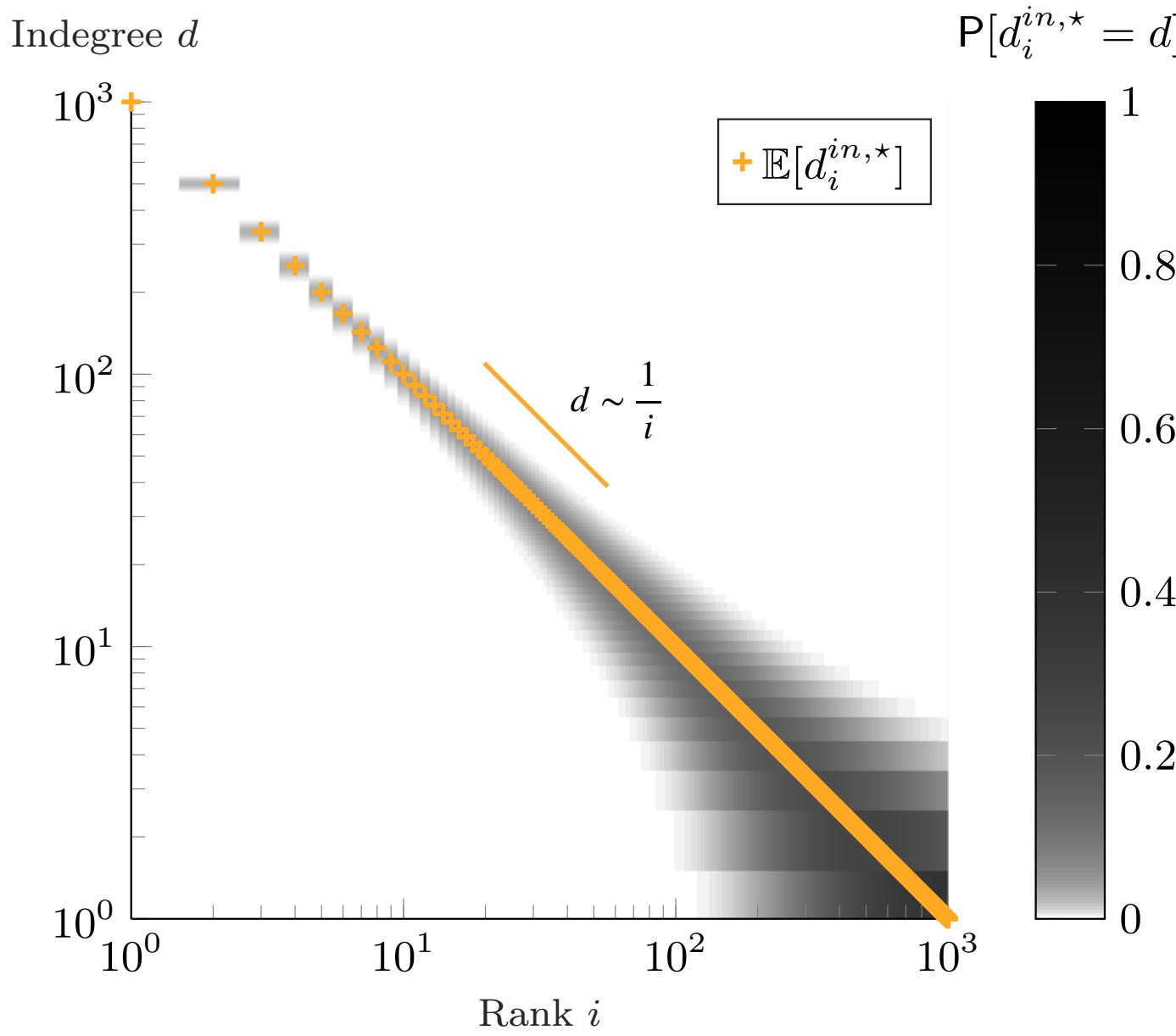


Fig. Theoretical probability density function of the nodes' indegree in a network of $N=1000$ agents.

$$P[d_i^{in,\star} = d] = \frac{1}{N} \sum_{i=1}^N P[d_i^{in,\star} = d]$$

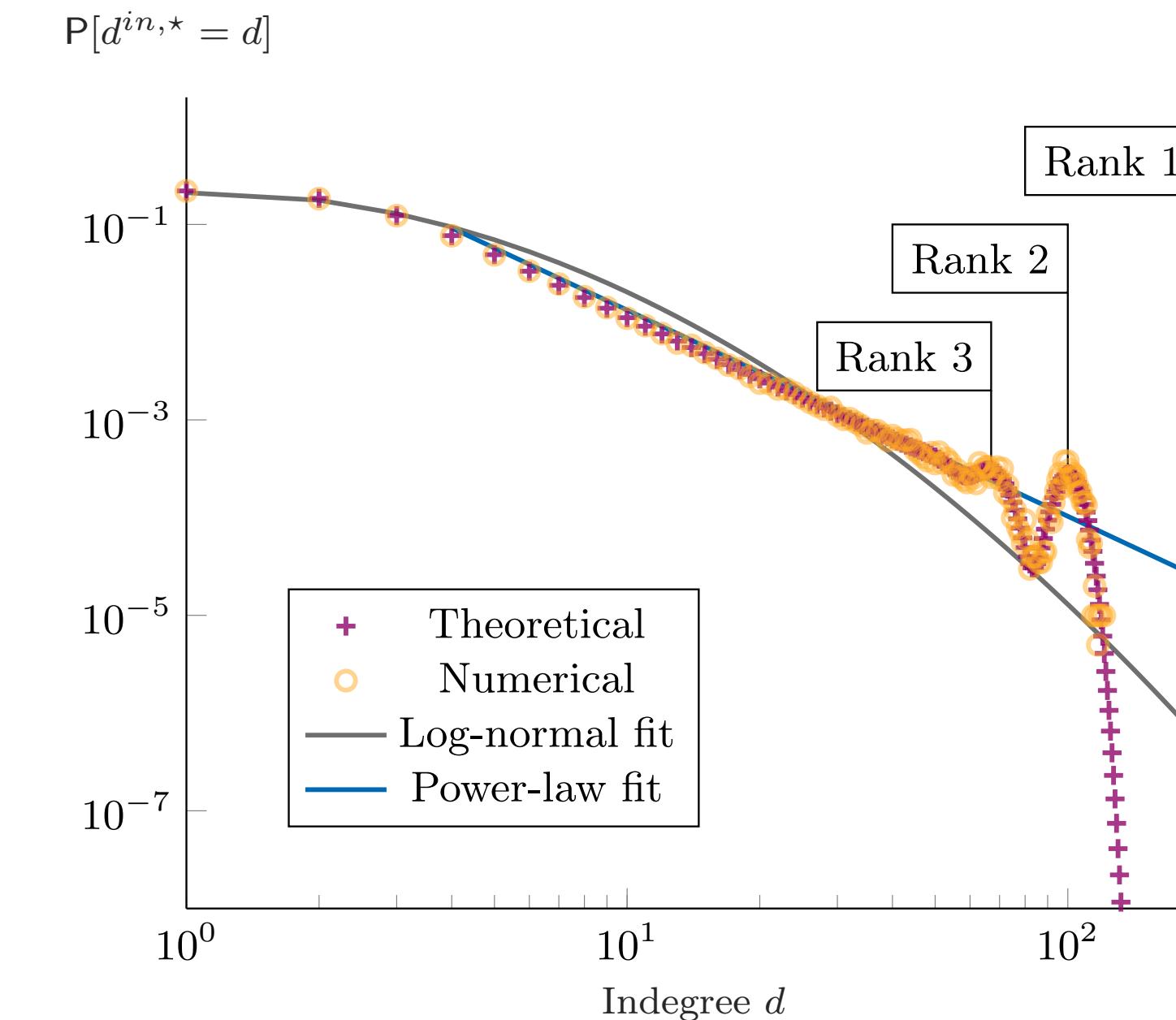


Fig. Theoretical Probability density function of the **average** nodes' indegree in a network of $N=1000$ agents.

AUDIENCE OVERLAP

DEFINITION.

We define the Audience Overlap index as follows:

$$O(i,j) := \frac{|F(i) \cap F(j)|}{|F(i)|} \in [0,1],$$

if $|F(i)| > 0$, and 0 otherwise, where $F(i)$ denotes the set of followers of i .



$$O(i,j) = 1/2$$

$$O(j,i) = 1/8$$

RESULTS

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- $F(i), |F(i)| = 4$
- $F(j), |F(j)| = 16$
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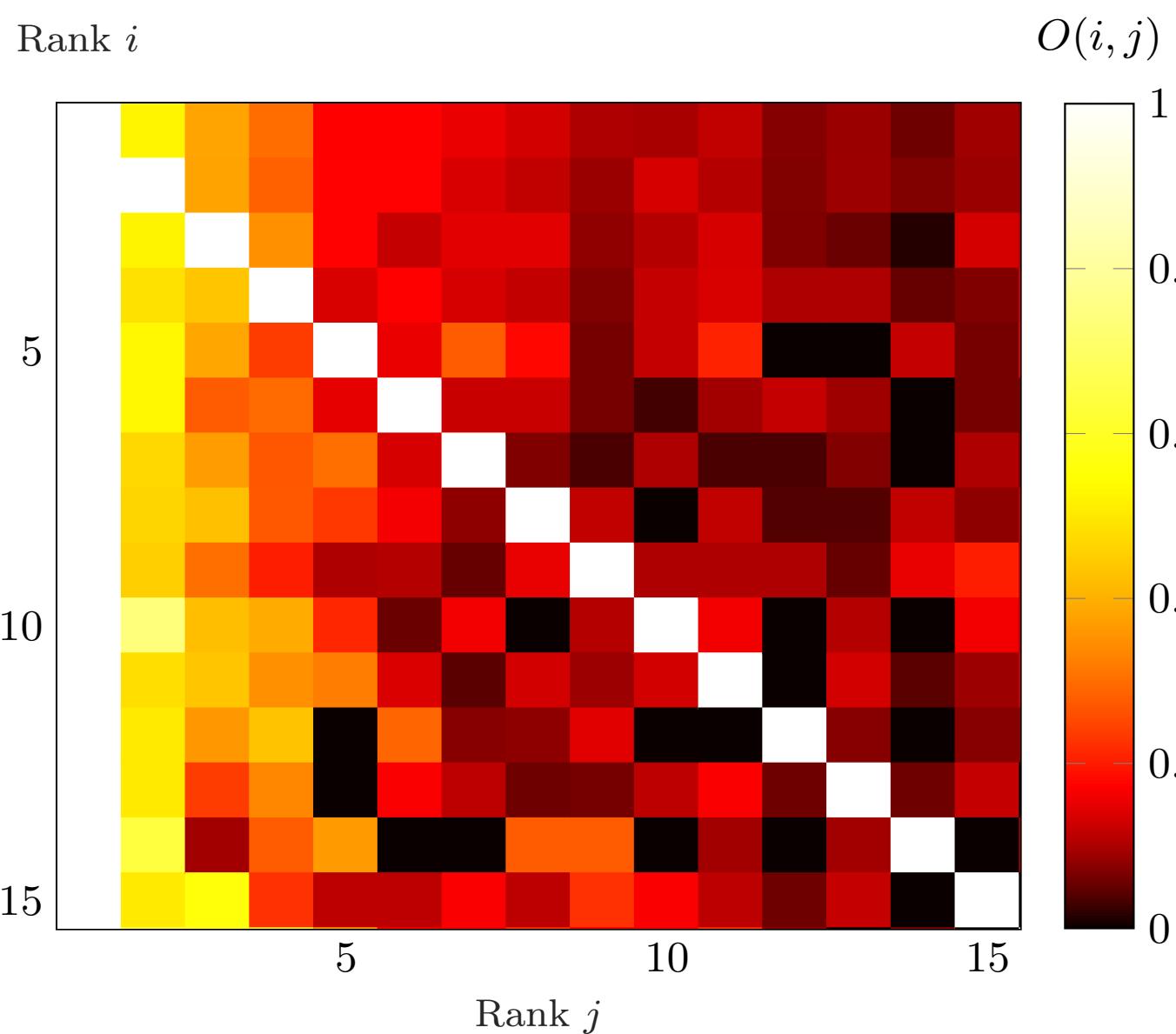


Fig. Numerical results on the followers' overlap among the top nodes. The result is obtained with $N=1000$ agents, upon reaching equilibrium.

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RESULTS

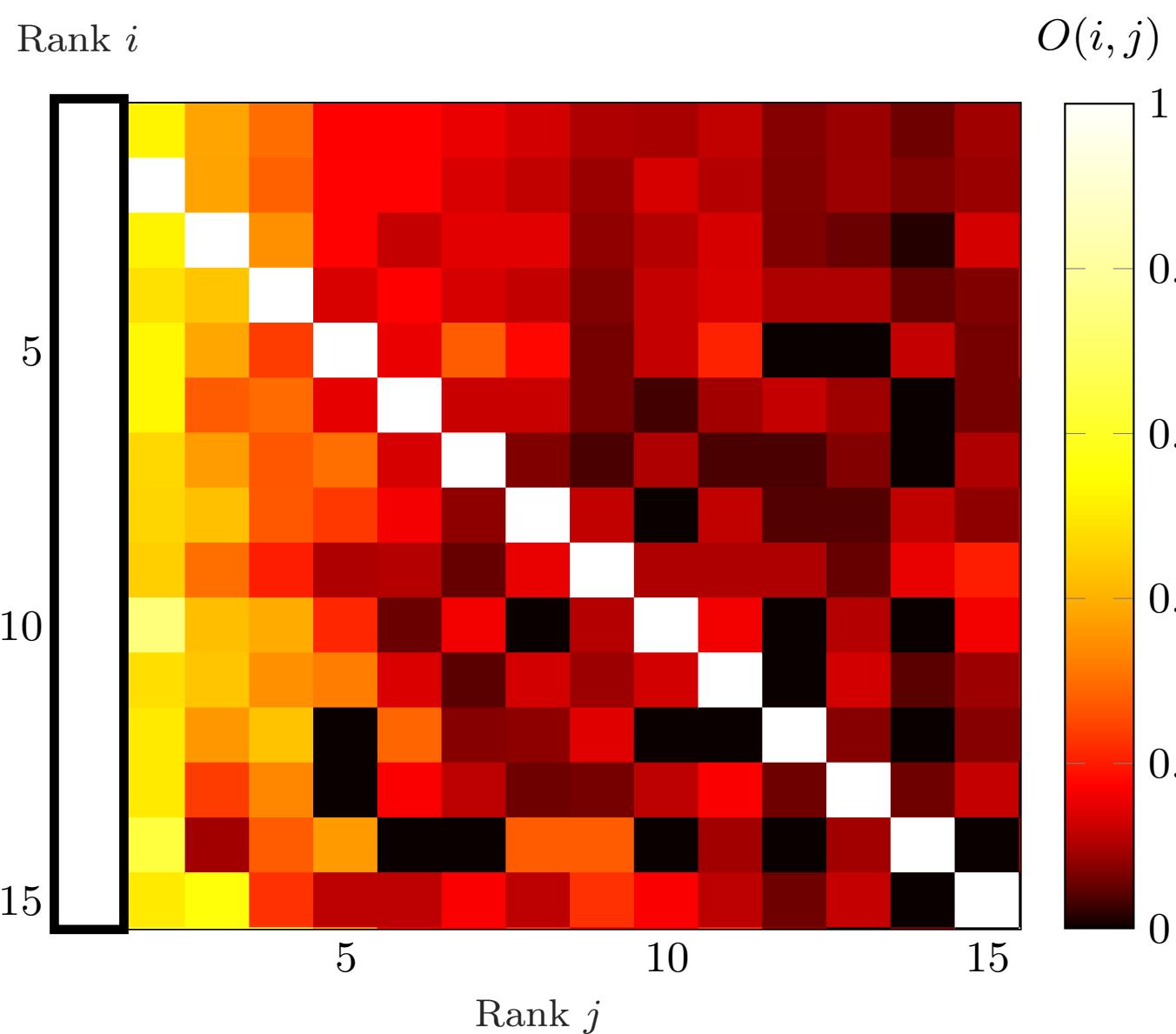


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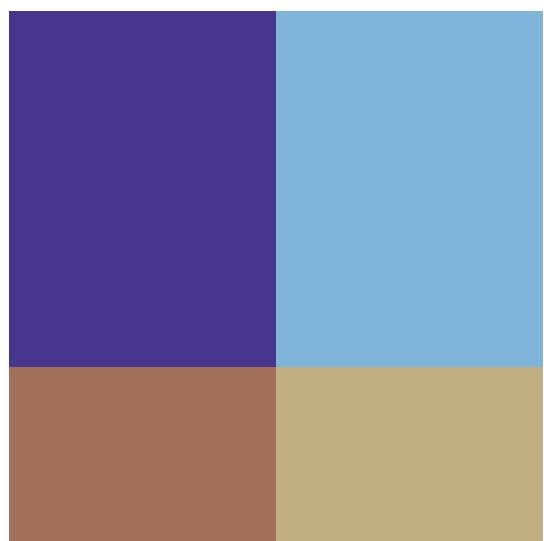
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RESULTS

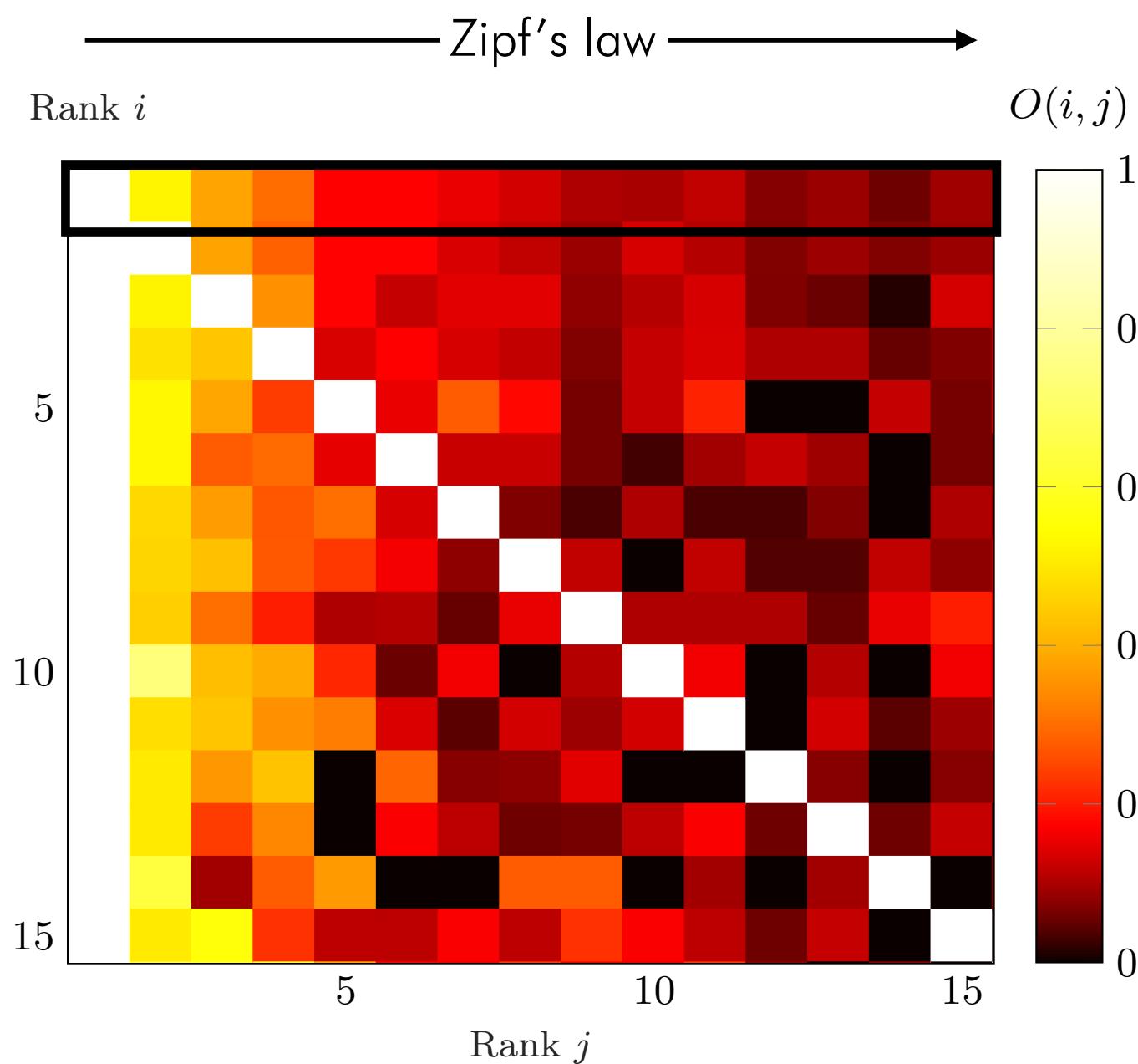


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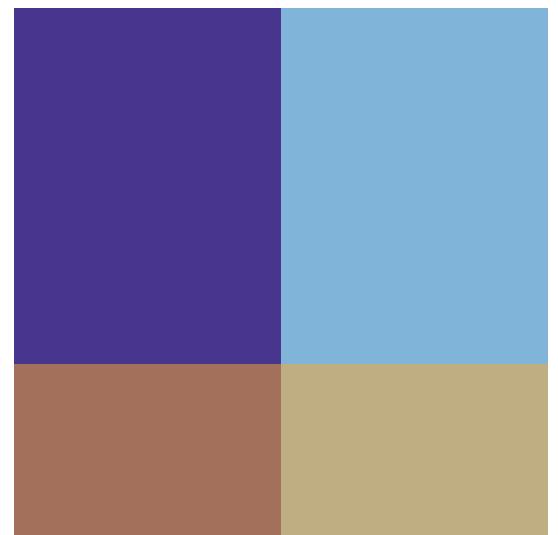
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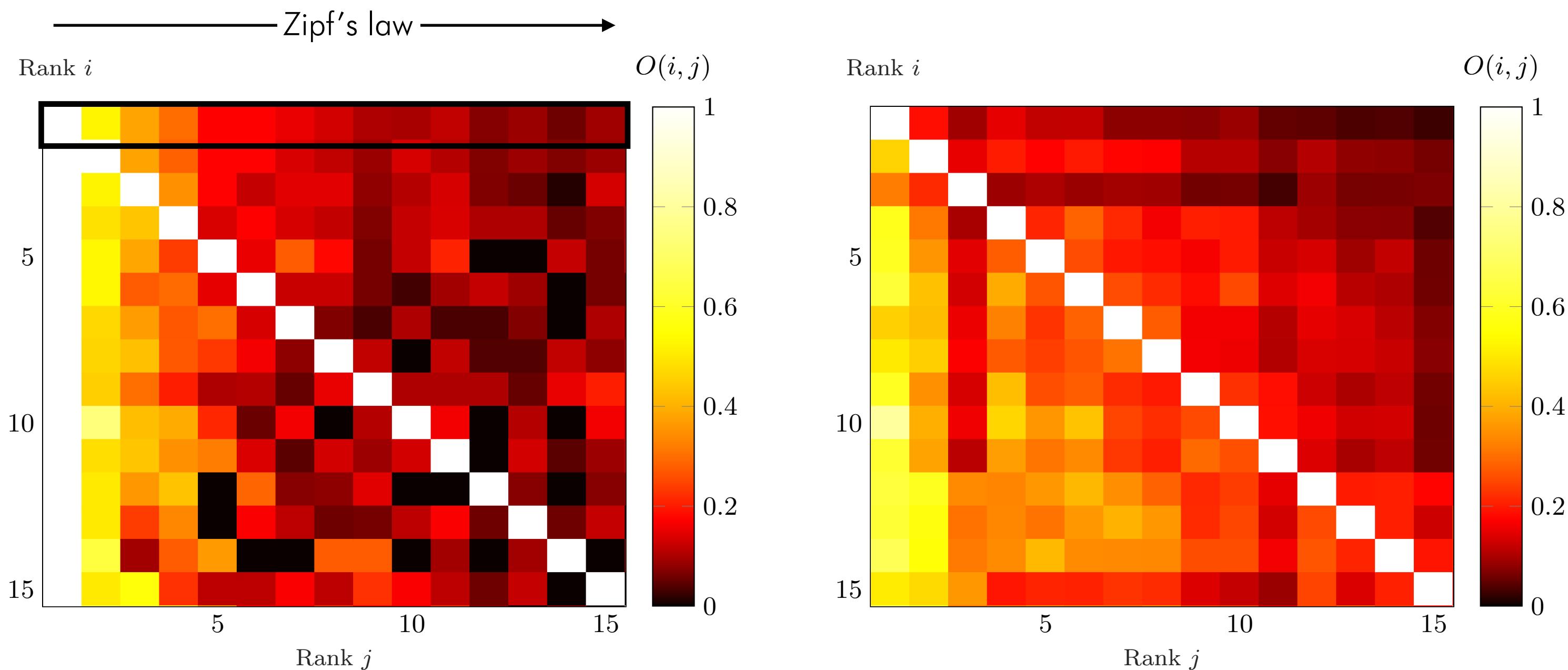


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Fig. Empirical results from our collected data-set.

OUTDEGREE DISTRIBUTION

- The outdegree probability density function is **homogeneous** for all the nodes.

$$\mathbb{P}[d_N^{out,*} = d]$$

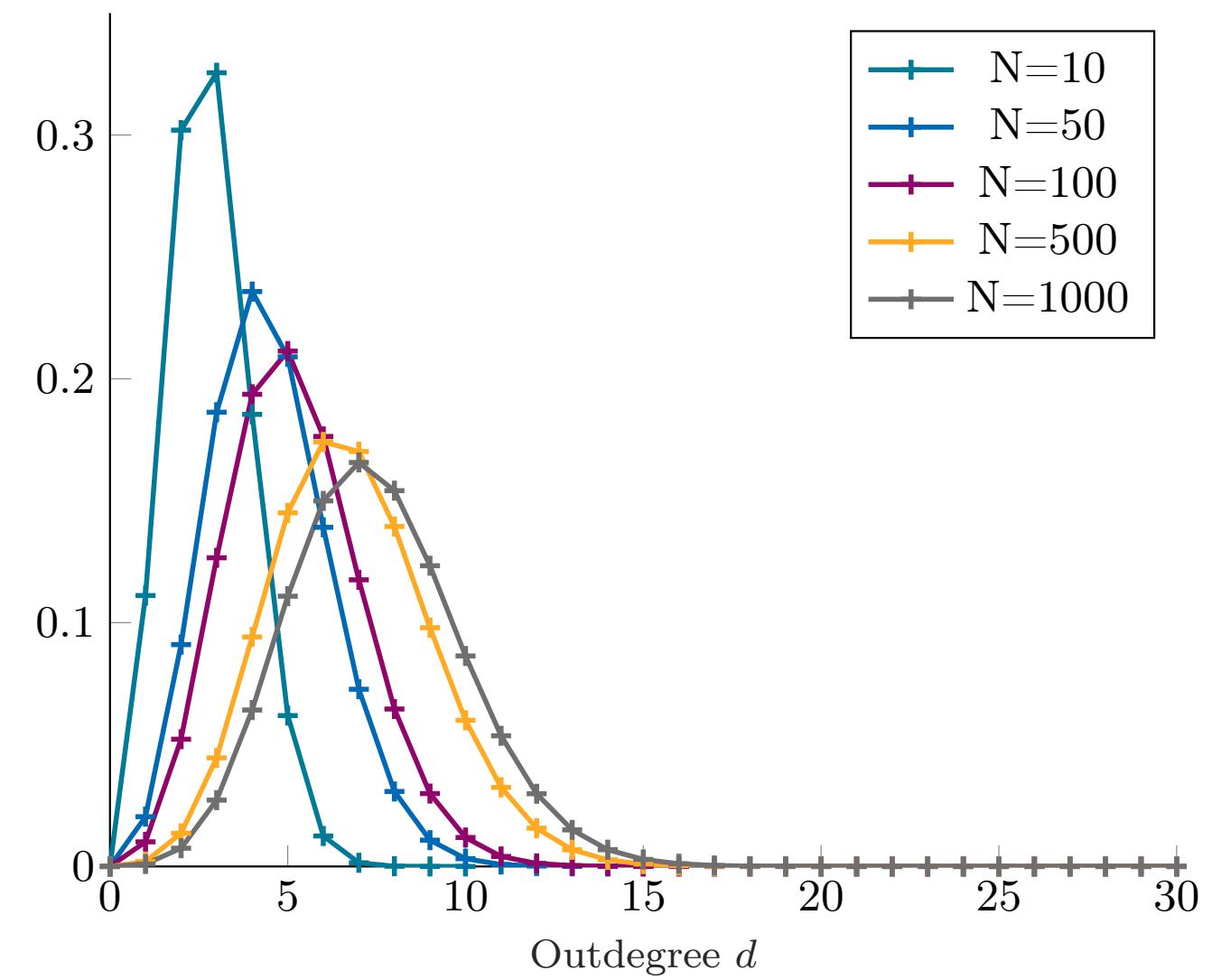


Fig. **Theoretical** outdegree distribution for different network size.

OUTDEGREE DISTRIBUTION

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The nodes' expected outdegree in a network of N agents equals the $(N-1)^{\text{th}}$ harmonic number:

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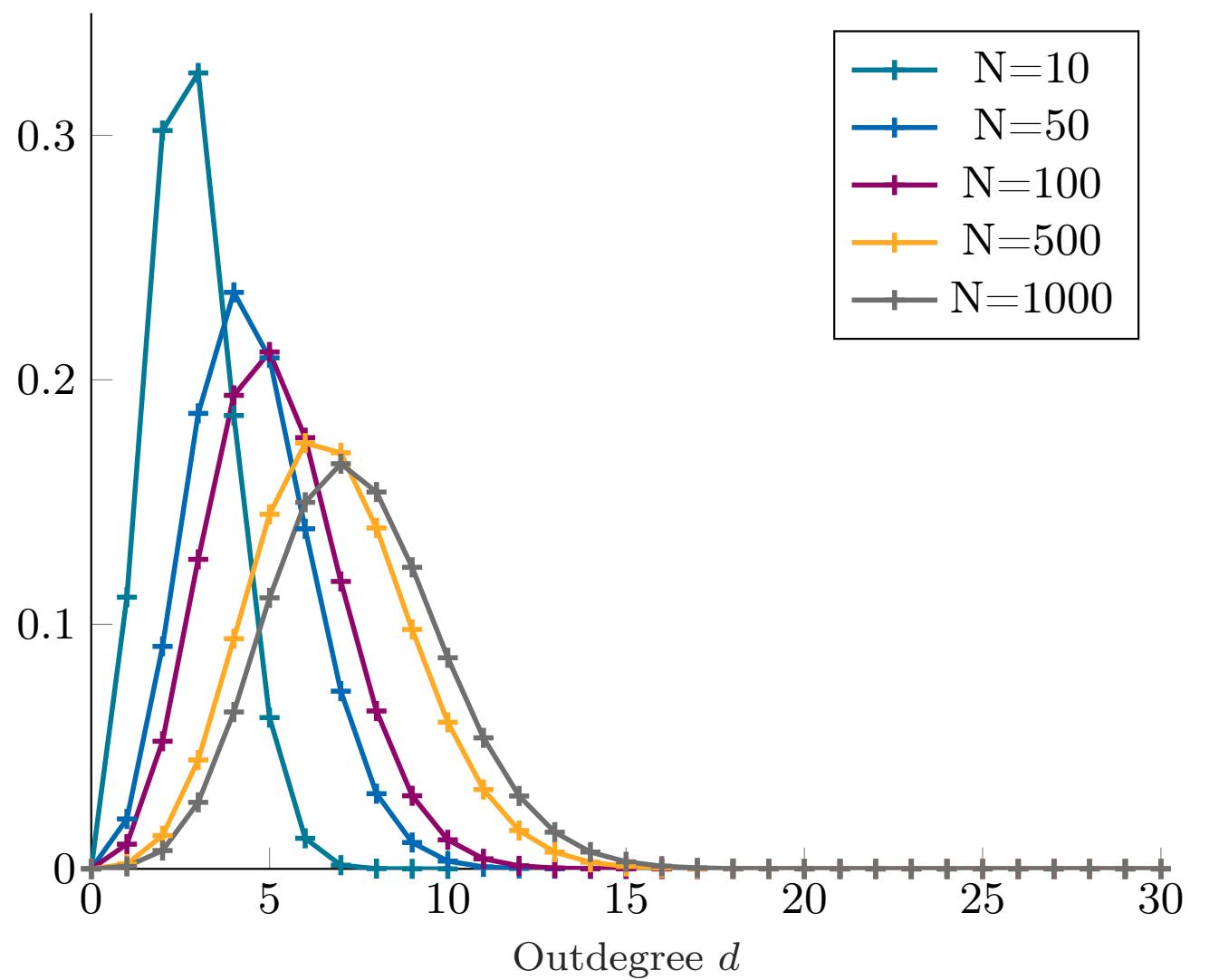


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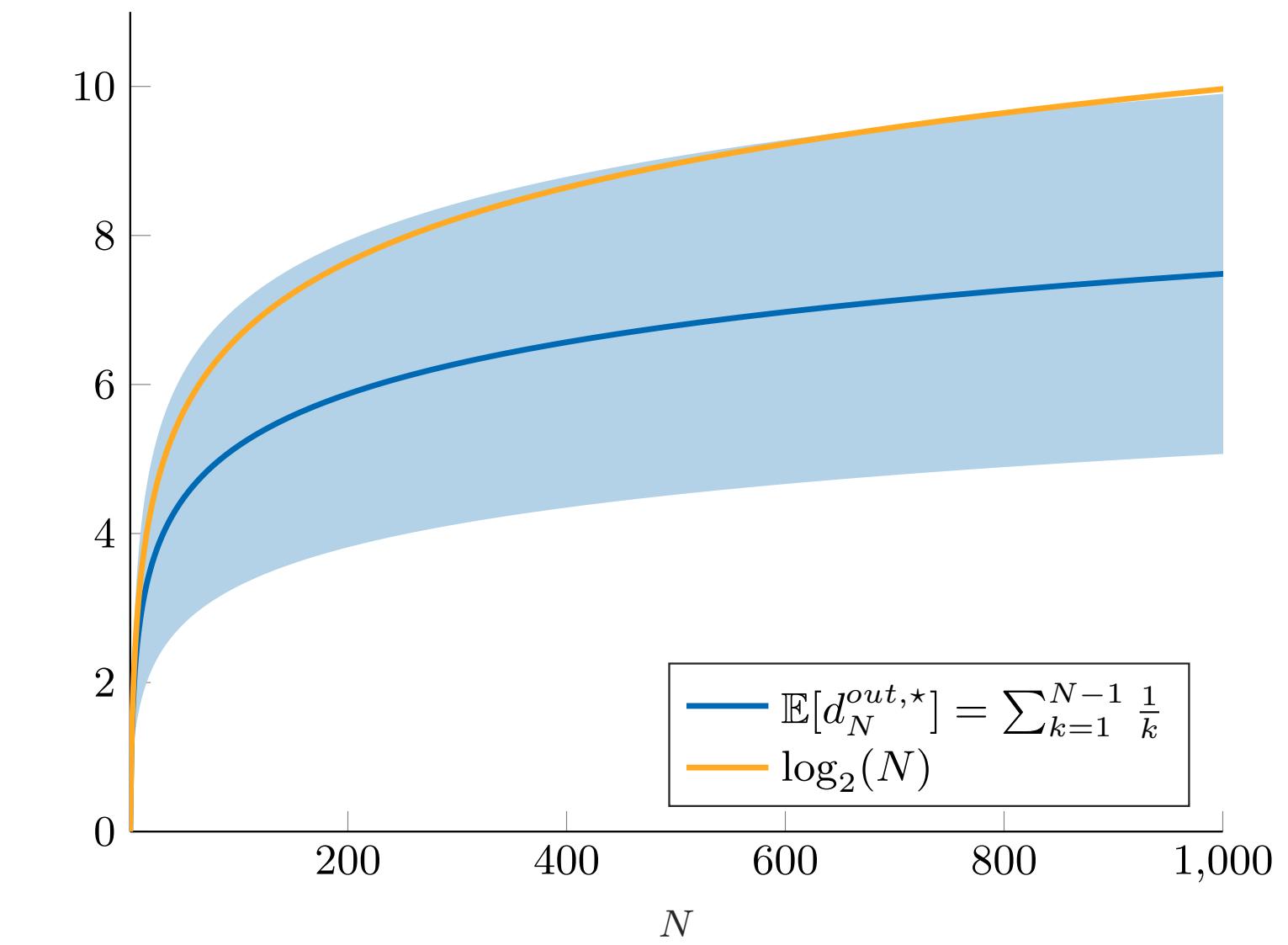


Fig. Theoretical expected outdegree as a function of the number of agents N .

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 - concentrated in the region $d \in [0,10]$;
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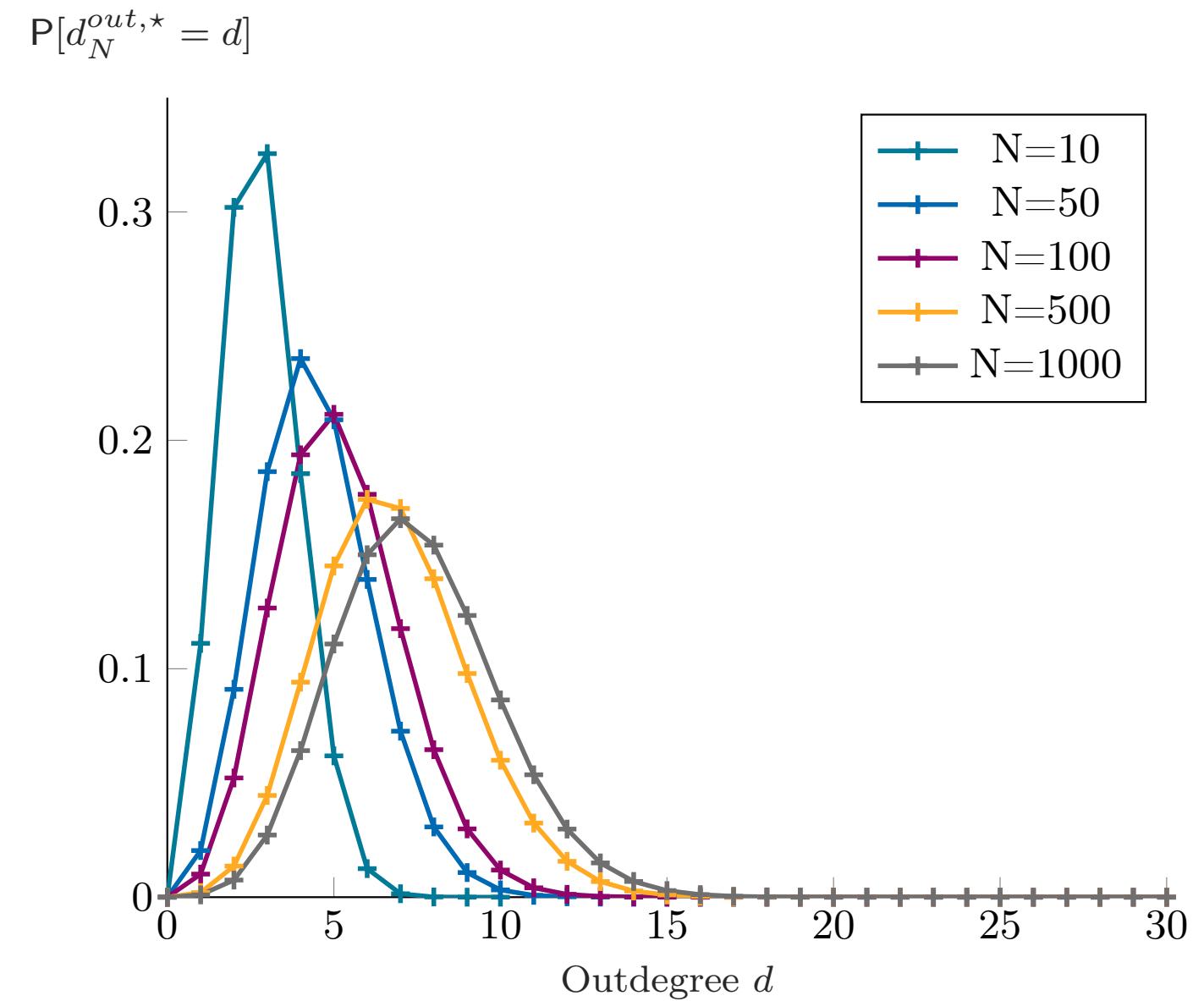


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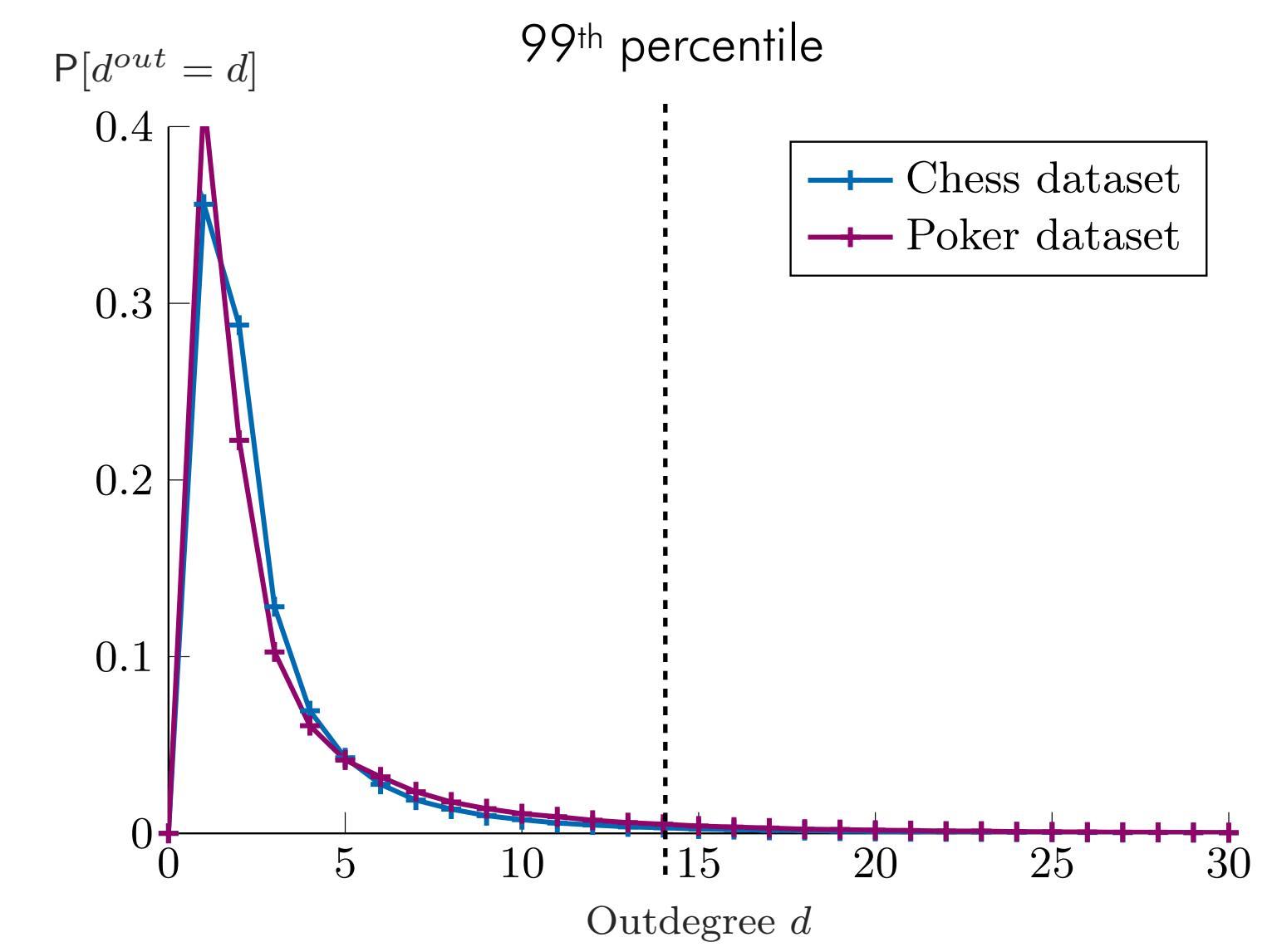


Fig. Empirical distribution of the outdegree in the collected data-sets.

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- This might be the effect of the **recommendation systems**, as it is more pronounced for the followers of the top nodes.

RESULTS

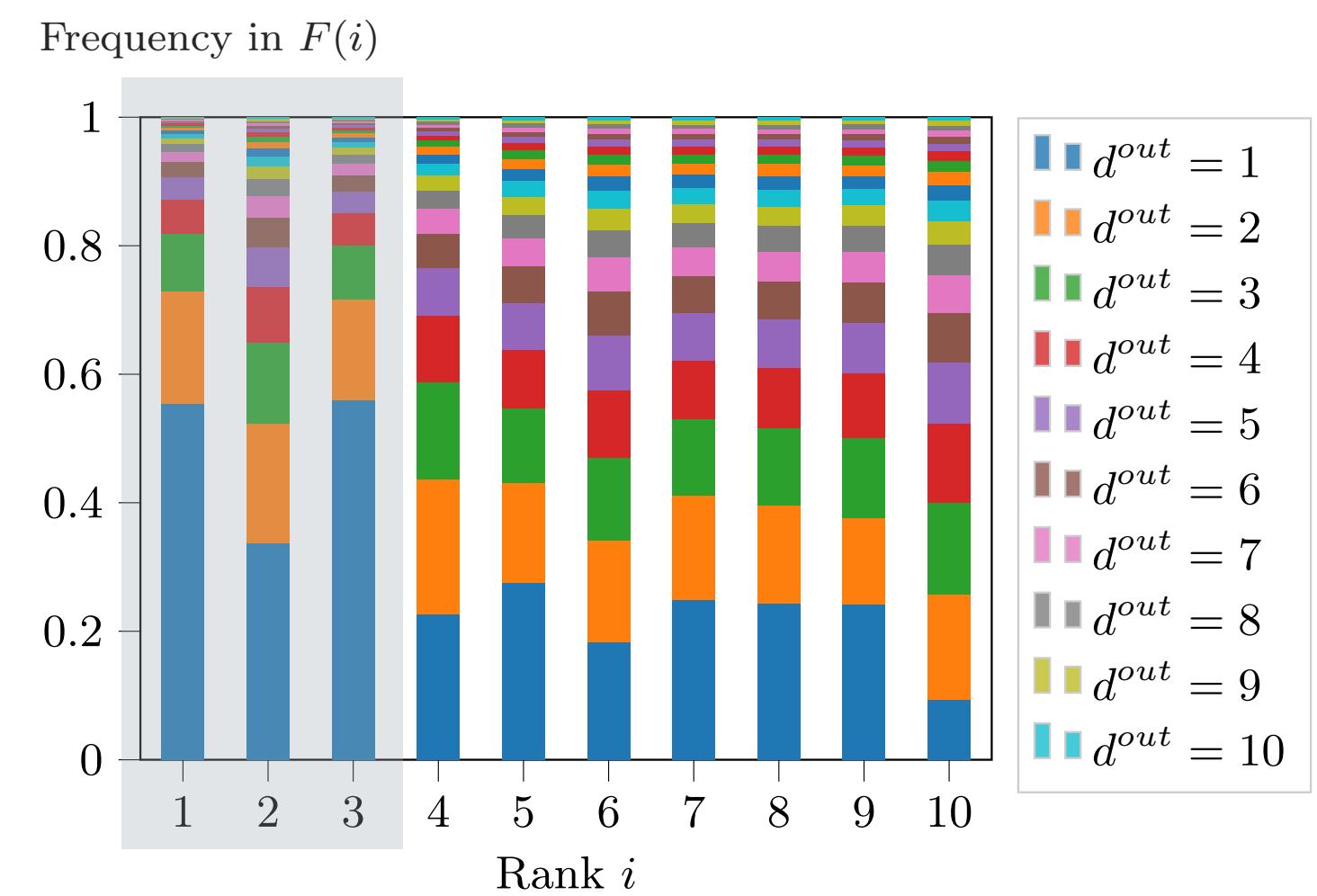


Fig. For each column i , the **empirical** distribution of the outdegree of the followers of node i (in the collected data-sets).

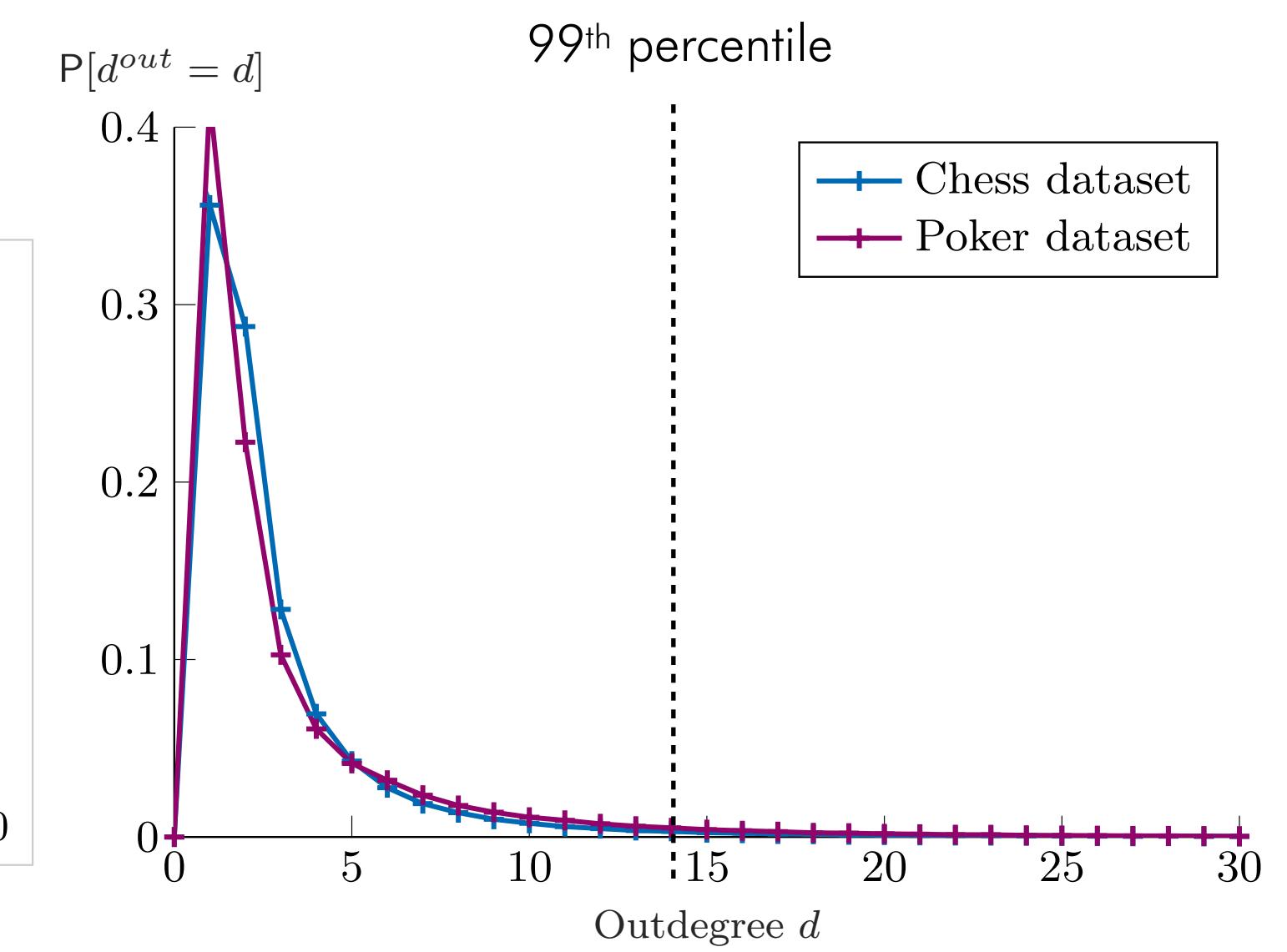


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CONCLUSIONS

SUMMARY AND OPEN DIRECTIONS

- We proposed a **quality-based** approach to model the social network formation on **UGC-based platforms**.
- We numerically **simulated** the dynamics and we studied the **theoretical properties** of the network dynamics and equilibria in terms of:
 - Indegree and Outdegree distribution;
 - Audience Overlap Index.
- Our results are cross-validated with two data-sets collected from the **Twitch** platform.
- The simple quality-based rule leads to a **Zipf's law** in the expected indegree of the **social media influencers**.

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- Study the network properties in terms of, e.g., **information spreading**, environmentally friendly habits adoption, ...
- Validate the model through **longitudinal** network data and potentially enrich the quality-based rule.
- Combine quality attributes with **socio-strategic incentives**.
- Model the role of the platforms' **recommendation systems** and study the interplay between individuals' and platforms' behavior.



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Dr. Wenjun Mei



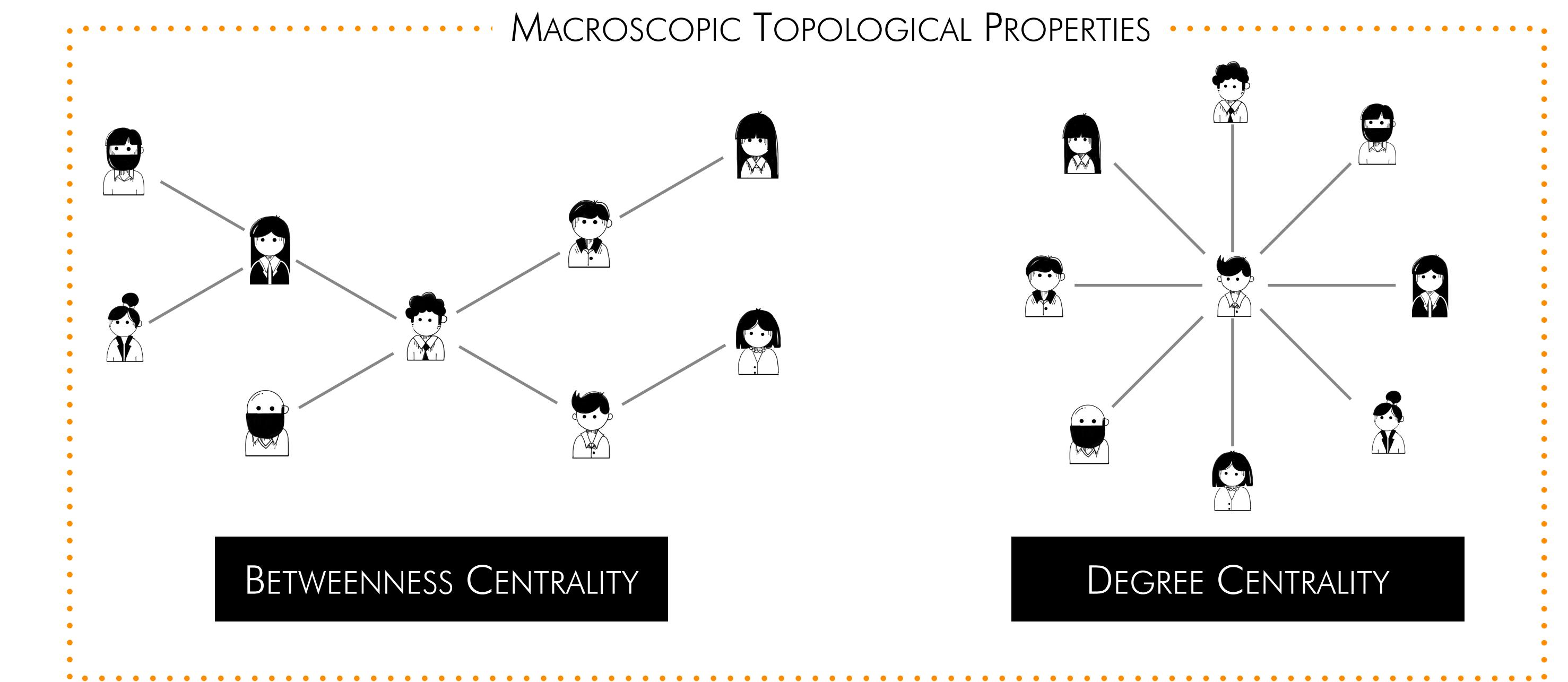
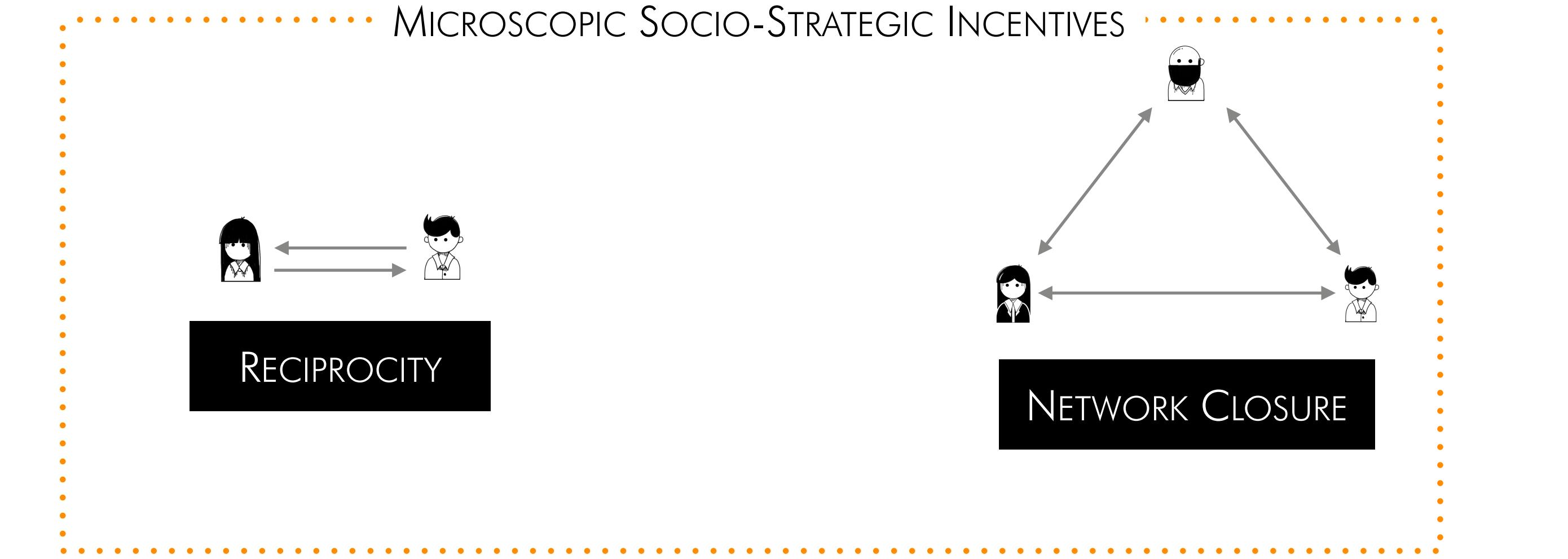
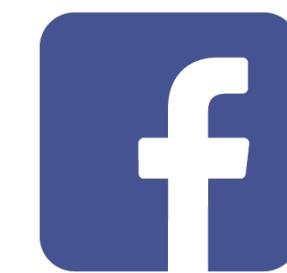
Prof. Florian Dörfler



BACK UP SLIDES

MOTIVATION

- Online Social Networks are ubiquitous.
- Researchers from different communities have started considering the problem of **Social Network Formation**.
- “Old-generation” Online Social Networks try to mimic offline Social Networks.



THEORETICAL RESULTS

THEOREM.

The probability of node i having indegree $d_i^{in}(t) = d \in [0, N-1]$ after t time-steps is given by

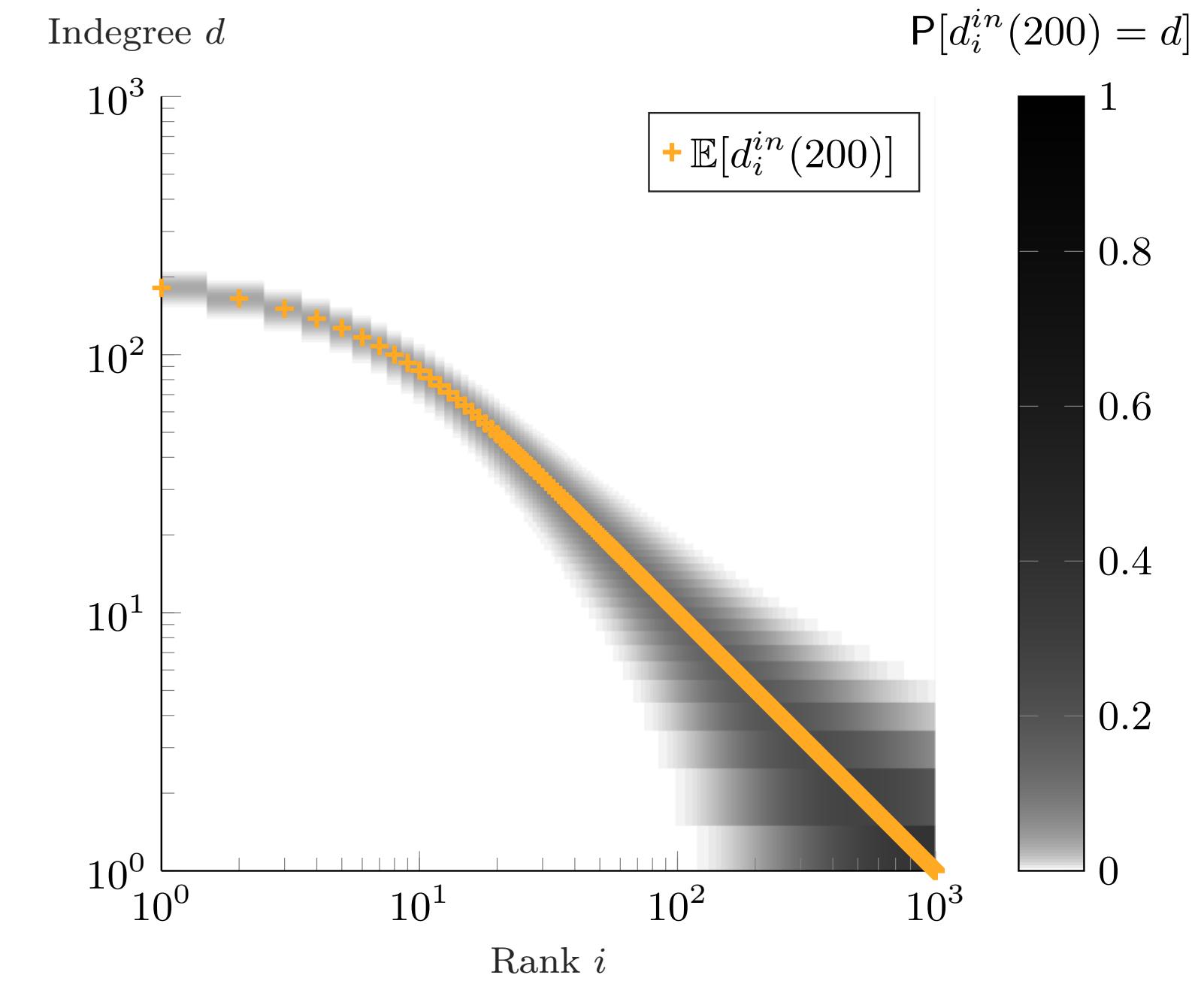
$$\mathbb{P}(d_i^{in}(t) = d) = \sum_{k=0}^d \binom{i-1}{k} \bar{p}_i^k (1 - \bar{p}_i)^{i-1-k} \binom{N-i}{d-k} \underline{p}_i^{d-k} (1 - \underline{p}_i)^{N-i-(d-k)},$$

where we omitted the time-step dependency on \bar{p}_i and \underline{p}_i and:

$$\mathbb{P}(a_{ji}(t) = 1) = \begin{cases} \bar{p}_i(t) := \frac{1}{i-1} \left(1 - \left(\frac{N-i}{N-1} \right)^t \right), & \text{if } j < i \\ \underline{p}_i(t) := \frac{1}{i} \left(1 - \left(\frac{N-i-1}{N-1} \right)^t \right), & \text{if } j > i. \end{cases}$$

Thus, the expected indegree of node i after t time-steps reads as:

$$\mathbb{E}(d_i^{in}(t)) = \frac{N}{i} - \left(\left(\frac{N-i}{N-1} \right)^t + \frac{N-i}{i} \left(\frac{N-i-1}{N-1} \right)^t \right).$$

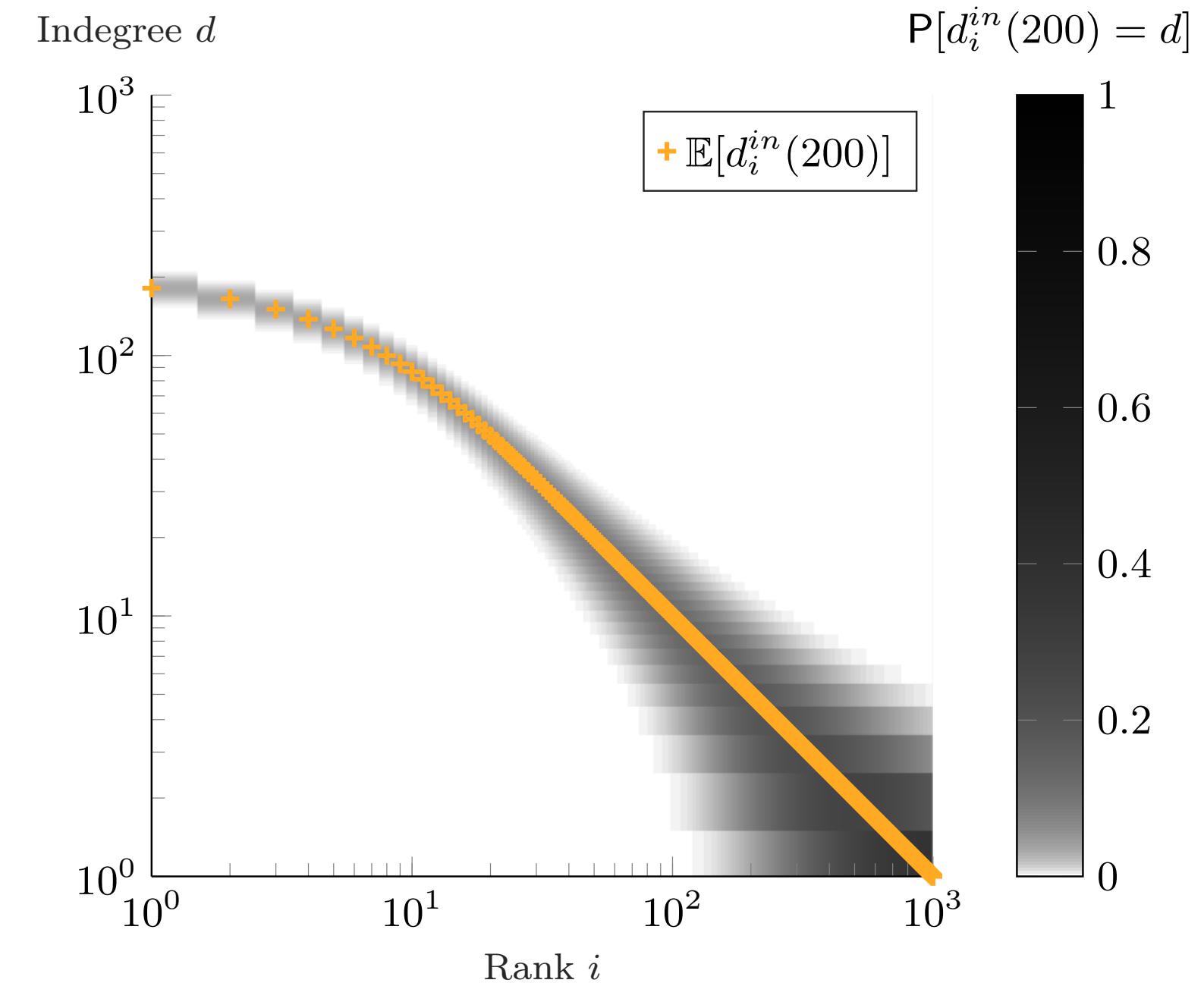
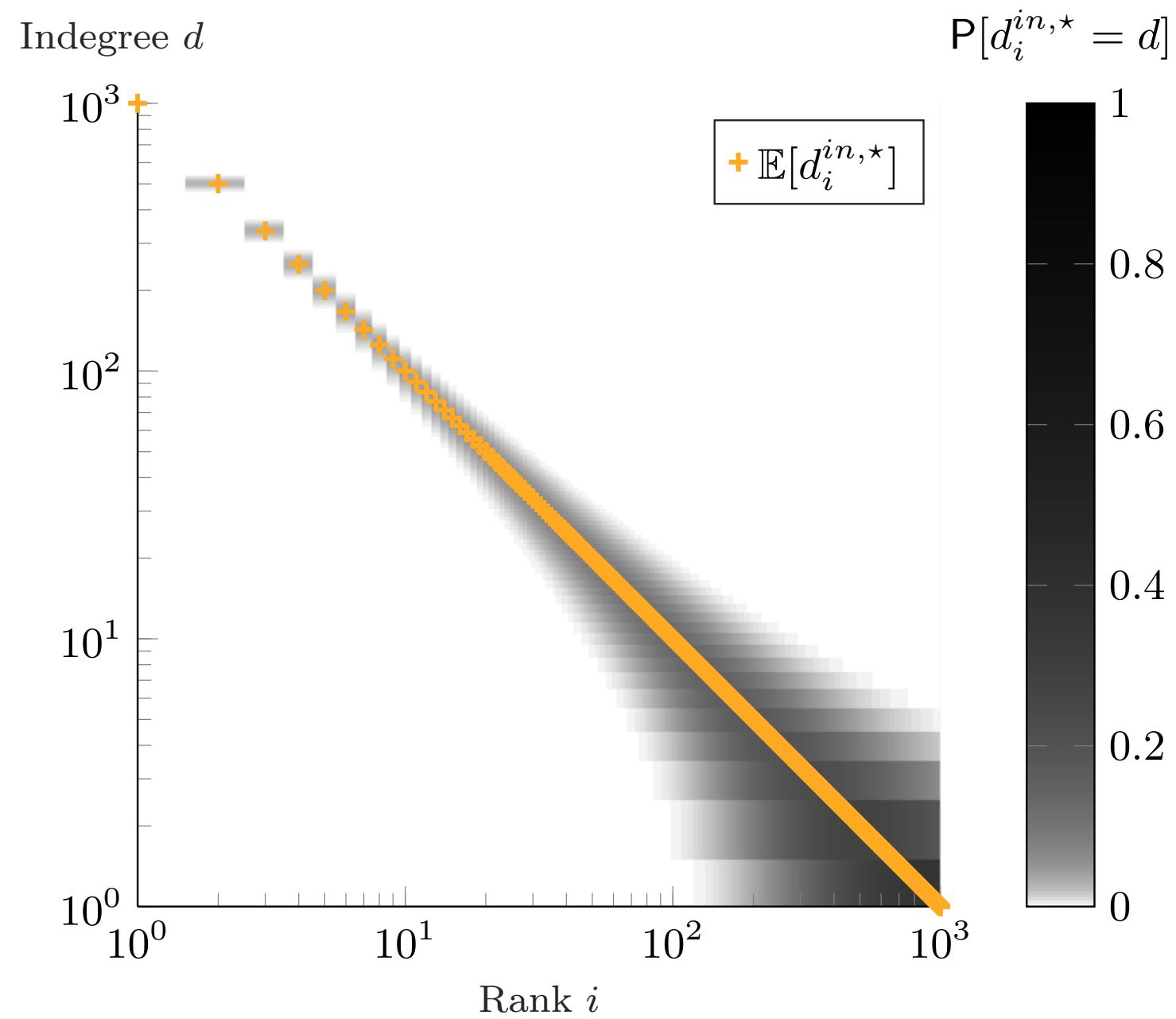


INDEGREE DISTRIBUTION

THEOREM.

At equilibrium, the expected indegree of node i reads as:

$$\mathbb{E}(d_i^{in,\star}) = \begin{cases} N-1, & \text{if } i=1, \\ \frac{N}{i}, & \text{otherwise.} \end{cases}$$



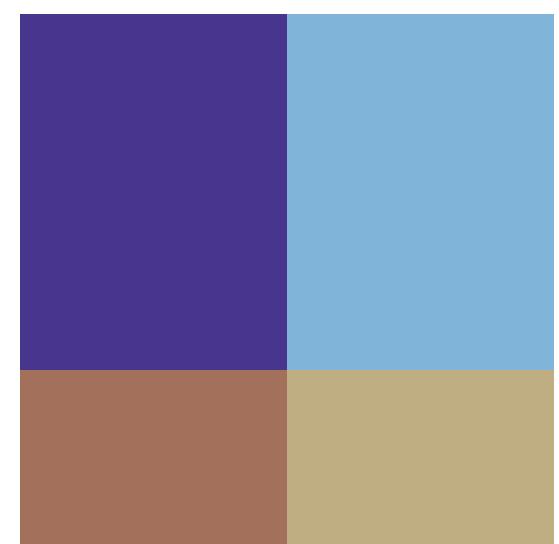
AUDIENCE OVERLAP

DEFINITION.

We define the Audience Overlap index as follows:

$$O(i,j) := \frac{|F(i) \cap F(j)|}{|F(i)|} \in [0,1],$$

if $|F(i)| > 0$, and 0 otherwise, where $F(i)$ denotes the set of followers of i .



$$O(1,2) = 1/2$$

$$O(1,3) = 1/3\dots$$

RESULTS

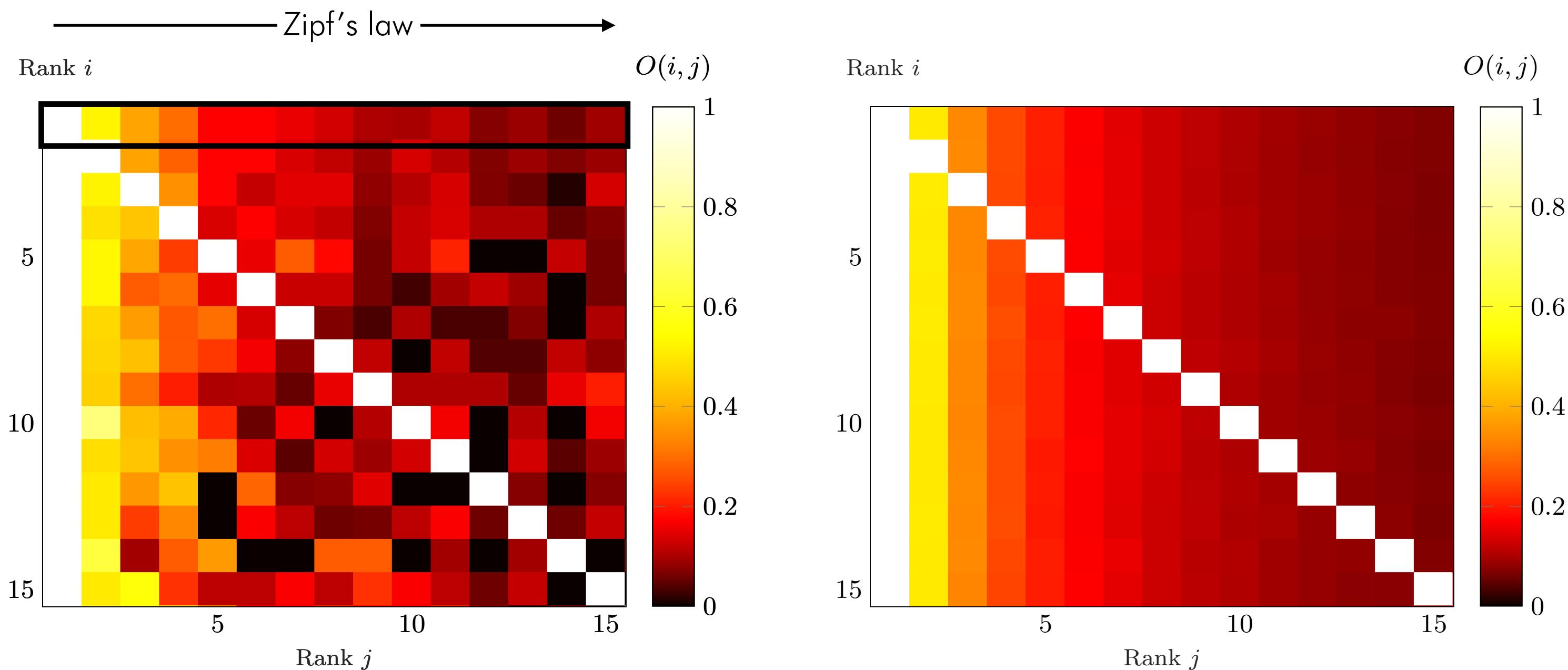


Fig. Numerical results on the followers' overlap among the top nodes. The result is obtained with $N=201$ agents, upon reaching equilibrium.

Fig. Average numerical results on the followers' overlap among the top nodes. The results are obtained from 1000 simulations with $N=201$ agents, upon reaching equilibrium.

AUDIENCE OVERLAP

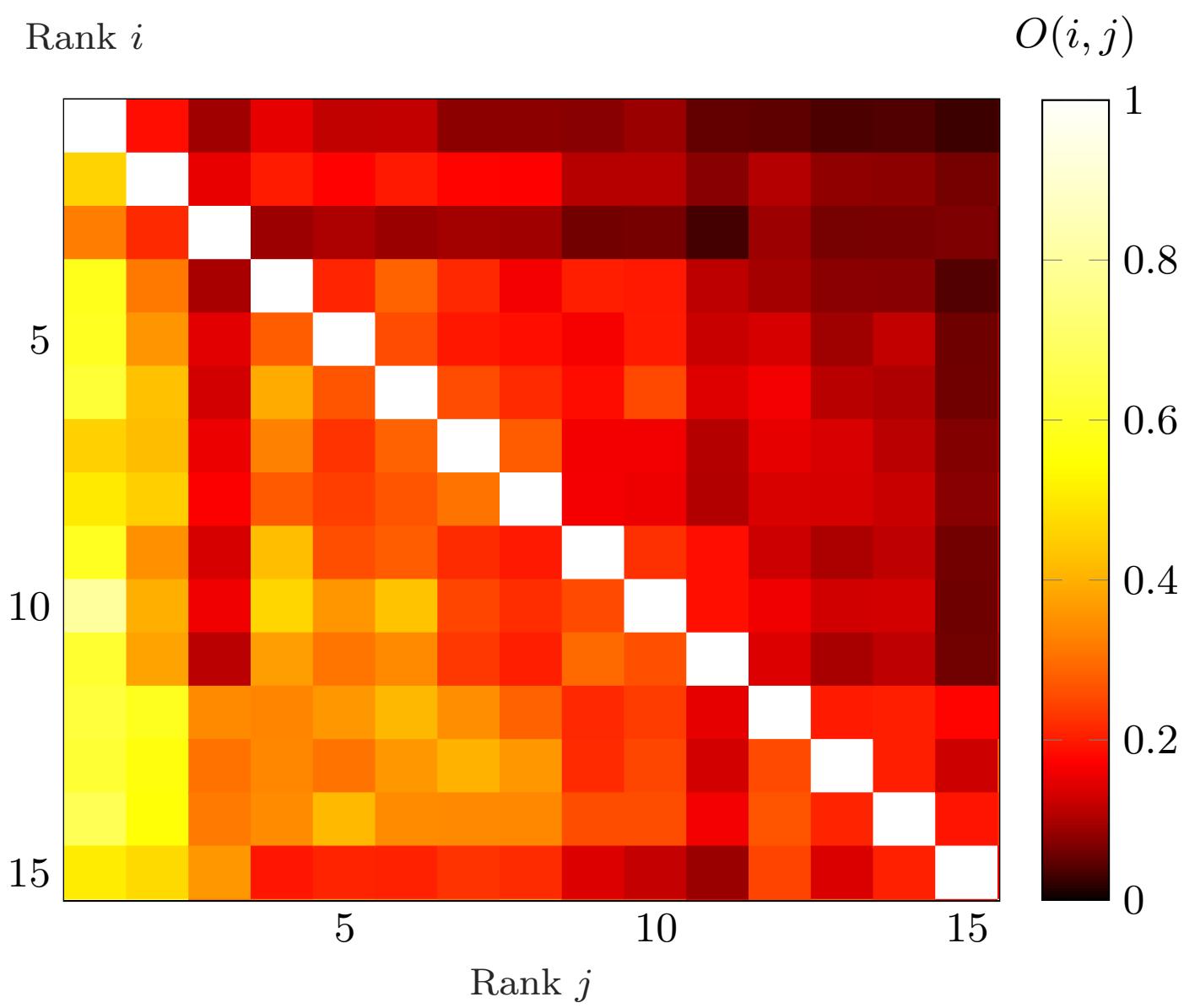


Fig. **Empirical** results from our collected data-set.

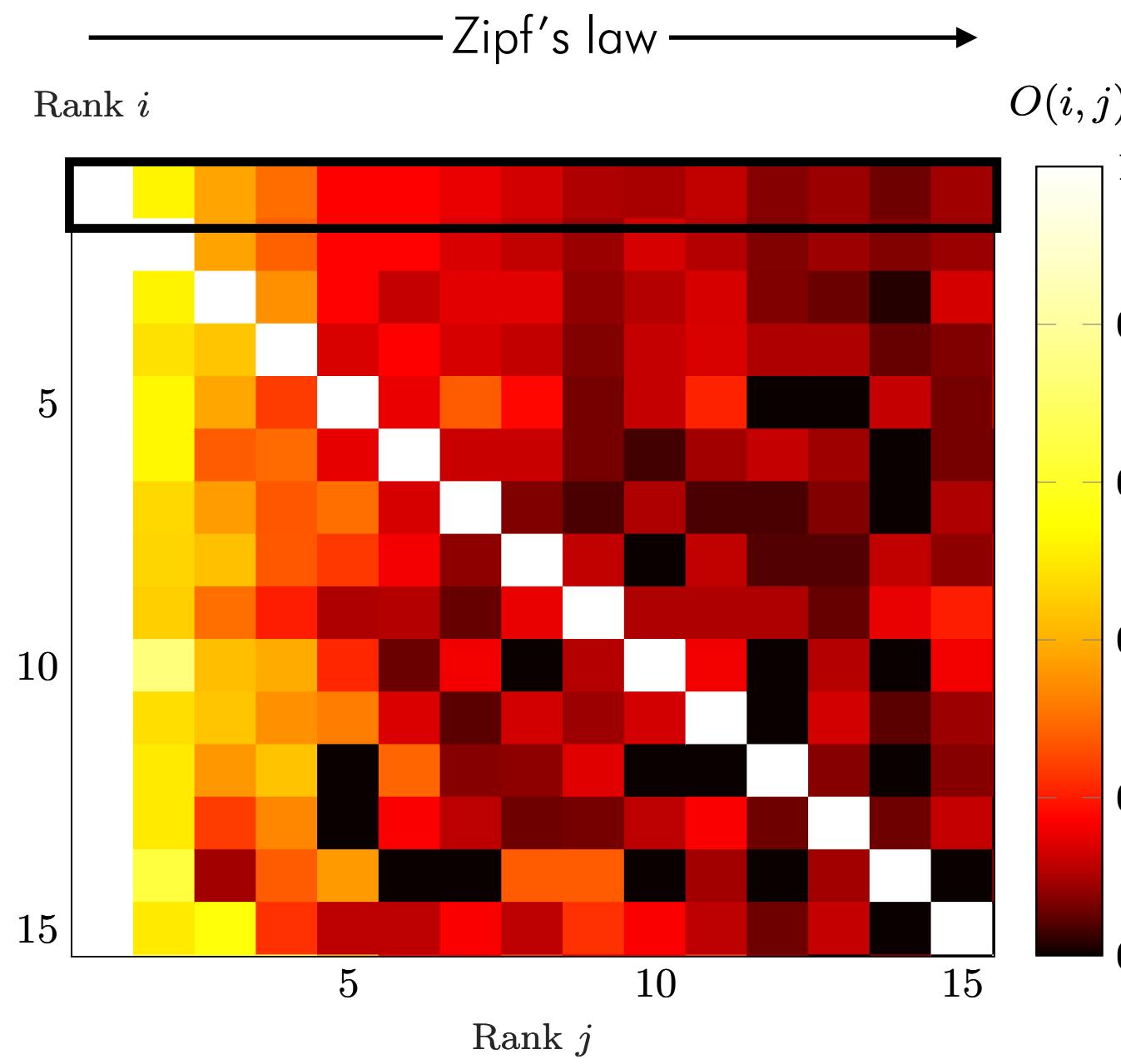


Fig. Numerical results on the followers' overlap among the top nodes. The result is obtained with $N=201$ agents, upon reaching equilibrium.

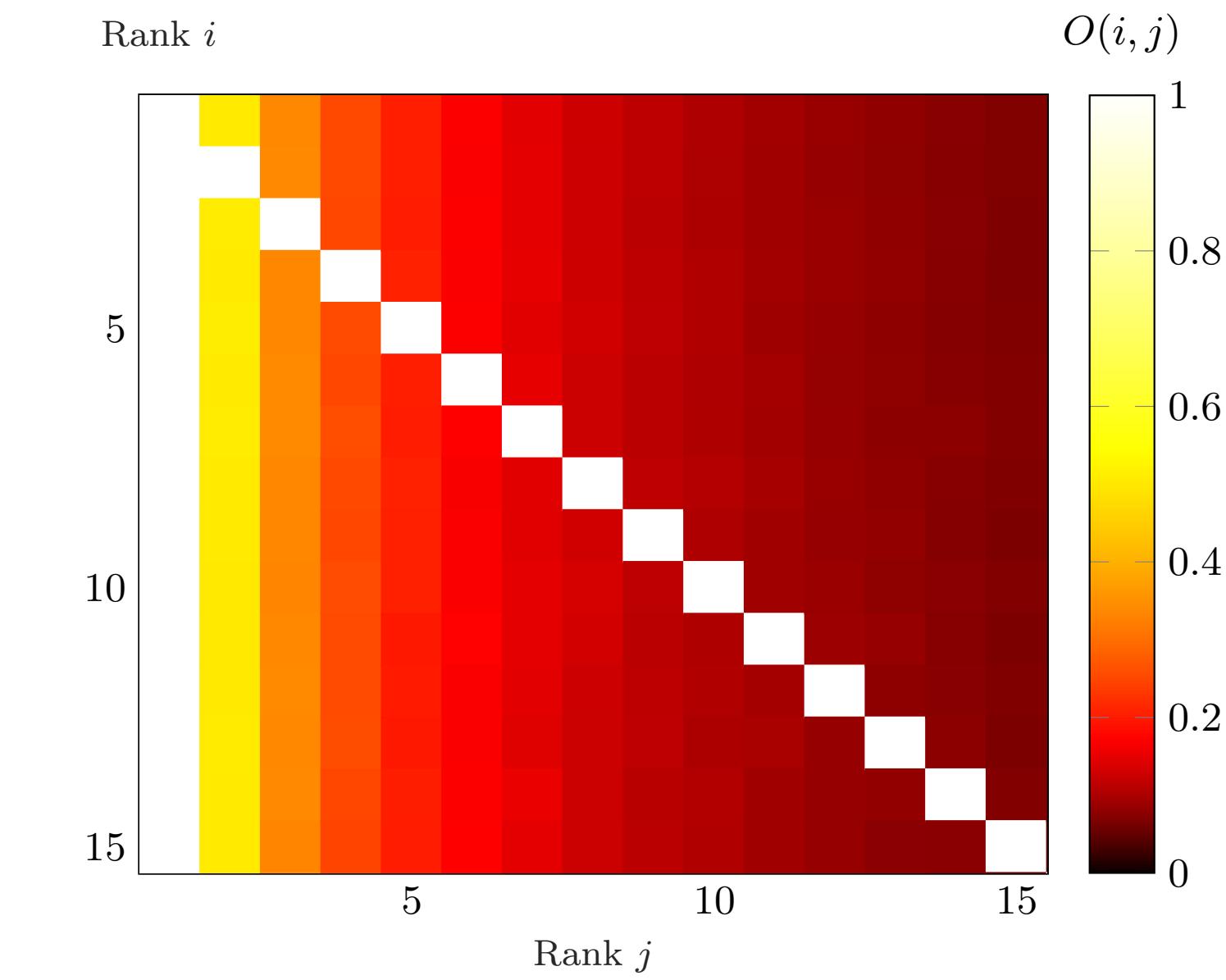


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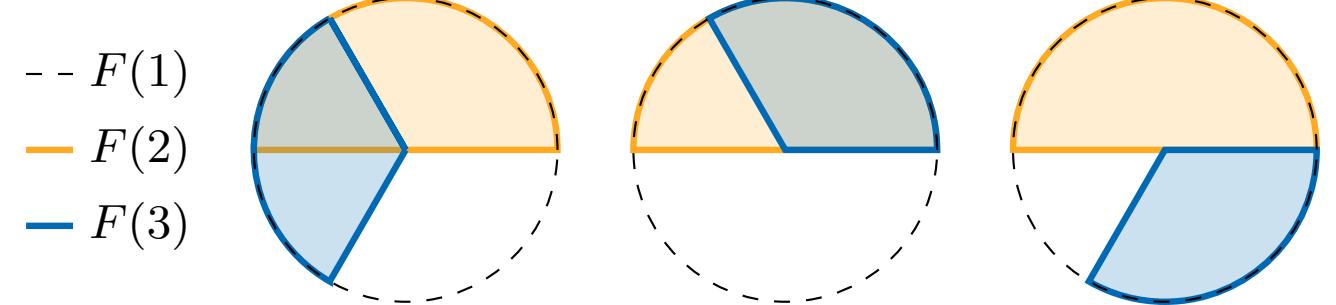


Fig. Sketch of the overlap between the followers' sets of the top 3 nodes.

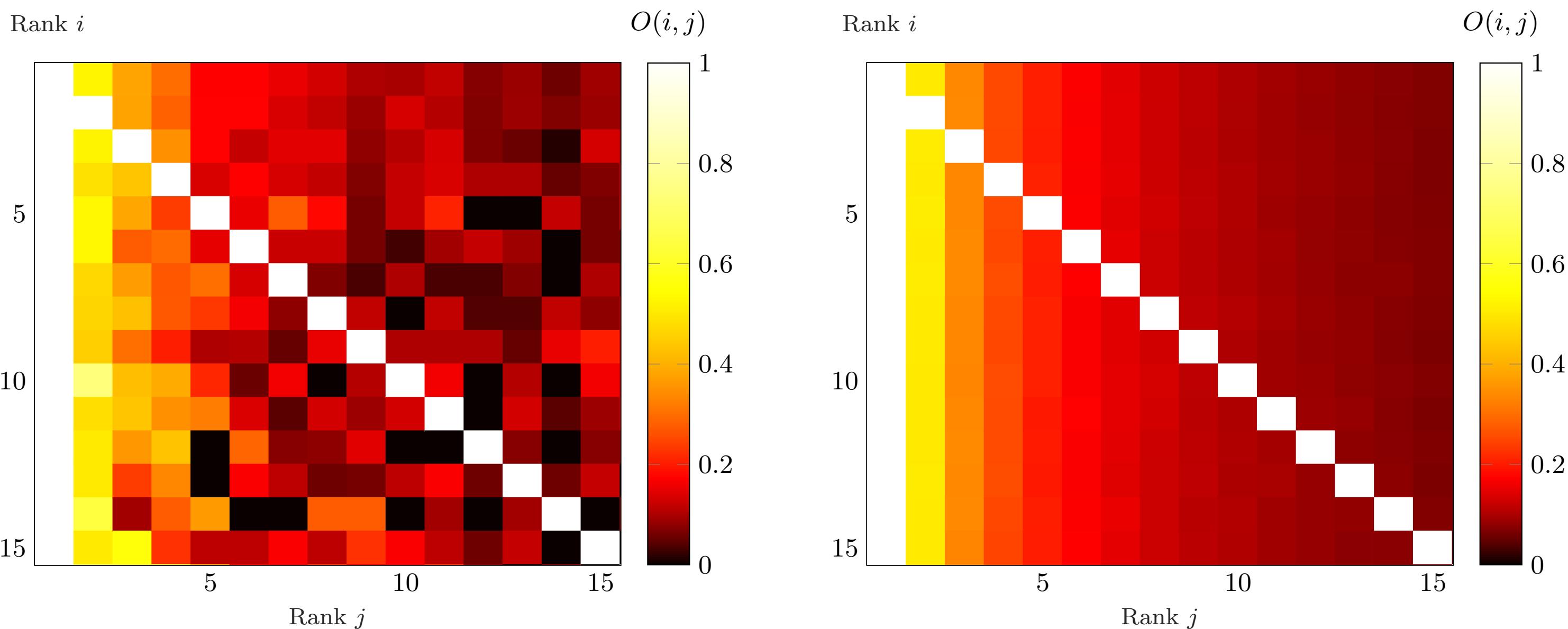
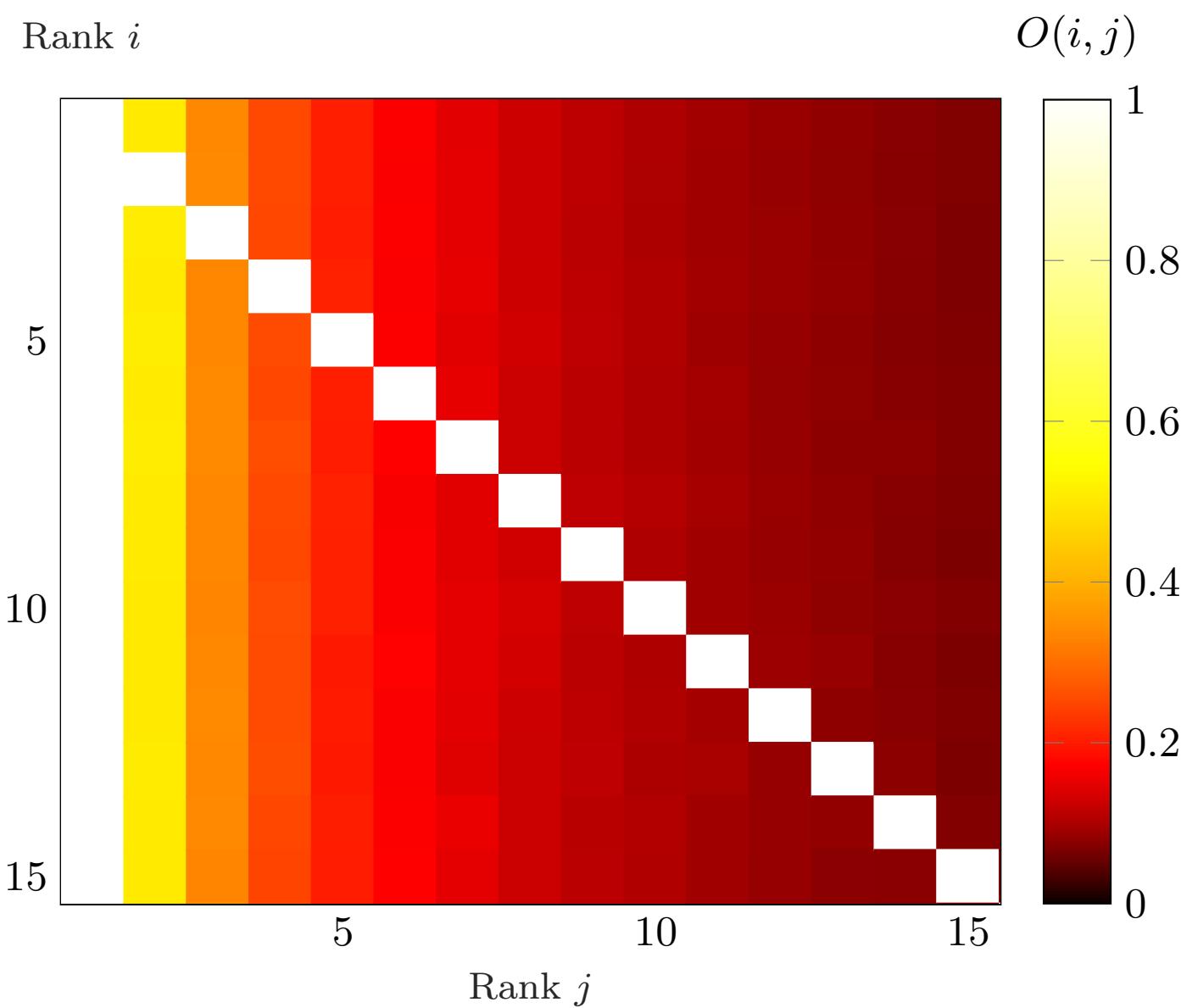


Fig. Numerical results on the followers' overlap among the top nodes. The results are obtained from 1000 simulations with $N=201$ agents, upon reaching equilibrium.

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AUDIENCE OVERLAP

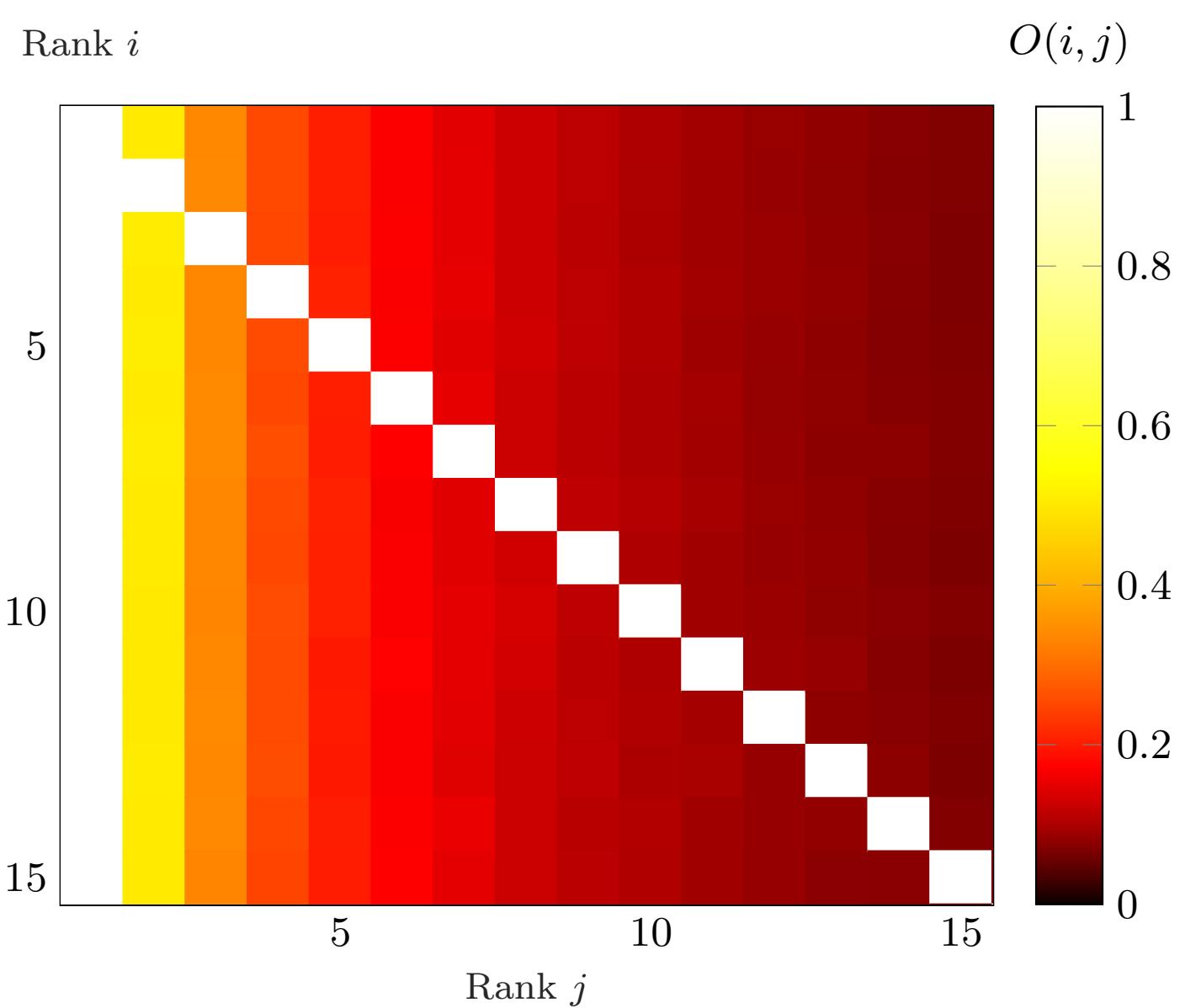


Fig. Average numerical results on the followers' overlap among the top nodes. The results are obtained from 1000 simulations with $N=201$ agents, upon reaching equilibrium.

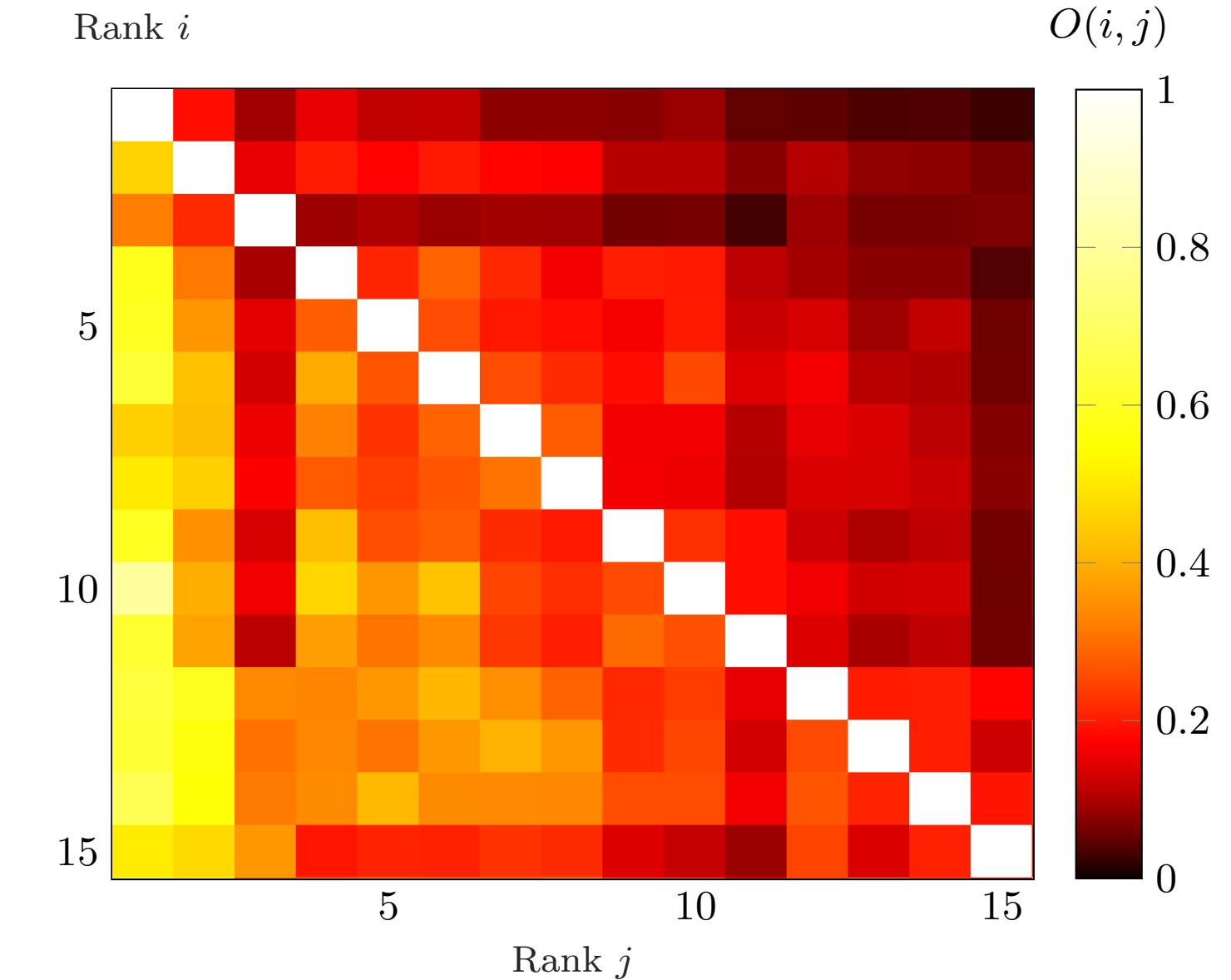


Fig. Average numerical results on the followers' overlap among the top nodes. The results are obtained from our collected data-set.

AUDIENCE OVERLAP

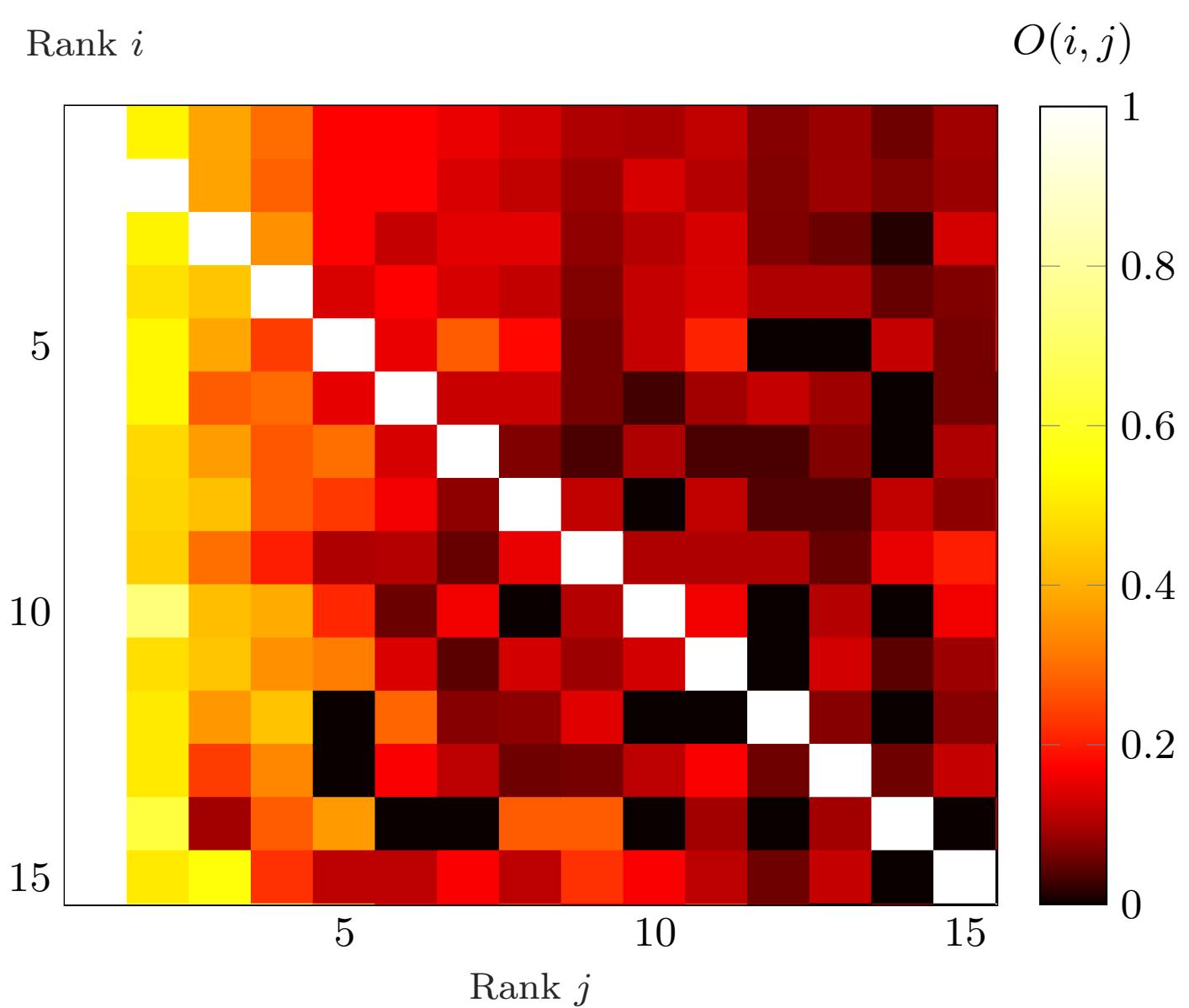


Fig. Numerical results on the followers' overlap among the top nodes. The results are obtained from 1000 simulations with $N=201$ agents, upon reaching equilibrium.

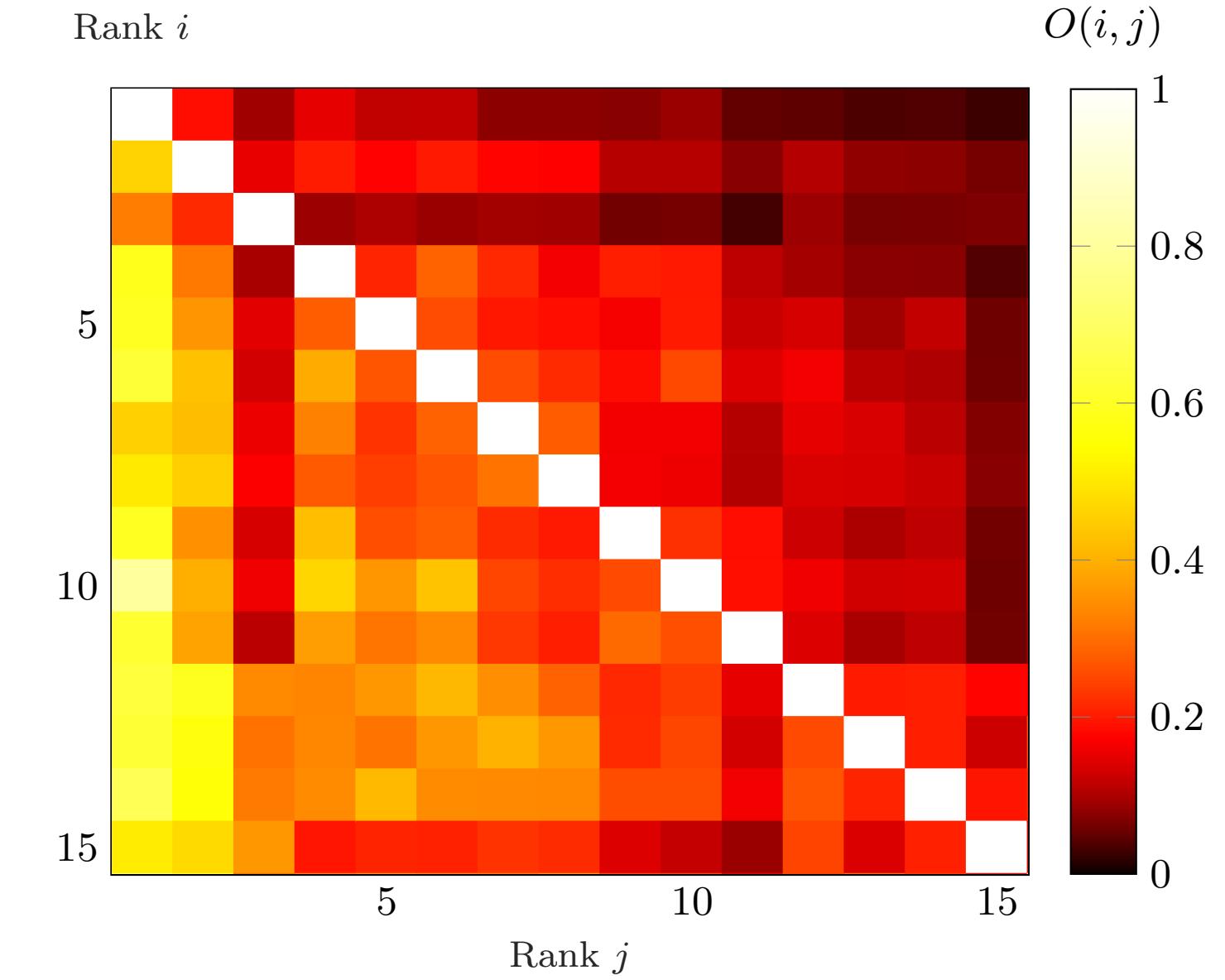


Fig. Average numerical results on the followers' overlap among the top nodes. The results are obtained from our collected data-set.

OUTDEGREE DISTRIBUTION

- The outdegree probability density function is homogeneous for all the nodes.

THEOREM.

The nodes' expected outdegree in a network of $N \geq 2$ agents equals the $(N-1)$ -th harmonic number:

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

- Compared to empirical data, the theoretical distribution seems to underestimate the low-outdegree nodes.
- This might be the effect of the recommendation systems, as it is more pronounced for the followers of the top nodes.

RESULTS

$$\mathbb{P}[d_N^{out,*} = d]$$

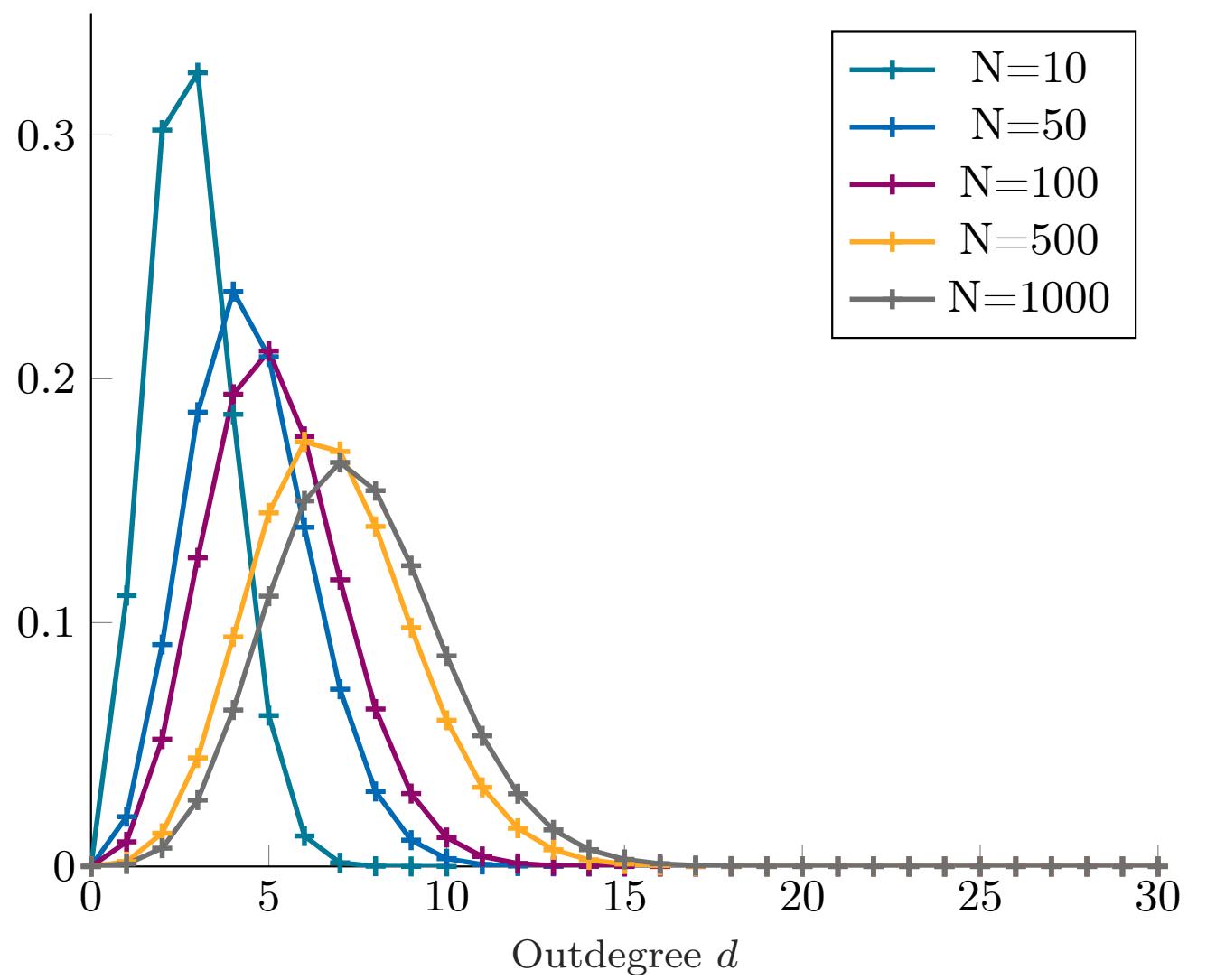


Fig. Analytical outdegree distribution for different network size.

- Simulation Results
- Theoretical Results
- Empirical Results

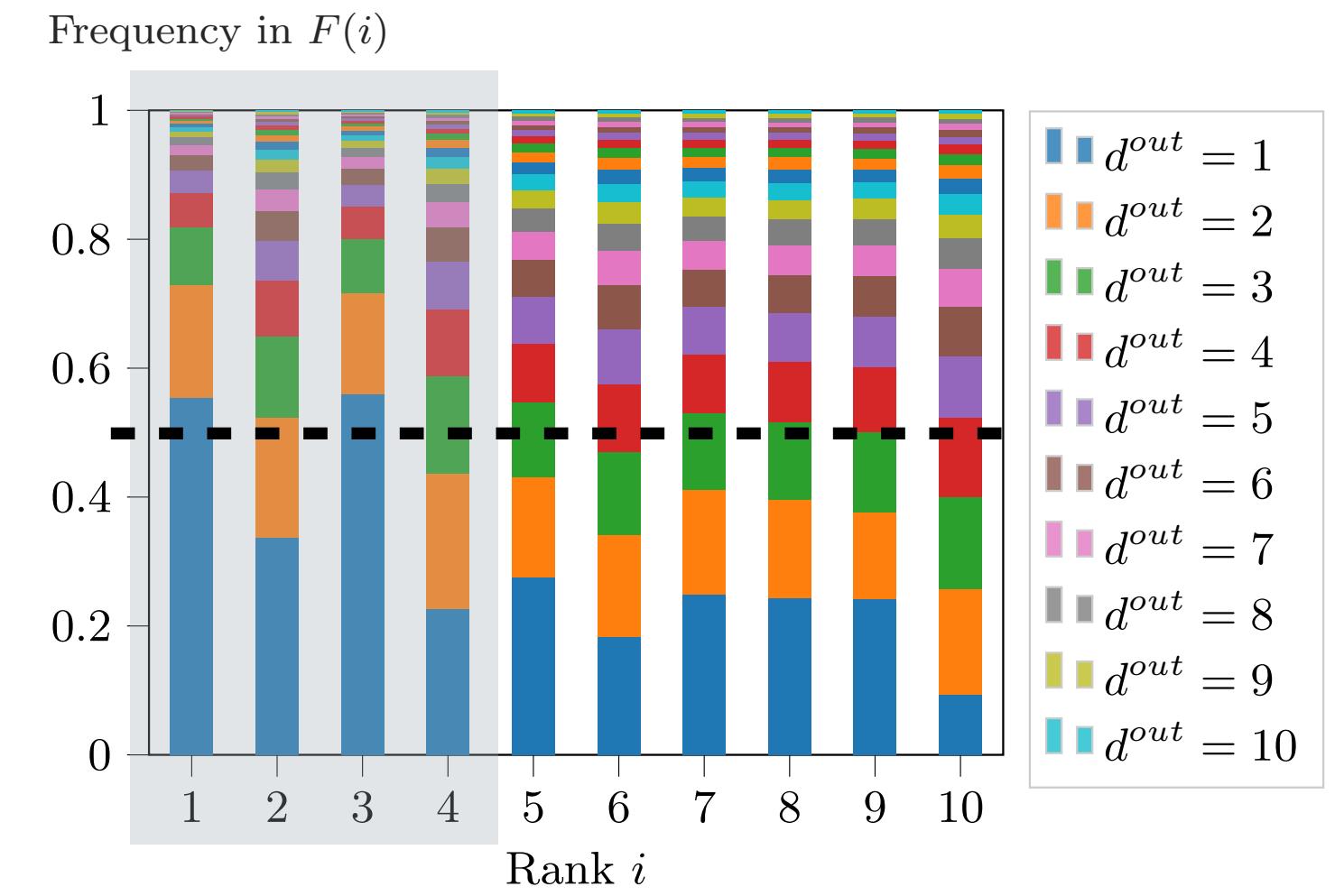


Fig. For each column i , the empirical distribution of the outdegree of the followers of node i (in the collected data-sets).