Machine Intelligence:: Deep Learning

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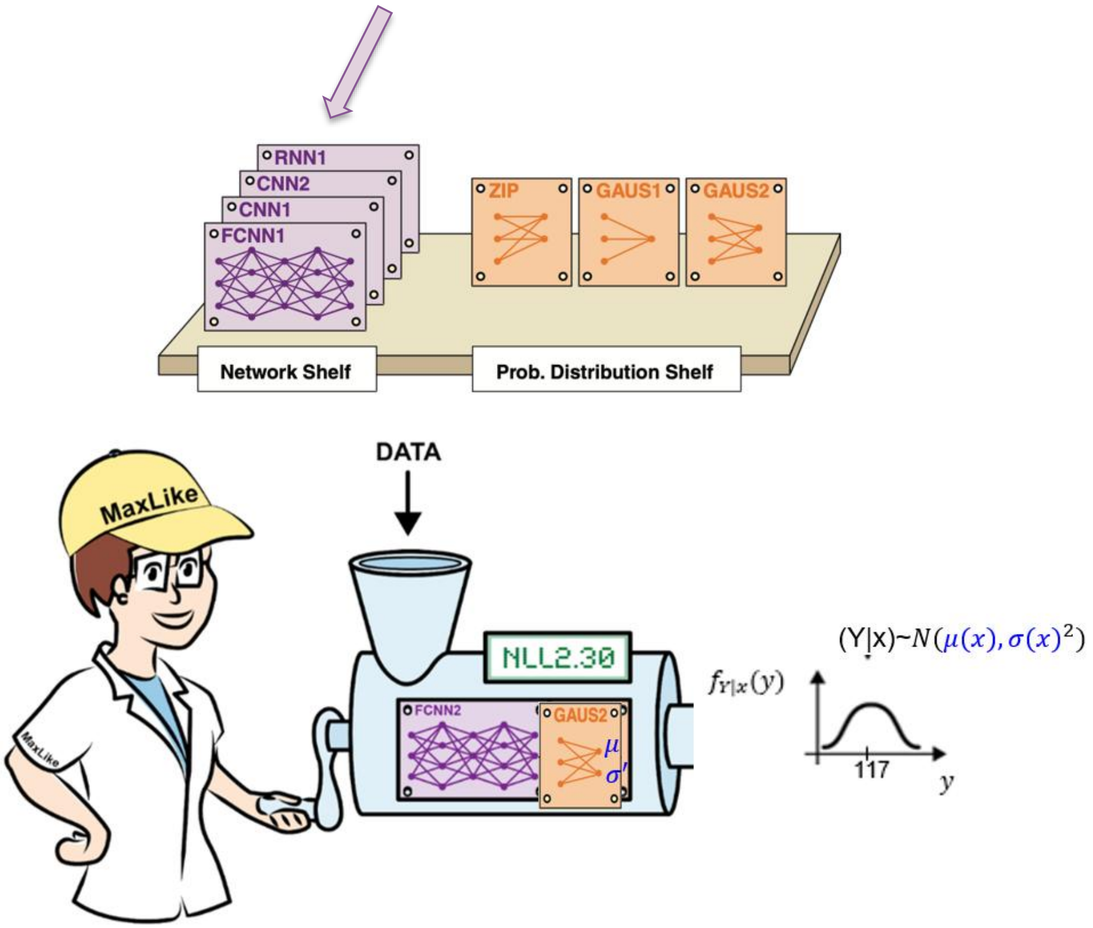
Most of the slides were developed by Oliver Dürr & Beate Sick

Outline of the DL Module (tentative)

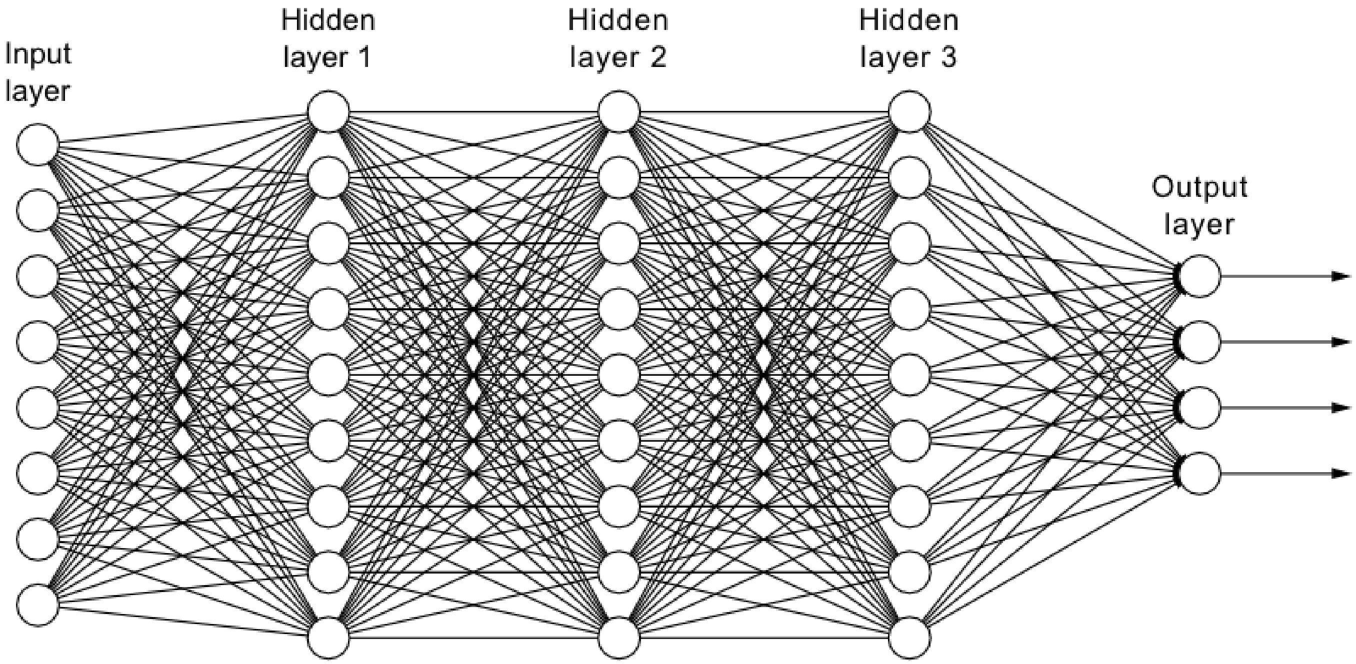
The course is split in 8 sessions, each 4 lectures long. Topics might be adapted during the course

Day	Date	Time	Topic
1	15.04.2025	09:00-12:30	Introduction to Deep Learning & Keras, first NNs
-	21.04.2025	-	FRÜHLINGS-FERIEN
-	28.04.2025	-	FRÜHLINGS-FERIEN
2	06.05.2025	09:00-12:30	Loss, Optimization, Regression, Classification
3	13.05.2025	09:00-12:30	Computer vision, CNN-archictecture
4	20.05.2025	09:00-12:30	DL in practice, pretrained (foundation) models
5	27.05.2025	09:00-12:30	Model evaluation, baselines, xAI, troubleshooting
6	03.06.2025	09:00-12:30	Generative Models, Transformer-architecture
7	10.06.2025	09:00-12:30	Vision Transformer
8	17.06.2025	09:00-12:30	Projects, deep Ensembling

NN architectures

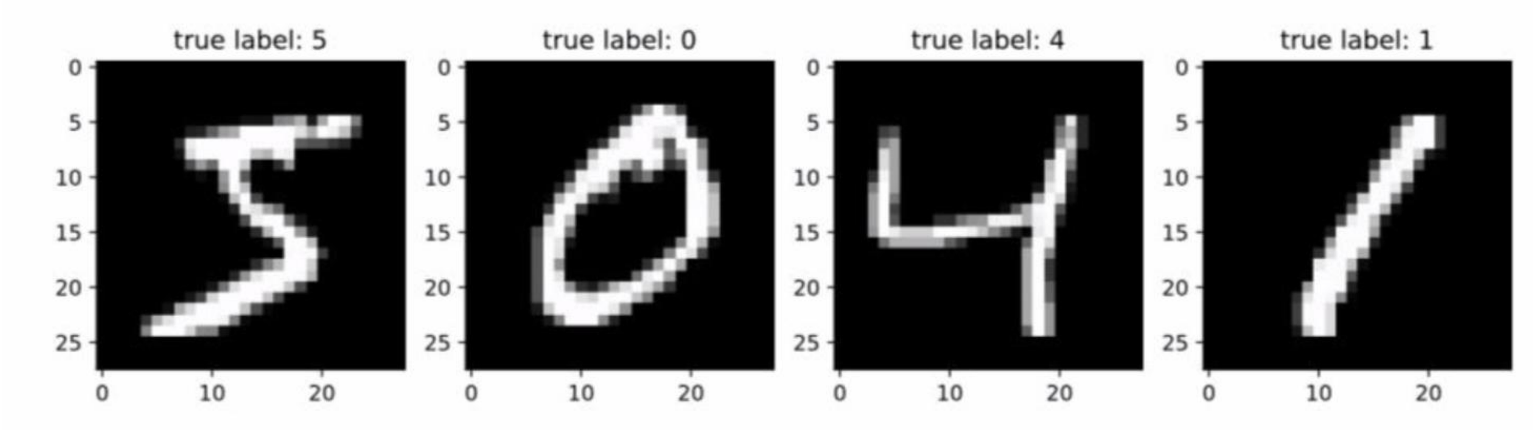


A fully connected NN



Probabilistic classification

- Usually in DL the model predicts a probability for each possible class
- Example:
  - Banknote from exercise – classes: “real” or “fake”
  - Typical example Number from hand-written digit – classes: 0, 1, …, 9



Classification: Softmax Activation

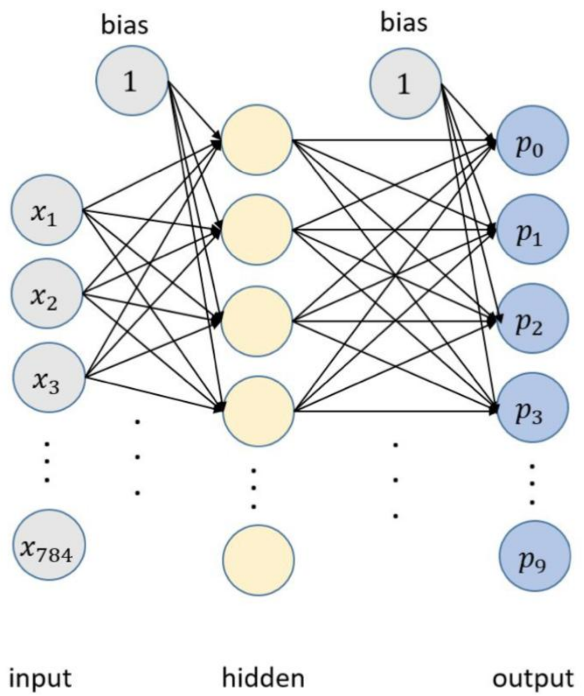


Figure 2.12: A fully connected NN with 2 hidden layers. For the MNIST example, the input layer has 784 values for the 28 x 28 pixels and the output layer out of 10 nodes for the 10 classes.

$p_o, p_1 \ldots p_9$ are probabilities for the classes 0 to 9.

Activation of last layer z_i incomming

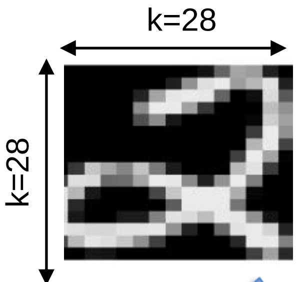
Makes outcome positive

$$p_i = \frac{e^{z_i}}{\sum_{j=0}^{9} e^{z_j}}$$

Ensures that pi's sum up to one

This activation is called softmax

NLL for multi-class = cross-entropy

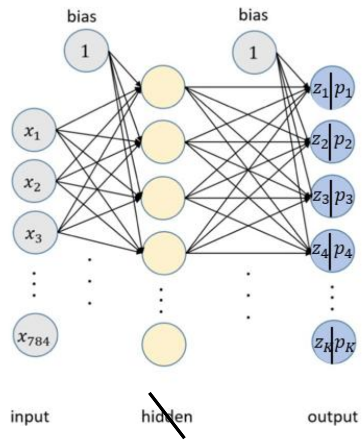


Flatten image_i

Input $\boldsymbol{x}_i$

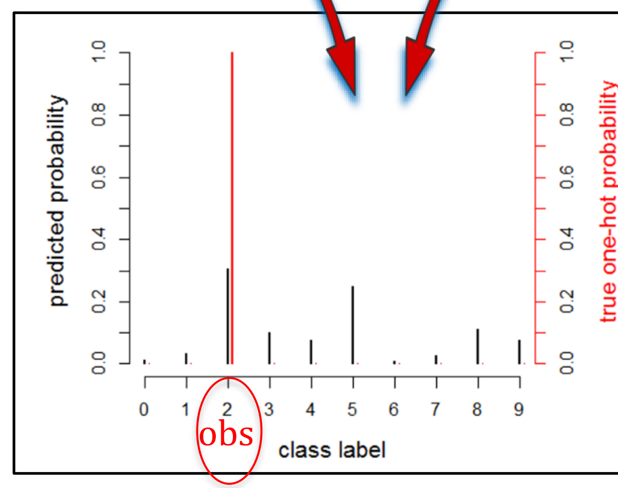
24.0
−5.1
12.2
89.9
:
3.2

$$\mathbf{x}_{(1,k^2)} \cdot \mathbf{W}_{(k^2,10)} + \mathbf{b}_{(1,10)} = \mathbf{z}_{(1,10)}$$



$$\hat{p}_k = \frac{e^{z_k}}{\sum_j e^{z_j}}$$

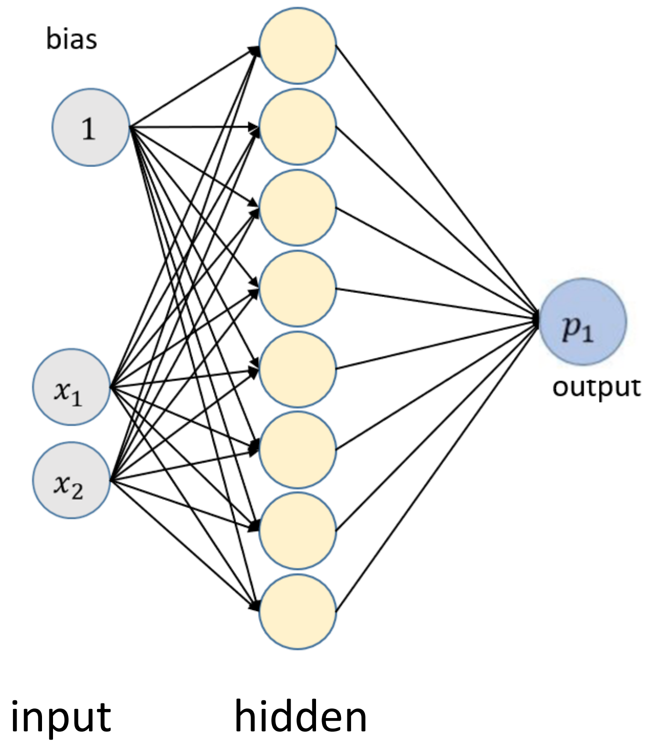
index	Score or logit $\boldsymbol{z}_i$	probability $\boldsymbol{p}_i$	1-hot labels $\boldsymbol{y}_i$
0	-3.89	0.02	0
1	-3.18	0.04	0
2	-0.80	0.31	1
3	-2.20	0.10	0
4	-2.44	0.08	0
5	-1.05	0.26	0
6	-4.60	0.01	0
7	-3.48	0.03	0
8	-2.09	0.11	0
9	-2.44	0.08	0

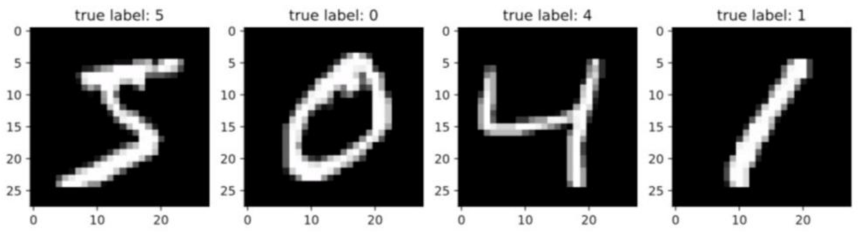


$$\text{loss} = \text{NLL} = \frac{1}{N_{\text{batch}}} \sum_{i=1}^{N_{\text{batch}}} l_i \quad \text{,with} \quad l_i = -\sum_{k=1}^{10} {}^{obs}y_{ik} \cdot \log(p_{ik})$$

Loss = NLL= cross-entropy ($-\sum p_i^{\text{obs}} \log p_i^{\text{pred}}$) averaged over all images in mini-batch

Exercise:

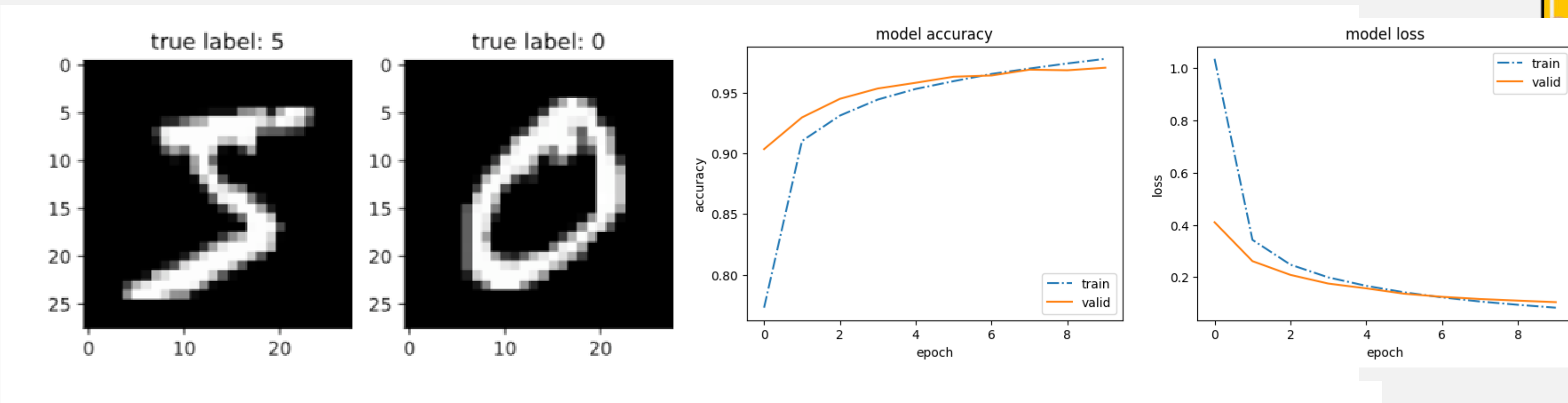


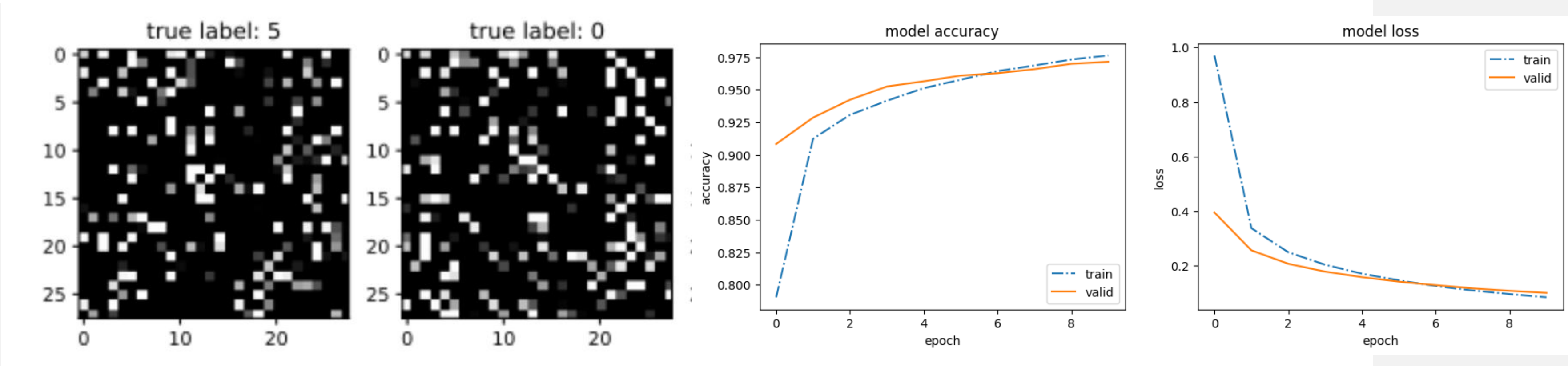


Use a fully connected NN to classify MNIST data to 10 possible classes

[03_fcnn_mnist_keras_torch.ipynb]

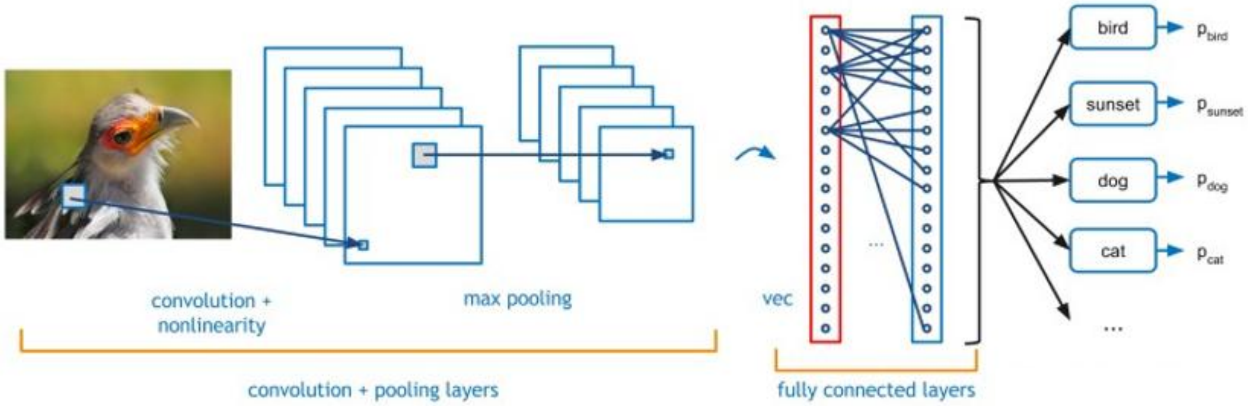
MNIST exercise: Does shuffling disturb a fcNN?





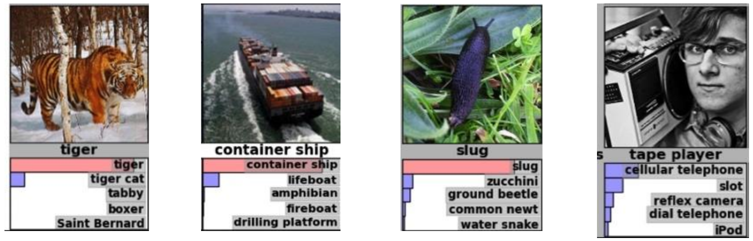
→ The performance of a fcNN is the same on original and shuffled images

Convolutional Neural Networks for image data

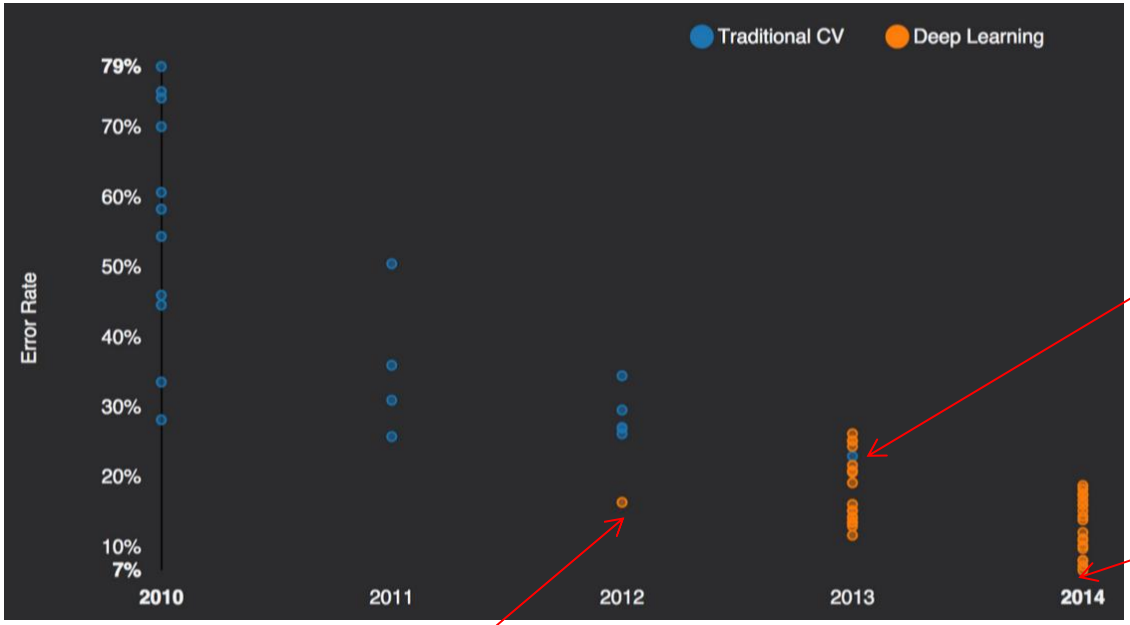


The first DL breackthrough: Imagenet challenge

1000 classes
1 Mio samples



…



Human: 5% misclassification

Only one non-CNN approach in 2013

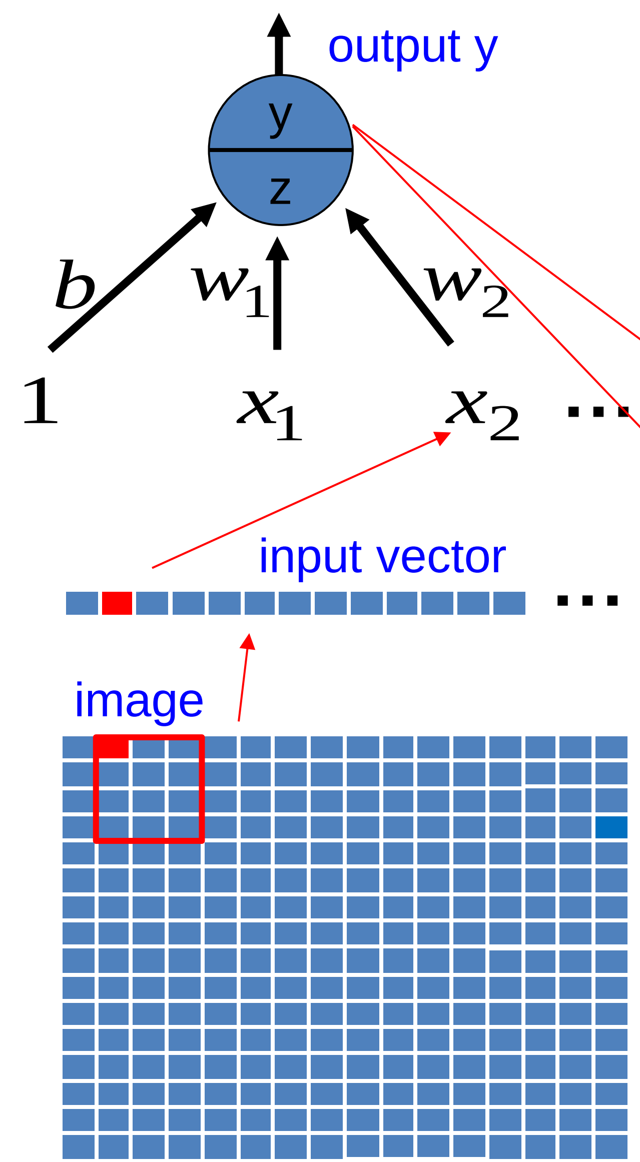
GoogLeNet 6.7%

A. Krizhevsky
first CNN in 2012
Und es hat zoom gemacht

[Figure: https://medium.com/global-silicon-valley/machine-learning-yesterday-today-tomorrow-3d3023c7b519](https://medium.com/global-silicon-valley/machine-learning-yesterday-today-tomorrow-3d3023c7b519)

11

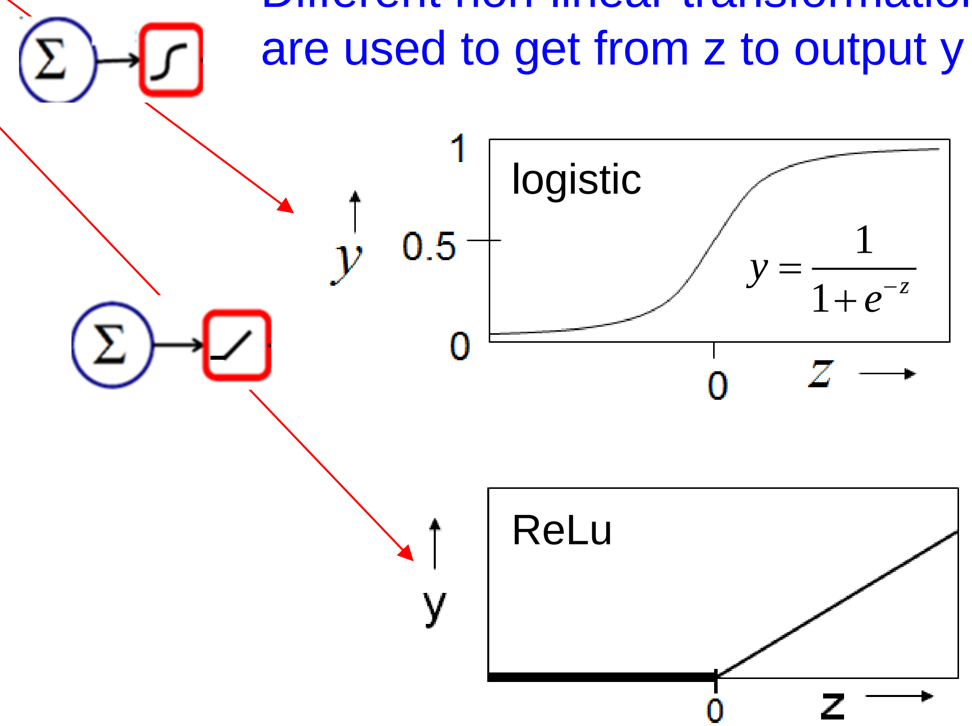
An artificial neuron



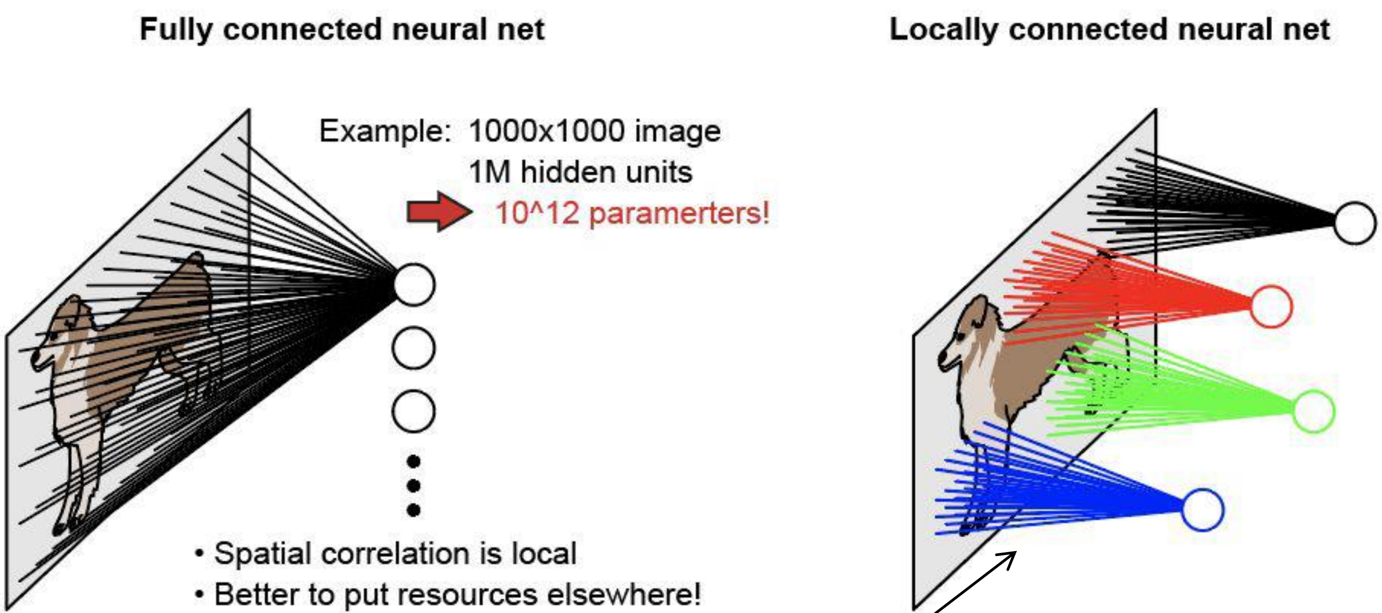
bias weights

$$z = b + \sum_i x_i w_i$$

Different non-linear transformations are used to get from z to output y



Convolution extracts local information using few weights



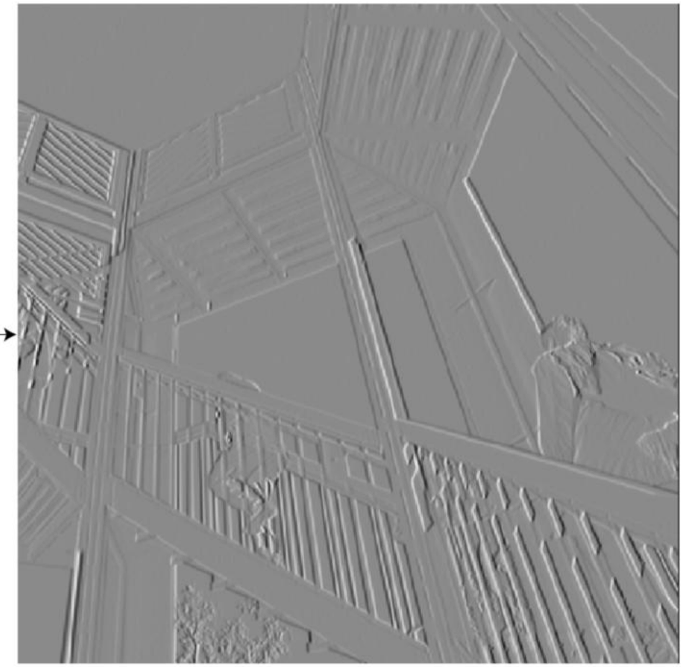
Shared weights:

by using the same weights for each patch of the image we need much less parameters than in the fully connected NN and get from each patch the same kind of local feature information such as the presence of an edge.

Example of designed Kernel / Filter

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

Horizontal Sobel kernel



Applying a vertical edge detector kernel

Taken from the great website on convolution: https://towardsdatascience.com/intuitively-understanding-convolutions-for-deep-learning-1f6f42faee1

Convolution

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Input X

1	0	1
0	1	0
1	0	1

Kernel W

4	3	4
2	4	3
2	3	4

Result Z

Convolution (let's ignore bias b):

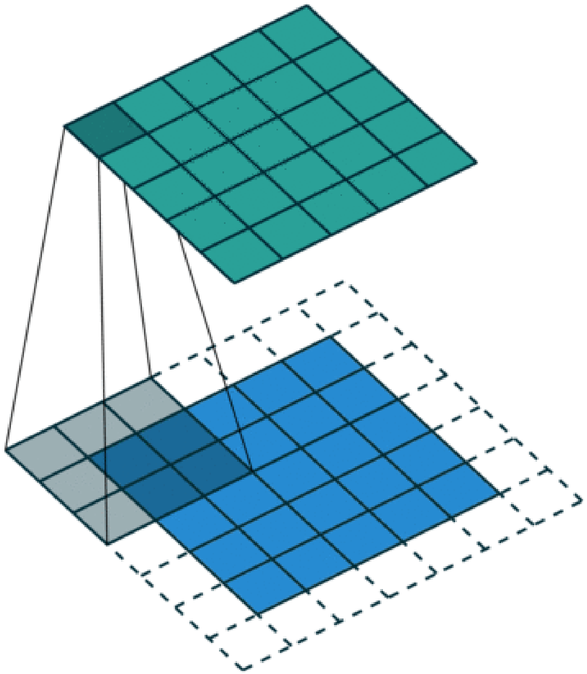
$$z = b + \sum_i x_i w_i$$

1x1	1x0	1x1	0	0
0x0	1x1	1x0	1	0
0x1	0x0	1x1	1	1
0	0	1	1	0
0	1	1	0	0

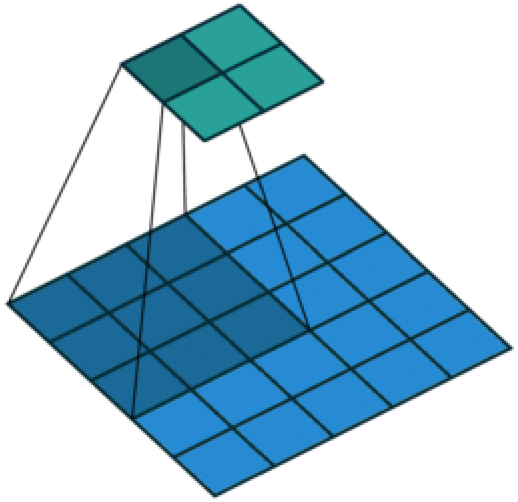
4		

https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Ingredient I: Convolution



Zero-padding to achieve
same size of feature and input



no padding to only use
valid input information

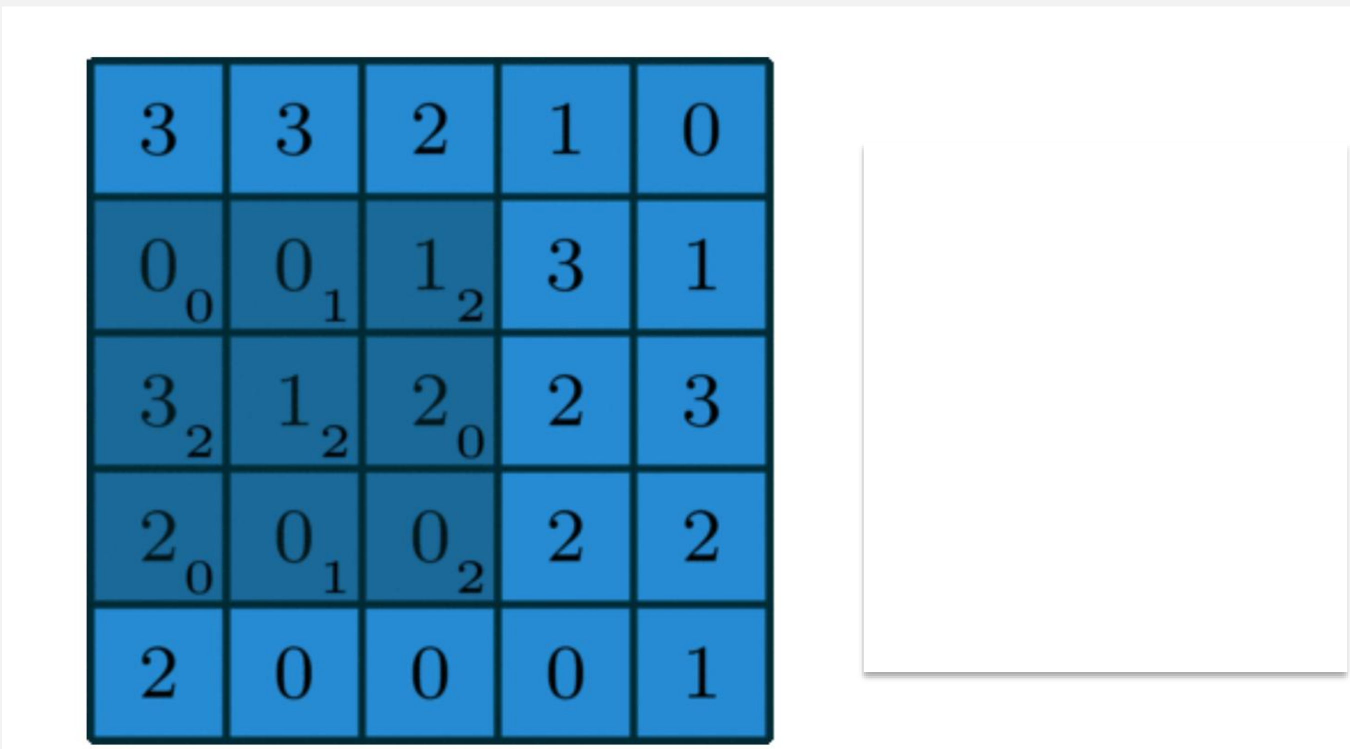
The *same* weights are used at each position of the input image.

Taken from the great website on convolution: https://towardsdatascience.com/intuitively-understanding-convolutions-for-deep-learning-1f6f42faee1

Exercise: Do one convolution step by hand

The kernel is 3x3 and is applied at each valid positon
– how large is the resulting activation map?

The small numbers in the shaded region are the kernel weights.
Determine the position and the value within the resulting activation map.



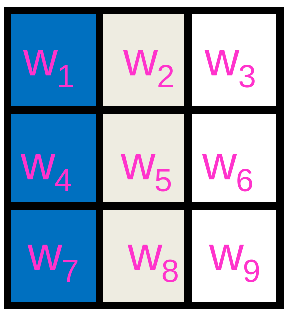
17

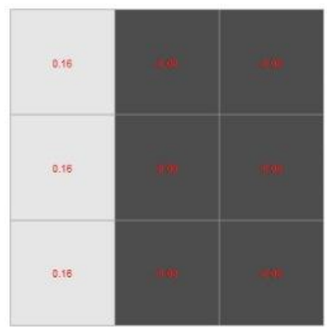
Convolutional networks use neighborhood information and replicated local feature extraction

In a locally connected network the calculation rule

$$z = b + \sum_i x_i w_i$$

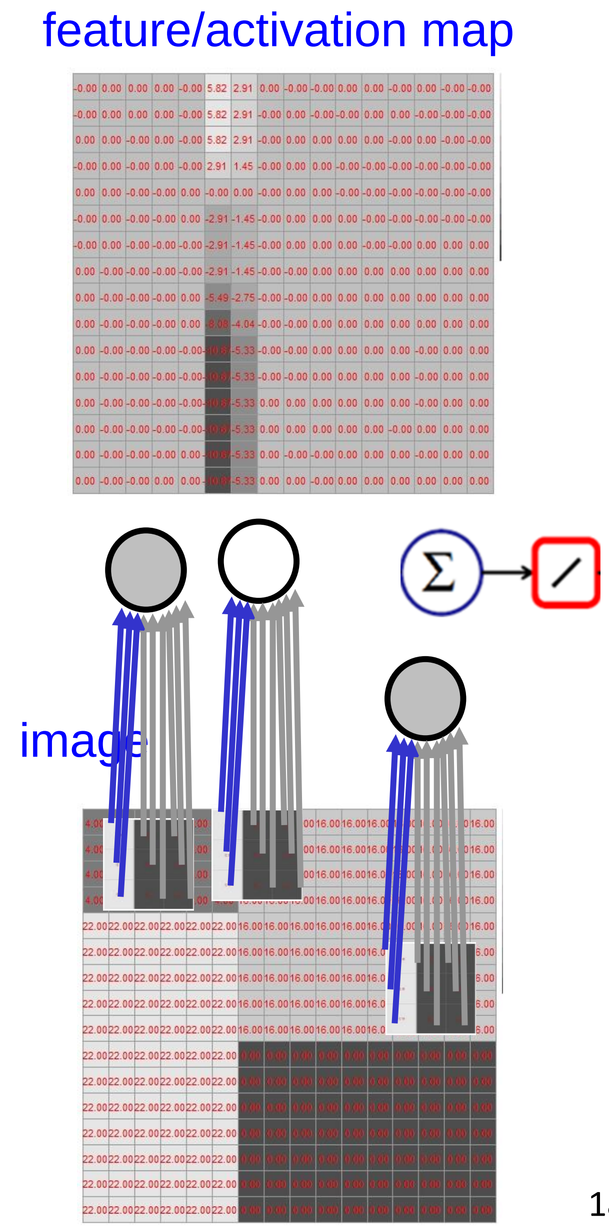
Pixel values in a small image patch are element-wise multilied with weights of a small filter/kernel:



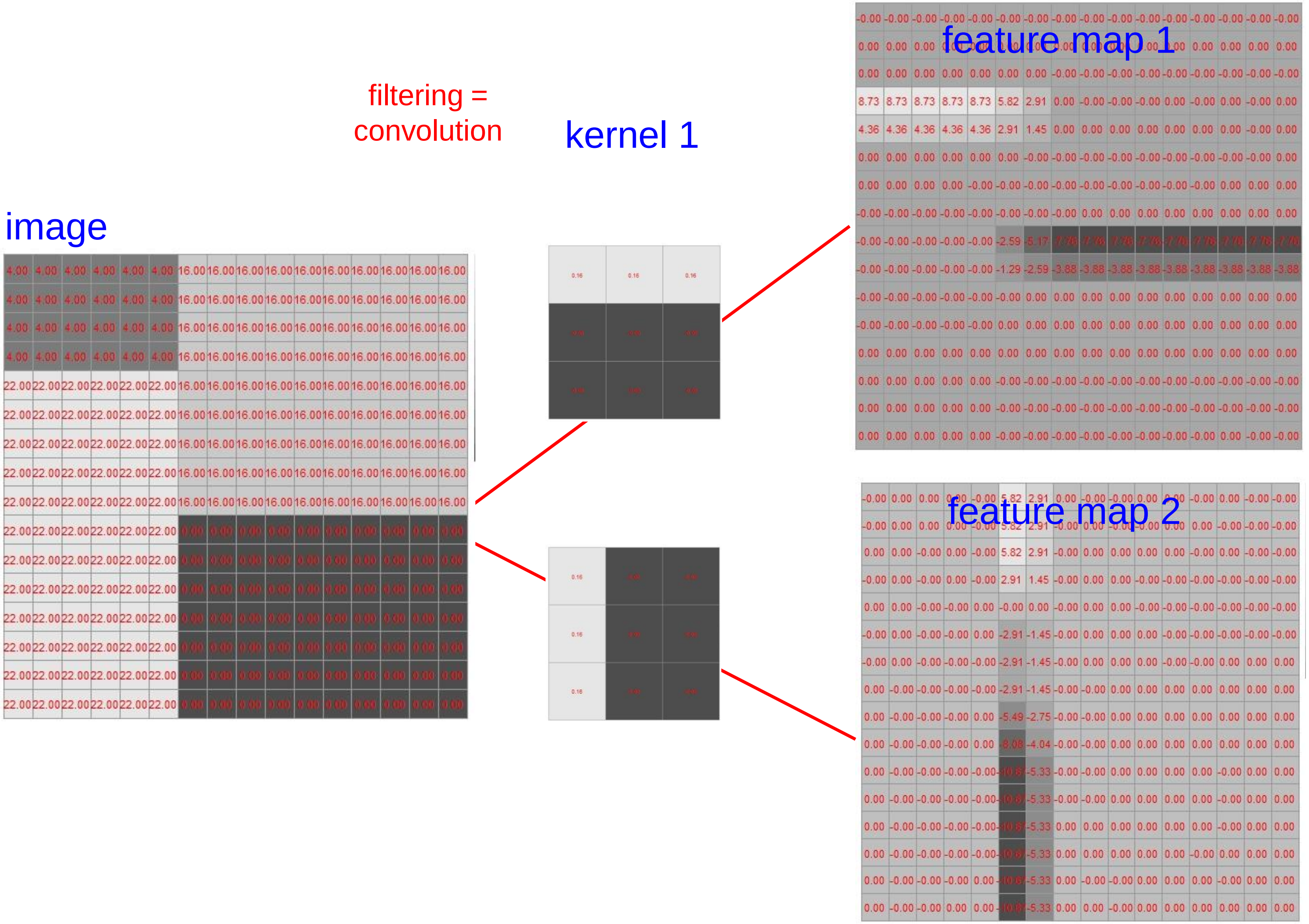


The filter is applied at each position of the image and it can be shown that the result is maximal if the image pattern corresponds to the weight pattern.

The results form again an image called feature map (=activation map) which shows at which position the feature is present.

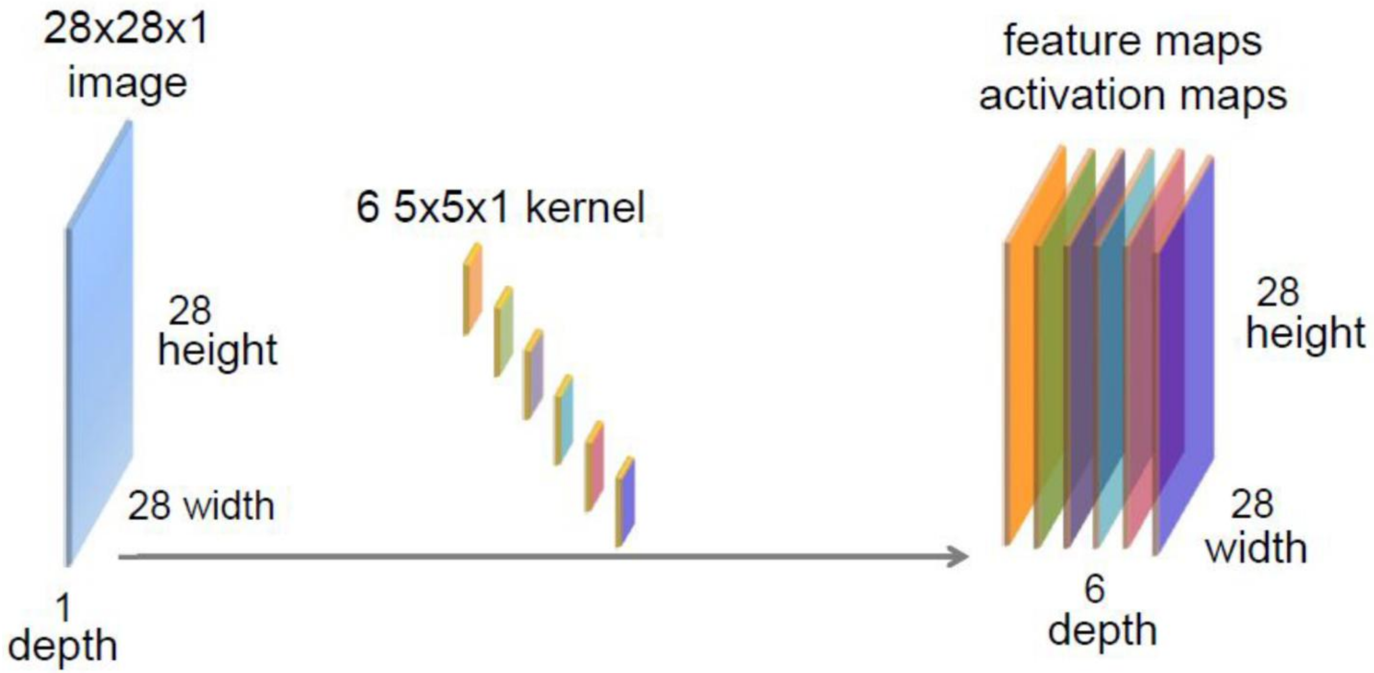


Convolutional networks use neighborhood information and replicated local feature extraction



The weights of each filter are randomly initiated and then adapted during the training.

Convolution layer with a 1-chanel input and 6 kernels

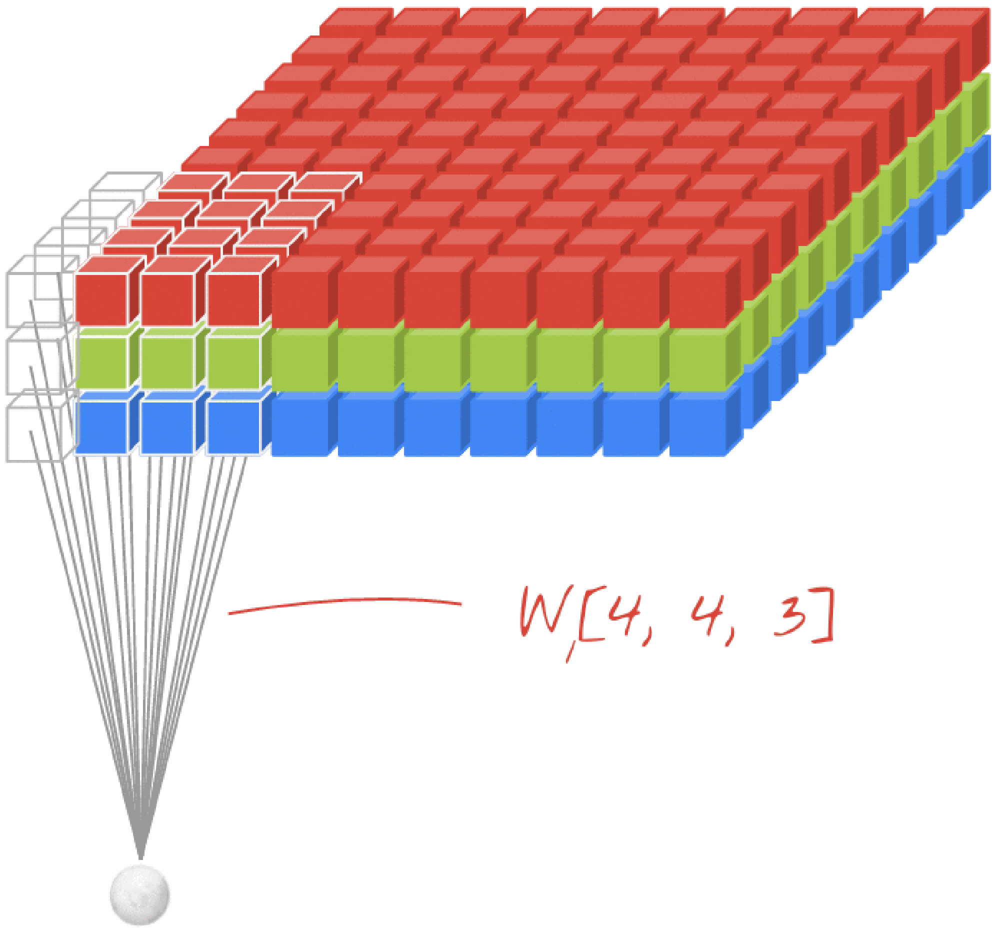


Convolution of the input image with 6 different kernels results in 6 activation maps.

If the input image has only one channel, then each kernel has also only one channel.

Animated convolution with 3 input channels

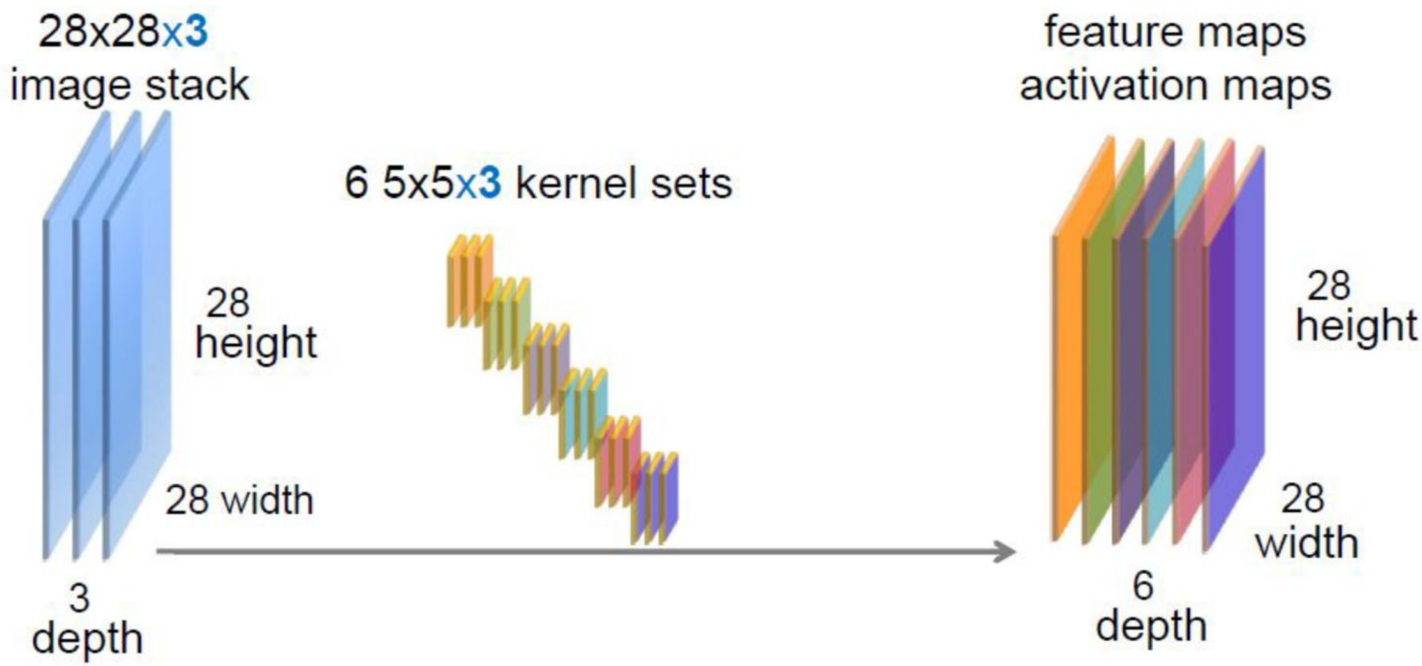
3 color channel input image



$$z = b + \sum_i x_i w_i$$

Animation credits: M.Gorner, https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#10
For an example with number see convolution demo in: https://cs231n.github.io/convolutional-networks/

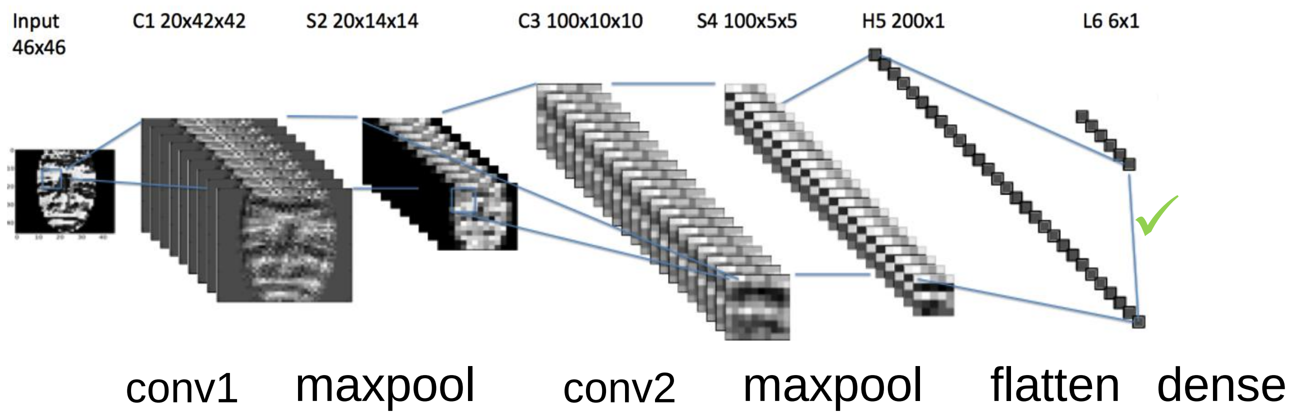
Convolution layer with a 3-chanel input and 6 kernels



Convolution of the input image with 6 different kernels results in 6 activation maps.

If the input image has 3 channels, then each filter has also 3 channels.

CNN ingredient II: Maxpooling Building Blocks reduce size



4x4

12	20	30	0
8	12	2	0
34	70	37	4
112	100	25	12

→

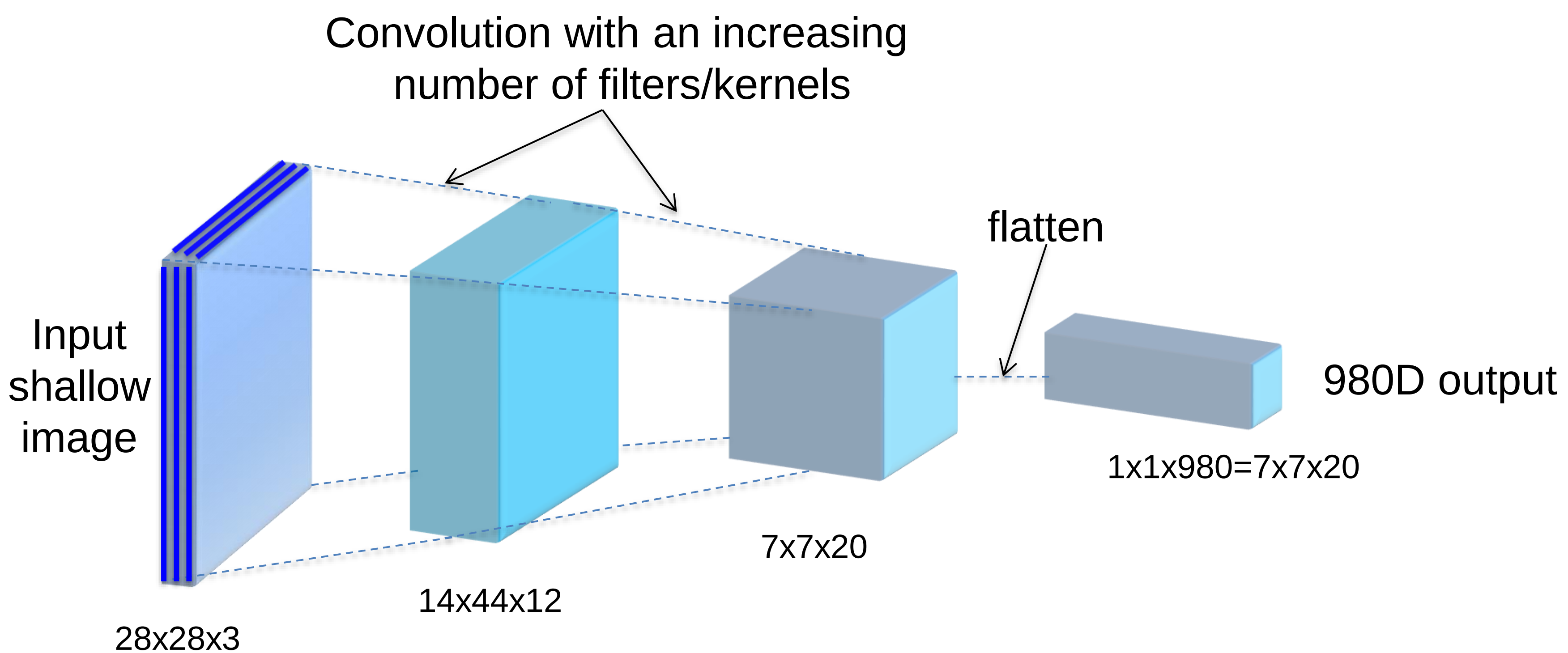
2x2

20	30
112	37

Simply join e.g. 2x2 adjacent pixels in one by taking the max.
→ less weights in model
→ Less train data needed
→ increased performance

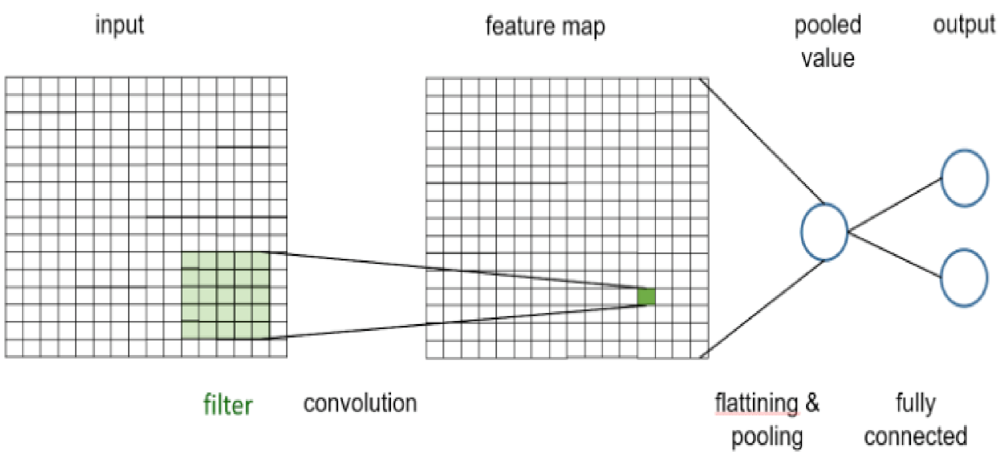
Hinton: „The pooling operation used in convolutional neural networks is a big mistake and the fact that it works so well is a disaster“

Typical shape of a classical CNN



Spatial resolution is decreased e.g. via max-pooling while more abstract image features are detected in deeper layers.

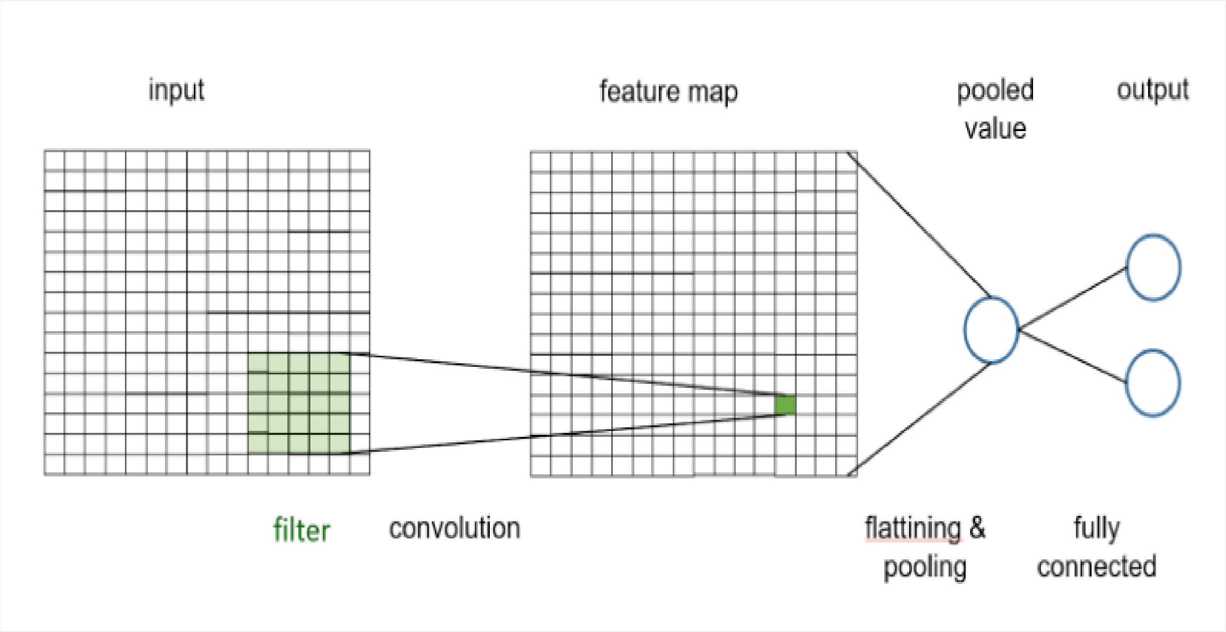
Building a very simple CNN with keras




```
model <- keras_model_sequential()
model %>%
  layer_conv_2d(filters=,
                kernel_size = c(5,5),
                padding = 'same',
…                input_shape = …,
                activation = 'linear') %>%
  # take the max over all values in the activation map
  layer_max_pooling_2d(pool_size = …) %>%
  layer_flatten() %>%
  layer_dense(units = 2,activation = 'softmax')
```

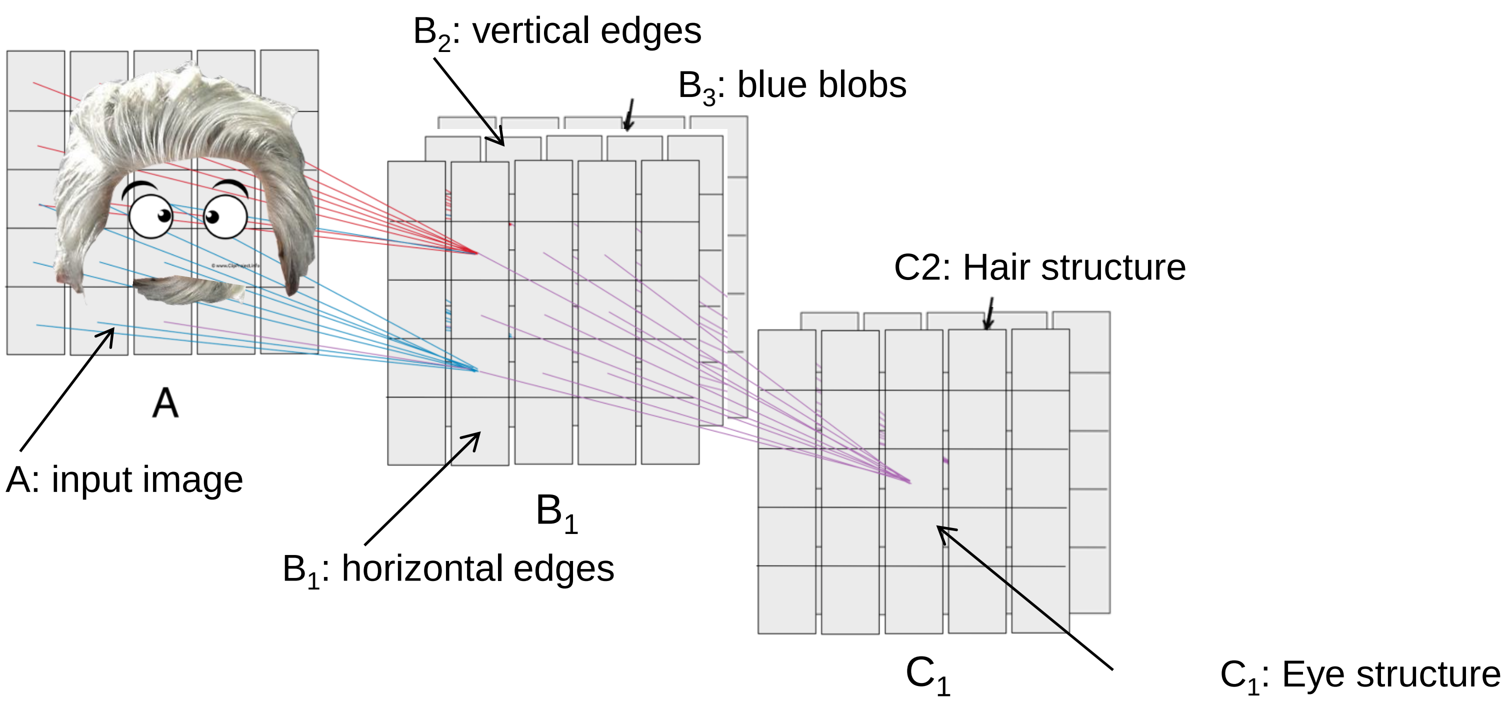
Fill the gaps!

Exercise: Artstyle Lover

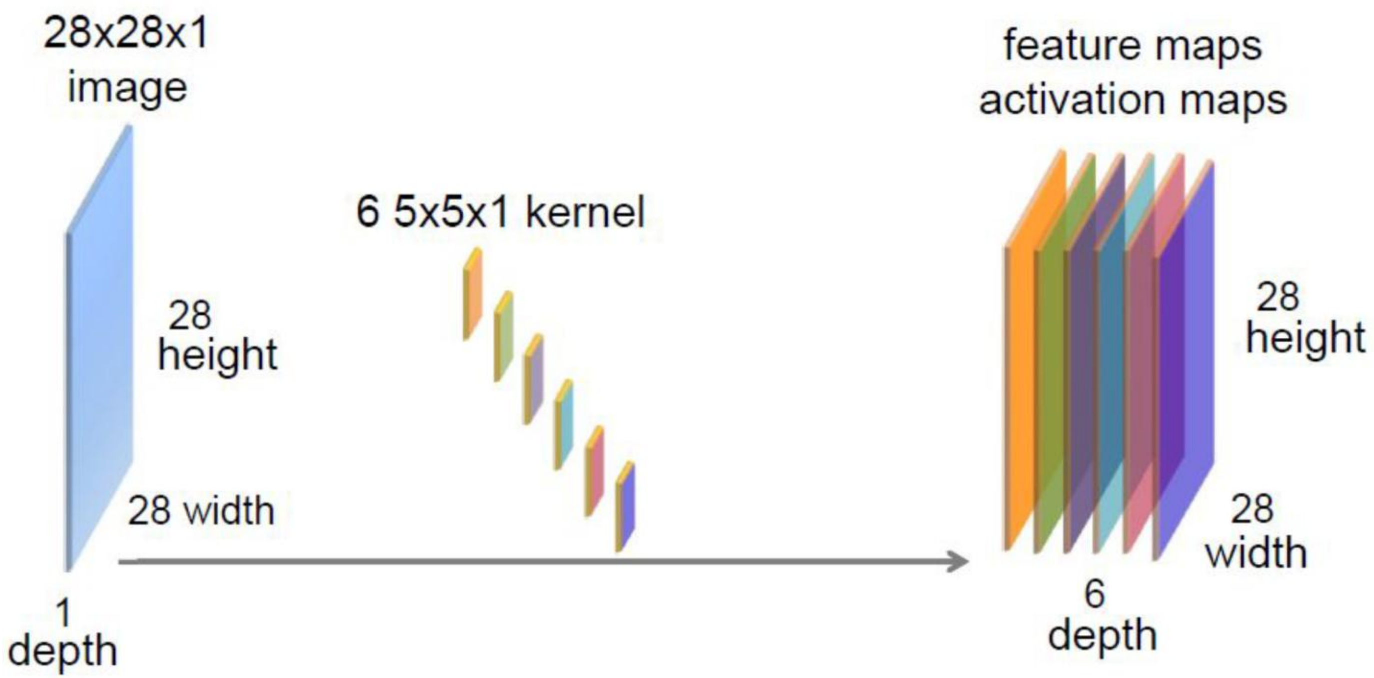


Open NB in: https://github.com/tensorchiefs/dl_course_2020/blob/master/notebooks/05_cnn_edge_lover.ipynb

More then one kernel (Motivatoion)



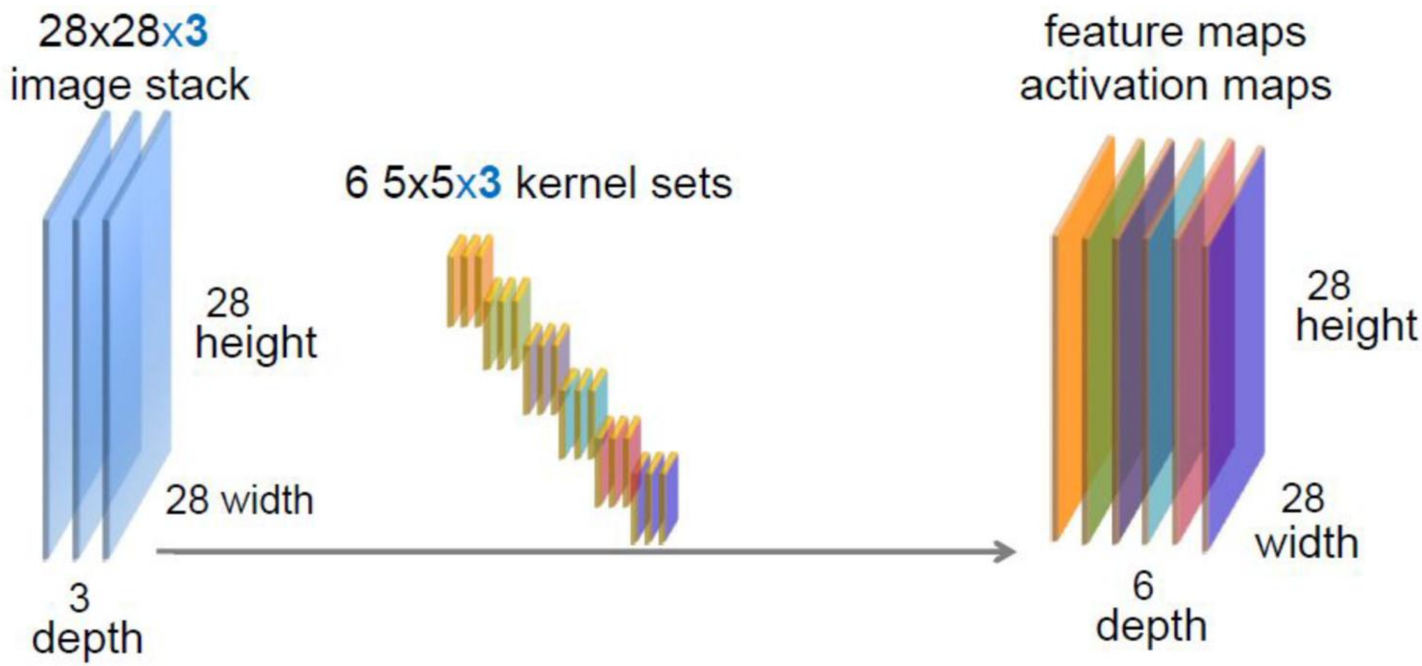
Convolution layer with a 1-chanel input and 6 kernels



Convolution of the input image with 6 different kernels results in 6 activation maps.

If the input image has only one channel, then each kernel has also only one channel.

Convolution layer with a 3-chanel input and 6 kernels



Convolution of the input image with 6 different kernels results in 6 activation maps.

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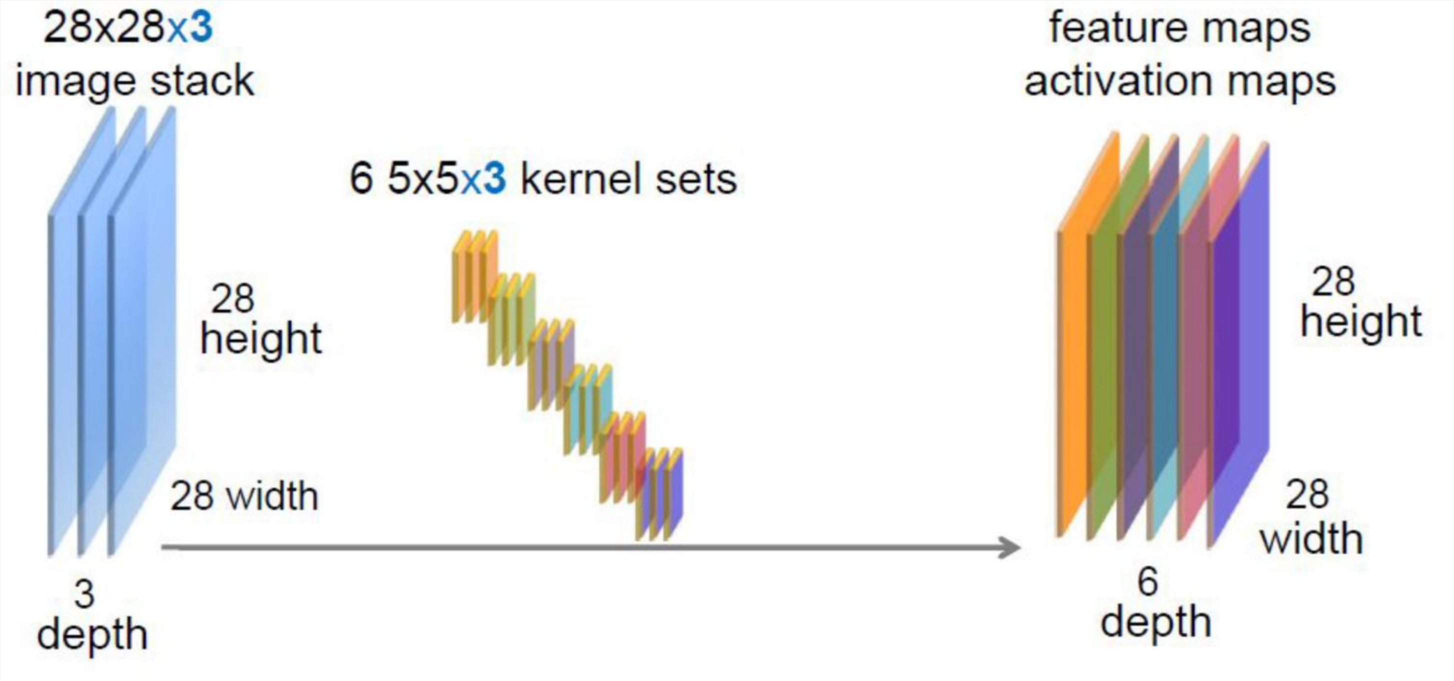
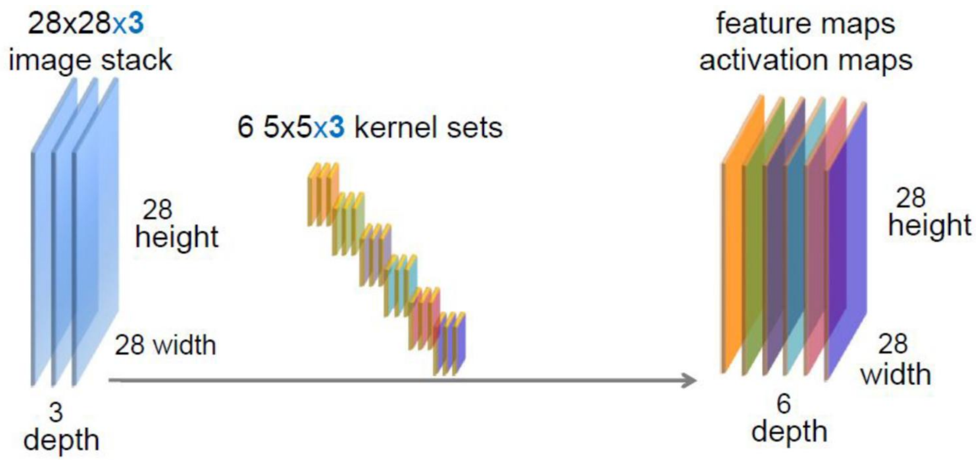
Convolution layer with a 3-chanel input and 6 kernels



How many weights?

Solution



6*5*5*3 + 6 = 456

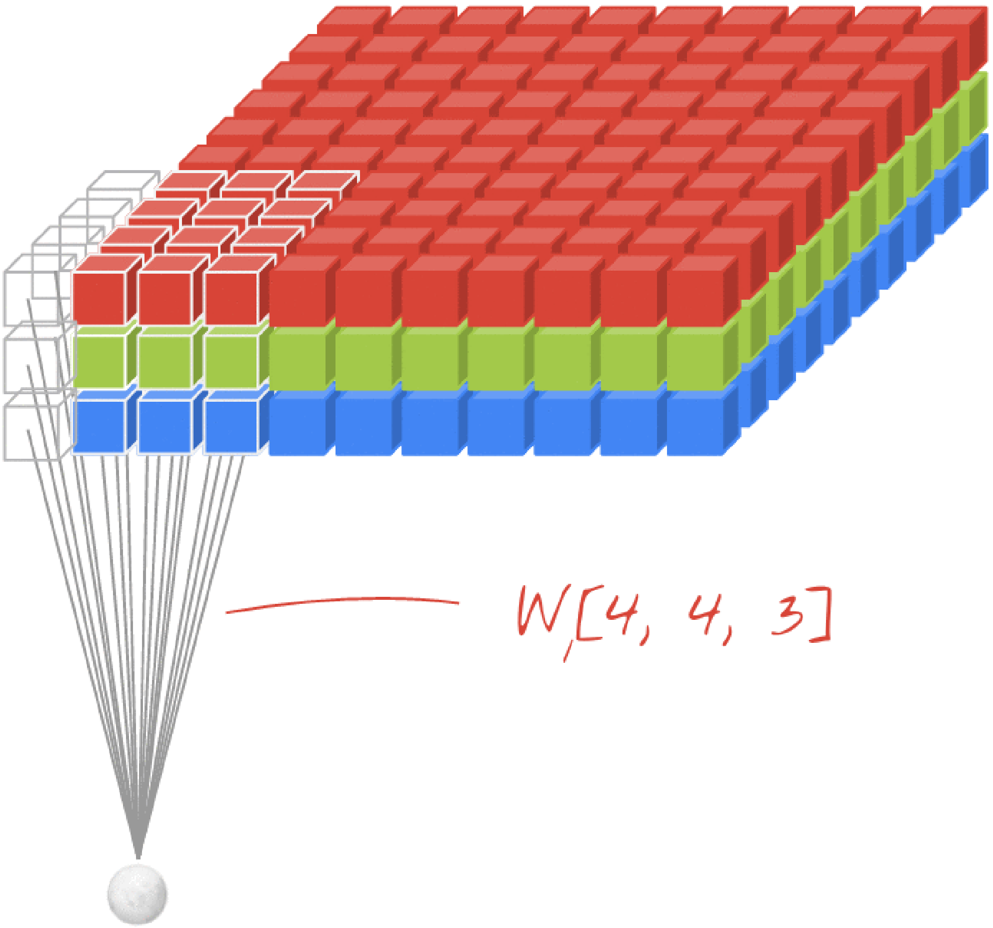
```
# Number of weights in Convolution
model = Sequential()
model.add(Convolution2D(6,kernel_size=(5,5),padding='same',input_shape=(28,28,3)))
model.summary()
```

Model: "sequential_11"

Layer (type)	Output Shape	Param #
conv2d_44 (Conv2D)	(None, 28, 28, 6)	456

Total params: 456 (1.78 KB)
Trainable params: 456 (1.78 KB)
Non-trainable params: 0 (0.00 B)

Animated convolution with 3 input channels



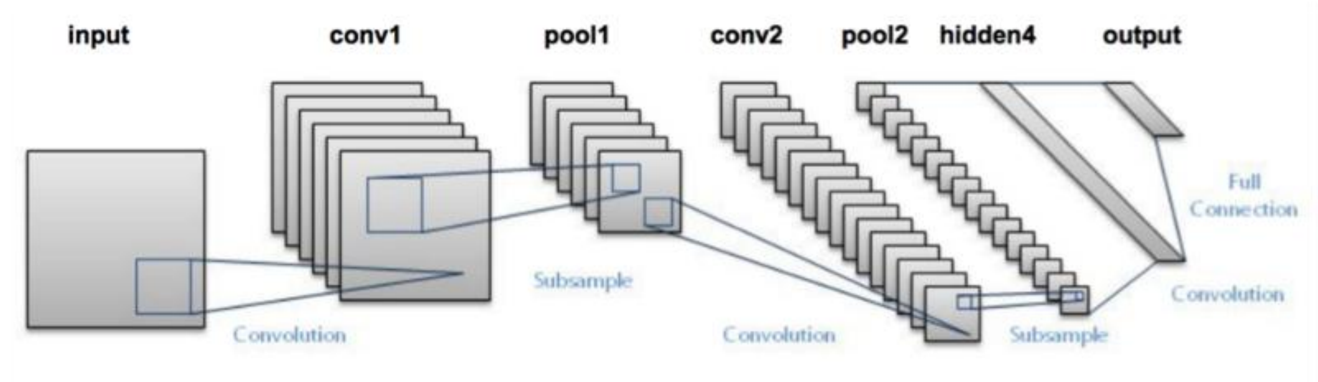
3 color channel input image

The value of neuron j in the k-th featuremap are computed from the weights in the k-th filter w_{ki} and the input values x_{ji} at the position j:

$$y_{j\mathrm{F_k}} = \mathrm{f}(\mathrm{z_{jF_k}}) = f(b_k + \sum x_{ji} \cdot w_{ki})$$

Animation credits: M.Gorner, https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist/#10

CNN for MNIST

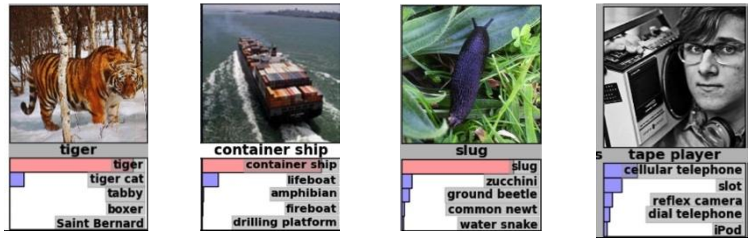



```
model = Sequential()

model.add(Convolution2D(filters=8,kernel_size=(3,3),
                        padding='same',input_shape=(28,28,1)))
model.add(Activation('relu'))
model.add(Convolution2D(16, (3, 3),padding='same'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Flatten())
model.add(Dense(40))
model.add(Activation('relu'))
model.add(Dense(10))
model.add(Activation('softmax'))

# compile model and intitialize weights
model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

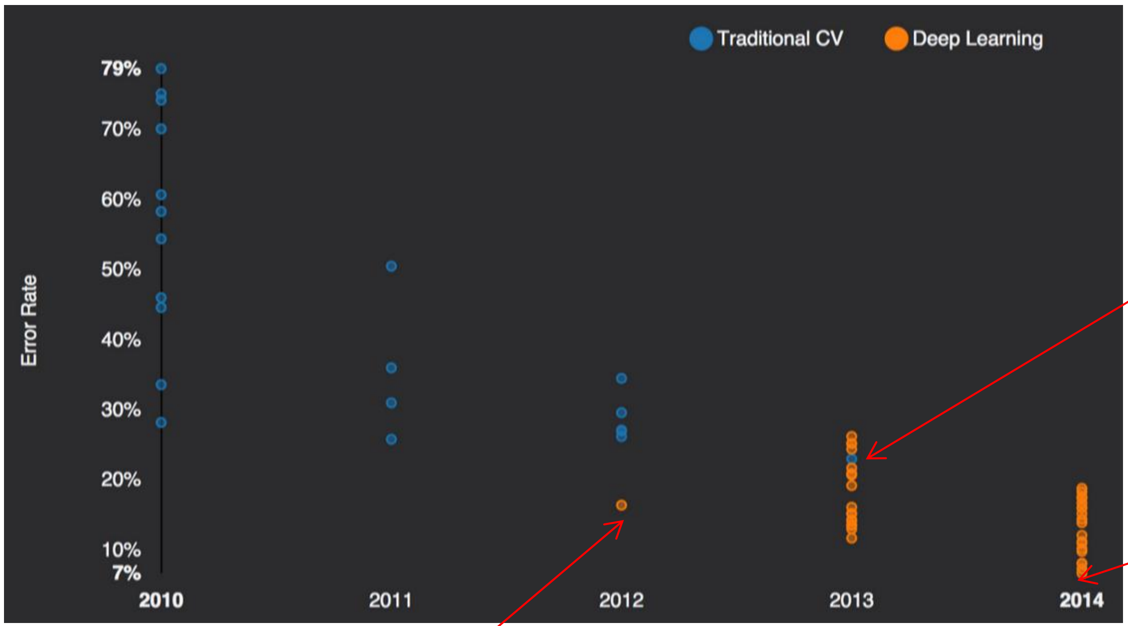
What is a good CNN architecture?

CNN breakthrough in 2012: Imagenet challenge

1000 classes
1 Mio samples



…



Human: 5% misclassification

Only one non-CNN approach in 2013

GoogLeNet 6.7%

A. Krizhevsky
first CNN in 2012
Und es hat zoom gemacht

Figure: https://medium.com/global-silicon-valley/machine-learning-yesterday-today-tomorrow-3d3023c7b519

Review of ImageNet winning CNN architectures

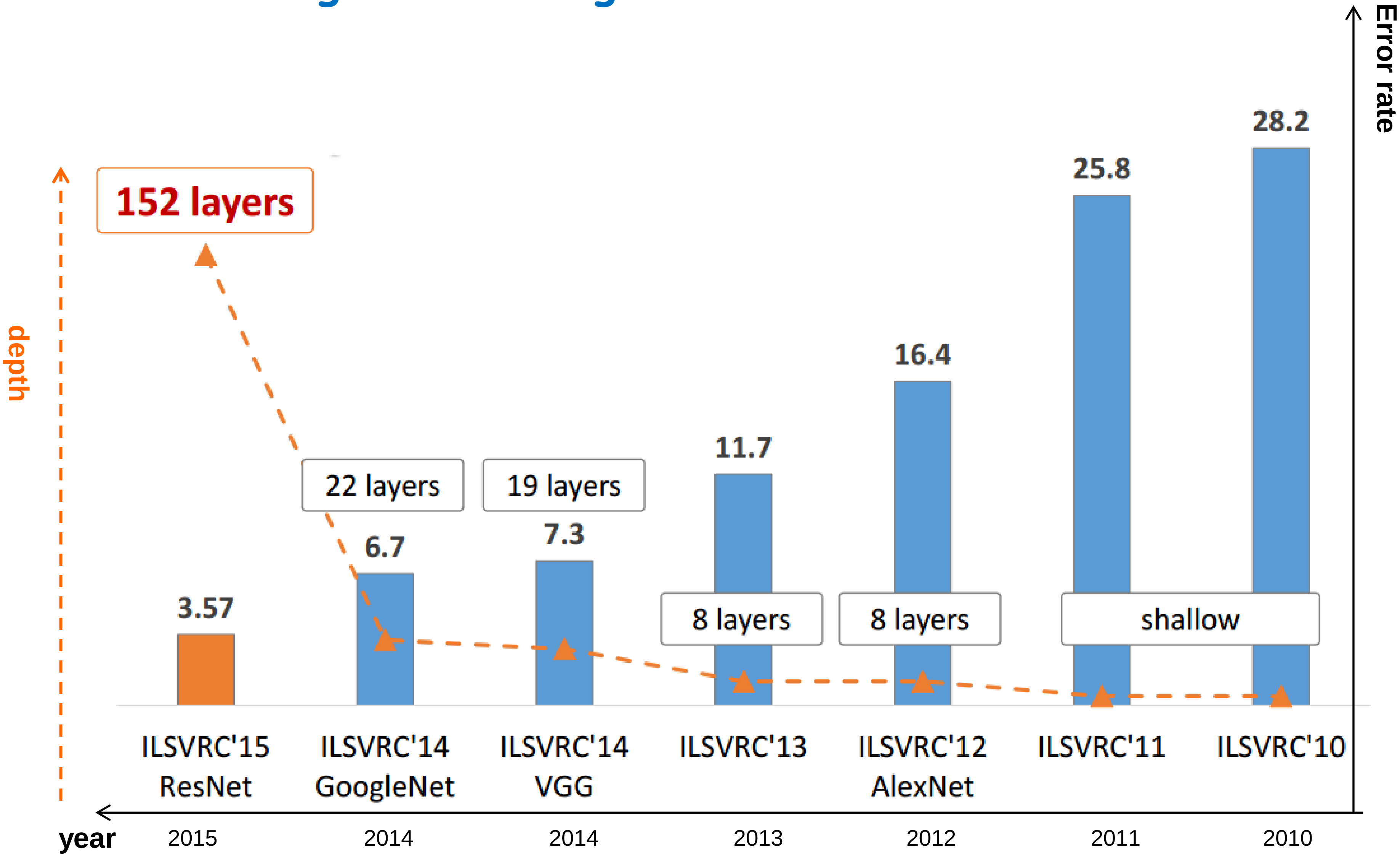


Image credits (modified): K.He, X.Zhang, S.Ren, J.Sun. "Deep Residual Learning for Image Recognition". arXiv 2015

LeNet-5 1998: first CNN for ZIP code recognition

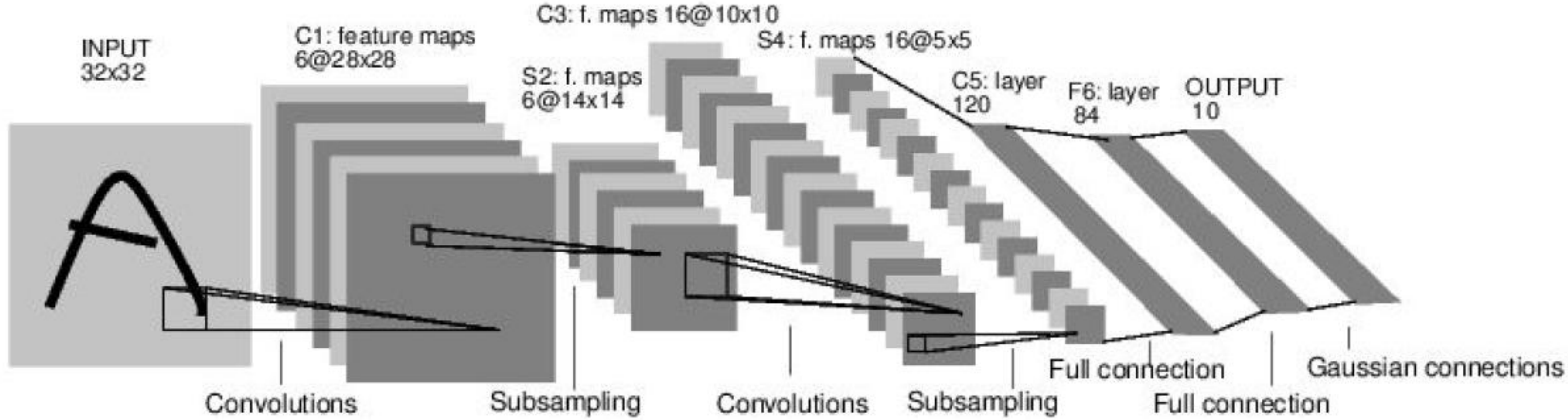


Image credits: http://yann.lecun.com/exdb/publis/pdf/lecun-98.pdf

[Demo von 1993](#) Yann LeCun

Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-CONV-FC]

http://yann.lecun.com/exdb/lenet/index.html

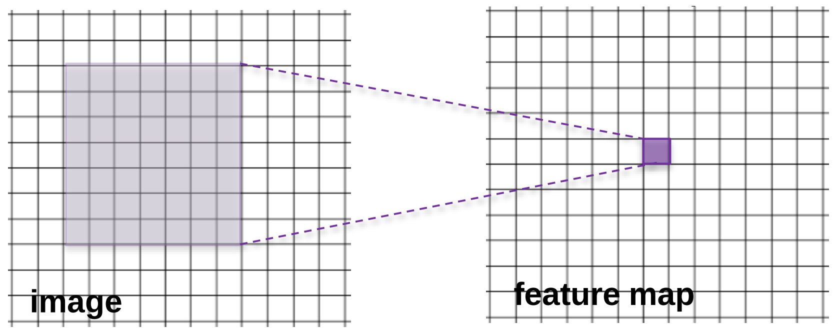
The trend in modern CNN architectures goes to small filters

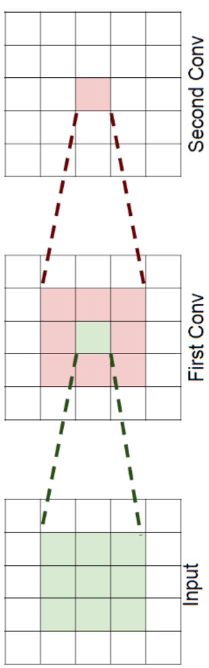
Why do modern architectures use very small filters?
Determine the receptive field in the following situation:

1) Suppose we have **one** 7x7 conv layers (stride 1)

49 weights

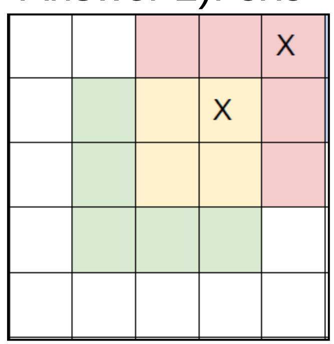
Answer1): 7x7





2) Suppose we stack **two** 3x3 conv layers (stride 1)

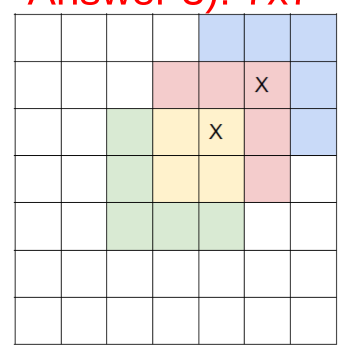
Answer 2): 5x5



3) Suppose we stack **three** 3x3 conv layers (stride 1)

3*9=27 weights

Answer 3): 7x7



We need less weights for the same receptive field when stacking small filters!

"Oxford Net" or "VGG Net" 2014 2nd place

- 2nd place in the imageNet challenge
- More traditional, easier to train
- Small pooling
- Stacked 3x3 convolutions before maxpooling

  -> large receptive field
- no strides (stride 1)
- ReLU after conv. and FC (batchnorm was not introduced)
- Pre-trainined model is available (see excercise)

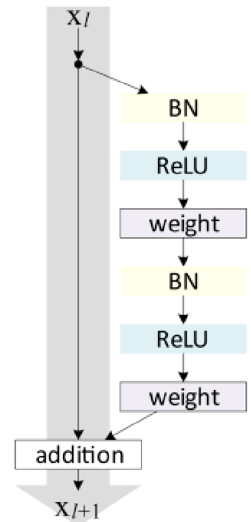
http://arxiv.org/abs/1409.1556

“ResNet” from Microsoft 2015 winner of imageNet

152
layers

ResNet basic design (VGG-style)

- add shortcut connections every two
- all 3x3 conv (almost)



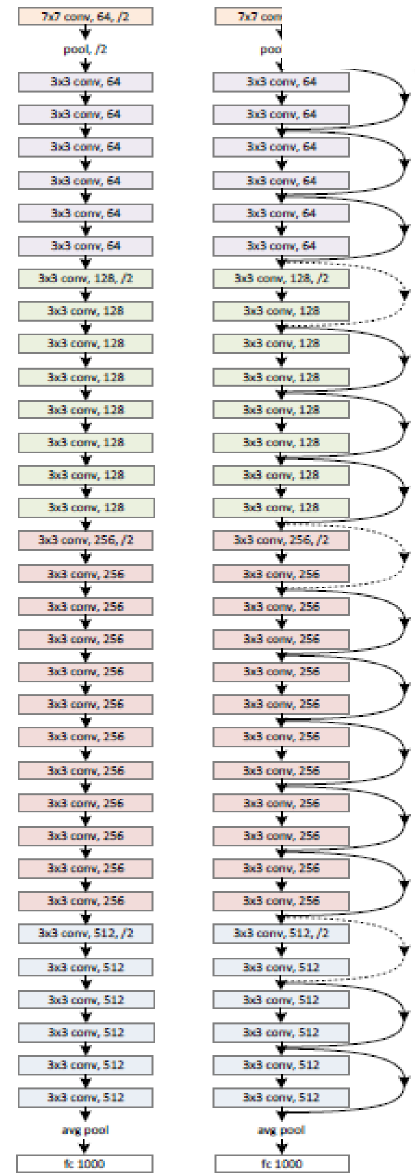
$F(x_l)$

$H(x_l)=x_{l+1} = x_l + F(x_l)$

152 layers:
Why does this train at all?

This deep architecture could still be trained, since the gradients can skip layers which diminish the gradient!

plain VGG



ResNet

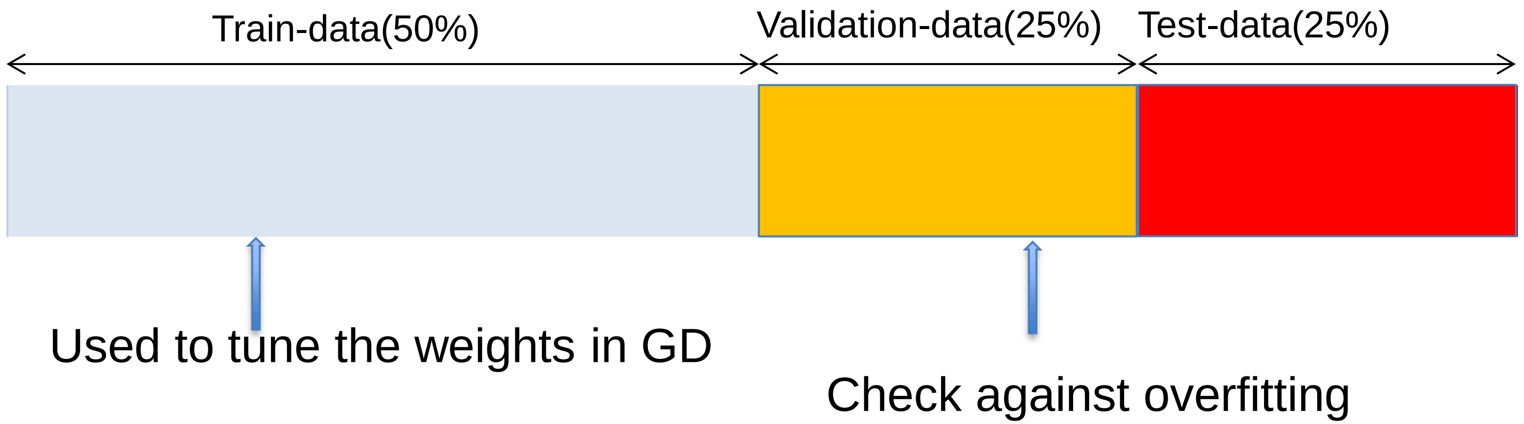
F(x) is called “residual” since it only learns the “delta” which is needed to add to x to get H(x)

credits: https://chatbotslife.com/resnets-highwaynets-and-densenets-oh-my-9bb15918ee32

Tricks of the trade

- Early stopping
- Input Standardization
- Batch Norm Layer
- Dropout
- Data augmentation

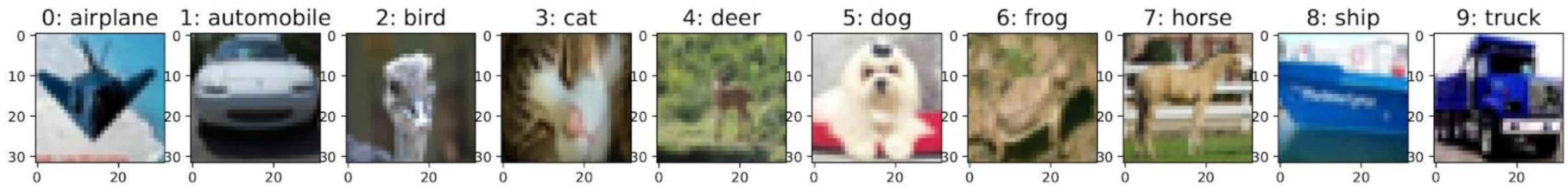
Best practice: Split in Train, Validation, and Test Set



Best practice: Lock an extra test data set away, and use it only at the very end, to evaluate the chosen model, that performed best on your validation set.
Reason: **When trying many models, you probably overfit on the validation set**.

Determine performance metrics, such as MSE, to evaluate the predictions **on new validation or test data**

CIFAR10 study with tensorflow notebook

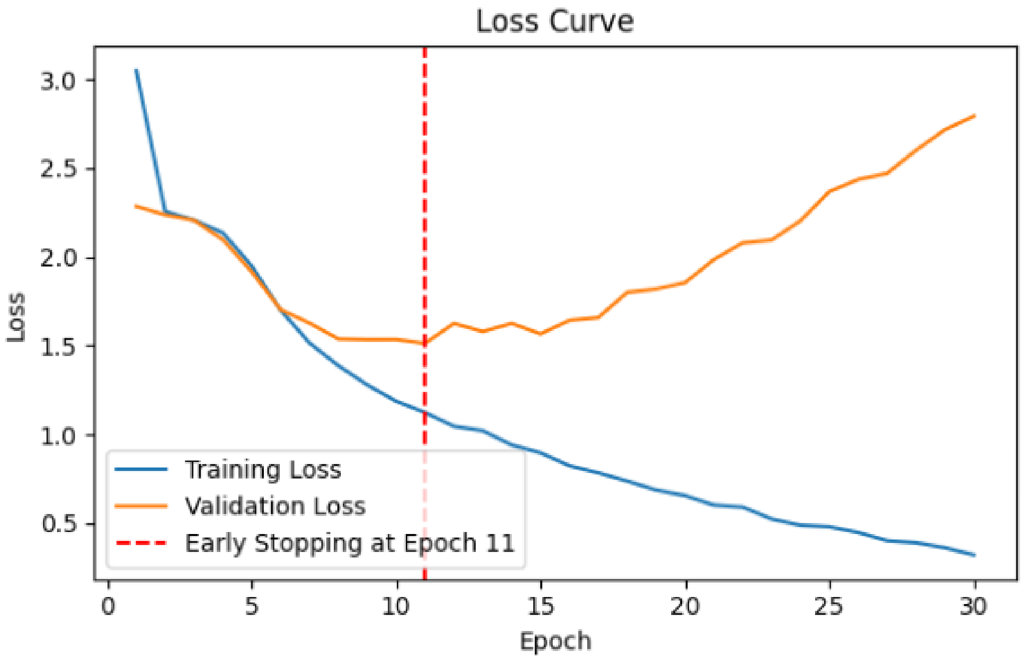


We define a CNN to classify cifar10 images (we have 10 classes)

Notebook:
https://github.com/tensorchiefs/dl_course_2020/blob/master/notebooks/07_cifar10_norm_sol.ipynb

Loss curve and early stopping

Very common check: Plot loss in train and validation data vs epoch of training.




```
Training completed all epochs.
Best model weights were restored from epoch 11
```

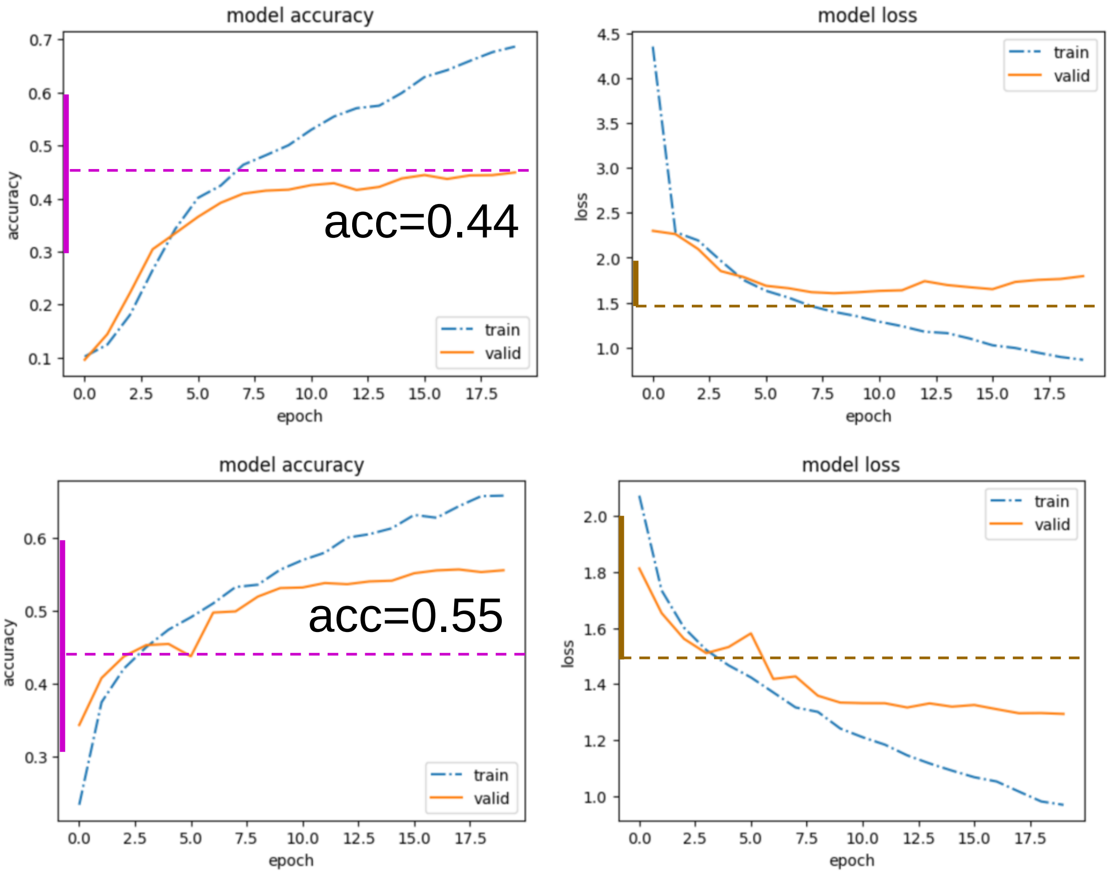
- If training loss does not go down to zero: model is not flexible enough
- Use weights @minimum of validation before overfitting
- Early stopping: stop to training if validation loss does not improve anymore

Take-home messages from CIFAR10 CNN study

- DL does not need a lot of preprocessing, but working with standardized (small-valued) input data often helps.

Without normalizing
the input to the CNN

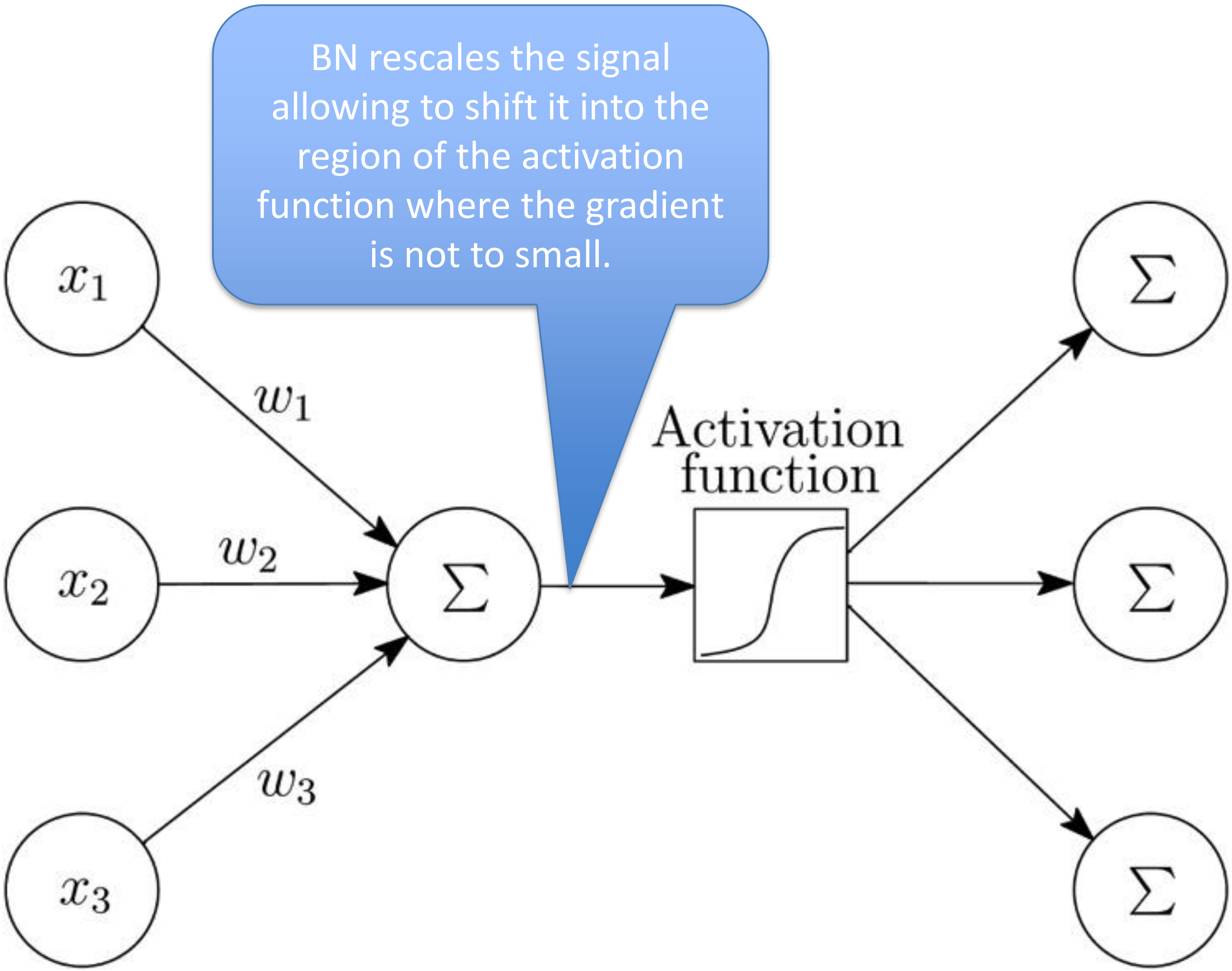
With normalizing
(pixel-value/255)
the input to the CNN



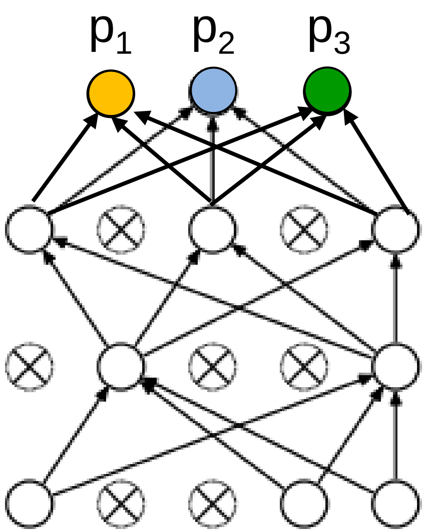
Regularization to avoid overfitting

- Batchnorm layer
- Dropout layer

What is the idea of Batch-Normalization (BN)



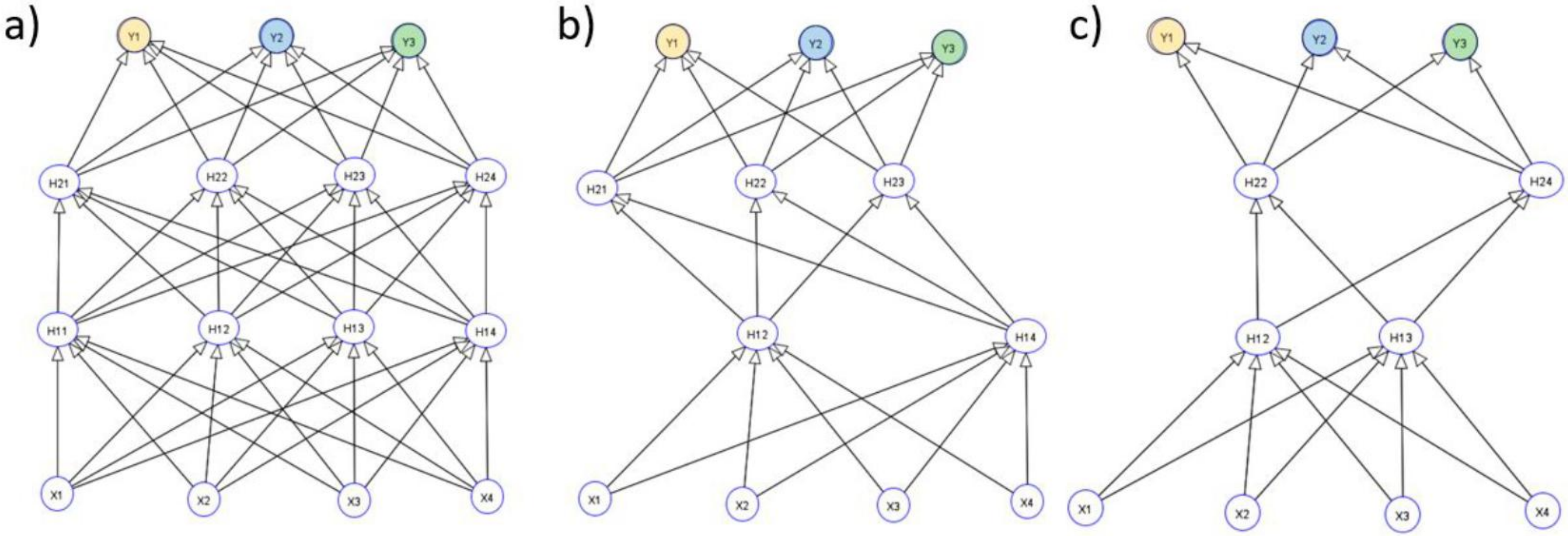
Dropout helps to fight overfitting



Using dropout during training implies:

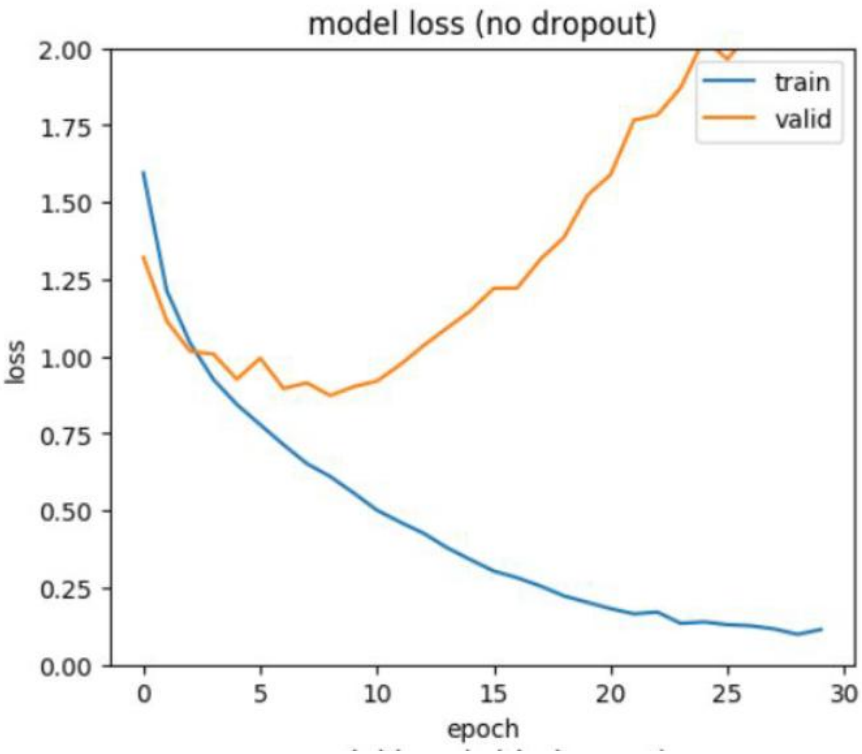
- In each training step only weights to not-dropped units are updated → we train a sparse sub-model NN
- For predictions with the trained NN we freeze the weights corresponding to averaging over the ensemble of trained models we should be able to “reduce noise”, “overfitting”
- JFI: To get same expected output in training (with dropout) and after training (test time - without dropout), the weights are multiplied after training by the dropout probability p=0.5.

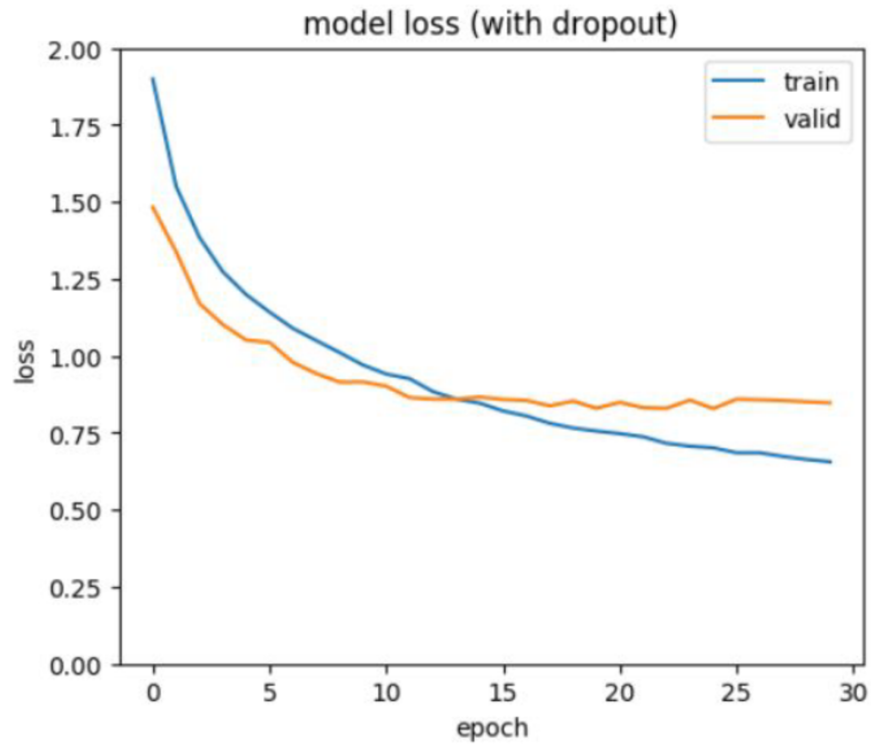
Dropout



Three NNs:
a) shows the full NN with all neurons (as used when NN is trained),
b) and c) show two versions of a thinned NN where some neurons are dropped (as done during training with dropout). Dropping neurons is the same as setting all connections that start from these neurons to zero.

Dropout fights overfitting in a CIFAR10 CNN





Summary

- The NN architecture choice depends on the structure of the data.
  - Fully connected NNs work best for tabular data
  - CNNs work best for images and other data with local order

- CNNs exploit the local structure of images by local connections and shared weight (same kernel is applied at each position of the image).

- Use tricks of the trade when building a CNN
  - Normalization of input data
  - Batchnorm
  - Dropout
  - Augmentation
  - Use challenge winning architectures