

Efficient and Reproducible Automated Deep Learning

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, **Xuanyi Dong** declare that this thesis, is submitted in fulfilment of the requirements for the award of **Doctor of Philosophy**, in the **School of Computer Science, FEIT** at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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ABSTRACT

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Deep learning has shown its power in a large number of applications, such as visual perception, language modeling, speech recognition, video games, etc. To deploy a deep learning model successfully, inevitable manual tuning is required for each component, such as neural architecture design, the choice of optimization strategy, data selection, augmentation, etc. Such manual tuning costs expensive computational resources and is labor-intensive. Moreover, this paradigm is not scalable when the model size or the data size significantly increases. Fortunately, AutoDL brings hope to alleviate this problem by making the tuning procedure automated. Despite the recent success of AutoDL, efficiency and reproducibility for AutoDL algorithms remain a tremendous challenge for the community.

In this thesis, we address this challenge in the following aspects. We comprehensively review the current state of AutoDL and set up six step-by-step objectives to further develop AutoDL. To achieve these objectives, we propose a series of efficient approaches to learning to search (1) neural architecture topology, (2) neural architecture size, and (3) hyperparameters by gradient descent. In addition to common empirical analysis on vision and NLP datasets, we build a systematical benchmark for neural architecture topology and neural architecture size. This benchmark aims to provide a fair and easy-to-use environment for our proposed algorithms as well as other AutoDL participants.

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List of Publications

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- J-[2] **Xuanyi Dong**, Yi Yang, Shih-En Wei, Xinshuo Weng, Yaser Sheikh, Shoou-I Yu. “Supervision by Registration and Triangulation for Landmark Detection”, *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)* (ERA CORE Rank A*, IF=17.861)
- J-[3] **Xuanyi Dong**, Liang Zheng, Fan Ma, Yi Yang, Deyu Meng. “Few-Example Object Detection with Model Communication”, *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)* (ERA CORE Rank A*, IF=17.861)
- J-[4] **Xuanyi Dong**, Yan Yan, Mingkui Tan, Yi Yang, Ivor W. Tsang. “Late Fusion via Subspace Search with Consistency Preservation”, *IEEE Transactions on Image Processing (TIP)* (ERA CORE Rank A*, IF=9.34)

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- C-[6] [ICLR-2020] **Xuanyi Dong**, Yi Yang. “NAS-Bench-201: Extending the Scope of Reproducible Neural Architecture Search”, International Conference on Learning Representations (ICLR) (H-index=150)

- C-[7] [NeurIPS-2020] Daiyi Peng, **Xuanyi Dong**, Esteban Real, Mingxing Tan, Yifeng Lu, Hanxiao Liu, Gabriel Bender, Adam Kraft, Chen Liang, Quoc V. Le. “PyGlove: Symbolic Programming for Automated Machine Learning”, *Advances in Neural Information Processing Systems (NeurIPS)* (ERA CORE Rank A*)
- C-[8] [NeurIPS-2019] **Xuanyi Dong**, Yi Yang. “Network Pruning via Transformable Architecture Search”, *Advances in Neural Information Processing Systems (NeurIPS)* (ERA CORE Rank A*)
- C-[9] [ICCV-2019] **Xuanyi Dong**, Yi Yang. “One-Shot Neural Architecture Search via Self-Evaluated Template Network”, *IEEE Conference on International Conference on Computer Vision (ICCV)* (ERA CORE Rank A*)
- C-[10] [ICCV-2019] **Xuanyi Dong**, Yi Yang. “Teacher Supervises Students How to Learn from Partially Labeled Images for Facial Landmark Detection”, *IEEE Conference on International Conference on Computer Vision (ICCV)* (ERA CORE Rank A*)
- C-[11] [CVPR-2019] **Xuanyi Dong**, Yi Yang. “Searching for A Robust Neural Architecture in Four GPU Hours”, *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (ERA CORE Rank A*)
- C-[12] [CVPR-2018] **Xuanyi Dong**, Shoou-I Yu, Xinshuo Weng, Shih-En Wei, Yi Yang, Yaser Sheikh. “Supervision-by-Registration: An Unsupervised Approach to Improve the Precision of Facial Landmark Detectors”, *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (ERA CORE Rank A*)
- C-[13] [CVPR-2018] **Xuanyi Dong**, Yan Yan, Wanli Ouyang, Yi Yang. “Style Aggregated Network for Facial Landmark Detection”, *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (ERA CORE Rank A*)
- C-[14] [CVPR-2017] **Xuanyi Dong**, Junshi Huang, Yi Yang, Shuicheng Yan. “More is Less: A More Complicated Network with Less Inference Complexity”, *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (ERA CORE Rank A*)

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Abbreviation

ML: Machine Learning

DL: Deep Learning

NN: Neural Network

CNN: Convolutional Neural Network

RNN: Recurrent Neural Network

NAS: Neural Architecture Search

HPO: Hyperparameter Optimization

AutoML: Automated Machine Learning

AutoDL: Automated Deep Learning

RL: Reinforcement Learning

ES: Evolutionary Strategy

FLOP: Floating Point Operation

GPU: Graphics Processing Unit

LSTM: Long Short-Term Memory

AOS: Alternative Optimization Strategy

SVD: Singular Value Decomposition

PPO: Proximal Policy Optimization