CVPR 2020 Tutorial on

From HPO to NAS: Automated Deep Learning

Hang Zhang[1], Cedric Archambeau[1], Song Han[2], Matthias Seeger[1],
Thibaut Lienart[1], Chongruo Wu[1,3], Ligeng Zhu[2], Haotian Tang[2], Aaron Klein[1]

Amazon[1], MIT[2], UC Davis[3]

Automated Deep Learning Tutorial Overview

- AutoML Background and Overview (by Cedric Archambeau)
- Introducing AutoGluon Toolkit (by Hang Zhang)
- AutoML for TinyML with Once-for-All Network (by Song Han)
- Hands-on Section
  - Quick Start and ProxylessNAS Tutorial (by Chongruo Wu)
  - Advanced HPO Algorithm (by Thibaut Lienart)
  - Once-For-All Network Tutorial (by Ligeng Zhu and Haotian Tang)
  - Code Example Walk-through (by Hang Zhang)

https://hangzhang.org/CVPR2020/
https://autogluon.mxnet.io/

Two Live Sections for (Check on Website)

Instructors

Cédric Archambeau
Amazon

Hang Zhang
Amazon

Song Han
MIT

Matthias Seeger
Amazon

Thibaut Lienart
Amazon

Chongruo Wu
UC Davis

Ligeng Zhu
MIT

Haotian Tang
MIT

Aaron Klein
Amazon

AutoGLUON: An AutoML Toolkit for Deep Learning

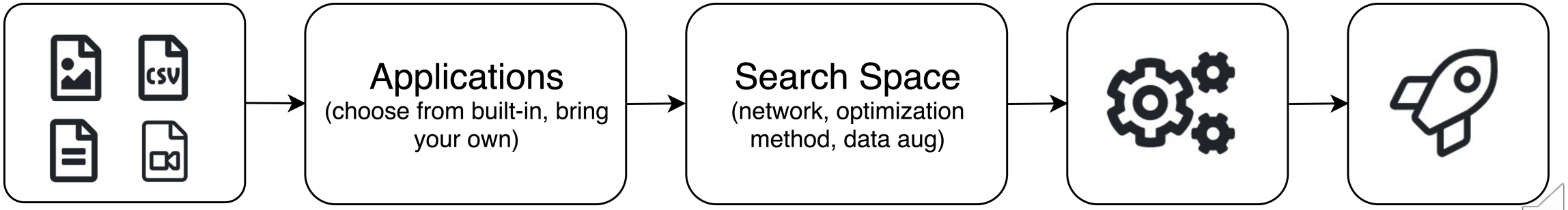
Hang Zhang

Applied Scientist, Amazon

CVPR Tutorial on From HPO to NAS: Automated Deep Learning (Jun 2020)

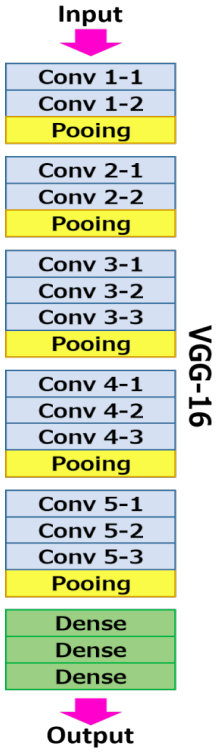
AutoGluon

- A Popular Toolkit:
  - 2.3K GitHub Starts, many media posts online
- AutoGluon Users:
  - DL expert/researcher (improves their model performance)
  - Researcher on AutoML/HPO algorithm
  - Developer conducting large scale distributed training (GPU management)
- Research Prototype => AutoML Production Pipeline (SageMaker)

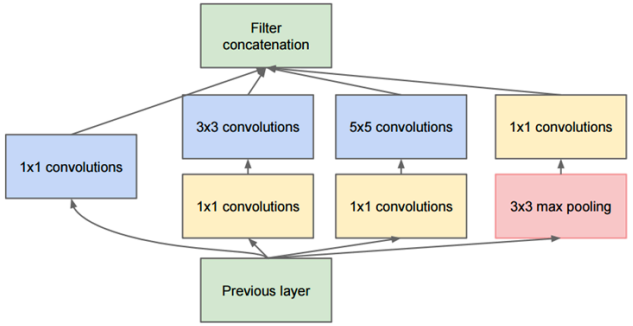


Why Do We Need HPO in Computer Vision?

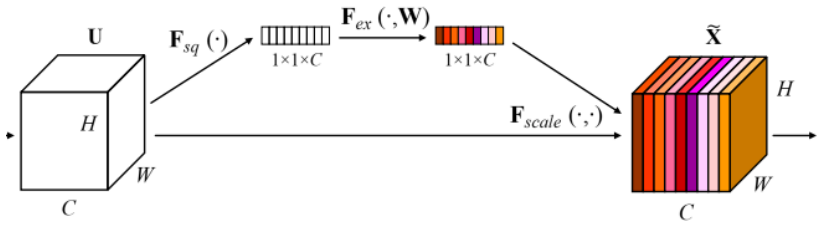
- Feature Engineering => Network Engineering => Neural Architecture Search
- Increasing number of design choices



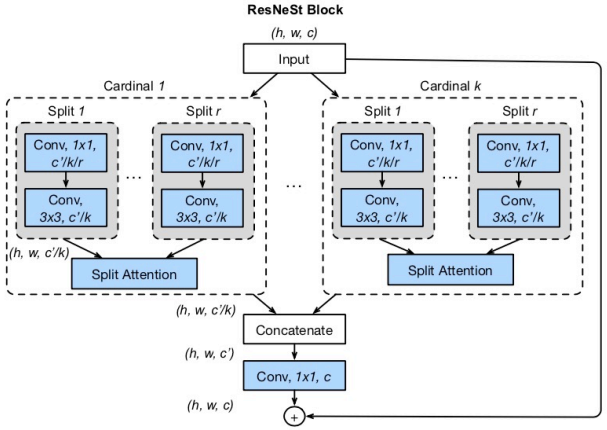
Very Deep Convolutional Networks for Large-Scale Image Recognition



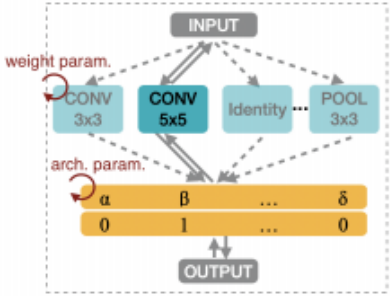
Going Deeper with Convolutions



Squeeze-and-Excitation Networks



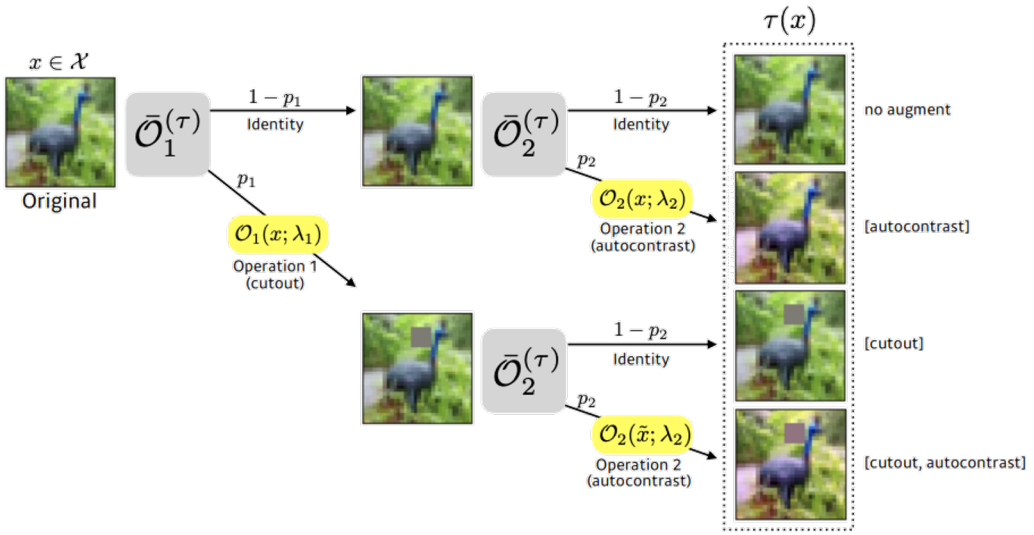
ResNeSt: Split-Attention Network



ProxylessNAS: Direct Neural Architecture Search on Target Task and Hardware

HPO for Computer Vision

- Optimization of training strategies and HPs
  - AutoAugment (Fast AA, RandAA)
  - FBNetV3 (joint optimization)
- Train recipe:
  - Data augmentation policies
  - Mix-up training
  - Label smoothing
  - Optimization HPs: learning rate, weight decay



How to Tune a Model Manually?

- Spinning up the experiments using different choices
- Learn lessons and suggest next choice

```
# change the rank for worker node
python train_dist.py --dataset imagenet --model resnest50 --lr-scheduler cos --epochs 270 --
checkname resnest50 --lr 0.025 --batch-size 64 --dist-url tcp://MASTER:NODE:IP:ADDRESS:23456 --
world-size 4 --label-smoothing 0.1 --mixup 0.2 --no-bn-wd --last-gamma --warmup-epochs 5 --rand-aug
--rank 0
```


What AutoGluon Provides

- AutoGluon Toolkit
  - Easy-to-use and easy-to-customize
  - Efficient in Search (BayesOpt, Hyperband, Reinforcement Learning)
  - Scalable (Distributed Search, AWS Batch, AWS SageMaker)

- Goal of this tutorial
  - Change the conventional way of doing research manually
  - Constructing search space and pass the workload to the machines

Easy to Use – Search Space

- Integer Space (similarly for Categorical and Real Space):

```
import autogluon as ag
a = ag.space.Int(lower=0, upper=10)
print(a)
print(a.rand)
```

```
Int: lower=0, upper=10
```

```
7
```

- Dict Space (similarly for List Space):

```
g = ag.space.Dict(key1=ag.space.Categorical('alpha', 'beta'),
                  key2=ag.space.Int(0, 3),
                  key3='constant' )
print(g.rand)
```

```
{'key1': 'beta', 'key2': 1, 'key3': 'constant'}
```

Easy to Customize – Training Function

- Allow HPO on python training scripts
  automatically generate search algorithm and conduct HPO

```
@ag. args(
        batch_size=128,
        lr=ag.Real(1e-4, 1e-2),
)
def train_fn(args, reporter):
        print(args.lr, args.batch_size)
        reporter(epoch=0, accuracy=0.9)

myscheduler = ag.scheduler.FIFOScheduler(train_fn, num_trials=25)
myscheduler.run()
```

https://autogluon.mxnet.io/tutorials/course/script.html

Easy to Customize – Searchable Objects

- Defining search space and constructing dynamic object in one go:
  - Searchable object from a function:

```
import gluoncv as gcv
@ag.func(multiplier=ag.Categorical(0.25, 1.0))
def get_mobilenet(multiplier):
    return gcv.model_zoo.MobileNetV2(multiplier=multiplier, classes=4)
```

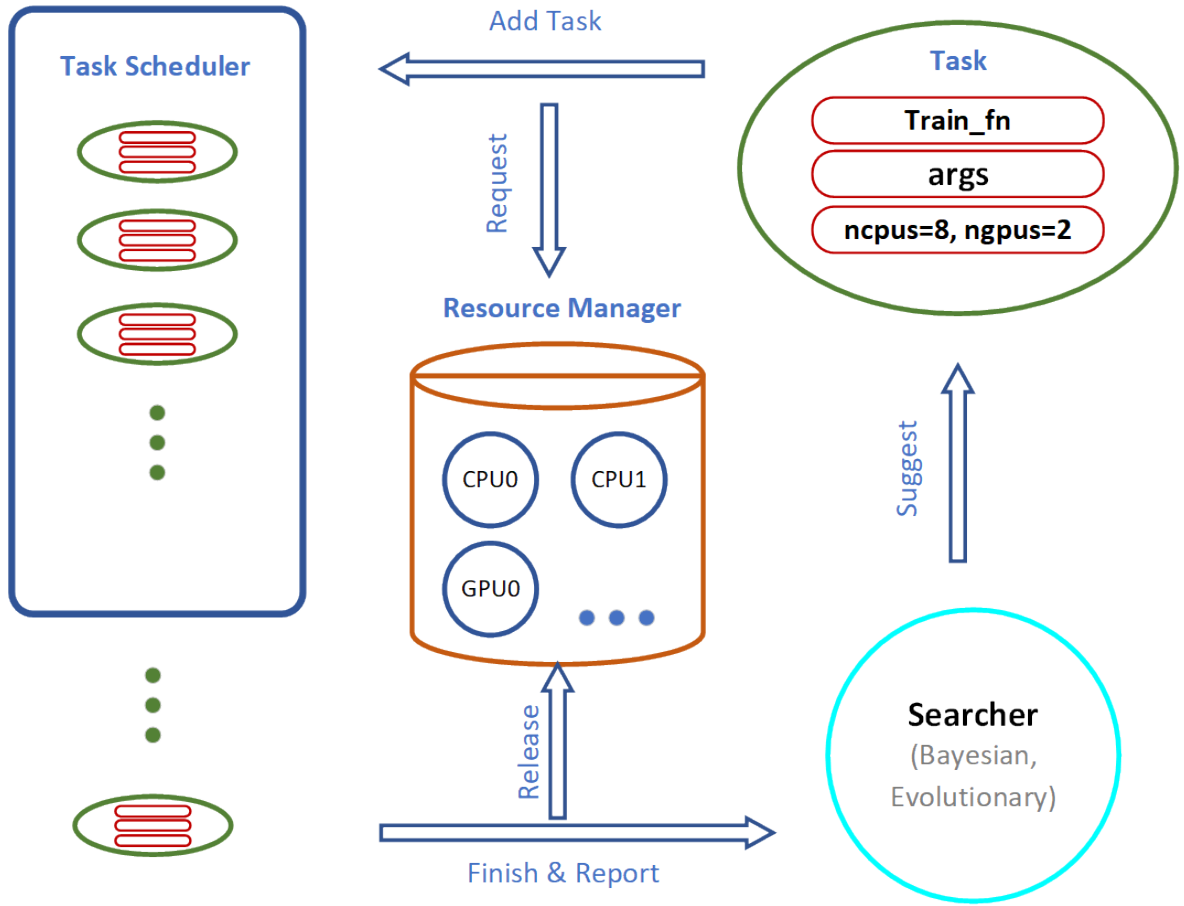
  - Searchable object from a class:

```
from mxnet import optimizer as optim
@ag.obj(learning_rate=ag.space.Real(1e-4, 1e-1, log=True),
        wd=ag.space.Real(1e-4, 1e-1))
class Adam(optim.Adam):
    pass
```

  - Pass the searchable object as the input of the train_fn:

```
@ag. args(net = get_mobilenet(), optim = Adam())
def train_fn(args, reporter):
    pass
```

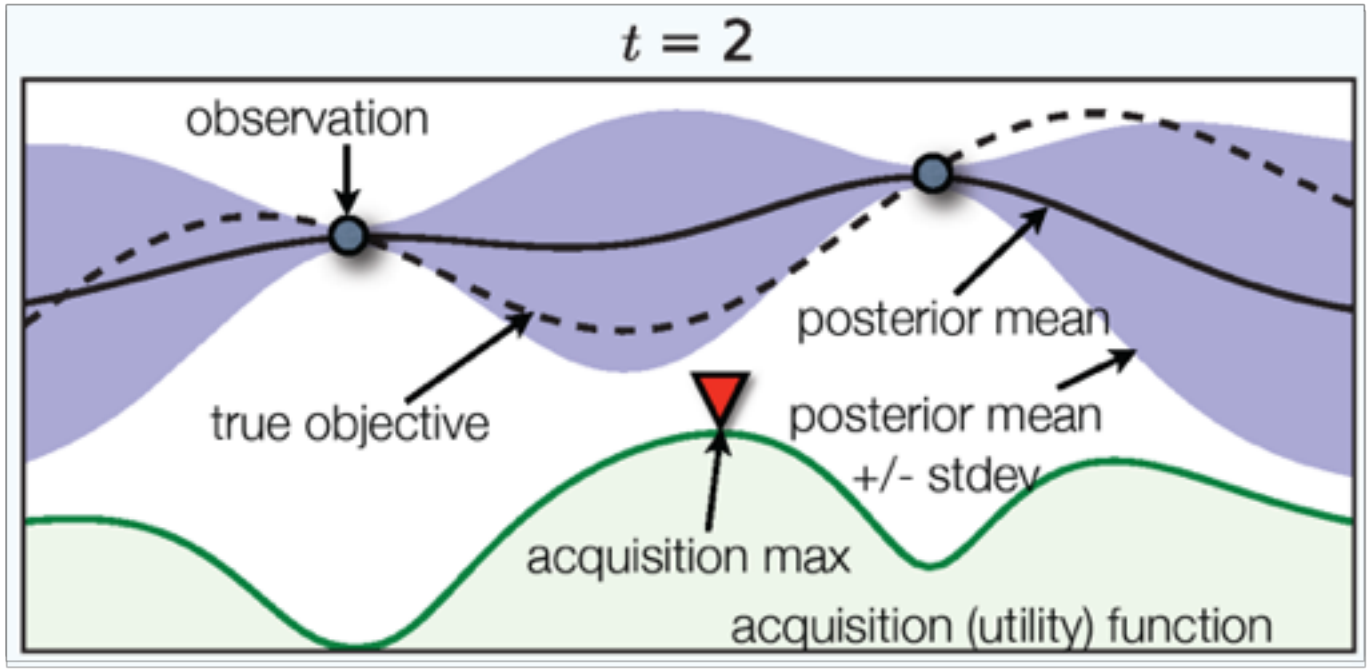
Efficient in Search – Advanced Search Strategies



- Searcher: suggests configurations for the next training jobs.
- Scheduler: schedules the training job when the computation resources are available.
- All components are modularized and easy to extend

Search Algorithms (Bayesian Optimization)

- Surrogate Model:
  reflects the probabilistic beliefs
- Acquisition function:
  which hyperparameter configuration to try next

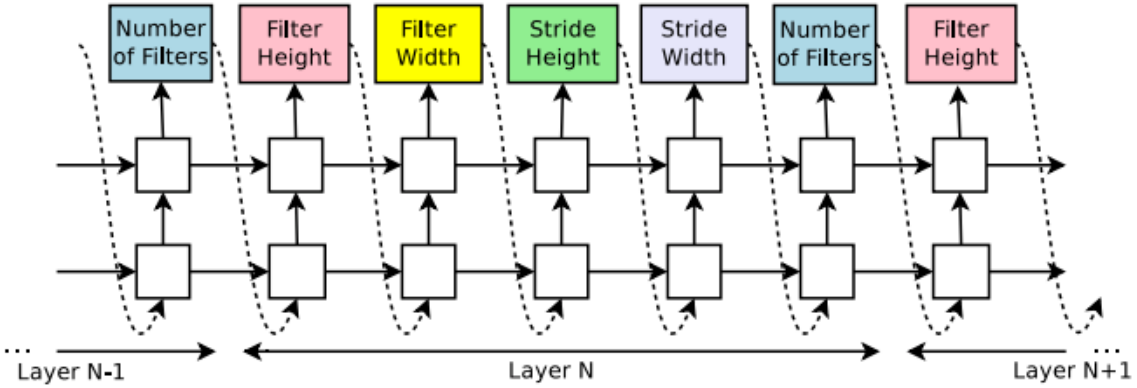



```
scheduler = ag.scheduler.FIFOScheduler(train_fn, searcher='bayesopt')
```

http://autogluon.s3.amazonaws.com/api/autogluon.searcher.html#skoptsearcher

Search Algorithms (RL, Gluon)

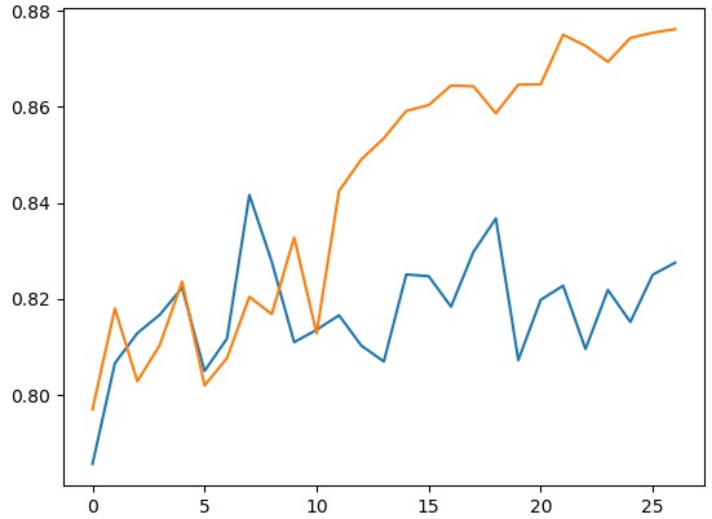
- Auto Construct a LSTM Controller based on Search Space



$$J(\theta) = E_{a\sim P(a;\theta)}[R(a)]$$

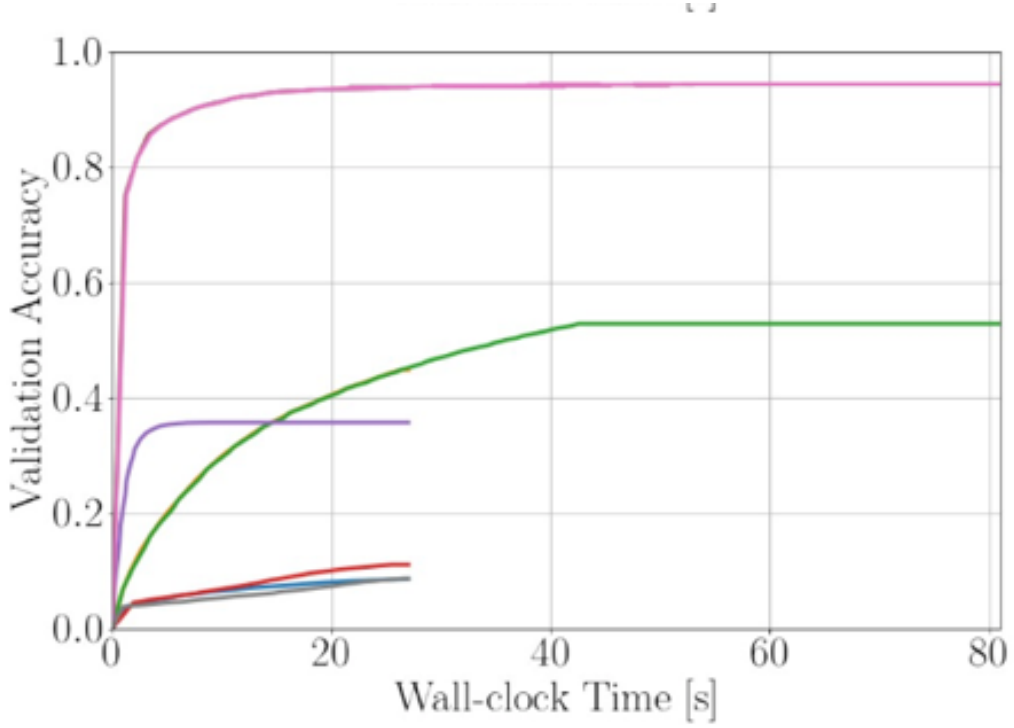
$$\nabla_\theta J(\theta) = E_{a\sim P(a;\theta)}[R(a)\nabla_\theta \log P(a;\theta)]$$

$$\frac{1}{m}\sum_{k=1}^{m}\sum_{t=1}^{T}\log P(a_t|a_{t-1};\theta)(R_k - b)$$



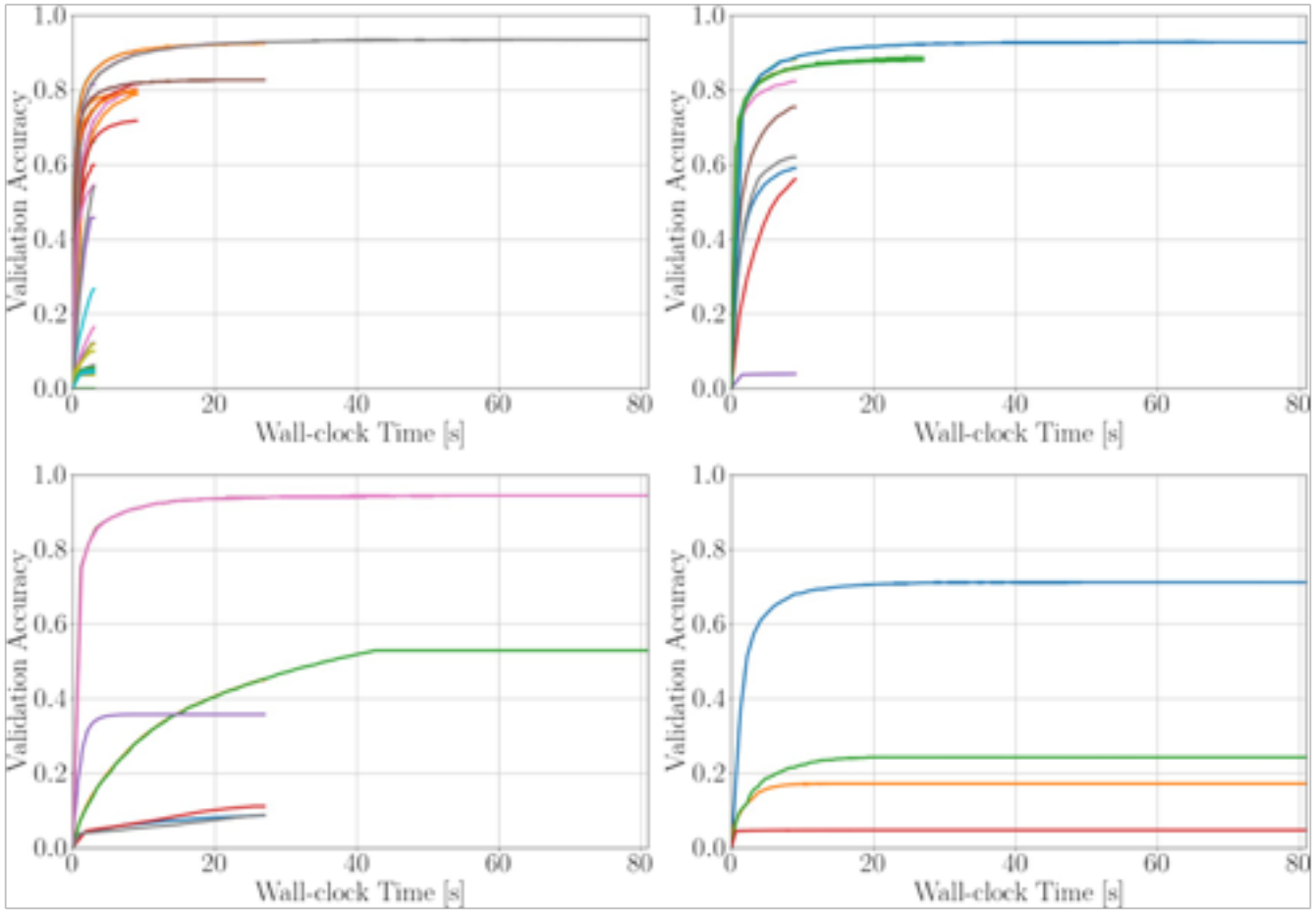
Zoph, Barret, and Quoc V. Le. "Neural architecture search with reinforcement learning."
Reinforce Algorithm http://cs231n.stanford.edu/slides/2019/cs231n_2019_lecture14.pdf

Early Stopping – Succesive Halving



- Randomly sample a set of configurations
- Evaluate the performances of all currently remaining configurations
- Throw out, the bottom half of the worst configurations
- Go back to 2. and repeat until one configuration remains.

Early Stopping – Hyperband



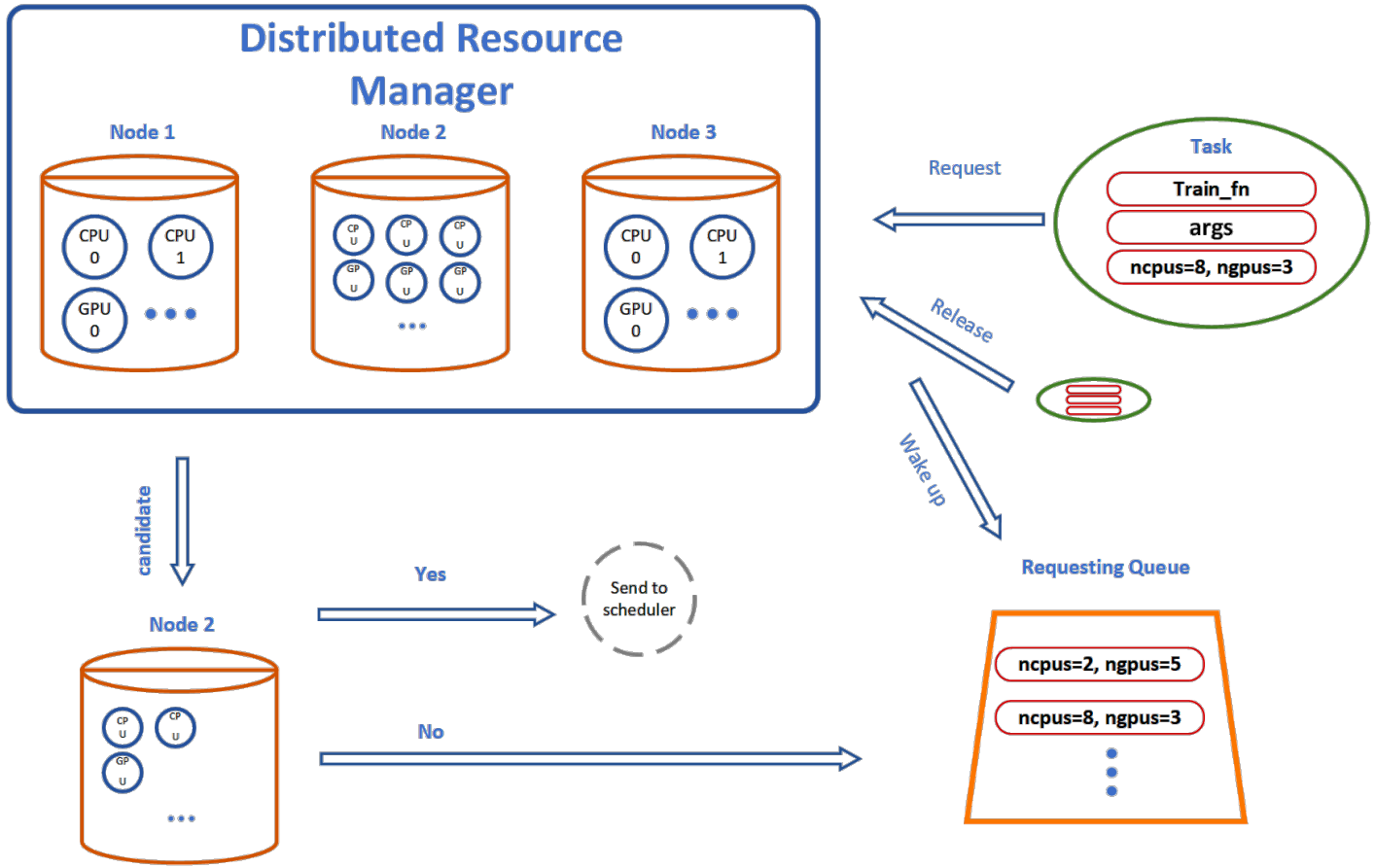
- Number of Total Iters: N
- Number of Successive Halving Brackets: $N_s = \log\left(\frac{N}{\eta}\right) + 1$, where η is a constant
- Number of iters per successive halving: $B = N_s \cdot N$

scheduler = ag.scheduler.
HyperbandScheduler(train_fn)

Scalable -- Distributed Search

- Seamless Experience on Multi-machines
- Automatically manage resource and schedule on remote machines:

```
ip_addrs = ['35.166.23.232',
            '35.166.30.159']
results = ag.schedule. FIFOScheduler(
        train_fn,
        dist_ip_addrs=ip_addrs)
```



http://autogluon.s3.amazonaws.com/tutorials/course/distributed.html

Running on AWS SageMaker

- SageMaker setup all the environment for you
- Upload dataset to S3

```
prefix = 'DEMO-autogluon-cifar10'
data_location = sess.upload_data('./data', key_prefix=prefix)
```

- Bring your own container:

```
from sagemaker.estimator import Estimator
estimator = Estimator(image_name=ecr_image,
                      role=get_execution_role(),
                      train_instance_count=4,
                      train_instance_type='p3.2xlarge')
estimator.fit(data_location)
```

- Download the models from S3

https://github.com/zhanghang1989/AutoGluon-Docker

Thank you!

See you at live Q&A section

- *06/15/2020 5:00 - 5:30 PM PST*
- *06/16/2020 8:00 - 8:30 AM PST*