Rebel Rebel

Implementation:

Assumptions:

For the implementation of this model, I used some assumptions when the instructions weren't conclusive or in order to make the model easier to implement.

- Jail: when an agent is put in jail, his spot becomes empty, resulting in more empty spots on the grid. At each round, the remaining time of all "prisoners" decrease and when their time is done, they will be placed back into a random empty spot on the grid.
- Rounds: to avoid asynchronous implementation, at each round we start by prompting the agents\cops actions from top left of the grid to bottom right. For each spot we check if it's empty, agent or cop. If it's not empty, we start by moving the person according to its vision and the model's rules and then we activate his action (decide if should be active or not for agents and put actives in jail for cops).
- Moving agents\cops: since the exact method of moving persons around wasn't explained, the way I chose is by checking all the empty spots a person's vision and then move it to one of them randomly. I realize it may not be exactly according to Epstein's model but I believe it's a reasonable assumption and it still represents the model loyally.

Questions

Question 3

In order to see the impact of different values for cop density, jail term and legitimacy level, I decided to perform 100 rounds for each value. At each round, the rebeliousness level is recorded and at the end of the 100 rounds, I saved the mean of the rebeliousness levels and this is what will be plotted for a specific value.

In addition, the rebeliousness level was measured by dividing the number of total active agents by the number of total agents. So the rebeliousness level is a percentage representing the ratio between active and total number of agents. The reason I did that instead of just the number of actives is because changing the cop density will mean there will be less agents in the first place and so less active agents will be logical eventhough it could be that there are more actives per agents. The agents in jail are not counted when calculating the rebeliousness levels.

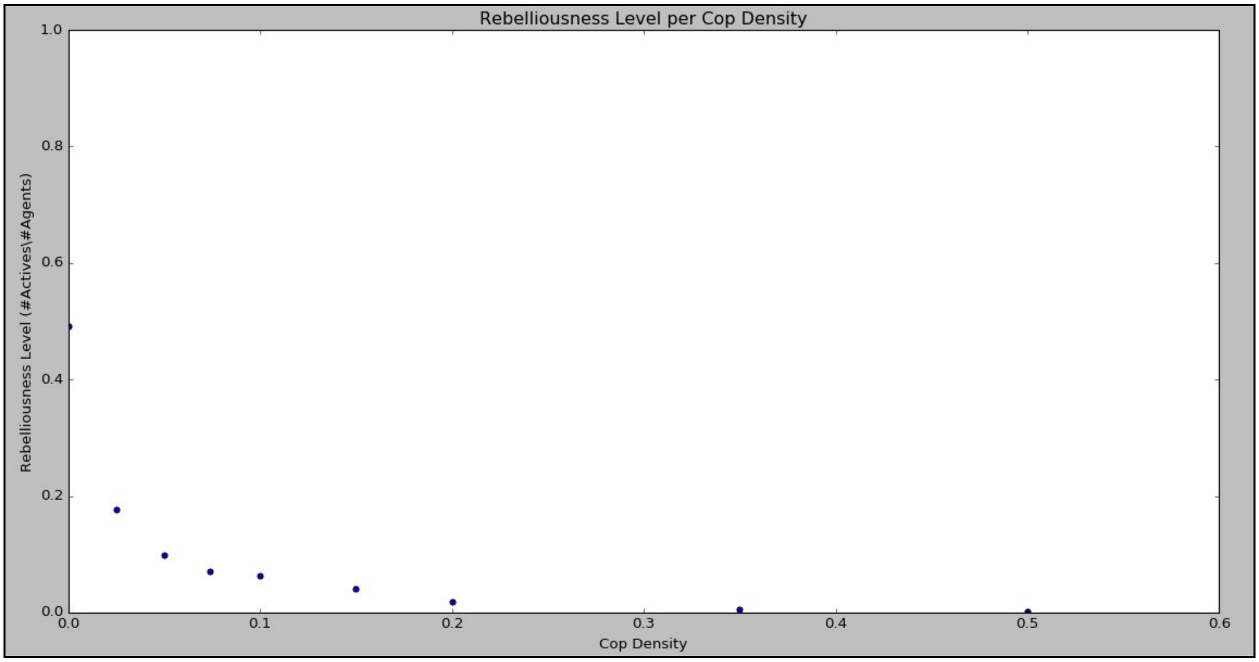
Cop Densities

As we can see in the following graph, increasing the cop density results in less rebeliousness. This makes sense due to two factors. Firstly, in expectation, there are more cops surrounding each agent and so the risk is higher when the agent thinks about going active and therefore more agents would rather not rebel. Secondly, more cops means more enforcement, therefore more agents going to jail, this means that there is less influence on other agents to rebel in addition to the fact that there are less actives since they are in jail. I'll remind that the agents in jail are still counted as agents when calculating rebelliousness levels.

So when the cop density is low, we can see that the rebeliousness level is high. The reason the rebeliousness is not 100% when the cop density is zero is because eventhough there are no cops at all, some agents will still choose not to rebel because they have different values for hardship, risk etc. This combined with a relatively high level of legitimacy and a low threshold means they don't believe the situation requires rebellion.

We can see that the rebeliousness levels quickly drops to zero as the cops density increases. I'll remind also that the density for entire players (non empty spots) is 0.7 and therefore a cop density of 0.35 means half of the "players" are cop and 0.5 means most of the "players" are cops.

Used values: 0, 0.025, 0.05, 0.074, 0.1, 0.15, 0.2, 0.35

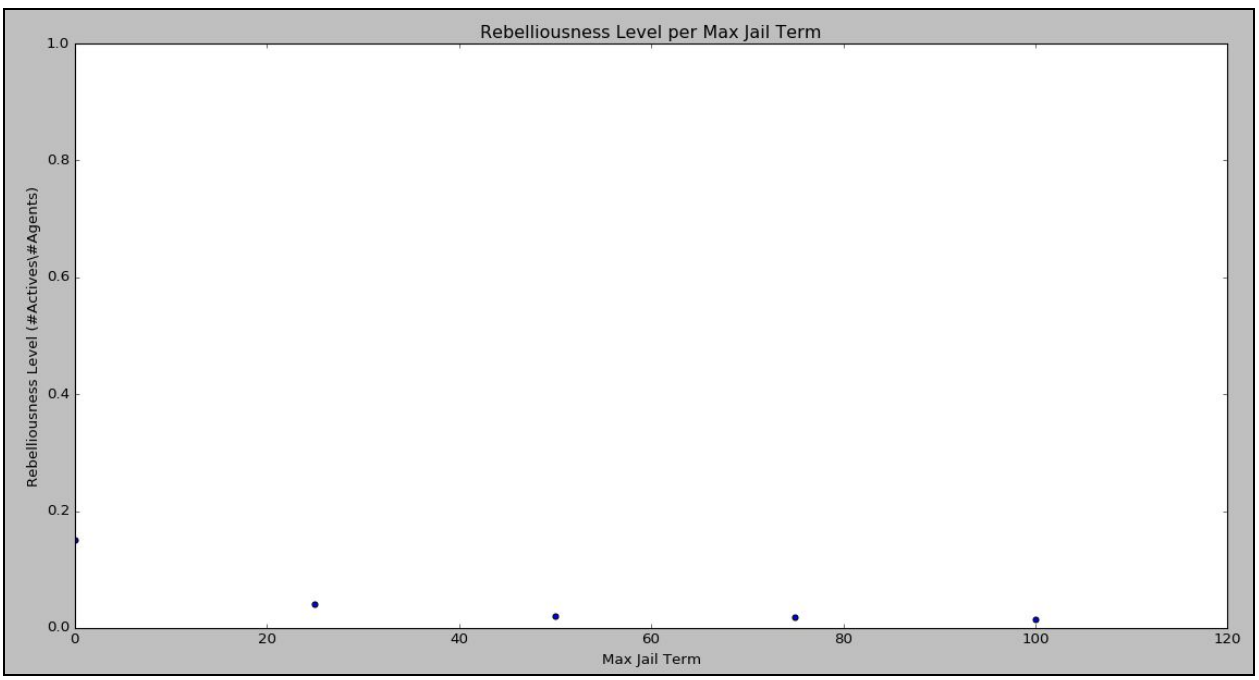


Rebelliousness Level per Cop Density
Rebelliousness Level (#Actives\#Agents)
Cop Density
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.1
0.2
0.3
0.4
0.5
0.6

Max Jail Terms

We can see that the max jail term does affect the rebeliousness level, but not as significantly as the cop density. While the rebeliousness decreases as the max jail term increases, the slope is less important than the cop density. This could be explain by the fact that in our model, the Alpha parameter is set to 0, therefore the max jail term doesn’t affect the reasoning of the agents when considering to go active.
The jail term does influence the rebelliousness in the sense that when agents are in jail, they’re not counted as actives but are counted as agents, which results in a lower rebelliousness level. Additionally, more agents in jail means less active agents encouraging other agent to rebel and consequently less rebelliousness.

Used values: 0, 25, 50, 75, 100

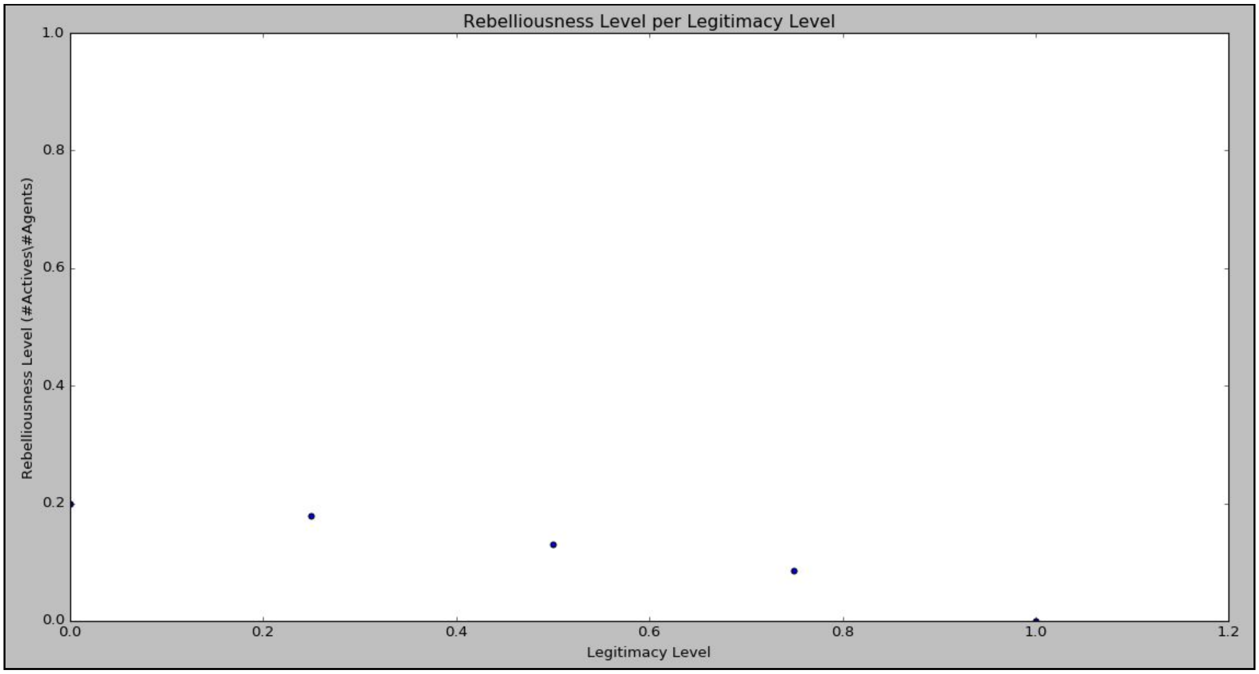


Legitimacy Levels

The results here are similar to the results of the max jail terms. We see that although the rebellious level decreases as the legitimacy increases, the slope is not as drastic as in the case of the cop density.

The legitimacy level affects the rebellious level when an agent considers if he should rebel or not. If the situation is legitimate, then the odds for an agent to rebel lessens.

Used values: 0, 0.25, 0.5, 0.75, 1



Question 4 and 5: Full Factorial and Multiple Regression

In order to run the full factorial, I used the followin values for each parameter:

Cops Density - 0, 0.025, 0.05, 0.1, 0.2, 0.35

Max Jail Term - 0, 25, 50, 75, 100

Legitimacy Level - 0, 0.25, 0.5, 0.75, 1

It is possible to use more values, however the values chosen seem to give a good understanding of the impacts of the different parameters on the Rebelliousness Level within a reasonable runtime.

After getting the results of the full factorial, I used Google Sheets to run a multiple regression. The results quite represent the graph from the previous question. We see that the parameter that has the most impact on the rebelliousness level is the Cop Density (-1.056) then the Legitimacy Level (-0.3) and lastly the Max Jail Term (-0.002).

The full factorial data can be found in the “Full Factorial Data” section at the bottom.

Regression Statistics						
Multiple R	0.6317598525					
R Square	0.3991205113					
Adjusted R Squa	0.3867736725					
Standard Error	0.2302360405					
Observations	150					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	3	5.140627551	1.713542517	32.32572462	0	
Residual	146	7.739260617	0.05300863437			
Total	149	12.87988817				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.5883342696	0.04602903995	12.78180623	0	0.497364978	0.6793035612
Cop Density	**-1.056235056**	0.1552067359	-6.805342887	0.00000000242	-1.36297721	-0.7494929033
Max Jail Term	**-0.00227938076**	0.00053170735	-4.286908427	0.00003275087	-0.00333021827	-0.00122854324
Legitimacy	**-0.302124423**	0.05317073599	-5.682156122	0.000000069777	-0.4072081744	-0.1970406717

Question 6:

In order to calculate the individual deceptive behavior, meaning the situation of him not to be active although he has a high level of hardship involves several factors. First of all, for the individual to have a deceptive behavior, there has to be a discrepancy between his feelings (hardship) and his rebellion state (active or passive). The inidividual’s deceptive behavior can be explained by the presence of cops around him.

(cop*hardship) * (1-is_active)

If the number is close to 1 then there is a high discrepancy since the hardship is high and the cop density is high, yet the individual is not active.
If it’s zero or close to zero then this means that either the indivual is active and therefore he doesn’t “hide” or that the cop and is low and hardship is low therfore there is no discrepancy as explained in the paper.

Pseudo Code

```
move_person(location):
        If  location is empty:
                Return
        Else:
                Empties = get_all_empty_spots_in_person_vision()
                move_person_to_random_empty(empties)
cop.arrest():
        Actives_coords = get_all_actives_in_vision(cop.vision)
        Random_active = random_pick(actives_coords)
        Random_active = empty
        get_person(random_active).set_jail_time(random(0, max_jail))
```

Full Factorial Data

Cop Density	Max Jail Term	Legitimacy	Rebel Level
0	0	0	0.896428571

0	0	0.25	0.853571429
0	0	0.5	0.771428571
0	0	0.75	0.610714286
0	0	1	0
0	25	0	0.897321429
0	25	0.25	0.872321429
0	25	0.5	0.826785714
0	25	0.75	0.596428571
0	25	1	0
0	50	0	0.892857143
0	50	0.25	0.878571429
0	50	0.5	0.800892857
0	50	0.75	0.596428571
0	50	1	0
0	75	0	0.904464286
0	75	0.25	0.869642857
0	75	0.5	0.800892857
0	75	0.75	0.597321429
0	75	1	0
0	100	0	0.894642857
0	100	0.25	0.858928571
0	100	0.5	0.8
0	100	0.75	0.6125
0	100	1	0

0.025	0	0	0.865462963
0.025	0	0.25	0.814907407
0.025	0	0.5	0.684351852
0.025	0	0.75	0.398703704
0.025	0	1	0
0.025	25	0	0.258611111
0.025	25	0.25	0.236203704
0.025	25	0.5	0.18537037
0.025	25	0.75	0.116944444
0.025	25	1	0
0.025	50	0	0.15962963
0.025	50	0.25	0.146388889
0.025	50	0.5	0.121388889
0.025	50	0.75	0.073611111
0.025	50	1	0
0.025	75	0	0.139444444
0.025	75	0.25	0.125185185
0.025	75	0.5	0.108518519
0.025	75	0.75	0.056759259
0.025	75	1	0
0.025	100	0	0.127592593
0.025	100	0.25	0.112685185
0.025	100	0.5	0.095833333
0.025	100	0.75	0.052962963

0.025	100	1	0
0.05	0	0	0.797305101
0.05	0	0.25	0.737824832
0.05	0	0.5	0.577478345
0.05	0	0.75	0.24533205
0.05	0	1	0
0.05	25	0	0.14080847
0.05	25	0.25	0.125890279
0.05	25	0.5	0.097978826
0.05	25	0.75	0.061405197
0.05	25	1	0
0.05	50	0	0.101154957
0.05	50	0.25	0.084696824
0.05	50	0.5	0.07093359
0.05	50	0.75	0.039653513
0.05	50	1	0
0.05	75	0	0.089316651
0.05	75	0.25	0.076130895
0.05	75	0.5	0.06053898
0.05	75	0.75	0.030317613
0.05	75	1	0
0.05	100	0	0.081424447
0.05	100	0.25	0.06987488
0.05	100	0.5	0.056207892

0.05	100	0.75	0.026467757
0.05	100	1	0
0.1	0	0	0.7034375
0.1	0	0.25	0.538645833
0.1	0	0.5	0.349166667
0.1	0	0.75	0.155
0.1	0	1	0
0.1	25	0	0.095104167
0.1	25	0.25	0.0734375
0.1	25	0.5	0.0565625
0.1	25	0.75	0.038333333
0.1	25	1	0
0.1	50	0	0.0696875
0.1	50	0.25	0.053229167
0.1	50	0.5	0.041458333
0.1	50	0.75	0.02625
0.1	50	1	0
0.1	75	0	0.058645833
0.1	75	0.25	0.048333333
0.1	75	0.5	0.027604167
0.1	75	0.75	0.016145833
0.1	75	1	0
0.1	100	0	0.059166667
0.1	100	0.25	0.041354167

0.1	100	0.5	0.025416667
0.1	100	0.75	0.013541667
0.1	100	1	0
0.2	0	0	0.543554443
0.2	0	0.25	0.385982478
0.2	0	0.5	0.222152691
0.2	0	0.75	0.087859825
0.2	0	1	0
0.2	25	0	0.04505632
0.2	25	0.25	0.036795995
0.2	25	0.5	0.025657071
0.2	25	0.75	0.011514393
0.2	25	1	0
0.2	50	0	0.030413016
0.2	50	0.25	0.021276596
0.2	50	0.5	0.014392991
0.2	50	0.75	0.007133917
0.2	50	1	0
0.2	75	0	0.026533166
0.2	75	0.25	0.016520651
0.2	75	0.5	0.010262829
0.2	75	0.75	0.004380476
0.2	75	1	0
0.2	100	0	0.017897372

0.2	100	0.25	0.009762203
0.2	100	0.5	0.007008761
0.2	100	0.75	0.004505632
0.2	100	1	0
0.35	0	0	0.434107143
0.35	0	0.25	0.279285714
0.35	0	0.5	0.153392857
0.35	0	0.75	0.042857143
0.35	0	1	0
0.35	25	0	0.025535714
0.35	25	0.25	0.020714286
0.35	25	0.5	0.012321429
0.35	25	0.75	0.002857143
0.35	25	1	0
0.35	50	0	0.014464286
0.35	50	0.25	0.010714286
0.35	50	0.5	0.006607143
0.35	50	0.75	0.002142857
0.35	50	1	0
0.35	75	0	0.01125
0.35	75	0.25	0.008928571
0.35	75	0.5	0.005535714
0.35	75	0.75	0.001428571
0.35	75	1	0

0.35	100	0	0.007321429
0.35	100	0.25	0.005357143
0.35	100	0.5	0.002142857
0.35	100	0.75	0.001607143
0.35	100	1	0