Optimizing Measurement Methods for Governmental Regulations to Slow Down COVID-19 Spread

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Abstract

COVID-19 has affected day to day life and slowed down the global economy. Most countries are locking their population and enforcing strict quarantine to control the spread of the havoc of this highly contagious disease. Since the outbreak of COVID-19, many data analyses have been done to provide a close support to decision makers. In this paper, we propose two different models of data analytics and statistics to help governmental decision support. Lockdown procedures are regularly reviewed by worldwide governments to enable a reasonable control over the outbreak increase. The first model aims to measure the lockdown efficiency for various countries. The model shows a good agreement between the lockdown efficiency and the infection rate increase. The lockdown efficiency is measured by finding a correlation coefficient between the lockdown attributes and the infection rate. The lockdown attributes include retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, residential and schools.

This second model aims to find out the outbreak growth by measuring the exponential tilt angle for predicting any future spike before its occurrence. The prediction chooses small intervals of three to four days. This is essential to closely monitor the sudden outbreak. The model measures the infection stability or instability and enables an appropriate comparison between countries. The model can measure any exponential or sigmoid growth of the infection rate.

Key Words: COVID-19, Pandemic, Outbreak, Government regulations, spread control

Introduction

Three major global pandemic outbreaks have spread in the last few decades, severe acute respiratory syndrome (SARS), Middle East respiratory syndrome (MERS) and Ebolavirus (EVD). SARS and MERS are both caused by coronaviruses. This group of crown-like viruses can cause liver, neurologic, gastrointestinal and respiratory disease [1-3]. SARS first appeared in Southern China in November 2002, caused by the SARS-associated coronavirus (SARS-CoV) with readily transmission through droplets. The incubation period is typically 2 to 7 days. The outbreak is declared to be over by the late July 2003, this global pandemic resulted in a total of 8,098 probable cases with 774 associated deaths [2]. Compared to SARS, new MERS cases were being reported. Since first identified in Saudi Arabia in 2012, a total of 2,519 laboratory-confirmed cases, including 866 associated deaths were reported globally by the end of January 2020 [4]. With 79.6% similarity in sequence identity as SARS-CoV, the newest coronavirus (COVID-19) outbreak first started in Wuhan, China on 12 December 2019, had caused 113,702 laboratory-confirmed infections including 4,012 deaths by 10 March 2020 [5, 6]. Within 24 hours, 4,125 new confirmed cases and 203 new death cases occurred [5]. Considering a rapid spread over the globe and person-to-person transmission capability, the World Health Organization (WHO) declared COVID-19 as a Public Health Emergency of International Concern on 1 February 2020 [7].

Proactively predicting how COVID-19 might evolve is crucial at the current stage for the following reasons. Firstly, prediction can avoid pandemic expansion at an early stage. Learning from history, an increase in movement of disease vectors and the disease they carried due to the tourism, immigration and economic activity growth around the world is one of the primary factors of disease transmission [8]. Therefore, the severity of virus spread may be reduced through placing effective precautions like travel ban and lockdown in the next hot spots of emergency. Second, predictions save time for preparedness for the next country at risk. Under the unexpected health crisis, the rising global demand on personal protective equipment (PPE), life necessity disrupted the normal supply chain and left health workers worldwide in danger [9]. Predicting the spread of disease globally can foresee the impact of disease and effectively manage the supply chain prior to epidemic secure allocations for critically affected and at-risk countries, therefore reducing the shortage issue for those endangering health workers at the front line.

Possible Scenarios to Stop the COVID-19 Pandemic

The world has witnessed several pandemic outbreaks in mankind history. The knowledge base of the old civilizations pandemics is very limited, and did not accurately cover the diseases symptoms, number of death toll and the period of the disease. Due to the limited transportation methods in the old civilizations, outbreaks were spread on local or national levels, known by epidemics. Majority of the historical epidemics were caused by Plague, Smallpox, Cholera, Influenza, Malaria and Measles. The recent outbreaks have appeared in Africa with Ebolavirus, in China with SARS and Swine Flu, and in the Middle east with MERS.

Once a disease reaches that number of infections, then it is hard to stop the spread completely. However, most countries have already applied the lockdown plans to slow down the disease outbreak. The WHO found that the global fatality rate from COVID-19 seems to be at about 3.4 percent [10]. That may sound low, but the fatality rate from seasonal flu is about 0.1 percent. The fatality rate from the feared Spanish influenza, which killed about 50 to 100 million people in 1918, was about 2 percent. Despite worldwide efforts to contain the new Coronavirus, hotspots continue to emerge, and the number of cases is on the rise. So, how will this pandemic stop? Experts say that all pandemic within the history start decreasing when enough people develop immunity, either through infection or vaccination.

Another possible scenario is that the virus will continue to circulate and establishes itself as a common respiratory virus. At this point, it is very unlikely that the outbreak will be contained worldwide. Any pandemic may come to an end when the virus doesn't have enough susceptible people to infect. Vaccination can be the safest solution in developing an immune against this virus. For this reason, the largest world's research institute are racing to find a vaccine for coronavirus. Organizations work in a parallel phase process to produce the vaccine as early as possible [11]. Many organizations are in charged in developing a vaccine, so this may speed up the phases and gives a chance to develop more than one type of vaccination [12]. Nevertheless, developers and researchers may not be able to provide any formal statements about the deadline to produce the vaccine. Informally, they do not expect a ready vaccine for public before May 2021, which is around one year away from now.

Effect of temperature and humidity on COVID-19

Theoretically, environmental conditions may affect the viral life cycle and the transmission of a virus, and therefore, some viruses have seasonality. Several studies show that the risk of influenza incidence was significantly increased with low daily temperature and low relative humidity [13]. These findings are true with a wide range of germs like SARS, Malaria, and Tuberculosis. Researchers suggest a similar end to COIVID-19 as soon as summer hits the north part of the earth. Ma et al. states that a positive association with COVID-19 daily death counts was observed for diurnal temperature range, while negative association for relative humidity. Adly finds that the temperature range between 13 – 24 C is the ideal environment to spread the virus. The study compared between the number of infections in Egypt and Australia [14]. Others suggest that Initial geographical epicenters of disease were all roughly along the 30- 50 o N' zone; this includes South Korea, Japan, Iran, and Northern Italy. It was noticed that during the same time, COVID-19 failed to spread significantly to countries with temperature around zero Celsius such as Russia and Mongolia, or countries with high temperatures, around 30 Celsius [15]. These findings are not accurate, since many countries broke the temperatures roles such as India. The temperature of India in mid-April is around 36, while the number of infected cases has exceeded 10,000. However, it is a matter of few months before confirming the impact percentage on COVID-19 spread.

Comparison Between Four Diseases

There are similarities between SARS, MERS and EVD. However, none of the mentioned diseases have caused a global outbreak as COVID-19 did. It is hard to predict the major circumstances that gave a good chance for COVID-19 to spread that fast. Table 1 explains the differences between them and may partially find out the major spreading reasons.

	COVID-19	SARS	MERS	EVD [16]
Incubation period	2-14 days	2-10 days	2-14 days	2-21 days
Contagious during incubation	Yes	Yes	Yes	No
Vaccine Release Year	N/A	N/A	N/A	Dec-19
Infected Body part	Blood vessels	Respiratory system	Respiratory system	All muscles
Latest outbreak	Dec 2019	Nov 2002 - July 2003	Apr-12 Jul-15	Dec 2013 - June 2016
Winter/Summer impact	Likely	Likely	Not likely	Not likely
Main Transmission	respiratory droplet secretions	respiratory droplet secretions	respiratory droplet secretions	Body Fluids
Shape & Size in nm	Spherical 80-120nm	Spherical 80-90 nm	Spherical 90-125 nm	Filament 14,000 X 80 nm
Temperature impact	Likely	Likely	likely	Likely
Mortality rate	2.65%	14-15%	34%	Up to 90%
Pronounced R-naught	2-2.5	3.1-4.2	<1	1.5-1.9

Table 1: Comparison between COVID-19, SARS, MER and EVD

A quick comparison between the four viruses may concludes that MERS and COVID-19 are very similar. COVID-19 has recorded the highest Pronounced R-naught (RO). However, the reason of COVID-19 fast spread may refer to other factors that are not confirmed yet. It is obvious that there is a minimum number of infections are required to ignite any outbreak as a threshold number. It is known that the threshold number is large enough in urban areas and crowded cities. In a rough estimation, it is enough to infect a minimum of 0.2% of the inhabitance out of any cities' population to reach the outbreak threshold value. This estimation depends on the RO value of the virus and on the population density. For instance, 0.2% is not enough percentage for creating an outbreak in a suburban or less density cities. Wuhan /Hubei is one of the highest increase of population rate in China, its average annual increase rate is 7.9% with a population number of 11 million [17]. the density of the city center of Wuhan city is unknown, but the average of world's medium metropolitans is around 29,000 person/kilometer. This number is usually doubled or tripled during the daytime in the city center.

Various factors have created an ideal environment to spread out the virus, the city center density, the outbreak core center, the high seasonal shopping celebrating upcoming Chinese spring festival, the large number of international students and worldwide visitors are good reasons for such an environment. On the contrast, Most probably that MERS and SARS have started in suburban areas [16]. MERS has appeared in places far away from main cities in Saudi Arabia. Camel's farms are available in unoccupied areas of deserts.

Pandemic and Economy

This paper presents some suggested methods for measuring the RO speed on the short run. This is to provide better measurement tools for the governmental body, so they promptly decide in accordance to the spread development. During the past few months, the spread measurements have adapted the value of RO=2.5. This value was calculated during the initial stages of the pandemic. The calculation method has considered the incubation period of 14 days for the virus. With the time pass, the RO rate has dramatically dropped down as a reason of the lockdown procedures, self-quarantine, and people's awareness of the disease. Moreover, the uncertainty of giving infection numbers, in the early stages, was high. Currently, the uncertainty percentage rate is lower, and the scan rate of suspected patients is higher. Also, the virus test results period is much shorter than before, which may not exceed few hours. For these reasons, we need to find a faster and more accurate measurement tool that gives governments a better understand to the outbreak growth.

The measurements models in this paper are divided into two types, one for measuring the lockdown procedures and finding out the most appropriate regulation that governments should take. The second measurement model enables a better prediction for the near future diseases spread. Both methods adapt a short period of measurement, which should not exceed four days. This may not look accurate for measuring RO, but however, it can be considered another model of measurement. This is essential to closely monitor the social distancing efficiency.

Governments should have a long-term plan for this outbreak, this includes a continues revision for the lockdown polices restrictions and procedures. The policies should compromise between preventing an over limit outbreak and mitigating economical loss. The limited capacity is defined by the ultimate capacity for intensive care units in the public health system. Governments are concerned about finding the optimal planning response, since they are unable to determine the outbreak spread time, and social activities that cause the highest spread. Future modelling will account for the actions taken by governments, which include restricting travel, isolating people with the virus and their contacts, social distancing, growing health system capacity and others [18].

For approximate evaluation, we built a naïve model that may support decision making. The model should provide a short period of reading the exponential spread of the diseases. A period of four days is defined as a short time to re-review the public health policy. The governments respond should act promptly according the resulted output.

Measuring Lockdown Efficiency

To implement a proper model for measuring the lockdown efficiency, the model is supposed to measure some factors that have direct impact on the lockdown procedures. The RO value was calculated on daily basis, and then it was grouped by interquartile ranges. The RO can be calculated by subtracting the number of infections in previous day from the current day infections. The equation is given by $\frac{x_i - x_{(i-1)}}{x_{(i-1)}}$. Suppose the that the number of infections is denoted by X, where X is defined as:

$$X = \{x_0, x_1, x_2, \dots . x_n\} \tag{1}$$

$$where\ x_n\ presents\ the\ number\ of\ infections\ in\ n\ days$$

The dispersion value is calculated by finding the interquartile mean of RO for each interquartile range. Two interquartile values of Q1 and Q3 are found as follows:

$$Q1 = N/4 \tag{2}$$

$$Q3 = 3 \times Q1 \tag{3}$$

Where N denotes the number of days

Three interquartile ranges are defined by finding the mean of the values between zero and Q1, and then the mean of the values between Q1 and Q3, and finally the mean of all the values greater than Q3. Close monitoring to the mean values of RO would give a good indication about the daily social distancing efficiency. The mean value is not a unique value in this case, it is a value that keeps changing daily. Calculating the mean value on a daily basis is essential to reduce the error rate caused by underestimating the actual number of daily infections. The mean value for each quartile is defined as follow:

$$\bar{x}_{Qp} = \begin{cases} \dfrac{\sum_{i=1}^{Q1} \frac{x_i - x_{(i-1)}}{x_{(i-1)}}}{Q_1+1}, & p = 1 \\ \dfrac{\sum_{i=Q1+1}^{Q3} \frac{x_i - x_{(i-1)}}{x_{(i-1)}}}{Q_3-Q_1}, & p = 2 \\ \dfrac{\sum_{i=Q3+1}^{N} \frac{x_i - x_{(i-1)}}{x_{(i-1)}}}{N-Q_3}, & p = 3 \end{cases} \quad (4)$$

$where\ \overline{x}\ denotes\ the\ mean\ value\ for\ each\ interquartile, and\ p\ presents\ the\ quarter\ number.$

Google report for social distancing was used in this measurement tool. Google has developed a COVID-19 Community Mobility Report for various countries. They abstracted data from length of stay on different locations. The length of stay is a good measurement tool that may partially provide some related information about the social distancing [19]. Google reports included the following locations, retail and recreation, grocery and pharmacy, parks, transit stations, workplaces and residential. All these values are given a percentage of comparison with baseline of zero. The minus value presents a very low length of stay, which can be interpreted as a lockdown policy. The higher value with minus sign presents the stricter lockdown. This is true for all attributes, except for the (residential), since residents will leave other places and stay the longest time at homes. Thus, data shows a decrease in six attributes and an increase in (residential) attribute simultaneously.

In addition to Google specified locations, we added one more location of schools, since it was ignored in Google report. The school's data were abstracted from UNESCO website and given a value of -30 on the closure date and onward. Zero value was assigned for the school opening dates [20]. The dataset was cleaned and prepared as shown in Table 2. Data are analyzed based on seven independent variables, as mentioned before, and one dependent class. The dependent class is chosen from the RO mean values of the interval > Q3. This interval was chosen since it measures the latest periods. The date chosen was between 15/02/2020 and 11/04/2020, for 98 countries. Table 2 lists a sample data for Australia with the dependent and independent attributes.

Country	**Date**	**> Q3**	**Retail and recreation**	**Grocery / pharmacy**	**Parks**	**Transit stations**	**Workplaces**	**Residential**	**School**
Australia	3/20/20	0.22	-12	20	-12	-22	0	6	0
Australia	3/21/20	0.25	-17	11	-9	-28	-4	7	0
Australia	3/22/20	0.26	-18	10	-11	-34	-12	6	0
Australia	3/23/20	0.25	-17	17	-27	-36	-6	8	0
Australia	3/24/20	0.25	-30	4	-30	-45	-19	12	-30
Australia	3/25/20	0.25	-31	2	-33	-50	-23	14	-30
Australia	3/26/20	0.25	-34	2	-23	-53	-27	16	-30
Australia	3/27/20	0.24	-35	2	-30	-53	-26	17	-30

Table 2: Dataset abstracted from UNESCO and Google reports

The aim of this dataset is studying the efficiency of social distance at any time. The data was classified using various models of Decision Table, Random Forest and K-Nearest Neighbor (KNN). In the initial stage of analytics, the dataset was classified for all countries. Two models were used in this analytics, KNN and Random Forest. The data split was conducted by the test mode of 3-fold cross-validation for all datasets. KNN was used for the combination of all independent attributes' classifications, while Random Forest was used for individual attributes' classifications. Graph 1 shows the correlation coefficient and the mean absolute error (MAE) for all countries.

It was concluded from Figure1 that individual factors do not have direct impact on lockdown efficiency. All independent attributes are found to be between 0.32 and 0.38 correlation values with RO mean values. The correlation value was higher when combining all independent attributes since it reached up to 0.68. Moreover, the MAE was found the least value when the combination of all attributes was chosen.

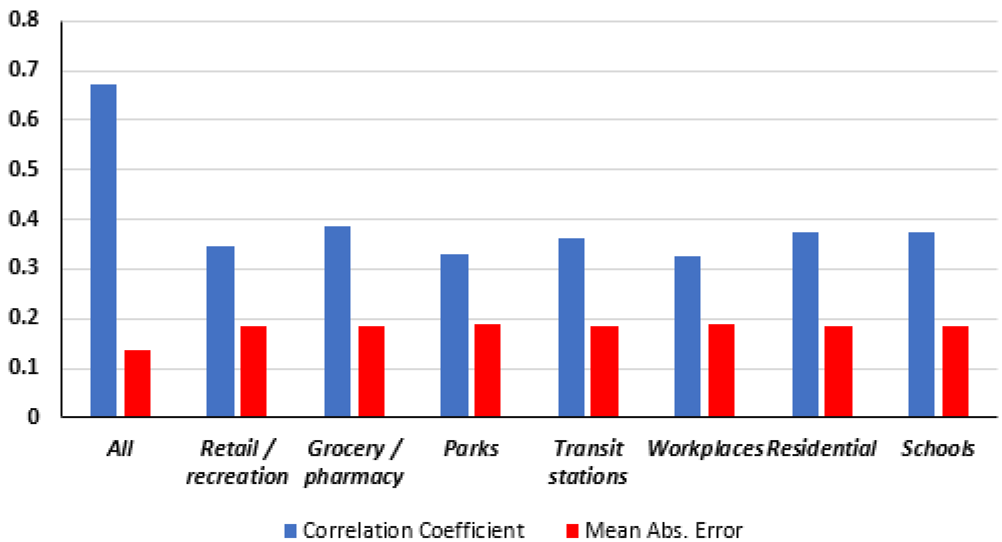


Figure 1: Correlation Coefficient for all countries

In the second stage of data analytics, we compared between several countries. We chose few countries a with a very high level of lockdown with a curfew, such as Italy, Jordan, and Indonesia. Then, we compared these countries with less restrictions on lockdown procedure's countries. The results show a large variance in correlation value between countries. Figure 2 illustrates the correlation coefficients and MAE for 13 countries. We only considered the models that provide the highest value of CC and the lowest value of MAE. In all experiments, we insured that the Relative Absolute Error should not exceed 50% as possible. The resulted values indicated that some countries have forced the lockdown policy, while it is ineffective enough, such as Italy and India. Based on the resulted output of analyzing various countries, lockdown efficiency can be categorized into four main RO groups, high (A), medium (B), low (C), and a very low (D).

- RO Group A: The high lockdown efficiency is given by (CC>=80%)
- RO Group B: The medium lockdown efficiency is given by (60%<= CC <80%).
- RO Group C: The low lockdown efficiency is given by (40%<= CC <60%).
- RO Group D: The very low lockdown efficiency is given by (- 40%< CC <40%).

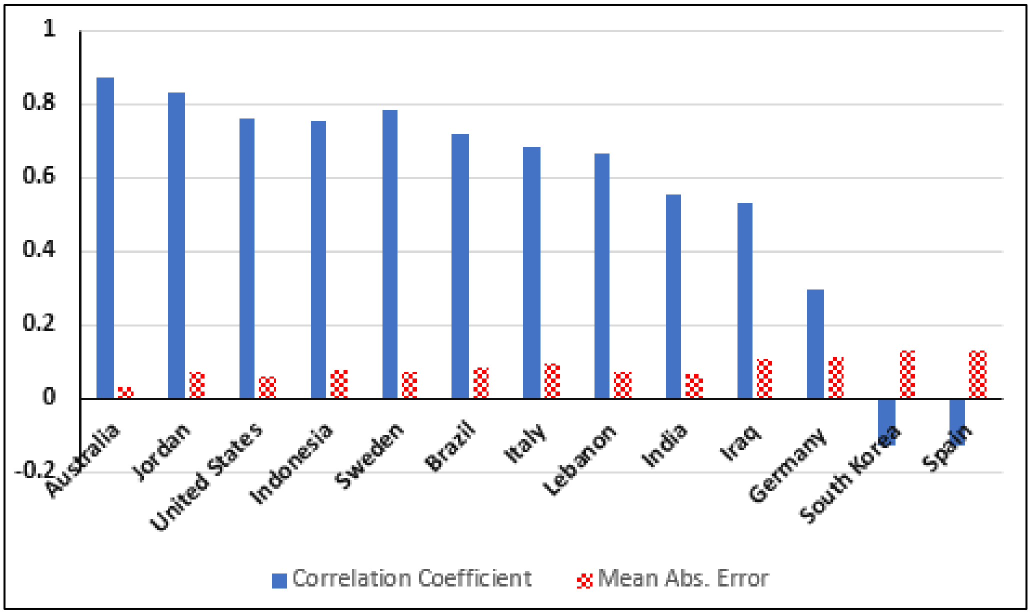


Figure 2: Correlation Coefficient for 13 countries

Figure 2 shows 3 countries with a group D, Germany, South Korea and Spain. This may indicate that Germany and Spain are not gaining any productive results out of the lockdown procedures. However, South Korea is exempted since it did not apply any lockdown procedures. South Korea is a good model of conquering the pandemic without a lockdown. These findings are volatile such as in India case. As shown in the diagram, India is currently in Group C, while started a very strict lockdown. Therefore, this may improve the lockdown efficiency in the coming weeks.

The high value of MAE may indicate that the seven factors are not the only factors. There might be other unknown factors that have negative impact on the lockdown efficiency. This measurement does not give a direct indication about the exponential increase or decrease of the infection numbers. Instead, it only indicates the lockdown efficiency.

Measuring the Outbreak Growth

The aim of this tool is measuring the growth angle of the exponential diagram. This is to compare between countries without considering the accumulative number of infections. Moreover, governments recognized that the actual number of infections is inaccurate on a daily basis. The infection number is based on the number of COVID-19 tests performed in every country. A larger test rate may result a larger infection rate. For this reason, zero infection that sometimes was recorded in some countries may not reflect the actual values. For this reason, we ignored the zero infections that appear within few days, by removing the repeated infection numbers.

Moreover, the exponential increase of infection rate is unsteady, then the prediction error rate remains high. It is essential to closely monitor the changes that occur on the exponential growth. The related dN/dt, with the number of daily infected persons accumulatively or based on newly informed cases, is necessary to avoid any undesired outbreak. The general growth of dN/dt for COVID-19 usually follows a skewed pattern. The rapid growth is usually followed by sigmoid when the growth of cases stops or reduces to the minimal. However, the new lockdown policies and producers made it hard for scientists to predict a correct model. Various models were proposed to predict the future growth of infections, death toll and recovered. One of the most popular models is called Susceptible-Infected-Recovered (SIR) model [21] , Other models focused on finding the number of probable infections only such as Generalized Richard Model (GRM) [22]. Nevertheless, the aim is not only predicting the number of infections, but also finding a mechanism of early alerting governments before another wave of outbreak starts.

The outbreak wave should count the number of infections during the last few days, so the model can describe a possible growth of infected numbers. In this paper we introduce a naïve model based on basic exponential equation to predict the number of infections Y as follow:

$$Y = \alpha \times \beta^{X} \tag{5}$$

where α denotes a magnitude that presents the growth stability rate, while β presents the decline rate.

This simple presentation of the exponential equation provides an exponential smoothing for the number of infection cases. The exponential function is attributed to Poisson as an extension of a numerical analysis technique [23]. Exponential smoothing is essential to avoid rough increase or decrease of infection cases on a daily basis. The zigzag line may not provide an accurate reading for the previous, current and future growth. In exponential graphs, several smoothing models were proposed such as General Exponential Smoothing [24], seasonal exponential smoothing, least-square fitting [25], Broydon method, Newton method and others.

We implemented Broydon method to smooth a small interval of four days counting the number of infections. Broydon's method is recommended for small and medium numbers. Since the number of infections did not exceed hundreds of thousands for each country, therefore; it is reasonable to use this method to smoothen the exponential curve. Equation 5 presents two main values of α and β, while X presents the number of days. The predicted number of infections Y is calculated after removing the repeated values. Variable α

presents the stability or non-stability growth. In every small interval, there is one unique value of α and β. These two values may look like linear, curvy or fixed. The curvy line may show a curve with a high, medium or low speed. Variable β is highly stable

The value of α and β were calculated based on Broydon method. They are valid for four consecutive days with ignoring the repeated numbers. Suppose that the predicted Y of the four days interval is Y={Y1, Y2, Y3, Y4}, hence the growth distance (D) between the fourth day and the first day is given by this equation:

$$D = Y_4 - Y_1 \tag{6}$$

This equation provides a simple comparison tool between countries and may build a simple graph for each country's expected growth in the future. The D value was multiplied by 100 to avoid the small decimal numbers for a better comparison rate. Th results of calculate D value for many countries show a stable D after the lockdown polices around the world. Most countries gained a value of D≈110. We built our dataset based on the statistical numbers of COVID-19 data [26]. We merged country's states and converted dates to numbers. Next, we built Python scripts to calculate the values of α and β [27]. Graphs 3 to 10 show various figures for different countries. Table 3 illustrates the method of calculating the distance D value by abstracting Y4 from Y1. Figures 3 to 10 show the values of α and D for several countries within the period between 22/01/2020 and 11/04/2020.

A	**B**	**X**	**Y**	**D=(Y4-Y1) ×100**
1.504609	1.143343	1	Y1=1.720284	85.08797
1.504609	1.143343	2	Y2=1.966875	
1.504609	1.143343	3	Y3=2.248812	
1.504609	1.143343	4	Y4=2.571164	
19.07286	1.019324	5	Y1=20.98829	124.0394
19.07286	1.019324	6	Y2=21.39386	
19.07286	1.019324	7	Y3=21.80728	
19.07286	1.019324	8	Y4=22.22868	
24.61267	1.014774	9	Y1=28.08543	126.3248
24.61267	1.014774	10	Y2=28.50036	
24.61267	1.014774	11	Y3=28.92141	
24.61267	1.014774	12	Y4=29.34868	

Table 3. Method of calculating Y and D values

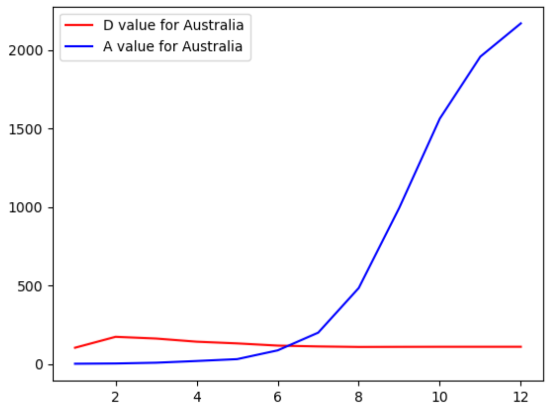


Figure 3. Australia D and α values

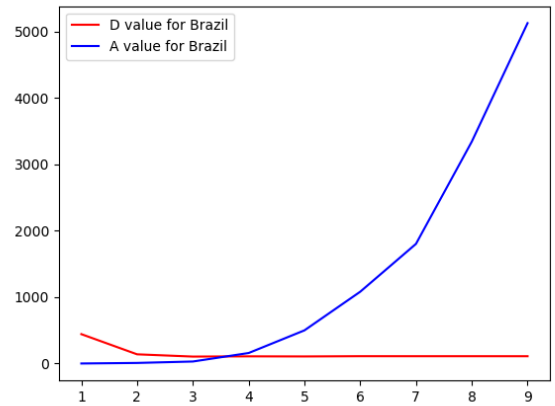


Figure 4. Brazil D and α values

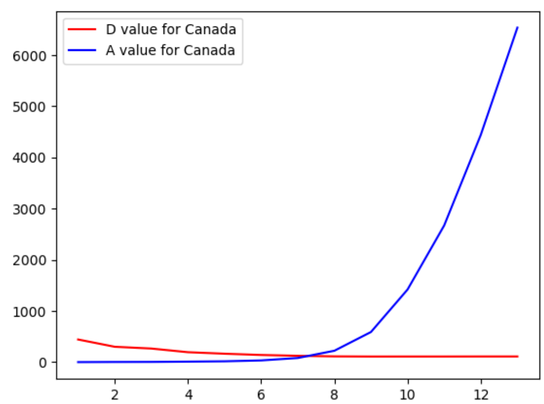


Figure 5. Canada D and α values

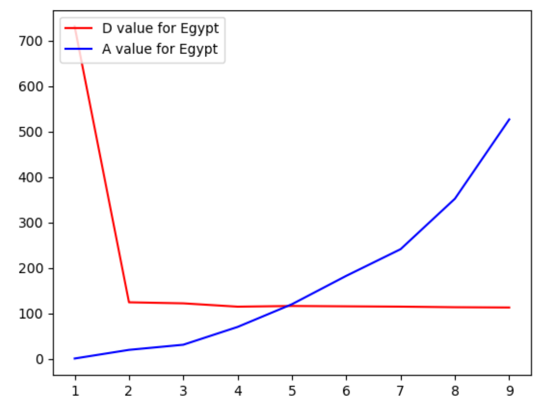


Figure 6. Egypt D and α values

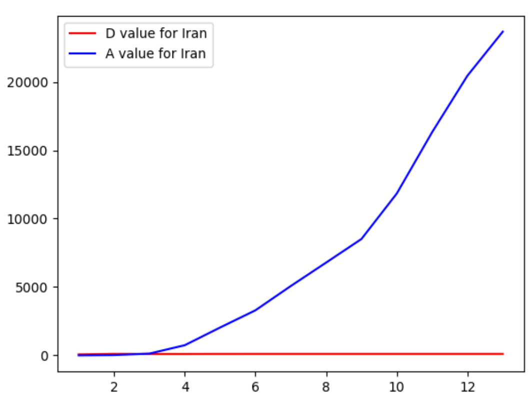


Figure 7. Iran D and α values

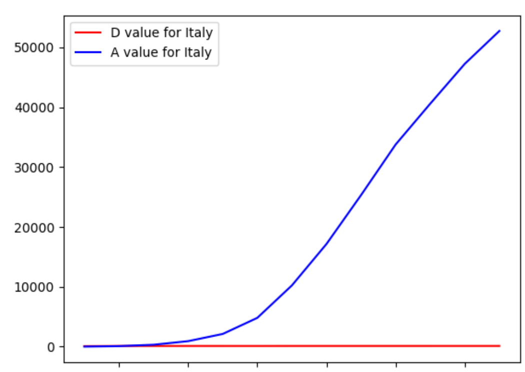
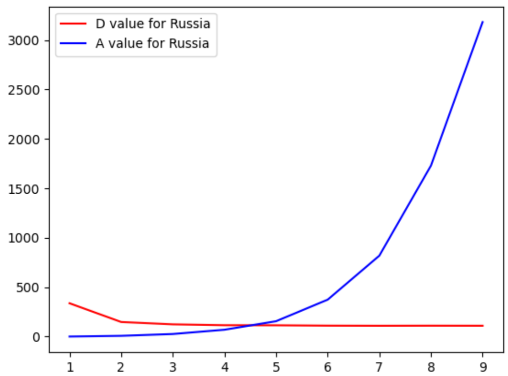


Figure 8. Italy D and α values



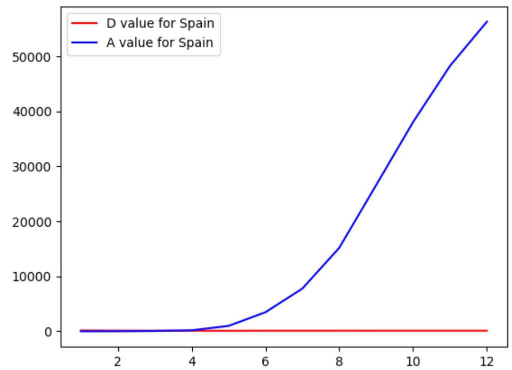


Figure 9. Russia D and α values

Figure 10. Spain D and α values

This method enables an easier comparison between countries. Here are some examples that show the comparison between various countries. Figure 11 illustrates a comparison between five countries Canada, France, Spain, Germany, and Australia. It is clear that Canada had the highest tilt of the exponential increase. This indicates a sharp growth of infection cases, which may describe a high rate of RO as well. However, the line graph shows a stable value after day 8 with a Y value around 110.

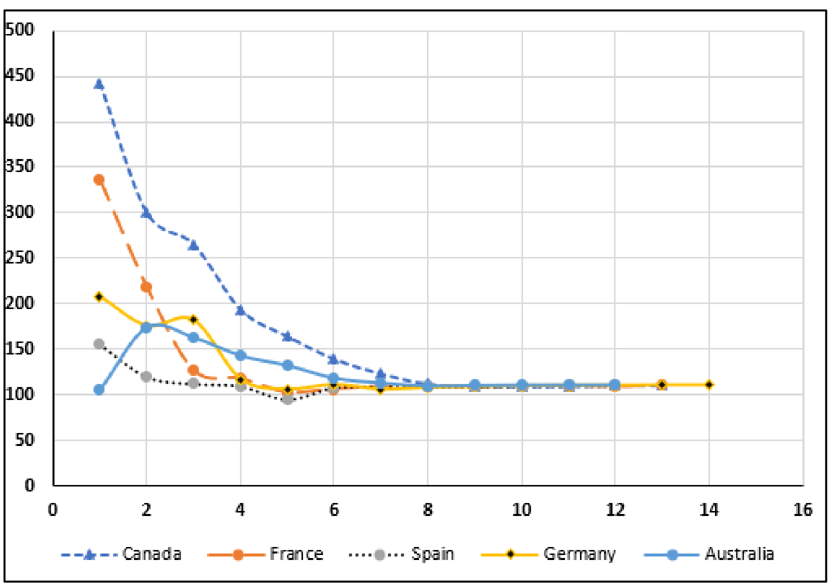


Figure 11: The distance value of D for five countries

Conclusion

Two statistical models are defined in this paper. These calculations may support governmental plans and decision making. Since this pandemic may last a year or more, then there should be a well-structured plan to bring life to usual activities with a high level of cautious. The first statistical model was based on Google report for social distancing for measuring the lockdown efficiency. The aim was finding the correlation coefficient for seven independent attributes with one class related to RO value abstracted from the third part (Q3) of the interquartile range. The lockdown efficiency was categorized into four main RO groups, high (A), medium (B), low (C), and a very low (D).

The second statistical model was for measuring the outbreak growth, this can be conducted by measuring the exponential tilt angle for predicting any future spike before its occurrence. A small interval of four days was smoothened using Broydon's method. The predicted smoothed values have measured the exponential equation's variable of A and B. The predicted Y_4 value of the fourth day interval was abstracted from the predicted Y_4 value of the first day to conclude the distance value D. The value D denotes the growth speed of the infection cases rather than measuring the number of infected cases. It is an independent method of calculating and comparing the growth changes. The statistical were applied on various countries and the results show a good agreement between countries' pandemic growth and our results.

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