

COVID-19 Analysis

Gabriel Lapointe

March 29, 2020

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1 Introduction

1.1 Context Summary

The COVID-19 is infecting many hundred of thousands people in the world and is very virulent. Among these people, many recovered from the infection while some of them died. These statistics increase day after day and many scientists are working to understand the virus and find out a vaccin to stop the propagation. While the COVID-19 is propagating around the world, safety measures have been enforced in many countries in order to reduce the propagation between infected people and non infected people. However, they discovered that elder people and people with chronic diseases are more at risk to die.

Here are some safety measures applied in Canada:

- Social distancing rule where people have to be at a distance of at least 2 meters between each other. People that are not respecting that rule could get a fine (from 1500\$ to 6000\$). It also means that gatherings of people are strongly forbidden and is punishable by fine.
- Non-essential services and stores are closed. Services like hospitals, police, gas stations, drug stores, grocery stores are considered essential services and stores.
- There is a limitation of people that can enter the stores considered as essential. Also, people have to wash their hands with purell when entering the store. In grocery stores, baskets are all disinfected once a client finished his grocery and leave the store.

1.2 Problem and Questions

The COVID-19 is not fully understood and many thousands of people are getting infected and die day after day. Some safety measures are in place in many countries, but other problems of psychologic nature may arise from these measures. Are those safety measures really as efficient as we thought? We would say yes because it seems to be the common sense for many people to reduce the propagation. However, other factors might be important to consider and might have more impacts on the propagation than we may think.

Since the virus is not fully understood, many questions have to be answered. Here are some of these questions:

1. In which countries the propagation of the virus slowed down the most quickly?
2. Which countries have the greater ratio of deaths over the population and the total infected people?
3. Which countries have the greater ratio of recovery over the population and the total infected people?
4. What is the age category that is more susceptible to die from the COVID-19 after being infected?
5. What is the age category that got mostly infected.
6. Is there a correlation between the sex of a person and the infection rate, death rate and recovery rate?
7. Which chronic diseases are the most vulnerable against the COVID-19?
8. Does the weather have an impact on the COVID-19 propagation?
9. Do the pollution rates have an impact on the COVID-19 propagation?
10. Does the hospitals capacity have an impact on the number of deaths caused by the COVID-19? Which countries are mostly impacted?
11. Is there a correlation between the density of the population and the propagation velocity of the COVID-19?

1.3 Objective

The objective of this analysis is to understand the propagation of the COVID-19 in countries and more precisely in Canada and in the province of Québec. It means to identify factors that appear to impact the propagation velocity of the COVID-19. Understanding these factors will help to understand the propagation of the virus and know how to slow it down quicker.

2 Data Preparation

The objective is to gather necessary data in order to answer our questions. The following datasets are used in our analysis:

- [Total population by country](#);
- [Worldwide Covid-19 cases](#) prepared by the John Hopkins University Center for Systems Science and Engineering.

The dataset shared by the John Hopkins University Center for Systems Science and Engineering provides the information on the:

- Country or region
- Province or state for some countries

- Latitude
- Longitude
- Date
- Cumulative number of people confirmed with the COVID-19
- Cumulative number of people that died from the COVID-19
- Cumulative number of people that recovered from the COVID-19

Number of countries or regions: 188

Start date: 2020-01-22

End date: 2020-06-25

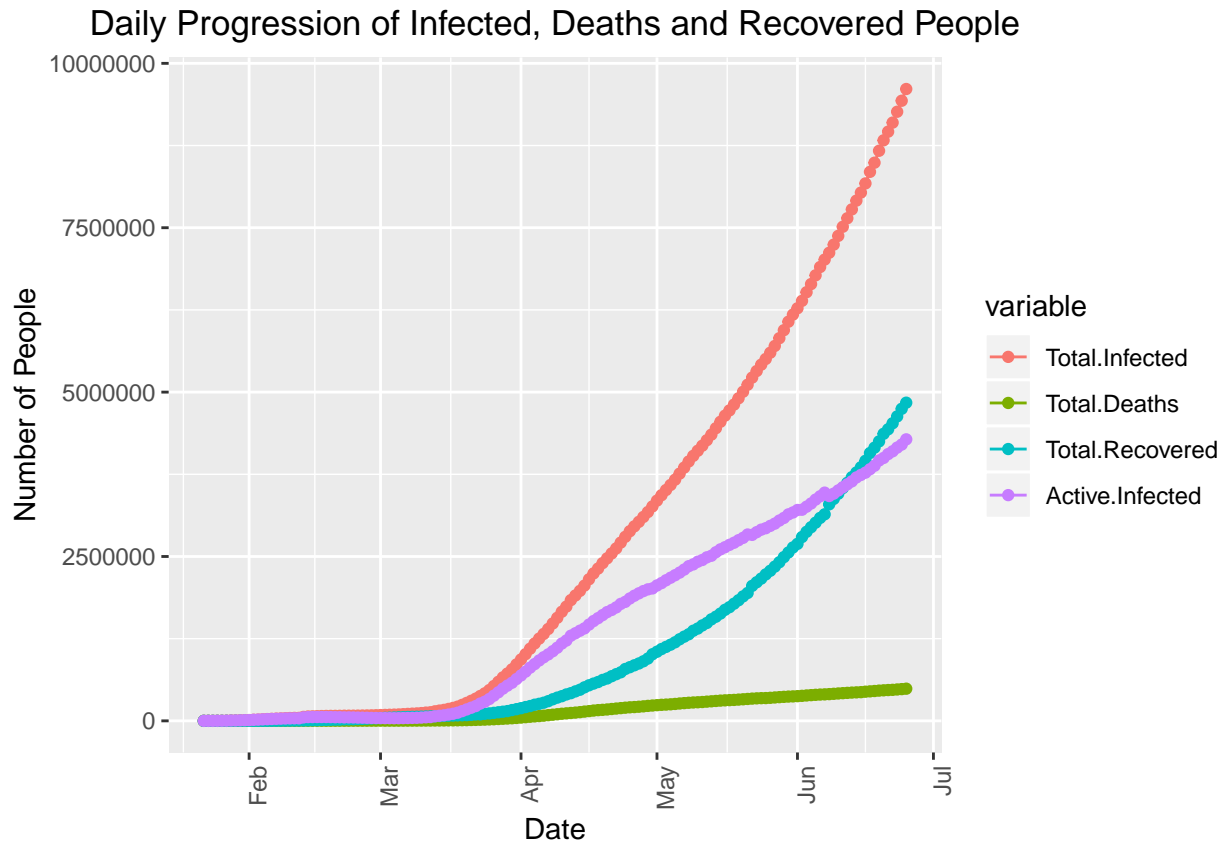
3 Dataset Exploration

3.1 Worldwide Propagation

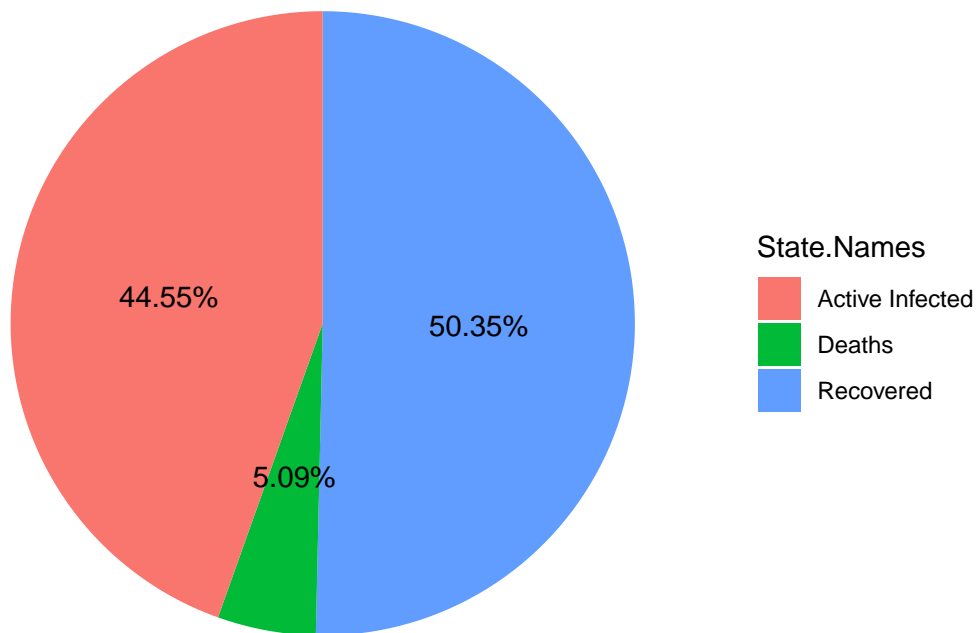
3.1.1 Daily Progression

The objective is to know the distribution of the number of people infected, dead and that recovered from the COVID-19 over days in the world.

Date	Total.Infected	Total.Deaths	Total.Recovered	Active.Infected
2020-06-12	7644260	425780	3620412	3598068
2020-06-13	7778881	430047	3706353	3642481
2020-06-14	7912426	433391	3777131	3701904
2020-06-15	8034461	436899	3857338	3740224
2020-06-16	8173940	443685	3955169	3775086
2020-06-17	8349950	448959	4073955	3827036
2020-06-18	8488976	453979	4155099	3879898
2020-06-19	8670323	460268	4250107	3959948
2020-06-20	8829186	464522	4365932	3998732
2020-06-21	8960607	468583	4434628	4057396
2020-06-22	9098643	472171	4526333	4100139
2020-06-23	9263935	477587	4630391	4155957
2020-06-24	9431350	482758	4746118	4202474
2020-06-25	9609829	489312	4838921	4281596



Pie Chart of the COVID-19 Propagation States Percentage

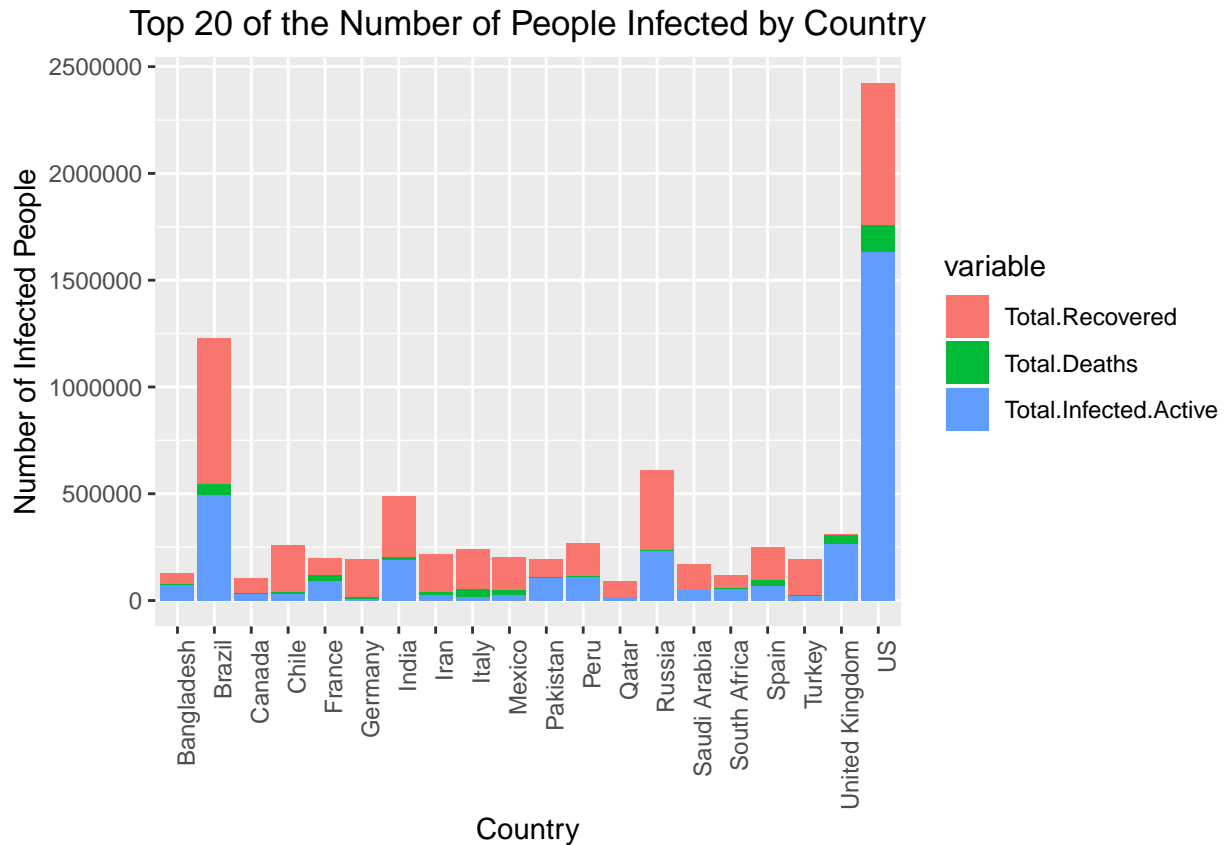


The distribution of the number of people infected, dead or recovered seems to be exponential. This would make sense because if we assume that all people will be infected one day or another, we expect that the curve will describe a sigmoid curve. The reasons behind this is explained in the **Propagation Model section**.

3.1.2 Countries With Highest Number of People Infected

The objective is to show in which countries there are the most infected people until today. Since there are many countries and because the list may be huge enough, we only display the 20 countries with the greatest number of infected people.

Country.Region	Total.Infected	Total.Deaths	Total.Recovered	Total.Infected.Active
US	2422299	124410	663562	1634327
Brazil	1228114	54971	679524	493619
Russia	613148	8594	374557	229997
India	490401	15301	285637	189463
United Kingdom	309455	43314	1361	264780
Peru	268602	8761	151225	108616
Chile	259064	4903	219327	34834
Spain	247486	28330	150376	68780
Italy	239706	34678	186725	18303
Iran	215096	10130	175103	29863
Mexico	202951	25060	152362	25529
France	197885	29755	75475	92655
Pakistan	195745	3962	84168	107615
Germany	193371	8940	176764	7667
Turkey	193115	5046	165706	22363
Saudi Arabia	170639	1428	117882	51329
Bangladesh	126606	1621	51495	73490
South Africa	118375	2292	59974	56109
Canada	104463	8567	66869	29027
Qatar	91838	106	74544	17188



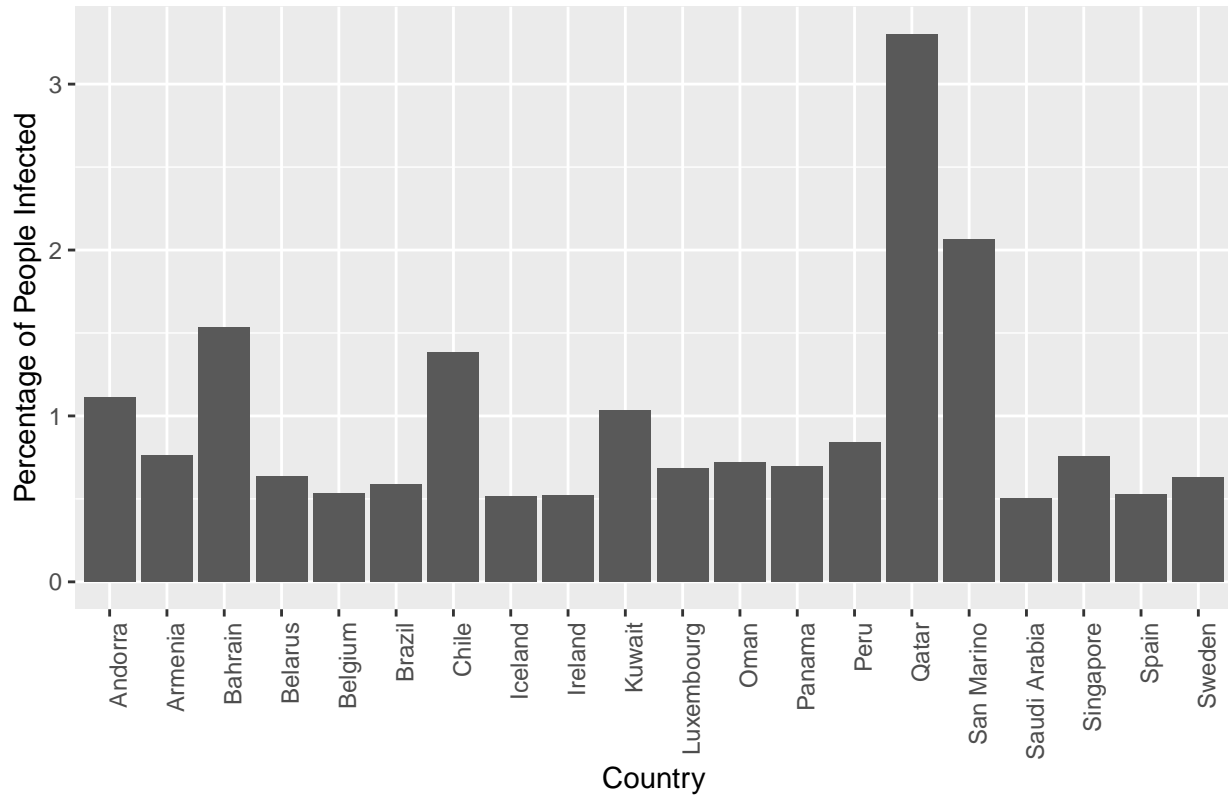
3.1.3 Countries Worst Ratio of Infected and Death People

The objective is to know which countries have the worst ratio of deaths and infected people over their population.

Country.Region	Population	Percent.Infected
Qatar	2781677	3.3015336
San Marino	33785	2.0660056
Bahrain	1569439	1.5343699
Chile	18729160	1.3832121
Andorra	77006	1.1103031
Kuwait	4137309	1.0341988
Peru	31989256	0.8396632
Armenia	2951776	0.7618464
Singapore	5638676	0.7579084
Oman	4829483	0.7226861
Panama	4176873	0.6951851
Luxembourg	607728	0.6830358
Belarus	9485386	0.6365793
Sweden	10183175	0.6274075
Brazil	209469333	0.5862978
Belgium	11422068	0.5341152
Spain	46723749	0.5296792
Ireland	4853506	0.5234360
Iceland	353574	0.5175720
Saudi Arabia	33699947	0.5063480

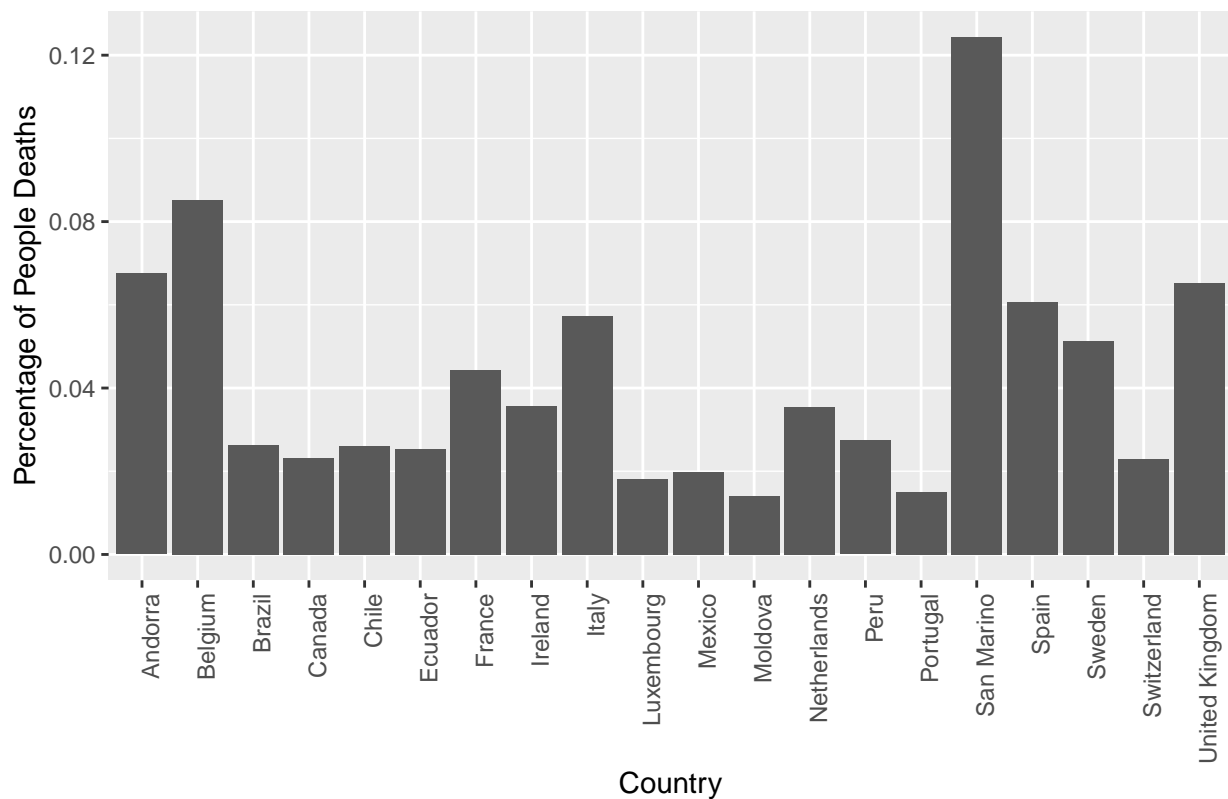
Country.Region	Population	Percent.Infected
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Top 20 of the Percentage of People Infected by Country



Country.Region	Population	Percent.Deaths
San Marino	33785	0.1243155
Belgium	11422068	0.0851510
Andorra	77006	0.0675272
United Kingdom	66488991	0.0651446
Spain	46723749	0.0606330
Italy	60431283	0.0573842
Sweden	10183175	0.0513592
France	66987244	0.0444189
Ireland	4853506	0.0355825
Netherlands	17231017	0.0355115
Peru	31989256	0.0273873
Brazil	209469333	0.0262430
Chile	18729160	0.0261784
Ecuador	17084357	0.0254209
Canada	37058856	0.0231173
Switzerland	8516543	0.0229905
Mexico	126190788	0.0198588
Luxembourg	607728	0.0181002
Portugal	10281762	0.0150655
Moldova	3545883	0.0141573

Top 20 of the Percentage of People Deaths by Country



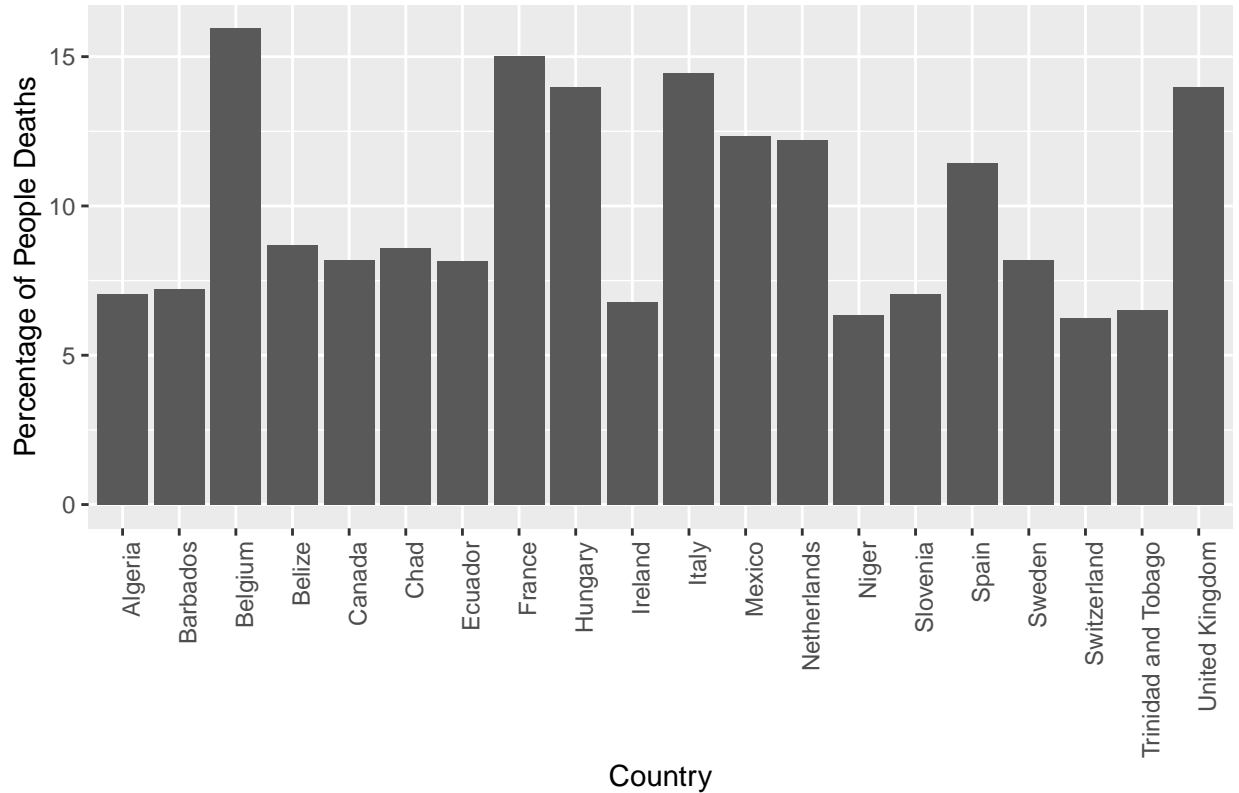
3.1.4 Countries Worst Ratio of Deaths Over Cumulative Infected People

The objective is to know which countries (top 20) have the worst ratio of dead people over the cumulative infected people.

Country.Region	Total.Infected	Total.Deaths	Percent.Deaths
Belgium	61007	9726	15.942433
France	197885	29755	15.036511
Italy	239706	34678	14.466889
United Kingdom	309455	43314	13.996866
Hungary	4123	577	13.994664
Mexico	202951	25060	12.347808
Netherlands	50122	6119	12.208212
Spain	247486	28330	11.447112
Belize	23	2	8.695652
Chad	863	74	8.574739
Canada	104463	8567	8.200990
Sweden	63890	5230	8.185945
Ecuador	53156	4343	8.170291
Barbados	97	7	7.216495
Algeria	12445	878	7.055042
Slovenia	1547	109	7.045895
Ireland	25405	1727	6.797874
Trinidad and Tobago	123	8	6.504065
Niger	1056	67	6.344697
Switzerland	31428	1958	6.230113

Country.Region	Total.Infected	Total.Deaths	Percent.Deaths
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Top 20 of the Percentage of People Deaths by Country

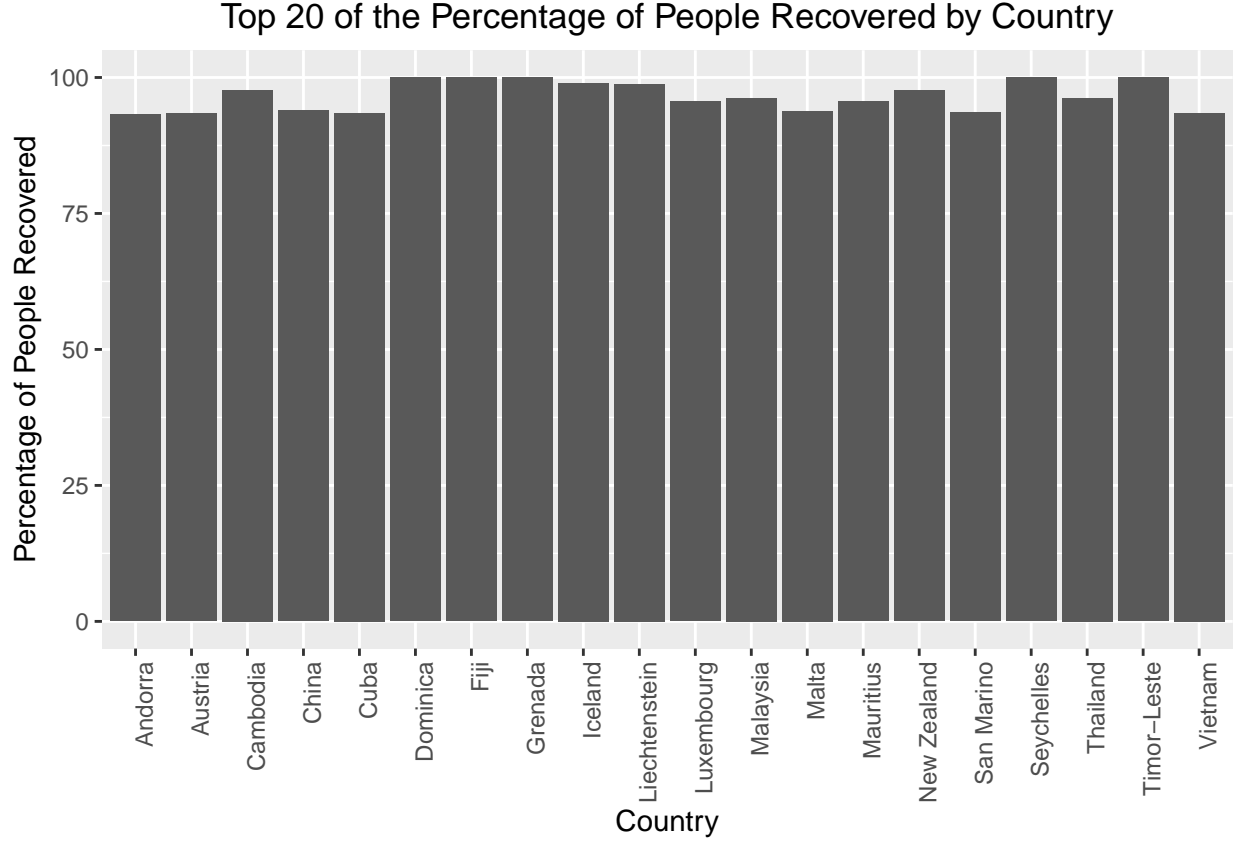


3.1.5 Countries Best Ratio of Recovers Over Cumulative Infected People

The objective is to know which countries (top 20) have the best ratio of recovered people over the cumulative infected people.

Country.Region	Total.Infected	Total.Recovered	Percent.Recovered
Timor-Leste	24	24	100.00000
Grenada	23	23	100.00000
Dominica	18	18	100.00000
Fiji	18	18	100.00000
Seychelles	11	11	100.00000
Iceland	1830	1811	98.96175
Liechtenstein	82	81	98.78049
Cambodia	130	127	97.69231
New Zealand	1520	1484	97.63158
Thailand	3158	3038	96.20013
Malaysia	8600	8271	96.17442
Mauritius	341	326	95.60117
Luxembourg	4151	3968	95.59142
China	84701	79572	93.94458
Malta	668	627	93.86228
San Marino	698	653	93.55301

Country.Region	Total.Infected	Total.Recovered	Percent.Recovered
Cuba	2321	2171	93.53727
Vietnam	352	329	93.46591
Austria	17477	16320	93.37987
Andorra	855	797	93.21637



3.2 Countries With Stable or Decreasing Propagation

The objective is to identify all countries whose propagation is stable or decreasing. In order to find these countries, we have to define what precisely is the meaning of *stable* or *decreasing* propagation.

Let $I(t)$ be the cumulative number of infected people at day $t \in \mathbb{N}$. If we take the difference between $I(t)$ at day t and $t + 1$, we get the **propagation velocity**. In mathematical terms, it is expressed as

$$\Delta I(t) = \frac{I(t+1) - I(t)}{(t+1) - t} = I(t+1) - I(t)$$

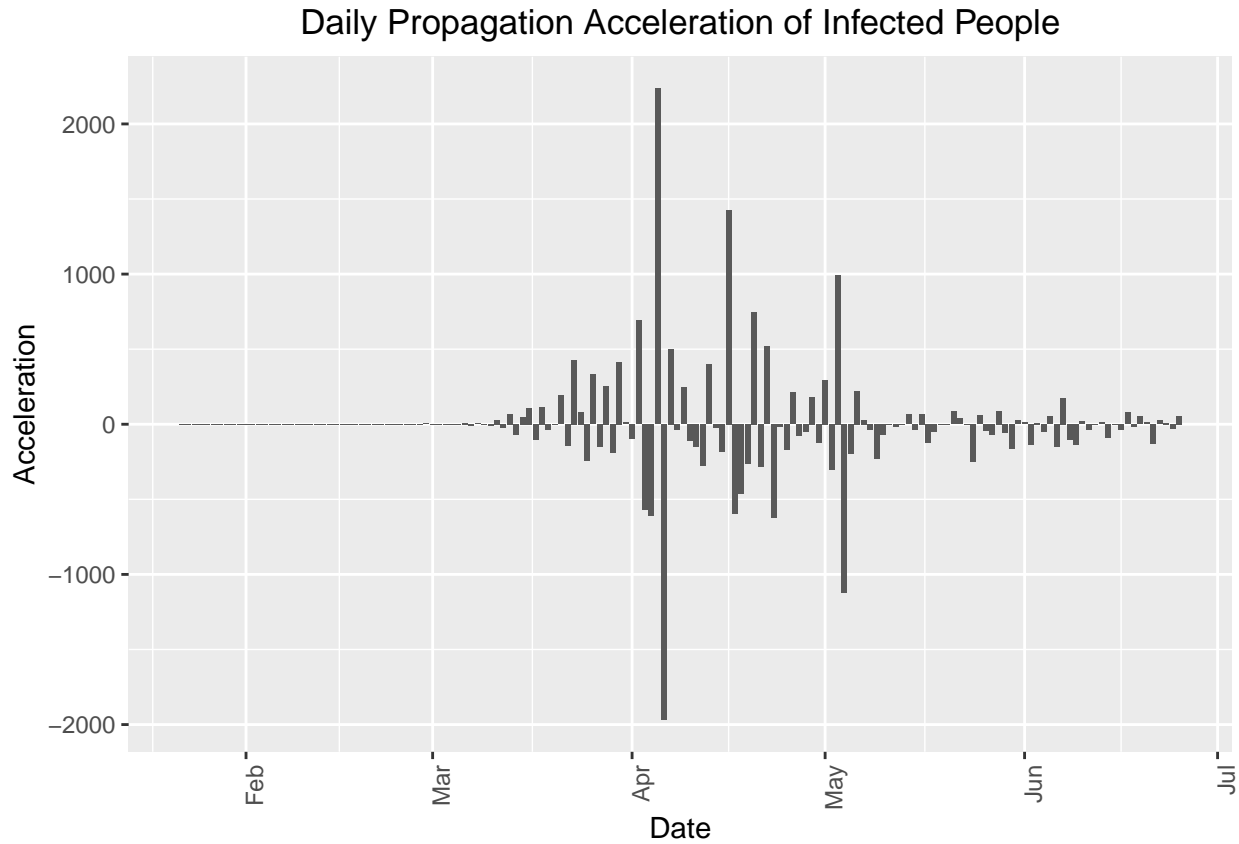
which can be seen as the derivative of $I(t)$ but in a discrete case. The same method is used to define the **propagation acceleration** where we look at the difference between the propagation velocity at day t and $t + 1$ expressed as

$$\Delta^2 I(t) = \frac{\Delta I(t+1) - \Delta I(t)}{(t+1) - t} = \Delta I(t+1) - \Delta I(t) = I(t+2) - 2I(t+1) + I(t).$$

The propagation is said **stable** if and only if the acceleration or deceleration is negligible which means that $\Delta^2 I(t) \approx 0$. Therefore, we need to find countries whose propagation acceleration is $\Delta^2 I(t) \lesssim 0$. However,

some of the values of $I(t)$ contained in the dataset may be aberrant values. The first step is to determine and remove those aberrant values. The second step is to determine when the propagation is accelerating, stabilized and decelering.

Date	Total.Infected	infected.delta	infected.acceleration
2020-06-12	99595	436	-3
2020-06-13	100043	448	12
2020-06-14	100404	361	-87
2020-06-15	100763	359	-2
2020-06-16	101087	324	-35
2020-06-17	101491	404	80
2020-06-18	101877	386	-18
2020-06-19	102314	437	51
2020-06-20	102762	448	11
2020-06-21	103078	316	-132
2020-06-22	103418	340	24
2020-06-23	103767	349	9
2020-06-24	104087	320	-29
2020-06-25	104463	376	56



It comes now the following questions:

1. What are the conditions to determine that a propagation velocity $\Delta I(t)$ is categorized as an aberrant value?
2. What is the range of propagation accelerations considered as approximative to 0 in the expression $\Delta^2 I(t) \approx 0$ and how to determine it?

3.2.1 Aberrant Propagation Acceleration Detection Model

The objective is to define what is an aberrant value based on our context and remove them in order to get a better estimation on the propagation acceleration. An aberrant value is a value that seems to be out of the “normality” according to our context. For example, if $\Delta^2(t)$ oscillates normally between -250 and 300 and at a day k , $\Delta^2(k) = 1500$, then $\Delta^2(k)$ could be considered as an aberrant value.

Since we want to find when the propagation speed is stable or is decreasing over days, the *value* here is the propagation acceleration. Assuming that the propagation accelerations are independent and identically distributed (i.i.d.) between days, the idea is to assume that the propagation acceleration is normally distributed (equivalently $\Delta^2 I(t) \sim N(\mu, \sigma^2)$). The mean μ is expressed as

$$\mu = \frac{1}{n-2} \sum_{t=1}^{n-2} \Delta^2 I(t)$$

where n is the number of observations in the dataset. Because there are n observations in the dataset, it follows that there are $n-2$ propagation accelerations. The variance is expressed as

$$\sigma^2 = \frac{1}{n-2} \sum_{t=1}^{n-2} (\Delta^2 I(t) - \mu)^2.$$

Let’s take the data of the Canada as an example. The mean of the propagation accelerations is $\mu = 2.4102564$ and the variance is $\sigma^2 = 118836.1144748$. Therefore, we have $\Delta^2 I(t) \sim N(2.4102564, 118836.1144748)$ where the positive standard deviation is $\sigma = 344.7261442$.

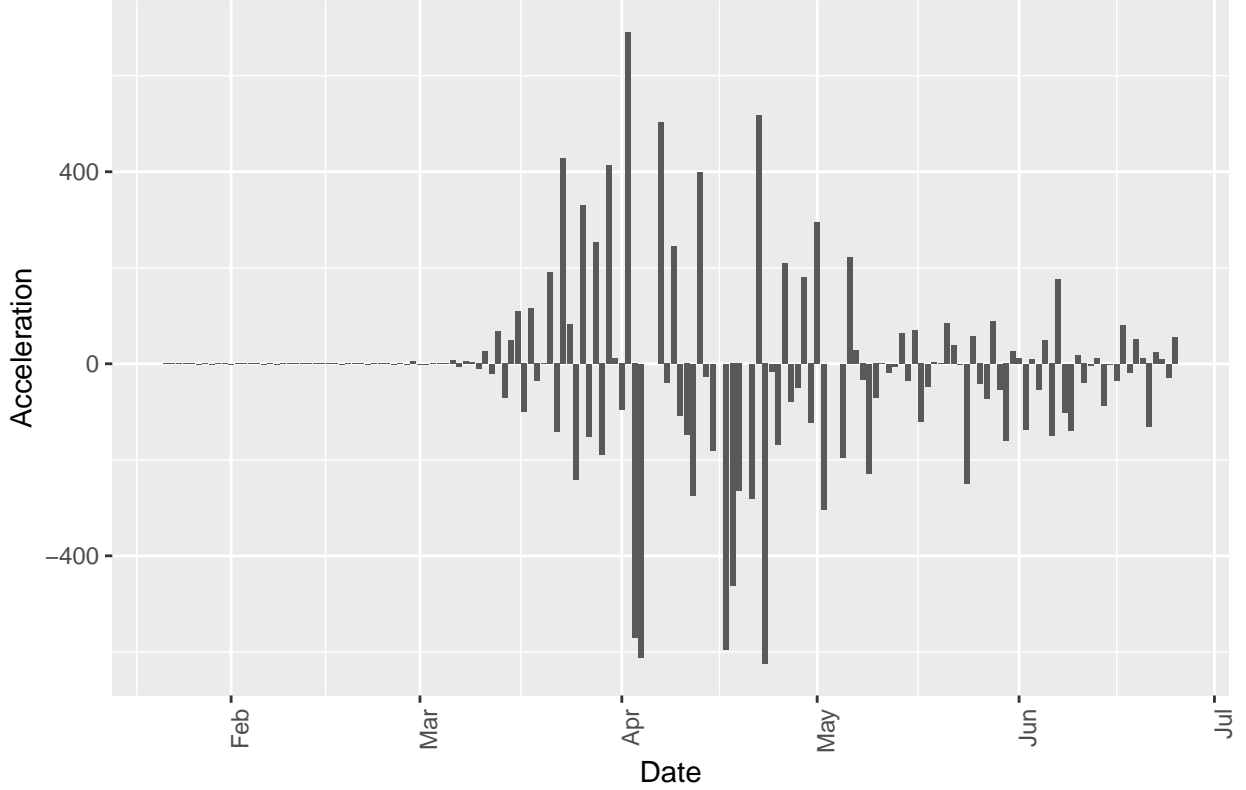
Therefore, the propagation acceleration is **aberrant** if and only if

$$\Delta^2 I(t) \in]-\infty, \mu - k\sigma] \cup [\mu + k\sigma, \infty[.$$

where $k \in \mathbb{R}$ is the parameter to provide. For example with $k = 2$, non-aberrant propagation accelerations in the Canada have to be exclusively between 2 standard deviations -687.0420319 and 691.8625448 .

Actually, there are 3.8461538 % of the propagation accelerations that are aberrant.

Daily Propagation Acceleration of Infected People



3.2.2 Propagation Phases Model

We know that a propagation can accelerate, become stable and decelerate on its curve. The objective is to find a model that determines if the propagation is still accelerating, stabilized or decelerating based on a set of points chronologically ordered. The idea is to find the global maximum among the non-aberrant propagation accelerations and define what is considered as an acceleration, a stabilization and a deceleration on the curve.

We define a **propagation cycle** when the 3 propagation phases occur in this order: Acceleration, Stabilization and Deceleration. We saw that a propagation is stable if $\Delta^2(t) \approx 0$. This is equivalent to say that a propagation is **stable** if and only if

$$|\Delta^2(t)| < \epsilon$$

where $\epsilon \in \mathbb{N}_*$. The stabilization phase may take many days and for this reason, we have to extend this definition to $|\Delta^2(t+k)| < \epsilon$ where $t+k \leq n$. However, this is not enough because it may happen that, between days t and $t+k$, the propagation is not stable. But overall, the bar chart will show that the propagation is stable. Therefore, we have to consider that a propagation is stable if the average of accelerations within a range of k days is near 0. In other terms, the **propagation is stable** between days t and $t+k$ if and only if

$$|\mu(\Delta^2(t), k)| = \frac{1}{k} \left| \sum_{i=1}^k \Delta^2(t+i) \right| < \epsilon.$$

We define the **propagation acceleration** as an acceleration of the number of infected people between day t and day $t+k$. The same method as the stabilization is used:

$$\mu(\Delta^2(t), k) = \frac{1}{k} \sum_{i=1}^k \Delta^2(t+i) \geq \epsilon.$$

We define the **propagation deceleration** as a deceleration of the number of infected people between day t and day $t + k$. The same method as the acceleration is used:

$$\mu(\Delta^2(t), k) = \frac{1}{k} \sum_{i=1}^k \Delta^2(t + i) \leq -\epsilon.$$

It follows that we have to provide the following parameters:

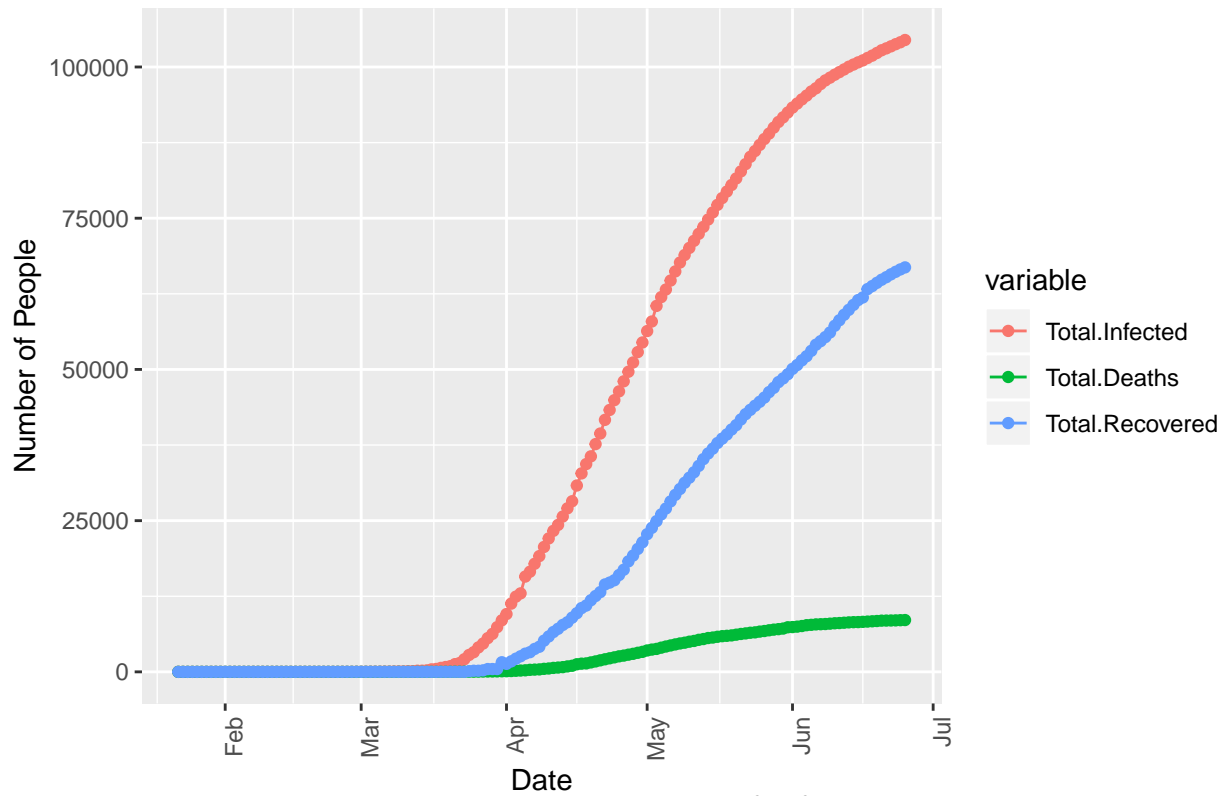
- the stabilization upper bound ϵ ;
- the number of days k on which the mean $\mu(\Delta^2(t), k)$ will be calculated.
- The step of days s between the calculation of means.

3.3 Canada Propagation Overview

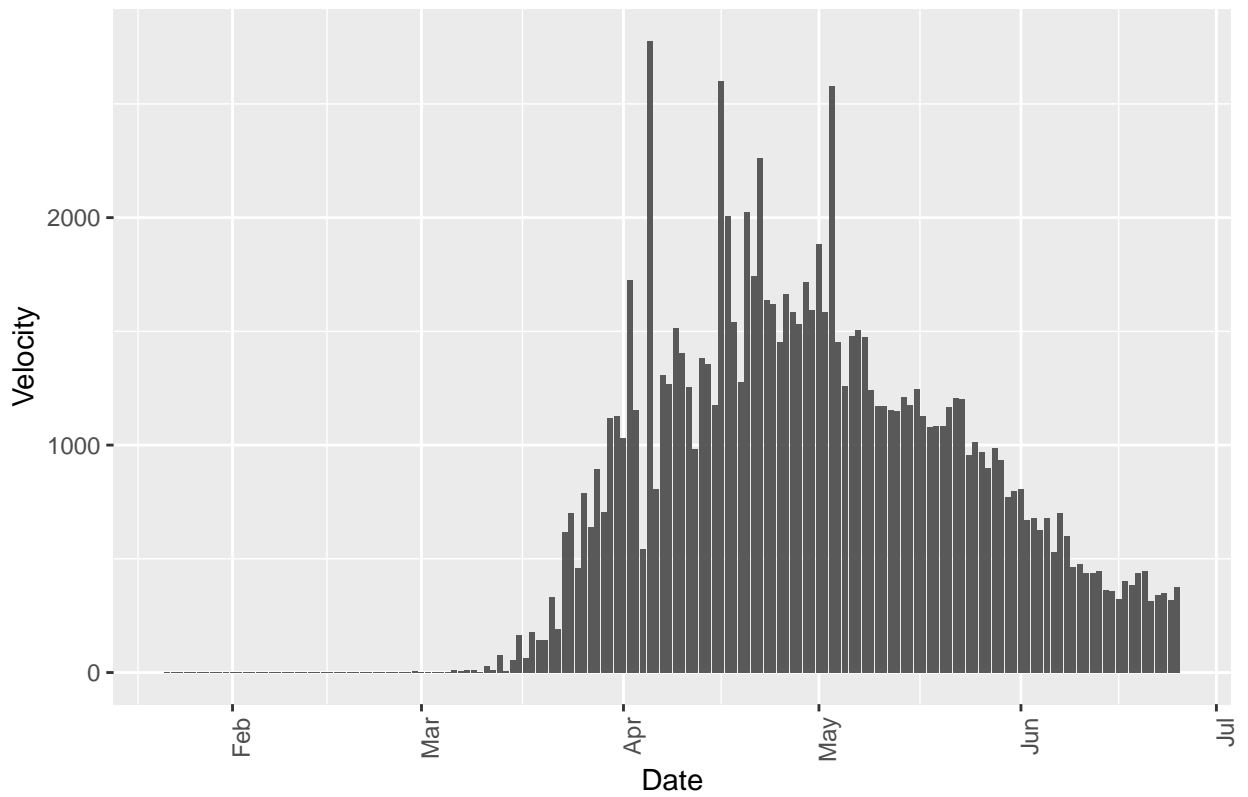
The objective is to know the overall propagation in Canada.

Date	Total.Infected	Total.Deaths	Total.Recovered	infected.delta	deaths.delta	recovered.delta
2020-06-12	99595	8125	59034	436	54	903
2020-06-13	100043	8183	59851	448	58	817
2020-06-14	100404	8218	60668	361	35	817
2020-06-15	100763	8228	61466	359	10	798
2020-06-16	101087	8271	61899	324	43	433
2020-06-17	101491	8312	63280	404	41	1381
2020-06-18	101877	8361	63782	386	49	502
2020-06-19	102314	8408	64318	437	47	536
2020-06-20	102762	8466	64826	448	58	508
2020-06-21	103078	8482	65249	316	16	423
2020-06-22	103418	8494	65721	340	12	472
2020-06-23	103767	8512	66135	349	18	414
2020-06-24	104087	8544	66533	320	32	398
2020-06-25	104463	8567	66869	376	23	336

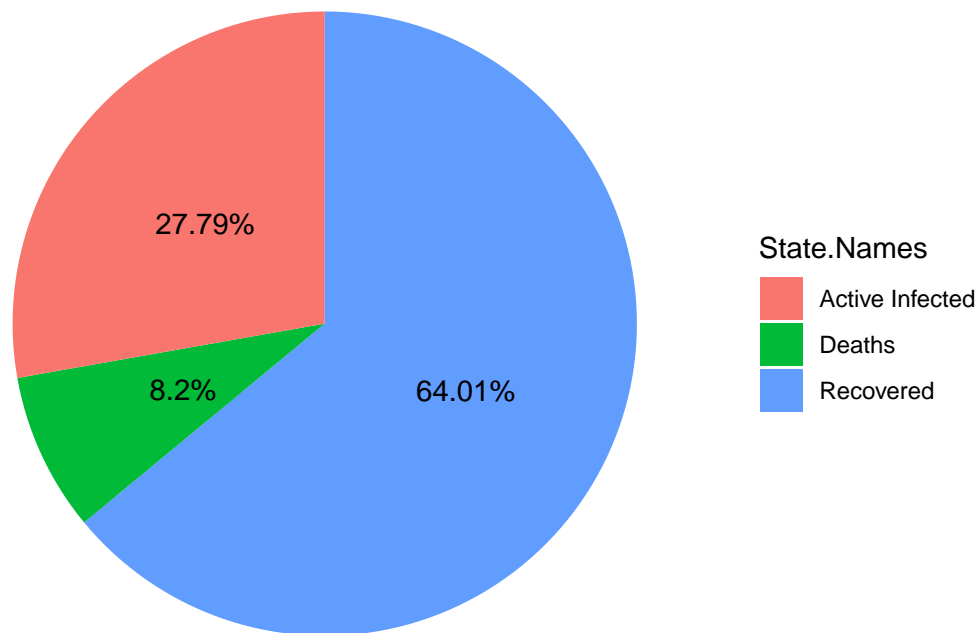
Daily Progression of Infected, Deaths and Recovered People



Daily Propagation Velocity of Infected People



Pie Chart of the COVID–19 Propagation States Percentage



4 Propagation Model

The COVID-19 is currently a worldwide pandemic virus which is considered very virulent. It means that it propagate from infected people to non-infected people by direct or indirect contacts. For exemple, if an infected person touches an object, a non-infected person touching the same object after a short time is mostly at risk to be infected.

The objective is to define a model that represents the propagation of the COVID-19 based on assumptions. However, we should take a look on variables that could have an impact on the propagation of the virus. Here is a list of some of those variables:

1. *Population density*: Countries with high population density should be more at risk because the contact between people is much easier hence more at risk to propagate the virus.
2. *Age of people*: Elder people are mostly to die after being infected by the virus because they are more fragile than younger people.
3. *People with chronic diseases*: People with chronic diseases like heart disease, lung disease, kidney disease, cancer, Alzheimer, diabetes, asthma and many others are more at risk to die after being infected.
4. *Births and deaths*: Since the propagation of the virus is a long time period, during this peiod, some people will die from any other causes than the COVID-19 which will decrease the population. In the other case, some women will give birth which will increase the population.
5. *Safety measures*: During the pandemic, many countries adopted safety measures in order to help reducing the contamination between people.
6. *Number of COVID-19 tests*: Since these tests are expensive, they are limited. Coutries that are part of the third world coutries will have less tests than the other countries. Therefore, the number of tests should at least be function of the country.

7. *Number of infected people not tested*: Some people that want to be tested because they might be infected by the COVID-19 are not tested because they are not considered as *essential*. By essential, we mean that the probability they infect others is much greater than other people that do not interact with people in their work (examples of essential people: police officers, nurses, doctors). Other people could be infected and prefer to stay at home without asking to be tested.
8. *Infected error factor*: It may happen that a person has been tested positive to the COVID-19 but is not infected at all. Thus, errors when testing could happen.
9. *Recovery error factor*: Errors could happen when people are considered to have recovered but in fact, they did not recover yet. They identified them as recovered too soon.
10. *Death error factor*: It may happen that a person has not died from the COVID-19 but is counted as being dead because of the COVID-19.

We did not consider the immunity against the COVID-19 because we are uncertain if there are people that will never be infected by the COVID-19 because they are immune. The same uncertainty holds for people recovering from the COVID-19. We do not know if they are immune for the rest of their life or it is like the Influenza; they can be infected after a period of time (virus mutation for example).

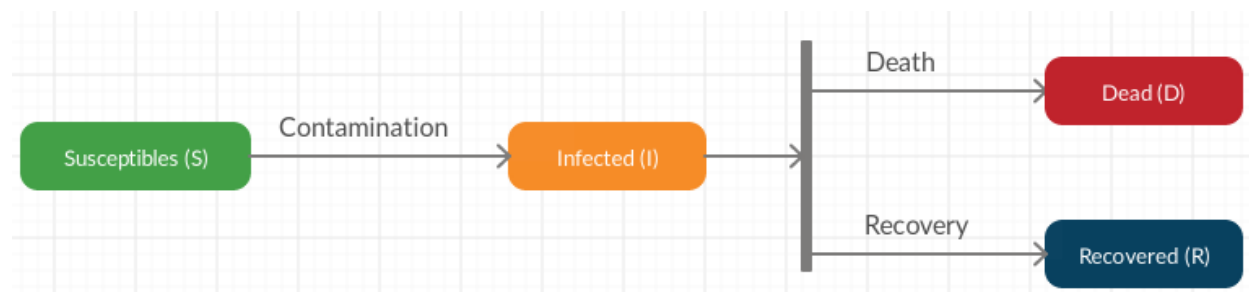
4.1 States and Transitions

A person can be in one of the following states during the propagation:

- Susceptible (noted $S(t)$): People susceptible to be infected by the COVID-19 at day t .
- Infected (noted $I_a(t)$): People tested positive to the COVID-19 at day t but did neither recovered nor died yet.
- Dead (noted $D(t)$): People died from the COVID-19 at day t .
- Recovered (noted $R(t)$): People recovered from the COVID-19 at day t .

Initially, all people in the population are in the *Susceptible* state. Then, it needs at least one person to start the propagation of the virus. This starts at day 1 (2020-01-22) given in our dataset and ends actually on 2020-06-25.

Here is a state diagram describing the interaction between the states:



The arrows between the states represent the transitions between 2 states.

4.2 Assumptions

The following assumptions are made to simplify the model:

1. A person taken randomly in the population has the same probabilities to be infected than any other person taken randomly in the population (it follows a uniform distribution). Therefore, any people have the same probabilities (homogenous population) to be infected without considering their age or if they have a chronic diseases.

2. An infected person could stay infected, recover or die the next day. There is no error made when a person is categorized as infected by the COVID-19. It means that it is not possible for a person to be in the *Infected* state and then transits back to the *Susceptible* state because an error has been made.
3. Every person that recovers from the COVID-19 are immune against it. It means that once a person recovered, that person cannot be infected anymore. Therefore, there is no transition between the *Recovered* state and the *Susceptible* state or *Infected* state.
4. During the propagation of the virus, there are neither births nor deaths (demography is ignored). The initial population is fixed to a constant N .
5. We know that there are more people infected than what the dataset is providing. Many circumstances make that these people have not been tested yet against the COVID-19. For simplicity, we assume that the dataset provides the right values of infected people. It means that we will not add an additional estimator to estimate the number of susceptible people that are in fact infected but not tested yet. However, we know that this assumption is not representative of the reality because the number of tests is limited. Indeed, some people that want to be tested because they have the COVID-19 symptoms are not tested because they are not considered as *essential*. By essential people, we mean that the probability that they infect others is greater than other people that do not interact with people in their work (e.g. police officers, nurses, doctors). These tests are also expensive which also explain why they are limited.
6. There are no safety measures taken during the pandemy. It means that there is no quarantine and social distancing between people, and any other safety measures.
7. All the population will have been infected one day. It does **not** take for account that some of the susceptible people could be immune against the virus, could never be infected or have not been tested but got infected by the COVID-19 and recovered.
8. The density of the population is independent of the propagation of the COVID-19.

4.3 SIR Epidemic Model

According to the assumptions, there are 3 transition phases between states on which our model is based:

- From *Susceptible* to *Infected* between days t and $t + 1$
- From *Infected* to *Recovered* between days t and $t + 1$
- From *Infected* to *Dead* between days t and $t + 1$

For exemple, if at day $t = 1$ there are 2 infected people and at day $t = 2$, there are 5 infected people and 1 dead, then between days $t = 1$ and $t = 2$, there are 4 people that transited from the *Susceptible* state to the *Infected* state and 1 person transited from the *Infected* state to the *Dead* state.

Per assumption 4, let the initial fixed population noted N be

$$N = S(t) + I_a(t) + R(t) + D(t)$$

where $S(t)$ will decrease while $I_a(t) + R(t) + D(t)$ will increase over days. On the first day of the propagation, there has to have at least one person infected in order to prapagate the virus to susceptible people. Generally, at this initial state, there are neither recovered nor dead people because they have to be infected before. However, it depends on the initial values given in the dataset. It may happen that the data have been gathered later like it is for our dataset.

We introduce $I_c(t)$ the **cumulative number of infected people** at day t because our dataset provides this feature. It means that $N = S(t) + I_c(t)$.

Per assumption 1, each infected person can be in contact with susceptible people and has the probability β to infect each of them. Therefore, each infected person generates $\beta S(t)$ infected people every day. This is true for all infected people ($I_c(t)$), therefore the total number of infected people generated is $\beta S(t) I_c(t)$. The population will then decrease at this rate.

The transition between the susceptible state and the infected state is represented by the equation

$$\frac{\partial S(t)}{\partial t} = -\beta S(t)I_c(t).$$

Per assumption 2, there is a probability γ that active infected people will recover (transition from *Infected* to *Recovered* state) or a probability of α that an active infected person will die (transition from *Infected* to *Dead* state) from day $t - 1$ to t . The transitions between the *Infected* state and the *Recovered* state or *Dead* state are given by

$$\begin{aligned}\frac{\partial R(t)}{\partial t} &= \gamma I_a(t) \\ \frac{\partial D(t)}{\partial t} &= \alpha I_a(t).\end{aligned}$$

We know that the number of susceptible people decreases when they become infected. It follows that the number of infected people increases by the same value. Therefore, we have that

$$\frac{\partial I_c(t)}{\partial t} = -\frac{\partial S(t)}{\partial t} = \beta S(t)I_c(t).$$

We did not remove the deaths and recovered people from the infected ones because in our case, the number of infected people is cumulative (I_c). However, to fit with our state diagram, we have to consider the **active** infected people ($I_a(t)$). This means that these people are infected by the COVID-19 but did neither recovered or died yet. Therefore, we have to subtract the deaths and recovered from the number of infected people:

$$\frac{\partial I_a(t)}{\partial t} = -\frac{\partial S(t)}{\partial t} - \frac{\partial R(t)}{\partial t} - \frac{\partial D(t)}{\partial t} = \beta S(t)I_c(t) - (\gamma + \alpha)I_a(t).$$

We have the following equations that represent our state transition model:

$$\begin{aligned}\frac{\partial S(t)}{\partial t} &= -\beta S(t)I_c(t) \\ \frac{\partial I_c(t)}{\partial t} &= \beta S(t)I_c(t) \\ \frac{\partial I_a(t)}{\partial t} &= \beta S(t)I_c(t) - (\gamma + \alpha)I_a(t) \\ \frac{\partial R(t)}{\partial t} &= \gamma I_a(t) \\ \frac{\partial D(t)}{\partial t} &= \alpha I_a(t)\end{aligned}$$

Let $R_0 = \frac{\beta}{\gamma + \alpha}$ be the number of infected people over the recovered and dead ones where $0 < \gamma + \alpha \leq 1$. We expect that $R_0 > 1$ will increase during the rising part of the propagation (contamination phase). Then, we expect that R_0 will decrease over the days and be nearer to 0 because the contamination phase will slow down while the recovery and death phases will increase faster. Finally, all phases will stabilize slowly to $R_0 = 1$.

4.4 Example

The example is based on the data we have for the Canada in this dataset. The first infected person appears to be on 2020-01-26.

Thus, let $I_c(0) = 1$, $R(0) = 0$, $D(0) = 0$ and fix the population to $N = 37058856$ people. It follows that $S(0) = 37058855$. Lets also fix the model parameters to $\alpha = 0.0065$, $\beta = 0.0000000045$ and $\gamma = 0.045$.

Lets see the results of the first iteration:

$$\begin{aligned}\frac{\partial S(t)}{\partial t} &= -0.0000000045 \times 37058855 \times 1 = -0.1667648475 \\ \frac{\partial I_a(t)}{\partial t} &= 0.0000000045 \times 37058855 \times 1 - 0.045 \times 1 - 0.0065 \times 1 = 0.1152648475 \\ \frac{\partial R(t)}{\partial t} &= 0.045 \times 1 = 0.045 \\ \frac{\partial D(t)}{\partial t} &= 0.0065 \times 1 = 0.0065\end{aligned}$$

Therefore, we obtain $I(1) = 0.8332351525$, $S(1) = 37058854.8332352$, $R(1) = 0.045$ and $D(1) = 0.0065$.

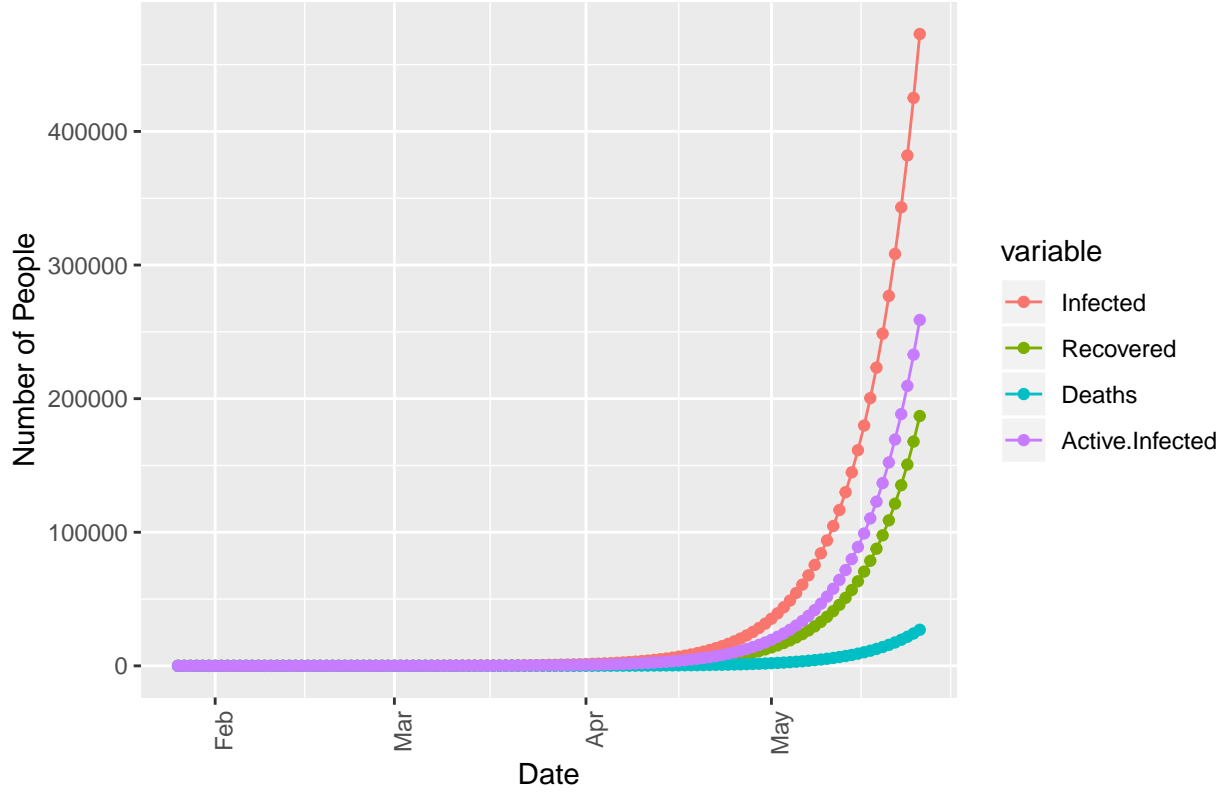
Lets simulate our model for 120 days to see the proppression of each state over the days.

Date	Susceptibles	Infected	Recovered	Deaths	Active.Infected
2020-01-26	37058855	1	0	0	1
2020-01-27	37058854	1	0	0	1
2020-01-28	37058854	1	0	0	1
2020-01-29	37058854	1	0	0	1
2020-01-30	37058854	1	0	0	1
2020-01-31	37058853	1	0	0	1
2020-02-01	37058853	1	0	0	1
2020-02-02	37058853	2	0	0	2
2020-02-03	37058852	2	0	0	2
2020-02-04	37058852	2	0	0	2
2020-02-05	37058852	2	0	0	2
2020-02-06	37058851	3	0	0	3
2020-02-07	37058851	3	1	0	2
2020-02-08	37058850	4	1	0	3
2020-02-09	37058849	4	1	0	3
2020-02-10	37058849	5	1	0	4
2020-02-11	37058848	5	1	0	4
2020-02-12	37058847	6	2	0	4
2020-02-13	37058846	7	2	0	5
2020-02-14	37058844	7	2	0	5
2020-02-15	37058843	8	3	0	5
2020-02-16	37058842	9	3	0	6
2020-02-17	37058840	11	3	0	8
2020-02-18	37058838	12	4	0	8
2020-02-19	37058836	13	4	0	9
2020-02-20	37058834	15	5	0	10
2020-02-21	37058831	17	6	0	11
2020-02-22	37058828	19	7	1	11
2020-02-23	37058825	21	7	1	13
2020-02-24	37058822	23	8	1	14
2020-02-25	37058818	26	9	1	16
2020-02-26	37058813	29	11	1	17
2020-02-27	37058808	32	12	1	19
2020-02-28	37058803	36	13	2	21
2020-02-29	37058797	40	15	2	23
2020-03-01	37058790	45	17	2	26
2020-03-02	37058782	50	19	2	29
2020-03-03	37058774	56	21	3	32
2020-03-04	37058765	63	24	3	36

Date	Susceptibles	Infected	Recovered	Deaths	Active.Infected
2020-03-05	37058754	70	27	3	40
2020-03-06	37058742	78	30	4	44
2020-03-07	37058729	87	33	4	50
2020-03-08	37058715	97	37	5	55
2020-03-09	37058698	108	42	6	60
2020-03-10	37058680	121	47	6	68
2020-03-11	37058660	135	52	7	76
2020-03-12	37058637	151	58	8	85
2020-03-13	37058612	168	65	9	94
2020-03-14	37058584	187	73	10	104
2020-03-15	37058553	209	81	11	117
2020-03-16	37058518	233	90	13	130
2020-03-17	37058479	260	101	14	145
2020-03-18	37058435	290	113	16	161
2020-03-19	37058387	324	126	18	180
2020-03-20	37058333	361	140	20	201
2020-03-21	37058272	403	157	22	224
2020-03-22	37058205	449	175	25	249
2020-03-23	37058130	501	195	28	278
2020-03-24	37058046	559	218	31	310
2020-03-25	37057953	624	243	35	346
2020-03-26	37057849	696	271	39	386
2020-03-27	37057733	776	302	43	431
2020-03-28	37057603	865	337	48	480
2020-03-29	37057459	965	376	54	535
2020-03-30	37057298	1076	420	60	596
2020-03-31	37057118	1201	468	67	666
2020-04-01	37056918	1339	522	75	742
2020-04-02	37056695	1493	582	84	827
2020-04-03	37056446	1665	650	93	922
2020-04-04	37056168	1857	725	104	1028
2020-04-05	37055858	2072	808	116	1148
2020-04-06	37055512	2310	901	130	1279
2020-04-07	37055127	2577	1005	145	1427
2020-04-08	37054697	2874	1121	162	1591
2020-04-09	37054218	3205	1251	180	1774
2020-04-10	37053684	3574	1395	201	1978
2020-04-11	37053087	3986	1556	224	2206
2020-04-12	37052423	4446	1735	250	2461
2020-04-13	37051681	4958	1935	279	2744
2020-04-14	37050854	5530	2158	311	3061
2020-04-15	37049932	6167	2407	347	3413
2020-04-16	37048904	6878	2685	387	3806
2020-04-17	37047757	7670	2994	432	4244
2020-04-18	37046479	8554	3340	482	4732
2020-04-19	37045053	9539	3724	538	5277
2020-04-20	37043462	10638	4154	600	5884
2020-04-21	37041689	11864	4633	669	6562
2020-04-22	37039711	13231	5166	746	7319
2020-04-23	37037506	14755	5762	832	8161
2020-04-24	37035047	16454	6426	928	9100
2020-04-25	37032304	18349	7166	1035	10148

Date	Susceptibles	Infected	Recovered	Deaths	Active.Infected
2020-04-26	37029247	20462	7992	1154	11316
2020-04-27	37025837	22817	8913	1287	12617
2020-04-28	37022035	25444	9940	1435	14069
2020-04-29	37017796	28373	11085	1601	15687
2020-04-30	37013070	31638	12361	1785	17492
2020-05-01	37007800	35278	13785	1991	19502
2020-05-02	37001925	39337	15373	2220	21744
2020-05-03	36995375	43861	17143	2476	24242
2020-05-04	36988073	48904	19117	2761	27026
2020-05-05	36979933	54525	21317	3079	30129
2020-05-06	36970859	60791	23771	3433	33587
2020-05-07	36960746	67774	26506	3828	37440
2020-05-08	36949473	75556	29556	4269	41731
2020-05-09	36936910	84227	32956	4760	46511
2020-05-10	36922910	93890	36747	5307	51836
2020-05-11	36907310	104655	40972	5918	57765
2020-05-12	36889929	116646	45681	6598	64367
2020-05-13	36870565	130003	50930	7356	71717
2020-05-14	36848995	144877	56780	8201	79896
2020-05-15	36824971	161440	63300	9143	88997
2020-05-16	36798219	179878	70565	10192	99121
2020-05-17	36768432	200401	78659	11361	110381
2020-05-18	36735274	223239	87677	12664	122898
2020-05-19	36698371	248645	97723	14115	136807
2020-05-20	36657309	276902	108912	15731	152259
2020-05-21	36611631	308319	121373	17531	169415
2020-05-22	36560835	343237	135247	19535	188455
2020-05-23	36504364	382030	150693	21766	209571
2020-05-24	36441608	425112	167884	24250	232978
2020-05-25	36371895	472932	187014	27013	258905

Daily Progression of Infected, Deaths and Recovered People



4.5 Model Representation With Markov Chain

Let $X = (X_t)_{t \geq 0}$ be a sequence of random variables where each random variable is representing a person X at day $t \geq 0$. Let $\mathbb{E} = \{S, I, R, D\}$ the COVID-19 state space. At any day t , a person X_t has to be in a state of \mathbb{E} . If $i, j \in \mathbb{E}$, then $\mathbb{P}(X_t \in j | X_{t-1} \in i) = p_{i,j}$. A person at day $t = 0$ as to start in a state of \mathbb{E} .

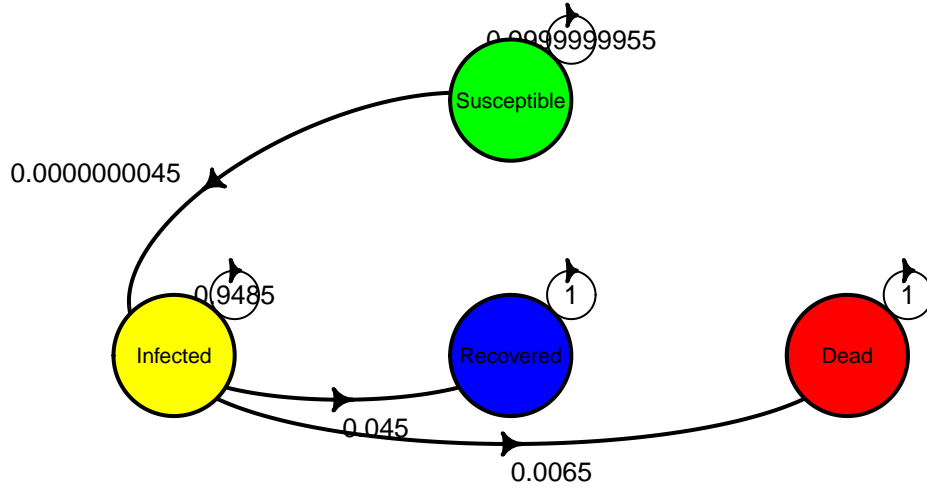
The probability that a susceptible person becomes infected at day t is defined as $\mathbb{P}(X_t \in I | X_{t-1} \in S) = \beta$. The susceptible people that do not transit to the infected state is expressed as $\mathbb{P}(X_t \in S | X_{t-1} \in S) = 1 - \beta$. Per assumption 5, it is impossible to transit from the *Infected* state to the *Susceptible* state. Therefore, we have $\mathbb{P}(X_t \in S | X_{t-1} \in I) = 0$.

The assumption 2 states that an infexcted person can transit to the death state or to the recovery state. It means that $\mathbb{P}(X_t \in R | X_{t-1} \in I) = \gamma$ and $\mathbb{P}(X_t \in D | X_{t-1} \in I) = \alpha$. Since the sets of recovered R and deaths D are mutually disjoint, we have that

$$\mathbb{P}(X_t \in R \cup D | X_{t-1} \in I) = \mathbb{P}(X_t \in R | X_{t-1} \in I) + \mathbb{P}(X_t \in D | X_{t-1} \in I) = \gamma + \alpha$$

We deduce that the remaining infected people that will stay in the *Infected* state (will not transit to another state on the next day) from day $t - 1$ to day t is $\mathbb{P}(X_t \in I | X_{t-1} \in I) = 1 - \alpha - \gamma$.

COVID-19 Markov Chain State Diagram



The transition matrix (noted P) is the following considering the order in \mathbb{E} and the transition between day $t - 1$ and day t :

$$P = \begin{bmatrix} p_{S,S} & p_{S,I} & p_{S,R} & p_{S,D} \\ p_{I,S} & p_{I,I} & p_{I,R} & p_{I,D} \\ p_{R,S} & p_{R,I} & p_{R,R} & p_{R,D} \\ p_{D,S} & p_{D,I} & p_{D,R} & p_{D,D} \end{bmatrix} = \begin{bmatrix} 1 - \beta & \beta & 0 & 0 \\ 0 & 1 - \alpha - \gamma & \gamma & \alpha \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Let's assume that there is an infected person, no deaths and no recovery on the first day. Including that there are $N - 1$ susceptible people, this means that if $\mathbf{x}^{(0)}$ is the initial vector, we have

$$\mathbf{x}^{(1)} = \mathbf{x}^{(0)} P = \begin{bmatrix} N - 1 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 - \beta & \beta & 0 & 0 \\ 0 & 1 - \alpha - \gamma & \gamma & \alpha \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} (N - 1)(1 - \beta) & (N - 1)\beta + (1 - \alpha - \gamma) & \gamma & \alpha \end{bmatrix}$$

On the second day, we have

$$\mathbf{x}^{(2)} = \mathbf{x}^{(1)} P = \begin{bmatrix} (N - 1)(1 - \beta)^2 \\ \beta(N - 1)((1 - \beta) + (1 - \alpha - \gamma)) + (1 - \alpha - \gamma)^2 \\ \beta(N - 1)\gamma + \gamma((1 - \alpha - \gamma) + 1) \\ \beta(N - 1)\alpha + \alpha((1 - \alpha - \gamma) + 1) \end{bmatrix}^T$$

For n days, we have $\mathbf{x}^{(n)} = \mathbf{x}^{(0)} P^n$. By induction on $n \geq 1$, one shows that

$$\mathbf{x}^{(n)} = \mathbf{x}^{(0)} P^n = \begin{bmatrix} (N - 1)(1 - \beta)^n \\ \beta(N - 1) \sum_{i=0}^{n-1} (1 - \beta)^{n-1-i} (1 - \alpha - \gamma)^i + (1 - \alpha - \gamma)^n \\ \beta(N - 1)\gamma \sum_{i=0}^{n-2} (1 - \beta)^i (1 - \alpha - \gamma)^{n-2-i} + \gamma \sum_{i=0}^{n-1} (1 - \alpha - \gamma)^i \\ \beta(N - 1)\alpha \sum_{i=0}^{n-2} (1 - \beta)^i (1 - \alpha - \gamma)^{n-2-i} + \alpha \sum_{i=0}^{n-1} (1 - \alpha - \gamma)^i \end{bmatrix}^T$$

Let's see what is the probability law \mathbf{x} . We have to find $\mathbf{x} = \lim_{n \rightarrow \infty} \mathbf{x}^{(n)}$. We calculate this limit term by term in $\mathbf{x}^{(n)}$. The first term:

$$\lim_{n \rightarrow \infty} (N - 1)(1 - \beta)^n = 0$$

because $0 < \beta \leq 1$ then $0 \leq (1 - \beta) < 1$. For the second term, we have that

$$\lim_{n \rightarrow \infty} \beta(N-1) \sum_{i=0}^{n-1} (1-\beta)^{n-1-i} (1-\alpha-\gamma)^i + (1-\alpha-\gamma)^n = \beta(N-1) \lim_{n \rightarrow \infty} \sum_{i=0}^{n-1} (1-\beta)^{n-1-i} (1-\alpha-\gamma)^i + \lim_{n \rightarrow \infty} (1-\alpha-\gamma)^n = 0.$$

Indeed, we get $\lim_{n \rightarrow \infty} (1-\alpha-\gamma)^n = 0$ because $0 \leq (1-\alpha-\gamma) < 1$. We also have that $\lim_{n \rightarrow \infty} \sum_{i=0}^{n-1} (1-\beta)^{n-1-i} (1-\alpha-\gamma)^i = 0$ because $\lim_{n \rightarrow \infty} (1-\beta)^{n-1-i} = 0$ since $0 \leq \beta < 1$. For the third term, we have that

$$\beta(N-1)\gamma \lim_{n \rightarrow \infty} \sum_{i=0}^{n-2} (1-\beta)^i (1-\alpha-\gamma)^{n-2-i} + \gamma \lim_{n \rightarrow \infty} \sum_{i=0}^{n-1} (1-\alpha-\gamma)^i = \gamma \lim_{n \rightarrow \infty} \sum_{i=0}^{n-1} (1-\alpha-\gamma)^i = \gamma \sum_{i=0}^{\infty} (1-\alpha-\gamma)^i$$

because using the same properties as for the second term, the first limit is evaluated to 0. For the second limit, we have a geometric series of ratio $(1-\alpha-\gamma) < 1$. Note that it is impossible to have $(1-\alpha-\gamma) = 1$ because it would mean that $\alpha = \gamma = 0$ which contradicts our assumption stating that an infected person at day t has to transit to either the *Recovered* state or the *Dead* state at day $t+k$ where $k \geq 1$.

Therefore, we have that

$$\gamma \sum_{i=0}^{\infty} (1-\alpha-\gamma)^i = \frac{\gamma}{1 - (1-\alpha-\gamma)} = \frac{\gamma}{\alpha + \gamma}.$$

For the fourth term, we use the same logic as the third term

$$\beta(N-1)\alpha \lim_{n \rightarrow \infty} \sum_{i=0}^{n-2} (1-\beta)^i (1-\alpha-\gamma)^{n-2-i} + \alpha \lim_{n \rightarrow \infty} \sum_{i=0}^{n-1} (1-\alpha-\gamma)^i = \alpha \lim_{n \rightarrow \infty} \sum_{i=0}^{n-1} (1-\alpha-\gamma)^i = \frac{\alpha}{\alpha + \gamma}.$$

Therefore, the final result is

$$\mathbf{x} = \begin{bmatrix} 0 & 0 & \frac{\gamma}{\alpha + \gamma} & \frac{\alpha}{\alpha + \gamma} \end{bmatrix}.$$

We expect that with the SIR model based on our assumptions, all susceptible people will be infected and then, all infected people will either recover or die. In other terms, we expect that at the end of the COVID-19 pandemic, a percentage of the population will recover while the rest of the population will die. Therefore, our vector \mathbf{x} makes sense because $\frac{\gamma}{\alpha + \gamma} + \frac{\alpha}{\alpha + \gamma} = 1$.

If we take back our example where $\gamma = 0.045$ and $\alpha = 0.0065$, we obtain

$$\frac{\gamma}{\alpha + \gamma} = \frac{0.045}{0.0515} = 0.8737864078$$

This means that 87.3786407767 % of the population will recover and 12.6213592233 % will die once the pandemic will end.

4.6 SIR Model Solutions

The objective is to solve the first-order differential equations defined for the 3 transitions in order to find $S(t)$, $I_a(t)$ and $R(t)$ in function of t . However, it is useful to mention that the propagation is described basically by the 3 following phases:

1. **Initialization** The propagation will start and slowly progress; only a small number of people will be infected at the beginning of the pandemic.
2. **Acceleration** The propagation will increase quickly because every person infected will infect other people that were not infected making the progression increasing exponentially.
3. **Resolution** The worst case is when the majority of the population is infected. Indeed, there are less non-infected people remaining and the progression will have no choice but to slow down until all people of the population are infected.

These phases justify why the sigmoid function is a good choice. This sigmoid function $I_c(t)$ starts at $t = 0$ and ends until all the population is infected. Therefore, we deduce that the bounds of t and $I_c(t)$ are $t \in [0, \infty[$ and $I_c(t) \in [0, N]$ where $I_c(t)$ will increase over days (cumulative function). It also follows that $\lim_{t \rightarrow \infty} I_c(t) = N$.

4.6.1 Cumulative Infected and Susceptible People Models

We know that when susceptible people are getting infected, the same number of people decreases from susceptible to increase in the infected state from day $t - 1$ to day t . It means that $I_c(t) = N - S(t)$. Therefore, we have

$$\frac{\partial I_c(t)}{\partial t} = \beta I_c(t)(N - I_c(t)).$$

We have $\frac{\partial I_c(t)}{\partial t} = N\beta I_c(t) - \beta I_c^2(t)$ which is a Bernoulli's differential equation. Dividing the equation by $I_c^2(t)$ gives

$$\frac{\frac{\partial I_c(t)}{\partial t}}{I_c^2(t)} - \frac{N\beta}{I_c(t)} = -\beta.$$

Let $y(t) = -\frac{1}{I_c(t)}$. Then, we have $\frac{\partial y(t)}{\partial t} = \frac{1}{I_c^2(t)} \frac{\partial I_c(t)}{\partial t}$. Replacing in the equation above, we get

$$\frac{\partial y(t)}{\partial t} = -\beta(1 + Ny(t)).$$

Dividing by $1 + Ny(t)$ on both sides gives

$$\frac{\frac{\partial y(t)}{\partial t}}{1 + Ny(t)} = -\beta.$$

Since $\int \frac{1}{1 + Ny(t)} dt = \frac{1}{N} \ln(1 + Ny(t))$, we have, after multiplying by N on both sides, that

$$\frac{\partial(\ln(1 + Ny(t)))}{\partial t} = -N\beta.$$

We know that $t \geq 0$, hence we have to integrate this last equation from 0 to t on both sides:

$$\int_0^t \frac{\partial(\ln(1 + Ny(x)))}{\partial x} dx = -N\beta \int_0^t dx$$

which gives:

$$\ln(1 + Ny(t)) - \ln(1 + Ny(0)) = -N\beta t.$$

Using the subtraction of logarithms property, we have:

$$\ln\left(\frac{1 + Ny(t)}{1 + Ny(0)}\right) = -N\beta t.$$

Applying the exponential function on both sides, it follows that

$$\frac{1 + Ny(t)}{1 + Ny(0)} = e^{-N\beta t}$$

which is equivalent to

$$y(t) = \frac{(1 + Ny(0))e^{-N\beta t} - 1}{N}.$$

Since $y(t) = -\frac{1}{I_c(t)}$ and then $y(0) = -\frac{1}{I_c(0)}$, we have

$$I_c(t) = \frac{N}{1 - \left(1 - \frac{N}{I_c(0)}\right) e^{-N\beta t}}$$

where $I_c(0) > 0$ because having $I_c(0) = 0$ implies that there are no infected people and then the propagation cannot start. Using the same method to solve $\frac{\partial S(t)}{\partial t} = -\beta S(t)(N - S(t))$, we obtain

$$S(t) = \frac{N}{1 + \left(\frac{N}{S(0)} - 1\right) e^{N\beta t}}$$

where $S(0) > 0$ because having $S(0) = 0$ implies that there is no population initially which is impossible.

We know that $t \in [0, \infty[$ and $S(t), I_c(t) \in [0, N]$. Taking the limit to infinite days, we have for $I_c(t)$ that:

$$\lim_{t \rightarrow \infty} \frac{N}{1 - \left(1 - \frac{N}{I_c(0)}\right) e^{-N\beta t}} = N$$

and for the initial day:

$$\lim_{t \rightarrow 0} \frac{N}{1 - \left(1 - \frac{N}{I_c(0)}\right) e^{-N\beta t}} = I_c(0).$$

Taking the limit to infinite days, we have for $S(t)$ that:

$$\lim_{t \rightarrow \infty} \frac{N}{1 + \left(\frac{N}{S(0)} - 1\right) e^{N\beta t}} = 0$$

and for the initial day:

$$\lim_{t \rightarrow 0} \frac{N}{1 + \left(\frac{N}{S(0)} - 1\right) e^{N\beta t}} = S(0).$$

4.6.2 Number of Recovered and Deaths Models

We know that $\frac{\partial R(t)}{\partial t} = \gamma I_a(t)$. But $I_a(t) = I_c(t) - R(t) - D(t)$ hence

$$\frac{\partial R(t)}{\partial t} = \gamma(I_c(t) - R(t) - D(t)).$$

However, $R(t)$ and $D(t)$ are the same except that the constant α is used instead of γ . Let $R_D(t) = R(t) + D(t)$ and $k = \gamma + \alpha$. It comes that

$$\frac{\partial R_D(t)}{\partial t} = k(I_c(t) - R_D(t))$$

which is equivalent to:

$$\frac{\partial R_D(t)}{\partial t} + kR_D(t) = kI_c(t).$$

This is a first-order differential equation. First, let's solve the homogeneous equation

$$\frac{\partial R_D(t)}{\partial t} + kR_D(t) = 0.$$

Hence, we have to solve the separated-variable equation:

$$\frac{\partial R_D(t)}{\partial t} = -kR_D(t).$$

After dividing by $R_D(t)$ on both sides:

$$\frac{\partial R_D(t)}{R_D(t)} = -k\partial t.$$

Then integrating both sides we obtain the general solution:

$$R_D(t) = R_0 e^{-kt}$$

where $R_0 \in \mathbb{R}$ is the integration constant. Suppose that R_0 is function of t in $R_D(t)$ where $R_D(t) = R_0(t)e^{-kt}$ and substitute it in the initial equation:

$$\begin{aligned} kI_c(t) &= \frac{\partial R_0(t)e^{-kt}}{\partial t} + kR_0(t)e^{-kt} \\ &= \frac{\partial R_0(t)}{\partial t}e^{-kt} + R_0(t)\frac{\partial e^{-kt}}{\partial t} + kR_0(t)e^{-kt} \\ &= \frac{\partial R_0(t)}{\partial t}e^{-kt} - kR_0(t)e^{-kt} + kR_0(t)e^{-kt} \\ &= \frac{\partial R_0(t)}{\partial t}e^{-kt} \end{aligned}$$

It follows that

$$\frac{\partial R_0(t)}{\partial t} = kI_c(t)e^{kt}.$$

Knowing $I_c(t)$, we have to solve:

$$R_0(t) = kN \int \frac{e^{kt} dt}{1 - \left(1 - \frac{N}{I_c(0)}\right) e^{-N\beta t}}.$$

Let $\delta = 1 - \frac{N}{I_c(0)}$. The previous equation is then written as

$$R_0(t) = kN \int \frac{e^{kt} dt}{1 - \delta e^{-N\beta t}}.$$

The result of this integral is given by:

$$R_0(t) = \frac{-kNe^{t(N\beta+k)} {}_2F_1\left(1; \frac{k}{N\beta} + 1; \frac{k}{N\beta} + 2; \frac{e^{N\beta t}}{\delta}\right)}{\delta(N\beta + k)} + D_0$$

where ${}_2F_1(\cdot)$ is the Gauss's hypergeometric function and $D_0 \in \mathbb{R}$ is the integration constant. Substituting $R_0(t)$ in $R_D(t) = R_0(t)e^{-kt}$ gives:

$$R_D(t) = \frac{-kNe^{N\beta t} {}_2F_1\left(1; \frac{k}{N\beta} + 1; \frac{k}{N\beta} + 2; \frac{e^{N\beta t}}{\delta}\right)}{\delta(N\beta + k)} + D_0e^{-kt}.$$

We can conclude on the following equations for $R(t)$:

$$R(t) = \frac{-\gamma Ne^{N\beta t} {}_2F_1\left(1; \frac{\gamma}{N\beta} + 1; \frac{\gamma}{N\beta} + 2; \frac{e^{N\beta t}}{\delta}\right)}{\delta(N\beta + \gamma)} + D_0e^{-\gamma t}$$

and for $D(t)$:

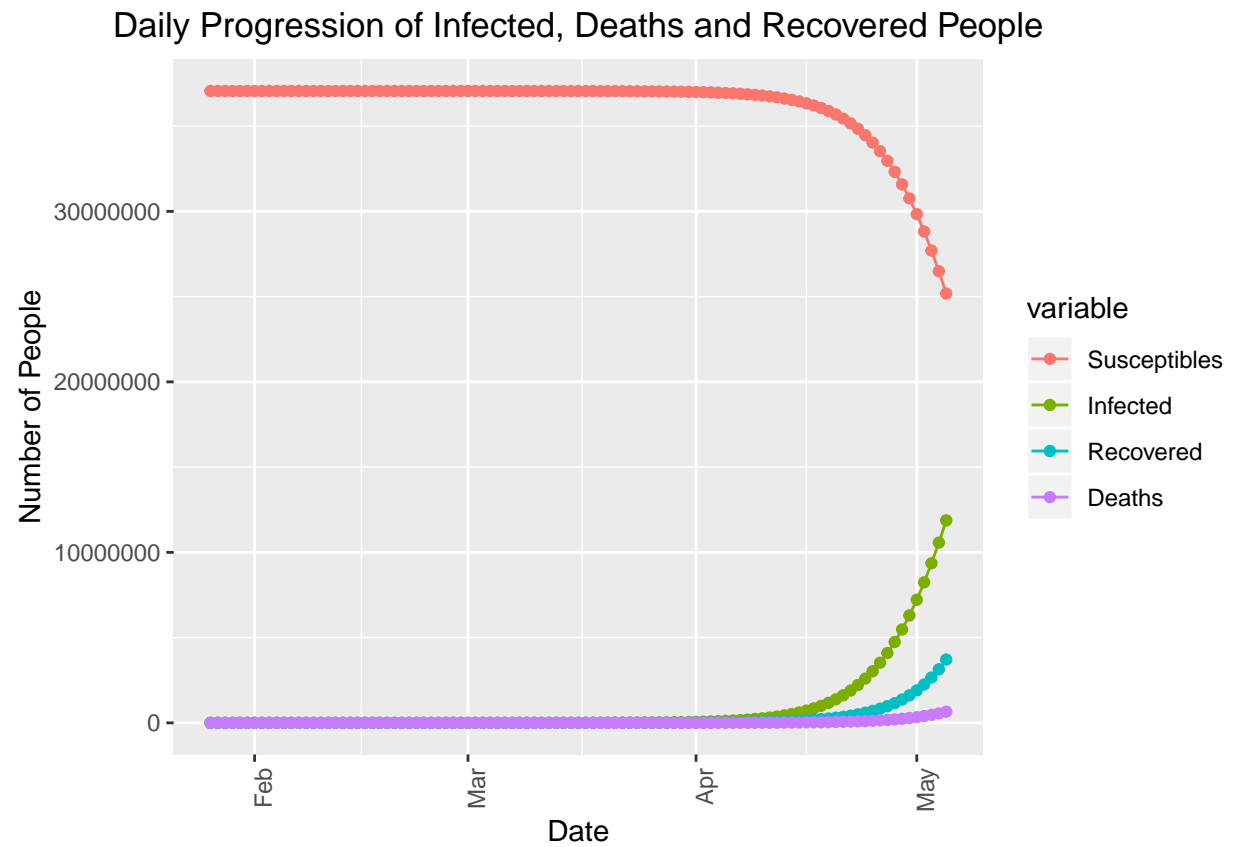
$$D(t) = \frac{-\alpha Ne^{N\beta t} {}_2F_1\left(1; \frac{\alpha}{N\beta} + 1; \frac{\alpha}{N\beta} + 2; \frac{e^{N\beta t}}{\delta}\right)}{\delta(N\beta + \alpha)} + D_0e^{-\alpha t}.$$

4.6.3 Simulation

Date	Susceptibles	Infected	Recovered	Deaths
2020-01-26	37058855.00	1.000000000	0.000000000	0.000000000
2020-01-27	37058854.82	1.181476405	0.2510635708	0.0443228779
2020-01-28	37058854.60	1.395886494	0.2966256866	0.0523664347
2020-01-29	37058854.35	1.649206954	0.3504562515	0.0618697073

Date	Susceptibles	Infected	Recovered	Deaths
2020-01-30	37058854.05	1.948499097	0.4140557942	0.0730975997
2020-01-31	37058853.70	2.302105698	0.4891971536	0.0863630898
2020-02-01	37058853.28	2.719883547	0.5779748972	0.1020359533
2020-02-02	37058852.79	3.213478208	0.6828637071	0.1205530719
2020-02-03	37058852.20	3.796648639	0.8067873618	0.1424306107
2020-02-04	37058851.51	4.485650724	0.9532002365	0.1682784067
2020-02-05	37058850.70	5.299690401	1.1261835942	0.1988169680
2020-02-06	37058849.74	6.261459031	1.3305593508	0.2348975578
2020-02-07	37058848.60	7.397765916	1.5720244862	0.2775259234
2020-02-08	37058847.26	8.740285606	1.8573098477	0.3278903319
2020-02-09	37058845.67	10.326440825	2.1943677727	0.3873946925
2020-02-10	37058843.80	12.200445626	2.5925937601	0.4576976909
2020-02-11	37058841.59	14.414537847	3.0630883704	0.5407590251
2020-02-12	37058838.97	17.030435237	3.6189666539	0.6388940321
2020-02-13	37058835.88	20.121055821	4.2757237332	0.7548382279
2020-02-14	37058832.23	23.772550471	5.0516667299	0.8918235603
2020-02-15	37058827.91	28.086704337	5.9684250768	1.0536684991
2020-02-16	37058822.82	33.183774068	7.0515534380	1.2448844765
2020-02-17	37058816.79	39.205839912	8.3312440467	1.4708016432
2020-02-18	37058809.68	46.320766130	9.8431683140	1.7377174464
2020-02-19	37058801.27	54.726880100	11.6294711708	2.0530721717
2020-02-20	37058791.34	64.658500548	13.7399458586	2.4256563405
2020-02-21	37058779.61	76.392468968	16.2334219180	2.8658557471
2020-02-22	37058765.74	90.255866287	19.1794050631	3.3859409620
2020-02-23	37058749.36	106.635129826	22.6600146557	4.0004093751
2020-02-24	37058730.01	125.986824665	26.7722727847	4.7263893103
2020-02-25	37058707.15	148.850369583	31.6308087594	5.5841174785
2020-02-26	37058680.14	175.863072216	37.3710544045	6.5975030762
2020-02-27	37058648.22	207.777892420	44.1530192267	7.7947942549
2020-02-28	37058610.52	245.484428810	52.1657506831	9.2093655394
2020-02-29	37058565.97	290.033713205	61.6326038851	10.8806481434
2020-03-01	37058513.33	342.667503809	72.8174676280	12.8552291160
2020-03-02	37058451.15	404.852893149	86.0321202986	15.1881499563
2020-03-03	37058377.68	478.323194808	101.6449207061	17.9444408974
2020-03-04	37058290.87	565.126247700	120.0910760946	21.2009336258
2020-03-05	37058188.32	667.681483047	141.8847735565	25.0484029664
2020-03-06	37058067.15	788.847342934	167.6335130124	29.5940972336
2020-03-07	37057924.00	932.000927129	198.0550412880	34.9647277812
2020-03-08	37057754.87	1101.132084717	233.9973593270	41.3100010845
2020-03-09	37057555.05	1300.954568264	276.4623602405	48.8067918125
2020-03-10	37057318.96	1537.037341885	326.6337571054	57.6640732145
2020-03-11	37057040.04	1815.959693561	385.9100789996	68.1287422551
2020-03-12	37056710.51	2145.494461683	455.9436550380	80.4925018737
2020-03-13	37056321.18	2534.824464056	538.6866730933	95.0999922122
2020-03-14	37055861.20	2994.798135497	636.4455970861	112.3583974684
2020-03-15	37055317.77	3538.231462480	751.9454597314	132.7487961671
2020-03-16	37054675.74	4180.264579013	888.4058229004	156.8395712371
2020-03-17	37053917.22	4938.782890948	1049.6305229974	185.3022537007
2020-03-18	37053021.09	5834.914365787	1240.1137030045	218.9302416202
2020-03-19	37051962.38	6893.616707965	1465.1650868421	258.6609160908
2020-03-20	37050711.63	8144.370588964	1731.0579880700	305.6017707639
2020-03-21	37049234.00	9621.997979614	2045.2041786768	361.0612832643

Date	Susceptibles	Infected	Recovered	Deaths
2020-03-22	37047488.37	11367.628009911	2416.3604924297	426.5853890394
2020-03-23	37045426.16	13429.836741674	2854.8729218578	504.0005743531
2020-03-24	37042990.01	15865.991874772	3372.9650130813	595.4647896410
2020-03-25	37040112.16	18743.838824034	3985.0785974974	703.5276024384
2020-03-26	37036712.63	22143.370919417	4708.2763582312	831.2012666460
2020-03-27	37032696.97	26159.033826800	5562.7174529005	982.0446891911
2020-03-28	37027953.68	30902.322802049	6572.2194506928	1160.2626346563
2020-03-29	37022351.16	36504.841225675	7764.9222477662	1370.8229332094
2020-03-30	37015734.10	43121.900171058	9174.0724676347	1619.5949590064
2020-03-31	37007919.25	50936.751680752	10838.9502117198	1913.5132391590
2020-04-01	36998690.44	60165.563087669	12805.9639932658	2260.7707538698
2020-04-02	36987792.74	71063.256203901	15129.9443759323	2671.0473159828
2020-04-03	36974925.65	83930.353519721	17875.6723772754	3155.7793960341
2020-04-04	36959735.01	99120.993600624	21119.6852414071	3728.4789141854
2020-04-05	36941803.70	117052.299349409	24952.4099167952	4405.1098853727
2020-04-06	36920640.69	138215.305147413	29480.6837099574	5204.5334166648
2020-04-07	36895668.33	163187.671137634	34830.7323783407	6149.0334611458
2020-04-08	36866207.57	192648.433523761	41151.6886768073	7264.9379837242
2020-04-09	36831460.94	227395.056389913	48619.7494373085	8583.3528538849
2020-04-10	36790492.94	268363.059743140	57443.0870604568	10141.0289226621
2020-04-11	36742207.50	316648.495285019	67867.6523269611	11981.3864536308
2020-04-12	36685322.48	373533.518864231	80184.0302824534	14155.7254639565
2020-04-13	36618340.74	440515.257066822	94735.5403036865	16724.6557137953
2020-04-14	36539517.93	519338.072057246	111927.8061356733	19759.7862050375
2020-04-15	36446826.82	612029.176593508	132240.0626648177	23345.7212842193
2020-04-16	36337918.68	720937.318295927	156238.5146046508	27582.4189910266
2020-04-17	36210082.09	848773.911654693	184592.1194679081	32587.9773914204
2020-04-18	36060200.48	998655.515634053	218091.2347757316	38501.9265644983
2020-04-19	35884710.10	1174145.897841589	257669.6492954694	45489.1180073146
2020-04-20	35679560.94	1379295.056118555	304430.6124284378	53744.3198749281
2020-04-21	35440184.55	1618671.453753314	359677.5873175501	63497.6461481213
2020-04-22	35161473.65	1897382.350708482	424950.5849185396	75020.9710669898
2020-04-23	34837780.50	2221075.499819260	502069.0918480192	88635.5076329177
2020-04-24	34462942.30	2595913.702825055	593182.7886233302	104720.7614298913
2020-04-25	34030344.04	3028511.958009627	700831.4720665249	123725.1093531670
2020-04-26	33533030.52	3525825.482125952	828015.8522111481	146178.2981276497
2020-04-27	32963879.78	4094976.224296817	978281.1971775634	172706.2110125271
2020-04-28	32315849.74	4743006.262744494	1155816.1576200332	204048.3143144600
2020-04-29	31582306.51	5476549.495484716	1365569.5254797610	241078.2700313694
2020-04-30	30757436.84	6301419.157102739	1613388.1816973640	284828.2892048339
2020-05-01	29836737.42	7222118.586236479	1906180.0781810875	336517.9048314724
2020-05-02	28817559.54	8241296.461109583	2252106.7971576559	397587.9663790159
2020-05-03	27699671.45	9359184.547514625	2660811.0555029497	469740.8035051383
2020-05-04	26485782.41	10573073.588338261	3143685.4957421012	554987.6785438312
2020-05-05	25181958.53	11876897.471322054	3714190.2562755286	655704.8504986896



5 Model Parameters Learning