Cascade Dynamics Modeling with Attention-based Recurrent Neural Network

Abstract

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1 Introduction

The emergence of Social Media platform has revolutionized dissemination of information via its great ease in inforamtion delivery, accessing and filtering. In Social Media, pieces of information, posted by users spontaneously, propagate along social relationships between users, explict or implict, forming cascade dynamics. Modeling cascade dynamics is the fundamental to understand information propagation and launch series of social applictions, i.e., viral marketing, popularity prediction and rumor detection.

The key to cascade dynamics modeling is to find a well-defined function in hypothesis space based on observed cascades. Existed methods for this problem fall into three main paradigms: pairwise, nodewise and eventwise modeling. The majority works in cascade dynamics modeling focus on pairwise modeling, defining the propagation probability of information between all pairs of users [Saito *et al.*, 2008; Goyal *et al.*, 2010; Gomez-Rodriguez *et al.*, 2013]. However, pairwise models suffer severe overfitting and overrepresentation problems especially in sparse social data, proved in [Wang *et al.*, 2015]. Nodewise modeling learn latent user-specific characteristics instead of pairwise manners, effectively combating overfitting and overrepresentation problems. Bourigault et.al. [Bourigault *et al.*, 2016] learn user-specific latent space in Independent Cascade (IC) model. Wang et.al [Wang *et al.*, 2015] capture users' influence and susceptibility in latent space and define propagation probability according to users latent characteristics. Kurashima et.al. [Kurashima *et al.*, 2014] embeded users into low-dimensional visualization space in Continous Time Independent Cascade (CTIC) model. But nodewise models require strong prior knowledge on generation processes of cascades in order to better fit the observations. Recently, eventwise models received great success in modeling sequence data.

Eventwise methods aims to learn history embedding in order to model the generation of next event, e.g., cascade. Manavoglu [Manavoglu *et al.*, 2003] propose users behavior generation method based on maxent and Markov mixture model. Recently, the efficient way of eventwise modeling can be achieved by Recurrent Neural Network (RNN) [Bengio *et al.*, 2003; Goldberg and Levy, 2014; Mikolov *et al.*, 2010; Sundermeyer *et al.*, 2012]. Du et.al. [Du *et al.*, 2016] proposed a Recurrent Marked Temporal Point Process (RMTPP) for event streams. The outputs of hidden layer in Recurrent Neural Network (RNN) represents the embedding of the event histories, then parameterizing the random process. The benefits of eventwise modeling are two folds: 1) avoiding strong prior knowledge on models and networks with respect to different observed cascades; 2) enlarging the functional space when searching the optimal cascade dynamics models, which may have great probability to better model cascade dynamics.

Despite of advantages in eventwise modeling, the traditional sequence models may meet "crossing dependency" problem in cascade dynamics modeling. The crossing dependencies problem is mainly caused by tree structure of propagation. Fig. 1 shows two typical crossing dependency cases in practical. For modeling dependence between 1st and 3rd event, we must use redundant information passing from 2nd event, called "redundant modeling". If we abandon useful information inherited by 3rd event when modeling the 4th event, the generation of 5th event would lose useful information from 3rd event, called "cut-off modeling". Crossing dependency problems limit the efficiency of sequence modeling.

In this paper, we propose a **C**ascade d**Y**namics modeling with **A**ttentio**N**-based RNN, named (CYAN-RNN). We construct a pooling layer above the output of hidden layer in RNN, aggregating event embedding in history. The weights in pooling layer pointing to each historical event embedding refers to connections between current event and history. We choose attention mechanism [Bahdanau *et al.*, 2014] to realize the pooling layer, automatically learned the connection weights. The benifits of our proposed model are three-fold: 1) We propose a eventwise method, using sequence modeling, for cascade dynamics modeling; 2) We point out crossing dependency problem in traditional sequence modeling when model cascade dynamics. Thus, we proposed CYAN-RNN to solve the problem; 3) We conduct experiments on synthetic and real-world datasets to show that our model consistently outperform than previous modeling methods in cascade dynamics modeling.

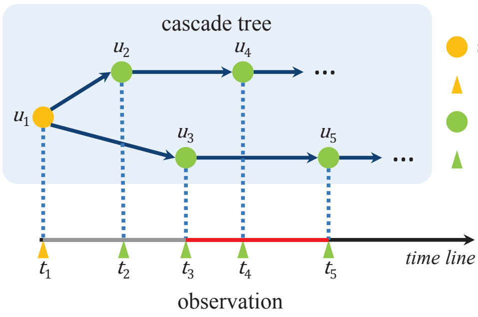


Figure 1: Tree structure of propagation and crossing dependency problems in sequence modeling. For modeling dependence between 1st and 3rd event, we must use redundant information passing from 2nd event, called "redundant modeling". If we abandon useful information inherited by 3rd event when modeling the 4th event, the generation of 5th event would lose useful information from 3rd event, called "cut-off modeling".

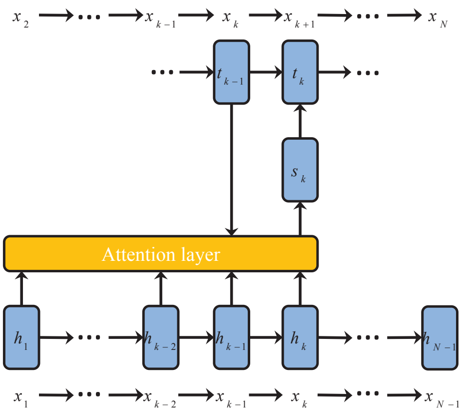
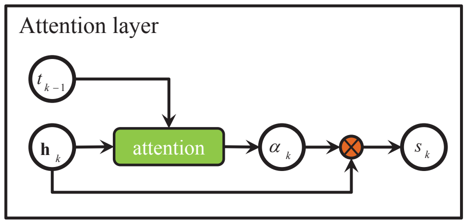
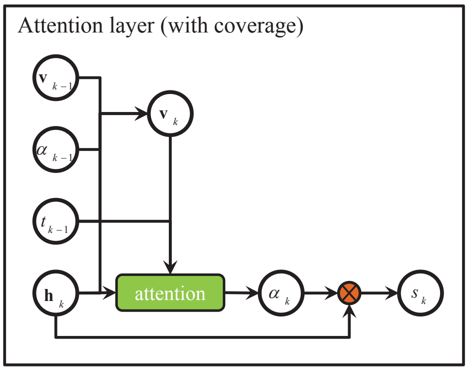


Figure 2:



(a)



(b)

Figure 3:

2 Model

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