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Building a Timeline Network for Evacuation in Earthquake Disaster

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Abstract

In this paper, we propose an approach that automatically extract users' activities in sentences retrieved from Twitter. We then design a timeline action network based on Web Ontology Language (OWL). By using the proposed activity extraction approach, we can automatically collect data for the action network. Finally, we propose a novel action-based collaborative filtering, which predicts missing activity data, in order to complement this timeline network. Moreover, with a combination of collaborative filtering and natural language processing (NLP), our method can deal with minority actions such as successful actions. Based on evaluation of tweets which related to the massive Tohoku earthquake, we indicated that our timeline action network can provide useful action patterns in real-time. Not only earthquake disaster, our research can also be applied to other disasters and business models, such as typhoon, travel, marketing, etc.

Introduction

The ability of computers to recommend useful action patterns based on users' behaviors is now an important issue in context-aware computing (Matsuo et al. 2007), ubiquitous computing (Poslad 2009), and can be applied to assist people in disaster areas. When the massive Tohoku earthquake and Fukushima nuclear disaster occurred in March 2011, many people felt panic, and wanted to know "what did other people do to go to a safe place", "how to come back home", etc. Since the train system in Tokyo was stopped after the earthquake, there are about 3 million people in Tokyo who had difficulties returning home (AsahiShimbun 2011). The Japanese government said that there is 87% of chance of an approximately 8.0-magnitude earthquake occurring in the Tokai region within the next 30 years (Nikkei 2011). In this case, temporary homeless people who are unable to return home, are expected to reach an amount of 6.5 million (Nakabayashi 2006).

To recommend useful action patterns, it is necessary to have a *collective intelligence of these action patterns*. During the massive Tohoku earthquake, while landlines and mobile phones got stuck, Twitter was used to exchange information related to evacuation, traffic, etc. On 11 March, 2011 the number of tweets from Japan dramatically increased to about 33 million (Biglobe 2011), 1.8 times higher than the average figure. Therefore, we can say that Twitter is becoming the *sensor* of the real world. In other words, we can collect activities of people in earthquake disaster from Twitter. We can consider these activities as the collective intelligence. However, sentences retrieved from Twitter which are more complex than other media texts, are often structurally various, syntactically incorrect, and have many user-defined new words (Nguyen et al. 2012).

In emergency situations, it is important to let the computers make a useful recommendation *in time*. This means that the activities should be collected, and represented in real-time. However, since tweets depend on users' autonomy, it is highly probable that the users do not post their activities in real-time. Thus, we need to solve the problem of missing activity data in order to have activity data in real-time. Additionally, to help the computer understand the meaning of the data, we should build the collective intelligence based on OWL.

In this paper, we first use our previous work (Nguyen et al. 2012) to automatically extracts human activities from Twitter. And then, we design a timeline action network (TiAN) to represent these activities in real-time. Finally, we propose a novel action-based collaborative filtering, which predicts missing activity data, to complement the action network. Moreover, with a *combination of collaborative filtering and NLP*, our method can handle *minority actions* such as successful actions.

The main contributions of our work are summarized as follows:

- We has successfully designed the TiAN based on OWL in order to represent the activities in real-time.
- We also proposed a method that can predict missing activity data to complement the action network. Moreover, this method can handle *minority actions*.

The remainder of this paper is organized as follows. We first explain how to extract human activity from Twitter. Secondly, we design TiAN to represent the extracted activities. Thirdly, we explain how to predict missing activity data. We then report our experimental results, and explain how to apply the action network. After considering related works, this paper concludes with some discussions of the future work.

Extraction of Human Activity

In this paper, we define an activity by five attributes namely *actor*, *act*, *object*, *time* and *location*. And an *action* consists of a combination of *act* with *object*. For example, in the sentence "Tanaka is now taking refuge at Akihabara", *actor*, *act*, *time* and *location* are "Tanaka", "take refuge", "now", "Akihabara" respectively.

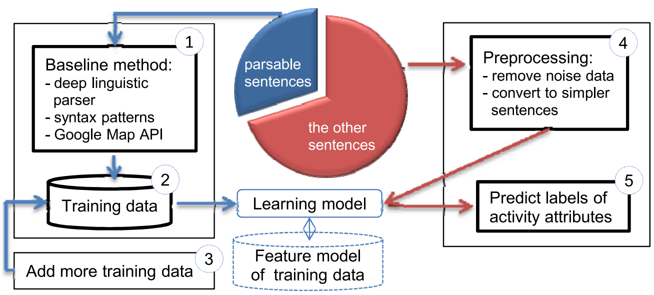

Figure 1: Approach of extracting activities.

As shown in Figure 1, our key ideas for extracting activity attributes in each sentence retrieved from Twitter, are summarized as follows:

- We deploy self-supervised learning (Banko and Etzioni 2008), and use the linear-chain conditional random field (CRF) (Lafferty, McCallum, and Pereira 2001) as a learning model.
- Using deep linguistic parser (Kudo and Matsumoto 2002), 8 syntax patterns, and Google Map API to make initial training data from parsable sentences.
- Based on the initial training, we collect more trustworthy training from weblogs.
- Since sentences retrieved from Twitter often contain noise data, we remove these noise data before testing. Additionally, to avoid error when testing, we convert complex sentences to simpler sentences by simplifying noun phrases and verb phrases.
- We consider not only time stamp of tweets, but also time expression (now, this evening, etc) to decide time of activities in these tweets.

Building Timeline Action Network

In this section, we first design TiAN. We then explain how to create semantic data for TiAN.

Designing Timeline Action Network

To represent human activities in real-time, we add time information into TiAN. As shown in Figure 2, TiAN is expressed as a directed graph whose nodes are activity attributes, and whose edges are relations between these activity attributes.

It is important to help the computers understand the meaning of data, thus we design TiAN based on OWL. Since N3

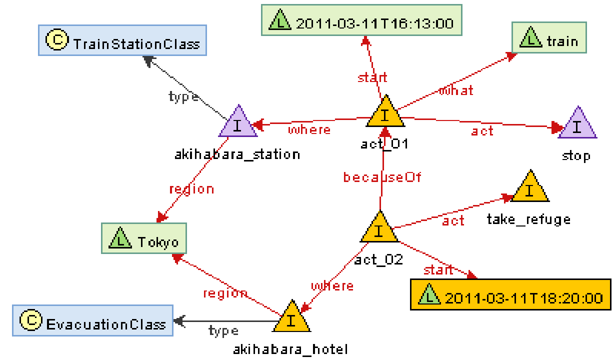

Figure 2: An excerpt from timeline action network (C, I, L represent class, instance, label of activity attributes respectively).

(W3C 2006) is a compact and readable alternative to RDF's XML syntax, we use N3 to describe data of TiAN.

:stop	a	:ActClass ;
	rdfs:label	"stop"@en .
:akihabara_station	a	:TrainStationClass ;
	rdfs:label	"Akihabara station"@en ;
	vcard:region	"Tokyo"@en ;
	vcard:locality	"Chiyoda-ku"@en ;
	vcard:street-address	"1-17-6 Sotokanda"@en ;
	geo:lat	35.69858 ;
	geo:long	139.773108 .
:act_01	a	:ActionClass ;
	:act	:stop ;
	:what	"train"@en ;
	:where	:akihabara_station ;
	tl:start	2011-03-11T16:13:00^^xsd:dateTime ;
	tl:end	2011-03-11T23:45:00^^xsd:dateTime .

Figure 3: An example of TiAN data.

To represent data of TiAN, we create classes and properties as below:

- ActionClass, ActClass, WhereClass, and WhatClass are classes of activity, act, location, object respectively.
- EvacuationClass, ShopClass, RestaurantClass, TrainStationClass are classes of evacuation, shop, restaurant, train station respectively.
- TiAN has five properties: act, what, where, next, and becauseOf, which correspond to activity attributes, and relations between activities.

To easily link to external resource, TiAN inherits Geo (Geo 2003), Time line (Raimond and Abdallah 2007), and vCards (Halpin et al. 2010) ontologies. Geo (Geo 2003) is used for representing latitude and longitude of a location. Time line (Raimond and Abdallah 2007) is used for representing time. And, vCards (Halpin et al. 2010) is used for representing an address of a location.

Based on the above classes, properties, and inherited ontologies, we can describe data of TiAN. For example, Figure 3 represents the activity in the sentence “The train has stopped at Akihabara Station at 16:13:00”.

Creating Semantic Data

Figure 4 explains how to create semantic data for TiAN. We first use #jishin (#earthquake) tag which relates to earthquake to collect activity sentences from Twitter. Secondly, we use our activity extraction method to extract activity attributes, and relationships between activities. Finally, we convert the extracted data to RDF/N3 to make semantic data for TiAN.

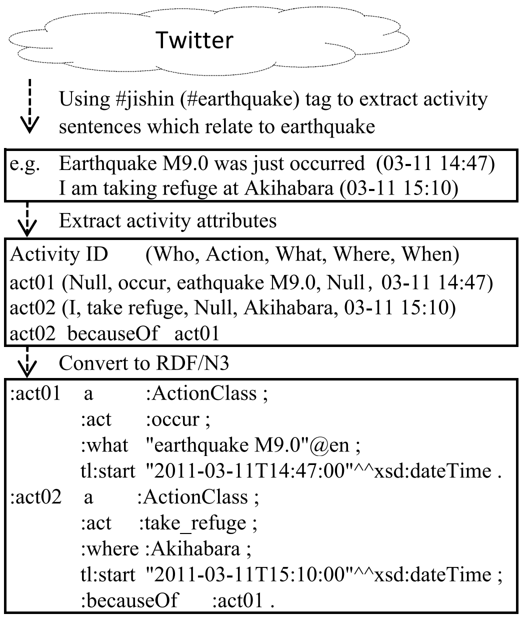

Figure 4: Method of creating semantic data for TiAN.

Prediction of Missing Activity

Let $Can_{act} = \{act_1, act_2, .., act_t, ...\}$ is the set of candidate actions of the active user u_a at time t. Predicting the action of u_a at time t can be considered as choosing the action in Can_{act}, which has the most highest probability. Therefore, we need to calculate probability of u_a did act_t at time t ($P_{u_a \rightarrow act_t}$).

As shown in Figure 5, we can use collaborative filtering approach (CF) to calculate $P_{u_a \rightarrow act_t}$. However, while traditional CF (Ma, King, and Lyu 2007; Koren 2009; Sandholm and Ung 2011) is trying to recommend suitable products on internet for users, our work tries to predict missing action data in real-world. Different from products, users' actions strongly depend on location, time, and before-after actions. Additionally, we need to consider execution time of each action. This means that it is not suitable to use traditional CF for our work.

Below, we propose a novel action-based CF to calculate $P_{u_a \rightarrow act_t}$.

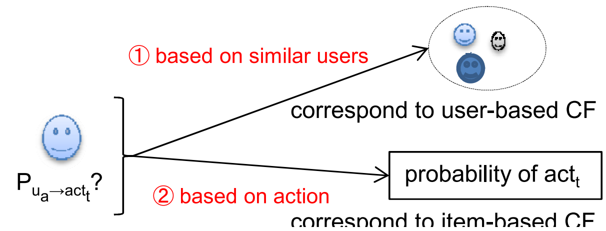

Figure 5: Approach of predicting missing activity.

Prediction based on Similar Users

Based on the following ideas, we calculate similarity between two users in emergency situations.

- It is highly probable that as same as user u_a, similar users also did before action ($Did(a_{before})$) and after action ($Did(a_{after})$) of the candidate action act_tD
- If users had the same goal (e.g. wanted to evacuate in Shinjuku), then they had same action patterns ($SameTarget(a_t, l_t)$).
- It is highly probable that user did the same actions if they were in the same location ($SameLocation(l)$).

Therefore, the similarity between user u_j and user u_a will be calculated as Equation 1.

$$\begin{aligned} S(u_j, u_a) = &\beta Did\left(\{a_{before}, l_{before}\}, \{a_{after}, l_{after}\}\right) \\ &+ \gamma SameTarget\left(a_t, l_t\right) \\ &+ (1 - \beta - \gamma) SameLocation(l) \end{aligned} \tag{1}$$

Where:

- Parameters β, γ satisfy $0 \leq \beta, \gamma, \beta + \gamma \leq 1$. These parameters depend on each particular problem.
- If u_j did action act_t in location l, then $Did(act_t, l) = 1$, otherwise $Did(act_t, l) = 0$.
- If u_j and user u_a has the same goal (want to do action a_t in target location l_t), then $SameTarget(a_t, l_t) = 1$, otherwise $SameTarget(a_t, l_t) = 0$.
- If u_j and user u_a were in the same location l at the time t, then $SameLocation(l) = 1$, otherwise $SameLocation(l) = 0$.

Prediction based on Probability of Action

In real-world, an action depends on location, time and its before-after actions. Therefore, probability of act_t at the time t can be calculated as Equation 2.

$$\begin{aligned} P(act_t) = &\rho_a \left\{F(a_{before} \rightarrow act_t) + F(act_t \rightarrow a_{after})\right\} \\ &+ \rho_t F(act_t, t) + (1 - \rho_a - \rho_t) F(act_t, l) \end{aligned} \tag{2}$$

Where:

- Parameters ρ_a, ρ_t satisfy $0 \leq \rho_a, \rho_t, \rho_a + \rho_t \leq 1$.
- $F(a_{before} \rightarrow act_t)$ is frequency of $a_{before} \rightarrow act_t$ (transition from a_{before} to act_t).

- $F(act_t \rightarrow a_{after})$ is frequency of $act_t \rightarrow a_{after}$ (transition from act_t to a_{after}).
- $F(act_t, t)$ is frequency of act_t at time t.
- $F(act_t, l)$ is frequency of act_t in location l.

Prediction based on Execution Time of Action

Figure 6 explains an example of plural missing actions. In this example, we need to determine that u_a did act_1 or act_2 at time t. We can solve this problem based on the execution time of these actions done by user u_j.

Let $time\_b$, $time\_1$ are execution time of before action, act_1 done by the similar user u_j respectively. We suppose that it took the same execution time for u_a and u_j did the same action. Based on this supposition, we can use Equation 3 to determine that u_a did act_1 or not.

$$T(u_j, act_1) = \begin{cases} \frac{time\_t}{time\_b} & (\text{diff} < 0) \\ 1 & (0 \leq \text{diff} \leq \text{time\_1}) \\ \frac{time\_1}{diff} & (\text{time\_1} < \text{diff}) \end{cases} \quad (3)$$

$$where, diff = time\_t - time\_b.$$

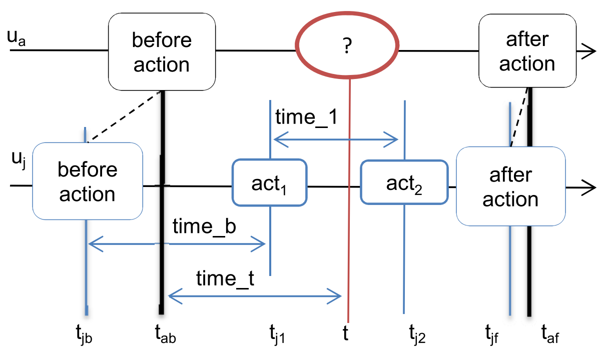

Figure 6: An example of plural missing actions.

Prediction Formula

Combination of Equation 1, Equation 2, and Equation 3, we can calculate $P_{u_a \rightarrow act_t}$ as Equation 4.

$$P_{u_a \rightarrow act_t} = \alpha \left(\frac{\sum_{j=1,L} \omega(u_j, act_t) * S(u_j, u_a) * T(u_j, act_t)}{L} \right) + (1-\alpha) P(act_t) \quad (4)$$

Where:

- L is number of all users similar to u_a.
- $\omega(u_j, act_t)$ is a weighting factor. If user u_j did act_t, then $\omega(u_j, act_t) = 1$, otherwise $\omega(u_j, act_t) = 0$.
- Parameters α satisfies $0 \leq \alpha \leq 1$. It depends on each particular problem.

Handling Minority Action

In emergency situations, successful actions are often minority actions, and have a great value. Therefore, we need a method that can handle not only the majority actions but also the minority actions. However, frequency-based method such as CF can easily handle the majority actions, but it is difficult to handle minority actions.

To deal with the minority action, we propose the following approach.

1. Using NLP to extract successful actions in feedbacks (tweets) from users. For example, if the users said that "it is a **good decision** when staying at company", then we can consider "stay at company" as a successful action.
2. Predicting probability of u_a who did a successful action, based on the following idea.
   - Probability of u_a who did a successful action is proportional to percentage of successful actions.
   - The degree of success of an action is proportional to number of good feedbacks from the users.

   Therefore, we can calculate probability of u_a who did a successful action by Equation 5.

$$DidSuccess_{u_a \rightarrow act_t} = f(u_a) * Success(act_t) \quad (5)$$

Where:

$$f(u_a) = \frac{number\ of\ successful\ actions}{number\ of\ actions}$$

$$Success(act_t) = \frac{number\ of\ good\ feedbacks\ about\ act_t}{total\ number\ of\ good\ feedbacks}$$

Finally, the formula to predict missing action will be complemented as Equation 6.

$$P^*_{u_a \rightarrow act_t} = DidSuccess_{u_a \rightarrow act_t} + P_{u_a \rightarrow act_t} \quad (6)$$

Evaluation

In this section, we first evaluate our activity extraction approach. Secondly, we use SPARQL (SPARQL Protocol and RDF Query Language) (W3C 2008) to evaluate our timeline action network. Then, we evaluate our proposed approach which predicts missing activities. Finally, we discuss the usefulness of the action network.

We collected 416,463 tweets which related to the massive Tohoku earthquake. And then, to create data-set for the evaluations, we selected tweets which were posted by users in Tokyo from 2011/03/11 till 2011/03/12.

Activity Extraction

Table 1 shows the comparison results of our approach with baseline method, and Nguyen et al. (Nguyen et al. 2011). Based on the results, we can see that the baseline has high precision but low recall. The reason is that sentences retrieved from twitter are often diversified, complex, syntactically wrong. Nguyen et al. also used self-supervised learning and CRF, but it could not handle complex sentences.

Table 1: Comparison of our approach with baseline, and Nguyen et al, (2011).

@	Method	Activity	Actor	Act	Object	Time	Location
Precision	Baseline	81.17%	86.32%	98.13%	84.14%	87.96%	88.25%
	Nguyen et al.	57.89%	72.79%	82.98%	67.01%	76.40%	80.20%
	Our approach	**73.21%**	**82.25%**	**97.11%**	**81.23%**	**80.04%**	**82.11%**
Recall	Baseline	23.86%	26.38%	28.87%	24.77%	26.20%	26.02%
	Nguyen et al.	51.13%	69.13%	90.23%	62.11%	73.51%	77.67%
	Our approach	**66.54%**	**80.11%**	**93.18%**	**76.57%**	**79.75%**	**81.02%**
F-measure	Baseline	36.88%	40.41%	44.61%	38.27%	40.37%	40.19%
	Nguyen et al.	54.30%	70.91%	86.45%	64.47%	74.93%	78.91%
	Our approach	**69.72%**	**81.17%**	**95.10%**	**78.83%**	**79.89%**	**81.56%**

```
SELECT   DISTINCT   ?location_name   ?street_address   ?end_time
WHERE {?action   :act   :open .
     ?action   tl:start   ?start_time .
     ?action   tl:end   ?end_time .
     ?action   :where   ?location .
     ?location   rdf:type   :EvacuationClass .
     ?location   rdfs:label   ?location_name .
     ?location   vcard:locality   "Chiyoda-ku"@en .
     ?location   vcard:street-address   ?street_address .

     FILTER(?start_time <= "2011-03-11T17:00:00"^^xsd:dateTime &&
          ?end_time >= "2011-03-11T17:00:00"^^xsd:dateTime &&
          lang(?street_address) = "en" &&
          lang(?location_name) = "en"
     )
}
```

Figure 7: An example query for looking up opening evacuation centers based on time and location.

Timeline Action Network

We used SPARQL to make RDF queries to evaluate our timeline action network. For example, Figure 7 shows the query that looks up an opening evacuation center based on the current time (2011-03-11T17:00:00), and the current location (Chiyoda-ku) of the active user. The result of this query is shown in Figure 8. Therefore, we can say that our action network is working properly with RDF queries.

location_name	"Akihabara Washington Hotel"@en
street_addresss	"1-8-3 Sakuma-cho, Kanda"@en
start_time	2011-03-11T16:00:00
end_time	2011-03-12T09:00:00

Figure 8: An example result of opening evacuation center.

Missing Activity Prediction

To evaluate our proposed approach, we first created correct action data of 3,900 Twitter users in Tokyo, after the massive earthquake occurred. Secondly, we repeated 10 times of the following experiment.

1. Randomly select 39 users as the active users.
2. Randomly delete activity data of these active users.
3. Consider the active users' names and time of deleted activities as input data, using our approach to determine whether the deleted activity data is reproduced or not.

The average results are shown in Table 2. In this table, baseline is the following method:

1. Look up the most similar user $most\_similar_{u_a}$ to the active user u_a.
2. Based on $most\_similar_{u_a}$, we predict missing activity of u_a.

Table 2: Recall of Deleted Activity Data.

Method	Action	Location	Action and Location
Baseline@	31.48%	43.09%	27.56%
Our method	**69.23%**	**76.92%**	**43.59%**

From the above results, we can say that:

- Our approach can reproduce 69.23% of missing actions, 76.92% of missing locations, and 43.59% of missing activities (both of action and location).
- Not only the most similar user, our method considers all similar users and candidate actions. This is the reason why our method outperforms baseline.

Application of Timeline Action Network

If data on Twitter is real-time data, then we can say that TiAN reflects real-world activities in real-time. By using SPARQL (SPARQL Protocol and RDF Query Language), computers can grasp situations of trains, evacuation centers, food shops, etc. Therefore, we can use TiAN to find the nearest available evaluation center for disaster victims.

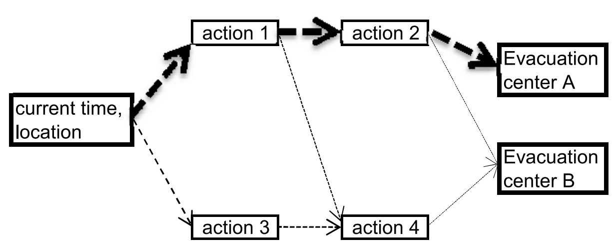

Figure 9: Using TiAN to recommend action patterns for reaching to available evacuation centers.

The computers also can recommend "what should to do" for the active user, based on action patterns of other users in TiAN. For example, as shown in Figure 9, if there is an user who did {action 1, action 2} to reach to the available "evacuation center A". Then, the computer can recommend {action 1, action 2} and "evacuation center A" for the current user.

Related Work

Action Network

ConcepNet (MIT Media Lab) (Liu and Singh 2004) is a well known action network. This action network is a semantic network of commonsense knowledge, based on the information in OpenMind commonsense corpus (OMCS) (MIT 2011).

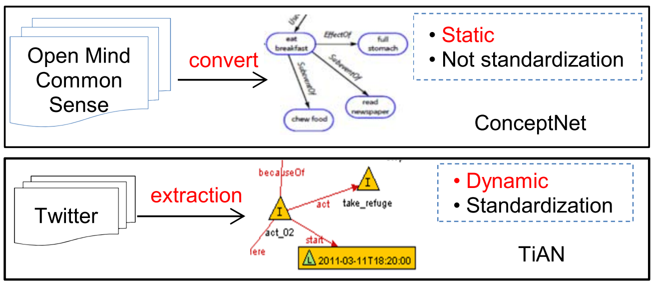

Figure 10: Comparison with ConcepNet.

Figure 10 shows comparisons of TiAN and ConcepNet. ConceptNet prepared a list of patterns in advance, and then it uses these patterns to obtain concepts, and the relations between these concepts. For example, given "A pen is made of plastic" as an input sentence, it uses "NP is made of NP" to get two concepts (a pen, plastic), and the relation (is made of) between these concepts. However, it is not practical to deploy this method for extraction of human activities from Twitter, because sentences retrieved from twitter are often diversified, complex, syntactically wrong. Additionally, TiAN is standardized based on OWL. Moreover, TiAN is a dynamic collaborative intelligence that represents instances of human activities in real-world.

Collaborative Filtering

(Ma, King, and Lyu 2007; Koren 2009) are the state-of-art approaches of the traditional CF. (Ma, King, and Lyu 2007) proposed a combination item-based CF and user-based CF, but it did not consider time and location. (Koren 2009) considered time, but did not consider location.

While traditional CF is trying to recommend suitable products on internet for users, our work is trying to predict missing action data in real-world. Different from products, user actions strongly depend on location, time, and before-after actions. Additionally, we need to consider execution time of each action. Moreover, we need to deal with minority actions.

Conclusions

In this paper, we have designed a timeline action network. Additionally, we used our previous work to automatically extract human activities from Twitter for this action network. We then proposed a novel action-based collaborative filtering, which predicts missing activity data. We also explained how to use this action network to assist disaster victims.

We are improving the approach of predicting missing activity data to complement the action network. We also need to consider reliability of activity data retrieved from Twitter as future work.

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