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Optimizing Deep Learning Systems for Hardware

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Next: Part III.b

- PIII.a : Model compression
- PIII.b : Efficient Architectures

Part III.b: Efficient Architectures

- a) Model Compression
  - Pruning
  - Quantization
  - Knowledge Distillation
- b) Efficient architectures
  - Case: Efficient CNNs

Efficient Architecture?

- Definition: An efficient architecture is a model design that
  - reduces computational cost, memory usage, and latency,
  - **through structural choices**,
  - (hopefully) without significantly sacrificing accuracy.
- Architectural Efficiency
  - Smarter building blocks (i.e. layers)
  - Better use of compute
  - Hardware-aware design

Efficient Dimensions

- Compute Efficiency
  - Minimize the number of operations (e.g., FLOPs)
    → Faster inference/training, lower energy cost

- Memory Efficiency
  - Reduce model size (parameters) and runtime memory (activations)
  → Enables deployment on edge devices, fits more in (GPU) memory

- Latency & Hardware Friendliness
  - Optimize for speed on real hardware
  → Fewer sequential operations, better dataflow, hardware-aligned ops

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through structural choices!

CNNs: Early Efficiency Tricks

- MobileNet Family
  - MobileNetV1: depthwise separable conv
  - MobileNetV2: inverted residuals & linear bottlenecks

- Key idea: reduce multiply-adds without losing too much accuracy

MobileNet V1

arXiv > cs > arXiv:1704.04861

Computer Science > Computer Vision and Pattern Recognition

(Submitted on 17 Apr 2017)

MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications

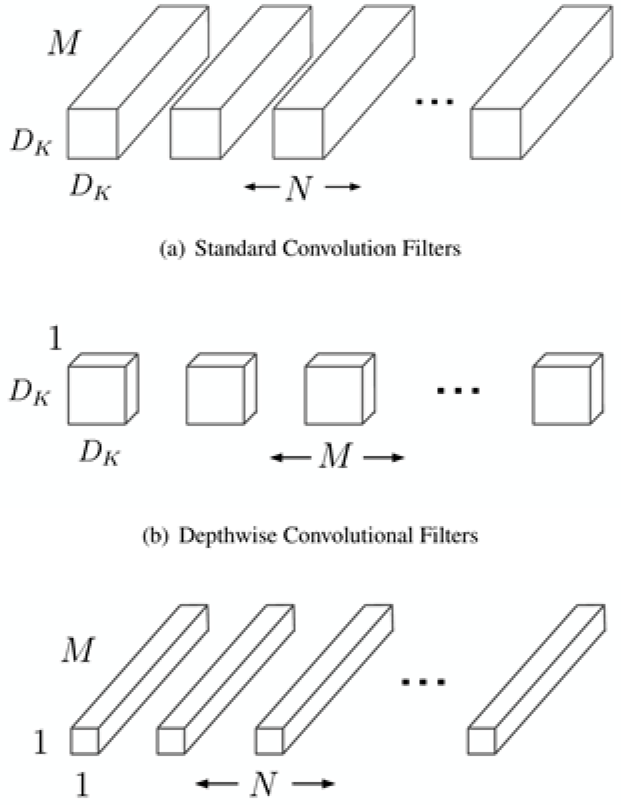
Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, Hartwig Adam

- MobileNet V1: depthwise separable convolution
  - Depthwise convolution

    (one 3×3 filter per input channel, no mixing)
  - Pointwise convolution

    (a 1×1 convolution to mix channels)

- Standard convolution (kernel size k×k, input channels M, output channels N) has cost:
  - **k×k×M×N**
- Depthwise separable convolution has cost:
  - **k×k×M + 1×1×M×N**



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

Figure 2. The standard convolutional filters in (a) are replaced by two layers: depthwise convolution in (b) and pointwise convolution in (c) to build a depthwise separable filter.

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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× Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
5× 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	$1 \times 1 \times 1000$

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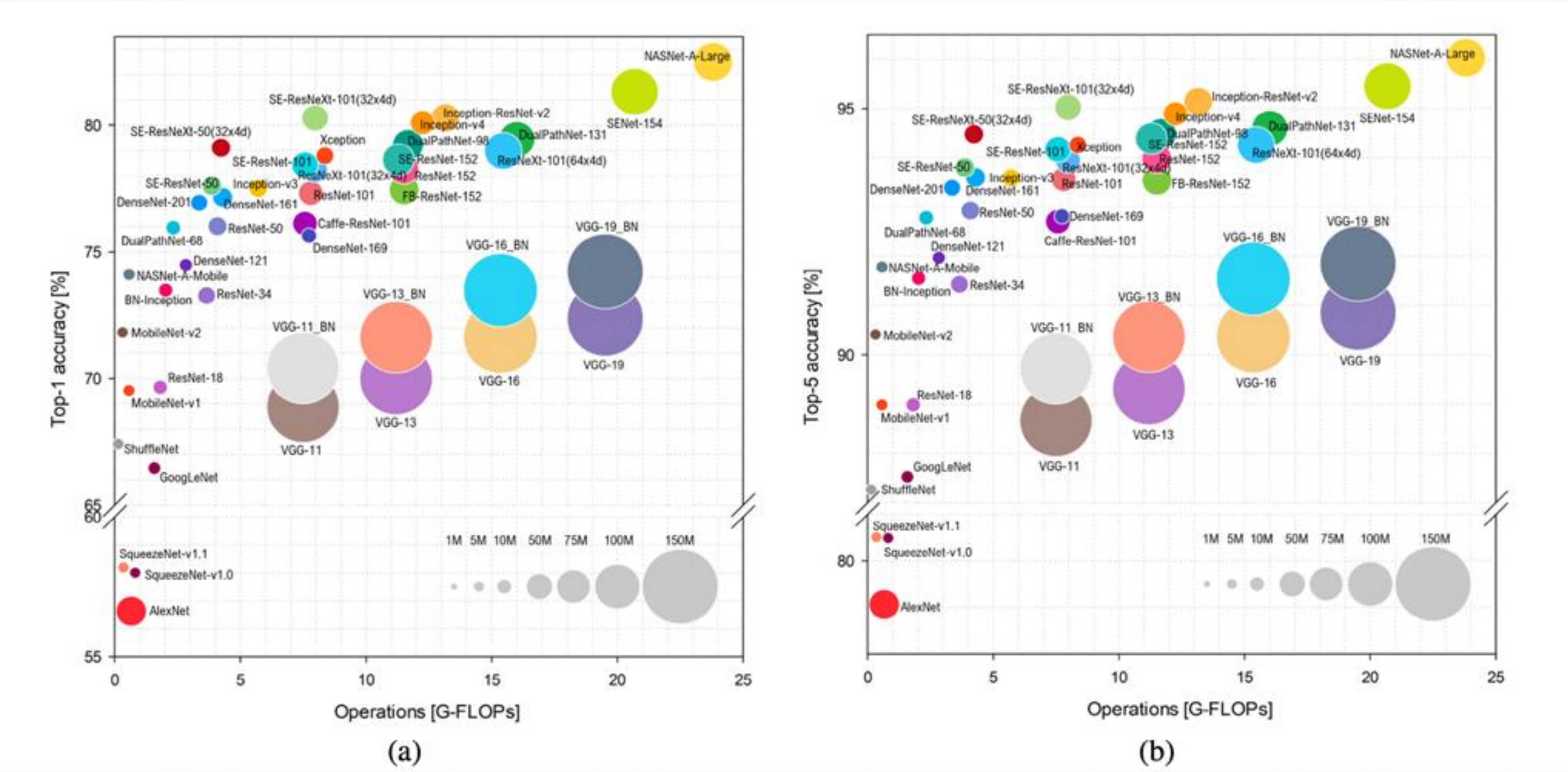

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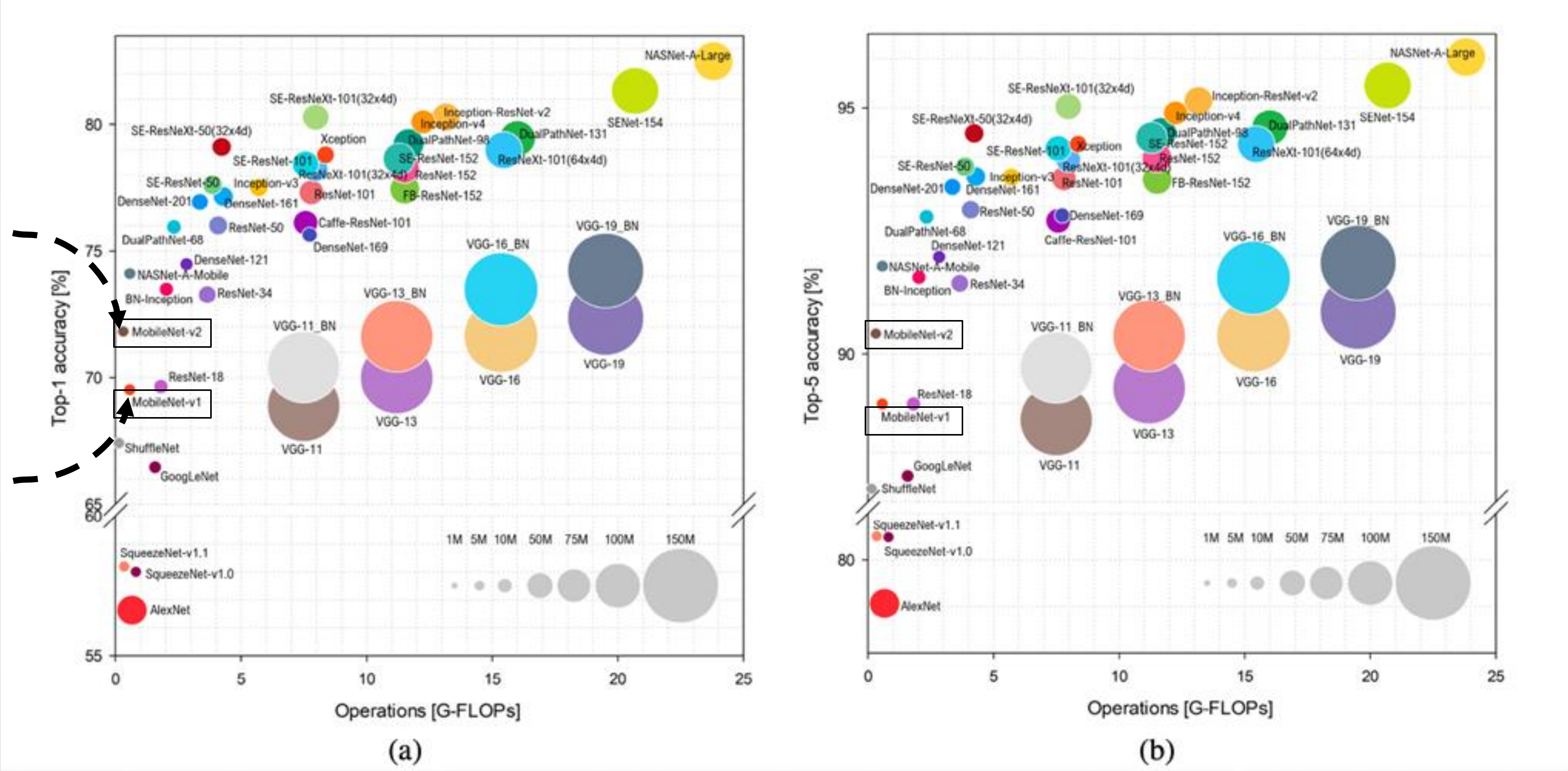

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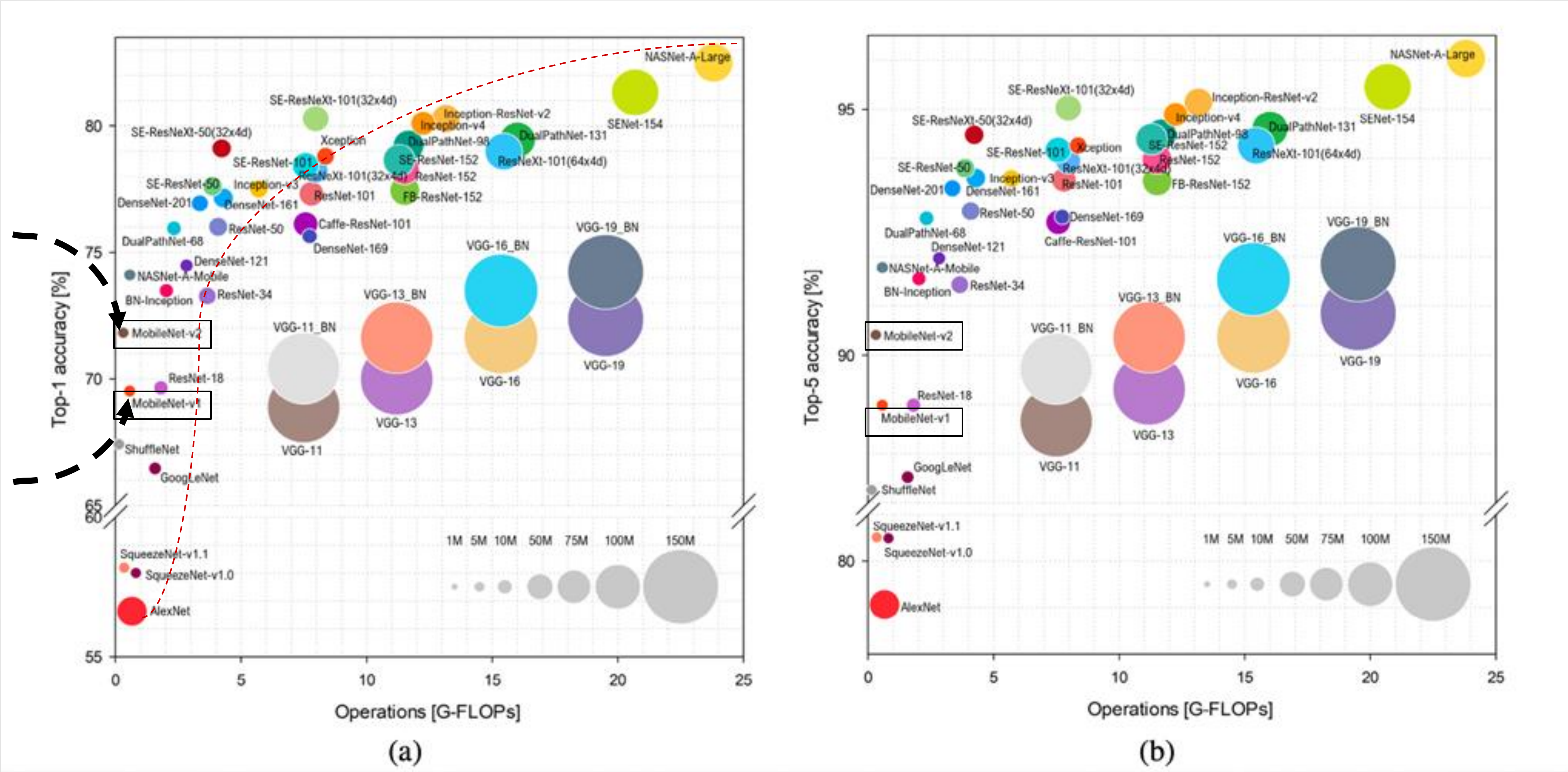


MobileNet V2


arXiv > cs > arXiv:1801.04381

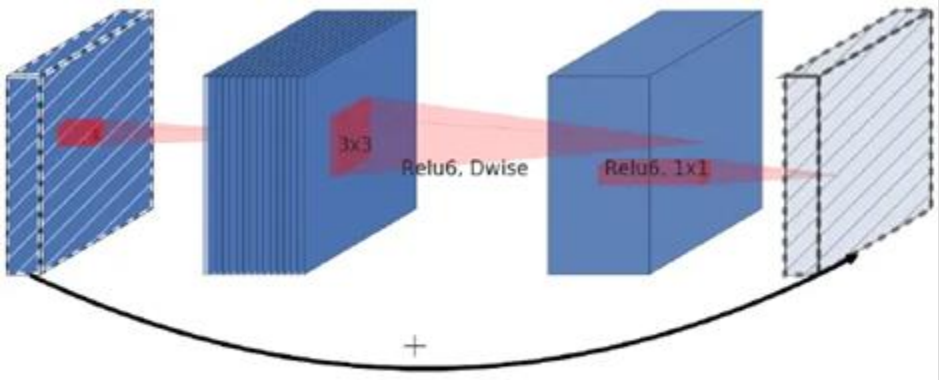
Computer Science > Computer Vision and Pattern Recognition

(Submitted on 13 Jan 2018 (v1), last revised 21 Mar 2019 (this version, v4))

MobileNetV2: Inverted Residuals and Linear Bottlenecks

Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, Liang-Chieh Chen

- **MobileNet V2: Inverted Residuals**
  - Residual blocks connect the beginning and end of a convolutional block with a skip connection.
  - This approach turned out to be essential in order to build networks of great depth.
  - An inverted residual block connects narrow layers with a skip connection while layers in between are wide
  - The authors describe this idea as an inverted residual block because skip connections exist between narrow parts of the network which is opposite of how an original residual connection works.
    - This is more efficient in OPs.



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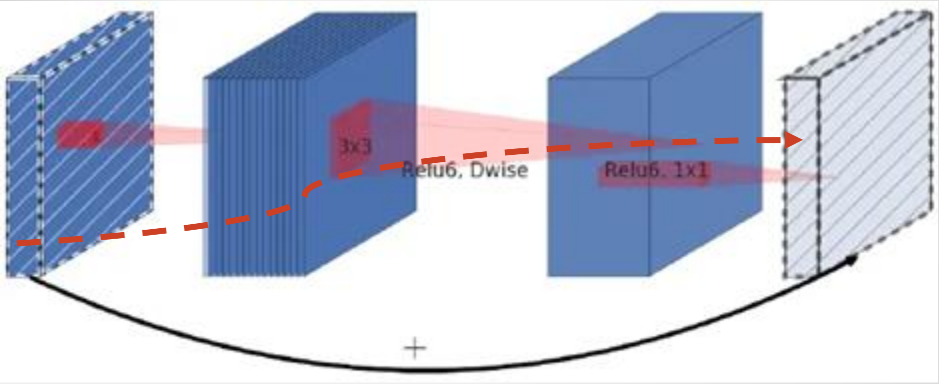
- **MobileNet V2: Linear Bottlenecks**
  - When we narrow the feature dimension (bottleneck), we reduce redundancy.
  - Applying non-linearities (like ReLU) after such layers can zero out important information.
  - To avoid this, we use a linear activation — that is, we apply no activation function after the bottleneck layer.

Linear
(i.e. no actv. func.)



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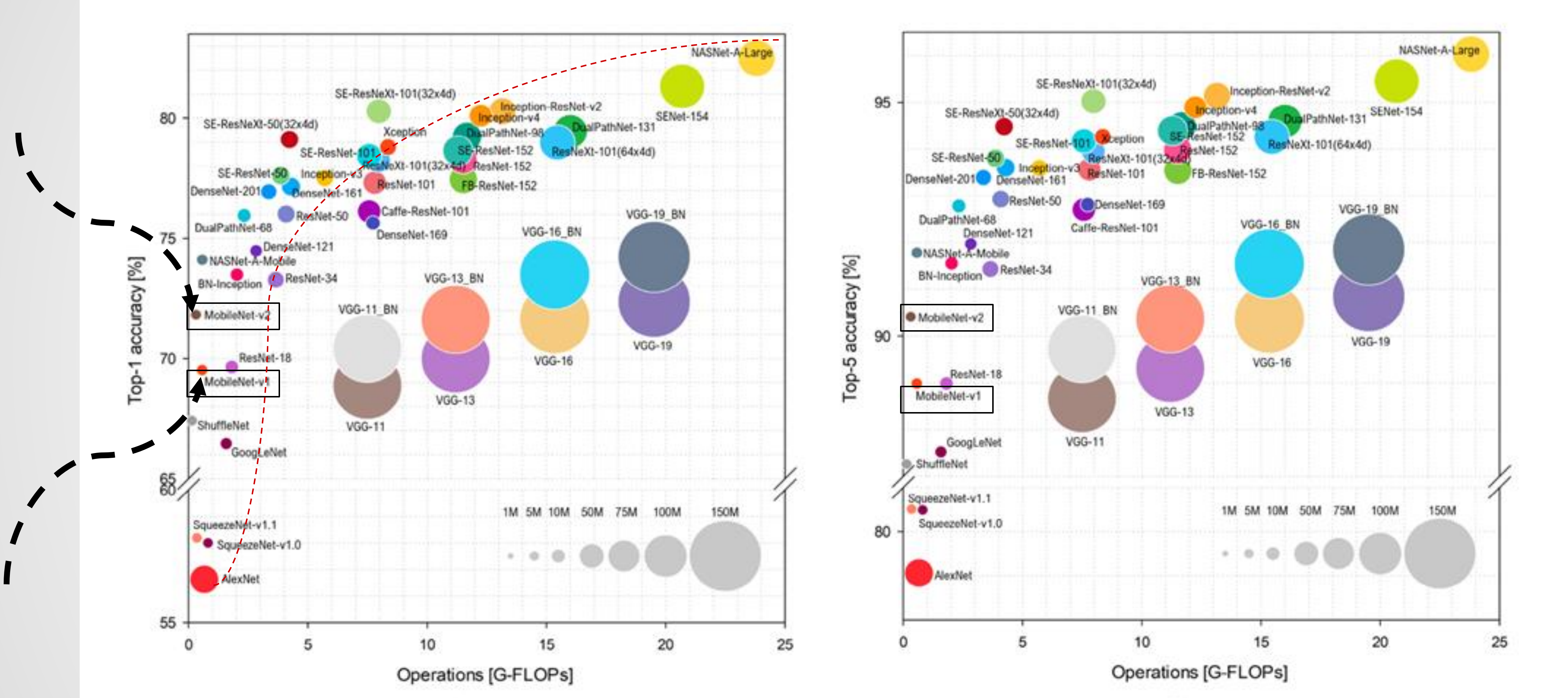

(a) (b)

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Next: Part IV

- Part I : Fundamentals
- Part II : Hardware Types & Memory Hierarchy
- Part III : Model-Level Optimizations
- **Part IV : System-Level Optimizations**
- Part V : Introduction to Scaling Deep Learning in HPC

Thanks!

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EuroHPC
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