

Derivations of Louvain Method Equations for Community Detection in Directed and Undirected Graphs

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Abstract—This is to summarize all the equations related to the Louvain Method in a single document

Keywords—Louvain Method, Directed Louvain Method

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1. Algorithm of Louvain Method

Initialization : Each node is in its own community
Algorithm:

1. Randomly sort the nodes (The order affects the resulting partition)
2. Loop through the nodes in the sorted order and **pop it from its original community** and **merge it to the neighboring community** that improves the modularity the most after merging. (Stay in original community if the change in modularity is negative)
3. If, after Step 1 and 2, modularity has increased (Or increased by more than the hyper-parameter **threshold**), merge all nodes in the same community into a single node and update all the edge weights accordingly. (The edges inside the same community become one self-loop edge of weight equal to the total sum of edge weights) (Inter-community edges between two communities merge into one with corresponding weight). Then repeat step 1 and 2. Otherwise, stop.

2. Undirected Louvain Method

2.1. Modularity (Q)

$$Q = \frac{1}{2m} \sum_i \sum_j (A_{ij} - \frac{d_i d_j}{2m}) \delta(c_i, c_j)$$

- Q = Modularity of the graph G
- A_{ij} = Entry $i \times j$ or Adjacency Matrix (Can be more than 1 in graph with weighted edges)
- d_i, d_j = the degree of node i and j
- c_i, c_j = communities of node i and j
- $\delta(c_i, c_j)$ = Kronecker Delta Function

$$\delta(c_i, c_j) = \begin{cases} 1 & \text{if } c_i \text{ and } c_j \text{ are the same cluster} \\ 0 & \text{otherwise} \end{cases}$$

2.2. Modularity of Each Cluster in Sum of Degree Format (Q_c)

$$Q_c = \frac{1}{2m} \sum_i \sum_j (A_{ij} - \frac{d_i d_j}{2m}) \mathbb{1}(c_i = c_j = c)$$

$$\begin{aligned} &= \frac{1}{2m} \sum_i \sum_j A_{ij} \mathbb{1}(c_i = c_j = c) - \frac{1}{2m} \sum_i \sum_j \frac{d_i d_j}{2m} \mathbb{1}(c_i = c_j = c) \\ &= \frac{1}{2m} \sum_i \sum_j A_{ij} \mathbb{1}(c_i = c_j = c) - \frac{1}{2m} \sum_i d_i \mathbb{1}(c_i = c) \frac{1}{2m} \sum_j d_j \mathbb{1}(c_j = c) \\ &= \frac{\Sigma_{in}^c}{2m} - (\frac{\Sigma_{tot}^c}{2m})^2 \end{aligned}$$

- Σ_{in}^c = the sum of edge weights between nodes within the community c (each edge is considered twice)
- Σ_{tot}^c = the sum of all edge weights for nodes within the community c (including edges which link to other communities).

$$2.3. Q = \sum_c Q_c$$

$$Q = \sum_c Q_c$$

Because every node pair from different communities do not contribute to the Modularity due to $\delta(c_i, c_j)$, we can calculate separately and add them up.

2.4. Change of Q (ΔQ) of node i changing community from c_i to c_j

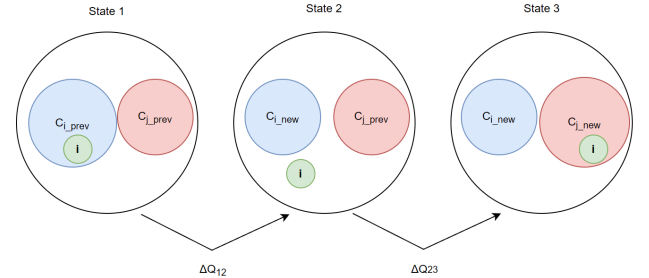


Figure 1. Node i leaving c_i and joining c_j

$$\Delta Q = \Delta Q_{12} \text{ (Removal Cost)} + \Delta Q_{23} \text{ (Merging Gain)}$$

2.4.1. ΔQ_{12} (Removal Cost)

$$\begin{aligned} \Delta Q_{12} &= (Q_{c_{i_new}} + Q_{node-i}) - (Q_{c_{i_prev}}) \\ &= (\frac{\Sigma_{in}^{c_{i_new}}}{2m} - (\frac{\Sigma_{tot}^{c_{i_new}}}{2m})^2 + \frac{\Sigma_{in}^{node-i}}{2m} - (\frac{\Sigma_{tot}^{node-i}}{2m})^2) - (\frac{\Sigma_{in}^{c_{i_prev}}}{2m} - (\frac{\Sigma_{tot}^{c_{i_prev}}}{2m})^2) \\ &= (\frac{\Sigma_{in}^{c_{i_prev}}}{2m} - \frac{d_i^{c_{i_prev}}}{2m} - (\frac{\Sigma_{tot}^{c_{i_prev}}}{2m} - d_i)^2 + 0 - (\frac{d_i}{2m})^2) - (\frac{\Sigma_{in}^{c_{i_prev}}}{2m} - (\frac{\Sigma_{tot}^{c_{i_prev}}}{2m})^2) \\ &= -\frac{d_i^{c_{i_prev}}}{2m} + \frac{d_i(\Sigma_{tot}^{c_{i_prev}} - d_i)}{2m^2} \end{aligned}$$

Where

- d_i^c = The degree of node i of edges only within community c (Each undirected edge is double counted for degree)
- d_i = Total degree of node i

The code inside the networkx python library (networkx.algorithms.community.louvain):

```

1 def _one_level(G, m, partition, resolution=1,
2   is_directed=False, seed=None):
3   ...
4   degree = degrees[u] #d_i
5   Stot[best_com] -= degree # (Sum_total - d_i)
6   remove_cost = -weights2com[best_com] / m +
7   resolution * (
8     Stot[best_com] * degree
9   ) / (2 * m**2) # weights2com[best_com] =
10  d_i^{c}/2
11  ...

```

Code 1. Snippet from networkx library.

2.4.2. ΔQ_{23} (Merging Gain)

$$\Delta Q_{23} = (Q_{c_j_new}) - (Q_{c_j_prev} + Q_{node-i})$$

With similar calculation,

$$= \frac{d_i^{c_j_new}}{2m} - \frac{d_i(\sum_{tot}^{c_j_new} - d_i)}{2m^2}$$

The code inside the networkx python library (networkx.algorithms.community.louvain):

```

1 def _one_level(G, m, partition, resolution=1,
2   is_directed=False, seed=None):
3   ...
4   gain = ( #gain = Delta Q
5     remove_cost # Q_12
6     + wt / m # wt = d_i^{c_j}/2
7     - resolution * (Stot[nbr_com] * degree)
8     / (2 * m**2)
9   )
10  ...

```

Code 2. Snippet from networkx library.

3. Directed Louvain Method

4. References

- Networkx louvain library
- Networkx modularity library
- Paper of Louvain Method
- Paper of Directed Louvain Method
- Louvain Method Wikipedia