Boulder

Computer Vision; Image Classification; Small Networks

YouTube Playlist

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Distilling the Knowledge in a Neural Network

YouTube Playlist

$z_i \rightarrow$ logits computed for each class

$q_i \rightarrow$ probability (using softmax)

$$q_i = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$

$T \rightarrow$ temperature (e.g., $T = 1$)

Higher $T \implies$ softer prob. distribution over classes

> Knowledge is transferred to the distilled model by training it on a transfer set and using a soft target distribution for each case in the transfer set that is produced by using the cumbersome model with a high temperature in its softmax. The same high temperature is used when training the distilled model, but after it has been trained it uses a temperature of 1.

Matching logits is a special case of distillation

$C = -\sum_i p_i \log q_i \rightarrow$ cross-entropy loss

$v_i \rightarrow$ logits of the cumbersome model

$$\frac{\partial C}{\partial z_i} = \frac{1}{T}(q_i - p_i) = \frac{1}{T}\left(\frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)} - \frac{\exp(v_i/T)}{\sum_j \exp(v_j/T)}\right)$$

If the temperature is high compared with the magnitude of the logits

$$\frac{\partial C}{\partial z_i} \approx \frac{1}{T}\left(\frac{1 + z_i/T}{N + \sum_j z_j/T} - \frac{1 + v_i/T}{N + \sum_j v_j/T}\right)$$

$$\frac{\partial C}{\partial z_i} \approx \frac{1}{NT^2}(z_i - v_i)$$

assume $\sum_j z_j = \sum_j v_j = 0$

equivalent to minimizing $1/2(z_i - v_i)^2$

Cumbersome Net	Smaller Net	Distilled Net
67	146	74

MNIST: Number of Errors

Performing inference with ensembles of specialists

$$KL(\mathbf{p}^g, \mathbf{q}) + \sum_{m \in A_k} KL(\mathbf{p}^m, \mathbf{q})$$

$p^g \rightarrow$ generalist model

$p^m \rightarrow$ specialist model

$A_k \rightarrow$ active set of specialists

classes k: $n = 1$ most probable classes (for each test case) according to the generalist model

A_k: All specialist models m whose special subset of confusable classes S^m has a non-empty intersection with k

confusable subset of the classes (like different types of mushroom)

JFT is an internal Google dataset that has 100 million labeled images with 15,000 labels

JFT 1: Tea party; Easter; Bridal shower; Baby shower; Easter Bunny; ...
JFT 2: Bridge; Cable-stayed bridge; Suspension bridge; Viaduct; Chimney; ...
JFT 3: Toyota Corolla E100; Opel Signum; Opel Astra; Mazda Familia; ...

System	Conditional Test Accuracy	Test Accuracy
Baseline	43.1%	25.0%
+ 61 Specialist models	45.9%	26.1%

Experiments on speech recognition

$$\boldsymbol{\theta} = \arg\max_{\boldsymbol{\theta}'} P(h_t|\mathbf{s}_t; \boldsymbol{\theta}')$$

$P \rightarrow$ acoustic model

$s_t \rightarrow$ acoustic observations

$P(h_t|\mathbf{s}_t; \boldsymbol{\theta}') \rightarrow$ prob. of the "correct" HMM state h_t

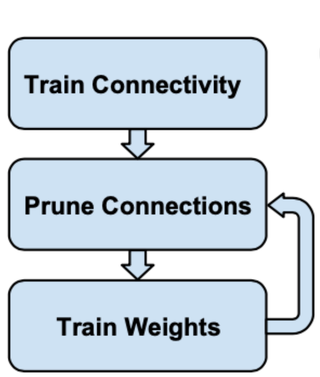
h_t is determined by a forced alignment with the correct sequence of words

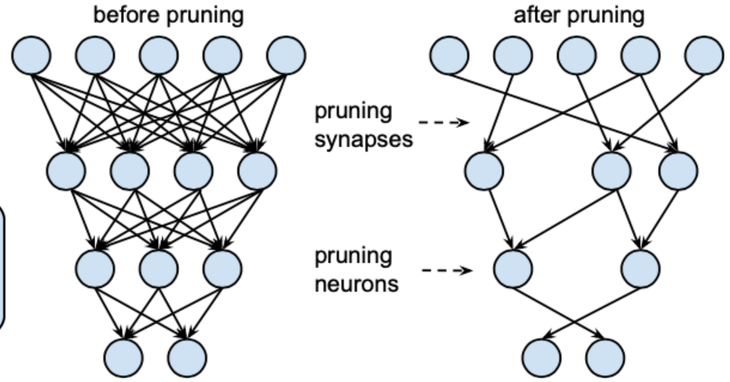
Word Error Rate (WER)

System	Test Frame Accuracy	WER
Baseline	58.9%	10.9%
10xEnsemble	61.1%	10.7%
Distilled Single model	60.8%	10.7%

Hinton, Geoffrey, Oriol Vinyals, and Jeff Dean. "Distilling the knowledge in a neural network." *arXiv preprint arXiv:1503.02531* (2015).

Learning both Weights and Connections for Efficient Neural Networks





Dropout Ratio Adjustment

$D_o \rightarrow$ original dropout rate

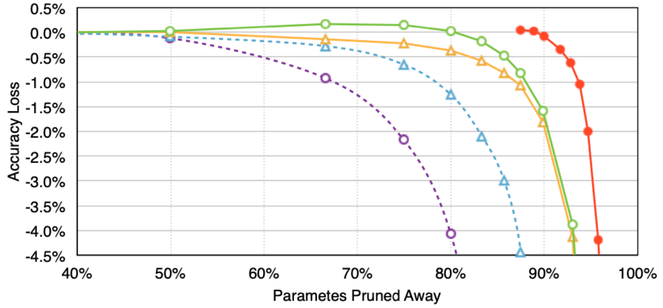
$D_r \rightarrow$ dropout rate during retraining

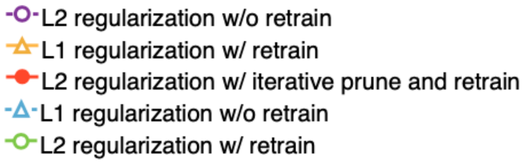
$C_{ir} \rightarrow$ number of connections in layer i for the network after retraining

$C_{io} \rightarrow$ number of connections in layer i for the original network

$$D_r = D_o \sqrt{\frac{C_{ir}}{C_{io}}}$$

Since C_{io} & C_{ir} vary quadratically with the number of neurons!





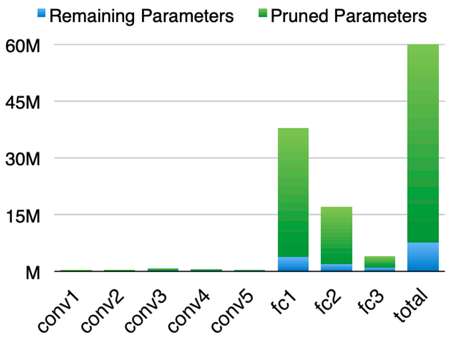
Layer	Weights	FLOP	Act%	Weights%	FLOP%
conv1_1	2K	0.2B	53%	58%	58%
conv1_2	37K	3.7B	89%	22%	12%
conv2_1	74K	1.8B	80%	34%	30%
conv2_2	148K	3.7B	81%	36%	29%
conv3_1	295K	1.8B	68%	53%	43%
conv3_2	590K	3.7B	70%	24%	16%
conv3_3	590K	3.7B	64%	42%	29%
conv4_1	1M	1.8B	51%	32%	21%
conv4_2	2M	3.7B	45%	27%	14%
conv4_3	2M	3.7B	34%	34%	15%
conv5_1	2M	925M	32%	35%	12%
conv5_2	2M	925M	29%	29%	9%
conv5_3	2M	925M	19%	36%	11%
fc6	103M	206M	38%	4%	1%
fc7	17M	34M	42%	4%	2%
fc8	4M	8M	100%	23%	9%
total	138M	30.9B	64%	**7.5%**	**21%**

Layer	Weights	FLOP	Act%	Weights%	FLOP%
conv1	0.5K	576K	82%	66%	66%
conv2	25K	3200K	72%	12%	10%
fc1	400K	800K	55%	8%	6%
fc2	5K	10K	100%	19%	10%
Total	431K	4586K	77%	**8%**	**16%**

Layer	Weights	FLOP	Act%	Weights%	FLOP%
fc1	235K	470K	38%	8%	8%
fc2	30K	60K	65%	9%	4%
fc3	1K	2K	100%	26%	17%
Total	266K	532K	46%	**8%**	**8%**

Network	Top-1 Error	Top-5 Error	Parameters	Compression Rate
LeNet-300-100 Ref	1.64%	-	267K	
LeNet-300-100 Pruned	1.59%	-	**22K**	**12×**
LeNet-5 Ref	0.80%	-	431K	
LeNet-5 Pruned	0.77%	-	**36K**	**12×**
AlexNet Ref	42.78%	19.73%	61M	
AlexNet Pruned	42.77%	19.67%	**6.7M**	**9×**
VGG-16 Ref	31.50%	11.32%	138M	
VGG-16 Pruned	31.34%	10.88%	**10.3M**	**13×**

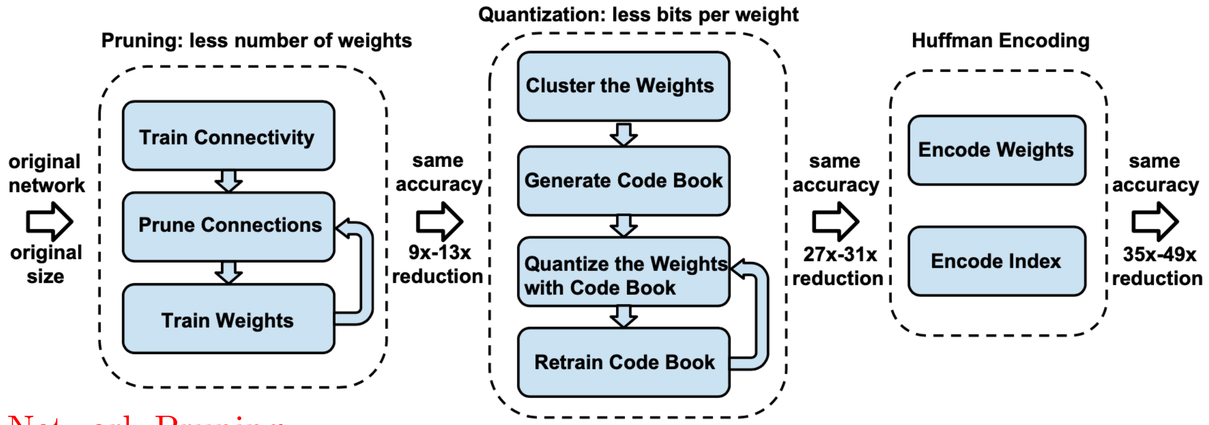
Layer	Weights	FLOP	Act%	Weights%	FLOP%
conv1	35K	211M	88%	84%	84%
conv2	307K	448M	52%	38%	33%
conv3	885K	299M	37%	35%	18%
conv4	663K	224M	40%	37%	14%
conv5	442K	150M	34%	37%	14%
fc1	38M	75M	36%	9%	3%
fc2	17M	34M	40%	9%	3%
fc3	4M	8M	100%	25%	10%
Total	61M	1.5B	54%	**11%**	**30%**



Han, Song, et al. "Learning both weights and connections for efficient neural network." *Advances in neural information processing systems*. 2015.

Deep Compression: Compressing Deep Neural Networks with Pruning, Trained Quantization and Huffman Coding

YouTube Playlist

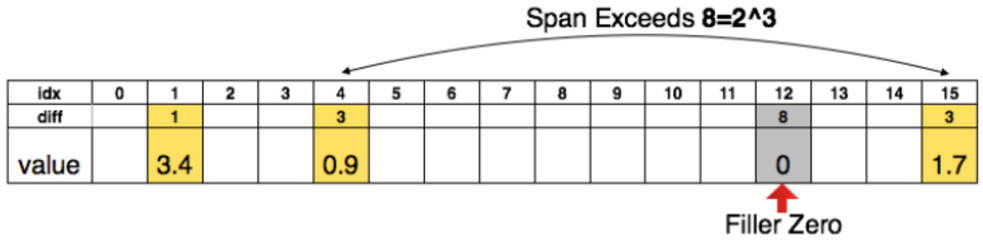


Network Pruning

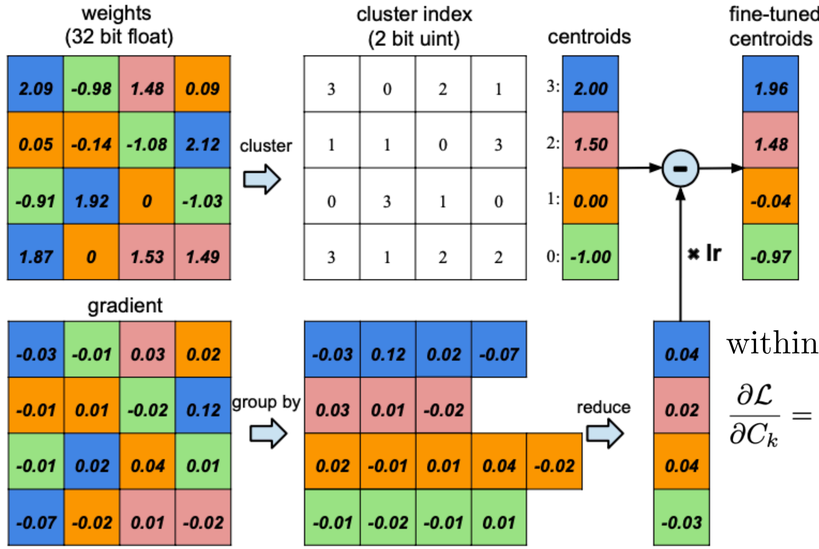
All connections with weights below a threshold are removed from the network

Compressed Sparse Row (CSR)
Compressed Sparse Column (CSC)
$\rightarrow 2a + n + 1$ numbers (a: number of non-zero elements, n: number of rows or columns)

To compress further, store the index difference instead of the absolute position, and encode this difference in 8 bits for conv layer and 5 bits for fc layer.



Trained Quantization & Weight Sharing



Quantize pruned AlexNet to 8-bits (256 shared weights) for each CONV layers, and 5-bits (32 shared weights) for each FC layer.

k-means clustering

$W = \{w_1, \ldots, w_n\}$ (n original weights)

$C = \{c_1, \ldots, c_k\}$ ($k \ll n$ clusters)

$$\arg\min_C \sum_{i=1}^{k} \sum_{w \in c_i} |w - c_i|^2$$

within-cluster sum of squares (WCSS)

$$\frac{\partial \mathcal{L}}{\partial C_k} = \sum_{i,j} \frac{\partial \mathcal{L}}{\partial W_{ij}} \frac{\partial W_{ij}}{\partial C_k} = \sum_{i,j} \frac{\partial \mathcal{L}}{\partial W_{ij}} \mathbb{1}(I_{ij} = k)$$

Huffman Coding

More common symbols are represented with fewer bits

$$r = \frac{nb}{n \log_2(k) + kb} = \frac{16 \times 32}{16 \times 2 + 4 \times 32} = 3.2$$

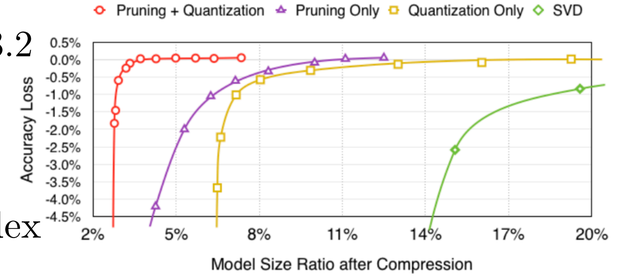
(r: compression rate)

$k \rightarrow$ number of clusters

$\log_2(k) \rightarrow$ required bits to encode the index

$n \rightarrow$ number of bits in a network

$b \rightarrow$ bits representing each connection



Han, Song, Huizi Mao, and William J. Dally. "Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding." *arXiv preprint arXiv:1510.00149* (2015).

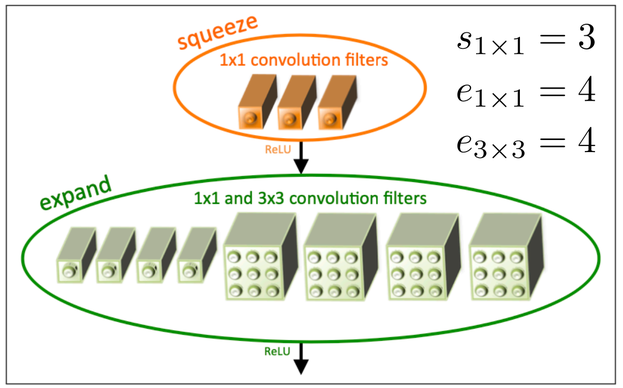
SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size

YouTube Video

$$X \in \mathbb{R}^{h \times w \times c} \xrightarrow{W \in \mathbb{R}^{k \times k \times c \times f}} Y \in \mathbb{R}^{h \times w \times f}$$

Strategy 1: Replace 3×3 filters with 1×1 filters
Strategy 2: Decrease the number of input channels to 3×3 filters
Strategy 3: Downsample late in the network so that convolution layers have large activation maps

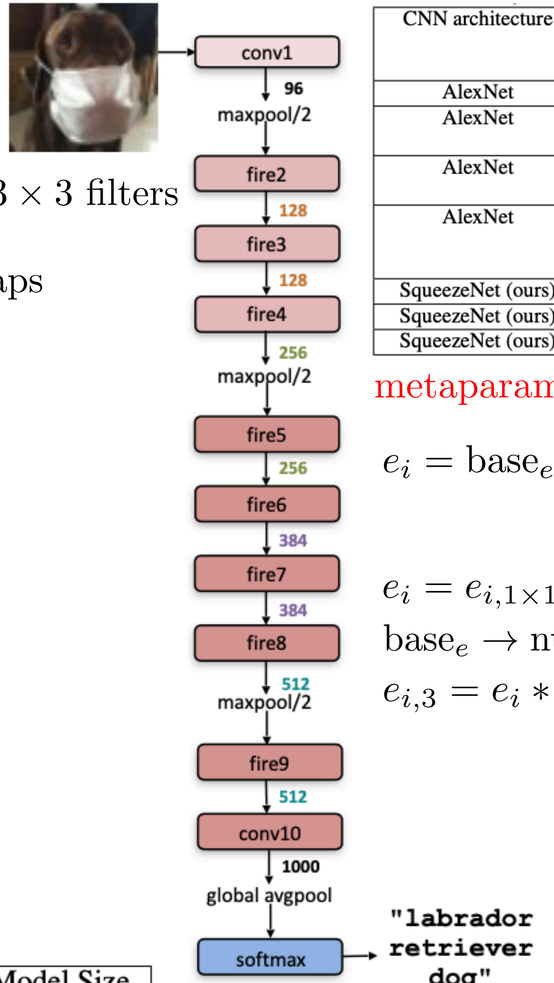
The fire module



$s_{1\times1} = 3$
$e_{1\times1} = 4$
$e_{3\times3} = 4$

$s_{1\times1} \rightarrow$ number of 1×1 filters in the squeeze layer
$e_{1\times1} \rightarrow$ number of 1×1 filters in the expand layer
$e_{3\times3} \rightarrow$ number of 3×3 filters in the expand layer
$s_{1\times1} < e_{1\times1} + e_{3\times3}$ as per strategy 2

Architecture	Top-1 Accuracy	Top-5 Accuracy	Model Size
Vanilla SqueezeNet	57.5%	80.3%	4.8MB
SqueezeNet + Simple Bypass	**60.4%**	**82.5%**	4.8MB
SqueezeNet + Complex Bypass	58.8%	82.0%	7.7MB

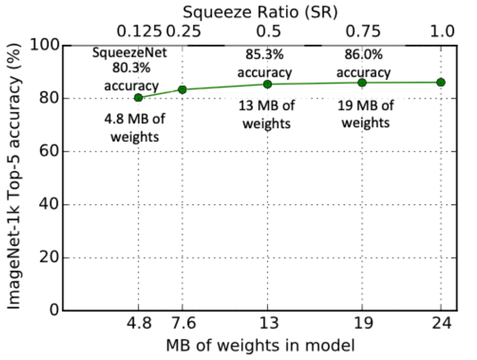


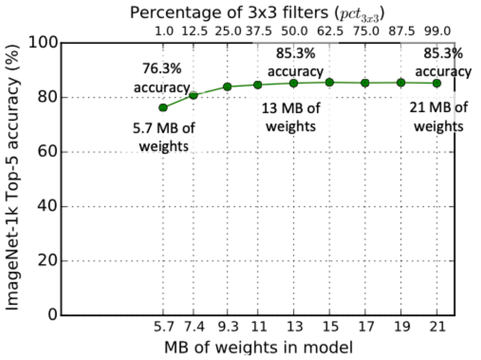
CNN architecture	Compression Approach	Data Type	Original → Compressed Model Size	Reduction in Model Size vs. AlexNet	Top-1 ImageNet Accuracy	Top-5 ImageNet Accuracy
AlexNet	None (baseline)	32 bit	240MB	1x	57.2%	80.3%
AlexNet	SVD (Denton et al., 2014)	32 bit	240MB → 48MB	5x	56.0%	79.4%
AlexNet	Network Pruning (Han et al., 2015b)	32 bit	240MB → 27MB	9x	57.2%	80.3%
AlexNet	Deep Compression (Han et al., 2015a)	5-8 bit	240MB → 6.9MB	35x	57.2%	80.3%
SqueezeNet (ours)	None	32 bit	4.8MB	**50x**	57.5%	80.3%
SqueezeNet (ours)	Deep Compression	8 bit	4.8MB → 0.66MB	**363x**	57.5%	80.3%
SqueezeNet (ours)	Deep Compression	6 bit	4.8MB → 0.47MB	**510x**	57.5%	80.3%

metaparameters

$$e_i = \text{base}_e + \underbrace{\left(\text{incr}_e * \left\lfloor \frac{i}{\text{freq}} \right\rfloor\right)}_{\text{after every freq fire modules increase the number of expand filters by incr}_e}$$

$e_i = e_{i,1\times1} + e_{i,3\times3} \rightarrow$ number of expand filters for fire module i
$\text{base}_e \rightarrow$ number of expand filters in the first fire module
$e_{i,3} = e_i * \underbrace{\text{pct}_{3\times3}}_{\text{percentage}}, \quad e_{i,1} = e_i * (1 - \text{pct}_{3\times3}), \quad s_{i,1\times1} = \underbrace{\text{SR}}_{\text{squeeze ratio}} * e_i$

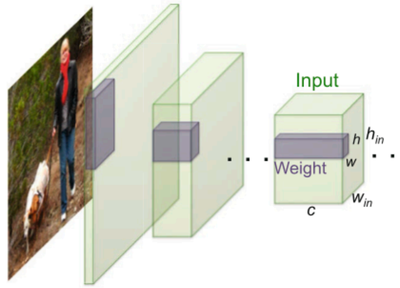




Iandola, Forrest N., et al. "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and< 0.5 MB model size." *arXiv preprint arXiv:1602.07360* (2016).

XNOR-Net: ImageNet Classification Using Binary Convolutional Neural Networks

YouTube Playlist



	Network Variations	Operations used in Convolution	Memory Saving (Inference)	Computation Saving (Inference)	Accuracy on ImageNet (AlexNet)
Standard Convolution	Real-Value Inputs: 0.11 -0.21 ... -0.34 / -0.25 0.61 ... 0.52; Real-Value Weights: 0.12 -1.2 ... 0.41 / -0.2 0.5 ... 0.68	+, −, ×	1x	1x	%56.7
Binary Weight	Real-Value Inputs: 0.11 -0.21 ... -0.34 / -0.25 0.61 ... 0.52; Binary Weights: 1 -1 ... 1 / -1 1 ... 1	+, −	~32x	~2x	%56.8
BinaryWeight Binary Input (**XNOR-Net**)	Binary Inputs: 1 -1 ... -1 / -1 1 ... 1; Binary Weights: 1 -1 ... 1 / -1 1 ... 1	XNOR, bitcount	~32x	~58x	%44.2

– virtual reality
– augmented reality
– smart wearable devices

$I \in \mathbb{R}^{c \times w_{in} \times h_{in}}$

$W \in \mathbb{R}^{c \times w \times h}, w \leq w_{in}, h \leq h_{in}$

$W \approx \alpha B$

$B \in \{+1, -1\}^{c \times w \times h} \rightarrow$ binary filter

$\alpha > 0 \rightarrow$ scaling factor

$I * W \approx (I \oplus B)\alpha$

convolution without any multiplications

$W, B \in R^n$ where $n = cwh$

$$B^* = \arg\max_B W^T B \text{ s.t. } B \in \{+1, -1\}^n$$

$$B_i = +1 \text{ if } W_i \geq 0$$
$$B_i = -1 \text{ if } W_i < 0 \implies B^* = \text{sign}(W)$$

$$\alpha^* = \frac{W^T B}{n} = \frac{W^T \text{sign}(W)}{n} = \frac{\sum_i |W_i|}{n} = \frac{1}{n}\|W\|_1$$

Given W_t

$$\alpha_t = \frac{1}{n}\|W_t\|_1$$

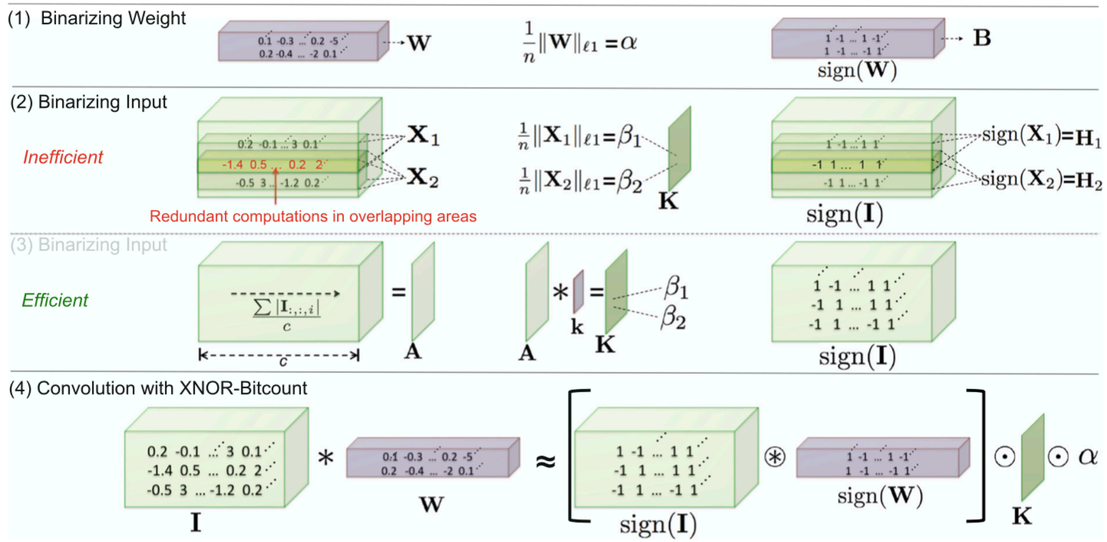
$$B_t = \text{sign}(W_t)$$

$$\widetilde{W}_t = \alpha_t B_t \qquad W_{t+1} = W_t - \eta \nabla_{\widetilde{W}_t} C$$

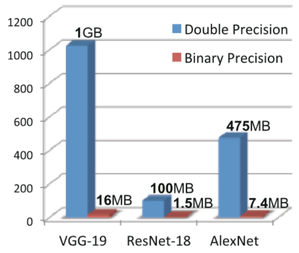
$$J(B, \alpha) = \|W - \alpha B\|^2 = \alpha^2 \underbrace{B^T B}_{=n} - 2\alpha W^T B + \underbrace{W^T W}_{:=c}$$

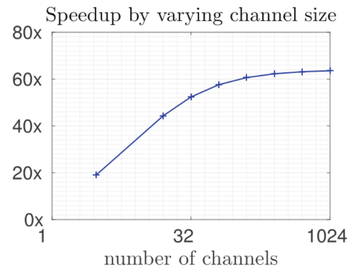
$=n$ since $B \in \{+1, -1\}^n$ $:=c$ is a constant since W is known

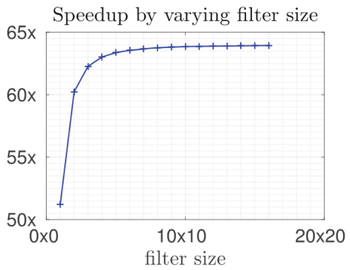
$$B^*, \alpha^* = \arg\min_{B,\alpha} J(B, \alpha)$$



$$\mathbf{A} = \frac{\sum |\mathbf{I}_{:,:,i}|}{c} \qquad \forall ij \ \mathbf{k}_{ij} = \frac{1}{w \times h}$$







Rastegari, Mohammad, et al. "Xnor-net: Imagenet classification using binary convolutional neural networks." *European conference on computer vision*. Springer, Cham, 2016.

MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications

YouTube Playlist

$F \in \mathbb{R}^{D_F \times D_F \times M}$ → input feature maps
$G \in \mathbb{R}^{D_F \times D_F \times N}$ → output feature maps
$K \in \mathbb{R}^{D_K \times D_K \times M \times N}$ → convolution kernel
$G_{k,\ell,n} = \sum_{i,j,m} K_{i,j,m,n} F_{k+i-1,\ell+j-1,m}$ → stride one and padding

Computational Cost: $D_K D_K M N D_F D_F$

$$\hat{G}_{k,\ell,m} = \sum_{i,j} \hat{K}_{i,j,m} F_{k+i-1,\ell+j-1,m}$$

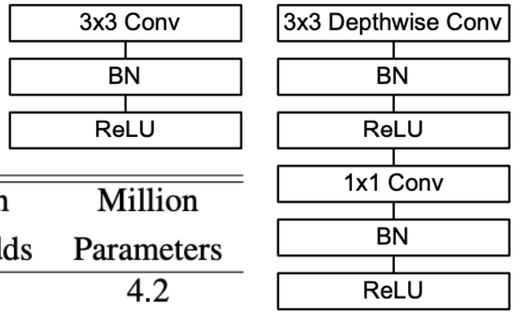
$\hat{K} \in \mathbb{R}^{D_K \times D_K \times M}$ → depth-wise (channel-wise) convolution kernel

Computational Cost: $D_K D_K M D_F D_F$

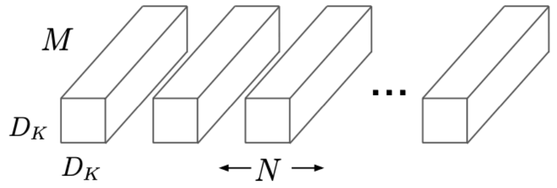
Depth-wise Separable Convolution Cost:

$$D_K D_K M D_F D_F + \underbrace{M N D_F D_F}_{1\times1 \text{ conv}}$$

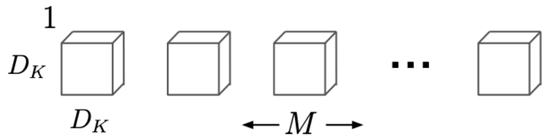
$\alpha \rightarrow$ width multiplier
$\alpha M, \alpha N$
$\rho \rightarrow$ resolution multiplier
ρD_F



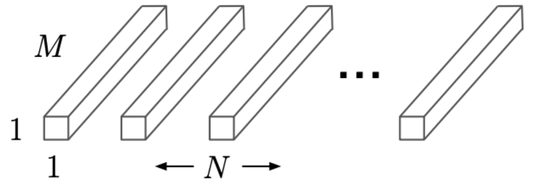
Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
GoogleNet	69.8%	1550	6.8
VGG 16	71.5%	15300	138



(a) Standard Convolution Filters



(b) Depthwise Convolutional Filters



(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
$5\times$ Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Width Multiplier	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
0.75 MobileNet-224	68.4%	325	2.6
0.5 MobileNet-224	63.7%	149	1.3
0.25 MobileNet-224	50.6%	41	0.5

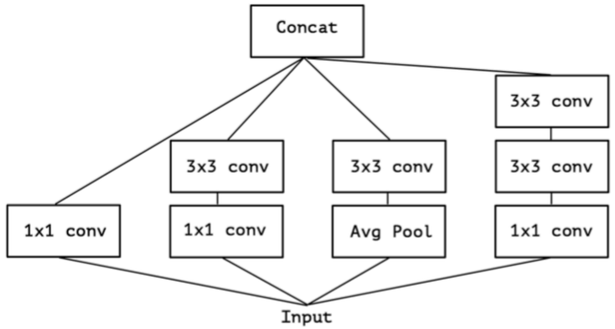
Resolution	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
1.0 MobileNet-192	69.1%	418	4.2
1.0 MobileNet-160	67.2%	290	4.2
1.0 MobileNet-128	64.4%	186	4.2

Howard, Andrew G., et al. "Mobilenets: Efficient convolutional neural networks for mobile vision applications." *arXiv preprint arXiv:1704.04861* (2017).

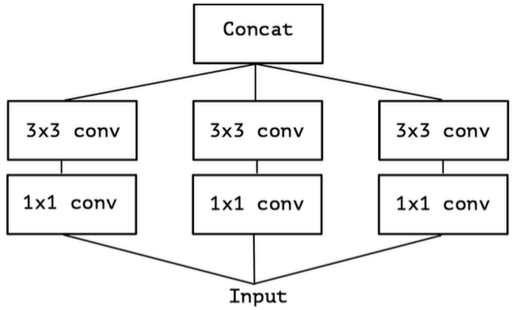
Xception: Deep Learning with Depthwise Separable Convolutions

YouTube Video

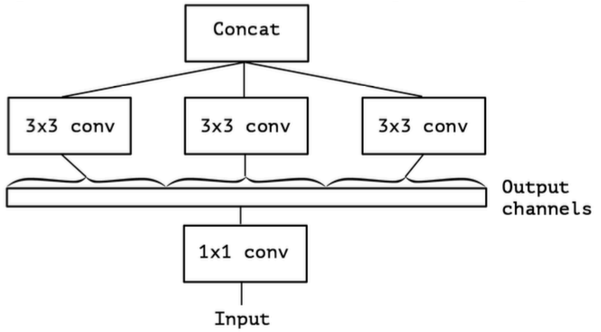
A canonical Inception module (Inception V3)



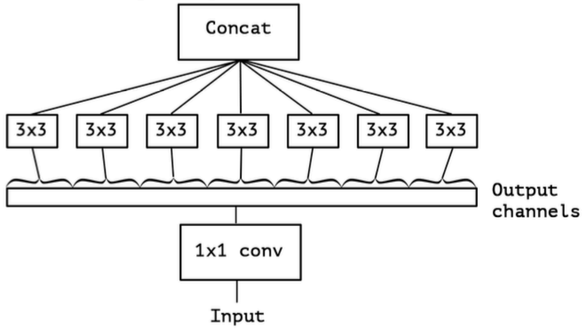
A simplified Inception module

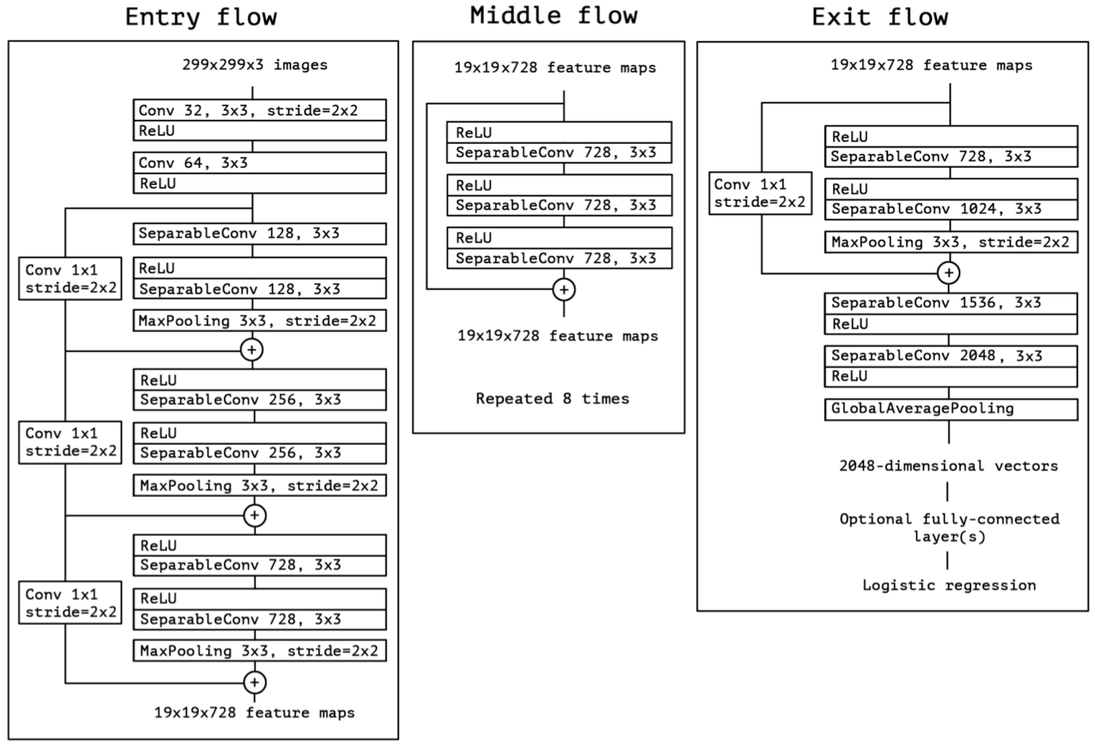


A strictly equivalent reformulation of the simplified Inception module



An "extreme" version of our Inception module, with one spatial convolution per output channel of the 1x1 convolution.

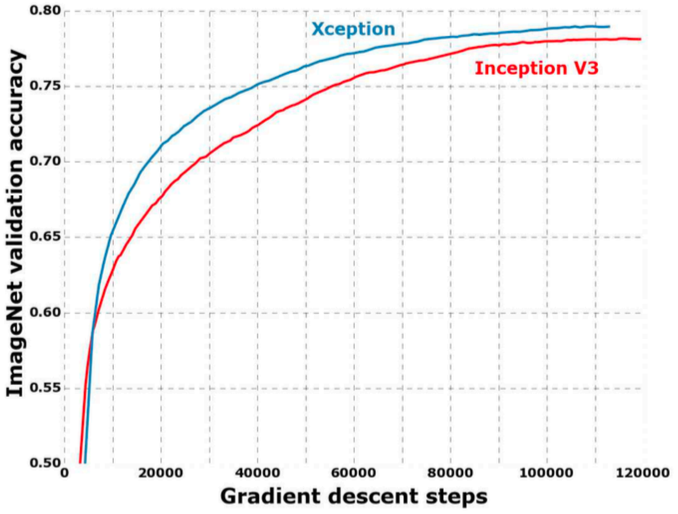


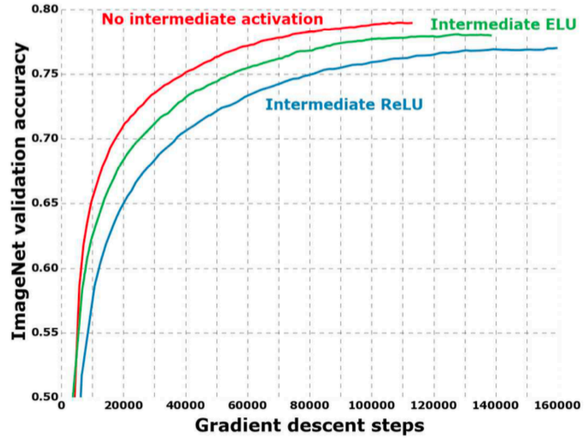


	Top-1 accuracy	Top-5 accuracy
VGG-16	0.715	0.901
ResNet-152	0.770	0.933
Inception V3	0.782	0.941
Xception	**0.790**	**0.945**

depthwise separable convolutions
depthwise convolution
pointwise convolution

	Parameter count	Steps/second
Inception V3	23,626,728	31
Xception	22,855,952	28

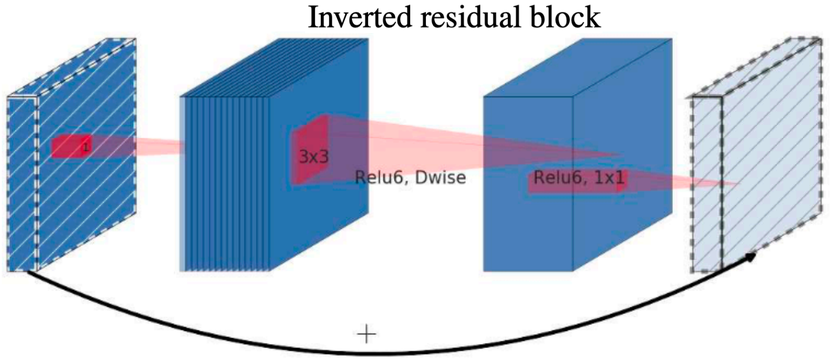




Chollet, François. "Xception: Deep learning with depthwise separable convolutions." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017.

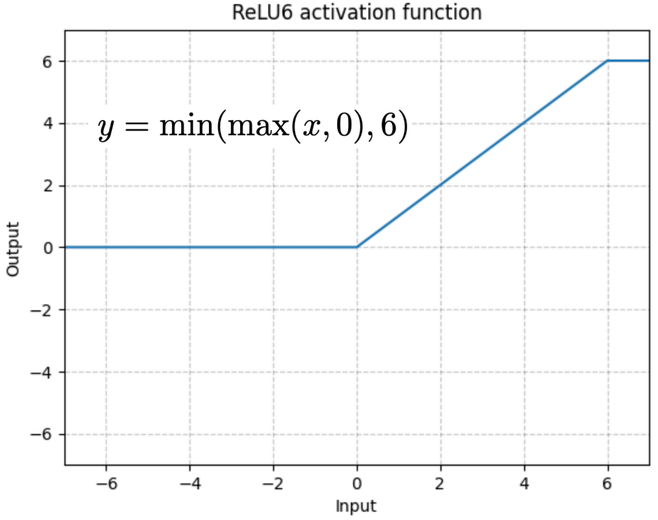
MobileNetV2: Inverted Residuals and Linear Bottlenecks

YouTube Video

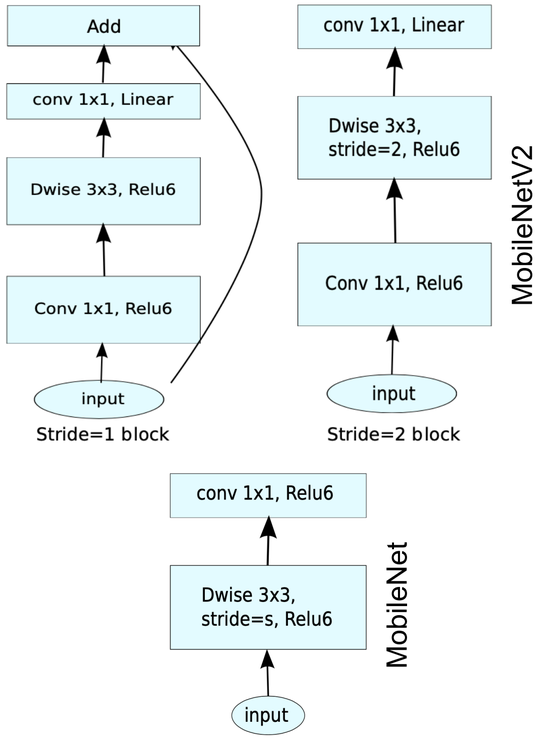


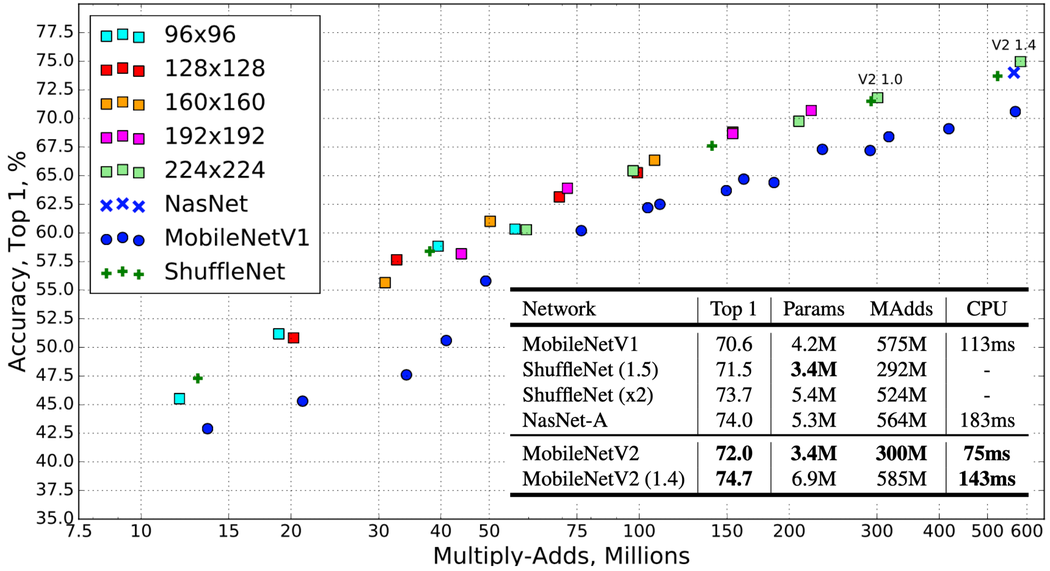
Input	Operator	Output
$h \times w \times k$	1x1 conv2d , ReLU6	$h \times w \times (tk)$
$h \times w \times tk$	3x3 dwise s=s, ReLU6	$\frac{h}{s} \times \frac{w}{s} \times (tk)$
$\frac{h}{s} \times \frac{w}{s} \times tk$	linear 1x1 conv2d	$\frac{h}{s} \times \frac{w}{s} \times k'$

Computational cost: $hwkt(k + 9 + k')$

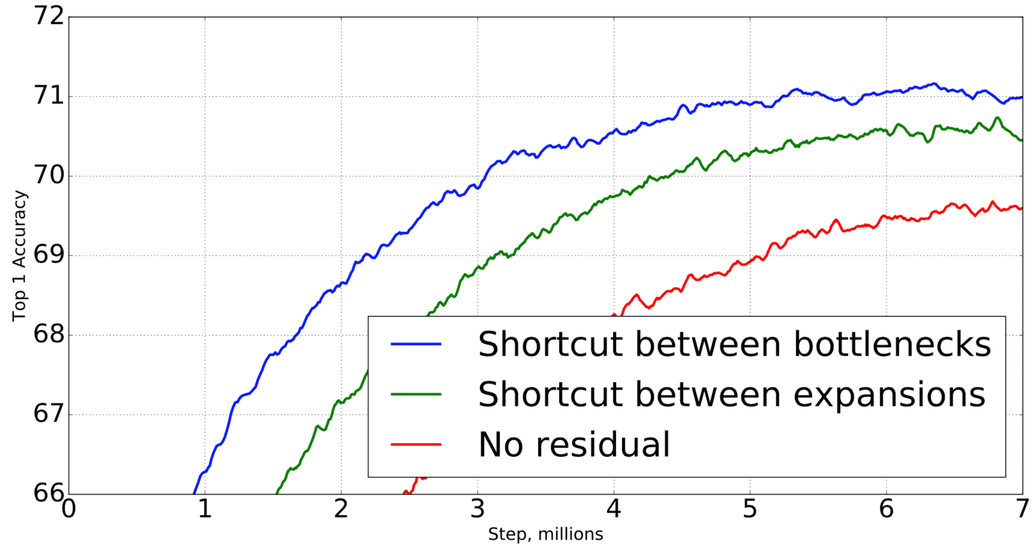


Input	Operator	t	c	n	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	avgpool 7x7	-	-	1	-
$1 \times 1 \times 1280$	conv2d 1x1	-	k	-	





Network	Top 1	Params	MAdds	CPU
MobileNetV1	70.6	4.2M	575M	113ms
ShuffleNet (1.5)	71.5	**3.4M**	292M	-
ShuffleNet (x2)	73.7	5.4M	524M	-
NasNet-A	74.0	5.3M	564M	183ms
MobileNetV2	**72.0**	**3.4M**	**300M**	**75ms**
MobileNetV2 (1.4)	**74.7**	6.9M	585M	**143ms**

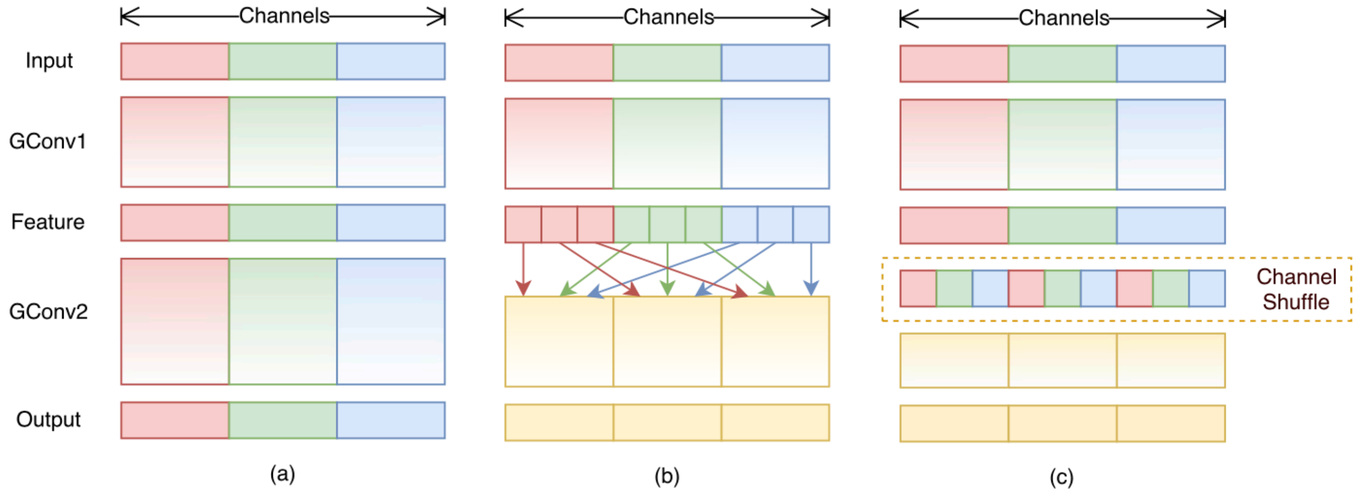


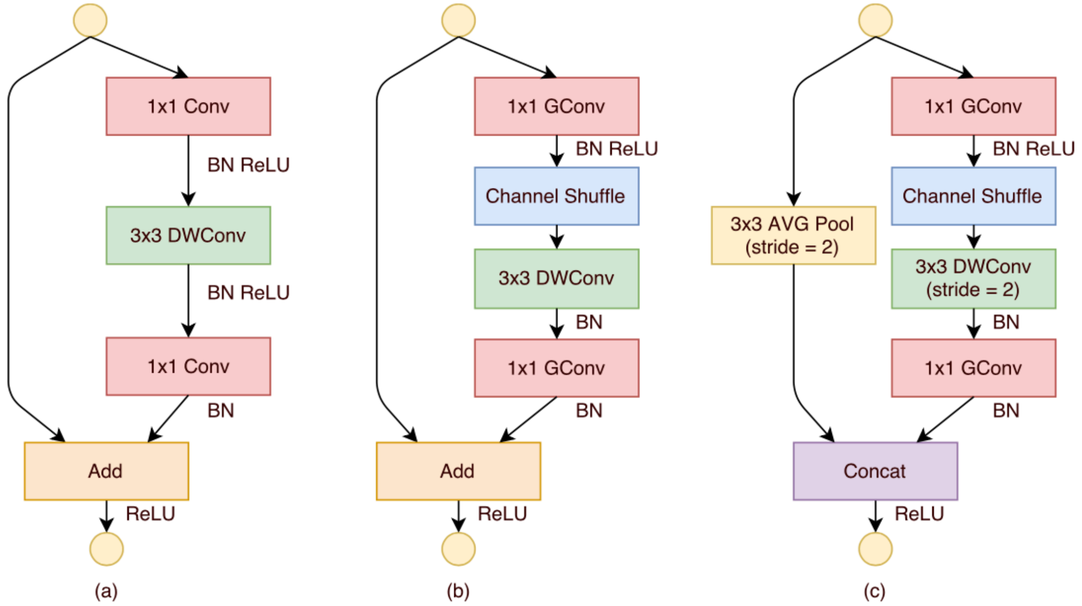
Sandler, Mark, et al. "Mobilenetv2: Inverted residuals and linear bottlenecks." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018.

ShuffleNet: An Extremely Efficient Convolutional Neural Network for Mobile Devices

Boulder

YouTube Video





– drones – robots – smartphones

channel shuffle

$g \rightarrow$ number of groups

$n \rightarrow$ number of channels per group

$gn \rightarrow$ number of channels

reshape to (g, n)

transpose

flatten

Model	Cls err. (%)	Complexity (MFLOPs)
VGG-16 [31]	28.5	15300
ShuffleNet 2× ($g = 3$)	26.3	**524**
GoogleNet [34]*	31.3	1500
ShuffleNet 1× ($g = 8$)	32.4	**140**
AlexNet [22]	42.8	720
SqueezeNet [14]	42.5	833
ShuffleNet 0.5× ($g = 4$)	41.6	**38**

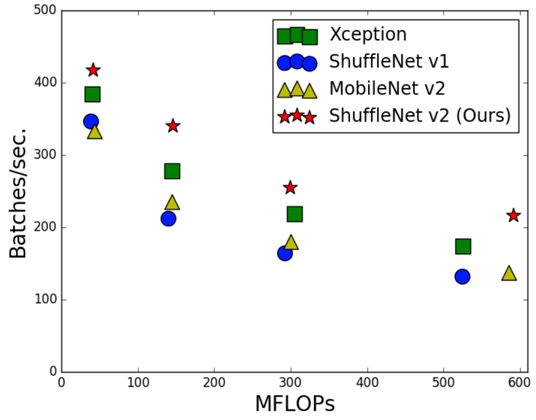
Model	Cls err. (%)	FLOPs	224 × 224	480 × 640	720 × 1280
ShuffleNet 0.5× ($g = 3$)	43.2	38M	15.2ms	87.4ms	260.1ms
ShuffleNet 1× ($g = 3$)	32.6	140M	37.8ms	222.2ms	684.5ms
ShuffleNet 2× ($g = 3$)	26.3	524M	108.8ms	617.0ms	1857.6ms
AlexNet [22]	42.8	720M	184.0ms	1156.7ms	3633.9ms
1.0 MobileNet-224 [12]	29.4	569M	110.0ms	612.0ms	1879.2ms

Layer	Output size	KSize	Stride	Repeat	Output channels (g groups)				
					$g = 1$	$g = 2$	$g = 3$	$g = 4$	$g = 8$
Image	224 × 224				3	3	3	3	3
Conv1	112 × 112	3 × 3	2	1	24	24	24	24	24
MaxPool	56 × 56	3 × 3	2						
Stage2	28 × 28		2	1	144	200	240	272	384
	28 × 28		1	3	144	200	240	272	384
Stage3	14 × 14		2	1	288	400	480	544	768
	14 × 14		1	7	288	400	480	544	768
Stage4	7 × 7		2	1	576	800	960	1088	1536
	7 × 7		1	3	576	800	960	1088	1536
GlobalPool	1 × 1	7 × 7							
FC					1000	1000	1000	1000	1000
Complexity					143M	140M	137M	133M	137M

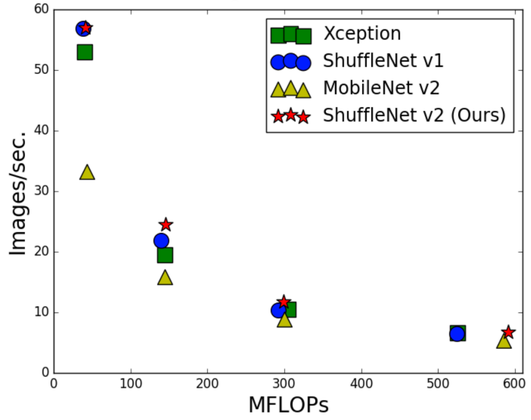
Zhang, Xiangyu, et al. "Shufflenet: An extremely efficient convolutional neural network for mobile devices." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018.

ShuffleNet V2: Practical Guidelines for Efficient CNN Architecture Design

Networks with similar FLOPs have different speeds!



(c) GPU



(d) ARM

– Memory Access Cost (MAC)
– degree of parallelism
– platform

G1) Equal channel width minimizes memory access cost (MAC).

$B = hwc_1c_2 \rightarrow$ FLOPs of a 1×1 convolution

$$\text{MAC} = \underbrace{hw(c_1 + c_2)}_{\text{input/output feature maps}} + \underbrace{c_1c_2}_{\text{kernel weights}}$$

$$\text{MAC} \geq 2\sqrt{hwB} + \frac{B}{hw} \text{ (equality when } c_1 = c_2)$$

G2) Excessive group convolution increases MAC.

$g \rightarrow$ number of groups

$B = hwc_1c_2/g$

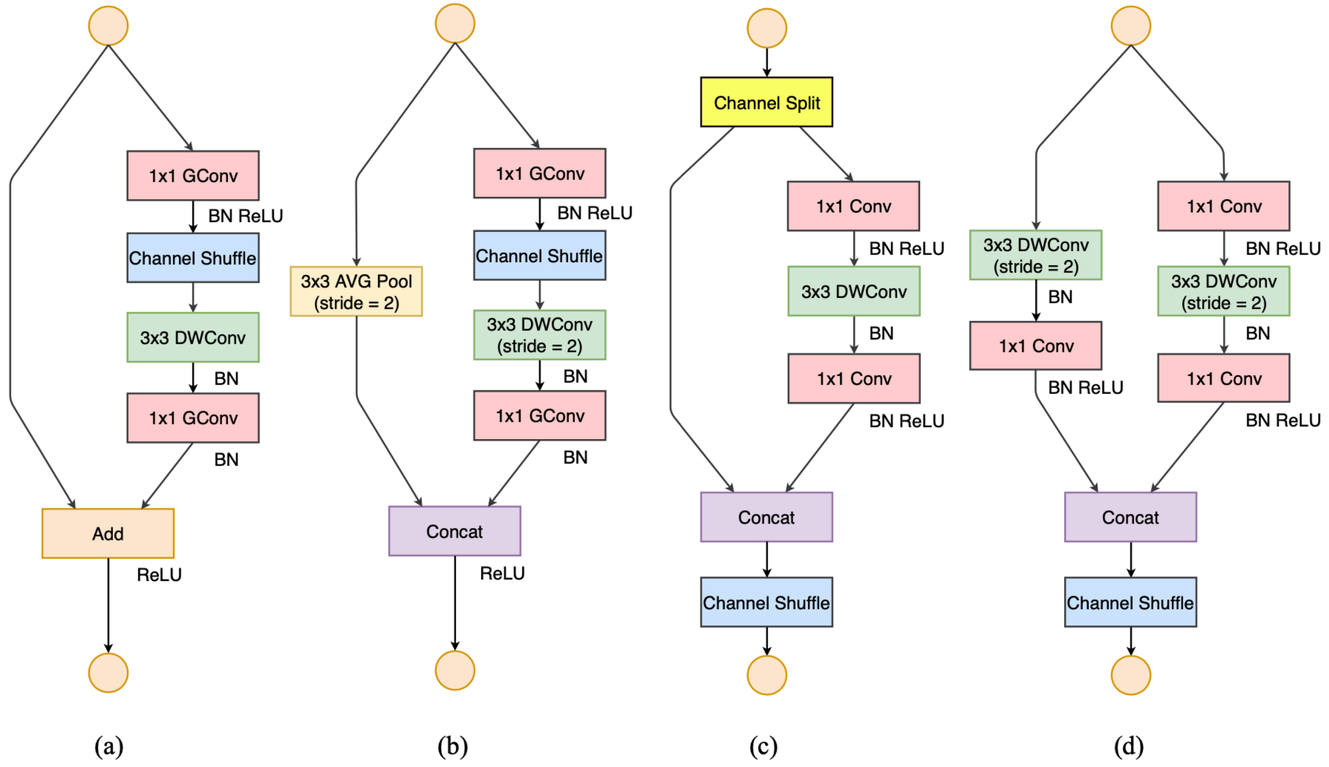
$\text{MAC} = hw(c_1 + c_2) + c_1c_2/g$

$\text{MAC} = hwc_1 + Bg/c_1 + B/(hw) \implies$ MAC increases by g

G3) Network fragmentation (e.g., Inception modules) reduces degree of parallelism.

G4) Element-wise operations are non-negligible (high MAC/FLOPs ratio).

– ShuffleNet v1 violates G2 (group convolutions) & G1 (bottleneck-like building blocks)
– MobileNet v2 violates G1 (inverted bottleneck structure) & G4 (depth-wise convolutions)
– auto-generated structures violate G3 high MAC/FLOPs ratio



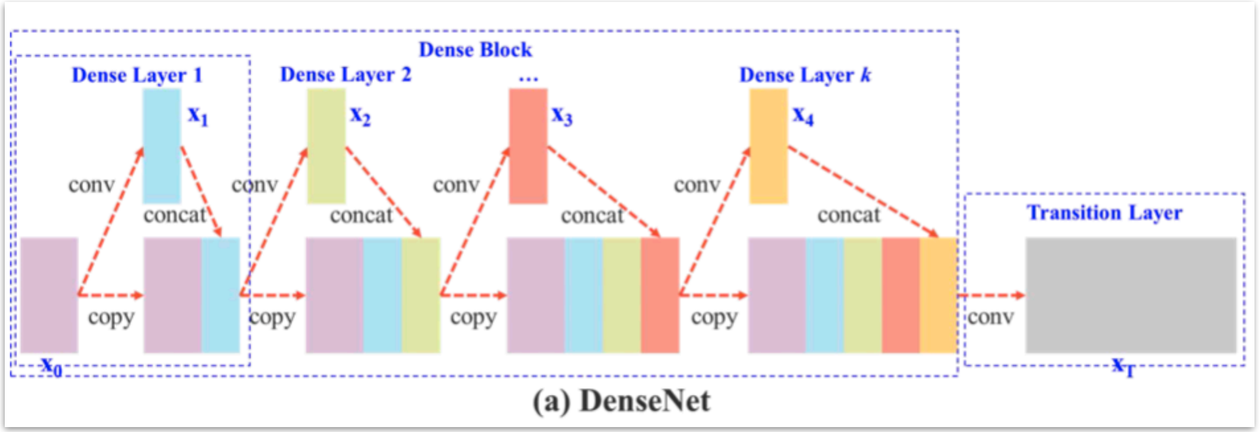
(a) (b) (c) (d)

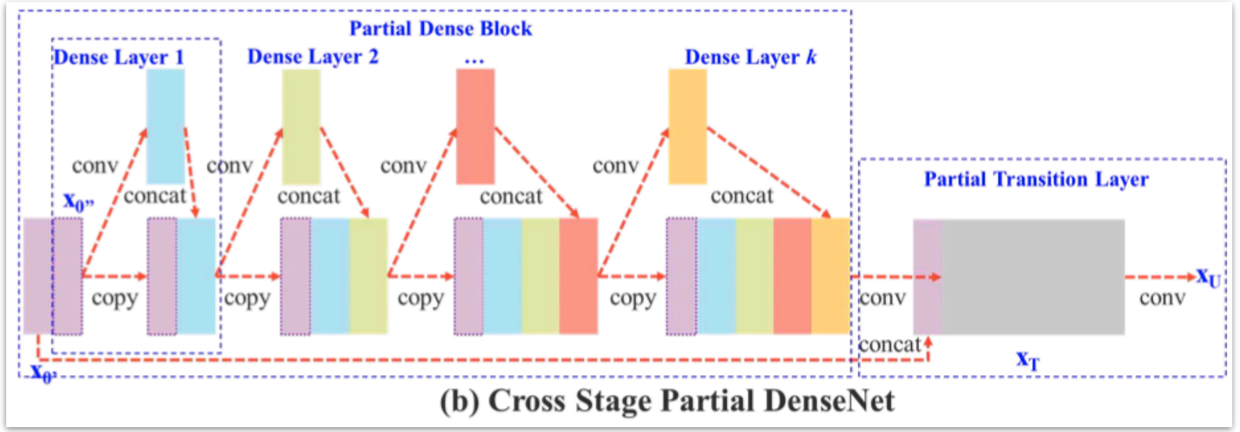
Channel Split

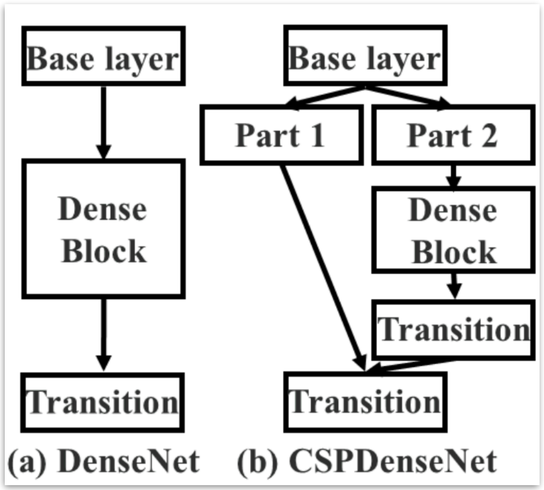
The input of c feature channels are split into two branches with $c - c'$ and c' channels ($c' = c/2$).

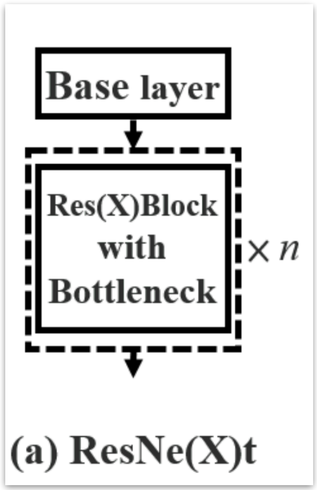
Ma, Ningning, et al. "Shufflenet v2: Practical guidelines for efficient cnn architecture design." *Proceedings of the European conference on computer vision (ECCV)*. 2018.

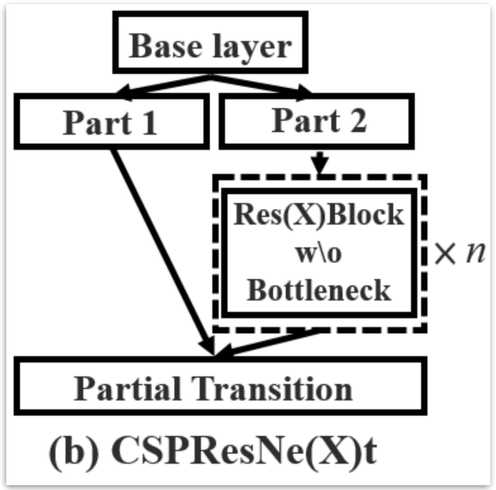
CSPNet: A New Backbone that can Enhance Learning Capability of CNN

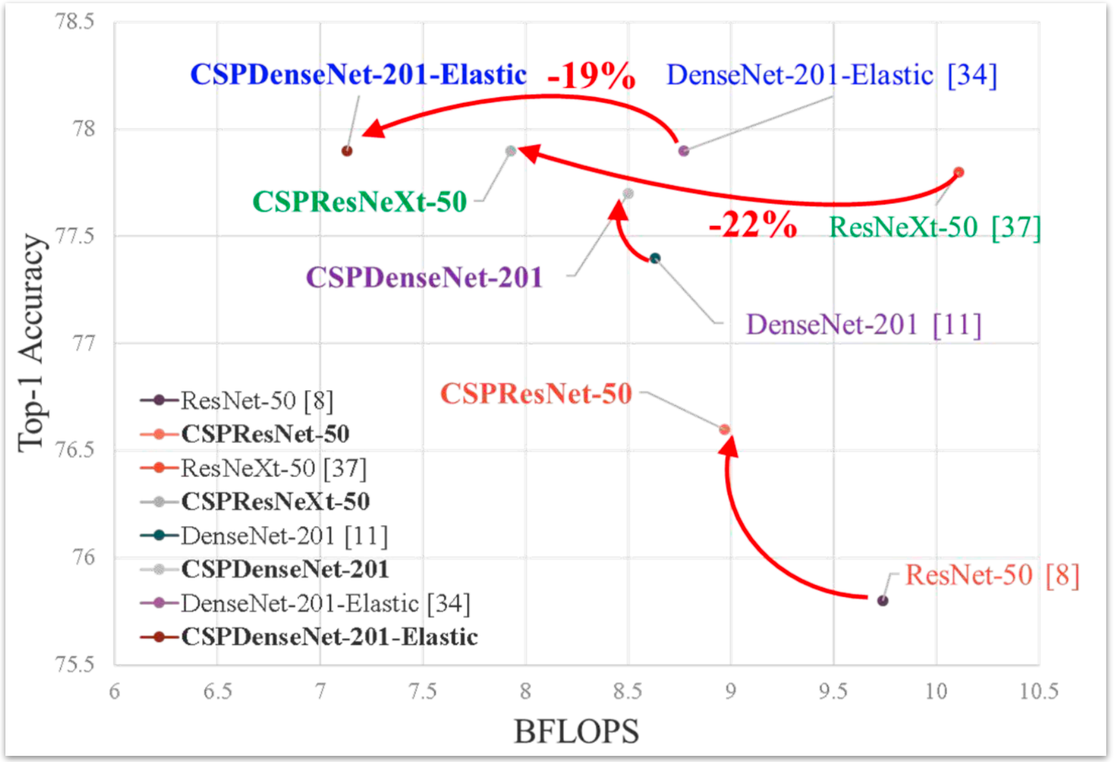












Wang, Chien-Yao, et al. "CSPNet: A new backbone that can enhance learning capability of CNN." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops*. 2020.

Boulder

Questions?

YouTube Playlist