Human Decision-making Strategy Analysis during Large-scale Disaster

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Human Decision-making Strategy Analysis during Large-scale Disaster

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Abstract

In recent decades, the frequency and intensity of natural disasters have increased significantly. Following these unexpected disasters, understanding and predicting human decision-making strategies during disasters will play a vital role in planning effective humanitarian relief, disaster management, and long-term societal reconstruction. However, such research is challenging due to the unavailability of reliable and large-scale human mobility data. In addition, these personal strategies during disasters become hard to predict due to the influences of multiple factors. In the decision-making process, what key (sometimes hidden) factors do people consider when making a particular mobility decision following a large-scale disaster? In this study, we construct a large human mobility database collected from mobile devices (GPS records of 66,598 users in the Greater Tokyo area), and analyze the human decision-making strategies following Japan’s 2011 Tohoku earthquake. Except for users’ location-based information, we also extract the grid-based stay areas from historical check-ins (normal days before disasters) and discover the functions of those areas combined with points of interest (POI) located in an area. In the final, we jointly model the users’ location-based factors and historical check-ins information, and develop an empirical prediction for decision-making strategies (i.e., destination, travel mode,
and departure time from their workplaces) following the Tohoku earthquake. An explainable analysis is conducted to explore the fundamental laws that govern human mobility following disasters. The results are encouraging to support future interventions in analyzing decision-making strategies during disasters, and understanding the relationship between decision making and considered multiple factors/features (as well as the relationship between feature values and possible predicted values).

Keywords: Emergency management · Big mobility data · Functional areas · Explainable knowledge · Decision-making Strategy Analysis

1 Introduction

Most serious disasters lead to massive movements and evacuations of the population. Human activity analysis is essential to plan effective humanitarian assistance and disaster control for long-term social stability and reconstruction. This work takes a “9.0” earthquake that occurred in the Pacific Ocean 130 kilometers off Sendai City, Japan, on March 11, 2011, as a case study [1–3]. The most threatening tsunami in history [4, 5], caused devastating damage to Japan and caused difficulty for people to return home due to the subway outage and road landslides. In the wake of a disaster of this magnitude, it is very crucial to record people’s movements following the event, analyze their behavioral patterns and develop predictive models for future disaster mitigation.

Although some works [6, 7] focus on the emergency management during earthquakes (e.g., crisis mapping and close range photogrammetry), how to analyze the human mobility pattern during natural disasters is still a burning question because of the difficulty of collecting representative vertical data where infrastructure and social order collapse. Fortunately, the constant maturity of the mobile Internet and popularization of intelligent terminals equipped with various sensors [8–10] have given birth to a new research field, namely the field of mobile sensing technology. Mobile sensing [11–14] is human-centered perception, and latent information plays an essential role in the perception process. Since the concept of mobile sensing was put forward, it has attracted extensive attention from academia and industry [15, 16]. Mobile sensing technologies have been widely applied in various fields such as transportation, medical care, and health care in daily life. Multiple works [17–19] have been proposed to predict human mobility in large-scale disasters (earthquakes, tsunamis, and hurricanes). However, they may lack the necessary analysis and enough knowledge to explain human decision-making strategies during disasters. Since large-scale disaster is rare, it’s challenging to understand human mobility from such data. Although there are many related works to predict the population flow [20, 21] after a large earthquake, little research considers the influence of personal factors on decision-making process for evacuation. In
addition, knowledge of what key factors propel a person to choose a return home strategy is vital to analyze human decisions during disasters.

Taking into account all these aspects, we address the following research questions:

**RQ1:** Based on large-scale human mobility data and POI, how can we discover and define the functions/topics of historical check-in points before disasters?

**RQ2:** After obtaining the type and number of historical check-ins from mobile phone users, how can we build the relationship between considered factors (including location-based factors and historical check-ins) and decision-making strategies following disasters, and accurately predict mobile phone users’ return home strategy from their workplaces?

**RQ3:** Based on the prediction of decision making, what key factors/characteristics compel users to choose the return home strategy? How do the certain feature values influence the predicted results?

In this paper, to address these problems, we collect an anonymous GPS log dataset from real-world mobile phone users in Japan over 12 days (from March 1 to March 12, 2011), and intend to seek the clues of decision-making from considered factors. Further, we detect the home and workplace via the detection of stay points, which are extracted from time-series GPS data of those mobile phone users. And we conduct map-matching for each trajectory to map the GPS trajectory onto various segments of public transportation network (e.g., subway, highway, and footpath) and label the travel mode choice during return home process following the Tohoku earthquake. To endow the semantic information except for location-based factors, we use DRoF \[22\] to discover the functional areas (e.g., restaurants, entertainment areas and shopping center) for the stay areas of historical check-ins based on both human mobility and points of interest (POI) located in an area. The discovered functions/topics of historical check-ins help people effectively understand human mobility following disasters and provide the basis for exploring more reasons for the decision-making process. In the final, an empirical prediction is proposed to estimate how people choose to return home after the Tohoku earthquake, and an explainable analysis is also conducted to explore the fundamental laws that govern human mobility during large-scale disasters.

By addressing the above research questions, our work makes the following contributions:

**Contribution 1:** We collect large-scale mobile sensing GPS data during the Tohoku earthquake and implement a topic model to discover the functions/topics of historical check-in points. Based on these, we can obtain the inferred topic and the number of those historical check-ins for each mobile user.

**Contribution 2:** By incorporating the topics discovered about historical check-in with the location-based factors of the users, we build up the prediction models of decision-making strategies (i.e. destination, travel mode and departure time from the workplaces) during Tohoku earthquake based on the above factors/discoveries.
Contribution 3: We conduct an explainable analysis for two prediction tasks under two situations (without historical check-ins and with historical check-ins) and analyzed the key factors that influenced decision-making strategies during the Tohoku earthquake.

The remainder of this paper is structured as follows: Section 2 concludes the background and related work. We introduce the basic notation and formulations in Section 3, and Section 4 provides the details about the data, the prediction tasks about return home strategies, and the factors considered. The experimental results and explainable analysis are presented in Section 5, and the paper is finally summarized in Section 6.

2 Related Work

This section discusses the related works from three perspectives. First, we provide the research directions about emergency direction based on geospatial technology, and then we discuss the recent works about human behavior prediction during disasters. In addition, our study is related to the field of mobile phone sensing.

2.1 Emergency Management

Recently, emergency management has been one hot interdisciplinary in geographic information science, due to obvious spatial dimensions and multidimensional properties. On one hand, event detection from social media is a particularly popular solution for emergency management. Sakaki et al. [23] first detected tweets about “earthquake”, and then acquired the geographic regions of these events based on Kalman filtering method. Hua et al. [24] proposed a semi-supervised method for spatio-temporal event detection in Twitter, such as earthquakes and disease outbreaks. On the other hand, productive works exploded the mobility pattern [25–28] by smartphone datasets to analyze people’s disaster responses. For example, Song et al. [29] developed a general probabilistic model to simulate population evacuation on complex geographic features in Japan in response to future disasters. Reference [25] discovered the distributions of earthquake risk areas and simulated people’s emergency measures using GPS data. Especially, reference [30] pointed to the entire mobility trends by a simulator of human emergency mobility. However, those works ignore personal situations or factors when they make decisions since the disasters. For example, people’s emergency measures are closely related to their location information and historical check-ins. In this paper, we endow the semantic information for each trajectory by combing functional areas, and estimate how people chose the return home strategy after the Tohoku earthquake. In addition, we conduct an explainable analysis to explore the fundamental laws governing human mobility following disasters.
2.2 Human Behavior Prediction during Disasters

These research topics about human behavior prediction during disasters (e.g., crowd panics [31], fires [32, 33], and floods [34]) have received numinous attention, especially for small-scale or short-term emergencies. Therefore, the related research directions on the human mobility dynamics during large-scale disasters (such as earthquakes, tsunamis, and hurricanes) are minimal [35], which maybe due to the difficulties of collecting representative vertical data where infrastructure and social order collapse. Although there is some literature [30, 36–39] interested in human mobility prediction in response to the large-scale disasters, more detailed analysis and knowledge discovery are lacked. Meanwhile, they only tried to predict the overall movements of group-living species. For example, reference [36] develops a hidden Markov model-based method that considers different factors (such as the intensity of disaster and damage level) to predict the large population flow. Reference [37] proposed an intelligent system named DeepMob to understand and predict human evacuation behavior and mobility following different types of natural disasters. By contrast, we focus more on explainable analysis for single individual’s decision-making process during disasters, which extracts the semantic information from trajectories (e.g., the distance between home & workplace and functional types of historical check-ins) to predict each mobile user’s strategy through an explainable model.

2.3 Mobile Phone Sensing

With the development of positioning equipment, numerous GPS data with high-precision sampling signals are constantly analyzed for human location-based and social information [40–43]. Meanwhile, the advance in mobile phone technology and the corresponding massive users have led the mobile phone to become one of the most critical sensing devices. Mobile phone signals can represent these location-sensing data, bus card swipes, and taxi track data, and can be used to understand people’s mobility patterns and social customs. Reference [44] discovered closed gathering practices from a large-scale trajectory database. Furthermore, reference [45] explored asynchronous periodic patterns in the trajectory. Reference [46] divided the urban area of city into disjoint regions, and studied the problem of detecting spatio-temporal outlier and their causal interactions from traffic data streams. Especially, anomalous connections between the two regions are collected based on the driving path of the vehicles between the two regions. As we mentioned, many works have been devoted to exploring human mobility’s potential pattern. In this work, we are the first to predict the human return home strategy after a large-scale disaster and provide the explainable analysis for supporting future interventions on understanding human mobility and decision-making strategy that incorporates both location-based information and historical check-ins.
3 Preliminaries

In this section, we will briefly introduce the definitions used in human decision-making strategy prediction.

**Definition 3.1. Human Mobility.** The human trajectory collected for an individual person essentially comprises a 3-tuple sequence: \((\text{timestamp}, \text{latitude}, \text{longitude})\), which can indicate a person’s location according to a captured timestamp. It can be further denoted as a sequence of \((t, l)\)-pairs to which the user ID \(uid\) is attached by simplifying \(\text{timestamp}\) as \(t\) and \((\text{latitude}, \text{longitude})\) as \(l\).

\[
\text{traj} = \{uid, (t_1, l_1), (t_2, l_2), \ldots, (t_n, l_n)\}
\]  

(1)

**Definition 3.2. Citywide Human Mobility.** Citywide human mobility \(\Gamma\) refers to a large group of user trajectories in a given urban area. Given a user ID \(uid\), we can retrieve their personal trajectory \(\Gamma_{uid}\) from \(\Gamma\) as \\{\((t_1, l_1), (t_2, l_2), \ldots, (t_n, l_n)\)\}.

**Definition 3.3. Return Home Trajectory.** A trajectory, named return home trajectory, is satisfied that its origin should be near the workplace and its destination should be near home during 15:00 PM ∼ 08:00 AM the next day.

**Definition 3.4. Travel Mode Choice.** The travel mode choice indicates the sequences of travel modes for a specific return home trajectory \((\text{traj})\). Taking the following example, Tom usually walks to the subway station from his workplace and return home by train directly. Thus, his trajectory can be defined as

\[
\text{traj} = \{\text{uid}, (\underbrace{t_1, l_1}_{\text{Walk}}), (\underbrace{t_2, l_2}_{\text{Train}}), (\underbrace{t_3, l_3}_{\text{Walk}}), \ldots, (\underbrace{t_{n-1}, l_{n-1}}_{\text{Train}}), (t_n, l_n)\}
\]  

(2)

Mathematically, given a \(\text{traj}\), its travel modes can be formulated as

\[
\text{tmod} = \{\text{uid}, (t_1, m_1), (t_2, m_2), \ldots, (t_n, m_n)\},
\]  

(3)

where \(m_i\) represents one of the travel modes, such as train, walk or car.

**Definition 3.5. Historical Check-ins.** Each historical check-in denotes a grid-based stay point during return home trajectory from this mobile phone user’s workplace before the Tohoku earthquake, which stays in a geographic area for more than a certain time interval \((\geq 20\text{mins})\).

**Definition 3.6. Functional Areas.** Functional areas (e.g., developed commercial areas, entertainment, education and parks, and restaurants) are detailedly developed to support different needs of people’s urban lives and become vital parts of urban planning in a city. In this study, we discover and infer five functions/topics (i.e. restaurant, public place, commuting, shopping, and entertainment) for those historical check-ins. See Table 1 for more detailed information.
4 Data, Tasks, and Considered Factors

4.1 Framework Overview

We here introduce the framework overview shown in Figure 1. We split our system into three steps: data mining, decision-making strategies, and explainable knowledge. In data mining, we first extract the grid-based stay points during return home trajectories (in normal days before disasters) as historical check-ins, and then discover the functional areas of these historical check-ins. More specifically, each stay point from historical check-ins is regarded as a document, and we infer the topic/function of historical check-ins using Dirichlet Multinomial Regression (DMR) model [47]. Next, we conduct home & work detection and travel mode choice detection for mobile phone users in Greater Tokyo area. Based on the above mining and discovery, we acquire the considered features/factors (i.e., users’ location-based information and historical check-ins) and label the decision-making strategies following large-scale disasters. After that, we define the decision-making prediction tasks including both return-home based strategy and departure time from the workplace, and conduct the explainable analysis based on considered factors/features. Especially, the explainable analysis not only provides the feature importance on decision-making strategies, but also conducts two case studies to analyze the relationship between specific feature values and possible predicted results, and demonstrate that the feature importance comparison between all mobile users and those users whose workplaces were in target region (i.e., Shinjuku, Tokyo).
Table 1  Detailed information of used City POI Data.

<table>
<thead>
<tr>
<th>Coarse POI types</th>
<th>Fine POI types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commuting</td>
<td>Bus stop, Railway station</td>
</tr>
<tr>
<td>Public place</td>
<td>Gym, Park, Temple, Shrine</td>
</tr>
<tr>
<td>Shopping</td>
<td>Supermarket, Shopping mall, Store</td>
</tr>
<tr>
<td>Restaurant</td>
<td>Restaurant, Caffe/Tea, Bar</td>
</tr>
<tr>
<td>Entertainment</td>
<td>Art gallery, Theater, Museum</td>
</tr>
</tbody>
</table>

4.2 Data Descriptions

**City POI Data.** We collect the Telepoint Pack DB of POI data in February 2011 provided by ZENRIN DataCom Co., Ltd [48]. Each record is a registered landline telephone number in the original database with its coordinates (latitude, longitude) and industry category information. Here, We treat each “telepoint” as one specific POI and use five coarse POI types (i.e., public transportation facilities, public places, shopping, restaurant, and entertainment) and the corresponding acceptable POI types. Detailed information on POI can be found in Table 1.

**Human Mobility Data.** We anonymously collect a GPS log dataset from approximately 1.6 million real mobile phone users in Japan over 12 days (from March 1st to March 12th, 2011). This dataset contains about 30 billion GPS records, covering approximately 1% of the real-world population. And it was collected by a mobile operator (NTT DoCoMo, Inc.) and a private company (ZENRIN DataCom Co., Ltd.) with the consent of the mobile phone users. At the same time, the data was processed collectively and statistically to conceal personal information such as gender or age. By default, the positioning function on the users’ mobile phones was activated every 5 min. However, data acquisition is affected by several factors, such as loss of signal or low battery power. In addition, the age distribution of this dataset skews slightly toward young users because the young preferred to use a mobile phone with a positioning function compared to users from other age groups (e.g., the elderly) in 2011. To verify the representativeness of our dataset, we refer to previous work [49] in which the quality of our dataset was evaluated. In this study, in order to analyze the human mobility after the Tohoku Earthquake, the analyzed period of our experiment is from March 1 to March 12, 2011.

In this study, we select the Greater Tokyo Area (including Tokyo Metropolis and the prefectures of Kanagawa, Chiba, and Saitama) as the target area for simulation. The user is selected in our experimental data if both his/her home and work locations are located in the target area.
Fig. 2  Traffic volume and ratio change of each travel mode choice ("Stay", "Walk", "Train" and "Car") before/during/after Tohoku Earthquake (March 9/10/11/12) in the Great Tokyo area. The earthquake happened at 14:46 PM on March 11, and the horizontal axis is the 24 hours of one day.

4.3 Mobile Data Processing and Region Function Discovery

4.3.1 Home & Workplace Detection

When it comes to the return home strategy, we need to extract the significant locations of places, particularly home and workplace. Most human activities are routine, and people tend to spend time in the same places in their daily life. In this work, we detect the locations of home and workplace based on individual’s GPS records, which is used as the users’ location-based factors. For implementation details, we first detect stay points for each individual’s trajectories during selected time periods (from March 1 to March 10, 2011). Stay points are detected when an individual spends at least one hour within 500 meters of a given GPS trajectory point. Every stay point’s coordinates are the median latitude and longitude values of the points found within the specified distance. Then we compute the grid-based mesh ID based on the coordinates of these stay points (500 m Grid Square, based on the Python library jismesh), which is used to obtain mobile users’ mesh IDs that correspond to home and workplace. By analyzing the time duration of each stay mesh for one mobile user during the day of the 24 hours, home and workplace can be possibly derived. We use periods from 00:00 AM to 06:00 AM as nighttime and 11:00 AM to 17:00 PM as daytime. Some periods are omitted due to the high possibility of commuting time, and the percentage is calculated by comparing the sum of all values in every mesh. Finally, we determine the grid-based
locations of home and workplace where a mobile user spent more than 80% of their total stay time during the night and morning, respectively. According to this standard, we select 66,598 mobile phone users whose activities are mainly located in the Greater Tokyo area to conduct a human decision-making strategy analysis during the Tohoku earthquake.

### 4.3.2 Travel Mode Choice Detection

To analyze the return home strategy during the Tohoku earthquake, it is necessary to mark the travel mode choice of the GPS data from mobile detection. Relying on a self-developed visualization system, we first divide a small portion of mobile GPS data into several segments based on map-matching algorithm [50], and manually label the ground-truth travel model choice for each segment of GPS trajectory based on corresponding speed, distance and matching result of public transportation network (e.g., subway, highway, and footpath). Then we implement a Random Forest Classifier [51] for the remaining datasets based on those train data samples, labeled travel mode choice. Traffic volume and ratio change for each travel mode choice before/during/after the Tohoku Earthquake can be seen in Figure 2. We can find the corruption of the public transportation network due to the damages of the Tohoku earthquake (At about 14:46 on March 11, 2011), and it validates the effectiveness of travel mode choice detection.

**Algorithm 1:** Function Discovery Process based on DMR

**Input:** number of areas $N$, POI feature vector $x_n$, mobility pattern $p_{n,r}$, number of topics $K$

**Output:** topic assignment $z_{n,r}$ for the $r$th mobility pattern in the $n$th area

1. **for each area topic $k$, do**
   2. (a) draw $\lambda_k \sim \mathcal{N}(0, \sigma^2 I)$; // $\mathcal{N}$ is the Gaussian distribution.
      (b) draw $\beta_k \sim \text{Dir}(\eta)$. // Dir is the Dirichlet distribution.

3. **for each area $n$, do**
   4. **for each area topic $k$, do**
      5. $\alpha_{n,k} = \exp(x_n^T \lambda_k)$;
   6. **end**
   7. draw $\theta_n \sim \text{Dir}(\alpha_n)$;
   8. **for the $r$th mobility pattern in the $n$th area $p_{r,n}$, do**
      9. draw $z_{n,r} \sim \text{Mult}(\theta_n)$; // Mult is the multinomial distribution.
      10. draw $p_{n,r} \sim \text{Mult}(\beta_{z_{n,r}})$;
   11. **end**
   12. **end**
13. **return** topic assignment $z_{n,r}$
4.3.3 Function Discovery for Historical Check-ins

How to make decisions after an earthquake may be related to personal interest/custom. For example, he may choose to wait near the station for the recovery of public transportation if someone likes to go to a bar for a drink after work. In this work, we aim to discover the function of historical check-ins during return home trajectory before disaster, and explore its influence on decision-making strategy under disaster emergency in the subsequent sections.

Therefore, we first detect the most frequently visited stay points (500 m Grid Square, based on the Python library jismesh) during return home trajectory from the workplace before March 11. Experimentally, we set the number of grid-based areas as $N = 3200$ in the Greater Tokyo area. Then we follow the instruction [22] to discover the functions of each area by using DMR [47], a generative probabilistic topic model. The basic idea of topic model is to learn the topic of each document based on the distribution over words for given all words of each document in a corpus. DMR can consider the influence of metadata of a document compared with other topic models. More specifically, we deem each grid-based area $n \in N$ as a document containing different topics, and generate mobility pattern $p_{n,r}$ (i.e., arriving and leaving matrix) as rth word. In addition, we calculate the POI feature vector $x_n$ (i.e., frequency intensity) as metadata of each area $n$. Then the topic assignment $z_{n,r}$ are induced by both the POI information and mobility patterns. The detailed function discovery process for historical check-ins can be found in Algorithm 1. Here, the heatmap of the most frequent 3200 staying grids during the return home process is shown in Figure 3 (left), and the topic assignment result obtained by DMR with $K = 4$ is visualized in Figure 3 (right).

![Image](image-url)

**Fig. 3** The most frequently visited 3200 grid-based stay points for historical check-ins during the return process in the Greater Tokyo area (left) and generated functional areas for four classes of topics (right).

We also consider five types of POI (i.e., commuting, public place, shopping, restaurant, and entertainment) to validate the inferred topics, which are represented in Table 1. The corresponding statistics for the inferred topic of each area are shown in Table 2 and Figure 4, respectively. By incorporating the POI number and temporal analysis (including arrival time and stay time) for the functional areas of each topic, we could infer possible topic types of
those stay points of historical check-ins. For example, cluster 2 (Green) has relatively more public sites and also shows a longer stay time than the historical check-ins of other topics. Thus, “Topic: public” is a reasonably inferred result.

![Diagram of stay time of each inferred topic](image1)

![Diagram of arrive time of each inferred topic](image2)

**Fig. 4** Temporal analysis for each inferred topic based on historical check-ins during return home trajectories.

**Table 2** Number of five coarse POI types and inferred topic for each functional cluster.

<table>
<thead>
<tr>
<th>Functional Clusters</th>
<th>Restaurant</th>
<th>Public place</th>
<th>Commuting</th>
<th>Shopping</th>
<th>Entertainment</th>
<th>Inferred Topic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster 0 (Red)</td>
<td>46553</td>
<td>2338</td>
<td>6371</td>
<td>6786</td>
<td>3454</td>
<td>Market/Commute</td>
</tr>
<tr>
<td>Cluster 1 (Yellow)</td>
<td>18887</td>
<td>91</td>
<td>604</td>
<td>1996</td>
<td>995</td>
<td>Restaurant</td>
</tr>
<tr>
<td>Cluster 2 (Green)</td>
<td>13835</td>
<td>1918</td>
<td>3173</td>
<td>2649</td>
<td>715</td>
<td>Public place</td>
</tr>
<tr>
<td>Cluster 3 (Blue)</td>
<td>8398</td>
<td>75</td>
<td>439</td>
<td>1433</td>
<td>1542</td>
<td>Entertainment</td>
</tr>
</tbody>
</table>
4.4 Decision-making Strategy Inference Tasks and Corresponding Influence Factors

4.4.1 Task Introduction

In this study, for those mobile phone users who stayed at the workplaces before the start of the Tohoku earthquake, we divide proposed decision-making strategies into return home strategy-based prediction and departure time estimation tasks from the workplace. Here, return home strategy-based prediction includes two three-class prediction sub-tasks. One is the post-disaster destination prediction, and the other is the travel mode choice prediction.

First, as shown in Figure 2c, most of the subway lines or highways were halted due to damages from the big earthquake. This caused the train-based and car-based traffic volumes to decline sharply. However, the main subway transportation network would resume from 11:00 PM on March 11, 2011. This raises a question: when comes to the big earthquake, which post-disaster destination did one mobile phone user choose to go during the time period from 16:00 PM on March 11 to 8:00 AM on March 12? The possible choice for them would be Choice 1 - Still return home; Choice 2 – Go to other places instead of returning home, e.g., hotels or refuges, and Choice 3 – Stay in the workplace to wait for the recovery of the public transportation network. As a result, sub-task one is a three-class classification problem.

Second, except for the post-disaster destination prediction, we also conduct a travel mode choice prediction for those mobile phone users who returned home after the Tohoku earthquake, that is, train-based, walk-based (including walk and bike), and car-based travel mode.

In addition, the departure time estimation from the workplace also plays a vital role in analyzing decision-making behaviors during big disasters. For example, the Tohoku earthquake happened at 14:46 on March 11, 2011 (Japanese standard time), and many workplaces let most employees leave work directly. However, due to the corruption of the transportation network, many people still chose to stay at their workplace to wait for the recovery of public transportation. Therefore, we estimate the departure time from the workplace for those mobile phone users who chose to return home after the earthquake.

4.4.2 Influence Factors

As Figure 5 shows, we conclude all analyzed factors/features for the return home strategy-based tasks. These factors can be divided into users’ historical check-ins and location information. For the first aspect, mobile phone users’ historical check-in information comprises the functional type, corresponding visit number for each check-in region, and the total stay time of all check-in records. For convenience analysis, we represent these features as the number of check-ins for each inferred topic and the whole stay time, which is represented as "topic_xxx" and "total stay_time". And for the second aspect, users’ location-based information includes the (latitude, longitude) of both home and workplace location of each mobile phone user, the total distance between
home and workplace, and the nearest subway station & bus stop and the corresponding distance with both home and work location.

5 Decision-making Strategy Inference

This section provides a descriptive analysis to predict decision-making strategy for mobile phone users after the Tohoku earthquake with the objective of understanding the nature of human behaviors during disasters. In the experimental phase, we use the Scikit-learn \cite{52} framework with Python, and conduct inference experiments with several model types: (1) LightGBM \cite{53}; (2) Random Forest \cite{51}; (3) Naive Bayes \cite{54}; (4) XGBoost \cite{55}; (5) AdaBoost \cite{56}. In addition, we use the k-fold cross-validation (k = 5) when conducting inference experiments, i.e., randomly selecting 75% of the mobile phone users as the train set, and the remaining users are used as a test set.

5.1 Return Home Strategy-based Prediction

This prediction task can be divided into two three-class sub-tasks defined in Section 4.4.1. One is the post-disaster destination prediction for experimental mobile phone users; the other is the direct travel mode prediction for those who choose to return home. The statistics of two sub-tasks can be seen in Table 3, which shows the detection result of the population number of each class for both two sub-tasks. Here, we detect the population number of each class for both sub-task 1 and sub-task 2 from total mobile phone users. Class 1, Class 2, and Class 3 denote the To home/Train-based travel mode, To other places/Walk-based mode, and At workplace/Car-based mode for
sub-task 1/sub-task 2. In our decision-making strategy prediction, we use corresponding features/factors described in Section 4.4.2, including two situations of "With HCs" (historical check-ins) and "No HCs".

Table 3 Statistics of both two sub-tasks.

<table>
<thead>
<tr>
<th>Tasks</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Number of people</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sub-task 1</td>
<td>13894</td>
<td>11451</td>
<td>16157</td>
<td>41502</td>
</tr>
<tr>
<td>Sub-task 2</td>
<td>1905</td>
<td>7233</td>
<td>2639</td>
<td>11777</td>
</tr>
</tbody>
</table>

Table 4 summarizes the prediction results of two three-class sub-tasks for return home strategy-based prediction. Two three-class sub-tasks achieved prediction accuracy of over 60% and 65%, respectively. Furthermore, when considering input factors/features, adding "With HCs" always performs better than "No HCs" and has relatively more minor standard deviations. This validates our topic discovery for historical check-in plays an essential role in return home strategy-based prediction. In the following explainable analysis, we will also discuss this point. Moreover, when considering model types, LightGBM and Random Forest often perform well, and Naive Bayes has worse prediction results across five model types. Generally, all the models implemented in this task, except for Naive Bayes, perform reasonably well. These results suggest that our selected factors/characteristics could contribute to the return home strategy-based prediction with good performance.

Table 4 Performance (mean. ± std.) for return home strategy-based prediction by using 5-fold cross validation. Here, "HC" denotes the adding factors for "Users' historical check-ins".

<table>
<thead>
<tr>
<th>Factors</th>
<th>Sub-task 1</th>
<th>Sub-task 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No HCs</td>
<td>HCs</td>
</tr>
<tr>
<td>LightGBM</td>
<td>62.14±2.14%</td>
<td>64.06±2.53%</td>
</tr>
<tr>
<td>Random Forest</td>
<td>61.29±2.59%</td>
<td>63.35±2.12%</td>
</tr>
<tr>
<td>Naive Bayes</td>
<td>58.71±3.36%</td>
<td>60.29±2.88%</td>
</tr>
<tr>
<td>XG Boost</td>
<td>61.30±2.12%</td>
<td>62.42±2.37%</td>
</tr>
<tr>
<td>Ada Boost</td>
<td>62.36±2.31%</td>
<td>63.88±1.76%</td>
</tr>
</tbody>
</table>

5.2 Departure Time Estimation from Workplace

When people come to the return home strategy, the workplace’s departure time is a crucial decision for analyzing human behavior during disasters. In addition, departure time also has different patterns for each travel mode (i.e., walk-based travel mode, car-based mode, and train-based mode). For example, suppose one mobile phone user chose to return home by train. In that case, they may decide to wait for the recovery of the train at a workplace
or other places near the subway station. The distribution plot of departure time from the workplace among the three travel mode choices can be seen in Figure 6, we can observe that mobile users who decided to choose a walk-based travel mode often intended to depart the workplace directly when the earthquake happened, and on the contrary, those users who chose the train-based mode were more likely to wait in their workplaces, until the recovery of public transportation network.

Table 5 shows the departure time estimation result, we here implement the mean absolute error (MAE), and root mean squared error (RMSE) as the evaluation metrics. We can find that adding our proposed "HCs" factors also improves estimation accuracy and achieves a slight standard deviation compared with "No HCs". Furthermore, the XGBoost and AdaBoost models can perform better than these five models. Nevertheless, all five models have relatively stable and consistent performance for departure time estimation from the workplace.

<table>
<thead>
<tr>
<th>Factors</th>
<th>RMSE No HCs</th>
<th>RMSE HCs</th>
<th>MAE No HCs</th>
<th>MAE HCs</th>
</tr>
</thead>
<tbody>
<tr>
<td>LightGBM</td>
<td>2.787±0.081</td>
<td>2.544±0.057</td>
<td>1.923±0.068</td>
<td>1.639±0.052</td>
</tr>
<tr>
<td>Random Forest</td>
<td>2.865±0.090</td>
<td>2.597±0.093</td>
<td>1.956±0.107</td>
<td>1.652±0.095</td>
</tr>
<tr>
<td>Native Bayes</td>
<td>2.974±0.083</td>
<td>2.604±0.071</td>
<td>2.015±0.124</td>
<td>1.803±0.037</td>
</tr>
<tr>
<td>XG Boost</td>
<td><strong>2.736±0.063</strong></td>
<td>2.502±0.043</td>
<td><strong>1.889±0.076</strong></td>
<td>1.587±0.059</td>
</tr>
<tr>
<td>Ada Boost</td>
<td>2.749±0.076</td>
<td><strong>2.467±0.075</strong></td>
<td>1.912±0.053</td>
<td><strong>1.622±0.046</strong></td>
</tr>
</tbody>
</table>

Fig. 6 The distribution plot of departure time from the workplaces among three travel mode choices ("Train", "Walk", and "Car"). Here, we analyze the mobile users who returned home during the time periods from 15:00 PM (March 11) to 8:00 AM (March 12) from total mobile users, and the horizontal axis is the elapsed time since the start of Tohoku earthquake (Hour).
5.3 Feature Importance Analysis

Although we have already known the feature contribution of "HCs" from the inference results, we also provide some interesting and reasonable discoveries for decision-making strategies based on feature importance analysis. In Figure 7, Figure 8 and Figure 9, we show the all considered factors/features importance values for two prediction sub-tasks and one estimation task, respectively. These SHAP values [57–59] were captured by the Shapash library when using all features in the LightGBM model. The higher values in these figures mean the big feature importance. Generally, users’ location information stays stable under the situations of both "No HCs" and "With HCs" for two prediction sub-tasks and one estimation task.

For the post-disaster prediction (sub-task 1), location information (especially "distance") has relatively higher important values than users’ historical check-in information. For example, "distance" has the most obvious influence
on the categories of “To Home” and “To Other Places”, and the location of the workplace is critical for the category of “At Workplace”. Therefore, it can be inferred that the workplace near the shelters is essential for those users who were challenged to return home and choose the destination to avoid the disaster. Moreover, users’ historical check-in information also plays an important role, and their destination choices are associated with different topics. For example, if one user intended to return home, the feature “topic_Entertainment” and total stay time of historical check-ins have high importance values. It is reasonable because phone users who often visited the environment venues, as usual, were more likely to return home because of the closure of environment venues. On the contrary, if one user chooses to go to other places (such as shelters), the feature “topic_Public” should also be important because shelters are often set in prominent public places. Our feature importance result for the category of “To other places” in Figure 7 validates this assumption. Significantly, the category of “At Workplace” doesn’t have very related topics (relatively low importance values with “topic_xxx”), only has specific importance values for the features of both “topic_Entertainment” and “topic_Restaurant”.

Also, for the travel mode choice prediction, Figure 8 shows that the travel mode choices have low correlations with topics of historical check-ins compared with post-disaster destination prediction. However, there are some exciting and reasonable discoveries from the feature importance analysis. For example, “work&subway_stop distance” is significantly crucial for the categories of “Train-based” and “Car-based” because Japan has developed subway lines for commuting. If one mobile user’s workplace is nearby the subway stop, they will intend to choose the train. And if the opposite is true, they will intend to select the bus (car). In addition, the feature “topic_Restaurant” and total stay time of historical check-ins have relatively higher importance values than other topics for the categories of both “Car-based” and “Train-based”. It could be interpreted because mobile phone users could wait for a subway/bus recovery in restaurants. At the same time, “topic_Public” means the visit of prominent public places such as parks and art galleries, and it associates with the category of “Walk-based” because mobile phone users have enough physical strength to walk for a long time.

Finally, as Figure 9 shows, the feature importance for the departure time estimation from the workplace also represents the same pattern with the category of “Train-based” in travel mode inference, which equally shows the high importance values in “topic_Restaurant” and “total stay_time” when considering the “HCs” factors. In sum, this suggests that both two factors easily influenced the decisions of mobile phone users for departure workplace time. Moreover, it is reasonable because both departure time and “Train-based” are relevant if the mobile phone users wait for the recovery of train.
5.4 Case Study

Except for the feature importance analysis (what is important), we also need to know the positive/negative correlation between feature importance and feature value (how important). As is shown in Figure 10, contribution plots for departure time estimation from the workplace provide this correlation between feature importance and feature value. We plot the SHAP (contribution) values, feature values and predicted values of each observation sample for the top 2 features in two feature groups (users’ location information and historical check-in information). Here, positive contribution means that the feature value is positively correlated with the predicted value (what time did mobile phone users depart from the workplace, the unit is PM) of each observation sample for the top 2 features in two feature groups, respectively. We can find four key feature values - {10km, 1km, 400mins, 5times}, which is viewed as the positive and negative conversion of SHAP values in four contribution plots (distance, work&subway_stop distance, total stay_time, and topic_Restaurant), respectively.

Fig. 9 Feature importance analysis for departure time estimation from workplace.

Fig. 10 Contribution plots for departure time estimation from the workplace. Here, we plot the SHAP (contribution) values, feature values, and predicted values (when did user depart from the workplace, the unit is PM) of each observation sample for the top 2 features in two feature groups, respectively. We can find four key feature values - {10km, 1km, 400mins, 5times}, which is viewed as the positive and negative conversion of SHAP values in four contribution plots (distance, work&subway_stop distance, total stay_time, and topic_Restaurant), respectively.
users depart from the workplace?\), and negative contribution to the contrary. For example, Figure 10a, if the total distance between home and workplace is far, they will intend to depart from the workplace late. And the predicted value can validate this pattern. We can also conclude that when the distance is less than 10 km, the predicted value could be contradictory (samples that have a very negative contribution but have a relatively significant predicted value) between the predicted value and contribution value in specific samples. This means poor prediction performance in samples of low distance. Moreover, from the contribution plots of features - "total stay time" and "topic_Restaurant", we can conclude that more times of visits for "topic_Restaurant" and longer stay time of historical check-ins would intend to depart from the workplace late. It’s very reasonable because of the previous explanation for users who waited for the recovery of the train. In sum, we can find four fundamental feature values - \{10km, 1km, 400mins, 5times\} in Figure 10, which is viewed as positive and negative conversion of SHAP values in four contrition plots (distance, work & subway_stop distance, total stay_time and topic_Restaurant), respectively. In addition, to validate these assumptions, we conduct a departure time distribution analysis for every key value detected from contribution plots in Figure 11. We can find different departure time distributions for the key values in contribution plots from these plots. These key threshold values would inspire the government to find different influences of key factors in the decision-making process during disasters and formulate the policy.

We also provide an explainable case study for total mobile phone users and those phone users whose workplaces were nearby Shinjuku station. We select Shinjuku of Tokyo because the Shinjuku area has numerous shopping
(a) The heatmap for all users’ (66,598 mobile phone users) stay point during the time period from 19:00 PM to 11:59 PM on March 11.

(b) Feature importance comparison for departure time estimation between “Global” (all users) and “Subset” (about 7% of users who worked in the Shinjuku area.)

Fig. 12 Cases of mobile phone users whose workplaces were in Shinjuku, Tokyo.

centers and an important railway station in the public transportation network of Tokyo. Especially according to the media reports, there are still many people waiting around the Shinjuku station until the recovery of the subway/bus after the Tohoku earthquake. It can be validated by Figure 12a. The comparative feature importance in Figure 12b also validates this news report. When it comes to the departure time estimation from the workplace, the scenario of “HCs” shows more importance in “topic_Market/Commuting” and “topic_Entertainment” compared with the total mobile phone users. In addition, the increased feature importance for “topic_Public” means that some people are stuck in nearby public venues.

6 CONCLUSION

In this study, we collected large-scale mobile sensing datasets and analyzed the decision-making strategies of mobile phone users during the Tohoku earthquake. Our work emphasized the importance of understanding the topics of the historical check-ins to obtain a holistic view of the human behaviors of different functional topics/types. Then all influence factors, including both users’ historical check-ins and location-based factors, could inform the decision-making strategy inference during disasters. We defined and evaluated two main prediction tasks (i.e., return home strategy-based prediction and departure time estimation from the workplace), showing the feasibility of using smartphone sensing to detect historical check-ins. In addition, we performed an explainable analysis of the critical factors/features that impel phone users to make a decision. We believe that these findings could be helpful to the government in implementing future mobile disaster evacuation systems by accurately predicting human decisions during large-scale disasters.

Declarations

Competing Interests The authors have no competing interests to declare that are relevant to the content of this article.
Authors’ Contributions Zhiwen Zhang and Hongjun Wang wrote the main manuscript text, and Zipei Fan provided the ideas and guidance for this manuscript. All authors reviewed the manuscript.

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Availability of Data and Materials The used large-scale GPS data and materials can only be requested at https://www.zenrin-datacom.net/ for the sensitivity reasons.

References


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