University of Western Australia
CITS4403 - Computational Modelling
Project Report

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Background

Virus epidemics in most forms would always tend to have a significant negative impact on the economics and the society (Madhav et al., 2017). According to ABS in 2022, Covid-19 has caused Australia to lose around 156 billion dollars in GDP. Therefore, it is important to understand different pandemics and look for intervention strategies. With the increase of population, urbanisation and an increase in travelling around the globe, the likelihood of pandemics is also increasing (Jones et al., 2008). Furthermore, most pandemics such as the plague are expected to emerge from time to time (World Health Organisation, 2022).

With the pandemics expected to inevitably happen in the future, the only effective action is to prepare and control. Detecting the pandemics early along with a large portion of the population vaccinated could greatly reduce the impact (Eubank et al,. 2004). In the sense of a model, the spread of epidemics can be expressed as a combination of some parameters (Marion et al., 2022). Therefore, creating a simulation on a model of the pandemic could be a cheap and effective way to find out the effectiveness of different intervention strategies.

This report describes the use of an agent based model for simulation to represent the spread of epidemics in a small town. The purpose is to allow different scenarios of epidemic to be represented by a combination of parameters. Experiments can also be run to find out an estimate of the behaviour and impact of the epidemic in a small town. A common pattern shown in the experiment is the higher the density of the town, the faster the epidemic would spread. Intervention techniques such as vaccinate and lockdown are also shown to be able to greatly reduce the impact of an epidemic.

Model Description

The epidemic model created attempts to simulate a small town with agents representing the population. Agents would be represented by a set of variables defining their properties and uniqueness, such as different agents having different strengths of immune systems. To make the model realistic, the virus in the epidemic would imitate that in reality. In the case of Covid, the virus inside the infected agents would first stay in a latent period and then become active.

A mix of cellular automata and agent based models is used to represent the small town and the agents. The cellular automaton is used to represent the space of the town, where each cell would represent an empty space or an agent. With the 2D grid, graphs can be easily made to visualise the spread of different agents; those healthy, infected and active. Moreover, having a 2D grid representing the infected agents makes it possible to calculate the spread of virus using the correlate function and a kernel. Agent based simulation can represent a realistic estimate of the population and different parameters can be used to simulate the spread of virus (Eubank et al,. 2004). Each agent has different properties and may take some actions at each round. Agents could randomly move around and infected agents may also infect other agents.

Assumption and rules of the model

Simplified actions: Agents in the model can only perform simple actions, such as moving randomly. Complex activities in reality are not captured and are abstracted to just movement in the town. Agents will move randomly at each time step in the simulation.

Agent status: Agents in the simulation can be in different status of infection. Healthy to represent healthy agents, dead for fatality from epidemic and infection can be latent or active.

Spaces: The town represented by a 2D grid has limited spaces for the agent to move around. Each cell could represent empty space or only an agent.

Diseases spread: The spread of the epidemic comes from the interactions of the healthy and infected agents. In the 2D grid space, the probability of a healthy agent becoming infected is the sum of all 8 neighbours based on if infected. The correlate2d function can be used with a kernel to calculate the sum of infection probabilities of each cell.

Immune system: Humans have an immune system that can combat the intrusion of viruses. Agents have a property that imitates the effect of the immune system against probability of getting infected.

Decay resistance against infection: Vaccination and recovery from an infection can greatly boost an agent's resistance to the infection. The effectiveness of the resistance would decrease over time until a threshold level is reached.

Transition of infection: Most virus infections have different states. Latent state of the virus causes no visible effect to the agent, but may transition into an active state. Active infections would damage an agent causing fatality or spreading the infection to others.

Intervention methods: Measures can be placed to try and actively control the epidemic. Vaccination can be represented as an overall increase in resistance to infections. Lockdown can be represented as a set of non-moving agents with an increased resistance to infections.

Initialisation and Parameters

Initialisation

A class in python is written to represent the epidemic simulation. Cellular automata technique is used, where a 2D grid is created to represent the limit space of the town. The size of the grid is defined by the parameter value n. A list of agents is created to represent the population in the town based on the input parameter pop. The 2D grid would define the spaces that the agents may move in. Each agent on initialization would also be spawned randomly in the 2D grid to represent the spread of population. Based on the num_infect parameter, a subset of the agents are randomly chosen to become infected. This would represent the start of the epidemic outbreak. Different intervention measures can also be placed, such as lockdown or vaccination.

Parameters

Parameters are chosen to best represent the actual epidemic spread that would exist in real life. Only a subset of the important properties of real life epidemics are included in the simulation.

Parameter	Description
n	The size of the 2D grid or the town, where the available cells would be n*n.
pop	The population in the town or the number of agents to create for the simulation.
infect_prob	The probability an agent gets infected in one time step when interacting with an infected agent.
latent_period	How many time steps or days would the virus be in latent mode in an agent.
fatal_rate	The probability of an active infected agent dying in a time step.
recovery_period	How many time steps would agents need to recover from an infection.
infec_resist_dec	How much the agent's immunity to the virus would decrease each time step. Agents may have a boost in the immune system after recovery from infection or from vaccines.
agent_move_size	How far the agent can move in each time step. This defines the distance in a square with the agent's position in the middle.
lock_down_resist	The effect of lockdown on agent infection rate.
num_infect	Defines how many agents are infected at the very beginning.

Results

The simulation will be conducted based on similar properties of the Covid virus. The size of the grid will be 100 * 100 and with a population of 2000. The outbreak will be represented by the number of initial infected agents, which will be 10.

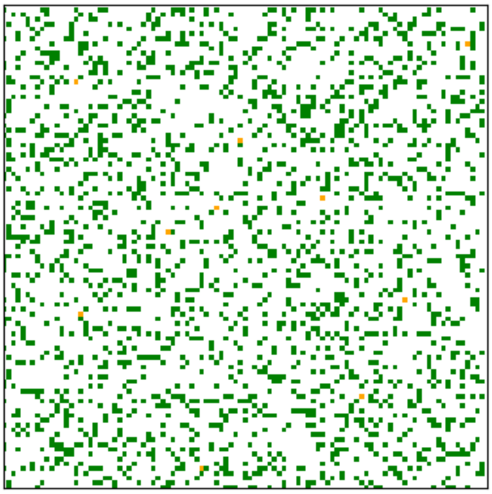

Figure 1. Spatial graph of agents right after initialisation.

Above figure shows a spatial view of the initially configured town in the simulation. It can be seen that some cells are coloured orange, which shows the latent infected agent.

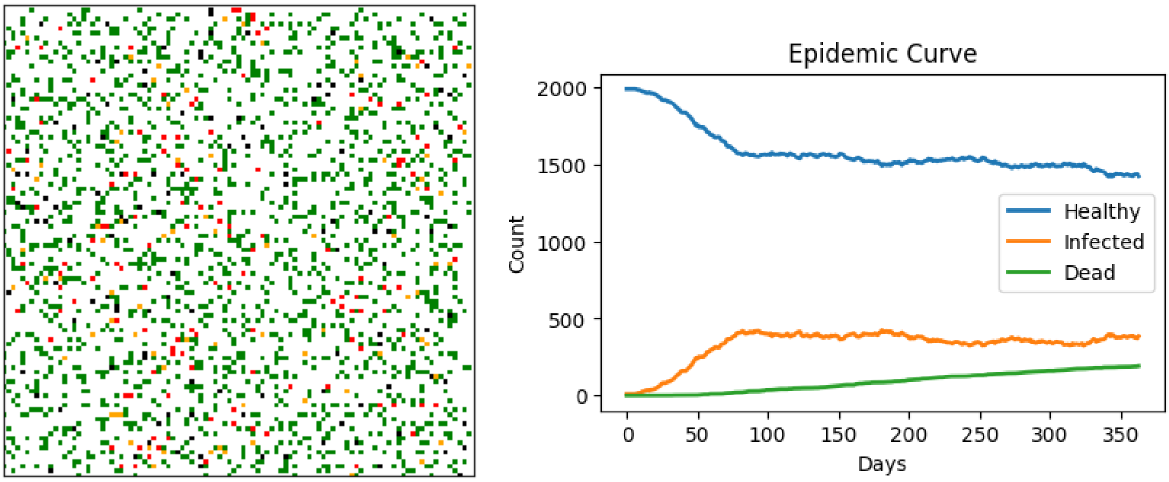

Figure 2. Spatial graph of the agents and epidemic curve after 365 time steps.

It can be seen that the number of infected agents is not too high after 365 days. The number of infected agents seems to stabilise after day 75.

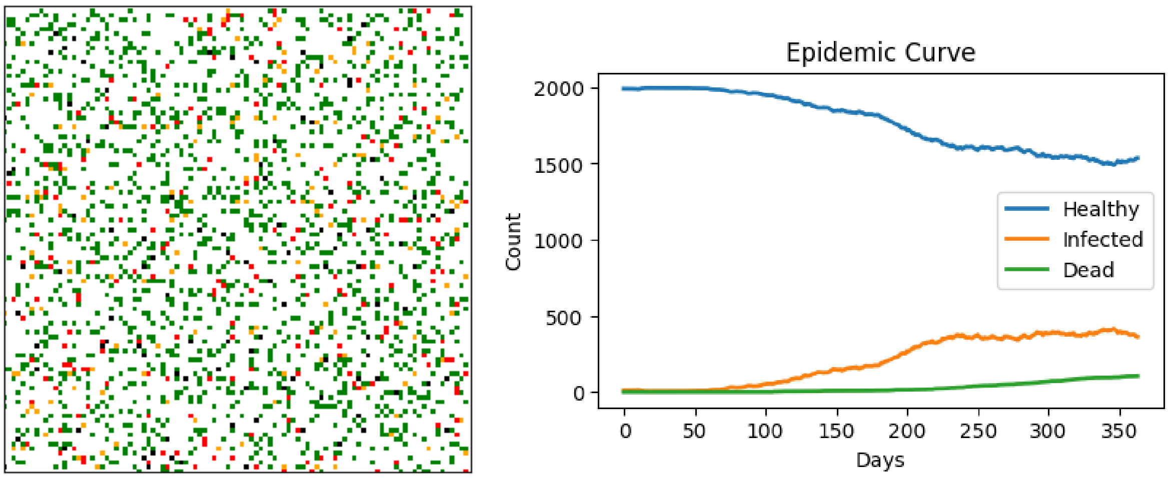

Figure 3. Spatial graph of the agents and epidemic curve with 70% population vaccinated after 365 time steps.

With vaccines applied to most of the agents, it can be seen that the number of infections after 365 days seems to be the same as if the vaccine wasn't applied. However, the graph shows that it is only after around 225 days until the number of infected agents stabilises. Furthermore, It can be seen that the reason for increase in the number of infected agents is the vaccine effect wearing out over time.

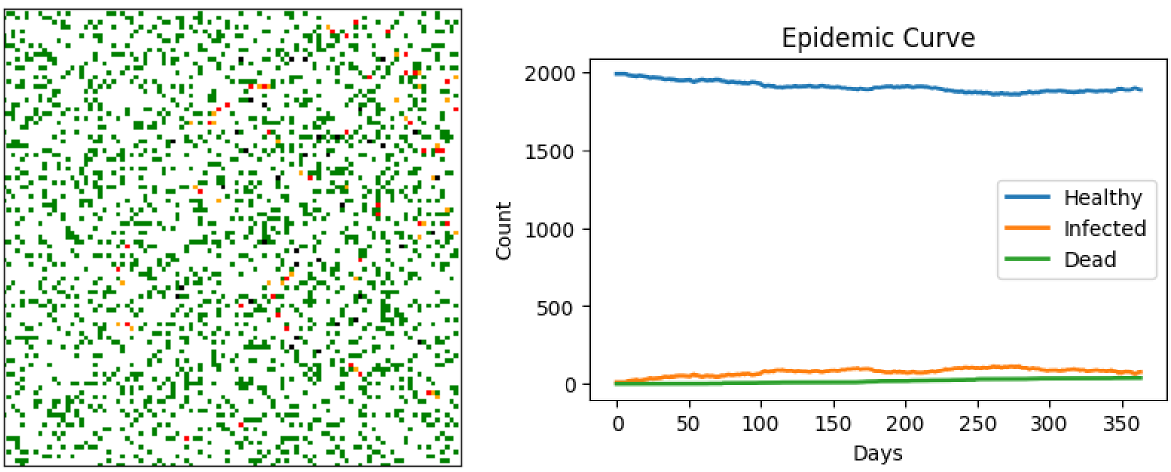

Figure 4. Spatial graph and epidemic curve with 70% population in lockdown after 365 days.

With lockdown applied, the number of infected agents is very low. This shows that lockdown is the most effective intervention strategy.

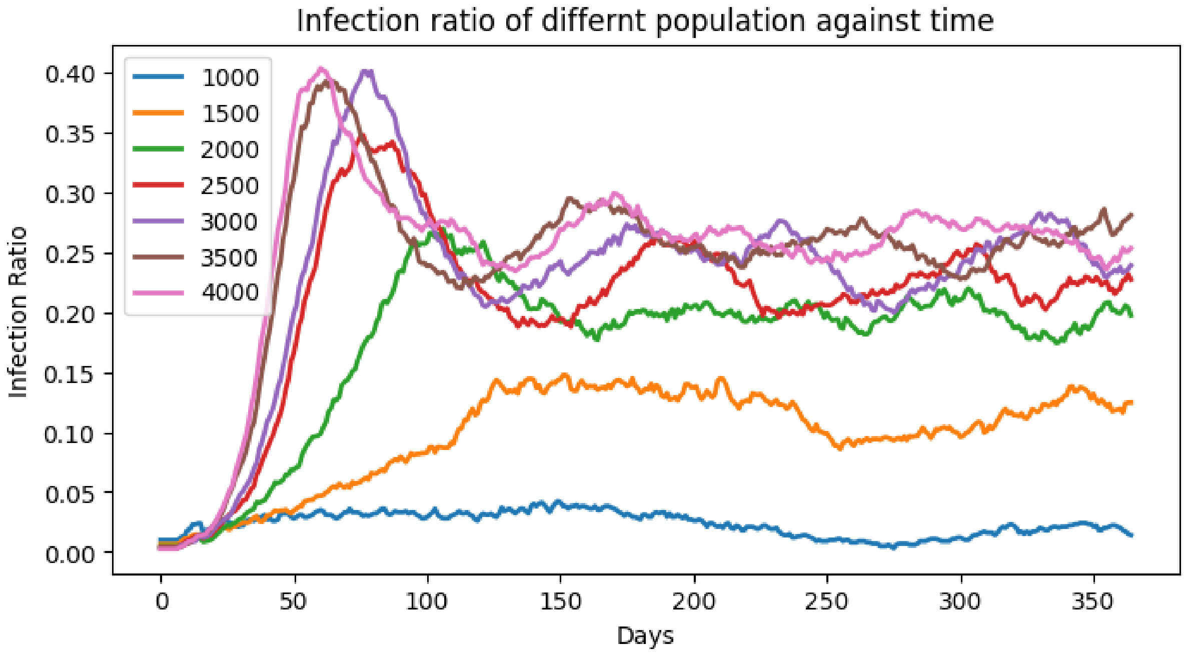

Figure 5. Line graph of infection ratio against days for a range of population on the same size grid.

From the above, it can be seen that a higher density means a higher infection rate. This is as expected, since agents interact a lot more in a more dense space. The trend of the ratio seems to be in the same pattern for populations over 2500. In this set, the peak in the infection ratio is around 50 days. In later days, it seems that the infection ratio stabilises around 0.25 percent of the population. A reason for this is likely to be that the interaction between infected agents and healthy agents stabilised.

Conclusion

In conclusion, the model proposed is very simplified compared to the actual problem. However, it does provide some simple estimate on the behaviour of the epidemic in different environments. The results of experiments from above shows that vaccination can effectively reduce the infection rate, but not in the long term; as the vaccination effect wears out in time. Lock down would be a better intervention method, as the experiment showed it can greatly reduce the infection ratio. The more dense the space is, the faster and more of the infection will spread. However, the number of infected ratio seems to stabilise after some time.

The stabilisation observed might not be a great estimate of the real problem. This is a particular downside of the model, agents are not smart and would only move randomly. Therefore, as the number of infected agents increase, the ratio of interactions of infected agents against the healthy agents also stabilises. This is likely not the case in the real world, since people are very much more connected and hence more interactions.

A solution to the weakness would be implemented in the future. The current model does not represent the real world that well. With more rules and a smarter agent, such as human connections and agent moment routines would better estimate the real problem.

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