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# Multi-agent Simulation of Violence Emergence in Protests

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Abstract. This paper presents an agent-based model to understand the emergence of aggressive mob during a protest. We study to what extent (1) protester behavior can lead to violence and (2) protest policing doctrine. The multi-agent architecture relies on the Belief Desire Intention paradigm, enriched with emotions, norms and personality. Indeed, to reproduce phenomena such as tension-building, the protester model includes emotional components that are added to Epstein's model of civil violence. In Epstein's model, aggressive behavior is triggered as a trade-off between grievance and perceived risk of arrest.

Our model is implemented on the open-source GAMA platform and applied to the study of two factors observed in real-life situations: policeprotester ratio and protest configuration (police blockade of escape routes, also called kettling, or police moving in the crowd). Simulations show that the key parameters are not necessarily the police-protester ratio but rather the protest configuration.

**Keywords:** Crowd Simulation  $\cdot$  Agent-based  $\cdot$  Emotion Modelling  $\cdot$  Protest  $\cdot$  Violence.

# 1 Introduction

Spurred by an increase of fuel taxes planned for 2019 that raised resentment towards economic inequalities, the Yellow Vests Protests started in France in November 2018 and gave rise to violent confrontations between police force and citizens. By December 20, 2018, injured people amounted to 1843 among civilians and 1048 among police officers [56]. One of the cause of the excessive violence is a reinterpretation by the government of the State's legitimacy to use force in order to maintain order [55]. For instance, it undermined the reversibility principle which states that the use of force should stop as soon as the problem it tried to quell down has disappeared [55]. On the one hand, without a better understanding of violence emergence during protests, the riots could become rampant since the number of political protests around the globe already skyrocketed on average of 11.5 percent each year between 2009 and 2019 [11]. On the other hand, from statistical analysis of campaigns originating from 1900 to 2006, Stephan and Chenoweth [52] questioned the necessity of using force through two

main results: violence to repress a movement statistically does not impact the outcomes of a campaign; and nonviolent resistances are almost twice as likely to reach their goals than violent ones.

In this context, research has been conducted on protest management. Riot forecasting is investigated in order to understand radicalization processes [1] or shed light on the circumstances that are more likely to precede the riot such as recent repressions and the protest organization [33]. At the level of the event itself, norms and practical guidelines are examined for police force to keep the protest peaceful [44]. Those guidelines strongly rely on an understanding of the causal mechanisms turning a protest into a riot. To do so, a first approach is to empirically analyze what occurs during peaceful protests and before riots, and to relate it to theoretical research. Along that line, Anne Nassauer grounds her work on many different kinds of documents like videos and reports from the police, the court and researchers [45]. Another approach is to use simulations. It allows to explore theories as well as formulate new hypotheses [20]. It also shows advantages in substituting to real experiments when experimenting is too expensive, impracticable or unethical.

The goal of this article is to follow-up on this question: can we understand how violence emerges during protests? To answer it, we pursue a computational approach called multi-agent modeling where the endeavour is to reproduce violence emergence within a crowd through the formulation of individual rules for the protesters and police officers.

The article is organized as follows. Section 2 studies the theories in social sciences that endeavour to tackle this issue along with computational approaches. Section 3 introduces the agent model we propose to study the emergence and dynamics of violence in protests. Section 4 examines the obtained experimental results. Finally, Section 5 summarizes the conclusions.

# 2 Related Work

According to the literature [13], a distinction can be made between passive crowds, called audiences, and active crowds, called mobs. Those latter crowds can be further categorized into four subgroups: aggressive, escaping, acquisitive, or expressive [13]. We call aggressive mob or riot a crowd trying to physically hurt others or damage objects [21]. We will first explain insights coming from social sciences on the appearance of aggressive behavior before presenting computational models that try to tackle the same issue, focusing on the emotional factors that should be taken into account.

## 2.1 Social Sciences' Approach

As we intend to better understand violence emergence within crowds, the model introduced in this article is grounded on studies in social sciences. We can distinguish these related works on violence emergence between the ones focusing on the individual and the others focusing on the group. At the individual level, the General Aggression Model (GAM) [2] bridges the gap between different theories like excitation transfer theory [58,57] and social learning theory [4] to highlight the main factors involved in aggression behavior. It separates dispositional causes, such as personality, from situational causes, which are composed of the environment the subject evolves in and of the subject's current mental states on the current event. Although it may have less predictive power than domain-specific theories for certain behaviors [21], the model gives a general toolbox of the factors that underlie individual aggression behavior.

At the scale of the crowd, the individual may indulge in violence after weighting up the relative cost of this behavior [34]. It explains the influence of recent repressions on crowd behavior found by Ives and Lewis [34] as well as the influence of forbidding nonviolent protests: if the peaceful protest is as hazardous as the riot, it translates into a low relative cost of violence and protesters are more likely to become aggressive. Although the less organized the protest, the more likely it may turn into a riot [34], multimedia data analysis reveals that riots cannot only be due to a violent group infiltrating the crowd [45]. Riots mostly emerge after a first nonviolent phase of tension-building in parallel with an increase of fear [16,45]. This first phase lasting between one and three hours makes way for a riot that is ignited once a side loses the advantage: the police–protester lines breaks up, some are outnumbered by the opposing group or even fall down on the ground [45].

The multi-agent model undertaken in this article consequently formalizes the individual decision-making processes and the course of tension-building leading to aggressive behavior. This model has the objective of enlightening the influence of violent subgroups over the rest of the crowd thanks to the study of the spread of aggressive behavior.

#### 2.2 Computational Approach

Several computational models are already designed to simulate aggressive behavior in different situations [28]. Some are used to reproduce the behavior of aggressive car drivers [19,46,31], or for linking biological factors such as testosterone, adrenalin and blood sugar with situational factors with the aim of understanding the behavior of people affected by psychological disorders [8].

The most referenced model of civil violence is the threshold-based model of Epstein [24]. This model is abstract in the sense that police officers and citizens are set on a fictive environment in a grid, and that the condition for an individual to turn from passive to active is based on abstract concepts. A citizen agent engages in a rebellion by computing its relative cost of turning in, which compares its grievance with its net risk of being active. The grievance is fixed at initialization by a combination of the perceived hardship and the legitimacy of the government. Subsequent models succeed in clarifying some of its facets. In the scenario of worker protest, Kim and Hanneman [36] expressed the grievance in terms of a comparison between the agent's wage and the perceived mean wage

around it. To clarify spatial phenomena, Davies, Fry and Wilson's model [17] reckoned with the selection of the assembling site for each citizen agent.

Nonetheless, such models do not consider what happens during the protest itself. To cope with this shortcoming, Torrens and McDaniel [54] designed geographic functionalities for agents within crowds. Their model takes into account collisions avoidance, social steering, way-finding and object obstruction within the vision field by means of ray-casting. Those functionalities can easily be combined with other models, either physical or psychological. The authors used Epstein's work [24] with the exact same condition ruling behavior shifts, and biased the movement of rebels and police officers with a set of weights. Six scenarios were investigated including a walled space which entailed lower time periods for riot peak and duration compared to a square-type setting. One of the limitations of this article was the possible roles of the agents. Lemos [39] extended Epstein's model by differentiating "active" from "violent" protesters and initializing protester agents into one of three sub-types defined according to their propensity for violence.

In this article, we focus on the transitions between one state to another without considering any sub-type within protesters. We assume to achieve the same outcomes since the agents' initial grievances against the government, inhibition thresholds for violence and personalities already delimit those sub-types. Rather than visual obstruction because of objects, we take a closer look at the impact of emotions on perception and decision.

#### 2.3 Emotions and Violence

Emotions are empirically found in protest visual recordings [45] and can better reflect the decision-making process of protesters before engaging in violence. However, scarce are the micro-level models of riot events taking emotions into account.

Emotions have significant influences on judgement and decision-making [42] and were noticed during protests on visual data and reports [45]. Extensive research has identified anger as a measure of desire to fight [38] or desire for revenge [48]. Anger was also found to reduce risk aversion [40], and to more easily blame [29] and patronize others [7]. Besides, emotions can arise a specific phenomenon within groups called emotional contagion, which is the influence on an agent's emotions from the perception of the neighboring agents' own emotions [5]. This phenomenon can be relevant to explain social mechanisms [9].

Interestingly, the emotion detected during protests is mostly fear [45] which contradicts the traditional view that the action tendency for fear is avoidance [27]. A middle ground can be found in excitation transfer theory where residues of excitation created by fearful events can transform into a misattributed anger [58]. The attribution of intent to the agent who causes negative emotions may be key for aggressive behavior analysis or modeling because hostile attribution was robustly related to aggressive behavior [18]. Additionally, other negative emotions than those reported and detected on images may be involved. Research in fight-or-flight mechanisms [14] already draws links between aggression and negative emotions, like anxiety [37] and frustration [26]. Anxiety, which is related to uncertainty about a future threat [30], will be subsumed under the risk assessment of the given situation in our model; and frustration, associated to uncertainty about the causes of the events that created them [51], seems unrelated to the studied situations at the microscopic level. Protesters have only one source of threat: the police force. At the macroscopic level, however, frustration can fuel the resentment felt against the government and motivate aggression.

We agree with the EROS (Enhance Realism Of Simulation) paradigm, which states designing social models from psychological theories improves realism and validity of results [35], and argue for emotions as a main component for aggressive behavior emergence within protests. Therefore, we endeavour to reproduce emotion dynamics and their impacts on decision-making in our model.

# 3 Model

#### 3.1 Overview

The purpose of our model is to understand how aggressive behavior can emerge in a decision-making process by modeling how situations create emotions and how emotions impact the participants behaviour.

Protesters, police officers, buildings, walls and damageable items are the only physical entities among agents. Added to those entities, teams and arrest teams are abstract agents representing collectives of police officers to better coordinate them and reflect the hierarchical structure of police force.

The police officers' and the protesters' decision process rely on the Belief Desire Intention (BDI) paradigm [12] to explain and reproduce their actions as a result of interactions between the agents' beliefs, desires and intentions. Structured around this paradigm and the OCC model of emotions [47], the protester's emotions are modeled using the BEN (Behavior with Emotions and Norms) architecture [10]. The emotion decay of the BEN architecture is adapted so that an emotion only lasts during the event that sparked it as per the definition that "emotions are short-lived psychological-physiological phenomena that represent efficient modes of adaptation to changing environmental demands" [41].

In this model, we denote an emotion  $Em_{emotionName}$  with emotionNamethe name of the emotion (fear, sadness, anger...) and a belief  $B_{beliefName}$  with beliefName the name of the belief. An agent a at time t has an emotion base Em(a, t), a belief base B(a, t) and a current intention I(a, t).

#### 3.2 Damageable Items

Damageable items are inanimate physical objects such as street lamps or trash cans. They have a specific attribute R standing for the current resistance before being broken or not being of interest for the protesters anymore. Once the resistance falls below zero, the item disappears from the simulation. Depending on the scenario, it can reappear after a period of time.

#### 3.3 Police Force

Officer agents detect violent offenders at perception distance at 360 degrees around them. When a rioter disappears from the perception field, the officer immediately forgets about the rioter, emulating strategies of hiding among the crowd or fleeing. Officers share the offenders they detected with their team.

Police officers are always affiliated to a team agent that sends them their specific locations within the formation. Those locations can be set before simulation, or adapted by the team during the simulation to barricade the road or position police officers regularly on lines and columns. Officers are assumed to obey their affiliated teams' orders and adapt their desires' priorities accordingly.

The team is the one dispatching the members to apprehend a violent offender by creating a specific arrest team agent for them. A team dispatches members for an arrest when violent offenders are recorded around and the current number of members is sufficiently high. The target of arrest is the violent offender who is the closest to the center of the team and who is not targeted by another arrest team. The dispatched members are the ones closest to the arrest target.

A member of an arrest team tracks the target of this arrest team and sends contributions whenever it is close enough to the target. When the contributions are higher than the initial resistance  $R_{arrestInit}$  of the target, the arrest team ends the process and disappears, which lets former members go back to their team positions. An arrested protester disappears to represent its removal from the protest.

When a police officer involved in an arrest strays too far from its assigned position within the original team, he leaves the arrest team and goes back to his position in the team's formation. This is useful when enforcing line formation across streets or maintaining the police officers united.

Police officers can be targeted by rioters but never disappear from the simulation.

#### 3.4 Protesters

Protester agents are characterized by an energy value and a state which can take three distinct values: "peaceful", "violent" or "retreat".

In **peaceful** state, the agent participates in the protest. To implement group behavior of a protest march, peaceful agents follow the three flocking rules of boids [49], which are the rules of separation, cohesion and imitation. The equations for those are taken from Rochefort et al. [50].

In **attack** state, the agent considers its mere presence not enough to express its demands and its violent desire translates into the intention Attack(v) with v another agent, object or police officer. The agent  $a_0$  in this state can attack an object at time t only if its current energy  $E(a_0, t)$  is positive. The victim v is chosen by maximizing a utility function U defined as:

$$U: \mathcal{A}_{I} \cup \mathcal{A}_{O} \times \mathcal{A}_{P} \times \mathbb{R} \to \mathbb{R}$$
$$a, a_{0}, t \mapsto \frac{log_{2}(2 + card(\{a': \mathbf{I}(a', t) = Attack(a)\})}{d(\lambda(a, t), \lambda(a_{0}, t))^{2}}$$

with  $\lambda$  the function giving the location of an agent at a given time and d a distance function.  $\mathcal{A}_I$ ,  $\mathcal{A}_O$  and  $\mathcal{A}_P$  are the respective sets for damageable item, police officer and protester agents. The  $log_2$  function was chosen to saturate the influence of the number of agents on the attractiveness of a target. At some point, if many offenders are already on a target, the violent agent would not bring a significant help to the rest of the group either and will account for this into its decision.

In **retreat** state, the agent is scared of police officers and flees from them as long as its current energy is positive. This energy emulates exhaustion from running or vandalizing, and is never recharged.

The priorities of protesters' desires evolve with their perceptions, beliefs and emotions. The main attributes ruling state transitions of any given protester agent a among the set of agents  $\mathcal{A}$  at a time t are the intensity  $G(a) \in [0,1]$  of its complaints against the government,  $R(a) \in [0,1]$  summarizing its preference to stay safe in uncertain situations, the threshold  $T_v \in [0,1]$  inhibiting its violent behavior, a probability of arrest P(a,t) identical to Epstein's model [24] and  $\mathcal{L}_b^t(a) \in [-1,1]$  the attitude of the agent towards another agent b from which is derived  $\overline{\mathcal{L}_p^t(a)}$  the aggregation of its attitude towards police officers. This attitude partly encodes the hostility perceived from another agent. The transitions are handled by the subsequent Algorithm 1 executed during each agent's time step where  $\forall x \in \mathbb{R}$ ,  $f(x) := 1 - 0.5 \times |x| \times \mathbb{1}_{\mathbb{R}^-}(x)$  function completes the Epstein's model [24] by involving emotions in the decision.

<b>Algorithm 1</b> Protester $a_0$ 's Desires Adaptation
switch $state(a_0)$ do
$\mathbf{case} \ peaceful$
if $G(a_0) - R(a_0) \times P(a_0, t) > T_v \times f(\overline{\mathcal{L}_p^t(a_0)})$ and $E(a, t) > 0$ then
$state(a_0) \leftarrow violent$
else if $\exists \boldsymbol{E} \boldsymbol{m}_{fearConfirmed} \in \boldsymbol{E} \boldsymbol{m}(a_0)$ then
$state(a_0) \leftarrow retreat$
end if
case violent
if $\exists Em_{fearConfirmed} \in Em(a_0)$ and $\nexists B_{triedRetreat} \in B(a_0)$ then
$state(a_0) \leftarrow retreat$
else if $\exists B_{arrestOtherAround} \in B(a_0)$ and
$G(a_0) - R(a_0) \times P(a_0, t) < 0.5 \times T_v \times f(\overline{\mathcal{L}_p^t(a_0)})$ then
$state(a_0) \leftarrow peaceful$
end if
case retreat
if $[\exists \boldsymbol{E} \boldsymbol{m}_{fearConfirmed} \in \boldsymbol{E} \boldsymbol{m}(a_0) \text{ and } E(a,t) < 0]$ or
$\exists m{B}_{surrounded} \in m{B}(a_0)  ext{ then }$
$state(a_0) \leftarrow violent$
$\mathbf{else ~if}~\nexists \boldsymbol{Em}_{fearConfirmed} \in \boldsymbol{Em}(a_0)~\mathbf{then}$
$state(a_0) \leftarrow peaceful$
end if

This algorithm can be explained as follows. A peaceful protester agent becomes violent if its energy is not depleted and its grievance is greater than its net risk of becoming violent of an inhibition threshold  $T_v$  that can be lowered because of its hatred for police officers. It can also starts fleeing if one of its fear is confirmed. From a "violent" state, the protester agent can start fleeing if one of its fear is confirmed and it does not remember fleeing. It can also go back to the "peaceful" state in case its situation has become significantly more risky. The protester agent trying to retreat can deem running as a lost cause and start to struggle against officers. The agent gives up when it feels surrounded or its energy is not sufficient to run anymore. Potentially without energy, it will not attack officers or items but may be a motivation for neighboring protesters to rebel. Naturally, if its confirmed fear is reassessed and disappears, the agent calms down.

The advantage of using the emotion  $Em_{fearConfirmed}$  is being a proxy for the various events that lead to that emotion. Within the BEN architecture, emotion is derived from desires, ideals and beliefs. The desires that generate fear in our model are the desire of being safe, while the desire and ideal of justice are the ones creating anger. Those two emotions of interest are caused by police officers on protesters. Table 1 introduces triggering events caused by the police force and the emotions they raise within the protester.

The emotions depend on the current protester's state since appraisal theory argues that an event is partly perceived with respect to the current goals and needs of the individual [23]. This is why a fleeing protester agent in our model construes every introduced event as a confirmation of its belief of not being safe. This accentuates its fear and extend its state of panic (see 1). Furthermore, feeling or being arrested while being peaceful turns the agent both fearful, to not be arrested, and angry, against the arrest perceived as unjust.

	Event	State "peaceful"	State "violent"	State "retreat"	
Γ	spatial incursion	fear	fear	fearConfirmed	
	outnumbered	fear	fear	fearConfirmed	
	feeling arrested	fearConfirmed, anger	fear	fearConfirmed	
	being arrested	fearConfirmed, anger	fearConfirmed	fearConfirmed	
	surrounded	fear	fear	fearConfirmed	

 Table 1. Protester agent emotions raised by events depending on the agent's state when interacting with the police force.

Spatial incursion is detected when a police officer is closer than 2.1 meter to the agent, which is the upper bound of the near mode in social distances [32]. The protester feels outnumbered when there are three times more officers than protesters around them, which is the amount of officers usually required for an arrest [45]. The agent feels arrested if an arrest team goes in its direction, and knows it is arrested when it detects an arrest team with itself as target. It feels surrounded when three out of its four cardinal directions are obstructed by police officers or walls. Additionally, the protester is subjected to emotional contagion [5] and follows the rules set in the BEN architecture [10] with the exception of the fear confirmed emotion that translates into fear when perceived in neighbors in the "violent" state. The reason is that the "violent" protester agent confirms its fears only when an arrest team is directly against it.

From those emotions is estimated the police liking value of protesters. It is inspired from the degree of liking introduced in BEN model [10] and adapted to dismiss the formulation of emotion intensity:

$$\forall (a,b,t) \in \mathcal{A}^2 \times \mathbb{R}^+, \ \mathcal{L}_b^{t+h}(a) - \mathcal{L}_b^t(a) = k_L(1 - N(a))(nP_{b,a} - nN_{b,a})(1 - |\mathcal{L}_b^t(a)|)h(a) = k_L(1 - N(a))(nP_{b,a})(1 - |\mathcal{L}_b^t(a)|)h(a) = k_L(1 - N(a)$$

with h > 0 the time step of the simulation.  $k_L \in \mathbb{R}^+$  is a parameter that adapts the speed of liking variations while N(a) is the agent's neuroticism coming from BEN architecture [10]. For all a and b in  $\mathcal{A}$ ,  $nP_{b,a}$  is the number of positive emotions caused by b felt by a; similarly,  $nN_{b,a}$  is the number of positive emotions caused by b felt by a. Positive emotions include joy and hope; negative emotions sadness and fear [10]. Then,  $\overline{\mathcal{L}_p^t}(a)$  is the average liking for the police officers met by a.

It is important to notice that anger in BEN architecture [10] results from reproach and sadness, and is thereby counted in the negative emotions. Furthermore, this liking value finds a middle ground between the empirical findings of Nassauer [45] supporting fear is a crucial emotion to understand shifts to aggressiveness, and theories about emotions advocating anger as the motivation for revenge, even through violence [38,48]. This middle ground revolves around the formalisation of hostility attribution which motivates aggression behavior [18].

# 4 Simulations

#### 4.1 Overview of the simulations

The two scenarios we have retained for our simulations are a protest taking place in a large public square patrolled by a single police team and a protest contained within a street because police officers are blocking both ends of the street using the kettling tactic. Those scenarios were selected because they represent the two opposites of observed situations in western protests' configurations [22,15]. Kettling is also a controversial tactic because it may infringe on the citizen's freedom of movement or of protesting. The press release from the French Conseil d'Etat of June 10, 2021 forbid the kettling tactic in the absence of specific conditions, which the release does not specify [6]. Thus, it is of interest to provide new tools to analyze the necessary conditions for kettling management. Finally, those scenarios were selected to reproduce the variety of behaviors that arise during protests. For instance, the kettling setting may spur anxiety and turn people violent more easily than in the public square setting.

### 4.2 Implementation

The simulation platform chosen is the open-source GAMA platform [53]. The main benefit of using an already existing platform is to clearly delineate the model we formulated from its implementation. Moreover, the GAMA platform comes with its own language that is easy to understand for non computer scientists, a lot of services such as loading Geographic Information System (GIS), and an already existing implementation of the BEN architecture we use [10].

In our implementation, every dynamic agents, which are of species protester, police officer, team or arrest team, are activated at every step. The implementation is done in an asynchronous fashion. To limit simulation artifacts, the order of agents' execution is shuffled at every step. One step represents 1 seconds in the simulation. One simulation is equivalent to 3 hours of protest.

The world in the kettling setting comes with a main road of 50 meters over 20 meters. The public square spreads over a 80 meters by 80 meters area in a toric world. While the number of protesters is set at 200 for all simulations, the number of officers varies from 10 to 40 with a step of 10. Table 2 summarizes those settings.

	Square	Kettling
Dimensions	$80m \times 80m$	$50m \times 20m$
Toric	True	False
Number of protesters	200	200
Number of police officers	10/20/30/40	10/20/30/40

 Table 2. Scenarios' parameters.

Regarding parameters calibration, we chose to set the vision distance to 7 meters for both protesters and police officers [43]. For protesters, the boid's rule of separation has a span of 0.5 meter [32]. The distance required to arrest a protester is the same. While protesters have  $R_{arrestInit}$  set so that they can be arrested in 5 seconds by three officers, damageable items can be destroyed in 1 minute by three violent protesters and reappear after 5 minutes. Thanks to this setting, items draw rioters' interest regularly. The energy consumption from attacking or fleeing is the same, and the protester is initially endowed with enough energy to flee for 5 minutes. Then, we chose  $k_L$  equal to  $8.5 \times 10^{-4}$  so that the social liking reaches the minimum -1 when an agent causes another two negative emotions for an hour and a half. Finally, the inhibition threshold  $T_v$  is set to 1.0 for every protester which allows violence only through a drop in police social liking, whereas the grievance G, the risk aversion R and the neuroticism N are heterogeneous and sampled uniformly over [0, 1] at initialization.

#### 4.3 Results and analysis

For each of the 8 different configurations, varying the protest configuration as well as the Police Officer-Protester Ratio (POPR), 5 simulations are executed. The means of the results of those simulations are introduced in Table 3 while their standard errors are in Table 4.

Config.	Square			Kettling				
POPR (%)	5	10	15	20	5	10	15	20
TBB1	02:00:06	02:10:30	02:04:53	01:19:14	00:01:57	00:01:47	00:04:29	00:36:49
TBA1	02:03:42	01:49:49	01:16:47	01:33:02	01:49:39	01:26:23	01:50:51	01:45:32
NbA	1.2	2	2	1.8	14.8	12.4	17.2	18.4
MaxVP $(\%)$	0.50	0.50	0.70	0.50	23.42	22.04	24.61	26.48
TVP	01:52:09	01:30:26	01:07:07	01:30:12	00:23:15	00:19:28	00:16:56	00:48:43
MaxFP $(\%)$	1.90	2.40	3.00	2.40	35.58	35.03	33.75	34.57
TFP	01:34:39	01:01:05	00:48:10	00:52:10	00:02:20	00:02:27	00:03:12	00:03:15
TR1	02:00:43	00:43:16	00:29:51	00:47:47	01:48:09	01:24:23	01:48:03	01:43:05
MPSL	-0.007	-0.009	-0.010	-0.008	-0.294	-0.277	-0.222	-0.196

**Table 3.** Means of the results obtained for different police officer-protester ratios (POPR) over 5 simulations. Measures are Time Before Breaking The First Item (TBB1), Time Before First Aggression on Police (TBA1), Number of Arrests (NbA), Maximum Ratio of Violent Protesters (MaxVP), Time of Maximum Ratio of Violent Protesters (TVP), Maximum Ratio of Fleeing Protesters (MaxFP), Time of Maximum Ratio of Fleeing Protesters (TFP), Time First Retreat (TR1), Min Mean PSL (MPSL)

In a basic situation with 5% of police officers compared to protesters in a square, the protest never turns violent. Increasing the number of police officers, thereby increasing the number of interactions between police officers and protesters and potentially heightening the tension between the two groups, we notice that the square scenario never reaches a riot. Only a few protesters become violent, and are thereafter quickly handled by the police force. Indeed, the Maximum Ratio of Violent Protesters (MaxVP) is on average below 0.70% and the Number of Arrests (NbA) is below 2. The Maximum Ratio of Fleeing Protesters (MaxFP) consequently remains low and its mean never exceeds 3.00%. This peaceful situation is due to the Mean Police Social Liking (MPSL) staying close to zero. Furthermore, this situation is stable across the simulations with low standard errors in Table 4. Especially, the MPSL is null because the police officers are always wandering across the plaza.

On the reverse side of the spectrum, kettling does result in aggressive behaviors among the crowd. The MaxVP stands at 23.42% on average with 5% of POPR. On the one hand, this value remains approximately constant when the number of officers increases. On the other hand, the Time of Maximum Ratio of Violent Protesters (TVP) decreases before attaining one hour and seven minutes when the POPR is at 20%. An explanation to this result is that the number of

Config.	Square				Kettling			
POPR (%)	5	10	15	20	5	10	15	20
TBB1	00:59:03	01:09:40	01:16:11	00:40:52	00:00:14	00:00:07	00:02:13	01:15:07
TBA1	00:41:19	00:55:22	01:00:27	00:53:16	01:36:21	01:14:06	01:34:42	01:30:09
NbA	0.8	0.7	1.2	0.8	20.3	17.34	23.6	25.4
MaxVP (%)	0.00	0.00	0.44	0.00	30.70	28.82	31.89	35.12
TVP	00:33:54	00:40:26	00:25:51	00:29:26	00:36:32	00:28:03	00:16:09	01:06:53
MaxFP (%)	1.24	0.42	1.17	0.41	48.74	47.96	46.22	47.35
TFP	01:00:17	00:32:39	00:20:18	00:13:08	00:03:12	00:03:24	00:04:23	00:04:29
TR1	00:42:41	00:19:23	00:19:01	00:11:31	01:38:25	01:16:49	01:38:32	01:33:30
MPSL	0.000	0.000	0.000	0.000	0.142	0.130	0.112	0.118

**Table 4.** Standard errors of the results obtained for different police officer-protester ratios (POPR) over 5 simulations. Measures are Time Before Breaking The First Item (TBB1), Time Before First Aggression on Police (TBA1), Number of Arrests (NbA), Maximum Ratio of Violent Protesters (MaxVP), Time of Maximum Ratio of Violent Protesters (TVP), Maximum Ratio of Fleeing Protesters (MaxFP), Time of Maximum Ratio of Fleeing Protesters (TFP), Time First Retreat (TR1), Min Mean PSL (MPSL)

officers plays a role in dissuading protesters for indulging in violence. For lower values of POPR, the tension created by interacting with police officers exceeds the dissuasion power.

What is prominent in the kettling scenario is the significant variations in its results. Further inquiries show that one out of two simulations becomes violent with around 50% of protesters turning violent until the end of the simulation, no matter the POPR value. This happens because of the presence of arrests. In our simulations, when police officers start an arrest, peaceful protesters around will get scared and start to panic. They will therefore enter the "retreat" state and spread their fears with others more quickly.

The reason it does not occur in every simulation is that the individual factors inhibiting aggressive behavior (the grievance G and the risk aversion R) are randomly sampled and may let appear more or less violence-prone protester agents. These agents are qualified as violence-prone since even a high inhibition  $T_v \times f(\overline{\mathcal{L}_p}(.))$  enables these agents to turn violent. Events, such as the spatial incursion or feeling outnumbered, will be deemed as a sufficient reason to turn aggressive. In future work, it may be of interest to study in more detail the circumstances leading to this phenomenon and understand why it does not occur in the previous square scenario.

## 5 Conclusion

This article has introduced a first emotional multi-agent model to reproduce violence emergence within the protest. Starting from the BEN architecture [10], the model adapted the former degree of liking to embody the attitude of protesters towards police officers, including the tension-building observed in Nassauer's data analysis [45]. By using emotions in its formulation, the model can be a base for future extensions.

The model was implemented in the GAMA platform [53] and was tested on two features: the protest configuration and the ratio of police officers versus protesters. The protest configurations are a square patrolled by a single police team and officers employing a kettling tactic to block the street. While the first scenario presented a good situation for peacekeeping, violence sometimes appeared in the second. In the future, the reasons for this emergence could be further investigated by running and studying more configurations. Also, the kettling scenario demonstrated a change in dynamics when the number of police officers increased sufficiently. It could be interesting to characterize when the number of police officers becomes more dissuasive than a source of conflict, or the reverse.

New insights can ensue from drawing further attention to the macroscopic phenomena involved in this work. For instance, the existence and properties of the resulting macroscopic equilibrium states of the current study may be explained by the macroscopic model of Filatova and Baratgin [25] who studied a phenomenon of hesitation between two opposites, like fight and flight, but for political preferences.

Finally, this model focused only on psychological facets. Yet, Torrens and McDaniel [54] argued for the importance of realistic physical behavior on agents within the crowd. These physical properties could further allow new perceptions for our model. For instance, feeling tightly packed could be a new source of tension for the agent, or heat, rising because of people movements, could be reckoned with since it has also been shown to make people more aggressive [3].

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