Audio file

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Transcript

Hi, my name is Justin Mittereder and this semester I have done research in agent-based modeling field of opinion dynamics.

So specifically, my project was modeling polarization in mass populations using opinion agent-based modeling in novel opinion dynamics.

So first, what is agent-based modeling?

So, agent-based modeling is using large scale simulations to model a population of agents and agents, in this case represent humans most times, but not always.

And then second, what is opinion dynamics?

So, opinion dynamics is studying how agents interact and how influence travels throughout a population.

So, first kind of just go over to the agenda of the presentation.

We're going to go over key vocabulary first.

Obviously, because polarization is a large top topic, we need to specify what we're specifically talking about.

Next, we're going to define polarization.

Like I said, to define sort of the exact polarization we're talking about.

Then go into quantifying polarization in terms of how are we going to get polarization down to a number.

Next, we're going to see how we can add a more human like behavior in the agents of our simulation because we want the agents of our simulation to behave like humans do in real life.

Next, we're going to go into the implementation of the model.

So how do we actually code our simulation?

Next, we're going to go into the research questions that we came up with and the next.

After that, the results that we found.

So first to go into the key vocabulary.

First, we're going to talk about Diametricity City.

So Diametricity is if you were to think of having an opinion from a on a range from zero to 1.

Diametricity City is the tendency for those opinions to be closer to the polls, so closer to zero and closer to one.

And this is what a lot of people talk about when they talk about polarization.

Uhm, next we have clustering. So clustering is when you have multiple different areas where agents could cluster. So, for example if you had agents with an opinion of .1 and then a bunch of agents of the opinion of .5 and then a bunch of agents with an opinion of .9.

We would say that that in that society there's three clusters of opinions.

And then next we're going to talk about openness, so openness is the willingness of an agent to change their opinion.

And then Lastly, we're going to get into Assortativity and this is something that was very important for us this semester because it's ultimately how we measured polarization in our society.

So, I'll get into that more in just a second.

Uhm, but let's go into defining polarization.

So, one of our main problems we ran into was that when we were talking about polarization amongst the four of us who did this research, we would kind of be conflating different types of polarization.

We would be saying about Diametricity City.

Versus sort being more sorted.

Uhm, so uhm that in terms of having multiple types of polarization, we wanted to distinguish Diametricity City which is being closer to the extremes in terms of having an opinion and also being more sorted.

Which means being connected to those that are similar in opinion to you.

Uhm, we also recognize that polarization is not only a state, but it's also a process.

So, you can say that a society is polarized, and that's a state, and you could also say that they're undergoing the process of polarization.

So next we define polarization rate.

We hadn't quantified it, and we needed to make sure that we could get it down to a number, because this is ultimately what we're going to be using as our proxy for polarization.

So, the way we're going to get it down to a number is calculating numerical assortativity coefficient for each issue and then taking the average of all of those, and that'll become a little bit clearer with the next slides, so.

So.

And this is an example of just a graph with eight nodes.

So not too big and this graph shows a higher assortativity because agents that are closer in opinion to each other are have a higher likelihood of being connected with agents that also have a similar opinion, right?

So, you have a point nine have a higher chance of being connected to another 0.8 than they would with a .1 and vice versa.

This graph shows the opposite. Shows low sort activities, so it's kind of more densely connected. You don't see only .7's and .8's connected to each other, and you see a .1 connected to a point 6.4 connected to a .8. It's just more densely connected.

So, after we figured out how we're going to measure polarization, we wanted to make sure that agents acted in a way that was similar to the way humans behave.

So, part of that was implementing some of the different parameters of the model that we ended up implementing, which you'll see in a little bit.

Little bit.

One of those things we found from previous research is that most times when people were simulating.

On simulating a society and doing opinion dynamics, they would have agents with only one opinion, and that opinion would be a zero or one.

And for us we thought that it would be more similar to real society if we had agents had multiple opinions rather than just.

One opinion and those opinions also existed on a continuum from zero to 1, so you could have an opinion that was .5 or .7 and have multiple opinions on different issues.

And then the last thing was that we wanted to have agents with a limited number of social connections.

So, in real life there's we found in research that there's actually a limited number of people that can influence you, like there is.

Obviously, you can have access to a lot of people.

Nowadays with social media, but there is a limit to the number of people that can influence you, which is represented as having an edge between a node and another node, versus or not having an edge there.

So last, we are going to get into the implementation of the model and the research questions that we had in our ultimately our results.

So first, how were we going to generate our graph?

So, there's multiple different graph generation algorithms.

The one that we used is.

Here it is rainy, which is what you're seeing here.

So, this graph has.

Uhm, two different.

This graph generation algorithm has two different parameters.

It has a number of nodes, which is pretty obvious.

It's just how big do you want the graph?

And then it also has the edge probability.

So, with the edge probability, means is what's the chance.

If you had any two nodes that there's an edge between those.

So obviously if there's a higher edge.

Probability that means you are going to have more edges in the graph.

And also, we wanted to make sure that our graph was connected.

So, what that means is that if you were to take any node on the graph, you can get to any other node via some number of edges.

Uhm, in going through the other nodes, we didn't have any lone nodes that weren't connected to any other nodes and we didn't have any distinct physical clusters that were separated by not having any edges.

So then moving onto specifically our model first.

Like I said before for that Erdos-Renyi graph generation, we have the number of agents, and then we have the edge probability and this is two things that I had just mentioned.

So next, we're going to talk about the comparison thresholds.

This was another important parameter of our model, so the comparison threshold is how we were able to gauge and change.

The openness of an agent.

So, for our model the comparison threshold was defined as the threshold and.

How similar an opinion of 1 agent needed to be to another agent in order for persuasion to take place between those two agents in a persuasion.

It's basically one agent changing their opinion, so next we have the number of issues, so obviously.

In previous research and in the previous literature, some research has only used one issue and we wanted to use multiple because we thought that more closely related to how real-life individuals act.

And then Lastly, we just have Max steps so Max steps is nothing too crazy, it's just the cut off for how long we wanted the simulation to run.

And this is just some noteworthy code.

Our code is hundreds of lines, but this is just a short method that we wrote that calculates the average assortativity.

So, we would take the assortativity for each issue and then get the average for all the issues.

So next, we're going to move into our research questions.

So, one research question that we had is, what effect does edge probability have on assortativity?

And by assortativity we mean polarization.

And then next we had.

What effect does the comparison threshold have one issue clustering?

So.

First, we're going to go into Assortativity and edge probabilities.

So, we found that with lower edge probabilities you would actually have a higher sort activity.

So, what does that mean exactly?

So, if you have lower edge probability, that means that you have fewer social connections, because the chance of there being an edge between you and other nodes is lower and we found that in cases in the simulations where we have fewer social connections, you would actually have higher assortativity rates.

And then next we had on the comparison threshold and issue clustering hypothesis.

So, we hypothesized that lower comparison thresholds would actually result in more issue clustering because if people were less open to changing their opinion because the comparison threshold was lower.

You would actually see more clusters of issues and this is something that we want to research more in the future, but we haven't been able to get to that yet, so we will be doing that this summer and then next fall as I continue my research.

And just some more things for future research.

Obviously the first thing on our plate is to test the comparison threshold issue clustering hypothesis and that is our number one priority and then after that we wanted to research what effect agent stubbornness has on our model.

So, agent stubbornness would be a reluctance of agents to change.

Their opinion, we hypothesized that having agent stubbornness could lead to more polarization and then next we could also research opinion diversion which would be.

If, uh, you run into an agent that is one of your neighbors and by neighbor I just mean you are connected with an edge to that person, and if your opinions are far enough apart and then you can push each other away closer to the polls in terms of polls being a zero or one and then.

Last, we wanted to get into intelligent versus unintelligent agents and unintelligent intelligent agents in the sense that intelligent agents would be less likely to change their opinion and have more nuanced opinion rather than unintelligent agents, which would just flip their opinion more easily.

thank you for listening my presentation.

You can email me for feedback or questions or you can email Professor Davies at that email listed.

Thank you.