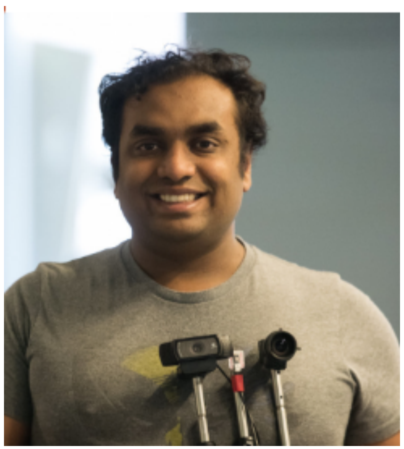
Practical Neural Network Design Using Reinforcement Learning

Bowen Baker
Media Lab
bowen@mit.edu

Co-authors



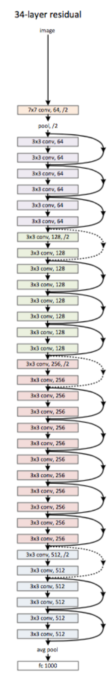
Otkrist Gupta
MIT Media Lab

Nikhil Naik
Harvard

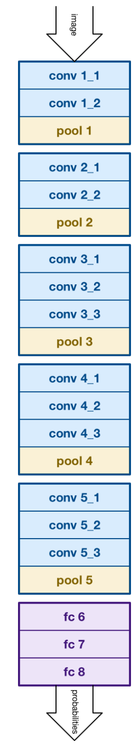
Ramesh Raskar
MIT Media Lab

Popular Deep Neural Networks

Inception



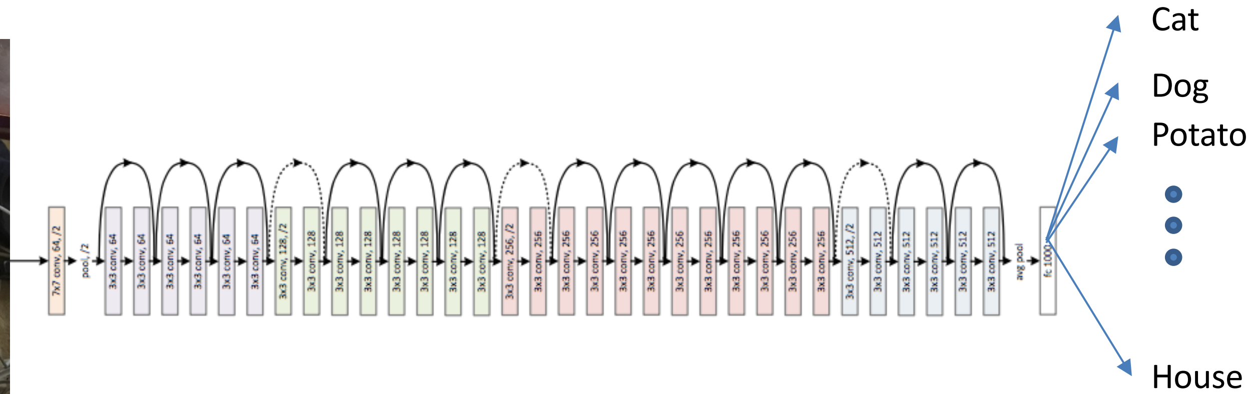
Resnet



VGG

Really good at recognizing cats!

Taro



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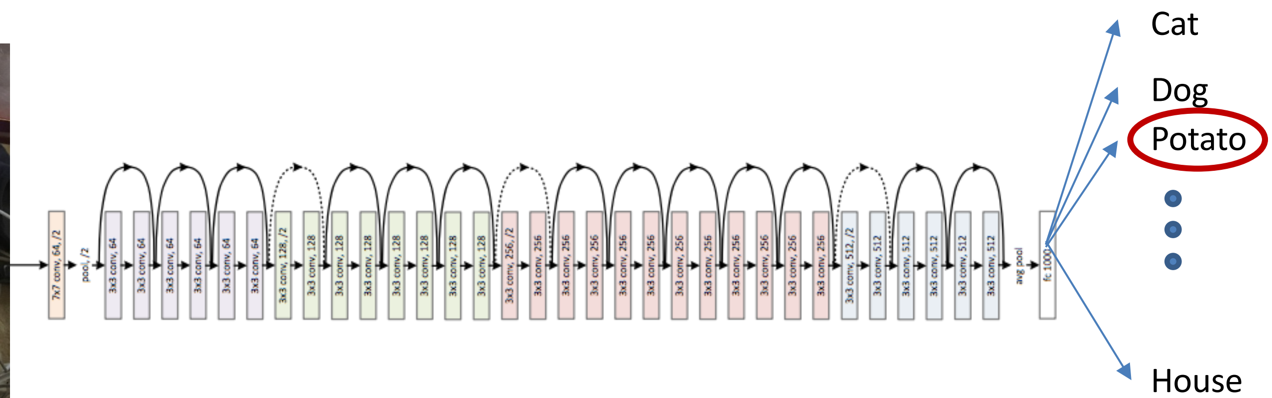
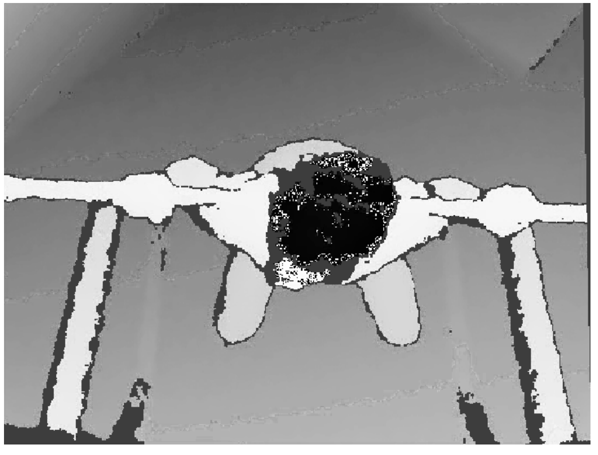


They may not be the best in other domains!

- Example:
  - Perch – An MIT workout tracking startup



Depth Image

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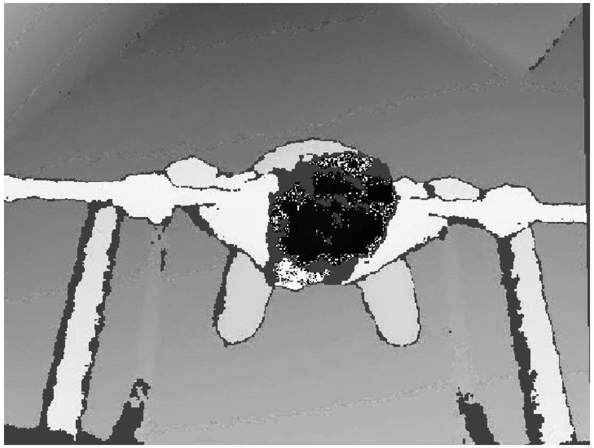
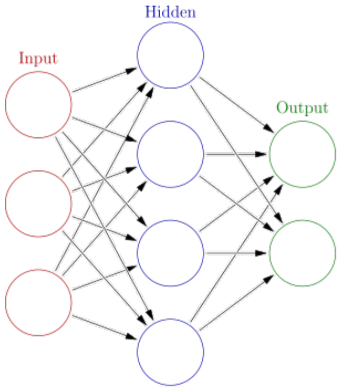


Depth Image



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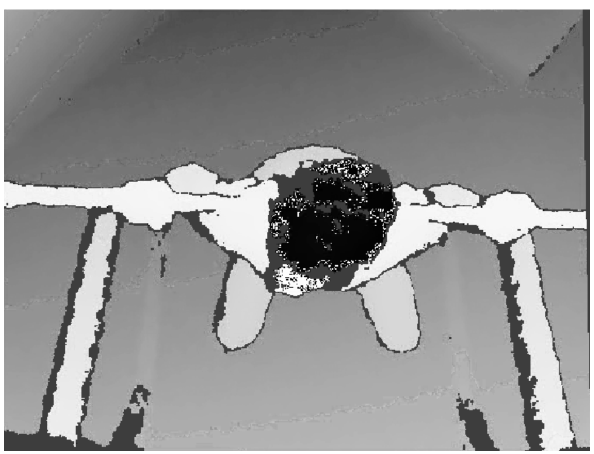

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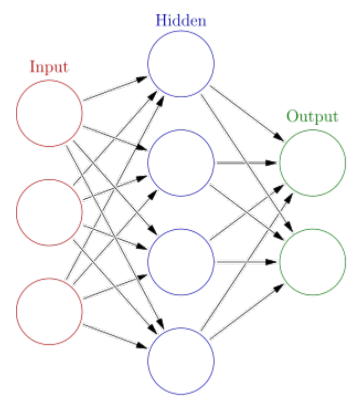

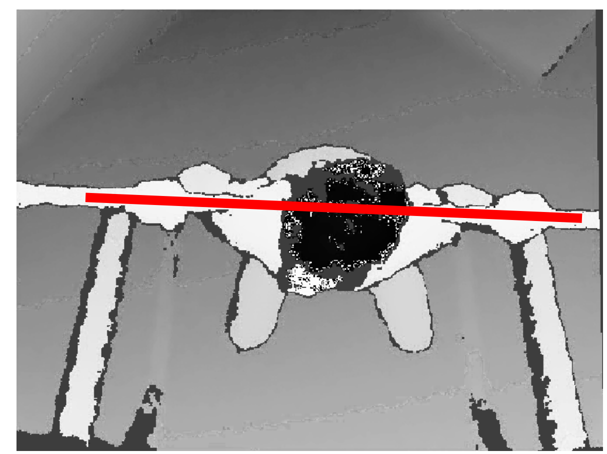

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- They need to use a $100 GPU to run this network at 30 fps

So what do we do?

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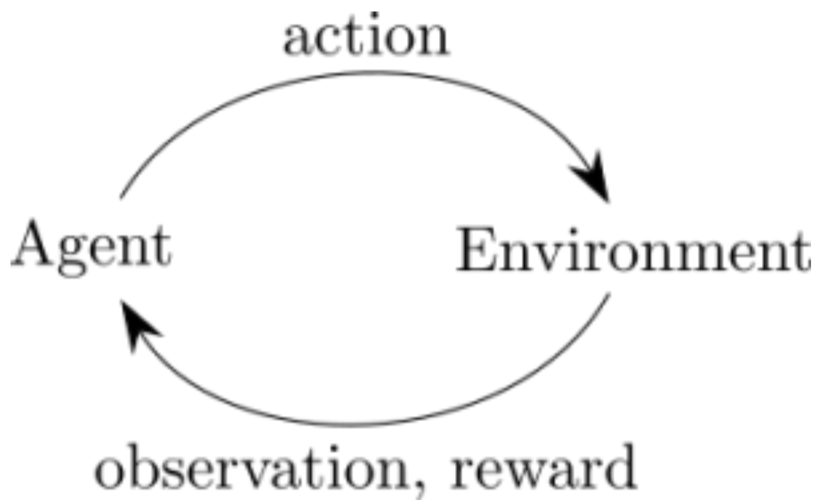
- Idea #2: Use reinforcement learning!

Automating Tasks With Reinforcement Learning



Automating Tasks With Reinforcement Learning

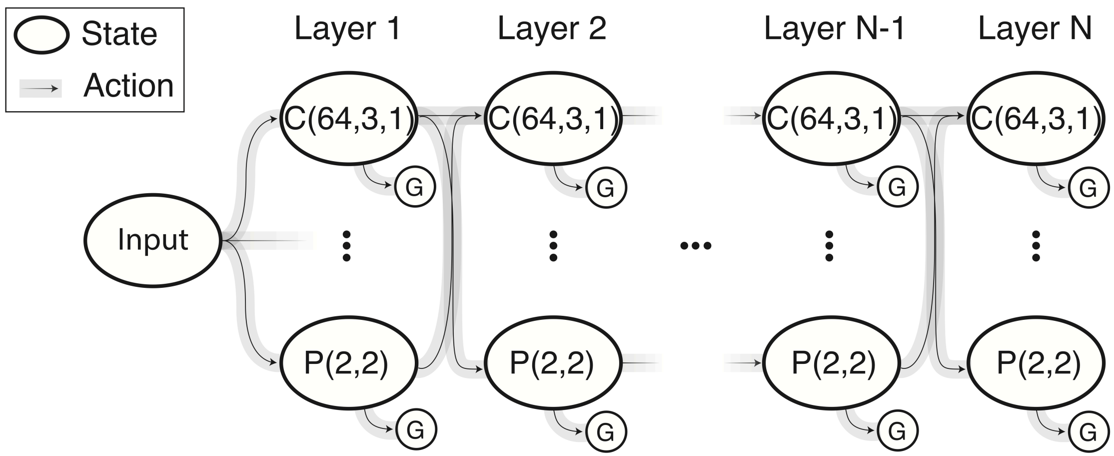




Outline

1. Modeling Architecture Selection as a Markov Decision Process
2. Reinforcement Learning Background
3. Results with Q-Learning
4. Accelerating Architecture Selection with Simple Early Stopping Algorithms

Modeling Architecture Selection as a Markov Decision Process



- C(64,3,1) – Convolutional Layer with 64 learnable kernels, 3x3 kernel size, and stride of 1

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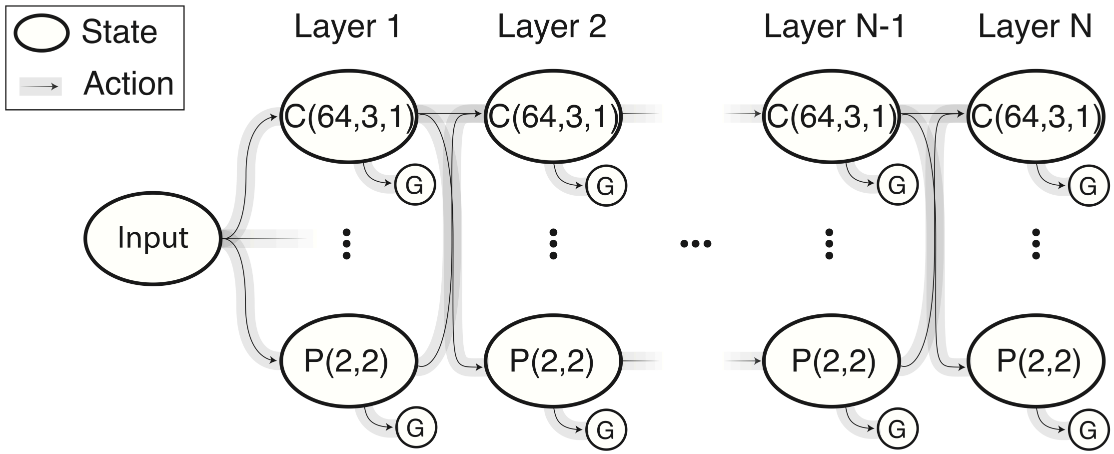

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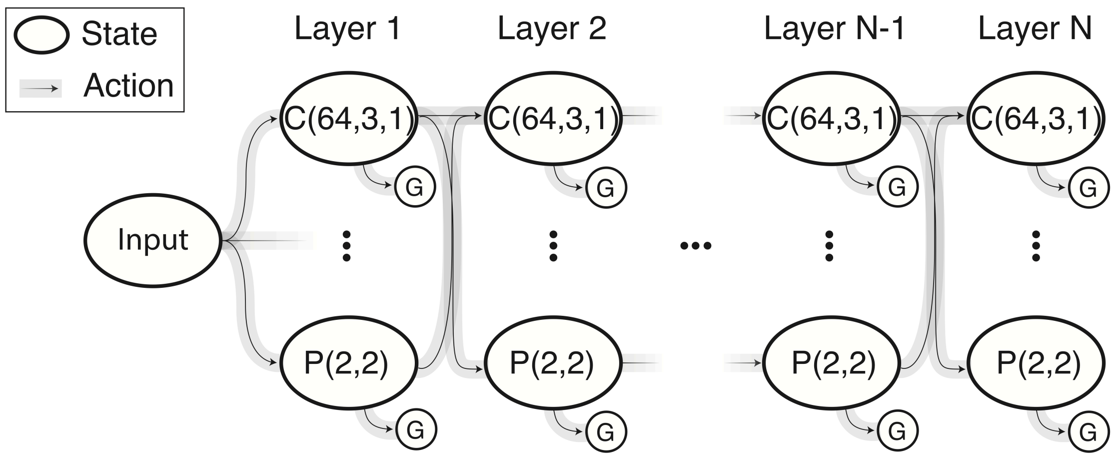

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- G – Termination State (e.g. Softmax)

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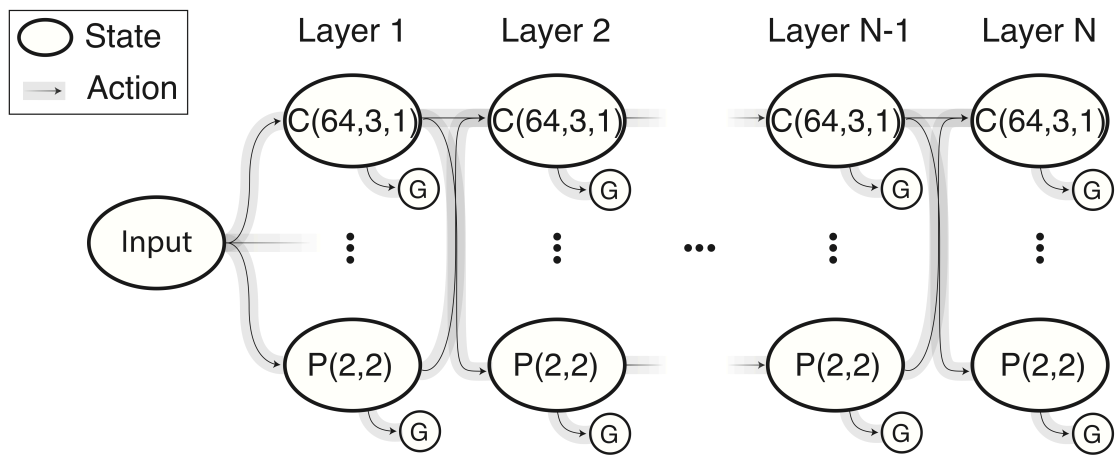
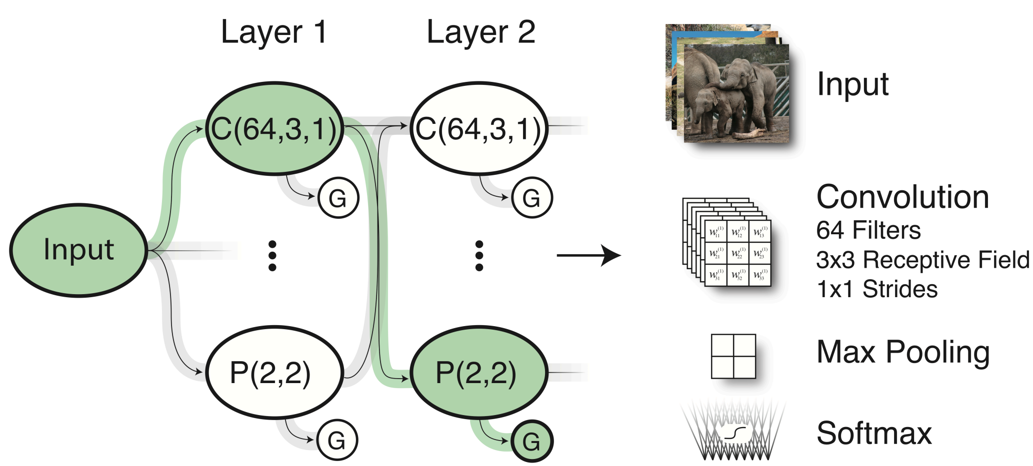




Q-Learning

$Q^*(s, u)$ -- Denotes the expected reward when following an optimal policy after taking action *u* at state *s*

Q-Learning

$$Q^*(s_i, u) = \mathbb{E}\left[r + \gamma \max_{u' \in \mathcal{U}(s_j)} Q^*(s_j, u')\right]$$

γ -- Discount Factor

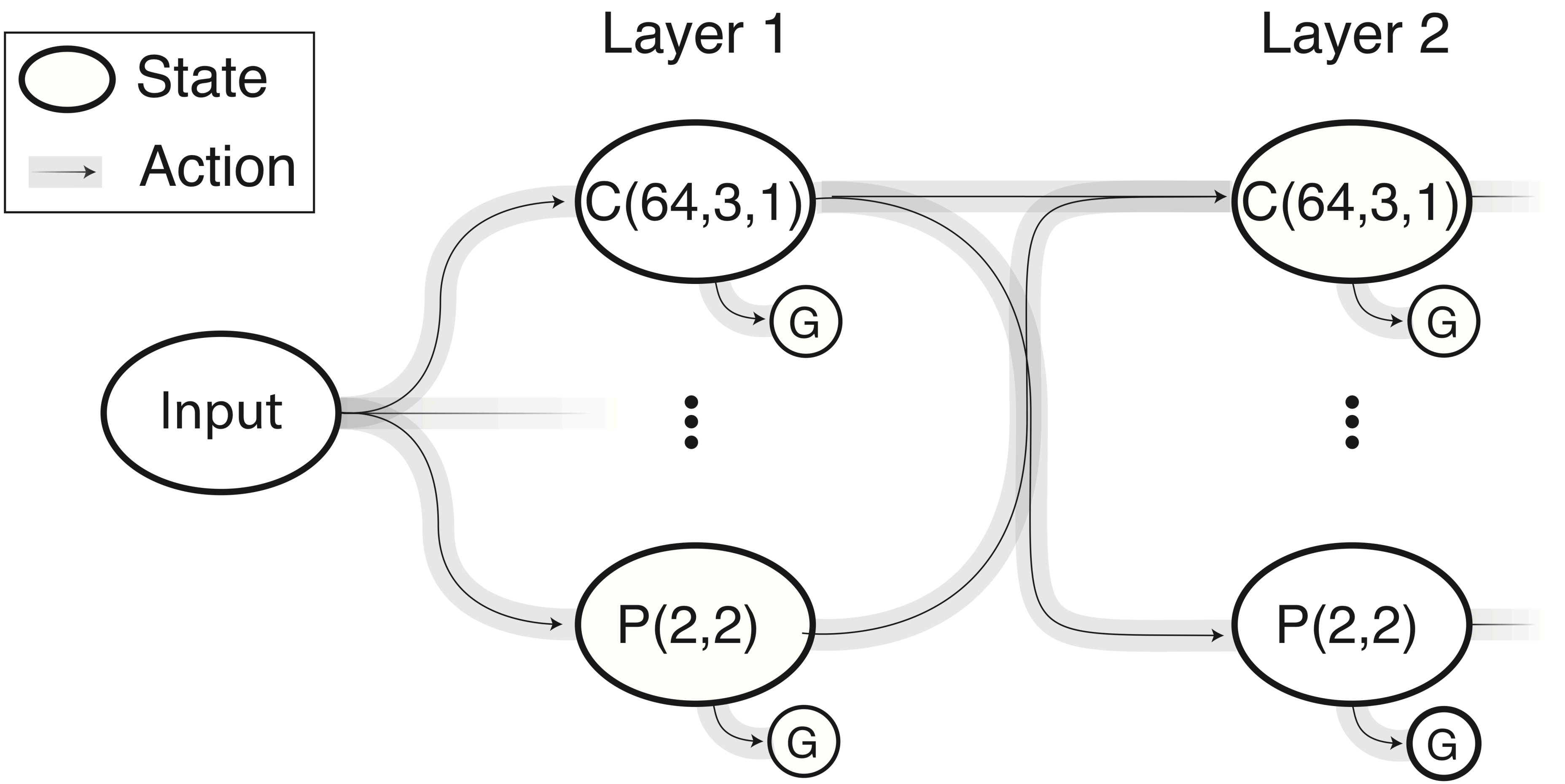
r -- Reward received from the (s_i, u, s_j) transition

Q-Learning

$$Q^*(s_i, u) = \mathbb{E}\left[r + \gamma \max_{u' \in \mathcal{U}(s_j)} Q^*(s_j, u')\right]$$

$$Q_{t+1}(s_i, u) = (1 - \alpha) Q_t(s_i, u) + \alpha \left[r_t + \gamma \max_{u' \in \mathcal{U}(s_j)} Q_t(s_j, u')\right]$$

Q-Value Update (Example)



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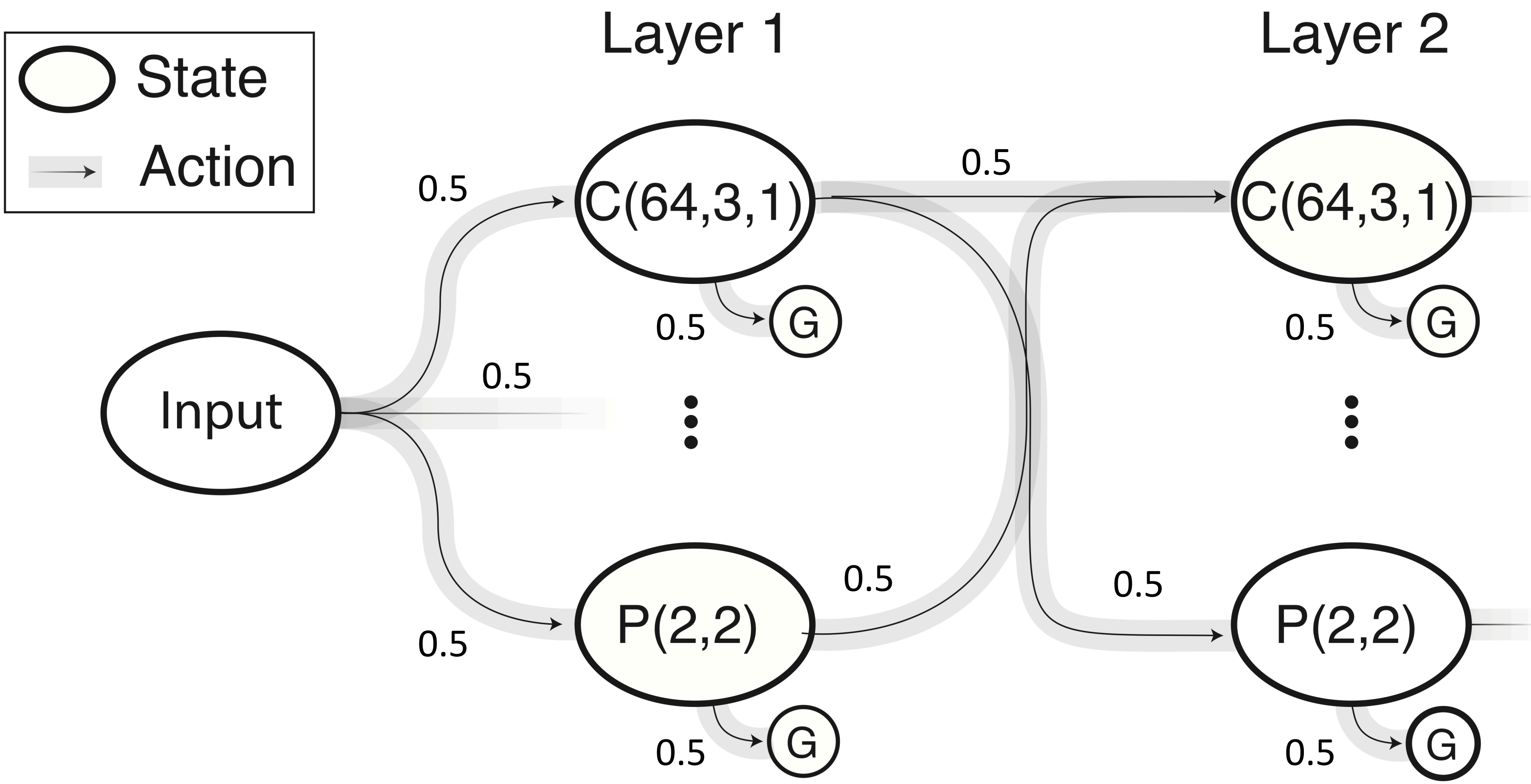

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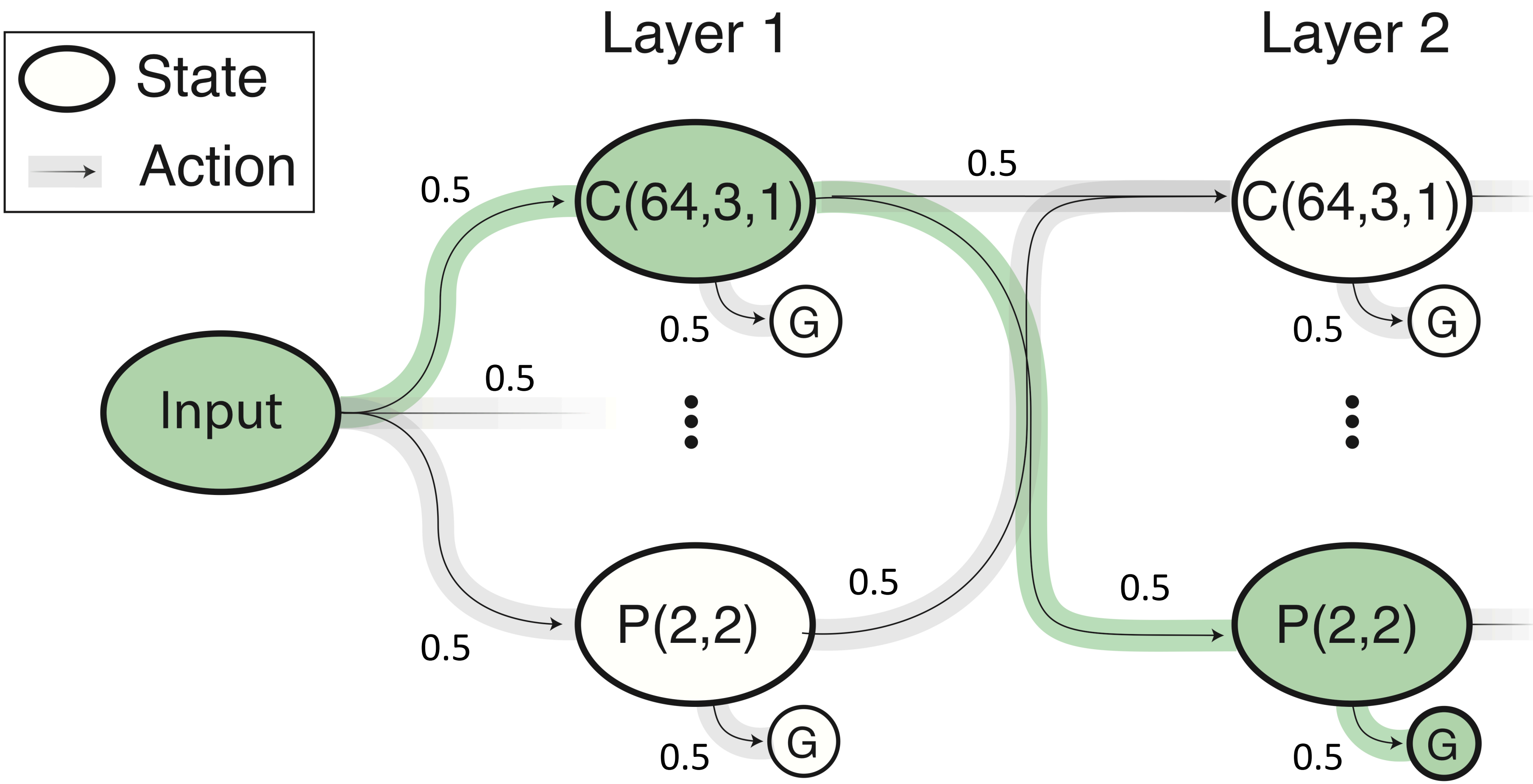

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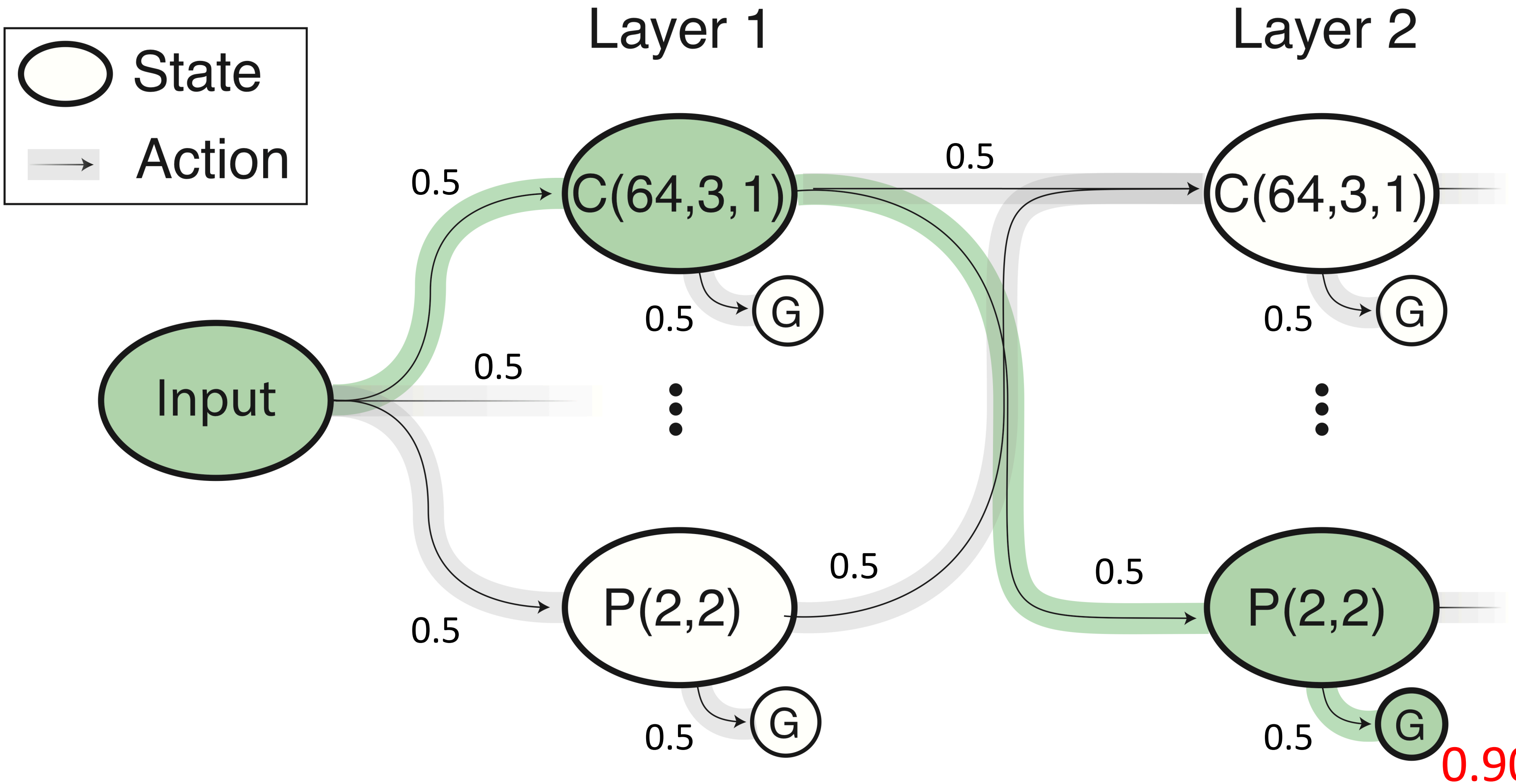

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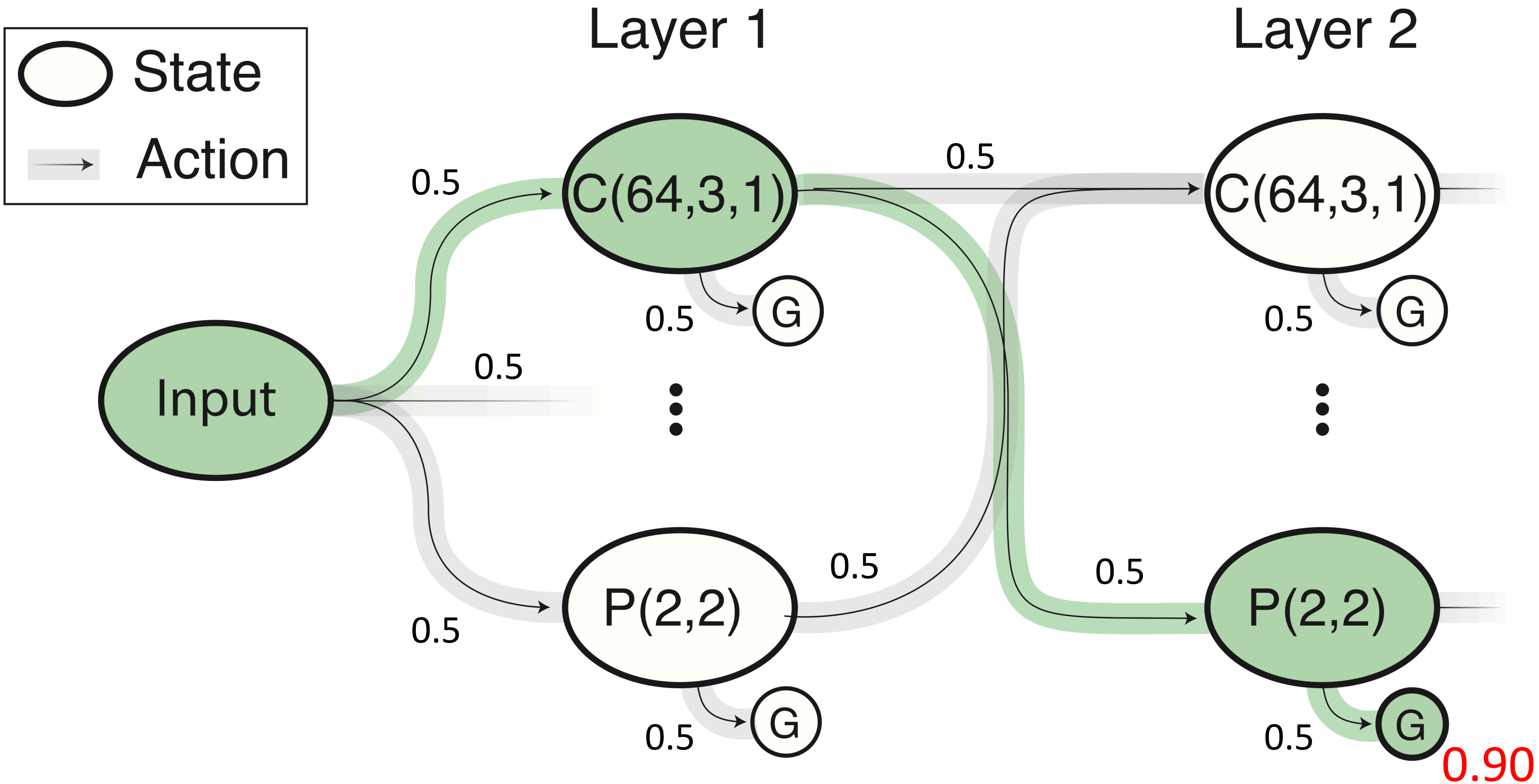

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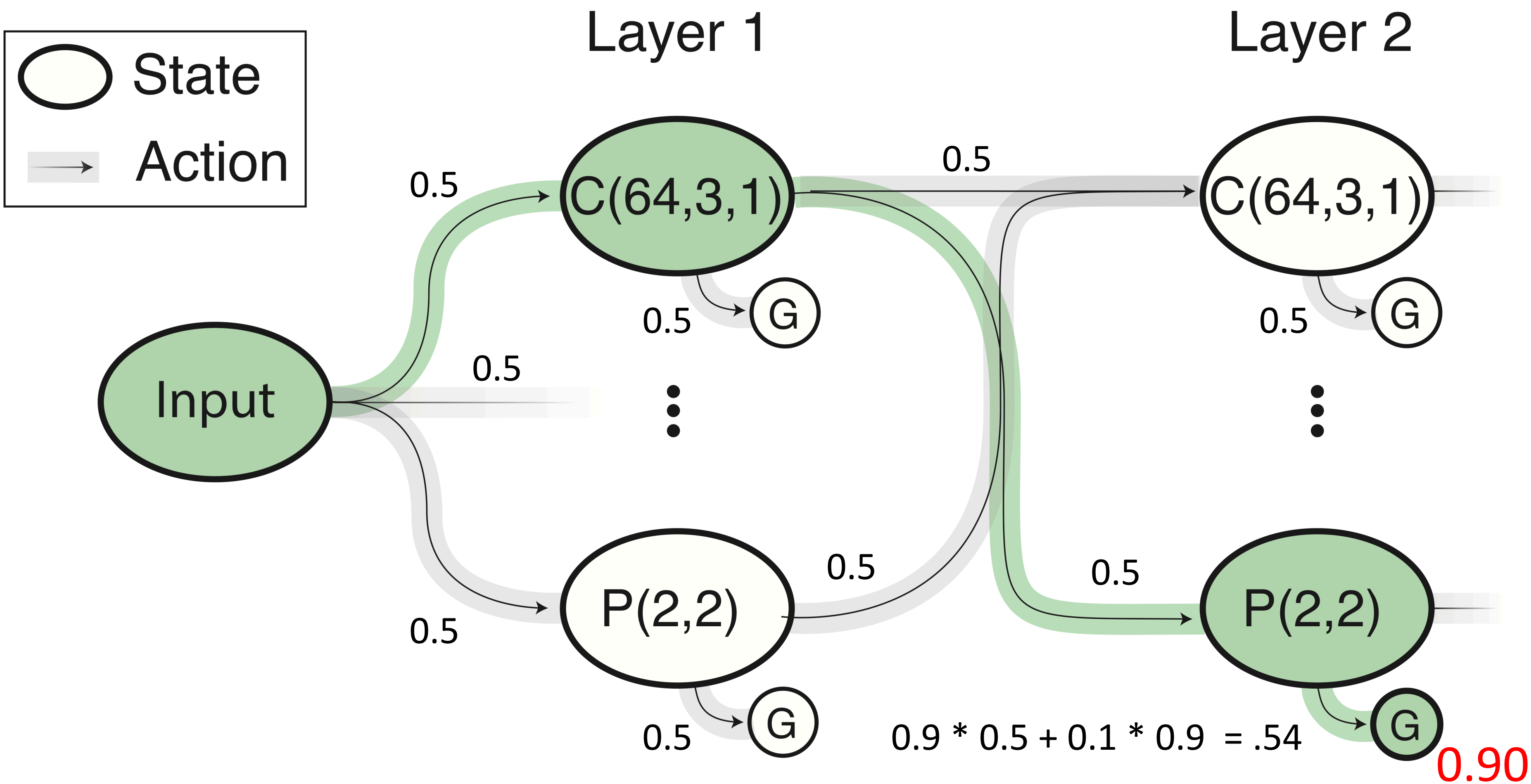

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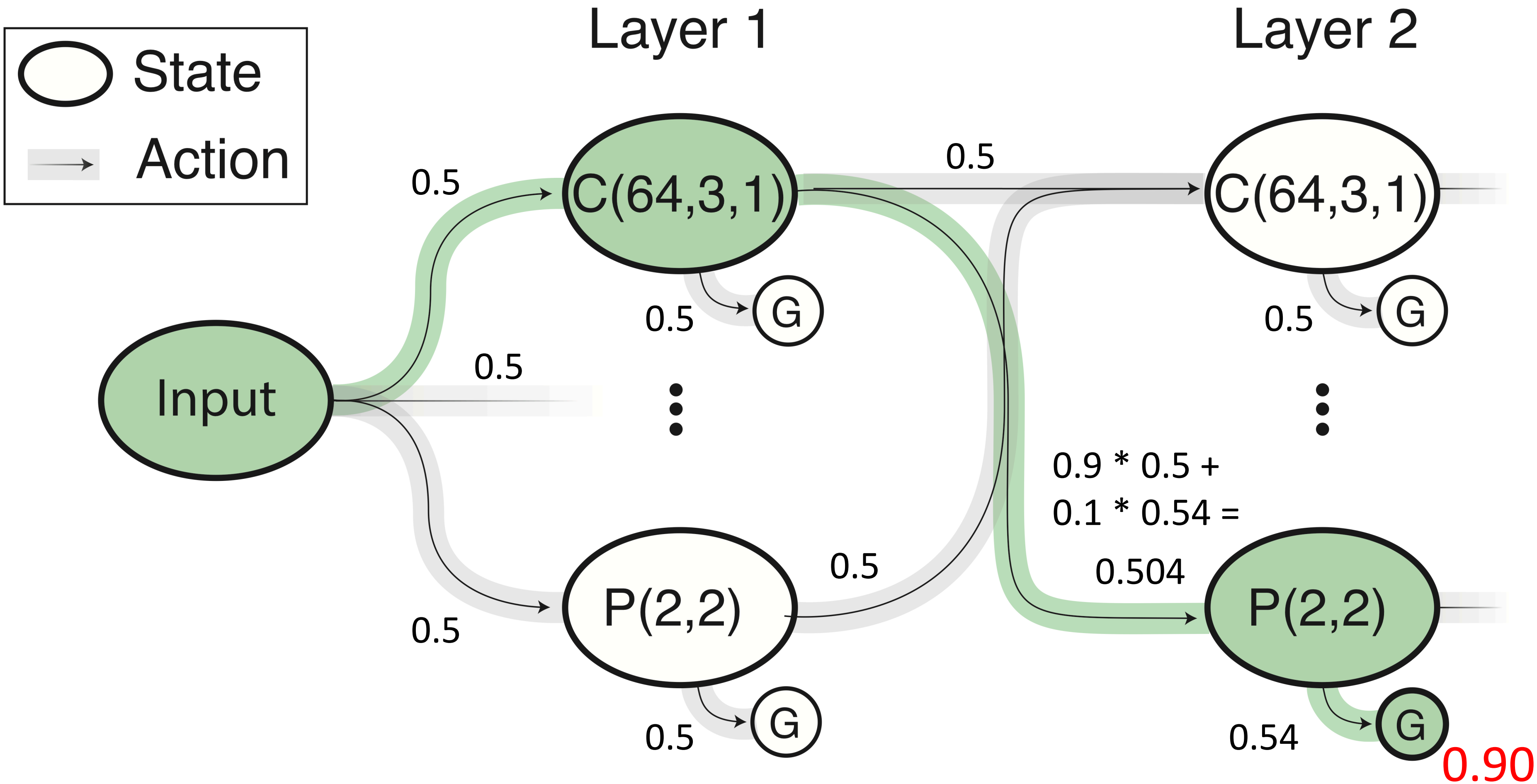

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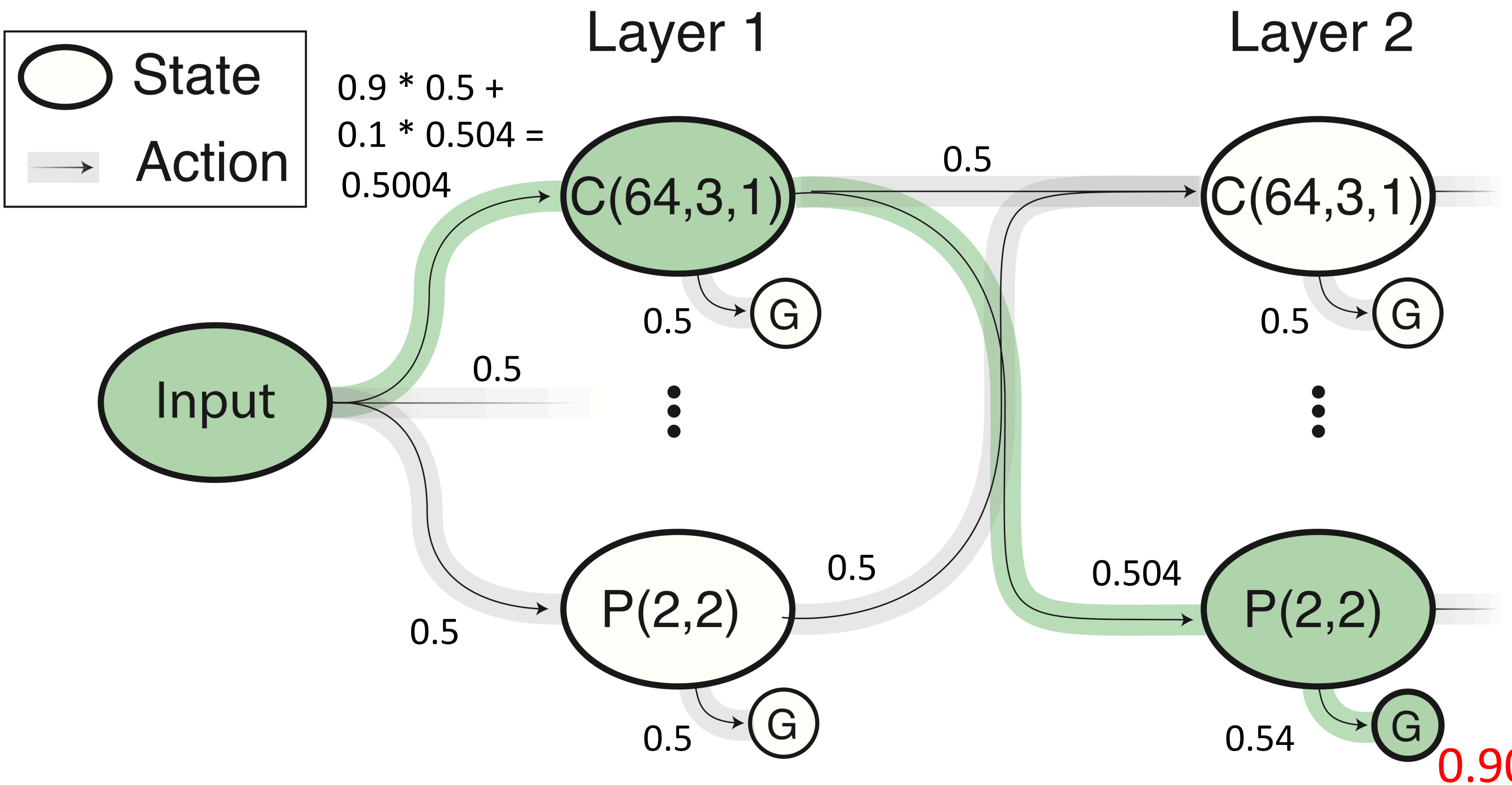
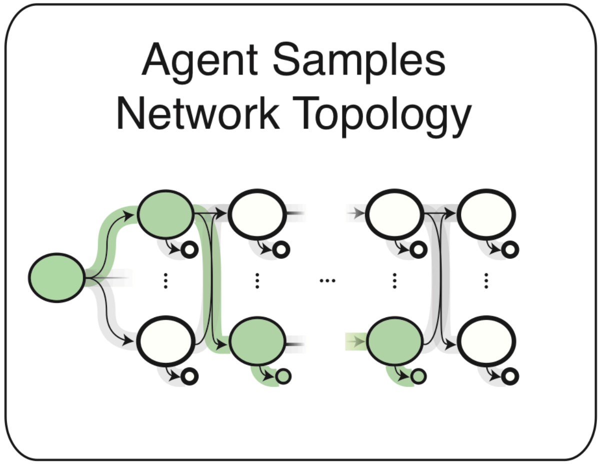


MetaQNN



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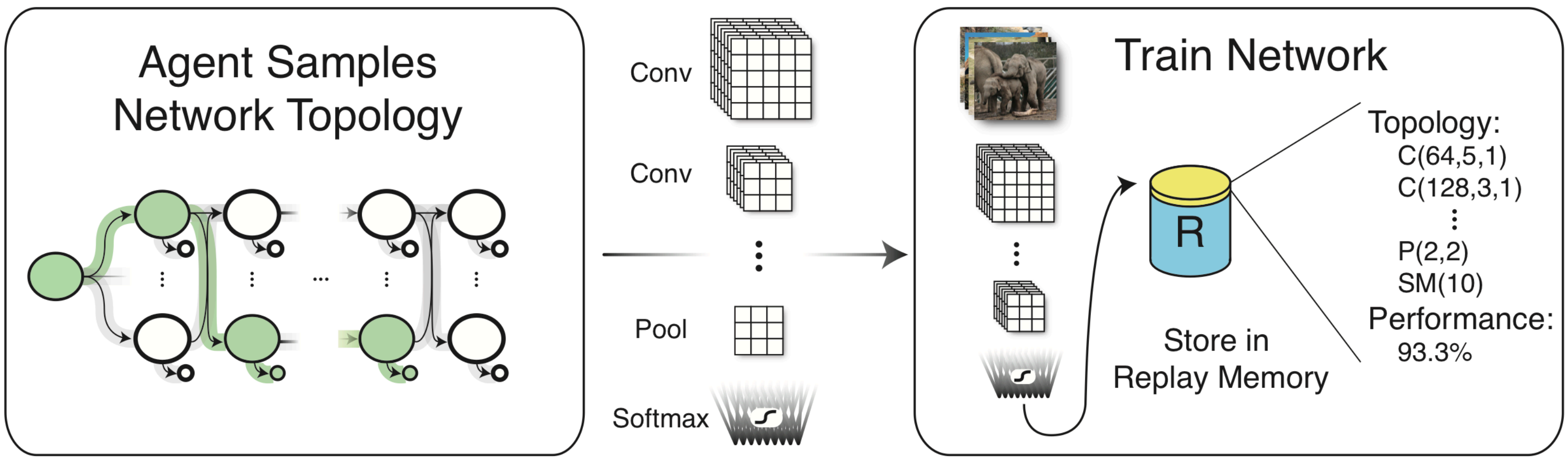
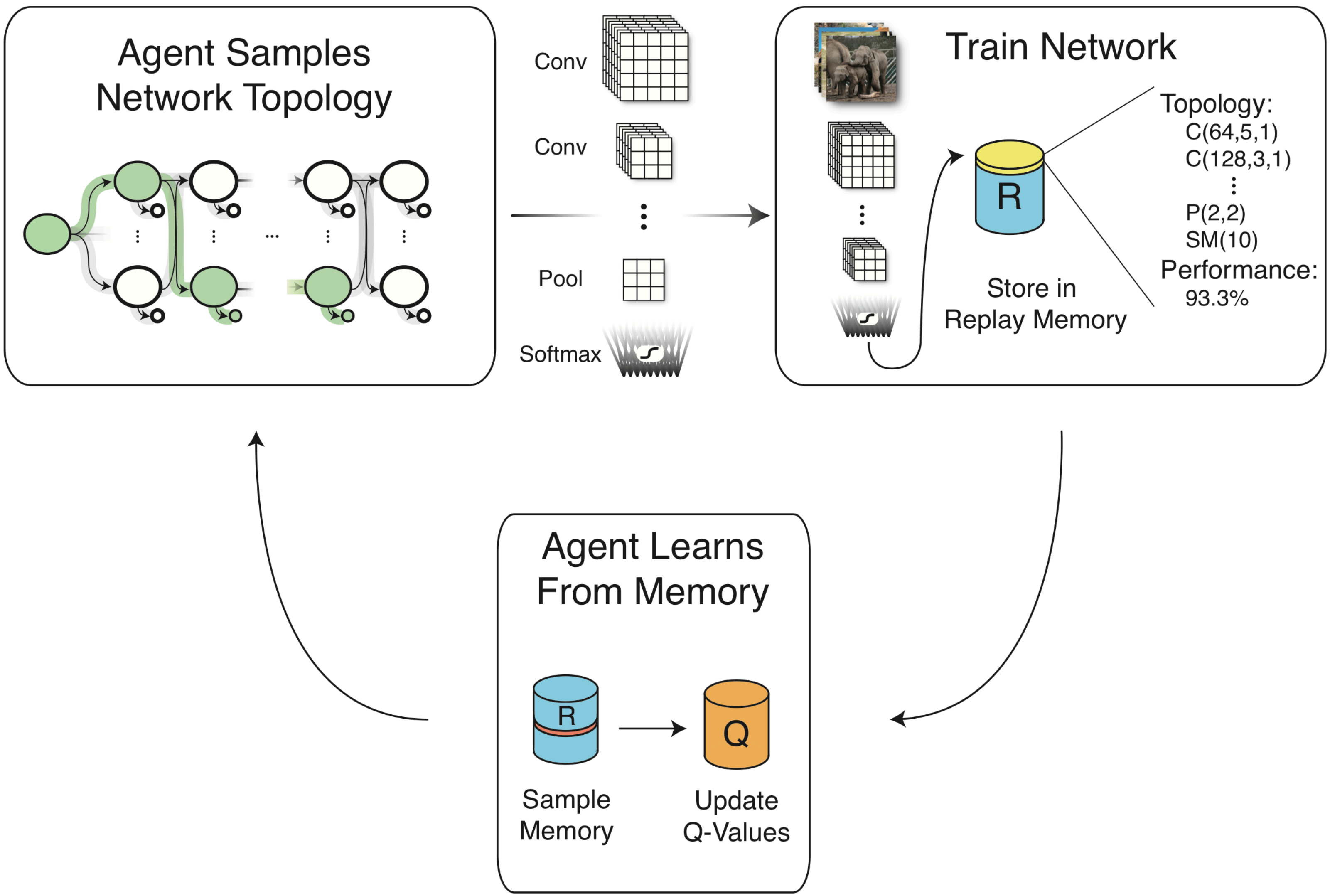


Agent Samples
Network Topology
Conv
Conv
Pool
Softmax
Train Network
R
Store in
Replay Memory
Topology:
C(64,5,1)
C(128,3,1)
P(2,2)
SM(10)
Performance:
93.3%

MetaQNN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R
Store in
Replay Memory
Agent Learns
From Memory
R
Q
Sample
Memory
Update
Q-Values

Sampling Networks

Epsilon-Greedy Exploration:

- State *s* corresponds the last layer chosen
- Action *u* corresponds to the next layer chosen

$$u = \begin{cases} \text{Uniform}[\mathcal{U}(s)] & \text{with probability } \epsilon \\ \arg\max_{u' \in \mathcal{U}(s)} [Q(s, u')] & \text{with probability } 1 - \epsilon \end{cases}$$

State Space

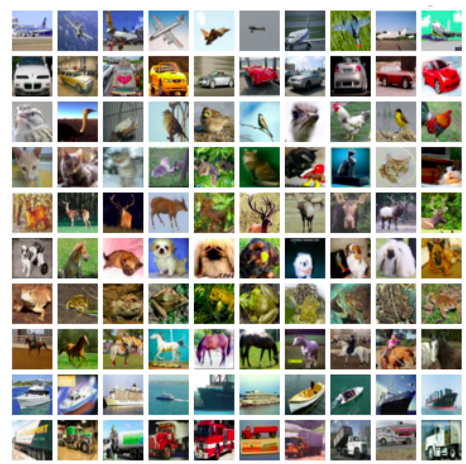
Layer Type	Layer Parameters	Parameter Values
Convolution (C)	$i \sim$ Layer depth $f \sim$ Receptive field size $\ell \sim$ Stride $d \sim$ # receptive fields $n \sim$ Representation size	< 12 Square. $\in \{1, 3, 5\}$ Square. Always equal to 1 $\in \{64, 128, 256, 512\}$ $\in \{(\infty, 8], (8, 4], (4, 1]\}$
Pooling (P)	$i \sim$ Layer depth $(f, \ell) \sim$ (Receptive field size, Strides) $n \sim$ Representation size	< 12 Square. $\in \{(5, 3), (3, 2), (2, 2)\}$ $\in \{(\infty, 8], (8, 4]$ and $(4, 1]\}$
Fully Connected (FC)	$i \sim$ Layer depth $n \sim$ # consecutive FC layers $d \sim$ # neurons	< 12 < 3 $\in \{512, 256, 128\}$
Termination State	$s \sim$ Previous State $t \sim$ Type	 Global Avg. Pooling/Softmax

Experiments

MNIST

- Hand Written Digits
- 60,000 Training Examples
- 10,000 Testing Examples
- 10 classes

CIFAR-10



- Tiny Images
- 50,000 Training Examples
- 10,000 Testing Examples
- 10 classes

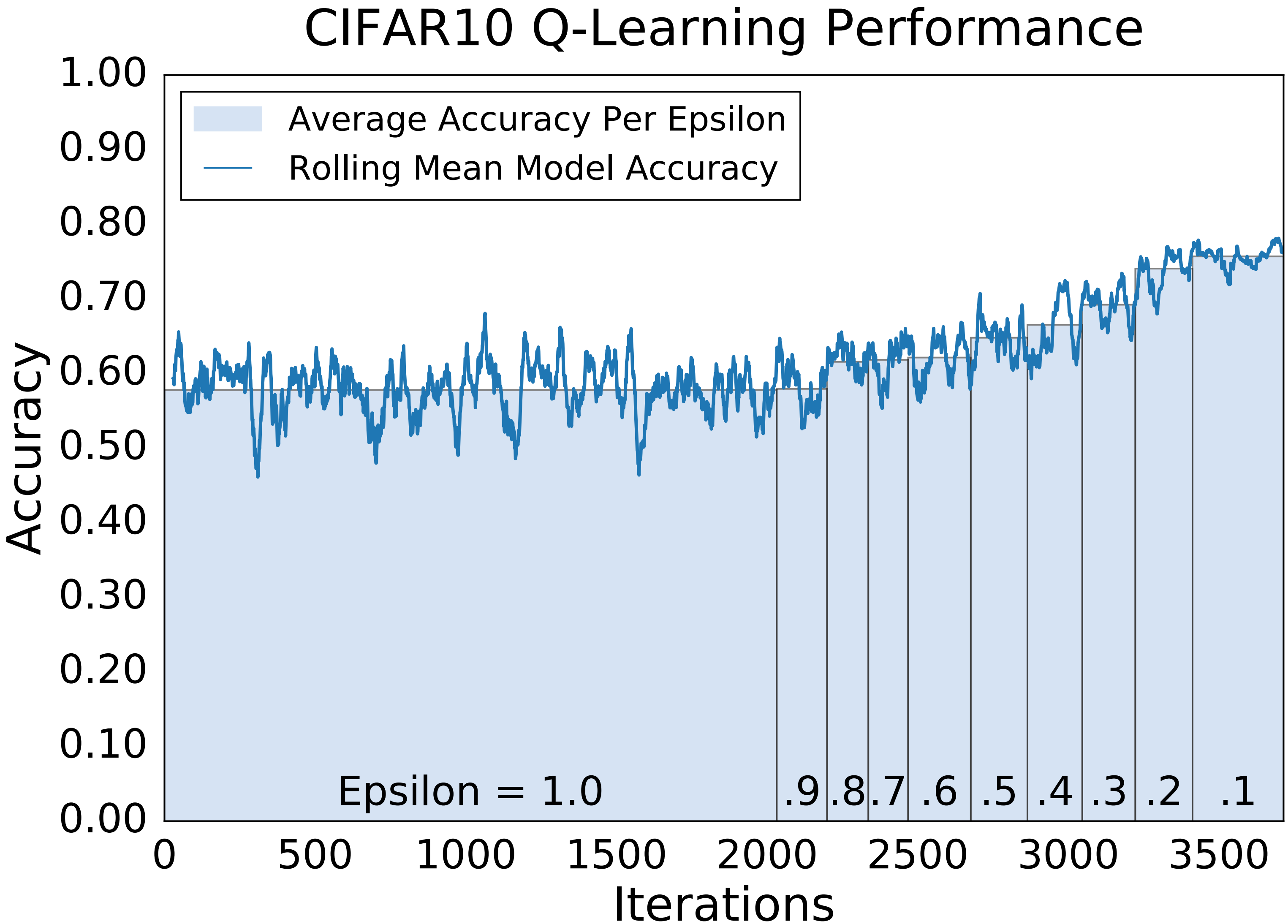
SVHN

- Street View House Digits
- 73257 Training Examples
- 26032 Testing Examples
- 531131 ‘Extra’ Examples
- 10 classes

Hardware

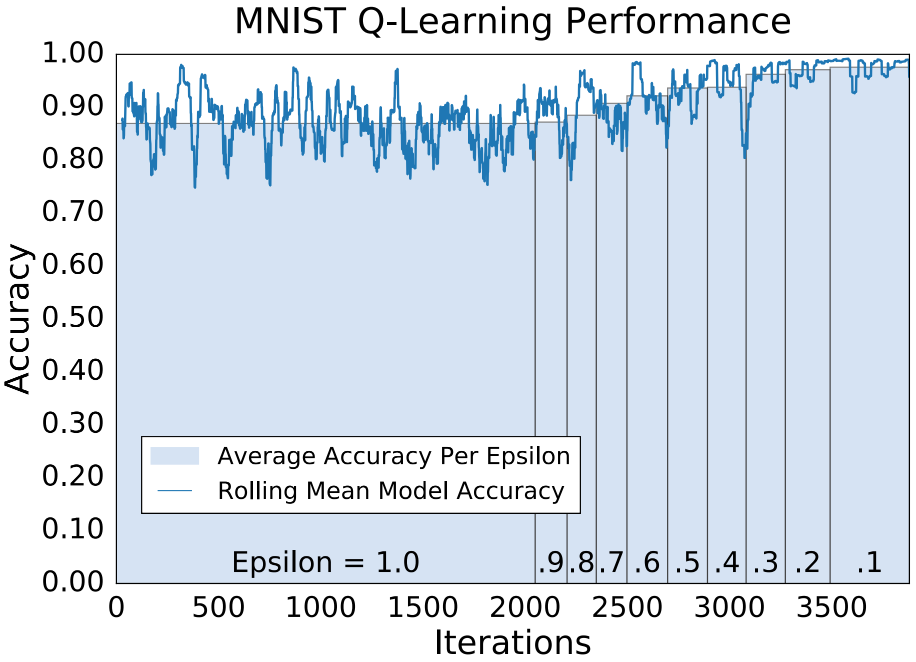
- ~10 GPU’s
  - Mostly 2015 Titan Xs
  - Some GTX 1080s
- Each experiment took ~10 days
  - Roughly 100 GPUdays

Results



CIFAR10 Q-Learning Performance
Average Accuracy Per Epsilon
Rolling Mean Model Accuracy
Accuracy
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Epsilon = 1.0
.9
.8
.7
.6
.5
.4
.3
.2
.1
0
500
1000
1500
2000
2500
3000
3500
Iterations

Results



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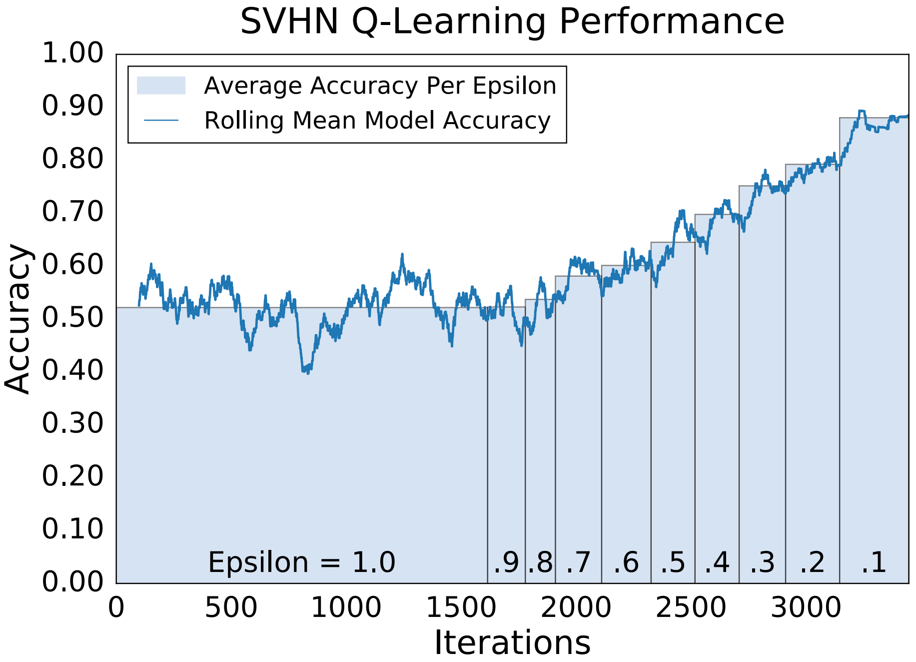

SVHN Q-Learning Performance
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Results

Comparison Against Models with similar design modules:

Method	CIFAR-10	SVHN	MNIST	CIFAR-100
Maxout (Goodfellow et al., 2013)	9.38	2.47	0.45	38.57
NIN (Lin et al., 2013)	8.81	2.35	0.47	35.68
FitNet (Romero et al., 2014)	8.39	2.42	0.51	35.04
HighWay (Srivastava et al., 2015)	7.72	-	-	-
VGGnet (Simonyan & Zisserman, 2014)	7.25	-	-	-
All-CNN (Springenberg et al., 2014)	7.25	-	-	33.71
MetaQNN (ensemble)	7.32	**2.06**	**0.32**	-
MetaQNN (top model)	**6.92**	2.28	0.44	**27.14***

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Comparison Against more complex modules:

Method	CIFAR-10	SVHN	MNIST	CIFAR-100
DropConnect (Wan et al., 2013)	9.32	1.94	0.57	-
DSN (Lee et al., 2015)	8.22	1.92	0.39	34.57
R-CNN (Liang & Hu, 2015)	7.72	1.77	**0.31**	31.75
MetaQNN (ensemble)	7.32	2.06	0.32	-
MetaQNN (top model)	6.92	2.28	0.44	27.14*
Resnet(110) (He et al., 2015)	6.61	-	-	-
Resnet(1001) (He et al., 2016)	**4.62**	-	-	**22.71**
ELU (Clevert et al., 2015)	6.55	-	-	24.28
Tree+Max-Avg (Lee et al., 2016)	6.05	**1.69**	**0.31**	32.37

Meta-Modeling Comparison on CIFAR-10

Method	Test Error on CIFAR-10	# Samples	Estimated Computation (GPU-Days)
MetaQNN (Ours)	6.92	2,700	100
Neural Architecture Search (Zoph et al., 2016)	3.65	12,800	10,000
Large Scale Evolution (Real et al., 2017)	5.4	-	2,600
Bayesian Optimization (Snoek et al., 2012)	9.5	50	-

Updated Results:

Different Model Depths Don’t Train Equally

Model Depth	20 Epoch Accuracy	300 Epoch Accuracy
9	84.78	93.08
15	81.2	94.7

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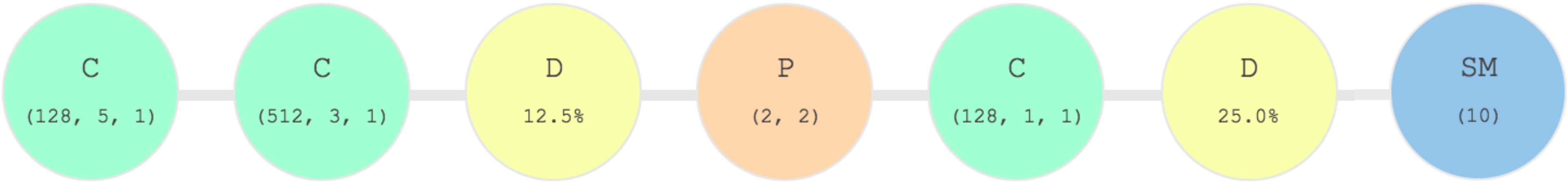

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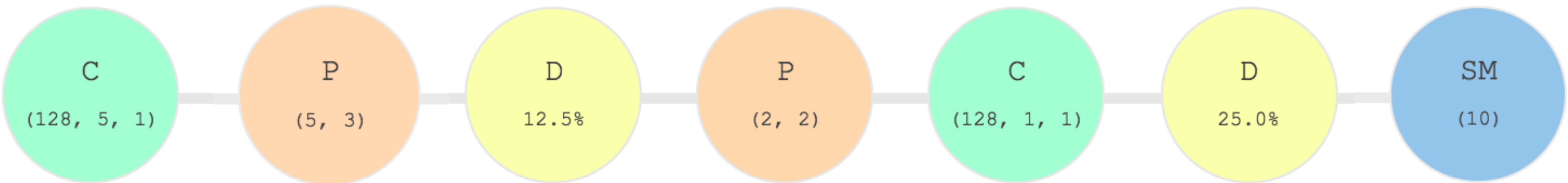

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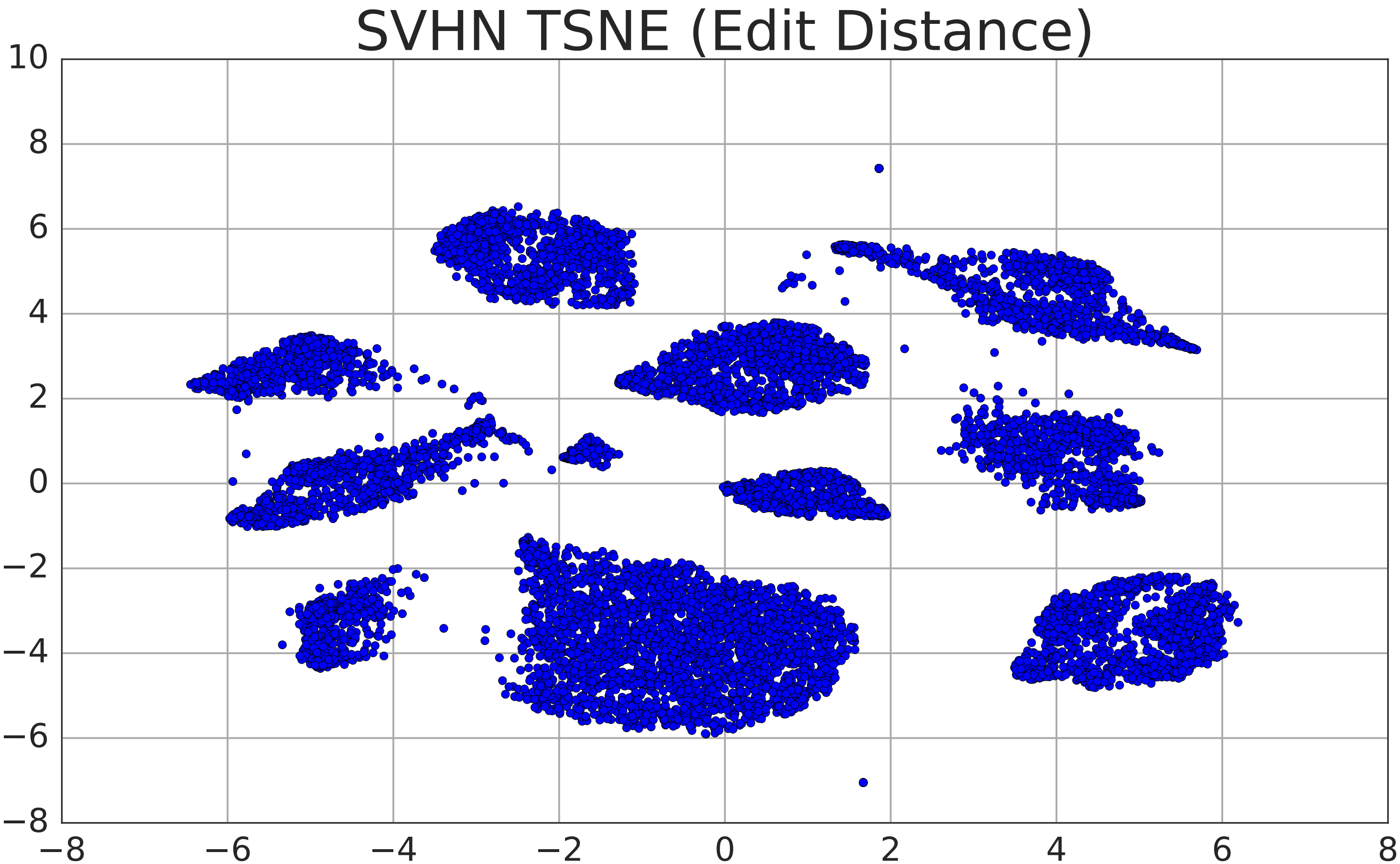

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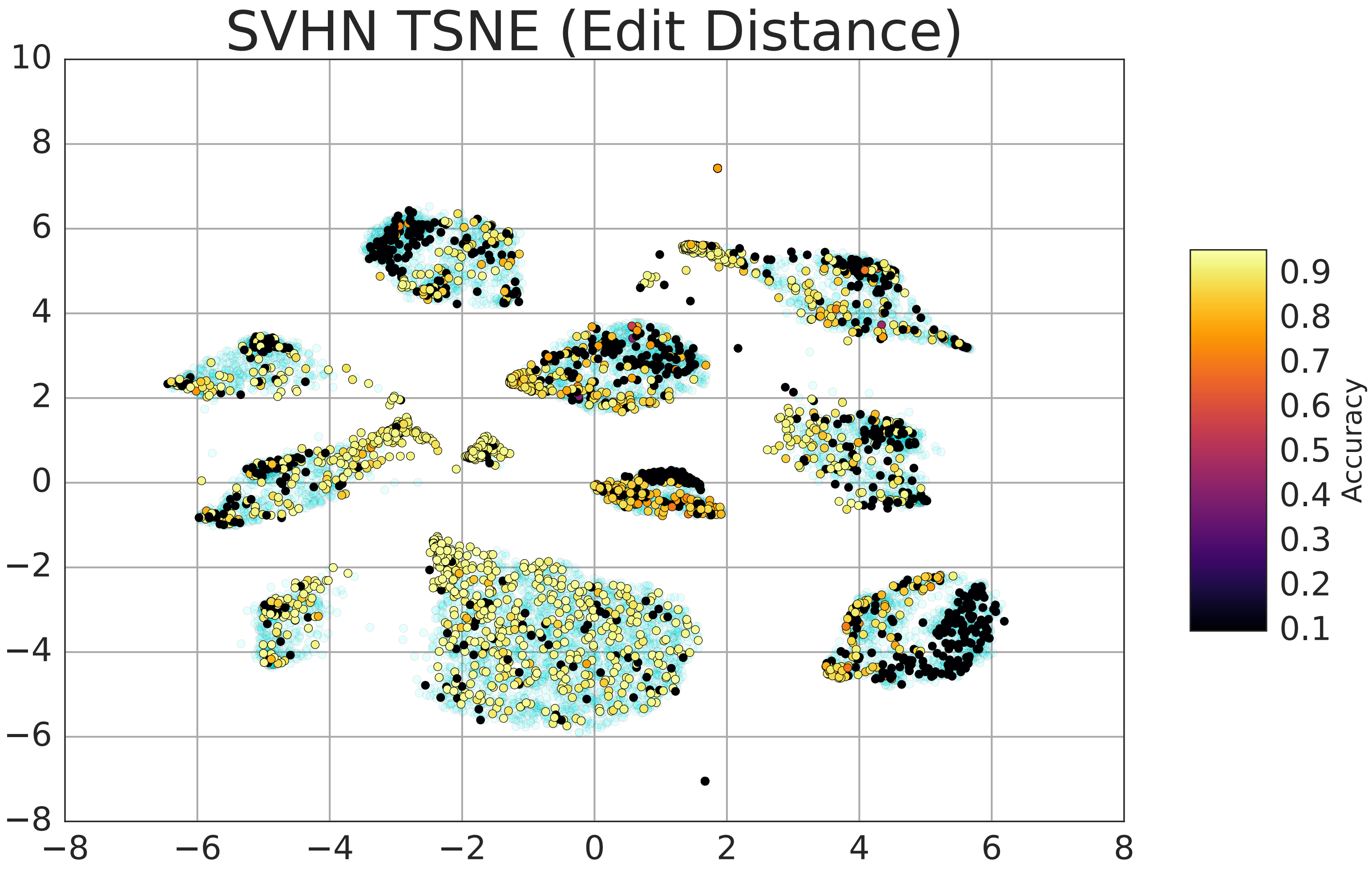

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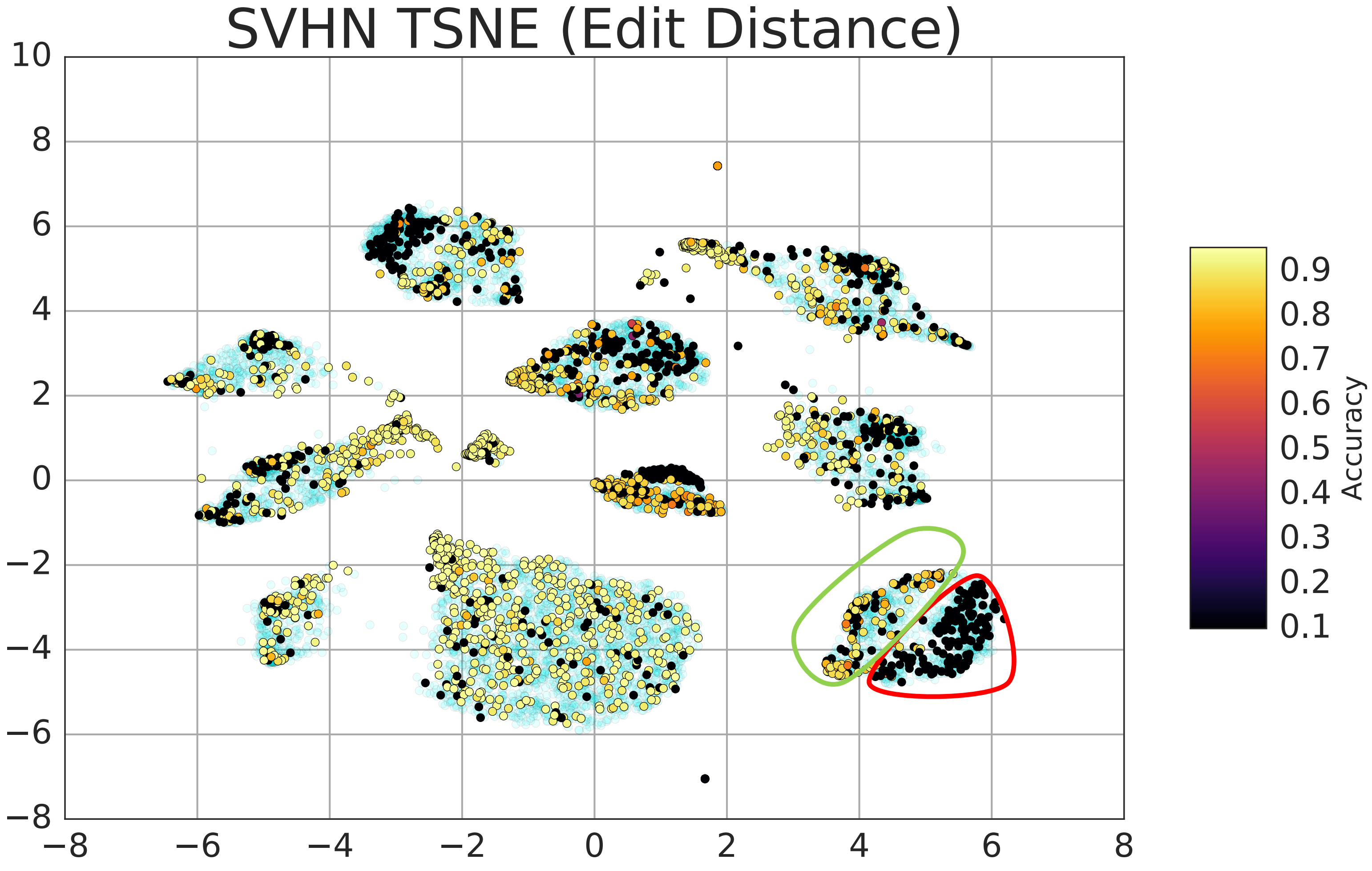

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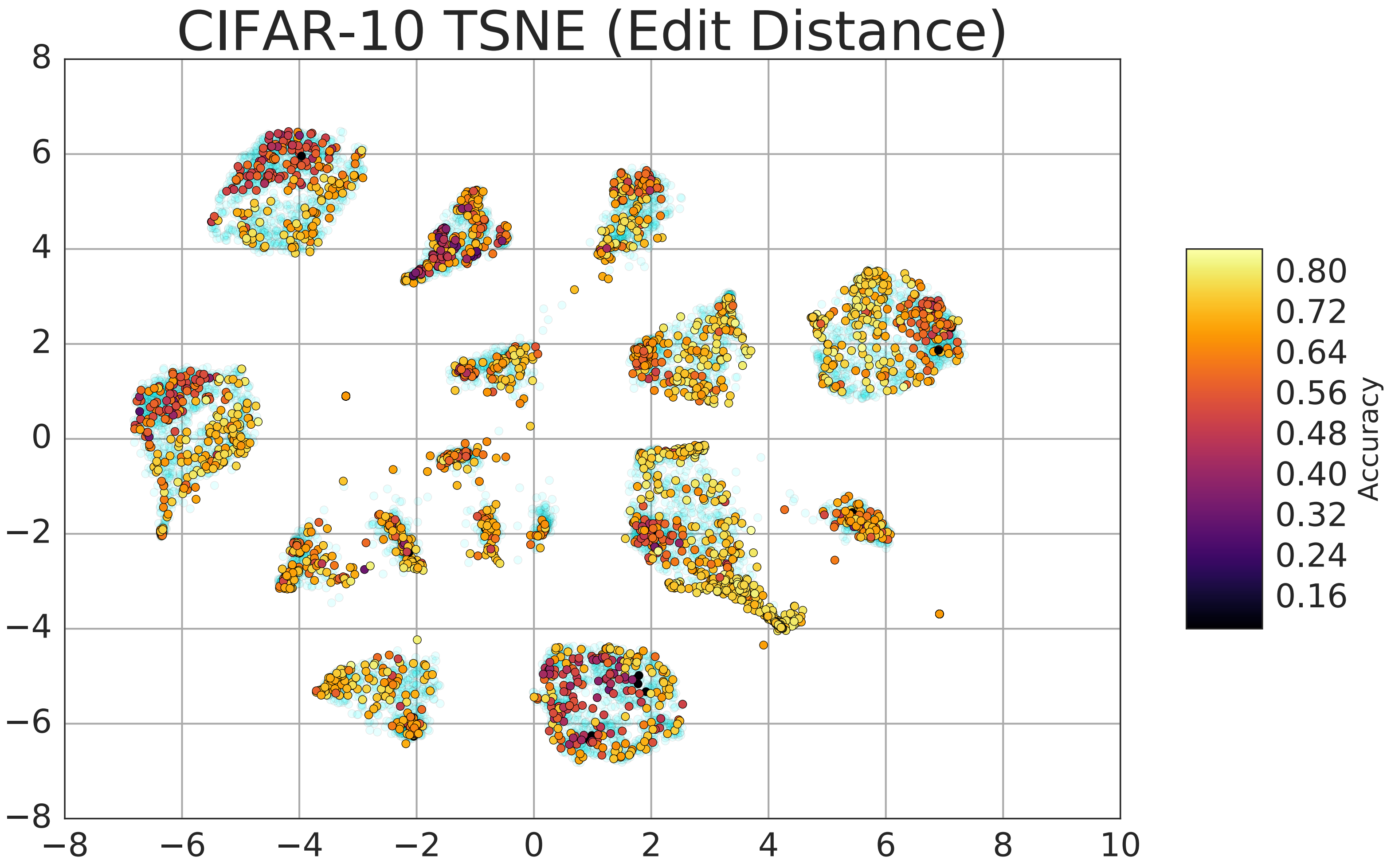

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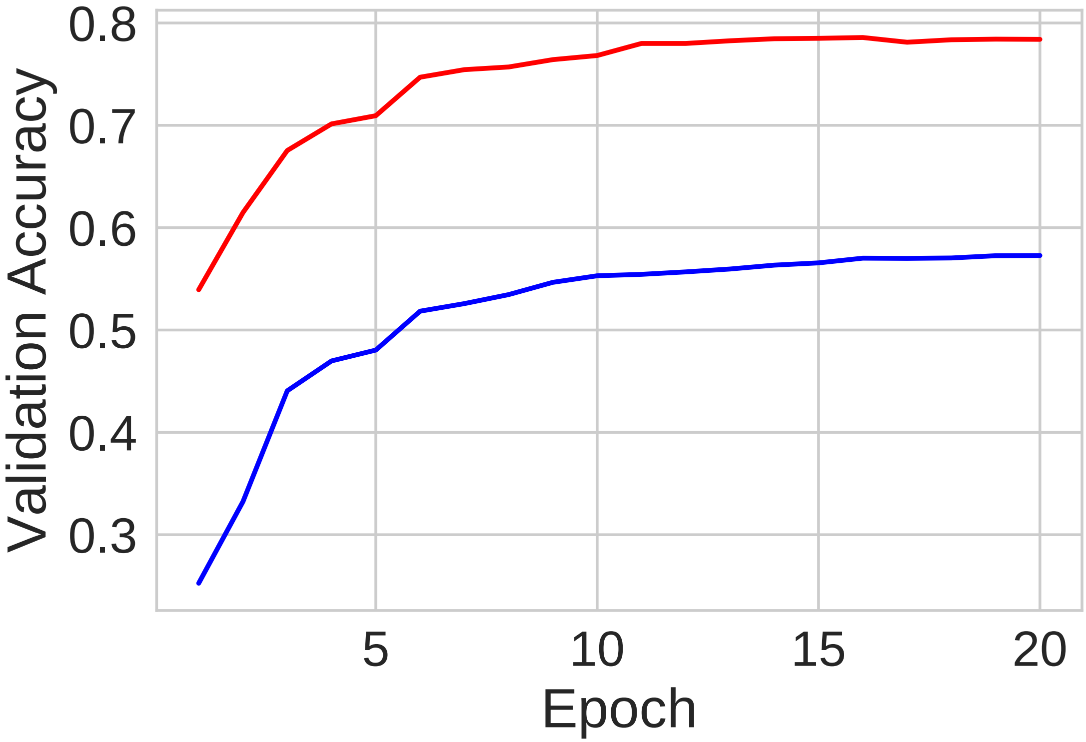
MetaQNN (Ours)	6.92	2,700	**100**
Neural Architecture Search (Zoph et al., 2016)	3.65	12,800	**10,000**
Large Scale Evolution (Real et al., 2017)	5.4	-	**2,600**
Bayesian Optimization (Snoek et al., 2012)	9.5	50	-

Early Stopping

- Humans are pretty good at recognizing sub-optimal training configurations



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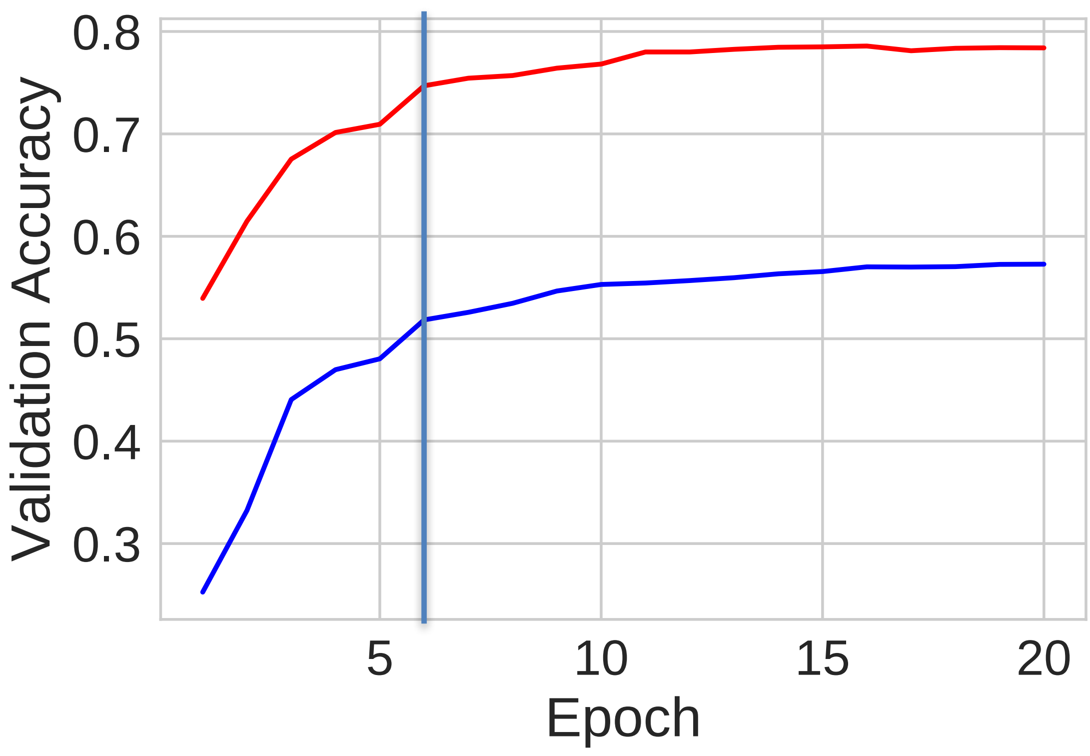
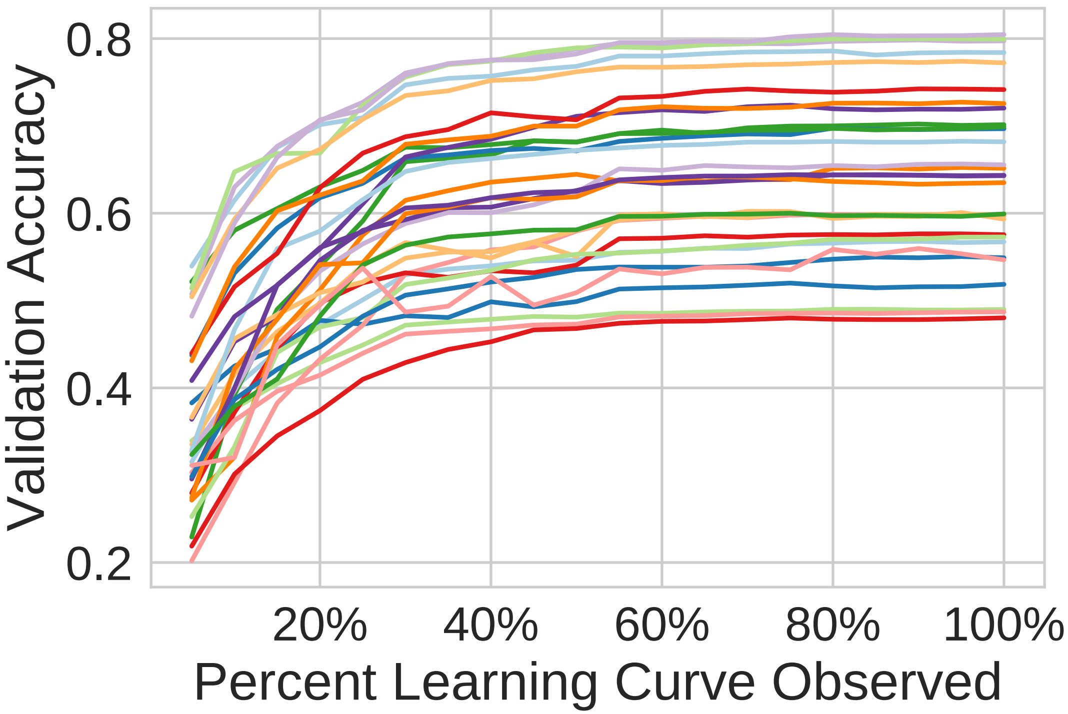


Early Stopping Using Partially Observed Learning Curves

- Use a simple model to predict final accuracy given a partially observed learning curve



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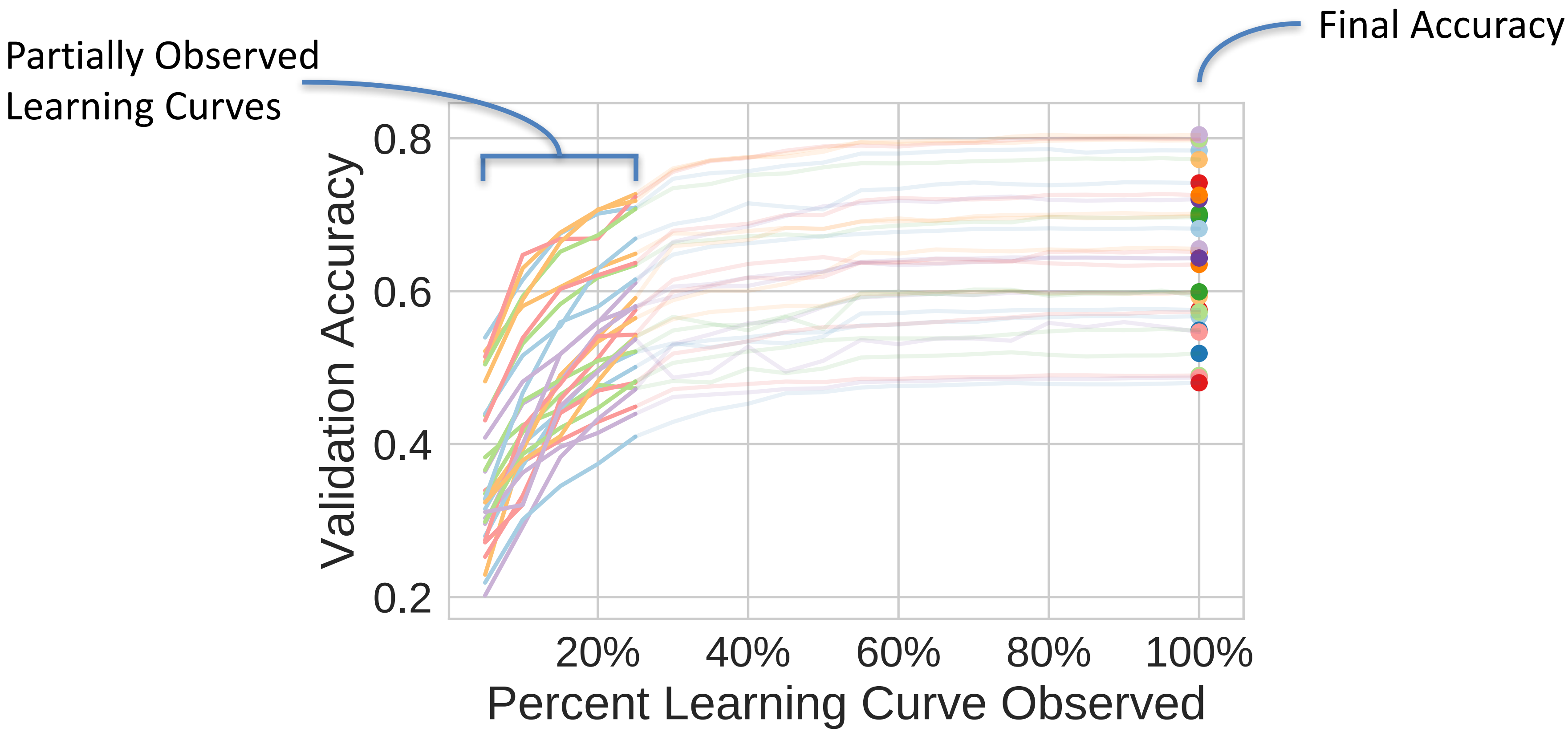

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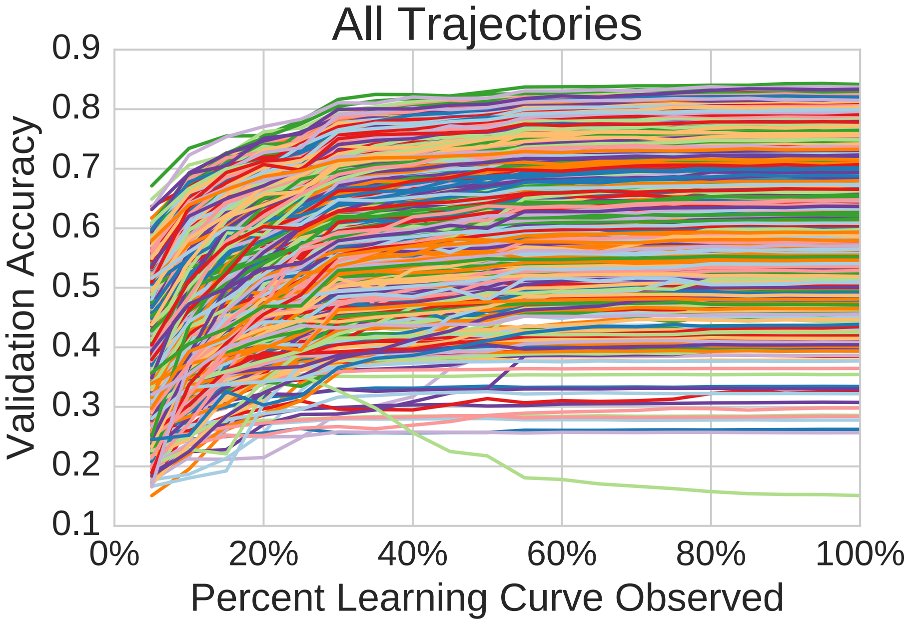
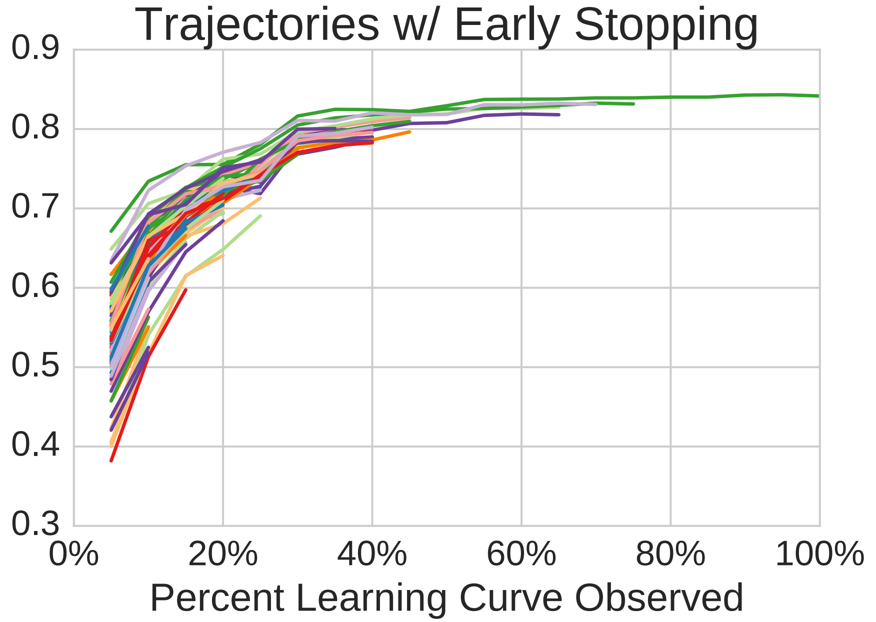
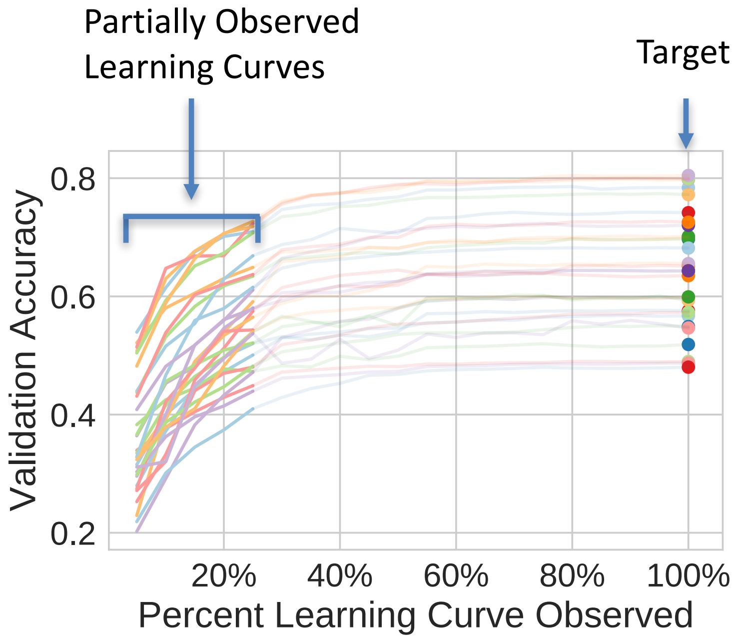




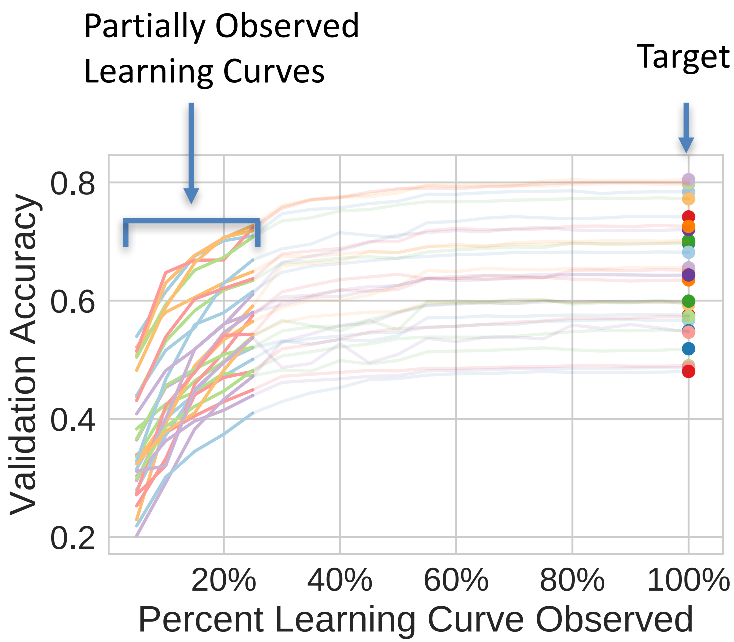
Performance Prediction Model

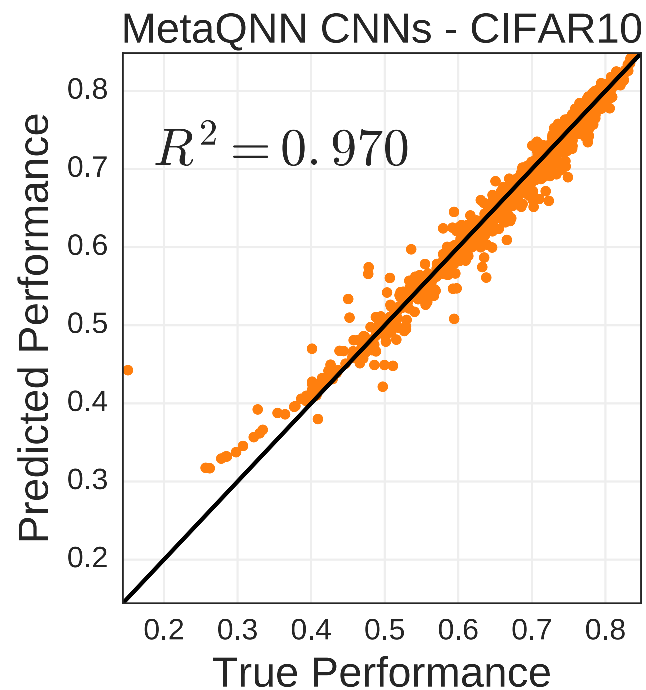
- Features:
  - $y_{1 \ldots t}$ Partially observed learning curves
  - x_f Model features, e.g. # layers, # weights, etc.
- Target
  - y_T Final Accuracy
- Works for both hyperparameter optimization and meta-modeling

Meta-Modeling Example (CIFAR-10)



Meta-Modeling Example (CIFAR-10)





- 100 training examples
- 25% learning curve observed

Early Stopping

1. Given performance prediction model

$$\hat{y}_T(t) = f\left(y_{1\ldots t}, x_f\right)$$

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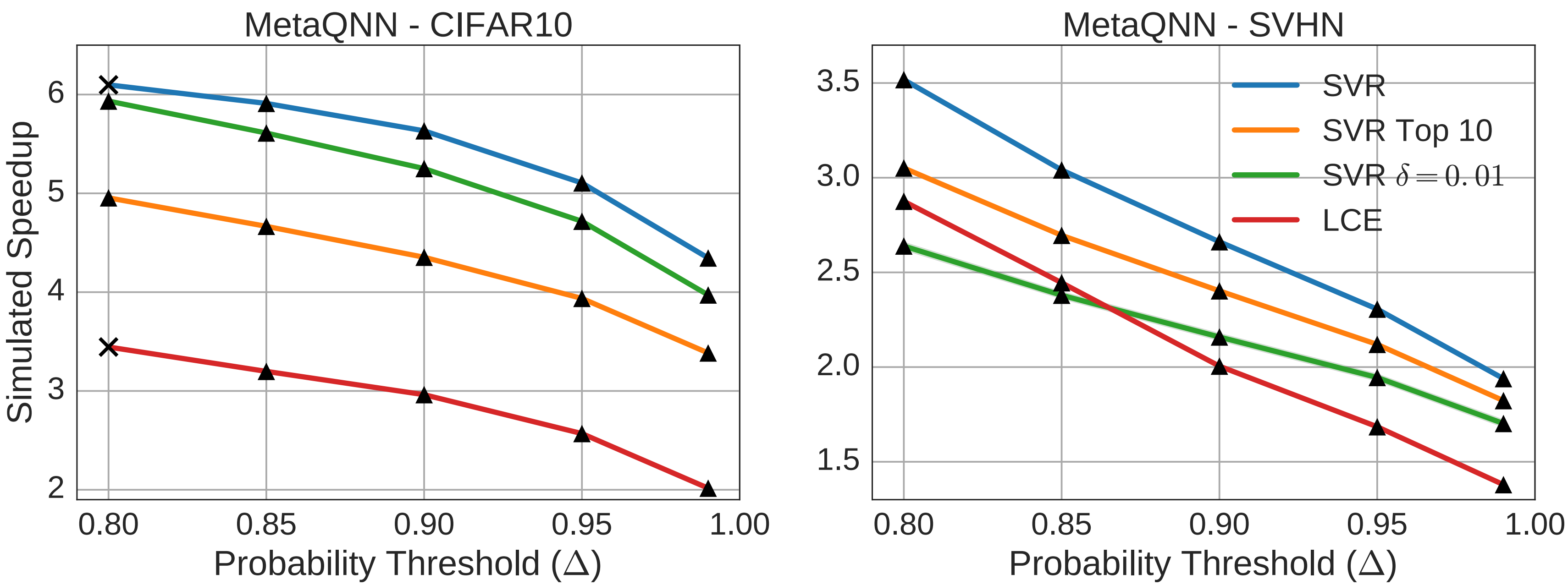
5. Define acceptance probability threshold Δ such that training is terminated at time-step t if

$$p(\hat{y}_T(t) < y_{BEST}) > \Delta$$

Early Stopping Results



X ~ On average does not recover best model

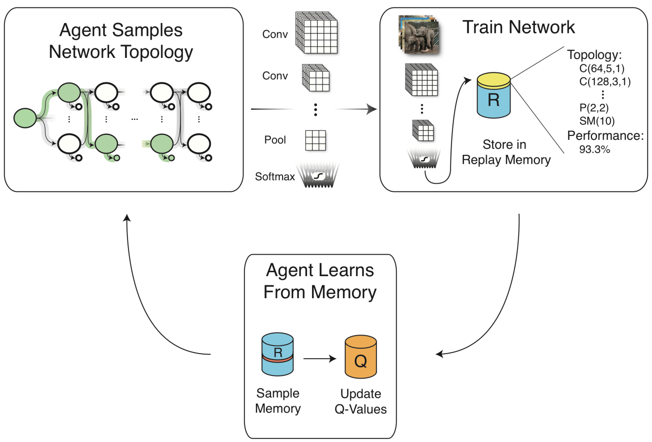
▲ ~ On average recovers best model

δ ~ Termination rule $p(\hat{y}_T(t) < y_{BEST} - \delta) > \Delta$

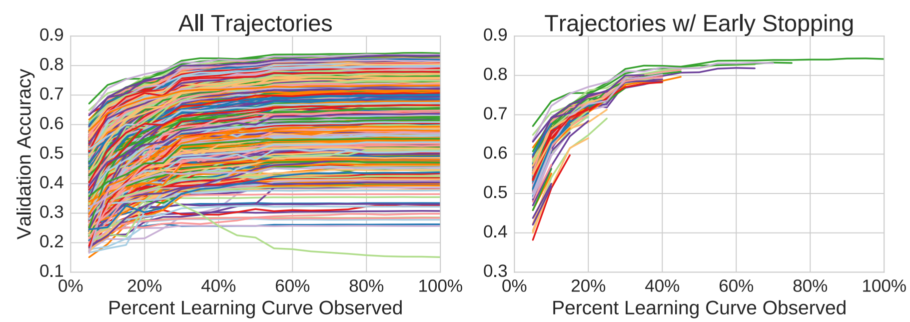
Top 10 ~ Termination rule $p(\hat{y}_T(t) < y_{10^{th}\ BEST}) > \Delta$

Summary

Designing neural network architectures using reinforcement learning [1]



Practical Neural Network Performance Prediction for Early Stopping [2]



Contact: bowen@mit.edu
Slides: bowenbaker.github.io
MetaQNN Code: github.com/bowenbaker/metaqnn

1. Bowen Baker, Otkrist Gupta, Nikhil Naik, and Ramesh Raskar. “Designing neural network architectures using reinforcement learning.” *International Conference on Learning Representations*, 2017.
2. Bowen Baker*, Otkrist Gupta*, Ramesh Raskar, and Nikhil Naik. "Practical Neural Network Performance Prediction for Early Stopping.” *Under Submission*, 2017.