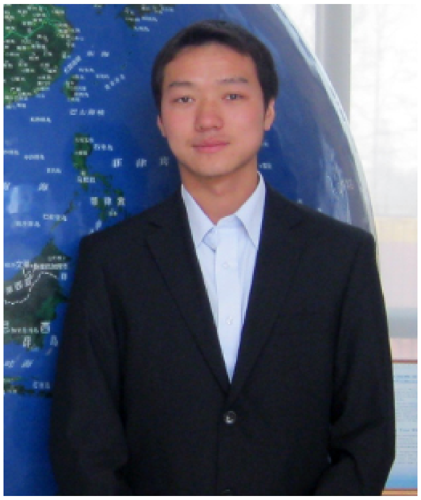
COVID Information Commons (CIC) Research Lightning Talk

Transcript of a Presentation by Song Gao (University of Wisconsin-Madison), April 14, 2021



Title: *RAPID: Geospatial Modeling of COVID-19 Spread and Risk Communication by Integrating Human Mobility and Social Media Big Data*

Song Gao CIC Profile

NSF Award #: 2027375

YouTube Recording with Slides

April 2021 CIC Webinar Information

Transcript Editor: Macy Moujabber

Transcript

Song Gao:

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Thank you Helen. Hello everyone, my name is Song Gao. My topic today is mapping human mobility and close contacts for the geospatial model in COVID-19 spread. This is a joint work with my colleagues with Qin Li from Mathematics, Kaiping Chen from Life Sciences Communication, and Jonathan Patz from Public Health. So all of us are at the UW Madison and funded by NSF as a social and behavioral science. So this is a different aspect that are very relevant to previous talks.

Slide 2

And for us, at the beginning during the pandemic, you know, first thing we are interested to look at how different community neighborhoods responded to the stay at home was - the home orders. So by tracking the mobility patterns, as you can see from the dashboard, and if it is a- if the colors used blue mean that on a particular day in a particular county, there is a reduced mobility measure by the median with individual maximum distance, and the red color showed increase mobility. By tracking the mobility patterns, we can further associate the mobility pattern with the COVID-19 confirm case growth rate and what we found was that there exists a statistic significant association regarding the mobility pattern and then the COVID-19 infection rate, also with some temporal lag. And if we compare the before stay at home and after stay at home order, we found the doubling time, you know, increase which also shows the effectiveness of the stay at home orders.

Slide 3

And then, in order to do the modeling, one critical dataset was missing from the open, you know, mobility dataset is about the travel flows between different places. So this is why we collaborated with SafeGraph and to aggregate the anonymized mobile phone data and to provide the state to state and county to county and also the track to track spatial interaction flow data set. And this is the open data repository available on GitHub and we still maintain the weekly updates, but the resolution is daily updates. And if people are interested, you can still incorporate this data set into your research.

Slide 4

And at the local level, in addition to the travel distance and then the stay at home time, we also utilize individual level mobile phone data to measure the closed contacts information as a proxy, you know, whether they are crowd events. As you can see on the map this is around our University of Wisconsin Madison compressed area, also the downtown of Madison, and as we know there was a surge in last summer, when our campus reopens. So this is why we hope to utilize such a, you know, mobile phone tracking platform to understand, you know, whether people have some gathering events. And as you can see from the map, we measure at the specific sensor block groups and the darker color is and then the higher of the close contact means that there might exist something in a gathering. So this is as a proxy and to inform some of the local decision making.

Slide 5

And utilizing the mobility and then the close country information, we further view the mobility augmented traditional, you know, SAER or academic model to understand the geospatial spread of the disease. And one innovation of our model was that we specifically take the spatial induction we mentioned earlier into the, you know, this compartment modeling effort and to consider the impact of the, you know, interstate travels. And so we evaluate three specific measures: travel flow restriction, the testing or reporting rate, and the social distancing, you know, policy, which is directly linked to the transmission rate. And so what we found was that, actually ,the travel flow instruction you know regarding the impact is not as, you know, important as you know social distancing and also the testing reporting rate. At the beginning of March 2020 in the U.S. average, there are only about 22 percent of the confirmed cases has been reported based on our modeling effort. So as shown in the plot on the right, we also quantify the impact of the timely quarantine in isolation of the infected cases and the x-axis shows the delay in time of days and the y shows the logarithm of the set of people. So you can see that in some state at that time like New York and Michigan, if the, you know, infected cases not isolated or quarantined in, you know, about two days, then the majority of people in these two states will be, you know, largely infected. So again to show the important importance of the timely quarantine isolation.

Slide 6

So finally at the inter-county level, we also take the spatial heterogeneity into consideration in our modeling effort. Specifically, these are two typical counties in Wisconsin. So within country as we know, there is a large age structure in the criterogenity because of the existence of their university and versus Milwaukee county. We know that Milwaukee is one of the most, you know, segregated metropolitan areas in the US. So there is a large you know race and ethnicity heterogeneity. So this is why if we compare the, you know, COVID-19 infection rate versus the spatial heterogeneity of the race and age structure, we can find the- is actually correlated with the infection case you know very well. So again, we try to use different demographics to explain the spatial heterogeneity of the COVID-19 spread. So that's all for my presentation. Thank you for your attention.