# Graph community detection

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# **Outline**

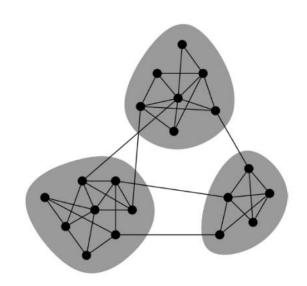
- Louvain Algorithm
  - Single pass

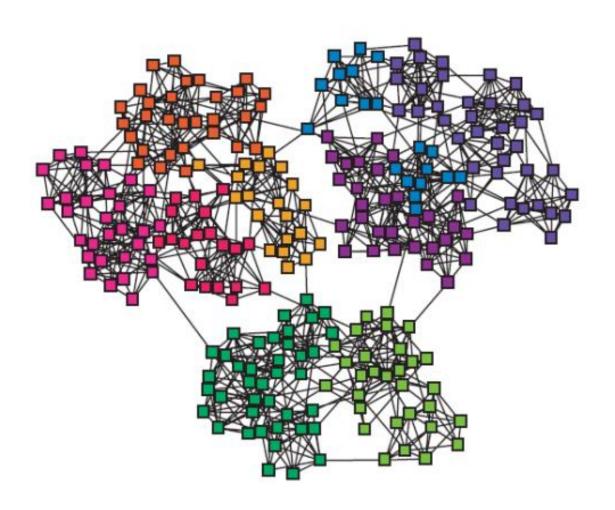
- Multi-pass Louvain Algorithm
  - (non-examinable!)

Many slides are from:

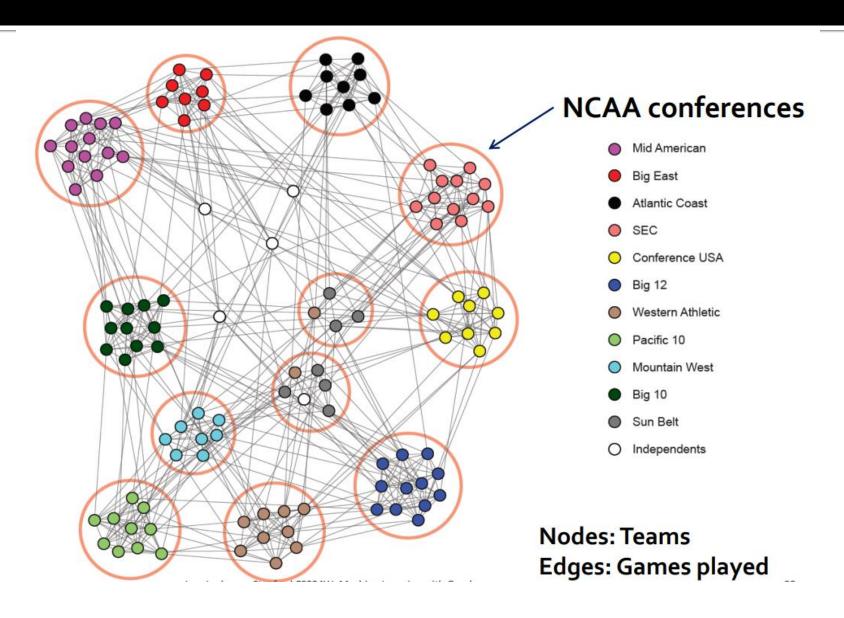
http://snap.stanford.edu/class/cs224w-2020/slides/13-communities.pdf

- One community in a graph:
  - A cluster of nodes
  - a group of tightly (densely) connected nodes
  - many internal connections and few external connections (to the rest of the network)
  - A community is also called: A cluster, A group, A module
- Community detection
  - A graph clustering task
  - Automatically find densely connected groups/clusters





# NCAA football network



# Louvain Algorithm

- Community detection on graphs
  - Greedy algorithm
    - Make locally optimal decision at each step
  - Supports weighted graphs
  - Provides hierarchical communities
  - Widely utilized to study large networks
    - Fast, rapid convergence
    - Produce high-quality results

# Modularity score

Use this equation to calculate the modularity score for a community:

$$Q(C) = rac{\Sigma_{in}}{2m} - (rac{\Sigma_{tot}}{2m})^2$$

- 1. Modularity score: measure the quality of a community
- 2. We aim to maximize the total Modularity score of all communities.

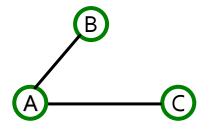
$$\Sigma_{in} \equiv \sum_{i,j \in C} A_{ij}$$
: Sum of the weights of internal edges in the community C. (double count each edge) (high value indicates strong internal connections)

$$\Sigma_{tot} \equiv \sum_{i \in C} k_i$$
: Sum of the weighted degrees of all nodes in the community C

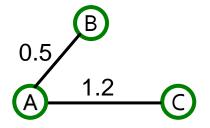
: the sum of all edge weights in the undirected graph

## Node degree

- Un-weighted graph:
  - Node degree: the number of connected edges.
  - all edge weights equal to 1
- Weighed graph:
  - Node degree (weighted): the sum of the weights of connected edges.



Un-weighted graph D(A)=2

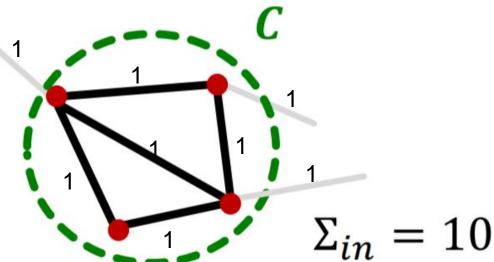


Weighted Graph D(A)=1.7

For un-weighted graph: the weight for each edge is 1

 $\Sigma_{in}$ :

The index i and j indicate the nodes in the community C



$$\Sigma_{in} \equiv \sum_{i,j \in C} A_{ij}$$

: Sum of all internal edge weights of the community (each internal edge will be double counted in the summation)

A<sub>ii</sub> is the edge weight for the edge connecting the nodes (i, j)

In the undirected graph, the edge weight:  $\,A_{i,j} = A_{j,i}\,$ 

For the example here, the internal edges will be double counted in the summation:

$$(1+1+1+1+1) \times 2=10$$

# Another example

Community B

For the community A, there are three internal nodes  $\{1,2,3\}$  We calculate  $\Sigma_{in}$  for community A:

$$\Sigma_{in} = \sum_{i,j \in C} A_{ij}$$
 (i,j indicate the internal nodes)  $= [A_{1,1} + A_{1,2} + A_{1,3}] + [A_{2,2} + A_{2,1} + A_{2,3}] + [A_{3,3} + A_{3,1} + A_{3,2}]$ 

There is no self links:  $A_{1,1}=0; A_{2,2}=0; A_{3,3}=0$ 

There is no edge between node 2 and 3:  $A_{2,3}=A_{3,2}=0$ 

In the undirected graph, the edge weight:  $\,A_{i,j} = A_{j,i}\,$ 

$$A_{1,2}=A_{2,1}=0.1; \quad A_{1,3}=A_{3,1}=0.2;$$

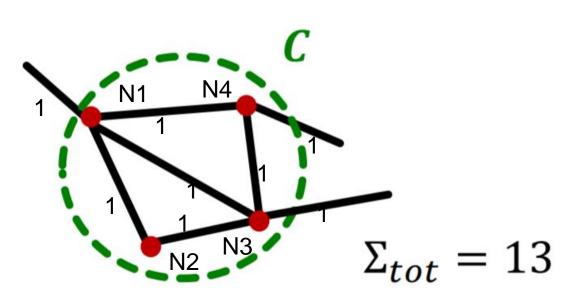
Community A

With the above, we can calculate  $\Sigma_{in}$  for community A as:

$$\Sigma_{in} = \sum_{i,j \in C} A_{ij} = (A_{1,2} + A_{1,3}) imes 2 = (0.1 + 0.2) imes 2 = 0.6$$
 (sum the internal edge weights and multiply 2)

For un-weighted graph: the weight for each edge is 1





 $\Sigma_{tot} \equiv \sum_{i \in C} k_i$ : Sum of the degrees of all internal nodes in the community C.

Here k<sub>i</sub> is the node degree of node i.

Sum of the node degrees of all internal nodes in C:

$$4 + 2 + 4 + 3 = 13$$

(for node N1, N2, N3, N4, respectively)

# Example: an extreme case

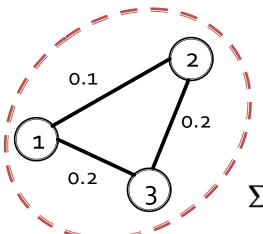
- An extreme case: all nodes belong to 1 community
  - This trivial clustering strategy provides a baseline score

$$Q(C) \qquad = \quad rac{\Sigma_{in}}{2m} - (rac{\Sigma_{tot}}{2m})^2 = rac{2m}{2m} - (rac{2m}{2m})^2 = 0$$

We have:  $\Sigma_{in}=2m$ 

$$\Sigma_{tot} = 2m$$

Example for the left graph:



community

n : the sum of all edge weights in the undirected graph

$$m = 0.1 + 0.2 + 0.2 = 0.5$$

$$\Sigma_{in} = (0.1 + 0.2 + 0.2) imes 2 = 1$$

$$\Sigma_{tot} = (0.1 + 0.2) + (0.1 + 0.2) + (0.2 + 0.2) = 1$$

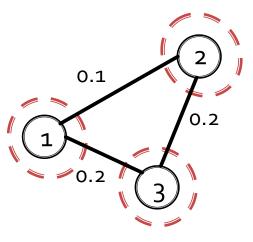
$$Q(C)=0$$

# Example: another extreme case

Another extreme case: one node forms one community

$$Q(C_i)=rac{\Sigma_{in}}{2m}-(rac{\Sigma_{tot}}{2m})^2=rac{0}{2m}-(rac{k_i}{2m})^2=-(rac{k_i}{2m})^2$$
 We have:  $\Sigma_{in}=0$   $k_i$  : the node degree of node i  $\Sigma_{tot}=k_i$ 

#### Example for the left graph:



3 communities

$$m=0.1+0.2+0.2=0.5$$
  $Q(\{1\})=-(rac{k_1}{2m})^2=-(rac{0.1+0.2}{1})^2=-0.09$   $Q(\{2\})=-(rac{k_2}{2m})^2=-(rac{0.1+0.2}{1})^2=-0.09$   $Q(\{3\})=-(rac{k_3}{2m})^2=-(rac{0.2+0.2}{1})^2=-0.16$ 

# Example: another extreme case

Another extreme case: one node forms one community The modularity score for the community formed by node i:

$$Q(C_i) = rac{\Sigma_{in}}{2m} - (rac{\Sigma_{tot}}{2m})^2 = rac{0}{2m} - (rac{k_i}{2m})^2 = -(rac{k_i}{2m})^2$$

We have: 
$$\Sigma_{in}=0$$
  $\Sigma_{tot}=k_i$ 

 $k_i$  : the node degree of node i

The total modularity score of all communities: (N indicates the total number of communities)

$$\sum_{i=1}^N Q(C_i) = -\sum_{i=1}^N (rac{k_i}{2m})^2$$
 The total score is less than 0

# Modularity score (discussion)

#### What is a good community:

The nodes in the community have lots of internal connections and very few external connections (to the rest of the network)

Modularity score: measure the quality of a community

A large value indicates a lot of internal connections

$$Q(C) = \left(rac{\Sigma_{in}}{2m}
ight) - \left(\left(rac{\Sigma_{tot}}{2m}
ight)^2
ight) = rac{\Sigma_{in}}{2}$$

- 1. A large value indicates a large community or large node degrees.
- 2. This term will penalize large community and the external connections.
  - The node degree includes the internal and external links of the node.
  - A large number of external links will lead to a large node degree.
- 3. Intuitively, the square operation is to downgrade the impact of the second term: e.g.  $(0.1)^2 < 0.1$

- Louvain Algorithm
  - aims to greedily maximize the Modularity score.
  - Modularity score: a metric to measure the quality of a community

- Single pass Louvain Algorithm
  - Community generation
    - Also called modularity optimization

# Louvain Algorithm: community generation

- Initialization: each node forms a distinct community
- A: generate a random list of nodes (start one scan)
- B: (one scan) sequentially process each node in the list for community update
- Repeat A, B until converge
  - Converge: there is no update of the community in the last scan

- B: sequentially process each node for community update
  - 1) Node movement step.
    - Identify possible movements by finding neighboring communities (directly connected external communities)
    - For each movement: compute the modularity gain ( $\Delta Q$ ) as the movement score.

$$\Delta Q = Q_{
m after} - Q_{
m before}$$

- 2) Community update step.
  - Move the node to a community that yields the largest positive score ( $\Delta Q$ ). If the largest score is not positive, there is no movement of the node.

# Modularity gain (movement score)

Directly use this equation to calculate the modularity score for each community:

$$Q(C) = rac{\Sigma_{in}}{2m} - (rac{\Sigma_{tot}}{2m})^2$$

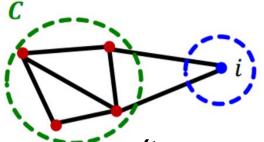
Modularity gain:

$$\Delta Q = Q_{
m after} - Q_{
m before}$$

Before merging

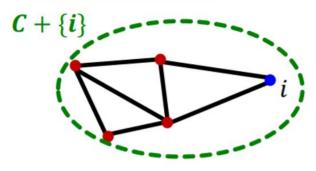
Merging i into C

$$\Delta Q(i \rightarrow C)$$



Isolated community of node *i* 

(two communities)



$$Q_{\text{before}} = Q(C) + Q(\{i\})$$

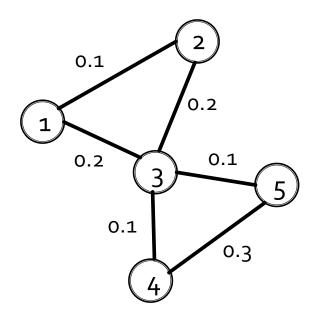
$$Q_{after} = Q(C + \{i\})$$

Modularity gain: 
$$\Delta Q(i o C) = Q_{
m after} - Q_{
m before}$$

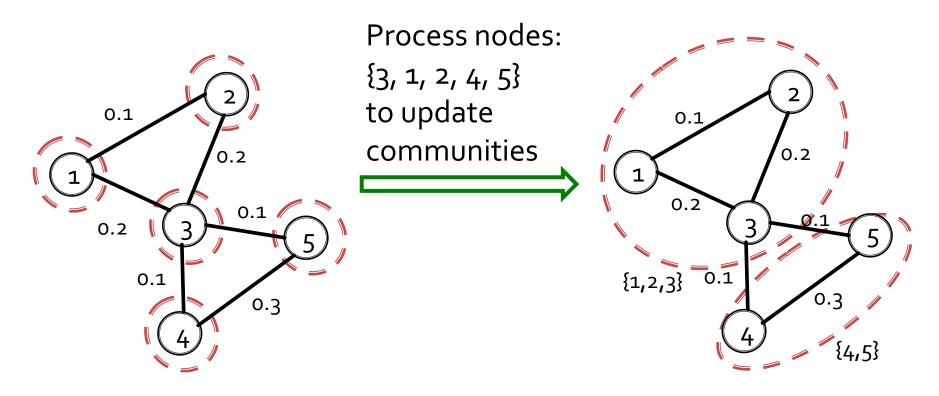
# Example: community update

Q: A graph is given below.

In the initialization, each node forms a distinct community. Use Louvain algorithm to sequentially process the nodes in the order {3, 1, 2, 4, 5} to update the communities given in the initialization.



# Result



In the initialization, each node forms a distinct community

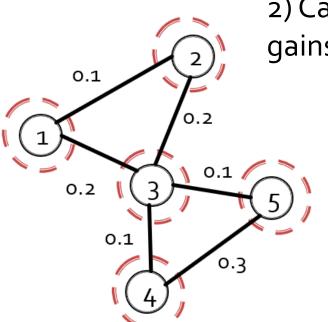
After processing, the communities are updated

# Intermediate steps

Sequentially process the node list {3, 1, 2, 4, 5}

## processing node 3

1) Identify neighbouring communities of node 3: {1}, {2}, {4} and {5}



2) Calculate the movement scores (modularity gains) for the following 4 movements:

$$\Delta Q(3 
ightarrow \{1\})$$

$$\Delta Q(3 
ightarrow \{2\})$$

$$\Delta Q(3 
ightarrow \{4\})$$

$$\Delta Q(3 
ightarrow \{5\})$$

# Intermediate steps

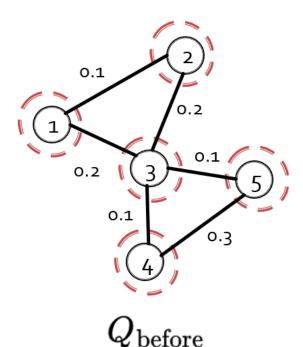
$$Q(C) = rac{\Sigma_{in}}{2m} - (rac{\Sigma_{tot}}{2m})^2$$

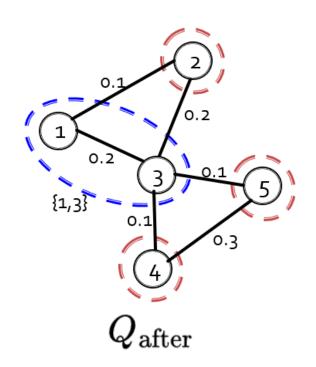
Sequentially process the node list {3, 1, 2, 4, 5}

## processing node 3

Movement score (Modularity gain) of moving node 3 to community {1}:

$$egin{array}{lll} \Delta Q(3 
ightarrow \{1\}) &=& Q_{after} - Q_{before} \ &=& Q(\{1\} + \{3\}) - igl[Q(\{1\}) + Q(\{3\})igr] \end{array}$$





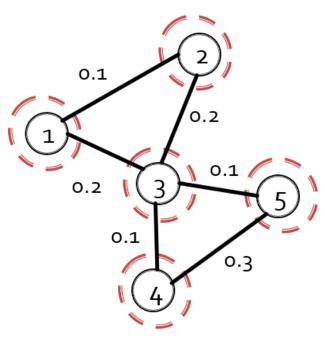
# Intermediate steps

$$Q(C) = rac{\Sigma_{in}}{2m} - (rac{\Sigma_{tot}}{2m})^2$$

Sequentially process the node list {3, 1, 2, 4, 5}

## processing node 3

$$egin{array}{lcl} \Delta Q(3 
ightarrow \{1\}) & = & Q_{after} - Q_{before} \ & = & Q(\{1\} + \{3\}) - igl[Q(\{1\}) + Q(\{3\})igr] \end{array}$$



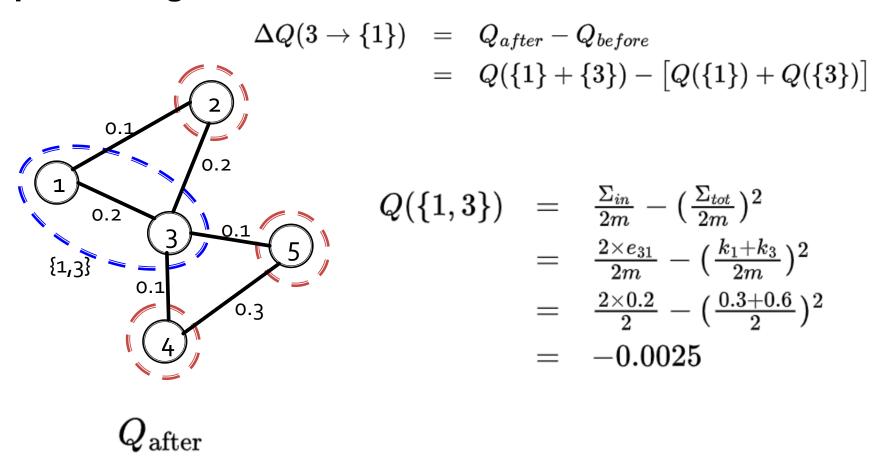
$$k_1 = 0.1 + 0.2 = 0.3$$
;  $k_3 = 0.2 + 0.2 + 0.1 + 0.1 = 0.6$ ;

$$m = 0.1 + 0.2 + 0.2 + 0.1 + 0.1 + 0.3 = 1$$

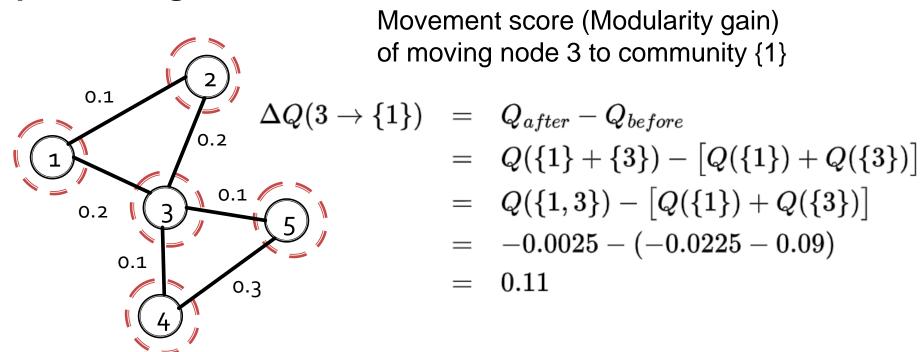
$$Q(\{1\}) = \left[0 - (\frac{k_1}{2m})^2\right] = -0.0225$$

$$Q({3}) = \left[0 - \left(\frac{k_3}{2m}\right)^2\right] = -0.09$$

## processing node 3

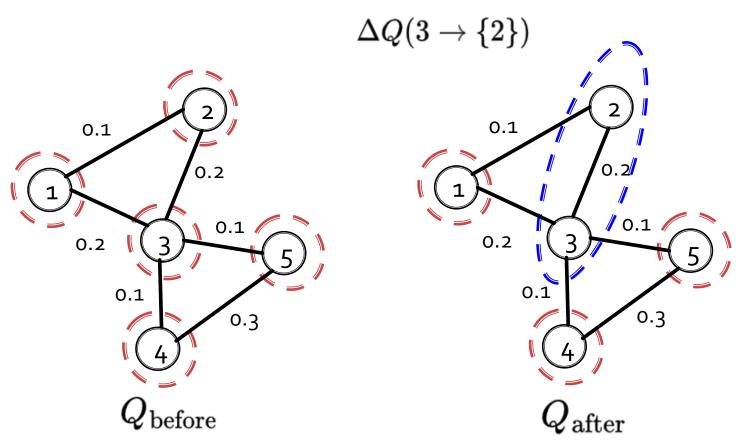


#### processing node 3

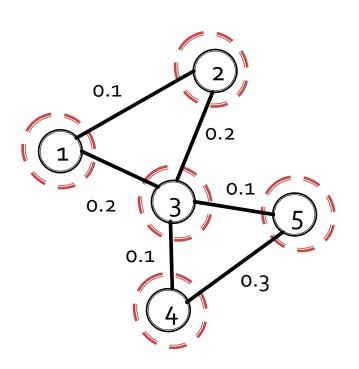


## processing node 3

Movement score (Modularity gain) of moving node 3 to community {2}



#### processing node 3



Movement score (Modularity gain) of moving node 3 to community {2}

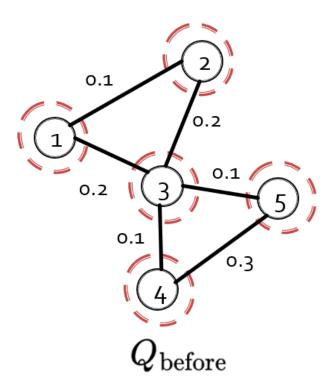
The link (1,3) and (2,3) have the same weight.

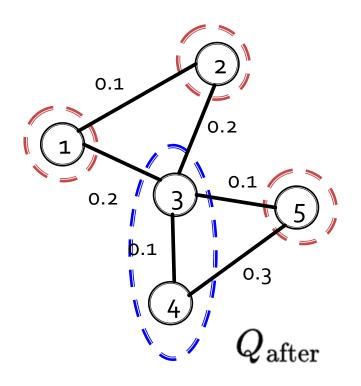
The gain of moving node 3 to  $\{2\}$  is the same as  $\Delta Q(3 o \{1\})$ 

$$\Delta Q(3 
ightarrow \{2\}) = 0.11$$

**processing node 3** The movement score of moving node 3 to {4}:

$$egin{array}{lll} \Delta Q(3 
ightarrow \{4\}) & = & Q_{after} - Q_{before} \ \\ & = & Q(\{4,3\}) - igl[Q(\{4\}) + Q(\{3\})igr] \end{array}$$





#### processing node 3

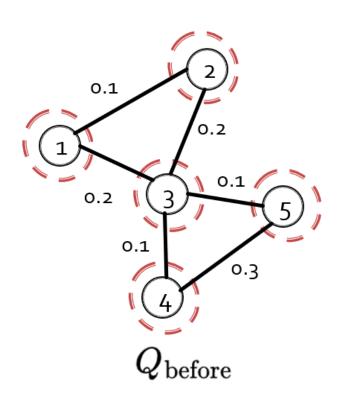
The movement score of moving node 3 to {4}:  $\Delta Q(3 \to \{4\}) = Q_{after} - Q_{before} \\ = Q(\{4\} + \{3\}) - \left[Q(\{4\}) + Q(\{3\})\right] \\ = Q(\{4,3\}) - \left[Q(\{4\}) + Q(\{3\})\right] \\ = -0.15 - (-0.04 - 0.09) \\ = -0.02$   $k_3 = 0.2 + 0.2 + 0.1 + 0.1 = 0.6; \quad k_4 = 0.1 + 0.3 = 0.4$ 

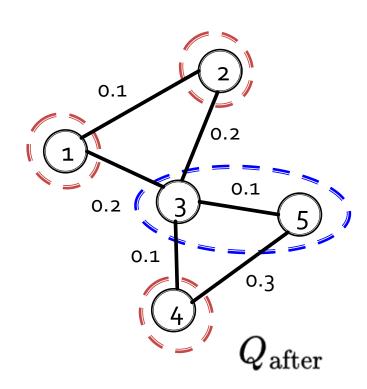
$$egin{array}{lll} Q(\{4,3\}) &=& rac{\Sigma_{in}}{2m} - (rac{\Sigma_{tot}}{2m})^2 & Q(\{3\}) &=& \left[0 - (rac{k_3}{2m})^2
ight] \ &=& rac{2 imes e_{34}}{2m} - (rac{k_4 + k_3}{2m})^2 &=& -0.09 \ &=& rac{2 imes 0.1}{2} - (rac{0.4 + 0.6}{2})^2 & Q(\{4\}) &=& \left[0 - (rac{k_3}{2m})^2
ight] \ &=& -0.15 & -0.04 \end{array}$$

## processing node 3

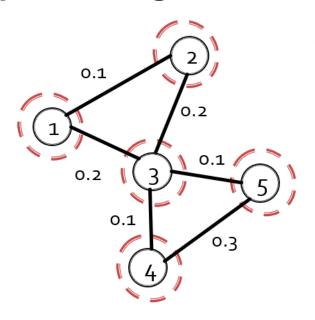
The movement score of moving node 3 to {5}:

$$\Delta Q(3 
ightarrow \{5\})$$





## processing node 3

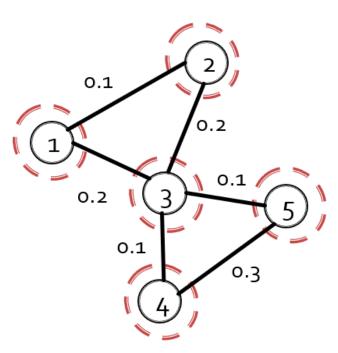


The movement score of moving node 3 to {5}:

The gain of moving node 3 to  $\{5\}$  is the same as:  $\Delta Q(3 o \{4\})$ 

$$\Delta Q(3 
ightarrow \{5\}) = -0.02$$

#### processing node 3



Summary:

Scores for all possible movements:

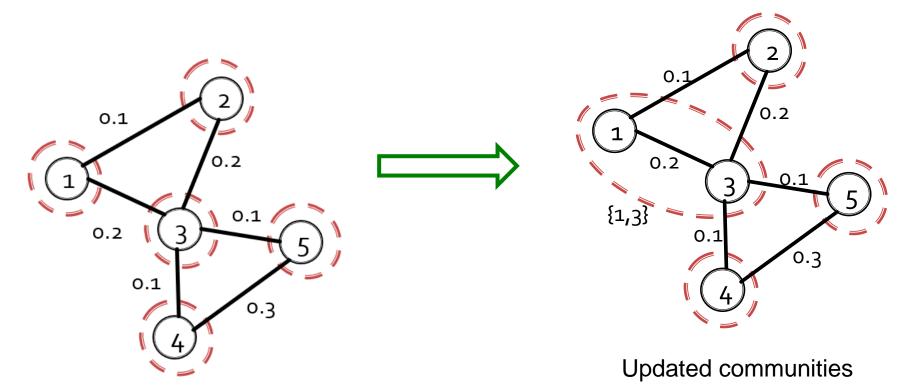
$$\Delta Q(3 
ightarrow \{1\}) \;\;\; = \;\; \Delta Q(3 
ightarrow \{2\}) \;\;\; = \;\; 0.11$$

$$\Delta Q(3 
ightarrow \{4\}) = \Delta Q(3 
ightarrow \{5\}) = -0.02$$

There is a tie for 3->{1} and 3->{2}. Randomly choose one community to proceed.

Here we choose {1}. Move node #3 to community {1}, now we have {1,3}.

## processing node 3



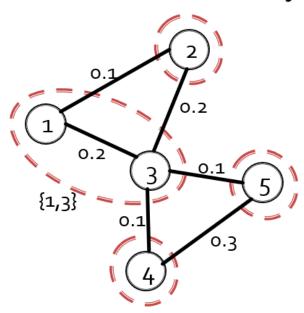
After processing node 3, we move node 3 to {1}.

## processing node 1

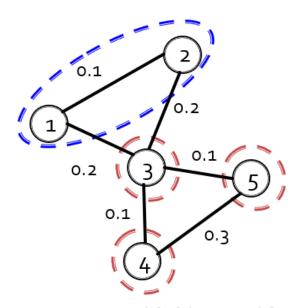
The neighbouring (directly connected) communities of node 1: Community {2} Only one possible movement:

Move node 1 out from {1, 3} and add node 1 to {2}:

$$\Delta Q(\{1,3\} 
ightarrow 1 
ightarrow \{2\}) = Q_{
m after} - Q_{
m before}$$



$$Q_{
m before} = Q(\{1,3\}) + Q(\{2\})$$



$$Q_{
m after} = Q(\{3\}) + Q(\{1,2\})$$

## processing node 1

The neighbouring (directly connected) communities of node 1: Community {2} Only one possible movement:

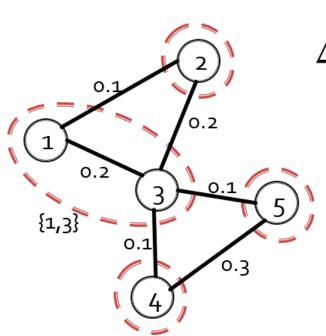
Move node 1 out from {1, 3} and add node 1 to {2}:

$$\Delta Q(\{1,3\} 
ightarrow 1 
ightarrow \{2\}) = Q_{
m after} - Q_{
m before}$$

$$Q_{
m before} = Q(\{1,3\}) + Q(\{2\})$$

From the previous steps, we already have the following values:

$$egin{aligned} Q(\{1,3\}) &= -0.0025 \ Q(\{2\}) &= Q(\{1\}) = -0.0225 \end{aligned}$$



Current communities

### processing node 1

Move node 1 out from {1, 3} and add node 1 to {2}:

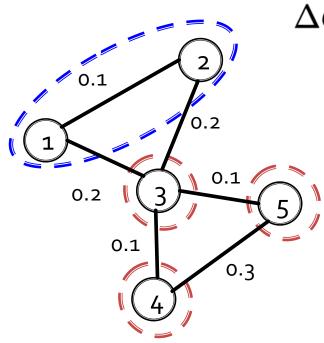
$$\Delta Q(\{1,3\} 
ightarrow 1 
ightarrow \{2\}) = Q_{
m after} - Q_{
m before}$$

$$Q_{
m after} = Q(\{3\}) + Q(\{1,2\})$$

$$egin{array}{lll} Q(\{1,2\}) & = & rac{\Sigma_{in}}{2m} - (rac{\Sigma_{tot}}{2m})^2 \ & = & rac{2 imes e_{12}}{2m} - (rac{k_2 + k_1}{2m})^2 \ & = & rac{2 imes 0.1}{2} - (rac{0.3 + 0.3}{2})^2 \ & = & 0.01 \end{array}$$

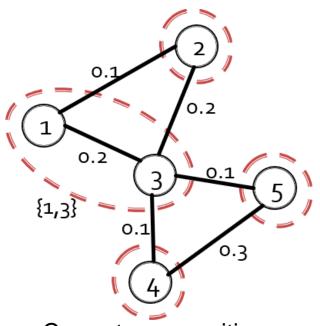
From the previous steps, we already have the following values:

$$Q(\{3\}) = -0.09$$



$$Q_{\mathrm{after}} = Q(\{3\}) + Q(\{1,2\})$$

## processing node 1



Move node 1 out from {1, 3} and add node 1 to {2}:

$$egin{aligned} \Delta Q(\{1,3\} 
ightarrow 1 
ightarrow \{2\}) &= Q_{
m after} - Q_{
m before} \ &= Q(\{3\}) + Q(\{1,2\}) - (Q(\{1,3\}) + Q(\{2\})) \ &= -0.09 + 0.01 - \left(-0.0025 - 0.0225
ight) \ &= -0.055 \end{aligned}$$

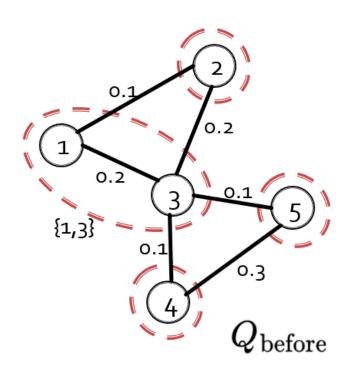
Current communities

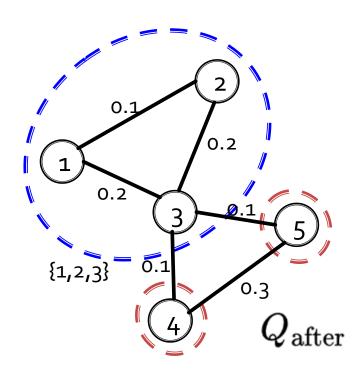
The largest gain is a negative value (there is only one neighboring community), do not move node 1 to {2}

## processing node 2

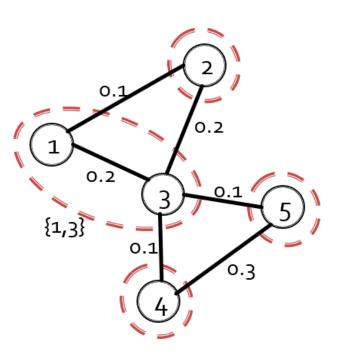
The neighbouring communities of node 2: Community {1, 3}. Only one possible movement:

$$egin{array}{lll} \Delta Q(2 
ightarrow \{1,3\}) & = & Q_{after} - Q_{before} \ & = & Q(\{1,2,3\}) - Q(\{1,3\}) - Q(\{2\})) \end{array}$$





## processing node 2



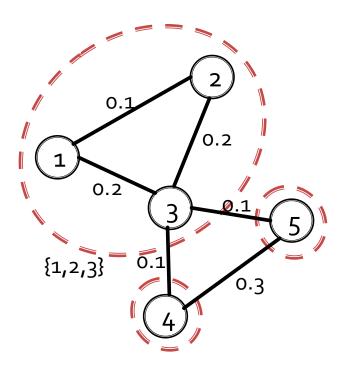
The neighbouring communities of node 2: Community {1, 3} Only one possible movement:

$$egin{array}{lll} \Delta Q(2 
ightarrow \{1,3\}) &=& Q_{after} - Q_{before} \ &=& Q(\{1,3\} + \{2\}) - igl[Q(\{1,3\}) + Q(\{2\})igr] \ &=& Q(\{1,2,3\}) - Q(\{1,3\}) - Q(\{2\})) \end{array}$$

$$egin{array}{lll} Q(\{1,2,3\}) & = & rac{\Sigma_{in}}{2m} - (rac{\Sigma_{tot}}{2m})^2 \ & = & rac{2 imes(e_{13} + e_{21} + e_{23})}{2m} - (rac{k_1 + k_2 + k_3}{2m})^2 \ & = & 0.14 \end{array}$$

$$egin{array}{lcl} Q(\{2\}) & = & -(rac{k_2}{2m})^2 & & Q(\{1,3\}) & = & rac{\Sigma_{in}}{2m} - (rac{\Sigma_{tot}}{2m})^2 \ & = & -0.0225 & & = & rac{2 imes e_{13}}{2m} - (rac{k_1 + k_3}{2m})^2 \ & = & -0.0025 \end{array}$$

## processing node 2

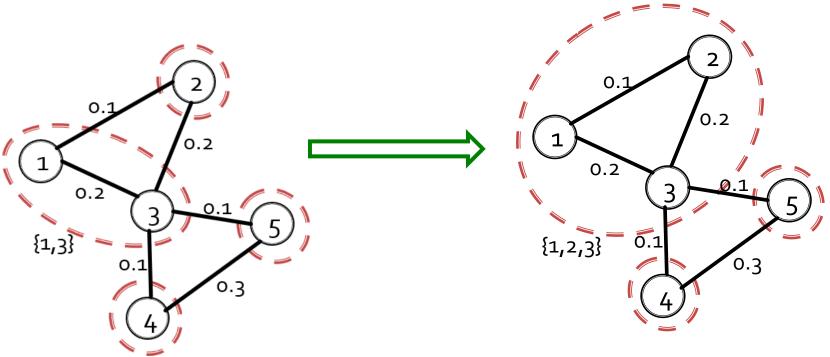


Updated communities after processing node 2

$$egin{array}{lll} \Delta Q(2 
ightarrow \{1,3\}) &= Q_{after} - Q_{before} \ &= Q(\{1,3\} + \{2\}) - igl[Q(\{1,3\}) + Q(\{2\})igr] \ &= Q(\{1,2,3\}) - Q(\{1,3\}) - Q(\{2\})) \ &= 0.165 \end{array}$$

The gain is a positive value, and there is only 1 neighboring community, so it's the largest positive gain. We move 2 to {1,3}.

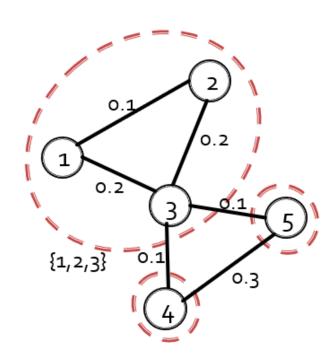
## processing node 2



Updated communities

After processing node 2, we move node 2 to {1,3}.

## processing node 4



Current communities

The neighbouring communities of node 4:

- 1. Community {1, 2, 3}
- 2. Community {5}

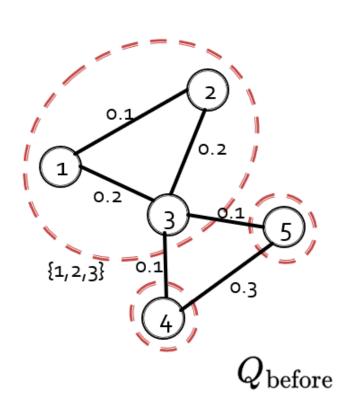
There are 2 possible movements. We need to calculate the following two modularity gains:

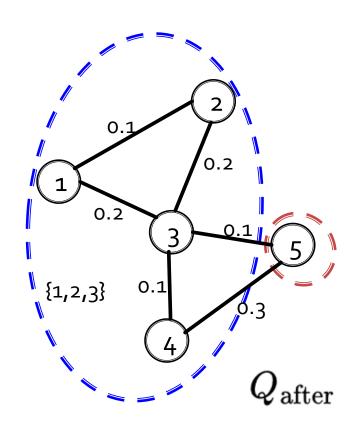
$$\Delta Q(4 
ightarrow \{1,2,3\})$$

$$\Delta Q(4 o\{5\})$$

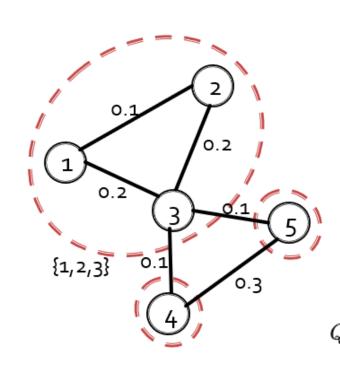
## processing node 4

$$\Delta Q(4 
ightarrow \{1,2,3\}) \; = \; \; Q_{after} - Q_{before}$$





## processing node 4



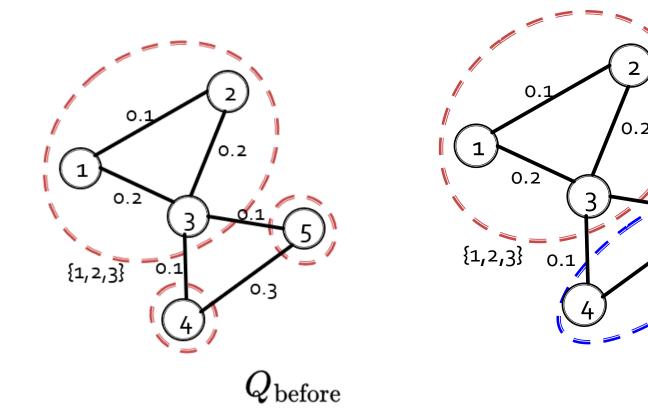
Current communities

$$egin{aligned} \Delta Q(4 
ightarrow \{1,2,3\}) &= Q_{after} - Q_{before} \ &= Q(\{4\} + \{1,2,3\}) - \left[Q(\{4\}) + Q(\{1,2,3\})
ight] \ &= Q(\{1,2,3,4\}) - Q(\{4\}) - Q(\{1,2,3\}) \ &= (-0.04) - (-0.04) - 0.14 \ &= -0.14 \end{aligned} \ egin{aligned} \mathsf{k}_4 = 0.1 + 0.3 = 0.4 \ Q(\{4\}) &= -(rac{k_4}{2m})^2 &= -0.04 \ Q(\{1,2,3\}) &= 0.14 \end{aligned} \ egin{aligned} Q(\{1,2,3\}) &= 0.14 \ Q(\{1,2,3,4\}) &= rac{\Sigma_{in}}{2m} - (rac{\Sigma_{tot}}{2m})^2 \ &= rac{2 imes (e_{12} + e_{13} + e_{23} + e_{34})}{2m} - (rac{k_1 + k_2 + k_3 + k_4}{2m})^2 \ &= rac{2 imes (0.1 + 0.2 + 0.2 + 0.1)}{2} - (rac{0.3 + 0.3 + 0.6 + 0.4}{2})^2 \end{aligned}$$

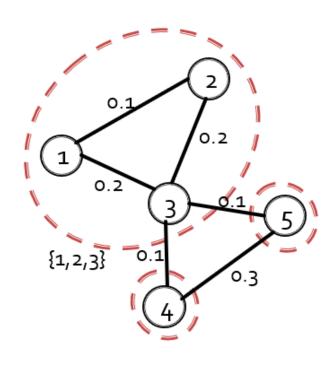
-0.04

## processing node 4

$$\Delta Q(4 
ightarrow \{5\}) = Q_{after} - Q_{before}$$

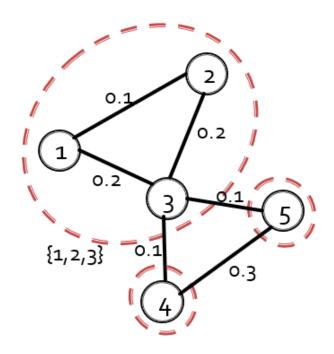


## processing node 4



$$egin{array}{lll} \Delta Q(4 
ightarrow \{5\}) &=& Q_{after} - Q_{before} \ &=& Q(\{4\} + \{5\}) - \left[Q(\{4\}) + Q(\{5\})
ight] \ &=& Q(\{4,5\}) - Q(\{4\}) - Q(\{5\}) \ &=& 0.14 - (-0.04) - (-0.04) \ &=& 0.22 \ &=& Q(\{4\}) &=& -(rac{k_4}{2m})^2 &=& -0.04 \ &=& Q(\{5\}) &=& -(rac{k_5}{2m})^2 &=& -0.04 \ &=& Q(\{4,5\}) &=& rac{\Sigma_{in}}{2m} - (rac{\Sigma_{tot}}{2m})^2 \ &=& rac{2 imes e_{45}}{2m} - (rac{k_4 + k_5}{2m})^2 \ &=& 0.14 \ \end{array}$$

## processing node 4



Current communities

Summary:

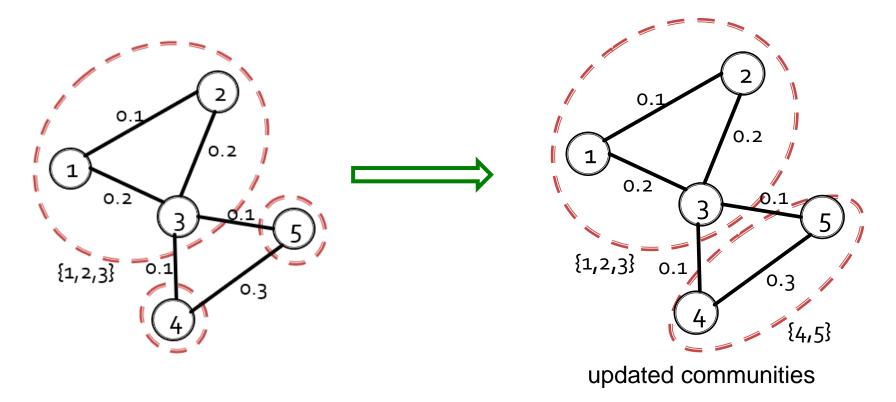
Scores for the 2 possible movements

$$\Delta Q(4
ightarrow\{1,2,3\})= -0.14$$

$$\Delta Q(4 
ightarrow \{5\}) = 0.22$$

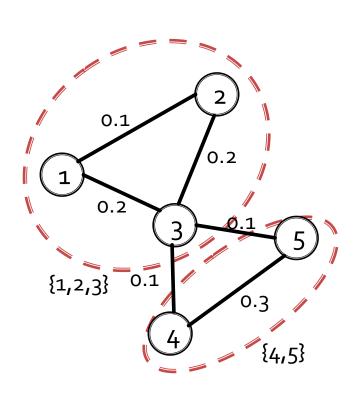
 $\Delta Q(4 
ightarrow \{5\})$  has the largest positive gain. We move node 4 to  $\{5\}$ .

## processing node 4



After processing node 4, we move node 4 to {5}.

## processing node 5



The neighbouring communities of node 5: Community {1, 2, 3}

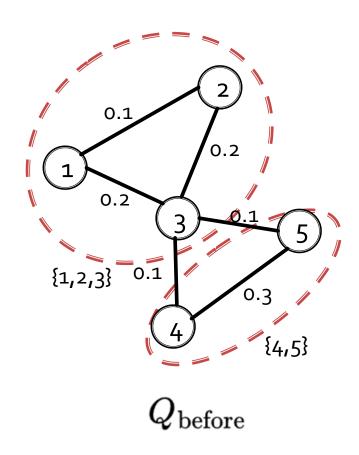
There is only one neighbouring community for node 5, so there is only one possible movement

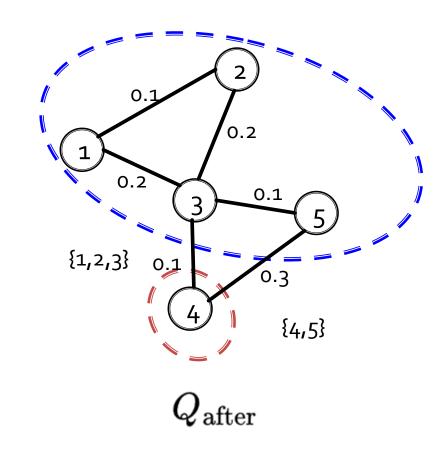
We need to calculate the following modularity gain:

$$\Delta Q(\{4,5\}
ightarrow 5
ightarrow \{1,2,3\})$$

## processing node 5

$$\Delta Q(\{4,5\}
ightarrow 5
ightarrow \{1,2,3\})$$





## processing node 5

$$\Delta Q(\{4,5\} o 5 o \{1,2,3\}) = Q_{after} - Q_{before}$$
 $= Q(\{4\}) + Q(\{1,2,3,5\}) - [Q(\{4,5\}) + Q(\{1,2,3\})]$ 
 $Q(\{1,2,3,5\}) = \frac{\Sigma_{in}}{2m} - (\frac{\Sigma_{tot}}{2m})^2$ 
 $= \frac{2 \times (e_{12} + e_{13} + e_{23} + e_{35})}{2m} - (\frac{k_1 + k_2 + k_3 + k_5}{2m})^2$ 
 $= \frac{2 \times (0.1 + 0.2 + 0.2 + 0.1)}{2} - (\frac{0.3 + 0.3 + 0.6 + 0.4}{2})^2$ 
 $= -0.04$ 

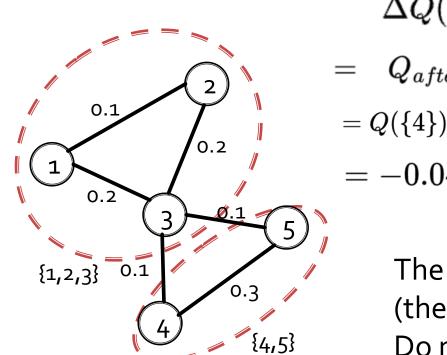
The below values can be obtained from previous steps:

$$Q(\{4\}) = -(\frac{k_4}{2m})^2 = -0.04$$

$$Q(\{4,5\})=0.14$$

$$Q(\{1,2,3\}) = 0.14$$

## processing node 5



$$\Delta Q(\{4,5\}
ightarrow 5
ightarrow \{1,2,3\})$$

$$= Q_{after} - Q_{before}$$

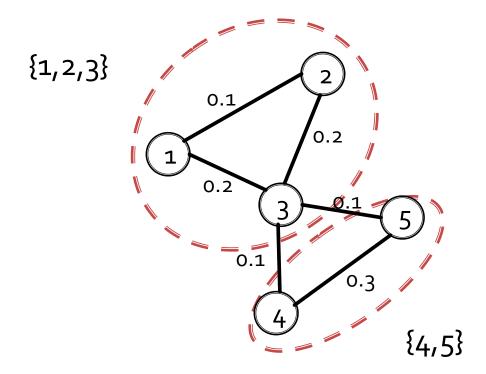
$$=Q(\{4\})+Q(\{1,2,3,5\})-[Q(\{4,5\})+Q(\{1,2,3\})]$$

$$=-0.04-0.04-(0.14+0.14)=-0.36$$

The largest gain is a negative value (there is one neighboring community). Do not move node 5.

## Result

After processing the node list {3, 1, 2, 4, 5}, we have two communities: {1, 2, 3} and {4, 5}.



Additional discussion: (beyond the question)

We have finished the 1st scan after processing the node list.

To fully complete community generation, continue to do the 2<sup>nd</sup> scan, 3<sup>rd</sup> scan, ....

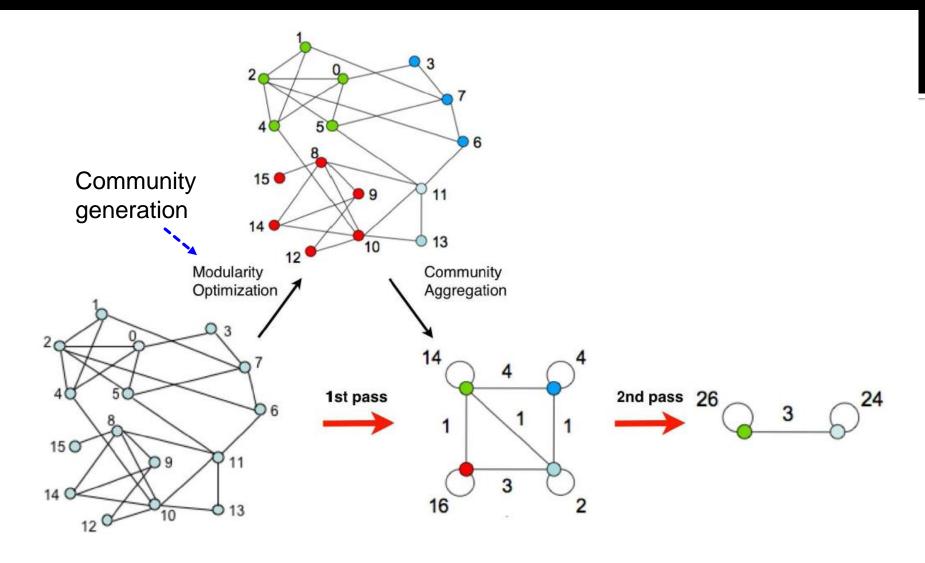
In each scan, we randomly generate a node list for processing.

#### Converge:

if there is no node movement in one scan, the community generation step converges.



- Multi-pass Louvain Algorithm
  - Multiple passes.
    - Produce hierarchical results
    - One pass corresponds to one hierarchical level
  - Each pass is made of 2 phases:
    - Phase 1: community generation (we have learnt)
    - Phase 2: community aggregation

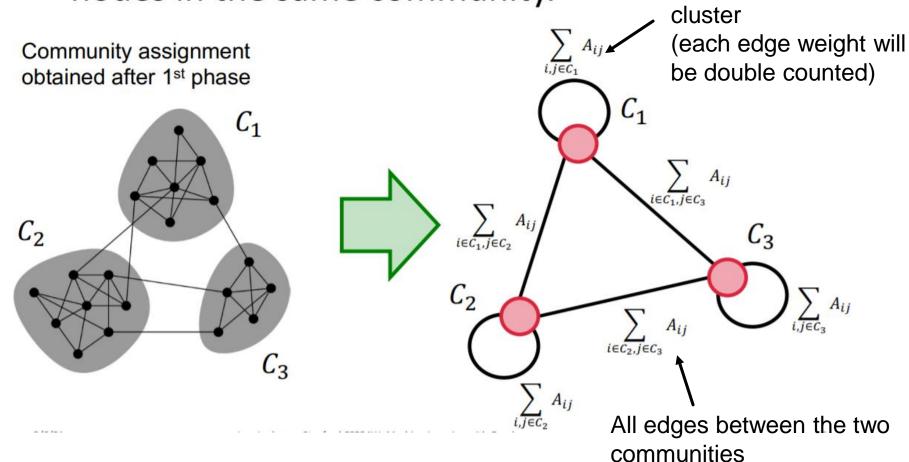


Multi-pass Louvain Algorithm high-level illustration

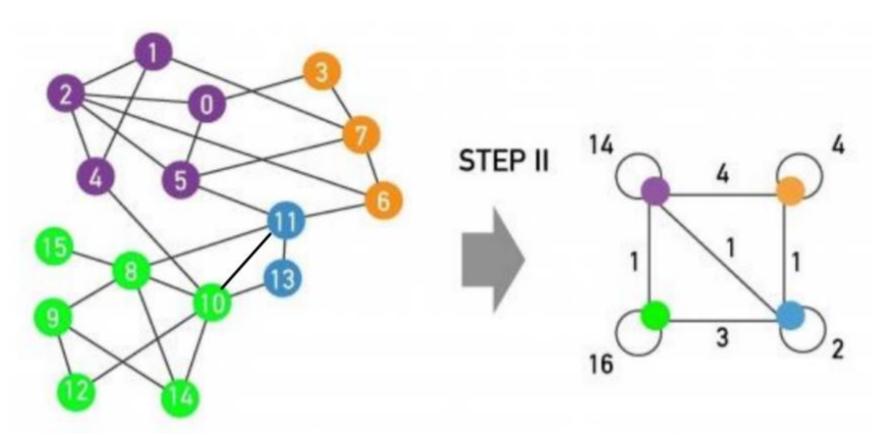
For un-weighted graph: the weight for each edge is 1

- Phase 2: community aggregation
  - Generate a new graph based on the communities
    - Create one node (super node) for one community in the new graph
    - Create edges of the super nodes if the original communities are connected by at least one edge
      - The weight of the edge between the two super nodes is the sum of the edge weights between the original communities
    - Create self-connections of the super nodes based on the internal connections of the original communities.

 Super nodes are constructed by merging nodes in the same community.



# Example

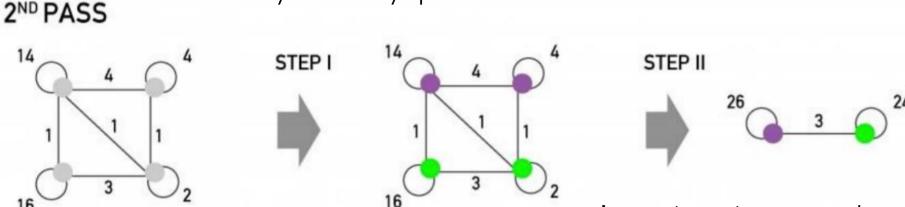


generate communities in phase 1 (step 1) generate new graph in phase 2 (step 2)

The 1<sup>st</sup> pass.

## Example

phase 1 (step1): community generation
by modularity optimization



phase 2 (step2): merge nodes and
generate a new graph

In the 2<sup>nd</sup> pass: run phase 1 (step 1 in the figure) and phase 2 (step 2) again on the new graph

## Further reading

- BigCLAM
  - For overlapping community detection

- Spectral clustering
  - A well-know clustering method on graph
  - http://snap.stanford.edu/class/cs224w-2019/
  - https://en.wikipedia.org/wiki/Spectral\_clustering