

ECCV 2020 Tutorial on

# From HPO to NAS: Automated Deep Learning

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# CVPR Tutorial Review <https://hangzhang.org/CVPR2020/>

- AutoML Background Overview (by Cedric Archambeau)
- Introduction to an AutoML Toolkit (by Hang Zhang)
- Once-for-All Network (by Song Han)
- Hands-on Sections:
  - ProxylessNAS
  - OFA-Net
  - Fast AutoAugment

# NAS: Neural Architecture Search

- What is NAS?

We want the architecture that maximize the reward with the corresponding network weights that minimize training loss.

$$\max_a R(\hat{w}(a), a) \text{ st. } \hat{w}(a) = \operatorname{argmin}_w \ell_{train}(w, a)$$

# Different Way of Approaching NAS

- NAS with RL:  
Sampling a set of configurations and calculate reward and update  $\theta$

$$J(\theta) = E_{a \sim P(a; \theta)}[R(a)]$$
$$\frac{1}{m} \sum_{k=1}^m \log P(a_k; \theta)(R(a_k) - b)$$

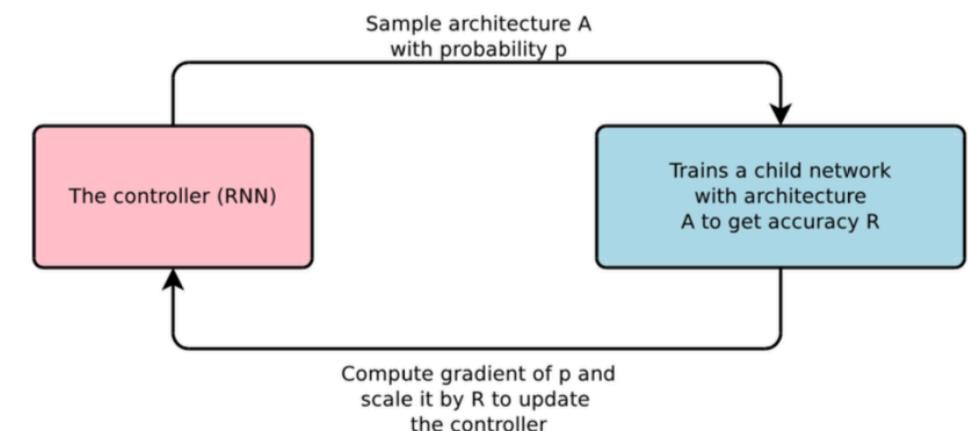
- Policy improves over time

Zoph, Barret, and Quoc V. Le. "Neural architecture search with reinforcement learning."

Reinforce Algorithm [http://cs231n.stanford.edu/slides/2019/cs231n\\_2019\\_lecture14.pdf](http://cs231n.stanford.edu/slides/2019/cs231n_2019_lecture14.pdf)

NASNet, MobileNetV3, MNASNet, AutoDeepLab

<http://autogluon.s3.amazonaws.com/tutorials/course/object.html>



# Different Way of Approaching NAS

- Differentiable Architecture Search:

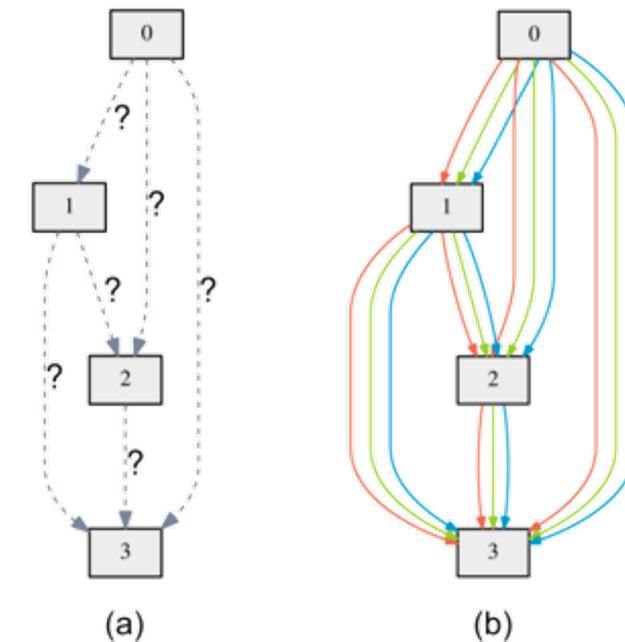
$$J(\theta) = E_{a \sim P(a; \theta)}[R(a)] \approx R(E_{P(a; \theta)}[a])$$

- Soft combination of different ops:

$$O(x) = \sum_i softmax(\theta_i) \cdot o_i(x)$$

- GumbleSoftMax( $\theta_i$ ) =  $\frac{\exp(\theta_i + g_i)/\tau}{\sum_j \exp(\theta_j + g_j)/\tau}$

- Difficulties: memory and computation



Liu, Hanxiao, Karen Simonyan, and Yiming Yang. "Darts: Differentiable architecture search."

Xie, Sirui, et al. "SNAS: stochastic neural architecture search."

Wu, Bichen, et al. "Fbnet: Hardware-aware efficient convnet design via differentiable neural architecture search."

# Scalable & Efficient Neural Architecture Search

- ENAS via parameter sharing (reward per-epoch)

$$J(\theta) = E_{a \sim P(a; \theta)} [R(a, w^*)]$$

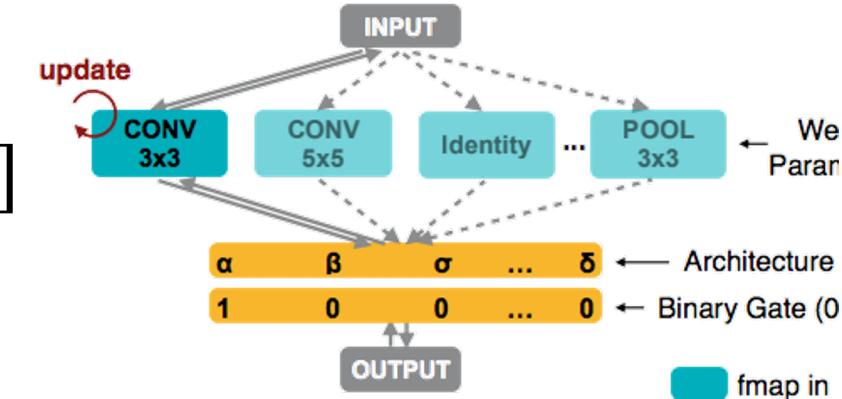
- ProxylessNAS:  $g = [0, 0, \dots, 1, \dots, 0]$

$$O(x) = \sum g_i(\theta_i) \cdot o_i(x)$$

$$\frac{d\ell}{d\theta_j} = \sum_i \frac{d\ell}{d\theta_j} \cdot \frac{d_{g_i}}{d\theta_j} \approx \sum_i \frac{d\ell}{d_{g_i}} \cdot \frac{d_{p_i}}{d\theta_j}$$

$$\frac{d_{g_i}}{d_{O(x)}} = \frac{d_{O(x)}}{d_{g_i}}$$

$$\frac{d_{g_i}}{d_{g_i}} \approx o_i(x)$$



Pham, Hieu, et al. "Efficient neural architecture search via parameter sharing."

Cai, Han, Ligeng Zhu, and Song Han. "Proxylessnas: Direct neural architecture search on target task and hardware."

# Tutorial Overview

- Introduction to Neural Architecture Search for Computer Vision (by Linjie Yang)
- Hardware-aware Deep Neural Architecture Search (by Peizhao Zhang)
- Model-based Asynchronous Hyperparameter and Neural Architecture Search (by Matthias Seeger)
- Does Unsupervised Architecture Representation Learning Help Neural Architecture Search (by Mi Zhang)
- AutoML for 3D Deep Learning (by Haotian Tang)