Designing neural networks through neuroevolution

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Designing neural networks through neuroevolution

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Much of recent machine learning has focused on deep learning, in which neural network weights are trained through variants of stochastic gradient descent. An alternative approach comes from the field of neuroevolution, which harnesses evolutionary algorithms to optimize neural networks, inspired by the fact that natural brains themselves are the products of an evolutionary process. Neuroevolution enables important capabilities that are typically unavailable to gradient-based approaches, including learning neural network building blocks (for example activation functions), hyperparameters, architectures and even the algorithms for learning themselves. Neuroevolution also differs from deep learning (and deep reinforcement learning) by maintaining a population of solutions during search, enabling extreme exploration and massive parallelization. Finally, because neuroevolution research has (until recently) developed largely in isolation from gradient-based neural network research, it has developed many unique and effective techniques that should be effective in other machine learning areas too. This Review looks at several key aspects of modern neuroevolution, including large-scale computing, the benefits of novelty and diversity, the power of indirect encoding, and the field's contributions to meta-learning and architecture search. Our hope is to inspire renewed interest in the field as it meets the potential of the increasing computation available today, to highlight how many of its ideas can provide an exciting resource for inspiration and hybridization to the deep learning, deep reinforcement learning and machine learning communities, and to explain how neuroevolution could prove to be a critical tool in the long-term pursuit of artificial general intelligence.

Classic neuroevolution

- A major inspiration for the investigation of neuroevolution is the evolution of brains in nature.
- By the 1980s, the notion of an artificial neural network was well established.
- Researchers began to ask whether these rough abstractions of brains themselves might be evolved artificially through evolutionary algorithms.
- Through mutation and crossover, the population gradually evolves to increasing levels of fitness.
- Researchers saw in such algorithms an opportunity to optimize neural networks.
- They were motivated by nature's own achievements through evolution.
  - alternative to backpropagation

Classic neuroevolution

- Fixed Architecture -> Evolving the Architecture of NN, intra-life learning
  - protecting more complex structures from dying became important.
  - NEAT(NeuroEvolution Augmenting Topology)
- NEAT prevented premature extinction of augmented structures through a mechanism called speciation.
- The early successes in the field often concerned evolving neural network controllers for robots, known as evolutionary robotics.
  - Sony-Aibo
- Tevatron particle collider (입자충돌기의 쿼크질량의 측정)
- Neuroevolution has also been used to study open questions in evolutionary biology.
- Tiny neural networks composed of hundreds or thousands of connections instead of the millions of connections commonly seen in modern deep neural network (DNN) research.

The new era of neuroevolution at scale

- Neuroevolution algorithms also perform far better when scaled to take advantage of modern computing resources.
- Neuroevolution is a competitive alternative to gradient-based methods for training deep neural networks for reinforcement learning problems.
- Natural evolutionary strategy (NES) performs competitively with the best deep reinforcement learning algorithms, including DQN and A3C. (Salimans. 2017)
  - But, NES can be interpreted as gradient-based method
- Simple genetic algorithm also competitive with DQN and A3C (and NES) on Atari games. (Such. 2017)
  - more quick, less sample efficient
- NES performs well at enabling a humanoid robot controlled by a two-layer neural network to walk. (Salimans. 2017)

The new era of neuroevolution at scale

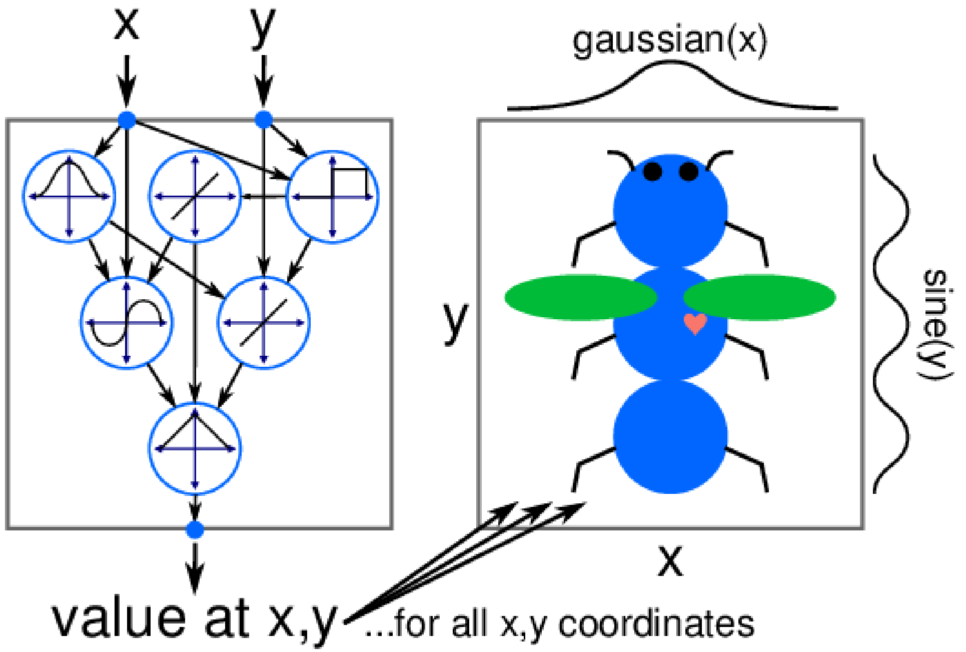
- GA can also perform well on this task, although with worse sample complexity. (Such. 2017)
- Simplified neuroevolution, training a singlelayer neural network, produces state-of-the-art results on these simulated robot control tasks. (Mania. 2018)
- 비교적 간단한 구조의 로봇 컨트롤 문제에서 뛰어난 퍼포먼스를 보여줌
- Hybridizing the gradient-based methods of deep learning with neuroevolution.
  - safe mutation
  - 정책평가의 cost는 큼(에피소드가 끝나야 함), DNN의 output의 평가의 cost는 작음
  - mutation할 때 gradient정보를 사용
- Combining such ideas with those from deep learning and deep reinforcement learning is a research area that should continue to deliver many breakthroughs.

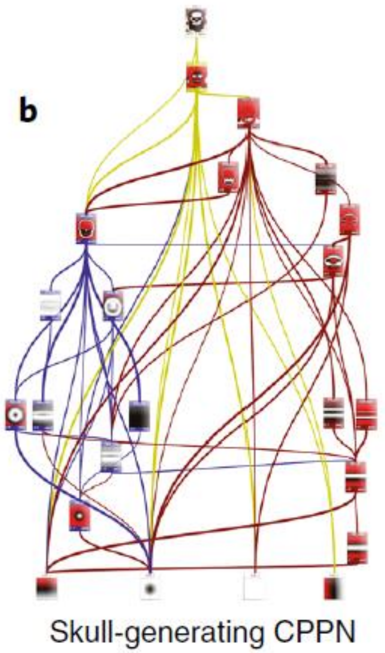
Indirect encoding

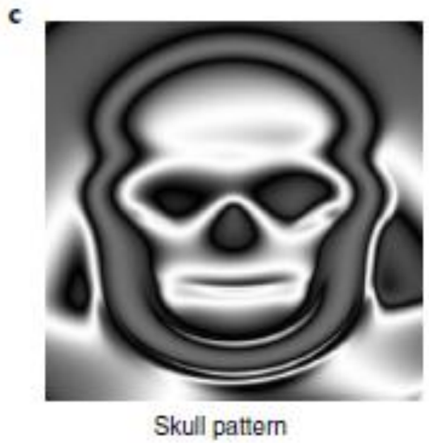
- The human brain far exceeds the size of any modern neural network.
- How is this astronomical structure encapsulated within our DNA-based genetic code, whose capacity is only about 30,000 genes?
- The need to encode all these components requires regularity and the compression that it enables, so that the genome can be reasonably compact.
- Convolution is a particular regular pattern of connectivity. (사람이 만들었음)
- Powerful regularities need not fall ultimately to the hands of human designers. (사람이 만들 필요 없음)
- It would be ideal if machine learning could discover such patterns, including convolution, on its own.
- researchers explored evolvable encodings for a wide range of structures. (Stanley. 2003)

Indirect encoding

- compositional pattern-producing networks(CPPNs) (Stanley. 2007)
- early in the development of the embryo, chemical gradients help to define axes from head to tail, front to back, and left to right. -> fingers
- 더 적은 노드로 더 복잡한 구조를 표현 가능







Indirect encoding

- Beyond these applications, perhaps the most important role of CPPNs is to generate the patterns of weights in neural networks themselves in an approach called HyperNEAT.
- The main idea is to generate the pattern of weights as a function of the geometry of the inputs and outputs of the domain.
  - for example, if there are multiple layers then their respective connectivity patterns can be generated by separate CPPN outputs.
- If there should be a correlation between weights of nearby neurons, then that can only be learned as a general pattern if the positions of the neurons are known. Covolution.
- Recent variants of HyperNEAT-based neuroevolution that combine neuroevolution and indirect encoding with SGD have indeed discovered convolutional patterns on their own.
- Hypernetworks help to enhance the performance of LSTMs in language modelling.

Indirect encoding

- Great benefit of HyperNEAT and indirect encoding in general is that they enable very large neural networks to be evolved through compact encoding.

- Interestingly, although the work of DeepMind had a strong impact on the field of reinforcement learning for learning to play Atari directly from pixels, HyperNEAT was the first system for which direct pixel-to-action Atari results were reported. (Hausknecht. 2014)

Meta-learning and architecture search

- learning how to learn (Meta-learning)
- Architecture Search
- Natural evolution, after all, is intrinsically a powerful meta-learning algorithm.
- Evolution can be viewed as an outer loop search algorithm that produced organisms (including humans) with extraordinarily sophisticated(복잡한) learning capabilities of their own.
- Much of the meta-learning work within neuroevolution has focused on synaptic plasticity (신경 가소성).
- It is even possible for an indirect encoding to generate a pattern of learning rules with adaptive HyperNEAT (Convlution) (Risi. 2010)
  - 웨이트 간의 패턴을 학습하는 것도 일종의 학습전략

Meta-learning and architecture search

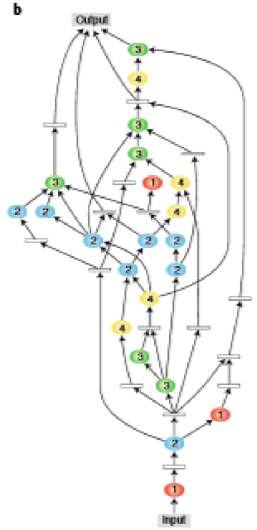
- The plasticity of connections themselves can be made to vary over the lifetime of the agent through the mechanism of neuromodulation.
  - 강화학습에서 한 에피소드동안 학습전략을 조정할 수 있다는 뜻 같음…
  - for example by locking in weights (by turning off plasticity) when they yield high rewards, or increasing plasticity when expected reward does not materialize.
- Catastrophic forgetting
  - Artificial neural networks learn new skills, they do so by erasing what they have learned about previous skills.
- Turning plasticity on only in the subset of neural weights relevant for the task currently being performed. (Ellefsen. 2015)

Meta-learning and architecture search

- Architecture Search
- Network architectures have become so complex that it is difficult to design them by hand
- Often innovations within a computer vision domain come from the discovery of different, better architectures, and each type of computer vision problem tends to require its own specialized architecture.
- NEAT represents an early advance in evolving network architecture (along with weights) at small scales, recent work has focused on evolving deep neural networks.
- A variant of the approach57 further improved performance by evolving small neural network modules that are repeatedly used in a larger hand-coded blueprint.
  - Inception, DenseNet, ResNet
- more computationally expensive tasks of image classification on the CIFAR and ImageNet datasets.
  - State of the art

Meta-learning and architecture search

- LSTM cell
  - Interestingly, the structure of the LSTM node has remained relatively constant since its inception 25 years ago.
  - The variations that have been proposed do not significantly improve on the standard LSTM.
- It has become possible to search automatically for better gated recurrent network designs, using, for example, reinforcement learning and evolution. (Zoph. 2017)
- A fruitful approach is to encode the structure of the gated recurrent node as a program.
- complex structures that are several times larger than the standard LSTM.
  - 15% better
  - 다른 도메인에서도 12% 좋음



Meta-learning and architecture search

- multitask learning
  - It has long been known that training a neural network on multiple tasks at once can make learning each task easier.
- But how should the requirements of the different tasks be best combined?
  - Architecture Search로 해결 가능 (CMTR)

Look forward

- hybridization of evolution and gradient descent
  - This trend is likely to accelerate especially as computational resources expand.
  - large-scale discovery
- The other side of the convergence between neuroevolution and deep learning is the importation of conceptual approaches from neuroevolution into gradient-based implementations without using any evolution.
- Neuroevolutionary ideas have also inspired progress in other areas of deep reinforcement learning.
- A final critical opportunity for neuroevolution is to lead the effort to construct 'open-ended' algorithms.
- generating more and more complex brain-like structures indefinitely.