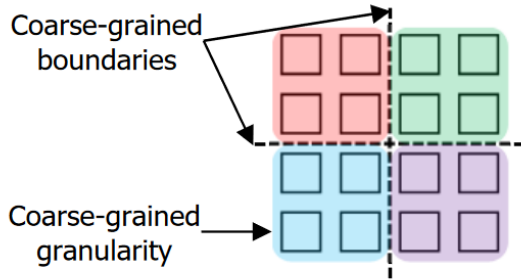
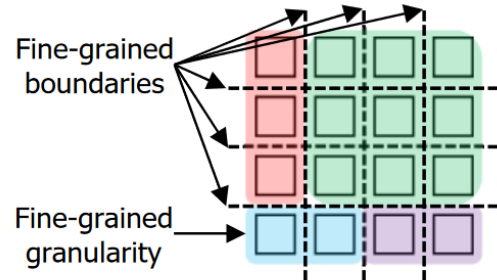


Dataflow Mirroring: Architectural Support for Highly Efficient Fine-Grained Spatial Multitasking on Systolic-Array NPU

DAC-21



(a) Coarse-grained [5]



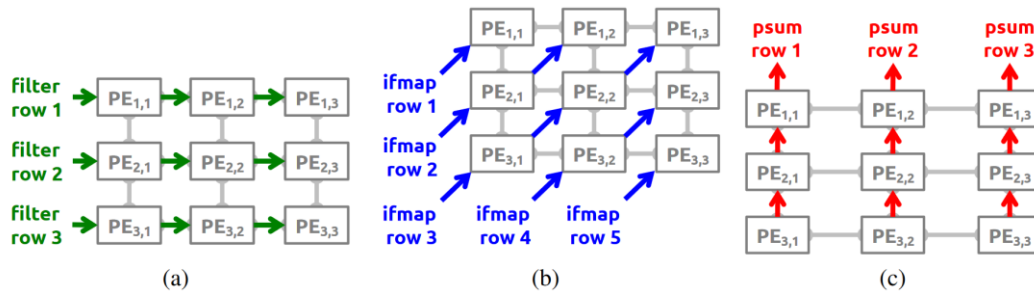
(b) Fine-grained (Ours)

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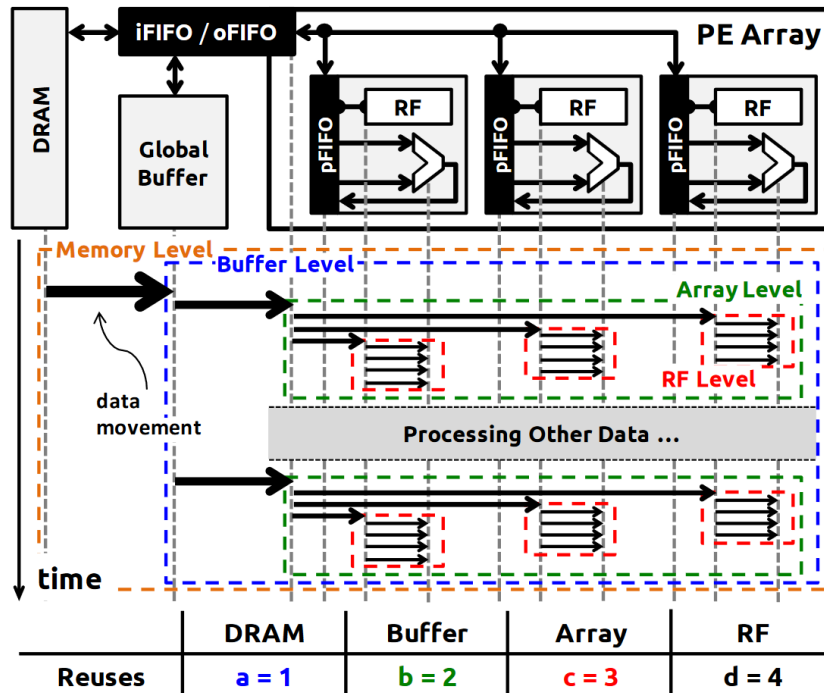
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Eyeriss: A Spatial Architecture for Energy-Efficient Dataflow for Convolutional Neural Networks

ISCA-16



Dataflow	Data Handling
WS	Maximize <i>convolutional reuse</i> and <i>filter reuse</i> of weights in the RF.
SOC-MOP OS	Maximize <i>psum accumulation</i> in RF. <i>Convolutional reuse</i> in array.
MOC-MOP OS	Maximize <i>psum accumulation</i> in RF. <i>Convolutional reuse</i> and <i>ifmap reuse</i> in array.
MOC-SOP OS	Maximize <i>psum accumulation</i> in RF. <i>Ifmap reuse</i> in array.
NLR	<i>Psum accumulation</i> and <i>ifmap reuse</i> in array.



Efficient Processing of Deep Neural Networks: A Tutorial and Survey

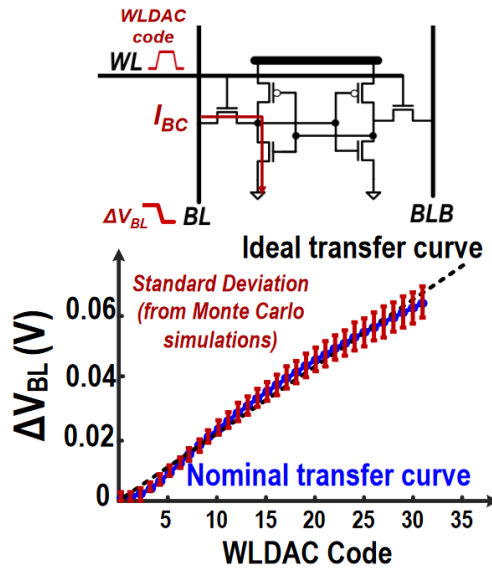
MICRO-17

1. DNN 基础

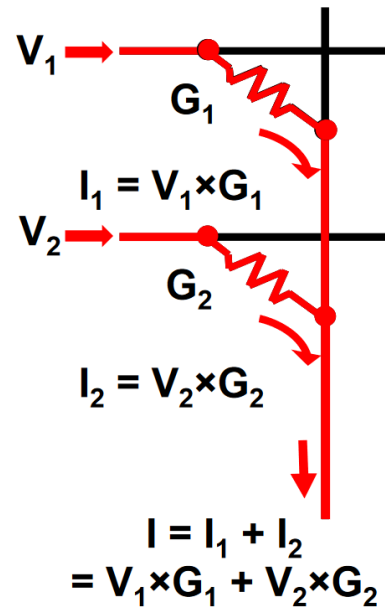
2. 众多用于 DNNs 的硬件平台和优化技术（不损失精度）

- For *temporal* architectures such as CPUs and GPUs, we will discuss how *computational transforms* on the kernel can reduce the number of multiplications to *increase throughput*.
- For *spatial architectures* used in accelerators, we will discuss how *dataflows* can increase *data reuse* from low cost memories in the memory hierarchy to *reduce energy consumption*.

3. 近数据处理(NDP)解决数据搬移的功耗



(a) Multiplication performed by bit-cell (Figure from [102])



(b) G_i is conductance of resistive memory (Figure from [104])

4. 通过降低精度提升吞吐量和能效的联合算法和硬件平台

- *Reduce precision of operations and operands*. This includes going from floating point to fixed point, reducing the bitwidth, non-linear quantization and weight sharing.
- *Reduce number of operations and model size*. This includes techniques such as compression, pruning and compact network architectures.

5. 对比不同硬件效果必须考虑的关键矩阵负载

- DNN model 需要用到的矩阵特性
- DNN hardware 需要用到的矩阵特性