How to design

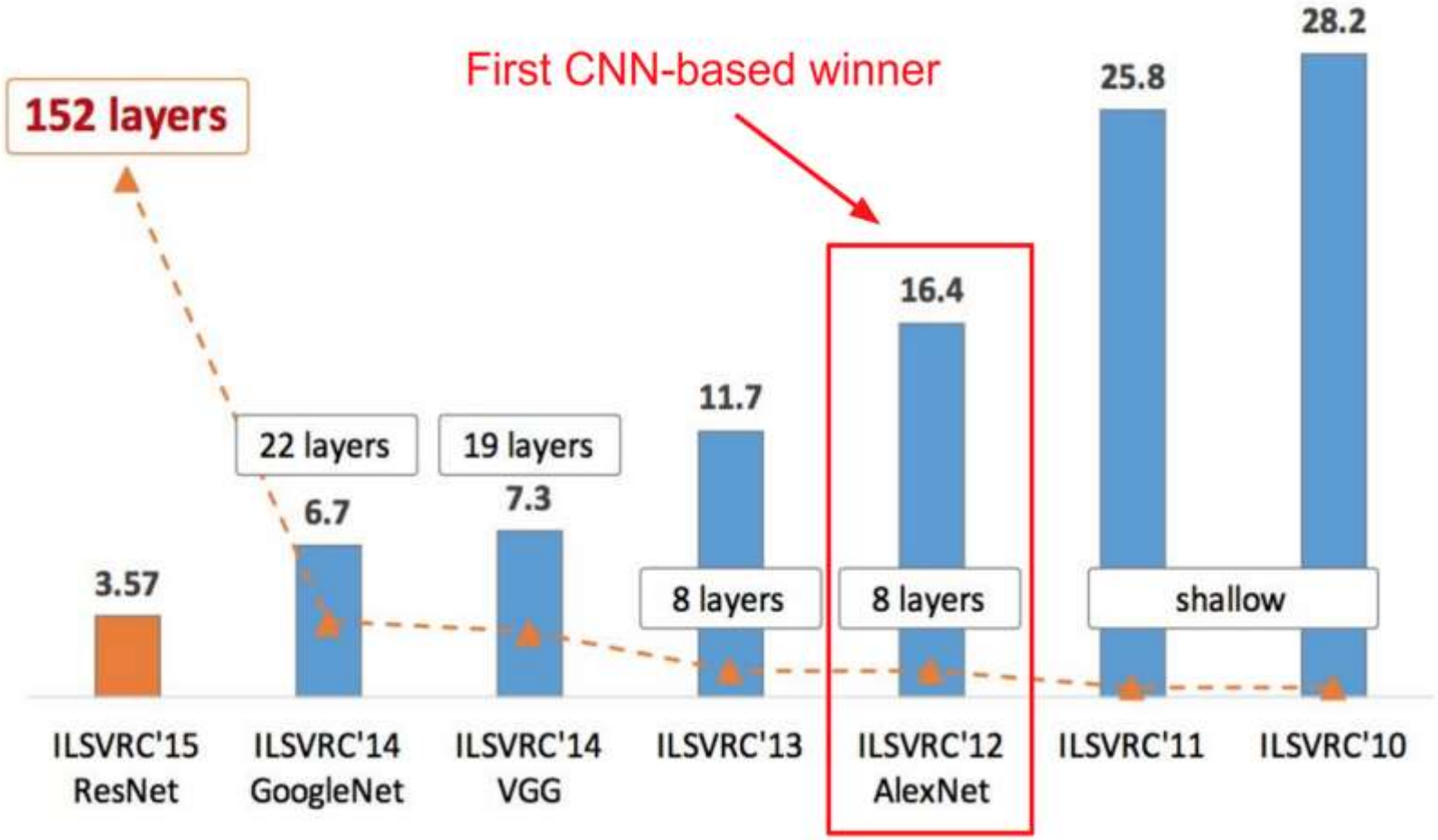
Deep Networks to process images on mobile devices

by SK Reddy
Chief Product Officer AI & ML
Digitalist (www.digitalist.global)
linkedin.com/in/sk-reddy/

Digitalist

H2O WORLD 2017

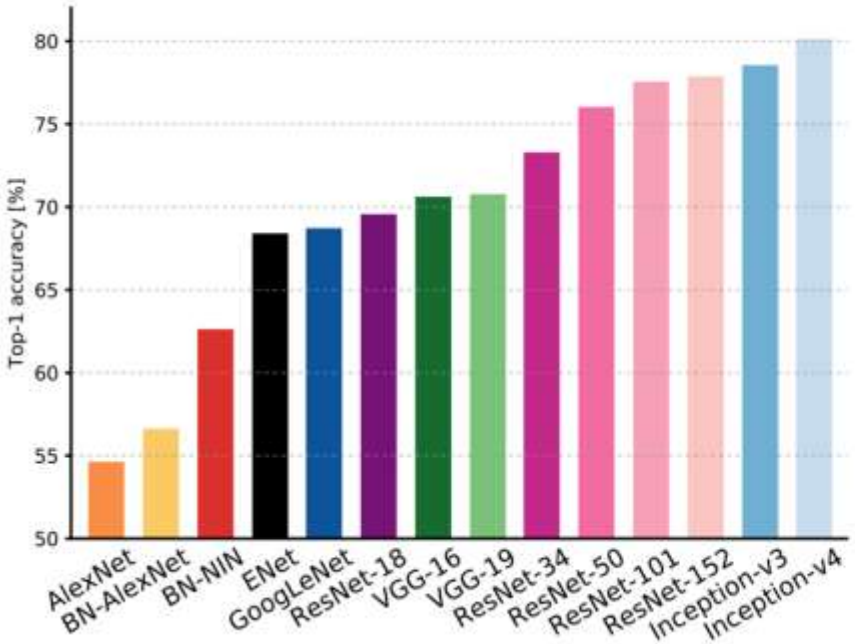
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

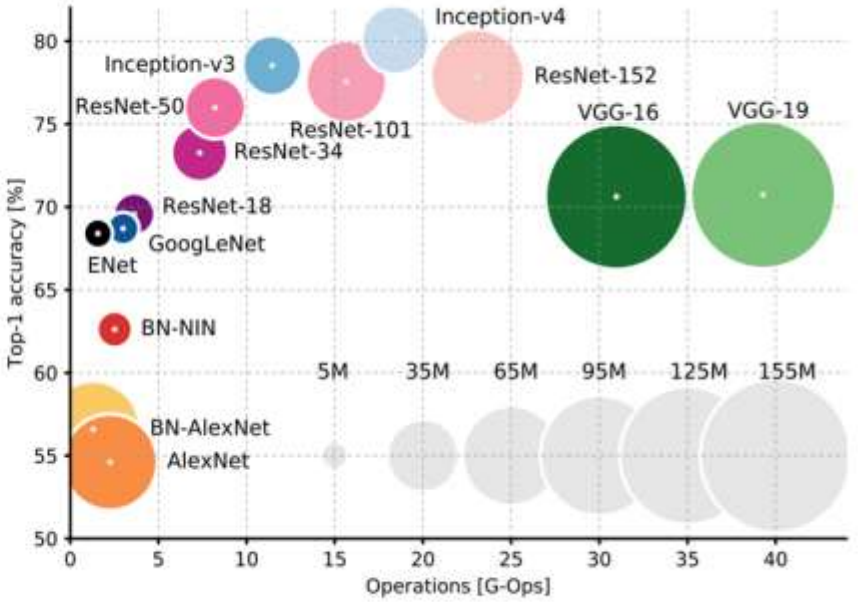


Digitalist

H2O WORLD 2017

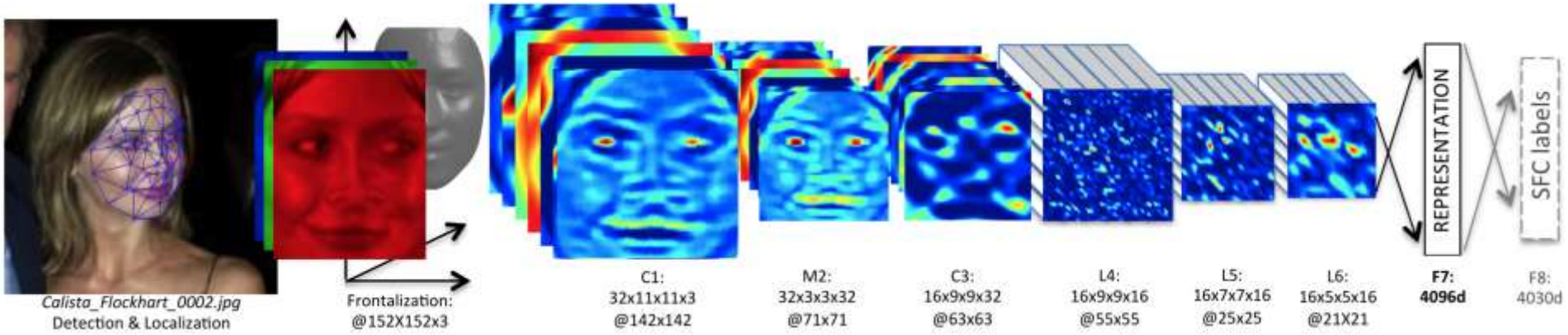
AN ANALYSIS OF DEEP NEURAL NETWORK MODELS FOR PRACTICAL APPLICATIONS





Ref: https://arxiv.org/pdf/1605.07678.pdf

DeepFace (facebook 2014)



Accuracy: 97.35% on the Labeled Faces in the Wild (LFW) dataset

DeepFace: Closing the Gap to Human-Level Performance in Face Verification;
https://www.cs.toronto.edu/~ranzato/publications/taigman_cvpr14.pdf

Digitalist

H2O WORLD 2017

FaceNet (Google, 2015)

Accuracy

- 99.63% for Labeled Faces in the Wild (LFW) dataset
- 95.12% for YouTube Faces DB

layer	size-in	size-out	kernel	param	FL
conv1	220×220×3	110×110×64	7×7×3, 2	9K	11
pool1	110×110×64	55×55×64	3×3×64, 2	0	
rnorm1	55×55×64	55×55×64		0	
conv2a	55×55×64	55×55×64	1×1×64, 1	4K	13
conv2	55×55×64	55×55×192	3×3×64, 1	111K	33
rnorm2	55×55×192	55×55×192		0	
pool2	55×55×192	28×28×192	3×3×192, 2	0	
conv3a	28×28×192	28×28×192	1×1×192, 1	37K	29M
conv3	28×28×192	28×28×384	3×3×192, 1	664K	521M
pool3	28×28×384	14×14×384	3×3×384, 2	0	
conv4a	14×14×384	14×14×384	1×1×384, 1	148K	29M
conv4	14×14×384	14×14×256	3×3×384, 1	885K	173M
conv5a	14×14×256	14×14×256	1×1×256, 1	66K	13M
conv5	14×14×256	14×14×256	3×3×256, 1	590K	116M
conv6a	14×14×256	14×14×256	1×1×256, 1	66K	13M
conv6	14×14×256	14×14×256	3×3×256, 1	590K	116M
pool4	14×14×256	7×7×256	3×3×256, 2	0	
concat	7×7×256	7×7×256		0	
fc1	7×7×256	1×32×128	maxout p=2	103M	103M
fc2	1×32×128	1×32×128	maxout p=2	34M	34M
fc7128	1×32×128	1×1×128		524K	0.5M
L2	1×1×128	1×1×128		0	
total				140M	1.6B

Zeiler&Fergus

type	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj (p)	params	FLOPS
conv1 (7×7×3, 2)	112×112×64	1							9K	119M
max pool + norm	56×56×64	0						m 3×3, 2		
inception (2)	56×56×192	2		64	192				115K	360M
norm + max pool	28×28×192	0						m 3×3, 2		
inception (3a)	28×28×256	2	64	96	128	16	32	m, 32p	164K	128M
inception (3b)	28×28×320	2	64	96	128	32	64	L_2, 64p	228K	179M
inception (3c)	14×14×640	2	0	128	256,2	32	64,2	m 3×3,2	398K	108M
inception (4a)	14×14×640	2	256	96	192	32	64	L_2, 128p	545K	107M
inception (4b)	14×14×640	2	224	112	224	32	64	L_2, 128p	595K	117M
inception (4c)	14×14×640	2	192	128	256	32	64	L_2, 128p	654K	128M
inception (4d)	14×14×640	2	160	144	288	32	64	L_2, 128p	722K	142M
inception (4e)	7×7×1024	2	0	160	256,2	64	128,2	m 3×3,2	717K	56M
inception (5a)	7×7×1024	2	384	192	384	48	128	L_2, 128p	1.6M	78M
inception (5b)	7×7×1024	2	384	192	384	48	128	m, 128p	1.6M	78M
avg pool	1×1×1024	0								
fully conn	1×1×128	1							131K	0.1M
L2 normalization	1×1×128	0								
total									7.5M	1.6B

GoogleNet (Inception)

$$\sum_i^N \left[\|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha \right]_+$$

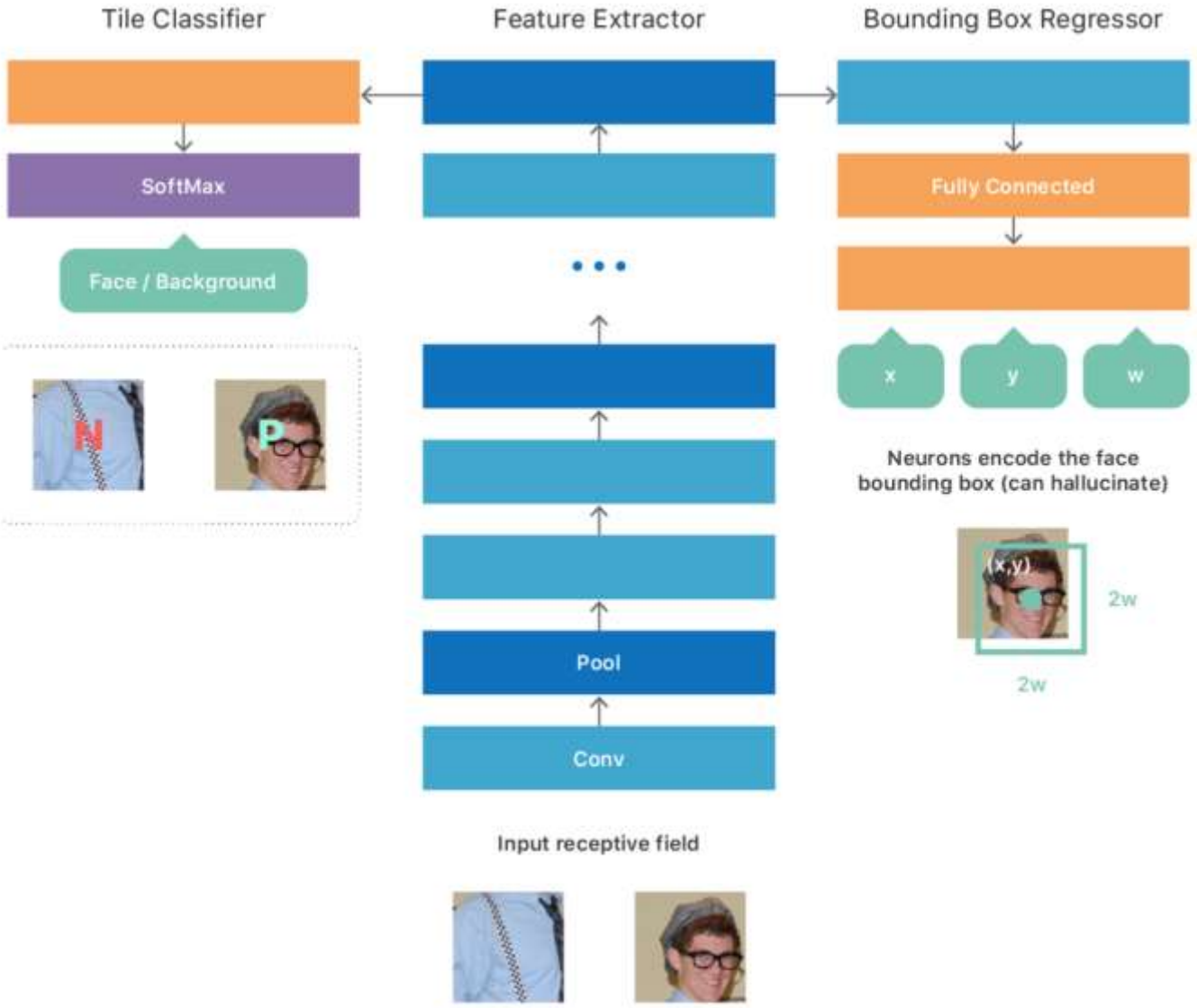
Triplet loss equation

FaceNet: A Unified Embedding for Face Recognition and Clustering; https://arxiv.org/pdf/1503.03832.pdf;
https://hackernoon.com/building-a-facial-recognition-pipeline-with-deep-learning-in-tensorflow-66e7645015b8

Digitalist

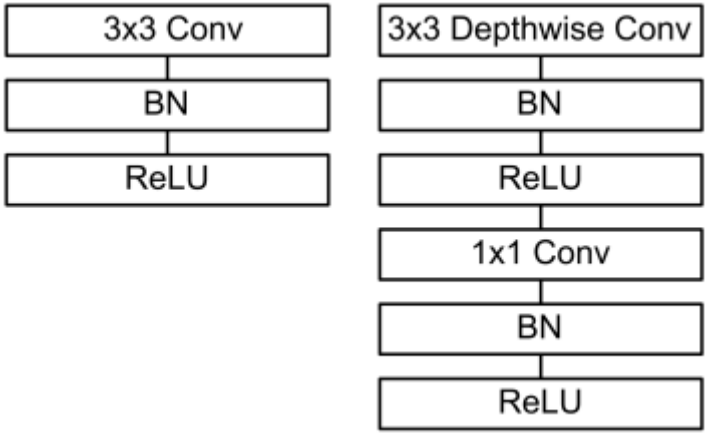
H2O WORLD 2017

Apple 2017: An On-device Deep Neural Network for Face Detection



https://machinelearning.apple.com/2017/11/16/face-detection.html#2

MobileNets 2017



Left: Standard convolutional layer with BN and ReLU.
Right: Depthwise Separable conv with Depthwise and Pointwise layers followed by BN and ReLU

Table 1. MobileNet Body Architecture

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	$1 \times 1 \times 1000$

Depthwise Separable vs Full Convolution MobileNet

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
Conv MobileNet	71.7%	4866	29.3
MobileNet	70.6%	569	4.2

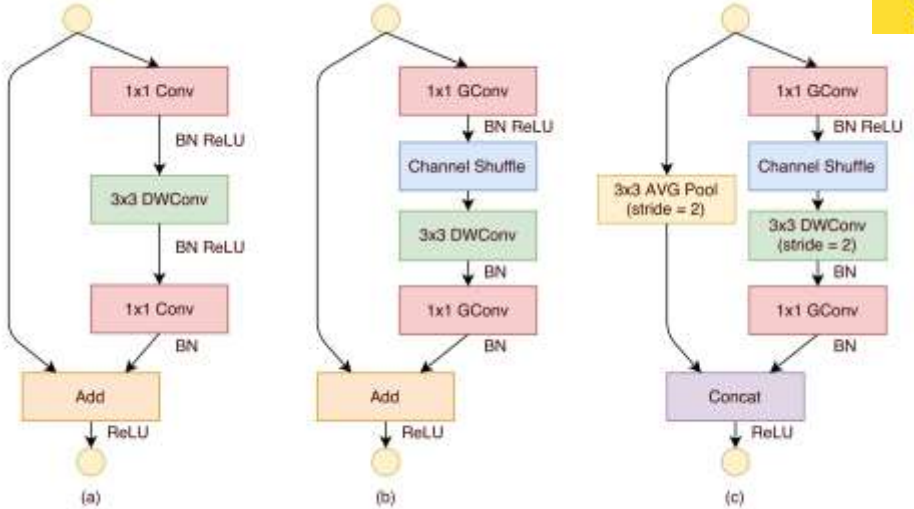
MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications; https://arxiv.org/pdf/1704.04861.pdf

ShuffleNet 2017:

An Extremely Efficient Convolutional Neural Network for Mobile Devices

Ref: https://arxiv.org/pdf/1707.01083.pdf

For mobile devices for 10-150 MFLOPS



ShuffleNet Units. a) bottleneck unit with depthwise convolution (DWConv); b) ShuffleNet unit with pointwise group convolution (GConv) and channel shuffle; c) ShuffleNet unit with stride = 2

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[1]	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[2]					143M	140M	137M	133M	137M

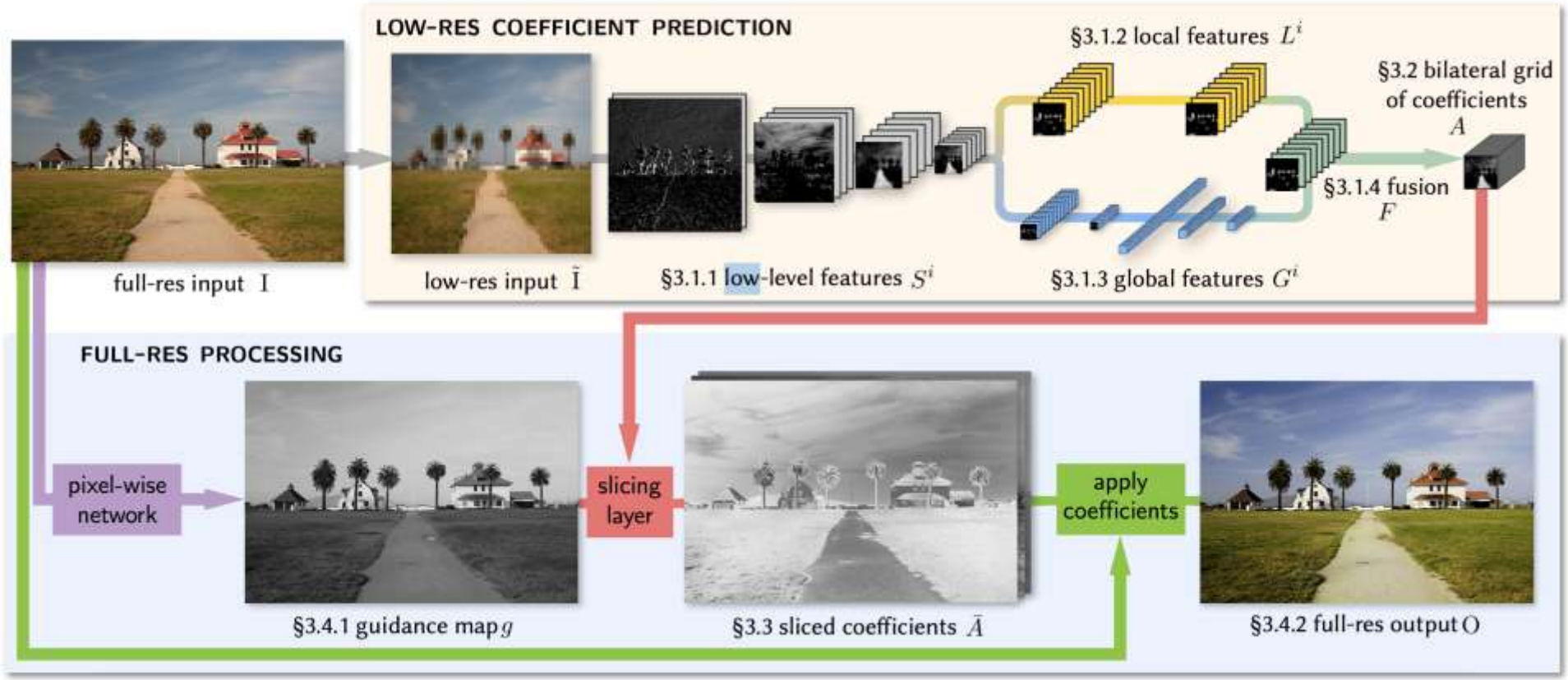
ShuffleNet vs. MobileNet [12] on ImageNet Classification

Model	Complexity (MFLOPs)	Cls err. (%)	Δ err. (%)
1.0 MobileNet-224	569	29.4	-
ShuffleNet $2\times$ ($g = 3$)	524	**29.1**	0.3
0.75 MobileNet-224	325	31.6	-
ShuffleNet $1.5\times$ ($g = 3$)	292	**31.0**	0.6
0.5 MobileNet-224	149	36.3	-
ShuffleNet $1\times$ ($g = 3$)	140	**34.1**	2.2
0.25 MobileNet-224	41	49.4	-
ShuffleNet $0.5\times$ (arch2, $g = 8$)	40	**42.7**	6.7
ShuffleNet $0.5\times$ (shallow, $g = 3$)	40	45.2	4.2

Digitalist

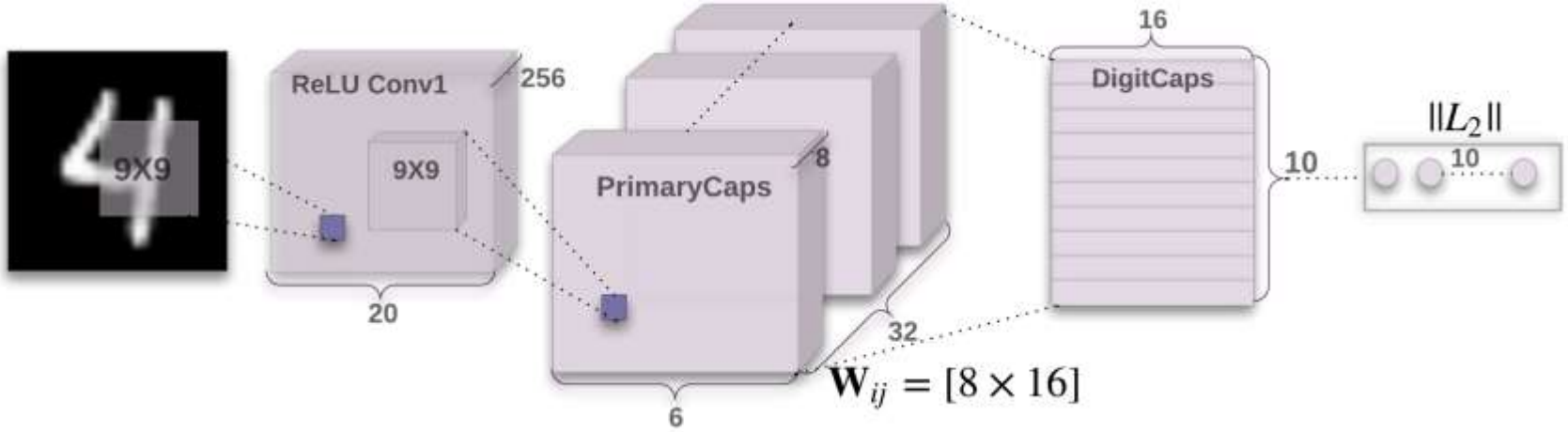
H2O WORLD 2017

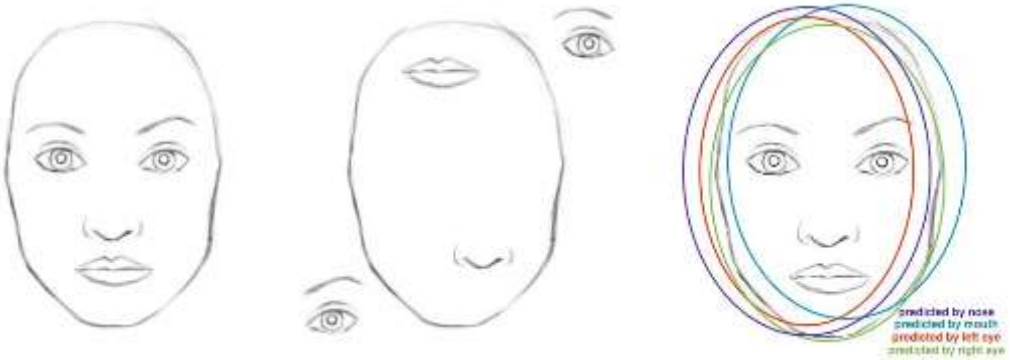
Deep Bilateral Learning for Real-Time Image Enhancement (2017)



Ref: https://groups.csail.mit.edu/graphics/hdrnet/data/hdrnet.pdf

CapsuleNet 2017: Dynamic Routing Between Capsules





https://medium.com/ai%C2%B3-theory-practice-business/understanding-hintons-capsule-networks-part-i-intuition-b4b559d1159b; https://arxiv.org/pdf/1710.09829.pdf

Thank you

SK Reddy
www.linkedin.com/in/sk-reddy/

We are hiring!!