MAT238 Project Report Cover Sheet – Fall 2024

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1.1 Question

The research question, “How did the lockdown measures implemented in Ontario during the COVID-19 pandemic affect the spread of the virus?” focuses on assessing the effectiveness of lockdown measures in Ontario and aims to determine whether this form of intervention reduced the transmission rate of COVID-19. A reduction consequently would lead to the slowing down of the spread of the disease. In order to explore our question more thoroughly, it is suitable to utilize the SIR model to simulate different scenarios and assess the impact of lockdown intervention on the pandemic.

1.2 Interest

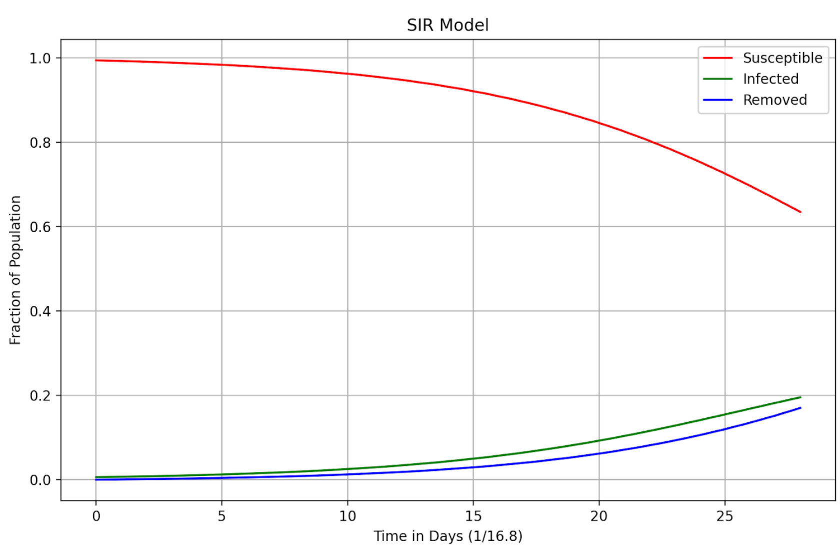
The COVID-19 pandemic is one of the most important global health crises in modern history. It affected nearly every single aspect of daily life. In order to reduce the spread of the virus, the Ontario government implemented lockdown measures that restricted movement and social interaction. To assess the effectiveness and reliability of lockdowns for future pandemics, we must be able to analyze and understand their impacts. The research question struck our interest due to how it provides insights into the balance between public health measures and their effects on community health outcomes. The analysis of real data through the SIR model helps us evaluate whether the lockdowns were effective enough to reduce transmission rates and help us understand their role in managing infectious disease outbreaks.

1.3 Overview

Our group began research by finding appropriate data from Ontario’s public health records [7]. We narrowed down our data to a specific period of 470 days (April 1st, 2020 to August 13th, 2021). Furthermore, we were able to find *N*, *v, I(t), death count, active cases and resolved cases* from Canada’s official public health record [1][4]. We created a spreadsheet with all the data and calculated *S(t)* and *R(t)*. We used Python to then extend Euler’s Method. The R_0 and v were also found in public health records [3][5] and were used to estimate the β value from the equation $R_0 = \frac{\beta}{v}$. After finding all the necessary values, we used the SIR model to analyze our research question and predict future outcomes.

2.1 Model

Graph 1: Simulated Data from the Python SIR Model



The SIR model was used to study the spread of COVID-19. It divides the population into three groups: Susceptible, Infected, and Removed. It models how individuals transition between these groups over time, capturing the dynamics of disease transmission and recovery. The simulated data is derived by extending the Euler’s Method from a set of initial parameters (see Appendix B).

2.2 Sources

The data from the dataset we used was from the first 470 days (April 1st 2020 to August 13th 2021). We normalized our data to better view changes in the infection rate.

2.3 Data Processing

To address the issue of disproportionality in the COVID-19 dataset for Ontario, we normalized the data to make the trends in the susceptible (S(t)), infected (I(t)), and recovered (R(t)) populations more visible and comparable (see Appendix A). Initially, the susceptible population was disproportionately large compared to the infected and recovered populations, which obscured the trends and made the visualizations uninformative. This imbalance also made it difficult to compare the observed data with the outputs of our SIR model, which operates on proportional values to estimate key epidemiological parameters such as the transmission rate (β), recovery rate (ν), and the basic reproductive number (R_0) (see Appendix B).

We refined our dataset to focus exclusively on the policy period from April 1, 2020, to August 13, 2021, ensuring alignment with the scope of our research question and enabling a precise examination of trends relevant to the policies under investigation [2]. Narrowing the dataset to this timeframe eliminates extraneous data, reducing noise and enhancing our ability to detect meaningful patterns influenced by the policies. Real-world data is often complex, with subtle trends obscured by broader fluctuations, but this targeted approach allows us to isolate the effects of the policies more effectively. By concentrating on a manageable and relevant subset of data, we can conduct a more detailed and focused analysis, leveraging statistical and graphical tools to uncover insights that directly address our research objectives and strengthen the validity of our findings.

2.4 Modelling

The Python code for the model data begins by defining the differential equations for S(t), I(t) and R(t) as outlined in the project instructions. It then employs Euler's method to calculate the trends over time, updating the values for these equations based on the initial parameters. These initial parameters were derived from our dataset, with the normalized dataset used to align with the trends in our Excel graph. The total population, as well as the initial counts of removed, infected, and susceptible individuals, were matched to those in our real-world dataset. To determine the value of β, we researched the average duration of the COVID-19 infectious period, estimated at 10 days, and used a transmission rate (R_0) of 2.6 [3][4]. By applying the formula $\beta = R_0 \bullet \frac{1}{\nu}$, we calculated the value of β [6].

3.1 Analysis

In the SIR Model, the Infectious population gradually grows past the Removed Population and the overall model shows a continuous exponential growth. In the experimental data, a trend can be observed where although the Removed Population follows a curve similar to the SIR Model, the Infectious Population dips above and below the Removed creating peaks.

The first observable deviation from the model occurs on Day 35 (May 4th 2020), the first instance where the Infectious Population falls below the Removed and then plateaus indicating a reduction in the beta value as a result of a reduced encounter rate, a trend which continues until Day 170. In 2020 a state of emergency was declared on March 17th and ended on July 13th (Day 105), during this time there was little to no change in the rate of increase.

From Day 170 (September 16th 2020) the experimental data begins to resemble the SIR Model once again as the Infectious Population rises above the Removed Population and forms an exponential curve.

The Infectious Population then peaks at around Day 280 (January 4th 2021) before starting to deviate from the model once again and gradually declining. Between Day 170 to Day 280 there was an increase in the beta value signifying an increase in the encounter rate, however the decline signifies a decrease in the encounter rate. These dates coincide with the start of the reopening period (October 9th 2020), second lockdown (December 26th 2020) and Second State of Emergency (January 13th 2021).

At around Day 340 (March 5th 2021) the decline ends and the Infectious Population begins to rapidly increase again, rising above the Removed Population at Day 375 (April 9th 2021) and reaching a peak around Day 380 (April 14th 2021). This indicates an increase in the beta value, likely a result of an increased encounter rate. From there a gradual decline begins, with the Infectious Population falling below the Removed Population at Day 390 (April 24th 2021) and continues to decline, indicating a reduction in the beta value as a result of a reduced encounter rate. On February 10th 2021, the state of emergency ended coinciding with the start of the rapid increase in infection. On April 8th 2021 a stay at home order was issued coinciding with the beginning of the decline in cases.

The gradual decline continues and then plateaus at Day 430 (June 3rd 2021) indicating a decrease in the beta value likely a result of a decreased transmission rate. On June 2nd 2021, the stay at home order expired and stage 1 of reopening began (Strikeman Elliot, 2020).

It is evident that the lockdowns coincide with the deviation between the modelled trajectory of the epidemic and the experimental data. The trajectory predicts that the spread will grow exponentially till the values gradually plateau, however the lockdowns have the same effect of "changing the beta value". The lockdowns reduced the number of encounters reducing the spread of the infection. As the spread of the infection declines the Infectious Population declines proportionally resulting in the observed deviation. Additionally during stages of reopening, where the number of encounters increases, raising the beta value the Infectious Population grows rapidly and begins to steer toward the predicted trajectory for the epidemic.

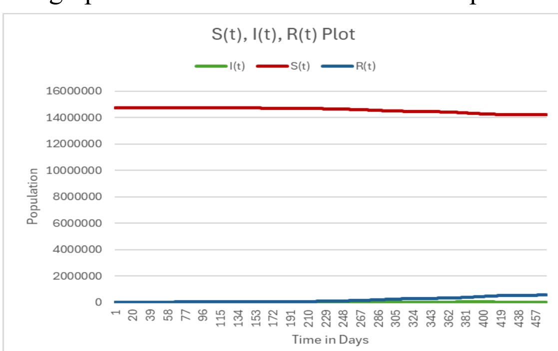
The observed trend is that lockdowns have a major impact on the beta value as it restricts the encounter rate of people limiting the growth of the Infectious Population.

3.2 Graphs

The graphs of the real-world dataset and **normalized** real-world dataset are provided below.

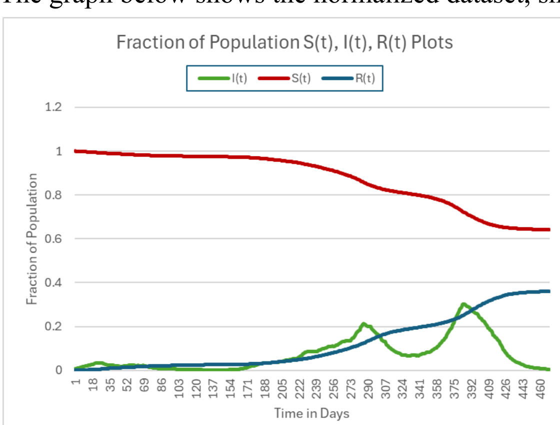
Graph 2: Plot of Experimental Data

The graph below shows the initial dataset plotted.



Graph 3: Plot of Normalized Experimental Data

The graph below shows the normalized dataset, showcasing a clearer comparison of relative change



4.1 Practical Implications of Results

In Ontario, the sharp decline in the infectious population during lockdowns can be attributed to several specific public health measures aimed at curbing COVID-19 transmission. The province declared a state of emergency on March 17, 2020, which led to the closure of all non-essential services, including dine-in restaurants, bars, libraries, theaters, and recreational facilities, and limited public gatherings initially to 50 and then to five people as of March 28 [2]. These measures were escalated with subsequent stay-at-home orders, the closure of non-essential retail, and interregional travel restrictions, all designed to minimize person-to-person contact. Although these interventions significantly decreased the number of infectious cases, fluctuations in infection rates were noted, particularly during holidays or warmer weather when people were more likely to gather outdoors. Prolonged periods of isolation also contributed to 'lockdown fatigue,' impacting overall compliance with the restrictions as the pandemic progressed.

4.2 Limitations

See Appendix C for the Strengths and Weaknesses of the model.

- Every individual is assumed to have an equal chance of contact with each other, though this is not the case in a real-life situation.
- β does not change on its own, it has to be adjusted manually. This value can also change due to other measures such as vaccination rollouts or new COVID-19 variants.
- The removed population includes recovered and dead but does not distinguish between them. This oversimplifies the outcomes of COVID-19 since recovered people can be reinfected.
- Other factors such as economic situations, policy enforcement, or healthcare limitations can also influence the measure's effectiveness.
- The transmission and recovery rates are assumed to be constant, which doesn't reflect real-world dynamics.
- We assume people are following all mandates, however this is not the case.
- The model does not assess specific policy impacts like partial vs. full lockdowns.

4.3 Future Research

The team could upgrade the SIR model to an SEIR model to account for COVID-19's latency period - the time between exposure to COVID and being infectious. We could also incorporate regulatory compliance into the model, noting that it likely decreases over time but may increase with the emergence of deadlier variants. Additionally, a time-dependent SIR model with variable $\beta(t)$, could better capture the real-time impact of lockdowns, predicting significant declines in infection rates with stricter measures, as seen in (Hong and Li, 2020).

5.1 Conclusion

The project used a SIR model and Ontario government data to investigate the impact of the province's COVID-19 lockdown measures on the virus's spread [2]. We got parameters such as β, v, and N from prior research, and then used Python to extend Euler's Method to build the SIR model (see Appendix B). The team then normalized the government data from April 1, 2020, to August 13, 2021, to align with the SIR model's proportional framework (see Appendix A). Finally, we analyzed key policy periods and simulated infection trends to assess changes in transmission rate (β), infected population $I(t)$ and the susceptible population $S(t)$ to answer our research question. We learnt that lockdowns tended to reduce transmission and relaxing measures were associated with a steady increase in infections. We also saw that strict interventions like stay-at-home orders were most effective at decreasing infections.

Given our findings, the team has concluded that the lockdown measures implemented in Ontario reduced the transmission of COVID-19. While there were limitations to our study methodology - as mentioned in the previous section - the team is confident in our answer for several reasons. The first reason is that the theoretical predictions from our SIR model were similar to the observed trends in the government's data. Secondly, we noticed consistent declines in infections during stricter lockdowns. Also, infections increased as the province moved forward in its reopening process, demonstrating that lockdowns curbed the spread of the virus. Therefore, we hope that this paper will shed light on the effectiveness of lockdowns in controlling pandemics.

6.1 Appendix

Appendix A. Excel Dataset

Figure 1. The First 10 Lines of the Processed Dataset

FILE_DATE	RESOLVED_CASES	DEATHS	ACTIVE_CASES	SUSCEPTIBLE	REMOVED	t	NORMALIZED_I(t)	NORMALIZED_S(t)	NORMALIZED_R(t)	Delta R(t)
4/1/2020	689	0	1703	14,749,982	689	1	0.005929193	1	0	
4/2/2020	831	53	1909	14,749,581	884	2	0.007404331	0.999736016	0.00012889	195
4/3/2020	1023	67	2165	14,749,119	1,090	3	0.009237511	0.999431875	0.00026505	206
4/4/2020	1219	94	2317	14,748,744	1,313	4	0.010325962	0.999185008	0.000412447	223
4/5/2020	1449	119	2470	14,748,336	1,568	5	0.011421574	0.998916416	0.000580995	255
4/6/2020	1624	132	2591	14,748,027	1,756	6	0.012288038	0.998712997	0.000705257	188
4/7/2020	1803	152	2771	14,747,648	1,955	7	0.013576994	0.998463496	0.000836791	199
4/8/2020	2075	173	3028	14,747,098	2,248	8	0.015417335	0.998101424	0.001030456	293
4/9/2020	2306	199	3254	14,746,615	2,505	9	0.01703569	0.997783458	0.001200325	257
4/10/2020	2575	221	3441	14,746,137	2,796	10	0.018374771	0.997468784	0.001392668	291

Table 1. Sample Calculations for Normalizing the Processed Dataset in Excel

I(t)	`=(D2 - MIN($D$2:$D$974))/(MAX($D$2:$D$974) - MIN($D$2:$D$974))`
S(t)	`=(E2 - MIN($E$2:$E$974))/(MAX($E$2:$E$974) - MIN($E$2:$E$974))`
R(t)	`=(F2 - MIN($F$2:$F$974))/(MAX($F$2:$F$974) - MIN($F$2:$F$974))`

Appendix B. Simulated Model

Figure 2. Python Code for the Simulated Data of the SIR model

```python
import numpy as np
import matplotlib.pyplot as plt
from scipy.integrate import odeint

# Define the SIR model differential equations
def sir_model(y, t, beta, gamma, N):
    S, I, R = y
    dS_dt = -beta * S * I / N
    dI_dt = beta * S * I / N - gamma * I
    dR_dt = gamma * I
    return [dS_dt, dI_dt, dR_dt]

# Set parameters
N = 1               # Total population
I0 = 0.005929193    # Initial number of infected individuals
R0 = 0              # Initial number of recovered individuals
S0 = N - I0 - R0    # Initial number of susceptible individuals
beta = 0.26         # Transmission rate
gamma = 0.1         # Recovery rate
R0_value = beta / gamma # Basic reproduction number

# Time points (days)
t = np.linspace(0, 28, 28)

# Initial conditions vector
initial_conditions = [S0, I0, R0]
```

```python
# Implement Euler's method
S = np.zeros(len(t))
I = np.zeros(len(t))
R = np.zeros(len(t))

# Initial conditions
S[0], I[0], R[0] = S0, I0, R0

# Time step size
h = t[1] - t[0]

# Perform Euler's method
for i in range(1, len(t)):
    dS_dt = -beta * S[i-1] * I[i-1] / N
    dI_dt = beta * S[i-1] * I[i-1] / N - gamma * I[i-1]
    dR_dt = gamma * I[i-1]

    # Update values for S, I, R
    S[i] = S[i-1] + h * dS_dt
    I[i] = I[i-1] + h * dI_dt
    R[i] = R[i-1] + h * dR_dt

# Plotting the results
plt.figure(figsize=(10, 6))
plt.plot(t, S, label='Susceptible', color='red')
plt.plot(t, I, label='Infected', color='green')
plt.plot(t, R, label='Removed', color='blue')
plt.xlabel('Time in Days (1/16.8)')
plt.ylabel('Fraction of Population')
plt.title('SIR Model')
plt.legend()
plt.grid()
plt.show()
```

Table 2. Variables Utilized to Set Up the Parameters for the SIR Model

Variable	***Definition***	***Variable***	***Definition***
s(t)	$s(t) = \frac{S}{N}$ A fraction of the population that are susceptible.	N	Total Population of Ontario: 14 749 982 Government of Canada Website.
i(t)	$i(t) = \frac{I}{N}$ A fraction of the population that are infectious.	β	Sufficient number of encounters a day to spread COVID-19. Encounter rate * transmission rate = 0.19
r(t)	$r(t) = \frac{R}{N}$ A fraction of the population that are removed.	ν	The removal rate of infectious individuals per day. $\nu = \frac{1}{10}$ (individuals/day)
R_0	$R_0 = \frac{\beta}{\nu}$ The transmission rate of COVID-19 Centre for Evidence-Based Medicine.	$\frac{1}{\nu}$	The average duration of the infectious period. $\frac{1}{\nu} = 10$

Appendix C. Strengths and Weaknesses

Strengths:

- The graph is easy to interpret as the trends are clearly outlined.
- The parameters like β and γ are customizable and therefore can result in accurate representation of the data
- Python code helps with computing Euler's method and therefore gives a more accurate model.

Weaknesses:

- The model assumes a constant total population, which ignores changes in demographics such as birth rates and deaths that are unrelated to the disease.
- Reinfection is not considered
- Euler's method is an approximation and not an exact representation of the real situation.

Citations:

[1] Status of COVID-19 cases in Ontario by Public Health Unit (PHU) - Status of COVID-19 cases in Ontario by Public Health Unit (PHU) - Ontario Data Catalogue. (2020). Ontario.ca. https://data.ontario.ca/dataset/1115d5fe-dd84-4c69-b5ed-05bf0c0a0ff9/resource/d1bfe1ad-6575-4352-8302-09ca81f7ddfc/

[2] Stikeman Elliott. (2020). Business Law Firm | Stikeman Elliott. https://stikeman.com/en-ca/kh/corporations-commercial-law/ontarios-economic-reopening--history-of-announced-measures

[3] Achaiah, N. C., Subbarajasetty, S. B., & Shetty, R. M. (2020). R0 and Re of COVID-19: Can We Predict When the Pandemic Outbreak will be Contained? Indian Journal of Critical Care Medicine : Peer-Reviewed, Official Publication of Indian Society of Critical Care Medicine, 24(11), 1125–1127. https://doi.org/10.5005/jp-journals-10071-23649

[4] Public. (2020). COVID-19: How long are people infectious, CCDR 46(11/12) - Canada.ca. Canada.ca.https://www.canada.ca/en/public-health/services/reports-publications/canada-communicable-disease-report-ccdr/monthly-issue/2020-46/issue-11-12-november-5-2020/covid-19-length-illness.html

[5] "When will it be over?": An introduction to viral reproduction numbers, R0 and Re. (n.d.). CEBM. https://www.cebm.net/covid-19/when-will-it-be-over-an-introduction-to-viral-reproduction-numbers-r0-and-re/

[6] Hong, H. G., & Li, Y. (2020). Estimation of time-varying reproduction numbers underlying epidemiological processes: A new statistical tool for the COVID-19 pandemic. PLOS ONE, 15(7), e0236464. https://doi.org/10.1371/journal.pone.0236464

[7] Canada,. (2024, September 25). Population estimates, quarterly. Statcan.gc.ca; Government of Canada, Statistics Canada. https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1710000901&cubeTimeFrame.startMonth=04&cubeTimeFrame.startYear=2020&cubeTimeFrame.endMonth=04&cubeTimeFrame.endYear=2021&referencePeriods=20200401%2C20210401