Intergroup Conflict Escalation Leads to more Extremism

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Abstract

Empirical findings in the intergroup conflict literature show that individuals' beliefs that mark differentiation from out-groups become radicalized as intergroup tensions escalate. They also show that this differentiation is proportional to tension escalation. In this paper, we are interested to develop an agent-based model which captures these findings in order to explore the effect of perceived intergroup conflict escalation on the average number of emergent extremists and opinion clusters in the population. The proposed model builds on the 2-dimensional bounded confidence model proposed by Huet et al (2008). The results show that the average number of extremists has a negative correlation with intolerance threshold and positive correlation with the amount of opinion movement when two agents are to reject each other's belief. In other words, the more tensions exist between groups, the more individuals getting extremists. We also found that intergroup conflict escalation leads to lower opinion diversity in the population compared with normal situations.

Keywords:
Intergroup conflict, Opinion Dynamics, Differentiation, Bounded Confidence, Extremism.

1- Introduction

Typically people are more comfortable with those who are similar with themselves or with those who perceived as in-group members. The phenomenon is called *homophily* and is one of the most widely accepted and empirically proven observation in the social psychology (Lazarsfeld and Merton 1954; Burt 1991). With homophilous behaviors comes ignorance of or differentiation from people of out-groups. This discriminatory and biased behavior of people based on the perceived in-group/out-group membership may trigger or intensify the intergroup conflict.

There are several social psychological theories which have tried to explain the underlying cognitive mechanisms of differentiation. *Cognitive Dissonance* theory is an attitude formation paradigm proposed by Festinger (1957). Cognitive dissonance occurs when there is an inconsistency between two or more beliefs which are hold simultaneously. This dissonance is "psychologically uncomfortable" and therefore motivate people to achieve a balanced state which may achieved by differentiating from opposing beliefs. Other theories such as the reactance theory (Brehm 1966) and social judgment theory (Sherif and Hovland 1961) assert that in some cases people shift their attitudes in the opposite direction of whom they are interacting with.

Differentiation is the underlying mechanism which leads to the emergence of pluralism, polarization, and radicalization in the society (Isenberg 1986). The aim of differentiation could be to maintain or to achieve superiority over out-groups (Tajfel and Turner 1986), to avoid betraying in-groups (Tajfel and Turner 1986), to maintain in-group solidarity (Bulbulia and Sosis 2011), or to protect in-group sacred values (Atran and Ginges 2012). However, categorization of people into different groups itself does not trigger intergroup conflict. There should be some sort of motivation that activates the discriminatory behaviors toward out-groups (Fiske 2002). Several social psychological theories have attempted to provide a plausible explanation for the forces that cause intergroup conflicts. These theories vary from interpersonal to social influence based theories.

Early theories on intergroup conflict tried to explain the emergent intergroup conflict as a result of individuals' prejudice and discrimination. Theories like the theory of *Authoritarian Personality* (Adorno et al 1950) and different versions of the Theory of Frustration, Aggression, and Displacement (Berkowitz 1962) are well-known instances of this category. The main drawback of this line of theories is the ignorance of social influence over individuals' behavior.

From the social influence point of view, the *Realistic Group Conflict Theory* (Sherif 1966) postulates that the real conflict of interest between groups triggers the intergroup conflict. Another theory concerning the cognitive basis of intergroup differentiation is the well-known *Social Identity Theory* (Tajfel 1978). Social Identity Theory states that group membership creates in-group feelings which may cause to favor in-group traits, values, and characteristics. However, the social identity theory (Tajfel 1978) and the subsequent self-categorization theory (Turner et al 1987) fail to provide a motivational driver for the process of in-group identification and intragroup derogation, particularly that of chronic and long-term identification.

Social pressures to favor one's own group through in-group/out-group bias lead groups to differentiate themselves from one another (Tajfel 1974, 1975; Turner 1975). The amount of differentiation varies by degree, from neglecting out-groups to murderous hostility toward threateningly perceived out-groups. The presence of explicit conflicts of group interests intensifies the positive attachment to in-groups and leads to antagonistic inter-group relations (Tajfel and Turner 1986). The more intense the inter-group conflict, the more likely that competing groups will act based on their group identification (Tajfel and Turner 1986).

Social psychologists studying intergroup conflict show that individuals' out-group attitudes can be predicted by the extent to which they are identified with in-group values. Deschamps and Brown (1983) found that when subjects are primed to categorization, the comparability of groups' roles increases the intergroup differentiation. In an attempt to empirically examine the utility of different social psychological approaches on intergroup relations, Brown et al. (1986) conducted an experiment among shop floor workers in a factory. They found that perceived intergroup conflict has strong positive correlation with differentiation. They also found that the amount of contact is negatively and the strength of group identification is positively correlated with differentiation, but these correlations are weak. To examine the relationship between strength of identification with a political party and the amount of differentiation from other political out-groups, Kelly (1988) showed that "in-group identification and perceived material conflict were consistent predictors of intergroup differentiation along evaluative and affective dimensions but not along the dimension of perceived intragroup homogeneity". Moreover, empirical findings show that when differentiation need is activated in individuals, they generate more negatively evaluated categories compared to when the inclusion need is activated (Leonardelli et al. 2010).

Despite the rich literature on intergroup conflict and intergroup differentiation, there is a need to build computational models to explore the emergent high-level patterns of individuals' opinion formation in presence of intergroup conflict. A plausible direct consequence of the presence of intergroup conflict is the emergence of individuals with radical beliefs. The process is called *Radicalization* and has received attention within social psychology from its inception. One important research question in studying extremism is to investigate *why* and *how* individuals with radical beliefs come to believe what they believe. Are they holding radical beliefs because they have interacted with other extremists or they could become radical just by interacting with moderate people? What are different plausible pathways or mechanisms for becoming an extremist?

So far, we discussed that the amount of differentiation does increase in certain situations (Deschamps and Brown 1983), and that perceived intergroup conflict has strong positive correlation with differentiation (Brown et al. 1986). The aim of this paper is to analyze the effect of perceived intergroup conflict escalation on the average number of emergent extremists in the society. We develop an agent-based model that links the micro-level findings of intergroup conflict and intergroup differentiation literature to the macro-level behavior of the population. The proposed model is an extension of the 2-dimensional Bounded Confidence model with rejection mechanism (2D BCR) proposed by Huet et al (2008). We randomly assign the agents to m groups and by assuming that the intergroup conflict exists *a priori* in the population, and that agents differentiate more if they perceive more intergroup conflict (Brown et al. 1986), we let agents to move farther from out-groups' opinion compared to in-group fellows. Before going through the model, we briefly review related agent-based opinion dynamics models in section 2. In section 3, we present our extended model that captures intergroup conflict escalation and differentiation. Then we discuss the simulation results for various parameters in section 4. Finally, we conclude the paper in section 5.

2- Agent-based Opinion Dynamics Models

Agent-based modeling is the fast growing approach to study the collective behavior of large number of people. Many agent-based models have been proposed for opinion dynamics using the social psychology theories. Most of the existing ones are based on the fact that people get closer together after interaction. The underlying interpretation of these models is that of homophily. They assume that there exist some “attractive forces” between individuals when they hold similar beliefs. Two widely used models of this category are Bounded Confidence (BC) model (Deffuant et al 2000; Hegselmann and Krause 2002) and Relative Agreement (RA) model (Deffuant et al 2002).

There are two well-known opinion dynamics under bounded confidence models that have been independently proposed by Deffuant, Weisbuch and others (DW) and Hegselmann and Krause (HK) in 2000. The two models are very much alike, but differ mainly in their communication regimes and slightly in updating mechanisms. While DW model considers random pairwise encounters at each time step in which agents may compromise or not, the HK model allows agents to communicate with all other agents and adopt the average opinion of those who fall in their area of confidence. For a survey of continuous opinion dynamics under bounded confidence models see Lorenz (2007). Similar to Huet et al (2008), we follow the DW version of the BC model in this paper.

In the DW model, agents have continuous belief, ranging from 0 to 1. The agents interact in randomly dyadic encounters and they are allowed to adjust their belief if their difference in belief is less than a pre-defined threshold called “uncertainty”. As the uncertainty increases, the agents converge to an average belief, but the number of opinion clusters reduces. The DW model fails to create extremists agents because it only considers the attractive forces between individuals. While in the DW model the uncertainty thresholds are assumed to be equal for all agents, in the RA model, the authors let the uncertainty change as a function of time. As a result, after each random pair interaction, both agents’ belief and uncertainty are updated and therefore the influence is no longer symmetric. However, similar to DW model, the RA model fails to capture the differentiation mechanism in dyadic interaction.

Several researchers have tried to model the emergence and propagation of extremists in the population using agent-based opinion dynamics models. They attempt to study radicalization by adding some extremist agents in the population with extreme belief but much lower uncertainty threshold (Deffuant et al. 2002), asymmetric confidence and biased confidence (Hegselmann and Krause 2002), weighting the influence of agents through a Gaussian function with uncertainty as standard deviation (Deffuant et al. 2004), examining the effect of network topology (Amblard and Deffuant 2004), assigning separate uncertainty thresholds for attraction and rejection (Jager and Amblard 2005), incorporating findings from Self-Categorization theory (Salzarulo 2006), comparing different continuous opinion dynamics models including the BC model, the Gaussian BC model, the RA model, and the Gaussian BC model with interlocutor uncertainty (Deffuant 2006), examining the striving for uniqueness among agents (Mäs, Flache, and Helbing, 2010), and introducing open- and close-minded agents in the population (Lorenz 2010).

In an effort to include the rejection mechanism in the DW model, Huet et al (2008) propose a 2-dimensional BC model which allows the agents to reject other's belief when they are in a dissonance situation. That is, when two agents are close in one attitude and far enough in another, they are in a dissonance state and therefore they want to resolve it by shifting away from each other in that close attitude. By incorporating this repulsive force into the BC model, some linear clusters form in attitude borders representing the emergence of extremism in the population. In another work, Huet and Deffuant (2010) introduce a new version of the BC model which is based on the Wood et al (1996) empirical results. While the model is still 2-dimensional, one attitude is considered as a main or important one and the other as a secondary. If two agents are close in primary attitude (difference is less than attraction threshold), they get closer in both attitudes. However, if they are far enough in primary attitude (difference is greater than rejection threshold), then they are in dissonance state and try to solve it by shifting away in secondary attitude. The results showed that high rejection threshold leads to the formation of clusters having extreme opinions for the secondary belief.

To extend the BC model, Kurmyshev et al (2011) used a heterogeneous population by incorporating two types of agents: friendly agents and partial antagonistic agents. While the first type always tries to reach people and get closer to them, the latter exhibits repulsive behavior in its interactions. They found that in high uncertainty situation and in equal proportion of two agent types, radical opinion changes would arise.

3- Intergroup Differentiation Escalation Model

In this section we present our agent-based model which is an extension of the 2-dimensional BC model with rejection mechanism proposed by Huet et al (2008). Our modifications derived from the well-grounded social psychological findings (Deschamps and Brown 1983; Brown et al. 1986; Kelly 1988; Leonardelli et al. 2010). For clarification purposes, first we describe the Huet et al's (2008) model and then describe our modifications. Let's consider a set of N individuals each having the following characteristics:

1) ***Opinion***: a 2-dimensional vector containing x_1 and x_2 representing real numbers ranging from -1 to +1, reflecting the belief of node over two different issues. The continuous opinion can be interpreted as the extent to which agents are in favor of or against to a given issue.
2) ***Uncertainty***: a 2-dimensional vector containing u_1 and u_2 representing by real numbers between 0 and 1 reflecting uncertainties related to x_1 and x_2 respectively.

At each simulation time step, instead of allowing each agent to interact with all of its neighbors, a pair of individuals is randomly selected to interact and update their belief. Here they condition the updating process based on the values of beliefs and uncertainties. Suppose agent *i* has beliefs x_{1i} and x_{2i} with uncertainties u_{1i} and u_{2i}, and agent *j* has beliefs x_{1j} and x_{2j} with uncertainties u_{1j} and u_{2j}. For sake of simplicity, they assume that all nodes have same uncertainties *U*. Then, agent *i* compares its beliefs with *j*'s and updates its beliefs. The general rule is that agents approach each other if they are close enough in both beliefs. Otherwise, they may ignore each other or reject and shift away. More formally, if:

$$\left|x_{1i}^t - x_{1j}^t\right| \le U \quad and \quad \left|x_{2i}^t - x_{2j}^t\right| \le U$$

Then the two agents' beliefs fall in their bounded confidence interval. Thus, they get closer to each other based on the following equations:

$$x_{1i}^{t+1} = x_{1i}^t + \mu \left(x_{1j}^t - x_{1i}^t\right) \qquad (1)$$
$$x_{2i}^{t+1} = x_{2i}^t + \mu \left(x_{2j}^t - x_{2i}^t\right) \qquad (2)$$

In these equations, μ is a constriction factor used to limit the convergence velocity. The assumption is that μ is constant and equal for all agents throughout the simulation. Another possible state is the case that two agents are close in one belief but far in another one:

$$\left|x_{1i}^t - x_{1j}^t\right| > U \quad and \quad \left|x_{2i}^t - x_{2j}^t\right| \le U$$

Here, depending on whether the difference is less than a certain threshold or not, two cases arise. To represent that threshold, they consider the "intolerance threshold" δ. Therefore, if the difference is below the predefined threshold, meaning:

$$\left|x_{1i}^t - x_{1j}^t\right| \le (1+\delta)U$$

The dissonance is not strong enough to trigger the rejection. Therefore, the two agents ignore each other in belief 1 and approach each other in belief 2.

$$x_{1i}^{t+1} = x_{1i}^t \qquad (3)$$
$$x_{2i}^{t+1} = x_{2i}^t + \mu \left(x_{2j}^t - x_{2i}^t\right) \qquad (4)$$

However, if the difference is significant enough, meaning:

$$\left|x_{1i}^t - x_{1j}^t\right| > (1+\delta)U$$

then the conflict is enough to make agents feel dissonance and thus trigger repulsive action. So the two agents shift away from each other in belief 2 and ignore belief 1. The movement should be large enough to resolve the dissonance.

$$x_{2i}^{t+1} = x_{2i}^{t} - \mu \, psign\left(x_{2j}^{t} - x_{2i}^{t}\right)\left(U - \left|x_{2i}^{t} - x_{2j}^{t}\right|\right) \quad (5)$$

$$x_{1i}^{t+1} = x_{1i}^{t} \quad (6)$$

Here *psign*(.) is similar to *sign* function, except that it returns +1 if the argument is 0. Moreover, the belief values are limited between -1 and +1 by incorporating the following rule:

$$if \left|x_{2i}^{t+1}\right| > 1 \; then \; x_{2i}^{t+1} = sign\left(x_{2i}^{t+1}\right)$$

Since the model has been built on the cognitive dissonance theory, it assumes that for cases in which two agents are far in both beliefs, there is no dissonance between them and therefore there is no influence from one to another and they simply ignore each other on both beliefs.

For our modeling purposes, we modify the 2D BCR model in three ways. First, to make the model more realistic by letting agents to interact in a social network structure in which each agent has limited number of neighbors. While in 2D BCR model agents are allowed to interact with any random agent in the population, we limit this communication to only their immediate neighbors. Second, to capture the group identification mechanism, we randomly assign all agents to *m* different groups. Third, we modify the belief updating rule to incorporate empirical findings from social psychology literature. In general, the findings state that escalation of the perceived intergroup tensions leads individuals to differentiate more from out-groups (Deschamps and Brown 1983; Brown et al. 1986). In our proposed model, we assume that a tension between groups exist *a priori* in the population. Moreover, since the findings just held true for "differentiating beliefs", we assume that x_1 and x_2 are differentiating beliefs. An example of differentiating beliefs can be "moral beliefs", including religious beliefs. The differentiation escalation mechanism occurs when the two encountering agents are from different groups. We capture the increase in opinion movement by entering an *intergroup differentiation escalation* coefficient β ($\beta > 1$) in equation 5:

$$x_{2i}^{t+1} = x_{2i}^{t} - \beta \, \mu \, psign\left(x_{2j}^{t} - x_{2i}^{t}\right)\left(U - \left|x_{2i}^{t} - x_{2j}^{t}\right|\right) \quad (7)$$

The second term in the right hand side of the equation 5 determines the amount that agents shift away from each other in dissonance situation. By multiplying the coefficient β ($\beta > 1$) in this quantity, we increase the movement and let the agents to shift farther away in their beliefs compared to the 2D BCR model. As the tension escalates between groups of people, we can increase the coefficient β to make agents move farther away. If there is no tension between groups, β is set to 1. Based on these modifications, we expect to see more extremists in the population, as we increase the intergroup differentiation escalation coefficient β. In other words, the number of emergent extremists is a function of β and δ:

$$N^t(e) = f(I^t, \beta, \delta) \quad (8)$$

where the $N^t(e)$ represents the number of extremists at time step t, I^t is the interaction situation at time step t (attraction or rejection), β is the intergroup differentiation escalation coefficient ($\beta > 1$), and δ is intolerance threshold. Table 1 compares the key features of the proposed model with some existing agent-based opinion dynamics models in the literature.

Table 1: Lite Docking the Agent-based Opinion Dynamics Models

Variables	BC (Deffuant et al 2000)	RA (Deffuant et al 2002)	Salzarulo (2006)	Huet et al (2008)	Differentiation Escalation
Supporting Theory	Cognitive Dissonance	Cognitive Dissonance	Self-Categorization	Cognitive Dissonance	Brown et al (1986)
Dimension	1	1	n	2	2
Uncertainty	Constant	Dynamic	N.A.	Constant	Constant
Communication Regime	Dyadic	Dyadic	Group	Dyadic	Dyadic
Rejection Mechanism	×	×	✓	✓	✓
Differentiation Escalation Mechanism	×	×	×	×	✓
Initial Groupings	×	×	✓	×	✓

4- Analysis of the Results

In this section, we present and analyze our agent-based simulation results. First we show the general behavior of the model and compare it to the original Huet et al (2008) model. Then, by designing a virtual experiment, we conduct a series of experiments to examine the effect of key factors on the number of emergent extremists in the population.

4.1. General Comparison with the 2D BCR Model

We consider a population of 1000 agents each having two beliefs. The initial beliefs are randomly assigned to the agents using the uniform distribution between -1 and 1. The uncertainties u_1 and u_2 are assumed to have equal values and held constant throughout the simulation. The assumption is that x_1 and x_2 are differentiating beliefs and agents are in conflict escalation situation (i.e. $\beta > 1$). Since our main focus in this paper is to test the effect of intergroup differentiation escalation, we leave out the network structure in this section and set the communication regime same to the 2D BCR model.

Figure 1 compares the evolution of opinions between the Huet et al (2008) model and the modified model. In each of the figures, the two axes represent the beliefs which are bounded between -1 and 1 and each dot on the figure represents an agent's opinion. Our assumption in the proposed model is that both beliefs are differentiating and there is a tension between groups of people. All other parameters are the same. Therefore, we can interpret the results as the changes in populations' belief when the beliefs become differentiating and tensions arise between groups.

Similar to the 2D BCR model, after some point, several stable equilibrium points emerge and opinion clusters form around those points. Two interaction social forces cause the creation of the clusters. On one hand, those agents which are close in both beliefs tend to get closer and form groups of like-minded agents. On the other hand, those who hold similar belief in one dimension and far enough in another one are separated and pushed away from each other. As a result, after some point, some dominant equilibrium points emerge in the population (Huet et al 2008). These “meta-clusters” are permanent and do not change their position on the figure.

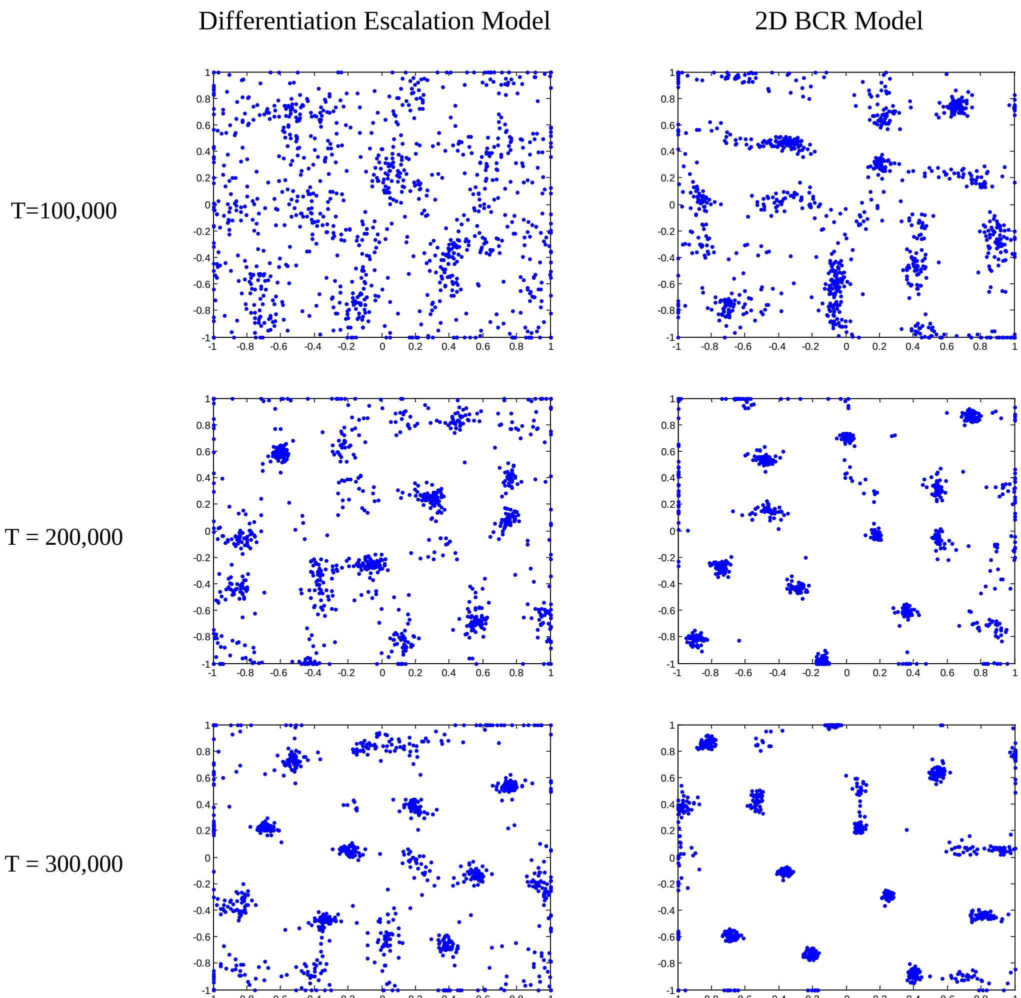

Figure 1: Comparison of the differentiation escalation model and the 2D BCR model (U=0.2, m=3, μ=0.3, δ=1, β=1.5). Both axes represent individuals’ opinion.

An interesting difference between the results is that the number of emergent opinion clusters is less in the differentiation escalation model than in the 2D BCR model. In order to compute the number of the clusters, we use the algorithm used by Deffuant (2006) and Huet et al (2008). That is, we define a minimum distance ε between the agents’ beliefs under which they assign to same cluster. In practice we set the minimum distance at ε = 0.15 and neglected the clusters of size lower than %1 of the population size. We run the model for 25 times and report the average number of clusters.

The results reveal that while the 2D BCR model produces 19 opinion clusters with at least 10 members, the differentiation escalation model leads to 16 opinion clusters. The reason can be explained by the role of β which increases fluctuations of individuals within the clusters. This increase in fluctuations enhances the instability of the clusters which in turn increases the likelihood of merging between clusters, or in rare cases, the explosion of clusters. This mechanism eventually leads to the formation of less number of opinion clusters in the final configuration of individuals. This implies that in presence of escalating tensions and differentiating opinions, not only the equilibrium points are changed, but also we see lower opinion diversity in the society. We explore this phenomenon more in section 4.2.1.

4.2. Virtual Experiments

In this section, we design a virtual experiment to test the effect of key variables of the proposed model on the average number of emergent extremists in the population. Here we define an agent as extremist if the absolute value of at least one of its beliefs is equal or greater than 0.9. Previous works have examined the effect of intolerance threshold (Deffuant 2006; Huet et al. 2008), the initial uncertainty of the moderates (Deffuant 2006), the initial proportion of extremists (Deffuant 2006), level of uncertainty (Huet et al 2008), and network topology (Amblard and Deffuant, 2004; Weisbuch 2004) on the dynamics and number of emergent extremist. Therefore, to avoid the analysis being too complicated and lengthy, here we control the convergence parameter, level of uncertainty, and number of agents and just vary the new introduced parameters along with the influential intolerance threshold variable. We assign three levels of value for the intergroup differentiation escalation coefficient β, intolerance threshold δ, and number of initial groupings m. We also examine the effect of the presence of random social network by adding an indicator variable which takes 1 if the agents can only interact with their immediate neighbors, and 0 if there is no network structure. We use an Erdös-Rényi random network with connectivity probability of p = 0.05. We run each combination 25 times. Table 2 illustrates our virtual experiment configuration.

The ANOVA table contains the sources of variation, degrees of freedom, sum of squares (SS), mean square (MS), F-ratio test statistics, and the corresponding significance levels (p-values). In general, the higher the F-ratio value, or the smaller the probability, the more important the corresponding factor. Table 3 presents the result of the ANOVA test for the average number of extremists. The results illustrate a significant difference between the various levels of intergroup differentiation escalation coefficient β (F (2, 1296) = 3.002, p = 0.050) and intolerance threshold δ (F (2, 1296) = 1229.465, p = 0.000). When examining the initial number of groupings m, we observed a significant difference (F (2, 1296) = 24.525, p = 0.000). Finally, we found that the absence or presence of random network is also significant (F (1, 1296) = 13.694, p = 0.000).

Table 2: Design of Experiments Configuration

Independent Variables	No. of Test Cases	Values Used
Beta	3	1, 1.5, 2
Intolerance threshold	3	1, 1.5, 2
Number of initial groupings	3	3, 5, 7
Social Network	2	Random (p = 0.05), No network
Control Variables	**No. of Test Cases**	**Values Used**
Uncertainty (U)	1	0.2
Convergence Parameter ($\boldsymbol{\mu}$)	1	0.3
Initial Belief Distribution	1	Random
Maximum Iteration	1	500,000
Number of Agents	1	1000
Number of Runs	1	25
Dependent Variables	**No. of Test Cases**	**Values**
Average Number of Extremists	-	-

The ANOVA table also reveals that there are significant interactions between the intergroup differentiation escalation coefficient β × intolerance threshold δ (F (4, 1296) = 22.577, p = 0.000), the number of initial groupings m × β (F (4, 1296) = 2.558, $p \leq 0.05$), β × random network existence (F (2, 1296) = 8.274, p = 0.000), $\delta \times m$ (F (4, 1296) = 5.892, p = 0.000), and m × random network existence (F (2, 1296) = 9.239, p = 0.000). This means that the simultaneous influence of independent variables on the average number of emergent extremists is not additive. That is, the relationship between each of the interacting variables and the dependent variable depends on the value of the other interacting variable. Further analysis of the effect of independent variables is presented in the following three sub-sections.

Table 3: ANOVA Table for Tests of Between-Subjects Effects

Source	SS	Degrees of Freedom	MS	F	P-Value
Beta	2505.975	2	1252.987	3.002	.050
Delta	1026453.255	2	513226.627	1229.465	.000
m	20475.539	2	10237.770	24.525	.000
Network	5716.507	1	5716.507	13.694	.000
Beta * Delta	37698.167	4	9424.542	22.577	.000
Beta * m	4271.563	4	1067.891	2.558	.037
Beta * Network	6907.471	2	3453.736	8.274	.000
Delta * m	9838.776	4	2459.694	5.892	.000
Delta * Network	880.164	2	440.082	1.054	.349
m * Network	7713.524	2	3856.762	9.239	.000
Beta * Delta * m	4398.121	8	549.765	1.317	.231
Beta * Delta * Network	32612.404	4	8153.101	19.531	.000
Beta * m * Network	524.271	4	131.068	.314	.869
Delta * m * Network	4917.298	4	1229.324	2.945	.019
Beta * Delta * m * Network	8721.520	8	1090.190	2.612	.008
Error	541000.720	1296	417.439		
Total	67483898.00	1350			

Dependent Variable: Number of Extremists
R Squared = .684 (Adjusted R Squared = .672)

4.2.1. Analyzing the effect of β

In this section, we analyze the effect of intergroup differentiation escalation coefficient β from two perspectives: 1) the effect of β on the average number of emergent extremists in the society, and 2) the effect of β on the number of opinion clusters. Figure 2 compares the number of extremists in the original 2D BCR model and the intergroup differentiation escalation model resulting from 25 numbers of runs. We show the number of extremists for when the interactions are restricted by random network and for when there is no network structure. In general, we can see that whether the interactions are restricted in a random network structure or not, the differentiation escalation model produce more number of extremists compared to the 2D BCR model. Also it appears that as the β goes up, the average number of extremists monotonically increases up to the β = 1.8 point, but decreases afterward.

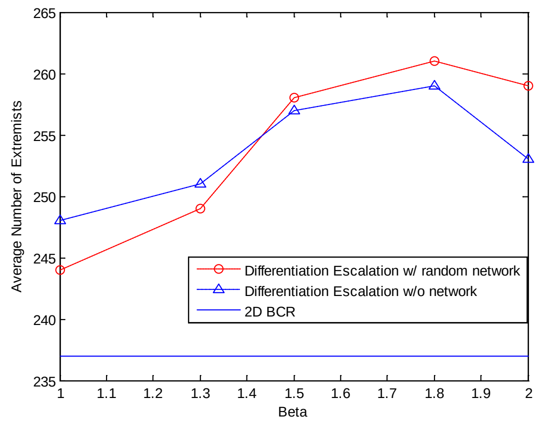

Figure 2: Comparing the effect of β on the average number of extremists between the 2D BCR and differentiation escalation models (U = 0.2, m = 3, μ = 0.3, δ = 1, iterations=500,000).

The reason could be traced to the amount of movement that the encountering agents undertake to differentiate from each other. By pushing agents to shift farther away from each other when they are in dissonance condition, more agents tend to reach the opinion borders and become extremists. This is an interesting result because it shows that just by changing the social interaction regime, more extremists emerge in the population. This supports the claim of Self-Categorization Theory (Turner et al. 1987) that extremists are the product of simple social interactions and that extremism is more likely to be an emerging phenomena rather than an intrinsic feature of individuals. That is, even without having individuals interacting with extremists in the society, they still can become extremists themselves just by interacting with those who holds less extreme beliefs (Urbig and Malitz 2007). The results also are in accordance with Isenberg's (1986) argument that group polarization is a function of "persuasive arguments" and "social comparison" and therefore existence of extremists is not necessary for polarization and radicalization to occur.

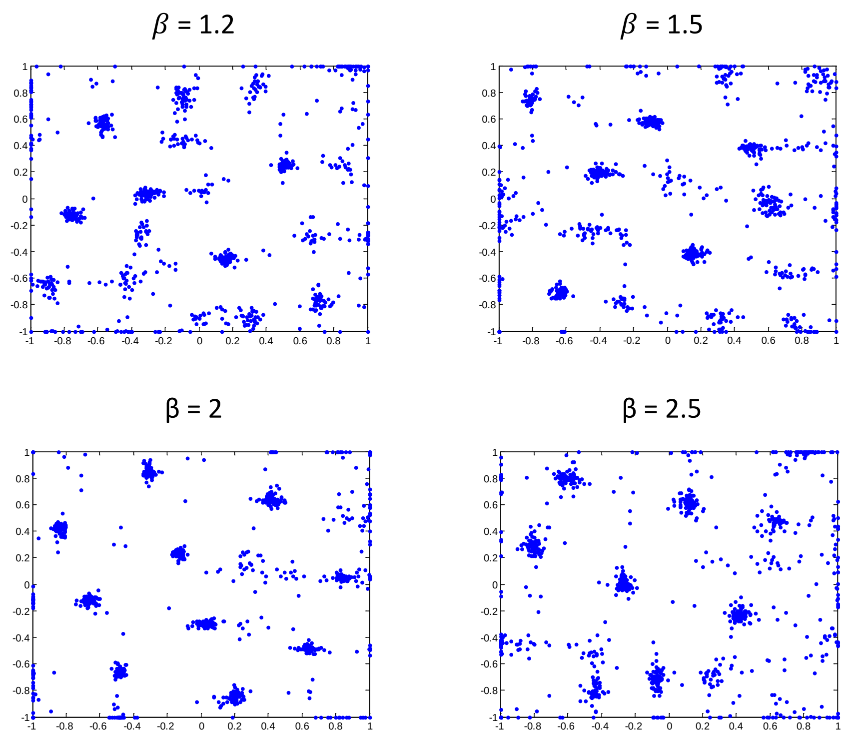

Figure 3: Effect of β on the number of extremists and clusters
(U=0.2, μ=0.3, δ=1, random network, iteration=500,000)

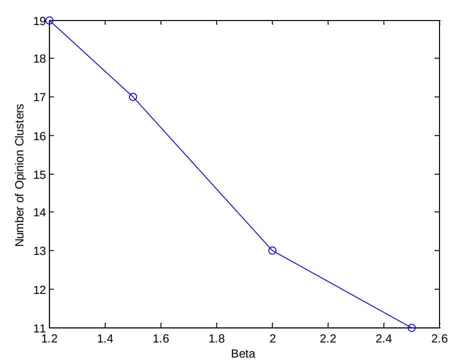

Figure 4: Analyzing the effect of β on the average number of emergent opinion clusters
(U=0.2, μ=0.3, δ=1, random network, iteration=500,000)

We discussed in section 4.1 that increasing the amount of movement at the time of differentiation increases the instability of the opinion clusters by increasing the likelihood of merging or disintegration of clusters which in turn decreases the final number of opinion clusters. Here we go more in depth and test the effect of increasing the β on the number of emerging opinion clusters in the population. Figure 3 illustrates the simulation results for different values of β and Figure 4 show the corresponding average number of opinion clusters obtained by Huet et al's (2008) algorithm. We run the algorithm for maximum number of 500,000 iterations and replicate for 25 times. Both figures suggest that the number of emergent opinion clusters decreases with intergroup differentiation escalation coefficient β. Indeed, as we push agents to shift their belief farther away from each other, the equilibrium points relocate and the distance between new clusters expands. This suggests that intergroup differentiation escalation reduces the opinion diversity in the society and in a way produced a radicalized population.

4.2.2. Analyzing the effect of intolerance threshold

Intolerance threshold plays an important role in agents' selection process of whether to attract or differentiate from others. Figure 5 shows simulation results for four different values of intolerance threshold δ (δ =1, 1.5, 2 and 2.5), while holding all other variables constant. Observationally, we can see that the number of opinion clusters strikingly increase as the rejection condition is restricted. Figure 6 illustrates the corresponding average number of opinion clusters (iterations = 500,000; replications = 25), where an increase from δ = 1 to δ = 2.5 increases the average number of opinion clusters from 16 to 29. Thus, we conclude that in intergroup differentiation escalation situation, restricting the differentiation mechanism would increase the opinion diversity in population. It is worth mentioning that the same trend has been found in 2D BCR model by Huet et al (2008).

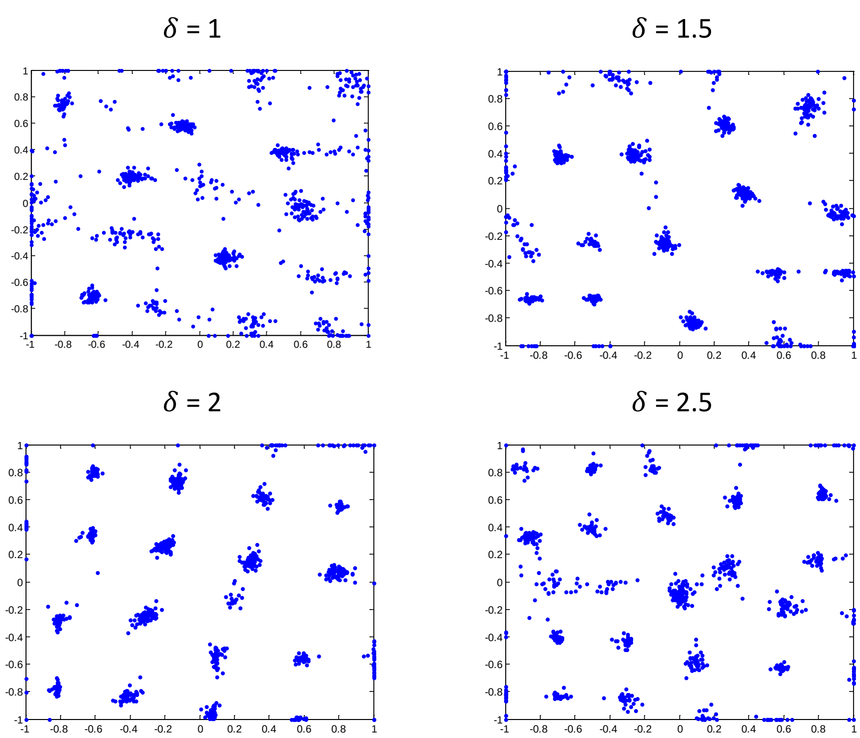

Figure 5: Effect of intolerance threshold δ on the opinion dynamics
(U=0.2, μ=0.3, β=1.5, random network, iterations=500,000)

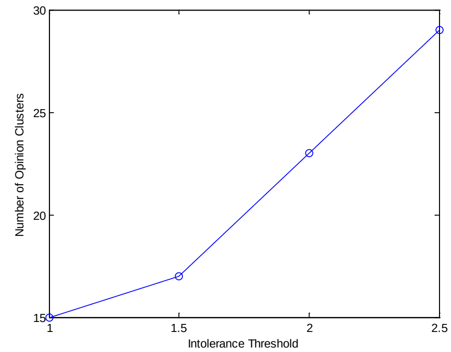

Figure 6: Analyzing the effect of intolerance threshold δ on the average number of emergent opinion clusters (U=0.2, μ=0.3, β=1.5, random network, iterations=500,000)

The ANOVA test result in Table 3 showed us that the intolerance threshold δ has a significant effect on the average number of emerging extremists. Figure 7 illustrates the average number of extremists when the intolerance threshold δ moves from 1 to 2.5. We observe that by increasing the intolerance threshold, the number of emerging extremists monotonically decreases. This is due to fact that by restricting the rejection conditions, people tend to get closer to each other or at most ignoring each other's opinion rather than rejecting and shifting away. The results also show that except for δ = 2.5, at other corresponding intolerance threshold values, the differentiation escalation model (with or without existence of random network) produces more number of extremists.

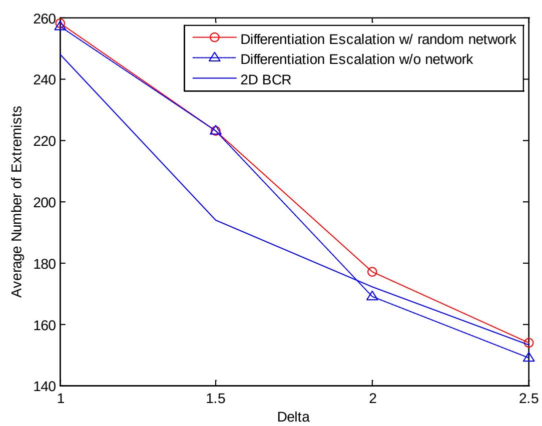

Figure 7: Effect of intolerance threshold δ on the average number of extremists (U=0.2, μ=0.3, β=1.5, m = 3, iteration=500,000)

4.2.3. Analyzing the Effect of the Number of Initial Groupings

In this subsection we examine the effect of number of initial groupings m on the average number of emergent extremists and number of final opinion clusters. Figure 8 shows the final distribution of the opinions after 500,000 iterations for different number of initial groupings. Figure 9 illustrates the corresponding number of final opinion clusters for each value of initial number of groupings. Both figures suggest that the average number of final opinion clusters slightly decreases with initial number of groupings *m*. This could be explained by the fact that increasing the number of initial groupings increases the differentiation among agents which leads to less number of opinion clusters.

Table 3 illustrated that changes in the initial number of groupings is highly correlated with the average number of emergent extremists in the population. Figure 10 shows the corresponding average number of extremists for various values of initial number of groupings *m* both in presence and absence of random network topology. We can see that whether the agents' interactions are restricted only to immediate neighbors on a random network or not, the average number of extremists increases with the number of initial groupings *m*. The underlying reason is that on the one hand, the opinions are bounded, and on the other hand, the differentiation occurs more when there is more number of pre-defined groupings in the initial population. Therefore, more agents are pushed to the extreme limits of the opinions. The results also reveal that random network generates more extremists in this configuration of parameters.

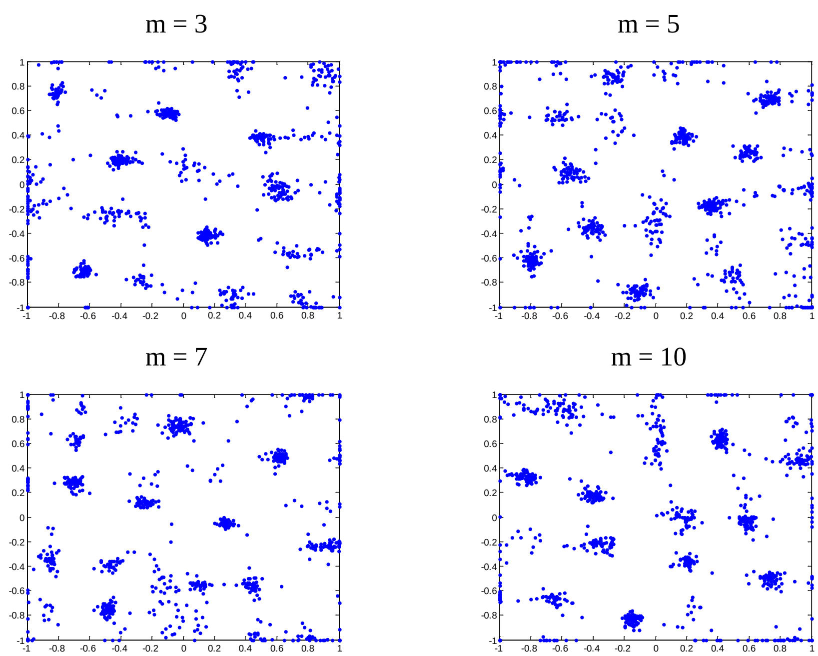

Figure 8: Analyzing the effect of the number of initial groupings on the opinion dynamics (U=0.2, μ=0.3, β=1.5, random network, iterations=500,000)

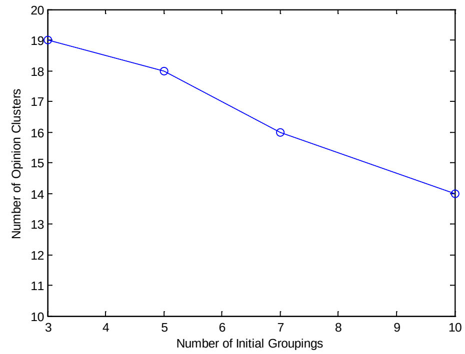

Figure 9: Analyzing the effect of initial number of groupings on the average number of emergent opinion clusters (U=0.2, μ=0.3, δ=1.5, β=1.5, random network, iterations=500,000)

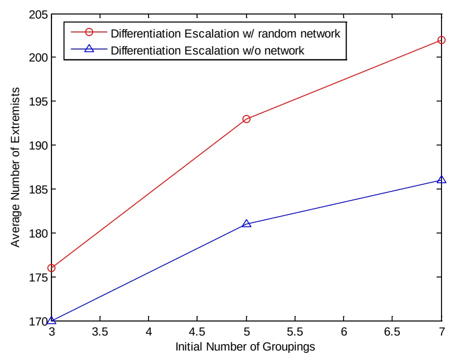

Figure 10: Effect of initial number of groupings m on the average number of extremists (U=0.2, μ=0.3, β=2, δ=1.5, iteration=500,000)

5- Discussion and Conclusion

Assuming that there is an interest to control and mitigate the spread of radical beliefs in the society, there would be a need for informed policies based on deep understanding of different conditions under which one could develop radical beliefs. For example, one could derive from the self-categorization theory that the existence of extremists in the society is an emergent phenomena rather than an intrinsic property of the individuals. That is, the extremists are not the cause of extremism but they are the product of social interactions.

A body of literature explored the idea that individuals' beliefs that mark differentiation from out-groups become radicalized as intergroup tensions escalate (Deschamps and Brown 1983; Brown et al. 1986; Kelly 1988; Leonardelli et al. 2010). Their results show that conflict triggers identification and differentiation dynamics. Moreover, they find that the more intense the intergroup tensions, the more identification and, hence, the more differentiation occurs between individual's opinions. That is, participants in the high conflict condition identified more with their in-group than participants in the low conflict condition, who in turn, identified more with their in-group than participants in the collaboration condition. The main idea is that individuals may not follow rational decision making when they are in serious conflict. In this situation, they may consider some issues as sacred values and become reluctant or even sensitive to compromise (Atran and Ginges 2012).

In this paper, we are interested in exploring the collective behavior of individuals when there exist some tensions between groups of people that trigger in-group opinions. Particularly, we want to test the effect of conflict escalation on the average number of extremists that are emerged as a result of social interactions. We developed our model based on two critical assumptions. First we assume that the tensions exist a priori in the society. Second we assume that the beliefs that agents are interacting on are differentiating beliefs. The proposed agent-based belief differentiation model is a modified version of 2-dimensional bounded confidence with rejection mechanism model proposed by Huet et al (2008). We randomly assigned the agents to m groups and let them to shift more away from each other if they are from different groups. We captured this increase in opinion rejection by introducing the intergroup differentiation escalation coefficient β into the model. We also incorporate a social network structure which allows agents to only interact within their neighborhood. We ran the model for various ranges of parameters and observed for difference in number of opinion clusters, change in equilibrium points, and level of consensus. We also designed a virtual experiment to systematically test the effect of intergroup conflict escalation on the average number of emerging extremists.

The ANOVA test results support the hypothesis that the average number of extremists is a function of the intolerance threshold and the amount of attitude shifting when two agents are to reject each other's belief. In other words, the increase in the amount of opinion differentiation would eventually lead to more extremism in the society. By varying the intergroup differentiation escalation coefficient between 1 and 2, we see more agents at the border of opinions meaning the emergence of more extremists in the population. The reason can be traced to the role of β which increases the amount of movement when the agents reject each other. In our model, in rejection situations, the agents are pushed farther away from the cluster by other clusters compared to the 2D BCR model. Since the beliefs are bounded between -1 and 1, this increase in the amount of movement increases the distance between clusters which in turn reduces the number of emerging clusters. The results also show that the modified model produces less opinion clusters which imply that in the presence of tension and differentiating beliefs, not only that the equilibrium points are changed, but also we observe less opinion diversity in the society.

Another interesting result coming from our virtual experiments is about the role of social network structure on opinion dynamics. Through the ANOVA test, we find that the presence of the random network structure does not have a statistically significant effect on the average number of emerging extremists in the society. However, the results show that as a result of restricting individuals' interaction in a social network structure, the equilibrium points are changed, meaning that opinion clusters are relocated.

Analyzing the effect of intolerance threshold δ on the dynamics of opinion reveals that it has an inverse correlation with the average number of emerging extremists. That is, as we restricted the rejection condition by expanding the intolerance threshold, on average we see less extremists at the final step. This is mainly due to the fact that people are more likely to attract to or at most ignore each other's opinion rather than differentiating. We also find that more opinion clusters emerge as the δ gets up which means more opinion diversity in the society.

Future works can test the effect of control variables. Particularly, analyzing the effect of different initial belief distribution would be of interest. In this paper, we assume that the initial beliefs are uniformly assigned to the agents. One can use other distributions such as normal distribution and measure its impact on the dynamics. Another possible direction to extend this work is to create the social network structure based on the homophily effect and then assign the initial beliefs respectively. That is, people who are connected to each other in the network tend to have more similar characteristics and beliefs compared to those who are not connected to them. Finally, exploring the effect of conflict escalation and presence of differentiating beliefs on the co-evolution of the opinion dynamics and the structure of the social network structure at the group level would shed lights on dynamics of group membership and the emergence of radical groups in the society.

Note

The Python code of the model is available in CoMSES Net Computational Model Library at http://www.openabm.org/model/4154/version/2/view.

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