

MAPPADEMICS

EVELYN, JAMES, AMNI

To what extent are we able to use a computer model to determine an optimum response to epidemics?



Aims and Objectives



Localisation

Malaysian-specific statistics for added relevance and accuracy, promoting SDG 3 (Good Health and Wellbeing) within the country



Real-World Applications

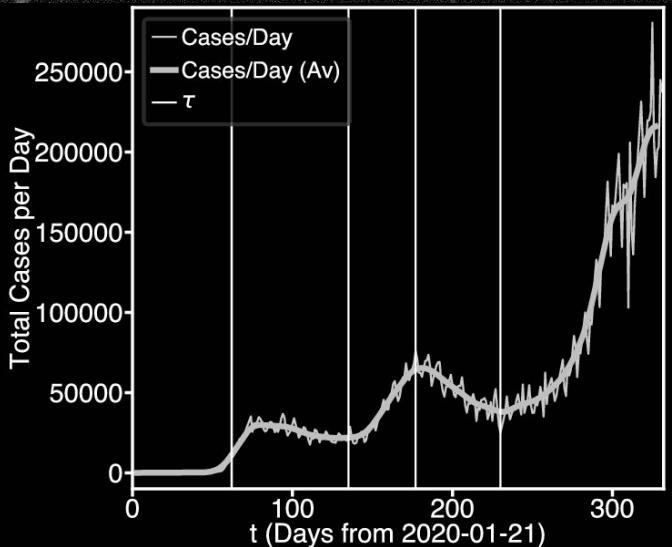
Model can be used to track/model a variety of different diseases in different areas, improving SDG 3 all over the world



Easily Accessible and Useful

To show how epidemics come to be and to provide a visually engaging and easy-to-understand way and for people to understand how to stop them

Existing Models



Limitations

- ✖ Lack of interactivity and visual elements
- ✖ Mathematically challenging to understand
- ✖ Created with a more generalised perspective, as compared to a specialised "by country" perspective

Inspirations

Simulating a Pandemic - a video by
3Blue1Brown

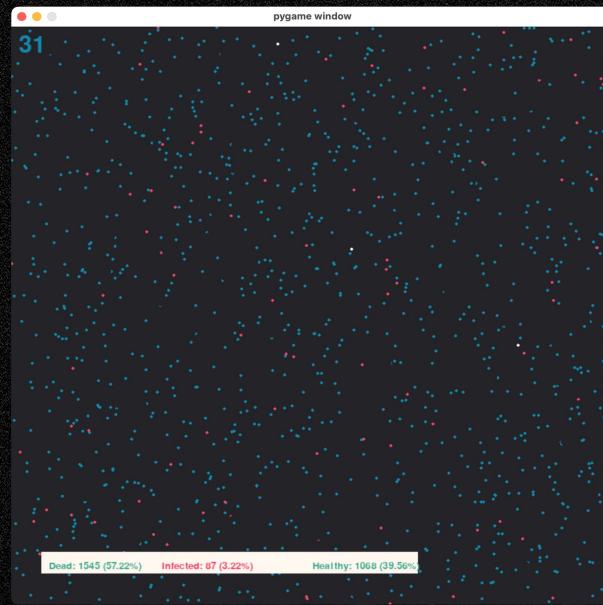
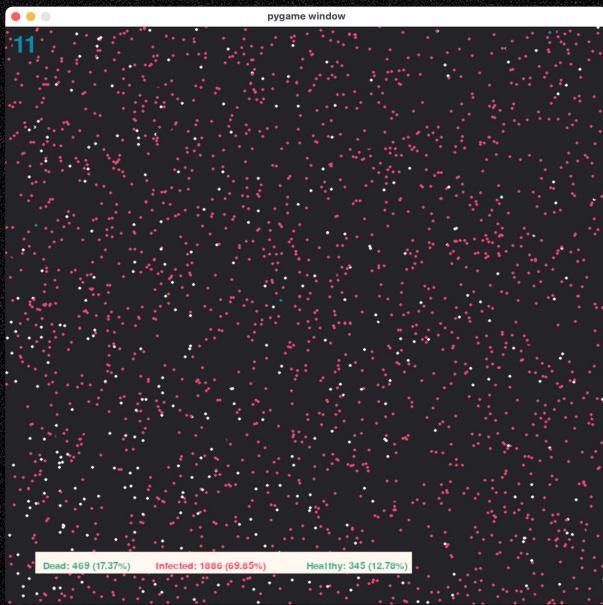
An abandoned project based off a
YouTube tutorial

The effects of the COVID-19 pandemic

The hope for improved healthcare for all

Improvements to our Model

Our model is inspired by the simulation of disease spreading, except it is modified to a Malaysian specific context. We also include the use of masks and vaccines.



How It Works: Our Code

```
def infect_people(self):
    for c in self.grid.cells:
        states = [p.state for p in c.people]
        if states.count("infected") == 0:
            continue
        people_in_area = []
        for index in c.get_neighboring_cells(self.grid.n_rows, self.grid.n_cols):
            people_in_area += self.grid.cells[index].people
        infected_people = [p for p in people_in_area if p.state == "infected"]
        healthy_people = [p for p in people_in_area if p.state == "healthy"]

        if len(healthy_people) == 0:
            continue
        for i in infected_people:
            for h in healthy_people:
                dist = math.sqrt((i.x-h.x)**2 + (i.y-h.y)**2)
                if dist < self.infect_dist:
                    if random.uniform(0,1) < self.prob_catch:
                        h.get_infected(self.recover_time)

def summarize(self):
    time_index = range(1,len(self.record)+1)
    infected = [r[0] for r in self.record]
    dead = [r[1] for r in self.record]

    newly_dead = [0]
    for i in range(1,len(dead)):
        newly_dead.append(dead[i] - dead[i-1])
    newly_dead = moving_average(newly_dead, 20)
    newly_dead = newly_dead[:len(time_index)]

    fig, ax = pyplot.subplots()
    ax.plot(time_index, infected, color = "red")
    ax.set_xlabel("Period")
    ax.set_ylabel("People currently infected", color = "red")

    ax2 = ax.twinx()
    ax2.plot(time_index, newly_dead, color = "black")
    ax2.set_ylabel("20 period moving average of fatalities", color = "black")
    pyplot.show()
```

- Uses grids to minimise processing
- Summarises the process to create a graph
- Can be run on any computer

Selection of Regions

Kuala Lumpur

Population density:
8500 people per
 km^2

https://iknselangor.moh.gov.my/hsis/images/covid19/Panduan-Pesakit-Covid19-di-HSDG-BM/Kit Covid-19_EN.pdf

Kuching

Population density:
750 people per km^2

Georgetown

Population density:
2600 people per
 km^2

A wide range of data...

Diseases Selected

Influenza A

Tracking common
epidemics

COVID-19

Tracking newly
discovered
diseases

Measles

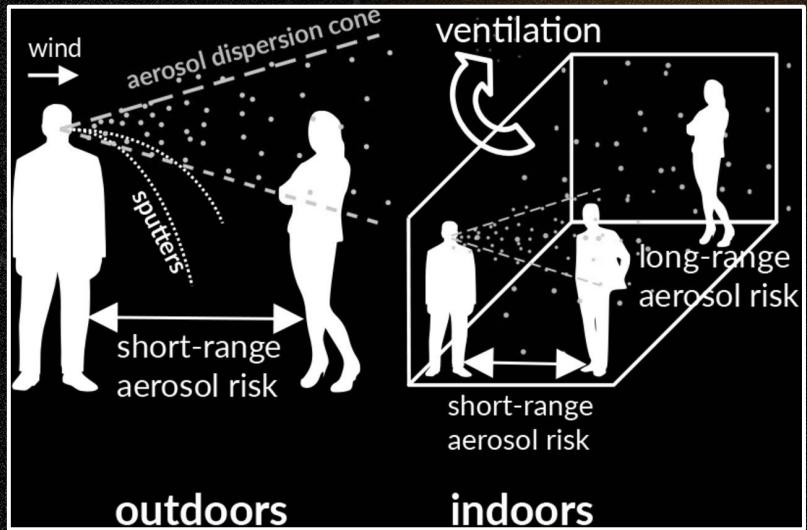
A case study on
the crucial role of
vaccines

Plague

Worst-case
scenario
(biosecurity!)

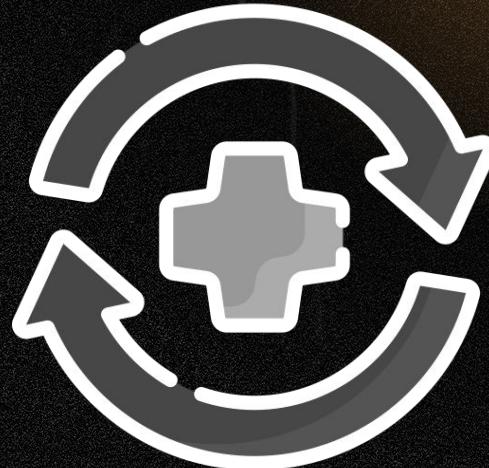
Variable: Infection Distance

How far a disease can spread from the first infected person; can travel through air droplets from coughing and sneezing



Variable: Recovery Time

Average length of time
between a person getting
infected and the body
fighting off the disease



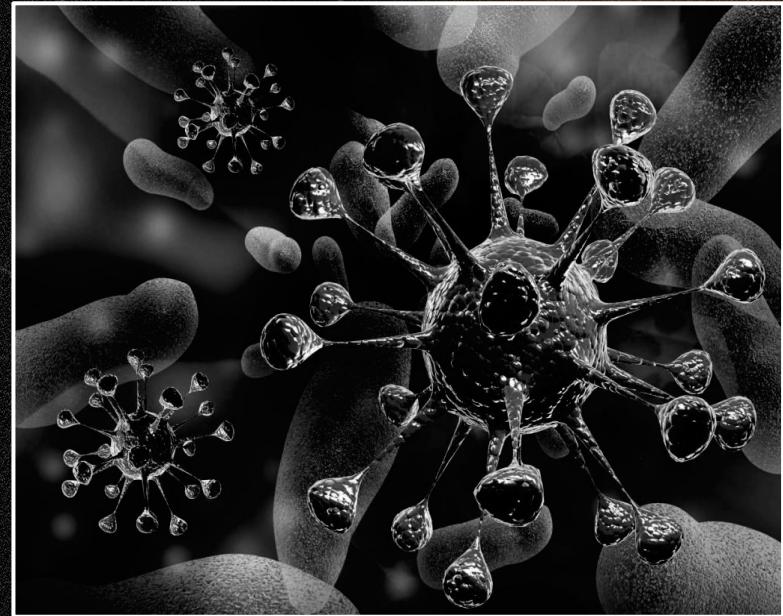
Variable: Immunity Time

Average length of times
antibodies specific to the
disease remain in the body,
preventing one from further
illness



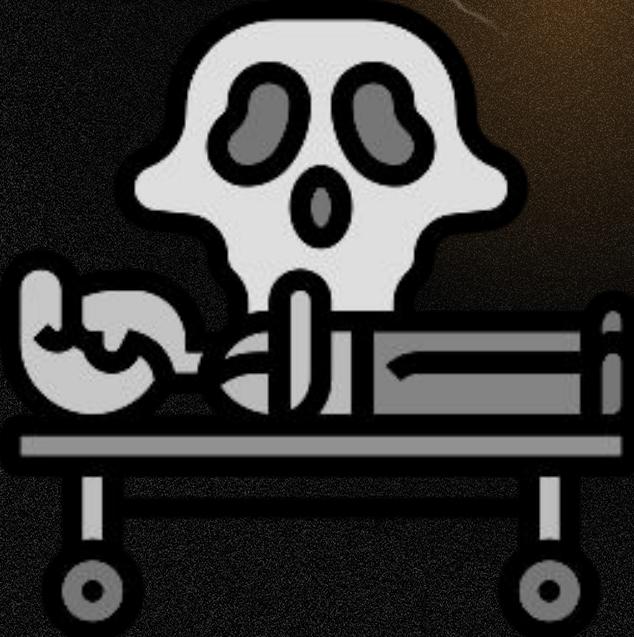
Variable: Infection Probability

Likelihood of catching a disease when one is exposed to an infected person



Variable: Probability of Death

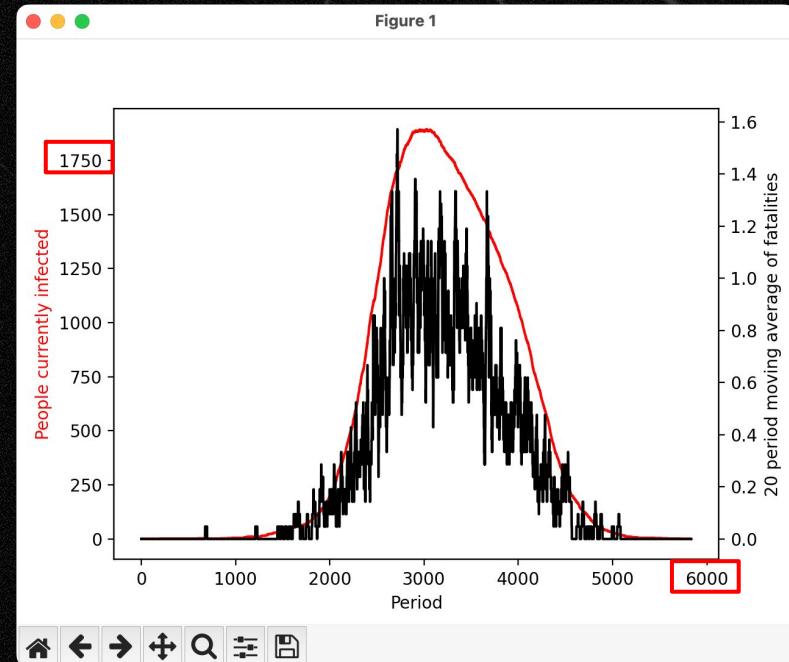
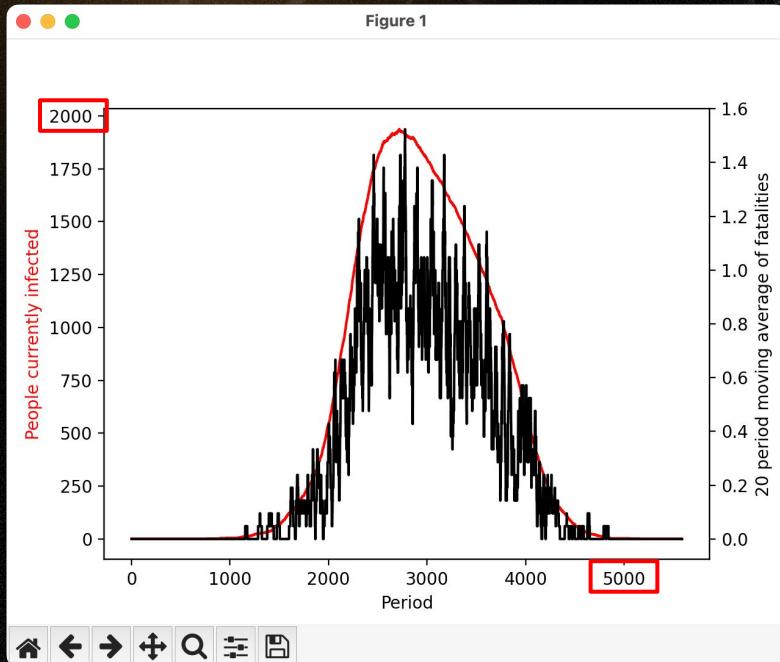
Probability for an infection to become fatal for the infected



Statistics

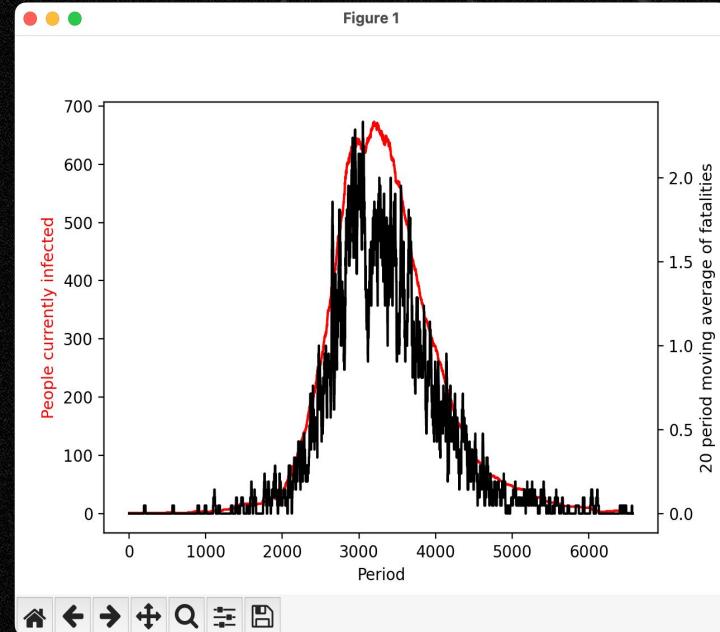
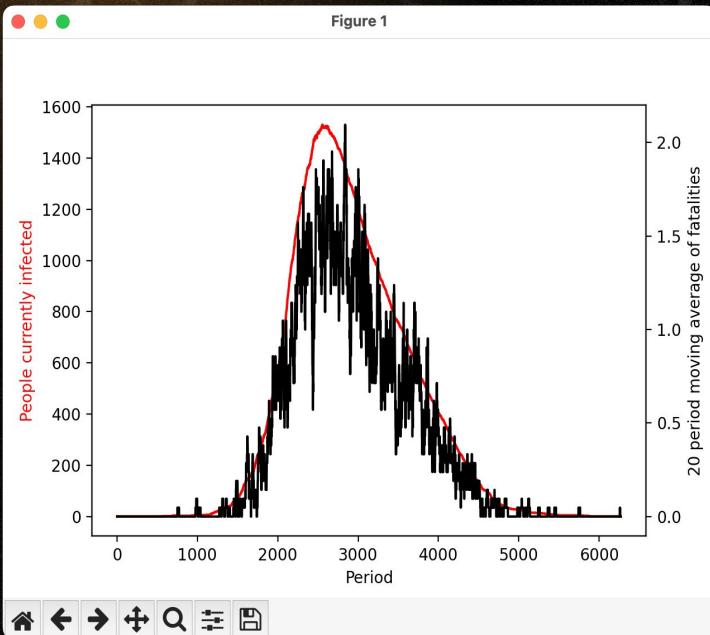
	Influenza A	COVID-19	Pre-Vaccine Measles	Post-Vaccine Measles	Plague
Recovery Time	10 days (1750 frames)	20 days (3500 frames)	20 days (3500 frames)	12 days (2100 frames)	20 days (3500 frames)
Immune Time	18 months (94500 frames)	4 months (21000 frames)	Lifelong	Lifelong	~1 year (80000 frames)
Infection Probability	0.2	0.2	0.9	0.7	0.9
Death Probability	0.0005	0.001	0.0025	0.001	0.0015

Mask Feature



Flattening the curve works (with and without masks enabled)

Vaccinations



Flattening the curve works (pre-vaccine and post-vaccine)

Limitations and Future Developments

3 GOOD HEALTH AND WELL-BEING



Other Variables

Increase in population, viral mutation, quarantine, vaccinations, and other government-related responses are not included in the model



Assumptions

Masks being enabled assumes that 100% of the population wears masks correctly



Proportionalities

City size, population density and R_0 values could all be made more realistic and mathematically accurate



Community-Community Interaction

City size, population density and R_0 values could all be made more realistic and mathematically accurate

Thank You

The Mappademics Team

Contacts

Evelyn Teng:

evelynteng.github.io
linkedin/in/evelyn-teng

James Ng:

linkedin.com/in/james-kbn

Amni Amin:

linkedin.com/in/amni-amin