



Community Detection ·

Active Semi-supervised Community Detection based on Pair-wise Constraints

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Concepts about community detection

Complex network

 A **complex network** is an undirected and unweighted graph $G = (V, E)$, where V represents the node set, and E represents the edges set.



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Concepts about community detection

Complex network

-  A **complex network** is an undirected and unweighted graph $G = (V, E)$, where V represents the node set, and E represents the edges set.
-  The node can be a people in the social network, a web page in the internet web graph, a paper in the citation network, *etc.*, and each edge in the network can represent the interaction or relationship between two people, can be a hyperlink between the web pages, a reference relationship between the papers, *etc.*



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Concepts about community detection

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-  A common property or characteristic of the complex network is its “**Community Structure**”.



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-  A common property or characteristic of the complex network is its “**Community Structure**”.
-  A **Community** is a group of densely connected nodes in the network, such that the nodes within a group are much more connected to each other than to the rest of the network.



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Concepts about community detection

Complex network

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-  A common property or characteristic of the complex network is its “**Community Structure**”.
-  A **Community** is a group of densely connected nodes in the network, such that the nodes within a group are much more connected to each other than to the rest of the network.
-  Communities are of interest because they often correspond to functional units of the networks, and community detection may shed light on the structural and functional characteristics of the network.



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Semi-supervised learning



Classification: supervised learning



Clustering: unsupervised learning



Semi-supervised learning: semi-supervised classification, semi-supervised clustering



Two kinds of semi-supervised components: **labeled data** and **must-link constraints**, **cannot-link constraints**

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must-link constraints and cannot-link constraints



Must-link constraints C_{ML} : $\forall v_i, v_j \in V, (v_i, v_j) \in C_{ML}$ indicates the two nodes v_i and v_j must belong to the same community.



Cannot-link constraints C_{CL} : $\forall v_i, v_j \in V, (v_i, v_j) \in C_{CL}$ indicates the two nodes v_i and v_j cannot be classified into the same community, and they must be allocated into different communities.

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Active learning



A strategy to select those data examples actively to annotate, such that the learner could achieve higher performance as compared with random selection



its goal is to maximize the learner's ability at a minimum cost



pool-based and **stream-based**



the most informative data or the data with least certainty are selected to annotate by an **oracle**



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Semi-supervised community detection algorithm based on the must-link constraints and cannot-link constraints



Augment the must-link constraint set and Cannot-link constraint set using the transitive property of must-link constraints



Construct the skeleton of the initial community structure from cannot-link constraints and must-link constraints



Expand communities by greedily select the (*community, unclassified node*) pair from all the pairs, and insert the selected unclassified node into the corresponding community iteratively



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Random walk based algorithm to compute the similarity matrix



A walker is placed in the network, at each time step, the walker is on a vertex and randomly jumps from the vertex to one of its neighbors following the edge between them



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Random walk based algorithm to compute the similarity matrix



A walker is placed in the network, at each time step, the walker is on a vertex and randomly jumps from the vertex to one of its neighbors following the edge between them



The walker tends to be trapped in a group of densely connected vertices corresponding to a community rather than walk across communities boundaries within limited number of steps



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The walker tends to be trapped in a group of densely connected vertices corresponding to a community rather than walk across communities boundaries within limited number of steps



Can be used to compute the similarity matrix: in each walk, we keep track of the visited nodes in a set, the possibility that these nodes in the set belong in the same community is high, so the similarity values between each pair of the nodes in the set should be increased



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The algorithm in literatures increased the similarity values between all pairs of the nodes in the set with a unique increment, i.e., it treated all the nodes in the set equally, without considering the order of nodes been visited during the walk



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The node sequence have been visited in each walk forms a path from the start node to the end node, intuitively, on that path, the start node is more similar with the nodes been reached earlier than with the nodes been visited later, i.e., the similarities between nodes have some relationships with the order of nodes been visited



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We alter the similarity computation strategy of this method, add the consideration of nodes' order been visited during the random walk



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Active learning strategy to generate the must-link constraints and cannot-link constraints



Every node compete with all its neighbors to be the candidate of the selection according to their degrees:

$\forall v \in V, u \leftarrow \arg \max_{n \in N(v)} (\text{degree}(n))$; if $\text{degree}(u) > \text{degree}(v)$, then the node v votes for the node u , otherwise, the node v vote for itself



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all the nodes with larger degree in local are extracted into the candidate set SC of the selection from the network



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Partition the candidate set SC into some clusters: every node in SC is taken as a cluster initially, and for every two nodes u and v in SC , if the number of their shared neighbors is larger than half of the degree of either of them, we merge the two clusters in which u and v belongs respectively into one; this merge operation is repeated until some termination criteria are met



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From every cluster, the node with the largest degree and the node(s) with edge(s) connected with node(s) in other cluster(s) are selected into a set S



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For each pair of nodes in S , we access a noiseless oracle to query the relationship between them



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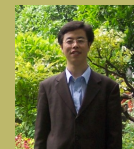


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The most informative nodes and the nodes with least uncertainty are selected to access a noiseless oracle to query the relationship between them



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