Simple and Efficient Architecture Search for Convolution Neural Networks

—— ICLR 2018 Workshop

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Background

Introduction

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Neural Networks have rapidly gained popularity over the last few years

However, In most cases Neural Networks are designed by hand, which is

exhausting

time-consuming

A Natural goal : design optimization algorithms to automate search process

Similar to Model Selection

Related Work

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Bayesian Optimization

Reinforcement Learning

Evolutionary Algorithms

However….
Most methods are very costly (requiring hundreds or thousands of GPU days)

Approach in this paper

Overview

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Hill Climbing Strategy(local search)

Starting with a small, (**possibly**) pretrained network, then apply **network morphisms** to generate larger ones that may perform better

Network Morphisms:

Make the network deeper

Make the network wider

Add a skip connection from layer i to layer j

Search Method

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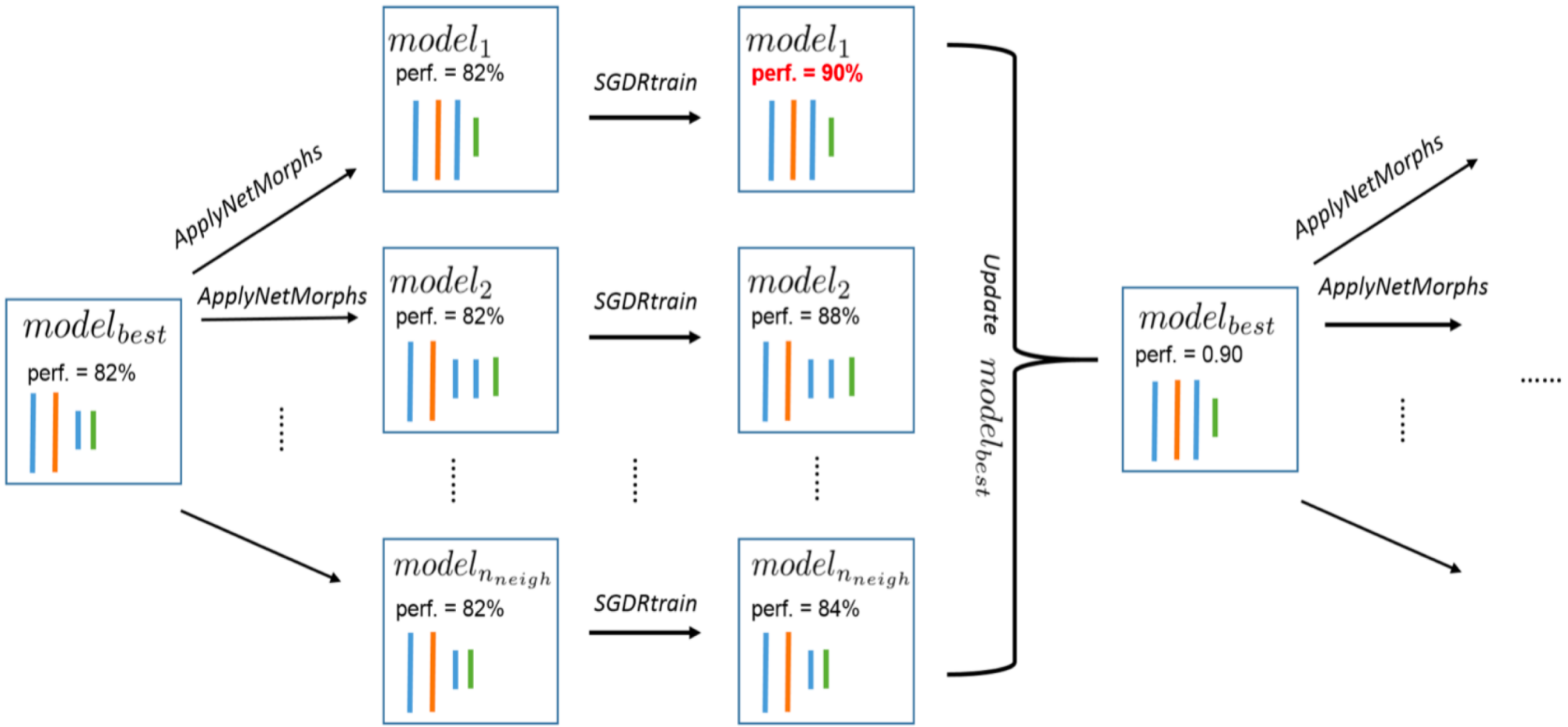

Network Morphism

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Tianqi Chen, Ian J. Goodfellow, and Jonathon Shlens. Net2net: Accelerating learning via knowledge transfer. arXiv 2015, ICLR 2016.

Suppose a parent network is $\boldsymbol{y} = f(\boldsymbol{x}; \boldsymbol{\theta})$, where $\boldsymbol{x}$ is the input to the network, $\boldsymbol{y}$ is the output of the network, $\boldsymbol{\theta}$ is the parameters of the network

The strategy of network morphism is to choose a new set of parameters $\boldsymbol{\theta}'$ for a child network, such that

$$\forall \boldsymbol{x}, f(\boldsymbol{x}; \boldsymbol{\theta}) = g(\boldsymbol{x}, \boldsymbol{\theta}')$$

Two basic operations: Net2WiderNet Net2DeeperNet

Example: Net2WiderNet

Suppose layer i and layer $i+1$ are both fully-connected

Weight matrix $W^{(i)} \in \mathrm{R}^{m \times n}, W^{(i+1)} \in \mathrm{R}^{n \times p}$

Replace layer i with a new layer with q outputs, with $q > n$

Introduce a random mapping function:

$$g(j) = \begin{cases} j & j \leq n \\ \text{random sample from } \{1, 2, \cdots n\} & j > n \end{cases}$$

$U^{(i)}$ and $U^{(i+1)}$ are new weight matrices, with

$$\boldsymbol{U}_{k,j}^{(i)} = \boldsymbol{W}_{k,g(j)}^{(i)}, \quad \boldsymbol{U}_{j,h}^{(i+1)} = \frac{1}{|\{x|g(x) = g(j)\}|} \boldsymbol{W}_{g(j),h}^{(i+1)}.$$

Example: Net2WiderNet

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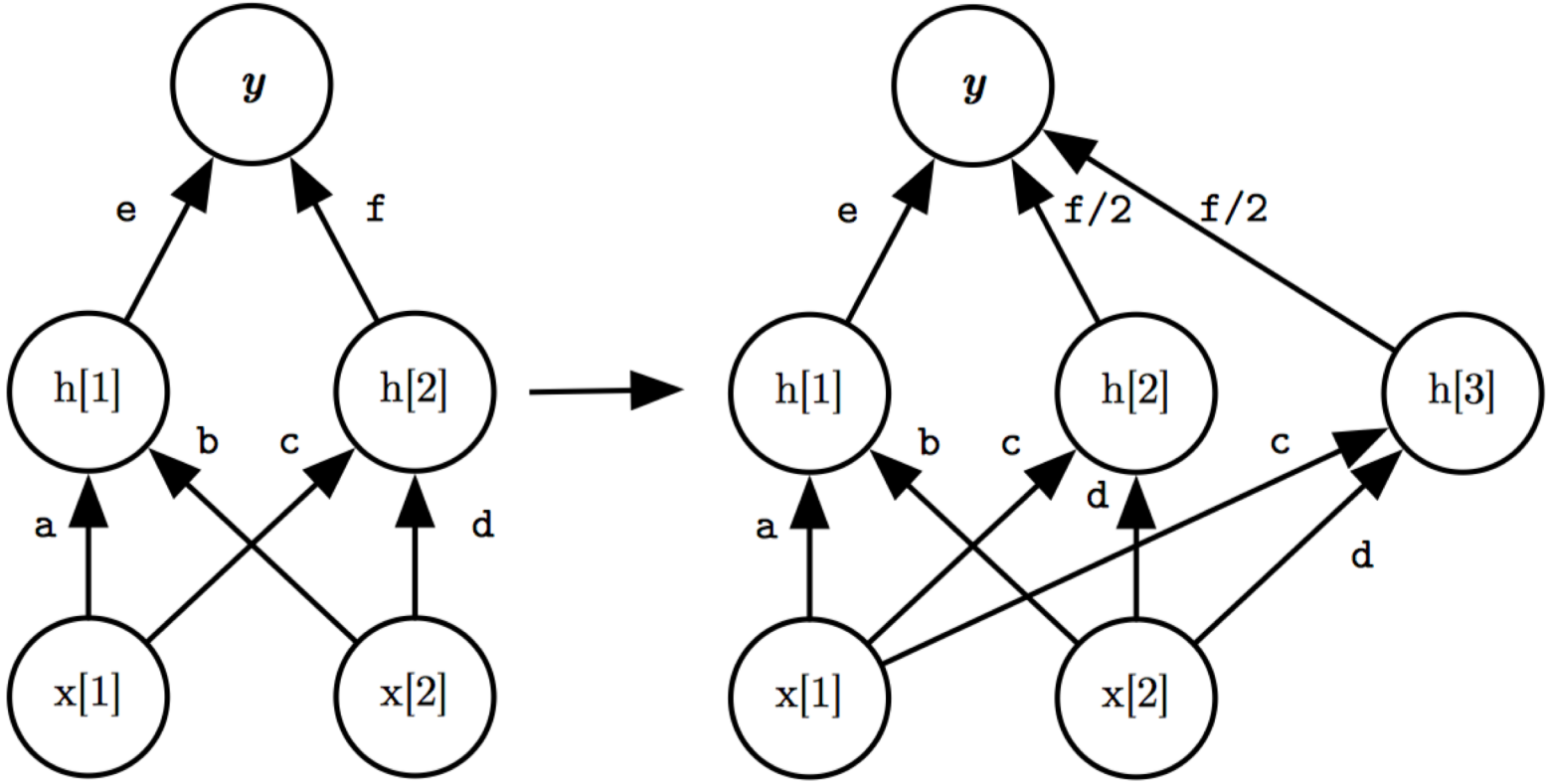

Network Search by hill climbing

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function NASH($model_0, n_{steps}, n_{neigh}, n_{NM}, epoch_{neigh}, epoch_{final}, \lambda_{end}, \lambda_{start}$)

$model_0 \triangleq$ model to start with, $n_{steps} \triangleq$ number of hill climbining steps
$n_{neigh} \triangleq$ number of neighbours, $n_{NM} \triangleq$ number of net. morph. applied
$epoch_{neigh} \triangleq$ number of epochs for training every neighbour
$epoch_{final} \triangleq$ number of epochs for final training
initial LR λ_{start} is annealed to λ_{end} during SGDR training

$model_{best} \leftarrow model_0$
# start hill climbing
for $i \leftarrow 1, \ldots, n_{steps}$ **do**
  #get n_{neigh} neighbors of $model_0$ by applying n_{NM} network morphisms to $model_{best}$
  for $j \leftarrow 1, \ldots, n_{neigh} - 1$ **do**
    $model_j \leftarrow ApplyNetMorphs(model_{best}, n_{NM})$
    # train for a few epochs on training set with SGDR
    $model_j \leftarrow \text{SGDRtrain}(model_j, epoch_{neigh}, \lambda_{start}, \lambda_{end})$
  end for
  # in fact, last neighbor is always just the current best
  $model_{n_{neigh}} \leftarrow \text{SGDRtrain}(model_{best}, epoch_{neigh}, \lambda_{start}, \lambda_{end})$
  # get best model on validation set
  $model_{best} \leftarrow \underset{j=1,\ldots,n_{neigh}}{arg\,max} \{performance_{vali}(model_j)\}$
end for
# train the final model on training and validation set
$model_{best} \leftarrow \text{SGDRtrain}(model_{best}, epoch_{final}, \lambda_{start}, \lambda_{end})$
return $model_{best}$
end function

Experiments

Experiments Setting

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Dataset:

Cifar10/Cifar100

Standard Data Augmentation Scheme

40000 training samples, 10000 valid samples, 10000 test samples

Nvidia Titan X

Baseline

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algorithm setting	runtime (hrs)	# params (mil.)	error $\pm$ std. (%)
$n_{neigh} = 8$	12.8	5.7	5.7 ± 0.35
Random networks ($n_{neigh} = 1$)	4.5	4.4	6.5 ± 0.76
models from line 1 retrained from scratch	5.3	5.7	6.1 ± 0.92
$n_{neigh} = 8$, no SGDR	10.6	5.8	6.4 ± 0.70
$n_{neigh} = 8$, no net. morph.	6.6	2.9	6.1 ± 0.30

Baseline experiments. Runtime, # params and error rates are averaged over 10 runs and 30 runs respectively.

Comparison on Cifar10

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model	resources spent	# params (mil.)	error (%)
Shake-Shake (Gastaldi, 2017)	4 GPU days, 2 GPUs	26	2.9
WRN 28-10 (Loshchilov & Hutter, 2017)	1 GPU day	36.5	3.86
Baker et al. (2016)	80-100 GPU days	11	6.9
Cai et al. (2017)	15 GPU days	19.7	5.7
Zoph & Le (2017)	16.000-24.000 GPU days	37.5	3.65
Real et al. (2017)	2500 GPU days	5.4	5.4
Saxena & Verbeek (2016)	?	21	7.4
Brock et al. (2017)	3 GPU days	16.0	4.0
Ours (random networks, $n_{steps} = 5, n_{neigh} = 1$)	0.2 GPU days	4.4	6.5
Ours ($n_{steps} = 5, n_{neigh} = 8$, 10 runs)	0.5 GPU days	5.7	5.7
Ours ($n_{steps} = 8, n_{neigh} = 8$, 4 runs)	1 GPU day	19.7	5.2
Ours (snapshot ensemble, 4 runs)	2 GPU days	57.8	4.7
Ours (ensemble across runs)	4 GPU days	88	4.4

Generate competitive network architectures in only 12 hours

Comparison on Cifar100

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model	resources spent	# params (mil.)	error (%)
Shake-Shake (Gastaldi, 2017)	14 GPU days	34.4	15.9
WRN 28-10 (Loshchilov & Hutter, 2017)	1 GPU day	36.5	19.6
Real et al. (2017)	250 GPUs	40.4	23.7
Brock et al. (2017)	3 GPU days	16.0	20.6
Ours ($n_{steps} = 8, n_{neigh} = 8$, 5 runs)	1 GPU day	22.3	23.4
Ours (snapshot ensemble, 5 runs)	2 GPU days	73.3	20.9
Ours (ensemble across runs)	5 GPU days	111.5	19.6

Baseline experiments. Runtime, # params and error rates are averaged over 10 runs and 30 runs respectively.

Concolusion

Conclusion

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Less computational resources than most alternative approaches

How to escape the local optima

Serve as a basis for the development of more sophisticated methods that yield further improvements of performance

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Q & A