Lecture 18:

Efficiently Evaluating DNNs

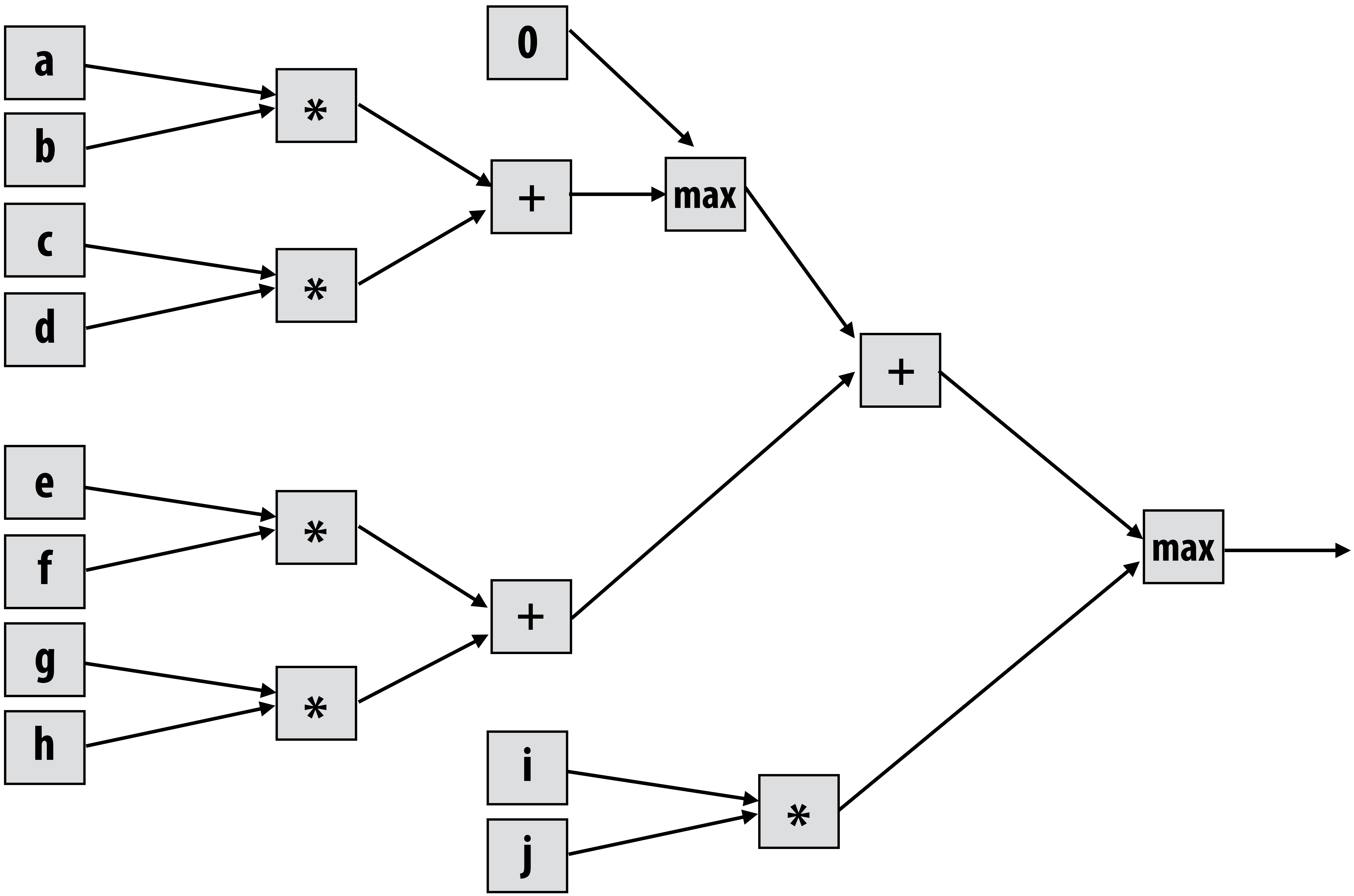
Parallel Computing

Stanford CS149, Winter 2019

Today

- We will discuss the workload of <u>evaluating</u> deep neural networks (performing "inference")
  - This lecture will be heavily biased towards concerns of DNNs that process images (to be honest, it's because that is what your instructor knows best)
  - Which admittedly, is not the majority of DNN evaluation in the world right now
- We will focus on the parallelism challenges of <u>training</u> deep networks next time

Consider the following expression

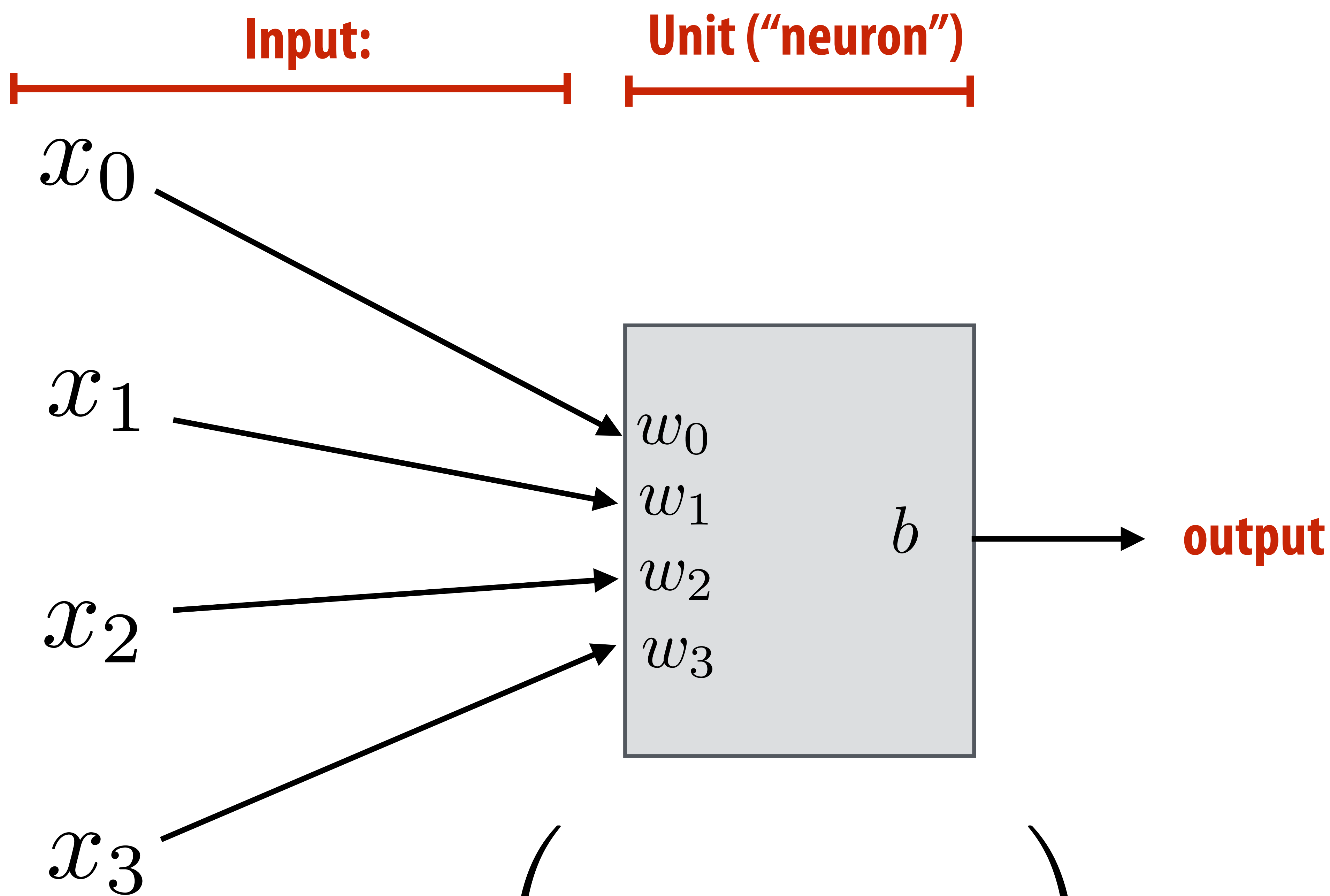



```
max( max(0, (a*b) + (c*d)) + (e*f) + (g*h), i*j)
```

What is a deep neural network?

A basic unit:

Unit with *n* inputs described by *n+1* parameters (weights + bias)



$$f\left(\sum_i x_i w_i + b\right)$$

Example: rectified linear unit (ReLU)

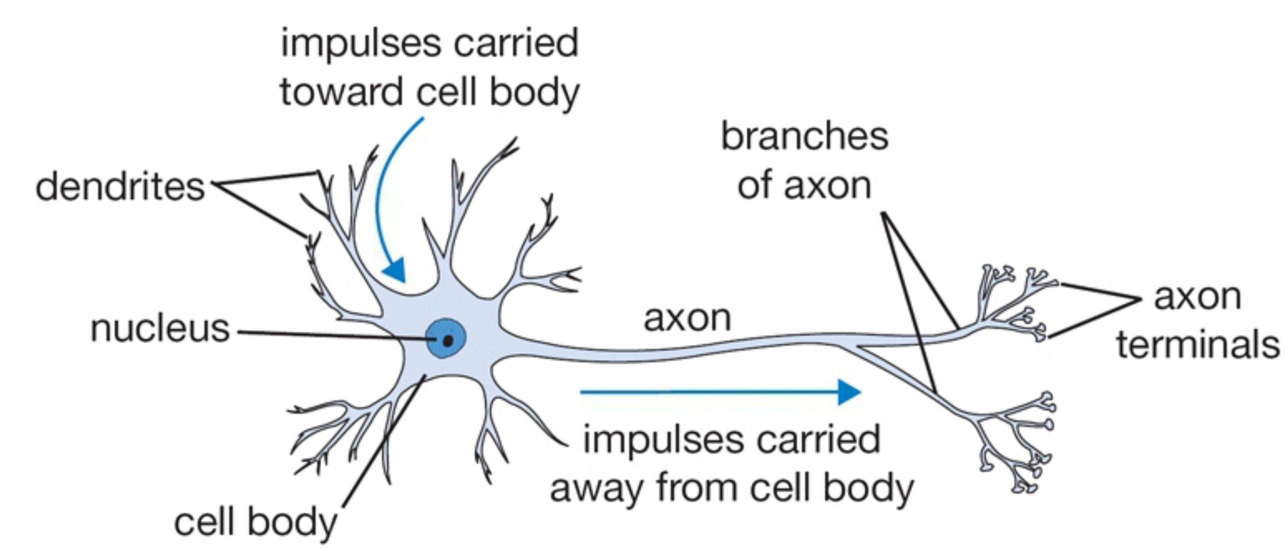
$$f(x) = max(0, x)$$

Basic computational interpretation:

It is just a circuit!

Biological inspiration:

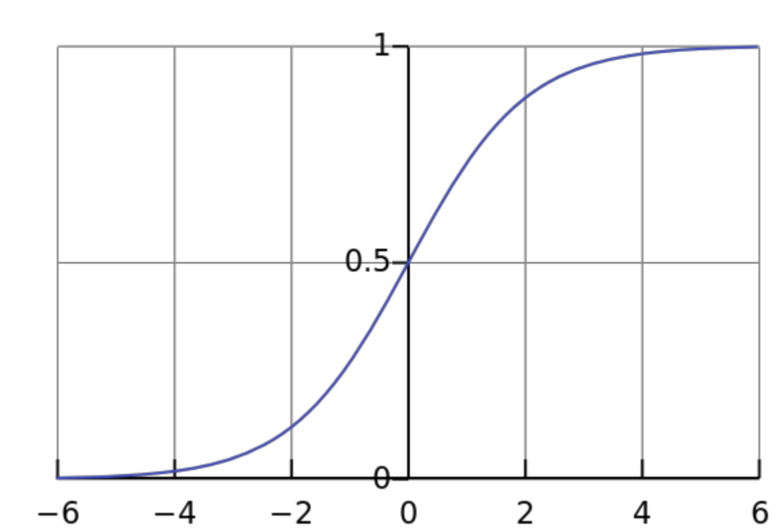
unit output corresponds loosely to activation of neuron



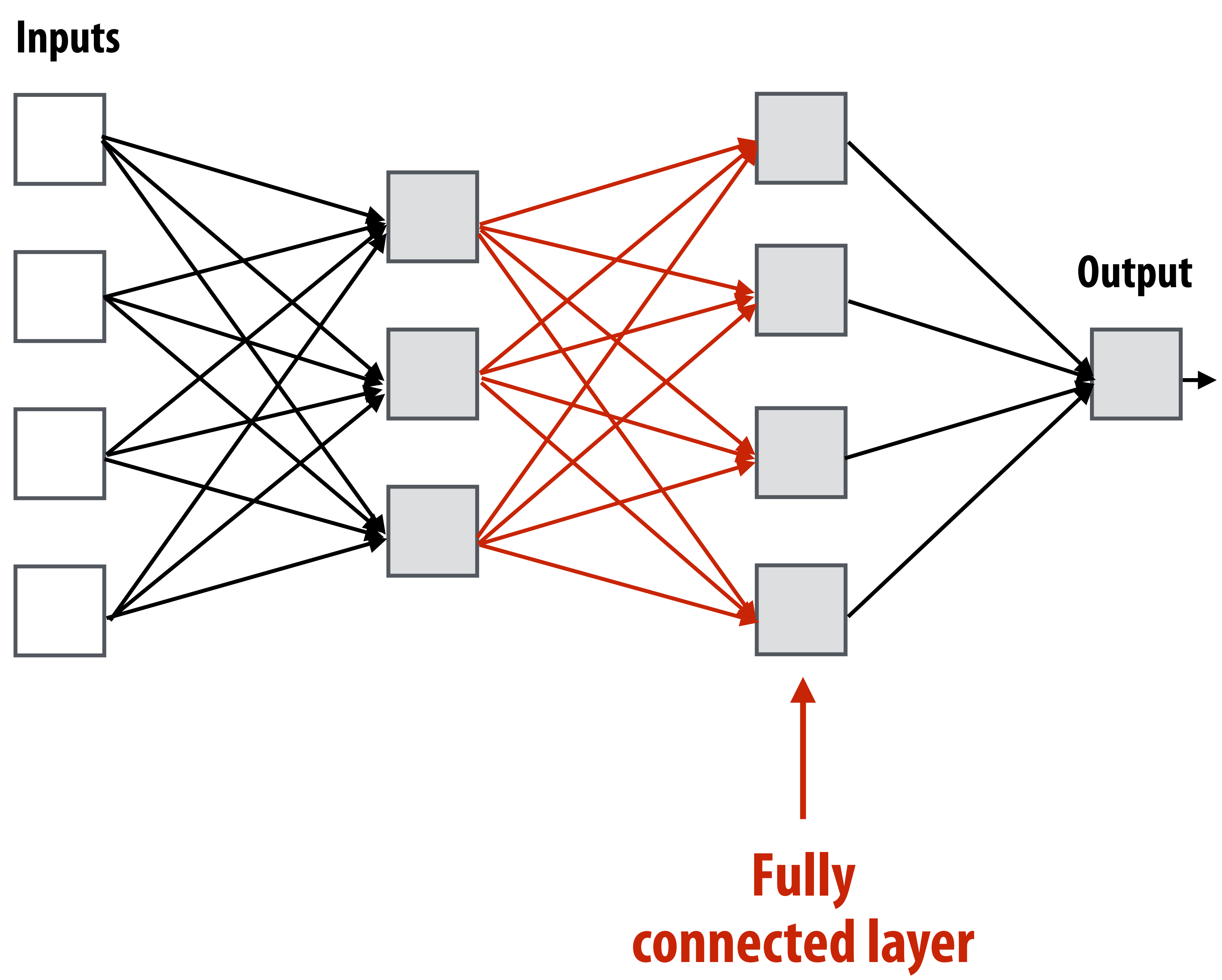
Machine learning interpretation:

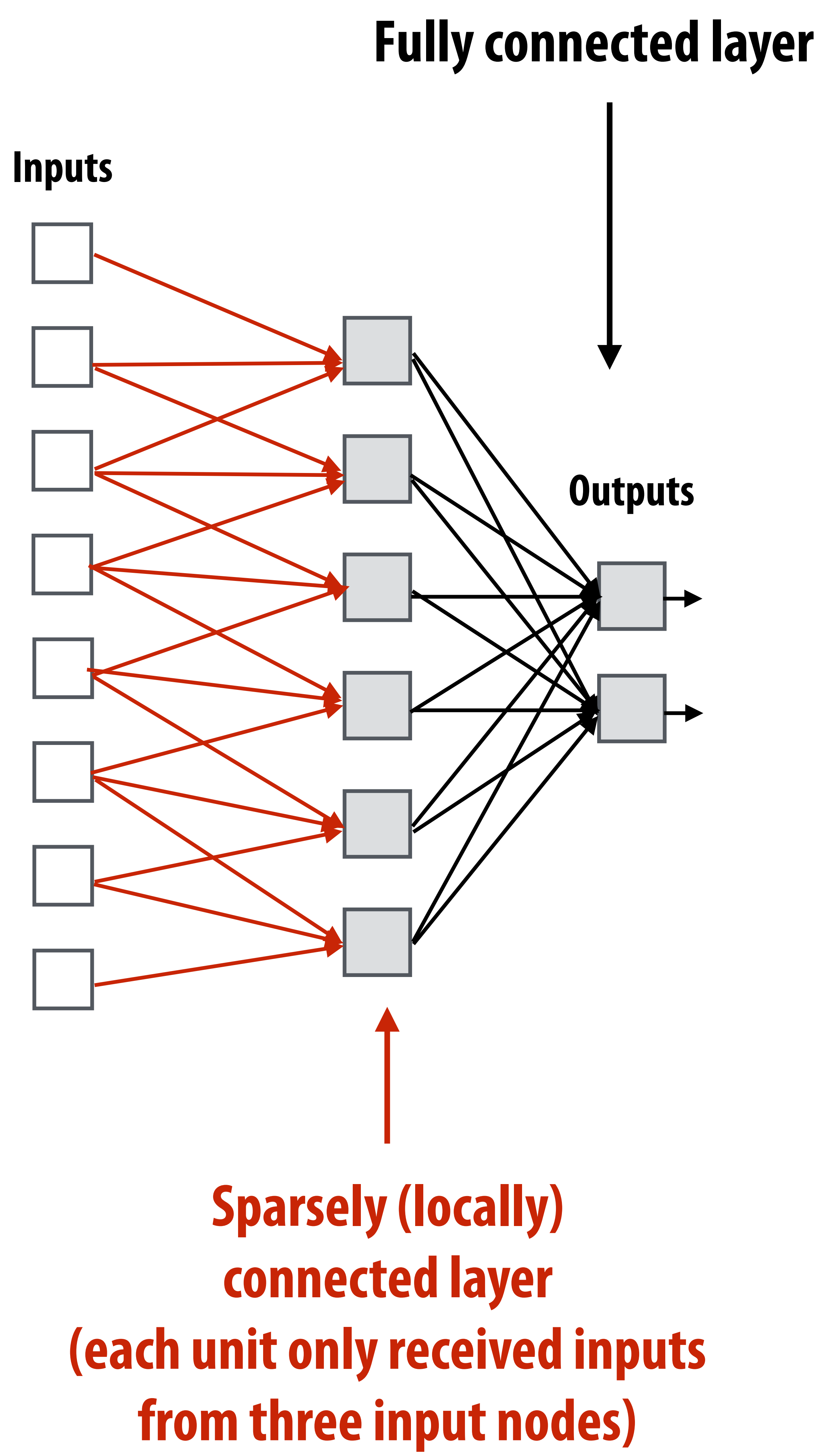
binary classifier: interpret output as the probability of one class

$$f(x) = \frac{1}{1 + e^{-x}}$$



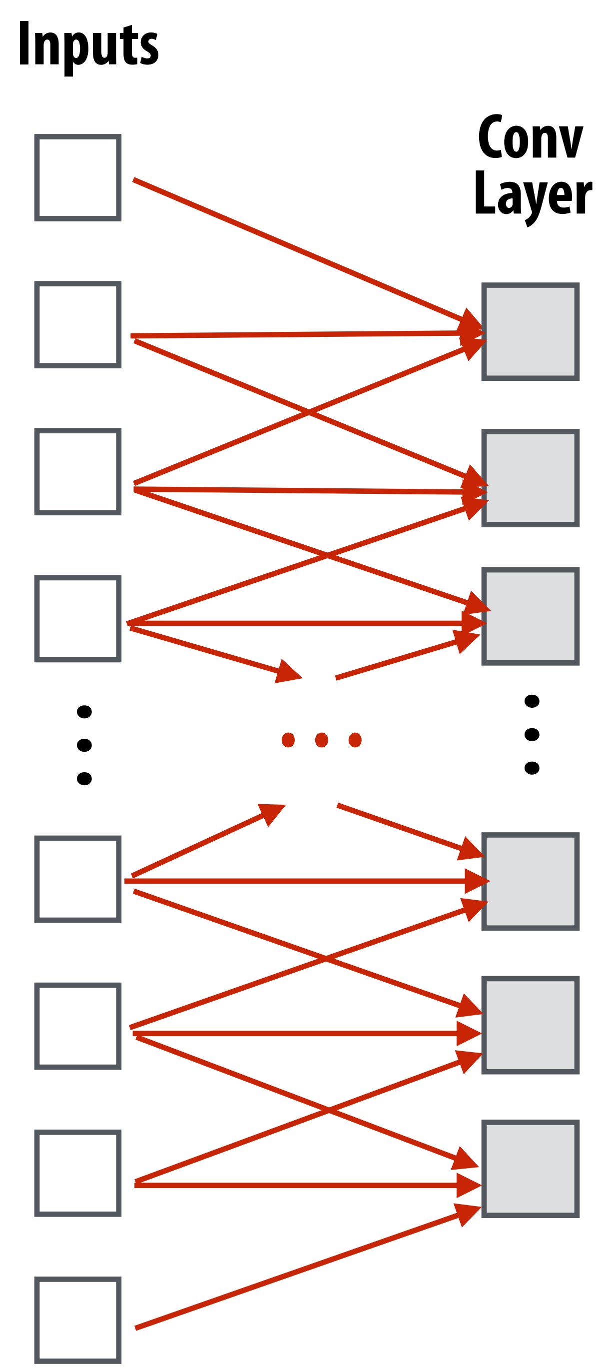
Deep neural network: topology

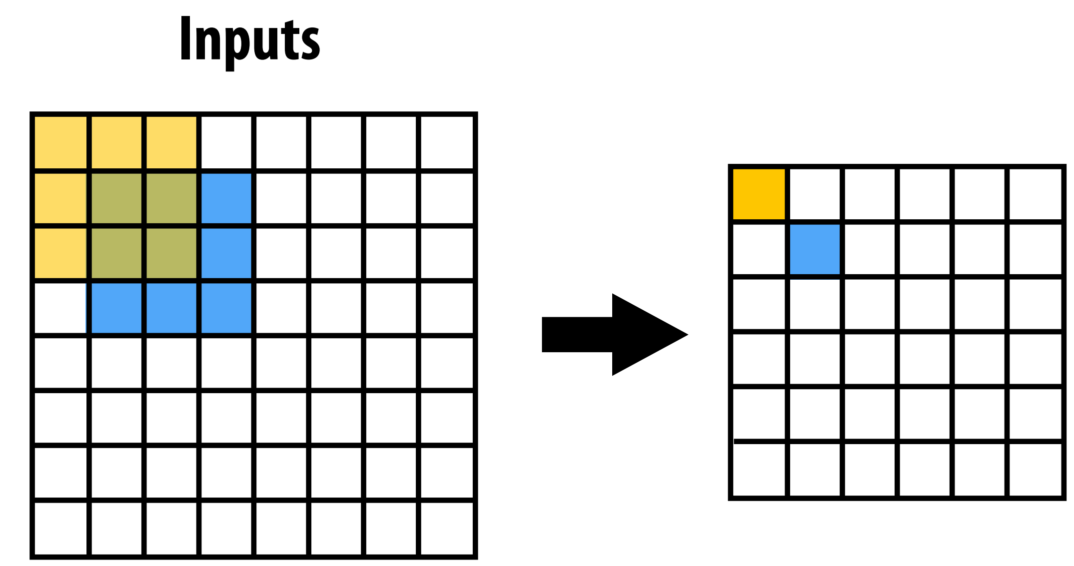




Recall image convolution (3x3 conv)

```
int WIDTH = 1024;
int HEIGHT = 1024;
float input[(WIDTH+2) * (HEIGHT+2)];
float output[WIDTH * HEIGHT];


float weights[] = {1.0/9, 1.0/9, 1.0/9,
                   1.0/9, 1.0/9, 1.0/9,
                   1.0/9, 1.0/9, 1.0/9};


for (int j=0; j<HEIGHT; j++) {
  for (int i=0; i<WIDTH; i++) {
    float tmp = 0.f;
    for (int jj=0; jj<3; jj++)
      for (int ii=0; ii<3; ii++)
        tmp += input[(j+jj)*(WIDTH+2) + (i+ii)] * weights[jj*3 + ii];
    output[j*WIDTH + i] = tmp;
  }
}
```



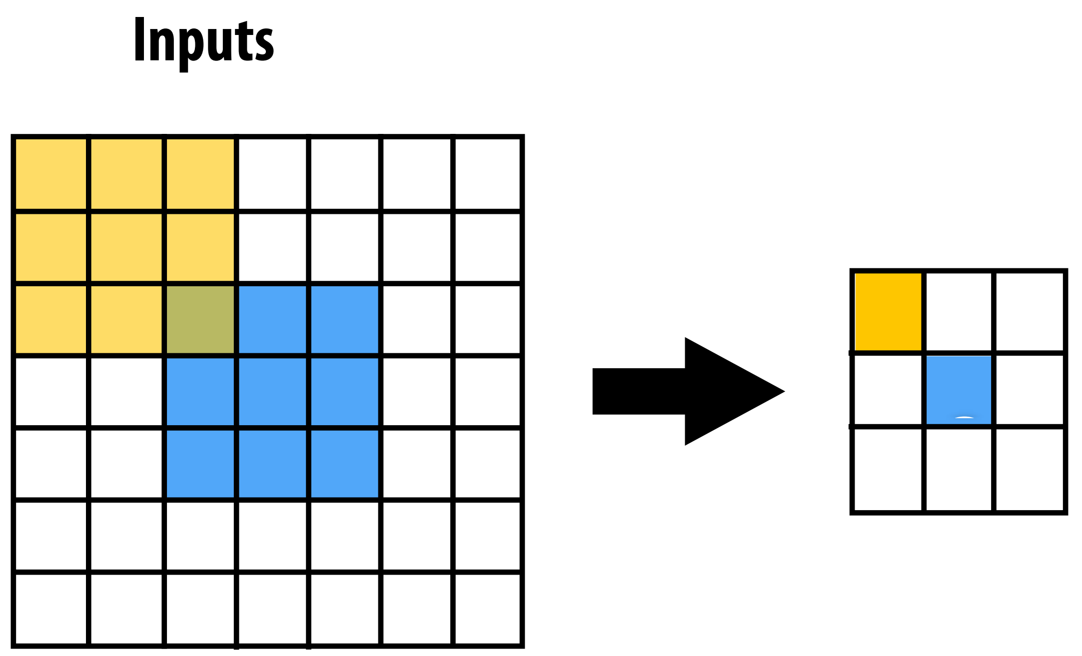


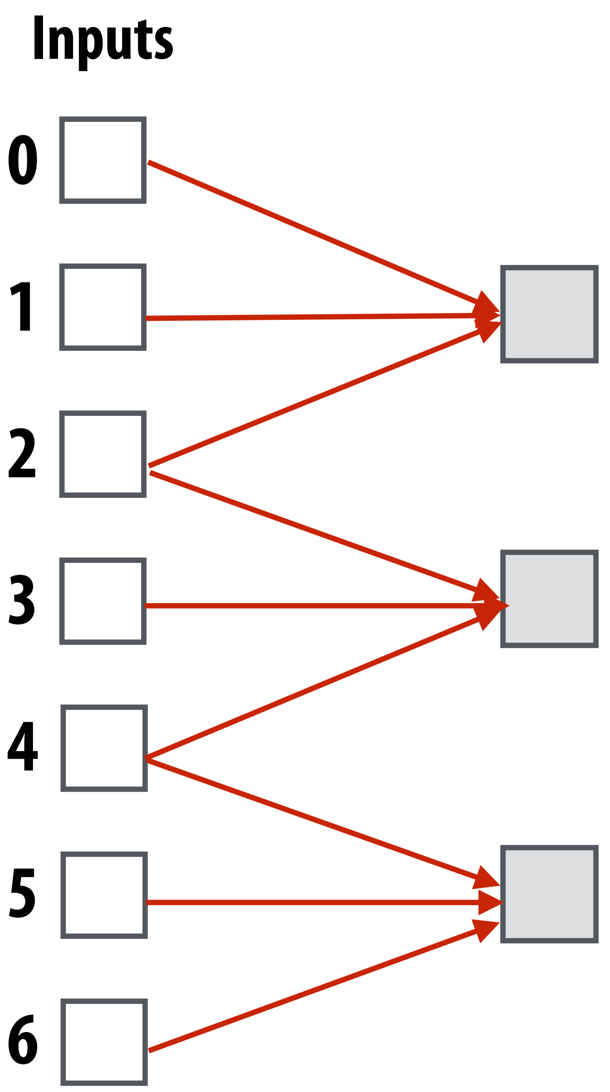
Convolutional layer: locally connected AND all units in layer share the same parameters (same weights + same bias):

(note: network illustration above only shows links for a 1D conv: a.k.a. one iteration of `ii` loop)

Strided 3x3 convolution

```
int WIDTH = 1024;
int HEIGHT = 1024;
int STRIDE = 2;
float input[(WIDTH+2) * (HEIGHT+2)];
float output[(WIDTH/STRIDE) * (HEIGHT/STRIDE)];


float weights[] = {1.0/9, 1.0/9, 1.0/9,
                   1.0/9, 1.0/9, 1.0/9,
                   1.0/9, 1.0/9, 1.0/9};


for (int j=0; j<HEIGHT; j+=STRIDE) {
  for (int i=0; i<WIDTH; i+=STRIDE) {
    float tmp = 0.f;
    for (int jj=0; jj<3; jj++)
      for (int ii=0; ii<3; ii++) {
         tmp += input[(j+jj)*(WIDTH+2) + (i+ii)] * weights[jj*3 + ii];
      output[(j/STRIDE)*WIDTH + (i/STRIDE)] = tmp;
  }
}
```



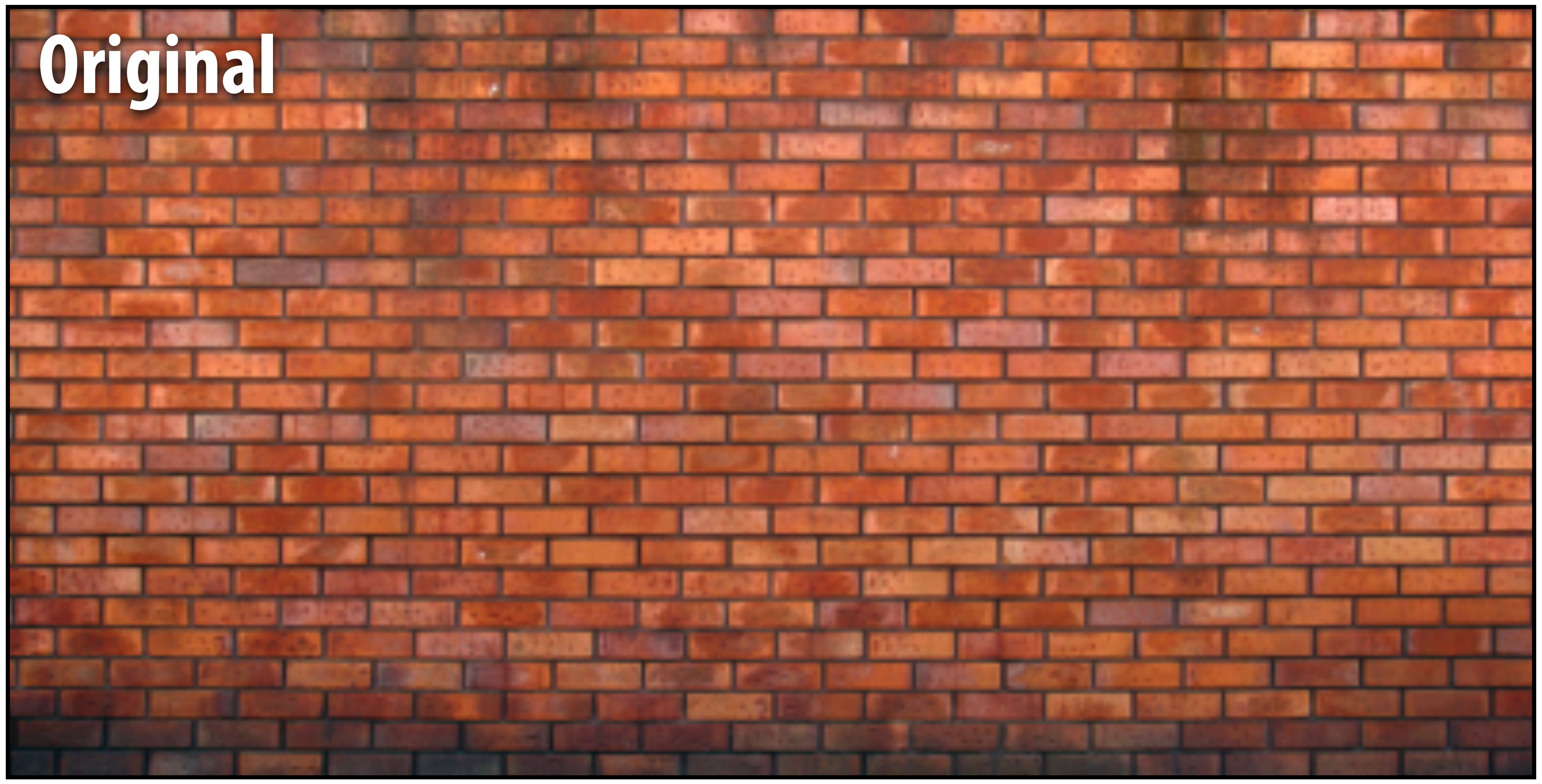


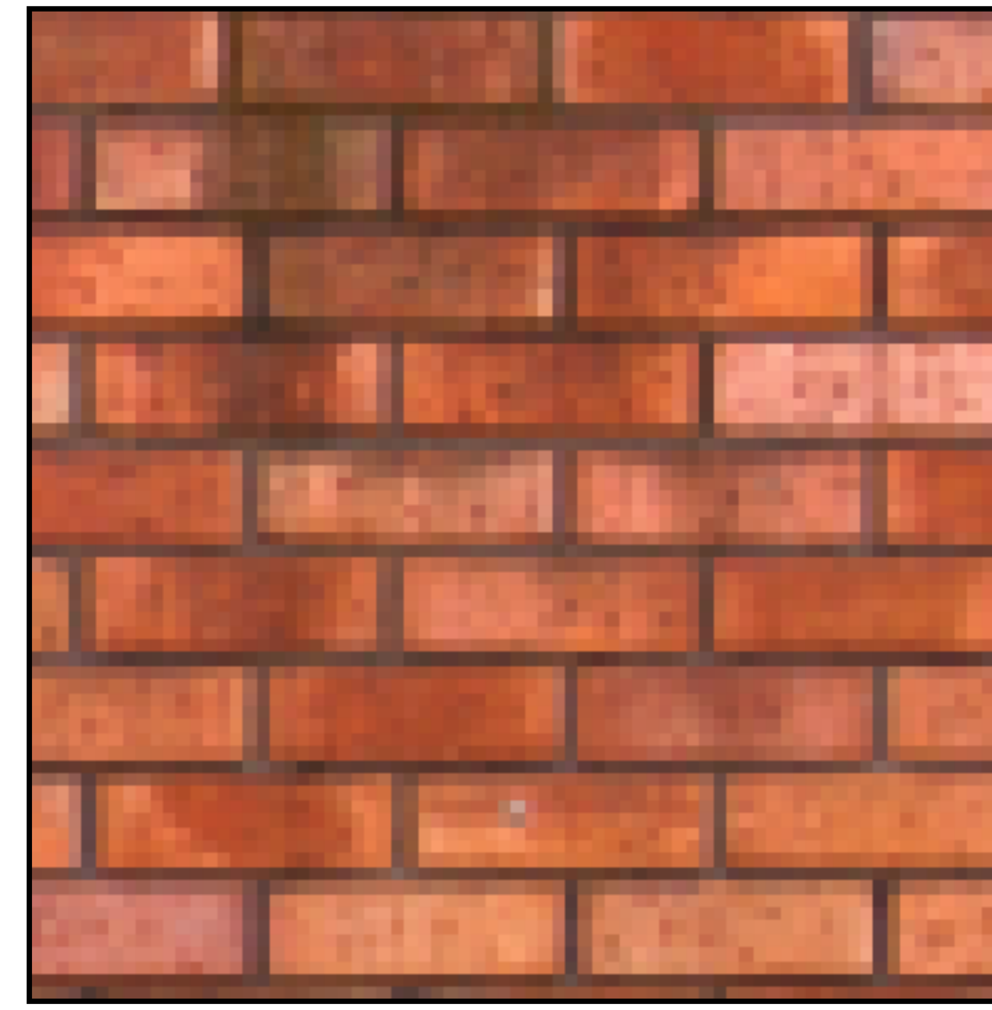
Convolutional layer with stride 2
(0,1,2) , (2,3,4) , (4,5,6) , …

What does convolution using these filter weights do?

$$\begin{bmatrix} .111 & .111 & .111 \\ .111 & .111 & .111 \\ .111 & .111 & .111 \end{bmatrix}$$

"Box blur"

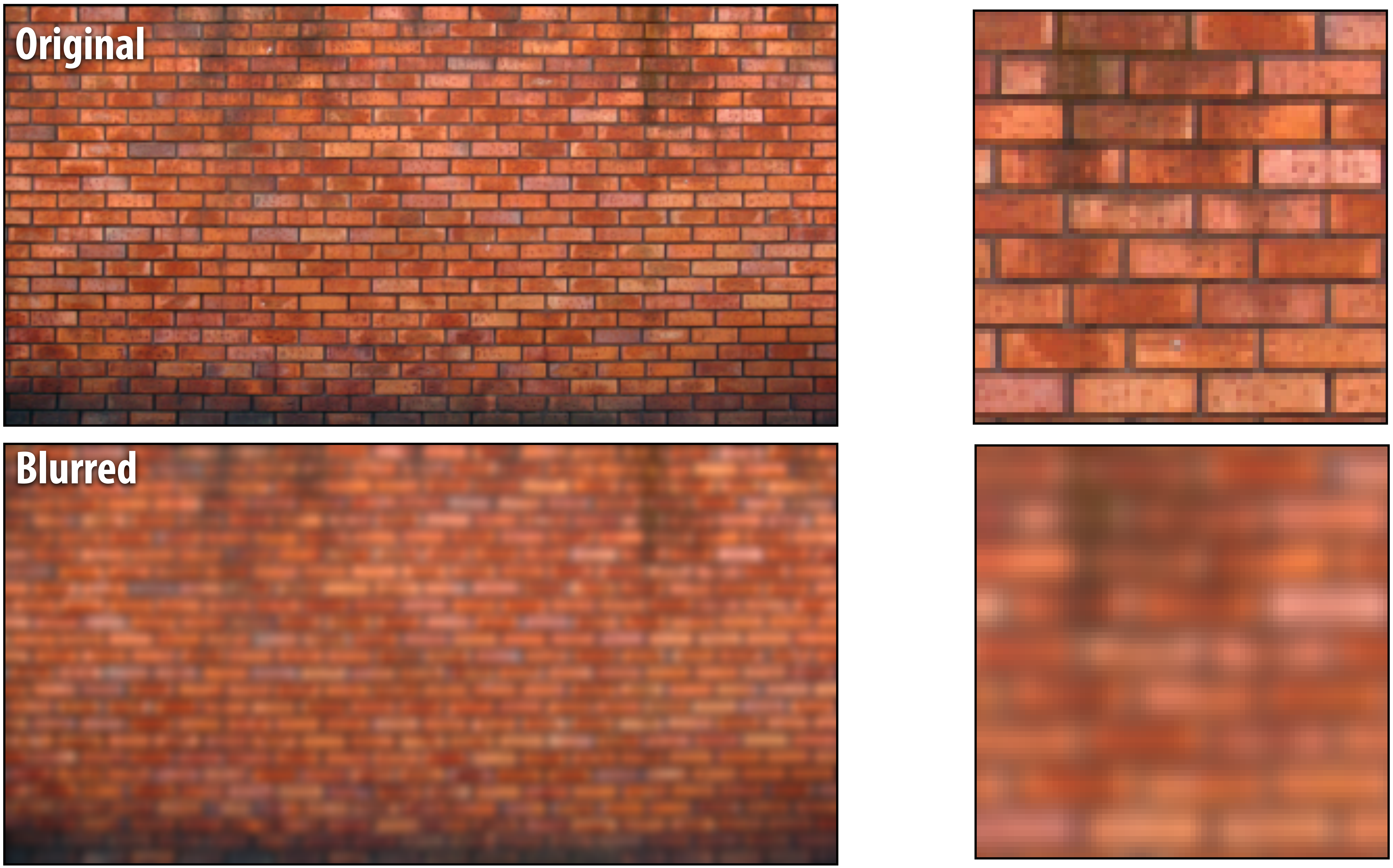




What does convolution using these filter weights do?

$$\begin{bmatrix} .075 & .124 & .075 \\ .124 & .204 & .124 \\ .075 & .124 & .075 \end{bmatrix}$$

"Gaussian Blur"



What does convolution with these filters do?

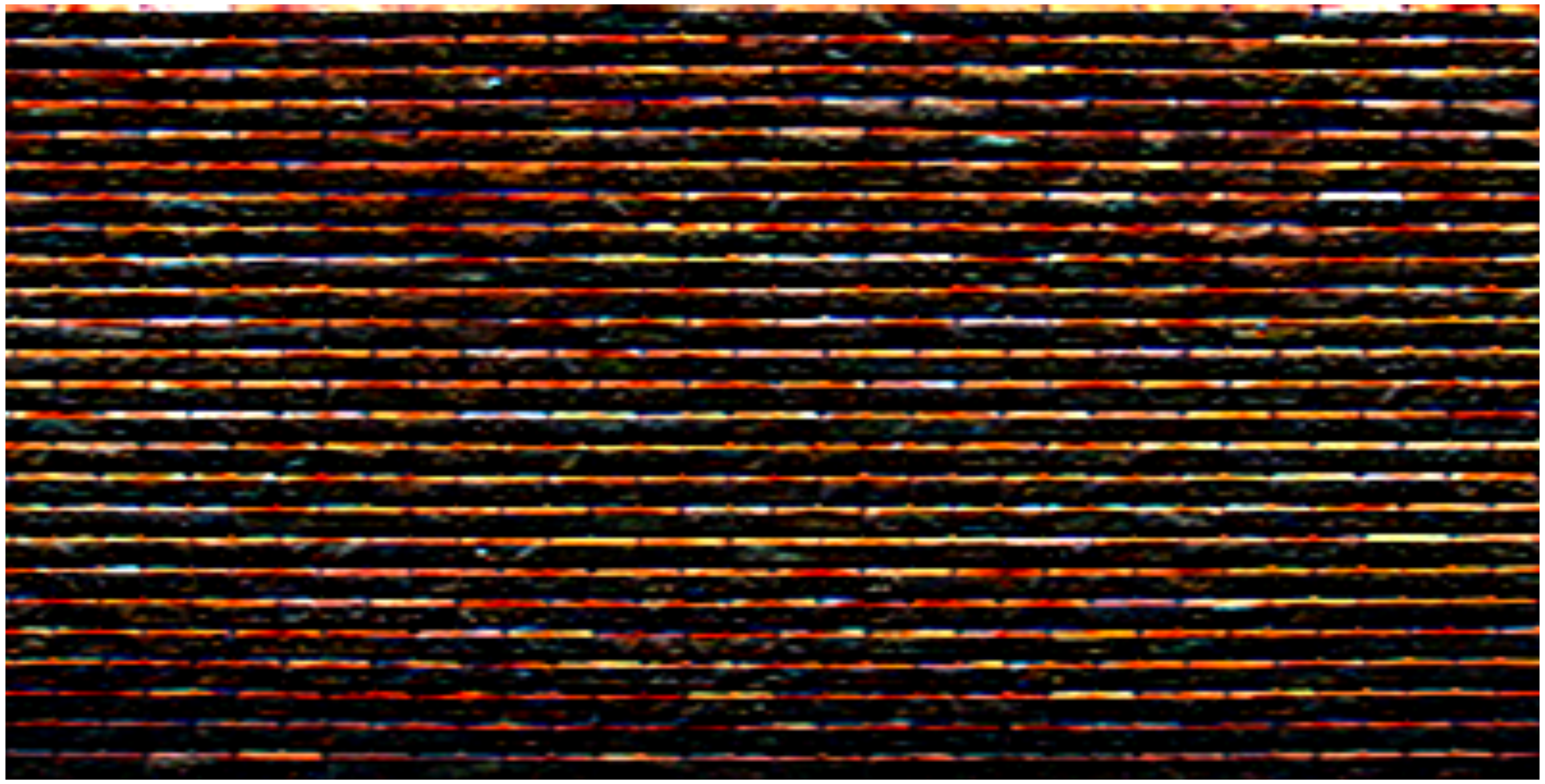
$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

Extracts horizontal gradients

Extracts vertical gradients

Gradient detection filters

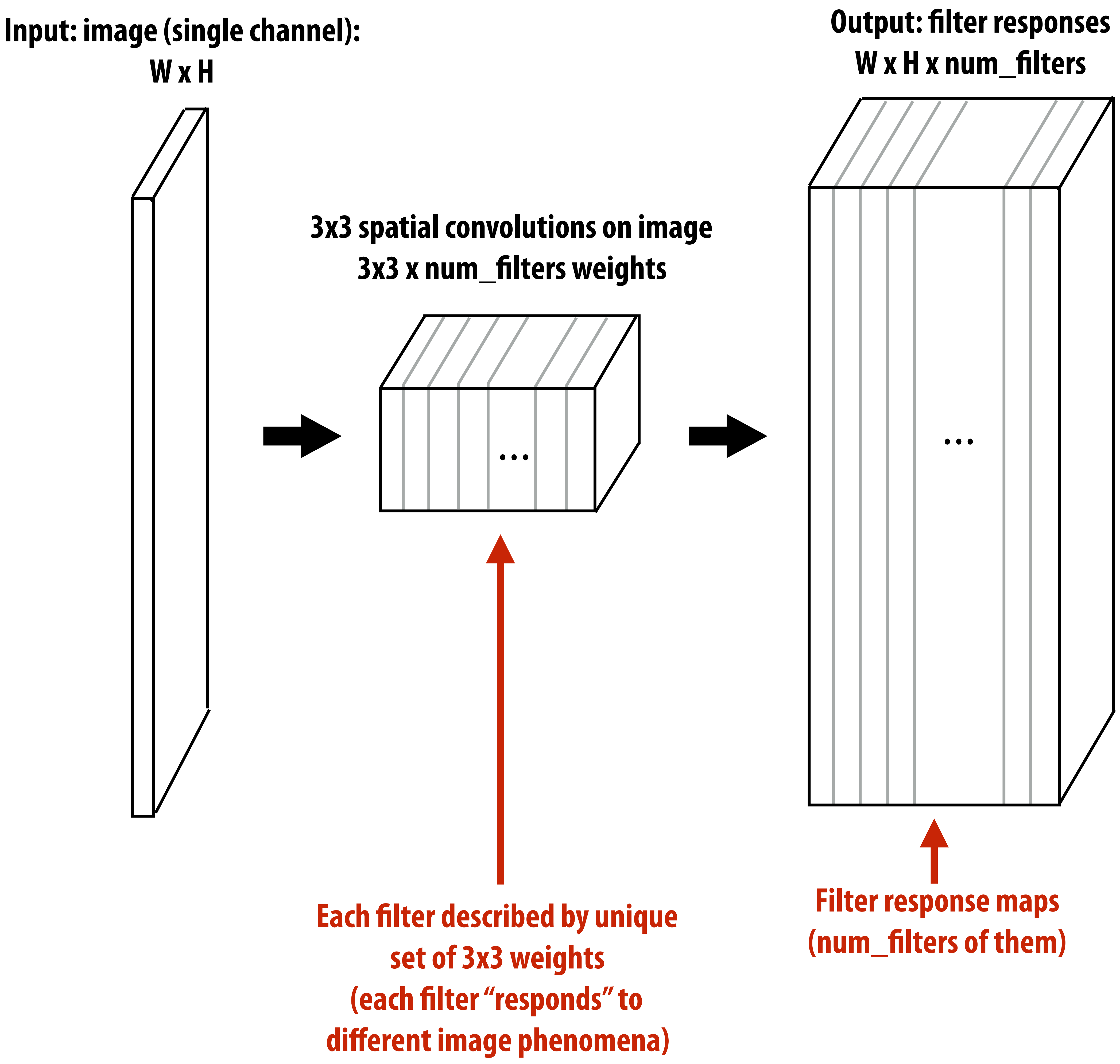
Horizontal gradients



Vertical gradients

Note: you can think of a filter as a "detector" of a pattern, and the magnitude of a pixel in the output image as the "response" of the filter to the region surrounding each pixel in the input image

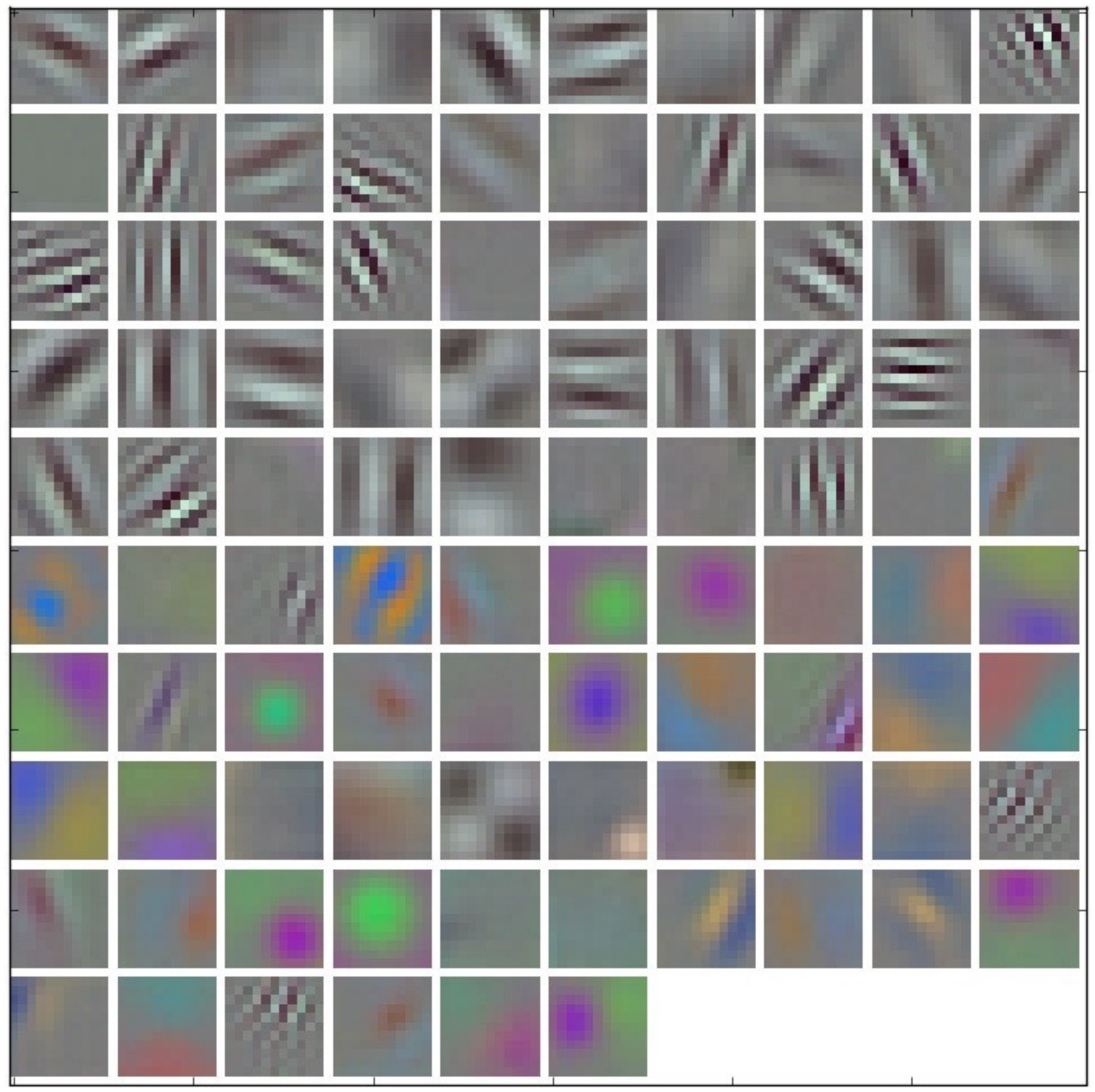
Applying many filters to an image at once



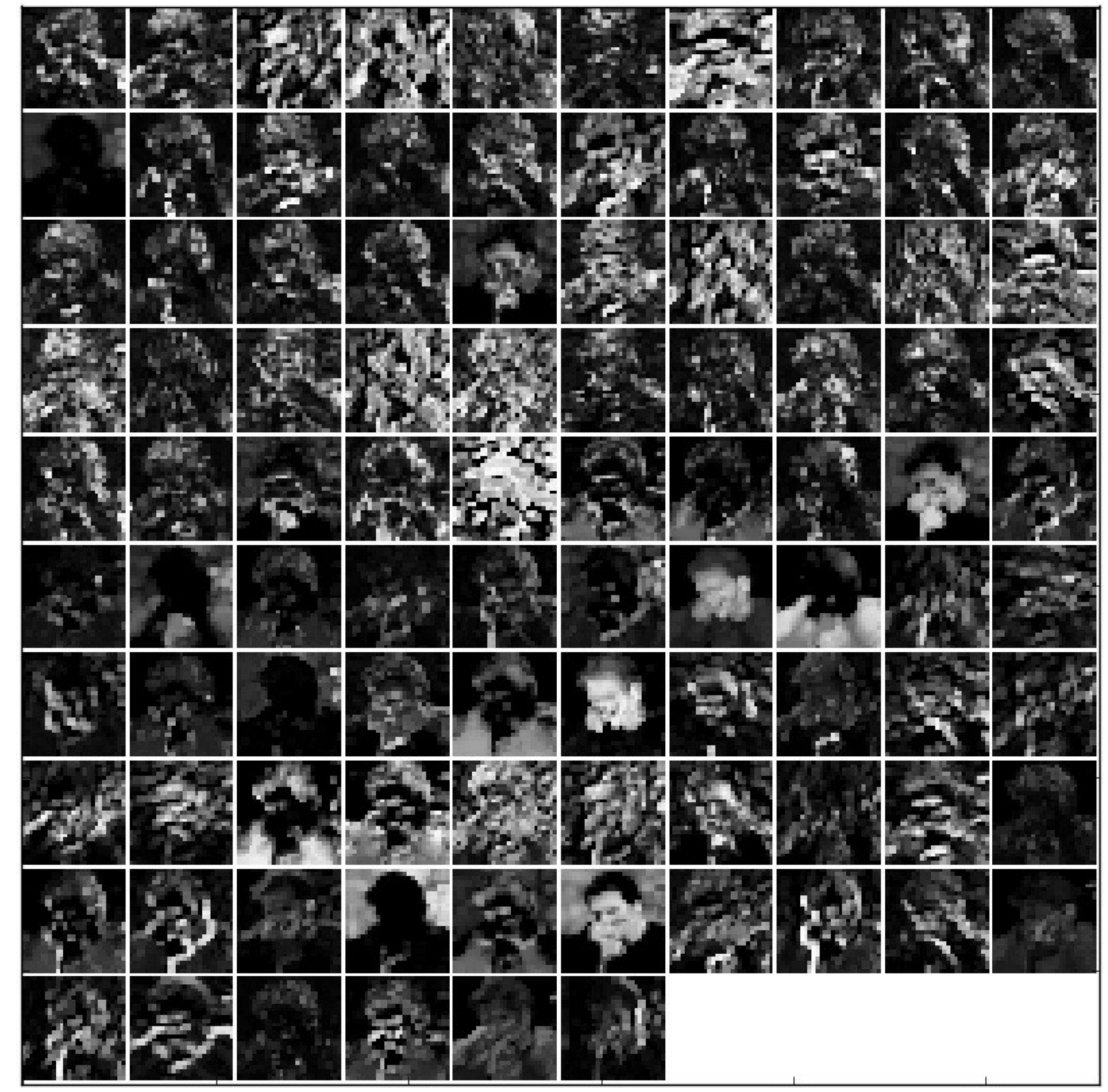
Applying many filters to an image at once

Input RGB image (W x H x 3)

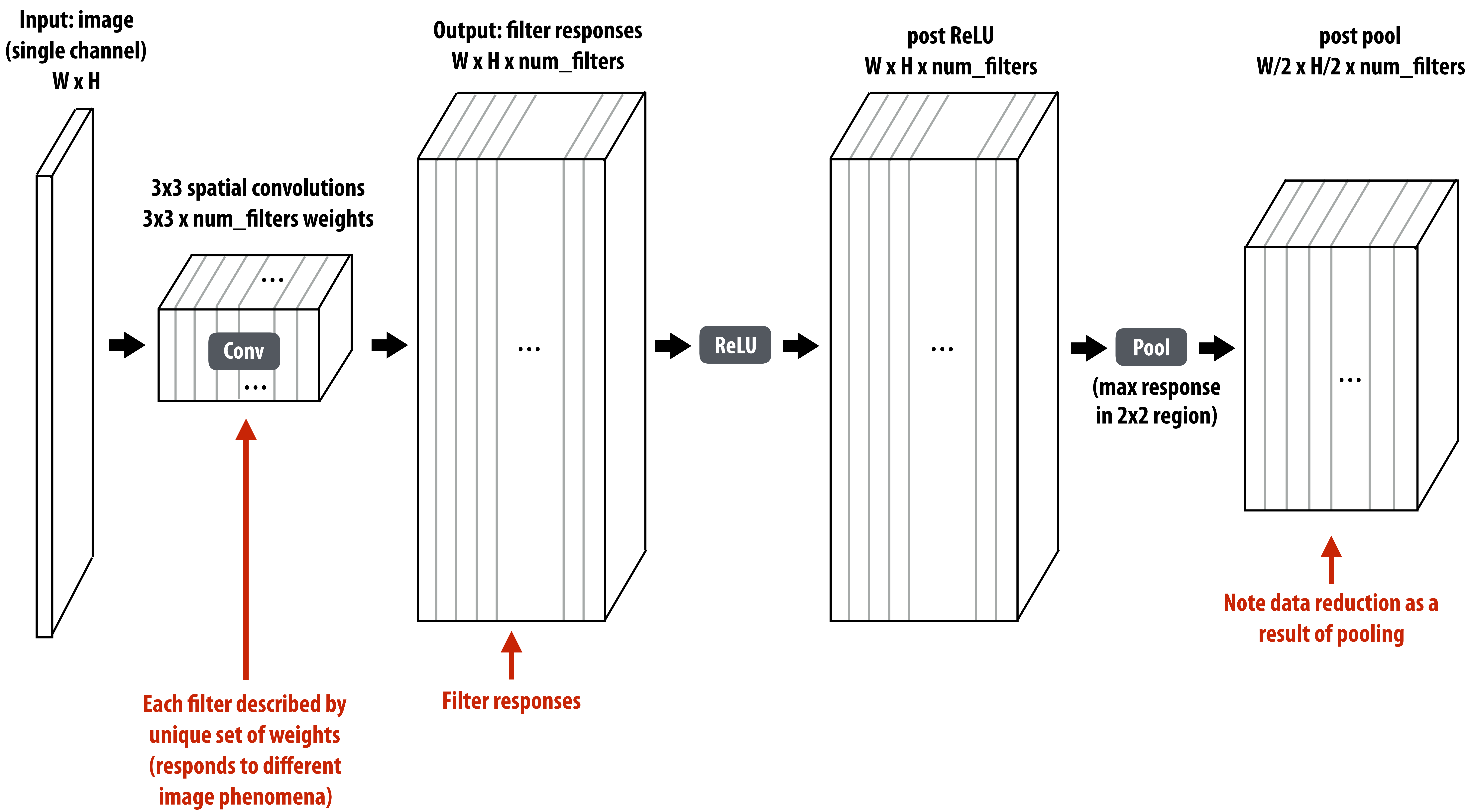
96 11x11x3 filters
(operate on RGB)



96 responses (normalized)



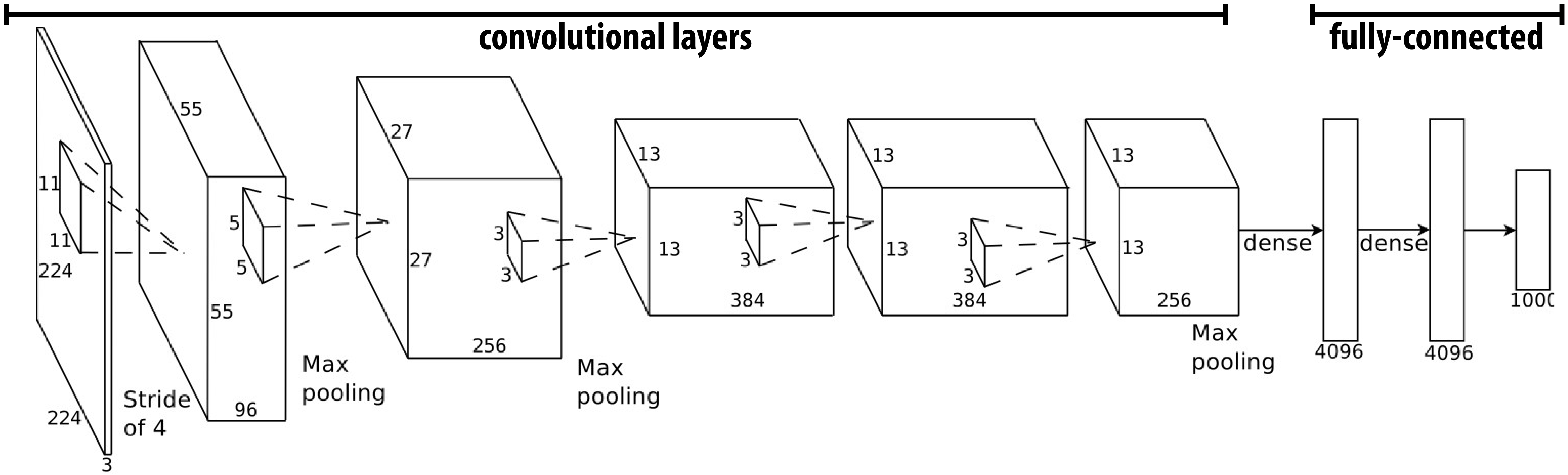
Adding additional layers



Example: "AlexNet" object detection network

Sequences of conv + reLU + pool (optional) layers

Example: AlexNet [Krizhevsky12]: 5 convolutional layers + 3 fully connected layers

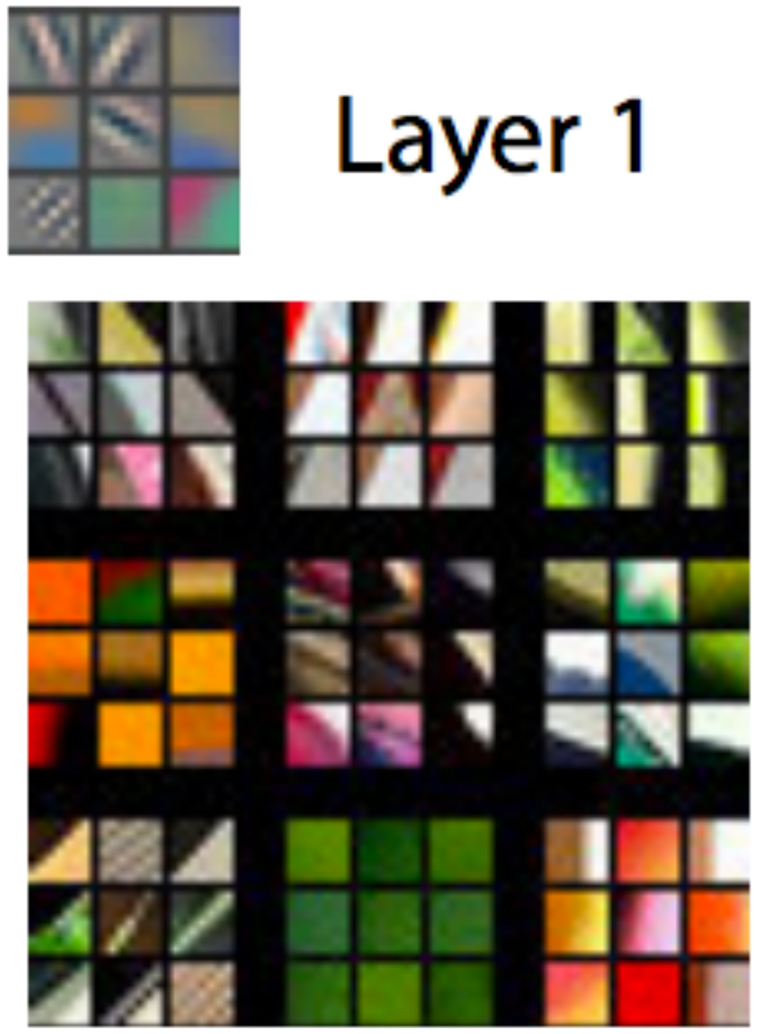


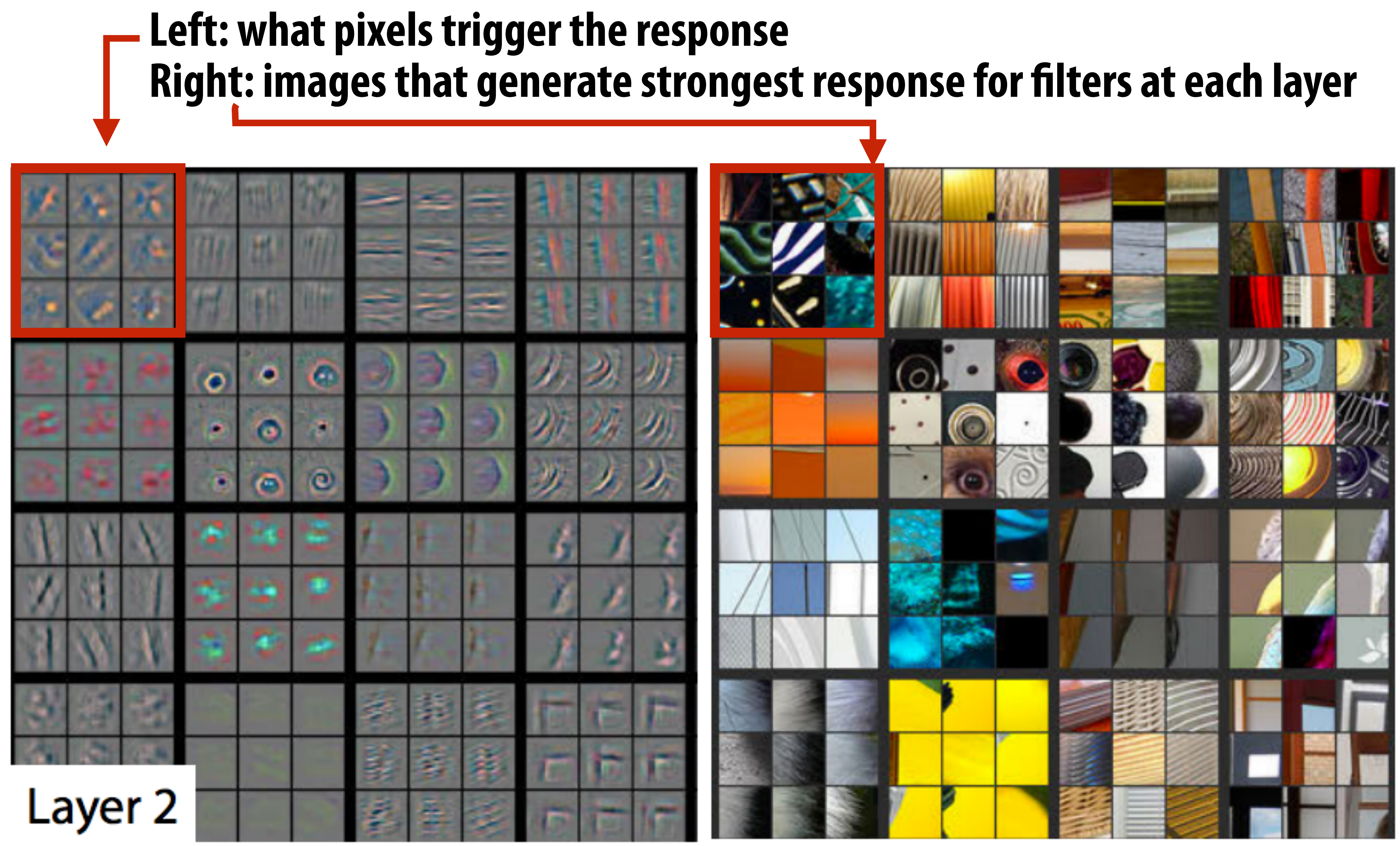
Another example: VGG-16 [Simonyan15]: 13 convolutional layers

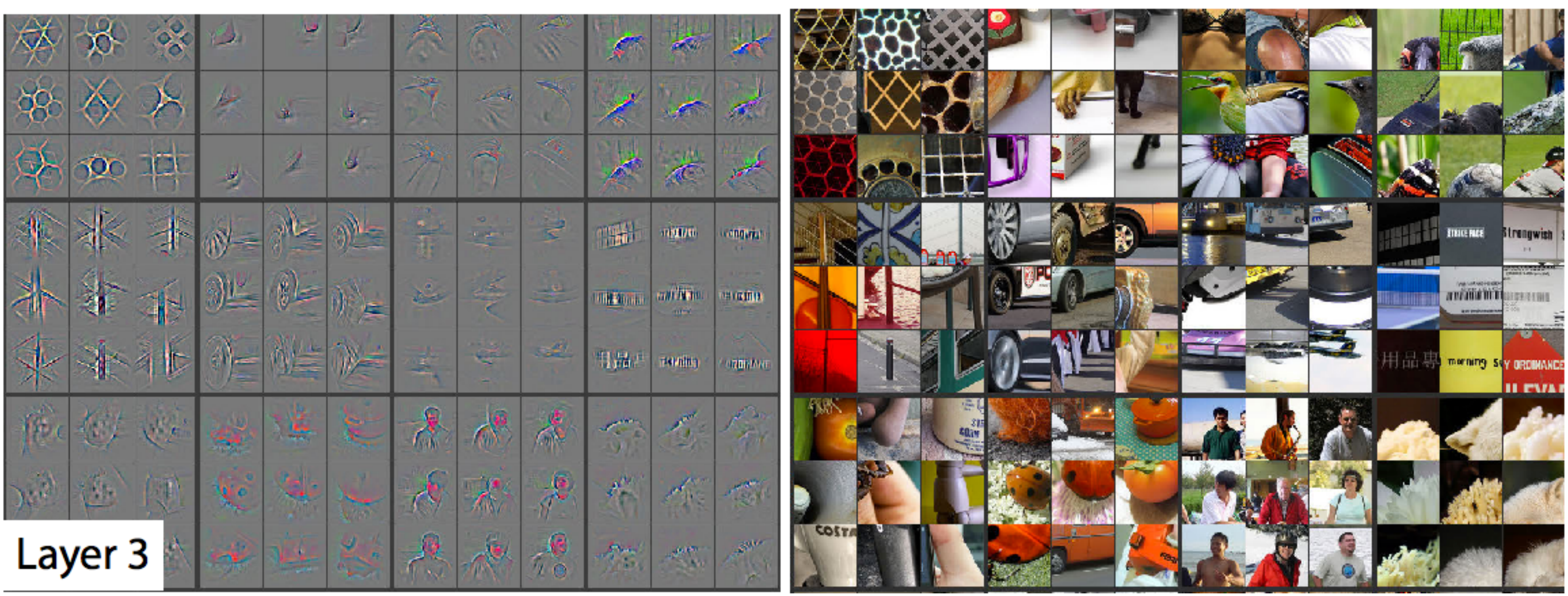
input: 224 x 224 RGB
conv/reLU: 3x3x3x64
conv/reLU: 3x3x64x64
maxpool
conv/reLU: 3x3x64x128
conv/reLU: 3x3x128x128
maxpool
conv/reLU: 3x3x128x256
conv/reLU: 3x3x256x256
conv/reLU: 3x3x256x256
maxpool
conv/reLU: 3x3x256x512
conv/reLU: 3x3x512x512
conv/reLU: 3x3x512x512
maxpool
conv/reLU: 3x3x512x512
conv/reLU: 3x3x512x512
conv/reLU: 3x3x512x512
maxpool
fully-connected 4096
fully-connected 4096
fully-connected 1000
soft-max

[VGG illustration credit: Yang et al.]

Why deep?

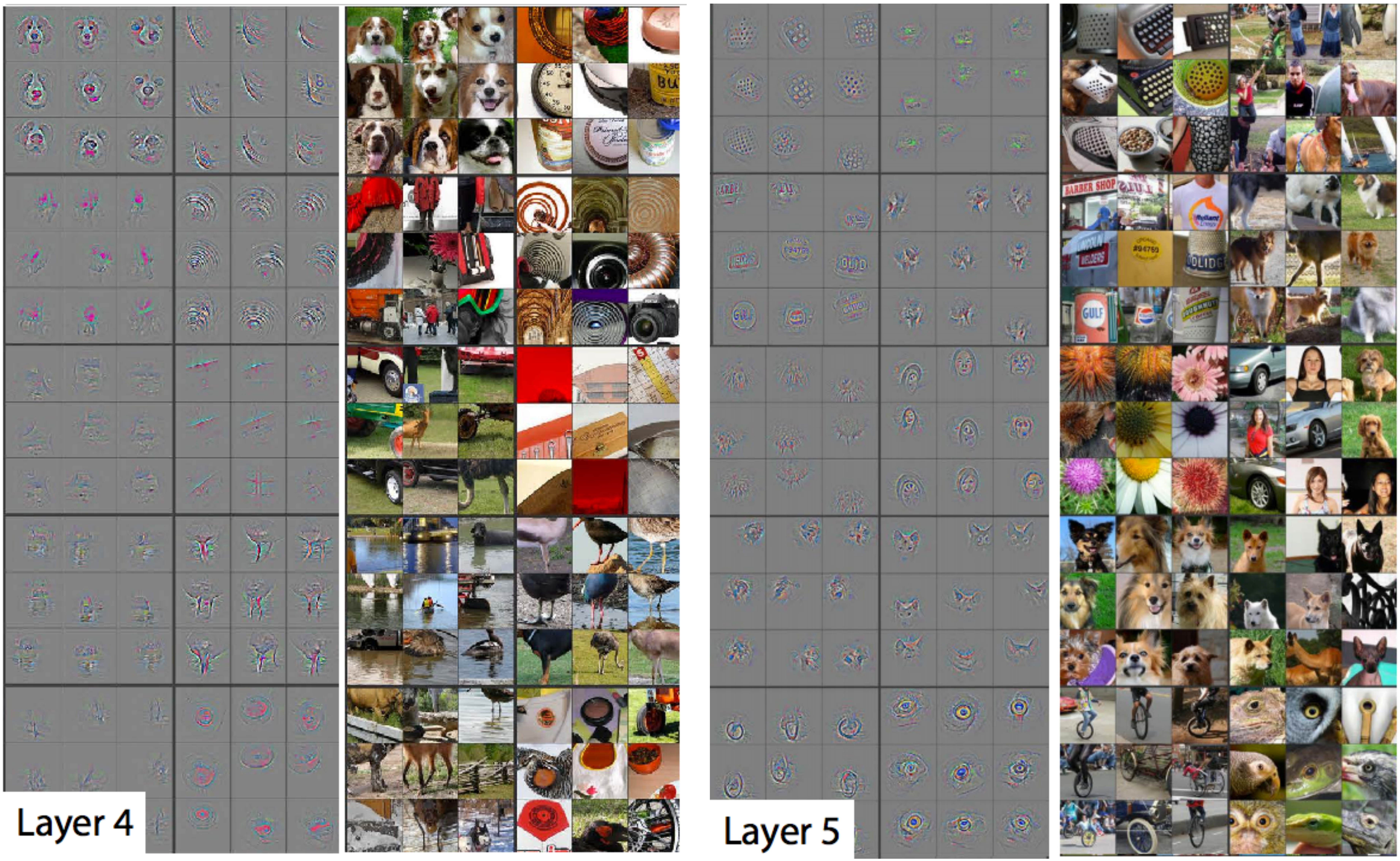






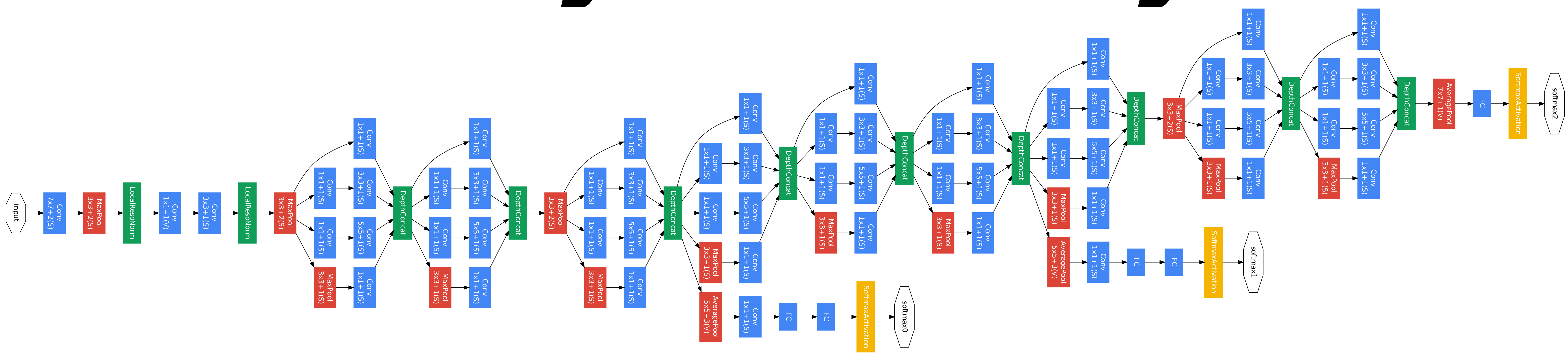
[image credit: Zeiler 14]

Why deep?

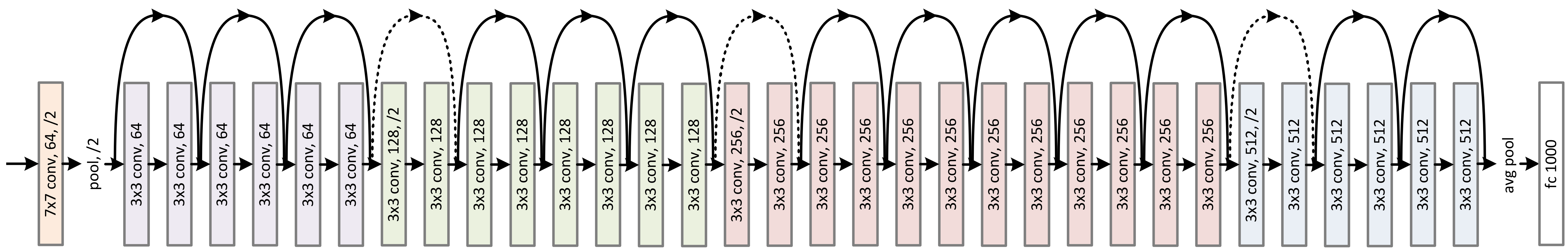


[image credit: Zeiler 14]

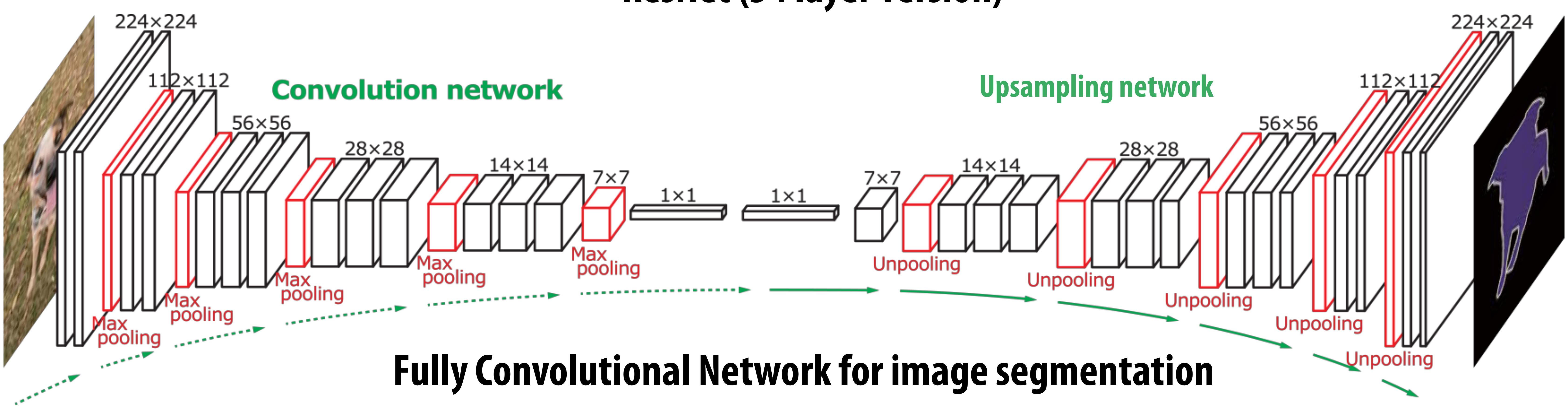
More recent image understanding networks



Inception (GoogleLeNet)



ResNet (34 layer version)



Fully Convolutional Network for image segmentation

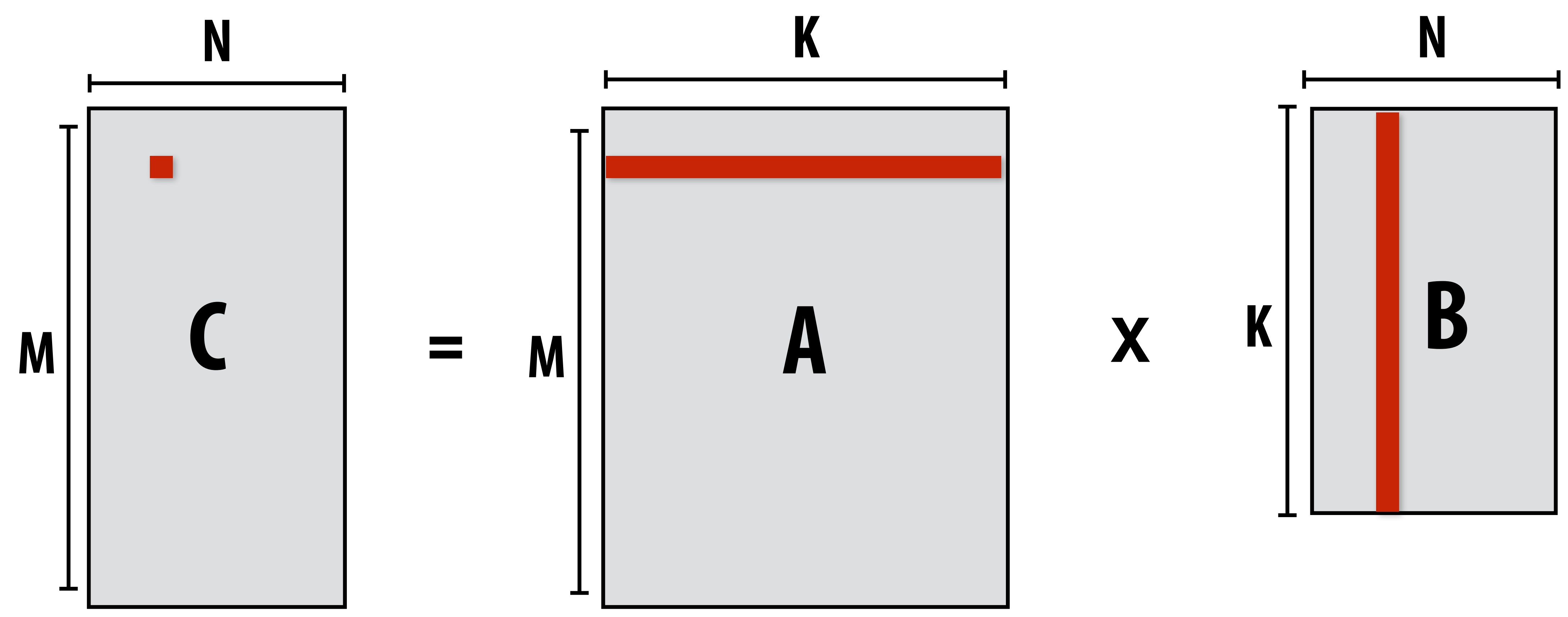
Deep networks learn useful representations

- Simultaneous, multi-scale learning of useful features for the task at hand
  - Example on previous slides: subparts detectors emerged in network for object classification
- But wait… how did you learn the values of all the weights?
  - For today, assume the weights are given (today is about evaluating deep networks, not training them)

Efficiently implementing convolution layers

Dense matrix multiplication

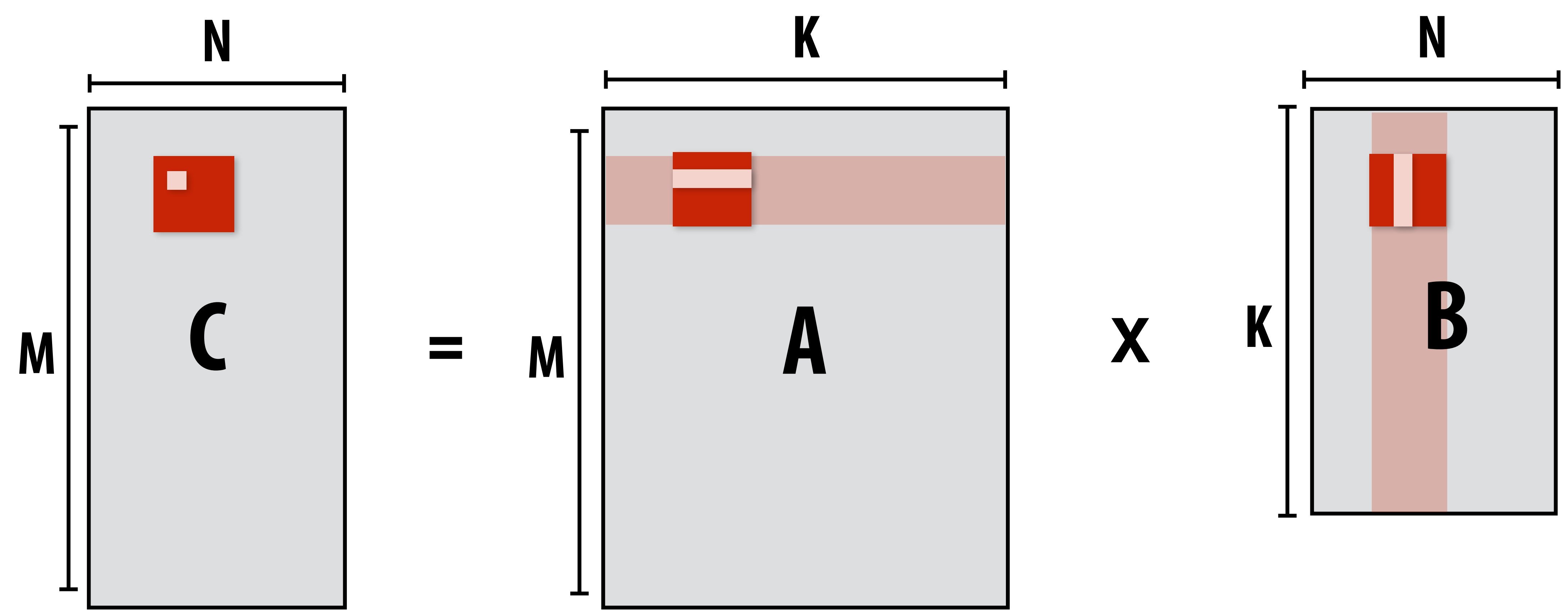
```
float A[M][K];
float B[K][N];
float C[M][N];

// compute C += A * B
#pragma omp parallel for
for (int j=0; j<M; j++)
  for (int i=0; i<N; i++)
     for (int k=0; k<K; k++)
         C[j][i] += A[j][k] * B[k][i];
```



What is the problem with this implementation?

Low arithmetic intensity (does not exploit temporal locality in access to A and B)

Blocked dense matrix multiplication




```
float A[M][K];
float B[K][N];
float C[M][N];

// compute C += A * B
#pragma omp parallel for
for (int jblock=0; jblock<M; jblock+=BLOCKSIZE_J)
  for (int iblock=0; iblock<N; iblock+=BLOCKSIZE_I)
     for (int kblock=0; kblock<K; kblock+=BLOCKSIZE_K)
        for (int j=0; j<BLOCKSIZE_J; j++)
           for (int i=0; i<BLOCKSIZE_I; i++)
              for (int k=0; k<BLOCKSIZE_K; k++)
                 C[jblock+j][iblock+i] += A[jblock+j][kblock+k] * B[kblock+k][iblock+i];
```

Idea: compute partial result for block of C while required blocks of A and B remain in cache (Assumes BLOCKSIZE chosen to allow block of A, B, and C to remain resident)

Self check: do you want as big a BLOCKSIZE as possible? Why?

Hierarchical blocked matrix mult

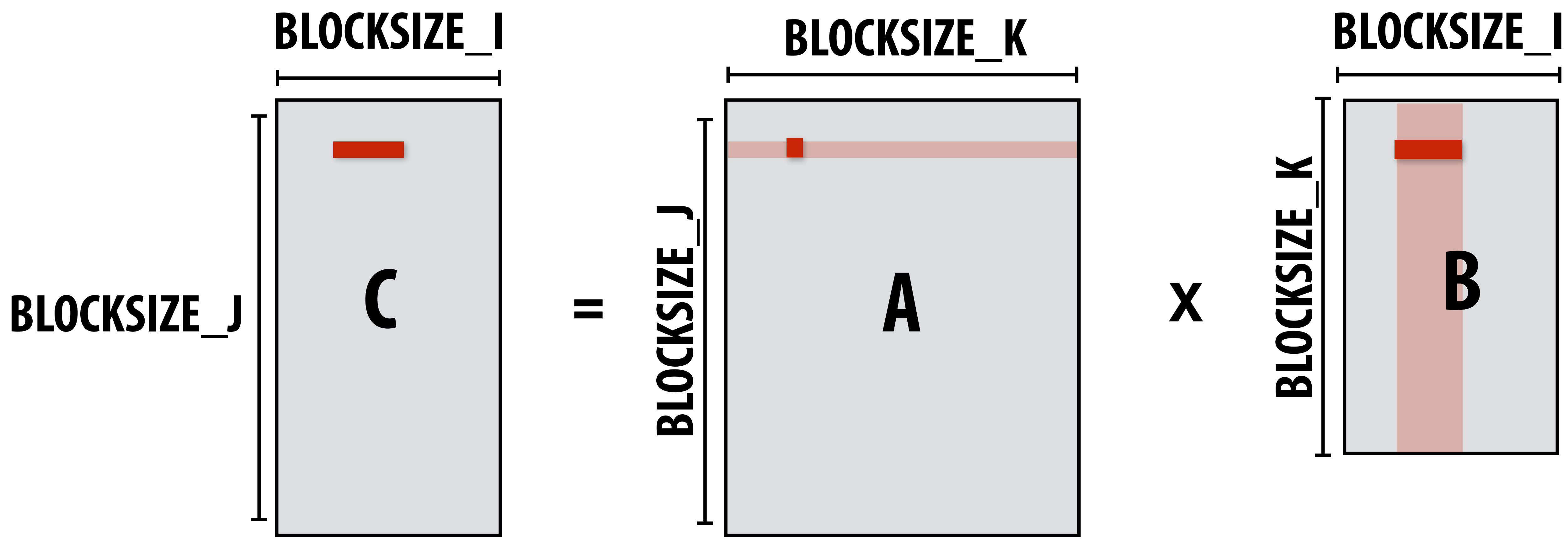
Exploit multiple levels of memory hierarchy

```
float A[M][K];
float B[K][N];
float C[M][N];

// compute C += A * B
#pragma omp parallel for
for (int jblock2=0; jblock2<M; jblock2+=L2_BLOCKSIZE_J)
  for (int iblock2=0; iblock2<N; iblock2+=L2_BLOCKSIZE_I)
     for (int kblock2=0; kblock2<K; kblock2+=L2_BLOCKSIZE_K)
        for (int jblock1=0; jblock1<L1_BLOCKSIZE_J; jblock1+=L1_BLOCKSIZE_J)
           for (int iblock1=0; iblock1<L1_BLOCKSIZE_I; iblock1+=L1_BLOCKSIZE_I)
              for (int kblock1=0; kblock1<L1_BLOCKSIZE_K; kblock1+=L1_BLOCKSIZE_K)
                  for (int j=0; j<BLOCKSIZE_J; j++)
                     for (int i=0; i<BLOCKSIZE_I; i++)
                        for (int k=0; k<BLOCKSIZE_K; k++)
                           ...
```

Not shown: final level of "blocking" for register locality…

Blocked dense matrix multiplication (1)

Consider SIMD parallelism within a block



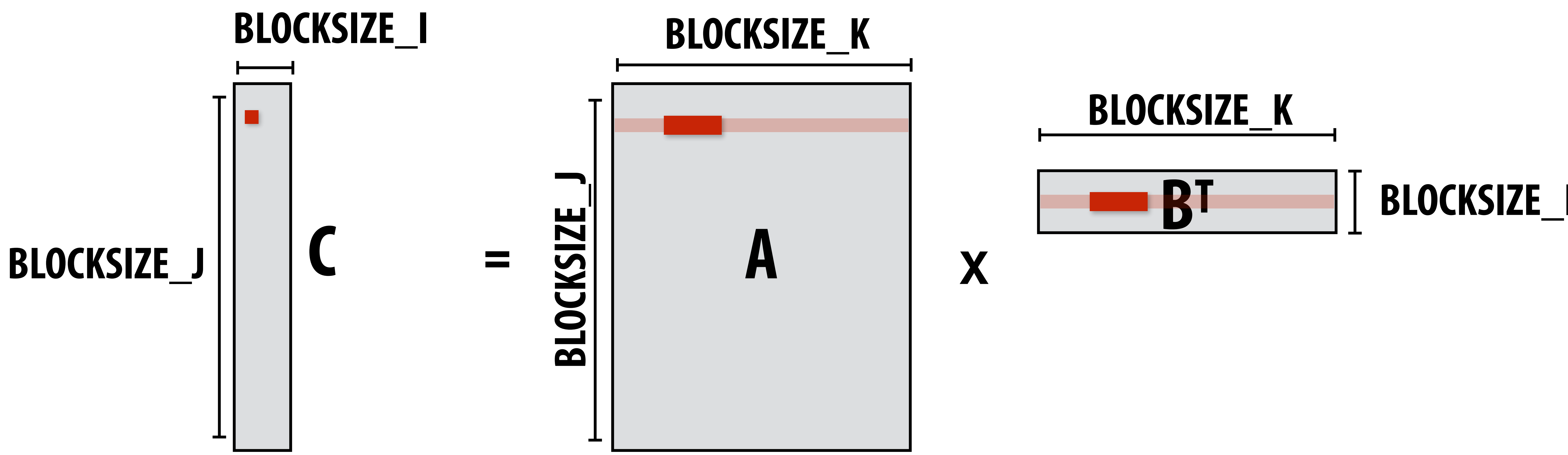

```
...
for (int j=0; j<BLOCKSIZE_J; j++) {
   for (int i=0; i<BLOCKSIZE_I; i+=SIMD_WIDTH) {
      simd_vec C_accum = vec_load(&C[jblock+j][iblock+i]);
      for (int k=0; k<BLOCKSIZE_K; k++) {
         // C = A*B + C
         simd_vec A_val = splat(&A[jblock+j][kblock+k]); // load a single element in vector register
         simd_muladd(A_val, vec_load(&B[kblock+k][iblock+i]), C_accum);
      }
      vec_store(&C[jblock+j][iblock+i], C_accum);
   }
}
```

Vectorize i loop

Good: also improves spatial locality in access to B

Bad: working set increased by SIMD_WIDTH, still walking over B in large steps

Blocked dense matrix multiplication (2)



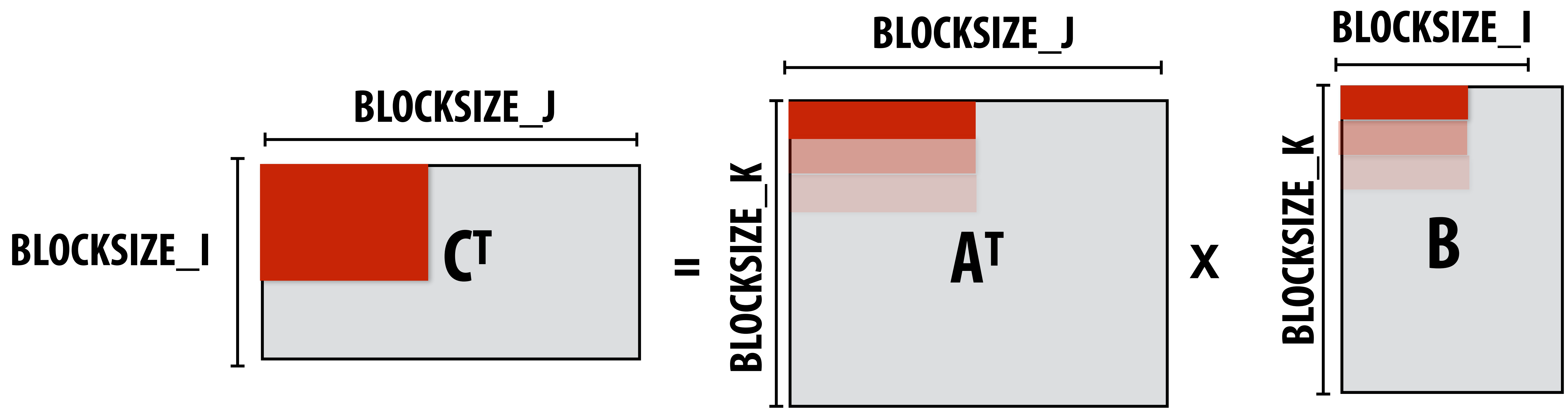

```
...
for (int j=0; j<BLOCKSIZE_J; j++)
   for (int i=0; i<BLOCKSIZE_I; i++) {
      float C_scalar = C[jblock+j][iblock+i];
      // C_scalar += dot(row of A,row of B)
      for (int k=0; k<BLOCKSIZE_K; k+=SIMD_WIDTH) {
        C_scalar += simd_dot(vec_load(&A[jblock+j][kblock+k]), vec_load(&Btrans[iblock+i][[kblock+k]);
      }
      C[jblock+j][iblock+i] = C_scalar;
   }
```

Assume *i* dimension is small. Previous vectorization scheme (1) would not work well.

Pre-transpose block of B (copy block of B to temp buffer in transposed form)

Vectorize innermost loop

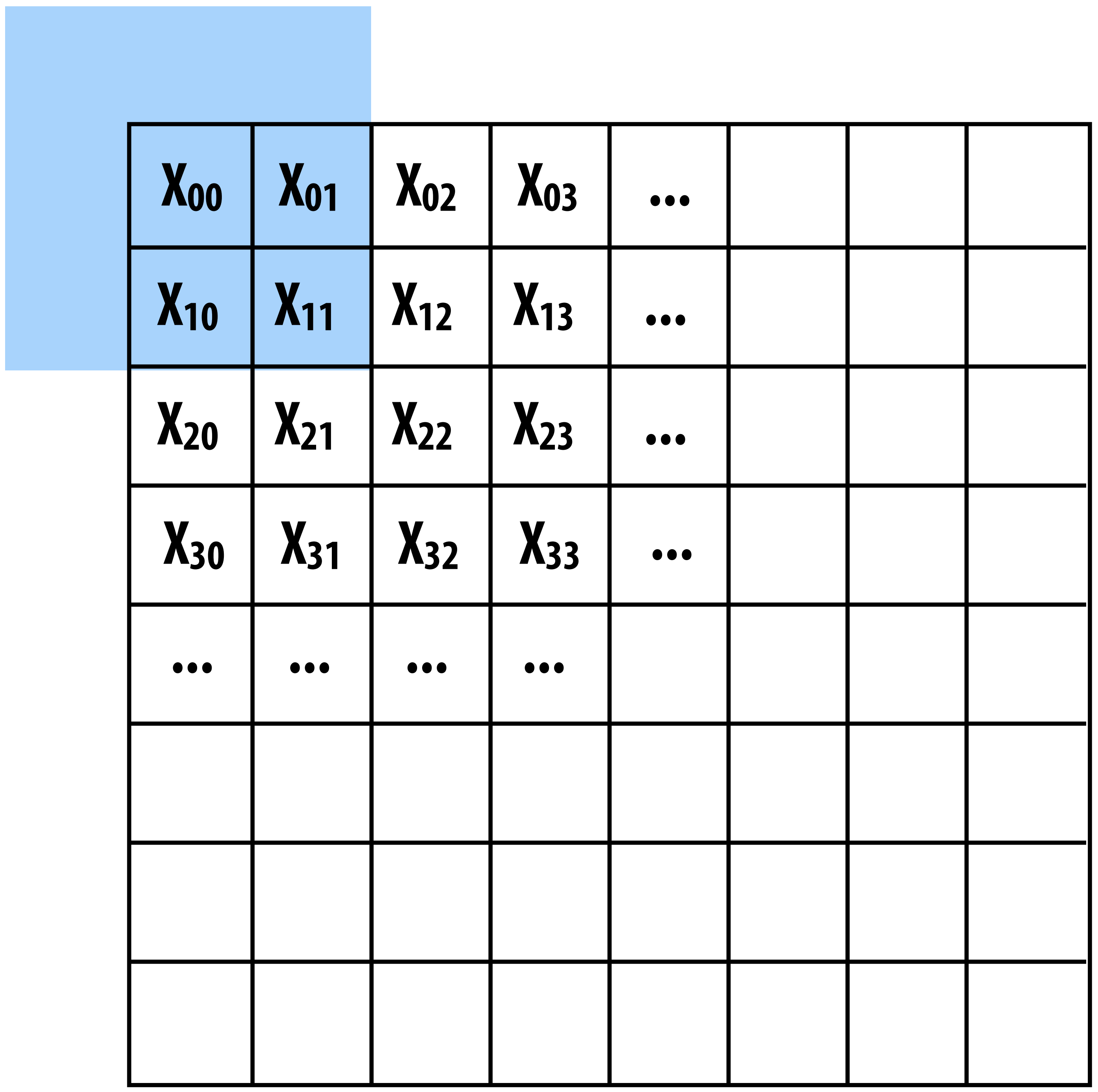
Blocked dense matrix multiplication (3)




```
// assume blocks of A and C are pre-transposed as Atrans and Ctrans
for (int j=0; j<BLOCKSIZE_J; j+=SIMD_WIDTH) {
   for (int i=0; i<BLOCKSIZE_I; i+=SIMD_WIDTH) {

      simd_vec C_accum[SIMD_WIDTH];
      for (int k=0; k<SIMD_WIDTH; k++)   // load C_accum for a SIMD_WIDTH x SIMD_WIDTH chunk of C^T
         C_accum[k] = vec_load(&Ctrans[iblock+i+k][jblock+j]);

      for (int k=0; k<BLOCKSIZE_K; k++) {
        simd_vec bvec = vec_load(&B[kblock+k][iblock+i]);
        for (int kk=0; kk<SIMD_WIDTH; kk++)  // innermost loop items not dependent
            simd_muladd(vec_load(&Atrans[kblock+k][jblock+j], splat(bvec[kk]), C_accum[kk]);
      }

      for (int k=0; k<SIMD_WIDTH; k++)
        vec_store(&Ctrans[iblock+i+k][jblock+j], C_accum[k]);
   }
}
```

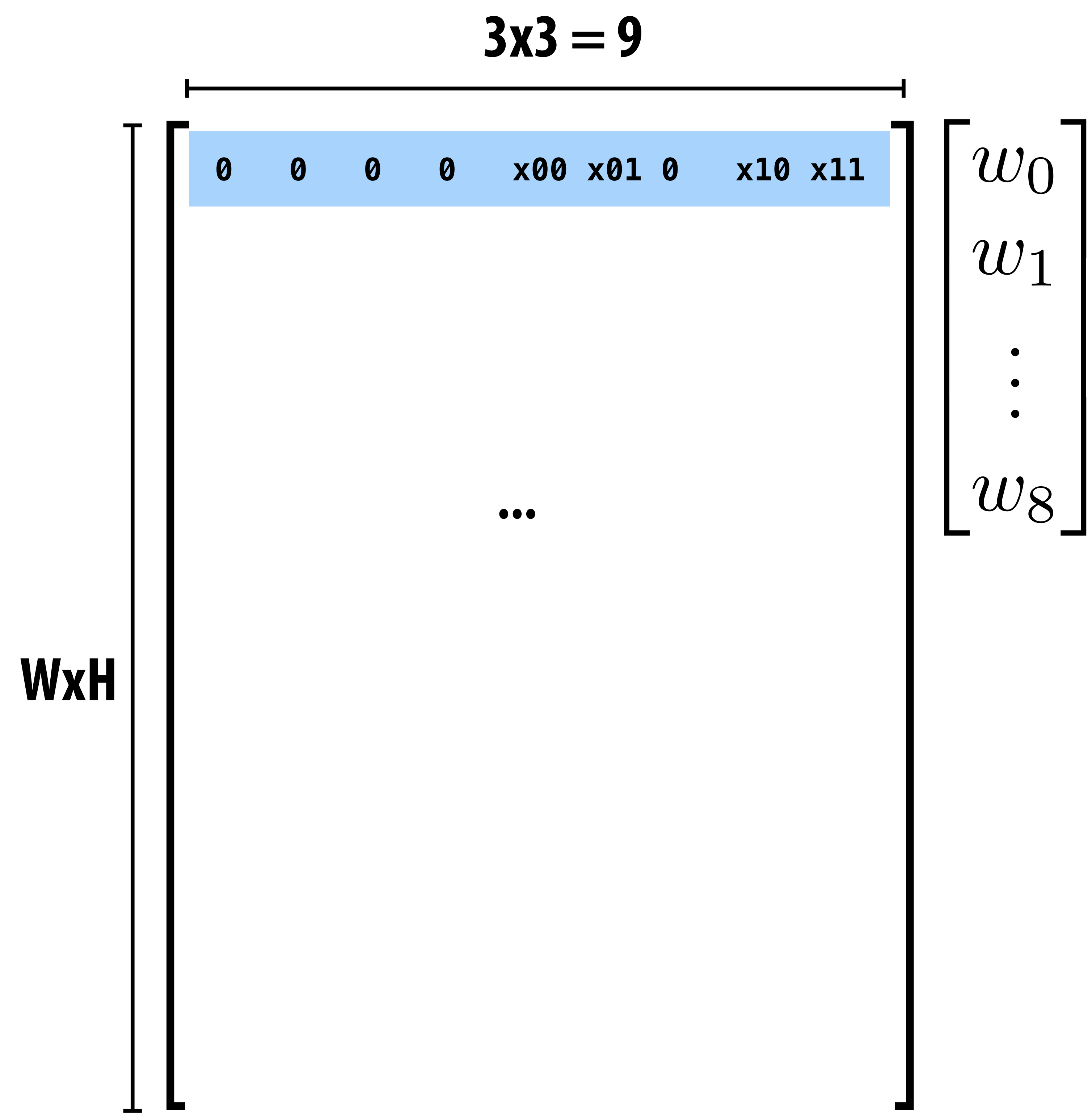
Convolution as matrix-vector product

Construct matrix from elements of input image



O(N) storage multiplier for filter with N elements

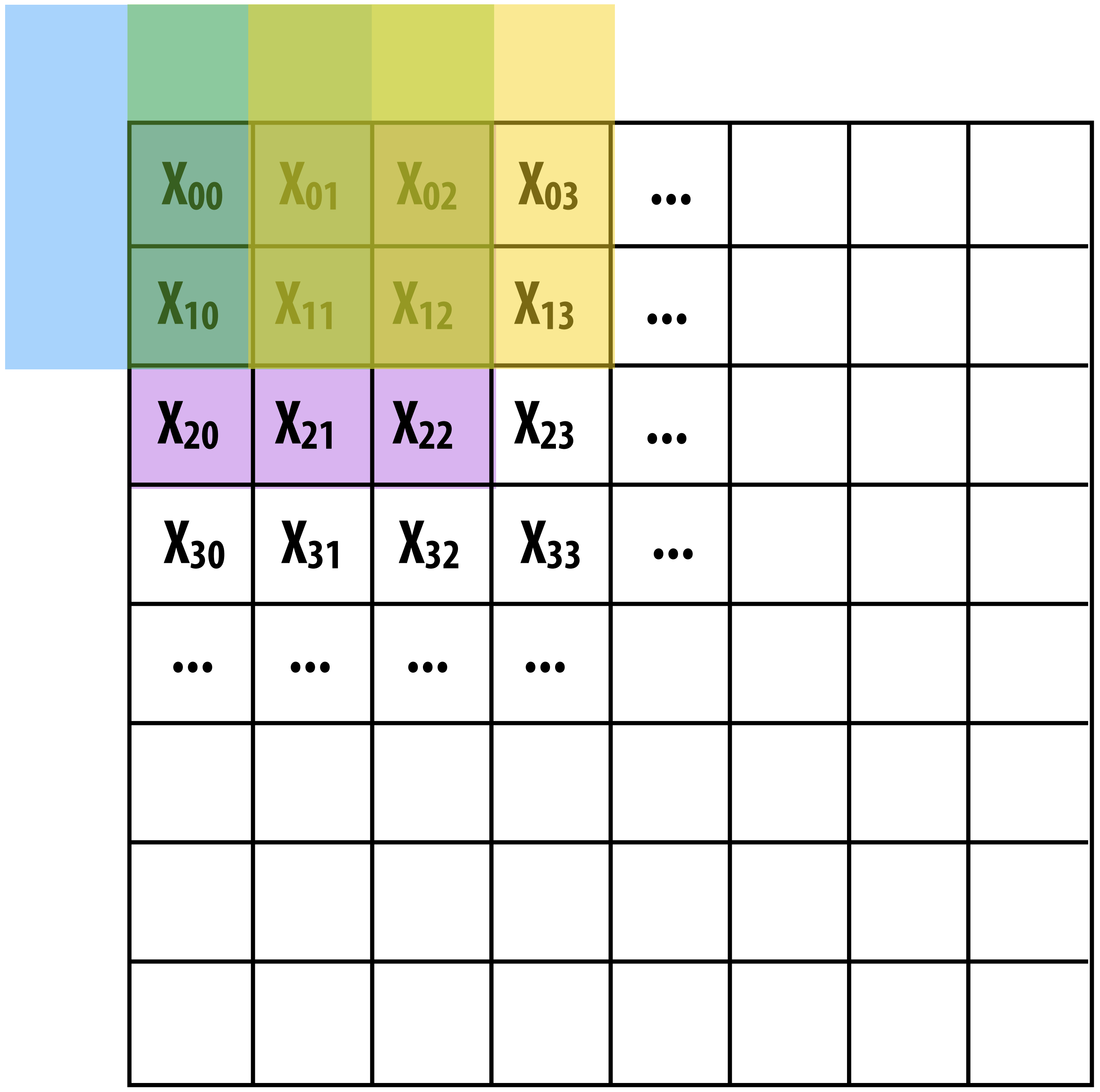
Must construct input data matrix



Note: 0-pad matrix

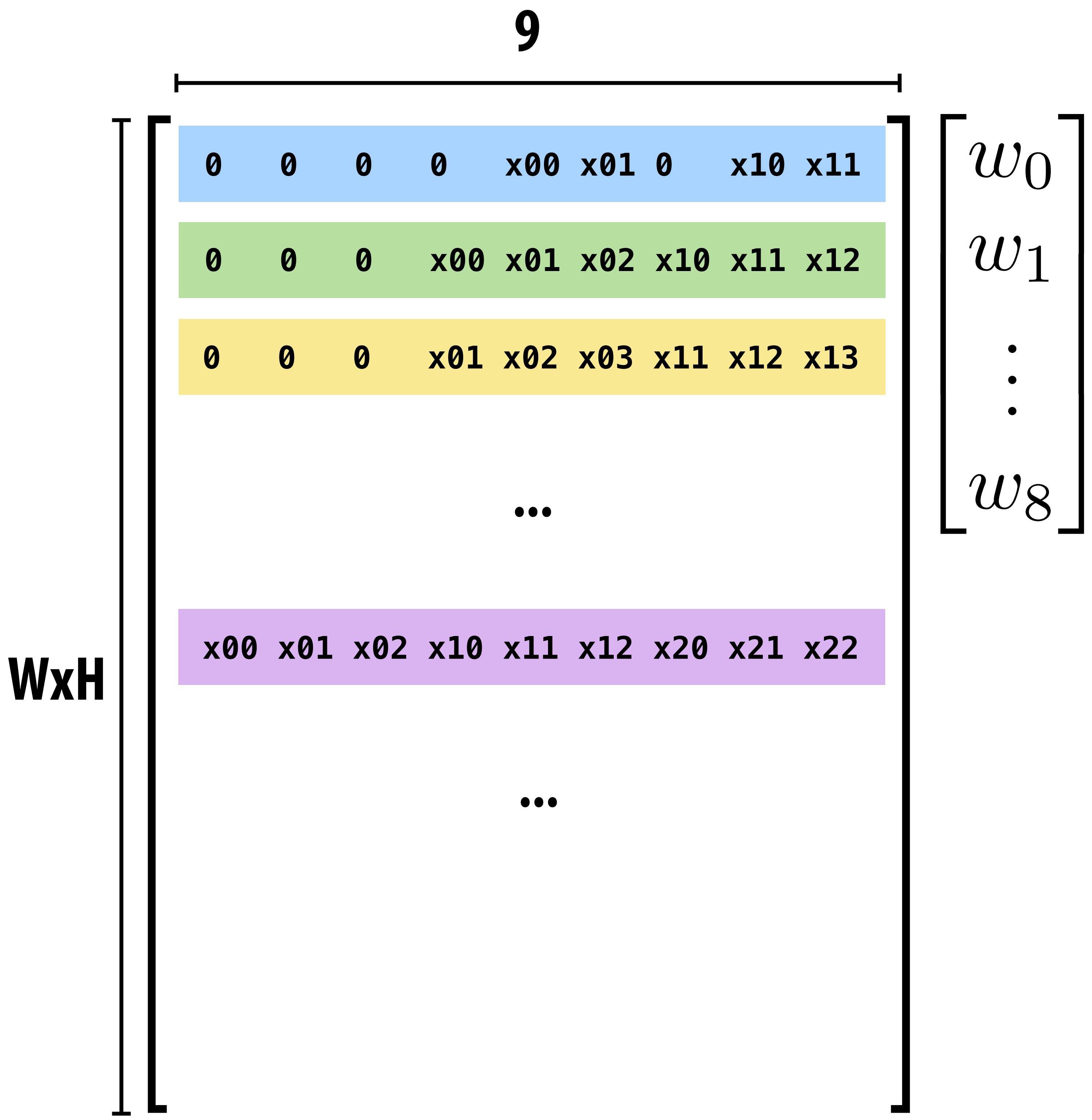
3x3 convolution as matrix-vector product

Construct matrix from elements of input image



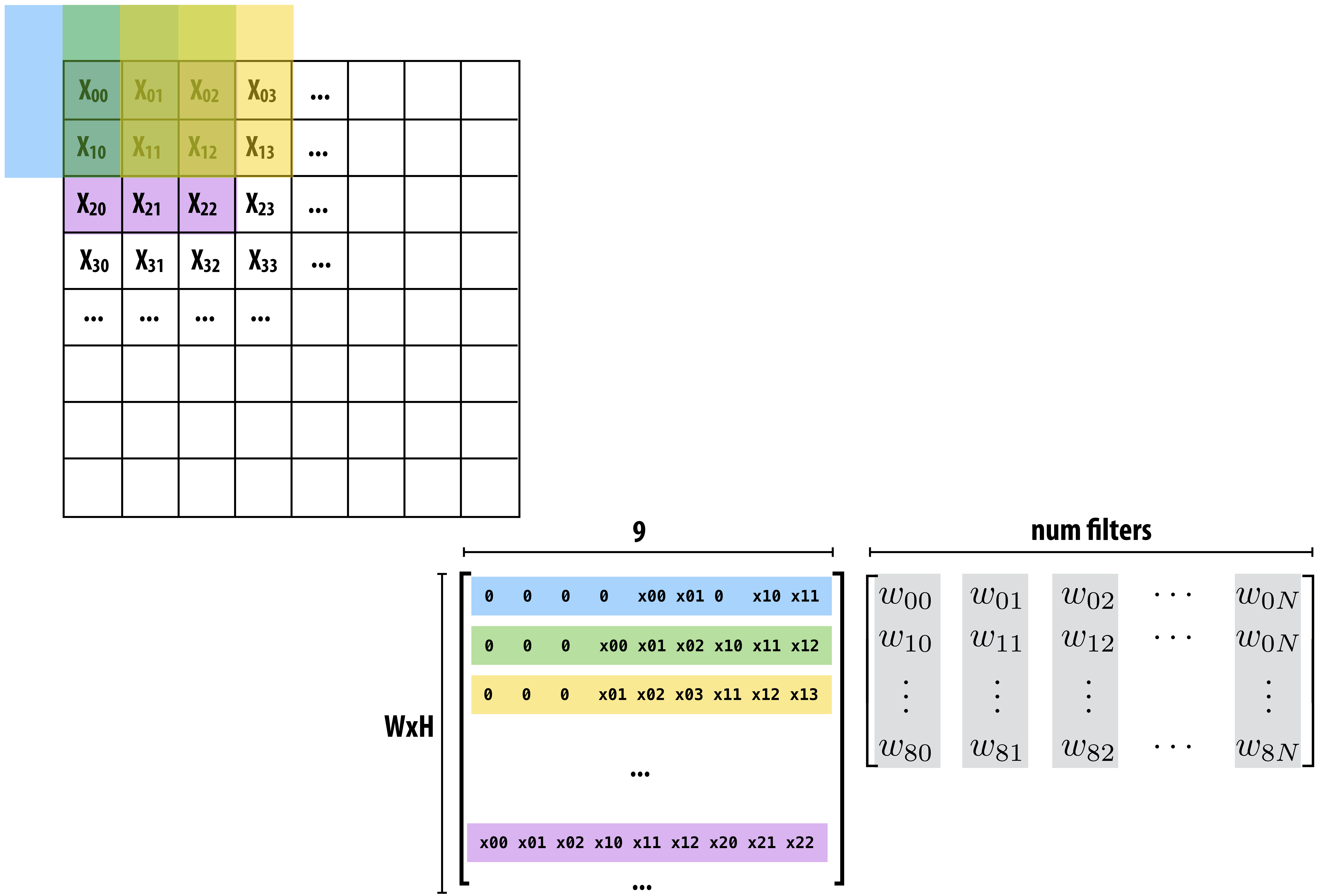
O(N) storage overhead for filter with N elements

Must construct input data matrix

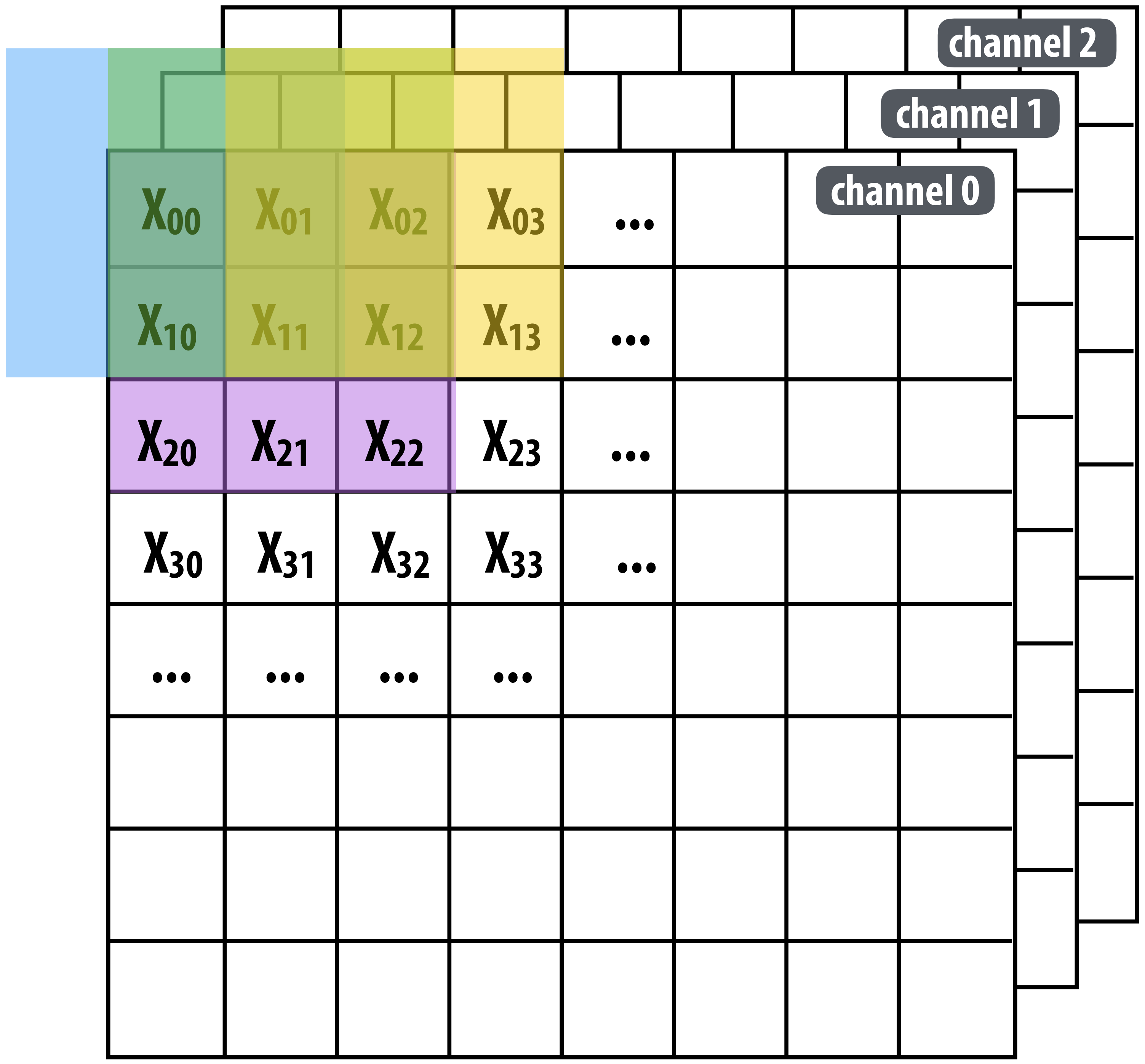


Note: 0-pad matrix

Multiple convolutions as matrix-matrix mult

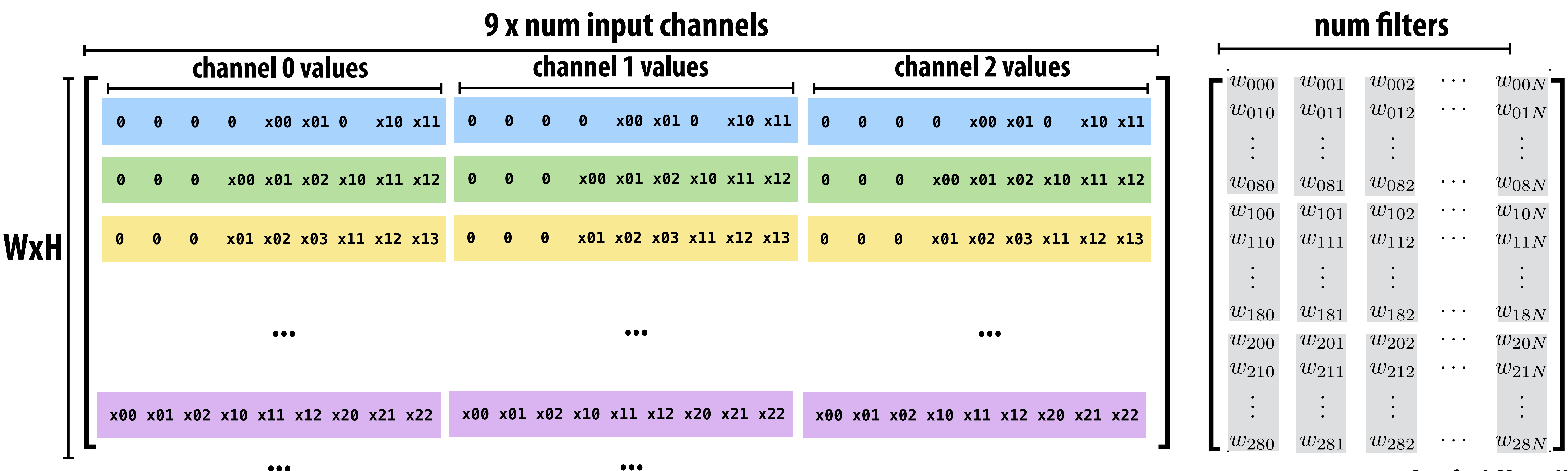


Multiple convolutions on multiple input channels



For each filter, sum responses over input channels

Equivalent to (3 x 3 x num_channels) convolution on (W x H x num_channels) input data



Direct implementation of conv layer

```
float input[IMAGE_BATCH_SIZE][INPUT_HEIGHT][INPUT_WIDTH][INPUT_DEPTH];
float output[IMAGE_BATCH_SIZE][INPUT_HEIGHT][INPUT_WIDTH][LAYER_NUM_FILTERS];
float layer_weights[LAYER_NUM_FILTERS][LAYER_CONVY][LAYER_CONVX][INPUT_DEPTH];

// assumes convolution stride is 1
for (int img=0; img<IMAGE_BATCH_SIZE; img++)
   for (int j=0; j<INPUT_HEIGHT; j++)
      for (int i=0; i<INPUT_WIDTH; i++)
         for (int f=0; f<LAYER_NUM_FILTERS; f++) {
            output[img][j][i][f] = 0.f;
            for (int kk=0; kk<INPUT_DEPTH; kk++)       // sum over filter responses of input channels
               for (int jj=0; jj<LAYER_FILTER_Y; jj++)    // spatial convolution (Y)
                  for (int ii=0; ii<LAYER_FILTER_X; ii+)  // spatial convolution (X)
                      output[img][j][i][f] += layer_weights[f][jj][ii][kk] * input[img][j+jj][i+ii][kk];
          }
```

Seven loops with significant input data reuse: reuse of filter weights (during convolution), and reuse of input values (across different filters)

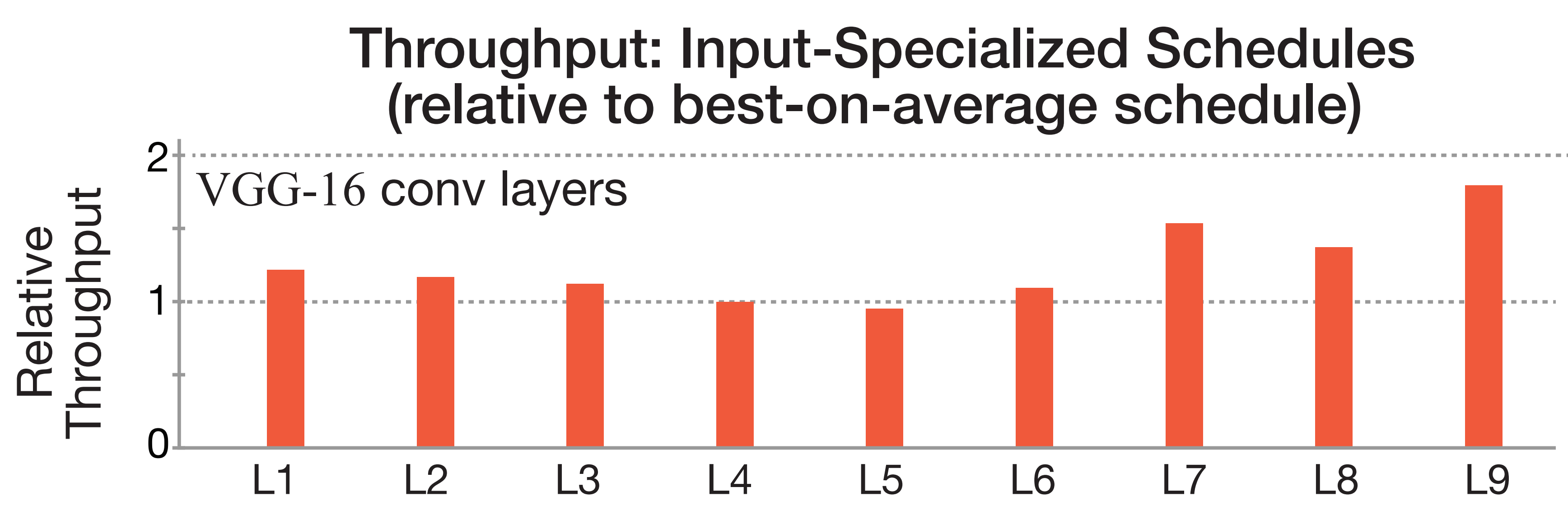
Avoids O(N) footprint increase by avoiding materializing input matrix
In theory loads O(N) times less data (potentially higher arithmetic intensity… but matrix mult is typically compute-bound)
But must roll your own highly optimized implementation of complicated loop nest.

Convolutional layer in Halide

```
int in_w, in_h, in_ch = 4;             // input params: assume initialized

Func in_func;                          // assume input function is initialized

int num_f, f_w, f_h, pad, stride;      // parameters of the conv layer

Func forward = Func("conv");
Var x, y, z, n;                        // n is minibatch dimension

// This creates a padded input to avoid checking boundary
// conditions while computing the actual convolution
f_in_bound = BoundaryConditions::repeat_edge(in_func, 0, in_w, 0, in_h);

// Create buffers for layer parameters
Halide::Buffer<float> W(f_w, f_h, in_ch, num_f)
Halide::Buffer<float> b(num_f);

// domain of summation for filter with W x H x in_ch
RDom r(0, f_w, 0, f_h, 0, in_ch);

// Initialize to bias
forward(x, y, z, n) =  b(z);
forward(x, y, z, n) += W(r.x, r.y, r.z, z) *
                       f_in_bound(x*stride + r.x - pad, y*stride + r.y - pad, r.z, n);
```

Consider scheduling this seven-dimensional loop nest!

Different layers of a single DNN may benefit from unique scheduling strategies



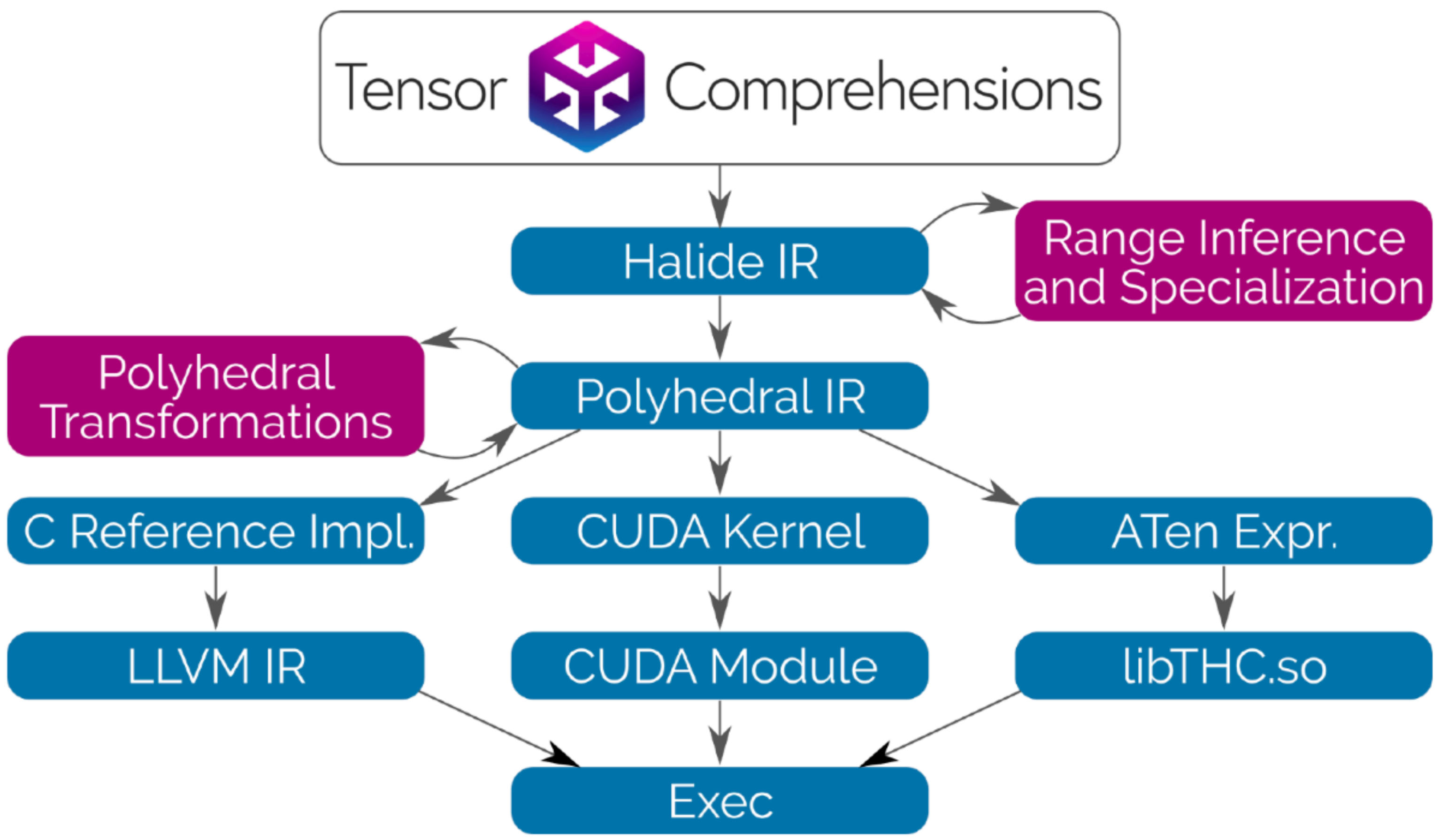
[Figure credit: Mullapudi et al. 2016]

Table 1. MobileNet Body Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
$5\times$ Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Notice sizes of weights and activations in this network: (and consider SIMD widths of modern machines). Ug!

Many efforts to automatically schedule key DNN operations



tvm Open Deep Learning Compiler Stack

license Apache 2.0 build passing

Documentation | Contributors | Community | Release Notes

TVM is a compiler stack for deep learning systems. It is designed to close the gap between the productivity-focused deep learning frameworks, and the performance- and efficiency-focused hardware backends. TVM works with deep learning frameworks to provide end to end compilation to different backends. Checkout the tvm stack homepage for more information.

NVIDIA TensorRT

Programmable Inference Accelerator

Reminder: energy cost of data access

Significant fraction of energy expended moving data to processor ALUs

Operation	Energy [pJ]	Relative Cost
32 bit int ADD	0.1	1
32 bit float ADD	0.9	9
32 bit Register File	1	10
32 bit int MULT	3.1	31
32 bit float MULT	3.7	37
32 bit SRAM Cache	5	50
32 bit DRAM Memory	**640**	**6400**

Estimates for 45nm process
[Source: Mark Horowitz]

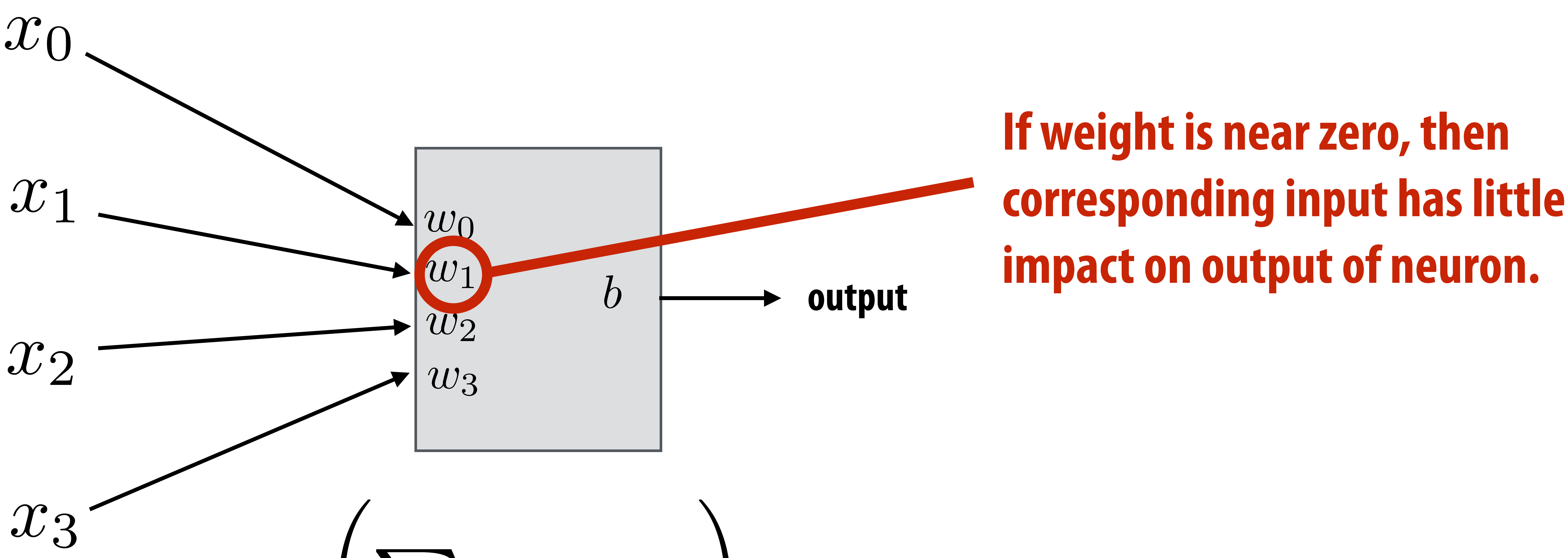
Reducing network footprint

- **Early DNN designs: large storage cost for model parameters**
  - AlexNet model: ~200 MB
  - VGG-16 model: ~500 MB
  - ResNet-50: 102 MB
  - Inception-v3: 91 MB

- **In many modern DNNs, activations (intra-layer intermediate buffers) require more storage than weights**
  - So bandwidth is often due to reading/writing intermediates

Is there an opportunity for compression?

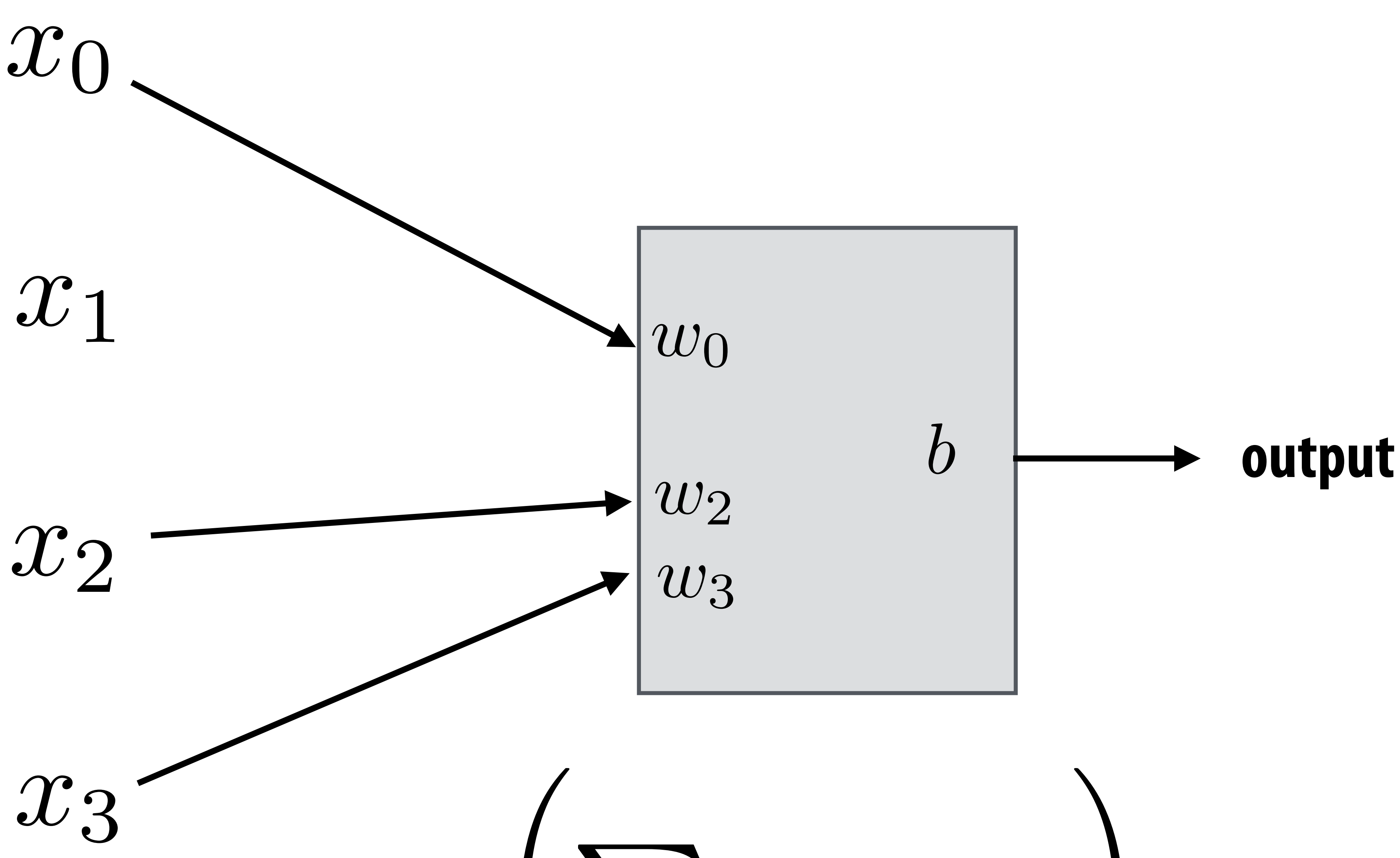
"Pruning" (sparsifying) a network



$$f\left(\sum_i x_i w_i + b\right)$$

$$f(x) = max(0, x)$$

"Pruning" (sparsifying) a network



$$f\left(\sum_i x_i w_i + b\right)$$

$$f(x) = max(0, x)$$

Idea: prune connections with near zero weight

Remove entire units if all connections are pruned.

Representing "sparsified" networks

Step 1: prune low-weight links (iteratively retrain network, then prune)

- Store weight matrices in compressed sparse row (CSR) format

```
Indices    1    4   9  ...
Value     1.8  0.5  2.1
```

0	1.8	0	0	0.5	0	0	0	0	1.1	...

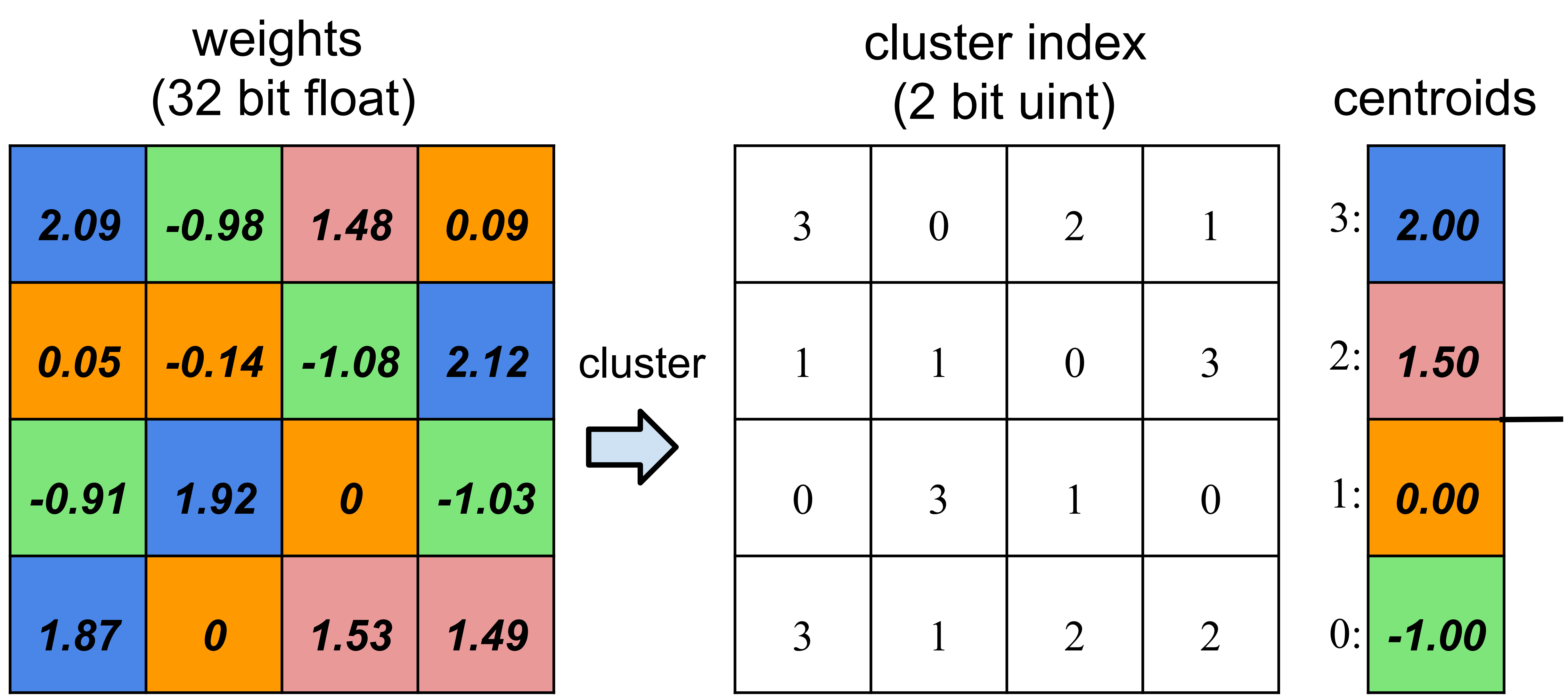
Reduce storage over head of indices by delta encoding them to fit in 8 bits

```
Indices   1    3    5  ...
Value     1.8  0.5  2.1
```

Efficiently storing the surviving connections

Step 2: Weight sharing: make surviving connections share a small set of weights

- Cluster weights via k-means clustering
- Compress weights by only storing index of assigned cluster (lg(k) bits)
- This is a form of lossy compression



Step 3: Huffman encode quantized weights and CSR indices (lossless compression)

[Figure credit: Han ICLR16]

VGG-16 sparsification

[Han ICLR16]

Large savings in fully connected layers due to combination of pruning, quantization, Huffman encoding *

Layer	#Weights	Weights% (P)	Weigh bits (P+Q)	Weight bits (P+Q+H)	Index bits (P+Q)	Index bits (P+Q+H)	Compress rate (P+Q)	Compress rate (P+Q+H)
conv1_1	2K	58%	8	6.8	5	1.7	40.0%	29.97%
conv1_2	37K	22%	8	6.5	5	2.6	9.8%	6.99%
conv2_1	74K	34%	8	5.6	5	2.4	14.3%	8.91%
conv2_2	148K	36%	8	5.9	5	2.3	14.7%	9.31%
conv3_1	295K	53%	8	4.8	5	1.8	21.7%	11.15%
conv3_2	590K	24%	8	4.6	5	2.9	9.7%	5.67%
conv3_3	590K	42%	8	4.6	5	2.2	17.0%	8.96%
conv4_1	1M	32%	8	4.6	5	2.6	13.1%	7.29%
conv4_2	2M	27%	8	4.2	5	2.9	10.9%	5.93%
conv4_3	2M	34%	8	4.4	5	2.5	14.0%	7.47%
conv5_1	2M	35%	8	4.7	5	2.5	14.3%	8.00%
conv5_2	2M	29%	8	4.6	5	2.7	11.7%	6.52%
conv5_3	2M	36%	8	4.6	5	2.3	14.8%	7.79%
fc6	103M	4%	5	3.6	5	3.5	1.6%	1.10%
fc7	17M	4%	5	4	5	4.3	1.5%	1.25%
fc8	4M	23%	5	4	5	3.4	7.1%	5.24%
Total	138M	7.5%(13×)	6.4	4.1	5	3.1	3.2% (**31×**)	2.05% (**49×**)

P = connection pruning (prune low weight connections)

Q = quantize surviving weights (using shared weights)

H = Huffman encode

ImageNet Image Classification Performance

	Top-1 Error	Top-5 Error	Model size	
VGG-16 Ref	31.50%	11.32%	552 MB	
VGG-16 Compressed	31.17%	10.91%	**11.3 MB**	49×

*** Benefits of automatic pruning apply mainly to fully connected layers, but unfortunately many modern networks are dominated by costs of convolutional layers**

Compressing weights (and activations)

- Many efforts to use low precision values for DNN weights and intermediate activations
- In the extreme case: 1-bit

XNOR-Net: ImageNet Classification Using Binary Convolutional Neural Networks

Mohammad Rastegari[†], Vicente Ordonez[†], Joseph Redmon[*], Ali Farhadi[†*]

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{mohammadr,vicenteor}@allenai.org
{pjreddie,ali}@cs.washington.edu

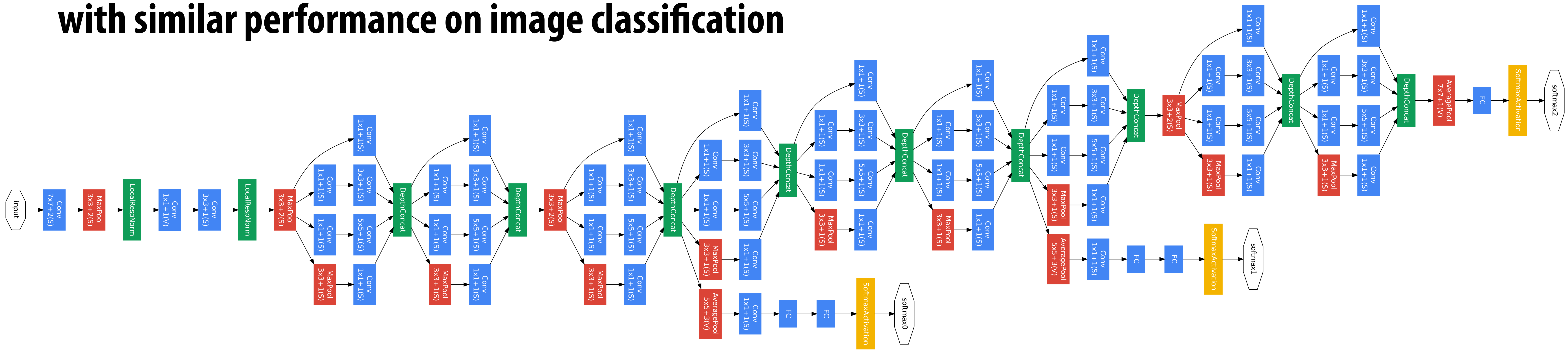
Abstract. We propose two efficient approximations to standard convolutional neural networks: Binary-Weight-Networks and XNOR-Networks. In Binary-Weight-Networks, the filters are approximated with binary values resulting in 32× memory saving. In XNOR-Networks, both the filters and the input to convolutional layers are binary. XNOR-Networks approximate convolutions using primarily binary operations. This results in 58× faster convolutional operations (in terms of number of the high precision operations) and 32× memory savings. XNOR-Nets offer the possibility of running state-of-the-art networks on CPUs (rather than GPUs) in real-time. Our binary networks are simple, accurate, efficient, and work on challenging visual tasks. We evaluate our approach on the ImageNet classification task. The classification accuracy with a Binary-Weight-Network version of AlexNet is the same as the full-precision AlexNet. We compare our method with recent network binarization methods, BinaryConnect and BinaryNets, and outperform these methods by large margins on ImageNet, more than 16% in top-1 accuracy. Our code is available at: http://allenai.org/plato/xnornet.

This a great example of non-domain-specific vs. domain-specific approach to innovation

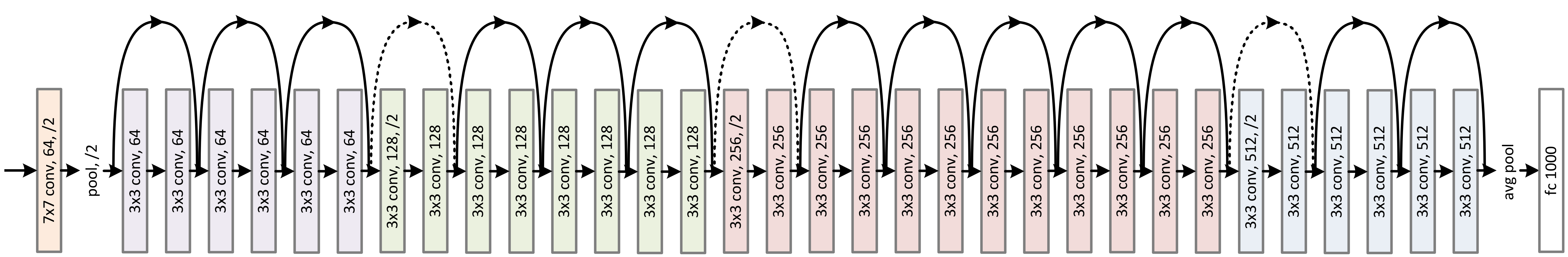
Leveraging domain-knowledge: more efficient topologies (aka better algorithm design)

- Original DNNs for image recognition where over-provisioned
  - Large filters, many filters
- Modern DNNs designs are hand-designed to be sparser

SqueezeNet: [Iandola 2017] Reduced number of parameters in AlexNet by 50x, with similar performance on image classification

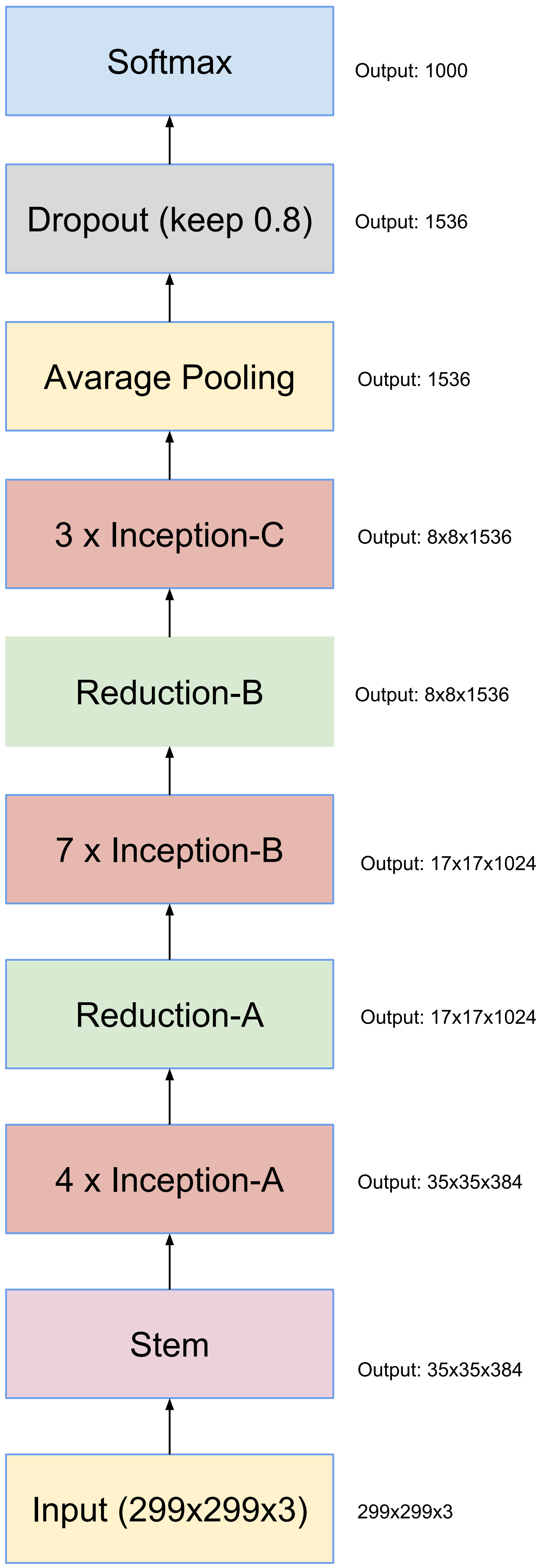


Inception v1 (GoogleLeNet) — 27 total layers, 7M parameters

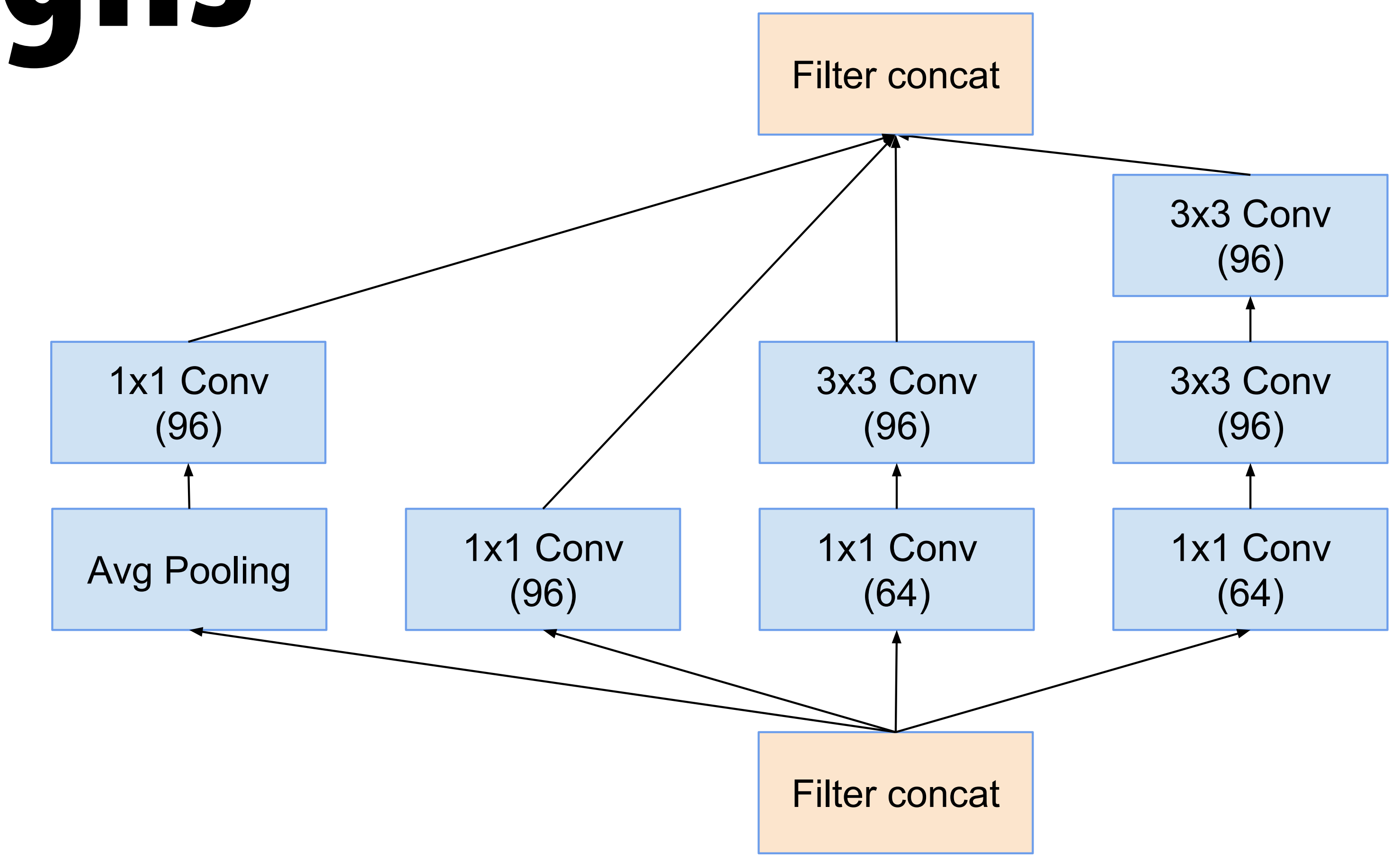


ResNet (34 layer version)

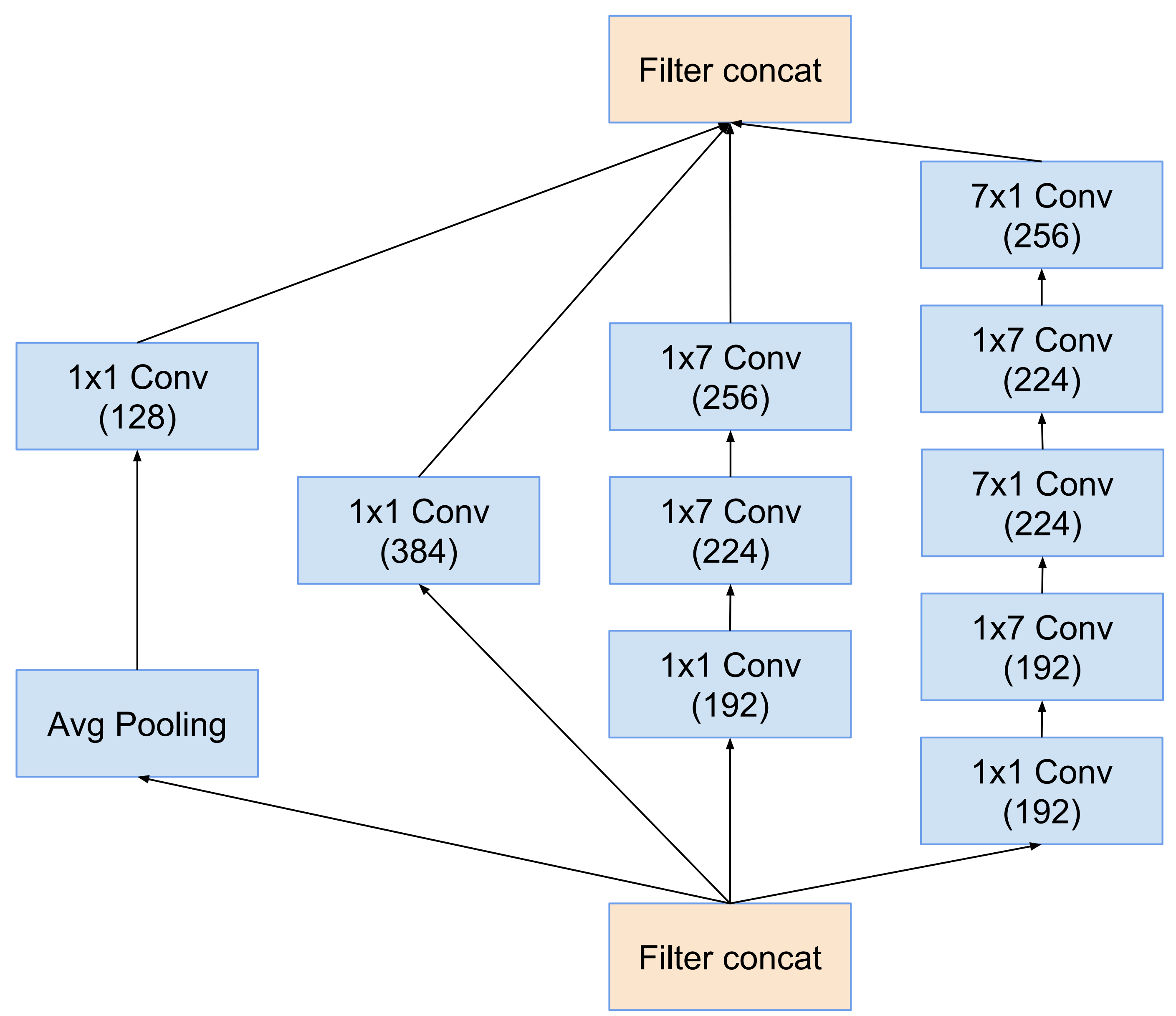
Modular network designs



Inception v4

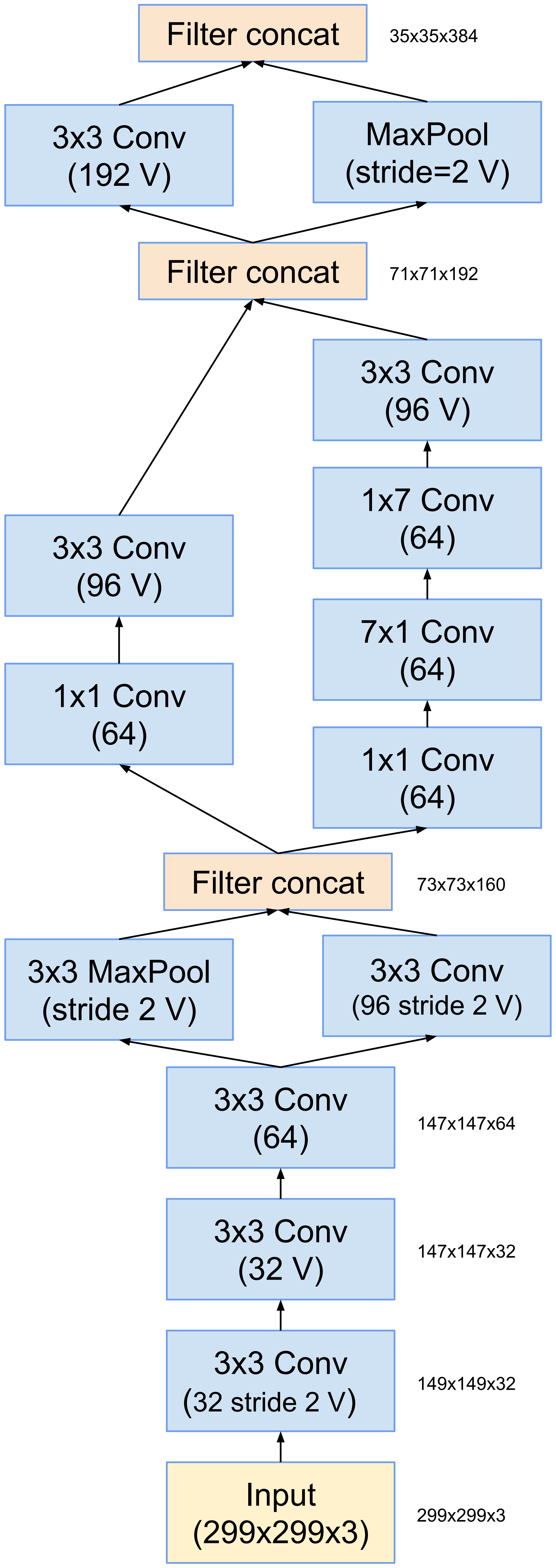


A block

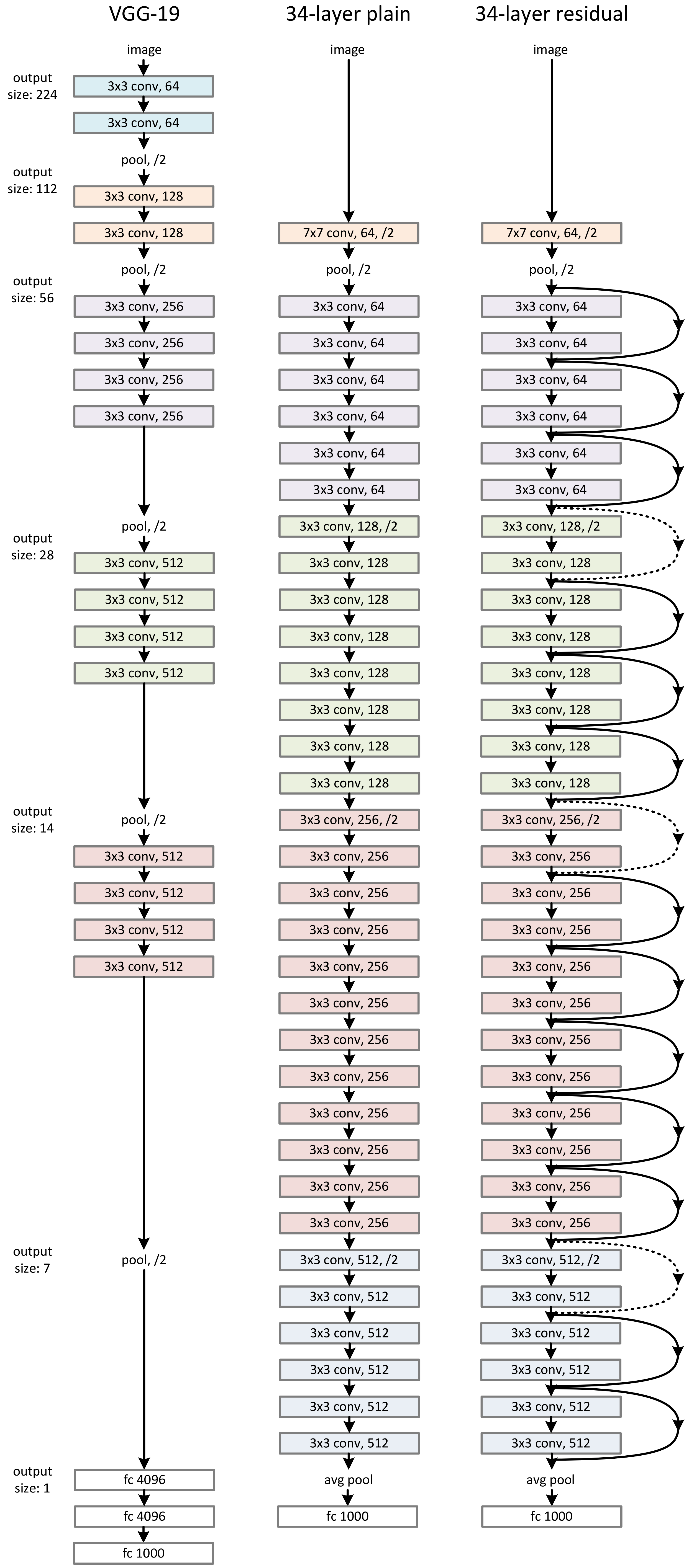


B block

Inception stem



ResNet



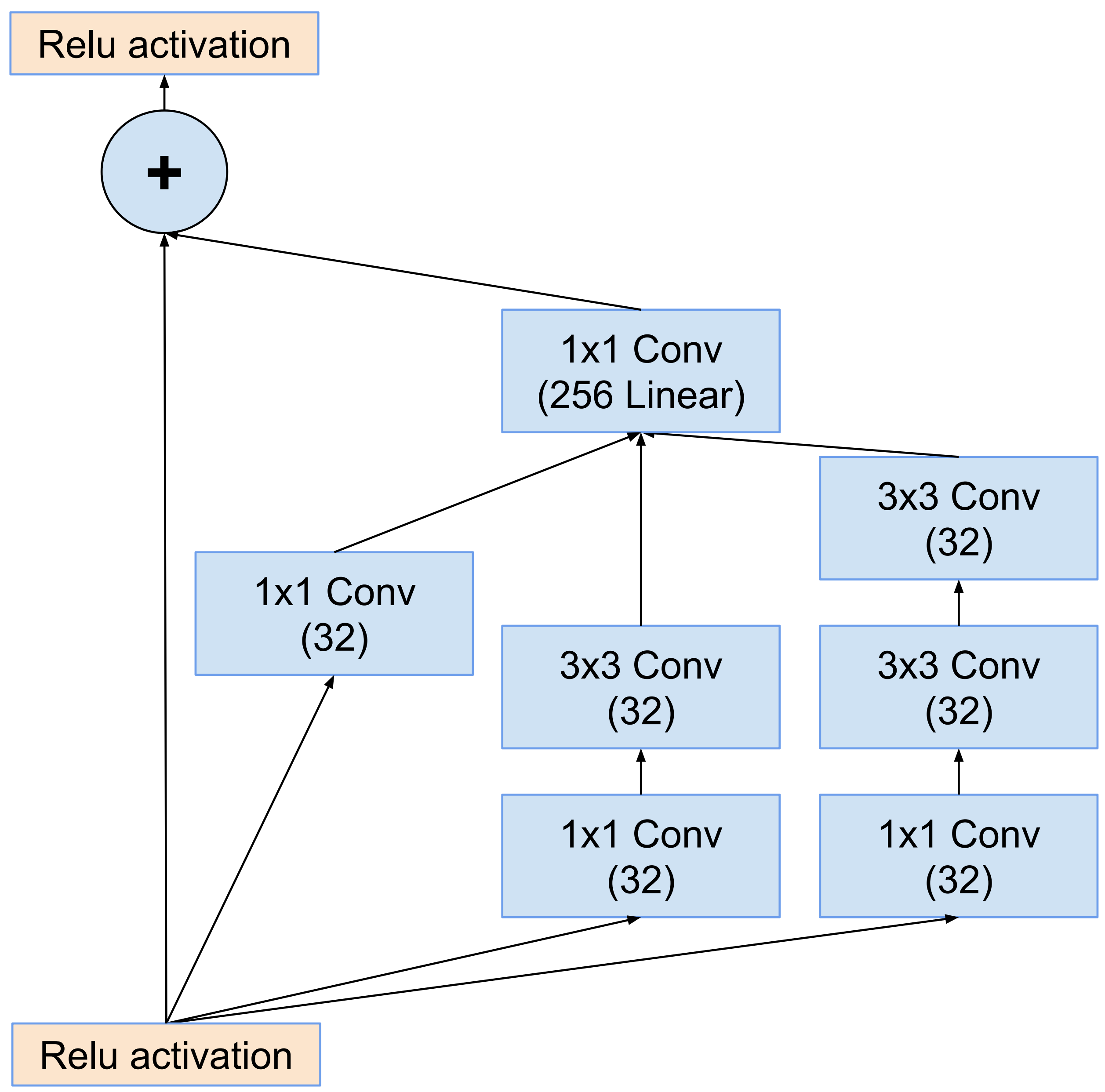
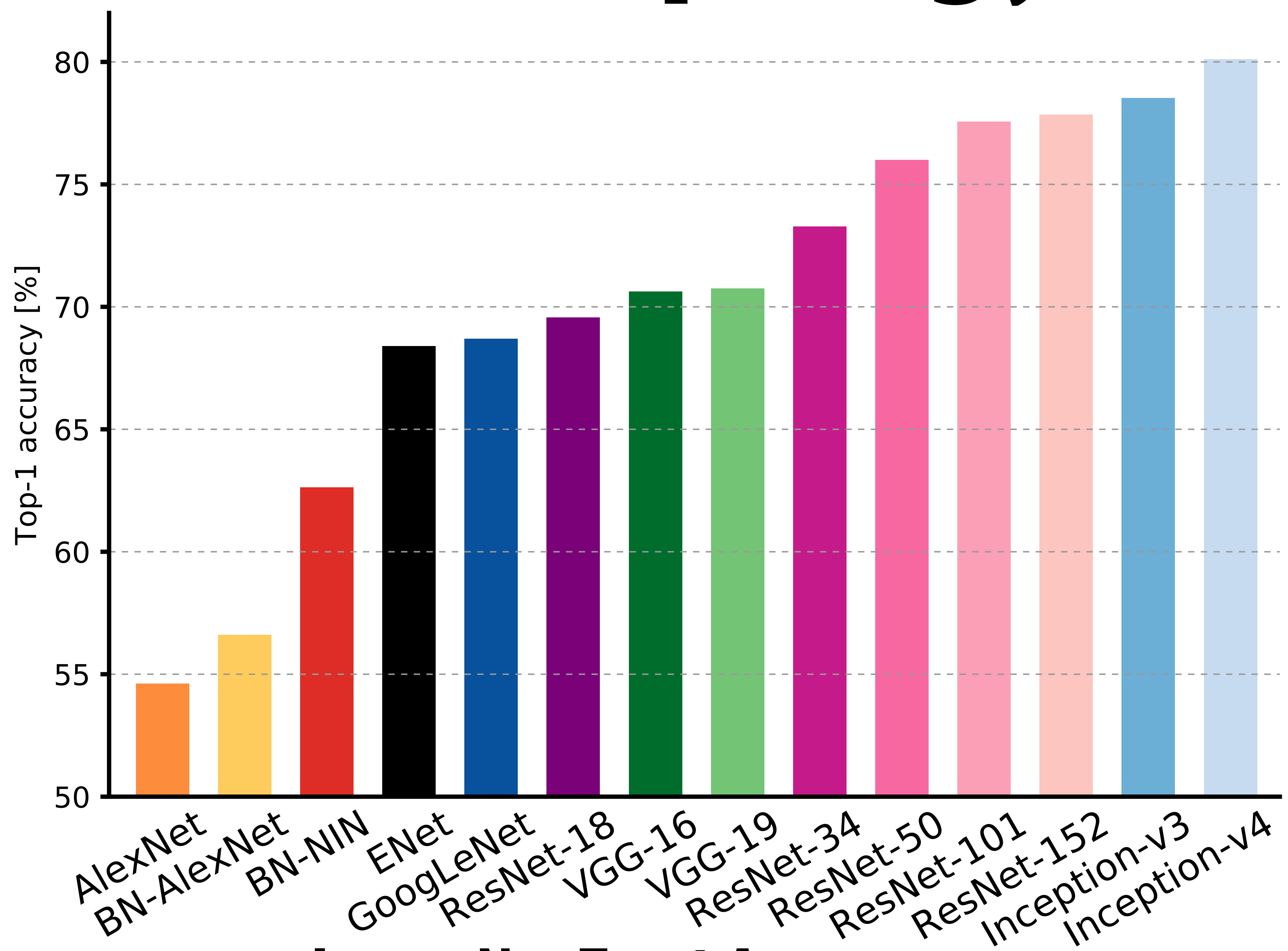
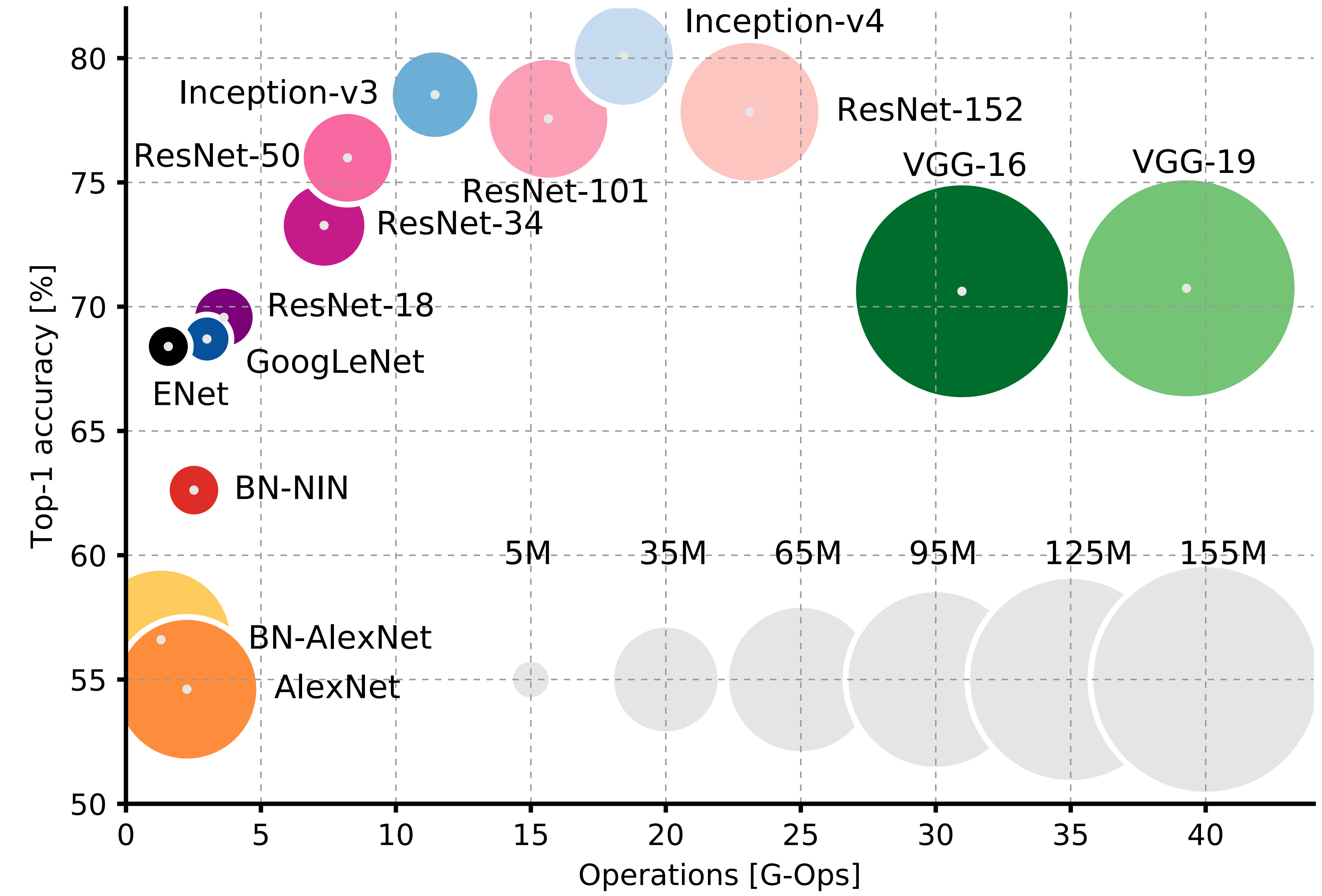


Figure 10. The schema for 35 × 35 grid (Inception-ResNet-A) module of Inception-ResNet-v1 network.

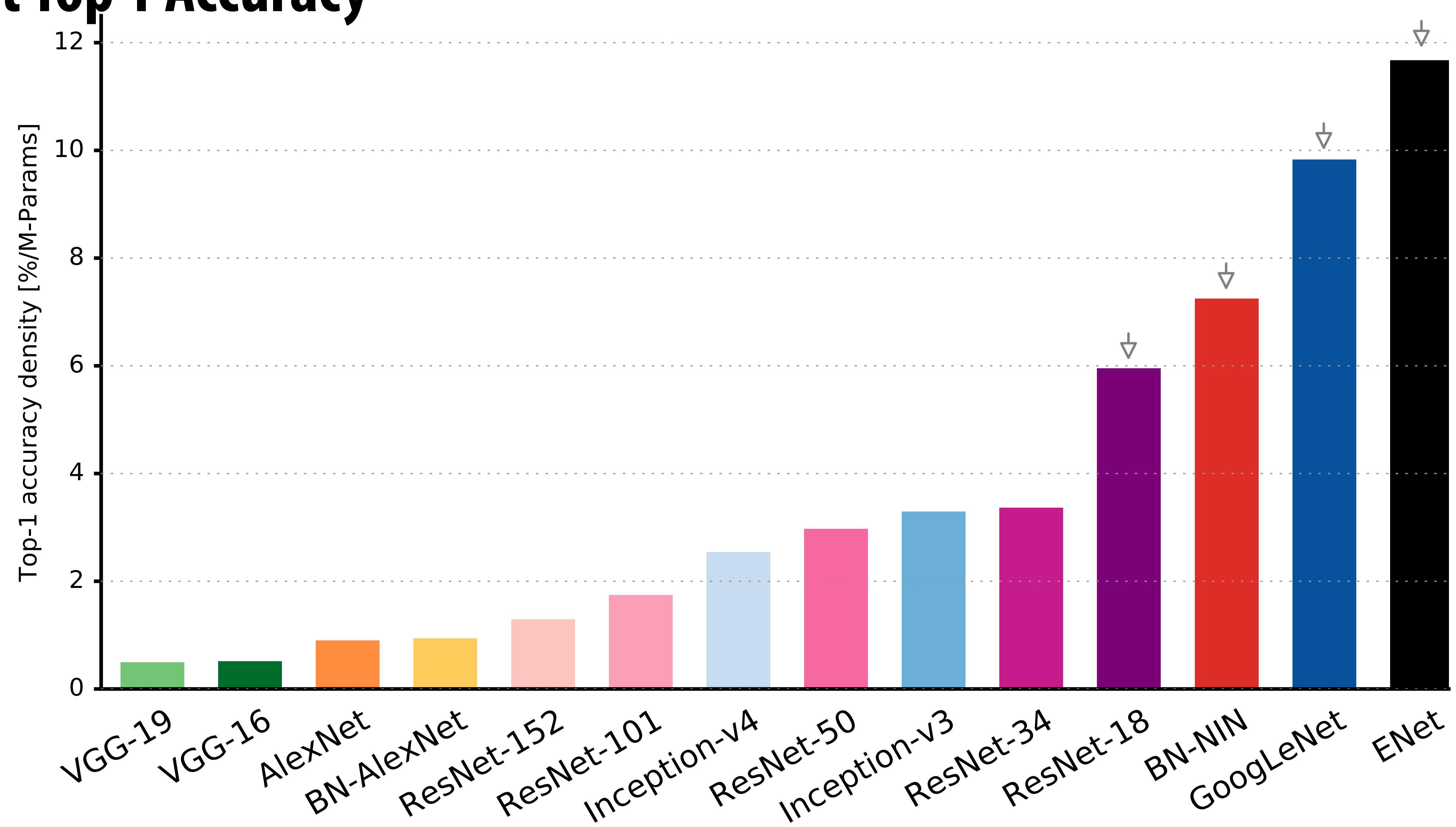
Effect of topology innovation



ImageNet Top 1 Accuracy



Flops cost (area of circle is # params)



Accuracy (points) per flop

Figure credit: Canziani et al 2017

Improving accuracy/cost (image classification)

2014 → 2017 **~ 25x improvement in cost at similar accuracy**

	ImageNet Top-1 Accuracy	Num Params	Cost/image (MADDs)	
VGG-16	71.5%	138M	15B	[2014]
GoogleNet	70%	6.8M	1.5B	[2015]
ResNet-18	73% *	11.7M	1.8B	[2016]
MobileNet-224	70.5%	4.2M	0.6B	[2017]

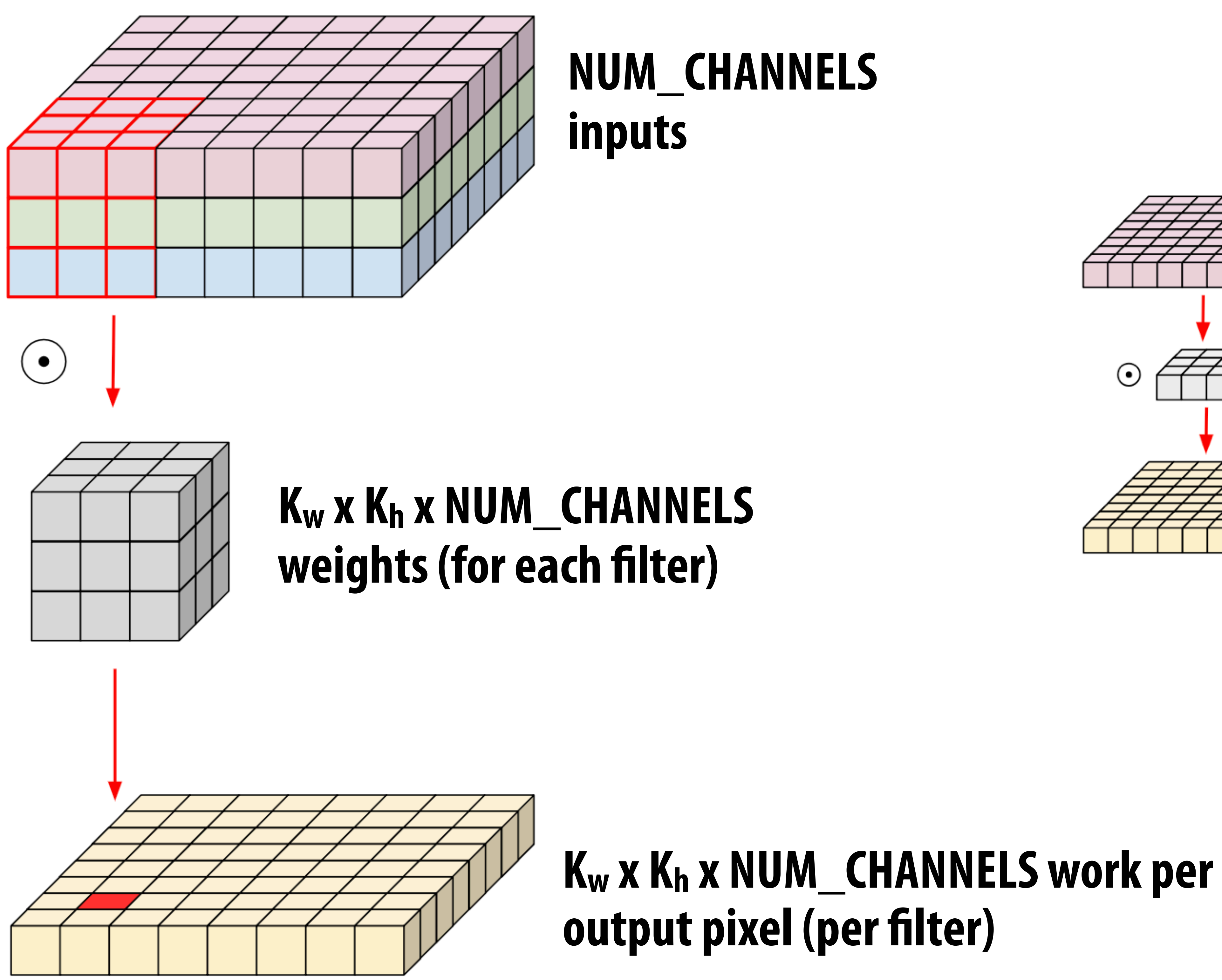
* 10-crop results (ResNet 1-crop results are similar to other DNNs in this table)

Depthwise separable convolution

Main idea: factor NUM_FILTERS 3x3xNUM_CHANNELS convolutions into:

- NUM_CHANNELS 3x3x1 convolutions for each input channel
- And NUM_FILTERS 1x1xNUM_CHANNELS convolutions to combine the results

Convolution Layer



Depthwise Separable Conv Layer

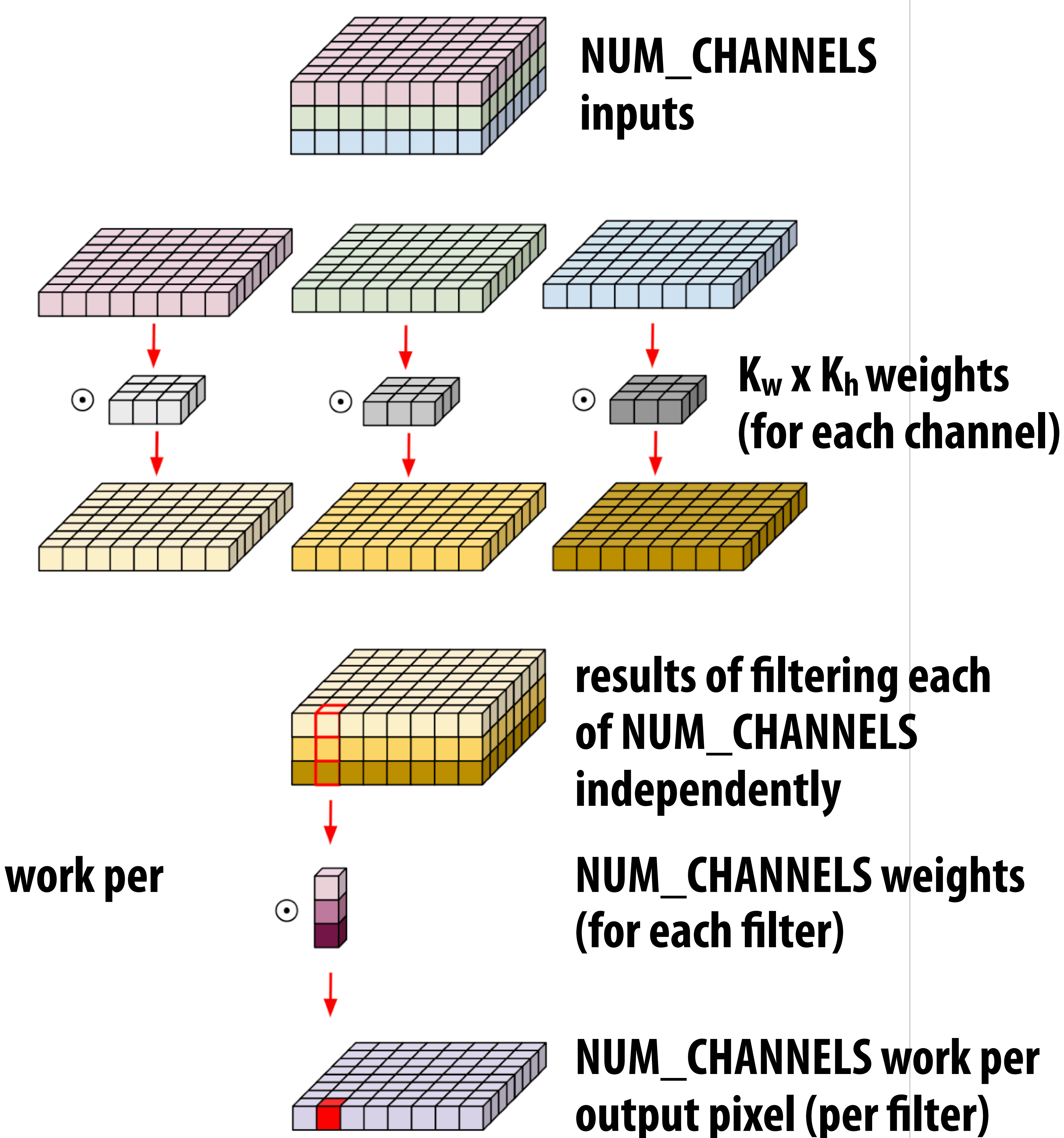
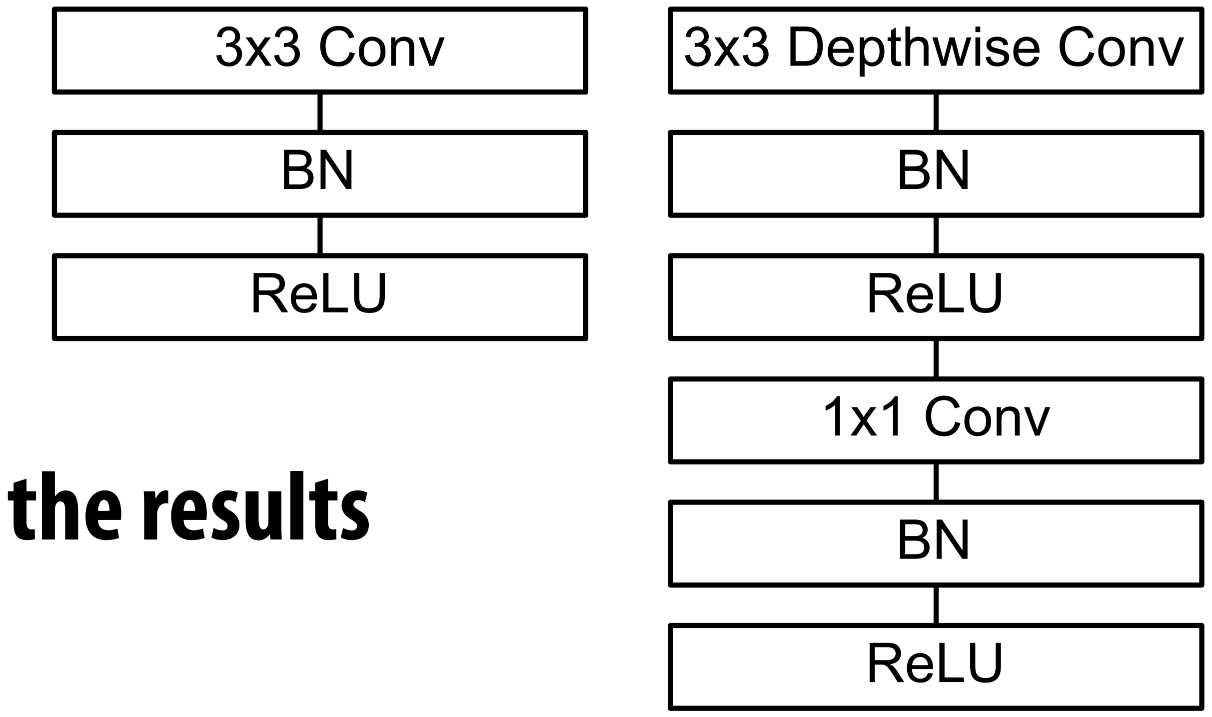


Image credit: Eli Bendersky
https://eli.thegreenplace.net/2018/depthwise-separable-convolutions-for-machine-learning/

MobileNet

[Howard et al. 2017]



Factor NUM_FILTERS 3x3xNUM_CHANNELS convolutions into:
- **NUM_CHANNELS 3x3x1 convolutions for each input channel**
- **And NUM_FILTERS 1x1xNUM_CHANNELS convolutions to combine the results**

Table 1. MobileNet Body Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1 Conv / s1	$3 \times 3 \times 512$ dw $1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$ $14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Image classification (ImageNet)
Comparison to Common DNNs

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
GoogleNet	69.8%	1550	6.8
VGG 16	71.5%	15300	138

Image classification (ImageNet)
Comparison to Other Compressed DNNs

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
0.50 MobileNet-160	60.2%	76	1.32
Squeezenet	57.5%	1700	1.25
AlexNet	57.2%	720	60

Value of improving DNN topology

- Increasing overall accuracy on a task (often primary goal of CV/ML papers)
- Increasing accuracy/unit cost
- What is cost of evaluating DNN?
  - Number of ops (often measured in multiply adds)
  - **Bandwidth!**
    - **Loading model weights + loading/storing intermediate activations**
    - **Careful! Certain layers are bandwidth bound, e.g., batch norm**

Depthwise separable convolutions add additional batch norm operations to network (after each step of depthwise conv layer)

Implication: number of ops can be a poor predictor of run time of network (too small to utilize processor, bandwidth bound, etc.)!

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \text{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \text{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

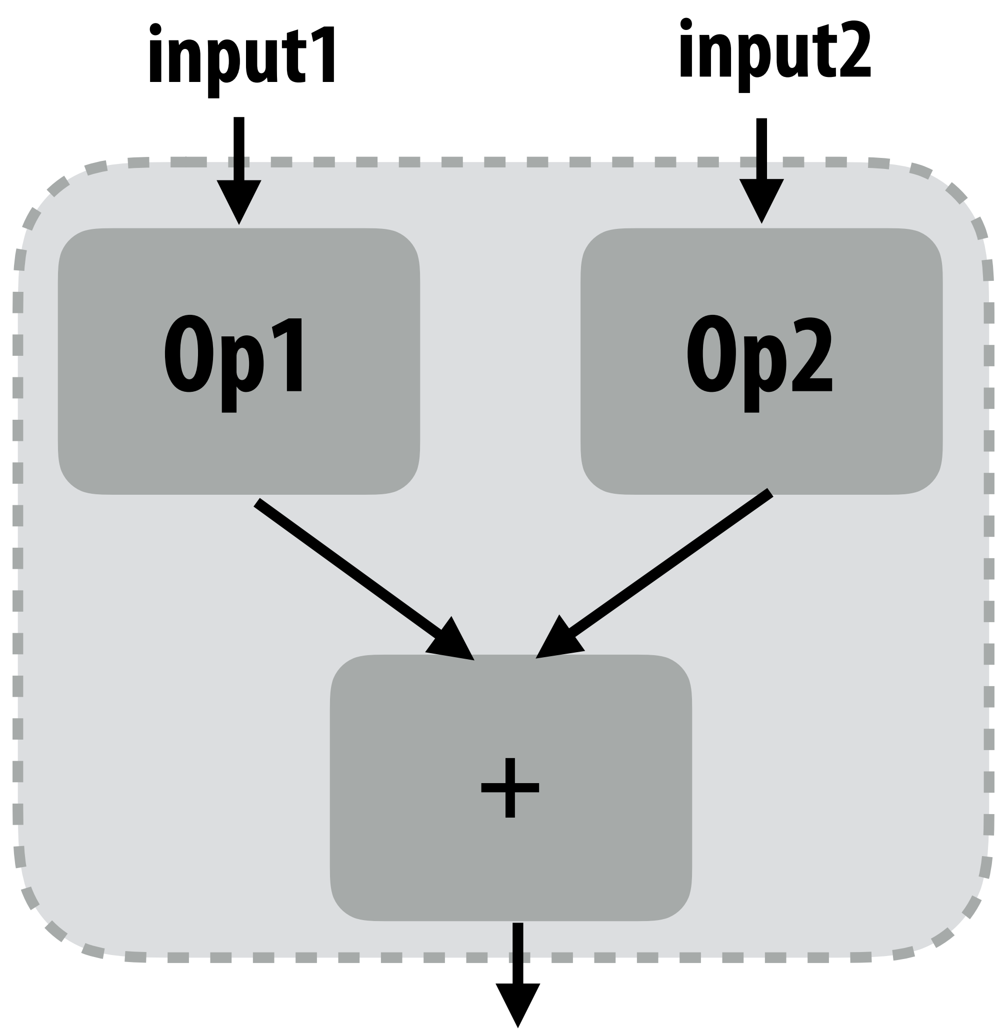
Model optimization techniques

- Manually designing better models
  - Common parameters: depth of network, width of filters, number of filters per layer, convolutional stride, etc.
- Good scheduling of performance-critical operations (layers)
  - Loop blocking/tiling, fusion
  - Typically optimized manually by humans (but significant research efforts to automate scheduling)
- Compressing models
  - Lower bit precision
  - Automatic sparsification/pruning
- **Automatically discovering efficient model topologies (architecture search)**

DNN architecture search

- Learn an efficient DNN topology along with associated weights
- Example: progressive neural architecture search [Liu et al. 18]

"Block" = (input1, input2, op1, op2)



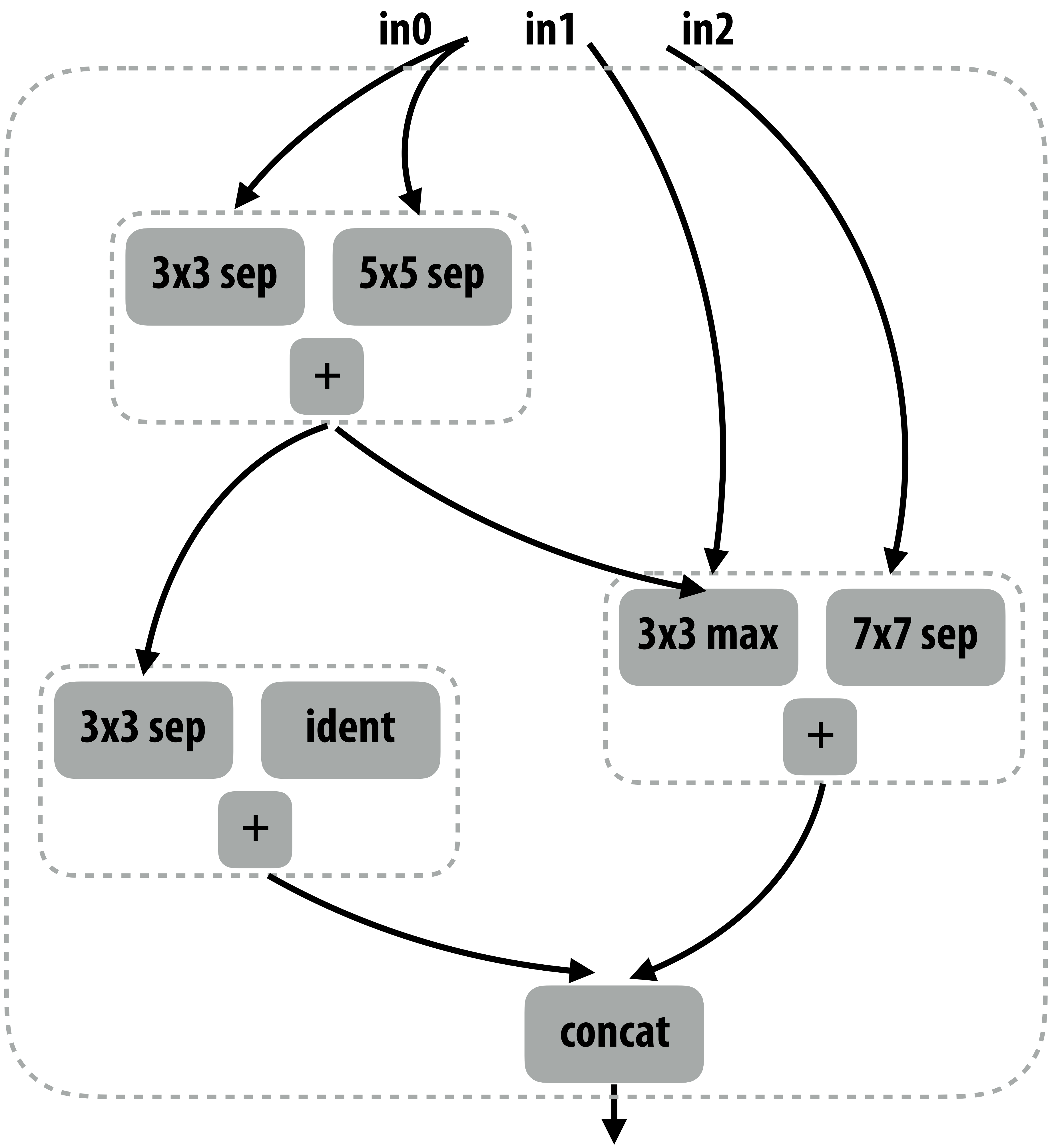
Eight possible operations:

3x3 depthwise-separable conv	identity
5x5 depthwise-separable conv	3x3 average pool
7x7 depthwise-separable conv	3x3 max pool
1x7 followed by 7x1 conv	3x3 dilated conv

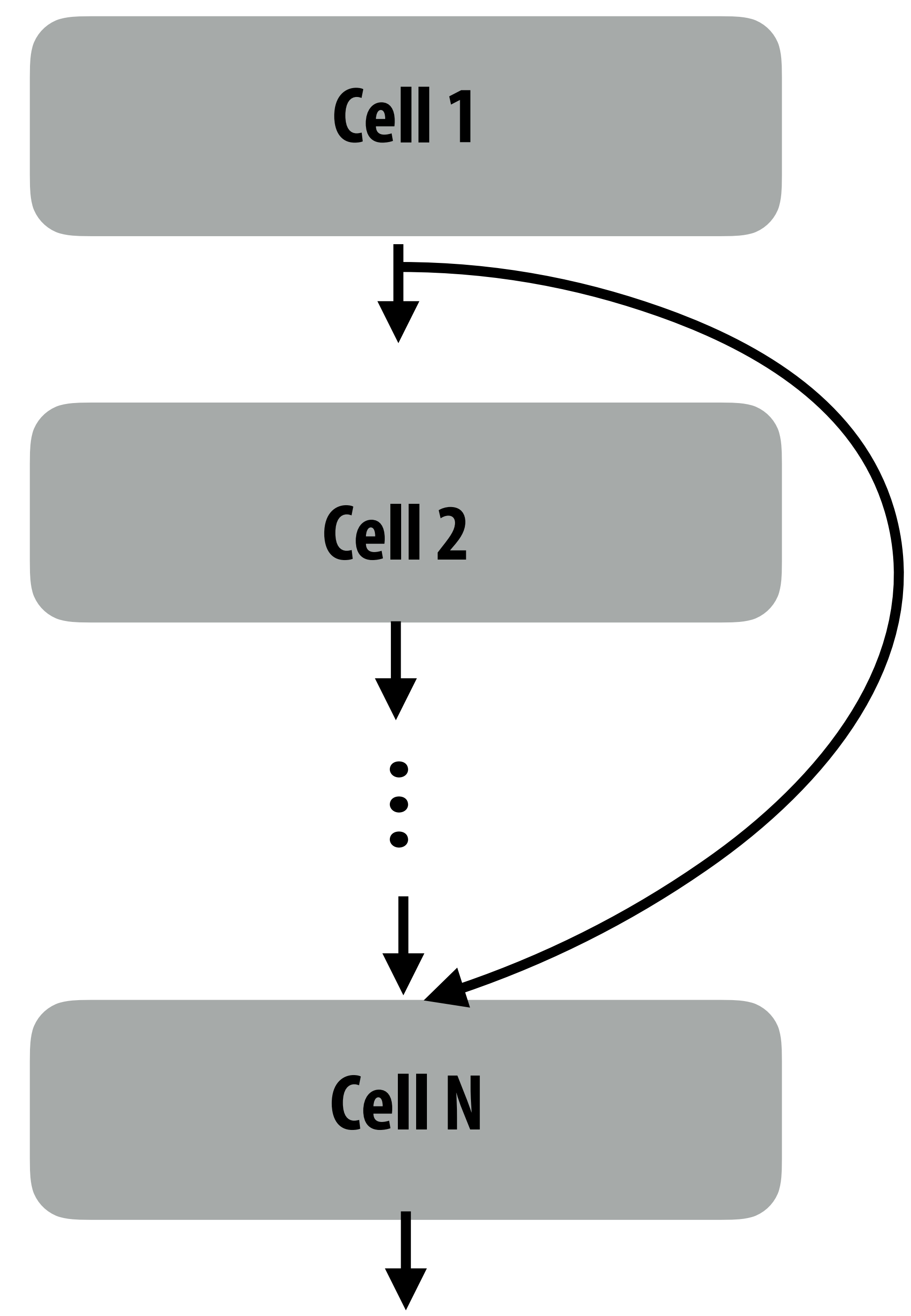
[Liu et al. 18]

Architecture search space

Cells are DAGs of *B* blocks



DNNs are sequences of *N* cells



Cells have one output, can receive input from all prior cells

Progressive neural architecture search results

- Automatic search was able to find model architectures that yielded similar/ better accuracy to hand designed models (and comparable costs)

Model	Params	Mult-Adds	Top-1	Top-5
MobileNet-224 [14]	4.2M	569M	70.6	89.5
ShuffleNet (2x) [37]	5M	524M	70.9	89.8
NASNet-A ($N = 4$, $F = 44$) [41]	5.3M	564M	74.0	91.6
AmoebaNet-B ($N = 3$, $F = 62$) [27]	5.3M	555M	74.0	91.5
AmoebaNet-A ($N = 4$, $F = 50$) [27]	5.1M	555M	74.5	92.0
AmoebaNet-C ($N = 4$, $F = 50$) [27]	6.4M	570M	75.7	92.4
PNASNet-5 ($N = 3$, $F = 54$)	5.1M	588M	74.2	91.9

- Forms of architecture search implemented by Cloud-based ML hosting services (user provides training data, service searches for good model)

Google Cloud

Cloud AutoML BETA

Why might a GPU be a good platform for DNN evaluation?

Deep neural networks on GPUs

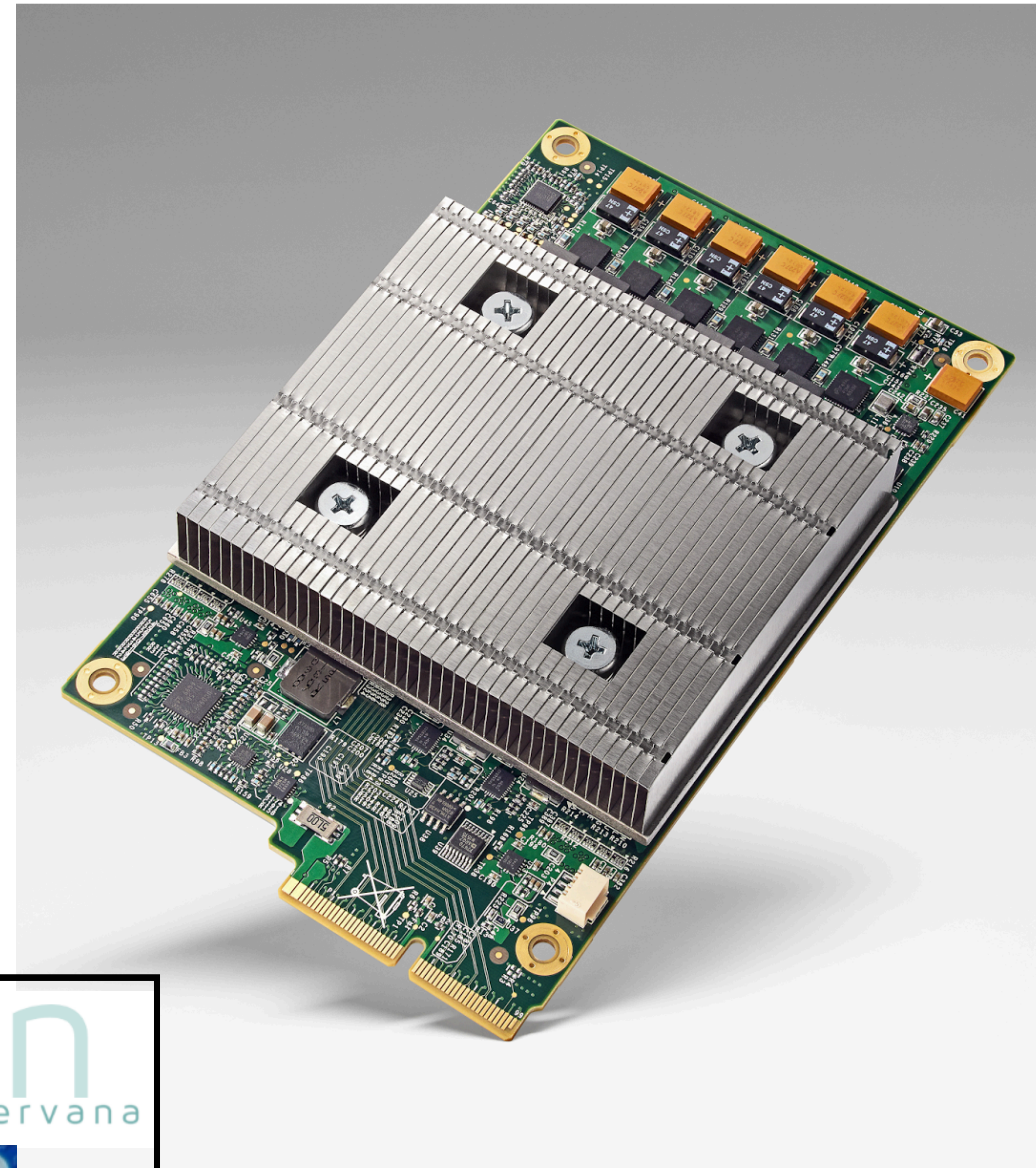
- Many high-performance DNN implementations target GPUs
  - High arithmetic intensity computations (computational characteristics similar to dense matrix-matrix multiplication)
  - Benefit from flop-rich architectures
  - Highly-optimized library of kernels exist for GPUs (cuDNN)
    - Most CPU-based implementations use basic matrix-multiplication-based formulation (good implementations could run faster!)

Facebook's Big Sur

Why might a GPU be a sub-optimal platform for DNN evaluation?

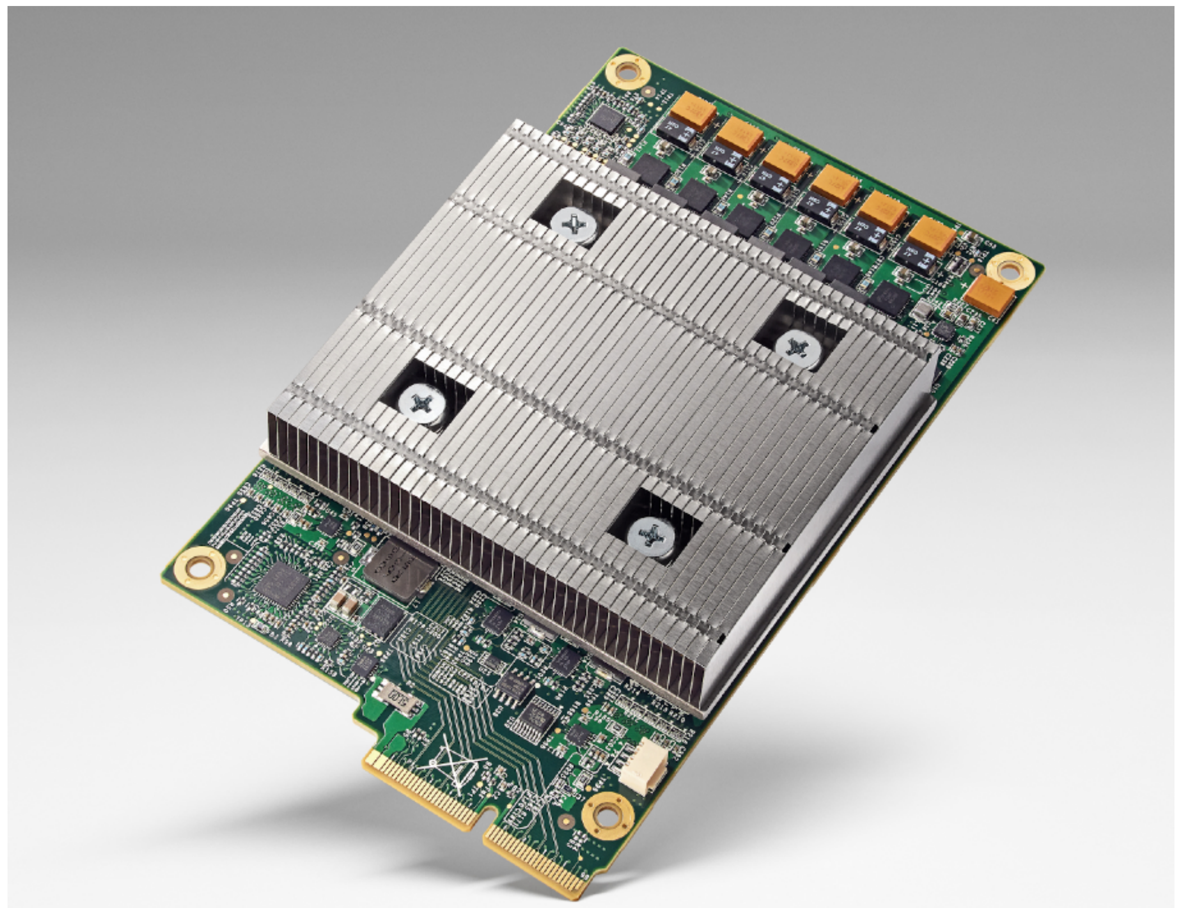
Increasing efficiency through specialization

Example: Google's Tensor Processing Unit (TPU)
Accelerates deep learning operations in Google datacenter

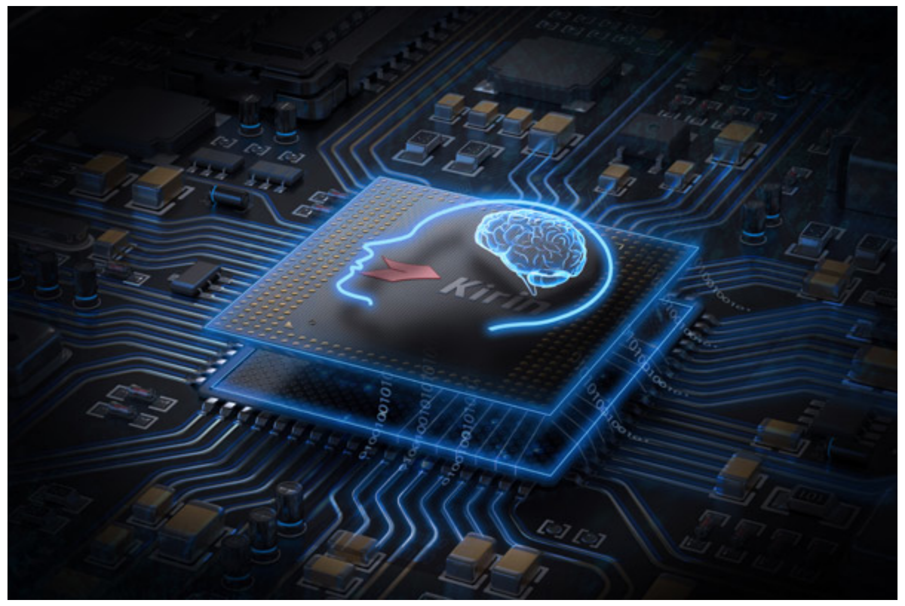


Intel has announced
Lake Crest ML accelerator
(formerly called Nervana)

Hardware acceleration for DNNs

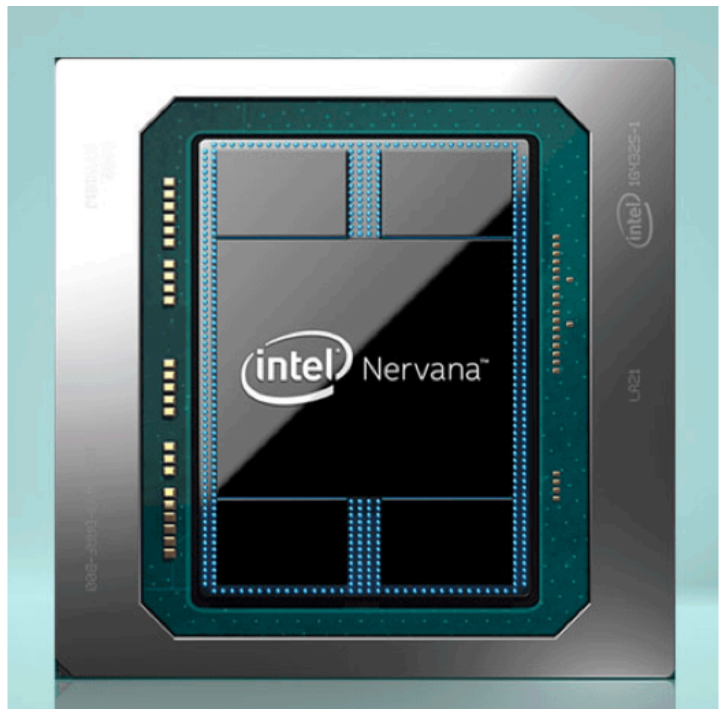


Google TPU:

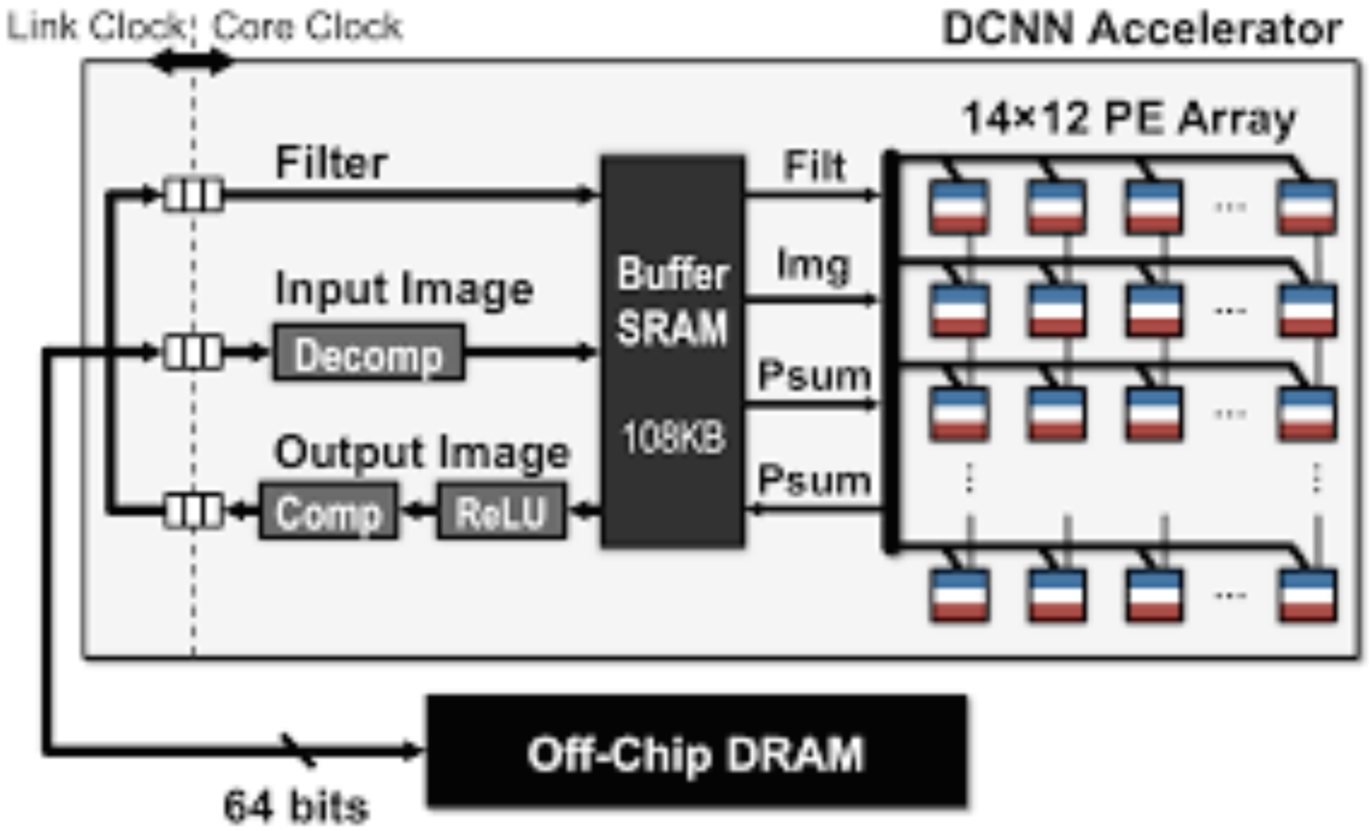


Huawei Kirin NPU

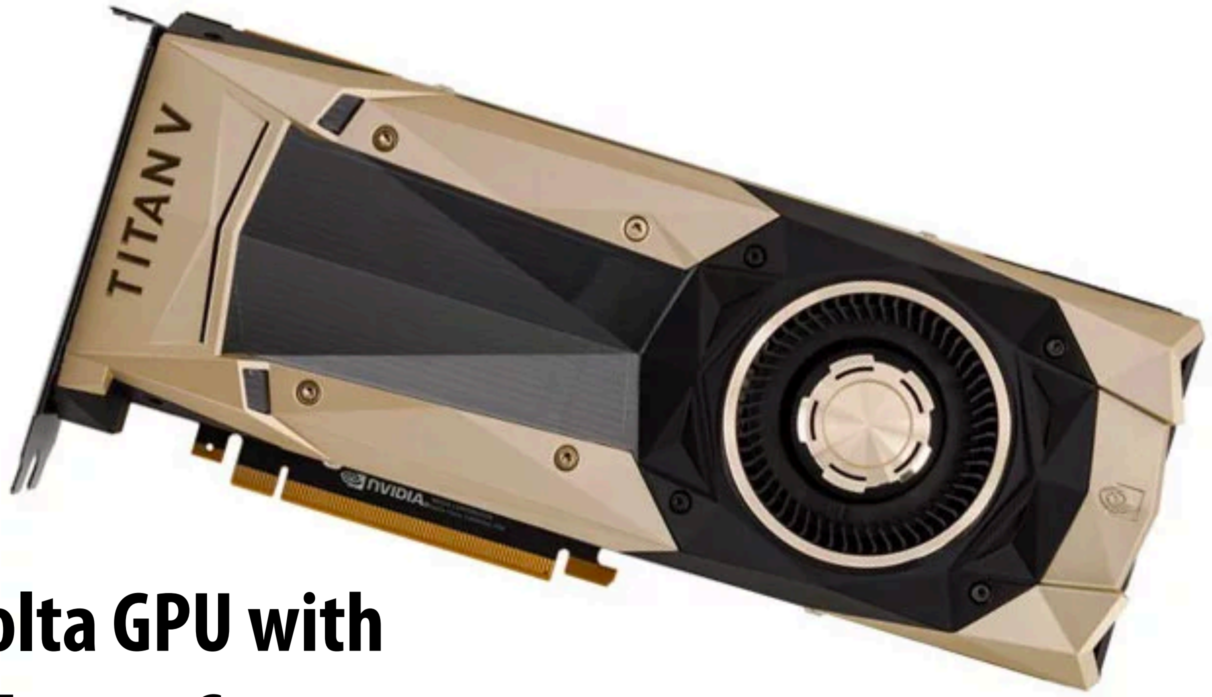
Apple Neural Engine



Intel Lake Crest
Deep Learning Accelerator



MIT Eyeriss



Volta GPU with
Tensor Cores

Slide credit: Xuan Yang

And many more…

IC Giants	Intel, Qualcomm, Nvidia, Samsung, AMD, Apple, Xilinx, IBM, STMicroelectronics, NXP, MediaTek, HiSilicon	12
Cloud/HPC	Google, Amazon_AWS, Microsoft, Aliyun, Tencent Cloud, Baidu, Baidu Cloud, HUAWEI Cloud, Fujitsu	9
IP Vendors	ARM, Synopsys, Imagination, CEVA, Cadence, VeriSilicon	6
Startups in China	Cambricon, Horizon Robotics, DeePhi, Bitmain, Chipintelli, Thinkforce	6
Startups Worldwide	Cerebras, Wave Computing, Graphcore, PEZY, KnuEdge, Tenstorrent, ThinCI, Koniku, Adapteva, Knowm, Mythic, Kalray, BrainChip, AImotive, DeepScale, Leepmind, Krtkl, NovuMind, REM, TERADEEP, DEEP VISION, Groq, KAIST DNPU, Kneron, Vathys, Esperanto Technologies	26

Image credit: Shan Tang [https://medium.com/@shan.tang.g/a-list-of-chip-ip-for-deep-learning-48d05f1759ae]

Modern NVIDIA GPU
(Volta)

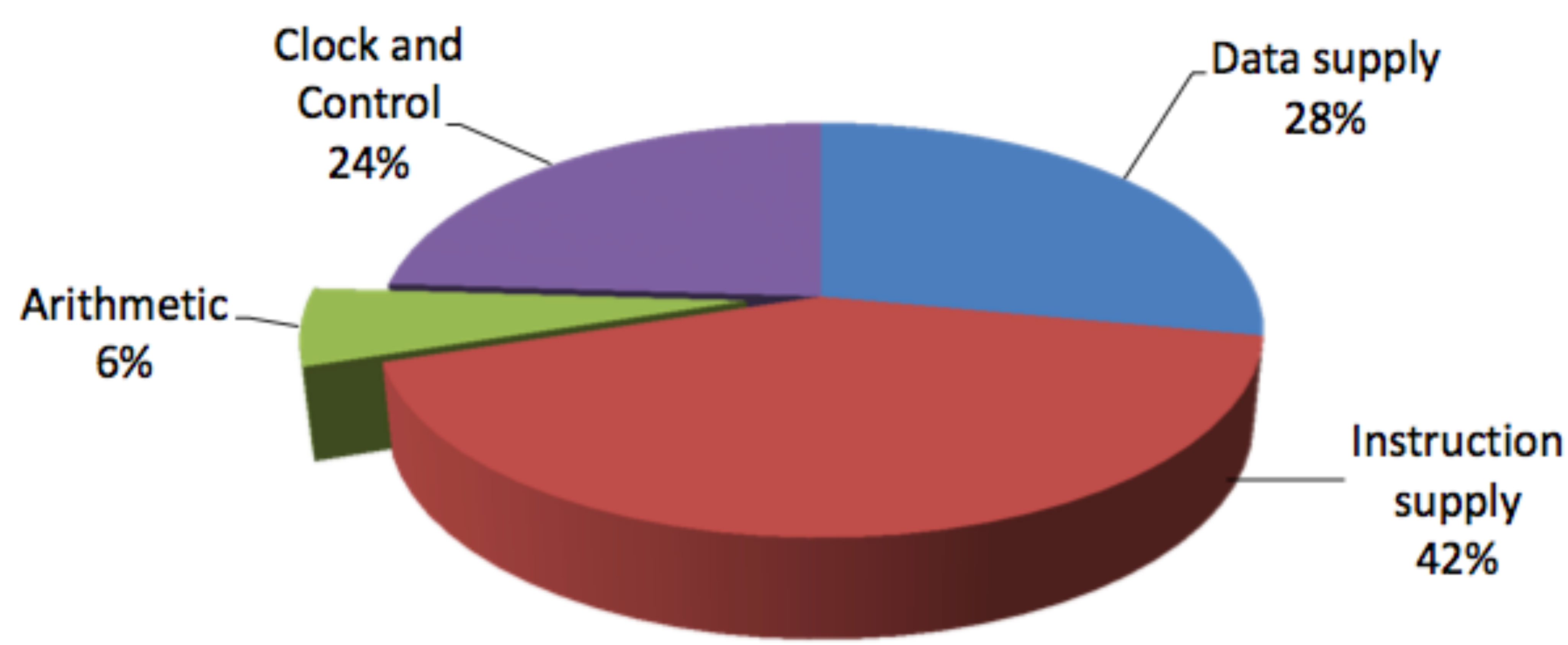
Recall: properties of GPUs

- "Compute rich": packed densely with processing elements
  - Good for compute-bound applications

- Good, because dense-matrix multiplication and DNN convolutional layers (when implemented properly) are compute bound

- But recall cost of instruction stream processing and control in a programmable processor:

Note: these figures are estimates for a CPU:



Efficient Embedded Computing [Dally et al. 08]
[Figure credit Eric Chung]

One solution: more complex instructions

- Fused multiply add ($ax + b$)
- 4-component dot product x = A dot B
- 4x4 matrix multiply
  - AB + C for 4x4 matrices A, B, C

- Key principle: amortize cost of instruction stream processing across many operations of a single complex instruction

Volta GPU

Single instruction to perform 2x4x4x4 + 4x4 ops

Each SM core has:

64 fp32 ALUs (mul-add)

32 fp64 ALUs

8 "tensor cores"

Execute 4x4 matrix mul-add instr

A x B + C for 4x4 matrices A,B,C

A, B stored as fp16, accumulation with fp32 C

GV100 GPU has 80 SM cores:

5,120 fp32 mul-add ALUs

640 tensor cores

6 MB of L2 cache

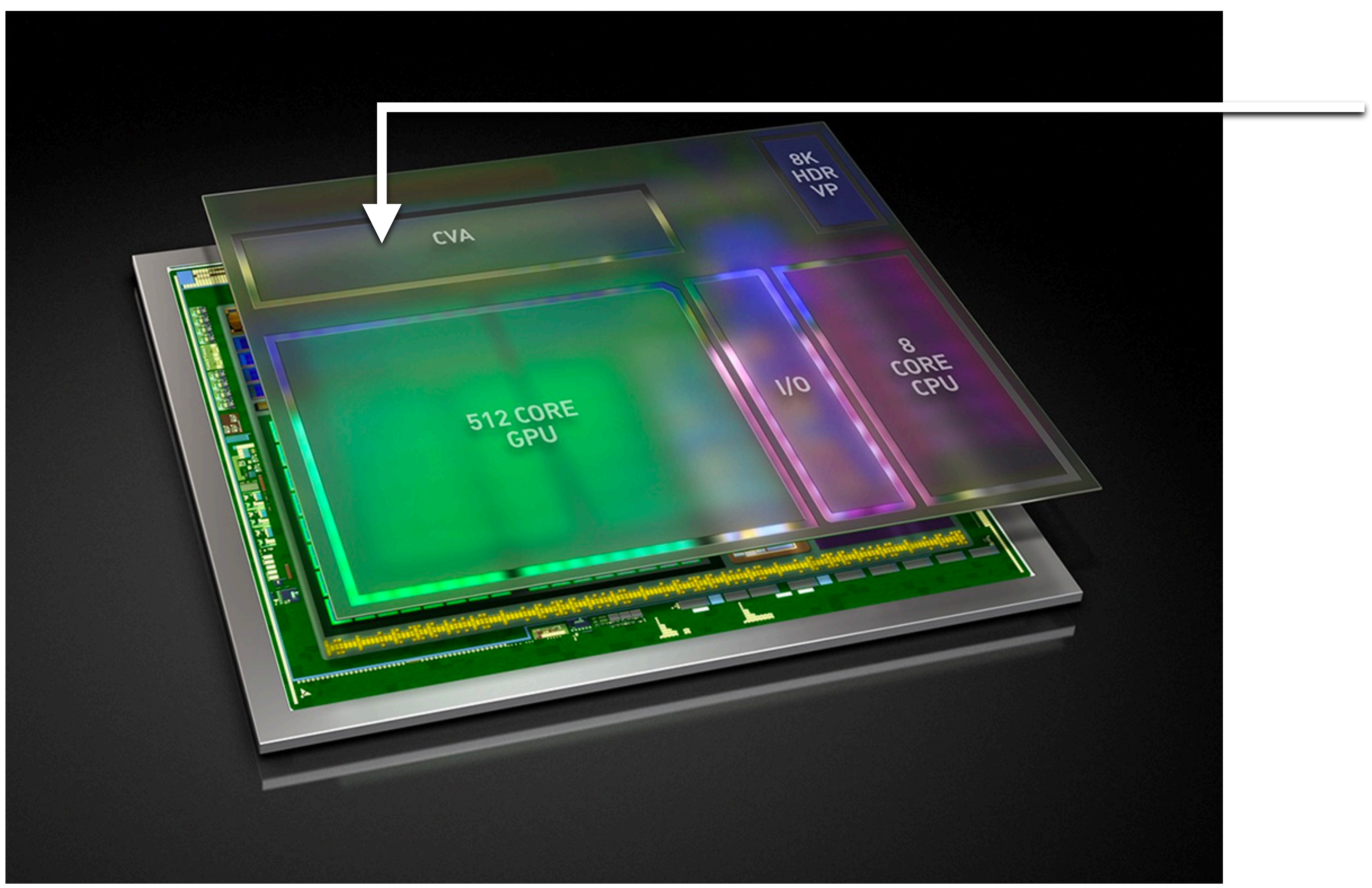
1.5 GHz max clock

= 15.7 TFLOPs fp32

= 125 TFLOPs (fp16/32 mixed) in tensor cores

Efficiency estimates *

- Estimated overhead of programmability (instruction stream, control, etc.)
  - Half-precision FMA (fused multiply-add) 2000%
  - Half-precision DP4 (vec4 dot product) 500%
  - Half-precision MMA (matrix-matrix multiply + accumulate) 27%



NVIDIA Xavier (SoC for automotive domain)

Features a Computer Vision Accelerator (CVA), a custom module for deep learning acceleration (large matrix multiply unit)

But only 2x more efficient than Volta MMA instruction despite being highly specialized component. (includes optimization of gating multipliers if either operand is zero)

* Estimates by Bill Dally using academic numbers, SysML talk, Feb 2018

Google TPU
(version 1)

Google's TPU

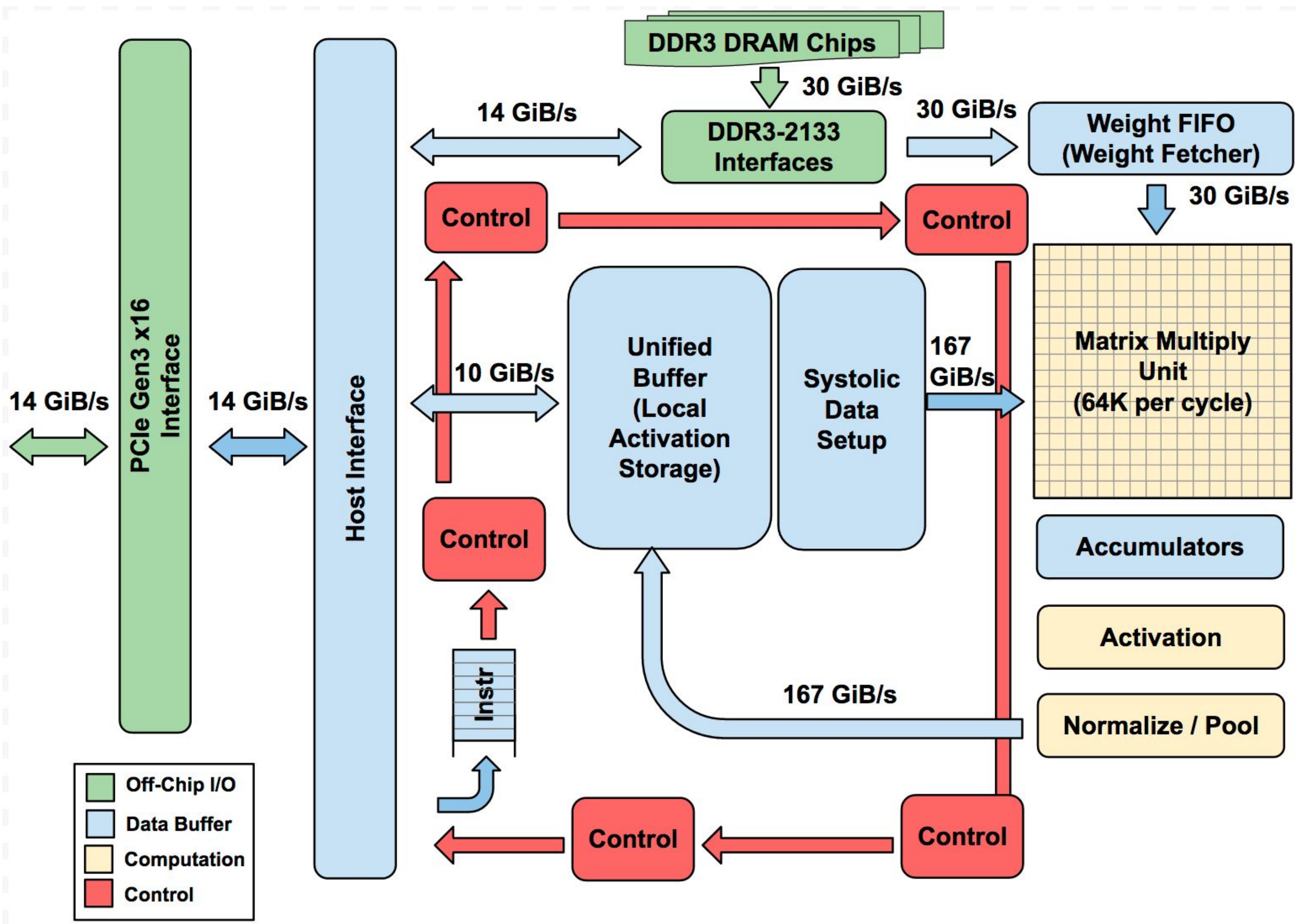
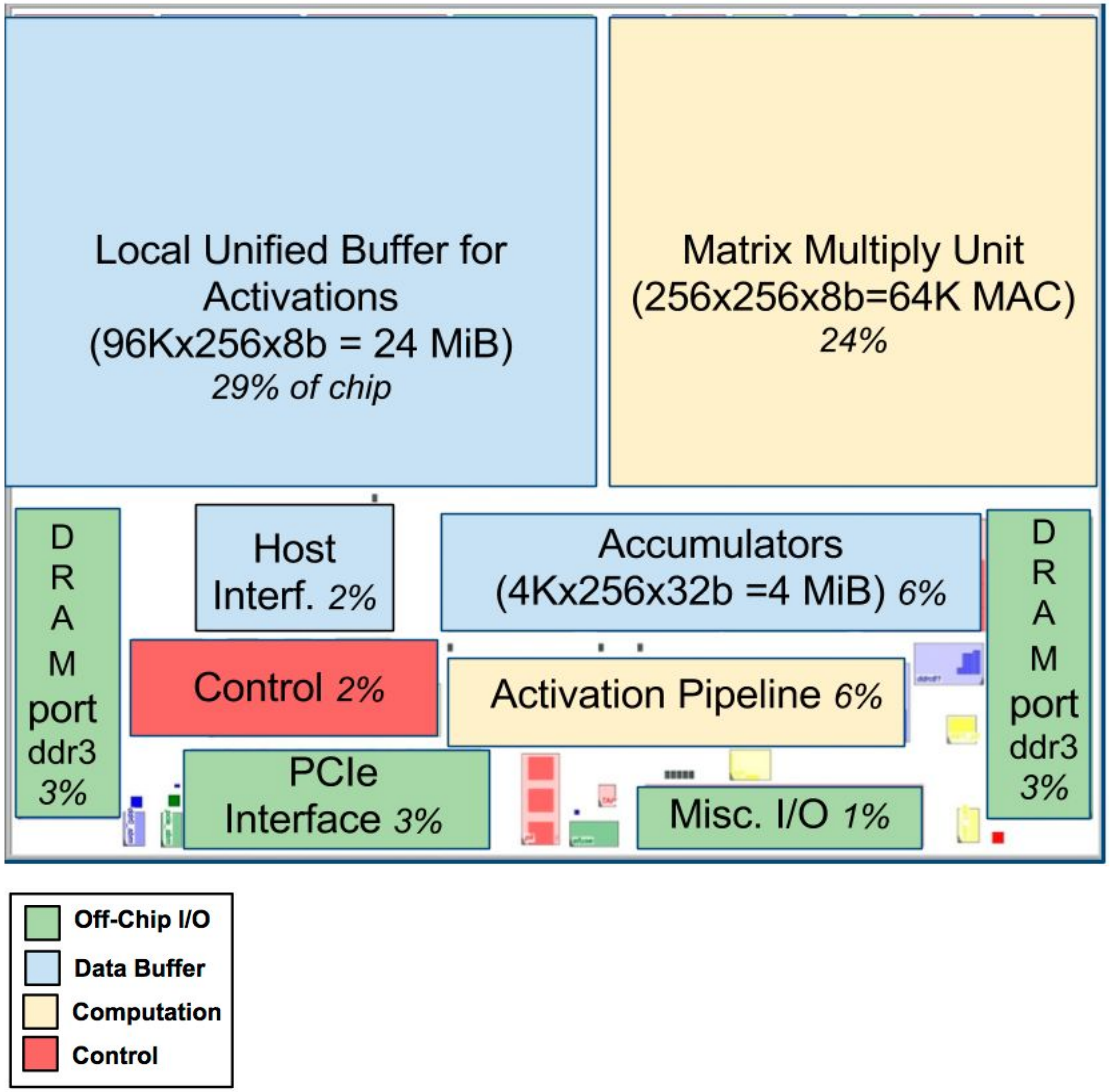


Figure credit: Jouppi et al. 2017

TPU area proportionality



Compute ~ 30% of chip

Note low area footprint of control

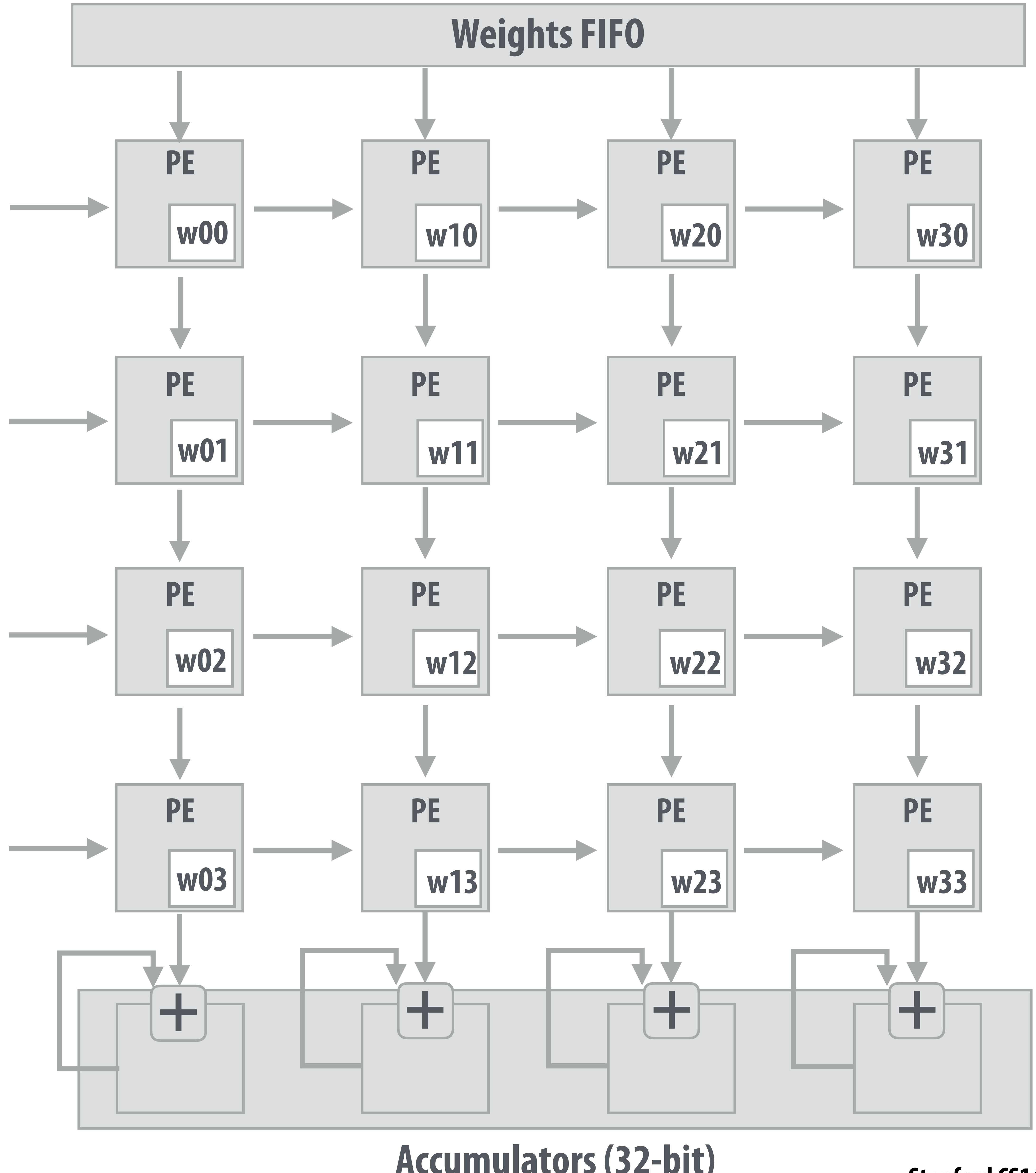
Key instructions:

- **read host memory**
- **write host memory**
- **read weights**
- **matrix_multiply / convolve**
- **activate**

Figure credit: Jouppi et al. 2017

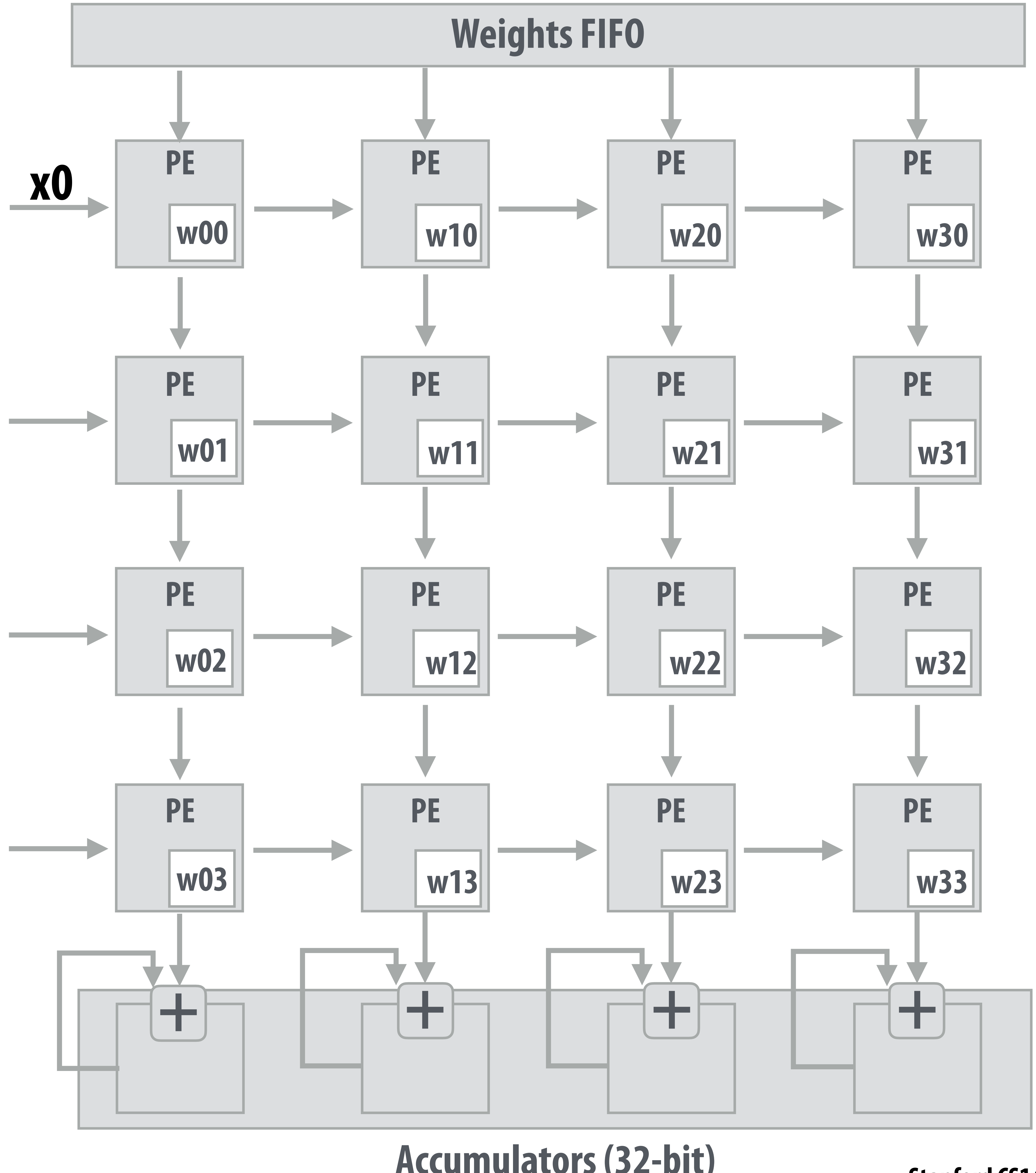
Systolic array

(matrix vector multiplication example: $y=Wx$)



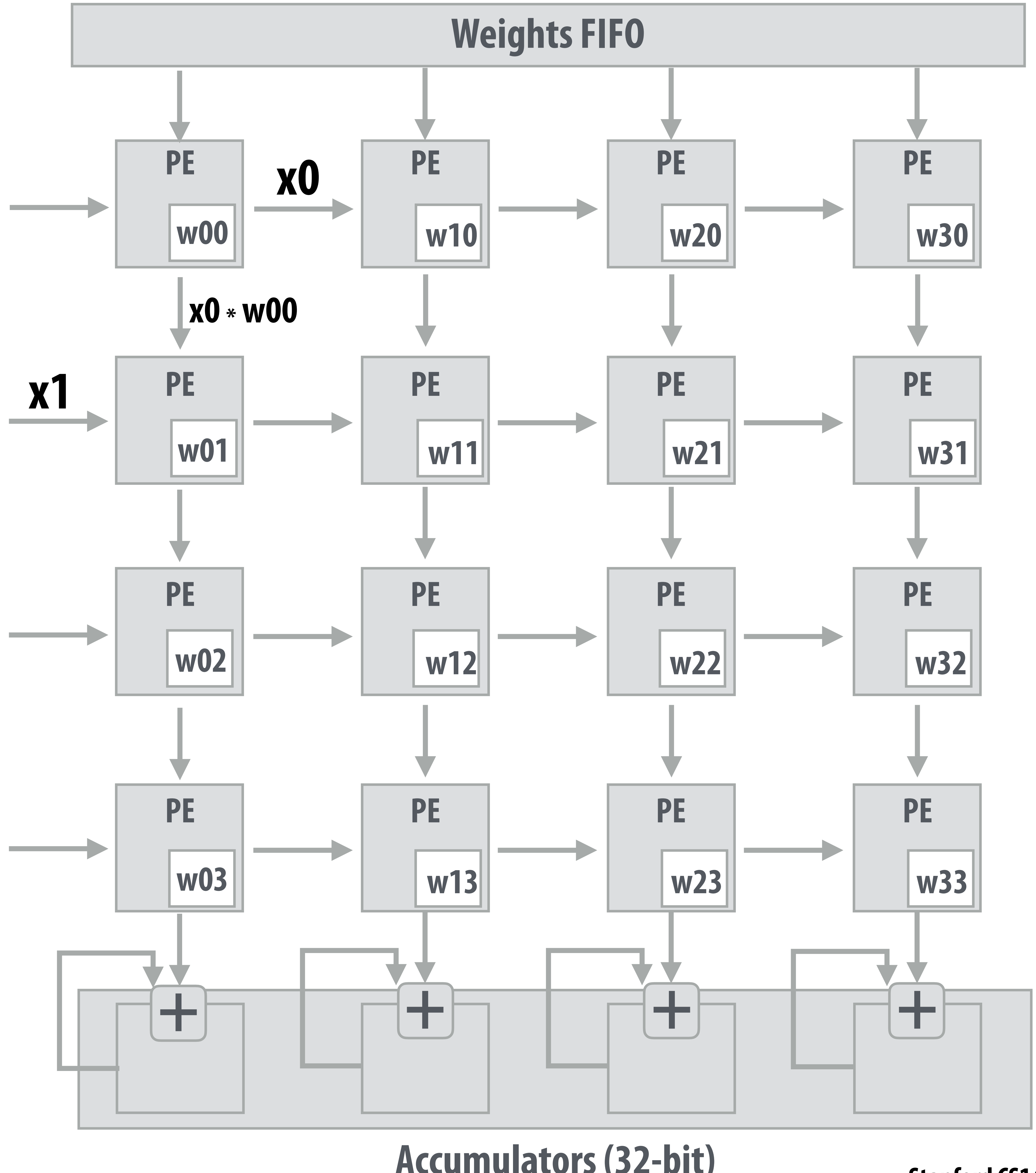
Systolic array

(matrix vector multiplication example: $y=Wx$)



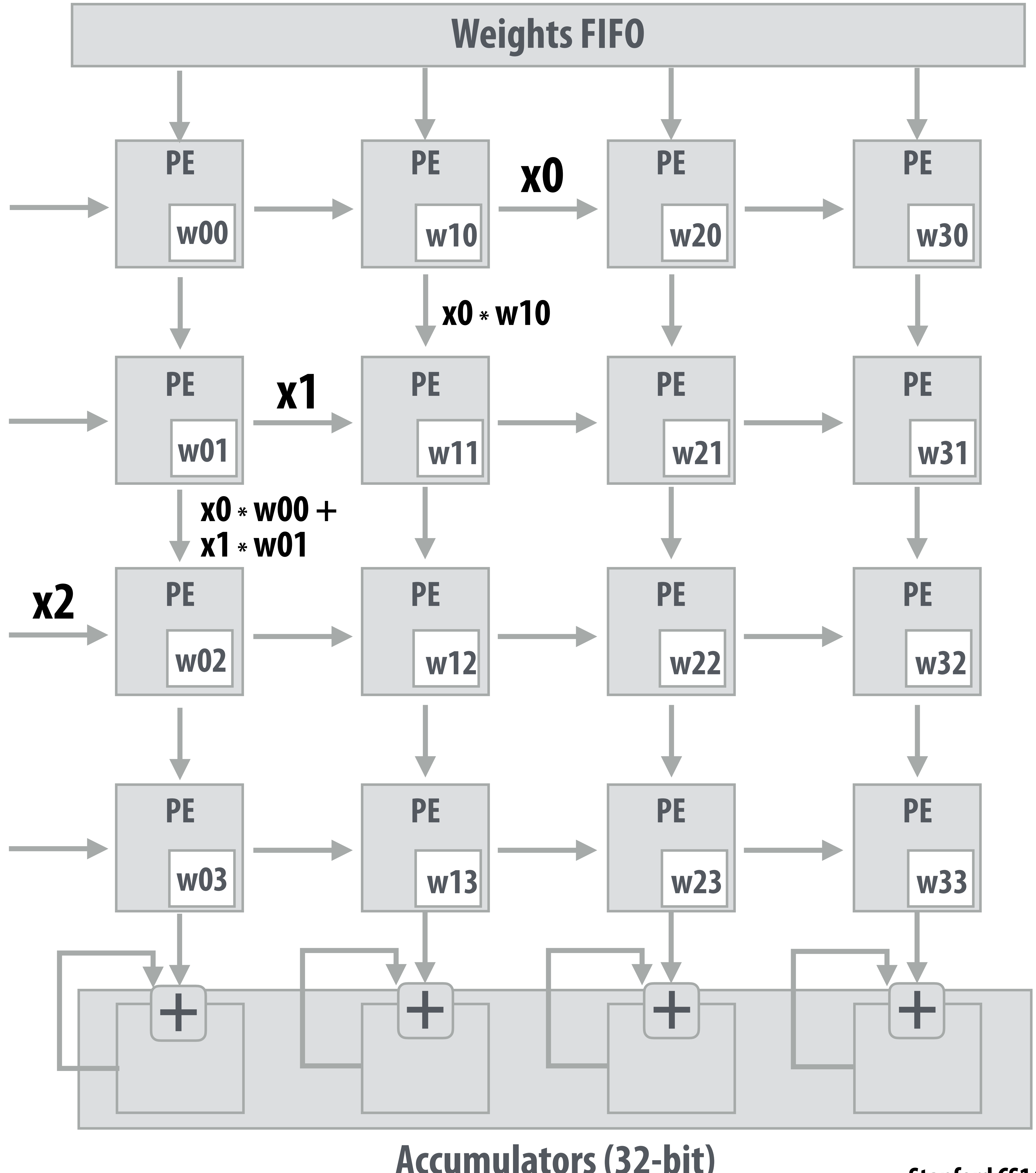
Systolic array

(matrix vector multiplication example: $y = Wx$)



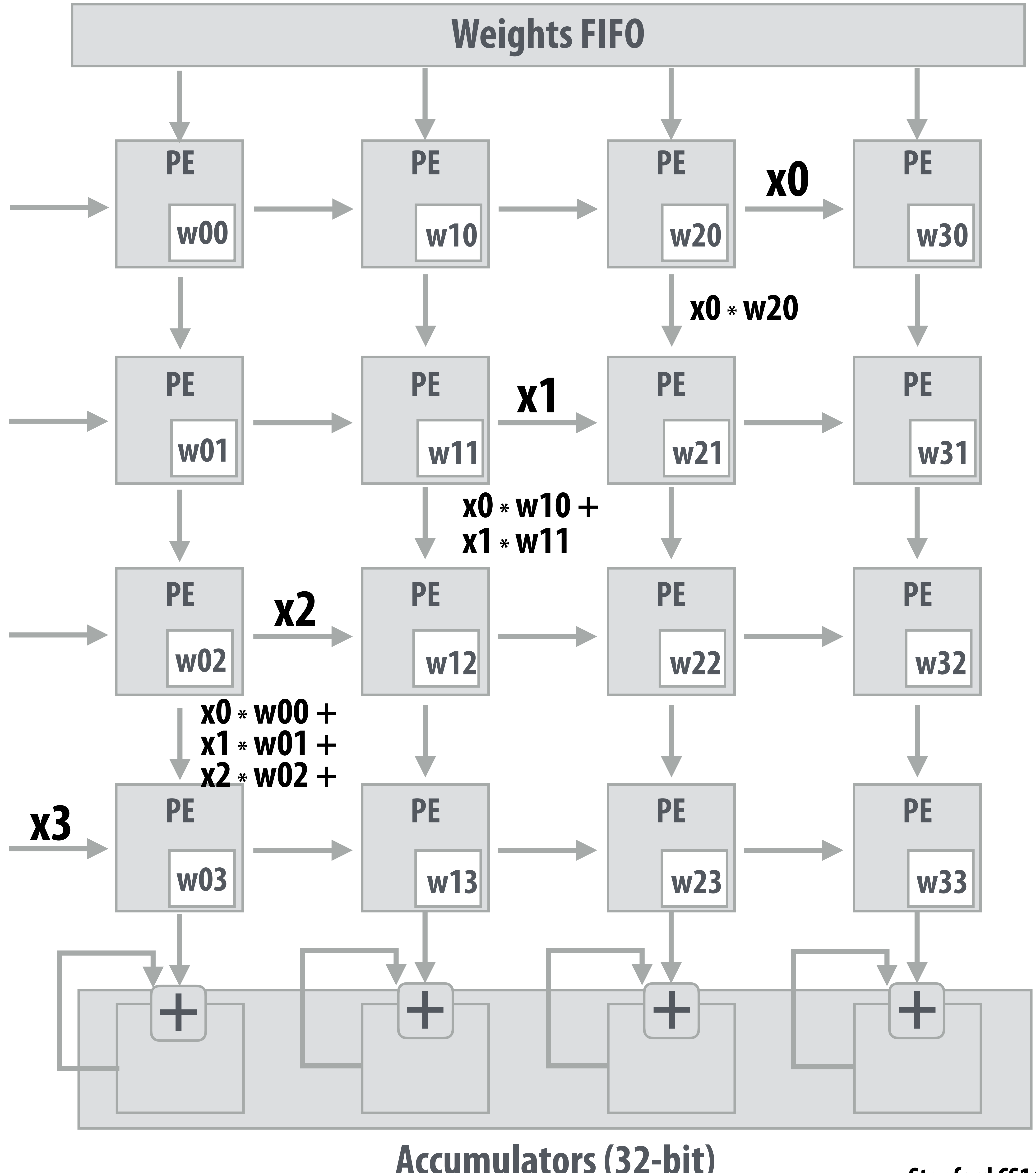
Systolic array

(matrix vector multiplication example: *y=Wx*)



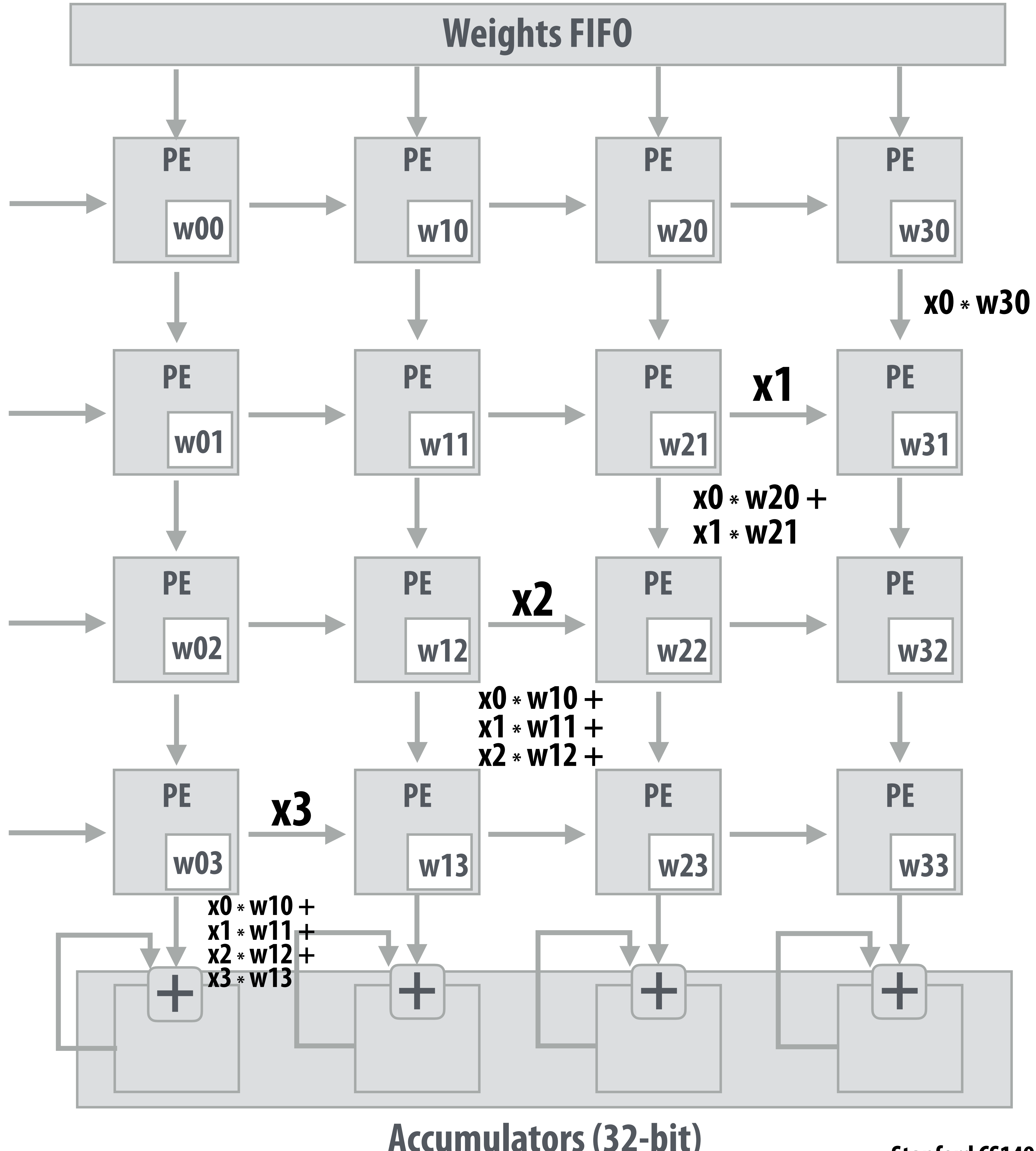
Systolic array

(matrix vector multiplication example: $y=Wx$)



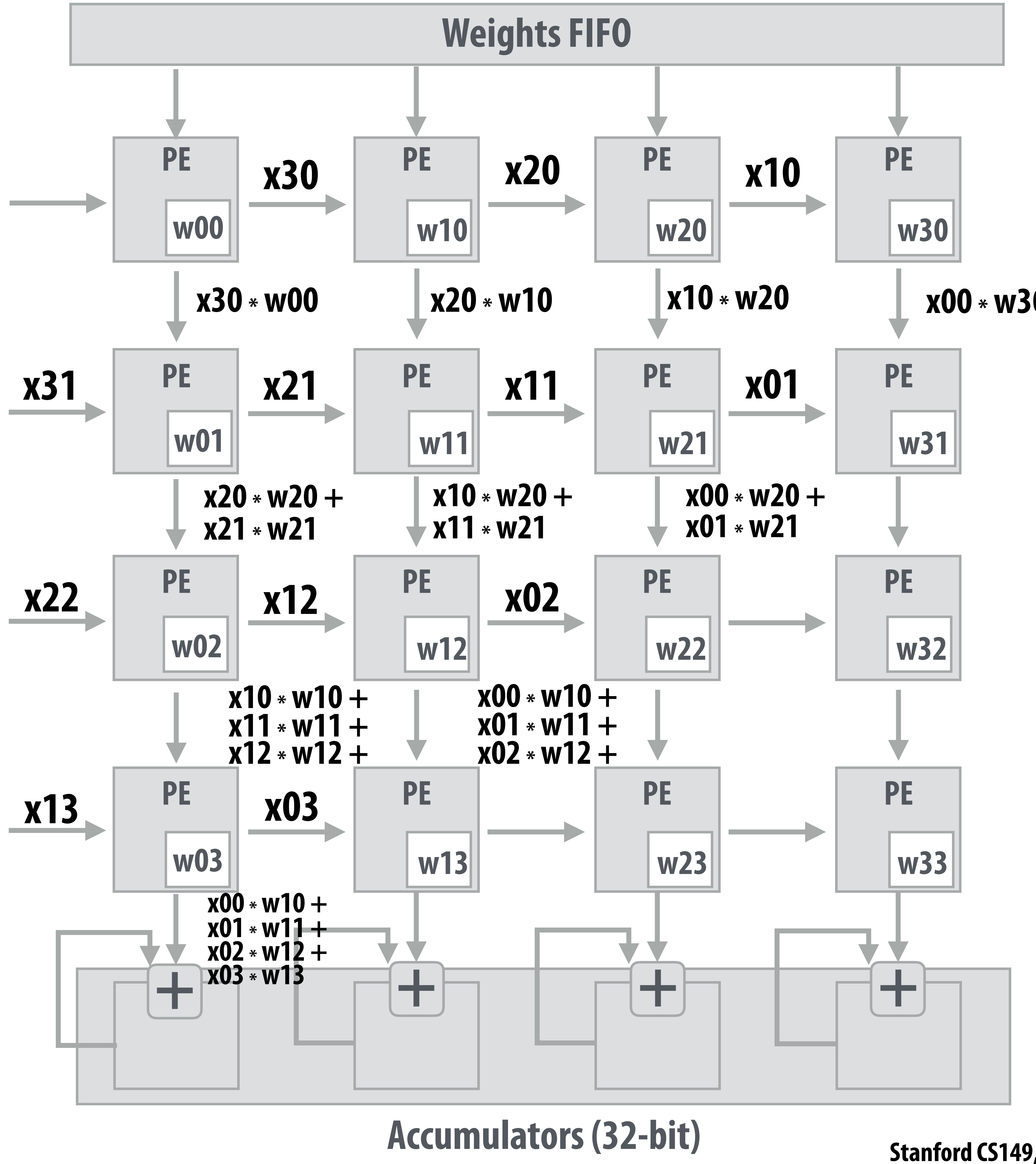
Systolic array

(matrix vector multiplication example: $y=Wx$)



Systolic array

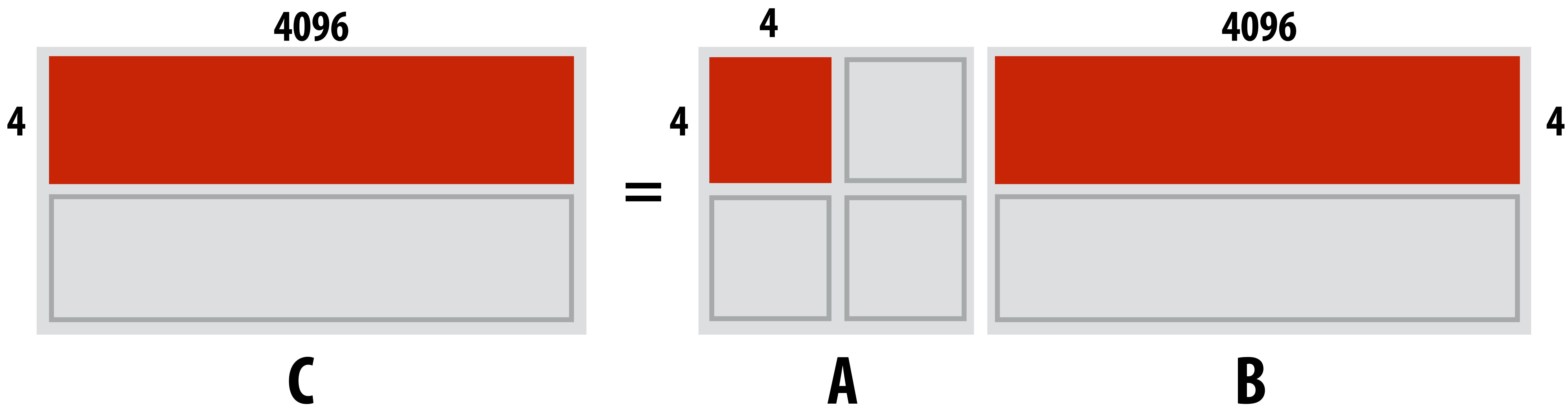
(matrix vector multiplication example: $y=Wx$)



Notice: need multiple 4x32bit accumulators to hold output columns

Building larger matrix-matrix multiplies

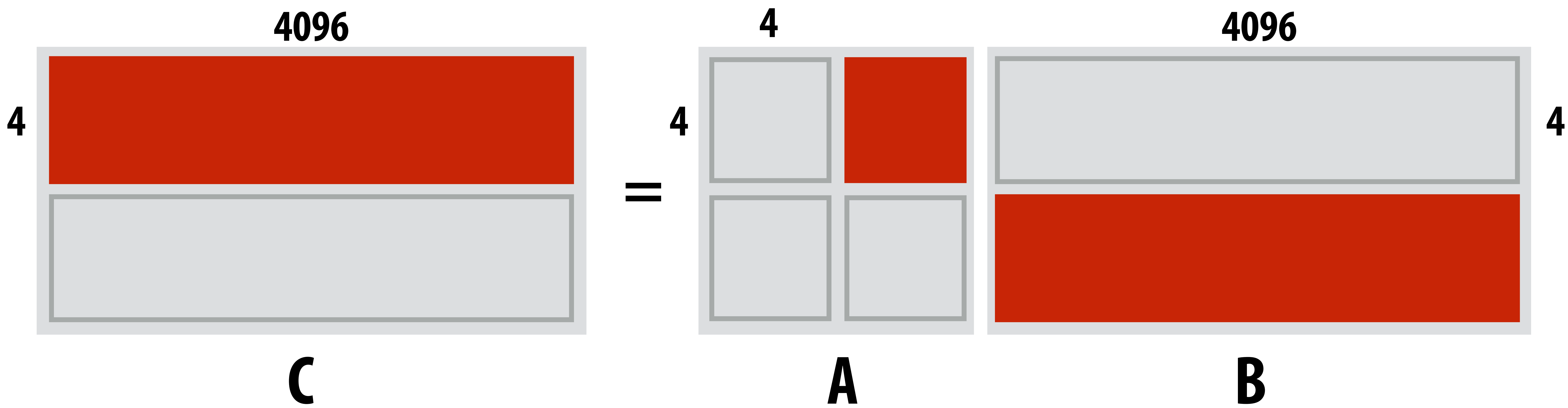
Example: A = 8x8, B= 8x4096, C=8x4096



Assume 4096 accumulators

Building larger matrix-matrix multiplies

Example: A = 8x8, B= 8x4096, C=8x4096



Assume 4096 accumulators

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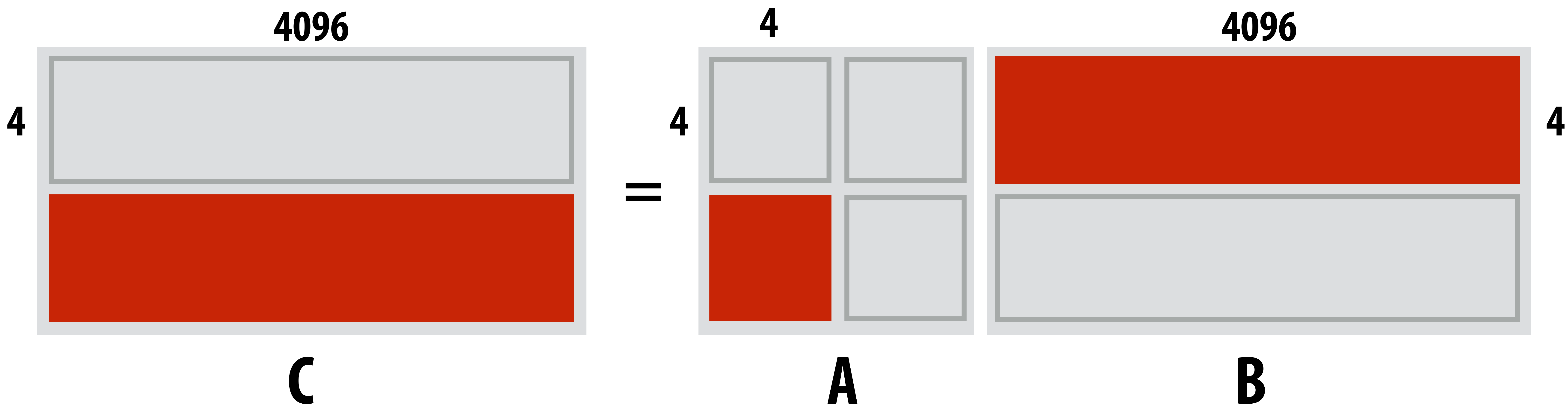

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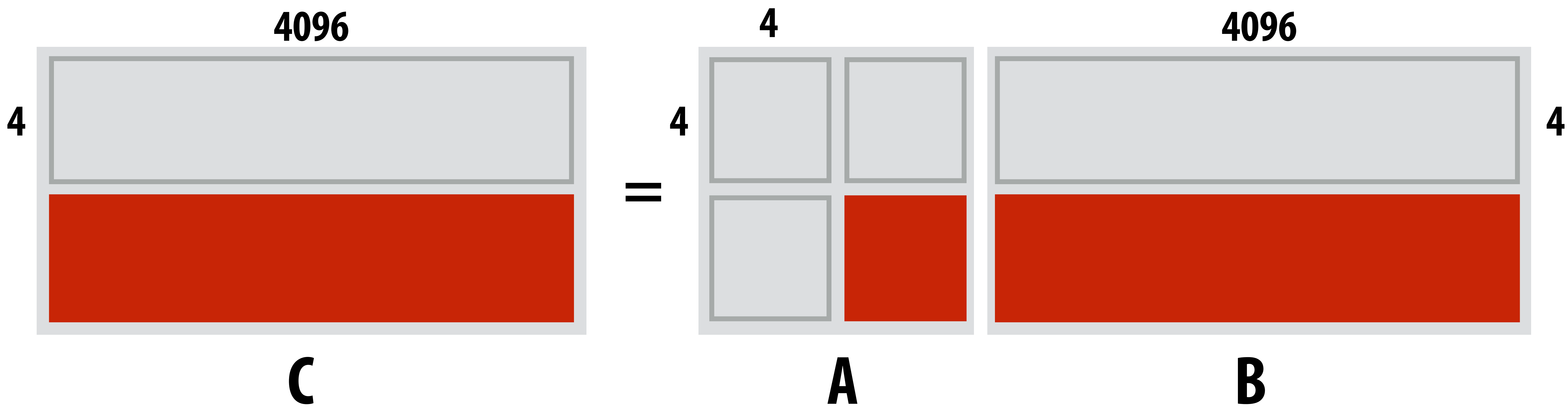
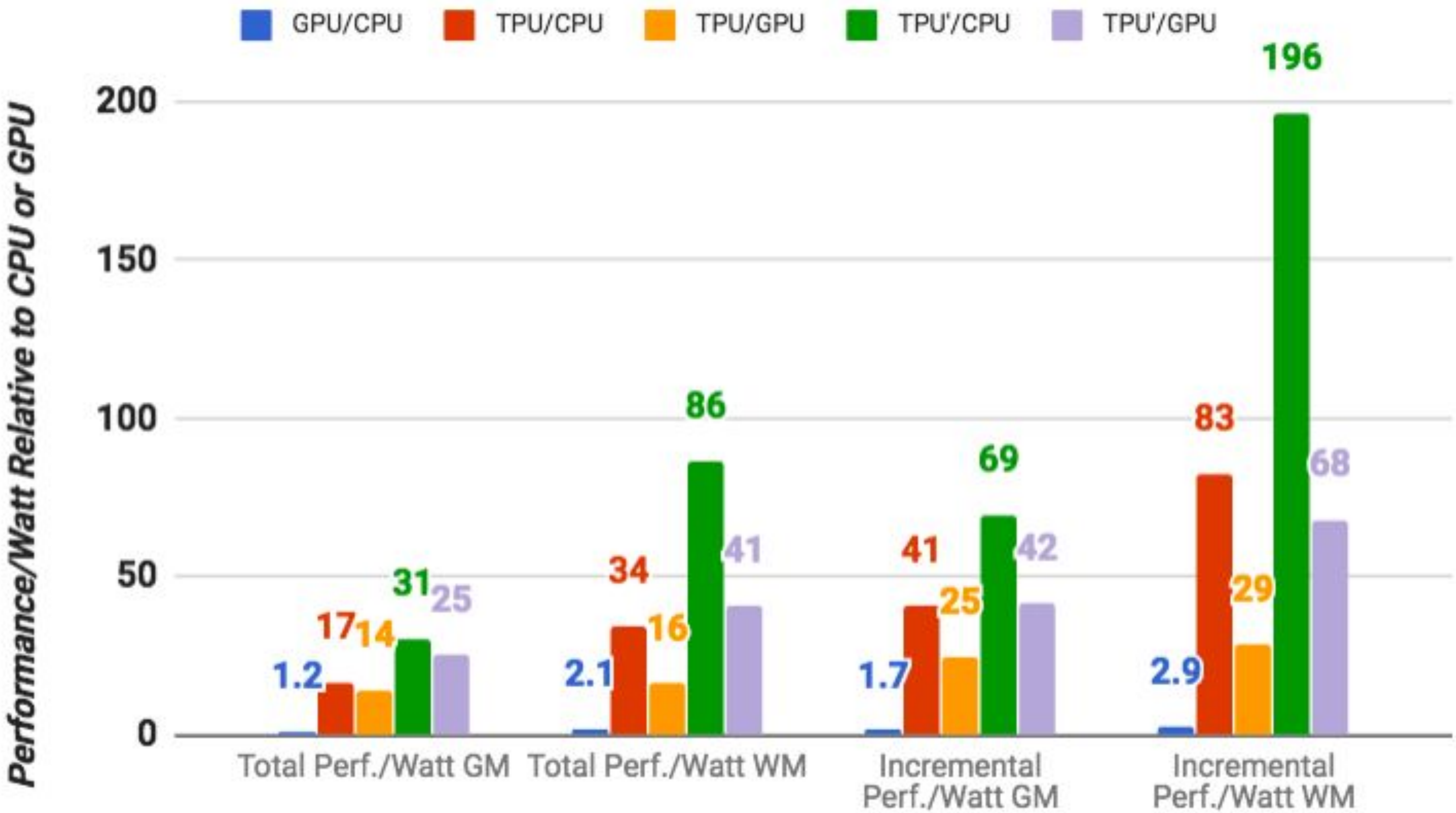


Assume 4096 accumulators

TPU Performance/Watt



GM = geometric mean over all apps
WM = weighted mean over all apps

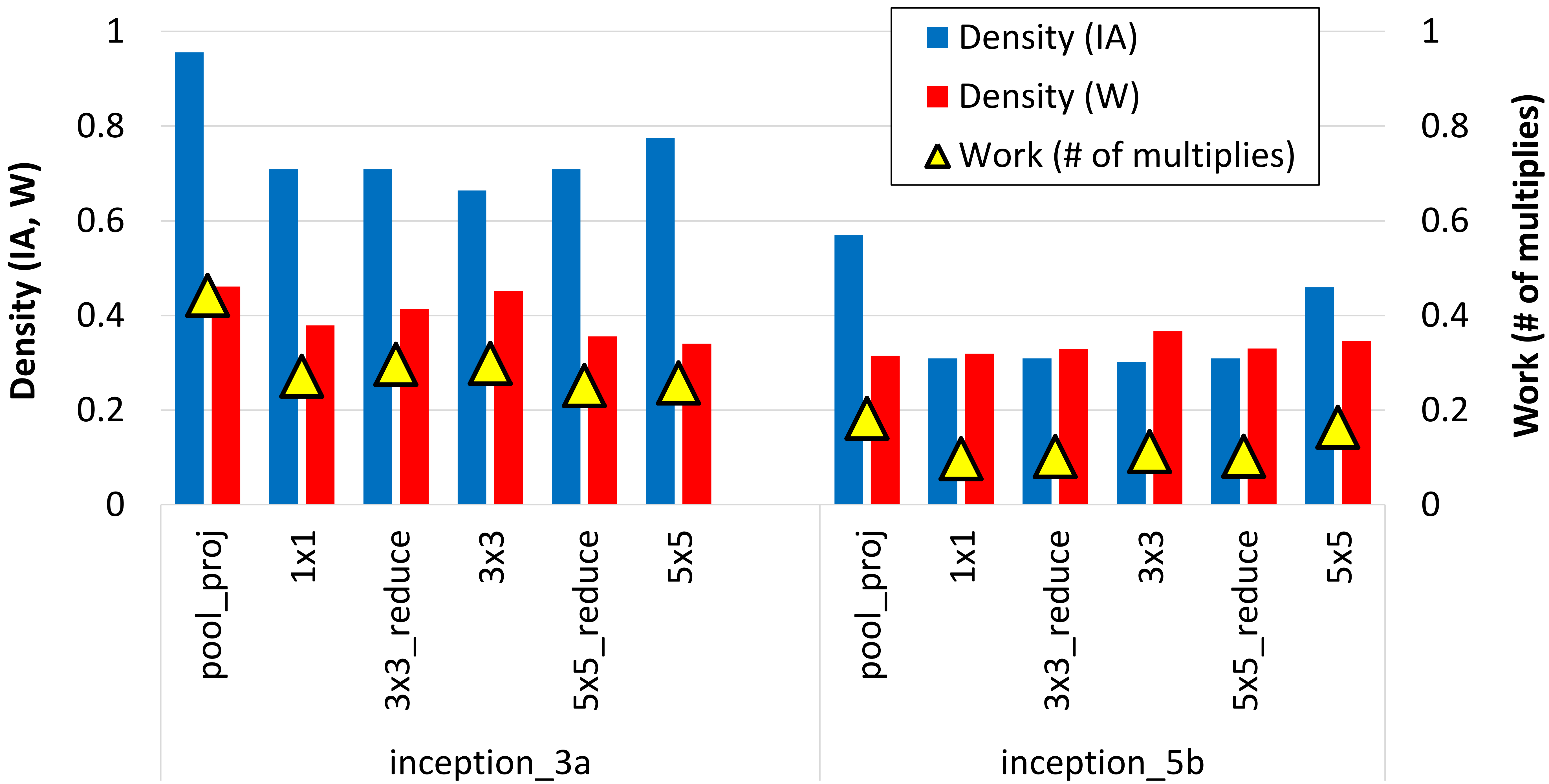
total = cost of host machine + CPU
incremental = only cost of TPU

Figure credit: Jouppi et al. 2017

Exploiting sparsity

Architectural tricks for optimizing for sparsity

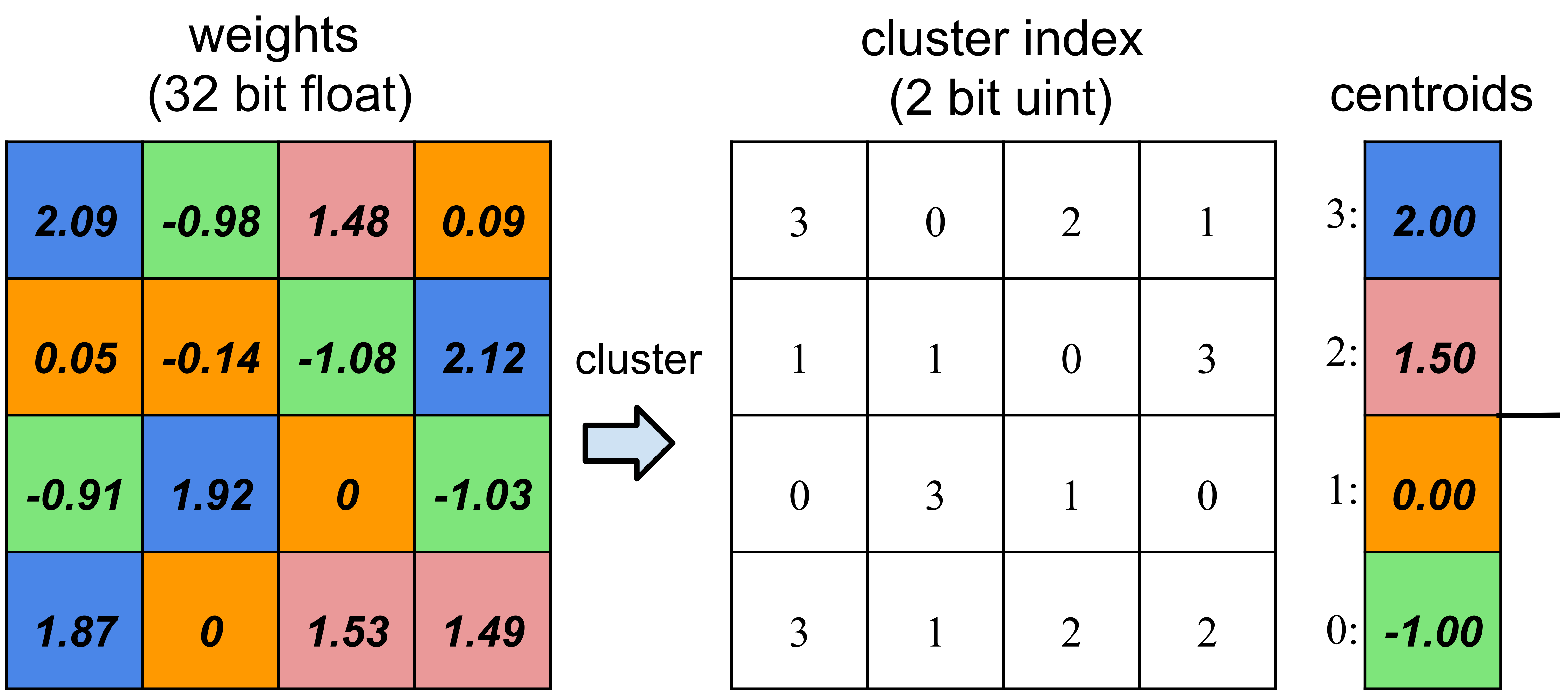
- Consider operation: result += x*y
- If hardware determines contents of register x or register y is zero…
  - Don't fire ALU (save energy)
  - Don't move data from register file to ALU (save energy)
  - But ALU is idle (so computation doesn't run faster, just saves energy)



(b) GoogLeNet

Recall: model compression

- Step 1: sparsify weights by truncating weights with small values to zero
- Step 2: compress surviving non-zeros
  - Cluster weights via k-means clustering
  - Compress weights by only storing index of assigned cluster (lg(k) bits)



[Han et al.]

[Figure credit: Han ICLR16]

Sparse, weight-sharing fully-connected layer

$$b_i = ReLU\left(\sum_{j=0}^{n-1} W_{ij}a_j\right)$$

Fully-connected layer:
Matrix-vector multiplication of activation vector a against weight matrix W

$$b_i = ReLU\left(\sum_{j \in X_i \cap Y} S[I_{ij}]a_j\right)$$

Sparse, weight-sharing representation:
I_{ij} = index for weight W_{ij}
S[] = table of shared weight values
X_i = list of non-zero indices in row i
Y = list of non-zero indices in vector a

Note: activations can be sparse due to ReLU

Sparse-matrix, vector multiplication

Represent weight matrix in compressed sparse column (CSC) format to exploit sparsity in activation vector:

```
for each nonzero a_j in a:
    for each nonzero M_ij in column M_j:
      b_i += M_ij * a_j
```

More detailed version (assumes CSC matrix):

```
int16* a_values;    // dense
PTR*   M_j_start;   // column j
int4*  M_j_values;
int4*  M_j_indices;
int16* lookup; // lookup table for
               // cluster values (from
               // deep compression paper)
```

```
for j=0 to length(a):
   if (a[j] == 0) continue;   // scan to next nonzero
   col_values = M_j_values[M_j_start[j]]; // j-th col
   col_indices = M_j_indices[M_j_start[j]]; // row idx in col
   col_nonzeros = M_j_start[j+1] - M_j_start[j];
   for i=0, i_count=0 to col_nonzeros:
      i    += col_indices[i_count];
      b[i] += lookup[col_values[i_count]] * a_values[j];
```

* Recall from deep compression paper: there is a unique lookup table for each chunk of matrix values

Parallelization of sparse-matrix-vector product

Stride rows of matrix across processing elements

Output activations strided across processing elements

$\vec{a}$ (0 0 $\mathbf{a_2}$ 0 a_4 a_5 0 a_7)

$\times$

									$\vec{b}$	$\overset{ReLU}{\Rightarrow}$
$PE0$	$w_{0,0}$	0	$\boldsymbol{w_{0,2}}$	0	$w_{0,4}$	$w_{0,5}$	$w_{0,6}$	0	b_0	b_0
$PE1$	0	$w_{1,1}$	**0**	$w_{1,3}$	0	0	$w_{1,6}$	0	b_1	b_1
$PE2$	0	0	$\boldsymbol{w_{2,2}}$	0	$w_{2,4}$	0	0	$w_{2,7}$	$-b_2$	0
$PE3$	0	$w_{3,1}$	**0**	0	0	$w_{0,5}$	0	0	b_3	b_3
	0	$w_{4,1}$	**0**	0	$w_{4,4}$	0	0	0	$-b_4$	0
	0	0	**0**	$w_{5,4}$	0	0	0	$w_{5,7}$	b_5	b_5
	0	0	**0**	0	$w_{6,4}$	0	$w_{6,6}$	0	b_6	b_6
	$w_{7,0}$	0	**0**	$w_{7,4}$	0	0	$w_{7,7}$	0	$-b_7$	0
	$w_{8,0}$	0	**0**	0	0	0	0	$w_{8,7}$	$-b_8$	0
	$w_{9,0}$	0	**0**	0	0	0	$w_{9,6}$	$w_{9,7}$	$-b_9$	0
	0	0	**0**	0	$w_{10,4}$	0	0	0	b_{10}	b_{10}
	0	0	$\boldsymbol{w_{11,2}}$	0	0	0	0	$w_{11,7}$	$-b_{11}$	0
	$w_{12,0}$	0	$\boldsymbol{w_{12,2}}$	0	0	$w_{12,5}$	0	$w_{12,7}$	$-b_{12}$	0
	$w_{13,0}$	$w_{13,2}$	**0**	0	0	0	$w_{13,6}$	0	b_{13}	b_{13}
	0	0	$\boldsymbol{w_{14,2}}$	$w_{14,3}$	$w_{14,4}$	$w_{14,5}$	0	0	b_{14}	b_{14}
	0	0	$\boldsymbol{w_{15,2}}$	$w_{15,3}$	0	$w_{15,5}$	0	0	$-b_{15}$	0

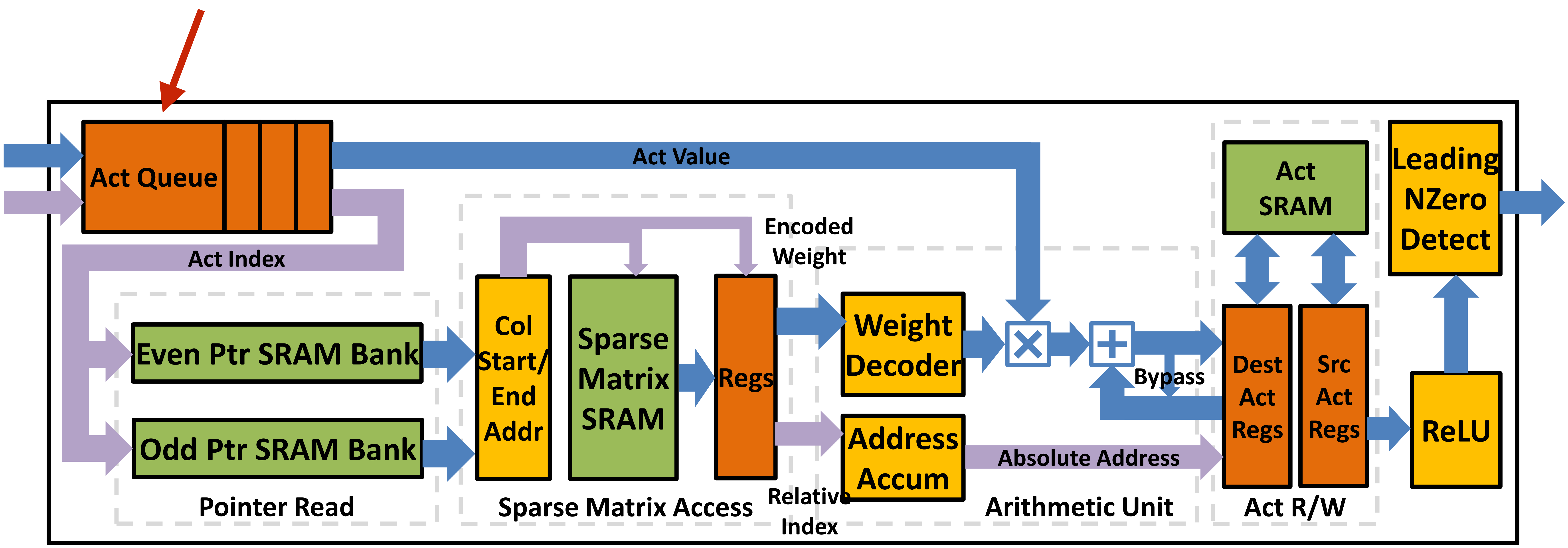
Weights stored local to PEs. Must broadcast non-zero a_j's to all PEs

Accumulation of each output b_i is local to PE

Efficient Inference Engine (EIE) for quantized sparse/matrix vector product

Custom hardware for decoding compressed-sparse representation

Tuple representing non-zero activation (a_j, j) arrives and is enqueued



Summary: efficiently evaluating deep nets

- **Workload characteristics**
  - **Convlayers: high arithmetic intensity, significant portion of cost when evaluating DNNs for image analysis and computer vision**
  - **Similar data access patterns to dense-matrix multiplication (exploiting temporal reuse is key), but implementation as matrix-matrix multiplication is sub-optimal**
- **Significant interest in reducing size of networks for both training and evaluation**
- **Algorithmic techniques (better model architectures) are responsible for huge speedups in recent years**
  - **Expect increasing use of automated model search techniques**
- **Model innovation complemented and extended by much ongoing work on efficient mapping of key layers to CPUs/GPUs and to custom hardware**