Modeling and Applications for Temporal Point Processes

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ABSTRACT

Real-world entities' behaviors, associated with their side information, are often recorded over time as asynchronous event sequences. Such event sequences are the basis of many practical applications, neural spiking train study, earth quack prediction, crime analysis, infectious disease diffusion forecasting, condition-based preventative maintenance, information retrieval and behavior-based network analysis and services, etc. Temporal point process (TPP) is a principled mathematical tool for the modeling and learning of asynchronous event sequences, which captures the instantaneous happening rate of the events and the temporal dependency between historical and current events. TPP provides us with an interpretable model to describe the generative mechanism of event sequences, which is beneficial for event prediction and causality analysis. Recently, it has been shown that TPP has potentials to many machine learning and data science applications and can be combined with other cutting-edge machine learning techniques like deep learning, reinforcement learning, adversarial learning, and so on.

We will start with an elementary introduction of TPP model, including the basic concepts of the model, the simulation method of event sequences; in the second part of the tutorial, we will introduce typical TPP models and their traditional learning methods; in the third part of the tutorial, we will discuss the recent progress on the modeling and learning of TPP, including neural network-based TPP models, generative adversarial networks (GANs) for TPP, and deep reinforcement learning of TPP. We will further talk about the practical application of TPP, including useful data augmentation methods for learning from imperfect observations, typical applications and examples like healthcare and industry maintenance, and existing open source toolboxes.

CCS CONCEPTS

• **Mathematics of computing** → **Stochastic processes**; • **Information systems** → **Temporal data**; • **Computing methodologies** → **Neural networks**; • **Theory of computation** → *Machine learning theory*.

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KEYWORDS

temporal point process; Hawkes processes; generative model; clustering; prediction

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1 OUTLINE

Part 1: Basics and typical models for TPP

– Event sequence modeling
– Conditional intensity functions and typical models
– Simulation of TPP
– Classic statistical learning of TPP
– Useful propositions of Hawkes processes

Partial list of references: [3, 4, 6, 11, 15, 16, 18, 26, 27]

Part 2: Deep networks for temporal point processes

– Brief on classic statistical learning of TPP
– Deep learning for TPP
– Adversarial learning for TPP
– Reinforcement learning for TPP
– Embedding for multi-dimensional TPP

Partial list of references: [10, 12, 19–25, 29–31].

Part 3: Temporal point processes in practice

– Inference from missing and noisy data
– Data augmentation strategies for TPP
– Learning from warped sequences
– Learning with marked events
– Applications: e.g. Social network analysis, Healthcare, Geophysics, Financial data, Crime analysis
– Open source packages

Partial list of references: [1, 2, 5, 7–9, 13, 14, 17, 28, 32]

2 INSTRUCTORS' BIOGRAPHY

Junchi Yan is an independent associate professor with Shanghai Jiao Tong University (SJTU), at Department of Computer Science and Engineering and AI Institute. Before joining SJTU in 2018, Junchi has been with IBM Research working on machine learning and computer vision since April 2011. He was once a Senior Research Staff Member with IBM China Research Lab, and extensively applied temporal point process model for preventative maintenance projects. He has been awarded the 2016 China Computer Federation Outstanding PhD Thesis Award and the nomination award of 2015 ACM China Distinguished PhD Thesis. His recent research interests include machine learning and data mining.

Hongteng Xu is a senior research scientist with Infinia ML, Inc. At the same time, he is a visiting faculty with Duke University, at Department of Electrical and Computer Engineering. Before joining Infinia ML in January 2018, Hongteng has been a postdoctoral researcher with Duke University since August 2017. Hongteng holds a Ph.D. in Electrical and Computer Engineering from Georgia Institute of Technology, a dual M.S. degree in Electrical and Computer Engineering from both Georgia Institute of Technology and Shanghai Jiao Tong University. Hongteng's research interests include temporal point process-based modeling and learning, applications for clinical data analysis, and connections with other machine learning techniques. He independently developed two point process toolboxes: the Matlab-based Hawkes process toolbox (THAP) and the PyTorch-based point process toolbox (PoPPy). Specifically, the THAP integrates most of existing models and algorithms of point processes proposed by Hongteng. The PoPPy provides a flexible framework to design various point process models and learn them efficiently on CPUs/GPUs in a stochastic manner.

Liangda Li is a senior research scientist at Yahoo Research, in the search and search ads team. He lead the vertical search ranking, query understanding, search ads, query linguistic analysis projects of Science team. Before joining Yahoo Research, he earned his Ph.D. degree in the School of Computer Science at Georgia Institute of Technology, under the supervision of Professor Hongyuan Zha. He received his B.S. degree in ACM honored class, at the School of Computer Science from Shanghai Jiao Tong University in 2010. He has been awarded the 2010 Microsoft Research Asia Young Research Fellow Award. His research interest includes machine learning and its applications in information retrieval and social network. In particular, his focus in on influence modeling in various real-world behavioral data, such as search intent understanding, urban intelligence and crisis/crime.

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