Voting Prediction Using New Spatiotemporal Interpolation Methods*

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ABSTRACT

Most spatial and spatiotemporal interpolation methods give back a surface function as the result. Instead of that we consider interpolation methods that yield a single value as the final result. *Voting prediction* is a natural example that requires this type of spatiotemporal interpolation, because the final result is the total percentage vote for a party or candidate. We propose a new spatiotemporal interpolation method for voting prediction and similar problems. The approach can also be used in election data verification for effective government. We test the new method using USA presidential election data from the states of California, Florida, and Ohio between 1972 and 2004. The experimental results show that our method can produce comparatively precise predictions (e.g., the difference between prediction and actual result is 1.09% for Florida in 2004).

1. INTRODUCTION

Spatial and spatiotemporal interpolations are important in many problems, such as, geographically distributed statistics for agricultural productions, disease prevalence, pollution levels, soil types, precipitation, and temperatures. Spatiotemporal interpolation is used to interpolate the original point-based Standardized Precipitation Index (SPI) data in a drought online analysis system [22]. These usually require the estimation of the unknown values at unsampled location-time pairs and yield as the final result a surface function. In contrast, we consider spatiotemporal interpolation methods that require only a single value as the final result. Aiming at effective government we choose predicting presidential election as the main application in this study.

Most presidential election forecasting models use *multi-variate ordinary least squares regression*, a common statistical method in the social sciences [9]. Those models compare calculations from previous elections of such independent variables as presidential popularity and economic growth with their current values to estimate the result in a future election. Among the simplest forecasting models are several that predict national two-party vote shares using time series data and sets of explanatory variables. Campbell and Wink use just two predictor variables, a trial-heat poll and second quarter GDP growth in the year of the election [2]. Lewis-Beck and Rice use a similar specification, but add variables capturing recent partisan trends [14].

As pointed out by Chappell [4], although the national models is widely accepted, predicting shares of the popular vote should not be the principal objective when the election winner is selected according to outcomes in the individual states. Several models such as the models proposed by Rosenstone[18] and Campbell [3] are designed for forecasts at the state-level. These models examine election outcomes across both states and time, using a mixture of national-level and state-level variables as explanatory variables.

Although both the national-level and state-level models introduced above are frequently cited for their use in forecasting and the accuracy is admirable, most of them share limitations. For example, the choice of factors to include in the model adds to the uncertainty. The decision to include one set of variables, such as presidential popularity and growth in GNP, rather than another, such as the rate of inflation and unemployment, changes the prediction outcome [9]. Also most models are limited by the lack of historical information on the relationship between political and economic fundamentals and elections [9]. In our research we turn the direction into the historical election data itself as the basis of spatiotemporal interpolations without a set of variables.

A key issue is the choice of an appropriate interpolation method for a given input data [1, 16]. Inverse distance weighting (IDW) [12, 17, 19, 20], kriging [6], shape functions [15], splines [8], and trend surface analysis [23] are some of the common spatial interpolation methods. We propose a novel and comparatively simple spatiotemporal interpolation method as a combination of spatial and temporal interpolation methods to predict the election at the state-level.

The rest of the paper is organized as follows. Section 2 reviews inverse distance weighting, which is a popular spatial interpolation method. We also use the IDW method in this

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study. Section 3 describes our spatiotemporal interpolation method. Section 4 describes the experimental methods and results. Finally, Section 5 presents some ideas for future work.

2. INVERSE DISTANCE WEIGHTING

Distance-based weighting methods have been used to interpolate spatial data by many authors, for example, by Legates and Willmont [12] and Stallings et al. [20]. The main assumption of IDW is that if A, B and C are three different locations, such that A is closer to B than to C, then the value we are interested in (temperature, precipitation, percentage of voters preferring a particular candidate, etc.) is also closer between A and B than between A and C. Hence, if the value at location A is unknown, while the values at locations B and C are known, then the value at B should be more important than the value at C in estimating the value at A.

The relative importance of the known values is reflected by the weights assigned by the IDW method to them. In the IDW method the sum of the weights is equal to 1, and the weights are assigned proportionally to the *inverse of the distance* between the known and unknown locations.

Let λ_i be the weight for the individual location, and y_i the variable observed in the sampled location.

IDW interpolations are of the form [10]:

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

$$\lambda_i = \frac{(\frac{1}{d_i})^p}{\sum_{k=1}^{N} (\frac{1}{d_k})^p} \tag{2}$$

For simplicity in the following we assume that $p = 1$. Therefore,

$$\lambda_i = \frac{\frac{1}{d_i}}{\sum_{k=1}^{N} \frac{1}{d_k}} \tag{3}$$

EXAMPLE 1. *Assume that $A = (5, 0)$, $B = (0, 0)$, and $C = (20, 0)$ and the value at A is unknown but the values at B and C are 100 and 200, respectively. Then, the number of known points is $N = 2$. We use the subscripts B and C instead of numbers in this simple example. We can calculate that:*

$$\lambda_B = \frac{\frac{1}{5}}{\frac{1}{5} + \frac{1}{15}} = 0.75 \qquad \lambda_C = \frac{\frac{1}{15}}{\frac{1}{5} + \frac{1}{15}} = 0.25$$

Hence the value of A will be interpolated based on B and C to be:

$$y_A = \lambda_B\ y_B + \lambda_C\ y_C = 0.75 \times 100 + 0.25 \times 200 = 125$$

Note that since point C is three times more distant than B is from point A, the weight λ_C is only a third of the weight λ_B. Hence y_A is much closer to y_B than to y_C.

3. NEW SPATIOTEMPORAL INTERPOLATION METHODS

Now we describe a new spatiotemporal interpolation method which is a combination of a spatial interpolation method with a temporal interpolation method. For the spatial interpolation part, we consider to use the IDW method as described in Section 2. We choose IDW because its ease of use and low computation charge [5]. For the temporal interpolation part, we consider two methods as described in Section 3.1.

For any location C, let $E_{t,C}$ be the estimated value using any chosen temporal interpolation method, and $E_{s,C}$ the estimated value using any spatial interpolation method, α_C the weight of $E_{t,C}$, and β_C the weight of $E_{s,C}$. We calculate the overall estimation value E_C for location C as follows:

$$E_C = \alpha_C \times E_{t,C} + \beta_C \times E_{s,C} \tag{4}$$

where $\alpha_C + \beta_C = 1$ and $0 \leq \alpha_C,\ \beta_C \leq 1$.

In interpolating the percentage vote for a given party in some county C for which we do not have information, we would naturally like to rely on the percentage votes in its neighboring counties if those values are known. Here we should notice that since election voting is not like some GIS applications like minimum or maximum temperatures in a weather station, where some data are missing because of broken instruments or data processing mistakes, hence interpolation is needed to find the replacing values. For election voting, it is very unlikely that previous voting result can not be found. And what people are most interested in is who will win in the coming election. Therefore, instead of doing a interpolation, we use our method to do a prediction.

Now we discuss how to determine $E_{t,C}$, $E_{s,C}$, α_C, and β_C in the following.

3.1 Temporal methods to determine $E_{t,C}$

3.1.1 Inverse linear temporal method

This is a variant of the IDW methods that measures "distance" in terms of time difference instead of spatial difference. That is, it treats time as a third dimension. Following the IDW method, the weights are assigned proportional to the inverse of the time difference, and again we assume that $p = 1$.

3.1.2 Inverse exponential temporal method

After some experimentation we realized that time is special and the inverse linear temporal method does not yield good results. Increasing p to a small constant 2 or 3 also does not yield a good result. Hence, we introduce another method that assigns weights that decrease exponentially with the time difference, i.e., if we look back in time n years and have one data in each of the past n years, then the weight of the data i years back in time will be $\frac{1}{2^i}$ for $1 \leq i \leq (n-1)$ and $\frac{1}{2^{n-1}}$ for n years back. Note that the last two weights will be the same and with this rule the sum of the weights is still 1.

Consider predicting the outcome of the USA presidential election of 2004 based on six previous election results, namely the presidential election votes in 2000, 1996, 1992, 1988, 1984, and 1980.

For inverse linear temporal interpolation, we use the time distance of one as the distance between two continuous USA presidential elections (even though it means four years). Hence we get the weights:

$$\lambda_i = \frac{\frac{1}{i}}{\frac{1}{1} + \frac{1}{2} + \ldots + \frac{1}{6}} = \frac{1}{2.45 \times i}$$

Using inverse exponential temporal interpolation, we assign the weights to the outcome of these elections (at any city or voting district) as $\frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{16}, \frac{1}{32}, \frac{1}{32}$, respectively. The weight $\frac{1}{32}$ occurring twice is to keep the sum of the weights still 1.

3.2 Spatial methods to determine $E_{s,C}$

As stated before, IDW is a very popular interpolation method, we use it as the spatial part for our method. However, a problem arises. For example, suppose we are back in November 2004 and want to predict the percentage vote for John Kerry in the 2004 USA presidential election in Alachua county, Florida. It is not reasonable to use the actual votes in Bradford, Clay, Columbia, Gilchrist, Levy, Marion, Putnam, and Union, which are the neighboring counties of Alachua, because those votes are not known yet. A possible solution is to use the estimated data in the neighboring counties, which can be created by many methods such as our inverse linear or inverse exponential temporal methods.

When we use the IDW method, we consider two versions. One is the IDW method with uniform distances and the other with real distances.

3.2.1 IDW with uniform distances

Suppose we want to predict the votes for county C, which has the following neighboring counties, $N_1, N_2, \ldots, N_k$. We assume all the distances between counties C and $N_i, 1 \leq i \leq k$, are the same. Hence by Equation (3) each neighbor N_i has exactly the same weight $\lambda_i = \frac{1}{k}$, $1 \leq i \leq k$.

3.2.2 IDW with real distances

When considering the real distance between counties C and $N_i, 1 \leq i \leq k$, we calculate the distances between the centroid of counties C and N_i, $1 \leq i \leq k$. Because of the near-spherical shape of the Earth, calculating an accurate distance between two points requires the use of spherical geometry and trigonometric math functions. In this study, we use the formulae introduced by Weisstein [21],

Table 1: Latitude and longitude of centroid of 67 counties of Florida, USA

County name	Latitude	Longitude
Alachua	29.676436	-82.379953
Baker	30.287517	-82.236268
Bay	30.219170	-85.638788
...		
Wakulla	30.144620	-84.366174
Walton	30.637995	-86.155962
Washington	30.630591	-85.638396

$$distance = \sqrt{(x_1 - x_0)^2 + (y_1 - y_0)^2 + (z_1 - z_0)^2} \quad (5)$$

where for $0 \leq i \leq 1$
$x_i = R \times \cos(long_i) \times sin(90^\circ - lat_i)$
$y_i = R \times \sin(long_i) \times sin(90^\circ - lat_i)$
$z_i = R \times \cos(90^\circ - lat_i)$
and $R = 6368KM$

The latitude and longitude of the centroid of a county are shown in Table 1, which is obtained from the official website http://www.census.gov.

Using the above distances we can get the weights of neighboring counties by Equation (3). Combined with the data of neighboring counties, we can use Equation (1) to estimate the votes for county C.

An interesting aspect is that in states with long and narrow shapes, such as Florida, there are fewer neighbors on average for each county than in counties with a more round shape such as Ohio. Therefore, we were concerned that the overall shape of a state can influence heavily the accuracy of our spatiotemporal interpolation method. Hence we choose three states, that is, Florida, Ohio, and California, with very different shapes as our test cases.

In each of our three test states, there are counties that have additional neighbors in other states. For example, some counties in Florida are neighbors of some counties in Georgia. However, we did not count neighbors in other states, because we did not have available data for them. Presumably the accuracy of our interpolation methods can be further improved by counting those neighbors too.

3.3 Determine α_C and β_C

3.3.1 Step function

When we consider this new method, the most natural way to determine α_C and β_C is a step function as shown in Figure 1. In a step function, we find some parameter σ_C and fix some threshold value θ (Details about σ_C and θ are in the following paragraphs). If $\sigma_C < \theta$, then we set $\alpha_C = 1$

Table 2: d_i and σ of 67 counties of Florida, USA

d_i in each county	00/96	96/92	92/88	88/84	84/80	σ
Alachua	1.353543	4.287756	0.781069	2.403800	5.863571	2.937948
Baker	4.927593	5.031435	0.896374	0.045522	24.17032	7.014248
Bay	0.951147	4.895554	1.633311	2.241453	11.67629	4.279550
...						
Wakulla	2.071604	8.078953	1.023610	1.278107	16.490388	5.7885324
Walton	3.626663	5.728941	1.235268	3.937664	20.734451	7.0525974
Washington	3.204958	5.745716	0.326218	3.265001	18.464455	6.2012696

and $\beta_C = 0$, which enforces that we use the temporal interpolation method; and if $\sigma_C \geq \theta$, then we set $\alpha_C = 0$ and $\beta_C = 1$, which enforces that we use the IDW spatial interpolation method. In summary,

$$\begin{cases} \alpha_C = 1,\ \beta_C = 0 & \text{if } \sigma_C < \theta \\ \alpha_C = 0,\ \beta_C = 1 & \text{if } \sigma_C \geq \theta \end{cases} \tag{6}$$

σ_C and θ are considered according to a specific application. For example, when we apply the method to USA presidential election data, we choose σ_C as the changes in the vote percentages of all pairs of subsequent presidential elections for a county C. We choose θ as a constant, say 1%, 2% and so on. Intuitively, a smaller σ_C means that the values in a county C are more consistent over time, hence we can rely more on the temporal interpolation method, which means that we should increase α_C and decrease β_C.

Let $M_{t,C}$ be the absolute difference between the temporal estimation value and the actual data at location C. Similarly, let $M_{i,C}$ be the absolute difference between the IDW estimation value and the actual data. If most counties with $\sigma_C < \theta$ have $M_{t,C} < M_{i,C}$ while most counties with $\sigma_C \geq \theta$ have $M_{t,C} \geq M_{i,C}$, then the step function makes an ideal choice. Intuition would suggest that $M_{t,C}$ and $M_{i,C}$ are independent, hence if a temporal method is more reliable because σ_C is small, then it is also usually the case that $M_{t,C} < M_{i,c}$.

3.3.2 Linear function

In addition to the step functions, we also experimented with linear functions of the form $\alpha = c\,\sigma + d$ with different values for the constants c and d. However, the linear functions did not work as well as the step functions. One likely explanation is that the temporal and IDW methods give similar variations for most counties, that is, when the temporal estimation value is higher (or lower) than the original data, then the IDW estimation value is also higher (or lower). That makes it difficult to find a good linear function.

3.3.3 σ_C in the election data

Suppose we would like to predict the outcome of the USA presidential election of 2004 in Alachua, Florida. Let us look at how to calculate $\sigma_{Alachua}$.

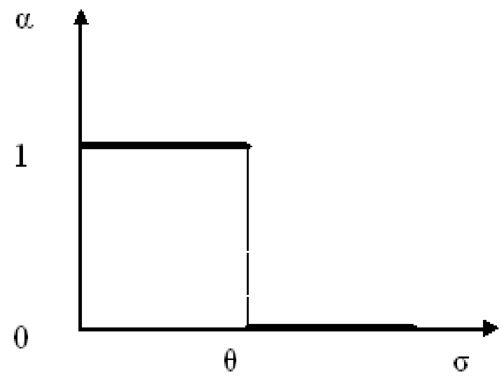

Figure 1: Step function

Let P_{year} be the percentage vote for the democratic candidate in the given year in Alachua and use P_{00} instead of P_{2000} and so on. We have $P_{00} = 55.249682\%, P_{96} = 53.896139\%, P_{92} = 49.608382\%, P_{88} = 48.827313\%, P_{84} = 46.423513\%$, and $P_{80} = 52.287084\%$.

Let d be the absolute difference between two continuous USA presidential elections, then $d_1 = |P_{00} - P_{96}|, \ldots, d_5 = |P_{84} - P_{80}|$. That is, $d_1 = |55.249682\% - 53.896139\%| = 1.353543\%$, $d_2 = 4.287756\%$, $d_3 = 0.781069\%$, $d_4 = 2.4038\%$, and $d_5 = 5.863571\%$.

Hence we get:

$$\sigma_{Alachua} = \frac{d_1 + d_2 + d_3 + d_4 + d_5}{5} = 2.937948\%$$

Table 2 gives d_i and σ of six counties of the state of Florida. We calculated similarly the σ for the remaining 61 counties in Florida, but we do not show them for space limitations.

4. EXPERIMENTAL METHODS AND RESULTS

4.1 USA presidential election data sets

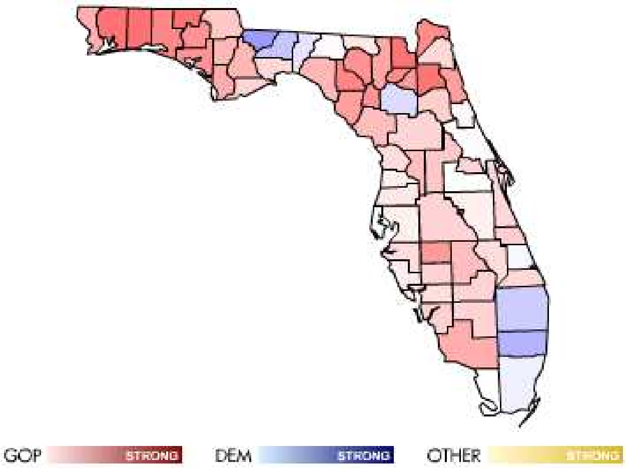

Figure 2: 2004 presidential votes by county in Florida (from http://www.cnn.com)

Table 3: Votes for 2000 USA presidential election in 67 counties of Florida, USA

County name	Total votes	Votes for Republican candidate	Votes for Democratic candidate
Alachua	85,757	34,135	47,380
Baker	8,155	5,611	2,392
Bay	58,876	38,682	18,873
...			
Wakulla	8,587	4,512	3,838
Walton	18,323	12,186	5,643
Washington	8,026	4,995	2,798

As stated before, in order to test our idea, we used the USA presidential election data for the states of California, Florida, and Ohio. For Florida, the data is obtained from the official website [24], which is maintained by the Florida Division of Elections and contains a comprehensive USA presidential voting data for 67 different counties in Florida between 1980 and 2004. Table 3 shows a part of the post-caculated data. The map in Figure 2 shows the 2004 presidential votes for each county in Florida. For California and Ohio, the data is obtained from [13], for the time period between 1972 and 2004. We estimated the votes for the 2004 democratic candidate for USA president (John Kerry) in those three states using our new method and compared them with the actual votes.

4.2 Prediction procedures

We tried out both the inverse linear and the inverse exponential temporal methods as described in Section 3.1. We used the two versions of the IDW methods described in Section 3.2 as our spatial interpolation method.

Once we get the temporal and spatial interpolation values, we apply Equation (4) to calculate the final estimation value. We test step functions to find the best estimation parameters α, β, and θ. For the threshold parameter θ we tried the ten values 1%, 2%, 3%, ..., 10%.

4.3 Evaluation method

Several measures are suitable for experimentally comparing the accuracy of interpolation methods. We use mean absolute error (MAE) and root mean square error (RMSE).

$$MAE = \frac{\sum_{i=1}^{N} |F_i - A_i|}{N} \quad (7)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (F_i - A_i)^2}{N}} \quad (8)$$

where
F_i: Prediction value.
A_i: Actual measurement.
N: Number of data.

Let $VPstate_e$ be the estimated statewide vote percentage for a given party. Similarly, let $VPstate_a$ be the actual statewide vote percentage for a given party.

$$VPstate_e = \frac{\sum E_i \times V_i}{\sum V_i} \quad (9)$$

where
E_i: Estimated vote percentage for a given party in county i.
V_i: The number of all voters in county i.

Then we can calculate the error of statewide total vote percentage (TE), which is a more interesting measure in the voting prediction area.

$$TE = |VPstate_e - VPstate_a| \quad (10)$$

EXAMPLE 2. *Assume that a state S has three counties A, B, and C. For some election the numbers of all voters in counties A, B, and C are 1000, 2000, and 3000, respectively. The estimated vote percentages for a given party in counties A, B, and C are 40%, 50%, 60%, respectively. And the actual vote percentage for a given party in state S is 58%. We can calculate that:*

$$TE = \left| \frac{40\% \times 1000 + 50\% \times 2000 + 60\% \times 3000}{1000+2000+3000} - 58\% \right| = 4.7\%$$

4.4 Evaluation

Figures 3-5 give the intuition for step functions, based on 67 counties in Florida. The x-axis is σ in each figure, while the y-axis is M_t in Figure 3, M_i in Figure 4, and their weighted

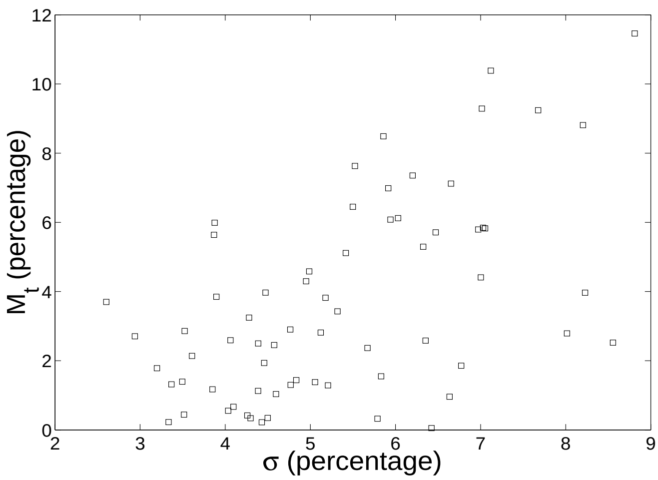

Figure 3: M_t of step function

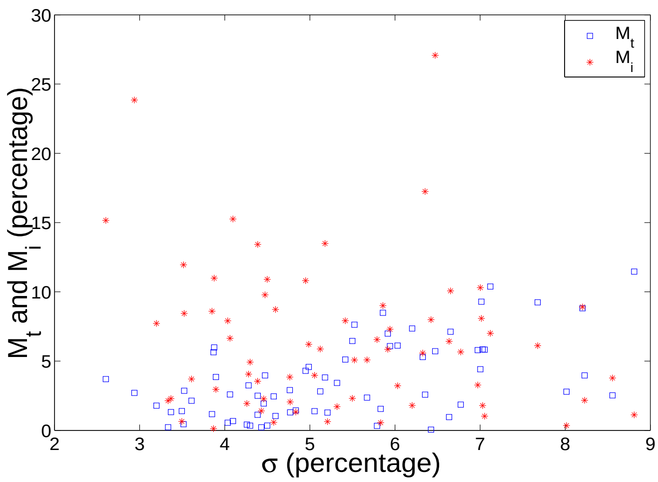

Figure 5: M_t and M_i of step function

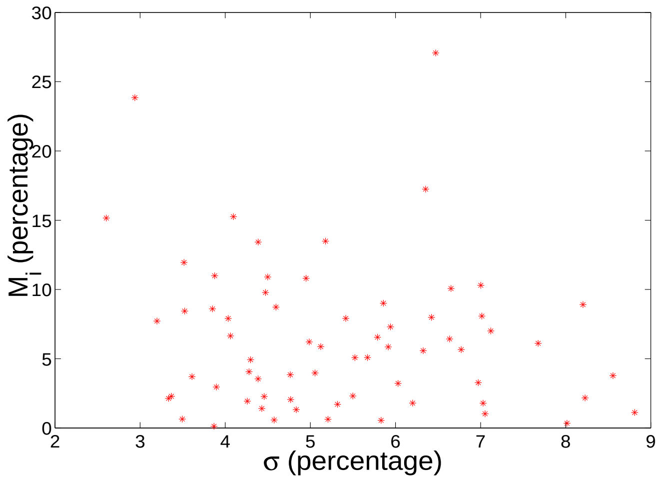

Figure 4: M_i of step function

linear combination in Figure 5. It can be seen that for this data set, 7% seems a reasonable threshold since most counties with $\sigma < 7\%$ have $M_t < M_i$, and most counties with $\sigma \geq 7\%$ have $M_t \geq M_i$. The experiments proved true our intuition.

Table 4 records our experimental results. We can see that the performance of spatiotemporal step functions and inverse exponential temporal methods is the best, getting comparatively precise predictions, especially in predicting the 2004 USA presidential election in Florida. Spatiotemporal step functions (with $\theta = 7\%$) predict for the 2004 USA presidential election, the democratic candidate (John Kerry) will win 46.00% votes in Florida, and the actual result is 47.09%, hence the discrepancy (TE) is only 1.09%. This contrasts favorably with a CNN poll which predicted only 42% for John Kerry shortly before the election [25], i.e., it had a TE of more than 5%.

The experimental results for California and Ohio are also impressive. Inverse exponential temporal method shows slightly better performance, TE is 3.46 and 3.18 in California and Ohio, respectively. For all three states, MAE and RMSE are reasonably low, between 2.39 and 6.83.

The experiment shows that the difference between the two versions of IDW methods with uniform distances and real distances are extremely small in our case. Therefore, the much more complicated standard IDW method using exact distances can be simplified by IDW method with uniform distances using topological neighbors without any significant change in the accuracy of the result.

Figure 6 shows the estimated vote percentages using step functions and the actual vote percentages over 67 counties in Florida. We can see that for most counties the discrepancy is low and it almost disappears for several counties.

5. CONCLUSION AND FUTURE WORK

The experimental results show that our new spatiotemporal interpolation method can be a basis for an effective voting prediction system. Of course, any real voting prediction system would need to be fine-tuned by considering many additional variables, such as a candidate's expenditures, gender, incumbency, and the interaction affects of those parameters. However, it is extremely interesting and encouraging that by combining a temporal and a spatial interpolation method, which in themselves are not too sophisticated, already yields prediction values that are more accurate than the results —published in various newspapers in the run-up to the elections— of much more sophisticated prediction systems. Hence our vote prediction system has a significant potential that we plan to exploit by factoring in more variables.

As this approach produced both county-level and state-level results, it can be used by election agencies in election data verification for effective government. We can compare the collected election results with the estimates at the county-level and identify possible suspected data when there is significant difference between them.

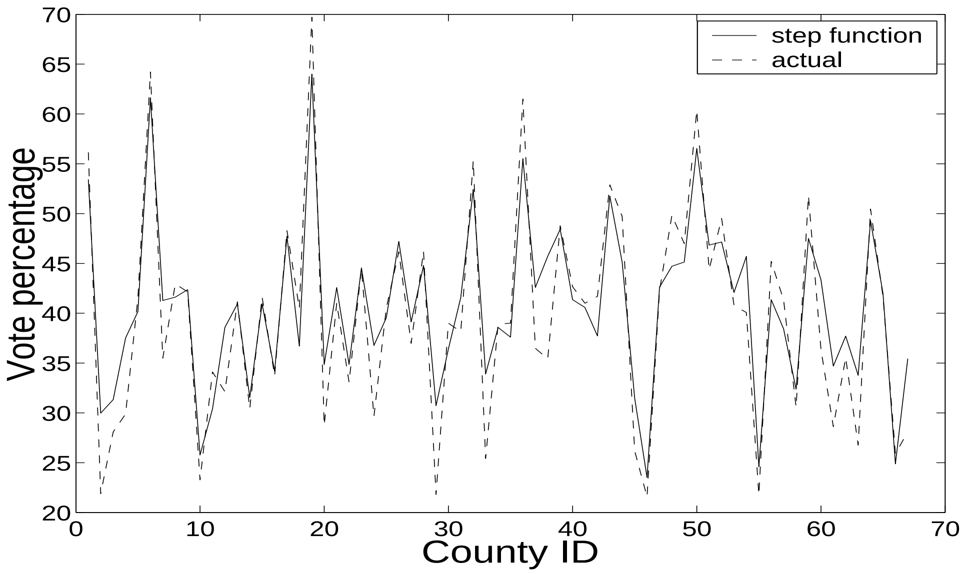

Figure 6: Estimated vote percentages using step functions and actual vote percentages over 67 counties in Florida, USA

Table 4: Comparison of step function, temporal and IDW methods

	California 2004			Florida 2004			Ohio 2004		
	TE	MAE	RMSE	TE	MAE	RMSE	TE	MAE	RMSE
IDW using uniform distances									
Spatial IDW	8.65	11.60	9.67	4.88	7.98	9.05	8.75	11.31	7.60
Spatiotemporal Step Function ($\theta = 7\%$)	3.49	4.51	6.26	1.09	2.40	5.18	3.57	4.37	3.57
Spatiotemporal Step Function ($\theta = 8\%$)	3.55	4.77	6.38	1.10	2.40	4.72	3.89	4.66	3.88
Spatiotemporal Step Function ($\theta = 9\%$)	3.49	4.51	6.26	1.10	2.39	4.61	3.27	4.05	3.14
IDW using real distances									
Spatial IDW	8.02	11.33	9.33	3.51	6.62	8.64	8.83	11.27	7.45
Spatiotemporal Step Function ($\theta = 7\%$)	3.58	4.63	6.83	1.10	2.39	4.84	3.45	5.06	4.88
Spatiotemporal Step Function ($\theta = 8\%$)	3.54	4.54	6.32	1.11	2.39	4.69	3.78	4.56	3.71
Spatiotemporal Step Function ($\theta = 9\%$)	3.50	4.51	6.03	1.11	2.39	4.59	3.25	4.03	3.10
Temporal Inverse Linear	5.46	6.66	7.25	2.68	3.81	5.12	4.10	5.09	3.74
Temporal Inverse Exponential	3.46	4.48	6.01	1.10	2.39	4.59	3.18	3.99	3.10

In the future, we also plan to look at other problems that require a single value as the outcome of the interpolation problem. For example, an aggregate health statistics, such as the number of persons infected with various specific diseases in a state or country would be another natural problem to look at. Another would be to predict human population changes in a country or worldwide. Both of these are known to be hard problems. For example, there are widely different values for the total number of AIDS cases predicted using different models or the predicted total human population in the world. By improving the estimation accuracy of these and similar types of problems, we can help governments and international health and environmental agencies to be better prepared in the future.

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