# **Epidemic Spreading Analysis Using Social Networks**

DIGITAL MEDIA AND SOCIAL NETWORKS

ECS637U/ECS757P

# Context

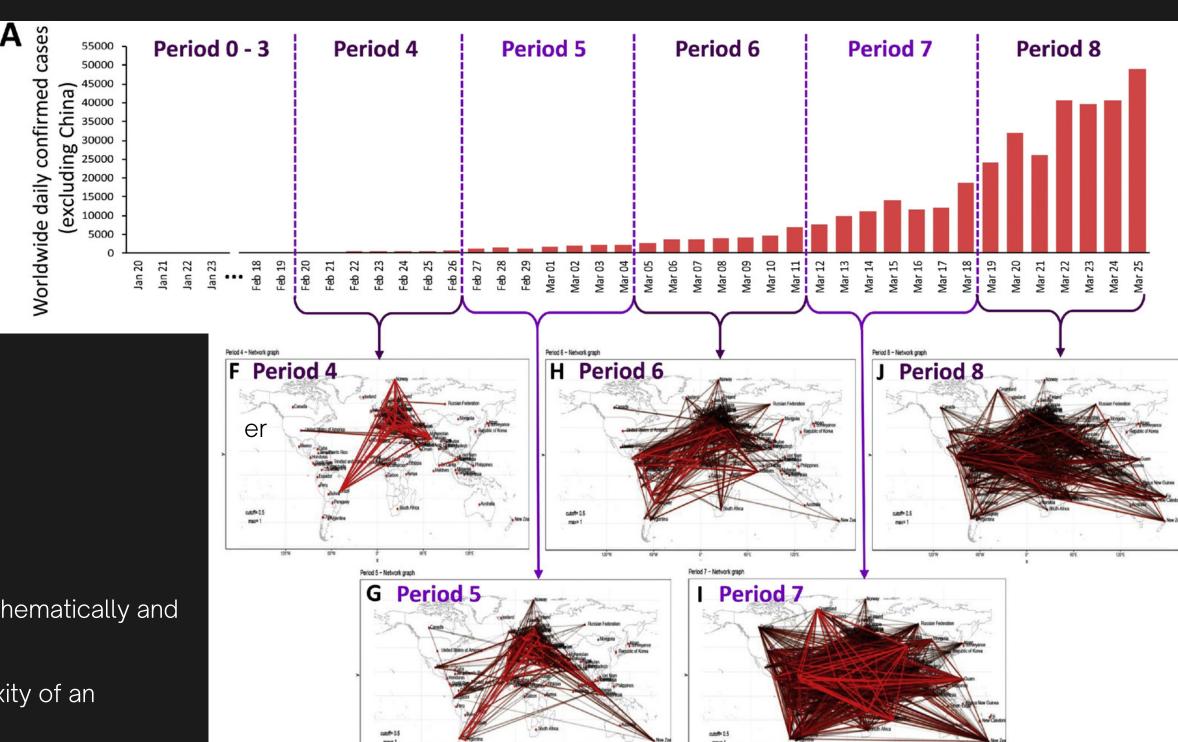
Assessments of epidemic spreading in a population usually focus on large scale analyses, e.g. movements of people between cities or countries. However, it is also interesting to elucidate how spreading works at a small scale (i.e. within cities or communities). To combat an epidemics, it is critical to take into account the structure of the social network and how it supports or slows down spreading, and to model the effects of local changes in the network (such as lockdown).

This project will rely on subsets of datasets available from the social network app Gowalla. Gowalla was a location-based social networking service. The first large-scale dataset is a friendship network, where each node is a user and each edge denotes friendship. The second large-scale dataset is a record of 6,442,890 checks-ins (including geographical coordinates) of these users over the period of Feb. 2009 - Oct. 2010. The project will be based on excerpts of these datasets, on a much smaller scale.

By combining these two dataset sources, one can simulate a hypothetical epidemic spreading between friends who meet in a same place within a given time window, and see how the network structure influence this spreading. Then, specific measures can be proposed: for example, to allow a maximum travel distance within the city, or a maximum of friends one could visit. The analysis and subsequent measures proposed have to be based on network key features such as eigenvector centrality, node removal analysis, or other methods covered in the module.

# Motivation

- Growing attention in estimating epidemic spread after Coronavirus outbreak.
- Graphs are extremely flexible for representing such complex processes. They capture interactions among the communities.
- Network centrality measures are effective in predicting the spread of diseases.
- Study the network to identify the hotspots and communities impacting them to define approaches to control the spread.



Ref:https://www.sciencedirect.com/science/article/pii/S1201971220303179

# Challenges

- Modelling transmission through networks is mathematically and computationally challenging.
- Difficult to understand the probabilistic complexity of an epidemic spread.
- A small part of the network is generally observed, hence could be misleading.
- The coarseness of the data being gathered is determined by the geographical locations. As a result, anyone suitable consistent approach not available

# ABOUT THE DATASET

# DATASET 1: FRIENDSHIP NETWORK

Friendship network defines the relationship (edges) between people (nodes) identifying various communities. This data would be used for targeted community based interventions.

- Identify the Giant component in the network.
- Undirected graph created with nodes as people and edges as their relationship.
   No relationship strength considered
- Partition the data with respect to modularity for overall max modularity value.

DATA PRE-PROCESSING

Nodes: 10001

Edges: 140869 Closeness Centrality: 2.897

Betweenness Centrality: 5

Modularity: 0.480

**STATISTICS** 

# DATASET 2:

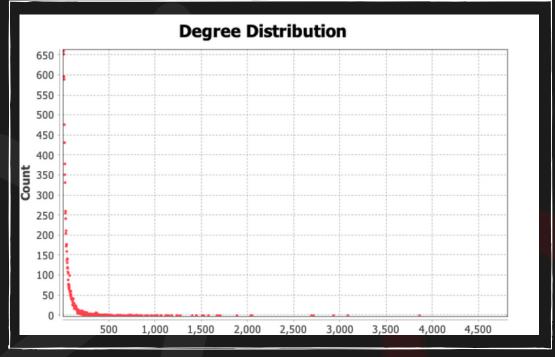
### **CHECKINS DATASET**

Checkins dataset provides an overview of the location where people usually interact. This will be used to identify targeted hotspot-based interventions.

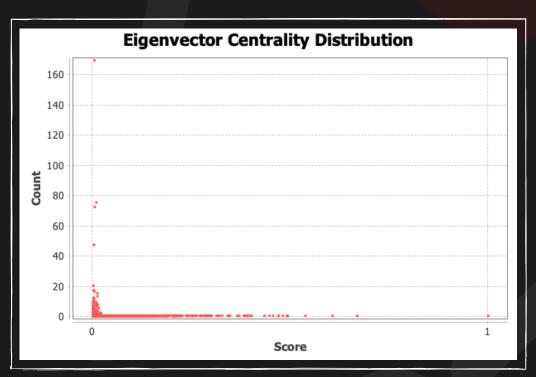
- Two datasets have been sampled:
  - Checkins data for the whole of September by location
  - Checkins data for a September evening to track interactions within a span of 4 hours.
- Two graphs created:
  - Directed Graph with nodes representing people pointing outwards to nodes representing location for September. Edge weight is the frequency of the checkins per location per person.
  - Undirected Graph, with nodes, representing people and locations, for checkins over an evening in 4 hours period

Nodes:	112501	Nodes:	1970
Edges:	138552	Edges:	1440
Average Degree:	2.463	Average Degree:	1.462
Network Diameter:	22	Network Diameter:	8
Modularity:	0.481	Modularity:	0.989
September Checkins		Evening Checkins	

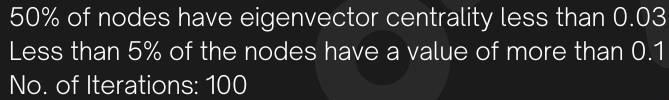
# NETWORK STATISTICS Friendship Network



50% of the nodes have a degree less than 12. Also, 80% nodes have a degree less than 50.

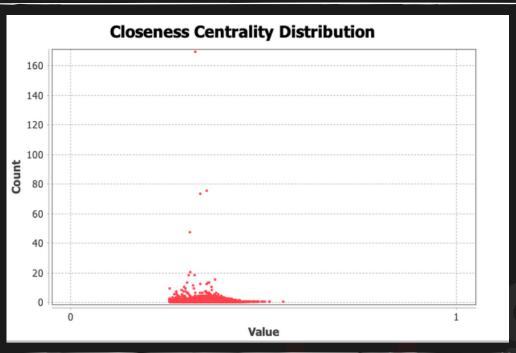


5 Major Communities can be clearly visualise.





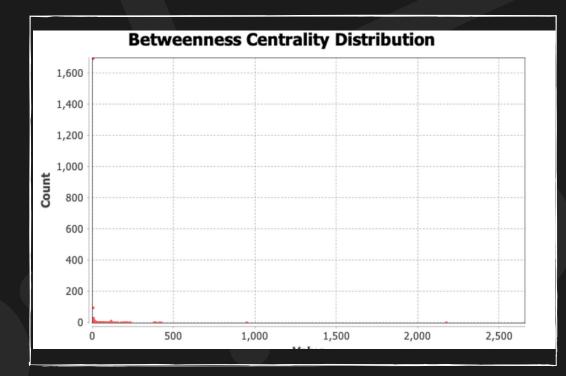
Modularity 0.48 No. of Communities 10 5 communities with more than 1K people.



Average path length 2.89 Network Diameter 4

# NETWORK STATISTICS Checkins Network

## September Evening Checkins



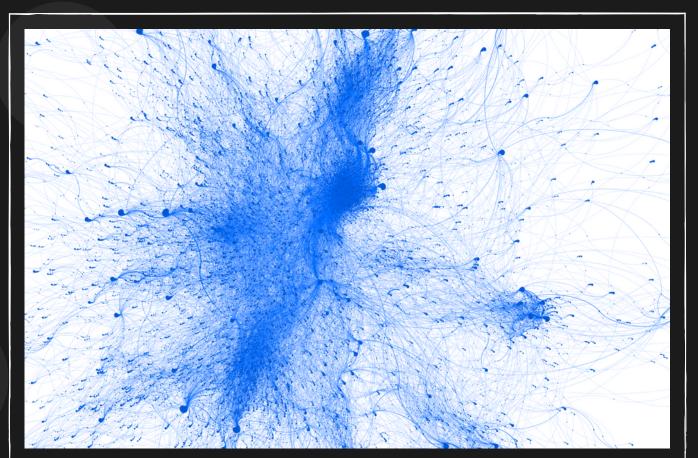
1.5% locations have betweeness more than 100

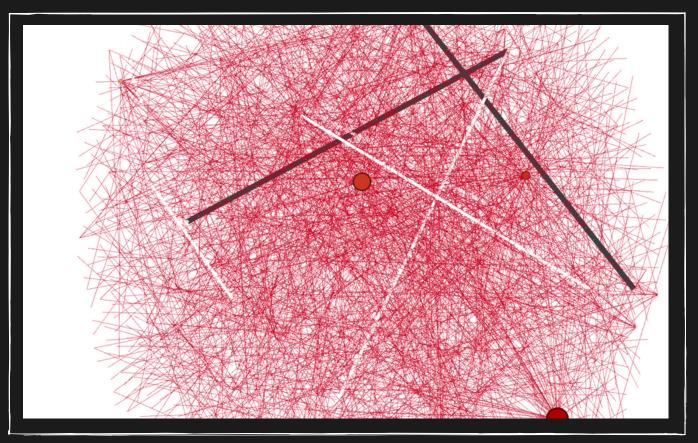
Average Path Length: 2.4

Approximately, 10% of people have a betweeness more than 100

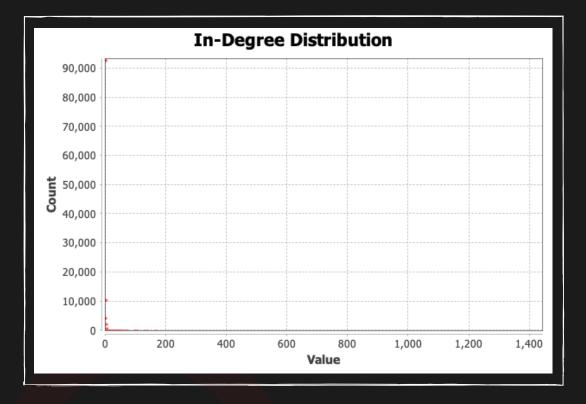
The large size nodes have large betweenness centrality hence maybe the hotspot.

Dense clouds may represent these hotspots (most visited location).









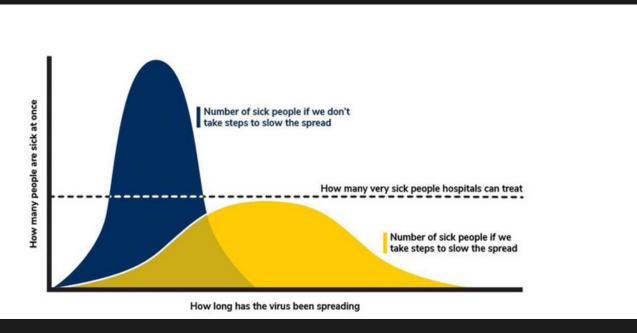
60% of people have an outdegree less than 18, 80% of the people have an outdegree less than 50.

Set of 13 locations which have indegree greater than 50

Captures the local hotspots which are the location visited the most. In the distribution we can see certain nodes having in-degree above 100, these could be the locations which are potential hotspot for spreading diseases.

# APPROACH

Epidemic Simulation in Community	Using SIR (Susceptible, Infectious, Recovered) model to simulate epidemic spread.		
	Identify potential hotspot locations and persons with maximum betweenness and degree centrality		
	Simulate epidemic spread considering a probability p to infect over coming in contact		
Centrality with Epidemic Spread	Identify the nodes with highest centrality over the friendship network		
	Consider betweenness, eigenvector, degree, closeness and other centrality measures		
	Simulate spread after removing 5%,10%,20% of nodes with highest centrality		
Community with Epidemic	Simulate epidemic spread within a community assuming epidemic triggers from a single person there		
	Identify key hotspots and persons removing which (whom) would slow the spread within community		
	Simulate epidemic spread between communities assuming epidemic triggers from a single community		



Ref:https://link.springer.com/article/10.1007/s13755-020-00121-9

# Key Metrics

**Spread** 

### **Epidemic Simulation**

- Size of Spread/ Final Size
- Time for spread of infection with number infected at a time
- R number by time

# Removing nodes with highest centrality

Identify key hotspots and persons removing which (whom) would slow the spread between communities

- How Size of Spread is reduced
- Time taken to spread increases
- R number along with max infected at a point is reduced

### Community with Epidemic Spread

- Size of Spread within a community is reduced
- Reduce time to spread between communities
- Overall R number impact with max infected at a point

# Thank You..