Infectious Disease Spread

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Complex Networks 2017/2018

**Introdution**

A complex network is a mathematical structure that models how a population of entities behaves with one another. This structure consists on a set of nodes, which represent the entities, and edges, which represent the relationships between nodes. Networks can be applied to almost anything in most study areas.

In this work, network science is used to model a human contact network related to the propagation of diseases in a population. It is based on a study done on Stanford University[1] (California, USA), where all credit for the previous analysis is due.

Infectious diseases are usually passed via droplets during the close proximity interactions, and thus the pandemic spread of an infectious disease poses a big threat to society in several ways.

This work aims to understand how a disease might spread across a population, so that us humans can understand how to fight it, by studying on a low-scale controled environment such as a highschool. Each individual was given a proximity sensor that registered it’s close proximity interactions. These devices have a radius of 3 meters and had a coverage of 94% of the total school’s interactions.

***“Schools are particularly vulnerable to infectious disease spread because of the high frequency of close proximity interactions”*[2]**

**The Dataset**

The dataset used consists of a single-day recording obtained from an American highschool. The network built is a weighted undirected network.

Nodes represent individuals (i.e., people) and edges represent close proximity interactions between said individuals.

There are 788 total nodes (655 students, 73 teachers, 55 staff, and 5 other persons). The edge representation is detailed in the next session.

The dataset can be found on the original’s study’s webpage[1]

**Edges – Contact Representation models**

Each edge represents a close proximity interaction between two individuals. An interaction between two individuals is defined by a continuous sequence of close proximity records, stored on the individual’s device. There are four considers a contact as the sum of all interactions. After recording for each individual all the close proximity records how do we build the edges? And what weight do we assign in order to differentiate contacts with bigger duration from the ones with small durations?

To do these 4 strategies are used in this dataset:

1. Add-then-chop
2. Chop-Then-Add
3. Chop-then-count
4. Just-Chop

The first 3 make use of the “minimum duration” parameter that defines the minimum duration (in CPRs) for an interaction must be set and the last one makes use of the “drop-off” parameter that defines the minimum CPR gap to be filled (allows you to assume that the dataset might be missing CPRs).

The first strategy first adds all interactions (CPRs) between two individuals to create the weight of the edge between the two, and then applies the minimum duration parameter, i.e. doesn’t consider edges with a weight less that the value of the minimum duration parameter. The second strategy first applies the minimum duration parameter to all interactions between two individuals and then adds everything in order to create the weight between the edges of the 2. The third …. To be continued

**Network Metrics**

[RR] Degree Study

ToDo

[RR] Average Path Length

ToDo

[JR] Clustering Coefficient

Average Clustering Coefficient: 0.005622395491693588

Node with lowest Clustering Coefficient 374(Role Here) -> ( 0.0013795108060206942 )

Node with highest Clustering Coefficient 25(Role Here) -> ( 0.04722572403965249 )

[RC] Diameter

ToDo

**Node Metrics**

[RC] Degree Centrality

ToDo

[RC] Eigenvector Centrality

ToDo

[JR] Closeness Centrality

Average Closeness Centrality: 0.6207525375025098

Node with lowest Closeness Centrality 375(Role Here) -> ( 0.3705273069679849 )

Node with highest Closeness Centrality 170(Role Here) -> ( 0.7509541984732825 )

[JR] Betweeness Centrality

Average Betweeness Centrality: 0.0011027788727294

Node with lowest Betweeness Centrality 266(Role Here) -> ( 0.0 )

Node with highest Betweeness Centrality 15(Role Here) -> ( 0.006957799391153176 )

**Conclusion**

ToDo

**References**

[1] <http://sing.stanford.edu/flu>

[2] <http://sing.stanford.edu/pubs/PNAS-2010-1009094108.pdf>