Balancing Efficiency and Flexibility for DNN Acceleration

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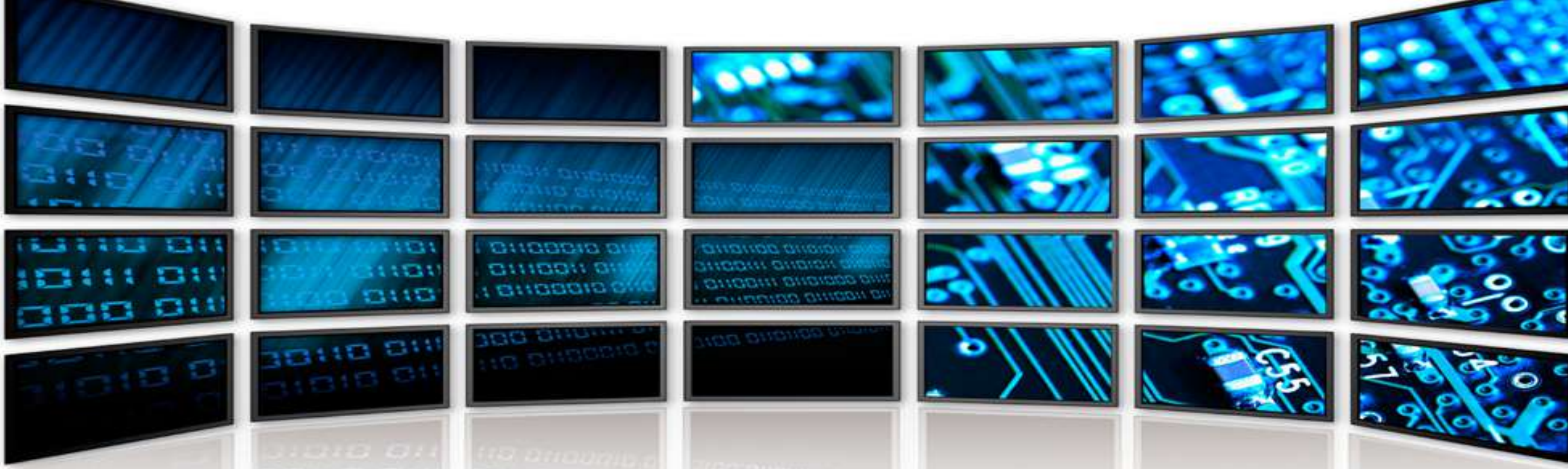

In collaboration with Yu-Hsin Chen, Joel Emer, Sertac Karaman, Fangchang Ma, Diana Wofk, Tien-Ju Yang, Zhengdong Zhang, Google Mobile Vision Team

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email: sze@mit.edu
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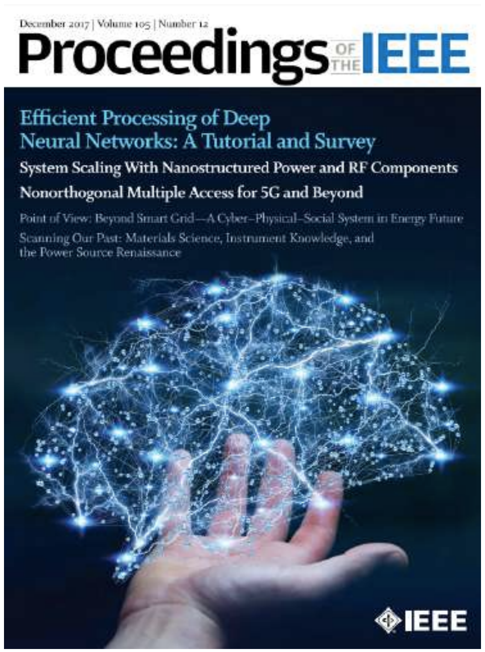
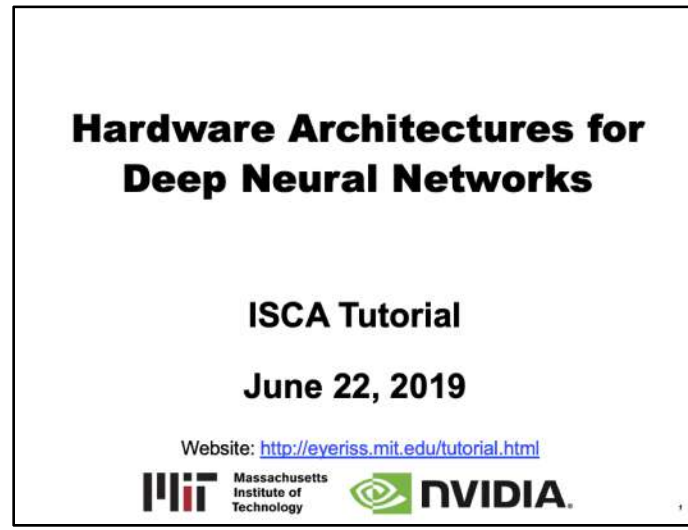
Energy-Efficient Processing of DNNs

A significant amount of algorithm and hardware research on energy-efficient processing of DNNs



V. Sze, Y.-H. Chen, T-J. Yang, J. Emer, "***Efficient Processing of Deep Neural Networks: A Tutorial and Survey***," Proceedings of the IEEE, Dec. 2017



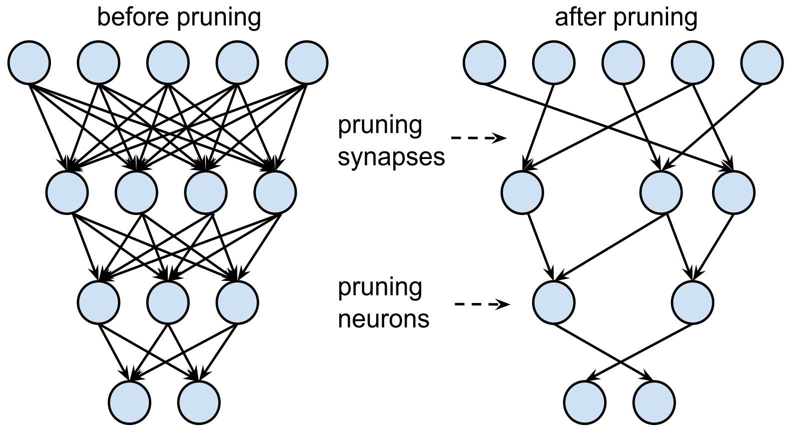
http://eyeriss.mit.edu/tutorial.html

We identified various challenges to existing approaches

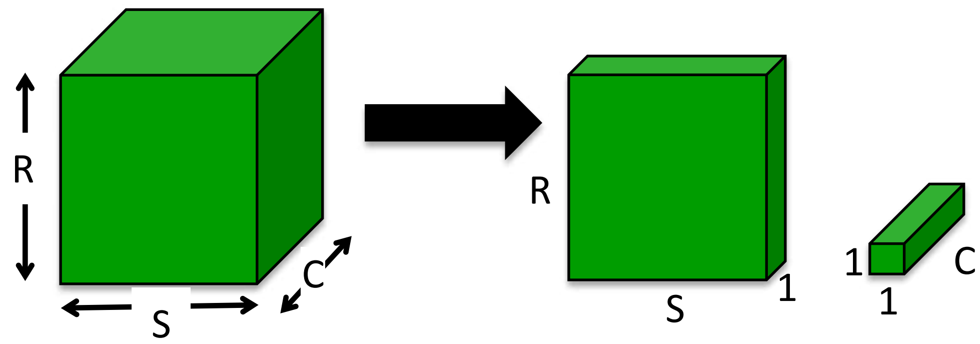
Design of Efficient DNN Algorithms

- Popular efficient DNN algorithm approaches

Network Pruning



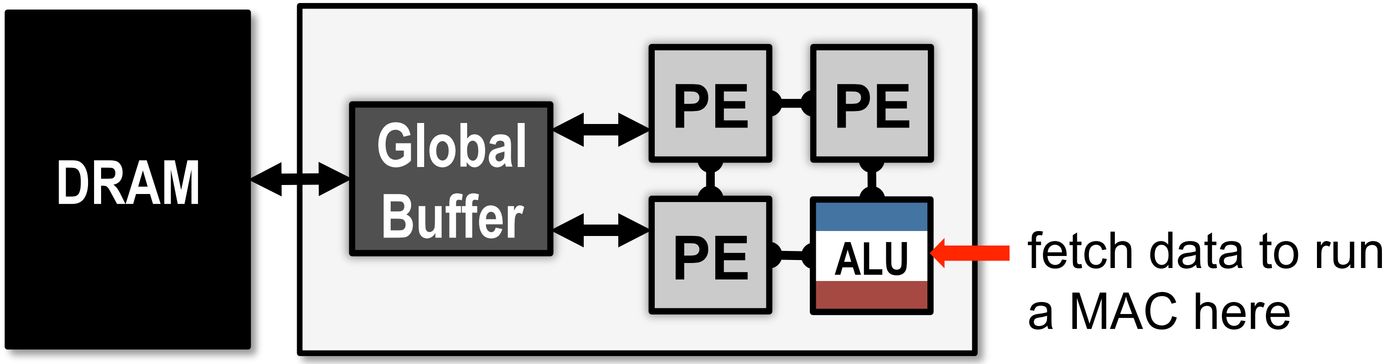
Compact Network Architectures

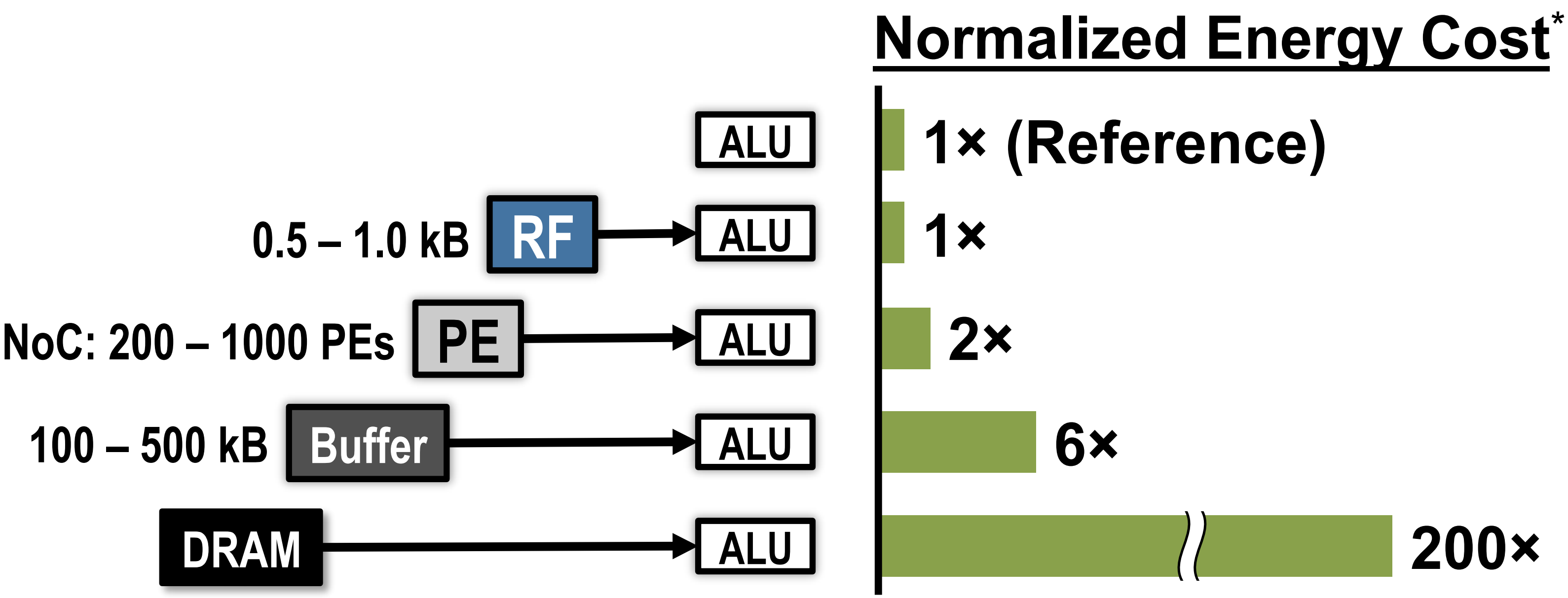


... also reduced precision

- Focus on reducing **number of MACs and weights**
- **Does it translate to energy savings and reduced latency?**

Data Movement is Expensive

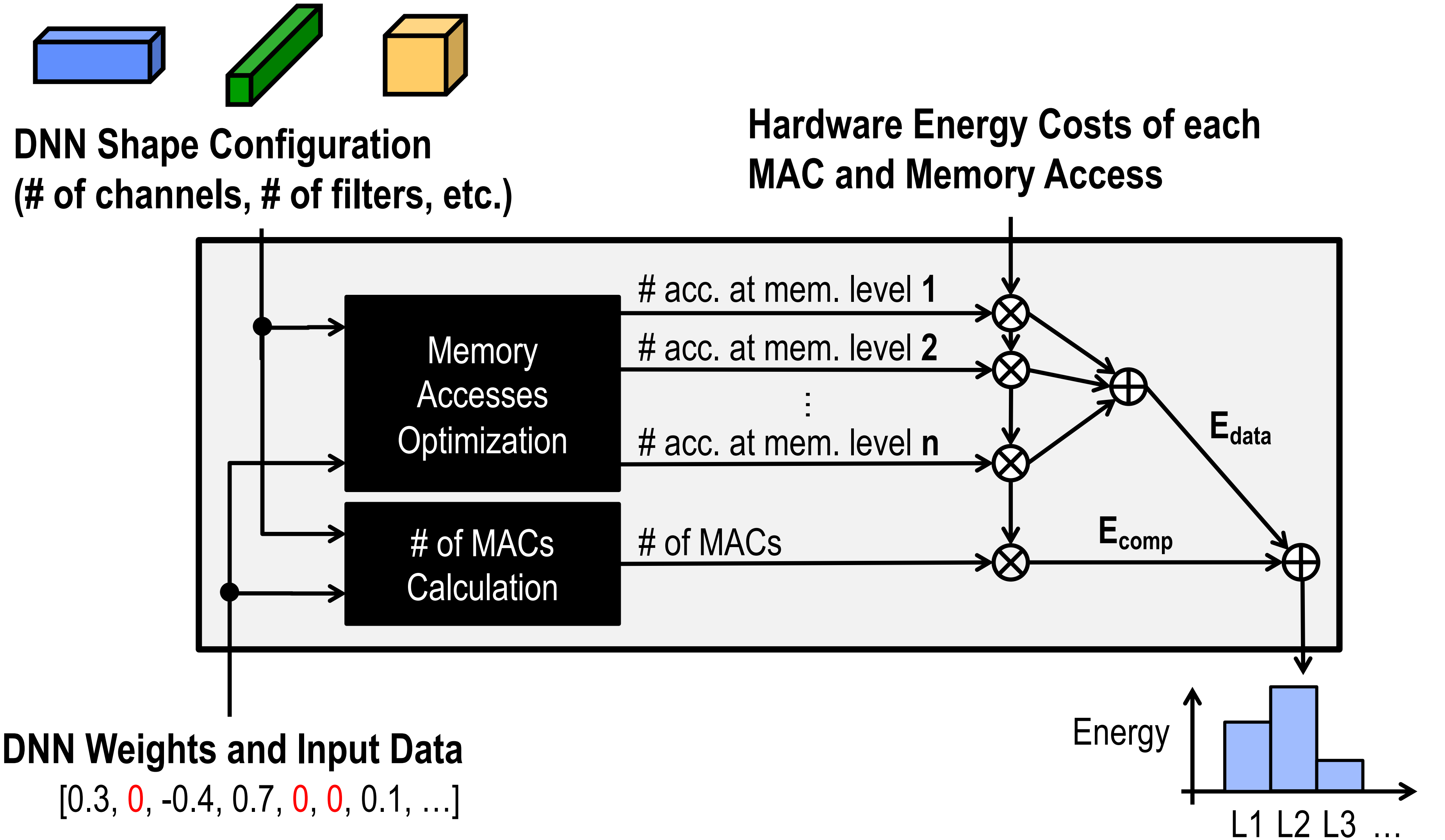




* measured from a commercial 65nm process

Energy of weight depends on **memory hierarchy** and **dataflow**

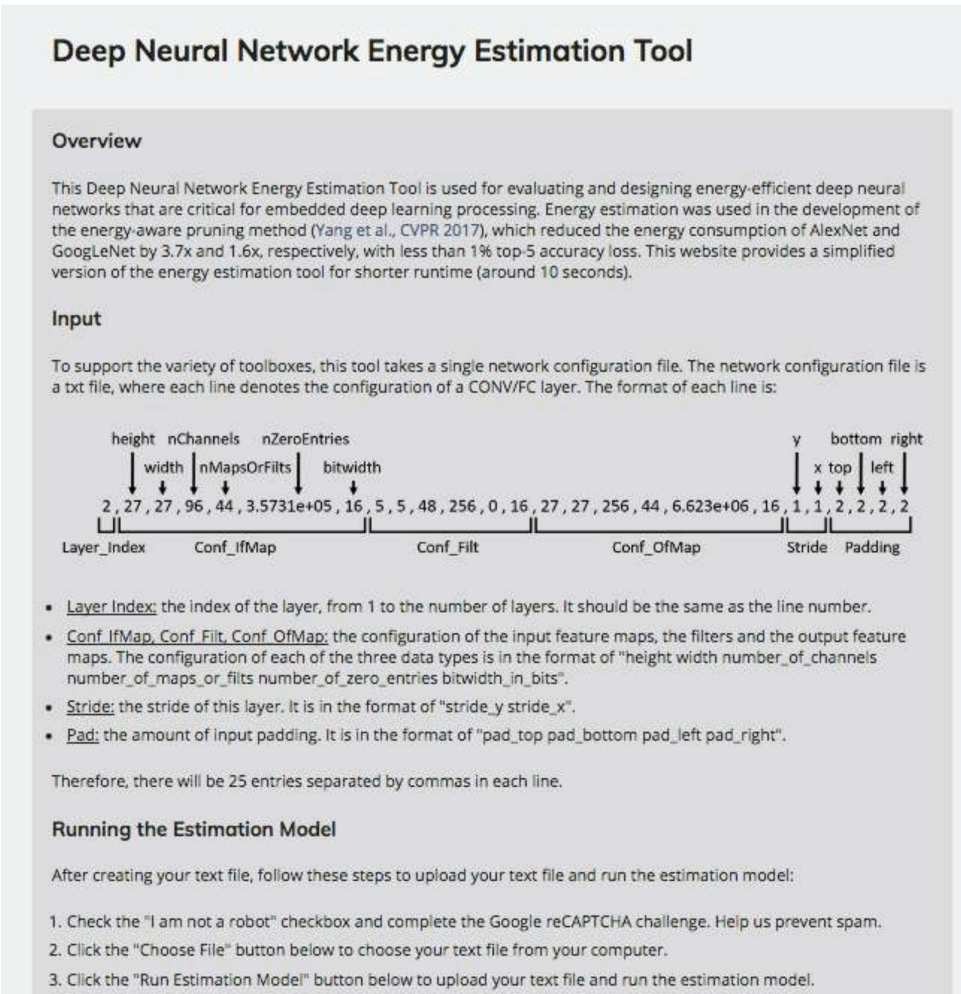
Energy-Evaluation Methodology



Tool available at: https://energyestimation.mit.edu/

Energy Estimation Tool

Website: https://energyestimation.mit.edu/



Deep Neural Network Energy Estimation Tool

Overview

This Deep Neural Network Energy Estimation Tool is used for evaluating and designing energy-efficient deep neural networks that are critical for embedded deep learning processing. Energy estimation was used in the development of the energy-aware pruning method (Yang et al., CVPR 2017), which reduced the energy consumption of AlexNet and GoogLeNet by 3.7x and 1.6x, respectively, with less than 1% top-5 accuracy loss. This website provides a simplified version of the energy estimation tool for shorter runtime (around 10 seconds).

Input

To support the variety of toolboxes, this tool takes a single network configuration file. The network configuration file is a txt file, where each line denotes the configuration of a CONV/FC layer. The format of each line is:

height nChannels nZeroEntries y bottom right
width nMapsOrFilts bitwidth x top left

2 , 27 , 27 , 96 , 44 , 3.5731e+05 , 16 , 5 , 5 , 48 , 256 , 0 , 16 , 27 , 27 , 256 , 44 , 6.623e+06 , 16 , 1 , 1 , 2 , 2 , 2 , 2

Layer_Index Conf_IfMap Conf_Filt Conf_OfMap Stride Padding

- Layer Index: the index of the layer, from 1 to the number of layers. It should be the same as the line number.
- Conf_IfMap, Conf_Filt, Conf_OfMap: the configuration of the input feature maps, the filters and the output feature maps. The configuration of each of the three data types is in the format of "height width number_of_channels number_of_maps_or_filts number_of_zero_entries bitwidth_in_bits".
- Stride: the stride of this layer. It is in the format of "stride_y stride_x".
- Pad: the amount of input padding. It is in the format of "pad_top pad_bottom pad_left pad_right".

Therefore, there will be 25 entries separated by commas in each line.

Running the Estimation Model

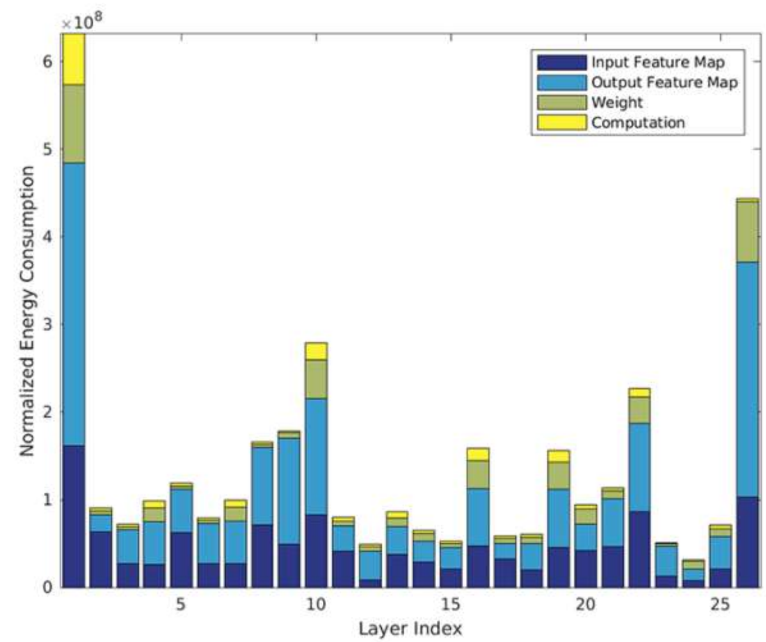
After creating your text file, follow these steps to upload your text file and run the estimation model:

1. Check the "I am not a robot" checkbox and complete the Google reCAPTCHA challenge. Help us prevent spam.
2. Click the "Choose File" button below to choose your text file from your computer.
3. Click the "Run Estimation Model" button below to upload your text file and run the estimation model.

Input DNN Configuration File

```
Layer_Index,Input_Feature_Map,Output_Feature_Map,Weight,Computation
1,161226686.785535,323273662,88858340.625,58290651
2,63540403.7543396,19104256.6840292,4770357.50868125,3263307.50868125
3,26787638.0555562,39583335.5555542,3272222.77777708,2285942.77777708
4,26018817.2746958,48841502.8019458,15927826.1926396,7847418.06763958
5,62285050.8236438,49433953.294575,4188476.6472875,3227376.6472875
6,27267689.7685187,45381705.7407417,3740581.20370417,2666586.20370417
7,26787131.0480146,48586492.3413917,16216779.2956958,8136371.17069583
```

Output DNN energy breakdown across layers

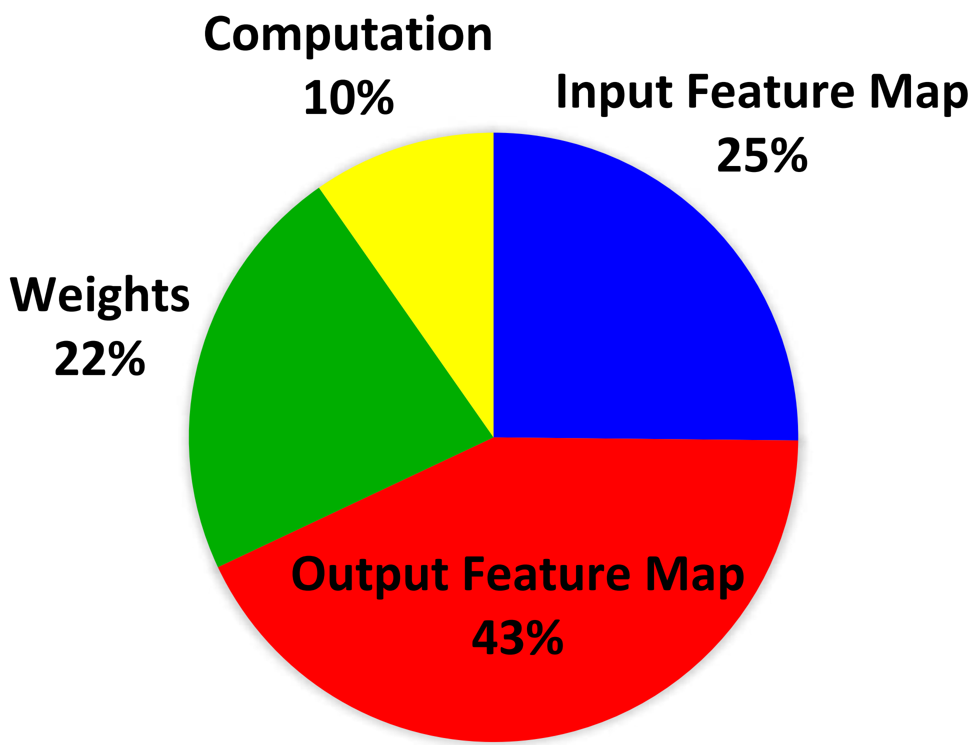


[Yang et al., CVPR 2017]

Key Observations

- Number of weights ***alone*** is not a good metric for energy
- **All data types** should be considered

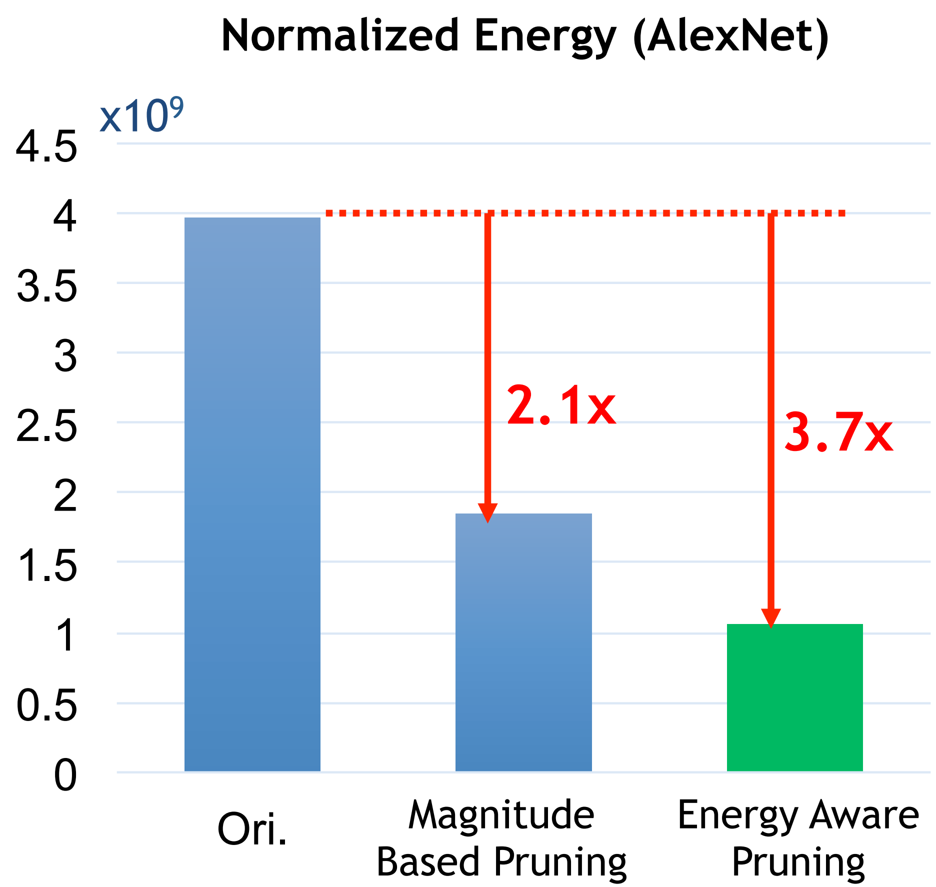
Energy Consumption of GoogLeNet



Energy-Aware Pruning

Directly target energy and incorporate it into the optimization of DNNs to provide greater energy savings

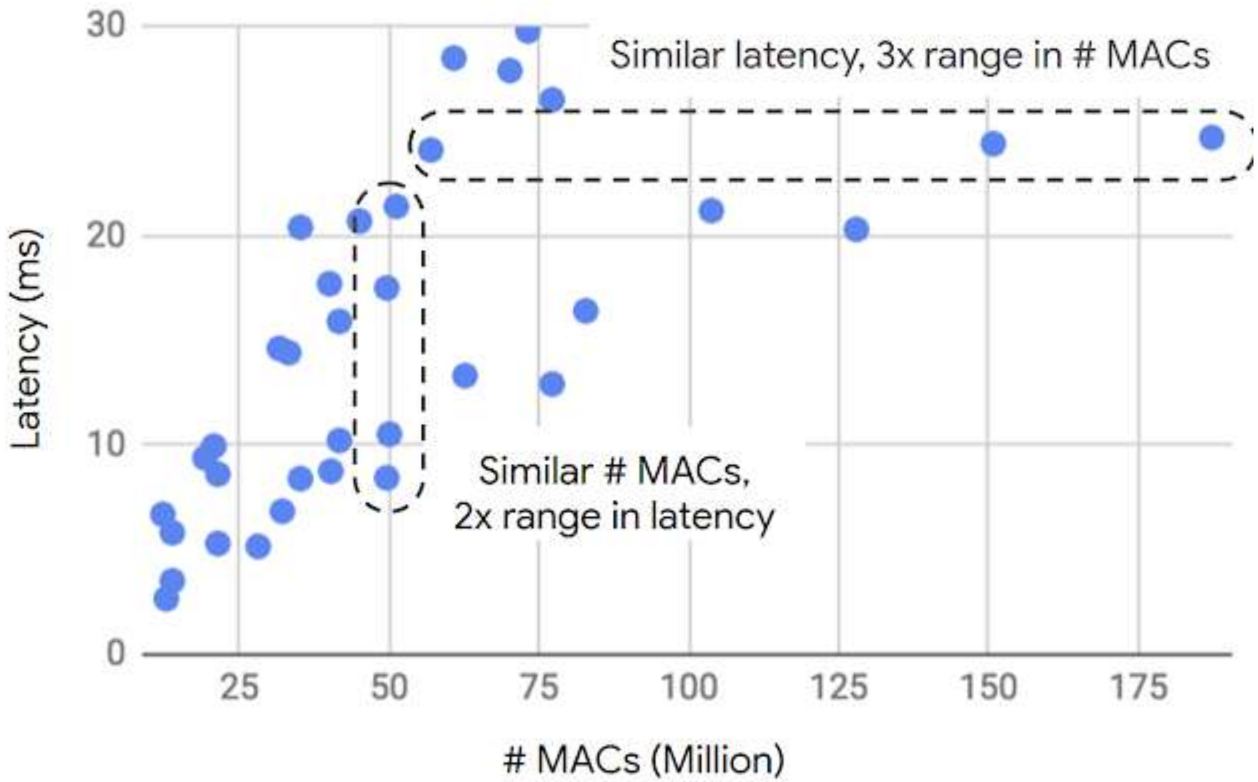
- Sort layers based on energy and prune layers that consume most energy first
- EAP reduces AlexNet energy by **3.7x** and outperforms the previous work that uses magnitude-based pruning by **1.7x**



Pruned models available at
http://eyeriss.mit.edu/energy.html

of Operations vs. Latency

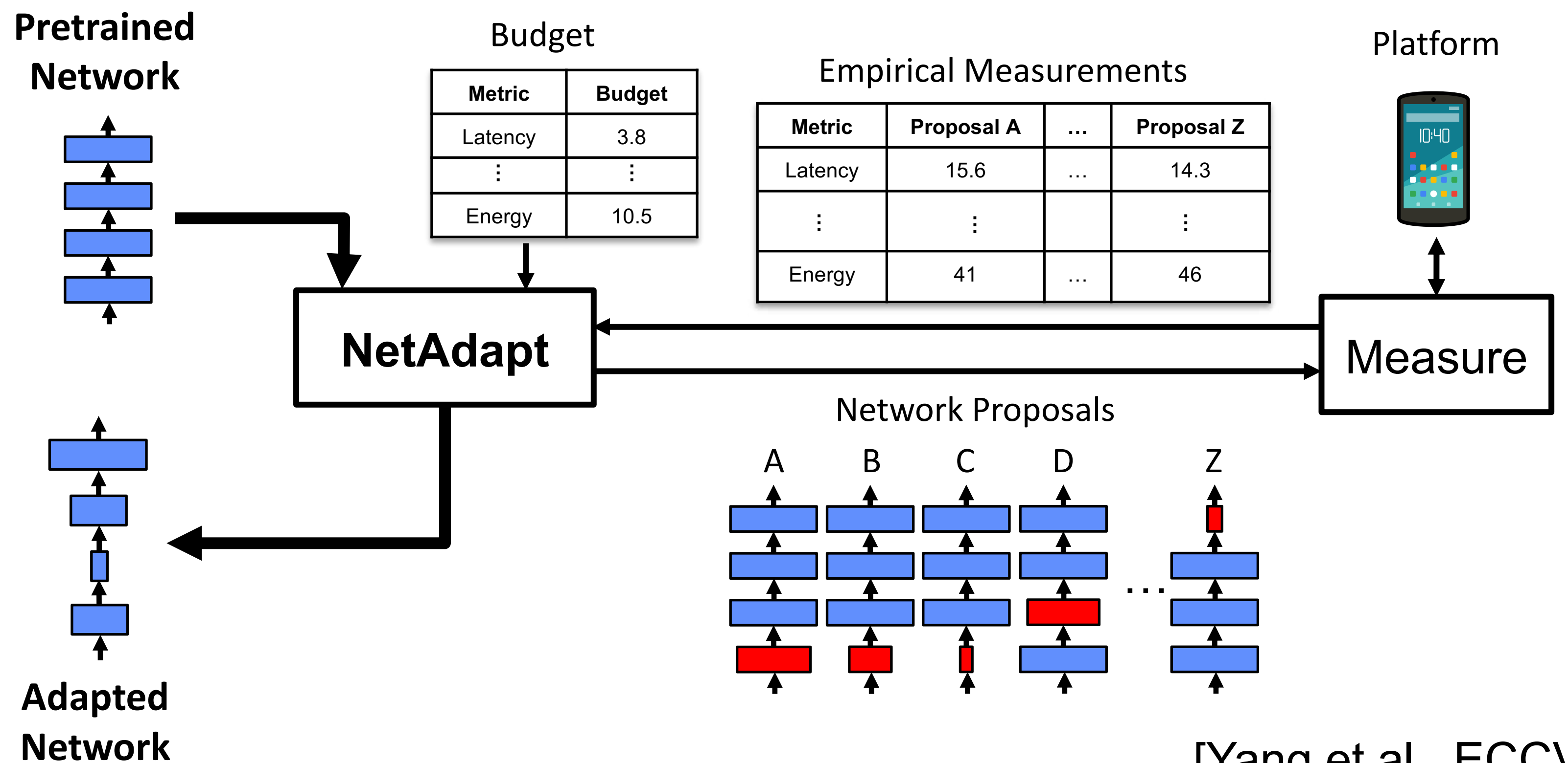
- # of operations (MACs) does not approximate latency well



Source: Google (https://ai.googleblog.com/2018/04/introducing-cvpr-2018-on-device-visual.html)

NetAdapt: Platform-Aware DNN Adaptation

- **Automatically adapt DNN** to a mobile platform to reach a target latency or energy budget
- Use **empirical measurements** to guide optimization (avoid modeling of tool chain or platform architecture)



Budget

Metric	Budget
Latency	3.8
⋮	⋮
Energy	10.5

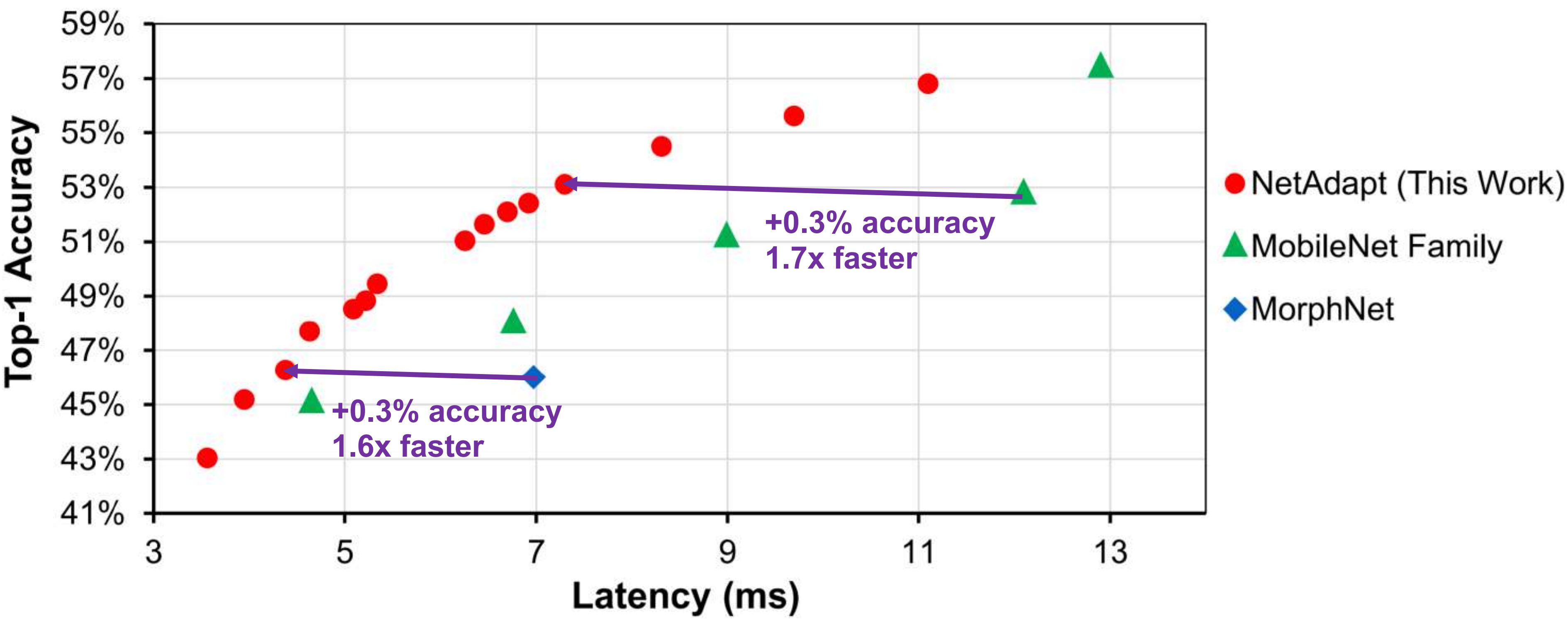
Empirical Measurements

Metric	Proposal A	…	Proposal Z
Latency	15.6	…	14.3
⋮	⋮		⋮
Energy	41	…	46

[Yang et al., ECCV 2018]

Improved Latency vs. Accuracy Tradeoff

- NetAdapt boosts **the real inference speed** of MobileNet by up to 1.7x with higher accuracy



*Tested on the ImageNet dataset and a Google Pixel 1 CPU

Reference:
MobileNet: Howard et al, "Mobilenets: Efficient convolutional neural networks for mobile vision applications", arXiv 2017
MorphNet: Gordon et al., "Morphnet: Fast & simple resource-constrained structure learning of deep networks", CVPR 2018

Problem Formulation

$$\max_{Net} Accuracy(Net) \;\; subject\ to\ Resource_j(Net) \leq Budget_j, j = 1, \cdots, m$$

Break into a set of simpler problems and solve iteratively

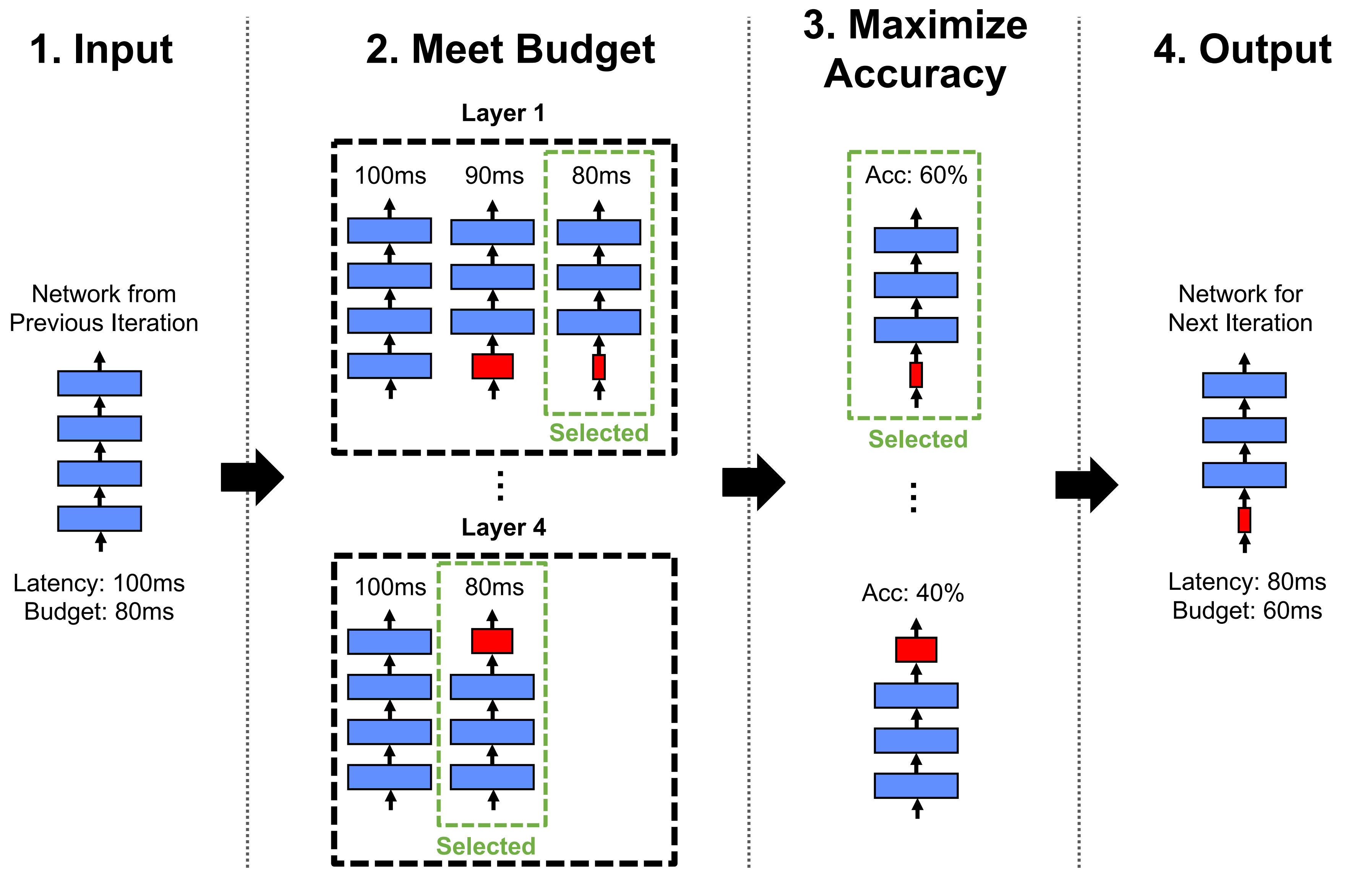
$$\max_{Net_i} Acc(Net_i) \;\; subject\ to\ Res_j(Net_i) \leq Res_j(Net_{i-1}) - \Delta R_{i,j}, j = 1, \cdots, m$$

**Acc*: accuracy function, *Res*: resource evaluation function,
***ΔR*: resource reduction**, *Bud*: given budget
Budget incrementally tightens $\boldsymbol{Res_j(Net_{i-1}) - \Delta R_{i,j}}$

- **Advantages**
  - Supports multiple resource budgets at the same time
  - Guarantees that the budgets will be satisfied because the resource consumption decreases monotonically
  - Generates a family of networks (from each iteration) with different resource versus accuracy trade-offs
  - Intuitive and can easily set one additional hyperparameter ($\boldsymbol{\Delta R_{i,j}}$)

[Yang et al., ECCV 2018]

Simplified Example of One Iteration

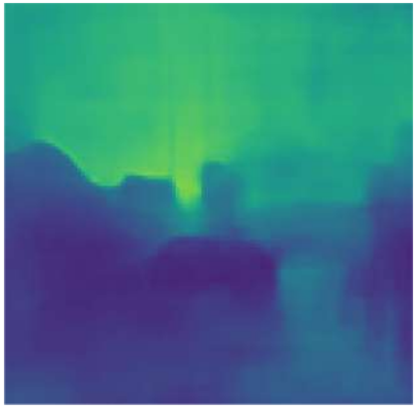


Code to be released at http://netadapt.mit.edu

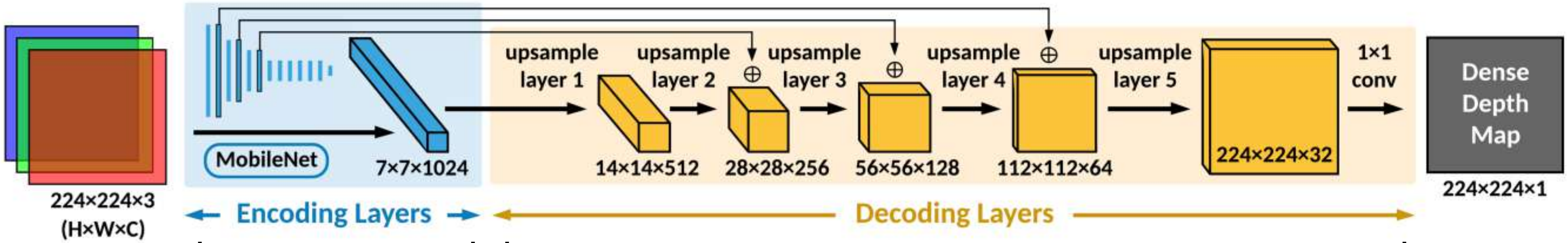
FastDepth: Fast Monocular Depth Estimation

Depth estimation from a single RGB image desirable, due to the relatively low cost and size of monocular cameras.

RGB **Prediction**



Auto Encoder DNN Architecture (Dense Output)



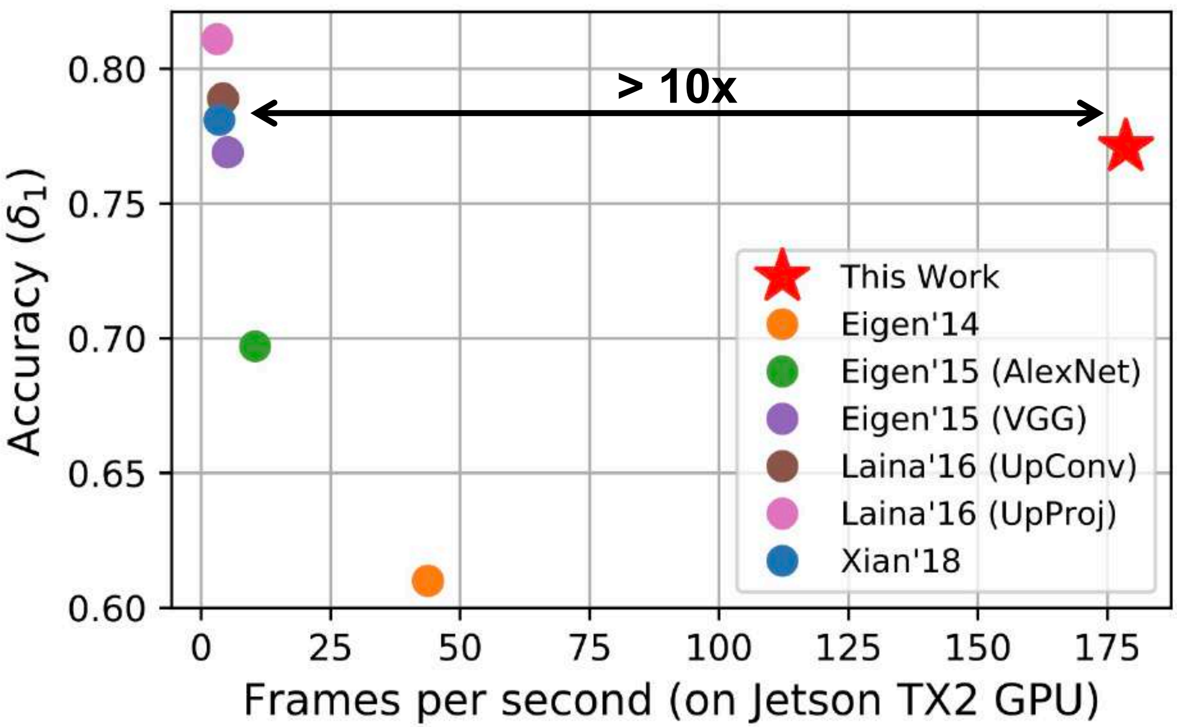
Reduction (similar to classification)

Expansion

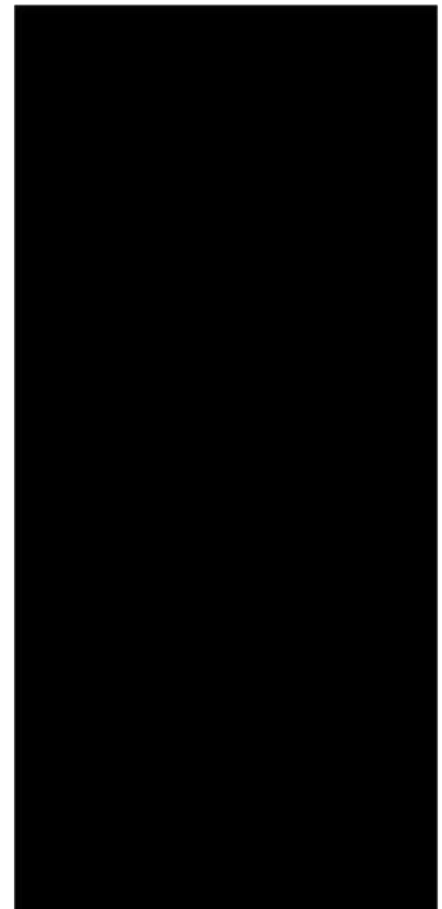
[Joint work with Sertac Karaman]

FastDepth: Fast Monocular Depth Estimation

Apply *NetAdapt*, *compact network design*, and *depth wise decomposition* to decoder layer to enable depth estimation at **high frame rates on an embedded platform** while still maintaining accuracy



Configuration: Batch size of one (32-bit float)



~40fps on an iPhone

Models available at *http://fastdepth.mit.edu*

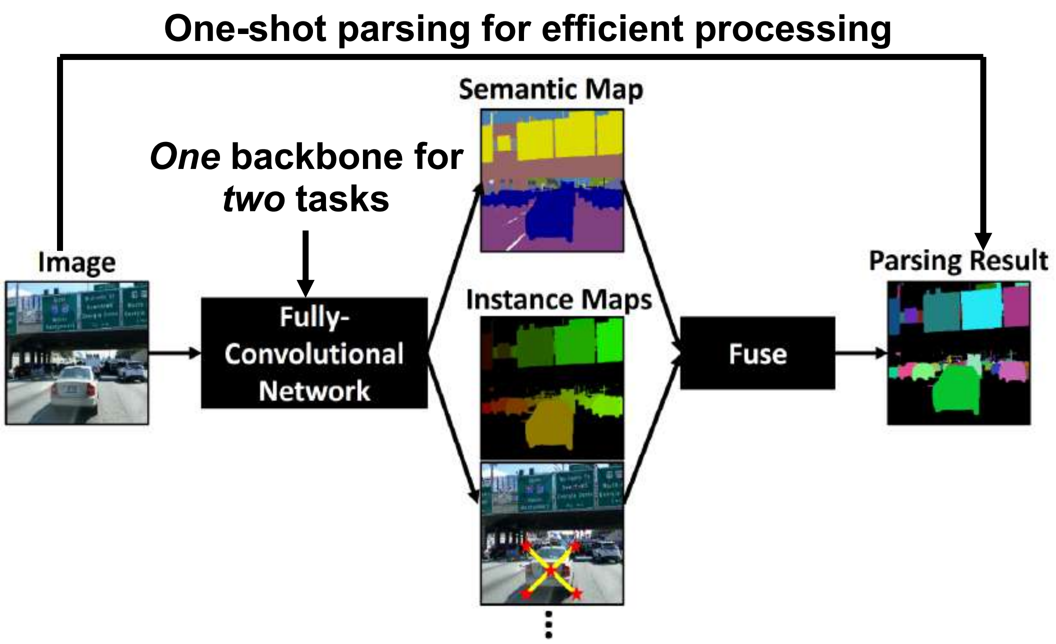
[Wofk*, Ma* et al., ICRA 2019]

DeeperLab: Single-Shot Image Parser

Results from Xception

Joint Semantic and Instance Segmentation (high resolution input image)

Fully convolutional, one-shot parsing
(bottom-up approach)



http://deeperlab.mit.edu/

[Yang et al., arXiv 2019]

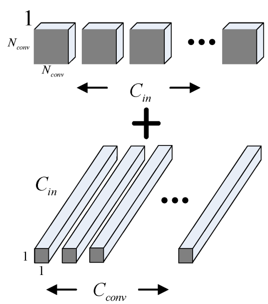
In collaboration with Google's Mobile Vision Team

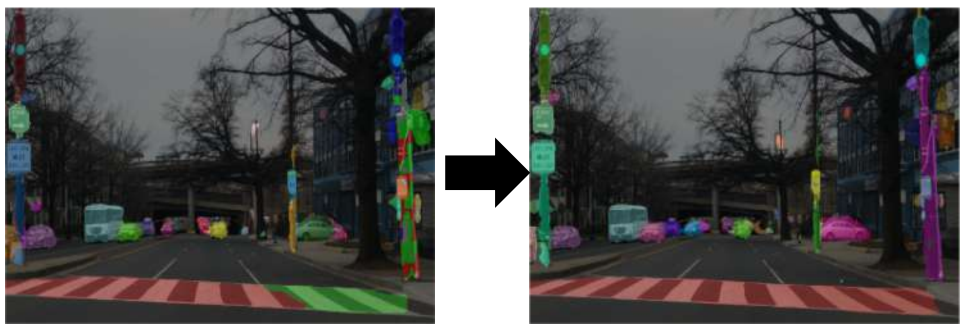
DeeperLab: Efficient Image Parsing

Address memory requirement for large feature map

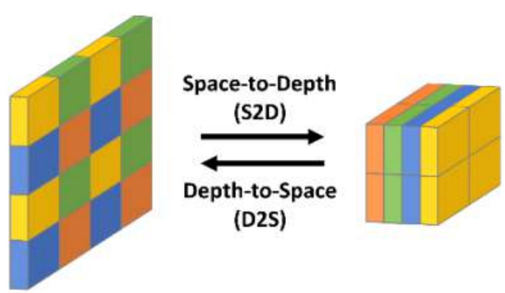
1 Wide MobileNet: Increase kernel size rather than depth

3x3 → 5x5





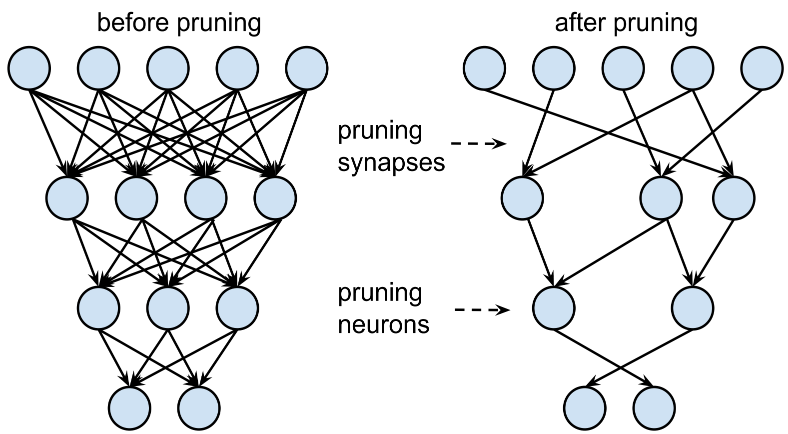
2 Space-to-depth/depth-to-space: Avoid upsampling



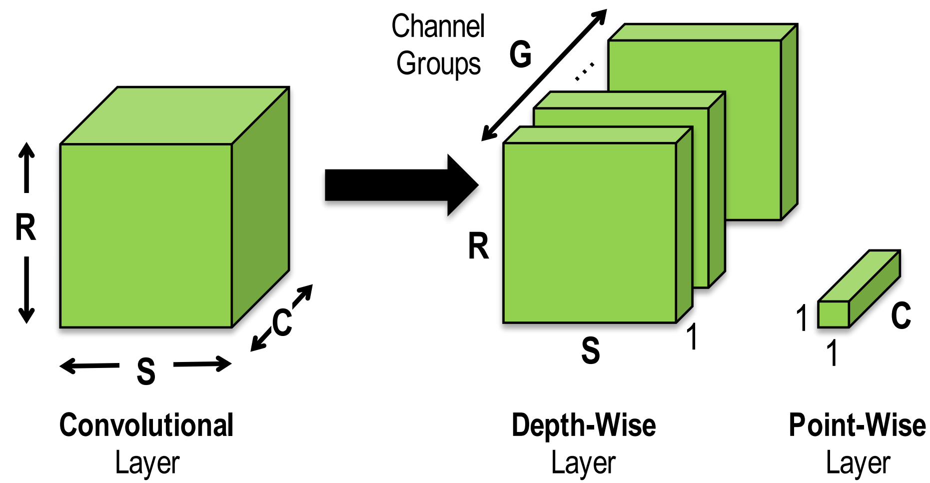
Achieves near real-time 6.19 fps on GPU (V100) with 25.2% PQ and 49.8% PC on Mapillary Vistas dataset

Many Efficient DNN Design Approaches

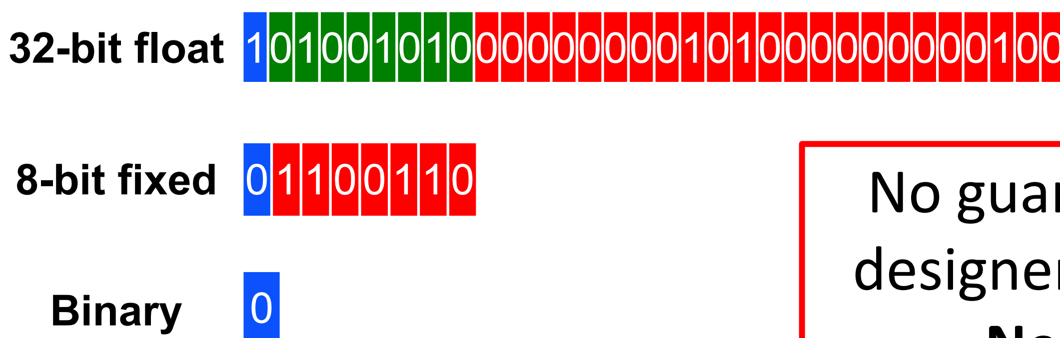
Network Pruning



Compact Network Architectures



Reduce Precision

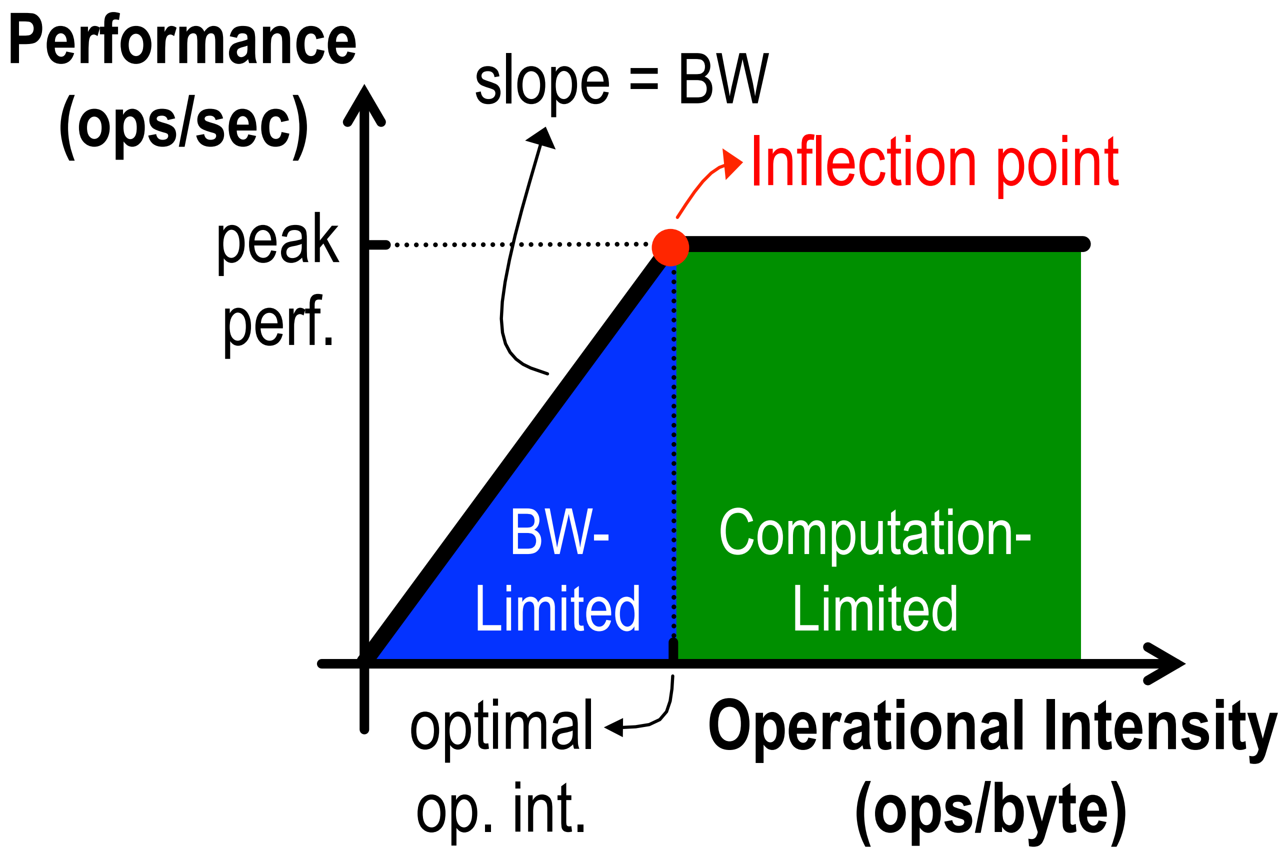


No guarantee that DNN algorithm designer will use a given approach.
Need flexible hardware!

[Chen et al., SysML 2018]

Roofline Model

A tool that visualizes the performance of an architecture under various degrees of operational intensity

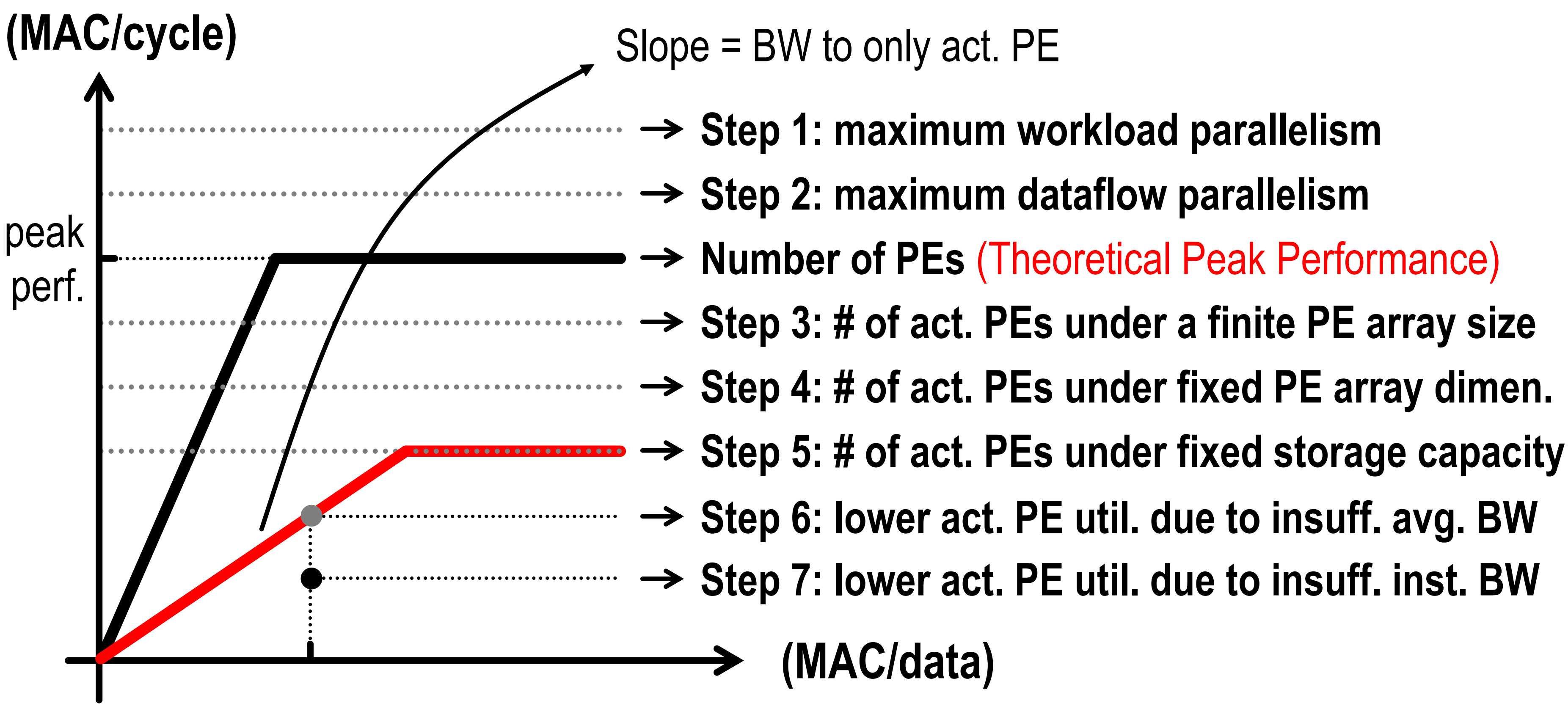


[Williams et al., Comm ACM 2009]

Eyexam: Inefficiencies in DNN Accelerators

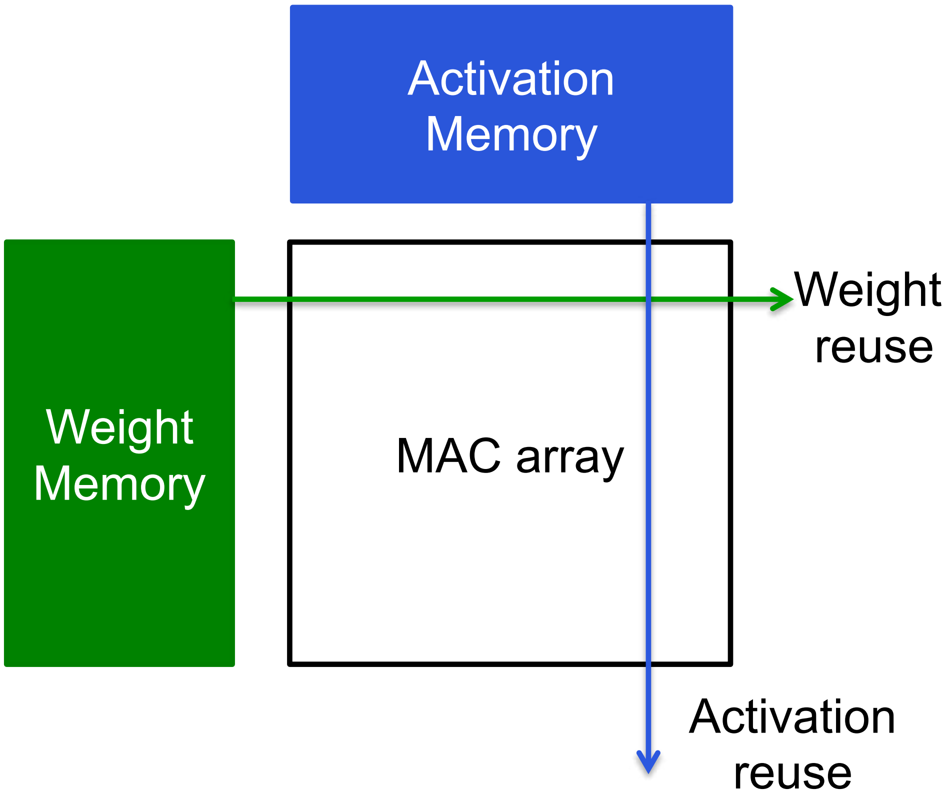
An analysis methodology that provides a systematic way of understanding the performance limits for DNN processors as a function of specific characteristics of the DNN model and accelerator design

Tightens the roofline model



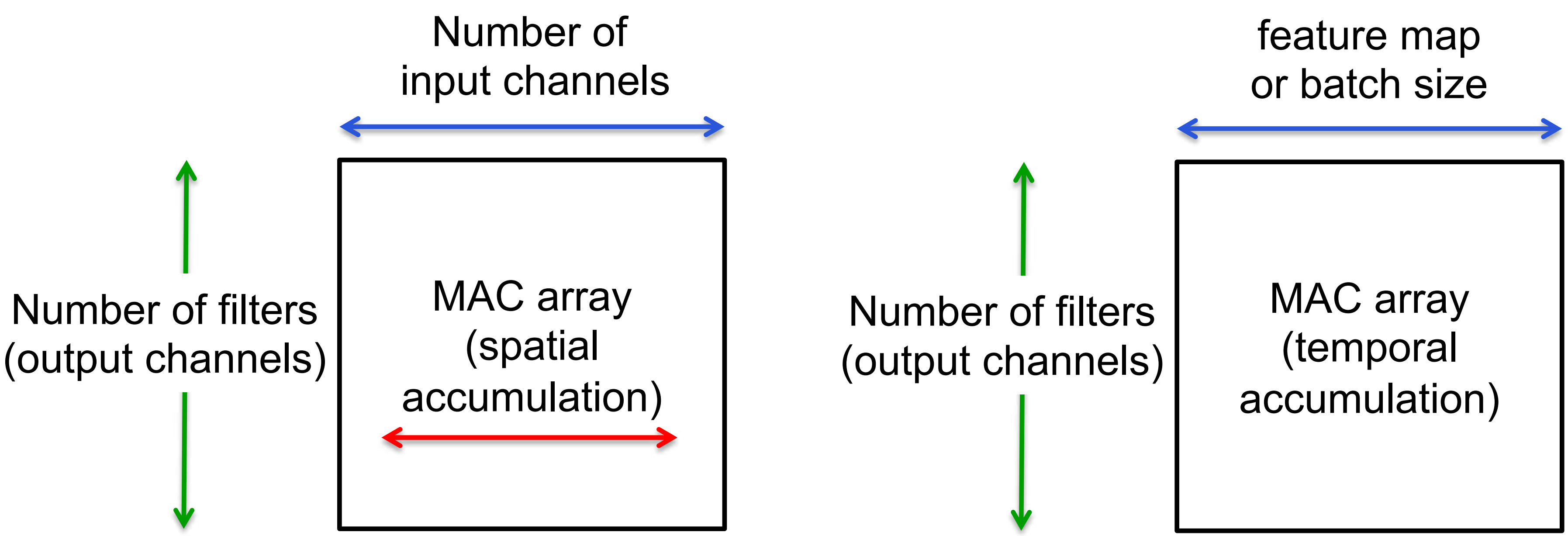
Existing DNN Architectures

- Specialized DNN hardware often rely on certain properties of DNN in order to achieve high energy-efficiency
- **Example:** Reduce memory access by amortizing across MAC array



Limitation of Existing DNN Architectures

- **Example:** Reuse and array utilization depends on # of channels, feature map/batch size
  - Not efficient across all network architectures (e.g., compact DNNs)



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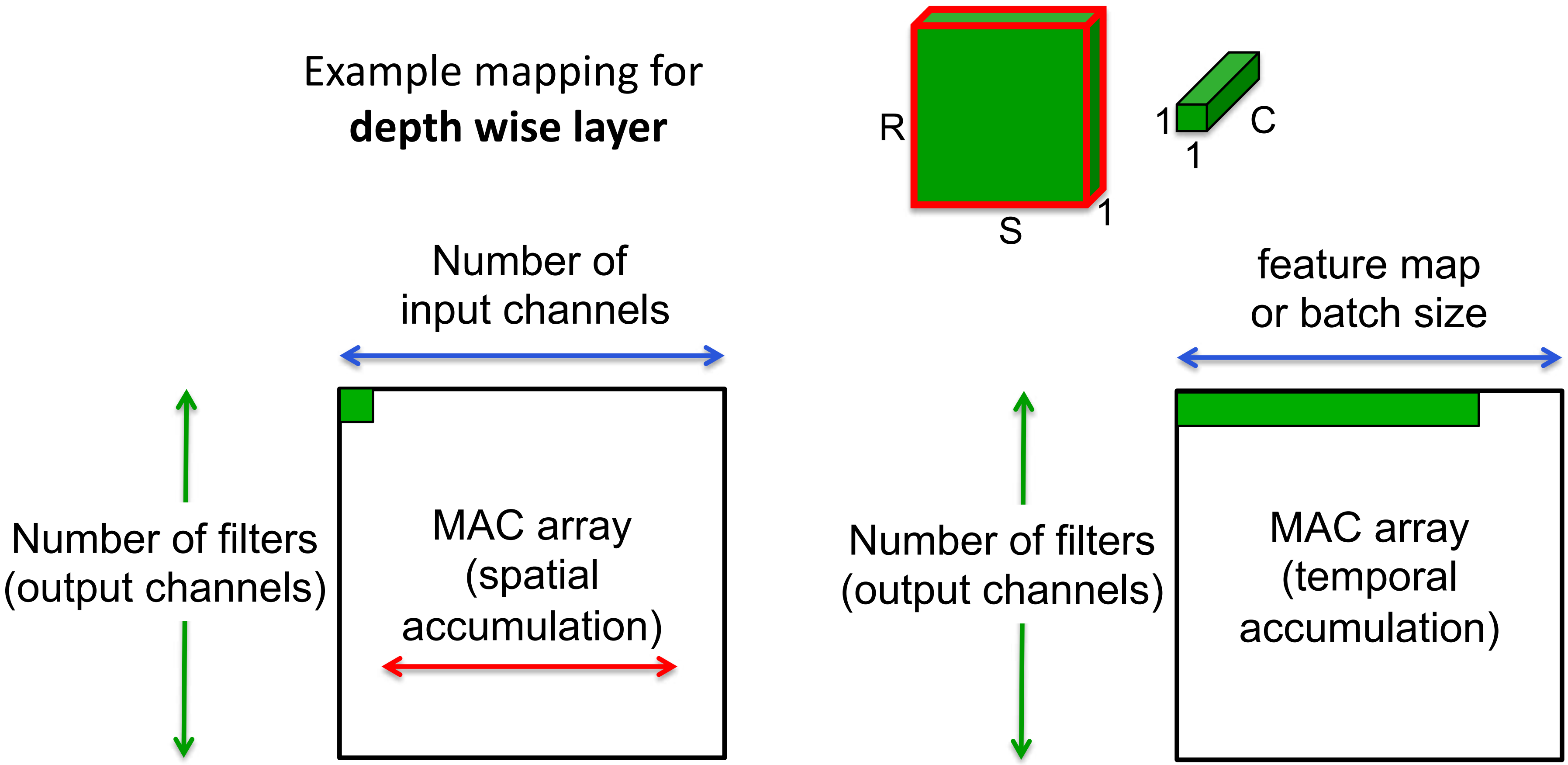
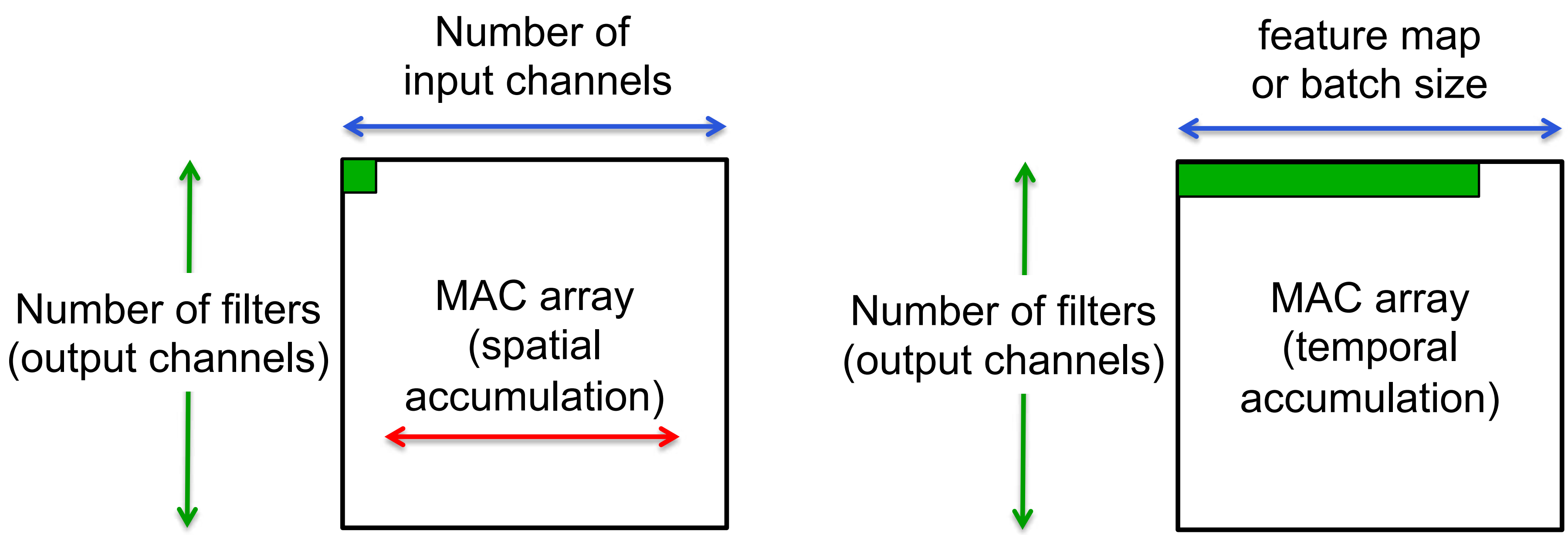


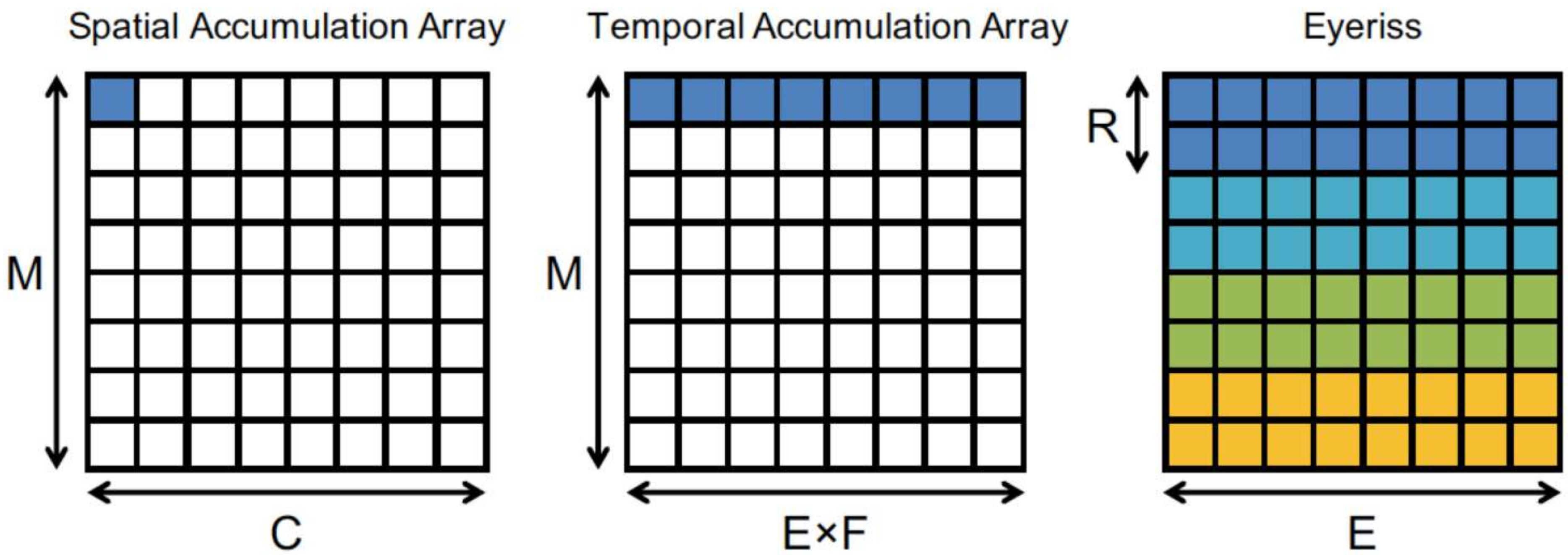
Limitation of Existing DNN Architectures

- **Example:** Reuse and array utilization depends on # of channels, feature map/batch size
  - Not efficient across all network architectures (e.g., compact DNNs)
  - Less efficient as array scales up in size
  - Can be challenging to exploit sparsity



Need Flexible Dataflow

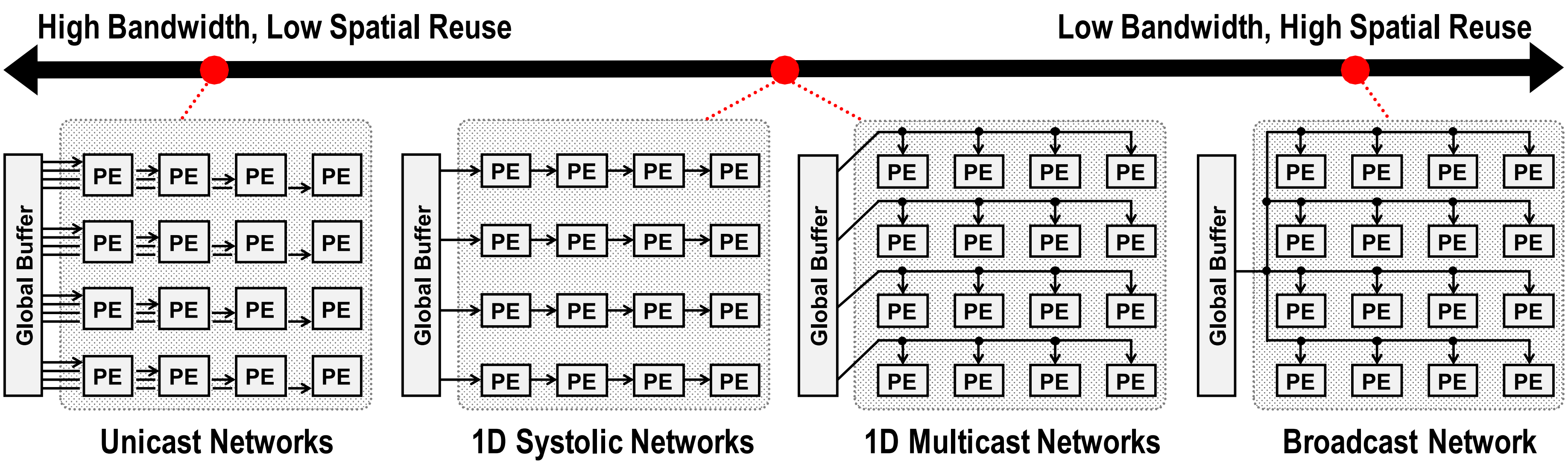
- Use flexible dataflow (**Row Stationary**) to exploit reuse in any dimension of DNN to increase energy efficiency and array utilization



Example: Depth-wise layer

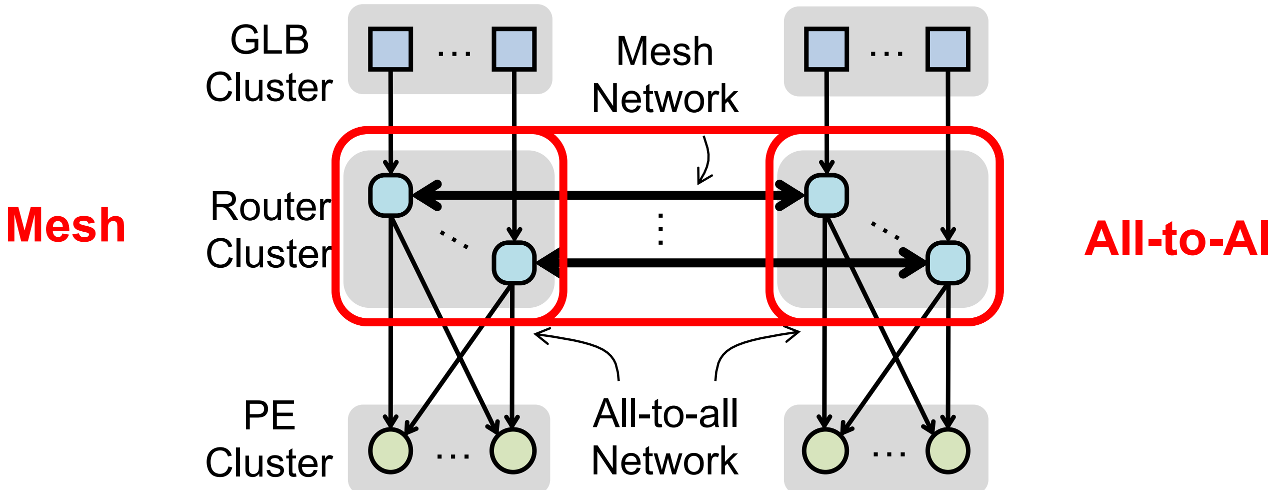
Need Flexible NoC for Varying Reuse

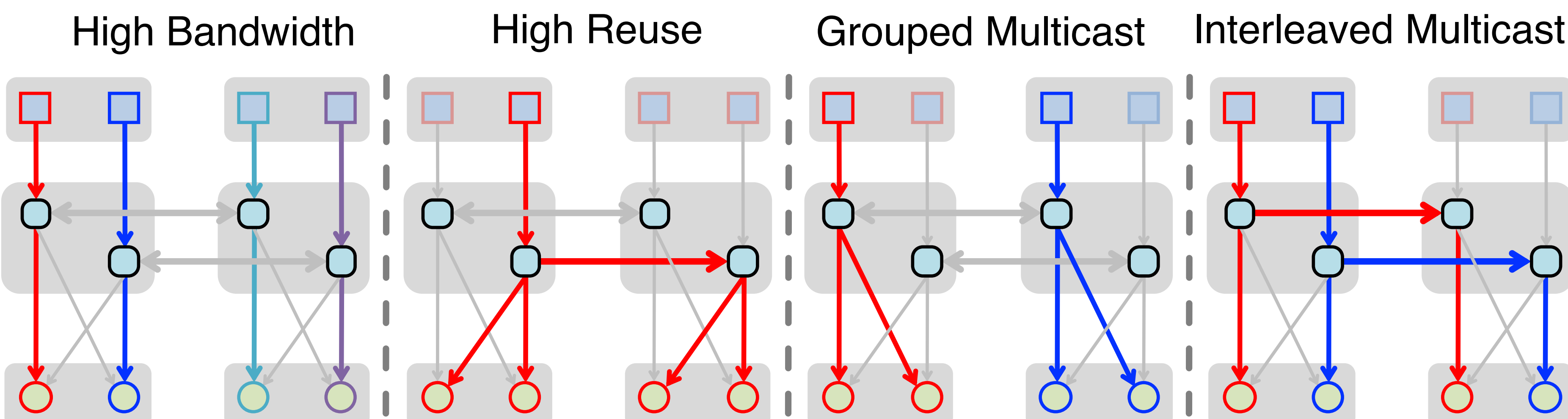
- When reuse available, need **multicast** to exploit spatial data reuse for energy efficiency and high array utilization
- When reuse not available, need **unicast** for high BW for weights for FC and weights & activations for high PE utilization
- An **all-to-all** satisfies above but too expensive and not scalable



[Chen et al., JETCAS 2019]

Hierarchical Mesh



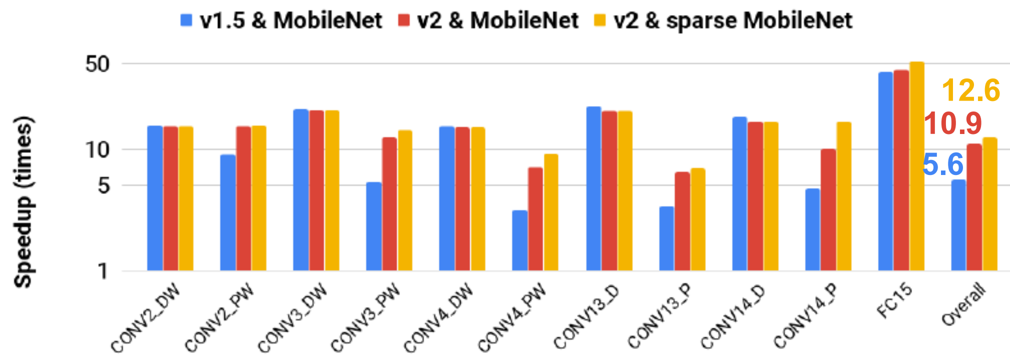


[Chen et al., JETCAS 2019]

Eyeriss v2: Balancing Flexibility and Efficiency

Efficiently supports

- Wide range of filter shapes
  - Large **and** Compact
- Different Layers
  - **CONV, FC, depth wise, etc.**
- Wide range of sparsity
  - Dense **and** Sparse
- **Scalable architecture**



Speed up over Eyeriss v1 scales with number of PEs

# of PEs	256	1024	16384
AlexNet	17.9x	71.5x	1086.7x
GoogLeNet	10.4x	37.8x	448.8x
MobileNet	15.7x	57.9x	873.0x

Over an order of magnitude faster and more energy efficient than Eyeriss v1

[Chen et al., JETCAS 2019]

[Joint work with Joel Emer]

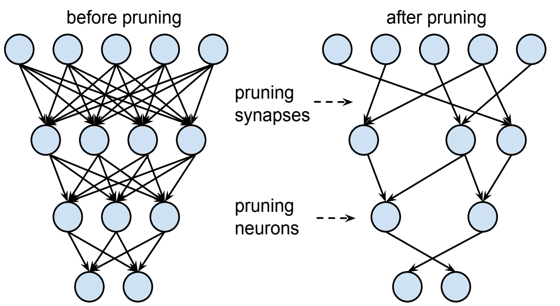
Need More Comprehensive Benchmarks

Processors should support a **diverse set of DNNs** that utilize different techniques

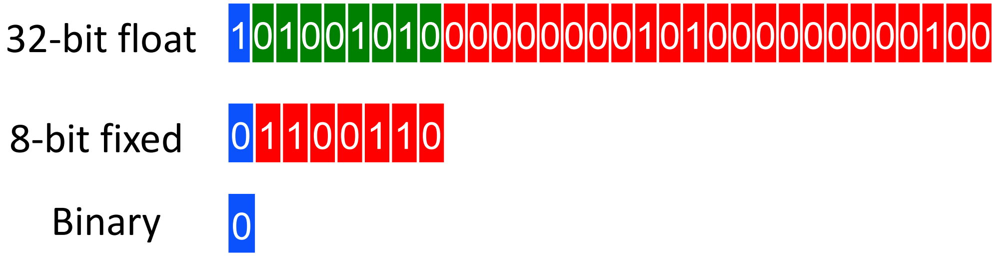
Example:

- Sparse **and** Dense
- Large **and** Compact network architectures
- Different Layers (e.g., CONV **and** FC)
- Variable Bit-width

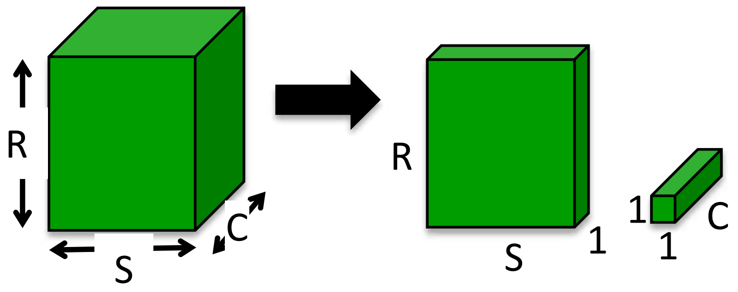
Network Pruning



Reduce Precision



Compact Network Architecture



Benchmarking Metrics for DNN Hardware

How can we compare designs?

V. Sze, Y.-H. Chen, T-J. Yang, J. Emer,
"***Efficient Processing of Deep Neural Networks: A Tutorial and Survey***,"
Proceedings of the IEEE, Dec. 2017

Metrics for DNN Hardware

- **Accuracy**
  - Quality of result for a given task
- **Throughput**
  - Analytics on high volume data
  - Real-time performance (e.g., video at 30 fps)
- **Latency**
  - For interactive applications (e.g., autonomous navigation)
- **Energy and Power**
  - Edge and embedded devices have limited battery capacity
  - Data centers have stringent power ceilings due to cooling costs
- **Hardware Cost**
  - $$$

Specifications to Evaluate Metrics

- **Accuracy**
  - Difficulty of dataset and/or task should be considered
- **Throughput**
  - Number of cores (include utilization along with peak performance)
  - Runtime for running specific DNN models
- **Latency**
  - Include batch size used in evaluation
- **Energy and Power**
  - Power consumption for running specific DNN models
  - Include external memory access
- **Hardware Cost**
  - On-chip storage, number of cores, chip area + process technology

Example: Metrics of Eyeriss Chip

ASIC Specs	Input
Process Technology	65nm LP TSMC (1.0V)
Total Core Area (mm^2)	12.25
Total On-Chip Memory (kB)	192
Number of Multipliers	168
Clock Frequency (MHz)	200
Core area (mm^2) /multiplier	0.073
On-Chip memory (kB) / multiplier	1.14
Measured or Simulated	Measured

Metric	Units	Input
Name of CNN Model	Text	AlexNet
Top-5 error classification on ImageNet	#	19.8
Supported Layers		All CONV
Bits per weight	#	16
Bits per input activation	#	16
Batch Size	#	4
Runtime	ms	115.3
Power	mW	278
Off-chip Access per Image Inference	MBytes	3.85
Number of Images Tested	#	100

Comprehensive Coverage

- **All metrics** should be reported for fair evaluation of design tradeoffs
- Examples of what can happen if certain metric is omitted:
  - **Without the accuracy given for a specific dataset and task**, one could run a simple DNN and claim low power, high throughput, and low cost – however, the processor might not be usable for a meaningful task
  - **Without reporting the off-chip bandwidth**, one could build a processor with only multipliers and claim low cost, high throughput, high accuracy, and low chip power – however, when evaluating system power, the off-chip memory access would be substantial
- Are results measured or simulated? On what test data?

Evaluation Process

The evaluation process for whether a DNN system is a viable solution for a given application might go as follows:

1. **Accuracy** determines if it can perform the given task
2. **Latency and throughput** determine if it can run fast enough and in real-time
3. **Energy and power consumption** will primarily dictate the form factor of the device where the processing can operate
4. **Cost**, which is primarily dictated by the chip area, determines how much one would pay for this solution

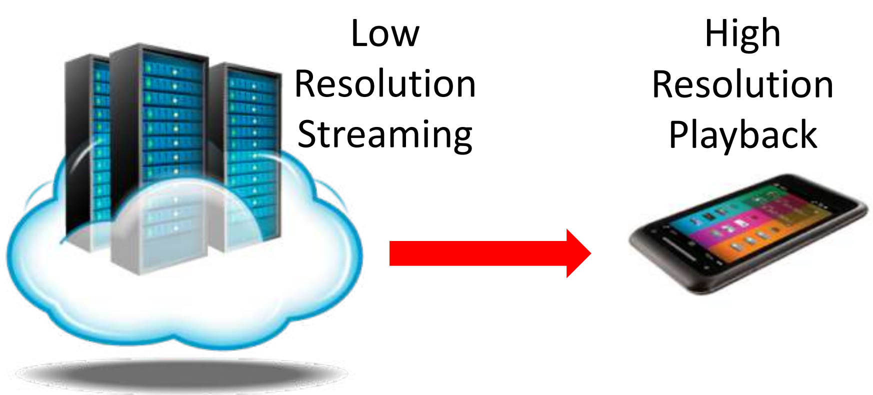
Summary

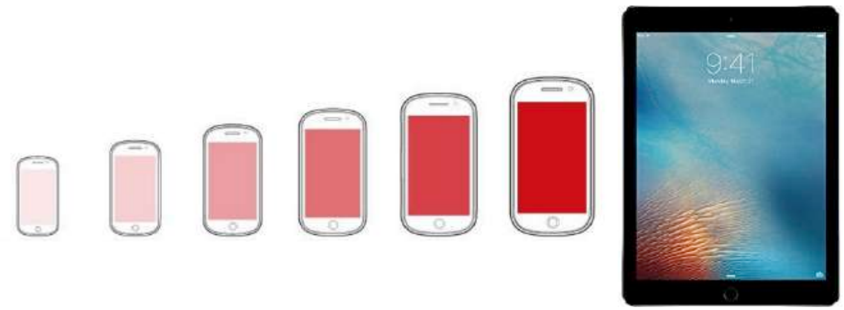
- The number of weights and MACs are not sufficient for evaluating the energy consumption and latency of DNNs
  - **Designers of efficient DNN algorithms should directly target direct metrics such as energy and latency and incorporate into the design**
- Many of the existing DNN processors rely on certain properties of the DNN which cannot be guaranteed as the wide range techniques used for efficient DNN algorithm design has resulted in a more diverse set of DNNs
  - **DNN hardware used to process these DNNs should be sufficiently flexible to support a wide range of techniques efficiently**
- Evaluate DNN hardware on a comprehensive set of benchmarks and metrics

Looking Beyond the DNN Accelerator for Acceleration

Z. Zhang, V. Sze, "**FAST: A Framework to Accelerate Super-Resolution Processing on Compressed Videos**," *CVPRW* 2017

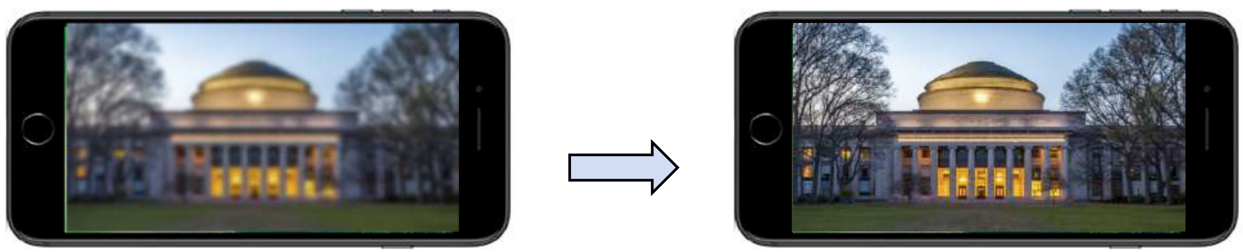
Super-Resolution on Mobile Devices





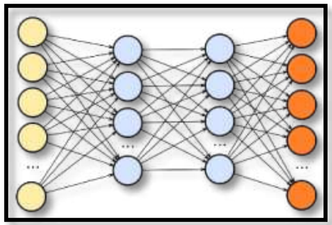
Transmit low resolution for lower bandwidth

Screens are getting larger



Use **super-resolution** to improve the viewing experience of lower-resolution content (*reduce communication bandwidth*)

FAST: A Framework to Accelerate SuperRes



SR algorithm

Compressed video

FAST

SR
15x faster

Real-time

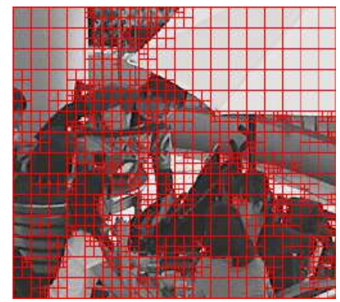
A framework that accelerates **any SR** algorithm by up to **15x** when running on compressed videos

Free Information in Compressed Videos

Compressed video

Decode

Pixels



Block-structure

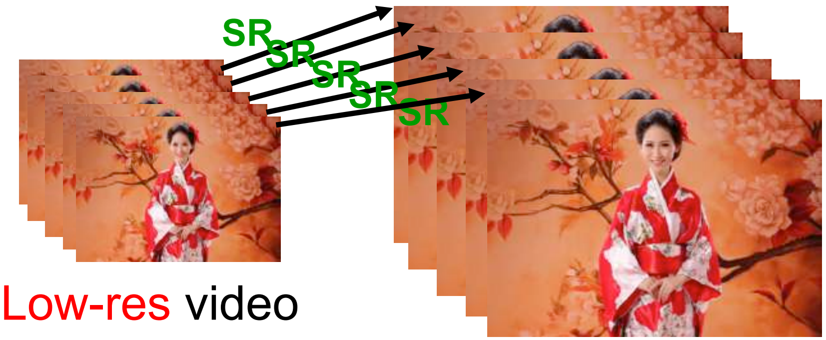
Motion-compensation

Video as a stack of pixels

Representation in compressed video

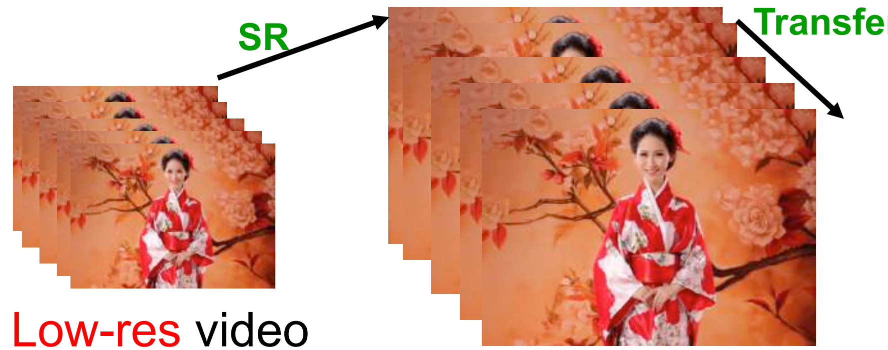
This representation can help **accelerate** super-resolution

Transfer is Lightweight



Low-res video

High-res video



Low-res video

High-res video

Transfer allows SR to run on only **a subset of frames**

Fractional Interpolation

Bicubic Interpolation

Skip Flag

The complexity of the transfer is comparable to bicubic interpolation.
Transfer **N** frames, accelerate by **N**

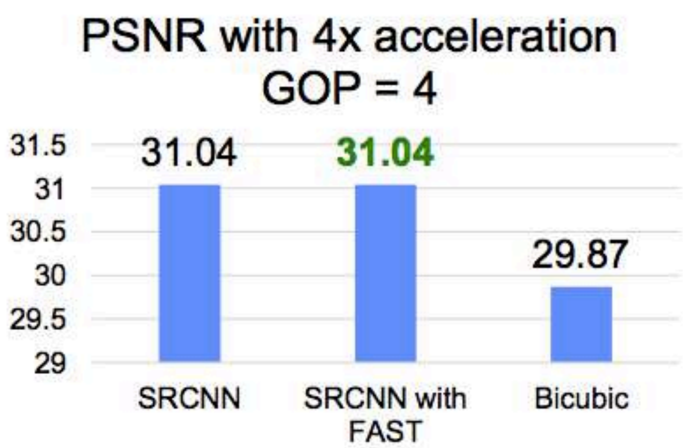
Evaluation: Accelerating SRCNN

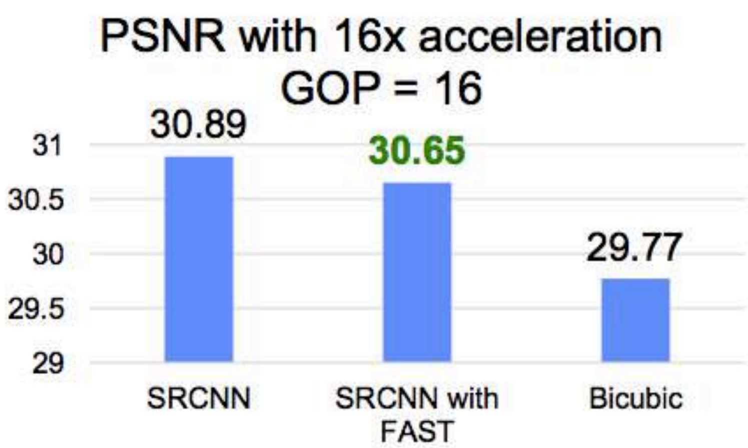
PartyScene

RaceHorse

BasketballPass

Examples of videos in the test set (20 videos for HEVC development)





$4\times$ acceleration with NO PSNR LOSS. $16\times$ acceleration with 0.2 dB loss of PSNR

Visual Evaluation

SRCNN **FAST + SRCNN** **Bicubic**

Look ***beyond*** the DNN accelerator for opportunities to accelerate DNN processing (e.g., structure of data and temporal correlation)

Code released at www.rle.mit.edu/eems/fast

Summary of Key Insights

- **Design considerations for co-design of algorithm and hardware**
  - Incorporate ***direct metrics*** into algorithm design for improved efficiency
  - Diverse workloads requires a ***flexible dataflow and NoC*** to exploit data ***reuse in any dimension*** and increase core utilization for speed and scalability
- **Accelerate deep learning by looking beyond the accelerator**
  - Exploit data representation for FAST Super-Resolution

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For updates on our research Follow @eems_mit

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