SAPE: A System for Situation-Aware Public Security Evaluation

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Abstract

Public security events are occurring all over the world, bringing threat to personal and property safety, and homeland security. It is vital to construct an effective model to evaluate and predict the public security. In this work, we establish a Situation-Aware Public Security Evaluation (SAPE) platform. Based on conventional Recurrent Neural Networks (RNN), we develop a new variant for temporal contexts in public security event datasets. This model can achieve better performance than the compared state-of-the-art methods. SAPE has two demonstrations, i.e., global public security evaluation and China public security evaluation. In the global part, based on Global Terrorism Database from UMD, for each country, SAPE can predict risk level and top-n potential terrorist organizations which might attack the country. Users can also view the actual attacking organizations and predicted results. For each province in China, SAPE can predict the risk level and the probability scores of different types of events in the next month. Users can also view the actual numbers of events and predicted risk levels of the past one year.

Introduction

Public security events happen all around the world, which bring threat to personal and property safety, and homeland security. Meanwhile, with rapid growth of available massive dataset of these events, constructing an effective model to predict event and evaluate the public security becomes possible and significant. The event prediction with temporal contexts is the most fundamental task of public security evaluation. Temporal contexts are the essential factors of an event, which are helpful in constructing prediction model for real-world applications. These techniques can also be used for e-commence and social good. For example, with user historical check-in data, we can analyze and predict where a user will go next. Using terrorist incidents of a country, we can predict the probability of attack of a terrorism organization.

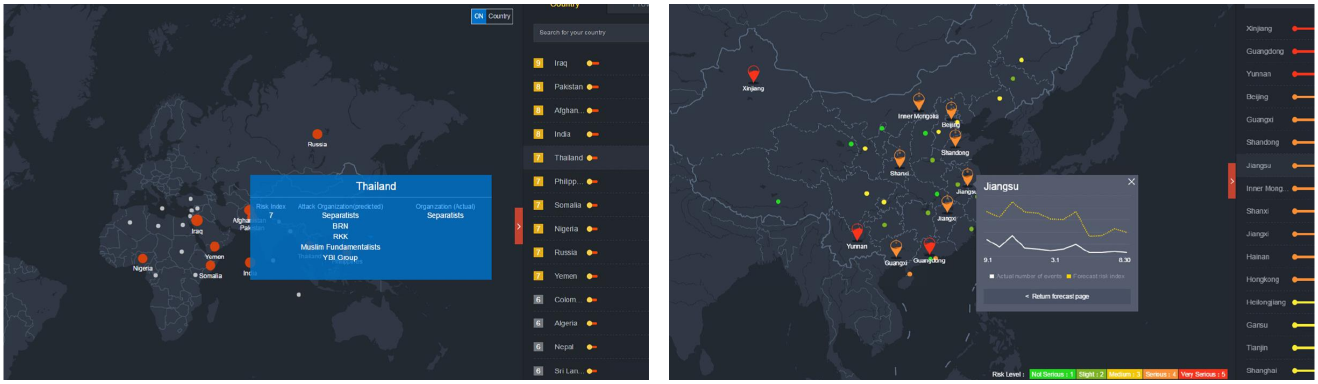
Event prediction with temporal contexts has been extensively studied. Neighborhood based models in the collaborative filtering approach (Lathia, Hailes, and Capra 2009) generate prediction based on instance weights, which are measured by the time proximity and provide more relevance to recent observations and less to others. The neighborhood based methods treat all events as separated and can not capture the sequential properties of historical events. Time-aware factorization models (Koren and Bell 2011) can also be implemented for event prediction and treat time bins as another dimension similar to that of other entities. However, factorization models have difficulty in generating latent representations of new time bins in the testing data, thus these methods have problem in predicting behaviors which occur in new time tins.

Markov chain is another popular approach for event prediction. Recently, factorizing personalized markov chain (Rendle, Freudenthaler, and Schmidt-Thieme 2010) extend the general markov chain model to be a personalized variant which has been applied in event prediction with temporal information. Finally this method is simplified to be a linearly combination of a matrix factorization and a factorized markov chain, but this independent assumption is not very suitable. Recently, RNN becomes popular in the research fields of computer vision and pattern recognition, and been successfully implemented for language modeling (Mikolov et al. 2011). RNN shows promising performance comparing with the conventional methods in sequence prediction, but is not capable to model the time interval between behaviors. In this work, we effectively extend the conventional RNN for event prediction with temporal information, by providing a fix time window and a time interval and assuming the blank time interval as a special empty event.

Model

The temporal information is intuitively essential for future event prediction, but is difficult to be handled by the conventional RNN. In this work, based on the conventional RNN, we develop an effective and efficient model to deal with temporal contexts. The new model can be used to make event prediction on public security event datasets.

Rather than considering only one existing element in the layer of RNN, each layer of proposed RNN model set a time window to model all the events inside. Besides, in each time window, we set a fix time interval and treat the empty time interval as the special event. For instance, in our applications, treating one month as the time window of a recurrent structure and one day as a time interval, all events have



(a) The terrorism incident prediction in SAPE. (b) The public security event prediction in SAPE.

Figure 1: Illustration of the SAPE system. The left part presents the potential terrorism organizations will attack a country and the right part shows the predicted risk levels of a province in China.

their corresponding transition matrices and the empty time interval also has a transition matrix. Comparing with RNN, the transition matrix of empty event can capture the local temporal contexts, this recurrent structure can better model temporal information and give more accurate prediction.

Mathematically, given a location k, the latent representation of the location at time t can be calculated as:

$$\mathbf{r}_t^k = f\left(\sum_{t-w<t_i<t} \mathbf{T}_{e_{t_i}^k} \mathbf{e}_{t_i}^k + \mathbf{C}\mathbf{r}_{t-w}^k\right), \qquad (1)$$

where w is the width of time window in which the elements are modeled in each recurrent layer. $\mathbf{e}_{t_i}^k$ is the latent vector of the event which happens at time t_i. $\mathbf{T}_{e_{t_i}^k}$ denotes the transition matrix for the event $\mathbf{e}_{t_i}^k$. When there does not exist an event, the $\mathbf{e}_{t_i}^k$ represents the latent vector of the empty event and corresponding matrix $\mathbf{T}_{e_{t_i}^k}$ means the transition matrix of the empty event. The transition matrix $\mathbf{C}$ is the recurrent connection of the previous status propagating sequential signals. $f(x)$ is the activation function which is chosen as a $sigmod$ function formulated as $f(x) = \frac{1}{1+e^{-x}}$. The new RNN considers several elements in the local temporal contexts in each layer and treat empty event as a specific event. Our model can achieve better performance than the compared state-of-the-art methods.

Applications

Based on the new variant of RNN, we establish a Situation-Aware Public Security Evaluation (SAPE) platform for two kinds of applications, which are global public security evaluation and China public security evaluation.

Global public security evaluation is conducted on the global terrorism dataset[1]. This dataset includes more than 125,000 terrorist incidents that have occurred around the world since 1970, which contains 168 countries and 998 terrorist organizations. The temporal information is collected based on the day level. Treating the temporal terrorist attacks of each country as a sequence and each terrorism incident with the organization as the corresponding event, we can implement the new RNN model and predict the potential terrorist organizations which may attack the province or state. In the implementation of our model on GTD, we provide one month with a recurrent structure and each day of the month with a temporal transition matrix. In the end, for each country, SAPE illustrates the risk level and top-n potential terrorist organizations which might attack the country. Fig. 1(a) also shows the actual attacking organizations and SAPE's predicted results.

For prediction of public security event in China, we crawl and clean the public security news from the website, and finally collect about 12324 public security events happened in different provinces of China since 1998. This dataset is also transformed based on the day level. Treating temporal events on different provinces as an instance and each kind of public security as event, we predict the potential public security events which may occur in this province. Besides, we use the same size of the time window and the time interval of GTD. Finally, for each province, SAPE can predict the risk level and the probability scores of different types of events in the next month. In Fig. 1(b), the demonstration shows the actual numbers of public security events and predicted risk levels of SAPE of the past one year.

[1]http://www.start.umd.edu/gtd/

Acknowledgments

This work is jointly supported by National Basic Research Program of China (2012CB316300) and National Natural Science Foundation of China (61403390, U1435221).

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