

## Repositório ISCTE-IUL

---

Deposited in *Repositório ISCTE-IUL*:

2022-06-09

Deposited version:

Accepted Version

Peer-review status of attached file:

Peer-reviewed

Citation for published item:

Lemos, C, Coelho, H. & Lopes, R. J. (2014). Agent-Based modeling of protests and violent confrontation: A micro-situational, multi-player, contextual rule-based approach. In Edward MacKerrow, Takao Terano, Flaminio Squazzoni, Jaime Simao Sichman (Ed.), Proceedings of the 5th World Congress on Social Simulation (WCSS 2014). (pp. 136-161). São Paulo

Further information on publisher's website:

<http://www.wcss2014.pcs.usp.br>

Publisher's copyright statement:

This is the peer reviewed version of the following article: Lemos, C, Coelho, H. & Lopes, R. J. (2014). Agent-Based modeling of protests and violent confrontation: A micro-situational, multi-player, contextual rule-based approach. In Edward MacKerrow, Takao Terano, Flaminio Squazzoni, Jaime Simao Sichman (Ed.), Proceedings of the 5th World Congress on Social Simulation (WCSS 2014). (pp. 136-161). São Paulo. This article may be used for non-commercial purposes in accordance with the Publisher's Terms and Conditions for self-archiving.

---

### Use policy

Creative Commons CC BY 4.0

The full-text may be used and/or reproduced, and given to third parties in any format or medium, without prior permission or charge, for personal research or study, educational, or not-for-profit purposes provided that:

- a full bibliographic reference is made to the original source
- a link is made to the metadata record in the Repository
- the full-text is not changed in any way

The full-text must not be sold in any format or medium without the formal permission of the copyright holders.

---

# Agent-Based modeling of protests and violent confrontation: a micro-situational, multi-player, contextual rule-based approach

Carlos Lemos<sup>1,2,3</sup>, Helder Coelho<sup>2</sup>, Rui J. Lopes<sup>3,4</sup>

<sup>1</sup> Portuguese Joint Command and Staff College, Lisbon, Portugal

<sup>2</sup> Faculty of Sciences of the University of Lisbon, Portugal

<sup>3</sup> ISCTE-IUL, Lisbon, Portugal

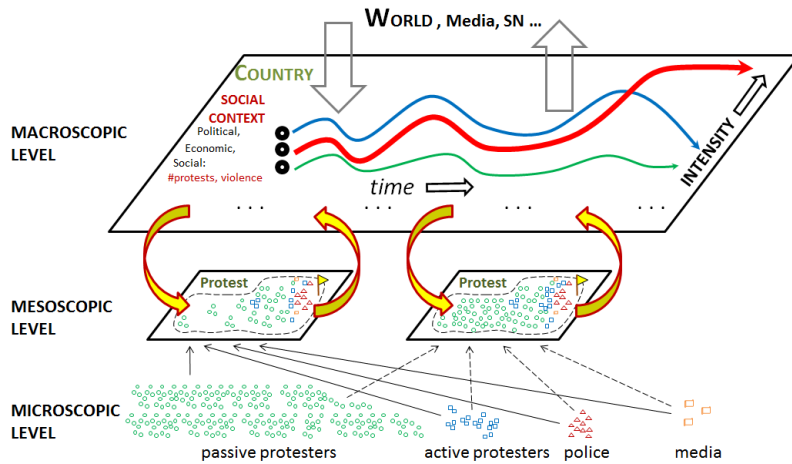
<sup>4</sup> Instituto de Telecomunicações IT-IUL, Lisbon, Portugal

**Abstract.** We propose an innovative Agent-Based model of street protests with multiple actors: police agents, three types of protesters (“hardcore”, “hangers-on” and “passers-by”), and “media” agents that seek to witness and publish episodes and situations of violence. Agents have multiple goals and action selection is performed using a “personality” vector together with context rules that provide adaptation. Protesters turn active or violent according to the threshold rule proposed by Epstein, and police agents arrest violent protesters within their move range if they have sufficient backup. The model was applied to a scenario where policemen defend a government building from protesters and described several emergent crowd patterns in real protests, such as clustering of violent and active protesters and formation of a confrontation line moving back and forth with localized fights. Violent behavior was restricted to the initially more aggressive protesters and did not propagate to the bulk of the crowd.

**Keywords:** Agent-Based model, protests, violence, complexity, social simulation, crowd dynamics.

## 1 Introduction

Protest demonstrations are both a manifestation of social conflicts and an instrument of political participation through which citizens press governments for political change. History provides startling examples of regimes being overthrown by the “power of the crowds” [1]. Media coverage and widespread access to Social Networks (SN) and Information and Communication Technologies (ICT) have been used by governments, parties or activists [2] to plan, coordinate and show the course of events in real time to a global audience (e.g. in Brazil, Turkey, and Ukraine). Understanding and, if possible, predicting or controlling how the social context leads to large protests and how these in turn change the social context, is a significant problem in sociology, social psychology, and political science. This problem is very difficult due to the number and diversity of players, the complexity of the links and interactions, and the multiple scales of the phenomena. Fig. 1 shows our conceptual framework for the relationship between protests and the intensity of a social conflict.



**Fig. 1.** Relation between protests and a social conflict viewed as a complex and path dependent process, with three distinct levels (macroscopic, mesoscopic and microscopic), types of relevant players (agents) and micro-macro and feedback (macro-micro) links.

In this paper, we present a new ABM of street protests with police agents (herein referred as “Cops”), protester and media agents, which is part of work in progress on the simulation of social conflict phenomena [3]. We consider three types of protesters, “hardcore”, “hanger-on” and “passer-by” (using the terminology adopted in [4]), with different behaviors. All protesters can be in four states, “quiet”, “active” (shouting, waving, etc.), “violent” (ripe to start a fight) and fighting with police agents. The spatial environment is a two dimensional grid that includes attraction points (sites that protesters try to occupy and police forces must protect), obstacles (walls or barriers) and entrances/exits (streets adjacent to the protest area). The purpose of the new model is to simulate the emergent patterns in protests and obtain quantitative measures of protest intensity, such as the number of violent confrontations and violent episodes covered by the media. These can be used to formulate the feedback links represented in Fig. 1. The research questions for which we seek answers are:

- How do the features of the protest space and the density, proportion and initial placement of each type of protester affect the crowd formation patterns (wandering, clustering and fighting) and protest intensity?
- How does violent confrontation arise? Once initiated, does it spread to the bulk of the crowd or remains confined to specific types and clusters of protesters?
- How does the presence of media agents affect the dynamics of protests?

The novel features of the model are the consideration of multiple types of agents and spatial features, using a simple but efficient agents’ architecture that allows the representation of a rich variety of states, behaviors and micro-interactions. The

combination of protester's state variables and measures of intensity (e.g. number of arrests and violent episodes registered by media agents) can also be used to formulate micro-macro links (such as legitimacy feedback).

The remainder of this paper is organized as follows. In section two, we present a summary of the theoretical background for the protest model. In section three we present a summary description of the model, which is complemented by a more detailed description according to the Overview, Design Concepts and Details (ODD) protocol [5] in Appendix A. Section four contains a description of the test cases and model parameters used in the simulations, together with results that show the model's capabilities and potential. Section five contains the discussion and in section six we present a summary of conclusions and prospects for the work in progress.

## **2 Theoretical background**

In this section, we present the theoretical background of the present work using the scale of social conflict phenomena as guideline, according to the conceptual framework sketched in Fig. 1.

### **2.1 Macro-scale social conflict phenomena. Issues and models**

Macro-scale conflict phenomena such as generalized uprisings of civil violence, insurgence or war involve a large part of the population (society). The concept of Relative Deprivation (RD) provides an explanation of the potential for social conflict within a society [6]. Indices of deprivation and social context variables derived from methods of objective analysis and extensive data bases [7], can be useful for parameterization of the individual agents.

Epstein introduced an ABM of rebellion against a central authority (Model I) or violence between two rival groups mediated by a central authority (Model II) with two types of agents, population and cops [8], [9]. Epstein's model successfully explains many features of civil violence processes at the macro-level, such as intermittent generalized bursts of violence, but has some drawbacks, like the crude representation of the "Cops" behavior and the agents' movement (see [3] for a review).

### **2.2 Meso-scale phenomena. Theories of crowd behavior**

Theories and studies of collective behavior in crowds (temporary gatherings of a significant and potentially very large number of persons at one place at a specific time) are an important source of knowledge for the formulation and interpretation of the results of ABM of protests. Some of the key questions in the study of crowds are the formation of collective behavior, the classification (or taxonomy) of crowds, the effects of heterogeneity and the symbolic value of the places.

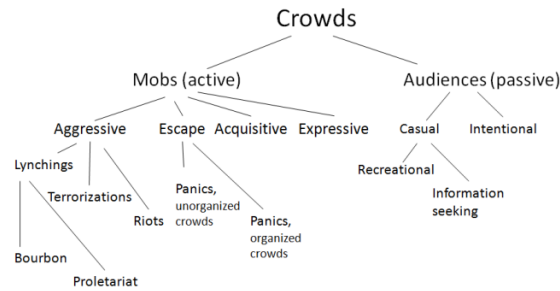


Fig. 2. Taxonomy of crowds, according to Brown [10].

Fig. 2 shows Brown’s proposed taxonomy of crowds [10]. According to this scheme, protests can be classified as Expressive Mobs, which may turn to Aggressive if part of the crowd engages in violent confrontation, or Escape if there is a police charge. Also, part of the crowd may be passive and thus behave as an Audience. This taxonomy is relevant in the formulation of ABM for defining the relevant types of agents, their proportions and interactions, the environment representation (obstacles, attraction points, escape points) and other features (e.g. events), as done in [4], [11]. From this viewpoint, protests are indeed complex crowd events which do not usually fit in a single category. Moreover, the agents in a protest model must be endowed with different behaviors and several possible states depending on their percepts and internal state to describe the timing, location and size of violent hot spots.

### 2.3 Micro-scale processes. Theory and models

At the micro-level, it is necessary to describe how the agents move and how they will become “active” (waving, shouting, etc.) or “violent” (throwing objects or fighting), to model protest dynamics in a realistic way. Existing models of crowd dynamics provide theoretical background for modeling the agents’ movement and micro-situational theories of violence provide guidelines for modeling the conditions for individuals to engage in violent confrontation and the spread of violence within a crowd.

The movement of pedestrians in crowds is an important topic in many contexts such as safety and architectural modeling, entertainment software, mathematics and physics, and has been studied using methods from fluid dynamics, cellular automata or particle dynamics [12]. The “Social Force Model” [13], [14] is an empirically based continuous space/continuous time description of the motion of pedestrians as self-propelled particles driven by three components that express individual motivations to: *i*) maintain a desired speed towards a wanted destination point; *ii*) keep clear from other pedestrians or obstacles; and *iii*) approach attractive features (such as other persons or displays). In discrete space/discrete time models with a large number of agents and one agent per cell, the agents’ movement can be modeled by minimizing/maximizing the distance to attraction/repulsion points weighted by individual “relative motivations”, because neither the repulsion forces (with shorter

range than the typical cell size) nor the acceleration due to variations of attractive forces within the vision radius can be represented. This (discrete space and time) approach was used in the present work, due to its simplicity and advantage for handling large numbers of agents.

The situational action theory (SAT) [15] and the micro-sociological theory of violence [16], [17] provide guidelines for modeling violent confrontation in protests. According to SAT, acts of violence result from the interaction of a person's propensity and the exposure to situational factors conducive to violence. If the individual has propensity but the context is not conducive to violent action, violence will depend on the level of deterrence [15]. According to the micro-sociological theory, the key factor for the outbreak of violence is the emotion of confrontational tension/fear. For violence to occur there must be pathways around the barrier posed by this emotion. Two such pathways are: *i*) to find a weak victim to attack, and *ii*) the "forward panic" reaction in group confrontation when one side gains overwhelming local advantage [16]. In the context of ABM, the most relevant findings of this theory are: *i*) in protest demonstrations only a few agitators engage in violent behavior, except when the crowd is already divided into antagonistic groups; *ii*) "forward panic" is typical of violent confrontations if local conditions set the pathways around the tension/fear barrier (e.g. indiscriminate police beating during a charge, or the overbeating of isolated protesters or police agents by the opposing group).

ABM of micro-interactions in violent confrontations takes into account some of these theoretical findings. Jaeger, Popping and van de Sande [4] presented an ABM of fighting between two parties (e.g. hooligans supporting two different football teams) and considered three types of agents, "hardcore", "hangers-on" and "passers-by" with a (typically) small proportion of "hardcore" agents. In this model, aggressiveness is a function of the number of local supporters on the current and past cycles but is not linked to social context variables, and there are no authority agents. Durupinar [11] presented a sophisticated ABM for different types of crowds with psychological effects, including various types of protesters (characters) and police agents. This model describes the micro processes in a very realistic way, but is computationally demanding for simulating large crowds. Ilachinski [18] developed an ABM of land combat in which the agents have a "personality vector" whose components are weights that set orientation to multiple goals, together with a set of meta-rules that provide adaptation to the local context. The agents' action selection is done by minimizing a penalty function computed for all positions accessible to the agent. This method allows the efficient implementation of goal-driven behavior.

### 3 Model description

In this section we present an overview of the ABM developed in this work, considering the model entities, main design concepts and development issues. The model was developed in the NetLogo simulation system [19]. A more complete description based on the ODD protocol is presented in Annex A.

### 3.1 Model entities. Agents and scenario

In our NetLogo implementation, the protester, cop and media agents are implemented as subclasses of the turtle agent type using the breed primitive. The three different subtypes of protesters are implemented using a protester-own variable kind. “Hardcore” protesters try to cluster, occupy attraction points and engage cops, and have the highest propensity for turning “violent”. “Hanger-on” protesters correspond to the more susceptible protesters in the crowd, with moderate incentive to approach “violent” and “active” protesters; when “quiet” they try to keep a minimum distance from violent and active protesters, cops and attraction points, but assume an increasing aggressive behavior if they turn “active” or “violent”. “Passer-by” protesters try to avoid “violent” protesters, “active” protesters and cops, but in exceptional conditions they can turn “active” or even “violent”. All kinds of protesters have moderate incentive to approach “Media” agents within their vision field. “Cops” try to defend attraction points from violent protesters and keep close to other cops. If they have sufficient backup they engage and arrest violent protesters. “Media” agents try to locate fights and record (“take pictures”) violent events. The various spatial features are implemented using patches-own Boolean variables. The class diagram for our ABM is presented in Annex A.

### 3.2 Basic design concepts

In our model the agents are reactive, move in discrete time and space increments (one agent per grid patch), are activated once per cycle in random order, and have one move rule and one behave rule. The move rule has the same form for all agent types and subtypes, as described below. The behave rule is different for each type of agent according to the qualitative behaviors described in 3.1 and in Annex A. Upon activation, agents typically perform a three step scan-plan-behave sequence, by which *i*) they form their percept  $P$  (other agents and spatial features in sight); *ii*) determine their next position and state, and *iii*) update their position and state. Agents determine their future positions by minimizing a penalty function involving a “personality vector” that allows the definition of multiple goals in an efficient way. The state of the “Protester” agents (“quiet”, “active” or “violent”) is updated using the rule proposed by Epstein, which is compatible with the micro-situational theories of violence.

### 3.3 Goal-driven agent movement

In the plan procedure, agents determine the center of the empty patch within their move range that minimizes a penalty function of the form  $V_A(x,y,I,P) = \omega_{A,c} \|\omega_{A,c}\|_1 \cdot (\mathbf{S}(x,y) - \mathbf{S}(x_0,y_0))$ , where  $I$  is the agent’s internal state,  $P$  is the percept,  $(x_0,y_0)$  is the current position of agent  $A$ ,  $\omega_{A,c}$  is a “personality vector” whose components are weights that determine the agent’s tendency to approach or avoid visible (perceived) features and  $\mathbf{S}_A$  is a vector whose components are the sum of distances from point  $(x,y)$  to each visible feature element. Table 1 shows the

correspondence between the weights in the personality vector and the feature elements that influence the agent’s movement. The weights range from +5 (strong attraction) to –5 (strong repulsion).

**Table 1.** Meaning of the components (weights) of the “personality vector”.

Component (weight)	$\omega_0$	$\omega_1$	$\omega_2$	$\omega_3$	$\omega_4$	$\omega_5$	$\omega_6$	$\omega_7$
Feature	“violent” protester	“active” protester	“quiet” protester	“Cop” agent	“Media” agent	Flag patch	Obstacle patch	Exit patch

Each agent has a pre-defined “default personality vector”  $\omega_{0,A}$  that determines its goal-directed movement, and a set of context-rules for changing the components of  $\omega_{0,A}$  according to the agent’s internal state and perceived features. For instance, “Hardcore” protesters try to pursue cops when they have local superiority but avoid them in the reverse case. The context-dependent personality vector  $\omega_{A,c}$  is then used to minimize the penalty function. Annex A contains a full description of the default personality and context rules for all agent types and subtypes. In the `behave` procedure, agents move to the optimal position with a probability  $p$  (set to 0.9) and to a random empty cell within their move range with probability  $(1 - p)$ . This represents the agents’ faults while assessing the local situation and adds realism to the simulations.

### 3.4 Behavior rules. Transition to “Active” and “Violent” behavior

Each type of agent has a different behavior rule (see 3.1 and Annex A). For “Protester” agents it is necessary to model the transitions from “quiet” to “active” and “violent” states and vice-versa, which are critical for describing emergent patterns of violent confrontation. In our model, these transitions are described using a variant of Epstein’s threshold rule  $G - N > T$ , where  $G = H \cdot (1 - L)$  is the level of grievance,  $N = R \cdot P$  is the net risk perception,  $T$  (constant exogenous variable) is a threshold,  $H$  is the (endogenous) perceived hardship,  $L \in [0,1]$  is the “perceived government legitimacy”,  $R$  is the (endogenous) risk aversion, and  $P$  is an estimated arrest probability which in our case depends on the ratio between the numbers of “cops” and “active” plus “violent” protesters within the agent’s vision field. This rule is consistent with the SAT and micro-sociological theories: predisposition can be modeled by the values of  $G$  and  $R$ , the situational and deterrence elements by the form of  $P$ , and the “barrier” by the threshold  $T$ . Annex A provides the implementation details.

### 3.5 Development issues

The use of a personality vector allows a simple and efficient implementation of goal orientation, for it avoids the combinatorial explosion problem that would arise from simple **if <context> then <action>** rule-based formulations. The relative importance of the goals is determined by the weights and measures associated with the perceived



features, not by the order by which simple rules are applied. However, it should be noted that although the “default personality vector” encodes an important part of the agent’s behavior, it is the context rules that provide adaptation and autonomous decision (fundamental attributes of agency). Furthermore, the context rules effectively connect the move and behave rules.

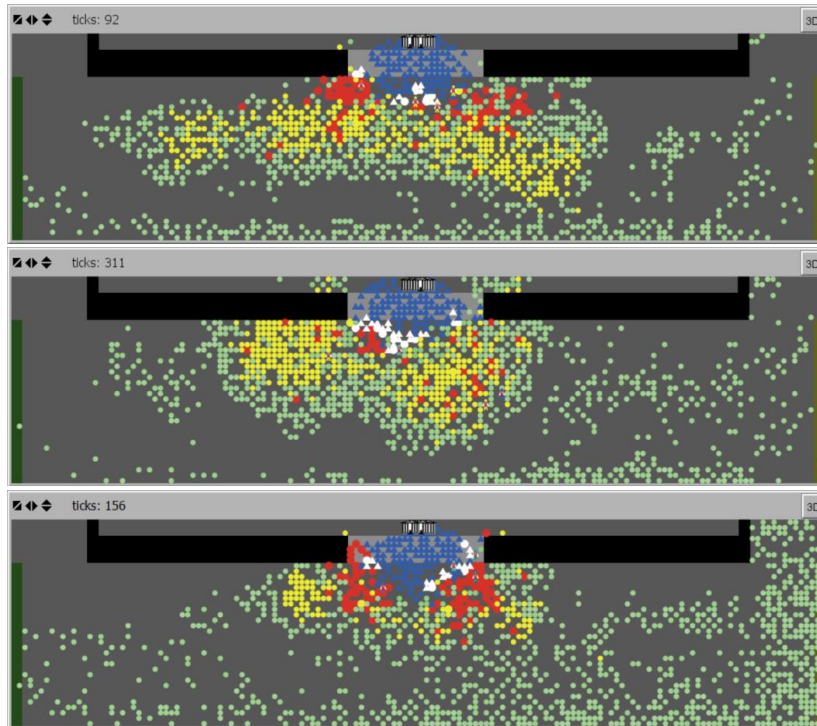
## 4 Results

We performed a set of simulations to test the model, for a case in which protesters try to reach the entrance of a government building and are opposed by a police force. This situation is typical of protests near the Parliament in Lisbon, Portugal, which is familiar to the authors. The scenario was defined by a  $150m \times 37m$  grid (closed boundaries). The access to an existing space in front of the main entrance of the Parliament where police forces usually stand (a wide stone staircase  $25 m$  wide) was defined by flagging a rectangle of cells near the top boundary. The defensive perimeter was defined by means of two sets of obstacle cells on each side of the central staircase, each with a width of  $48 m$ . The protest area was defined as a strip  $30 m$  wide in front of the staircase and obstacles, with an entrance on the right and an exit on the left. Table 2 summarizes the initial proportions of agents, type of placement and perceived government legitimacy used in the simulations.

**Table 2.** Initial numbers of “Cops”, “Hardcore”, “Hanger-on” and “Passer-by” protesters, value of perceived government legitimacy ( $L$ ), and initial placement (random or non-random).

Run:	# cops	# hardcore	# hanger-on	# passer-by	L	Initial placement	Comments
AR1	125	100	800	300	0.82	selective	Adopted reference condition
AR2	125	100	800	300	0.82	random	Random initial placement
AR3	125	100	300	800	0.82	selective	Invert proportions of hanger-on/passers-by protesters
AR4	65	50	400	150	0.82	selective	Lower density (1/2 reference)
AR5	125	100	800	300	0.79	selective	Lower perceived legitimacy

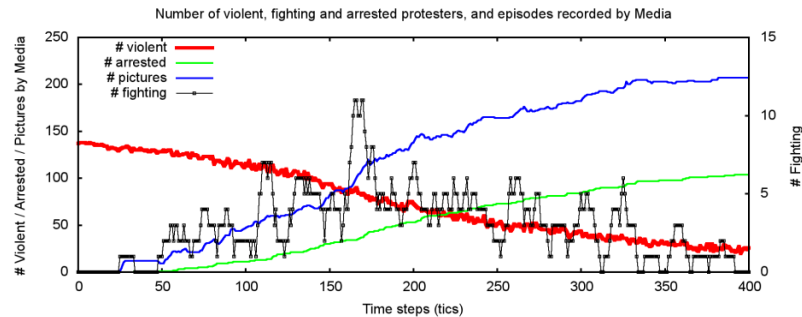
We introduced four “Media” agents (standing for the four Portuguese TV Channels). The “Cops” were placed on the “Parliament staircase” and their base personality as  $\omega_0 = (2 \frac{1}{2} \frac{1}{2} 5 0 5 \frac{1}{2} 0)$  so that cops would spread more uniformly in the defensive area and also react to approaching “active” and “quiet” protesters. In the selective initial placement, the four “Media” agents are stationed between the “Cops” and “Protesters”, with “Hardcore” in the front, then “Hangers-on” and finally “Passers-by”, all facing the police force and the “Parliament”. Fig. 3 shows three snapshots of the simulated protest space for simulations AR1 (top), AR2 (middle) and AR3 (bottom). These snapshots were chosen because they were representative of the emergent patterns obtained with the model (AR1), and of the variations resulting from: *i*) initial blocking by “active” and “quiet” protesters due to random placement (AR2), and *ii*) the reverse effect, due to the reversing of proportions of “Hanger-on” and “Passer-by” protesters. Lower density (AR4) had the same effect (initial blocking) as random placement.



**Fig. 3.** Snapshots of the simulation space obtained in simulations AR1 (top), AR2 (middle) and AR3 (bottom). “Cops” are represented by blue triangles, “Hardcore” protesters by large circles (size = 2), the remaining protesters by small circles (size = 1) and “Media” agents by little human figures. Fighting agents are represented in white, “violent” protesters in red, “active” protesters in yellow and “quiet” protesters in green. Obstacles are represented in black, flagged cells in gray, entrances in dark yellow and exits in dark green.

In Fig. 3 it can be observed that the model reproduced several crowd patterns observed in real protests, such as clustering of “violent” and “active” protesters, the formation of a confrontation line moving back and forth along which fights and occasional arrests occur. “Media” agents attracted nearby protesters (inducing local clustering) and moved to find “hot spots”. Many “quiet” (“Hanger-on”) protesters also clustered near the confrontation zone, whereas “Passers-by” remained “quiet” and walked from entrance to exit in wandering paths, avoiding the confrontation zone. Different initial placement and variations in the proportion of “Hanger-on” and “Passer-by” protesters had impact on the capability of the policemen to simultaneously protect the perimeter and engage and arrest “violent” protesters. Fig. 4 shows the time variation of some quantitative measures of violence intensity, for simulation AR5. 99 “Hardcore” and 39 “Hanger-on” turned “violent”, showing that in this case there was some contagion of “active” protesters to “violent” state. Fights

occurred in bursts (with a peak of 11 protesters fighting, the largest number in the simulation set) once “violent” agents reached contact with the “Cops”. The number of arrests increased steadily, with about two “Media” records for each arrest.



**Fig. 4.** Time history of the number of fighting (right vertical axis) and violent protesters, number of arrests and number of pictures taken by “Media” agents (left vertical axis), for simulation AR5.

## 5 Discussion

In all simulations the model reproduced in a realistic way several crowd patterns observed in real protests in this type of scenario, such as clustering of “violent”, “active” and “passive” protesters, wandering of “Passers-by”, formation of a confrontation line with localized fights and arrests, and “Media” agents attracting nearby protesters, moving near the “hot spots” and registering fight events. However, some results were somewhat unrealistic, such as some “quiet” and “active” protesters breaching the defensive perimeter due to “Cops” interacting weakly with these agents. The typical time variation of the crowd behavior was as follows. Transition to violent behavior occurred in the following sequence: *i*) “violent” protesters started clustering; *ii*) after clustering, they approached the “Cops” by breaching through the “active” and “quiet” protesters they found in between; and *iii*) they invested towards the policemen and tried to occupy the flagged area and began fighting with the “Cops”. The contact between “violent” protesters and “Cops” generally took the form of two wedges of “violent” protesters investing towards the police force from the flanks, not in the centerline of the staircase. This collective pattern behavior is often observed in real protests.

It is interesting to discuss how different conditions affected the outcome of the simulations, in terms of how well the police force copes with the tasks of protecting the perimeter and engaging protesters. The reference simulation (AR1) led to higher numbers of arrests (76 at  $t = 300$ ) and “Media” pictures (76 at  $t = 300$ ) than in the simulations with initial random placement and higher proportion of “Passers-by”, but also to a higher number protesters trespassing the defensive perimeter. In simulation AR3 there is less blocking by passive ones, and the police force appears to have

difficulty in controlling the larger clusters of “violent” protesters (Fig. 3). In this case, the number of arrests was lower (54 at  $t = 300$ ), but the number of protesters breaching the perimeter was also much smaller. Although the modeling of the police agents needs to be improved, the model already gives some hints on the tactical advantages and disadvantages for both sides in this “game”. For “violent” protesters, it is advantageous to invest from the flanks, have more confrontation spots (e.g. side accesses to the protest area that are usually less protected), attract support from “Actives” that may elude the “Cops” and trespass the defensive perimeter while the “Cops” are fighting, and avoid passive “Hanger-on” protesters blocking direct confrontation. For the “Cops”, it is advantageous to shorten the length of the confrontation zone, have a smaller number of fronts and avoid arrests that temporarily limit their mobility and give the “Media” opportunity to exploit the situation.

## 6 Conclusions and future developments

In this work an ABM of street protest dynamics was presented that includes multiple players (“Hardcore”, “Hanger-on” and “Passer-by” protesters, police agents, and “Media” agents). Agents can have multiple goals encoded in a “personality vector” plus a set of context rules that provide adaptation, and protesters can be “quiet”, “active” or “violent”. The model was applied to a typical protest situation in which a police force defends the entrance of a government building that protesters seek to occupy, and reproduced many features of real protests, such as clustering of “violent” and “active” protesters, the formation of a confrontation line moving back and forth, occasional fights and arrests and “Media” agents inducing local clustering and seeking the “hot spots”. It was found that with the transition rules and agents’ attributes used in the model, violent behavior was confined to the “Hardcore” and at most a small proportion of “Hanger-on” protesters, but did not propagate to the bulk of the crowd. The inclusion of multiple players with purposeful movement and multiple states allowed a more complete and realistic representation of micro-interactions than is found in previous models of civil violence, clustering and fighting.

Although the model represented well emergent crowd patterns found in real protests, it needs improvement in some aspects, such as: *i*) more advanced modeling of the police agents, with “Command”, “Defensive” and “Offensive” types; *ii*) additional context rules for “active” and “quiet” protesters when they are near police agents; *iii*) variable velocity (by subdividing the grid and using a variable move range), *iv*) legitimacy feedback mechanisms associated with the measures of intensity; and *v*) parameterization of the agents’ attributes using data collected in real protests. These developments are being considered as part of an ongoing work on ABM simulation of social conflict phenomena.

## References

1. Kuran, T.: Sparks and prairie fires: A theory of unanticipated political revolution.

- Public Choice, 61, 41--74 (1989)
2. Faris, D.: Revolutions Without Revolutionaries? Social Media Networks and Regime Response in Egypt. Ph. D. Thesis, University of Pennsylvania (2010)
  3. Lemos, C., Coelho, H., Lopes, R. J.: Agent-Based Modeling of Social Conflict, Civil Violence and Revolution: State-of-the-Art Review and Further Prospects, In Proceedings - EUMAS 2013, 124--138 (2013)
  4. Jager, W., Popping, R., van de Sande, H.: Clustering and Fighting in Two-party Crowds: Simulating the Approach-avoidance Conflict. *Journal of Artificial Societies and Social Simulation*, 4, no. 3, p. undefined (html document) (2001)
  5. Grimm, V., Berger, U., DeAngelis, D., Polhill, J., Giske, J., Railsback, S.: The ODD protocol: A review and first update. *Ecological Modelling*, 221, 2760--2768 (2010)
  6. Gurr, T.; Why Men Rebel. Paradigm Publishers, Anniversary Edition (2011)
  7. Baker, P.: The Conflict Assessment System Tool (CAST). The Fund for Peace, Tech. Rep. (2006)
  8. Epstein, J., Steinbruner, J., Parker, M.: Modeling Civil Violence: An Agent-Based Computational Approach, Center on Social and Economic Dynamics, Working Paper No. 20 (2001)
  9. Epstein, J.: Modeling civil violence: An agent-based computational approach. *Proceedings of the National Academy of Sciences of the United States of America*, 99, 7243--7250 (2002)
  10. Brown, R.: Mass Phenomena. In Lindzey, G. (Ed.) *The Handbook of Social Psychology*, Addison-Wesley, Cambridge, 833--876 (1954)
  11. Durupinar, F.: From Audiences to Mobs: Crowd Simulation with Psychological Factors. Ph.D. dissertation, Bilkent University (2010)
  12. Leggett, R.: Real-Time Crowd Simulation: a Review (2004)
  13. Helbing, D., Molnár, P.: Social Force Model for Pedestrian Dynamics. *Physical Review E*, 51, 4282--4286 (1995)
  14. Helbing, D., Molnár, P., Farkas, I., Bolay, K.: Self-Organizing Pedestrian Movement. *Environment and Planning B: Planning and Design*, 28, 361--383 (2001)
  15. Wikström, P., Treiber, K.: Violence as Situational Action. *International Journal of Conflict and Violence*, 3 75--96 (2009)
  16. Collins, R: *Violence: A Micro-sociological Theory*. Princeton University Press (2008)
  17. Collins, R.: Micro and Macro Causes of Violence. *International Journal of Conflict and Violence*, 3, 9--22 (2009)
  18. Ilachinsky, A.: Artificial War. Multiagent-Based Simulation of Combat, *World Scientific* (2004)
  19. Uri Wilenski, NetLogo, <https://ccl.northwestern.edu/netlogo/index.shtml> (1999)

## **Annex A – ODD Description of the Agent-Based Model of Protest and Violent Confrontation.**

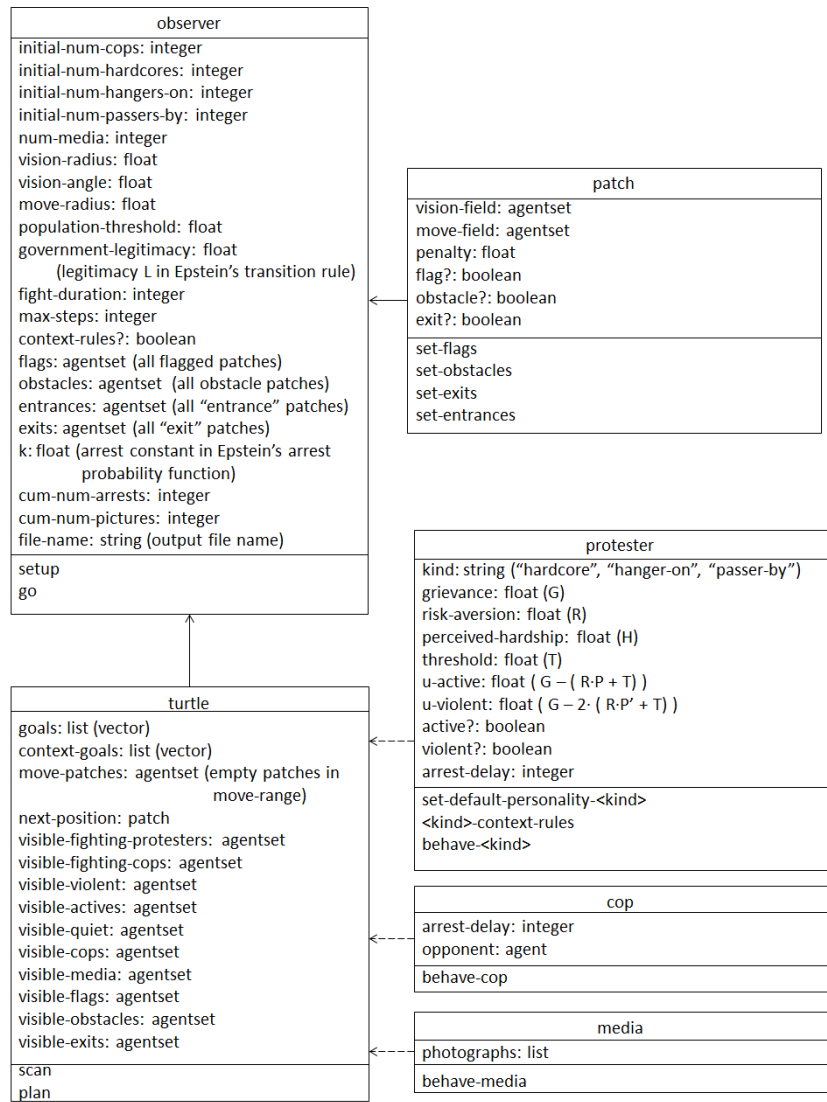
### **A.1 Purpose**

The purpose of the model is the simulation of the interaction between protesters, police forces and media agents in street protests, to understand emergent crowd patterns such as clustering of protesting or violent individuals, fighting and transition to violence, the influence of passive actors, and the effect of media coverage on the protest dynamics. The model allows the representation of spatial features such as attraction zones (symbolic sites within the protest space), obstacles (physical obstructions) and entrances/exits (adjacent streets and open spaces).

The key ideas and innovative features of the model are: *i*) consideration of three types of actors (“Protester”, “Cop” and “Media”) and three different kinds of protester personality and behavior (“Hardcore”, “Hanger-on” and “Passer-by”), for a more complete and realistic modeling of their micro interaction modes (movement and state transitions) than in currently available ABM; *ii*) introduction of media coverage effects, which change the micro behavior and help describing the feedback links between protests and the social context; *iii*) use of a “personality vector” and context rules (as proposed in [1] for land combat) for programming the agents’ action selection, taking into account theoretical results of crowd dynamics [2], and qualitative analysis of protest videos for setting the weights and context rules; *iv*) modeling the protesters’ state changes (“quiet”→ “active” and “active”→ “violent”) using the Epstein’s threshold rule (as in [3], [4]) with more stringent conditions for the transition to “violent” state; *v*) arresting of protesters is not instantaneous but requires a fighting arrest delay and local superiority of the cops.

### **A.2 Entities, state variables, and scales**

The model was implemented in NetLogo and consists of the following entities: Observer (World, global variables), agents and patches (space variables). Figure A.1 shows the class diagram for the model.



**Fig. A.1** Class diagram of the ABM of protest dynamics.

**Agents:** There are three types of agents, “Protesters”, “Cops” and “Media”. “Protester” agents can be of three subtypes (kinds): “Hardcore”, “Hanger-on” and “Passer-by”, each with a different behavior. “Hardcore” agents form the small proportion of protesters with highest propensity for violence, whereas “Hangers-on”

form the proportion of more or less “susceptible” protesters and “Passers-by” correspond to curious participants that try to avoid hotspots. Cops must protect specific sites within the protest space (for instance, the access to a government building) and keep near other cops, to avoid gaps or situations of dangerous local inferiority. “Media” agents try to approach hotspots and avoid uninteresting zones.

Table A.1 summarizes the qualitative behavior of all agent types and subtypes. From this table, the strengths and limitations of the model can be clearly understood. The implementation of the agents’ qualitative behavior is done using a “personality vector” and context rules as described in sections A.4 and A.7.

**Table A.1.** Qualitative behaviour of agent types and subtypes considered in the model.

Type/subtype	Description
Protester/ hardcore	<ul style="list-style-type: none"> <li>• Easily turn to “violent” state</li> <li>• Try to occupy the attraction points and engage cops</li> <li>• Cluster with “violent”/ “active” protesters to avoid being outnumbered by cops</li> <li>• Neutral to obstacles and entrance/exit points</li> </ul>
Protester/ hanger-on	<ul style="list-style-type: none"> <li>• Moderate incentive to approach attraction points and entrance/exit points</li> <li>• Low incentive to avoid obstacles</li> <li>• Low incentive to approach “violent” or “active” protesters and cops</li> <li>• Can turn “active” or even “violent” depending on their internal characteristics (hardship, risk aversion, threshold) and on the local context</li> </ul>
Protester/ passer-by	<ul style="list-style-type: none"> <li>• Low incentive to avoid “violent” or “active” protesters and cops when “quiet”, which reverses when “active” or “violent”</li> <li>• Other behavioral characteristics as for hangers-on</li> <li>• Usually remain passive, because they avoid clustering with “active” or “violent” protesters</li> </ul>
Cop	<ul style="list-style-type: none"> <li>• Try to defend attraction points from “violent” protesters and keep close to other cops, to avoid being outnumbered by “violent” protesters</li> <li>• Try to escape from “violent” protesters when outnumbered and alone</li> <li>• Moderate to high incentive to pursue “violent” protesters, when in local superiority</li> <li>• Engage and arrest “violent” protesters in their move range, when in local superiority and with sufficient backup</li> </ul>
Media	<ul style="list-style-type: none"> <li>• Try to locate “hot spots” and record (“take pictures”) of violent episodes (fights between violent protesters and cops)</li> <li>• Moderate incentive to approach attraction points and entrance/exit points</li> <li>• Moderate incentive to avoid “uninteresting” zones with many “quiet” protesters</li> </ul>

**Environment:** The spatial environment consists of a 2D grid (to represent a protest space with physical boundaries) of patches (sites). The patches can be marked as “flag” to represent attraction points that protesters try to occupy and police agents must defend, “obstacle” to represent obstructions (walls, barriers), and “exit” to represent open boundary sections (adjacent streets) of the protest area.



**Spatial and temporal scales:** The patch size, or space occupied by one agent, has dimensions  $1m \times 1m$ . The time scale is 1s, giving a constant speed of  $1 ms^{-1}$ . The user-defined global variable `arrest-delay` represents the number of seconds in a fight between protesters and police agents before an arrest is made.

### A.3 Process overview and scheduling

The model is based on discrete space and time representation, with a fixed time cycle and a 2D discrete grid of patches. Obstacle patches cannot be occupied by agents. The remaining patches can be occupied by only one agent at a time. The model is implemented in two procedures, `setup` and `go`, with the following operation sequences:

`setup`:

This procedure clears all variables from previous simulation; resets cycle counter; builds the environment (protest space); builds the agents list; and initializes the cumulative number of arrests and the cumulative number of “pictures” taken by “Media” agents in protest and plots the protest space (environment features and agents).

`go` (main cycle):

This procedure implements the main cycle of the ABM via the following actions: *i*) tests for termination (if `ticks > max-steps` the simulation halts); *ii*) resets the number of arrests and number of “pictures” taken by “Media” agents for the current cycle; *iii*) activates all agents not involved in fights (`arrest-delay = 0`) in random order, which perform the sequence `scan – plan – behave`; *iv*) activates all agents involved in fights (`arrest-delay > 0`), decrements their `arrest-delay` variable by one, and if the decremented value is zero, the agent is a “Protester” and the number of adjacent “Cops” exceeds twice the number of adjacent “violent” protesters, the agent is removed from the protest space (arrested); otherwise it is free to restart the `scan – plan – behave` sequence; *v*) updates the cumulative numbers of arrests and “pictures” taken by “Media” agents; and *vi*) updates the display of the protest space.

The `scan` procedure allows the agents to get information on the agents (“violent”, “active” and “quiet” protesters, “Cops”, and “Media”) and spatial features (flagged cells, obstacles and exits). In the `plan` procedure, agents decide where to move next (or stand in the same patch) and, in the case of “Protester” agents, update the auxiliary variables used to set their next state (“quiet”, “active” or “violent”). In the `behave` procedure, agents move to the next position and perform an action: *i*) “Protesters” update their state; *ii*) “Cops” try to engage violent protesters within their move range; and *iii*) “Media” agents try to take pictures of violent confrontations). The `scan`, `plan` and `behave` procedures as well as the auxiliary reporter procedures used in the model will be described in the Submodels section below.

## A.4 Design concepts

### A.4.1 Basic principles

The model is based on the following general concepts:

- All agents are reactive, goal driven and rule-based, move in discrete time an space increments (at most one agent per grid patch), and can have multiple goals that change according to the local context. This is consistent with the hypothesis that in protests, as in other crowd phenomena, people move and act according to simple motivations and rules, without sophisticated deliberation. Also, this approach permits simulations with large numbers of agents while retaining many important aspects of the multi-player micro-interactions in real protests;
- Agents' have one **move** rule and one **behave** rule.
- The **move** rule consists of moving to the patch within the move range that minimizes a penalty function with probability  $p = 0.9$  and to a random patch within the move range with probability  $p = 0.1$ . The penalty function involves weights that represent approach/avoid motivations to other agents or space features and of the relative proximity of such features. The weights of the move rule depend on a “personality vector” and on context rules, as proposed in [1] for land combat. This is consistent with simplifying the attraction forces and a neglecting the short-range repulsion forces in the social force model of crowd simulation [2] in the framework of our discrete time/discrete space representation. Random movement simulates errors in the agents' estimates, as described in A.4.9.
- The **behave** rule is different for each type of agent: “Protesters” determine their state (“quiet”, “active”, “violent”) according to Epstein's threshold rule, “Cops” try to protect the flag cells (defensive perimeter, or objective) and arrest violent agents within their move range, “Media” try to locate and record violent episodes;
- The **move** and **behave** rules are connected to the agent's overall goals. For instance:
  - Clustering of “violent” protesters facilitates not only their remaining in this state but also their advance towards attraction points and cop formations;
  - Cops remaining close to each other except when outnumbered by “violent” protesters and alone maximizes both the effectiveness of their protective action and the chances of arresting “violent” protesters.

The implementation of these rules is done by calls to NetLogo procedures upon agents' activation, as described in section A.7.

### A.4.2 Emergence

The model is expected to represent the following emergent patterns: clusters of “violent” and “active” protesters, localized fights between protesters and police, police forces either defending the perimeter or engaging violent protesters according to the local context, passers-by giving clearance to fights an active clusters, Media agents moving around the “hot spots”. Model output includes the time-history of the

number of quiet, active and violent protesters, as well as the number of arrests and violent fighting episodes registered by media agents.

#### A.4.3 Adaptation

Agents adapt their goals depending on their precepts and internal state in the previous time cycle, but have no internal representation of previous percepts or states, and thus have no evolutionary or learning capabilities.

#### A.4.4 Objectives

The agents' goals are programmed in their default "personality vector" and in the context rules, which are different for the various agent types and subtypes. The individual's success is determined by the values of the penalty function, which determines the next position. In the case of "Hardcore" protesters, the move rule also maximizes their chances of advancing towards the attraction points and engaging police agents without being arrested.

#### A.4.5 Learning

Agents have no learning capabilities.

#### A.4.6 Prediction

As described in A.4.4 and A.4.5.

#### A.4.7 Sensing

Agents' planning and decision is based on the percept constructed in the scan procedure. This percept is local for the other agents, obstacles and possible positions (empty patches within the move range) and global for attraction points and exits. This is consistent with the assumption that other agents and obstacles exert influence only when they are visible, but attraction points and exits are permanent features of the protest space known to all agents anywhere within the protest space. The local percept is constructed using NetLogo's `in-cone` primitive with range vision-radius (global variable in the interface tab, varying between 2 and 20 *m*) and vision angle 180° to detect all visible agents (turtles) and applying the appropriate logical conditions to identify: *i*) the visible "violent", "active" and "quiet" protesters; *ii*) the visible cops; *iii*) the visible "Media" agents; and *iv*) the visible obstacles. Attraction points and exits are identified as patches with [flag?] or [exit?], respectively. Sensory information is used to find the quantities (sum of distances) and context-adjusted goal-directing weights (via the context rules) in the penalty function (see section A.7 below).

#### A.4.8 Interaction

Agents interact in the following ways:

- Approach/avoid specific types of agents or agents in a certain state as determined by the positive or negative components of the "default" personality vector and the context rules, leading to clustering/dispersing patterns;

- Induce state changes, which may result from clustering (facilitates transition to active and violent behavior, mostly for “Hardcore” protesters but also for the other two protester profiles) or dispersion;
- Engage in fights between “violent” protesters and cops. This is modeled by immobilizing the fighting cops and protester (two cops for one potential detainee) during an arrest-delay period, thereby simulating the cost to the police force of doing one arrest and creating opportunities for “Media” agents to move towards hotspots and record violent episodes.

#### A.4.9 Stochasticity

Pseudo-random variables are used in NetLogo primitives, e.g. for setting the initial positions for all agents and the endogenous context variables (hardship and risk aversion) for protester agents, for activating the agents, and for selecting the next position when the penalty function has more than one local minimum within the agent’s move range. Epstein’s rule for protesters state changes involves an estimated arrest probability, but state transitions are based on a deterministic formula. The model has other features that induce stochasticity and complex behavior due to sensitivity to initial conditions, such as:

- Multiplicity of goals, personalities and context rules among the agents;
- Variations of the orientation of the vision cone, which lead to other agents and features to enter and leave the vision field from cycle to cycle;
- The agents’ next position is the center of the patch within their move radius that minimizes a penalty function (see section A.7) with a probability  $p = 0.9$ , and the center of a random patch with probability  $p = 0.1$ . This simulates random errors in the agents’ estimates of the optimal movement and increases the realism of the simulations.

#### A.4.10 Collectives

Collectives of agents form as emergent patterns resulting from clustering due to their “personality vector” and the effect of context rules:

- Cops aggregate in tight formations over attraction points (flagged cells);
- “violent” protesters also cluster and form patterns that advance towards attraction points and defending cop formations;
- Confronting cop and “violent” protester clusters tend to form lines (phalanxes) thus avoiding involvement and preventing the other side from acquiring overwhelming local superiority (consistent with the micro-sociological theory of violence)
- “Passer-by” protesters tend to avoid clusters of “violent” and “active” protesters thus forming gaps in the protest space.

These features are observable in many videos of street protests.

#### A.4.11 Observation

No empirical data were used for parameterization of the agent’s attributes, but information about hardship factors and perceived legitimacy in protest events in Portugal is being collected, using a specific questionnaire. This information may allow the formulation of more realistic distributions of the protesters’ attributes.

Videos of protest events in different parts of the world were analyzed to perform qualitative validation of the patterns of movement and violent confrontation obtained in the simulations.

### A.5 Initialization

Table A.2 describes the global variables, their initial default values and ranges (for global variables defined in sliders in NetLogo's interface tab).

**Table A.2.** Default values and ranges of the global variables for model initialization

Variable name	Description	Default value	Range
min-pxcor	minimum x-coordinate for patches	0	–
max-pxcor	maximum x-coordinate for patches	149	–
min-pycor	minimum y-coordinate for patches	0	–
max-pycor	maximum y-coordinate for patches	37	–
initial-num-cops	initial number of cops	125	[5,250]
initial-num-hardcores	initial number of hardcore protesters	100	[0,100]
initial-num-hangers-on	initial number of hanger-on protesters	800	[0,800]
initial-num-passers-by	initial number of passers-by protesters	300	[10,800]
num-media	number of "Media" agents	4	[0,5]
max-steps	maximum number of time steps	1200	[0,3600]
vision-radius	agents' vision radius	10	[2,20]
vision-angle	agents' vision angle	180	[90,185]
move-radius	agents' moving radius	1	[1,3]
population-threshold*	threshold for state transition	0.1	[0.0,1.0]
government-legitimacy*	government legitimacy	0.82	[0.0,1.0]
k*	arrest constant	2.3	–

\*the meaning of these variables is explained in section A.7

The initial positioning of the agents is programmed by hand according to the scenario to be simulated. The setup of the agents' personality vector, context rules and state transition formulae for protesters (which involve the last three variables in Table A.2) is described in section A.7.

### A.6 Input data

The present version of the model does not use empirical data or external files/sources for the parameterization of the agents' attributes. However, work is in progress to formulate the parameterization of the protester attributes that determine the state transitions according to data obtained in real protests using questionnaires.

### A.7 Submodels

This section contains a description of the submodels (NetLogo procedures) used in the two main procedures (setup and go) described in section A.3. We start by

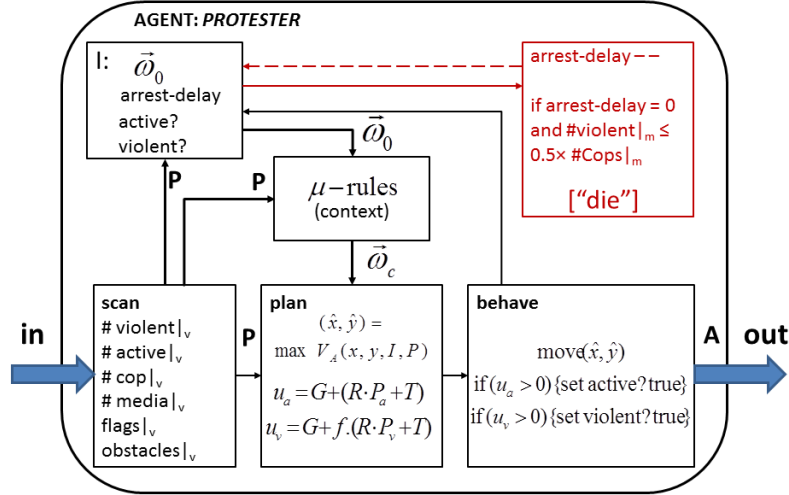
presenting the basic architecture common to all agents, followed by a description of the implementation of goal-driven agent movement and state transitions. We also include a list of auxiliary procedures used by the setup and go procedures to implement the agents' move and behave rules.

#### A.7.1 Agent architecture

We formally define the agents as a 5-tuple

$$\text{Agent} = \langle P, I, A, in, out \rangle, \quad (1)$$

where *in* is the input, *P* is the percept, *I* is the agent's internal state, *A* is the action and *out* is the output or change of the environment due to the agent's action. Fig. A.2 illustrates the implementation for the case of a "Protester" agent.



**Fig. A.2.** Agent architecture diagram for the "Protester" agent type. In this diagram  $|_v$  is the neighborhood within the vision cone of the agent,  $|_m$  is the move range,  $u_a$  and  $u_v$  are auxiliary functions that are positive when the agent is "active" or "violent" (respectively),  $V$  is the penalty function and  $(\hat{x}, \hat{y})$  is the position (patch center) that minimizes this function. "Cop" and "Media" agents have a similar architecture.

The agent's internal state consists of a "default personality" vector  $\omega_{A,0}$  of weights  $\omega_{A,i}$  which define the agent's goal orientations; two variables that indicate whether or not the agent is "quiet", "protesting" or "violent"; and an *arrest-delay* that identifies the agent as engaged in fighting with "Cops" and counts the number of cycles remaining before arrest. If the agent is fighting, the *arrest-delay* is decremented. If the decremented *arrest-delay* is zero and the number of "Cops" adjacent to the protesters

is equal or exceeds twice the number of adjacent “violent” protesters, the agent is arrested and disappears from the simulation space; if this condition is not verified (not enough local superiority of the “Cops”), the fight is broken and the agent becomes free. Otherwise, the agent scans the environment, resulting in a percept  $P$  with the relevant context features.

The **plan** procedure combines the “default personality” with the meta-rules that may be activated by  $P$ . The result is a context-adjusted vector  $\omega_{A,c}$  used to find the next position (analogous to the method in [1]) and compute the values of the auxiliary functions that define the agent’s state according to a variant of Epstein’s threshold-based transition rule [3], [4]. Finally, the **behave** procedure moves the agent and updates its state.

### A.7.2 Goal-driven agent movement

Agents move to the position (patch center of an empty patch) within their move radius that minimizes the penalty function

$$V_A(x, y, I, P) = \frac{\omega_{A,c}(I, P)}{\|\omega_{A,c}(I, P)\|_1} \bullet (\mathbf{S}(x, y) - \mathbf{S}(x_0, y_0)) \quad (2)$$

where  $\omega_{A,c}(I, P)$  is the context-adjusted personality vector,

$$\mathbf{S}(x, y) = \sum_{F_i \in P} \left( \sum_{j=1}^{N_{F_i}} D_{(x,y)F_{i,j}} \right) \quad (3)$$

is the sum of distances from element  $j$  (say, one violent protester) belonging to a feature  $F_i$  (say, the agent set of visible violent protesters) in percept  $P$  to the point  $(x, y)$ , and  $(x_0, y_0)$  is the current position of agent  $A$ .

The goals have absolute value between 5 (very high) and 0 (neutral). Table A.3 shows the default personality weights which sets the default goal-driven behavior for all agent types and subtypes. From this table, the default behavior of the agents can be inferred. For instance, Cops have a strong attraction towards other cops and flags and moderate attraction to violent agents, but have low attraction towards active protesters and are indifferent to all other features.

**Table A.3.** Default personality weights for all agent types and subtypes. A positive sign means attraction and a negative sign means repulsion.

Agent type/ subtype	violent	active	quiet	cops	media	flag	obstacle	exit
	$\omega_0$	$\omega_1$	$\omega_2$	$\omega_3$	$\omega_4$	$\omega_5$	$\omega_6$	$\omega_7$
hardcore	+5	+2	0	+4	+3	+5	-1	0
hanger-on	+1	+1	0	+1	+3	+1	-1	+1
passer-by	-1	-1	0	-1	+3	0	-1	+1
cop	+2	+1	0	+5	0	+5	0	0
media	+3	+1	-1	+3	+2	+2	-1	0

Depending on the internal state  $I$  and percept  $P$ , the default weights may be changed according to the local context by application of meta-rules, which are different for different type and subtype of agent. Table A.4 summarizes the context rules for each agent type and subtype.

**Table A.4.** Context rules for all agent types and subtypes.

Agent type/subtype	Context rule	Meaning	Condition*
hardcore	CLUSTER	Get support before confronting cops	Visible flags and $N_{viol} < \frac{1}{2} N_{cops}$
	PURSUE AVOID	Pursue cops when in advantage Avoid cops when outnumbered	$N_{active} + N_{viol} \geq 2 N_{cops}$ $N_{active} + N_{viol} < \frac{1}{2} N_{cops}$
hanger-on	KEEP CLEAR	Keep clear for other agents when “quiet”	Keep $2.5 m$ clearance from “quiet” and $5 m$ clearance from “violent” protesters and “Cops”
	CLUSTER	Approach other “actives” when “active”	$active? = true$
	TURN VIOLENT	Assume “Hardcore” personality when “violent”	$violent? = true$
passer-by	KEEP CLEAR	Keep clear for other agents when “quiet”	Keep $2.5 m$ clearance from “quiet” and $5 m$ clearance from “violent” protesters and “Cops”
	CLUSTER	Approach other “actives” when “active”	$active? = true$
	TURN VIOLENT	Assume “Hardcore” personality when “violent”	$violent? = true$
cop	ON-STATION	Increase attention towards nearby agents when in position (flagged cell)	$[flag?] \text{ of patch-here} = true$
	PURSUIT	Pursue “violent” protesters	$N_{violent} \leq \frac{1}{2} N_{cops}$
	RETREAT/AVOID	Avoid “violent” protesters when outnumbered and alone	$0 \leq N_{cops} \leq \frac{1}{2} N_{violent}$
	SUPPORT	Help comrades in “hot spots”	$0 \leq N_{cops}  _m \leq \frac{1}{2} N_{violent}  _m$
media	MINIMUM CLEARANCE	Keep good distance for “taking pictures”	Distance to nearest “violent” protester or “Cop” $\leq 3 m$

We used the following guidelines for implementation of context rules:

- Start with the two types of agents with strongest interaction (in this case, “Hardcore” Protesters and “Cops”) and successively add other agent types;
- Set and adjust the components of the “default personality vector” to define the intended goal-orientation for each agent type;
- Successively introduce and test the context rules and observe if they provide the intended behavior adaptation with respect to the default behavior;
- When implementing the context rules, it is necessary to pay attention to the following points: *i*) context rules should be as independent as possible from each other; *ii*) when two or more rules are dependent it is necessary to check carefully if they do not cancel each other or produce unrealistic effects; *iii*) effective context rules “focus the agent’s attention” by setting the default weights of less relevant features to zero and increasing the absolute value of the weights associated with the (context-dependent) important features.

#### A.7.3 Transition to “Active” and “Violent” behavior

In Epstein’s civil violence model [3], [4] transition from “quiet” to “active” (rebellious) behavior is determined by the rule  $G - N > T$ , where  $G = H \cdot (1 - L)$  is the level of grievance,  $N = R \cdot P$  is the net risk perception,  $T$  (constant exogenous



variable) is a threshold,  $H \sim U(0,1)$  is the (endogenous) perceived hardship,  $L \in [0,1]$  is the “perceived government legitimacy”,  $R \sim U(0,1)$  is the (endogenous) risk aversion, and  $P$  is the estimated arrest probability  $P = 1 - \exp(-k \lfloor C/(A+1) \rfloor_v)$  in which  $k$  is a constant and  $C$  and  $A$  are the number of “active” citizens and cops within the vision radius  $v$ . Although it was proposed for a macro-scale ABM, this rule is consistent with the main tenets of the SAT and micro-sociological theories: predisposition can be modeled by the values of  $G$  and  $R$ , the situational and deterrence elements by the form of  $P$ , and the “barrier” by the threshold  $T$ . In our model, a Protester’s transition from “quiet” to “active” and “violent” is determined by the following rules:

$$\text{if } G - (R \cdot P_a + T) > 0, \text{ turn to “active”} \quad (4)$$

$$\text{if } G - 2(R \cdot P_v + T) > 0, \text{ turn to “violent”} \quad (5)$$

where  $P_a = 1 - \exp(-k \lfloor C/(A+1) \rfloor_v)$ ,  $P_v = 1 - \exp(-k \lfloor 2 \cdot C/(A+1) \rfloor_v)$  and  $V$  is the number of active Protesters within the vision cone. The factor two is in Eq. (4) is arbitrary and accounts for the increased risk and need for local support in the transition to violence. Finding a more correct value for this parameter requires empirical analysis of real protest events.

### A.7.3 List of auxiliary procedures

The submodels described above, as well as some straightforward routines for defining the flag, obstacle and exit configurations of the protest space were implemented as NetLogo procedures and reporter procedures. Table A.5 contains a description of those auxiliary routines, and completes this section.

**Table A.5.** List of auxiliary NetLogo procedures used by the setup and go procedures.

Calling procedure	Submodel	Description
setup	set-flags	sets flag? = true and color = gray for flagged cells
	set-obstacles	sets obstacle? = true and color = black for obstacle cells
	set-exits	sets exit? = true and color = green - 3 for exit cells
	set-default-personality-<agent>*	sets the agents’ default “personality” vector
go	scan	gets the entities (agents and environmental features) necessary for agents’ planning using NetLogo’s in-cone primitive
	plan	computes the value of the penalty function for all patches in move field, and the variables used for updating the agent’s state in the case of “Protester” agents.
	<agent>-context-rules*	reports the context-dependent “personality vector” that results from changing the components of the default “personality” vector according to the percept received from the scan procedure. There are different procedures for each type and subtype of agent, which implement different rules.
	sum-distance [agentset]*	reports the sum of distances agent to perceived entities (agents of environmental features) in the agentset argument
	arrest-probability-active*	reports the estimated arrest probability of turning “active” for “Protester” agents
	arrest-probability-violent*	reports the estimated arrest probability of turning “violent” for “Protester” agents
	behave	makes agents move and act according to plan. There are different behave-<agent> procedures for each type of agent
	display-<agent>	displays agents (in either 2D or 3D NetLogo display)

\*procedure of the reporter type.

#### **References (for Annex)**

1. Andrew Ilachinsky, A.: Artificial War. Multiagent-Based Simulation of Combat. World Scientific (2004)
2. Helbing, D., Molnár, P.: Social Force Model for Pedestrian Dynamics. Physical Review E, 51, 4282--4286 (1995)
3. Epstein, J., Steinbruner, J., Parker, M.: Modeling Civil Violence: An Agent-Based Computational Approach. Center on Social and Economic Dynamics, Working paper No. 20 (2001)
4. Epstein, J.: Modeling civil violence: An agent-based computational approach. Proceedings of the National Academy of Sciences of the United States of America, 99, 7243--7250 (2002)

# From Anarchy to Monopoly: How Competition and Protection Shaped Mafia's Behavior

Luis G. Nardin<sup>1</sup>, Giulia Andrighetto<sup>1,2</sup>, Rosaria Conte<sup>1</sup>, and Mario Paolucci<sup>1</sup>

<sup>1</sup> Laboratory of Agent-Based Social Simulation – ISTC/CNR, Rome, Italy

<sup>2</sup> European University Institute – Dep. of Political and Social Sciences, Fiesole, Italy

{gustavo.nardin, giulia.andrighetto, rosaria.conte,  
mario.paolucci}@istc.cnr.it,

**Abstract.** Mafia-like organizations are characterized by their extortive activities that impact societies and economies in different modes and magnitudes. This renders the understanding of how these organizations evolved an objective of both scientific and application-oriented interests. We propose an agent-based simulation model – the *Extortion Racket System* model – aimed at understanding the factors and processes explaining the successful settlement of the Sicilian Mafia in Southern Italy, which may more generally account for the transition from an anarchical situation of uncoordinated extortion to a monopolistic social order. Our results show that in situations of anarchy, these organizations do not last long. This indicates that a monopolistic situation shall be preferred over anarchical ones. Competition is a necessary and sufficient condition for the emergence of a monopolistic situation. However, when combined with protection, the resulting monopolistic regime becomes even more preferable for societies in which extortion activities are endemic.

## 1 Introduction

Mafia-like organizations are remarkably prosperous organizations originating in Southern Italy at the end of the XIX century, if not earlier, and now widely spread all over the world. They are highly dynamic and organized criminal groups that impact societies and economies in different modes and magnitudes [5, 8].

The origins of the Mafia, however, are not yet well understood, mainly due to the lack of information, which is in part a consequence of their secret nature. Currently, an explanation largely supported among scholars proposes three main factors for its origins, (i) the *land reforms*, (ii) the *property rights* and (iii) the *weak State* institutions. These factors were present in the Sicilian transition from feudalism to pre-capitalism and in the typical market structure of the region in the XIX century [2–4, 10].

Following to this view, the Mafia phenomenon developed when the State was weakly represented in the Sicilian region and widespread criminals were freer to engage in repeated raids against properties and production, thereby creating a chaotic or anarchical situation all over Sicily [1].