**Summary**

In this paper (attached) we design a locally heterogeneous algorithm for community detection. To grasp the network structure, detecting the community framework in heterogeneous networks is beneficial. In heterogeneous networks, searching for similarity is a big challenge. It is interesting to find the similarities among multiple types of individuals and links. We shall discuss (later) some of the similarity measures used in a comparative analysis section.

The goal of local community detection is to design techniques which are sensitive to varying behavior of different parts of the network. Design an effective algorithm for community detection in locally heterogeneous networks. Present the effects of local heterogeneity on community detection on real network data sets. A fast and efficient method to detect community structure is proposed based on node similarity, which discovers the community based on distance measurement i.e. containing a node with maximum similarity. The presented method requires only the network's local information, and there is no need for prior community knowledge.

The basic idea of this algorithm is that there is more possibility of grouping node pairs with minimum distance into the same community.

1. Find local networks and generate sets of probabilities.

2. Calculating relative distance between each node pair.

3. Calculating similarity of each pair of nodes based on relative distance.

Hellinger distances a well-known metric to measure the distance between distributions is used to quantify the similarity between two distributions of probability.

This method shows more reasonable results in line with our common human judgment. This study suggests the idea of closed similarity to use local sub-networks to detect heterogeneous networks communities. To demonstrate the significance of this approach, we implemented and tested the algorithm on a few data sets. It turns out that distance measures are putting forward the best communities. We examined the algorithm on a large-scale network as well. Results show that closed similarity performs well, near Louvain, based on measurement of distance. Because social networks are very large, local analysis on such a network is challenging.

Theoretic definition of closed similarity

The previous similarity measures are tied to a particular application. Our

goal is to provide a formal definition of similarity, we first clarify our intuitions

about similarity.

Intuition 1: The similarity between x and y is related to their closeness.

Intuition 2: The more differences between x and y, the less similar they are.

Intuition 3: When x and y are identical their similarity is maximum, no matter

how much closeness they share.

We try to arrive at a definition of similarity that captures the above intuitions.

Since there are many alternative ways to define similarity.

In this section,

we first make a set of few assumptions about similarity that we believe to be

reasonable. A similarity measure can then be derived from those assumptions.

In order to capture the first intuition, we need a measure of closeness. Our first

assumption is:

Assumption 1: The closeness between x and y is measured by

I(closeness(x,y))

where closeness between x and y is a proposition that states the closeness be-

tween x and y; I(s) is amount of information about x and y. For example if x is

red and y is orange then the closeness between x and y is color(x) and color(y).

In information theory [31], the information contained in a statement is measured

by the negative logarithm of the probability of the statement. Therefore,

I(closeness(x,y) = −logP(color(x) and color(y))

Since knowing both the closeness and the differences between x and y means

knowing what x and y are, we assume.

Assumption 2: The differences between x and y is measured by

I(descriptions(x, y)) − I(closeness(x) and (y))