Supervised-CityProphet: Towards Accurate Anomalous Crowd Prediction

Soto Anno
Tokyo Institute of Technology
Tokyo, Japan
anno@miubiq.cs.titech.ac.jp

Kota Tsubouchi
Yahoo Japan Corporation
Tokyo, Japan
ktsubouc@yahoo-corp.jp

Masamichi Shimosaka
Tokyo Institute of Technology
Tokyo, Japan
simosaka@miubiq.cs.titech.ac.jp

ABSTRACT

Forecasting anomalies in urban areas is of great importance for the safety of people. In this paper, we propose Supervised-CityProphet (SCP), an anomaly score matching-based method towards accurate prediction of anomalous crowds. We re-formulate CityProphet as a regression model via data source association with mobility logs and transit search logs to leverage user's schedules and the actual number of visitors. We evaluate Supervised-CityProphet using the datasets of real mobility and transit search logs. Experimental results show that Supervised-CityProphet can predict anomalous crowds 1 week in advance more accurately than baselines.

CCS CONCEPTS

• **Information systems** → *Information systems applications*; • **Human-centered computing** → *Empirical studies in ubiquitous and mobile computing*;

KEYWORDS

Anomaly Prediction, Mobility Logs, Transit Search Logs, Urban Computing

ACM Reference Format:
Soto Anno, Kota Tsubouchi, and Masamichi Shimosaka. 2020. Supervised-CityProphet: Towards Accurate Anomalous Crowd Prediction . In *28th International Conference on Advances in Geographic Information Systems (SIGSPATIAL '20), November 3–6, 2020, Seattle, WA, USA.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3397536.3422219

1 INTRODUCTION

Crowd control by predicting anomalous urban congestion is a crucial topic for people's safety at various events, such as concerts, fireworks, or sports games. Such events attract many people and often cause unforeseen accidents due to unexpected anomalous crowds. For instance, the Akashi fireworks festival in 2001 caused the death of 11 people death and 247 serious injuries as people rushed and collapsed at the pedestrian bridge. To control such unexpected congestions and to ensure safety of visitors, predicting not only the occurrence of an anomalous crowd but also the number of people coming to the events is important. Hence, forecasting anomalous congestion degree quantitatively is crucial for efficient anomalous crowd management [5].

Meanwhile, the analysis of active population movements, so-called urban dynamics, has been intensively investigated with large-scale urban mobility data, such as GPS location history [7]. Anomaly detection in urban dynamics is one of the important research topics on urban dynamics analysis. Anomalous crowd can be detected under such techniques in a real time manner [6, 8]. However, as a typical aspect of anomaly detection, observing an anomalous crowd follows the occurrence of an anomaly, which would result in insufficient countermeasures due to lack of time. Therefore, the crucial technology which enables an appropriate crowd management for human safety is to forecast anomalous crowds in the future.

Recently, predicting anomalous crowds has started to be pioneered by Fan et al. [2], Jiang et al. [3] and Konishi et al. [4]. In particular, CityProphet [4] can provide anomaly prediction far into the future by applying new data sources for anomaly prediction, but not mobility logs. Assuming that the number of search queries for train transits increases according to the number of visitors to events, the researchers use transit search history data, which reflect user schedules of train travel. Anomalous crowds caused by events can be predicted 1 week in advance by this method. However, some people do not attend the event although they search for routes, while other people search for routes at least twice or more. Such a complex usage of transit search makes it unreliable for predicting the exact anomalous degree.

In this paper, we propose Supervised-CityProphet (SCP), a novel anomaly crowd prediction framework. To perform accurate predictions, we re-formulate CityProphet based on cross-modal data source association by leveraging mobility logs and transit search logs, and model optimization with anomaly score matching. Supervised-CityProphet outperforms the existing works for urban dynamics prediction and anomalous crowd prediction.

The contributions of our study are as follows:

- We propose a novel anomalous crowd prediction framework with direct anomaly score regression using mobility logs based on GPS signals and transit search logs.
- We evaluate our method on a real mobility dataset and transit search history. The results show that our model predicts anomalous urban dynamics accurately.

2 PRELIMINARIES

Before formally describing our investigated problem, we define necessary variables and provide the problem formulation of anomalous crowd prediction.

SIGSPATIAL '20, November 3–6, 2020, Seattle, WA, USA

ACM ISBN 978-1-4503-8019-5/20/11.
https://doi.org/10.1145/3397536.3422219

2.1 Variable and Problem Definition

Variable Definition. Let t be a time segment on 1 day, and each day is divided into T time segments (i.e. $t = 1, 2, ..., T$). In addition, l denotes the point of interest (POI), which is a certain urban region we are focusing on. The urban dynamics of active population based on mobility logs observed at the POI l on the date d and time segment t is denoted by $y^{(l)}_{d,t}$. We treat it as a ground-truth urban dynamics. In addition, transit search history consists of each query record q that contains the scheduled date d and time t, searching date d', and destination POI l as $q = (d, t, d', l)$. Then, the user's activity patterns in the future are described by the number of transit search queries as $s^{(l)}_{d,t|d'}$. In general, d' denotes the former day than d (i.e., $s^{(l)}_{d,t|d-i}$ denotes the number of logs searched i days before the scheduled date d). Finally, the schedule information $\mathcal{S}^{(l)}_{d,t}$ for date d and time t at a destination POI l is denoted by $\mathcal{S}^{(l)}_{d,t} = \{s^{(l)}_{d,t|d-i} | i = p_d, p_d + 1..., p_d + p_w\}$, where p_d is the earliest day before the scheduled date, and p_w denotes the range of days that we utilize.

Under anomalous events, anomalous score denoted by $v^{(l)}_{d,t}$ should be large to reflect the high congestion degree. In contrast, it should be close to zero if no events occur. Based on this notion, anomaly score of urban dynamics $v^{(l)}_{d,t}$ is defined as how much the ground-truth dynamics $y^{(l)}_{d,t}$ deviates from the normal dynamics $\hat{y}^{(l)}_{d,t}$ as $v^{(l)}_{d,t} = (y^{(l)}_{d,t} - \hat{y}^{(l)}_{d,t})/\hat{y}^{(l)}_{d,t}$.

Problem Definition. In this paper, we tackle the problem of accurate anomalous crowd prediction. During events, not only the occurrence of anomalous crowds but also the quantitative degree of congestion on anomalous crowd should be predicted. Specifically, we predict anomaly score of urban dynamics $v^{(l)}_{d,t}$ robustly and precisely when an anomalous event is held on date d and time t at POI l.

2.2 Anomaly Prediction with CityProphet and Challenges of Accurate Prediction

The aforementioned work CityProphet [4] has pioneered the prediction of anomalous crowds far into the future. In CityProphet, two prediction models, schedule-based population (SP) and descriptor-based population (DP), are proposed for the prediction of the number of search queries, and anomaly score is computed based on the comparison between the two models. Let $\hat{s}^{(l,\mathrm{SP})}_{d,t|d}$ and $\hat{s}^{(l,\mathrm{DP})}_{d,t|d}$ denote the predictions of SP and DP model respectively. SP model is formulated with the inputs of schedule information based on the auto regressive model [1] as $\hat{s}^{(l,\mathrm{SP})}_{d,t|d} = \sum_{i=p_d}^{p_d+p_w} \sum_{j=-q}^{q} \theta_{i,j} s^{(l)}_{d,t-j|d-i}$, where $\theta_{i,j}$ is the parameter.

In addition, DP model is formulated with the inputs of context information based on the bilinear Poisson regression [6] as $\hat{s}^{(l,\mathrm{DP})}_{d,t|d} = \mathbb{E}[\mathrm{Pois}(s^{(l)}_{d,t|d} | \pi^{(l)}_{\mathbf{c},t})] = \pi^{(l)}_{\mathbf{c},t}$. Then, anomaly score $\hat{v}^{(l),\mathrm{CP}}_{d,t}$ is calculated as $\hat{v}^{(l),\mathrm{CP}}_{d,t} = (\hat{s}^{(l,\mathrm{SP})}_{d,t|d} - \hat{s}^{(l,\mathrm{DP})}_{d,t|d})/\hat{s}^{(l,\mathrm{DP})}_{d,t|d}$.

Although CityProphet can predict anomalies 1 week in advance, predicted resuls are quite unstable due to the characteristics of transit search logs. To overcome the issue of instability and ensure the model robustness, we address the challenge of lack of data sources to capture anomalous urban dynamics precisely.

3 PROPOSED METHOD: SUPERVISED-CITYPROPHET

In this section, we describe our proposed method. As discussed in the previous section, we address the challenge of lack of data sources to capture urban dynamics precisely. To overcome this issue, we first build a prediction model that leverages mobility log-based urban dynamics $y^{(l)}_{d,t}$ and the user's schedule information $\mathcal{S}^{(l)}_{d,t}$.

To simplify handling the anomalous criteria, our method is based on the model that directly outputs the anomaly score $\hat{v}^{(l)}_{d,t}$. Specifically, we formulates the problem as a regression model that takes contextual information $\mathbf{c}$ and schedules $\mathcal{S}^{(l)}_{d,t}$ as inputs, and then we predict anomaly score $\hat{v}^{(l)}_{d,t}$. After regressing it, we rebate urban dynamics $y^{(l)}_{d,t}$ from its anomalous degree.

3.1 Anomaly Score Calculation

As discussed in the previous section, we establish a model whose inputs are contextual information $\mathbf{c}$ and schedules $\mathcal{S}^{(l)}_{d,t}$, and outputs are the prediction of anomaly score $v^{(l)}_{d,t}$. To calculate the anomaly score quantitatively, the normal dynamics pattern $\hat{y}^{(l)}_{d,t}$ should be defined. Although the ground truth of normal dynamics is unknown, the normal urban dynamics should not change suddenly in consecutive time segments. In addition, as discussed in the previous section, daily patterns of active population are affected by the context information such as holiday-or-not, weekday-or-weekend, or the weather. Based on these facts, we utilize the bilinear Poisson regression [6] to obtain normal population patterns.

In this model, the active population are described by a Poisson distribution as $y^{(\mathbf{c},l)}_{d,t} \sim \mathrm{Pois}(\cdot | \lambda^{(l)}_{\mathbf{c}_d,t})$, where λ denotes the parameter of the Poisson distribution. It is defined by using the context $\mathbf{c}_d$ of date d and time t as $\ln \lambda^{(l)}_{\mathbf{c}_d,t} = \varphi(\mathbf{c}_d)^{\top} W^{(l)} \phi(t)$, where $\varphi(\mathbf{c}) \in \mathbb{R}^C$ is the external factor vector expressing the contexts $\mathbf{c}$ by one-hot encoding method and $\phi(t) \in \mathbb{R}^T$ is time factor, which is denoted by $\phi(t) = \{t_s | t_s = \mathcal{N}(s|\tau, \sigma^2), s = 1, ..., T\}$, where $\mathcal{N}(\cdot)$ is a Gaussian distribution with mean τ and variance σ^2.

Following the definition of anomaly score, we calculate the anomaly score by the ground truth $y^{(l)}_{d,t}$ and the predicted results $\lambda^{(l)}_{\mathbf{c}_d,t}$ as $v^{(l)}_{d,t} = (y^{(l)}_{d,t} - \lambda^{(l)}_{\mathbf{c}_d,t})/\lambda^{(l)}_{\mathbf{c}_d,t}$.

3.2 Anomaly Score Prediction via Data Source Association

The discussion of CityProphet indicates the instability of future anomalous crowd predictions due to the characteristics of transit search history. To address this issue, we consider associating datasets to obtain a stable prediction performance.

Based on the previous work of CityProphet [4], we divided the explanatory variables to the context information and schedule information. As in normal urban dynamics, we build a model to predict the normal amount of queries searched on the same date as scheduled one by using only the context information as

$\hat{s}^{(l)}_{d,t|d} = \mathbb{E}[\mathrm{Pois}(s^{(l)}_{d,t|d}|\pi^{(l)}_{\mathbf{c}_d,t})] = \pi^{(l)}_{\mathbf{c}_d,t}$, where $\pi^{(l)}_{\mathbf{c}_d,t}$ is the parameter of the Poisson distribution, which is formulated in the same way as urban dynamics.

Given the prediction $\pi^{(l)}_{\mathbf{c}_d,t}$ and the numbers of logs $\{s^{(l)}_{d,t|d-i}\}^{p_d+p_w}_{i=p_d}$, we define the schedule features $\{\zeta^{(l)}_{d,t|d-i}\}^{p_d+p_w}_{i=p_d}$ to predict anomaly score $v^{(l)}_{d,t}$ as $\zeta^{(l)}_{d,t|d-i} = (s^{(l)}_{d,t|d-i} - \pi^{(l)}_{\mathbf{c}_d,t})/\pi^{(l)}_{\mathbf{c}_d,t}$. With this schedule features $\{\zeta^{(l)}_{d,t|d-i}\}^{p_d+p_w}_{i=p_d}$, the anomaly score $v^{(l)}_{d,t}$ is regressed by using an auto regressive model [1].

$$\hat{v}^{(l)}_{d,t} = \sum_{i=p_d}^{p_d+p_w} \sum_{j=-q}^{q} w_{i,j}\zeta^{(l)}_{d,t-j|d-i} + w_c, \tag{1}$$

where $w_{i,j}$ is parameter and w_c is the constant term. Further, q denotes the time range that affects the prediction of targets. The parameters are optimized by minimizing the negative log likelihood with $L2$ norm regularization.

3.3 Urban Dynamics Prediction in the Future

After training, the model can predict the anomalous score p_d days in advance from the contexts and the number of queries searched i days before ($i = p_d, p_d + 1..., p_d + p_w$). Consider a certain POI l. Given the context feature and time feature denoted by $\varphi(\mathbf{c}) \in \mathbb{R}^C$ and $\phi(t) \in \mathbb{R}^T$, and a set of the number of queries searched before denoted by $\{x^{(l)}_{d,t|d-i}\}^{p_d+p_w}_{i=p_d}$, the congestion score $\hat{v}^{(l)}_{d,t}$ is predicted by using SP and DP model with the optimized parameters. By the definition of the congestion score, it reflects the multiples of the actual number of visitor as normal density $y^{(\mathbf{c},l)}_{d,t}$. This is, we can rebate the urban dynamics $\hat{y}^{(l),\mathrm{SCP}}_{d,t}$ as $\hat{y}^{(l),\mathrm{SCP}}_{d,t} = (1 + \hat{v}^{(l)}_{d,t})y^{(\mathbf{c},l)}_{d,t}$.

4 EXPERIMENTS

In this section, we describe the experimental setup and results. We conducted the experiments using large-scale mobility logs based on GPS records and transit search history to evaluate the predictive performance of the proposed model.

4.1 Datasets

The mobility logs were collected by a disaster alert mobile application[1] from Yahoo! JAPAN. Each record of them are completely anonymized, and characterized by timestamp, latitude, and longitude. We utilized the data collected in six months (from October 1, 2019, to March 31, 2020).We also utilized massive transit search history data, which are searched by passengers of train, bus, or taxi. These logs are gathered by the transit search application[2], also released by Yahoo! JAPAN. Each record contains anonymized user ID, searching timestamp, scheduled timestamp, and destination. The destination mainly denotes train stations, but it is sometimes set to places where events take place. Therefore, we also used such records as the transit search logs. The term of gathering data is same as the mobility logs. We selected 58 specific square areas as POIs and their corresponding stations. POIs contain not only the Greater Tokyo Area (where many people are observed daily) but also stadiums, shrines, and venues of the fireworks displays. The size of each POI was set to $600 \times 600m^2$. We aggregated the mobility logs in the POIs at each time segment and counted the number of it as an urban dynamics.

[1] http://emg.yahoo.co.jp/

[2] https://transit.yahoo.co.jp/smartphone/app/

4.2 Experimental Setup

Model Setting. We handle 1 day as a 24-hours period, and the number of time segments T is set to 24 (i.e., one time segment expresses 1-hour period). Moreover, we consider that the day starts at 3:00 AM and lasts for 24 hours, in accordance with the past research [6]. As for the inputs for the normal dynamics prediction model, we used holiday-or-not, weekday-or-weekend, and weather information. Based on one-hot encoding, holiday-or-not and weekday-or-weekend features are two-dimensional vectors. Weather information is a four-dimensional vector: sunny, cloudy, rainy, and the other. To avoid overfitting by reducing the number of parameters, we did not adopt a day-of-the-week feature assuming that daily urban dynamics are effectively determined by whether it is a holiday and the weather information. We used the tensor product to compose these features into one input vector. In addition, we used the schedule information observed 1 week in advance to conduct long-term anomalous crowd prediction. Thus, $p_d = 7$. We also set $p_w = 7$ to take the user's schedules specified 2 weeks before the day of events into account and $q = 1$ to cover the difference of scheduled arrival time among users.

Experimental setting and performance measures. We evaluated the performance for two types of predictions: *anomaly score prediction* and *urban dynamics prediction*. To evaluate the performance fairly, we conducted five-fold cross validation.

To evaluate the performance of our model, we adopt a mean absolute error (MAE)-based metric. In general, assessment not only on the accuracy for all predicted values but also on the normal sample accuracy (specificity) and anomalous sample accuracy (recall) is important when we handle the prediction of anomalies. To measure the model performance on both normal and abnormal patterns, we used MAE conditioned by the anomaly score-based threshold $\bar{v}$.

For the anomaly score predictions, we used the normal sample MAE (NS-MAE) defined as NS-MAE $= \frac{1}{DT}\sum_{d=1}^{D}\sum_{t=1}^{T}|v^{(l)}_{d,t} - \hat{v}^{(l)}_{d,t}|$ and anomalous sample MAE (AS-MAE) defined as AS-MAE $= \frac{1}{DT}\sum_{d=1}^{D}\sum_{t=1}^{T}|v^{(l)}_{d,t} - \hat{v}^{(l)}_{d,t}|$ where $v^{(l)}_{d,t} \geq \bar{v}$, D and T are the number of days and time segments, $\hat{v}^{(l)}_{d,t}$ is the predicted anomaly score at POI l on date d and time t, and $v^{(l)}_{d,t}$ is the ground truth.

Similarly, for the prediction of urban dynamics, we used NS-MAE defined as NS-MAE $= \frac{1}{DT}\sum_{d=1}^{D}\sum_{t=1}^{T}|y^{(l)}_{d,t} - \hat{y}^{(l)}_{d,t}|$ and AS-MAE defined as AS-MAE $= \frac{1}{DT}\sum_{d=1}^{D}\sum_{t=1}^{T}|y^{(l)}_{d,t} - \hat{y}^{(l)}_{d,t}|$ where $v^{(l)}_{d,t} < \bar{v}$, $\hat{y}^{(l)}_{d,t}$ is the predicted urban dynamics at POI l on date d and time t and $y^{(l)}_{d,t}$ is the ground truth.

4.3 Comparative Models

Anomalous Score Prediction. CityProphet (**CP**) [4] is used as a comparative model. CityProphet is the state-of-the-art method that takes the context information and the schedule information as input data. In CityProphet, two prediction models, schedule-based population (SP) and descriptor-based population (DP), are proposed for the prediction of the number of search queries, and anomaly score is computed based on the comparison between the two models.

Urban Dynamics Prediction. As models for comparison, we used the bilinear Poisson regression [6] (**BPReg**), bilinear Poisson regression with schedule information (**BPReg-with-SI**), and **CP** [4]. **BPReg-with-SI** uses the schedule information $S_{d,t}^{(l)}$ for modeling urban dynamics, in addition to the external factors that were stated before. In this model, the schedule information is formulated as a $p_w(2+q)$-dimensional vector, which includes each number of searched queries.

4.4 Experimental Results

Table 1: Performance Evaluation based on NS-MAE and AS-MAE for Anomaly Score Prediction.

Model	NS-MAE	AS-MAE	
$\bar{\nu}$	5.0	5.0	10.0
CP	3.66 ± 0.40	14.9 ± 16.6	23.4 ± 13.5
SCP	**0.54 ± 0.09**	**4.9 ± 1.2**	**16.2 ± 5.7**

Table 2: Performance Evaluation based on NS-MAE and AS-MAE for Urban Dynamics Prediction.

Model	NS-MAE	AS-MAE	
$\bar{\nu}$	5.0	5.0	10.0
BPReg	80.8 ± 40.1	54.3 ± 32.5	130.9 ± 66.2
BPReg-with-SI	79.1 ± 37.9	54.0 ± 32.2	130.2 ± 65.1
CP	204.5 ± 25.2	182.5 ± 279.7	234.2 ± 194.1
SCP	**46.2 ± 28.5**	**46.2 ± 28.5**	**119.4 ± 58.9**

4.4.1 Performance Evaluation. Table. 1 and 2 show the prediction performances of the anomaly score and urban dynamics, respectively. We evaluated them by the average of the prediction results of all POIs. From the results of NS-MAE-based evaluation, Supervised-CityProphet outperforms CityProphet by 85.2% on anomaly score prediction. In addition, from the results of urban dynamics prediction, Supervised-CityProphet achieved better performance than BPReg and BPReg-with-SI on normal dynamics prediction.

Moreover, from the results of AS-MAE-based evaluation, Supervised-CityProphet still predicts the anomaly score and urban dynamics more accurately than CityProphet for both of the thresholds. Supervised-CityProphet outperforms CityProphet by 48.9% on anomaly score prediction. Moreover, from the results of urban dynamics prediction, we can observe that Supervised-CityProphet achieves higher prediction accuracy than BPReg and BPReg-with-SI. At a larger threshold of $\bar{\nu} = 10$, our model outperforms CityProphet by 49.0%, BPReg by 8.7%, and BPReg-with-SI by 8.2% in urban dynamics prediction.

5 DISCUSSION

In this section, we discuss the prediction performance of the proposed model from the viewpoint of accurate prediction. As shown in the experimental results, CityProphet cannot provide accurate prediction towards anomalies compared to the proposed model. This is probably because CityProphet did not leverage the mobility log-based urban dynamics, and this resulted in the ability to predict the occurrence of anomalies, not its congestion degree. On the other hand, the prediction by BPReg-with-SI was quite unstable compared to the proposed method. We suppose that this is because the number of parameters of this model increased by adding the schedule feature to the inputs, which generally results in performance deterioration. Therefore, naive association of data sources does not work well. In contrast to that, the proposed model performed better than the comparative models both on normal situation and andanomalous crowds. This implies that both schedule information and the actual number of visitors should be taken into account, and the proposed method for data source association based on auto regressive model is very effective for accurate prediction.

6 CONCLUSION

In this paper, we proposed Supervised-CityProphet (SCP) for accurate prediction of anomalous crowds. We analyzed limitations of the conventional methods and their causes. To address these issues, we established an anomaly score matching-based model with data source association. The experimental results on real datasets demonstrate the superiority of our model to the existing approaches. Our approach shows better results in the prediction performance and the robustness. The proposed method outperforms CityProphet by 61.0% in anomaly score prediction. Our model is durable enough to be applied to real-world scenarios.

REFERENCES

[1] Hirotugu Akaike. 1969. Fitting autoregressive models for prediction. *Annals of the institute of Statistical Mathematics* (1969).

[2] Zipei Fan, Xuan Song, Ryosuke Shibasaki, and Ryutaro Adachi. 2015. CityMomentum: An Online Approach for Crowd Behavior Prediction at a Citywide Level. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*.

[3] Renhe Jiang, Xuan Song, Dou Huang, Xiaoya Song, Tianqi Xia, Zekun Cai, Zhaonan Wang, Kyoung-Sook Kim, and Ryosuke Shibasaki. 2019. DeepUrbanEvent: A System for Predicting Citywide Crowd Dynamics at Big Events. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*.

[4] Tatsuya Konishi, Mikiya Maruyama, Kota Tsubouchi, and Masamichi Shimosaka. 2016. CityProphet: City-Scale Irregularity Prediction Using Transit App Logs. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*.

[5] Y. Sekimoto, R. Shibasaki, H. Kanasugi, T. Usui, and Y. Shimazaki. 2011. PFlow: Reconstructing People Flow Recycling Large-Scale Social Survey Data. *IEEE Pervasive Computing* (April 2011).

[6] Masamichi Shimosaka, Keisuke Maeda, Takeshi Tsukiji, and Kota Tsubouchi. 2015. Forecasting Urban Dynamics with Mobility Logs by Bilinear Poisson Regression. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*.

[7] Xuan Song, Quanshi Zhang, Yoshihide Sekimoto, Teerayut Horanont, Satoshi Ueyama, and Ryosuke Shibasaki. 2013. Modeling and Probabilistic Reasoning of Population Evacuation during Large-Scale Disaster. In *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*.

[8] Akihito Sudo, Takehiro Kashiyama, Takahiro Yabe, Hiroshi Kanasugi, Xuan Song, Tomoyuki Higuchi, Shin'ya Nakano, Masaya Saito, and Yoshihide Sekimoto. 2016. Particle Filter for Real-Time Human Mobility Prediction Following Unprecedented Disaster. In *Proceedings of the 24th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*.