Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Lecture with Computer Exercises:
Modelling and Simulating Social Systems with MATLAB

Project Report

Influence of modern media on unstable social systems

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Zurich
December 2013

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1 Abstract

In the following study the influence of modern media on revolutionary civil violence is investigated. For our purpose we used an agent based model as proposed by Epstein et al [1]. The impact of media is described in two different ways. At first connectivity to media influences the decision of the people, in the second approach it modifies their direction of movement. It is shown that especially in societies with a high displeasure and an oppressive government the increasing connectivity to media has the ability to catalyze outbreaks in violence.

2 Individual contributions

All the members contributed equally to the project. In particular, after having worked on the initial code which is based on Epsteins model [1], we have continued our project with two different approaches. Federico and An-phi have worked on the implementation of directional movement of agents and have analyzed the results obtained with this major change of the initial model. On the other hand, Jessica and Robert have studied the influence of connectivity to modern media on agents decision by analyzing how this affects the inclination of agents to become active.

3 Introduction and Motivation

Social sciences include very complex processes. For this reason it is a great challenge to analyze adequately specific social events isolated from social processes as a whole. However, this is exactly how social sciences are organized. The division of the processes into more fundamental ones is crucial for trying to understand the underlying rules and mechanisms that govern social events. Another great challenge is represented by experimentation that needs to observe collective behavior of the society while actually looking at a restricted number of people [2]. In social sciences, a common method to deal with the above-mentioned issues, is to use models in order to try to reproduce social events and understand how different parameters influence their evolution. This permits the possibility to gain a better understanding of the underlying processes. For these reasons our goal is to use an agent-based model to analyze the recent revolutions in developing countries. In particular, we want to study the role of social media in these events. In fact, as recent revolutions in northern Africa have shown, media can have a big impact on the dynamics of insurgencies. It promotes for example the organization of revolutionary groups and events. It is therefore of great interest to analyze the influence of the information provided especially by *modern media* on the behavior of single people and the group dynamics.

For this purpose modeling of social behavior can play an important role. Another interesting aspect to analyze is the influence of oppressive governments that prevent the creation of large revolutionary groups by controlling and limiting the access to the web, which is having a deep impact in connecting people sharing the same ideals.

3.1 Main Questions

How does information availability influence revolutionary actions?

- Does the effect modern media has on the individual lead to a difference in the collective behavior?
- How do social networks affect the group dynamics during insurgencies?

4 Description of the Model

4.1 Original Model

Our model is inspired by the agent-based computational model of civil violence of J.M. Epstein [1]. In his paper J.M. Epstein describes two different types of models, but we focus on only one of them, where an authority tries to suppress rebellion. In this model there are two different groups of actors distributed on a two dimensional lattice. Every lattice position can only be occupied by one person. The first group of actors is formed by agents, which represent the population. These can be either active if they are rebellious or inactive if they stay quiet. The second group of actors is formed by the cops, which are members of a central authority. Their aim is to arrest the active agents and therefore to stop rebellions. A fundamental property of all the actors is their vision. This represents the number of lattice positions around the actor that it is able to inspect. In our model we used the same categories of actors and the basic principle is the same as found in J.M. Epsteins version. The following descriptions of cops and agents rules are useful for better understanding the model.

4.1.1 Cops

The most important parameter for cops is their vision. In fact, a cop will inspect all positions within its vision and will randomly arrest one of the active people in this region.

4.1.2 Agents

Agents are characterized by different parameters:

- Hardship H: This is the level of deprivation perceived by each individual, represented by a number randomly chosen between 0 and 1.
- Legitimacy L: This shows how much a government is perceived as just and righteous. Its value is between 0 and 1.
- Grievance G: The level of grievance perceived by each agent towards the regime depends on the two above-mentioned parameters. The relationship is described by the following equation:
$$G = H(1 - L)$$
where $(1 - L)$ can be seen as the illegitimacy.

Since H and L have values between 0 and 1, also G lies between 0 and 1. By increasing legitimacy, the grievance will decrease. Whereas if people are suffering more, which is shown by an increased hardship, also the value for G will increase.

- Risk aversion R: This represents the risk aversion of each agent and its value is randomly chosen between 0 and 1. This is an important variable since some agents are more inclined to take risk than others.
- Arrest probability P: This is the agents probability to be arrested and depends on the number of active people and of cops around them. In particular the relationship is:
$$P = 1 - e^{-k(\frac{C}{A})_v}$$
where $(\frac{C}{A})_v$ is the cop-to-active ratio within the vision and k is a constant chosen as $\log(0.1)$ to normalize P to a reasonable range . The more active people there are around, the smaller the arrest probability for an individual will be.
- Agents net risk N: It is the risk aversion of the individual multiplied by the arrest probability:
$$N = RP$$
The rule for the agents is based on the difference between the grievance and the net risk: $G - N$. If this difference exceeds a threshold T, then the agent becomes active, else it turns inactive:
$$G - N > T$$
In fact, the greater the grievance and the smaller the net risk, the more reasonable it seems for an agent to become active.

4.1.3 Jail

In our model, when an active agent is arrested, he disappears from our grid for a certain period, i.e. for a certain number of time steps randomly chosen between zero and the jail term J. The idea behind this is that the agent is captured in prison. After the arrest time, it will be free and go back to a random position in the grid. The above-mentioned parameters and rules are all based on the model of Epstein et al. [1]. Subsequently we have modified this model following two different approaches. At first we have analyzed how the connectivity to media influences the decision of the agents. Then, directional movement of the agents has been implemented.

4.2 Addition to Original Model

- The *first approach* is to consider that, if a person has access to media, this will influence its decision for going active or inactive. The threshold T can be now seen as the value that an agent must surpass to go active when only local information is available. But when the people are connected to social media like facebook or twitter they are provided global information about the system. In our model they get to know about all the active people, for example because of reading their decisions online. The knowledge that there are active people all around and not only in their direct range of vision lowers the risk felt by the individual agent and therefore its threshold. For deciding if a person has access to media they have been assigned a media value which was picked for each one individually randomly between 0 and 1. Subsequently by defining the media threshold globally between 0 and 1 it can be efficiently chosen how big the fraction of people with access to media should be. For people with access to media the threshold for going active is lowered by the media impact (*mediaimp*), yielding the rule $G - N < T - mediaimp$ for going active. The media impact is dependent on the fraction of free people being active and the initial threshold. For using this the formula

  $$mediaimp = m\,T\,\frac{N_{active}}{N_{free}}$$

  has been chosen. G-N can only lie between -1 and 1. If the net threshold under influence of media reaches strongly negative values this can cause all agents to turn active irreversibly. This definitely happens at -1 but is likely to happen for any negative value. For this reason it was made sure, that the net threshold *T-mediaimp* did not drop below 0. Also in the model proposed by Epstein [1] the threshold was meant to be nonnegative. We solved this with an *if condition* that sets the net thresholds to 0 if it would drop below 0. With low values of the factor m the availability of media had no observable effect on the behaviour of agents, since mediaimp was just too smalled compared to T. The factor m has been chosen to be equal to 5 since this yielded observable effects of connectivity to media. A linear dependence of *mediaimp* on active people has been chosen in order to keep the model simple.

- In the *second approach*, the agents are influenced by social media in a different way: we wanted to try to model another aspect of social networks, which is the ability to easily organize events that involve large groups of people. With regards to our model, this could represent the possibility to coordinate large demonstrations, such as those occurred during the recent Arab spring. We implemented this feature by orienting the people's movements. We can suppose that every person willing to take part in the riot tends somehow to move towards places where insurgencies are happening. In the same way, if an agent is active (i.e. is committing criminal acts), he will try to move as far away as possible from cops. Normally every agent has information only about his surroundings and will act consequently. However, thanks to the contribute provided by social media, this information becomes global, e.g. if a particular place has been chosen for a demonstration, active agents tend to get there. Therefore, we can model this phenomenon through a "social" force, that has the effect to push active people away from cops and, at the same time, get them closer to other active people. In this way we can easily implement the two cases mentioned above just by changing the range of the force.

5 Implementation

We now present the most important features of our code. For more details, we refer to the commented code itself.

5.1 Data Structures

In order to keep track of the evolution of our system, we decided to use three data structures:

- **Agents** A N_{ag} x 7 matrix: every row contains information about an agent (e.g. position, activity status, grievance, etc...);
- **Cops** A N_{cops} x 2 matrix: every row contains the position of the cops;
- **Grid** A N x N x 3 matrix: it displays position of agents (:,:,1), active agents (:,:,2) and cops (:,:,3) in a spatial domain.

5.2 Initialization

In this phase we set the parameters of the model and we create the data structures. First of all, we start by filling the grid of people and cops randomly according to some density value. Then, we assign to every agent a random value for G, H, R, a zero value for J. Finally, the Active Flag is put on 1 according to the general rule. We keep this information in the *Agents* data structure. Now the simulation can start.

5.3 Time Loop

Every time step is divided in several phases:

- **Data Collection** Data such as number of active people, mobs' sizes, etc... are gathered for analysis purpose. *Functions*: PostOnFacebook, Nfree.
- **People Movement** People are moved in a random order according to 2 different rules. In a case, agents and cops move randomly in a neighbouring cell, while, in the other, they tend to move in the direction provided by the "social" force applied to them. *Functions*: move_people, move_people_forces, choose_movement.
- **Update** In this phase, agents can change their "activity status" according to the general rule, cops arrest a random active agent in their field of view and jail term is updated for every agent. *Functions*: decide, Arrest, JailUpdate, UpdateMedia, decidemedia.

5.4 Boundary Conditions

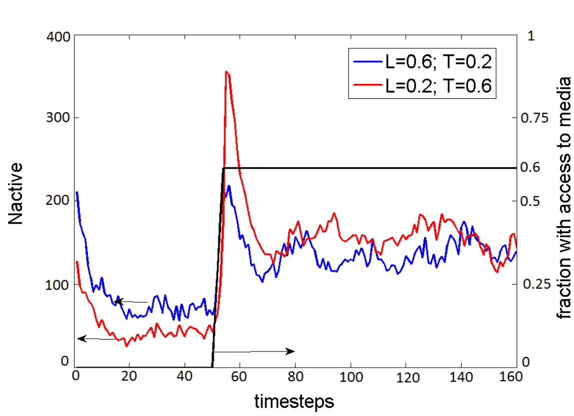
In order to avoid deviating behaviour at the boundaries, we chose periodic boundary conditions for functions decide and Arrest.
Since these conditions seemed unrealistic for function move_ people_ forces, we made so that, whenever a person exits the lattice, it reappears at a random boundary cell[1].

6 Simulation Results and Discussion

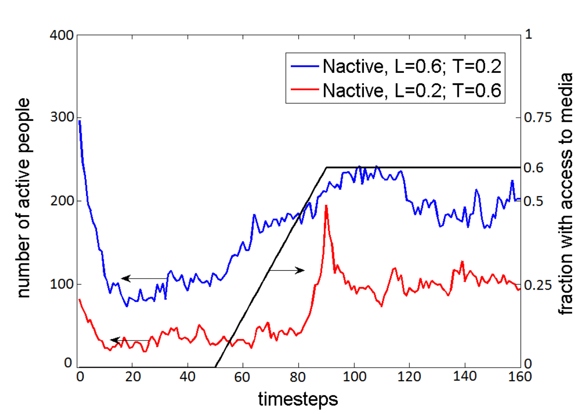
6.1 First Approach

The following simulations were all run on a 40x40 grid with an initial density of agents of 0.7, density of cops of 0.05 and a Jail term of 30. Since the behaviour

[1]Implemented only in the *second approach* because boundary issues, such as amassing of people at the border, arise only in the case of *oriented movements*.



(a) Access to media in 4 steps



(b) Access to media in 40 steps

Figure 1: Number of active people over time

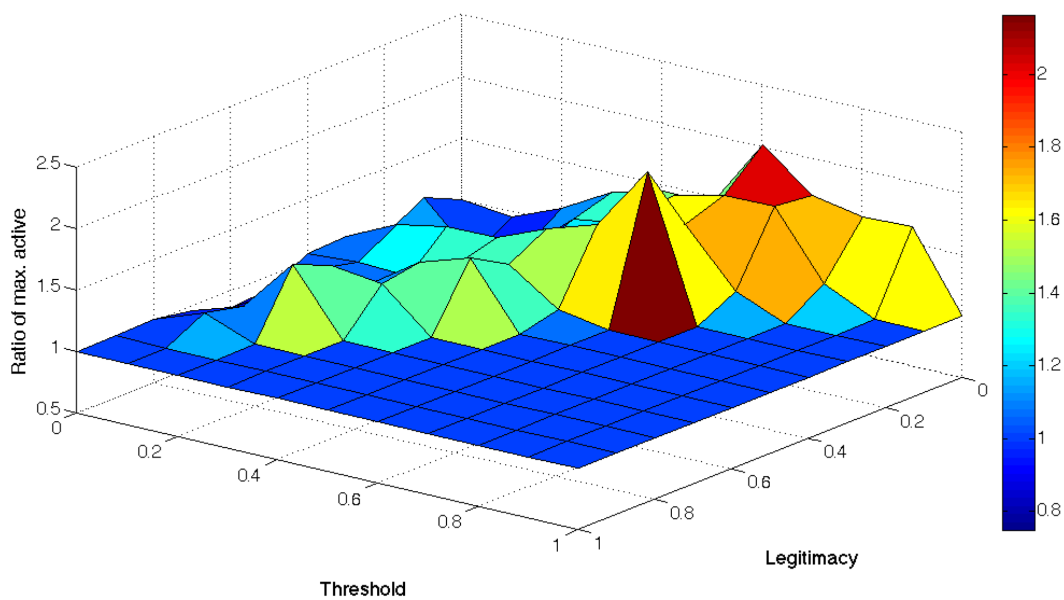


Figure 2: Ratio of maximum active people (fast increase of internet users / slow increase of internet users) as a function of threshold and legitimacy.

observed in this runs is due to the system not equilibrating fast enough, a high cop density greatly decreases the influence of media in this model[2]. This already offers a possibility for oppressive governments to deal with the increasing influence of media. The vision of both agents and cops was chosen as 2 lattice points in every vertical and horizontal direction, yielding a square. The taken values offered a good compromise between runtime of the program and system size.

To study how the velocity at which the media term changes influences the outbreak of a rebellion, we have fixed the maximum percentage of population that can access media and changed the number of time steps needed to reach this value. Having only a few time steps represents a quick increase in number of people having access to the web in the real world . This actually reflects what is happening in developing countries such as the ones in northern Africa (see Morocco and Egypt in Table 1). We have then used the same settings and simply increased the number of time steps needed to reach the maximum percentage of populations access to internet. In this case the number of people having access to the web increases gradually with no big changes between following time steps. Subsequently we compared the results in order to analyze the influence that this great outbreak in web access taking place in developing countries can have. This study has first been done using fixed parameters for legitimacy and threshold in order to see how the number of rebellious people changes over time. The same analysis has then been extended to different combinations of values of legitimacy and threshold changing between 0 and 1. The ratio of maximum number of rebellious people for fast increase to slow increase in media access has then been plotted in a 3-D plot over legitimacy L and threshold T.

First we have compared an increase of connectivity by 4 steps with one by 40. Essentially, we have compared how the maximum number of active people changes with the speed by which the media influence is increased. In both cases at first no people had access and in the end a maximum value of 60% of the population was reached. Figure 1 shows plots of the number of active people over time steps for a system with high legitimacy and low threshold (blue) and for low legitimacy and high threshold (red) where the access to media once gets increased in few (1a) and once in many steps (1b).The arrows in figure 1 indicate the axis the data is referring to. It is important to mention that these graphs show the output of one single run and are therefore not very representative. But the general behaviour is shown well nevertheless. For the system with high threshold there is always a clear and sharp peak in the number of active people when the maximum fraction has access to media. When then connection to media is increased fast this peak is significantly higher. For the high legitimacy system this effect is way less pronounced. Also the difference

[2]An example can be seen in the graph *High Cop Density* (https://github.com/jgenta/Civil_violence/blob/master/doc/high%20Cop%20density.png).

between fast and slow increase seems to be a lot smaller. To further investigate the behaviour, data for more different L and T configurations has been acquired. Figure 2 shows the ratio between the maximum number of active people obtained with the 4-steps runs and the 40-steps runs. Data has been obtained for different combinations of threshold and legitimacy between 0 and 1. Increasing the number of people with internet accesses rapidly leads to a much greater outbreak in comparison to the 40-steps increase. This is shown by high values in the 3D-plot. These results are easily recognizable in Figure 2. Here we see that in a certain regime, there is a flat surface at a z-value equal to 1. This is due to the number of active people being zero in both cases. The reason for that lies in the underlying formula stating that for $T + L \geq 1$ there can be no active people. For making the plot we set the ratio to 1 manually, which makes sense since it is the same value (0) in both cases.

One can observe that the greatest values for the ratio of maximum active people

Year	Country	Users	Population	% Penetration
2000	Switzerland	2134000	7407700	28.8 %
	Morocco	100000	29890700	0.3 %
	Egypt	450000	66303000	0.7 %
2006/2007	Switzerland	5097822	7523024	67.8 %
	Morocco	4600000	30534870	15.1 %
	Egypt	5100000	71236631	7.0 %
2010/2012	Switzerland	5739300	7623438	75.3 %
	Morocco	15656192	31968361	49.0 %
	Egypt	29809724	83688164	35.6 %

Table 1: Comparison of amount of internet users in different countries and years[3].

is present at low legitimacy and high threshold. It means that in these cases, if the access to internet increases rapidly, it is much more likely for outbreaks to occur. In fact, this reflects what recently happened in many Arabic countries, where the access to internet in the last years increased incredibly fast. This is shown in Table 1 and 2 where the number of internet users in Morocco and Egypt over time is compared with the one in Switzerland. By looking at the tables, it becomes immediately clear how great the increase in these two Arabic countries has been in the last year (Table 2).

In order to better analyze the results obtained in the 3-D plot, we have selected two points in the plot and have more deeply studied the system for these parameters. In particular we have selected the first point at a legitimacy L = 0.2 and a threshold

[3]http://www.internetworldstats.com, 02.12.2013

Years	2000-2006/2007	2006/2007-2011 ca	2000-2011 ca
Switzerland	2.39	1.13	2.69
Morocco	46	3.40	156.56
Egypt	11.33	5.85	66.24

Table 2: Increase in number of internet users within different time periods. The values represent the factor by which the initial number of users is increased[3].

T = 0.6 and the second point at L = 0.6 and T = 0.2. For each configuration the maximum number of active people has been obtained as a function of the number of steps needed to reach the maximum fraction of population with access to media (Figure 3). Every value has been averaged over 10 different runs and the standard deviation of the mean is represented in Figure 3 by an error bar. It can be observed that at low legitimacy and high threshold (blue graph) we have a high number of maximum active people, when the increase in access to media is fast, i.e. when the change is done in a few steps. By increasing the number of steps and therefore by increasing more gradually the access to media, we see that the maximum number of active people decreases until it apparently converges to a constant value at around 40 steps. This is consistent with the results obtained in the 3-D plot. In Figure 3 we also see in red the values obtained for L = 0.6 and T = 0.2. In this case, for a low threshold and a higher legitimacy, it can be observed that the number of active people, especially for a fast increase in access to media, is significantly lower. The graph also shows that even in this configuration the number of active people approaches a constant value of about 160-180 actives. These results confirm what previously stated. In fact, systems that experience low legitimacy are more sensitive to fast increases in access to media by showing a high number of maximum active people. In these systems it is therefore more likely that outbreaks and revolutions occur catalyzed by media.

6.2 Second Approach

In order to investigate the way social media incentivize formation of large groups of protesters, we ran several simulations setting different values for some of the model's parameters. In particular, the effects of legitimacy, threshold level and cops' density have been analyzed: for each of these parameters, we chose five different values, and for each combination of them we ran ten simulations implementing both local and global (i.e., with social media on) oriented movement. The other variables were set to: Grid Size = 20x20, Agents' Density = 0.2, Max Jail Term = 10 and Number of Time Steps = 200.

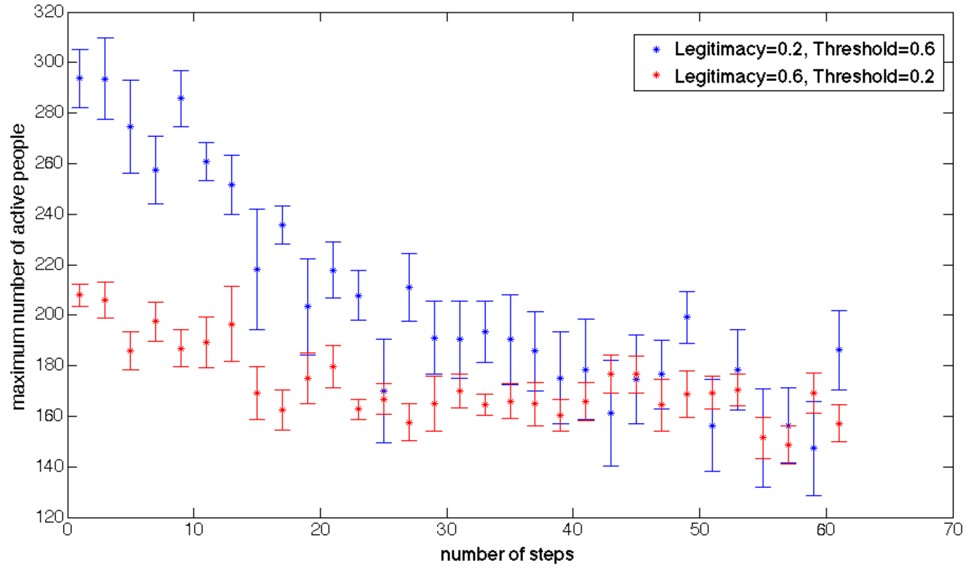


Figure 3: Maximum number of active people (average over 10 runs) for different number of steps needed to increase the fraction of population with access to media from 0 to 0.6.

We were interested in monitoring the variations in the total number of active people and in the size of their biggest aggregation. The results (average over 10 simulations) of these tests showed the following, which seems to validate the model:

1. As can be seen in Figure 4, the biggest cluster of active people maintains a larger size in the case of social media effect turned on. This results applies to all combinations of parameters and holds for the whole duration of the simulation.

2. Along time, there are wider oscillations in the size of the biggest cluster than in the normal case. We suppose this is a direct consequence of the boosted tendency of active people to aggregate: since more active people tend to group together, the cops can be more efficient in breaking up those groups. A good example of these behaviours is shown in Figure 5, which corresponds to a simulation run with a medium density of cops.

3. We suppose this increased efficiency in the cops' action is also the reason why, for low levels of threshold and a small density of cops, the number of active people tends to be lower than in the normal case. Again, since active people stay in compact groups, it is easier for cops to identify and capture them than if they were just randomly distributed. An example of the different numbers of

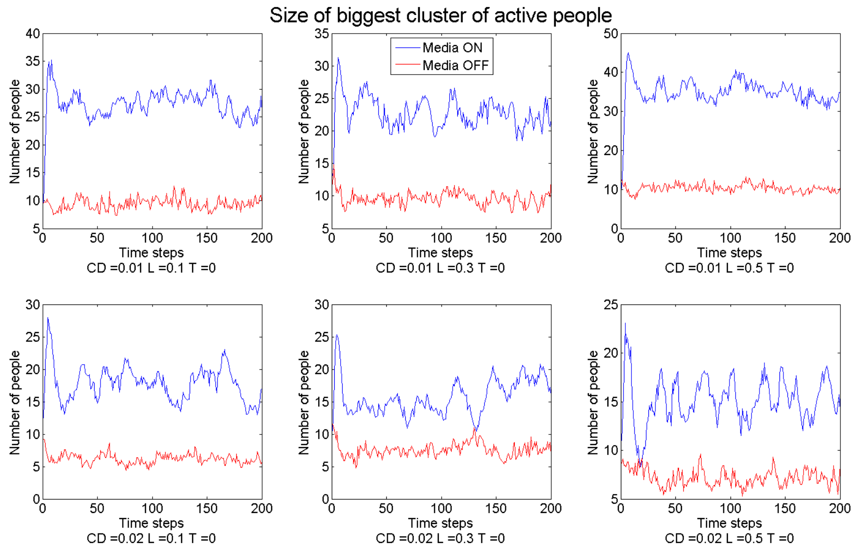


Figure 4: Size of biggest cluster obtained with a 200-steps simulation. Red graph is the *normal case*, while blue is *media case*.

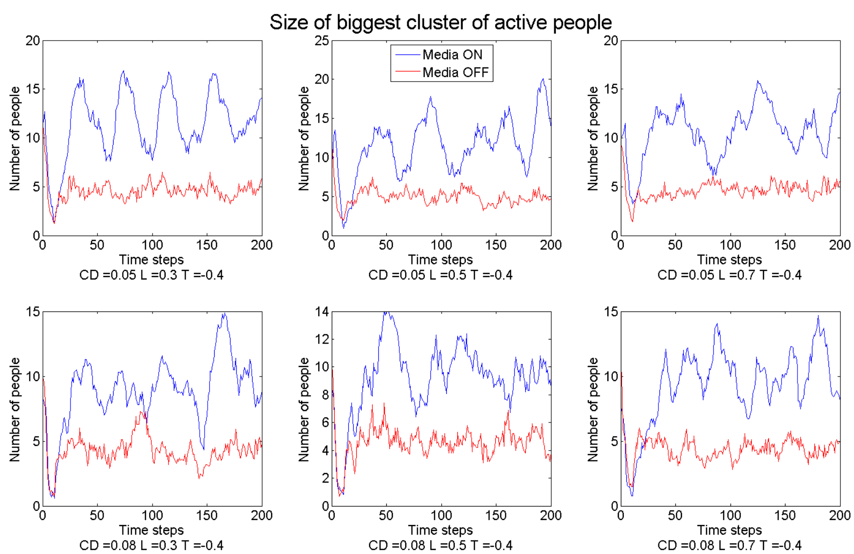


Figure 5: Plots of biggest mob against time. The density of cops is relatively high (Cd = 0.05,0.08). Note the fluctuations characterizing the *media case* graph.

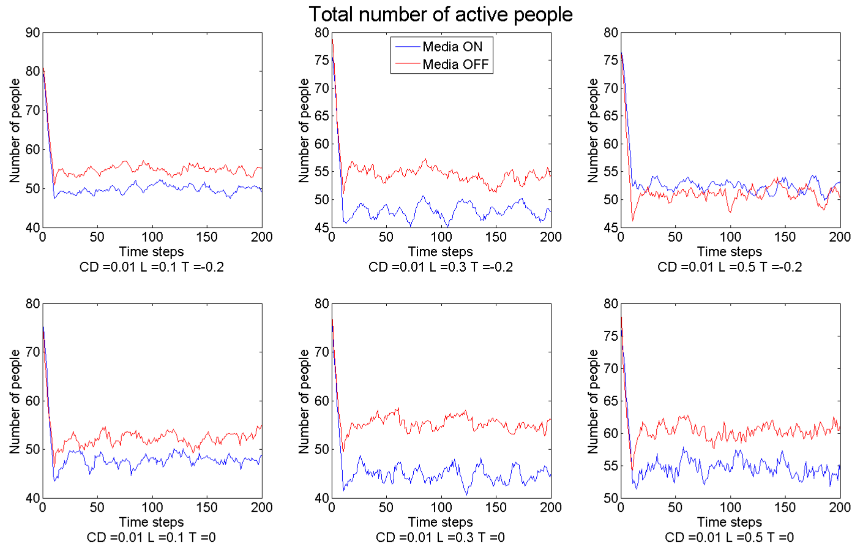


Figure 6: Simulations with low values of cops' density, legitimacy and threshold. They represent particularly unstable political situations without huge police forces.

active people in the two cases can be seen in Figure 6.

4. Lastly, as the cops' density is increased, the gaps in both the numbers of active people and the sizes of the biggest clusters between the two cases tend to become smaller, until eventually they overlap (Figure 7). This might be due to the fact that if the number of cops is sufficiently high, they do not leave any chance to the people to aggregate, thus neglecting *de facto* the effect of social media.

Against the background of the above, the model we implemented seems to behave as expected; we can now focus our attention on the actual social system we are interested in. We tuned our parameters in order to best describe the unstable situations that characterized the countries involved in the so-called Arab Spring. Therefore, we set a low level of legitimacy (L = 0.2) and a reasonably high threshold[4] (T = 0.6). About the cops' density, we chose it according to the previous results, so to allow cops to still represent an actual threat, without preventing agents from aggregate (Cd=0.03). Another series of 100 simulations were run under those values: statistical analysis[5] of the results showed that, after a transition period, the total number of active people

[4] Note that T influences an agent's tendency to turn active; we suppose that in a highly repressive legal system, this tendency is low and, consequently, the threshold is high.

[5] T-test: $\mu_{nomedia} = \mu_{socialmedia}$ vs $\mu_{nomedia} < \mu_{socialmedia}$. After about 40 time steps, the p-value drops definitely below 10^{-7}, hence we decide to reject the null hypothesis.

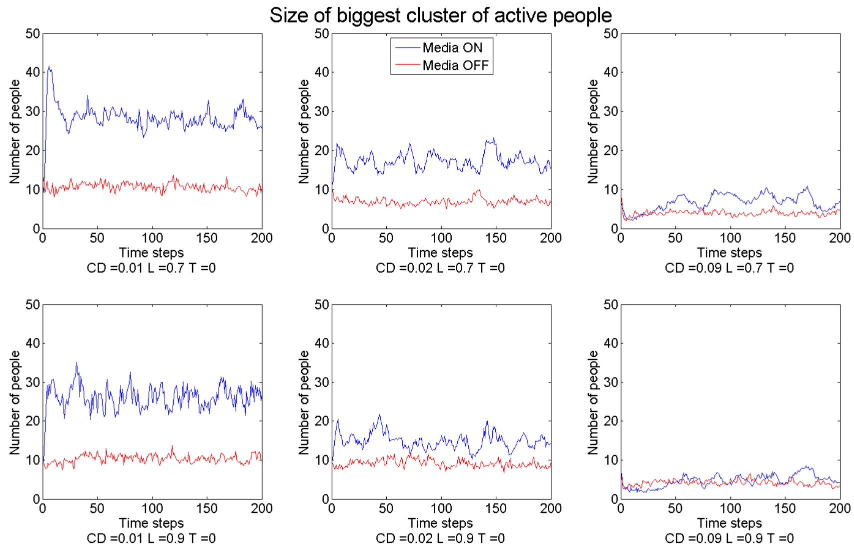


Figure 7: Different simulations with increasing cops' density. Legitimacy's value has been set to 0.7 or 0.9 to better appreciate the effect of cops.

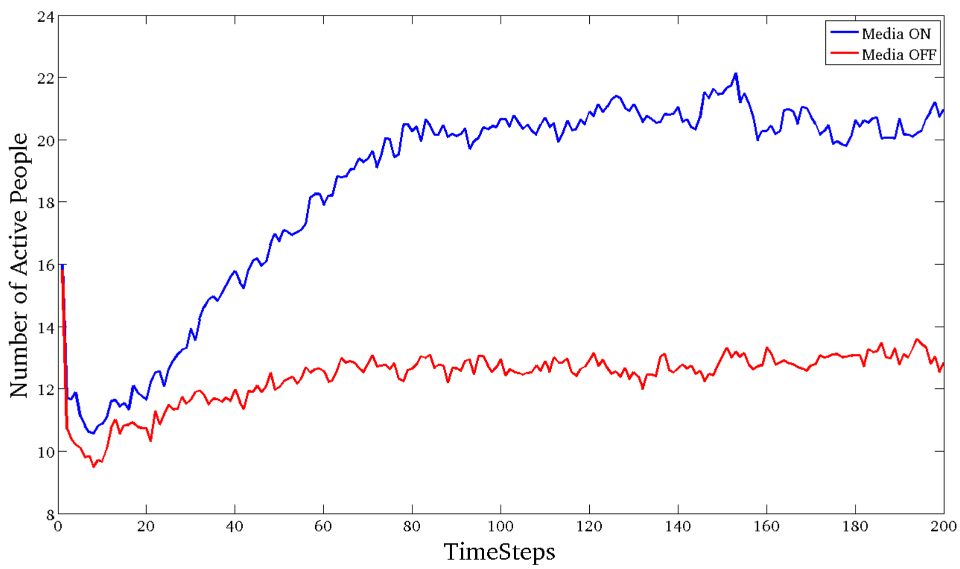


Figure 8: Simulation's output for a real world case, such as the Arab Spring. Parameters: Grid Dimension = 20x20, People Density = 0.2, Cops Density = 0.03, Legitimacy = 0.2, Threshold = 0.6, Max Jail Term = 10, Time Steps = 200.

stabilizes at a much higher value if they are connected through social media (Figure 8). Hence, our model suggests that some sort of global media connection helps sustaining the riots attracting more people to it.

7 Summary and Outlook

In our study we have used two different approaches to analyze how civil violence is influenced by modern media. The agent-based model that has been used for our purpose is found on Epsteins work [1]. The main modification done in our first approach is to add a media term, which influences the decision of people and is dependent on the fraction of agents being active. This term can be interpreted as the influence of modern media such as facebook or twitter. It has been shown that by fast increase in the number of people with access to media, outbreaks are more likely to occur. In particular this happens in a system with low legitimacy, which means in populations with high displeasure. It means that in these situations modern media heavily affects individual inclination to violence, which answers one of the initial questions. The result we obtained could explain one of the contributions that led to the revolutions northern Africa, where there was a huge increase in access to modern media in the last few years. On the other hand, it has been shown that by controlling the access to media, great violent outbreaks can be avoided. This can be referred to oppressive governments that keep under controlthe populationby limiting access to modern media.

With regards to the second approach, a law for orienting agents' movement has been implemented, which tends to group together people with a high level of grievance. According to our interpretation, this can be justified by the fact that the modern ways of communication, such as social networks, provide an easy way to organize large events and demonstrations. As a consequence, public manifestations can be sustained longer, and a higher number of participants can be involved; one could then expect this to have a direct result on the outcome of a social movement, especially in the conditions of political instabilities and high social tensions. Finally, we can conclude that accessibility to information and the possibility to use modern ways of communication can affect deeply the dynamics of large scale rebellious phenomena, eventually influencing their outcome.

Further investigations could be carried out by combining the two different approaches and by looking at collective effects. In addition, we could run a greater number simulations in order to obtain more statistically meaningful results.

8 References

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[2] Epstein J.M; Axtell R.L. *Growing Artificial Societies: Social Science From the Bottom Up (Complex Adaptive Systems).* MIT Press, October 1, 1996.