Neural Marked Temporal Point Process with Applications to Human Activities Predictions

ABSTRACT

Human activities constantly produce temporal-spatial sequences of events ranging from social interactions to financial transactions to electronic medical records. Are these activities predictable ? Can we forecast which activity people might take at what time in the future based on his (her) past history ? In this paper, we propose a novel random process, referred to as the Neural Marked Temporal Point Process, to take into account both the discrete action prediction (classification) task and the continuous time prediction (regression) task in a unified framework. An innovative feature of the proposed model is that we apply a Recurrent Neural Network to learn a unified representation of the past activities and time, conditioned on which we can jointly formulate the probability of the next activity and the density of the respective temporal interval. This new model establishes a previously under-explored general connection between recurrent neural network and marked temporal point process. We have conducted large-scale experiments on both synthetic and real world time series data and demonstrate that Neural Marked Temporal Point Process can capture meaningful dependency over the historical data, which leads to consistently better prediction performance compared to alternative competitors.

CCS Concepts

•**Computer systems organization** → **Embedded systems;** *Redundancy;* Robotics; •**Networks** → Network reliability;

Keywords

Recurrent neural network; Marked point process; Time series; Stochastic process

1. INTRODUCTION

Temporal-spatial event data have been becoming ubiquitous due to the fast development of modern communications,

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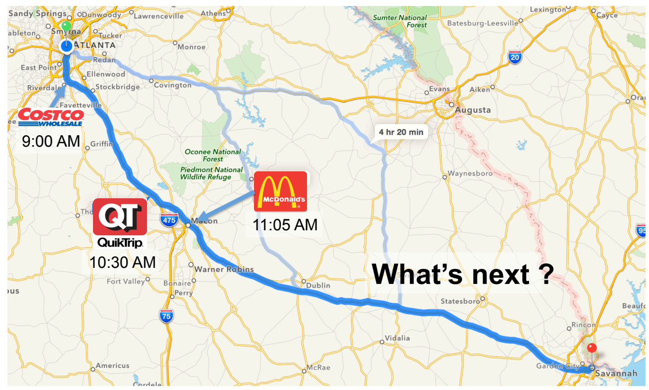

Figure 1: A user has visited Costco at 9:00AM, refilled the gas in QT at 10:30AM, and then had lunch in MacDonald at 11:05AM. Given the trace of these past locations and time, can we predict what the next stop will be and when it will happen in the future ?

mobile devices, and various wearable gadgets. Large collections of these data arise from social activities, to financial transactions, to electronic health records, which provide rich information about what type of event is happening between which entities at what time and place. Quite often, each set of temporal events associated with an involved entity (online user, stock ID, patients) is first ordered by time and then chained together to form a temporal sequence. The resulting collection of sequences capture the full traces of historical activities induced from the respective entities over time. For instance, people go to work, airports, gas stations, parks, cinemas, church, restaurants, groceries at different time of days in a week. Music streaming subscribers listen to different albums and watch various videos as time goes by. Professional trading systems buy and sell a bunch of stocks within short-time frames. Patients go to see the doctor with a time-stamped sequence of diagnoses of the concerned diseases.

Although the aforementioned situations come from different domains, we seek to capture them in a unified framework by addressing the key problem : can human activities be predictable ? Based on the sequence of past events, can we predict what kind of action people will take at what time in the future ? Accurately predicting the next activity at the right moment will have potential applications of great significance. For mainstream personal assistants, shown in

Figure 1, because people tend to visit different places dependent on the temporal/spatial contexts like morning vs. evening, weekdays vs. weekend, successfully predicting the next places that users will visit at the most likely time will make such services more relevant and usable. In stock market, accurately forecasting when to sell or buy a particular stock next means critical business success. Finally, for modern healthcare, patients may have several diseases that have complicated dependencies on each other. The occurrence of one disease can trigger the progression of others. Accurately estimating when a probable disease might occur can effectively help to take proactive steps to reduce the potential risks in the future.

Existing studies in literature attempt to solve this problem from two different perspectives. On the one hand, classic varying-order Markov models formulate the problem as a discrete-time sequence prediction task. Based on the history, they seek to predict the most likely state the process will go into on the next step. As a result, one limit of the Markov model is that it assumes the process proceeds by a unit time-step, so it cannot capture the heterogeneity of the time to predict the timing of the next event in the future. Furthermore, when the number of states is large, Markov model cannot have long dependency on the history since the overall state-space will grow exponentially. Semi-Markov model can capture the continuous interval between two successive states to some extent by assuming the intervals have exponential distribution. But still, it has the same state-space explosion issue when the order grows. On the other hand, classic marked temporal point process explicitly treat the time interval between two activities as continuous random variable. The type of each event can be modeled either as an explicit marker or as an independent dimension. However, most studies along this line are restricted to low dimension and small data settings for simple inference problems. The high dimensional nature, the complexity of the event features, the sheer volume of the data, and particularly the unique learning problems faced by modern emerging applications such as the ones mentioned above pose new great challenges in their modeling and learning. Therefore, in this work, we propose a novel random process, referred to as the Neural Marked Temporal Point Process, to take into account both sources of information from event types and timing to make future predictions. More precisely, we make the following contributions :

- We establish a previously under explored connection between Recurrent Neural Networks and Marked Temporal Point Processes, which enables joint predictions of event type and timing in the future by incorporating the long-term influence of the past history.
- We point out that the proposed Neural Marked Temporal Point Process has implications beyond temporal-spatial features and sequence predictions. We will show that our construction can be generalized to other settings by incorporating more rich contextual information and features.
- We conduct large-scale experiments on both synthetic and real-world datasets from a diverse range of domains to show that our model have consistently better predictive performance for both the event type and timing compared to alternative competitors.

2. RELATED WORK

This will include several related studies from varying Markov models, Semi-Markov models, RNN, LSTM, GRU, Temporal Point Process, Marked Temporal Point Process

3. HUMAN ACTIVITIES PREDICTIONS

3.1 Problem Definition

Graphical Model Representation

3.2 Marked Temporal Point Process

3.3 Recurrent Neural Network

3.4 Neural Marked Temporal Point Process

4. EXPERIMENTS

4.1 Synthetic Data

1. only considers time : autoregressive point process with exponential, Rayleigh duration distribution; Single Hawkes Process 2. Considers time and marker jointly : two dimensional Hawkes process, graphical models

4.2 Real Data

1. Stock, MIMIC2, NY Taxi, Alibaba, LastFM, StackOverFlow 2. Empirical patterns found in data : interval distributions (by week day vs. by weekend), history correlations (whether history will help), QQ-plot, 3. Visualization of NY Taxi, Visualization of RNN predictions

5. DISCUSSIONS

extend to consider other features, like spatial information, structure information

6. CONCLUSIONS