香港浸會大學理學院
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DEPARTMENT OF COMPUTER SCIENCE

PhD Degree Oral Presentation

PhD Candidate:	Mr. Qi TAN
Date	March 24, 2021 (Wednesday)
Time:	2:30 pm – 4:30 pm (35 mins presentation and 15 mins Q & A)
Venue:	Zoom ID: 910 7571 1443 (The password and direct link will only be provided to registrants)
Registration:	https://bit.ly/sem-zm (Deadline: 12:00nn, March 23, 2021)

Learning Complex Spatio-Temporal Dependency:
Model Design, Information-Theoretic Analysis, and Systematic Validation

Abstract

Predictive spatio-temporal analytics (PSTA) is of great importance in many real-world applications, such as disease prediction, climate forecast, and traffic prediction. One of the most challenging tasks in PSTA is to learn the complex and intrinsic dependency relationships among heterogeneous data, which generally manifest at multiple spatio-temporal scales. Several models have been proposed for such PSTA tasks, including time series models, tensor-based learning models and deep neural network models. However, these models have not explicitly addressed the issue of multi-scale dependency modeling and hence have presented certain limitations in their performance. In this thesis, we tackle the aforementioned issue in the following specific ways.

First, we develop and demonstrate a novel Interactively- and Integratively-connected Deep Recurrent Neural Network (I2DRNN) model. I2DRNN consists of three key modules: (i) an Input module that integrates data from heterogeneous sources; (ii) a Hidden module that captures the information at different scales while allowing the information to flow interactively between layers; and (iii) an Output module that models the integrative effects of information from various hidden layers to generate the output predictions.

Second, in order to theoretically prove that our designed model can learn multi-scale spatio-temporal dependency, we provide an information-theoretic framework to examine the underlying learning behavior of the proposed model. In so doing, we can tackle one of the open questions in deep learning, that is, how to determine the necessary and sufficient configurations of a certain designed deep learning model with respect to the given learning datasets.

Third, in order to validate the I2DRNN model and confirm its information-theoretically described behavior, we systematically conduct a series of experiments involving both synthetic datasets and real-world PSTA tasks. The experimental results show that the I2DRNN model outperforms both classical and state-of-the-art models on all datasets and PSTA tasks. More importantly, as readily validated, the proposed model captures the multi-scale spatio-temporal dependency, which is meaningful in the real-world context. Furthermore, the model configuration that corresponds to the best performance on a given dataset always falls into the range between the necessary and sufficient configurations, as described by the information-theoretic analysis.

In addition, we further explore two issues in practical PSTA, i.e., incomplete data and hidden interaction, which make the spatio-temporal dependency even more complex and difficult to capture. In order to infer the missing data, we propose a heterogeneous neural metric learning method to systematically restore the data integrity by referring to heterogeneous data sources. We examine the proposed method on a real-world spatio-temporal analytics task, malaria risk mapping, and show that the proposed method can produce accurate and reliable estimation. In order to characterize the hidden interaction among the spatio-temporal data, we develop two structure-aware methods to uncover the primitive motif prior and the mesoscale connection structure of the underlying interaction network, respectively. Results on various datasets validate the effectiveness of the proposed methods in capturing the hidden interaction for PSTA.

***** ALL INTERESTED ARE WELCOME *****