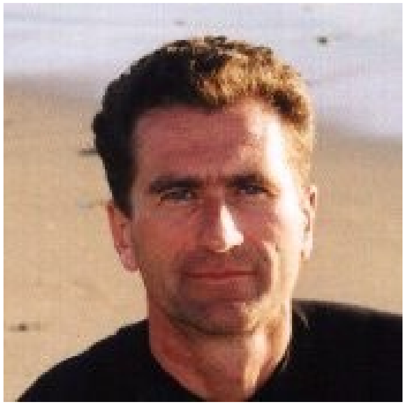
COVID Information Commons (CIC) Research Lightning Talk



Transcript of a Presentation by Peter Pirolli (Florida Institute for Human & Machine Cognition, Inc.), January 31, 2023

Title: Mobility Analysis for Pandemic Prevention Strategies (MAPPS)

Peter Pirolli CIC Database Profile

NSF Award #: 2200112

YouTube Recording with Slides

January 2023 CIC Webinar Information

Transcript Editor: Lauren Close

Transcript

Slide 1

Ok, great, thank you. So the title of my talk is - this is also the title of a proposal that we also put into the PIPPprogram that Mark [Lurie] just mentioned - this is work that I'm doing with my co-PIs Kathleen Carley, Christian Lebiere, and Mark Orr. I'm at IHMC and we've also involved researchers from Carnegie Mellon University and the University of Virginia.

Slide 2

Our proposed Grand Challenge is really around the development of novel computational theories and models of information flow, human behavior, and the transmission and evolution of pathogens.

Slide 3

Our work draws upon research from a variety of fields, mostly centering around the cognitive sciences, so it involves research on social and organizational systems, online social media analysis, machine learning, natural language processing, with a big focus on how to pull that all together into computational cognitive modeling of people.

Slide 4

This is sort of an outline of the kind of work that we have been doing and the kind of center that we're trying to pull together. We collect data from a large variety of sources, including online social media and polling data that has been made publicly available. We're looking into the kind of research that Mark is talking about where we want to employ mobile platforms to collect not only social distancing data but also ecological momentary assessments of what people are doing and what they're thinking. From all of these data, we're developing a variety of analytic methods to infer the perceptions, attitudes, beliefs, and intentions of people in different geographical areas.

We use that to see something that we call psychologically valid agents, which are based on a computational neurocognitive theory that I'll talk some more about. The aim of that is to really try to understand the behavior response profiles of people in these different regions - that is, given the current state of the world, how are they social distancing? Are they wearing masks? Are they making decisions to vaccinate or not? And so on. Those agents go into a kind of synthetic population or agent-based model in which the main thing that we're trying to predict is the time dynamics of these behaviors. Mostly we've been focusing in, so far, on mobility, predicting mobility, and predicting mask wearing. Of course, all of that is related to case rates and death rates as Mark was indicating.

Slide 6

What I'm going to focus on is a very thin slice through this that focuses on this idea of using computational cognitive models to make inferences about people's decision making.

Slide 7

I'm going to focus on this because I think it's probably novel in this space. We are working with a computational neurocognitive theory called ACT-R. This is a theory that's been developed for some decades now. It is partly a theory of how the mind works and it's also a theory of how it is implemented in the brain, so it covers a large variety - hundreds of experiments in cognitive psychology - but also makes predictions about the functioning of the brain. For example, FMRI data and EEG data that's collected as people do various kinds of tasks. It's been used in application in the development of cognitive tutoring systems. It's used a lot in human-computer interaction. Underlying these models are a lot of very complicated dynamical equations that I'm not going to go into, but they cover things like how memory works, how forgetting works, how practice and habit formation work, and so on. It's a unification of all these various aspects of cognition into a single theory in which we can do simulations.

Slide 8

For the purposes of this talk, I'm going to focus on a subset of the mechanisms that are involved in decision making that come from this cognitive theory. They are sometimes called instance-based learning or memory blending. This is a particular kind of decision making that we think we frequently see in people doing real world decisions where they are making decisions based on a generalization of their memories and experiences of previous situations. This primarily leverages the cognitive mechanisms that we know around memory - so how information decays in memory, how rehearsal increases the retention of those memories, how priming works - and it leverages a variety of cognitive mechanisms that are involved in what's called pattern matching.

That is, how memories are retrieved in accordance to how they match the current situation. It's also [related to] this mechanism called blending which essentially generalizes over these experiences to produce kind of the best result for the current situation. And individual biases in decision making result from the fact that people have different kinds of experiences and the way that these cognitive mechanisms actually work.

So, to give you a thumbnail sketch of how the theory works in the simulation - the idea is: every experience, every message, goes into memory as what is technically called a chunk. A chunk is just a unitary thing that captures the features of your particular experience or memory and stores that away.

Slide 9

Of course, over time you have lots of experiences that might be interrelated with respect to some situation or some decision. At the time that a new decision is needed, you perform this kind of memory, very quick memory retrieval, that essentially generalizes and summarizes all that past experience based on the likelihood that it would be retrieved in this particular context as well as the similarity and the inter-similarity of these experiences to the particular situation that you're making a decision about.

Slide 10

So we use these mechanisms to model attitudes and behavior. This is not very standard fare for how this kind of modeling has been done in this community. So this rather novel application - to try to make predictions about people's attitudes and how it influences behavior.

Slide 11

Attitude Theory really comes from social psychology and there's lots of attitude theories. Here's just a canonical theory to give you an idea of how it works. The idea is that your behavioral decisions, whether you're going to wear a mask or socially distance, are influenced by what are called intentions. Your intentions can vary in strength. Those intentions are related to your attitudes towards the likelihood that an outcome is going to happen and the value of that outcome. It's also influenced by subjective norms - what are other people doing? What do other people think about what you're doing? It's also related to what's called perceived behavioral control or what's often called self-efficacy, which is your belief or confidence and your ability to do something.

Slide 12

So those things combine to make predictions about attitudes and in the implementation of behaviors we implement this using this set of mechanisms called instance-based learning. The basic idea is you have a bunch of experiences that are positive around some behaviors, sometimes negative. You're getting social information, you're getting messaging information. At the time that you have to make a decision to exhibit to execute a behavior or not - all those pieces of information and memory and experiences are being combined into that particular decision to, for example, wear a mask or not.

Slide 13

Here's this kind of a toy simulation just to give you a sense of the impact of messages and experiences on intentions and decision making. So this is just a toy simulation in which we assume that there's no real value that you place on mask wearing. But then you get messages at discrete points in time that say it's highly valued. Those messages get stored as chunks and they influence your inferences about the subjective value of wearing a mask. If the cumulative effects of those messages and the timing of those effects of messages impact your overall intention and your expectations, then that has an impact on your decision making about whether to execute that behavior or not.

Slide 14

Just to go through another thing that influences behavior - this notion of self-efficacy. The idea is that you build up confidence every time you positively execute a behavior, when you think you may not have enough confidence or you may have some difficulty you might put additional intentional effort in. So over time, as you do something like wear a mask or socially distance, your self-efficacy builds up. The amount of additional intentional effort that you have to put in goes down, and overall the probability of that behavior goes up. So how does this all combine in some phenomena that we see in things like mask wearing in reaction to COVID?

Slide 15

One of the things that we have been modeling specifically is this idea that your awareness of what's going on in the pandemic around you and the messages that you're getting through mass media and social media have an impact on your awareness of the state of the pandemic. That then modulates your behavior, which then in turn modulates the transmission rates. This effective transmission number. However, there's delays in how this all propagates. So there's a delay between a point in time that people get infected, that the symptoms become apparent, to fatalities, and then to our awareness of all that. That results in a kind of oscillatory dynamic that you can see in the data themselves.

Slide 16

So this is the effective transmission number in ten carefully selected states. What you see is that this is over the first three waves of the COVID pandemic. There's this huge spike in transmission that is then brought down and kind of oscillates around one. Our simulations can reproduce that kind of oscillatory behavior. In the lower right corner there is kind of a phase-based diagram where the infection rate at time T is then related to the probability of people wearing a mask. The idea that people wear a mask in reaction to their awareness that things have gotten worse and then they may back off of that when they think things are getting better. One way to think of this is it's kind of like a pendulum is swinging back and forth. As the pendulum swings in one direction there's a behavior that kind of pushes it back in the other direction, then when it swings in the other direction there's a behavior that pushes it back towards the center, which causes it to kind of oscillate around this effective transmission number of one.

Slide 17

Now, when you look at the data it's actually a little more complicated than that. So this is the same kind of phase-based diagram where we're looking at the the the Rt values at one point in time related to the Rt values about two or three weeks in the future. You do see this kind of oscillation around one, but there's also this kind of spiraling where kind of is also moving up upward a little bit.

Slide 18

If we look at the actual relationship between transmission rates and people wearing masks slightly ahead in the future, we see an even more complicated picture where there is this kind of oscillation that as Rt values go up, people seem to wear masks, which brings it back down, swings leads back and forth. But it's also overall increasing again over the three waves of COVID such that people's reactions by the third wave are that when Rt values go up, they almost immediately start to wear masks and more people wear masks. We believe this is a reflection of the fact that there is this kind of learning effect that people are exhibiting. It fundamentally goes back to this notion that people are building up self-efficacy and they're also building up some habits around how to do that, which is perfectly captured within the model. So that's just one of the phenomena that we're looking at. We're looking at many other aspects of how people behaviorally react to information in their environment.

Slide 19

This, again, is just showing these data in a slightly different format. The top two graphs there show the Rt values across 3,000 counties over the first three waves of COVID. So the top left there is the first and second wave and you can kind of see that they all center around one and are basically the same across those two waves. You can see the same pattern as you go from wave two to wave three in that top right chart. But then if you look at the the charts below, this is the the percentage of people wearing masks over these three waves and you can see as you go from wave one to wave two, mask wearing goes up dramatically and then a little bit more when you go from wave two to wave three.

Slide 20

Ok, so we're doing additional work as I said, predicting other kinds of behaviors. We're looking at mask wearing, social distancing, and now we're turning towards an analysis of vaccine attitudes and decisions as well as people's attitudes towards alternative treatments besides vaccines. So we're looking at analytics around vaccination discussions in mass media and social media segmented geographically across the United States using a variety of machine learning and natural language processing to identify these beliefs and attitudes. We're also very interested in credibility judgments about how people perceive the sources of this information and then pulling that all into these psychologically valid agents that are built in ACT-R. And that's it, thanks.