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An Improved k-Nearest Neighbours Method for Traffic Time Series Imputation

1st Bin Sun

Blekinge Institute of Technology
Karlskrona 37179, Sweden
bin.sun@bth.se

2nd Liyao Ma

School of Electrical Engineering
University of Jinan
Jinan 250022, China
cse_maly@ujn.edu.cn

3rd Wei Cheng

Kunming University of Science and Technology
Kunming 650093, China
Blekinge Institute of Technology
Karlskrona 37179, Sweden
Corresponding Author: wei.cheng@bth.se

4th Wei Wen

Blekinge Institute of Technology
Karlskrona 37179, Sweden
wei.wen@bth.se

5th Prashant Goswami

Blekinge Institute of Technology
Karlskrona 37179, Sweden
prashant.goswami@bth.se

6th Guohua Bai

Blekinge Institute of Technology
Karlskrona 37179, Sweden
guohua.bai@bth.se

Abstract—Intelligent transportation systems (ITS) are becoming more and more effective, benefiting from big data. Despite this, missing data is a problem that prevents many prediction algorithms in ITS from working effectively. Much work has been done to impute those missing data. Among different imputation methods, k-nearest neighbours (kNN) has shown excellent accuracy and efficiency. However, the general kNN is designed for matrix instead of time series so it lacks the usage of time series characteristics such as windows and weights that are gap-sensitive. This work introduces gap-sensitive windowed kNN (GSW-kNN) imputation for time series. The results show that GSW-kNN is 34% more accurate than benchmarking methods, and it is still robust even if the missing ratio increases to 90%.

Index Terms—Traffic Time Series, Gap-Sensitive Windowed k-Nearest Neighbours (GSW-kNN), Missing Data Imputation

I. INTRODUCTION

Nowadays, intelligent transportation systems (ITS) are becoming more and more effective, benefiting from big data generated by modern sensors and devices [1]. Many prediction algorithms rely on such big data, for example, frequently used prediction methods, including auto regressive integrated moving average (ARIMA) [2], neural network [3]–[5], support vector regression (SVR) [6], kNN regression [7] among others. These methods cannot make full use of dataset in case of missing values [8]. While the amount of data captured by various devices is getting larger, the amount of missing data increases as well. The missing ratio of traffic data is usually 5% to 25%, sometimes more than 90% [8]–[10].

There has been much work on imputation for time series data and kNN has produced imputations accurately and efficiently [8], [11]. However, two key topics are not found in the literature. Firstly, missing values lead to gaps within time series which should be considered during neighbour distance measurement. Secondly, time series is continuous on time scale which is not considered in general kNN imputation. To solve the problems mentioned above, this work proposes a

gap-sensitive windowed kNN (GSW-kNN) to impute missing values in traffic time series.

II. BACKGROUND AND RELATED WORK

Data missing situation can be categorized into three types [12]–[14]. In the first type, the values are missing completely at random (MCR). The missing positions are completely unrelated with each other and are randomly located on the time scale. In the second type, the values are missing at random (MR) which means the missing positions are dependent on neighbouring samples. They are kind of clustered or continuous, but the clusters are randomly located on the time scale. The situation is usually due to device damage or maintenance. The third type is missing values not at random (MNR). The missing clusters are not randomly located on the time scale. There can be more types when considering spatial information such as multi-sensor station situation, which is out of the scope of this work [9].

To impute missing values, data imputation methods are developed which can be divided into three categories: prediction based, interpolation based and statistical/machine learning based [8], [15]. Prediction based methods, such as ARIMA and neural network, have the problem that they only make use of continuous chunks in the time series [8]. A typical interpolation based method is regression spline, which is a piecewise polynomial function that tries to approximate the unknown function [16], [17]. In the statistical/machine learning category, k-Nearest neighbours (kNN) [9], [18] and principal component analysis (PCA) based methods [8], [19] have shown great performance [8], [14] and efficiency [11]. It has been shown that different PCA based methods perform similar with regards to accuracy [14]. Another work introduces an ad hoc category which includes mean, median and last observation carried forward (LOF) [13]. Among those methods, kNN is accurate and efficient [8], [11].

Fig. 1. General kNN imputation matrix. Imputation for time t on day D using other days' data. The entire data of each day as a vector is taken to calculate similarity and the most similar days are selected. Three dashed dark green squares are the selected nearest neighbours' data at t of corresponding days ($k = 3$). 4 searchable history days (no shifts) lead to 4 potential neighbours.

The general kNN imputation of traffic data is shown in Fig. 1. One value at time t on day D is missing. Each searchable day in the history data is considered as a neighbour. The distance between the day D and other days are calculated and the nearest k days are selected as nearest neighbours. The values (white-dashed dark green squares) at time t of the k days are averaged to impute the missing value at time t on day D .

One problem is the general kNN imputation is that it is developed for matrix such as microarrays in human genes, which is not considering traffic data on the time scale. An important characteristic of time series is correlation and continuous change on the time scale. A possible approach to make use of such a characteristic is to use window based shifting, which have been used for kNN based time series prediction [20], [21]. Though this approach works well, it has not been used for imputation.

Another problem is that we can see that the general kNN is not considering the gap of missing data. Gaps occur if any values are missing. When the general kNN algorithm tries to impute a value, it measures its distance to neighbours with the positions of missing values ignored. However, missing values at different positions have diverse influences on the distance measurement. This gap matters, which has been shown in prediction-related work [22], [23], but the general kNN considers all elements in the vectors equally.

III. METHODOLOGY

This section proposes a gap-sensitive windowed kNN for imputation to solve the issues mentioned above. Later, the data

Fig. 2. Traffic prediction for time t using GSW-kNN. The position of missing data is (D, t) . The shown example window is $v = 1$, thus three shifts: $(-1, 0, +1)$. Three dashed dark green squares are the selected nearest neighbours' data at t or $t \pm 1$ of corresponding days ($k = 3$). 4 searchable history days with three shifts lead to 12 potential neighbours. Besides, the instances indexes are extended into the neighbouring previous or later day when the lag d is big.

and experimental setup are described.

A. GSW-kNN

As shown in Fig. 2, suppose the position of missing data is (D, t) which is at the time t on the day D . The search lag length is d on both sides of (D, t) , so the state vector of the missing data is:

$$\mathbf{r}_{D,t} = (r_{D,t-d}, \dots, r_{D,t-1}, r_{D,t+1}, \dots, r_{D,t+d}) \quad (1)$$

where $\mathbf{r}$ means traffic flow volume rate. As an example, one searchable neighbour vector on the previous day ($D - 1$) without window is:

$$\begin{aligned} \mathbf{r}_{D-1,t} \\ = (r_{D-1,t-d}, \dots, r_{D-1,t-1}, r_{D-1,t+1}, \dots, r_{D-1,t+d}) \end{aligned} \quad (2)$$

where $\mathbf{r}_{D-1,t}$ is the *matching point data*. This step is similar to the general kNN neighbours except that the state vector of missing data and searchable history neighbours $\mathbf{r}$ can extend to neighbouring days when d is big.

Here we add a window to the algorithm. A *window* (v) is a limitation of *shift* that can be applied to all searchable history day and its matching point. For example, if $v = 1$, the shift can be $-1, 0, 1$. If a shift 1 is applied to the neighbour vector $\mathbf{r}_{D-1,t}$ in (2), the neighbour vector becomes:

$$\begin{aligned} \mathbf{r}_{D-1,t+1} \\ = (r_{D-1,t-d+1}, \dots, r_{D-1,t}, r_{D-1,t+2}, \dots, r_{D-1,t+d+1}) \end{aligned} \quad (3)$$

Introducing window into kNN is a good way to make full use of data. Suppose the window size is v , then the shifts contained in the window are $-v, -v+1, \dots, -1, 0, 1, \dots, v-1, v$. Consequently, the non-zero shifts make the searchable dataset v times bigger than the original dataset. This is important due to the fact that machine learning algorithms heavily rely on the big amount of available data. Especially when there is not too much data, such as only one single station/sensor's data are available.

The distance between neighbours is measured by Euclidean distance as it is frequently used in literature [24]. Other distance metrics such as Mahalanobis distance [25] or dynamic time warping [18], [26] are sometimes used but out of the scope of this work. Due to the fact that the search length d is dynamic, using Euclidean distance is not suitable for d -dimension vectors. Also, to avoid the curse of dimension problem [27], we treat the time domain as one dimension instead of d -dimension by averaging the distance values from all search steps. The distance between the missing data vector (1) and one neighbour (2) is defined as follows:

$$\hat{\mathbf{r}} \times \mathbf{w} = (\mathbf{r}_{D,t} - \mathbf{r}_{D,t-1}) \times \mathbf{w} \quad (4)$$

where $\hat{\mathbf{r}}$ is the vector of absolute values of element-wise subtraction of $\mathbf{r}_{D,t}$ and $\mathbf{r}_{D,t-1}$. The $\mathbf{w}$ is the vector of weights for each search lag and it is gap-sensitive and is defined as follows.

Firstly, the initial scores are calculated:

$$\begin{aligned} \mathbf{w}^* &= (w_1^*, w_2^*, \dots, w_d^*) \\ &= (1, 2, \dots, d-1, d, d-1, \dots, 2, 1) \end{aligned} \quad (5)$$

Those scores are given according to how far each element is differing from the missing data position in (1) or matching point position in (2). Later, the remaining values in $\mathbf{w}^*$ are normalized so that the sum of elements is 1.

$$\mathbf{w} = \frac{\mathbf{w}^*}{\sum_{i=1}^{2d} w_i^*} \quad (6)$$

It is worth mentioning that any values of missing positions in either vectors (1) or (2) are deleted from both vectors. If any element is deleted, both vectors should extend to include more values from further time points to keep the number of elements on both sides of the missing/matching point as d . This is because the missing data cannot be used to calculate distance.

B. Data Specification

The real world data is collected by the PeMS system traffic management centre in the Bay Area [28]. Each device sends one statistical record at five-minute intervals. Each record contains a timestamp and some statistical values such as the number of vehicles passed during the last five minutes, i.e. the flow rate. Part of the data from one monitoring device on the road is used, which is the public Dodgers dataset [29]. The time range of data is from April 2015 to October 2015.

Fig. 3. RMSE of proposed GSW-kNN and four benchmarking methods. GSW-kNN is not only more accurate but also more stable when missing ratio is high.

The original dataset contains MCR and MR missing values which are 5%. To test missing ratios higher than the original 5%, MCR missing values are added.

C. Experimental Setup

The experiments are conducted using Python programming language version 2.7 [30] for GSW and with the main package impute version 0.0.4 [31] for the general kNN method in Ubuntu 16.04 LTS. Other methods are conducted in R programming language version 3.3.3 [32] and the package imputets version 2.5 [33] in Window 10. For each missing ratio, 5% non-missing instances are selected randomly as test data and each of them is marked as missing during one experiment so that the influence the missing ratio is negligible. Best parameter configurations are used if needed.

The imputation accuracy is measured by root mean square error (RMSE), which is also known as root mean square deviation. RMSE is selected as it is frequently used in previous literature to measure imputation results so it is easier for readers to compare with previous work. Later, the imputation results are analyzed using cross comparison and eigenvalues.

IV. RESULTS AND ANALYSIS

This section describes benchmarking results among five methods, followed by more detailed comparison between two kNN based methods.

The RMSE comparison results of different methods are shown in Fig. 3. The missing ratio ranges from 5% to 90%. It is shown that RMSE values of GSW-kNN are the smallest compared to the other four methods. GSW-kNN performs 14% to 59% better than others and 34% better on average. Also, the RMSE values of GSW-kNN are very stable and the algorithm is robust. Except our proposed method, the general kNN method works better than the other three methods.

Fig. 4. RMSE and variation (standard deviation) of general kNN and GSW-kNN methods. GSW-kNN is more robust to high missing ratio.

Now we focus on the comparison of two kNN based methods. Fig. 4 shows the improvement of accuracy using our proposed method than the general kNN w.r.t. RMSE. GSW-kNN is 18% to 46% better when being compared to general kNN. The squares represent the mean values of RMSE for each missing ratio and the bars indicate standard deviation. As it is shown in Fig. 4, GSW-kNN is consistently better than general kNN. GSW-kNN has smaller RMSE on average and less variation (standard deviation), which means it works more stable from 5% to 90% missing ratio than the general kNN method.

The traffic data used in the experiments are distributed between 0 and 60. To understand more about how GSW-kNN performs in different ranges of the traffic, several flow ranges are selected, say, 0 to 10, 10 to 20, 20 to 30 and 30 to 40. 40 to 60 is not used due to very few data. In each range, 200 values are randomly selected. The improvement of RMSE from general kNN to the proposed GSW-kNN is shown in Fig. 5, indicating that in each of the four ranges, our proposed method performs better than general kNN with few exceptions. Especially, when the missing ratio is higher than 70%, the accuracy improvement given by GSW-kNN increased dramatically in all the four ranges. Among the four ranges, the improvement in the range 0 to 10 is the highest. The reason is possibly that night traffic is more consistent across different days compared to day-time traffic which exhibits large variations during holidays. Thus, the windowed algorithm can make more use of existing night-time data [21].

Fig. 6 and Fig. 7 show the cross comparison plots of the ground truth and the imputed data from the general kNN and our proposed method. The x-axis represents the ground truth values, and the y-axis represents imputed values. When the missing ratio is lower than 70%, the shapes of point distributions from two methods are similar with each other, as well as among different missing ratios within the same method. This indicates that the two methods are both working in a stable way when the missing ratio is not too high. To describe the distribution of the cross comparison points in detail, the eigenvalues and eigenvectors of each covariance matrix is computed using singular value decomposition (SVD) method. According to the definition of the eigenvalues computed by SVD, the first eigenvalue depicts the data value range of the distribution, and the second eigenvalue represents the accuracy

Fig. 5. The improvement of accuracy w.r.t. RMSE, when comparing GSW-kNN with general kNN. GSW-kNN imputation is performing better especially in traffic flow range 1 (night time traffic) with high missing ratio.

of the data imputation. It means that the smaller the second eigenvalue is, the more accurate the imputation is. If the distribution of points is similar to a diagonal straight line, the imputed values are similar to the ground truth values.

Fig. 8 shows the second eigen values of the covariance matrix between ground truth value and the imputed value by the method of GSW-kNN and general kNN. Its results are consistent with our previous results discussion. Our proposed method, GSW-kNN works very stable and better than general kNN.

Additionally, we also compared to PCA imputation from [34]. However, it cannot perform imputation for datasets with very high missing ratio, such as 80% and 90%, so it is not included in the plots. The available results indicate that PCA is about 8% to 10% less accurate on average compared to GSW-kNN.

V. CONCLUSION

This paper proposes GSW-kNN for traffic time series imputation. The method takes gaps caused by missing values into consideration via using weights during distance measurement and uses windows to broaden the amount of neighbours. The experiment results from the public PeMS dataset are showing that GSW-kNN performs 14% to 59% better than benchmarking methods and 34% better on average. It is also more robust even for datasets with high missing ratios.

There are some issues that should be considered when using GSW-kNN. Firstly, more traditional time series based algorithms can be compared or used as part of ensemble methods as ensemble strategies are showing promising performance improvements compared to a single model for a variety of tasks [35], [36]. Secondly, our work does not distinguish data

Fig. 6. The cross comparison between ground truth values and the imputed values by general kNN. Its performance drops suddenly when the missing ratio is higher than 70%.

Fig. 7. The cross comparison between ground truth values and the imputed values by GSW-kNN. The distribution of points is more similar to a diagonal straight line than general kNN, especially when the missing ratio is higher than 70%. Thus, GSW-kNN is more accurate.

Fig. 8. The second eigenvalues of the cross comparison between ground truth values and the imputed values by the method of general kNN and GSW-kNN. GSW-kNN is giving smaller the second eigenvalues, hence the better imputation.

under normal situation with data under events. We plan to investigate those tasks in future work.

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