

Building Efficient CNN Models for Mobile and Embedded Vision Applications

facebook

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Higher Accurac y

Faster Speed

Smaller Size Smaller Memory





Model Architecture

Model Compression

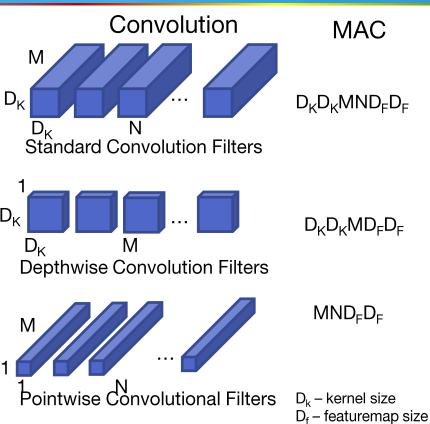
Realtime style transfer

Realtime pose estimation

MobileNet



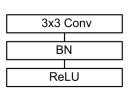
- MobileNet [Howard et al. 2017]
- Depthwise separable convolution
 - Depthwise convolution
 - Pointwise convolution
- Hyper-parameters to trade off between latency and accuracy
 - Width multiplier
 - Resolution multiplier







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- Depthwise separable convolution
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- Hyper-parameters to trade off between latency and accuracy
 - Width Multiplier
 - Resolution Multiplier



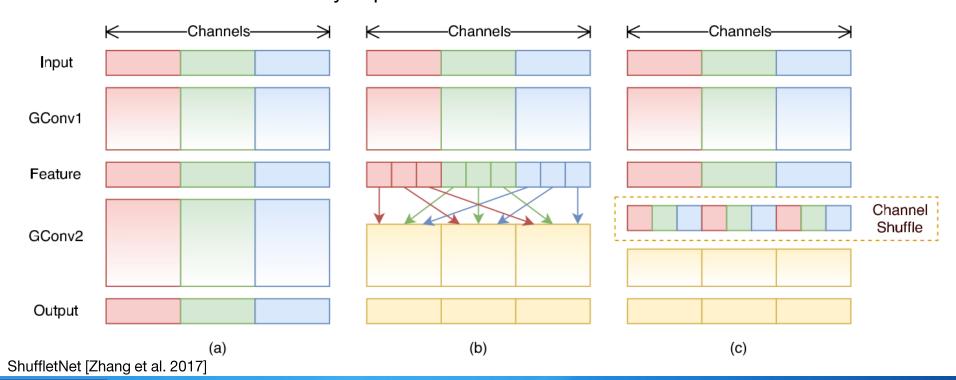
3x3 Depthwise Conv
BN
ReLU
1x1 Conv
BN
ReLU

Filter Shape
$3 \times 3 \times 3 \times 32$
$3 \times 3 \times 32 \text{ dw}$
$1 \times 1 \times 32 \times 64$
$3 \times 3 \times 64 \text{ dw}$
$1 \times 1 \times 64 \times 128$
$3 \times 3 \times 128 \text{ dw}$
$1 \times 1 \times 128 \times 128$
$3 \times 3 \times 128 \text{ dw}$
$1 \times 1 \times 128 \times 256$
$3 \times 3 \times 256 \text{ dw}$
$1\times1\times256\times256$
$3 \times 3 \times 256 \text{ dw}$
$1\times1\times256\times512$
$3 \times 3 \times 512 \text{ dw}$
$1 \times 1 \times 512 \times 512$
$3 \times 3 \times 512 \text{ dw}$
$1 \times 1 \times 512 \times 1024$
$3 \times 3 \times 1024 \text{ dw}$
$1 \times 1 \times 1024 \times 1024$
Pool 7 × 7
1024×1000
Classifier



ShuffleNet

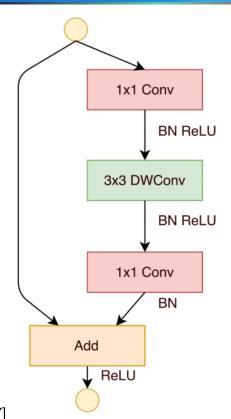
• Pointwise convolution is very expensive $M \cdot N \cdot D_F \cdot D_F >> D_K \cdot D_K \cdot M \cdot D_F \cdot D_F$



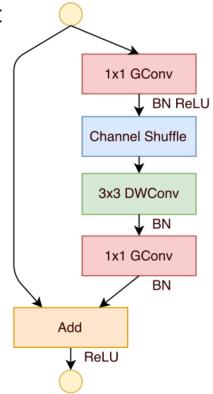


ShuffleNet

ResNet



ShuffleNet



ShuffletNet [Zhang et al. 2017]

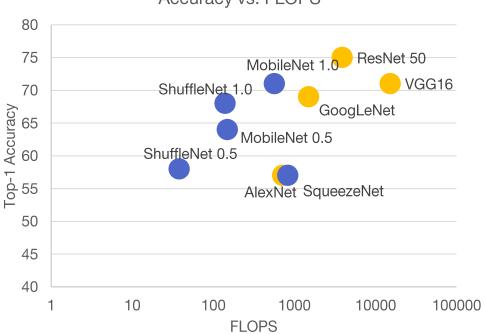
Full models

Mobile models

Accuracy vs. FLOPS



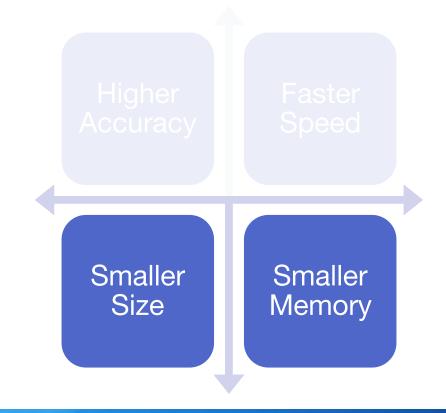




Model	FLOPS	Top-1 Accuracy [%]
AlexNet	720	57
VGG 16	15300	71
GoogLeNet	1500	69
Resnet 50	3900	75
SqueezeNet	833	57
MobileNet 1.0 - 224	569	71
MobileNet 0.5 - 224	149	64
ShuffleNet 1.0	140	68
ShuffleNet 0.5	38	58

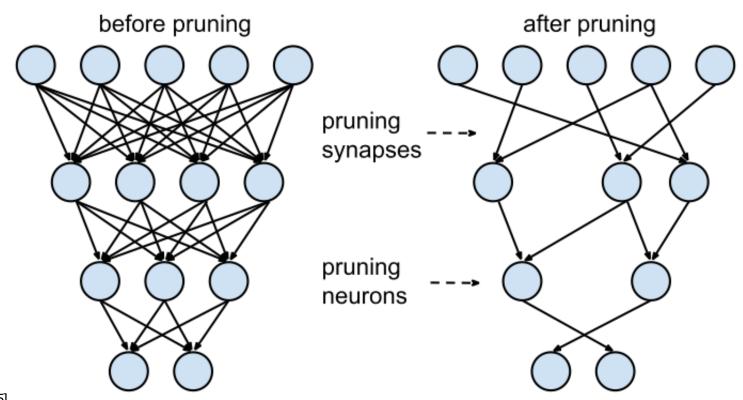








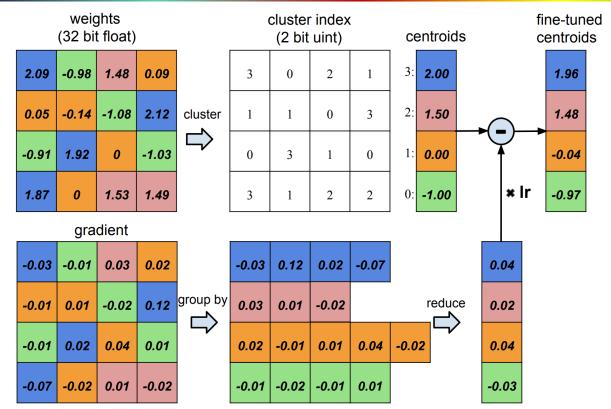




[Han et al. NIPS 2015]



Quantization



[Han et al. ICLR 2016]



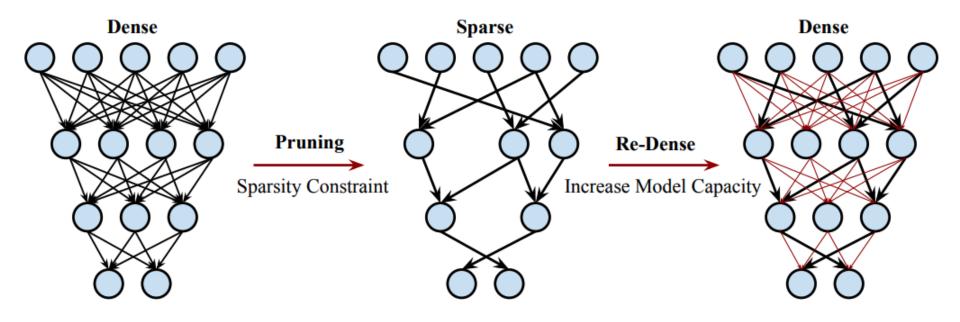
Pruning + Quantization







Dense-Sparse-Dense





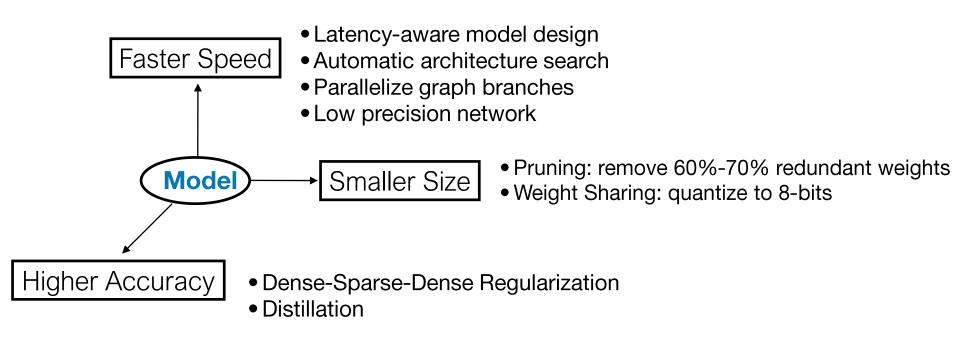


Dense-Sparse-Dense

Neural Network	Top-1 error	DSD training – Top-1 error
GoogLeNet	31.1%	30.0%
VGG-16	31.5%	27.2%
ResNet-18	30.4%	29.2%
ResNet-50	24.0%	22.8%



Summary of Model Optimization Approaches





Realtime Style Transfer







• Gatys et al. 2015



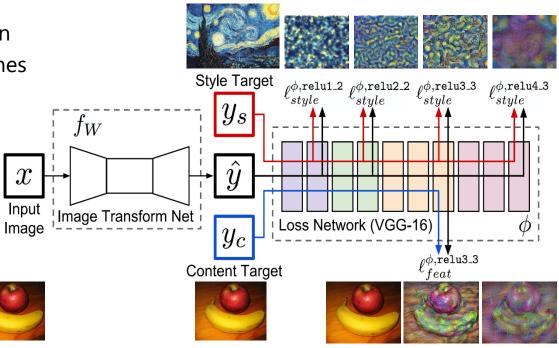


$$\mathbf{x}^* = \underset{\mathbf{x}}{\operatorname{argmin}} \left(\alpha \mathcal{L}_{\operatorname{content}}(\mathbf{c}, \mathbf{x}) + \beta \mathcal{L}_{\operatorname{style}}(\mathbf{s}, \mathbf{x}) \right)$$



Realtime Style Transfer

- Caffe2Go
 - NNPack, NEON optimization
 - Real time on high-end phones
 - Specific layer optimization
- Model
 - Reduce layer number
 - Reduce channel number
 - Model compression
 - Pruning
- Quality
 - A/B test



[Justin et al. ECCV 2016]









- Open-sourced optimized layers:
 - GenerateProposalsOp
 - BBoxTransformOp
 - BoxWithNMSLimit
 - RolAlignOp
- Use-cases
 - Gesture recognition
 - AR effects
 - Avatar for AR/VR
- Caffe2Go
 - Mobile CPU, GPU, DSP







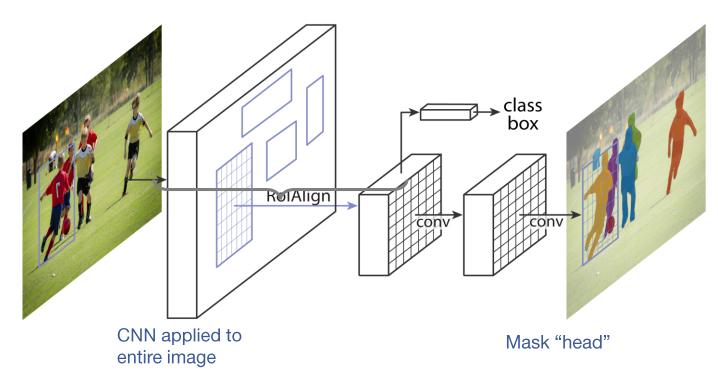






Images and annotations from COCO keypoint challenge





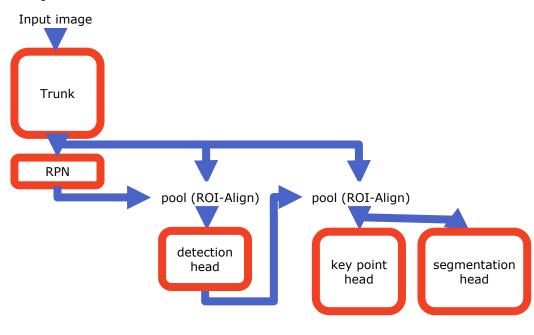
[Kaiming et al. ICCV 2017]



Region Proposal Network Class/box Class/box Class/box Shared region-wise subnetwork RolPool CNN applied to *In-network* region entire image proposals from RPN

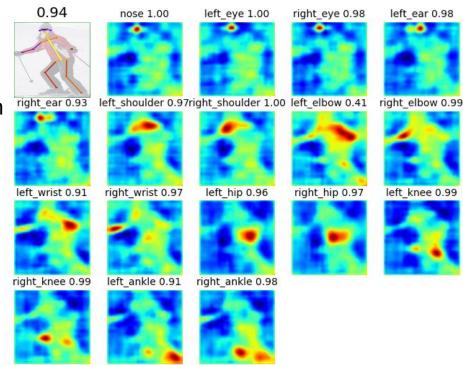


- Mask R-CNN2Go open-sourced layers
- Real-time on high-end phones
- Model
 - Reduce layer number
 - Reduce channel number
 - Model compression
 - Pruning
 - Split prev. nets to trunk, head
- Balanced blocks
 - Small detection head
 - Small number of proposals
 - High input resolution





- Challenges
 - Data, data, data...
 - Parameter search and optimization
 - Corner cases
 - Real-time benchmark MAC
- Keypoint = 1-hot mask
- Represent pose as 17 masks



Mask R-CNN2Go





More efficient model architectures

High-performance inference

Leveraging CPU, GPU and DSP on the phone



Take - away

VISION SUMMIT 2018

- Data, Data, ...
- Diverse hardware support for high/low end iOS/Android. Open sourced Caffe2/Pytorch 1.0 efficient implementation on CPU/GPU/DSP on phone.
- Efficient model architecture balanced optimization on hardware
 - Accuracy
 - Model/Memory size
 - Speeeeeed
- Download models from cloud and run on mobile
 - + Realtime interaction
 - + Low/No bandwidth needs
 - + Works offline
 - + Privacy

- Battery
- Low-end phone support
- Limited accuracy and data capacity

Resource Slide



- Peter Vajda: <u>vajdap@fb.com</u>
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