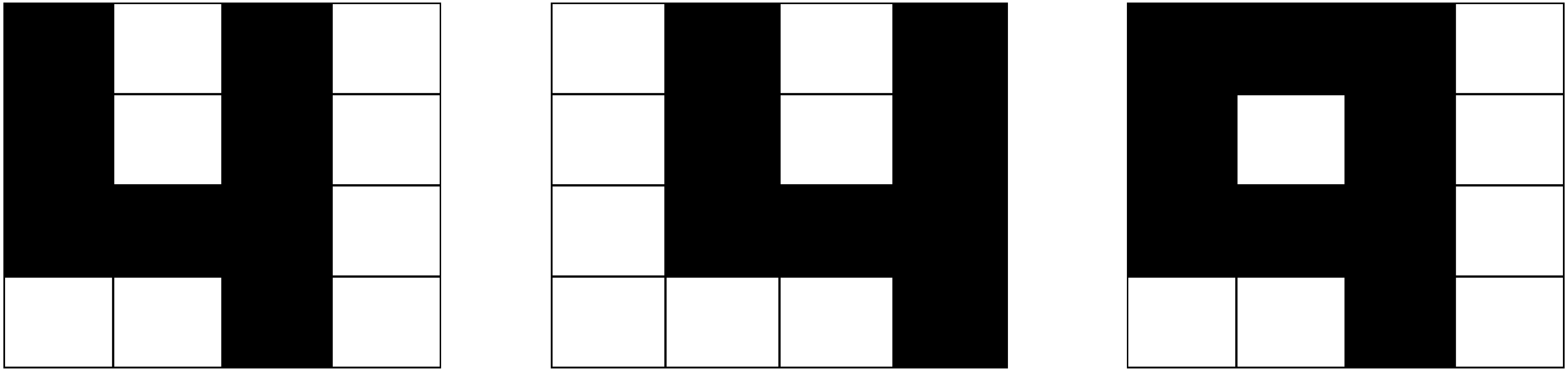
Non-linear classifiers
Neural networks

Linear classifiers on pixels are bad



- Solution 1: Better feature vectors
- Solution 2: Non-linear classifiers

A pipeline for recognition

Compute image gradients

Compute SIFT descriptors

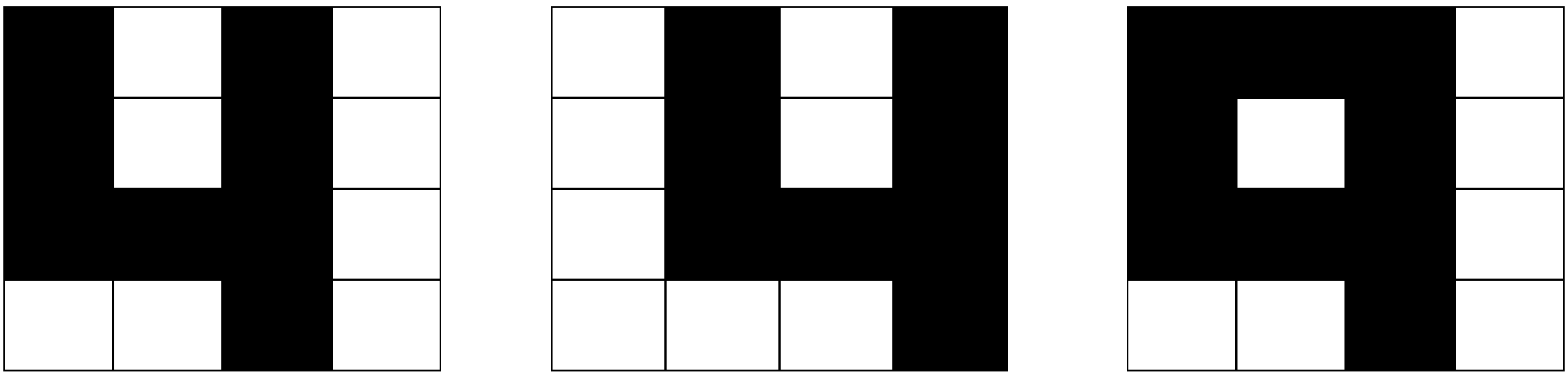
Assign to k-means centers

Compute histogram

Linear classifier

Horse

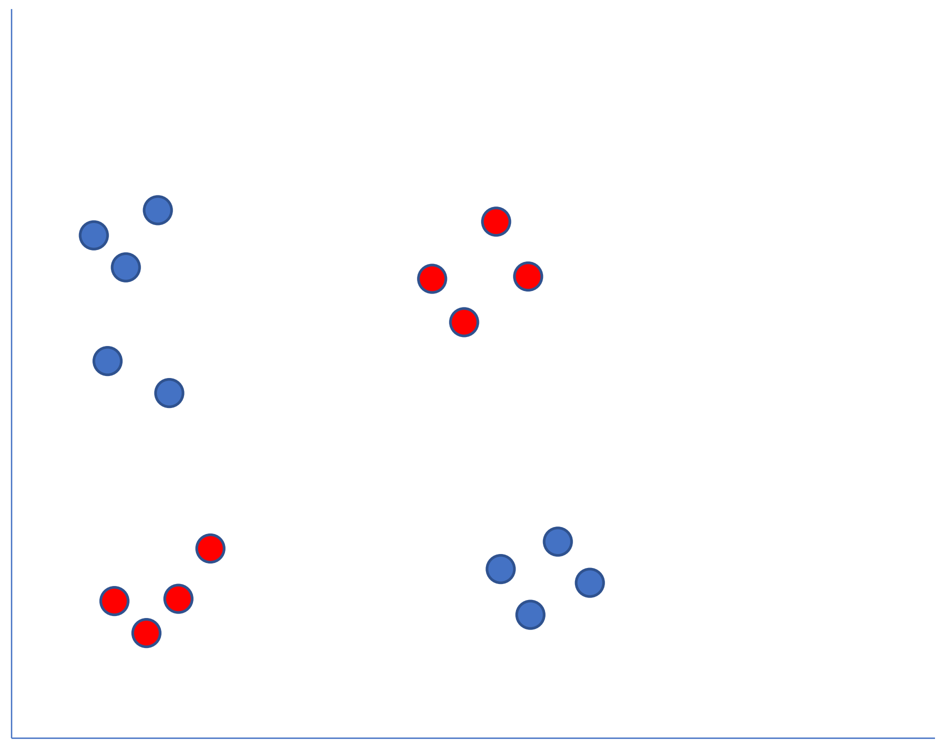
Linear classifiers on pixels are bad



- Solution 1: Better feature vectors
- Solution 2: Non-linear classifiers

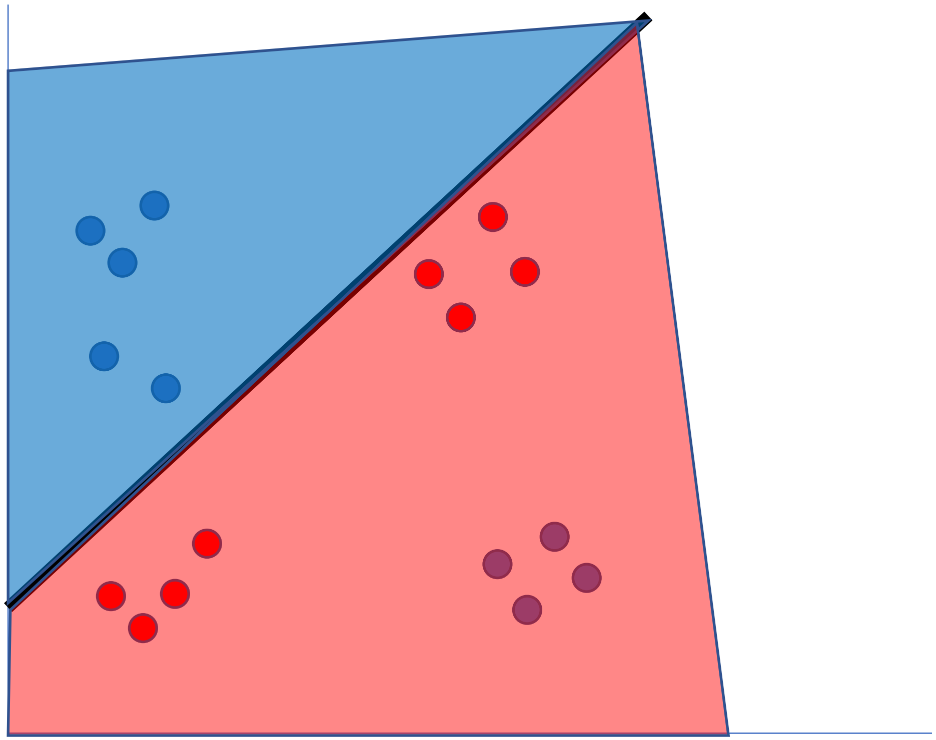
Non-linear classifiers

- Suppose we have a feature vector for every image



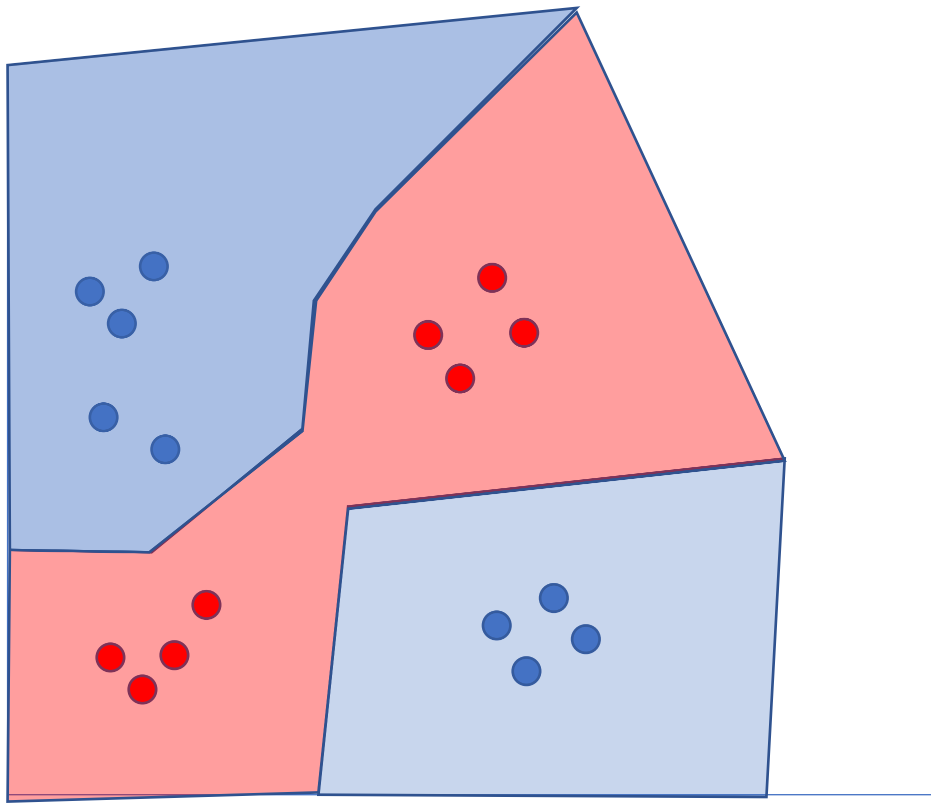
Non-linear classifiers

- Suppose we have a feature vector for every image
  - Linear classifier



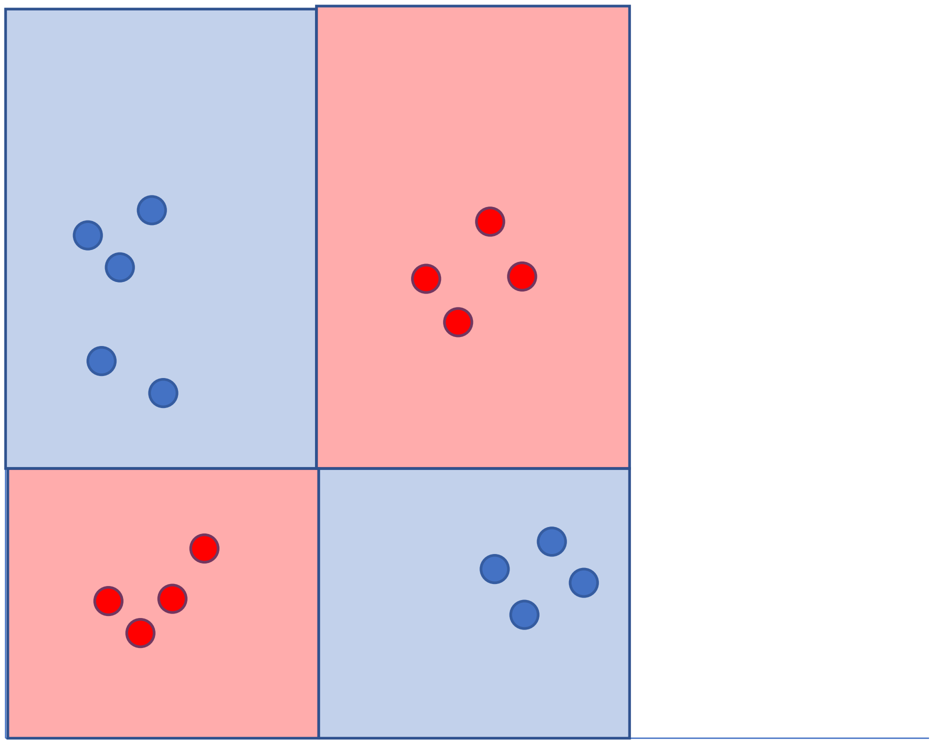
Non-linear classifiers

- Suppose we have a feature vector for every image
  - Linear classifier
  - Nearest neighbor: assign each point the label of the nearest neighbor



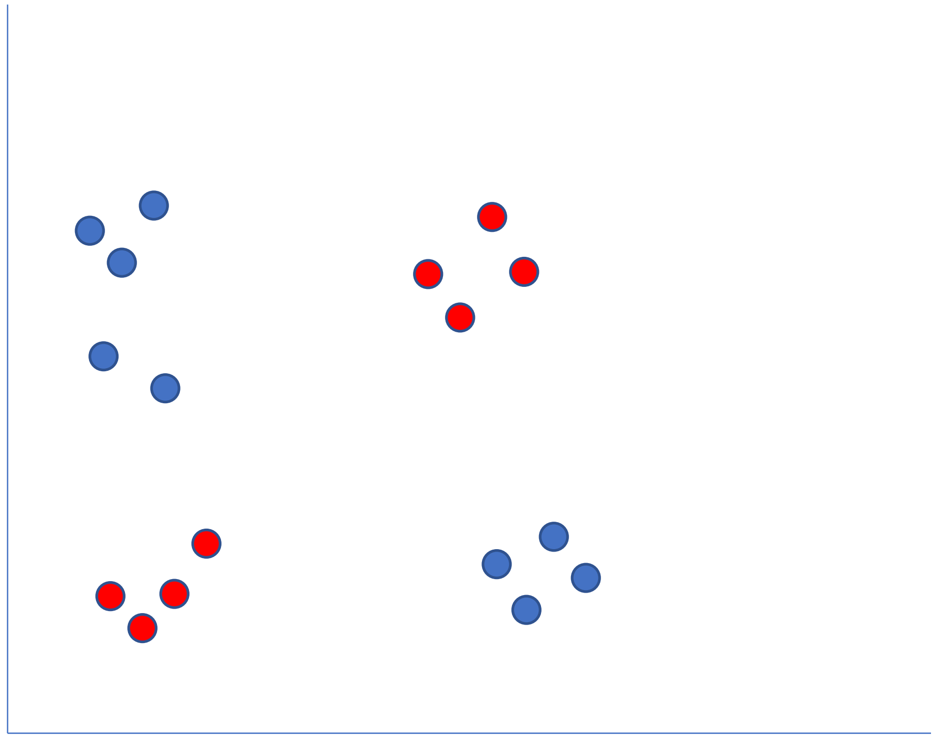
Non-linear classifiers

- Suppose we have a feature vector for every image
  - Linear classifier
  - Nearest neighbor: assign each point the label of the nearest neighbor
  - Decision tree: series of if-then-else statements on different features

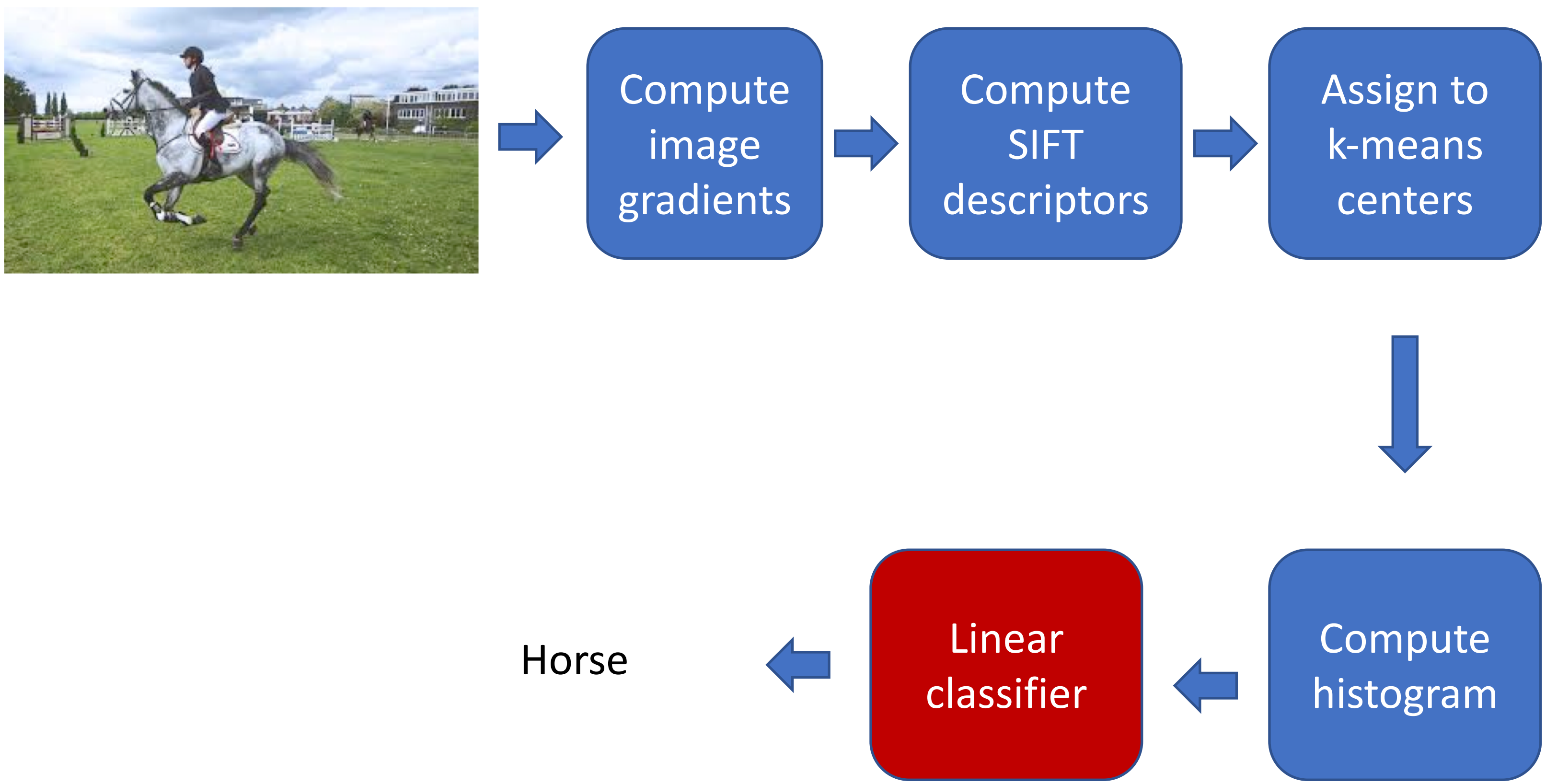


Non-linear classifiers

- Suppose we have a feature vector for every image
  - Linear classifier
  - Nearest neighbor: assign each point the label of the nearest neighbor
  - Decision tree: series of if-then-else statements on different features
  - Neural networks / multi-layer perceptrons



A pipeline for recognition



Multilayer perceptrons

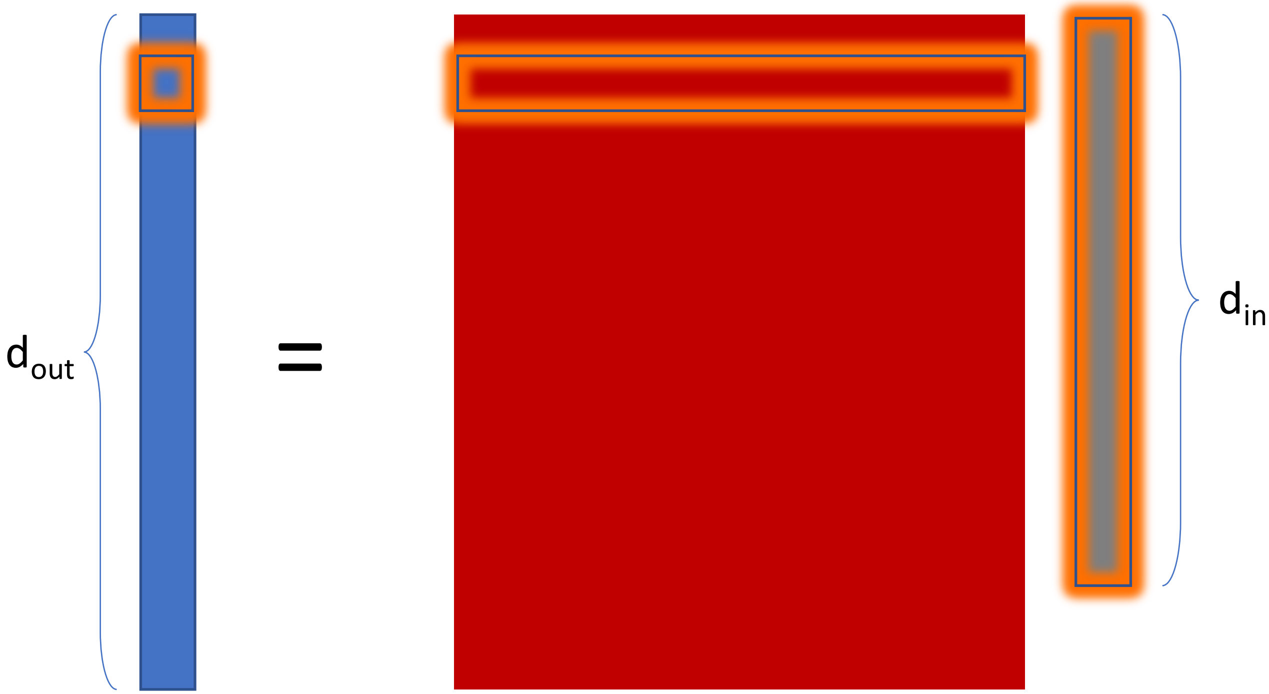
- Key idea: build complex functions by composing simple functions
- Caveat: simple functions must include non-linearities
- $W(U(Vx)) = (WUV)x$
- Let us start with only two ingredients:
  - *Linear: $y = Wx + b$*
  - *Rectified linear unit (ReLU, also called half-wave rectification): $y = \max(x,0)$*

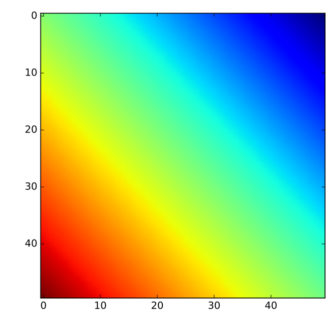
The linear function

- $y = Wx + b$
- Parameters: W,b
- Input: x (column vector, or 1 data point per column)
- Output: y (column vector or 1 data point per column)
- Hyperparameters:
  - Input dimension = # of rows in x
  - Output dimension = # of rows in y
  - W : outdim x indim
  - b : outdim x 1

The linear function

- $y = Wx + b$
- Every row of y corresponds to a hyperplane in x space

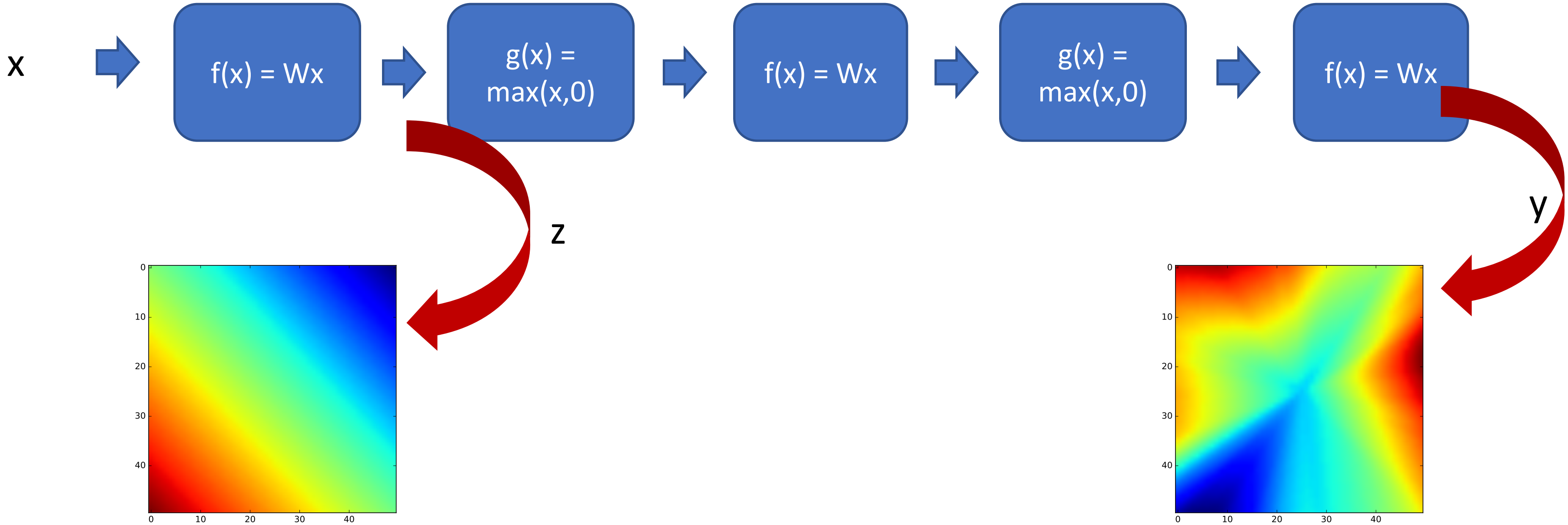




The case when $d_{in} = 2$. A single row in y plotted for every possible value of x

Multilayer perceptrons

- Key idea: build complex functions by composing simple functions

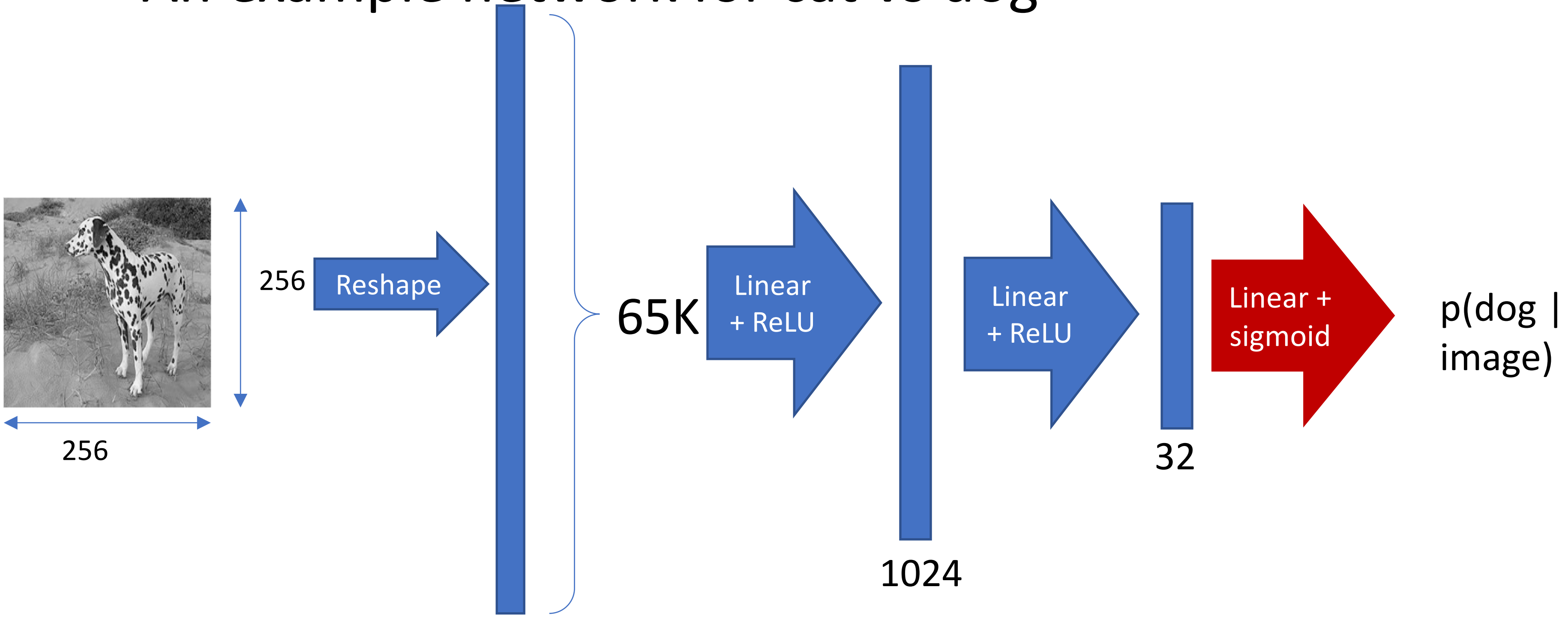


1 row of z plotted for every value of x

1 row of y plotted for every value of x

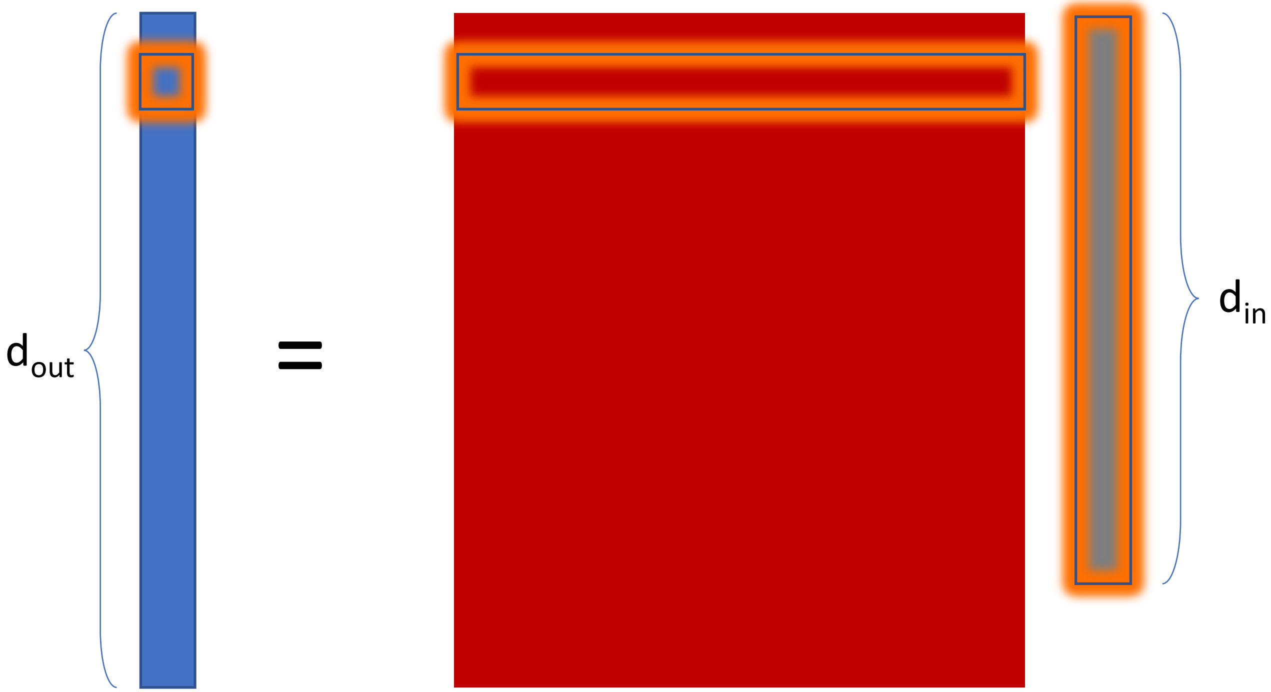
Multilayer perceptron on images

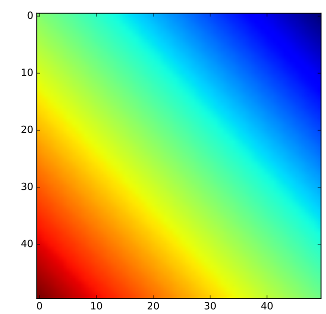
- An example network for cat vs dog



The linear function

- $y = Wx + b$
- How many parameters does a linear function have?

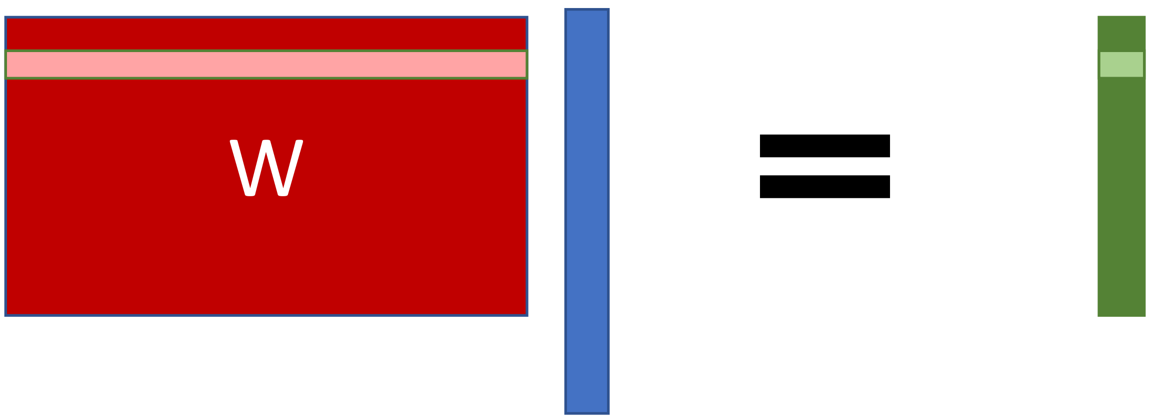




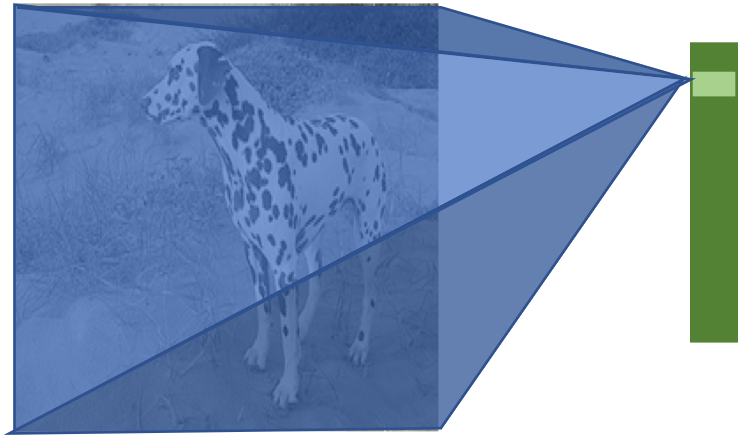
The case when d_{in} = 2. A single row in y plotted for every possible value of x

The linear function for images

Reducing parameter count

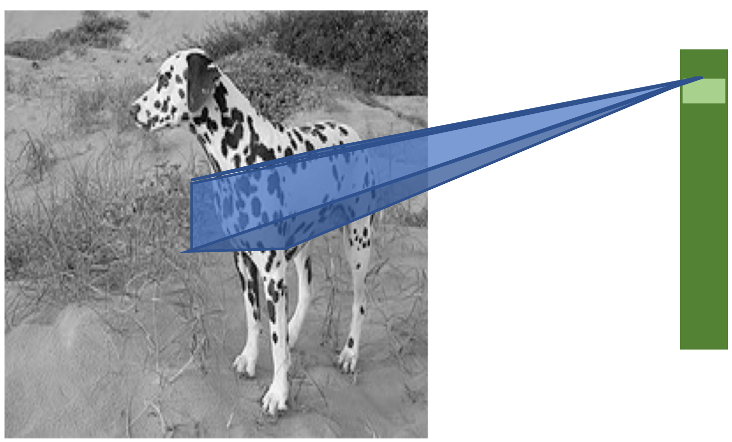


Reducing parameter count



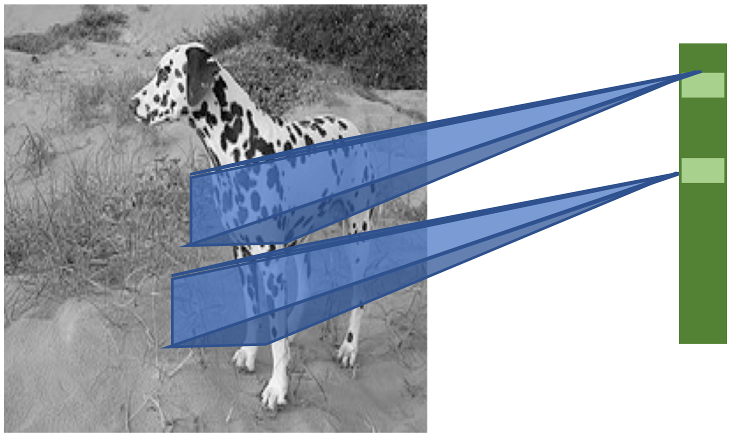
Idea 1: local connectivity

- Pixels only related to nearby pixels



Idea 2: Translation invariance

- Pixels only related to nearby pixels
- Weights should not depend on the location of the neighborhood



Linear function + translation invariance = *convolution*

- Local connectivity determines kernel size

5.4	0.1	3.6
1.8	2.3	4.5
1.1	3.4	7.2

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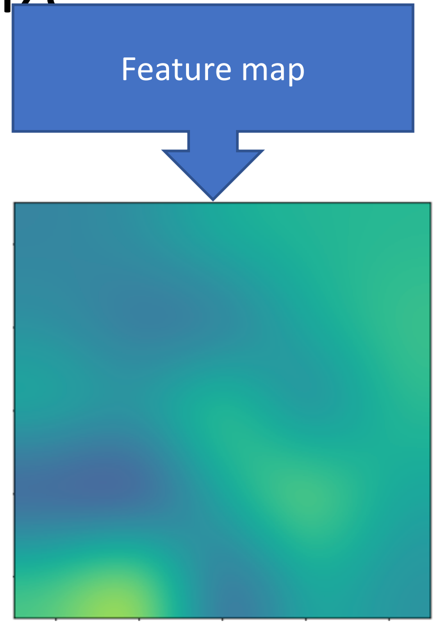
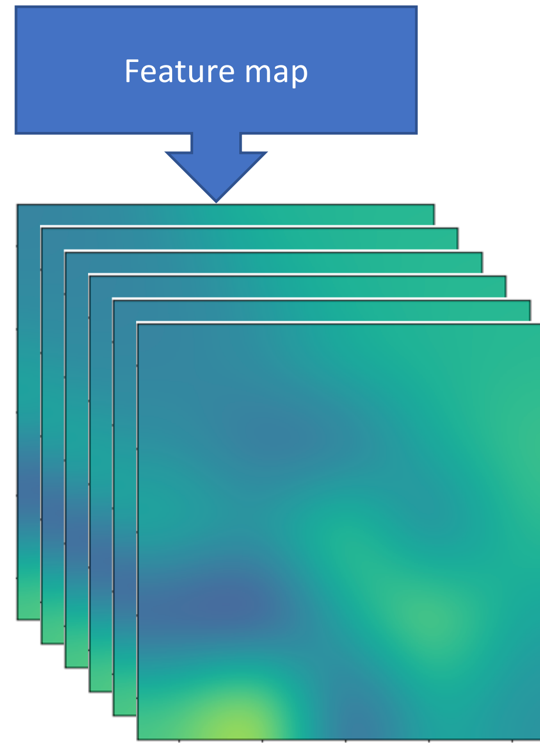
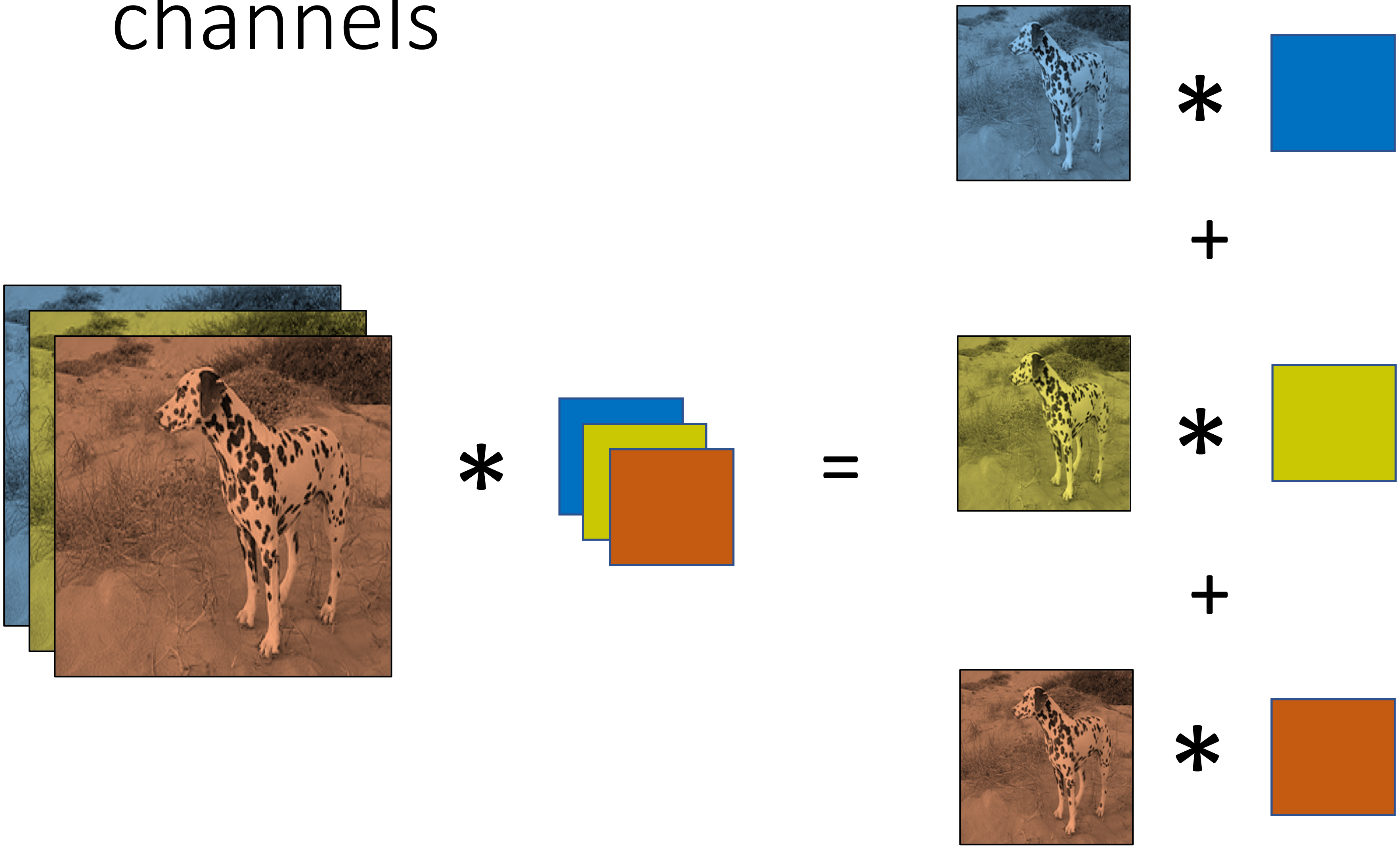


Convolution with multiple filters

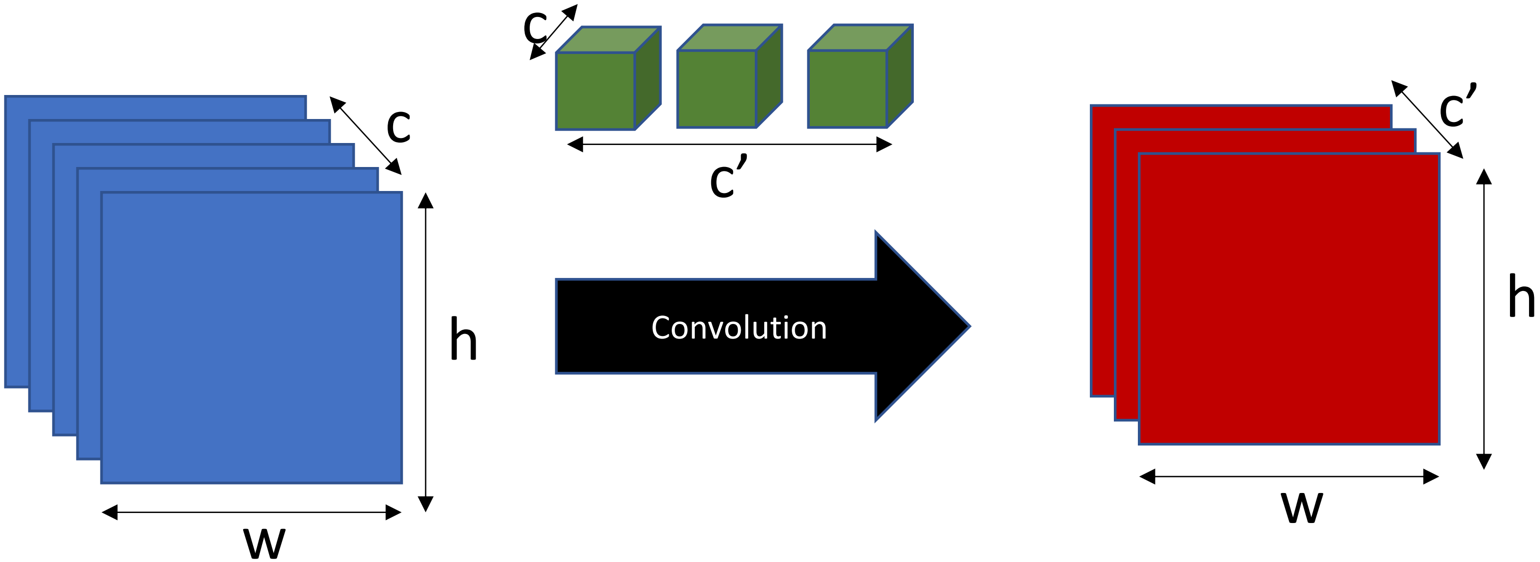
5.4	0.1	3.6
1.8	2.3	4.5
1.1	3.4	7.2



Convolution over multiple channels

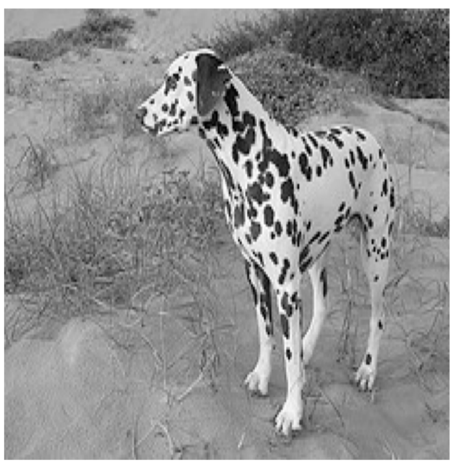


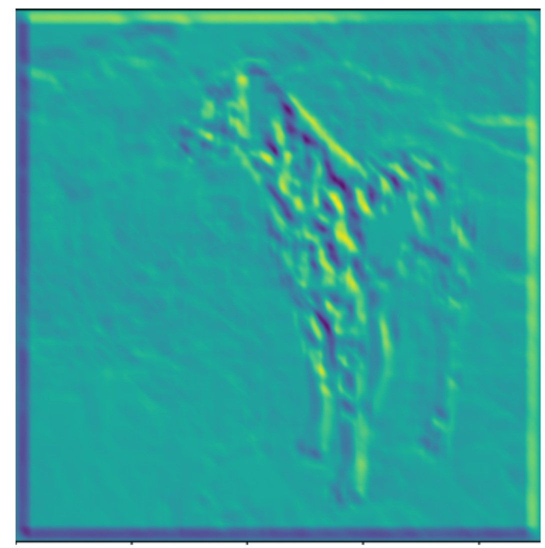
Convolution as a primitive



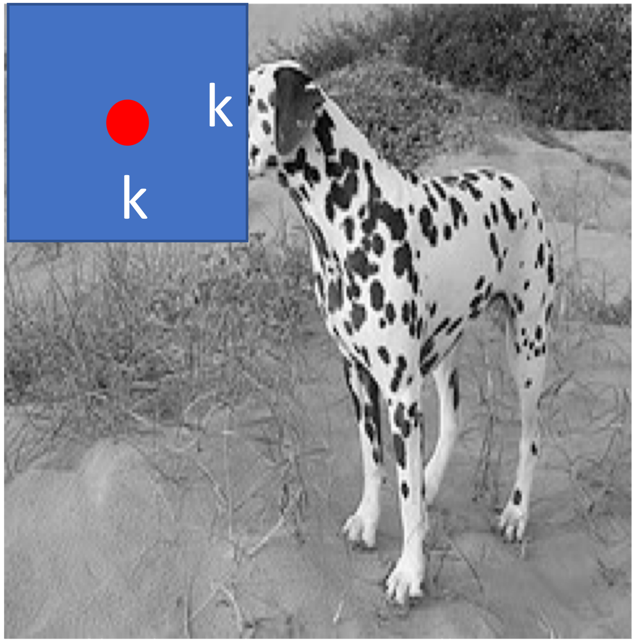
Convolution as a feature detector

- score at (x,y) = dot product (filter, image patch at (x,y))
- Response represents similarity between filter and image patch



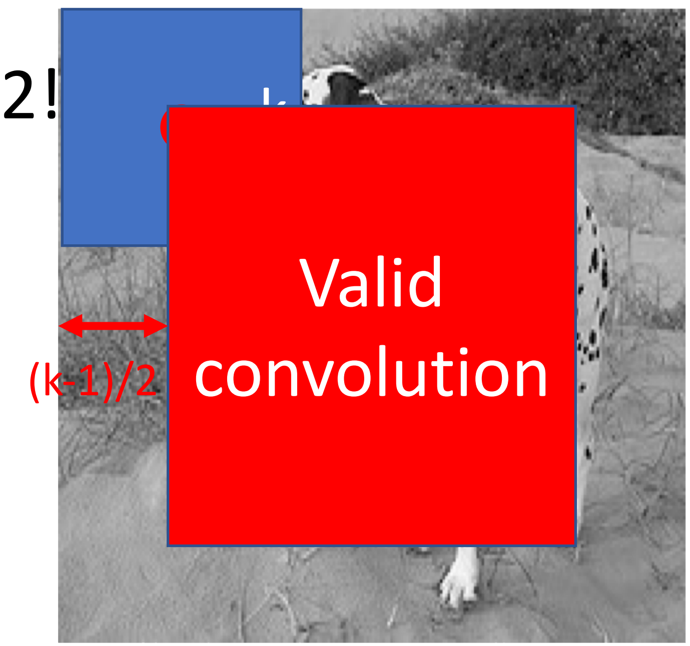


Kernel sizes and padding



Kernel sizes and padding

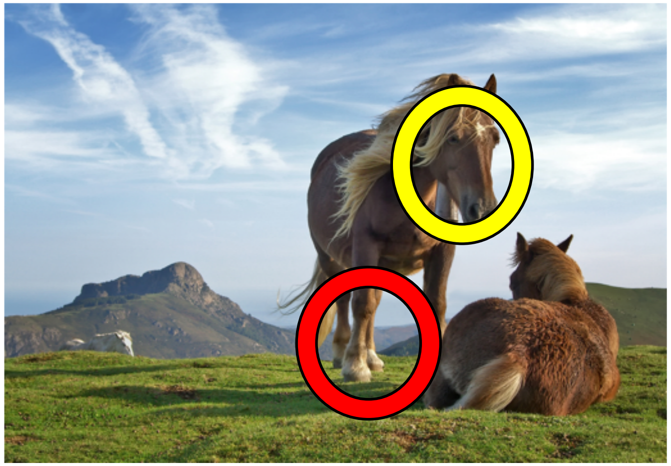
- Valid convolution decreases size by (k-1)/2 on each side
- Pad by (k-1)/2!



The convolution unit

- Each convolutional unit takes *a collection of feature maps* as input, and produces *a collection of feature maps* as output
- Parameters: Filters (+bias)
- If c_{in} input feature maps and c_{out} output feature maps
  - Each filter is k x k x c_{in}
  - There are c_{out} such filters
- Other hyperparameters: padding

Invariance to distortions



Invariance to distortions

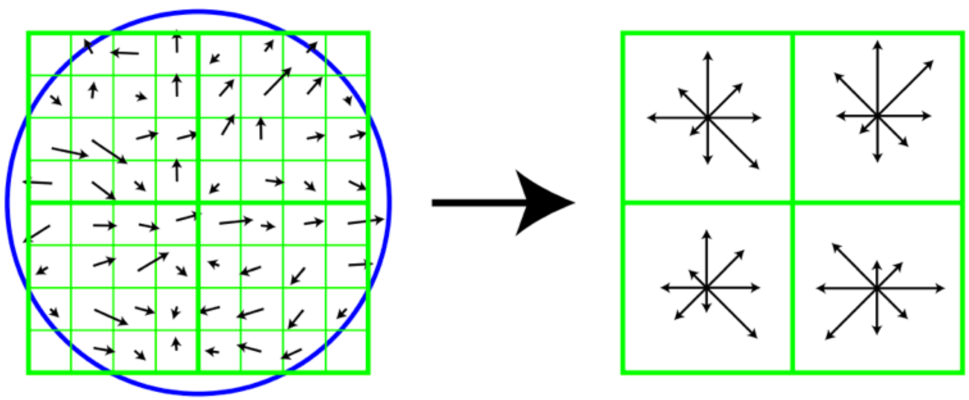
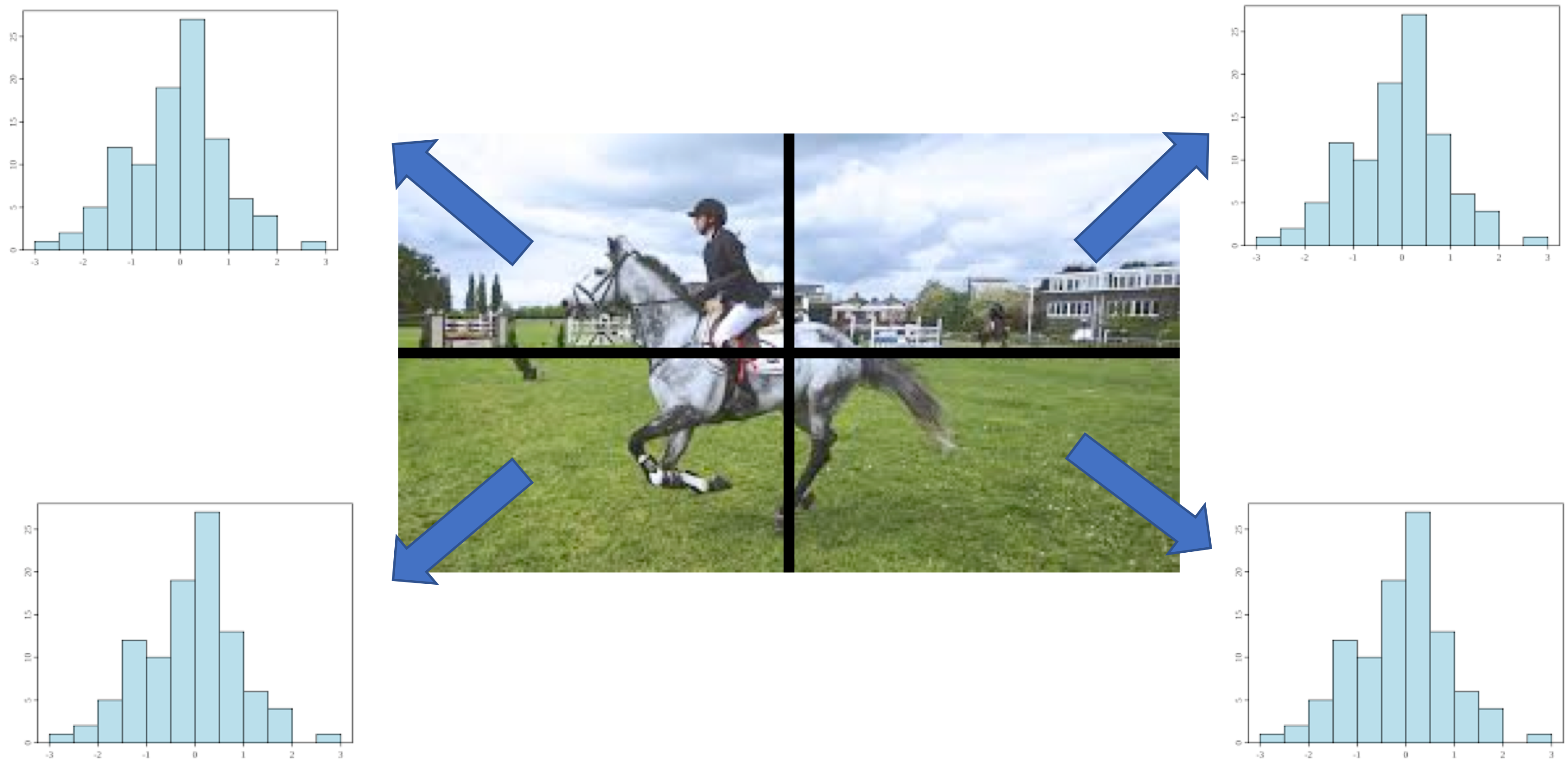
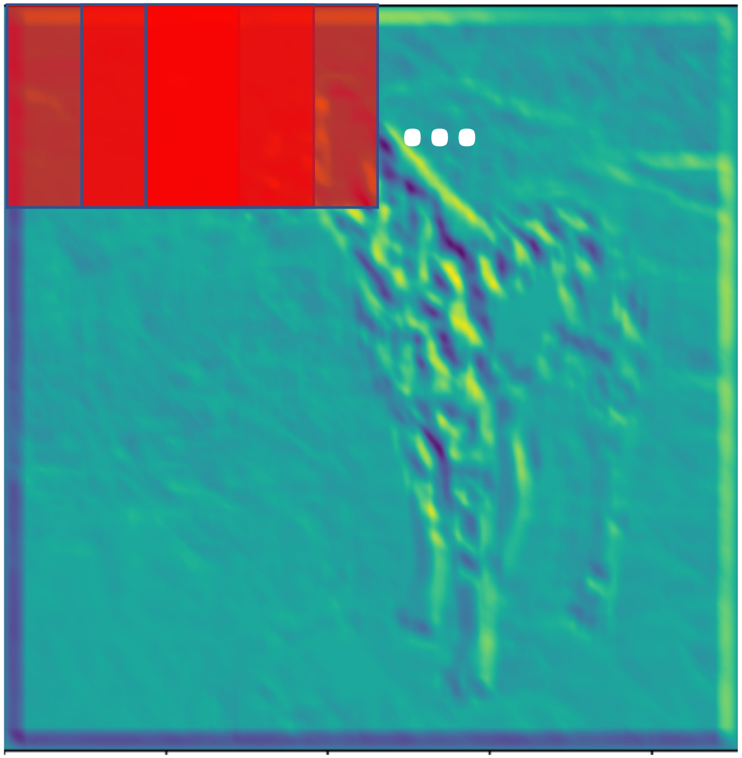


Image gradients Keypoint descriptor

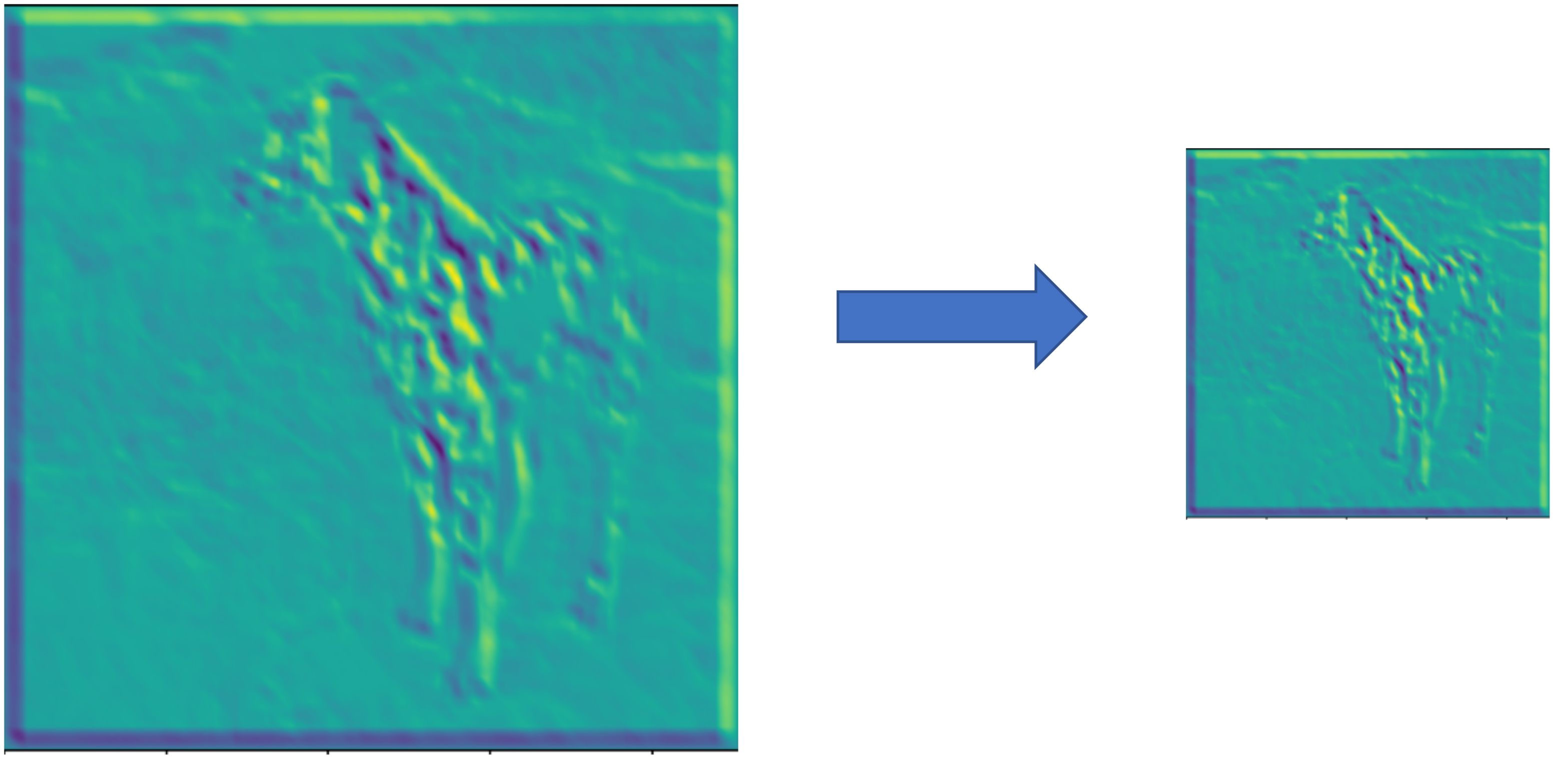
Invariance to distortions



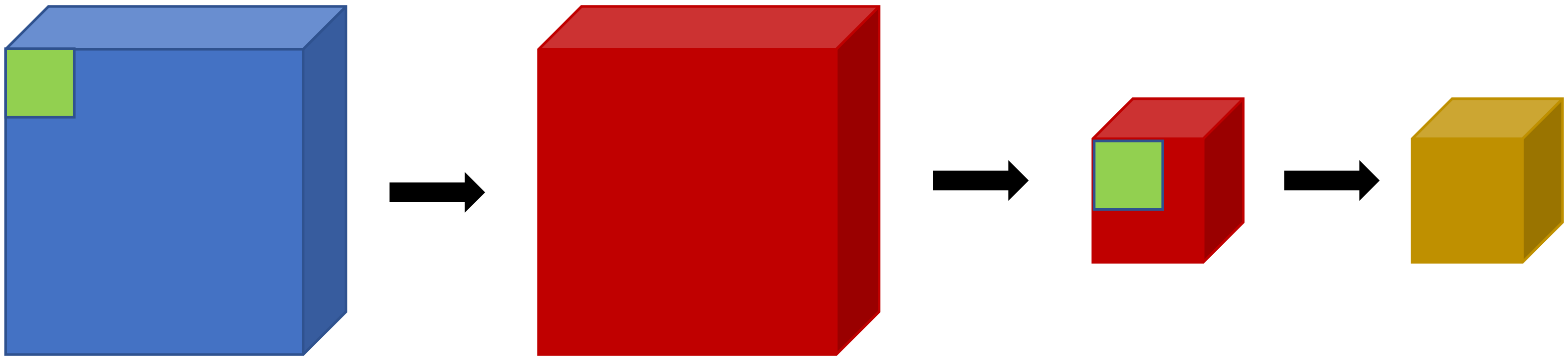
Invariance to distortions: Pooling



Invariance to distortions: Subsampling



Convolution subsampling convolution



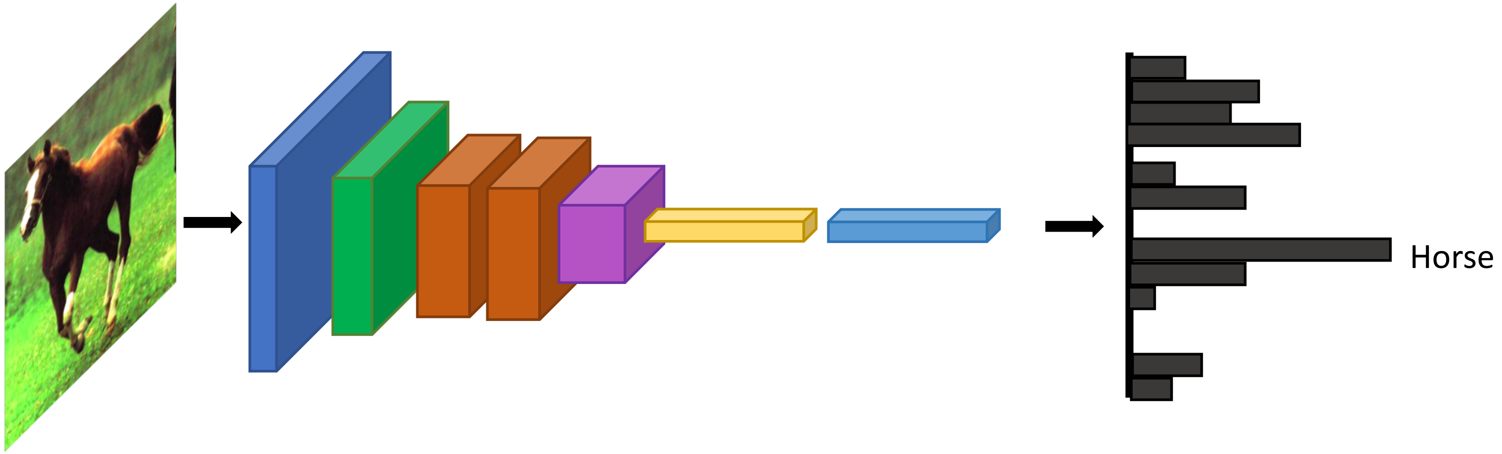
Convolution subsampling convolution

- Convolution in earlier steps detects *more local* patterns *less resilient* to distortion
- Convolution in later steps detects *more global* patterns *more resilient* to distortion
- Subsampling allows capture of *larger, more invariant* patterns

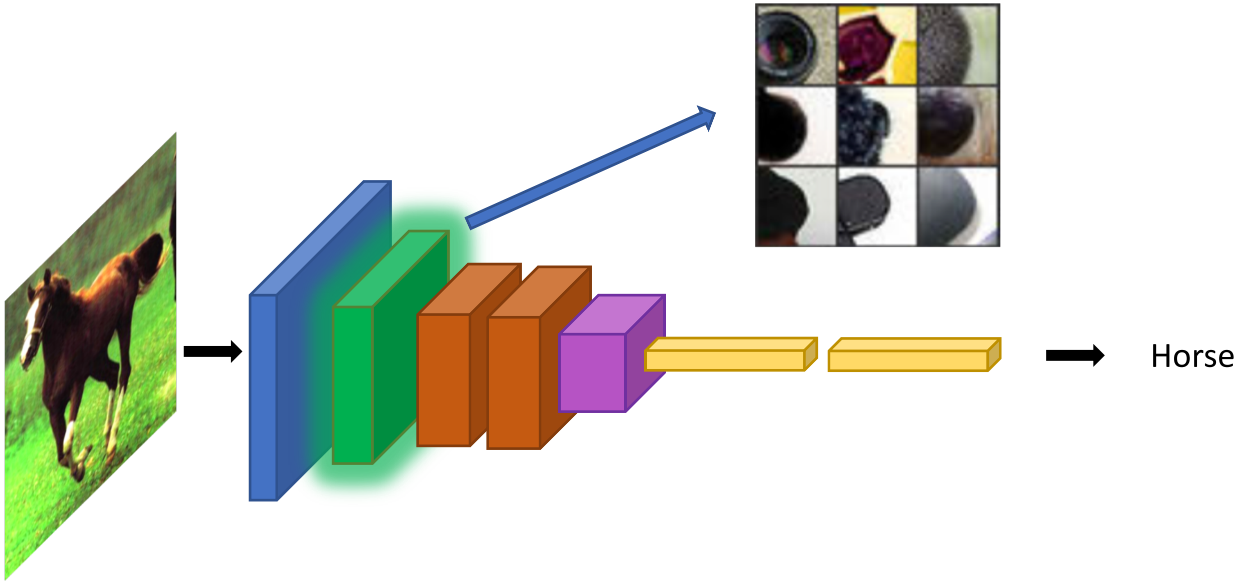
Strided convolution

- Convolution with stride s = standard convolution + subsampling by picking 1 value every s values
- Example: convolution with stride 2 = standard convolution + subsampling by a factor of 2

Convolutional networks

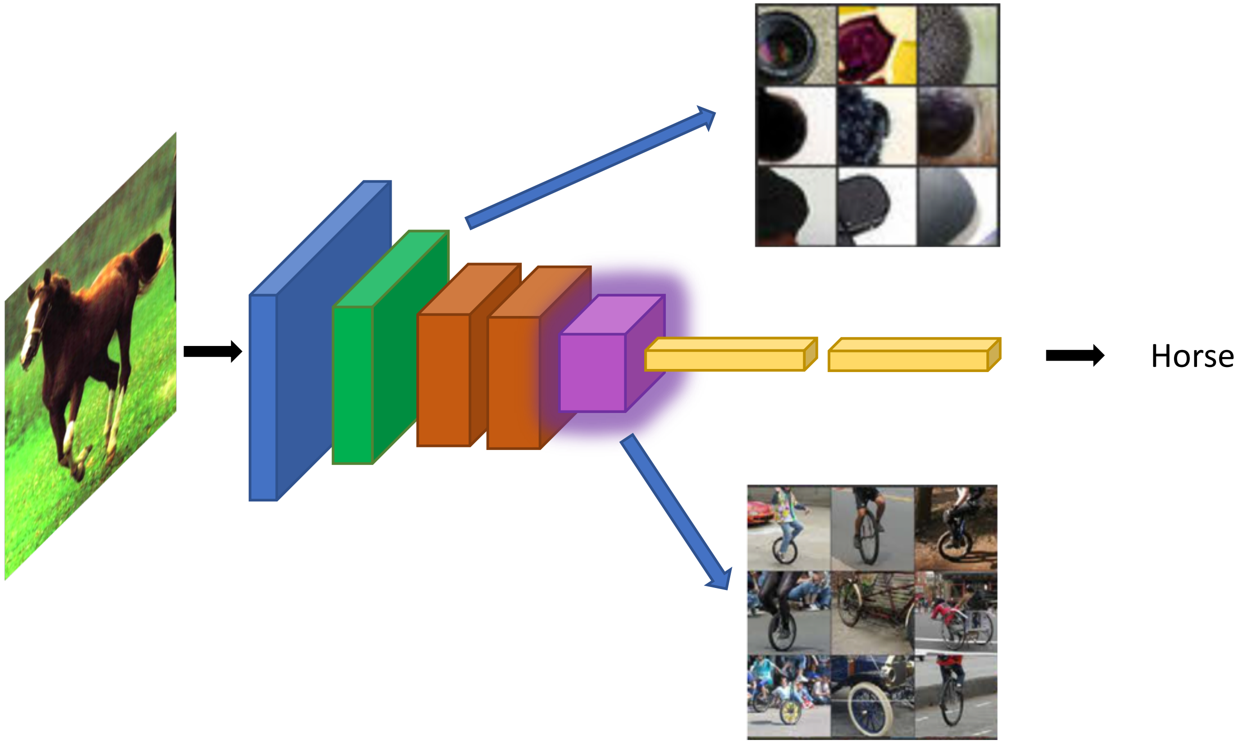


Convolutional networks



Visualizations from : M. Zeiler and R. Fergus. Visualizing and Understanding Convolutional Networks. In ECCV 2014.

Convolutional networks



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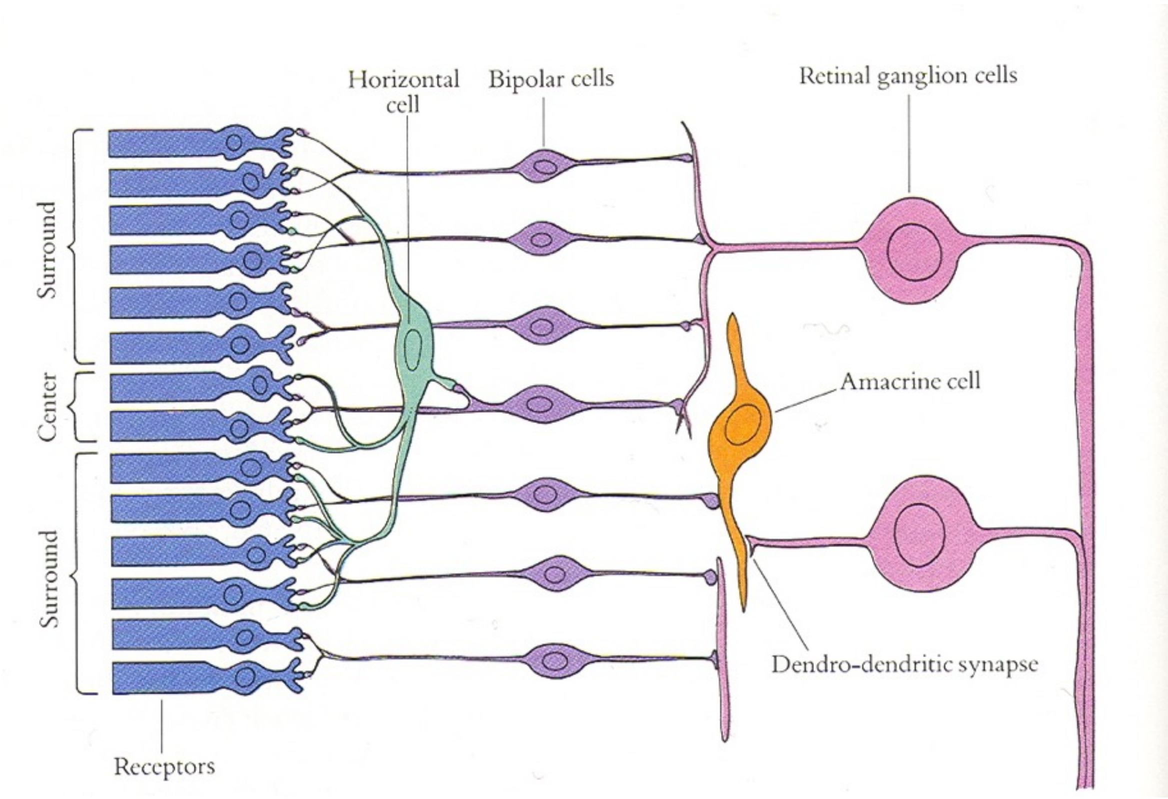
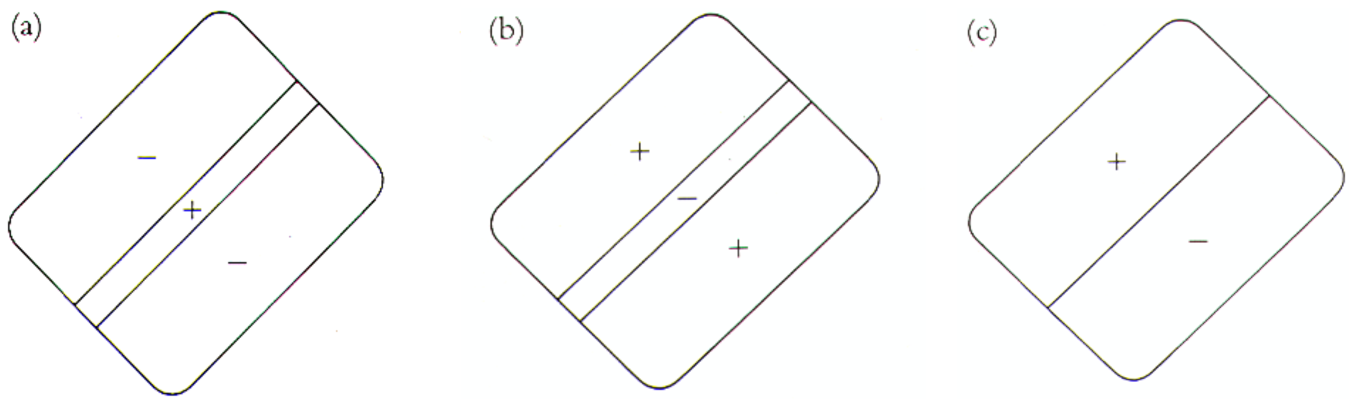
Convolutional Networks and the Brain



Slide credit: Jitendra Malik

Receptive fields of simple cells (discovered by Hubel & Wiesel)



Slide credit: Jitendra Malik

Convolutional networks

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE* 86.11 (1998): 2278-2324.

Convolutional networks

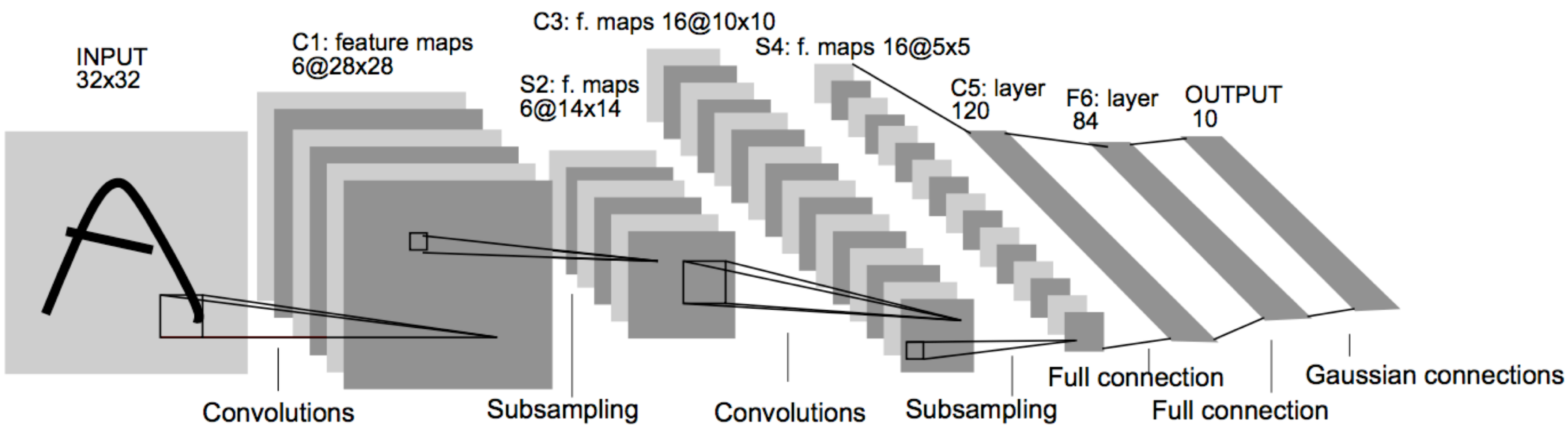


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

Convolutional networks