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A Novel Spatiotemporal Prediction Method of Cumulative Covid-19 Cases

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A NOVEL SPATIOTEMPORAL PREDICTION METHOD OF CUMULATIVE COVID-19 CASES

by

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Prediction methods are important for many applications. In particular, an accurate prediction for the total number of cases for pandemics such as the Covid-19 pandemic could help medical preparedness by providing in time a sufficient supply of testing kits, hospital beds and medical personnel. This thesis experimentally compares the accuracy of ten prediction methods for the cumulative number of Covid-19 pandemic cases. These ten methods include two types of neural networks and extrapolation methods based on best fit linear, best fit quadratic, best fit cubic and Lagrange interpolation [1], as well as an extrapolation method from Revesz [14]. We also consider the Kriging [8] and inverse distance weighting [18] spatial interpolation methods. We also develop a novel spatiotemporal prediction method by combining the Best fit linear and [18]. The experiments show that among these ten prediction methods, the spatiotemporal method has the smallest root mean square error and mean absolute error on Covid-19 cumulative data for counties in New York State between June and July, 2020.

DEDICATION

To the brighter tomorrow

ACKNOWLEDGMENTS

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Chapter 1

Introduction

In many applications, the value of a spatiotemporal variable needs to be predicted for some time in the future based on previously measured data at the same location and neighboring locations. Some well-known applications include the prediction of economic indicators, such as stock prices, GDP or unemployment figures. In this thesis, we take a look at predicting the number of cases of the Covid-19 pandemic [5], which is a novel type of pandemic with no well-tested prediction algorithms for it. Earlier epidemics prediction algorithms exist but they often require extra information like infected animals that are not available or applicable in this case [15]. Therefore, we focus on the Covid-19 pandemic in this thesis, although our novel spatiotemporal interpolation algorithm may also be applicable to other spatiotemporal interpolation problems [9].

There are only a few publications that use Covid-19 data together with geographic information. Liu et al. [10] analyzes the combination of Covid-19 data and travel data in Wuhan, China and showed that travel restrictions were useful in curbing the spread of the pandemic. Thakar [21] generates an approximate density map for Covid-19 patients using location information such as school or work location from publicly available news articles in Washington State. Wang et al. [24] developed an algorithm that can estimate if a ship contains a risk of Covid-19 infections based on some information about the ships and their travel paths. These works are applicable only when the required patient address or travel data are available. In contrast, our prediction algorithms work without the need for such detailed information. Thomas et al. [22] presented a Covid-19 diffusion model based on interpersonal contact networks. While this may give more accurate predictions than other pandemic models, it requires interpersonal contact information, which is not generally available.

The rest of this thesis is organized as follows. Section 2 reviews some previously proposed prediction methods. Section 3 presents a novel spatiotemporal prediction method. Section 4 presents an experiment that compares the various prediction methods on Covid-19 data from the state of New York. Finally, Section 5 presents some conclusions and future work.

1.1 List of Contributions

The main contributions of this thesis are the following:

- Doing the experimental comparison of the temporal and spatiotemporal methods described in Chapter 4.
- Developing a novel spatiotemporal method for the cumulative Covid-19 cases, which is presented in Chapter 3.2.

Part of the work in this thesis was already published in the *24th International Database Engineering and Applications Symposium* [2].

Chapter 2

Review of Previous Interpolation Algorithms and Basic Concepts

In this section we review previous prediction methods. The prediction methods include temporal extrapolation methods (Section 2.1), spatial extrapolation methods (Section 2.2), and neural networks (Section 2.3). In addition, Section 2.4 reviews the concept of moving average. Finally, Section 2.5 reviews the error measures used in this thesis. Every interpolation method has a function that can be applied to any temporal value even a value higher than all the values in the raw data. In this way, an interpolation method can be also used for extrapolation, that is, for predicting the outcome in the future.

2.1 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 *Best Fit Cubic* and the *Lagrange* interpolation methods [1] can be used to predict the number of cases of the Covid-19 pandemic at that location. These methods derive interpolation functions into which we can place any future time instance to get a prediction value. In addition, the exponential decay temporal method, which was highly accurate for predicting election outcomes [3], can be used to get an estimate for the current day using the following formula, which assumes that we know the number of cases during the six previous days:

$$y = \frac{y_1}{2} + \frac{y_2}{4} + \frac{y_3}{8} + \frac{y_4}{16} + \frac{y_5}{32} + \frac{y_6}{32} \tag{2.1}$$

The above formula can be extended for more numbers of days. The important feature is that the weights are successively diminishing by half except in the last instance, where the last weight is equal to the previous weight. Note that in this way, the sum of all the weights is exactly one. Finally, another prediction method that was proposed by Revesz [14] uses the following formula to predict the number of cases of the Covid-19 pandemic, where t is the number of days ahead 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.

$$y = \left(1 + t + \frac{t^2}{2}\right) y_1 + (t + t^2)y_2 + \frac{t^2}{2} y_3 \tag{2.2}$$

2.2 Spatial Extrapolation Methods

Inverse Distance Weighting (IDW) [18] is a common spatial interpolation method. 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 closer than another neighbor, then the weight of the former will be higher than the weight of the latter. We use λ_i as the weight, y_i as the interpolated variable, and d_i as the distance to the i^{th} neighbor [13]. Then the Inverse Distance Weighting equation for the interpolated variable y at a location can be written in terms of its neighbors as follows:

$$y = \sum_{i=1}^{N} \lambda_i \times y_i \tag{2.3}$$

where the equation for calculating λ_i can be written as follows:

$$\lambda_i = \frac{\left(\frac{1}{d_i}\right)^P}{\sum_{k=1}^{N}\left(\frac{1}{d_i}\right)^P} \tag{2.4}$$

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

Kriging is based on the work of Danie G. Krige [8]. Different from IDW, Kriging not only considers the distance, but also find the spatial structure inside the data. The basic formula for Kriging is the following:

$$Z(x_0) = \begin{bmatrix} z_1 & ... & z_n \end{bmatrix} * \begin{bmatrix} w_1 \\ ... \\ w_n \end{bmatrix} \tag{2.5}$$

Where $Z(x_0)$ is the predicted value at location x_0, $z_1 ... z_n$ are the values of the neighbors of x_0, and $w_1 ... w_n$ are the weights of the neighbors, which can be calculated as follows:

$$\begin{bmatrix} w_1 \\ ... \\ w_n \end{bmatrix} = \begin{bmatrix} c(x_1, x_1) & ... & c(x_1, x_n) \\ ... & ... & ... \\ c(x_n, x_1) & ... & c(x_n, x_n) \end{bmatrix}^{-1} * \begin{bmatrix} c(x_1, x_0) \\ ... \\ c(x_n, x_0) \end{bmatrix} \tag{2.6}$$

where $c(x, y)$ is the covariance function, that is, $c(x, y) = Cov(Z(x), Z(y))$.

2.3 Neural Networks

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

2.3.1 Backpropagation

Backpropagation is a learning algorithm that has been used very often in neural networks. 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 descent. 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 make sure that the neural network can produce an accurate prediction.

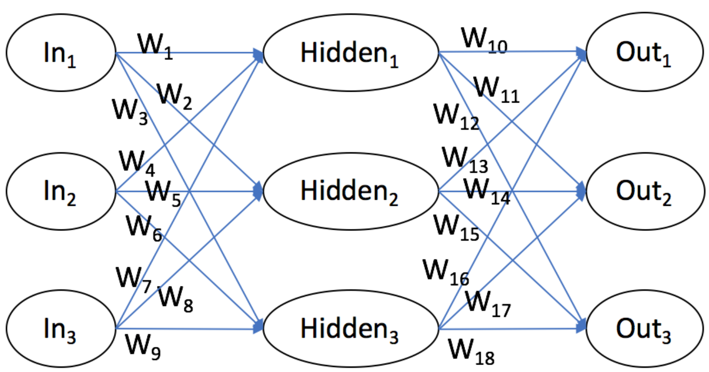

Figure 2.1: Backpropagation example.

Figure 2.1 shows the example of backpropagation structure. Where:

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

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

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

The goal of this step is to find the best weights (W_i) for the neural network to learn.

2.3.2 Recurrent Neural Networks

Recurrent Neural Networks (RNNs) [4] improve backpropagation with the goal of better predicting the outcomes of a time series, such as in motor control and rhythm detection. 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 extensions of RNN called LSTM (Long Short-Term Memory) allows the users to specify 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 widely used to forecast data in many areas. Kong et al. [7] used LSTM to forecast short-term resident load. Their experiment showed that among all the prediction methods they selected, LSTM has the most accuracy. 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 proves the ability of LSTM to predict PM 2.5. Sagheer et al. [17] developed a model based on LSTM that can deal with most time-series prediction problems. They verified experimentally that their model works well on time series problems regarding petroleum production.

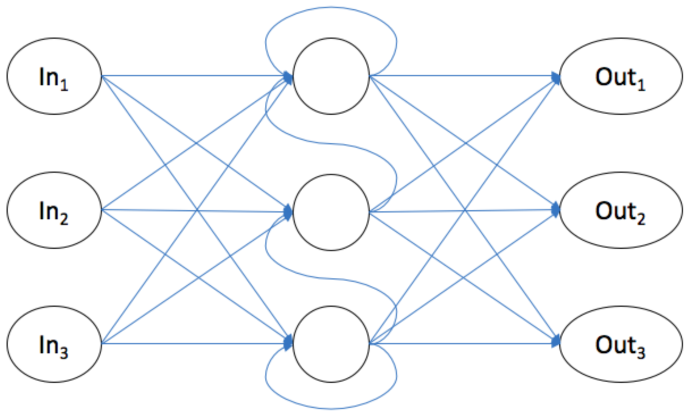

Figure 2.2: Architecture of Recurrent Neural Network.

2.4 Moving Average

In order to have smoother data, the moving average 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 and 2164. Hence the seven day moving average centered on July 4th is the average of these seven values divided by the population of that county, which is 0.3 million, which gives 7008.5 cases 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.

2.5 Error Measures

To experimentally evaluate the accuracy of the interpolation methods, we use the *Mean Absolute Error* (MAE) and the *Root Mean Square Error* (RMSE) measures, which are defined as follows, where F_i is the predicted value and A_i is the corresponding actual value and N is the number of items:

$$MAE = \frac{\sum_{i=1}^{N} |F_i - A_i|}{N} \tag{2.7}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (F_i - A_i)^2}{N}} \tag{2.8}$$

Chapter 3

Proposed Spatiotemporal Interpolation Method

In this section we propose a novel spatiotemporal interpolation method that works in general for many types of data, including cumulative Covid-19 pandemic data. Before describing our spatiotemporal extrapolation algorithm, we remark that not all temporal and spatial extrapolation methods can be applied to cumulative data. In fact, we can show the following.

Theorem 1. The exponential decay extrapolation method underestimates the real value when the measured value is monotonically increasing.

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

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

The above implies the following:

$$\frac{y_1}{2} + \frac{y_2}{4} + \frac{y_3}{8} + \frac{y_4}{16} + \frac{y_5}{32} + \frac{y_6}{32} < \frac{y_1}{2} + \frac{y_1}{4} + \frac{y_1}{8} + \frac{y_1}{16} + \frac{y_1}{32} + \frac{y_1}{32} = y_1$$

By Equation 1, the exponential decay extrapolation method's estimate for y is the left side of the above inequality. Hence the estimate for y is less than y_1, whereas $y > y_1$ because the measured value is monotonically increasing. Therefore, the exponential decay extrapolation method underestimates the value of y. $\square$

Theorem 1 implies that the exponential decay extrapolation method is not applicable for estimating cumulative data, which are inherently monotonically increasing. This theorem serves as a caution in applying known methods to our task.

3.1 Calculation of Distances between Neighboring Counties

Next we describe how we calculate the distances between neighboring locations. In the example below we consider the counties within the State of New York. Second, we calculate the distance between two counties i and j based on their centroids considering that they lie on the surface of the 3-dimensional earth, as follows. First, let R = 6368 kilometers (radius of the earth), and then take:

$x_i = \mathrm{R} \times \cos(long_i) \times \sin(90°\text{-}lat_i)$

$y_i = \mathrm{R} \times \sin(long_i) \times \sin(90°\text{-}lat_i)$

$z_i = \mathrm{R} \times \cos(90°\text{-}lat_i)$

Similarly, we have:

$x_j = \mathrm{R} \times \cos(long_j) \times \sin(90°\text{-}lat_j)$

$y_j = \mathrm{R} \times \sin(long_j) \times \sin(90°\text{-}lat_j)$

$z_j = \mathrm{R} \times \cos(90°\text{-}lat_j)$

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

$$distance = \sqrt{(x_1 - x_0)^2 + (y_1 - y_0)^2 + (z_1 - z_0)^2} \tag{3.1}$$

3.2 Combining Spatial and Temporal Extrapolation Methods to Form Spatiotemporal Methods

Intuitively, the number of cases of the Covid-19 pandemic can be better estimated by considering both temporal and spatial interpolations. If a county C has a very high number of Covid-19 cases, then the situation in its neighbors may not affect the development of the number of cases much and could even be ignored because most residents of C will catch the disease from other residents within county C. Therefore, the best temporal interpolation based on just that state's previous cases, denoted as $E_{t,C}$, likely would give the best prediction for the future.

On the other hand, if a county C has few Covid-19 cases relative to its neighbors, then the situation in its neighbors has to be carefully considered because in that case most residents of C could be infected by neighboring county residents when they travel and meet. Therefore, a spatial interpolation of the neighbors' future cases, denoted as $E_{s,C}$, likely would give the best prediction for the future cases in county C.

Preliminary experiments suggested that the above still needs to be refined because if one of the neighbors experiences an explosion in the number of cases, then it may not immediately cause an explosion in county C too. In other words, there is some time delay instead of an immediate effect. Therefore, in such cases the temporal interpolation $E_{t,S}$, would still likely give the most accurate prediction, while the spatial interpolation $E_{s,S}$ would be likely to give an overestimate of the number of Covid-19 pandemic cases. Therefore, we need to place some limit on the difference between the two estimates and ignore the spatial estimate if it is excessively larger than the temporal estimate. By testing values of multiples of ten, we found that 30 and 280 work best as the lower and upper bound values, respectively. Therefore, we refine the above formula as follows:

$$E_S = \begin{cases} E_{s,C} & \text{if } 30 < E_{s,C} - E_{t,C} < 280 \\ E_{t,C} & \text{otherwise} \end{cases} \tag{3.2}$$

Chapter 4

An Experimental Comparison of the Prediction Methods

In this section, we describe a computer experiment that compares several temporal, spatial and spatiotemporal extrapolation methods that are applicable to predicting the number of cumulative Covid-19 cases. This section is organized as follows. Section 4.1 describes the data sources. Section 4.2 describes the implementation of the algorithms that were tested. Section 4.3 explains the experimental procedure. Section 4.4 presents the experimental results.

4.1 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 other hand, some fluctuations may be due to the differences

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

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 and weekends when more people are more likely to go for Covid-19 testing. Hence, it makes sense to smoothen the data by taking a moving average. We computed a seven day moving average based on the raw data and divided it by the population of each county. The seven day moving average was calculated as explained in Section 2.4. In the Appendix, Tables A.1-A.5 show the refined data.

4.2 Implementation of the Algorithms

We implemented the temporal, IDW, and the spatiotemporal interpolation methods in MATLAB. For Kriging, we obtained the MATLAB function code from [11]. We obtained a MATLAB implementation of the LSTM recurrent neural network program from [12]. We adjusted the neural network structure to have an input layer with six nodes, a hidden layer with ten nodes, and an output layer with one nodes. We modified the code so that the recurrent neural network can accept six inputs and give one output.

For the backpropagation neural network, we used the program from [20]. We adjusted the neural network structure to have an input layer with six nodes, a hidden layer with ten nodes, and an output layer with one node. We modified the code so that the backpropagation neural network can accept six inputs and give one output.

4.3 Testing Procedure

We did some preliminary experiments to fine tune the parameters used in all of the algorithms. In particular, we compared the accuracies of the methods using the raw, the five days moving average and the seven days moving average data. In general, all methods performed best with the seven days moving average except for the Revesz method. We also compared 3 versus 6 previous days' values as inputs for the Lagrange method with the result that it was more accurate with only 3 inputs. For the neural networks we also considered using a single neural network for each county versus using sixteen different neural networks for each county, where each neural network predicted for a particular number of days ahead between one and sixteen. In general, using sixteen different neural networks was more accurate for most counties. We also experimented with five, ten and fifteen hidden nodes in the neural networks. There was a significant improvement from five to ten hidden nodes but little or no improvement from ten to fifteen hidden nodes. Therefore, we used ten hidden nodes in the hidden layer of all the neural networks. Finally, for fine tuning the parameters of our spatiotemporal method, we tested multiples of ten for possible upper and lower bounds. The lower bound of 30 and the upper bound of 280 produced the most accurate result.

After fine tuning, our goal was to compare how well the various prediction methods predicted the moving average centered on days 7/10 (1 day ahead), 7/11 (2 days ahead),

..., and 7/25 (16 days ahead). For our testing we divided the prediction methods into two groups based on the number of inputs that they use.

The first group used six inputs, which were the moving average data centered on days from 7/4 to 7/9. The first group included the Best Fit Linear, the Best Fit Quadratic and the Best Fit Cubic methods. The second group used only three inputs, which were the moving average data centered on days 7/7, 7/8 and 7/9. The second group included the Lagrange and the Revesz [14] methods. The Lagrange method was put into the second group because preliminary experiments showed that the Lagrange method with three inputs was more accurate than the Lagrange method with six inputs. On the other hand, the Best Fit Cubic and Best Fit Quadratic methods were better with six inputs than with three inputs. The Revesz method requires three inputs by definition.

A spatial interpolation-based way to predict n days ahead in county C_i the number of cumulative Covid-19 cases is the following two-step process. First, we predict n days ahead in all the neighbors of C_i the number of cumulative Covid-19 cases using the Best Fit Linear extrapolation. Second, we use either IDW or Kriging to predict n days ahead in county C_i the number of cumulative Covid-19 cases.

Our novel spatiotemporal prediction method chooses between either the above IDW-based prediction or the prediction n days ahead in county C_i of the number of cumulative Covid-19 cases using the Best Fit Linear extrapolation. The choice is guided by the conditions described in Section 3.2. The spatial interpolation-based and the novel spatiotemporal prediction methods are classified as belonging to the first group because they use the Best Fit Linear extrapolation method.

For the backpropagation and the recurrent neural networks, we collected raw data from 6/1 to 6/28 too. Then for each county, we generated moving average data divided by the population of the county from 6/4 to 6/25. Next we trained 16 separate neural networks for each county on the following set of training data, which are sequences with length 7:

1. Training Input: 6/4 to 6/9 Output: 6/10; Testing Input: 7/4 to 7/9 Output: 7/10
2. Training Input: 6/4 to 6/9 Output: 6/11; Testing Input: 7/4 to 7/9 Output: 7/11
3. Training Input: 6/4 to 6/9 Output: 6/12; Testing Input: 7/4 to 7/9 Output: 7/12
4. Training Input: 6/4 to 6/9 Output: 6/13; Testing Input: 7/4 to 7/9 Output: 7/13
5. Training Input: 6/4 to 6/9 Output: 6/14; Testing Input: 7/4 to 7/9 Output: 7/14
6. Training Input: 6/4 to 6/9 Output: 6/15; Testing Input: 7/4 to 7/9 Output: 7/15
7. Training Input: 6/4 to 6/9 Output: 6/16; Testing Input: 7/4 to 7/9 Output: 7/16
8. Training Input: 6/4 to 6/9 Output: 6/17; Testing Input: 7/4 to 7/9 Output: 7/17
9. Training Input: 6/4 to 6/9 Output: 6/18; Testing Input: 7/4 to 7/9 Output: 7/18
10. Training Input: 6/4 to 6/9 Output: 6/19; Testing Input: 7/4 to 7/9 Output: 7/19
11. Training Input: 6/4 to 6/9 Output: 6/20; Testing Input: 7/4 to 7/9 Output: 7/20
12. Training Input: 6/4 to 6/9 Output: 6/21; Testing Input: 7/4 to 7/9 Output: 7/21
13. Training Input: 6/4 to 6/9 Output: 6/22; Testing Input: 7/4 to 7/9 Output: 7/22
14. Training Input: 6/4 to 6/9 Output: 6/23; Testing Input: 7/4 to 7/9 Output: 7/23
15. Training Input: 6/4 to 6/9 Output: 6/24; Testing Input: 7/4 to 7/9 Output: 7/24
16. Training Input: 6/4 to 6/9 Output: 6/25; Testing Input: 7/4 to 7/9 Output: 7/25

There are 58 counties and 16 neural networks for each, which is a total of 928 sequences in the training data set. During testing, we gave as an input to the neural network the moving average data centered on days 7/4 ... 7/9.

For all methods, we compared the predictions for the moving average centered on days 7/10 (1 day ahead), 7/11 (2 days ahead), . . . , and 7/25 (16 days ahead) with the actual values in Tables A.4-A.5. We evaluated the root mean square error (RMSE) and the mean absolute error (MAE) measures for each prediction method as defined in Section 2.5.

Table 4.2: The RMSEs of the prediction methods

Type	Method	1	2	3	4	5	6	7	8
Temporal	BP	763.11	746.25	704.11	840.86	819.75	804.20	800.41	745.16
Temporal	RNN	717.57	704.70	689.94	676.62	662.48	650.01	637.60	618.29
Temporal	Lagrange	5.37	14.00	26.37	41.62	61.34	85.30	115.56	148.90
Temporal	Revesz	3.93	11.11	21.90	35.42	53.27	75.30	103.52	134.72
Temporal	Cubic	5.21	15.68	33.48	58.37	93.23	140.86	203.05	279.79
Temporal	Quadratic	6.19	14.64	27.13	43.15	63.81	88.13	115.28	143.85
Temporal	Linear	10.46	18.65	27.99	38.28	47.67	56.23	64.05	72.80
Spatial	Kriging	8375.16	8378.97	8383.33	8388.87	8394.33	8400.20	8405.39	8410.06
Spatial	IDW	3095.06	3096.19	3097.57	3099.77	3103.11	3107.46	3111.47	3115.72
Spatiotemp.	ST	17.74	23.75	30.46	38.49	45.93	52.73	58.68	65.76
Type	Method	9	10	11	12	13	14	15	16
Temporal	BP	815.84	807.15	750.80	879.84	750.45	849.66	788.08	846.86
Temporal	RNN	606.98	601.14	586.80	569.55	556.75	555.15	536.29	547.24
Temporal	Lagrange	186.94	228.66	274.96	323.36	375.64	430.90	490.15	553.12
Temporal	Revesz	170.73	210.31	254.58	300.98	351.24	404.64	461.87	522.89
Temporal	Cubic	374.79	490.02	625.62	782.50	963.68	1170.01	1403.81	1668.21
Temporal	Quadratic	175.38	209.64	247.25	287.34	330.52	376.87	428.01	483.01
Temporal	Linear	79.96	85.56	92.34	101.31	111.24	122.12	132.42	142.67
Spatial	Kriging	8412.73	8414.49	8415.58	8416.22	8416.68	8417.35	8418.45	8419.48
Spatial	IDW	3120.70	3125.66	3130.19	3133.49	3136.67	3139.77	3142.59	3145.07
Spatiotemp.	ST	71.99	77.42	84.11	92.94	102.85	113.87	123.84	133.71

4.4 Experimental Results

Table 4.2 shows the root mean square error (RMSE) for each prediction method when they were used to predict 1-16 days ahead. Similarly, Table 4.3 shows the mean absolute error (MAE) for each prediction method when they were used to predict 1-16 days ahead.

Table 4.3: The MAEs of the prediction methods

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 average of the seven day moving averages centered on July 25, that is, the average of the last column of Table A.5 is 7952.15. Hence the ST method's MAE of 102.87 is equivalent to about a 1.29 percent error. For testing the spatial interpolation, we use the predict result of the Best Fit Linear since it has the highest accuracy among all temporal method we tested. The result for the spatial Interpolation shows that for IDW, the predict result for Dutchess and Tompkins counties, the overall result for IDW has lower error than the the Best Fit Linear method in those three states. For Kriging, the predict result for Tompkins and Yates county, the overall result for Kriging has lower error than Revesz method in those two states but IDW has the lowest error. The Figures 5.3 and 5.4 show the RMSE and MAE of the combined spatiotemporal method. The experiment indicates that our spatiotemporal prediction method works well for cumulative Covid-19 cases.

We also analyzed the the results for New York State in further detail by considering separately the counties that are mostly metropolitan areas versus the other counties that are mostly rural areas. For the spatiotemporal method, Tables 4.4 and 4.5 show the MAEs and RMSEs of the mostly metropolitan counties, which are Erie, Monroe, New York City, Onondaga, Schenectady and Westchester, and rest of the counties, which are mostly rural. Table 4.4 also shows the absolute difference between the metropolitan and the rural MAEs. The absolute differences are always below 17 with a mean of 9.7 over the sixteen days. The average number of Covid-19 cases for all counties ranged from 6603.73 to 6950.04.

The last row of Table 4.4 shows that the absolute differences in the MAEs make up only a small percent of the average number of Covid-19 cases. These percentages fluctuate slightly from 0.10% for one day ahead to 0.02% for twelve days ahead and to 0.24% for sixteen days ahead. The last row of Table 4.5 shows that the absolute differences in the RMSEs also make up only a small percent of the average number of Covid-19 cases and also fluctuate slightly from 0.22% for one day ahead to 0.04% for thirteen days ahead and to 0.31% for sixteen days ahead. Hence according to both the MAE and the RMSE measures there was no significant differences between the mostly metropolitan and the mostly rural counties within New York State. This suggests that similar accuracies can be obtained when the method is applied to other states, including mostly metropolitan states such as Rhode Island and mostly rural states like most states in the Mid-West.

Table 4.4: The spatiotemporal method's MAEs for the Metropolitan and Rural counties

County	1	2	3	4	5	6	7	8
Metropolitan MAE	3.65	5.92	10.76	16.26	22.29	28.68	34.58	39.23
Rural MAE	10.39	16.45	22.56	28.34	33.99	39.93	45.51	51.83
Absolute Difference of MAEs	6.73	10.53	11.80	12.09	11.70	11.25	10.93	12.60
Average Number of Cases	6603.74	6627.28	6652.34	6677.43	6701.85	6725.55	6748.49	6771.51
Percentage Difference	0.10%	0.16%	0.18%	0.18%	0.17%	0.17%	0.16%	0.19%
County	9	10	11	12	13	14	15	16
Metropolitan MAE	45.38	52.06	60.62	69.88	81.41	93.24	106.20	118.10
Rural MAE	57.06	60.59	64.72	71.30	78.04	85.21	92.80	101.11
Absolute Difference of MAEs	11.68	8.53	4.11	1.42	3.36	8.03	13.39	16.99
Average Number of Cases	6793.62	6814.36	6835.62	6858.13	6881.07	6904.41	6927.87	6950.04
Percentage Difference	0.17%	0.13%	0.06%	0.02%	0.05%	0.12%	0.19%	0.24%

Table 4.5: The spatiotemporal method's RMSEs for the Metropolitan and Rural counties

County	1	2	3	4	5	6	7	8
Metropolitan RMSE	4.01	6.97	13.04	20.45	28.99	38.51	47.03	54.04
Rural RMSE	18.68	24.97	31.87	40.05	47.50	54.13	59.87	66.98
Absolute Difference of RMSEs	14.68	18.00	18.83	19.60	18.52	15.62	12.84	12.94
Average Number of Cases	6603.74	6627.28	6652.34	6677.43	6701.85	6725.55	6748.49	6771.51
Percentage Difference	0.22%	0.27%	0.28%	0.29%	0.28%	0.23%	0.19%	0.19%
County	9	10	11	12	13	14	15	16
Metropolitan RMSE	60.11	66.30	75.22	85.54	100.28	117.22	135.66	153.01
Rural RMSE	73.24	78.60	85.08	93.76	103.15	113.48	122.41	131.30
Absolute Difference of RMSEs	13.13	12.30	9.86	8.22	2.87	3.74	13.25	21.71
Average Number of Cases	6793.62	6814.36	6835.62	6858.13	6881.07	6904.41	6927.87	6950.04
Percentage Difference	0.19%	0.18%	0.14%	0.12%	0.04%	0.05%	0.19%	0.31%

Chapter 5

Conclusion

The thesis compared ten prediction methods for cumulative Covid-19 cases in the counties of New York State. One of these methods is a novel spatiotemporal method that combines a temporal extrapolation method with the IDW spatial interpolation method. Overall, this novel spatiotemporal prediction method was the best according to both the MAE and the RMSE error measures.

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 location 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.

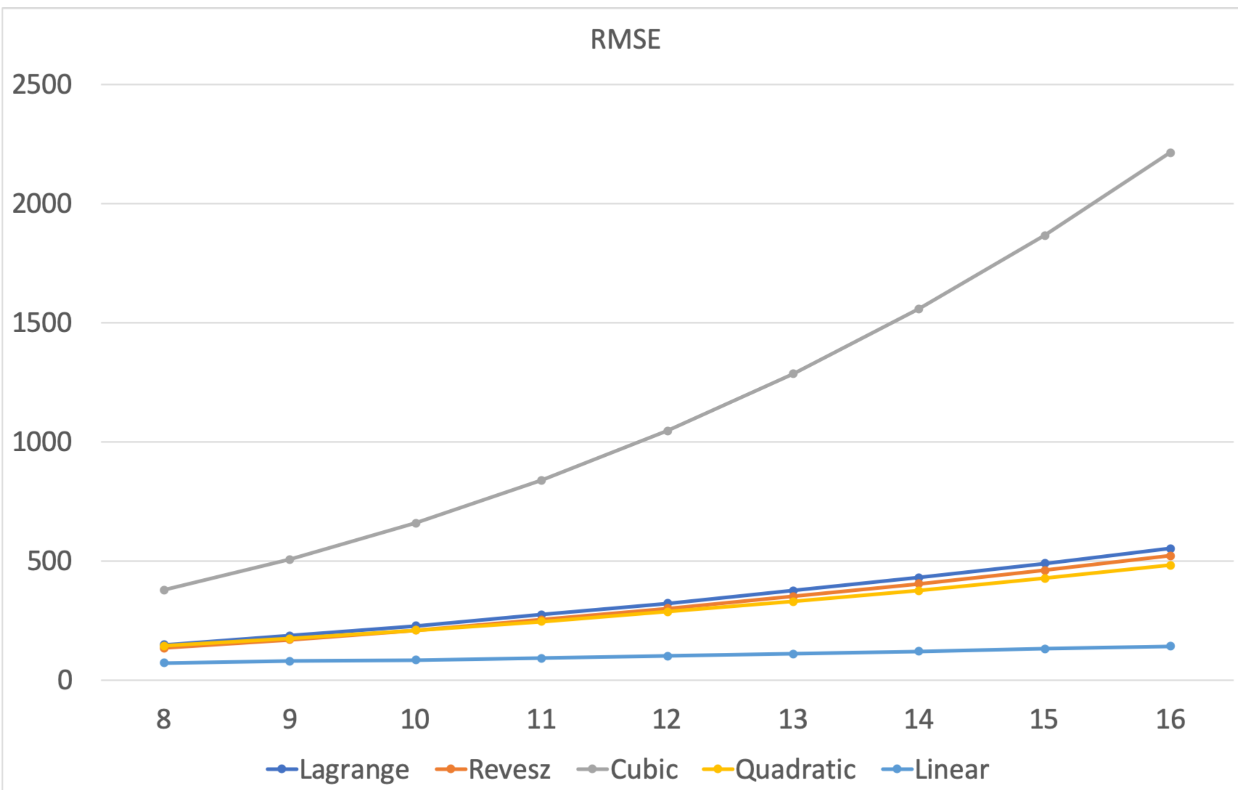

Figure 5.1: RMSE of Temporal Methods.

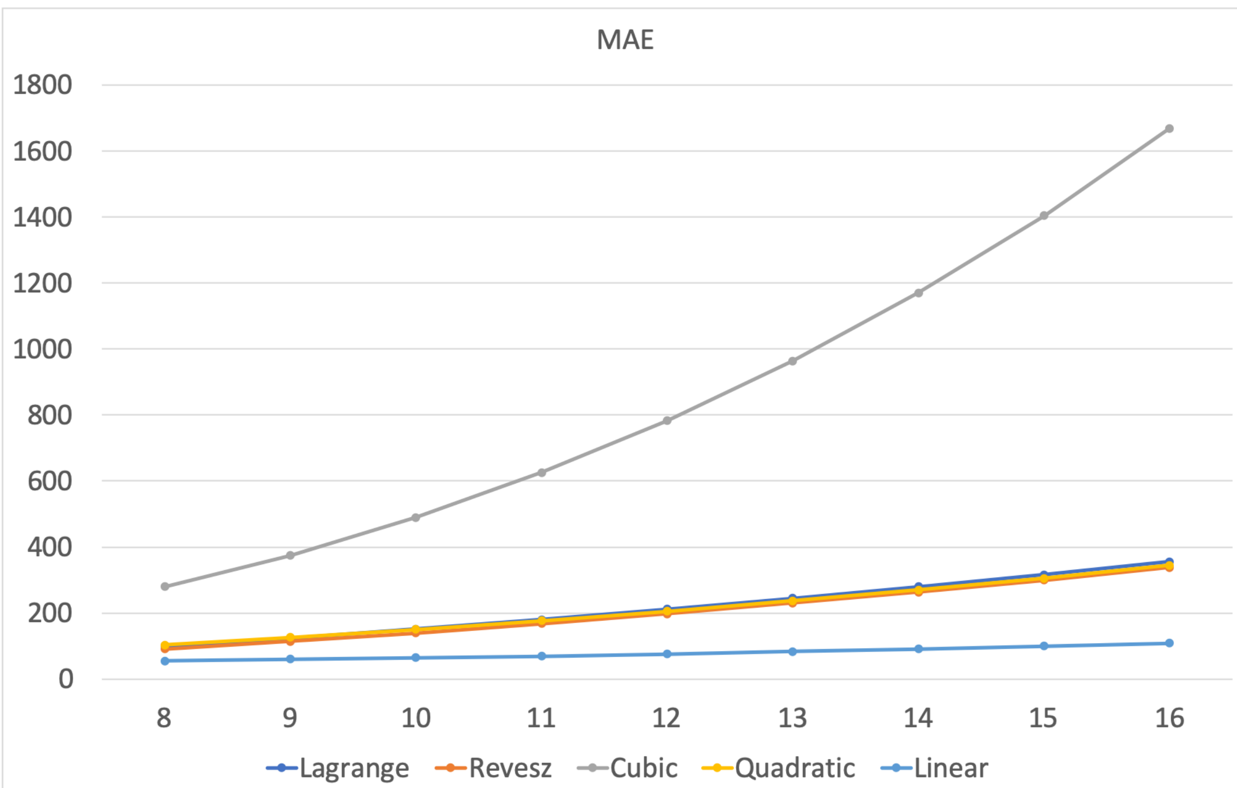

Figure 5.2: MAE of Temporal Methods.

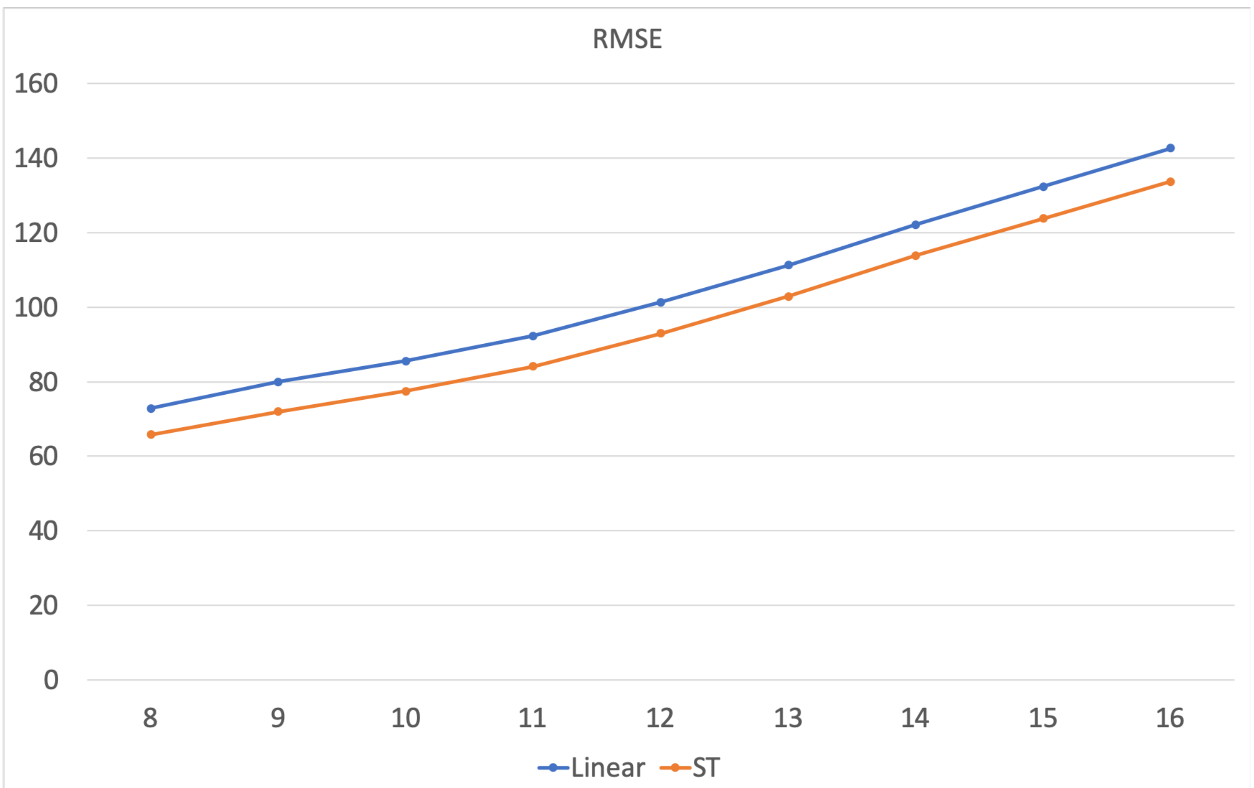

Figure 5.3: RMSE of spatiotemporal Methods.

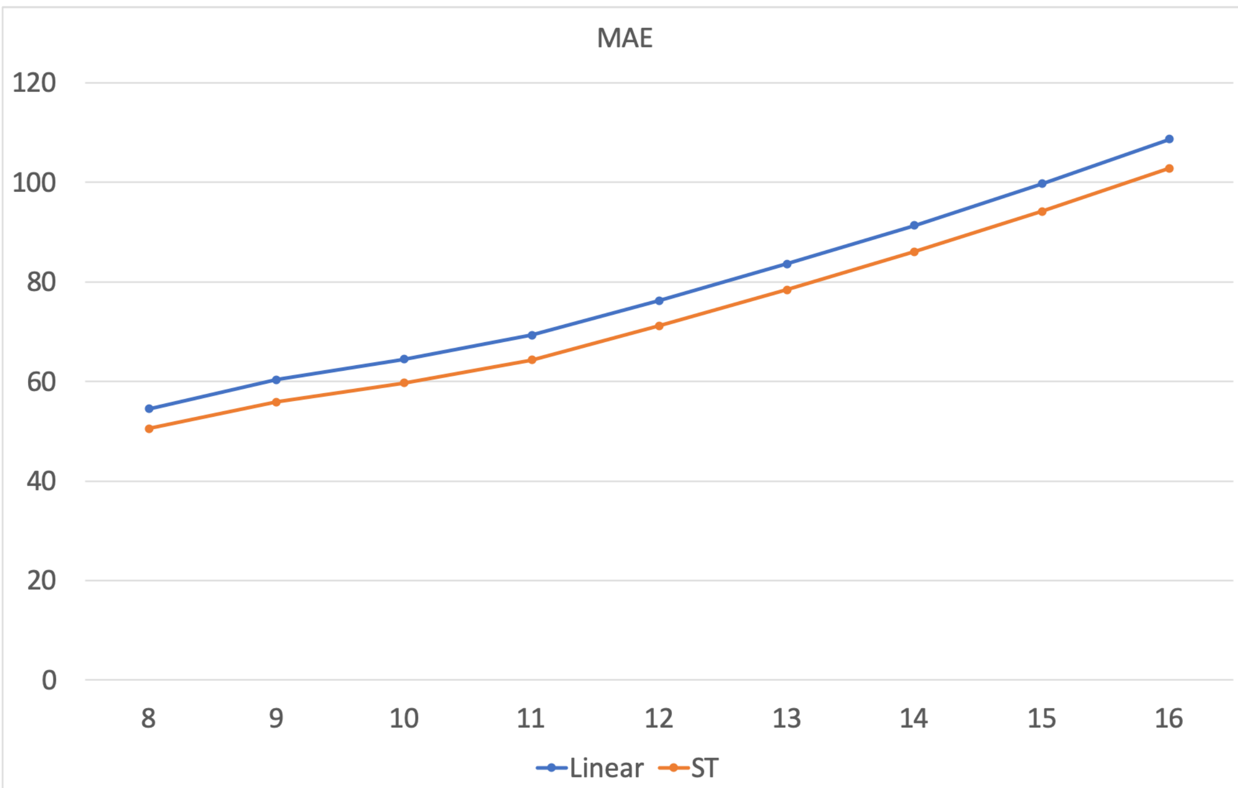

Figure 5.4: MAE of spatiotemporal Methods.

Finally, we would like to suggest some future work. Our spatiotemporal algorithm was fine tuned by finding the lower and upper bound values of 30 and 280. These values may be dependent on the characteristics of the raw data in each state. It would be good to find a mathematical relationship between the raw data and the upper and lower bounds. Such a mathematical relationship could be used to automatically adjust the lower and upper bound values.

In addition, if scientists find a vaccine against the Covid-19 virus, then a more complex model could be developed that takes into consideration the percentage of the population that was vaccinated or already had the disease and developed some immunity to it. While the consideration of these extra statistics could refine each of the prediction methods, we expect the improvements to be about the same percentage for all of the prediction methods. Hence our main conclusion that spatiotemporal extrapolation yields the most accurate prediction method will likely continue to hold with these extension too.

Appendix A

Table A.1: Moving Average of seven days COVID-19 cases divided by population in million centered on June 4-12, 2020. The dates shown are the middle of the seven days for the moving average. The data for New York City combine five counties.

County	6/4	6/5	6/6	6/7	6/8	6/9	6/10	6/11	6/12
Albany	6306.63	6351.52	6390.34	6421.20	6452.06	6482.92	6512.38	6539.97	6560.54
Allegany	1075.51	1084.81	1094.11	1103.41	1115.81	1122.00	1131.30	1140.60	1153.00
Broome	3128.81	3166.30	3203.05	3233.80	3269.80	3299.05	3324.54	3347.79	3371.04
Cattaraugus	1195.53	1206.79	1218.05	1229.31	1242.45	1259.34	1276.23	1295.00	1315.64
Cayuga	1261.12	1277.91	1294.70	1305.89	1317.09	1326.41	1332.01	1341.34	1350.67
Chautauqua	733.97	751.98	771.12	789.13	801.51	811.64	819.52	826.28	833.03
Chemung	1641.58	1641.58	1643.30	1645.01	1646.72	1648.43	1650.14	1651.85	1653.57
Chenango	2820.40	2826.46	2832.51	2844.61	2856.72	2871.85	2886.98	2899.09	2908.16
Clinton	1203.42	1205.19	1205.19	1205.19	1206.97	1208.74	1210.52	1212.29	1214.07
Columbia	6765.54	6825.60	6880.86	6931.31	6988.97	7029.82	7075.47	7128.32	7188.39
Cortland	861.69	864.69	867.69	870.70	873.70	876.70	879.70	882.71	882.71
Delaware	1880.59	1893.54	1906.49	1922.67	1942.09	1955.04	1964.75	1974.46	1984.17
Dutchess	13474.95	13514.76	13553.60	13588.08	13619.64	13644.40	13670.62	13697.81	13727.92
Erie	6859.37	6922.81	6988.43	7047.83	7102.41	7158.08	7208.46	7254.96	7299.43
Essex	1243.25	1250.99	1258.74	1266.48	1274.23	1281.98	1289.72	1297.47	1301.34
Franklin	459.80	459.80	459.80	459.80	459.80	462.65	468.37	474.08	479.79
Fulton	4054.26	4099.75	4142.57	4182.71	4222.85	4254.97	4281.73	4308.49	4329.90
Genesee	3566.44	3581.40	3601.36	3623.80	3641.26	3658.72	3673.68	3683.66	3696.13
Greene	5134.48	5158.70	5179.89	5204.11	5228.33	5249.52	5261.63	5276.77	5288.87
Hamilton	1132.25	1132.25	1132.25	1132.25	1132.25	1132.25	1132.25	1164.60	1196.95
Herkimer	1877.77	1912.71	1945.33	1973.29	2001.24	2029.20	2043.18	2054.83	2064.15
Jefferson	680.25	685.45	691.95	698.46	704.96	711.46	719.27	724.47	728.37
Lewis	760.57	760.57	760.57	760.57	760.57	760.57	760.57	760.57	760.57
Livingston	1909.64	1914.18	1918.72	1920.99	1923.26	1923.26	1925.53	1930.07	1934.61
Madison	4522.87	4545.02	4573.22	4597.38	4625.57	4645.71	4661.82	4675.92	4692.03
Monroe	4152.81	4198.84	4247.75	4287.62	4328.45	4367.55	4400.86	4435.53	4469.62
Montgomery	1938.78	1964.90	1985.22	2002.63	2017.14	2037.46	2051.97	2063.58	2075.19
Nassau	30000.84	30050.11	30093.06	30132.12	30168.65	30202.03	30235.61	30267.20	30298.04
New York C.	25265.15	25326.48	25382.70	25437.58	25489.85	25541.00	25591.96	25641.74	25691.35
Niagara	5164.62	5212.40	5264.97	5307.29	5342.10	5372.13	5402.85	5439.71	5475.89
Oneida	4722.32	4806.03	4890.99	4981.58	5073.41	5173.37	5252.09	5333.30	5402.02
Onondaga	4985.58	5051.03	5112.76	5167.67	5216.99	5261.97	5300.13	5339.52	5377.68
Ontario	1965.02	1981.94	1998.86	2007.97	2022.28	2036.60	2049.61	2065.23	2080.84
Orange	27244.69	27282.17	27313.35	27343.41	27372.73	27400.19	27420.60	27441.75	27460.31
Orleans	6110.51	6181.32	6237.96	6283.99	6330.01	6376.03	6400.82	6443.30	6485.78
Oswego	957.47	963.57	969.67	973.33	981.87	991.62	1001.38	1009.92	1023.34
Otsego	1229.44	1236.64	1241.44	1251.05	1263.05	1275.06	1289.47	1303.87	1315.88
Putnam	12890.85	12922.82	12948.97	12975.12	12995.47	13012.90	13028.89	13044.87	13062.30
Rensselaer	3126.02	3135.92	3146.72	3157.52	3169.22	3180.92	3191.72	3201.63	3211.53
Rockland	40729.25	40797.22	40854.23	40903.78	40949.82	40993.23	41035.32	41078.30	41122.58
Saratoga	2142.89	2155.94	2172.72	2186.40	2198.83	2210.01	2218.09	2226.17	2234.25
Schenectady	4523.99	4541.47	4558.95	4572.75	4587.46	4601.26	4613.22	4626.10	4644.50
Schoharie	1668.26	1686.69	1700.52	1714.34	1728.17	1741.99	1741.99	1741.99	1741.99
Schuyler	665.87	673.89	673.89	673.89	673.89	673.89	673.89	673.89	673.89
Seneca	1768.08	1776.47	1784.87	1789.07	1797.47	1805.87	1814.27	1822.67	1835.27
St. Lawrence	1919.97	1925.27	1930.57	1934.55	1941.18	1950.46	1957.09	1965.05	1973.00
Steuben	2574.69	2589.67	2604.65	2619.62	2633.10	2645.09	2651.08	2657.07	2664.56
Suffolk	27161.41	27226.43	27269.58	27308.47	27343.20	27374.16	27406.77	27438.69	27469.17
Sullivan	18586.28	18639.30	18688.54	18749.15	18788.92	18824.90	18860.89	18889.29	18917.70
Tioga	2753.24	2765.09	2773.98	2779.91	2785.84	2794.73	2803.62	2818.44	2833.26
Tompkins	1631.57	1641.36	1651.15	1659.54	1667.92	1674.92	1677.71	1680.51	1683.30
Ulster	9601.68	9625.82	9648.35	9668.46	9688.57	9707.07	9727.19	9745.69	9761.78
Warren	4003.50	4007.97	4012.44	4014.67	4016.91	4019.14	4019.14	4019.14	4019.14
Washington	3893.30	3904.97	3911.98	3916.64	3923.65	3928.31	3932.98	3939.99	3946.99
Wayne	1337.73	1352.03	1367.91	1377.45	1386.98	1398.10	1410.81	1425.11	1437.82
Westchester	34900.93	34967.08	35026.43	35083.28	35133.34	35180.73	35229.31	35278.92	35327.21
Wyoming	2193.45	2207.78	2225.70	2240.04	2254.38	2265.13	2272.30	2283.05	2290.22
Yates	1565.45	1565.45	1565.45	1565.45	1565.45	1565.45	1565.45	1571.18	1576.92

Table A.2: Moving Average of seven days COVID-19 cases divided by population in million centered on June 13-21, 2020. The dates shown are the middle of the seven days for the moving average. The data for New York City combine five counties.

County	6/13	6/14	6/15	6/16	6/17	6/18	6/19	6/20	6/21
Albany	6580.65	6600.76	6618.53	6638.17	6655.47	6671.37	6689.14	6705.97	6722.80
Allegany	1165.40	1174.69	1187.09	1202.59	1214.99	1227.39	1236.68	1245.98	1255.28
Broome	3392.79	3413.04	3425.04	3439.29	3452.79	3465.54	3476.78	3488.03	3498.53
Cattaraugus	1338.17	1362.56	1383.21	1398.22	1420.75	1441.39	1458.28	1478.93	1499.57
Cayuga	1358.13	1365.59	1373.05	1380.51	1389.84	1393.57	1397.30	1401.04	1406.63
Chautauqua	838.66	842.04	846.54	853.30	863.43	873.56	883.69	892.70	903.95
Chemung	1653.57	1653.57	1653.57	1655.28	1656.99	1658.70	1660.41	1662.12	1663.84
Chenango	2920.27	2926.32	2932.37	2935.40	2938.43	2941.45	2947.50	2953.56	2962.64
Clinton	1217.62	1221.17	1222.94	1224.72	1228.27	1231.82	1235.37	1237.14	1238.92
Columbia	7255.66	7308.51	7354.16	7397.41	7445.46	7481.49	7512.73	7541.56	7570.39
Cortland	882.71	882.71	888.71	894.71	900.72	906.72	912.73	918.73	924.74
Delaware	1990.65	1997.12	2000.36	2003.59	2010.07	2016.54	2023.01	2032.72	2039.20
Dutchess	13756.56	13783.27	13812.89	13849.30	13887.18	13926.99	13964.38	14000.79	14040.12
Erie	7339.39	7380.75	7421.34	7458.35	7493.65	7527.70	7561.60	7595.97	7631.11
Essex	1301.34	1301.34	1301.34	1301.34	1305.22	1309.09	1312.96	1316.83	1320.71
Franklin	485.50	491.21	499.78	508.35	514.06	519.77	525.48	534.05	542.62
Fulton	4351.30	4372.71	4388.77	4404.83	4434.26	4458.35	4482.43	4503.84	4525.25
Genesee	3703.61	3716.08	3728.55	3743.52	3768.46	3793.40	3823.32	3863.23	3898.14
Greene	5300.98	5310.07	5319.15	5334.29	5349.42	5364.56	5379.70	5391.81	5403.92
Hamilton	1229.30	1261.65	1294.00	1326.35	1358.70	1358.70	1358.70	1358.70	1358.70
Herkimer	2071.14	2078.13	2085.11	2094.43	2108.41	2127.05	2148.02	2168.99	2201.60
Jefferson	730.97	734.88	738.78	741.38	743.98	747.88	751.78	755.69	758.29
Lewis	760.57	766.00	771.44	776.87	787.74	804.03	820.33	842.06	858.36
Livingston	1939.16	1943.70	1948.24	1952.78	1955.05	1955.05	1957.32	1961.86	1966.40
Madison	4702.10	4716.19	4732.30	4750.43	4770.56	4792.72	4816.88	4839.03	4857.15
Monroe	4500.24	4531.63	4559.75	4586.91	4615.22	4639.87	4665.29	4691.87	4720.56
Montgomery	2086.80	2098.41	2110.02	2118.72	2127.43	2133.24	2144.85	2159.36	2176.77
Nassau	30330.68	30362.79	30393.22	30421.96	30450.49	30479.44	30508.18	30534.92	30562.82
New York C.	25740.68	25788.79	25835.87	25882.48	25926.45	25970.44	26012.96	26055.22	26096.48
Niagara	5507.29	5540.06	5572.14	5600.81	5624.02	5641.77	5658.15	5674.53	5689.55
Oneida	5474.49	5539.46	5611.93	5686.90	5764.99	5839.96	5924.92	5999.89	6086.10
Onondaga	5414.28	5453.06	5503.00	5552.63	5597.92	5643.52	5688.19	5736.89	5791.49
Ontario	2096.46	2112.07	2119.88	2131.59	2143.31	2152.42	2164.13	2174.54	2190.15
Orange	27477.75	27499.28	27519.32	27542.33	27570.16	27598.74	27628.80	27660.71	27686.69
Orleans	6524.73	6563.67	6602.61	6652.18	6701.74	6733.60	6761.92	6793.79	6818.57
Oswego	1052.61	1081.88	1112.37	1169.70	1227.03	1289.23	1346.56	1395.35	1455.11
Otsego	1330.29	1342.29	1351.90	1361.50	1366.31	1371.11	1378.31	1383.12	1385.52
Putnam	13079.74	13097.18	13116.06	13140.76	13164.01	13182.90	13203.24	13222.13	13239.57
Rensselaer	3219.63	3226.83	3233.13	3241.23	3250.23	3260.13	3272.73	3289.83	3306.94
Rockland	41169.50	41211.16	41250.19	41289.65	41326.49	41362.00	41394.01	41424.27	41453.65
Saratoga	2241.09	2248.54	2256.62	2265.32	2275.89	2287.08	2298.26	2308.21	2317.53
Schenectady	4662.89	4682.21	4701.53	4724.53	4748.44	4775.12	4801.80	4833.99	4866.19
Schoharie	1741.99	1746.60	1751.21	1755.82	1765.03	1778.86	1792.68	1806.51	1815.73
Schuyler	673.89	673.89	673.89	673.89	673.89	673.89	673.89	673.89	673.89
Seneca	1847.87	1860.47	1868.87	1873.07	1877.27	1881.47	1881.47	1881.47	1881.47
St. Lawrence	1980.96	1988.92	1992.89	1994.22	1996.87	1998.20	2000.85	2003.50	2006.15
Steuben	2672.05	2678.04	2682.53	2687.02	2696.01	2705.00	2715.48	2724.47	2733.46
Suffolk	27499.35	27528.96	27557.79	27587.30	27615.64	27645.92	27676.69	27707.46	27739.48
Sullivan	18946.11	18961.26	18976.41	18987.77	18997.24	19010.50	19021.86	19035.12	19061.63
Tioga	2851.04	2865.86	2880.67	2889.57	2898.46	2901.42	2904.38	2907.35	2910.31
Tompkins	1686.10	1688.90	1691.69	1693.09	1694.49	1697.28	1700.08	1702.88	1705.67
Ulster	9776.26	9790.74	9804.42	9816.49	9825.34	9835.79	9847.86	9859.93	9872.80
Warren	4019.14	4019.14	4021.38	4030.31	4039.25	4048.19	4059.36	4070.53	4081.70
Washington	3953.99	3960.99	3965.66	3967.99	3972.66	3975.00	3977.33	3979.67	3982.00
Wayne	1450.53	1468.00	1487.07	1506.13	1525.20	1541.09	1556.97	1574.45	1595.10
Westchester	35374.90	35420.53	35465.27	35506.61	35541.01	35575.12	35609.08	35642.01	35673.31
Wyoming	2297.38	2304.55	2311.72	2318.89	2326.06	2329.64	2333.22	2333.22	2333.22
Yates	1582.65	1588.38	1594.12	1599.85	1611.32	1617.06	1628.52	1645.73	1668.66

Table A.3: Moving Average of seven days COVID-19 cases divided by population in million centered on June 22 - July 8, 2020. The dates shown are the middle of the seven days for the moving average. The data for New York City combine five counties.

County	6/22	6/23	6/24	6/25	7/4	7/5	7/6	7/7	7/8
Albany	6742.44	6758.81	6776.58	6796.69	7008.51	7037.97	7065.09	7093.15	7122.61
Allegany	1258.38	1258.38	1258.38	1261.48	1357.56	1366.86	1373.06	1376.16	1385.46
Broome	3515.78	3541.28	3568.28	3594.53	3908.01	3941.01	3971.75	4007.75	4049.00
Cattaraugus	1522.09	1548.37	1567.14	1582.15	1653.47	1666.61	1679.74	1698.51	1719.16
Cayuga	1412.23	1415.96	1421.56	1430.88	1570.80	1576.40	1585.73	1593.19	1604.38
Chautauqua	916.34	927.59	936.60	944.48	1030.03	1054.80	1082.94	1112.21	1156.11
Chemung	1665.55	1665.55	1665.55	1667.26	1742.58	1747.71	1754.56	1759.70	1763.12
Chenango	2977.77	2995.92	3017.11	3038.29	3189.60	3228.94	3274.33	3328.80	3380.25
Clinton	1242.47	1246.02	1247.79	1249.57	1269.09	1277.97	1288.62	1299.27	1311.69
Columbia	7599.22	7632.85	7656.88	7685.71	7969.21	8007.65	8031.68	8050.90	8077.32
Cortland	924.74	924.74	924.74	930.74	1044.83	1065.85	1089.87	1113.89	1137.91
Delaware	2045.67	2052.15	2055.38	2058.62	2061.86	2061.86	2061.86	2061.86	2061.86
Dutchess	14082.85	14116.35	14147.43	14176.56	14393.60	14411.57	14426.13	14441.19	14456.24
Erie	7665.01	7700.15	7735.29	7770.12	8103.82	8144.10	8183.60	8219.83	8258.55
Essex	1324.58	1328.45	1332.33	1336.20	1467.88	1494.99	1529.85	1549.22	1564.71
Franklin	548.33	551.19	556.90	562.61	651.14	656.85	662.57	668.28	673.99
Fulton	4546.66	4576.10	4592.15	4624.27	4881.17	4894.55	4902.58	4910.61	4921.31
Genesee	3933.06	3967.98	4005.39	4045.29	4182.46	4197.43	4212.39	4229.85	4249.80
Greene	5419.05	5428.14	5443.27	5455.38	5555.29	5564.37	5573.45	5576.48	5582.53
Hamilton	1358.70	1358.70	1358.70	1358.70	1358.70	1358.70	1358.70	1358.70	1358.70
Herkimer	2236.55	2278.48	2325.08	2376.33	2802.67	2846.94	2888.87	2916.83	2954.11
Jefferson	762.19	766.09	768.69	769.99	840.23	848.03	854.54	857.14	859.74
Lewis	880.09	907.25	928.98	961.58	1162.59	1168.02	1173.45	1178.89	1178.89
Livingston	1973.22	1980.03	1986.84	1998.19	2089.02	2104.91	2127.62	2159.41	2191.20
Madison	4873.26	4891.39	4907.50	4921.59	5100.82	5122.97	5141.09	5163.24	5185.40
Monroe	4751.95	4786.62	4823.02	4860.00	5268.86	5320.09	5366.51	5411.77	5456.25
Montgomery	2194.19	2214.50	2243.53	2278.35	2423.47	2432.18	2449.59	2475.71	2507.64
Nassau	30594.09	30625.36	30655.05	30684.00	30938.67	30966.99	30993.73	31023.74	31053.11
New York C.	26137.96	26178.80	26219.22	26258.57	26594.49	26634.00	26671.02	26706.22	26740.34
Niagara	5703.20	5722.31	5746.20	5769.41	6071.81	6119.59	6165.33	6209.70	6248.60
Oneida	6177.93	6279.76	6385.34	6505.92	7495.48	7579.20	7653.54	7714.76	7772.86
Onondaga	5833.68	5879.59	5925.19	5971.72	6361.02	6412.52	6459.98	6512.40	6565.76
Ontario	2207.07	2223.99	2243.51	2264.33	2512.89	2540.21	2568.84	2592.27	2615.69
Orange	27714.52	27743.47	27770.19	27794.31	28003.62	28031.83	28056.32	28078.96	28102.71
Orleans	6846.89	6864.59	6882.29	6899.99	7002.66	7020.36	7034.52	7052.23	7069.93
Oswego	1512.44	1542.93	1573.42	1600.26	1753.94	1764.92	1771.02	1783.21	1799.07
Otsego	1387.92	1390.32	1395.12	1399.92	1431.14	1435.94	1440.75	1450.35	1455.15
Putnam	13262.82	13288.97	13315.12	13347.09	13573.75	13595.55	13618.80	13650.76	13688.54
Rensselaer	3330.34	3357.34	3383.44	3407.75	3543.66	3566.16	3593.17	3619.27	3646.27
Rockland	41486.54	41517.67	41548.80	41580.37	41849.17	41882.94	41914.07	41943.89	41975.02
Saratoga	2326.23	2333.69	2343.01	2352.33	2451.15	2471.04	2489.68	2505.84	2526.35
Schenectady	4902.98	4935.18	4969.22	5004.17	5327.05	5362.93	5392.36	5418.12	5441.12
Schoharie	1824.94	1834.16	1838.77	1843.38	1884.85	1894.07	1907.90	1926.33	1944.76
Schuyler	673.89	673.89	673.89	673.89	730.05	730.05	730.05	730.05	746.10
Seneca	1889.87	1910.87	1931.86	1952.86	2070.45	2074.65	2087.25	2099.85	2116.65
St. Lawrence	2008.80	2012.78	2015.43	2018.09	2068.47	2079.08	2088.36	2094.99	2104.27
Steuben	2743.94	2754.42	2758.92	2766.41	2823.32	2827.82	2833.81	2839.80	2847.29
Suffolk	27772.47	27805.75	27839.13	27871.44	28162.94	28198.93	28233.57	28269.65	28308.55
Sullivan	19088.15	19116.56	19146.86	19173.37	19294.58	19309.73	19322.99	19340.03	19355.18
Tioga	2913.27	2916.24	2922.17	2928.09	3017.00	3037.75	3061.46	3108.88	3153.33
Tompkins	1708.47	1711.27	1712.66	1714.06	1744.82	1749.01	1751.81	1756.00	1763.00
Ulster	9888.09	9903.37	9921.88	9941.18	10240.46	10291.14	10340.21	10370.79	10394.92
Warren	4092.87	4097.34	4101.80	4106.27	4188.93	4211.27	4231.38	4249.25	4262.66
Washington	3986.67	3991.34	3993.67	3998.34	4024.01	4026.35	4031.02	4038.02	4045.02
Wayne	1618.94	1647.53	1676.13	1706.32	2027.24	2057.43	2087.62	2119.39	2151.17
Westchester	35707.72	35743.89	35782.58	35820.82	36176.08	36218.60	36258.62	36294.94	36330.38
Wyoming	2333.22	2336.81	2343.98	2351.14	2408.49	2419.24	2433.58	2455.08	2473.00
Yates	1691.60	1720.27	1743.21	1766.15	1892.30	1903.77	1915.24	1926.70	1926.70

Table A.4: Moving Average of seven days COVID-19 cases divided by population in million centered on July 9-17, 2020. The dates shown are the middle of the seven days for the moving average. The data for New York City combine five counties.

County	7/9	7/10	7/11	7/12	7/13	7/14	7/15	7/16	7/17
Albany	7153.94	7184.33	7223.15	7272.24	7322.28	7378.39	7428.43	7474.72	7520.08
Allegany	1394.76	1404.05	1419.55	1435.05	1453.65	1475.34	1490.84	1506.34	1521.83
Broome	4099.25	4151.74	4210.99	4275.48	4343.73	4408.23	4460.72	4507.97	4564.22
Cattaraugus	1739.80	1758.57	1779.22	1799.86	1820.51	1841.15	1854.29	1867.43	1880.56
Cayuga	1615.58	1623.04	1632.37	1643.56	1651.02	1660.35	1665.95	1671.54	1680.87
Chautauqua	1198.89	1240.54	1291.20	1332.85	1376.75	1418.41	1445.42	1472.44	1498.33
Chemung	1766.54	1769.97	1773.39	1780.24	1785.37	1790.51	1799.07	1809.34	1821.32
Chenango	3428.67	3468.01	3510.38	3558.79	3604.19	3649.58	3698.00	3746.42	3791.81
Clinton	1322.34	1332.99	1341.86	1350.74	1357.84	1364.94	1370.26	1377.36	1384.46
Columbia	8103.75	8127.78	8151.80	8168.62	8185.44	8204.66	8219.07	8233.49	8245.50
Cortland	1158.93	1179.94	1197.96	1218.97	1242.99	1276.02	1306.04	1339.07	1369.09
Delaware	2065.09	2068.33	2071.57	2074.80	2078.04	2081.28	2087.75	2090.99	2094.22
Dutchess	14472.26	14488.77	14522.76	14565.00	14614.53	14663.57	14714.07	14762.62	14809.23
Erie	8300.06	8341.43	8386.37	8432.24	8479.35	8529.43	8576.85	8622.41	8665.95
Essex	1576.33	1584.07	1591.82	1599.57	1599.57	1599.57	1599.57	1599.57	1599.57
Franklin	682.56	691.12	699.69	711.12	722.54	733.96	748.24	759.67	771.09
Fulton	4932.01	4940.04	4950.75	4961.45	4969.48	4974.83	4977.51	4982.86	4988.21
Genesee	4277.23	4297.19	4322.13	4347.07	4372.01	4391.96	4414.41	4431.86	4451.82
Greene	5591.62	5600.70	5612.81	5637.03	5661.25	5682.44	5700.60	5718.77	5736.93
Hamilton	1358.70	1358.70	1358.70	1358.70	1358.70	1358.70	1358.70	1358.70	1358.70
Herkimer	2998.37	3030.99	3063.60	3100.88	3147.47	3194.07	3231.35	3263.96	3294.25
Jefferson	863.64	870.14	877.95	885.75	894.86	905.26	916.97	927.37	936.48
Lewis	1178.89	1178.89	1184.32	1189.75	1195.18	1200.62	1206.05	1216.92	1227.78
Livingston	2225.26	2257.05	2295.65	2327.44	2356.96	2381.94	2409.18	2434.16	2461.41
Madison	5207.55	5229.70	5247.82	5263.93	5282.06	5298.17	5314.28	5332.40	5350.52
Monroe	5499.39	5542.92	5589.72	5634.98	5681.78	5726.65	5770.95	5814.09	5856.84
Montgomery	2545.37	2583.10	2641.15	2699.20	2745.63	2783.36	2821.10	2853.02	2882.05
Nassau	31082.17	31113.86	31149.13	31184.92	31220.93	31254.94	31289.36	31322.52	31356.64
New York C.	26776.19	26812.16	26848.86	26886.94	26926.81	26966.92	27008.43	27049.28	27090.68
Niagara	6286.83	6322.33	6359.19	6392.64	6426.08	6456.12	6484.11	6512.77	6541.44
Oneida	7823.47	7874.07	7928.42	7980.90	8029.00	8093.35	8167.69	8240.79	8310.75
Onondaga	6620.04	6675.57	6732.02	6786.00	6840.29	6890.54	6940.79	6988.56	7034.47
Ontario	2641.72	2667.75	2698.98	2732.81	2767.95	2801.78	2838.22	2869.45	2900.69
Orange	28124.98	28147.24	28166.54	28193.26	28224.81	28257.46	28291.24	28326.86	28362.86
Orleans	7087.63	7098.25	7108.87	7115.95	7123.03	7126.57	7130.11	7133.65	7137.19
Oswego	1816.15	1835.66	1857.62	1877.13	1896.65	1910.06	1922.26	1933.24	1941.78
Otsego	1462.36	1469.56	1479.17	1491.17	1505.58	1519.99	1534.39	1556.01	1577.62
Putnam	13724.86	13765.55	13817.85	13873.07	13926.83	13971.87	14014.01	14057.60	14096.83
Rensselaer	3692.18	3736.28	3784.89	3831.69	3879.39	3928.90	3980.21	4011.71	4044.11
Rockland	42004.84	42032.46	42060.97	42089.03	42124.11	42160.94	42197.78	42231.54	42266.18
Saratoga	2548.72	2572.34	2595.96	2621.44	2645.68	2672.40	2697.26	2719.01	2737.03
Schenectady	5468.71	5496.31	5533.11	5576.34	5620.49	5666.49	5716.16	5763.08	5806.31
Schoharie	1958.59	1972.41	1986.24	1995.46	2000.06	2000.06	2000.06	2000.06	2000.06
Schuyler	762.14	778.19	794.23	810.28	826.32	842.37	850.39	858.41	898.52
Seneca	2129.25	2141.85	2154.45	2175.45	2188.05	2204.84	2221.64	2246.84	2272.04
St. Lawrence	2112.23	2118.86	2128.14	2137.42	2150.68	2165.27	2181.18	2197.09	2216.98
Steuben	2853.28	2860.77	2871.25	2883.23	2893.72	2904.20	2913.19	2923.67	2932.66
Suffolk	28345.89	28387.20	28434.03	28479.31	28526.13	28571.70	28615.53	28657.90	28695.05
Sullivan	19372.23	19387.38	19400.63	19413.89	19430.93	19440.40	19457.45	19472.60	19487.75
Tioga	3197.79	3236.31	3268.91	3307.44	3343.00	3369.68	3396.35	3423.02	3458.59
Tompkins	1772.78	1782.57	1792.36	1817.52	1842.69	1866.45	1888.82	1919.58	1951.74
Ulster	10415.03	10432.73	10456.06	10490.66	10525.25	10561.45	10597.65	10631.44	10662.82
Warren	4280.53	4298.40	4314.04	4338.62	4365.43	4392.24	4419.05	4441.39	4457.02
Washington	4052.02	4056.69	4063.69	4070.70	4075.36	4077.70	4080.03	4082.37	4084.70
Wayne	2182.94	2219.48	2256.02	2300.51	2344.99	2379.95	2414.90	2449.85	2480.04
Westchester	36367.88	36403.76	36442.15	36477.59	36512.88	36547.87	36583.75	36615.94	36649.02
Wyoming	2487.34	2505.26	2526.76	2544.68	2559.02	2566.19	2576.94	2587.69	2594.86
Yates	1926.70	1926.70	1932.44	1943.91	1955.38	1972.58	1989.78	2006.98	2024.19

Table A.5: Moving Average of seven days COVID-19 cases divided by population in million centered on July 18-25, 2020. The dates shown are the middle of the seven days for the moving average. The data for New York City combine five counties.

County	7/18	7/19	7/20	7/21	7/22	7/23	7/24	7/25
Albany	7568.71	7610.33	7662.23	7716.47	7773.99	7836.18	7897.44	7952.15
Allegany	1534.23	1543.53	1549.73	1559.03	1568.33	1577.62	1586.92	1593.12
Broome	4621.21	4679.71	4734.46	4797.45	4864.20	4935.44	4998.44	5054.69
Cattaraugus	1895.58	1906.84	1918.10	1927.48	1936.87	1948.13	1963.14	1974.40
Cayuga	1688.33	1699.53	1712.58	1727.51	1746.16	1764.82	1781.61	1798.40
Chautauqua	1527.60	1554.62	1578.26	1600.77	1625.54	1652.56	1679.57	1694.21
Chemung	1831.59	1840.15	1850.42	1862.40	1874.38	1884.65	1893.21	1901.77
Chenango	3843.26	3891.67	3940.09	3985.49	4049.04	4112.59	4170.08	4215.48
Clinton	1391.56	1396.89	1402.21	1412.86	1427.06	1439.49	1451.91	1467.89
Columbia	8259.92	8279.14	8298.36	8317.58	8339.20	8358.42	8384.85	8406.47
Cortland	1411.13	1459.17	1510.21	1555.24	1603.28	1651.32	1705.36	1753.40
Delaware	2097.46	2100.70	2110.41	2126.59	2142.78	2158.96	2175.14	2194.57
Dutchess	14839.34	14863.61	14884.49	14906.34	14925.28	14949.07	14980.15	15012.68
Erie	8708.40	8746.35	8786.78	8825.96	8867.32	8908.69	8952.38	8992.50
Essex	1599.57	1611.19	1622.80	1634.42	1646.04	1657.66	1673.15	1688.65
Franklin	788.22	802.50	813.93	822.50	828.21	839.63	851.05	865.33
Fulton	4990.89	4993.56	4998.92	5004.27	5014.97	5023.00	5031.03	5039.06
Genesee	4466.78	4476.76	4491.72	4509.18	4521.65	4539.11	4559.06	4579.01
Greene	5752.07	5755.10	5761.15	5782.34	5806.56	5833.81	5864.08	5897.38
Hamilton	1358.70	1358.70	1358.70	1391.05	1423.40	1455.75	1488.10	1520.45
Herkimer	3324.53	3357.15	3382.78	3427.04	3473.64	3529.55	3594.78	3660.02
Jefferson	952.09	968.99	992.41	1018.42	1047.03	1075.65	1104.26	1125.07
Lewis	1233.21	1238.65	1249.51	1260.38	1271.24	1276.67	1282.11	1287.54
Livingston	2481.85	2504.55	2522.72	2536.34	2547.70	2556.78	2563.59	2568.13
Madison	5372.67	5396.84	5418.99	5441.14	5457.25	5471.35	5483.43	5491.48
Monroe	5896.32	5936.96	5974.32	6009.76	6045.58	6082.17	6120.30	6154.97
Montgomery	2890.75	2899.46	2911.07	2925.58	2937.19	2951.70	2966.21	2989.43
Nassau	31388.85	31420.75	31453.39	31485.50	31519.29	31554.88	31590.57	31625.31
New York C.	27133.36	27175.74	27218.19	27260.56	27302.14	27342.33	27382.72	27419.81
Niagara	6566.70	6593.32	6621.31	6646.57	6677.28	6704.59	6731.89	6756.47
Oneida	8382.60	8454.44	8524.41	8575.01	8614.37	8651.86	8694.34	8735.57
Onondaga	7075.73	7113.88	7150.80	7188.02	7224.01	7258.44	7291.94	7325.13
Ontario	2929.32	2956.64	2978.77	3002.19	3020.41	3042.53	3064.65	3085.48
Orange	28401.09	28431.52	28458.61	28483.85	28510.94	28535.80	28562.52	28588.87
Orleans	7137.19	7137.19	7137.19	7140.73	7144.27	7151.35	7158.43	7165.51
Oswego	1949.09	1956.41	1964.95	1973.49	1982.03	1993.00	2005.20	2014.96
Otsego	1601.63	1625.64	1649.65	1668.86	1690.47	1702.48	1714.49	1726.49
Putnam	14121.53	14138.96	14156.40	14175.29	14194.18	14213.07	14236.31	14263.92
Rensselaer	4073.81	4106.22	4133.22	4162.92	4190.83	4220.53	4251.13	4279.94
Rockland	42298.19	42328.45	42353.44	42377.56	42400.80	42420.97	42439.83	42456.93
Saratoga	2755.68	2772.46	2796.70	2818.45	2845.79	2875.63	2906.08	2934.05
Schenectady	5845.87	5887.26	5933.26	5982.01	6041.80	6108.03	6177.02	6243.26
Schoharie	2009.28	2018.50	2036.93	2059.97	2083.02	2110.67	2138.32	2156.75
Schuyler	938.64	978.75	1018.86	1058.97	1091.06	1123.15	1123.15	1123.15
Seneca	2297.24	2314.04	2330.84	2356.03	2377.03	2389.63	2402.23	2419.03
St. Lawrence	2235.54	2256.76	2277.97	2299.19	2319.08	2340.29	2356.20	2370.79
Steuben	2940.15	2946.14	2953.63	2962.62	2974.60	2985.08	2994.07	3003.06
Suffolk	28729.98	28764.23	28801.18	28839.01	28875.97	28916.31	28961.88	29005.32
Sullivan	19501.01	19512.37	19523.73	19535.10	19540.78	19546.46	19552.14	19557.82
Tioga	3497.11	3532.68	3568.24	3591.95	3618.62	3645.30	3666.04	3683.83
Tompkins	1983.89	1999.27	2020.24	2052.40	2085.95	2108.32	2130.69	2153.06
Ulster	10690.17	10707.07	10720.74	10732.00	10744.88	10764.18	10784.30	10813.26
Warren	4474.90	4483.83	4495.00	4508.41	4524.05	4539.69	4555.33	4577.67
Washington	4084.70	4087.03	4091.70	4096.37	4101.04	4108.04	4117.38	4126.71
Wayne	2508.63	2532.47	2556.30	2581.72	2605.55	2627.79	2651.62	2669.10
Westchester	36681.65	36717.38	36753.56	36788.55	36823.25	36861.93	36898.55	36935.61
Wyoming	2609.20	2627.12	2645.04	2670.13	2691.63	2713.14	2734.64	2748.98
Yates	2035.66	2041.39	2047.12	2047.12	2047.12	2047.12	2052.86	2058.59

Table A.6: Raw data of COVID-19 cases from 5/30 to 6/10. The data for New York City combine five counties.

County	5/30	5/31	6/1	6/2	6/3	6/4	6/5	6/6	6/7	6/8	6/9	6/10
Albany	1843	1860	1882	1900	1920	1930	1941	1953	1961	1978	1983	1986
Allegany	45	45	48	48	49	49	51	51	51	51	51	52
Broome	561	566	574	578	589	593	605	613	620	624	627	630
Cattaraugus	87	88	89	89	90	91	92	92	94	95	95	96
Cayuga	90	91	92	93	96	96	98	100	101	101	102	102
Chautauqua	83	84	85	86	89	95	97	99	101	101	103	105
Chemung	137	137	137	137	137	137	137	137	137	137	138	138
Chenango	132	133	133	133	133	133	133	133	134	135	135	137
Clinton	95	95	96	97	97	97	97	97	97	97	97	97
Columbia	383	387	389	391	399	400	411	412	414	414	414	420
Cortland	41	41	41	41	41	41	41	41	41	42	42	42
Delaware	79	79	81	82	82	82	84	85	85	85	86	87
Dutchess	3899	3909	3924	3936	3951	3962	3984	3995	4000	4006	4016	4022
Erie	6014	6070	6123	6173	6234	6308	6359	6429	6486	6531	6595	6616
Essex	44	45	45	46	46	46	46	46	46	47	48	48
Franklin	22	22	23	23	23	23	23	23	23	23	23	23
Fulton	207	208	210	212	213	215	219	222	224	227	228	228
Genesee	200	202	202	202	202	205	205	206	208	208	210	211
Greene	238	238	239	241	241	241	242	246	246	247	248	249
Hamilton	5	5	5	5	5	5	5	5	5	5	5	5
Herkimer	107	108	109	111	113	113	115	122	123	124	125	125
Jefferson	74	74	74	74	74	74	75	75	77	78	79	79
Lewis	20	20	20	20	20	20	20	20	20	20	20	20
Livingston	118	119	119	119	120	120	121	121	121	121	121	121
Madison	311	316	316	317	319	319	323	325	327	327	331	331
Monroe	2910	2943	2965	2990	3049	3082	3118	3168	3191	3204	3244	3256
Montgomery	89	91	91	93	94	96	96	98	100	100	100	100
Nassau	40307	40396	40479	40572	40644	40713	40797	40853	40904	40947	40980	41015
New York C.	207539	208085	208550	209195	209688	210227	210728	211274	211728	212122	212469	212884
Niagara	1020	1037	1046	1048	1067	1085	1099	1109	1112	1116	1125	1129
Oneida	1006	1027	1036	1049	1058	1069	1077	1127	1143	1170	1185	1203
Onondaga	2133	2170	2197	2228	2256	2295	2329	2375	2392	2408	2427	2433
Ontario	206	207	208	209	215	218	219	220	221	221	222	222
Orange	10404	10421	10437	10464	10475	10486	10499	10523	10529	10538	10548	10556
Orleans	228	229	236	241	246	247	247	254	255	256	257	259
Oswego	108	109	110	110	112	112	112	114	115	115	115	115
Otsego	71	72	72	73	73	73	73	74	74	75	75	77
Putnam	1248	1252	1257	1262	1264	1268	1270	1274	1277	1279	1280	1282
Rensselaer	486	491	492	493	495	495	497	499	502	503	505	507
Rockland	13128	13151	13185	13223	13259	13280	13297	13315	13325	13340	13353	13372
Saratoga	477	480	483	484	489	493	496	501	502	504	511	511
Schenectady	686	689	693	696	701	701	706	710	711	712	715	716
Schoharie	50	50	50	51	51	51	51	54	54	54	54	54
Schuyler	11	11	11	12	12	12	12	12	12	12	12	12
Seneca	58	58	59	59	60	60	61	61	61	61	61	61
St. Lawrence	202	204	205	205	206	207	207	209	209	209	209	209
Steuben	241	241	241	242	243	245	246	251	251	251	252	253
Suffolk	39532	39643	39705	39980	40062	40153	40239	40278	40329	40377	40426	40464
Sullivan	1375	1387	1389	1392	1393	1405	1409	1411	1415	1417	1418	1425
Tioga	128	130	130	131	133	133	134	134	134	134	134	135
Tompkins	161	164	164	164	165	165	167	171	171	171	171	171
Ulster	1678	1685	1691	1696	1701	1704	1711	1714	1718	1721	1724	1726
Warren	255	255	255	255	256	256	256	257	257	257	257	257
Washington	235	235	235	237	238	238	240	240	240	240	240	240
Wayne	113	115	116	116	120	121	122	123	124	125	126	126
Westchester	33428	33480	33551	33632	33690	33766	33853	33923	33953	33999	34034	34075
Wyoming	84	86	86	86	87	87	88	89	89	90	91	91
Yates	39	39	39	39	39	39	39	39	39	39	39	39

Table A.7: Raw data of COVID-19 cases from 6/11 to 6/22. The data for New York City combine five counties.

County	6/11	6/12	6/13	6/14	6/15	6/16	6/17	6/18	6/19	6/20	6/21	6/22
Albany	1996	2007	2016	2020	2022	2026	2029	2034	2049	2053	2054	2060
Allegany	53	53	54	54	55	55	55	57	58	58	58	58
Broome	641	644	647	651	655	656	657	657	663	665	668	670
Cattaraugus	98	101	101	104	106	107	109	109	109	113	115	115
Cayuga	102	103	103	106	106	106	106	106	107	108	108	108
Chautauqua	106	106	106	107	107	108	108	110	112	115	116	116
Chemung	138	138	138	138	138	138	138	138	139	139	139	139
Chenango	137	138	138	138	138	139	139	139	139	139	139	140
Clinton	98	98	98	98	98	99	99	99	99	100	100	100
Columbia	424	428	431	436	439	442	442	443	446	451	451	452
Cortland	42	42	42	42	42	42	42	44	44	44	44	44
Delaware	88	88	88	88	88	88	89	89	89	90	90	90
Dutchess	4027	4035	4049	4056	4068	4075	4077	4088	4110	4127	4138	4145
Erie	6659	6717	6753	6785	6817	6852	6882	6920	6955	6980	7004	7035
Essex	48	48	48	48	48	48	48	48	48	49	49	49
Franklin	23	24	25	25	25	25	25	26	27	27	27	27
Fulton	230	231	232	234	235	236	236	236	237	243	243	244
Genesee	212	212	212	212	213	213	216	217	218	222	222	225
Greene	249	249	250	251	251	252	252	252	254	255	256	256
Hamilton	5	5	5	6	6	6	6	6	6	6	6	6
Herkimer	125	127	128	128	128	128	128	128	131	134	136	137
Jefferson	79	80	81	81	81	81	82	82	82	83	84	84
Lewis	20	20	20	20	20	20	21	21	21	22	23	23
Livingston	121	121	122	123	123	123	123	123	123	123	123	124
Madison	333	333	333	334	335	336	338	341	342	343	345	347
Monroe	3294	3321	3341	3371	3381	3403	3419	3440	3462	3488	3499	3513
Montgomery	101	103	103	104	104	104	104	105	106	106	106	108
Nassau	41060	41114	41172	41204	41240	41290	41320	41349	41387	41443	41479	41513
New York C.	213271	213707	214242	214627	215011	215342	215686	216013	216421	216803	217189	217487
Niagara	1136	1143	1154	1166	1169	1171	1177	1183	1185	1188	1192	1193
Oneida	1216	1237	1253	1273	1280	1301	1307	1332	1357	1378	1393	1416
Onondaga	2454	2474	2498	2519	2531	2545	2558	2615	2634	2644	2666	2675
Ontario	229	230	230	233	233	234	234	235	239	239	240	242
Orange	10565	10573	10578	10586	10588	10595	10614	10619	10635	10653	10663	10669
Orleans	260	260	261	267	268	268	270	271	274	275	276	276
Oswego	119	120	122	122	126	139	139	144	167	169	173	173
Otsego	78	78	80	80	80	81	82	82	82	82	82	83
Putnam	1282	1282	1285	1288	1291	1292	1294	1295	1299	1301	1301	1305
Rensselaer	508	510	511	513	514	514	515	515	519	521	524	528
Rockland	13385	13396	13411	13423	13441	13460	13467	13474	13486	13495	13504	13514
Saratoga	513	514	514	515	517	522	523	526	528	531	533	535
Schenectady	717	721	723	725	732	735	737	738	746	749	754	761
Schoharie	54	54	54	54	54	54	55	55	55	56	57	57
Schuyler	12	12	12	12	12	12	12	12	12	12	12	12
Seneca	62	63	63	63	64	64	64	64	64	64	64	64
St. Lawrence	212	214	214	215	215	215	215	215	215	216	216	217
Steuben	254	254	255	255	256	257	257	257	257	261	261	263
Suffolk	40512	40559	40615	40659	40692	40738	40770	40810	40864	40908	40972	41010
Sullivan	1426	1428	1430	1430	1432	1433	1433	1434	1434	1435	1437	1438
Tioga	135	137	137	139	139	140	140	140	140	140	140	140
Tompkins	171	172	173	173	173	173	173	173	173	174	175	175
Ulster	1729	1734	1739	1741	1741	1742	1744	1746	1749	1750	1754	1756
Warren	257	257	257	257	257	257	257	258	261	261	261	262
Washington	241	242	242	243	243	243	243	243	243	244	244	244
Wayne	127	129	131	133	133	134	137	139	141	143	143	143
Westchester	34105	34174	34252	34289	34326	34357	34384	34408	34454	34485	34520	34556
Wyoming	91	91	91	92	92	93	93	93	93	93	93	93
Yates	39	39	39	40	40	40	40	40	40	41	41	42

Table A.8: Raw data of COVID-19 cases from 6/23 to 7/4. The data for New York City combine five counties.

County	6/23	6/24	6/25	6/26	6/27	6/28	6/29	6/30	7/1	7/2	7/3	7/4
Albany	2062	2065	2076	2084	2091	2097	2099	2102	2112	2125	2130	2145
Allegany	58	58	58	58	58	59	59	59	61	62	63	63
Broome	671	671	680	697	701	703	710	716	722	729	736	752
Cattaraugus	118	120	121	123	123	123	123	123	123	124	124	127
Cayuga	108	109	109	109	111	113	114	115	119	119	120	120
Chautauqua	116	118	121	122	123	123	123	127	127	127	129	131
Chemung	139	139	139	139	139	140	140	141	144	144	145	146
Chenango	141	142	144	145	146	146	146	146	146	148	148	149
Clinton	100	100	101	101	101	101	101	101	101	101	101	101
Columbia	454	454	455	460	461	463	463	464	466	472	474	474
Cortland	44	44	44	44	44	46	47	47	47	47	48	50
Delaware	91	91	91	91	91	91	91	91	91	91	91	91
Dutchess	4150	4158	4176	4179	4191	4198	4201	4207	4213	4225	4231	4238
Erie	7073	7108	7138	7181	7206	7228	7249	7292	7337	7370	7427	7462
Essex	49	49	49	49	50	50	50	50	50	50	54	55
Franklin	28	28	28	28	29	29	30	30	31	32	33	33
Fulton	244	244	244	248	249	255	256	256	257	260	261	261
Genesee	229	230	231	232	237	238	238	238	238	238	239	239
Greene	256	256	257	257	260	260	260	260	260	260	263	263
Hamilton	6	6	6	6	6	6	6	6	6	6	6	6
Herkimer	137	142	143	149	154	158	159	159	162	164	172	172
Jefferson	84	84	85	85	85	85	86	86	88	90	93	93
Lewis	24	24	25	26	26	29	30	30	30	30	30	31
Livingston	125	125	126	126	126	128	128	129	130	130	130	131
Madison	347	347	349	351	351	352	353	357	357	359	360	363
Monroe	3541	3568	3603	3642	3677	3691	3710	3743	3781	3834	3886	3923
Montgomery	109	110	111	113	116	118	118	118	118	119	119	119
Nassau	41544	41585	41646	41684	41725	41754	41780	41807	41853	41910	41947	41988
New York C.	217803	218089	218429	218799	219157	219481	219670	219844	220143	220567	221028	221395
Niagara	1195	1199	1203	1213	1223	1226	1228	1234	1237	1248	1262	1277
Oneida	1421	1445	1479	1520	1547	1586	1616	1627	1642	1672	1708	1725
Onondaga	2702	2734	2751	2782	2791	2816	2822	2842	2863	2897	2909	2928
Ontario	242	246	248	252	254	256	257	259	265	268	275	278
Orange	10681	10684	10694	10713	10725	10728	10731	10738	10745	10759	10774	10781
Orleans	277	277	279	279	280	281	281	281	281	282	282	282
Oswego	179	188	191	192	194	195	196	197	201	206	206	206
Otsego	83	83	83	83	84	84	84	84	84	84	84	86
Putnam	1305	1306	1311	1317	1319	1323	1325	1326	1329	1332	1333	1335
Rensselaer	533	534	541	549	550	551	553	553	555	556	559	563
Rockland	13529	13534	13549	13557	13566	13576	13580	13590	13602	13612	13623	13629
Saratoga	538	538	540	540	546	548	549	549	550	555	561	562
Schenectady	770	772	778	781	786	792	799	800	805	816	824	831
Schoharie	57	57	57	57	57	58	58	58	58	58	58	58
Schuyler	12	12	12	12	12	12	12	12	13	13	13	13
Seneca	64	64	66	69	69	69	69	69	70	70	70	70
St. Lawrence	217	217	217	218	218	218	219	219	219	220	222	223
Steuben	263	263	264	264	264	266	266	266	268	268	268	269
Suffolk	41056	41101	41151	41208	41253	41306	41339	41385	41427	41491	41538	41585
Sullivan	1440	1447	1448	1449	1451	1451	1451	1451	1452	1453	1455	1456
Tioga	141	141	141	141	142	142	142	143	143	143	143	145
Tompkins	175	175	175	175	175	176	177	177	177	178	178	178
Ulster	1757	1760	1765	1768	1773	1778	1778	1781	1782	1790	1815	1825
Warren	262	262	263	263	263	263	263	263	263	264	266	268
Washington	244	244	245	245	245	246	246	246	246	246	246	246
Wayne	145	150	154	159	161	162	165	170	174	176	181	183
Westchester	34580	34596	34641	34699	34747	34779	34797	34837	34865	34911	34979	35019
Wyoming	93	93	93	94	95	95	95	95	95	95	95	96
Yates	43	44	44	45	45	45	46	46	46	46	46	48

Table A.9: Raw data of COVID-19 cases from 7/5 to 7/16. The data for New York City combine five counties.

County	7/5	7/6	7/7	7/8	7/9	7/10	7/11	7/12	7/13	7/14	7/15	7/16
Albany	2152	2160	2164	2175	2183	2190	2208	2219	2225	2247	2280	2290
Allegany	63	63	63	64	64	64	66	66	66	68	69	70
Broome	753	757	762	766	770	784	807	820	827	841	852	861
Cattaraugus	127	128	128	130	131	134	138	138	138	139	141	142
Cayuga	120	122	122	122	124	124	126	126	126	127	128	128
Chautauqua	132	134	135	149	152	155	170	170	171	180	186	191
Chemung	146	146	147	147	148	148	148	148	148	149	151	151
Chenango	150	156	157	159	163	166	166	166	169	171	175	178
Clinton	103	103	105	106	107	107	108	109	109	110	111	111
Columbia	475	477	479	482	482	482	485	486	487	489	489	489
Cortland	51	52	53	54	55	56	58	58	59	59	61	63
Delaware	91	91	91	91	91	91	91	92	92	92	92	92
Dutchess	4243	4246	4248	4250	4255	4262	4269	4276	4280	4318	4337	4357
Erie	7475	7500	7544	7596	7624	7660	7711	7742	7766	7833	7891	7927
Essex	56	57	57	57	59	59	59	59	59	59	59	59
Franklin	33	33	33	33	34	35	35	36	36	36	37	38
Fulton	261	262	262	262	263	264	265	265	265	266	266	266
Genesee	239	242	242	244	244	246	247	250	250	252	254	254
Greene	263	263	263	263	263	264	265	266	266	267	271	271
Hamilton	6	6	6	6	6	6	6	6	6	6	6	6
Herkimer	173	179	181	181	182	184	188	192	193	195	197	202
Jefferson	94	94	94	94	95	95	95	97	99	100	100	102
Lewis	31	31	31	31	31	31	31	31	31	32	32	32
Livingston	132	133	134	137	140	144	145	147	147	151	151	153
Madison	363	364	367	368	368	371	374	374	375	376	376	377
Monroe	3954	3975	4005	4047	4075	4121	4154	4178	4201	4248	4282	4318
Montgomery	119	120	121	121	125	128	130	132	133	141	141	141
Nassau	42031	42053	42088	42122	42164	42232	42267	42307	42354	42423	42462	42506
New York C.	221637	221882	222156	222444	222723	223078	223382	223725	223977	224293	224662	225045
Niagara	1284	1290	1297	1307	1315	1327	1334	1340	1342	1351	1356	1364
Oneida	1742	1749	1760	1776	1791	1806	1818	1823	1830	1847	1860	1868
Onondaga	2949	2963	2997	3029	3050	3078	3100	3124	3142	3179	3203	3225
Ontario	280	282	283	286	290	293	296	300	302	307	312	317
Orange	10790	10796	10813	10821	10825	10835	10845	10850	10856	10865	10893	10910
Orleans	282	284	285	286	286	287	287	287	287	288	288	288
Oswego	206	206	207	210	211	216	219	220	222	225	226	227
Otsego	86	86	86	86	86	88	88	89	89	90	91	92
Putnam	1336	1337	1340	1344	1348	1355	1361	1361	1365	1376	1382	1385
Rensselaer	565	568	571	580	586	588	593	616	617	625	632	639
Rockland	13648	13656	13668	13679	13683	13691	13700	13716	13719	13733	13743	13763
Saratoga	566	572	578	582	585	587	595	602	610	616	623	624
Schenectady	834	838	843	844	848	852	856	864	868	883	891	896
Schoharie	59	59	59	60	61	62	62	62	62	62	62	62
Schuyler	13	13	13	13	13	13	15	15	15	15	15	15
Seneca	71	71	71	71	73	73	74	74	74	74	76	76
St. Lawrence	224	226	226	227	227	227	230	230	231	233	234	237
Steuben	270	271	271	271	272	272	274	274	276	278	279	279
Suffolk	41642	41685	41730	41799	41849	41911	41987	42028	42112	42214	42267	42333
Sullivan	1456	1457	1459	1460	1460	1464	1464	1465	1465	1466	1467	1469
Tioga	146	148	150	150	151	159	160	161	161	161	163	163
Tompkins	179	179	179	180	180	181	183	186	186	186	198	198
Ulster	1834	1840	1843	1845	1851	1853	1855	1859	1862	1872	1888	1894
Warren	269	272	273	273	273	274	274	277	280	280	284	285
Washington	246	247	247	247	248	249	249	249	249	250	250	250
Wayne	185	186	191	193	195	201	203	205	209	214	221	223
Westchester	35042	35083	35105	35153	35182	35225	35259	35296	35326	35365	35393	35421
Wyoming	97	97	97	98	99	101	101	101	102	103	103	103
Yates	48	48	48	48	48	48	48	48	48	49	50	50

Table A.10: Raw data of COVID-19 cases from 7/17 to 7/28. The data for New York City combine five counties.

County	7/17	7/18	7/19	7/20	7/21	7/22	7/23	7/24	7/25	7/26	7/27	7/28
Albany	2310	2315	2318	2322	2351	2369	2401	2426	2438	2451	2453	2468
Allegany	71	71	71	71	72	72	72	74	74	74	74	74
Broome	870	877	883	902	917	930	934	954	966	978	986	992
Cattaraugus	145	145	145	145	147	147	148	150	150	151	153	153
Cayuga	129	129	129	131	131	134	135	137	139	139	140	140
Chautauqua	192	194	194	194	206	210	212	212	216	218	218	219
Chemung	151	153	154	155	155	156	157	158	160	160	160	160
Chenango	181	182	182	184	188	191	194	196	203	203	203	203
Clinton	111	111	113	113	114	114	114	117	119	120	120	123
Columbia	490	491	492	492	495	497	497	498	500	500	503	504
Cortland	67	68	69	69	73	77	80	82	84	85	87	89
Delaware	92	93	93	93	93	93	95	97	98	98	98	99
Dutchess	4363	4373	4376	4376	4380	4387	4400	4408	4412	4425	4440	4447
Erie	7982	8016	8035	8046	8106	8135	8187	8234	8282	8301	8327	8364
Essex	59	59	59	59	59	62	62	62	62	62	63	63
Franklin	39	40	40	40	42	42	42	42	42	44	44	47
Fulton	266	266	267	267	267	267	268	268	270	270	270	270
Genesee	254	256	257	258	258	258	260	261	261	264	266	266
Greene	271	271	272	272	272	272	273	278	279	281	282	283
Hamilton	6	6	6	6	6	6	6	7	7	7	7	7
Herkimer	204	204	206	206	208	211	213	223	224	230	234	236
Jefferson	103	104	105	106	112	113	120	123	126	127	128	128
Lewis	32	32	33	33	33	33	34	34	34	34	34	34
Livingston	155	157	158	159	160	161	161	161	162	162	162	162
Madison	379	382	383	384	387	388	388	390	390	390	390	391
Monroe	4354	4384	4402	4423	4453	4493	4512	4538	4570	4592	4621	4633
Montgomery	141	143	143	143	144	144	145	146	147	148	148	152
Nassau	42555	42594	42622	42678	42729	42765	42816	42860	42915	42960	43017	43059
New York C.	225414	225799	226104	226388	226779	227130	227517	227882	228220	228445	228740	228939
Niagara	1371	1375	1382	1384	1388	1395	1405	1408	1420	1422	1424	1424
Oneida	1909	1937	1940	1942	1962	1975	1980	1990	2000	2000	2010	2028
Onondaga	3240	3262	3278	3290	3312	3326	3344	3360	3378	3389	3398	3419
Ontario	319	324	324	326	329	333	334	337	338	341	343	345
Orange	10923	10936	10946	10953	10968	10975	10983	10991	11009	11013	11025	11039
Orleans	288	288	288	288	288	288	288	289	289	290	290	290
Oswego	227	229	229	229	231	232	234	234	236	238	239	239
Otsego	94	94	98	98	100	101	102	102	103	103	103	105
Putnam	1386	1390	1391	1392	1393	1394	1397	1399	1403	1404	1408	1412
Rensselaer	643	650	651	653	658	668	669	676	681	684	687	690
Rockland	13775	13784	13793	13798	13806	13812	13820	13830	13837	13839	13841	13845
Saratoga	630	635	637	639	646	650	663	665	679	685	688	691
Schenectady	902	910	915	915	926	936	946	955	975	987	990	998
Schoharie	62	62	62	62	64	64	66	67	67	68	68	68
Schuyler	15	16	16	20	20	20	20	20	20	20	20	20
Seneca	77	78	80	80	80	80	80	83	83	83	83	84
St. Lawrence	238	242	242	246	247	250	253	254	257	258	258	258
Steuben	279	280	281	282	283	283	284	285	288	288	288	289
Suffolk	42382	42440	42466	42496	42575	42621	42715	42773	42822	42883	42967	43024
Sullivan	1469	1473	1473	1473	1473	1473	1475	1475	1476	1476	1476	1476
Tioga	168	169	170	173	174	175	175	176	178	179	180	180
Tompkins	198	199	208	209	209	209	213	221	223	224	225	225
Ulster	1898	1900	1901	1901	1906	1909	1911	1912	1916	1925	1926	1942
Warren	286	286	287	287	288	288	290	292	293	294	294	298
Washington	250	250	250	250	250	251	252	252	252	253	254	254
Wayne	223	225	227	228	232	236	238	239	240	241	243	243
Westchester	35462	35502	35514	35550	35586	35635	35666	35699	35737	35776	35798	35837
Wyoming	103	104	104	104	107	108	108	110	110	110	110	111
Yates	51	51	51	51	51	51	51	51	51	51	52	52

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