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Root Cause Analysis of Traffic Anomalies Using Uneven Diffusion Model

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ABSTRACT Detection and analysis of traffic anomalies are important for the development of intelligent transportation systems. In particular, the root causes of traffic anomalies in road networks as well as their propagation and influence to the surrounding areas are highly meaningful. The root cause analysis of traffic anomalies aims to identify those road segments, where the traffic anomalies are detected by the traffic statuses significantly deviating from the usual condition and are originated due to incidents occurring in those roads such as traffic accidents or social events. The existing methods for traffic anomaly root cause analysis detect all traffic anomalies first and then apply, implicitly or explicitly, specified causal propagation rules to infer the root cause. However, these methods require reliable detection techniques to accurately identify all traffic anomalies and extensive domain knowledge of city traffic to specify plausible causal propagation rules in road networks. In contrast, this paper proposes an innovative and integrated root cause analysis method. The proposed method is featured by 1) defining a visible outlier index as the probabilistic indicator of traffic anomalies/disturbances and 2) automatically learning spatiotemporal causal relationship from historical data to build an uneven diffusion model for root cause analysis. The accuracy and effectiveness of the proposed method have been demonstrated by experiments conducted on a trajectory dataset with 2.5 billion location records of 27 266 taxies in Shenzhen city.

INDEX TERMS Root cause analysis, traffic anomalies, spatiotemporal causal relationship, visible outlier index, uneven diffusion model.

I. INTRODUCTION

Detection and analysis of traffic anomalies / disturbances are important for the development of intelligent transportation systems. In particular, the analysis of root cause is of great significance. It carries information about propagation of traffic disturbance in the surrounding parts of road networks, which can provide in-depth understanding of the traffic dynamics to the decision makers of transport department, and assist them to sharply grasp the key point, control situations, and benefit long-term planning for the further development. Recently, this problem has been studied in [1]–[5].

Most existing approaches are based on the analysis of detected anomalous links or regions. They typically comprise two steps. First, a certain method is used to detect traffic anomalies. Then the spatiotemporal interrelationships between the detected traffic anomalies are analyzed following implicitly or explicitly defined causal propagation rules to trace back to the road segment where the very original traffic anomaly occurs due to local incidents, such as traffic accidents or social events. However, there are shortcomings in both of the two steps which together undermine the effectiveness of root causal analysis.

The first step is to detect traffic anomalies. Unfortunately, no method can accurately detect all traffic anomalies since traffic anomaly detection is a probabilistic problem. The traffic situation in a road segment (or in a region) is considered anomalous if a traffic indicator, such as traffic flow (i.e., the number of vehicles passing per time unit) or average traffic speed, deviates from the normal value in history. A threshold is required to determine whether the deviation is significant or not. In the second step, existing methods require implicit or explicit rules of causal propagation between traffic anomalies in road networks. However, no universal rule can be applied in all situations due to the inhomogeneity of traffic on different road segments and time periods. For example, some road segments have a large amount of traffic flow while other road segments have a small amount of traffic flow; a traffic anomaly may influence one nearby road much more significant than other nearby road segments in the morning but not in the afternoon. To understand the differences, extensive domain knowledge of both road networks and traffic on them across the entire city is required.

To overcome these shortcomings, we propose an innovative and integrated root cause analysis of traffic anomalies method. First, we define a *Visible Outlier Index* (VOI) which represents the possibility of the traffic anomaly occurring in a road segment (or in a region) at a certain time bin. And then the expected VOI in each region at the current time bin is estimated using the VOIs of its neighborhoods and itself in the past time bin using an *Uneven Diffusion Model*, which learns the causal propagation of traffic anomalies in road networks from historical data. By comparing the expected VOI and the true VOI observed, if the difference is notable, the traffic anomaly originated by local incidents such as traffic accidents or social events can be identified. The original traffic anomaly may propagate to surrounding parts of road networks and cause more traffic anomalies such that they are called root cause. The contribution of this paper is three-folds:

- We propose an innovative and integrated solution of root cause analysis of traffic anomalies in road networks which overcomes the shortcomings of current state-of-the-art methods. The effectiveness of proposed solution has been verified by experiments using a trajectory dataset with 2.5 billions location records of 27,266 taxis.
- We measure the traffic anomaly using a new probabilistic metric, VOI, instead of detecting all traffic anomalies as the first step of causal analysis. It reduces the uncertainty introduced during traffic anomaly detection.
- We use the deep learning architecture model with *Stacked AutoEncoder* (SAE) to automatically learn spatiotemporal causal relationship, based on which an uneven diffusion model is built for analysis of traffic anomalies in different regions at different time periods. As a result, the requirement of extensive domain knowledge of road networks can be minimized.

The rest of the paper is organized as follows. In Section II, we present the related work. The probabilistic indicator of traffic anomaly is defined in Section III, the Uneven Diffusion Model is proposed in Section IV, and the root cause identification is discussed in V. Then, Section VI demonstrates the effectiveness of the proposed method by experimental results. Finally, this paper is concluded in Section VII.

II. RELATED WORK

Mining causal relationship of traffic anomalies has attracted widespread attention. The existing studies identify the traffic anomalies first, and then infer the root cause following the implicitly or explicitly specified causal propagation rules.

A. SPATIOTEMPORAL CAUSAL RELATIONSHIP

Xing *et al.* [4] construct *directed acyclic graph* (DAG) which explores spatial-temporal density to reveal the outlier causal relationship of traffic anomalies. Liu *et al.* [3] propose outlier causality trees with attempt to capture the relationships between spatiotemporal outliers detected. Pang *et al.* [5] have proved that Likelihood Ratio Text based solution is effective in spatiotemporal outlier detection. But it requires complex parameter determination process which is tailored to different types of traffic anomalies and highly depend on informed dataset. In [3]–[5], the prerequisite is that the traffic anomalies have been detected by identifying behaviors deviating from regular patterns; and the propagation rules of traffic anomalies have been well defined based on domain knowledge of traffic across the city. In particular, the propagation rules must be spatiotemporally continuous, otherwise, these methods fail to infer the root cause.

Chawla *et al.* [1] infer the origin-destination routes which cause the anomalous links observed between regions. Here, a route consists of a sequence of links while links connect regions directly. In the first step, the principle component analysis (PCA) has been applied to detect anomalous links connecting regions based on their historical pattern. Then, a link-route matrix is created, where the detected anomalous links haven been represented, finally the optimized $L1$ technique is used to infer the routes causing the link anomalies. Note that this problem is very different from our problem of identifying the links/regions where the root cause of the detected anomalies occurs, other than origin-destination routes. Subsequently, the methods developed in [1] cannot resolve our problem.

B. HEAT DIFFUSION MODEL

The work most related to this study finds the major anomaly causes based on heat diffusion model [2]. Traffic anomalies are assumed to be like heat sources, which propagate energy to surrounding parts in road networks. Initially, the traffic anomalies are detected. It assumes that the traffic flow distribution of any road segment is normal. Given a road segment, the mean of traffic flows is obtained using historical data and an anomaly is detected if the observed traffic flow at a time bin deviates from the mean significantly. Then, the traffic anomalies as the heat sources spread energy to nearby road segments and decay progressively.

By capturing how a road segment is influenced by the spreading energy from all neighboring road segments and itself in the current time period, a model has been proposed to predict the expected traffic flow of the road segment in the next time period. If the observed traffic flow in the next time period deviates a lot from the expected, there is a *major anomaly cause* in this road segment; otherwise, no major anomaly cause is reported even though the observed traffic flow deviates from its mean significantly. This method borrows the idea of heat diffusion in thermal physics to model the causal propagation of traffic anomalies in road networks.

However, the heat diffusion model assumes the uniform diffusion of energy to the periphery. In fact, the distribution of the traffic flow in road networks is uneven. This can be explained by a large amount of traffic flow on some road segments and a small amount of traffic flow on other road segments. Also, a traffic anomaly can influence one nearby road segment much more significant than other nearby road segments. Therefore, simply using the heat diffusion model to infer the root cause of traffic anomalies is theoretically inaccurate. Not to mention the uncertainty introduced by the results obtained from anomaly detection stages.

C. DISCUSSIONS

For the first step in the existing methods, the traffic anomalies are detected. However, no method can accurately detect all traffic anomalies since it is a probabilistic problem. For the second step in existing methods, the causal propagation rules are specified, implicitly or explicitly. However, no universal rule can be applied in all situations due to the inhomogeneity of traffic on different road segments. Even though domain knowledge of traffic in city road networks helps solve the problem, it is hard to completely obtain and maintain such domain knowledge due to the scale and dynamic nature of city road networks.

In this paper, we have the following improvement. First, we introduce the probability-based traffic anomaly indicator called visible outlier index (VOI) for each road segment to measure traffic anomaly at a specifical time bin instead of detecting all traffic anomalies directly. Second, an uneven diffusion model based on spatiotemporal neighborhoods are applied to automatically learn causal propagation rules from historical data instead of manually defined by domain experts. The proposed method takes into account the comprehensive effect of both spatial and temporal domain on the observed region, and minimizes errors introduced by detection methods or human factors. In theory, it has the ability to dig into the root causes of traffic anomalies more accurately.

III. PROBABILITY-BASED TRAFFIC ANOMALY INDICATORS

The trajectory of a vehicle is a sequence of location records continuously captured by the GPS devices equipped on the vehicle. A location record is represented as $<lon, lat, timestamp, speed>$, where (*lon*, *lat*) and *speed* are longitude, latitude and speed of the vehicle at time *timestamp*. In order to gain insight into the traffic dynamics of the whole city, we partition the road networks by dividing the city area into small and uniform regions. For example, if we select lon=0.005 and lat=0.004 as a criterion to divide, each region represents an approximate $500m \times 500m$ region. In temporal dimension, each hour is divided into uniform time bins where each bin spans δ mins (e.g., 5 mins or 20 mins). For each spatiotemporal partition, the traffic condition can be extracted using the trajectory data falling in the partition.

There are different ways of partition in the context of specific applications, for example, partition by road links [2], or by dividing city areas using main road segments [5], or using road network Voronoi diagram [6]. Note the city area partition method and the time bin span are independent of the root cause analysis proposed in this study. That is, the proposed solution works no matter how the road networks are partitioned.

The traffic situation can be measured using different indices such as traffic flow or average traffic speed. In a region at a time bin, if the value of traffic indicator significantly deviates from the regular value in the same region at the same time bin, a traffic anomaly is reported [1]–[5]. However, these indices are not considered to depict traffic situation accurately since traffic flow and average traffic speed are aggregated information. We need a more accurate indicator in this study to describe the nuances of traffic situations. To this end, we measure the traffic speed distribution, i.e., the distribution of individual vehicles in different speed ranges. For example, 30% vehicles are in the speed range of 40-50km/h, 40% vehicles in the range of 50-60km/h, and 30% vehicles are in the range of 60-70km/h. Given a region at a time bin, the speed distribution in different days should be similar if the traffic situation is normal. If the speed distribution in a particular day differs from the distribution in most other days, it indicates traffic anomaly.

To measure traffic situation based on speed distribution, the two-sample Kolmogorov-Smirnov test (KS-test) is applied in this study. In statistics, KS-test is a nonparametric test of the similarity of continuous, one dimensional probability distributions. KS-test can be used to compare a sample with a reference probability distribution. The distance between the empirical distribution function of the sample and the cumulative distribution function of the reference is quantified by the KS statistic, which determines whether the sample is from the reference distribution. This feature of KS-test can help us quantify the extent of a traffic anomaly that happens in a specified spatiotemporal space. Specifically, given the speed distribution extracted from trajectory data across all days as the reference distribution and the speed distribution extracted from trajectory data in a particular day as the empirical distribution, their mismatch of KS-test is calculated.

In KS statistics, the empirical distribution function F_n for n samples and identically distributed observations X_i is defined as:

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} I_{[-\infty,x]}(X_i) \tag{1}$$

where $I_{[-\infty,x]}(X_i)$ is the indicator function, equal to 1 if $X_i \leq x$ and equal to 0 otherwise. When the two-sample KS-test is used in the latter case, the KS-statistic is:

$$D_{n,m} = max \left|F_{e,n}(x) - F_{r,m}(x)\right| \tag{2}$$

where $F_{e,n}$ and $F_{r,m}$ are the empirical distribution functions of the sample in a particular day and the reference distribution of the data across all days respectively, n and m are the sizes of the sample and the data across all days respectively. The null hypothesis is that the sample is drawn from the reference distribution. The null hypothesis is rejected at significance level α if

$$D_{n,m} > c(\alpha)\sqrt{\frac{n+m}{nm}}. \tag{3}$$

where the value of $c(\alpha)$ is given by table of critical values for the two-sample test.[1]

In context of this paper, in a region A at time bin t of a particular day d, the traffic data are extracted from trajectories of taxis and they are viewed as a sample. For the same spatiotemporal partition in all different days, the speeds of all vehicles together form the reference distribution in the partition. If the null hypothesis is rejected, it means traffic anomaly happens in a region A at time bin t of a particular day d; otherwise, traffic is in the normal situation.

According to KS-test, the hypothesis test calculates value-asymptotic p_{value}, the probability of observing a test statistic as extreme as, or more extreme than, the observed value under the null hypothesis. Comparing p_{value} with a significance level α, if p_{value} is less than the significance level α, we can reject the null hypothesis; otherwise, accept it. Instead of specifying the significance level α, we define a new concept known as *visible outlier index* to indicate how likely a traffic anomaly happens.

Definition 1 (Visible Outlier Index (VOI)):

$$VOI = |log(p_{value})|\,. \tag{4}$$

Note that VOI is the rescaled p_{value}. The value of p_{value} is in the range of [0,1] and the value of VOI is in the range of [0,∞]. Changing the scale is for the following reason. Only when p_{value} is very close to 0 (typically [0, 0.05]), it is regarded as an unusual situation. So, the difference between p_{value}s when they are very closer to 0 is particularly important and will be used in the following processing. After rescaling, VOI can properly capture any change in this range.

IV. UNEVEN DIFFUSION MODEL

In this section, we propose an uneven diffusion model which can be trained in advance using historical data to learn the propagation relationship of traffic disturbances between the target region and the surrounding parts in road networks. Then, the model can be used to predict the traffic situation of the target region at the next time bins.

A. TRAFFIC SPATIOTEMPORAL NEIGHBORHOODS

Through road networks in a city, it takes time for a vehicle to move from a region to a neighboring region. Likewise, a traffic disturbance in one region propagates progressively and eventually causes other traffic disturbances in nearby regions after a period of time. So, a concept called *traffic spatiotemporal neighborhoods* is introduced to represent the regions covered.

Definition 2 (Traffic Spatiotemporal Neighborhoods): Given a road segment A in road networks, A's traffic spatiotemporal neighborhoods at time bin t are all regions from which vehicles in one time bin can reach A by driving through road networks in time bin $t-1$.

[1] http://sparky.rice.edu/astr360/kstest.pdf

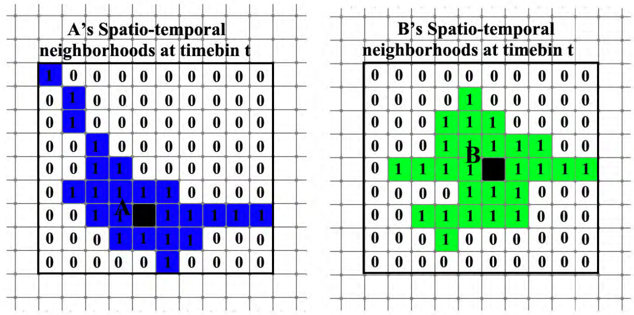

FIGURE 1. An example of traffic spatiotemporal neighborhoods.

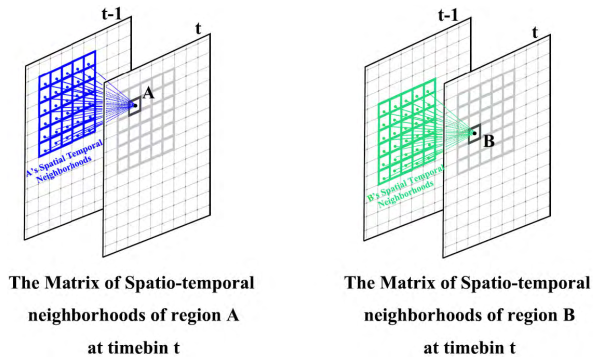

FIGURE 2. The matrix of spatiotemporal neighborhoods as the input of the uneven diffusion model.

Note the traffic spatiotemporal neighborhoods of region A include region A itself. An example of traffic spatiotemporal neighborhoods is illustrated in the Fig. 1. For region A at time bin t, its traffic spatiotemporal neighborhoods are marked in blue. For region B at time bin t, its spatiotemporal neighborhoods is marked in green. If the traffic situations in region A's traffic spatiotemporal neighborhoods in the past time bin $t-1$ are known, the traffic situation of region A in time bin t should be able to be predicted accurately if no incident like traffic accident happens in region A in time bin t, so does region B.

For the same region, the propagation pattern of traffic disturbances from traffic spatiotemporal neighborhoods is considered relatively stable. So, training the Uneven Diffusion Model using historical data is possible to learn the propagation pattern from spatiotemporal neighborhoods. An example is illustrated in Fig. 2. Given a region A at a time bin t, the traffic disturbances of A's *traffic spatiotemporal neighborhoods* at time bin $t-1$ are represented as $VOIs(R_A, t-1)$. The value of VOI in one neighboring region is greater, the greater the traffic disturbances and thus more impact to region A. Let the traffic disturbance of region A at time bin t be $VOI(A, t)$. The Uneven Diffusion Model can be used to predict $VOI(A, t)$ using $VOIs(R_A, t-1)$.

$$VOI(A, t) = D(VOIs(R_A, t-1)) \tag{5}$$

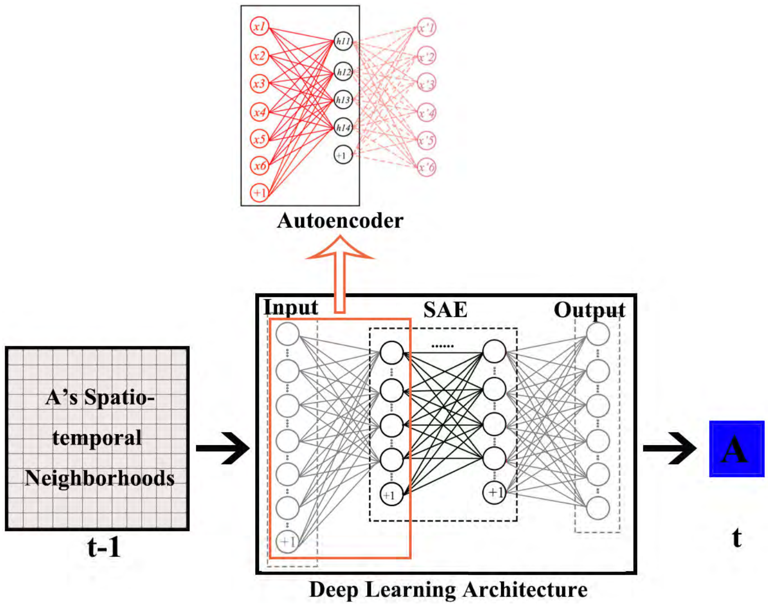

FIGURE 3. Training uneven diffusion model for region A.

Clearly, for different regions, the propagation patterns of traffic disturbances from their traffic spatiotemporal neighborhoods are intrinsically different because the underlying road networks in different regions have different topology. For region B as shown Fig. 1, the traffic disturbance of region B at time bin t is represented by $VOI(B, t)$ which can be estimated by traffic disturbances of its traffic spatiotemporal neighborhoods, i.e., $VOIs(R_B, t-1)$. Note that it requires to train a different Uneven diffusion Model for region B.

B. DEEP LEARNING ARCHITECTURE

For region A, we learn the traffic disturbance propagation pattern in road networks using the Uneven Diffusion Model so as to predict VOI of region A at the next time bin. A deep learning network is adopted. Actually, there are varieties of traffic prediction approaches that have been proposed, including traffic status prediction (e.g. traffic flow [7]–[9], traffic speed [10], [11]), anomaly relevant information prediction [12], [13] and anomalous level prediction [17]. In these studies, the advantage of *Neural Network* and *Deep Learning* have been acknowledged in prediction performance.

Deep learning is a multilayer neural network and abstracts the input data into a series of feature data (hidden layers) and then maps to the specified output. It typically uses unsupervised or semi-supervised feature learning and hierarchical feature extraction algorithm to obtain the relationship between input and corresponding output. The major improvement of the deep network comprises the following stages. Hinton *et al.* [14] proposed a greedy learning algorithm for *Deep Belief Networks* (DBN) in 2006. A classical DBN consists of several RBM (Restricted Boltzmann Machines) layer and a BP (Back Propagation) layer. Bengio *et al.* [15] developed an unsupervised pre-training algorithm and *Stacked Auto-Encoder* (SAE) model which uses auto-encoder instead of RBM as a layer building block for deep networks. They have also proved its effectiveness. In this paper, we use the deep learning architecture with SAE to build the Uneven Diffusion Model illustrated in Fig. 3. Inputs of the model are the VOIs of traffic spatiotemporal neighborhoods at the previous time bin, and outputs of the model are the VIO of the target region at current time bin.

1) STACKED AUTO-ENCODER (SAE)

SAE is a stack of autoencoders and it is the important components of the model. An autoencoder is a network structure which usually has one input layer, one hidden layer and one output layer as shown in Fig. 3 (marked in red). For example, there is a sample $X = x_1, x_2, x_3, \cdots, x_n$. First, X as input maps to a hidden representation H according to Eq. (6). This process is known as encoder procedure.

$$H = f(W_1X + b_1) \tag{6}$$

where W_1 is a weight matrix and b_1 is an encoding bias vector. We consider function $f(x)$ as logistic sigmoid function (i.e., $\frac{1}{1+exp(-x)}$). And then, H is used to reconstruct X' according to Eq. (7),

$$X' = g(W_2H + b_2) \tag{7}$$

where W_2 is decoding weight matrix and b_2 is decoding bias vector. This process is called *decoder* procedure. The model parameters can be obtained by minimizing reconstruction error between X and X' (such as sum of squared errors). In fact, only some of the parameters of autocoders are used in the SAE model (marked in red rectangle in Fig. 3), i.e., W_1, b_1

and b_2. That is, the output of the previous layer of autoencoder is used as the input of the next layer of autoencoder.

2) TRAINING ALGORITHM

As shown in Fig. 3, the training process of the model is essential. The implicit relationship between the target region and its spatiotemporal neighborhoods can be captured. The VOIs of spatiotemporal neighborhoods at the previous time bin is the input while the VOI of the corresponding region at the current time bin is the output. At the output of the deep learning architecture, *Back Propagation* (BP) is adapted to adjust the error in order to optimize training. BP is a multi-layer perceptron proposed by Rumelhart *et al.* [16] and can learn any complex function. The greedy learning algorithm proposed by Hinton *et al.* [14], and the unsupervised pre-training algorithm and the SAE mode developed by Bengio *et al.* [15] make deep networks more efficient after pre-training the network layer in a bottom-up way. The training procedure is as follows:

(1) Train the first layer in SAE as an autoencoder according to Eq. (6) and Eq. (7) by minimizing the reconstruction error using the input data;

(2) Train each of the following layers in SAE as an autoencoder in order, where the output of the previous layer is the input of the next layer;

(3) Feed the output of the last layer in SAE as the input of a predictor;

(4) Initialize the deep network using the weights obtained by training each layer separately, and then fine-tune the parameters of the entire network in a supervised way.

V. ROOT CAUSE ANALYSIS

Given region A at time bin t, the root cause analysis aims to report whether there are traffic anomalies due to occurrence of significant traffic disturbance in region A at time bin t. Note that the originated traffic disturbance can be the consequence of any irruptive city incidents like traffic accident or social events. Identifying the types and characters of such city incidents behind traffic disturbance is an interesting topic which requires analyzing additional information such as social media and local news. But this is out of the scope of this study.

For each region, its Uneven Diffusion Model has been trained before being used for prediction. The VOI at time bin t can be estimated by using VOIs of its spatiotemporal neighborhoods at time bin $t-1$ as inputs of the uneven diffusion model. If the predicted VOI in A is similar to the truly observed VOI in A at time bin t, there is no root cause of traffic anomaly in region A at time bin t. It indicates one of the two situations: (i) the traffic situation of A is normal, or (ii) the traffic disturbance happens in A but it is caused by the traffic disturbances of spatiotemporal neighborhoods. On the other hand, if the predicated VOI in A is significantly less than the truly observed VOI in A at time bin t, it indicates

Algorithm 1 Finding Root Causes of Traffic Anomalies for Region r During (T_{min}, T_{max})

Input: significant threshold α, region r.
Output: A set of root causes RC.
Initial RC;
$\Delta t \rightarrow 5$ mins ;
$t \leftarrow T_{min} + \Delta t$;
$STN_r \rightarrow$ r's spatiotemporal neighborhoods ;
if $D(r)$ *is not trained* **then**
  training $D(r)$;
else
  while $t < T_{max}$ **do**
    $RVOI_{r,t} \rightarrow VOI(r, t)$;
    $PVOI_{r,t} \rightarrow D(VOIs(STN_r, t - \Delta t))$ Eq. (5);
    if $(RVOI_{r,t} - PVOI_{r,t}) > \alpha$ **then**
      $RC \rightarrow RC \cup (r, t)$;
    end
    $t = t + \Delta t$;
  end
end

that traffic disturbance of noticeable level is originated in A at time bin t. The detail is shown in Algorithm 1. The significant threshold α can be defined by users according to different aims. Such originated traffic disturbance may propagate to surrounding regions in the following time bins and thus it is the root cause of traffic disturbances. The root cause analysis sorts regions in descending order in terms of the difference between the predicated VOI and the truly observed VOI. The regions with higher difference deserve more attention. Using the output of the root cause analysis, further analysis tasks can be performed such as the frequent patterns detection, the relation between the time of a day and the occurrence of originated traffic disturbance, and the propagation direction and path of traffic disturbance in road networks.

An example is shown in Fig. 4 and Fig. 5, where the regions are marked in different colors to represent the VOIs in corresponding regions. In Fig. 4, the predicted VOIs of regions at time bin t are shown using the trained Uneven Diffusion Model based on the VOIs of their traffic spatiotemporal neighborhoods. In Fig. 5, the truly observed VOIs of regions at time bin t are presented.

Note that the truly observed VOIs of both region A and B are high as shown in Fig. 5. It means region A has a significant traffic disturbance, so does region B. Comparing the predicted VOI and the truly observed VOI in region A, the difference is trivial, it means the disturbance of region A is mainly due to the traffic disturbances from traffic spatiotemporal neighborhoods at time bin $t-1$. In contrast, comparing the predicted VOI and the truly observed VOI in region B, the difference is significant. It means the traffic disturbance is mainly originated in region B at time bin t. Compared with region B, the predicted VOI and the truly observed VOI in

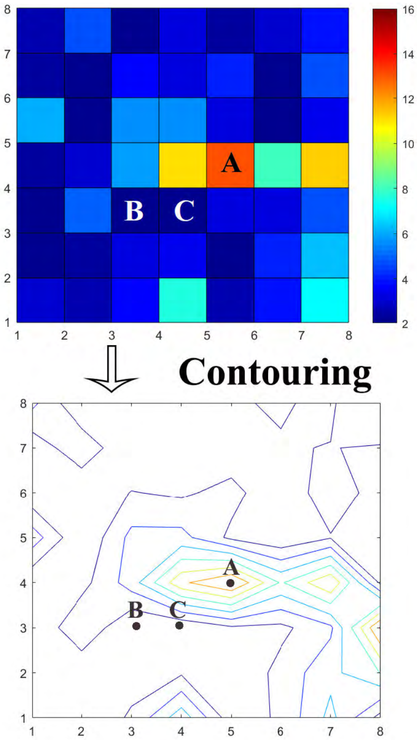

FIGURE 4. Predicted VOIs at time bin t.

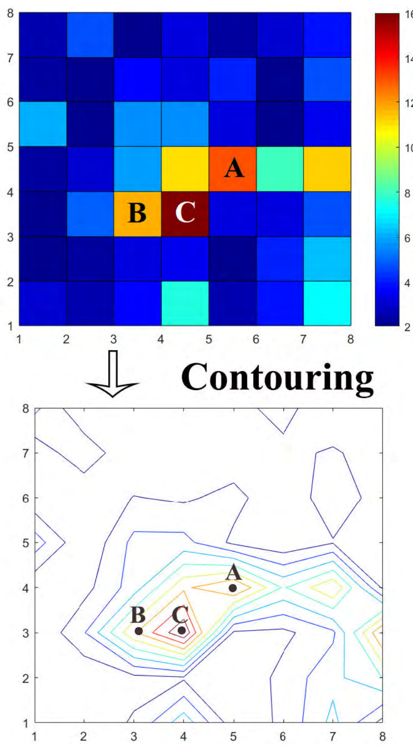

FIGURE 5. Truly observed VOIs at time bin t.

region C differs much more significantly. It reveals that more significant traffic disturbance is originated in region C at time bin t.

In addition to the distribution of VOIs in city, the contour of traffic disturbance is generated as shown in Fig. 4 and Fig. 5 by connecting neighboring regions with the equal value. The contours give a better understanding how traffic disturbances diffuse to surrounding regions smoothly.

It is worthy to point out that, to understand what have happened in the road segments in region C and region B, it is straightforward to partition road networks by road segments instead of regions. Also, the time bin can be split into finer granularity. The same methodology can be applied without any adaption to detect the road segment and the time bin where traffic disturbance is originated.

VI. EXPERIMENTAL STUDY

All experiments have been conducted on a PC with 64-bit Windows 7, 8GB RAM and Intel CPU $i7-4790$ @ 3.60GHz. The algorithms are implemented by Matlab and Python. We use a real-world trajectory data set with total of 2.5 billion data points from 27, 266 taxis during 1/12/2014 – 31/12/2014 in Shenzhen City, China. Each trajectory data point is sampled every $15-30$ seconds. In the experiment, the time is partitioned uniformly into 12 time bins per hour with 5 mins each. The geographical area of Shenzhen City studied in this paper is $[113.75'E - 114.64'E]$ and $[22.44'N - 22.85'N]$. We divide the city area into 42×90 regions of equal size where each region spans 0.01 in latitude and 0.01 in longitude. For every region at every time bin, the location records are extracted from trajectory data and the VOI is computed according to Eq. (4). Among all regions and time bins, 80% are selected as the training data set of Uneven Diffusion Model, and remaining 20% as the testing data set.

A. PERFORMANCE EVALUATION

In this section, we test the performance of the proposed Uneven Diffusion Model, i.e., SAE+BP. by comparing with other three models: (i) SdAE model which is proposed in [17] using Stack denoise Autoencoder to form a deep architecture, (ii) Back-propagation Neural Network (BP NN) which is a classic neural network model and is developed in [16], and (iii) SAE+LR model which is a SAE network with a logistic regression layer on top of the network [18]. The performance metrics are *mean absolute error* (MAE), *mean relative error* (MRE) and *root mean square error* (RMSE) which are defined below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y_i}| \tag{8}$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \widehat{y_i}|}{y_i} \tag{9}$$

$$RMSE = (\frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \widehat{y_i}|^2}{y_i})^{\frac{1}{2}} \tag{10}$$

1) VOI PREDICTION

The test results are presented in Table 1. It is clear that SAE+BP outperforms other models in all three metrics. Although BP NN is generally an effective learning model,

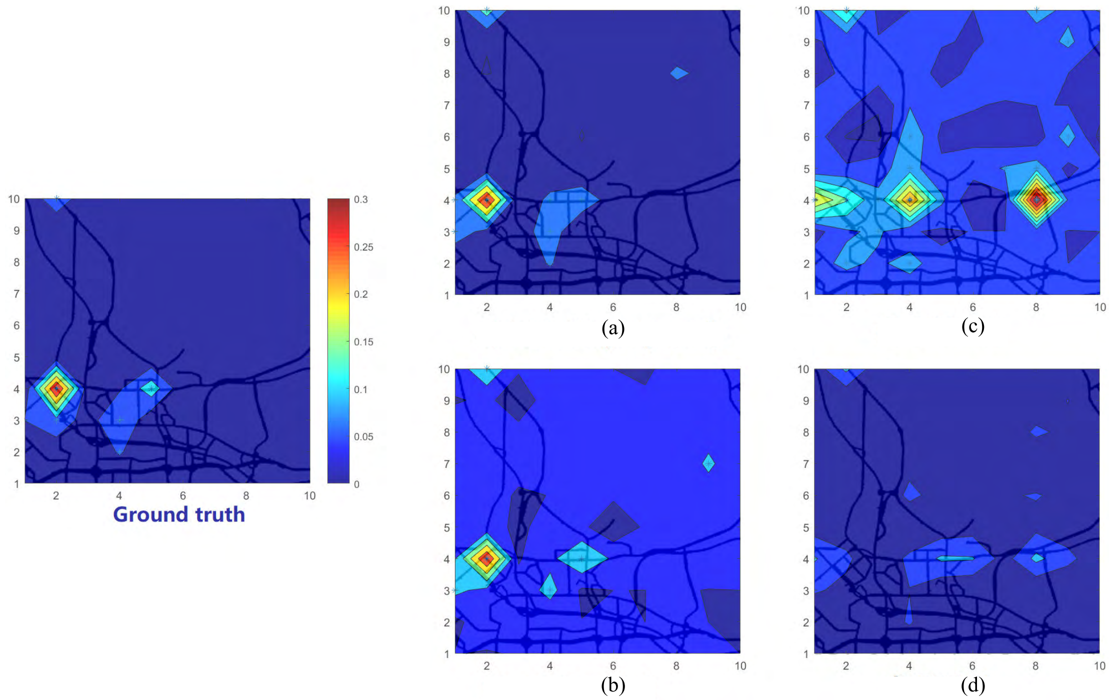

FIGURE 6. **Predicted VOIs in one area of Shenzheng city. a) SAE+BP (proposed). b) SdAE model. c) SAE+LR. d) BP NN.**

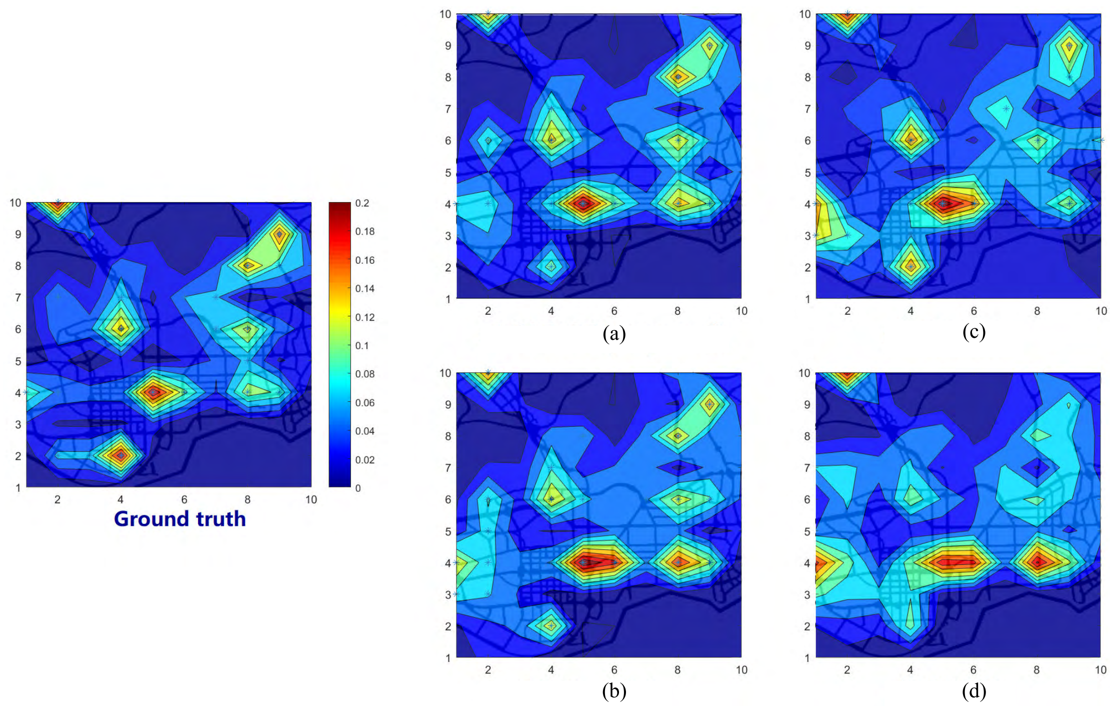

FIGURE 7. **Predicted VOIs in another area of Shenzhen city. a) SAE+BP (proposed). b) SdAE model. c) SAE+LR. d) BP NN.**

there is a relatively high prediction error. Compared to other models, BP NN has the worst performance. SAE+LR uses SAE network plus a logistic regression layer. It is slightly better than BP NN, but not as good as SdAE which uses stacked denoise autoencoder to form deep networks. Denoise autoencoder is characterized by filtering values of some layers by a certain probability.

In Fig. 6 and 7, the contour contrastive diagram of VOI predicted using different models (SdAE, BP NN, SAE+LR and SAE+BP) for a small region in Shenzheng City and

TABLE 1. Predicted values.

	MAE	MRE	RMSE
SAE+BP	**0.0273**	**3.7406**	**0.0470**
SdAE model [17]	0.0315	4.2172	0.0499
SAE+LR [18]	0.0399	5.0566	0.0712
BP NN [16]	0.0417	6.5072	0.0622

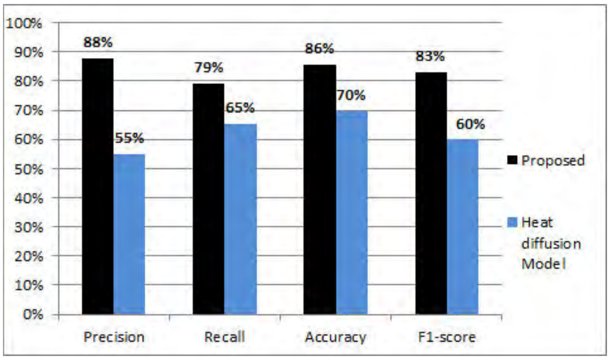

FIGURE 8. Comparison with heat diffusion model [2].

the ground truth are illustrated respectively. We can observe that the predicted VOIs using SAE+BP model are almost the same as the ground truth. It is followed by SdAE where minor errors occur. While many disturbances can be predicted by SAE+LR, there are many false reports. BP NN has the worst performance.

2) COMPARE HEAT DIFFUSION MODEL

We compare our Uneven Diffusion Model with the *heat diffusion model* [2] which is the most relevant study to this work. To be fair in comparison, the traffic anomaly detection in [2] is skipped over since parameter settings in the detection may lead to different set of traffic anomalies (see Section II-B). That is, both Uneven Diffusion Model and the heat diffusion model use VOIs observed a time bin to predict the VOI at the next time bin; and compare the predicted VOI against the truly observed VOI to figure out where the originated traffic disturbances occurs.

For this test, we manually identify 100 regions where originated traffic disturbances happened as the ground truth. The evaluation metrics include *precision*, *recall*, *accuracy* and *F1-score*. The test results are shown in Fig. 8. It is unsurprised that Uneven Diffusion Model dominates the heat diffusion model. While Uneven Diffusion Model learns traffic disturbance propagation from historical data to fit the situations in different locations and orientations in road network, the heat diffusion model directly applies uniform propagation pattern everywhere across the city.

B. CASE STUDY

Three scenarios have been closely investigated on 07/12/2014 in Shenzheng City which is the day of Shenzhen International Marathon. Shenzhen International Marathon is held at Shennan Road in Shenzhen City at $8:00-14:00$. As a massive event, it impacts the city traffic widely and significantly due to temporal road controls in many parts of the city. That is, we can observe many significant traffic disturbances and they are mainly caused due to the road controls. Using the case studies, the proposed root cause analysis solution are tested to report where significant traffic disturbances are originated.

1) SCENARIO ONE

The first scenario is in time bin $08:00-08:05$ of the day. As shown in Fig. 9, the red dots indicate the starting/ending locations of the Marathon, i.e., Shenzhen City Civic Center. The red line with arrows indicates the Marathon route and direction to the Return point, i.e., Nantou Middle School. Fig. 9 shows two regions with traffic disturbances originated in time bin $08:00-08:05$ which are marked with two white circles and denoted as *Cause*. The discovery can be well justified.

The two regions are next to the starting location of the Marathon. The traffic control around this area begins before $08:00$ and remains after $08:00$. This naturally causes unexpected traffic disturbances. Meanwhile, we can observe other areas along the Marathon route mainly do not have

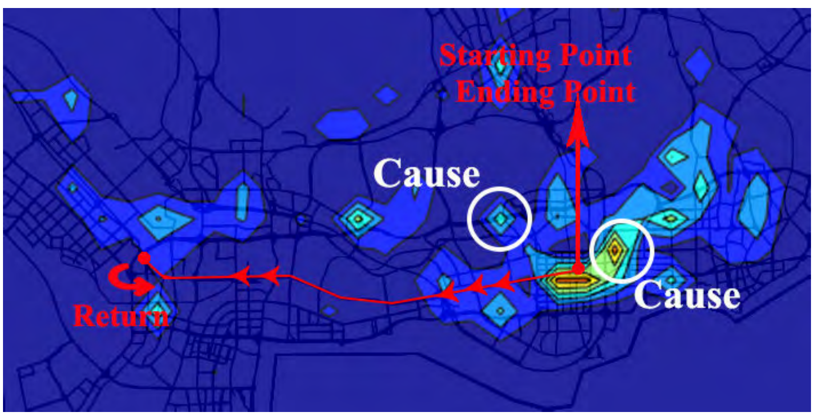

FIGURE 9. Scenario 1: Causality analysis for traffic disturbance at 8:05 a.m. on 07/12/2014.

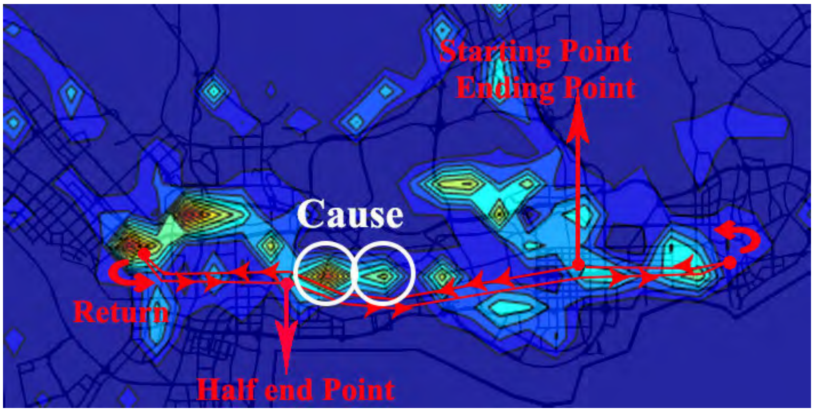

FIGURE 10. Scenario 2: Causality analysis for traffic disturbance at 9:10 a.m. on 07/12/2014.

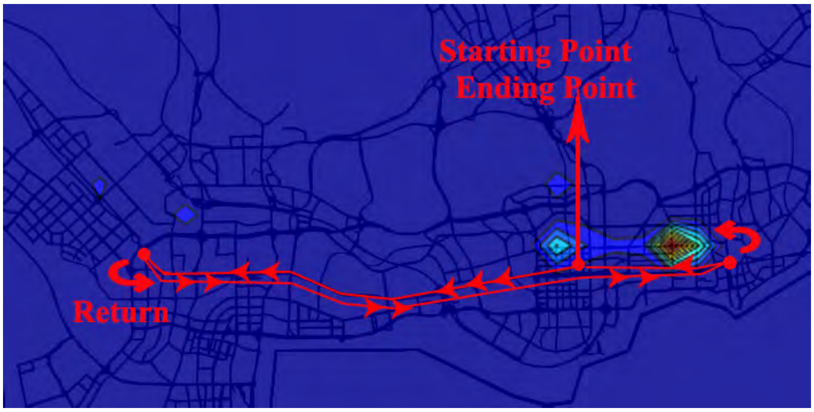

FIGURE 11. Scenario 3: Causality analysis for traffic disturbance at 11:00 a.m. on 07/12/2014.

traffic disturbance originated locally. This situation can be justified by the sectional traffic control, i.e., the roads are closed only when the runners are close.

2) SCENARIO TWO

The second scenario is in time bin $09:05-09:10$ of the day. As shown in Fig. 10, two regions with traffic disturbances originated by local incidents have been identified in the time bin. Similarly, they are marked with white circles. At the same time, we notice that there are more other traffic disturbances compared to the situation in time bin $08:00-08:05$ as shown in Fig. 9, but they are not originated by local incidents in time bin $09:05-09:10$. Instead, they are the consequence of traffic disturbances of spatiotemporal neighborhoods in the past time bin. This can be well justified by the actual situation where most marathoners in $09:05-09:10$ were close to the Return point after running one hour. Around these areas, traffic control applied and audiences aggregated originate new traffic disturbances.

3) SCENARIO THREE

The third scenario is in time bin $10:55-11:00$ of the day. Fig. 11 shows few traffic disturbance has been identified and no new traffic disturbance originated by local incidents. If we look closely, in the half of the Marathon in time bin $10:55-11:00$, most traffic controls have been released. In particular, the day 07/12/2014 is Sunday. The traffic in almost all areas comes back to regular situations. Only few traffic disturbances can be observed around the ending point, but they are not new.

VII. CONCLUSIONS AND FUTURE WORK

Understanding root cause of traffic disturbance in a city is a significant problem because it provides the knowledge of traffic dynamics to the decision makers of transport department, and assist them to sharply grasp the key point, control situations, and benefit long-term planning for the further development. By getting over the shortcomings of the state-of-the-arts, this study has provided innovative solutions to represent the traffic disturbance instead of identifying traffic anomalies and propose Uneven Diffusion Model to learn traffic disturbance propagation rules from historical data. The robustness of the solutions have been verified by extensive testing on a large real-world dataset and case studies.

Along this line of study, more analysis tasks can be performed using the output of the root cause analysis, such as the frequent pattern detection, the relation between the time of a day and the occurrence of originated traffic disturbance, and the propagation direction and path of traffic disturbance in road networks. More interesting, the originated traffic disturbance can be the consequence of any irruptive city incidents like traffic accidents or social events. Identifying the types and characters of such city incidents behind traffic disturbances is an interesting topic, which requires analyzing additional information such as social media and local news.

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