Quantifying the effect of quarantine policies on the spread of COVID 19 with neural network

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Abstract

Up to now, the Coronavirus Disease 2019(COVID-19) has become a global pandemic. The current research papers have contributed to the formulation of national policies on COVID-19. We use publicly available data from the China and South Africa as samples, and through the SIR (susceptible infectious recovered) model we have an in-depth understanding of the impact of policies formulated in different countries on the number of infections, cures, and deaths through analysis. Our model combining SIR and neural network suggests that international travel controls and restriction of internal movements are the most effective policy for the disease control. This is very valuable for trying to understand and formulate a reasonable new coronary pneumonia policy.

1. Introduction

This world is living under the threat of the corona virus. According to the World Health Organization (https://www.who.int), up until 9 September 2021, 08:39 am GMT-7, there have been 222,406,582 people in the whole world who were diagnosed with COVID-19, and 4,592,934 people died because of it, not even including people who were infected and died without being tested due to limited medical conditions.

In order to deal with the coronavirus pandemics, governments around the world have put forward policies that restrict the spread of the disease, including social distancing, mask-wearing, travel restriction etc. However, due to the different policies and implementation of different countries, the degree of control of COVID-19 varies greatly. We take China and the South Africa as examples to simulate the effects of policy interventions at different levels of prevention and control.

The data of COVID-19, collected and updated on a daily basis, thanks to people devoted to this, show us information of the pandemic's spread trend. By laws of natural, the number of people infected firstly goes up, and then decreases, forming a peak-like shape. What a government willing to do in a modern society, is to use medical and political systems, to make the curve as flat and small as possible. In order to do that, governments brought up series of policies throughout the process. However, how the policies can affect the shape of the curve is not directly seen. Here, we parameterized the curves by a mathematical model, whose parameters determine the shapes of the curves. A neural network is then applied to map policies to the parameters in the model, which determine the shapes of the curves. We hope to understand the influence of policies in this manner, and hopefully provide some hints for the future.

The remainder of this paper is structured as follows: Section 2 gives an overview of related work. Section 3 explains the data collected and collection methods. Section 4 presents the analysis and results and section 5 concludes.

2. Related work

It has been shown that in some countries, quarantine and other policies have effectively suppressed the spread of COVID-19. Yubo Huang etc. al shown that the comprehensive identification and isolation policies have effectively suppressed the spread of COVID-19 in Wuhan, China. And postponing or weakening such policies would undoubtedly exacerbate the epidemic. Since January 2020, China has taken many measures in response to the new crown epidemic, including extensive quarantine, and strict controls on travel and extensive monitoring of suspected cases. Zifeng Yang etc. showed how these control measures impacted the containment of the epidemic and concluded that the implementation of control measures on January 23 2020 was indispensable in reducing the eventual COVID-19 epidemic size.

Basic SIR model has a good fit for the transmission mechanism of COVID-19. Taking the research of multi-risk SIR model with optimally targeted lockdown (Daron Acemoglu, 2020) as an example, SIR model successfully assisted the study of impacts of quarantine policies when the COVID-19 pandemic spreading. It has been revealed that through the SIR model, a significant impact of the quarantine factors on the prevention and control of the epidemic has been found and the protection can be improved.

Neural networks have been used as multiple tools. It has been used as PC tools (RC Eberhart, 2014), serves as model for forecasting (Young Tae Chae, 2015). And the applications of it in finance has been extensively studied. (Bo K Wong, 2010).In the last decade, the use of neural networks as a variable selection tool is shown and the advantage of networks as a nonlinear data modelling device is discussed.(D.J. Livingstone etc. 1997) Requiring less formal statistical training, Neural networks has been widely known for its ability to implicitly detect complex nonlinear relationships between dependent and independent variables, and to detect all possible interactions between predictor variables, and the availability of multiple training algorithms. (Jack V. Tu, 2010)

3. Data Preparation

The data used for the SIR model is from Our World in Data, researched and organized by Max Roser, Esteban Ortiz-Ospina and others. We downloaded data about the policy from the following fifteen aspects: School Closures, Workplace Closures, Cancellation of Public Events, Restriction of Public Gatherings, Stay-at-home Restrictions, Face coverings, Public information campaigns, Public Transport, Restrictions on internal movement, International travel controls, Testing policy, Contact tracing, Vaccination, Income support, Debt and contract relief.

All data are classified according to the grades of policies. For example, among the data of Stay-at-Home Restrictions policy, the numbers corresponding to each country have different meanings, 0 means No Measures, 1 means Recommended Not to Leave the House, and 2 means Required to Not Leave the House with Exceptions for Daily Exercise, Grocery Shopping, and Essential Trips, 3 stands for Required to Not Leave the House with Minimal Exceptions.

We chose China and South Africa as our analyzing targets. Both of the countries have updated data for the number of confirmed, recovery, and death cases. (https://github.com/CSSEGISandData/COVID-19) Their policies in response to COVID-19 were also available from https://ourworldindata.org. For China, we analyzed data from 1/22/2020 to 7/19/2021. For South Africa, we analyzed data from 3/21/2020 to 8/1/2021, as the outbreak started latter than China.

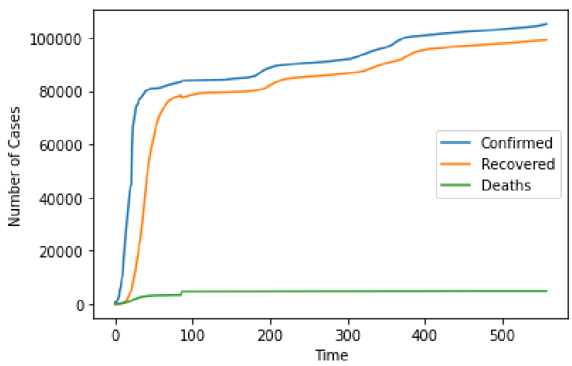


Figure 1 The number of confirmed, recovered, and death cases in China, from 1/22/2020 to 7/19/2021

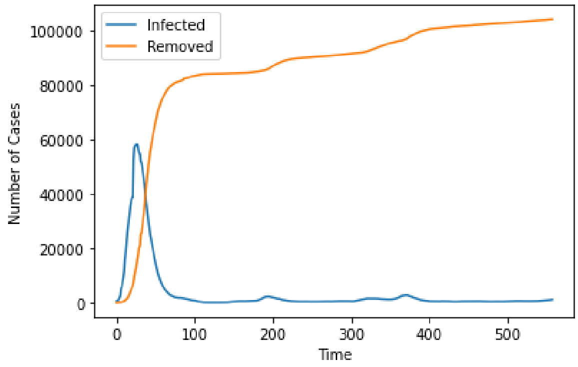


Figure 2 The number of infected and removed cases in China, from 1/22/2020 to 7/19/2

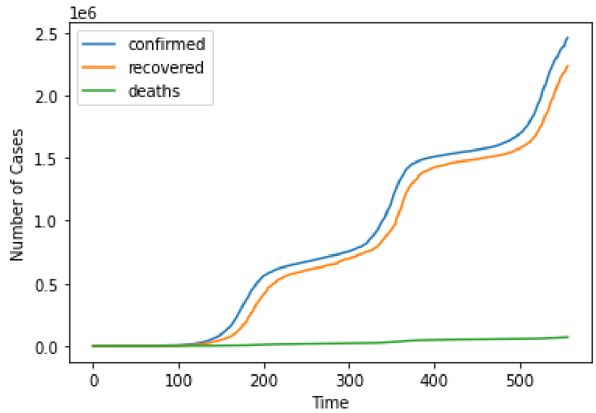


Figure 3 The number of confirmed, recovered, and death cases in South Africa, from 1/22/2020 to 8/1/2021

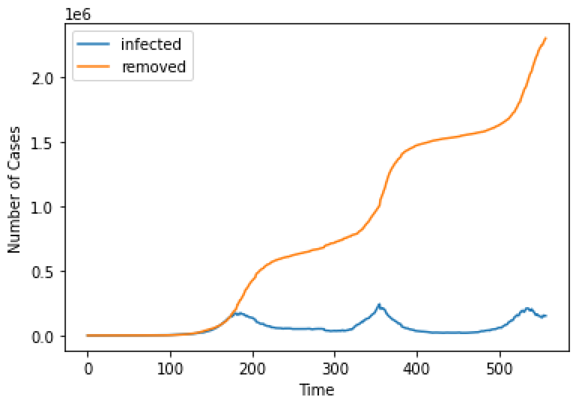


Figure 4 The number of infected and removed cases in South Africa, from 1/22/2020 to 8/1/2021

China and South Africa have very different social conditions, as while as policy responses, therefore are suitable for a comparative study.

4. Analysis and Results

SIR Model

Compartmental models are commonly used to describe the dynamics of pandemics. The population is divided into several compartments. As the timeline advances, population switches from one compartment to another, which is described by a set of differential equations. SIR is one of the most classic compartmental models. In SIR, the population is divided into the susceptible, the infected, and the removed, represented by S, I, R, respectively. When people infected recover from the disease, or die from it, they add to the removed sector, meaning they are no longer susceptible to the disease. Even though there has been news reporting re-infection after recovered from COVID-19, the proportion is relatively low, so we did not take this into account. COVID-19 does not cause significant number of deaths, so the removed section can also be represented as recovery.

$$\frac{dS}{dt} = -\frac{\beta S(t)I(t)}{N}$$

$$\frac{dI}{dt} = \frac{\beta S(t)I(t)}{N} - \gamma I(t)$$

$$\frac{dR}{dt} = \gamma I(t)$$

β is the infection rate, γ is the recovery rate, and N is the total population. N = S + I + R. With values of beta, gamma, and initial value of ***s***, ***i***, and ***r*** at time 0, the shape of the SIR curve is determined by the differential equations.

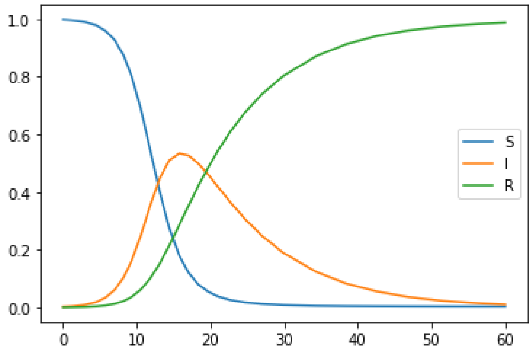


Figure 5 Plot SIR model with given parameters and initial conditions. s(0)=0.998, i(0)=0.002, r(0)=0, beta=0.6, gamma=0.1.

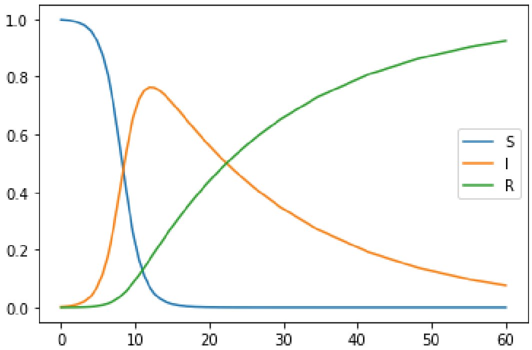


Figure 6 Plot SIR model with given parameters and initial conditions. s(0)=0.998, i(0)=0.002, r(0)=0, beta=0.8, gamma=0.05.

Other than SIR model, there are other compartmental models, such as SEIR, SIRD, etc. While introducing more compartments, the number of parameters increases. While adding more compartments might be useful in certain research work, they do not generally change the shape of the curve. Since the spread of COVID-19 in our case does not stress any additional process other than infection and recovery, we chose SIR model instead of others. SIR has only two parameters, which also decreases the variance of our parameter estimation.

Parameter Estimation

The SIR model has two parameters to be determined, beta the infection rate, and gamma the recovery rate. Even though these rates have specific meanings, we are unable to know estimate them directly. With data for the infection cases and recovery cases, we can use gradient descent to find the parameters that minimize our loss function, being the sum of square errors between modelled infection and documented infection.

Dictated by the differential equations, the SIR curve only has one peak, while in reality, both China and

South Africa have experienced several peaks. This makes sense, as SIR does not consider the effect of virus mutation, human affairs such as International transmission and big gathering and festivals, and the change of seasons. We modelled 3 peaks for both China and South Africa. This also gives us opportunity to understand how policies during each outbreak could potentially influence the shape of the peaks.

We model the influence of polices, by allowing them to change the parameters in our SIR model, which are beta and gamma. For South Africa, the total population of the model is chosen to be the real population, 58,560,000. While for China, we use 140,000 as the total modelling population, instead of the real population of China. This is because the real population of China is too large for the hidden premise of SIR model, which is all population is uniformly mixed. For China's huge population and geographical area, as well as strict travel restrictions implemented by Chinese government, the modelling total population should be smaller than the real one. Our choice makes statistical sense, while small inconsistency can be adjusted by the other two parameters. The initial conditions of the second and third peak of China are set to be satisfy that the ratio of infected and removed population is the same as that of the first peak.

Even within the same peak, governmental policies can change, which might influence of the trend of the pandemic. In order to capture such effect, we perform fitting multiple times within a same peak. Starting from day 0, we firstly only use part of the data to obtain a set of parameters, and add on data from more days gradually. During this process, we can observe how the prediction varies as more data is used.

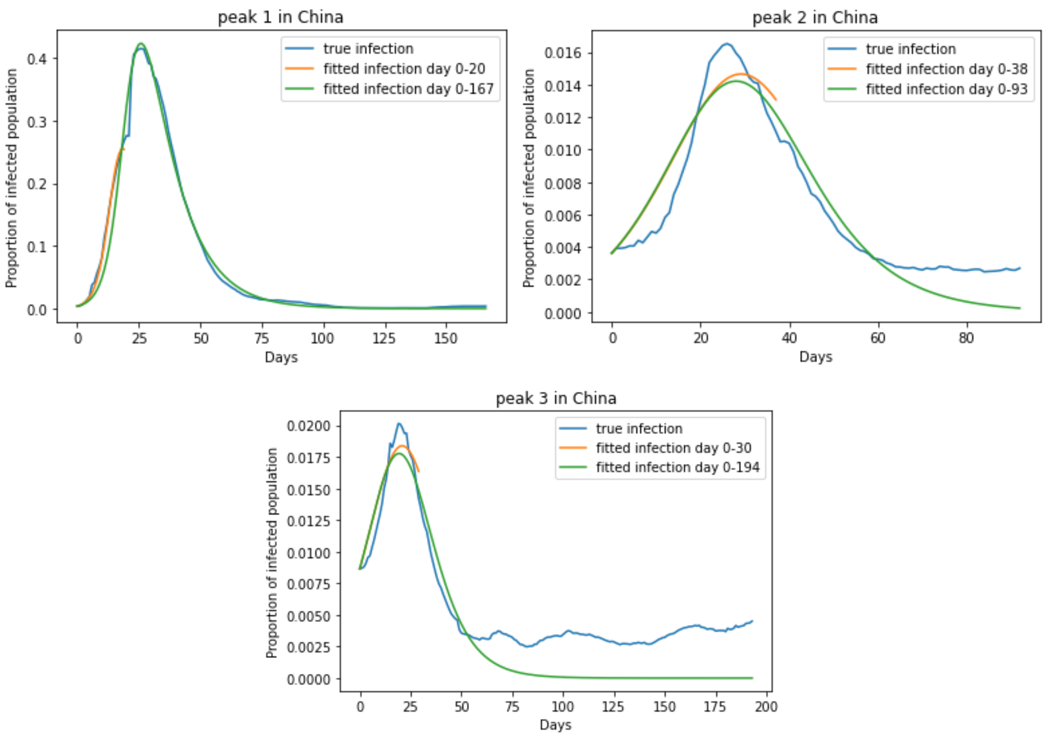


Figure 1 Fitting results of the 3 peaks in China.

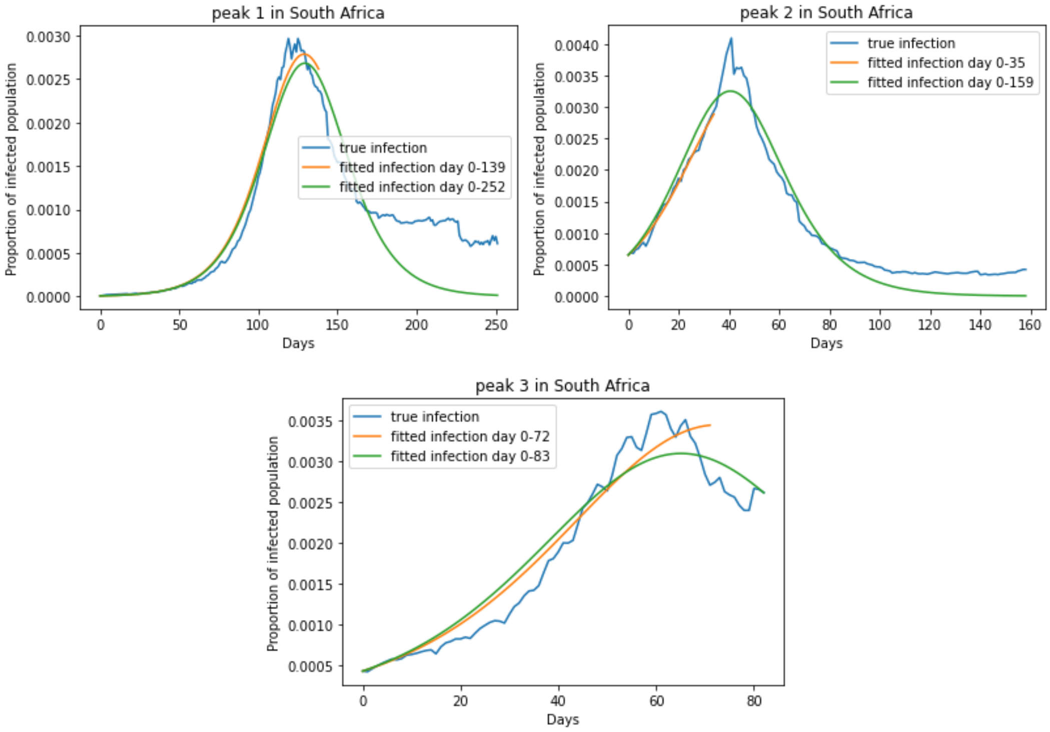


Figure 2 Fitting result of the first peak in South Africa

Parameters and Policies

We start fitting using the first 20 days, and add 1 more day for every following training. However, 20 days can still be too short for effective fitting. We select the fitting results by restricting the relative error of all parameters to be less than 5%. When training data is insufficient, the resulting fitting parameters usually have huge variance. For the 545 days of data in China, we eventually obtained 141, 56, 165 sets of parameters that meet our standard, for 3 peaks respectively. For the 497 days of data in South Africa, we obtained 151, 116, 15 sets of qualified parameters for the 3 peaks respectively. The optimization is performed with the 'lmfit' library.

We take into consideration a total of 15 different policies in response to the COVID-19 pandemic from website https://ourworldindata.org/. The policies are assigned into categories and quantified by numbers like 0, 1, 2, 3, 4, 5. The categories are different according to the specific policy. A full table of policy categories and their meanings can be provided, and also be seen on the website. As for our purpose, we rescale all policies uniformly from 0-1.

For every set of SIR parameters we obtain from fitting, we calculate the time average of policies during the corresponding time period. In this way, every set of SIR parameters, which is a 2-dimensional vector, matches a 15-dimensional policy vector.

Neural Network

Intuitively, governmental policies during a pandemic outbreak can affect the trend. We quantify the trend with SIR parameters fitted with the SIR curve, which are beta, the infection rate, and gamma, the recovery rate. Now we use neural network to quantify the internal relationship between the policies and the beta, gamma parameters. This requires a neural network with 15-dimensional input and 2-dimensional output. The training data is generated as previously described. A few architectures are tested with data from China and South Africa separately. For China, we test 4 models, with architecture of 15/8/2, 15/10/6/2, 15/12/8/4/2, 15/12/10/6/4/2. For South Africa, we test 3 models, with architecture of 15/8/2, 15/10/6/2, 15/12/8/4/2. Training is performed using the ‘keras’ library.

It is worth mentioning that due to the scarcity of our training data, training is unstable, falling into local minima very often. Therefore, we train 100 networks for every architecture and every country, and then select the ones that do successfully reduce the loss function. For the 4 model architectures of China, the numbers of successfully trained models are 39, 35, 37, 35 (out of 100 trainings each). For the 3 model architectures of South Africa, the numbers of successfully trained models are 52, 49, 38 (out of 100 trainings each).

The final prediction of each architecture and country is taken as the average of the successfully trained models. After examination, we observe that neural networks with simpler architectures (15/8/2, 15/10/6/2) would have unreasonable outputs if we test inputs that are not in the training set, while more complicated architectures (15/12/8/4/2, 15/12/10/6/4/2) would not. The outputs of the two complicated architectures are very similar. This suggests to us that simple networks are unable to capture the complex relations behind our data. The relations also do not depend on the network architecture. Therefore, we choose the 15/12/8/4/2 neural network for our following analysis, for this is just complicated enough to capture the relations and has fewer parameters to avoid possible overfitting.

This architecture is used for both prediction of China and South Africa.

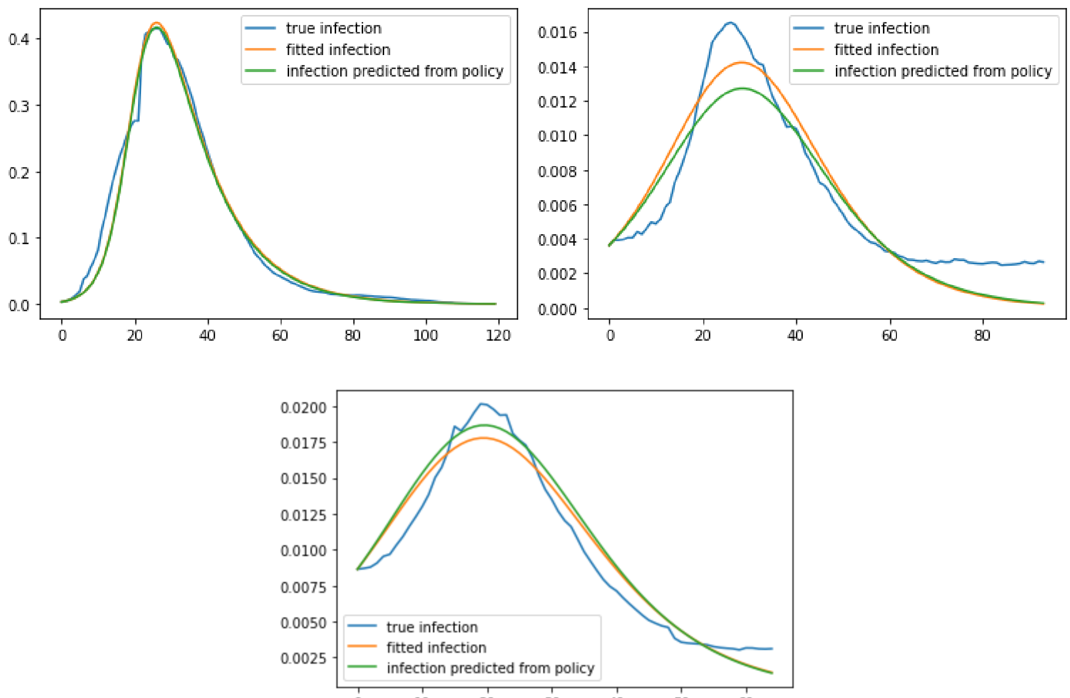


Figure 3 Prediction of trained neural network for 3 peaks of China.

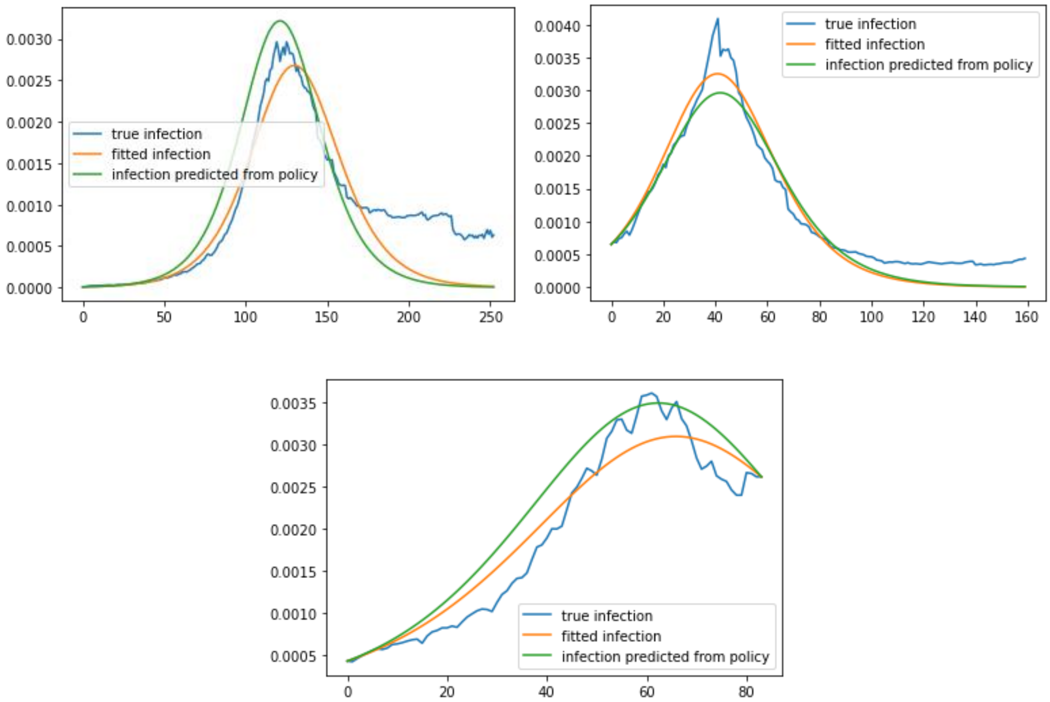
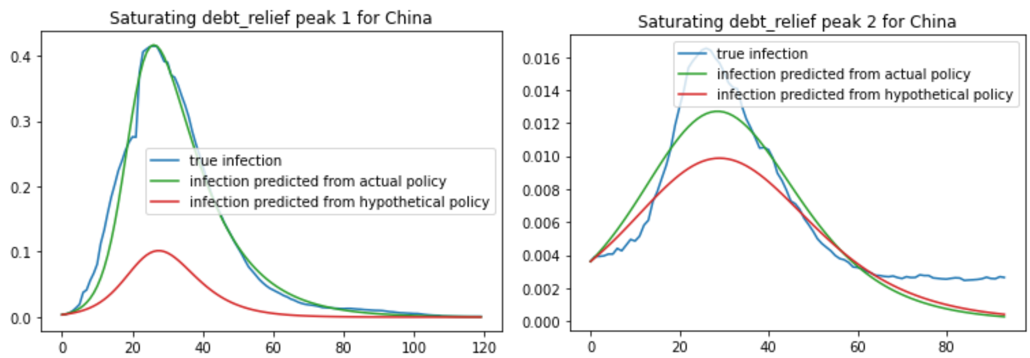


Figure 10 Prediction of trained neural network for 3 peaks of South Africa.

We further test the networks with hypothetical policy vectors. We ask the networks to deal with inputs they never saw, and answer questions like what will happen if country X implemented policy Y during their outbreak. For each peak of each country, we take the time average of the policy vector, and generate a series of 15 new policy vectors, each one of which has one of the 15 policies set directly to 1, the highest level of policy. We also generate another series of 15 policy vectors that removes one the polices, meaning setting it to 0, and test the effects of the previously trained models.

For most policies in China, after changed to 1, the differences are minor. This could be because China's original policies were already very strict and close to 1. For some policies, where the original number is small, the neural networks predict a huge reduction in the peaks.



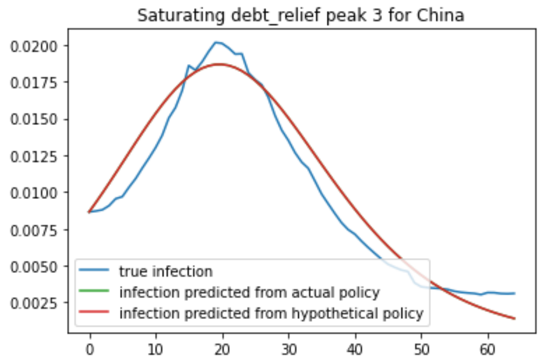


Figure 4 Prediction of trained neural network after saturating debt relief policy in China.

Other policies that exhibit significant reduction of infections are income support and international travel control.

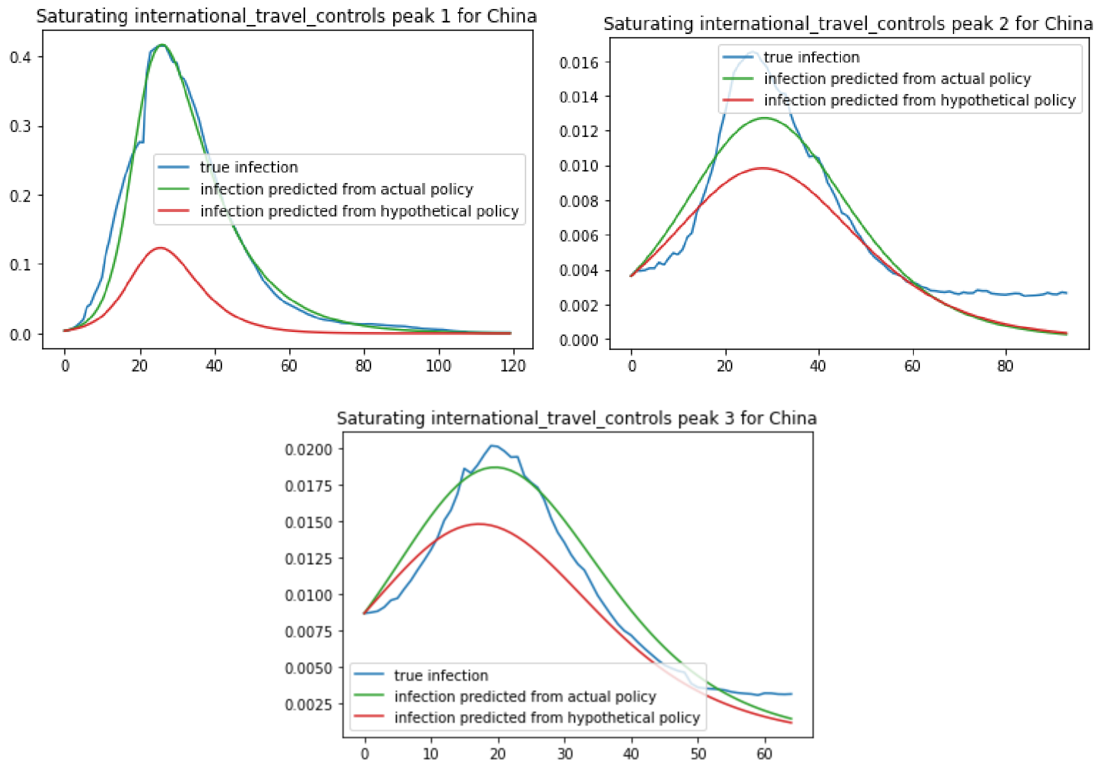
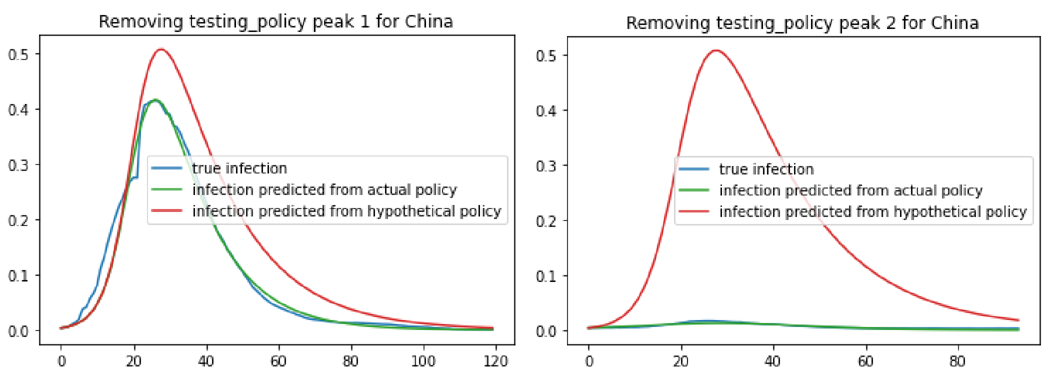


Figure 5 Prediction of trained neural network after saturating international travel control policy in China.

Removing almost any policy will cause a huge increase of infections for the second and third peak, while effect on the first peak is relatively small. This could be because the original policies during second and third peak are close to 1, while policies during the first peak are relatively closer to zero.



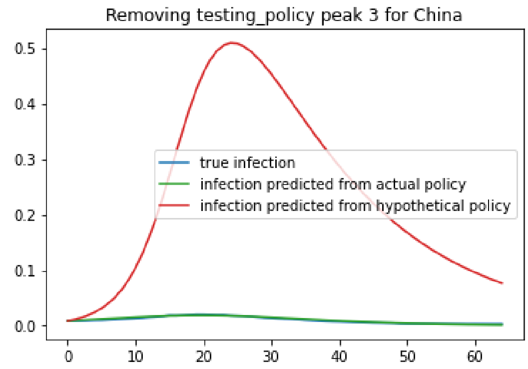


Figure 6 Prediction of trained neural network after removing testing policy in China.

For South Africa, we perform similar analysis to China, where we firstly saturate each policy, and then remove them. Saturating most policies results in a decrease of infections to some extent (similar to the example shown below).

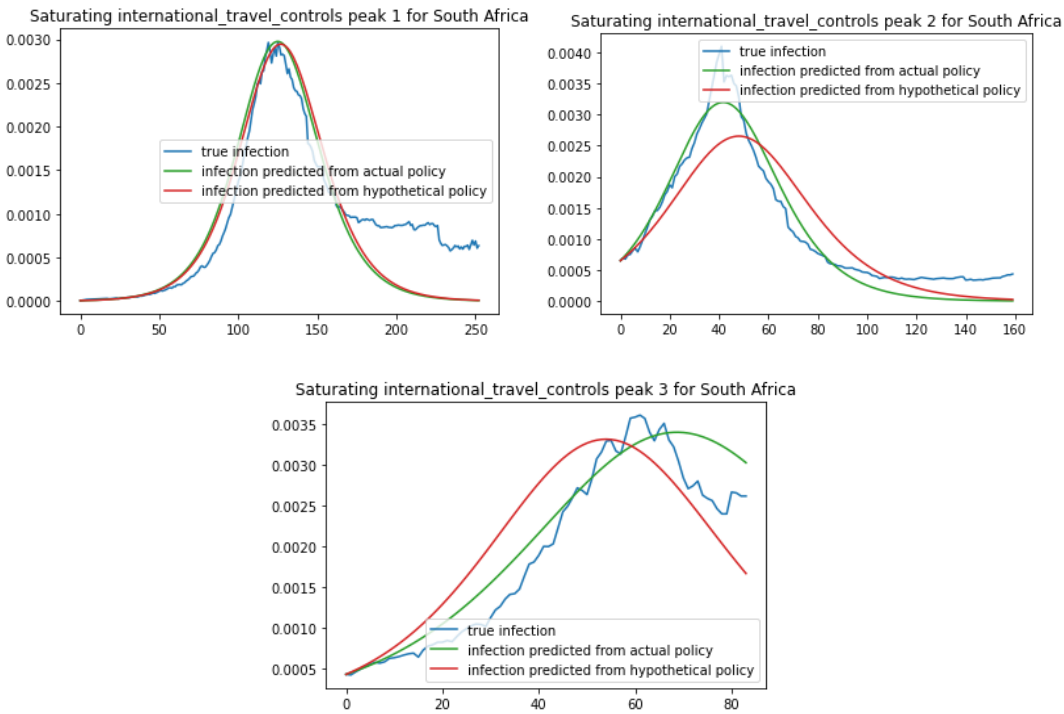


Figure 7 Prediction of trained neural network after saturating the international travel control policy in South Africa.

In the experiments that remove one of the policies, most changes do not produce significant differences. We observe some horizontal shift of peaks after removing some policies, while the height remains largely the same.

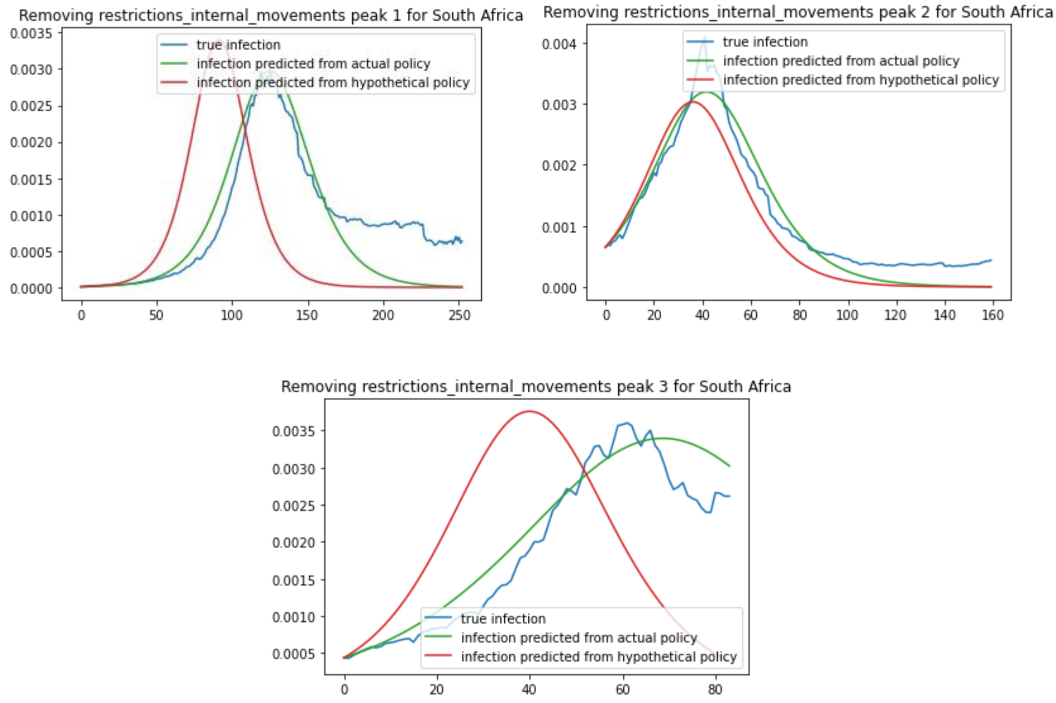


Figure 8 Prediction of trained neural network after removing the internal movement restriction policy in South Africa.

However, there are some unexpected cases, where stricter policies result in worse infections. These are vaccination and face covering, which are widely believed to be positive in dealing with pandemics.

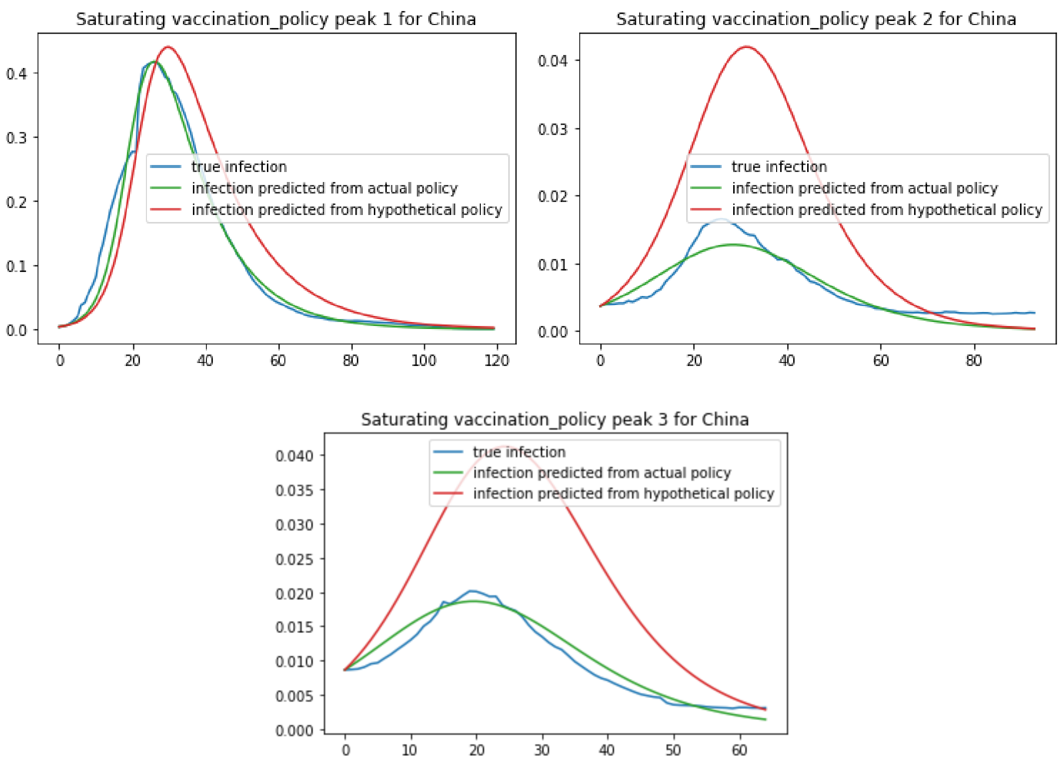


Figure 9 Prediction of trained neural network after saturating vaccination policy in China

The following two tables summarize results of our experiments on all policies.

	peak 1			peak 2			peak 3		
	Mean value	Set to 1	Set to 0	Mean value	Set to 1	Set to 0	Mean value	Set to 1	Set to 0
testing_policy	0.52777778	↓↓↓	↑	1	*	↑↑↑↑↑	1	*	↑↑↑↑↑
contact_tracing	1	*	↓↓	1	*	↑↑↑↑↑	1	*	↑↑↑↑↑
vaccination_policy	0	~	*	0	↑↑↑	*	0.21333333	↑↑↑	↑↑↑↑↑
debt_relief	0	↓↓↓↓	*	0.5	↓↓	↑↑↑↑↑	1	*	↑↑↑↑↑
facial_coverings	0.75	~	↓↓	0.5	↑↑	↑↑↑↑↑	0.89166667	↑	↑↑↑↑↑
income_support	0	↓↓↓↓	*	0.5	↓↓↓	↑↑↑↑↑	0.5	↓↓↓↓	↑↑↑↑↑
restrictions_internal_movements	0.98333333	↓	↓	0.96666667	~	↑↑↑↑↑	0.89166667	~	↑↑↑↑↑
international_travel_controls	0.21666667	↓↓↓	↑	0.75	↓↓	↑↑↑↑↑	0.75	↓↓	↑↑↑↑↑
public_information_campaigns	1	*	↓	1	*	↑↑↑↑↑	1	*	↑↑↑↑↑
cancel_public_events	1	*	↓	1	*	↑↑↑↑↑	1	*	↑↑↑↑↑
restriction_gatherings	1	*	↓↓	1	*	↑↑↑↑↑	1	*	↑↑↑↑↑
close_public_transport	0.98333333	~	↓↓	0.93333333	~	↑↑↑↑↑	0.89166667	~	↑↑↑↑↑
school_closures	0.93333333	~	↓↓	0.66666667	↑	↑↑↑↑↑	0.93333333	~	↑↑↑↑↑
stay_home_requirements	0.88333333	~	↓↓	0.93333333	~	↑↑↑↑↑	0.85555556	~	↑↑↑↑↑
workplace_closures	0.93333333	↓	↓↓	0.95555556	~	↑↑↑↑↑	0.66666667	~	↑↑↑↑↑

Figure 10 Summary of the effects of changing policies on the infection curve of China. Arrows up suggest an increase of infection, and arrows down suggest a decrease of infection. The number of arrows semi-quantifies the degree of increase or decrease. An asterisk means no change to the original policy. A wavy line means the effect is minimal.

	peak 1			peak 2			peak 3		
	Mean value	Set to 1	Set to 0	Mean value	Set to 1	Set to 0	Mean value	Set to 1	Set to 0
testing_policy	1	*	↗	0.91091954	↓	→	0.8	↙	↖
contact_tracing	1	*	→	1	↓	↘	1	↙	←
vaccination_policy	0	↗	*	0.21724138	↗	↓	0.6	↑	←
debt_relief	0.97350993	~	~	1	*	↓	0.5	←	←
facial_coverings	0.75	↑	↓↓	0.76293103	~	↓↓	0.75	↖	↓↓
income_support	0.5	↑	↓	0.5	~	↓	0.43333333	↖	↓
restrictions_internal_movements	0.57284768	~	↖↖	0.01293103	↓↓	~	0.6	↙	↖↖
international_travel_controls	0.81125828	~	↘↘	0.42456897	↓↓	↘↘	0.25	←	↓
public_information_campaigns	1	*	↗	1	*	↗	1	*	↗
cancel_public_events	0.77152318	~	→	0.51724138	↓↓	↓	0.8	←	↙
restriction_gatherings	0.69039735	~	↘↘	0.75646552	↓	↘↘	0.9	←	↓
close_public_transport	0.13576159	↑↑	↓	0.5	↗	↓	0.5	↖	↓
school_closures	0.5187638	~	→	0.54022989	↓	↘	0.53333333	←	↓
stay_home_requirements	0.64238411	↖	↘	0.66666667	↓	↘	0.66666667	←	↓
workplace_closures	0.51434879	~	~	0.42241379	↓	↓	0.66666667	←	↙

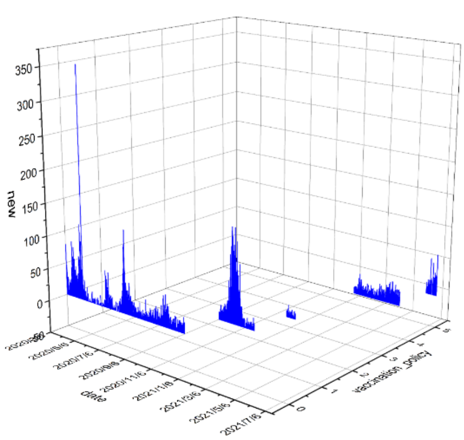
Figure 11 Summary of the effects of changing policies on the infection curve of South Africa. Arrows up suggest an increase of infection, and arrows down suggest a decrease of infection. The direction of arrows means the moving direction of the peak. The number of arrows semi-quantifies the degree of increase or decrease. An asterisk means no change to the original policy. A wavy line means the effect is minimal.

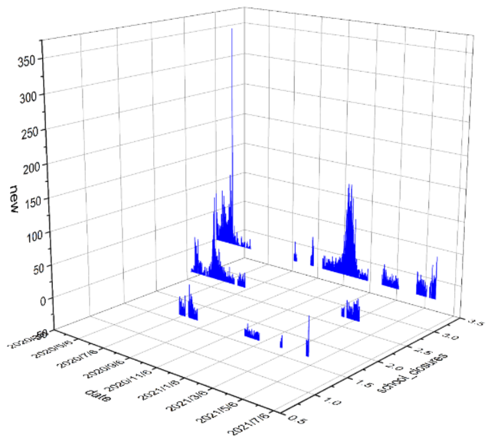
RESULTS

Our model enables a two-tailed Pearson correlation analysis of 14 policy data and new cases, by testing policy containment index, stringency index, vaccination policy, debt relief, income support, restrictions internal movements, international travel controls, cancel public events, restriction gathering, close public transport, school closures, stay home requirements, workplace closures.

For this kind of correlation analysis, we expect to see that the policy has a negative correlation with the number of new cases, that is, the implementation of the policy will lead to a decline in the number of new cases.

After drawing 2D maps of policies and new cases, we found and stress that some of the policies have an impact immediately, while some of them started to have the impact on new cases dozens of days later. As shown below:





The above two pictures are for China. Vaccination will affect the new cases in real time, but the impact of school closure will lag for a while, but it will also have a better effect on the control of cases.

Therefore, in combination with the above situation, we will analyze the impact of the policy on the new cases that day and 30 days later, 40 days later, 50 days later, and 60 days later.

Correlations for China

		testing_policy	containment_index	stringency_index	vaccination_policy	debt_relief	income_support	restrictions_internal_movements
new_cases	Correlation	-.593**	-.083*	0.056	-.117**	-.269**	-.412**	0.077
	Sig. (2-tailed)	0.000	0.042	0.169	0.004	0.000	0.000	0.059
new_cases_30	Correlation	-.463**	-.184**	-0.075	-0.011	-.143**	-.309**	.083*
	Sig. (2-tailed)	0.000	0.000	0.067	0.794	0.001	0.000	0.043
new_cases_40	Correlation	-.221**	0.033	0.078	.126**	0.055	-.141**	.146**
	Sig. (2-tailed)	0.000	0.429	0.061	0.002	0.190	0.001	0.000
new_cases_50	Correlation	-0.071	.174**	.156**	.155**	.151**	-0.013	.131**
	Sig. (2-tailed)	0.093	0.000	0.000	0.000	0.000	0.765	0.002
new_cases_60	Correlation	-.093*	0.005	-0.021	.176**	.167**	0.021	0.072
	Sig. (2-tailed)	0.027	0.904	0.628	0.000	0.000	0.626	0.090

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations for China

		international_travel_controls	cancel_public_events	restriction_gatherings	close_public_transport	school_closures	stay_home_requirements	workplace_closures
new_cases	Correlation	-.568**	0.034	0.040	.137**	.114**	0.079	.136**
	Sig. (2-tailed)	0.000	0.410	0.330	0.001	0.005	0.061	0.001
new_cases_30	Correlation	-.438**	0.055	0.049	.113**	-0.045	.104*	-0.056
	Sig. (2-tailed)	0.000	0.186	0.234	0.006	0.271	0.014	0.174
new_cases_40	Correlation	-.250**	.099*	.094*	.105*	0.074	.167**	0.060
	Sig. (2-tailed)	0.000	0.018	0.024	0.012	0.075	0.000	0.152
new_cases_50	Correlation	-.162**	.086*	.098*	0.048	.145**	.213**	.267**
	Sig. (2-tailed)	0.000	0.040	0.019	0.258	0.001	0.000	0.000
new_cases_60	Correlation	-.180**	0.060	0.079	-0.058	-0.078	.260**	.139**
	Sig. (2-tailed)	0.000	0.159	0.061	0.173	0.067	0.000	0.001

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

After conducing a two-tailed Pearson variable analysis on China's data, we can see that testing policy, vaccination policy, debt relief, income support, and international travel controls have a timely impact on new cases. Close public transport and school closures will have a impact in 60 days, while the workplace closures only takes up to 30 days.

Correlations for South Africa

		testing_policy	containment_index	stringency_index	vaccination_policy	debt_relief	income_support	restrictions_internal_movements
new_cases	Correlation	0.061	.234**	.114**	.345**	0.074	0.062	.156**
	Sig. (2-tailed)	0.148	0.000	0.007	0.000	0.078	0.141	0.000
new_cases_30	Correlation	.131**	-0.078	-.188**	.169**	.094*	-0.037	-0.058
	Sig. (2-tailed)	0.002	0.069	0.000	0.000	0.027	0.389	0.175
new_cases_40	Correlation	.106*	-.148**	-.242**	.198**	.100*	0.027	-.098*
	Sig. (2-tailed)	0.014	0.001	0.000	0.000	0.020	0.528	0.023
new_cases_50	Correlation	0.043	-.173**	-.249**	.250**	0.037	0.078	-.139**
	Sig. (2-tailed)	0.322	0.000	0.000	0.000	0.394	0.075	0.001
new_cases_60	Correlation	-0.031	-.214**	-.264**	.286**	-0.025	.115**	-.179**
	Sig. (2-tailed)	0.476	0.000	0.000	0.000	0.573	0.009	0.000

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations for South Africa

	international_travel_controls	cancel_public_events	restriction_gatherings	close_public_transport	school_closures	stay_home_requirements	workplace_closures

new_cases	Pearson Correlation	-.263**	.202**	.349**	.303**	-0.077	.140**	0.069
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.066	0.001	0.101
	N	565	566	566	566	564	566	566
new_cases_30	Pearson Correlation	-.343**	-.154**	-0.055	.268**	-.298**	0.018	-.117**
	Sig. (2-tailed)	0.000	0.000	0.203	0.000	0.000	0.681	0.006
	N	546	546	546	546	546	546	546
new_cases_40	Pearson Correlation	-.340**	-.267**	-.150**	.184**	-.313**	0.069	-.110*
	Sig. (2-tailed)	0.000	0.000	0.001	0.000	0.000	0.113	0.011
	N	536	536	536	536	536	536	536
new_cases_50	Pearson Correlation	-.324**	-.359**	-.247**	.145**	-.238**	.145**	-0.026
	Sig. (2-tailed)	0.000	0.000	0.000	0.001	0.000	0.001	0.554
	N	526	526	526	526	526	526	526
new_cases_60	Pearson Correlation	-.285**	-.451**	-.336**	0.025	-.155**	.213**	0.024
	Sig. (2-tailed)	0.000	0.000	0.000	0.566	0.000	0.000	0.585
	N	516	516	516	516	516	516	516

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

After conducting a two-tailed Pearson variable analysis on South Africa's data, we can see that income support, international travel controls, workplace closures will take up to 30 days to make an influence.

Testing policy, debt relief, restrictions internal movements, cancel public events, restriction gatherings, school closures will have the greatest impact within 60 days of the policy adjustment.

Limitations

In this correlation analysis, we only considered the impact of a single policy on new cases at different times, and did not combine two or more policies for simultaneous analysis. It is possible that the decline in the number of cases at a certain moment is due to other policies that took effect at the previous time, resulting in inaccurate correlations, but this still has a certain reference value.

Discussion

We devise this work following the idea that polices governments implemented during the COVID-19 pandemic will influence the spread of the disease, shown as the infection curve. We build neural networks that map the relation between policies and the shape of the infection curve, characterized by SIR model. After training, our neural networks will predict the shape of infection curves from the policy inputs. With these networks, we test the effects of saturating and removing one of the policies on the predicted infections. We hope this method can imply which are the most important and effective policies.

However, we do need to be critical about the results, for the limitations we see in our work. Since our training input, the policies, only comes from real-world decisions made by governments, it is impossible to obtain a satisfying data distribution for machine learning. Certain policies, like vaccination, may take months for its effects to be seen, so our neural network may not be able to capture such long-term dependence. There can also be a feedback in policy making, meaning governments tend to choose stricter policy when the pandemics is more outrageous. This causal relationship can be misinterpreted by our neural network, which can produce the positive correlations we see between strictness of policies and infections.

Despite the limitations discussed, we still want to conclude our positive results that appear robustly in both countries and all peaks analyzed. 'International travels controls', 'restrictions on internal movements' and 'testing policy' are the most effective policies according to our analysis. Though our method is not perfectly satisfactory, we hope our effort can make a little contribution to this global challenge.

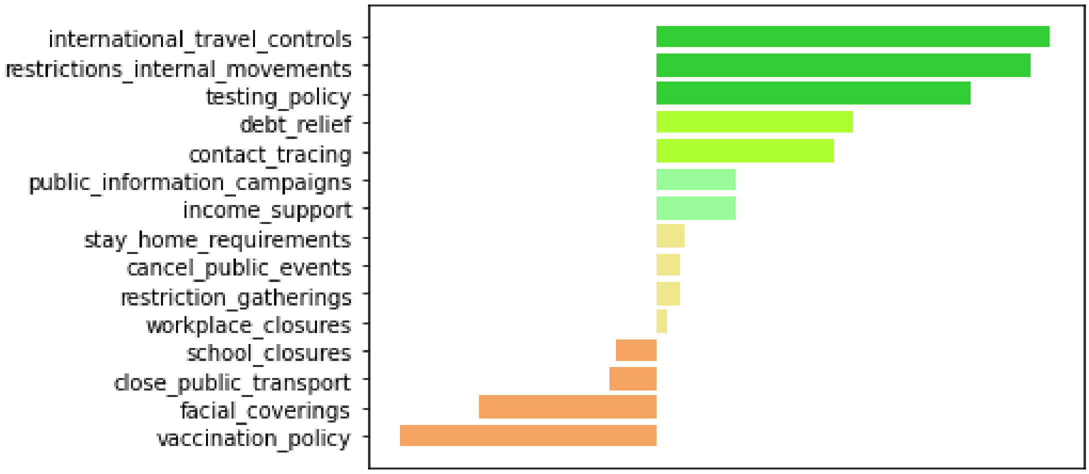


Figure 12 The effectiveness of policies analyzed. The top three lime-green lines are recommended according to our model.

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