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# Uncovering Overlap Community Structure in Complex Networks using Particle Competition


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# Introduction

- Communities are defined as a subgraph whose nodes are densely connected within itself but sparsely connected with the rest of the network.
- However, in practice there are common cases where some nodes in a network can belong to more than one community.
  - Example: in a social network of friendship, individuals often belong to several communities:
    - their families,
    - their colleagues,
    - their classmates,
    - etc.
  - These nodes are called overlap nodes, and most known community detection algorithms cannot detect them
  - Uncovering the overlapping community structure of complex networks becomes an important topic in data mining. [1 – 3]

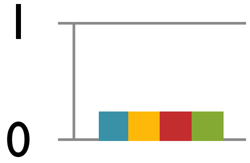

1. Zhang, S.,Wang, R.S., Zhang, X.S.: Identication of overlapping community structure in complex networks using fuzzy c-means clustering. Physica A Statistical Mechanics and its Applications 374 (January 2007) 483-490.
2. Palla, G., Derenyi, I., Farkas, I., Vicsek, T.: Uncovering the overlapping community structure of complex networks in nature and society. Nature 435(7043) (2005) 814-818 .
3. Zhang, S., Wang, R.S., Zhang, X.S.: Uncovering fuzzy community structure in complex networks. Physical Review E (Statistical, Nonlinear, and Soft Matter Physics) 76(4) (2007) 046103.

# Proposed Method

- Particles competition
  - For possession of nodes of the network
  - Rejecting intruder particles
- Objectives
  - Detect community structure
  - Uncover overlap community structure

# Initial Configuration

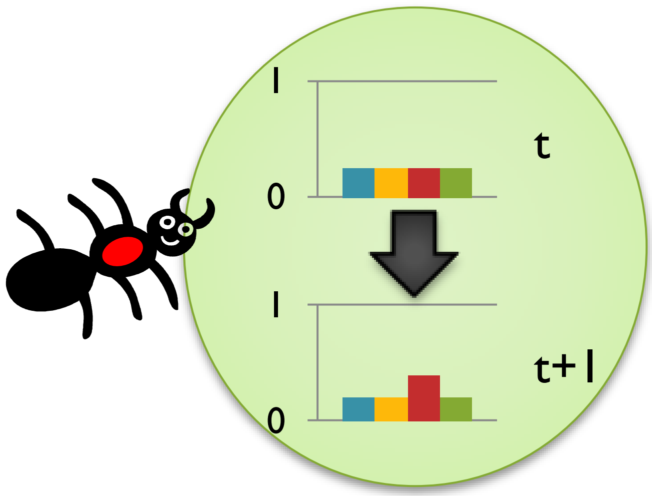
- A particle is generated for each community to be detected
- Nodes have an ownership vector
  - Initially, nodes have levels set equally for each particle
    - Ex: [ 0.25 0.25 0.25 0.25 ] (4 classes)




- Particles initial position is set randomly.

# Node Dynamics

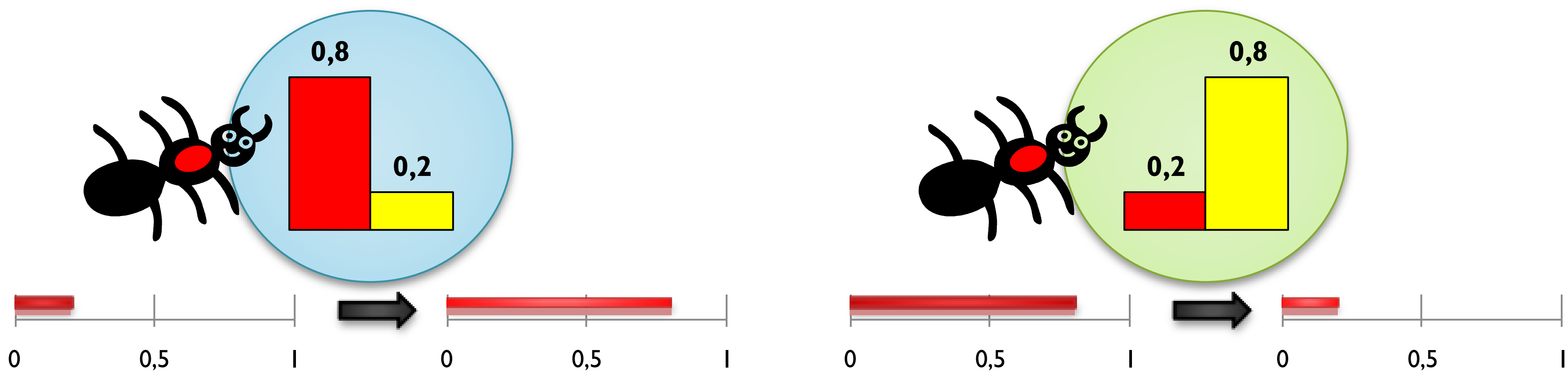
- When a particle selects a neighbor to visit:
  - It decreases the ownership level of other particles
  - It increases its own ownership level




$$v_i^{\omega_k}(t+1) = \begin{cases} \max\{\omega_{\min}, v_i^{\omega_k}(t) - \frac{\Delta_v \rho_j^{\omega}(t)}{c-1}\} & \text{if } k \neq j \\ v_i^{\omega_k}(t) + \sum_{q \neq k} v_i^{\omega_q}(t) - v_i^{\omega_q}(t+1) & \text{if } k = j \end{cases}$$

# Particle Dynamics

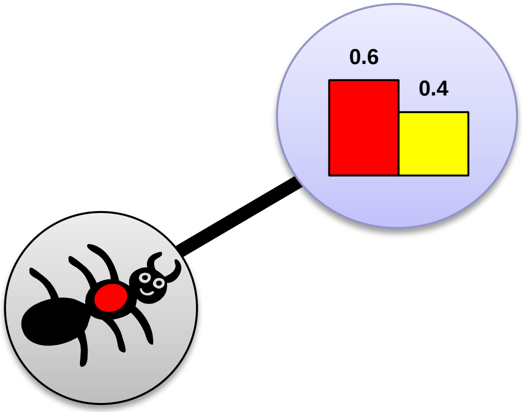
- A particle will get:
  - stronger when it is targeting a node being dominated by it
  - weaker when it is targeting a node dominated by other particles

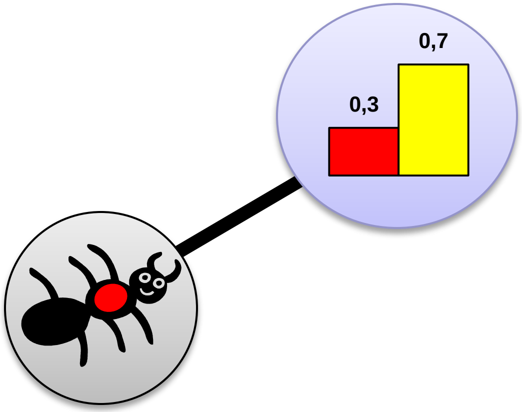



$$\rho_j^{\omega}(t+1) = \rho_j^{\omega}(t) + \Delta_{\rho}(v_i^{\omega_j}(t+1) - \rho_j^{\omega}(t))$$

# Particles Walk

- Shocks
  - A particle really visits a target node only if its ownership level on that node is higher than others;
  - otherwise, a shock happens and the particle stays at the current node until next iteration.
- How a particle chooses a neighbor node to target?
  - Random walk
  - Deterministic walk



# Random-deterministic walk

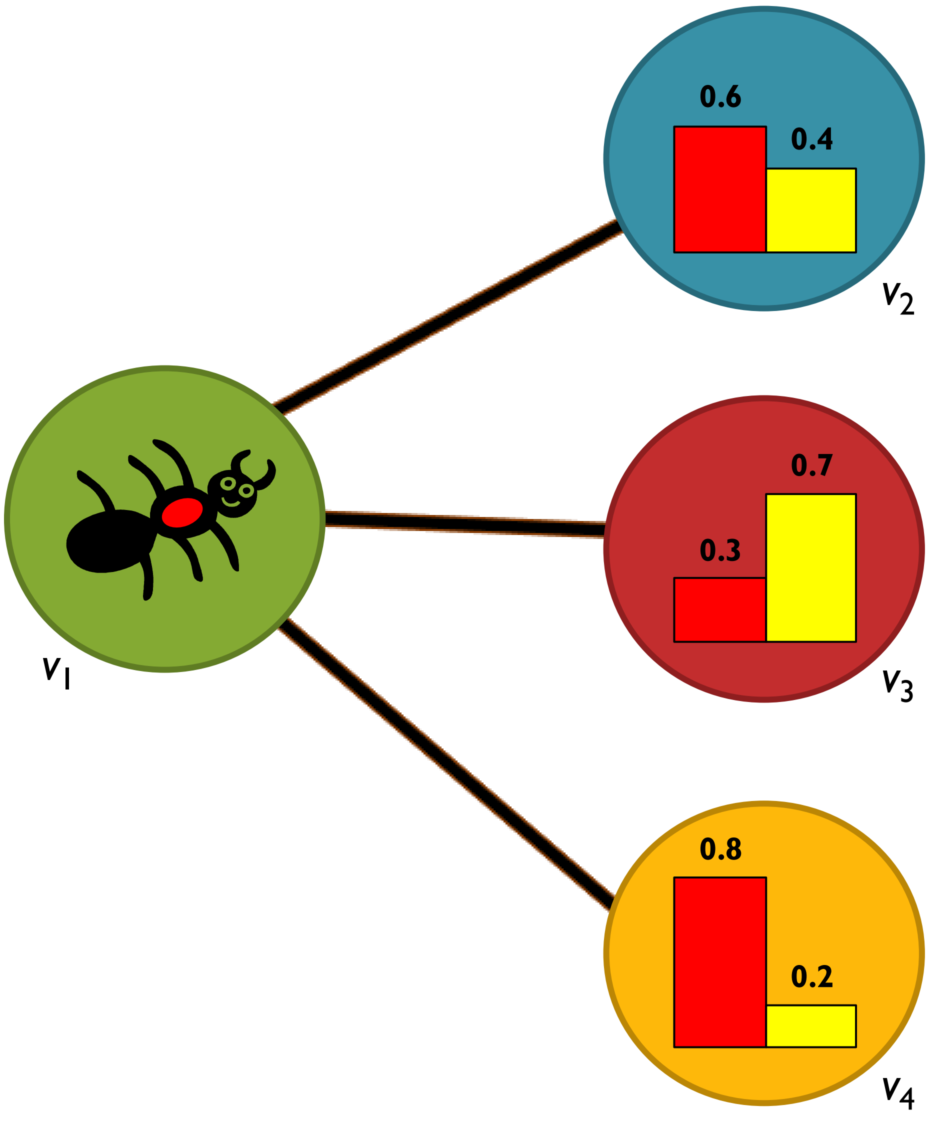
- Random walk
  - The particle randomly chooses any neighbor to visit with no concern about ownership levels

$$p(v_i|\rho_j) = \frac{W_{ki}}{\sum_{q=1}^{n} W_{qi}}$$

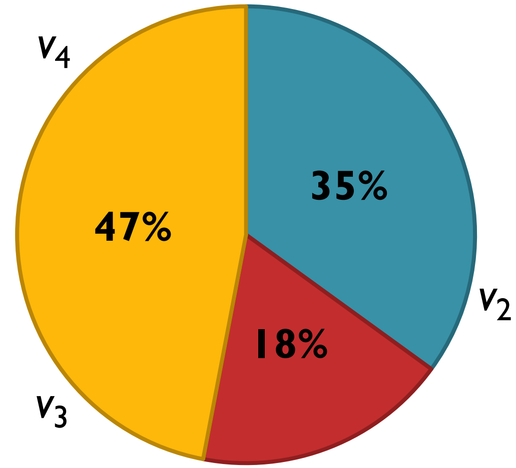
- Deterministic walk
  - The particle will prefer visiting nodes that it already dominates

$$p(v_i|\rho_j) = \frac{W_{ki} v_i^{\omega_j}}{\sum_{q=1}^{n} W_{qi} v_i^{\omega_j}}$$

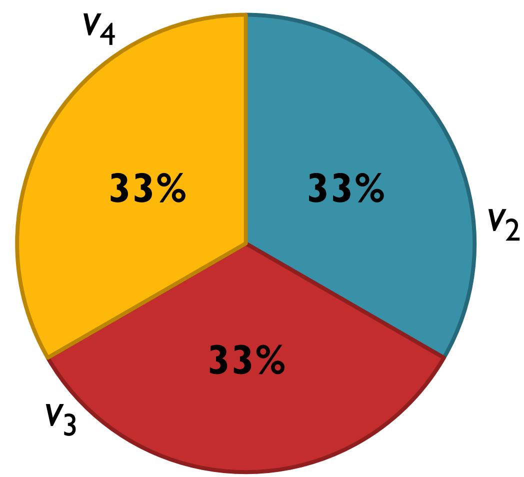
**The particles must exhibit both movements in order to achieve an equilibrium between exploratory and defensive behavior**




**Deterministic Moving Probabilities**




**Random Moving Probabilities**



# Fuzzy Output

- Instantaneous ownership levels
  - Very volatile under certain conditions
    - In overlap nodes the dominating team changes frequently
    - Levels do not correspond to overlap measures
- Long-term ownership levels
  - Temporal averaged domination level for each team at each node
    - Weighted by particle strength
    - Considers only the random movements

$$v_i^{\lambda_j}(t+1) = v_i^{\lambda_j}(t) + \rho_j^{\omega}(t)$$

# Fuzzy Output

- At the end of the iterations, the degrees of membership for each node are calculated using the long term ownership levels

$$f_i^j = \frac{{v_i}^{\lambda_j}(\infty)}{\sum_{q=1}^{c} {v_i}^{\lambda_q}(\infty)}$$

# Algorithm

1) Build the adjacency matrix,
2) Set nodes domination levels,
3) Set initial positions of particles randomly and set particle strength
4) Repeat steps 5 to 8 until convergence or until a predefined number of steps has been achieved,
5) For each particle, complete steps 6 to 8,
6) Select the target node by using the combined random-deterministic rule,
7) Update target node domination levels,
8) Update particle strength,
9) Calculate the membership levels (fuzzy classication) based on long-term ownership levels

# COMPUTER SIMULATIONS

| Connections | Fuzzy Classification | | | |
|---|---|---|---|---|
| A-B-C-D | A | B | C | D |
| 16-0-0-0 | 0.9928 | 0.0017 | 0.0010 | 0.0046 |
| 15-1-0-0 | 0.9210 | 0.0646 | 0.0079 | 0.0065 |
| 14-2-0-0 | 0.8520 | 0.1150 | 0.0081 | 0.0248 |
| 13-3-0-0 | 0.8031 | 0.1778 | 0.0107 | 0.0084 |
| 12-4-0-0 | 0.7498 | 0.2456 | 0.0032 | 0.0014 |
| 11-5-0-0 | 0.6875 | 0.3101 | 0.0016 | 0.0008 |
| 10-6-0-0 | 0.6211 | 0.3577 | 0.0111 | 0.0101 |
| 9-7-0-0 | 0.5584 | 0.4302 | 0.0011 | 0.0103 |
| 8-8-0-0 | 0.4949 | 0.4944 | 0.0090 | 0.0017 |
| 8-4-4-0 | 0.5025 | 0.2493 | 0.2461 | 0.0021 |
| 7-4-4-1 | 0.4397 | 0.2439 | 0.2491 | 0.0672 |
| 6-4-4-2 | 0.3694 | 0.2501 | 0.2549 | 0.1256 |
| 5-4-4-3 | 0.3144 | 0.2491 | 0.2537 | 0.1828 |
| 4-4-4-4 | 0.2512 | 0.2506 | 0.2504 | 0.2478 |

Table 1. Fuzzy classification of a node connected to network with 4 communities generated with $z_{out}/k = 0.125$

| Connections | Fuzzy Classification | | | |
|---|---|---|---|---|
| A-B-C-D | A | B | C | D |
| 16-0-0-0 | 0.9912 | 0.0027 | 0.0024 | 0.0037 |
| 15-1-0-0 | 0.9318 | 0.0634 | 0.0026 | 0.0023 |
| 14-2-0-0 | 0.8715 | 0.1219 | 0.0023 | 0.0044 |
| 13-3-0-0 | 0.8107 | 0.1827 | 0.0036 | 0.0030 |
| 12-4-0-0 | 0.7497 | 0.2437 | 0.0044 | 0.0022 |
| 11-5-0-0 | 0.6901 | 0.3036 | 0.0034 | 0.0029 |
| 10-6-0-0 | 0.6298 | 0.3654 | 0.0020 | 0.0028 |
| 9-7-0-0 | 0.5584 | 0.4360 | 0.0026 | 0.0030 |
| 8-8-0-0 | 0.4952 | 0.4985 | 0.0027 | 0.0036 |
| 8-4-4-0 | 0.5060 | 0.2485 | 0.2427 | 0.0028 |
| 7-4-4-1 | 0.4442 | 0.2477 | 0.2429 | 0.0652 |
| 6-4-4-2 | 0.3762 | 0.2465 | 0.2514 | 0.1259 |
| 5-4-4-3 | 0.3178 | 0.2500 | 0.2473 | 0.1849 |
| 4-4-4-4 | 0.2470 | 0.2518 | 0.2489 | 0.2523 |

Table 2. Fuzzy classification of a node connected to network with 4 communities generated with $z_{out}/k = 0.250$

| Connections | Fuzzy Classification | | | |
|---|---|---|---|---|
| A-B-C-D | A | B | C | D |
| 16-0-0-0 | 0.9709 | 0.0092 | 0.0108 | 0.0091 |
| 15-1-0-0 | 0.9160 | 0.0647 | 0.0093 | 0.0101 |
| 14-2-0-0 | 0.8571 | 0.1228 | 0.0104 | 0.0097 |
| 13-3-0-0 | 0.8008 | 0.1802 | 0.0100 | 0.0090 |
| 12-4-0-0 | 0.7422 | 0.2385 | 0.0095 | 0.0098 |
| 11-5-0-0 | 0.6825 | 0.2958 | 0.0123 | 0.0093 |
| 10-6-0-0 | 0.6200 | 0.3566 | 0.0111 | 0.0123 |
| 9-7-0-0 | 0.5582 | 0.4181 | 0.0128 | 0.0109 |
| 8-8-0-0 | 0.4891 | 0.4846 | 0.0130 | 0.0133 |
| 8-4-4-0 | 0.5045 | 0.2437 | 0.2406 | 0.0113 |
| 7-4-4-1 | 0.4397 | 0.2461 | 0.2436 | 0.0705 |
| 6-4-4-2 | 0.3797 | 0.2471 | 0.2445 | 0.1287 |
| 5-4-4-3 | 0.3175 | 0.2439 | 0.2473 | 0.1913 |
| 4-4-4-4 | 0.2462 | 0.2494 | 0.2549 | 0.2495 |

Table 3. Fuzzy classification of a node connected to network with 4 communities generated with $z_{out}/k = 0.375$

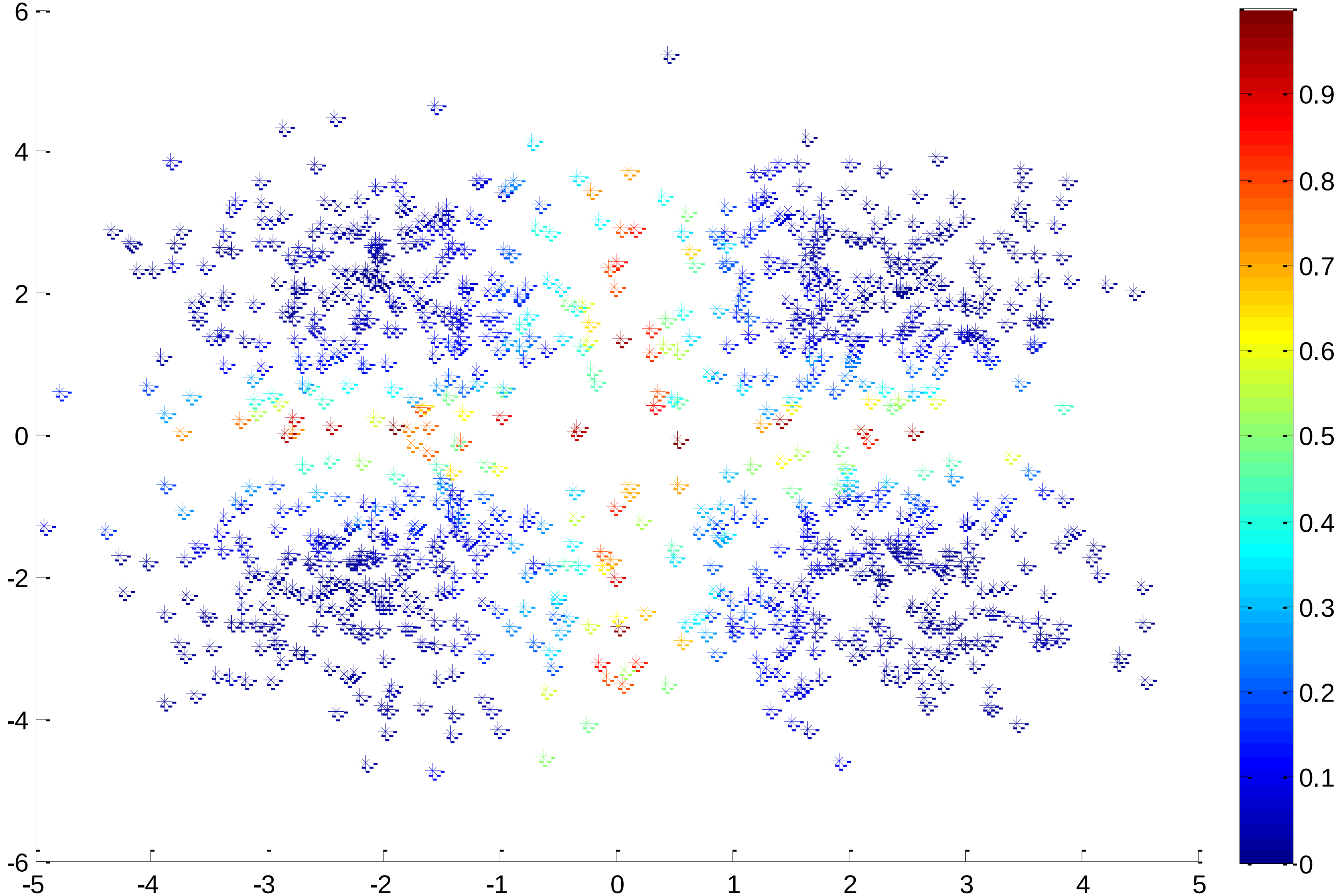



Fig. 1. Problem with 1000 elements split into four communities, colors represent the overlap index from each node, detected by the proposed method.

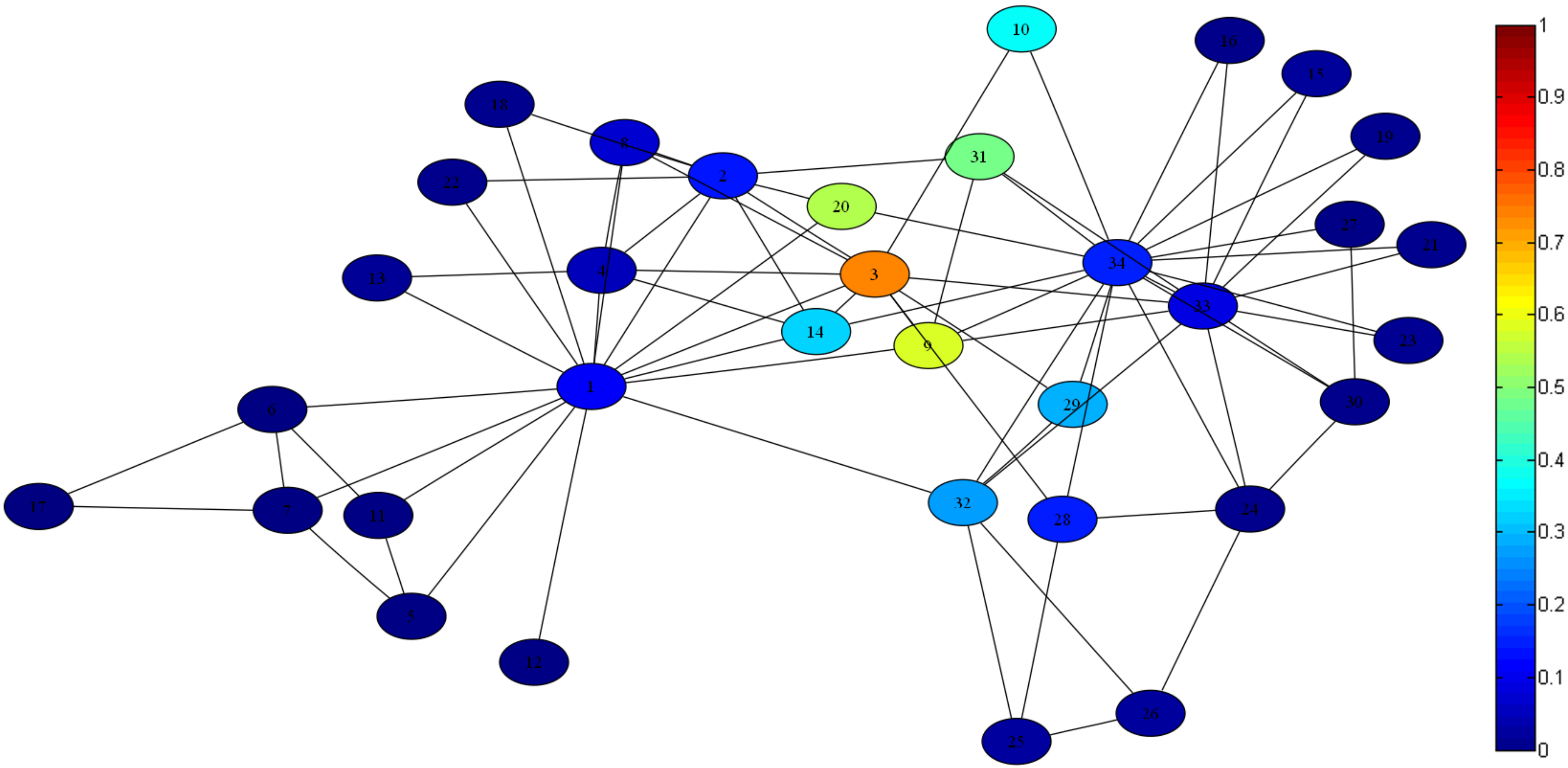



Fig. 2. The karate club network, colors represent the overlap index from each node, detected by the proposed method.

# Conclusions

- The algorithm outputs not only hard labels, but also soft labels (fuzzy values) for each node in the network, which corresponds to the levels of membership from that node to each community.
- Computer simulations were performed in both synthetic and real data, and the results shows that our model is a promising mechanism to uncover overlap community structure in complex networks.

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