香港浸會大學理學院
HKBU Faculty of Science

DEPARTMENT OF COMPUTER SCIENCE

PhD Degree Oral Presentation

PhD Candidate:	Mr. HE Xin
Date	5 May 2023 (Friday)
Time:	3:30 pm – 5:30 pm (35 mins presentation and 15 mins Q & A)
Venue:	ZOOM (Meeting ID: 943 4379 1472) (The password and direct link will only be provided to registrants)
Registration:	https://bit.ly/bucs-reg (Deadline: 6:00 pm, 4 May 2023)

Automated Machine Learning and Its Applications

Abstract

Deep learning (DL) has been successfully applied to many complex cognitive tasks. However, deploying DL in under-explored fields can be challenging due to the need for ML expertise to design data augmentations and develop new neural architectures, which can be both time-consuming and laborious. Automated machine learning (AutoML) is a promising solution to these problems, as it aims to enable even beginners with limited ML expertise to build high-quality ML models with minimal effort. In this thesis, we investigate AutoML in the context of DL and provide a comprehensive survey of AutoML from the perspective of the ML pipeline, including data preparation, feature engineering, model generation, and model estimation. We focus on neural architecture search (NAS), which is a hot subtopic of AutoML. To this end, we build an easy-to-use NAS framework called Hyperbox and develop several NAS applications for image classification and image generation tasks.

For image classification, we present two NAS applications. First, we propose a differentiable NAS to discover a family of 3D models to classify COVID-19 3D CT scans, called COVIDNet3D, which outperform human-designed 3D models on three public datasets. Second, we propose an evolutionary multi-objective NAS approach, called EMARS, to alleviate the search instability of weight-sharing NAS. By combining potential, accuracy, and model size as objectives, the proposed method can balance exploration and exploitation in the search process and efficiently find more competitive models.

For image generation, we propose an efficient two-stage evolutionary algorithm-based NAS framework, called EAGAN, to search generative adversarial networks (GANs). GAN training suffers from instability and is prone to collapse, which can be further exacerbated when using NAS to search GANs. Experiments on CIFAR-10 and STL-10 datasets demonstrate that the proposed EAGAN can find better GANs than previous NAS-GAN methods.

Finally, we propose an end-to-end differential approach called MedPipe to jointly search for data augmentation policy (DAP) and neural architecture (NA). Experiments on nine different medical datasets empirically validate MedPipe's effectiveness and superiority. Our work has contributed to the AutoML field by advancing the latest technologies in NAS and developing new methods for end-to-end AutoML, which can improve the efficiency and accessibility of DL model development.

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