Yi-Qi Hu

Gender	Male	**Date of Birth**	6^{th} Match 1993
Position	Ph.D. Candidate	**Homepage**	`http://lamda.nju.edu.cn/huyq/`
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Experience

- **September 2015 ∼ Present**
  Ph.D. Candidate: Department of Computer Science, Nanjing University, China.
  Supervisor: Assoc. Prof. Yang Yu.
- **February 2019 ∼ Present**
  Senior Algorithm Researcher: Zhuiyi Technology Co., Ltd., Nanjing, China.
- **May 2018 ∼ November 2018**
  Research Intern: 4Paradigm Inc., Beijing, China.
- **September 2011 ∼ June 2015**
  B.Sc. degree: College of Computer Science, Nanjing University of Aeronautics and Astronautics, China.

Research Interests

I am focusing on finding efficient derivative-free optimization approaches and employing derivative-free optimization on real machine learning applications. Optimization is the core issue in machine learning. With the growing complexity of machine learning tasks, the formulated optimization problems are losing good mathematic properties, e.g., continuous, convex and so on. Especially on reinforcement learning and automatic machine learning (AutoML), plenty of optimization problems are non-convex. The widely used gradient-based optimization techniques, however, are showing limitations for these complex problems. Meanwhile, derivative-free optimization involves kinds of methods that performs optimization through sampling, instead of using gradients, which has great potential for complex problems. I am currently working on:

1. **Developing high-efficiency derivative-free optimization tools**
   Previous studies on derivative-free optimization usually suffer from low-efficiency, weak-theoretical foundation and poor scalability. For examples, most of evolutionary algorithms lack theoretical analysis, and Bayesian optimization methods are hard to handle high-dimensional optimization problems. Our work developed a classification-based derivative-free optimization method in [AAAI'16]. This method has been proved to have polynomial time complexity for approximating Local Lipschitz Continuity functions, which covered a wide range of non-convex problems. Further more, our work developed the sequential random embedding technique for scaling up derivative-free optimization in [IJCAI'16], which has been shown to solve problems with dimensionality more than tens of thousands.
2. **Applying derivative-free optimization to solve complex machine learning problems**
   We are interested in applying derivative-free optimization to search policies directly for reinforcement learning tasks. However, due to the sequential property of policy evaluation, most derivative-free optimization methods use batch sampling and could have low efficiency. Our work developed the sequential classification-based optimization method in [AAAI'17], which was improved from the original batch sampling classification-based optimization. Our method has shown outstanding performance on GYM reinforcement learning tasks.

3. **Automatic machine learning (AutoML): full automatic pipeline for real-world applications**
The purpose of AutoML is to find the best machine learning configurations without any human participation. Following the general pipeline, the machine learning process includes data pre-processing, algorithm selection and hyper-parameter optimization. Our works recently focus on the hyper-parameter optimization and algorithm selection.

    - **High-efficient derivative-free hyper-parameter optimization**
    The hyper-parameter tuning is usually formulated as optimizing the hyper-parameter for an algorithm on an evaluation criterion, such as accuracy, AUC score, and so on. Because the evaluation criterion is non-differential, non-convex and non-continuous. The high-efficient derivative-free optimization is urgently-needed. In [AAAI'17], we proposed the classification-based derivative-free optimization method. It has been empirically and theoretically proved that the classification-based optimization has high-efficiency. For hyper-parameter tuning, we further improve the optimization efficiency from two complementary ways. In [IJCAI'18], we extract the experience from the optimization processes on the source tasks and apply it to the target tasks. The experience makes the optimization process converge on a better solution with fewer evaluations. In [AAAI'19], we consider a multi-fidelity optimization setting on AutoML tasks and propose the transfer series expansion method to correct the bias between low and high fidelity evaluations. By replacing high-fidelity evaluations with corrected low-fidelity evaluations, the evaluation cost can be significantly reduced. It provides derivative-free optimization with more evaluation times.
    - **Cascaded algorithm selection with bandit strategy**
    In the algorithm selection phase, we want to find the algorithm which potentially has the best performance. Thus, the hyper-parameter optimization is still a core part. Our work considers the cascaded algorithm selection, which has a two-level process. In the first level, we optimize hyper-parameters for algorithms separately. In the second level, we allocate the limited resources to hyper-parameter optimization processes. In [IJCAI'19], we formulate the cascaded algorithm selection as a multi-armed bandit problem. However, AutoML tends to choose maximum performance. Thus, we proposed the extreme-region UCB (ER-UCB) strategy for the fixed feedback distributions. ER-UCB focuses on extreme feedbacks. In algorithm selection tasks, ER-UCB can discover the algorithm which potentially has the best performance, and allocates the most of the resources to it. Further, we extend the ER-UCB from the fixed distributions to the dynamic distributions. In this situation, some smart derivative-free optimization methods can be applied in the hyper-parameter optimization level.

4. **Practical neural architecture search for deep learning tasks**
Deep learning has been proved as the widely-used technique for real-world applications, such as computer vision, natural language processing, recommendation systems, etc. In recent decades, the advances in deep learning focused on the architectures of neural networks. For example, the convolutional neural network (CNN) was proposed in 1990s. But the architectures of CNN have been developed fast in recent ten years. Many novel architectures are proposed and greatly improve the performances on the computer vision tasks. However, manual architecture designing needs a lot of expert knowledge and manpower. The neural architecture search is proposed to customize high-quality architecture for deep learning tasks. Now, we are trying to apply reinforcement learning, evolutionary learning, and derivative-free optimization approaches to develop a general neural architecture search framework. And this framework will be employed to automatically design the architectures for kinds of real-world tasks.

Publication List

- **Yi-Qi Hu**, Yang Yu, Jun-Da Liao. *Cascaded Algorithm-Selection and Hyper-Parameter Optimization with Extreme-Region Upper Confidence Bound Bandit.* In: **Proceedings of the 28th International Joint Conference on Artificial Intelligence (IJCAI'19)**, Macao, China, 2019.

- **Yi-Qi Hu**, Yang Yu, Wei-Wei Tu, Qiang Yang, Yuqiang Chen, Wenyuan Dai. *Multi-Fidelity Automatic Hyper-Parameter Tuning via Transfer Series Expansion.* In: **Proceedings of the 33rd AAAI Conference on Artificial Intelligence (AAAI'19)**, Honolulu, HI, 2019, pp.2286-2292.

- **Yi-Qi Hu**, Yang Yu, Zhi-Hua Zhou. *Experienced Optimization with Reusable Directional Model for Hyper-Parameter Search.* In: **Proceedings of the 27th International Joint Conference on Artificial**

Intelligence (IJCAI'18), Stockholm, Sweden, 2018, pp.2276-2282.

- **Yi-Qi Hu**, Hong Qian, Yang Yu. *Sequential classification-based optimization for direct policy search.* In: **Proceedings of the 31st AAAI Conference on Artificial Intelligence (AAAI'17)**, San Francisco, CA, 2017, pp.2029-2035.
- **Yi-Qi Hu**, Yang Yu. *A Multi-Task Learning Approach by Combining Derivative-Free and Gradient Methods.* In: **Proceedings of 11th Bio-Inspired Computing-Theories and Applications (BIC-TA'16)**, Xi'an, China, 2016, pp.456-465.
- Hong Qian, **Yi-Qi Hu**, Yang Yu. *Derivative-free optimization of high-dimensional non-convex functions by sequential random embeddings.* In: **Proceedings of the 25th International Joint Conference on Artificial Intelligence (IJCAI'16)**, New York, NY, 2016, pp.1946-1952.
- Yang Yu, Hong Qian, **Yi-Qi Hu**. *Derivative-free optimization via classification.* In: **Proceedings of the 30th AAAI Conference on Artificial Intelligence (AAAI'16)**, Phoenix, AZ, 2016, pp.2286-2292.
- Xin Li, Yong-Juan Liang, Hong Qian, **Yi-Qi Hu**, Lei Bu, Yang Yu, Xin Chen, Xuan-Dong Li. *Symbolic execution of complex program driven by machine learning based constraint solving.* In: **Proceedings of the 31st IEEE/ACM International Conference on Automated Software Engineering (ASE'16)**, Singapore, 2016, pp.554-559.

Services

- **Conference PC Member**:
  AAAI'19, ICML'19, NeurIPS'19.
- **Volunteer**:
  The 14th China Workshop on Machine Learning and Applications (MLA'16), Nanjing, China, 2016.
  The 25th International Joint Conference on Artificial Intelligence (IJCAI'16), New York, NY, 2016.
  The 13rd China Workshop on Machine Learning and Applications (MLA'15), Nanjing, China, 2015.

Selected Awards

- Artificial Intelligence Industrial Talent Scholarship for Ph.D. Candidates. Nanjing, 2018.
- Nanrui Scholarship in Nanjing University. Nanjing, 2017.
- The First Class Academic Scholarship in Nanjing University. Nanjing, 2016.
- The First Class Academic Scholarship in Nanjing University. Nanjing, 2015.
- The First Price Scholarship in Nanjing University of Aeronautics and Astronautics. Nanjing, 2013.
- The First Price Scholarship in Nanjing University of Aeronautics and Astronautics. Nanjing, 2012.

Talks

- Some Progress from Derivative-Free Optimization to Experienced Derivative-Free Optimization. PRICAI AutoML Workshop, Nanjing, China, Aug. 28, 2018.

Teaching Assistant

- Introduction to Machine Learning. (With Prof. Zhi-Hua Zhou, Assoc. Prof. De-Chuan Zhang; For Undergraduate Students, Spring, 2018)
- Advanced Machine Learning. (With Prof. Zhi-Hua Zhou, Assoc. Prof. De-Chuan Zhan, Assoc. Prof. Yang Yu; For Graduate Students, Autumn, 2017)