Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Complex Social Systems:
Modeling Agents, Learning, and Games

Project Report

A discrimination-based Civil Violence Model

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Zürich
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1 Abstract

Thanks to its solid formulation and its simplicity, Epstein's agent-based model of civil violence [Eps02] makes it possible to describe different types of social conflict phenomena. A possible revision of the standard model is suggested by the recent protests, concerning the social movement Black Live Matters, against black people discrimination and police violence. In order to model the latter, we consider two different types of agent and a discrimination factor, which influences the behaviour of agents and makes them more likely to join a rebellion.

2 Individual contributions

The project ran on two parallel paths. Barandun Silvio (B.S.), Fritzsche Alice (F.A.) and Guzzi Emanuele (G.E.) worked predominantly on the two-agent based model. Schmid Nicolas (S.N.) and Wöhler Jakob (W.J.) mostly on the bad-cops model.

The structure of the Python program was developed by G.E. and S.B.. Individual modifications integrated by each member of the team were adopted for the different scopes. Equal work contributions was achieved by increased responsibilities taken by other members in later stages of the project (e.g. tuning and analysing).

The present text was written according the distribution shown in Table 1.

S.B.	Sections 6.1.3-6.1.5
F.A.	
G.E.	Sections 6.1.1-6.1.2
S.N.	Simulation results and discussion of the bad cops model, Summary
W.J.	

Table 1: Written Contribution

3 Introduction and Motivations

3.1 Background

The social movement Black Lives Matter (BLM) began in 2013 in the USA. The mission of its supporter is to defeat white supremacy and police brutality against black people. After African-American George Floyd was killed in Minneapolis during a violent arrest on the 25th May 2020, BLM protests also took place in Australia, Asia and Europe; which made the national social movement become global.

Inspired by the recent events involving the social movement Black Lives Matter, we implemented the agent-based computational model of civil violence described by Epstein [Eps02] and we introduced some modifications, which will be presented in Section 4.

3.2 Epstein's model

In the agent-based computational model of civil violence described by Epstein, a central authority seeks to suppress rebellions. To represent the central authority and the rebels, the model introduces two categories of actors. The "Agents" are members of the general population and may be actively rebellious (so-called "active") or not (so-called "quiet"). The "Cops" are the forces of the central authority, their job is to arrest actively rebellious agents.

3.2.1 Specification of Agents and Cops

We start by describing the more complex one: the agent.
In order to model rebellions, we first need to represent the level of political grievance (**G**) that

any agent perceives from the government. **G** depends on only two components: hardship (**H**) and legitimacy (**L**). **H** is the agent perceived hardship, i.e., physical or economic privation. **L** is the perceived legitimacy of the regime, or central authority. **G** is now defined through the product of perceives hardship and the perceived "illegitimacy":

$$G = H(1 - L).$$

The next variable we need to represent is motivated by the fact that there are agents which are more inclined then others to take risks. For this purpose we define the agents level of risk aversion **R**. The last thing we need to take into account is that any agent, before joining a revolution, will estimate his probability of getting arrested. In order to model this, we first define the agents vision **v** as the number of position that the agent is able to inspect, i.e. "how far he can see", and then, we denote by $(\mathbf{C}/\mathbf{A})_{\mathbf{v}}$ the cop-to-active ratio within vision **v**. The value of **P** is given by the following equation:

$$P = 1 - e^{-k(C/A)_v}. \tag{3.1}$$

The constant k is set to 2.3 in order to have consistent values for $\mathbf{P} = 0.9$ when $\mathbf{C} = 1$ and $\mathbf{A} = 1$. Using the agent's risk aversion **R** and the estimated arrest probability **P**, we define the agent's net risk (**N**) as the product of the two: **N**=**RP**. We now have everything needed to define when an agent changes from a quiet to an active status or the other way around. If for a quiet agent the difference $\mathbf{G} - \mathbf{N}$ exceeds some non-negative threshold **T**, then that agent goes active. Otherwise, he stays quiescent. Moreover, if for an active agent the difference exceeds **T**, then he stays active. Otherwise, he goes quiescent. To conclude the agent's description, we define the agent's rule:

$$\text{If } G - N > T \text{ be active: otherwise, be quiet.} \tag{Agent rule A}$$

The description of the cops is much simpler. Analogously to the agent's vision we define the cops vision $\mathbf{v}^*$, with the property that $\mathbf{v} \geq \mathbf{v}^*$. Their behavioural rule is:

$$\text{Inspects all sites within } \mathbf{v}^* \text{ and arrest a random active agent.} \tag{Cop rule C}$$

In order to describe the way agents and cops move around we define for both the same movement rule:

$$\text{Move to a random site within your vision.} \tag{Movement rule M}$$

When a cop arrests an active agent, the latter goes to jail for a while and during this period he does not interfere with the system. The jail term is assumed to be drawn randomly from $U(0, \mathbf{J}_{\max})$, where $\mathbf{J}_{\max}$ is the maximum jail time. This term acts as a deterrent. Higher Jail time makes agents less active since they risk an higher punishment if they would.

3.2.2 The Run

We now have everything we need to run the model. The first thing to do is to set the values $\mathbf{L}$,$\mathbf{v}$, $\mathbf{v}^*$, $\mathbf{J}_{\max}$ and the initial agents and cops densities. Agents and cops are situated at random positions and agents are assigned random values of **H** and **R**. The model then iterates the three rules (Agent rule A), (Cop rule C) and (Movement rule M) until the user quits. An agent or a cop is selected at random, he moves according to rule M to a random position within his vision and then, depending on whether he is an agent or a cop, he acts with respect to rule A or C.

4 Description of the Model

In this section we will present our modifications to the model of Epstein.

4.1 Two-agent based model

The first modification we make to the original model is to consider two types of agents instead of one: the type 0 and the type 1 agents. The type 1 agents represent the discriminated part of the population. The type 0 agents represent the rest of the population. To implement the two different agents in the model, we introduce three new variables. The first one is the probability for an agent to be in class 1 (denoted by `p_class_1`). The second one gives us the probability, given an arrested is made, that the arrested agent is of type 1 (denoted by `prob_arrest_class_1`). The third one defines how many times $\mathbf{J}_{\text{max}}$ is bigger for type 1 then for type 0, i.e. how much longer then type 0 does type 1 stay in jail (denoted by `factor_Jmax1`).

The second modification introduces a discrimination factor $\mathbf{D}$ for the two types of agents. Our aim is to measure how much type 1 is discriminated, by taking the ratio

$$\frac{\#\text{ type 1 arrested}}{\#\text{ total arrested}}.$$

If the ratio is larger then `p_class_1` we could make the hypothesis that type 1 is discriminated. We want $\mathbf{D}$ to depend on the type of agent. In fact, it makes sense to assume that the discriminated agents type 1 have a higher discrimination factor then the type 0, since they are directly involved. We can think about the value of $\mathbf{D}$ for type 0 as a "discrimination of solidarity". This means that, although they are not directly discriminated, they feel empathy for the type 1 agent. The discrimination factor $\mathbf{D}$ is then given by:

$$\mathbf{D} = \mathbf{D}_{\text{const}} \cdot \left| \texttt{p\_class\_1} - \frac{\#\text{ type 1 arrested}}{\#\text{ total arrested}} \right|$$

Where the constant $\mathbf{D}_{\text{const}}$ depends on the type of agent.
Agents who feel discriminated are more likely to become active, therefore we need to take into account the value of $\mathbf{D}$ and change the agent's rule (Agent rule A) into:

New Agent rule: If $G - N + D > T$ be active: otherwise, be quiet.

On Section 6 we will see how these new variables are set in the standard model and discuss our results. Some of our runs will also include realistic data: in 2018 blacks represented 12% of the U.S. adult population (`p_class_1`) and 33% of the sentenced prison population (`prob_arrest_class_1`)[Gra20]. From 2012 to 2016 black men served sentences that were on average about 20% percent longer than those for white men for similar crimes (`factor_Jmax1`)[Com17]. We also need to consider that on average this minority has a shorter life expectancy and might easily bypass the census.

4.1.1 Expectations

We expect discrimination to increase activity of the agents but not in a drastic way. Actually, discrimination and activeness of the population could mutually influence each other in a non trivial way. Furthermore, analysing Epstein's model, we expect our model to be depended on randomness. Thus, for quantitative results, many runs might be necessary.

4.2 Bad cops model

4.2.1 Model

For the second model, the goal is to analyse the effect police brutality has on the general population. The original model of Epstein already provides the basis used. In the original model, the legitimacy of the government is equal across all agents and is varied as an input. Regarding police brutality, the model can be applied to this problem by defining the legitimacy

not from the government, but from the police as the force of the government itself.
If we do that, we need to simulate the change of legitmacy based on the police around the agents. As everybody has different experiences with the police, this means we change the legitimacy from a global variable across all agents to a variable different for each agent which is changed by the experiences done with police officers in vision.
To model the change in legitimacy, we need to simulate the police violence. The violence of each police officer is difficult to measure, as there are many reasons for a police officer to become violent. There are some officers which are turning violent faster then others, and the intensity of the aggressiveness is not similar for every officer. In order to keep the model simple, all these factors are reduced into a probability of bad_cops. This means that there is a certain fraction of cops which will be violent in every turn, and the rest will be peaceful. For this, each cop gets a factor `aggressiveness`. This factor will be picked up by each agent in vision, and will in turn affect the perceived legitimacy of each agent.

$$\text{perceived\_aggressiveness} = \sum_{\text{cops in vision}} \text{aggressiveness}$$

This means that the effect includes all cops in vision of the agent. In case there is a bad cop but a lot of good cops, the good cops will restrain the bad cop and lessen the effect. In case there are only good cops, this will lead to an increase in legitimacy.

The change of legitimacy based on the perceived aggressiveness is, regarding a lack of data, done with an exponential function. We use the illegitimacy instead of the legitimacy, as this is used anyway for the calculation of the net risk.

$$Il(n) = Il(n-1) \cdot e^{\text{perceived\_aggressiveness}}$$

The values used for a default run are shown in the Implementation.

4.2.2 Expectations

Epstein mentions an intelligent behaviour by avoiding cops and popping up in groups in case there are only few cops around. So there are outbreaks in case there are no cops. It is to be expected that there will be similar outbreaks in case there is a lack of cops in an area. It is to be expected as well that there will be similar outbreaks around bad cops, as the bad cops will influence the legitimacy and with this the grievance of the agents. On the other side, the presence of only good cops should help calming outbreaks, by reducing the active-to-cop ratio and increasing the legitimacy at the same time.

5 Implementation

We implemented the models presented in Section 4 in Python. The code is available here. Our run time analysis for both models concludes a asymptotic of $\mathcal{O}(T \cdot n^2)$ where n is the nation's dimension and T the total number of runs. (An initial naive $\mathcal{O}(T \cdot n^4)$ asymptotic was perfected by linear memory increase.)

6 Simulation Results and Discussion

6.1 Two-agent based model

6.1.1 Typical simulation

To start with, we discuss how does a typical simulation looks like: we will describe the qualitative behaviour of the system and some of the important aspects that are recurrent in our simulations. In this discussion we will encounter some of the main phenomena already presented in Epstein, as well as some new dynamics related to the discrimination[1] that we introduced in the model. In Figure 6.1 we can see how a typical run of our model goes: at random time we have peaks of active agents that disappear once the active agents get arrested or quiet. We can also observe that towards the end of the simulation the peaks get larger and more frequent and the system loses its stability.

We will now describe what are the causes of these peaks and how the discrimination influences them. The main reasons for peaks in activity of agents are: a random configuration of the nation, a peak in the discrimination and a combination thereof. In equation (3.1), we can see that a local depression of the cop-to-active ratio leads to a decrease of the agents' perceived arrest probability. Therefore, when at some iteration we have an area with a small number of cops, it will be more likely to get a peak of active agents there (an example of this phenomena can be seen in Figure 6.8). While this was already observable in Epstein model, we will now concentrate on the role played by discrimination, which is an aspect particular to our model. To start with, we expect a two-ways relation between discrimination and activity of the agents. On one hand, we implemented the agent to be sensitive to discrimination (see Section 4.1). Therefore, a peak in discrimination will lead to a peak of active agents. On the other hand, we biased the way agents get arrested in our model. Therefore, a peak of active agents will lead to a peak of arrested agents and since type 1 agents are more likely than type 0 agent to get arrested an increase in the discrimination will follow.

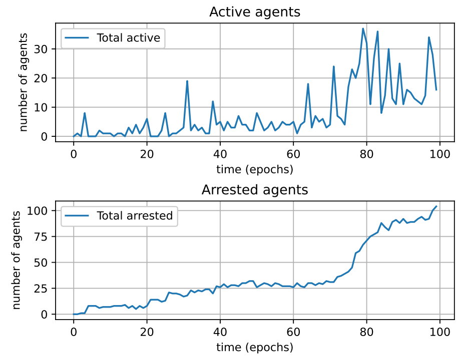


Figure 6.1: Number of active and arrested agents over time.

In Figure 6.2 we see that our expectation is met. Indeed, at the beginning of the simulation we have peak in discrimination that induces a peak in active agents[2] , while around epoch 40 we have a peak in active agents preceding a peak in discrimination. Note that towards the end of the simulation we have peaks that are not related to particular changes in the discrimination. They might be due to some random configuration of the nation (as we mentioned above) or to the fact that the system loses its stability (it presents larger and more frequent peaks of active agents) after some iterations. We also can observe that the value of discrimination, even if it oscillates a lot, does not present large peaks and after some iteration it converges to a certain value. We observed the same behaviour (with even more accentuate convergence of the discrimination) also for simulation carried out over a longer period of time. Varying the probability of arrest type 1 agent, brought also no substantial changes in the qualitative evolution of discrimination over time; however, an increase in the previous mentioned probability make the discrimination

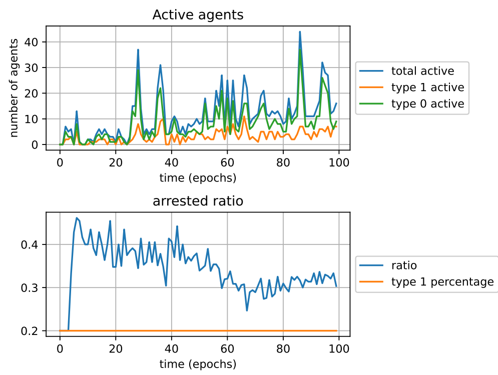


Figure 6.2: Number of active and type 1 arrested/total arrests ratio over time.

[1]We decided to measure discrimination as the ratio between the number of arrested type 1 agents and the total number of arrests. Therefore, when referring to discrimination we will actually refer to this ratio.

[2]Note that the peak in active agents at the beginning is small even though the peak in discrimination is large. This is due to the fact that we decided to reduce the weight of discrimination until at least 10 arrests are made. Indeed, if the first agent arrested is of type 1, then we will have a discrimination of 1. This shows why at the beginning the ratio we are considering is not a good indicator of discrimination.

converge to a larger value.

6.1.2 Inducing peaks of discrimination

Motivated by the observation of the previous section, we tried to substantially change the evolution of discrimination in the model by inducing artificially peaks in discrimination. In order to achieve that, we constructed the following two scenarios in our model. In scenario 1, we changed the model such that 80 type 1 agents, independently on whether they are active or quiet, get arrested at epoch 20. While in the second scenario, from epoch 10 up to epoch 20, at each iteration 10 agent of type 1 get arrested (again independently on their status). We will now discuss the results of this experiments.

In Figure 6.4, we can observe how at epoch 10 a large peak in discrimination is artificially induced. By looking at the arrested agents, we see that, as a consequence of the massive arrest of type 1 agents, a large amount of type 0 agent (the non discriminated type) arrests follows. Even though agent of type 0 are not systematically arrested, after epoch 10 the peak of arrests of type 0 agents is comparable to the peak of type 1 agent arrests at epoch 20. Moreover, in the following epochs the number of type 0 agents that get arrested continue to grow. In this way the model reduces the discrimination and tries to reach a more stable configuration. This is even more apparent in the second scenario: instead of growing until epoch 20 the discrimination stabilises and then start decreasing already around epoch 15. Indeed, by looking at Figure 6.4, it can be seen that around epoch 15 type 0 agents get arrested at the same speed as type 1 agents (even though they are not systematically discriminated). This phenomena stops the discrimination to grow further and make the system converge to a more stable configuration. Finally, we remark that the qualitative influence on the model is similar for both the scenario: Indeed, it can be noticed that, even though the maximal jail term in our simulation is around 23 epochs [3], the two perturbation considered in scenario 1 and 2 have a much longer influence. Indeed the mean number of active agents and the peaks are larger in Figure 6.3 and 6.4 than in Figure 6.2 even after epoch 50. Moreover, we notice that also the discrimination converges slower and stays higher for a longer period. We can conclude that the model present some inertia in its discrimination dynamics: On one hand, as we discussed in Section 6.1.1, the discrimination converges and does not allow for large changes in its value; On the other hand if we induce artificially some perturbations as in scenario 1 e 2, the model will need a relative long time to reach a more stable configuration and to erase the effects of the perturbations.

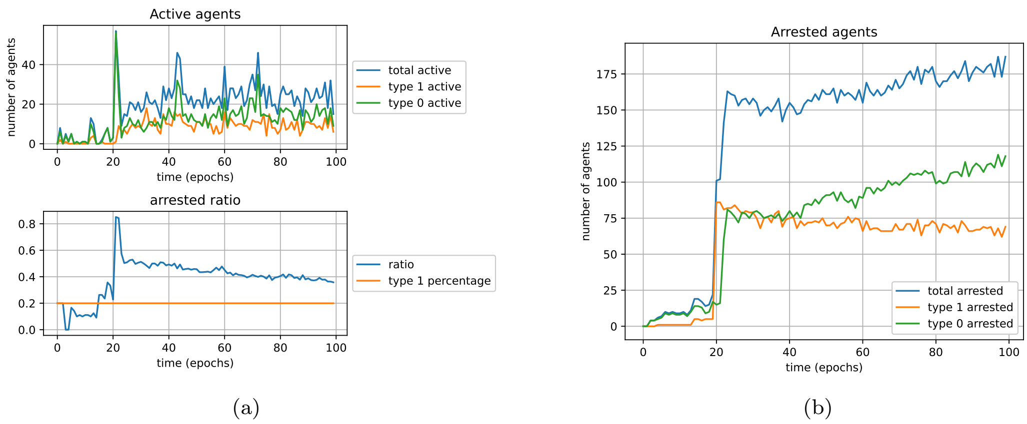
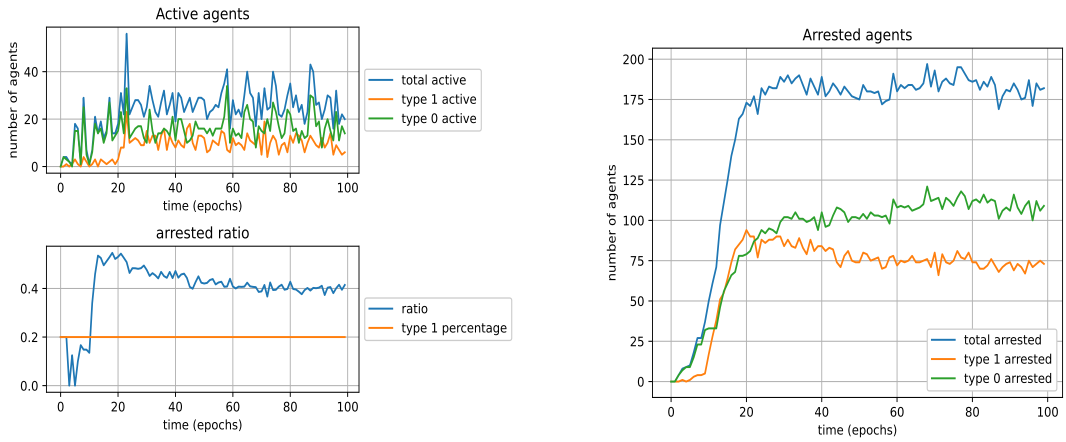


Figure 6.3: Scenario 1 results

6.1.3 Discrimination does stir up rebels

We want to analyse now, if the model behaves as expected when we introduce discrimination. In order to do that we run both the Epstein model (with two classes of agents) which has

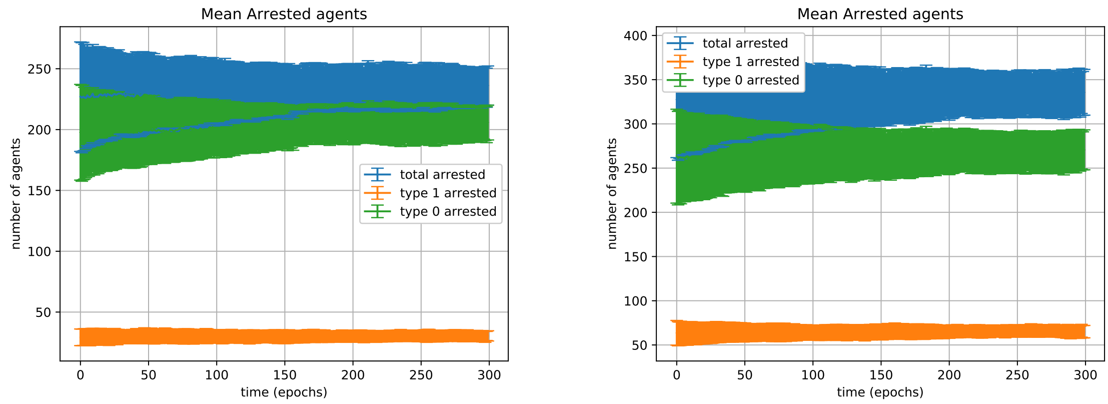
[3]For this simulation the maximal jail term was set to 15, but for type 1 agent the jail term might be 1.5 times longer.



(a) (b)

Figure 6.4: Scenario 2 results

no discrimination parameters and our model presented in Section 4.1. The discrimination parameters are demographically realistic as presented there. The simulation runs for 300 time iterations (i.e. 300 days) and in order to reduce the dependency on random choices we compute averages over 30 simulations. The results are shown in Figure 6.5.



(a) No discrimination (b) Discrimination

Figure 6.5: Comparison of arrested agents over time with and without discrimination.

We observe a substantial increase, about 40% higher, from Figure 6.5(a) without discrimination to Figure 6.5(b) with discrimination. Similar behaviour is observed in the evolution of active agents as shown in Figure A.1.

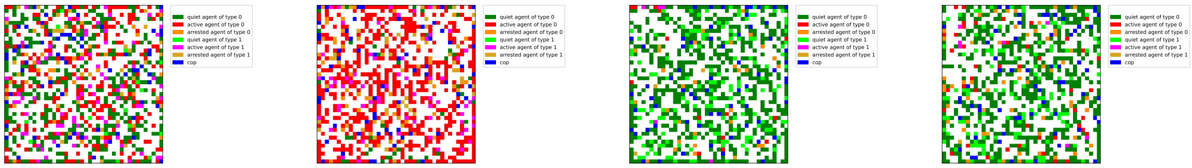
We particularly observe that in both model the standard deviation firstly reduces and then stabilises. In Figure A.2 we compare the results of a mean over 30 and over 150 rounds. Dependency on randomness is shown to be particularly present in the short term.

From the above presented results we can conclude that the model indeed behaves as expected after introducing the discrimination parameters.

6.1.4 Extreme government discrimination stabilises the nation

The phenomena we want to present here need the chance for very active agents, so as presented in Section 3.2.1 we will reduce the $\mathbf{J}_{\text{max}}$ parameter to 5 days.

We first look at an introductory example where type 1 agents represent 20% of the total population. In a first scenario, we consider very discriminating cops but a correct government, i.e. `prob_arrest_class_1 = 0.6, factor_Jmax1 = 1`. In a second scenario, we consider the same kind of cops, but with a very discriminating government, i.e. `prob_arrest_class_1 = 0.6, factor_Jmax1 = 5`. In Figure 6.6, the influence of government discrimination is made very clear. Despite our forecasts, government discrimination seems not to not stir revolutions, but rather to discourage them.



(a) No Discrimination, 5$^{\text{th}}$ Day (b) No Discrimination, 15$^{\text{th}}$ Day (c) Discrimination, 5$^{\text{th}}$ Day (d) Discrimination, 15$^{\text{th}}$ Day

Figure 6.6: Simulation snapshots with and without discriminating government.

A natural question one might ask now, is if this qualitative behaviour in rather unrealistic example may also be observed in more realistic situations.

This is indeed the case, as if we consider the realistic demographical parameters from Section 4.1 we observe the values presented in Figure A.5.

Despite the high variance in both graphs, we can clearly observe a significantly smaller number, about 70% less, of active agents in the case of government discrimination. Furthermore, the short term behaviour exposed in Figure 6.6 is confirmed in the long term without notable differences.

The same behaviour might be observed looking at the numbers of arrested agents as shown in Figure A.3. The clear conclusion from this observation is the following. In presence of police discrimination (i.e. there is a type of agent more likely to be arrested), as presented in Section 6.1.3, agents are more keen to get active, so rebellions and revolutions are more likely. An effective method to repress these rebels is to introduce government discrimination (i.e. increase jail time for the type discriminated by the police). We refer to Figure A.4 for a quantitative asymptotic behaviour of the "unrealistic" example exposed above. Comparing this last mentioned figures and Figure A.5 one notices that the effectiveness of this measure in reducing the active agents is much higher with strongly discriminating cops.

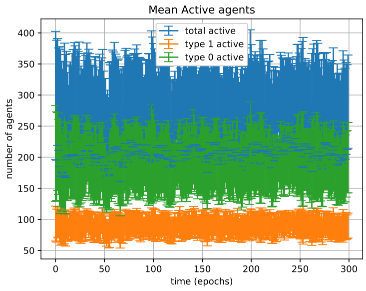
Despite effective, this method is obviously ethically not correct and as such does not present a solution to the police-discrimination induced rebellions.

6.1.5 Locally discrimination-sensitive agents are less rebellious

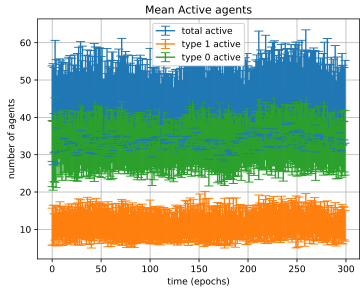
As described in Section 4.1, our model assumes that agents are able to perceive the discrimination the whole nation. This is realistic in the view of presence of social media, news channels etc. Nevertheless, we investigate here which is the influence of a local discrimination sensibility to the revolutionary set-up of Section 6.1.4. The working hypothesis is that, as discriminating governments are generally less fair and thus more likely to operate censure, a reduced discrimination vision is realistic in the a discriminating government set-up.

We summarise in Figure 6.7 the results obtained for the four possible cases. "Global discrimination-vision" means that the agents are able to compute the ratio $\frac{\#\text{ type 1 arrested}}{\#\text{ total arrested}}$ of the whole nation; while "Local discrimination-vision" means that they are only able to compute that ration considering agents within their vision $\mathbf{v}$.

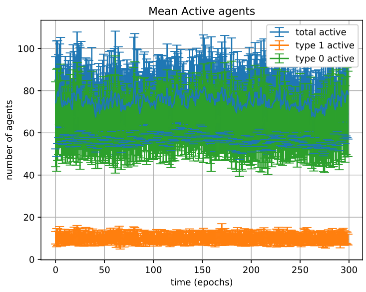
One might observe that the scenario with less rebelling agents is the one with local discrimination vision and a discriminating government. However, the introduction of a second discriminating factor (i.e. comparing it with Figure 6.7(b) and Figure 6.7(c)) is no much less effective in reducing active agents than the first introduced discrimination.



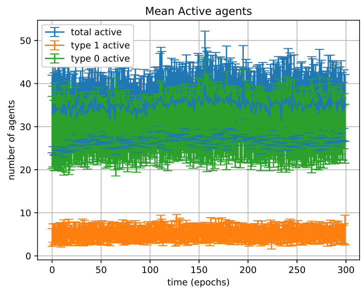
(a) Global discrimination-vision (non-discriminating government).



(b) Local discrimination-vision (non-discriminating government).



(c) Global discrimination-vision (discriminating government).



(d) Local discrimination-vision (discriminating government).

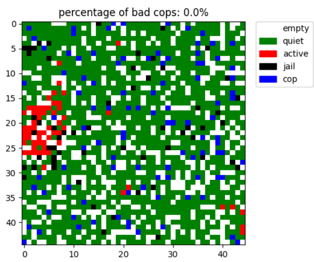
Figure 6.7: Global vs local discrimination vision.

6.2 Bad Cops Model

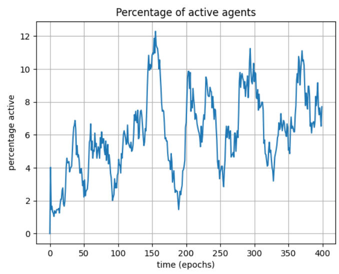
6.2.1 Reproducing Epstein's model

The most sensitive factor in the model was the ratio between the influence of the perceived illegitimacy and the estimated arrest probability. This means we had to choose if we gave more importance to the fear of being caught or the indignation caused by the bad cops. There it was due to a lack of real data that we decided to go with a model where agents behaved in an intelligent way - an increase around bad cops, but not a complete outbreak. To verify the model, we started with some results that we got with 0% of bad cops, which should behave the same as Epstein's model.

We see on the left of Figure 6.8 that a lack of blue cops in a small region leads to a cluster of those red active agents there, which is what we expected and it is the behaviour which is analysed. Because the more agents are active in a region, the lower is the cop-to-active ratio and the more agents get active. Looking at the percentage of active agents in Figure 6.8 we can notice peaks, which correspond to the appearance of those clusters.



(a) Cluster of active agents



(b) Percentage of active agents

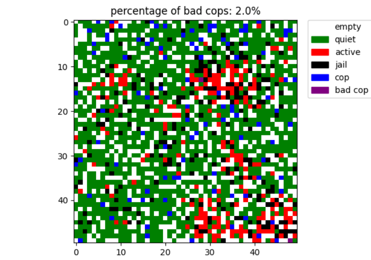
Figure 6.8: Simulation with 0% of bad cops

In this configuration of the parameters, the number of active agents actually stays pretty low and the peaks always come down again after a certain amount of time. This fits to the periodical development Epstein describes, and the model works as intended.

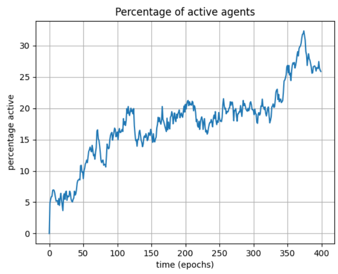
6.2.2 Influence of the bad cops

The simulation shown here was with 1750 agents, 100 cops, we gave the bad cops an aggressiveness of 1 and the good cops an aggressiveness of -0.12, and the vision of cops and agent was 4. Furthermore we had some fixed general scaling factors as seen in the code.

For the bad cop model, what interested us was to see how a change in the percentage of bad cops influences the number of active agents, and whether a higher number of cops would calm the agents or make them more active because of the bad cops. In Figure 6.9 we put in a very small percentage of bad cops, in this example 2%, without changing any other parameter. If we compare the initial situation with no bad cops, we can notice here that there also are some peaks but they don't really come down, they seem to add up. After a longer amount of iteration, we see that the amount of active agents stabilises at a percentage of active agents which is 3 to 4 times higher than with no bad cops. We also noticed that in the simulation that some of the clusters occur at random positions, but most of them are around one or two bad cops as you can see in Figure 6.9. With 5% of bad cops, the percentage of active agents goes up to 40% of the population, and almost 20% of the agents are in jail as you can see in Figure 6.10. This situation would be unsustainable for any government. Of course, this is only a qualitative approach of the problem, and absolutely not a quantitative one.

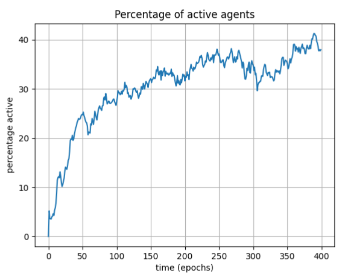


(a) Cluster of active agents next to the bad cops

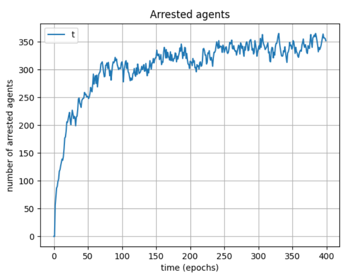


(b) Percentage of active agents

Figure 6.9: Simulation with 2% of bad cops



(a) Percentage of active agents



(b) Number of arrested agents

Figure 6.10: Simulation with 5% of bad cops, 100 cops and 1750 agents

We thought it would be interesting to see what happens if the cop density is higher. Normally, in the Epstein model, more cops means less active agents. But with this model, more cops also means more bad cops (if we keep the percentage of bad cops the same). So, we put 200 cops instead of a hundred in our simulation, keeping the percentage of bad cops at 5%. We observe in Figure 6.11 that the percentage of active agents goes down to 25%, which is lower than what we got with 100 cops and 5% of bad cops, but about the same as if there were 100 cops and

2% of bad cops. In this model, more cops means also more people in jail, because at every iteration, each cop can arrest one active agent, so the limit of people in jail is twice as much as with 100 cops. That means that if we see less active agents, it is also due to the fact that more of them are in jail.

It is obvious that those results do not represent the reality, but we can observe interesting behaviours. The first noticeable observation is how the clusters around the bad cops can be way bigger than the vision of the cops (which was 4 in these simulations) as you could see in Figure 6.9. In other words, the bad influence of a policeman can spread on a large region. The second observation is that even with bad cops, if we have a higher amount of cops, the agents will be less active. But we saw that when we set the percentage of bad cops from 2% to 5% we had to double the amount of cops to get about the same amount of active agents. So, if too many cops behave badly, we need to have a lot of cops to compensate those negative effects, which could result in a police state.

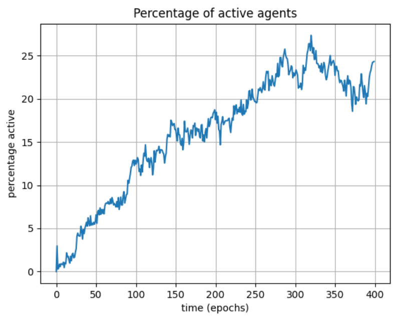


Figure 6.11: Simulation with 5% of bad cops, 200 cops and 1750 agents

7 Summary and Outlook

7.1 Summary

These two models of civil violence are oversimplifications of reality and thus can't represent quantitative results. The parameters we chose in a rather arbitrary way also have a big influence on the results. However, these results can be interpreted qualitatively, by observing how a change in one parameter influences the system. Here are three observations that we think we can learn from those simulations:

- Discrimination has some inertia and the model does not allow rapid changes in its value.
- Discrimination substantially increases civil rebellion.
- The easiest way to avoid rebellion is to decrease the number of bad cops. But if we can't, adding way more cops also solves the problem.

7.2 Outlook

References

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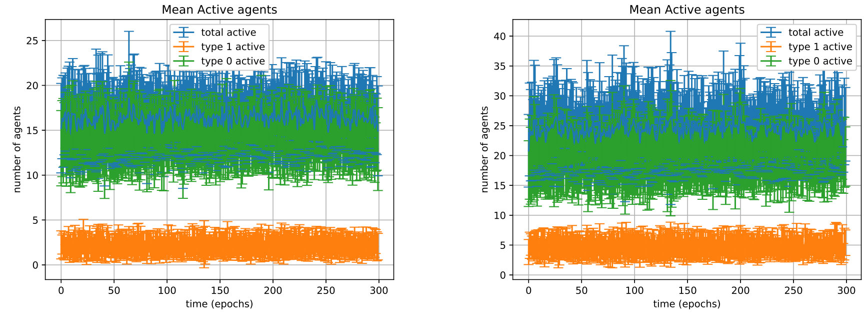
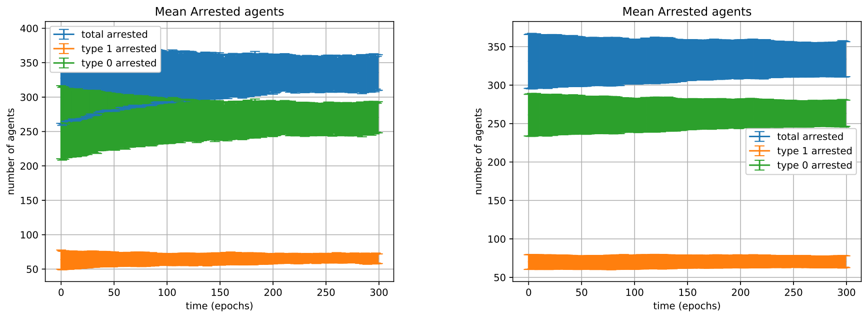
A Extra figures



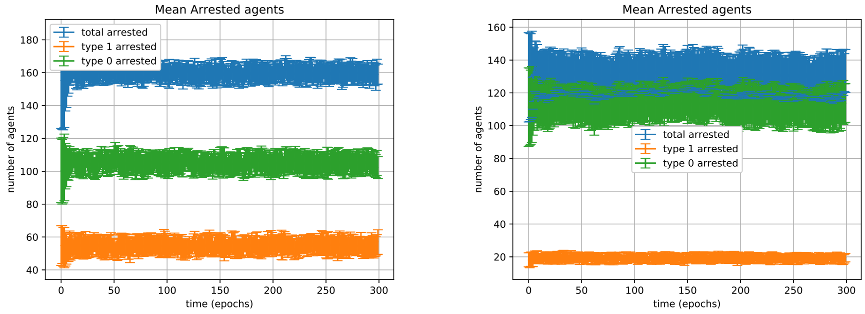
(a) No discrimination (b) Discrimination

Figure A.1: Comparison of active agents over time with and without discrimination.



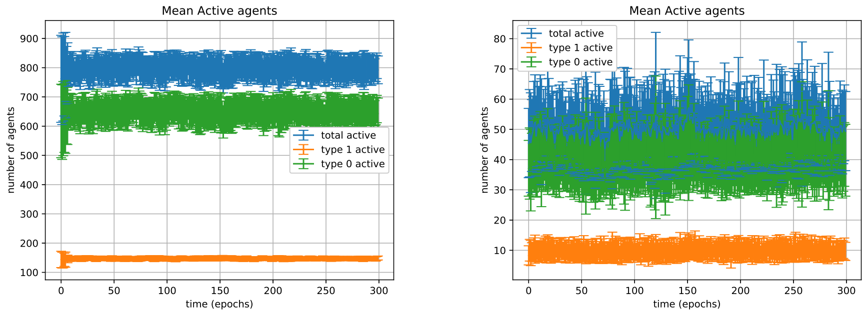
(a) 30 validation rounds (b) 150 validation rounds

Figure A.2: Comparison of random dependency of arrested agents over time with discrimination.



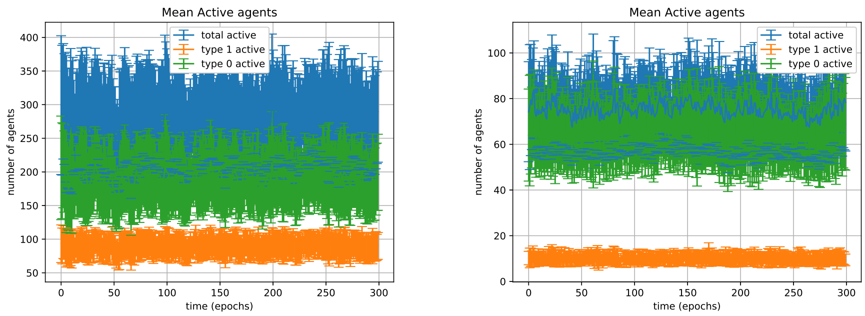
(a) Same jail time (b) 5 times more jail for Type 1

Figure A.3: Arrested Agents realistic example



(a) Same jail time (b) 5 times more jail for Type 1

Figure A.4: Active Agents borderline example



(a) Same jail time (b) 5 times more jail for Type 1

Figure A.5: Active agents with and without government discrimination.