Lecture 24:

Parallel Deep Neural Networks

Parallel Computer Architecture and Programming
CMU 15-418/15-618, Spring 2020

Training/evaluating deep neural networks

Technique leading to many high-profile AI advances in recent years

Speech recognition/natural language processing

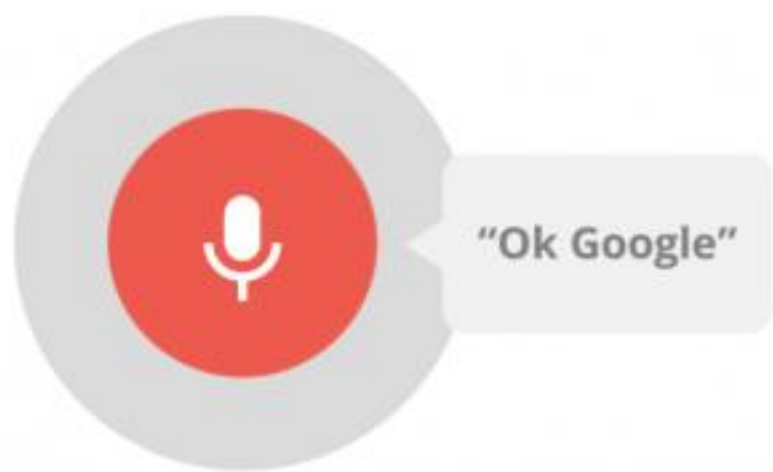
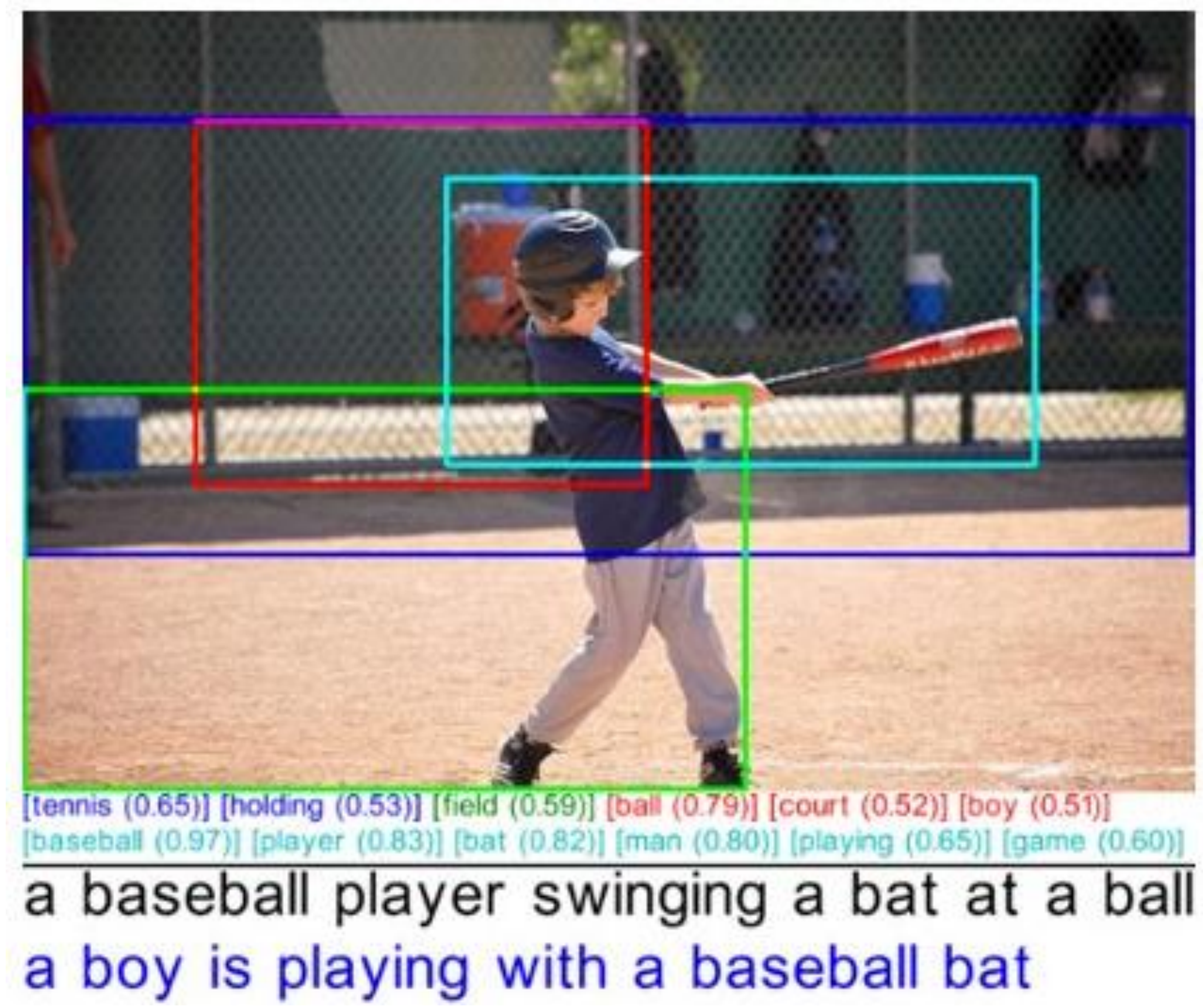
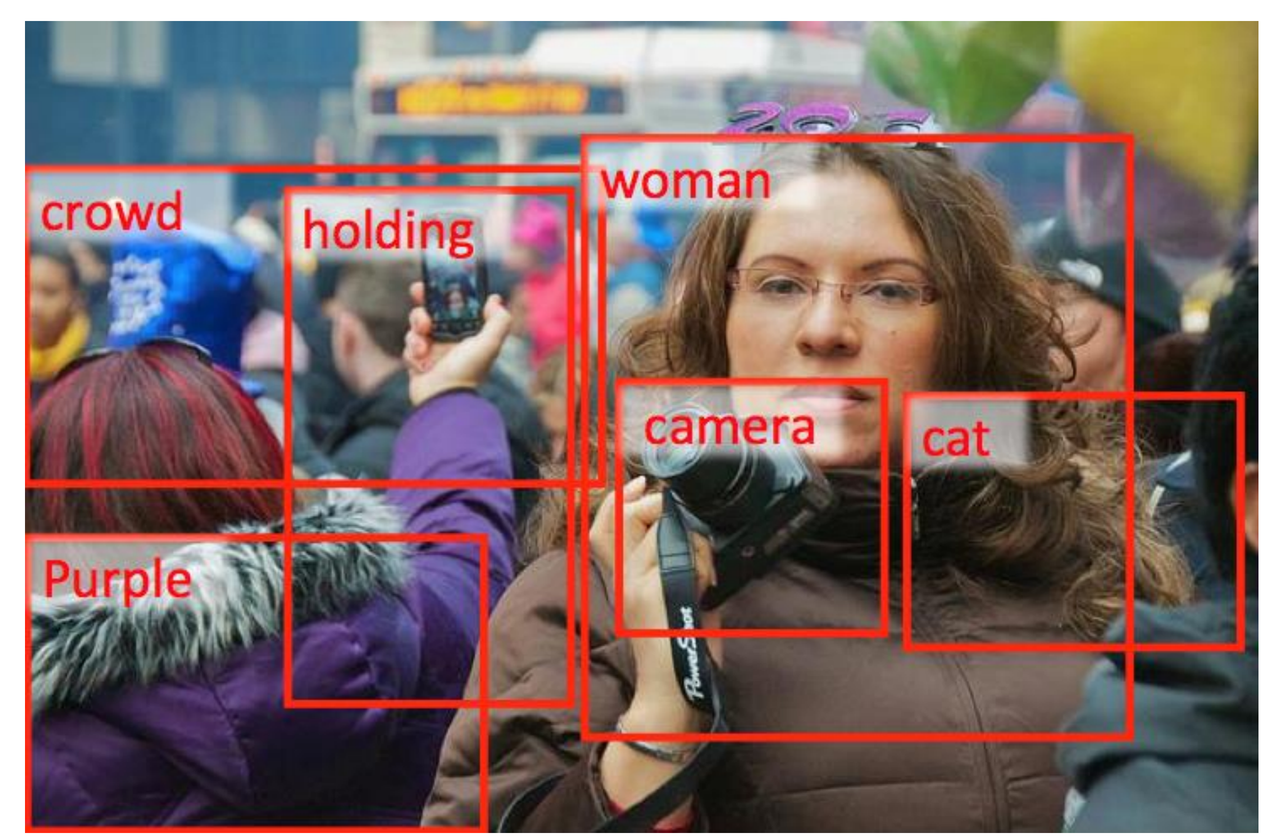


Image interpretation and understanding

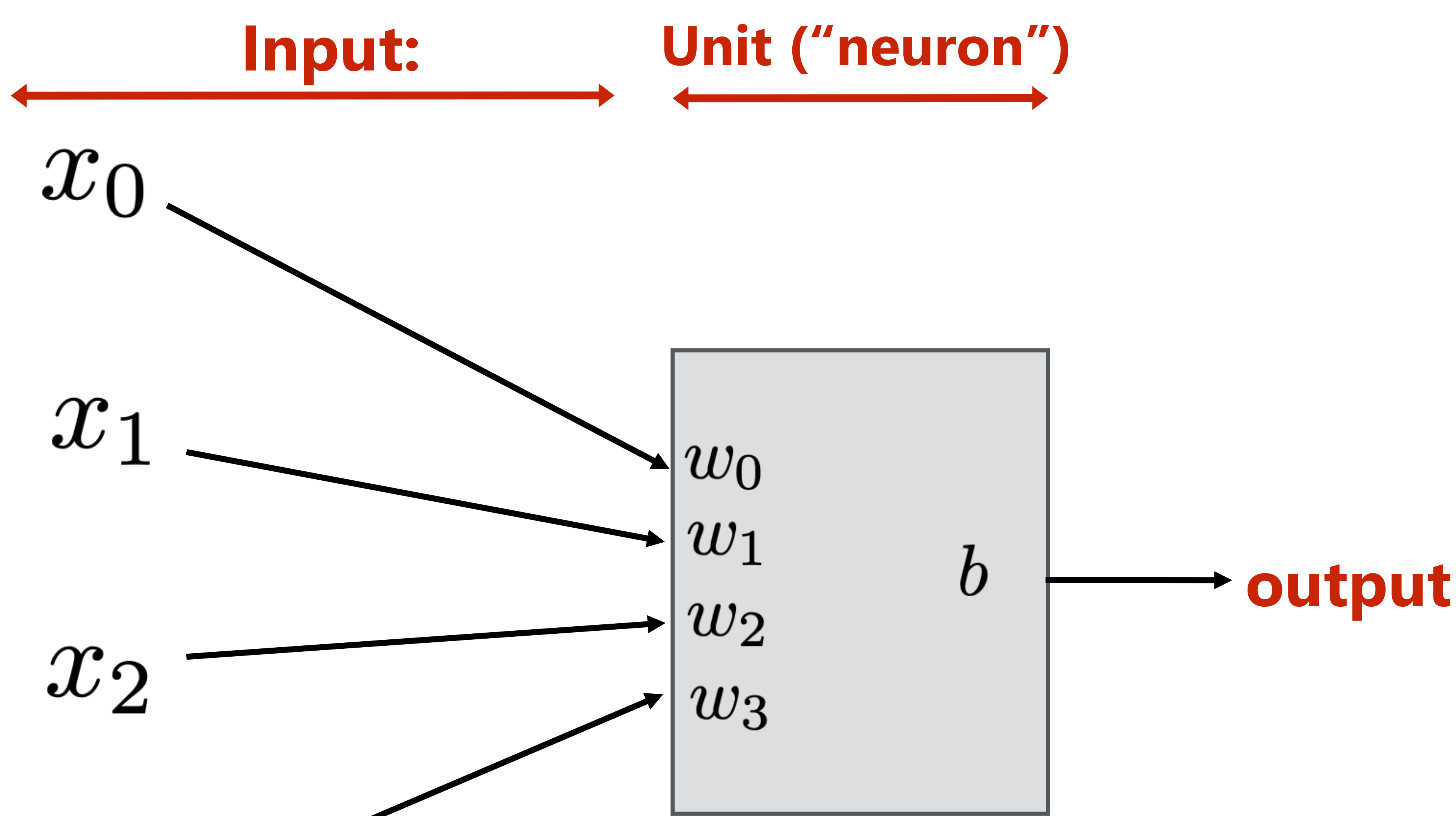




What is a deep neural network?

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 f: rectified linear unit (ReLU)

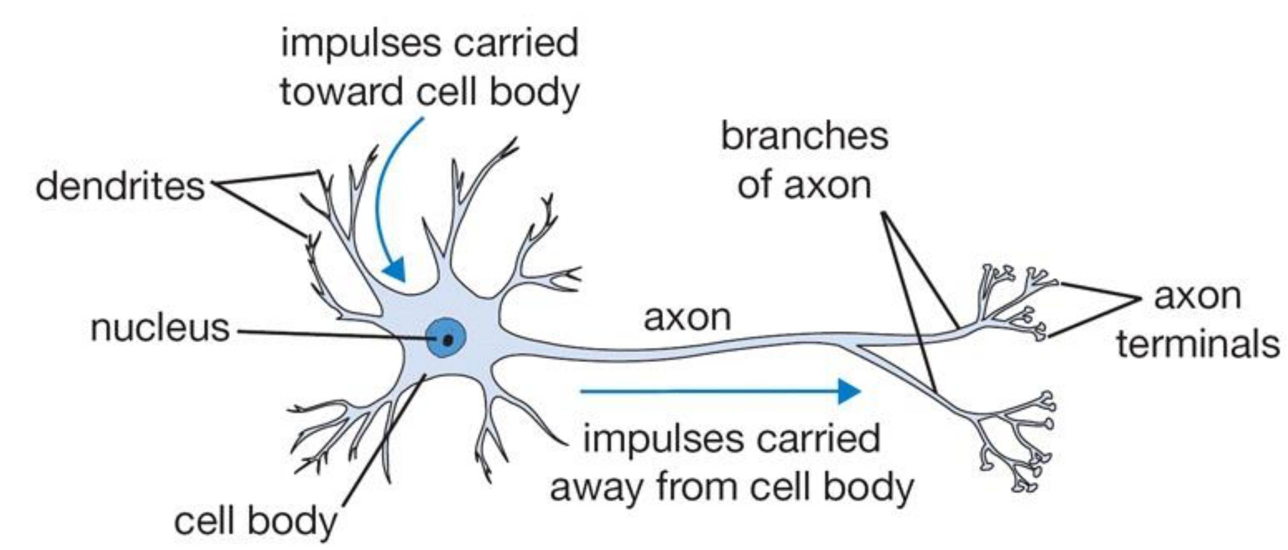
$f(x) = max(0, x)$

Basic computational interpretation:

It's just a circuit!

Biological inspiration:

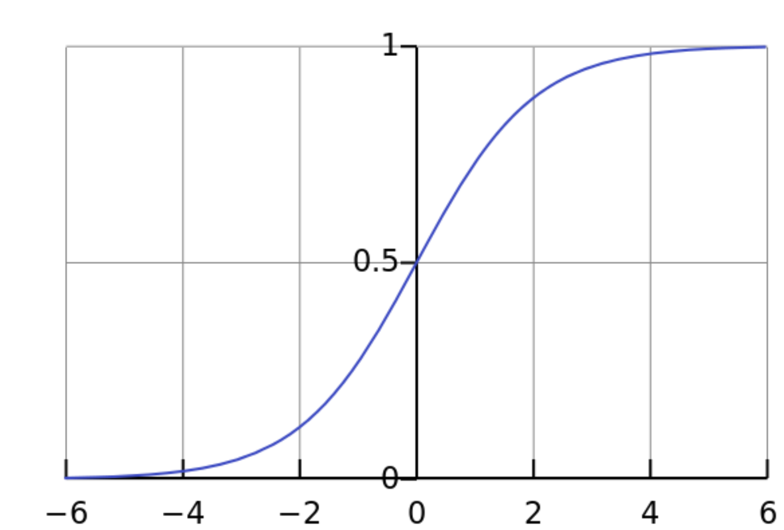
unit output corresponds loosely to activation of neuron



Machine learning interpretation:

binary classifier: interpret output as the probability of one class

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



Deep Learning Heros

Type to enter a caption.

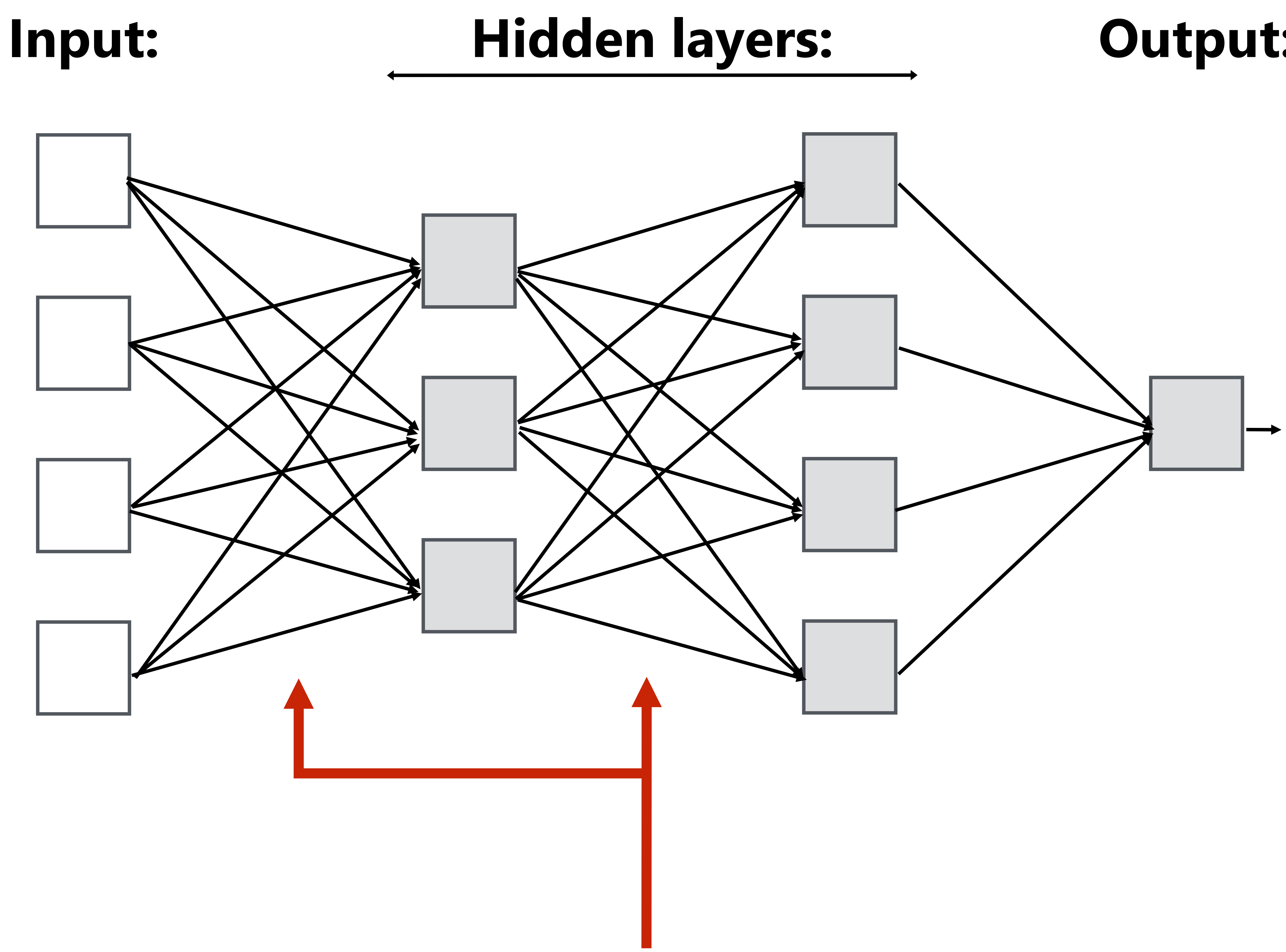
- **2019 Turing Award Winners**
  - Yoshua Bengio
  - Geoff Hinton
  - Yann LeCun

Two Distinct Issues with Deep Networks

- **Evaluation/Inference**
  - often takes milliseconds
- **Training**
  - often takes hours, days, weeks

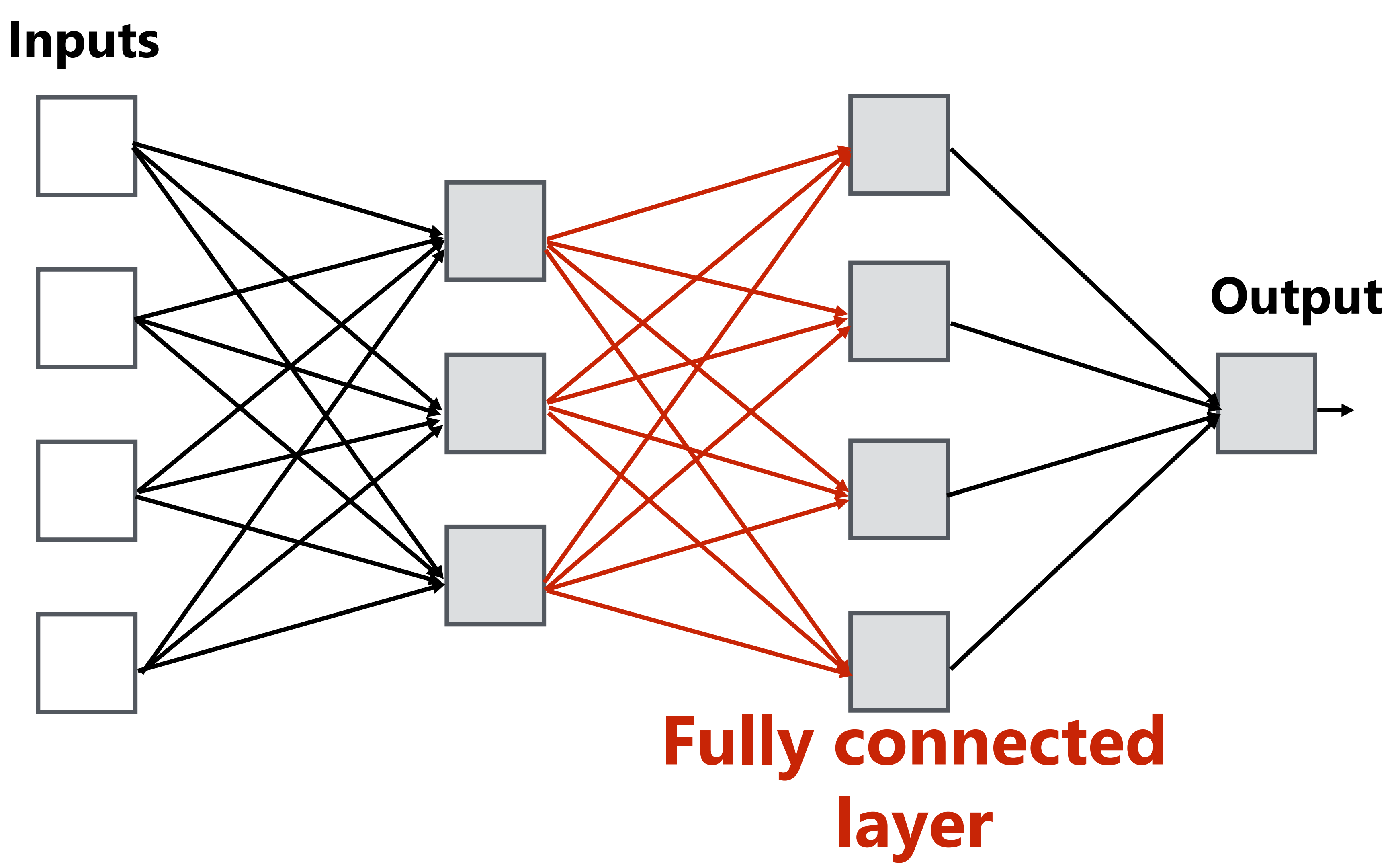
What is a deep neural network? topology

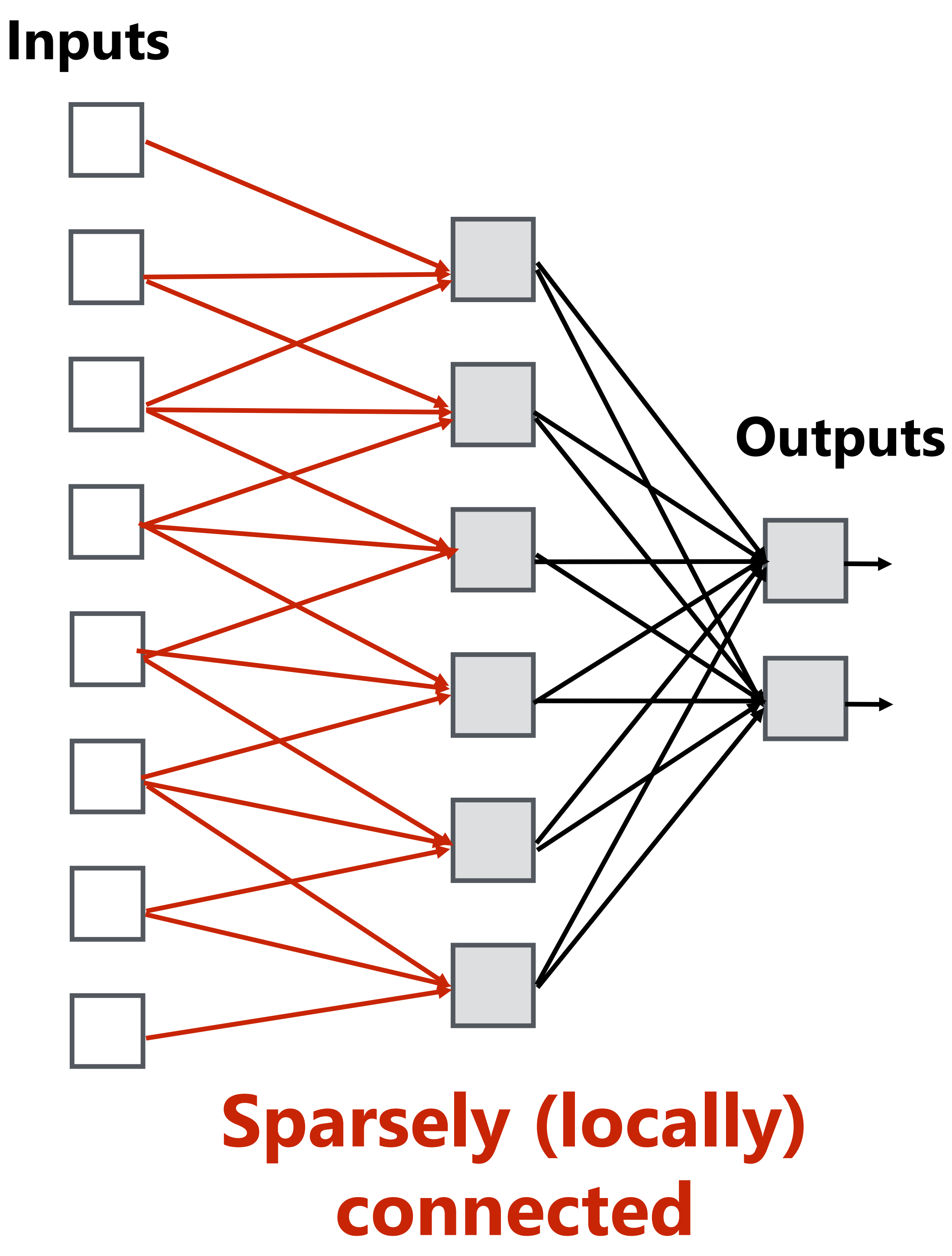
This network has: 4 inputs, 1 output, 7 hidden units
"Deep" > one hidden layer
Hidden layer 1: 3 units x (4 weights + 1 bias) = 15 parameters
Hidden layer 2: 4 units x (3 weights + 1 bias) = 16 parameters



Note fully-connected topology in this example

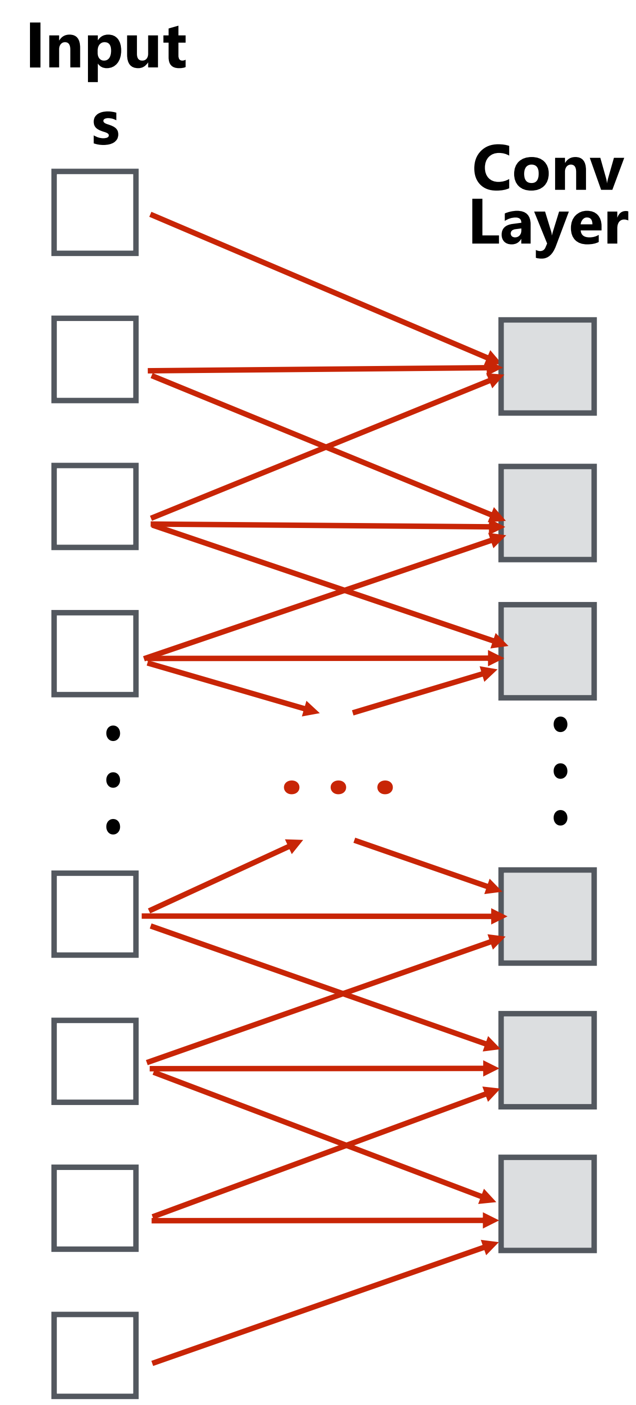
What is a deep neural network? topology

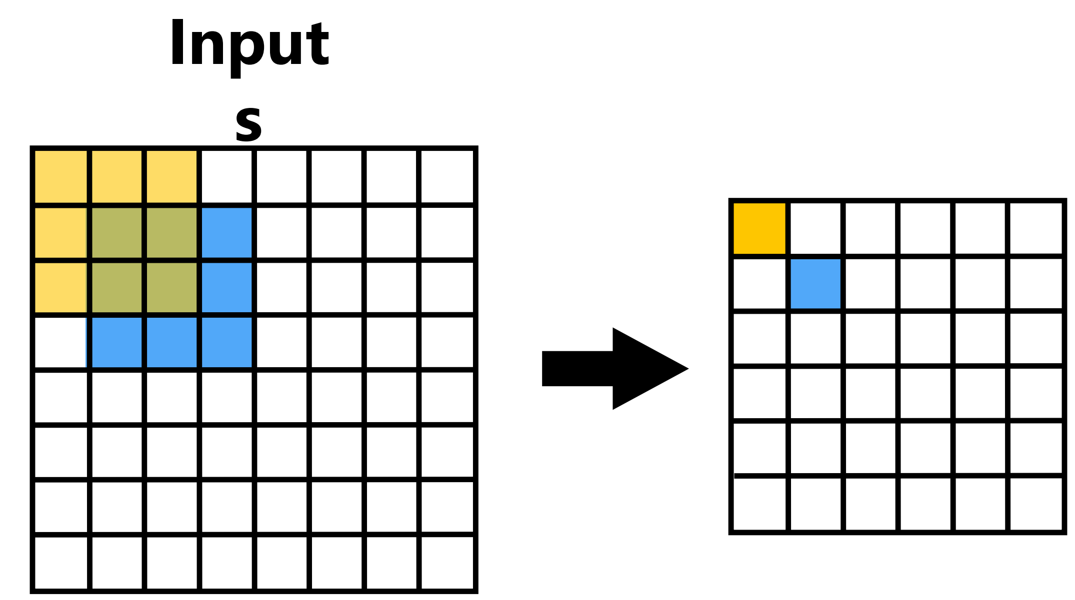




Recall image convolution (3x3 conv)

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

float bias = 0.f;
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};
```

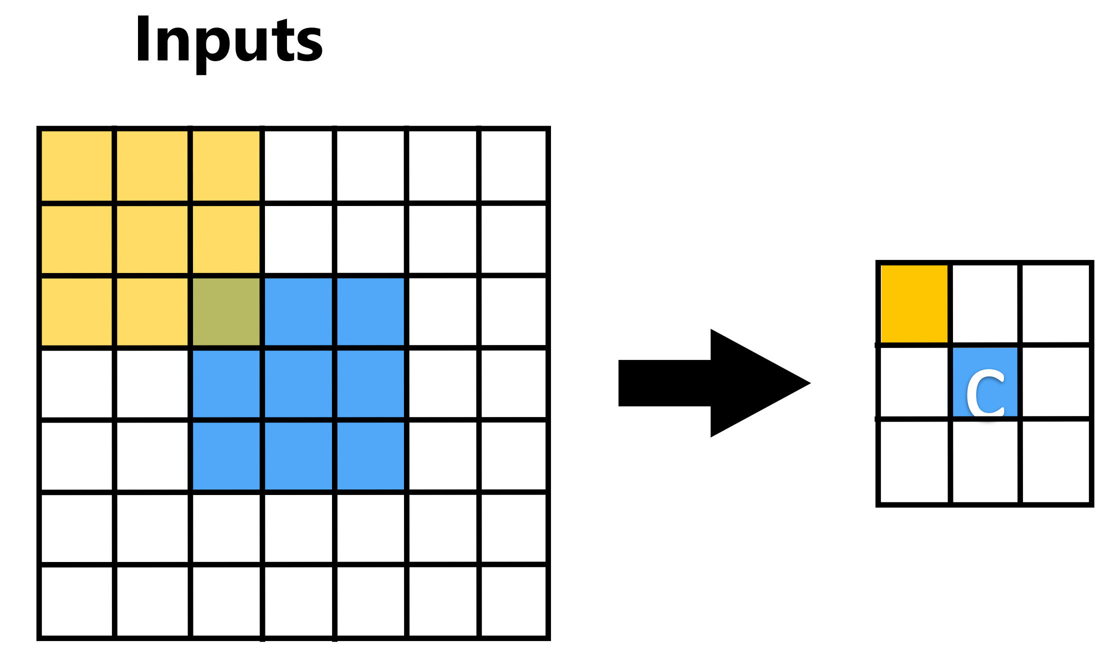




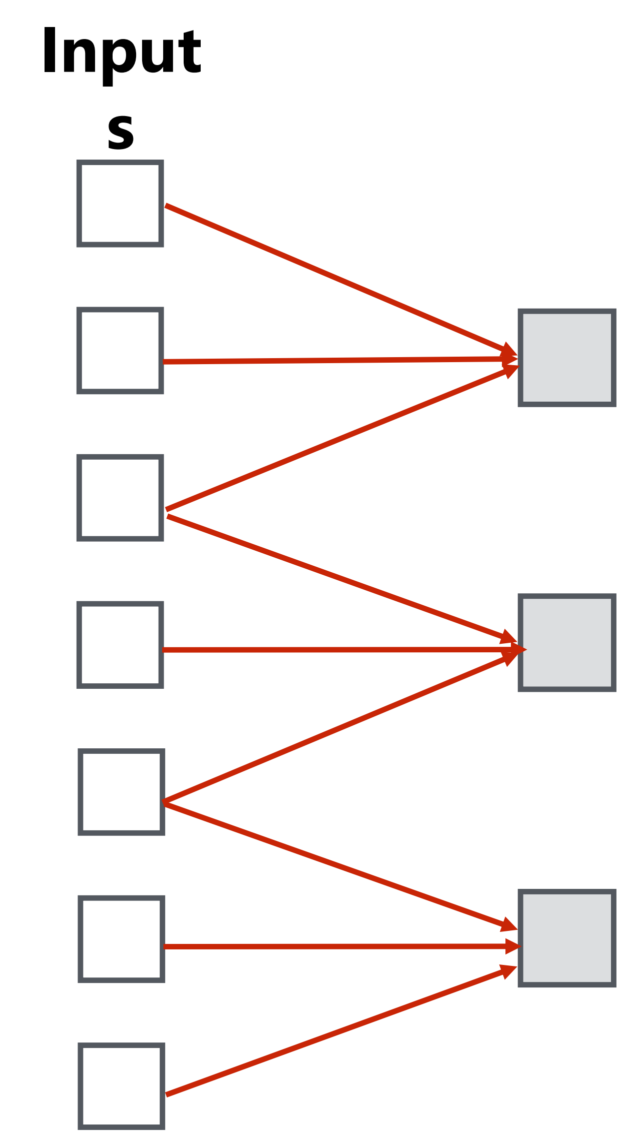

```
for (int j=0; j<HEIGHT; j++) {
  for (int i=0; i<WIDTH; i++) {
    float tmp = bias;
    for (int jj=0; jj<3; jj++)
      for (int ii=0; ii<3; ii++)
        tmp += input[(j+jj)*(WIDTH+2) + (i+ii)] * weights[jj*3 + ii];
    output[j*WIDTH + i] = tmp;
  }
}
```

Convolutional layer: locally connected AND all units in layer share the same parameters (same weights + same bias):
(note: network diagram only shows links due to 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 bias = 0.f;
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 = bias;
    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;
  }
}
```

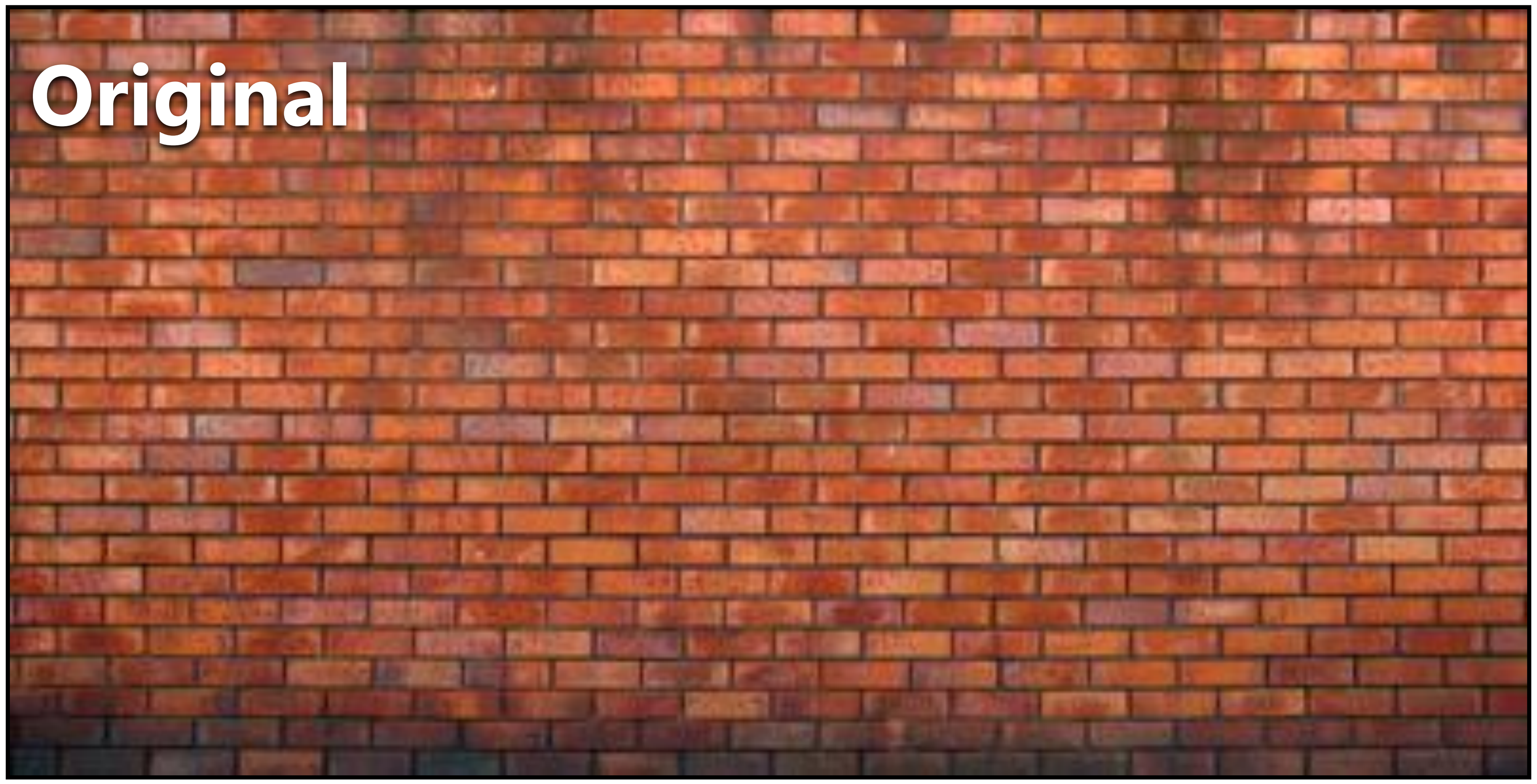


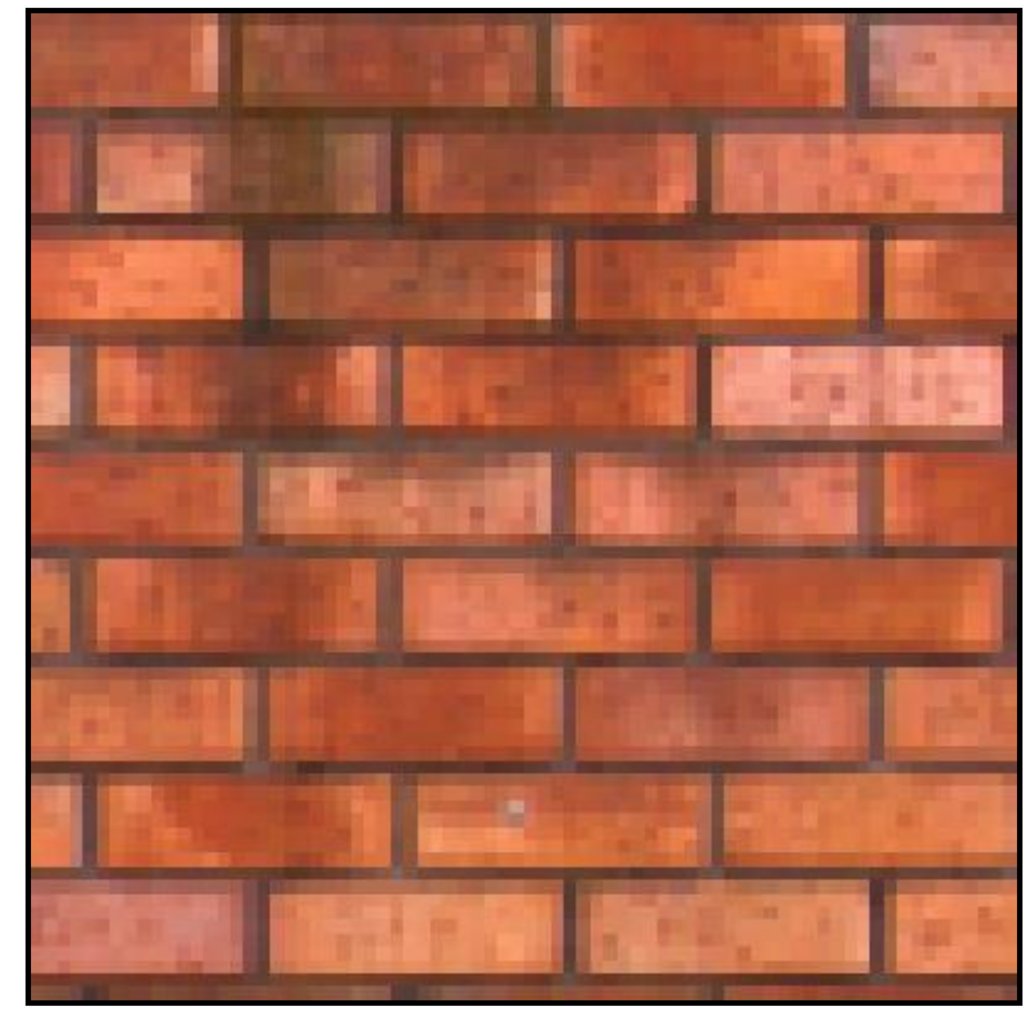
Convolutional layer with stride 2

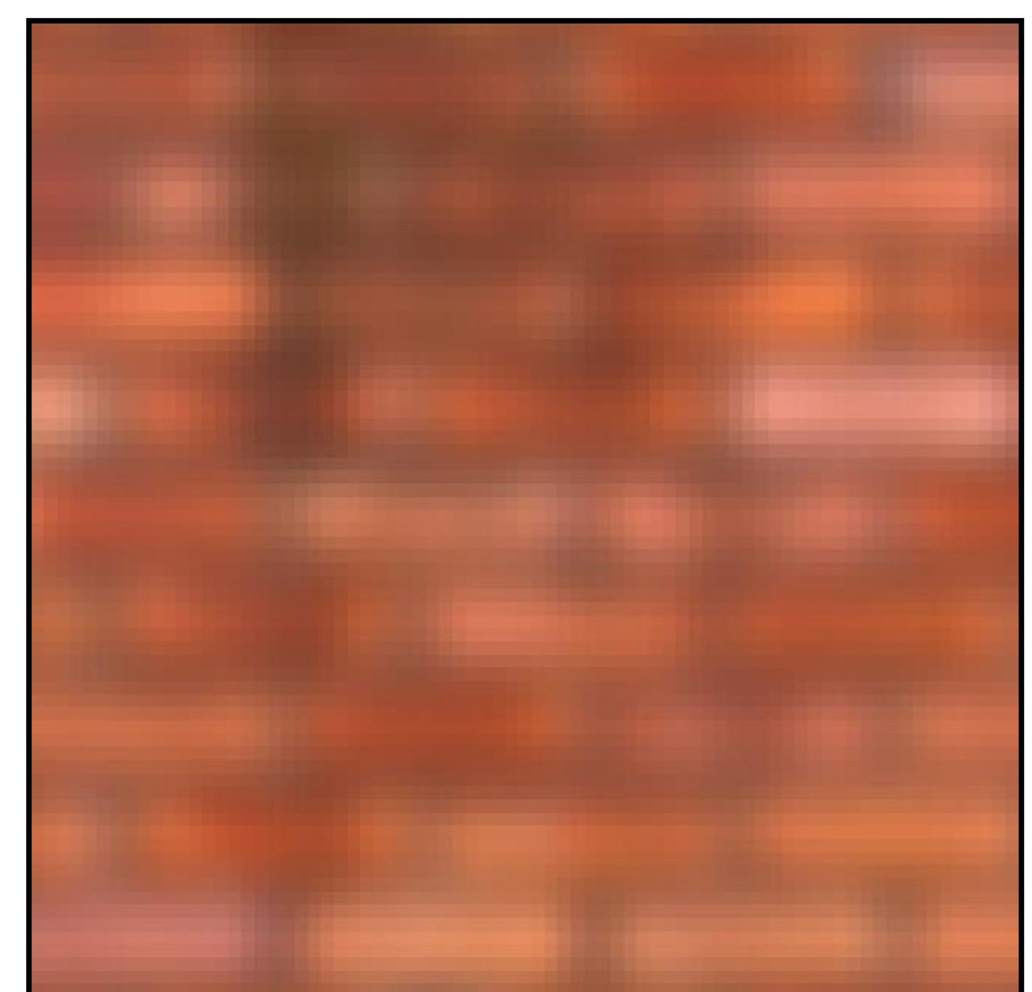
What does convolution using these filter weights do?

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

"Gaussian Blur"







What does convolution with these filters do?

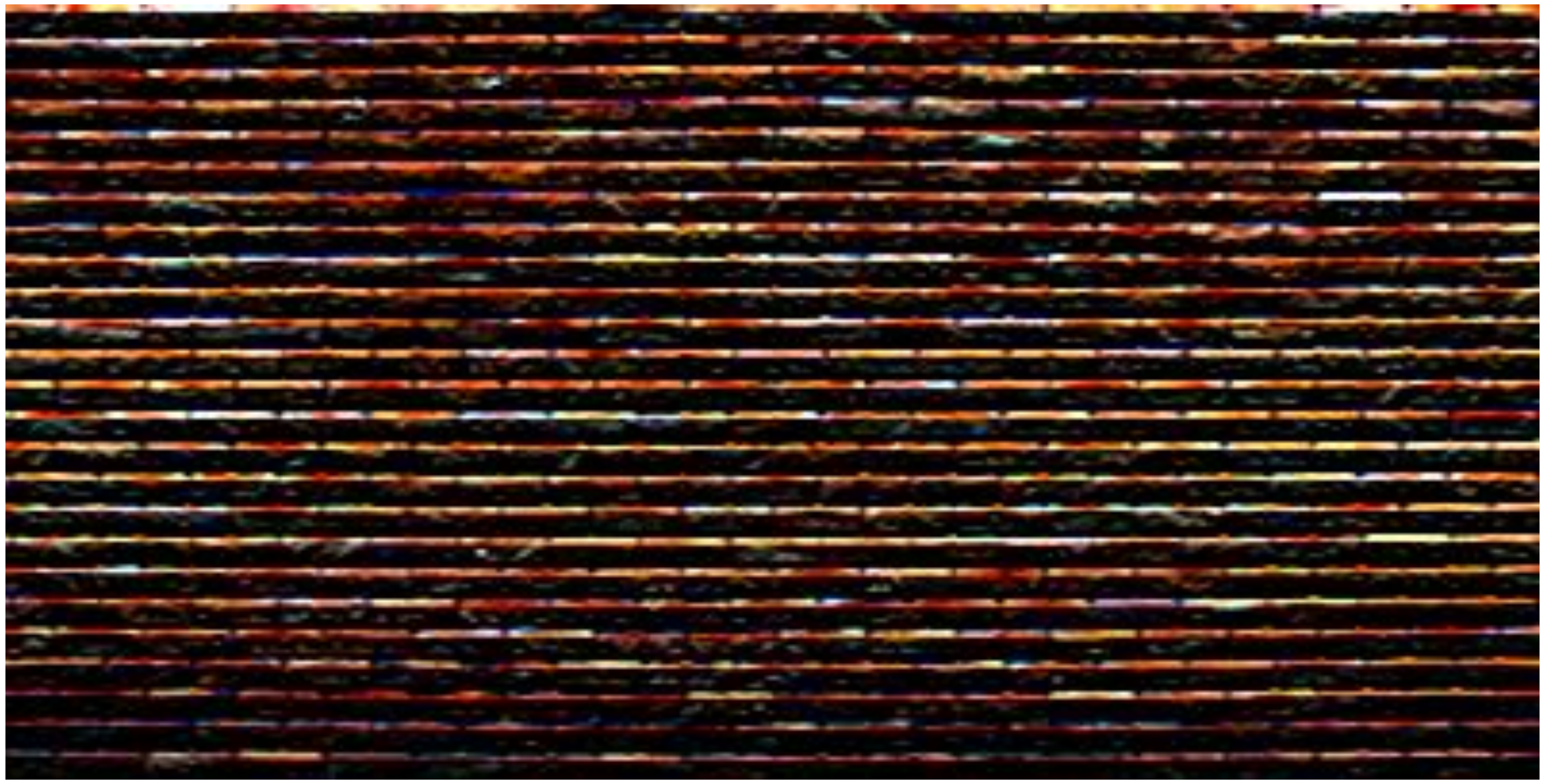
$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

Extracts horizontal gradients

Extracts vertical gradients

Gradient detection filters

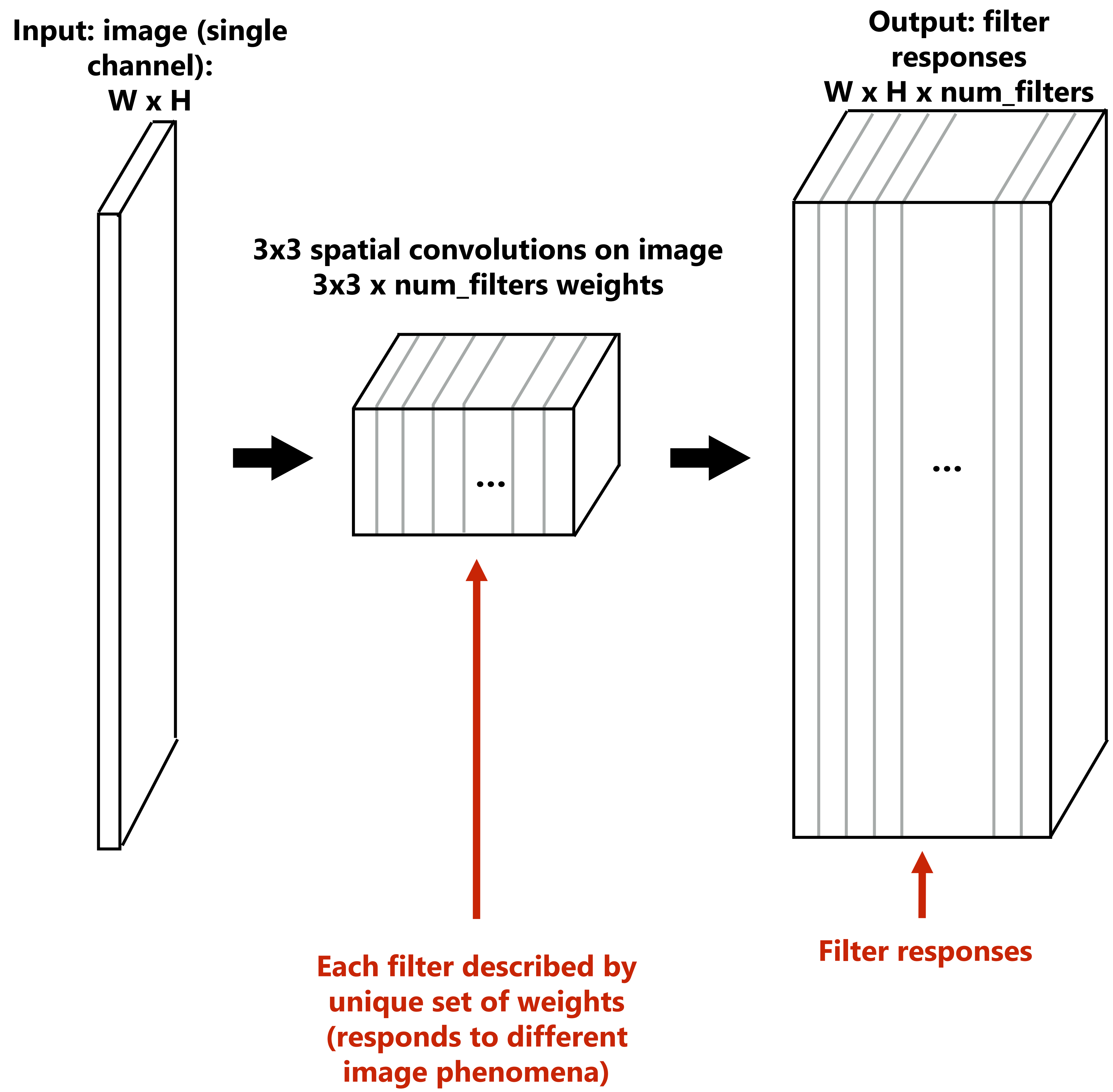
Horizontal gradients



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

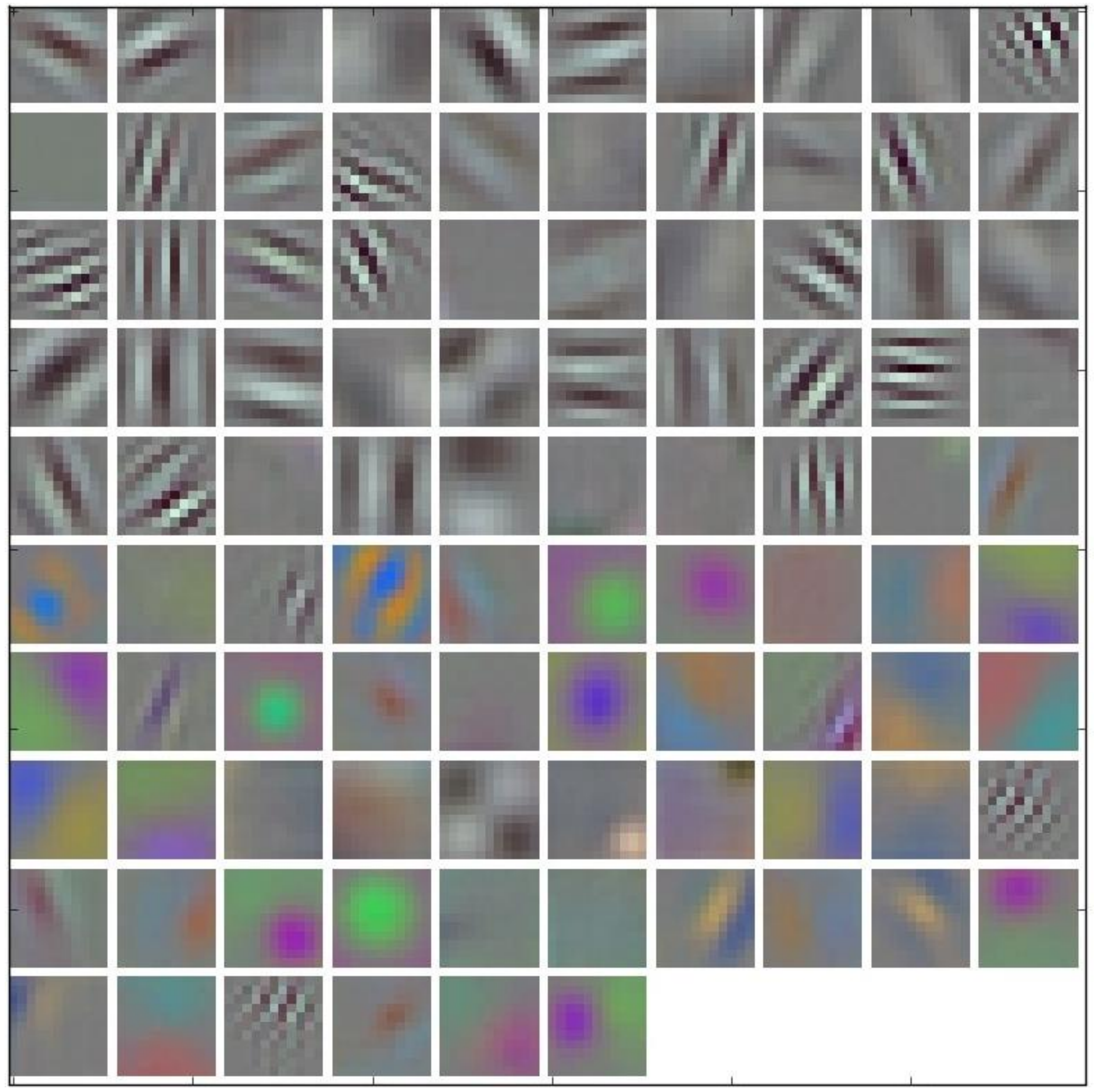
Applying many filters to an image at once



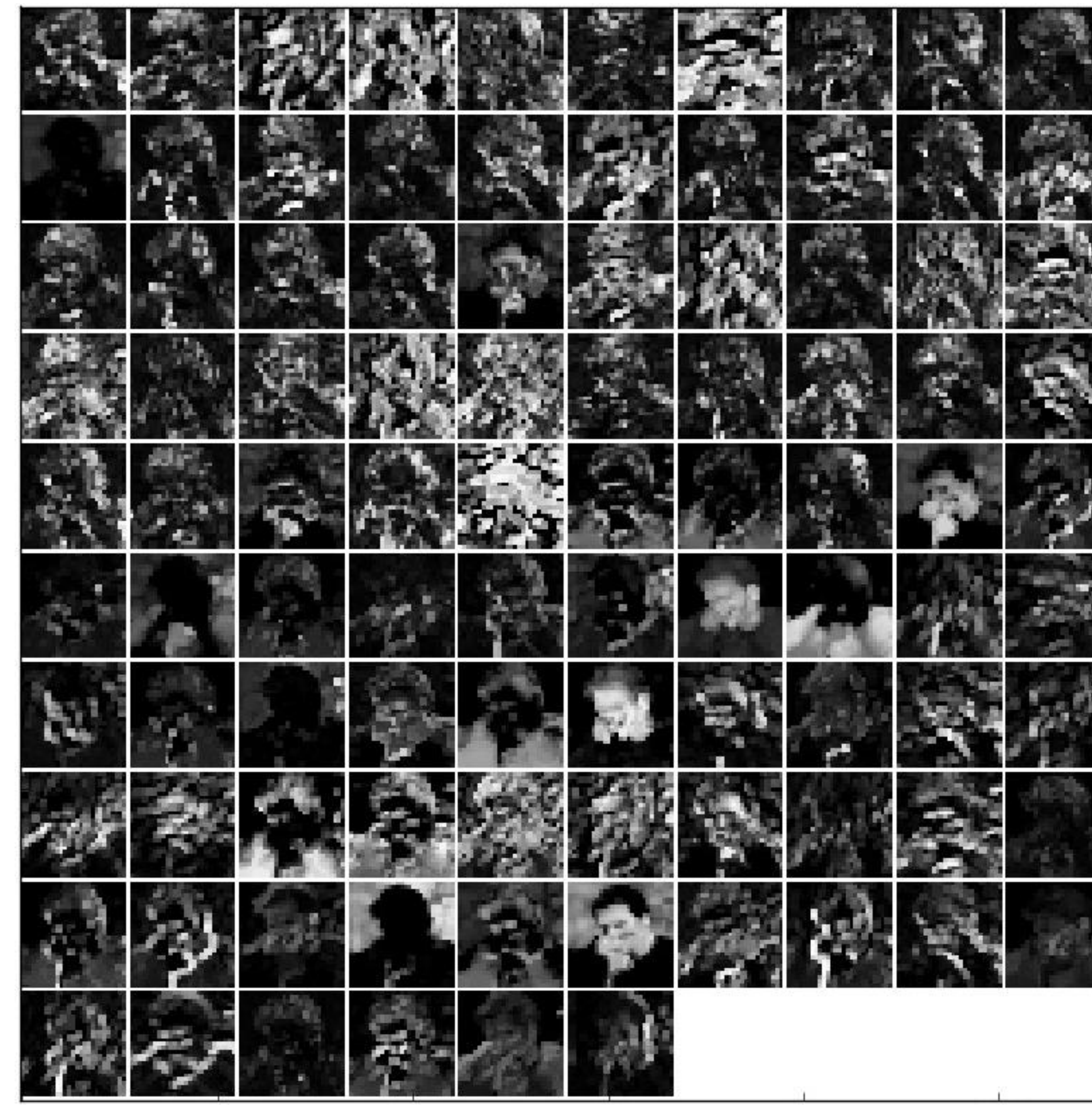
Applying many filters to an image at once

Input RGB image (W x H x 3)

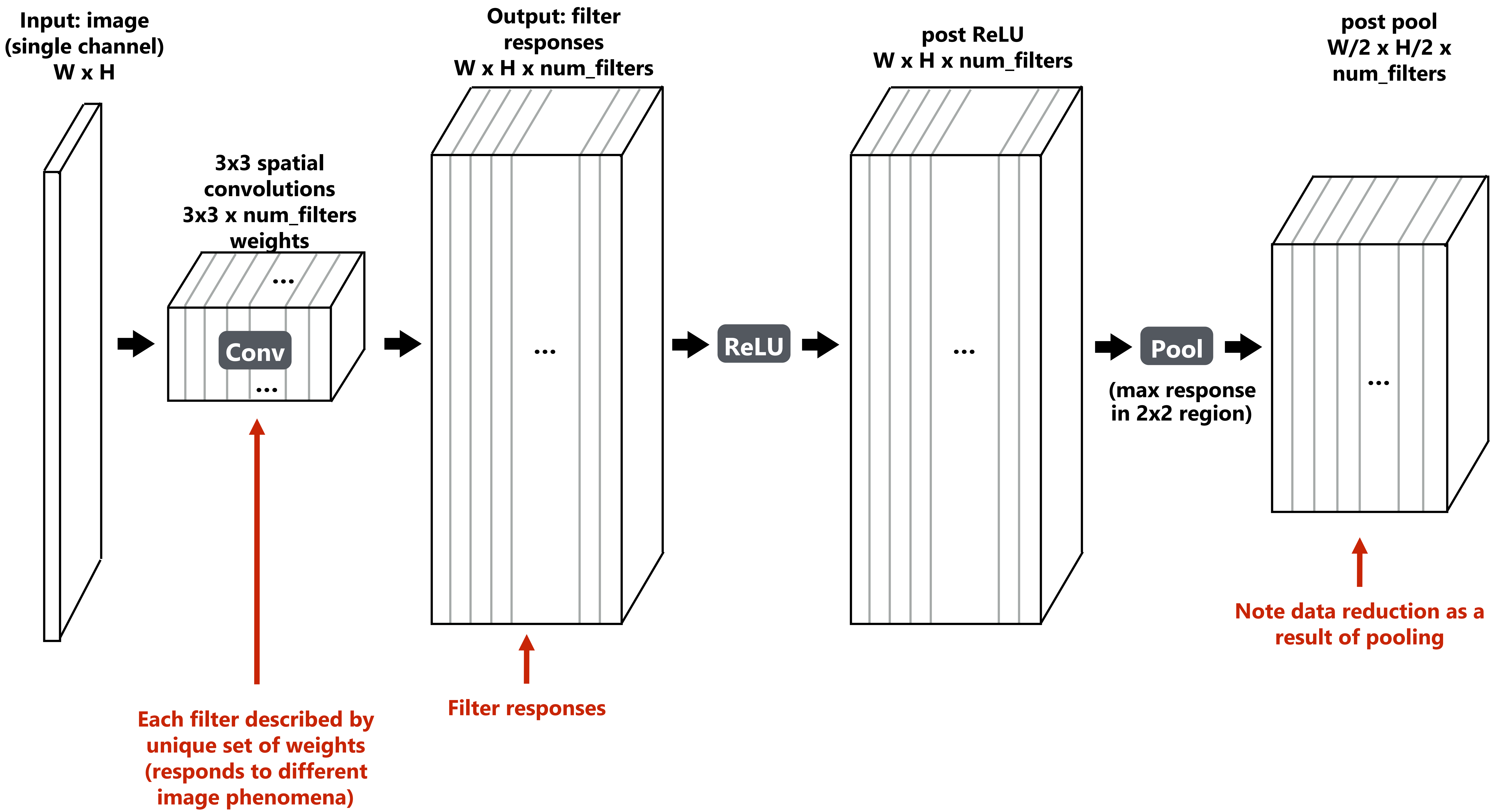
96 11x11x3 filters
(operate on RGB)



96 responses (normalized)



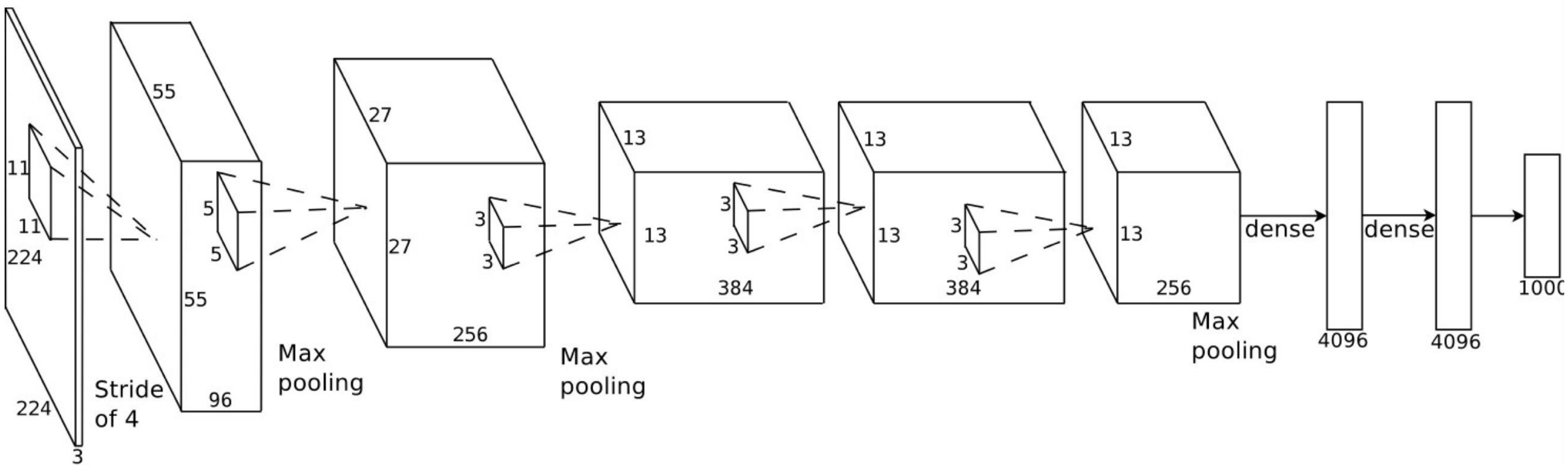
Adding additional layers



Modern object detection networks

Sequences of cont + reLU + (optional) pool layers

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



VGG-16 [Simonyan15]: 13 convolutional layers

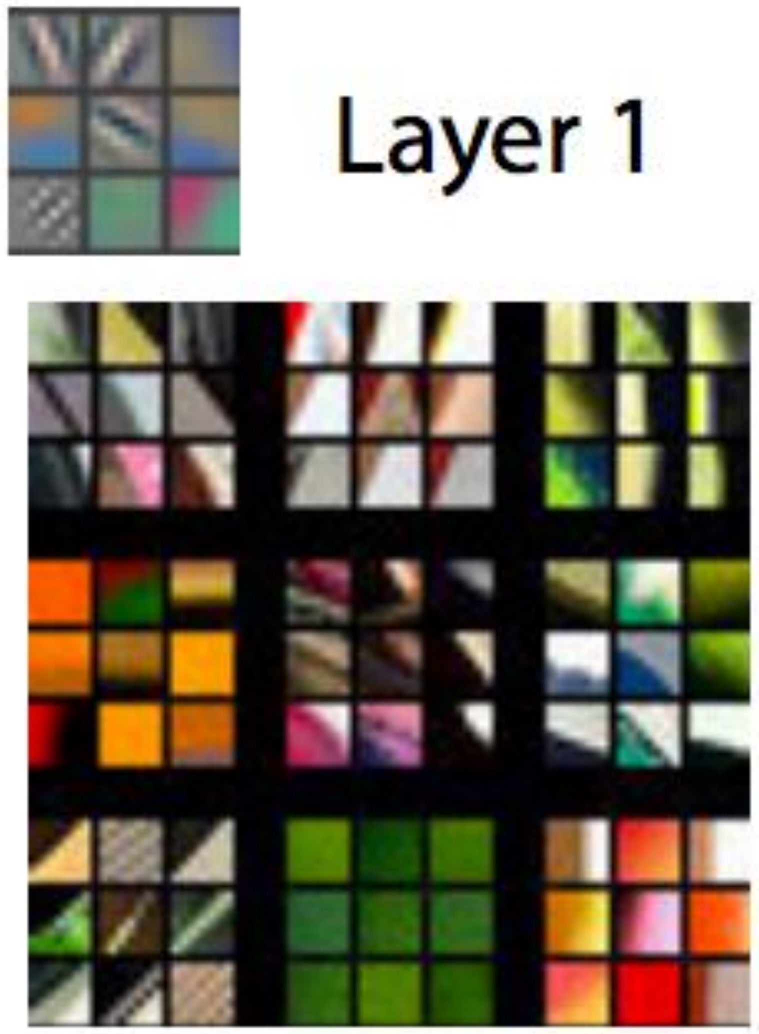
input: 224 x 224 RGB
conv/reLU: 3x3x3x64
conv/reLU: 3x3x64x64
maxpool
conv/reLU: 3x3x64x128
conv/reLU: 3x3x128x128
maxpool
conv/reLU: 3x3x128x256
conv/reLU: 3x3x256x256
conv/reLU: 3x3x256x256
maxpool
conv/reLU: 3x3x256x512
conv/reLU: 3x3x512x512
conv/reLU: 3x3x512x512
maxpool
conv/reLU: 3x3x512x512
conv/reLU: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

[VGG illustration credit: Yang et al.]

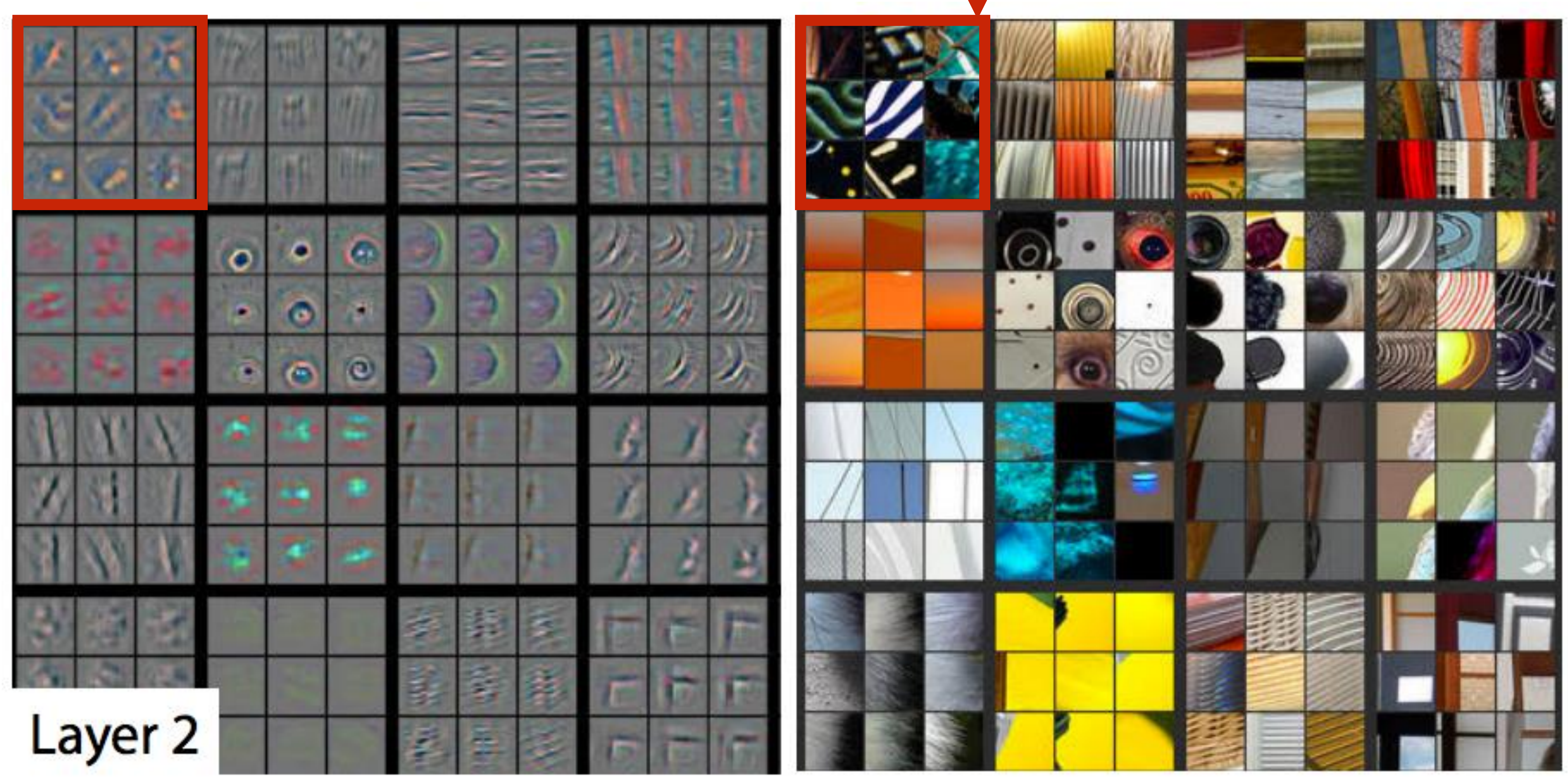
Why deep?

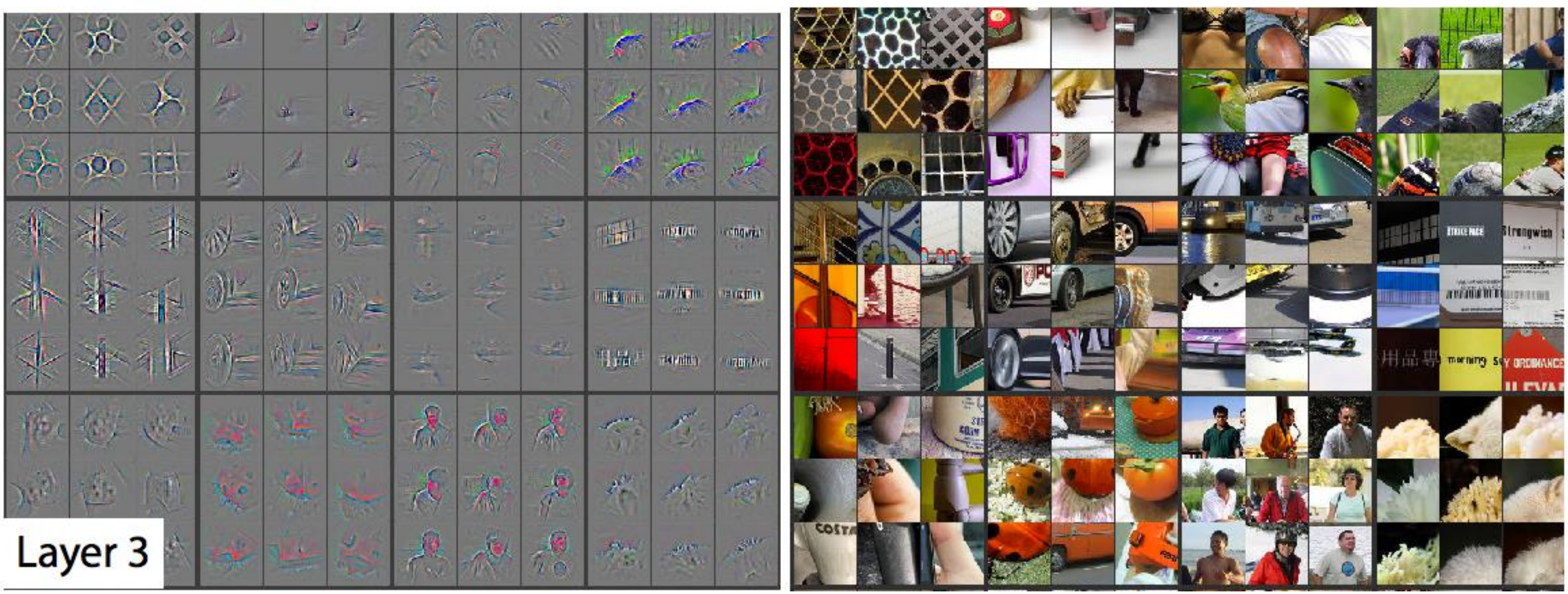
Left: what pixels trigger the response

Right: images that generate strongest response for filters at each layer



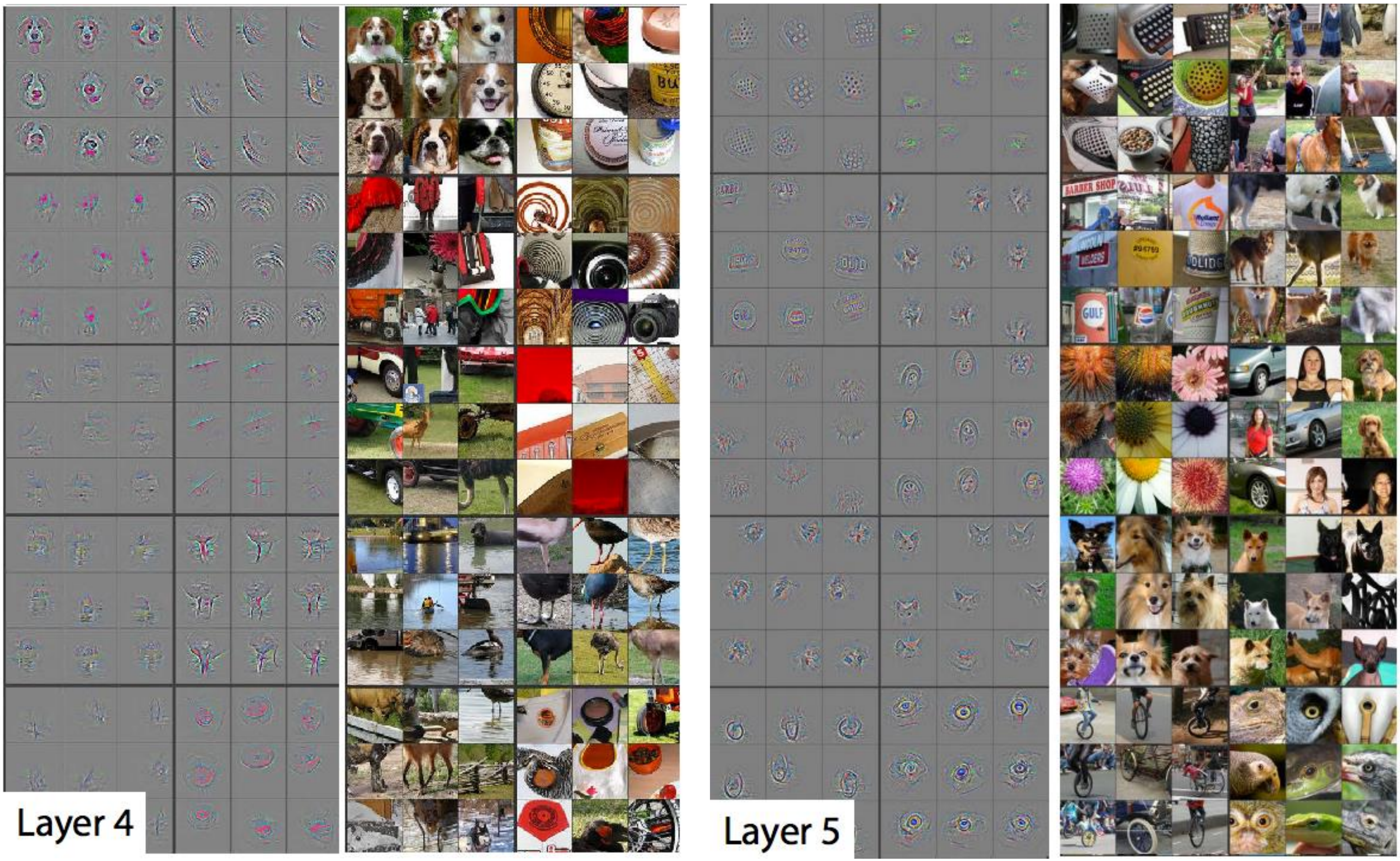
Layer 1





[image credit: Zeiler 14]

Why deep?



[image credit: Zeiler 14]

Efficiently implementing convolution layers

Direct implementation of conv layer

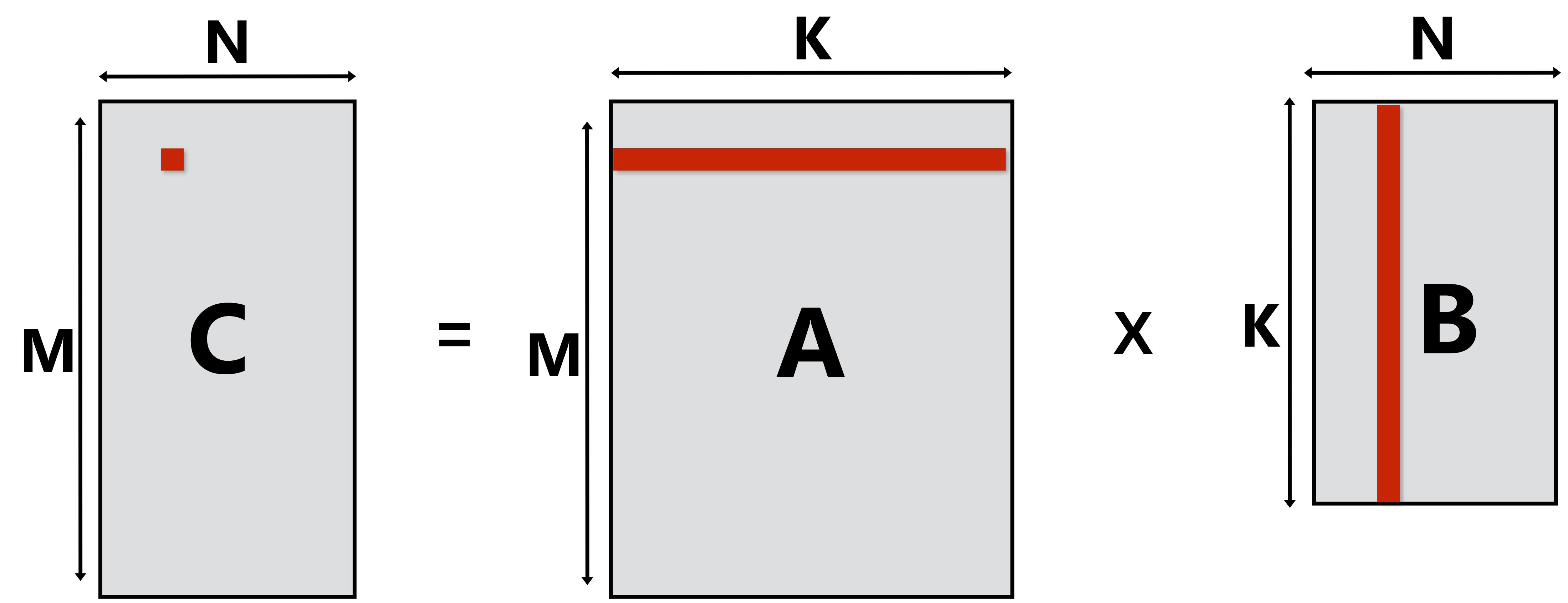
```
float input[INPUT_HEIGHT][INPUT_WIDTH][INPUT_DEPTH];
float output[INPUT_HEIGHT][INPUT_WIDTH][OUTPUT_DEPTH];
float layer_weights[OUTPUT_DEPTH][INPUT_DEPTH][LAYER_CONVY][LAYER_CONVX];
float layer_biases[OUTPUT_DEPTH];
// assumes convolution stride is 1
// Note that code does not handle boundary conditions
for (int img=0; img<IMAGE_BATCH_SIZE; img++)  // Optional outer loop for multiple images
   for (int j=0; j<INPUT_HEIGHT; j++)
      for (int i=0; i<INPUT_WIDTH; i++)
         for (int f=0; f<OUTPUT_DEPTH; f++) {
            float tmp = layer_biases[f];
            for (int kk=0; kk<INPUT_DEPTH; kk++)  // sum over filter responses of input channels
               for (int jj=0; jj<LAYER_CONVY; jj++) // spatial convolution
                  for (int ii=0; ii<LAYER_CONVX; ii+)  // spatial convolution
                      tmp += layer_weights[f][kk][jj][ii] * input[j+jj][i+ii][kk];
            output[j][i][f] = tmp; // Use Max(0.f, tmp) for ReLU
         }
```

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

But must roll your own highly optimized implementation of a complicated loop nest.

Dense matrix multiplication

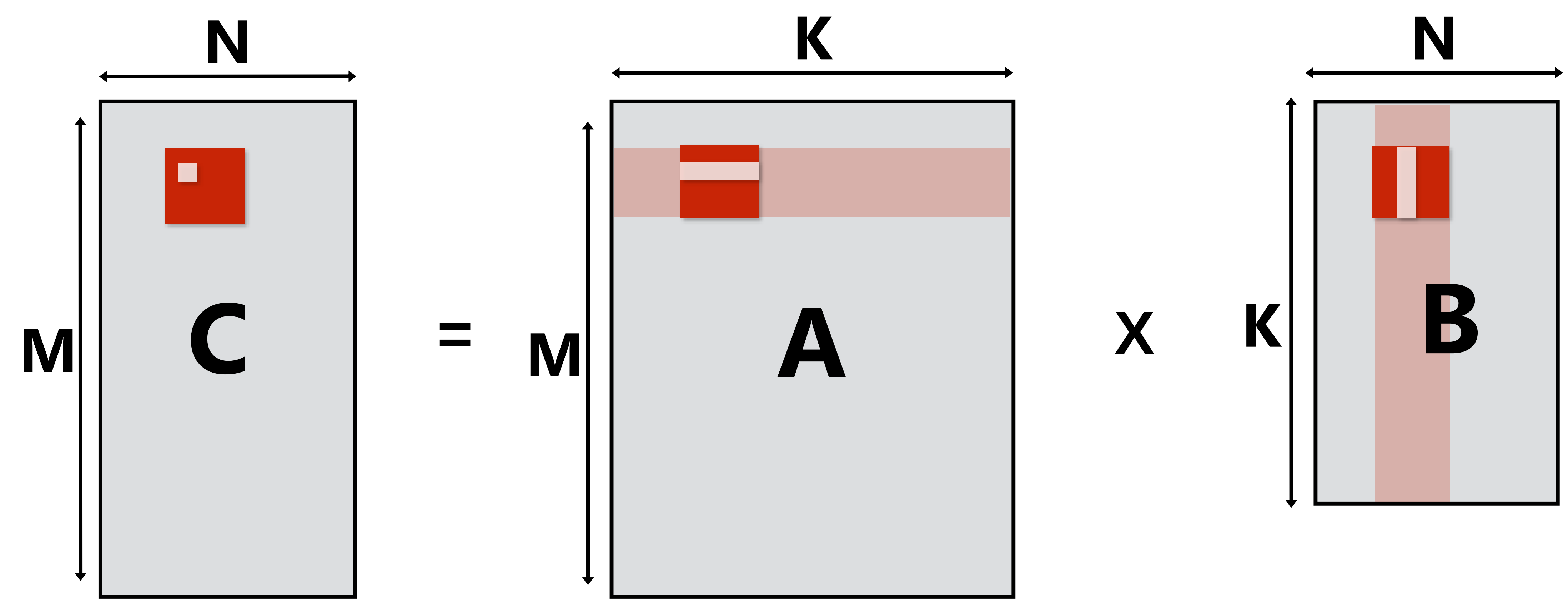
```
float A[M][K];
float B[K][N];
float C[M][N];

// 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

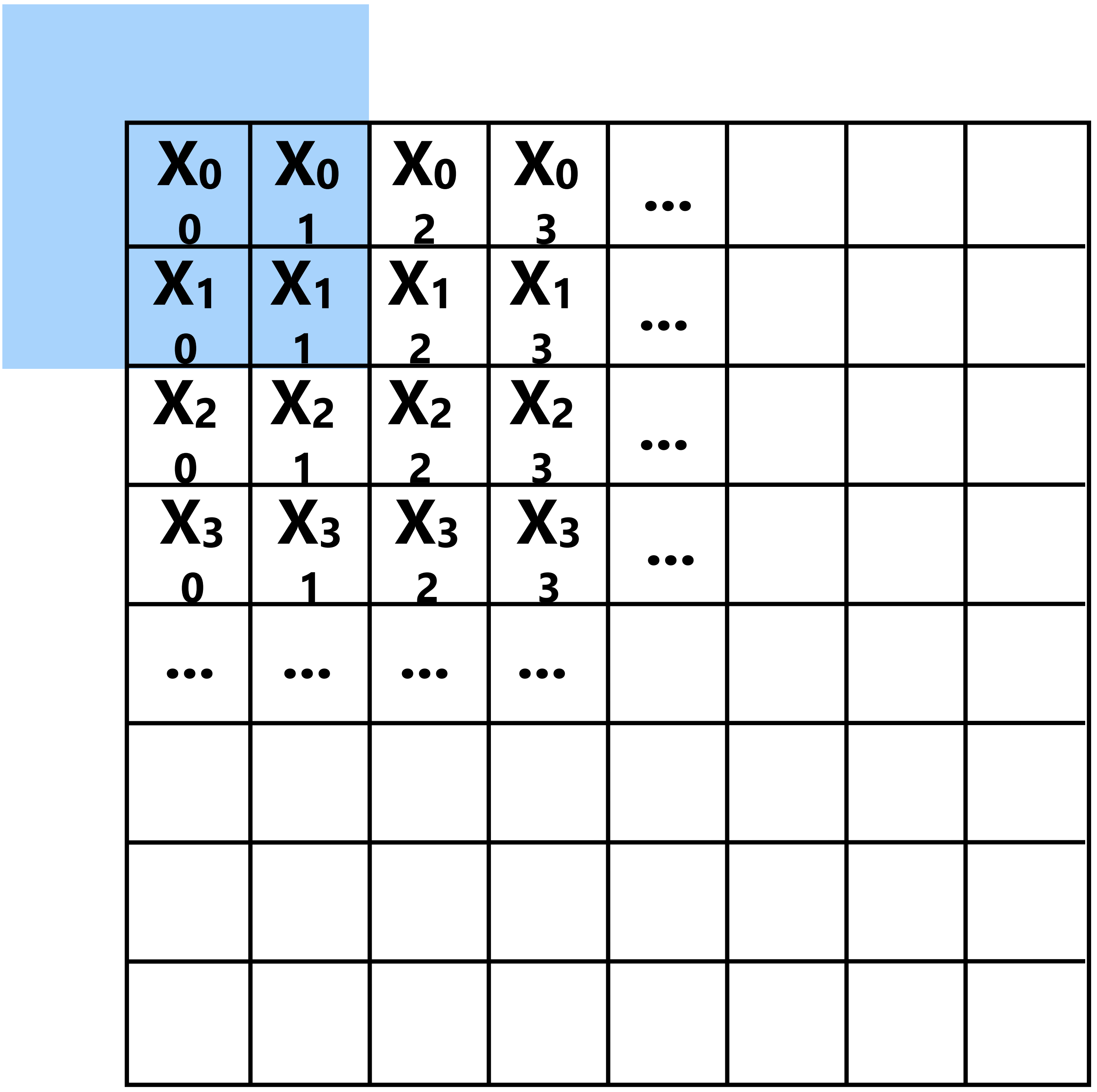



```
float A[M][K];
float B[K][N];
float C[M][N];

// 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?

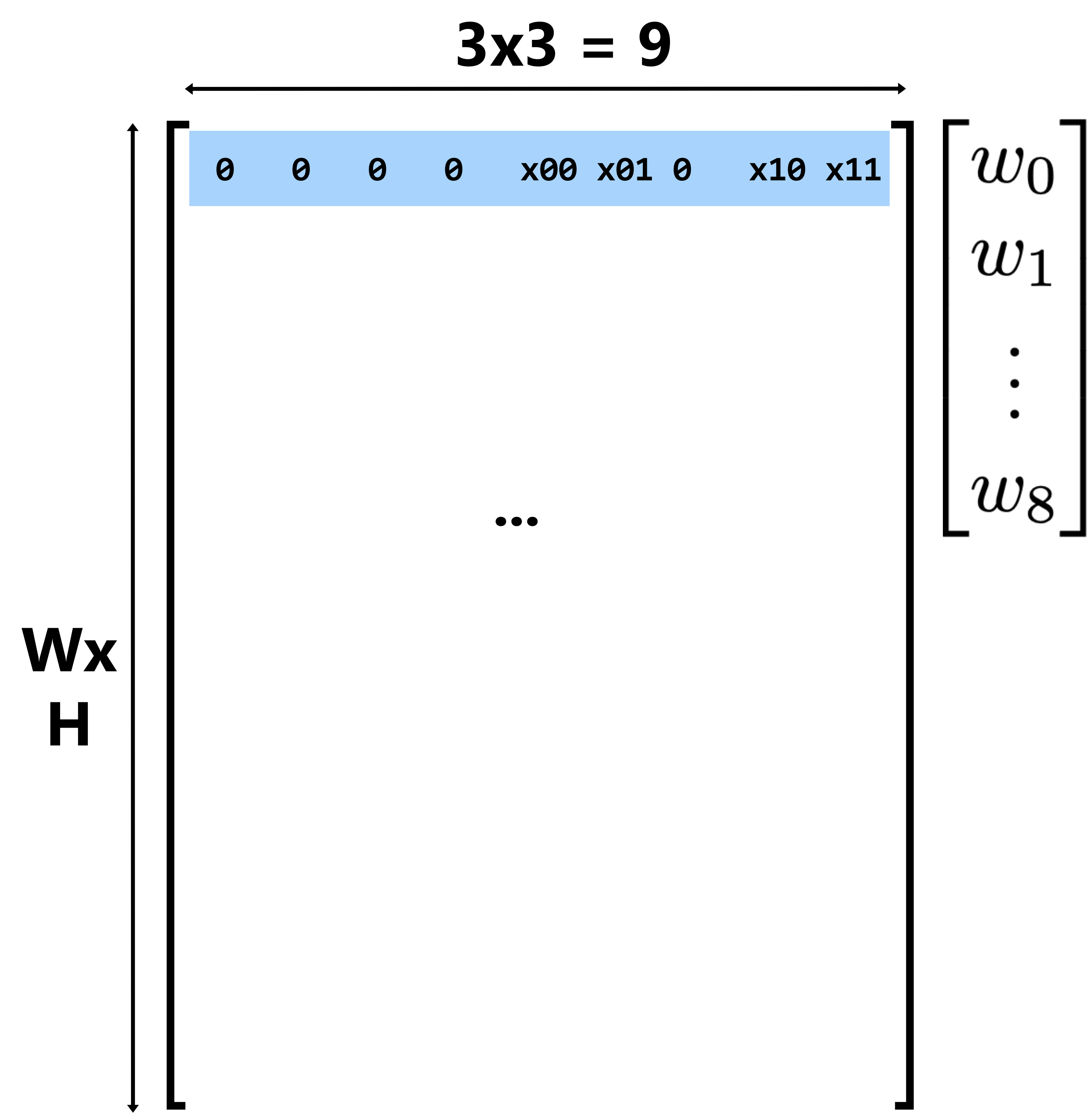
Convolution as matrix-vector product

Construct matrix from elements of input image



O(N) storage overhead for filter with N elements

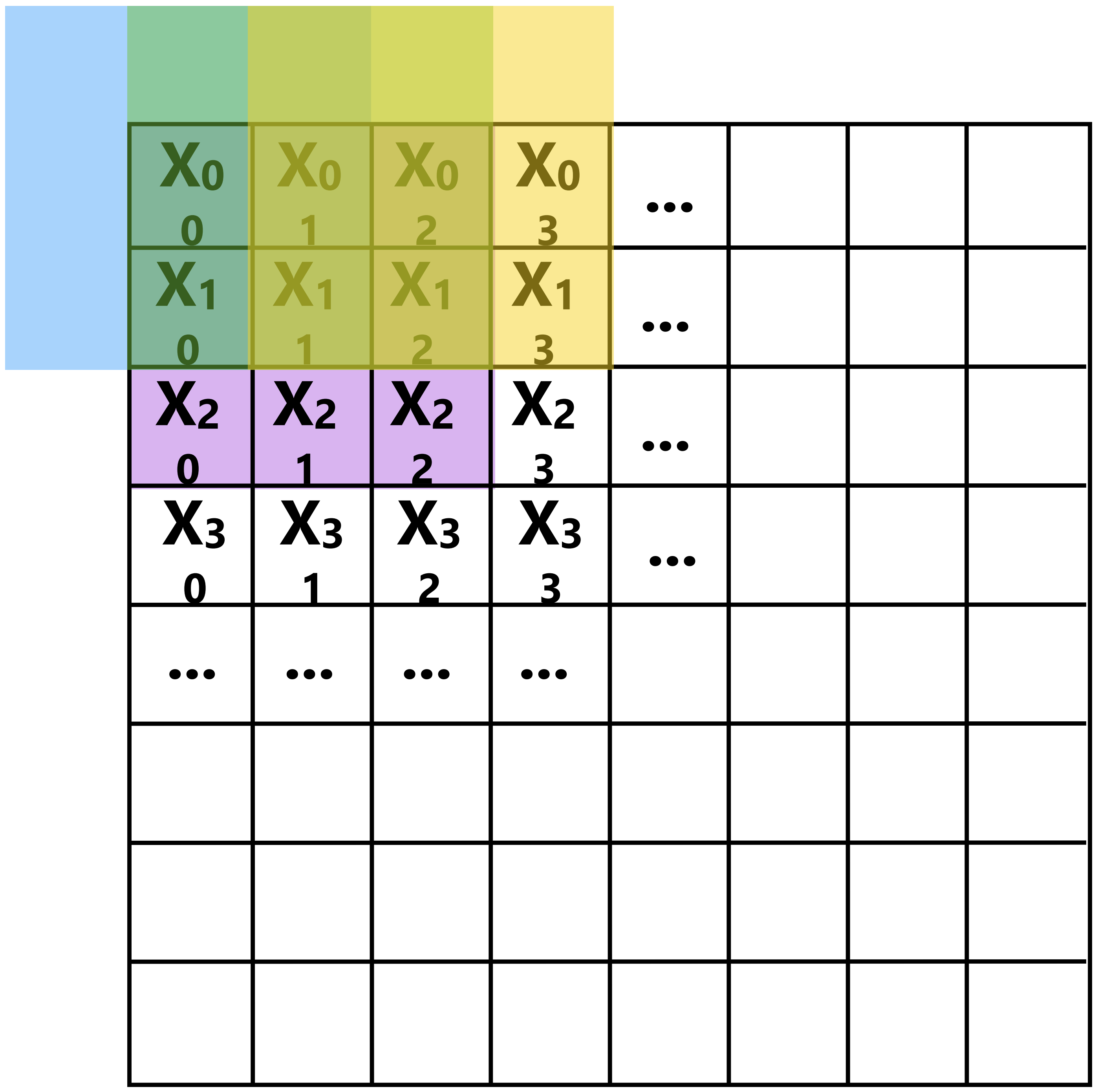
Must construct input data matrix



Note: 0-pad matrix

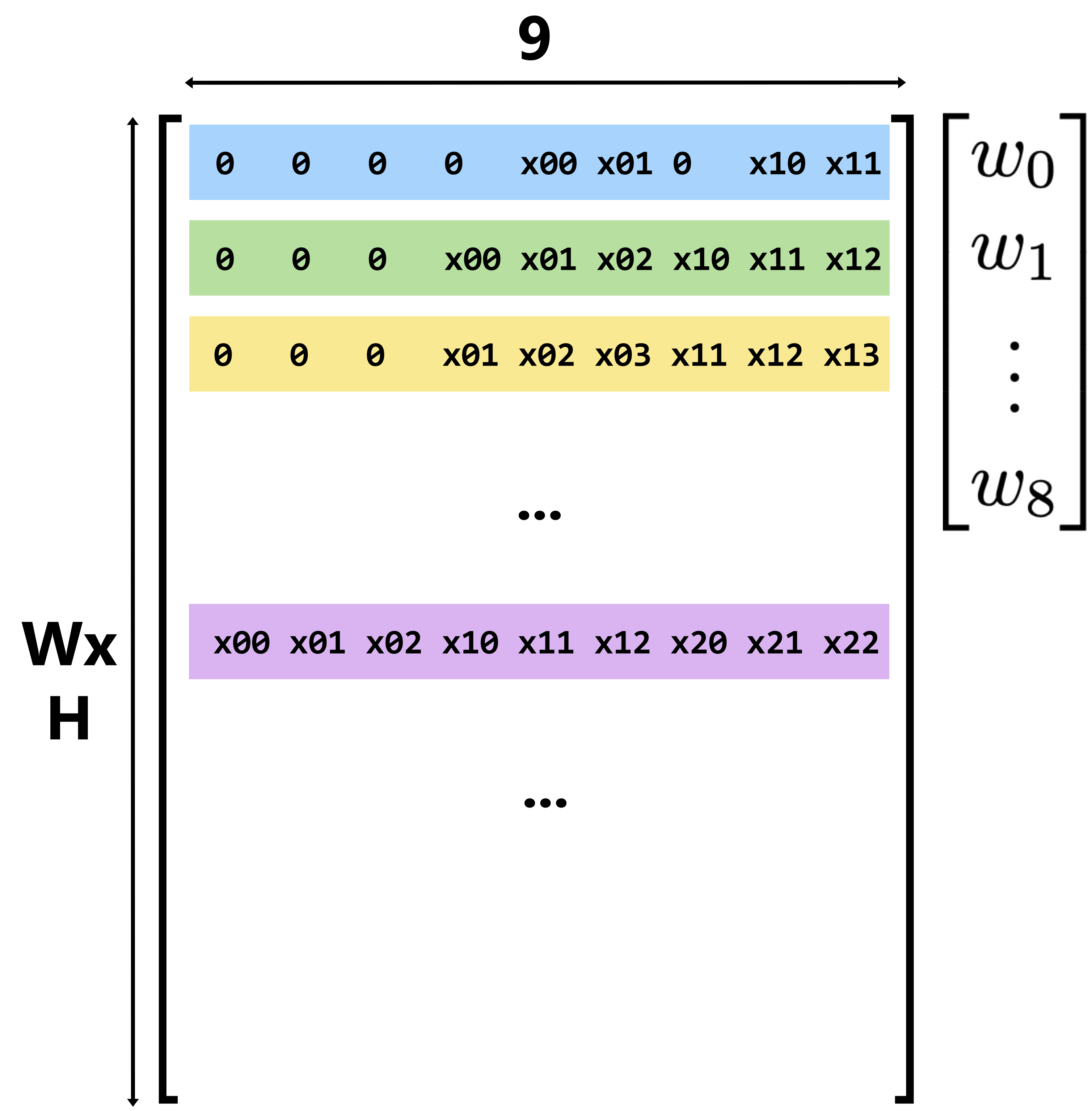
3x3 convolution as matrix-vector product

Construct matrix from elements of input image



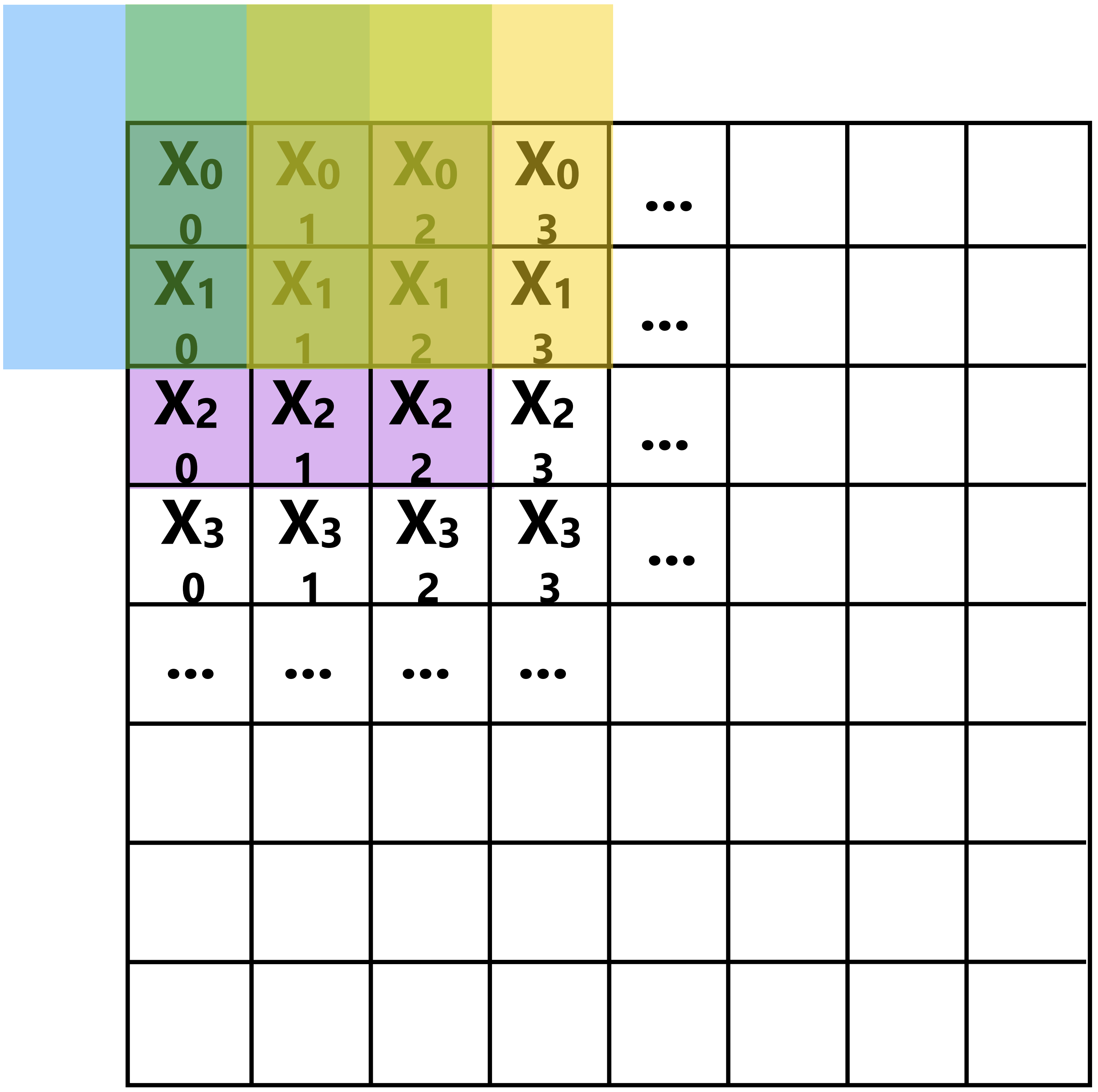
O(N) storage overhead for filter with N elements

Must construct input data matrix



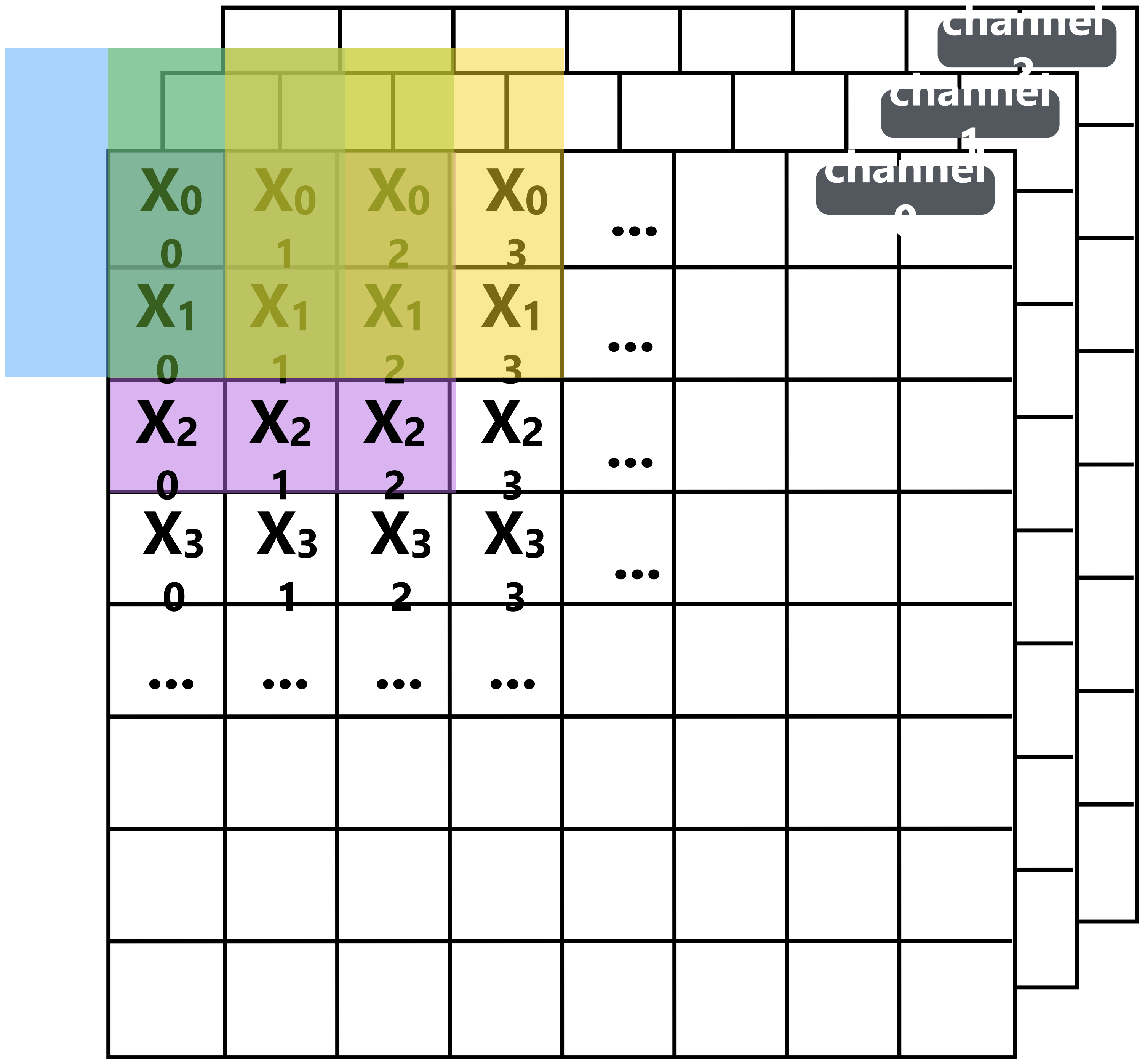
Note: 0-pad matrix

Multiple convolutions as matrix-matrix mult



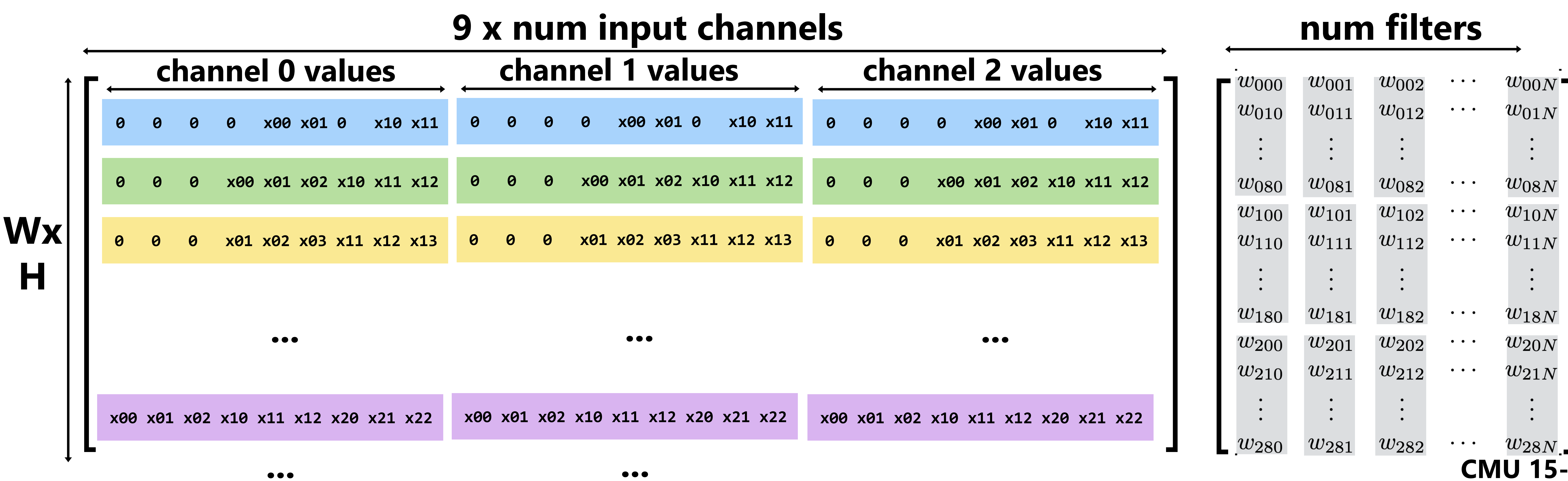
$$
\begin{array}{cc}
 & \overset{9}{\longleftrightarrow} \\
W\mathrm{x}H &
\begin{bmatrix}
0 & 0 & 0 & 0 & x00 & x01 & 0 & x10 & x11 \\
0 & 0 & 0 & x00 & x01 & x02 & x10 & x11 & x12 \\
0 & 0 & 0 & x01 & x02 & x03 & x11 & x12 & x13 \\
 & & & & \dots & & & & \\
x00 & x01 & x02 & x10 & x11 & x12 & x20 & x21 & x22 \\
 & & & & \dots & & & &
\end{bmatrix}
\end{array}
\quad
\begin{array}{c}
\overset{\text{num filters}}{\longleftrightarrow} \\
\begin{bmatrix}
w_{00} & w_{01} & w_{02} & \cdots & w_{0N} \\
w_{10} & w_{11} & w_{12} & \cdots & w_{0N} \\
\vdots & \vdots & \vdots & & \vdots \\
w_{80} & w_{81} & w_{82} & \cdots & w_{8N}
\end{bmatrix}
\end{array}
$$

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



VGG memory footprint

inputs/outputs get multiplied by image batch size

multiply by next layer's conv window size to form input matrix to next conv layer!!! (for VGG, this is a 9x data amplification)

Calculations assume 32-bit values (image batch size = 1)

	weights mem:	output size (per image)	(mem)
input: 224 x 224 RGB image	—	224x224x3	150K
conv: (3x3x3) x 64	6.5 KB	224x224x64	12.3 MB
conv: (3x3x64) x 64	144 KB	224x224x64	12.3 MB
maxpool	—	112x112x64	3.1 MB
conv: (3x3x64) x 128	228 KB	112x112x128	6.2 MB
conv: (3x3x128) x 128	576 KB	112x112x128	6.2 MB
maxpool	—	56x56x128	1.5 MB
conv: (3x3x128) x 256	1.1 MB	56x56x256	3.1 MB
conv: (3x3x256) x 256	2.3 MB	56x56x256	3.1 MB
conv: (3x3x256) x 256	2.3 MB	56x56x256	3.1 MB
maxpool	—	28x28x256	766 KB
conv: (3x3x256) x 512	4.5 MB	28x28x512	1.5 MB
conv: (3x3x512) x 512	9 MB	28x28x512	1.5 MB
conv: (3x3x512) x 512	9 MB	28x28x512	1.5 MB
maxpool	—	14x14x512	383 KB
conv: (3x3x512) x 512	9 MB	14x14x512	383 KB
conv: (3x3x512) x 512	9 MB	14x14x512	383 KB
conv: (3x3x512) x 512	9 MB	14x14x512	383 KB
maxpool	—	7x7x512	98 KB
fully-connected 4096	392 MB	4096	16 KB
fully-connected 4096	64 MB	4096	16 KB
fully-connected 1000	15.6 MB	1000	4 KB
soft-max		1000	4 KB

Reducing network footprint

- Large storage cost for model parameters
  - AlexNet model: ~200 MB
  - VGG-16 model: ~500 MB
  - This doesn't even account for intermediates during evaluation

- Footprint: cumbersome to store, download, etc.
  - 500 MB app downloads make users unhappy!

- Consider energy cost of 1B parameter network
  - Running on input stream at 20 Hz
  - 640 pJ per 32-bit DRAM access
  - (20 x 1B x 640pJ) = 12.8W for DRAM access

(more than power budget of any modern smartphone)

Compressing a network

[Han ICLR16]

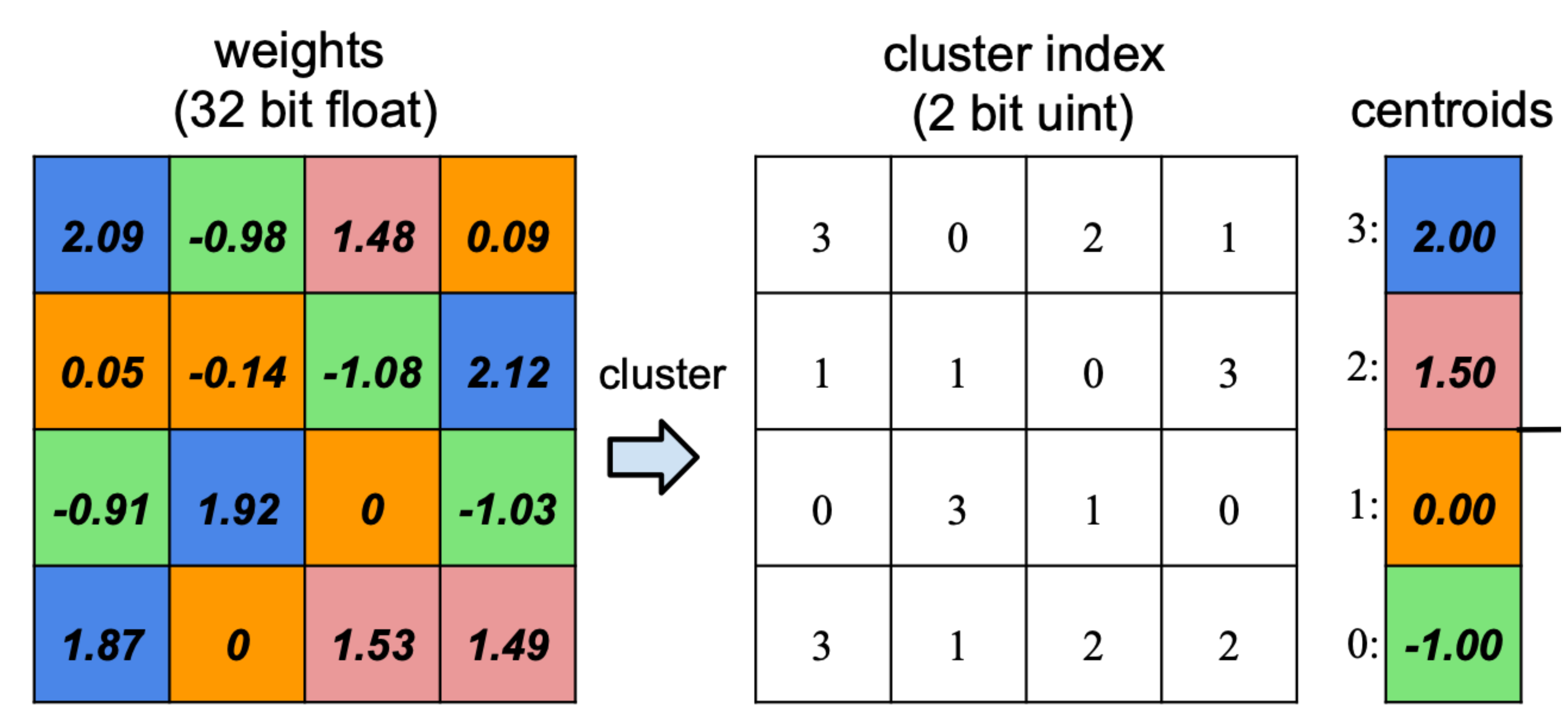
Step 1: prune low-weight links (iteratively retrain network, then prune)
- Over 90% of weights can be removed without significant loss of accuracy
- Store weight matrices in compressed sparse row (CSR) format

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

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

Step 2: weight sharing: make surviving connects share a small set of weights
- Cluster weights via k-means clustering (irregular ("learned") quantization)
- Compress weights by only storing cluster index (lg(k) bits)
- Retrain network to improve quality of cluster centroids

Step 3: Huffman encode quantized weights and CSR indices



[Han ICLR16]

VGG-16 compression

Substantial savings 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×

Deep neural networks on GPUs

- 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)

Facebook's Big Sur

Emerging architectures for deep learning

- NVIDIA Pascal (most recent GPU)
  - Adds double-throughput 16-bit floating point ops
  - Feature that is already common on mobile GPUs
- Google TensorFlow Processing Unit
  - Hardware accelerator for array computations
  - Used in Google data centers
- Apple Neural Engine
  - On A11 & A12 processor chips in iPhones & iPads
- XNOR Networks
  - Reduce weights & data to single bits
- FPGAs, ASICs?
  - Microsoft "BrainWave" on FPGAs within data centers
  - Not new: FPGA solutions have been explored for years
- …A million startups…

Programming frameworks for deep learning

- Heavyweight processing (low-level kernels) carried out by target-optimized libraries (NVIDIA cuDNN, Intel MKL)

- Popular frameworks use these kernel libraries
  - Caffe, Torch, Theano, TensorFlow, MxNet

- DNN application development = constructing novel network topologies
  - Programming by constructing networks
  - Significant interest in new ways to express network construction

Summary: efficiently evaluating convnets

- Computational structure
  - Convlayers: high arithmetic intensity, significant portion of cost of evaluating a network
  - Similar data access patterns to dense-matrix multiplication (exploiting temporal reuse is key)
  - But straight reduction to matrix-matrix multiplication is often sub-optimal
  - Work-efficient techniques for convolutional layers (FFT-based, Winograd convolutions)
- Large numbers of parameters: significant interest in reducing size of networks for both training and evaluation
  - Pruning: remove least important network links
  - Quantization: low-precision parameter representations often suffice
- Many ongoing studies of specialized hardware architectures for efficient evaluation
  - Future CPUs/GPUs, ASICs, FPGS, …
  - Specialization will be important to achieving “always on” applications

Two Distinct Issues with Deep Networks

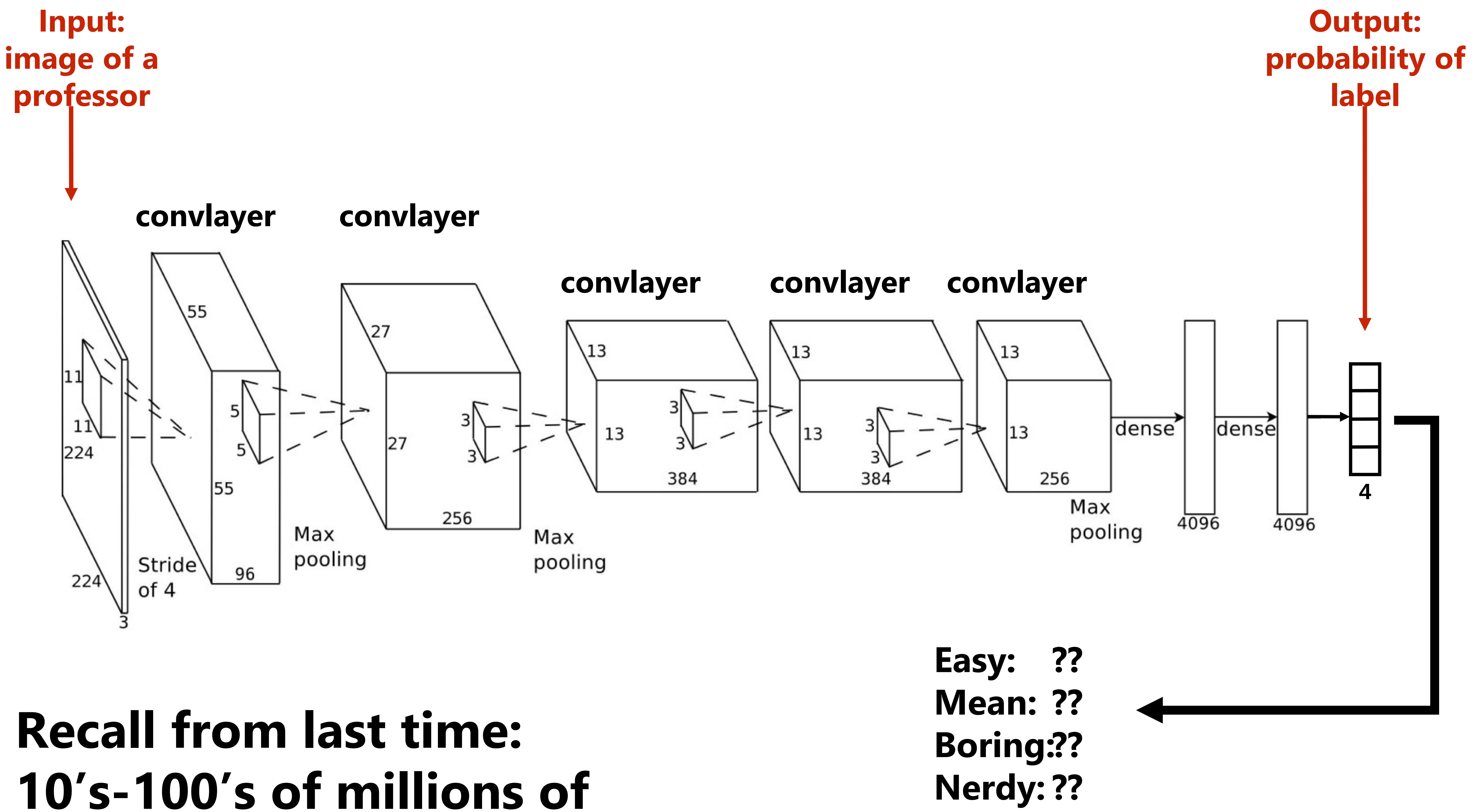
- **Evaluation/Inference**
  - **often takes milliseconds**
- **Training**
  - **often takes hours, days, weeks**

“Training a network”

- **Training a network is the process of learning the value of network parameters so that output of the network provides the desired result for a task**
  - **[Krizhevsky12] task = object classification**
    - **input 224 x 224 x 3 RGB image**
    - **output probability of 1000 ImageNet object classes: “dog”, “cat”, etc…**
    - **~ 60M weights**

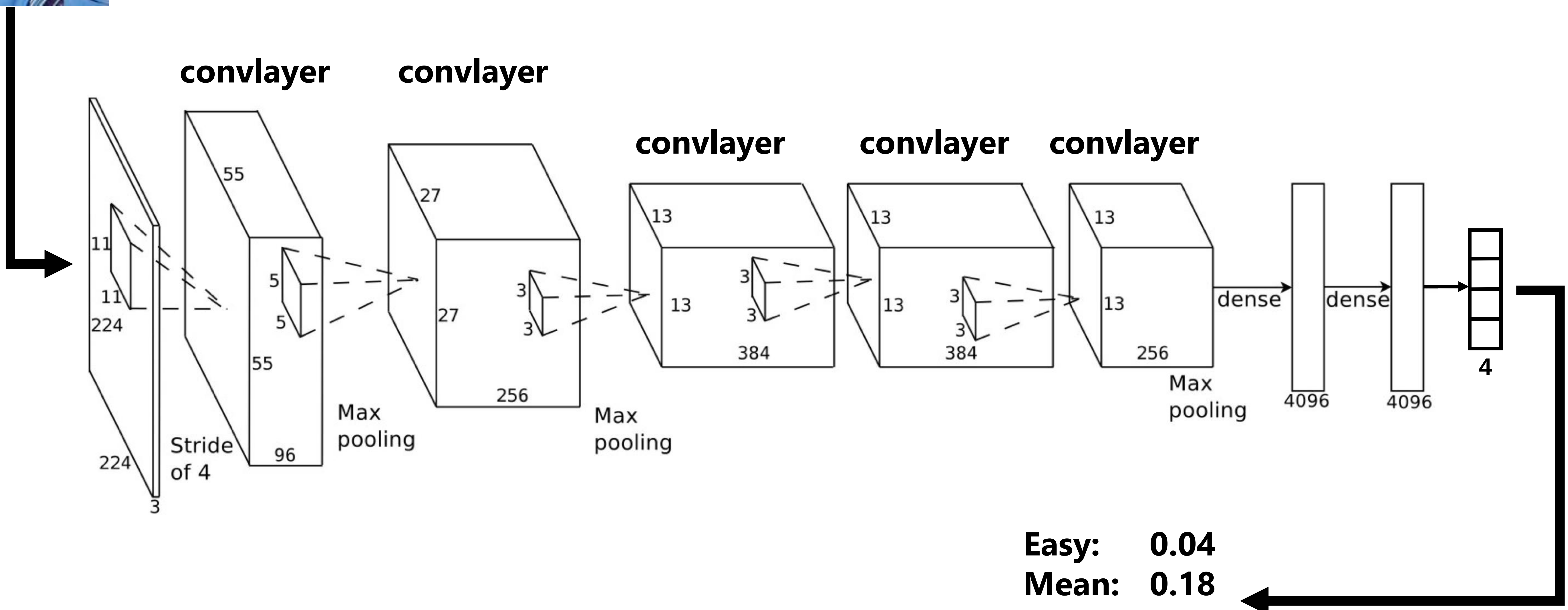
Professor classification network

Classifies professors as easy, mean, boring, or nerdy based on their appearance.



Recall from last time: 10's-100's of millions of parameters

Professor classification network



Easy: 0.04
Mean: 0.18
Boring: 0.27
Nerdy: 0.51

Where did the parameters come from?

Training data (ground truth answers)

[label omitted]

[label omitted]

[label omitted]

[label omitted]

[label omitted]

[label omitted]

[label omitted]

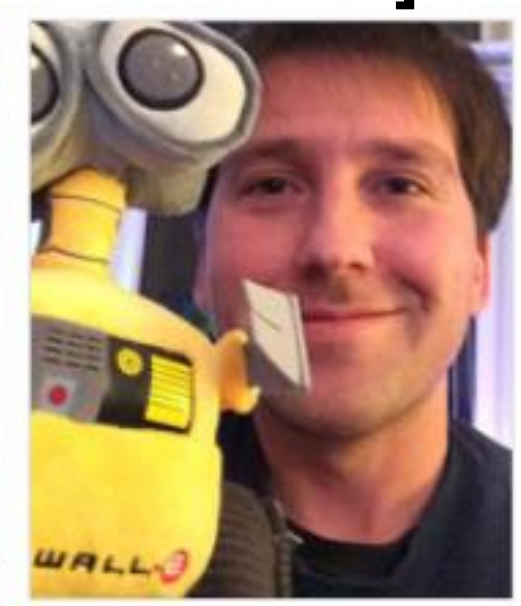
[label omitted]

[label omitted]

[label omitted]

[label omitted]

[label omitted]



[label omitted]

[label omitted]

[label omitted]

[label omitted]

[label omitted]

[label omitted]

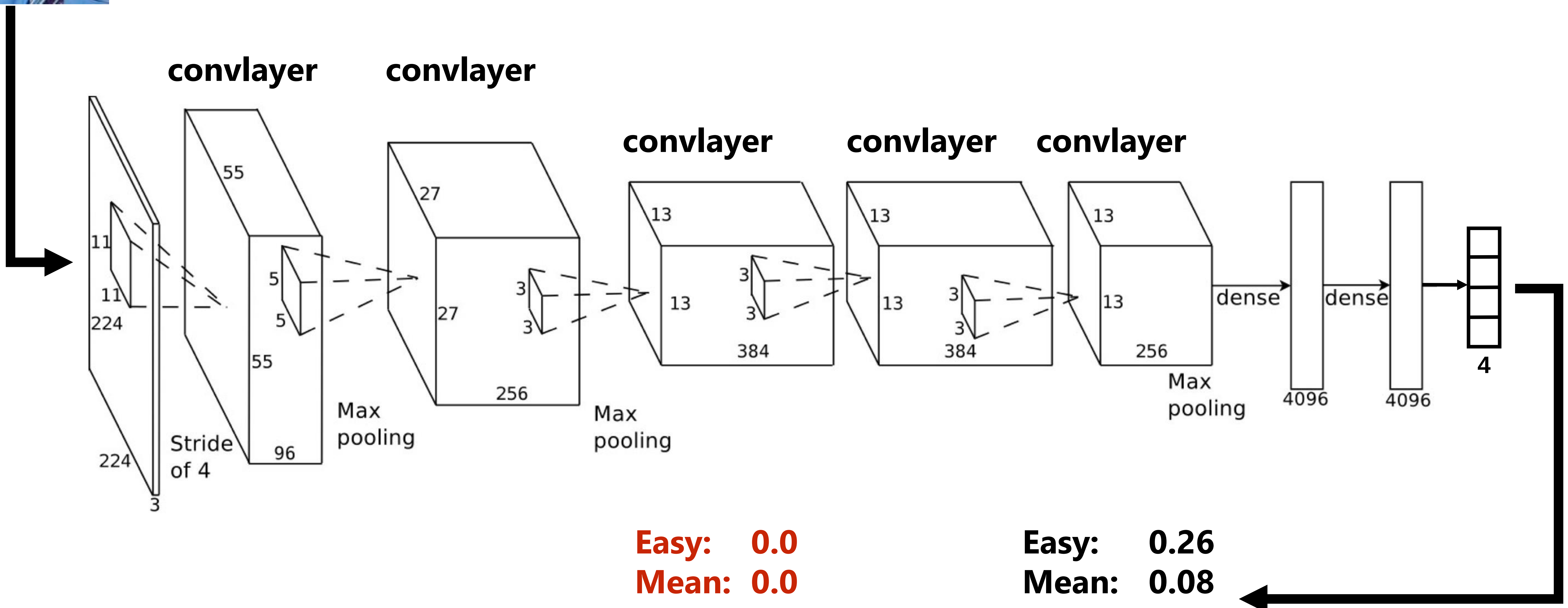
[label omitted]

[label omitted]

[label omitted]

Professor classification network

New image of Bryant
(not in training set)



Easy:	0.0	Easy:	0.26
Mean:	0.0	Mean:	0.08
Boring:	0.0	Boring:	0.14
Nerdy:	1.0	Nerdy:	0.52

Ground truth
(what the answer should be)

Network output

Error (loss)

Ground truth:
(what the answer should be)

Easy:	0.0
Mean:	0.0
Boring:	0.0
Nerdy:	1.0

Network output: *

Easy:	0.26
Mean:	0.08
Boring:	0.14
Nerdy:	0.52

Common example: softmax loss:

$$L = -log\left(\frac{e^{f_c}}{\sum_j e^{f_j}}\right)$$

Output of network for correct category

Output of network for all categories

* In practice a network using a softmax classifier outputs unnormalized, log probabilities (f_j), but I'm showing a probability distribution above for clarity

Training

Goal of training: learning good values of network parameters so that network outputs the correct classification result for any input image

Idea: minimize loss for all the training examples (for which the correct answer is known)

$$L = \sum_i L_i$$

(total loss for entire training set is sum of losses L_i for each training example x_i)

Intuition: if the network gets the answer correct for a wide range of training examples, then hopefully it has learned parameter values that yield the correct answer for future images as well.

Intuition: gradient descent

Say you had a function *f* that contained a hidden parameters $f(x_i)$
***p_1 and p_2*:**

And for some input *x_i*, your training data says the function should output 0.

But for the current values of *p_1 and p_2*, it currently outputs 10.

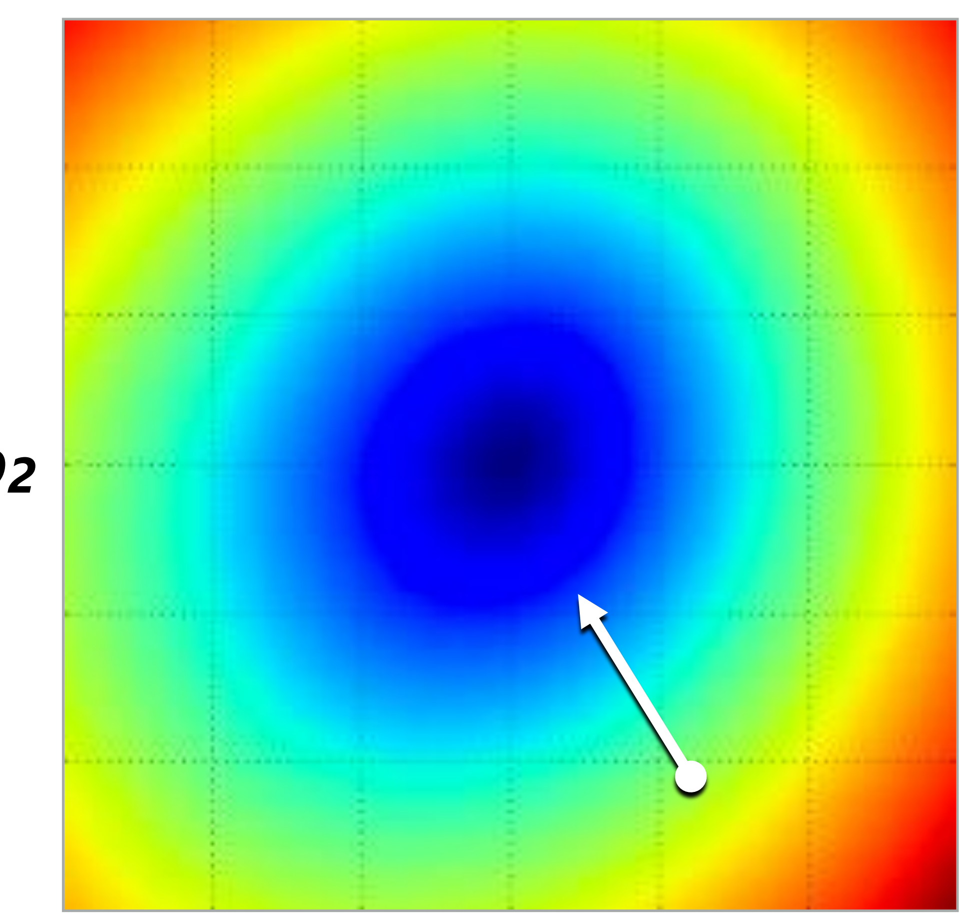
$$f(x_i, p_1, p_2) = 10$$

And say I also gave you expressions for the derivative of *f* with respect to *p_1 and p_2* so you could compute their value at *x_i*.

$$\frac{df}{dp_1} = 2 \quad \frac{df}{dp_2} = -5 \qquad \nabla f = [2, -5]$$

red = high values of f
blue = low values

p_2



p_1

How might you adjust the values *p_1 and p_2* to reduce the error for this training example?

Basic gradient descent

```
while (loss too high):

   for each item x_i in training set:
      grad += evaluate_loss_gradient(f, loss_func, params, x_i)

   params += -grad * step_size;
```

Mini-batch stochastic gradient descent (mini-batch SGD): choose a random (small) subset of the training examples to compute gradient in each iteration of the while loop

How to compute df/dp for a complex neural network with millions of parameters?

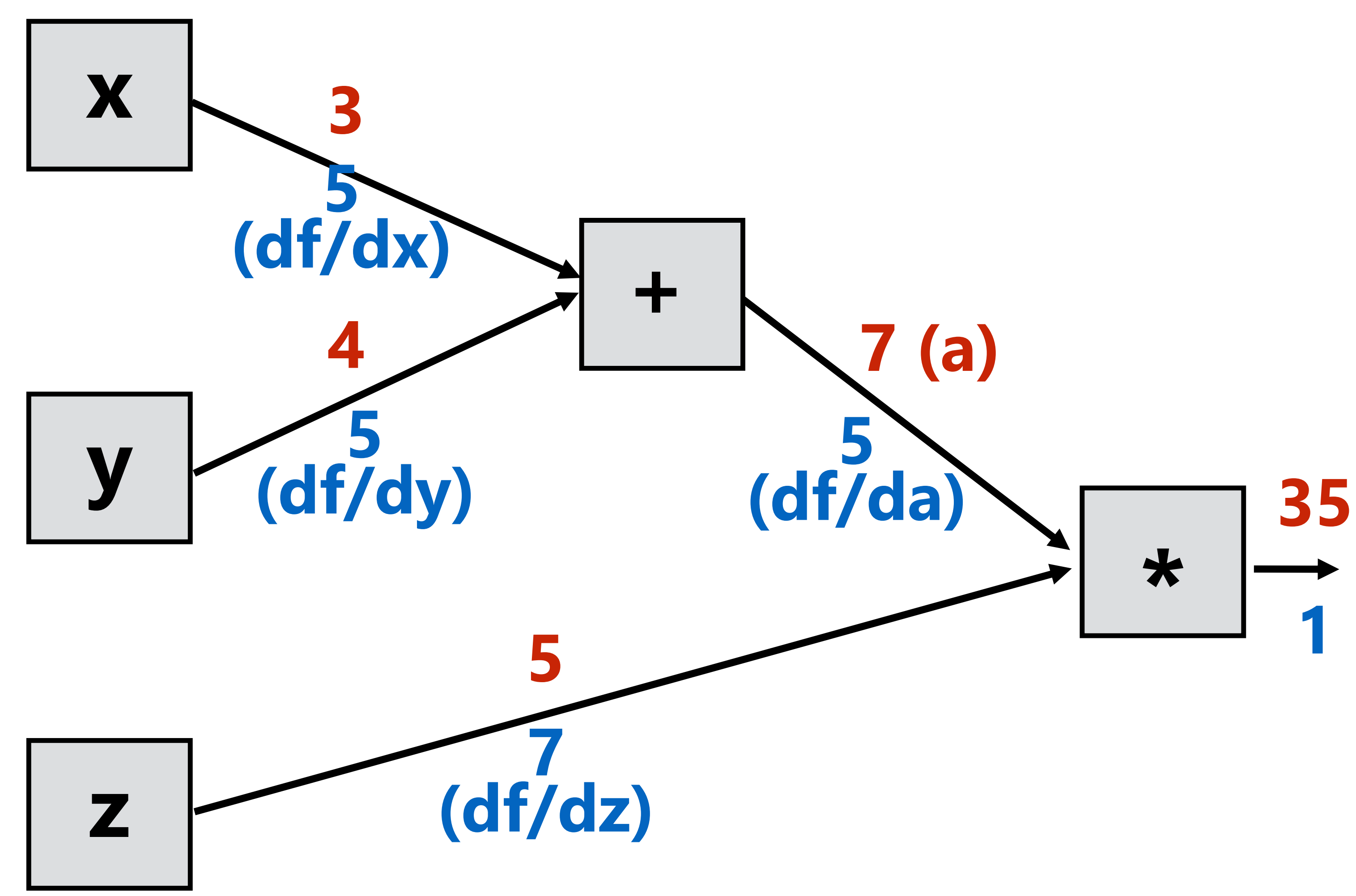
Derivatives using the chain rule

$$f(x, y, z) = (x + y)z = az$$ **Where:** $a = x + y$

$$\frac{df}{da} = z \quad \frac{da}{dx} = 1 \quad \frac{da}{dy} = 1$$

So, by the derivative chain rule:

$$\frac{df}{dx} = \frac{df}{da}\frac{da}{dx} = z$$



Red = output of node

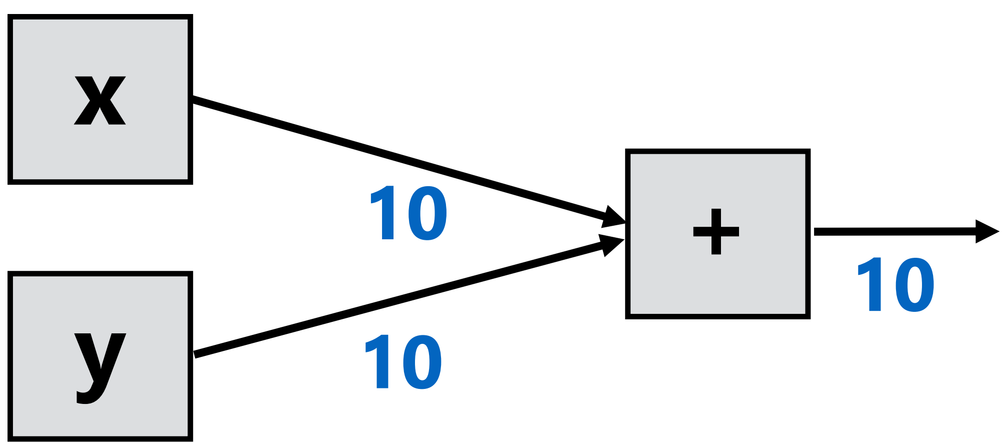
Blue = df/dnode

Backpropagation

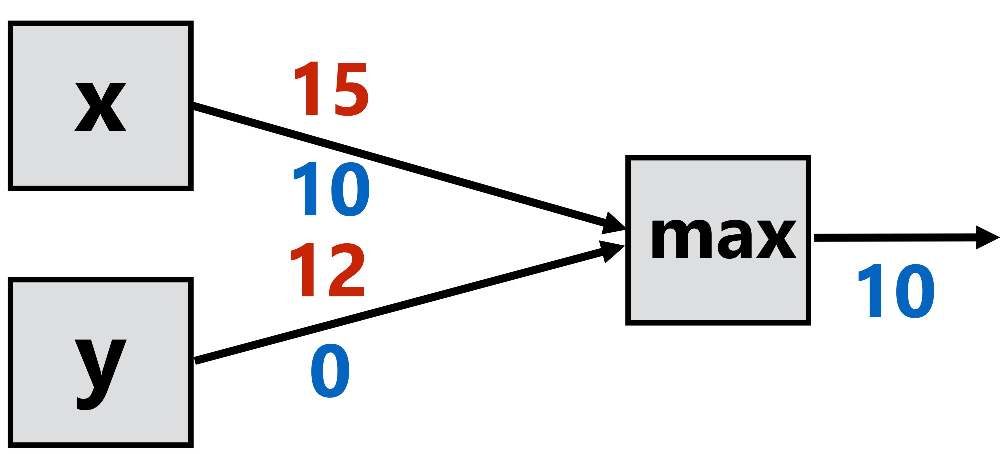
Red = output of node

Blue = df/dnode

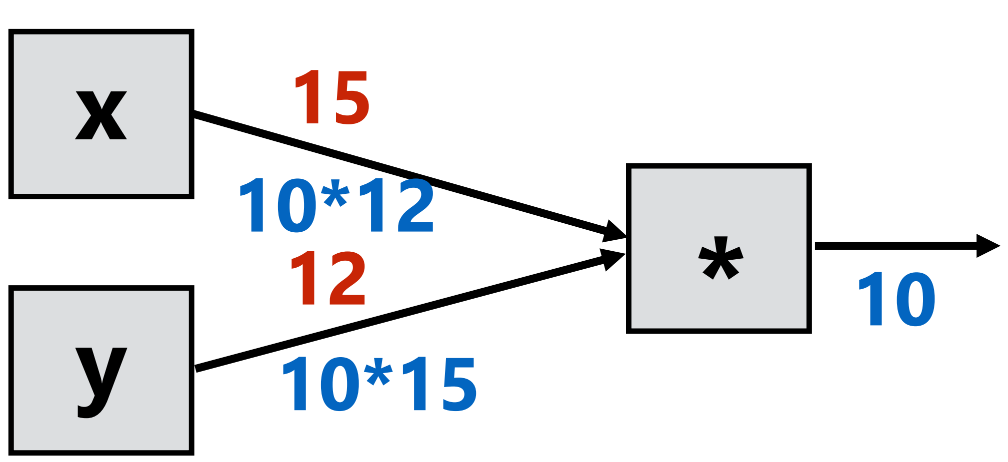
Recall: $$\frac{df}{dx} = \frac{df}{dg}\frac{dg}{dx}$$



$$g(x,y) = x + y \qquad \frac{dg}{dx} = 1\,,\ \frac{dg}{dy} = 1$$



$$g(x,y) = \max(x,y) \qquad \frac{dg}{dx} = \begin{cases} \text{1, if x > y} \\ \text{0, otherwise} \end{cases}$$



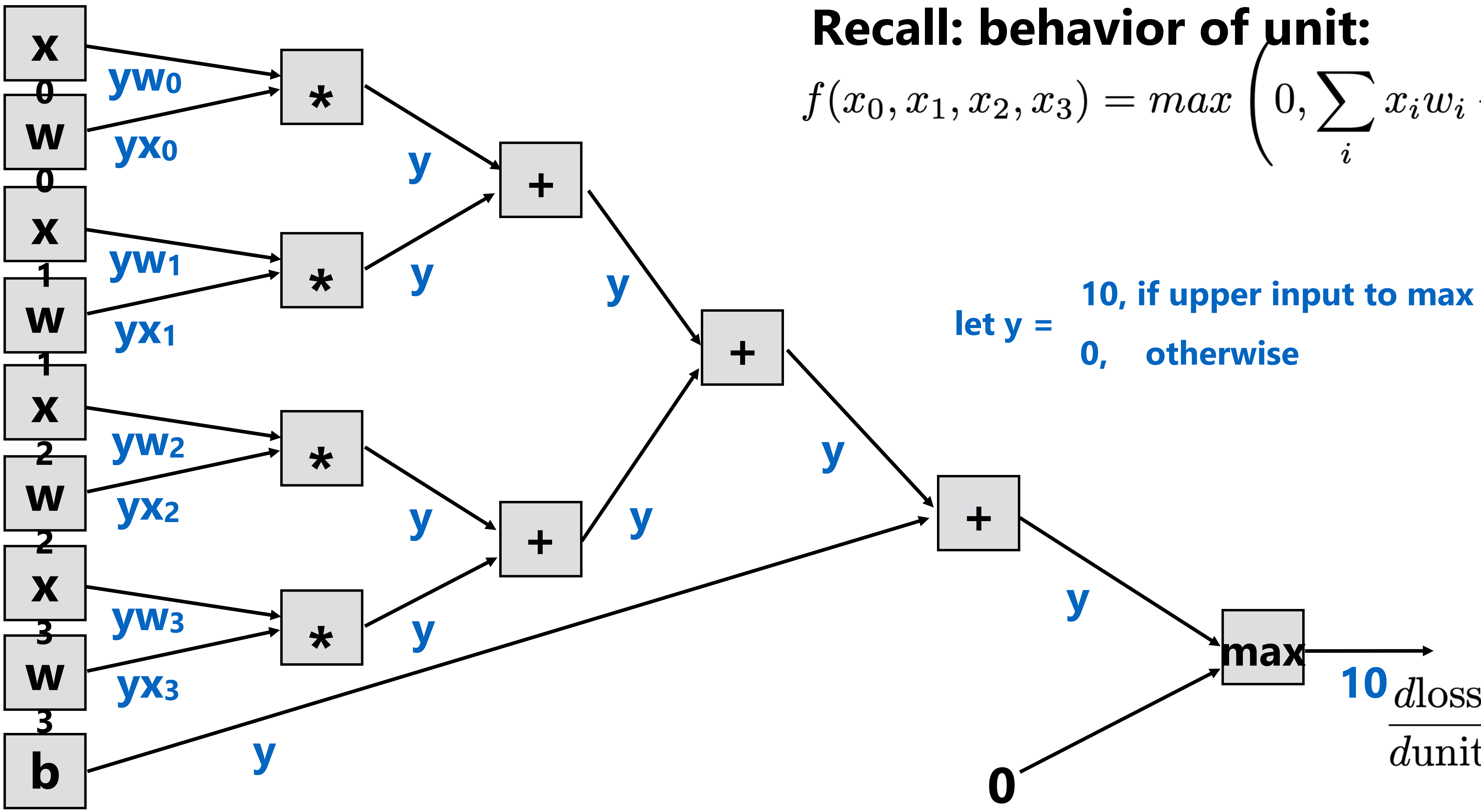
$$g(x,y) = xy \qquad \frac{dg}{dx} = y\,,\ \frac{dg}{dy} = x$$

Backpropagating through single unit

Recall: behavior of unit:

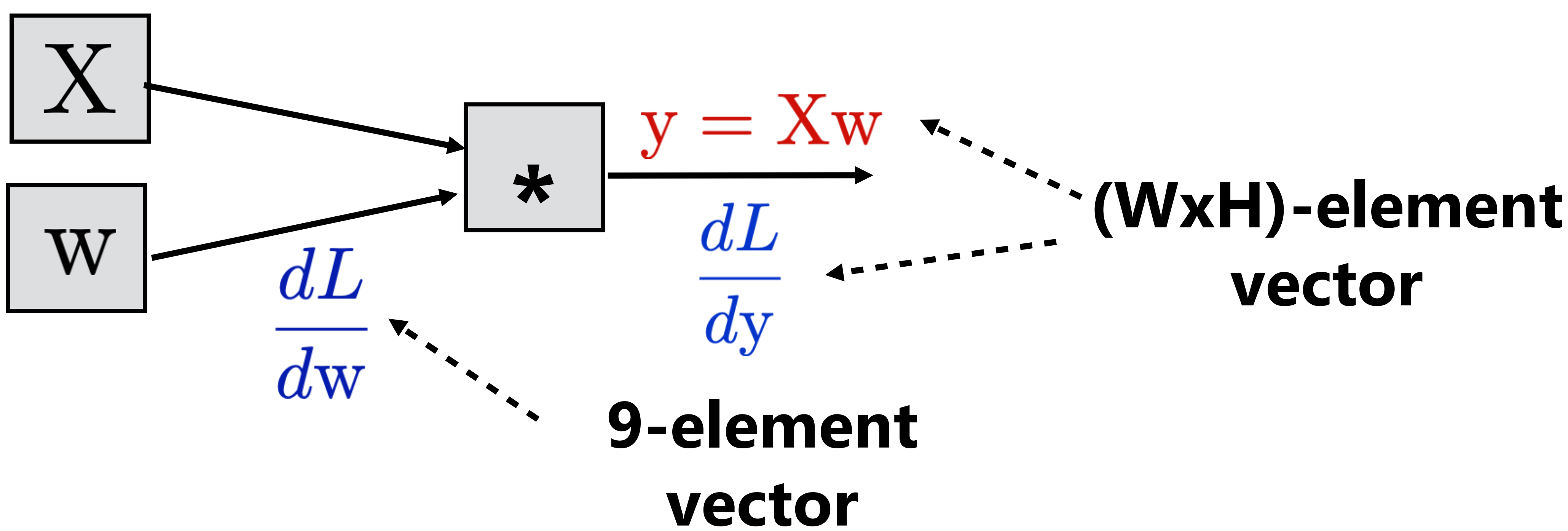
$$f(x_0, x_1, x_2, x_3) = max\left(0, \sum_i x_i w_i + b\right)$$

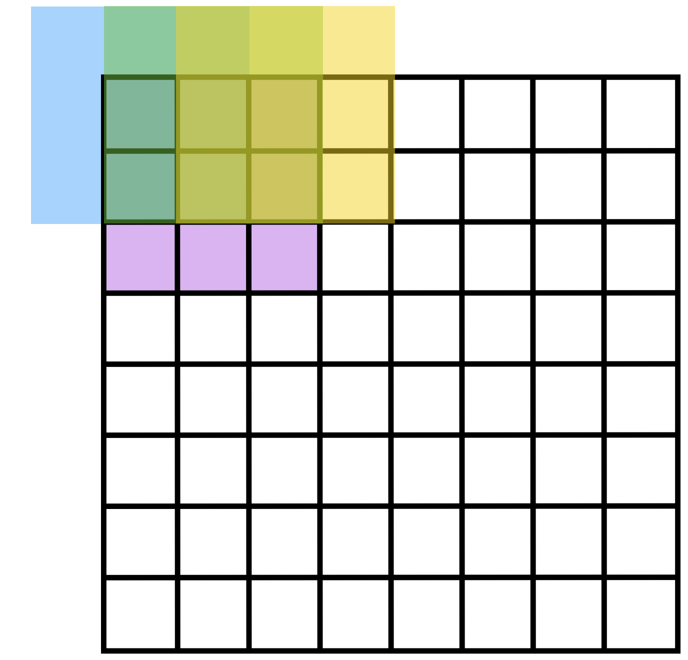
let y =
10, if upper input to max is > 0
0, otherwise



Observe: output of prior layer (x_i's) and output of this unit must be retained in order to compute weight gradients for this unit during backprop.

Backpropagation: matrix form





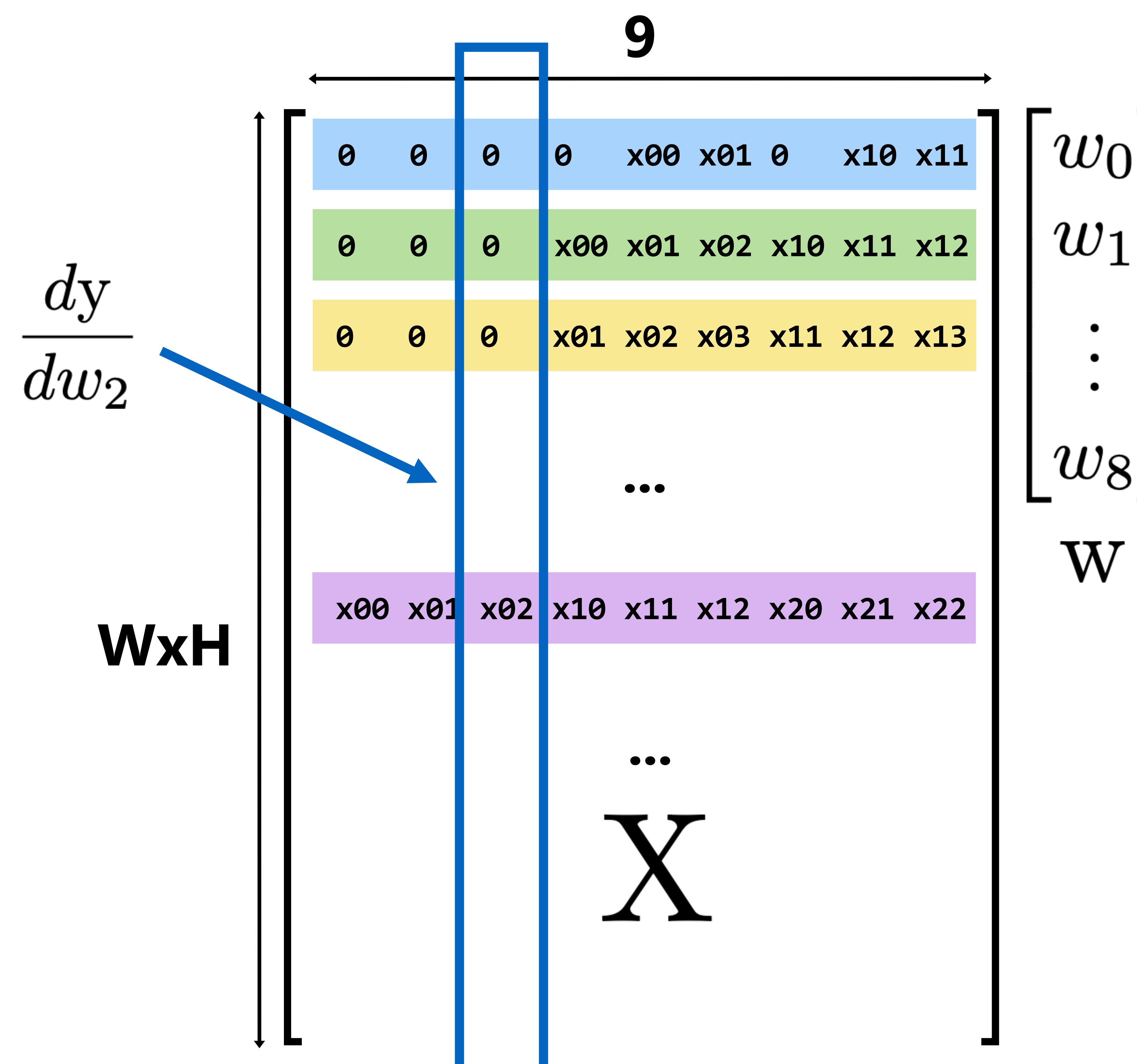
$$\frac{dy_j}{dw_i} = X_{ji}$$

$$\frac{dL}{dw_i} = \sum_j \frac{dL}{dy_j}\frac{dy_j}{dw_i}$$

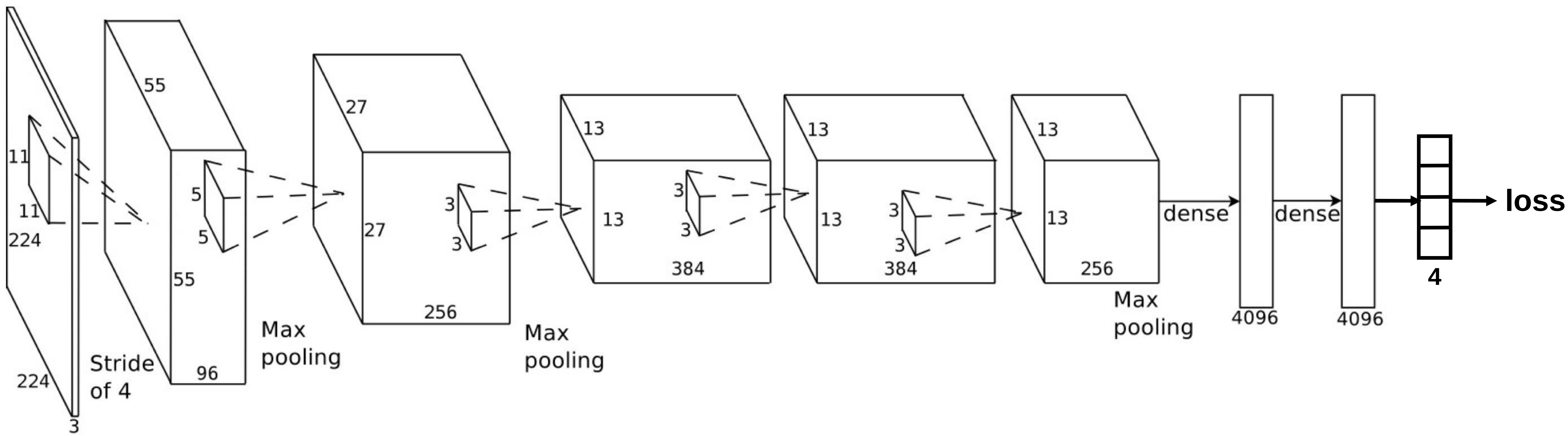
$$= \sum_j \frac{dL}{dy_j} X_{ji}$$

Therefore:

$$\frac{dL}{dw} = X^T \frac{dL}{dy}$$



Backpropagation through the entire professor classification network



For each training example x_i in mini-batch:

Perform forward evaluation to compute loss for x_i

Note: must retain all layer outputs + output gradients (needed to compute weight gradients during backpropagation)

Compute gradient of loss w.r.t. final layer's outputs

Backpropagate gradient to compute gradient of loss w.r.t. all network parameters

Accumulate gradients (over all images in batch)

Update all parameter values: w_i_new = w_i_old - step_size * $grad_i$

VGG memory footprint

Calculations assume 32-bit values (image batch size = 1)

inputs/outputs get multiplied by mini- batch size

Unlike forward evaluation:
1. must store outputs and gradient of outputs
2. cannot immediately free outputs once consumed by next level of network

Must also store per-weight gradients

Many implementations also store gradient "momentum" as well (multiply by 3)

	weights mem:	output size (per image)	(mem)
input: 224 x 224 RGB image	—	224x224x3	150K
conv: (3x3x3) x 64	6.5 KB	224x224x64	12.3 MB
conv: (3x3x64) x 64	144 KB	224x224x64	12.3 MB
maxpool	—	112x112x64	3.1 MB
conv: (3x3x64) x 128	228 KB	112x112x128	6.2 MB
conv: (3x3x128) x 128	576 KB	112x112x128	6.2 MB
maxpool	—	56x56x128	1.5 MB
conv: (3x3x128) x 256	1.1 MB	56x56x256	3.1 MB
conv: (3x3x256) x 256	2.3 MB	56x56x256	3.1 MB
conv: (3x3x256) x 256	2.3 MB	56x56x256	3.1 MB
maxpool	—	28x28x256	766 KB
conv: (3x3x256) x 512	4.5 MB	28x28x512	1.5 MB
conv: (3x3x512) x 512	9 MB	28x28x512	1.5 MB
conv: (3x3x512) x 512	9 MB	28x28x512	1.5 MB
maxpool	—	14x14x512	383 KB
conv: (3x3x512) x 512	9 MB	14x14x512	383 KB
conv: (3x3x512) x 512	9 MB	14x14x512	383 KB
conv: (3x3x512) x 512	9 MB	14x14x512	383 KB
maxpool	—	7x7x512	98 KB
fully-connected 4096	392 MB	4096	16 KB
fully-connected 4096	64 MB	4096	16 KB
fully-connected 1000	15.6 MB	1000	4 KB
soft-max		1000	4 KB

SGD workload

```
while (loss too high):
```

At first glance, this loop is sequential (each step of "walking downhill" depends on previous)

```
    for each item x_i in mini-batch:
        grad += evaluate_loss_gradient(f, loss_func, params, x_i)
```

Parallel across images

sum reduction

large computation with its own parallelism (but working set may not fit on single machine)

```
    params += -grad * step_size;
```

trivial data-parallel over parameters

Deep network training workload

- **Huge computational expense**
  - **Must evaluate the network (forward and backward) for millions of training images**
  - **Must iterate for many iterations of gradient descent (100's of thousands)**
  - **Training modern networks takes days**
- **Large memory footprint**
  - **Must maintain network layer outputs from forward pass**
  - **Additional memory to store gradients for each parameter**
  - **Recall parameters for popular VGG-16 network require ~500 MB of memory (training requires GBs of memory for academic networks)**
  - **Scaling to larger networks requires partitioning network across nodes to keep network + intermediates in memory**
- **Dependencies /synchronization (not embarrassingly parallel)**
  - **Each parameter update step depends on previous**
  - **Many units contribute to same parameter gradients (fine-scale reduction)**
  - **Different images in mini batch contribute to same parameter gradients**

Data-parallel training (across images)

```
for each item x_i in mini-batch:
   grad += evaluate_loss_gradient(f, loss_func, params, x_i)
params += -grad * step_size;
```

Consider parallelization of the outer for loop across machines in a cluster


```
partition mini-batch across nodes
for each item x_i in mini-batch assigned to local node:
   // just like single node training
   grad += evaluate_loss_gradient(f, loss_func, params, x_i)
barrier();
sum reduce gradients, communicate results to all nodes
barrier();
update copy of parameter values
```

Challenges of computing at cluster scale

- **Slow communication between nodes**
  - Clusters do not feature high-performance interconnects typical of supercomputers

- **Nodes with different performance (even if machines are the same)**
  - Workload imbalance at barriers (sync points between nodes)

Modern solution: exploit characteristics of SGD using asynchronous execution!

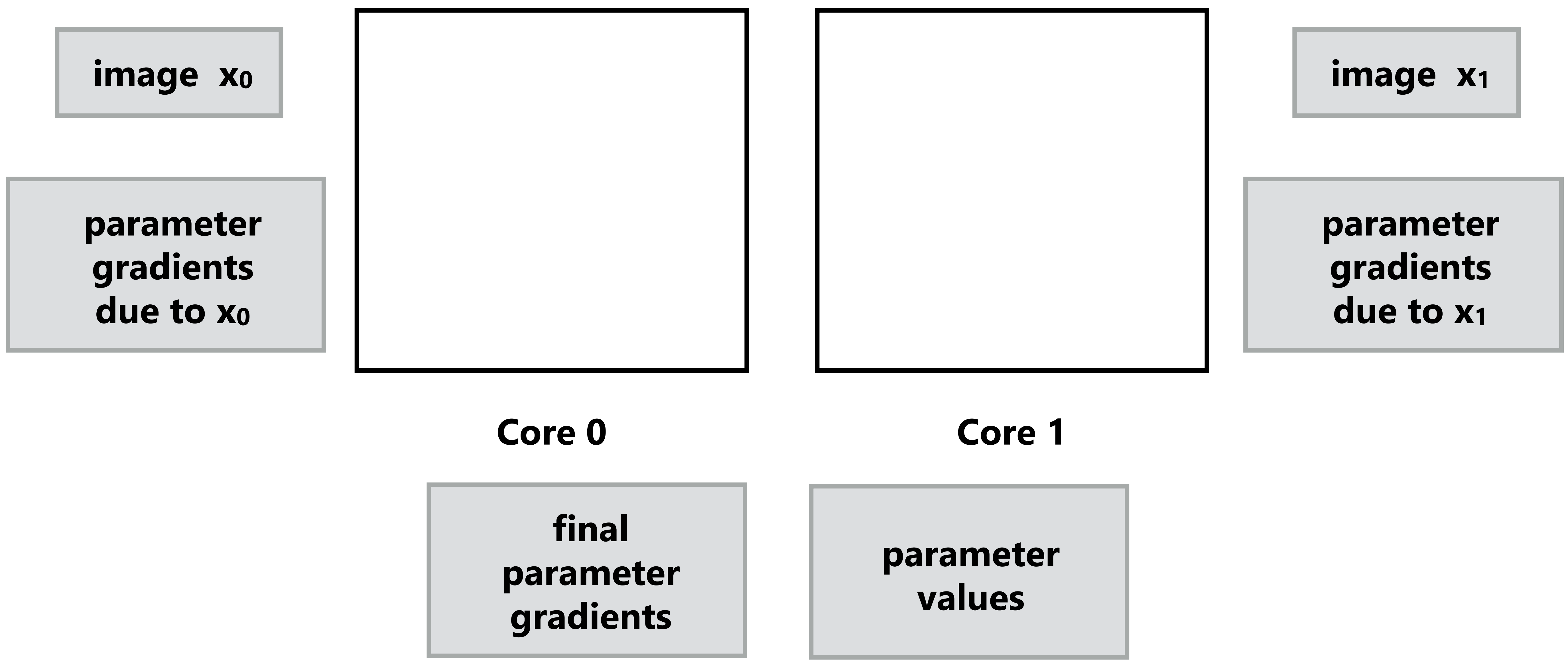
Exploiting SGD Characteristics

- Convergent computation
  - Update ordering does not matter
  - OK to have small errors in weight updates
- How used
  - Within machine: Don’t synchronize weight updates across threads
  - Between machines:
    - OK to do some computations using stale data
    - Ordering of updates not critical
    - Incomplete or redundant coverage of data set acceptable

Parallelizing mini-batch on one machine

```
for each item x_i in mini-batch:
   grad += evaluate_loss_gradient(f, loss_func, params, x_i)
params += -grad * step_size;
```

Consider parallelization of the outer for loop across cores



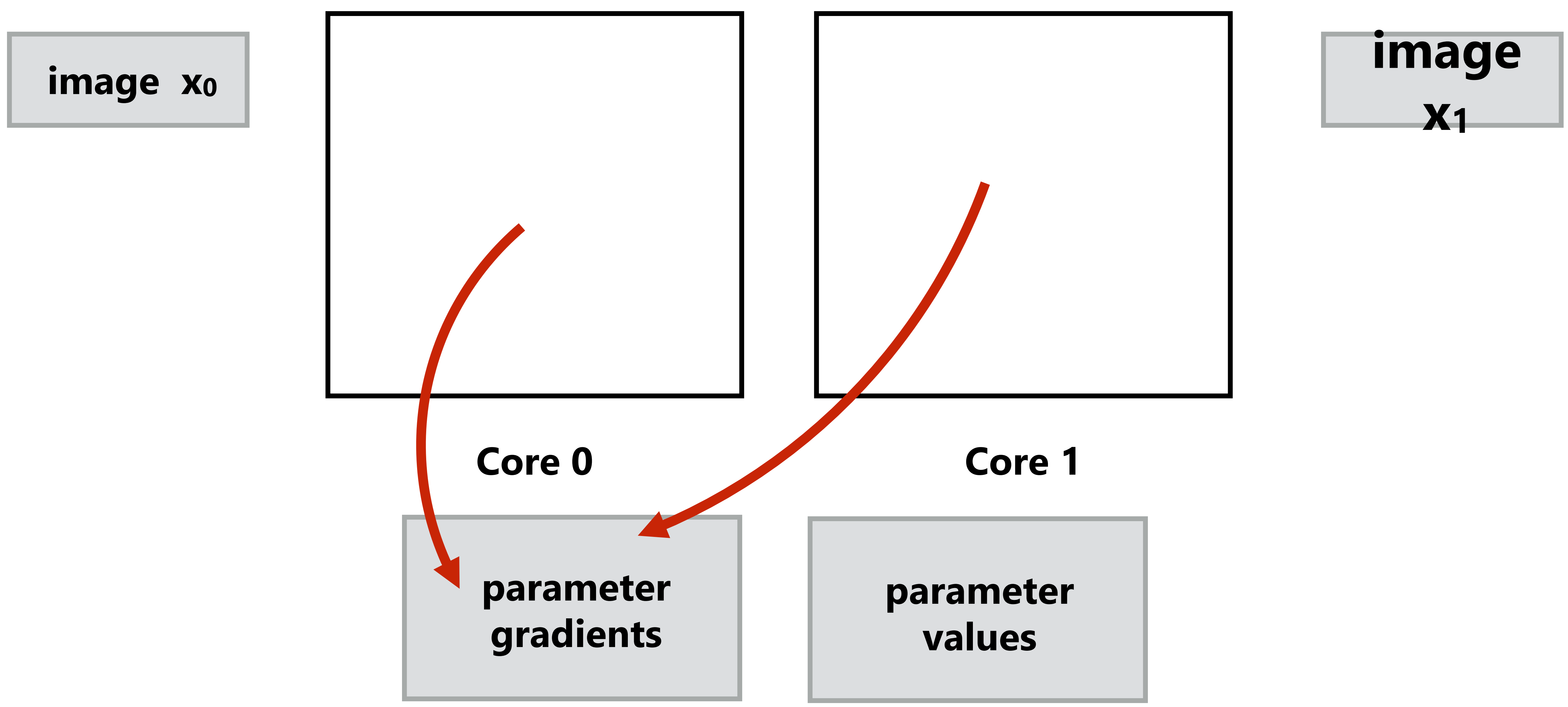
Good: completely independent computations (until gradient reduction)

Bad: complete duplication of parameter gradient state (100's MB per core)

Asynchronous update on one node

```
for each item x_i in mini-batch:
   grad += evaluate_loss_gradient(f, loss_func, params, x_i)
params += -grad * step_size;
```

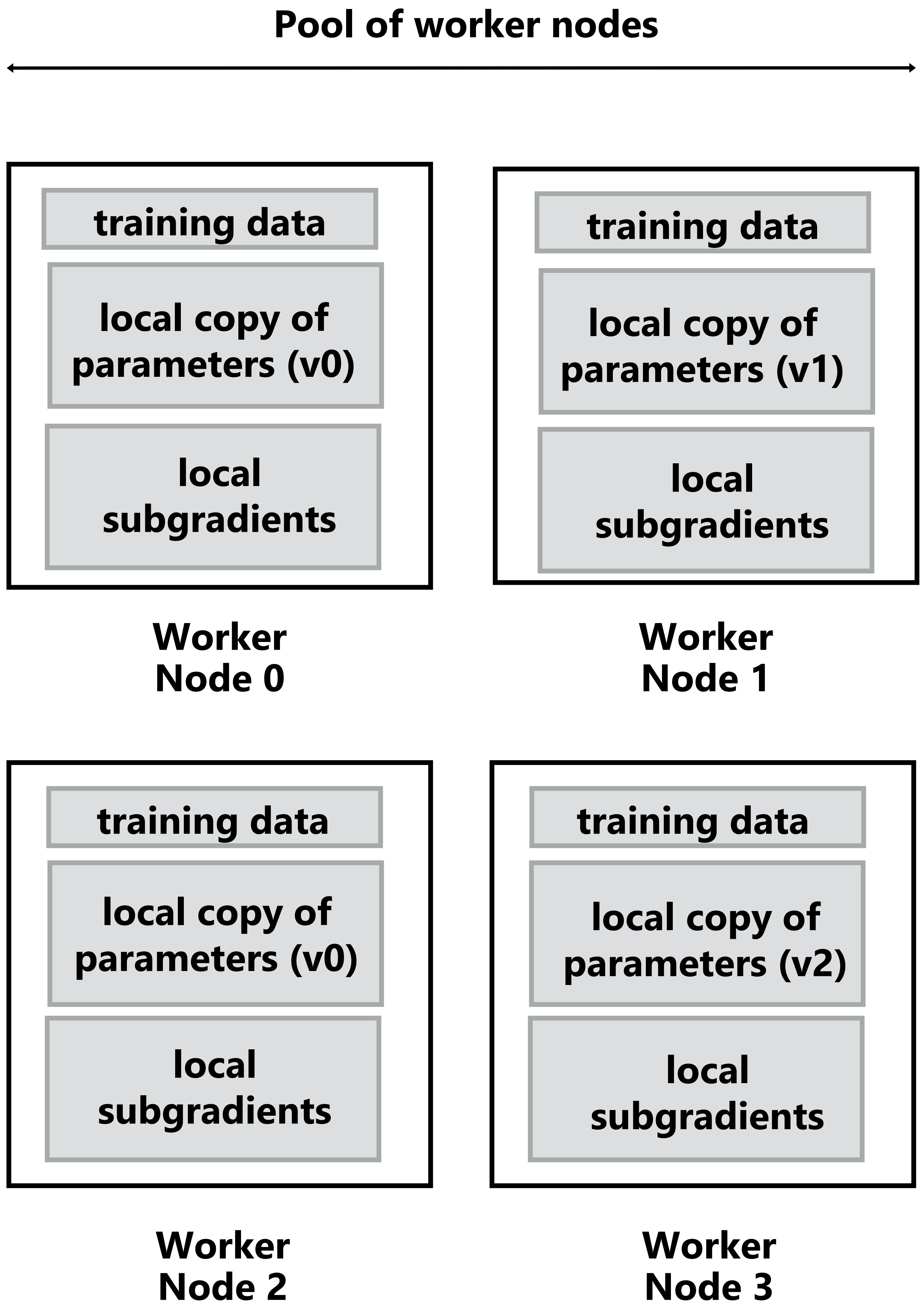
Cores update shared set of gradients.
Skip taking locks / synchronizing across cores: perform "approximate reduction"

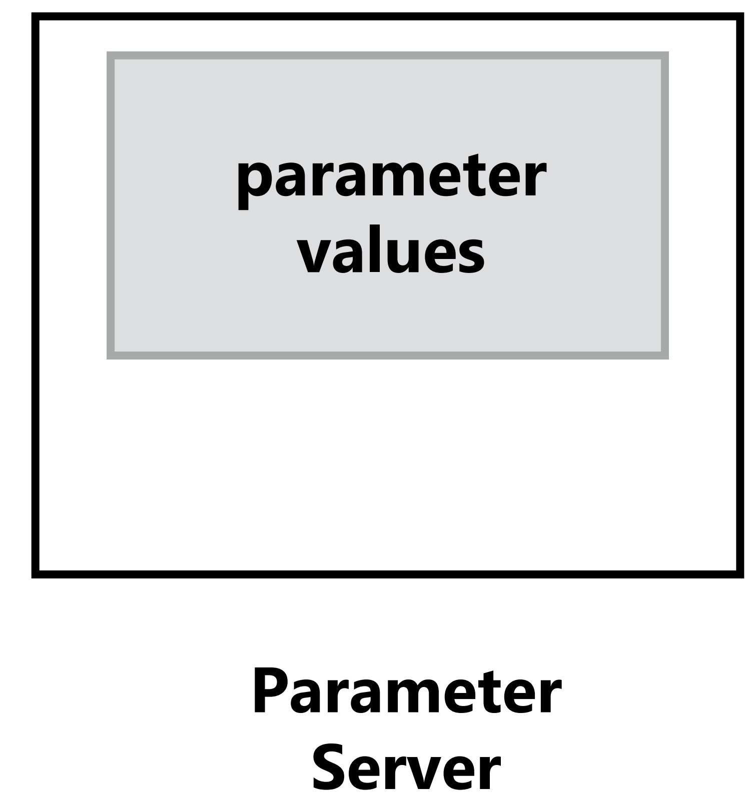


Project Adam [Chilimbi OSDI14]

Parameter server design

Parameter Server [Li OSDI14]
Google's DistBelief [Dean NIPS12]
Microsoft's Project Adam [Chilimbi OSDI14]





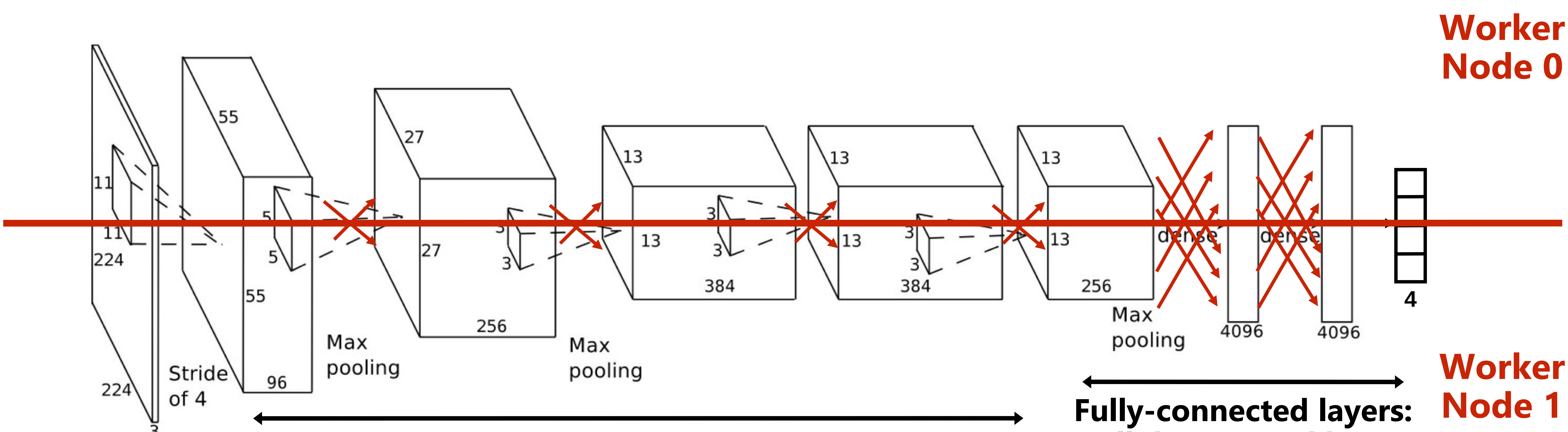
- **Separate set of machines to maintain DNN parameters**
- **Highly fault tolerant (so that worker nodes need not reliable)**
- **Accept updates from workers asynchronously**

Model parallelism

Partition network parameters across nodes (spatial partitioning to reduce communication)

Reduce internode communication through network design:

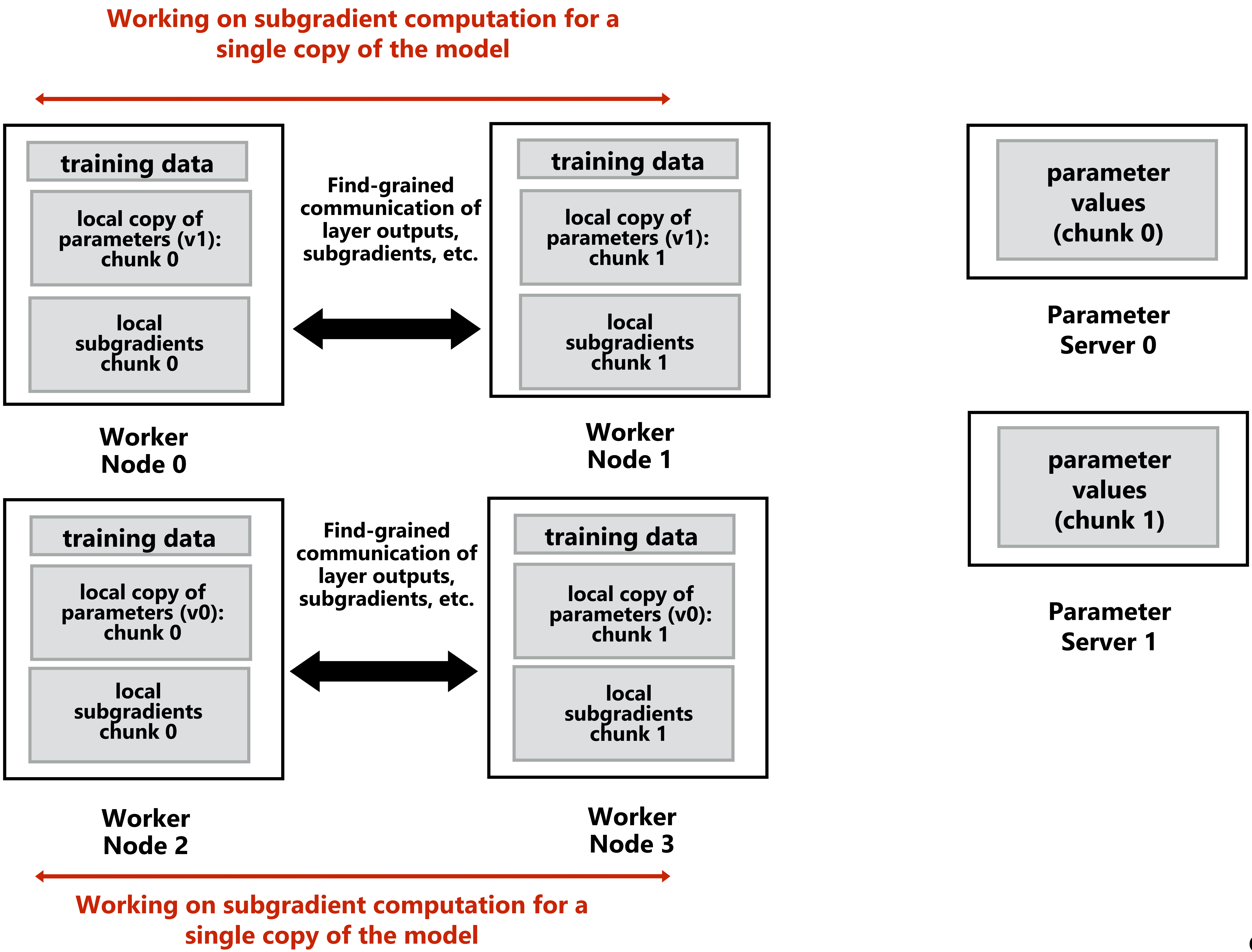
- Use small spatial convolutions (1x1 convolutions)
- Reduce/shrink fully-connected layers



Convolutional layers: only need to community outputs near spatial partition

Fully-connected layers: all data owned by a node must by communicated to other nodes

Training data-parallel and model-parallel execution



Using supercomputers for training?

- Fast interconnects critical for model-parallel training
  - Fine-grained communication of outputs and gradients
- Fast interconnect diminishes need for async training algorithms
  - Avoid randomness in training due to computation schedule (there remains randomness due to SGD algorithm)

OakRidge Titan Supercomputer

NVIDIA DGX-1: 8 Pascal GPUs connected via high speed NV-Link interconnect

Summary: training large networks in parallel

- **Most systems rely on asynchronous update to efficiently used clusters of commodity machines**
  - **Modification of SGD algorithm to meet constraints of modern parallel systems**
  - **Open question: effects on convergence are problem dependent and not particularly well understood**
  - **Tighter integration / faster interconnects may provide alternative to these methods (facilitate tightly orchestrated solutions much like supercomputing applications)**
- **Open question: how big of networks are needed?**
  - **>90% of connections could be removed without significant impact on quality of network**
  - **High-performance training of deep networks is an interesting example of constant iteration of algorithm design and parallelization strategy**

(a key theme of this course! recall the original grid solver example!)