Optimizing implementation of CNN inferences:

change the model or the architecture?

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Plan

The problem of CNN hyperparameters

What architecture to consider for CNN?

What if CNN have dynamic parts?

Is it better to change the model or the architecture?

The problem of CNN hyperparameters

Tons of parameters...

AlexNet: ≈ 1.4 millions of parameters

Parameters coming from neuron weights, deduced from hyperparameters (#layers and their type, #neurons, conv. sizes)

More parameters $\rightarrow$ more computations

- because training might converge slowly or overfit
- **because more data must be stored and more Mult-Add are needed**

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How to reduce the number of parameters? Pruning!

Pruning what?

Q1. Prune connections, neurons, layers?

Q2. With what objective?

$\Rightarrow$ very long if pruning during learning

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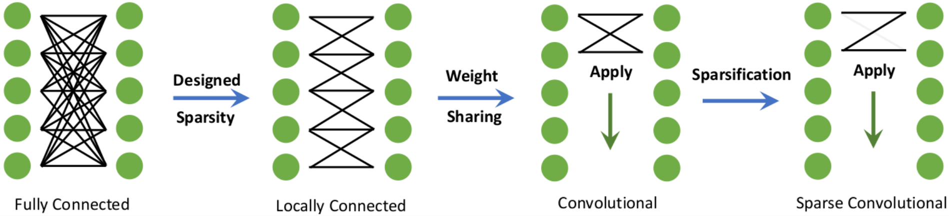
Convolutions already are reducing the number of parameters!



©Sparsity in Deep Learning(...), Figure 3

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Pruning the parameters or their related values?

Quantization and weight sharing

Select numerical representation with less bits (after training).

e.g. `char` instead of `long`

Ref: Deep Compression: Compressing Deep Neural Network with Pruning, Trained Quantization and Huffman Coding, ICLR 2016, quoted 4963 (Google) times

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Network	Top-1 Error	Top-5 Error	Parameters	Compress Rate
LeNet-300-100 Ref	1.64%	-	1070 KB	
LeNet-300-100 Compressed	1.58%	-	**27 KB**	**40**×
LeNet-5 Ref	0.80%	-	1720 KB	
LeNet-5 Compressed	0.74%	-	**44 KB**	**39**×
AlexNet Ref	42.78%	19.73%	240 MB	
AlexNet Compressed	42.78%	19.70%	**6.9 MB**	**35**×
VGG-16 Ref	31.50%	11.32%	552 MB	
VGG-16 Compressed	31.17%	10.91%	**11.3 MB**	**49**×

©Deep Compression(...), Table 1

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Do not forget hyperparameters and network topology!

Reorder the computations of convolution layers

Reduce data movements by splitting the convolutions.

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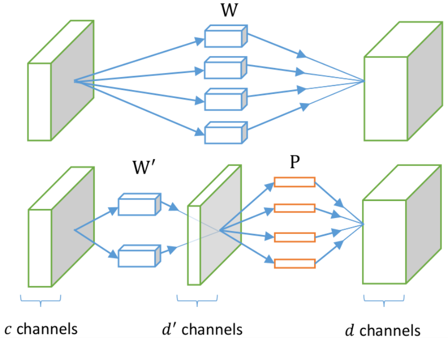

©Accelerating Very Deep Convolution Networks(...), Figure 1

Examples

- SqueezeNet
- MobiletNets

Problem

Requires linear separability.

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What architecture to consider for CNN?

What architectures?

CNN are heavily data-parallel, slightly task-parallel

The number of pixels in images usually exceeds the number of processing elements.
If feed-forward, CNN can be considered layer by layer.

Architectures

- CPU ≈ (task parallelism, not enough cores)
- GPU ++ (data parallelism, perfect)
- **FPGA** + (streamed data parallelism + task parallelism, but not enough memory)
- ASIC ++ (whatever you want, but costly)
- MPSoC+ (quantity of CPU/GPU/... is predefined)

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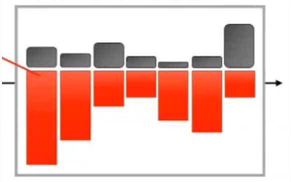
Easier to pipeline if layers have balanced computations.
(otherwise we might merge them)



©Tutorial ISFPGA'21: Neural Network Accelerator Co-Design with FINN (2 min 06 sec)

FINN-R framework of Xilinx

- claim higher throughput than GPU (not higher energy efficiency?)
- claim easy reconfiguration (scaling) when changing of FPGA
- intrinsic quantization

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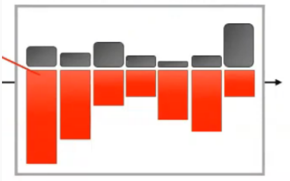

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The case of ~~FPGA~~: two examples

Extreme quantization

Binary Neural Networks have all weights on 1 bit.

Extreme (down)scaling

MobileNets can be easily adapted to constrained architectures by sacrificing accuracy.

Ref: FracBNN: Accurate and FPGA-Efficient Binary Neural Networks with Fractional Activations, FPGA 2021
Ref: Multi-Objective Autotuning of MobileNets across the Full Software/Hardware Stack, ReQuEST 2018

The case of ~~FPGA~~: data ordering

Matrix multiplication is already highly optimized...

...but it requires to copy and reorder the data (im2col)

$$\begin{pmatrix} k1 & k2 & 0 & k3 & k4 & 0 & 0 & 0 & 0 \\ 0 & k1 & k2 & 0 & k3 & k4 & 0 & 0 & 0 \\ 0 & 0 & 0 & k1 & k2 & 0 & k3 & k4 & 0 \\ 0 & 0 & 0 & 0 & k1 & k2 & 0 & k3 & k4 \end{pmatrix} \cdot \begin{pmatrix} x1 \\ x2 \\ x3 \\ x4 \\ x5 \\ x6 \\ x7 \\ x8 \\ x9 \end{pmatrix}$$

©StackOverflow: 2-D convolution as a matrix-matrix multiplication

Best reordering (tested on CPU)

kn2row seems to have better data locality.

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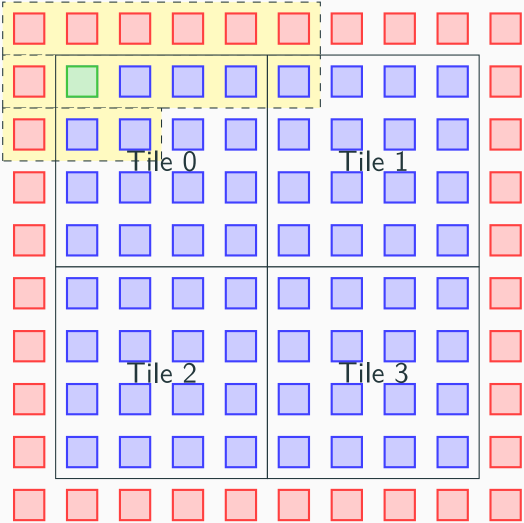

Input image is streamed and a 3x3 convolution is applied per tile.

Requires previous reorder but reduce FIFO sizes.

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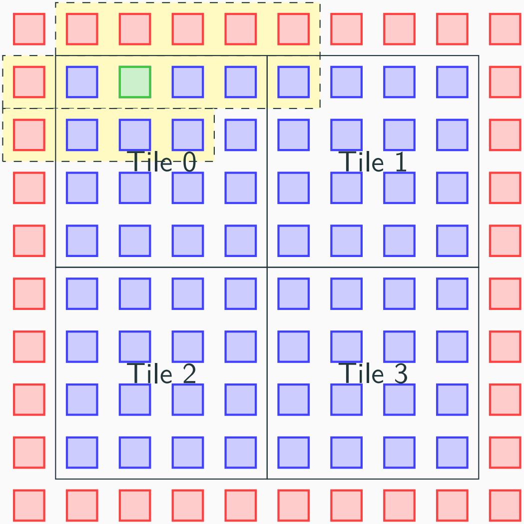

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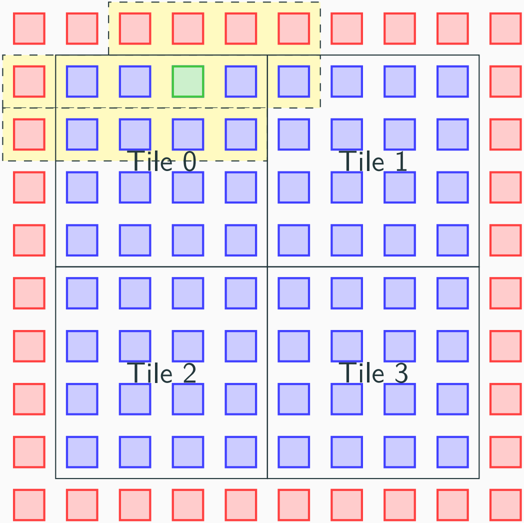

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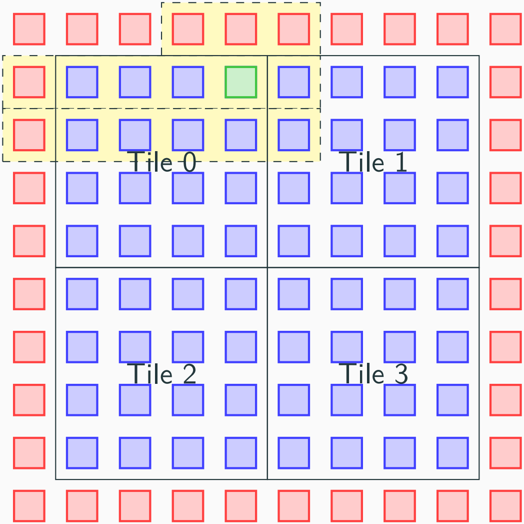

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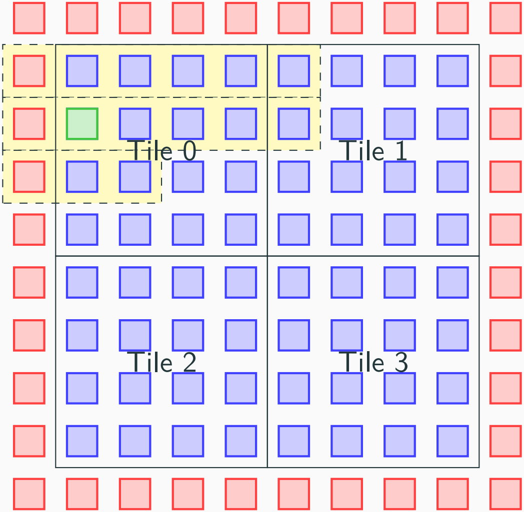

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Vendors know their circuits better

Even on FPGA, some circuits are hard-wired (as full-adder).

Specialized per layer type?

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Dynamic filter pruning

Prune some filters during inference

Remove redundant ones or select the ones with more saliency.

Problem

P1. Modify the balance of computations between processing elements.

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Pyramidal and dynamic pooling

Dynamic image size before k-max pooling

Input image size may vary for convolutions, but k is constant and keep spatial properties.

Dynamic k-max pooling

Sentence size varies and k depends on the input.

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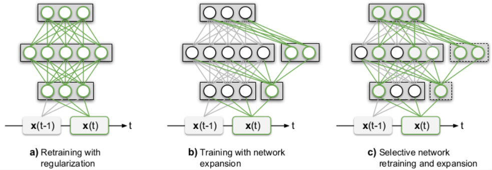

©Continual lifelong learning(...), Figure 2

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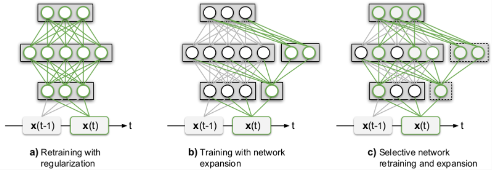

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Is it better to change the model or the architecture?

Conclusion: better to change model and architecture

ML project management

Architecture selection comes at stage 5 out of 10.

Options to not change the hardware

- everything is static and data parallel
- narrow convolutions even if adding more layers

Otherwise

Test and retry! (probably layer per layer)

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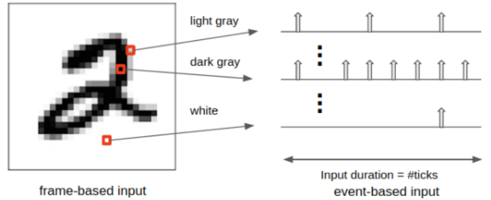

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For what architecture?

Initially ASICs, and now FPGA (using FINN-R).

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Opening 1: Spiking Neural Networks

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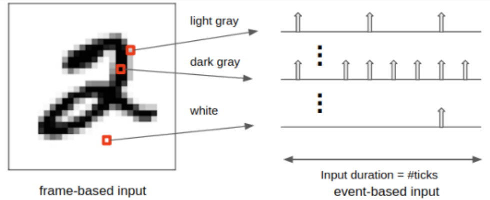

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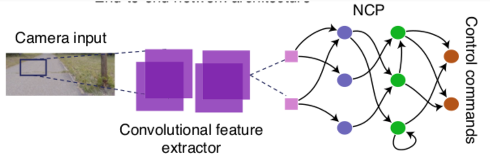
Opening 2: NN with Ordinary Differential Equations

NCP are still time dependent, but after a regular CNN!

$$\frac{d\mathbf{x}(t)}{dt} = -\left[\frac{1}{\tau} + f(\mathbf{x}(t), \mathbf{I}(t), t, \theta)\right]\mathbf{x}(t) + f(\mathbf{x}(t), \mathbf{I}(t), t, \theta)A. \quad (1)$$

©Liquid Time-constant Networks, Equation 1



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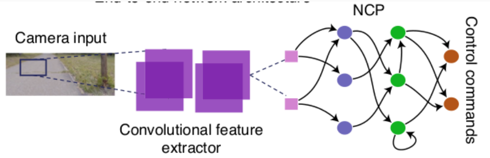

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