Neural Architecture Search

Neural Networks Design And Application

A framework for NAS

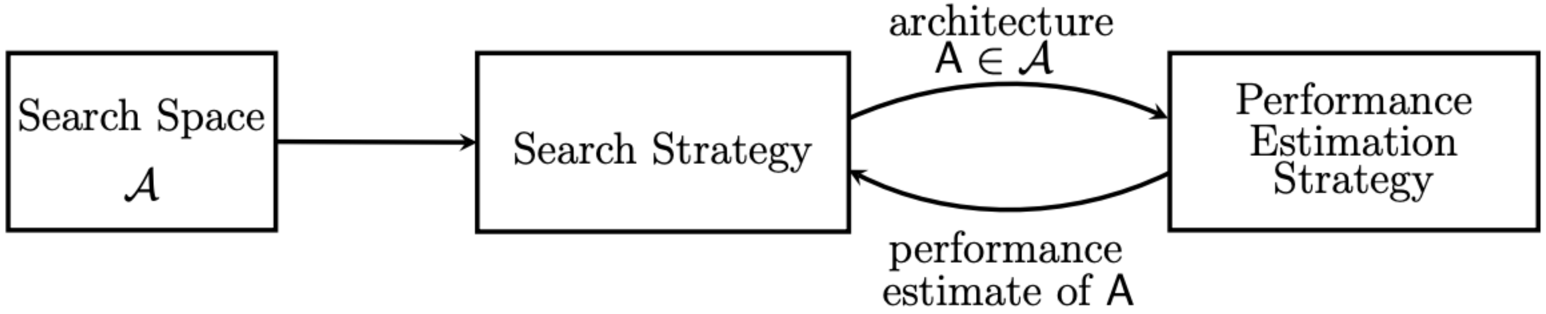

Image credit:
Elsken, Thomas, Jan Hendrik Metzen, and Frank Hutter. "Neural architecture search: A survey." *J. Mach. Learn. Res.* 20, no. 55 (2019): 1-21.
https://arxiv.org/pdf/1808.05377.pdf

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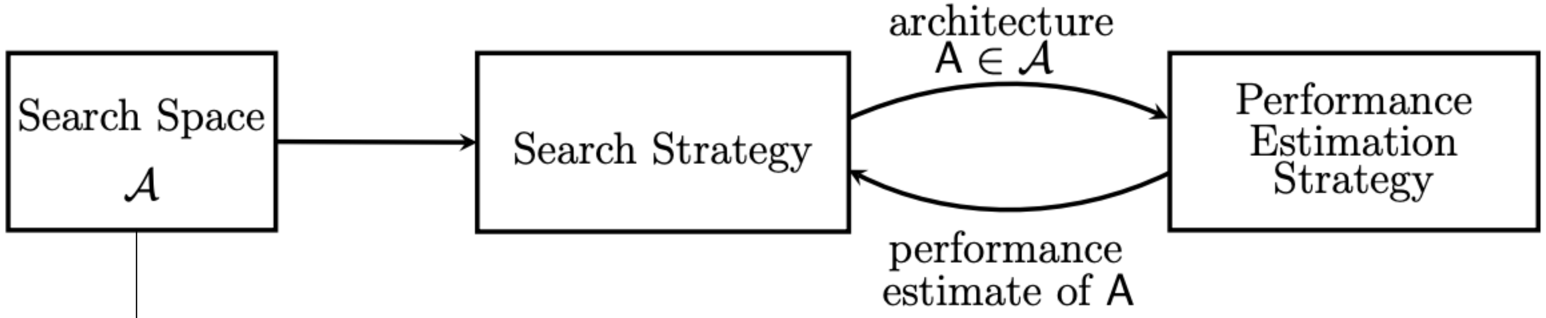
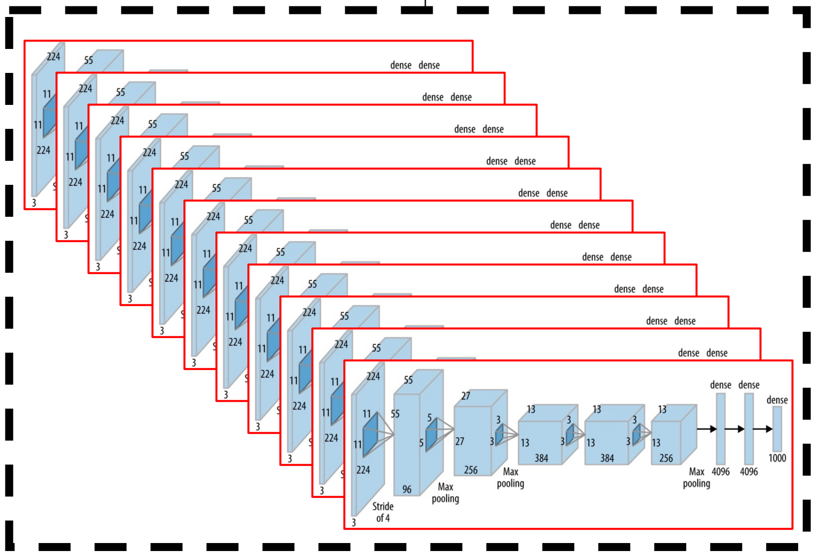


Exponentially large
number of elements



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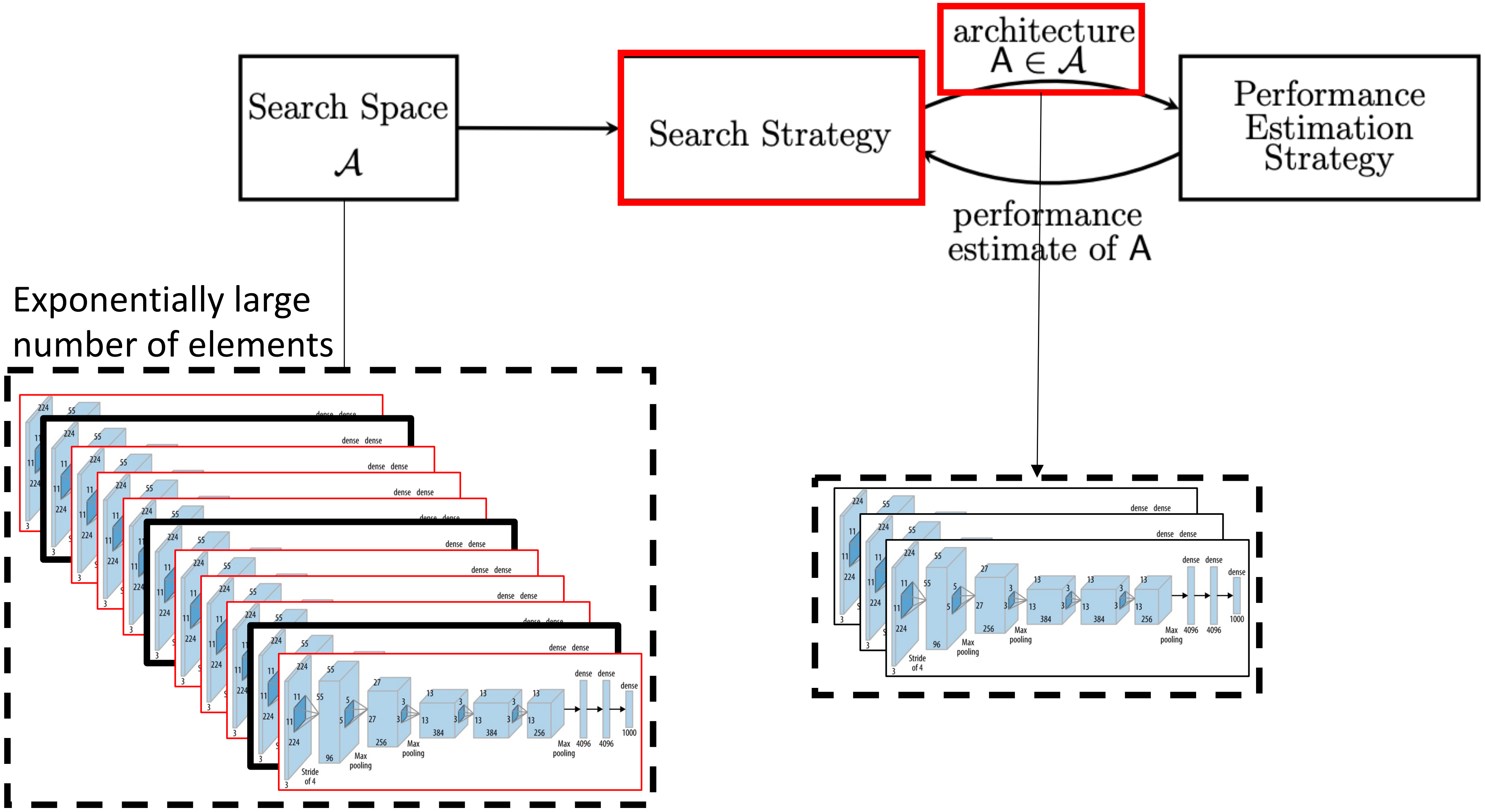

Random search

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- Weight decay (L2 regularization): {0.0001, 0.001, 0.01, 0.1, 1, 10}

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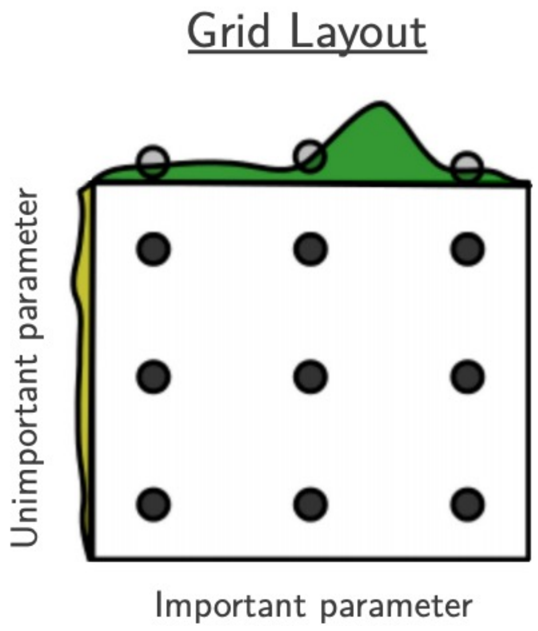

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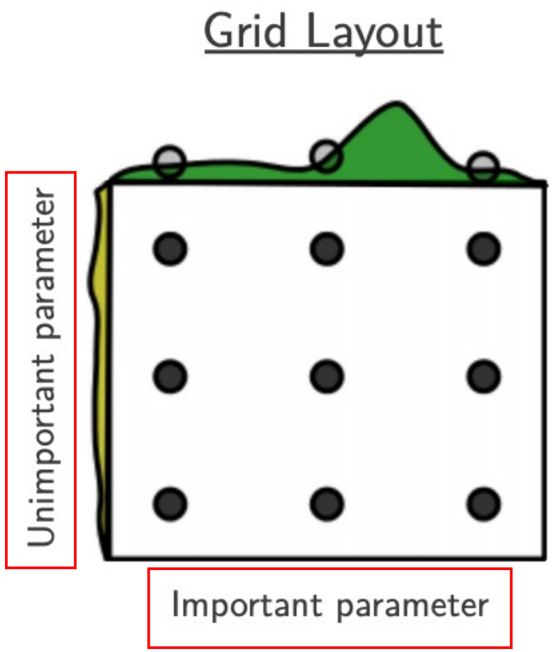

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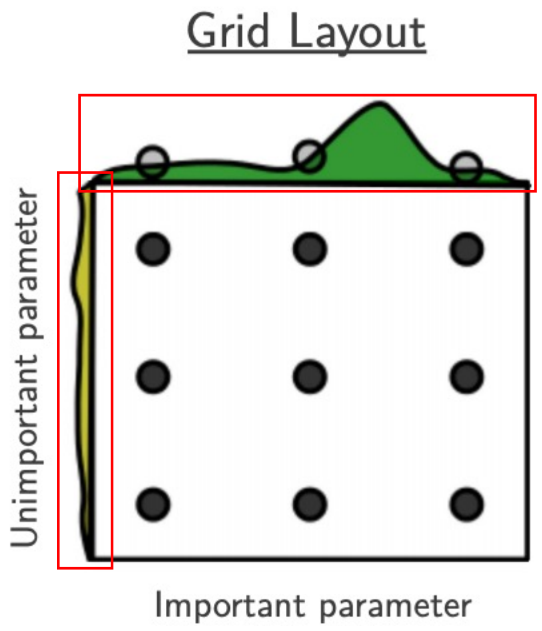

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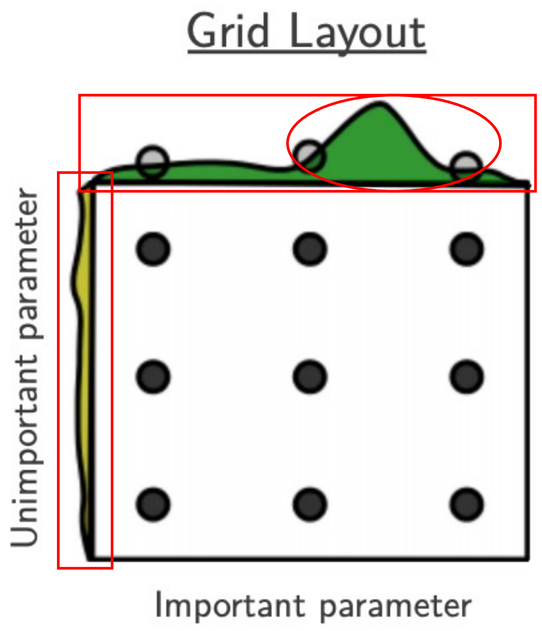

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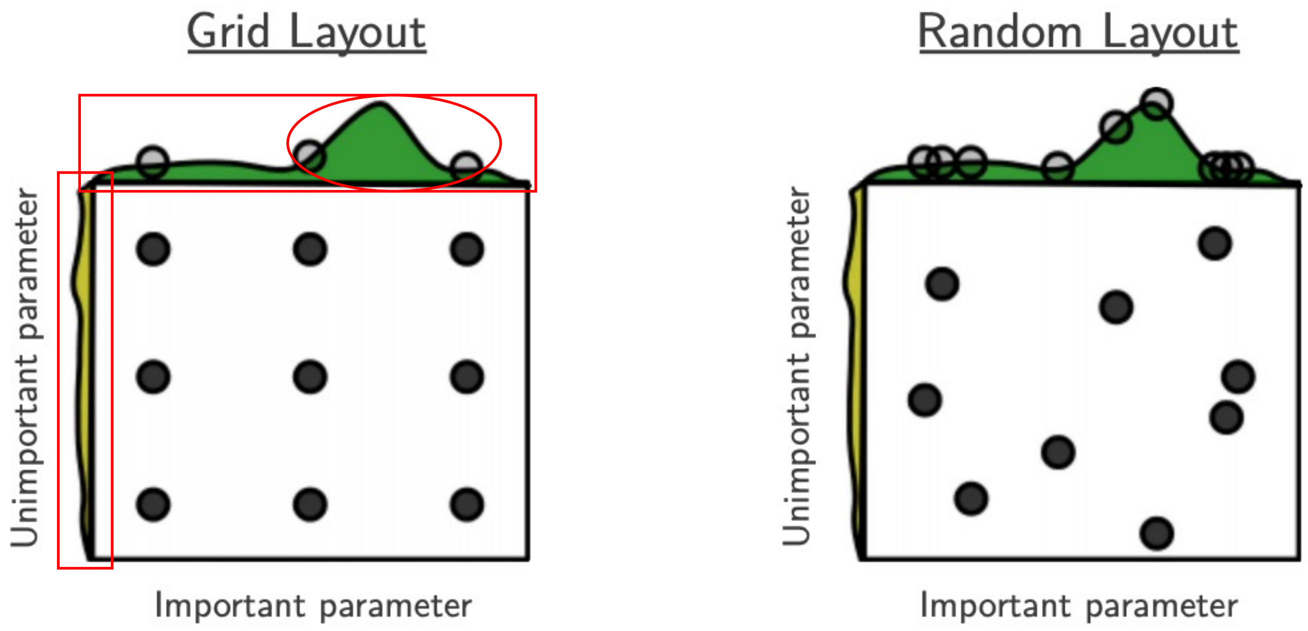

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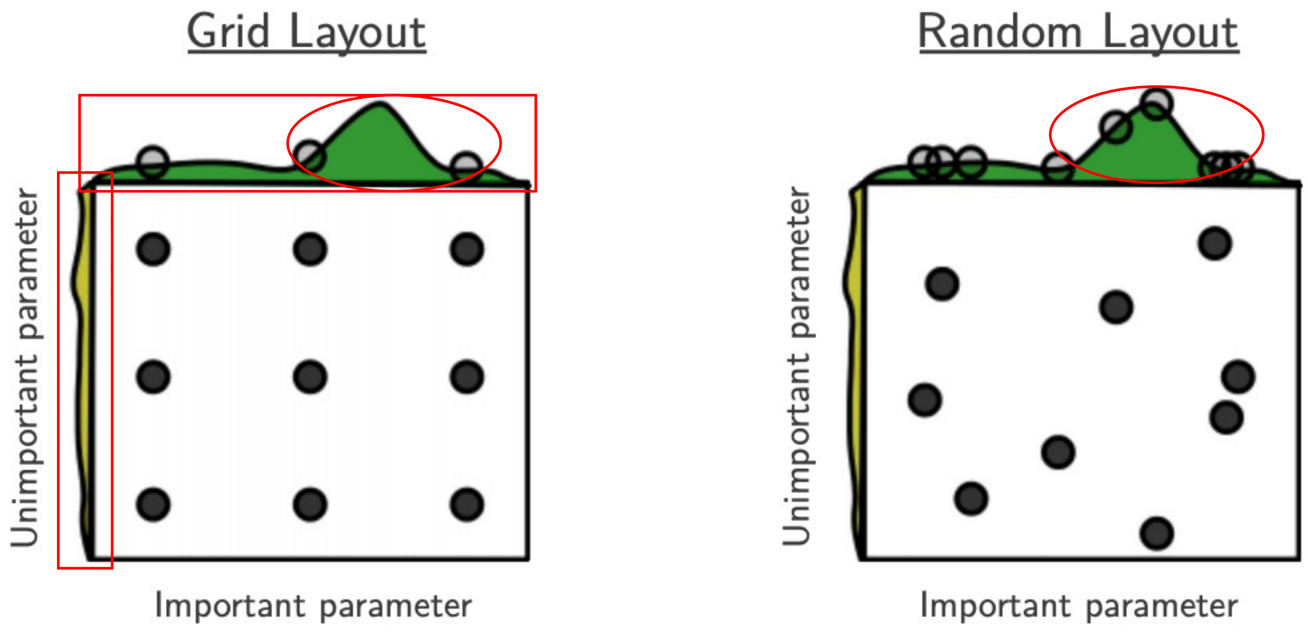

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Reinforcement learning

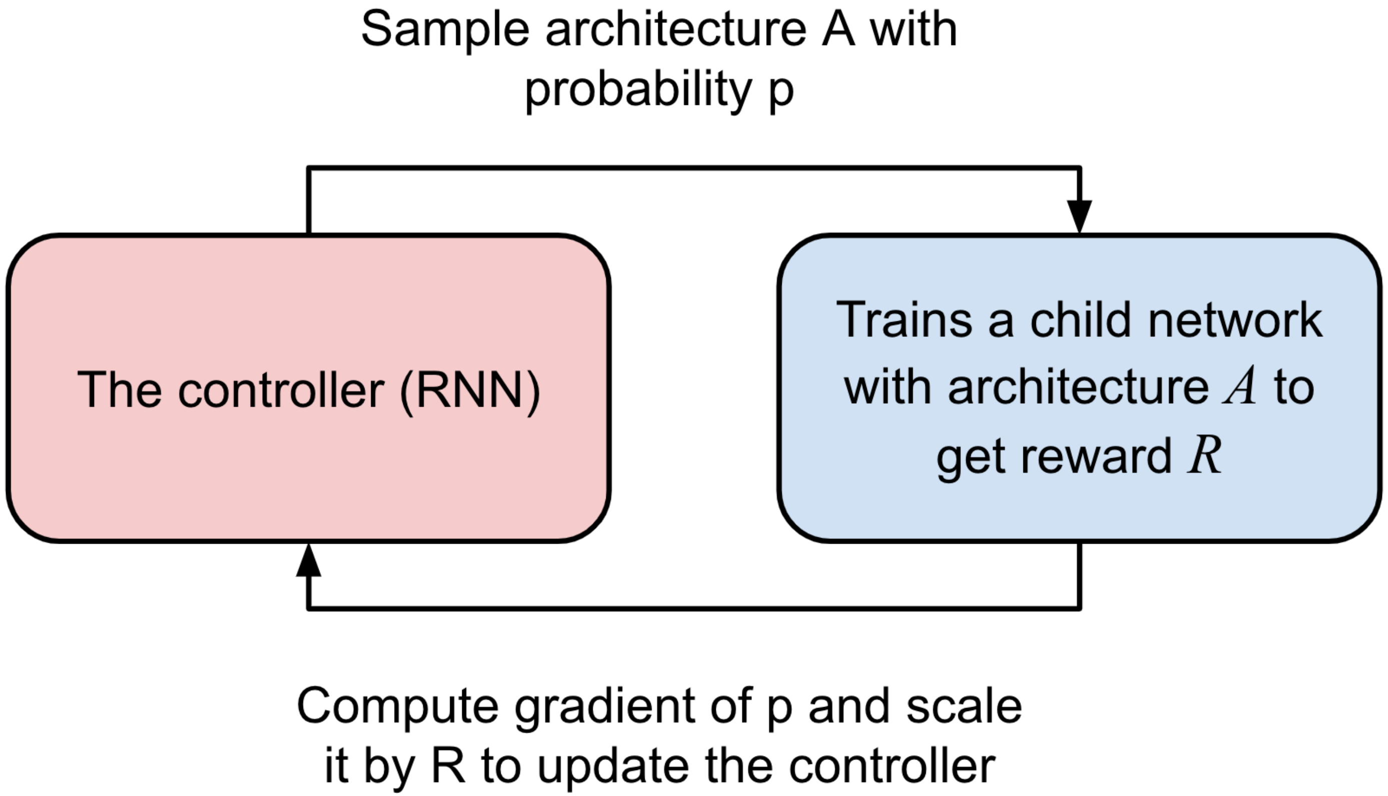

Image credit: https://lilianweng.github.io/lil-log/2020/08/06/neural-architecture-search.html

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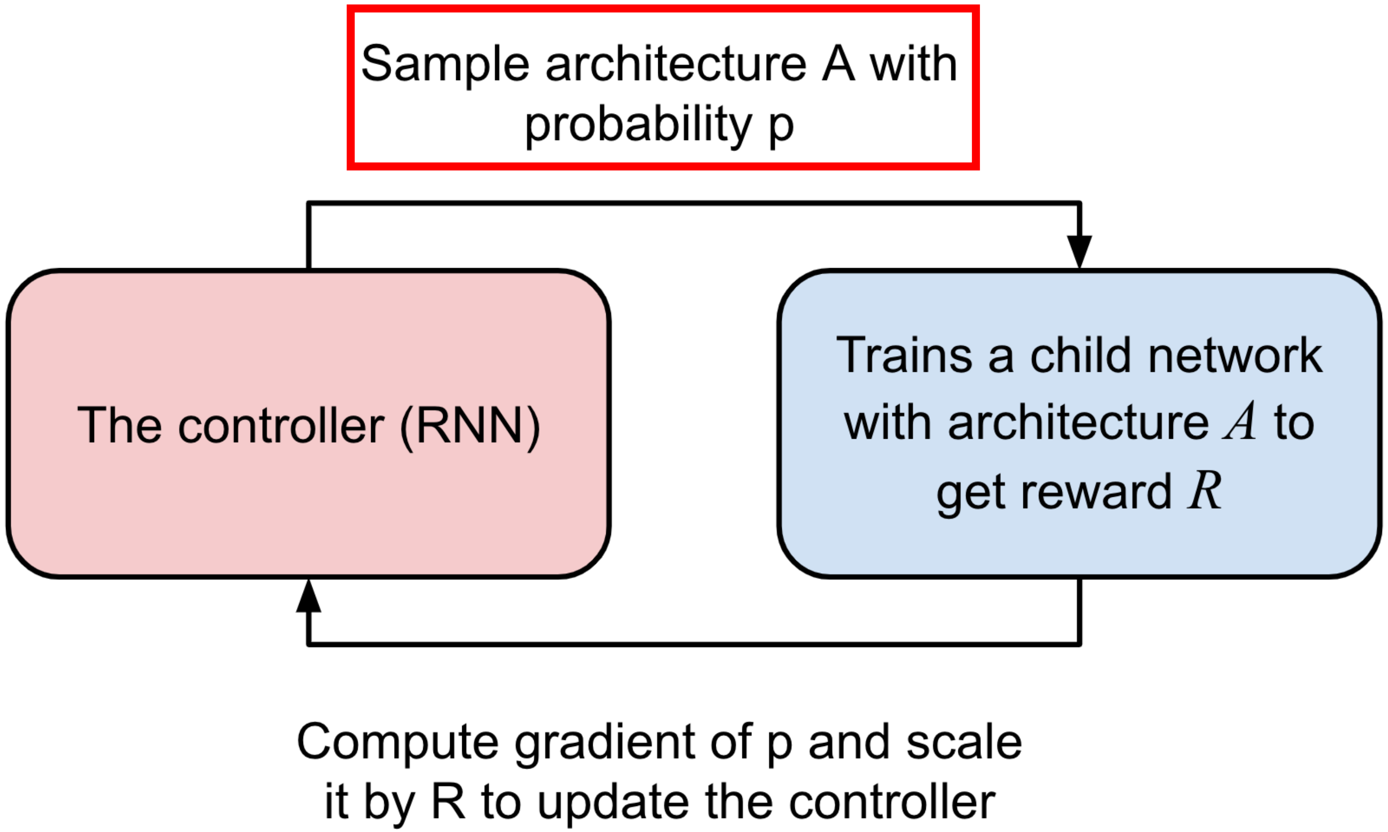

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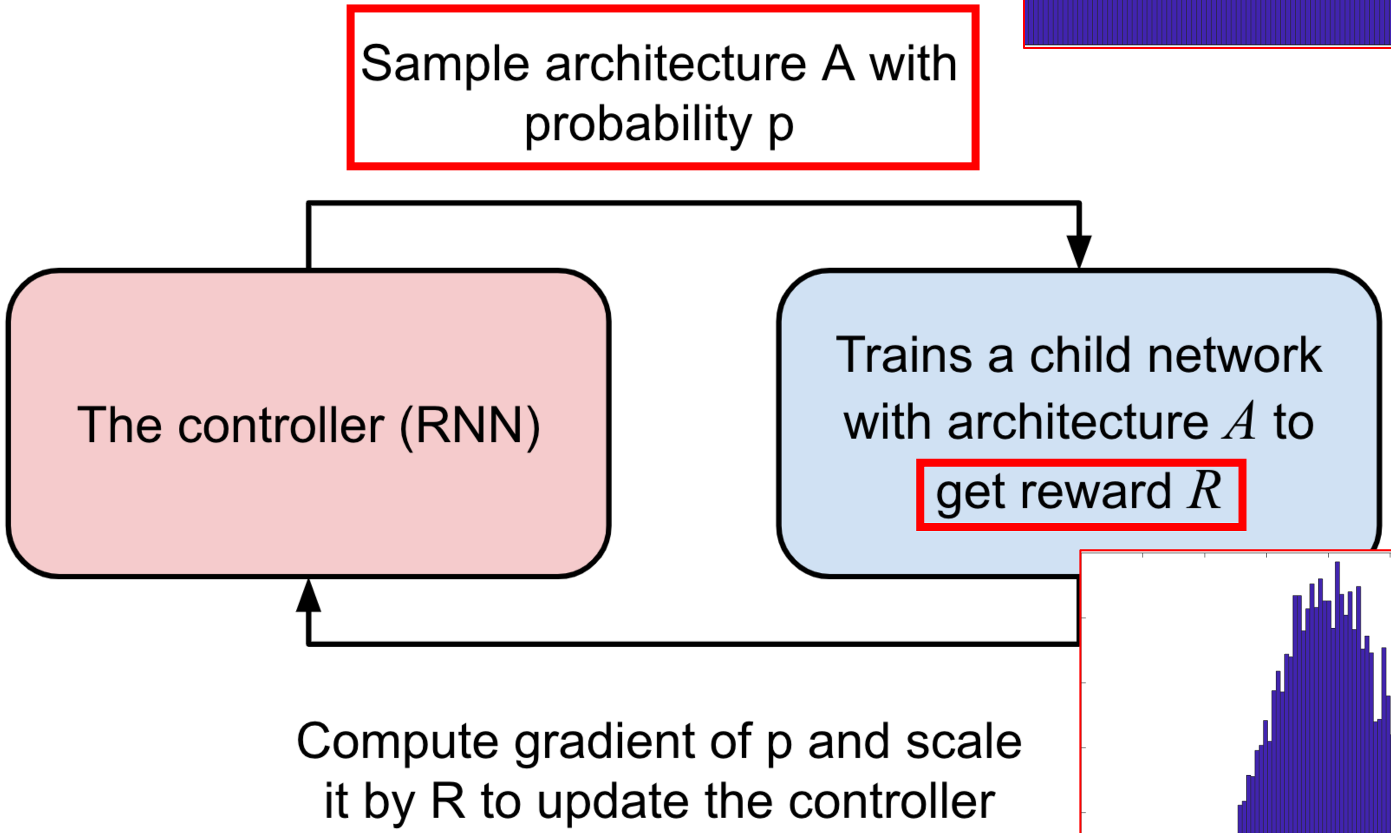

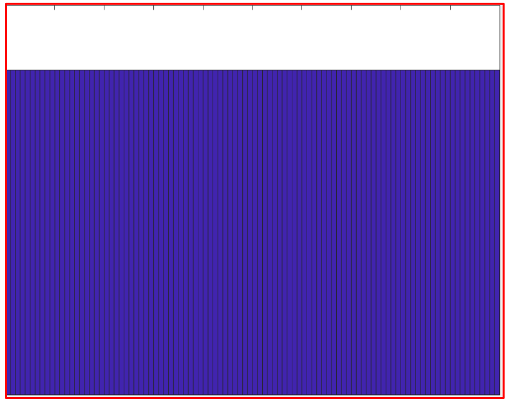

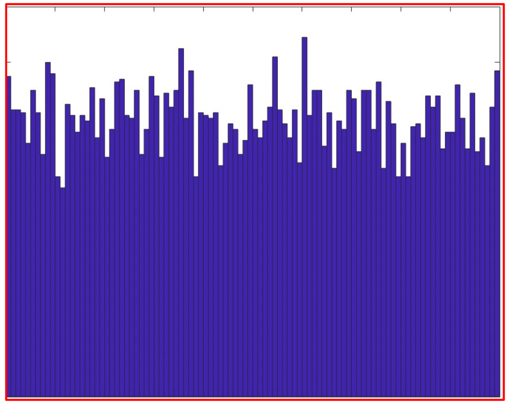

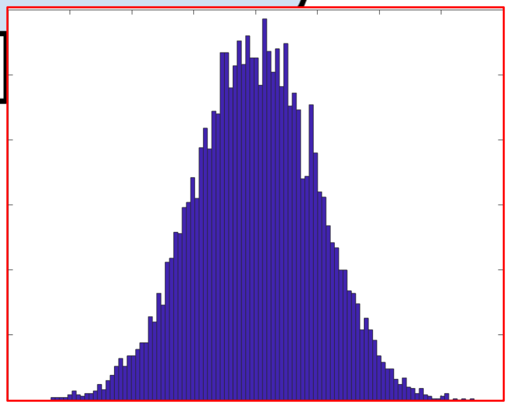

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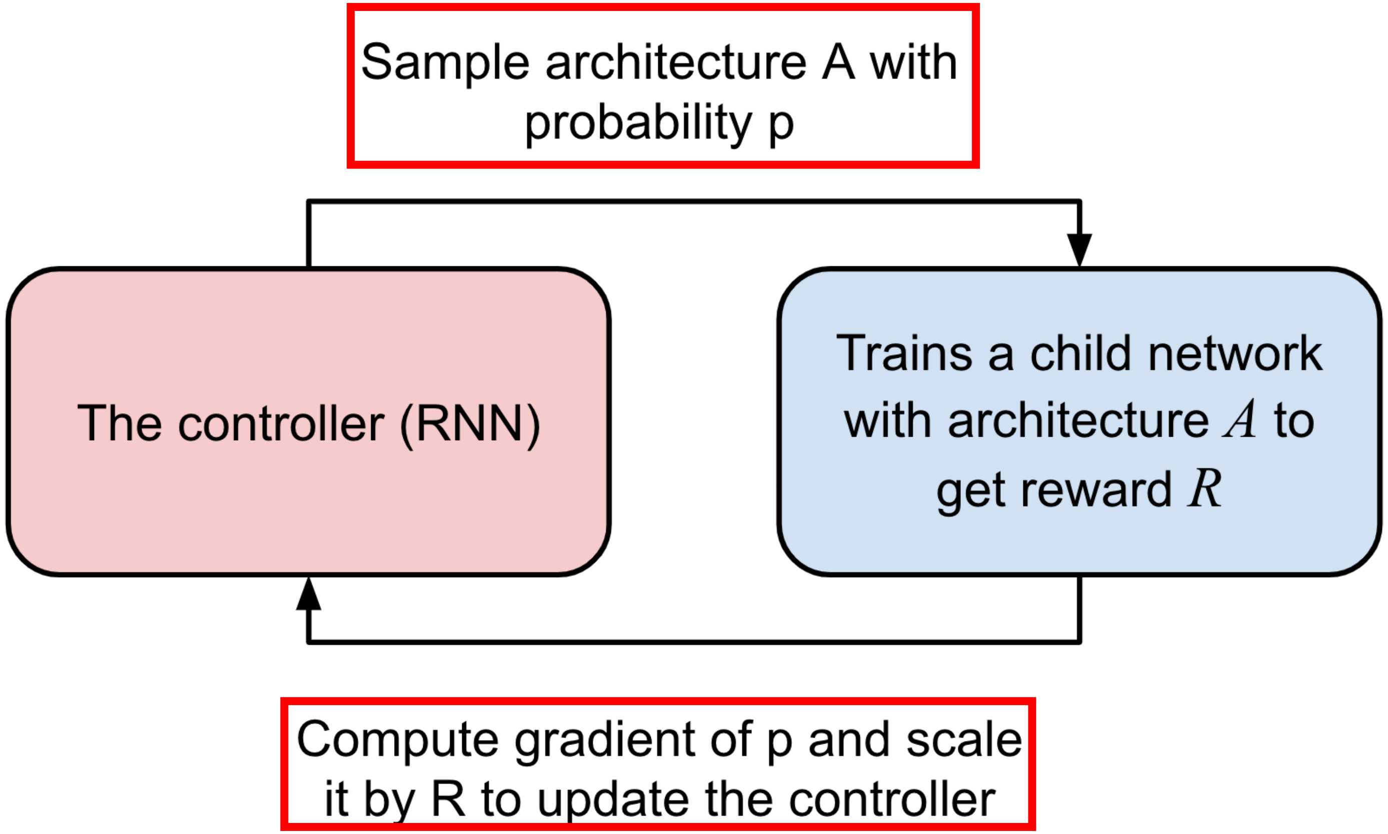

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- **Reward**: The accuracy of a child network that can be achieved at convergence is the reward for training the controller, R.
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$$\nabla_\theta J(\theta) = \sum_{t=1}^{T} \mathbb{E}[\nabla_\theta \log P(a_t | a_{1:(t-1)}; \theta) R]$$

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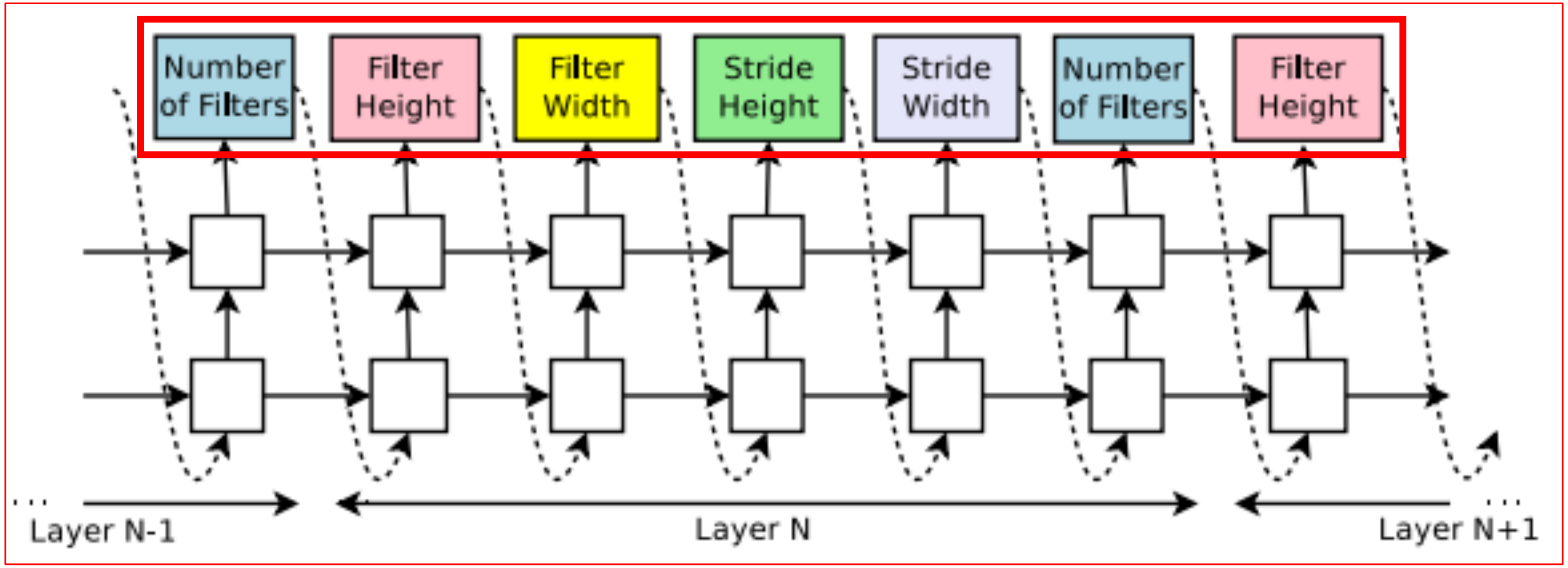
Defining search space



A RNN network

Zoph, Barret, and Quoc V. Le. "Neural architecture search with reinforcement learning." *arXiv preprint arXiv:1611.01578* (2016). https://arxiv.org/pdf/1611.01578.pdf

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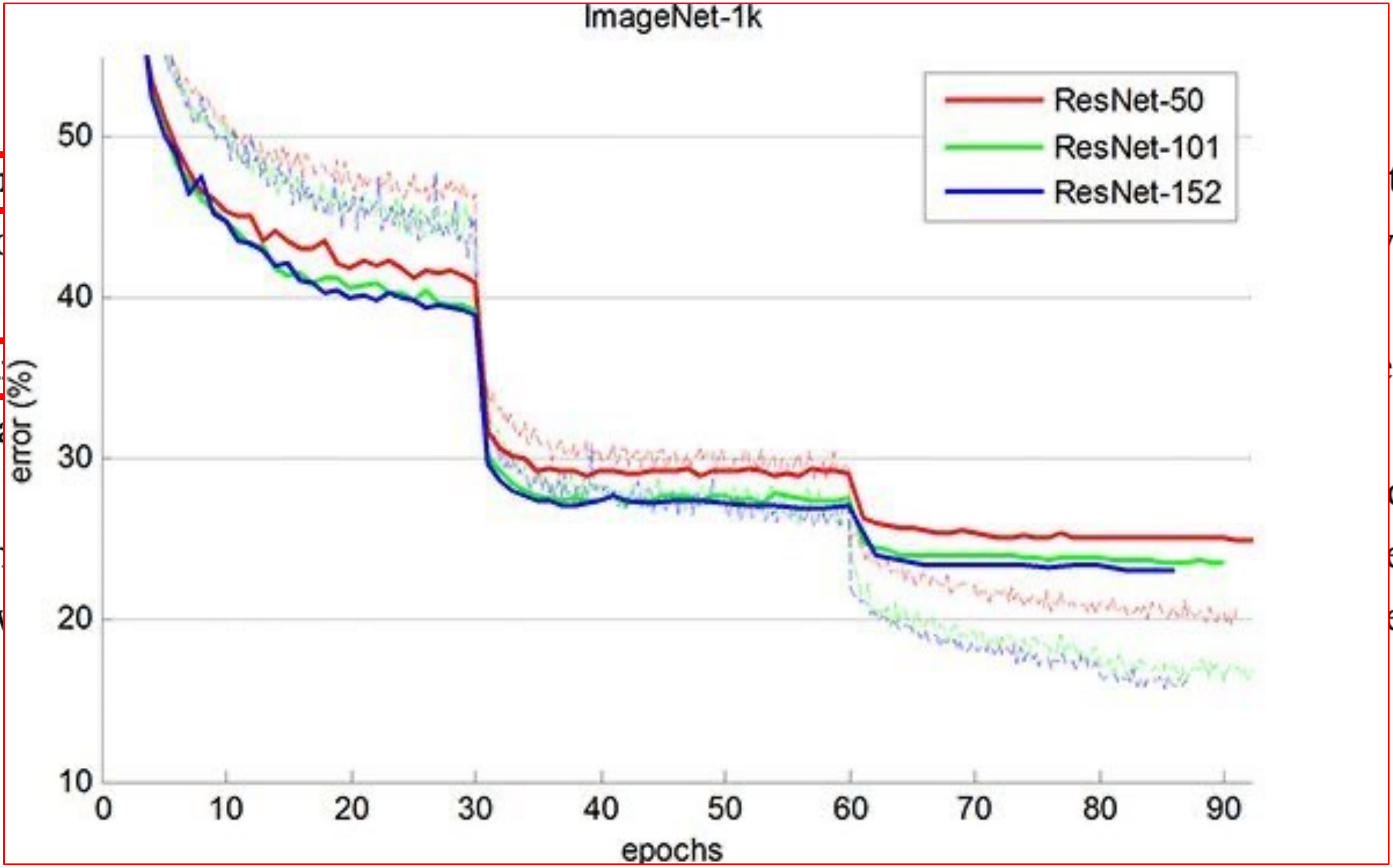
Reinforcement learning

- **Actio** ... ted by
  the co ... here T
  is the
- **Rewa** ... reward
  for tra
- **Loss:** ... o
  maxin ... e thing
  here v ... e.



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$$\boxed{\mathrm{E}[X] = \sum_{i=1}^{k} x_i\, p_i = x_1p_1 + x_2p_2 + \cdots + x_kp_k.}$$

$$\boxed{L(\theta \mid x) = \prod_{i=1}^{n} p_X(x_i \mid \theta)}$$

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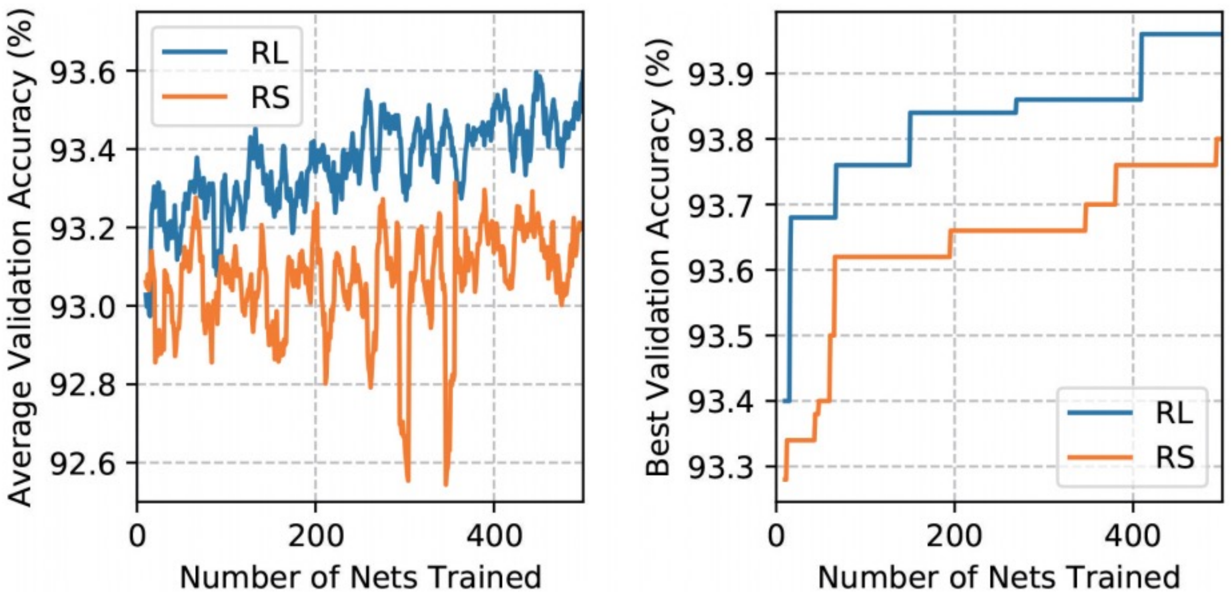
RS vs RL



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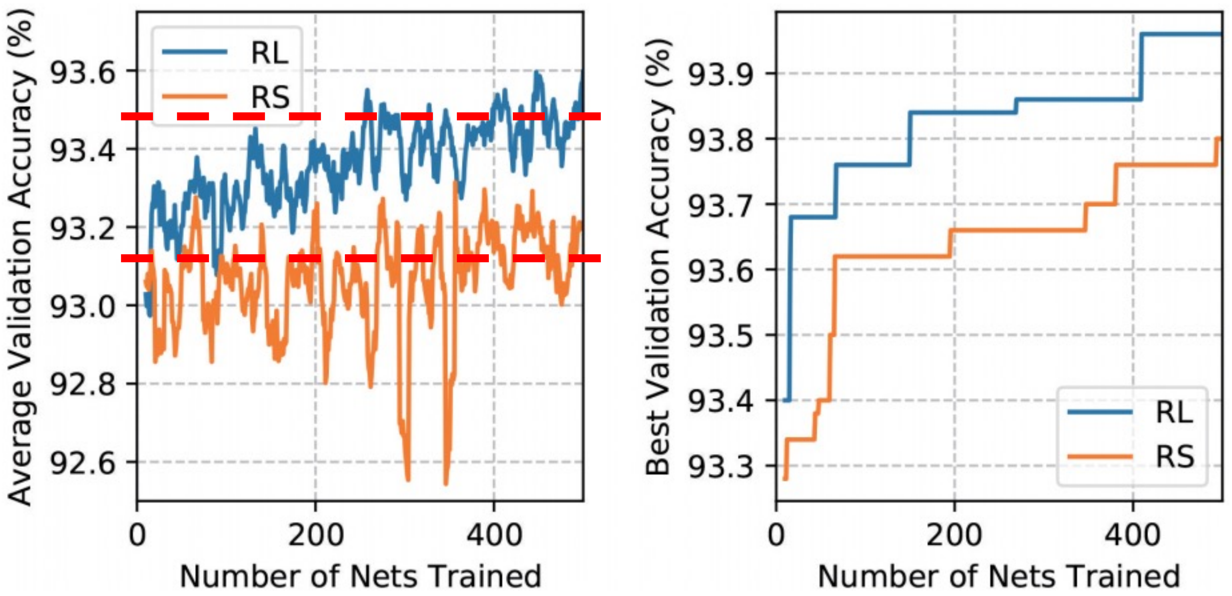

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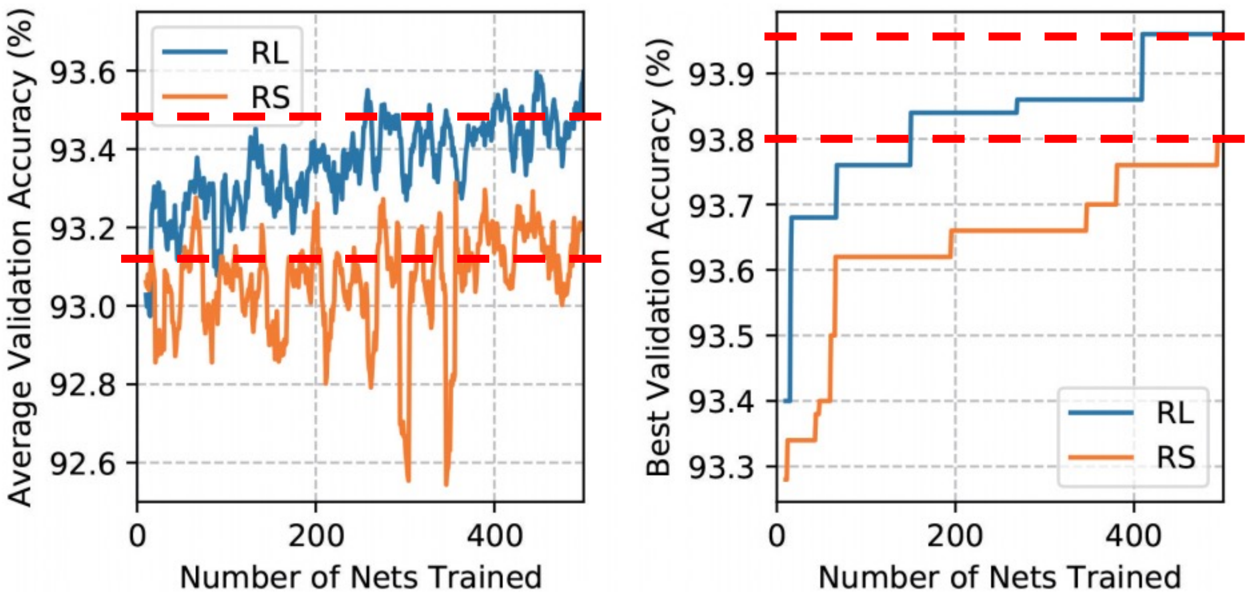

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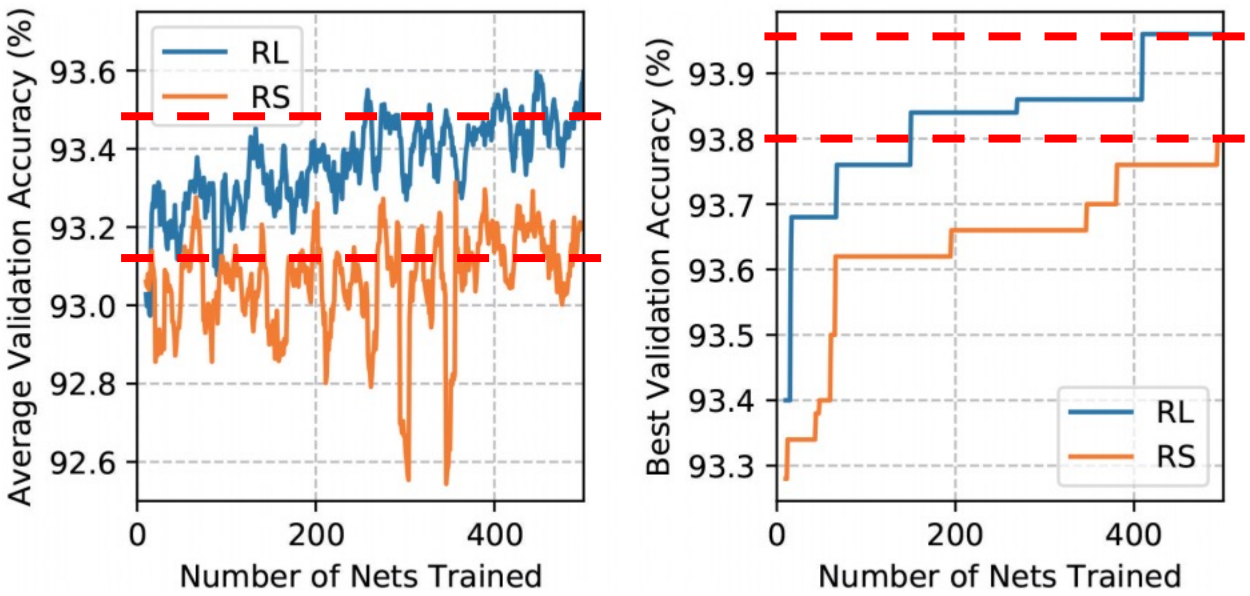
RS vs RL

Q: what conclusion can we make?



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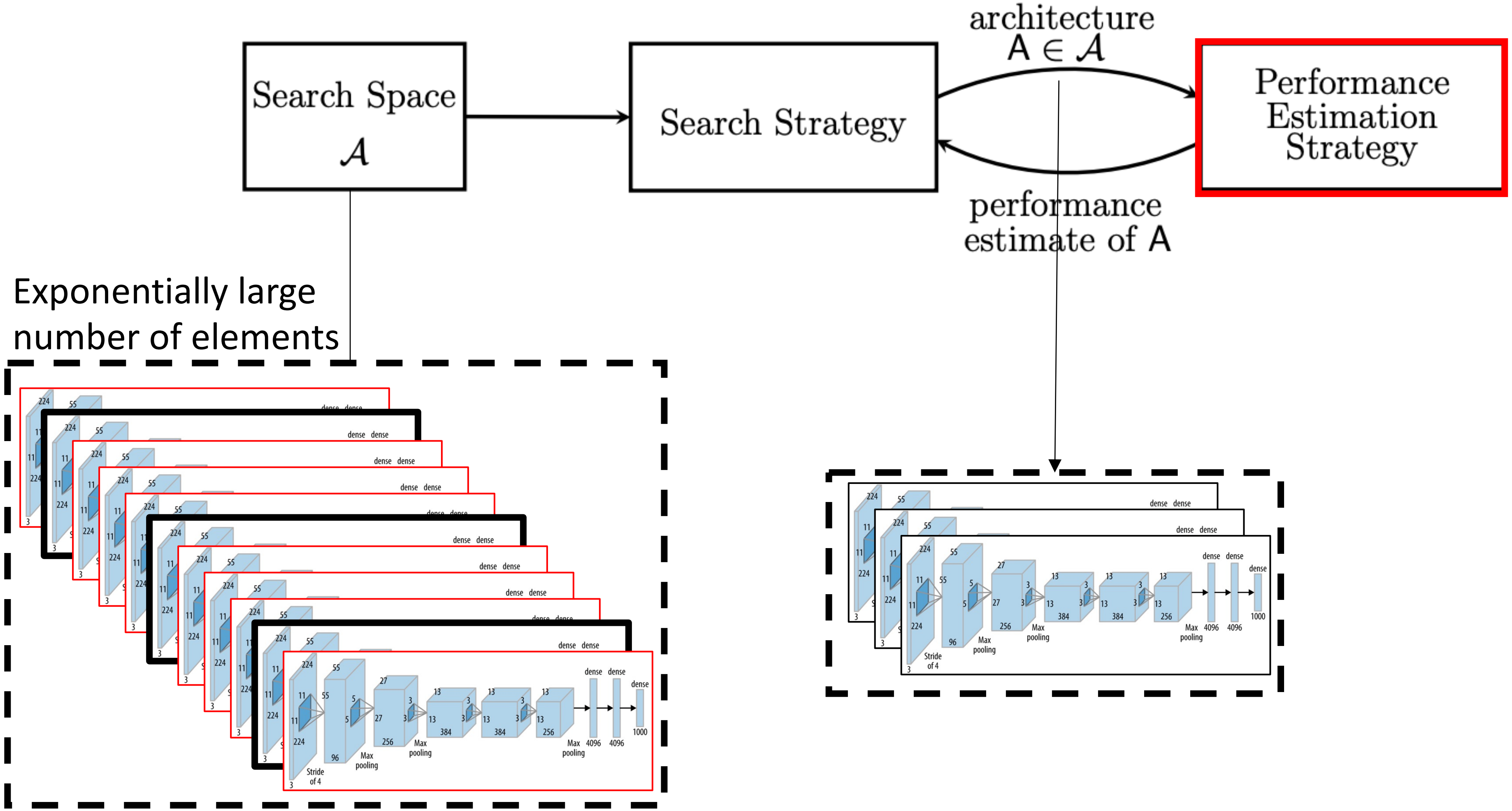

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    - E.g., once a cell structure is learned, the final architecture is determined by selecting a number of cell repeats https://arxiv.org/pdf/1707.07012.pdf

putational budget. After having learned the convolutional cells, several hyper-parameters may be explored to build a final network for a given task: (1) the number of cell repeats N and (2) the number of filters in the initial convolutional cell. After selecting the number of initial filters, we use a

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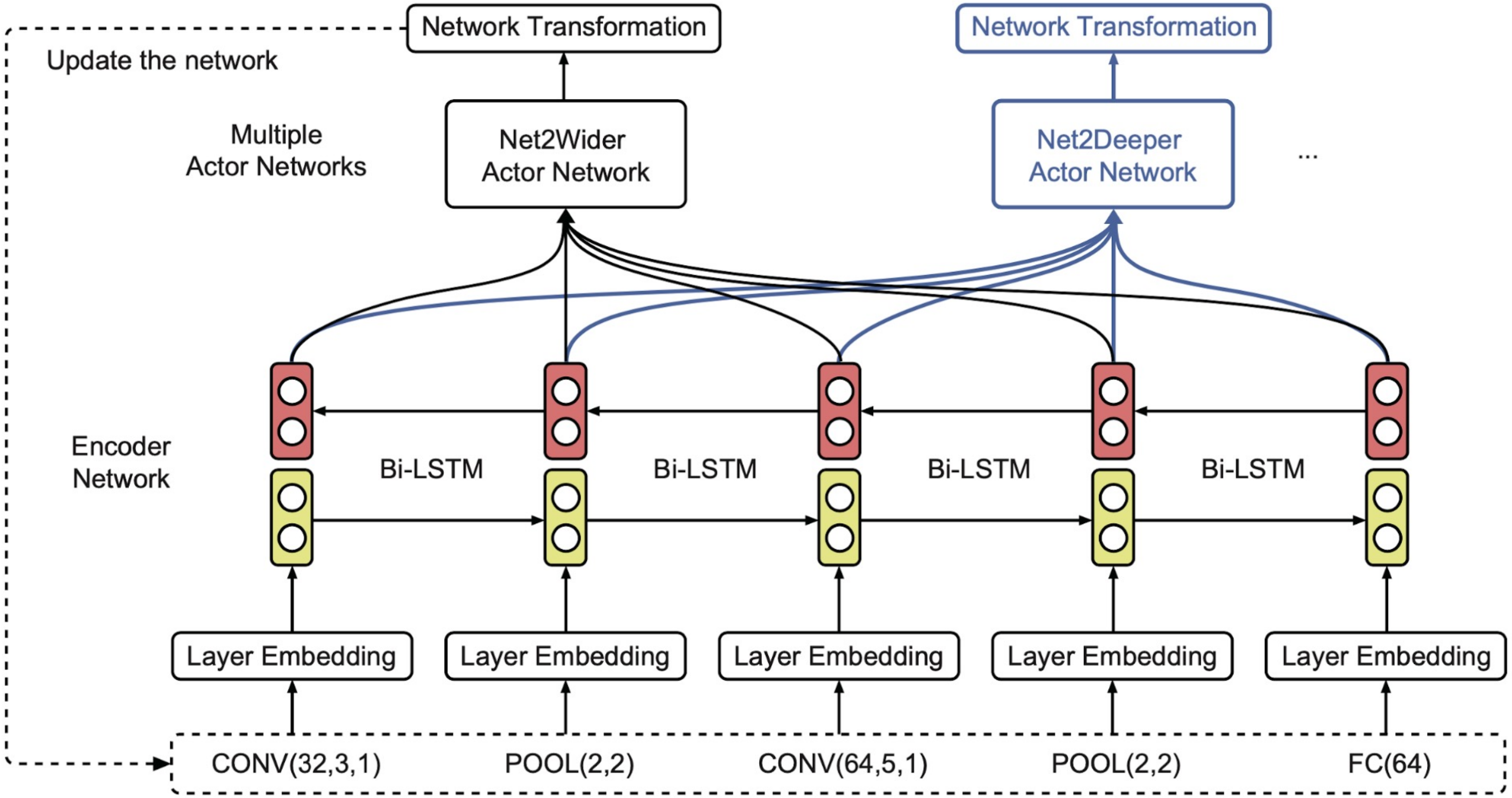
- Parameter Sharing

Parameter Sharing



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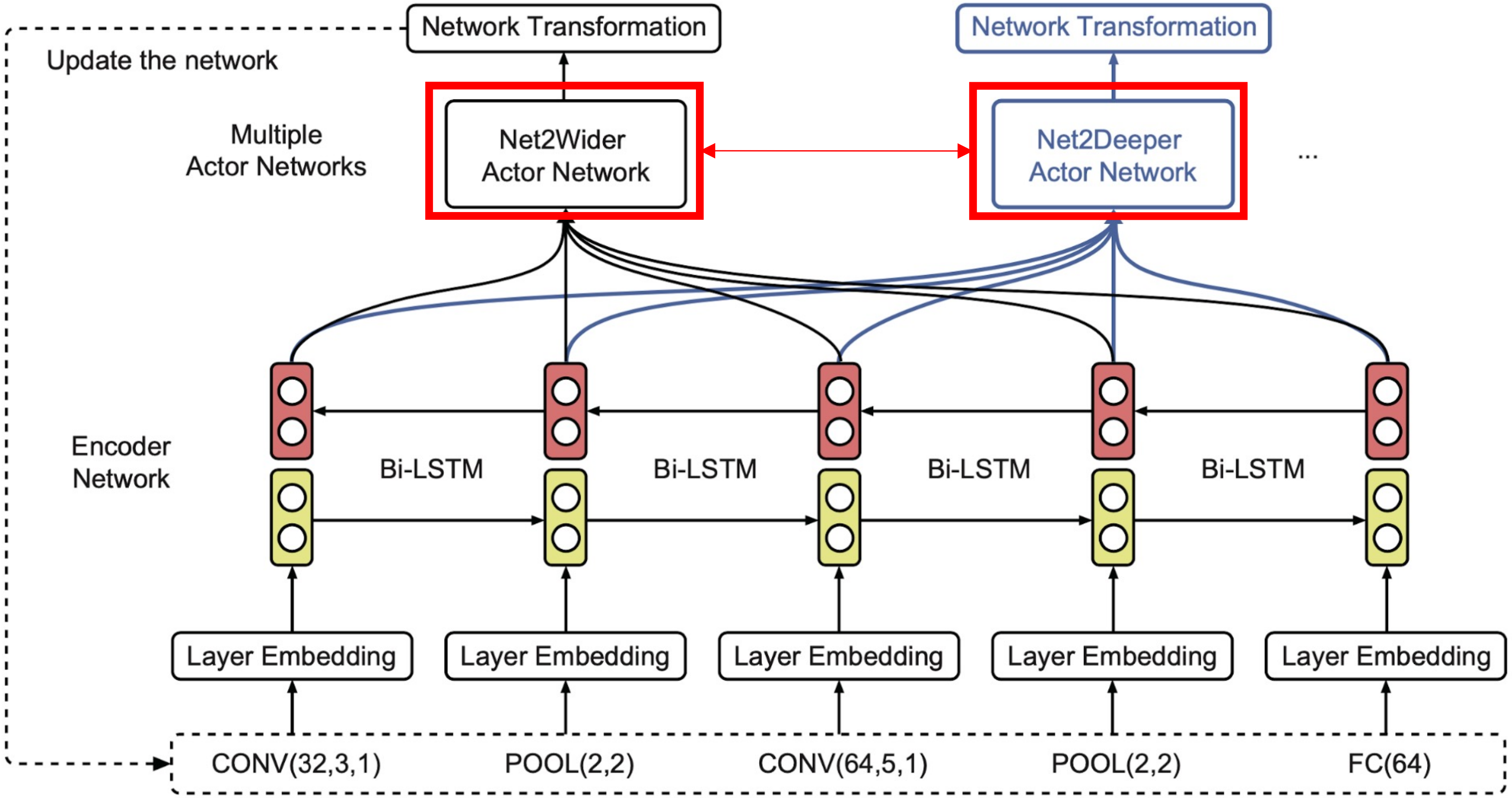

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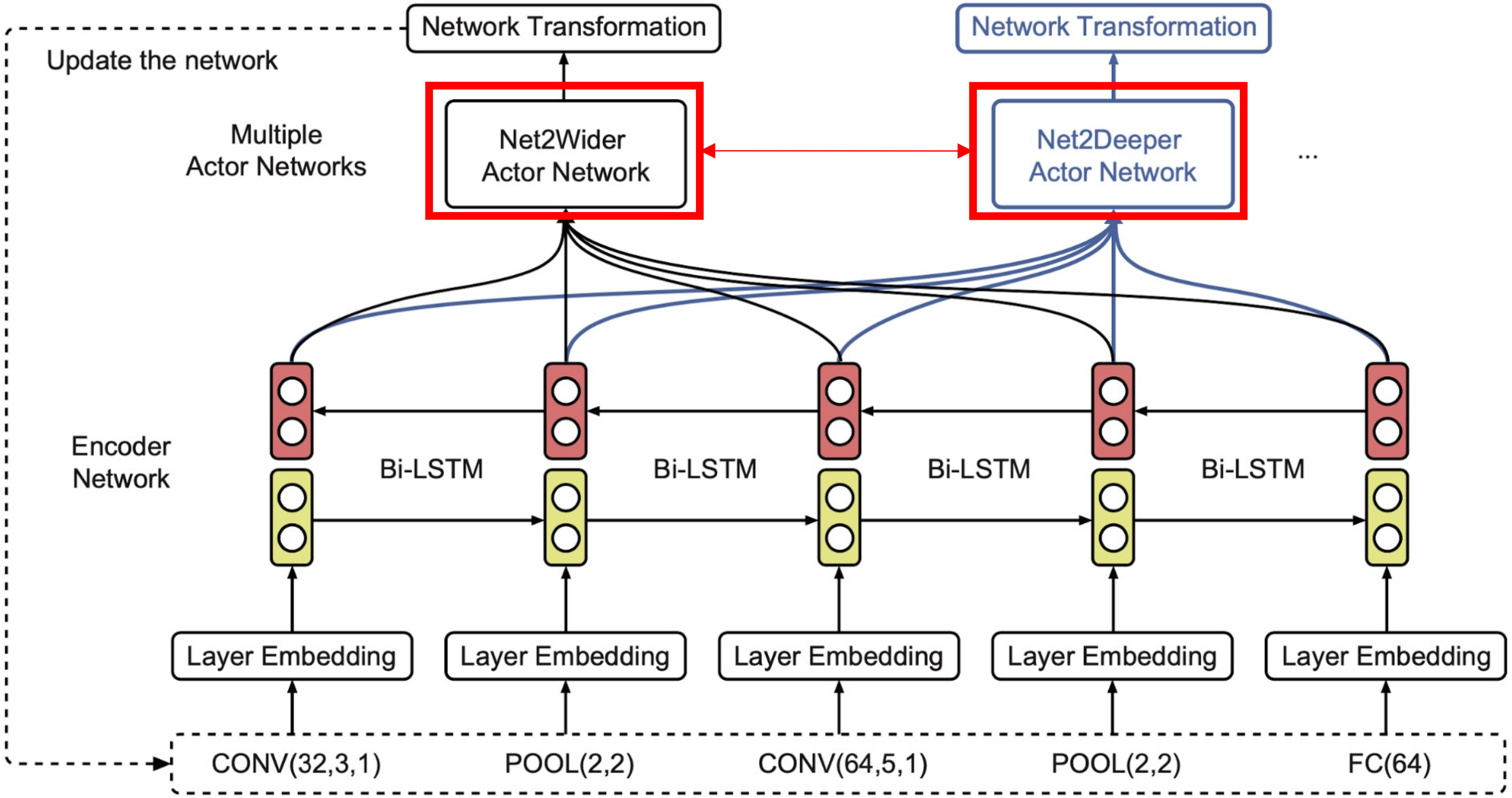
more units for fully-connected layers
more filters for convolutional layers



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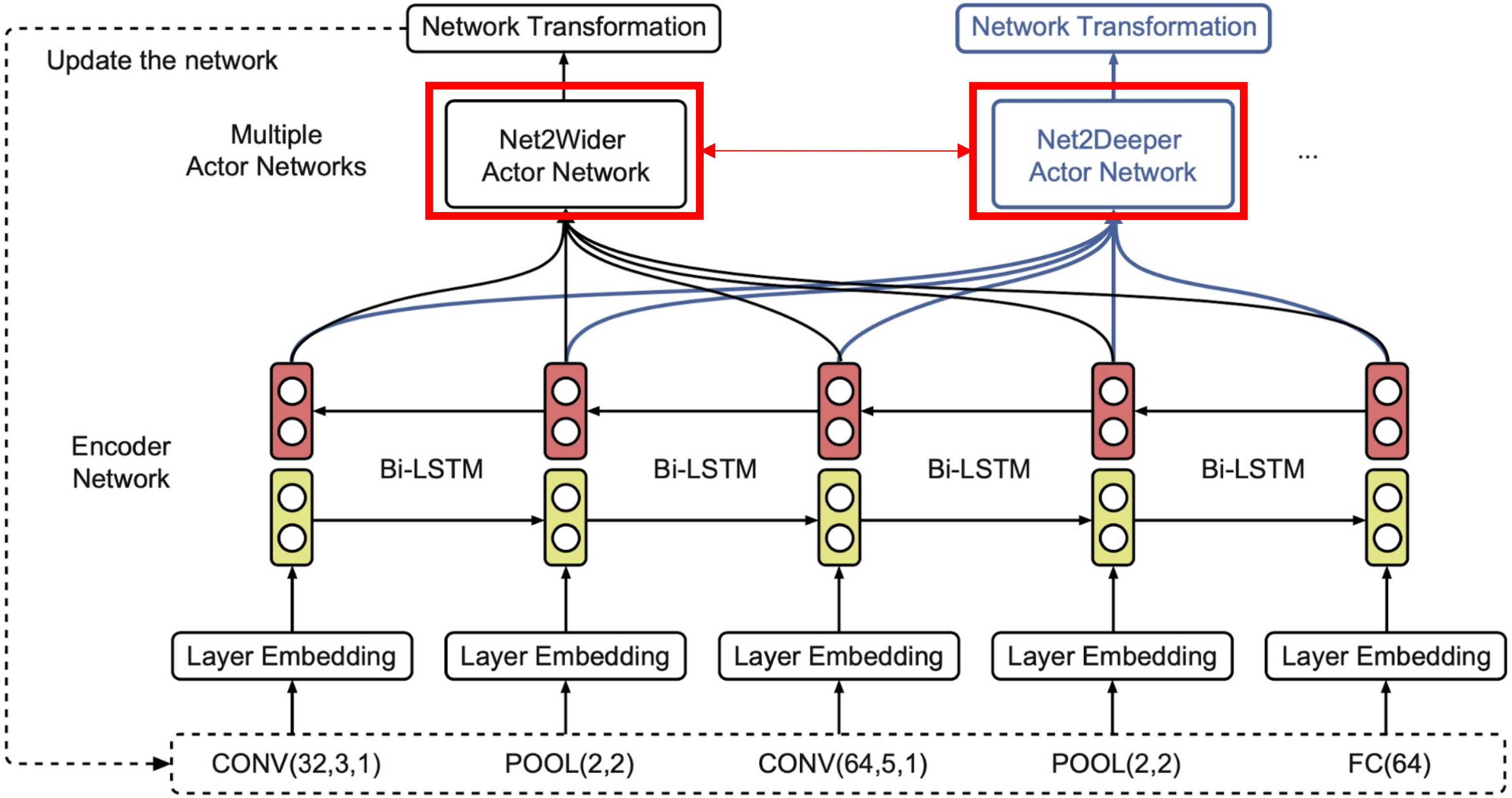
insert a new layer
convolutional layer: the kernel is set to be identity filters
fully-connected layer: the weight matrix is set to be identity matrix



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DARTS: differentiable architecture search

Algorithm 1: DARTS – Differentiable Architecture Search

Create a mixed operation $\bar{o}^{(i,j)}$ parametrized by $\alpha^{(i,j)}$ for each edge (i,j)
while *not converged* **do**
  1. Update weights w by descending $\nabla_w \mathcal{L}_{train}(w, \alpha)$
  2. Update architecture α by descending $\nabla_\alpha \mathcal{L}_{val}(w - \xi \nabla_w \mathcal{L}_{train}(w, \alpha), \alpha)$

Replace $\bar{o}^{(i,j)}$ with $o^{(i,j)} = \mathrm{argmax}_{o \in \mathcal{O}}\, \alpha_o^{(i,j)}$ for each edge (i,j)

$$\min_{\alpha} \mathcal{L}_{\text{validate}}(w^*(\alpha), \alpha)$$
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Replace $\bar{o}^{(i,j)}$ with $o^{(i,j)} = \mathrm{argmax}_{o \in \mathcal{O}} \, \alpha_o^{(i,j)}$ for each edge (i, j)

$$\min_{\alpha} \boxed{\mathcal{L}_{\text{validate}}(w^*(\alpha), \alpha)}$$
$$\text{s.t.} \boxed{w^*(\alpha) = \arg\min_{w} \mathcal{L}_{\text{train}}(w, \alpha)}$$

Architecture

Corresponding weights

DARTS: differentiable architecture search

Algorithm 1: DARTS – Differentiable Architecture Search

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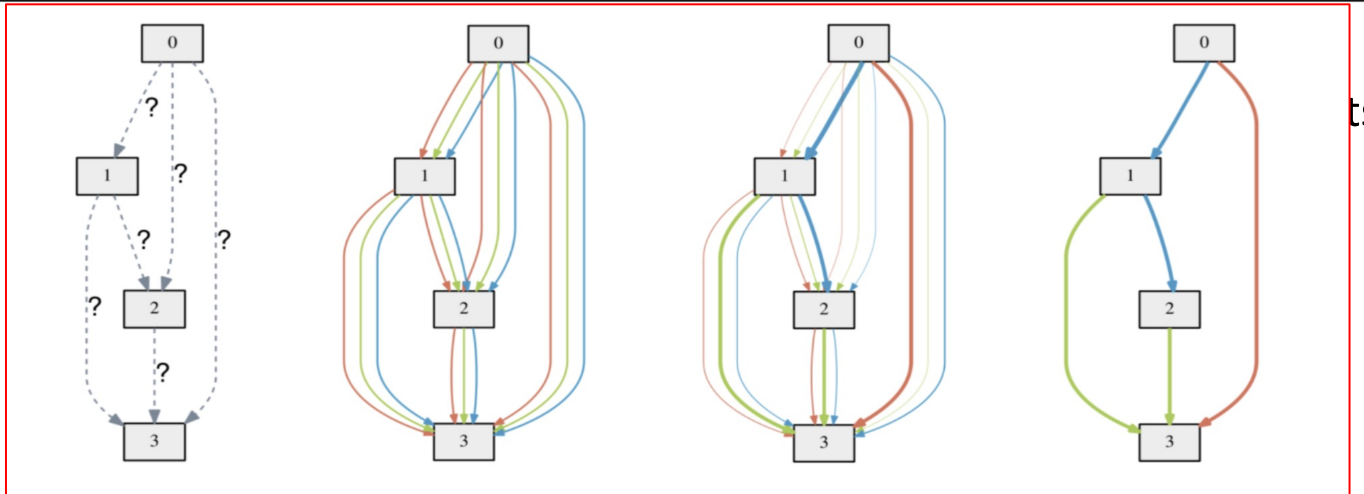

(a) Initially unknown operations on the edges.

(b) Continuous relaxation by placing a mixture of operations on each edge.

(c) Bilevel optimization to jointly train mixing probabilities and weights.

(d) Finalized the model based on the learned mixing probabilities.

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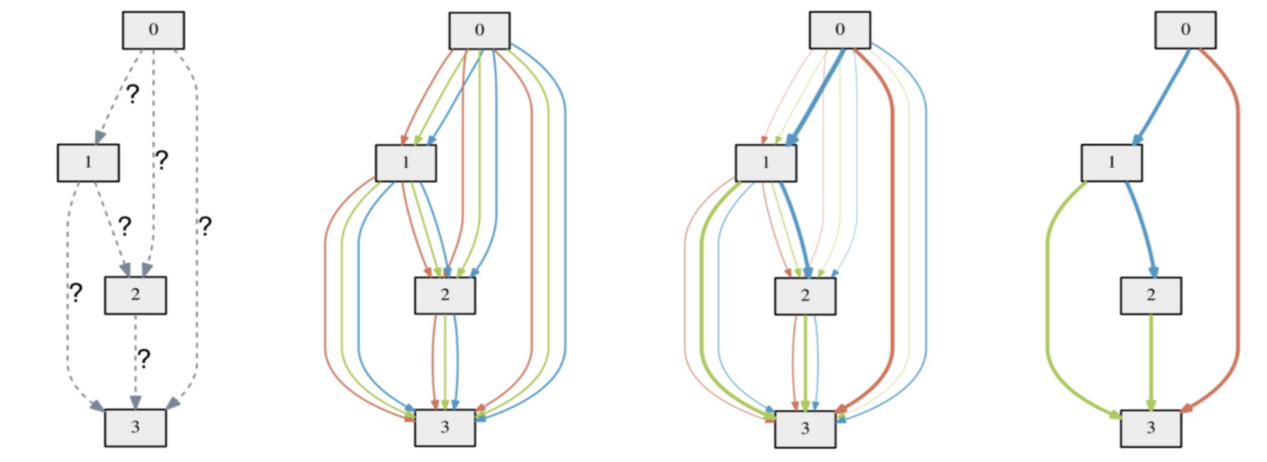
ts



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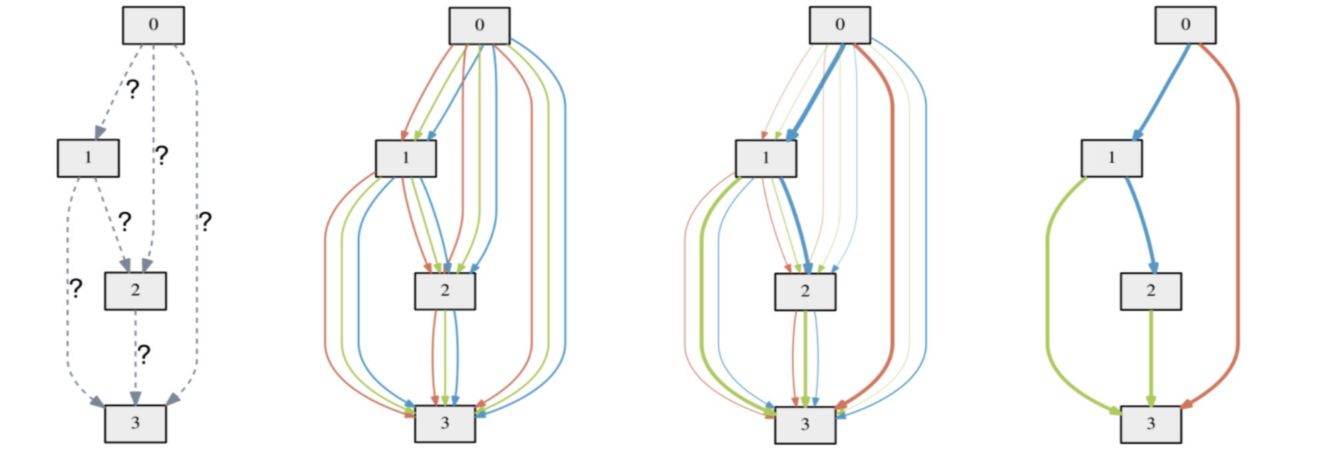

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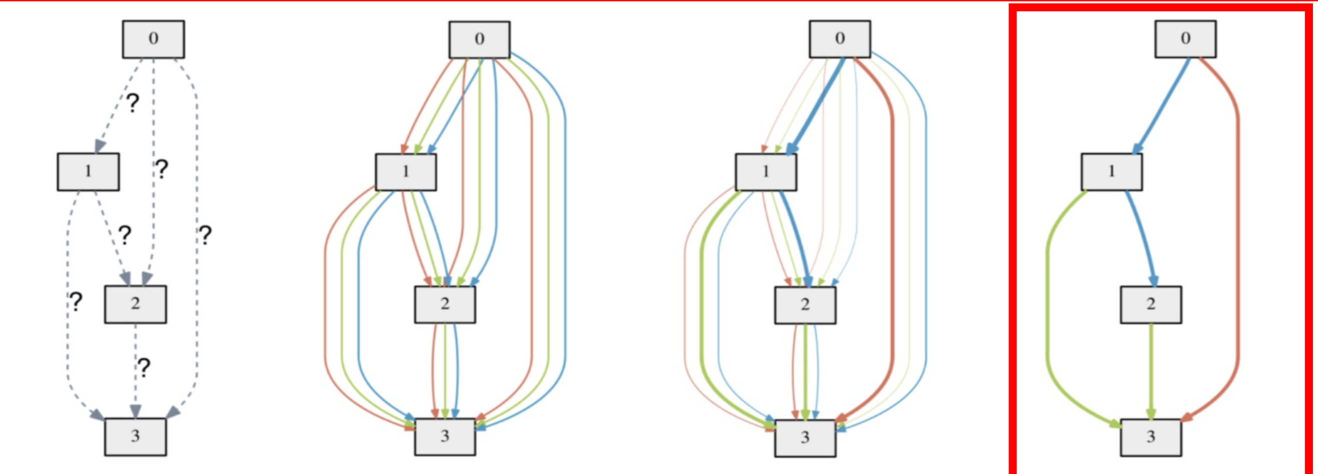

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