香港浸會大學理學院
HKBU Faculty of Science

DEPARTMENT OF COMPUTER SCIENCE

PhD Degree Oral Presentation

PhD Candidate:	Mr. Qingxiong TAN
Date	July 8, 2021 (Thursday)
Time:	1:30 pm – 3:30 pm (35 mins presentation and 15 mins Q & A)
Venue:	Zoom ID: 968 7786 3247 (The password and direct link will only be provided to registrants)
Registration:	https://bit.ly/sem-zm (Deadline: 1:00 pm, July 7, 2021)

Deep Learning Models for Irregular Electronic Health Record Data Analysis

Abstract

The wide adoption of electronic health records (EHRs) produces a large quantity of health data, such as laboratory parameters, disease diagnoses, and treatment reports, which provides unprecedented opportunities for developing advanced machine learning models to help improve healthcare quality. However, the analysis of EHRs data is highly challenging because real-world medical data is irregular and heterogeneous. Influenced by dynamic changes in the severity of illness, patients usually go to hospitals to take examinations irregularly, producing a large volume of irregular medical data with varying intervals. Meanwhile, certain physiological variables are not examined during some visits, causing the missing data problem. Furthermore, there are usually influencing relationships between different types of medical data, e.g., basic health data may influence future trajectories of dynamic variables.

In this thesis, we focus on the analysis of irregular EHRs data to achieve the accurate prediction of clinical outcomes. Firstly, an explainable uncertainty-aware neural network is proposed to incorporate the uncertainty information in the generated data to dynamically learn contribution weights of different data and introduce filters to adaptively adjust the unity of components in each sub-series and the diversity of components between different sub-series. Meanwhile, an attention module is incorporated to identify key features and provide explainable prediction results. Secondly, varying time intervals and missing values provide valuable information in promoting clinical predictions because visit intervals are usually determined by the health status of patients while missing values are caused by changes in symptoms of patients. Therefore, a dual-attention time-aware neural network is introduced to jointly deal with the two key challenges (i.e., varying visit intervals and missing values) in irregular EHRs data by directly modeling the contained useful information on dynamic changes in the health conditions of patients while avoiding damaging the structure of irregular EHRs. Lastly, to effectively promote the clinical outcome prediction results, we further design an end-to-end importance-aware approach to simultaneously model multiple data sources, including both static and dynamic health data, while adaptively learning fusion weights for different deep features and assign larger weights to important features.

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