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# A Novel Spatiotemporal Prediction Method of Cumulative Covid-19 Cases

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## ABSTRACT

***Prediction methods are important for many applications. In particular, an exact estimate for the total number of cases for plagues such as the Covid-19 contagion could help medical awareness by providing in time a adequate supply of testing kits, hospital beds & medical people. This thesis experimentally equivalences the accuracy of ten estimate methods for the swelling number of Covid-19 plague cases. These ten methods embrace 2 types of neural networks & extrapolation methods based on best fit rectilinear, best fit quadratic, best fit cubic & Lagrange interpolation [1], as well as an extrapolation method from Revest [14]. We also reflect the Kriging [8] & converse distance weighting [18] latitudinal outburst methods. We also develop a novel spatiotemporal prediction method by combination the Best fit linear and [18]. The researches drawing that amid these ten supposition methods, the spaciotemporal method has the slenderest root mean square fault & mean utter fault on Covid-19 upward data for areas 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 many claims, the value of a spatiotemporal flexible desires to be foretold for some time in the imminent based on earlier measured data at the same location & neighboring locations. Some well-known applications include the prediction of economic indicators, such as stock prices, GDP or unemployment figures. In this thesis, we revenue a look at expecting the number of cases of the Covid-19 plague [5], which is a innovative type of plague with no well-tested estimate systems for it. Former crazes estimate algorithms exist but they often need extra material like infested animals that are not offered or applicable in this case [15]. The respite of this thesis is strategic as follows. Section 2 analyses some hitherto proposed estimate methods. Section 3 presents a novel spatiotemporal estimate method. Section 4 presents an trial that equivalences the various prophecy methods on Covid-19 data from the public of New York. Finally, Section 5 grants some conclusions & future work.

## List of Contributions

The main donations of this thesis are the following:

- Doing the trial comparison of the temporal & spatiotemporal methods labelled in Chapter 4.
- Evolving a novel spatiotemporal method for the growing Covid-19 cases, which is obtainable in Chapter 3.2.

Part of the labor in this thesis was already published in the 24th International Database Engineering & Applications Conference [2].

## Review of Previous Interpolation Algorithms & Basic Concepts

In this section we review previous prediction methods. The prediction methods include sequential extrapolation methods (Section 2.1), spatial 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 reviews the fault measures used in this thesis. Every outburst method has a meaning that can be everyday to any sequential value even a value complex than all the ethics in the rare data. In this way, an speaking method can be also used for extrapolation, that is, for expecting the product in the future.

## Proposed Spatiotemporal Interpolation Method

In this slice we propose a fresh spatiotemporal outburst method that works in overall for several types of data, scounting growing Covid-19 plague data. Before relating our spaciotemporal extrapolation system, we remark that not all temporal & spatial extrapolation methods can be useful to growing data. In fact, we can show the following.

**Theorem 1.** The exponential decline extrapolation method underrates the real value when the leisurely value is monotonically increasing.

*Proof.* When the measured value is monotonically increasing, then we have the following conditions:

$$y > y_1 > y_2 > y_3 > y_4 > y_5 > y_6$$

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By Equation 1, the exponential decay extrapolation method's guesstimate for $y$ is the left side of the upstairs variation. Hence the guess for $y$ is less than $y_1$, however $y > y_1$ because the leisurely value is monotonically growing. Therefore, the exponential decayextrapolation method underestimates the value of $y$.

Theorem 1 infers that the exponential decline extrapolation method is not related for assessing swelling data, which are intrinsically monotonically increasing. This theorem serves as a caution in applying known methods to our task.

## Calculation of Distances between Neighboring Counties

Next we pronounce how we calculate the reserves between sadjoining locations. In the ex- ample below we consider the counties within the State of New York. Second, we estimate the distance between two counties $i$ & $j$ based on their centroids seeing that they lie on the exterior of the 3-dimensional soil, as follows. First, let R = 6368 kilometers (radius of the earth), and then take: $x_i$ = R × cos($long_i$) × sin(90°-$lat_i$) $y_i$ = R × sin($long_i$) × sin(90°-$lat_i$) $z_i$ = R × cos(90°-$lat_i$)

Similarly, we have:

$x_j$ = R × cos($long_j$) × sin(90°-$lat_j$) $y_j$ = R × sin($long_j$) × sin(90°-$lat_j$) $z_j$ = R × cos(90°-$lat_j$)

Finally, the Euclidean distance in 3-dimensions between the two centroids can be found as follows:

$$distance = \sqrt{(x_1 - x_0)^2 + (y_1 - y_0)^2 + (z_1 - z_0)^2} \quad (3$$

## An Experimental Comparison of the Prediction Methods

In this sector, we designate a computer trial that equivalences several sequential, spatial & spatiotemporal extrapolation methods that are related to envisaging the number of snowballing Covid-19 cases. This segment is prepared as follows. Section 4.1 defines the data causes. Section 4.2 pronounces the employment of the systems that were vexed. Section 4.3 explains the experimental procedure. Section 4.4 presents the experimental results.

## Data Sources

First, we collected population data for each county of New York State from the *World Population Review* website [25]. Second, we obtained the centroid latitude and longitude of each county from the United State Census Bureau website [23]. Table 4.1 shows the latitude and the longitude of the centroid and the population of each county of New York State. Next, we also obtained data about the cumulative number of Covid-19 cases in the counties of New York State during July 2020 from the *New York Times* [19]. In the Appendix, Tables A.6-A.10 present the raw data. The raw data show some fluctuations in the daily increases in the number of Covid-19 cases. Some of these fluctuations may reflect the true expansion of the disease. On the extra arrow, some oscillations may be owing to the alterations

Table 4.1: Latitude, longitude and population (in millions) of the counties in New York State. The data for New York City cartel 5 regions.

| County | Latitude | Longitude | Population | County | Latitude | Longitude | Population |
|---|---|---|---|---|---|---|---|
| Albany | 42.58824 | -73.97401 | 0.31 | Niagara | 43.456731 | -78.792142 | 0.21 |
| Allegany | 42.247853 | -78.026153 | 0.05 | Oneida | 43.242727 | -75.434282 | 0.23 |
| Broome | 42.161977 | -75.830283 | 0.19 | Onondaga | 43.006516 | -76.196134 | 0.46 |
| Cattaraugus | 42.239099 | -78.662332 | 0.08 | Ontario | 42.856357 | -77.303497 | 0.11 |
| Cayuga | 43.008546 | -76.574587 | 0.08 | Orange | 41.40241 | -74.306252 | 0.38 |
| Chautauqua | 42.304216 | -79.407595 | 0.13 | Orleans | 43.502287 | -78.229726 | 0.04 |
| Chemung | 42.15528 | -76.747179 | 0.08 | Oswego | 43.461443 | -76.209262 | 0.12 |
| Chenango | 42.478024 | -75.602241 | 0.05 | Otsego | 42.629776 | -75.028841 | 0.06 |
| Clinton | 44.752712 | -73.705643 | 0.08 | Putnam | 41.427907 | -73.743861 | 0.10 |
| Columbia | 42.247729 | -73.626806 | 0.06 | Rensselaer | 42.710421 | -73.513845 | 0.16 |
| Cortland | 42.594039 | -76.07624 | 0.05 | Rockland | 41.154628 | -74.024662 | 0.33 |
| Delaware | 42.193986 | -74.966728 | 0.04 | Saratoga | 43.106135 | -73.855387 | 0.23 |
| Dutchess | 41.75477 | -73.740041 | 0.29 | Schenectady | 42.817552 | -74.043559 | 0.16 |
| Erie | 42.752759 | -78.778192 | 0.92 | Schoharie | 42.591294 | -74.438172 | 0.03 |
| Essex | 44.109601 | -73.778431 | 0.04 | Schuyler | 42.419776 | -76.938603 | 0.02 |
| Franklin | 44.594376 | -74.31067 | 0.05 | Seneca | 42.782294 | -76.827088 | 0.03 |
| Fulton | 43.115609 | -74.423678 | 0.05 | St. Lawrence | 44.488112 | -75.074311 | 0.11 |
| Genesee | 43.00091 | -78.192778 | 0.06 | Steuben | 42.266725 | -77.385525 | 0.10 |
| Greene | 42.279821 | -74.142025 | 0.05 | Suffolk | 40.943554 | -72.692218 | 1.48 |
| Hamilton | 43.657879 | -74.502456 | 0.00 | Sullivan | 41.719993 | -74.771577 | 0.08 |
| Herkimer | 43.407489 | -75.011683 | 0.06 | Tioga | 42.178057 | -76.297456 | 0.05 |
| Jefferson | 43.996389 | -76.052968 | 0.11 | Tompkins | 42.453006 | -76.473483 | 0.10 |
| Lewis | 43.782681 | -75.44414 | 0.03 | Ulster | 41.947212 | -74.265458 | 0.18 |
| Livingston | 42.727485 | -77.769779 | 0.06 | Warren | 43.555105 | -73.838139 | 0.06 |
| Madison | 42.910026 | -75.663575 | 0.07 | Washington | 43.312377 | -73.439428 | 0.06 |
| Monroe | 43.464484 | -77.664658 | 0.74 | Wayne | 43.458758 | -77.063164 | 0.09 |
| Montgomery | 42.900891 | -74.435357 | 0.05 | Westchester | 41.152686 | -73.745753 | 0.97 |
| Nassau | 40.729612 | -73.589414 | 1.36 | Wyoming | 42.701363 | -78.228567 | 0.04 |
| New York C. | 40.776642 | -73.970187 | 8.18 | Yates | 42.638237 | -77.104324 | 0.02 |

between weekdays &weekends when extra people are extra expected to go for Covid-19 testing. Hence, it types sagacity to shine the data by enchanting a affecting usual. We computed a seven day moving average based on the raw data and divided it by the population of each county. The 7 day poignant usual was intended as explicated in Sector 2.4. In the Appendix, Tables A.1-A.5 show the refined data.

## Experimental Results

Table 4.2 shows the cause cruel square blunder (RMSE) for each estimate method when they were used to foresee 1-16 days gaining. Similarly, Table 4.3 shows the cruel utter blunder (MAE) for each estimate method when they were used to predict 1-16 days ahead.

Table 4.3: The MAEs of the estimate systems

| Type | Method | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| Temporal | BP | 603.70 | 604.99 | 586.89 | 647.06 | 635.28 | 647.69 | 642.94 | 624.43 |
| Temporal | RNN | 570.61 | 564.97 | 558.30 | 552.10 | 544.88 | 535.46 | 530.61 | 517.38 |
| Temporal | Lagrange | 3.56 | 9.42 | 17.56 | 27.97 | 41.81 | 58.24 | 78.11 | 99.69 |
| Temporal | Revesz | 2.65 | 7.64 | 15.02 | 24.23 | 36.76 | 51.75 | 70.59 | 90.99 |
| Temporal | Cubic | 7.33 | 21.17 | 44.84 | 78.47 | 125.58 | 190.35 | 275.01 | 379.09 |
| Temporal | Quadratic | 4.37 | 10.35 | 19.34 | 31.21 | 46.26 | 63.74 | 83.43 | 103.68 |
| Temporal | Linear | 7.01 | 12.94 | 19.99 | 27.07 | 34.13 | 41.21 | 47.70 | 54.52 |
| Spatial | Kriging | 3951.21 | 3960.78 | 3970.85 | 3981.79 | 3992.73 | 4003.48 | 4013.01 | 4021.52 |
| Spatial | IDW | 2003.26 | 2005.42 | 2007.66 | 2010.24 | 2013.33 | 2017.80 | 2022.77 | 2027.74 |
| Spatiotemp. | ST | 9.69 | 15.36 | 21.34 | 27.09 | 32.78 | 38.77 | 44.38 | 50.53 |
| Type | Method | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
| Temporal | BP | 663.29 | 675.90 | 640.45 | 708.22 | 651.38 | 706.29 | 679.51 | 723.15 |
| Temporal | RNN | 510.66 | 500.89 | 490.46 | 479.87 | 476.62 | 470.24 | 452.53 | 470.71 |
| Temporal | Lagrange | 124.45 | 151.33 | 180.32 | 211.49 | 244.58 | 279.46 | 316.52 | 355.91 |
| Temporal | Revesz | 114.58 | 140.01 | 168.08 | 198.13 | 230.07 | 263.94 | 299.85 | 338.04 |
| Temporal | Cubic | 506.55 | 659.14 | 839.51 | 1047.27 | 1286.93 | 1559.27 | 1867.56 | 2214.14 |
| Temporal | Quadratic | 126.21 | 150.58 | 177.11 | 205.77 | 236.75 | 269.58 | 305.65 | 344.20 |
| Temporal | Linear | 60.32 | 64.46 | 69.33 | 76.27 | 83.59 | 91.32 | 99.75 | 108.71 |
| Spatial | Kriging | 4028.28 | 4033.79 | 4038.63 | 4043.29 | 4047.75 | 4052.93 | 4059.25 | 4065.45 |
| Spatial | IDW | 2032.73 | 2036.99 | 2040.92 | 2043.76 | 2046.84 | 2049.61 | 2052.07 | 2054.57 |
| Spatiotemp. | ST | 55.85 | 59.71 | 64.30 | 71.16 | 78.39 | 86.04 | 94.19 | 102.87 |

The usual of the 7 day moving medians centered on July 25, that is, the usual of the last spilaster of Table A.5 is 7952.15. Hence the ST method's MAE of 102.87 is correspondent to around a 1.29 % fault. For taxing the latitudinal outburst, we use the expect result of the Best Fit Rectilinear since it has the highest exactness among all historical method we tested. The result for the latitudinal Outburst shows that for IDW, the assume result for Dutchess & Tompkins counties, the global result for IDW has minor mistake than the Best Fit Linear method in those three statuses. For Kriging, the expect result for Tompkins & Yates county, the global result for Kriging has lower blunder than Revesz method in folks 2 states but IDW has the deepest fault. The Figures 5.3 & 5.4 show the RMSE & MAE of the united spatiotemporal method. The trial specifies that our spatiotemporal estimate method works well for swelling Covid-19 cases.

## Conclusion

The thesis linked ten estimate methods for growing Covid-19 cases in the districts of New York State. One of these methods is a original spaciotemporal method that blocs a temporal extrapolation method with the IDW latitudinal outburst method. Global, this original spatiotemporal estimate way was the best conferring to both the MAE & the RMSE fault dealings.

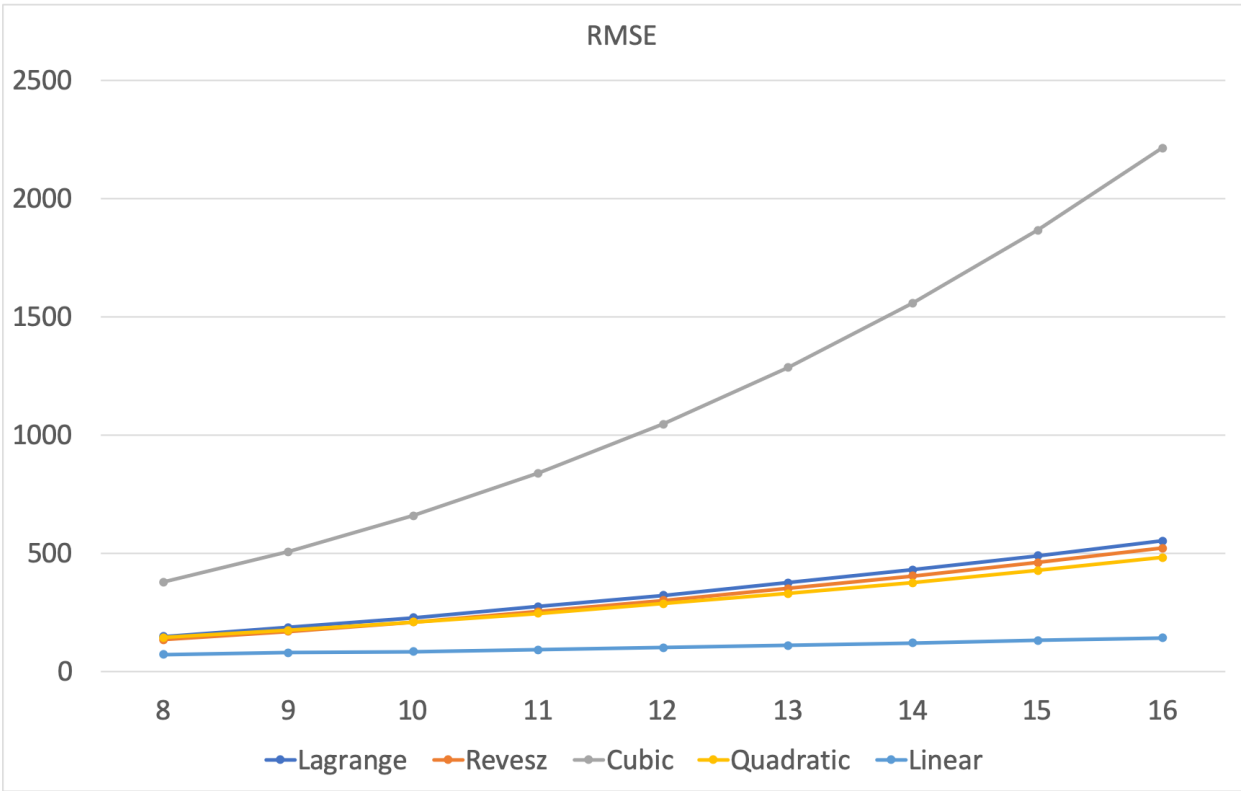


Figure 5.1: RMSE of Temporal Methods.

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