Paper

Searching for MobileNetV3

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Abstract

We present the next generation of MobileNets based on a combination of complementary search techniques as well as a novel architecture design. MobileNetV3 is tuned to mobile phone CPUs through a combination of hardwareaware network architecture search (NAS) complemented by the NetAdant algorithm and then subsequently improved through novel architecture advances. This paper starts the exploration of how automated search algorithms and network design can work together to harness complementary approaches improving the overall state of the art. Through this process we create two new MobileNet models for release: MobileNetV3-Large and MobileNetV3-Small which are targeted for high and low resource use cases. These models are then adapted and applied to the tasks of object detection and semantic segmentation. For the task of semantic segmentation (or any dense pixel prediction), we propose a new efficient segmentation decoder Lite Reduced Atrous Snatial Pyramid Pooling (LR-ASPP). We achieve new state of the art results for mobile classification, detection and segmentation. MobileNetV3-Large is 3.2% more

curate on ImageNet classification while reducing latency
'% compared to MobileNetV2. MobileNetV3-Small is
'ore accurate compared to a MobileNetV4 model
'arable latency. MobileNetV3-Large detection
'aster at roughly the same accuracy as Mo'OCO Astestima MobileNetV4. Jame 1 B.

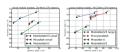


Figure 1. The trade-off between Pixel 1 latency and top-1 ImageNet accuracy. All models use the input resolution 224. V3 large and V3 small use multipliers 0.75, 1 and 1.25 to show optimal frontier. All latencies were measured on a single large core of the same device using 'FFLite[1]. MobileNetV3-Small and Large are our proposed next-generation mobile models.

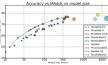


Figure 2. The trade-off between MAdds and top-1 accuracy. This allows to compare models that were targeted different hardware or

Gray Literature

Everything you need to know about MobileNetV3



When MobileNet VI came in 2017, it essentially started a new section of deep learning research in computer vision, i.e. coming up with models that can run in embedded systems. This lead to several important works including but not limited to ShuffleNet(VI and V2), MNasNet, CondenseNet, EffNet, among others. Somewhere in between came the second version of MobileNet as well last year. Now, this year's iteration gives us the third version of MobileNet as well last year. Now, this year's iteration gives us the third version of MobileNet called MobileNetV3. This story is a review of MobileNetV3 from Google that was presented at ICCV in Seoul, South Korea this year.

Contents:

- 1. Efficient Mobile Building Blocks
- 2. Neural Architecture Search for Block-Wise Search
- 3. NetAdapt for Layer wise search

Network Improvements - Layer removal and H-swish

U Structure

Model Card

This model is an implementation of MobileNet-03-Small found beze. This repository provio. to run MobileNet-03-Small an Qualcomm* devices. More details on model performance across various devices, can be found here.

Model Details

Model Type: Image classification

Model Stats:

Model checkpoint: Imagenet

· Mo	del size: 9.72 M	В					
Device	Chipset	Target Runtime	Inference Time (ms)	Peak Memory Range (MB)	Precision	Primary Compute Unit	Targ Mod
Samsung Galaxy S23 Ultra (Android 13)	Snapdragon ^e 8 Gen 2	TFLite	0.844 ms	0 - 2 MB	FP16	NPU	MobileN v3- Small.tf
Samsung Galaxy S23 Ultra (Android 13)	Snapdragon [®] 8 Gen 2	QNN Model Library	0.879 ms	1-5 MB	FP16	NPU	Mobilet v3-Smail
Installation							

AI Label



Benchmark (PWC)



Platform (PWC)



