COVID Information Commons (CIC) Research Lightning Talk

Transcript of a Presentation by Michael Chertkov (University of Arizona), November 15, 2021

Title: *Graphical (and Agent Based) Models of Pandemic*

Michael Chertkov CIC Database Profile

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Transcript

Michael Chertkov:

*Slide 1*

Thank you very much. My name is Misha Chertkov, and I'm telling you about graphical models of the pandemic. Also, I will be mentioning agent-based models, so I'm on the applied mass side of the aisle. Let's go on.

*Slide 2*

That's my kind of road map of activities which we started, well, this pandemic, basically. What I'll be telling you about is based on those two papers which are available on archive. Only entry of some portions of this road map is covered, and specifically I'll be talking about inference and prediction and prevention of pandemics. There are many other aspects which we are planning to go ahead with, and one reason for me to talk here is maybe to look for collaborators.

*Slide 3*

It all started with data, and we got quite a lot of data on how the pandemic expressed. There are all kinds of biological, epidemiological, geographic, environment mobility, which is very important for what we are doing, etc. data. I don't mean to read this table literally, but I wanted to emphasize that it's an important new ingredient for modelers like myself to start thinking, and you or for that matter, to start new projects to model the pandemic.

*Slide 4*

On the level of modeling, we talk about very different levels of resolution and very different sources of information, in particular from data which I mentioned, and different expertises which are certainly needed. My position today for the purpose of this talk will be somewhere kind of in the middle in a sense that we'll be talking about the geographical maps and geographs (how we call them). I'll not be discussing a very aggregated model, what we call compartmental models, even though those were very significant first steps in modeling the pandemic in general, not only COVID. By the way, everything which I'll be talking about is generalizable to other pandemics and other situations, actually, not only viral but also social. I'll be mainly discussing what you're calling graphical models but also will be mentioning agent-based.

*Slide 5*

That's another diagram which basically puts scales into the play. We are mainly interested in these projects on a neighborhood scale, maybe a city like Tucson, or maybe a county, but of course this modeling or kind of paradigm extends to different scales. We are predicting what will happen if there is an injection of infection in a particular city, for example, through a super spreader, and projecting now what will happen two or three weeks from now. They of course also mean not only to predict but also to prevent. In the first place, I mentioned data. We want to learn parameters in our model, so all of that is a one-to-one umbrella.

*Slide 6*

Very high-resolution models are known under the name of agent-based models. Before the pandemic started, we had quite a lot of expertise on that in the world, but very few of those, actually only one, was an open source. Now you see the list of ABMs (that's how we call agent-based models) which are now all pretty much open source. We can all play with them and extend them. They account for different effects like masking, quarantining, etc., and that's ongoing work, which is very exciting and very important.

*Slide 7*

Now we are also developing agent-based model software. We are not yet public, but we are heading towards that. Actually, well, in there too, we'll put a paper about that on the archive.

*Slide 8*

Well, features of agent-based models. They're basically the working horse of epidemiology. They're resolving individual people. We are talking about the city of Seattle, for example 700 000 people. So, 700,000 agents, it's extremely heavy. You cannot model and you cannot prevent this resolution, so you need to have reduced models. That's what I'll start talking about very soon.

*Slide 9*

Graphical models is one way of doing this course graining model reduction. It's macroscopic as opposed to ABMs, which were microscopic, they're supposed to be efficient. They're probabilistic, so they count. They are not answering questions affirmatively but giving you estimations of probabilities, and they are data-driven. There are various inputs and various questions you can ask, in particular, what is the probability of injection of infection you happen to have as a threat.

*Slide 10*

Here I'll put a very schematic slide, and it's actually based on a paper which is very famous, very well known, but not in epidemiology, in computer science. That paper discussed the spread of, well, misinformation or information through the internet. Now I'm putting it in a little bit with epidemiological swing. Imagine that I have this grid, and each node in a grid represents a neighborhood. In fact, that one neighborhood is at moment of time 'zero,' and red is infected. So, the rule of the game is that I stay infected only for one step, and then I become black. Black means removed, and otherwise if I am blue, I am susceptible to it. This is a probabilistic model. It basically resolves through connections possible spread. You end up with a particular sample, which is two colors: black and blue. That's a sample, which means that there is a certain probability of this to happen depending on initial infection. You want to answer the question: What is the most probable configuration, or what is the probability of some particular infection?

*Slide 11*

That's if I map to the city of Seattle. It's an illustration of how this type of model would work, so parameters are now characterizing these probabilities of infection between neighbors. You need to learn to extract from the data. I'm putting it all on the rack. I'm showing you how I started. Suppose I have an infection here and that's where I end up. It is a number of steps, so one particular step is intermediate. You see that black is quite spread, but not uniformly, and that's what we want to study.

*Slide 12*

So, the model which describes this final state happened to be a model which is known on the statistical side but also the physics side under the name of 'Ising model.' It's not exactly the same. It's a graph which is a graph of this connection between different neighborhoods. Those 'j's' represent strengths of interaction— how often people travel and how serious, significant [throughout?]. Age is a local bias. It is how much you protect it, how much you are masking, what is the policy, etc..

*Slide 13*

Now, you can ask questions like I mentioned before. What is the probability that infection spreads? Let's say half of the city of Seattle three [days?] after this initial infection is basically infected (initial infection injection). There are a lot of different questions, a lot of conclusions you can draw. You can see that basically very often in this densely populated city, it goes from either everybody getting infected or nobody, so there is a sharp transition which is called an applied mass physics phase transition. You depend very much on data. Data is how you calibrate your model, and you can resolve it not only on a city level. You can go to Wisconsin, for example, which is much more rural in comparison with the West Coast.

*Slide 14*

Again, different questions, but let me now jump to what you can do prevention-wise.

*Slide 15*

You can put these graphical models in this prevention framework, and in the prevention framework you're basically asking questions like “how I can change?”, “How I can introduce, and if I need to, enforce the mask mandate if I want to maybe limit traffic?”

*Slide 16*

Think about it a little bit abstractly as this polytope in a space of characteristics. If I'm within this polytope, I'm green. I'm good. If I'm outside, I'm bad, and then I need to project myself back to this point. This is the type of mathematical formulation which you have for this prevention problem.

*Slide 17*
We play with that. What we care about there is a development methodology. Methodology should be efficient, and that's what we are testing. So again, methodology, but we of course want to be practical and project real problems, to real, well for example, the city of Seattle.

*Slide 18*

Quite a lot of staff work in progress. I've been telling you a little bit about inference, but I didn't tell you much about learning and the overall modeling pipeline from data, to high resolution, into low resolution. That's what is ahead of us.

*Slide 19*

This is a team not only from Tucson but also from San Diego.

*Slide 20*

Thank you very much.

<u>Lauren Close:</u>

Thank you, Misha. That was great. As a reminder to all of our audience members please, remember to share your questions either in the chat or hang on to them for our moderated Q&A session at the end of the presentations. Florence will collect everyone's questions, and we'll talk about them at the conclusion of today's webinar. Next, I'd like to welcome Amanda Leggett, who's coming to us from the University of Michigan.