Firefly Neural Architecture Descent

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Motivation

Biological brains can grow new neurons (neurogenesis). Artificial neural networks are fixed in size.

The *benefits* of growing a dynamic architecture:

1. Learning capacity is enlarged on demand (adaptive, energy efficient).
2. Dynamic architecture has been shown effective to mitigate *catastrophic forgetting* in continual learning (Rusu et al., 2016, Yoon et al., 2017, Li et al., 2019).

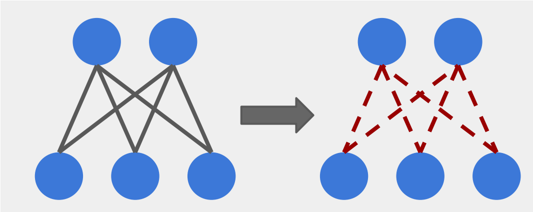
Motivation

Limitations of existing growing methods:

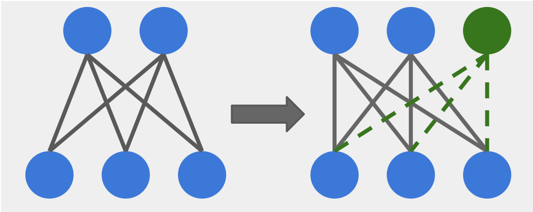
1. Previous growing methods are often based on heuristics.
2. An exception is *splitting steepest descent* (Liu et al., 2019) that progressively splits neurons greedily. But the method is *limited to* splitting (does not consider new neurons/layers) and has *high time complexity* (requires solving an eigen-problem per growth).

Joint Parametric & Architecture Descent

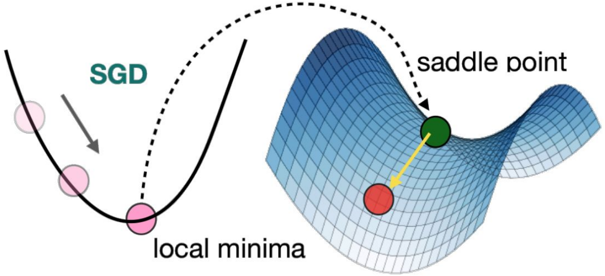
A neural network consists of both its *parameters* and its *architecture*. In this work, we propose to jointly optimize both.



Parametric Descent



Architecture Descent



(SGD refers to Stochastic Gradient Descent; Image from Wang et al., 2019)

When a network grows, the previous local minima can become a saddle point in the larger space.

A General Framework for Network Optimization

Assume the current neural network is f_t . Then we looks for

$$f_{t+1} = \arg\min_{f} \left\{ L(f) \quad s.t. \quad f \in \mathcal{B}(f_t,\ \epsilon), \qquad C(f) \leq C(f_t) + \eta_t \right\}$$

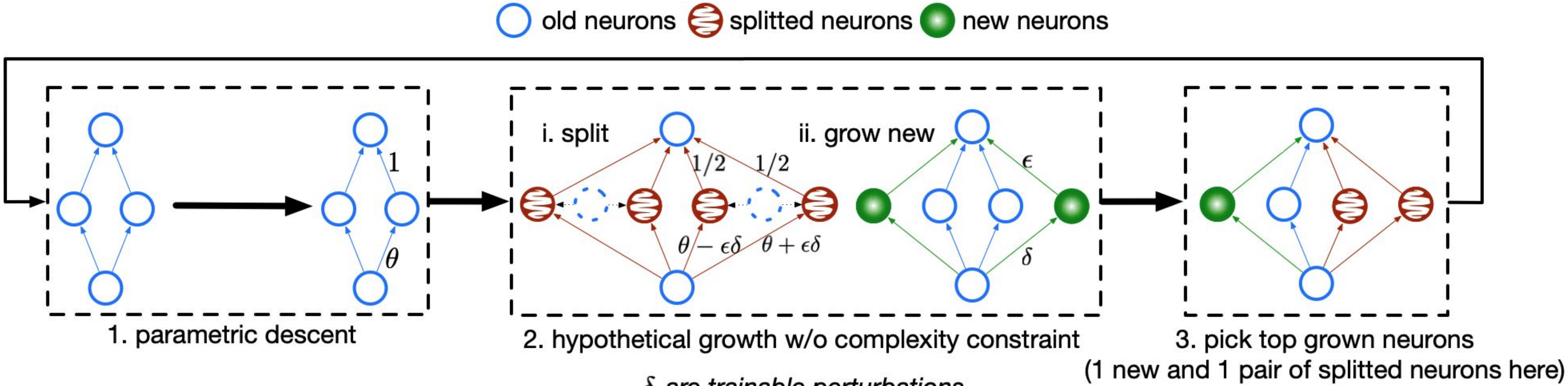
- $L(\cdot)$ denotes the loss function;
- $\mathcal{B}(f_t,\ \epsilon)$ represents a ball of radius ϵ centered at f .
- $C(\cdot)$ measures the complexity of the network, i.e. the FLOPs.

Firefly Neural Architecture Descent

We introduce *firefly neural architecture descent* to solve

$$f_{t+1} = \arg\min_{f} \left\{ L(f) \quad s.t. \quad f \in \mathcal{B}(f_t,\ \epsilon), \qquad C(f) \le C(f_t) + \eta_t \right\}$$

Specifically, we propose parametric descent + 2-step growing:



δ *are trainable perturbations*

Experiments (neural architecture search)

We compare against some previous growing methods.

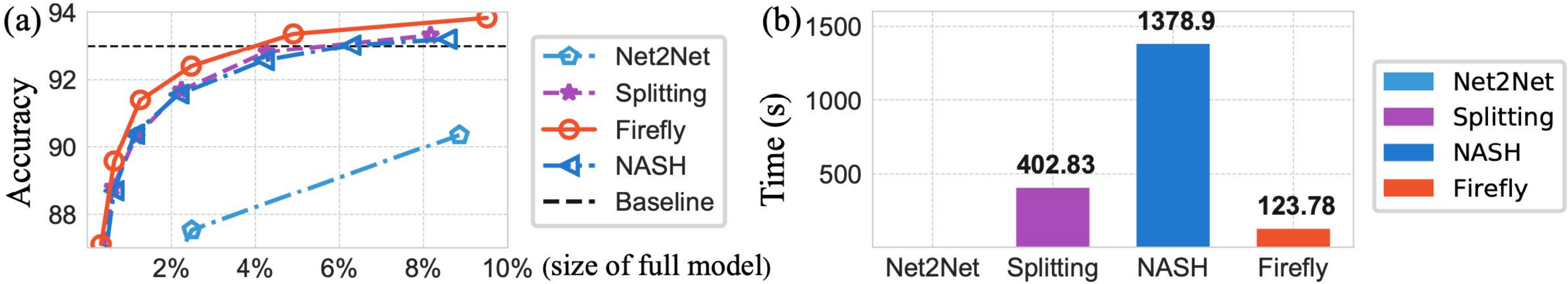


Figure 4: (a) Results of growing increasingly wider networks on CIFAR-10; VGG-19 is used as the backbone. (b) Computation time spent on growing for different methods.

Experiments (continual learning)

We apply Firefly to continual image classification task on the CIFAR dataset. Firefly outperforms state-of-the-art dynamic architecture approaches.

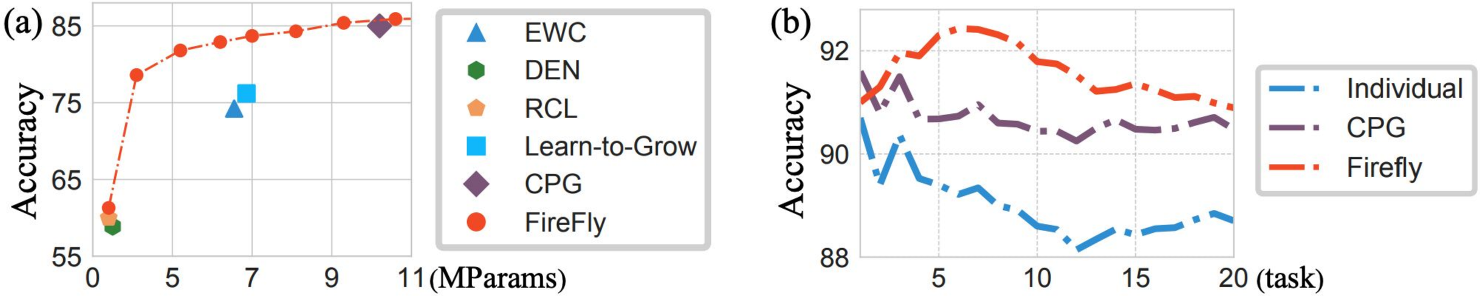


Figure 5: (a) Average accuracy on 10-way split of CIFAR-100 under different model size. We compare against Elastic Weight Consolidation (EWC) (Kirkpatrick et al., 2017), Dynamic Expandable Network (DEN) (Yoon et al., 2017), Reinforced Continual Learning (RCL) (Xu & Zhu, 2018) and Compact-Pick-Grow (CPG) (Hung et al., 2019a). (b) Average accuracy on 20-way split of CIFAR-100 dataset over 3 runs. Individual means train each task from scratch using the Full VGG-16.

References

[1] Liu, Qiang, Wu, Lemeng, and Wang, Dilin. Splitting steepest descent for growing neural architectures. Neural Information Processing Systems (NeurIPS), 2019.

[2] Wang, Dilin, Li, Meng, Wu, Lemeng, Chandra, Vikas, and Liu, Qiang. Energy-aware neural architecture optimization with fast splitting steepest descent. arXiv preprint arXiv:1910.03103, 2019.

[3] Rusu, Andrei A, Rabinowitz, Neil C, Desjardins, Guillaume, Soyer, Hubert, Kirkpatrick, James, Kavukcuoglu, Koray, Pascanu, Razvan, and Hadsell, Raia. Progressive neural networks. arXiv preprint arXiv:1606.04671, 2016.

[4] Yoon, Jaehong, Yang, Eunho, Lee, Jeongtae, and Hwang, Sung Ju. Lifelong learning with dynamically expandable networks. International Conference on Learning Representation (ICLR), 2018.

[5] Li, Xilai, Zhou, Yingbo, Wu, Tianfu, Socher, Richard, and Xiong, Caiming. Learn to grow: A continual structure learning framework for overcoming catastrophic forgetting. International Conference on Machine Learning (ICML), 2019.

[6] Hung, Ching-Yi, Tu, Cheng-Hao, Wu, Cheng-En, Chen, Chien-Hung, Chan, Yi-Ming, and Chen, Chu-Song. Compacting, picking and growing for unforgetting continual learning. In Advances in Neural Information Processing Systems (NeurIPS), 2019.

[7] Xu, Ju and Zhu, Zhanxing. Reinforced continual learning. In Advances in Neural Information Processing Systems (NeurIPS), 2018.

[8] Kirkpatrick, James, Pascanu, Razvan, Rabinowitz, Neil, Veness, Joel, Desjardins, Guillaume, Rusu, Andrei A, Milan, Kieran, Quan, John, Ramalho, Tiago, Grabska-Barwinska, Agnieszka, et al. Overcoming catastrophic forgetting in neural networks. Proceedings of the national academy of sciences, 114(13):3521–3526, 2017.