COMP4641: Social Information Networks Analysis and Engineering

2020 Spring Semester Assignment 1

Date assigned:

Due time: 23:59pm, Apr 01 (Wed), 2020.

IMPORTANT NOTES

- Your grade will be based on the correctness, efficiency and clarity.
- Late submission: 25 marks will be deducted for every 24 hours after the deadline.
- ZERO-Tolerance on Plagiarism: All involved parties will get zero mark.

Problem 1 (40%)

Given the definition of following models:

- Static geographic model: Given N nodes randomly dispersed in the space, each node has a fixed position and each node is connected to its m nearest neighburs, m is the same for all the nodes.
- Random growth model: Similar with preferential attachment growth model (Barabasi-Albert model), except that for each new added node, the probability pi that the new node is connected to node i is the same for all the existed nodes $p_i = \frac{1}{\sum_i 1} = \frac{1}{n}$, n is the total number of existed nodes when the new node is added.

In this question we will compare these two models with Erdos-Renyi model and preferential attachment model.

- (a) For an Erdos-Renyi model with N nodes and link probability p, what is the expected degree \bar{k} ?
- (b) Consider a static geographic model with N nodes and $m \approx \bar{k}$, then compare it with the previous Erdos-Renyi model, whether the following statements are true or false, and give your explainations?
 - 1) the static geographic model has stronger locality
 - 2) the static geographic model has shorter average shortest path
- (c) Compare random growth model with Erdos-Renyi model, explain why links are unevenly distributed in random growth model? Which model has more nodes with degree 1?
- (d) Compare random growth model with preferential attachment model, for the following two pictures, each has 500 nodes, which model fits best to each picture and explain why?
- (e) Suppose for random growth model, when each new node is added, it's connected to m other nodes, and at each time only one new node is added, then at time t, consider the degree $K^{t_0}(t)$ of the node which was added at time t_0 , it satisfies

$$\frac{dK^{t_0}(t)}{dt} = \frac{m}{t}$$

with $K^{t_0}(t_0) = m$, give the solution for $K^{t_0}(t)$?

(f) For preferential attachment model,

$$K^{t_0}(t) = m \left(\frac{t}{t_0}\right)^{\frac{1}{2}}$$

when t_0 is small, $K^{t_0}(t)$ is large, which means old nodes have large degrees at time t. Now consider when t is large, the percentage of nodes with degree smaller than $K^{t_0}(t)$ is

$$P(k \le K^{t_0}(t)) = \frac{t - t_0}{t} \tag{1}$$

explain why and give the degree distribution P(k)?

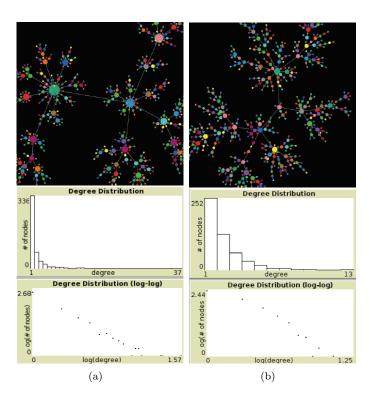
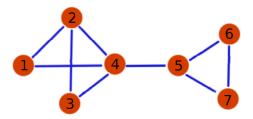


Figure 1: (a) Model 1; (b) Model 2.

Problem 2 (30%) Given the following network,



- (a) What is the normalized degree centrality for node 2? What are the normalized betweenness centrality, normalized closeness centrality and clustering coefficient for node 4?
- (b) What is the value of network constraint for node 5?
- (c) What is the modularity matrix for this network? You can check with the provided notebook's results and also see how a brutal force search is used to find the optimum community structure with maximum modularity.

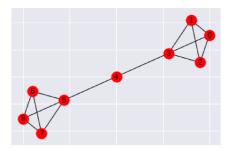
Problem 3 (Programming) (30%)

Given a adjacency matrix of some undirected graph, you are required to write a python program that performs the following two functions:

- (a) Implements the Girvan-Newman algorithm and outputs the resultant hierarchical decomposition of the network. If there are multiple edges have the same highest betweenness score, remove all of them simultaneously.
- (b) Implements the calculation of modularity, and outputs the corresponding cluster structure.

Implementation Details:

For example, given the following graph (Note: A graph different from the example graph above will be used in grading. So do NOT hard-code this graph in your program)



• Your program should first read the input file:

- the first line contains the number of nodes;
- the remaining lines contain the adjacency matrix.
- Your program output should have two parts:
 - 1) The first part outputs the hierarchical decomposition produced by the Girvan-Newman algorithm, in the following format:

```
network decomposition:
([0, 1, 2, 3], [5, 6, 7, 8], [4])
([0], [1], [2], [3], [5], [6], [7], [8], [4])
```

2) The second part outputs the modularity results, in the following format:

```
3 clusters: modularity 0.4209
9 clusters: modularity -0.1148
optimal structure: ([0, 1, 2, 3], [5, 6, 7, 8], [4])
```