BMI 500: Model-Based Machine Learning
Problem Set 1

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GitHub Repository: `https://github.com/kcampbell824/campbell-bmi500-week11`

1. Simple SIR Model for Pandemic Spread

1a/b. The implemented SIR model can be found in `problem1/Campbell_HW1.ipynb` in the github repository linked above. The code for this implementation was inspired by the OSET model described in lecture[1]. Figure 1 illustrates the results of running the model with S(0) = 999, I(0) = 1, R(0) = 0, beta = 0.3, and gamma = 0.1. The infectious population peaks around 40 days with about a third of the population actively infected. Note that the recovered proportion converges below 1 and the susceptible proportion converges to a nonzero value, indicating that not all people in this population are infected over the course of the simulation.

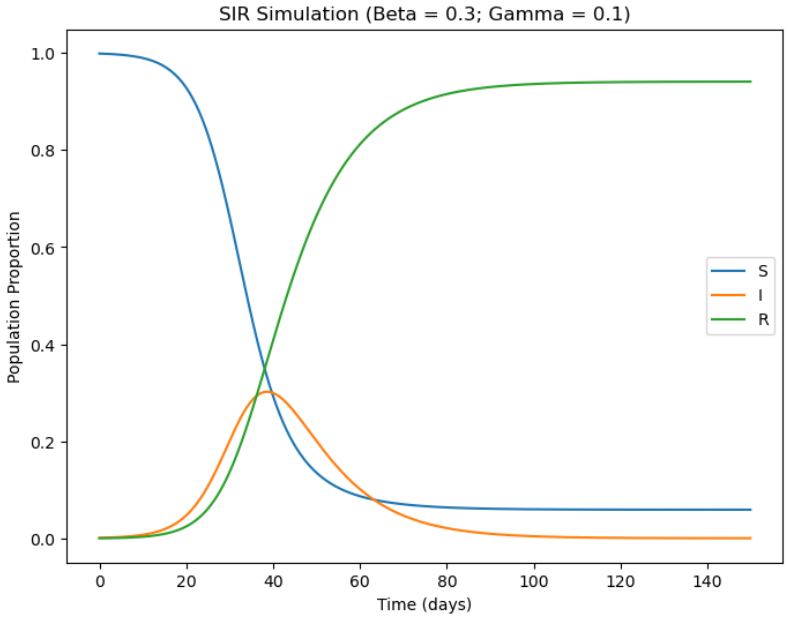

Figure 1: SIR simulation of pandemic spread over 150 days. Infection rate (beta) = 0.3 and recovery rate (gamma) = 0.1

1c. Figure 2 below demonstrates how different combinations of beta and gamma affect pandemic dynamics. We can explore the impact of increasing basic reproductive rate by holding recovery rate constant and increasing the infection rate (moving down a column in Figure 2). Increasing basic reproductive rate causes the infected curve peaks to a higher proportion earlier in the simulation, illustrating that the infection is spreading much faster in the population. Increasing basic reproductive number also makes it more likely that all people will eventually become infected through the course of the simulation, so the recovered population will rise to 1 and susceptible population will drop to 0 earlier in the simulation. Instead, if we hold infection rate constant and increase recovery rate (decreasing basic reproductive rate along a row of Figure 2), the infected population curve exhibits a lower peak amplitude and larger spread. Additionally, more individuals make it through the entire simulation without an infection (i.e. susceptible proportion converges to a larger, nonzero value).

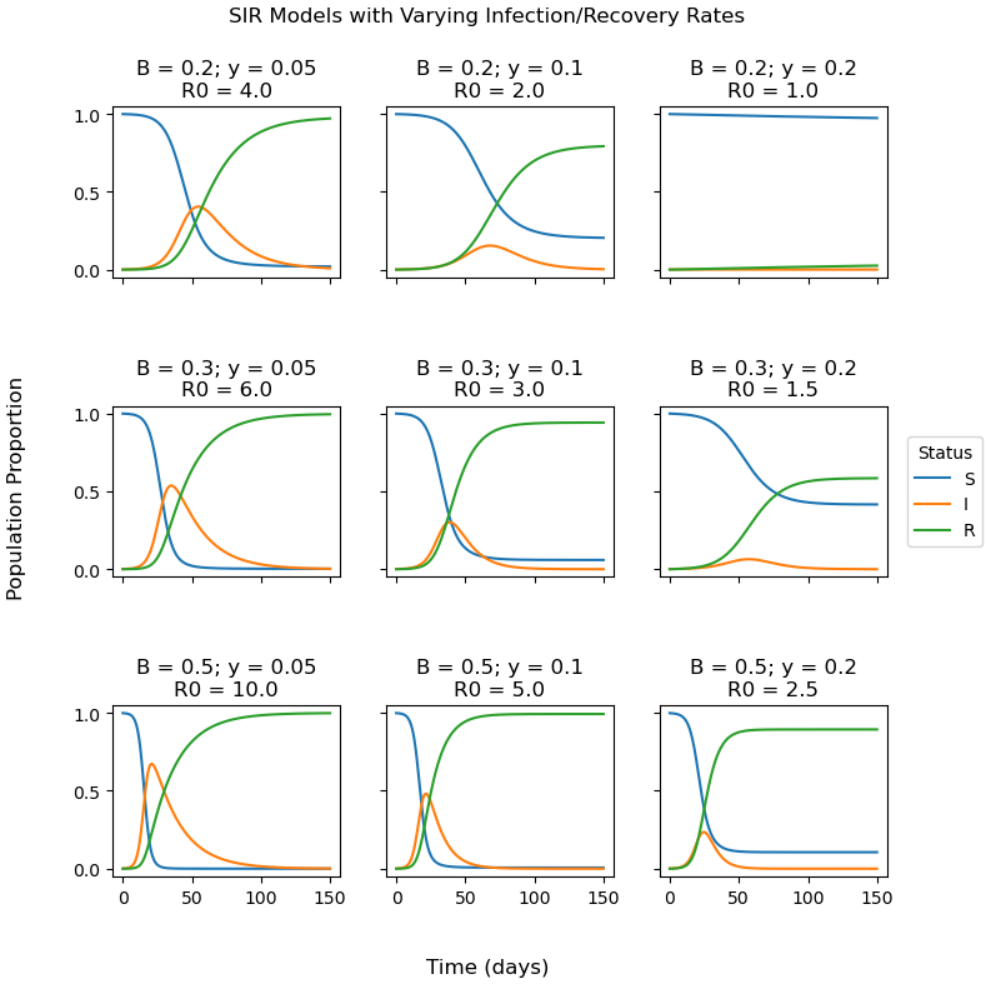

Figure 2: Pandemic dynamics over 150 days with varying infection (beta) and recovery (gamma) rates. R0 represents the basic reproductive number (beta/gamma)

4. Agent-based Modeling of Pandemic Spread

4a-c. Environment and Agent behavior are defined in `problem4/environment.py` and `problem4/agent.py`, respectively in the GitHub repository linked above. A simulation can be run using the following set of calls:

```
from environment import Environment
from agent import Agent

# Define environment & run simulation of 200 time steps
size = 50
p = 0.05
q = 0.02

e = Environment(size, p, q)
e.populate_all(n_sus = 95, n_inf = 5, n_recov = 0)
results = e.run_simulation(200)
```

4d. Visualizing the desired agent-based simulation can be achieved using `visualize_simulation(results)` using the results variable defined above and visualization function defined in `problem4/Campbell_HW4.ipynb`

4e. Analysis results were executed using `problem4/Campbell_HW4.ipynb`.

– Running the simulation with p = 0.05 and q = 0.02 over 200 days is visualized in Figure 3 below. The infection spread is quite minimal, with the number of infected agents never exceeding about 6 agents. This makes sense since the grid is quite large so the likelihood of a susceptible and infected agent occupying the same cell is quite low. Additionally the infection rate is low, so even if an susceptible and infected agent share the same cell, there's only a 5% chance of infection. The infection takes a while to die out due to the low recovery rate, ending around day 125. So while the infection isn't spreading to a large proportion of the population, it take a while for the infected agents to recover.

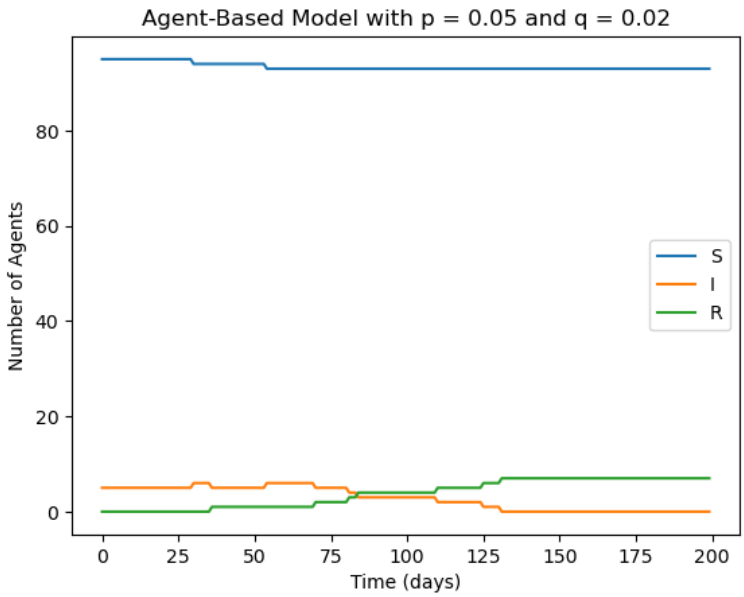

Figure 3: Agent-based model in 50x50 grid with infection rate = 0.05 and recovery rate = 0.02

– Figure 4 below demonstrates how different values of p (infection rate) and q (recovery rate) impact model dynamics. When q increases, the infection dies out quickly because the infected agents are more likely to recover in a given timestep. Since this is a large grid, it decreases the probability that an infected agent encounters a susceptible agent before they recover, which is why the infection dies out so quickly. If p increases, then each infected agent is more likely to infect a susceptible agent when they land in the same cell, so the infection spreads faster and lasts longer. Note that across all combinations of parameters tested, a large proportion of the susceptible population remains uninfected by the end of the simulation. This is likely because the grid is large relative to the number of agents.

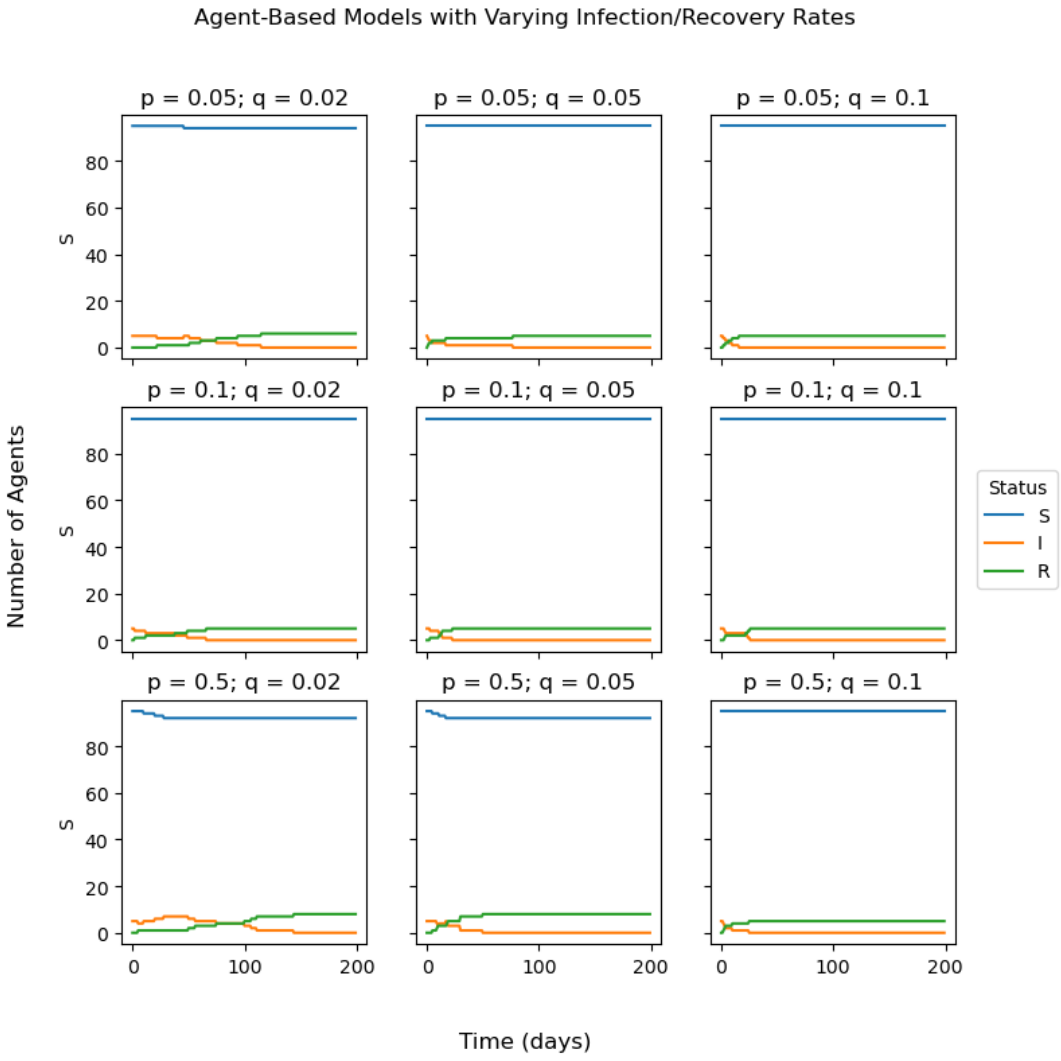

Figure 4: Pandemic dynamics over 200 days with varying infection (p) and recovery (q) rates in an agent-based model

References

1. R. Sameni, OSET: The open-source electrophysiological toolbox. Version 3.14, URL: http://www.oset.ir