Network Simulation

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Author Note

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Network Simulation

The purpose of this model is to explore the interaction between people's opinions and the strength of their social connections. To do so, I modified the existing rules of the social dynamics model which we discussed in Session 7.2.

Model Modifications

1. *Multiple Opinions*

The basic version was based on a few unrealistic assumptions. First of all, the model assumed that people only have one general opinion which defines the strength of their social connections. Since people have different views on different topics, I implemented three opinions for each node. Opinions form our worldview, and so I decided to add a new attribute which combines different opinions. I assumed that some views are more formational than others (politics vs. food) and randomly picked one opinion which has the highest importance (0.8) for each node. The other two opinions also matter but have a less significant effect on the worldview, 0.1 each. When people interact, they only discuss one topic, and so only one opinion changes according to the rules of the basic model. In case people strongly disagree, they have an argument after which their opinion become less radical, and their social connection is getting weaker. People with similar views have a lovely conversation which strengthens their relationship and doesn't have a significant effect on the opinion itself.

2. Persuasiveness

Another modification that I've implemented is persuasiveness. Some people are more convincing than others, and can, therefore, influence others' opinions to a larger extent. Persuasiveness is an attribute of every node which is drawn from a normal distribution. The majority of people's persuasiveness is centered around the mean of 0.5. However, in some cases, due to the nature of normal distribution, we can experience significant outliers which have very high or very low (negative) level of persuasiveness. In the update function, after the change in the opinion has been calculated, it is further modified according to one's persuasiveness. In case it's very high (around 1), the opinion can be further modified by up to 0.1 of the change calculated. In case an opponent has negative persuasiveness, the difference in the opinion decreases.

3. New Relationships

I also implemented a different mechanism for creating new relationships. In the original model, it was not entirely random, and new edges were given a weight of 0.5. My model adds new connections according to the following rules:

1. With a probability prob_new, find two nodes that are not connected.
2. Check for the mutual connections. Nodes that have friends in common are more likely to meet, so they'll definitely form a connection.
3. The weight of their edge is determined as the average of the weights of all mutual connections. If let's say, they have two friends in common one of which has the weights of 0.7 and 0.6 while the other 0.5 and 0.4 with node 1 and node 2 respectively, the resulting edge will have a weight of 0.55.
4. If these people don't have any mutual connections, the probability of their meeting decreases to 0.1 * prob_new. The weight is chosen randomly from the uniform distribution in the range from 0.3 to 0.7. This range assures that we have some variety but doesn't allow for radical relationships. The initial weights are also designed to be in this range.

Parameters and Update Rules

Parameter	Description	Default
network_size (int)	The number of nodes in the network.	50
alpha (float)	The rate at which nodes adjust their opinions to match neighboring nodes' opinions during interactions.	0.03
beta (float)	The rate at which edge weights are changed in response to differing opinions.	0.3
gamma (float)	The pickiness of nodes. Nodes with opinions differing by more than 1/gamma will result in an edge weight decreasing.	4
prob_new (float)	The probability of forming a new edge during each update.	0.02
graph_type (integer)	The type of the graph used to build the network. If it equals 1, the model uses watts_strogatz_graph; erdos_renyi_graph otherwise. I only compared these two graphs in my model, but other types can be added as well.	1

Table 1. Parameters of the simulation

The “update” method consists of two parts. The first part adds new connections as described in the “New Relationships” section above. The other part updates the opinions and edges based on the interaction. It first chooses one edge and the topic (one of the opinions) randomly. Then it recalculates the opinions based on the input parameters and adjusts it based on person’s persuasiveness. After that, the worldview and the edge weight are being updated. Finally, the model removes week edges which have the value of less than 0.05.

Major Improvements

I believe that this model is an improvement over the basic version for several reasons. First of all, it is more flexible since it can be initialized using different user specified random graphs. This modification makes it easier to play around with different graphs and compare them if there is a need.

Another modification is the way new relationships are being formed. In reality, if you're going to a party, professional meeting or any other event, it is highly likely that your friends' friends will be there and you'll be introduced to them. At the same time, it's very difficult to meet someone outside of your regular social circle. That's why the model assumes different probabilities for these events. This model also uses the principle "tell me who your friend and I'll tell you who you are". It's highly likely that you'll find a person who is close to your friends to be more attractive than a member of a group which has people you don't get on well with. This principle is closer to real life than the initial assignment of same weights for everyone

Two other modifications, different opinions and persuasiveness, have been described earlier in this paper. Persuasiveness makes it possible to differentiate among people and have individuals who are poor at persuasion as well as real manipulators as it often happens in real life. Different opinions make the model less extreme. It is rarely the case that the group splits based solely on a single opinion everyone holds as the initial model assumes. Instead, multiple opinions assure that the worldview is adjusted gradually, without major shifts. For this reason, even when two separate clusters are formed, the opinions of their members are not as radical and people often still have connections with members of other clusters as it happens in real life (different parties, religious/ethnic groups). The last improvement that I find important is the fact that one's worldview is represented as the node's label which is much more informative than the node's number.

Local Analysis

1. *Relationship between Two People*

The change in opinions happens according to the following rule:

$$\Delta o_i = \alpha w_{ij}(o_j - o_i)$$

In case two people interact, their opinions converge. In case the opinion has a higher value, the change in the opinion will be negative, and so the value will decrease. Otherwise, the change will be positive. A new opinion is formed using one's persuasiveness (p):

$$o_i' = o_i + \Delta o_i + 0.1 p_j \Delta o_i$$

If one's opponent is very persuasive, the change in the opinion can be raised up to 110%, and so different views will diverge faster. However, it is still not the end of the interaction, since this single opinion only has a limited effect on the worldview (wv) which is illustrated on the graph:

$$wv = 0.8 * o_1 + 0.1 * o_2 + 0.1 * o_3$$

This equation assumes that opinion 1 is the most formational. Since people have different formational opinions, the interaction will have a different influence on one's worldview. In case the topic that has been discussed is of one's major interest, 80% of the total change (including the persuasiveness factor) will be incorporated into the new worldview while the other opinions remain unchanged. This modification makes the model more conservative: people are less likely to change their views dramatically based on a single conversation.

The equation of the change in the weight of the edge has a slight modification:

$$\Delta w_{ij} = \beta w_{ij} (1 - w_{ij}) (1 - \gamma |wv_i - wv_j|)$$

Since we now base the equation on the difference in the worldviews, the drop or increase in the weight of the edge will be based on people's "general impressions" and not a specific conversation.

2. Analysis of Major Parameters

Alpha $\in$ *(0, 0.5]* is a parameter responsible for the rate at which nodes adjust their opinions to match neighboring nodes' opinions during interactions. The larger α is, the faster people change their opinions to match other people's.

As you might've noticed from the change in opinions equation, nodes' views can only **converge** after the conversation no matter how bad their relationship is. Let's look at the case where the difference in opinions is the highest - 1, and the relationship is extremely bad - 0.05. In this case, the change in opinion will be a maximum of 0.025 for each node (assuming $\alpha = 0.5$), which means that the total difference in opinions will decrease by 5%. If we consider an average case scenario where $w_{ij} = 0.5$ and $o_j - o_i = 0.5$, the opinions will get 25% closer which is a significant change! If we assume a two-node network, it will take approximately two steps for a complete convergence. Since we want to run the simulation longer, α of around 0.01 will be the best choice since the number will increase to at around 50 steps. Since I'm working with a network of 50 nodes and there are approximately 125 edges, the probability of picking an edge is 1/125. The probability of checking this particular opinion is ⅓, which results in the final number of steps of around 20000 for opinions to converge. This number is ideal for exploring the dynamic change in the simulation.

Beta is the rate at which edge weights are changed in response to differing opinions.

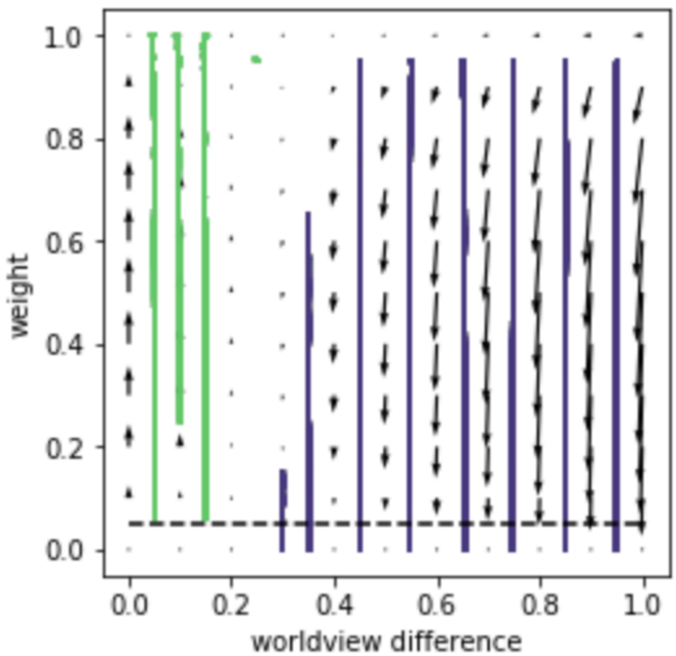
$$\Delta w_{ij} = \beta\, w_{ij}\,(1 - w_{ij})\,(1 - \gamma|wv_i - wv_j|)$$

If β is around 0, the change in the relationship will be barely noticeable so the nodes will have a chance to interact pretty often before breaking their relationship. On the other hand, the influence of β increases a lot when it approaches 1. As a result, we would expect a fast formation of clusters. A reasonable value is somewhere in between, so I'll use $\beta = 0.3$ as a default since it assures that the relationship changes at a rate comparable to the rate of alpha derived above.

The direction of the change in the relationship highly depends on the value of γ. If $\gamma \leq 1$, all weights will converge to 1 since the difference in opinions is not significant enough to decrease edge weights. I will demonstrate it in the simulation below. If $\gamma > 1$, the weight between two nodes will decrease based on how dramatic this difference is. We would assume the network to split much faster if this rate is high (8). In reality, it has a moderate rate of $\gamma = 4$ which was used in the initial simulation as well.

3. Vector Field Plot

A vector field plot demonstrates for which opinion and relationship strength values we can expect clusters to form or split apart. The plot below is based on several assumptions. First of all, I couldn't plot individual opinions since every person has three of them. Instead, I plotted worldviews. Worldviews are based on opinions which have different importance. To incorporate it into the plot I looked at two cases. The first case assumes that people are exchanging opinions that are not very important which happens in ⅔ of the cases. These opinions do not have a significant effect, so I drew them from the uniform distribution. The second case assumes an exchange of important views where the number is chosen to be pretty close to the worldview since it accounts for 80%. The resulting plot shows that the network's behavior is similar to the behavior of the original model where the purple lines result in an edge disappearing (which leads to the formation of a cluster, while green lines result in an edge with a weight of 1. However, it also incorporates the randomness that is involved in the new model, that's why the prediction can be slightly off in some cases.



Pic. 1. Vector Field Plot for parameters alpha = 0.01, beta = 0.3, gamma = 4

4. Random Graphs

For the purpose of this simulation, I looked at two different graphs: Watts-Strogatz and Erdos-Renyi. I believe that both graphs are useful in modeling different scenarios. However, the first graph is a more realistic illustration of real-life networks. It is initialized in a way that every node is connected to its closest neighbors. As a result, all the nodes have the same number of edges, and the probability of changing any of them is the same. As a result, at least at the very beginning, the simulation doesn't prioritize any nodes. However, in the middle of this random rewiring process, the network gets the "small-world" property while still maintaining locally clustered topologies which is thought to be a nice illustration of how real-life networks work.

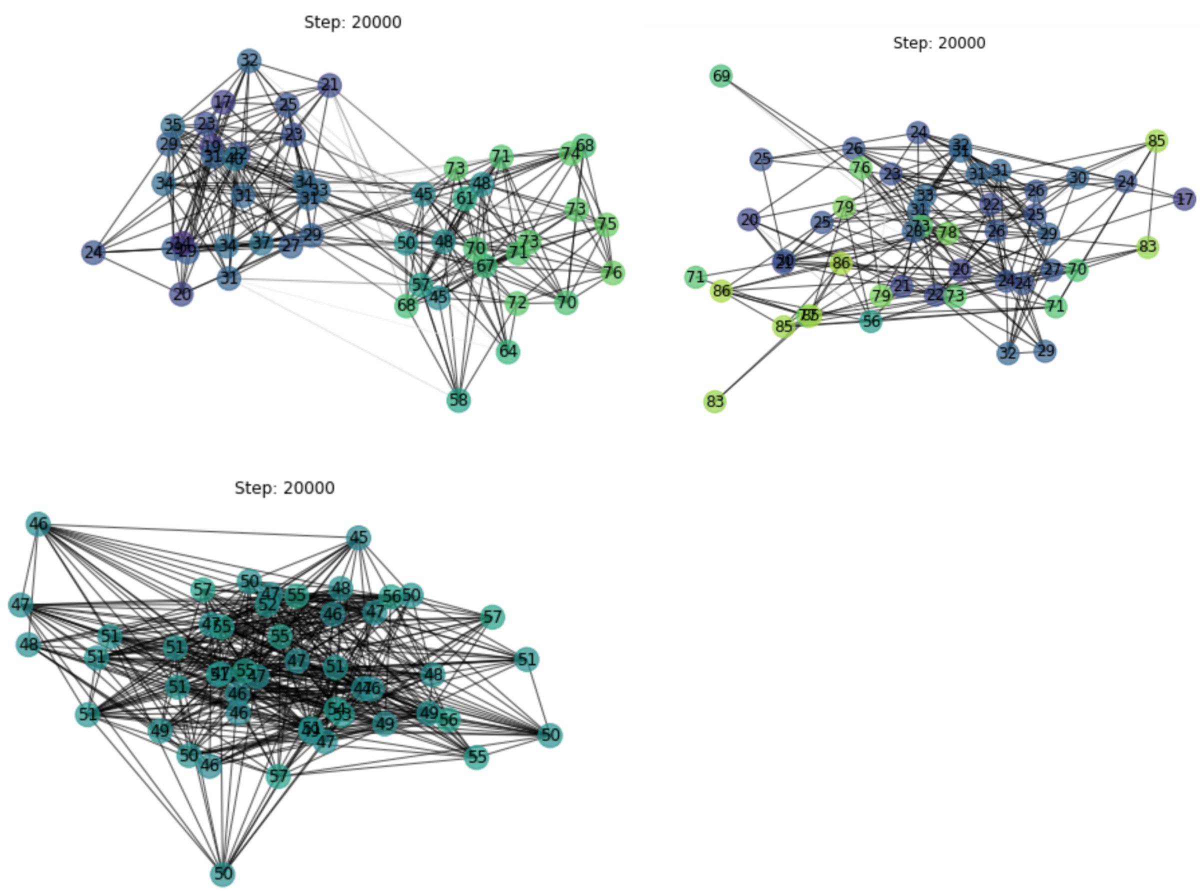
The second random graph edges are initialized randomly with a certain probability. As a result, it doesn't exhibit the small-world property described above but can still be useful for some specific simulations, especially if the number of nodes is small so that there is no problem of local clusters formation.

Simulation

I ran the simulation with low, optimal, and high values of parameters alpha, beta, and gamma on both graphs while holding the other parameters constant.

1. Alpha

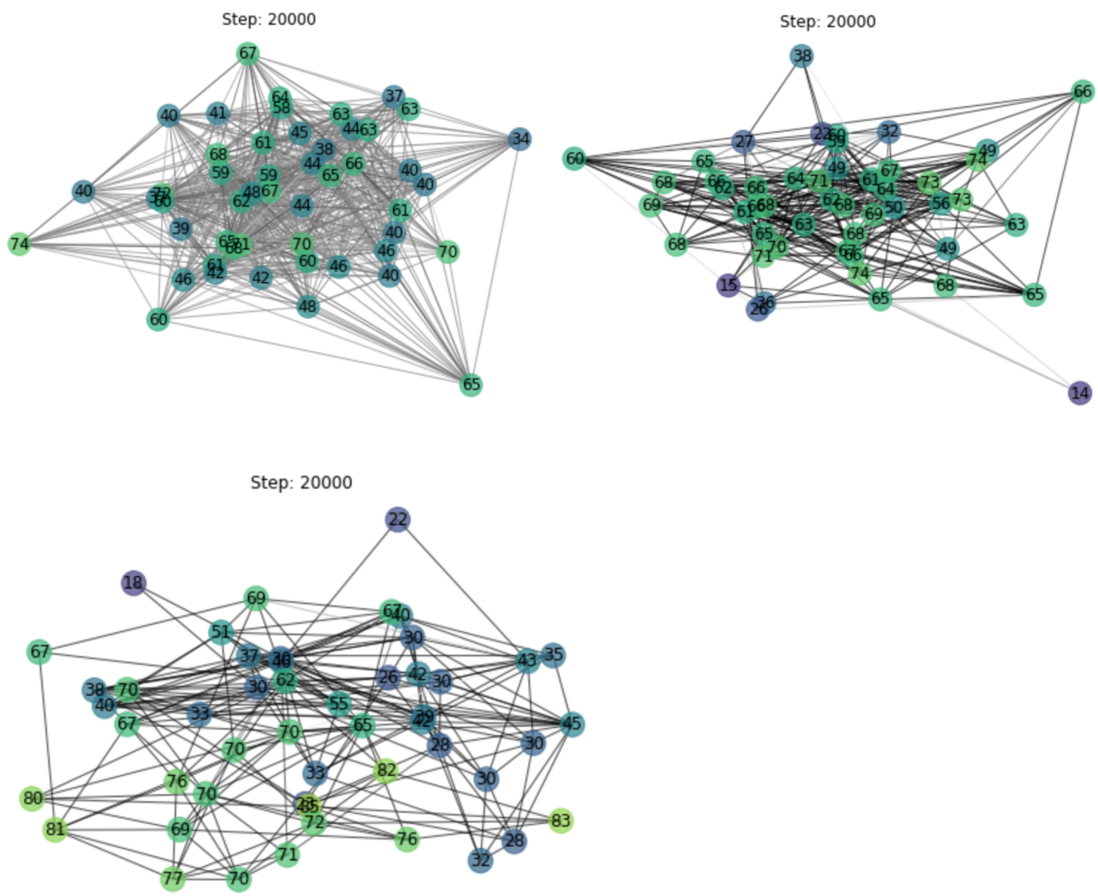
The simulation output is similar to the predicted results where low alpha results in a split of the network, and high alpha leads to the convergence of the worldviews. The moderate value needs more steps to either converge or split, and the result can be different.



Pic. 2. The result of the simulation after 20000 steps for $\alpha = 0.001,\ 0.01,\ 0.03$.

2. Beta

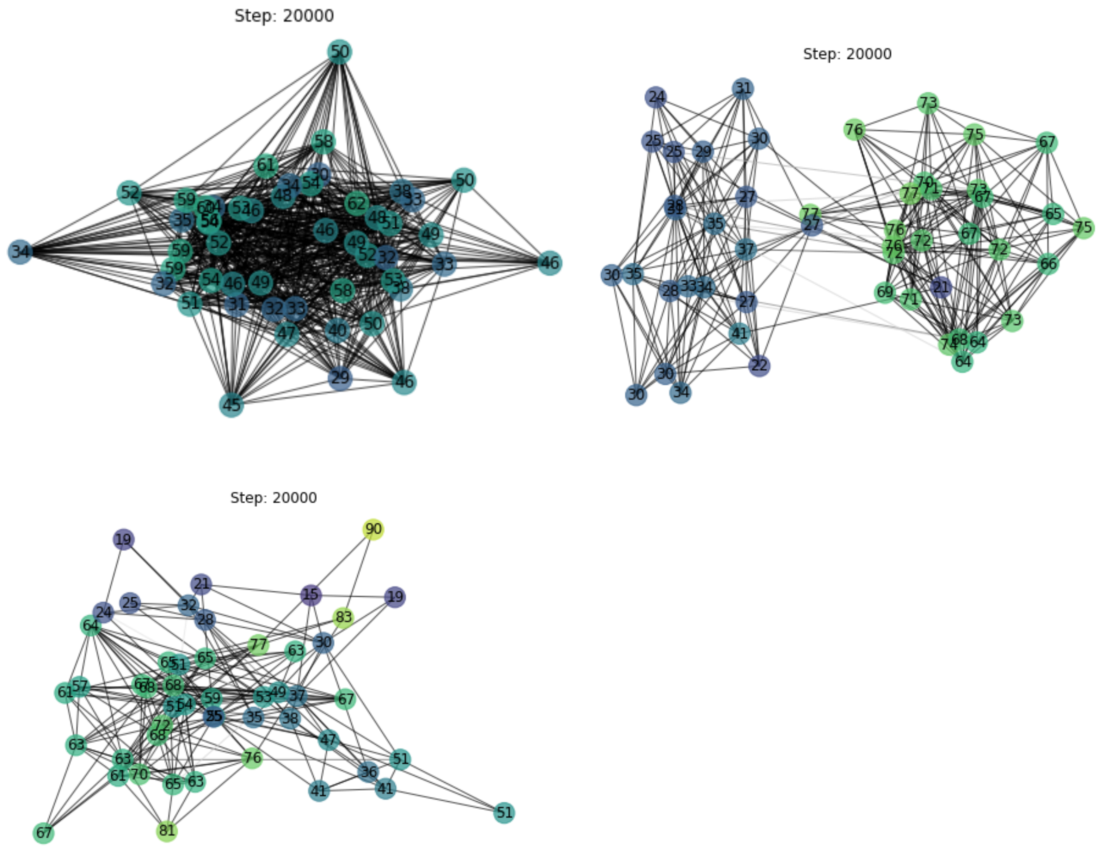
One important observation is that the number of edges is much bigger for lower values of β which is, of course, not very realistic. For high values, I expected to have a formation of clusters. However, it didn't really happen since I haven't account for the fact that the edge is removed before the nodes manage to converge. The optimal value has a reasonable number of edges so that the nodes can interact with each other a reasonable amount of time while still leaving a possibility for an edge to break.



Pic. 3. The result of the simulation after 20000 steps for $\beta = 0.01, 0.3, 0.99$.

3. Gamma

In the last experiment, I used different values of gammas. As expected, the network never splits and never loses edges if γ is below 0, so the network converged. For a high value, the distribution of the worldviews looks pretty random which can be explained by the fact that the nodes split too fast without actually adjusting their worldviews. For the optimal case, two clusters are being formed.



Pic. 4. The result of the simulation after 20000 steps for $\beta = 0.01, 0.3, 0.99$.

I ran these experiments on both random graphs, the main trends were the same. The only difference that I've noticed is that Erdos-Renyi forms the clusters or converges faster. I think the reason for that is its initial random structure. For the Watts-Strogatz graph, it takes time to connect some nodes which are far away from each other.