Глубокое обучение на примере компьютерного зрения

Занятие 2
Метод обратного распространения ошибки. Сверточные нейронные сети.

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IntelliVision

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Last time: **Классификация изображений**

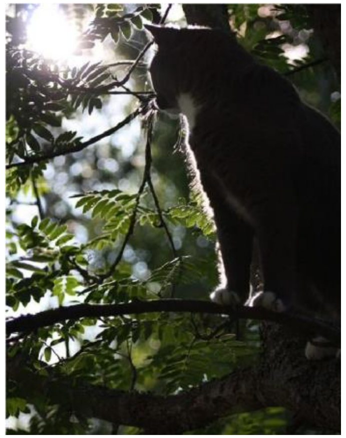
Ключевая задача компьютерного зрения

К какому классу принадлежит изображение?
классы: человек, животное, автомобиль …

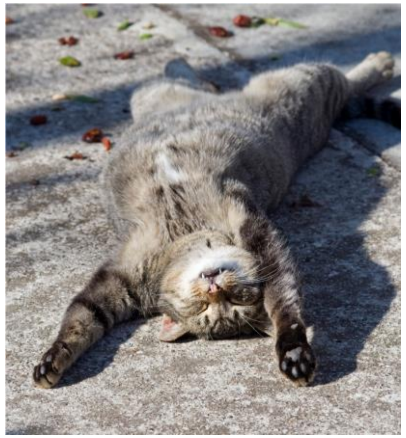
кот

Last time: **Сложности классификации изображений**

Освещение



Форма



Заслонение

Фон

Вариативность классов

Last time: **Линейный классификатор**

Image

$$\underbrace{s=\boxed{f(x,W)}}_{10x1} = \underbrace{\boxed{W}}_{10x3072}\overbrace{\boxed{x}}^{3072x1} + \boxed{b}\ 10x1$$

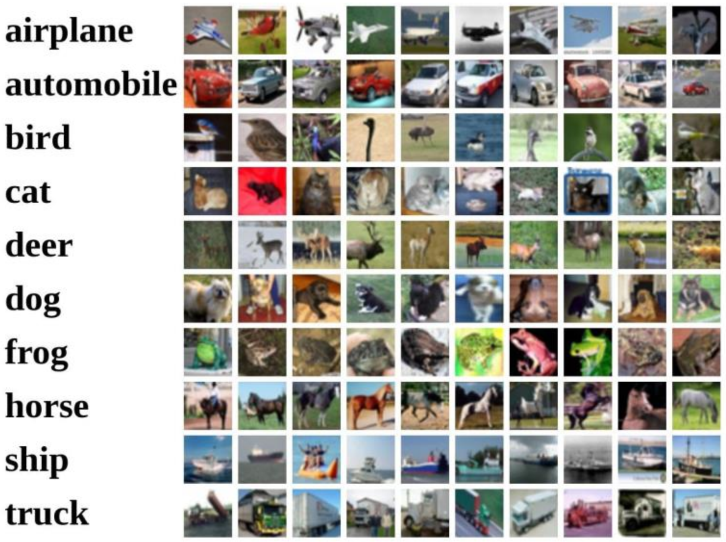
s – scores
W – weights or parameters
x – image pixels
b – bias

Array of **32x32x3** numbers (3072 numbers total)

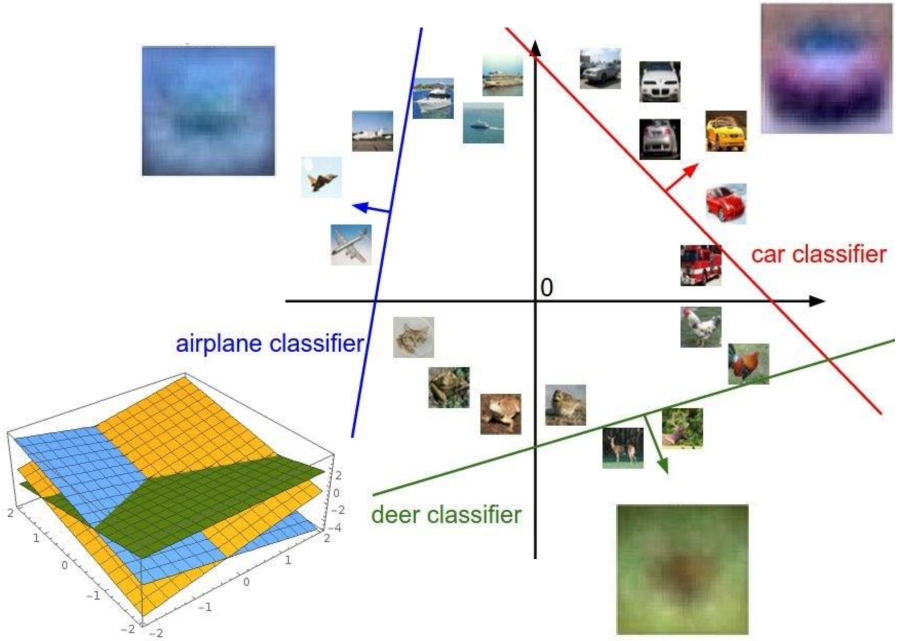
CIFAR-10
50,000 training images
10,000 testing images
10 classes

Last time: **Интерпретация линейного классификатора**

CIFAR-10



$$f(x,W) = Wx + b$$



Example trained weights of a linear classifier trained on CIFAR-10:

Last time: **Функции потерь**

Image

x_i - image
y_i - label, element of a set {0, 1, …}

scores $s = f(x_i, W) = [s_0, \dots s_{y_i}, \dots]$

Loss over dataset:

$$L = \frac{1}{N}\sum_{i=1}^{N} L_i$$

Multiclass SVM (hinge) loss:

$$\boxed{L_i = \sum_{i \neq y_i} \max(0, s_i - s_{y_i} + 1)}$$

Cross-entropy (softmax) loss:

$$\boxed{L_i = -\log \frac{e^{s_{y_i}}}{\sum_j e^{s_j}}}$$

Last time: **Регуляризация**

Softmax or SVM

λ - regularization strength (hyperparameter)

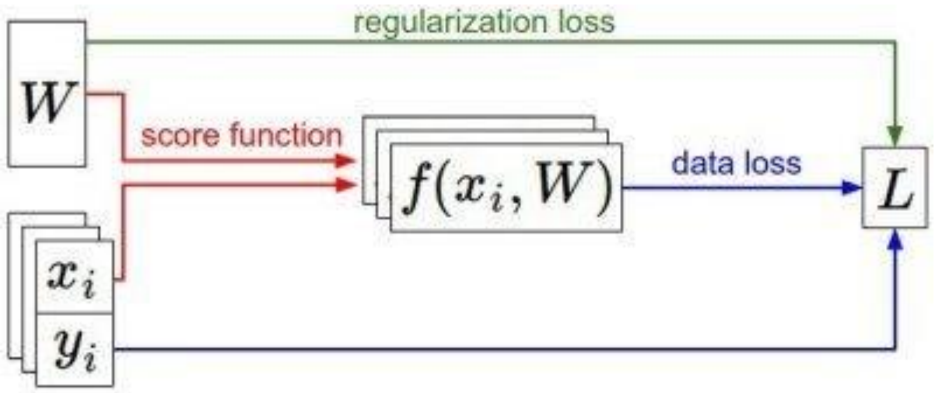
Full loss $$L = \underbrace{\frac{1}{N}\sum_{i=1}^{N} L_i}_{\text{Data loss}} + \underbrace{\lambda R(W)}_{\text{Regularization}}$$

How do we find the best W?

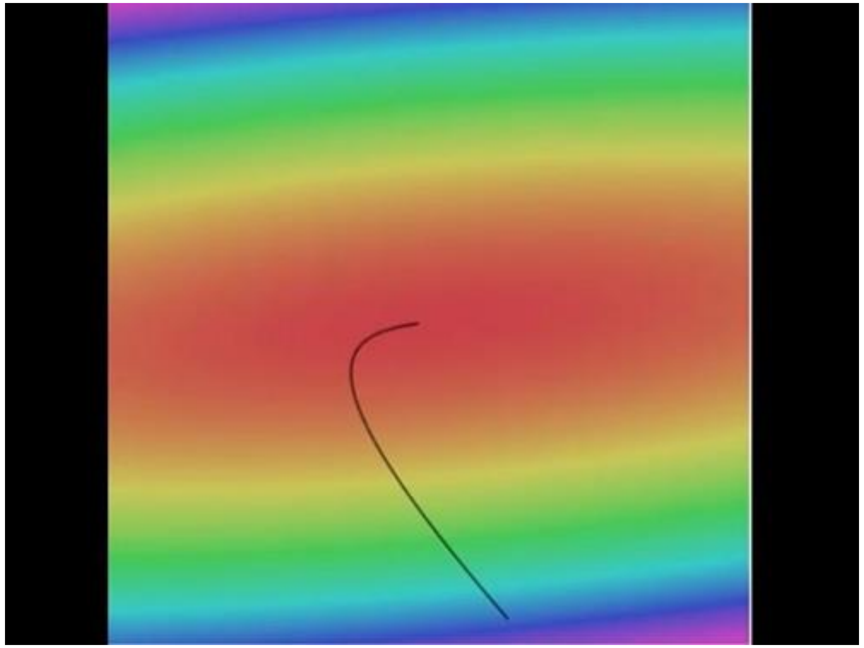
L2 regularization $R(W) = \sum_k \sum_l W_{k,l}^2$

L1 regularization $R(W) = \sum_k \sum_l |W_{k,l}|$

Elastic net (L1 + L2) $R(W) = \sum_k \sum_l \beta W_{k,l}^2 + |W_{k,l}|$



Оптимизация



```
# Vanilla Minibatch Gradient Descent

while True:
  data_batch = sample_training_data(data, 256) # sample 256 examples
  weights_grad = evaluate_gradient(loss_fun, data_batch, weights)
  weights += - step_size * weights_grad # perform parameter update
```

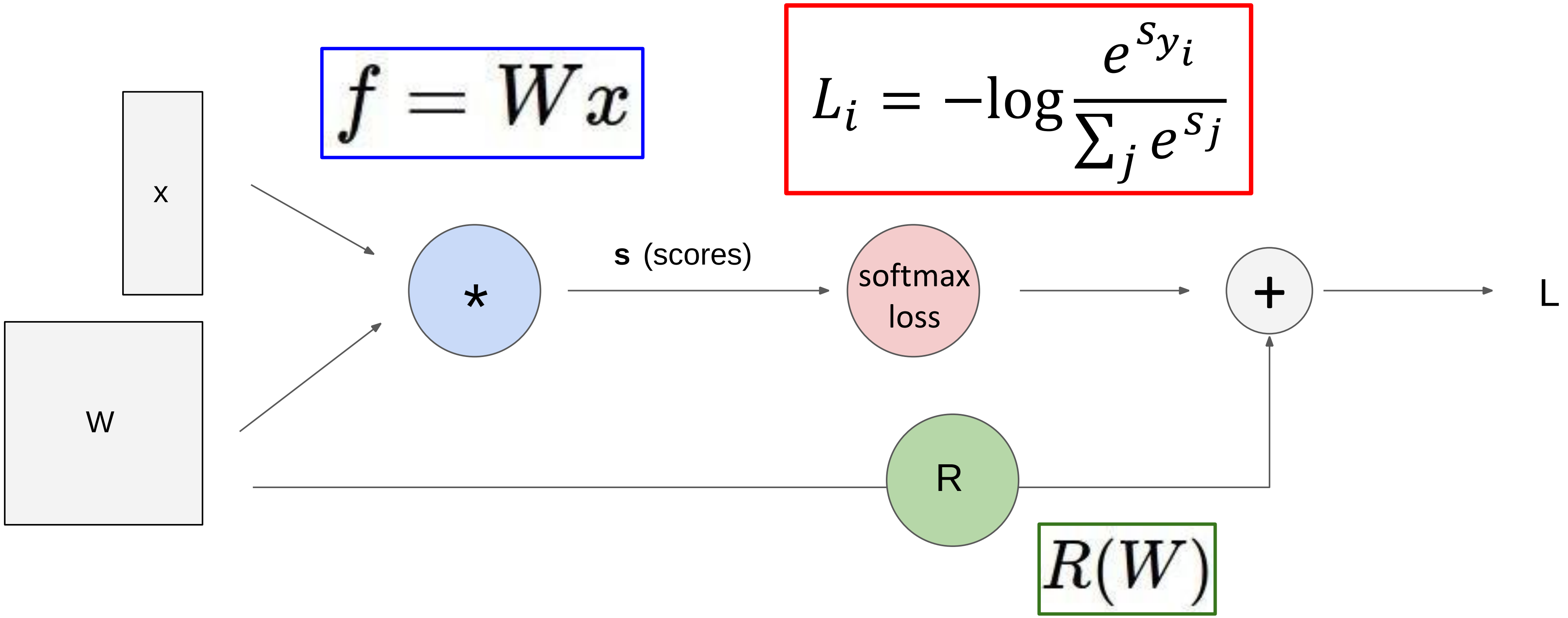
Градиентный спуск

$$\frac{dL(w)}{dw} = \lim_{h \to 0} \frac{L(w+h) - L(w)}{h}$$

Численные градиенты: медленно, не точно, быстро реализовать

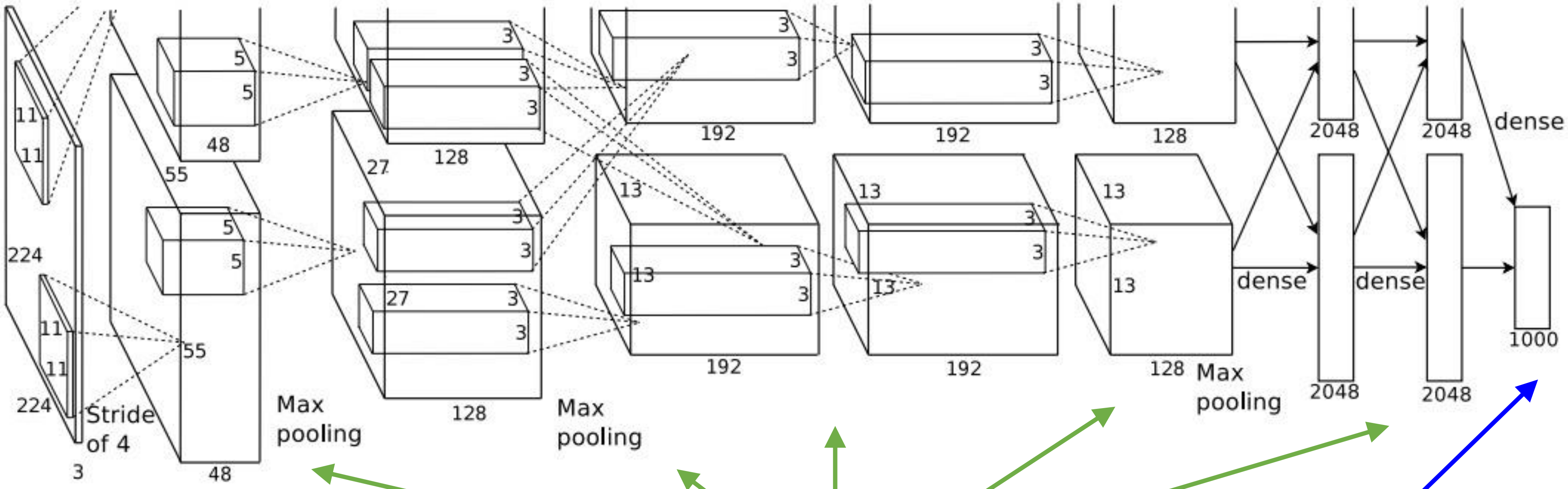
Аналитические градиенты: быстро, точно, можно ошибиться

Вычислительный граф



Вычислительный граф: **Convolutional Network**

AlexNet



input image

weights

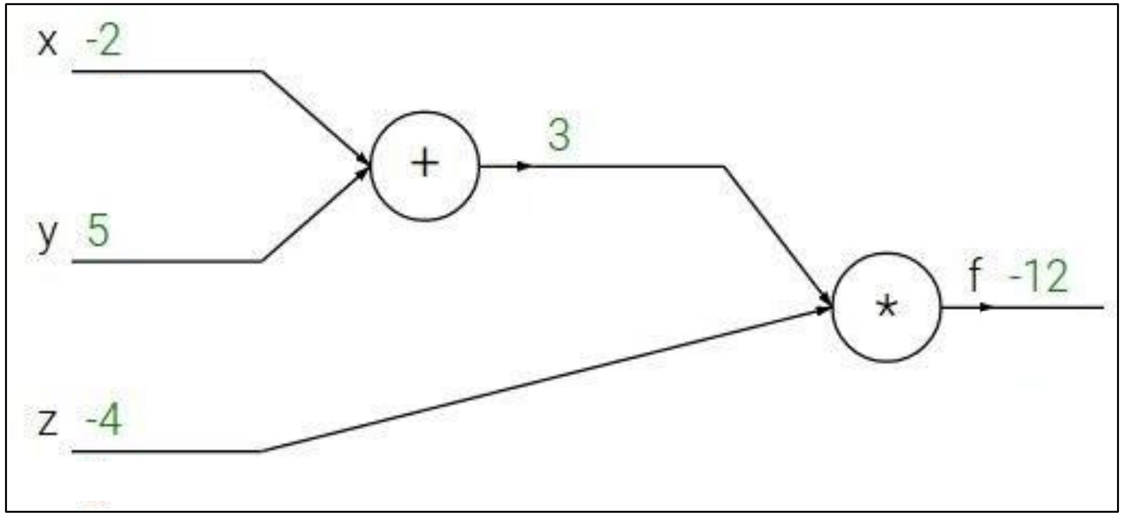
loss

Backpropagation

Backpropagation: a simple example

$$f(x, y, z) = (x + y)z$$

e.g. x = -2, y = 5, z = -4



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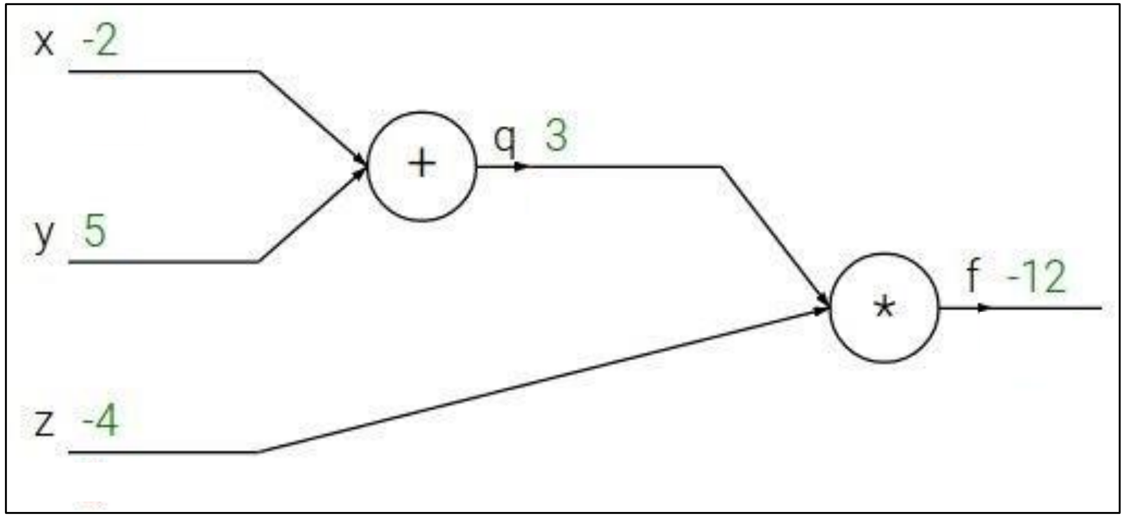
Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



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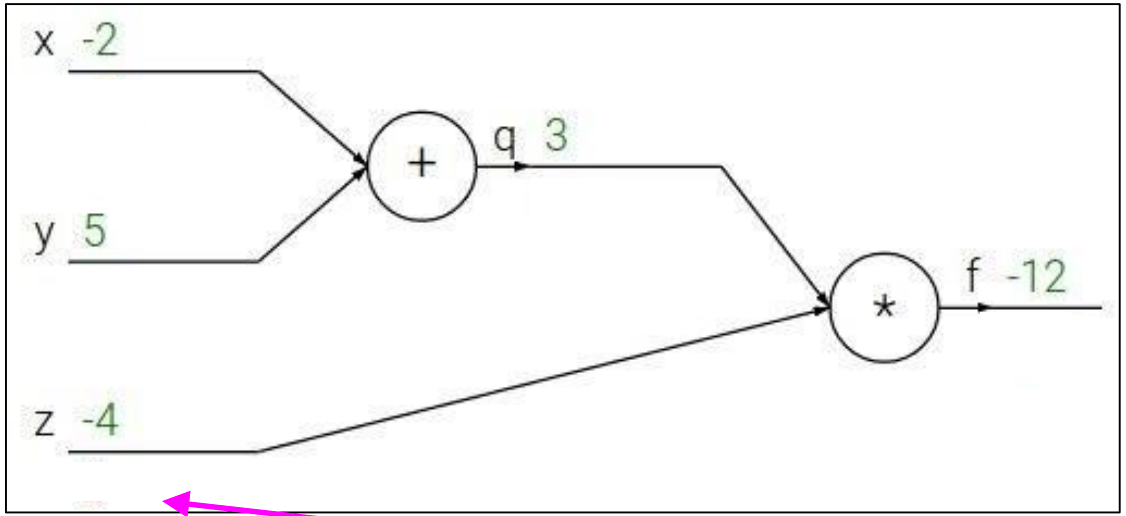

$$\frac{\partial f}{\partial z}$$

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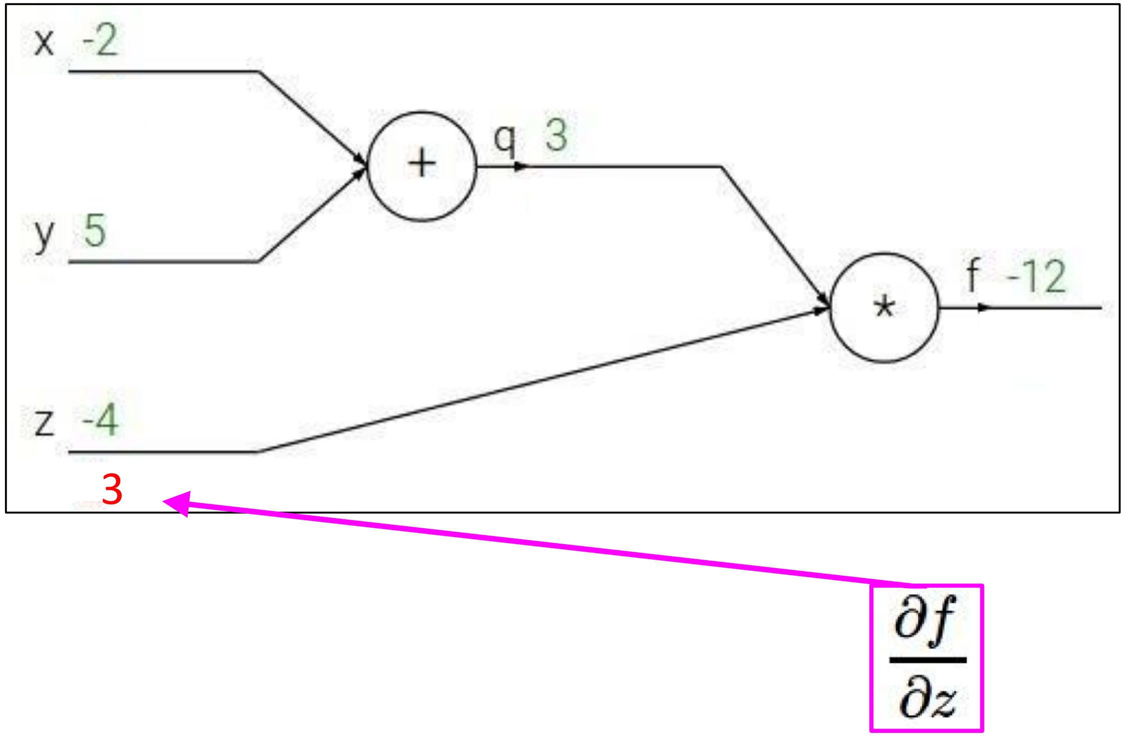

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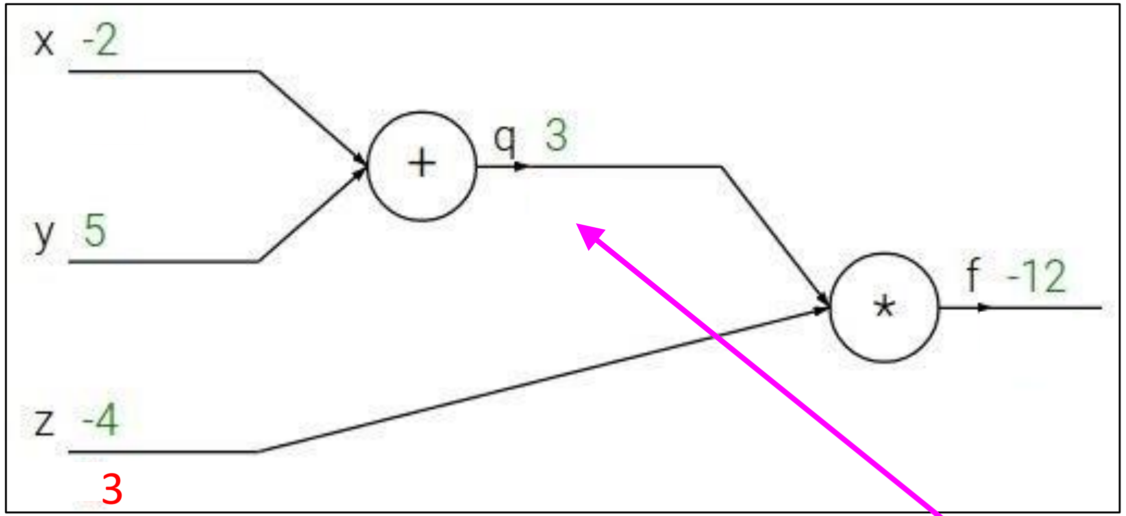

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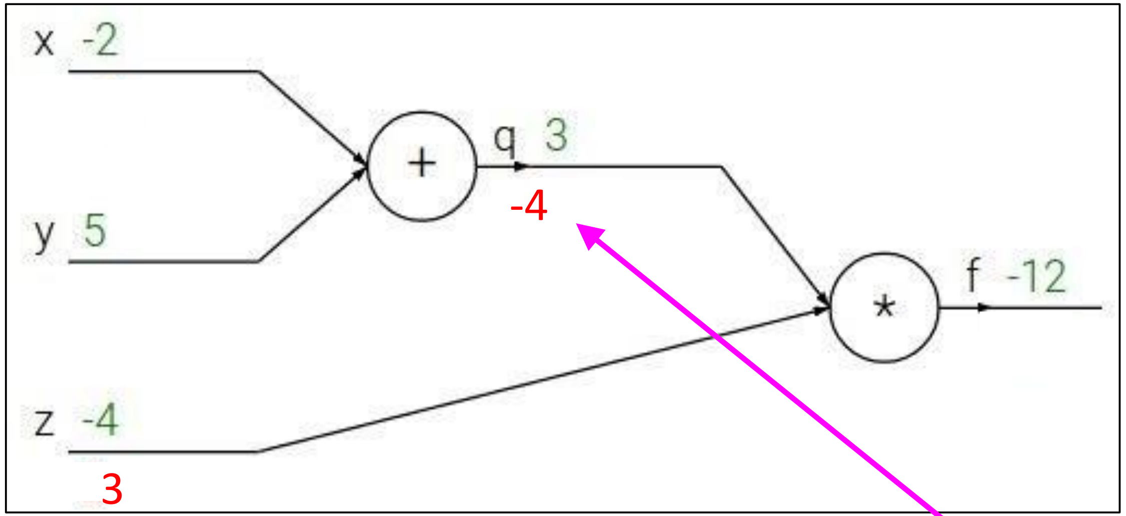

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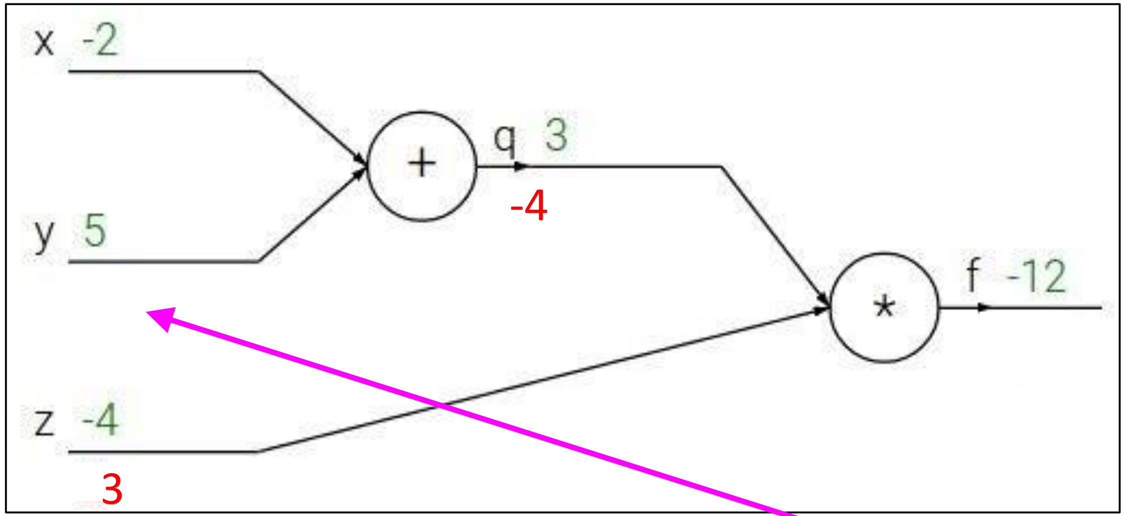

$\frac{\partial f}{\partial y}$

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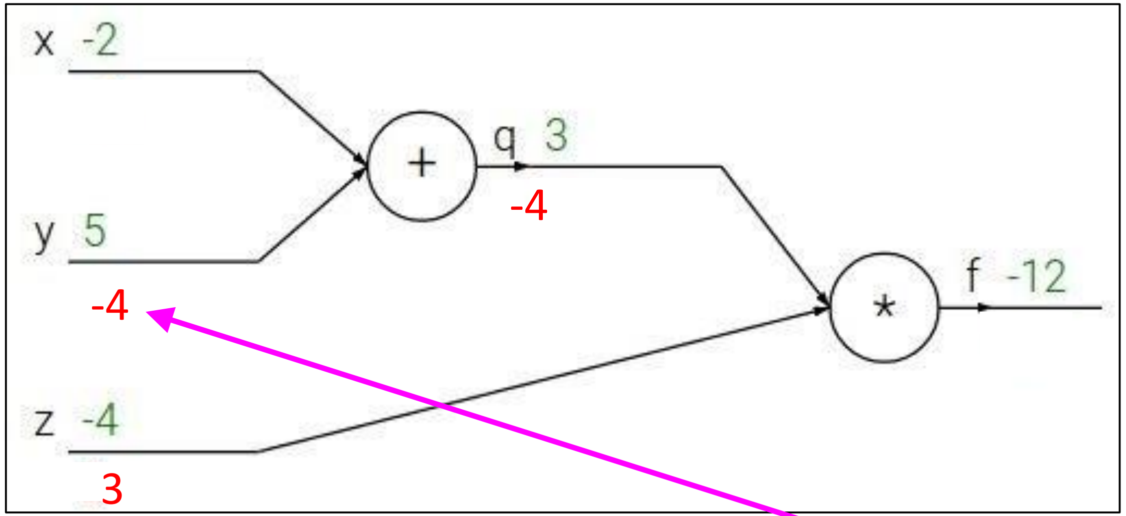

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$$\frac{\partial f}{\partial y}$$

Chain rule:

$$\frac{\partial f}{\partial y} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial y}$$

Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$

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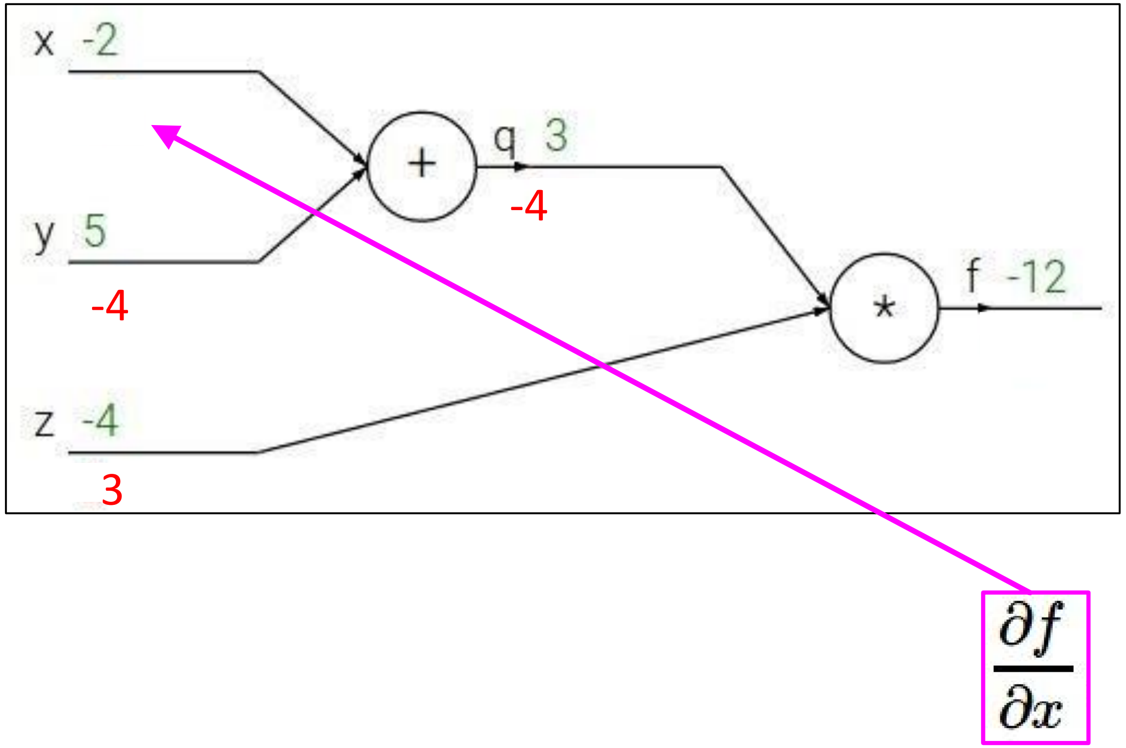

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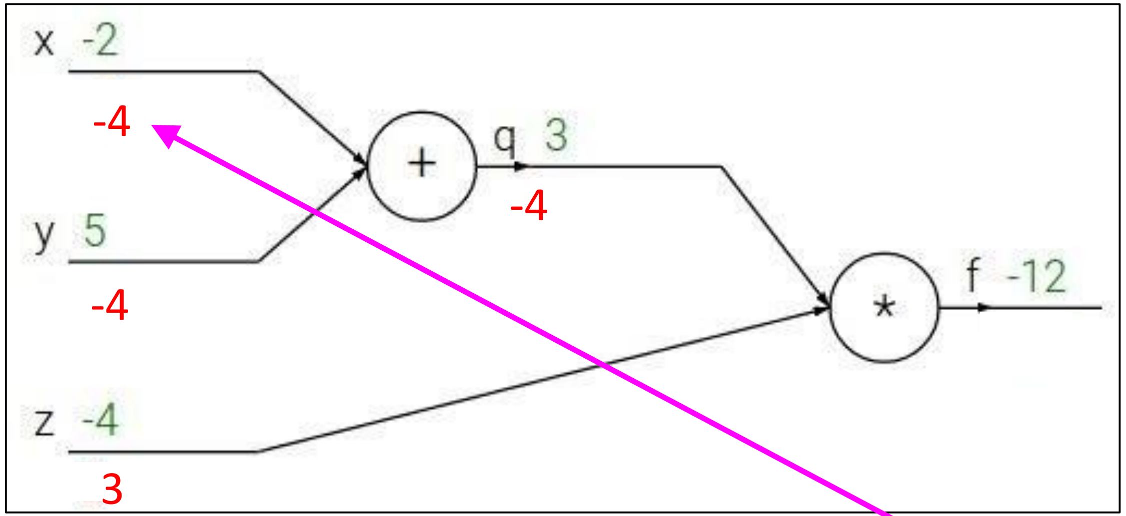
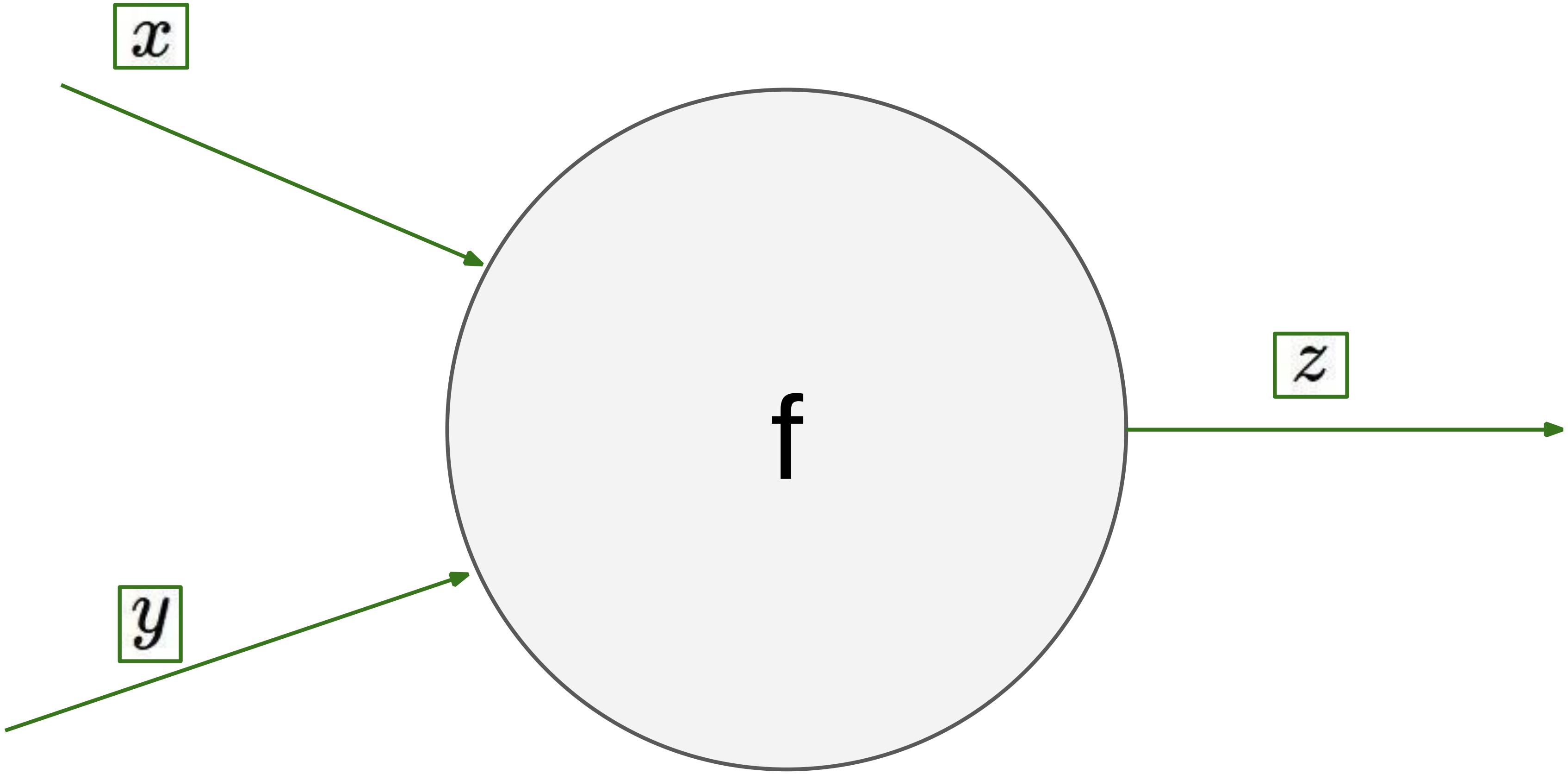


$$\frac{\partial f}{\partial x}$$

Chain rule:

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial x}$$

Backpropagation: общий случай



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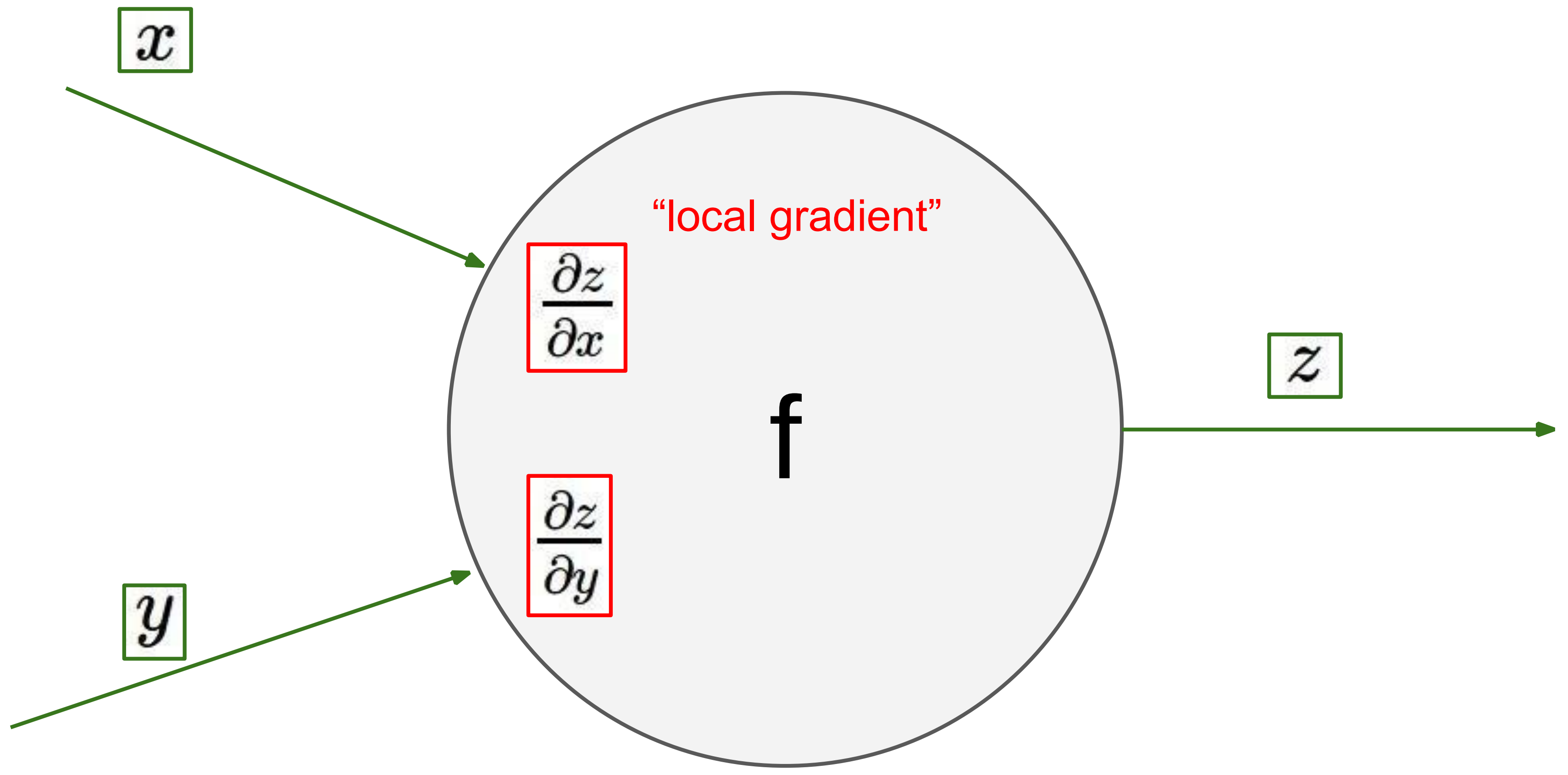

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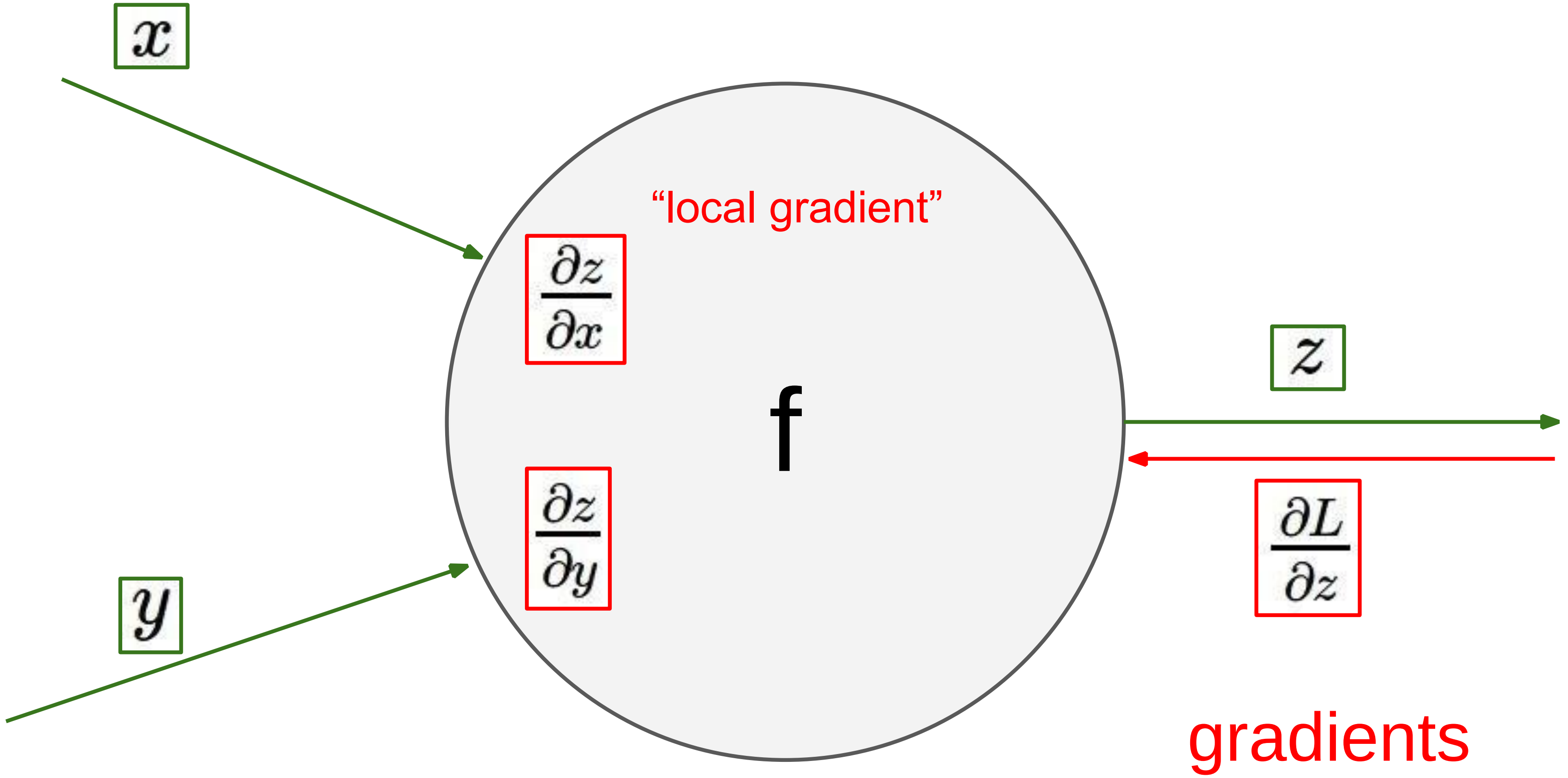

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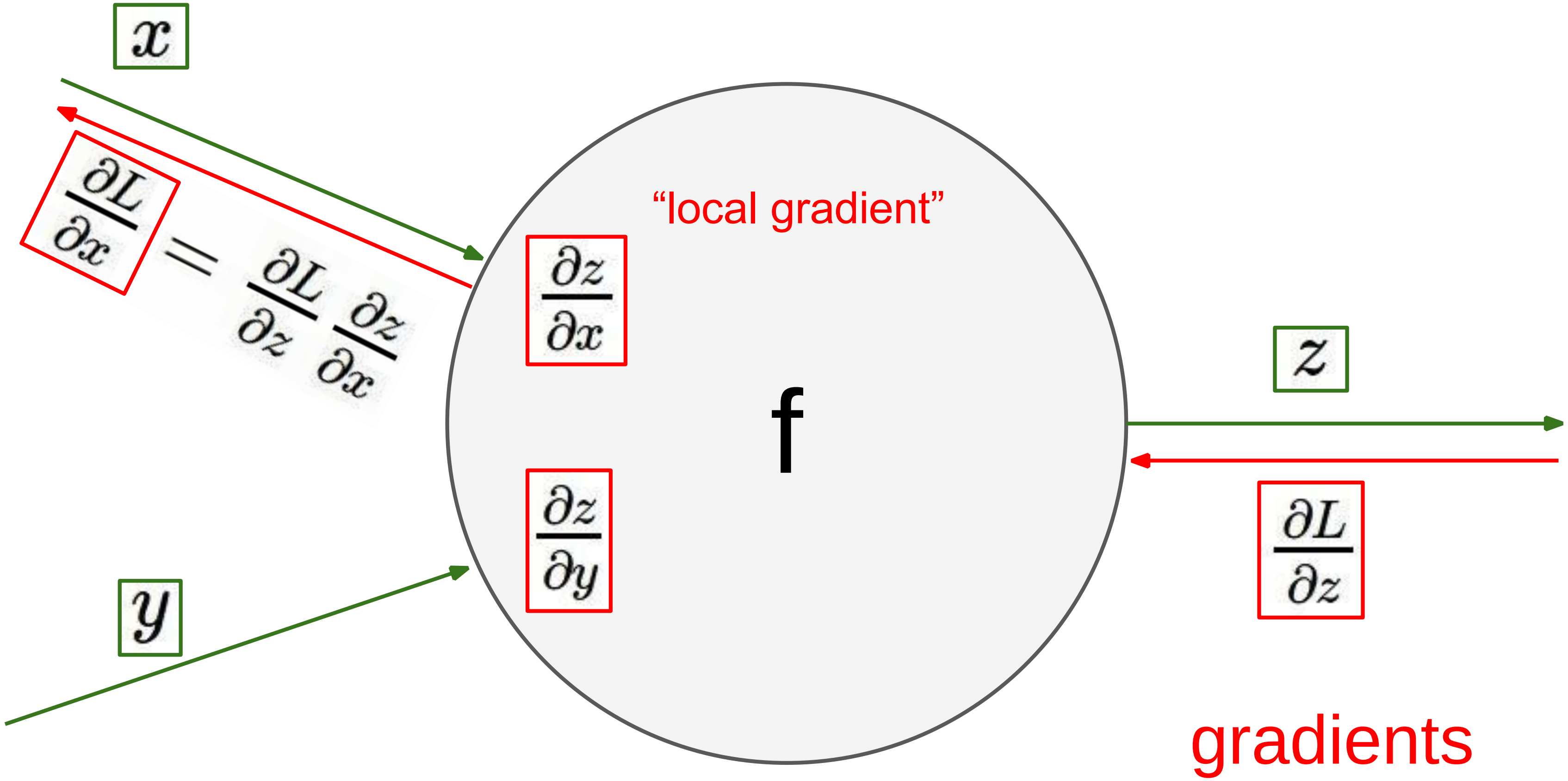

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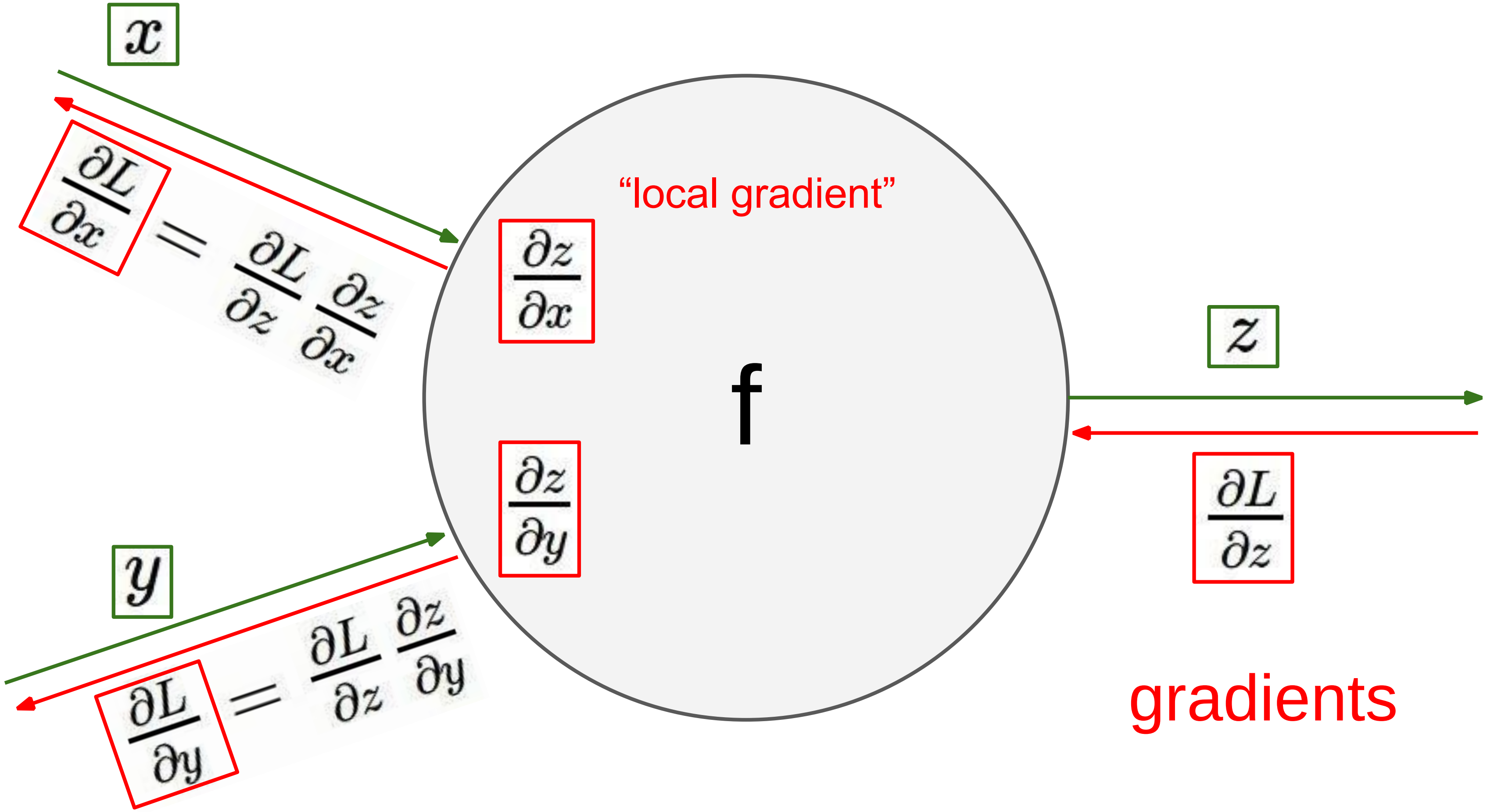

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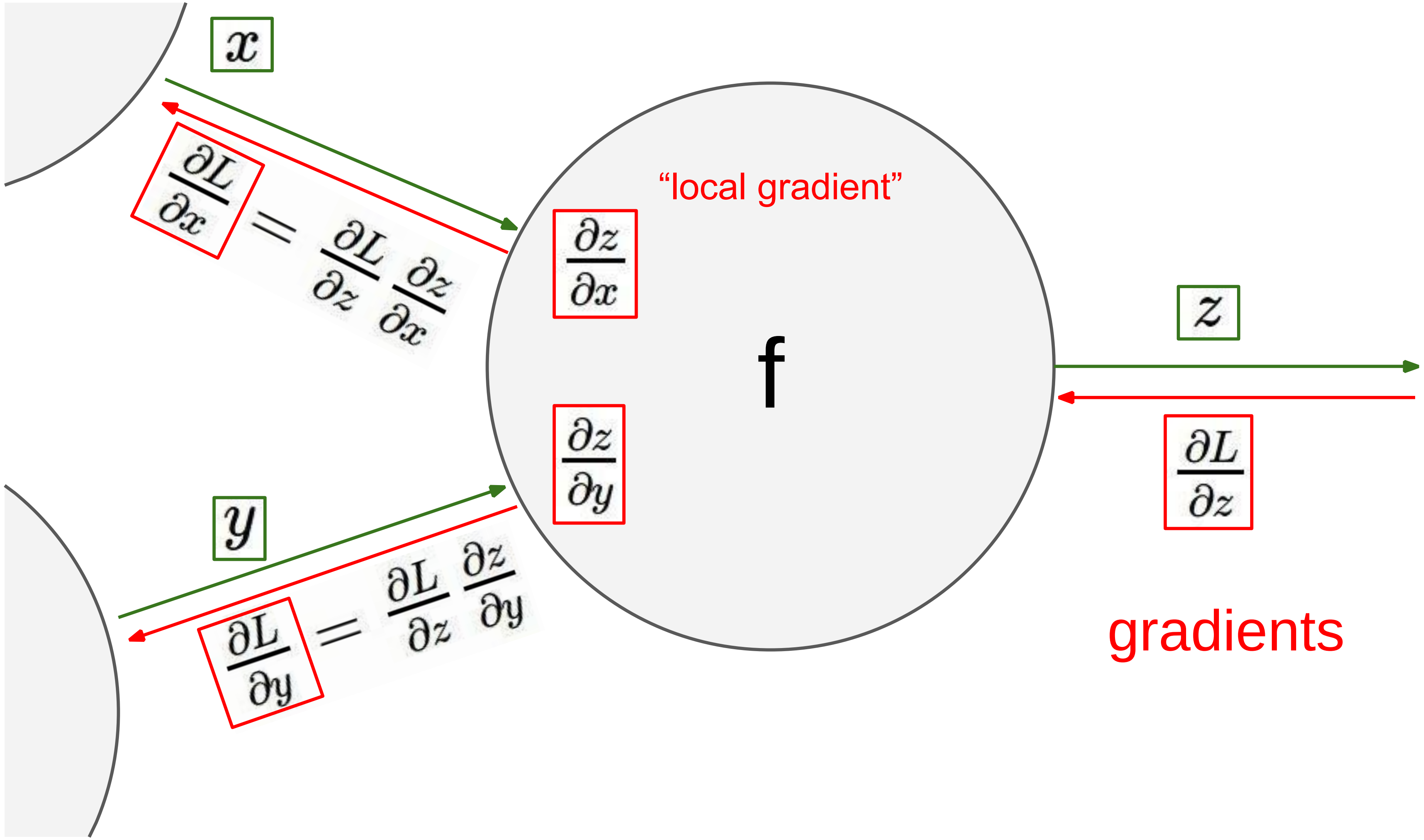
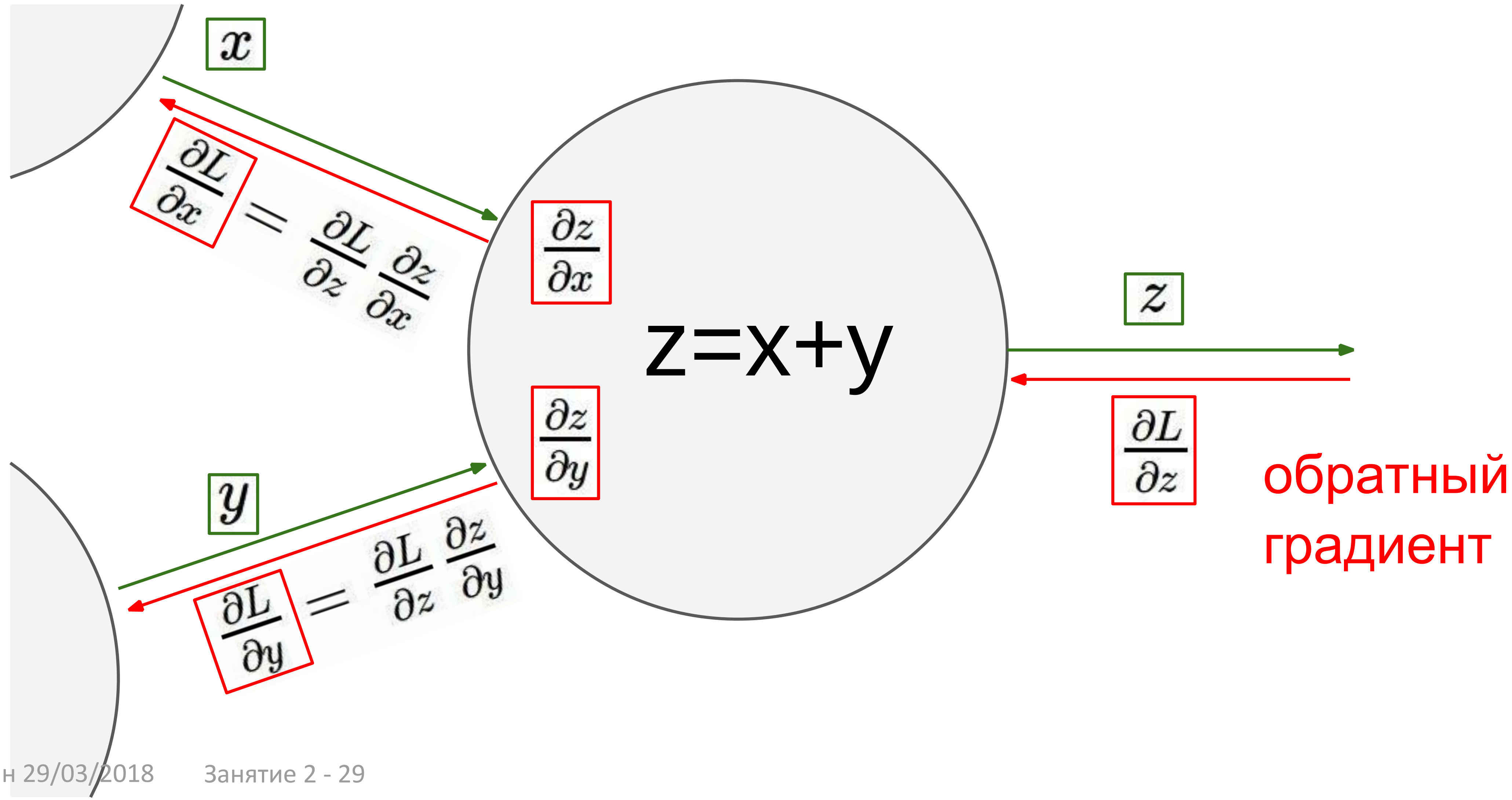


Обратный градиент при суммировании



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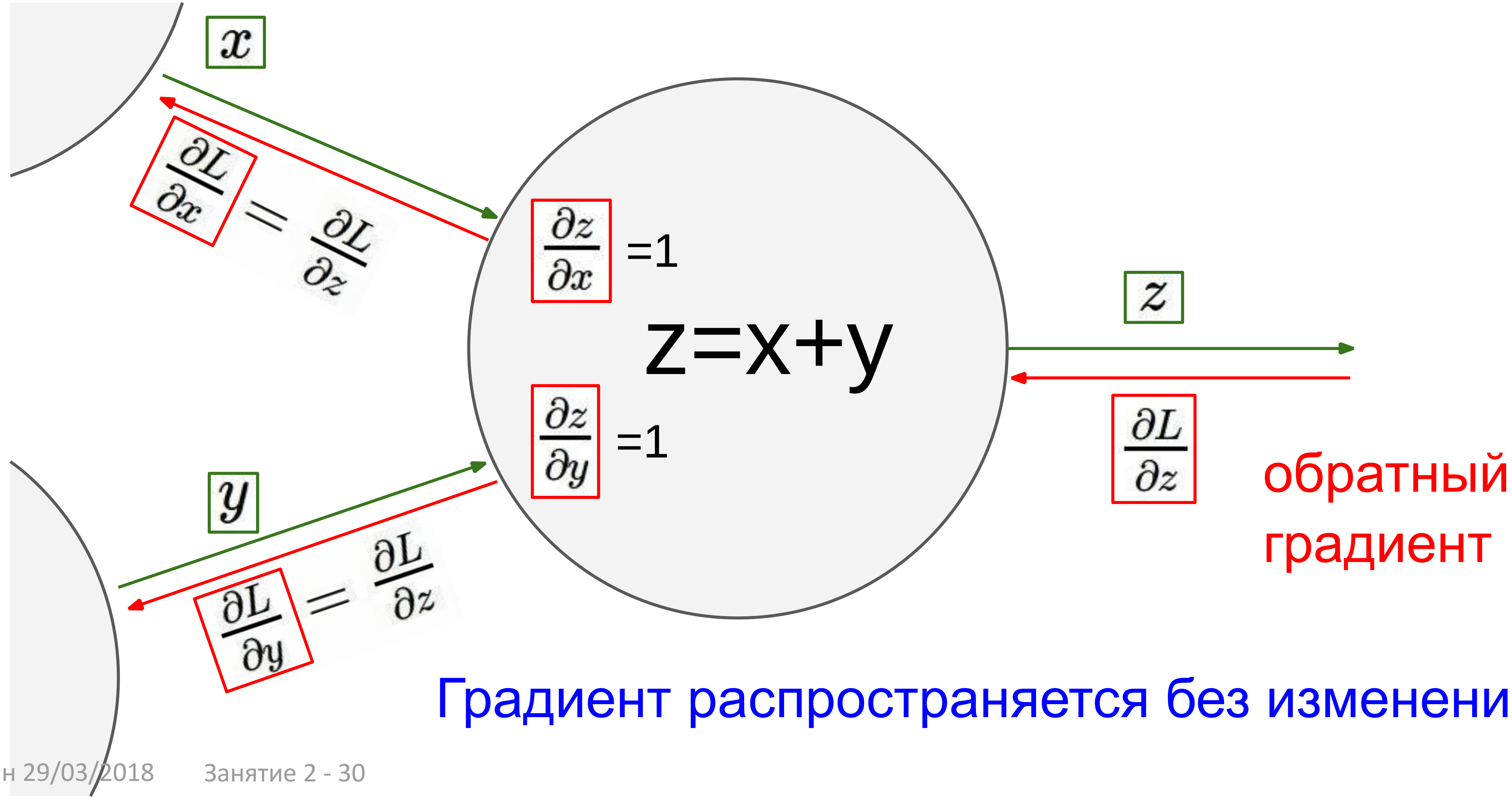
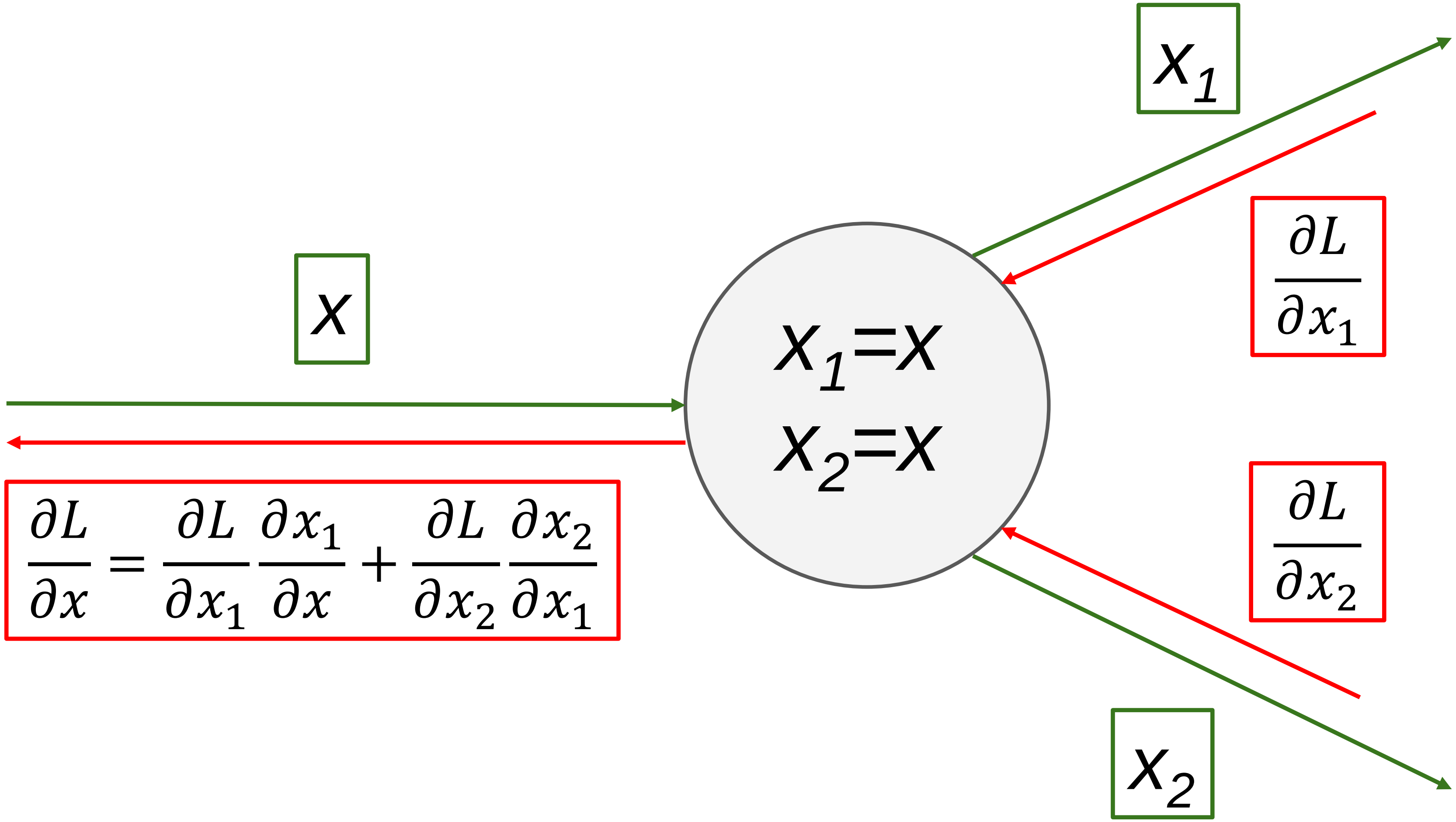


Градиент распространяется без изменений

Обратный градиент при переиспользовании переменной



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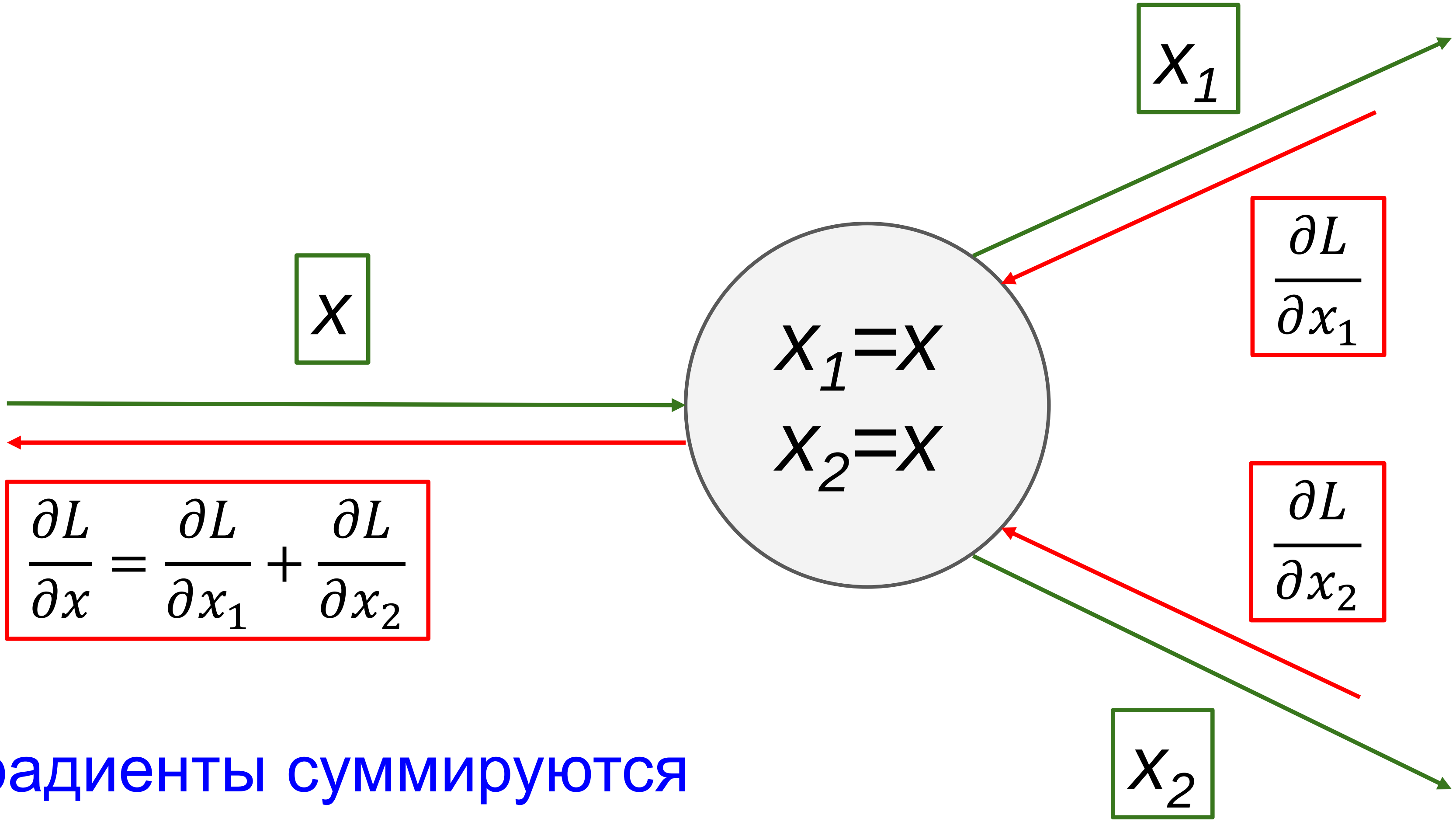
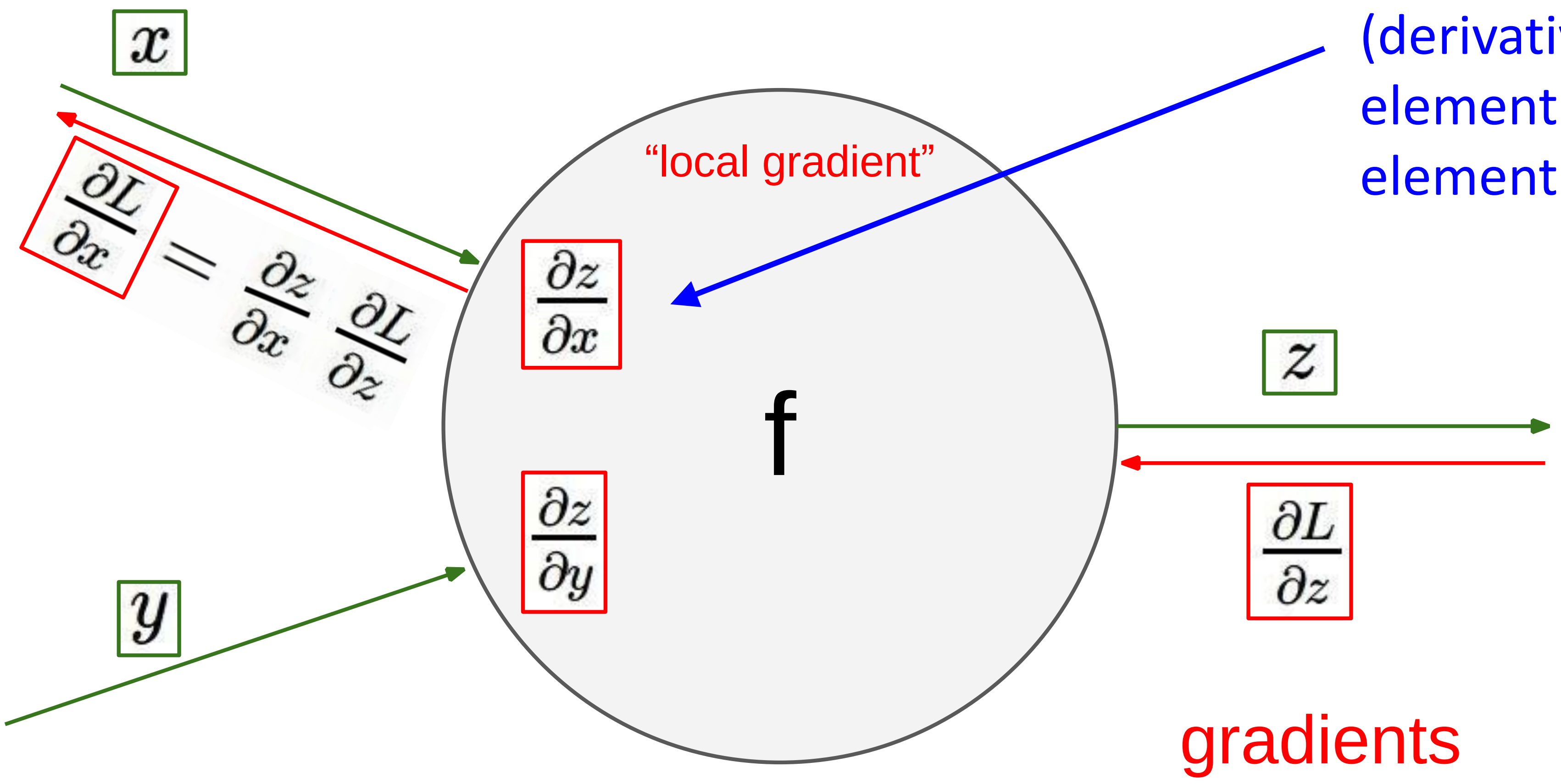


Градиенты суммируются

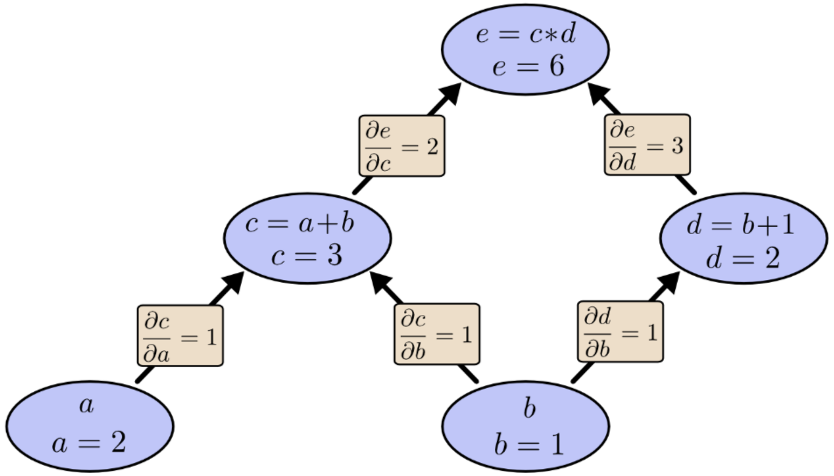
Backpropagation: векторный случай

(x,y,z are now vectors)

This is now the **Jacobian matrix** (derivative of each element of z w.r.t. each element of x)



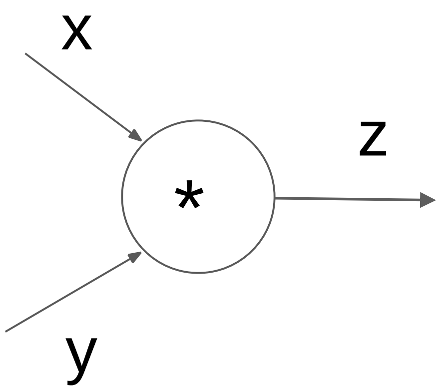
Modularized implementation: forward / backward API



Graph (or Net) object *(rough psuedo code)*

```
class ComputationalGraph(object):
    #...
    def forward(inputs):
        # 1. [pass inputs to input gates...]
        # 2. forward the computational graph:
        for gate in self.graph.nodes_topologically_sorted():
            gate.forward()
        return loss # the final gate in the graph outputs the loss
    def backward():
        for gate in reversed(self.graph.nodes_topologically_sorted()):
            gate.backward() # little piece of backprop (chain rule applied)
        return inputs_gradients
```

Modularized implementation: forward / backward API



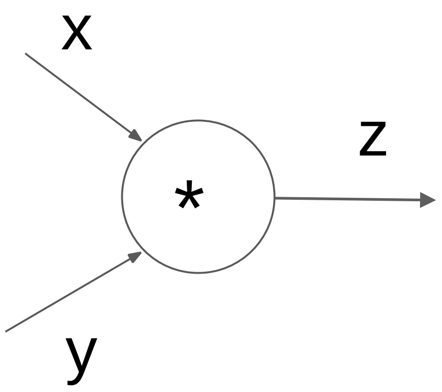
(x,y,z are scalars)

```python
class MultiplyGate(object):
    def forward(x,y):
        z = x*y
        return z
    def backward(dz):
        # dx = ... #todo
        # dy = ... #todo
        return [dx, dy]
```

$$\boxed{\frac{\partial L}{\partial z}}$$

$$\boxed{\frac{\partial L}{\partial x}}$$

Modularized implementation: forward / backward API



(x,y,z are scalars)

```
class MultiplyGate(object):
    def forward(x,y):
        z = x*y
        self.x = x # must keep these around!
        self.y = y
        return z
    def backward(dz):
        dx = self.y * dz # [dz/dx * dL/dz]
        dy = self.x * dz # [dz/dy * dL/dz]
        return [dx, dy]
```

Example: Caffe layers

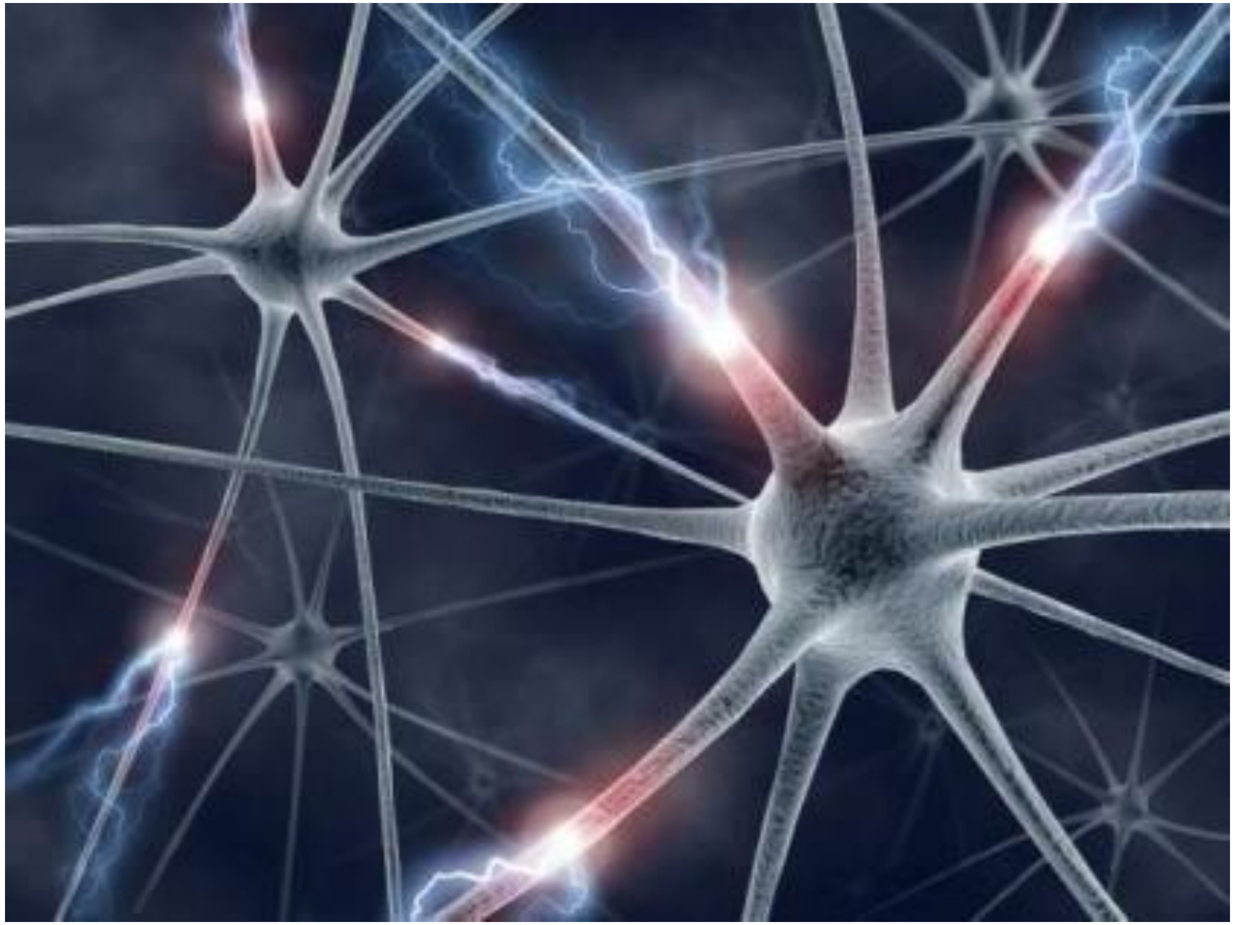
Branch: master ▾ caffe / src / caffe / layers / — Create new file | Upload files | Find file | History

shelhamer committed on GitHub Merge pull request #4630 from BlGene/load_hdf5_fix … — Latest commit e687a71 21 days ago

..		
absval_layer.cpp	dismantle layer headers	a year ago
absval_layer.cu	dismantle layer headers	a year ago
accuracy_layer.cpp	dismantle layer headers	a year ago
argmax_layer.cpp	dismantle layer headers	a year ago
base_conv_layer.cpp	enable dilated deconvolution	a year ago
base_data_layer.cpp	Using default from proto for prefetch	3 months ago
base_data_layer.cu	Switched multi-GPU to NCCL	3 months ago
batch_norm_layer.cpp	Add missing spaces besides equal signs in batch_norm_layer.cpp	4 months ago
batch_norm_layer.cu	dismantle layer headers	a year ago
batch_reindex_layer.cpp	dismantle layer headers	a year ago
batch_reindex_layer.cu	dismantle layer headers	a year ago
bias_layer.cpp	Remove incorrect cast of gemm int arg to Dtype in BiasLayer	a year ago
bias_layer.cu	Separation and generalization of ChannelwiseAffineLayer into BiasLayer	a year ago
bnll_layer.cpp	dismantle layer headers	a year ago
bnll_layer.cu	dismantle layer headers	a year ago
concat_layer.cpp	dismantle layer headers	a year ago
concat_layer.cu	dismantle layer headers	a year ago
contrastive_loss_layer.cpp	dismantle layer headers	a year ago
contrastive_loss_layer.cu	dismantle layer headers	a year ago
conv_layer.cpp	add support for 2D dilated convolution	a year ago
conv_layer.cu	dismantle layer headers	a year ago
crop_layer.cpp	remove redundant operations in Crop layer (#5138)	2 months ago
crop_layer.cu	remove redundant operations in Crop layer (#5138)	2 months ago
cudnn_conv_layer.cpp	dismantle layer headers	a year ago
cudnn_conv_layer.cu	Add cuDNN v5 support, drop cuDNN v3 support	11 months ago

=

Neural Networks



Neural Networks

(**Before**) Linear score function: $f = Wx$

Neural Networks

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(**Now**) 2-layer Neural Network: $f = W_2 \max(0, W_1 x)$

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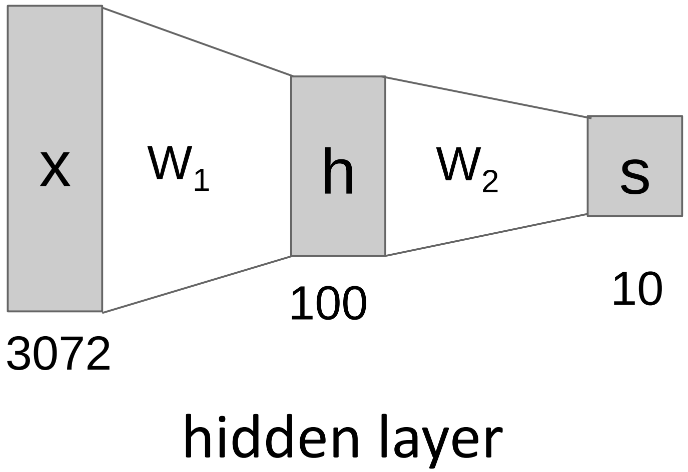
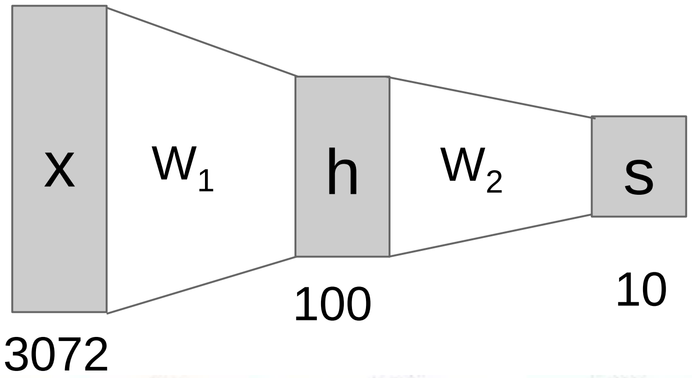


Neural Networks

(**Before**) Linear score function: $f = Wx$

(**Now**) 2-layer Neural Network: $f = W_2 \max(0, W_1 x)$



Neural Networks

(**Before**) Linear score function: $f = Wx$

(**Now**) 2-layer Neural Network: $f = W_2 \max(0, W_1 x)$

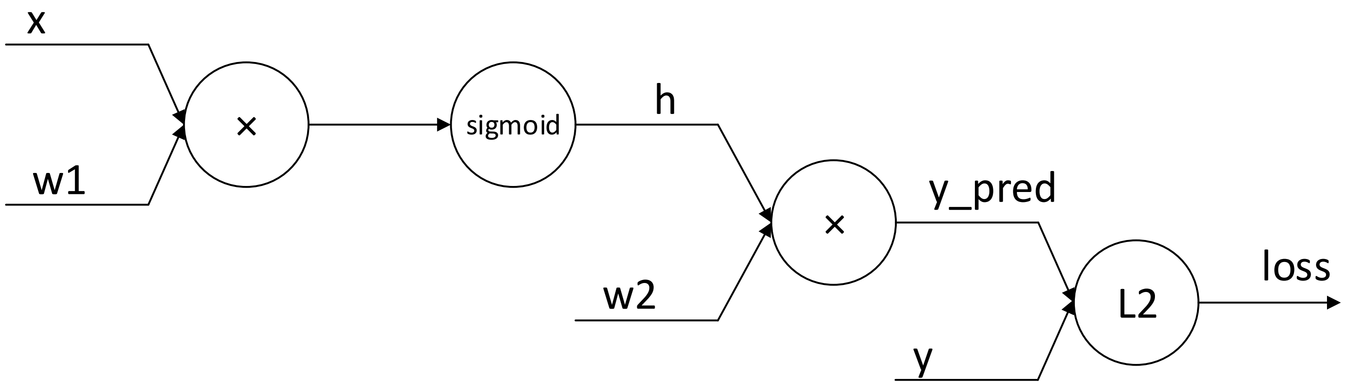
we can go deeper

3-layer Neural Network $f = W_3 \max(0, W_2 \max(0, W_1 x))$

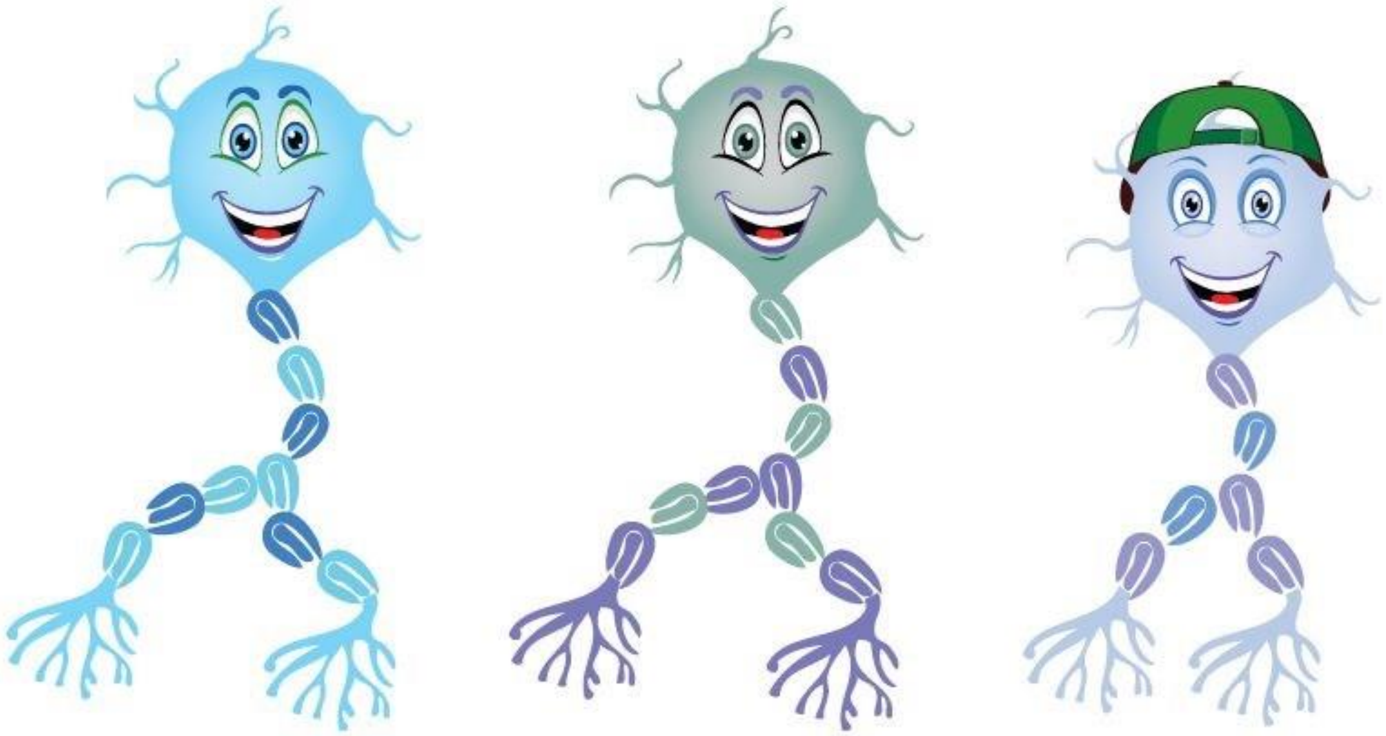
Full implementation of training a 2-layer Neural Network needs ~20 lines:

```python
import numpy as np
from numpy.random import randn

N, D_in, H, D_out = 64, 1000, 100, 10
x, y = randn(N, D_in), randn(N, D_out)
w1, w2 = randn(D_in, H), randn(H, D_out)

for t in range(2000):
  h = 1 / (1 + np.exp(-x.dot(w1)))
  y_pred = h.dot(w2)
  loss = np.square(y_pred - y).sum()
  print(t, loss)

  grad_y_pred = 2.0 * (y_pred - y)
  grad_w2 = h.T.dot(grad_y_pred)
  grad_h = grad_y_pred.dot(w2.T)
  grad_w1 = x.T.dot(grad_h * h * (1 - h))

  w1 -= 1e-4 * grad_w1
  w2 -= 1e-4 * grad_w2
```

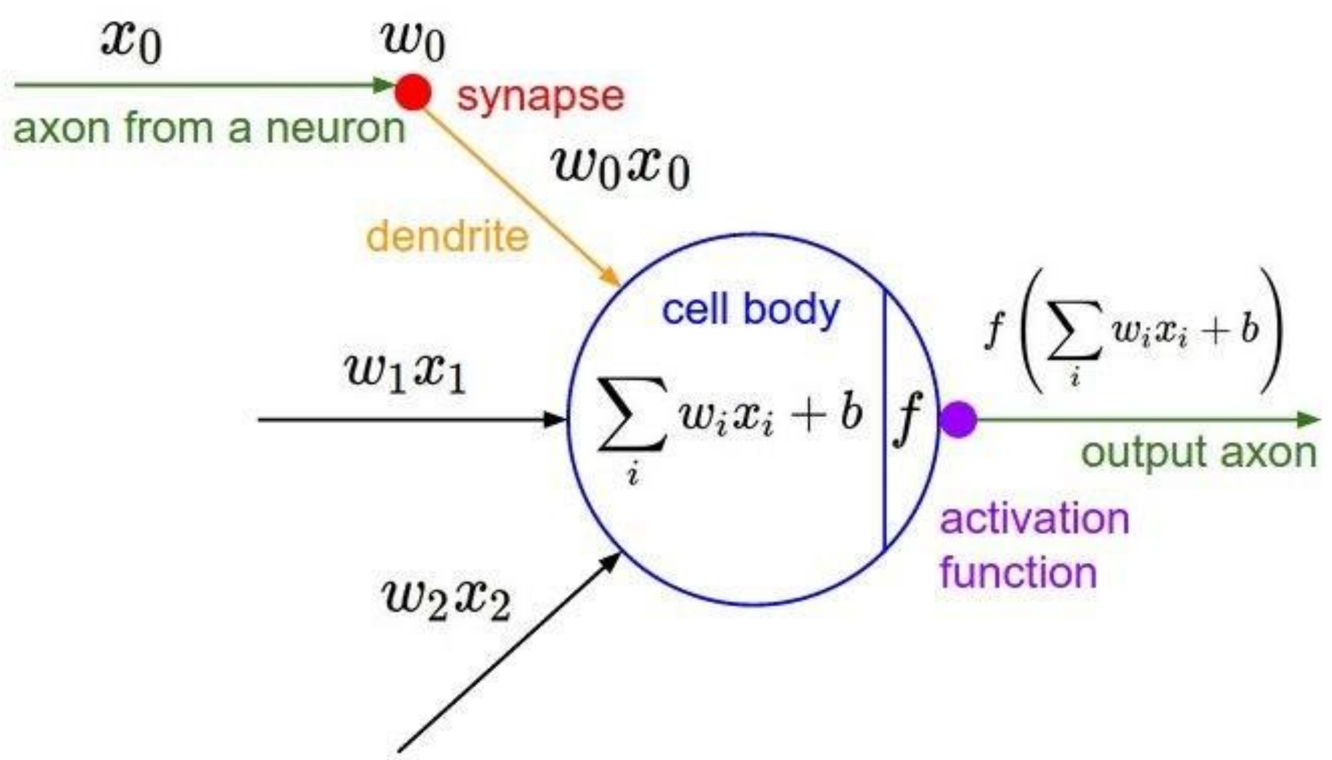
$$\sigma(x) = \frac{1}{1+e^{-x}}$$ sigmoid function



Artificial neuron



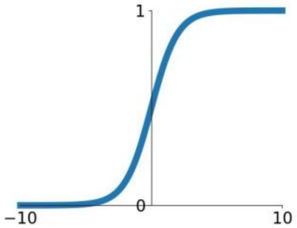
Artificial neuron



Activation functions

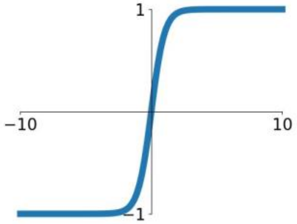
Sigmoid

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



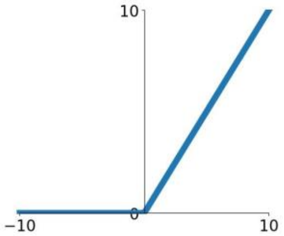
tanh

$\tanh(x)$



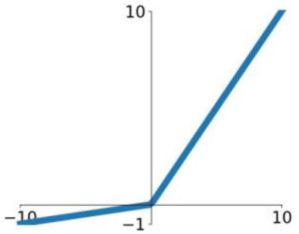
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

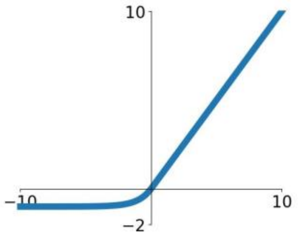


Maxout neuron

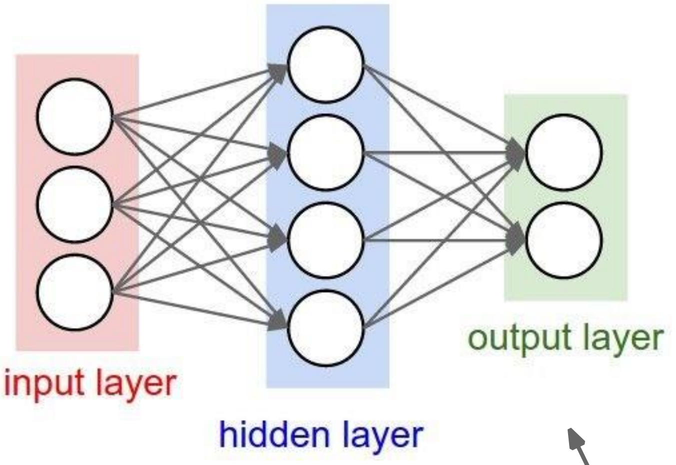
$\max(w_1^T x + b_1, w_2^T x + b_2)$

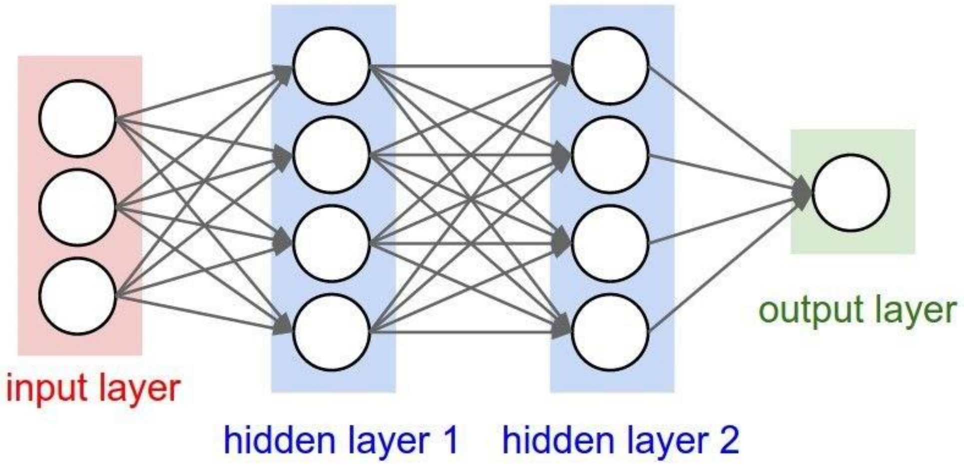
ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



Neural networks: fully-connected architectures



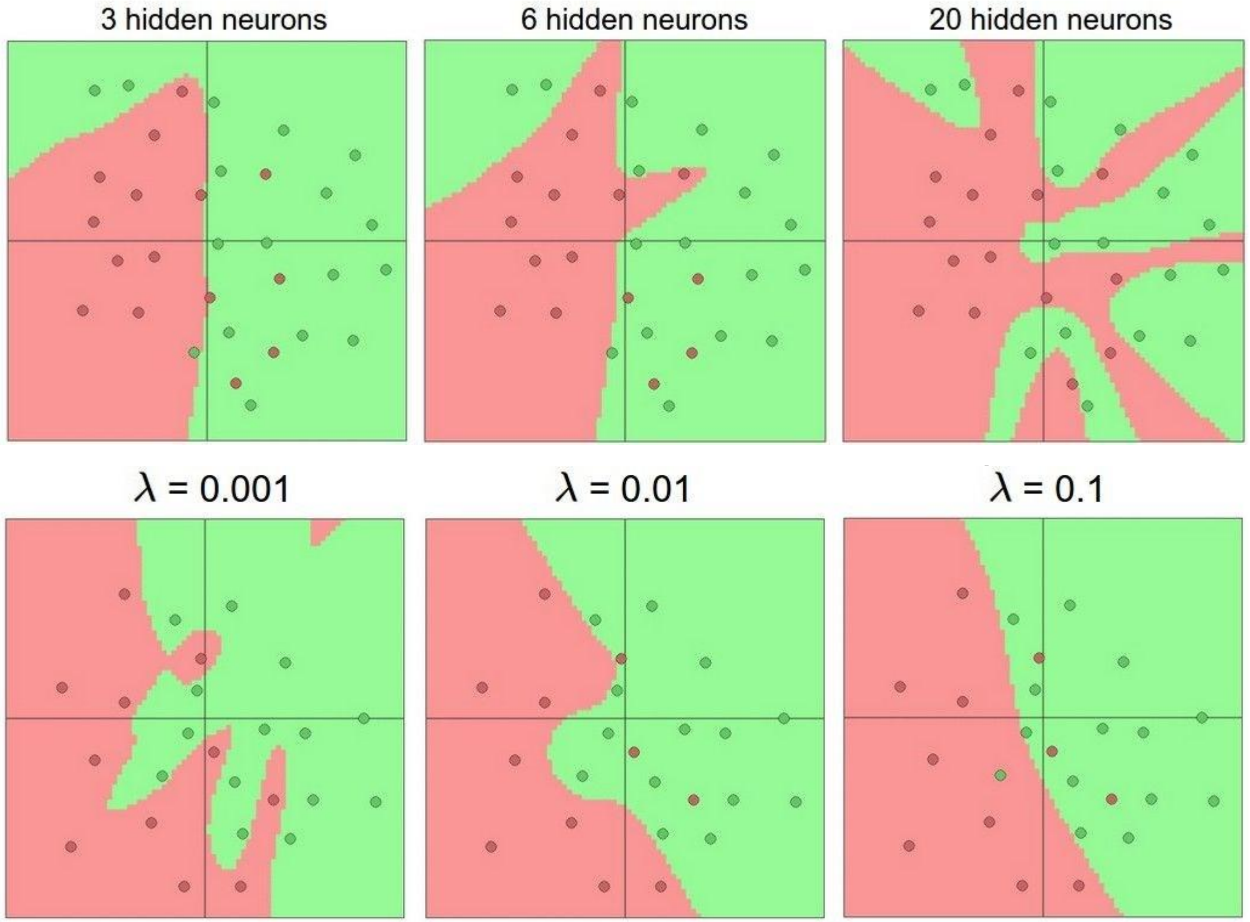


“2-layer Neural Net”, or
“1-hidden-layer Neural Net”

“3-layer Neural Net”, or
“2-hidden-layer Neural Net”

“Fully-connected” layers

Demo time



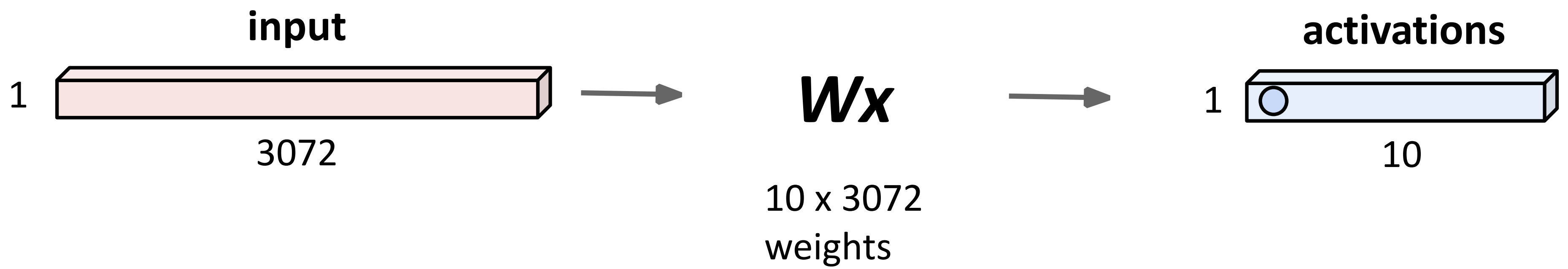
Setting the number of layers and their sizes

Setting regularization

http://cs.stanford.edu/people/karpathy/convnetjs/demo/classify2d.html

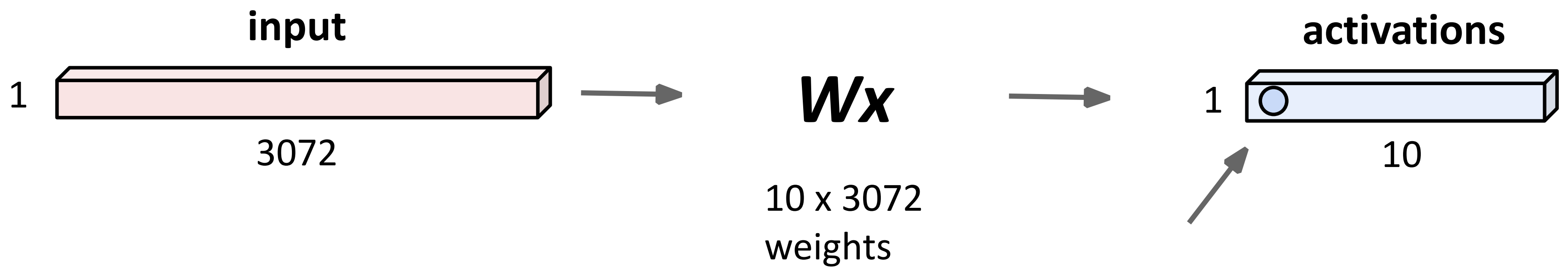
Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1



Fully Connected Layer

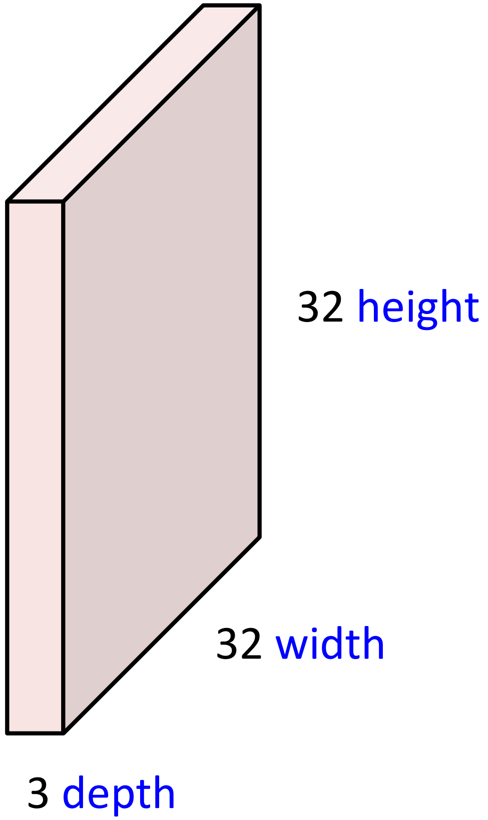
32x32x3 image -> stretch to 3072 x 1



1 number:
the result of taking a dot product between a row of W and the input (a 3072-dimensional dot product)

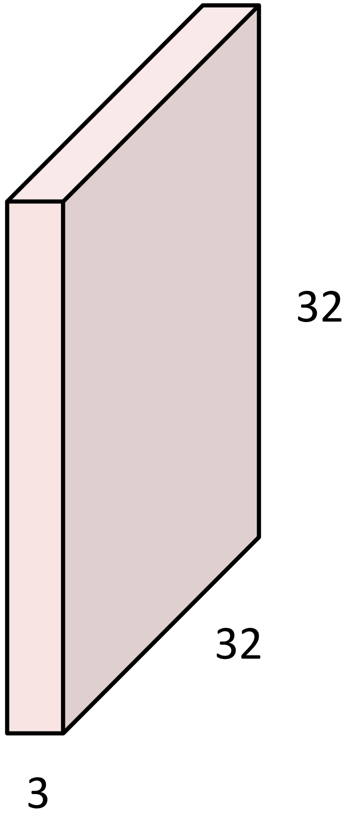
Convolutional Layer

32x32x3 image -> preserve spatial structure

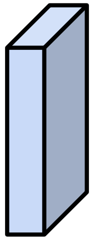


Convolutional Layer

32x32x3 image



5x5x3 filter

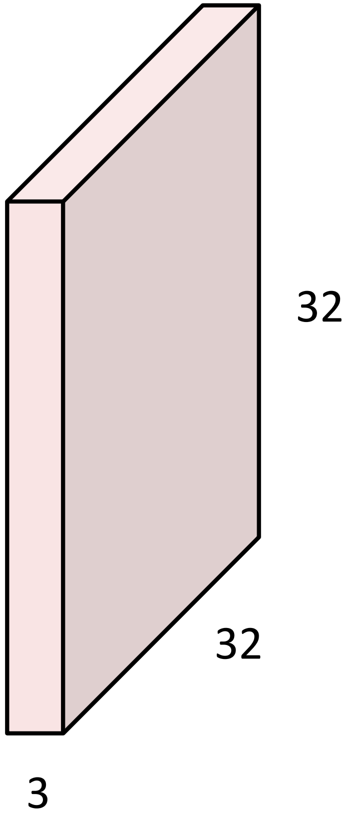


Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

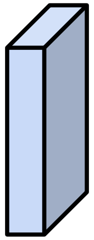
Convolutional Layer

Filters always extend the full depth of the input volume

32x32x3 image



5x5x3 filter

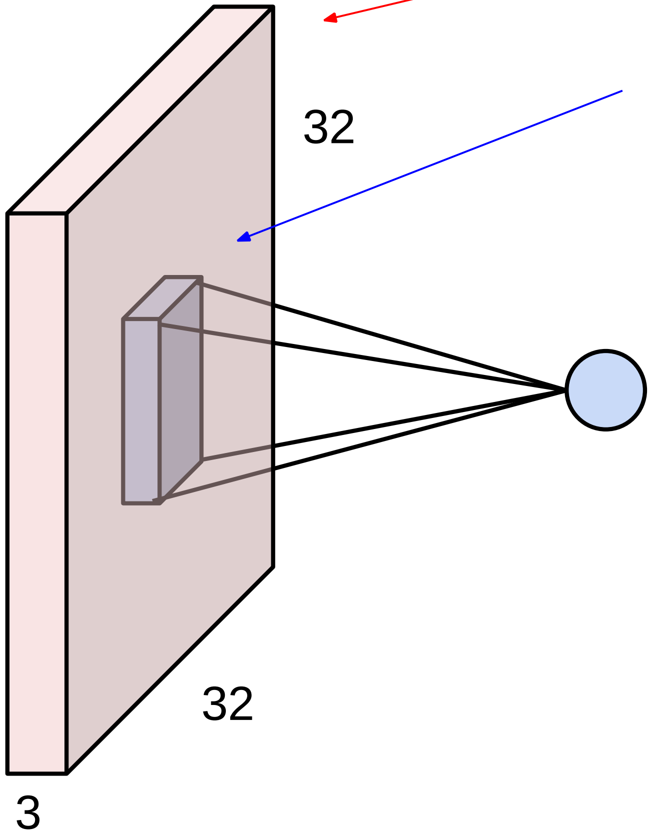


Convolve the filter with the image i.e. “slide over the image spatially, computing dot products”

Convolutional Layer

32x32x3 image

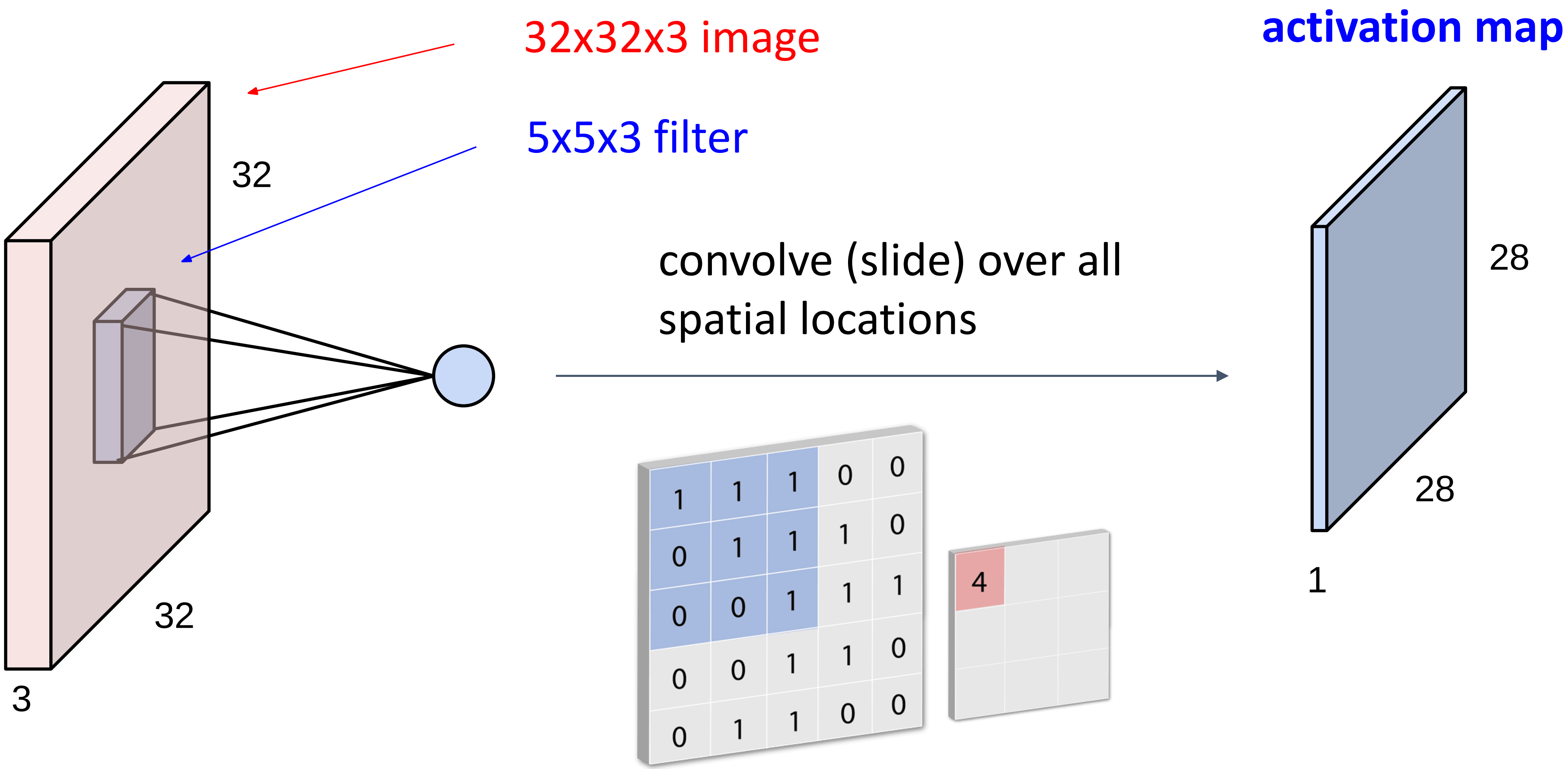
5x5x3 filter w



1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$wx + b$$

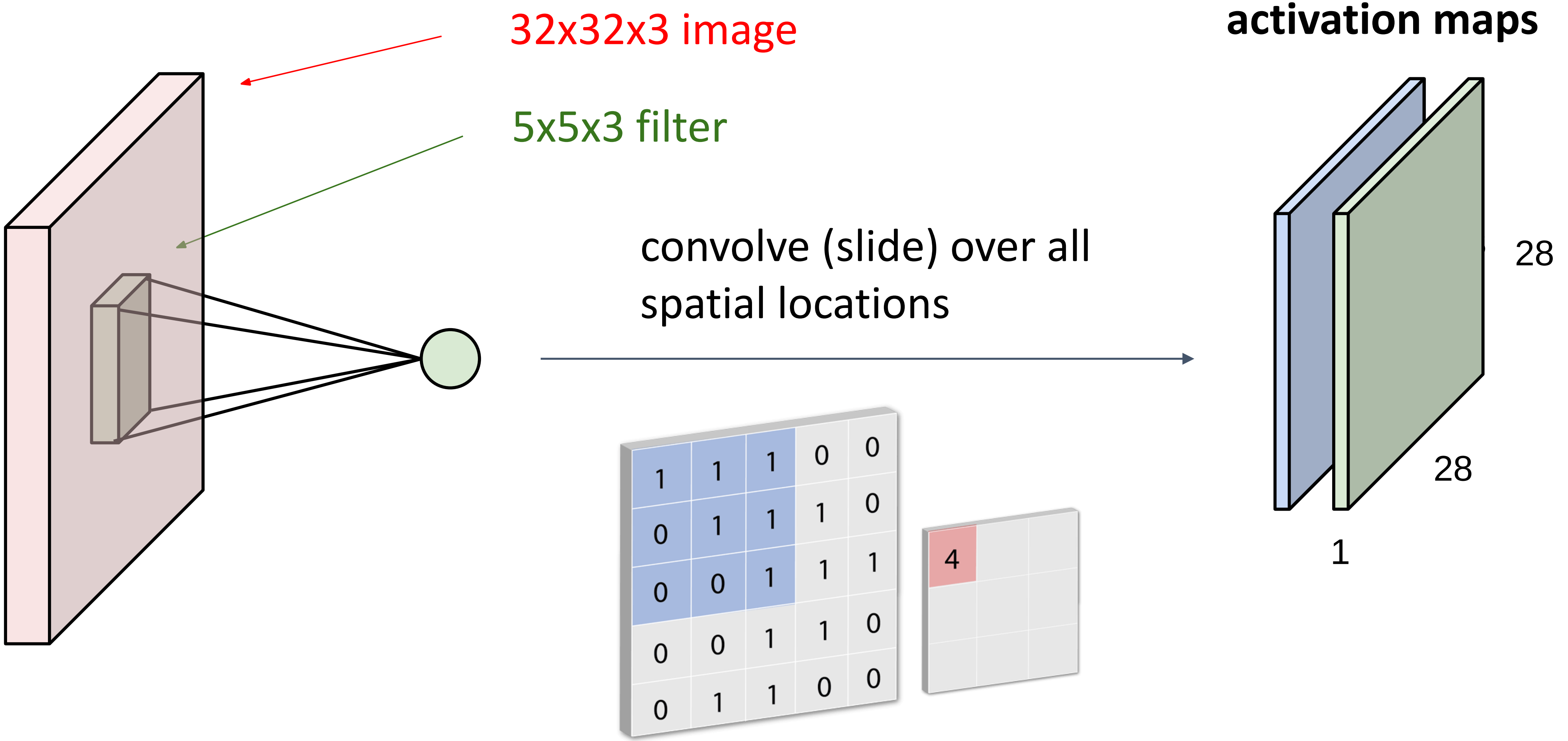
Convolutional Layer



example: image 5x5, filter 3x3

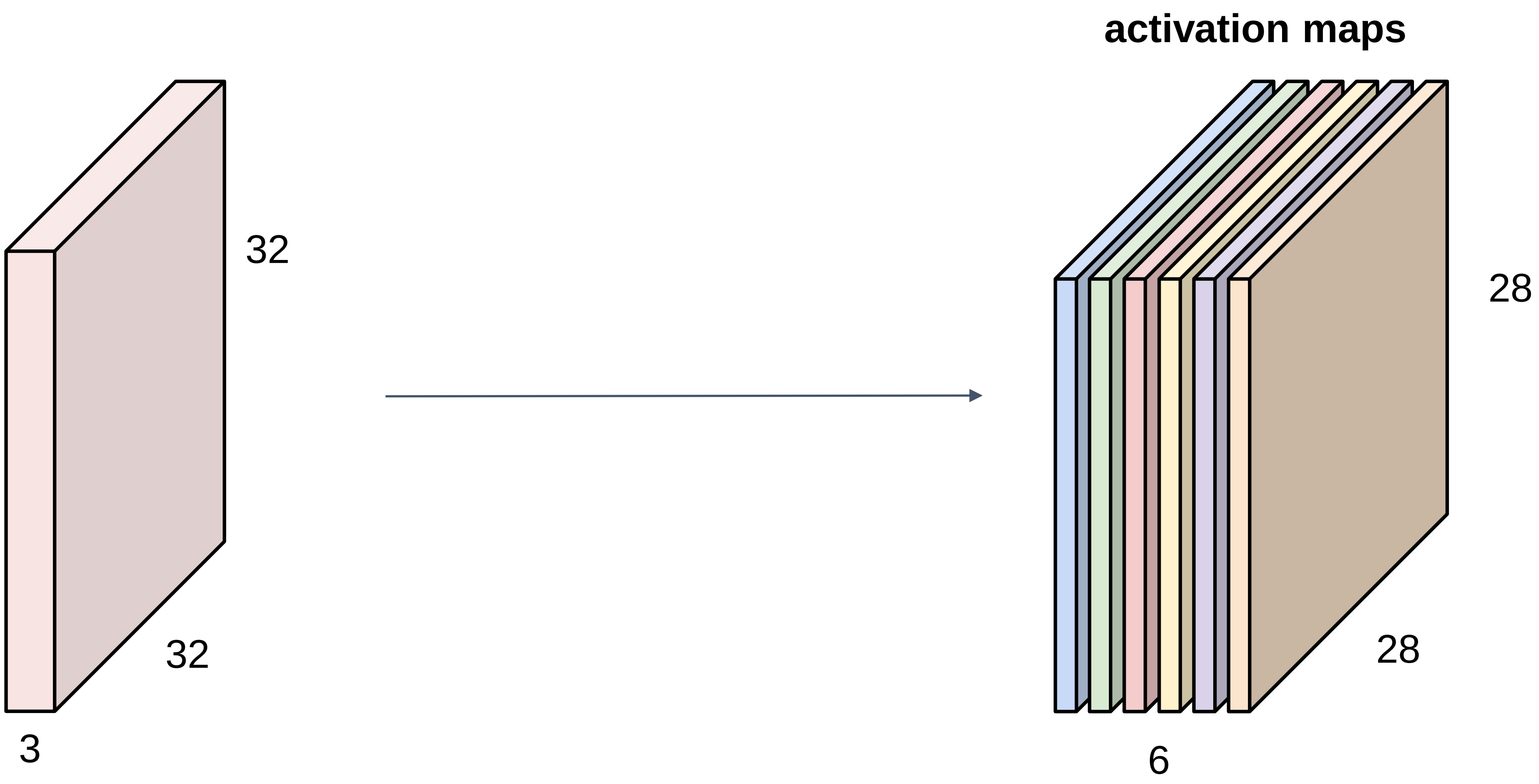
Convolutional Layer

consider a second, green filter



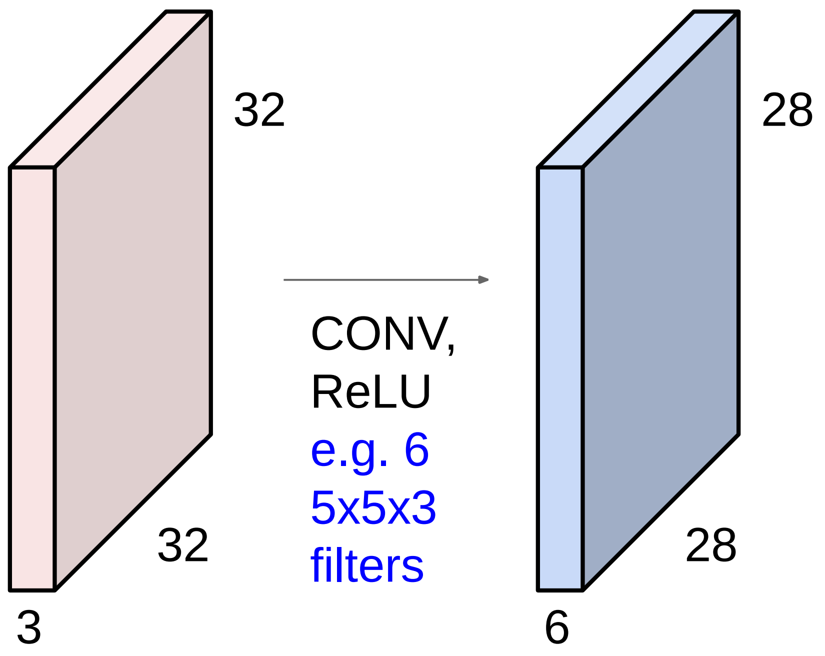
example: image 5x5, filter 3x3

For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:

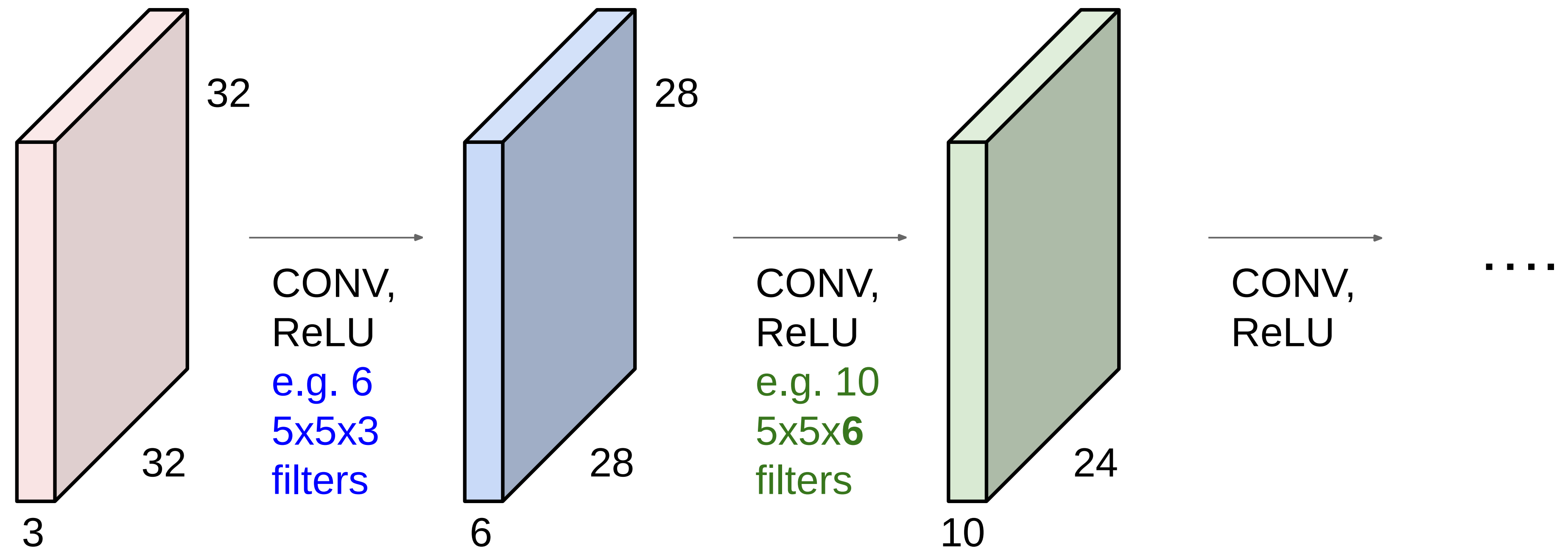


We stack these up to get a "new image" of size 28x28x6!

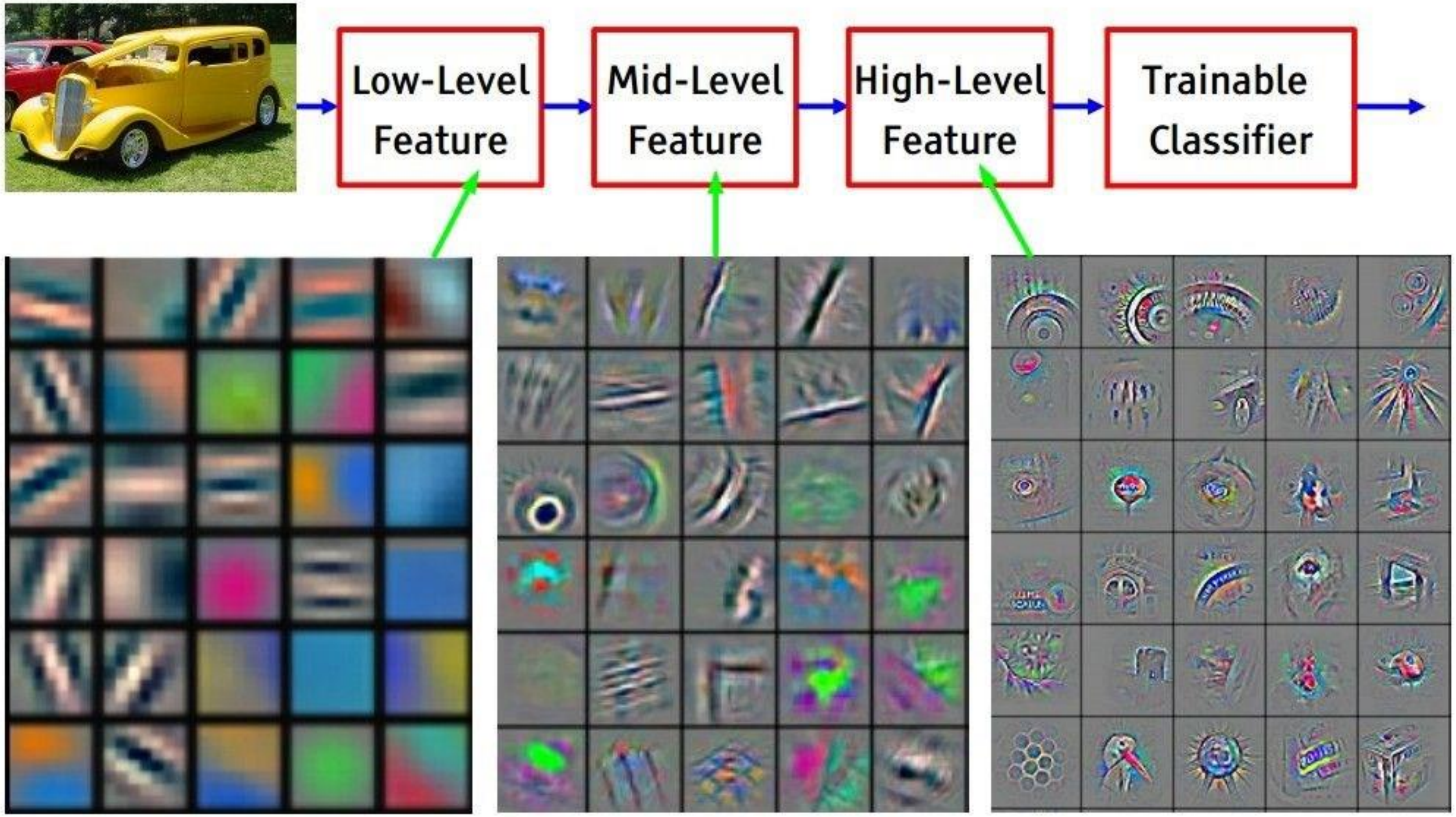
ConvNet is a sequence of Convolution Layers, interspersed with activation functions



ConvNet is a sequence of Convolution Layers, interspersed with activation functions

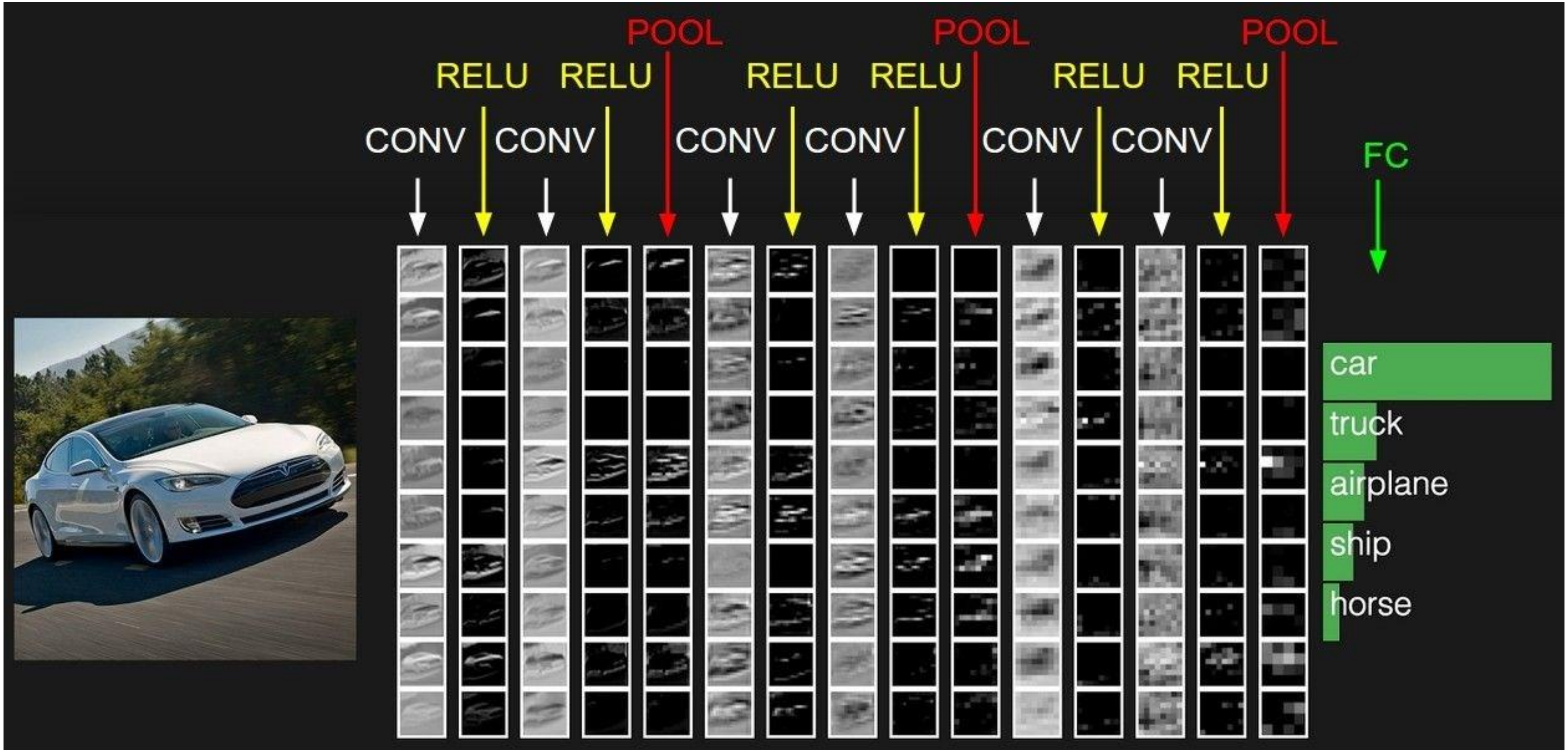


Визуализация признаков нейронной сети

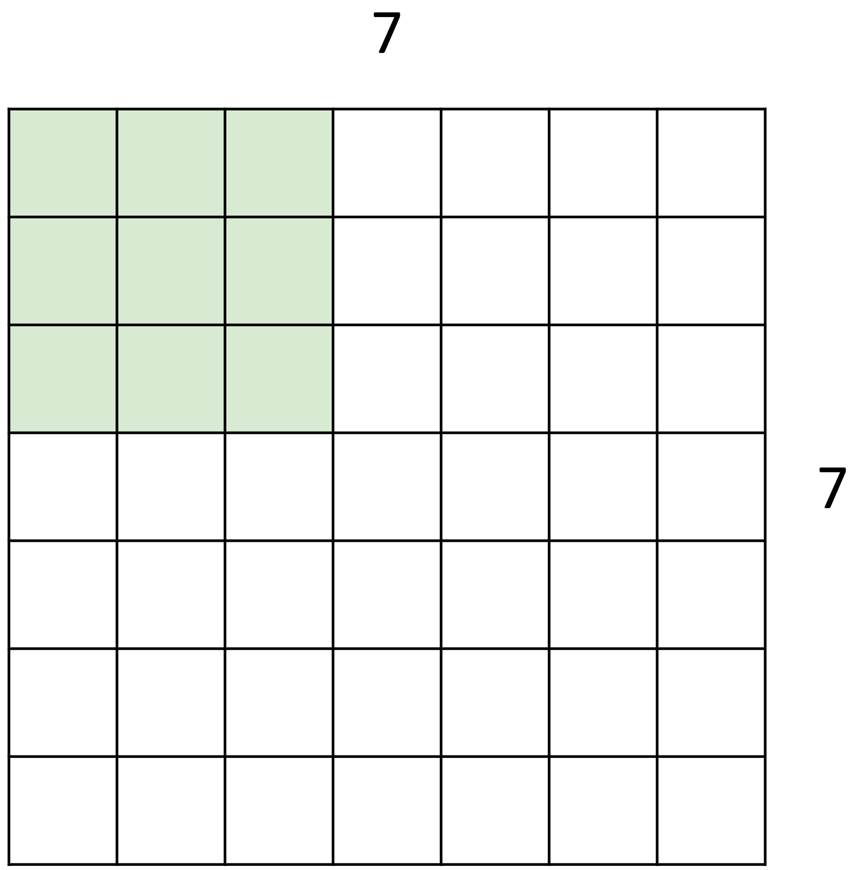


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Сверточная нейронная сеть

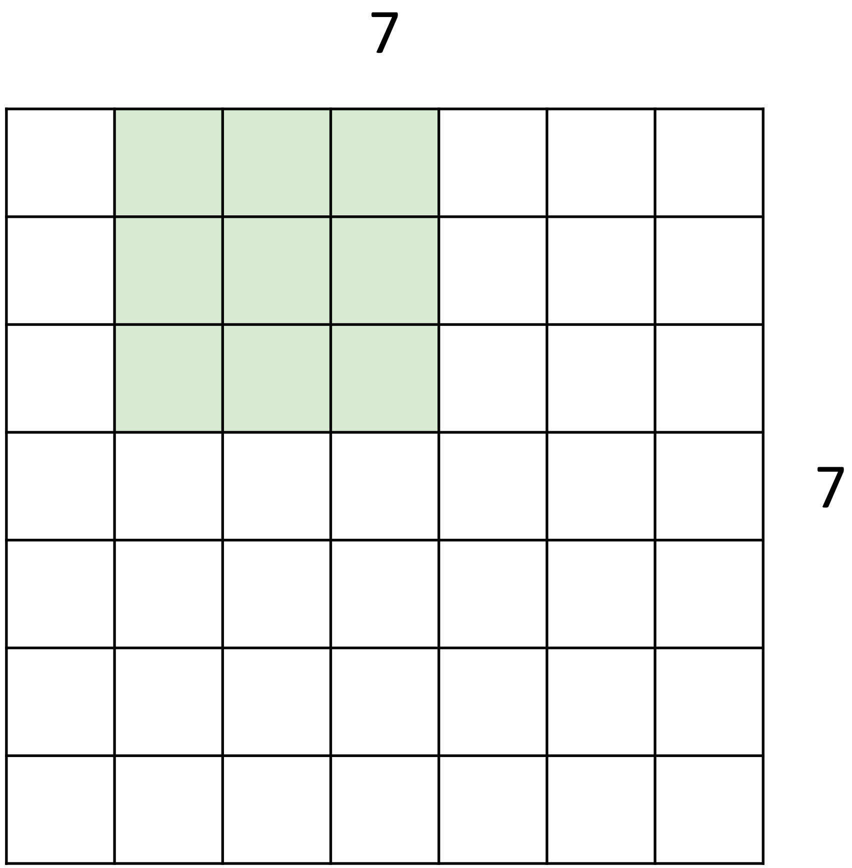


A closer look at spatial dimensions:



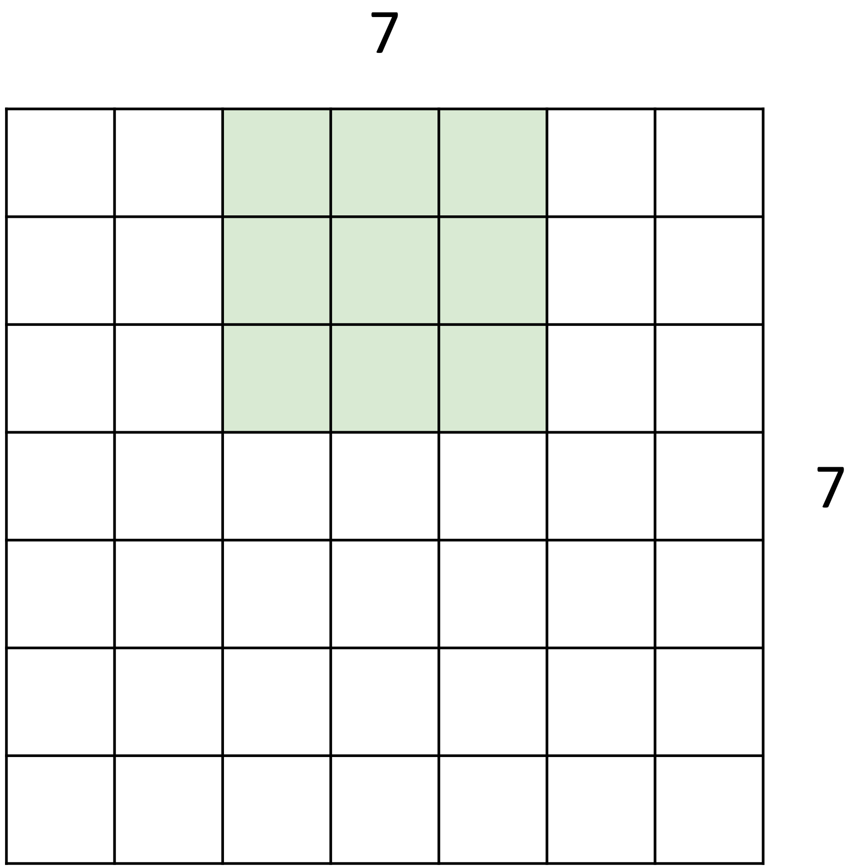
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



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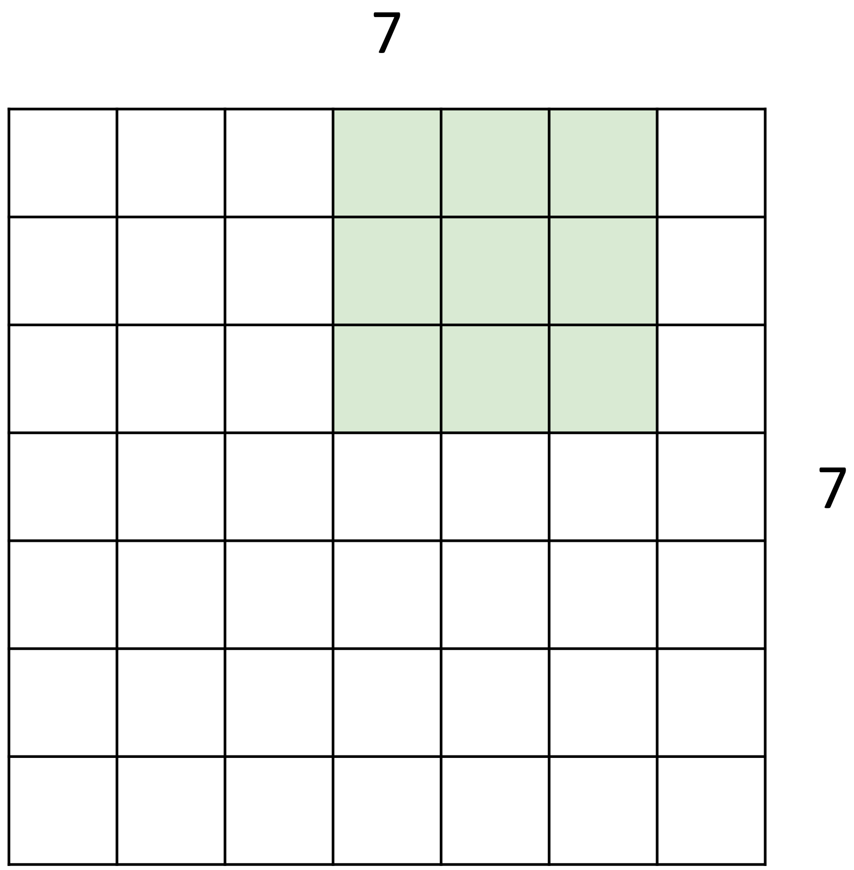
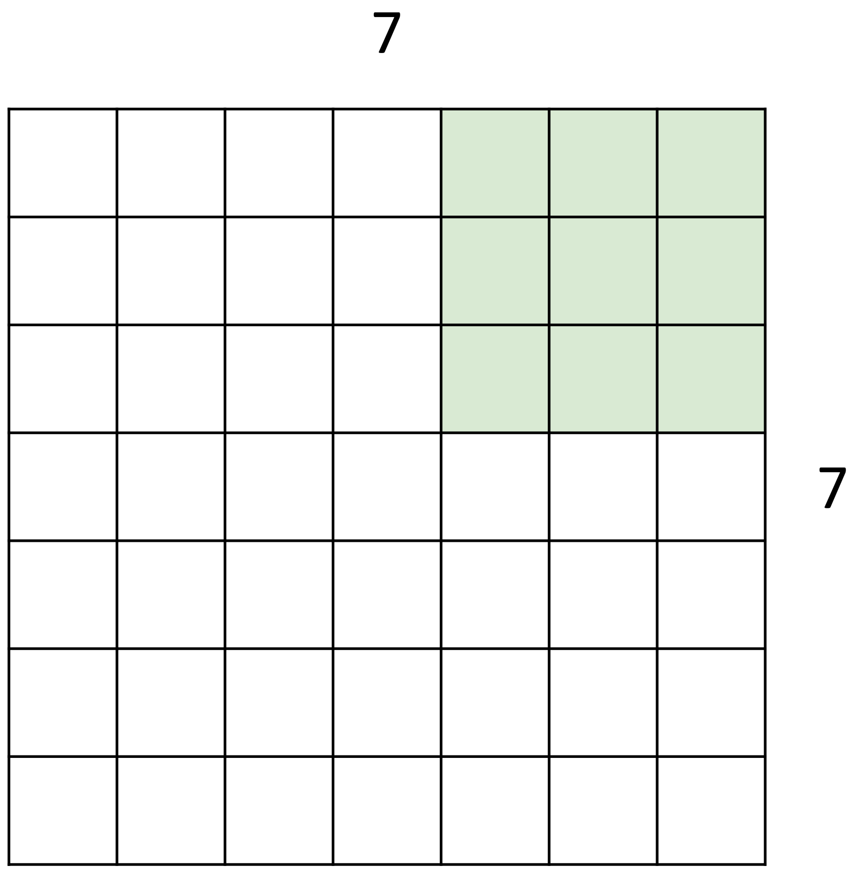
assume 3x3 filter

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

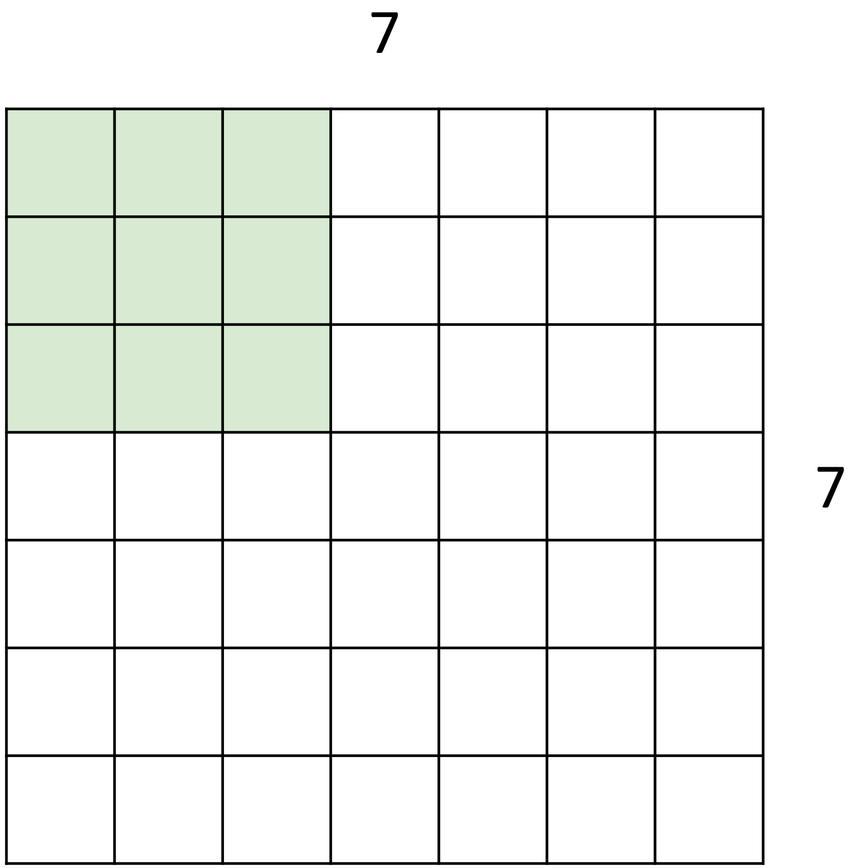
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

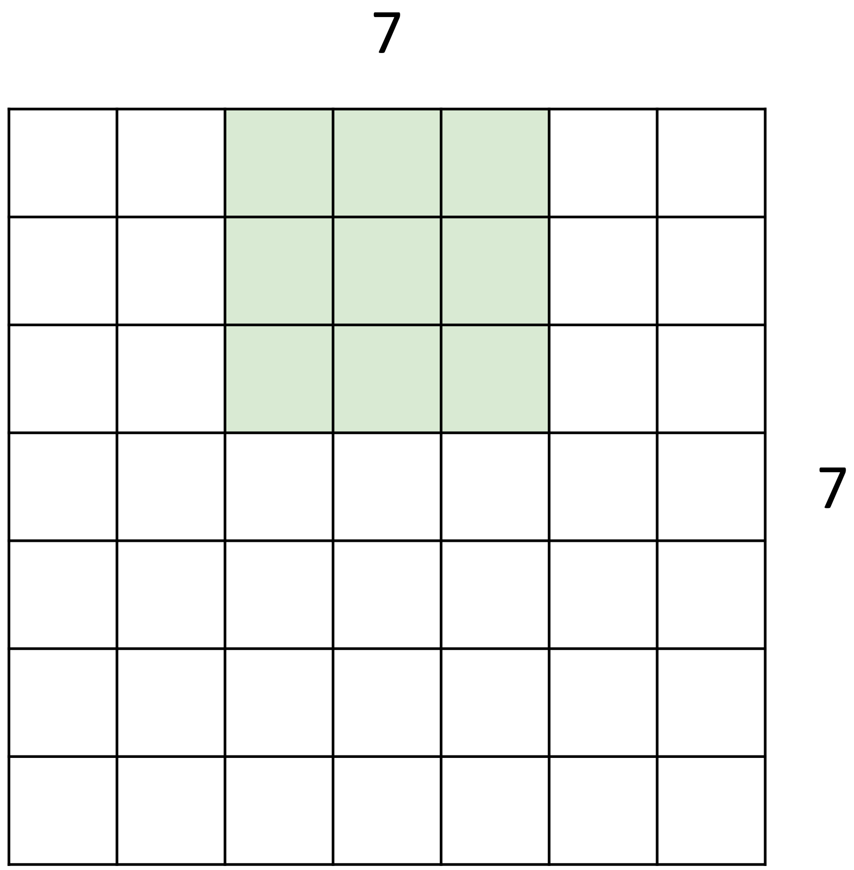
=> 5x5 output

A closer look at spatial dimensions:



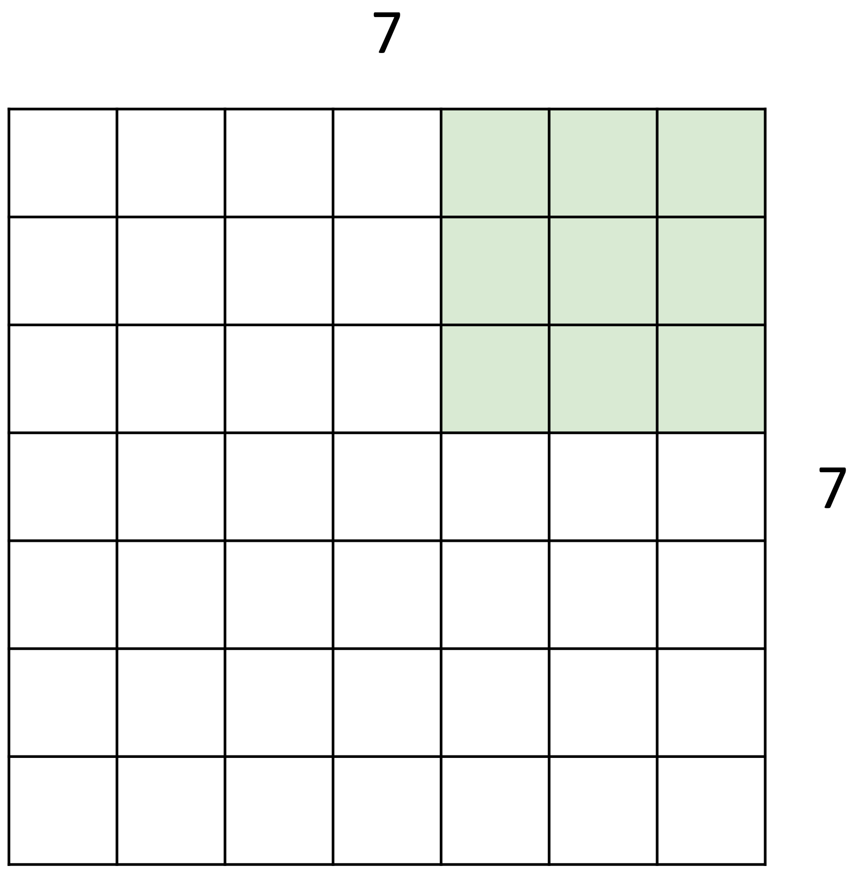
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



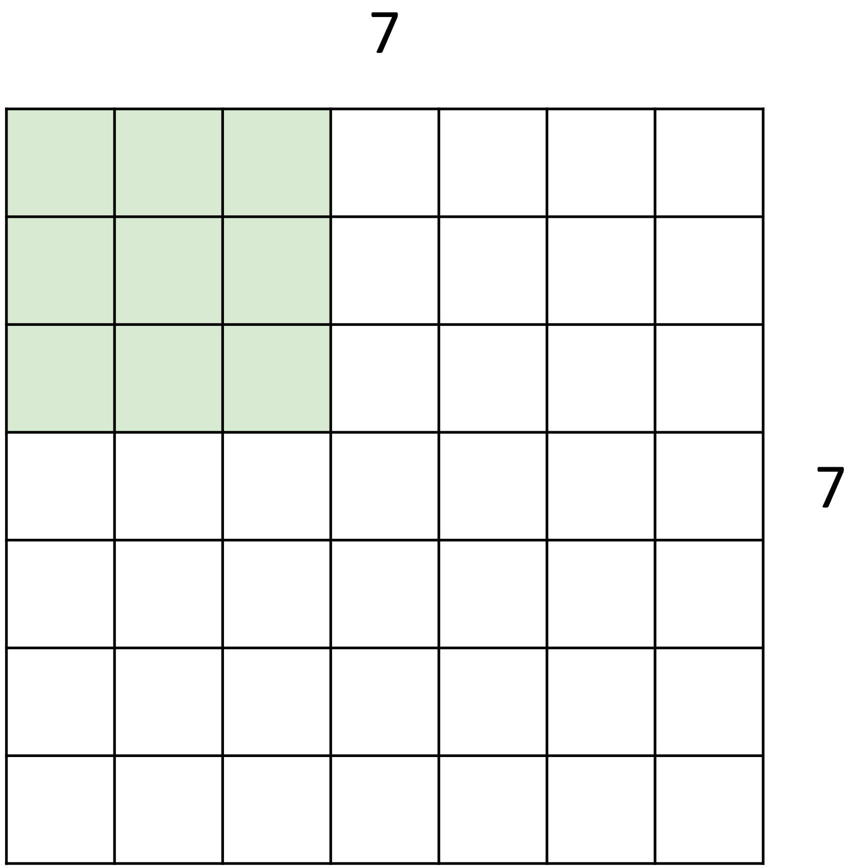
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



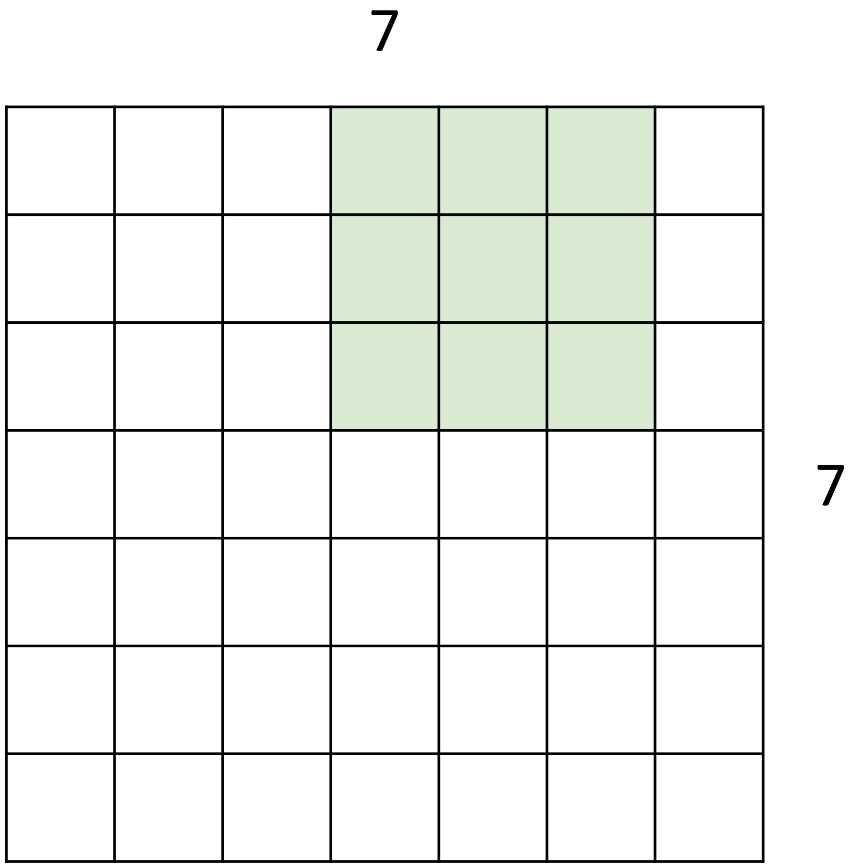
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

A closer look at spatial dimensions:



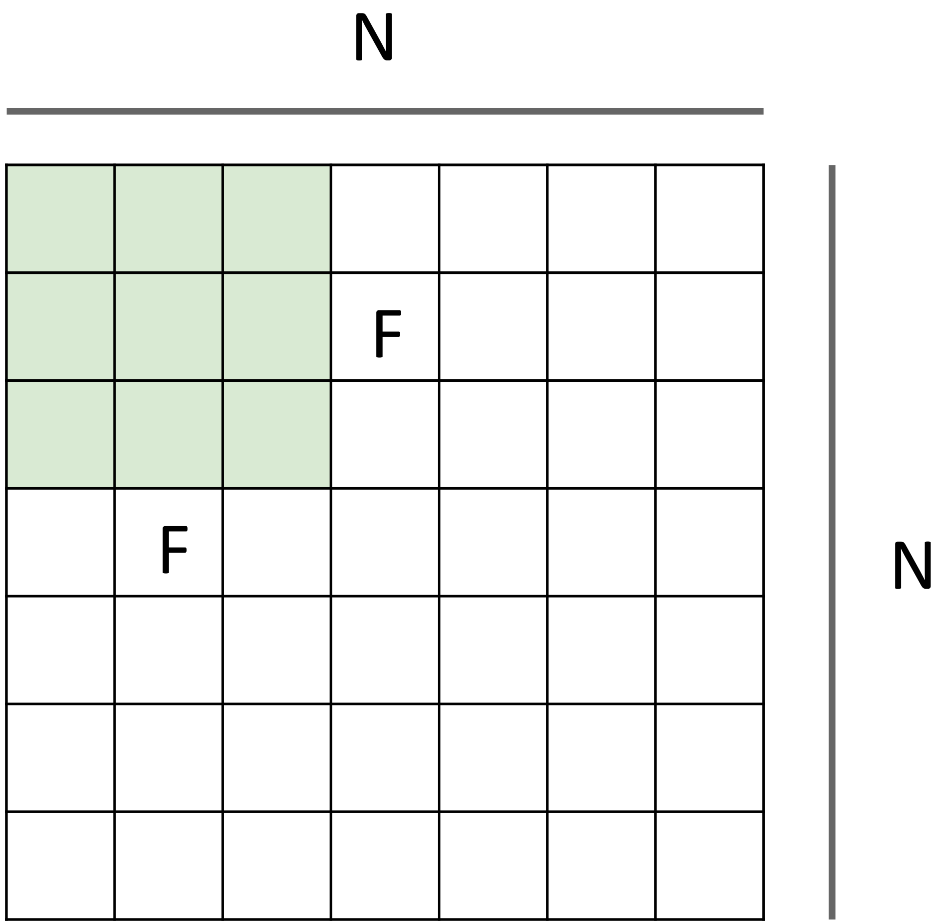
7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

doesn't fit!
cannot apply 3x3 filter on
7x7 input with stride 3.

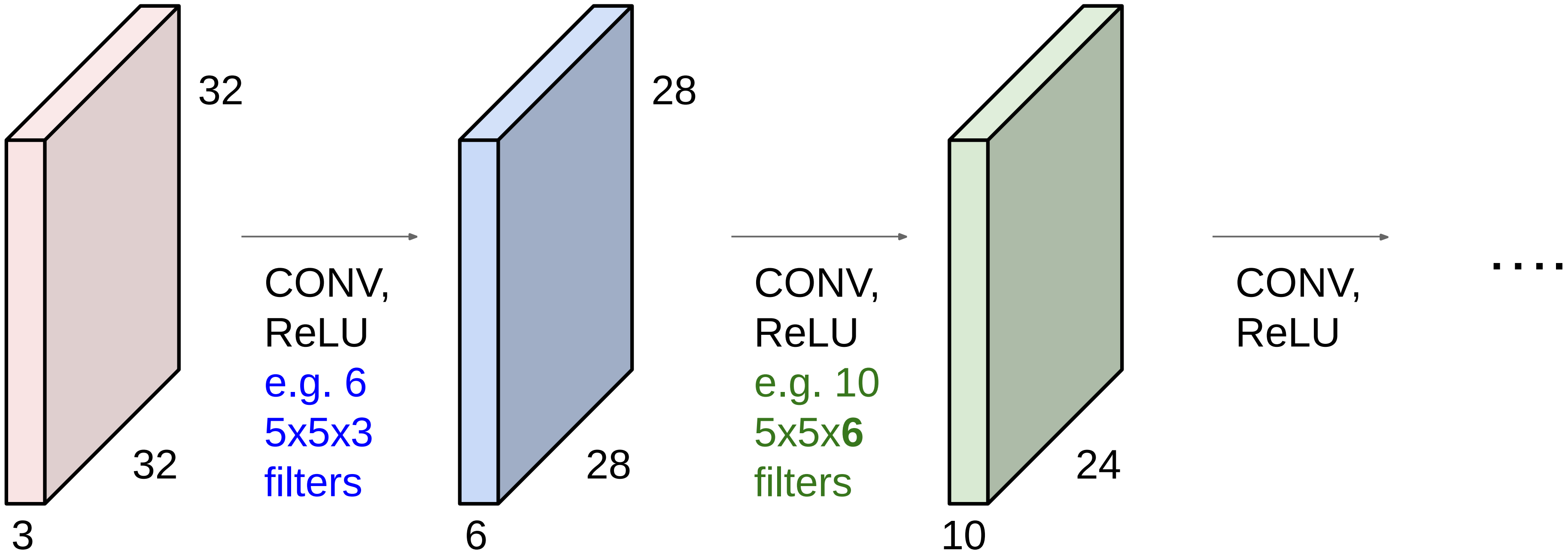


Output size:
(N - F) / stride + 1

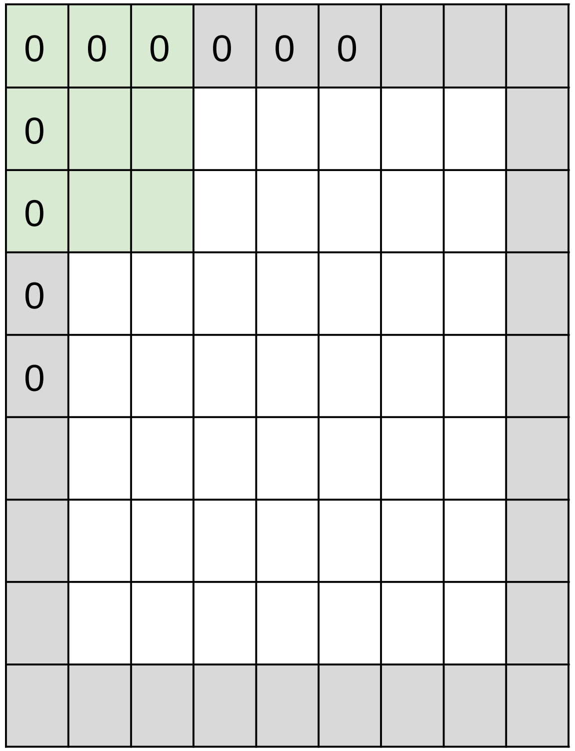
e.g. N = 7, F = 3:
stride 1 => (7 - 3)/1 + 1 = 5
stride 2 => (7 - 3)/2 + 1 = 3
stride 3 => (7 - 3)/3 + 1 = 2.33 :\

Remember back to…

E.g. 32x32 input convolved repeatedly with 5x5 filters shrinks volumes spatially!
(32 -> 28 -> 24 ...). Shrinking too fast is not good, doesn't work well.



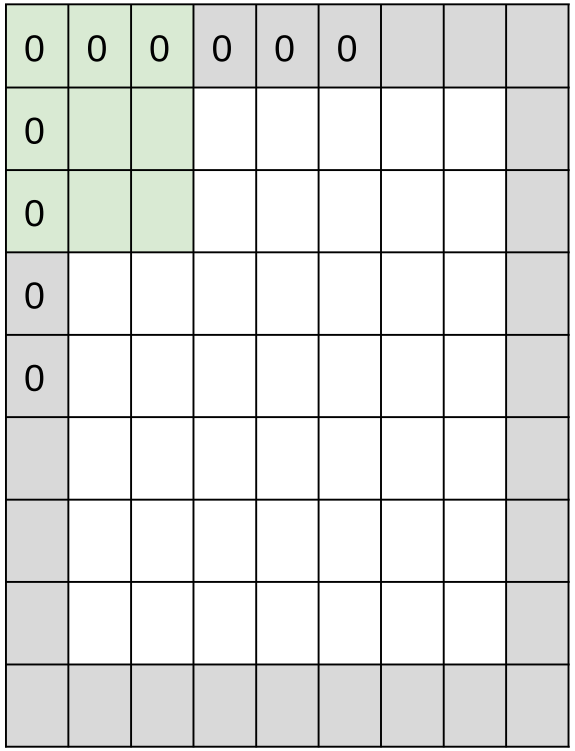
In practice: Common to zero pad the border



e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

(recall:)
(N - F) / stride + 1

In practice: Common to zero pad the border



e.g. input 7x7
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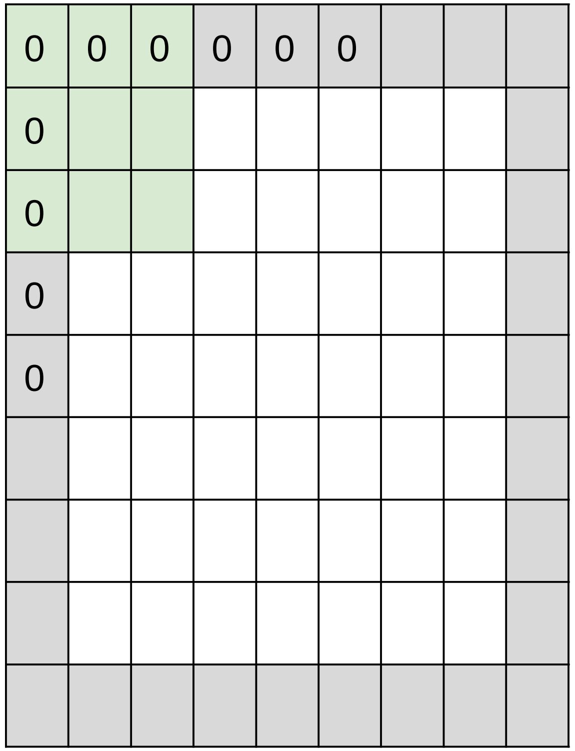
pad with 1 pixel border => what is the output?

7x7 output!

In practice: Common to zero pad the border



e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

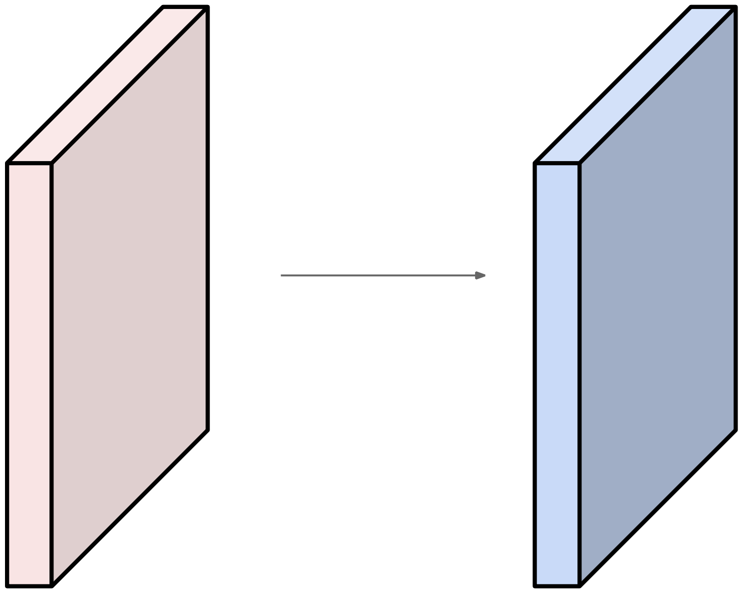
7x7 output!

in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

Examples time:

Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

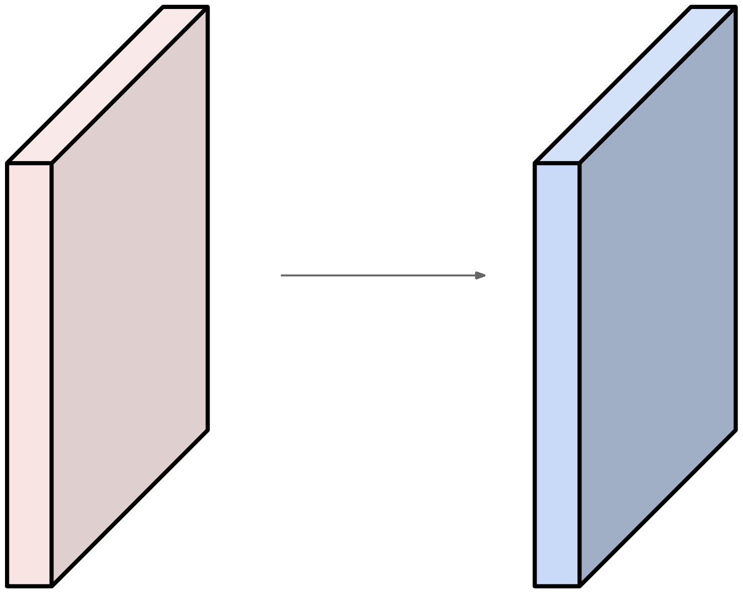
Output volume size: ?



Examples time:

Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

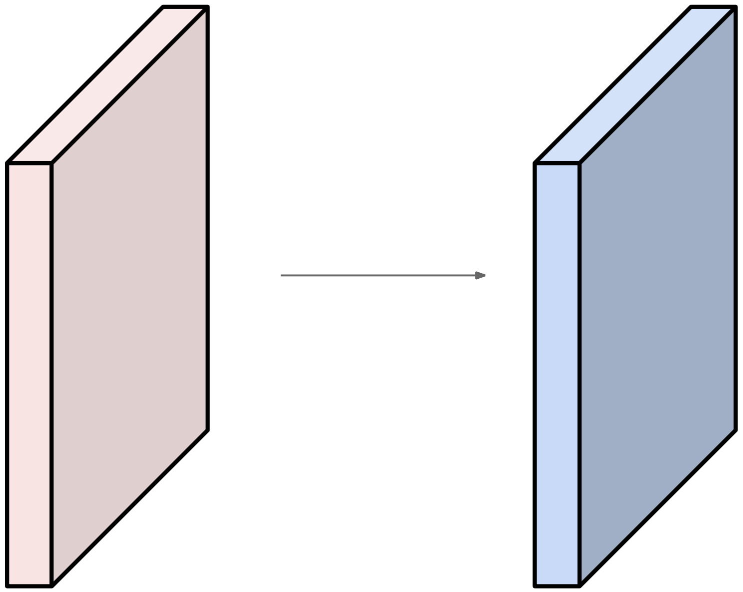
Output volume size:
(32+2*2-5)/1+1 = 32 spatially, so
32x32x10



Examples time:

Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

Number of parameters in this layer?



Examples time:

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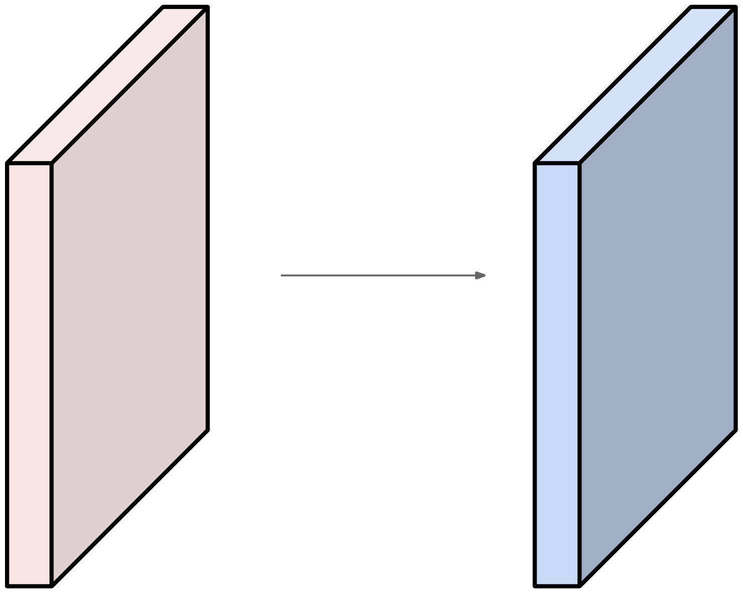

Number of parameters in this layer?

each filter has 5*5*3 + 1 = 76 params (+1 for bias)

=> 76*10 = **760**

Summary. To summarize, the Conv Layer:

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
    - Number of filters K,
    - their spatial extent F,
    - the stride S,
    - the amount of zero padding P.
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
    - $W_2 = (W_1 - F + 2P)/S + 1$
    - $H_2 = (H_1 - F + 2P)/S + 1$ (i.e. width and height are computed equally by symmetry)
    - $D_2 = K$
- With parameter sharing, it introduces $F \cdot F \cdot D_1$ weights per filter, for a total of $(F \cdot F \cdot D_1) \cdot K$ weights and K biases.
- In the output volume, the d-th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d-th filter over the input volume with a stride of S, and then offset by d-th bias.

Summary. To summarize, the Conv Layer:

- Accepts a volume of size $W_1 \times H_1 \times D_1$
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  - Number of filters K,
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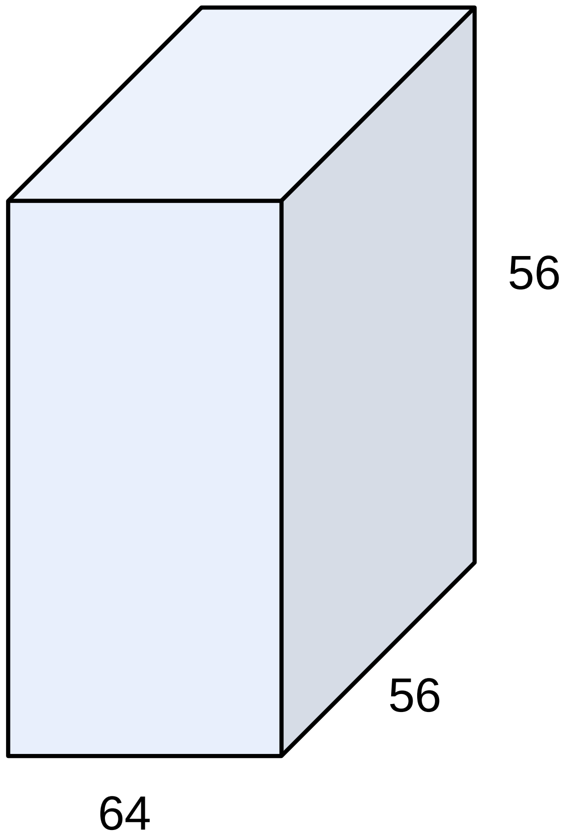
- In the output volume, the d-th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d-th filter over the input volume with a stride of S, and then offset by d-th bias.

Common settings:

K = (powers of 2, e.g. 32, 64, 128, 512)

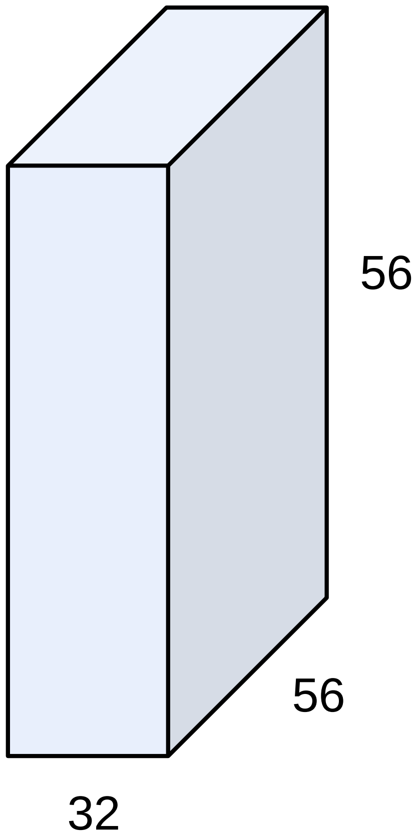
- F = 3, S = 1, P = 1
- F = 5, S = 1, P = 2
- F = 5, S = 2, P = ? (whatever fits)
- F = 1, S = 1, P = 0

1x1 convolution layers make perfect sense



1x1 CONV
with 32 filters

(each filter has size 1x1x64, and performs a 64-dimensional dot product)



Example: CONV layer in Caffe

```
layer {
  name: "conv1"
  type: "Convolution"
  bottom: "data"
  top: "conv1"
  # learning rate and decay multipliers for the filters
  param { lr_mult: 1 decay_mult: 1 }
  # learning rate and decay multipliers for the biases
  param { lr_mult: 2 decay_mult: 0 }
  convolution_param {
    num_output: 96     # learn 96 filters
    kernel_size: 11    # each filter is 11x11
    stride: 4          # step 4 pixels between each filter application
    weight_filler {
      type: "gaussian" # initialize the filters from a Gaussian
      std: 0.01        # distribution with stdev 0.01 (default mean: 0)
    }
    bias_filler {
      type: "constant" # initialize the biases to zero (0)
      value: 0
    }
  }
}
```

Summary. To summarize, the Conv Layer:

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.

Example: CONV layer in TensorFlow

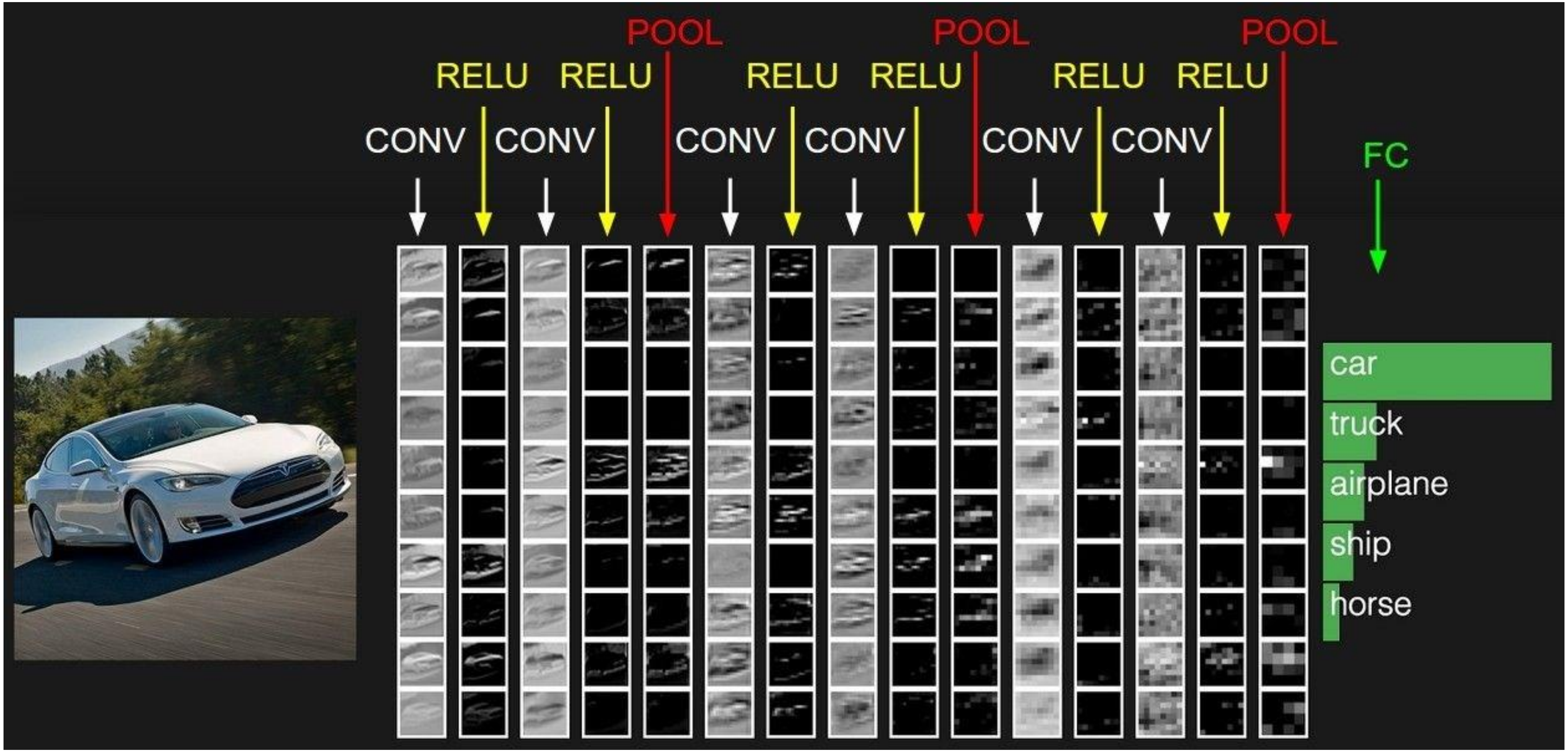
```
conv2d(
    inputs,
    filters,
    kernel_size,
    strides=(1, 1),
    padding='valid',
    data_format='channels_last',
    dilation_rate=(1, 1),
    activation=None,
    use_bias=True,
    kernel_initializer=None,
    bias_initializer=tf.zeros_initializer(),
    kernel_regularizer=None,
    bias_regularizer=None,
    activity_regularizer=None,
    trainable=True,
    name=None,
    reuse=None
)
```

Summary. To summarize, the Conv Layer:

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.

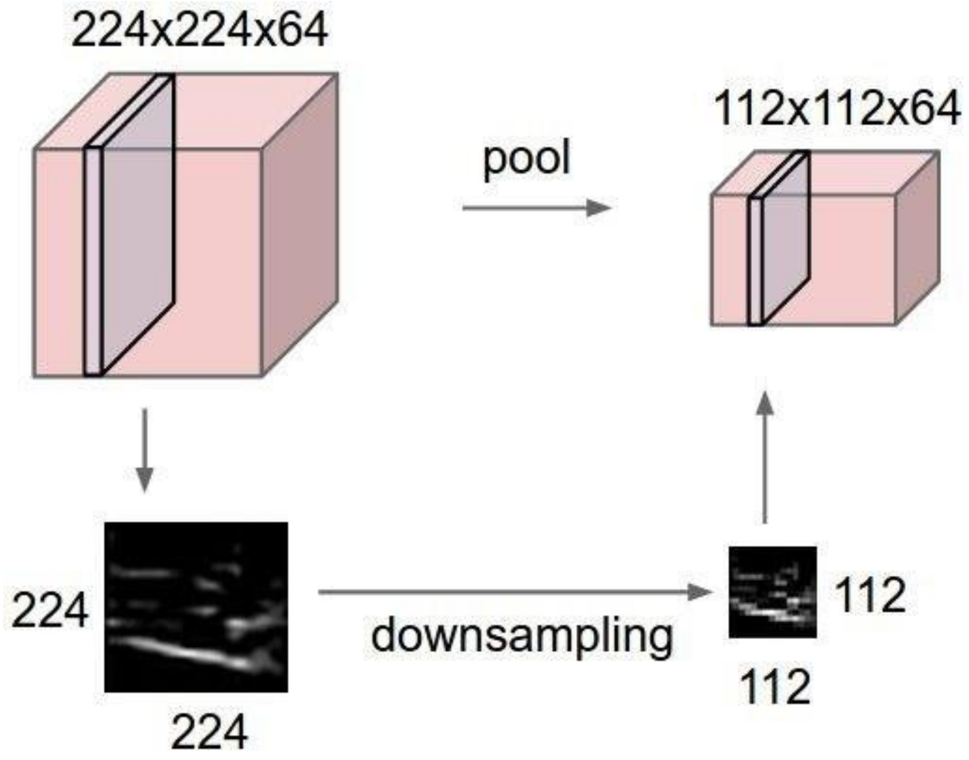
```
# Input Layer
input_layer = tf.reshape(features, [-1, 28, 28, 1])

# Convolutional Layer #1
conv1 = tf.layers.conv2d(
    inputs=input_layer,
    filters=32,
    kernel_size=[5, 5],
    padding="same",
    activation=tf.nn.relu)
```

Сверточная нейронная сеть: **Pooling**

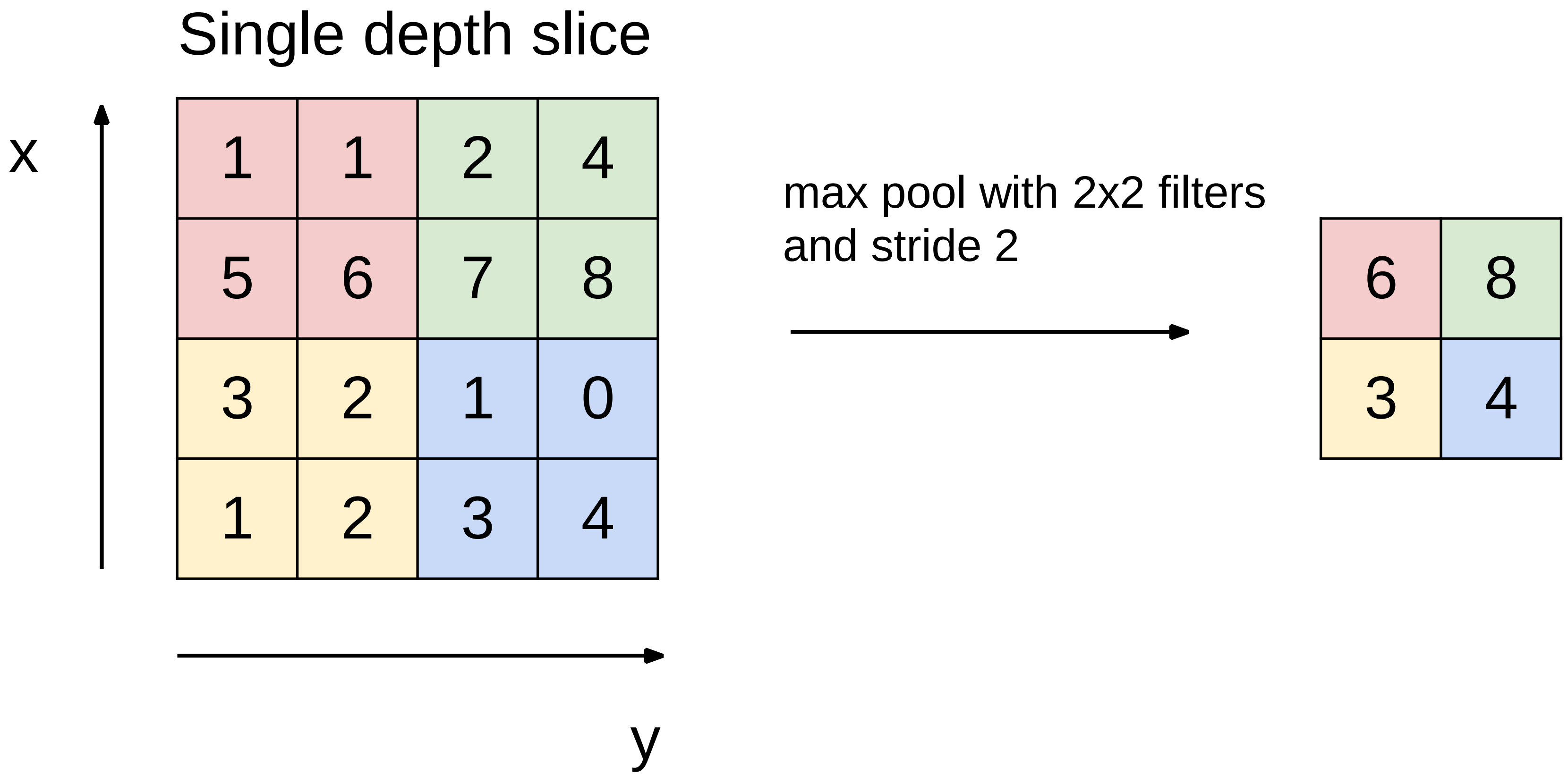


Pooling layer

- makes the representations smaller and more manageable
- operates over each activation map independently:



MAX POOLING


Single depth slice
x
1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
y
max pool with 2x2 filters
and stride 2
6 8
3 4

Pooling

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires three hyperparameters:
  - their spatial extent F,
  - the stride S,
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F)/S + 1$
  - $H_2 = (H_1 - F)/S + 1$
  - $D_2 = D_1$
- Introduces zero parameters since it computes a fixed function of the input
- Note that it is not common to use zero-padding for Pooling layers

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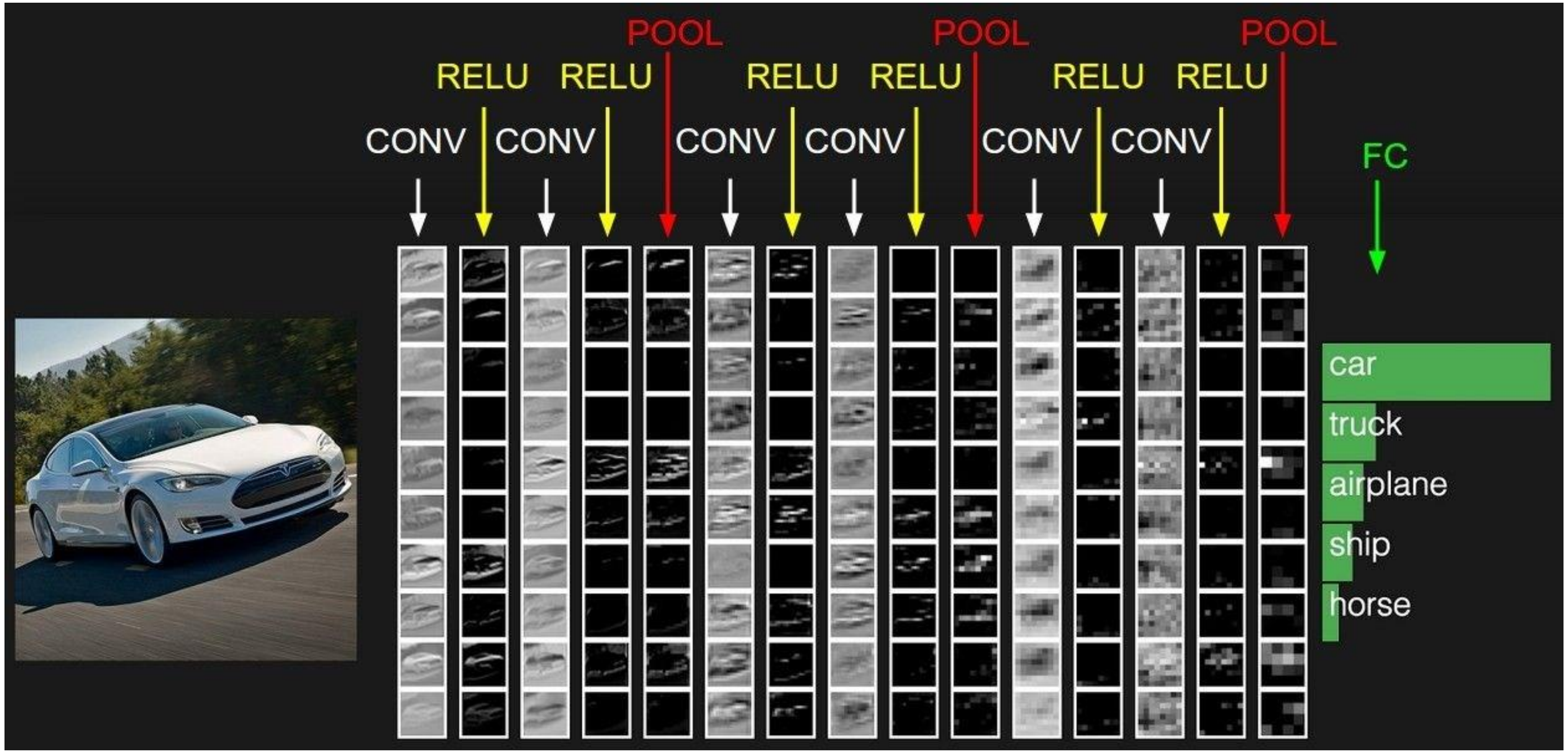
Common settings:

F = 2, S = 2
F = 3, S = 2

Сверточная нейронная сеть: Fully Connected Layer (FC layer)

Contains neurons that connect to the entire input volume, as in ordinary Neural Networks



[ConvNetJS demo: training on CIFAR-10]

ConvNetJS CIFAR-10 demo

Description

This demo trains a Convolutional Neural Network on the CIFAR-10 dataset in your browser, with nothing but Javascript. The state of the art on this dataset is about 90% accuracy and human performance is at about 94% (not perfect as the dataset can be a bit ambiguous). I used this python script to parse the original files (python version) into batches of images that can be easily loaded into page DOM with img tags.

This dataset is more difficult and it takes longer to train a network. Data augmentation includes random flipping and random image shifts by up to 2px horizontally and verically.

By default, in this demo we're using Adadelta which is one of per-parameter adaptive step size methods, so we don't have to worry about changing learning rates or momentum over time. However, I still included the text fields for changing these if you'd like to play around with SGD+Momentum trainer.

Report questions/bugs/suggestions to @karpathy.

http://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html

Заключение

- Нейронная сеть:
  линейные классификаторы + нелинейные активационные функции
- Backpropagation – метод вычисления градиентов
- Сверточная нейронная сеть:
  CONV + POOL + FC слои
- Типичная архитектура классической сверточной сети
  [(CONV-RELU)*N-POOL]*M-(FC-RELU)*K,SOFTMAX
  где N до ≈5, M большое до ≈15, 0 <= K <= 2.

  современные нейронные сети ResNet, DenseNet имеют более сложные архитектуры

В следующий раз

- Активационные функции
- Стратегии изменения весов нейронной сети
- Инициализация весов
- Knowledge transfer - перенос знаний из одной нейронной сети в другую