Prediction of Human Emergency Behavior and their Mobility following Large-scale Disaster

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The frequency and intensity of natural disasters has significantly increased over the past decades and this trend is predicted to continue. **Urban emergency management** has become the especially important issue for the whole governments around the world.

**Japan** is one of the countries **most affected by natural disasters**. Two out of the five most expensive natural disasters (big earthquakes) in recent history have occurred in Japan, costing $181 billion in the years 2011 and 1995 only. Japan has also been the site of some of the 10 worst natural disasters of the 21st century.
Urban Emergency Management and Big Data

Human mobility during the Great East Japan Earthquake 2011 in Rikuzentakata and Minamisanriku (Mobile Phone GPS Data)

Recently, the mobile phone data, GPS trajectories data, location-based online social networking data, and IC card data have emerged and increased explosively. The explosive increasing of these human mobile sensing data becomes the “Big Data”, and offer a new way to perform the next-generation urban emergency management.
What happened in Tokyo during the Great East Japan Earthquake in 2011?

The Greater Tokyo Area (the largest metropolitan area in the world)
If some similar disasters happen, can we predict human behavior and their mobility?

- By modeling human past movements following disasters?

If some future disaster occur, given person’s current observed movements:
- **which place** will it go next time period?
- How about its **traveling routes**?
Therefore, in this research, we try to develop a model for accurately predicting human behavior and their mobility following large-scale disaster.
Data and Empirical Analysis
The Database for this Research

- **Mobile Phone GPS Data:** Auto-GPS mobile sensing data
  - 1.6 million users, in one year (now we have three years data)
  - Total size 600GB in CSV
  - 9.2 billion records.
  - Auto GPS function
  - GPS data provided by individual users of mobile-phone navigation with their permission.
  - 5 min (at least) interval, for a whole year.

- **Disaster Information Data**
  - Disaster intensity data
  - Disaster reporting data

- **Hadoop Cluster**
  - 32 cores, 32GB memory, 16TB storages
  - run 28 tasks at the same time
  - provide indexing, retrieval, editing and visualization services
Pre-processing of Data (important places discovery)

- Even though human movement and mobility patterns have a high degree of freedom and variation, the majority of human movement is based on periodic movement between a small set of important places.
- We compute distribution of geographic location for individual people and analyze it with time. It is easy for us to find and recognize some important places of individual people.
Human behaviors after the Great East Japan Earthquake and Fukushima nuclear accident

(a) Human Behaviors after 24 hours of the Earthquake

The Greater Tokyo Area

- at home
- working
- social relationship
- unknown places

(b) Human Behaviors after 24 hours of the Earthquake

Fukushima, Miyagi, Iwate prefectures

- at home
- working
- social relationship
- unknown places

(c) Human Behaviors after 19 Days of the Earthquake

The Greater Tokyo Area

- at home
- working
- social relationship
- unknown places

(d) Human Behaviors after 19 Days of the Earthquake

Fukushima, Miyagi, Iwate prefectures

- at home
- working
- social relationship
- unknown places

Fukushima Nuclear Event

3/11
March 11th, 2:45 pm
Earthquake & Tsunami

11th, 2:45 pm
Emergency declared

4:36 pm
Unit 1 Hydrogen Explosion

8:41 am
Unit 3 Explosion

11:15 am
Unit 3 Explosion

6:06 am
Unit 4 Explosion

5:45 am
Unit 4 2nd Fire

7:00 am
Unit 4 Storage pool boiling

3:00 am
Thirty-five fire engines

3:10 am
Bottled water scarce

3:55 pm
Unit 3 Gray smoke appears

3:55 pm
Radiation leaks

126x > iodine limit

3:55 pm
IAEA Tracks

Elevated levels outside 30km

Workers touch radiation

100,000x > norm

13x > norm, 16km away

28x > norm, 10km away

1:00 pm
Unit 3 Gray smoke again

1:00 pm
Unit 3 Containment vessel breach

2:30 pm
Unit 4 Storage pool boiling

7:00 pm
Unit 4 Helicopter water

Unit 1, 2, 3 Seawater cooling continues

Unit 2 Radioactive seawater leaking to outside

Unit 2 Radioactive seawater leaking to outside

3:36 pm
Unit 1 Hydrogen Explosion

3:36 pm
Unit 1 Hydrogen Explosion

3:36 pm
Unit 1 Hydrogen Explosion

10/11

News Reporting

NHK

CNN

FOX

REUTERS

Fukushima probably exceeds Chernobyl and there is no end in sight

Radiation test 10,000,000 times above normal

(retracted)

Utility retests reactor water

100,000X > coolant norm/yr

330>/ave per person

Japan mulls new steps.

335X > legal water limit
Approach
Our approach decomposes the predicting problem into two sub-problems:

- We use people’s past movements during disasters, and its important places to train a HMM-based human behavior model. Then, given person’s current observed movements and disaster states, our model predicts its possible behavior at next time period.

- We use the whole collected population movements of a specific urban areas to train the urban mobility model. Then, our model predicts person’s possible movements given its predicted behavior at next time period.
The following three key parameter components of HMM model need to be learned:

- Initial state probability for each hidden states;
- State transition probability between hidden states;
- State-dependent output probability $P(Z|S)$, which determines the probability of the people’s mobility given the hidden behavior state.
A Simple Example (Normal Case)
Cont.

The morning of 2011 July 13th (Friday)
Cont.
Cont.
Then, we also need to predict people’s possible mobility or evacuation routes, which will play a vital role on effective humanitarian relief and disaster management. Given a predicted place and its current location, it is not difficult to find a possible route for a specific person. However...
Prediction of human mobility and its traveling routes

- Almost the whole public transportations (whole metro or railway services) in Tokyo were unavailable!!
- This earthquake caused large traffic chaos and urban disorders

Human Mobility following The Great East Japan Earthquake

- Given a predicted place and its current location, it is easy to think of using transportation networks to plan and predict its possible movements. However, most public transportation systems are usually not available after the earthquake occurred.
- Furthermore, human’s mobility following disaster usually will be impacted by other people, and they usually tend to find a much safer routes for evacuations.
Urban mobility modeling following disasters

Human Mobility During The Great East Japan Earthquake

- To understand, simulate and predict large number of population movements in the urban areas (urban mobility), we need a concise model to effectively represent population movements in a specific urban areas.
- To model urban mobility following the earthquake, there are mainly two stages: mobility graph construction and inference model learning.
Given the population movements, constructed some important regions as the nodes for the graph. Utilize these movements traversing the regions to derive edge connections. The final mobility graph was illustrated.
Mobility Graph Model Learning

Based on the constructed mobility graph, the model was able to be developed by using the Markov Decision Process (MDPs). The mobility graph provided us a deterministic MDP, the urban region (nodes) was able to be seen as state, the edge was the action, and the path was the parameterized trajectories by their path feature. We utilized the Inverse Reinforcement Learning to train the overall model.
The nodes denote the important locations of people (e.g. home or working), and edges represent human movements. The size of the circles denote the node weights. Here, it shows population density. The edge color indicates the edge parameters. Here, it shows the travel frequency. In addition, the circle’s color indicates the population change. Warner values represent decrease of population, and cooler values represent increase.
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Human Mobility Prediction through Urban Mobility Graph Model
Evaluation
To evaluate the performance of different predictive models (PMM, MF, GM and ours), we use three metrics: predictive accuracy, Log-likelihood, and expected distance error.
Evaluation of mobility prediction

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Matching</th>
<th>90% Matching</th>
<th>Log-Prob</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our Method (the Greater Tokyo Area)</td>
<td>80.68%</td>
<td>58.73%</td>
<td>-6.53</td>
</tr>
<tr>
<td>Method [15] (the Greater Tokyo Area)</td>
<td>72.76%</td>
<td>51.27%</td>
<td>-7.15</td>
</tr>
<tr>
<td>Our Method (Other three prefectures)</td>
<td>83.39%</td>
<td>63.36%</td>
<td>-5.97</td>
</tr>
<tr>
<td>Method [15] (Other three prefectures)</td>
<td>73.28%</td>
<td>52.28%</td>
<td>-7.33</td>
</tr>
</tbody>
</table>

To evaluate the performance, we use three metrics: Matching percentage, 90% Matching percentage, and Log-Prob.
Conclusion and Future Work

We develop a model of human behavior that takes into account different disaster factors for accurately predicting their behavior and mobility. The experimental results and validations demonstrate the efficiency of our behavior model.

Future work:
Currently, the learnt behavior model is only able to applied to a specific person (learnt with its movements after disaster). In the future, we try to extend our behavior model into a general one by using transfer learning technology.
Thank you very much for your attentions!