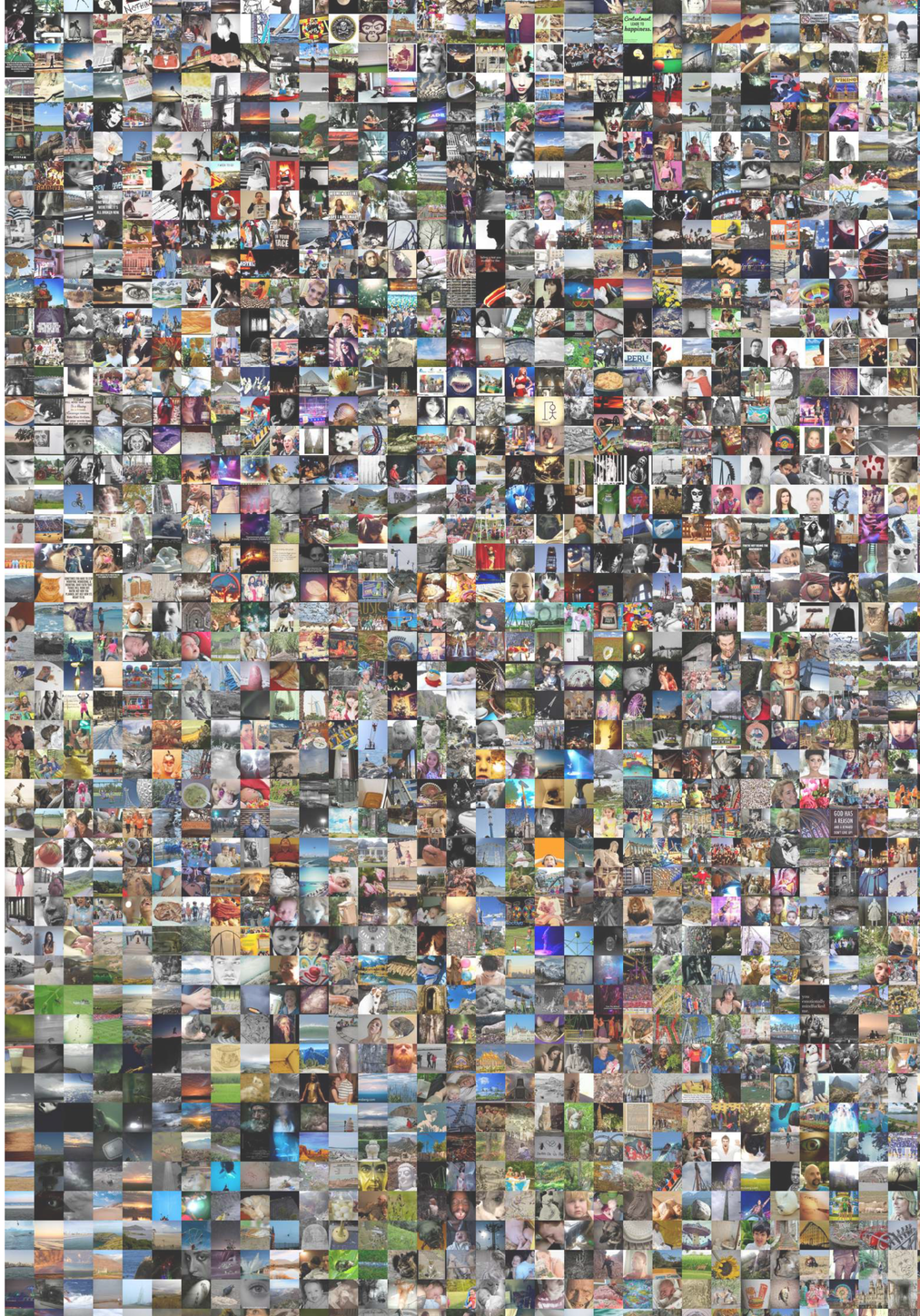
Neural Architecture Search

CS 4803 / 7643 Deep Learning

Erik Wijmans, 11/18/2021

Background



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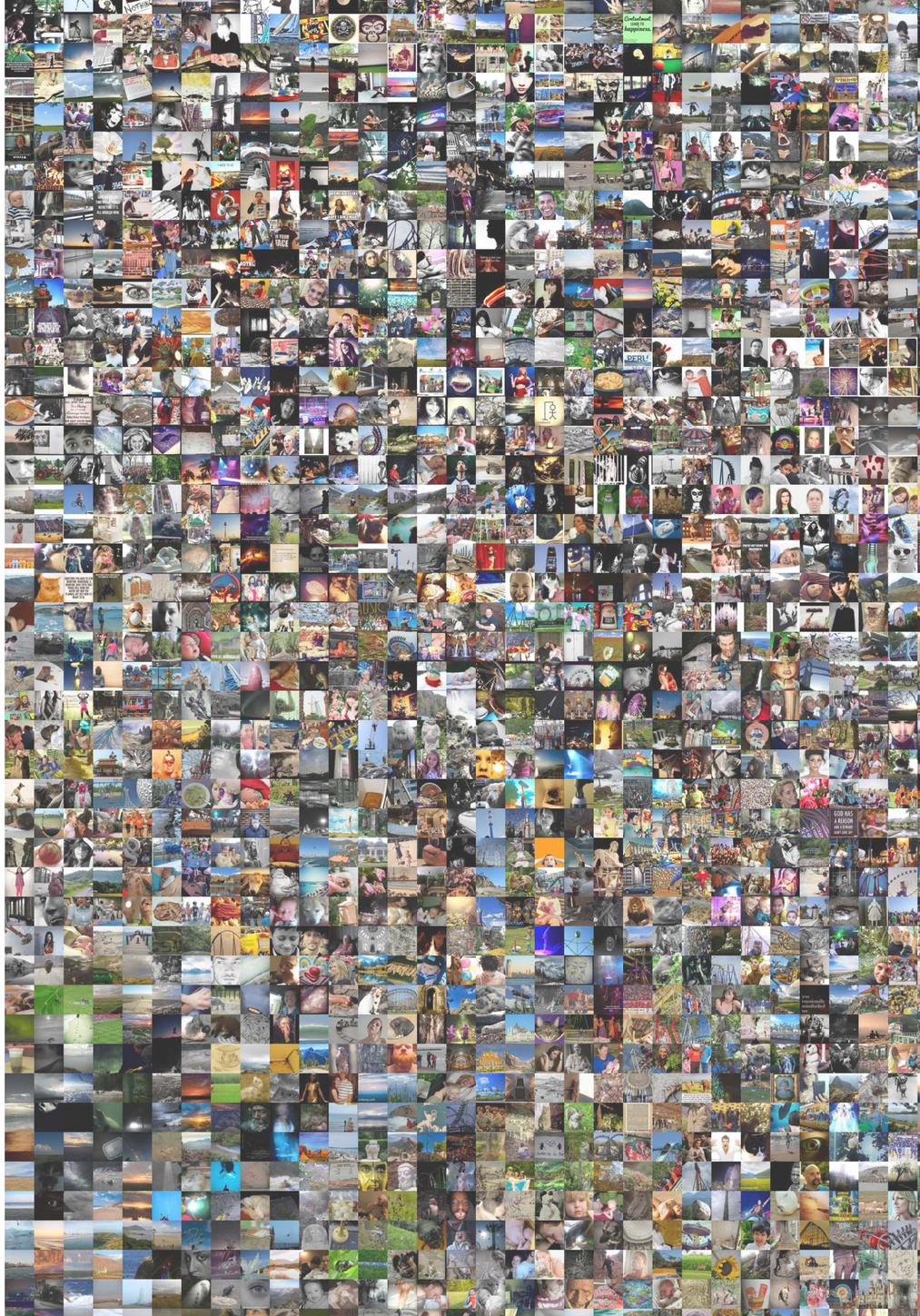
$$\min_{\theta} \mathbb{E}_{(x,y)\sim\mathcal{D}} \left[\mathcal{L}\left(f\left(x;\theta\right),y\right)\right]$$



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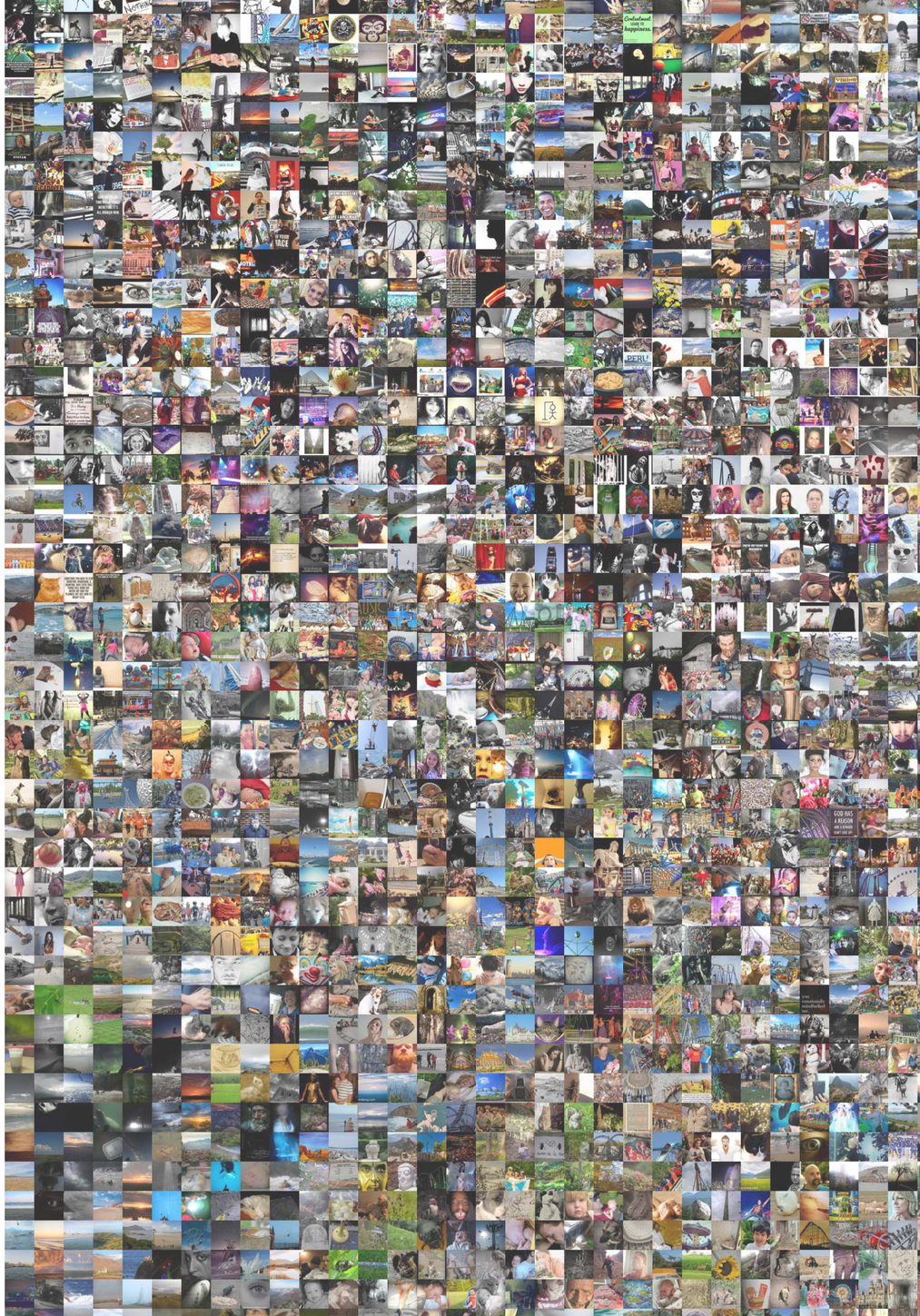

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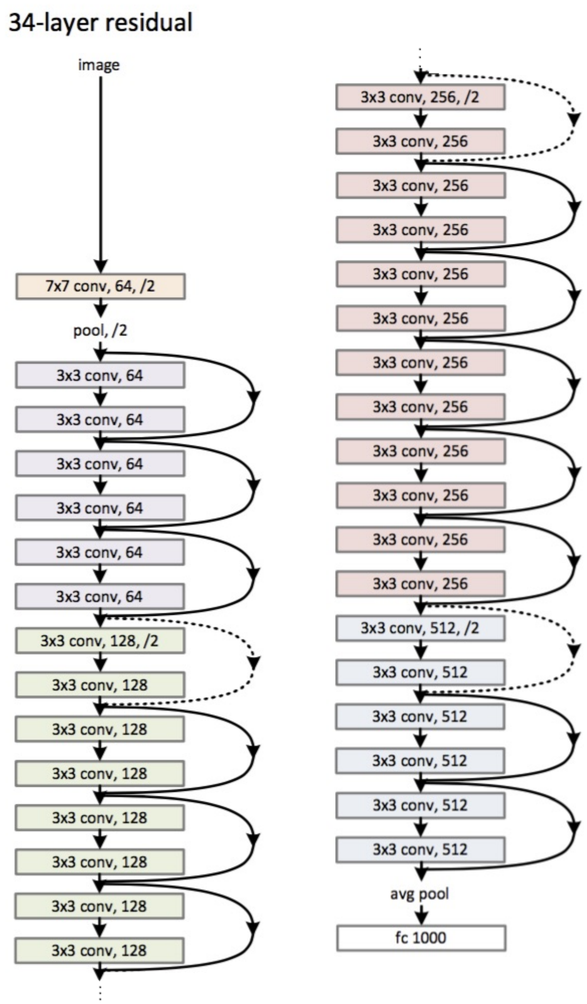
34-layer residual
image
7x7 conv, 64, /2
pool, /2
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 128, /2
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128
3x3 conv, 256, /2
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 512, /2
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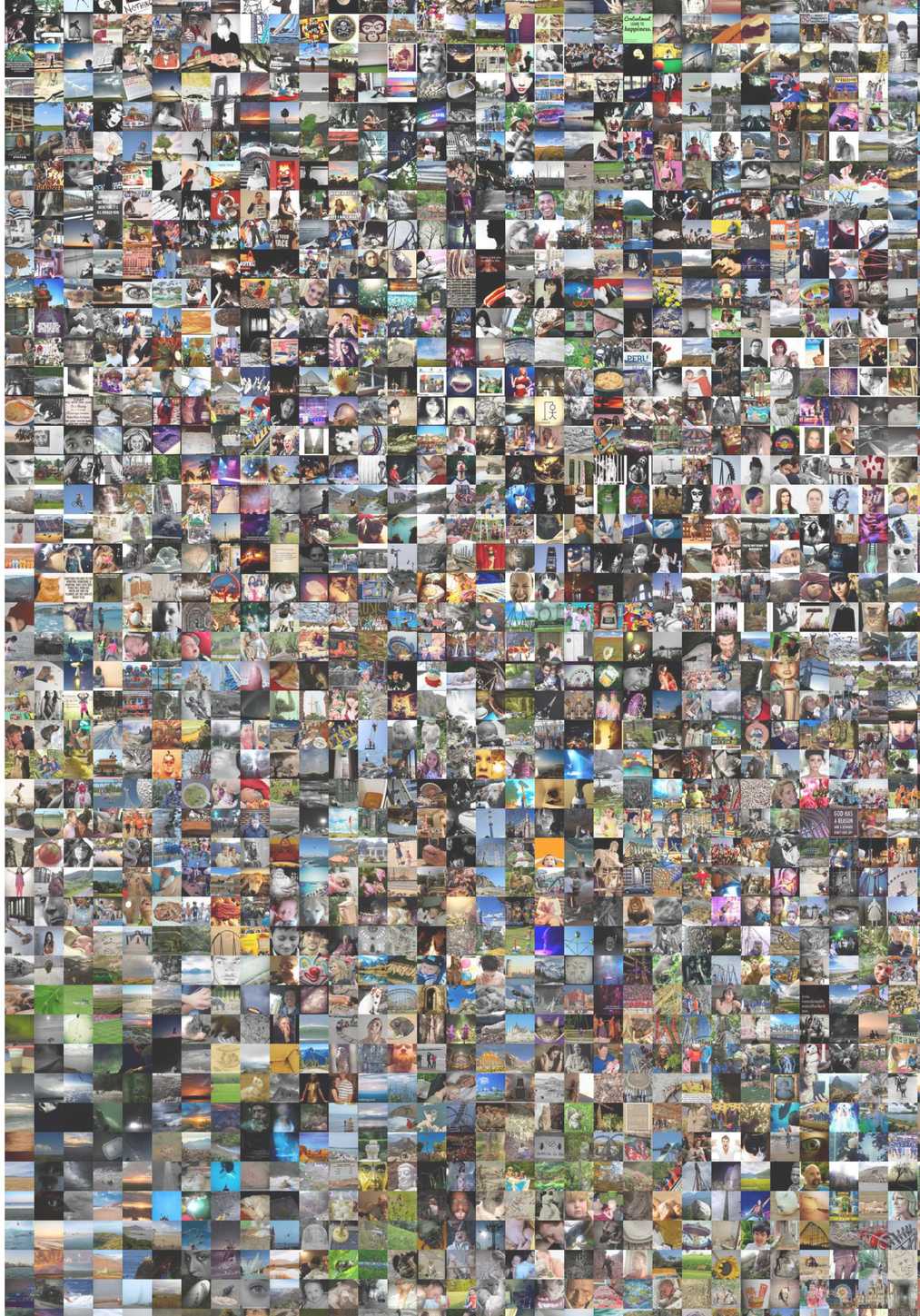
3x3 conv, 512
3x3 conv, 512
avg pool
fc 1000



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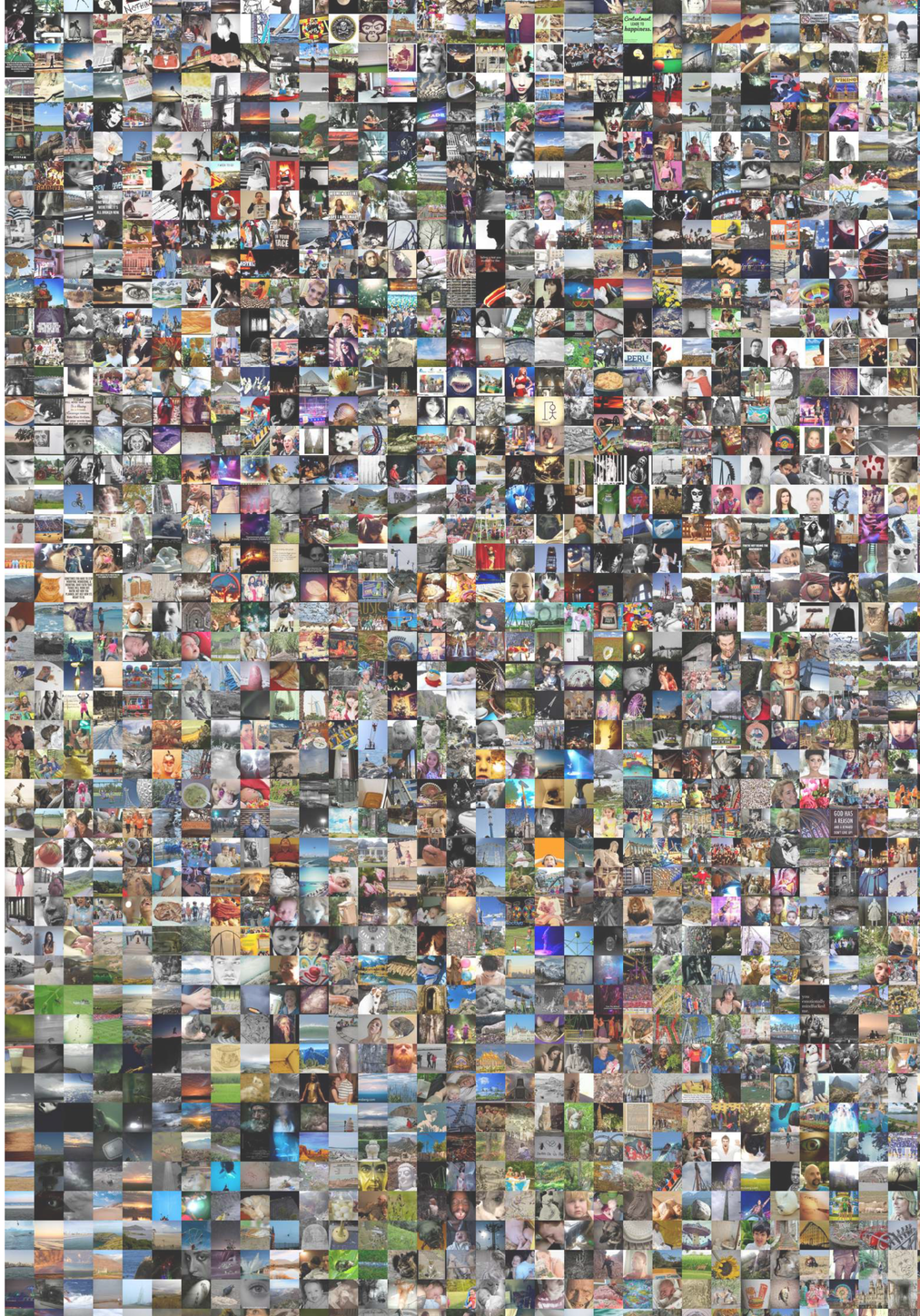

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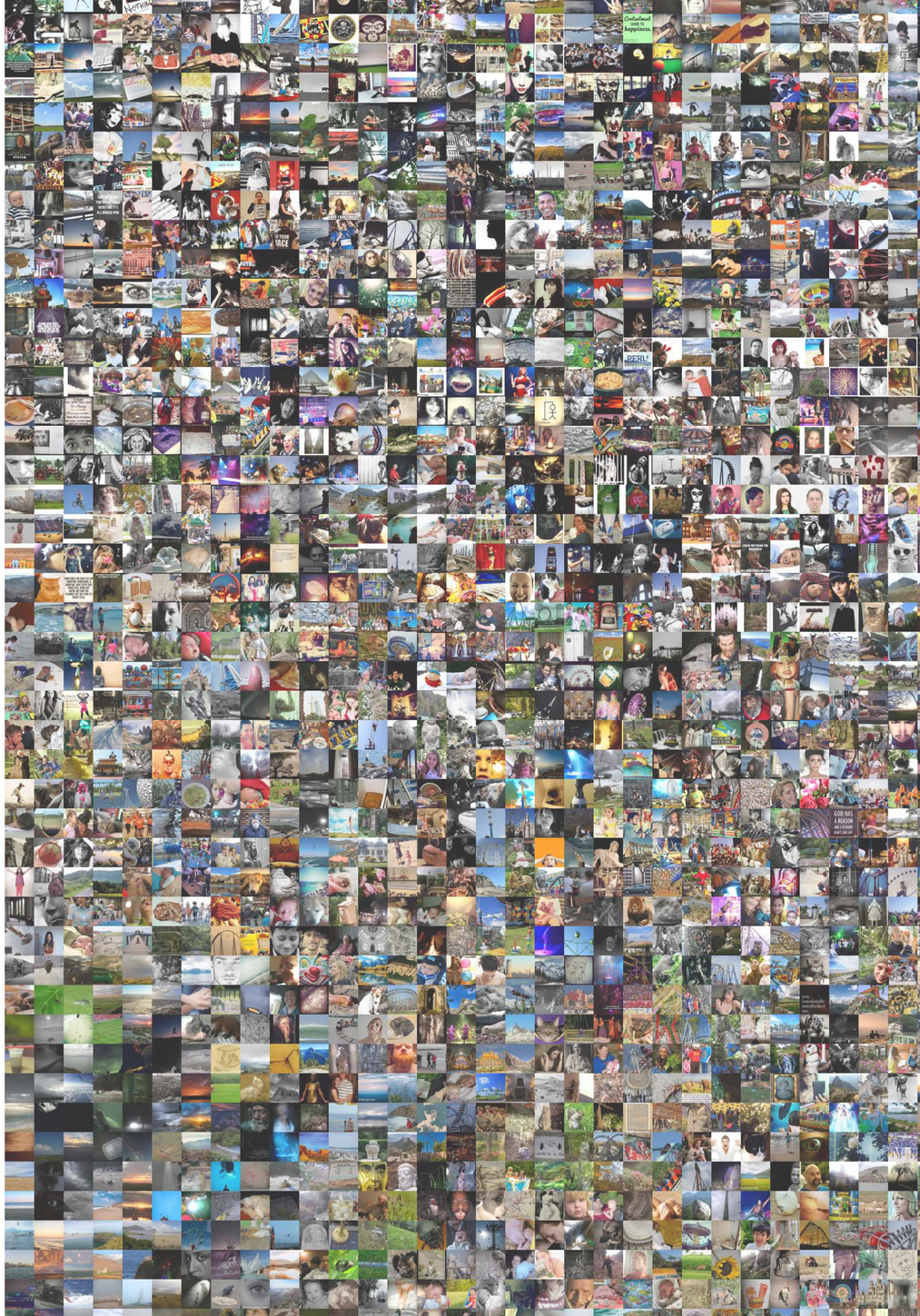
Set of networks



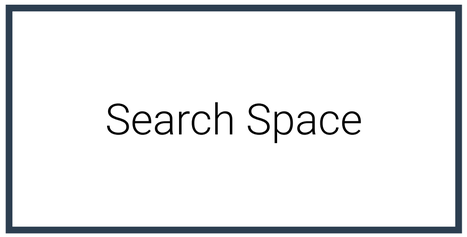
Neural Architecture Search

Neural Architecture Search

High Level Overview

Neural Architecture Search

High Level Overview



Neural Architecture Search

High Level Overview

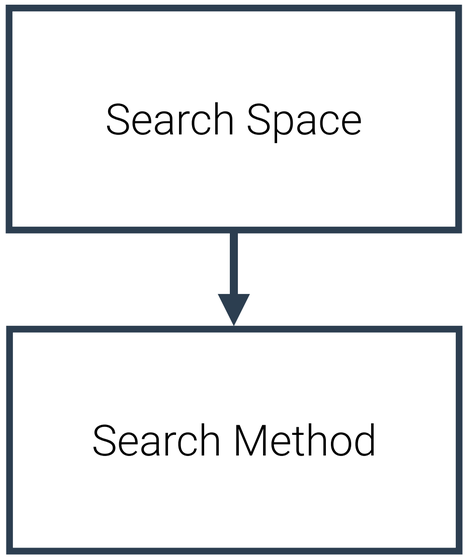
Search Space

$$\min_{f \in \mathcal{F}} \min_{\theta} \mathbb{E}_{(x,y)\sim\mathcal{D}} \left[\mathcal{L} \left(f \left(x; \theta \right), y \right) \right.$$

Set of networks

Neural Architecture Search

High Level Overview



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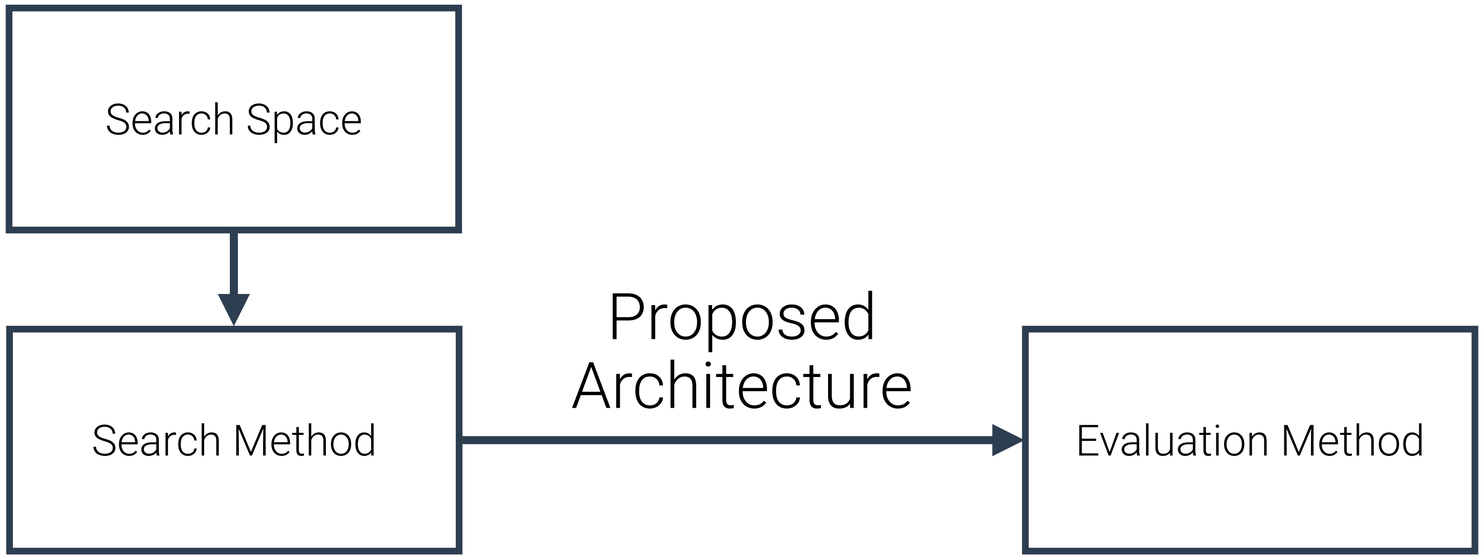

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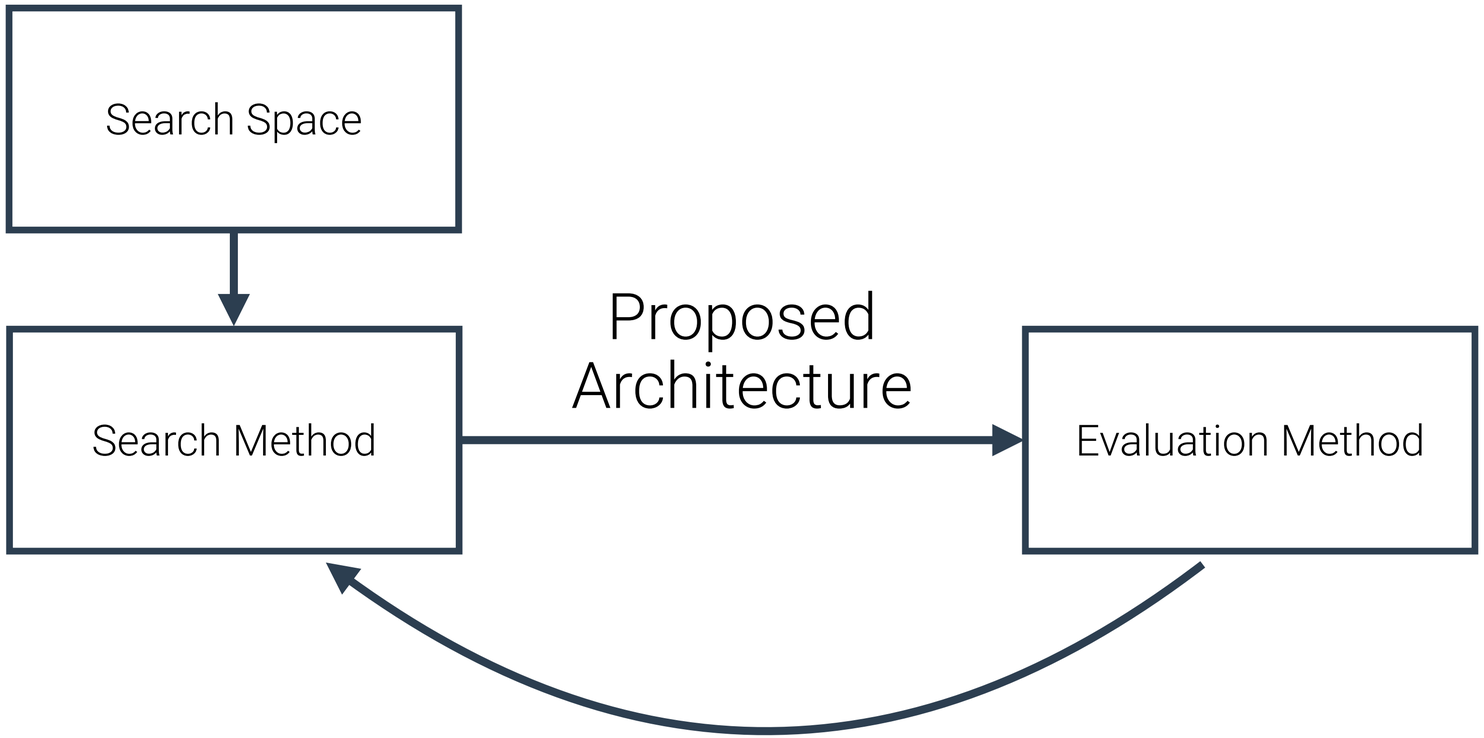

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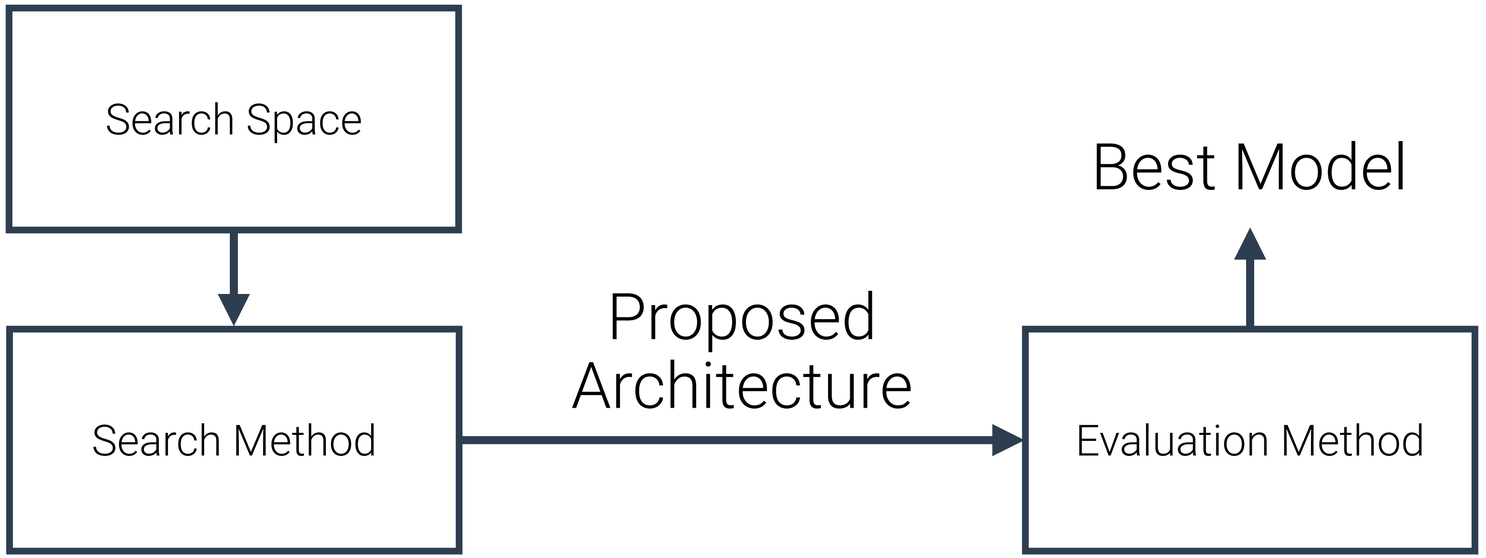

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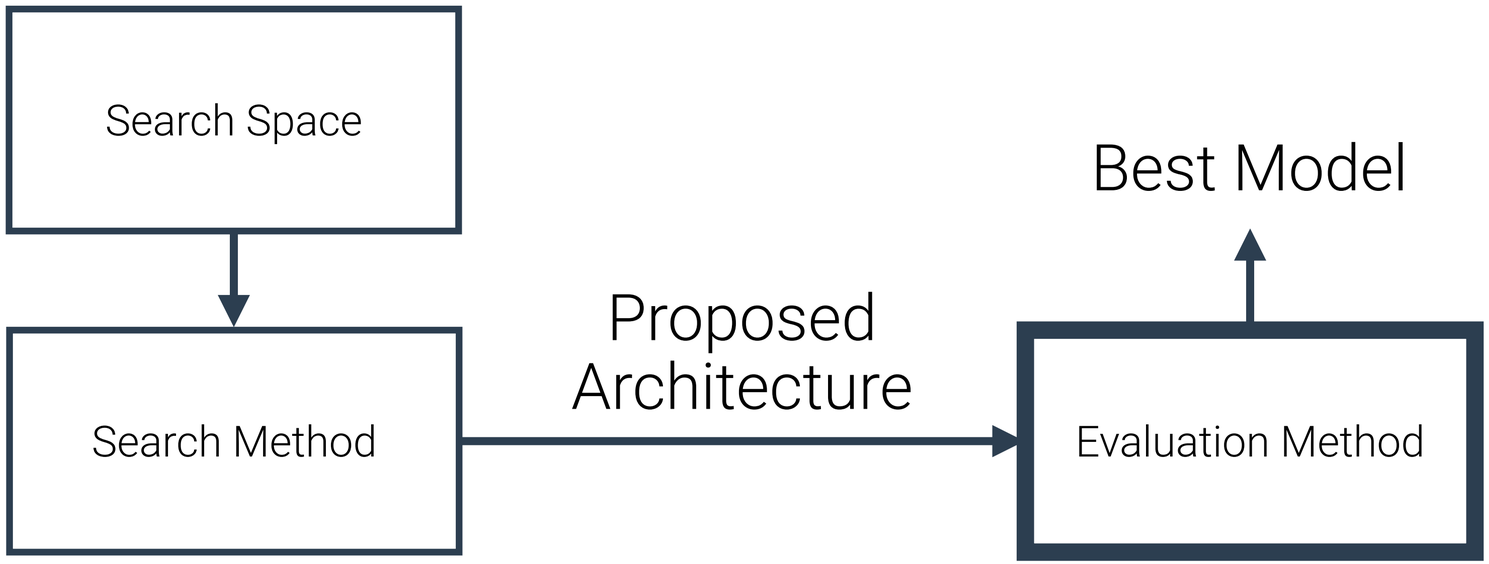

Neural Architecture Search

Evaluation Method

Neural Architecture Search

Evaluation Method

- Generally, this is performance on held-out data.

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- Generally, this is performance on held-out data.
- Evaluation is typically done by (partially) training the network and evaluating its performance on held-out data.

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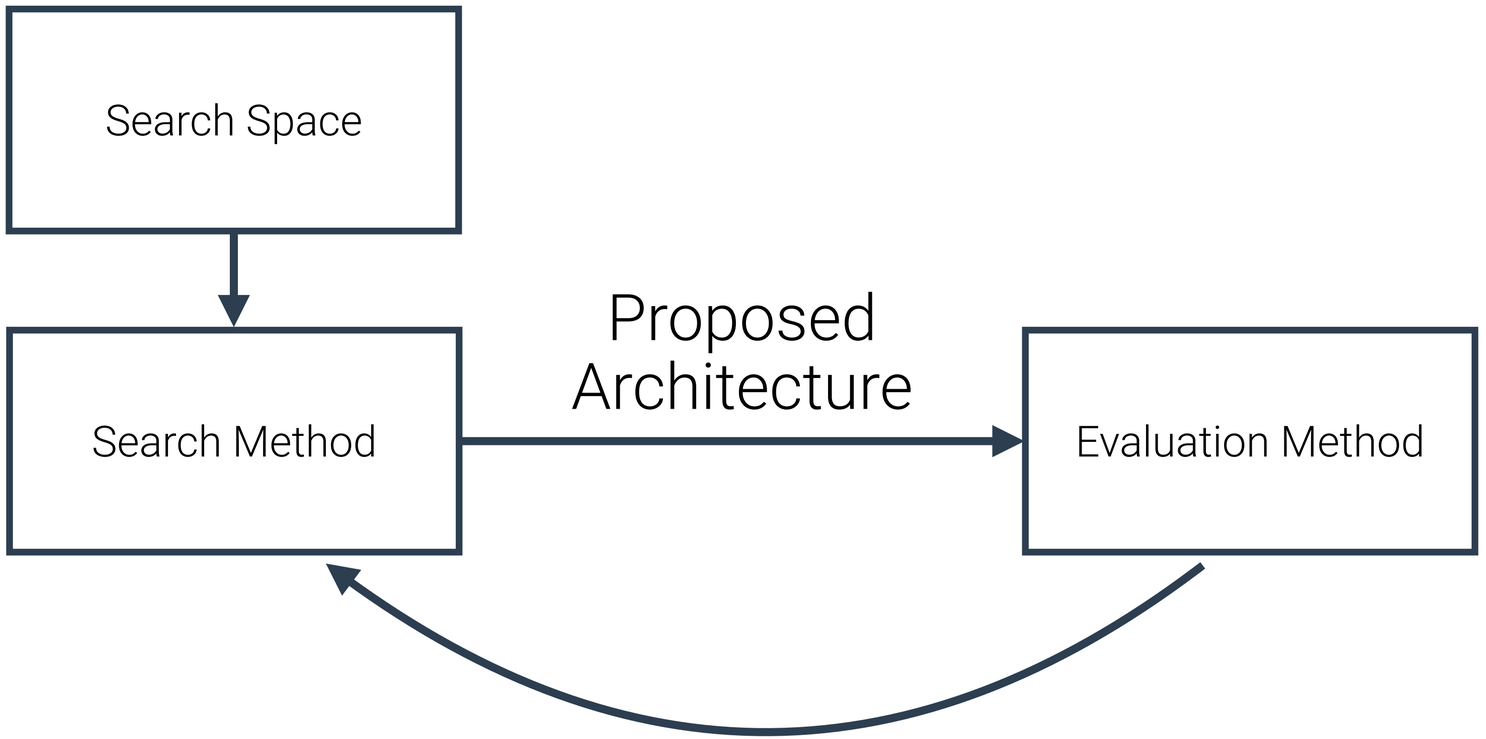

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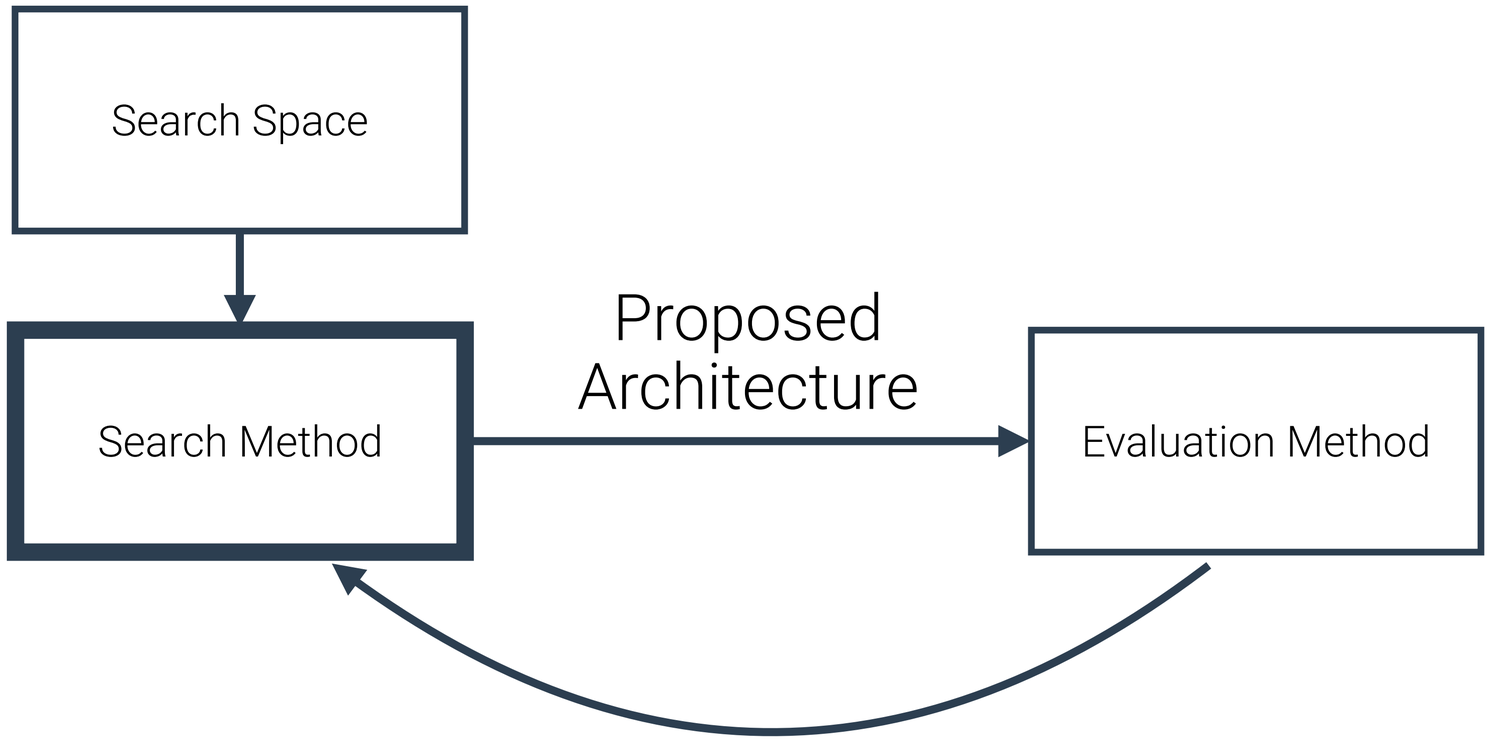

Search via Reinforcement Learning

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NAS-RL

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NAS-RL

- Motivated by the observation that a DNN architecture can be specified by a string of variable length (i.e. Breadth-first traversal of their DAG)

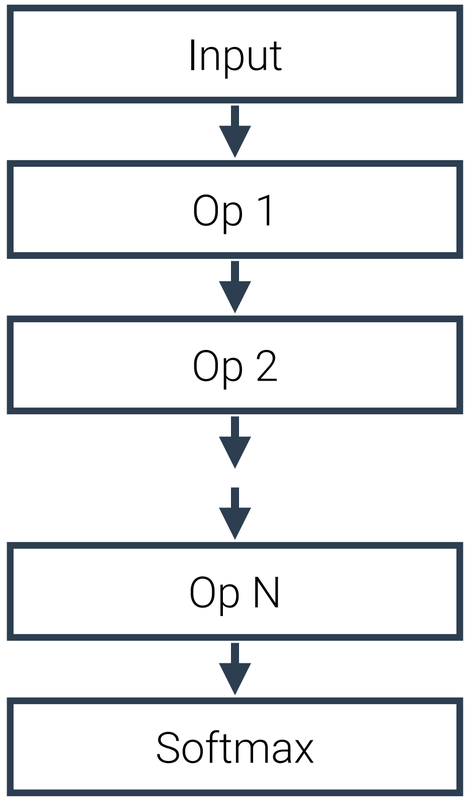
Search via Reinforcement Learning

NAS-RL

- Motivated by the observation that a DNN architecture can be specified by a string of variable length (i.e. Breadth-first traversal of their DAG)
- Use reinforcement learning to train an RNN that builds the network

Search via Reinforcement Learning

NAS-RL



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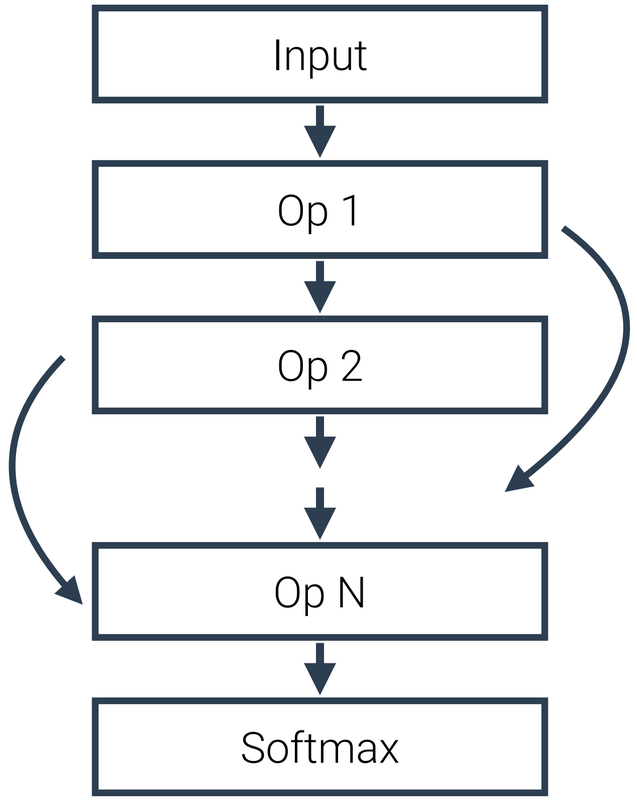

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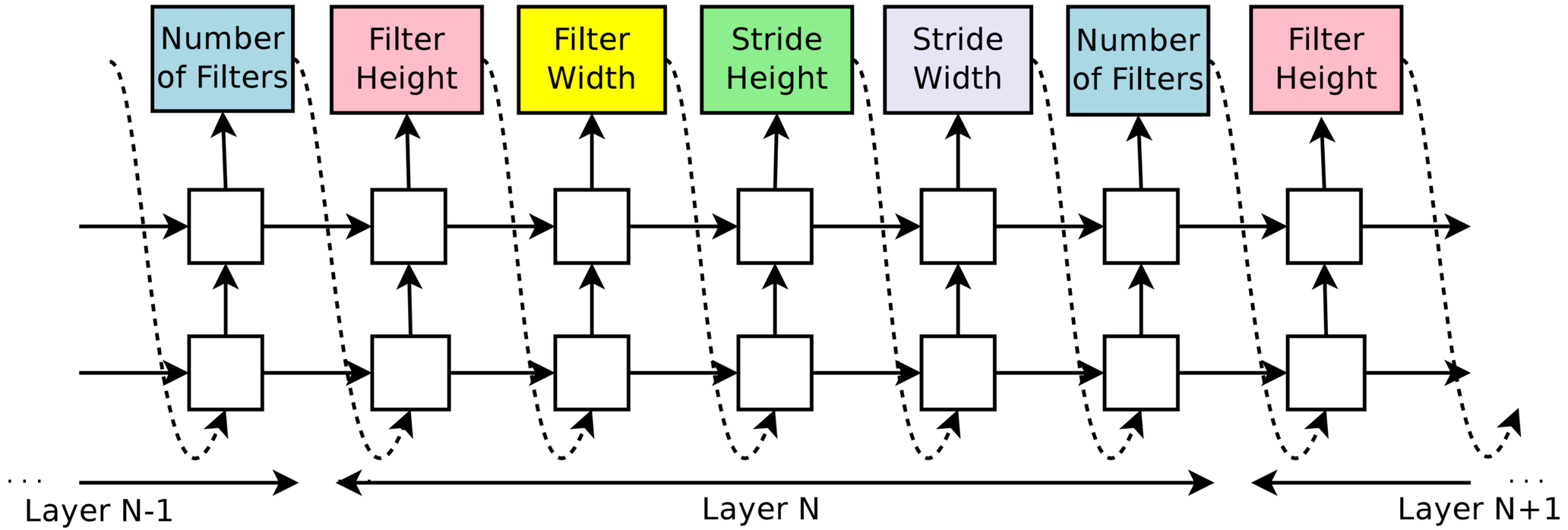

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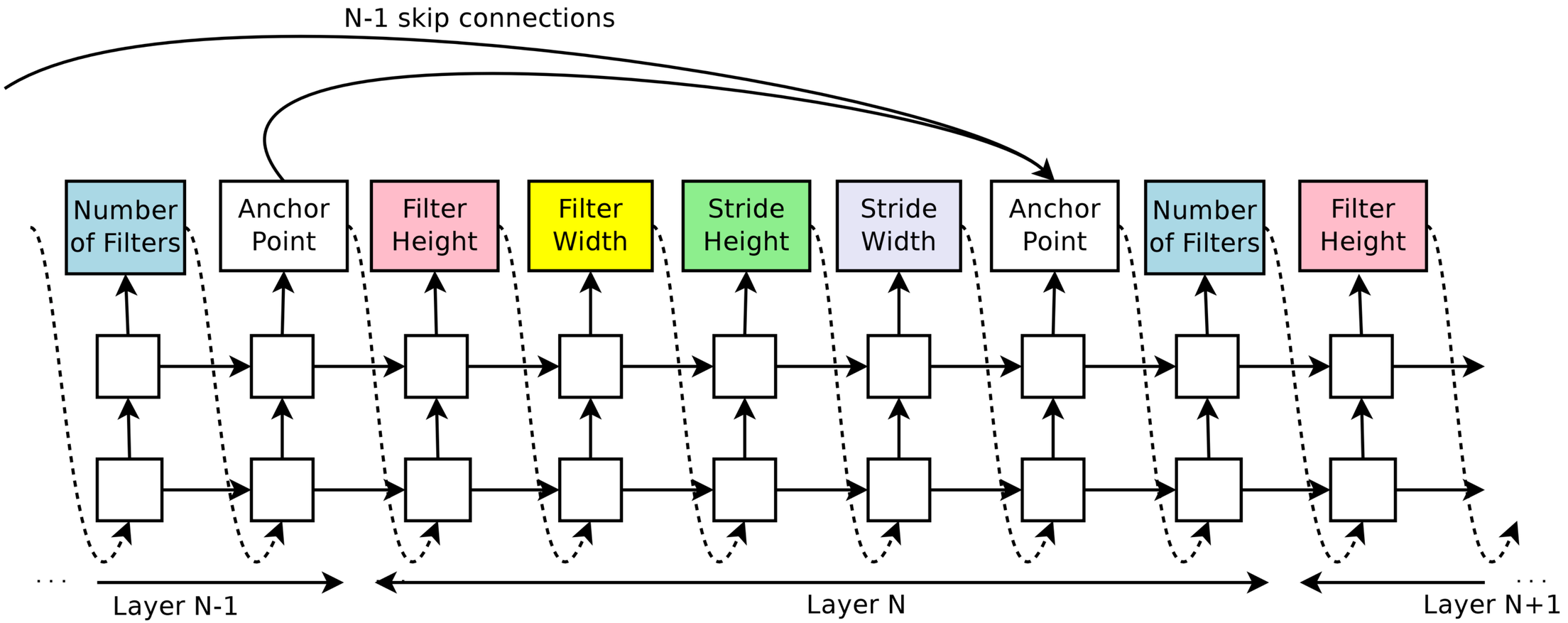

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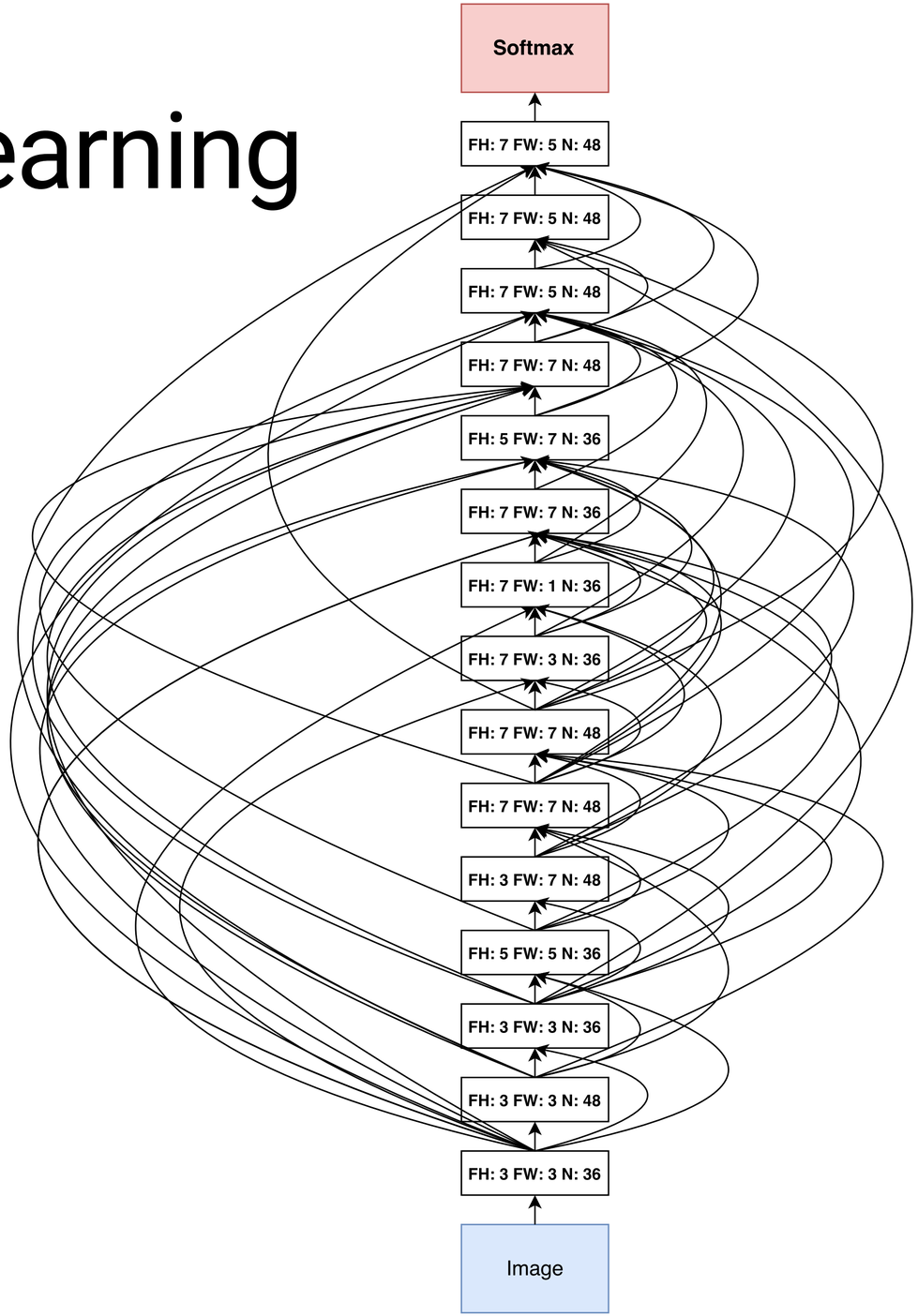
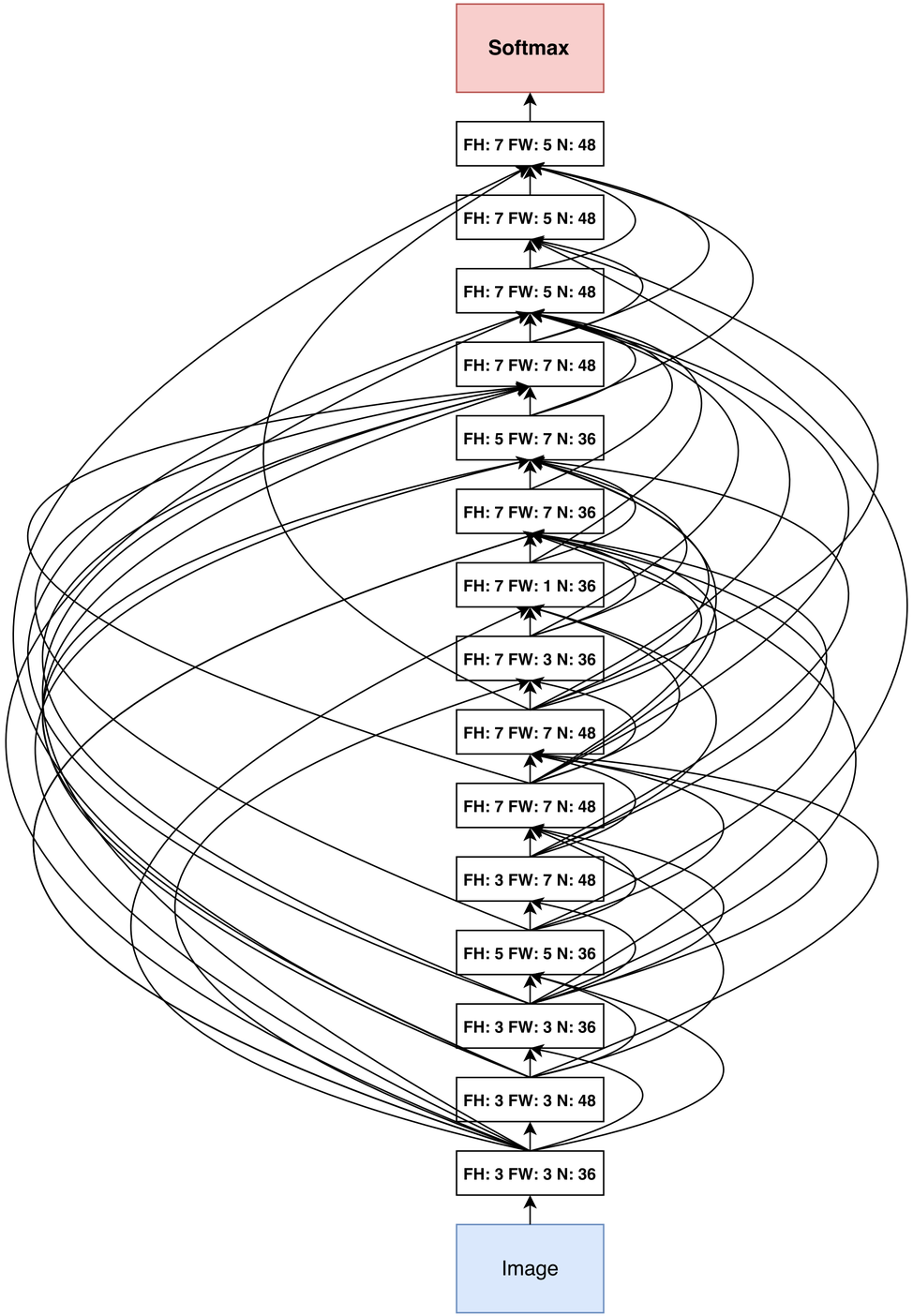


Search via Reinforcement L

NAS-RL

- Performance is on-par with other CNNs of the time



Search via Reinforcement Learning

NAS-RL

- This is a very general method

Search via Reinforcement Learning

NAS-RL

- This is a very general method
- The cost of that is compute: This used 800 GPUs (for an unspecified amount of time) and trained >12,000 candidate architectures

Search via Reinforcement Learning

NASNet

- Instead, limit the search space with “blocks”

Search via Reinforcement Learning

NASNet

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- This is similar to “Human Neural Architecture Search”

Search via Reinforcement Learning

NASNet

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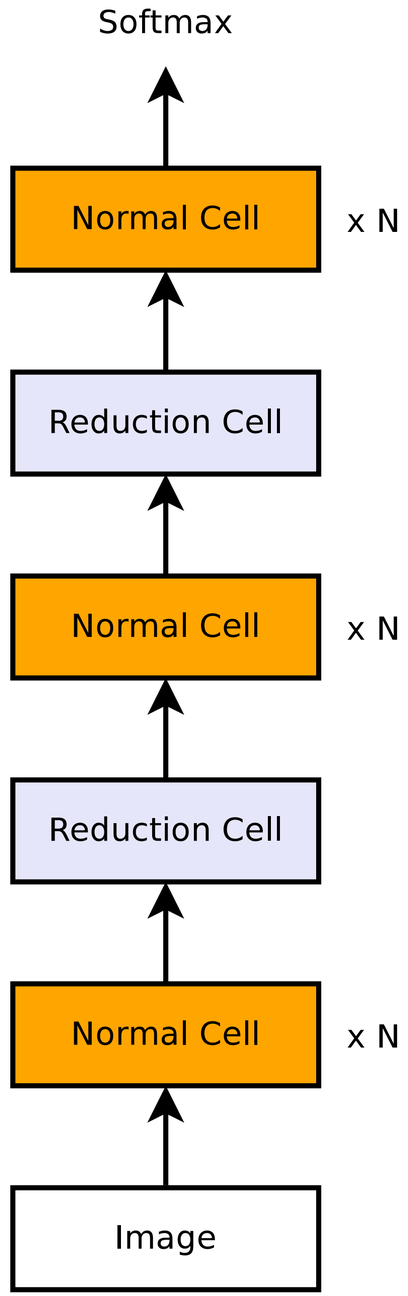

Search via Reinforcement Learning

NASNet

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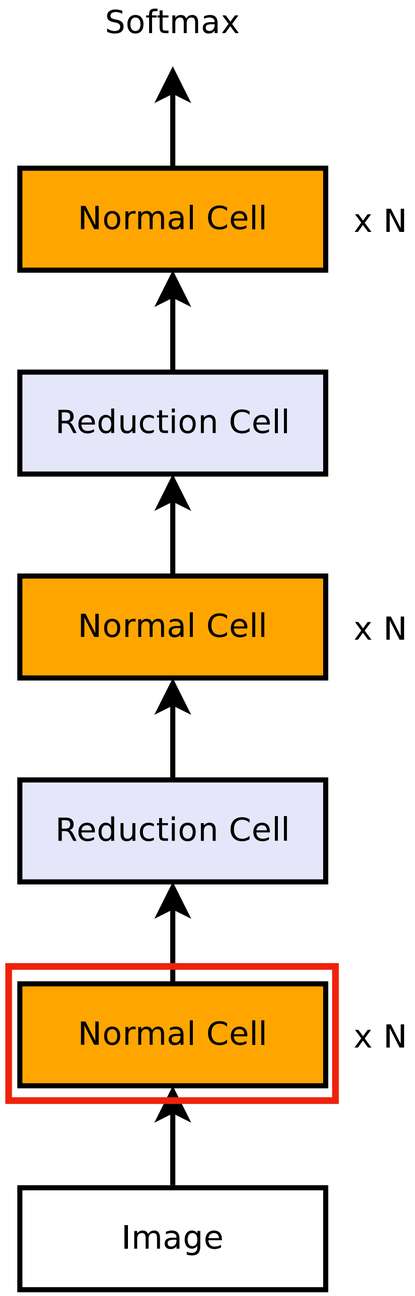

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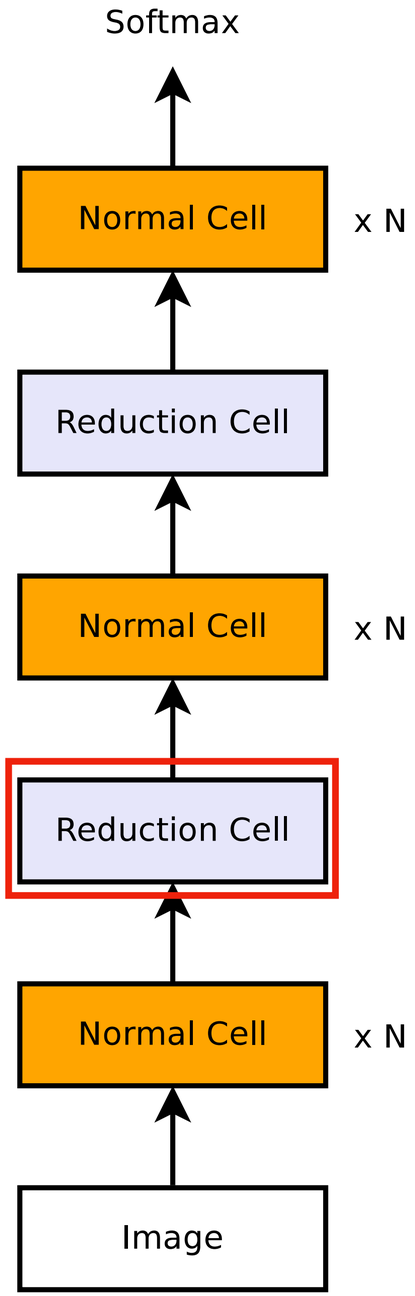

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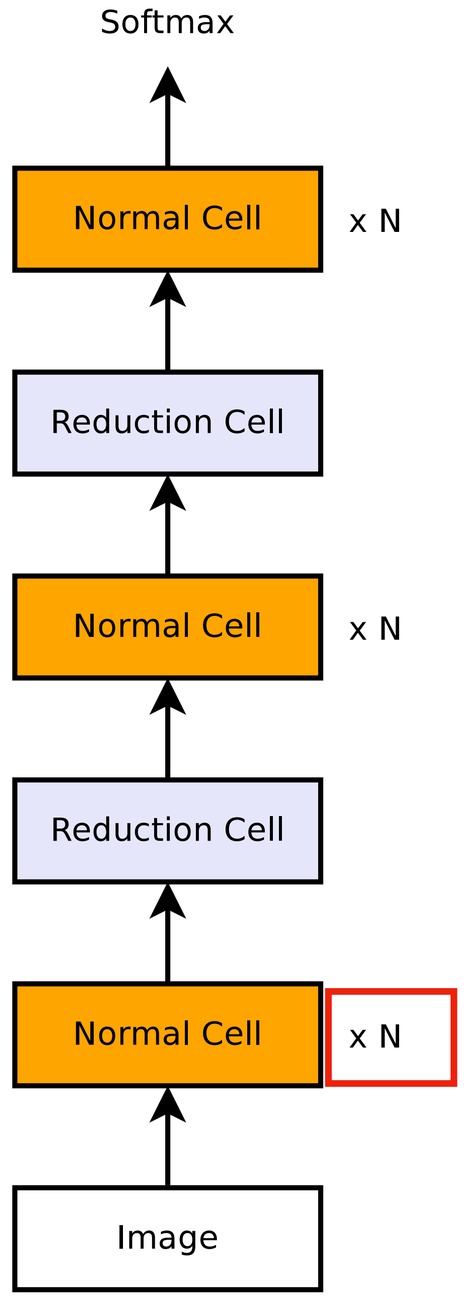

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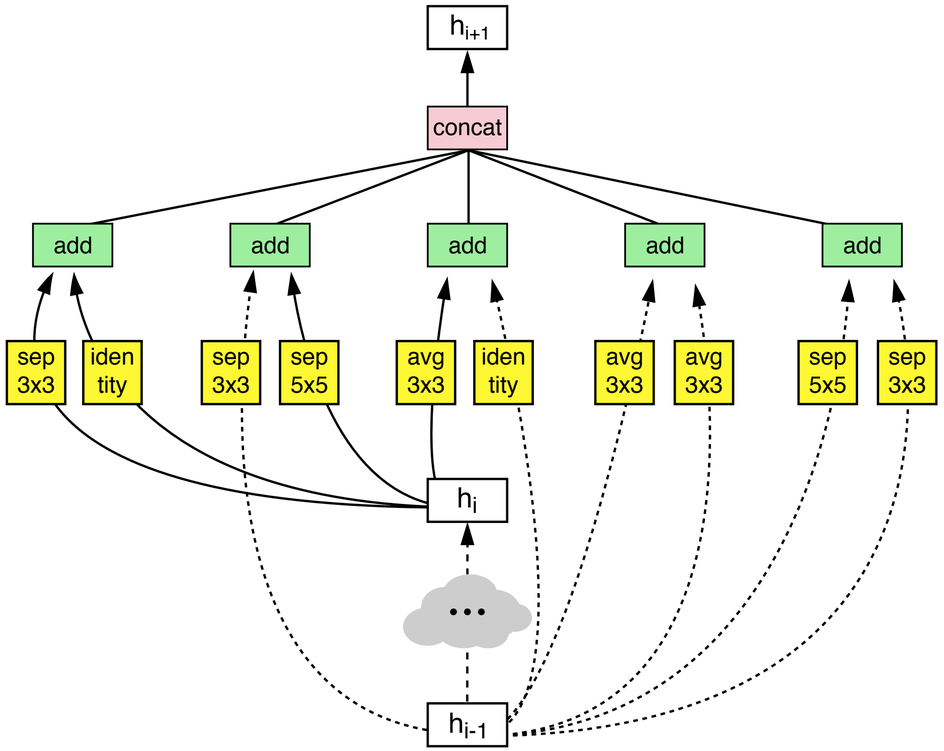
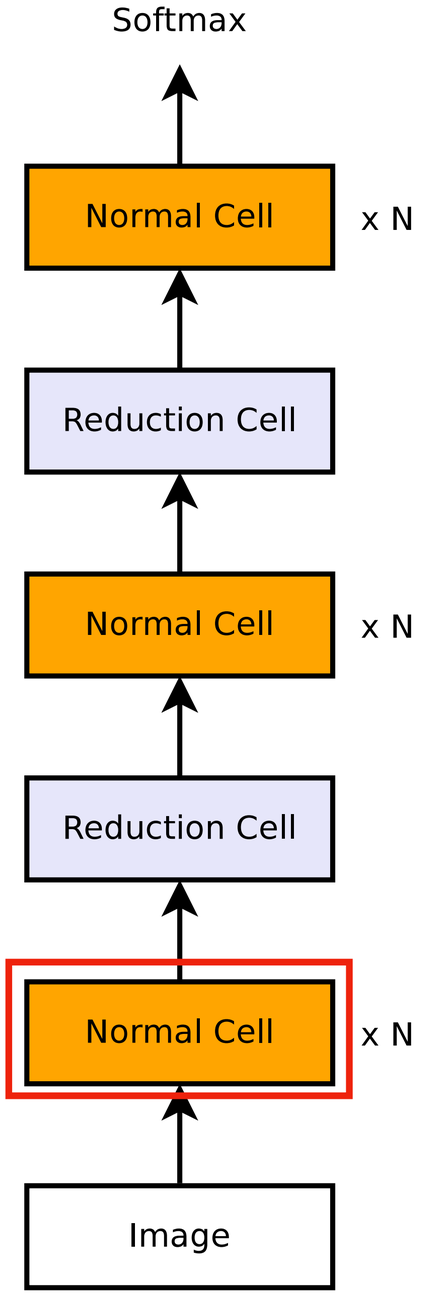


Normal Cell



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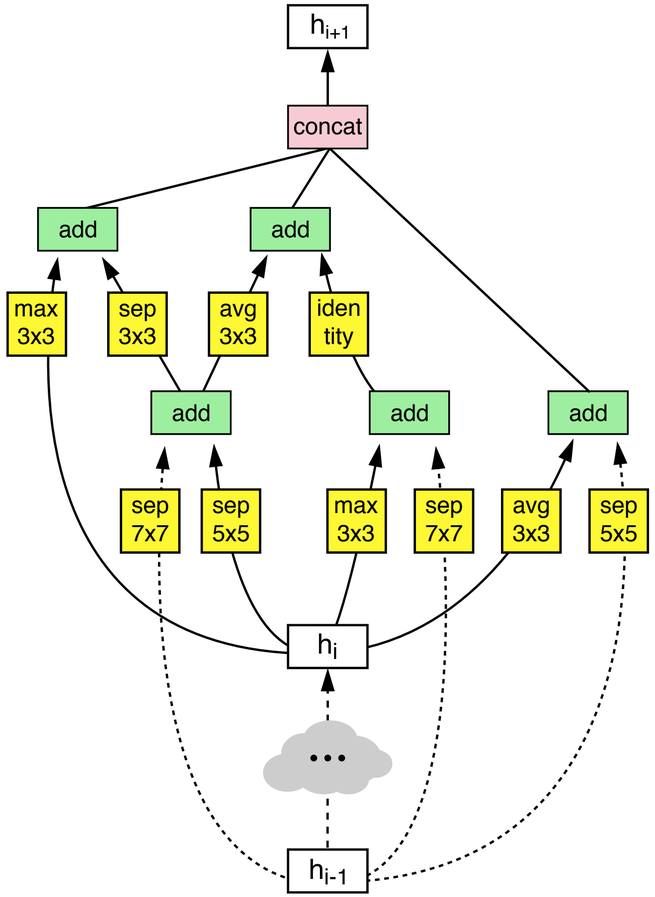
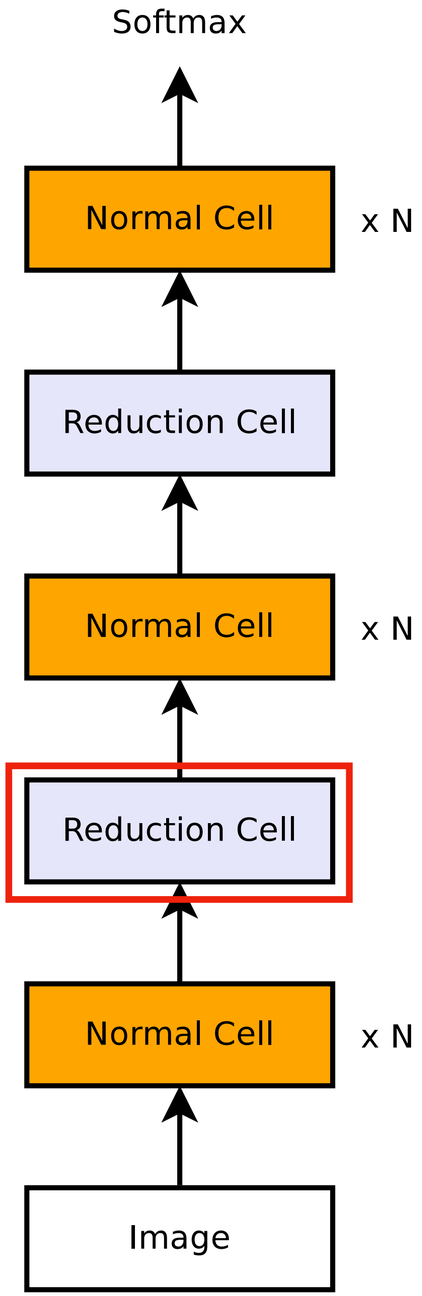


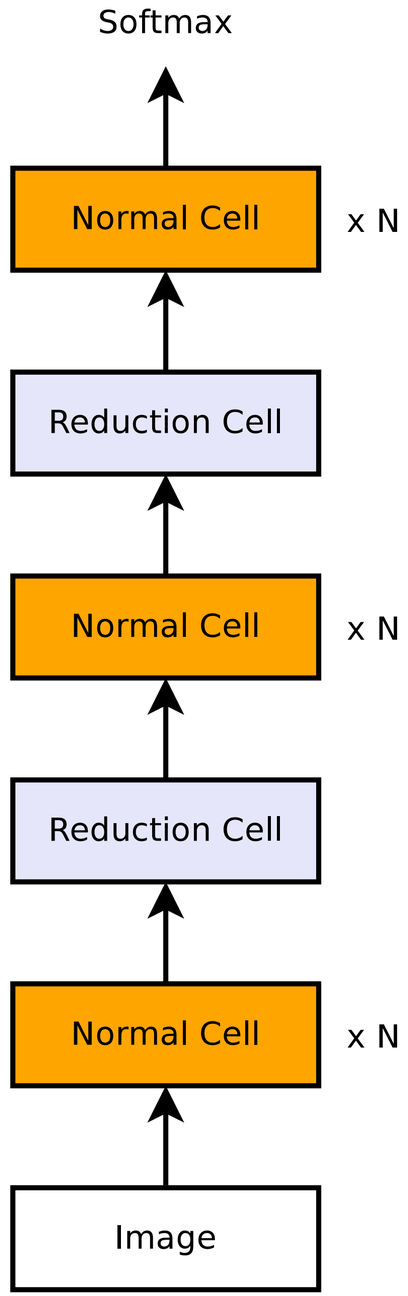
Reduction Cell



Search via Reinforcement Learning

NASNet

- Performance is on-par with other CNNs at the time but with less parameters/compute



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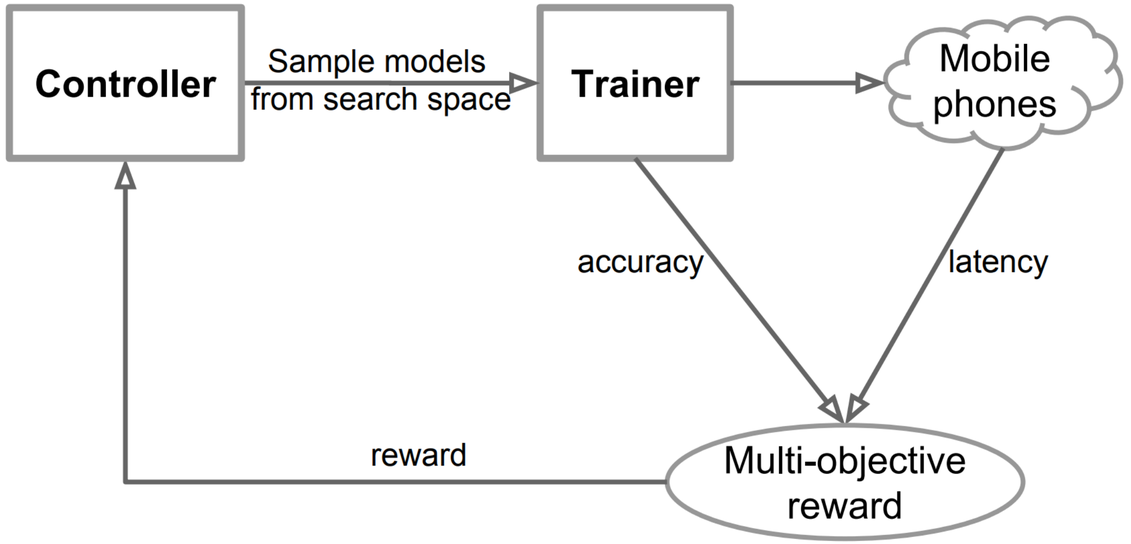

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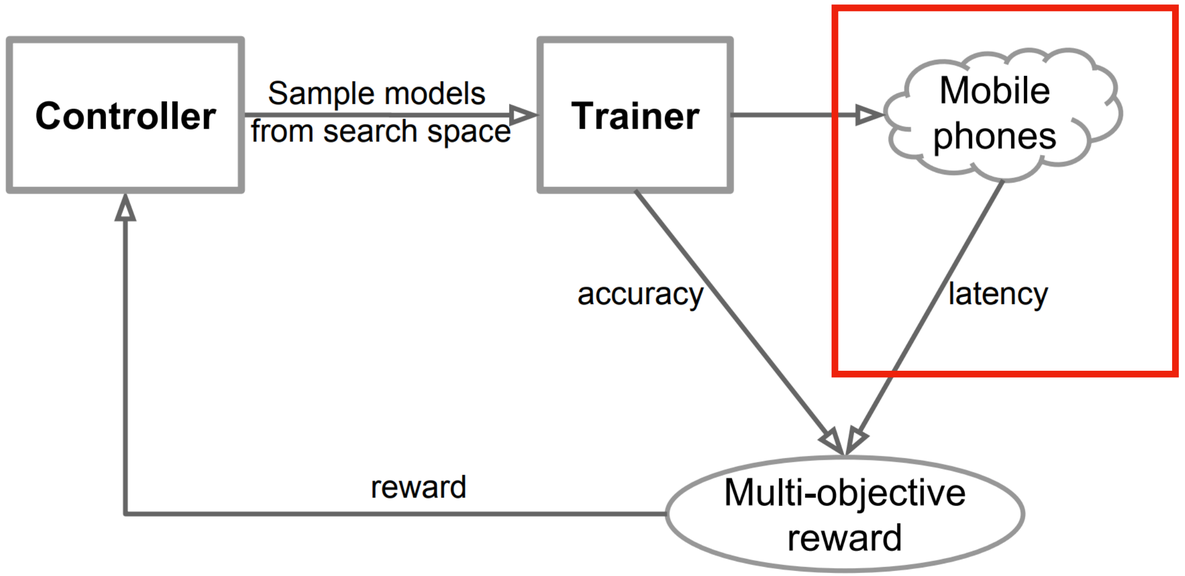

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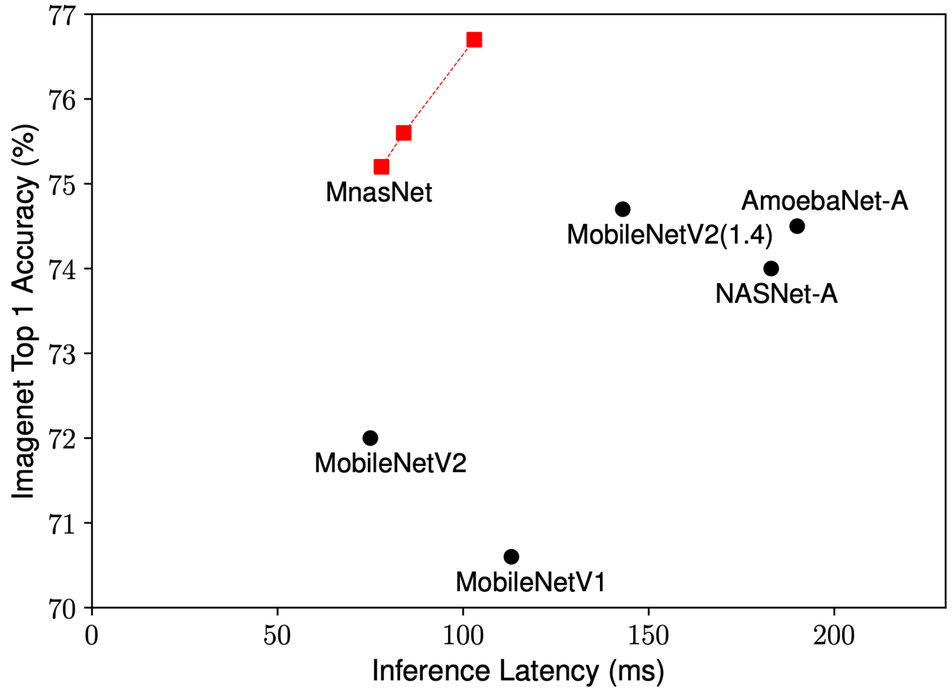

Search via Gradient Optimization

Differentiable Architecture Search (DARTS)

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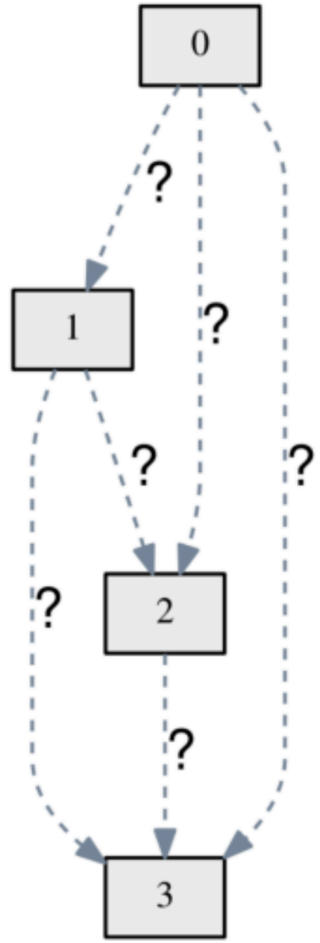

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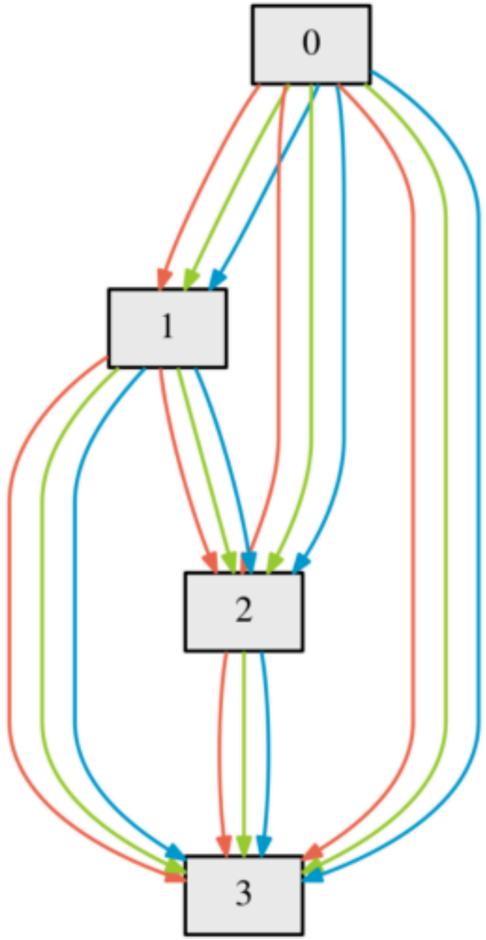

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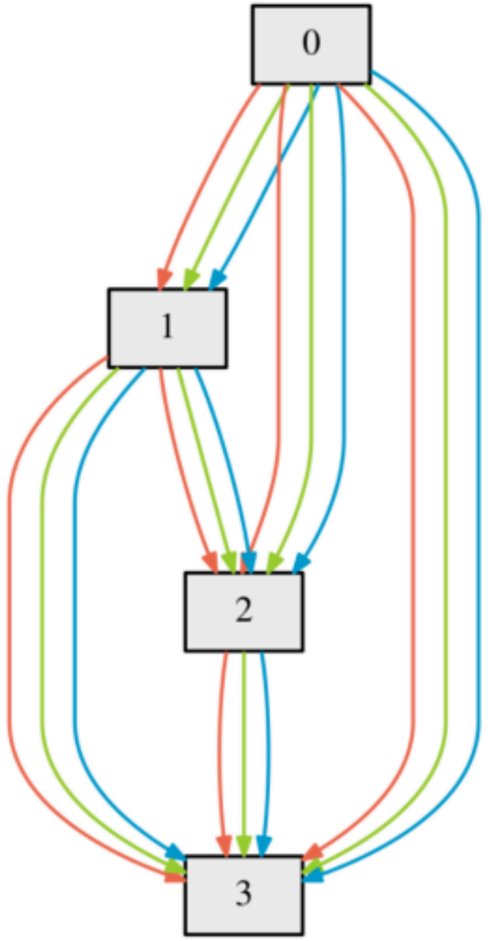

1x1 Conv

Search via Gradient Optimization

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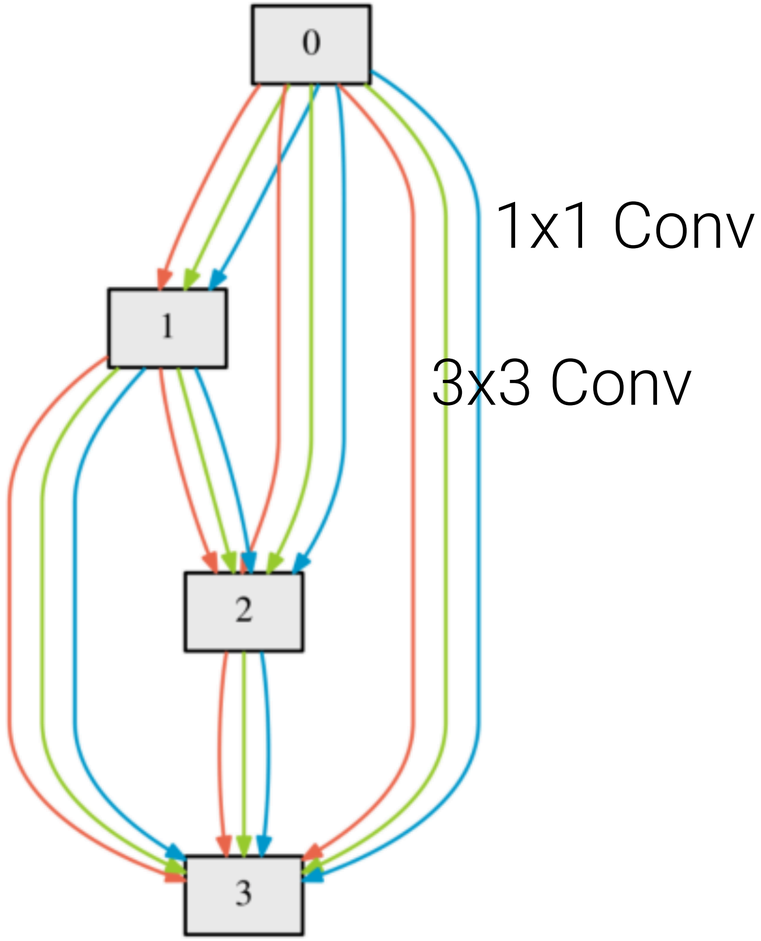

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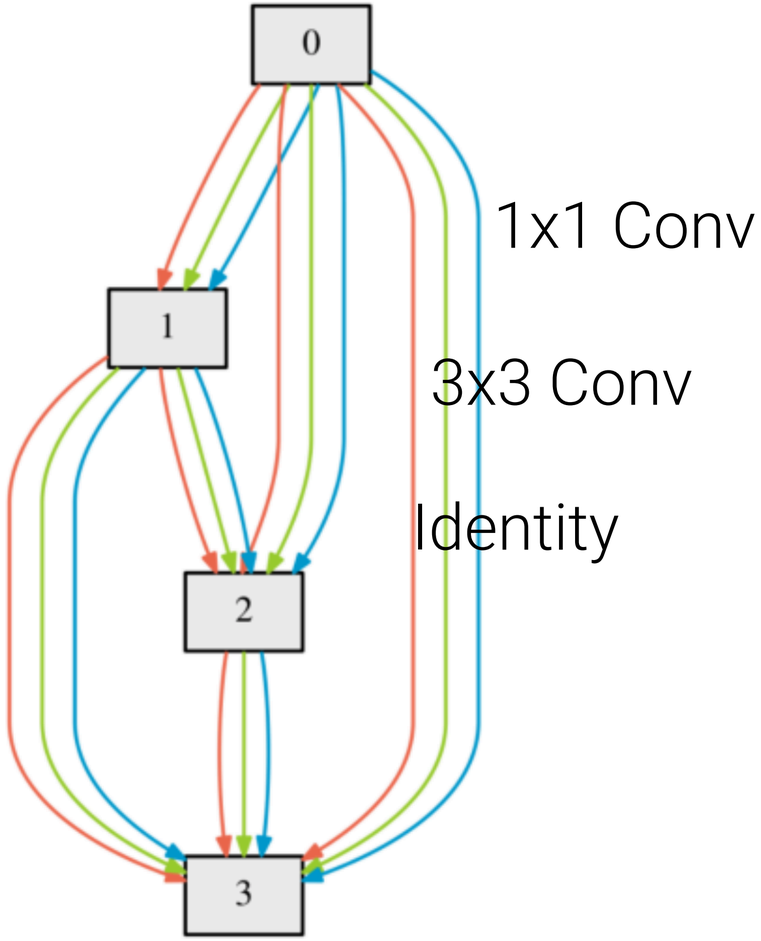

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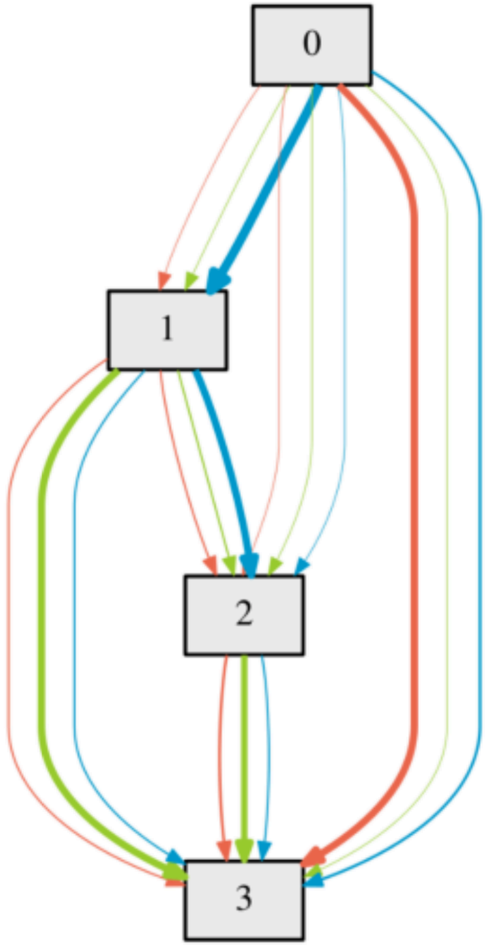

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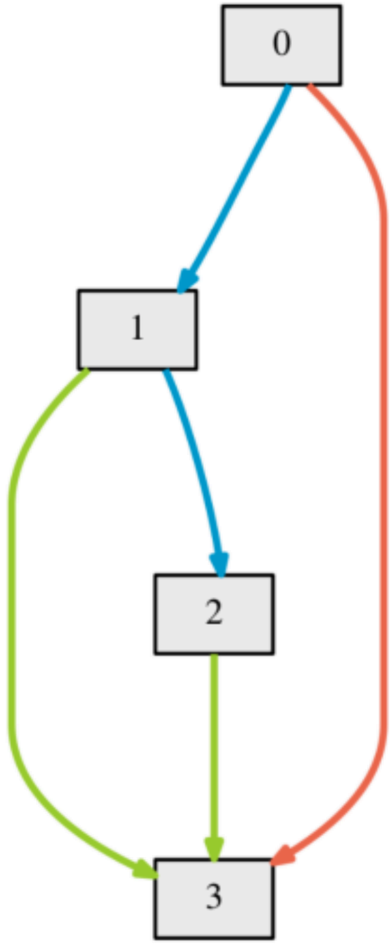

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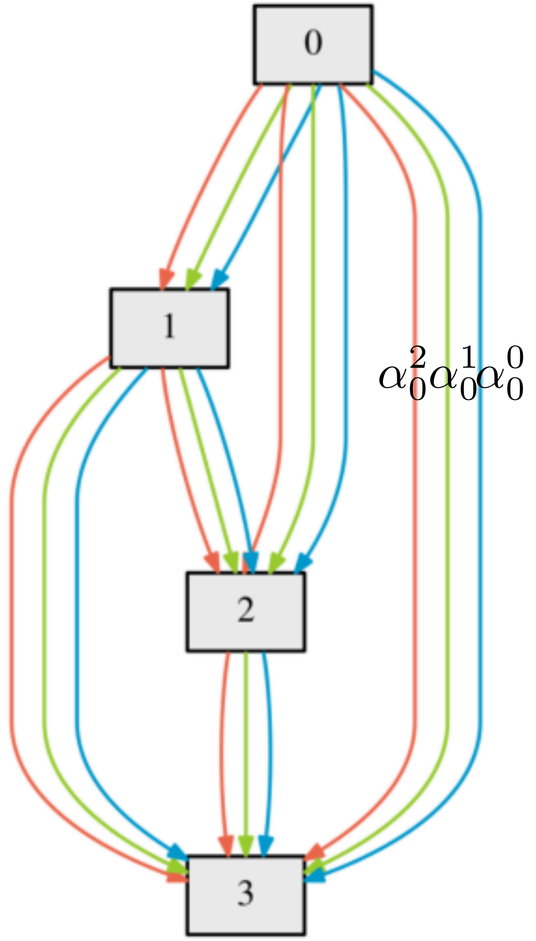

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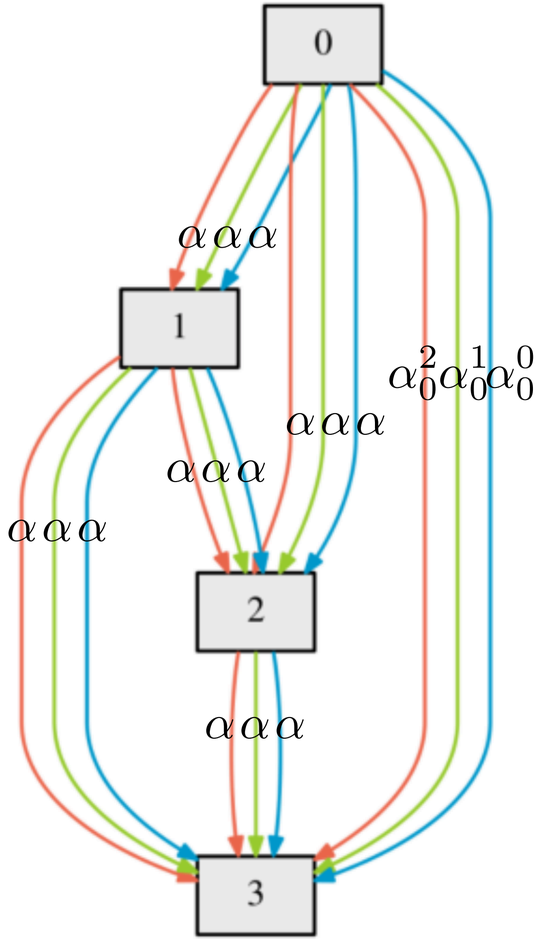
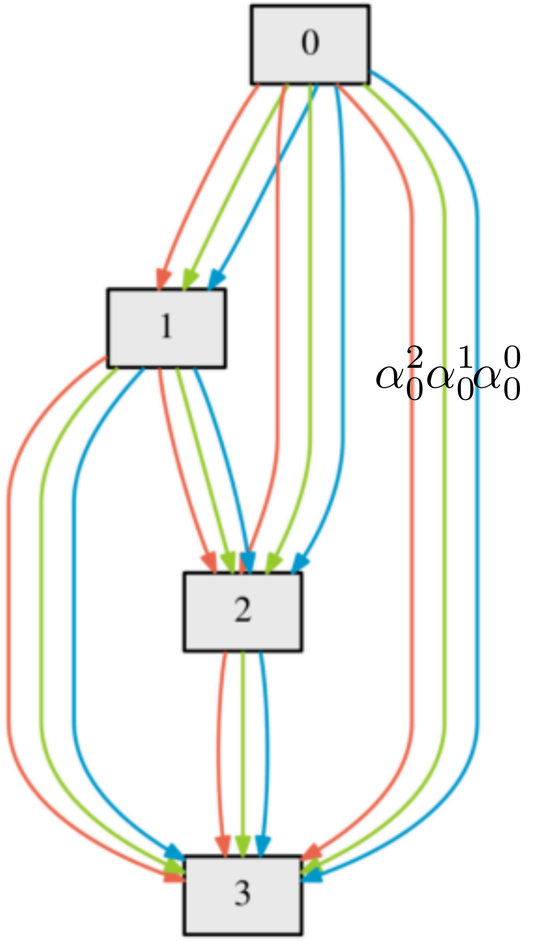


Search via Gradient Optimization

Differentiable Architecture Search (DARTS)

$$w_0^i = \frac{e^{\alpha_0^i}}{\sum_j e^{\alpha_0^j}}$$

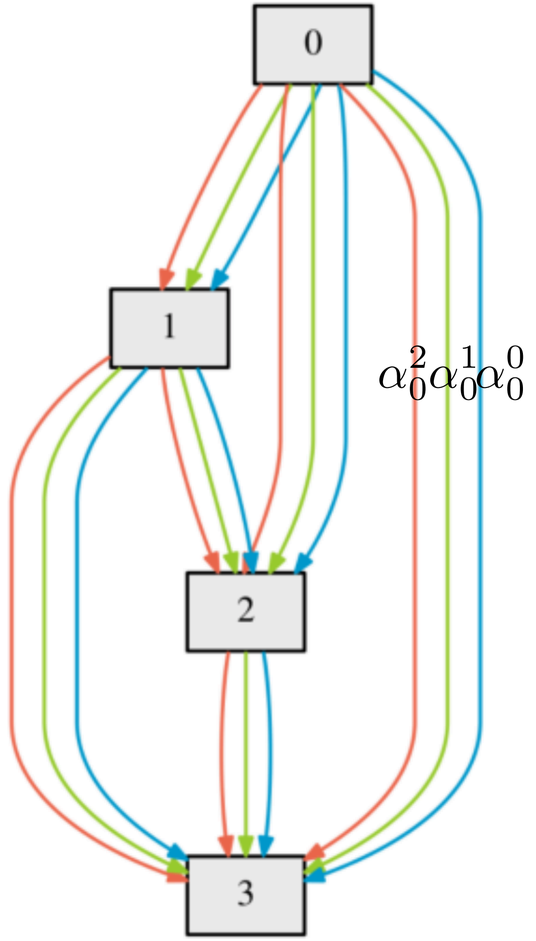


Search via Gradient Optimization

Differentiable Architecture Search (DARTS)

$$w_0^i = \frac{e^{\alpha_0^i}}{\sum_j e^{\alpha_0^j}}$$

w_0^0 1x1Conv $+w_0^1$ 3x3Conv $+w_0^2$ Identity



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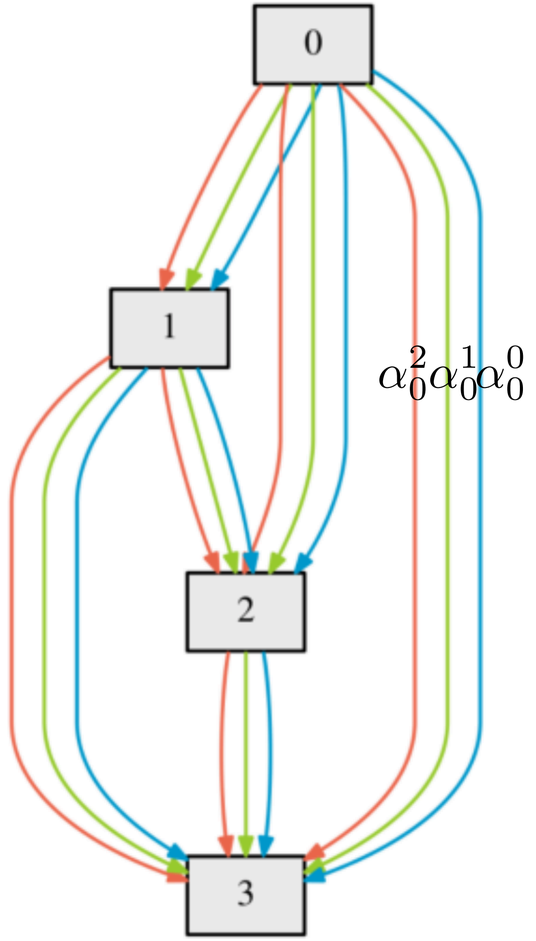
Differentiable Architecture Search (DARTS)

$$w_0^i = \frac{e^{\alpha_0^i}}{\sum_j e^{\alpha_0^j}}$$

$$\min_{\alpha} \mathcal{L}_{val}(\theta^*(\alpha), \alpha)$$

$$\text{s.t.} \quad \theta^*(\alpha) = \min_{\theta(\alpha)} \mathcal{L}_{train}(\theta, \alpha)$$



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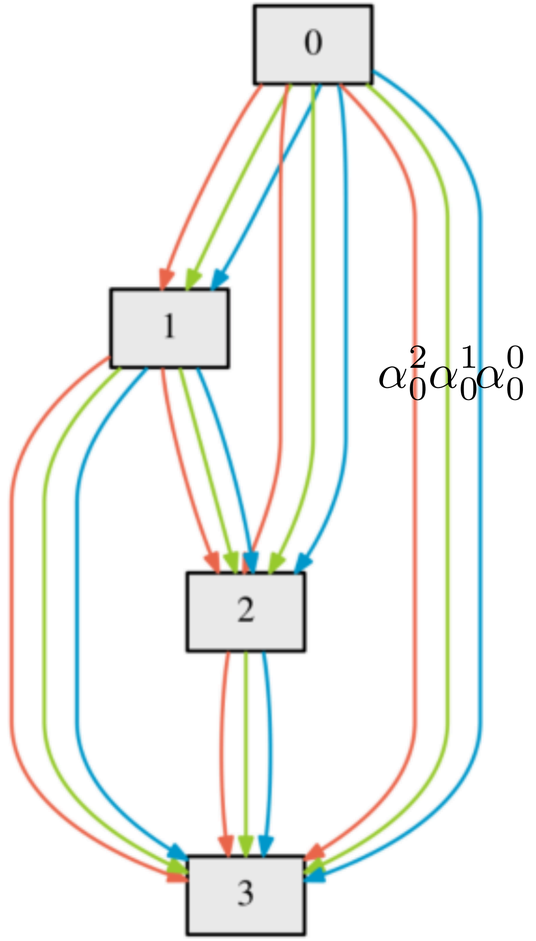

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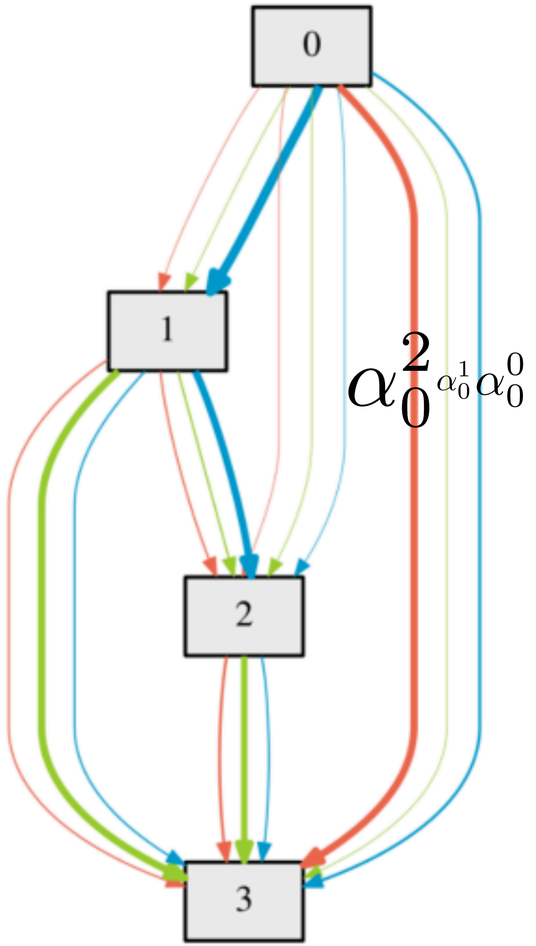

$$\min_{\alpha} \mathcal{L}_{val}(\theta^*(\alpha), \alpha)$$

$$\text{s.t.} \quad \theta^*(\alpha) = \min_{\theta(\alpha)} \mathcal{L}_{train}(\theta, \alpha)$$

Search via Gradient Optimization

Differentiable Architecture Search (DARTS)

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Differentiable Architecture Search (DARTS)

$$\nabla_\alpha \mathcal{L}_{val}(\theta^*(\alpha), \alpha)$$

$$\approx \nabla_\alpha \mathcal{L}_{val}(\theta - \nabla_\theta \mathcal{L}_{train}(\theta, \alpha), \alpha)$$

Search via Gradient Optimization

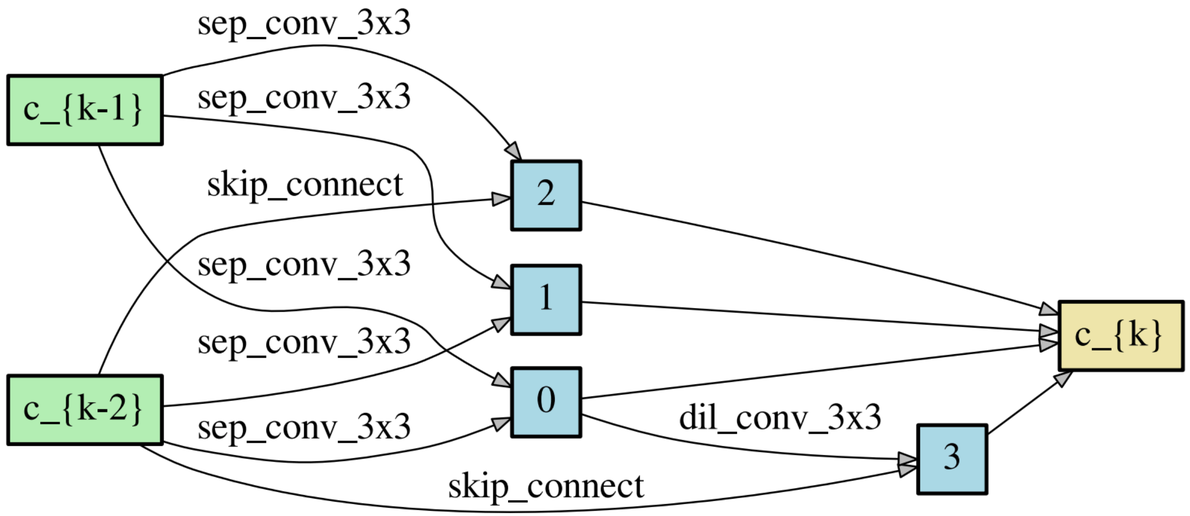
Differentiable Architecture Search (DARTS)

$$\nabla_\alpha \mathcal{L}_{val}(\theta^*(\alpha), \alpha)$$
$$\approx \nabla_\alpha \mathcal{L}_{val}(\theta - \nabla_\theta \mathcal{L}_{train}(\theta, \alpha), \alpha)$$
$$\approx \nabla_\alpha \mathcal{L}_{val}(\theta, \alpha)$$

Search via Gradient Optimization

Differentiable Architecture Search (DARTS)

- Finds networks with very little computation cost (~1 GPU day) that perform better or on-par with existing NAS methods



Search via Scoring

Search via Scoring (without training)

Neural Architecture Search without Training

Search via Scoring (without training)

Neural Architecture Search without Training

- How well a given architecture will do when fully trained can be approximated by how “flexible” the network is.

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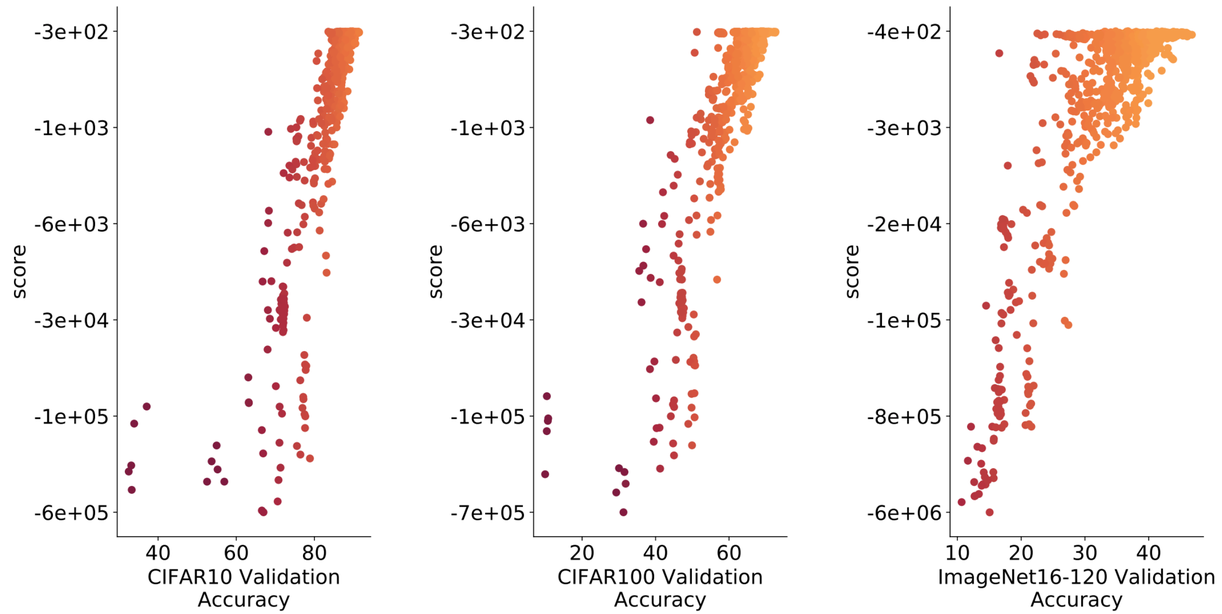

Summary

- Neural Architecture Search (NAS) focuses on automatically finding highly performant network architectures

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Google’s AutoML

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- Neural Architecture Search (NAS) focuses on automatically finding highly performant network architectures
- Search is commonly done with either RL or gradient methods (e.g. DARTS)
- One fruitful use has been searching for compute efficient networks