IT/PC/B/T/411

Machine Learning

Deep Learning Basics

Lecture 06: Convolutional NN

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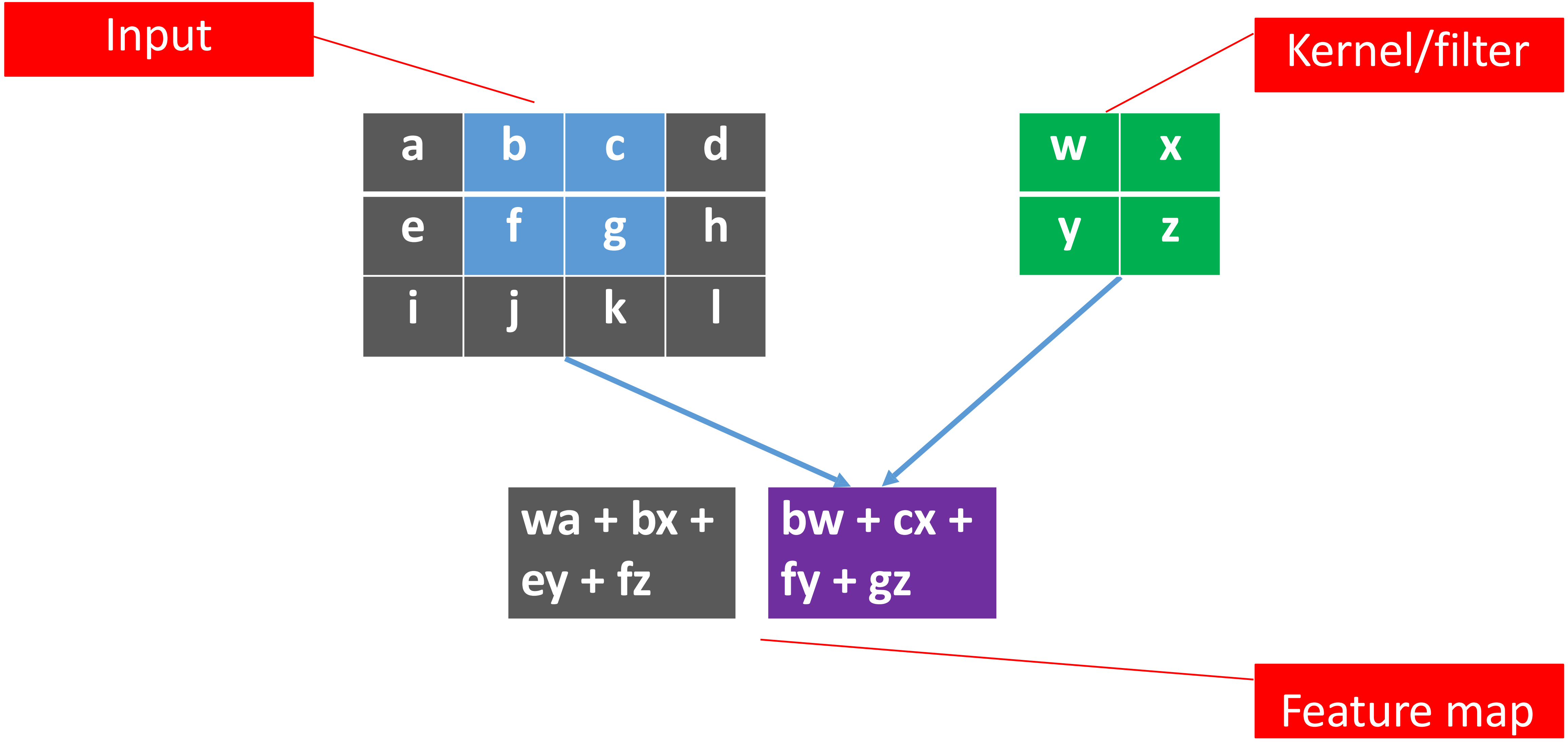
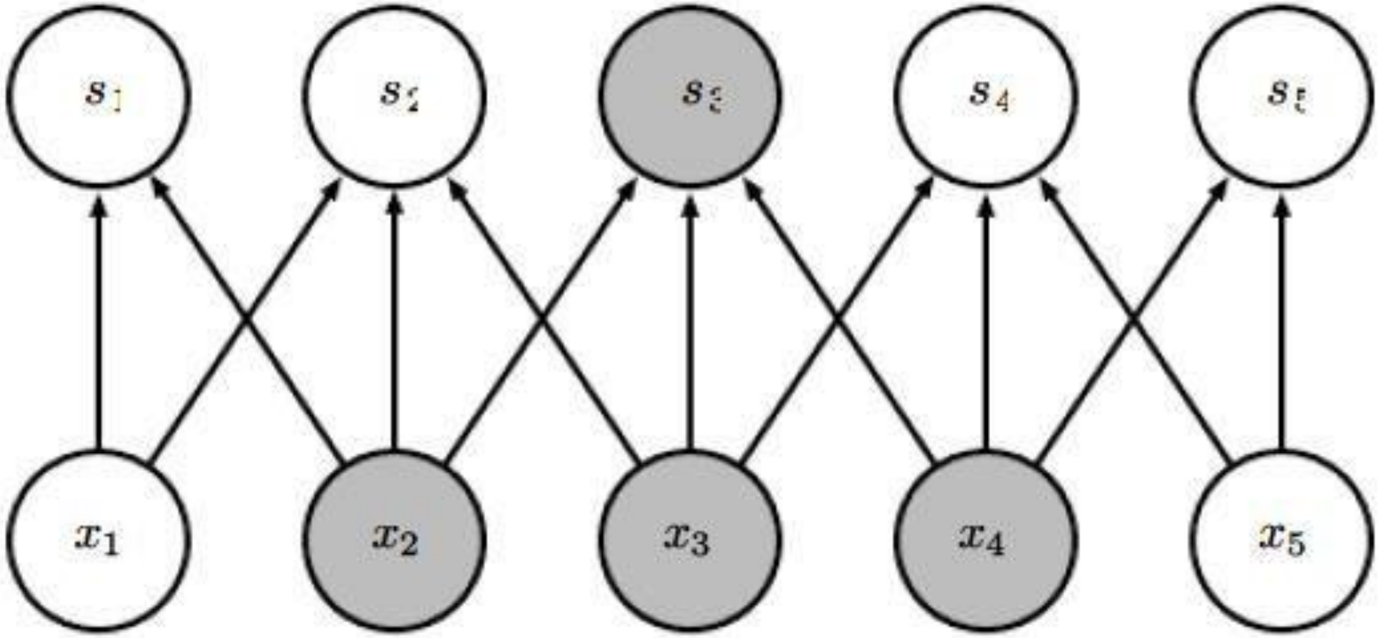
Review: convolutional layers

Convolution: two dimensional case



Convolutional layers

the same weight shared for all output nodes



m output nodes

k kernel size

n input nodes

Figure from *Deep Learning,* by Goodfellow, Bengio, and Courville

Terminology

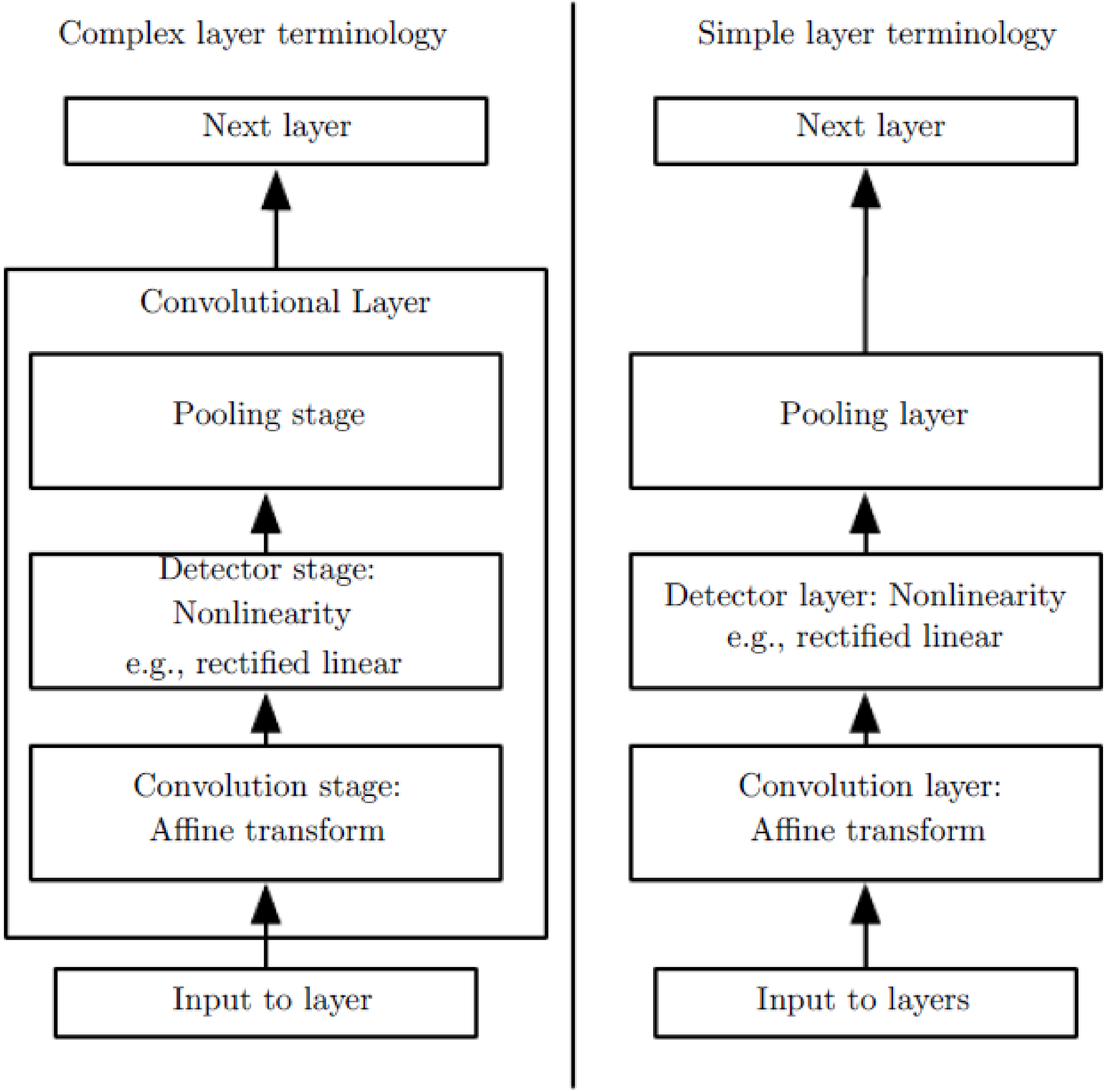


Figure from *Deep Learning,* by Goodfellow, Bengio, and Courville

Case study: LeNet-5

LeNet-5

- Proposed in "Gradient-based learning applied to document recognition", *by Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, in Proceedings of the IEEE, 1998*

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- Apply convolution on 2D images (MNIST) and use backpropagation

LeNet-5

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- Apply convolution on 2D images (MNIST) and use backpropagation

- Structure: 2 convolutional layers (with pooling) + 3 fully connected layers
  - Input size: 32x32x1
  - Convolution kernel size: 5x5
  - Pooling: 2x2

LeNet-5

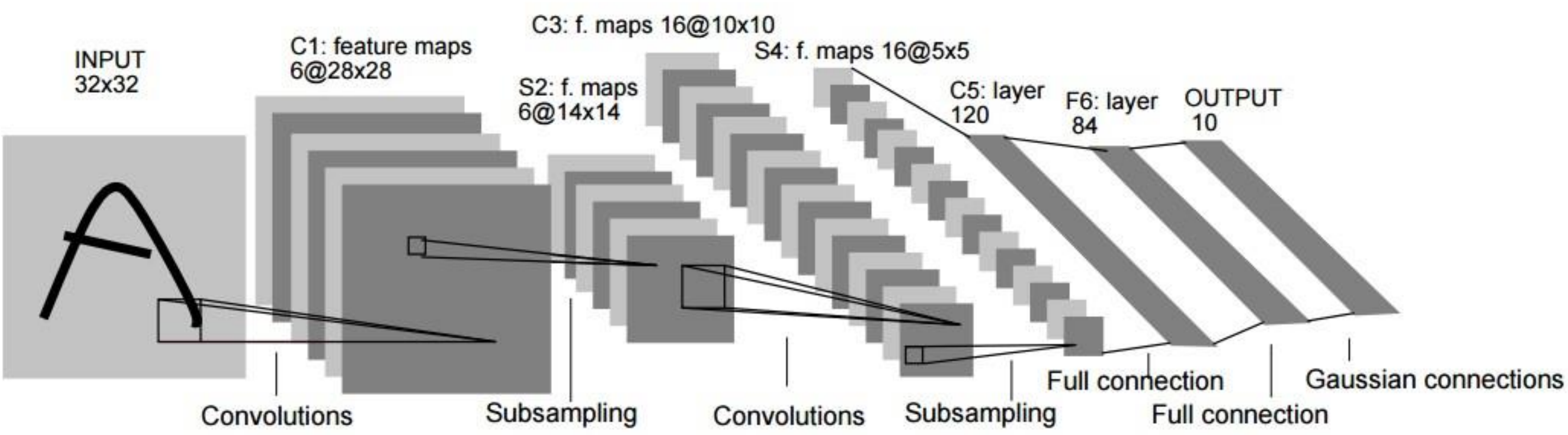


Figure from Gradient-based learning applied to document recognition, *by Y. LeCun, L. Bottou, Y. Bengio and P. Haffner*

LeNet-5

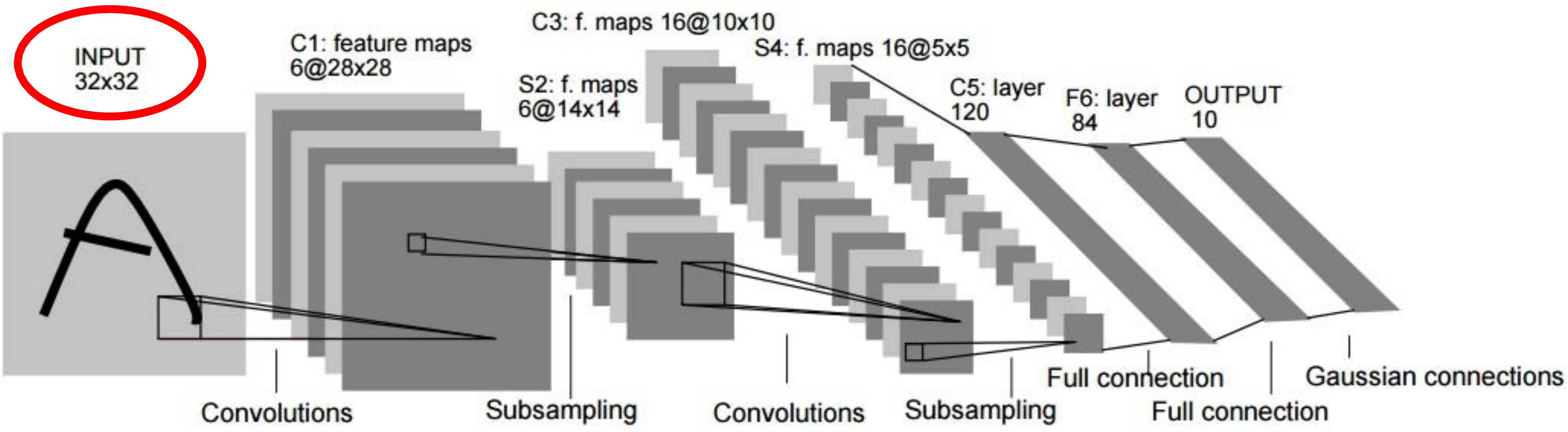


Figure from Gradient-based learning applied to document recognition, *by Y. LeCun, L. Bottou, Y. Bengio and P. Haffner*

LeNet-5

Filter: 5x5, stride: 1x1, #filters: 6

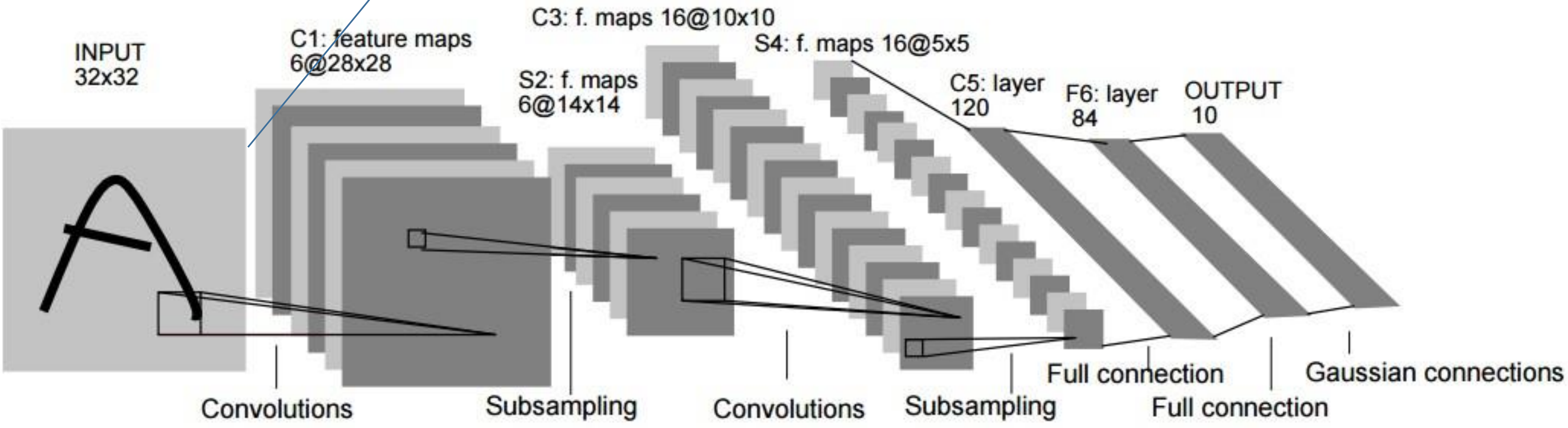


Figure from Gradient-based learning applied to document recognition, *by Y. LeCun, L. Bottou, Y. Bengio and P. Haffner*

LeNet-5

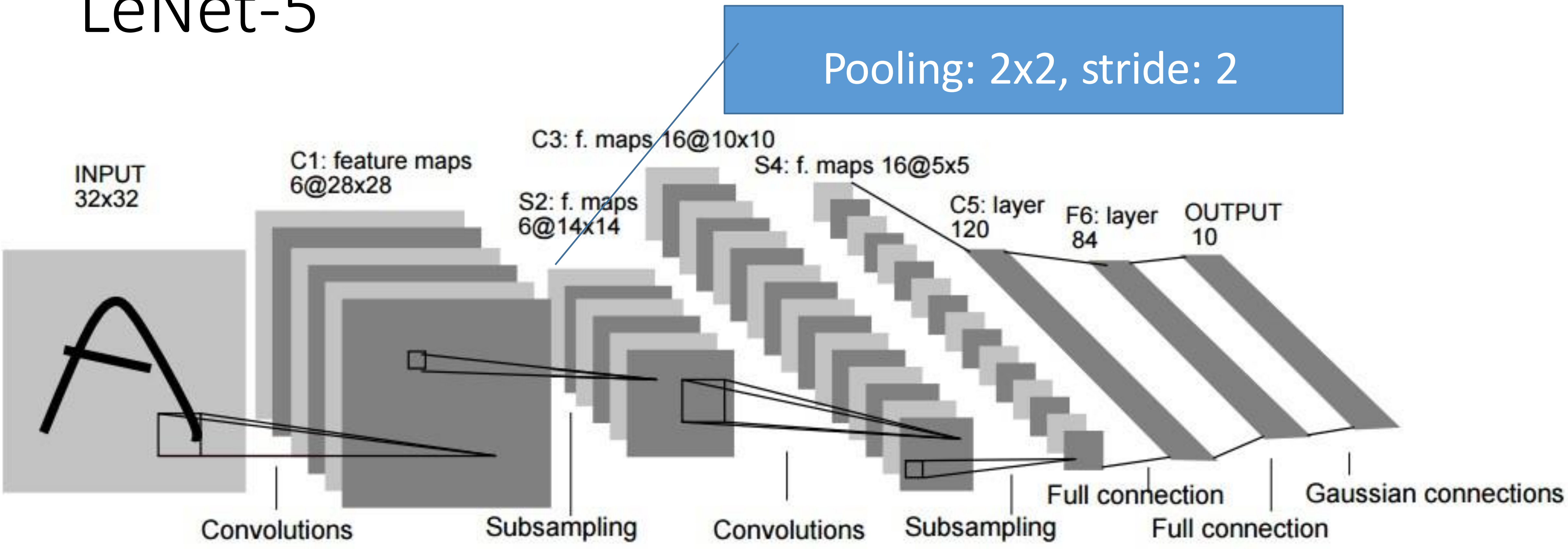


Figure from Gradient-based learning applied to document recognition, *by Y. LeCun, L. Bottou, Y. Bengio and P. Haffner*

LeNet-5

Filter: 5x5x6, stride: 1x1, #filters: 16

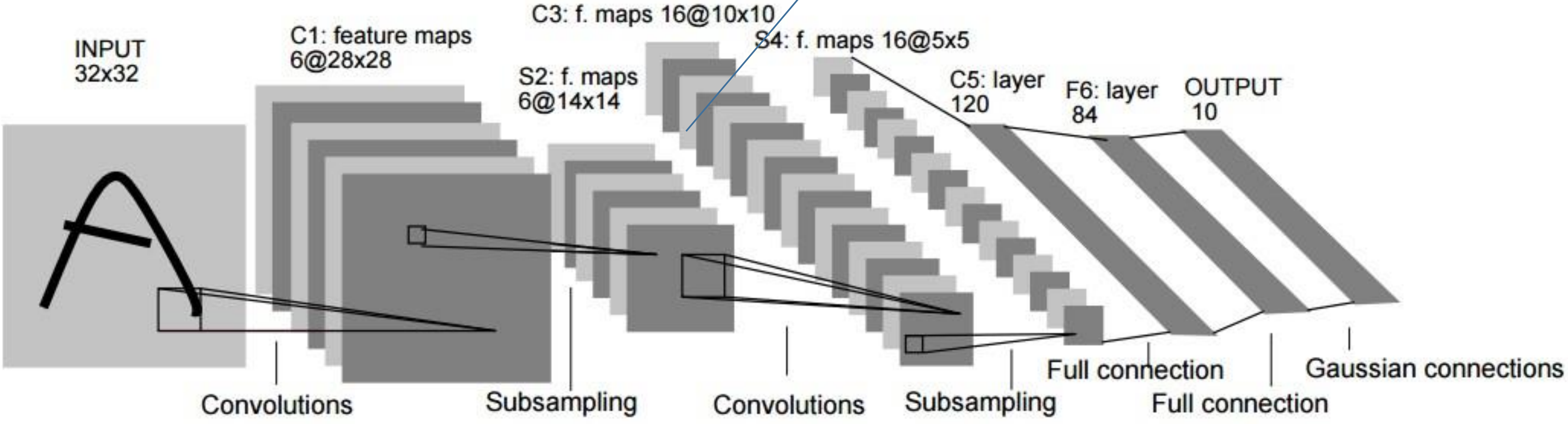


Figure from Gradient-based learning applied to document recognition, *by Y. LeCun, L. Bottou, Y. Bengio and P. Haffner*

LeNet-5

Pooling: 2x2, stride: 2

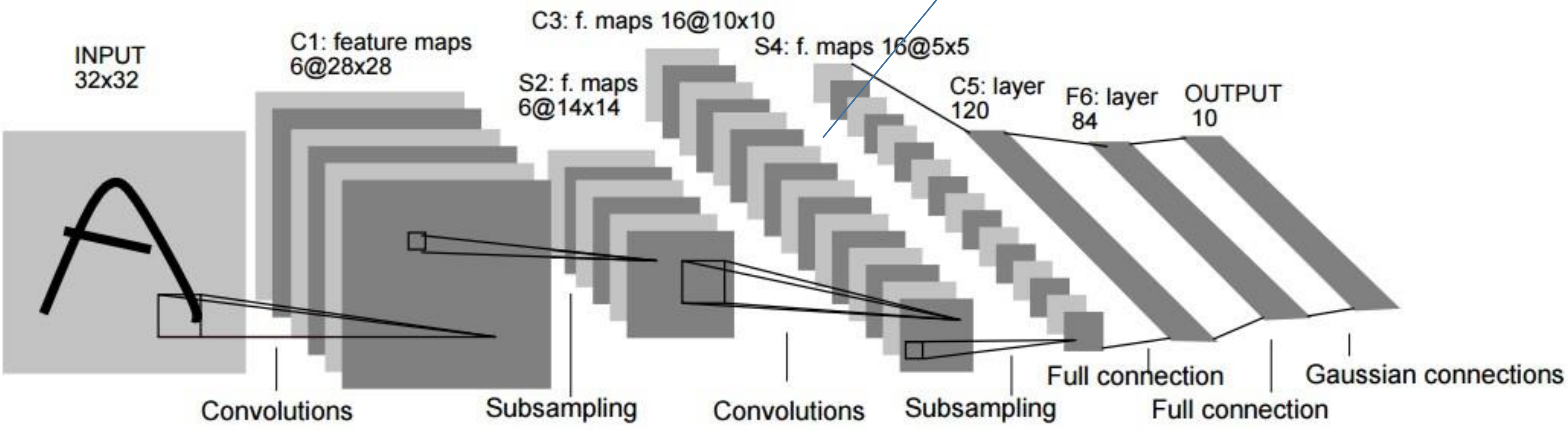


Figure from Gradient-based learning applied to document recognition, *by Y. LeCun, L. Bottou, Y. Bengio and P. Haffner*

LeNet-5

Weight matrix: 400x120

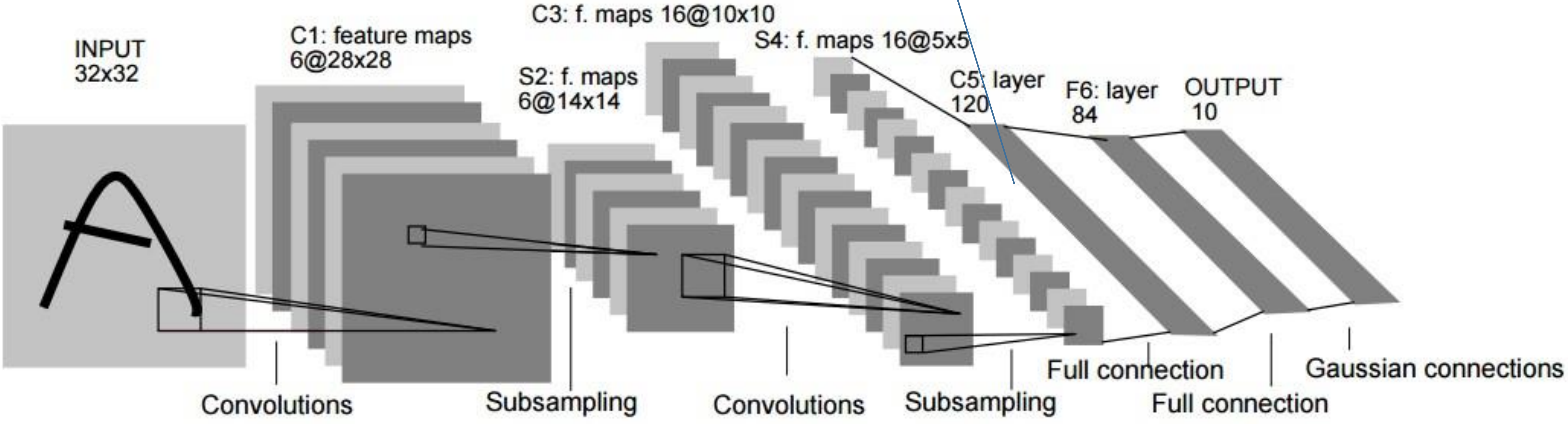


Figure from Gradient-based learning applied to document recognition, *by Y. LeCun, L. Bottou, Y. Bengio and P. Haffner*

LeNet-5

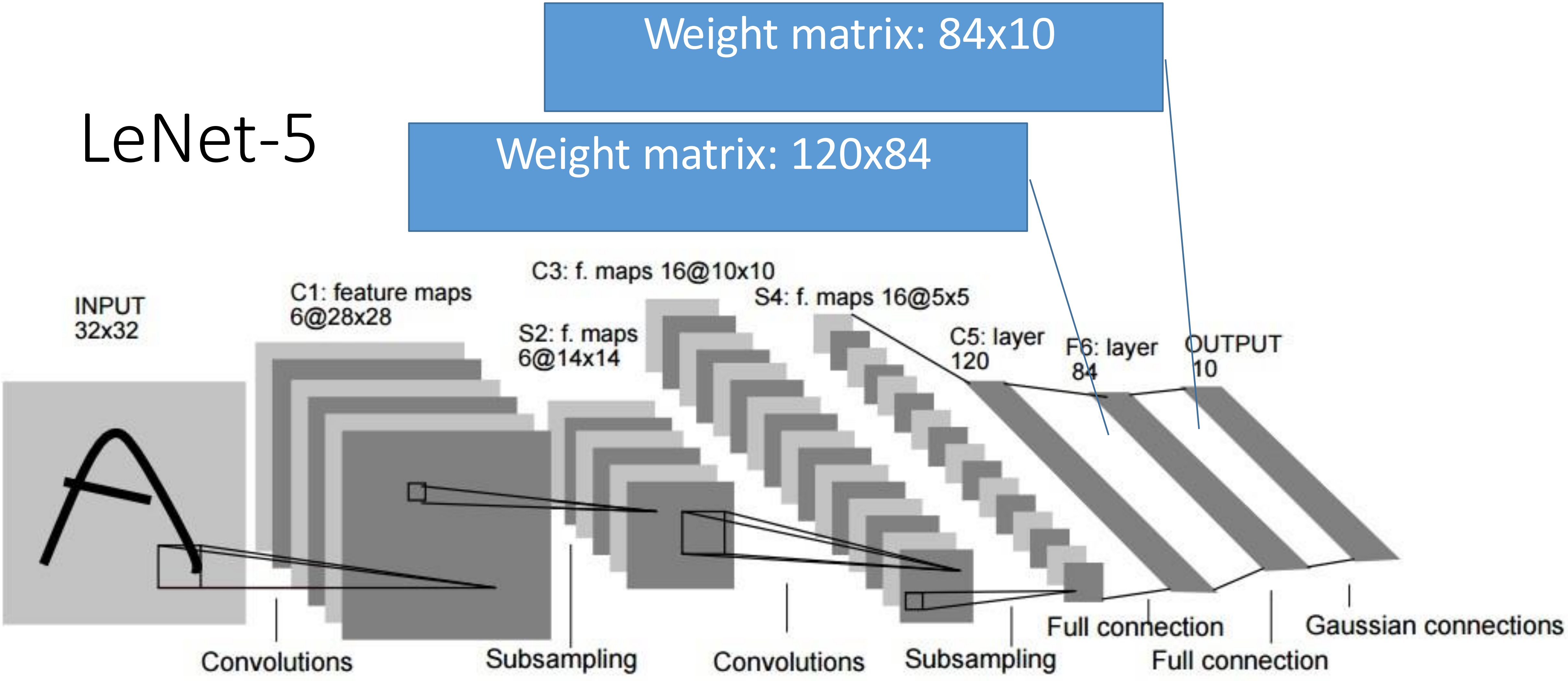
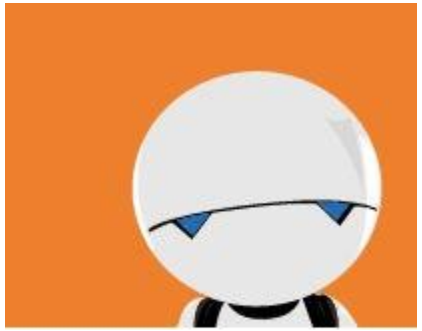


Figure from Gradient-based learning applied to document recognition, *by Y. LeCun, L. Bottou, Y. Bengio and P. Haffner*

Software platforms for CNN

Updated in April 2016; checked more recent ones online

Platform: Marvin (marvin.is)



Marvin

A minimalist GPU-only N-dimensional ConvNet framework

Learn more | Questions?

Marvin thinks, therefore Marvin is.

Never before has it been so easy to learn so deeply. Marvin was born to be hacked, relying on few dependencies and basic C++. All code lives in two files (`marvin.hpp` and `marvin.cu`) and all numbers take up two bytes (FP16). Win friends and influence people in four easy steps:

Platform: Marvin by

LeNet in Marvin: convolutional layer

```
{
    "in": ["data"],
    "type": "Convolution",
    "name": "conv1",
    "num_output": 20,
    "window": [5,5],
    "padding": [0,0],
    "stride": [1,1],
    "upscale": [1,1],
    "weight_lr_mult": 1.0,
    "weight_filler": "Xavier",
    "bias_lr_mult": 2.0,
    "bias_filler": "Constant",
    "bias_filler_param": 0.0,
    "out": ["conv1"]
},
```

LeNet in Marvin: pooling layer

```
{
    "in": ["conv1"],
    "type": "Pooling",
    "name": "pool1",
    "mode": "max",
    "window": [2,2],
    "padding": [0,0],
    "stride": [2,2],
    "out": ["pool1"]
},
```

LeNet in Marvin: fully connected layer

```
{
    "in": ["pool2"],
    "type": "InnerProduct",
    "name": "ip1",
    "num_output": 500,
    "weight_lr_mult": 1.0,
    "weight_filler": "Xavier",
    "bias_lr_mult": 2.0,
    "bias_filler": "Constant",
    "bias_filler_param": 0.0,
    "out": ["ip1"]
},
```

Platform: Caffe (caffe.berkeleyvision.org)

Caffe

Deep learning framework by the BVLC

Created by
Yangqing Jia
Lead Developer
Evan Shelhamer

Caffe

Caffe is a deep learning framework made with expression, speed, and modularity in mind. It is developed by the Berkeley Vision and Learning Center (BVLC) and by community contributors. Yangqing Jia created the project during his PhD at UC Berkeley. Caffe is released under the BSD 2-Clause license.

Check out our web image classification demo!

LeNet in Caffe

```
layer {
  name: "conv1"
  type: "Convolution"
  bottom: "data"
  top: "conv1"
  param {
    lr_mult: 1
  }
  param {
    lr_mult: 2
  }
  convolution_param {
    num_output: 20
    kernel_size: 5
    stride: 1
    weight_filler {
      type: "xavier"
    }
    bias_filler {
      type: "constant"
    }
  }
}
```

Platform: Tensorflow (tensorflow.org)

Platform: Tensorflow (tensorflow.org)

```
conv = tf.nn.conv2d(data,
                    conv1_weights,
                    strides=[1, 1, 1, 1],
                    padding='SAME')
# Bias and rectified linear non-linearity.
relu = tf.nn.relu(tf.nn.bias_add(conv, conv1_biases))
# Max pooling. The kernel size spec {ksize} also follows the layout of
# the data. Here we have a pooling window of 2, and a stride of 2.
pool = tf.nn.max_pool(relu,
                      ksize=[1, 2, 2, 1],
                      strides=[1, 2, 2, 1],
                      padding='SAME')
```

Platform: Tensorflow (tensorflow.org)

```
# Fully connected layer. Note that the '+' operation automatically
# broadcasts the biases.
hidden = tf.nn.relu(tf.matmul(reshape, fc1_weights) + fc1_biases)
# Add a 50% dropout during training only. Dropout also scales
# activations such that no rescaling is needed at evaluation time.
if train:
  hidden = tf.nn.dropout(hidden, 0.5, seed=SEED)
```

Others

- **Theano** – CPU/GPU symbolic expression compiler in python (from MILA lab at University of Montreal)
- **Torch** – provides a Matlab-like environment for state-of-the-art machine learning algorithms in lua
- **Lasagne** - Lasagne is a lightweight library to build and train neural networks in Theano

- See: http://deeplearning.net/software_links/

Optimization: momentum

Basic algorithms

- Minimize the (regularized) empirical loss

$$\hat{R}(\theta) = \frac{1}{n} \sum_{t=1}^{n} l(\theta, x_t, y_t) + R(\theta)$$

where the hypothesis is parametrized by θ

- Gradient descent

$$\theta_{t+1} = \theta_t - \eta_t \nabla \hat{R}(\theta_t)$$

Mini-batch stochastic gradient descent

- Instead of one data point, work with a small batch of b points

$$(x_{tb+1}, y_{tb+1}), \ldots, (x_{tb+b}, y_{tb+b})$$

- Update rule

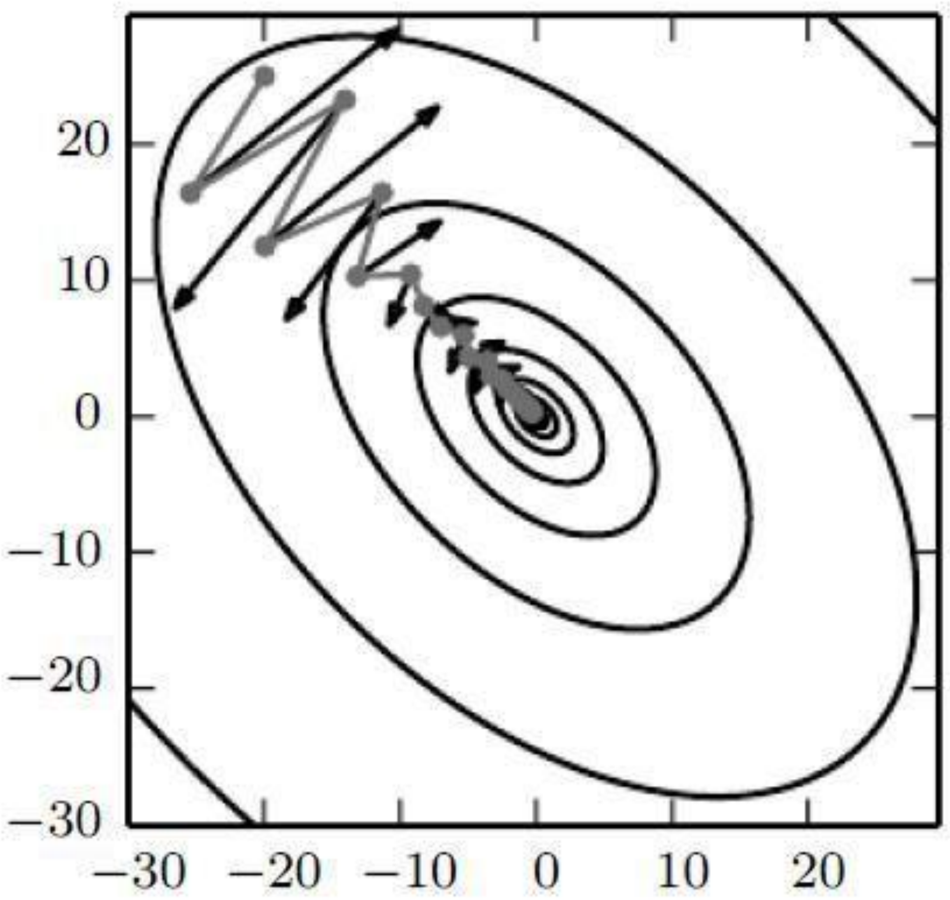
$$\theta_{t+1} = \theta_t - \eta_t \nabla \left(\frac{1}{b} \sum_{1 \le i \le b} l(\theta_t, x_{tb+i}, y_{tb+}) + R(\theta_t) \right)$$

Momentum

- Drawback of SGD: can be slow when gradient is small

- Observation: when the gradient is consistent across consecutive steps, can take larger steps
- Metaphor: rolling marble ball on gentle slope

Momentum



Contour: loss function
Path: SGD with momentum
Arrow: stochastic gradient

Figure from *Deep Learning,* by Goodfellow, Bengio, and Courville

Momentum

- work with a small batch of b points

$$(x_{tb+1}, y_{tb+1}), \ldots, (x_{tb+b}, y_{tb+b})$$

- Keep a momentum variable v_t, and set a decay rate α
- Update rule

$$v_t = \alpha v_{t-1} - \eta_t \nabla \left(\frac{1}{b} \sum_{1 \le i \le b} l(\theta_t, x_{tb+i}, y_{tb+}) + R(\theta_t) \right)$$

$$\theta_{t+1} = \theta_t + v_t$$

Momentum

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$$\theta_{t+1} = \theta_t + v_t$$

- Practical guide: α is set to 0.5 until the initial learning stabilizes and then is increased to 0.9 or higher.