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A Review on A Novel Spatiotemporal Prediction Method of Cumulative Covid-19 Cases

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ABSTRACT

Estimate methods are vital for sundry applications. In specific, an exact estimate for the total number of belongings for plagues such as the Covid-19 sickness couldhelp medical readiness by providing in time a enough supply of taxing kits, hospital beds & medical workers. This notion experimentally equivalences the precision often estimate methods for the growing number of Covid-19 plague cases. These ten methods embrace 2 types of nervousnetworks & extrapolation methods based on best fit rectilinear, best fit quadratic equation, best fit cubic & Lagrange outburst [1], as well as an extrapolation method from Revesz [14]. We also consider the Kriging [8] & reversedistance weighting [18] spatial outburst methods. We also mature a novel spaciotemporal estimate method by uniting the Best fit linear & [18]. The trials show that among these ten estimate methods, the spatiotemporal method has the least root mean right-angled error & mean unqualified erroron Covid-19 snowballing data for counties in New York State between June &July, 2020.

Keyword: - COVID-19, SARS-CoV-2, Covid-19 diseases expecting, spatio-temporal study, spatio- temporal evaluation, cardinal epidemiology

Introduction

In various bids, the value of a spatiotemporal flexible desires to be forecast for some time in the future based on earlier measured data at the same location & adjoining locations. There are only a few publications that use Covid-19 data together with geographic in- formation. Liu et al. [10] analyzes the recipe of Covid- 19 data & travel data in Wuhan, China & exhibited that travel borders were useful in restriction the supper of the contagion. Thakkar [21] creates an near density map for Covid-19 affected role using location evidencesuch as school or work site from widely available news pupillages in Capital State. Wang et al. [24] developed an algorithm that can estimate if a ship comprises a riskof Covid-19 infections based on some information about the ships and their travel paths. These works are valid only when the mandatory enduring address or travel data are available. In distinction, our estimate systems work without the necessity for such comprehensive evidence. Thomas et al. [22] presented a Covid-19 diffusion model based on interpersonal contact networks. While this may give more exact forecasts than other sickness mockups, it entails interpersonal contact evidence, which is not largely existing.

Review of Previous Outburst Algorithms & Basic Concepts

In this segment we review prior guess methods. The estimate methods embrace temporal extrapolation methods (Section 2.1), latitudinal extrapolation methods (Section 2.2), & neural networks (Section 2.3). In addition, Section 2.4 reviews the concept of moving aver- age. Finally, Section 2.5 evaluations the blunder trials used in this theory. Each outburst method has a purpose that can be everyday to any sequential value even a value complex than all the morals in the raw data. In this technique, an outburst system can be also used for extrapolation, that is, for envisaging the upshot in the imminent.

Temporal Extrapolation Methods

Let y_i be the number of cases of the Covid-19 pandemic at some location i days ago. Hence y_1 is the number of cases yesterday, and y_2 is the number of cases the day before yesterday etc. Then the *Finest Fit Cubic* & the *Lagrange* outburst methods [1] can be used to envisage the number of suitcases of the Covid-19 plague at that scene. These devices spring outburst occupations into which we can residence any imminent time illustration to get a estimate value. In count, the exponential decline sequential method, which was decidedly precise for expecting voting outcomes [3], can be used to get an evaluation for the existing day using the following formula, which accepts that we know the amount of cases over the six earlier days:

$$y = \frac{y1}{2} + \frac{y2}{4} + \frac{y3}{8} + \frac{y4}{16} + \frac{y5}{32} + \frac{y6}{32} \qquad (2.1)$$

The above formula can be prolonged for added facts of days. The imperative chin is that the hefts are sequentially waning by half excluding in the last occurrence, where the past bulk is equal to the prior weight. Note that in this way, the sum of all the weights is exactly one. Finally, additional estimate method that was anticipated by Revesz [14] uses the following method to envisage the number of cases of the Covid-19 disease, where t is the number of days forward from the last data. In other words, if the last data is for yesterday, then predicting for today means $t = 1$ and for tomorrow $t = 2$ etc.

$$y = \frac{-\quad t^2}{1 + t + \frac{\quad}{2}} \; y_1 + (t + t^2) y_2 + \frac{t^2}{2} y_3 \qquad (2.2)$$

Spatial Extrapolation Methods

Converse Reserve Premium (IDW) [18] is a common latitudinal outburst way. It is used when the interpolated variable at a location has a weighted relationship with its neighbors and when that relationship varies with distance. If a neighbor is quicker than alternative national, then the bulk of the prior will be complex than the heft of the latter. We use λ_i as the weight, y_i as the included variable, & d_i as the reserve to the i^{th} neighbor [13]. Then the Contrary Reserve Premium comparation for the interposed flexible y at a site can be printed in relations of its neighbors as follows:

$$y = \sum_{i=1}^{N} \lambda_i \times y_i \qquad (2.3)$$

where the reckoning for shrewd λ_i can be written as follows:

$$\lambda_i = \frac{\sum 1 \frac{P}{d_i}}{\sum^{N} 1^{P}} \qquad (2.4)$$

The p (power) worth can be any number ≥ 1. For simplicity, in this thesis we assume that p = 1.

Kriging is built on the labor of Danie G. Krige [8]. Different from IDW, Kriging not only considers the distance, but also find the spatial structure inside the data.

Neural Networks

We use two different types of neural networks in this thesis: backpropagation neural networks and recurrent neural networks.

Backpropagation

Backpropagation is a culture system that has been used very often in nervous webs. Backpropagation first appeared in the work of Rumelhart et al. [16] in 1988. Their work shows that applying backpropagation often results in useful discoveries using gradient de- scent. During the training, when the hidden layer passes the values to the output layer, the backpropagation method will calculate the differences between the hidden layer values and the actual values. Backpropagation will then adjust the weight on the edges between the two layers and repeat passing the values back to hidden layer until the error is small enough to kind sure that the nervous network can yield an exact estimate.

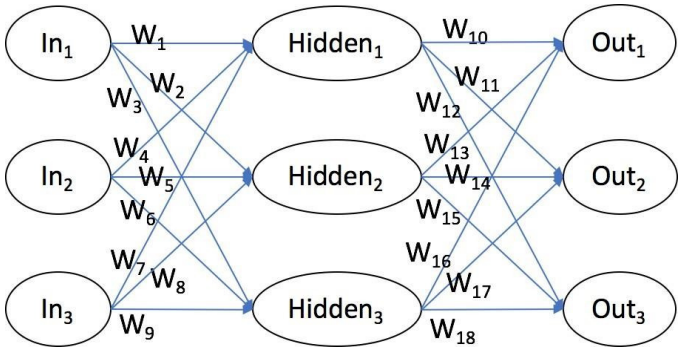

Figure 2.1: Backpropagation example.

Figure 2.1 displays the example of backpropagation building.

Where:

$$Hidden_1 = In_1 \times W_1 + In_2 \times W_4 + In_3 \times W_7$$

$$Out_{Hidden}1 = \frac{}{1 + e^{-Hidden_1}}$$

$$Out_1 = Out_{Hidden_1} \times W_{10} + Out_{Hidden_2} \times W_{13} + Out_{Hidden_2} \times W_{16}$$

The goalmouth of this pace is to find the best hefts (W_i)for the neuronic web to cram.

Recurrent Neural Networks

Recurrent Neural Networks (RNNs) [4] progress backpropagation with the box of better envisaging the upshots of a time series, such as in motor control & pace exposure. Figure 2.2 shows the architecture of the RNN, which differs from other neural networks in that RNN contains one or more than one loop between nodes. RNN has a limit when dealing with back-propagated error. One of the delays of RNN called LSTM (Long Short-Term Memory) slets the users to stipulate a limit. Different from Traditional RNN, LSTM only reads the input from the current time when doing a time series prediction which makes it more efficient than the traditional RNN [4].

LSTM is broadly used to estimate data in various areas. Kong et al. [7] used LSTM to forecast short-term resident load. Their testing exposed that among all the estimate methods they certain, LSTM has the most precision. Huang et al. [6] used the past PM 2.5 concentration and weather report data to predict the PM 2.5 concentration in the future. The result verifies the capacity of LSTM to foresee PM 2.5. Sagheer et al. [17] developed a model based on LSTM that can deal with most time-series prediction problems. They verified empirically that their archetypal works well on time series problems about petroleum creation.

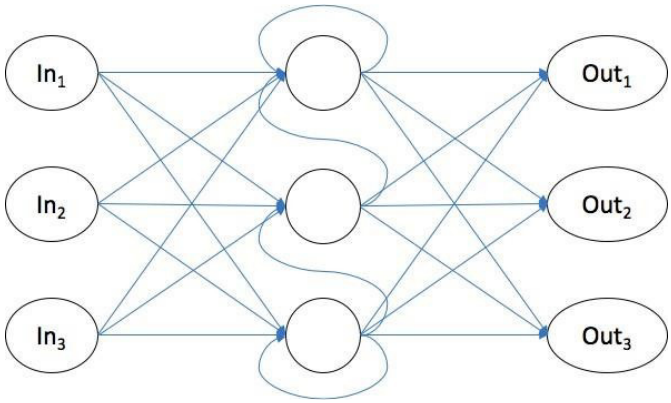

Figure 2.2: Architecture of Recurrent Neural Network.

Moving Average

In order to have sander data, the stirring usual is applied. Rather than using the data for a single day, we use the moving average value for seven days. For example, as shown in Tables A.8 and A.9, in the county of Albany in the state of New York, the number of Covid-19 cases for the days from July 1 to July 7 were the following in order: 2112, 2125, 2130, 2145, 2152, 2160 & 2164. Hence the seven- day stirring average placed on July 4th is the average of these 7 values divided by the populace of that section, which is 0.3 million, which gives 7008.5 gears per million people. That explains the value of the entry of Table A.3 in the row of that starts with Albany and the fifth column.

Conclusion

The thesis related ten estimate methods for growing Covid-19 cases in the sections of New York State.
It remains to be seen whether the prediction method can be further improved. Generally, the spatial prediction methods are more accurate with denser spatial locations with measurement data. Hence the IDW method could improve if we have more than a single lo- cation for each county. Each county may be subdivided into smaller districts with their own separate measurements. With increased accuracy of the IDW method, our spatiotemporal interpolation method could also improve.

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