Summary of GECCO 2018 Kyoto

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1 Tutorials

1.1 Evolution of Neural Networks, by Risto Miikkulainen from Sentient

Miikkulainen presented an interesting talk on their work of customizing the architecture of neural networks with Deep Learning, which I was greatly encouraged. There are two key points that he has covered in his tutorial.

1.1.1 Optimization of Deep Learning Architecture

Miikkulainen argued that evolution can help in improving the architecture of neural networks. His work suggested that different neural network architectures can mean significant performances. During the evolution, he also implemented the idea of **modularity**. For instance, he evolves different modules within a neural network separately by, e.g., doing crossover different modules. He has demonstrated good results on optimizing structures of current prevailing networks, including CNN and LSTM.

1.1.2 Neuroevolution for Sequential Tasks

People have started tackling the classical sequential problems, e.g., MDP, with neural networks. Miikkulainen utilized the evolution to optimize the structures of these networks. In order to make the search tractable, they invented a concept called **indirect encodings**. Personally, this is an interesting technique, since repetition and symmetry, just like our brains, can emerge. They also claimed that the protection of novelty is essential.

1.1.3 Discussion

I managed to have a personal talk with both Miikkulainen and his former PhD student Stanley and asked them the question "under what conditions will modular structures of neural networks evolve out"? Both of them, including a lot of other researchers at GECCO, all pointed out the work done by Jeff Clune et al., who claimed that modularity is due to the cost associated with connections. Personally, I do not believe this is the case. Therefore, I asked their opinions on functional conditions. They suggested me to have a look at indirect encoding.

1.2 Neuroevolution for Deep Reinforcement Learning Problems, by David Ha from Google Brain

David Ha is a senior researcher at Google Brain in Tokyo. He published a paper with Schimihuber this year as the first author. Personally, his contribution is mainly on how to leverage virtual environments to train neural networks. Within this technique, he utilized neuroevolution to optimize the network structures. For example, he built a virtual environment and evolved virtual robots within this environment. Afterwards, he built physical robots according to the structures of evolved robots. Up to here, this is similar to Bongard's work. However, robots that work well in virtual environments usually do not perform well in the physical world. He and his team may have some secret ideas on how to deal with this difference.

More interestingly, they can have agents evolve out models of the environments and train these agents with these models, instead of training agents by letting them directly engaging with environments. This concept is called **world model**, which is quite of a hot topic now. Their way of combining world models and evolution computation can be interesting.

1.3 Evolutionary Computational for Digital Art, by Aneta Neumann et al. from the University of Adelaide

Personally, their work is not that interesting. They proposed a method of how to convert an artwork A to B, so that the generated artwork will have characteristics of both A and B. What they have done was randomly picking some positions, and randomly walk to left, right, up or down. This technique reminded me of cellular automatons. Specifically, the basic movements of cellular automatons are as simple, but these simple movements can eventually lead to very complex behaviors.

1.4 Others

I also attended four other tutorials, namely *Introduction to Genetic Programming for EC*, *Decomposition multi-objective optimisation: current developments and future opportunities* and *Evolutionary Computation - an Unified Approach*. The only evolution part of the former was a mention of an algorithm called *polish*, the latter I did not quite understand. As to the third, it did not cover many new things, just a review of the history of EC.

2 Parallel Sessions

Two presentations impressed me, whose titles are *Data-efficient Neuroevolution with Kernel-Based Surrogate Models* and *Evolving Mario Levels in the Latent Space of a Deep Convolutional Generative Adversarial Network*. One take-away is the evaluation of distances between two individuals by using the path of ancestors. I need to read papers to fully understand the details.