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Networked Weighted Balance Theory: Extensions and Criticism

Introduction:

In 1824, the first opinion polls took place in the United States to better understand public opinion concerning elections (Smith, 1990). Since then, numerous methods have been used to study opinions, from surveys to agent-based models to social network analysis (Newman, 2018; Squazzoni, 2012). Through the implementation of an agent-based model, we explore the nonlinear dynamics at play in the study of opinion, such as the relationship between an agent's position in the network and aggregate levels of polarization or alignment. Noticeably, this is not a question concerning the grand theories of sociology, but instead inquires into how micro-level causes may lead to macro-level effects. Thus, in a more broad focus, agent-based models may play a positive role in creating middle-range theories in analytical sociology. This may offer a pathway into bringing consensus to theories of certain general social phenomena based upon theoretically driven models, however, issues concerning full demonstrations of causality may impede models created using this methodology.

To begin, this essay first displays the final concept map created in the building of the agent-based model used for the factorial experiment. Following this, section 1 is an ODD of the agent-based model implemented. Section 2 delves into the use of this particular agent-based model in terms of the middle-range theories and how agent-based models more broadly can be a tool for such endeavors into the middle-range. Finally, Section 3 critiques the agent-based model employed in terms of a lack of empirical calibration and validation for demonstrating causality as well as a more comprehensive overview into the requirements of input and output realisms needed for agent-based models claim of causality. While this may increase the argument of the model and thus may encourage the use of agent-based models, it may be high thresholds for researchers to bear and dissuade those from using this methodology. But firstly, we begin with the display of Figure 1, the final concept map; an accompanied file is also included in order to zoom into elements of the final concept map.

Figure 1: Final Concept Map

Section 1

ODD

1.1: Overview

1.1a: Purpose

The purpose of this model is to simulate the opinion dynamics of different types of network using the Weighted Balanced Model. More specifically, this model simulates how individuals change their opinion based upon their neighbors opinions and the equanimity their neighbor's have. The individuals can only access other neighbors to update their opinion that are a distance of 1 from them in a certain type of network. Depending on the position of the individual in the network, they may update their opinion if and only if they are below a certain threshold in terms of their Burt's constraint value, that is to say, individuals can only update their opinion if they fall below a threshold, otherwise their opinions remain the same. An aggregate score of the polarization, the alignment, and the extremeness of all individuals in the network is taken at each time step. These scores allow for the simulation to explore the followings impact on opinion dynamics :

1) The type of the network
2) The amount of individuals
3) The amount of opinions
4) The individuals place within the network

1.1b: Entities, State Variables, and Scale

The following paragraph explains the structure of the model, in terms of the entities, their low level state-variables, and the spatial and temporal scales within the model. Each entity in the model represents an individual. Each individual is placed in a position within a certain type of network, thus each individual has their own position. From this position, each individual is given a Burt's Score, to identify the structural hole value they have within the network. In terms of temporality, each individual agent is able to update their opinions during each step, as long as their Burt's Score is less than the threshold value. Thus, certain individual agents experience time at each time step, while others do not. Each agent is also given their own opinions, which are represented as numerical values. Lastly, each agent is given an equanimity score, also a numerical value, which represents how well liked they are by other individuals within the network. For this model, these agent entities that represent individuals do not have many low-level state variables. This distinguishable characteristic can be explored in further development of the agent-based model for future research.

1.1c: Process Overview and Scheduling

Furthermore, it is important to consider the processes and scheduling that occurs within the agent-based model. First, a network is created and subsequently the structural hole value is calculated based upon the positions of nodes within the network. For the initialization of the agents, which will be discussed in further detail below in the initialization section, an opinion matrix which contains the varied opinions is created which is based upon the number of agents and the number of opinions. This is also accompanied by the creation of an epsilon matrix that contains the varied equanimity scores. The two matrix creations allow for the following to happen in which each agent is placed in a node in the network and given opinion values, an epsilon value (equanimity score), their Burt score and the threshold value which will determine if they can update their opinions in the interaction with other agents each step. After the initiation of the model, in terms of scheduling for each step, if an agent has a Burt score less than the threshold, they choose at random a neighbor with a distance of one from their position in the network and updates their opinions based upon their neighbors opinions and the epsilon value (equanimity score). If an agent has a Burt score equal or greater than the threshold value given by the modeler to the model, then the agent keeps their initial opinion. At each step, it is determined the aggregate elements of polarization, alignment, and extremeness of all the agents within the network. The code for all of the above descriptions can be seen in the table below.

<table>
<tr>
<td>Initiation phase</td>
<td><pre>if network == None:
        self.G = nx.barabasi_albert_graph(n=self.num_nodes, m=2)
        struct_hole = nx.constraint(self.G)
        self.grid = mesa.space.NetworkGrid(self.G)
      elif network == 'Wattz-Strogatz':
        self.G = nx.watts_strogatz_graph(n=self.num_nodes, k=2, p = .3)
        struct_hole = nx.constraint(self.G)</pre></td>
</tr>
</table>

```
    self.grid = mesa.space.NetworkGrid(self.G)
  elif network == 'Connected Wattz-Strogatz':
    self.G = nx.connected_watts_strogatz_graph(n=self.num_nodes, k=2, p = .3)
    struct_hole = nx.constraint(self.G)
    self.grid = mesa.space.NetworkGrid(self.G)


  self.datacollector = mesa.DataCollector(
      #agent_reporters={"OpinionValues": "opinion_values"},
      model_reporters={"Polarization": Polarization2,
                  "Alignment" : Alignment2,
                  "Extremeness": Extremeness2}
  )

  #create agents
  agent_id = 1
  e = create_epsilon_array(n_agents=self.num_nodes,
        n_opinions=self.num_opinions,
         mode='column_vec')
  O = initiate_opinion_matrix(n_agents=self.num_nodes,n_opinions=self.num_opinions)
  for i, node in enumerate(self.G.nodes()):
      epsilon_value = e[i] if i < len(e) else 0
      opinion_values = O[i]
      burt_score = 1 - struct_hole[i]
      thresh = self.threshold
      agent = MyAgent(agent_id, self, epsilon_value, opinion_values, burt_score, thresh  )
      self.schedule.add(agent)
      agent_id += 1
      #add agent to the network
      self.grid.place_agent(agent, node)
```

Agent Interaction per step

```
def step(self):
  if self.burt_score < self.threshold:
    neighbors_nodes = self.model.grid.get_neighborhood(self.pos, include_center=False,
      radius = self.radius)
    each_neighbor = self.model.grid.get_cell_list_contents(neighbors_nodes)
    chosen_neighbor = self.random.choice(each_neighbor)
    q = chosen_neighbor.opinion_values
    R = relation_vec(O=self.opinion_values, Q=q, e=chosen_neighbor.epsilon_value)
    B = balanced_mat(R, Q=q, e=chosen_neighbor.epsilon_value)
    X = update_opinion_mat(O=self.opinion_values, Q=q, R=R,
          e=chosen_neighbor.epsilon_value, alpha=self.alpha)
    self.X = X
```

	elif self.burt_score >= self.threshold:
	X = self.opinion_values
	self.X = X
	
	def advance(self):
	self.opinion_values = self.X

Calculate Aggregate Scores	**def Polarization2(model)**: *""Computes the polarization of the network based upon the opinion matrix of all agents."""* exp = 2 agent_opinions = [agent.opinion_values for agent in model.schedule.agents] *#create the matrix* matrix = np.vstack(agent_opinions) *# Sum of: Minkowski distance between all row vectors of M raised to the power of exp:* dist_sum = np.power(distance_matrix(matrix,matrix,p=2),exp).sum() *# Maximum possible distance:* max_dist = distance.minkowski(np.ones(model.num_opinions),-np.ones(model.num_opinions),p=2)**exp *# Maximum number of pairs with maximum distance:* max_pairs = (model.num_nodes**2)/2 *# Divide sum of distances by product of maximum distance and maximum number of pairs at max distance:* normalized_dist_sum = dist_sum/(max_dist*max_pairs) *# Take exp-th root of normalized_dist_sum*: polarization = normalized_dist_sum**(1/exp) return(polarization) **def Extremeness2(model**): *"""Computes extremeness (mean absolute value of elements) of opinion matrix of all agents."""* agent_opinions = [agent.opinion_values for agent in model.schedule.agents] *#create the matrix of opinions* matrix = np.vstack(agent_opinions) *#calculate the absolute value* O_matrix = np.absolute(matrix) *#calculate the mean* extremeness = O_matrix.mean() return(extremeness) **def Alignment2(model)**: *"""Performs a PCA on opinion matrix of all agents and returns the proportion of*

	variance explained by the first component.""" agent_opinions = [agent.opinion_values for agent in model.schedule.agents] matrix = np.vstack(agent_opinions) expected = 1/matrix.shape[1] sm = StandardScaler().fit_transform(matrix) pca = PCA(n_components=1) principalComponents = pca.fit_transform(sm) explained_variance = pca.explained_variance_ratio_[0] alignment = (explained_variance - expected)/(1-expected) return(alignment)

1.2 Design Concepts

1.2a Basic Principles

The model is designed to investigate whether an individual's position in a network can affect the polarization and alignment of the group with the opinion dynamics. The design of the model is heavily based upon the previous work of the Weighted Balanced Model (Scweighofor et al., 2020), in which Balance Theory in opinion dynamics is updated to include not just if an individual is liked or disliked, but the extent to which someone is liked or disliked. In Heider's (1946) original work on Balance Theory, an individual's attitude can have negative or positive valence regarding objects, people, ideas, and events. Individuals attempt to increase the balance within themselves by having similar views on objects with those that they have positive attitudes towards, and reversely strive for balance by having the opposite opinion on attitudes towards objects that individuals they have negative attitudes towards. Cartwright and Harray (1956) extend this to include social networks and make the specification that an individual i, an alter j, and an object d can only be in balance if each relation between i, j, and d is the product of the signs(positive or negative) of the other two's relation. The Weighted Balance Model extends this by not making the relations just positive or negative represented in a binary by 1 and -1, instead the relations are weighted with values between 1 and -1, as can be seen in Figure 2. They further incorporate the concept of issue constraint by adding the possibility of equanimity and a certain level of equanimity that individuals may have within the group. However, what is lacking in the Weighted Balance Model is the inclusion of networks as the Weighted Balance Model has individuals interacting with all others at random and are thus not embedded in networks.

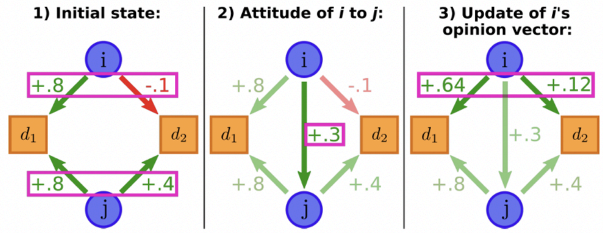


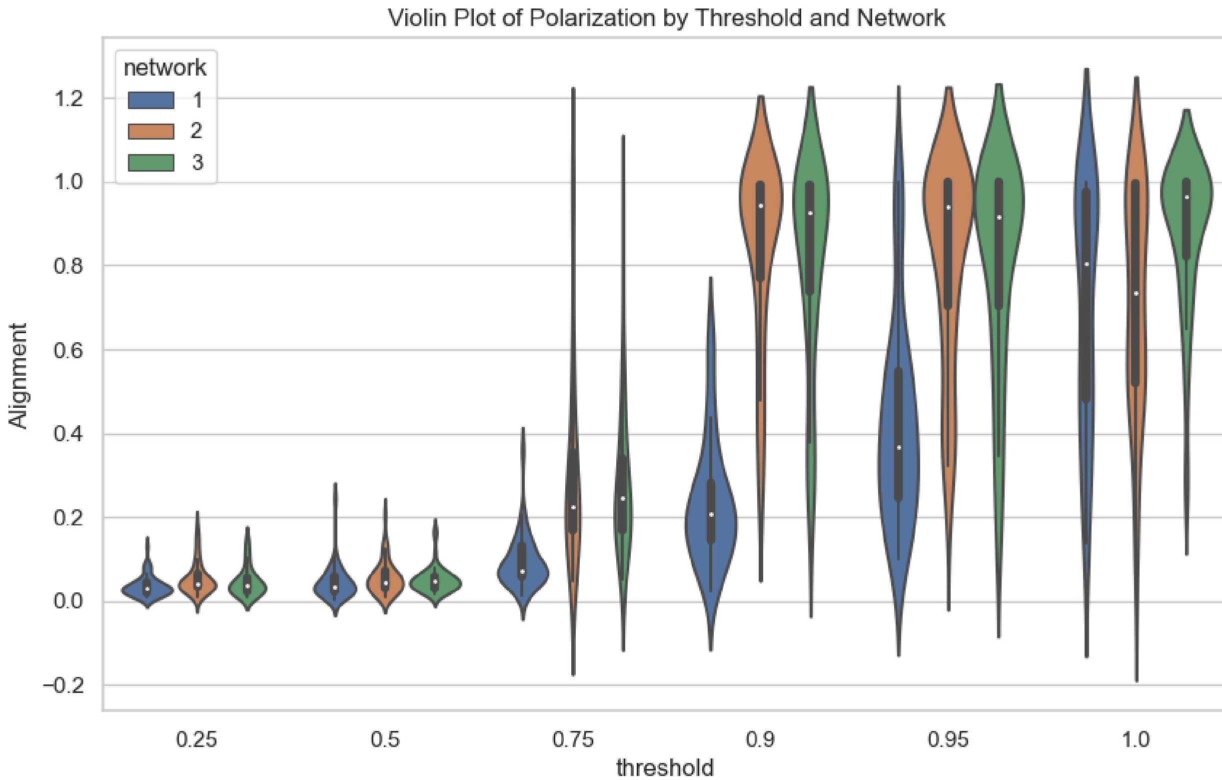
Figure 2. Schematic of Opinion Exchange under WBT. Agents *i* and *j* have attitudes to policy issues d_1 and d_2 (1), i creates a interpersonal attitude towards j based on these policy attitudes (2), *i* modifies its opinion vector to increase balance (3).

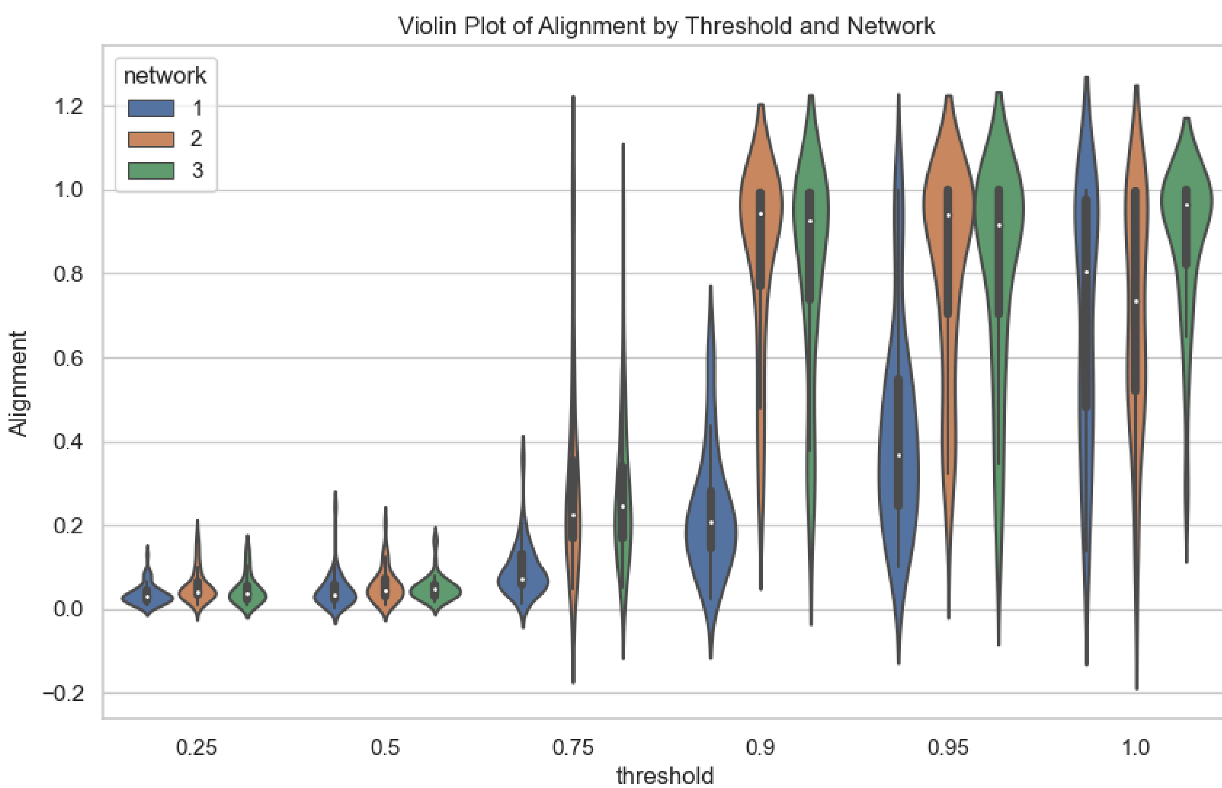
Therefore, we extend the Weighted Balance Model to include networks and to also discover how the position individuals may have in the network can play a role. This is based on the work of Burt's Structural Holes (2018), in which individuals who sit in between two different clusters of networks may have more social capital as they have the ability to control the information between the two groups. Thus, we test this theory in the Weighted Balance Model by not allowing certain individuals with a Burt's Constraint (2004) value to update their opinions. Importantly, we did not remove these nodes from the network, as that would only lead to testing of a different type of network and would not reveal much about the original network, opinion flow, and the social capital an individual may have from their position in the network. Instead, we chose to keep the individuals above a certain threshold of 1-Burt's Constraint from updating their opinions. This is important as it stops those above this threshold from spreading their opinions and importantly, they cannot update their opinion based upon one cluster and transfer that updated opinion to another cluster. Thus, the basic principle of the agent-based model is one in which the Weighted Based Model is updated to include networks, and explores the notion that those within certain positions in the network cannot update their opinions nor spread the opinions from one cluster to another. The notions revealed from this exploration demonstrates that when below a certain threshold, that of .75, polarization in the network can remain. However, above this threshold, the agents who have a higher structural hole value can decrease the amount of polarization and alignment in the network. This demonstrates the social capital, in terms of Burt's structural hole's, and the ability for the agents at the micro level, in terms of updating or not updating opinions, to lead to macro level outcomes.

1.2b Emergence

The emergence of alignment and polarization occurs in three different types of networks dependent on the set threshold of the Burt Constraint, as seen in Figure 3.

Figure 3: The below images demonstrate the Polarization and Alignment at time step 100.





1.2c Adaption

Agents adept their opinions based upon the Weighted Balance Theory. More specifically, as discussed above, agents adept their opinions based on their interpersonal attitudes of other agents' opinions they interact with as well as their level of equanimity.

1.2d Objectives

Agents' objective is to increase the cognitive balance based upon their interactions with others and their opinions.

1.2e Learning

There is no learning in this model.

1.2f Predicting

There is no predicting in this model.

1.2g Sensing

Agents adept their opinions based upon those within 1 degree to them in the network. As addressed in Grennoveter's Strength of Weak Ties (1973), if an individual A has a strong tie with individual B, and individual A also has a strong tie with individual C, individual B and C will either have a connection or there will emerge a connection between the two. Thus, for this reason, agents adept their opinion, not only based upon the weighted balanced model, but with individuals with whom they sense are a distance of one in the network. This is important as it demonstrates that the network is static and the network is not dynamic. It is only the agents that adapt their opinions that can be sensed.

1.2h Interaction

At each time step, only agents with below the set threshold value of the Burt Constraint score interact with other agents to update their opinions. First, agents choose at random a neighbor and then they compute the updated balanced opinion. While the code in Table 1 describes both the interaction in the step function, the following code in Table 2 describes the helper functions that determine the relationship and the updated balance opinion values. Then, each agent simultaneously updates their opinion, either with the newly computed opinion or with their original opinion. The simultaneous update is chosen as if not, who goes first may have an impact on the outcomes of the model (Comer, 2014). The purpose of setting a threshold value which determines which agents can update their opinion is not arbitrary, but is used as a test for the mechanism at play within the model. The particular values chosen do not have a strong theory behind them and further research should be explored in determining these values. In the code below, the alpha value as well as the e value are both stylized facts that remain from the original Weighted Balanced Model and they do not appear to have any theory or empirical evidence in the choice of these values. This code is mainly that of the original model, although some was missing and was updated in attempts to replicate their meaning from the original paper.

Table 2:

<table>
<tr>
<td>Balanced opinion</td>
<td>

```
def relation_vec(O,Q,e=0.5,aggregation_method = 'mean'):
    """
    Compute vector of relations R between agents in corresponding rows of opinion
matrices O, for the agent's opinion and Q for the agent's chosen neighbor.
    Parameter e determines degree of 3 in agents.
    The aggregation_method determines how the SGMs of various issue dimensions
are integrated:
    If aggregation_method == 'mean', SGMs are averaged with the arithmetic
mean.
    If aggregation_method == 'abs_weighted_mean', a weighted average of the
SGMs is computed, with the
    absolute SGMs as weights.
    If aggregation_method == 'self_weighted_mean', the weights are set to the
absolute opinion vector of agent i.

    """


    # Pointwise product of O and Q:
    p_mat = np.multiply(O,Q)
    # Multiply signs of p_mat with absolute p_mat to the power of e:
    m_mat = np.sign(p_mat)*np.power(np.abs(p_mat),e)
    # Average the resulting products row-wise:
    if aggregation_method == 'mean':
        R = np.mean(m_mat,axis=0)
    # Row-wise average, weighted by absolute magnitude of m_mat entries (so that
stronger agreement/disagreement counts more):
```

</td>
</tr>
</table>

	elif aggregation_method == 'abs_weighted_mean':
	    R_ = np.average(m_mat, axis=1, weights=np.abs(m_mat))
	  # Row-wise average, weighted by absolute magnitude of O entries (so that stronger opinions of i count more):
	  elif aggregation_method == 'self_weighted_mean':
	    R = np.average(m_mat, axis=1, weights=np.abs(O))
	  else:
	    print('ERROR: Aggregation Method "' + str(aggregation_method) + '" not recognized!')
	  return(R)

Balanced opinion	def balanced_mat(R,Q,e=0.5): *"""* *Compute balanced opinion matrix B in which R is the relationship computed earlier and Q is the chosen neighbors opinion values.* *"""* p_mat = np.multiply(R,Q) B = np.sign(p_mat)*np.power(np.abs(p_mat),e) return(B)
Updated Opinions	def update_opinion_mat(O,Q,R,e=.5,alpha=.05): *# Compute the balanced opinion matrix B* B = balanced_mat(R, Q, e=e) *# Update the opinion matrix O_new* O_new = O + alpha * (B - O) return (O_new)

1.2i Stochasticity

Stochasticity plays a role in the model in the creation of the three types of networks and within the interaction of the agents. In terms of the creation of the networks, the three types of networks the traits of Barabasi's preferential attachment network, Watt-Strogatz's small world network, or Connected Watts-Strogatz small world connected network, but are randomly generated in python at the initiation of the model. The interaction between agents also contains a random element as some agents will only pick one agent at random with whom they will use to calculate their updated opinion.

1.2j Collectives

There are no collectives in the model as agents are not grouped socially.

1.2k Observations

The data collected from the model is the agent's opinions at each time step as well as the aggregate level of polarization, alignment, and extremeness.

1.3 Details

1.3a Initialization

The model is initialized with one of three types of networks as well as with placing individuals within the network. The agents are each given opinions, the equanimity score, and their Burt Score, which is one minus their Burt constraint. The initial parameters of the model are then the type of network, the threshold value that will determine the individuals who are below a certain Burt Score, the number of agents in the network, as well as the number of opinions. The code above in Table 1 demonstrates this initiation phase in action.

1.3b Input

The model does not use any external inputs.

1.3c Submodels

The model does contain any submodels.

Section 2

FCP, FE, and Middle Range Theories

One may note the linkage involved in the creation of agent-based models to that of the investigation and explanation of middle-range theories in analytical sociology. Beginning firstly with the arguments of both Coleman's (1986) and Merton's (1948) critique of Parson's structuralism, these two authors stress the need for middle-range theories in sociology alongside their critique of the notion of one specific grand theory that can attempt to explain all human social phenomena. A middle-range theory can be defined as a distinct and clear theory which attempts to explain a range of phenomena without the use of extreme reductionism in their explanation (Hedstrom, 2011). One of the foundational approaches in analytical sociology, that of structural individualism which focuses on the interaction between the micro and macro level of phenomena, attempts to aid researchers in their aim of understanding a range of social phenomena and thus answer the call of Coleman and Merton in the generation of middle-range theories. Indeed, structural individualism as argued by Manzo (2014) is one in which "*From an explanatory point of view, the only requirement is that it should be possible to indicate at least one micro-level element through which the macro/ meso-to-micro causal effect is generated—no matter if consciously or unconsciously from the point of view of the micro-level entity at hand.*". Manzo expands the notion further in stating that the macro and the meso-level factors demonstrate emergent properties in relation to micro-level aspects explanations, thus the macro and meso-level elements of the explanation cannot be reduced solely to the individual. Instead, explanations should be constructed into multi-level models that incorporate structure, emergent properties, and dynamics of aggregation. In this light, modeling complex social systems requires a tool that allows for complexity that can often arise from the interdependence and interaction of different agents and their environment (Lucas, Feliciani, 2023). Agent-based models may provide such a tool as they are computer models that have the ability to model and simulate diverse systems with autonomous, interactive agents. Agent-based models have three main components, the agents, the environment, and the rules of interaction. These three main components are customized by the modeler and can allow for the building of models in a vast range between one end of a highly specified applied situation to the other end in which models are entirely artificial and abstract in nature (Squazzoni, 2012). In the center of this range, there is the ability for the researcher to craft middle-range models, perhaps the goldilocks of the range of agent-based models, which rely on and strengthen the connection between theory and empirical evidence in the explanation of empirical puzzles of social phenomena without venturing too far in the abstract or highly specific.

One may note the connection between the final conceptual map (FCP), the factorial experiment (FE), and the middle-range theories. More specifically, the exploration in opinion dynamics through the Weighted Balance Model and the investigation of social capital in terms of

Coleman's closures and Burt's structural holes. The idea of closures can be first linked to Coleman, Katz, and Menzel (1957) found the diffusion of a drug within the Chicago-land region of the United States was due to four individual physicians who all had strong ties with each other. Coleman later expands on this idea in which it is the dense networks in which strong ties connect the group, transmit information, and increase trust are key to increasing social capital (Coleman, 1988; Burt, 2017). Opposite of this, Burt's structural holes argument is that it is the individuals between different clusters that may have the most advantage in terms of social capital as it allows for them to be the brokers between two or more groups (Burt, 2018). Thus, it isn't always the individuals who are in the most dense network, but those that lie between dense networks that can have greater amounts of social capital. As seen in the FCP and in the FE, we can test for these two in terms of opinion dynamics in the Weighted Balanced Model. As described above in the ODD, agents are encoded with set interactions consisting of those in the network only 1 distance away from themselves; this was chosen to represent the strong ties that Coleman argued were vital in terms of social capital. Agents are also assigned a Burt's Score, the value given by calculating their Burt's constraint given their position in the network. A threshold is set for each of the runs of the models that determines if agents with a Burt's Score above the threshold can update their opinions or not. As the model runs, there is a calculation of the overall polarization and alignment in the network at each time step and the formulas for calculation that were used were that of the previous Weighted Balanced Model. In terms of middle-range theories, this model is not intended to explain all social phenomena nor a specific applied situation, as one can note from the text in pink in the FCP that is left out of the model as it detracts away from the investigation and may lead to an agent-based model concerned with a particular case. Instead, a middle-range model is built that relies on the theories of Coleman and Burt in order to investigate how individual position in the network may cause macro level outcomes, with a focus on agent's Burt's score and the aggregate polarization or alignment in opinion. This then allows for the venture into an attempt at explaining the empirical puzzle of network structure and social capital in opinion dynamics, closely tying this type of model to that of the middle-range.

Section 3

Causality and ABM's

While the FE model is informed by theoretical works such as Coleman, Burt, and most heavily, the Weighted Balance Model, this FE has many shortcomings in attempts to reach satisfactory arguments for causality. The third section of this essay is highly reliant on Manzo's Agent-Based Models and Causal Inference (2022). My FE may be found lacking both in terms of empirical calibration and empirical validation. This leads to a model that may have "theoretical realism", but lacking in "input realism" and "output realism". In terms of empirical calibration, the model incorporates the network component that was absent from the original Weighted Balance Model but leaves these networks as static throughout the run of the model. This goes against the behavior of real world networks as there has been evidence that quite thoroughly demonstrates real world networks are dynamic and change over time (Newman, 2018). Secondly, while it was chosen by the modelers for agents to only choose a neighbor at a distance of one from themselves to update their opinion as to incorporate previous sociological theory, individuals do not act at random choosing with whom they discuss their opinions and more empirical calibrations could be added to the model to inform how agents choose their neighbor. Furthermore, when agents update their opinions, they are using the Weighted Balance Model, but in this model there is a constant alpha set as .02 which is intended to demonstrate that in the updating of the opinion to become "balanced", an individual does not just automatically adopt the "balanced opinion", but approaches it, scene in Table 2 in the Updated Opinions code in the ODD. However, this constant alpha set at 02 does not appear to have any theoretical or empirical evidence to suggest why .02 was chosen. As for empirical validation, there is none that is used to empirically validate the model. A group level experiment on aggregate opinions trends could have been used to validate the model if time and resources allowed for the collection of the data.

The failings of our specific model to fully incorporate the theoretical, input, and output realisms relate more broadly to the use of agent-based models' ability to demonstrate causality. Firstly, while models with theoretical realism may be easier to implement in a model, one of the strong justifications for theoretically informed agent-based models is the lack of consensus on the type of theories which attempt to explain social phenomena. Thus, agent-based models may play a role in forming consensus on possible middle-range theories that demonstrate the key causal mechanisms at play for the desired explanation of the phenomena. However, as the models need to have the empirical validation, consensus regarding the empirical validations representation of the social phenomena may cause difficulties in demonstrating the causality claims of the agent-based model, with the problem of data availability a major contribution. The question of how much data is required in order to establish the generative outcomes of an agent-based model is close enough to the empirical data as well as how to define close enough. This is an important part of empirical validation given that counterfactual arguments require this for the arguments concerning the extent of specific manipulation impact on a model. However, empirical validation data gathered that is both longitudinal and cross-sectional patterns may not best represent the model, as the model is concerned with the process and the mechanisms, and thus arguments for data collected should be instituted in order to create "process realism". This though could make the problem of data availability too exorbitant.

However, if one may include the critic of pragmatic sociology with its foci on the situation, there may be an allowance for the reduction in the amount of data needed for the creation of the "process realism" in an agent-based model as it is the situational data that must be available in the replication processes. Thus, researchers can focus more attention on the situation and not each individual agent at each moment. In line with pragmatic sociology, methodological localism (Little, 2007) can be employed, which is a method that allows for "*socially constructed and socially situated individual, who lives, acts, and develops within a set of local social relationships, institutions, norms, and rules*". This may still fall within the bounds of an agent-based model and within Manzo's view on structural individualism quoted earlier, but still may cause difficulties in terms of 'in practice' agent-based models as this still requires even more data than originally called for in the processes of increasing the empirical validation of the model, but may decrease the amount needed in the creation of "process realism".

Furthermore, researchers need to take into account that agent-based models must at the same time as increasing the empirical validation of the model, researchers also need to maximize the empirical calibration in order to fully represent causality. This may be easier if data is already being collected to fully represent the "process realism", but that is quite high of a bar to set for researchers as well as the fact that empirical calibration often used in models may cause increasing challenges in keeping empirical validation as the two can often push in different directions. As discussed in the ODD, the model created chooses to step each agent simultaneously, and as discussed, changing this can have an impact on the outcomes of the model as first-mover advantage or even randomness of which agent goes first can cause different outcomes in the same model. As there is no clear theory or data that may be used to inform the model on which agents should update their opinion in which order, this can cause strong arguments against the outcomes of the model as the mechanism at play could just be who goes first. Furthermore, there is no way to quantify the relational ties between individuals as either “strong” or “weak”, and thus, while I use previous theory to justify why agents should only interact with other agents at a distance of one because of the strong tie argument, this does not represent reality and people can and do update their opinions not solely based on interactions with their “strong” ties. There is also the issue of time, specifically what are standards for steps or ticks in netlogo. For our model, we chose to have the factorial experiment run for 100 steps as the original paper of the Weighted Balanced Model claimed after 60 steps there was an emergence of polarization or alignment. However, it may be quite difficult for a researcher to match steps or ticks to time in reality when attempting to either calibrate or validate the model. These examples are illustrations of the limits of the ability of empirical calibration of agent-based models and could be seen as an argument against their usage. Thus, as empirical calibration and empirical validation may cause extreme challenges for the use of agent-based models, Manzo argues for partial representation and the use of four different forms of analysis in terms of sensitivity, robustness, dispersion, and the internal workings of the model. This is used to strengthen the claims of causality, while allowing for looser regulations on input and output realism. This may be key for the usage of agent-based models as the requirements for causality are quite high, and thus creating a different avenue for the ability to argue for agent-based models without the stringent criteria needed for empirical calibration and validation may allow for the field to advance. While problems such as data availability, which may impact a large number of researchers who do not have the resources to access such data, may still exist, the use of agent-based models need not create inequalities within the research community in the attempt to generate new insights into social phenomena.

Conclusion:

Through the use of an agent-based model, we were able to explore the impact of where an individual may be embedded in a network has on opinion dynamics. This allowed for the further exploration between the two distinct views of Coleman and Burt in terms of structural position in the network and social capital. Thus we were able to see that theoretically informed agent-based models more broadly can have the ability for researchers to simulate and investigate theories of the middle-range. This may offer the ability for greater consensus concerning theories in sociology. However, the use of agent-based models may require high costs in terms of demonstrating causality and thus researchers should be forewarned if wanting to implement this methodology. Although, for further exploration on the topic, one may look to Netlogo's practice of giving access to models as well as Computational Model Library online which gives access and allows for researchers to easily upload their models. These two resources may lower the high cost of causality as it allows and is intended for fellow researchers to share in the creation and building of models, distributing the burden that does not need to be carried alone.

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