



Prediction of epidemic trends in COVID-19 with logistic model and machine learning technics

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ABSTRACT

COVID-19 has now had a huge impact in the world, and more than 8 million people in more than 100 countries are infected. To contain its spread, a number of countries published control measures. However, it's not known when the epidemic will end in global and various countries. Predicting the trend of COVID-19 is an extremely important challenge. We integrate the most updated COVID-19 epidemiological data before June 16, 2020 into the Logistic model to fit the cap of epidemic trend, and then feed the cap value into FbProphet model, a machine learning based time series prediction model to derive the epidemic curve and predict the trend of the epidemic. Three significant points are summarized from our modeling results for global, Brazil, Russia, India, Peru and Indonesia. Under mathematical estimation, the global outbreak will peak in late October, with an estimated 14.12 million people infected cumulatively.

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1. Introduction

An outbreak of atypical pneumonia [coronavirus disease 2019 (COVID-19)] caused by Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) since late December 2019 has made huge impact on people life and work. The virus may spread from bats to humans through another intermediate host and cause severe respiratory syndrome [1], characterized by strong human-to-human transmission through the air [2,3]. The world health organization (WHO) declared an international emergency on 31 January, 2020. Since initial identification, despite of strict control, now it becomes a pandemic in global, which is a big threat and challenge to world health and economy [4], the disease has spread to over 100 countries across the world (Fig. 1). As of 3:33 PM on 16 June, 2020, a total of 8,044,683 COVID-19 cases have been reported worldwide, with 437,131 deaths and 3,883,243 survivors, with an overall case fatality rate of 5.43% [5]. John Hopkins University is offering the current data [6]. The infectivity of COVID-19 is greater than that of influenza, with an estimated R_0 value (the basic reproduction number, representing viral infectivity) of 2.28 [7].

According to the statistics of WHO, the United States of America (US), Brazil, Russia, India, and the United Kingdom (UK) are the top 5 countries with the highest number of infections in the world by 16 June, 2020 (Fig. 2). More to the point, the number of infections worldwide is still increasing. A number of measures were taken to prevent the spread of the disease, including social distance, the closure of businesses and schools, and bans on travel and outdoor activities, beginning in the cited areas and later applied throughout the country. The degree of infection varies from country to country, and the control strategy and degree vary according to national conditions, too. How the global epidemic will peak or diminish is the most concerned problem worldwide. Therefore, it is of striking significance to predict the pandemic trends of infection worldwide.

Many scholars have developed a number of predicting methods for the trend forecasting of COVID-19, in some severe countries and global [8,9], debating about mathematical model, infectious disease model, and artificial intelligence model. The models based on mathematical statistics, machine learning and deep learning have been applied to the prediction of time series of epidemic development [10,11]. Logistic is often used in regression fitting of time series data due to its simple principle and efficient calculation. For example, in the Coronavirus case, Logistic growth is characterized by a slow increase in growth at the beginning, fast growth phase approaching the peak of the incidence curve,

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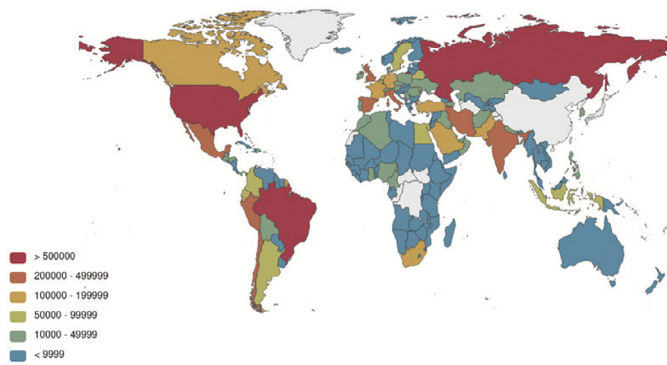


Fig. 1. All infected countries with COVID-19 pandemic by June 16, 2020. The warmer the color is, the more infections are in the country.

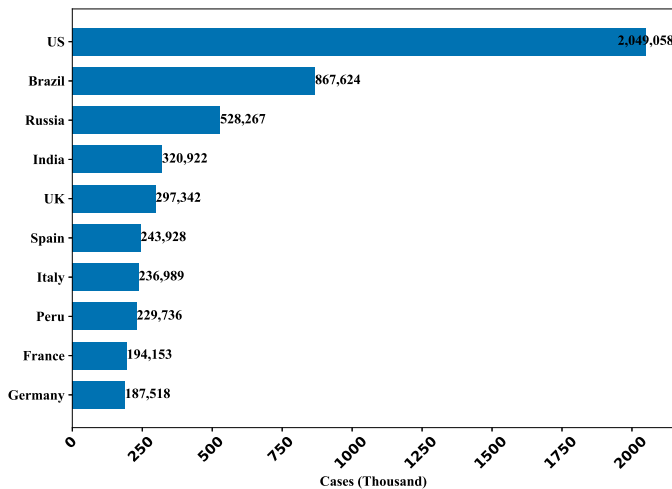


Fig. 2. The world's top 10 countries with the number of confirmed COVID-19 cases.

and a slow growth phase approaching the end of the outbreak, i.e., the maximum of infections. Wu et al. [12] have calibrated the logistic growth model, the generalized logistic growth model, the generalized growth model and the generalized Richards model to the reported number of infected cases in the COVID-19 epidemics, and their different models imply that Logistic model could provide upper and lower bounds of our scenario predictions. When the sample size of machine learning model is small, the model is easy to overfit, and the model performs well in the historical data set. Therefore, the prediction effect is not good enough in real scene. For instance, the short-term forecasts of machine learning are good, but long-term ones are inferior.

In order to obtain the long-term prediction curve, Yang et al. [8] train the Long Short-Term Memory (LSTM) model based on the 2003 severe acute respiratory syndrome (SARS) data because the times series data of SARS is complete. However, SARS and COVID-19 are different in many ways, such as incubation rate, incubation period and the development degree of the world at the time of the outbreak, so the simulation may be not reliable. FbProphet is an open source library of Facebook [13]. It uses the method of time series decomposition and machine learning fitting, and can predict time series with high accuracy with simple and intuitive parameters. However, it only has two types of prediction, linear and Logistic, which are more accurate for short-term prediction. If we want to use Prophet with Logistic growth for long-term prediction, a cap value must be specified. Therefore, we integrate the most updated COVID-19 epidemiological data before June 16, into the Logistic model to fit the cap of epidemic trend, and then feed the

cap value into FbProphet model, a time series prediction model to derive the epidemic curve and predict the long term of epidemic.

This paper aim at constructing a reliable model based on time series data to predict the long-time period trend of COVID-19 in global, also in some heavily infected countries. Forecasts about when the pandemic will reach the turning point and global maximum number of infections may be of great usefulness for public decision-makers and humans, as it could relieve people's emotions and give policy-makers the time to respond to the changes that the outbreak has brought.

The rest of this paper is structured as follows. In Section 2, data sources and our proposed method are introduced detailed. Experiments and results analysis are given in Section 3. Section 4 presents the discussion of our research. Finally, in Section 5, the main contribution of this paper is summarized.

2. Methodology

2.1. Data sources

The most recent daily COVID-19 outbreak epidemical data in global are collected form John Hopkins University, which released a dashboard at the country level. Data are available at an ArcGIS platform [6]. Therefore, we collected the time series at County level for the periodical analysis from January 22, 2020 to June 16, 2020. The 2003 SARS epidemic data between April and June 2003 across the whole of China retrieved from an archived news-site (SOHU) [14] was used for Logistic training.

2.2. A Logistic growth forecasting model

The Logistic model originated from the modeling of population growth in ecology [15]. As an improvement on the Malthus population model [16], in 1838, Pierre François Verhulst published the logistic equation:

$$\frac{dQ}{dt} = rQ\left(1 - \frac{Q}{K}\right) \quad (1)$$

where Q , r and K indicate the population size, intrinsic growth rate and maximum population size that the environment could carry, respectively. dQ/dt represents the growth of the population. r and K are constants number and the value of Q derives with time to produce an S-shaped curve in this Logistic equation.

The Logistic growth model was first used by LotKa [17]. Nowadays, Logical functions have been applied in a series time series prediction problem beyond their ecological roots, like epidemiology modeling. Logistic Growth is characterized by increasing growth in the beginning period, but a decreasing growth at a later stage, as you get closer to a maximum. Zhou and Yan [18] used the Richards model (a logistics type of model) to fit the cumulative number of SARS cases reported daily in Singapore, Hong Kong and Beijing. As is shown in Fig. 3, the cumulative number of SARS

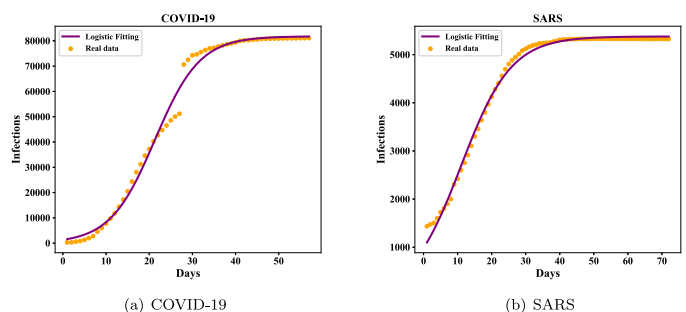


Fig. 3. The Logistic growth modeling of COVID-19 and SARS 2003 in China.

and COVID-19 in China are always be S-shaped curve which could be well described by Logistic fitting. At the beginning of the outbreak, people did not take strict measures, and the initial number of people infected is small, so the number of infections slowly increased. When the infection base reached a certain proportion, the epidemic situation showed an explosive exponential growth trend, and then with the government's regulation and public's cooperation, the epidemic situation gradually slowed down the spread speed, finally reached the maximal number of cumulative infected people. The key point is the time at which the cumulative situation curve turns, i.e., when rapid increases in the number of cases are replaced by slow increases. Because this inflection point specifies the point at which the daily number of cases increases to a maximum, this moment marks a critical turning point at which transmission of the disease begins to decline. As long as the data include this key point and the time interval shortly thereafter, the curve fitting and prediction of the future number of cases will be fairly accurate.

2.3. FbProphet model

Machine learning techniques for forecasting algorithms are a branch of computer science that is trained from historical data, such as artificial neural networks, deep learning, decision trees and Bayesian networks [19–21]. The idea of the algorithm is to select a suitable training model according to the characteristics of historical data and use it to predict the future observation results. We applied this technique to COVID-19 forecasting in the real world. Prophet is an open source framework of Facebook for time series forecasting based on additive model which is opened up to the public in 2017 [13,22]. The non-linear trends of Prophet are fitted with yearly, weekly, and daily seasonality, plus holiday effects. The perfect Prophet function can not only predict the future, but also fill in missing values and detect anomalies. In Prophet, the prediction model consists of superpositions $y(t) = g(t) + s(t) + h(t) + \epsilon_t$, where $g(t)$ is a trend function used to analyze the non-periodic changes of time series. $s(t)$ a periodic term, reflecting the periodic change, such as the periodicity of a week or a year. $h(t)$ is the influence of an occasional day or days, such as a holiday. ϵ_t is an error term, on behalf of the failed to consider the effect of the error of the model. Here in our research, we only consider about the non-periodic changes of time series.

We create an instance of the Prophet class and then call its fit and predict methods. The input to Prophet is always a time series with two features: date ds and value y . Here in our study, ds is the date of day, and y is the accumulated cases in a particular country.

2.4. Formulation of the proposed method

In this paper, We integrate the most updated COVID-19 epidemiological data before Jun 16, 2020 into the Logistic model to fit the cap of epidemic trend, and then feed the cap value into FbProphet model, a machine learning based time series prediction model to derive the epidemic curve and predict the trend of epidemic. The main steps of our method are described in Fig. 4.

To modeling the Logistic growth of COVID-19, Q , r and K in Eq. (1) indicate the size of accumulates infected cases, intrinsic growth rate and maximum cases size that the world or country could carry, respectively. dQ/dt represents the growth of the scale. r and K are constants number and the value of Q derives with time to produce an S-shaped curve in this Logistic equation. Logistic Growth is characterized as follows [23]:

$$Q(t) = \frac{K}{1 + a * e^{bt}} \quad (2)$$

where $Q(t)$ is the number of cases at time t , a is constant, b could be considered as incubation rate and K is the cap value, the maxi-

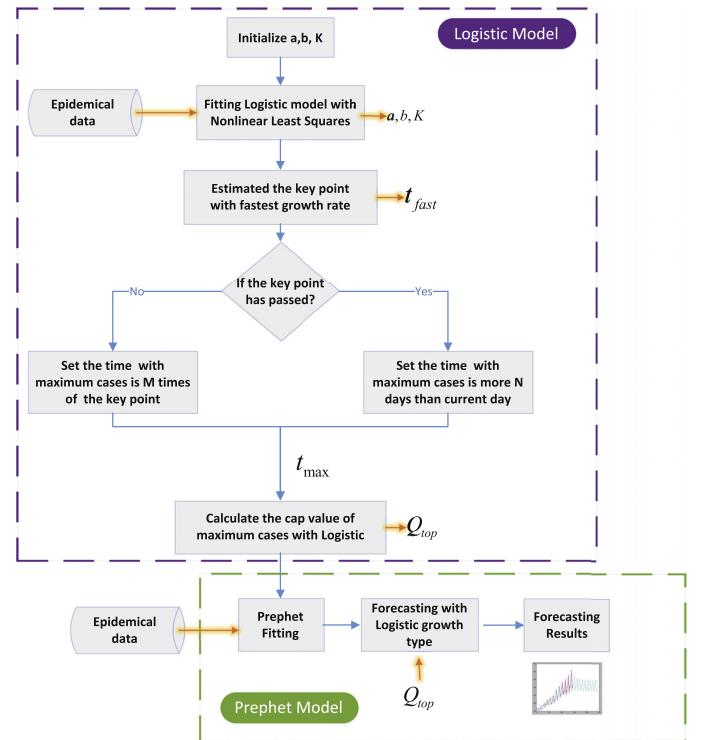


Fig. 4. Framework of forecasting the trend of COVID-19 with Logistic model and Prophet. The key point with fastest growth rate t_{fast} is fitted from Logistic model based on epidemical data of COVID-19. By estimating the time t_{max} with maximum cases, the cap value of epidemic size Q_{top} is calculated by using Logistic modeling method, then the cap value is used to the Prophet model, and model the full epidemic trend of COVID-19.

mal number of cases for $Q(t)$. Therefore, the number of cases at the very beginning is $K/(1+a)$, and the key point is $\ln a/b$ at which the cumulative situation curve turns, when rapid increases in the number of cases are replaced by slow increases. We initialize a , b and K randomly and update it by using Nonlinear Least Squares [24]. The upper bound of b is set according to the pandemic situation for each country. Hereafter, we could model the growth of COVID-19 with Logistic formula and learn the parameters a , b and K . Using calculated parameters from the Logistic growth model, Prophet is applied to forecast the trend of COVID-19.

Based on the key point calculated from Logistic model fitting with Nonlinear Least Squares method, we can forecast the maximal number of cases with a time interval P . A number of measures were taken to prevent the spread of the disease and the situation of infection varies from country to country. For example, the growth of COVID-19 in China has already stabled, while Brazil is still increasing at a scale. Therefore, the first step we need to do is identifying whether the virus is still growing sharply or have passed the exponential growth period and starts to reach the maximal cases size in a particular country. The key point t_{fast} and the accumulated cases $Q(t_{fast})$ at that time can be written as follow:

$$t_{fast} = \frac{\ln(a)}{b} \quad (3)$$

$$Q(t_{fast}) = \frac{K}{2} \quad (4)$$

If the current day in time series is less than t_{fast} , it means the key point is still ahead and the growth is increasing maybe exponential. Otherwise, it means that virus spread has been controlled and growth is going towards the end. We set the time t_{max} with maximum cases is three times of t_{fast} for the first kind of growth

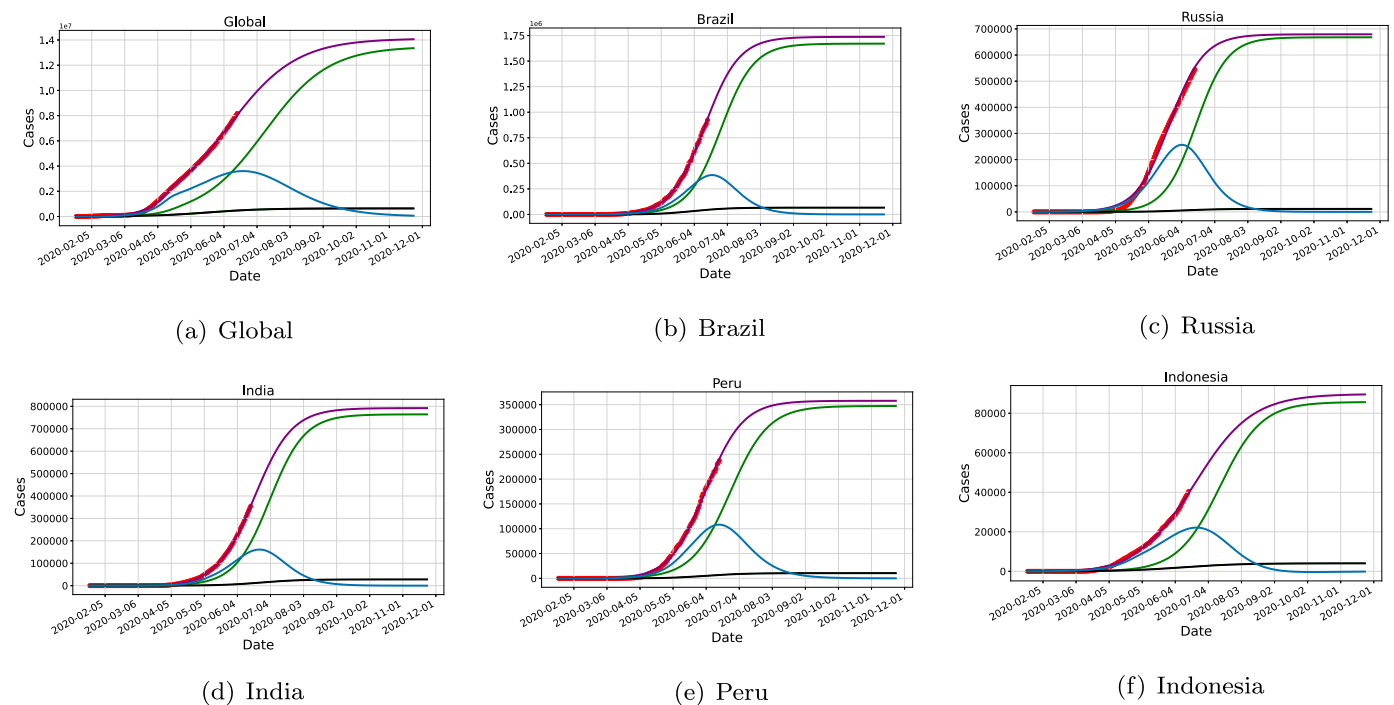


Fig. 5. Number of accumulated confirmed cases (purple), recovered (green), death (black), and active confirmed cases (blue) by the hybrid Logistic and Prophet model for Global (a), Brazil (b), Russia (c), India (d), Peru (e), and Indonesia (f). Actual data of accumulated confirmed infections were fitted onto the curve (red circles). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Implication of main points.

Main point name	Implication
Epidemic peak point	This peak means that the active infections has reach the top value and since then, the numberof active cases will decrease.
The fastest growth point	After this point, the epidemic gradually slows down and finally becomes stabled.
Turn point	This point occurred when the number of cumulative cured exceeds the number of active confirmedcases, marks an early victory in the control of the epidemic.

while it is more 20 days than current day for the second kind of growth. Then the estimated top number of infections Q_{top} can be calculated as follows:

$$Q_{top} = \frac{K}{1 + a * e^{(-bt_{max})}} \quad (5)$$

The aforementioned top number of infections Q_{top} will be feed into Prophet model with actual time series data. We perform around five to six months ahead forecasting by using Prophet, with 95% prediction intervals and logistic growth type. No tweaking of seasonality-related parameters and additional regressors are performed.

3. Results

In this section, experiments for forecasting the trend of COVID-19 in global and particular countries based on the epidemiological data (form January 22, 2020 to June 16, 2020) are conducted to analyze the effectiveness of our proposed model. There are 4 parameters in our experiments. The lower bounds of a,b and K in Logistic model are all set to be 0 and the upper bounds of them are set to be 1000,000, 5, and 7,000,000,000, respectively. The calibrated model is then employed to generate 160-day-ahead to 200-day-ahead (time interval P) dynamic forecast over the post-sample period: from June 16, 2020, to December 23, 2020 or January 2, 2021. All of our experiments are executed on the Colaboratory platform provided by Google.

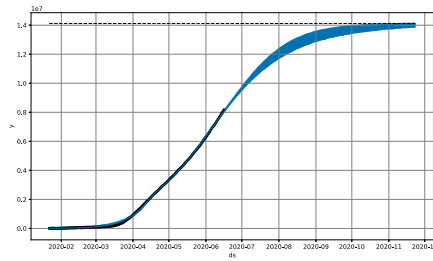
3.1. Forecasting the epidemic trend in global

Three time series are constructed from our collected data, namely confirmed cases, recovered cases and death cases series. In our experiment, we assume that each of these three sequences has a peak, in other words, the epidemic will end eventually. Obviously, the number of active confirmed cases is equal to the number of accumulated confirmed cases minus the number of recovered and deaths. We first apply Logistic model to fit the curve and calculate the time with fastest growing rate, then use Prophet to make a prediction. Fig. 5(a) shows the predicting results of Prophet model for the total case number in Global. We then plotted the number of accumulated, recovered, death and active confirmed cases derived from the hybrid Logistic and Prophet model and the actual reported total case numbers for global. There was a remarkable fit between the actual number of confirmed cases and the predicted curve between January 22, and the June 16.

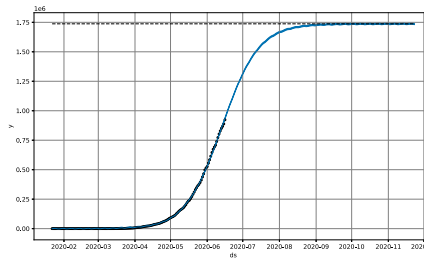
It is worth noting that there are three significant points in our forecasting results, as is described in Table 1. The first is the maximum number of existing infections (the time when the blue line reach peak in Fig. 5), i.e., epidemic peak point. The second point is the fastest growing point of the epidemic, after which, the epidemic gradually slows down and finally becomes stabled. The third point is the time when the number of cumulative cured (green line) exceeds the number of active confirmed cases (blue line), which marks an early victory in the control of the epidemic. Of course, the maximum number of total infections can also be obtained from the experimental results. Table 2 is given

Table 2
Summary of the main turning points from our study.

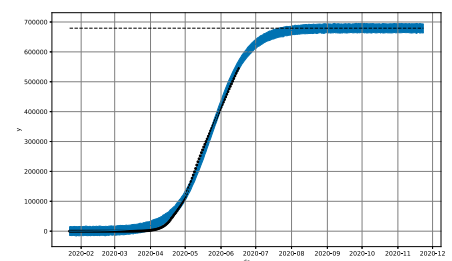
Area	Epidemic peak Cumulative active infections		The fastest growth point Cumulative infections		Turn point Cumulative recovered		Epidemic size
	Time	Number	Time	Number	Time	Number	
Global	2020/6/21	3,603,111	2020/5/16	4,706,052	2020/6/11	3,524,598	14,117,911
Brazil	2020/6/20	384,998	2020/6/10	742,424	2020/6/7	324,872	1,737,272
Russia	2020/6/4	256,535	2020/5/18	283,029	2020/6/10	252,753	679,269
India	2020/6/24	161,185	2020/6/14	330,043	2020/6/9	135,419	792,103
Peru	2020/6/16	108,217	2020/5/29	149,088	2020/6/12	107,906	357,812
Indonesia	2020/6/23	22,127	2020/6/4	29,914	2020/6/25	22,668	89,741



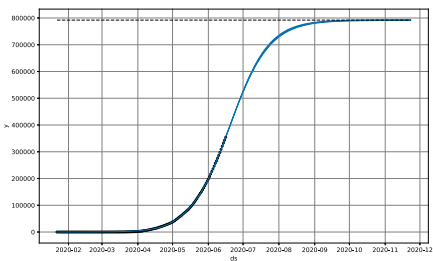
(a) Global



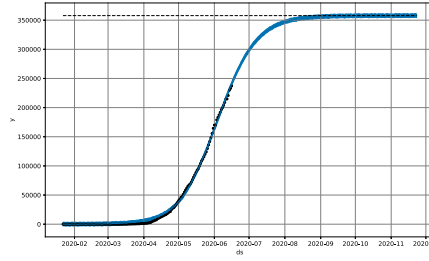
(b) Brazil



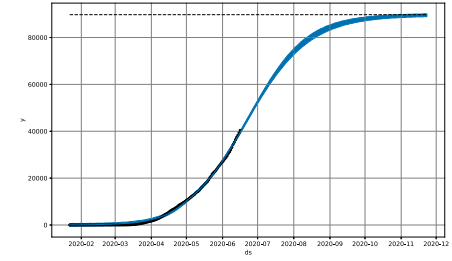
(c) Russia



(d) India



(e) Peru



(f) Indonesia

Fig. 6. The predicting results of Prophet model for the total confirmed case number in Global (a), Brazil (b), Russia (c), India (d), Peru (e), and Indonesia (f). The line with a 95% confidence interval is confirmed cases and the true reported values are marked as circles. The horizontal axis represents the date, and the vertical axis represents the cumulative number of infections.

to summarize the major turning points in global, Brazil, Russia, India, Peru and Indonesia, respectively. With current control, the total epidemic size in global is predicted to peak on June 21, with 3,603,111 active infections. The total epidemic size is predicted to be 14,117,911 by the end of October (Fig. 5(a)). The fastest growth point has passed on May 16. The actual reported cumulative number of infections is also in good agreement with our predicted curve.

3.2. Forecasting the epidemic trend in particular countries

We chose Brazil, Russia, India, Peru and Indonesia as the forecast countries, because these countries are among the highest in the world in the total number of confirmed COVID-19 infections and are the most concerned countries worldwide. We could summarize our basic predictions as follows:

As is shown in Table 2, the fastest growth point of those five countries has already passed. With current intervention, the total epidemic size in Brazil is predicted to peak on late June with 384,998 active infections. The total epidemic size is predicted to be 1,737,272 and the fastest growth point came on June 10. The turning point at which the cumulative recovered cases would greater than active ones came by the middle of June.

For Russia, the fastest growth point and epidemic peak has passed on May 18, and June 4, with an 283,029 and 256,535 active

infections, respectively. The turning point where cumulated recovered cases exceeded active infections came on June 10. In terms of India, the epidemic peak is still ahead, which is predicted on June 24. At that time, the number of active infections predicted by our model is 161,185. The fastest growth point came on June 14, with a total epidemic size of 330,043. And the turning point in India is predicted in early June.

Our hybrid Logistic and Prophet model predicted that the epidemic of Peru peaked on middle June, resulting in 108,217 active cases, and the scale of epidemic size will reach 357,812. We also predicted a peak of 22,127 active cases in Indonesia on June 23, and the epidemic size is expected to be 89,741. The cumulative recovered cases will be greater than active cases by late June according to the prediction of our model.

We plotted the actual reported cumulative active infections (red circles in Fig. 5(b)–(f)) up to June 16, 2020 for each country onto our predicted curve and the actual cumulative number of confirmed and predicted values were compared separately (Fig. 6). The results found that there was overall a good fit between our projected and reported data.

4. Discussion

According to the experimental results, the time at which the important inflection point arrives vary from country to country.

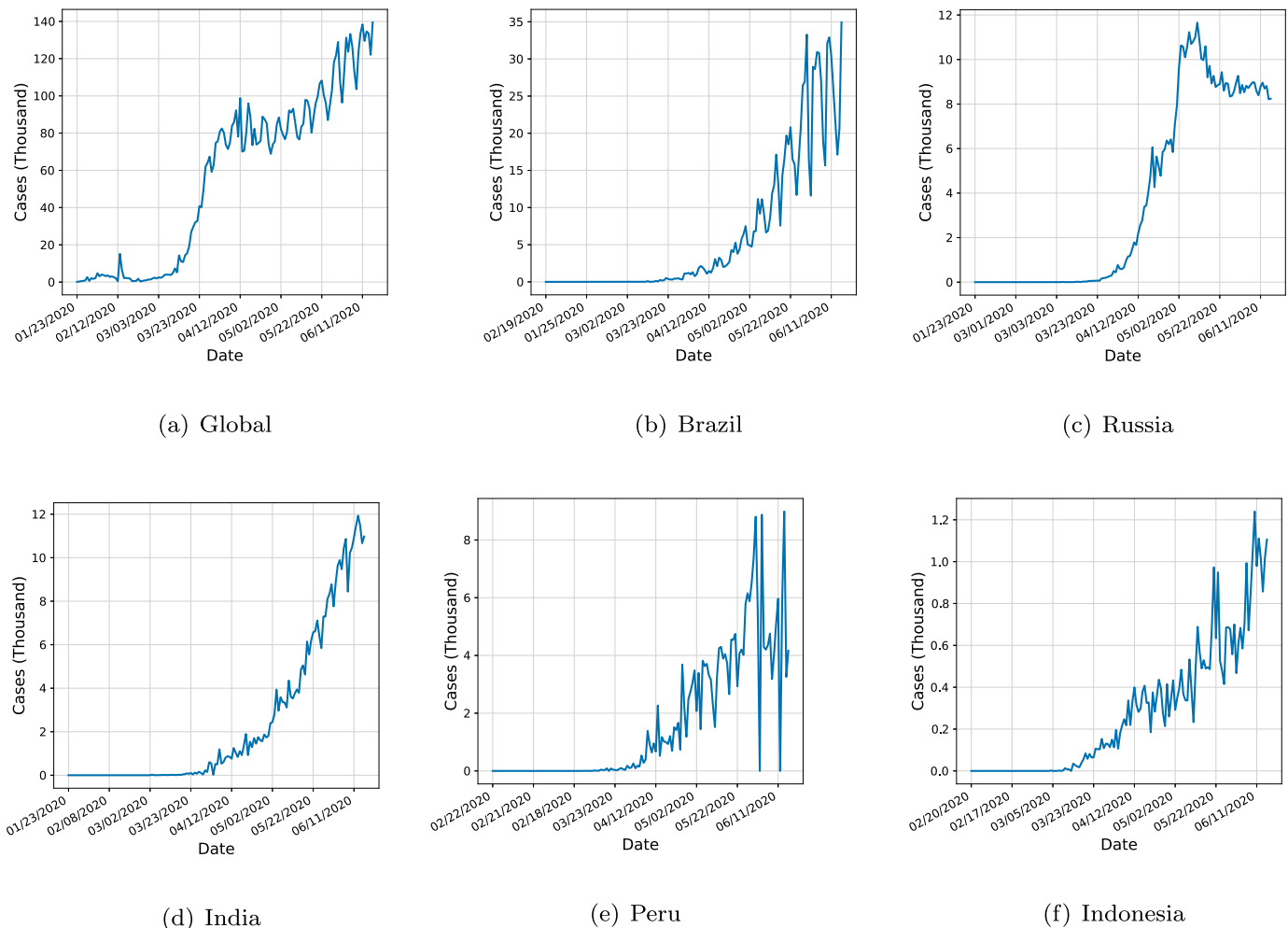


Fig. 7. Number of Daily confirmed cases in Global (a), Brazil (b), Russia (c), India (d), Peru (e), and Indonesia (f) by June 16, 2020.

The epidemic is projected to begin in early-August with the number of new daily deaths in Brazil edging toward 4600. This result is in accordance with the result of Institute for health measurement and evaluation, university of Washington [25]. Brazil has viewed a massive spread of the disease, in addition to the large number of deaths caused by COVID-19, the epidemic of Brazil will burden hospitals far beyond their current management capacity, especially in ICU care [26]. Once the outbreak exceeds the combination of national health resources, it will take a long time to recover. In our predicted results, by the late July or mid of August 2020, the healing rate will increase and Brazil will have about 1.7 million confirmed cases at the end.

Our study highlighted another key point, the strict control measures adopted since March by many countries are effective, leading to the decline in growth rate in global around middle May. But as outbreaks continue in some particular countries, the worldwide epidemic may rebound. Because when the epidemic goes beyond a certain scale, it becomes very difficult to control or get back to the previous level. Russia, for example, reported its first confirmed case on March 2, and launched prevention and control measures in early March. According to the Russian Health Ministry, as of 19 April 2020, the first decrease in the number of daily confirmed cases in Russia, to 4268. This may be due to the fact that severe control and isolation has been implemented in Russia, which shows that isolation is effective in reducing human exposure and controlling the epidemic. But in early May, there was a massive

outbreak in this country, with 11,656 new cases in a single day, leading to a modest slowdown despite strict control measures.

As of June 16, 2020, the case fatality rates in Russia, Brazil and Peru are 1.35%, 4.90% and 2.98%, respectively and there are still some increasing cases every day (Fig. 7). Because of the rapid outbreak in South American and European countries, the medical system nearly collapsed in a short period of time [27]. After strict control, the growth rate of the epidemic gradually slowed down, and the days when the cumulative cure was greater than the existing diagnosis came in mid-June, which means that South American and European countries still have a long way to fight in strictly controlling the outbreak.

While more data is needed to make more detailed predictions, these models could help predict future confirmed cases if the spread of the virus does not change in a way beyond expectation. As we all know, this virus is new and has the ability to spread seriously. This characteristic may affect all our predictions, but to our best knowledge at the time we spent writing this paper, the proposed model is effective.

5. Conclusion

In this article, a forecasting method with Logistic and Prophet model is proposed to analysis the COVID-19. The cap value is fitted by Logistic model through determining the fastest growing point, which is then feed into Prophet model for forecasting. We con-

ducted experiments for global pandemic and also in some particular countries to forecast the epidemic peak, growing fasted point and the turning point of recovered. The Results in Section 3 plot the predictive trend of global and five particular countries, and demonstrate the effectiveness of our model to predicting the turning point and epidemic size of COVID-19.

However, as is shown in Fig. 6, all of our predictions are based on the assumption of there will be a maximum of outbreak, and the epidemic curve is modeled based on a full Logistic curve. In real world, there maybe some small peak during the pandemic due to different intervention of the government and different public cooperation. Besides, when we forecasting the epidemic in some countries, the effects of input cases and spatial influence between countries are not taken into account.

To address the aforementioned limitations, the following aspects are worthy for our future research. First, piecewise prediction with a variant of Logistic model deserves further study. Second, Prophet is a perfect model based on additive model, and the non-linear trends of Prophet are fitted with yearly, weekly, and daily seasonality, plus holiday effects. In our research, we only applied times series data as trend term into the model, therefore, converting the control measures, like travel bans as holiday effects into Prophet model is a significant research.

As the research in this paper shows that a hybrid Logistic and Prophet model has a valuable advantage in terms of forecasting the epidemic trend, using our model can significantly improve estimates of the number of infections in global and particular countries and help public policymakers better plan health policy interventions.

Declaration of Competing Interest

There is no conflict of interest in this work.

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