**CSE 8803 EPI: Data Science for Epidemiology, Fall 2022**

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Lecture 7 : Network Construction

# 1 Lecture Summary

In this lecture, we discuss how to think of the SIR type models as networks to understand the spread of disease. We discuss the use of these networks for contact tracing as well as how networks can be built off of different data sources.

# 2 Common Network Models

In a network model, a circle represents a person, and square represents a location and a line represents a connecting edge. There are four common network models as seen in Fig 3. A person to person network involves unweighted connections. In a person to location network, people are interacting indirectly through a location. Locations can represent different zipcodes or even rooms within a building, like a hospital. A oneway population hcw can include directed edges. In the case of a travel city to city network, nodes can represent cities with weighted edges representing the volumn of travel between them.

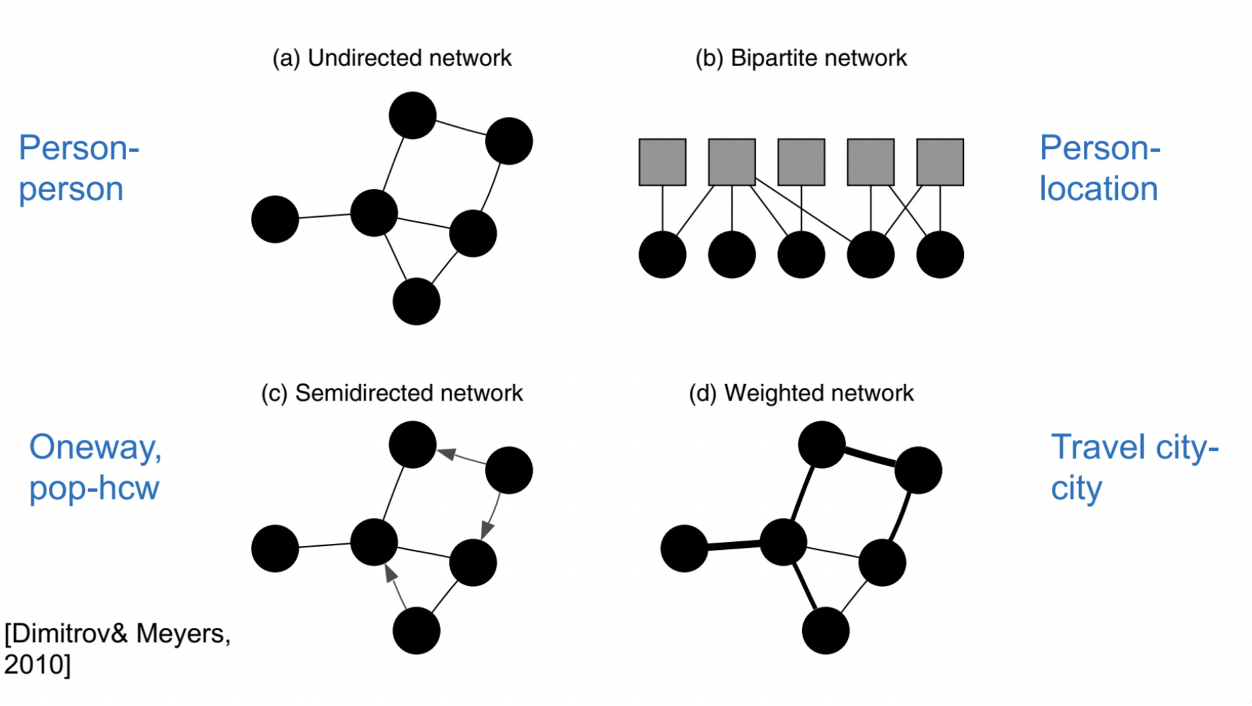
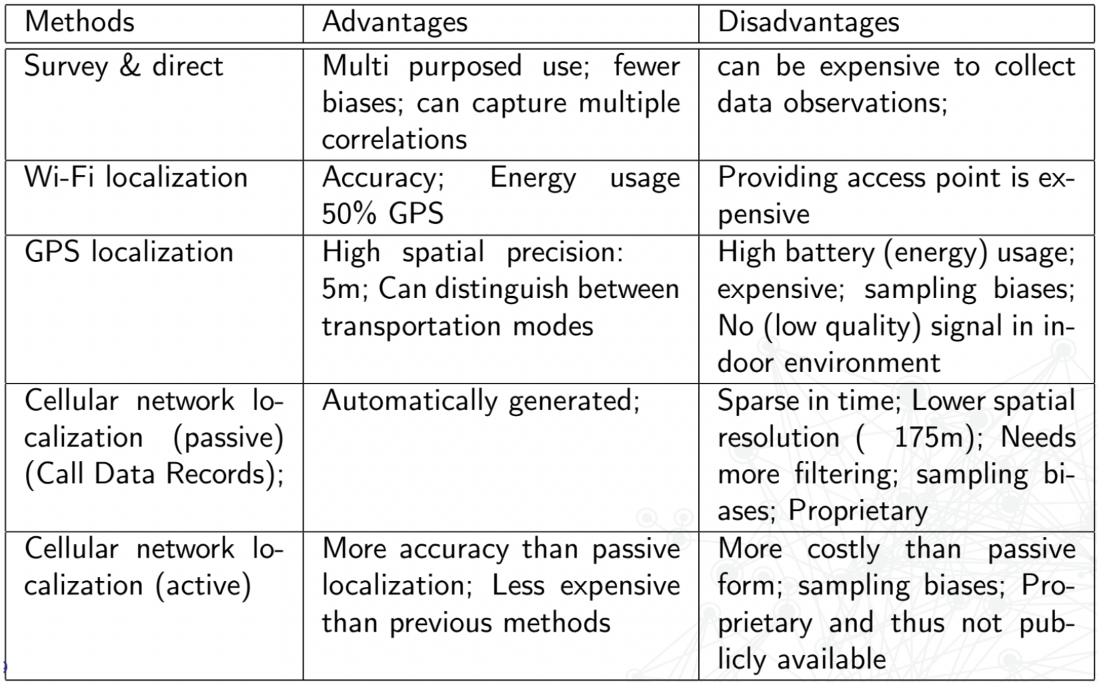


Figure 1: Common Network Models

# 3 Building a Network Model via Mobility Data

When building a network, one needs define the nodes involved in the model as well as what a contact edge would represent. For example, for respiratory diseases, and edge would represent close proximity. For sexually transmitted diseases, and edge would represent sexual contact, needle sharing, etc. A distribution of epidemiological contacts can be collected through mobility data[6]. Mobility can be acquired through a combination of surveys and trace data. Survey data includes census data, mobility statistics, activity surveys, etc. while trace data includes GPS, WLAN, cellular, or Bluetooth data. Mobility data would ideally be easy to collect and provide substantial information into transmission. This would involve a useful frequency of collection.



| Methods | Advantages | Disadvantages |
|---|---|---|
| Survey & direct | Multi purposed use; fewer biases; can capture multiple correlations | can be expensive to collect data observations; |
| Wi-Fi localization | Accuracy; Energy usage 50% GPS | Providing access point is expensive |
| GPS localization | High spatial precision: 5m; Can distinguish between transportation modes | High battery (energy) usage; expensive; sampling biases; No (low quality) signal in indoor environment |
| Cellular network localization (passive) (Call Data Records); | Automatically generated; | Sparse in time; Lower spatial resolution ( 175m); Needs more filtering; sampling biases; Proprietary |
| Cellular network localization (active) | More accuracy than passive localization; Less expensive than previous methods | More costly than passive form; sampling biases; Proprietary and thus not publicly available |

Figure 2: Advantages and disadvantages of mobility data [5].

## 3.1 Considerations of Mobility Data

Different types of mobility data have different pros and cons with respect to usefulness, data collection cost, etc. These pros and cons are described in Fig. 2.

When collecting mobility data - particularly trace data like GPS, which is collected without consent of the user - one must also consider what could happen if the data is being used with malicious intent. Often times, extra precautions are made to mask the individual's personally identifiable information.

Another thing to keep in mind is the potential socio-economic bias present in the data.

For example, trace data like GPS data might better describe sections of society with better technological availability. This might reduce the applicability of the mobility data to describe epidemiologically-relevant networks.

## 3.2 Examples of Systems using Mobility Data

### 3.2.1 RFID tags and Localization

One great example is the use of RFID (Radio Frequency Identification) tags paired with localization data. Recall from previous lectures, the MIT Reality dataset investigated the capability of smartphones to track human interaction in a certain community, and in this case around the MIT Media Laboratory [3][8]. They discovered that the decision of identifying one another as a friend is significantly correlated with spending time after work/at weekends, in other words, sharing the same localization information in certain time periods. They also claimed that there is periodicity in one person's behavior and the interaction between people can, in a way, be predicted.
Another example is located in a high school, where wireless sensor motes were distributed to students, faculty, and staff. Using the localization data, they built a social network with 762,868 CPIs (close proximity interactions) at a maximal distance of 3 meters across 788 individuals. They did 100 simulations on each of the 788 individuals with an SEIR model imposed over the network and found that the secondary infections and $R_0$ are in agreement with school absenteeism data during the experiment period.

**Impact of Attendance on Infections** An intriguing observation is the relationship between attendance rates and the number of secondary infections. Specifically, models that utilized RFID and localization data revealed that lower attendance rates were associated with a higher number of secondary flu infections. This counterintuitive finding underscores the complexity of disease transmission dynamics and highlights the value of real-time data for predictive modeling.

**HAI Example** A critical application of RFID technology is in healthcare settings for tracking Hospital-Acquired Infections (HAI). RFID tags can be attached to hospital staff ID badges, patient wristbands, and even medical equipment. By monitoring these tags, it's possible to construct a dynamic contact network within the hospital. This data can be used to identify high-risk areas for HAI transmission and assess the effectiveness of intervention strategies. Studies have shown that such a system can provide valuable insights into the spread of HAIs, enabling healthcare providers to take targeted actions to minimize infection rates.

### 3.2.2 COVID-19 examples

There are numerous examples used for COVID-19:

- Maps and directions in Apple [2]
- Location history in Google [4]

- High resolution imagery in Facebook
- POI access in Safegraph
- Mobile phone data for Cubeiq
- Immune response and inflammation [9].
- etc...

#### 3.2.3 First Principle Approach in Epidemiology

The first principle approach in epidemiology often involves the use of computational tools and methodologies to analyze large-scale data sets. One such example is PLINK, a toolset designed for whole-genome association studies. It focuses on data management, summary statistics, population stratification, and identity-by-descent estimation among other functionalities [7].

When building a contact network based on how agents are acting in the model, the first principle approach emphasizes some core aspects of one individual's information that need to be addressed:

- **Maps and directions in Apple**: Apple Maps has contributed to COVID-19 response by aggregating anonymized user mobility data to produce Mobility Trends Reports. These reports display changes in the volumes of people driving, walking, or taking public transit, providing valuable information for public health authorities to understand the effectiveness of social distancing measures. [2]
- **Location history in Google**: Google released COVID-19 Community Mobility Reports that use aggregated, anonymized data to chart movement trends in various places such as retail and recreation spots, parks, and workplaces. This data helps authorities assess how well social distancing guidelines are being followed and informs policy decisions. [4]
- **High-resolution imagery in Facebook**: Facebook's Data for Good program provides high-resolution population density maps, enabling researchers to better predict the spread of the virus. The maps use satellite imagery and machine learning to estimate population density and demographics, thereby enhancing the precision of epidemiological models.
- **POI access in Safegraph**: SafeGraph provides anonymized Point-of-Interest (POI) visitation patterns culled from mobile devices. The data includes visits to essential businesses like grocery stores and medical facilities, helping researchers and policymakers understand the impact of public health interventions on human mobility and virus transmission.
- **Mobile phone data for Cubeiq**: Cubeiq utilizes mobile phone geolocation data to analyze mobility patterns, including how often people leave their homes and the distance they travel. This data is useful for understanding how mobility is linked to COVID-19 transmission rates, thereby aiding in the formulation of targeted public health interventions.

- **Immune response and inflammation**: Some research efforts have utilized health data from wearables to study immune responses to COVID-19. For example, a study explored biomarkers and cytokine profiles to understand inflammation and immune response in COVID-19 patients, paving the way for potential treatment strategies. [9]

These are aspects that can change along the time as disease spread or other interventions go on. Noticeably, the challenge here is that usually there is no one dataset that will give all aspects of data one is looking for when building in this kind of agent-based model. Instead, one need to synthesize multiple datasets and domain knowledge to cover all the aspects needed for the first principle approach. After successfully aggregate all the information, one can use the network to model behavioral changes, such as hypothesizing the absence of certain conditions to observe the changes accordingly.

## 3.3 Aggregation data from various sources

One application example is shown in Figure 4. This is a good visualization of synthesizing multiple data streams into a social contact network. The "Who" data is collected from the census data of different areas combined with social media. Then they figure out the synthetic population (ex: who are in the same household) and their "When", "What", and "Where" through different sources. Aggregating all these information build the synthetic social contact network.

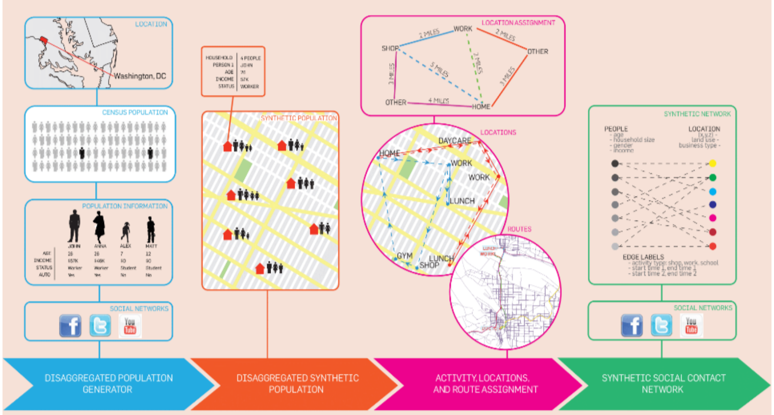


Figure 3: Synthetic Social Contact Network

## 3.4 Example: COVID-19 in MA

Since behaviors change after interventions, in order to accurately model the behavioral changes of people, one can split the mobility in terms of layers. As shown in Figure 5 [1], this is a mobility study in the Massachusetts. They split the population into children and adult to visualize their fraction vs. location accordingly. They investigate their movement throughout the day and separate the data in terms of location layers: school layer, workplace and community layer, and household layer. During COVID-19, many schools switched to remote and the network should change accordingly by removing the school layer to accurately reflect the mobility.

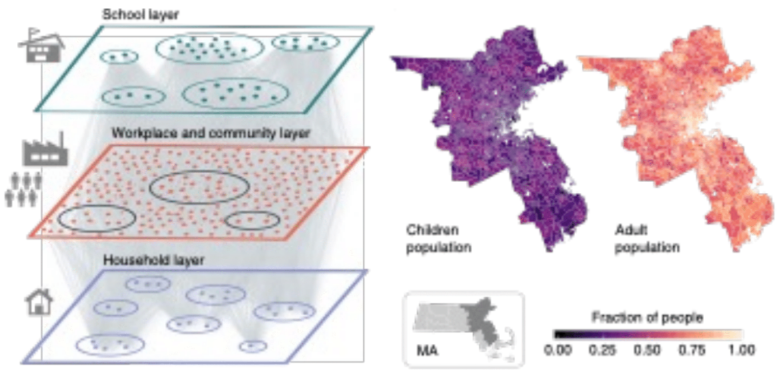


Figure 4: Layers of Mobility in MA

### 3.5 Multi-source data: Copenhagen Networks

Another example of a multi-source data aggregation is the Copenhagen Networks Study.They collected data from various sources uploaded by users and obtained from 3rd party servers. Users' data include WiFi access, Bluetooth scans, location estimates, etc. 3rd party servers like Facebook can provide friend list, likes, tags, etc, or like university administration can provide course grades. These various sources were aggregated into a single network and researchers can access the API to do investigation. They provided a temporal aggregation of the Bluetooth network as shown in Figure 6, showing how people are connected and how the structure changes along a small period of time, and the granularity here is very important for observation. The network is in use at GT for COVID-19 purpose, include phone-base proximity alerting and Infrastructure-based (WiFi) social interaction.

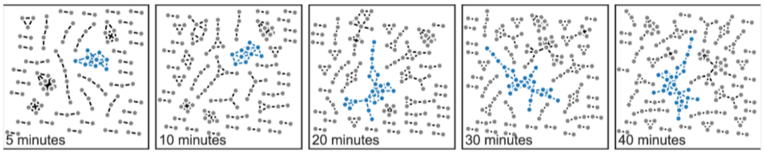


Figure 5: Copenhagen networks: temporal aggregation of Bluetooth network

### 3.6 WiFi as a coarse location sensor

Just as mentioned in the previous example, passive sensor stream can be extremely powerful when collecting data for analysis. Specifically, WiFi can act as a coarse location sensor, the regular authentication to the campus network from devices is the indication of location of the user. GT has over 7000 access points across 250 buildings, so these location information can be very accurate. For application in COVID-19, the WiFi information can provide details such as which students have close contact in a room for certain period to estimate risks.

An example of this is the WiMob application. Instead of route data that cover many places, WiFi Mobility data targets fewer spaces and can be more specific. Usual practice include remote classes/localized closures. One project done in Fall 2019 investigate the relationship between WiFi Mobility Network versus Enrollment. They visualize the enrollment and WiFi mobility in Figure 7. In the first week, there are plenty of enrollment and people come to classrooms, while in the 10th week there are fewer enrollment but fewer people come to classrooms. At the end of the semester, the network becomes very dense: enrollment and WiFi mobility paired very well because people come to take exams. In this case, since as the time goes, the enrollment does not change much but the attendance changes a lot during the semester, and in this case enrollment overestimates the efficacy of remote instruction.

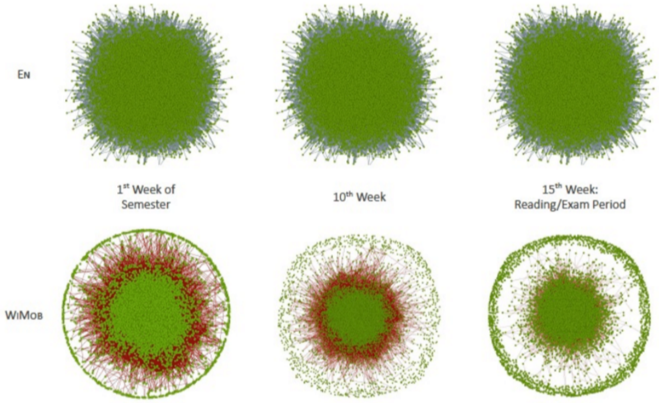


Figure 6: WiMob data vs. Enrollment

## 3.7 Dynamic COVID Model

One project focuses on building a dynamic COVID SEIR model. They used the dynamic collocation network as the underlying contact network. By capturing the asymptomatic transmissions and isolating symptomatic individuals and considering the external infections from the surrounding neighborhood, they calculate the confirmed cases real time.

## 3.8 Multi-network and Co-evolution

In the real world, many changes in the behaviors can only be explained when incorporating multiple networks. The diffusion of behaviors can be affected by different interventions in neighbor-networks, such as intervention/policies on social information networks that leads to diffusion of public information and disease dynamics on social contact networks that leads to epidemics changes. In this way, we can think of how misinformation can have huge impact on people behavior.

## 3.9 If data is plenty

Many of the times there are plenty of data, and some question cannot be answered just with collecting more data, such as on social.web cascades. But one can infer the underlying propagation network from set of observed cascades such as using Machine Learning methods or incorporating more generally surveillance information.

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