STOR566: Introduction to Deep Learning Lecture 20: Neural Architecture Search

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Materials are from Deep Learning (UCLA)

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Neural Architecture Search (NAS)

NAS: Background

Neural network architecture is important for both accuracy and efficiency



NAS: Why this Architecture?

- Architecture of VGG19 and ResNet34 on ImageNet
- How does people come up with this final architecture?
- Can we automatically design an architecture?





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Picture from Elsken et al., Neural Architecture Search: A Survey, JMLR, 2019

• Abstract illustration of Neural Architecture Search methods.

Search Space

- An illustration of different architecture spaces.
- Left: Chain-structured neural networks
- Right: A more complex search space with additional layer types



Picture from Elsken et al., Neural Architecture Search: A Survey,

Search Space: Parameters

For Chain-structured neural networks:

- n: the (maximum) number of layers
- the type of operation in a layer, e.g., pooling, convolution, full-connected, etc.

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• hyper-parameters associated with the operations

For more complex search space:

- Skip connection
- Dense net connection
- ...

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The optimization problem can be very hard!

Search Space: Cell-based

- Search the architecture for a cell (block)
- Build final architecture by stacking cells.
- Zoph et al., Neural architecture search with reinforcement learning. ICLR, 2017.: normal cell, reduction cell



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How to determine the macro-architecture?

Search Strategy

Overview of Search Strategies:

- Bayesian optimization
- Evolutionary methods
- Reinforcementt learning (RL)

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• Gradient-based methods

• ...

Search Strategy: RL

In 2016, Reinforcement learning (RL) is proposed for NAS

• A better (structured) representation of search space

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• Learning a controller to generate architectures

Search Strategy: RL

In 2016, Reinforcement learning (RL) is proposed for NAS

- A better (structured) representation of search space
- Learning a controller to generate architectures

Papers:

- Zoph et al., Neural Architecture Search with Reinforcement Learning. ICLR, 2017.
- Baker et al., Designing Neural Network Architectures using Reinforcement Learning. ICLR, 2017.

Architecture	Test Error (%)	Search Cost (GPU days)	Search Method
ResNet (He et al., 2016)	4.62	-	manual
DenseNet-BC (Huang et al., 2017)	3.46	-	manual
NAS-RL (Zoph & Le, 2017)	3.65	22,400	RL

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- Controller: a RNN to propose an architecture
- Train and evaluate proposed architecture
- Update the controller with the reward

Controller

- Controller to generate hyper-parameters of neural networks
- RNN as backbone
- Simple example: generate hyper-parameters of a chain-structured CNN



Figure from Zoph et al., Neural Architecture Search with Reinforcement Learning. ICLR, 2017.

Controller: Anchor Point

- Anchor point to form skip connection
- At layer N, N 1 sigmoids to indicate the previous connections



Evolutionary Algorithm



- A nature inspired approach to optimization
- Process of getting the most out of something
- Inspired by the notion of survival of the fittest from Darwinian Evolution and modern genetics

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The following slides are from

https://www.researchgate.net/publication/310365190_Introduction_to_Evolutionary_Algorithms



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- Goal achieved?
- Number of generations reached max?

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– Performance stagnating?







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NAS with EA

Real et al., Regularized Evolution for Image Classifier Architecture Search. AAAI, 2019.

Steps:

- Sample *S* models from the population
- Pick the one with the best performance as parent
- Mutate to generate child
- Train child, evaluate, add back to the population
- Discard the oldest from the population

```
Algorithm 1 Aging Evolution
population \leftarrow empty queue
                                         \triangleright The population.
                                ▷ Will contain all models.
history \leftarrow \emptyset
while |population| < P do
                                    ▷ Initialize population.
    model.arch \leftarrow RANDOMARCHITECTURE()
   model.accuracy \leftarrow TRAINANDEVAL(model.arch)
    add model to right of population
    add model to history
end while
while |history| < C do
                                    \triangleright Evolve for C cycles.
    sample \leftarrow \emptyset
                                      ▷ Parent candidates.
    while |sample| < S do
       candidate \leftarrow random element from population
                   ▷ The element stays in the population.
       add candidate to sample
   end while
   parent \leftarrow highest-accuracy model in sample
   child.arch \leftarrow MUTATE(parent.arch)
    child.accuracy \leftarrow TRAINANDEVAL(child.arch)
    add child to right of population
    add child to history
   remove dead from left of population
                                                  ⊳ Oldest.
   discard dead
end while
return highest-accuracy model in history
```

NAS is Expensive

- Experiments for NAS are typically time consuming to run
- RL or evolutionary algorithm often need to evaluate > 10,000 configs in a single run



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Differentiable NAS

• Significantly reduced search time since 2018

Architecture	Test Error (%)	Search Cost (GPU days)	Search Method	
DenseNet-BC (Huang et al., 2017)	3.46	-	manual	
NAS-RL (Zoph & Le, 2017)	3.65	22,400	RL	
NASNet-A (Zoph et al., 2018)	2.65	2000	RL	
BlockQNN (Zhong et al., 2018)	3.54	96	RL	
AmoebaNet (Real et al., 2019)	3.34 ± 0.06	3150	evolution	
Hierarchical GA (Liu et al., 2018)	3.75	300	evolution	
GCP (Suganuma et al., 2017)	5.98	15	evolution	
DARTS (1st) (Liu et al., 2019)	3.00 ± 0.14	0.4	differentiable	·
DARTS (2nd) (Liu et al., 2019)	2.76 ± 0.09	1.0	differentiable	
SNAS (moderate) (Xie et al., 2019)	2.85 ± 0.02	1.5	differentiable	Can run on a
GDAS (Dong & Yang, 2019)	2.93	0.3	differentiable	single GPU
ProxylessNAS (Cai et al., 2019) [†]	2.08	4.0	differentiable	machinal
PC-DARTS (Xu et al., 2020)	2.57 ± 0.07	0.1	differentiable	machine:
NASP (Yao et al., 2019)	2.83 ± 0.09	0.1	differentiable	
SDARTS-ADV (Chen & Hsieh, 2020)	2.61 ± 0.02	1.3	differentiable	
DrNAS (Chen et al., 2019)	2.46 ± 0.03	0.6^{\ddagger}	differentiable	
DARTS+PT (Wang et al., 2020)	2.61 ± 0.08	0.8	differentiable	

Weight Sharing



- Models defined by Path A and Path B should be trained separately
- $\bullet\,$ Can we assume Path A and Path B share the same weight at $1\to 2?\,$ Weight Sharing

Avoid retraining for each new architecture

Conclusions

- A brief introduction to NAS
- Multiple search strategies

Questions?