

# **Neural Architecture Search**

Quoc Le

Thanks: Barret Zoph, Vijay Vasudevan, Irwan Bello, Jon Shlens and others Google Brain team

# Importance of architectures for Vision

- Designing neural network architectures is hard
- Can we try and learn good architectures automatically?





Two layers from the famous Inception V4 computer vision model. Szegedy et al, 2017



# Neural Architecture Search

- Key idea is that we can specify the structure and connectivity of a neural network by using a configuration string
  - ["Filter Width: 5", "Filter Height: 3", "Num Filters: 24"]
- Our idea is to use a RNN ("Controller") to generate this string that specifies a neural network architecture
- Train this architecture ("Child Network") to see how well it performs on a validation set
- Use reinforcement learning to update the parameters of the Controller model based on the accuracy of the child model





#### Train & evaluate models









# Training with REINFORCE

Accuracy of architecture on Parameters of Controller RNN held-out dataset  $J(\theta_c) = E_{P(a_{1:T};\theta_c)}[R]$ Architecture predicted by the controller RNN viewed as a sequence of actions  $\bigtriangledown_{\theta_c} J(\theta_c) = \sum_{t=1}^T E_{P(a_{1:T};\theta_c)} \left[ \bigtriangledown_{\theta_c} \log P(a_t | a_{(t-1):1}; \theta_c) R \right]$ Number of models in minibatch  $\longrightarrow \frac{1}{m} \sum_{k=1}^{m} \sum_{t=1}^{T} \bigtriangledown_{\theta_c} \log P(a_t | a_{(t-1):1}; \theta_c) R_k$ 



# **CIFAR-10** Experiments

- We apply Neural Architecture Search to predicting convolutional networks on CIFAR-10
- Predict the following for a fixed number of layers (15, 20, 13):
  - Filter width/height
  - Stride width/height
  - Number of filters















# **CIFAR-10 Experiment Details**

- Method uses 800 GPUs concurrently at one time
- Reward given to the Controller is the maximum validation accuracy
- Each child model was trained for 50 epochs
- Run for a total of **12,800** child models



# **Distributed Training**







Model		Parameters	Error rate (%)	
Network in Network (Lin et al., 2013)		-	8.81	
All-CNN (Springenberg et al., 2014)	-	-	7.25	
Deeply Supervised Net (Lee et al., 2015)	-	-	7.97	
Highway Network (Srivastava et al., 2015)	-	-	7.72	
Scalable Bayesian Optimization (Snoek et al., 2015)	-	-	6.37	
FractalNet (Larsson et al., 2016)	21	38.6M	5.22	
with Dropout/Drop-path	21	38.6M	4.60	
ResNet (He et al., 2016a)	110	1.7M	6.61	
ResNet (reported by Huang et al. (2016c))	110	1.7M	6.41	
ResNet with Stochastic Depth (Huang et al., 2016c)	110	1.7M	5.23	
en e	1202	10.2M	4.91	
Wide ResNet (Zagoruyko & Komodakis, 2016)	16	11.0M	4.81	
	28	36.5M	4.17	
ResNet (pre-activation) (He et al., 2016b)	164	1.7M	5.46	
	1001	10.2M	4.62	
DenseNet $(L = 40, k = 12)$ Huang et al. (2016a)	40	1.0M	5.24	
DenseNet( $L = 100, k = 12$ ) Huang et al. (2016a)	100	7.0M	4.10	
DenseNet $(L = 100, k = 24)$ Huang et al. (2016a)	100	27.2M	3.74	
DenseNet-BC ( $L = 100, k = 40$ ) Huang et al. (2016b)	190	25.6M	3.46	
Neural Architecture Search v1 no stride or pooling	15	4.2M	5.50	
Neural Architecture Search v2 predicting strides	20	2.5M	6.01	
Neural Architecture Search v3 max pooling	39	7.1M	4.47	
Neural Architecture Search v3 max pooling + more filters	39	37.4M	3.65	

Best result of evolution (Real et al, 2017): 5.4% Best result of Q-learning (Baker et al, 2017): 6.92%



# Neural Architecture Search for ImageNet

• Neural Architecture Search directly on ImageNet is expensive

• Key idea is to run Neural Architecture Search on CIFAR-10 to find a "cell"

• Construct a bigger net from the "cell" and train the net on ImageNet



# Neural Architecture Search for ImageNet





#### Neural Architecture Search for ImageNet





#### Performance of cell on CIFAR-10

model	depth	# params	error rate (%)
DenseNet $(L = 40, k = 12)$ [26]	40	1.0M	5.24
DenseNet $(L = 100, k = 12)$ [26]	100	7.0M	4.10
DenseNet $(L = 100, k = 24)$ [26]	100	27.2M	3.74
DenseNet-BC $(L = 100, k = 40)$ [26]	190	25.6M	3.46
Shake-Shake 26 2x32d [18]	26	2.9M	3.55
Shake-Shake 26 2x96d [18]	26	26.2M	2.86
Shake-Shake 26 2x96d + cutout [12]	26	26.2M	2.56
NAS v3 [70]	39	7.1M	4.47
NAS v3 [70]	39	37.4M	3.65
NASNet-A (6 @ 768)	-	3.3M	3.41
NASNet-A (6 @ 768) + cutout	-	3.3M	2.65
NASNet-A (7 @ 2304)	-	27.6M	2.97
NASNet-A (7 @ 2304) + cutout	-	27.6M	2.40
NASNet-B (4 @ 1152)	-	2.6M	3.73
NASNet-C (4 @ 640)	-	3.1M	3.59



# Performance of cell on ImageNet







# Performance of cell on COCO (object detection)

Model	resolution	mAP (mini-val)	mAP (test-dev)	
MobileNet-224 [24]	$600 \times 600$	19.8%	-	
ShuffleNet (2x) [69]	$600 \times 600$	24.5% <sup>†</sup>	-	
NASNet-A (4 @ 1056)	$600 \times 600$	29.6%	-	
ResNet-101-FPN [35]	800 (short side)	-	36.2%	
Inception-ResNet-v2 (G-RMI) [28]	$600 \times 600$	35.7%	35.6%	
Inception-ResNet-v2 (TDM) [51]	$600 \times 1000$	37.3%	36.8%	
NASNet-A (6 @ 4032)	$800 \times 800$	41.3%	40.7%	
NASNet-A (6 @ 4032)	$1200 \times 1200$	43.2%	43.1%	
ResNet-101-FPN (RetinaNet) [36]	800 (short side)		39.1%	



Features Business	Explore Marketplace Pric	ing This repositor	ry Search		Sign in or Sign up
tensorflow / models		<b>O</b> w	/atch 1,763	★ Star 24,825	% Fork 12,212
<> Code Issues 438	ן Pull requests 164 🔲 Projec	ts 2 🗉 Wiki 📊	⊥ Insights		
Branch: master - models / I	research / slim / nets / <b>nasnet</b> /			Create new file	Find file History
<b>nealwu</b> Remove extraneous	print statement from nasnet_utils.py			Latest commit 7	7f2ea99 17 days ago
README.md	Minor fixes to README.md for N	ASNet for TF Slim.			a month ago
■initpy	PiperOrigin-RevId: 173907206				a month ago
🖹 nasnet.py	Fix nasnet image classification a	and object detection			a month ago
nasnet_test.py	Bring tensorflow/models slim up	to date.			a month ago
asnet_utils.py	Remove extraneous print statem	nent from nasnet_utils.p	У		17 days ago
nasnet_utils_test.py	Bring tensorflow/models slim up	to date.			a month ago

E README.md

#### TensorFlow-Slim NASNet-A Implementation/Checkpoints

