Hardware-aware Deep Neural Architecture Search

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Mobile Vision, Facebook

Acknowledge: Bichen Wu, Xiaoliang Dai, Alvin Wan, Peter Vajda

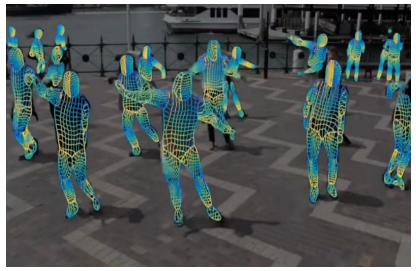
Outline

- Introduction
- Hardware-aware Architecture Search
  - Differentiable Search: **FBNet** and **FBNetV2**
  - Predictor-based Search: **ChamNet** and **FBNetV3**
- Applications

Goal: Accuracy and Efficiency

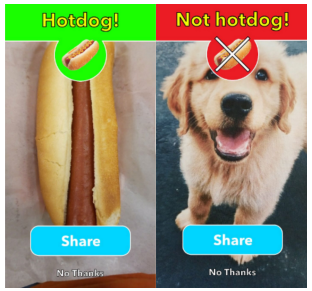
- Mobile and embedded computer vision applications require accurate and efficient ConvNets

Pose detection



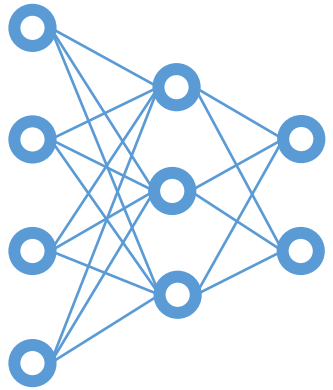
Dense pose

Style transfer



Classification

OCR



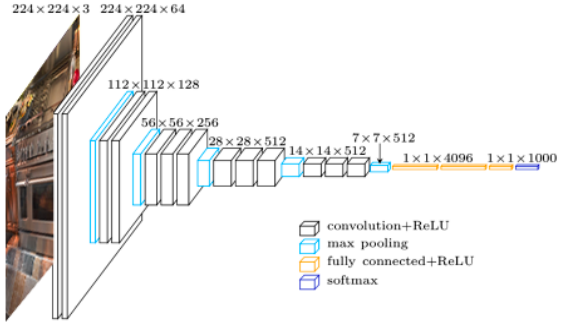
ConvNets

Mobile devices

VR headsets

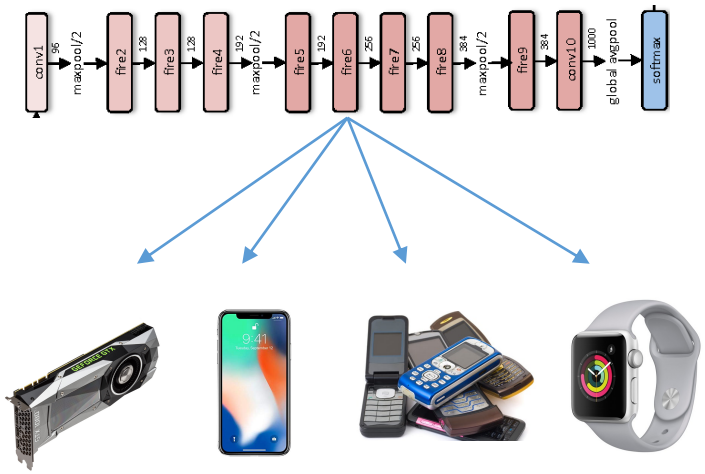
Challenges

- Intractable design space
- Conditional optimality
- Inaccurate metrics

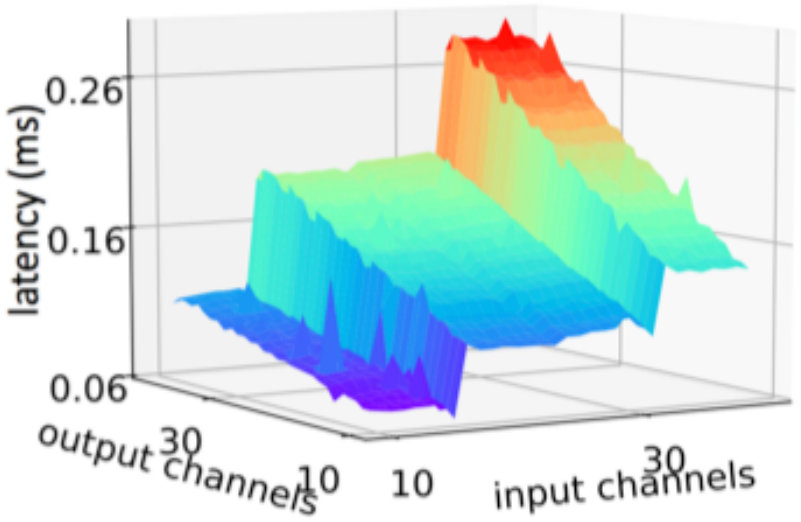


- Kernel size = {1, 3, 5}
- Channel size = {16, 32, 64, 128, 256}

(3x5)^16=2e15 possible architectures

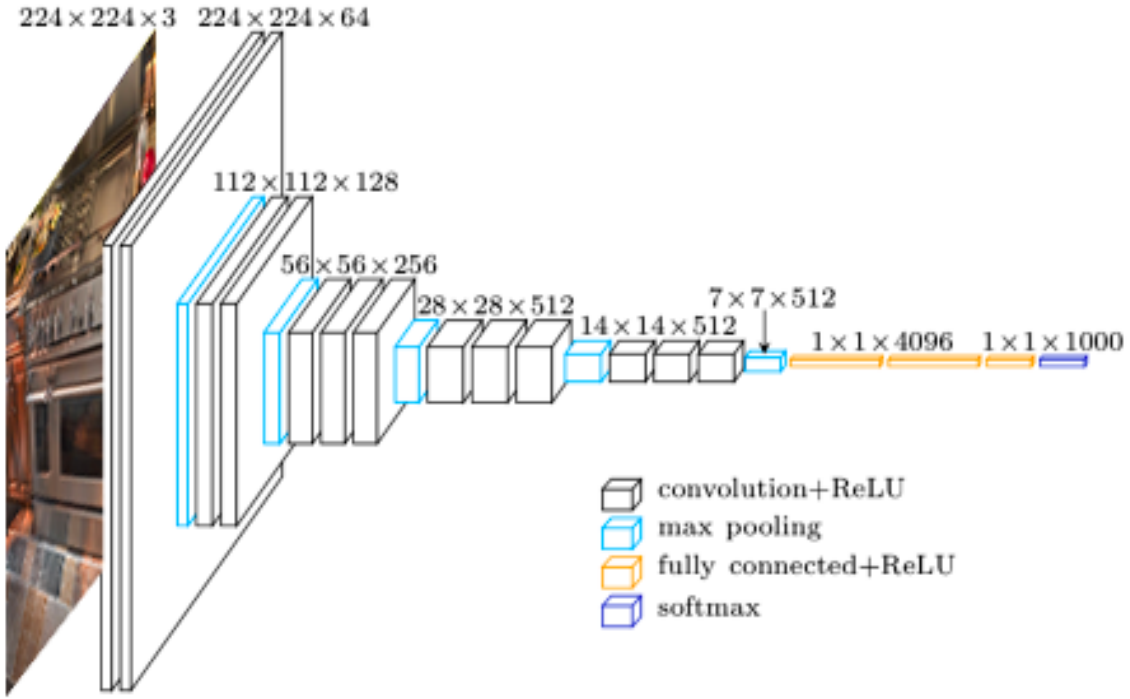


GPU | High-end phones | Low-end phones | Wearable devices



Challenges #1: Intractable design space

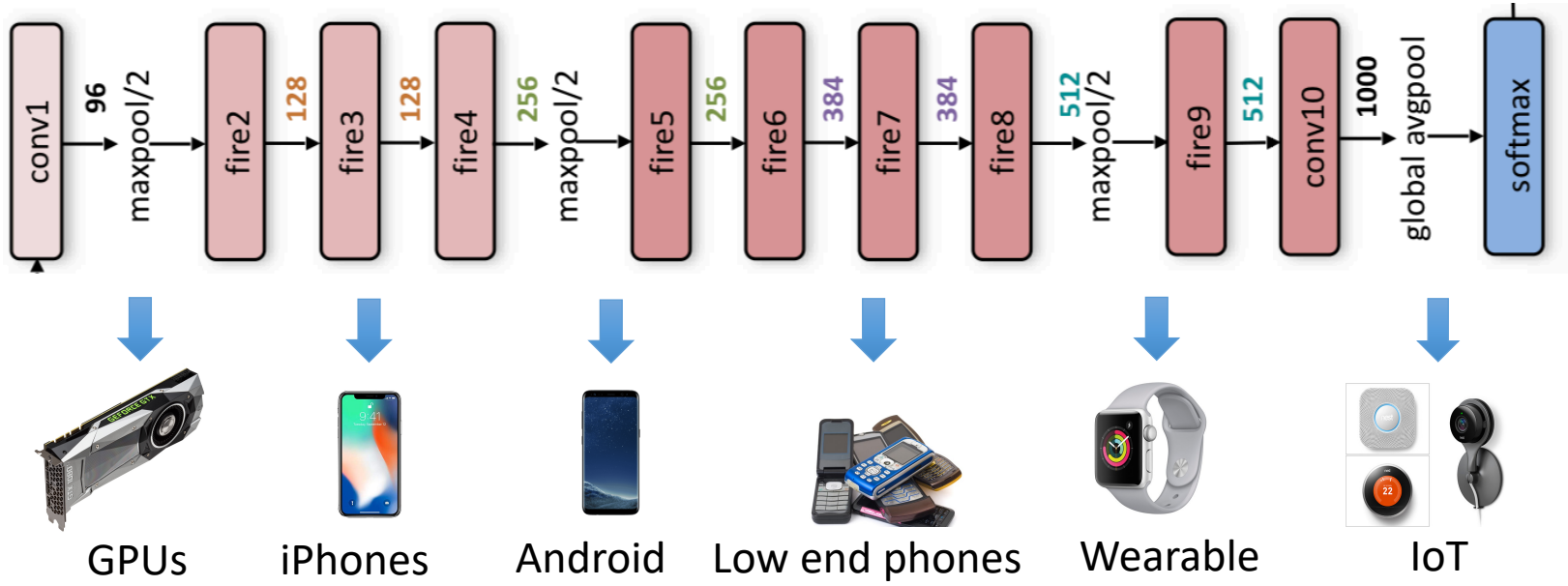
- Design space of Deep Neural Nets is huge!
  - VGG16[1] has 13 conv layers
  - Design choices for each layer:
    - kernel size = {1, 3, 5}
    - channel size = {32, 64, 128, 256, 512}
  - Search space = (3x5)^13 = 2e15



[1] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

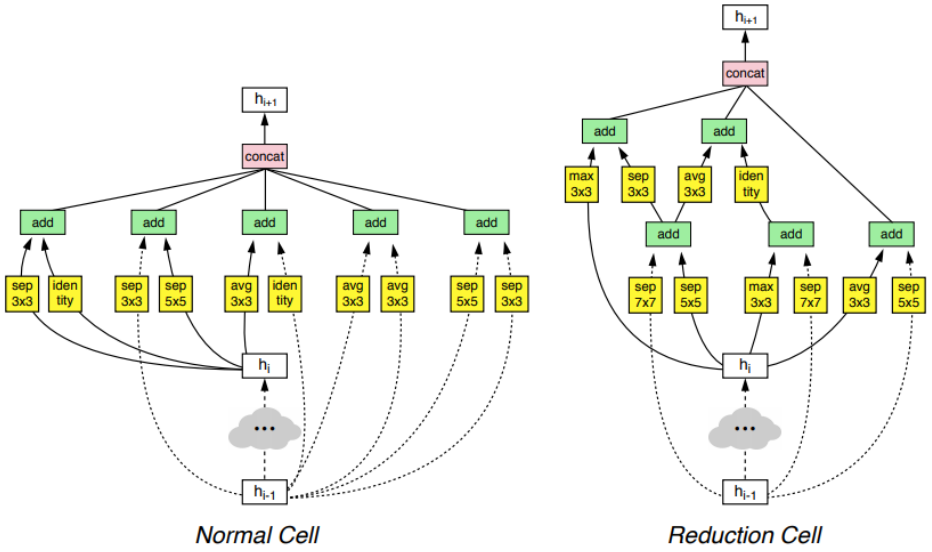
Challenge #2: Conditional optimality

- Ideally, we should design different ConvNets for different devices
- In reality, due to the cost of design & training ConvNets, we can only afford to **design one** and **deploy to all** conditions



Challenge #3: Inaccurate metrics

- Previous works focus on efficiency proxies: parameter size or FLOPs
- Proxies do not always reflect actual efficiency
  - NASNet-A[1] has slightly smaller FLOPs than MobileNetV1[2], but the latency is 1.6x slower

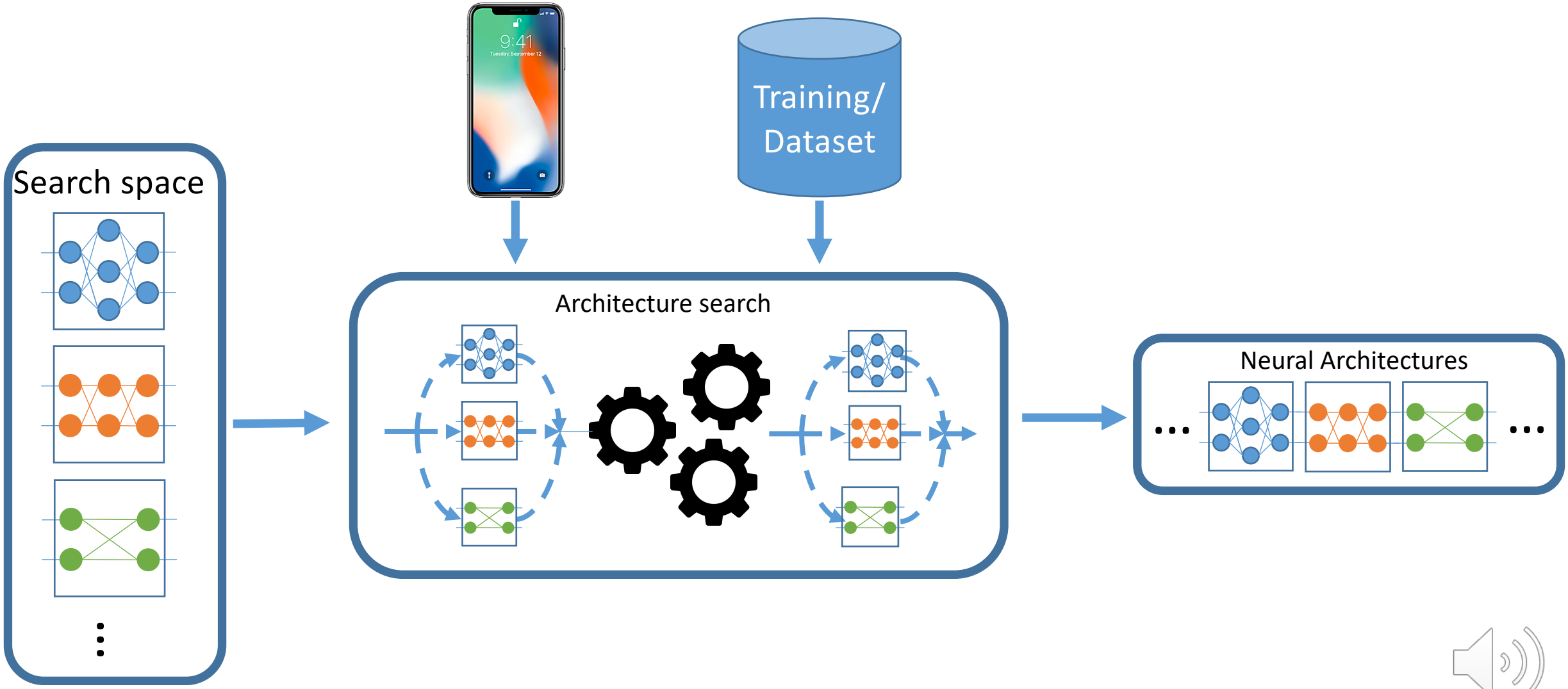


NASNet [2]

[1] Zoph, Barret, et al. "Learning transferable architectures for scalable image recognition." *CVPR18*

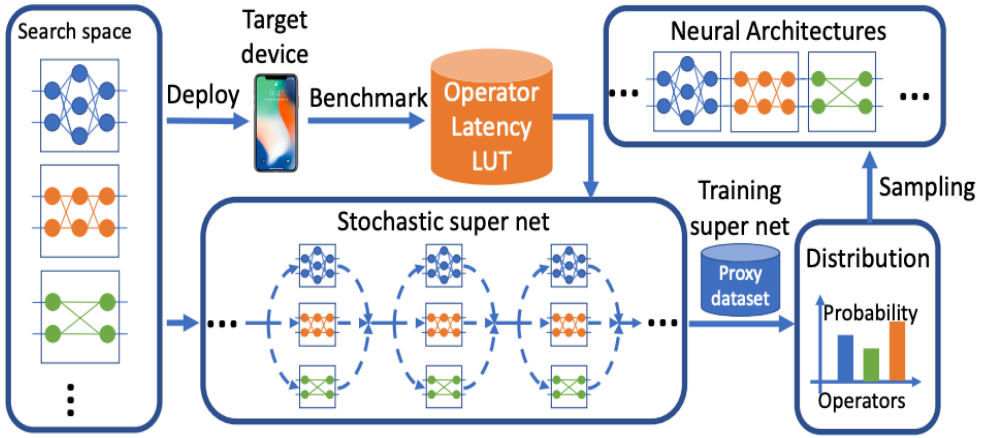
[2] Howard, Andrew G., et al. "Mobilenets: Efficient convolutional neural networks for mobile vision applications." arXiv:1704.04861

Hardware-aware Neural Architecture Search

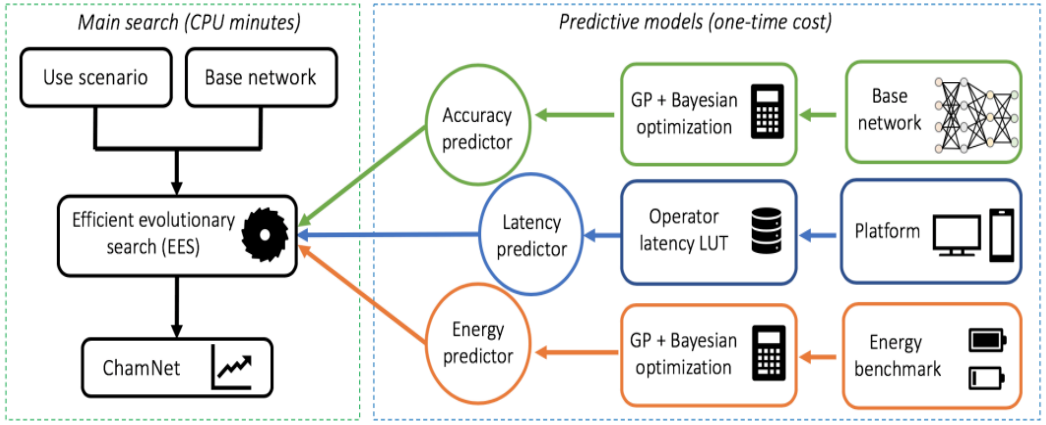


Hardware-aware Architecture Search

- Differentiable Architecture Search: **FBNet** and **FBNetV2**
- Predictor-based Architecture Search: **ChamNet** and **FBNetV3**



FBNet



ChamNet

- Wu et al., FBNet: Hardware-Aware Efficient ConvNet Design via Differentiable Neural Architecture Search, CVPR 2019
- Dai et al., ChamNet: Towards Efficient Network Design through Platform-Aware Model Adaptation, CVPR 2019
- Wan et al., FBNetV2: Differentiable Neural Architecture Search for Spatial and Channel Dimensions, CVPR 2020
- Dai et al., FBNetV3: FBNetV3: Joint Architecture-Recipe Search using Neural Acquisition Function, submitted

Hardware-aware Architecture Search

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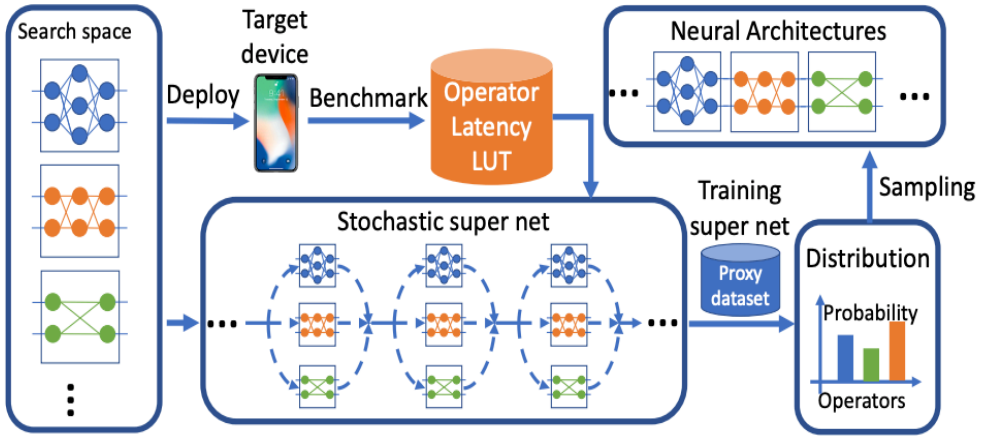
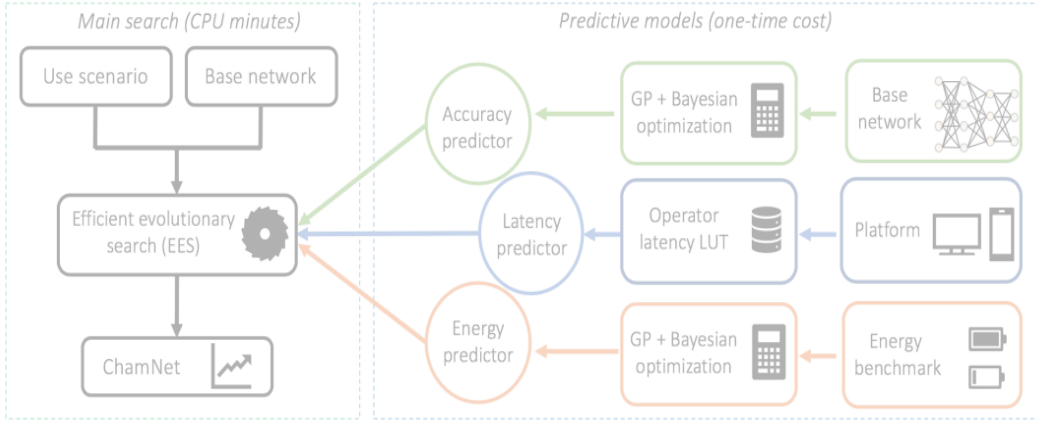
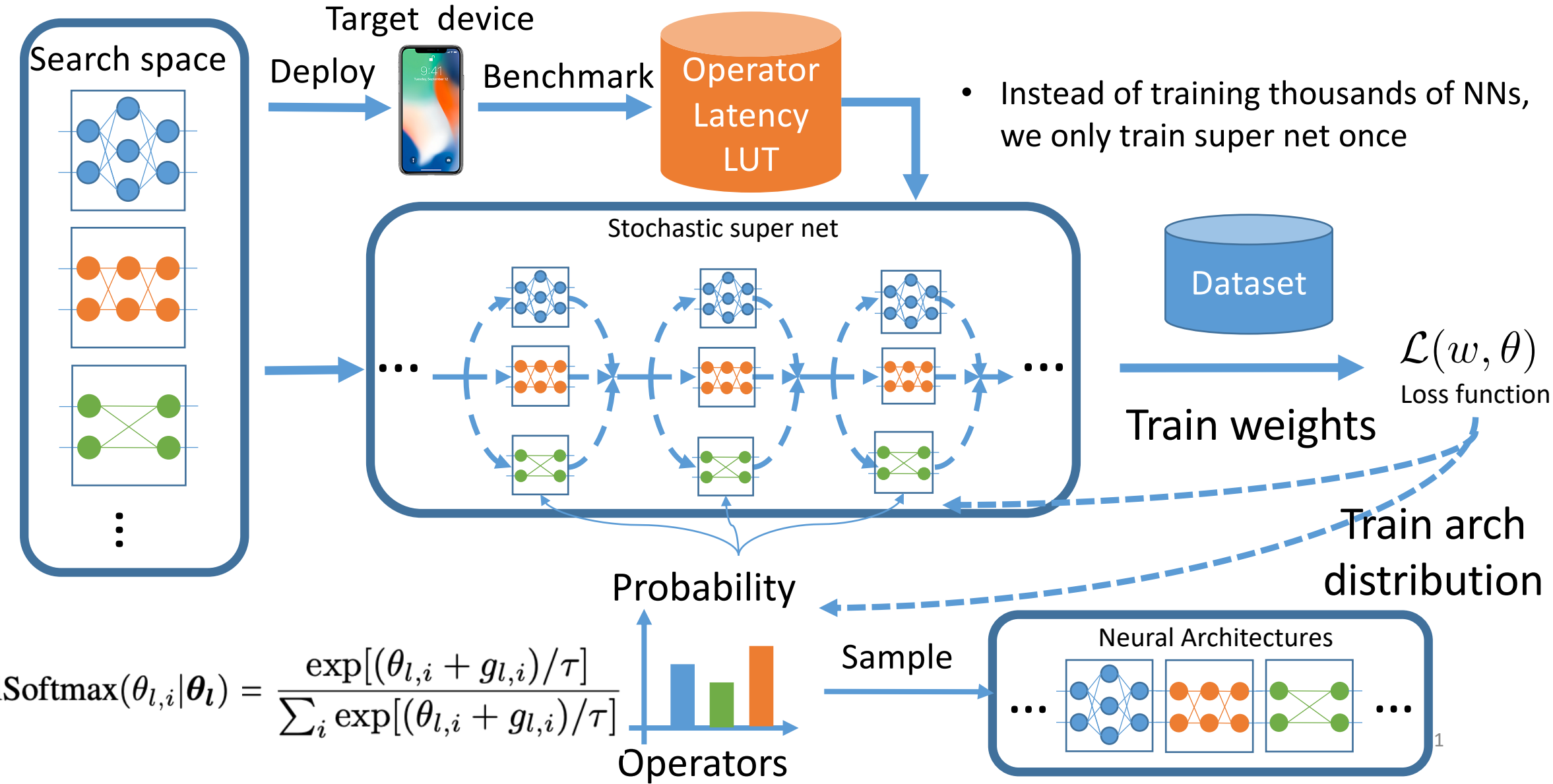


FBNet



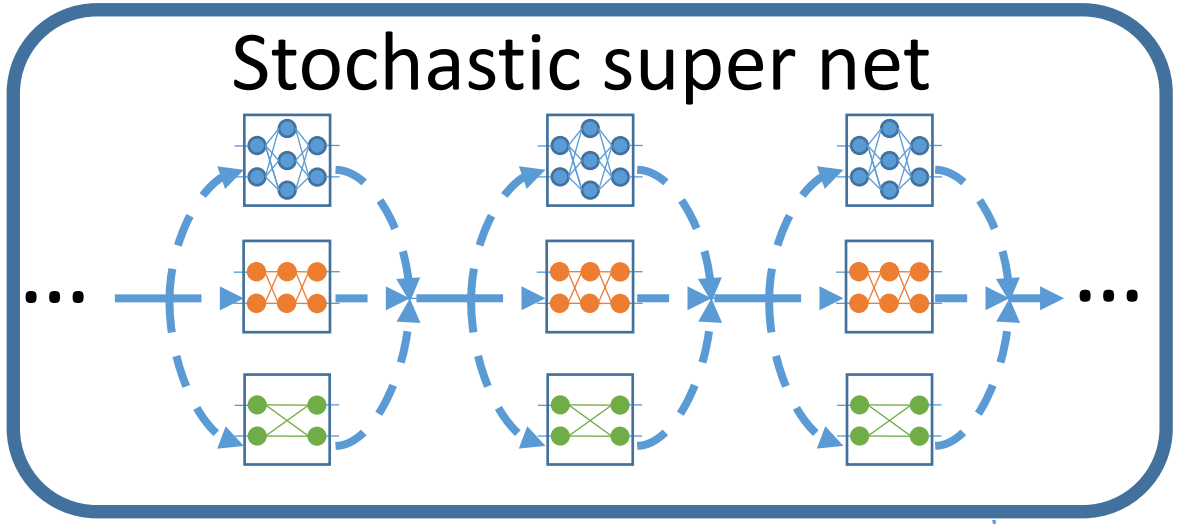
ChamNet

FBNet: Differentiable Neural Architecture Search



- Instead of training thousands of NNs, we only train super net once

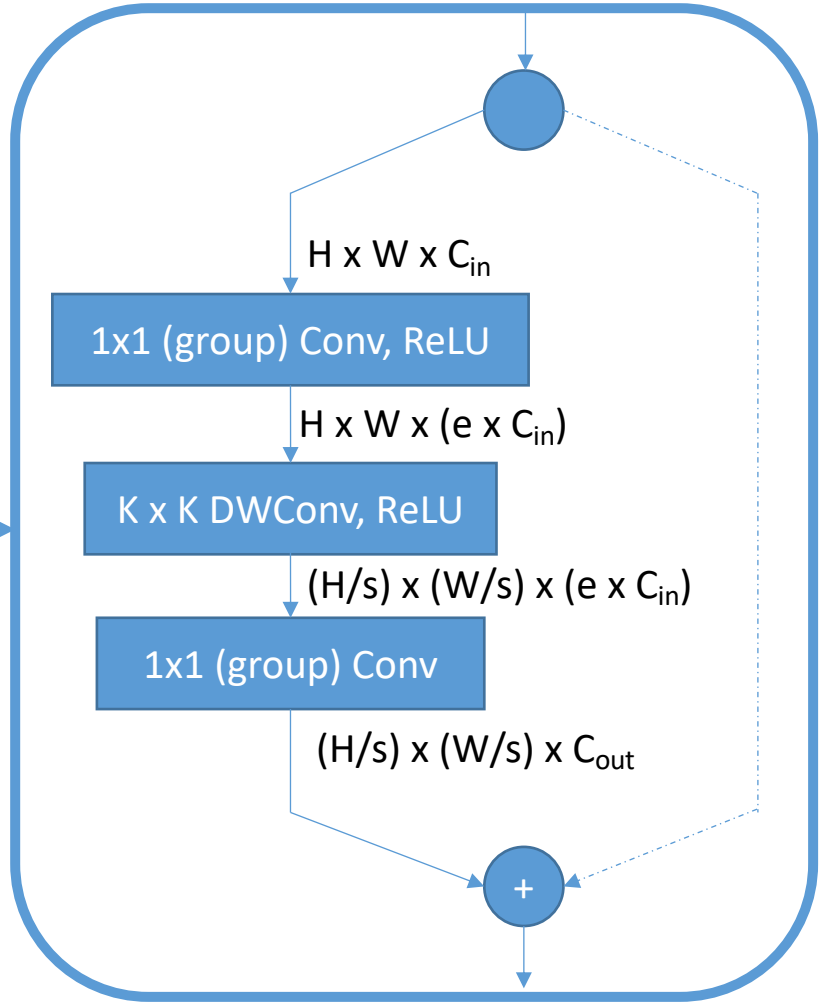
FBNets Search Space



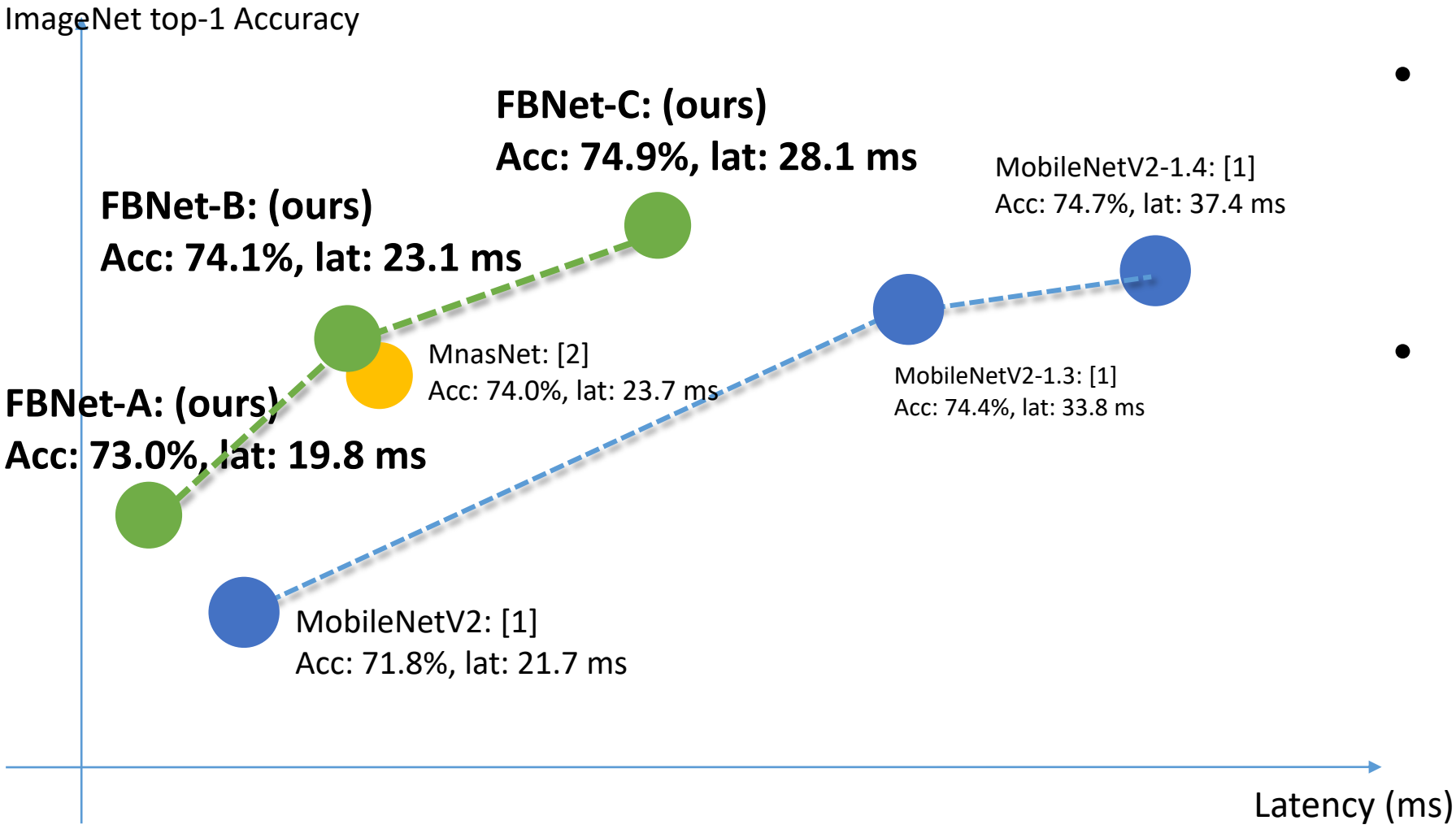
Each “layer” of a network can choose a different block

Candidate blocks with different hyper-parameters

- Kernel size: 3, 5
- Expansion rate: 1, 3, 6
- Skip: no-operation



FBNets vs. previous state-of-the-art



- FBNet-B vs MobileNetV2[1], same accuracy, **1.5x faster, 2.4x smaller FLOPs**
- FBNet vs. MnasNet[2], search cost is 8 GPUs x 24 hours, **421x** lower than MnasNet

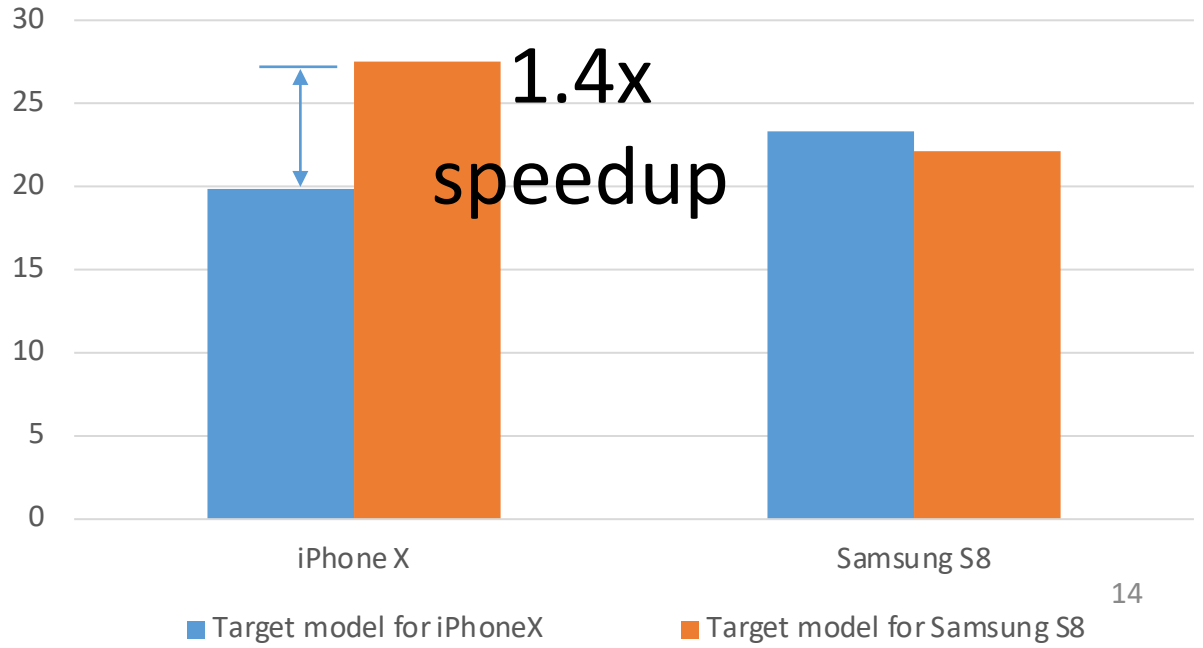
[1] Sandler, Mark, et al. "MobileNetV2: Inverted Residuals and Linear Bottlenecks." CVPR18
[2] Tan, Mingxing, et al. "Mnasnet: Platform-aware neural architecture search for mobile." *CVPR19*

FBNets for different target devices

- Apple A11
- Big: 2 ARMv8 @ 2.5 GHz
- Little: 4 ARMv8 @ 1.4 GHz
- Vectorization: 4-wide 32-bit MAC
- LPDDR4x memory (30 GB/s)
- GPU + Neural Processing Engine

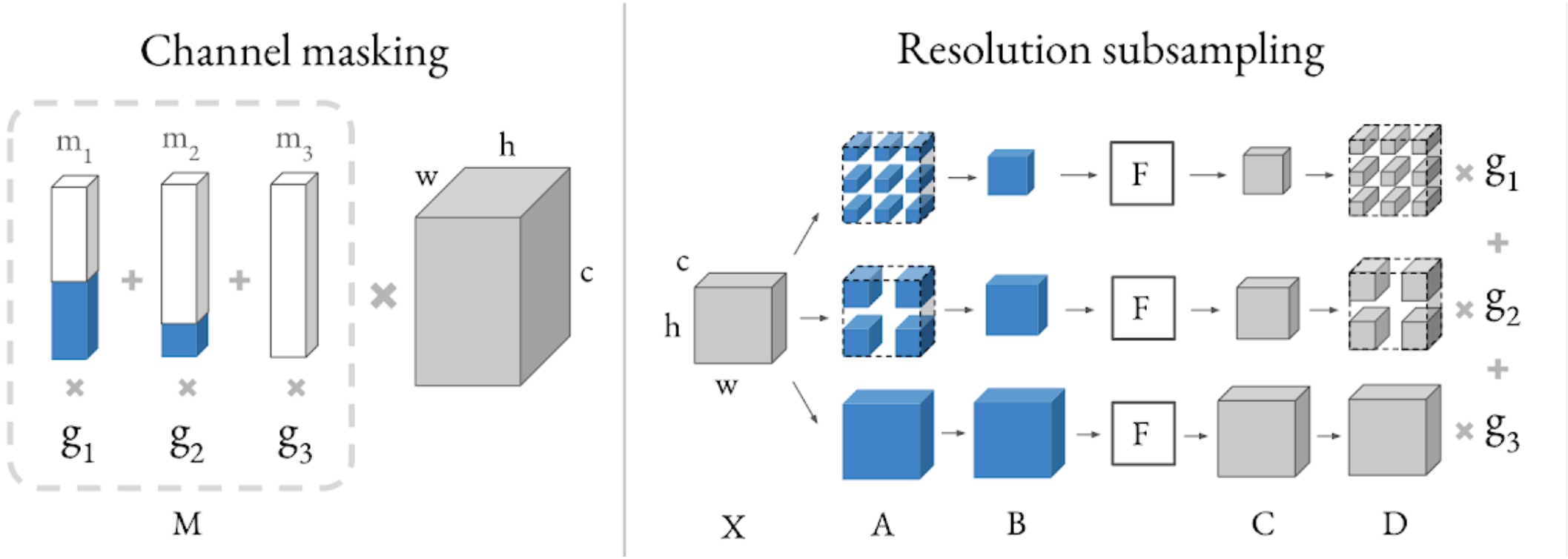
- Snapdragon 835
- Big: 4 ARMv8 @ 2.4 GHz
- Little: 4 ARMv8 @ 1.9 GHz
- Vectorization: 4-wide 32-bit MAC
- LPDDR4x memory (30 GB/s)
- Adreno 540 GPU

- Under similar accuracy constraint (73.27% vs 73.20%), FBNet optimized for iPhone-X achieves 1.4x speedup over the Samsung optimized model

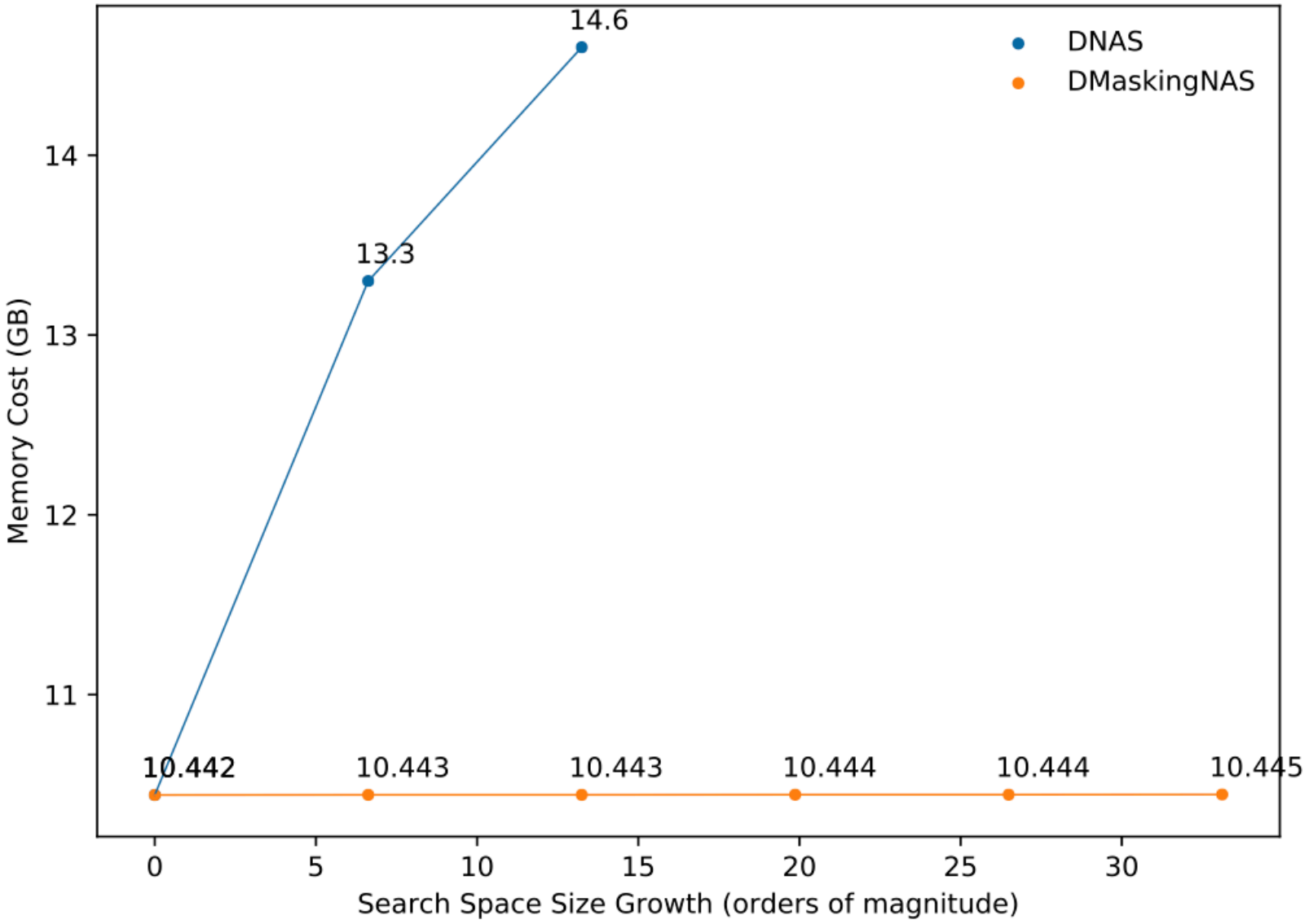


FBNetV2: Differentiable Neural Architecture Search for Spatial and Channel Dimensions

- Searches Channels, Input Resolution, and Expansion Rate
- Expands search space by 10^{14} times



Near-constant memory cost

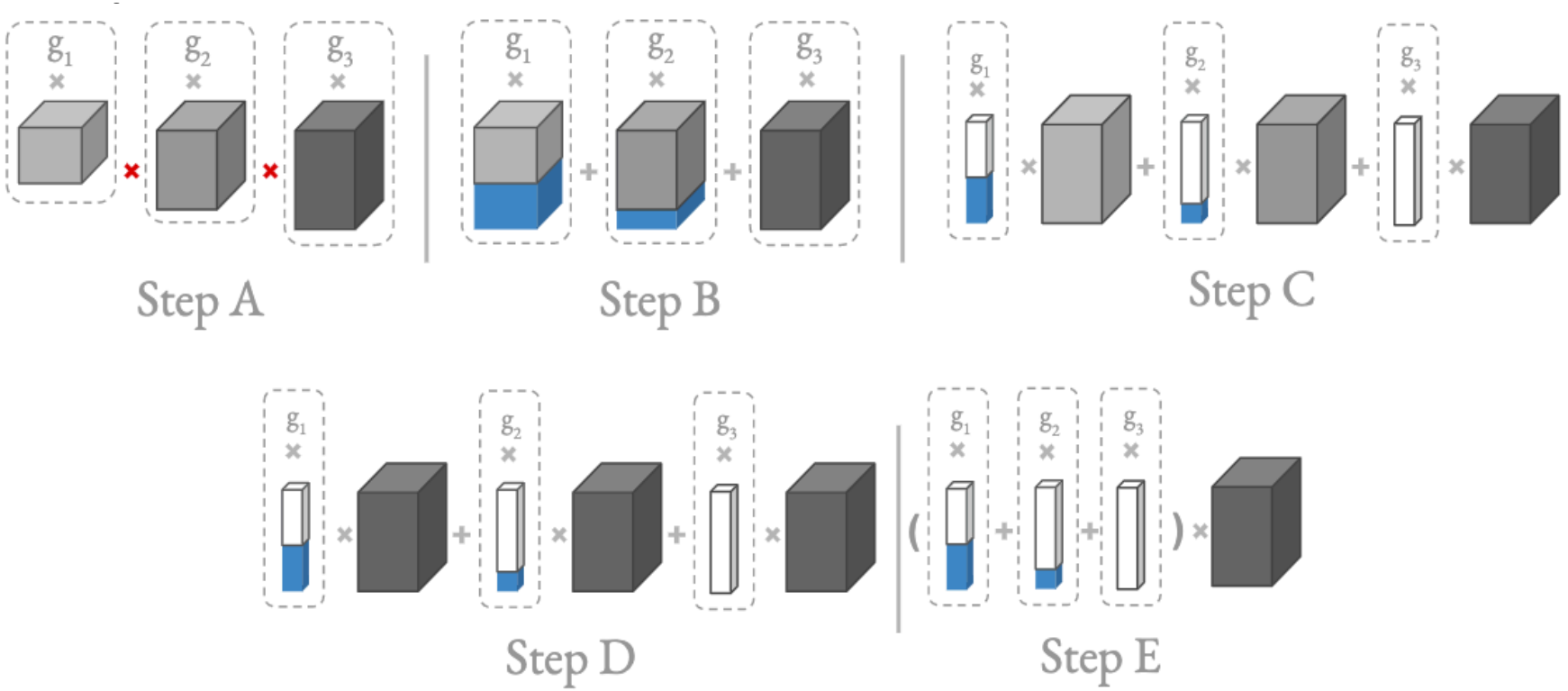


Search Complexity

	Memory Cost	Computational Cost
Channel	near-constant	near-constant
Expansion Rate	near-constant	near-constant
Input Resolutions	near-constant	sub-linear

Channel Masking

- Expanding search space using weight-sharing approximations



How Channel Search Works: convolutional outputs (gray), and their gumbel weights g_i

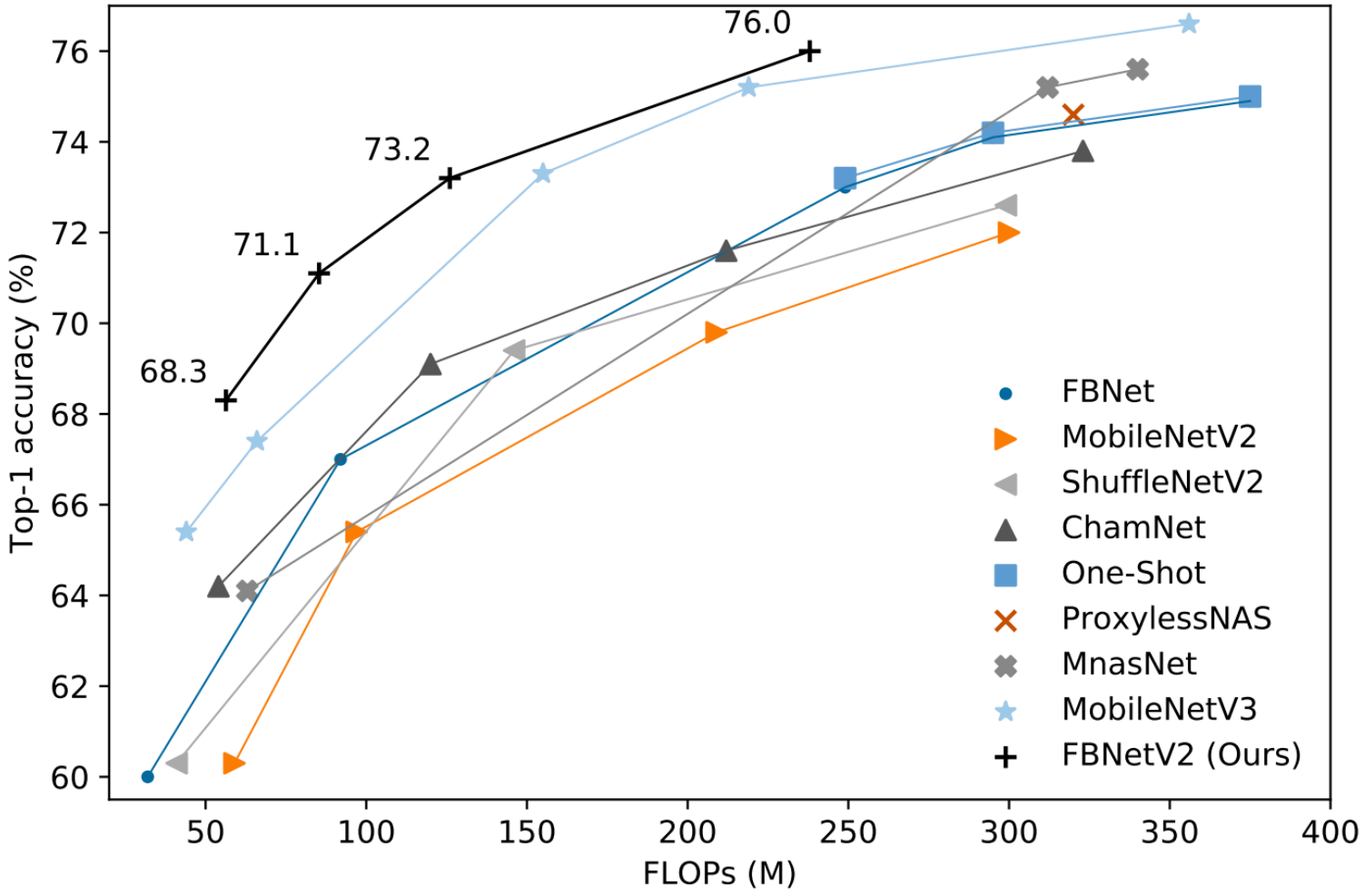
A. Cannot sum feature maps
B. Pad with zeros, but expensive
C. Equivalent to masking
D. Approximate by replacing all 3 convolutions with just 1 conv
E. Equivalent to summing masks

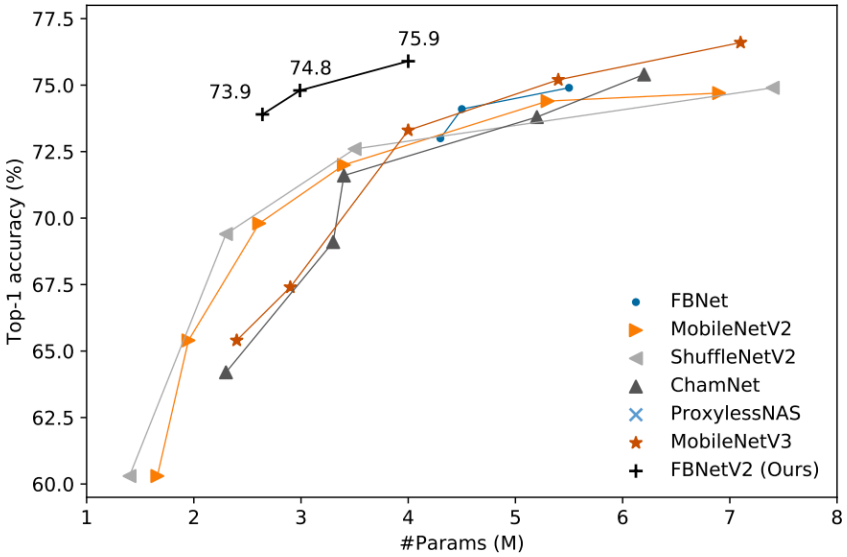
FBNetV2 Search Space

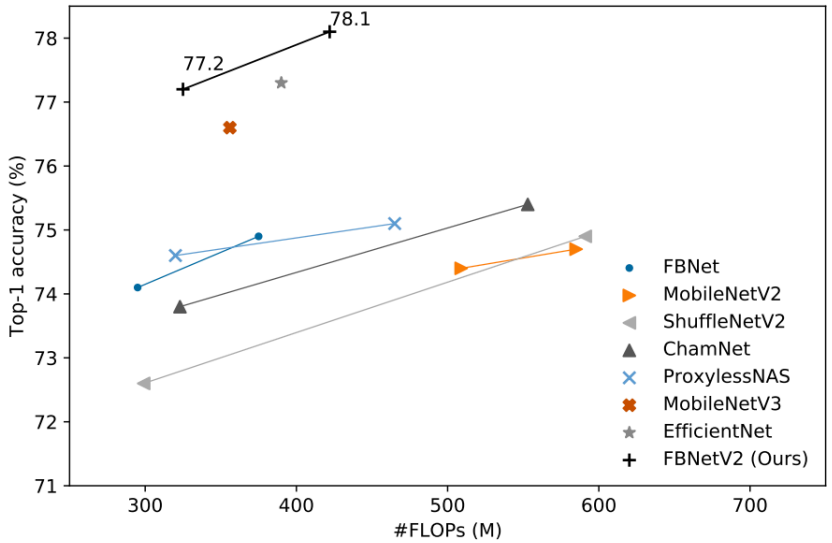
NAS algorithm	C	K	L	B	R	E
MnasNet [28]	✓		✓	✓		✓
ProxylessNAS [2]		✓	✓	✓		✓
Single-Path NAS [26]		✓	✓			✓
ChamNet [3]	✓		✓		✓	✓
FBNet [32]		✓	✓	✓		✓
DMaskingNAS	✓	✓	✓	✓	✓	✓

FBNetV2's search space (bottom row) **eclipses other NAS's**: Number of channels C, kernel size K, number of layers L, bottleneck type B, input resolution R, expansion rate E.

FBNetV2 vs. previous state-of-the-art

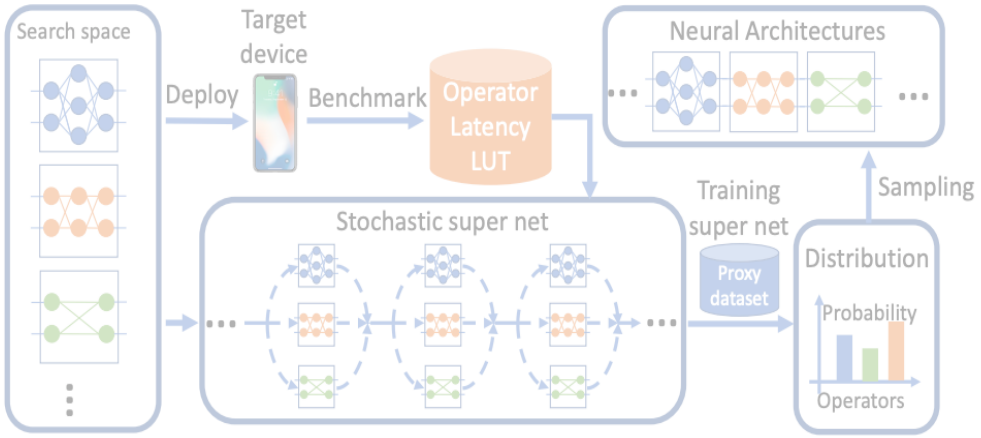




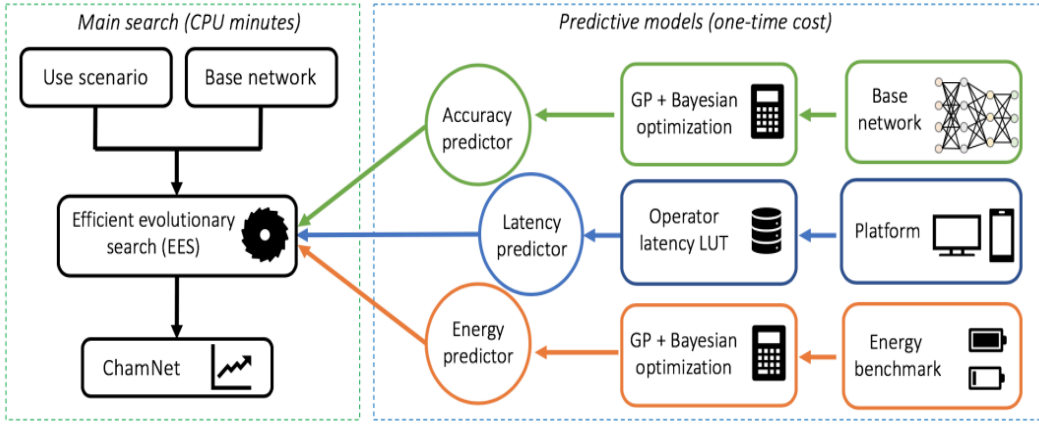


Hardware-aware Architecture Search

- Differentiable Architecture Search: FBNet and FBNetV2
- Predictor-based Architecture Search: ChamNet and FBNetV3



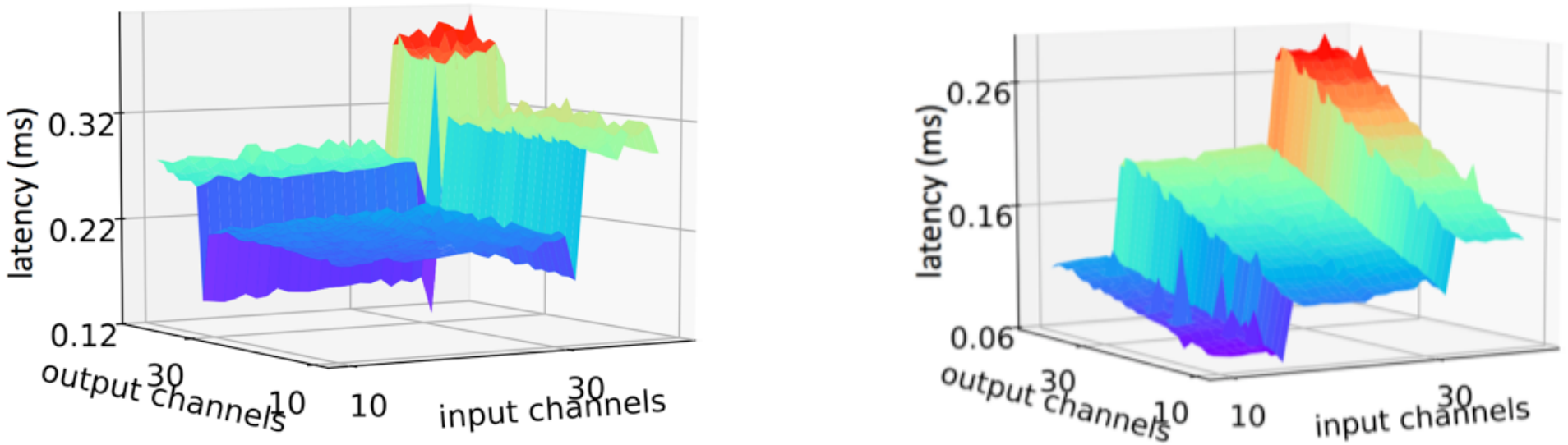
FBNet



ChamNet

Challenges

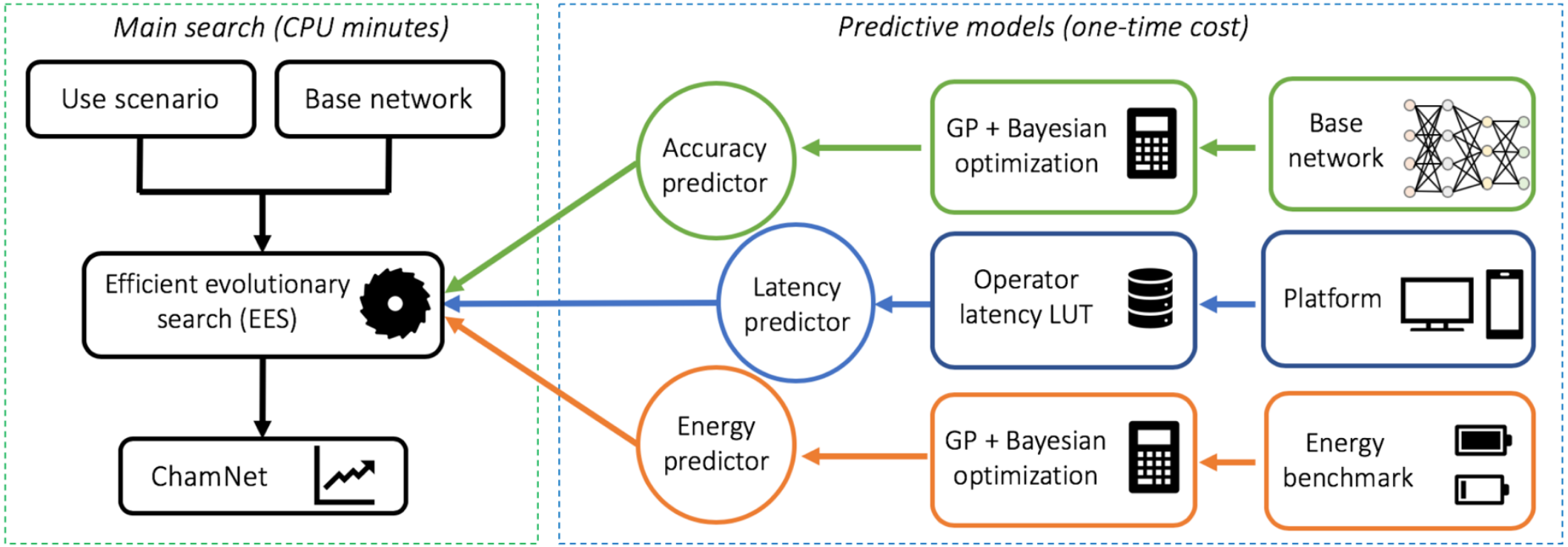
- One model does not fit all devices
- Too expensive to search per task per device



Latency vs. #Channels for a 1x1 convolution on an input image size of 56x56 and stride 1 on (left) Snapdragon 835 GPU and (right) Hexagon v62 DSP.

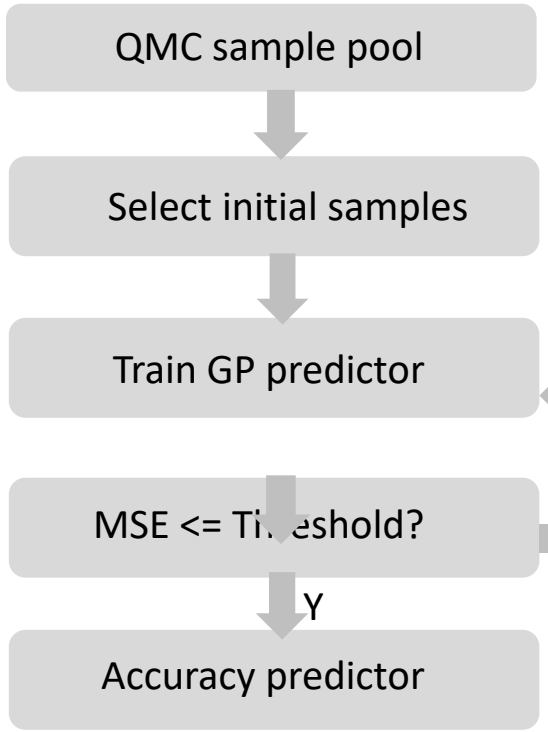
ChamNet: Towards Efficient Network Design through Platform-Aware Model Adaptation

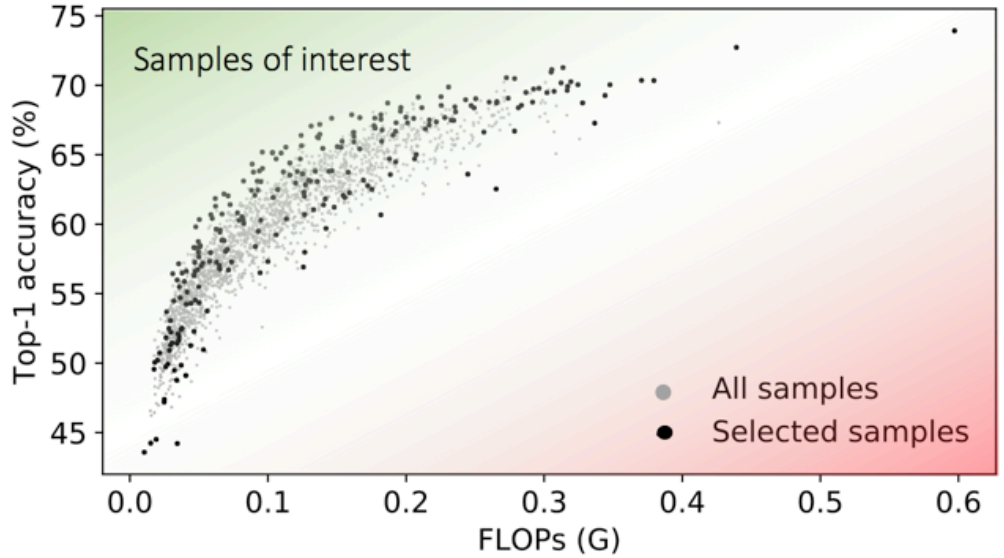
- Build predictive based models for **accuracy, latency,** and **energy**
- Search model for target devices in **minutes**



Accuracy Predictor

- Gaussian process (GP) accuracy predictor
- Bayesian optimization for sample selection





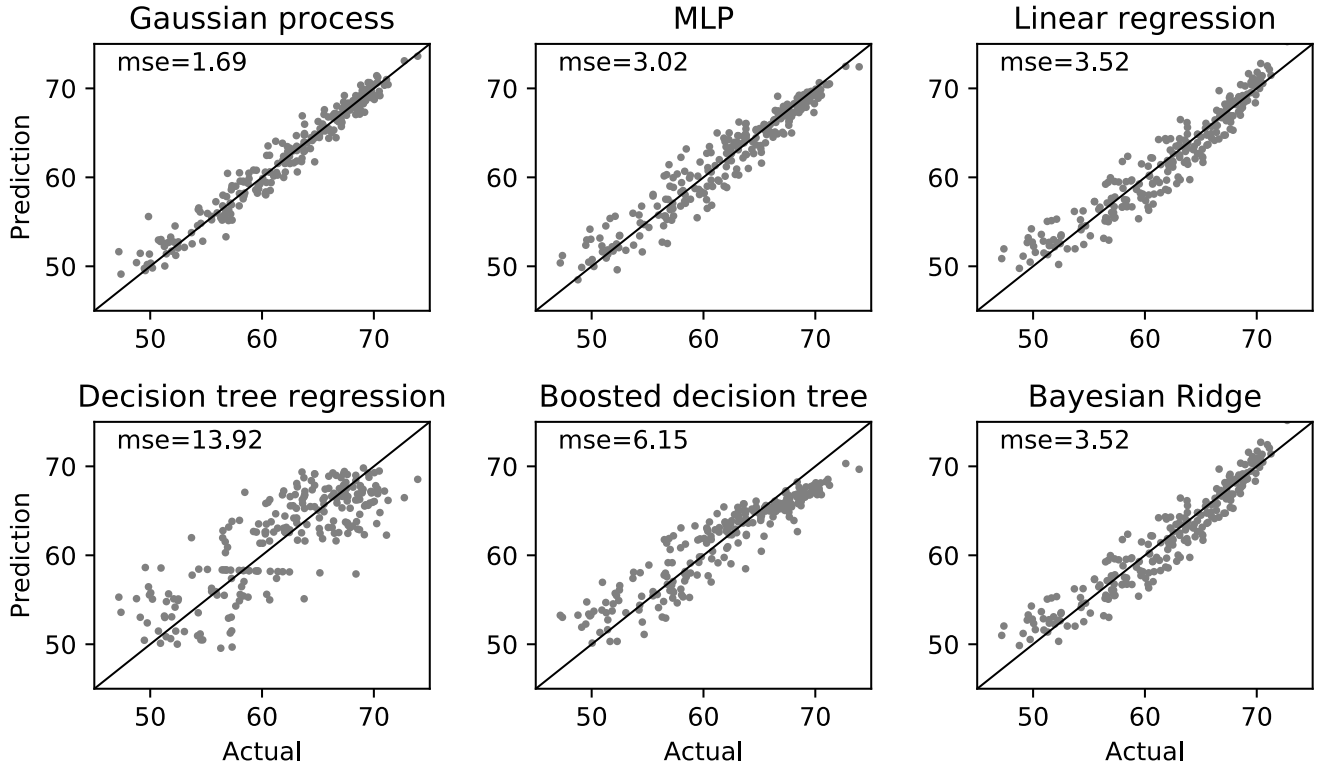
Add samples with large σ or A/FLOP

N *Evaluate uncertainty (σ) and accuracy (A)*

Steps involved to build an accuracy predictor

Accuracy Predictor

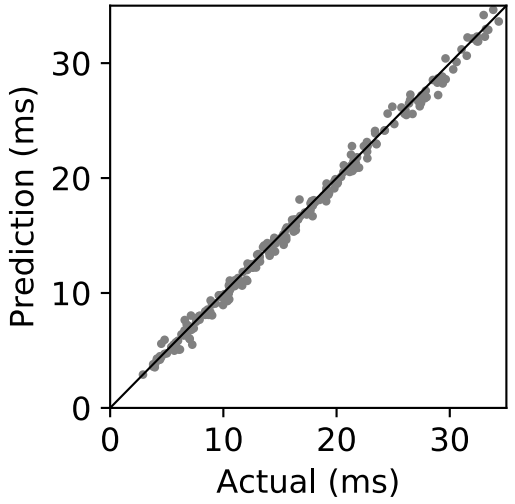
- Very efficient model evaluation
- No training during search



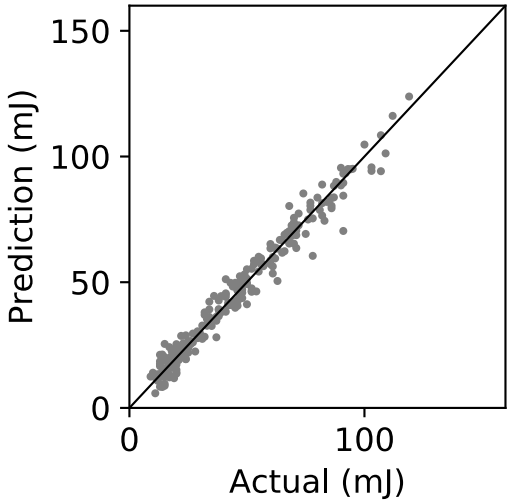
Performance comparison of different accuracy prediction models.

Latency/Energy Predictor

- CNN latency look-up table (LUT)
  - Fast and reliable latency estimation
- Energy predictor
  - Based on real measurements on hardware



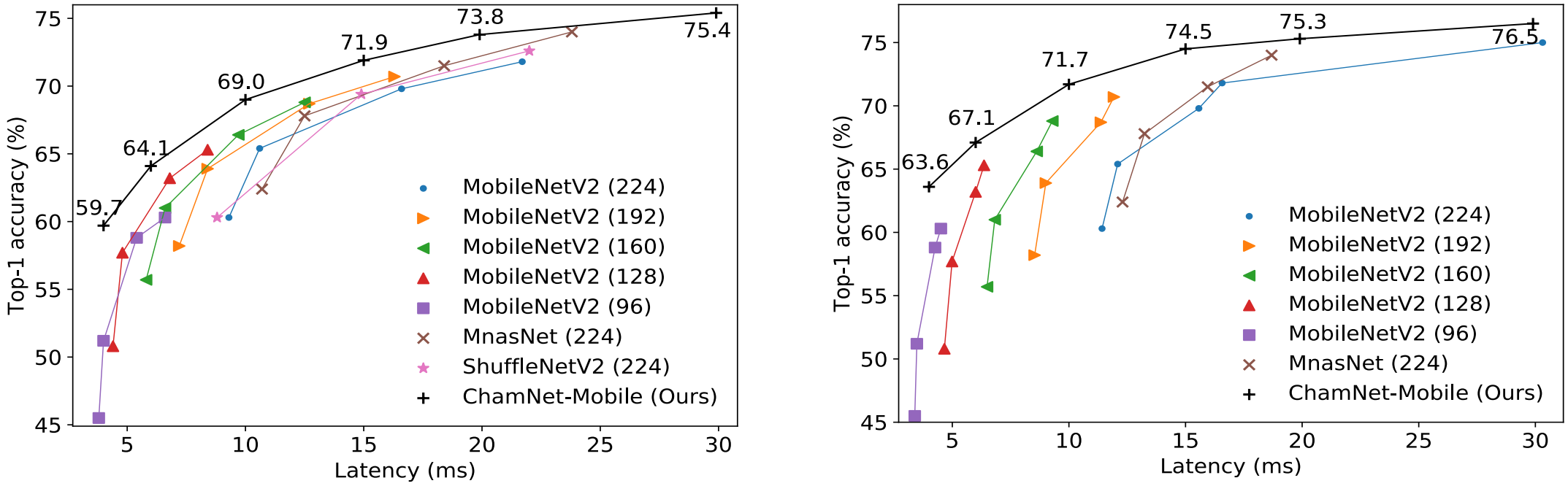
Latency predictor



Energy predictor

ChamNet on Mobile CPU and DSP

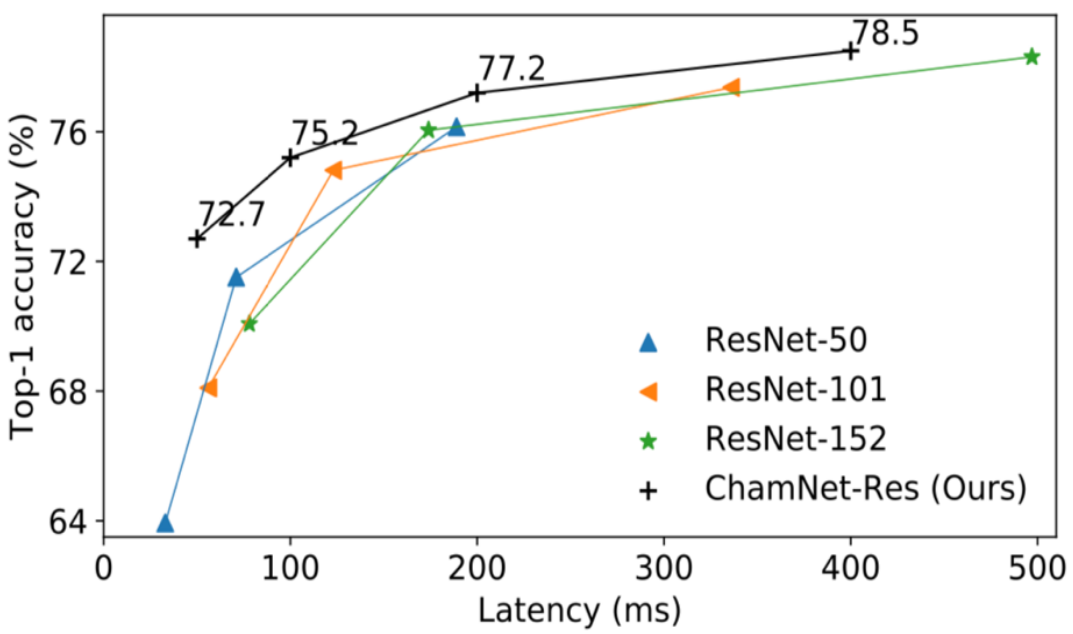
- Inverted residual block based search space
- 8.5% absolute accuracy gain at 4ms compared to MobileNetV2
- 6.6% absolute accuracy gain at 10ms compared to MnasNet

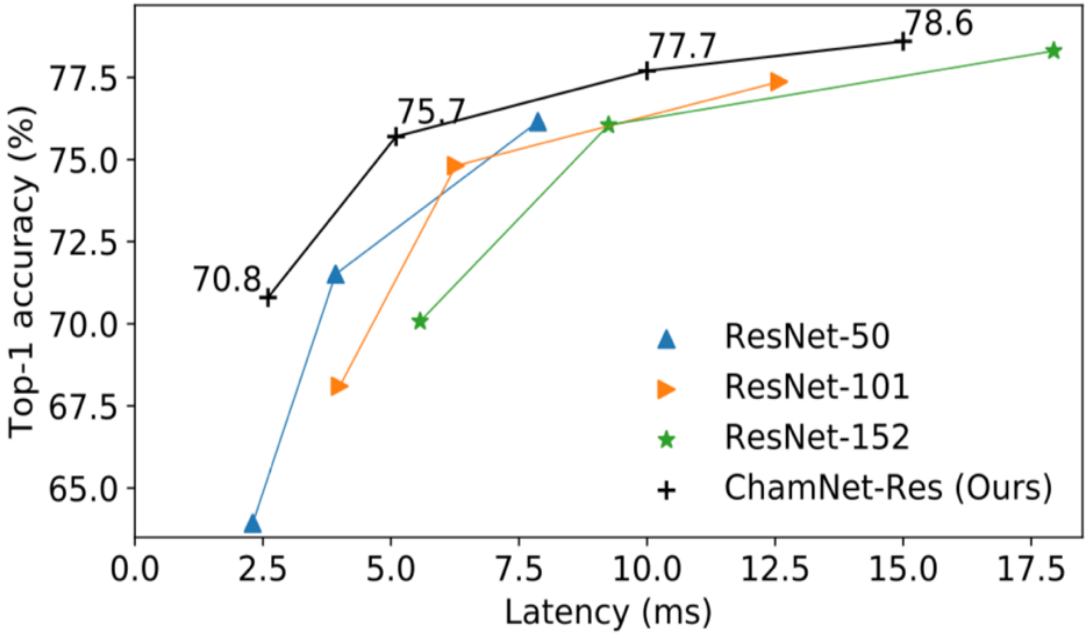


Performance of ChamNet-Mobile on (left) Snapdragon 835 CPU and (right) Hexagon v62 DSP. Numbers in parentheses indicate input image resolution.

ChamNet on Server CPU and GPU

- Residual block based search space
- Significant improvement against ResNet-101 and ResNet-152

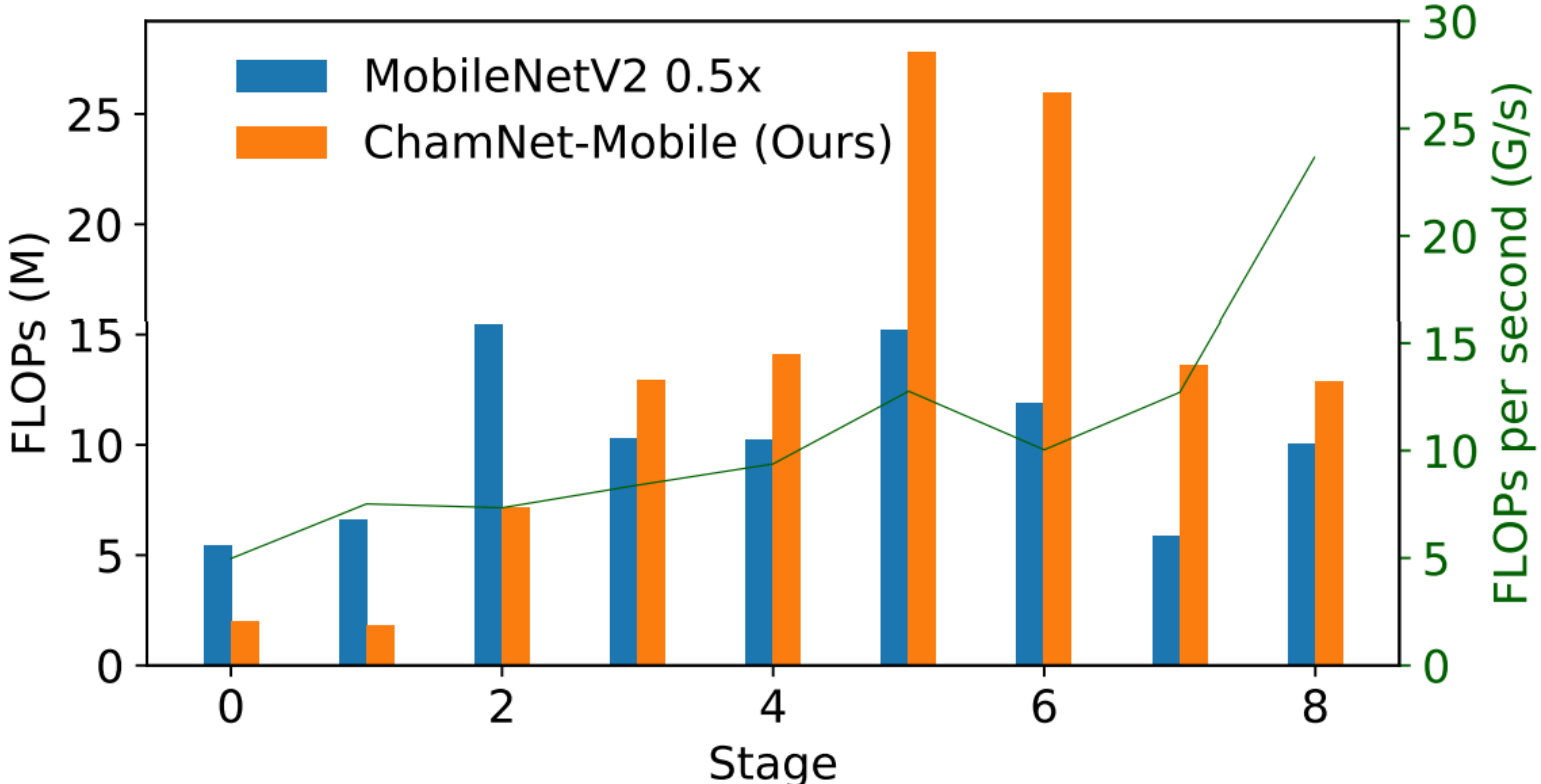




Performance of ChamNet on (left) Intel CPU and (right) Nvidia GPU

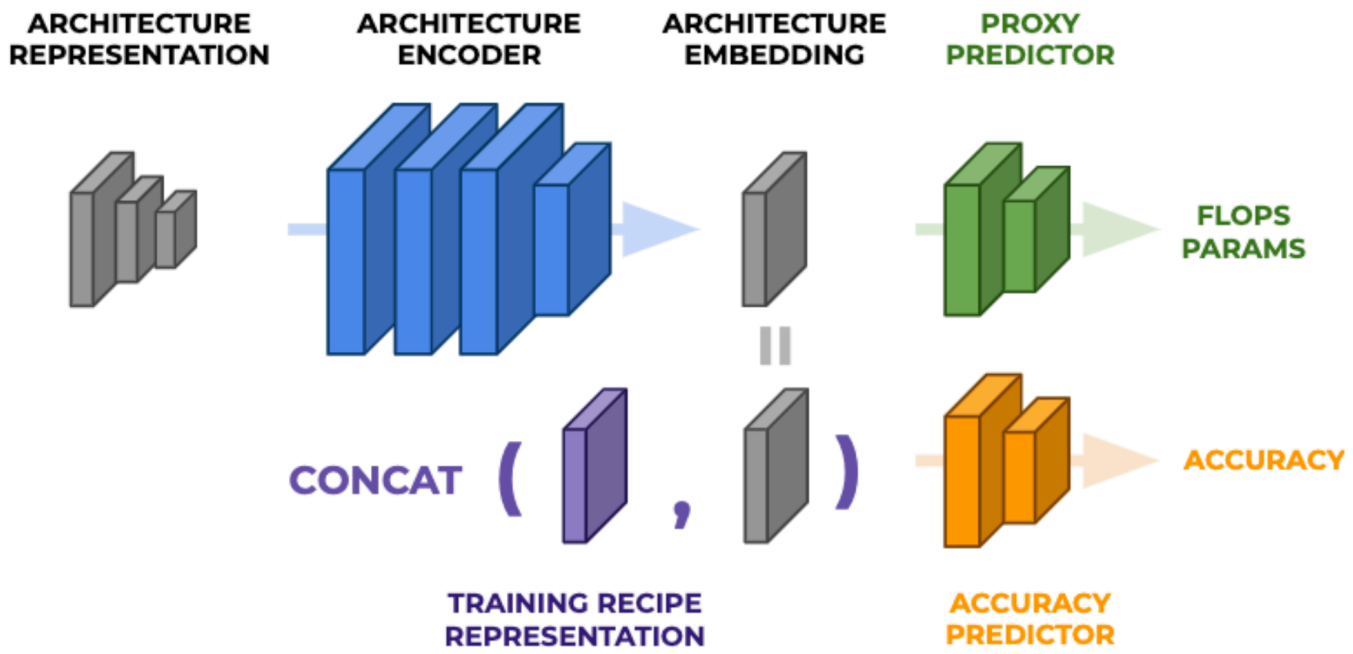
Model FLOPS distribution

- The searched layer distribution is **heavy tailed**
- The operators in early stages with large input image size have lower efficiency (FLOPs per second)



FBNetV3: Joint Architecture-Recipe Search using Neural Acquisition Function

- Joint search of efficient architecture and training hyper-parameters
- DNN-based accuracy predictor

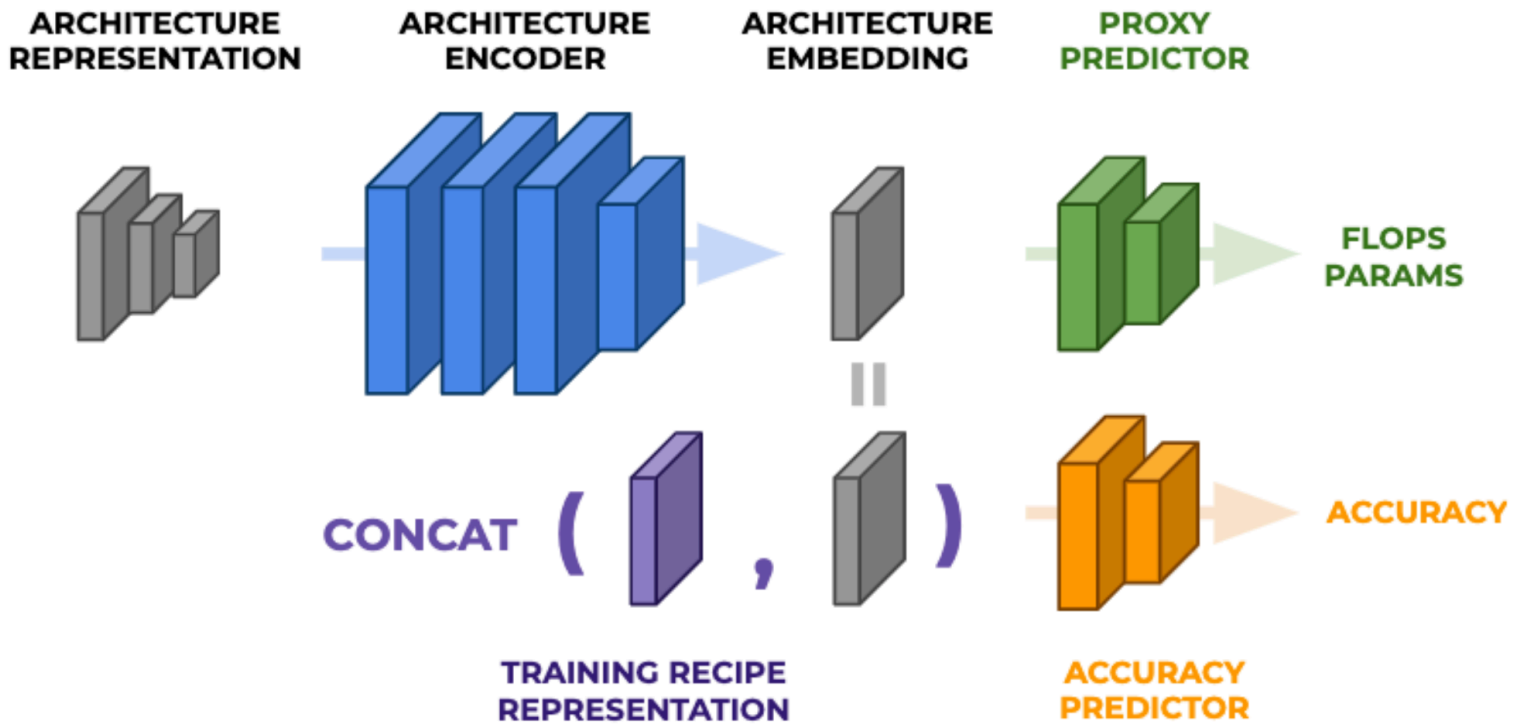


FBNetV3 Search Space

- Architecture
  - Inverted residual block (kernel, channel, expansion, stride)
  - Number of layers
  - Squeeze-and-Excite
  - Activation function
- Training hyper-parameters
  - Resolution
  - Optimizer (type, learning, rate, weight decay)
  - Regularization (dropout ratio, stochastic depth drop ratio, mix-up ratio)
  - EMA (exponential moving average)

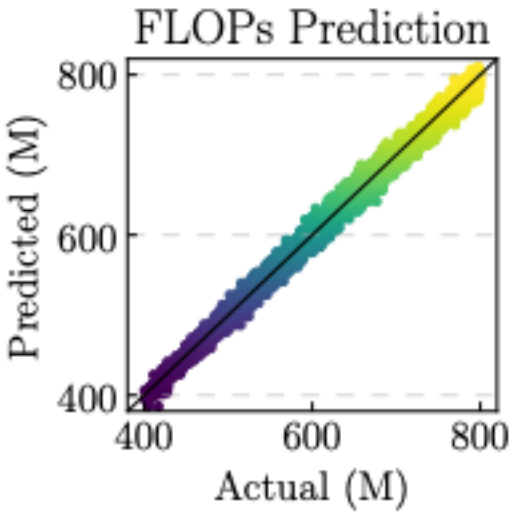
DNN-based Accuracy Predictor

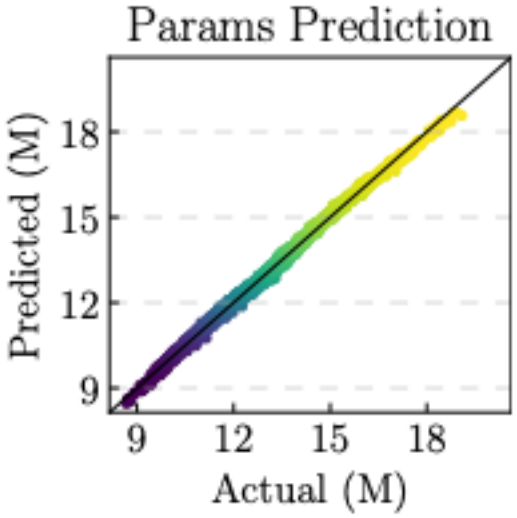
- Multi-layer perceptron with auxiliary head
  - One-hot categorical variables
  - Integral range variables

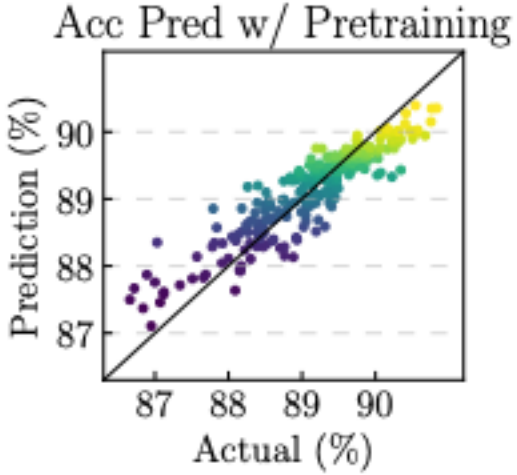


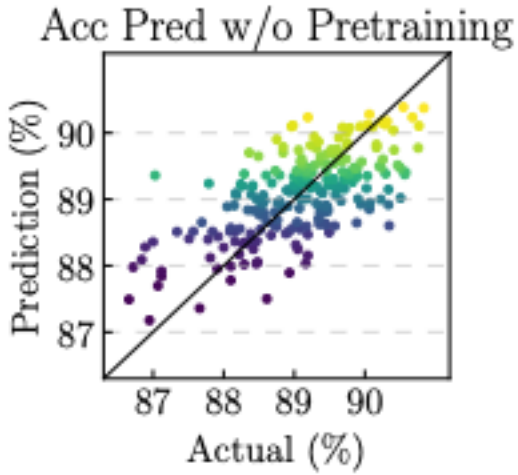
Accuracy Predictor Pre-training

- Pretrain architecture embedding layer using FLOPs/number of parameters



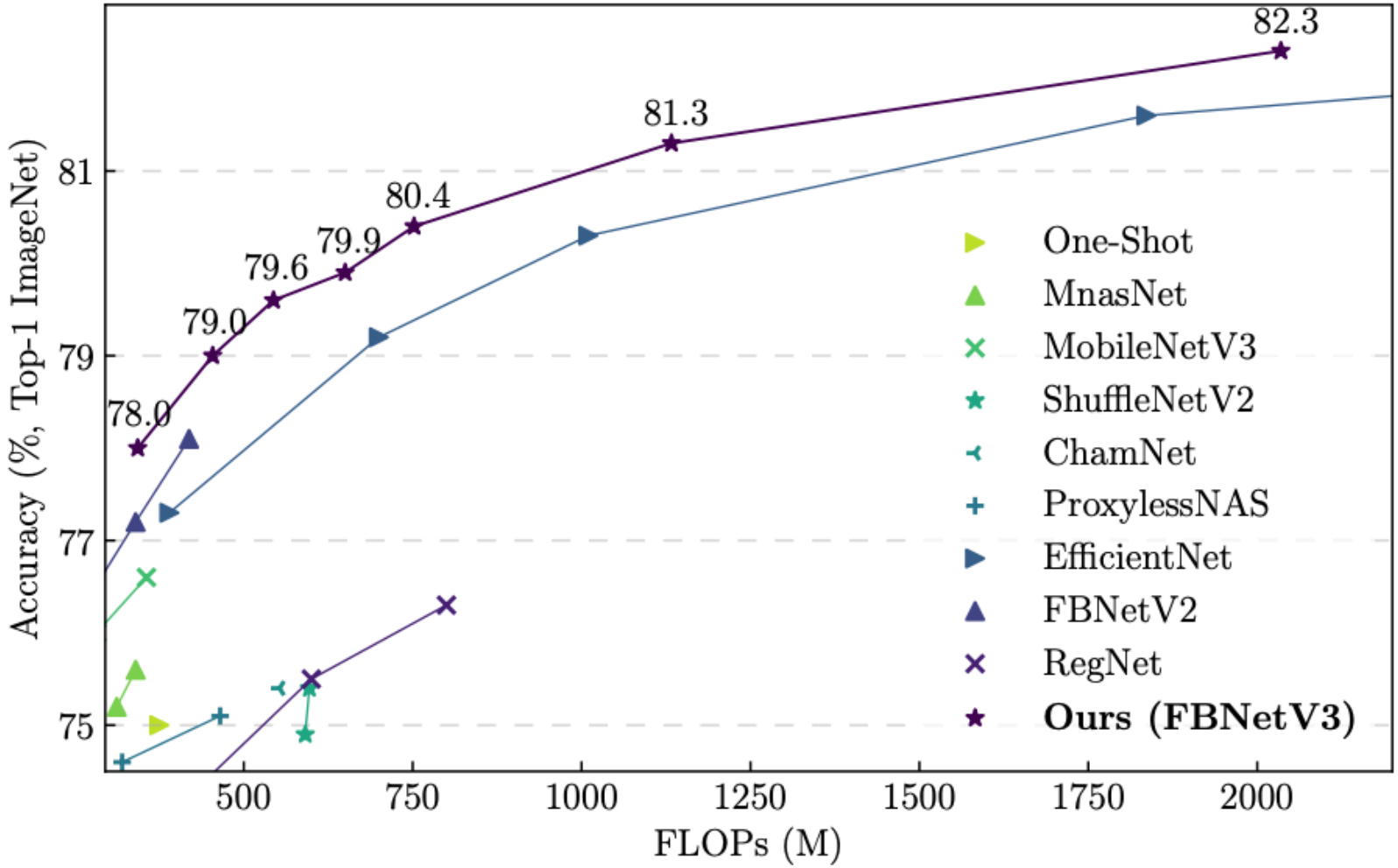






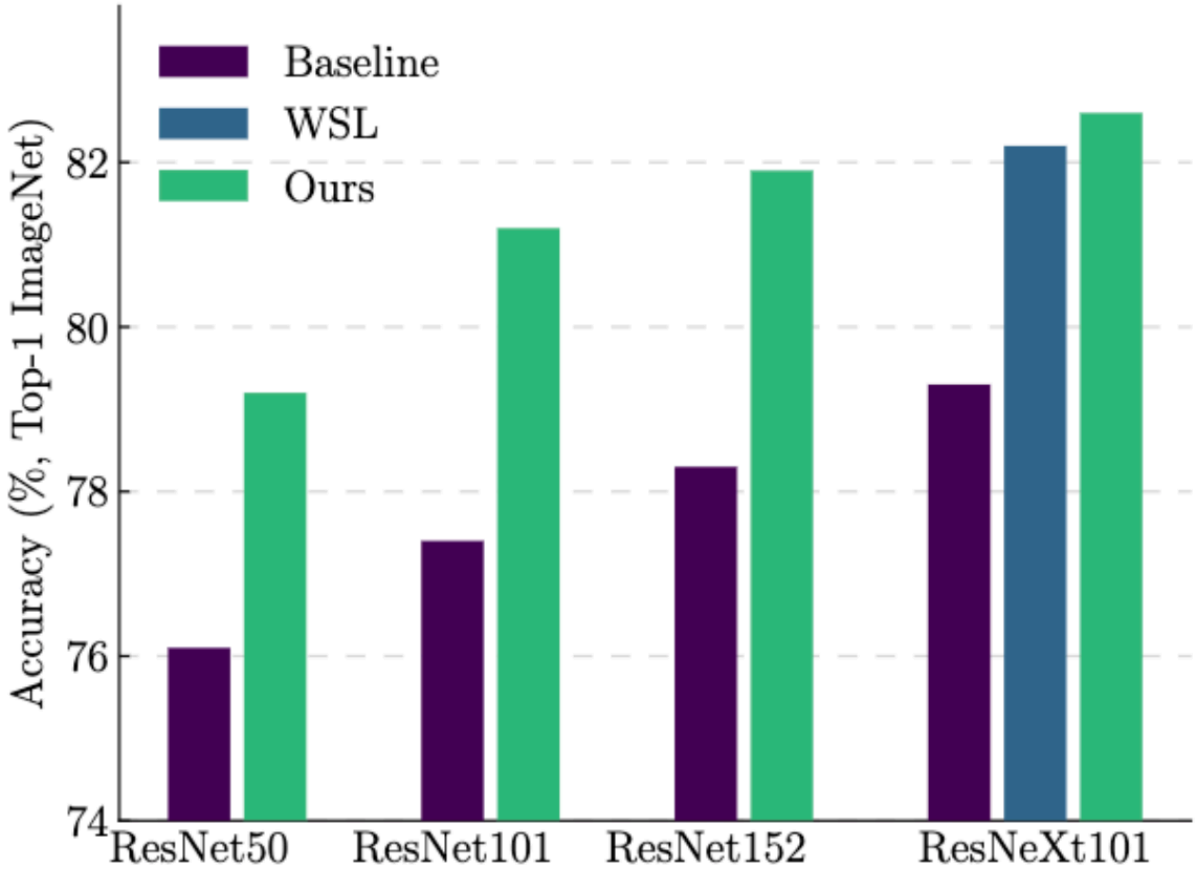
FBNetV3 vs. previous state-of-the-art

- 28% less FLOPs with same accuracy as EfficientNet



Training Hyperparameter Search

- Searched ResNet-50 shows **0.9**% better accuracy than ResNet-152
- Searched ResNext101 surpasses the **weakly supervised learning** (WSL) model without extra 1B training data



Architecture Search Applications for AR/VR

Single depth estimation for one shot 3D photography

Real-time hand tracking on device for VR

- Kopf et al, One Shot 3D Photography, SIGGRAPH 2020
- Han et al., MEgATrack: Monochrome Egocentric Articulated Hand-Tracking for Virtual Reality, SIGGRAPH 2020

Summary

- Hardware-aware Architecture Search
  - Direct metric search (latency, energy)
  - State-of-the-art performance (same accuracy, 28% less compute)
- Differentiable Architecture Search (FBNet, FBNetV2)
  - Extremely fast: 8 GPUs for 24 hours, 421x faster search
  - 10^{14}x larger search space with near-constant memory cost
- Predictor-based Architecture Search (ChamNet, FBNetV3)
  - Fast adaption for different devices
  - Training hyper-parameter search

Mobile Vision @ Facebook

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Thank you!

References

- Wu et al., *FBNet: Hardware-Aware Efficient ConvNet Design via Differentiable Neural Architecture Search*
- Wan et al., *FBNetV2: Differentiable neural architecture search for spatial and channel dimensions*
- Dai et al., *ChamNet: Towards Efficient Network Design through Platform-Aware Model Adaptation*
- Dai et al., *FBNetV3: Joint Architecture-Recipe Search using Neural Acquisition Function*

Models available:
https://github.com/facebookresearch/mobile-vision