Accepted Manuscript

Accepted Date:

Modeling Asynchronous Event Sequences with RNNs

Stephen Wu, Sijia Liu, Sunghwan Sohn, Sungrim Moon, Chung-il Wi, Young Juhn, Hongfang Liu

PII: DOI: Reference:	S1532-0464(18)30099-6 https://doi.org/10.1016/j.jbi.2018.05.016 YJBIN 2986
To appear in:	Journal of Biomedical Informatics
Received Date:	26 June 2017
Revised Date:	10 May 2018

26 May 2018



Please cite this article as: Wu, S., Liu, S., Sohn, S., Moon, S., Wi, C-i., Juhn, Y., Liu, H., Modeling Asynchronous Event Sequences with RNNs, *Journal of Biomedical Informatics* (2018), doi: https://doi.org/10.1016/j.jbi. 2018.05.016

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

Modeling Asynchronous Event Sequences with RNNs

Stephen Wu, Sijia Liu, Sunghwan Sohn, Sungrim Moon, Chung-il Wi, Young Juhn, Hongfang Liu

Abstract

Sequences of events have often been modeled with computational techniques, but typical preprocessing steps and problem settings do not explicitly address the ramifications of timestamped events. Clinical data, such as is found in electronic health records (EHRs), typically comes with timestamp information. In this work, we define event sequences and their properties: synchronicity, evenness, and co-cardinality; we then show how asynchronous, uneven, and multi-cardinal problem settings can support explicit accountings of *relative time*. Our evaluation uses the temporally sensitive clinical use case of pediatric asthma, which is a chronic disease with symptoms (and lack thereof) evolving over time. We show several approaches to explicitly incorporate relative time into a recurrent neural network (RNN) model that improve the overall classification of patients into those with *no asthma*, those with persistent *asthma*, those in long-term *remission*, and those who have experienced *relapse*. We also compare and contrast these results with those in an inpatient intensive care setting.

1. Introduction

Sequences of events have often been modeled with techniques such as Hidden Markov Models (HMMs), Conditional Random Fields (CRFs), Recurrent Neural Networks (RNNs), and their derivatives. Here, we zoom in on the typical temporal assumptions being made in these types of models, and provide evaluations on a use case of medical information (asthma diagnoses) that could intuitively benefit from more explicit accountings of event timing.

We will define event sequences and differentiate between *synchronous* v. *asynchronus, co-cardinal* v. *multi-cardinal*, and *even* v. *uneven* pairs of such sequences (see §3.1). In particular, where most methods transform event sequences to be synchronous, co-cardinal, and even, we will consider the ramifications of using event sequences that are either synchronous, co-cardinal, but *un*even; or synchronous, *multi*-cardinal, and *un*even.

To evaluate the representational power and computational tractability

© 2009, Elsevier Ltd. Bugs, feature requests, suggestions and comments shall be mailed to <elsarticle@river-valley.com>. **QUICK LINKS**

Version: 1.20 Date: April 6, 2018 Contact: wu.stephen.t@gmail.com Download English Version:

https://daneshyari.com/en/article/6927441

Download Persian Version:

https://daneshyari.com/article/6927441

Daneshyari.com