PART III:CONVOLUTIONAL NEURAL NETWORKS

THE BASIC BUILDING BLOCKS OF CNNs

Discrete Convolution

1D: [Spectra]

$$f(x) * g(x) = \sum_{k=-\infty}^{k=+\infty} f(k).g(k-x)$$

2D: [Images]

$$f(x,y) * g(x,y) = \sum_{k=-\infty}^{k=+\infty} \sum_{l=-\infty}^{l=+\infty} f(k,l).g(x-k,y-l)$$

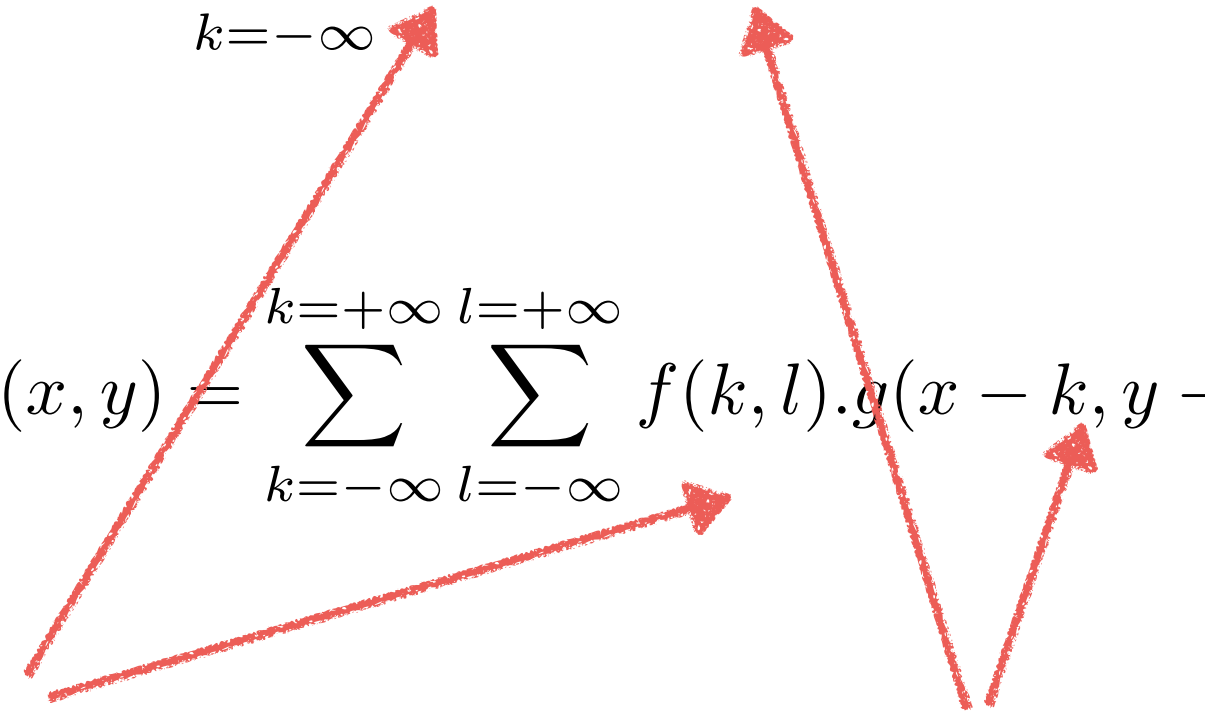
DISCRETE CONVOLUTION

1D: [Spectra]

$$f(x) * g(x) = \sum_{k=-\infty}^{k=+\infty} f(k).g(k-x)$$

2D: [Images]

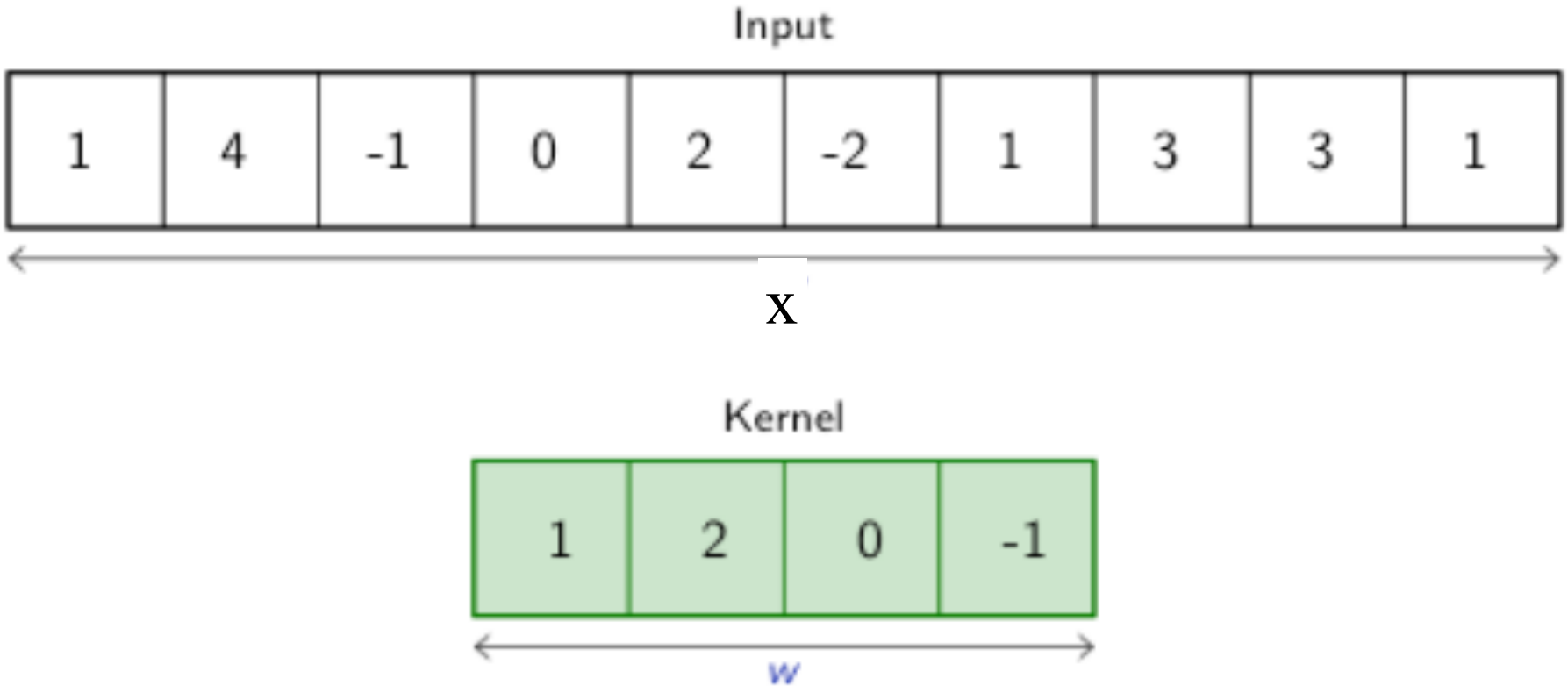
$$f(x,y) * g(x,y) = \sum_{k=-\infty}^{k=+\infty} \sum_{l=-\infty}^{l=+\infty} f(k,l).g(x-k,y-l)$$



CONVOLUTION KERNEL

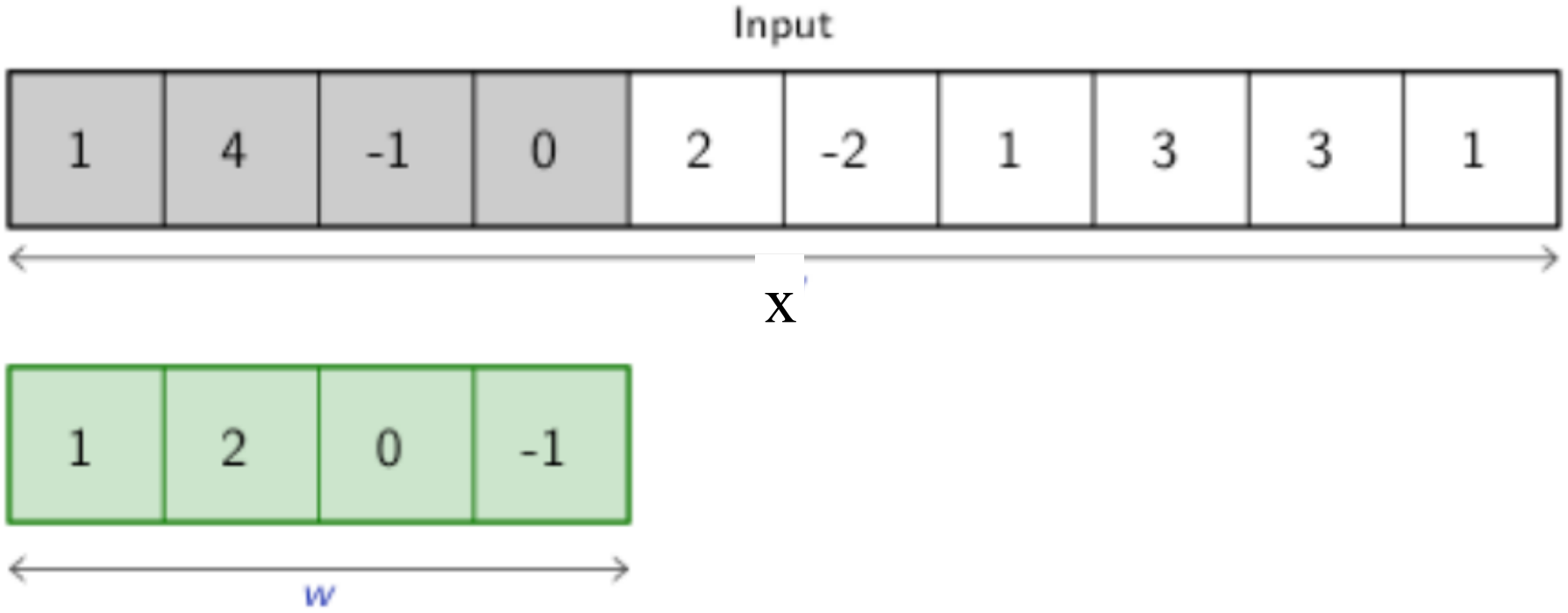
INPUT DATA

1-D CONVOLUTION



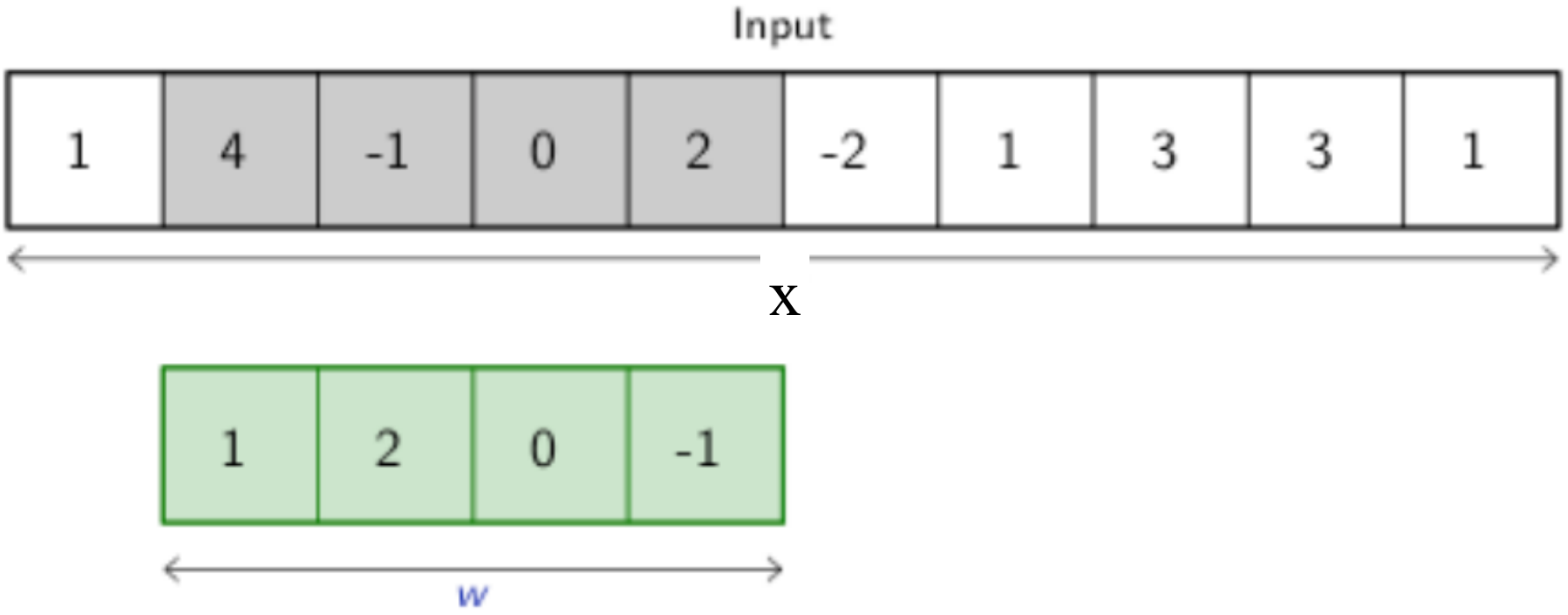
credit

1-D CONVOLUTION



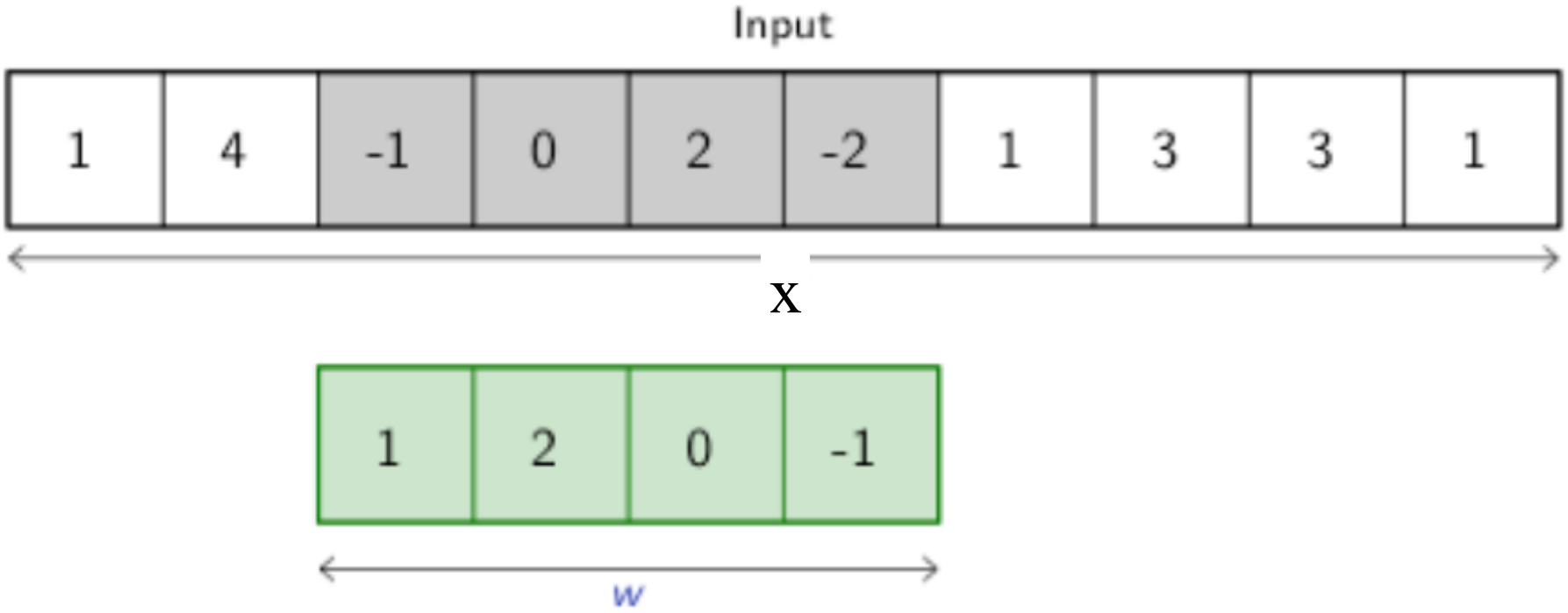
credit

1-D CONVOLUTION



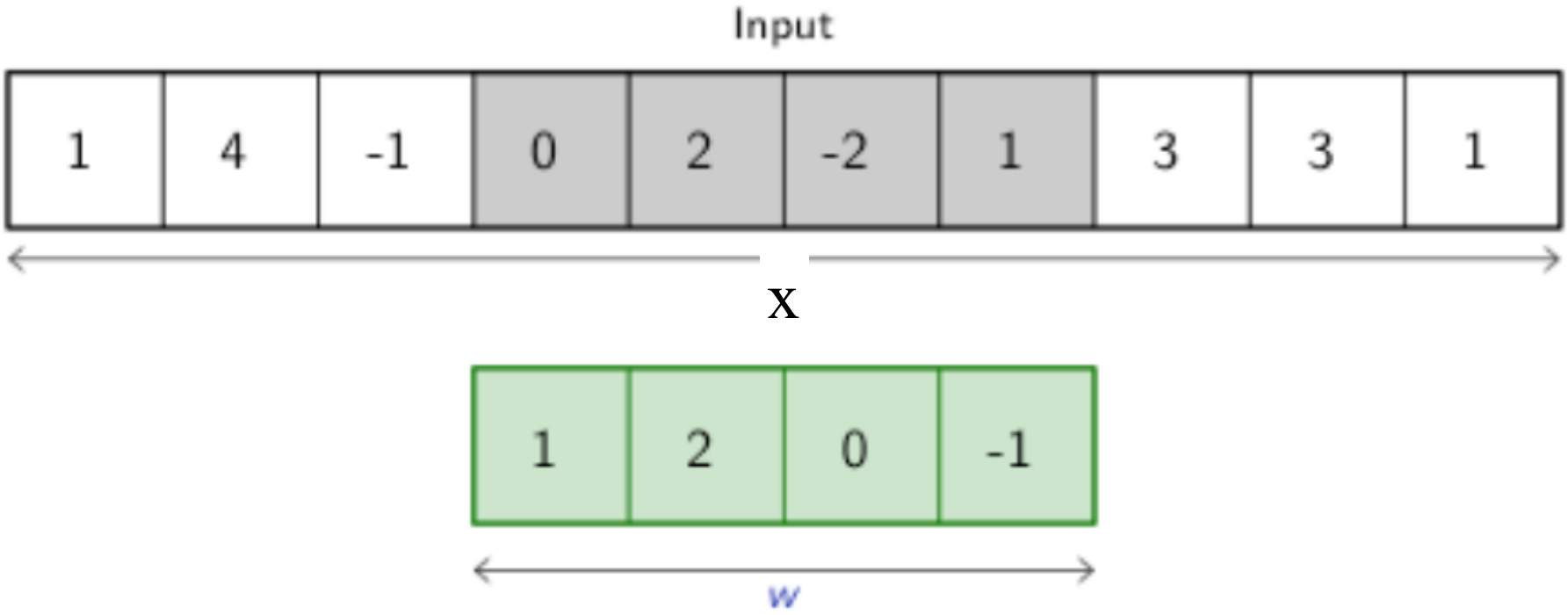
credit

1-D CONVOLUTION



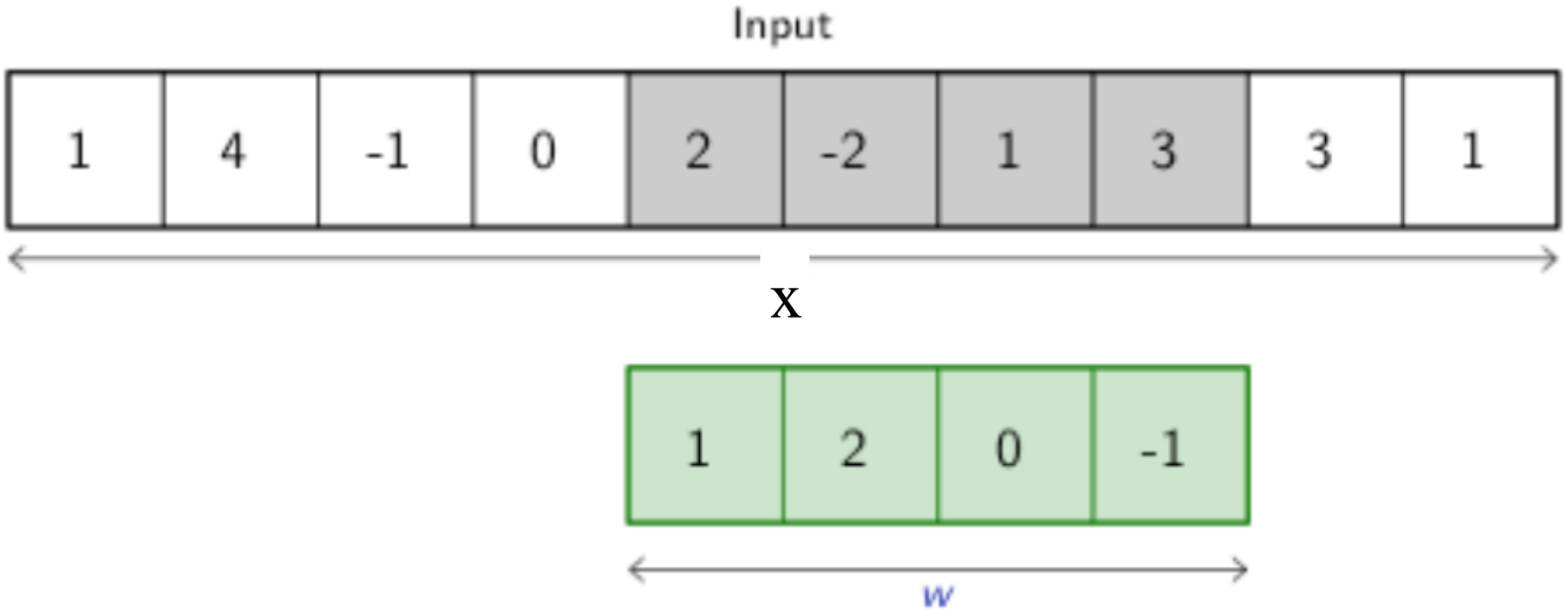
credit

1-D CONVOLUTION



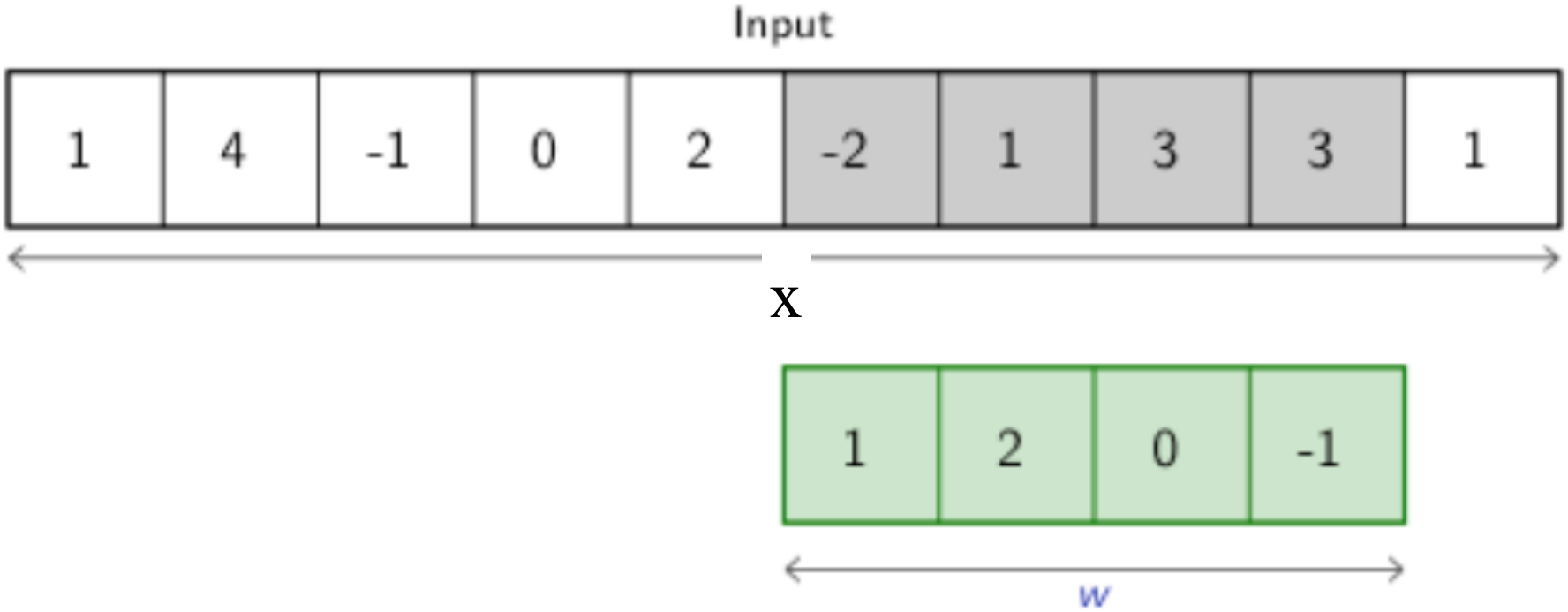
credit

1-D CONVOLUTION



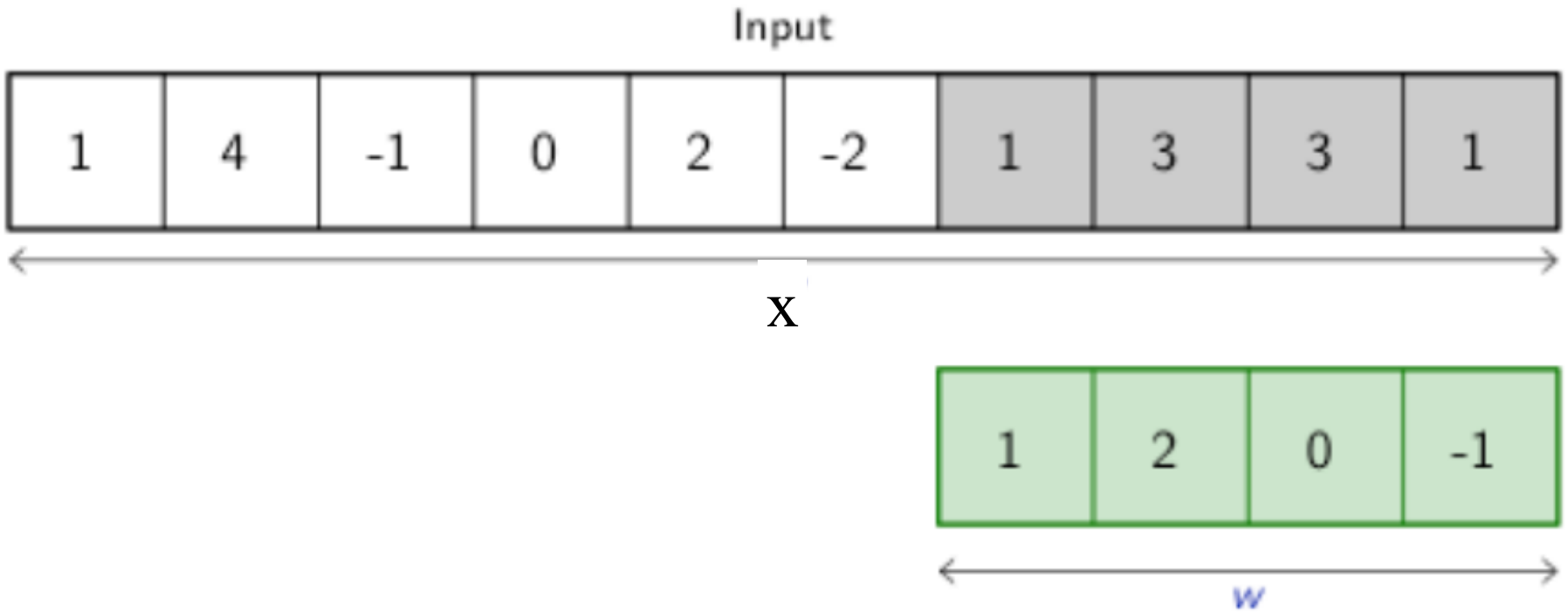
credit

1-D CONVOLUTION



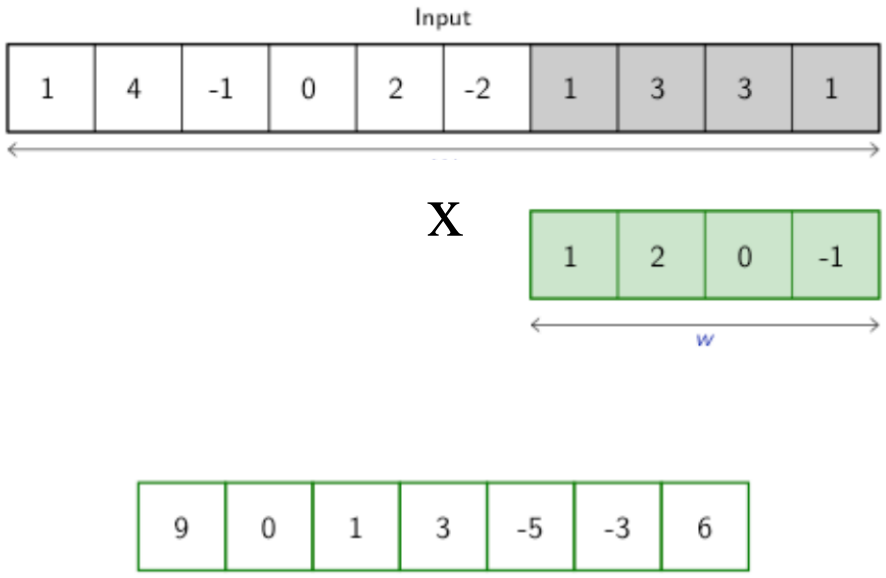
credit

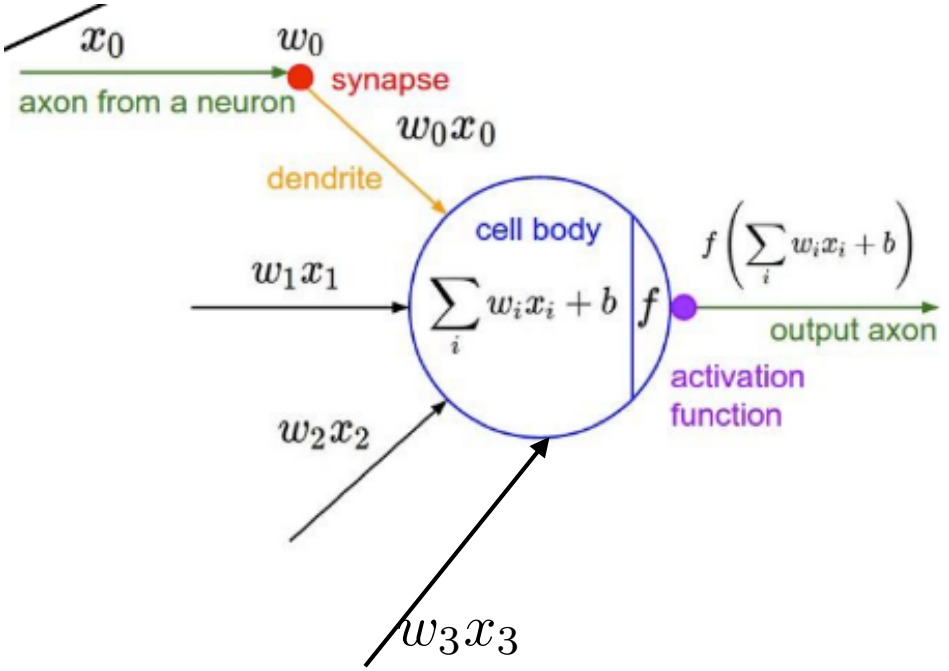
1-D CONVOLUTION



credit

THE CONVOLUTION BUILDING BLOCK OPERATION IS EQUIVALENT TO A NEURON WITH AS MANY INPUTS AS KERNEL ELEMENTS AND WEIGHTS EQUAL TO THE KERNEL





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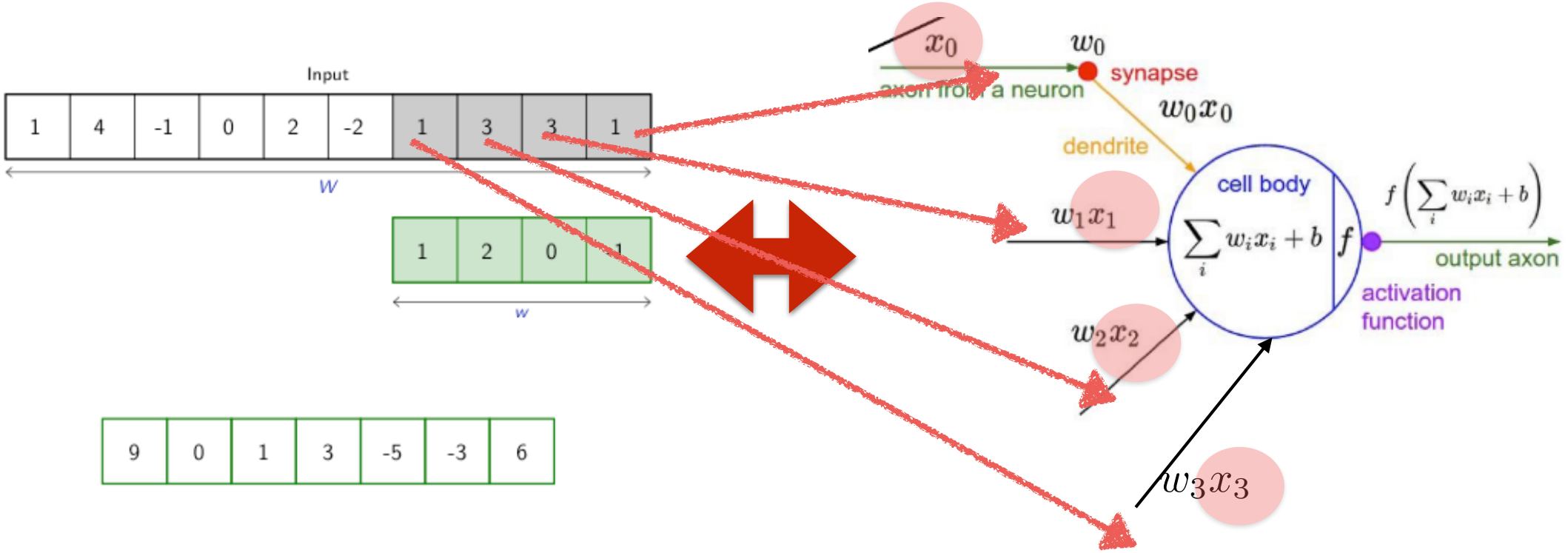
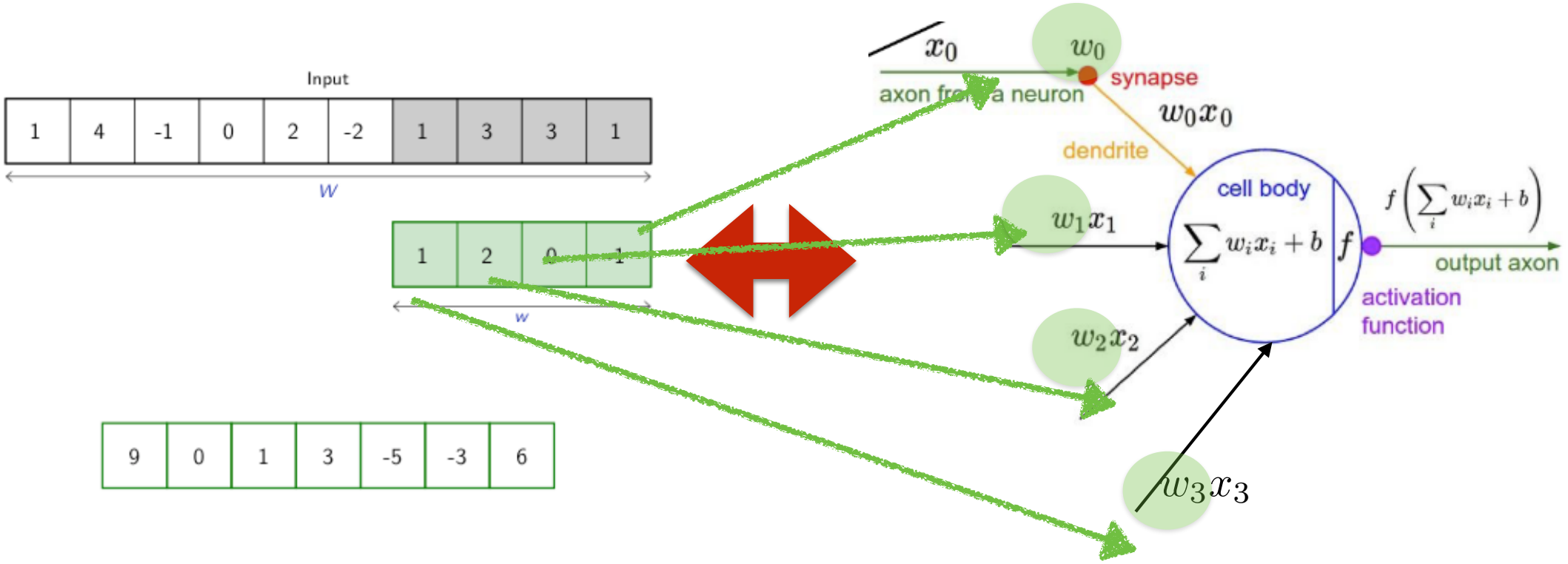
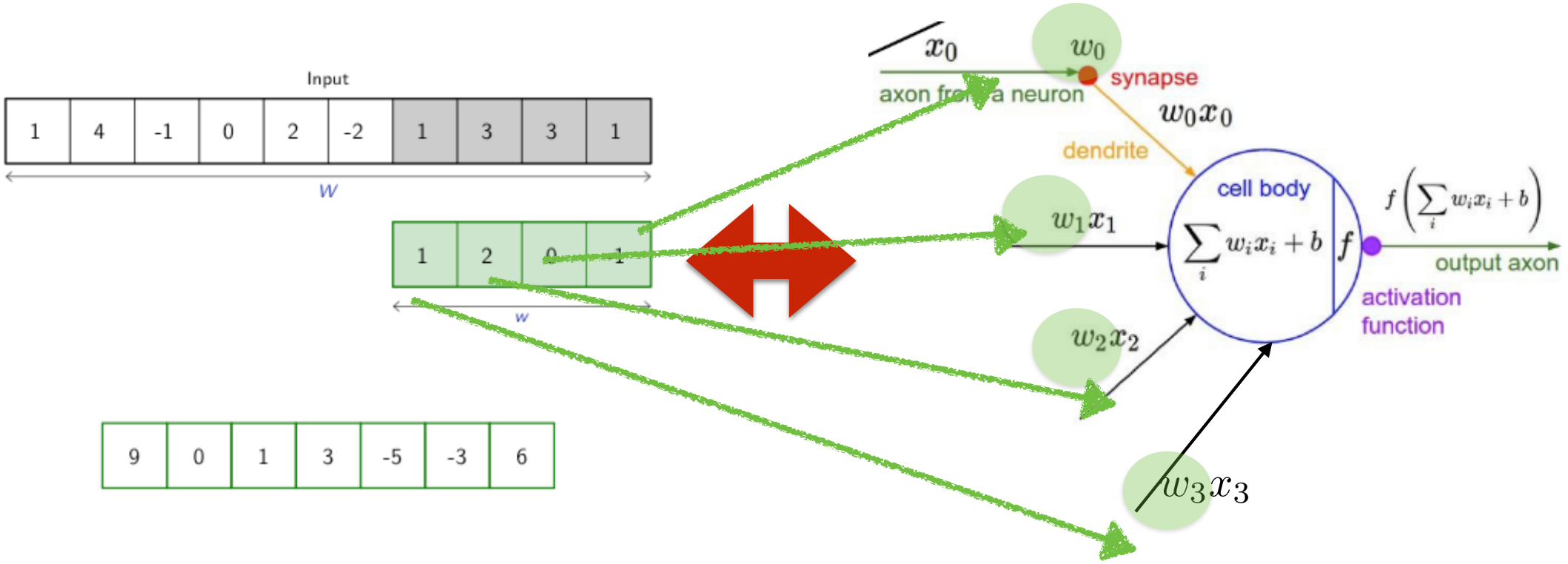


THE CONVOLUTION BUILDING BLOCK OPERATION IS EQUIVALENT TO A NEURON WITH AS MANY INPUTS AS KERNEL ELEMENTS AND WEIGHTS EQUAL TO THE KERNEL



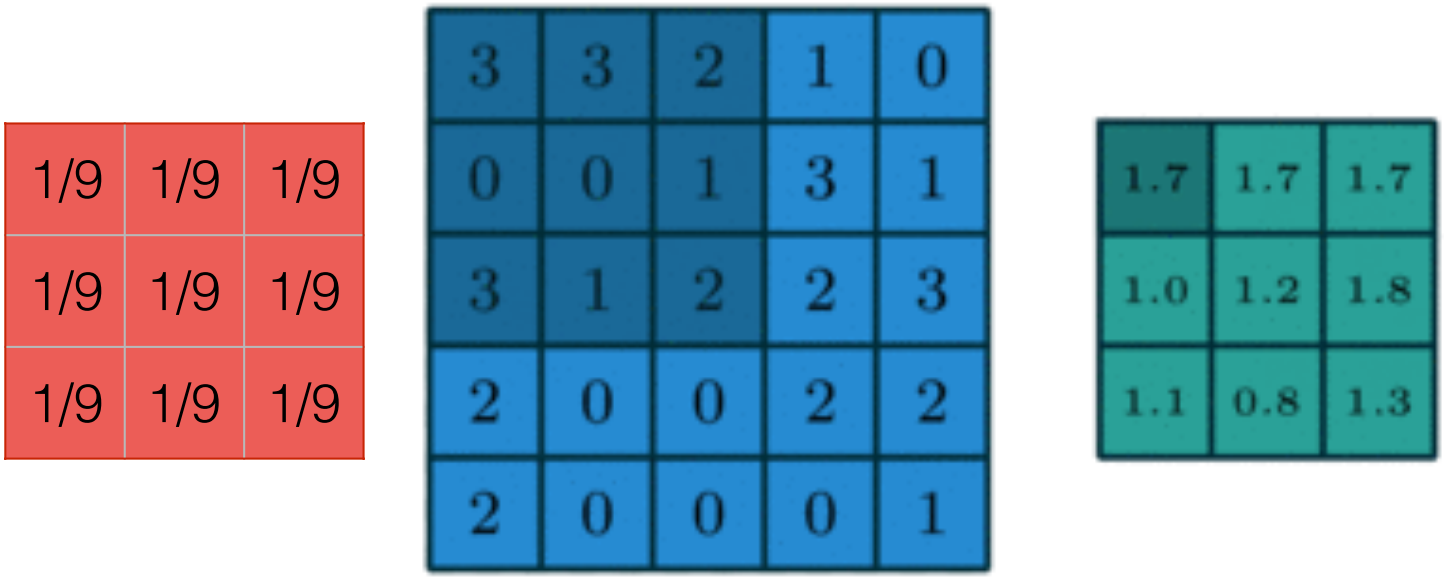
THE CONVOLUTION BUILDING BLOCK OPERATION IS EQUIVALENT TO A NEURON WITH AS MANY INPUTS AS KERNEL ELEMENTS AND WEIGHTS EQUAL TO THE KERNEL



WITH THE ADVANTAGE THAT THE SAME WEIGHTS ARE APPLIED TO ALL THE SIGNAL: TRANSLATION INVARIANCE

2-D CONVOLUTION

SAME IDEA, BUT THE KERNEL IS NOW 2D

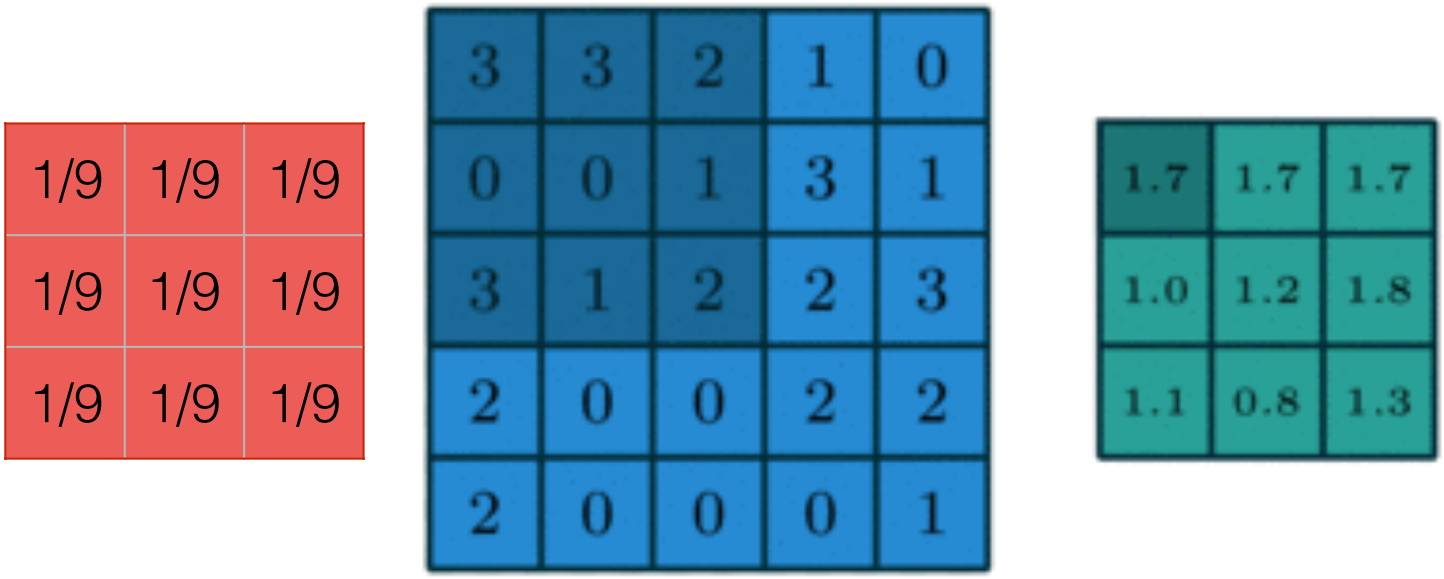


KERNEL **INPUT (IMAGE)** **OUTPUT**

Credit: animations from https://github.com/vdumoulin/conv_arithmetic

2-D CONVOLUTION

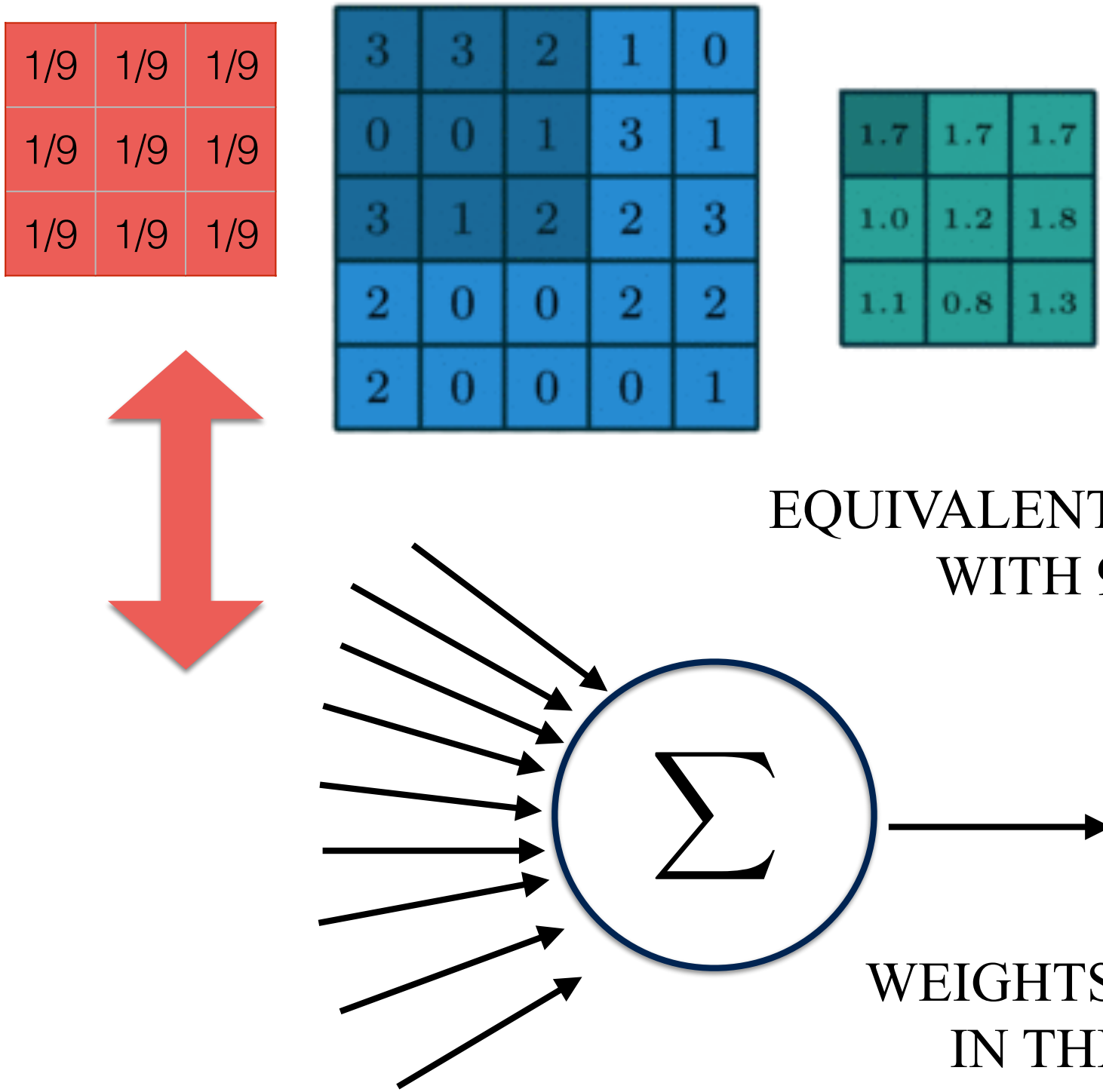
SAME IDEA, BUT THE KERNEL IS NOW 2D

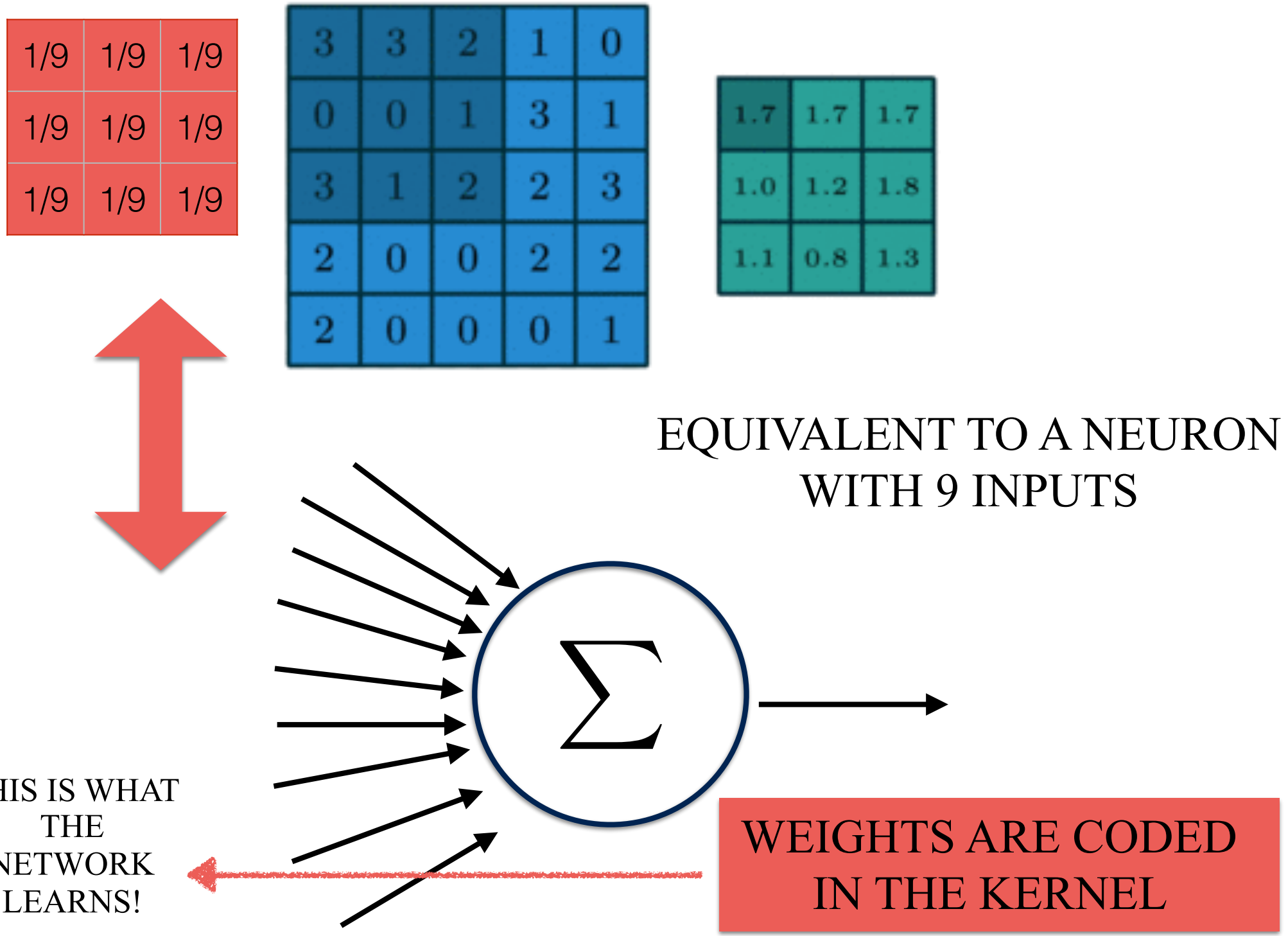


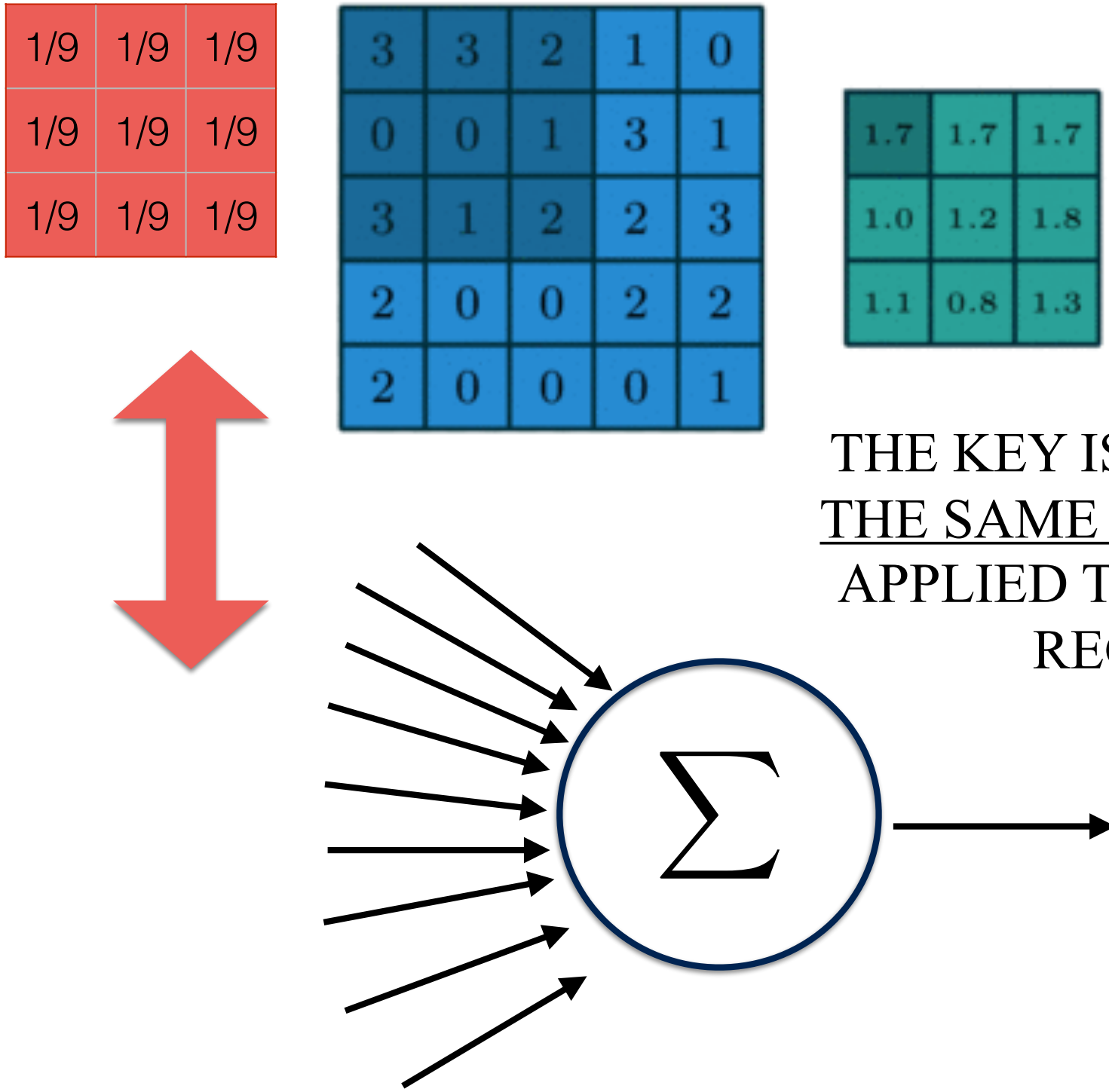
IN THE EXAMPLE: EACH 3x3 REGION GENERATES AN OUTPUT

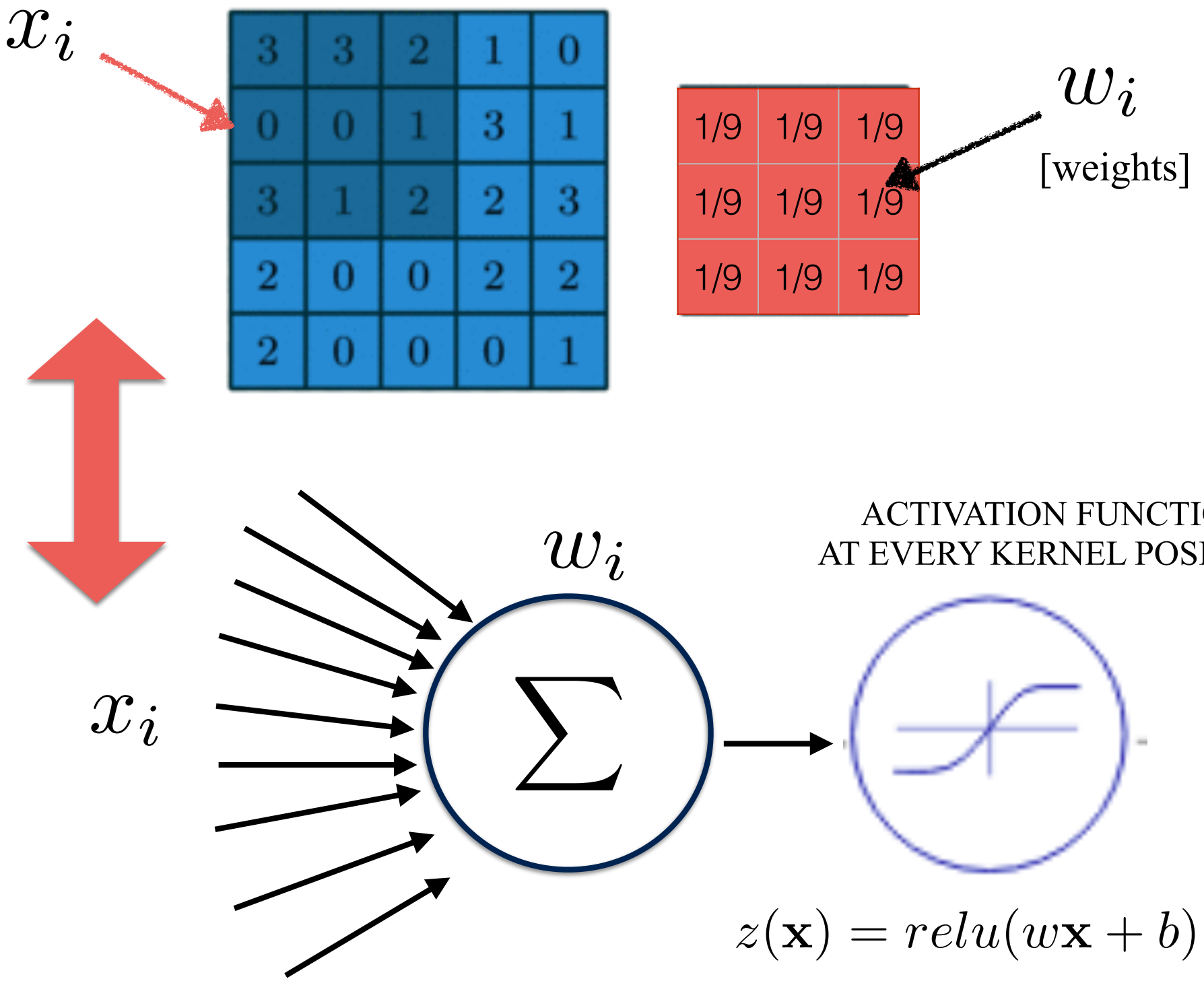
$$Size_{output} = Size_{input} - Size_{kernel} + 1$$

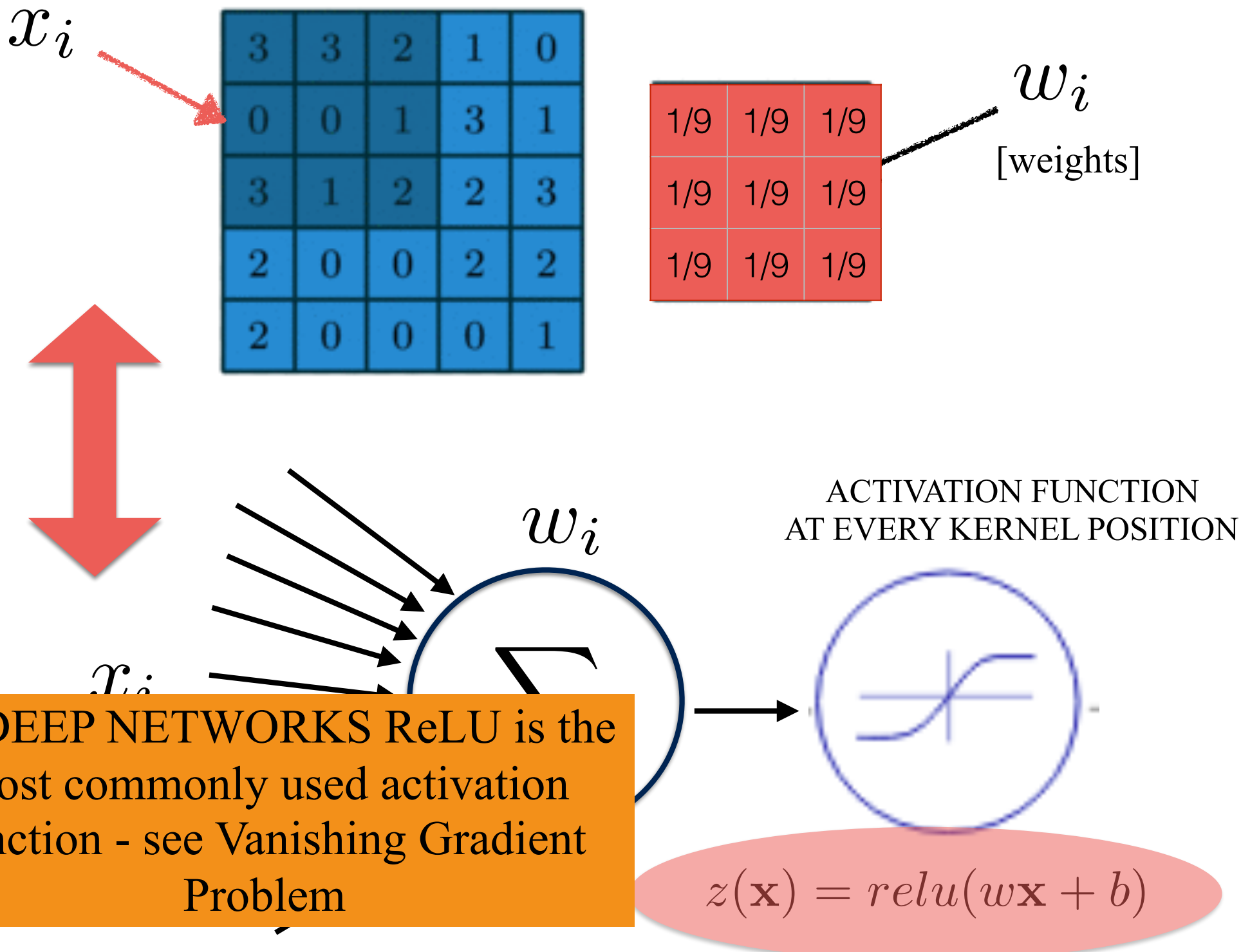
Credit: animations from https://github.com/vdumoulin/conv_arithmetic


1/9 1/9 1/9
1/9 1/9 1/9
1/9 1/9 1/9
3 3 2 1 0
0 0 1 3 1
3 1 2 2 3
2 0 0 2 2
2 0 0 0 1
1.7 1.7 1.7
1.0 1.2 1.8
1.1 0.8 1.3
EQUIVALENT TO A NEURON
WITH 9 INPUTS
Σ
WEIGHTS ARE CODED
IN THE KERNEL


1/9 1/9 1/9
1/9 1/9 1/9
1/9 1/9 1/9
3 3 2 1 0
0 0 1 3 1
3 1 2 2 3
2 0 0 2 2
2 0 0 0 1
1.7 1.7 1.7
1.0 1.2 1.8
1.1 0.8 1.3
EQUIVALENT TO A NEURON
WITH 9 INPUTS
Σ
THIS IS WHAT
THE
NETWORK
LEARNS!
WEIGHTS ARE CODED
IN THE KERNEL

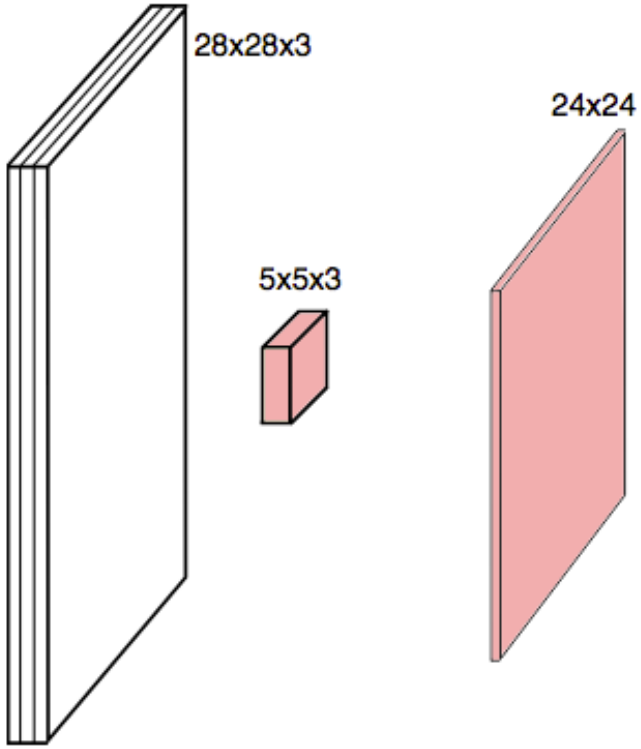

1/9 1/9 1/9
1/9 1/9 1/9
1/9 1/9 1/9
3 3 2 1 0
0 0 1 3 1
3 1 2 2 3
2 0 0 2 2
2 0 0 0 1
1.7 1.7 1.7
1.0 1.2 1.8
1.1 0.8 1.3
THE KEY IS AGAIN THAT
THE SAME WEIGHTS ARE
APPLIED TO ALL IMAGE
REGIONS
Σ

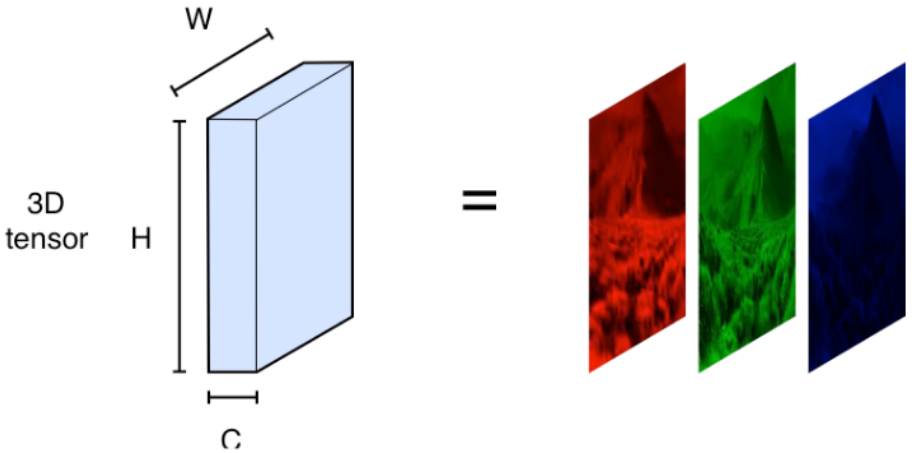

x_i
3 3 2 1 0
0 0 1 3 1
3 1 2 2 3
2 0 0 2 2
2 0 0 0 1
1/9 1/9 1/9
1/9 1/9 1/9
1/9 1/9 1/9
w_i
[weights]
w_i
x_i
$\sum$
ACTIVATION FUNCTION
AT EVERY KERNEL POSITION
$z(\mathbf{x}) = relu(w\mathbf{x} + b)$


x_i
3 3 2 1 0
0 0 1 3 1
3 1 2 2 3
2 0 0 2 2
2 0 0 0 1
1/9 1/9 1/9
1/9 1/9 1/9
1/9 1/9 1/9
w_i
[weights]
w_i
x_i
ACTIVATION FUNCTION
AT EVERY KERNEL POSITION
IN DEEP NETWORKS ReLU is the most commonly used activation function - see Vanishing Gradient Problem
$z(\mathbf{x}) = relu(w\mathbf{x} + b)$

CONVOLUTIONS CAN ALSO BE COMPUTED ACROSS CHANNELS (OR COLORS)

A COLOR IMAGE IS A TENSOR
OF SIZE height x width x channels





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A COLOR IMAGE IS A TENSOR
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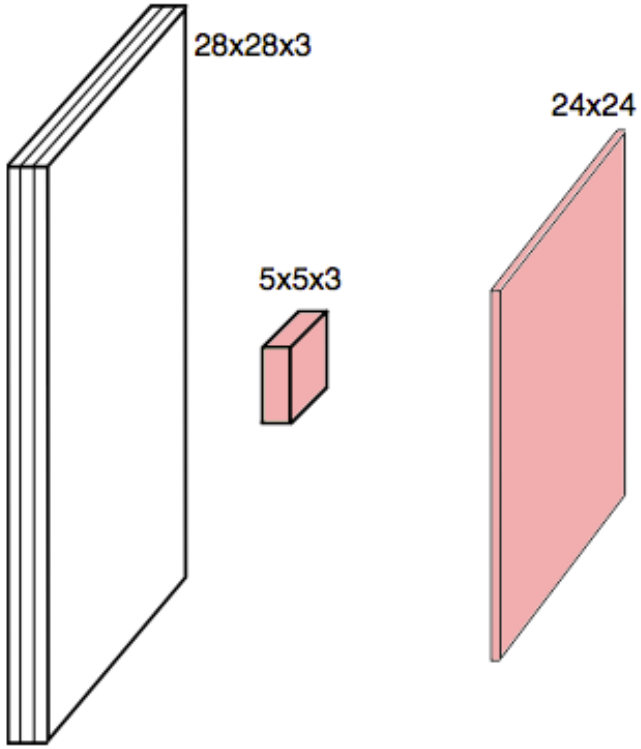
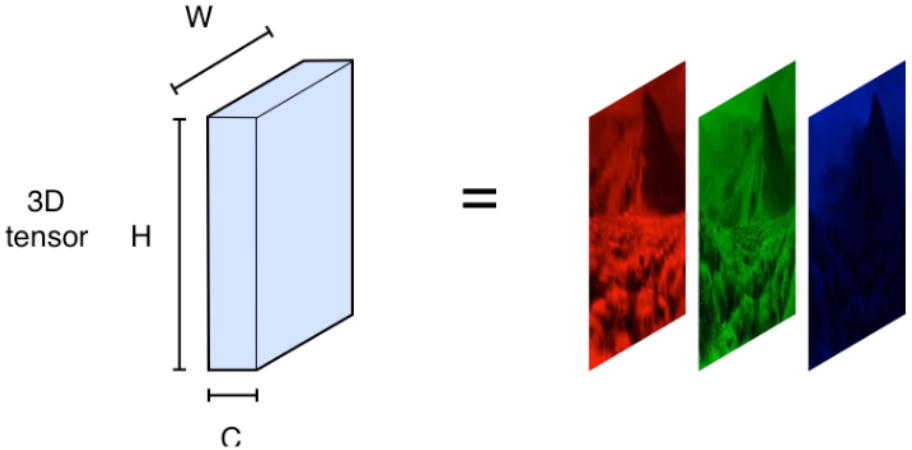


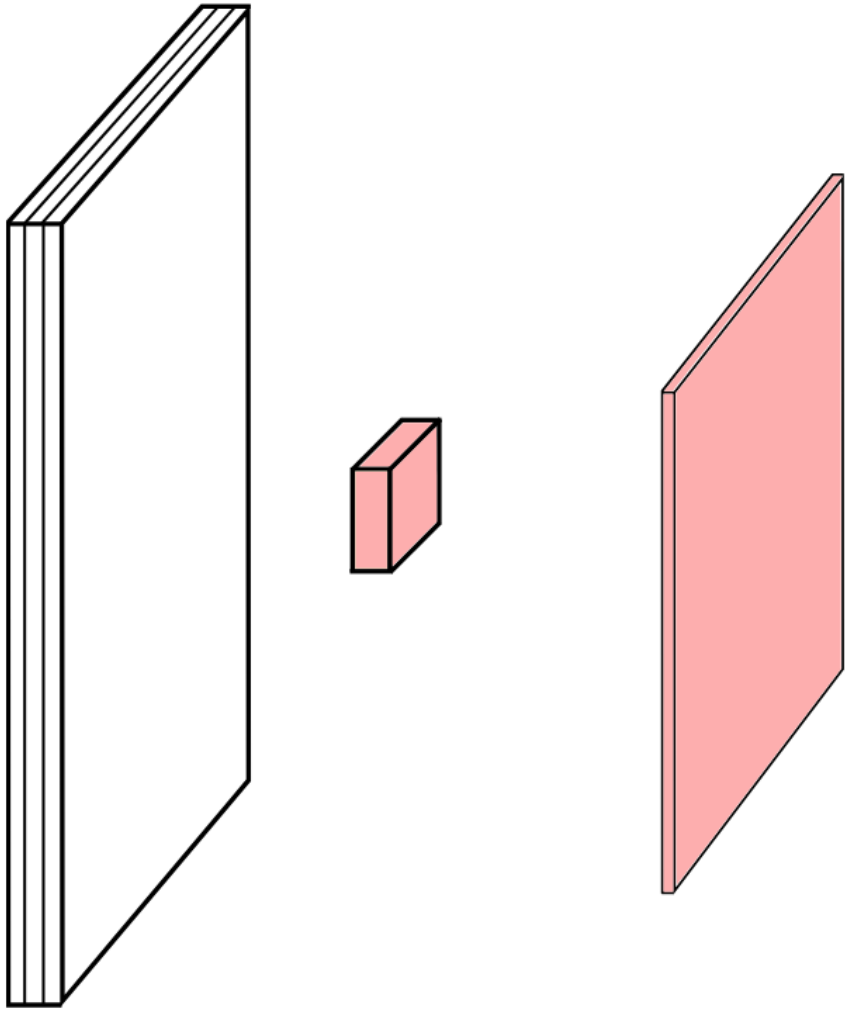


THEN THE KERNEL HAS ALSO 3 CHANNELS

IN ASTRONOMY …

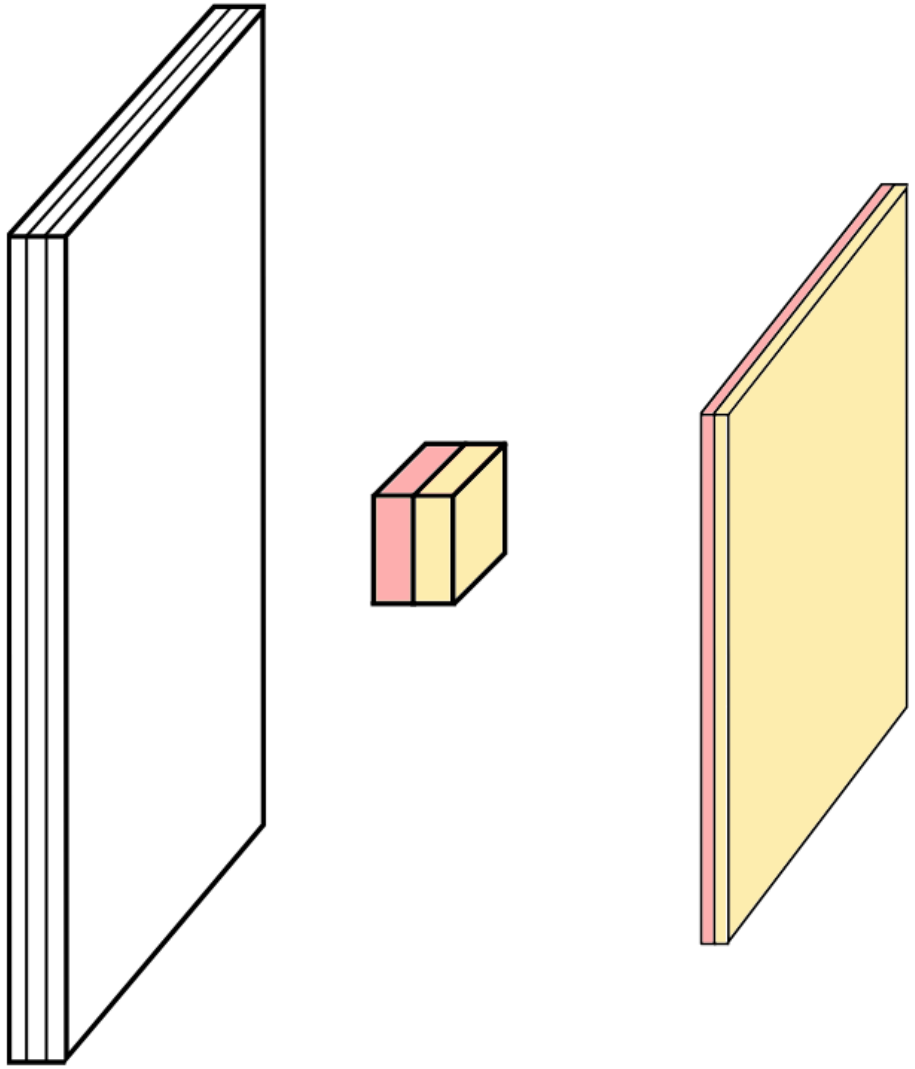
IT OPENS THE DOOR TO ANALYZE MULTIPLE FILTERS SIMULTANEOUSLY

MULTIPLE CONVOLUTIONS WITH DIFFERENT KERNELS CAN BE PERFORMED



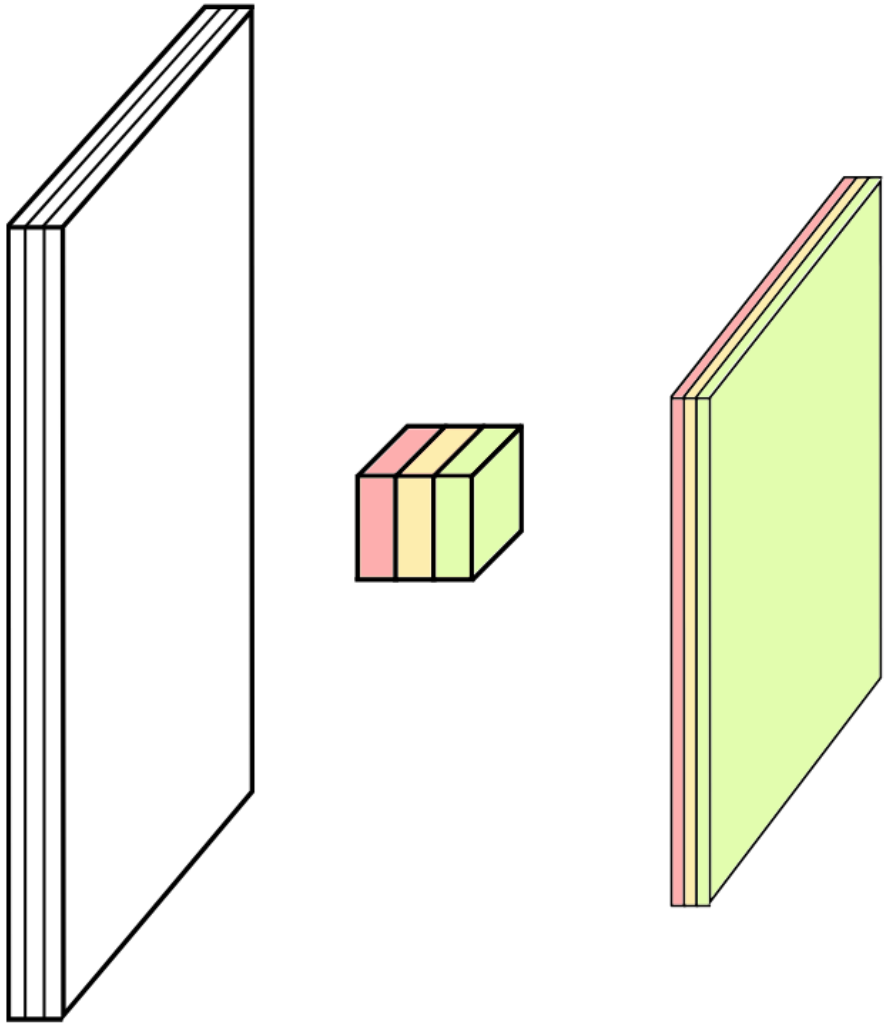
credit

MULTIPLE CONVOLUTIONS WITH DIFFERENT KERNELS CAN BE PERFORMED



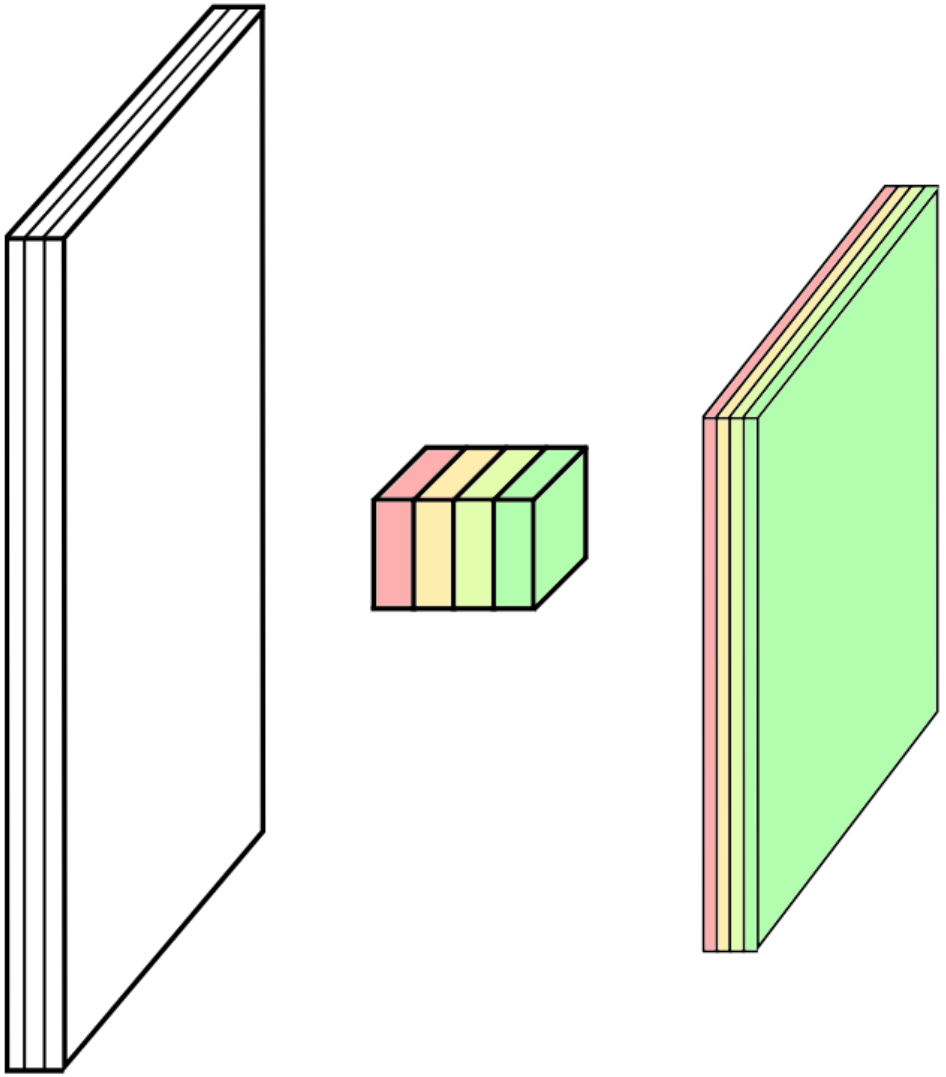
credit

MULTIPLE CONVOLUTIONS WITH DIFFERENT KERNELS CAN BE PERFORMED



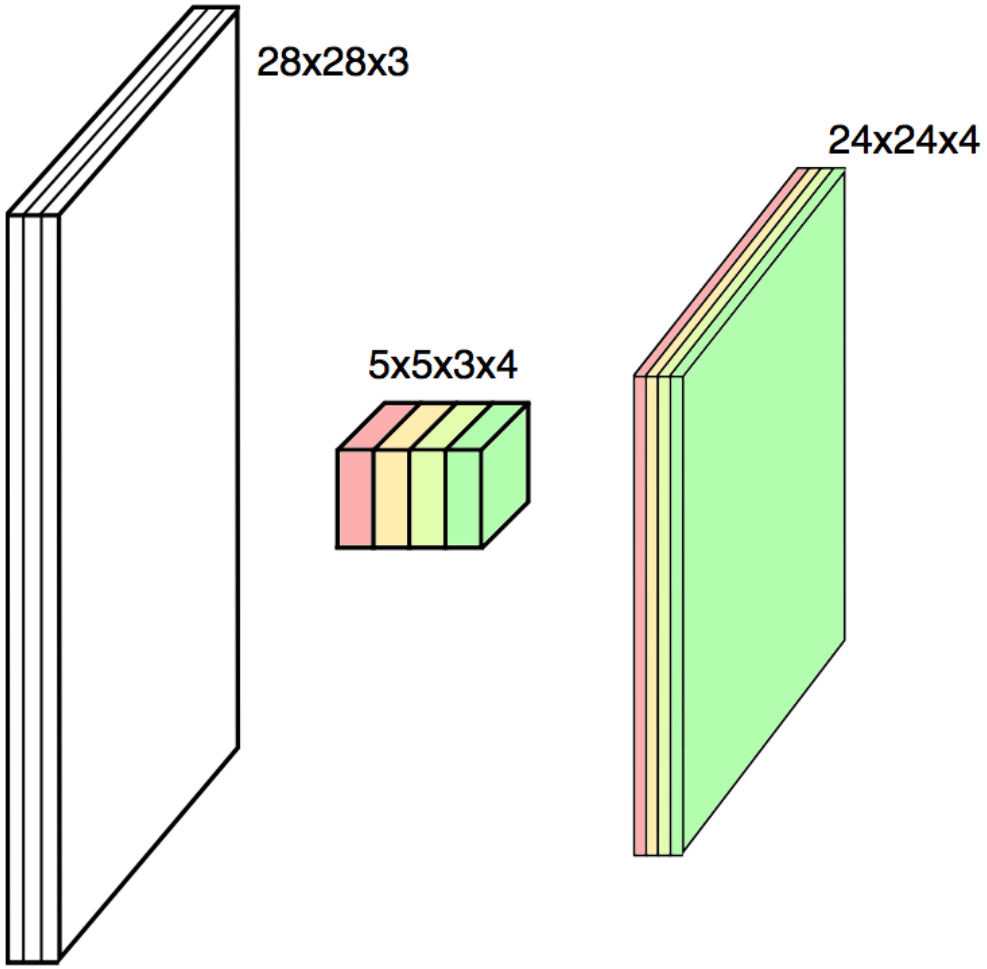
credit

MULTIPLE CONVOLUTIONS WITH DIFFERENT KERNELS CAN BE PERFORMED



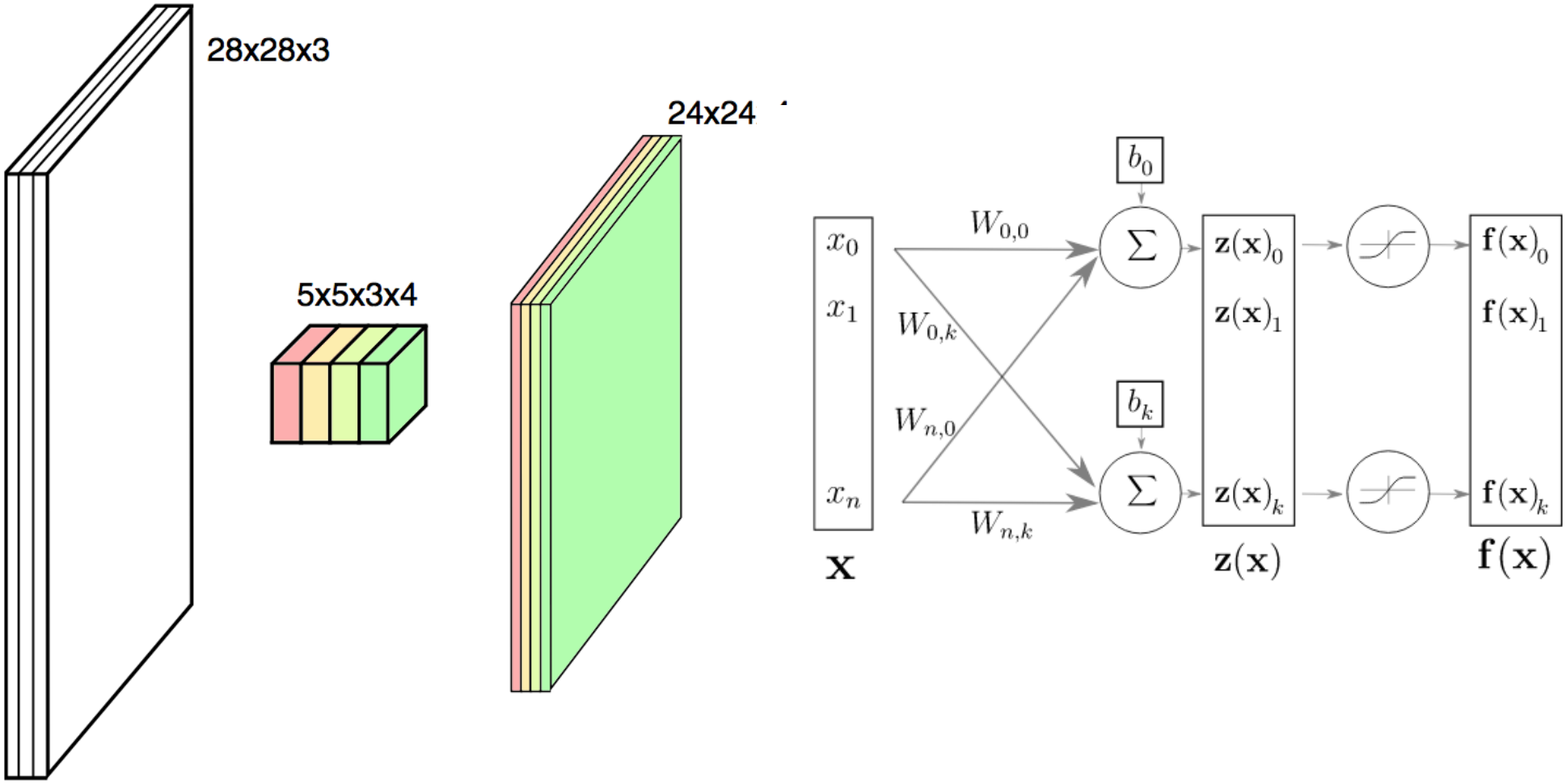
credit

MULTIPLE CONVOLUTIONS WITH DIFFERENT KERNELS CAN BE PERFORMED



credit

MULTIPLE CONVOLUTIONS WITH DIFFERENT KERNELS CAN BE PERFORMED



credit

IN KERAS…

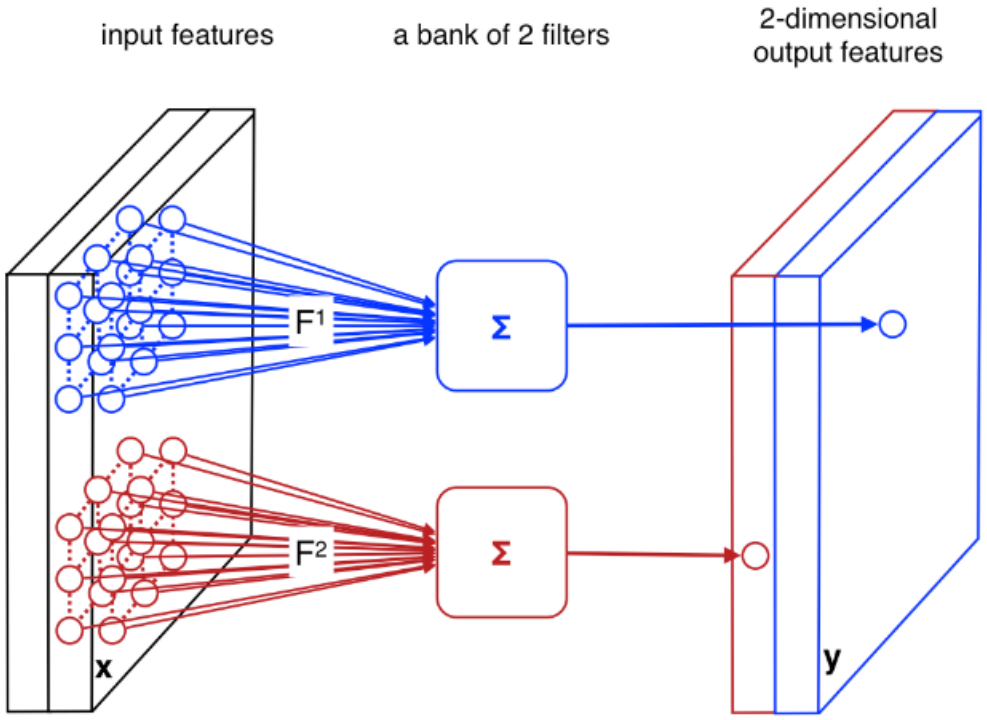
model = Sequential()

model.add(Convolution2D(4,5,5, activation="relu"))

depth

sizeX, sizeY

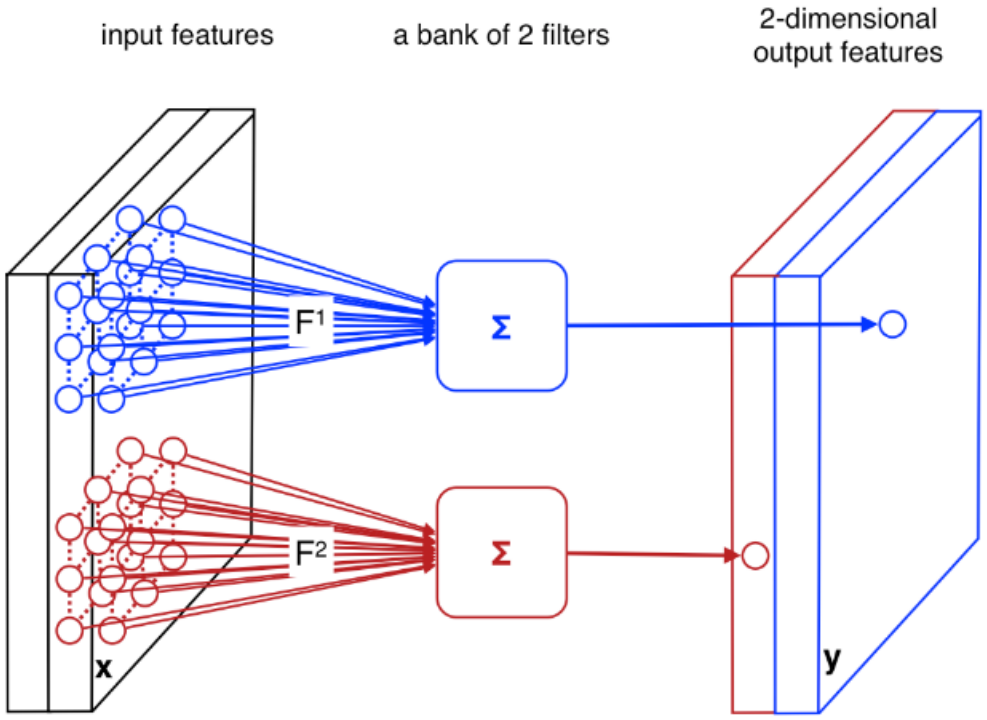
SINCE CONVOLUTIONS OUTPUT ONE SCALAR, THEY CAN BE SEEN AS AN INDIVIDUAL NEURON WITH A RECEPTIVE FIELD LIMITED TO THE KERNEL DIMENSIONS



Credit

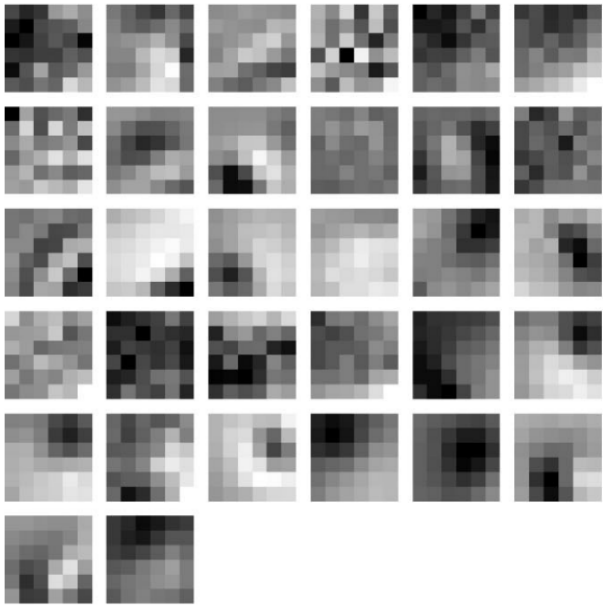
SINCE CONVOLUTIONS OUTPUT ONE SCALAR< THEY CAN BE SEEN AS AN INDIVIDUAL NEURON WITH A RECEPTIVE FIELD LIMITED TO THE KERNEL DIMENSIONS

THE SAME NEURON IS FIRED WITH DIFFERENT AREAS FROM THE INPUT

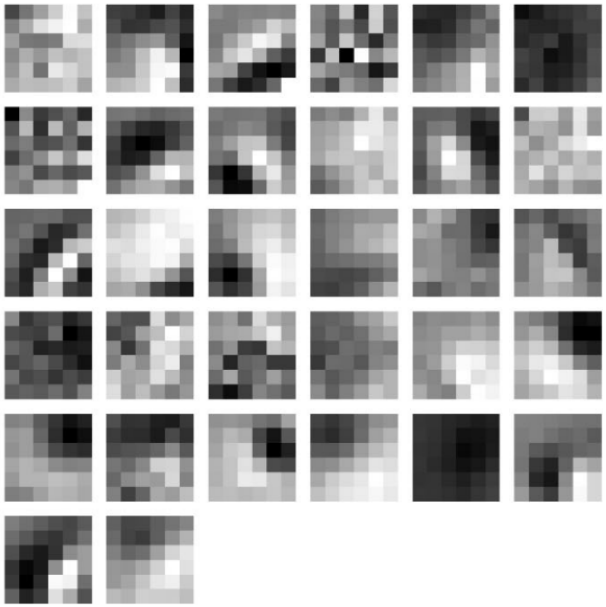


Credit

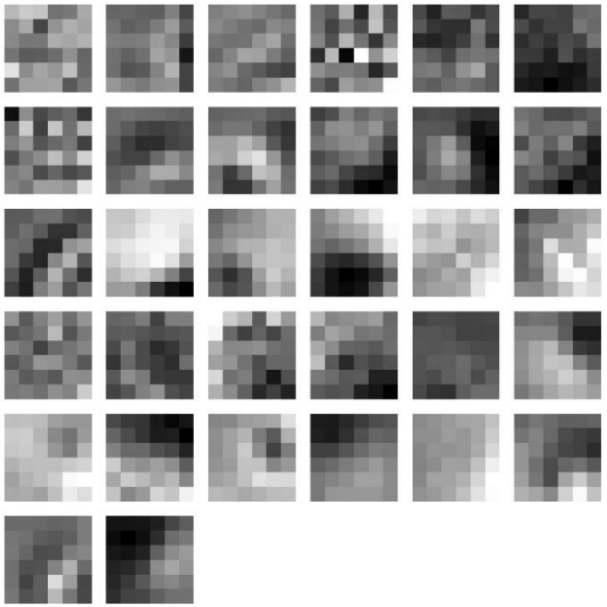
EXAMPLE OF 32 FILTERS LEARNED IN A CONVOLUTIONAL LAYER



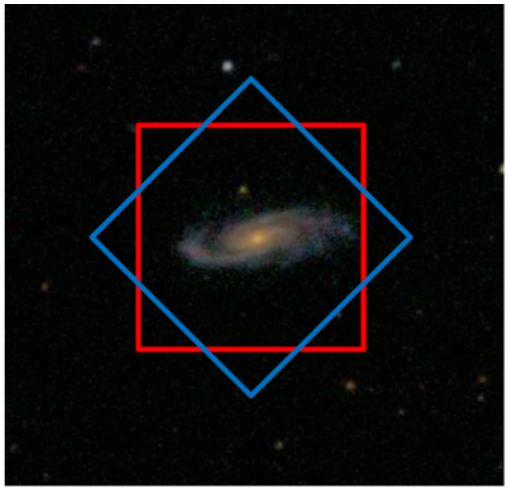
(a) red channel



(b) green channel

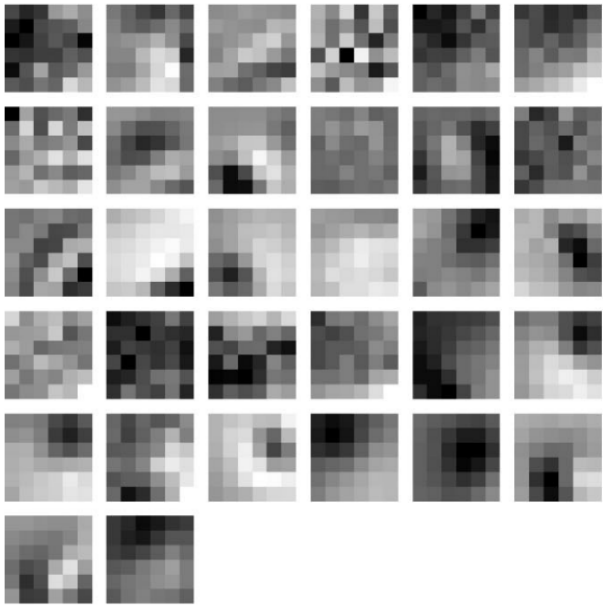


(c) blue channel

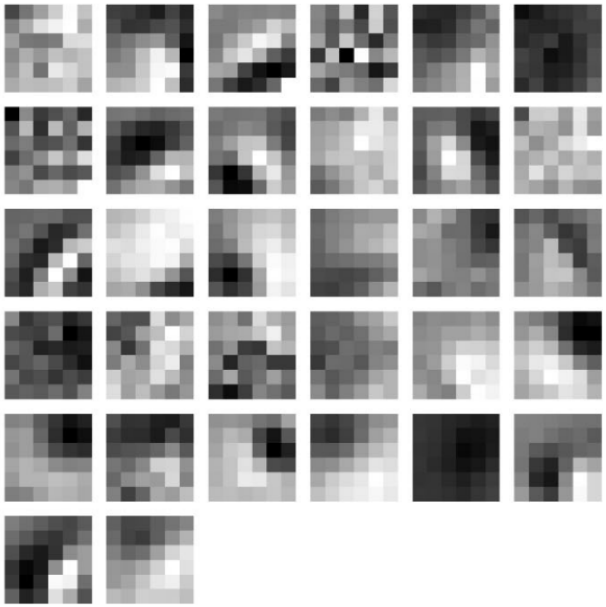


Dieleman+16

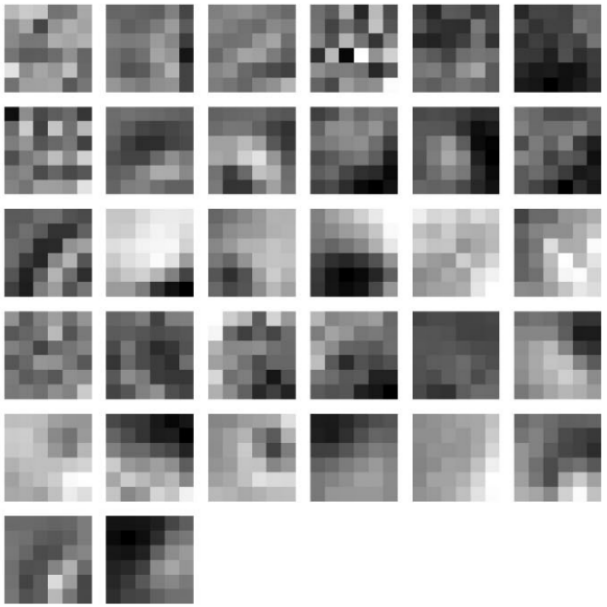
EXAMPLE OF 32 FILTERS LEARNED IN A CONVOLUTIONAL LAYER



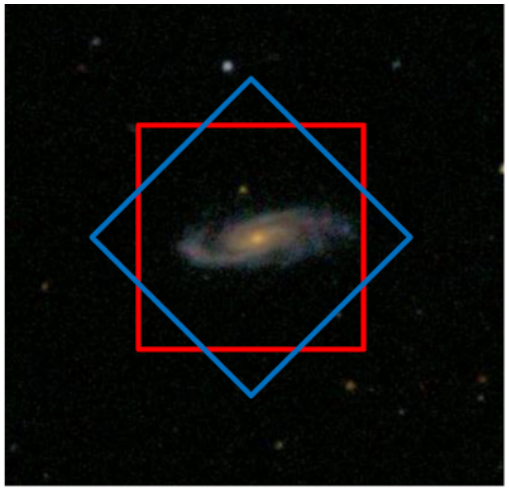
(a) red channel



(b) green channel



(c) blue channel



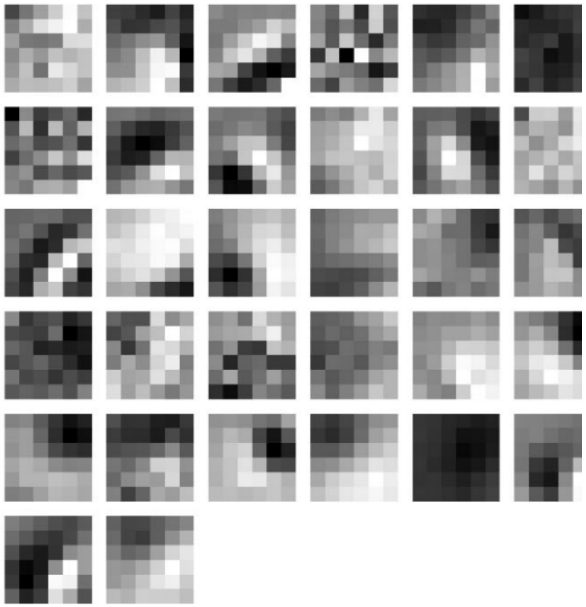
Dieleman+16

THESE ARE CALLED **FEATURE MAPS**

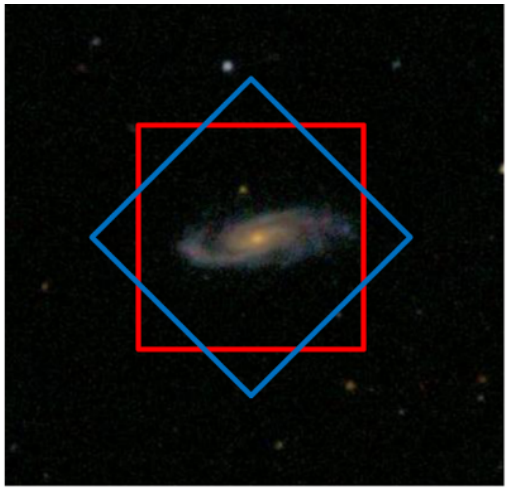
EXAMPLE OF 32 FILTERS LEARNED BY A CONVOLUTIONAL

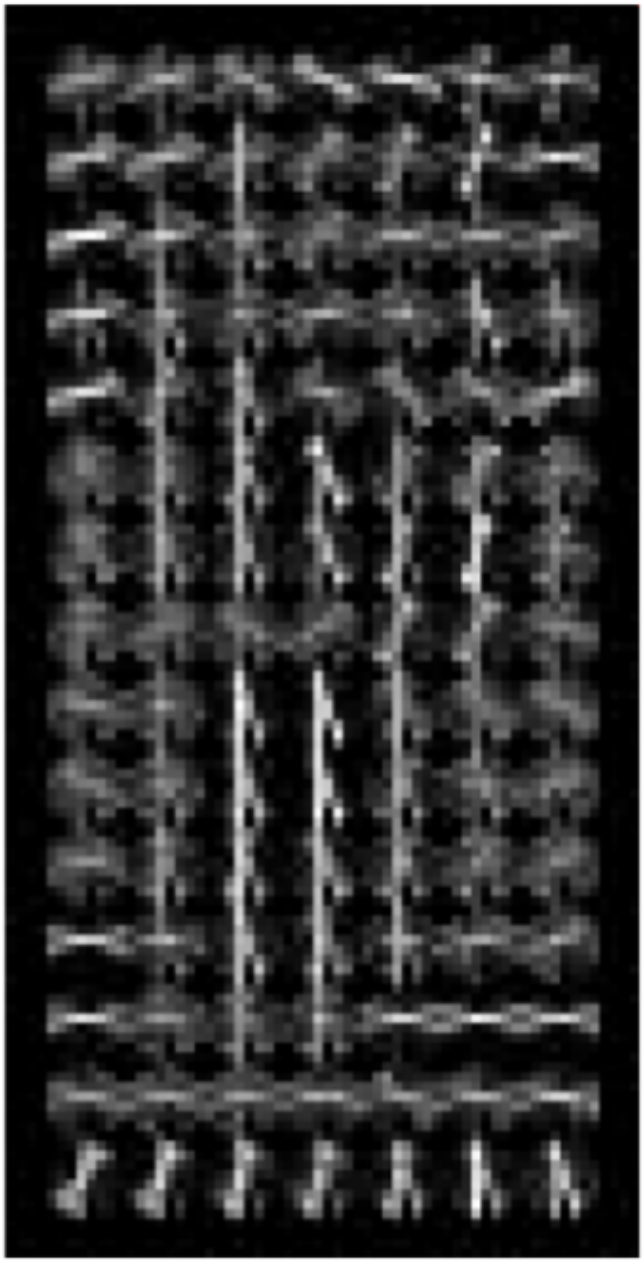
REMEMBER THE HoG ?

(a) red channel



(b) green channel





THESE ARE CALLED **FEATURE MAPS**

ESTIMATING SHAPES AND NUMBER OF PARAMETERS

KERNEL SHAPE:	PADDING:	STRIDES:
(F, F, C^i, C^o)	P	S

OUTPUT SIZE: $W_0 = (W^i - F + 2P)/S + 1$

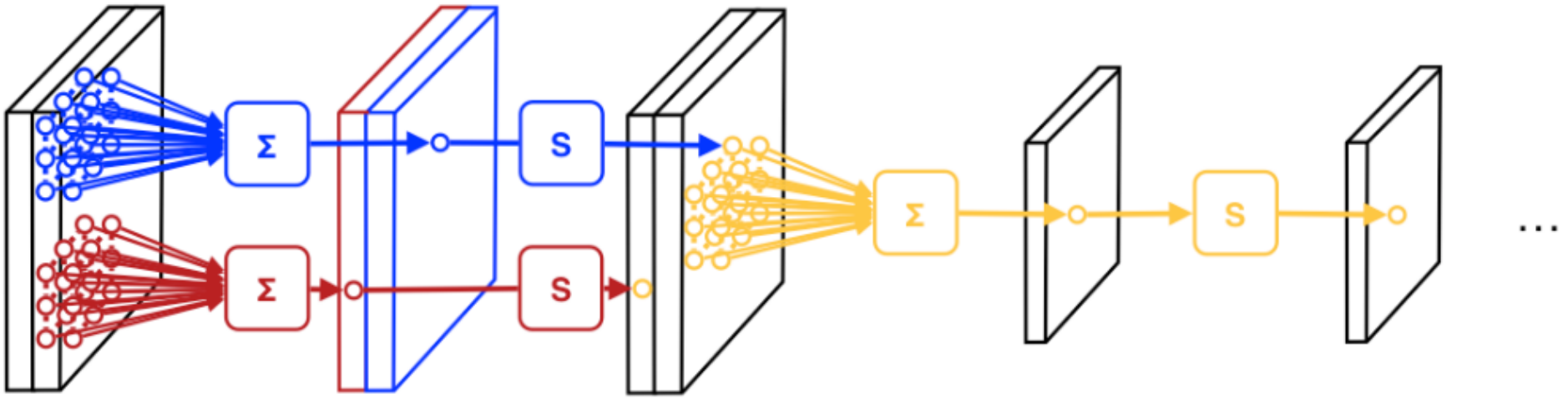
NUMBER OF PARAMETERS: $(F \times F \times C^i + 1) \times C^o$

→ the number of parameters increases fast!

32 filters of 5*5 on a color image —> 2432 parameters to learn

DOWNSAMPLING

DOWNSAMPLING IS APPLIED TO REDUCE THE OVERALL SIZE OF TENSORS



POOLING

CONVOLUTIONS ARE OFTEN FOLLOWED BY AN OPERATION OF DOWNSAMPLING [POOLING]

VERY SIMPLE OPERATION - ONLY ONE OUT OF EVERY N PIXELS ARE KEPT

OFTEN MATCHED WITH AN INCREASE OF THE FEATURE CHANNELS

TYPES OF POOLING

SUM POOLING $y = \sum x_{uv}$

SQUARE SUM POOLING $y = \sqrt{\sum x_{uv}^2}$

MAX POOLING $y = max(x_{uv})$

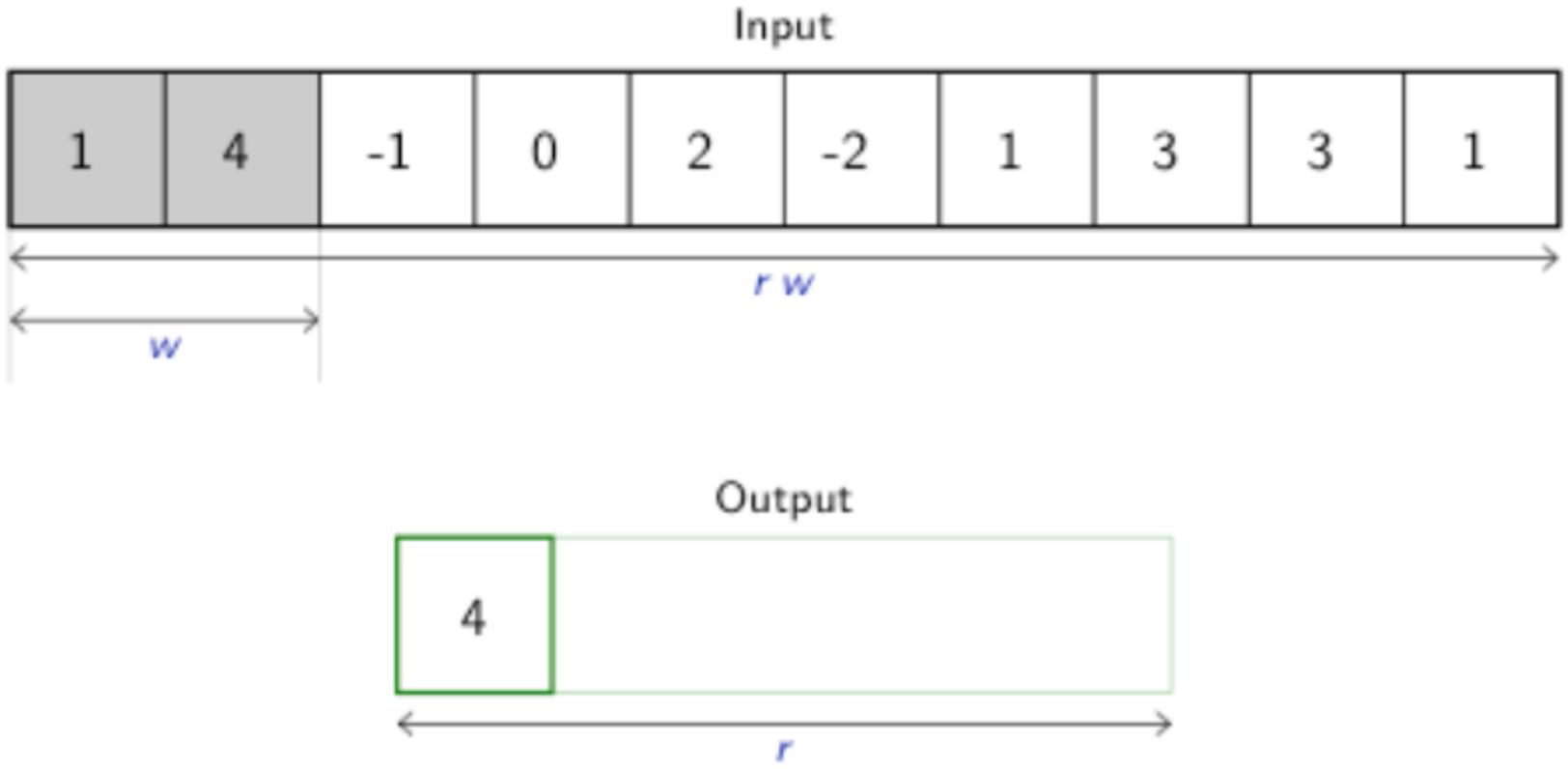
TYPES OF POOLING

SUM POOLING $y = \sum x_{uv}$

SQUARE SUM POOLING $y = \sqrt{\sum x_{uv}^2}$

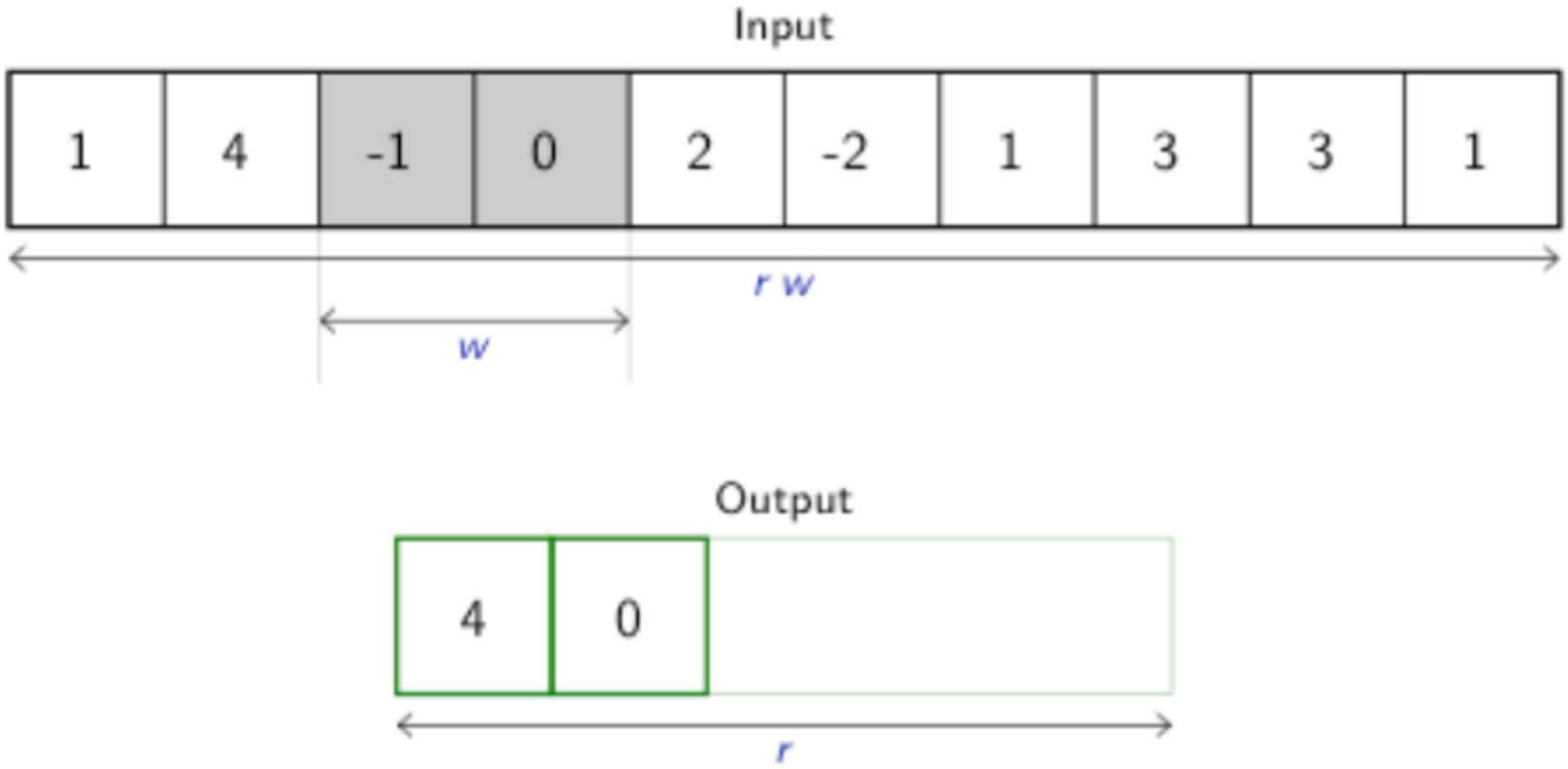
MAX POOLING $y = max(x_{uv})$

MAX POOLING 1D



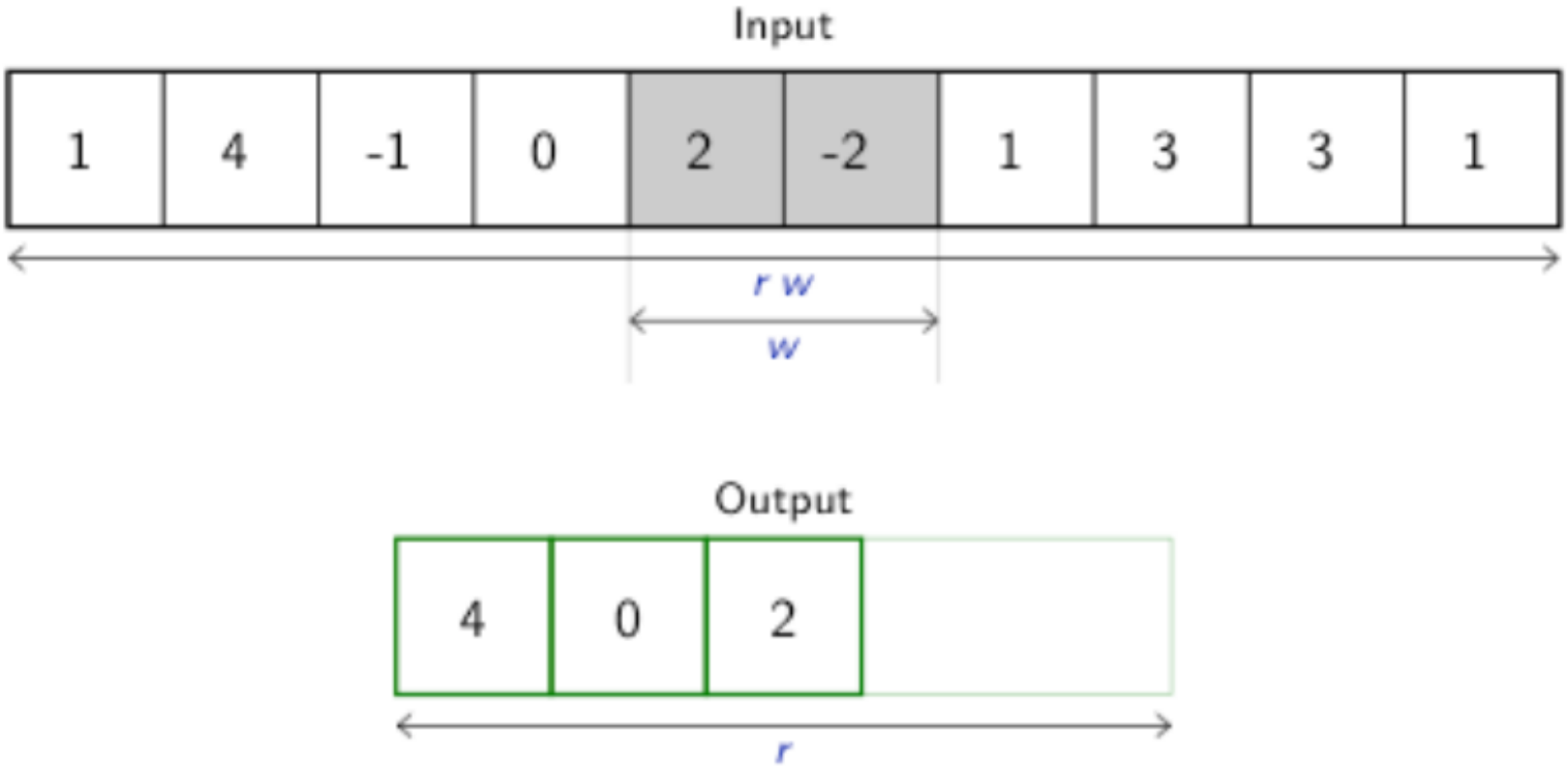
Credit: F. Fleuret

MAX POOLING 1D



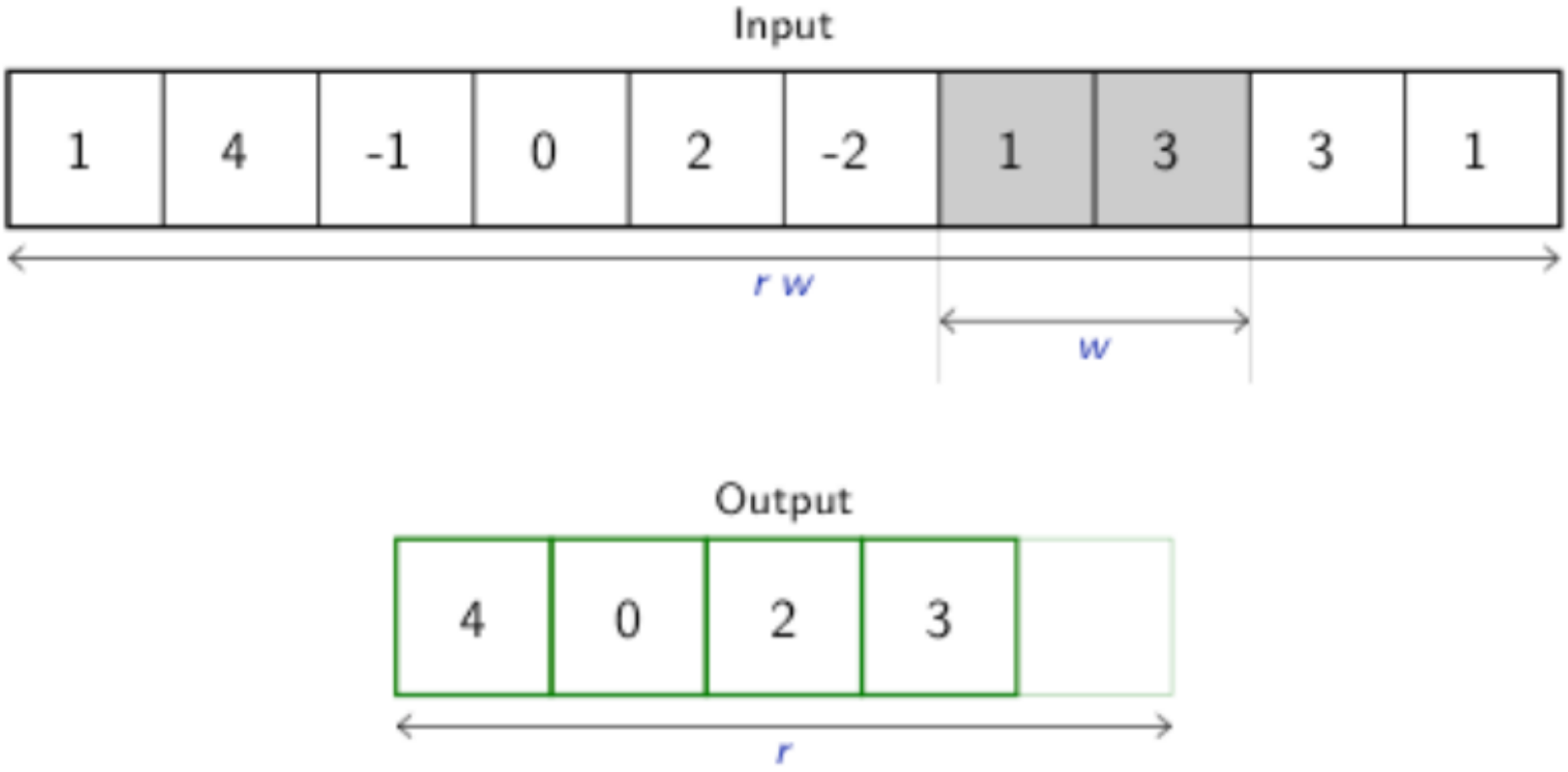
Credit: F. Fleuret

MAX POOLING 1D



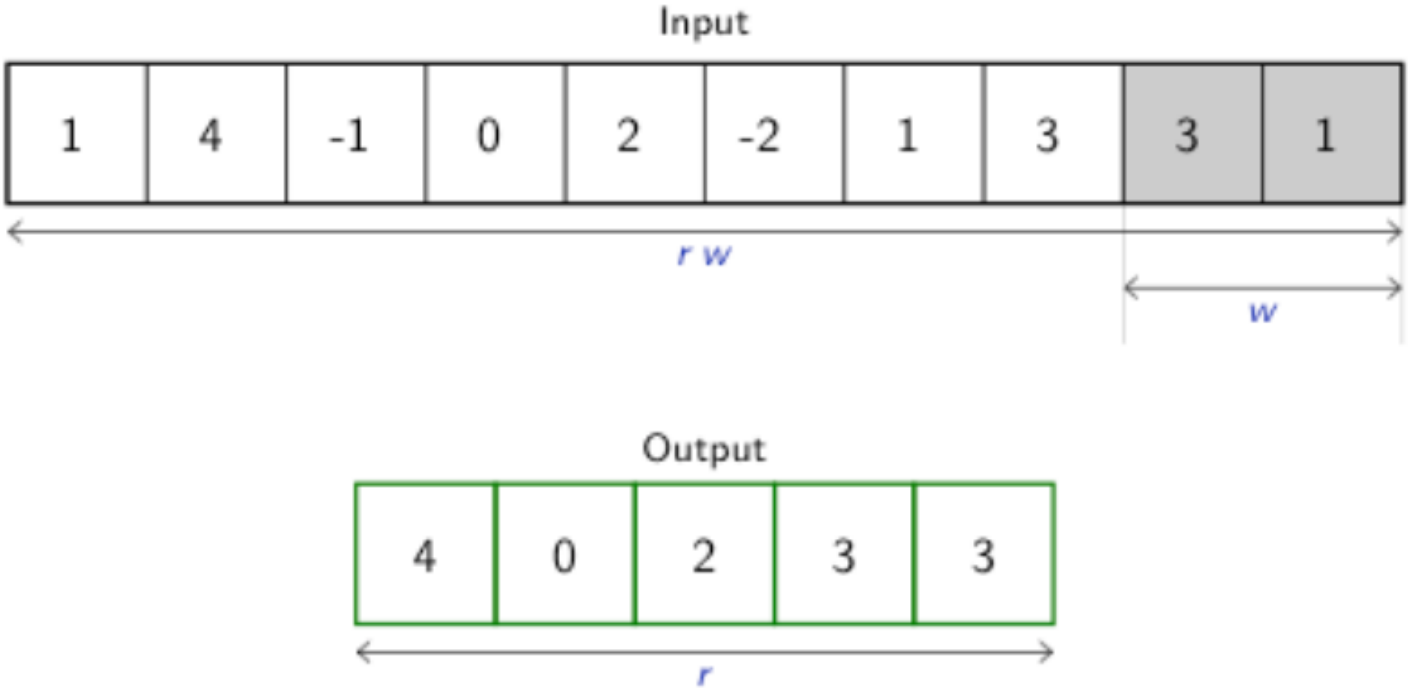
Credit: F. Fleuret

MAX POOLING 1D



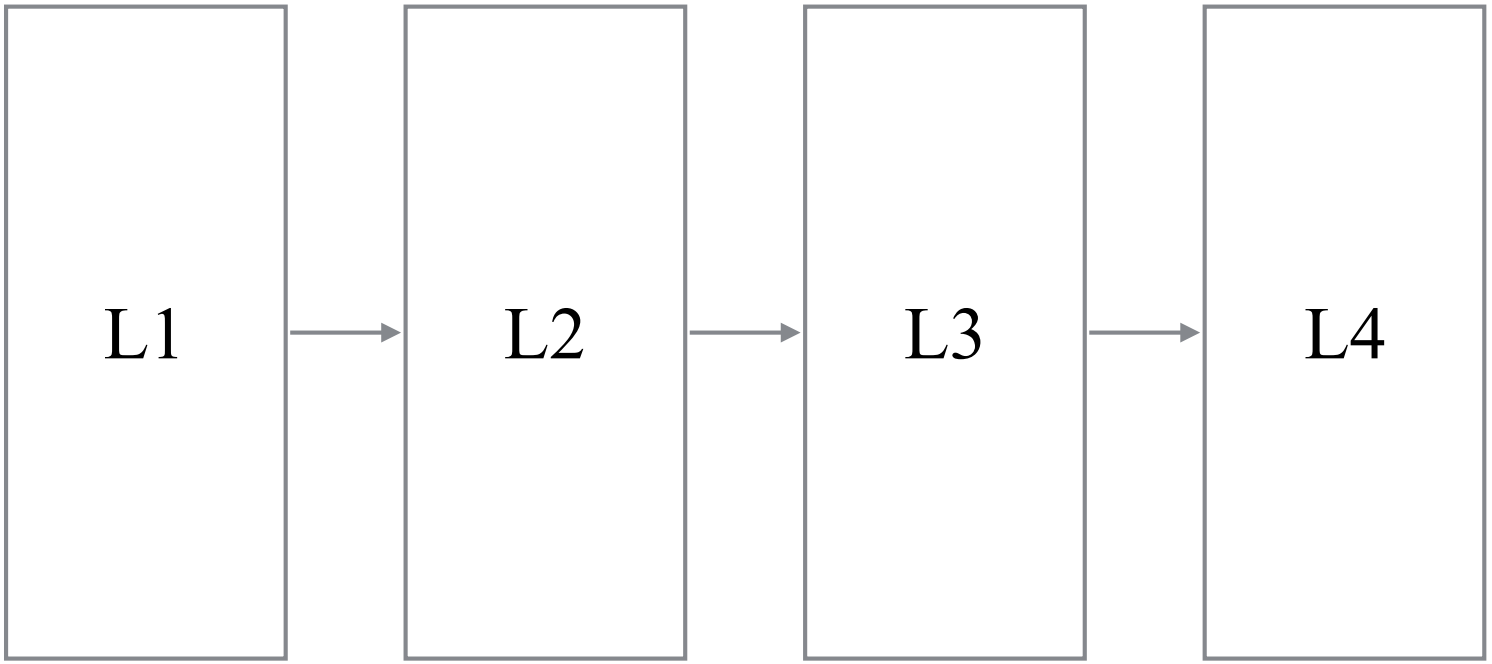
Credit: F. Fleuret

MAX POOLING 1D



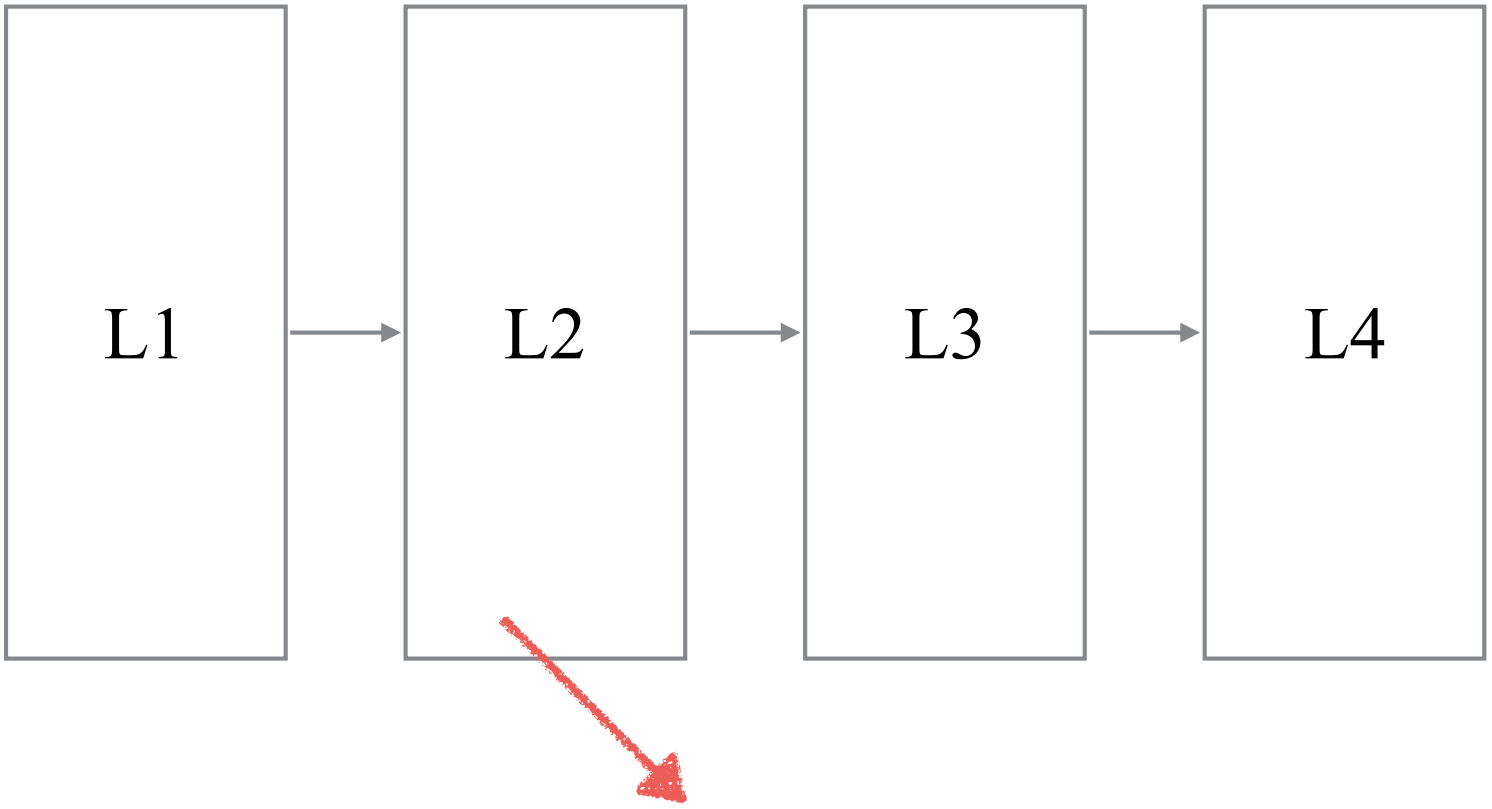
Credit: F. Fleuret

CONVNET OR CNN



A CONCATENATION OF MULTIPLE CONVOLUTIONAL BLOCKS

CONVNET OR CNN

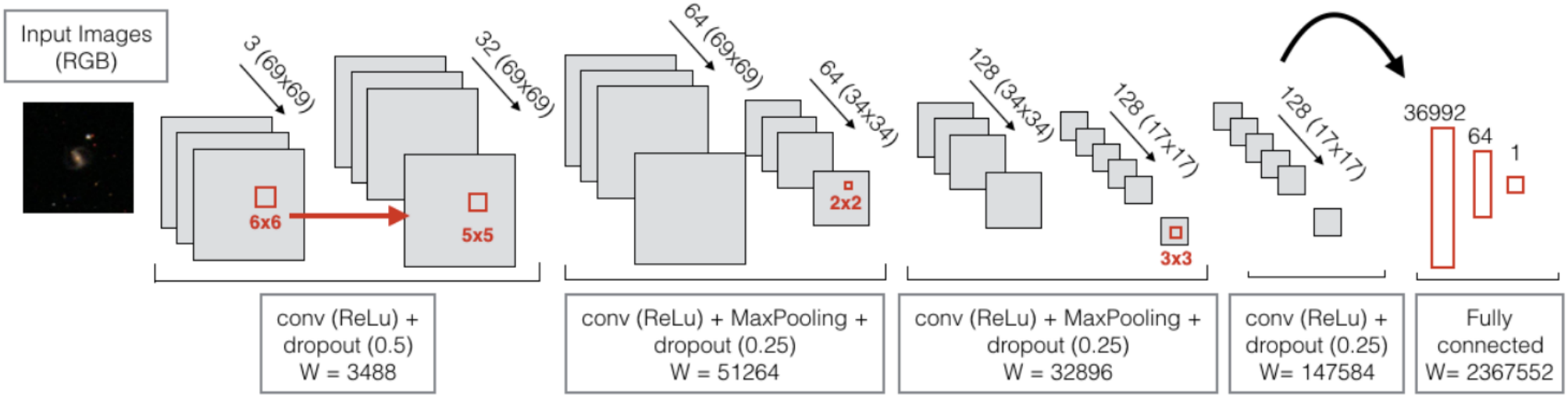


EACH BLOCK TYPICALLY MADE OF:

CONV | ACTIVATION | POOLING

(+dropout for training)

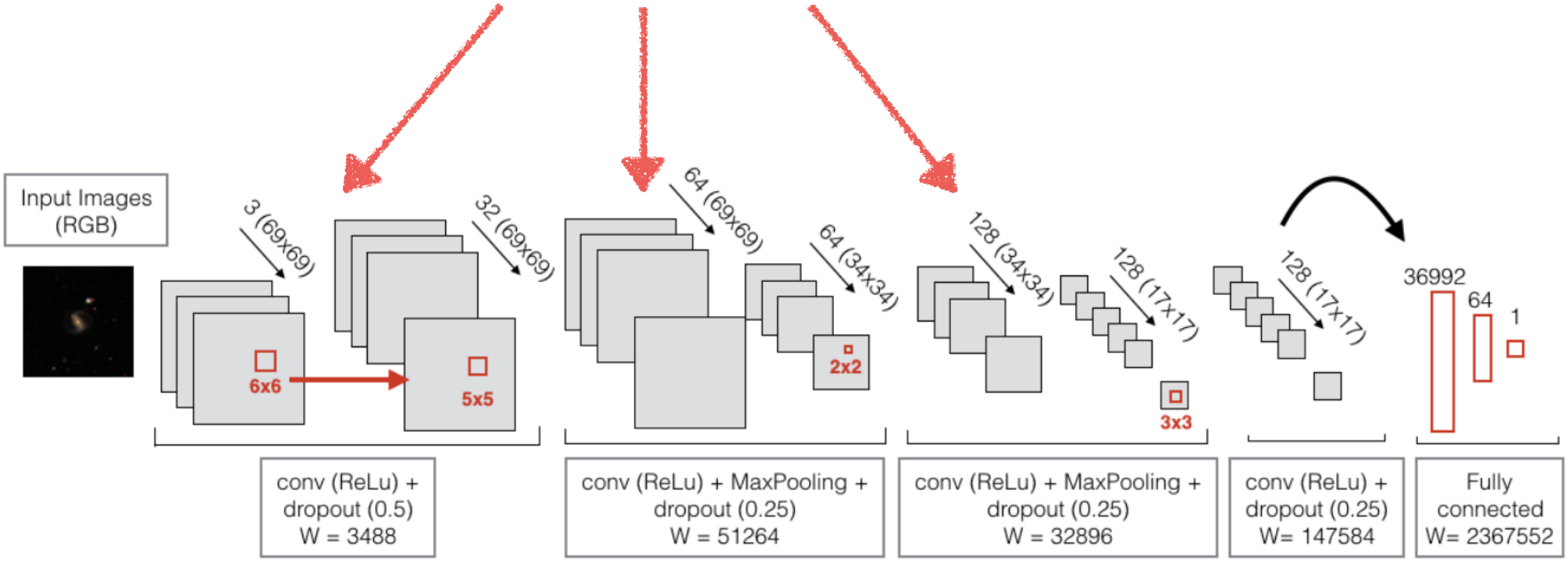
EXAMPLE OF VERY SIMPLE CNN



Dominguez-Sanchez+18

EXAMPLE OF VERY SIMPLE CNN

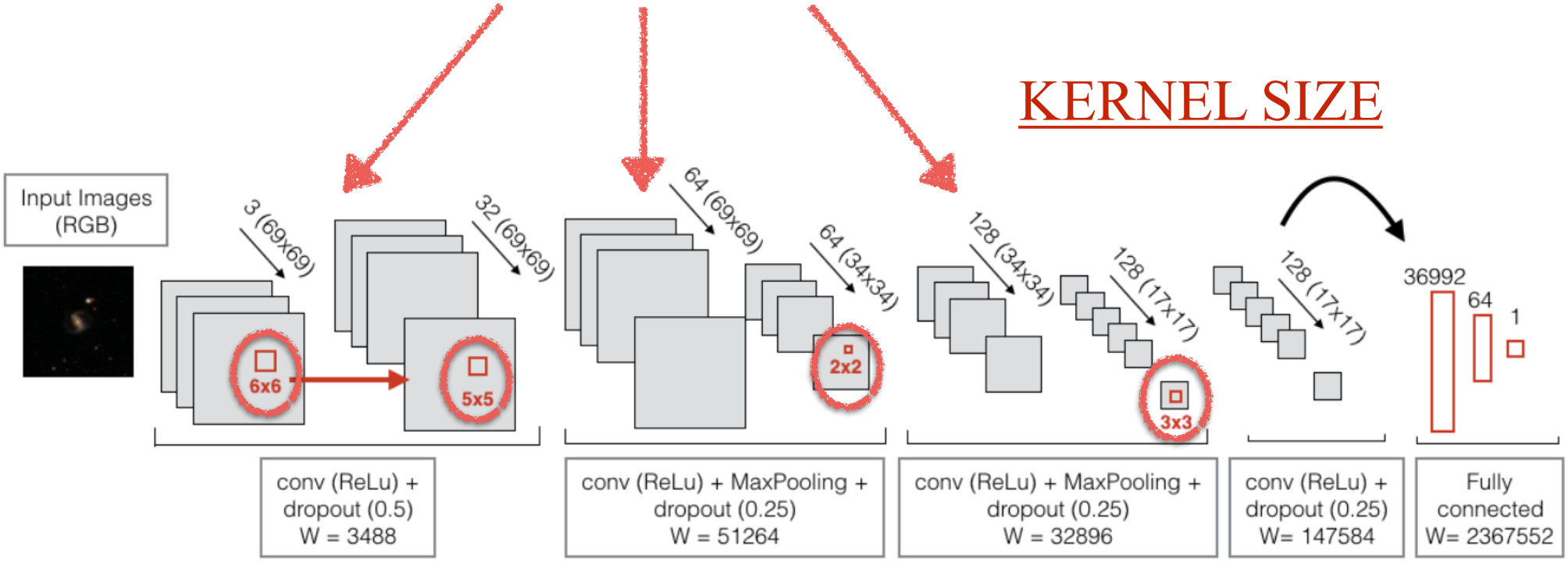
3 convolutional layers



Dominguez-Sanchez+18

EXAMPLE OF VERY SIMPLE CNN

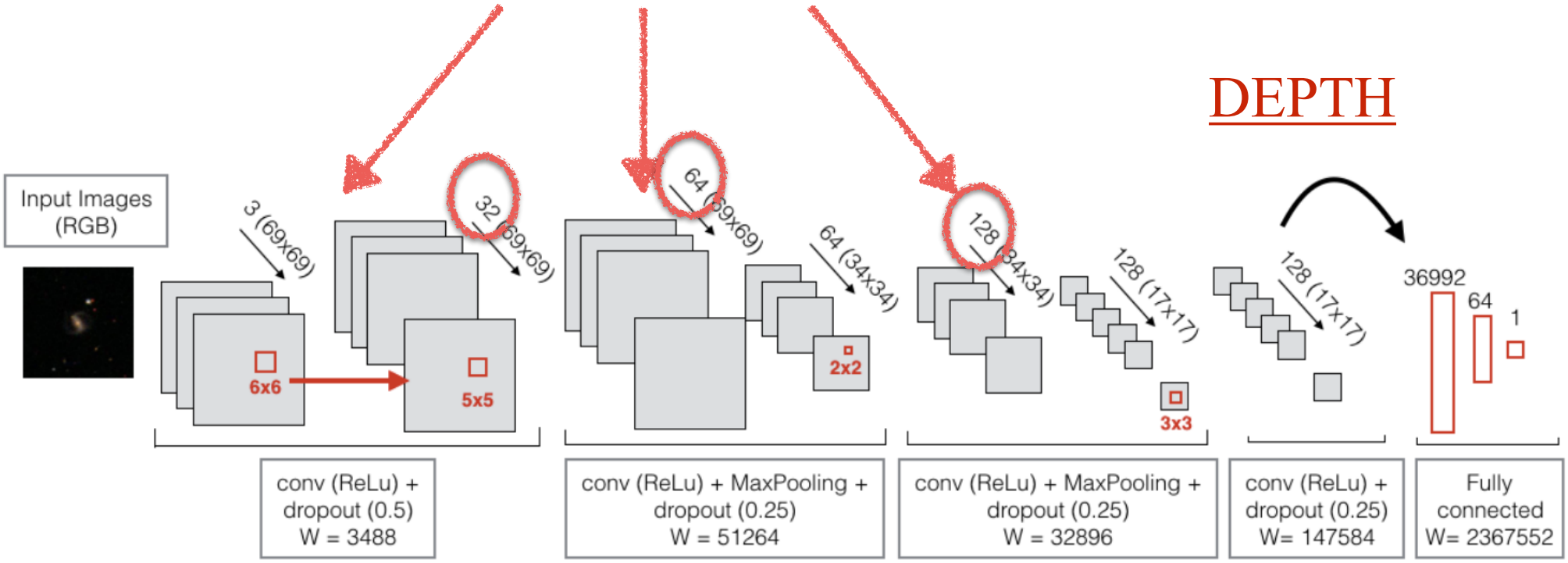
3 convolutional layers



Dominguez-Sanchez+18

EXAMPLE OF VERY SIMPLE CNN

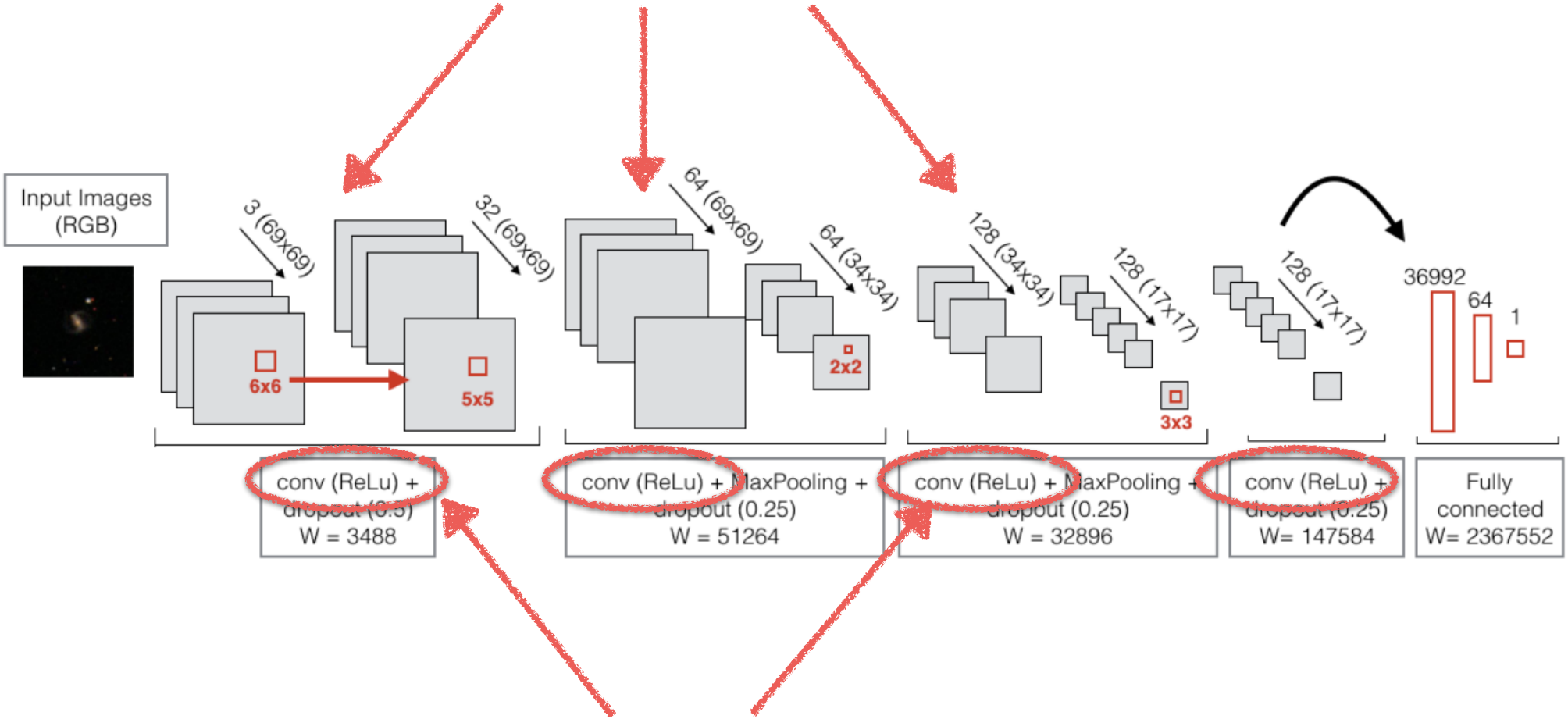
3 convolutional layers



Dominguez-Sanchez+18

EXAMPLE OF VERY SIMPLE CNN

3 convolutional layers

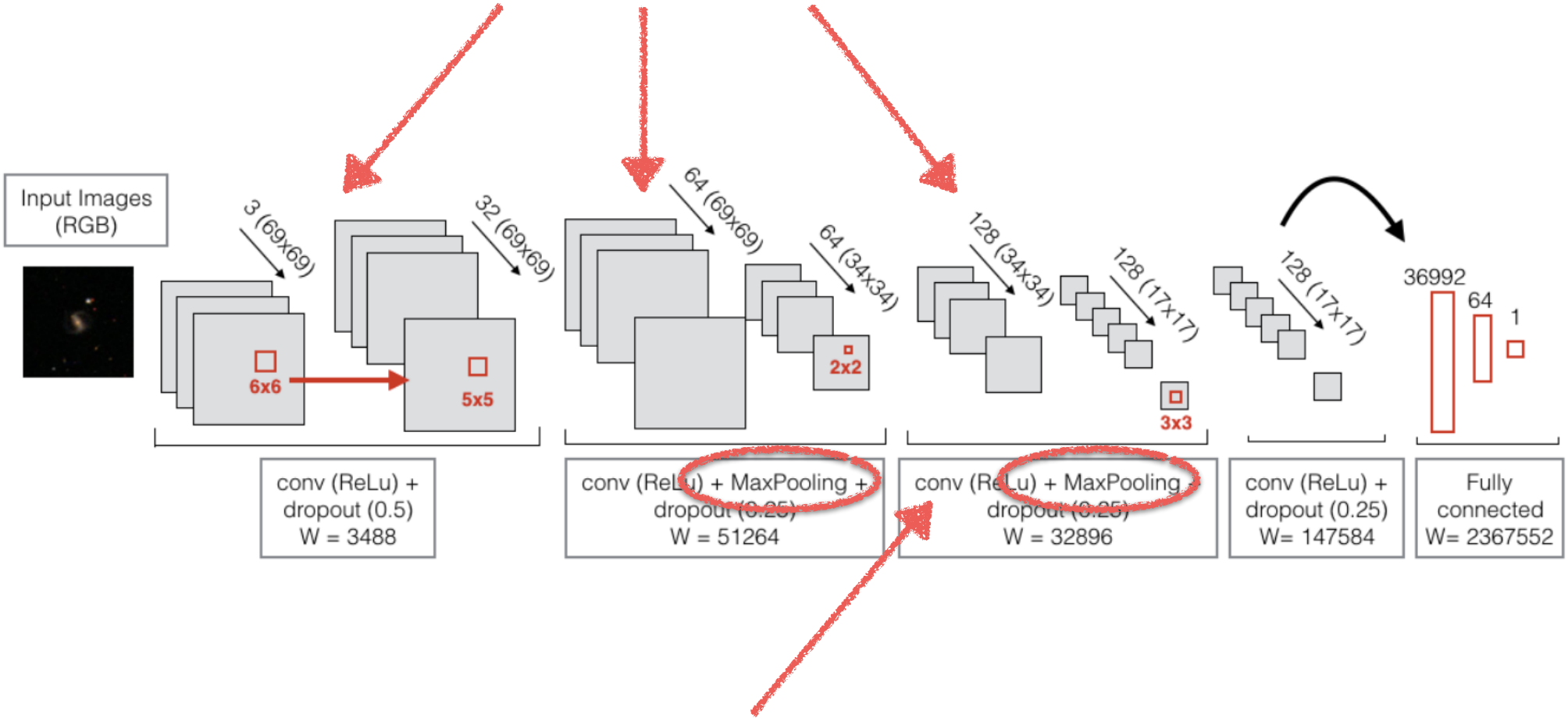


ReLu activation

Dominguez-Sanchez+18

EXAMPLE OF VERY SIMPLE CNN

3 convolutional layers



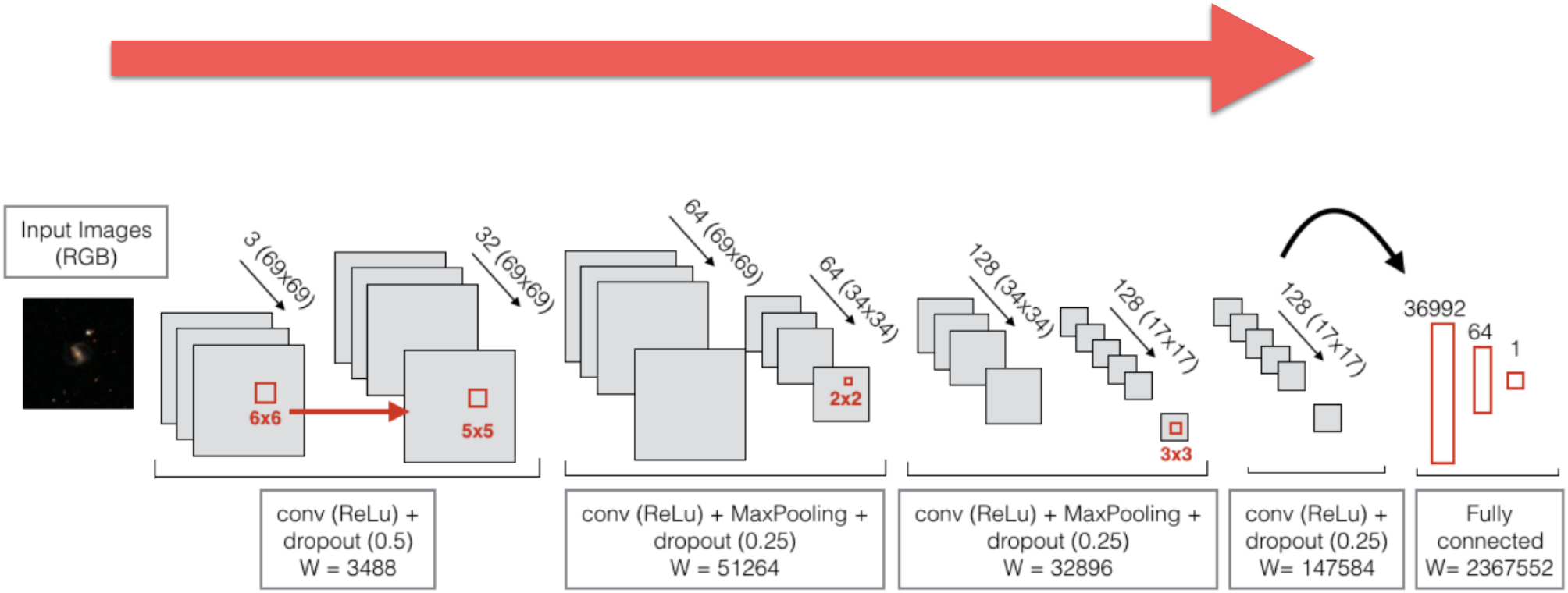
Pooling

Dominguez-Sanchez+18

EXAMPLE OF VERY SIMPLE CNN

OVERALL:

- decrease of tensor size
- increase of depth



Dominguez-Sanchez+18

IMPLEMENTATION IN KERAS

```
#========= Model definition=======

#Convolutional Layers

model = Sequential()
model.add(Convolution2D(32, 6,6, border_mode='same',
                        input_shape=(img_channels, img_rows, img_cols)))
model.add(Activation('relu'))
model.add(Dropout(0.5))

model.add(Convolution2D(64, 5, 5, border_mode='same'))
model.add(Activation('relu'))

model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Convolution2D(128, 2, 2, border_mode='same'))
model.add(Activation('relu'))

model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Convolution2D(128, 3, 3, border_mode='same'))
model.add(Activation('relu'))

model.add(Dropout(0.25))

#Fully Connected start here
#------------------------------#

model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dropout(.5))
model.add(Dense(1, init='uniform', activation='sigmoid'))

print("Compilation...")

model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
```

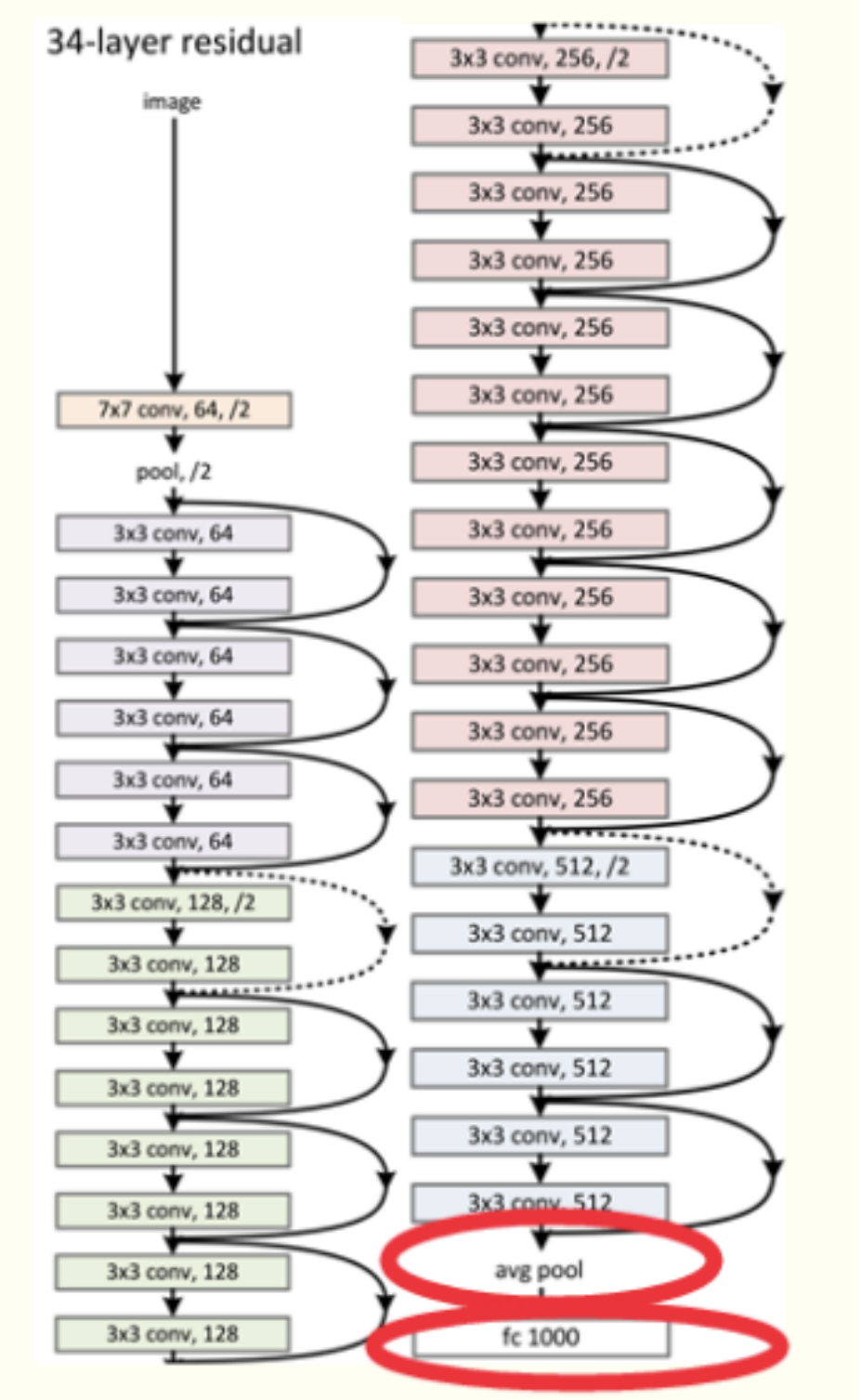
CHECKING THE NUMBER OF PARAMETERS / LAYERS WITH KERAS

model.summary()

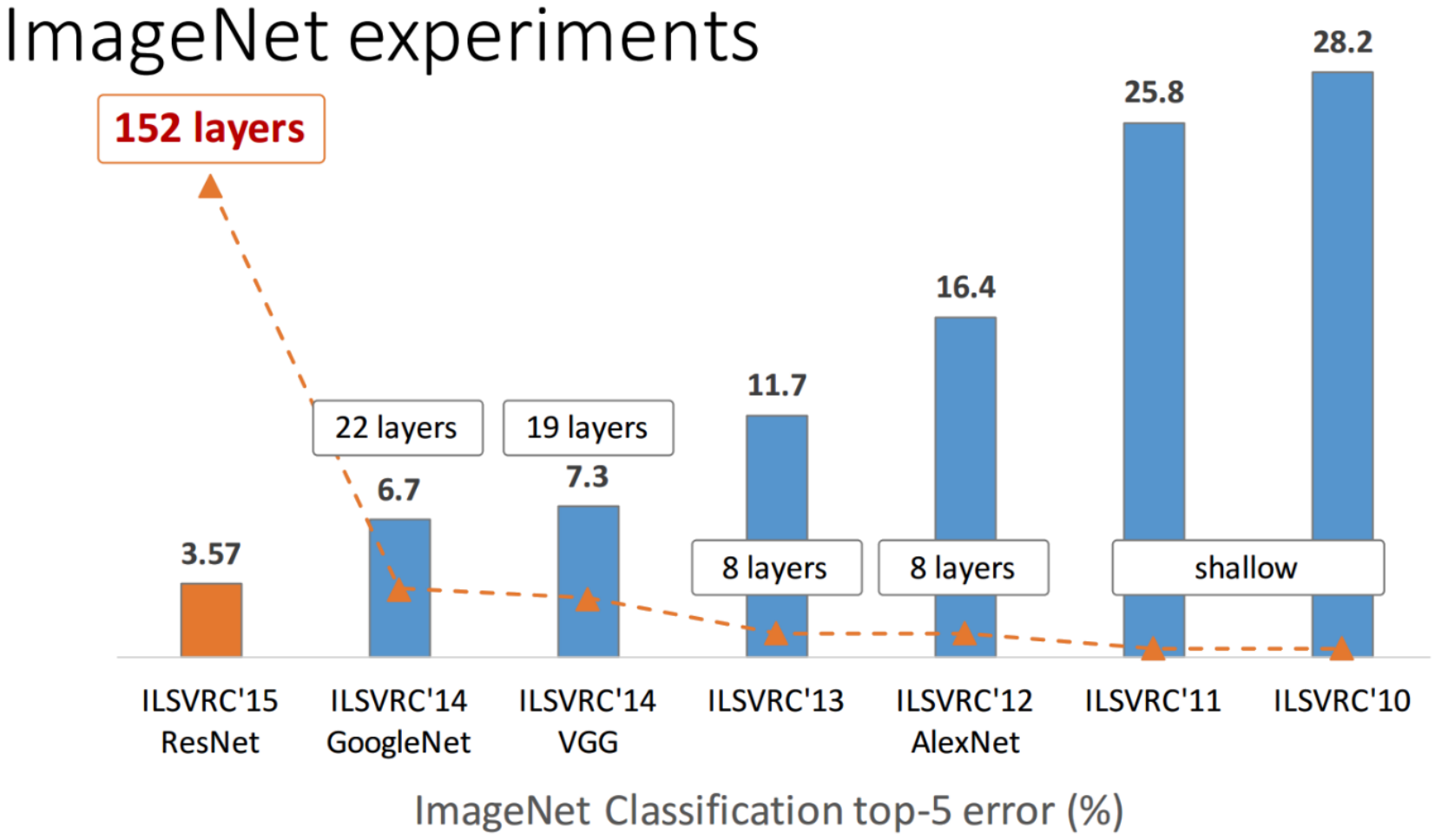
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 1, 16, 112, 112)   0
_________________________________________________________________
conv3d_1 (Conv3D)            (None, 16, 16, 112, 112)  448
_________________________________________________________________
batch_normalization_1 (Batch (None, 16, 16, 112, 112)  448
_________________________________________________________________
activation_1 (Activation)    (None, 16, 16, 112, 112)  0
_________________________________________________________________
max_pooling3d_1 (MaxPooling3 (None, 16, 8, 56, 56)     0
_________________________________________________________________
conv3d_2 (Conv3D)            (None, 32, 8, 56, 56)     13856
_________________________________________________________________
batch_normalization_2 (Batch (None, 32, 8, 56, 56)     224
_________________________________________________________________
activation_2 (Activation)    (None, 32, 8, 56, 56)     0
_________________________________________________________________
max_pooling3d_2 (MaxPooling3 (None, 32, 4, 28, 28)     0
_________________________________________________________________
conv3d_3 (Conv3D)            (None, 64, 4, 28, 28)     55360
_________________________________________________________________
batch_normalization_3 (Batch (None, 64, 4, 28, 28)     112
_________________________________________________________________
activation_3 (Activation)    (None, 64, 4, 28, 28)     0
_________________________________________________________________
max_pooling3d_3 (MaxPooling3 (None, 64, 2, 14, 14)     0
_________________________________________________________________
activation_12 (Activation)   (None, 64, 2, 14, 14)     0
=================================================================
Total params: 70,448
Trainable params: 70,056
Non-trainable params: 392
_________________________________________________________________
```

IN THE REAL LIFE…

RESNET



DEEPER TENDS TO BE BETTER…

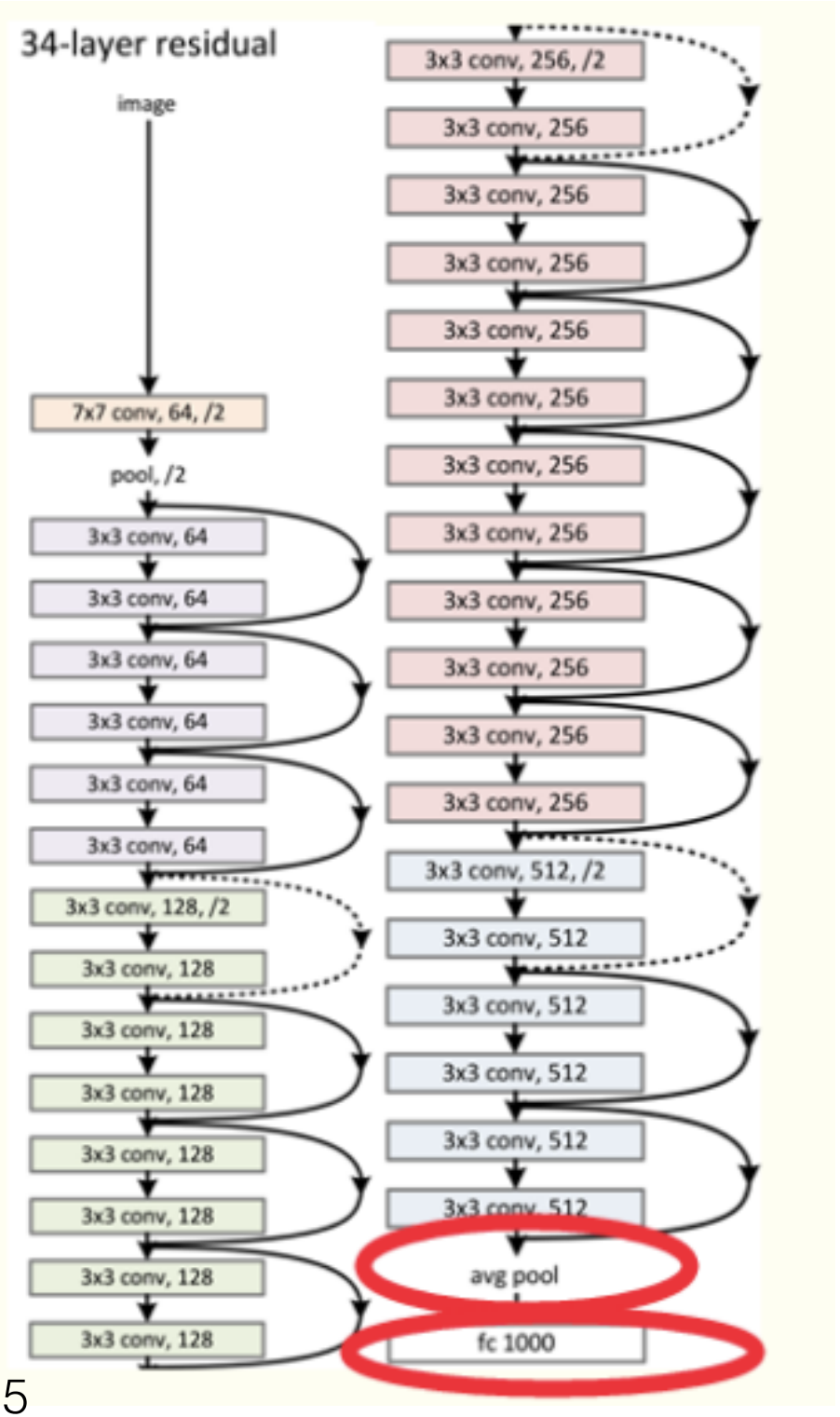


IN THE REAL LIFE…

RESNET

DO WE NEED TO GO THIS DEEP FOR ASTRONOMY APPLICATIONS?

[34 layers - authors explored up to 1202!]



He+15

THE PROBLEMS OF GOING TOO DEEP…

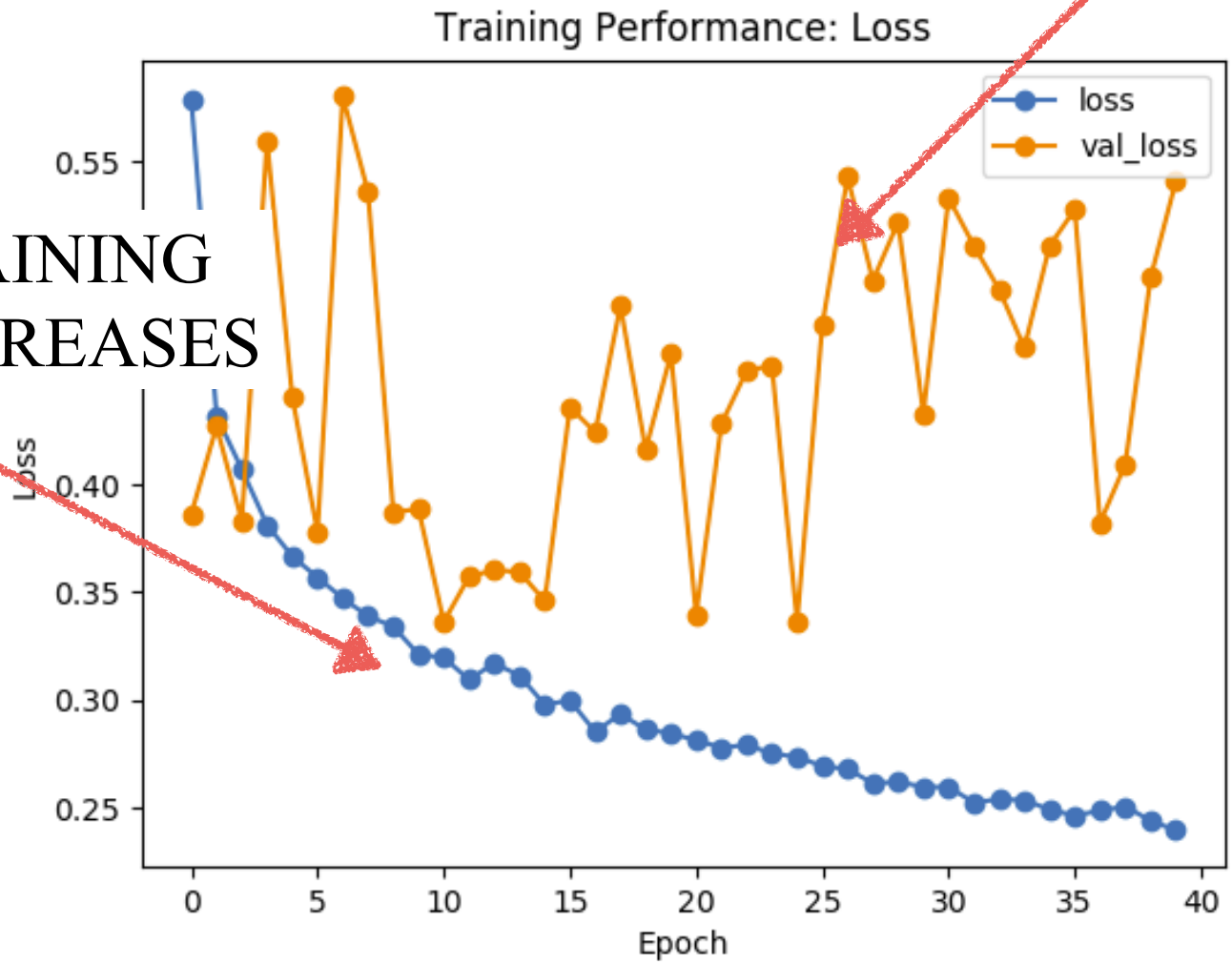
THE PROBLEMS OF GOING “TOO DEEP”

- DEEP NETWORKS ARE MORE DIFFICULT TO OPTIMIZE
- NEED MORE DATA - MORE SUBJECT TO OVER-FITTING
- AND ALSO NEED MORE TIME …

OVER-FITTING

THE TEST STAYS CONSTANT OR INCREASES

THE TRAINING LOSS DECREASES

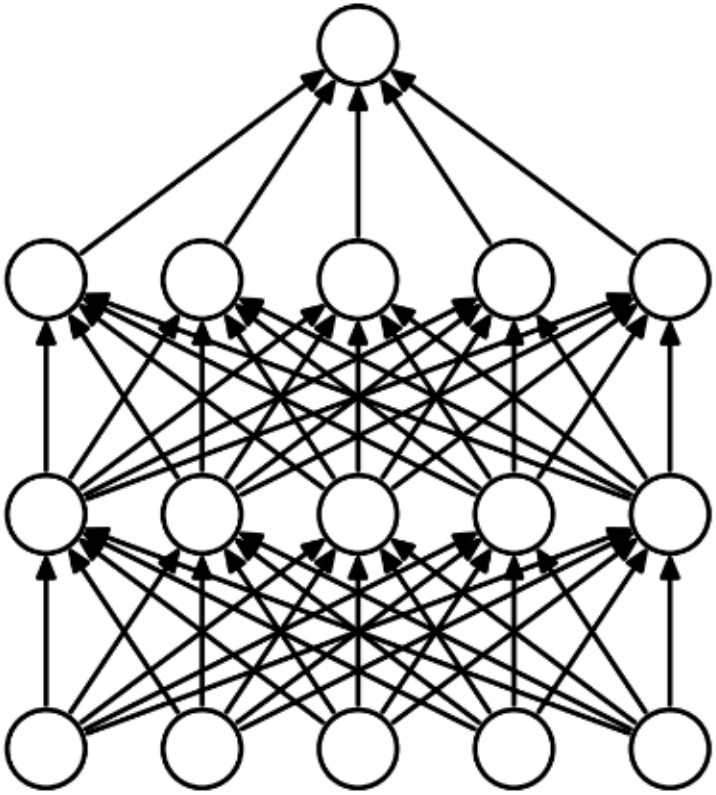


DROPOUT

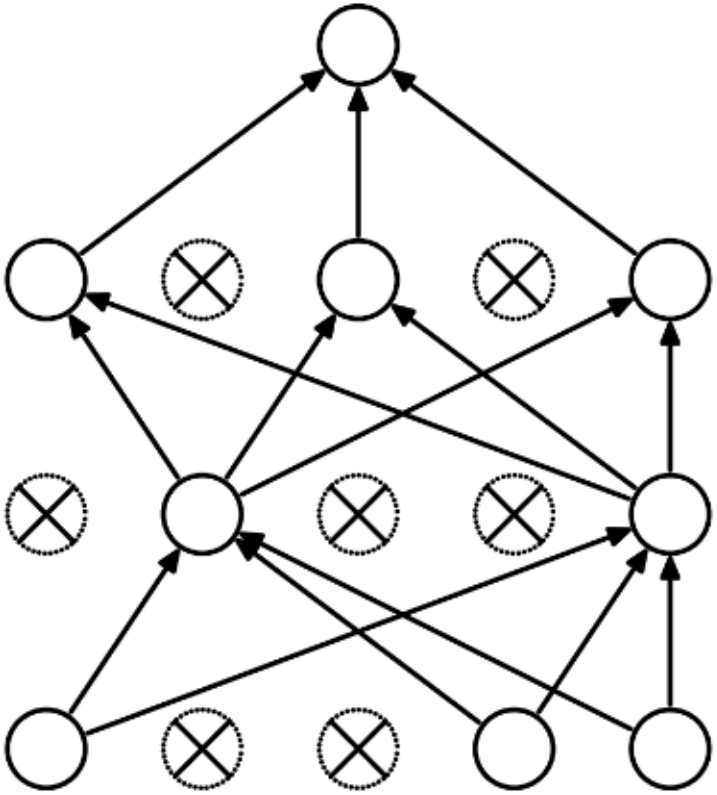
[Hinton+12]

- THE IDEA IS TO REMOVE NEURONS RANDOMLY DURING THE TRAINING

- ALL NEURONS ARE PUT BACK DURING THE TEST PHASE



(a) Standard Neural Net



(b) After applying dropout.

DROPOUT

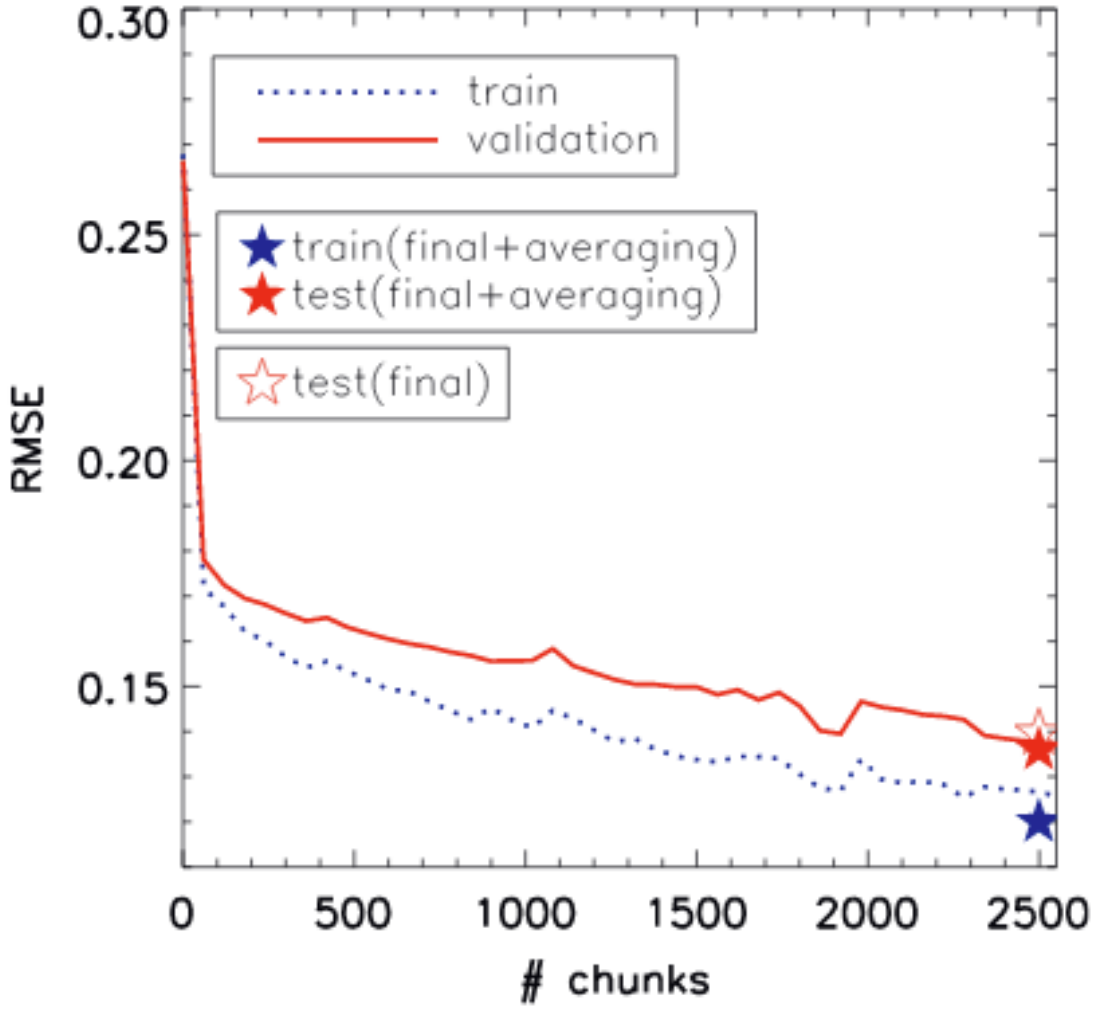
WHY DOES IT WORK?

1. SINCE NEURONS ARE REMOVED RANDOMLY, IT AVOIDS CO-ADAPTATION AMONG THEMSELVES

2. DIFFERENT SETS OF NEURONS WHICH ARE SWITCHED OFF, REPRESENT A DIFFERENT ARCHITECTURE AND ALL THESE DIFFERENT ARCHITECTURES ARE TRAINED IN PARALLEL. FOR N NEURONS ATTACHED TO DROPOUT, THE NUMBER OF SUBSET ARCHITECTURES FORMED IS 2^N. SO IT AMOUNTS TO PREDICTION BEING AVERAGED OVER THESE ENSEMBLES OF MODELS.

DROPOUT

WITH A LITTLE BIT
OF DROPOUT



Huertas-Company+15

IMPLEMENTATION IN KERAS / TENSORFLOW

```
#========= Model definition=======

#Convolutional Layers

model = Sequential()
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                        input_shape=(img_channels, img_rows, img_cols)))
model.add(Activation('relu'))
model.add(Dropout(0.5))

model.add(Convolution2D(64, 5, 5, border_mode='same'))
model.add(Activation('relu'))

model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Convolution2D(128, 2, 2, border_mode='same'))
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model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dropout(.5))
model.add(Dense(1, init='uniform', activation='sigmoid'))

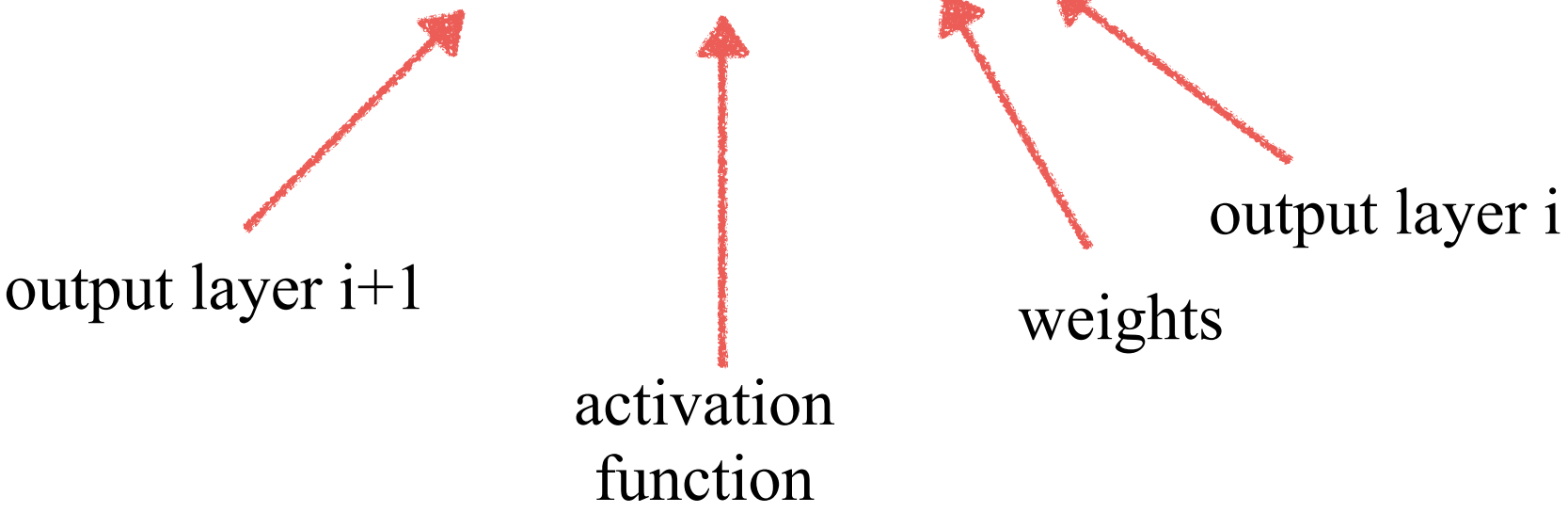
print("Compilation...")

model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
```

VANISHING / EXPLODING GRADIENT PROBLEM

REMEMBER THAT:

$$y_{i+1} = \sigma[\sum w_i y_i]$$

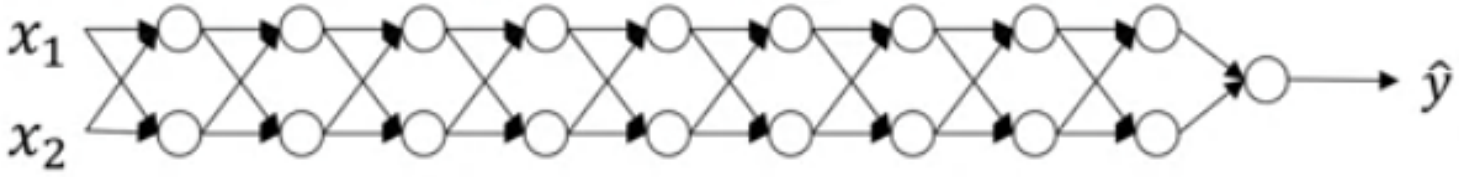


VANISHING / EXPLODING GRADIENT PROBLEM

WITH MANY LAYERS:

$$y_n = \sigma\left(...\sigma\left(...\sigma\left(\sum w_0 x\right)\right)\right)$$

VANISHING/EXPLODING GRADIENT PROBLEM



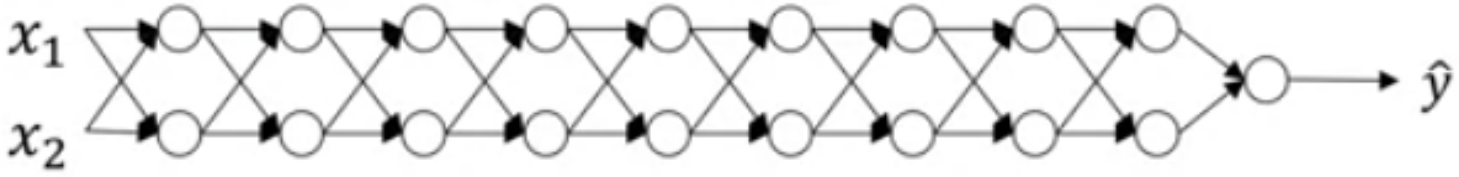
IF WE ASSUME AN IDENTITY ACTIVATION FUNCTION:

$$\hat{y} = x \prod_n w_i$$

with:

$$w_i = \begin{pmatrix} w_i^0 & 0 \\ 0 & w_i^1 \end{pmatrix} \qquad x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

VANISHING/EXPLODING GRADIENT PROBLEM



$$w_i = \begin{pmatrix} w_i^0 & 0 \\ 0 & w_i^1 \end{pmatrix} \qquad \hat{y} = x \prod_n w_i$$

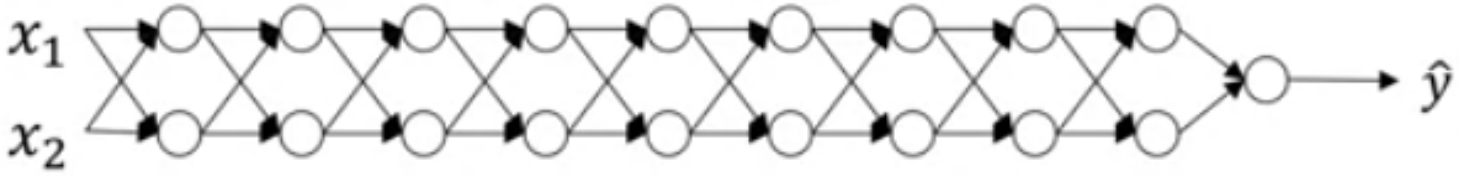
$$x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

IF WEIGHTS ARE ALL INITIALIZED TO VALUES <<1:

$$w_i^L \to 0$$

VANISHING GRADIENT

VANISHING/EXPLODING GRADIENT PROBLEM



$$w_i = \begin{pmatrix} w_i^0 & 0 \\ 0 & w_i^1 \end{pmatrix} \qquad \hat{y} = x \prod_n w_i$$

$$x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

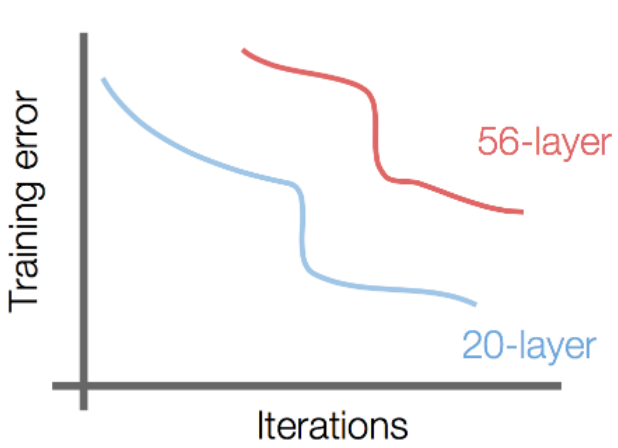
IF WEIGHTS ARE ALL INITIALIZED TO VALUES >1:

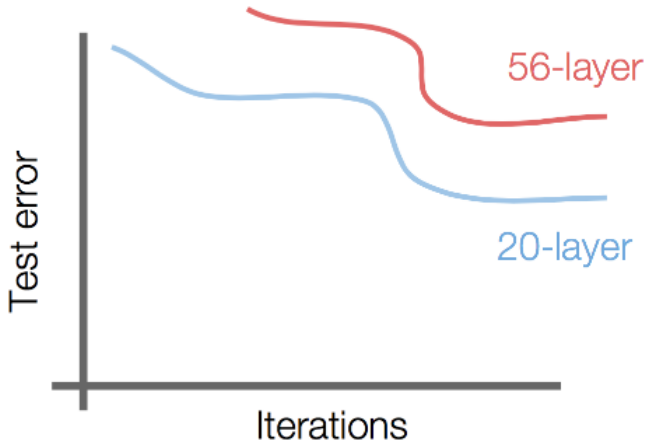
$$w_i^L \to \infty$$

EXPLODING GRADIENT

VANISHING/EXPLODING GRADIENT PROBLEM

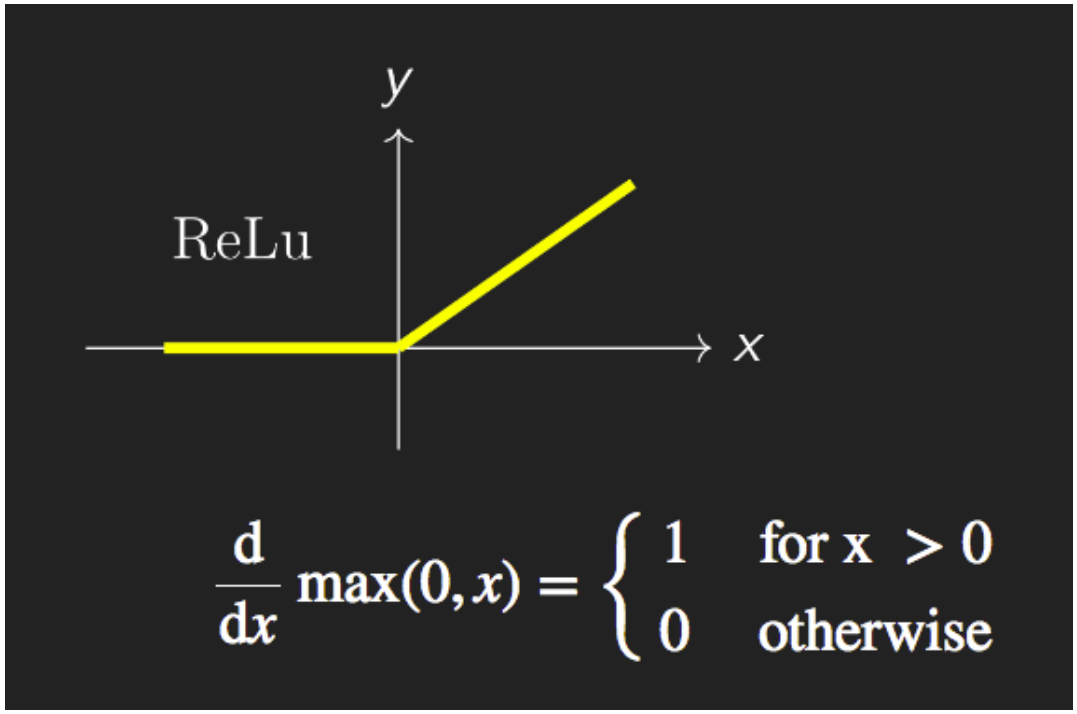
TRAINING BECOMES UNSTABLE
VERY SLOW OR NO CONVERGENCE





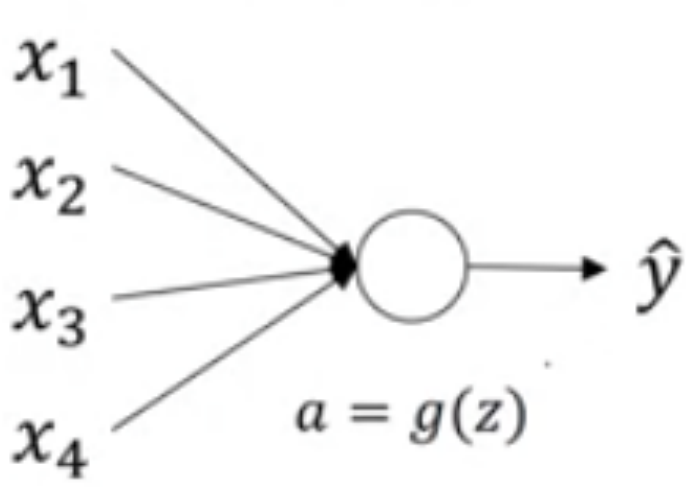
VANISHING GRADIENT PROBLEM

THE ReLU ACTIVATION FUNCTION HELPS PREVENTING VANISHING GRADIENTS



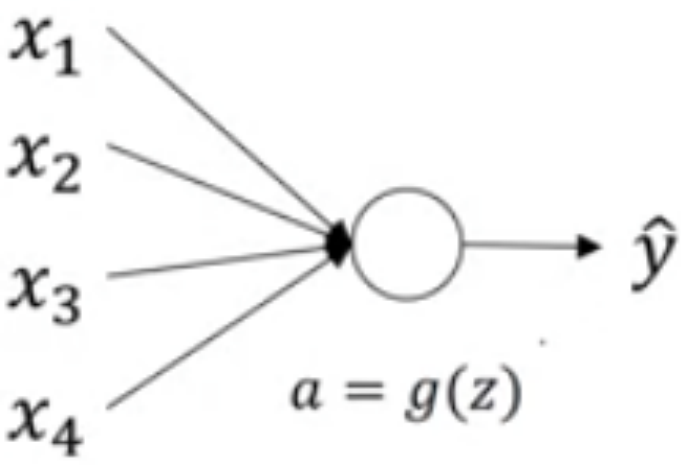
MOST WIDELY USED IN DEEP NETWORKS

WEIGHT INITIALIZATION IS A KEY POINT…



$$z = x_1 w_1 + x_2 w_2 + \ldots + x_n w_n$$

WEIGHT INITIALIZATION IS A KEY POINT…



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THE LARGER n, THE SMALLER WEIGHTS SHOULD BE…

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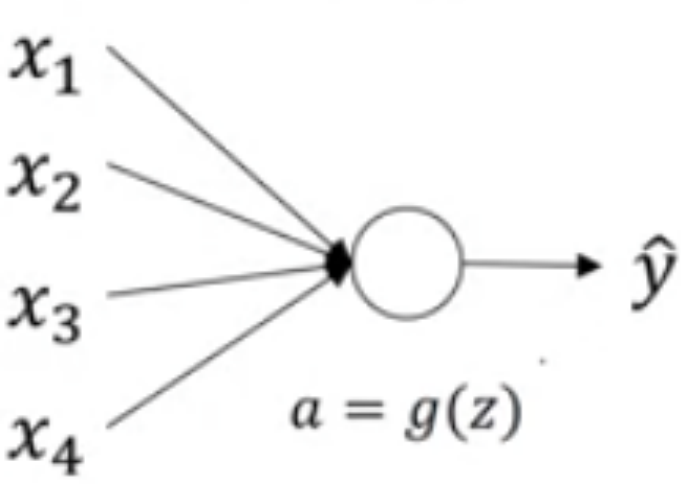

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variance

ONE SIMPLE SOLUTION: $\sigma^2(w_i) = \frac{1}{n}$ ← number of inputs

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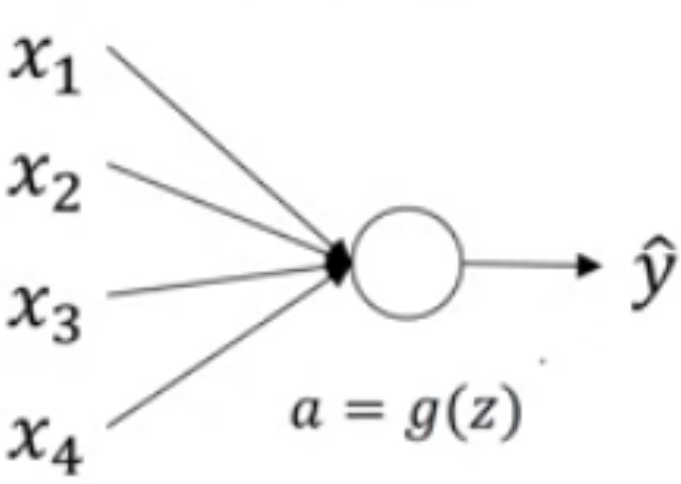

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WEIGHT INITIALIZATION IS A KEY POINT…

For ReLU activation functions we typically use:

$$\sigma^2(w_i) = \frac{2}{n}$$

[He initialization, He+15]

WEIGHT INITIALIZATION IS A KEY POINT…

IMPLEMENTATION IN KERAS:

```
initialization = 'he_normal'
act = 'relu'

model = Sequential()
model.add(Convolution2D(depth, conv_size, conv_size, activation=act, border_mode='same',
name = "conv%i"%(layer_n), init=initialization, W_constraint=constraint))
```

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```

MANY OTHER INITIALIZATIONS AVAILABLE:

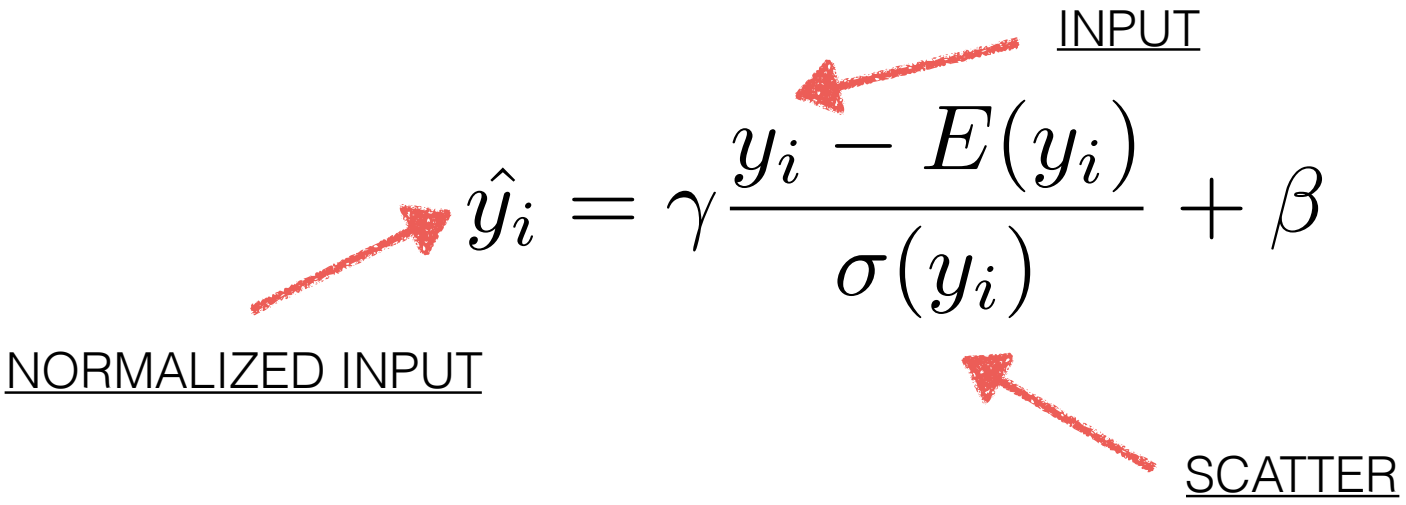
`keras.initializers` → https://keras.io/initializers/

BATCH NORMALIZATION

[SZEGEDY+15]

ANOTHER SOLUTION TO KEEP REASONABLE VALUES OF THE ACTIVATIONS IN DEEP NETWORKS

BATCH NORMALIZATION PREVENTS LOW OR LARGE VALUES BY RE-NORMALIZING THE VALUES BEFORE ACTIVATION FOR EVERY BATCH



BATCH NORMALIZATION

[SZEGEDY+15]

BATCH NORMALIZATION SPEEDS UP AND STABILIZES TRAINING

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

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

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

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

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

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

BATCH NORMALIZATION

[SZEGEDY+15]

IN KERAS, IT IS IMPLEMENTED AS AN ADDITIONAL LAYER

BatchNormalization [source]

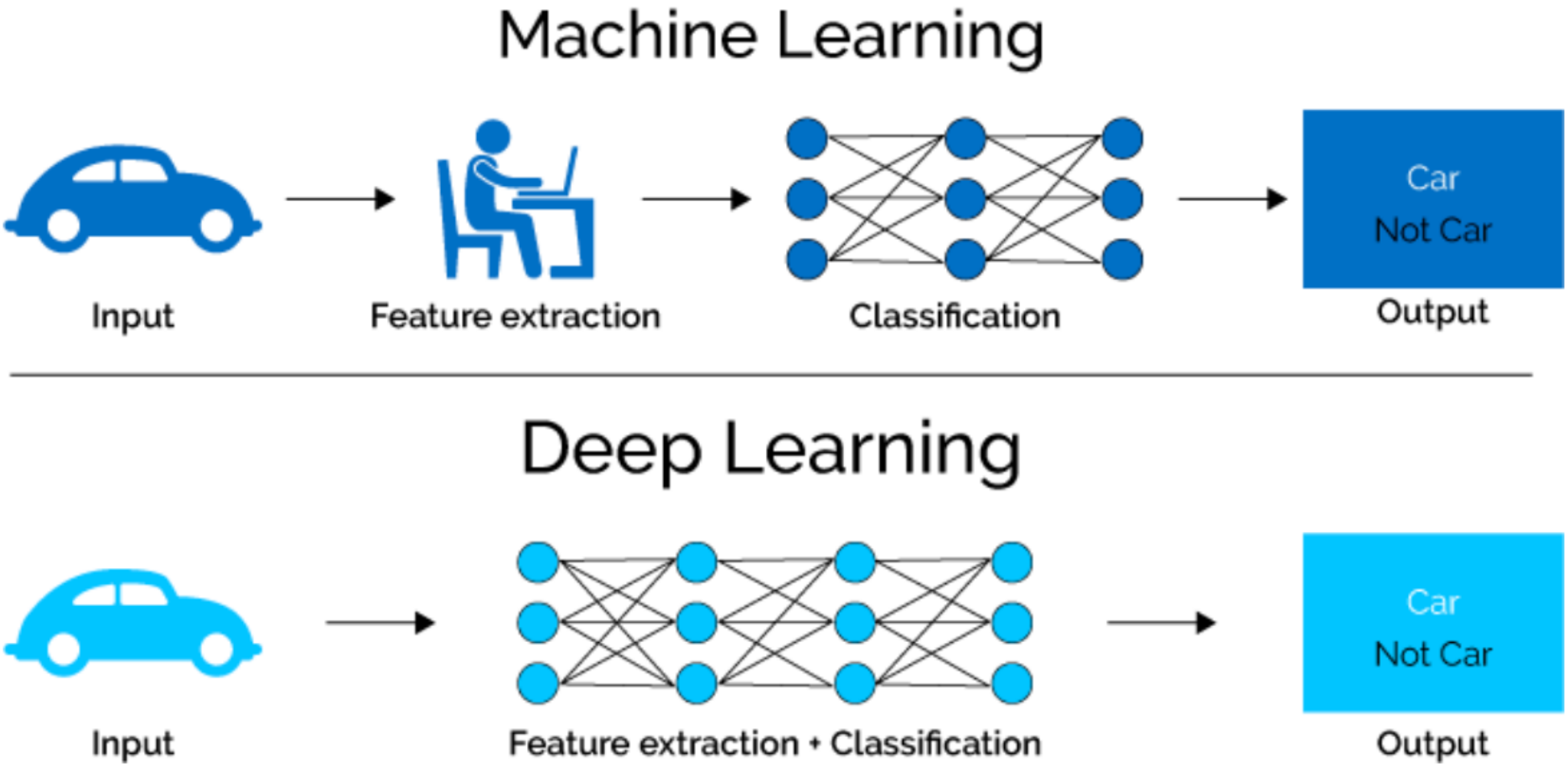
```
keras.layers.BatchNormalization(axis=-1, momentum=0.99, epsilon=0.001, center=True, scale=True, beta_initializer
```

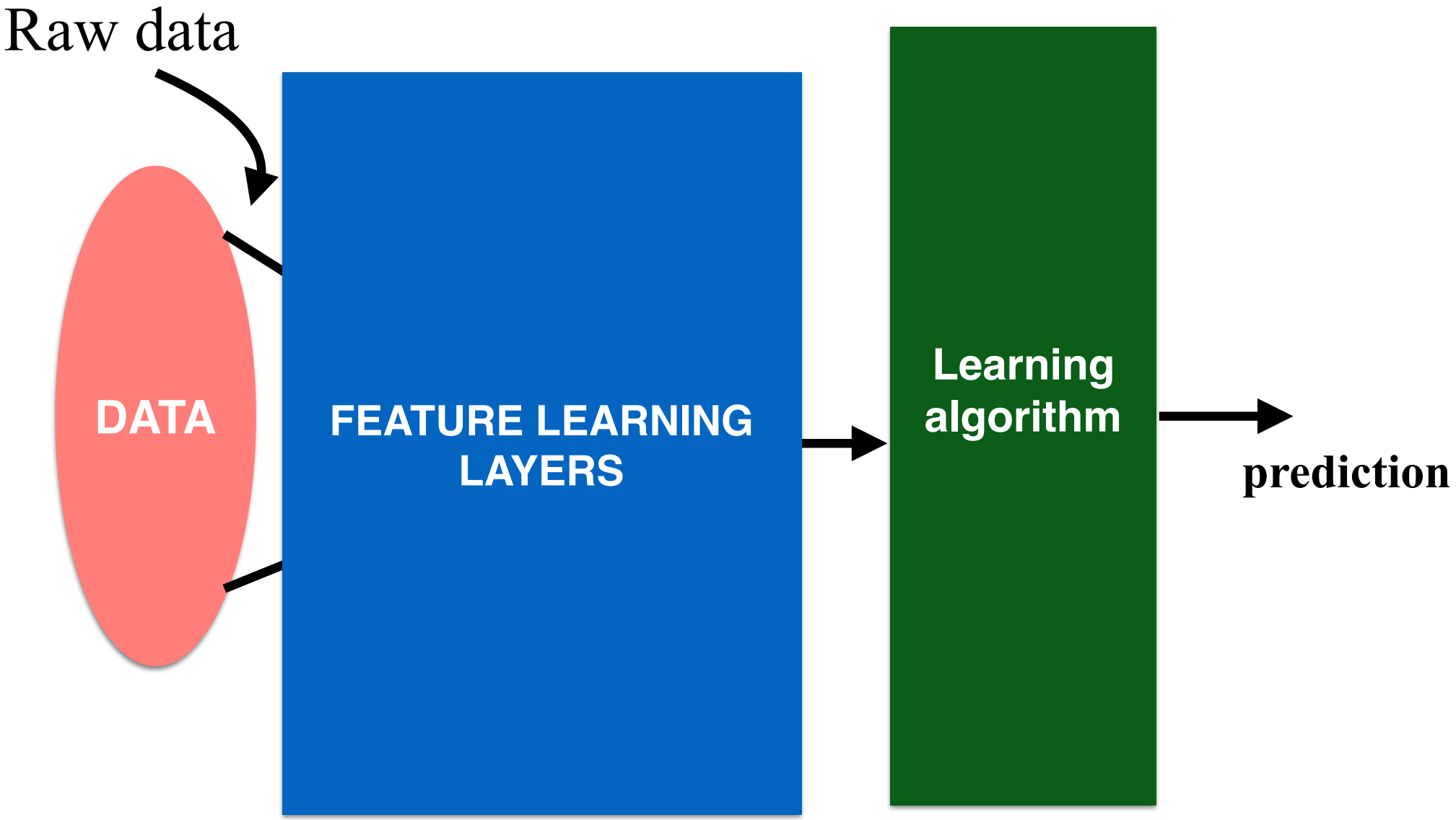
Batch normalization layer (Ioffe and Szegedy, 2014).

Normalize the activations of the previous layer at each batch, i.e. applies a transformation that maintains the mean activation close to 0 and the activation standard deviation close to 1.

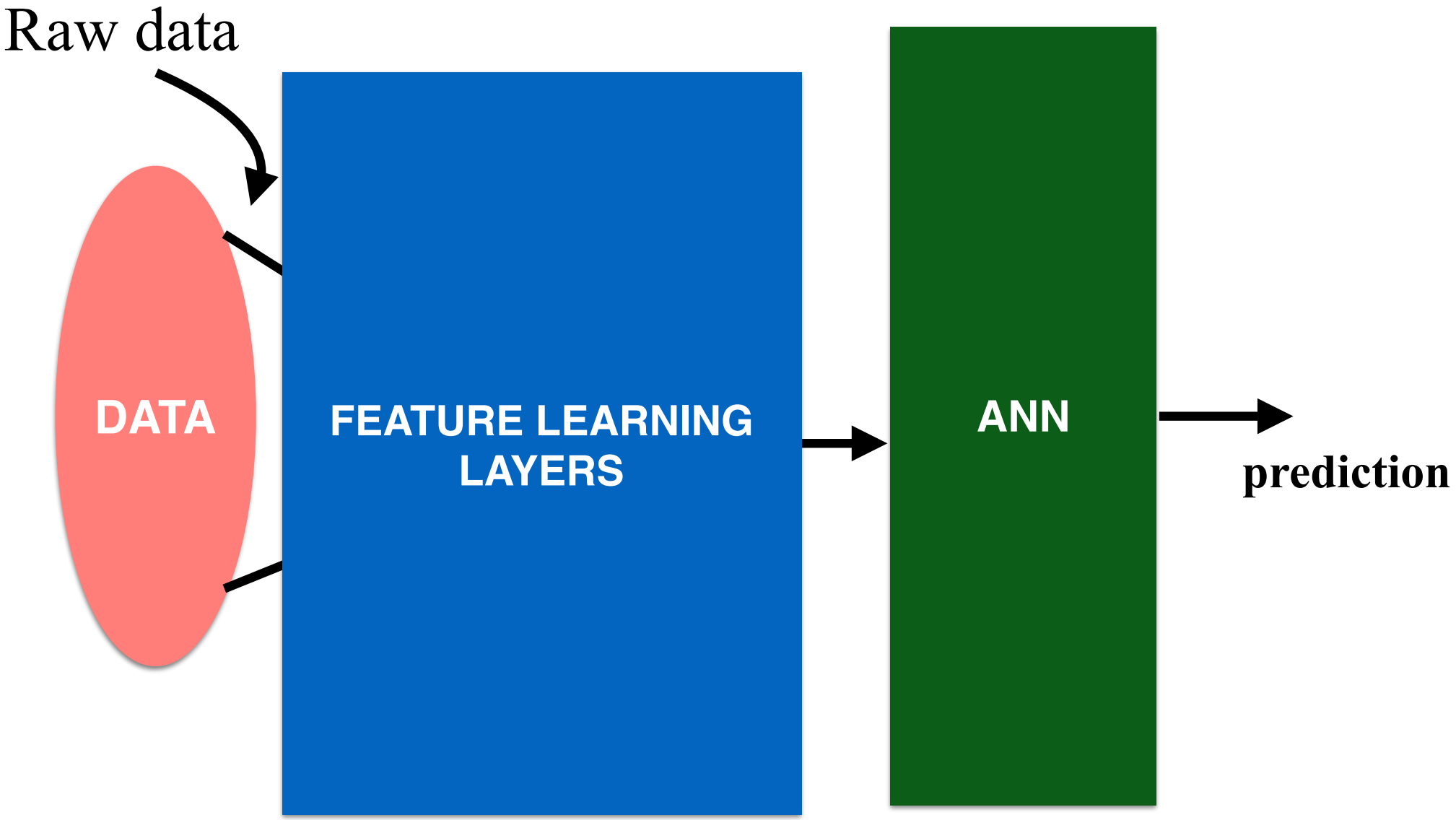
Arguments

THIS IS A CHANGE OF PARADIGM!




Raw data
DATA
FEATURE LEARNING LAYERS
Learning algorithm
prediction

THE LEARNING ALGORITHM CAN BE CHANGED



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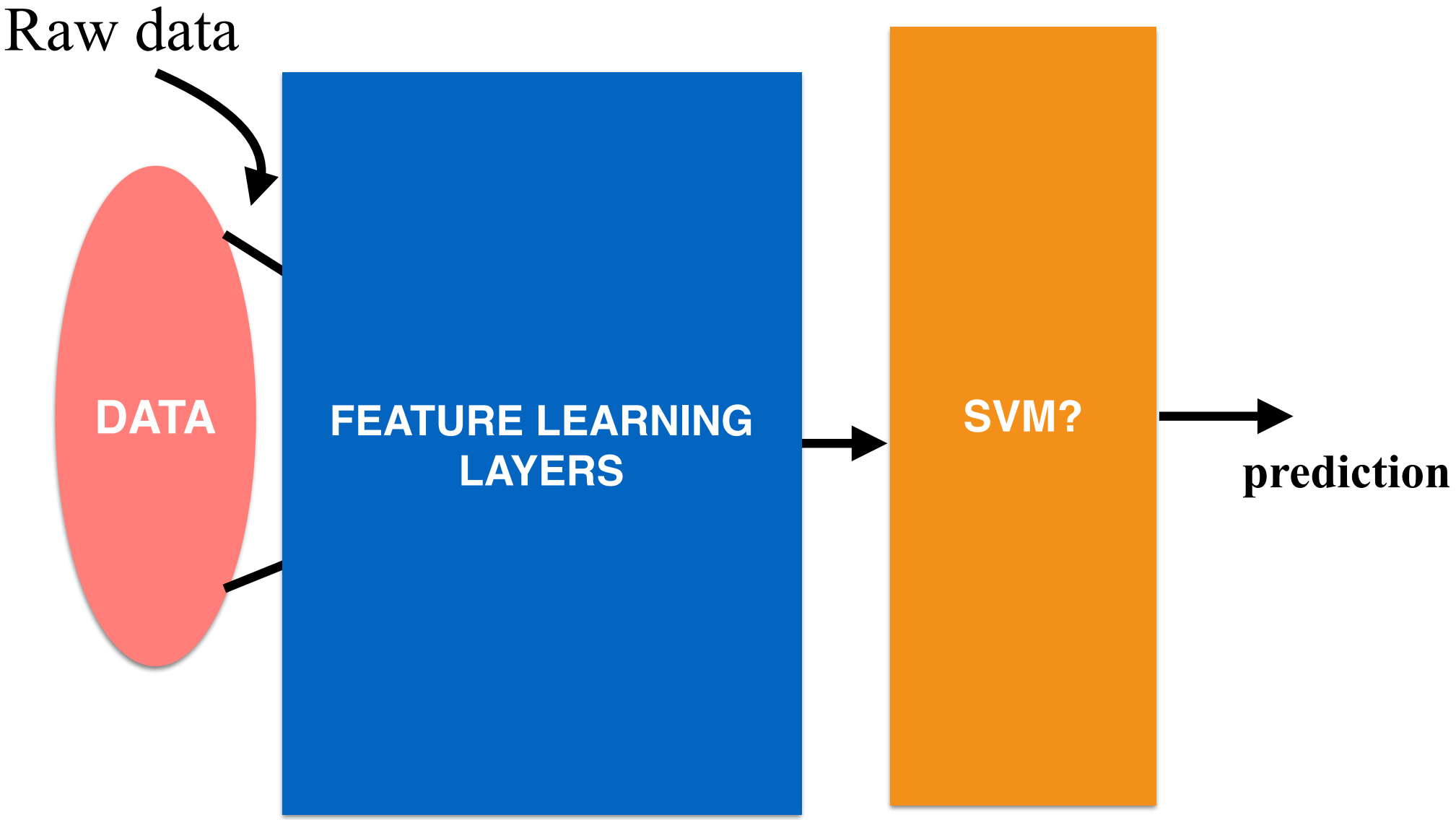

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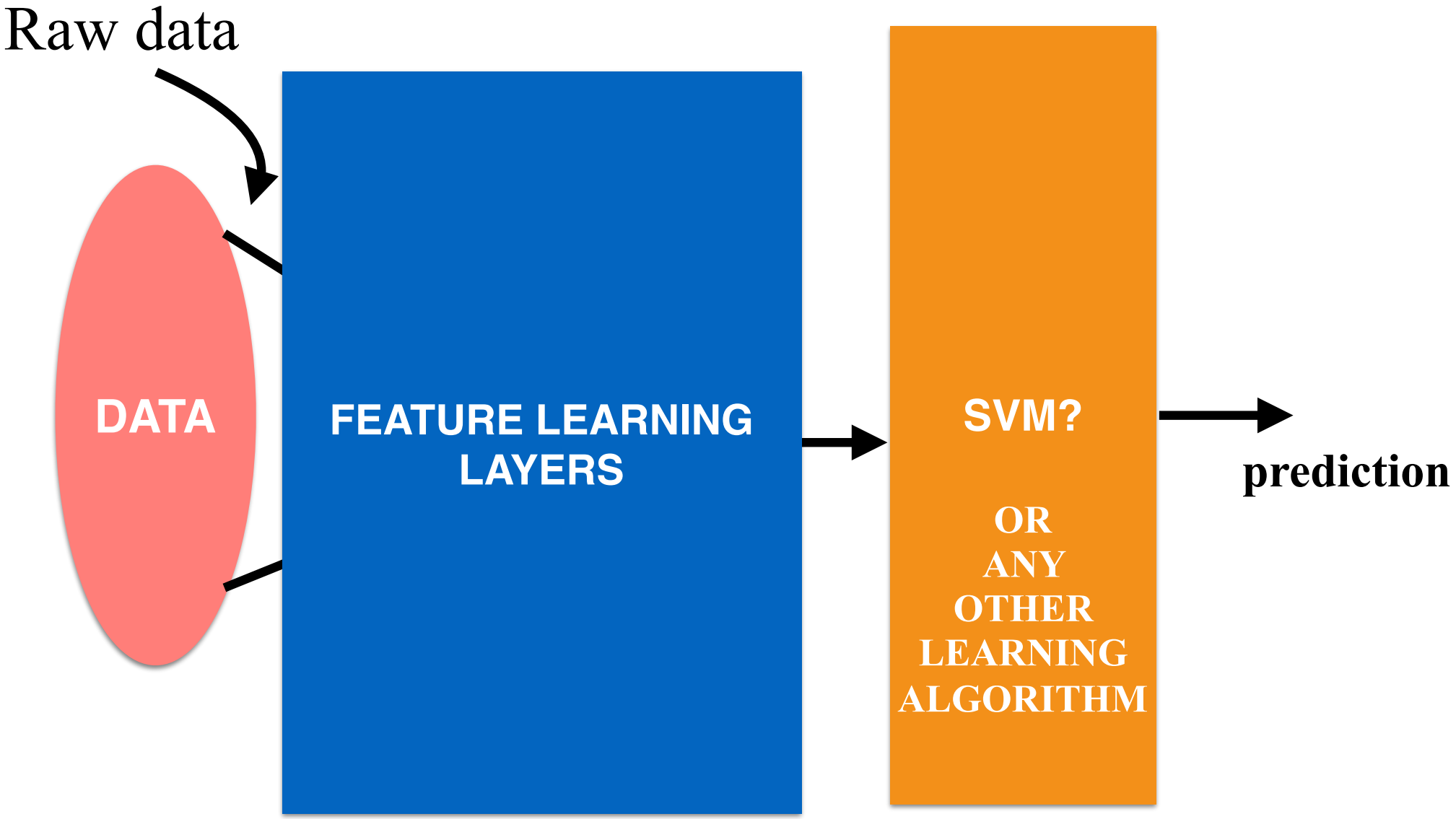
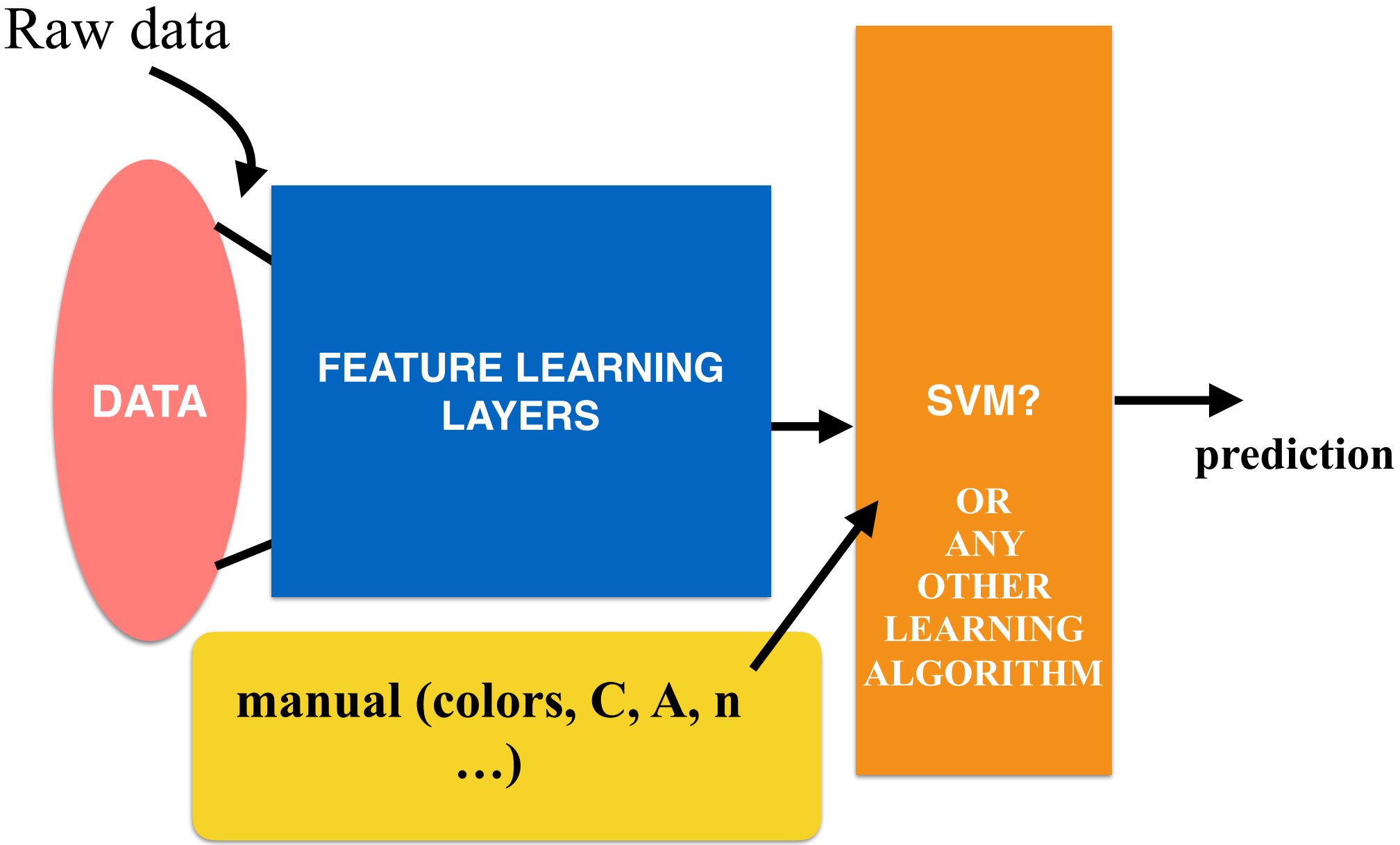
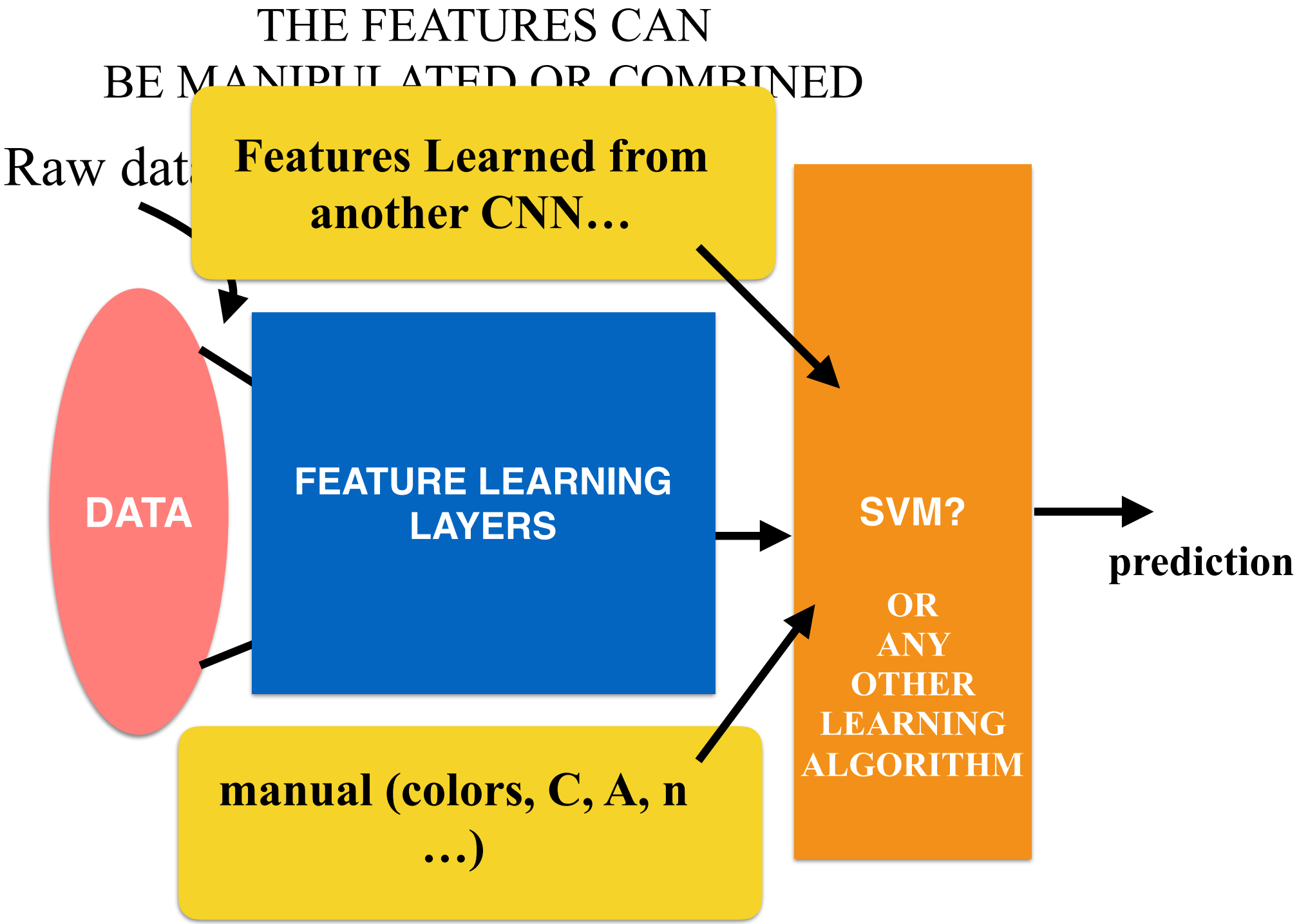
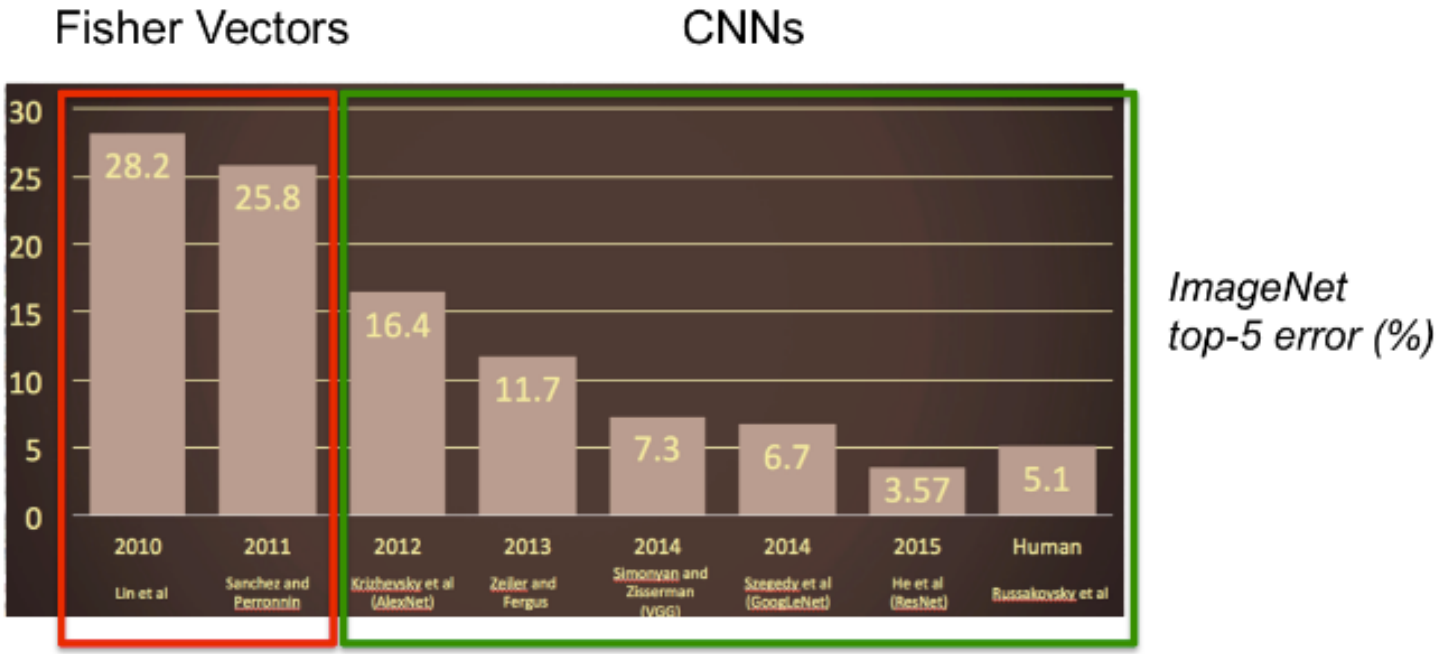


THE FEATURES CAN BE MANIPULATED OR COMBINED




THE FEATURES CAN
BE MANIPULATED OR COMBINED
Raw dat
Features Learned from another CNN…
DATA
FEATURE LEARNING LAYERS
SVM?
OR ANY OTHER LEARNING ALGORITHM
prediction
manual (colors, C, A, n …)

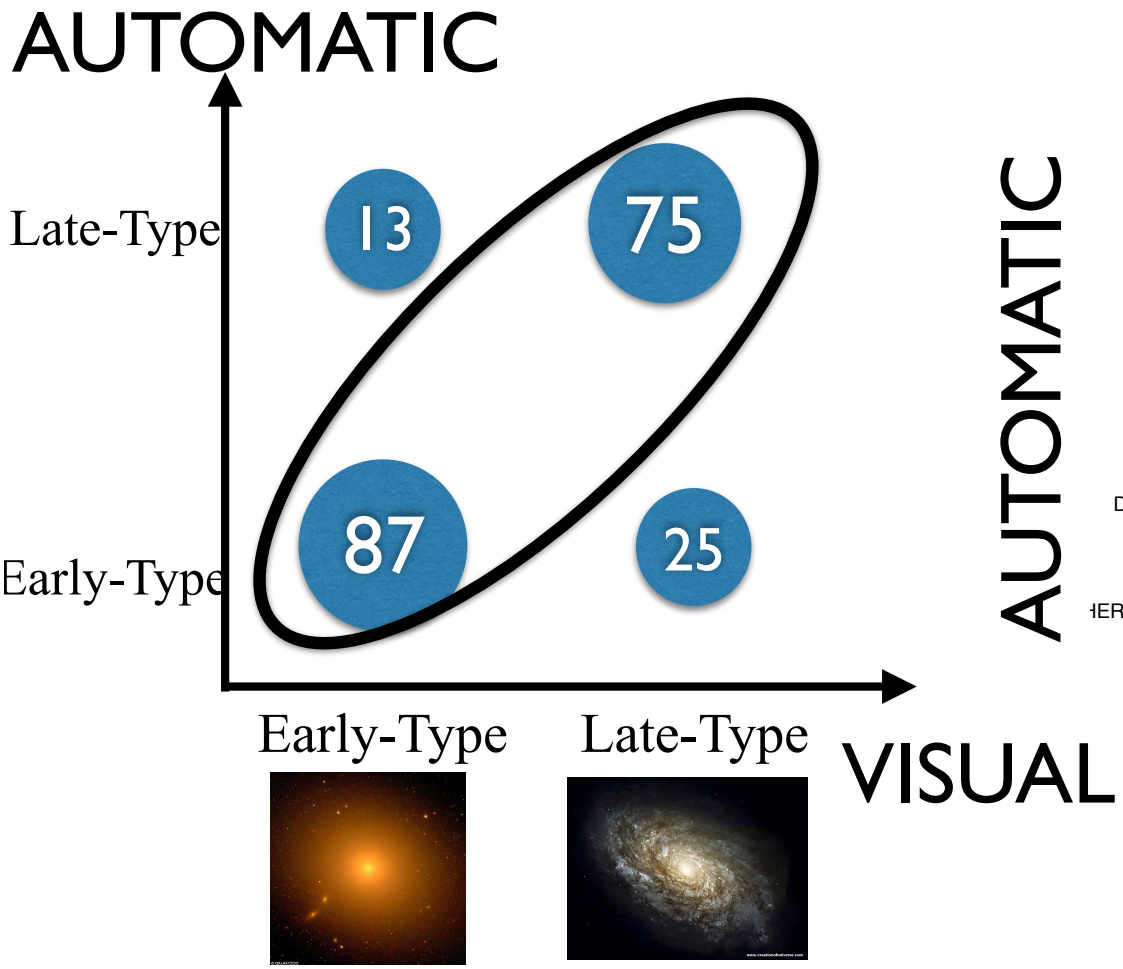
THIS IS A CHANGE OF PARADIGM!



ALSO FOR GALAXY MORPHOLOGY

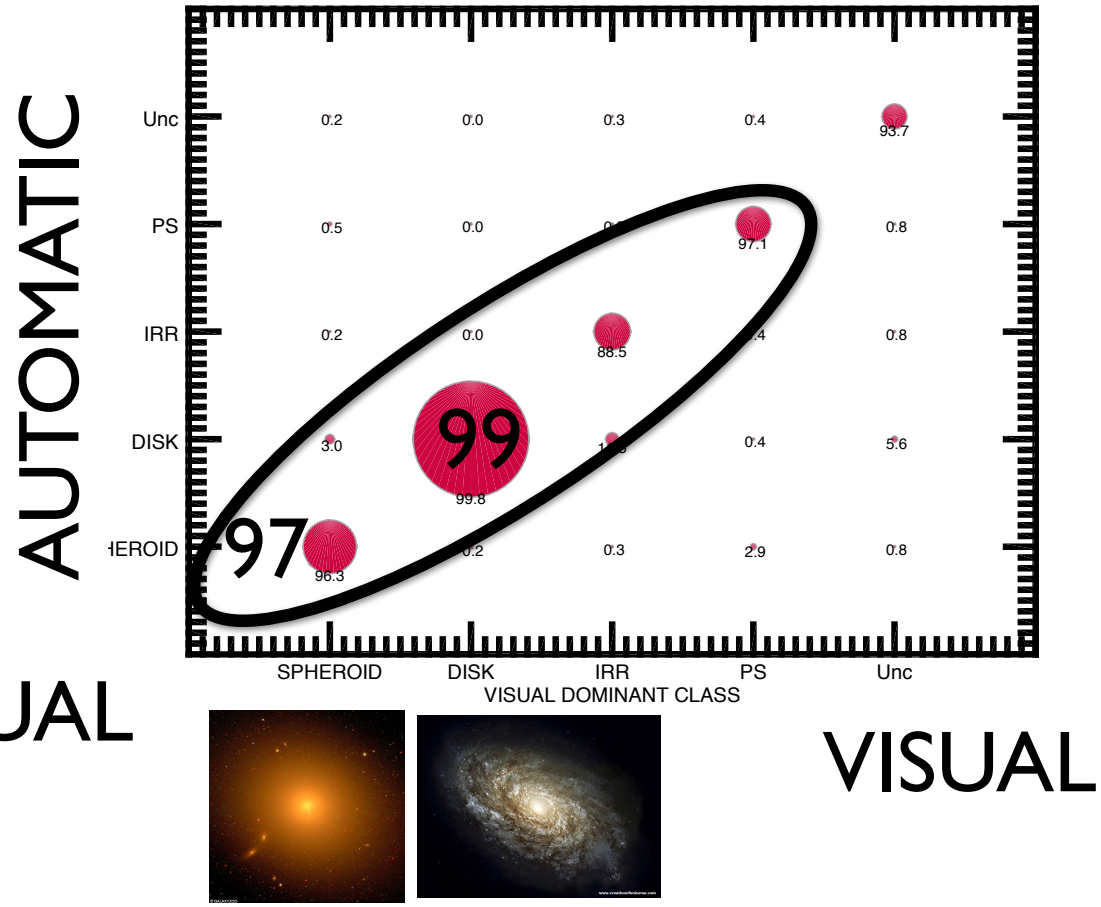
SVMs

[HUERTAS-COMPANY+14]

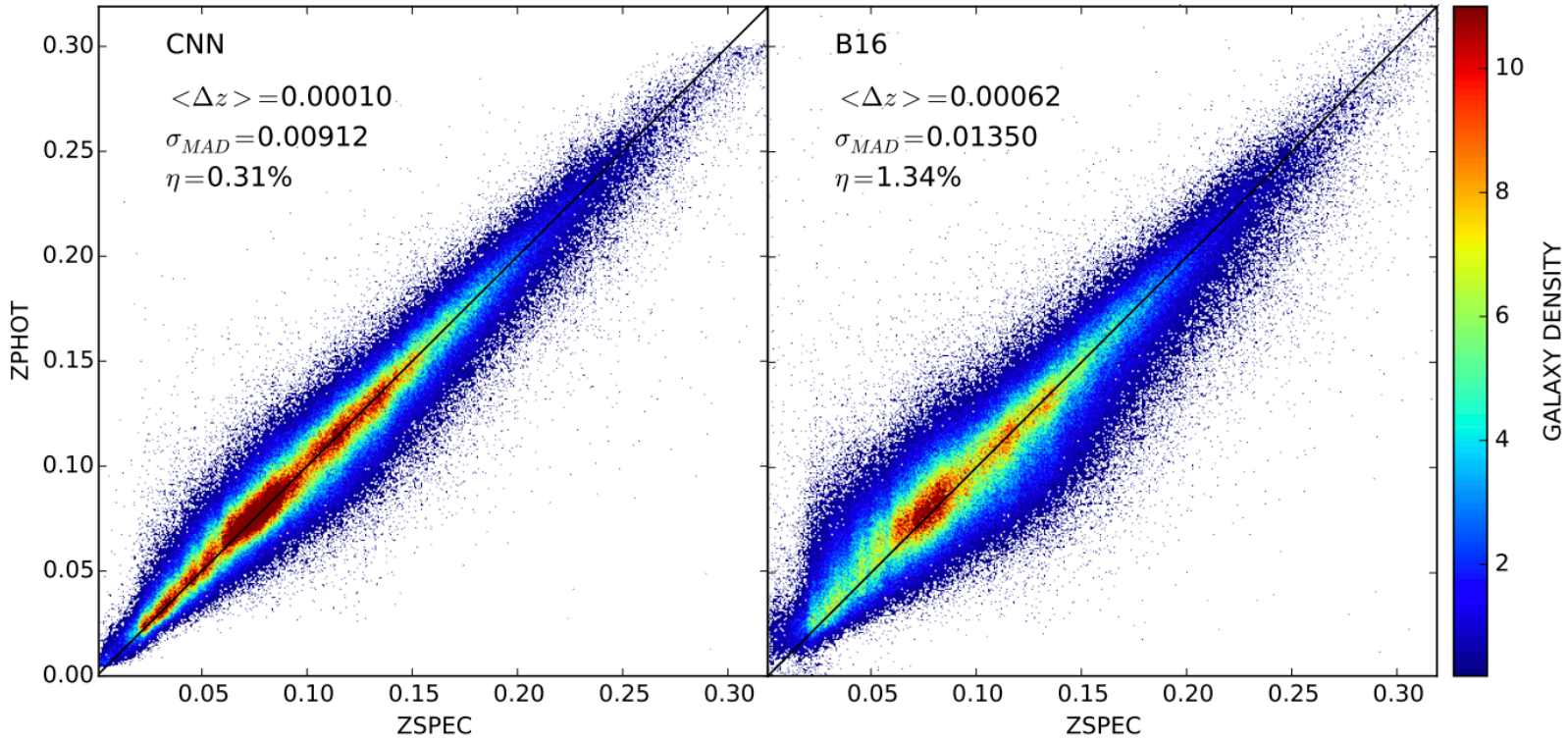


CNNs

[HUERTAS-COMPANY+15b]



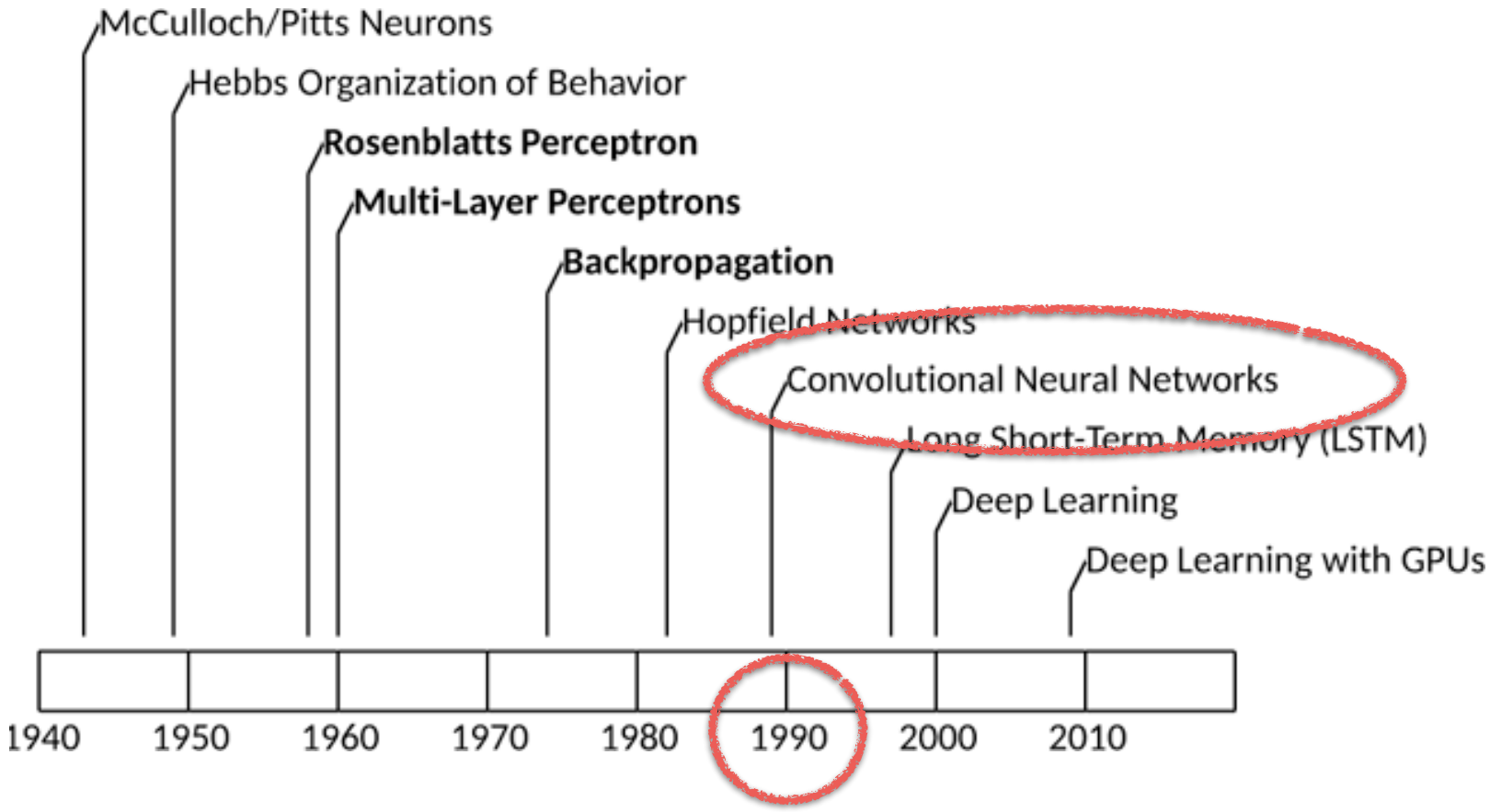
PHOTOMETRIC REDSHIFTS



Pasquet+18

AUTOMATICALLY COMBINING MORPHOLOGY AND COLOR FOR PHOTOZ ESTIMATION

WELL, BUT THIS IS AN "OLD" IDEA - WHY NOW?



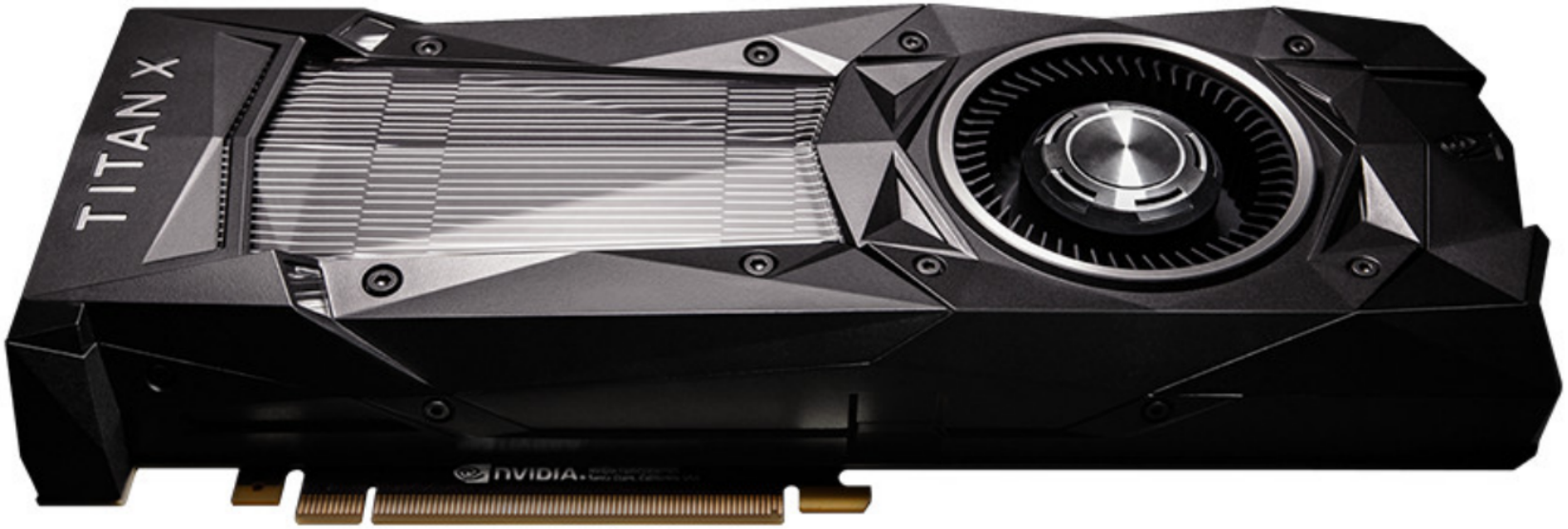
WELL, BUT THIS IS AN “OLD” IDEA - WHY NOW?

1 - MORE DATA TO TRAIN! DEEP NETWORKS HAVE A LARGE NUMBER OF PARAMETERS - THX TO SOCIAL MEDIA …

WELL, BUT THIS IS AN “OLD” IDEA - WHY NOW?

2 - GPUs - TRAINING OF THESE DEEP NETWORKS HAS REMAINED PROHIBITIVELY TIME CONSUMING WITH CPUs - THX TO VIDEO GAMES…

GPUs



NVIDA TITANX GPU

GPUs vs. CPUs

CPUs

FEWER CORES (~10x)

EACH CORE IS FASTER

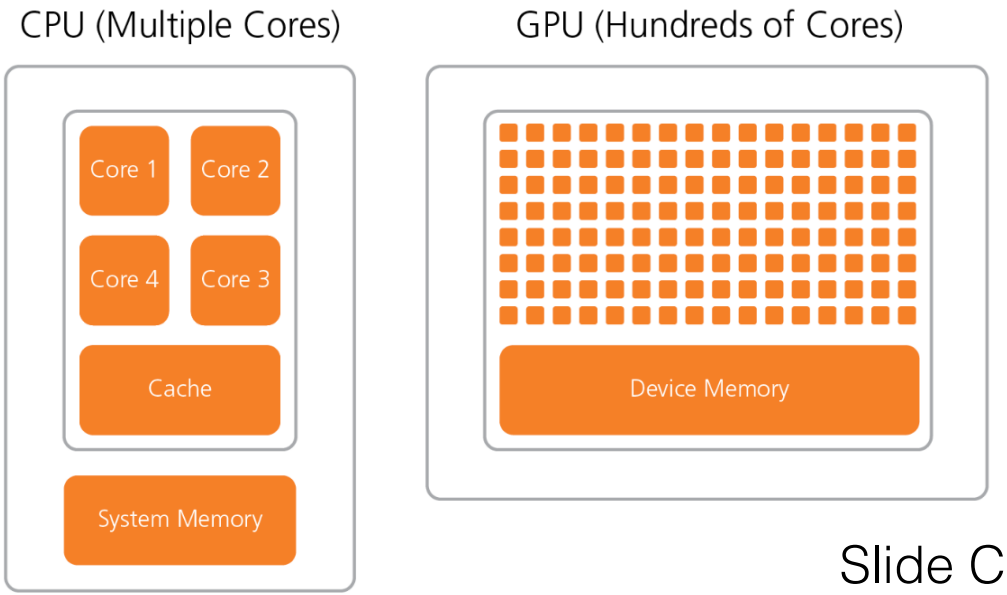
USEFUL FOR SEQUENTIAL TASKS

GPUs

MORE CORES (100x)

EACH CORE IS SLOWER

USEFUL FOR PARALLEL TASKS



Slide Credit:

GPUs vs. CPUs

More benchmarks available here.

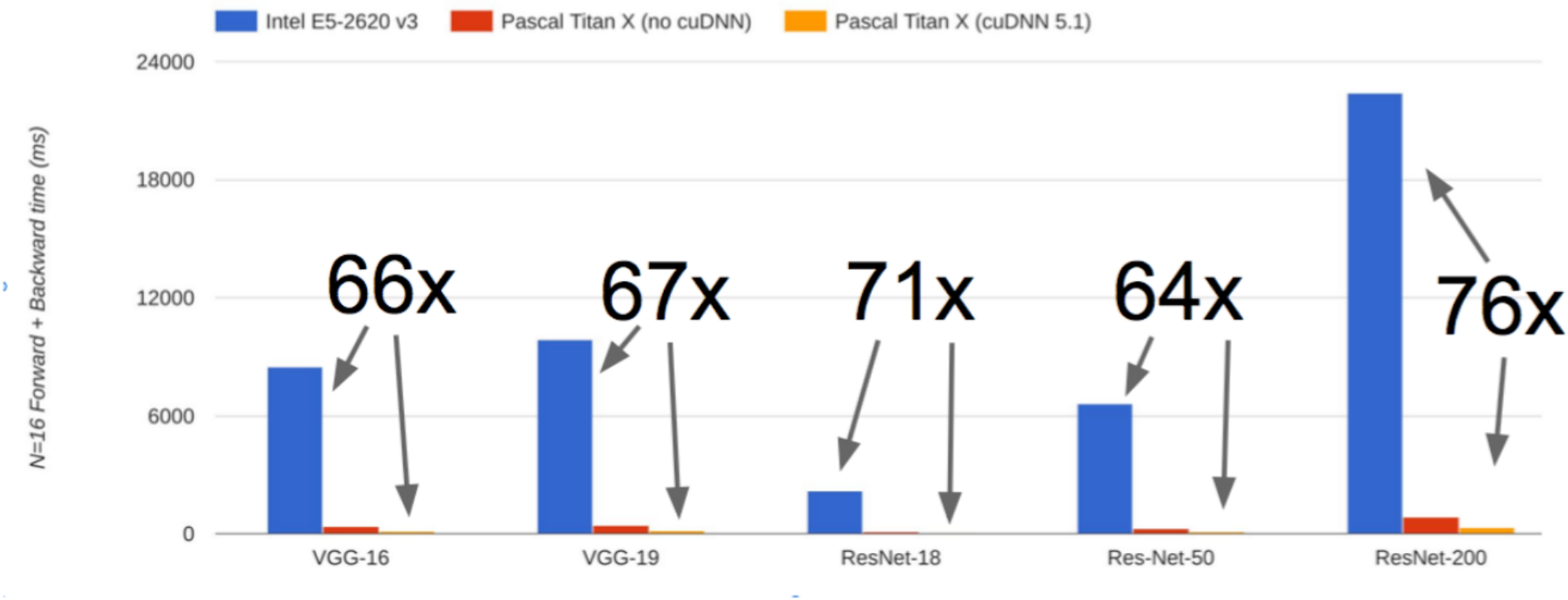


Figure credit: J. Johnson

GPUs for deep learning

NVIDIA GPUs ARE PROGRAMMED THROUGH CUDA [Compute Unified Device Architecture]

ANOTHER ALTERNATIVE IS OPENCL, SUPPORTED BY SEVERAL MANUFACTURES, LESS INVESTMENT [Way less used]

CuDNN IS A LIBRARY FOR SPECIFIC DEEP LEARNING COMPUTATIONS ON NVIDIA GPUs

THE PRICE TO PAY?

1. LARGE NUMBER OF PARAMETERS IMPLIES LARGE DATASETS TO TRAIN

2. LOOSE EVEN MORE DEGREE OF CONTROL OF WHAT THE ALGORITHM IS DOING SINCE THE FEATURE EXTRACTION PROCESS BECOMES UNSUPERVISED

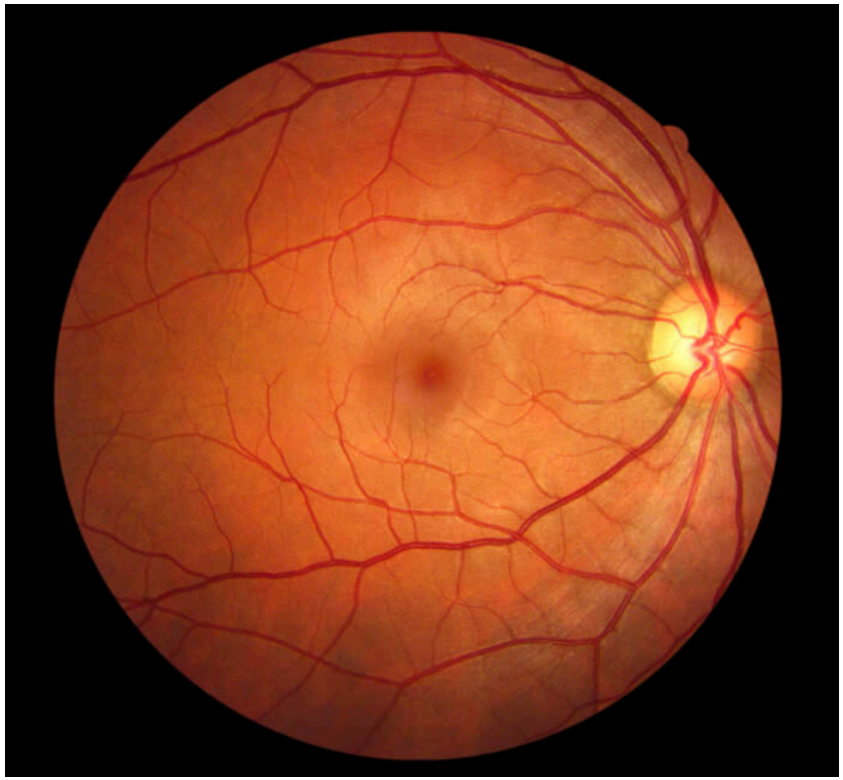


IMAGE OF THE BACK OF THE EYE

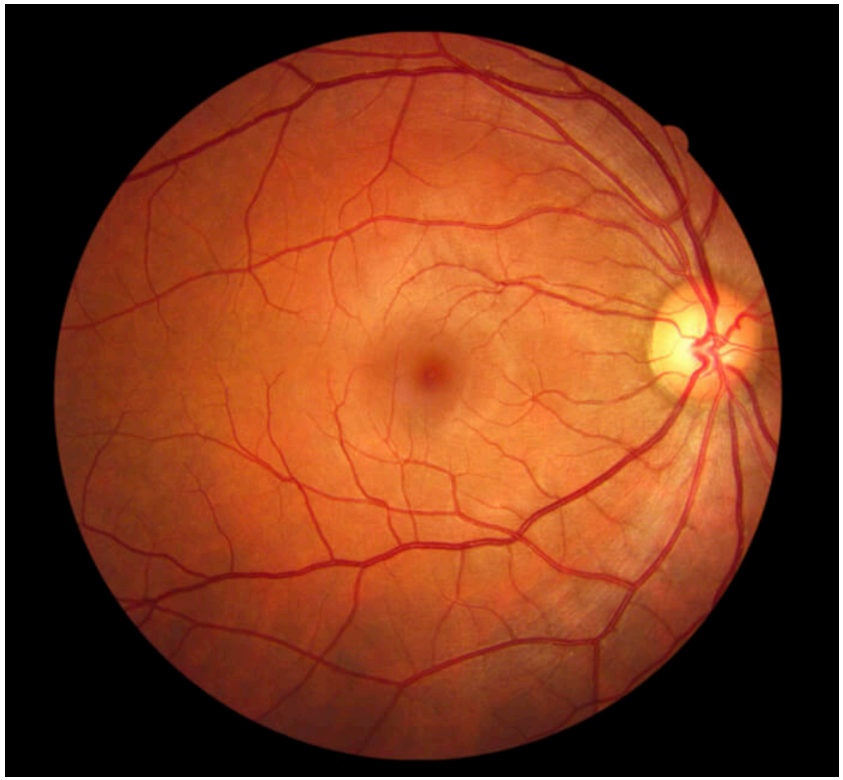


IMAGE OF THE BACK OF THE EYE

DEEP LEARNING CAN IDENTIFY THE PATIENT'S GENDER WITH 95% ACCURACY