Designing Neural Network Architectures Using Reinforcement Learning

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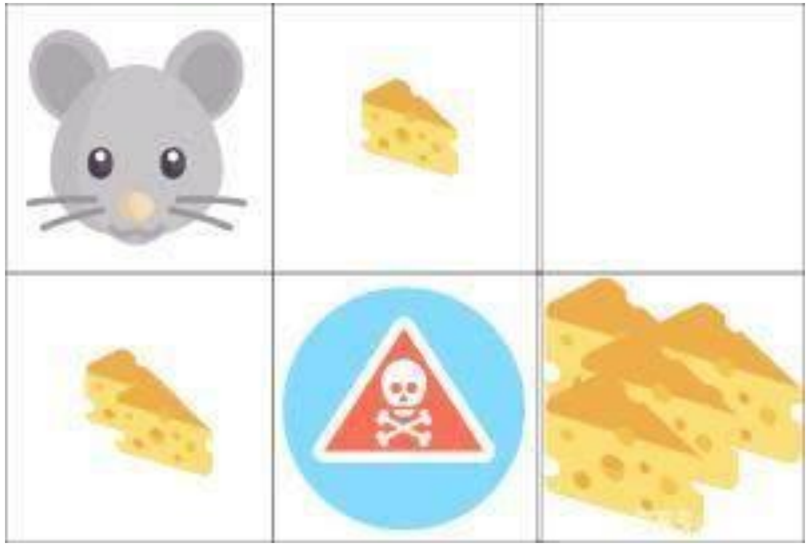
Abstract

At present, designing convolutional neural network (CNN) architectures requires both human expertise and labor. New architectures are handcrafted by careful experimentation or modified from a handful of existing networks. We introduce MetaQNN, a meta-modeling algorithm based on reinforcement learning to automatically generate high-performing CNN architectures for a given learning task. The learning agent is trained to sequentially choose CNN layers using Q-learning with an ϵ-greedy exploration strategy and experience replay. The agent explores a large but finite space of possible architectures and iteratively discovers designs with improved performance on the learning task. On image classification benchmarks, the agent-designed networks (consisting of only standard convolution, pooling, and fully-connected layers) beat existing networks designed with the same layer types and are competitive against the state-of-the-art methods that use more complex layer types. We also outperform existing meta-modeling approaches for network design on image classification tasks.

Q-Learning



Q-Table

	←	→	↑	↓
Start	0	0	0	0
Small cheese	0	0	0	0
Nothing	0	0	0	0
2 small cheese	0	0	0	0
Death	0	0	0	0
Big cheese	0	0	0	0

ε-Greedy Exploration

我们指定一个探索速率ε，一开始将它设定为 1。这个就是我们将随机采用的步长。在一开始，这个速率应该处于最大值，因为我们不知道 Q-table 中任何的值。这意味着，我们需要通过随机选择动作进行大量的探索。

生成一个随机数。如果这个数大于 ε，那么我们将会进行「利用」（这意味着我们在每一步利用已经知道的信息选择动作）。否则，我们将继续进行随机探索。即ε-greedy每次以ε的概率去探索，1-ε的概率来利用。

在刚开始训练 Q 函数时，我们必须有一个大的 ε以便掌握更多的信息。随着agent对估算出的 Q 值更有把握，我们将逐渐减小 ε。

Bellman 方程

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

The update equation has two parameters:
(i) α is a Q-learning rate which determines the weight given to new information over old information
(ii) γ is the discount factor which determines the weight given to short-term rewards over future rewards.

更新Q-Table

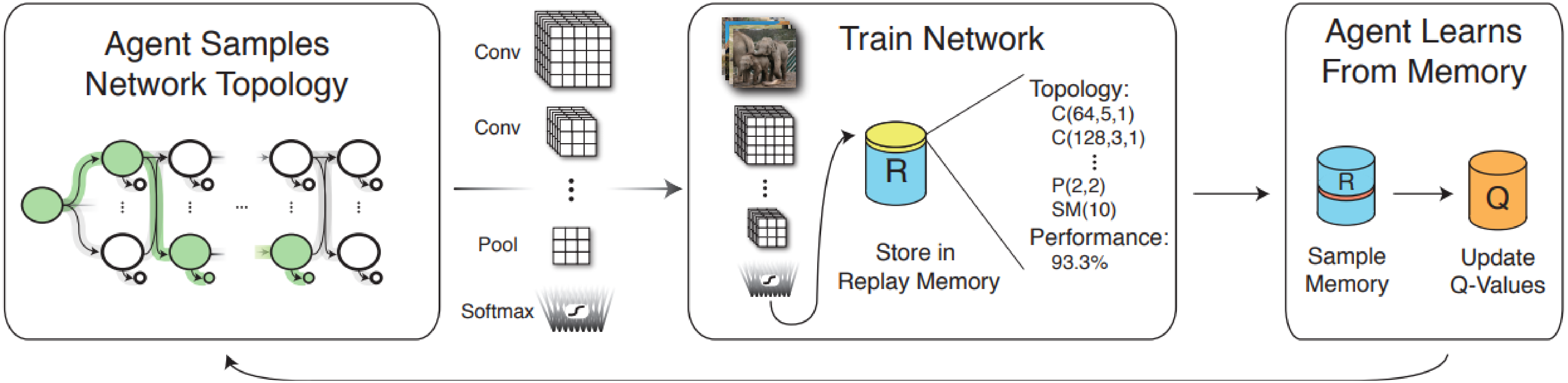
$$Q_{t+1}(s_i, u) = (1-\alpha)Q_t(s_i, u) + \alpha\left[r_t + \gamma \max_{u' \in \mathcal{U}(s_j)} Q_t(s_j, u')\right].$$

	←	→	↑	↓
Start	0	0	0	0
Small cheese	0	0	0	0
Nothing	0	0	0	0
2 small cheese	0	0	0	0
Death	0	0	0	0
Big cheese	0	0	0	0

	←	→	↑	↓
Start	0	0.1	0	0
Small cheese	0	0	0	0
Nothing	0	0	0	0
2 small cheese	0	0	0	0
Death	0	0	0	0
Big cheese	0	0	0	0

Experimental 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



Algorithm 1 Q-learning For CNN Topologies

Initialize:

replay_memory $\leftarrow [\,]$

$Q \leftarrow \{(s, u)\ \forall s \in \mathcal{S}, u \in \mathcal{U}(s)\ :\ 0.5\}$

for episode = 1 to M **do**

$S, U \leftarrow$ SAMPLE_NEW_NETWORK(ϵ, Q)

accuracy $\leftarrow$ TRAIN(S)

replay_memory.append((S, U, accuracy))

for memory = 1 to K **do**

S_{SAMPLE}, U_{SAMPLE}, accuracy$_{SAMPLE} \leftarrow$ Uniform{replay_memory}

$Q \leftarrow$ UPDATE_Q_VALUES(Q, S_{SAMPLE}, U_{SAMPLE}, accuracy$_{SAMPLE}$)

end for

end for

Sample New Network

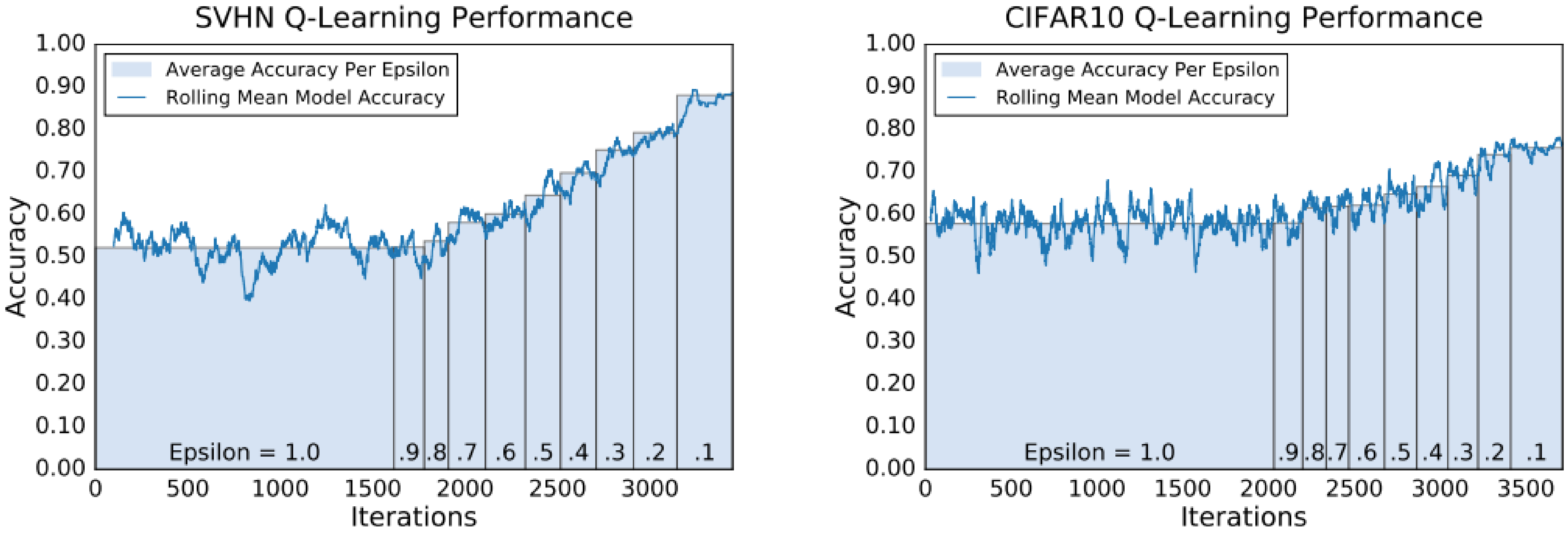
Algorithm 2 SAMPLE_NEW_NETWORK(ϵ, Q)

Initialize:
  state sequence $S = [s_{\text{START}}]$
  action sequence $U = [\ ]$
while $U[-1] \neq$ terminate **do**
  $\alpha \sim \text{Uniform}[0, 1)$
  if $\alpha > \epsilon$ **then**
    $u = \text{argmax}_{u \in \mathcal{U}(S[-1])} Q[(S[-1], u)]$
    $s' = \text{TRANSITION}(S[-1], u)$
  else
    $u \sim \text{Uniform}\{\mathcal{U}(S[-1])\}$
    $s' = \text{TRANSITION}(S[-1], u)$
  end if
  U.append(u)
  if u != terminate **then**
    S.append(s')
  end if
end while
return S, U

Update Q-Values

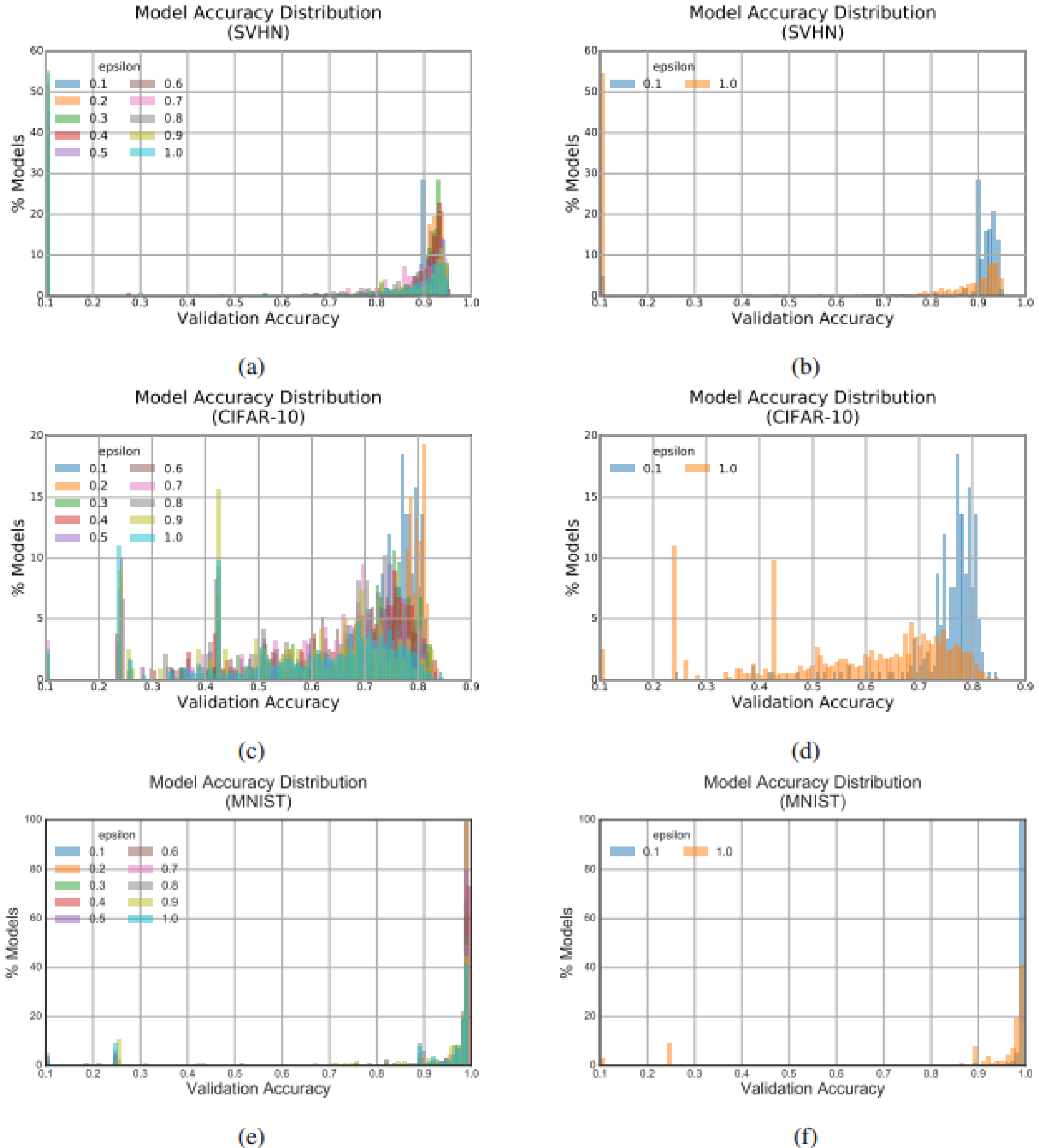
Algorithm 3 UPDATE_Q_VALUES(Q, S, U, accuracy)

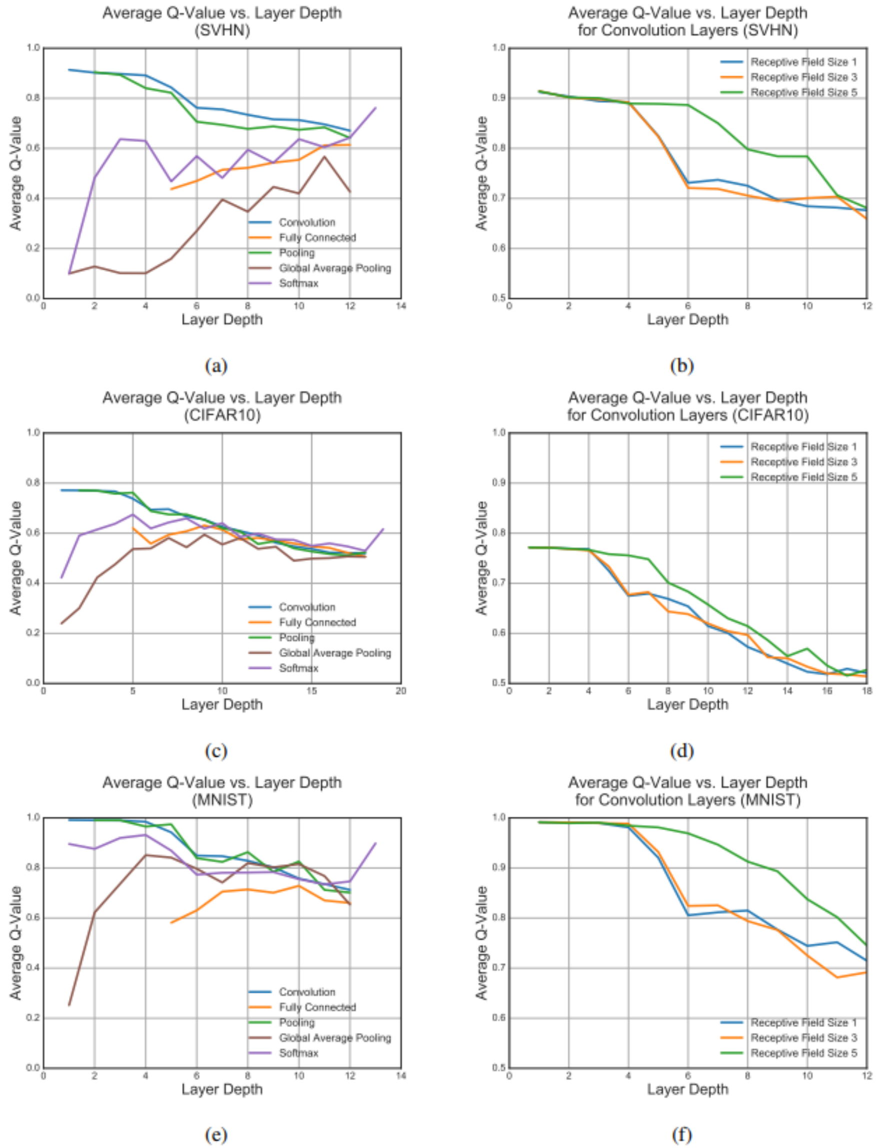
$Q[S[-1], U[-1]] = (1-\alpha)Q[S[-1], U[-1]] + \alpha \cdot \text{accuracy}$
for i = length(S) − 2 to 0 **do**
    $Q[S[i], U[i]] = (1-\alpha)Q[S[i], U[i]] + \alpha \max_{u \in \mathcal{U}(S[i+1])} Q[S[i+1], u]$
end for
return Q



ϵ	1.0	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
# Models Trained	1500	100	100	100	150	150	150	150	150	150

Accuracy Distribution versus εAnd Average Q-Value Versus Layer Depth for different layer types





Top Topologies Selected By Algorithm

Model Architecture	Test Error (%)	# Params (10^6)
[C(512,5,1), C(256,3,1), C(256,5,1), C(256,3,1), P(5,3), C(512,3,1), C(512,5,1), P(2,2), SM(10)]	6.92	11.18
[C(128,1,1), C(512,3,1), C(64,1,1), C(128,3,1), P(2,2), C(256,3,1), P(2,2), C(512,3,1), P(3,2), SM(10)]	8.78	2.17
[C(128,3,1), C(128,1,1), C(512,5,1), P(2,2), C(128,3,1), P(2,2), C(64,3,1), C(64,5,1), SM(10)]	8.88	2.42
[C(256,3,1), C(256,3,1), P(5,3), C(256,1,1), C(128,3,1), P(2,2), C(128,3,1), SM(10)]	9.24	1.10
[C(128,5,1), C(512,3,1), P(2,2), C(128,1,1), C(128,5,1), P(3,2), C(512,3,1), SM(10)]	11.63	1.66

Table A1: Top 5 model architectures: CIFAR-10.