Chapter 08. 좋은 딥러닝 구조를 찾아내는 딥러닝 (Neural Architecture Search)

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NAS Methods

Reinforcement Learning (RL)

Evolutionary Algorithm (EA)

Differentiable Architecture Search (DARTS)

다양한 종류의 NAS 방법을 소개하고자 한다.

NAS

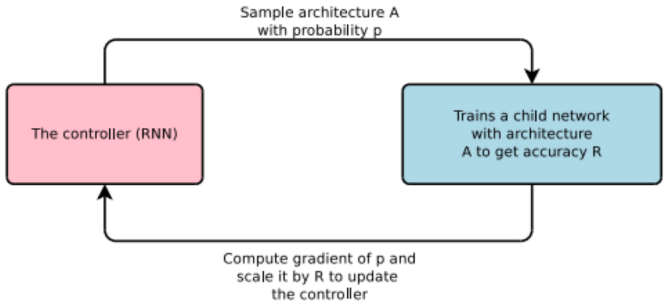
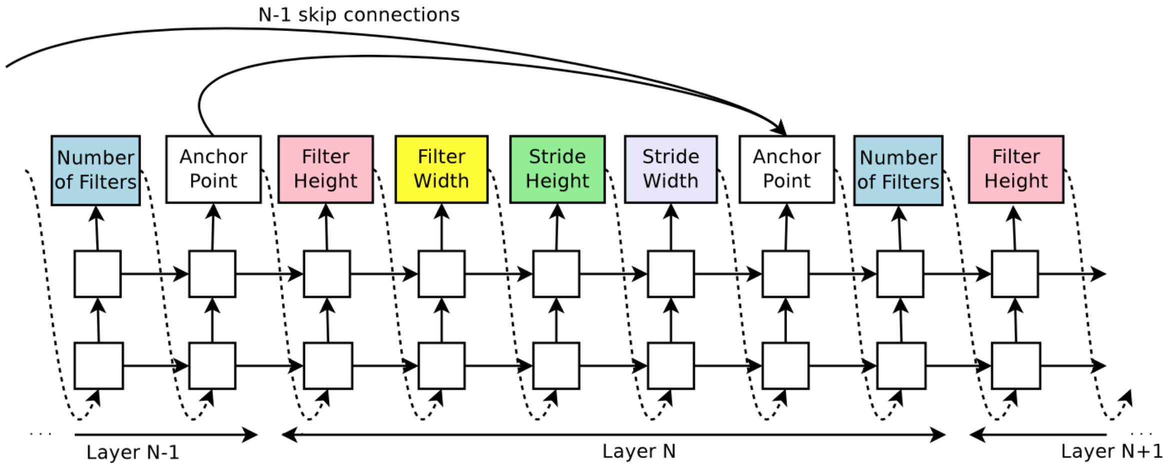


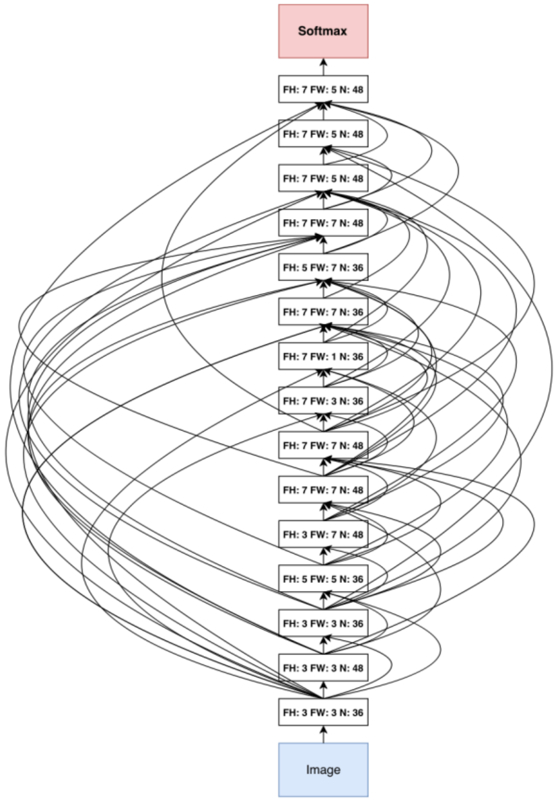
Figure 1: An overview of Neural Architecture Search.



Google Brain에서 제안한 첫 NAS 논문. RNN Controller를 이용한 RL 방법이다.

https://openreview.net/pdf?id=r1Ue8Hcxg

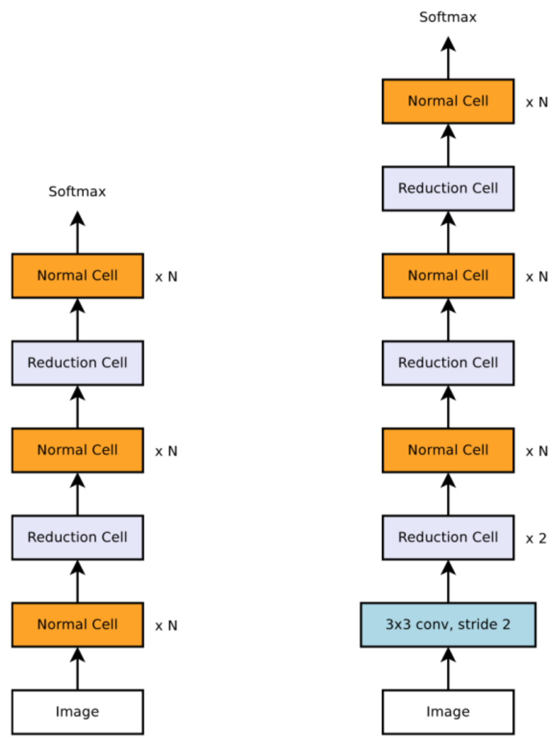
NAS



NAS로 도출한 Optimum Image Classifier. GPU Time으로 약 1000day가 들어갔다.

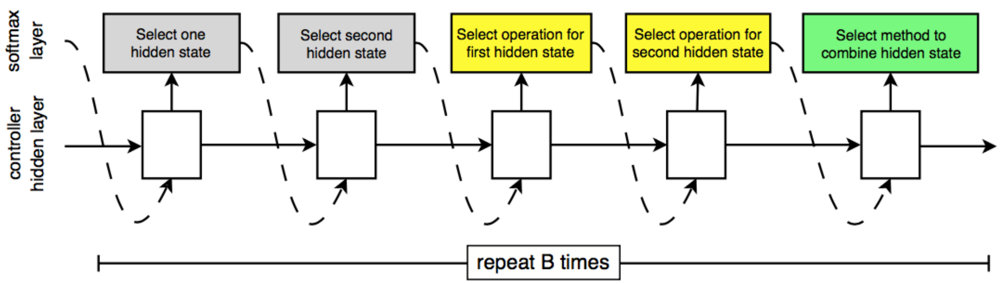
https://openreview.net/pdf?id=r1Ue8Hcxg

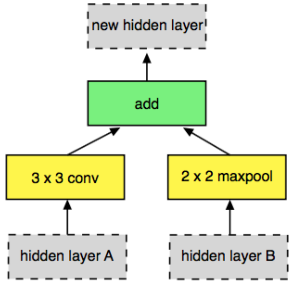
NASNet



CIFAR10 Architecture

ImageNet Architecture



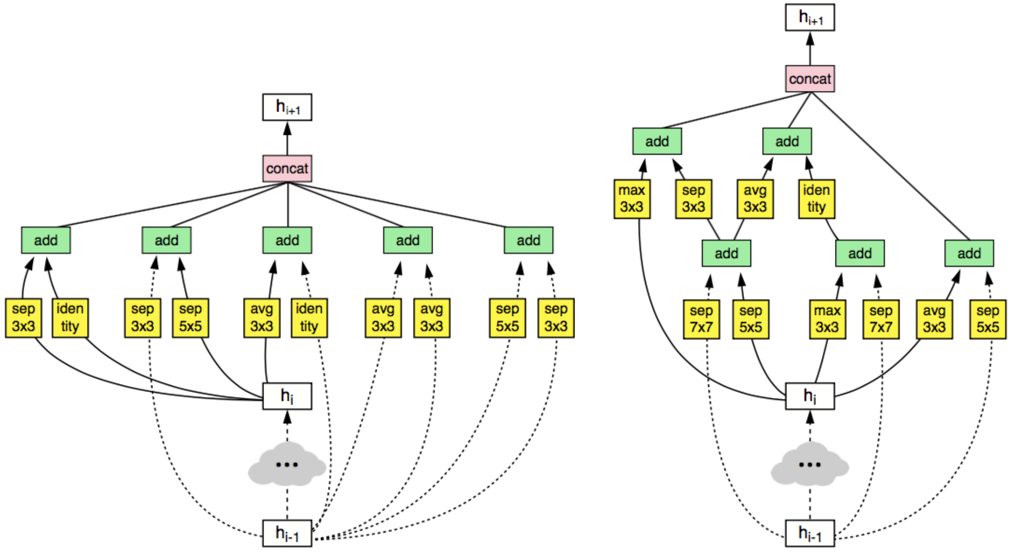


- identity
- 1x7 then 7x1 convolution
- 3x3 average pooling
- 5x5 max pooling
- 1x1 convolution
- 3x3 depthwise-separable conv
- 7x7 depthwise-separable conv
- 1x3 then 3x1 convolution
- 3x3 dilated convolution
- 3x3 max pooling
- 7x7 max pooling
- 3x3 convolution
- 5x5 depthwise-seperable conv

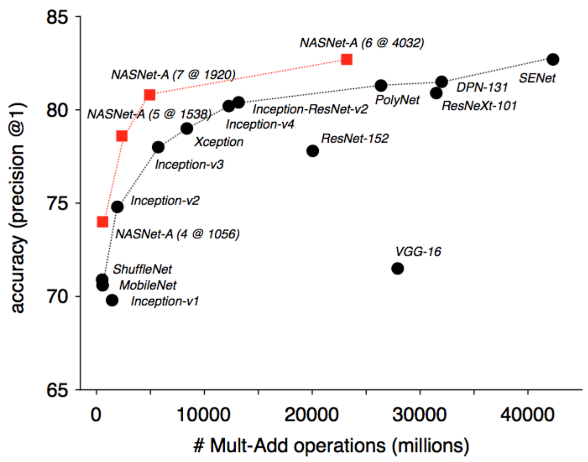
Normal Cell과 Reduction Cell로 나누고, 자주 쓰이는 Operation을 후보로 두었다.

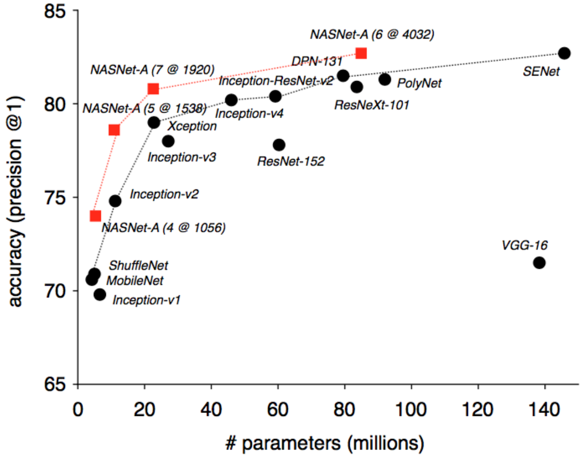
https://arxiv.org/pdf/1707.07012.pdf

NASNet



Normal Cell Reduction Cell

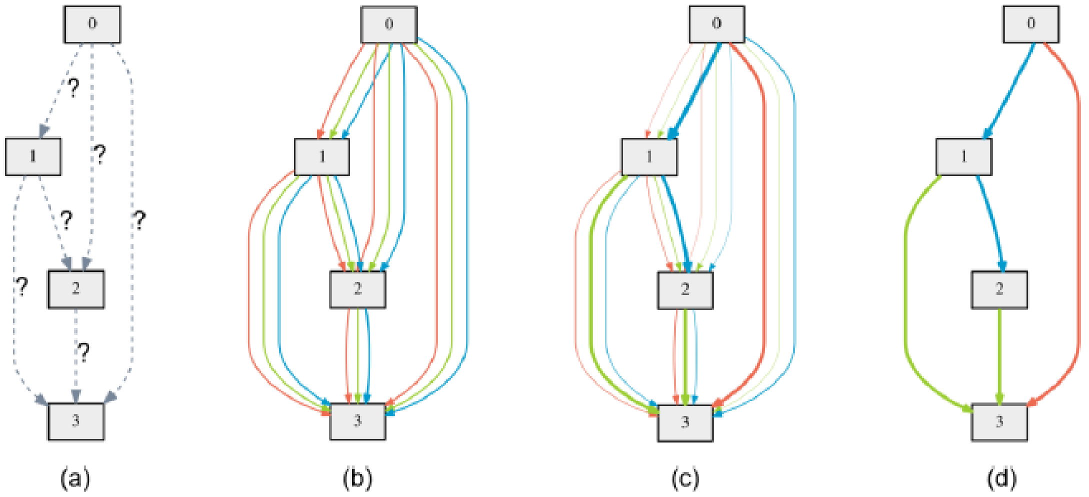




NASNet으로 찾은 구조로, ImageNet에서 SOTA의 성능을 보여주었다.

https://arxiv.org/pdf/1707.07012.pdf

DARTS



$$\min_{\alpha} \quad \mathcal{L}_{val}(w^*(\alpha), \alpha)$$
$$\text{s.t.} \quad w^*(\alpha) = \text{argmin}_w \; \mathcal{L}_{train}(w, \alpha)$$

Mixed Operation의 가중치를 이용해, Child network의 선택이 미분 가능하게 한다.

https://arxiv.org/abs/1806.09055

DARTS

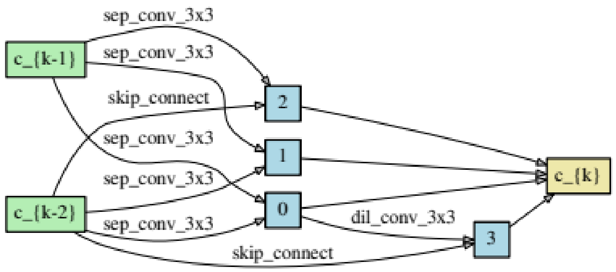


Figure 4: Normal cell learned on CIFAR-10.

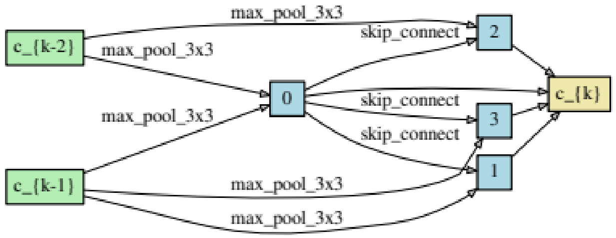


Figure 5: Reduction cell learned on CIFAR-10.

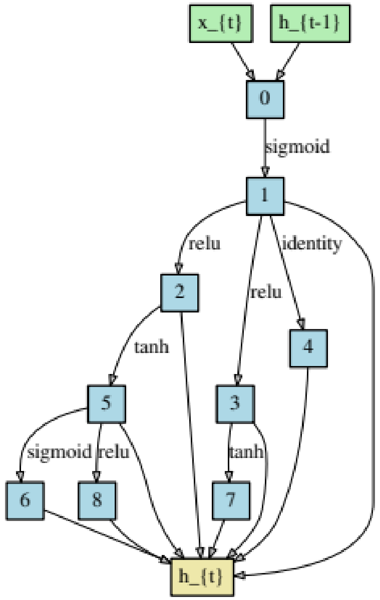


Figure 6: Recurrent cell learned on PTB.

DARTS에 의해 학습된 Cell Architectures

https://arxiv.org/abs/1806.09055

DARTS

Architecture	Test Error (%)	Params (M)	Search Cost (GPU days)	Search Method
DenseNet-BC (Huang et al., 2017)	3.46	25.6	–	manual
NASNet-A + cutout (Zoph et al., 2017)	2.65	3.3	1800	RL
NASNet-A + cutout (Zoph et al., 2017)†	2.83	3.1	3150	RL
AmoebaNet-A + cutout (Real et al., 2018)	3.34 ± 0.06	3.2	3150	evolution
AmoebaNet-A + cutout (Real et al., 2018)†	3.12	3.1	3150	evolution
AmoebaNet-B + cutout (Real et al., 2018)	2.55 ± 0.05	2.8	3150	evolution
Hierarchical Evo (Liu et al., 2017b)	3.75 ± 0.12	15.7	300	evolution
PNAS (Liu et al., 2017a)	3.41 ± 0.09	3.2	225	SMBO
ENAS + cutout (Pham et al., 2018b)	2.89	4.6	0.5	RL
Random + cutout	3.49	3.1	–	–
DARTS (first order) + cutout	2.94	2.9	1.5	gradient-based
DARTS (second order) + cutout	2.83 ± 0.06	3.4	4	gradient-based

GPU Hour 대비 매우 좋은 성능이 나타남을 알 수 있다.

https://arxiv.org/abs/1806.09055