DARTS: Differentiable ARchiTecture Search

Source Code, arXiv

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Paper Info

- Hanxiao Liu, Karen Simonyan, Yiming Yang
- Conference paper at ICLR 2019
- Neural Architecture Search (NAS)

Overview

- Scalable Architecture Search

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- Efficient search in a differential space using gradient descent

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- Efficient search in a differential space using gradient descent
- Faster than existing NAS algorithms
- Unified framework - works for both CNN and RNN architectures
- **Continuous Relaxation** of architectural search

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Proposed Speedup Methods

- Imposing a particular structure on the search space
- Weights/performance prediction for each individual architecture
- Weight sharing/inheritance across multiple architectures

Basic Idea

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- Search space is often discrete
- NAS: A black-box optimization problem over a discrete domain
  - Requires a large number of architecture evaluations
- Scalability is a fundamental challenge!

Paper Highlights

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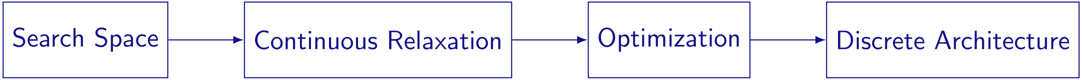
- Doesn't involve controllers, hypernetworks or performance predictors
- Simple, yet generic enough to handle convolutional and recurrent architectures.

Process Flow



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  - Output is obtained by a reduction operation on all intermediate nodes.

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- Continuous to discrete: replace with most likely op.

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- We use gradient descent

Speeding up GD

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- Notice the expensive computation i.e., product of Hessian and gradient – $\mathbf{O}(|\alpha||\mathbf{w}|)$

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- This is $\mathbf{O}(|\alpha| + |\mathbf{w}|)$
- **First Order Approximation**: Take $\xi = 0$. Leads to a faster heuristic but worse performance
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Deriving Discrete Architectures

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- Retain top-k strongest operations to form each node (excluding zero ops).
- For comparison with existing works, $k = 2$ for conv. and $k = 1$ for recurr.
- Zero ops are excluded as they do not affect the final classification outcome due to the presence of batch norm.

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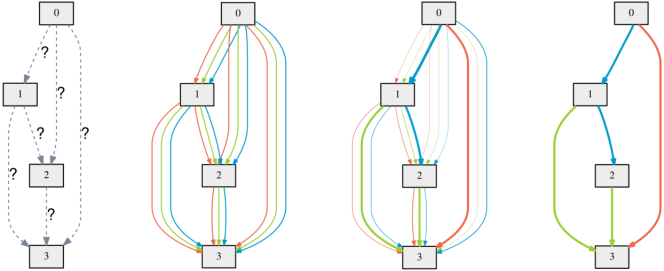

(a) (b) (c) (d)

Combining Everything

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 architecture α by descending $\nabla_\alpha \mathcal{L}_{val}(w - \xi \nabla_w \mathcal{L}_{train}(w, \alpha), \alpha)$
   ($\xi = 0$ if using first-order approximation)
2. Update weights w by descending $\nabla_w \mathcal{L}_{train}(w, \alpha)$

Derive the final architecture based on the learned α.

Experiments & Results

- Datasets: CIFAR-10 and Penn TreeBank (PTB)

Table 1: Comparison with state-of-the-art image classifiers on CIFAR-10 (lower error rate is better). Note the search cost for DARTS does not include the selection cost (1 GPU day) or the final evaluation cost by training the selected architecture from scratch (1.5 GPU days).

Architecture	Test Error (%)	Params (M)	Search Cost (GPU days)	#ops	Search Method
DenseNet-BC (Huang et al., 2017)	3.46	25.6	–	–	manual
NASNet-A + cutout (Zoph et al., 2018)	2.65	3.3	2000	13	RL
NASNet-A + cutout (Zoph et al., 2018)†	2.83	3.1	2000	13	RL
BlockQNN (Zhong et al., 2018)	3.54	39.8	96	8	RL
AmoebaNet-A (Real et al., 2018)	3.34 ± 0.06	3.2	3150	19	evolution
AmoebaNet-A + cutout (Real et al., 2018)†	3.12	3.1	3150	19	evolution
AmoebaNet-B + cutout (Real et al., 2018)	2.55 ± 0.05	2.8	3150	19	evolution
Hierarchical evolution (Liu et al., 2018b)	3.75 ± 0.12	15.7	300	6	evolution
PNAS (Liu et al., 2018a)	3.41 ± 0.09	3.2	225	8	SMBO
ENAS + cutout (Pham et al., 2018b)	2.89	4.6	0.5	6	RL
ENAS + cutout (Pham et al., 2018b)*	2.91	4.2	4	6	RL
Random search baseline‡ + cutout	3.29 ± 0.15	3.2	4	7	random
DARTS (first order) + cutout	3.00 ± 0.14	3.3	1.5	7	gradient-based
DARTS (second order) + cutout	2.76 ± 0.09	3.3	4	7	gradient-based

* Obtained by repeating ENAS for 8 times using the code publicly released by the authors. The cell for final evaluation is chosen according to the same selection protocol as for DARTS.

† Obtained by training the corresponding architectures using our setup.

‡ Best architecture among 24 samples according to the validation error after 100 training epochs.

Experiments & Results

Table 2: Comparison with state-of-the-art language models on PTB (lower perplexity is better). Note the search cost for DARTS does not include the selection cost (1 GPU day) or the final evaluation cost by training the selected architecture from scratch (3 GPU days).

Architecture	Perplexity valid	Perplexity test	Params (M)	Search Cost (GPU days)	#ops	Search Method
Variational RHN (Zilly et al., 2016)	67.9	65.4	23	–	–	manual
LSTM (Merity et al., 2018)	60.7	58.8	24	–	–	manual
LSTM + skip connections (Melis et al., 2018)	60.9	58.3	24	–	–	manual
LSTM + 15 softmax experts (Yang et al., 2018)	58.1	56.0	22	–	–	manual
NAS (Zoph & Le, 2017)	–	64.0	25	1e4 CPU days	4	RL
ENAS (Pham et al., 2018b)*	68.3	63.1	24	0.5	4	RL
ENAS (Pham et al., 2018b)†	60.8	58.6	24	0.5	4	RL
Random search baseline‡	61.8	59.4	23	2	4	random
DARTS (first order)	60.2	57.6	23	0.5	4	gradient-based
DARTS (second order)	58.1	55.7	23	1	4	gradient-based

* Obtained using the code (Pham et al., 2018a) publicly released by the authors.

† Obtained by training the corresponding architecture using our setup.

‡ Best architecture among 8 samples according to the validation perplexity after 300 training epochs.

Experiments & Results

Table 3: Comparison with state-of-the-art image classifiers on ImageNet in the mobile setting.

Architecture	Test Error (%) top-1	Test Error (%) top-5	Params (M)	$+\times$ (M)	Search Cost (GPU days)	Search Method
Inception-v1 (Szegedy et al., 2015)	30.2	10.1	6.6	1448	–	manual
MobileNet (Howard et al., 2017)	29.4	10.5	4.2	569	–	manual
ShuffleNet $2\times$ ($g = 3$) (Zhang et al., 2017)	26.3	–	$\sim$5	524	–	manual
NASNet-A (Zoph et al., 2018)	26.0	8.4	5.3	564	2000	RL
NASNet-B (Zoph et al., 2018)	27.2	8.7	5.3	488	2000	RL
NASNet-C (Zoph et al., 2018)	27.5	9.0	4.9	558	2000	RL
AmoebaNet-A (Real et al., 2018)	25.5	8.0	5.1	555	3150	evolution
AmoebaNet-B (Real et al., 2018)	26.0	8.5	5.3	555	3150	evolution
AmoebaNet-C (Real et al., 2018)	24.3	7.6	6.4	570	3150	evolution
PNAS (Liu et al., 2018a)	25.8	8.1	5.1	588	$\sim$225	SMBO
DARTS (searched on CIFAR-10)	26.7	8.7	4.7	574	4	gradient-based

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