Loss Landscape created with data from the training process of a convolutional network, Javier Ideami

COMP547

DEEP UNSUPERVISED LEARNING

Lecture #2 – Neural Networks Basics and Spatial Processing with CNNs

KOÇ UNIVERSITY

Aykut Erdem // Koç University // Spring 2021

Previously on COMP547

- course logistics
- course topics
- what is deep unsupervised learning

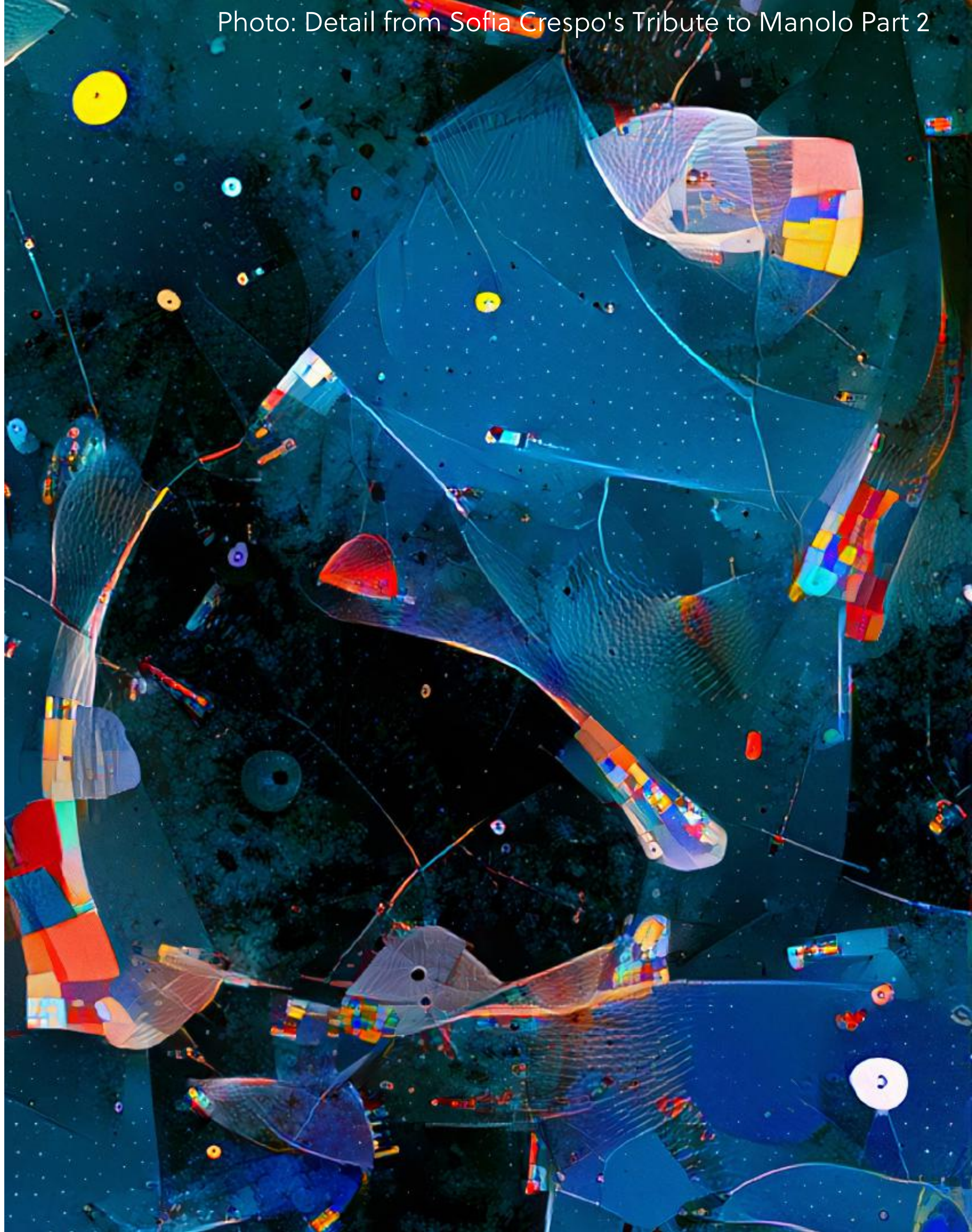


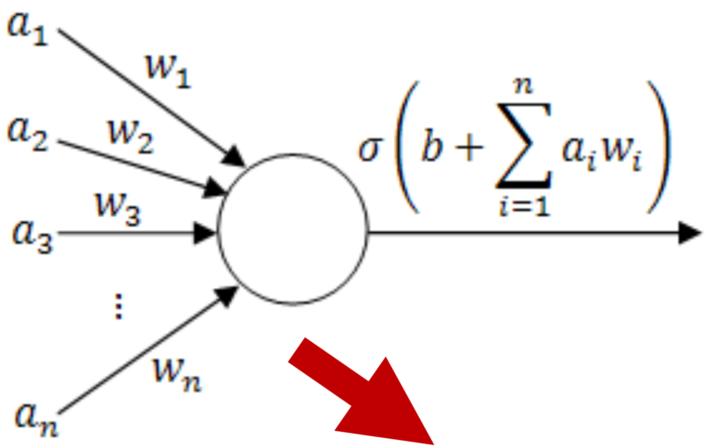
Photo: Detail from Sofia Crespo's Tribute to Manolo Part 2

Lecture overview

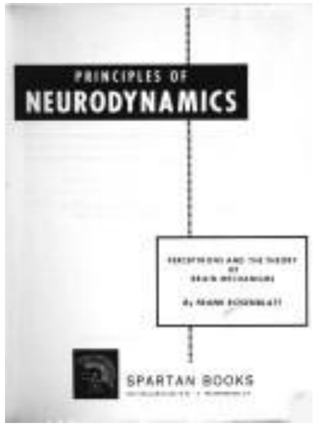
- deep learning
- computation in a neural net
- optimization
- backpropagation
- training tricks
- convolutional neural networks

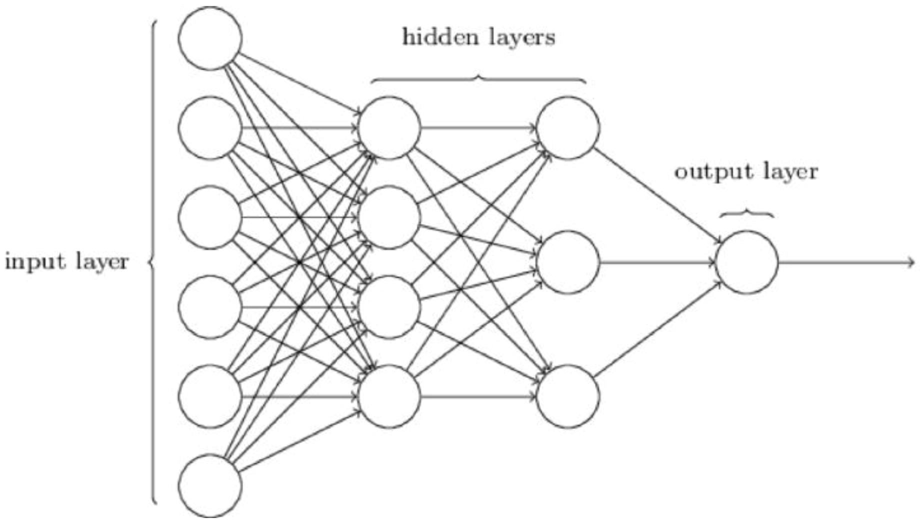
- **Disclaimer:** Much of the material and slides for this lecture were borrowed from
  —Costis Daskalakis and Aleksander Mądry's MIT 6.883 class
  —Bill Freeman, Antonio Torralba and Phillip Isola's MIT 6.869 class

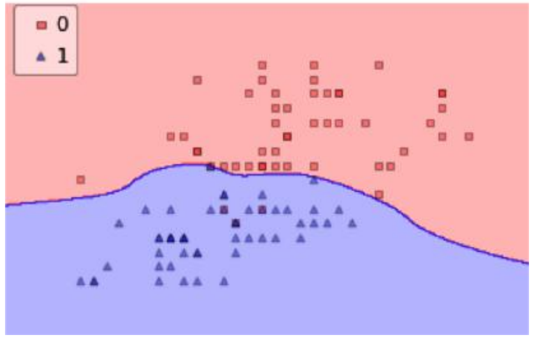
Humble beginnings

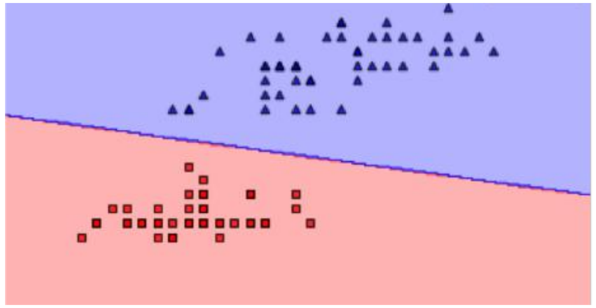


- Perceptron [Rosenblatt '58]

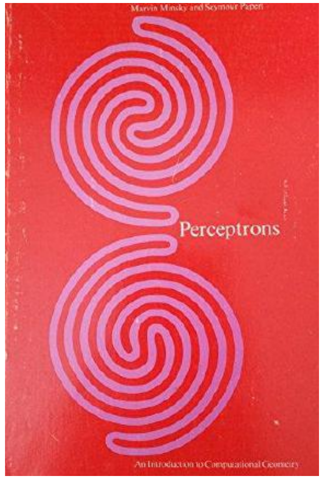




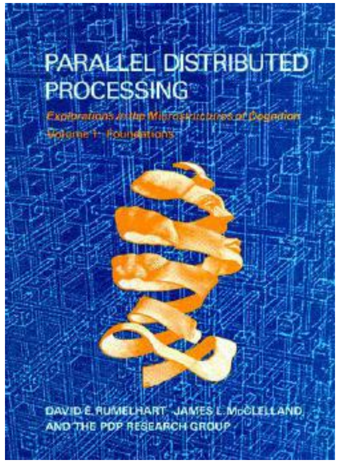




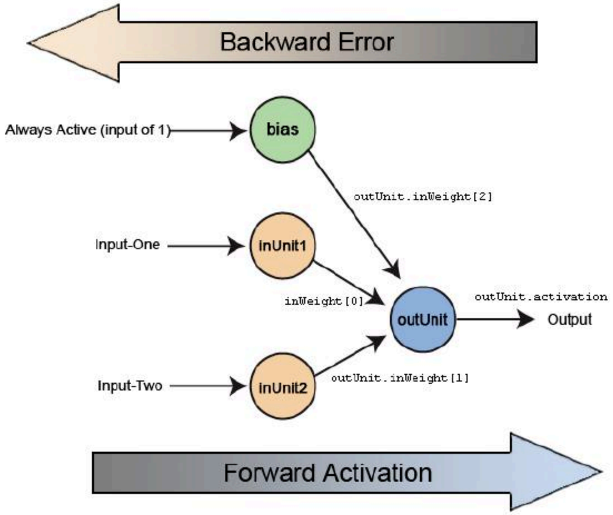
- Criticism of Perceptrons (XOR affair) [Minsky Papert '69]
  - Effectively causes a "deep learning winter"



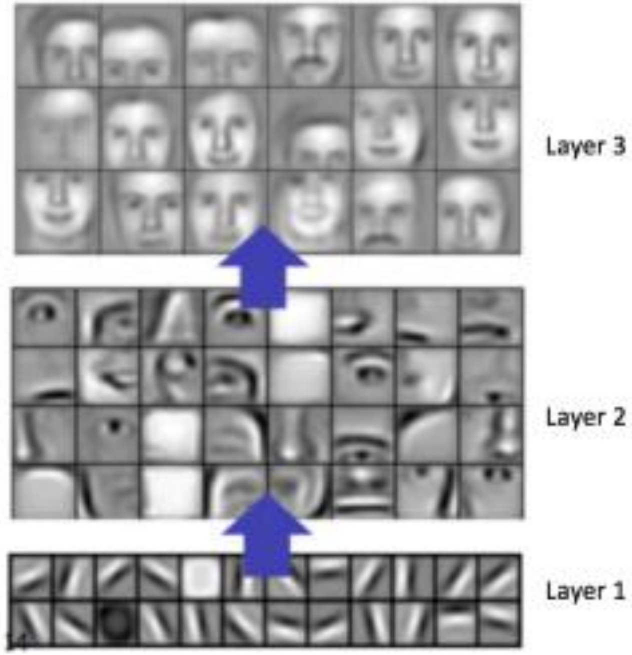
(Early) Spring



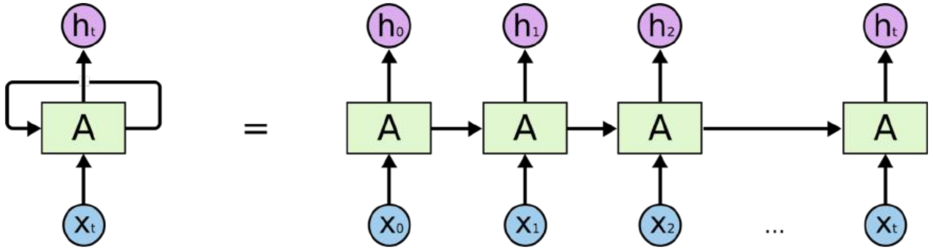
- Back-propagation [Rumelhart et al. '86, LeCun '85, Parker '85]



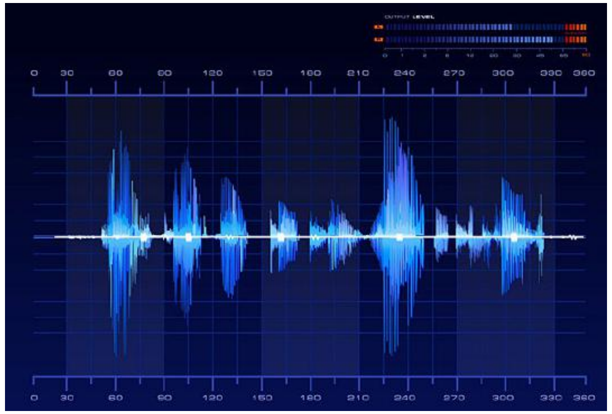
- Convolutional layers [LeCun et al. '90]



- Recurrent Neural Networks/Long Short-Term Memory (LSTM) [Hochreiter Schmidhuber '97]

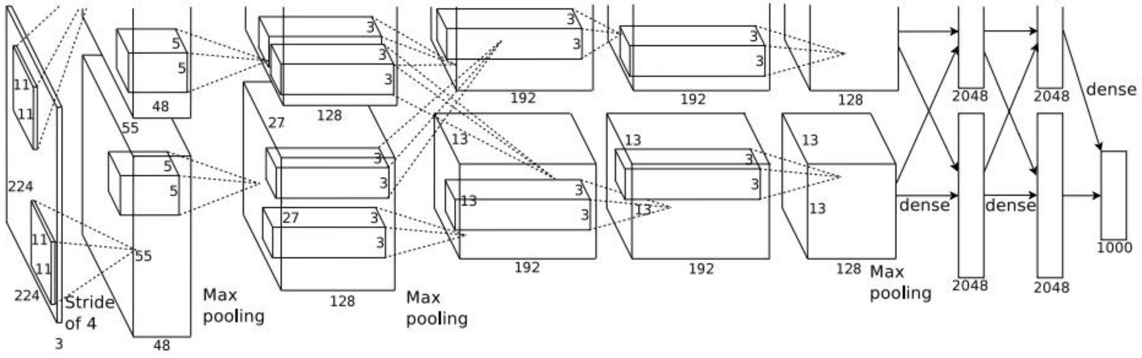


Summer

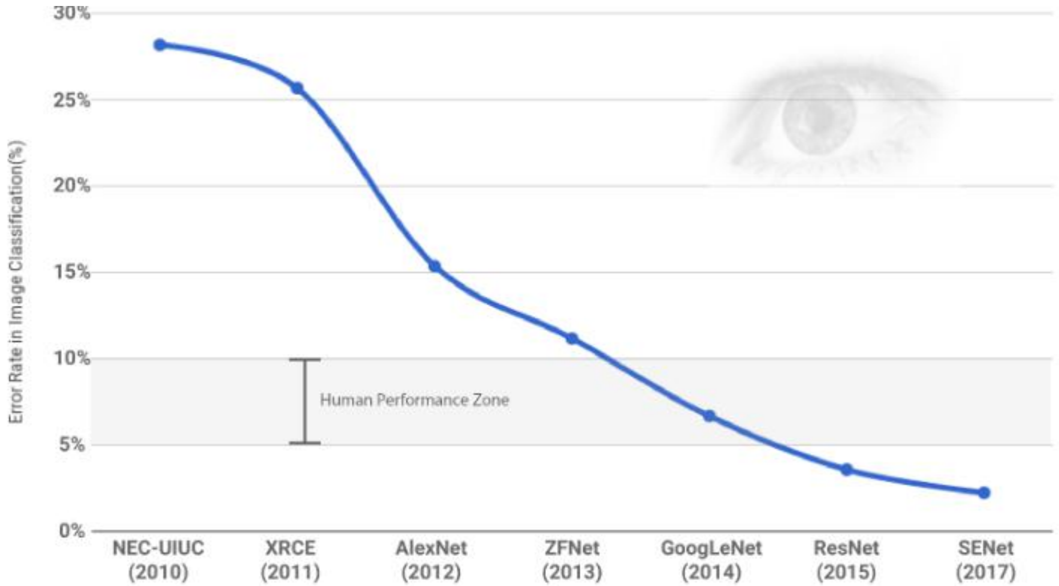


- **2006:** First big success: speech recognition

- **2012:** Breakthrough in computer vision: AlexNet [Krizhevsky et al. '12]



- **2015:** Deep learning-based vision models outperform humans



What enabled this success?

- Better architectures (e.g., ReLUs) and regularization techniques (e.g. Dropout)

IMAGENET

- Sufficiently large datasets

- Enough computational power

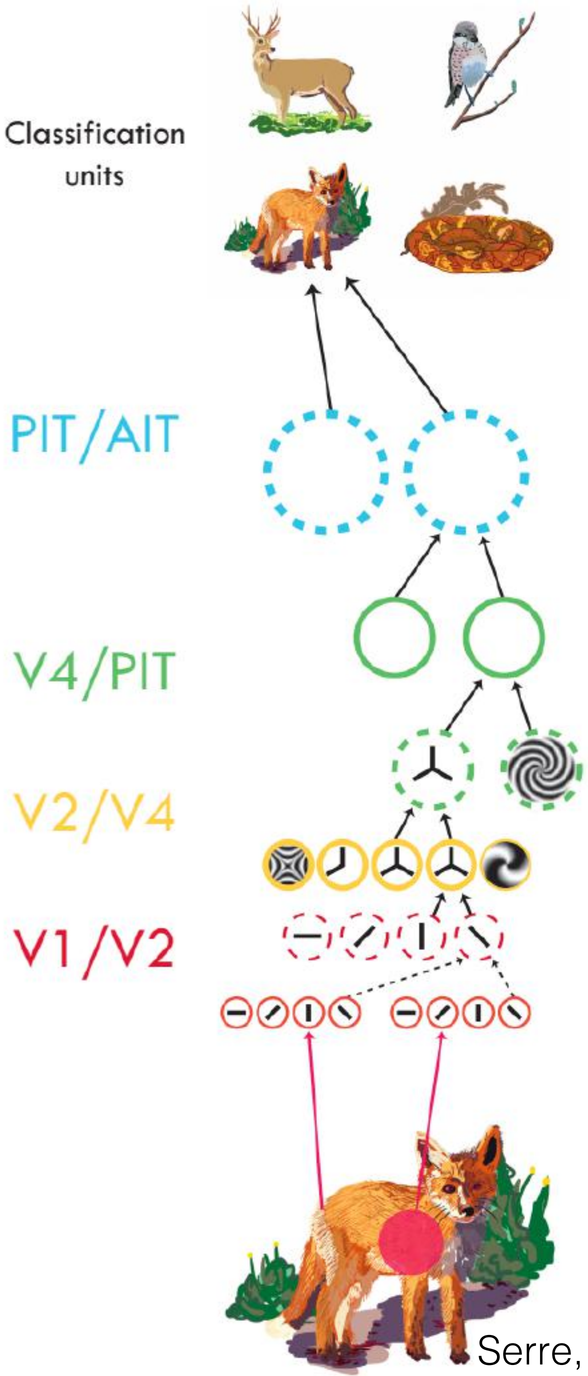
Deep learning

- Modeling the visual world is incredibly complicated. We need high capacity models.

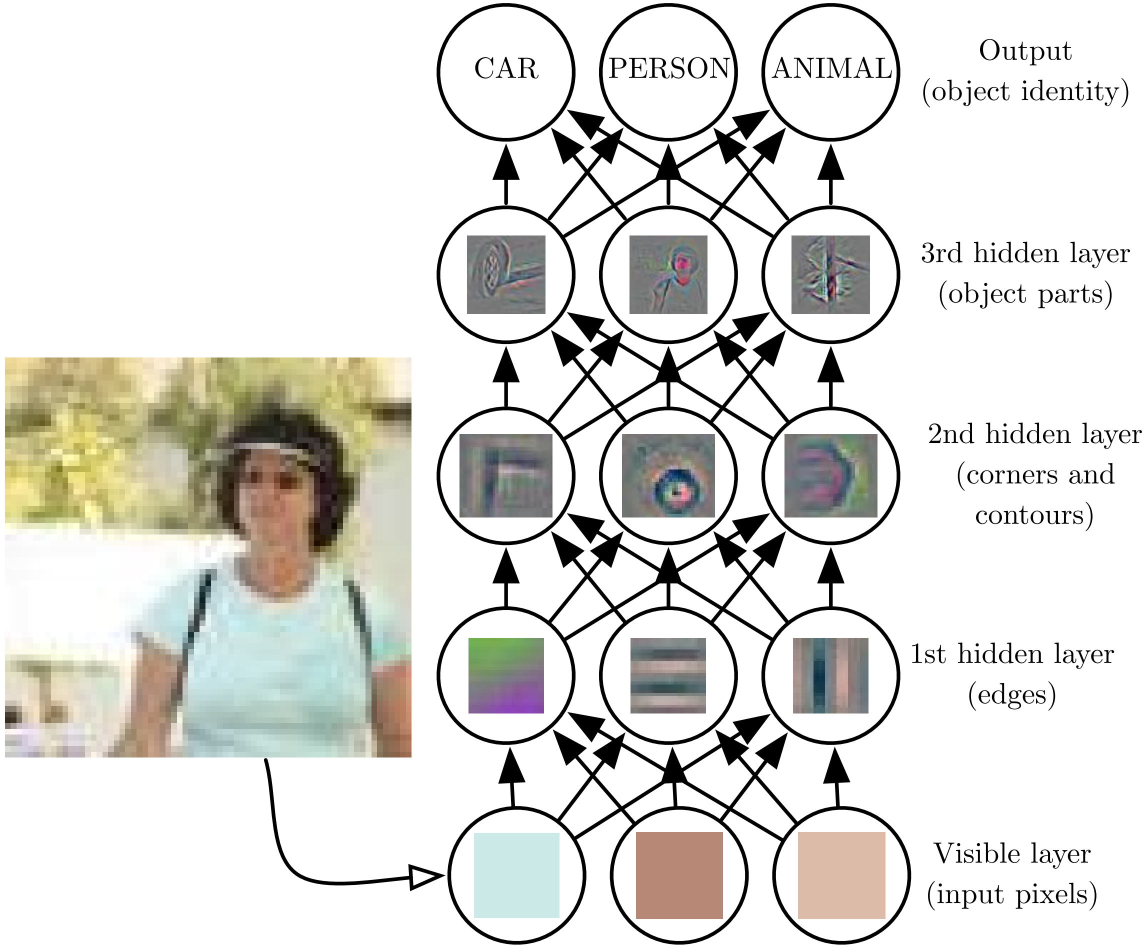
- In the past, we didn’t have enough data to fit these models. But now we do!

- We want a class of **high capacity models** that are **easy to optimize**.

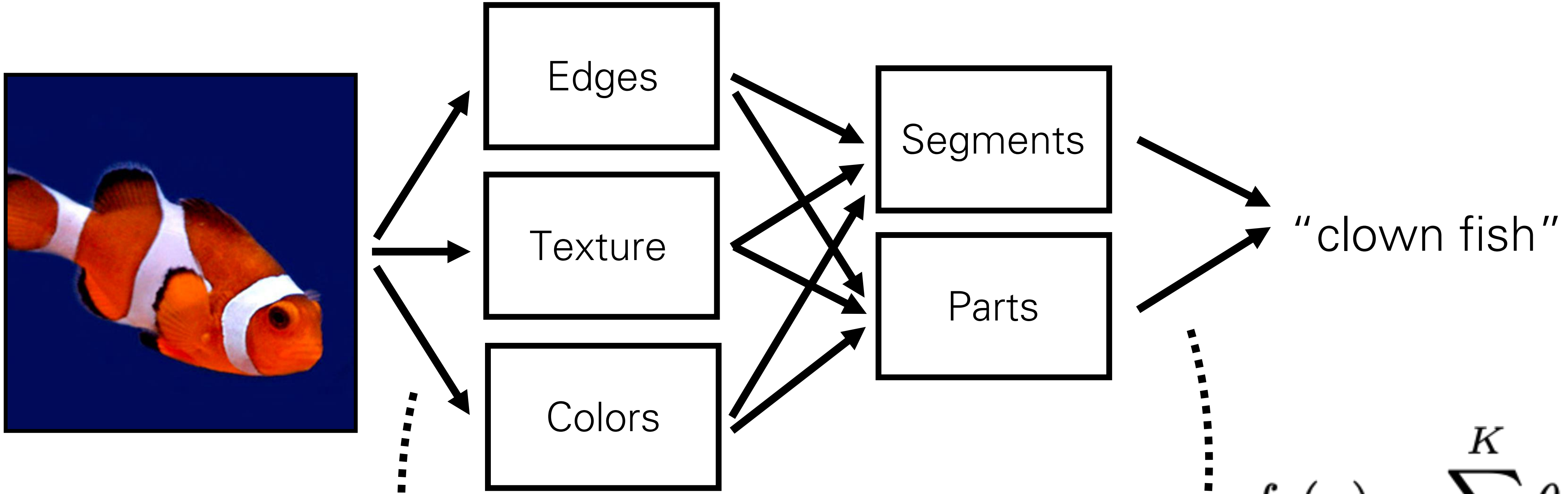
Deep neural networks!


Classification units
PIT/AIT
V4/PIT
V2/V4
V1/V2

Serre, 2014


CAR
PERSON
ANIMAL
Output (object identity)
3rd hidden layer (object parts)
2nd hidden layer (corners and contours)
1st hidden layer (edges)
Visible layer (input pixels)

Object recognition



$$\phi_k(x)$$

$$f_\theta(x) = \sum_{k=1}^{K} \theta_k \phi_k(x)$$

Feature extractors

Classifier

Object recognition

Learned

Edges

Texture

Colors

Segments

Parts

"clown fish"

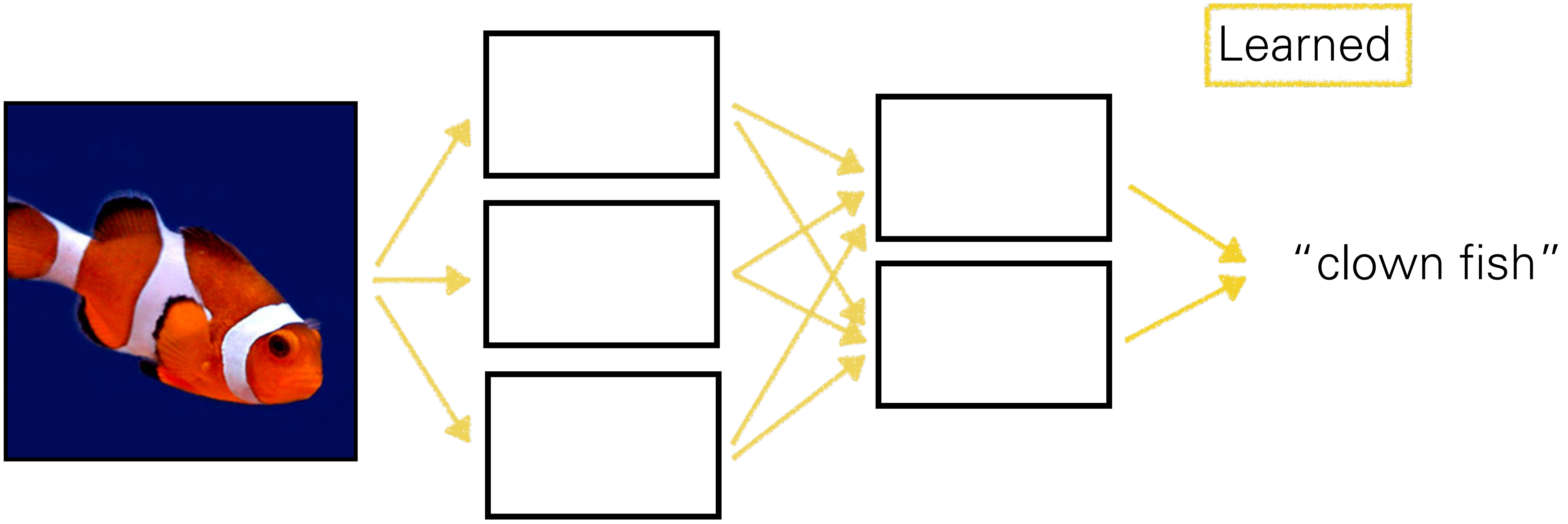
$\phi_k(x)$

$$f_\theta(x) = \sum_{k=1}^{K} \theta_k \phi_k(x)$$

Feature extractors

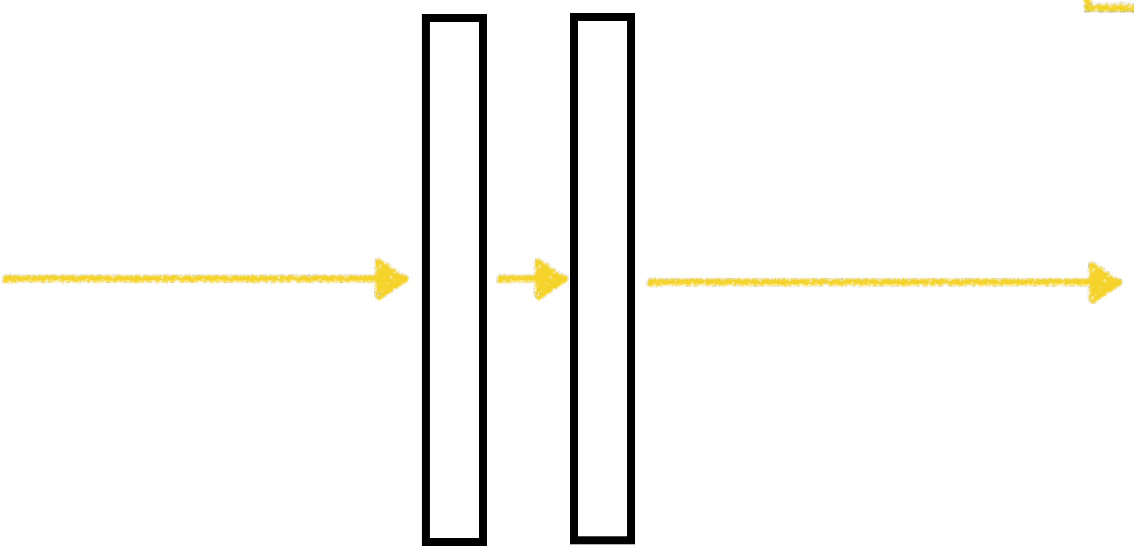
Classifier

Object recognition



Object recognition

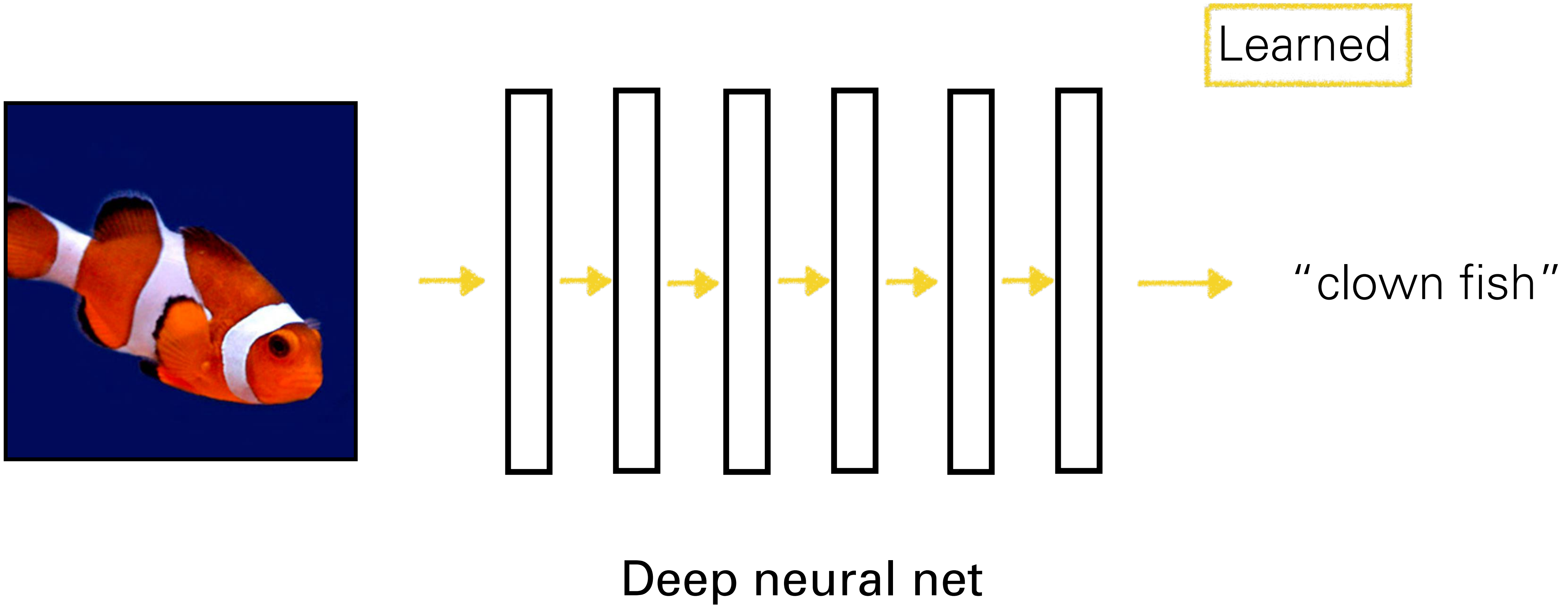
Learned



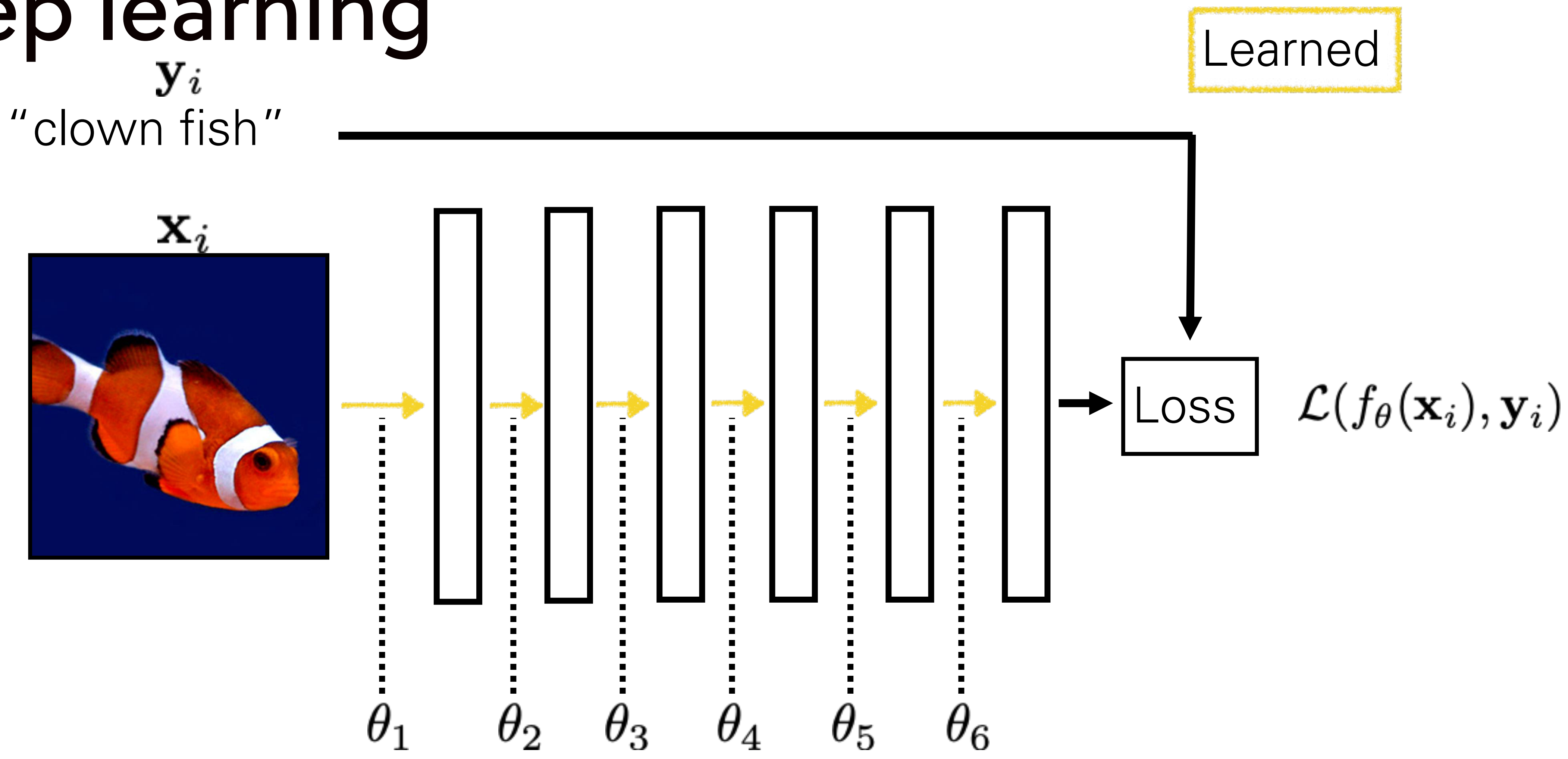
"clown fish"

Neural net

Object recognition



Deep learning

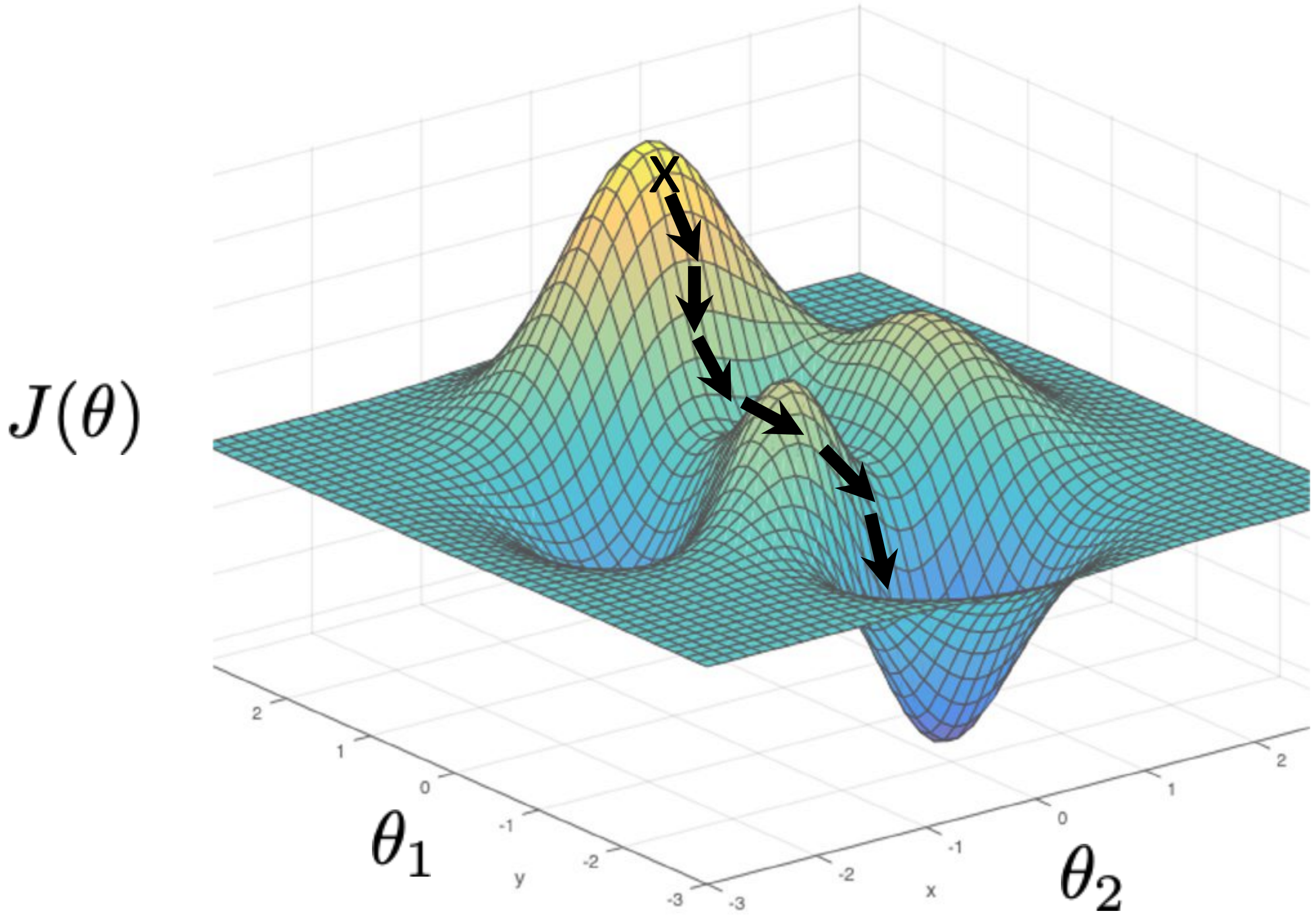


$$\boxed{\theta^* = \arg\min_\theta \sum_{i=1}^{N} \mathcal{L}(f_\theta(\mathbf{x}_i), \mathbf{y}_i)}$$

Gradient descent

$$\boxed{\theta^* = \arg\min_\theta \underbrace{\sum_{i=1}^{N} \mathcal{L}(f_\theta(\mathbf{x}_i), \mathbf{y}_i)}_{J(\theta)}}$$

Gradient descent



$$\theta^* = \arg\min_{\theta} J(\theta)$$

Gradient descent

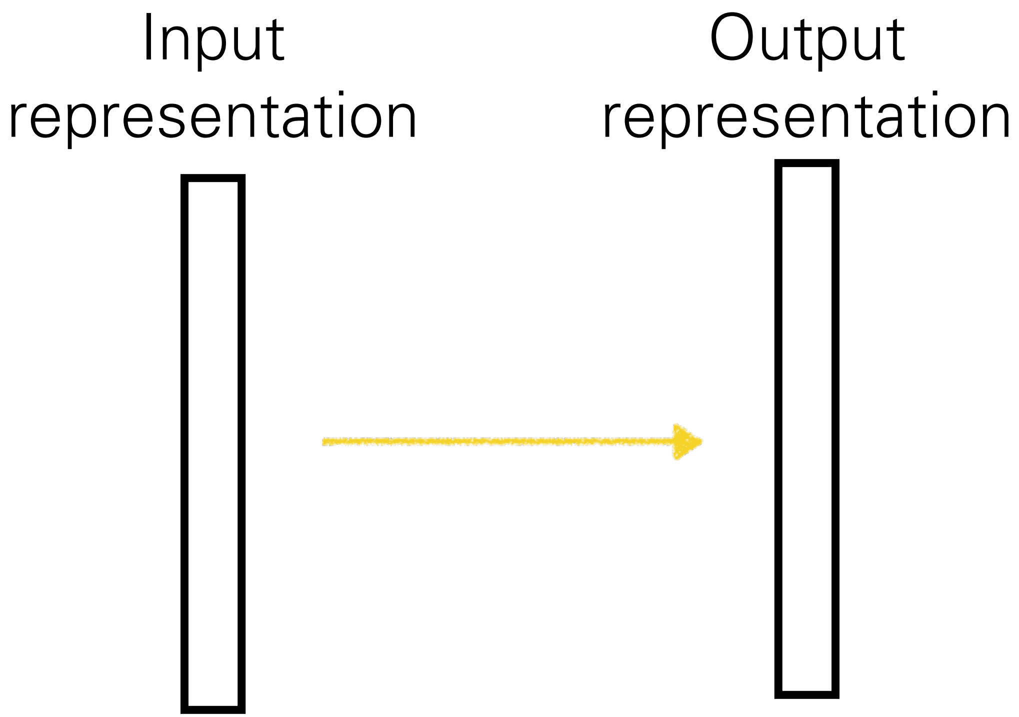
$$\boxed{\theta^* = \arg\min_\theta \underbrace{\sum_{i=1}^{N} \mathcal{L}(f_\theta(\mathbf{x}_i), \mathbf{y}_i)}_{J(\theta)}}$$

One iteration of gradient descent:

$$\theta^{t+1} = \theta^t - \eta_t \left.\frac{\partial J(\theta)}{\partial \theta}\right|_{\theta=\theta^t}$$

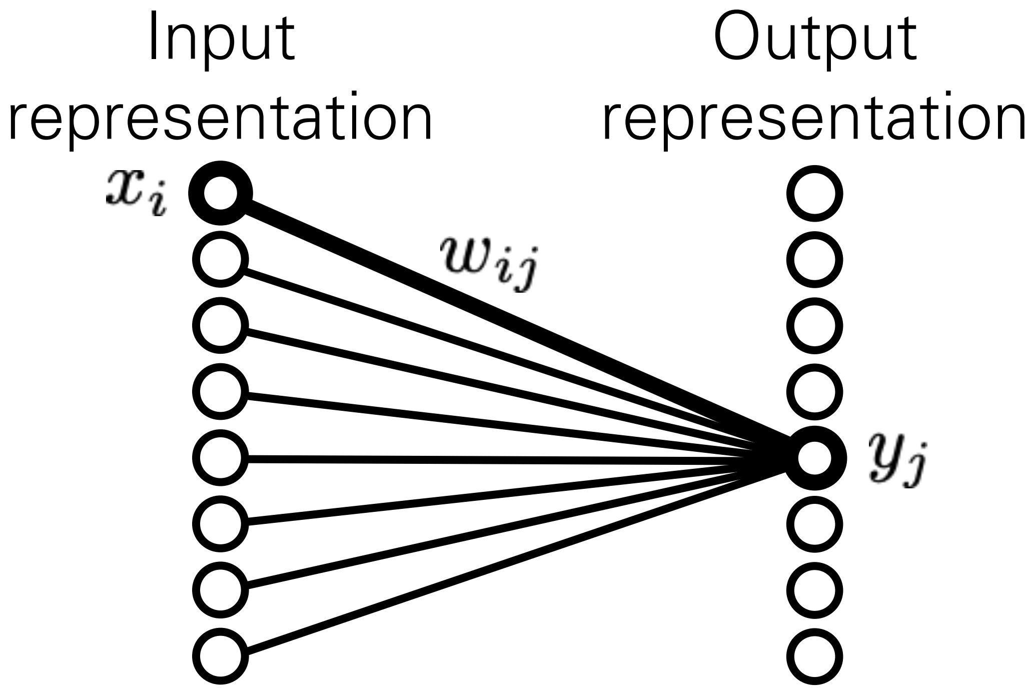
learning rate

Computation in a neural net



Computation in a neural net

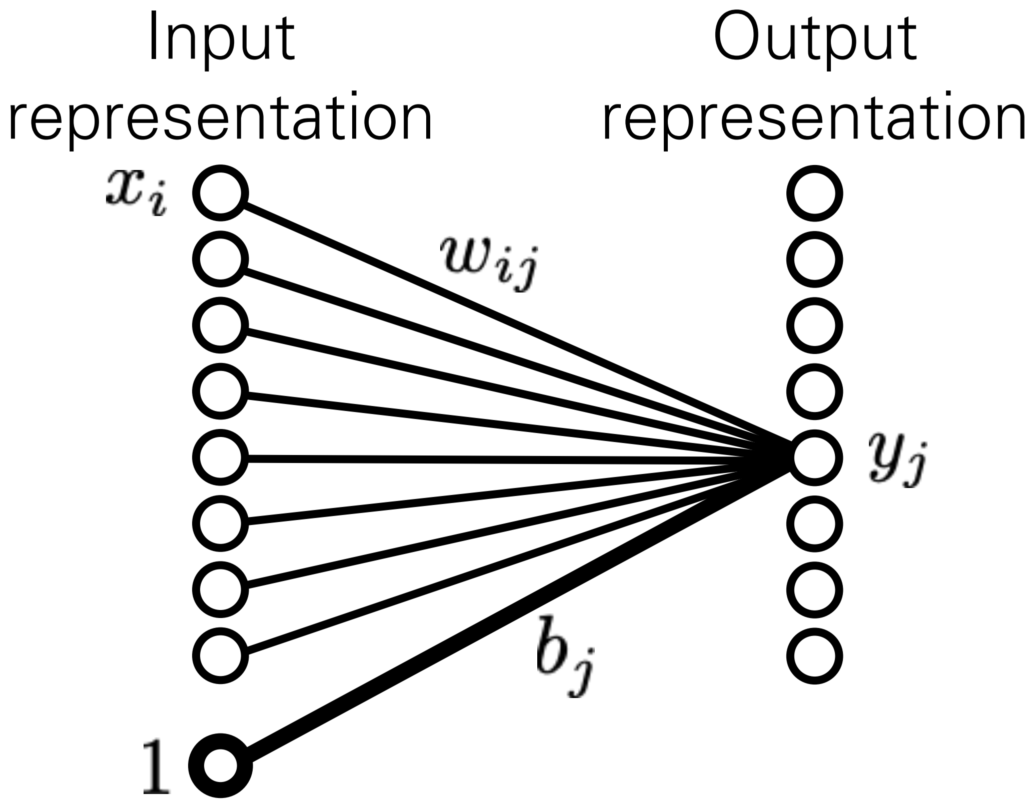
Linear layer



$$y_j = \sum_i w_{ij} x_i$$

Computation in a neural net

Linear layer



weights

$$y_j = \sum_i w_{ij} x_i + b_j$$

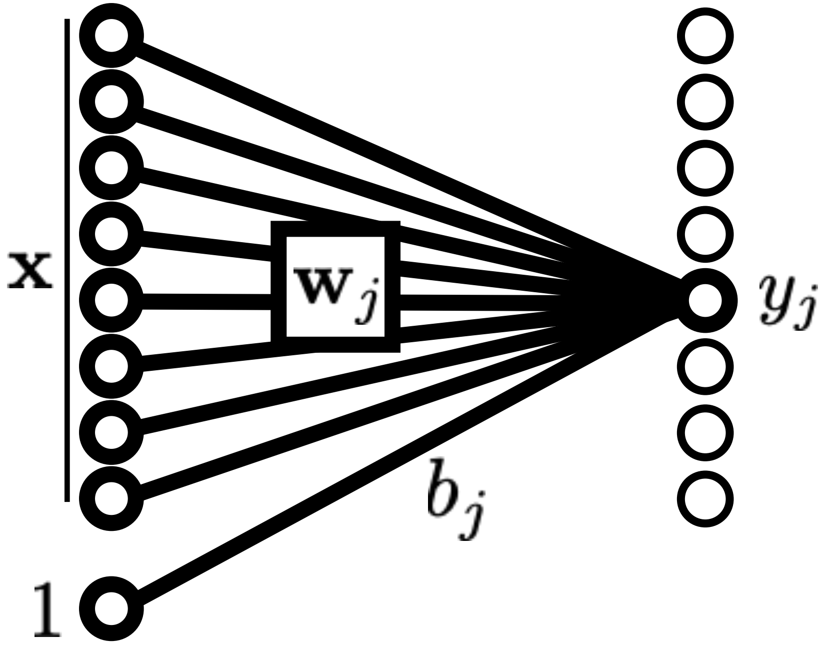
bias

Computation in a neural net

Linear layer

Input representation

Output representation



weights

$$y_j = \mathbf{x}^T \mathbf{w}_j + b_j$$

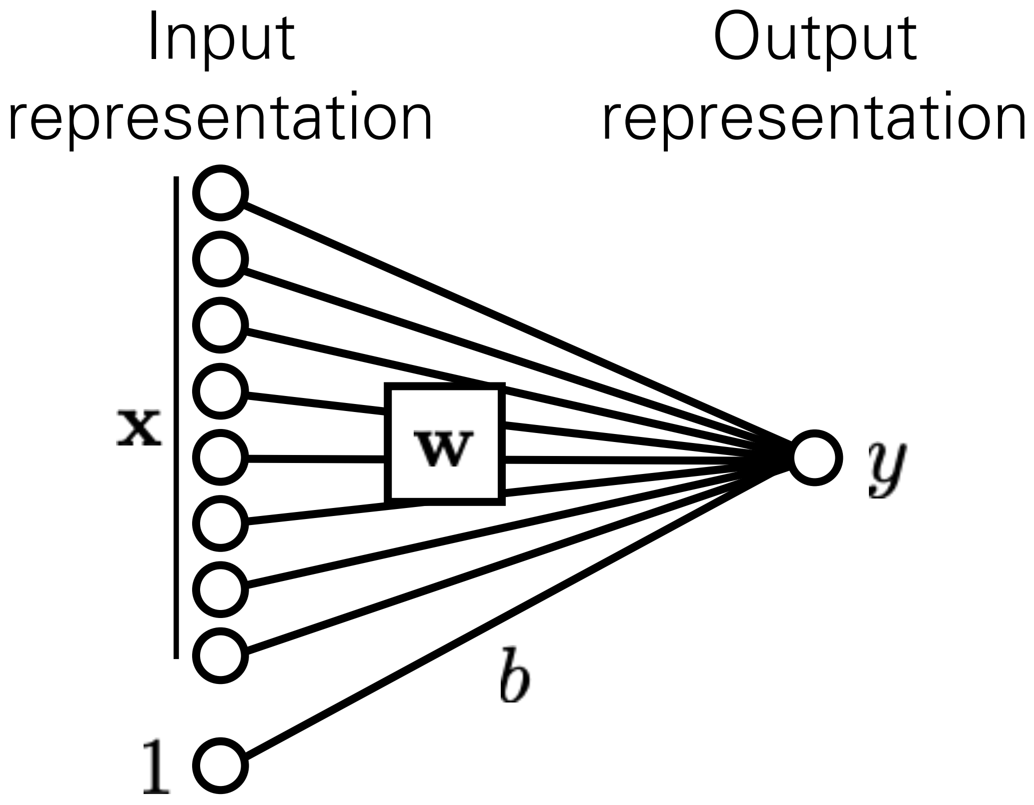
bias

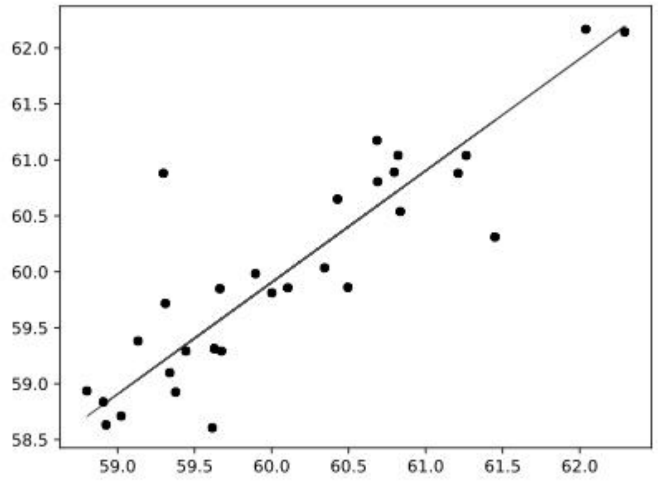
$$\theta = \{\mathbf{W}, \mathbf{b}\}$$

parameters of the model

Example: linear regression with a neural net

Linear layer





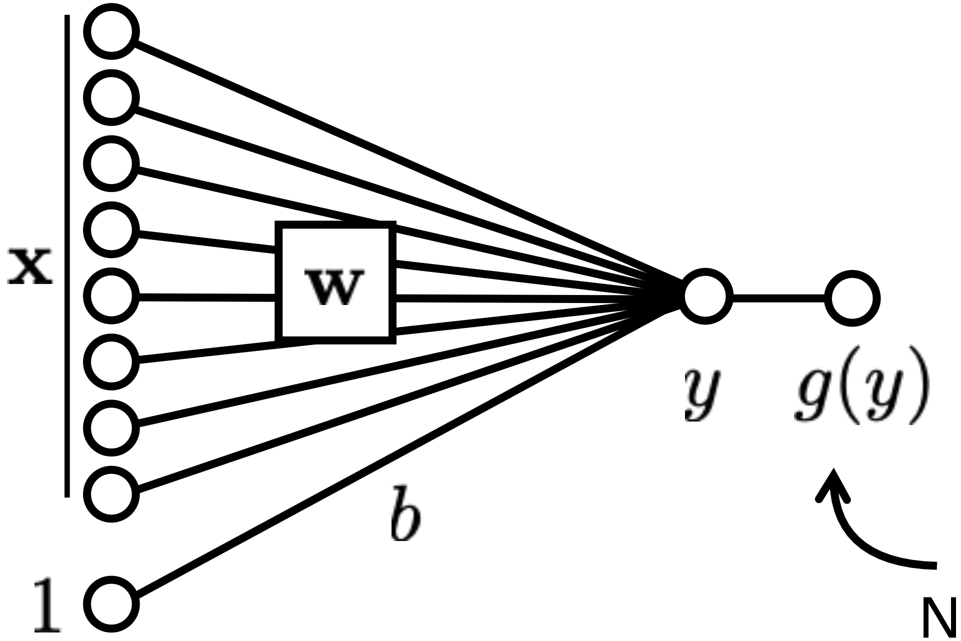
$$f_{\mathbf{w},b}(\mathbf{x}) = \mathbf{x}^T\mathbf{w} + b$$

Computation in a neural net

"Perceptron"

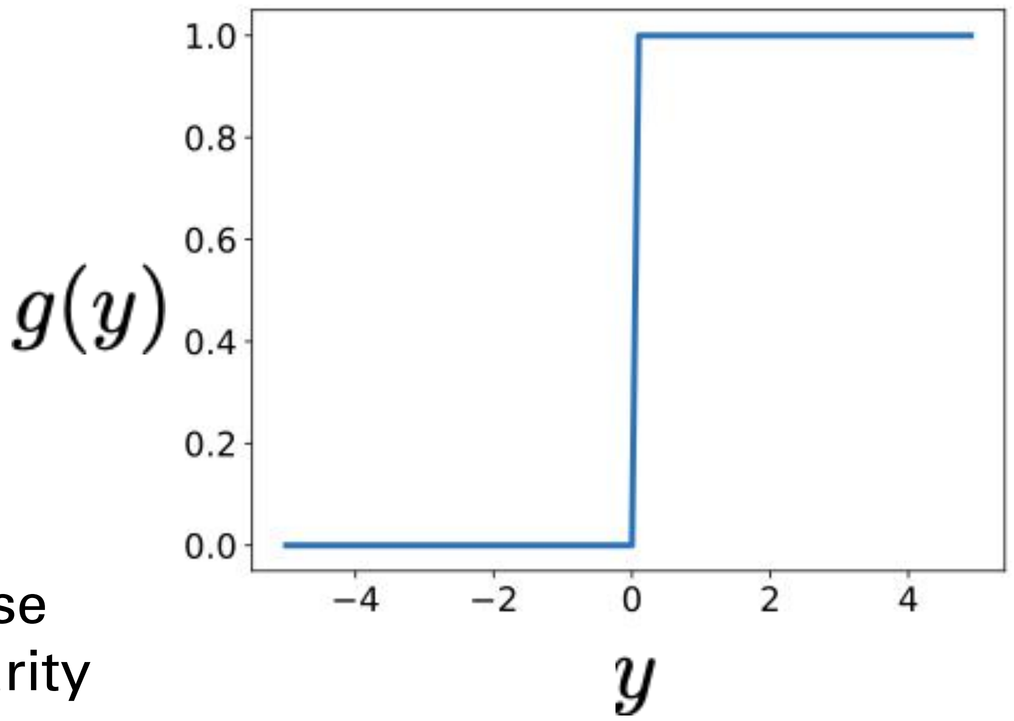
Input representation

Output representation

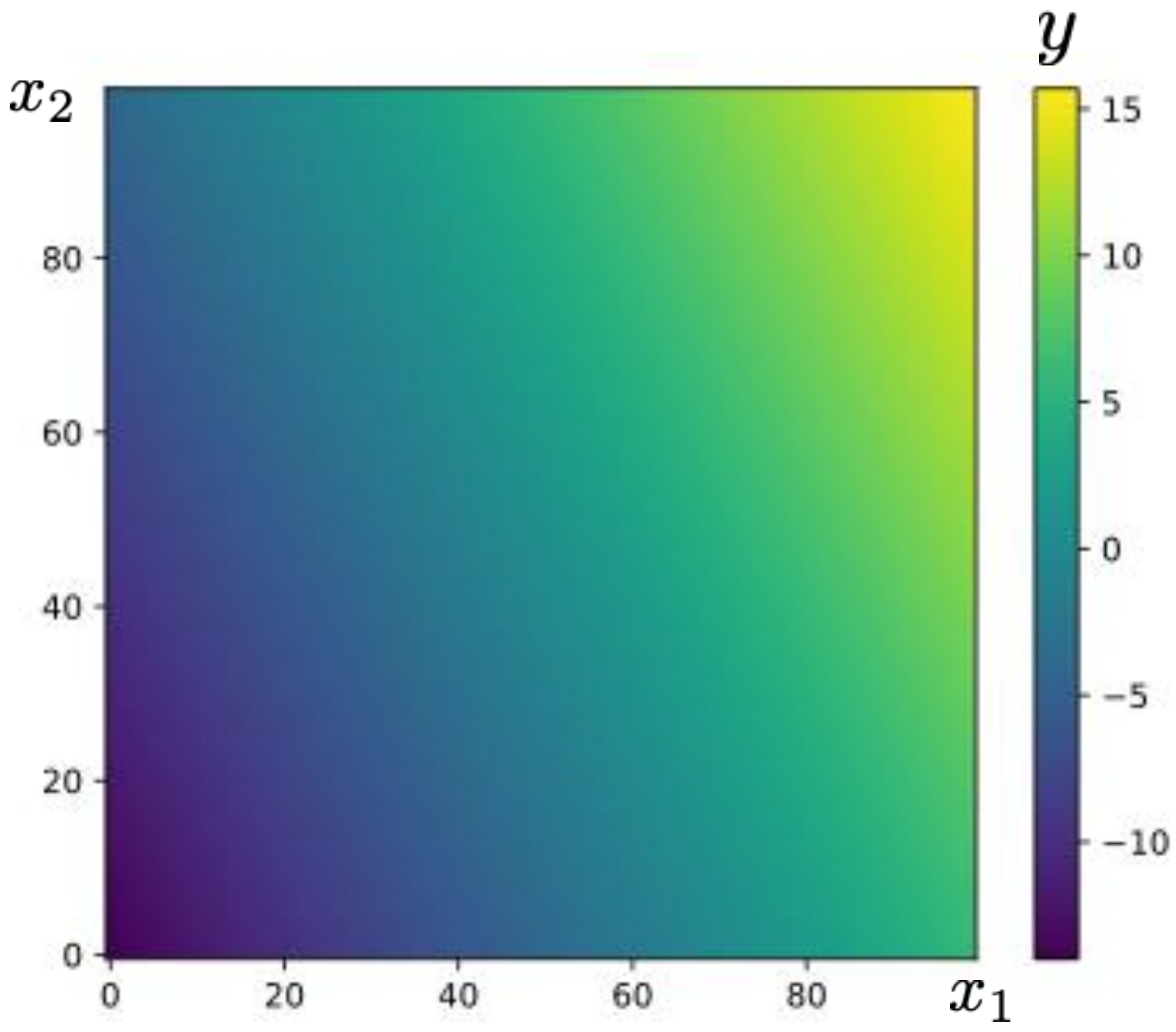


Pointwise Non-linearity

$$g(y) = \begin{cases} 1, & \text{if} \quad y > 0 \\ 0, & \text{otherwise} \end{cases}$$

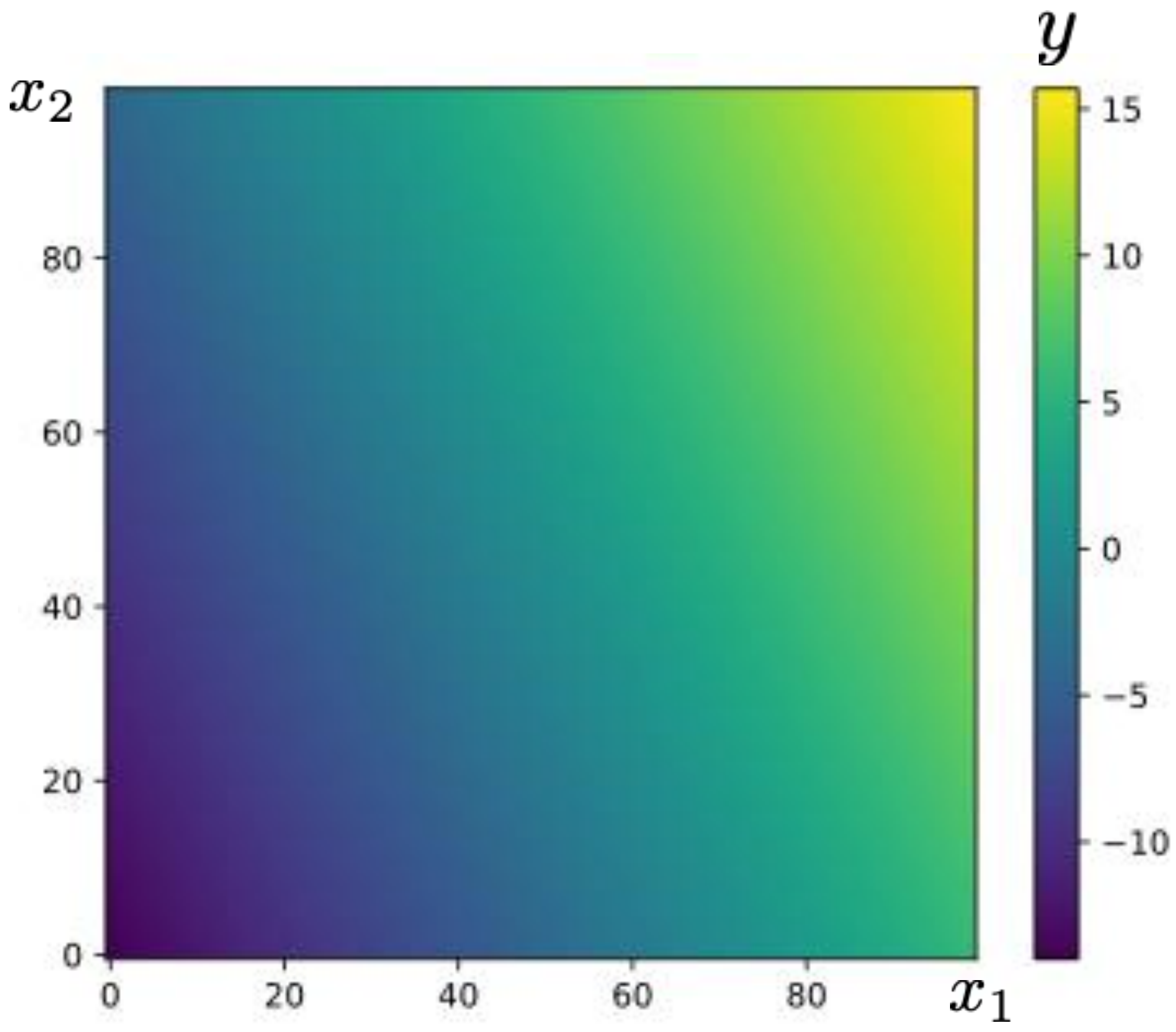


Example: linear classification with a perceptron



$$y = \mathbf{x}^T \mathbf{w} + b$$

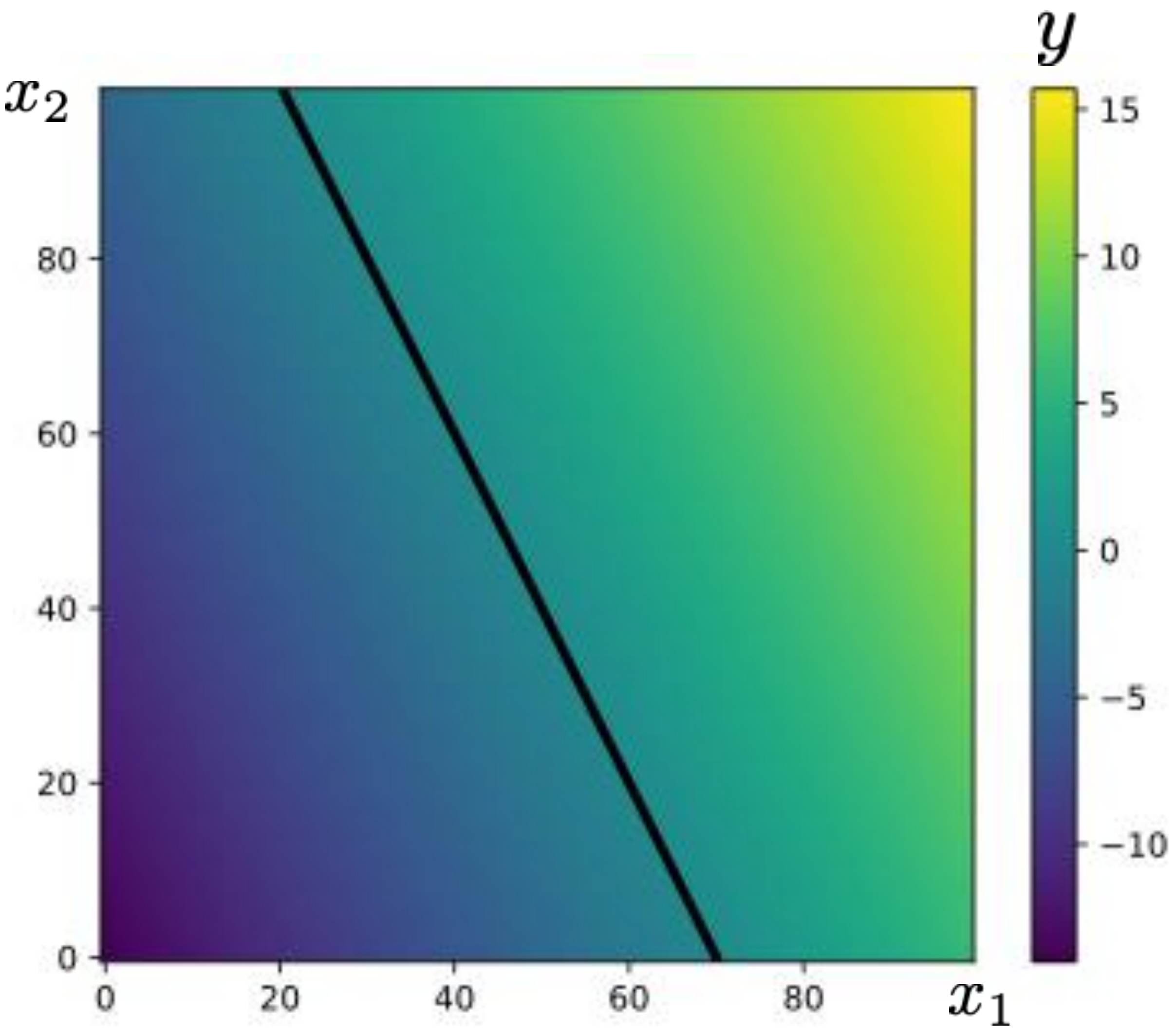
Example: linear classification with a perceptron



$$y = \mathbf{x}^T \mathbf{w} + b$$

$$g(y) = \begin{cases} 1, & \text{if} \quad y > 0 \\ 0, & \text{otherwise} \end{cases}$$

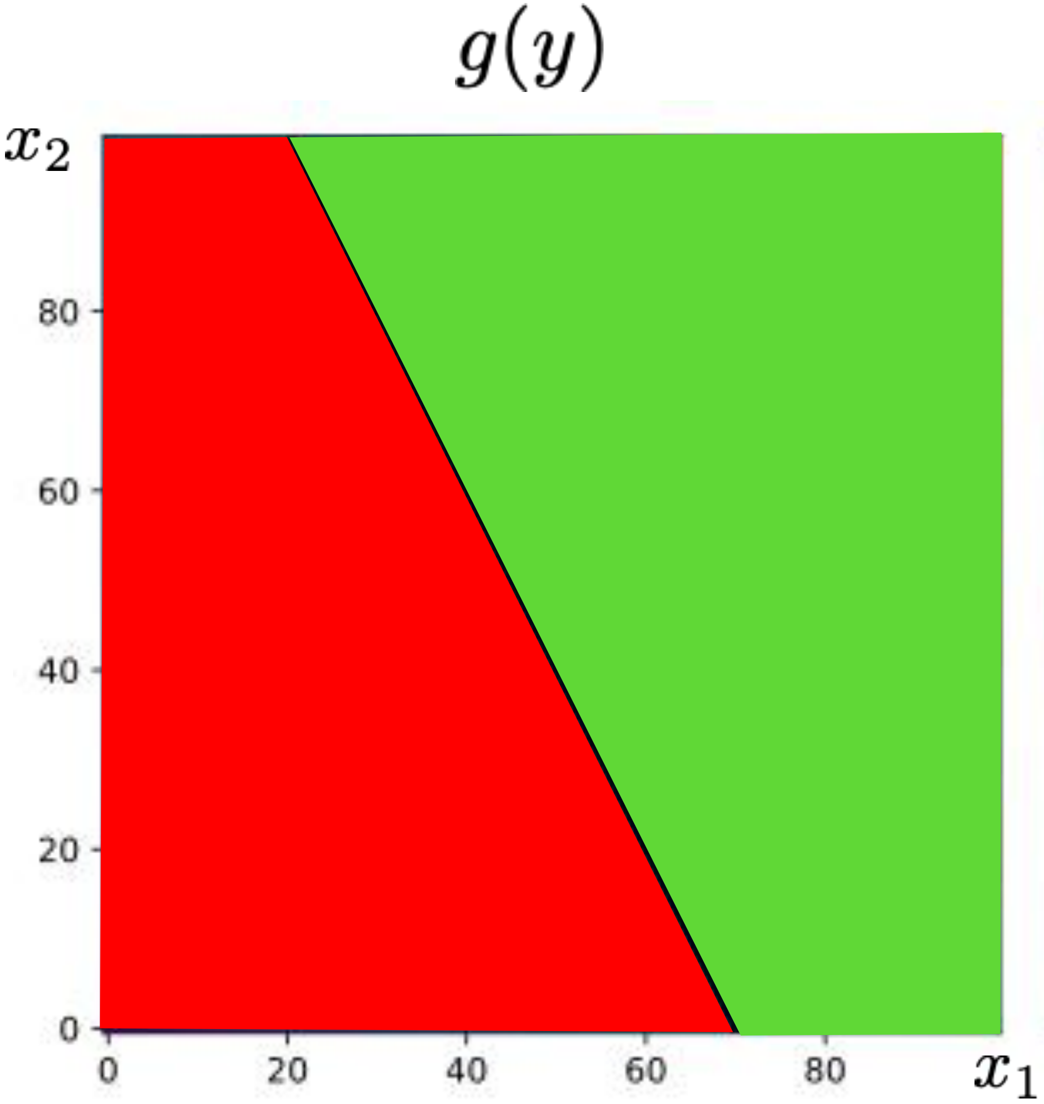
Example: linear classification with a perceptron



$$y = \mathbf{x}^T \mathbf{w} + b$$

$$g(y) = \begin{cases} 1, & \text{if} \quad y > 0 \\ 0, & \text{otherwise} \end{cases}$$

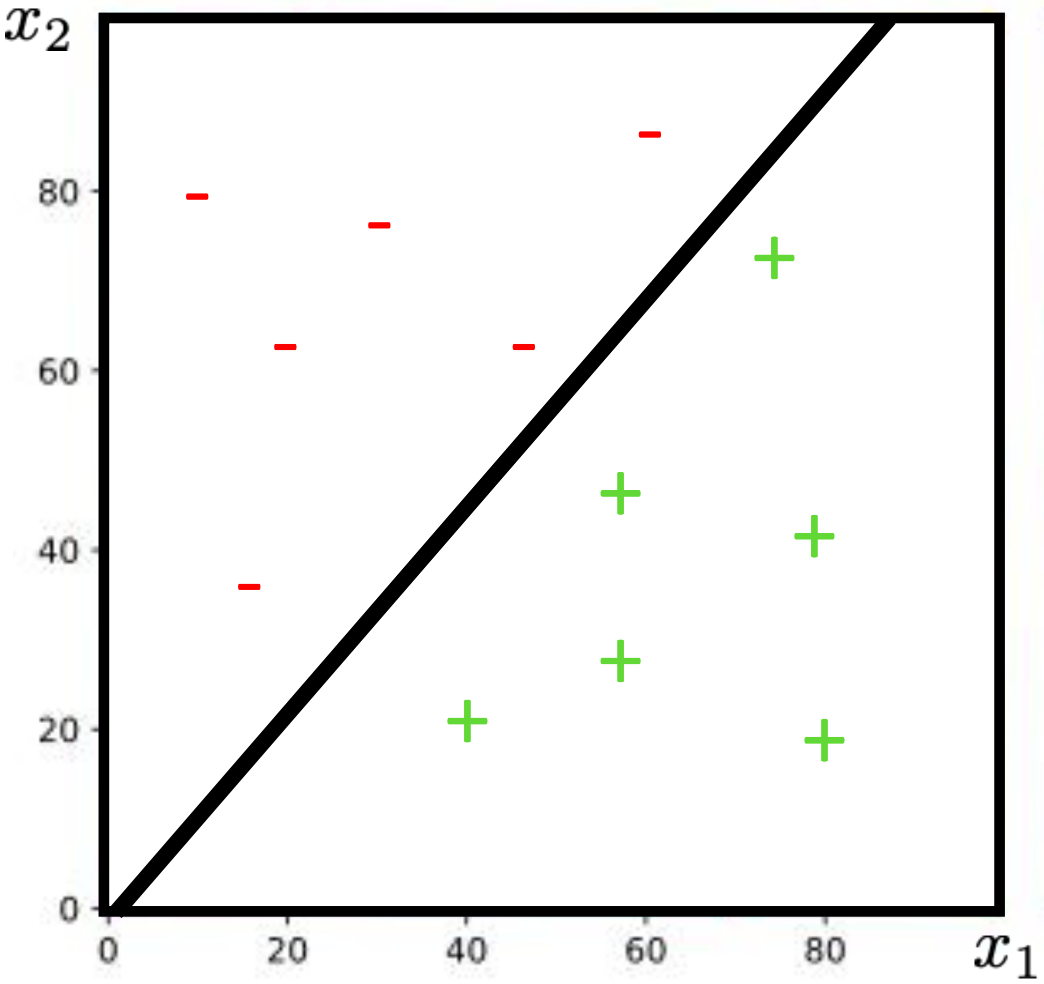
Example: linear classification with a perceptron



$$y = \mathbf{x}^T \mathbf{w} + b$$

$$g(y) = \begin{cases} 1, & \text{if} \quad y > 0 \\ 0, & \text{otherwise} \end{cases}$$

Example: linear classification with a perceptron

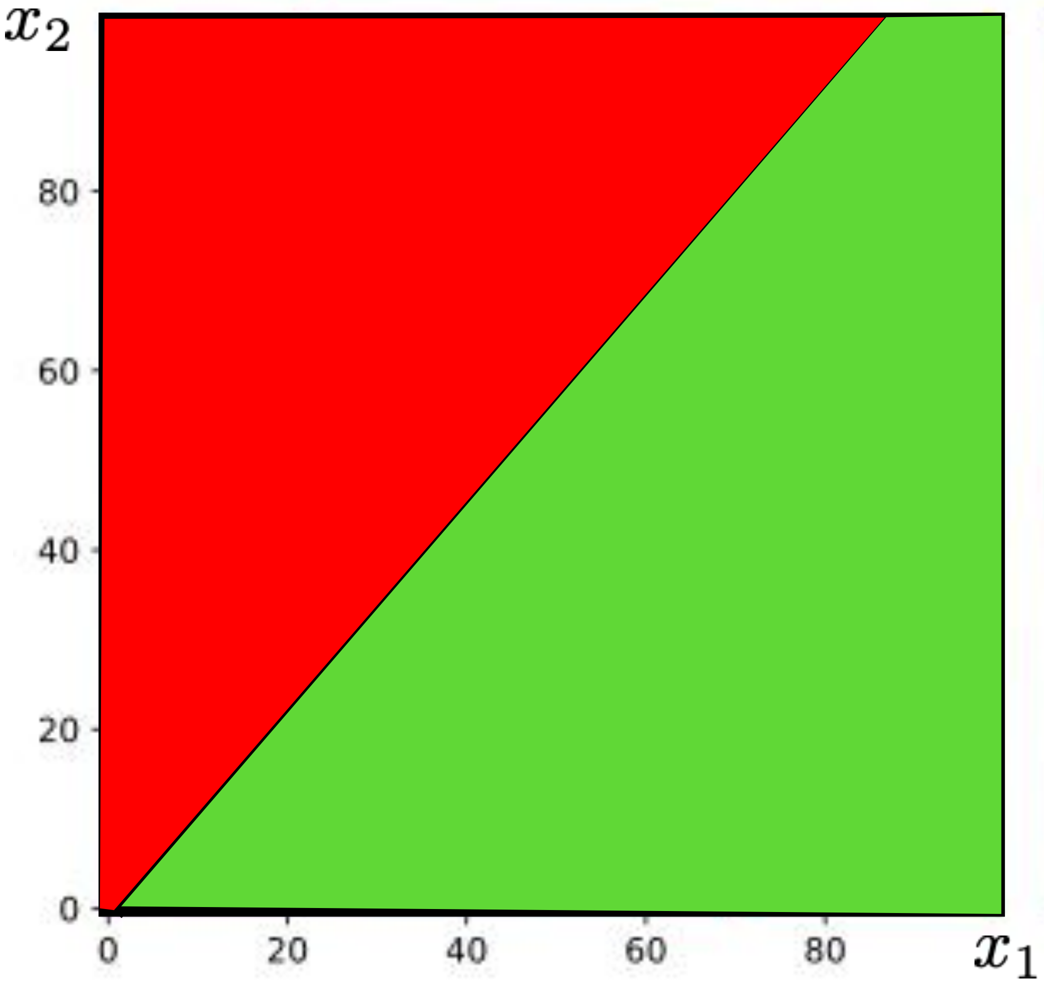


$$\hat{y} = \mathbf{x}^T \mathbf{w} + b$$

$$g(\hat{y}) = \begin{cases} 1, & \text{if} \quad \hat{y} > 0 \\ 0, & \text{otherwise} \end{cases}$$

$$\boxed{\mathbf{w}^*, b^* = \underset{\mathbf{w}, b}{\arg\min}\, \mathcal{L}(g(\hat{y}), y_i)}$$

Example: linear classification with a perceptron



$$\hat{y} = \mathbf{x}^T\mathbf{w} + b$$

$$g(\hat{y}) = \begin{cases} 1, & \text{if} \quad \hat{y} > 0 \\ 0, & \text{otherwise} \end{cases}$$

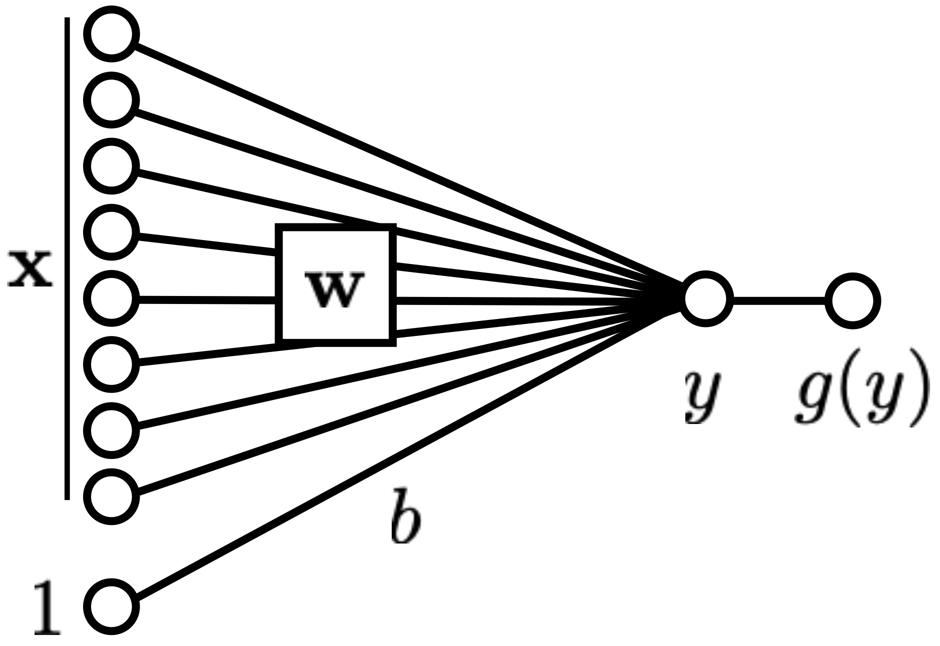
$$\boxed{\mathbf{w}^*, b^* = \arg\min_{\mathbf{w},b} \mathcal{L}(g(\hat{y}), y_i)}$$

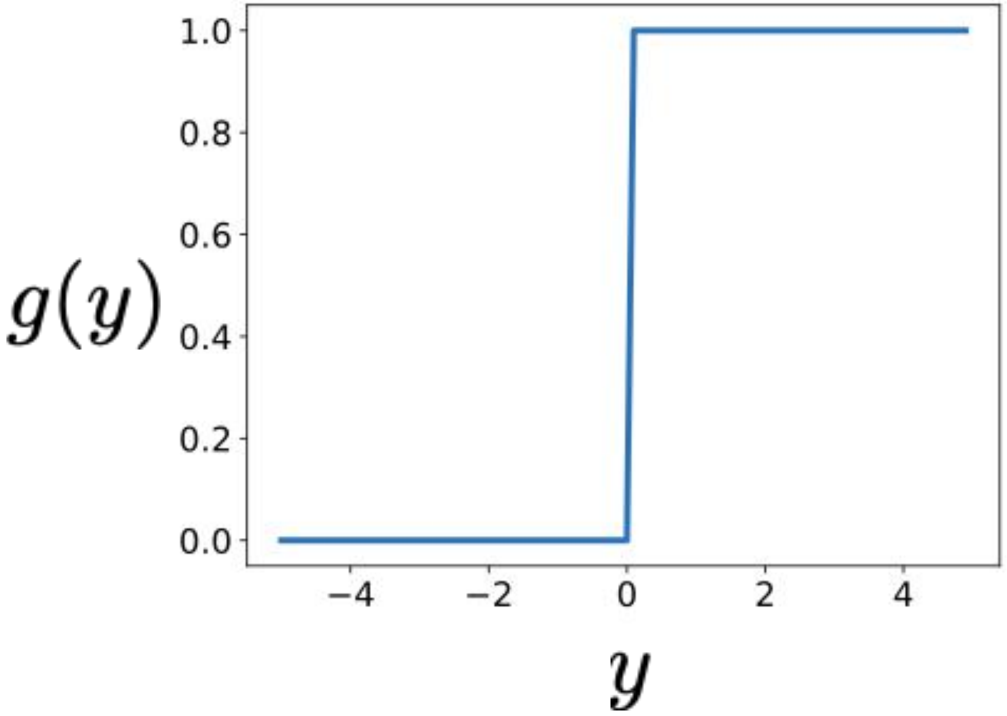
Computation in a neural net

$$g(y) = \begin{cases} 1, & \text{if} \quad y > 0 \\ 0, & \text{otherwise} \end{cases}$$

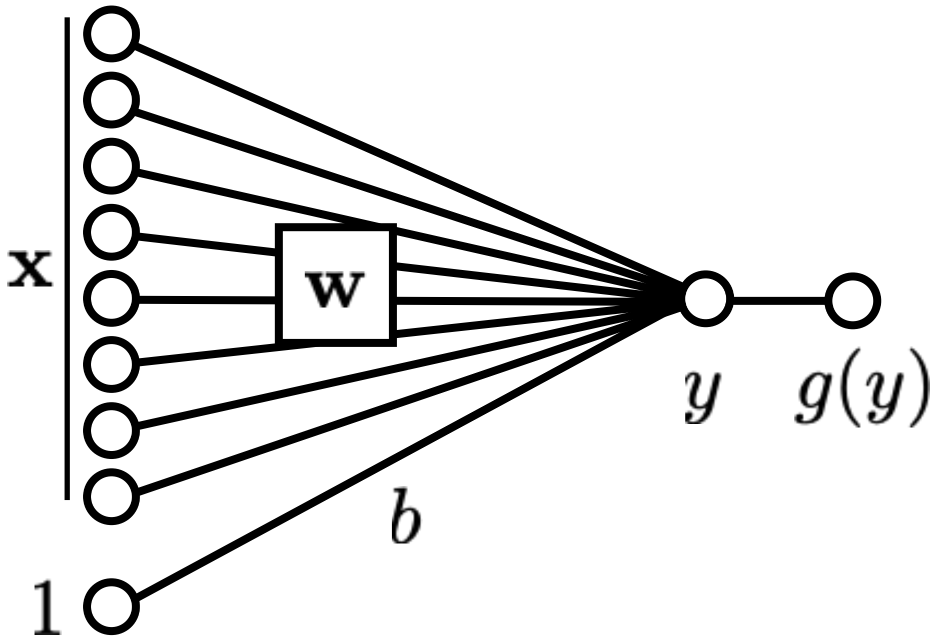
Input representation

Output representation



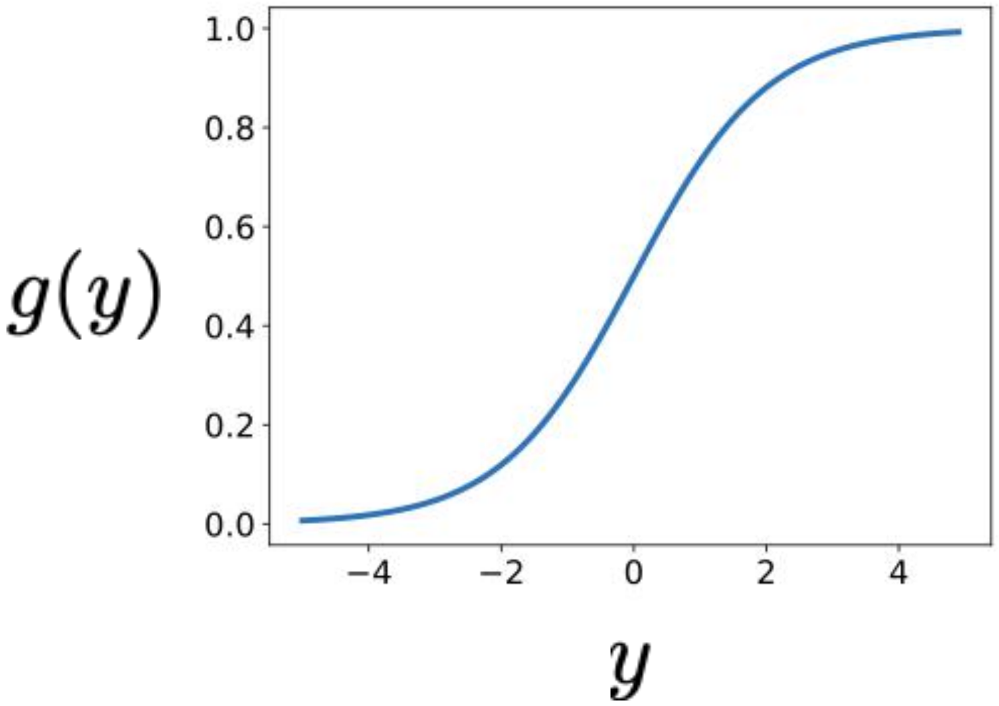


Computation in a neural net – nonlinearity



Sigmoid

$$g(y) = \frac{1}{1 + e^{-y}}$$

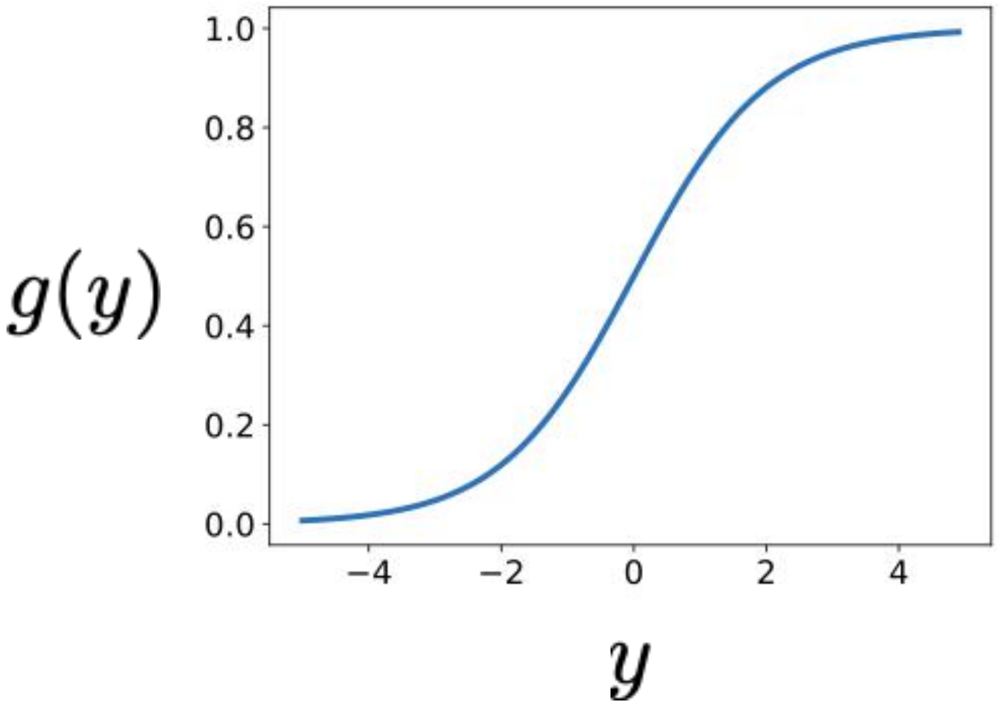


Computation in a neural net – nonlinearity

- Interpretation as firing rate of neuron
- Bounded between [0,1]
- Saturation for large +/- inputs
- Gradients go to zero
- Outputs centered at 0.5
  (poor conditioning)
- Not used in practice

Sigmoid

$$g(y) = \frac{1}{1 + e^{-y}}$$



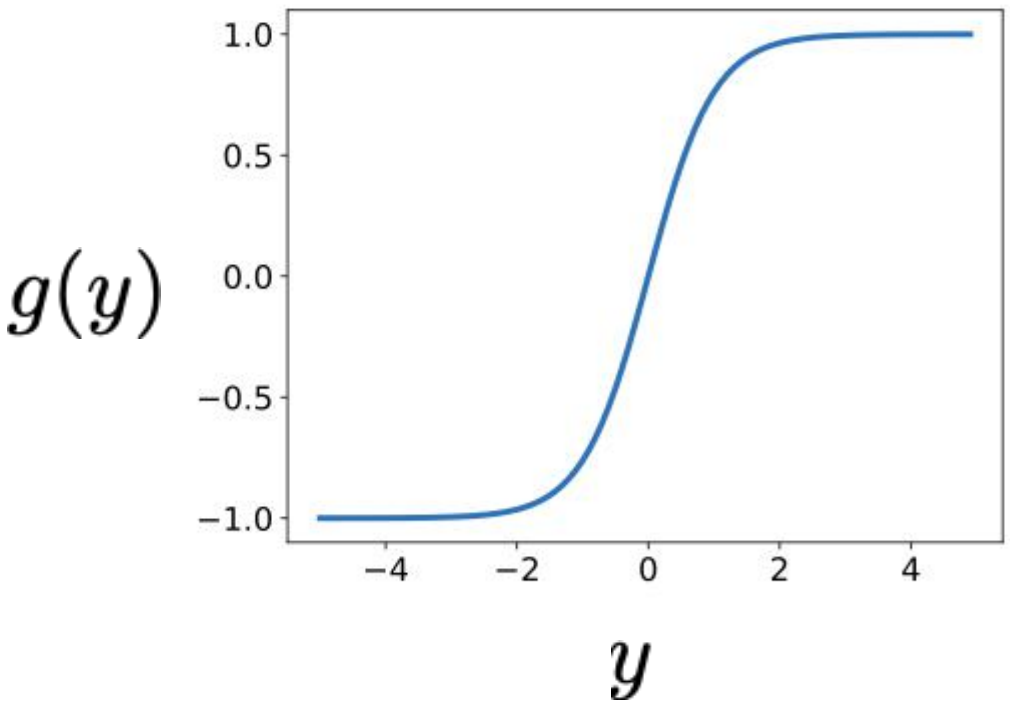
Computation in a neural net – nonlinearity

- Bounded between [-1,+1]
- Saturation for large +/- inputs
- Gradients go to zero
- Outputs centered at 0
- Preferable to sigmoid

tanh(x) = 2 sigmoid(2x) −1

Tanh

$$g(y) = \frac{e^y - e^{-y}}{e^y + e^{-y}}$$

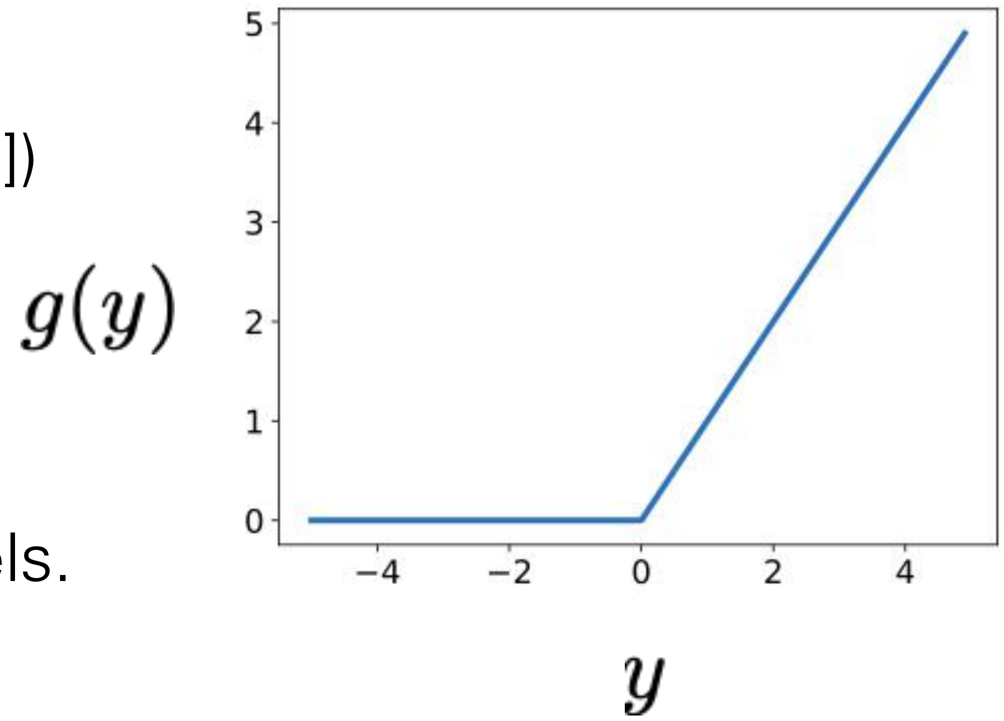


Computation in a neural net – nonlinearity

- Unbounded output (on positive side)
- Efficient to implement: $\frac{\partial g}{\partial y} = \begin{cases} 0, & \text{if} \quad y < 0 \\ 1, & \text{if} \quad y \geq 0 \end{cases}$
- Also seems to help convergence
  (see 6x speedup vs tanh in [Krizhevsky et al.])
- Drawback: if strongly in negative region,
  unit is dead forever (no gradient).
- Default choice: widely used in current models.

Rectified linear unit (ReLU)

$$g(y) = \max(0, y)$$



Computation in a neural net – nonlinearity

- where α is small (e.g. 0.02)

- Efficient to implement: $\frac{\partial g}{\partial y} = \begin{cases} -a, & \text{if} \quad y < 0 \\ 1, & \text{if} \quad y \geq 0 \end{cases}$

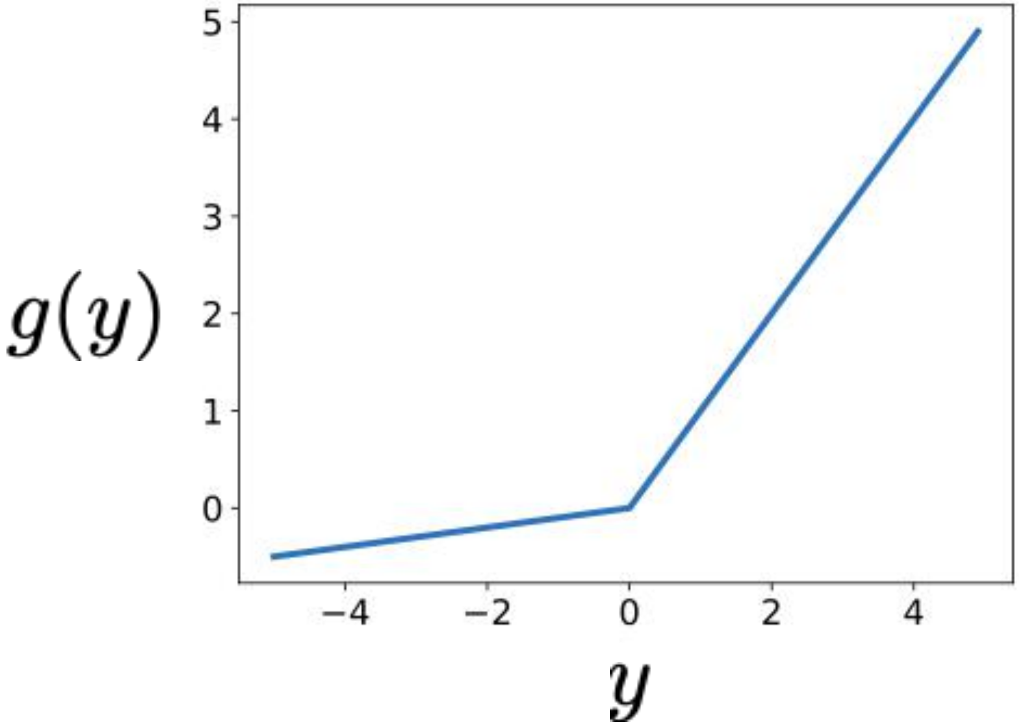
- Also known as probabilistic ReLU (PReLU)

- Has non-zero gradients everywhere (unlike ReLU)

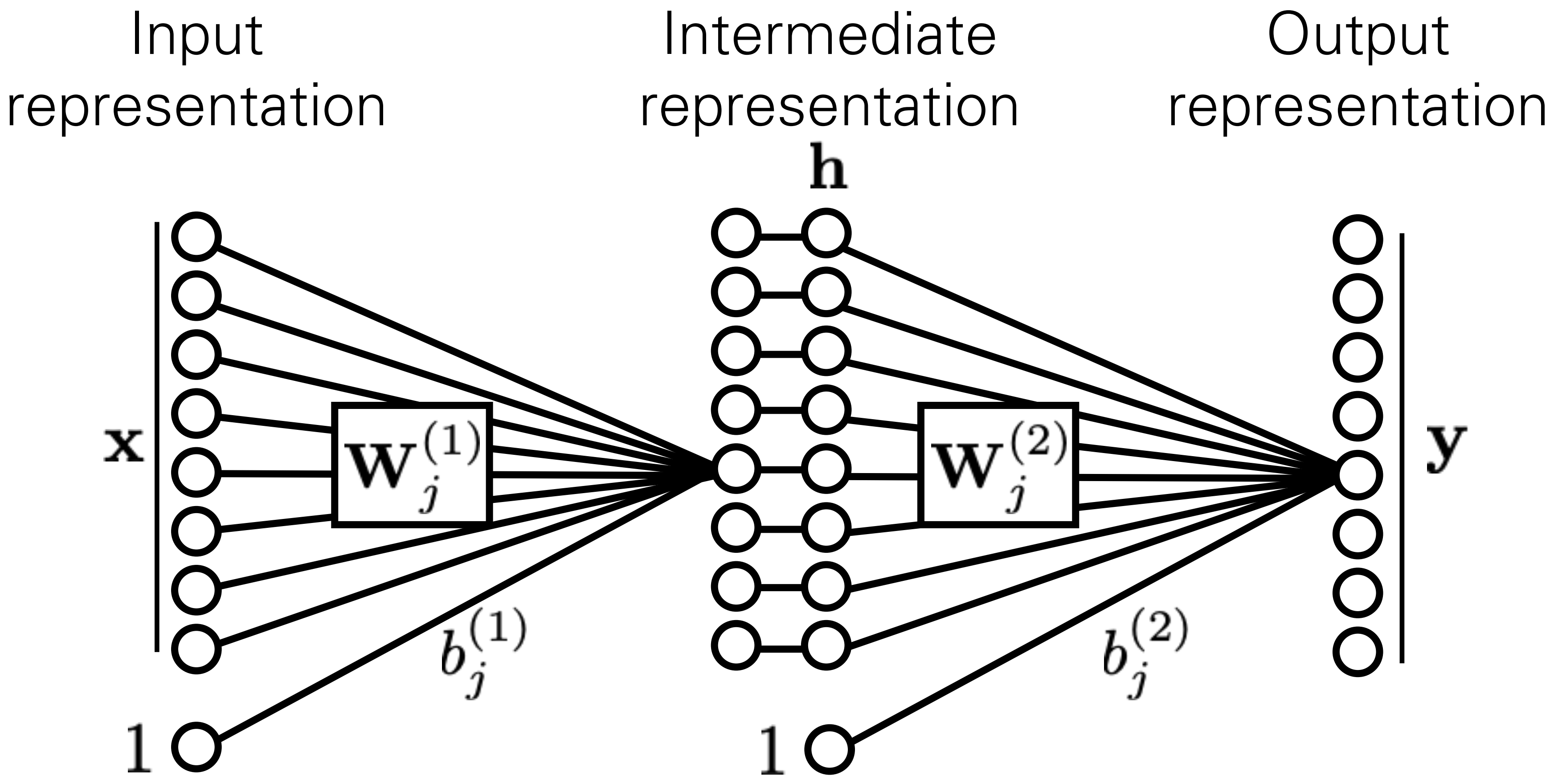
- α can also be learned (see Kaiming He et al. 2015).

Leaky ReLU

$$g(y) = \begin{cases} \max(0, y), & \text{if} \quad y \geq 0 \\ a\min(0, y), & \text{if} \quad y < 0 \end{cases}$$

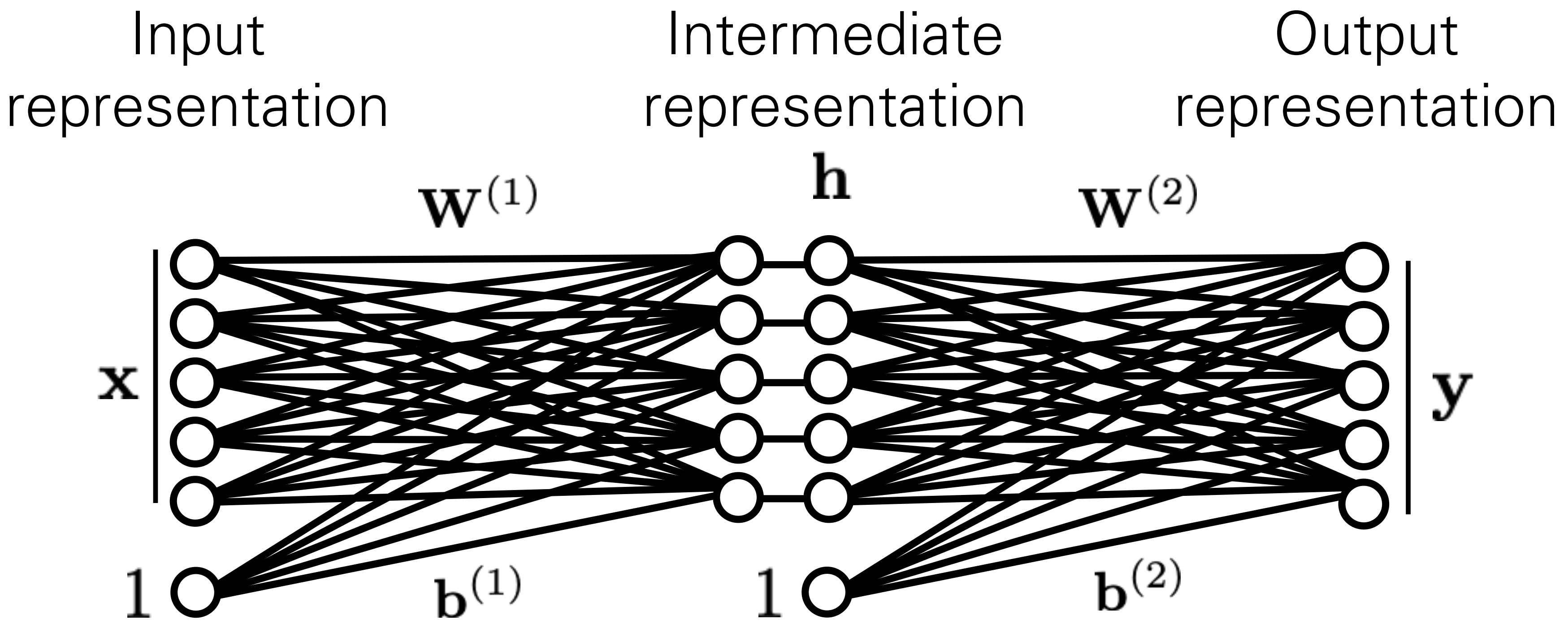


Stacking layers



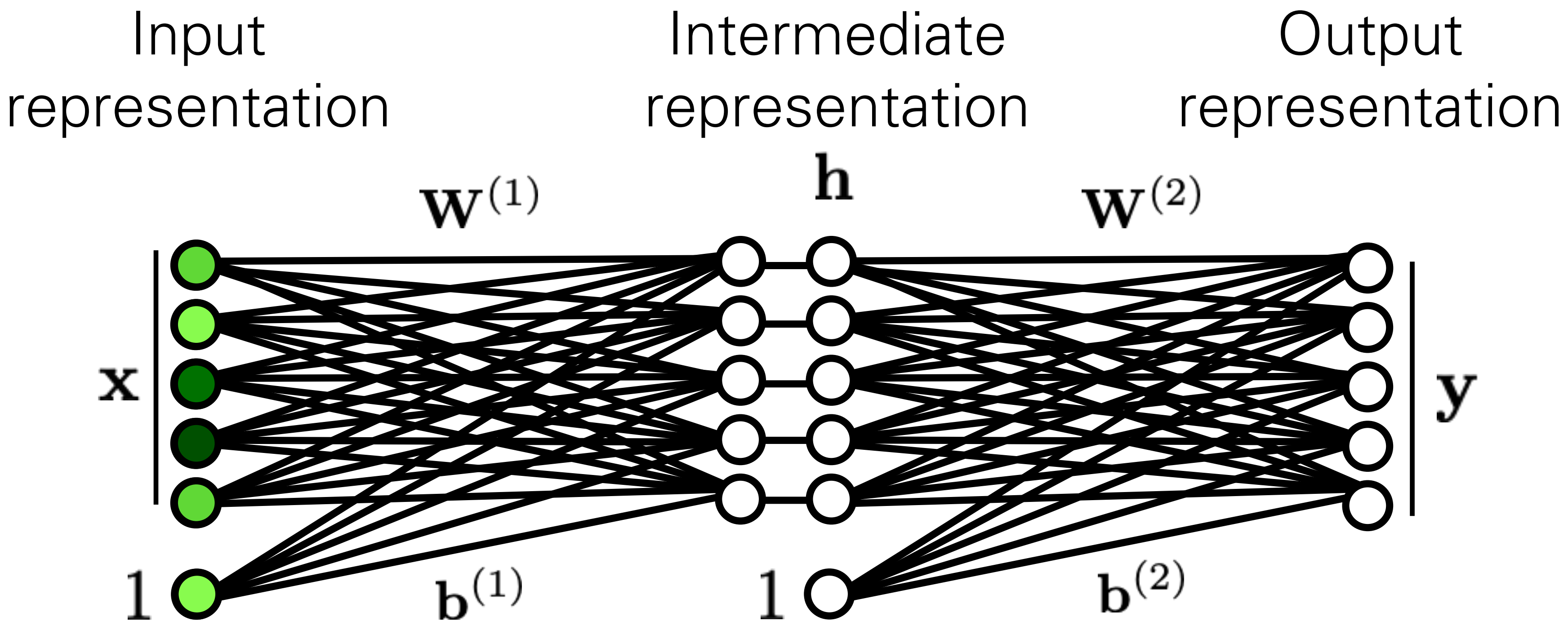
$\mathbf{h}$ = "hidden units"

Stacking layers



$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

Stacking layers

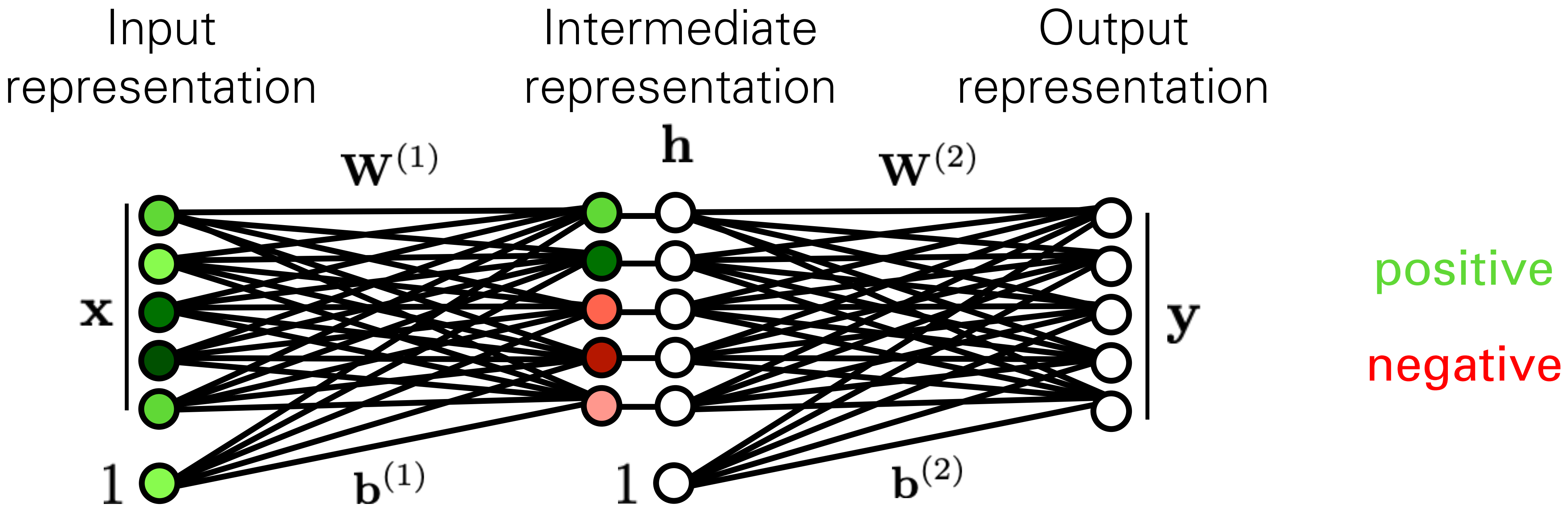


positive

negative

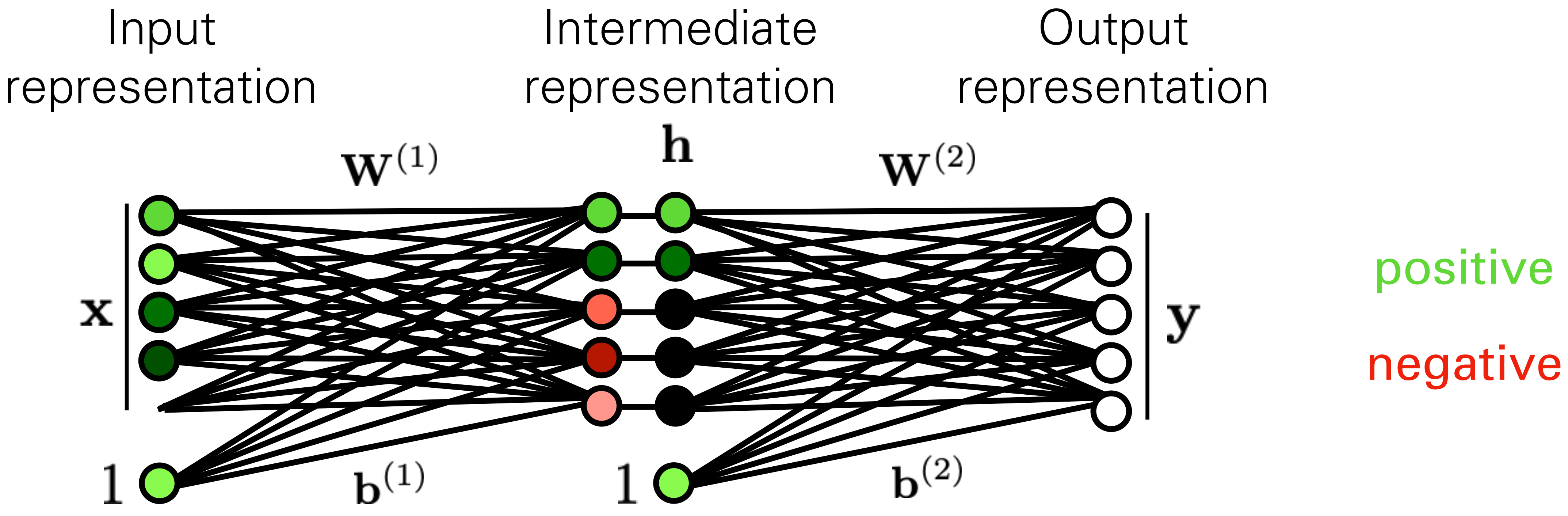
$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

Stacking layers



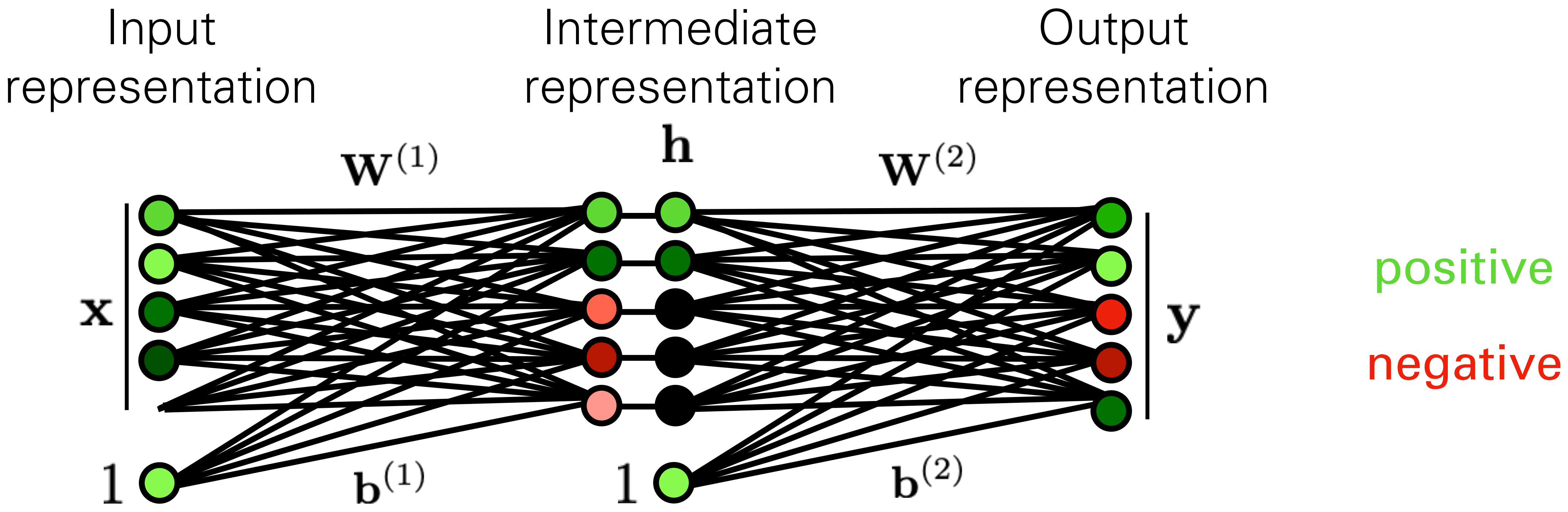
$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

Stacking layers



$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

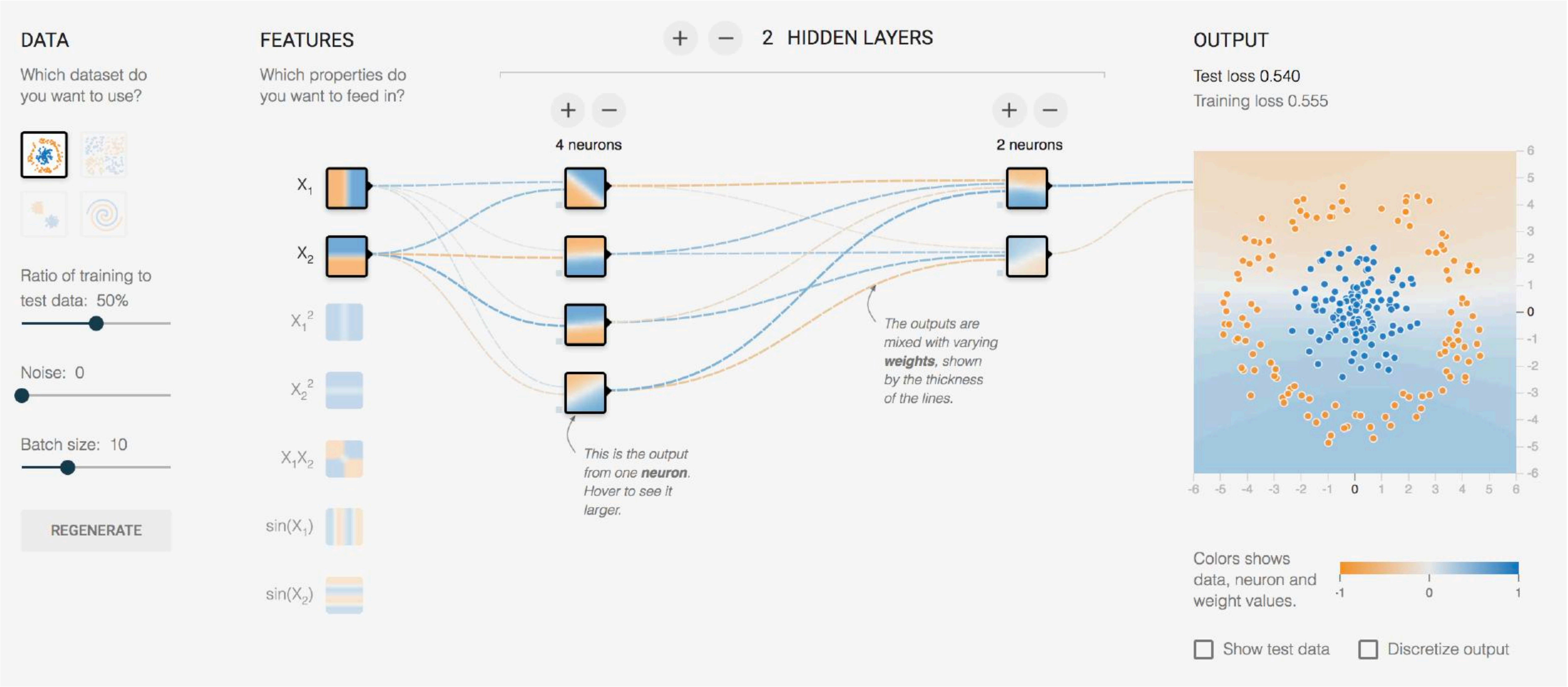
Stacking layers



$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

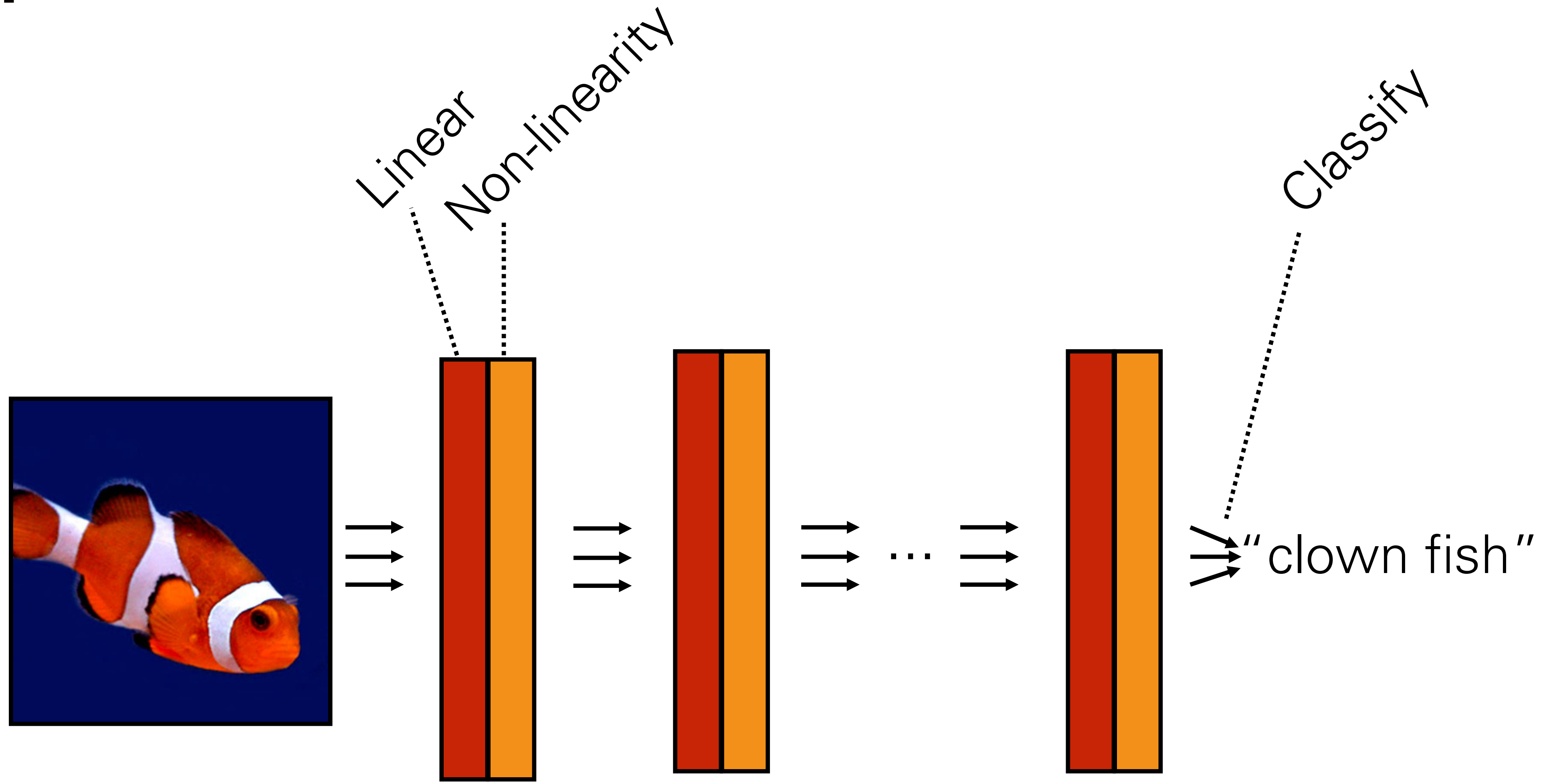
Representational power

- 1 layer? Linear decision surface.
- 2+ layers? In theory, can represent any function. Assuming non-trivial non-linearity.
  - Bengio 2009, http://www.iro.umontreal.ca/~bengioy/papers/ftml.pdf
  - Bengio, Courville, Goodfellow book http://www.deeplearningbook.org/contents/mlp.html
  - Simple proof by M. Neilsen http://neuralnetworksanddeeplearning.com/chap4.html
  - D. Mackay book http://www.inference.phy.cam.ac.uk/mackay/itprnn/ps/482.491.pdf
- But issue is efficiency: very wide two layers vs narrow deep model? In practice, more layers helps.



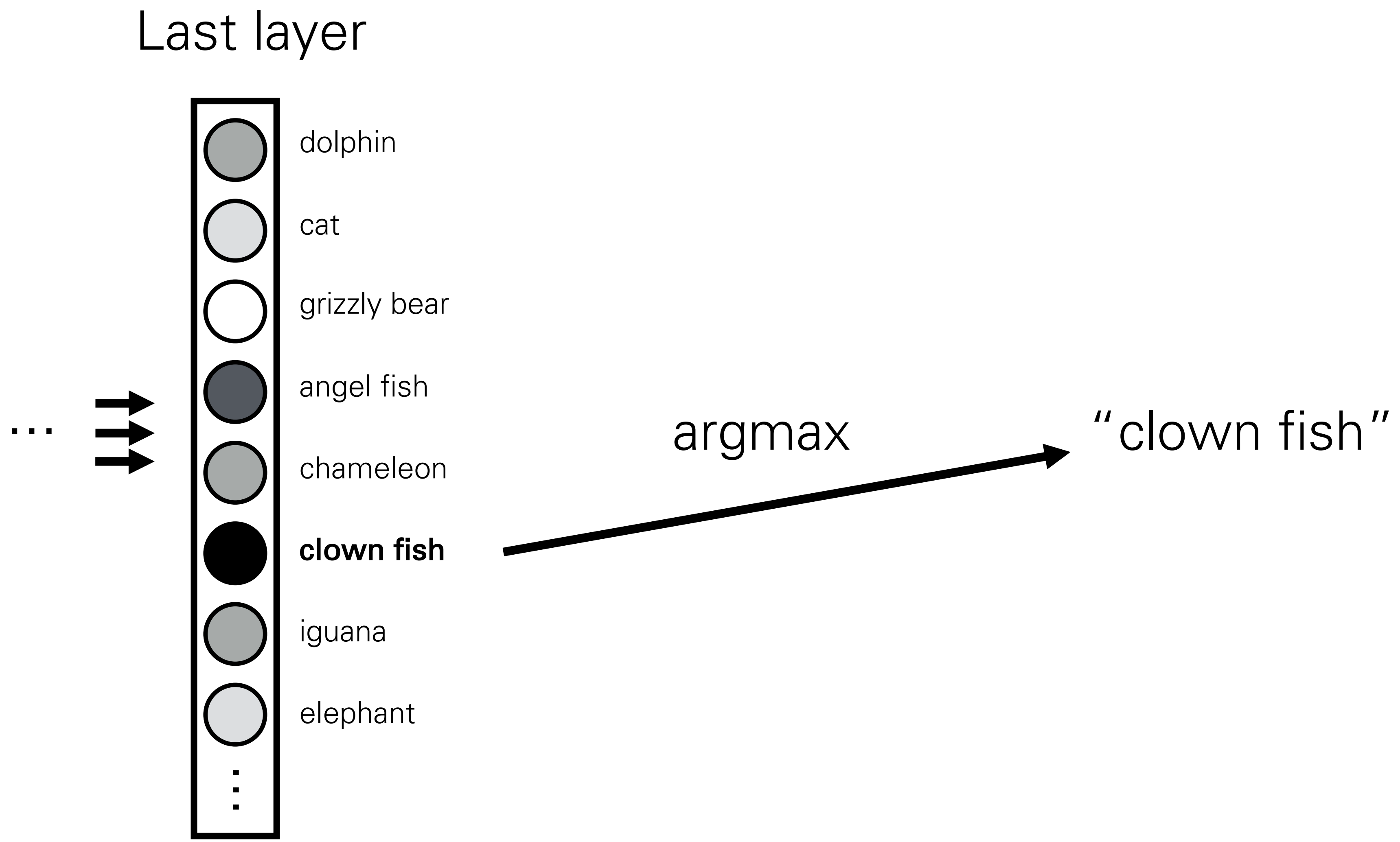
[http://playground.tensorflow.org]

Deep nets

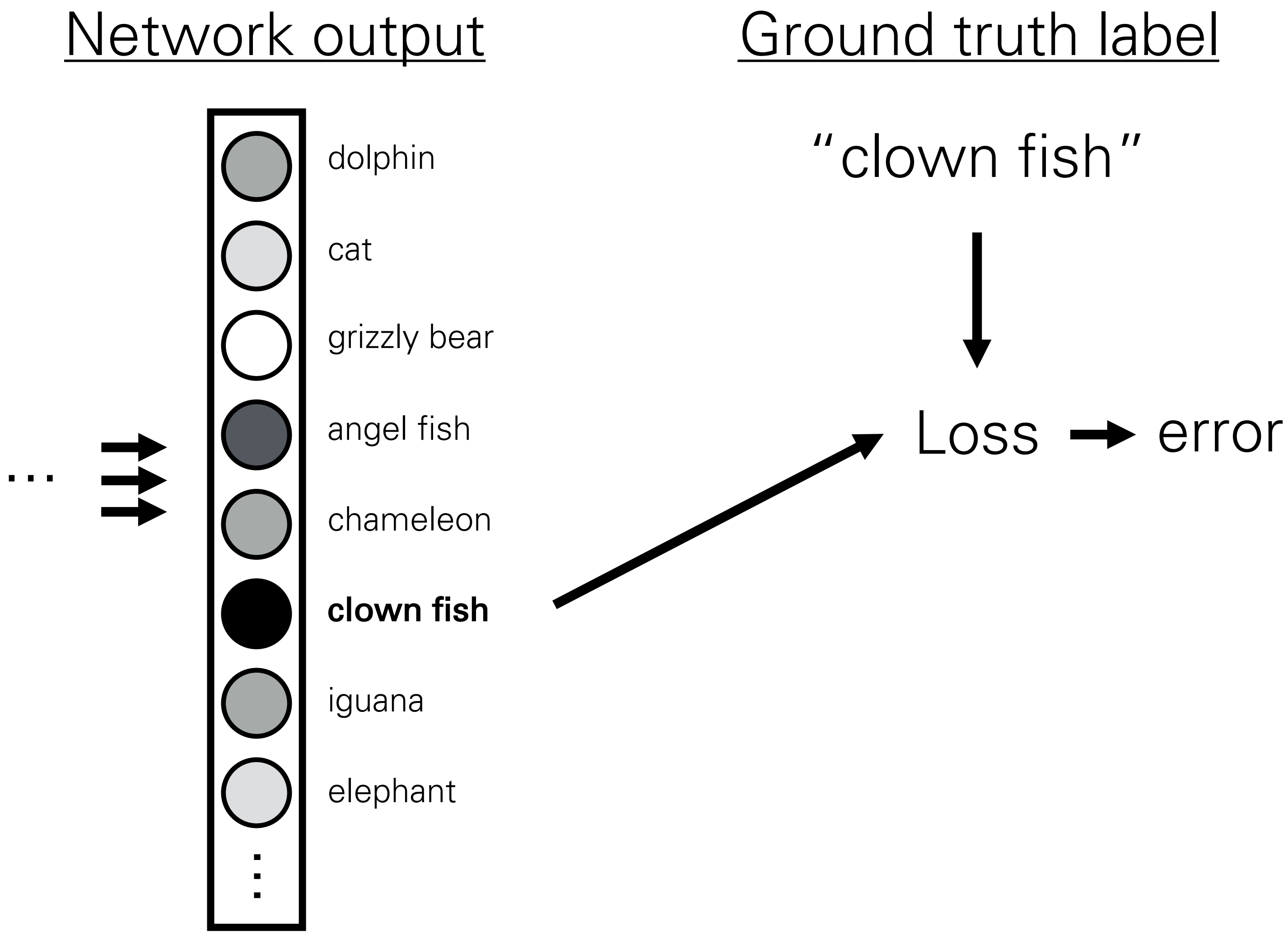


$$f(\mathbf{x}) = f_L(\dots f_2(f_1(\mathbf{x})))$$

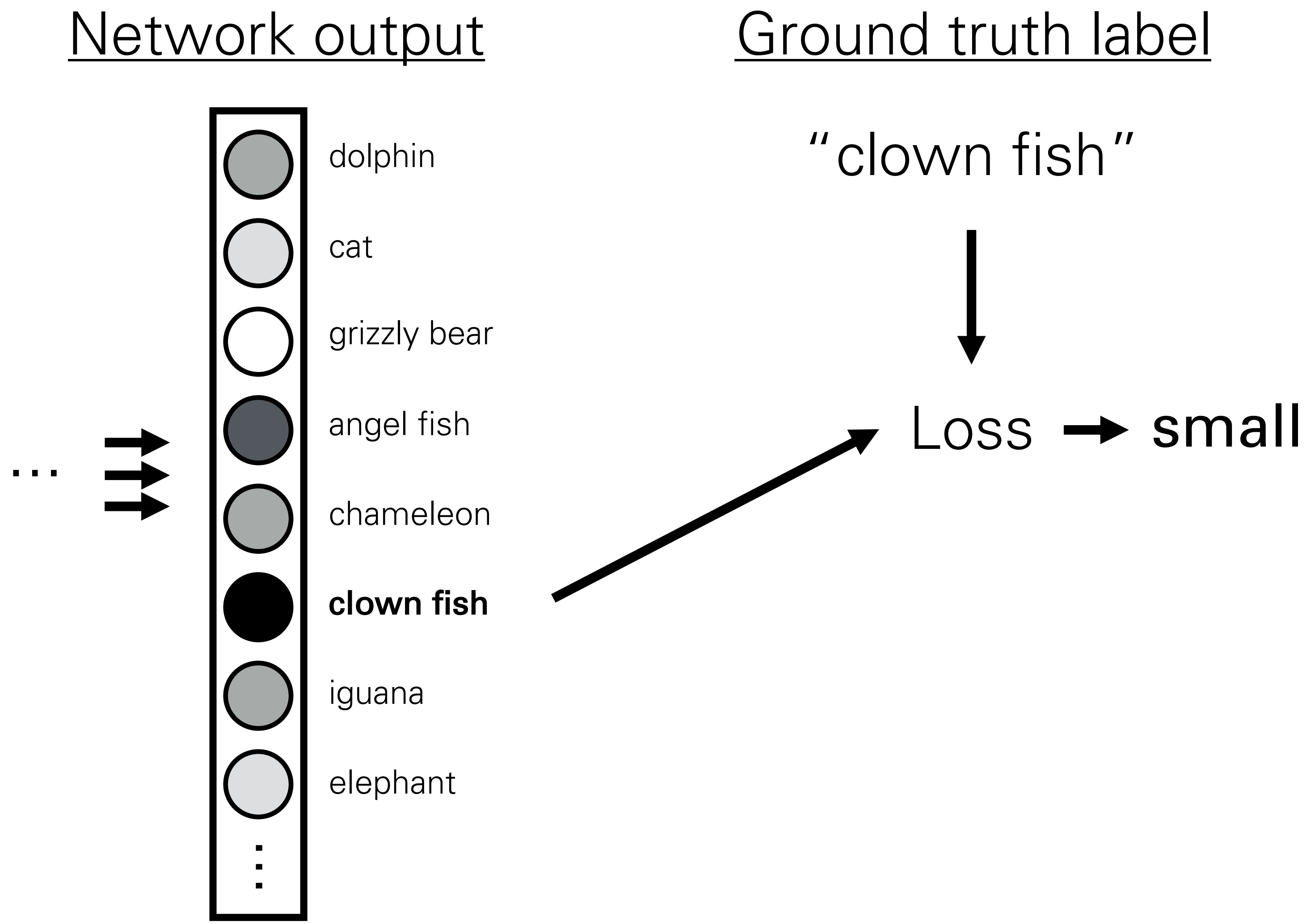
Classifier layer



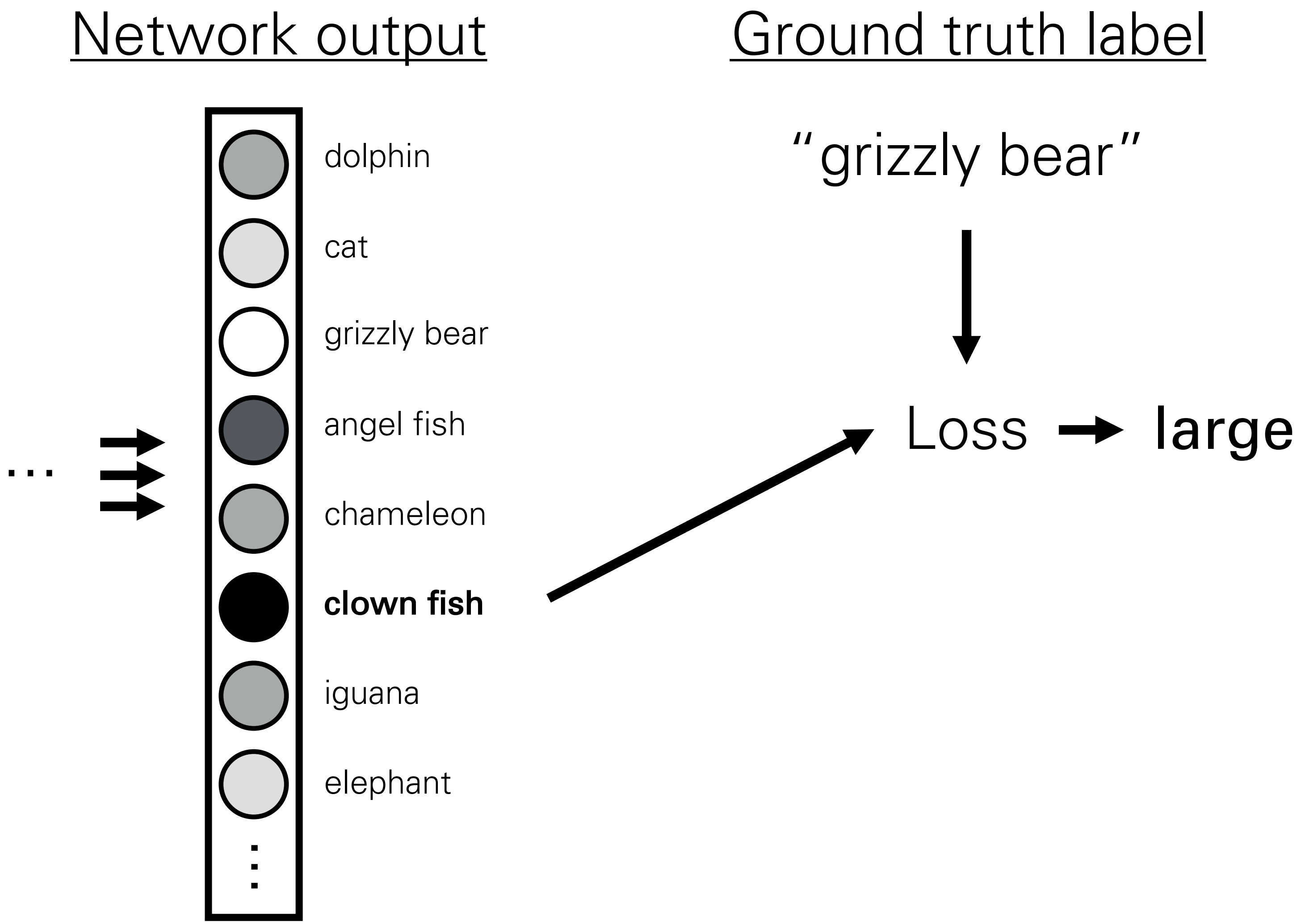
Loss function



Loss function

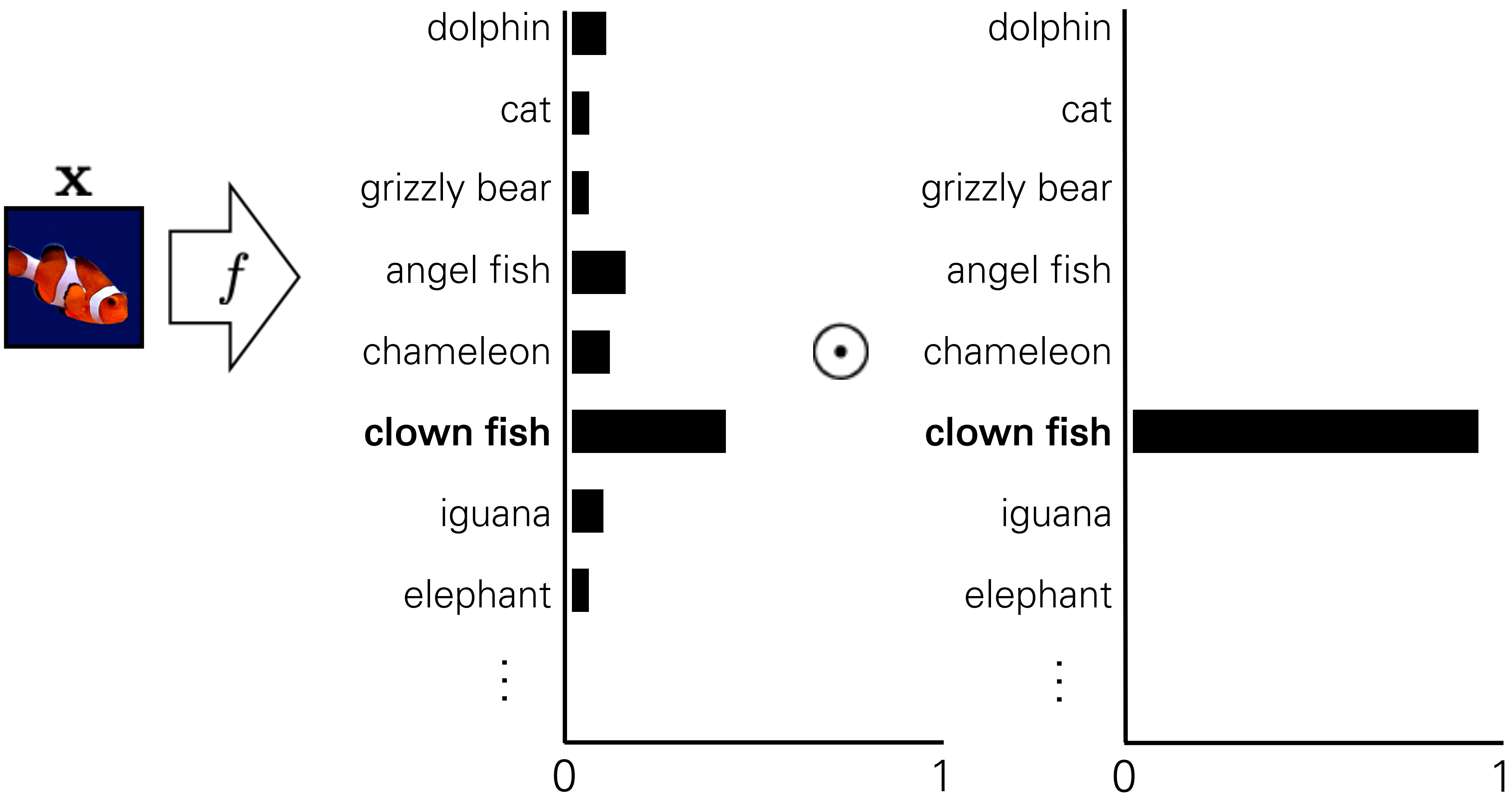


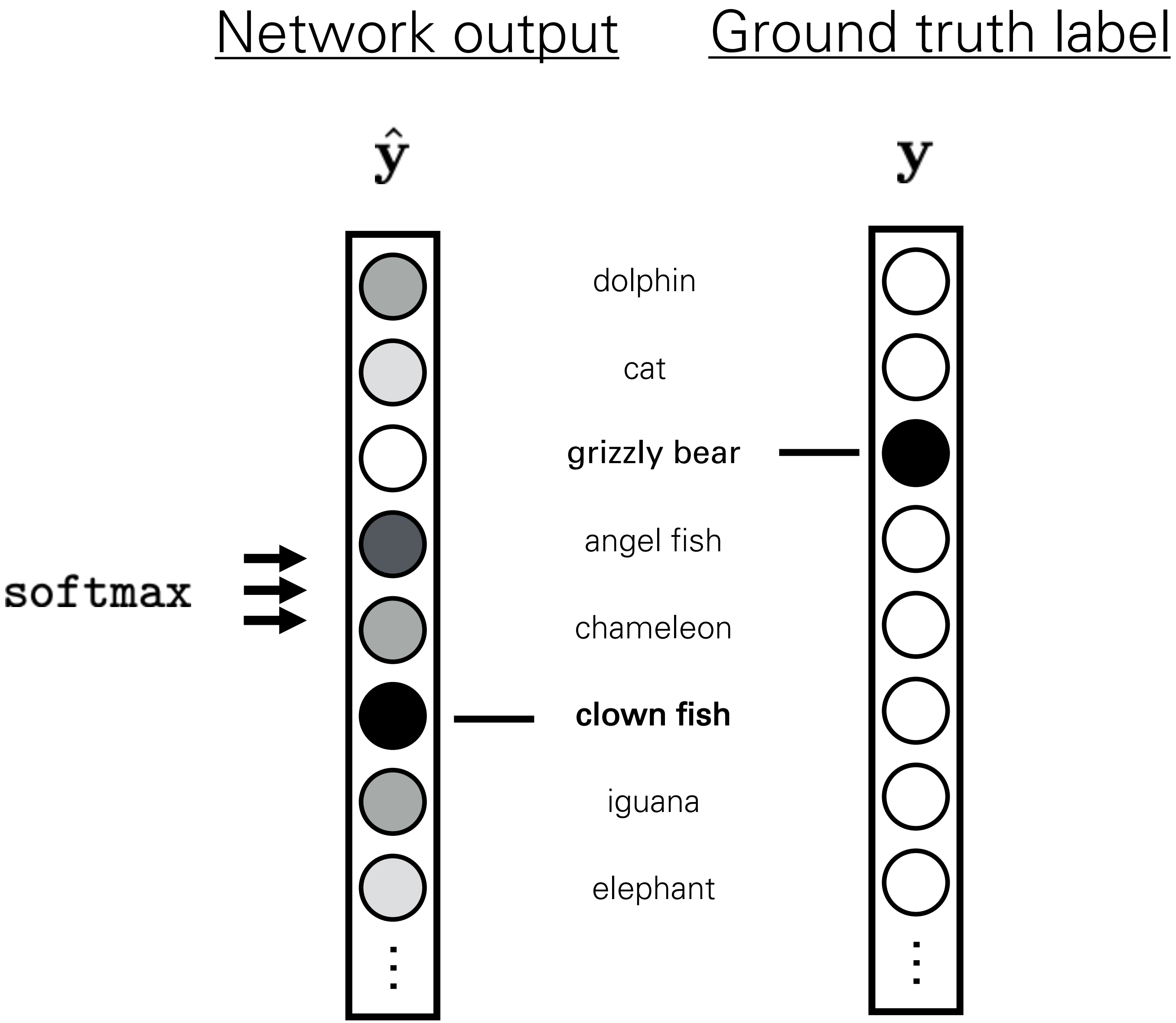
Loss function



Prediction $\hat{\mathbf{y}}$ Ground truth label $\mathbf{y}$

$$f_\theta : X \to \mathbb{R}^K$$



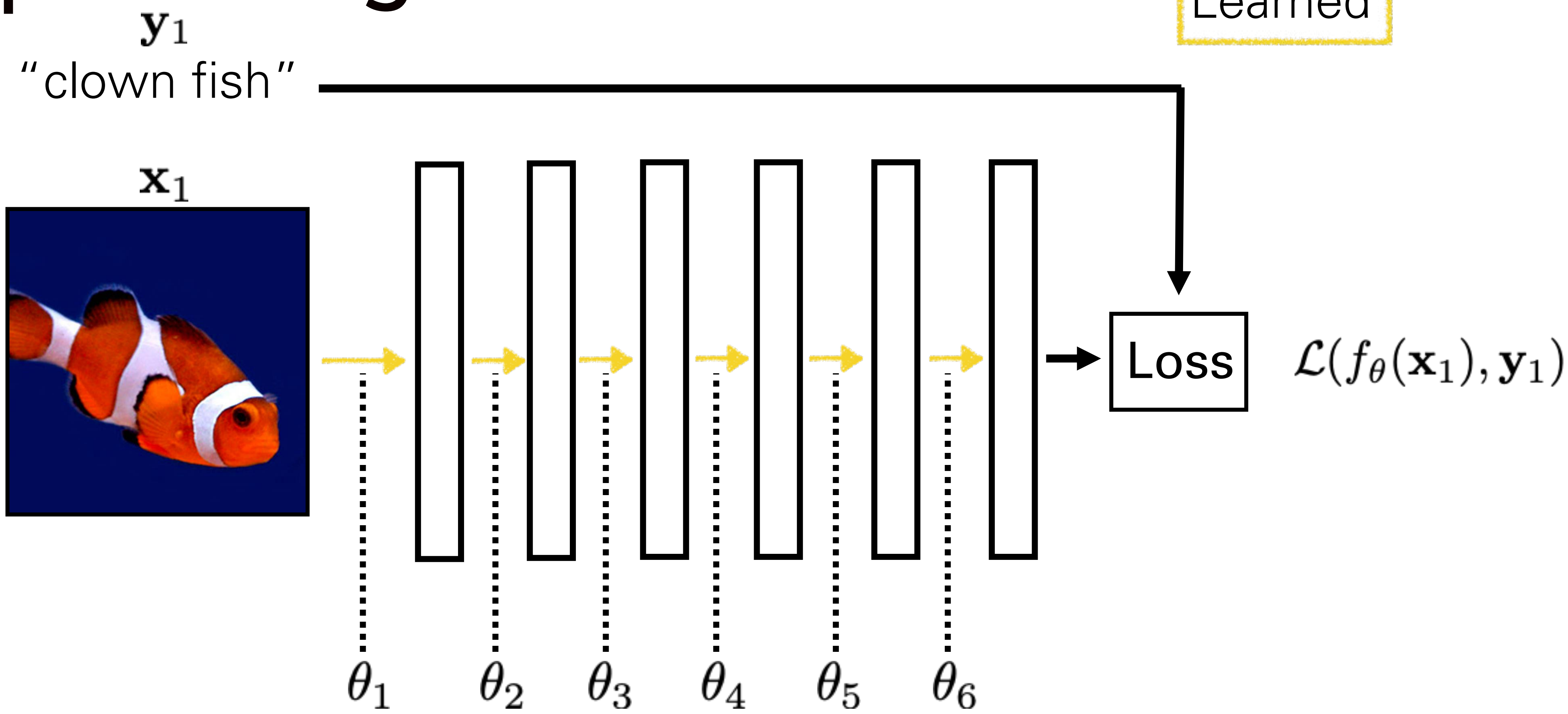


Probability of the observed data under the model

$$H(\mathbf{y}, \hat{\mathbf{y}}) = -\sum_{k=1}^{K} y_k \log \hat{y}_k$$

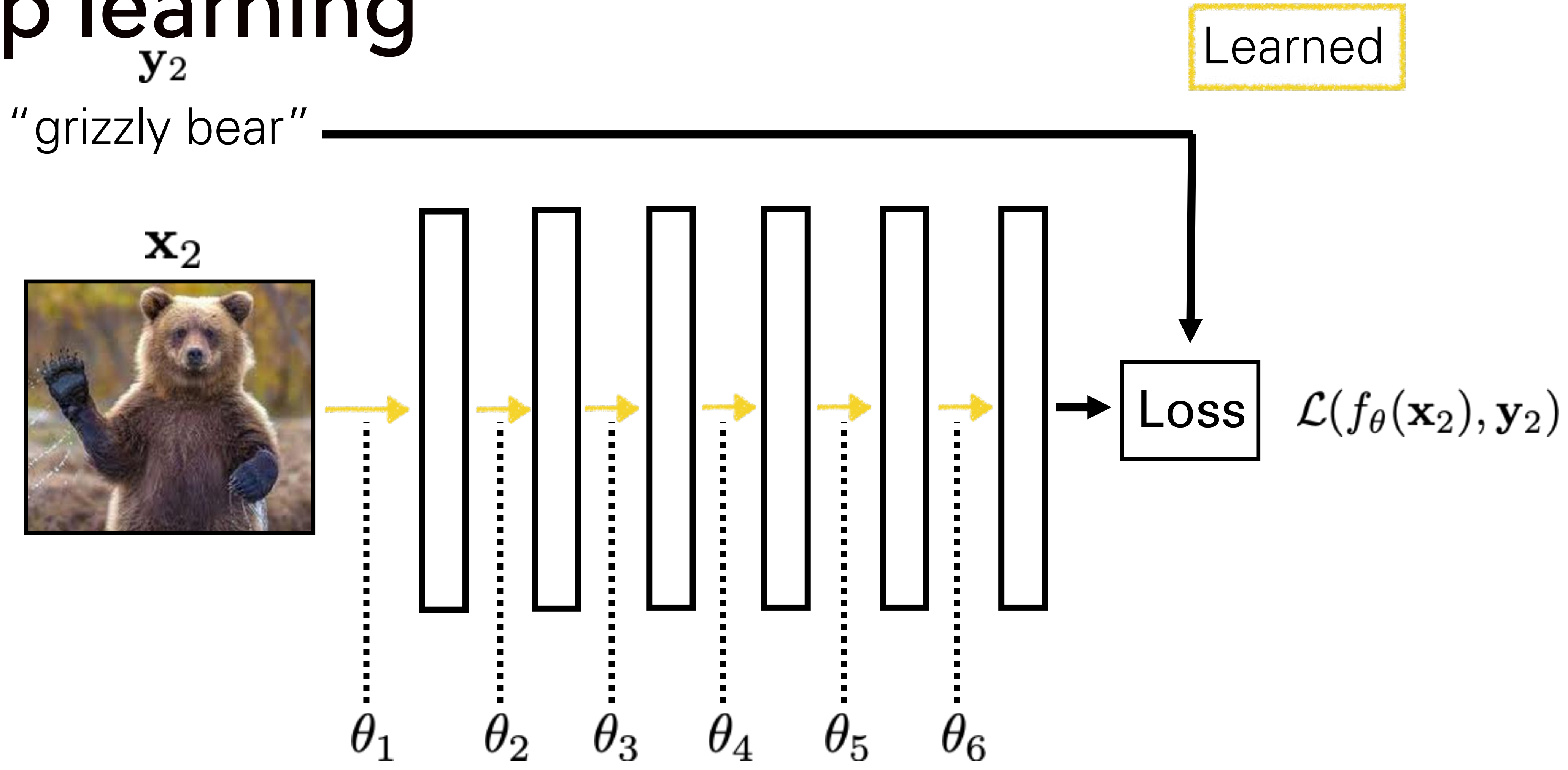
Deep learning

Learned



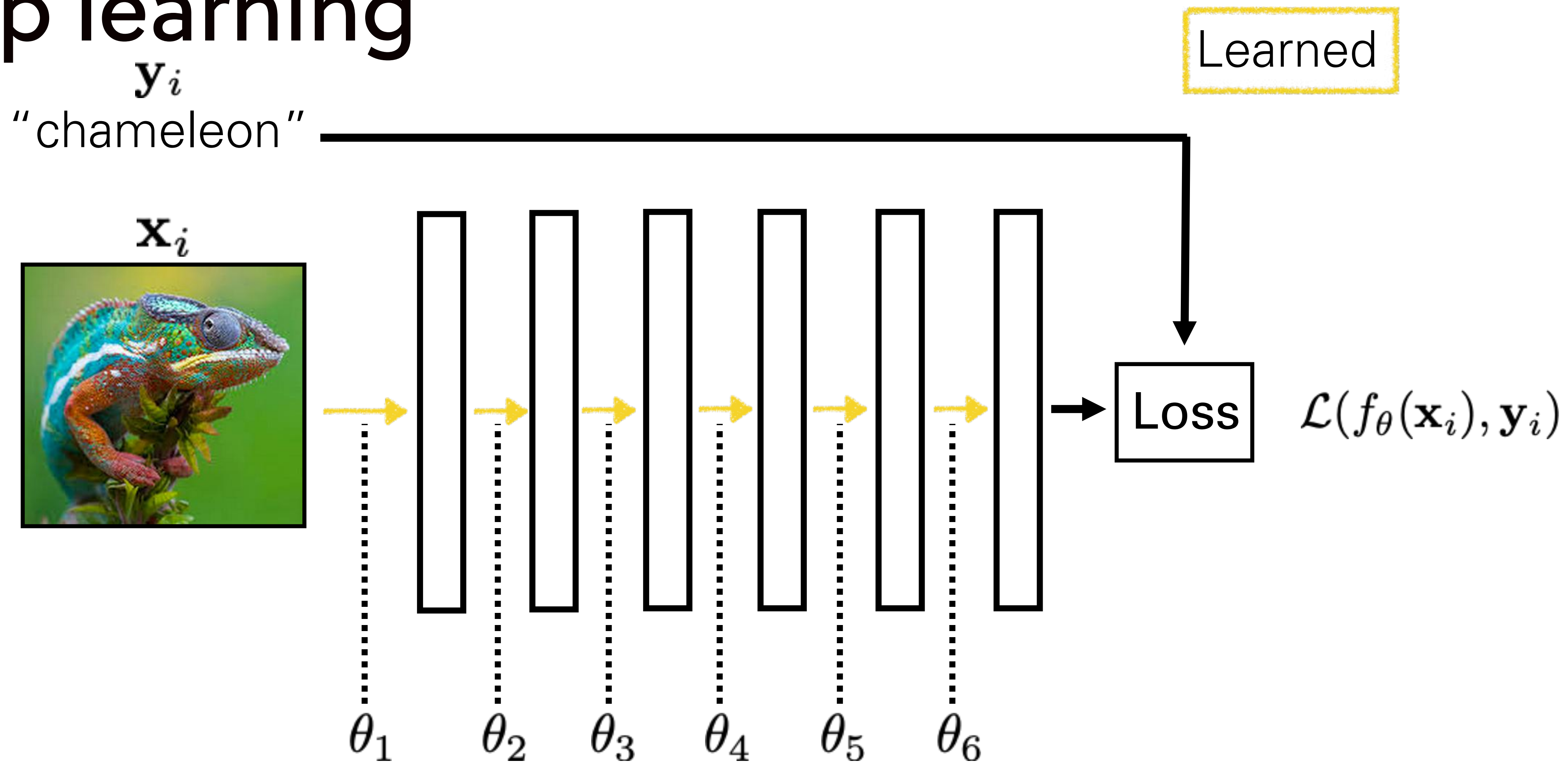
$$\theta^* = \arg\min_\theta \sum_{i=1}^{N} \mathcal{L}(f_\theta(\mathbf{x}_i), \mathbf{y}_i)$$

Deep learning



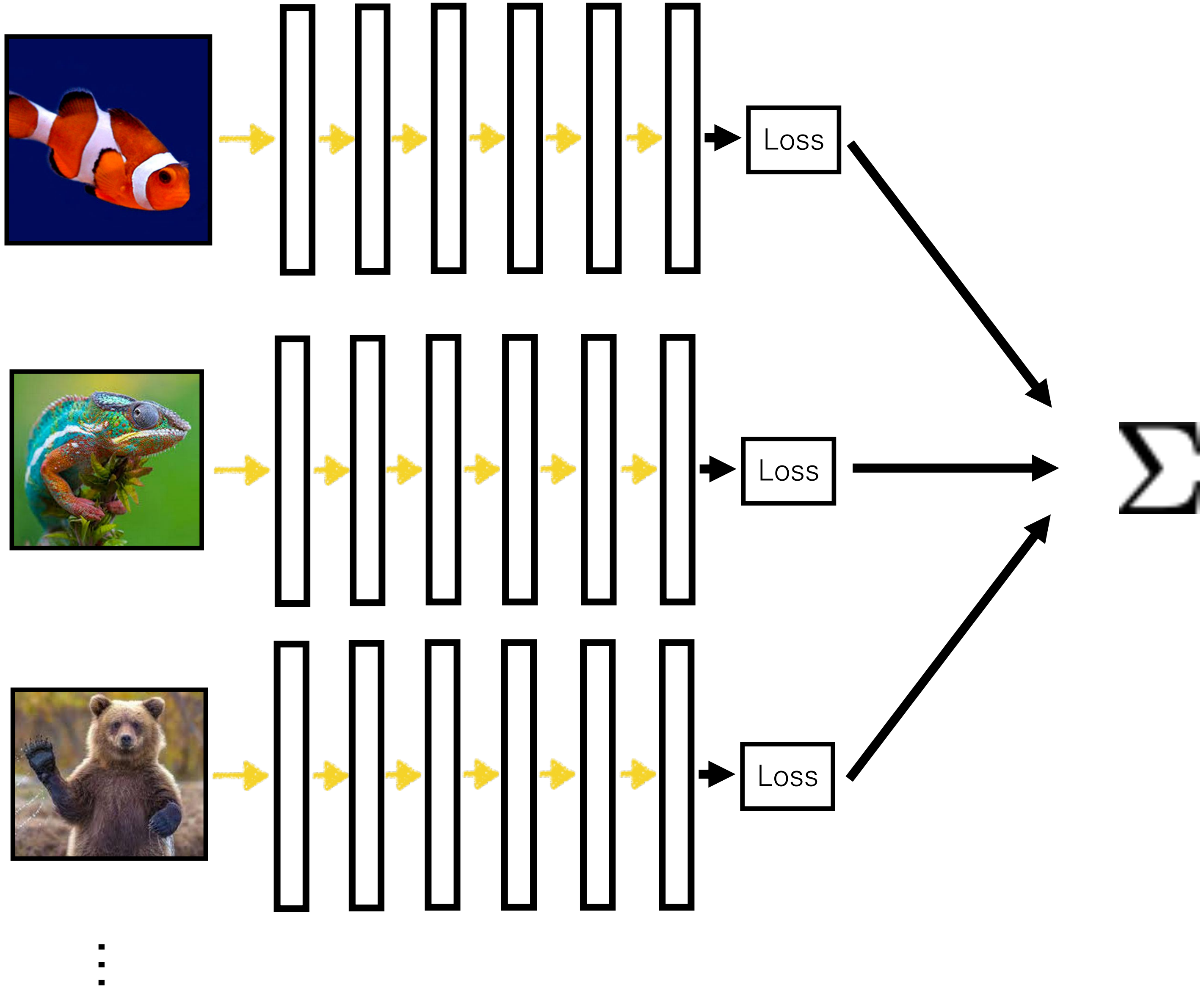
$$\theta^* = \arg\min_\theta \sum_{i=1}^{N} \mathcal{L}(f_\theta(\mathbf{x}_i), \mathbf{y}_i)$$

Deep learning



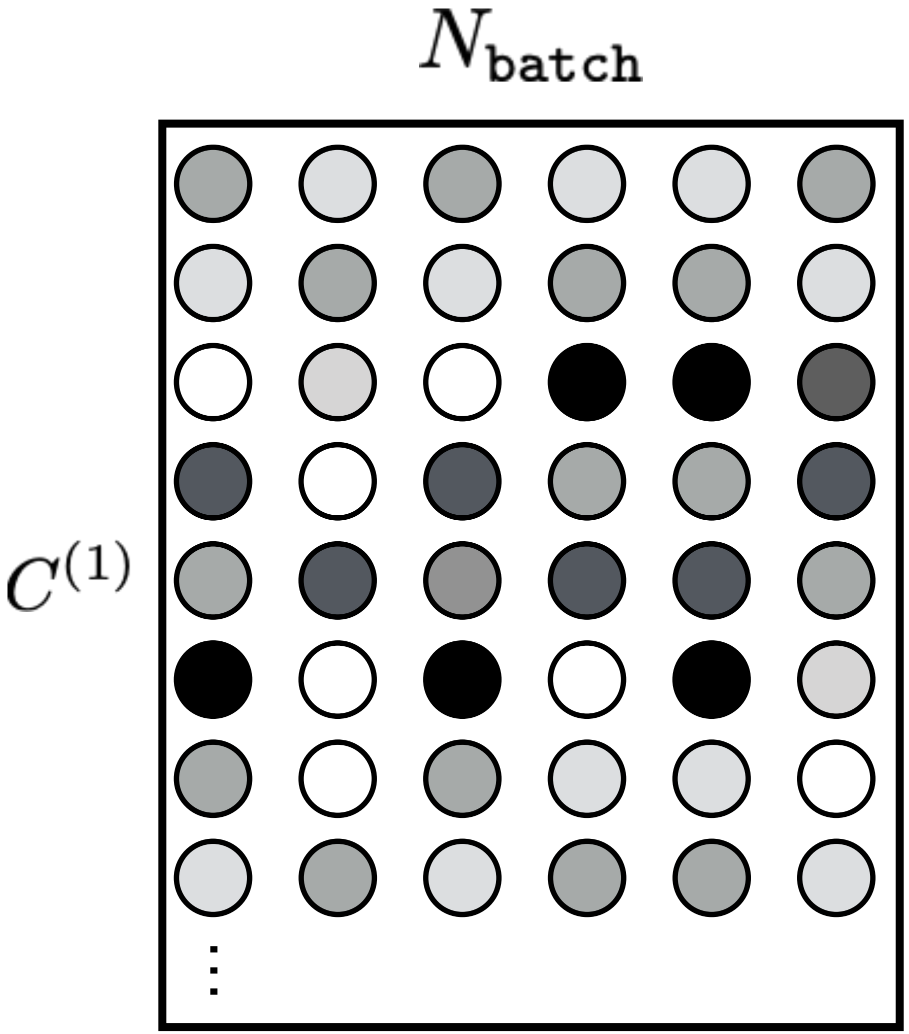
$$\theta^* = \arg\min_\theta \sum_{i=1}^{N} \mathcal{L}(f_\theta(\mathbf{x}_i), \mathbf{y}_i)$$

Batch (parallel) processing



Tensors

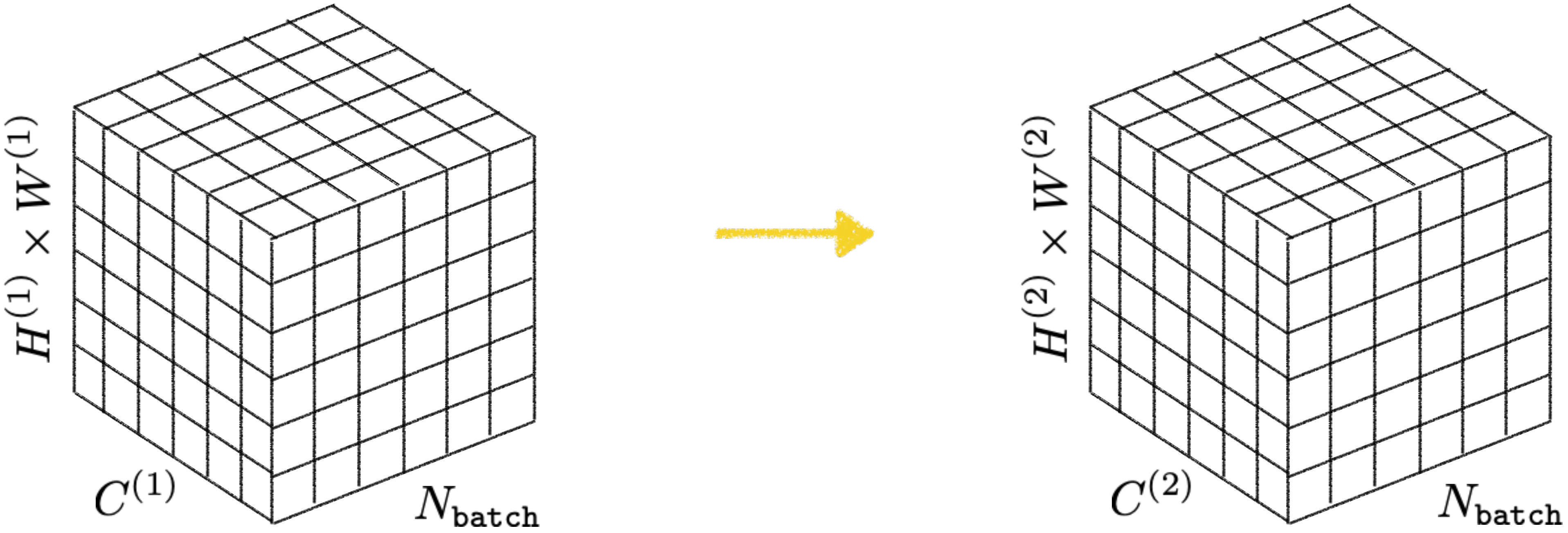
$$\mathbf{h}^{(1)} \in \mathbb{R}^{N_{\texttt{batch}} \times C^{(1)}}$$



"Tensor flow"

$\mathbf{h}^{(1)} \in \mathbb{R}^{N_{\texttt{batch}} \times H^{(1)} \times W^{(1)} \times C^{(1)}}$

$\mathbf{h}^{(2)} \in \mathbb{R}^{N_{\texttt{batch}} \times H^{(2)} \times W^{(2)} \times C^{(2)}}$



Regularizing deep nets

Deep nets have millions of parameters!

On many datasets, it is easy to overfit — we may have more free parameters than data points to constrain them.

How can we regularize to prevent the network from overfitting?

1. Fewer neurons, fewer layers
2. Weight decay
3. Dropout
4. Normalization layers
5. …

Recall: regularized least squares

$$f_\theta(x) = \sum_{k=0}^{K} \theta_k x^k$$

$$R(\theta) = \lambda \left\|\theta\right\|_2^2$$

Only use polynomial terms if you really need them! Most terms should be zero

ridge regression, a.k.a., **Tikhonov regularization**

Probabilistic interpretation: R is a Gaussian **prior** over values of the parameters.

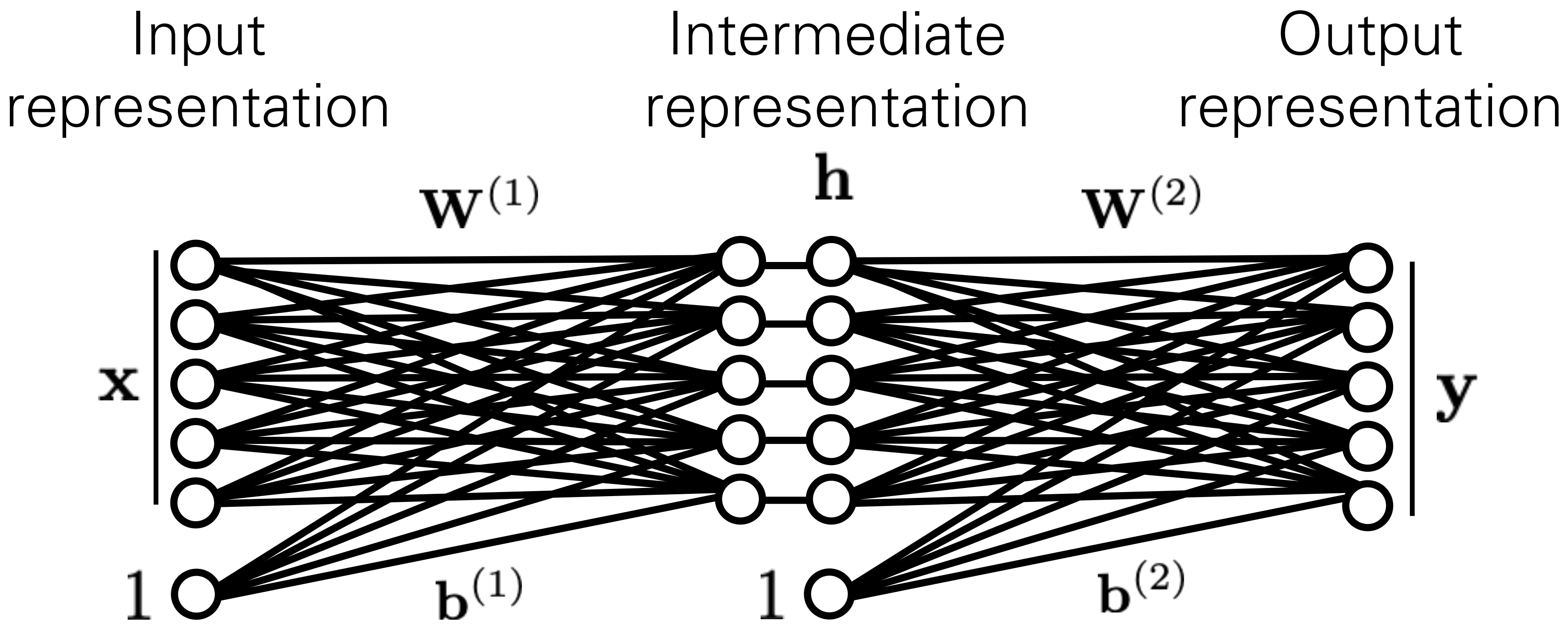
Recall: regularized least squares

$$\theta^* = \arg\min_{\theta} \sum_{i=1}^{N} \mathcal{L}(f_\theta(\mathbf{x}_i), \mathbf{y}_i) + R(\theta)$$

$$R(\mathbf{W}) = \lambda \|\mathbf{W}\|_2^2 \longleftarrow \text{weight decay}$$

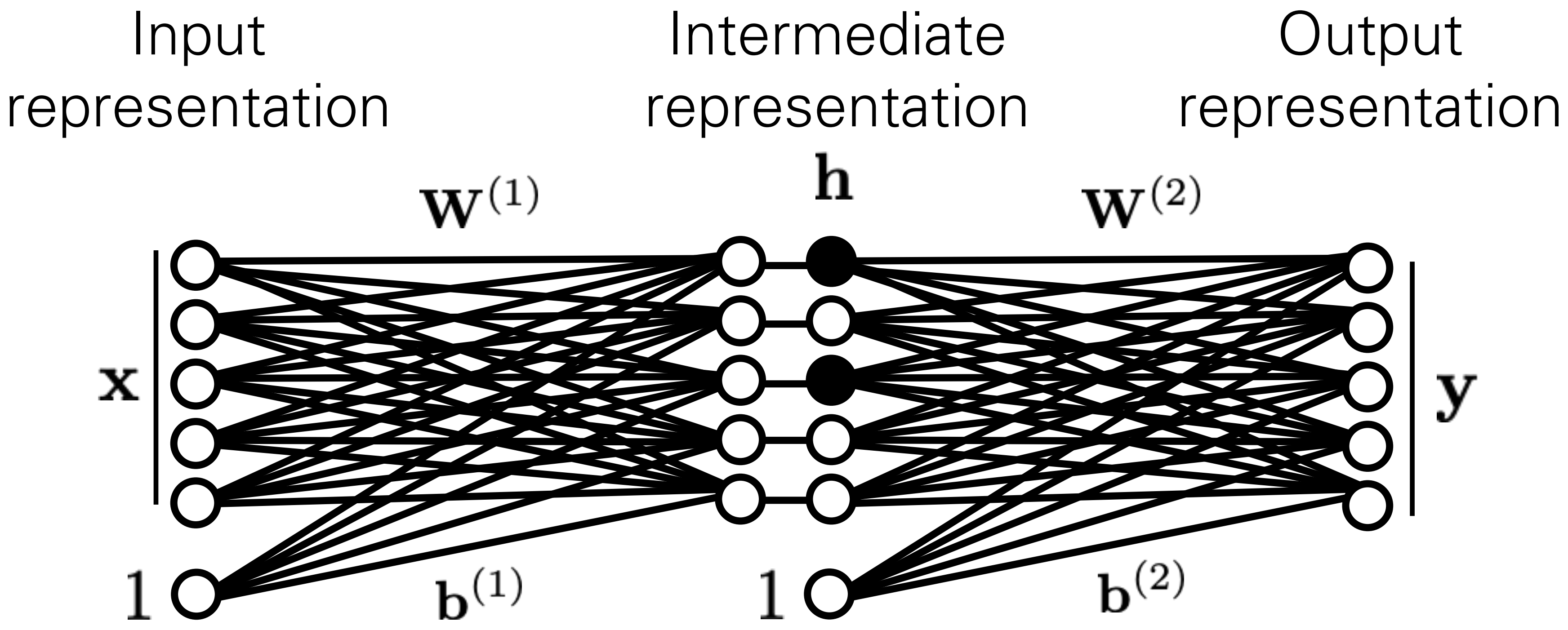
"We prefer to keep weights small."

Dropout



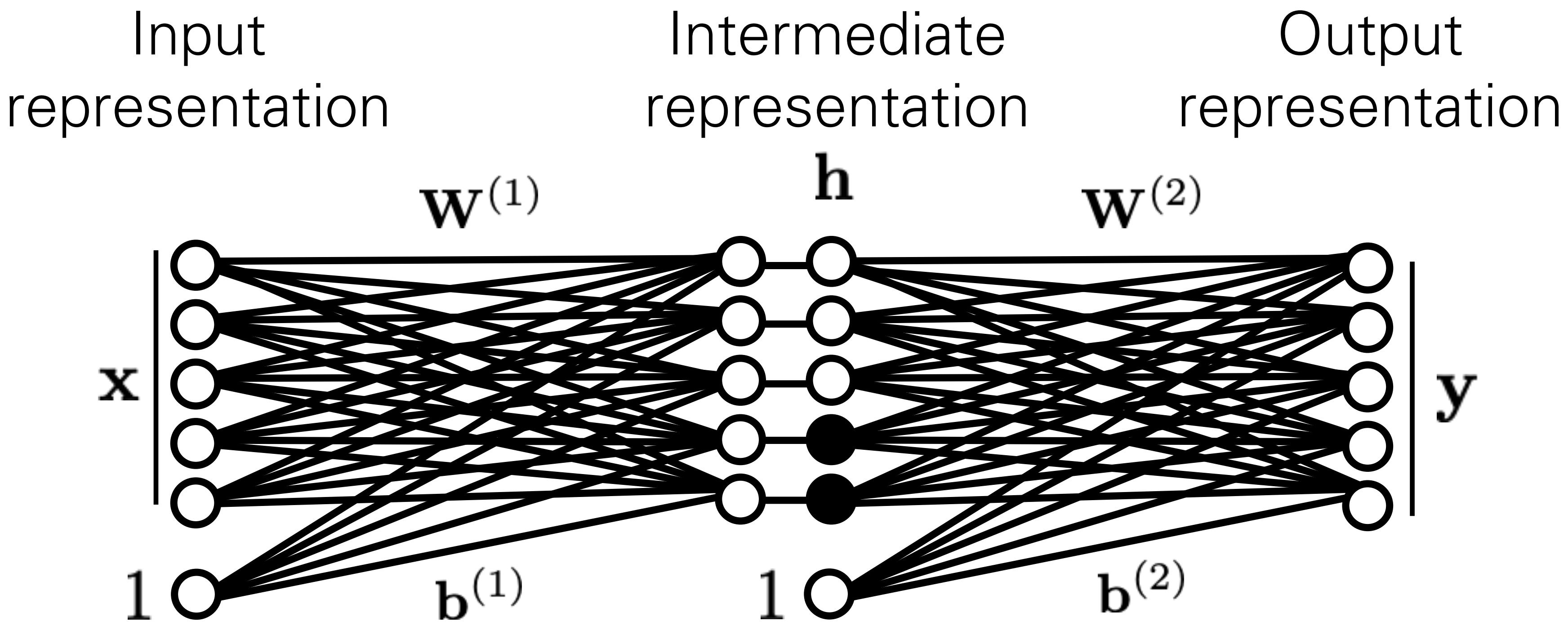
$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

Dropout



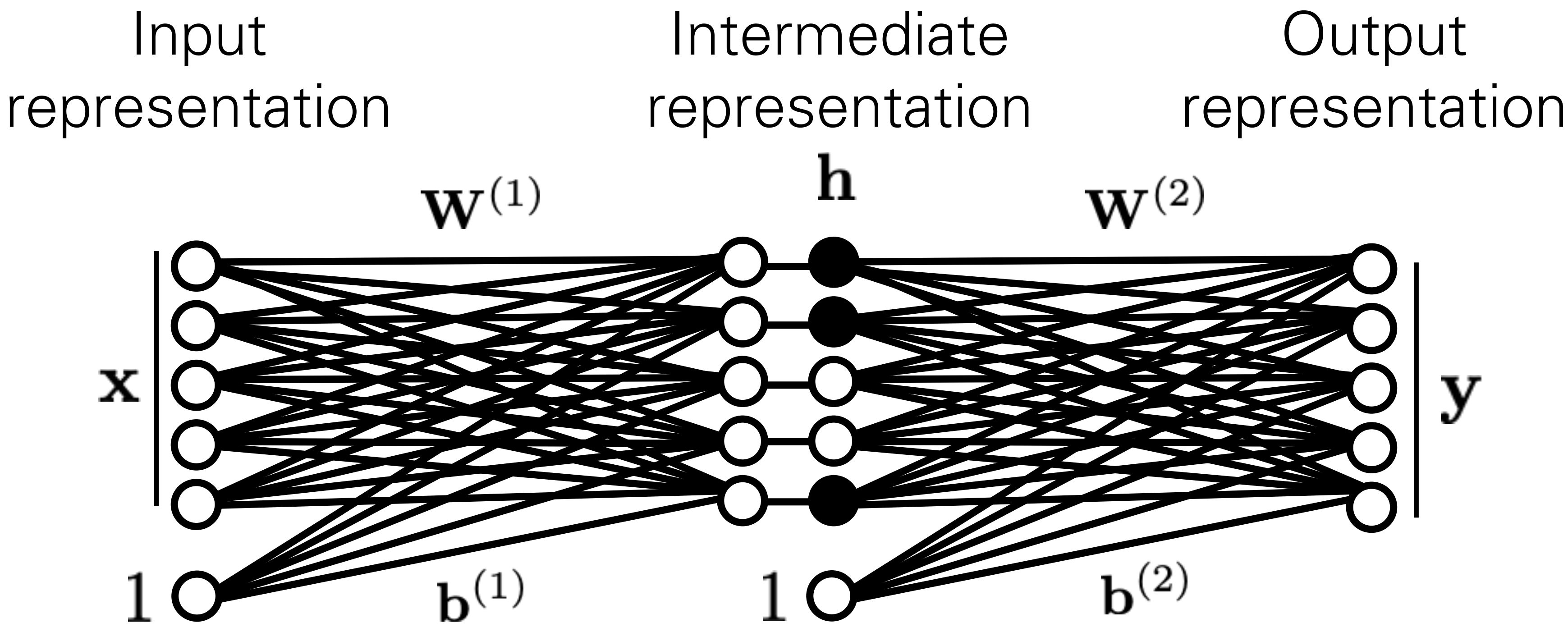
$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

Dropout



$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

Dropout



$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

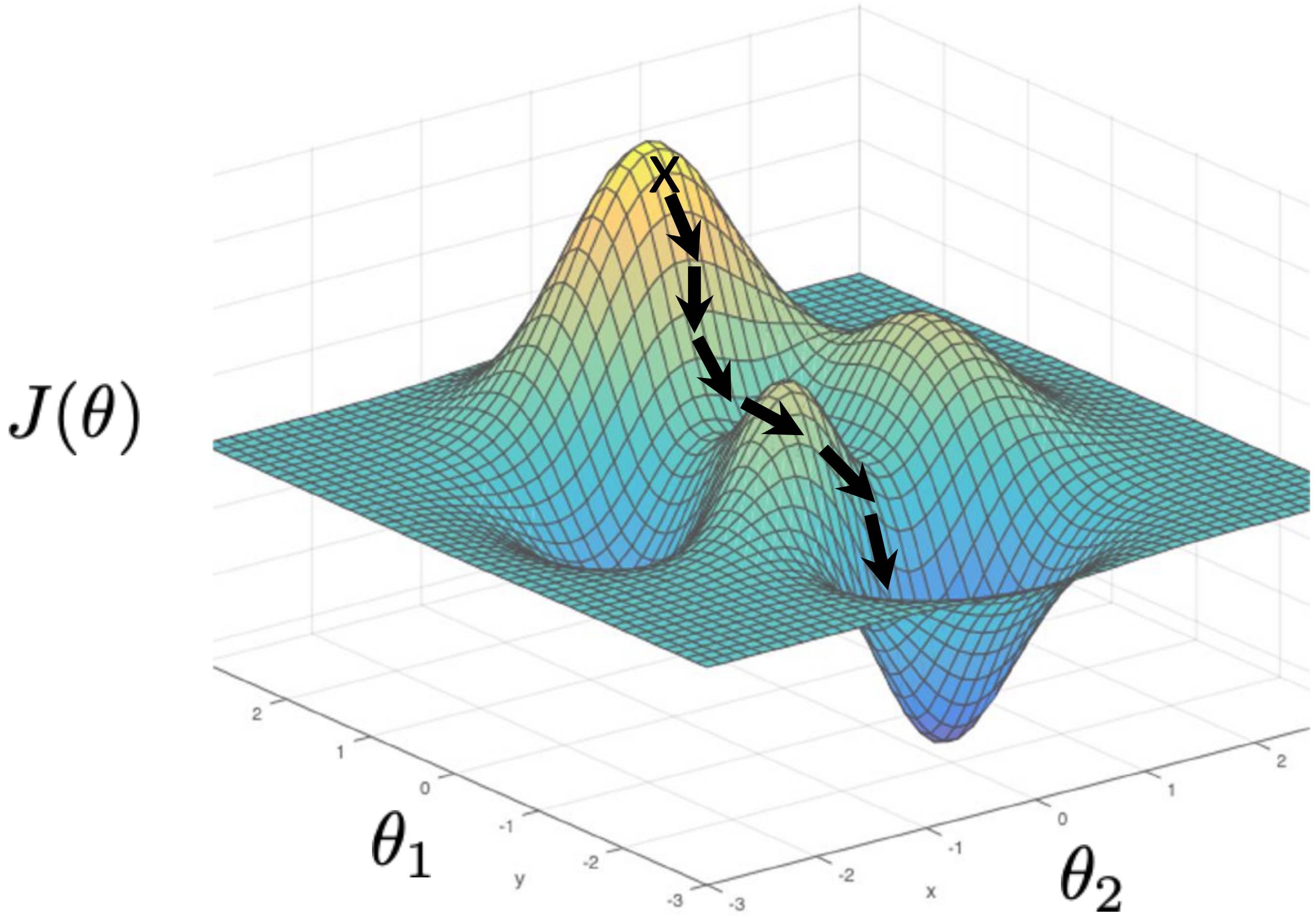
Dropout

Randomly zero out hidden units.

Prevents network from relying too much on spurious correlations between different hidden units.

Can be understood as averaging over an exponential **ensemble** of subnetworks. This averaging smooths the function, thereby reducing the effective capacity of the network.

Gradient descent



$$\theta^* = \arg\min_{\theta} J(\theta)$$

Gradient descent

$$\boxed{\theta^* = \arg\min_\theta \underbrace{\sum_{i=1}^{N} \mathcal{L}(f_\theta(\mathbf{x}_i), \mathbf{y}_i)}_{J(\theta)}}$$

One iteration of gradient descent:

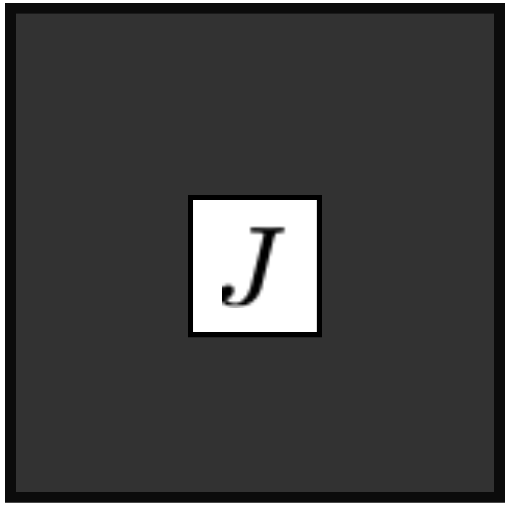
$$\theta^{t+1} = \theta^t - \eta_t \left.\frac{\partial J(\theta)}{\partial \theta}\right|_{\theta=\theta^t}$$

learning rate

Optimization

Params

$\theta \rightarrow$

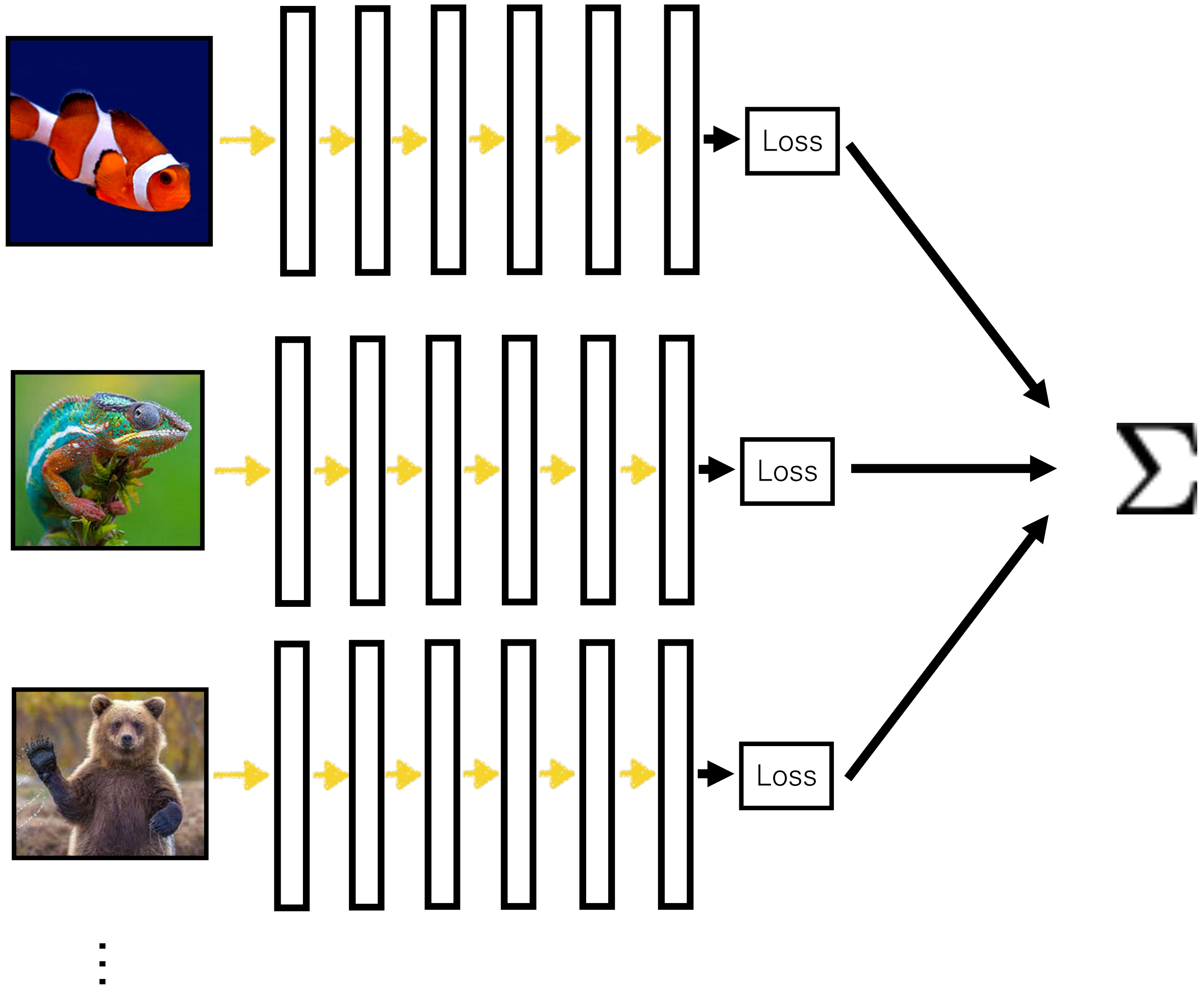


$\rightarrow$ $J(\theta)$
$\nabla_\theta J(\theta)$
$H_\theta(J(\theta))$

$$\theta^* = \arg\min_\theta J(\theta)$$

- What's the knowledge we have about J?
  - We can evaluate $J(\theta)$ ← Black box optimization
  - We can evaluate $J(\theta)$ and $\overbrace{\nabla_\theta J(\theta)}^{\text{Gradient}}$ ← First order optimization
  - We can evaluate $J(\theta)$, $\nabla_\theta J(\theta)$, and $\underbrace{H_\theta(J(\theta))}_{\text{Hessian}}$ ← Second order optimization

Batch (parallel) processing



Stochastic gradient descent (SGD)

- Want to minimize overall loss function J, which is sum of individual losses over each example.
- In Stochastic gradient descent, compute gradient on sub-set (batch) of data.

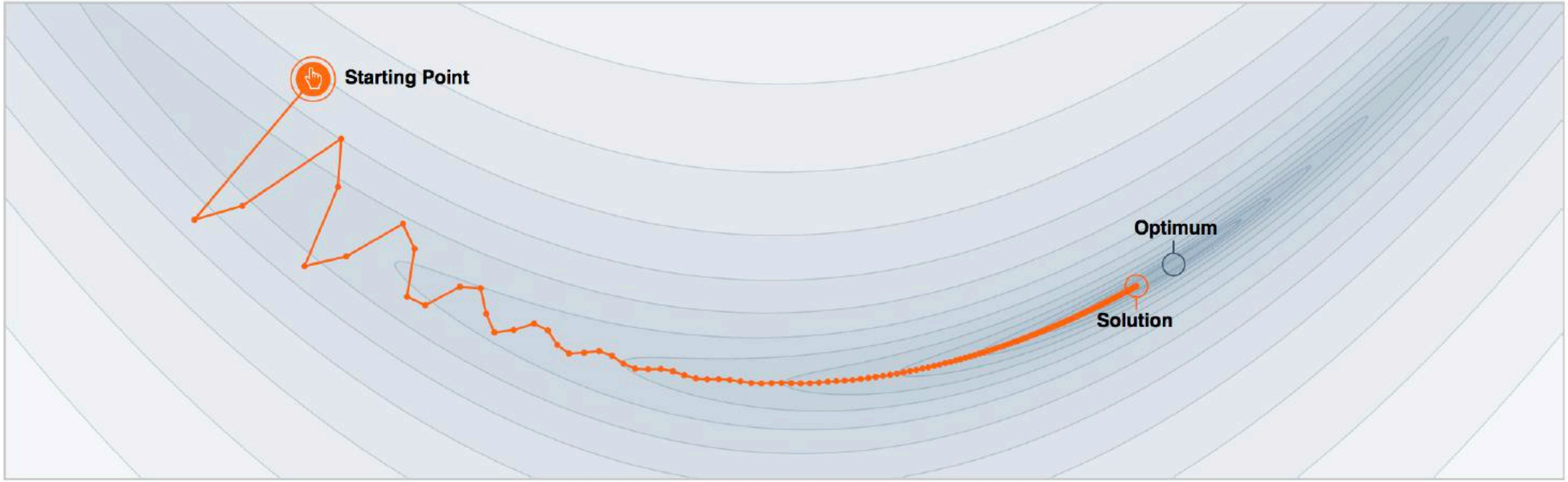
  If batchsize=1 then θ is updated after each example.

  If batchsize=N (full set) then this is standard gradient descent.
- Gradient direction is noisy, relative to average over all examples (standard gradient descent).
- Advantages
  - Faster: approximate total gradient with small sample
  - Implicit regularizer
- Disadvantages
  - High variance, unstable updates

Momentum

- Basic idea: like a ball rolling down a hill, we should build up speed so as to make faster progress when "on a roll"
- Can dampen oscillations in SGD updates
- Common in popular variants of SGD
  - Nesterov's method
  - RMSProp
  - Adam

Why Momentum Really Works



Step-size α = 0.02

0 0.003 0.006

Momentum β = 0.99

0.00 0.500 0.990

We often think of Momentum as a means of dampening oscillations and speeding up the iterations, leading to faster convergence. But it has other interesting behavior. It allows a larger range of step-sizes to be used, and creates its own oscillations. What is going on?

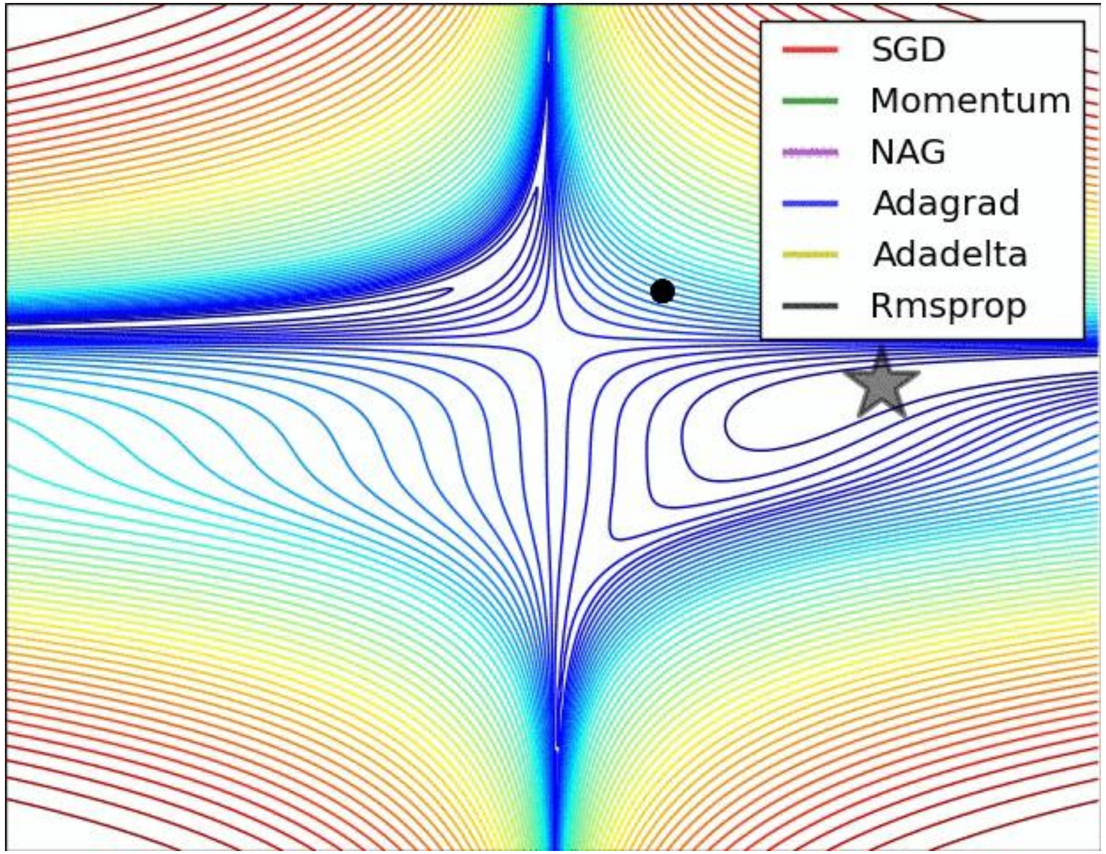
GABRIEL GOH
UC Davis

April. 4
2017

Citation:
Goh, 2017

[https://distill.pub/2017/momentum/]

Comparison of gradient descent variants



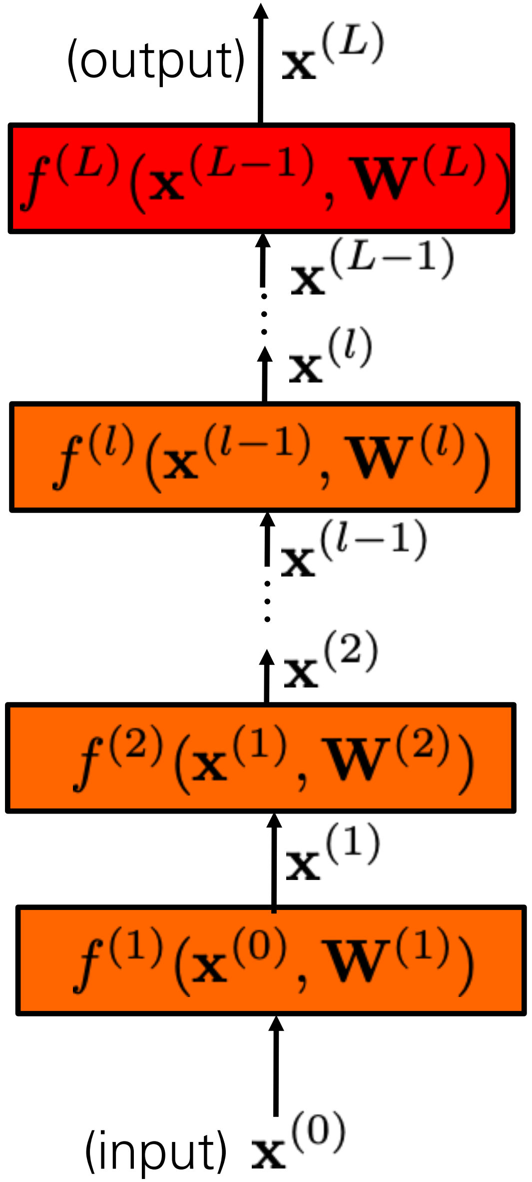
[http://ruder.io/optimizing-gradient-descent/]

Forward pass

- Consider model with L layers. Layer l has vector of weights $\mathbf{W}^{(l)}$
- **Forward pass:** takes input $\mathbf{x}^{(l-1)}$ and passes it through each layer $f^{(l)}$:

$$\mathbf{x}^{(l)} = f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})$$

- Output of layer l is $\mathbf{x}^{(l)}$.
- Network output (top layer) is $\mathbf{x}^{(L)}$.



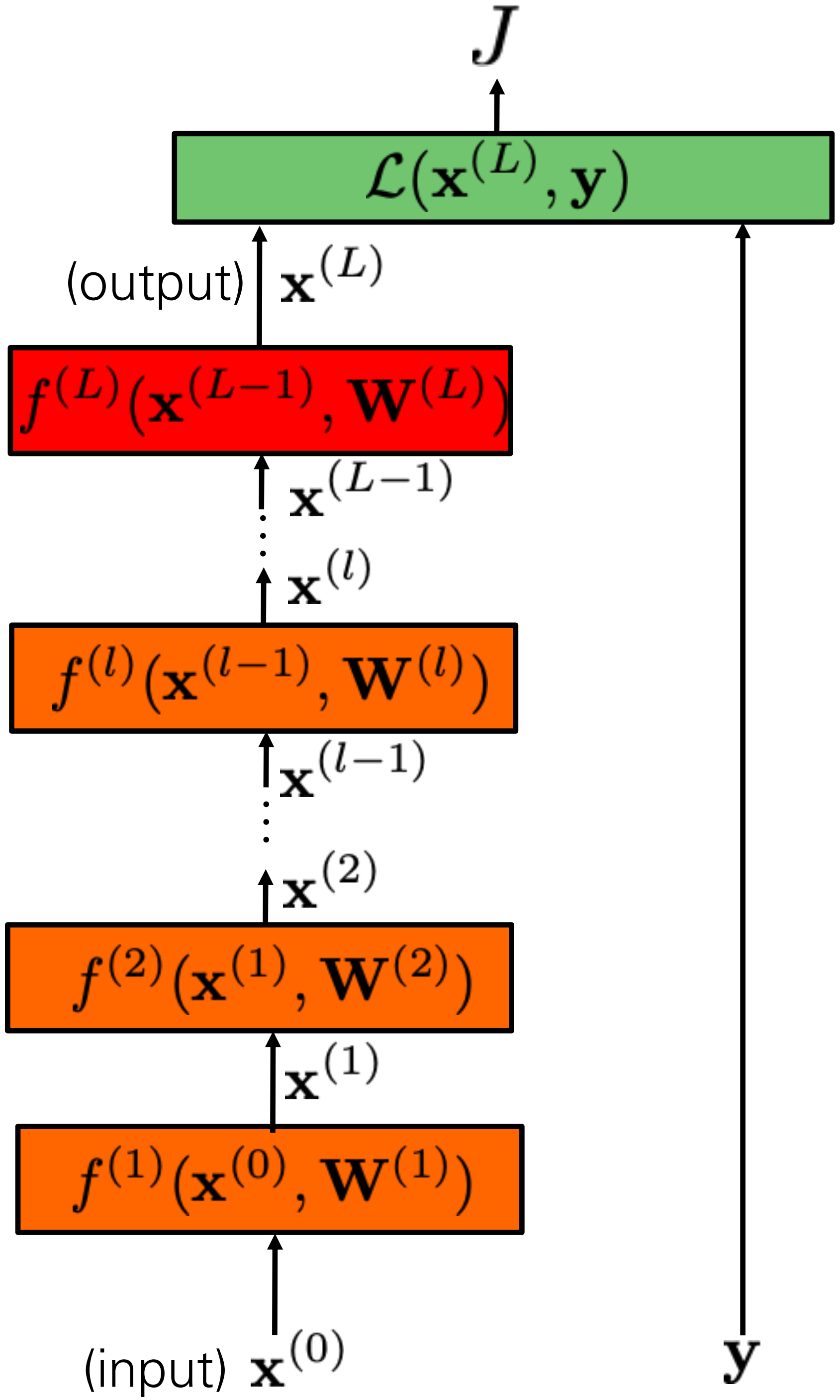
Forward pass

- Consider model with L layers. Layer l has vector of weights $\mathbf{W}^{(l)}$
- **Forward pass:** takes input $\mathbf{x}^{(l-1)}$ and passes it through each layer $f^{(l)}$:

$$\mathbf{x}^{(l)} = f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})$$

- Output of layer l is $\mathbf{x}^{(l)}$.
- Network output (top layer) is $\mathbf{x}^{(L)}$.

- **Loss function** $\mathcal{L}$ compares $\mathbf{x}^{(L)}$ to $\mathbf{y}$.
- Overall energy is the sum of the cost over all training examples: $$J = \sum_{i=1}^{N} \mathcal{L}(\mathbf{x}_i^{(L)}, \mathbf{y}_i)$$



Gradient descent

- We need to compute gradients of the cost with respect to model parameters $\mathbf{W}^{(l)}$.

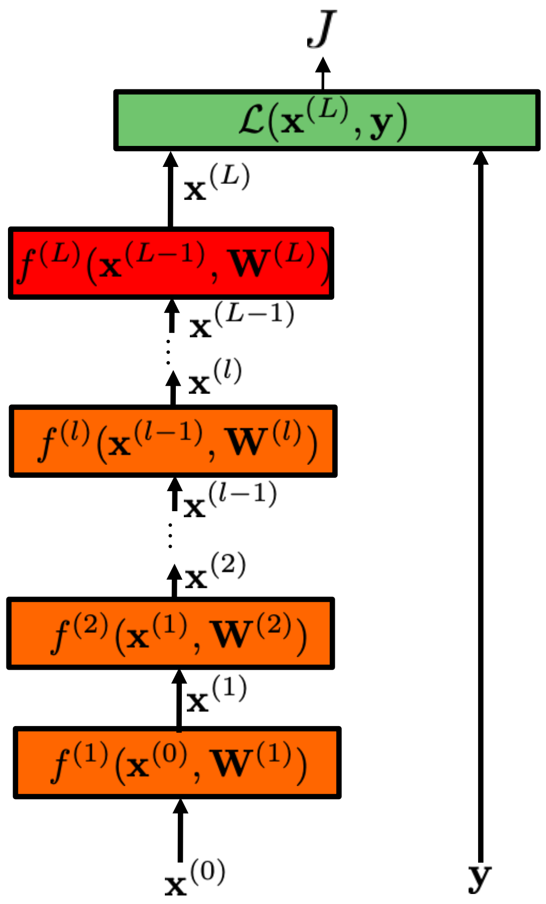
- By design, each layer is differentiable with respect to its parameters and input.

Computing gradients

To compute the gradients, we could start by writing the full energy J as a function of the network parameters.

$$J(\mathbf{W}) = \sum_{i=1} \mathcal{L}(f^{(L)}(\dots f^{(2)}(f^{(1)}(\mathbf{x}_i^{(0)}, \mathbf{W}^{(1)}), \mathbf{W}^{(2)}), \dots \mathbf{W}^{(L)}), \mathbf{y}_i)$$

And then compute the partial derivatives… instead, we can use the chain rule to derive a compact algorithm: **backpropagation**



Computing gradients

The energy J is the sum of the losses associated to each training example $\{\mathbf{x}_i^{(0)}, \mathbf{y}_i\}$

$$J(\mathbf{W}) = \sum_{i=1}^{N} \mathcal{L}(\mathbf{x}_i^{(L)}, \mathbf{y}_i; \mathbf{W})$$

Its gradient with respect to each of the network's parameters w is:

$$\frac{\partial J(\mathbf{W})}{\partial w} = \sum_{i=1}^{N} \frac{\partial \mathcal{L}(\mathbf{x}_i^{(L)}, \mathbf{y}_i; \mathbf{W})}{\partial w}$$

is how much J varies when the parameter w is varied.

Computing gradients

We could write the loss function to get the gradients as:

$$\mathcal{L}(\mathbf{x}^{(L)}, \mathbf{y}; \mathbf{W}) = \mathcal{L}(f^{(L)}(\mathbf{x}^{(L-1)}, \mathbf{W}^{(L)}), \mathbf{y})$$

If we compute the gradient with respect to the parameters of the last layer (output layer) $W^{(L)}$, using the **chain rule**:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{(L)}} = \frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(L)}} \cdot \frac{\partial \mathbf{x}^{(L)}}{\partial \mathbf{W}^{(L)}} = \frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(L)}} \cdot \frac{\partial f^{(L)}(\mathbf{x}^{(L-1)}, \mathbf{W}^{(L)})}{\partial \mathbf{W}^{(L)}}$$

(How much the cost changes when we change $W^{(L)}$ is the product between how much the loss changes when we change the output of the last layer and how much the output changes when we change the layer parameters.)

Computing gradients: loss layer

If we compute the gradient with respect to the parameters of the last layer (output layer) $W^{(L)}$, using the chain rule:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{(L)}} = \frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(L)}} \cdot \frac{\partial \mathbf{x}^{(L)}}{\partial \mathbf{W}^{(L)}} = \frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(L)}} \cdot \frac{\partial f^{(L)}(\mathbf{x}^{(L-1)}, \mathbf{W}^{(L)})}{\partial \mathbf{W}^{(L)}}$$

For example, for an Euclidean loss:

$$\mathcal{L}(\mathbf{x}^{(L)}, \mathbf{y}) = \frac{1}{2} \left\| \mathbf{x}^{(L)} - \mathbf{y} \right\|_2^2$$

The gradient is:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(L)}} = \mathbf{x}^{(L)} - \mathbf{y}$$

Will depend on the layer structure and non-linearity.

Computing gradients: layer l

We could write the full loss function to get the gradients:

$$\mathcal{L}(\mathbf{x}^{(L)}, \mathbf{y}; \mathbf{W}) = \mathcal{L}(f^{(L)}(\ldots f^{(2)}(f^{(1)}(\mathbf{x}^{(0)}, \mathbf{W}^{(1)}), \mathbf{W}^{(2)}), \ldots \mathbf{W}^{(L)}), \mathbf{y})$$

If we compute the gradient with respect to w_i, using the chain rule:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{(L)}} = \underbrace{\frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(L)}} \cdot \frac{\partial \mathbf{x}^{(L)}}{\partial \mathbf{x}^{(L-1)}} \cdot \frac{\partial \mathbf{x}^{(L-1)}}{\partial \mathbf{x}^{(L-2)}} \cdots \frac{\partial \mathbf{x}^{(l+1)}}{\partial \mathbf{x}^{(l)}}}_{\frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l)}}} \cdot \frac{\partial \mathbf{x}^{(l)}}{\partial \mathbf{W}^{(l)}}$$

And this can be computed iteratively!

$$\frac{\partial f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})}{\partial \mathbf{W}^{(l)}}$$

This is easy.

Backpropagation

$$\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{(L)}} = \underbrace{\frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(L)}} \cdot \frac{\partial \mathbf{x}^{(L)}}{\partial \mathbf{x}^{(L-1)}} \cdot \frac{\partial \mathbf{x}^{(L-1)}}{\partial \mathbf{x}^{(L-2)}} \cdots \frac{\partial \mathbf{x}^{(l+1)}}{\partial \mathbf{x}^{(l)}}}_{\frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l)}}} \cdot \frac{\partial \mathbf{x}^{(l)}}{\partial \mathbf{W}^{(l)}}$$

$$\frac{\partial f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})}{\partial \mathbf{W}^{(l)}}$$

If we have the value of $\frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l)}}$ we can compute the gradient at the layer below as:

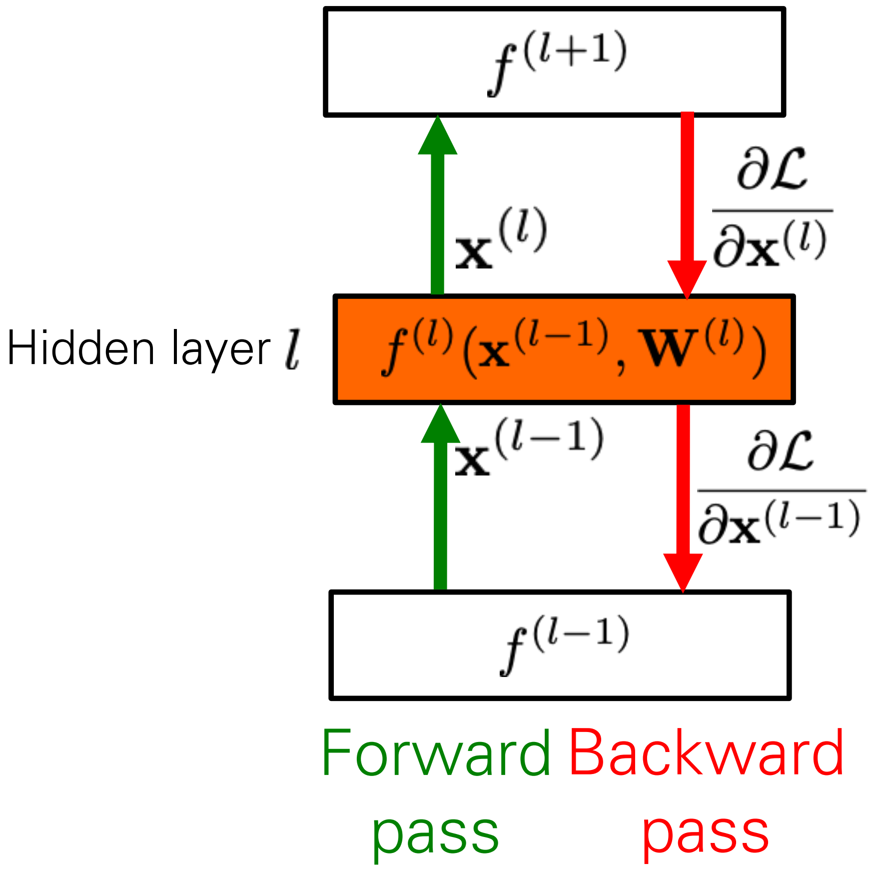
$$\frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l-1)}} = \frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l)}} \cdot \frac{\partial \mathbf{x}^{(l)}}{\partial \mathbf{x}^{(l-1)}}$$

Gradient layer l-1

Gradient layer l

$$\frac{\partial f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})}{\partial \mathbf{x}^{(l-1)}}$$

Backpropagation — Goal: to update parameters of layer l



- Layer l has two inputs (during training)

$$\mathbf{x}^{(l-1)} \qquad \frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l)}}$$

- We compute the outputs

$$\mathbf{x}^{(l)} = f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l-1)}} = \frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l)}} \cdot \frac{\partial f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})}{\partial \mathbf{x}^{(l-1)}}$$

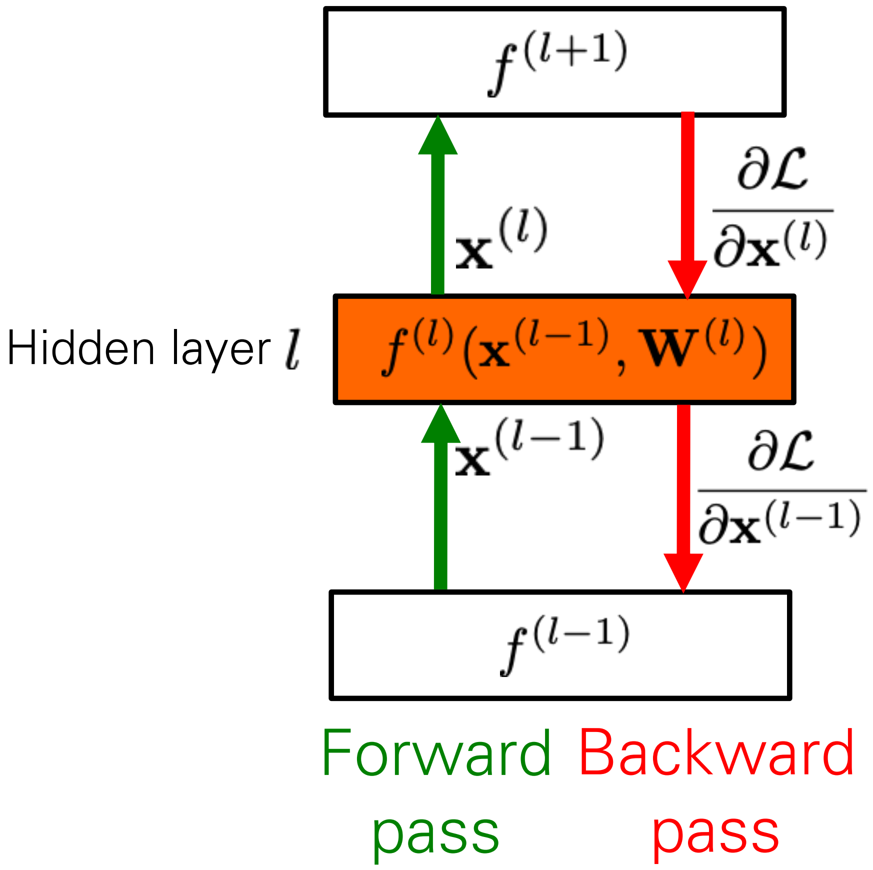
- To compute the output, we need:

$$\frac{\partial f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})}{\partial \mathbf{x}^{(l-1)}}$$

- To compute the weight update, we need:

$$\frac{\partial f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})}{\partial \mathbf{W}^{(l)}}$$

Backpropagation — Goal: to update parameters of layer l



- Layer l has two inputs (during training)

$$\mathbf{x}^{(l-1)}, \quad \frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l)}}$$

- We compute the outputs

$$\mathbf{x}^{(l)} = f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l-1)}} = \frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l)}} \cdot \frac{\partial f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})}{\partial \mathbf{x}^{(l-1)}}$$

- The weight update equation is:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{(l)}} = \frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l)}} \cdot \frac{\partial f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})}{\partial \mathbf{W}^{(l)}}$$

$$\boxed{\mathbf{W}^{(l)} \leftarrow \mathbf{W}^{(l)} + \eta \left(\frac{\partial J}{\partial \mathbf{W}^{(l)}} \right)^T}$$

(sum over all training examples to get J)

Backpropagation Summary

- Forward pass: for each training example, compute the outputs for all layers:

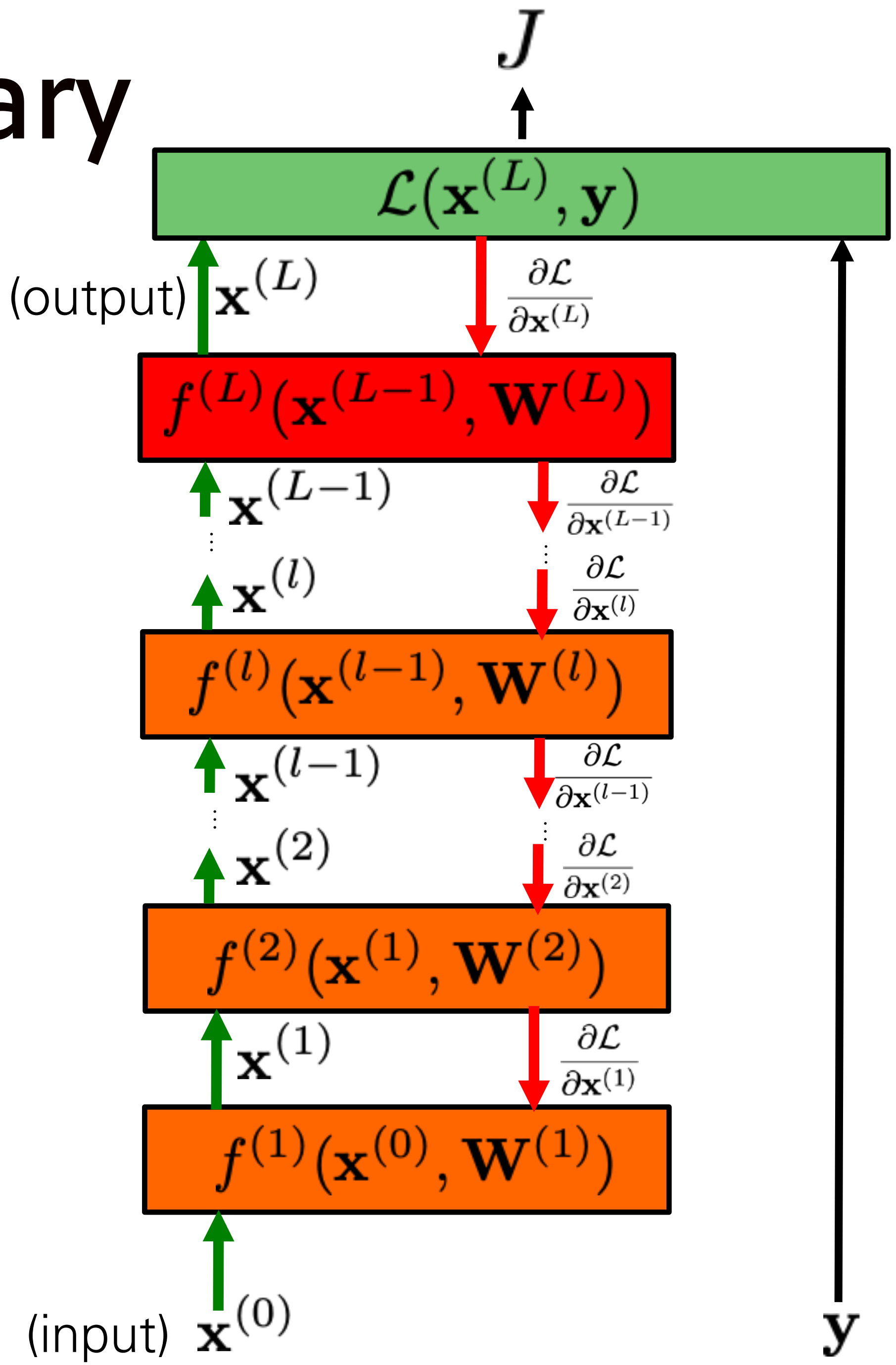
$$\mathbf{x}^{(l)} = f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})$$

- Backwards pass: compute loss derivatives iteratively from top to bottom:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l-1)}} = \frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l)}} \cdot \frac{\partial f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})}{\partial \mathbf{x}^{(l-1)}}$$

- Compute gradients w.r.t. weights, and update weights:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{(l)}} = \frac{\partial \mathcal{L}}{\partial \mathbf{x}^{(l)}} \cdot \frac{\partial f^{(l)}(\mathbf{x}^{(l-1)}, \mathbf{W}^{(l)})}{\partial \mathbf{W}^{(l)}}$$



Differentiable programming

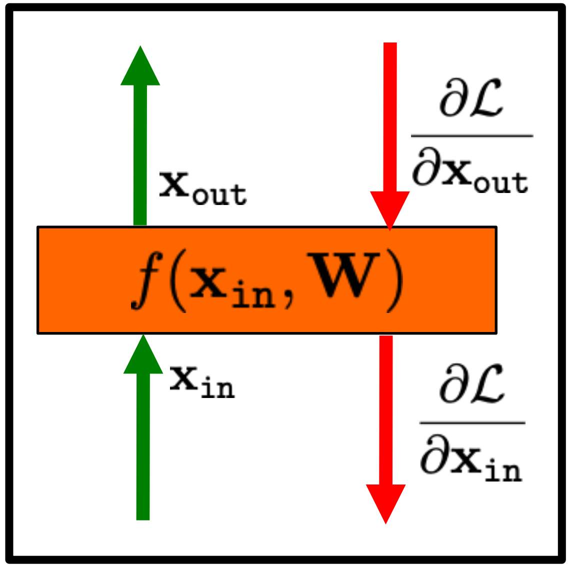
Deep nets are popular for a few reasons:

1. High capacity
2. Easy to optimize (differentiable)
3. Compositional "block based programming"

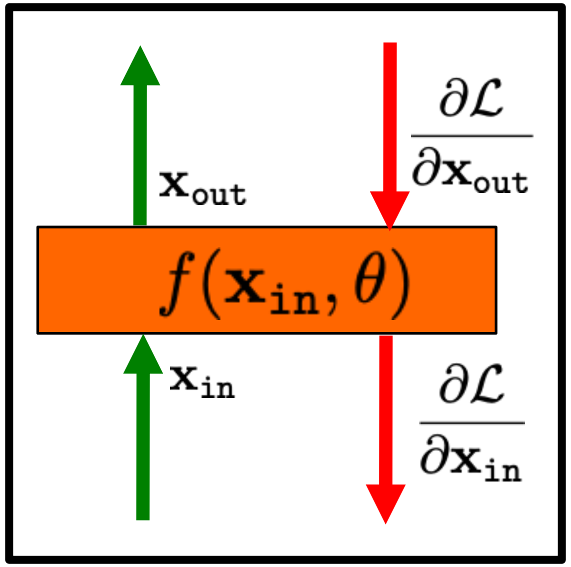
An emerging term for general models with these properties is **differentiable programming.**

Differentiable programming

Deep learning

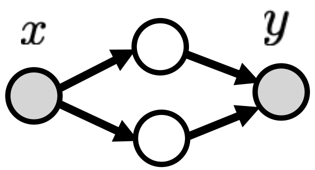


Differentiable programming



PyTorch

TensorFlow™




```
for i, data in enumerate(dataset):
  iter_start_time = time.time()
  if total_steps % opt.print_freq == 0:
      t_data = iter_start_time - iter_data_time
  visualizer.reset()
  total_steps += opt.batch_size
  epoch_iter += opt.batch_size
  model.set_input(data)
  model.optimize_parameters()
```

Convolutional Neural Networks

Convolutional Neural Networks

LeCun et al. 1989

Neural network with specialized connectivity

Tailored to processing natural signals with a grid topology (e.g., images).

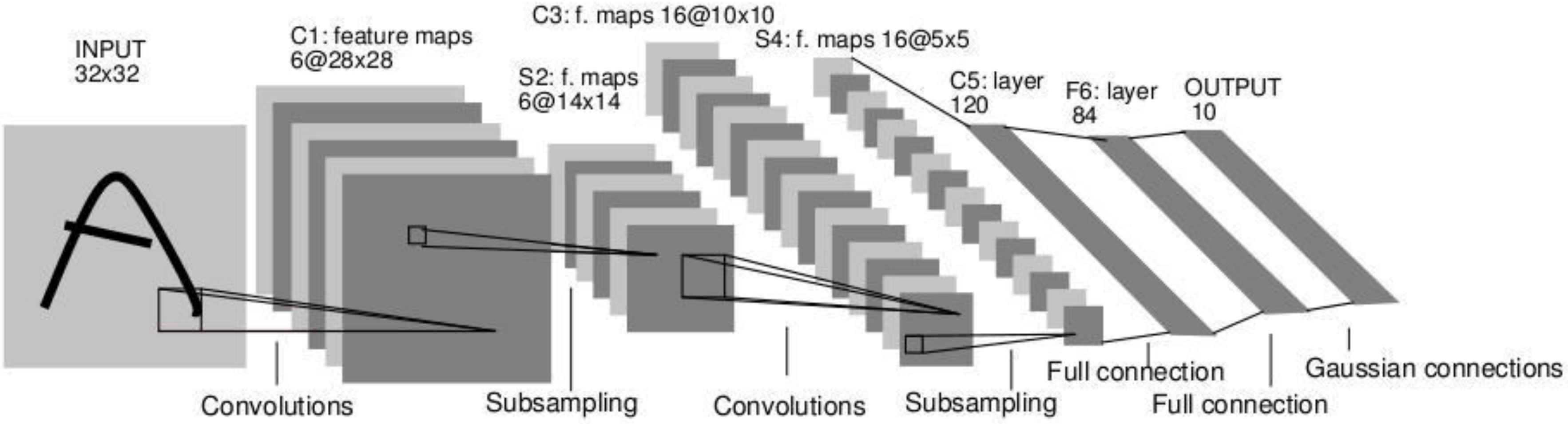


Image classification

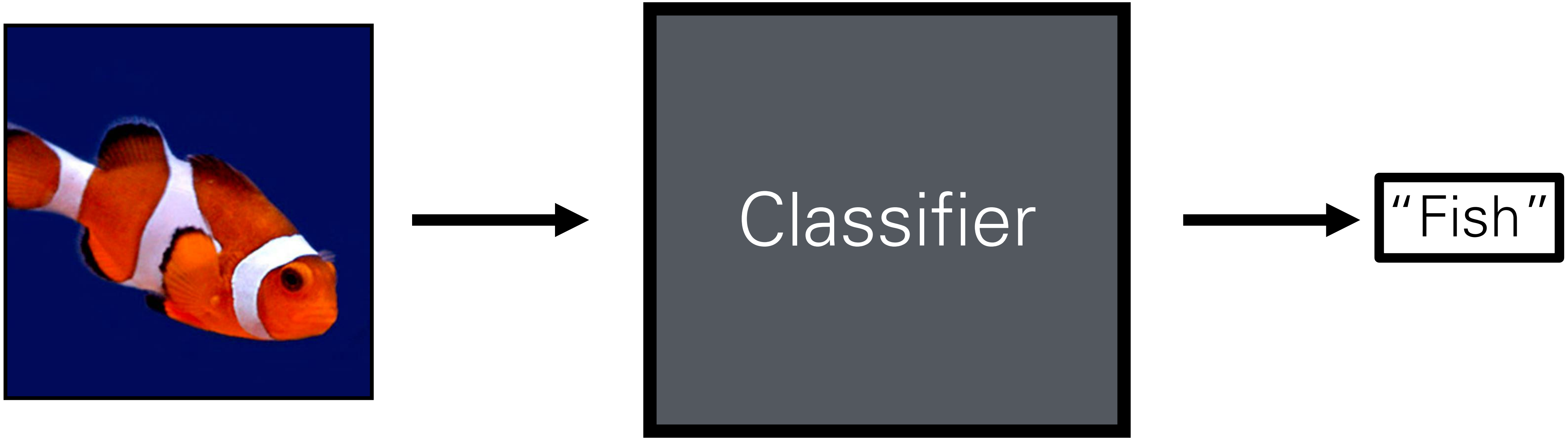
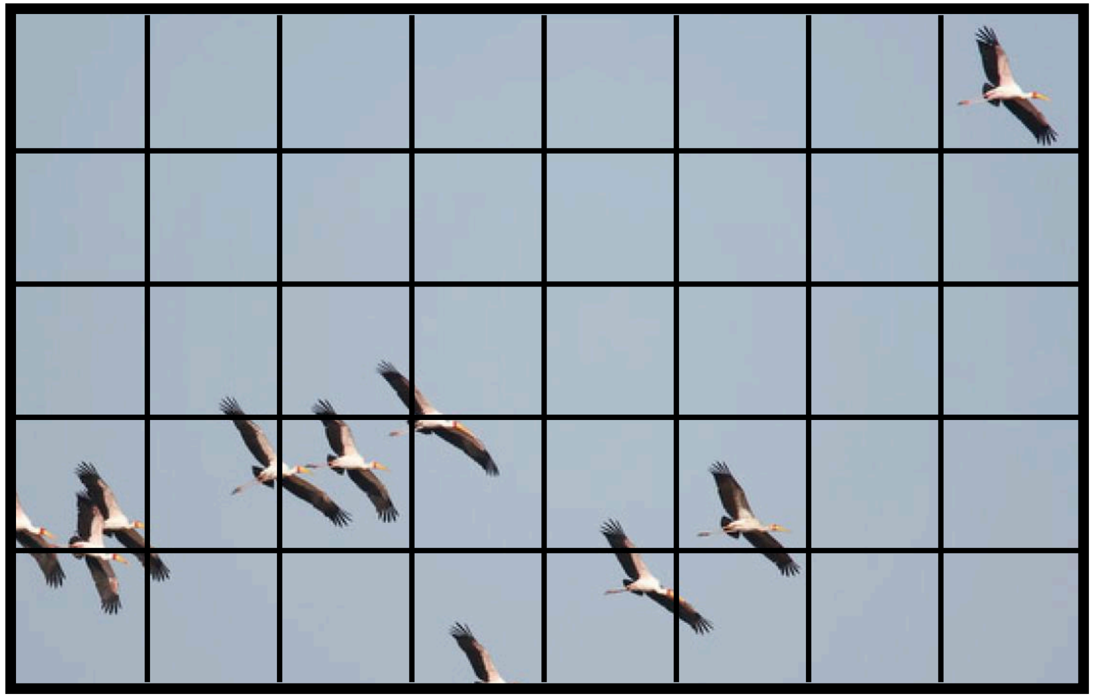
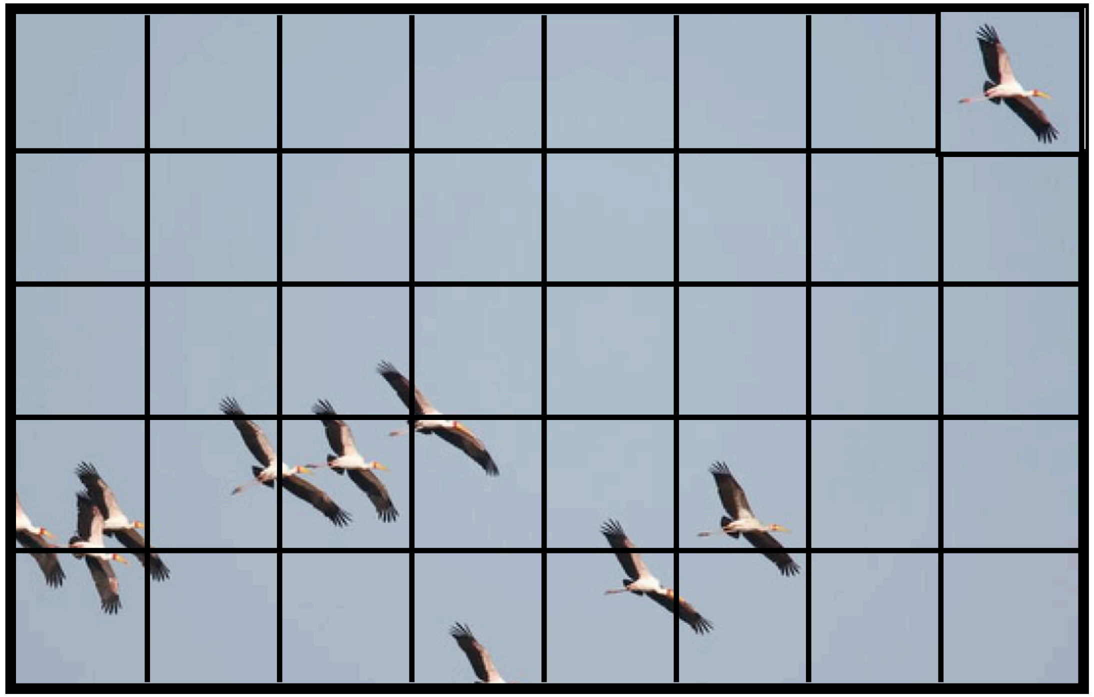
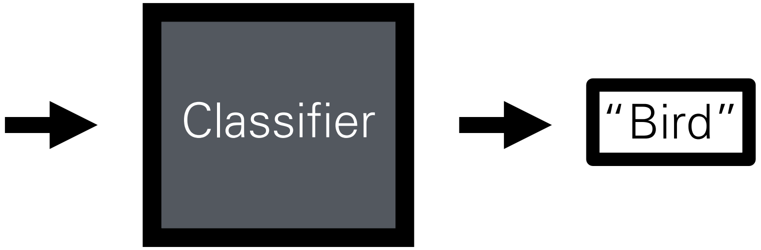


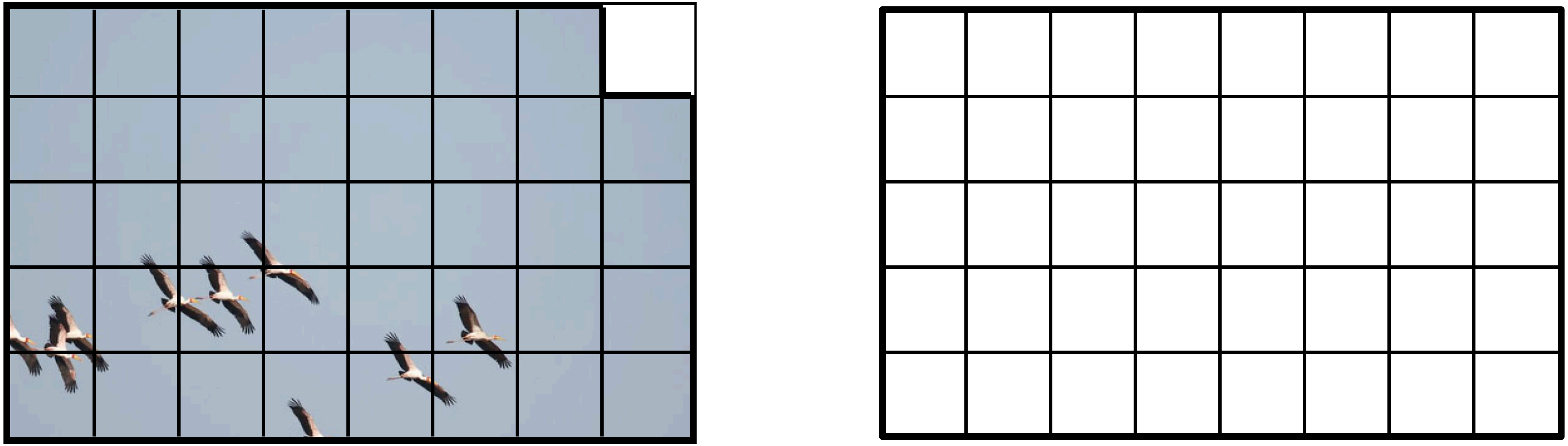
image **x** label y

Photo credit: Fredo Durand

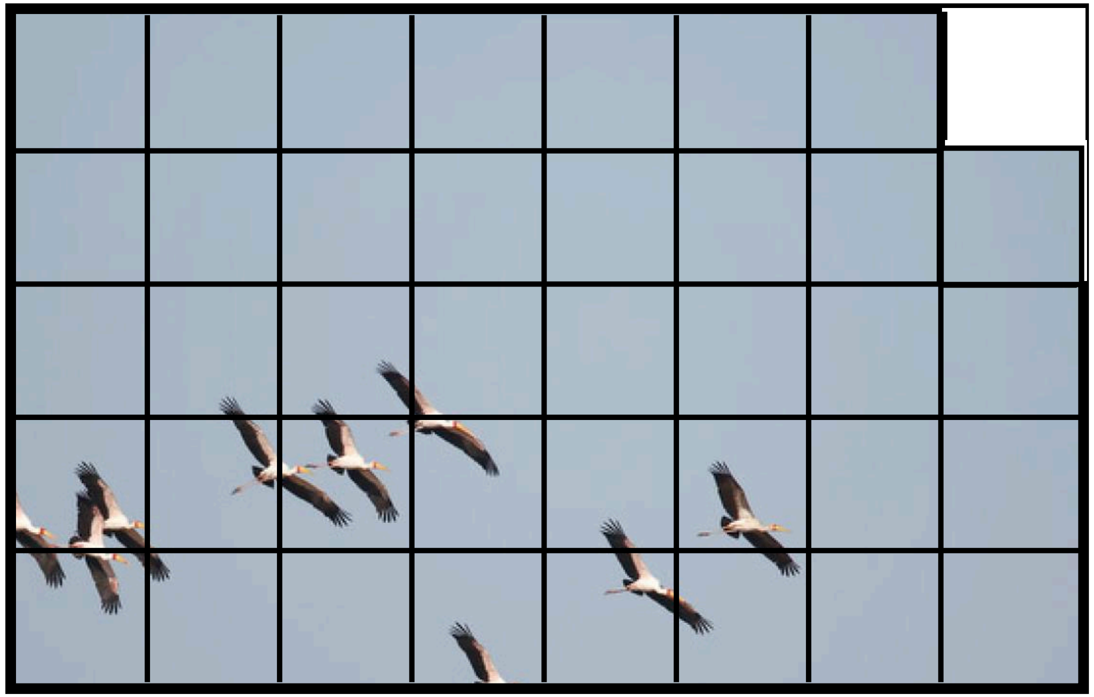


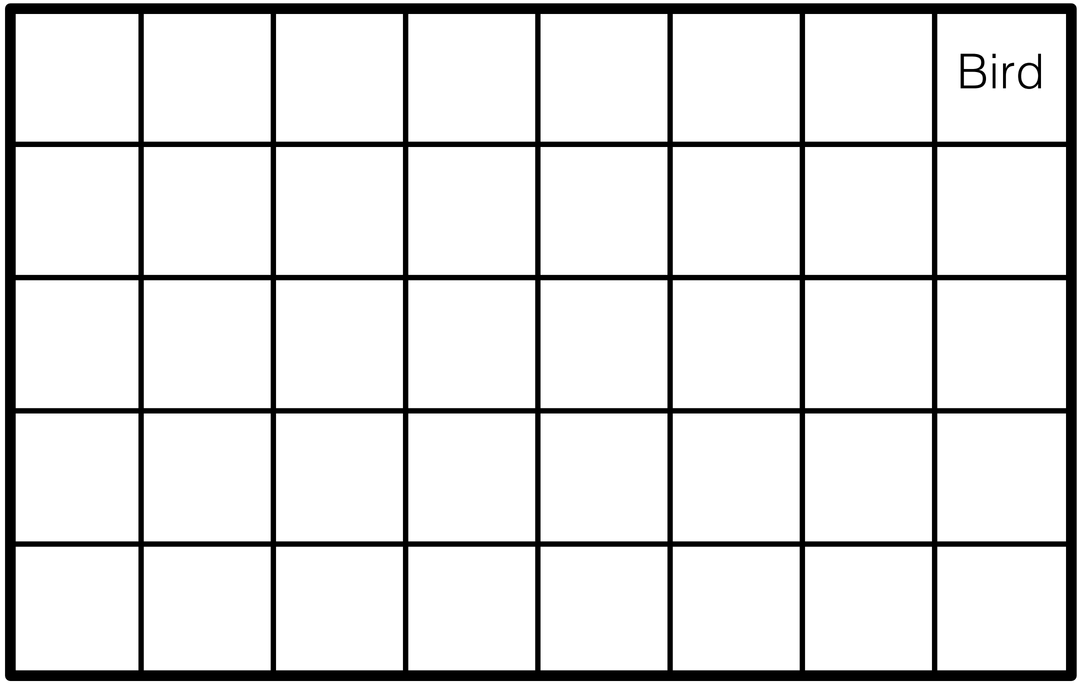



Classifier
"Bird"

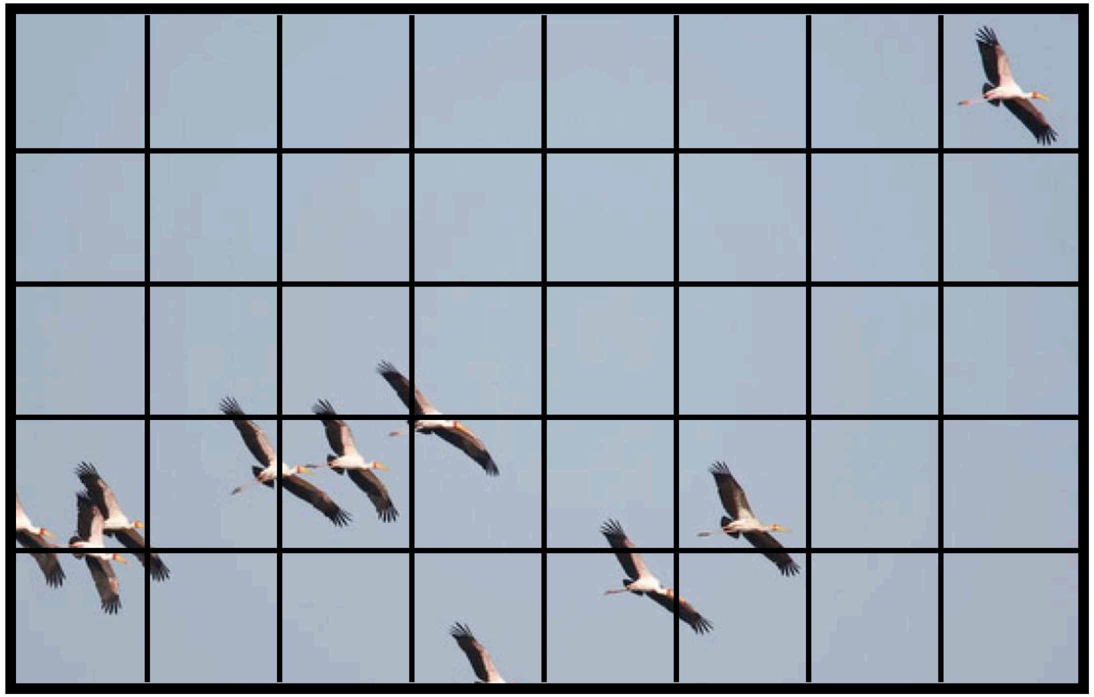



Classifier
"Bird"

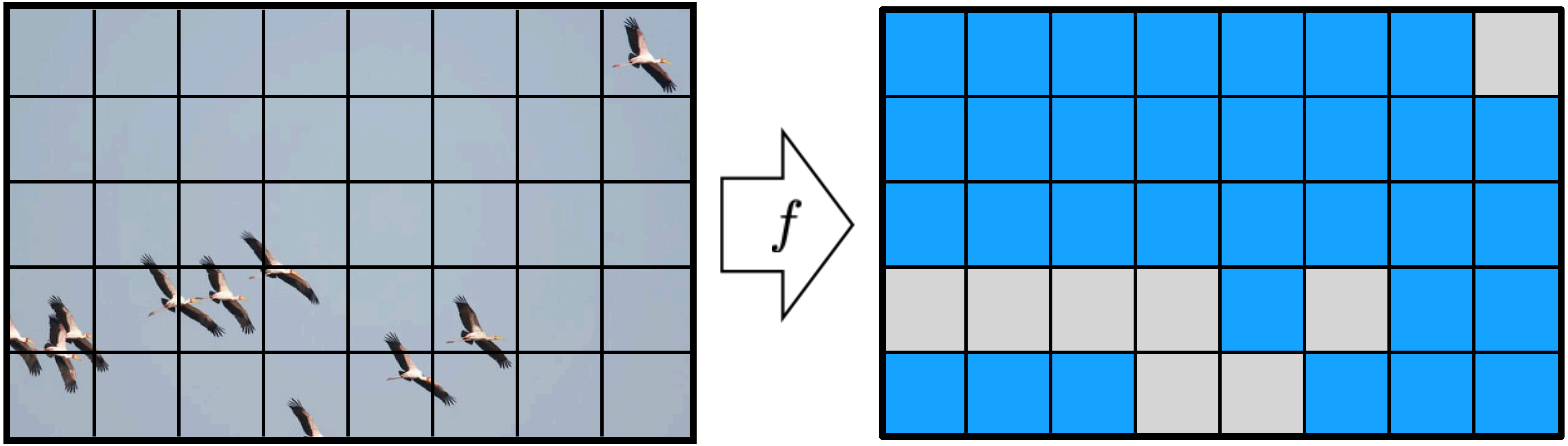


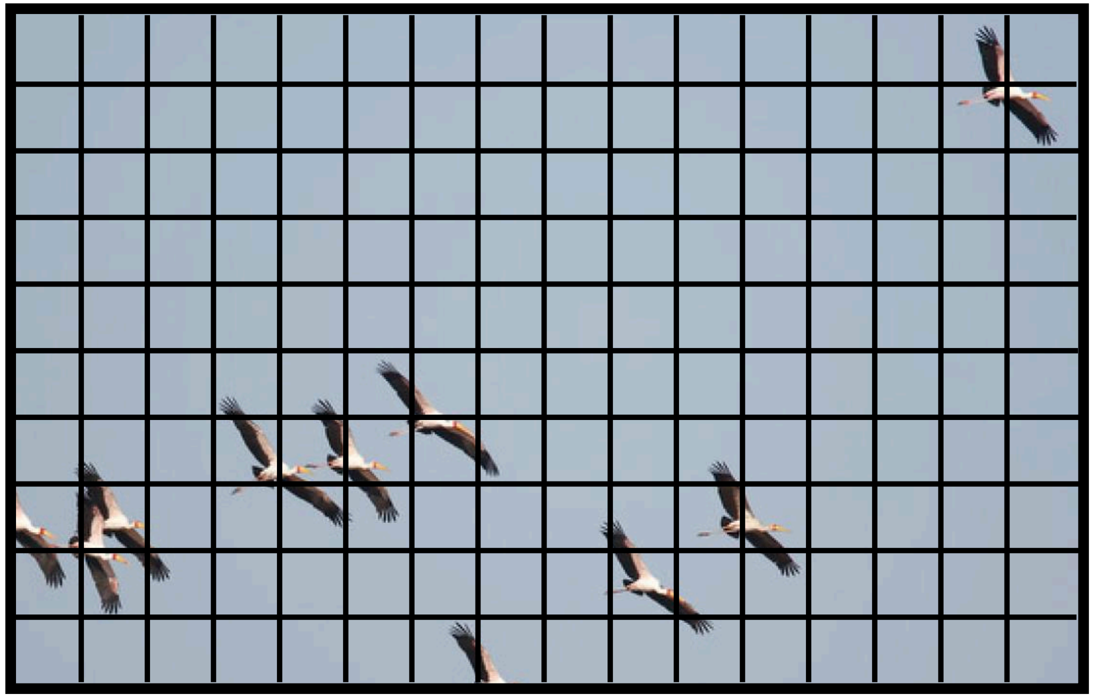

Bird


Classifier
"Sky"

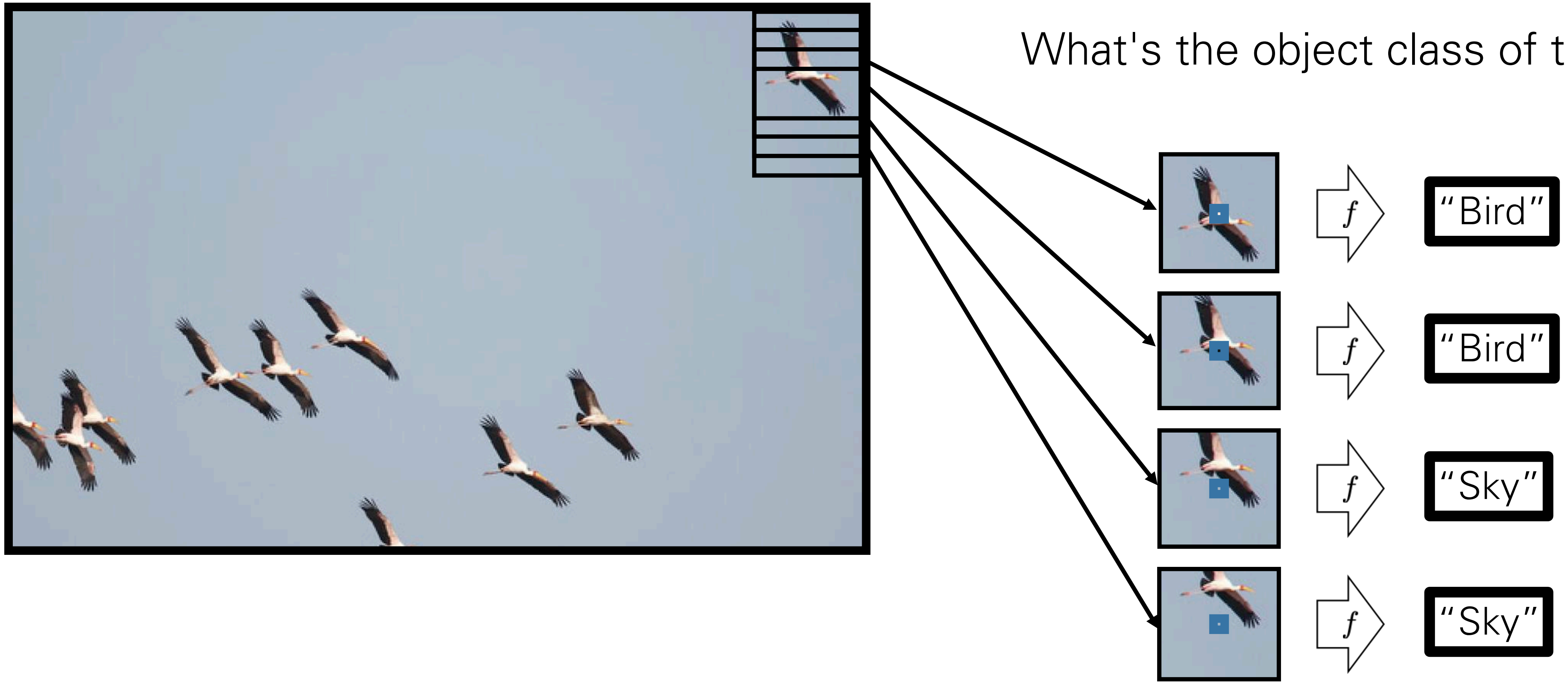


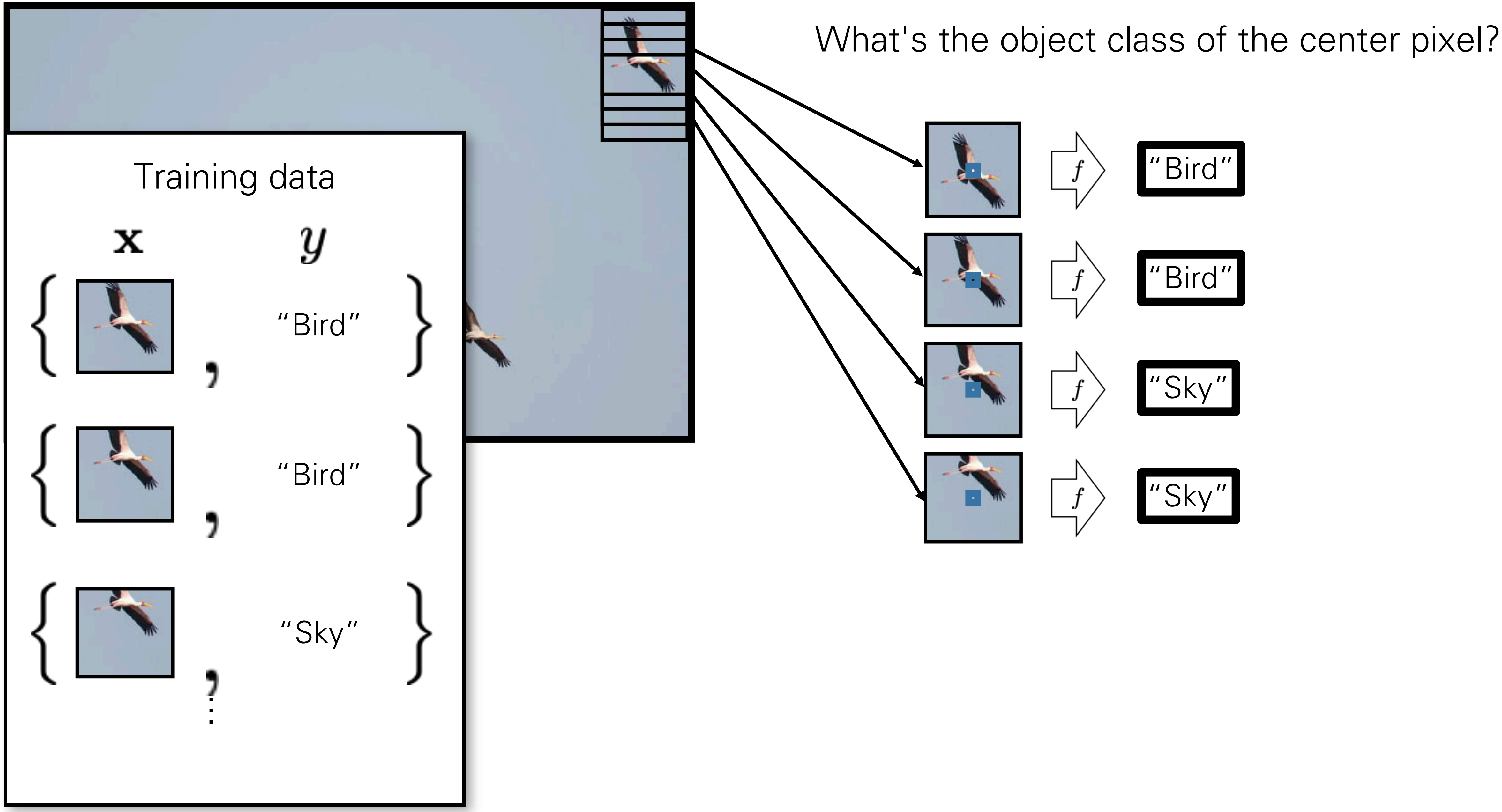
Sky	Sky	Sky	Sky	Sky	Sky	Sky	Bird
Sky	Sky	Sky	Sky	Sky	Sky	Sky	Sky
Sky	Sky	Sky	Sky	Sky	Sky	Sky	Sky
Bird	Bird	Bird	Sky	Bird	Sky	Sky	Sky
Sky	Sky	Sky	Bird	Sky	Sky	Sky	Sky

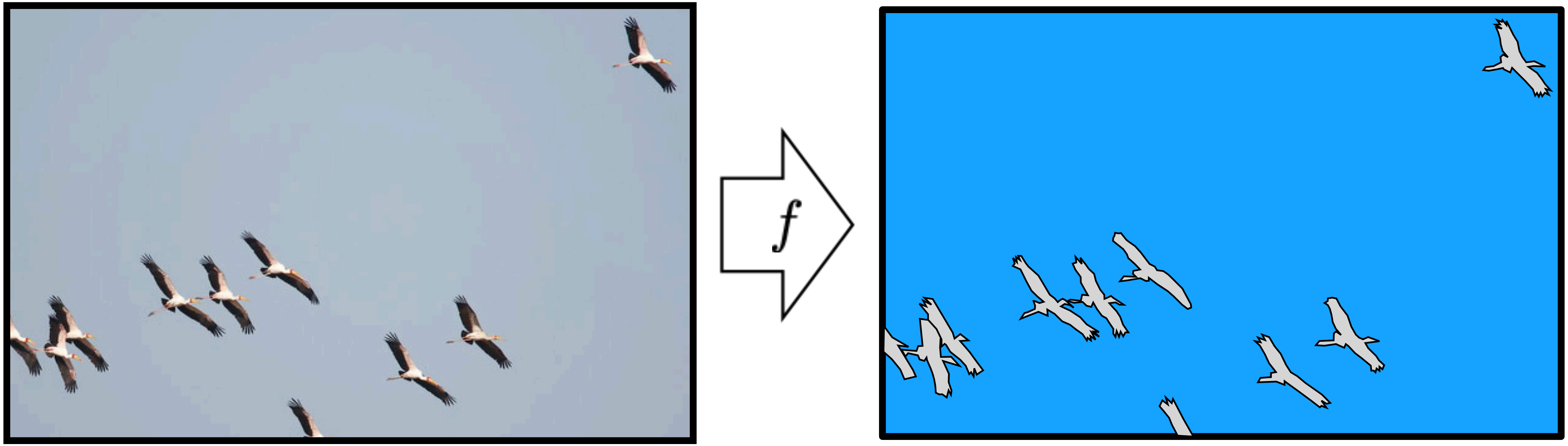

f



What's the object class of the center pixel?



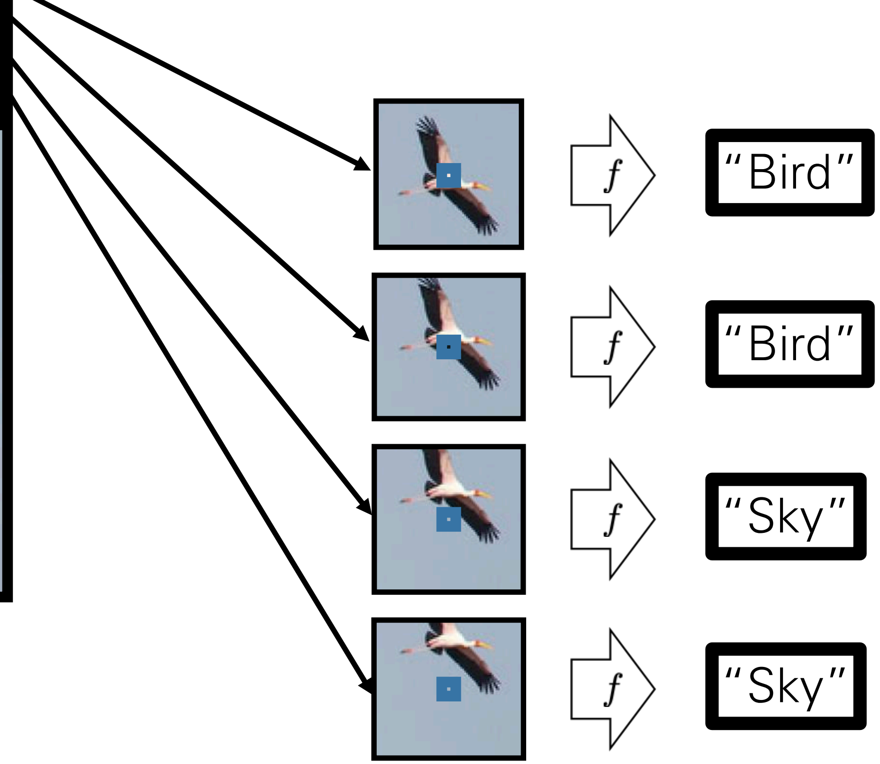

What's the object class of the center pixel?
Training data
x
y
"Bird"
"Bird"
"Sky"
f
"Bird"
"Bird"
"Sky"
"Sky"



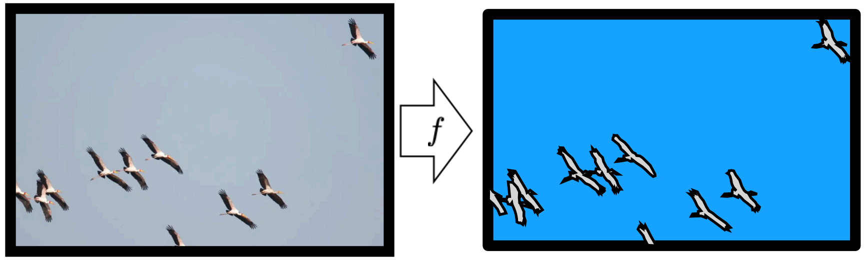
(Colors represent one-hot codes)

This problem is called **semantic segmentation**

What’s the object class of the center pixel?



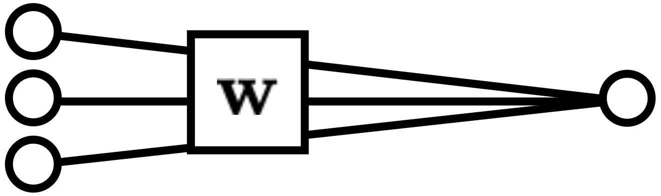
Translation invariance: process each patch in the same way.

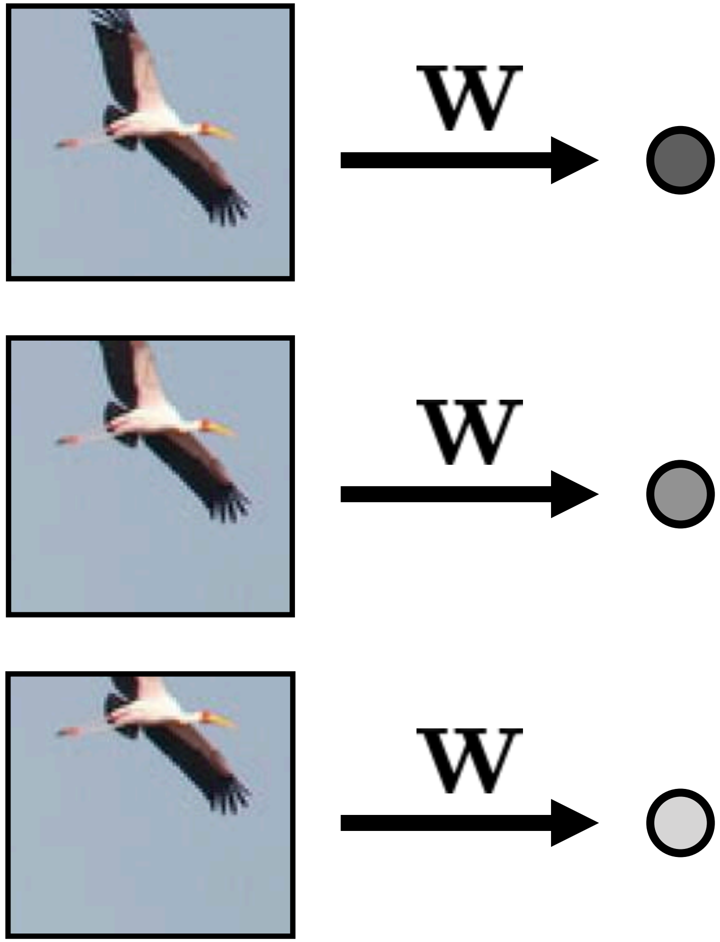


An equivariant mapping:

$$f(\texttt{translate}(x)) = \texttt{translate}(f(x))$$

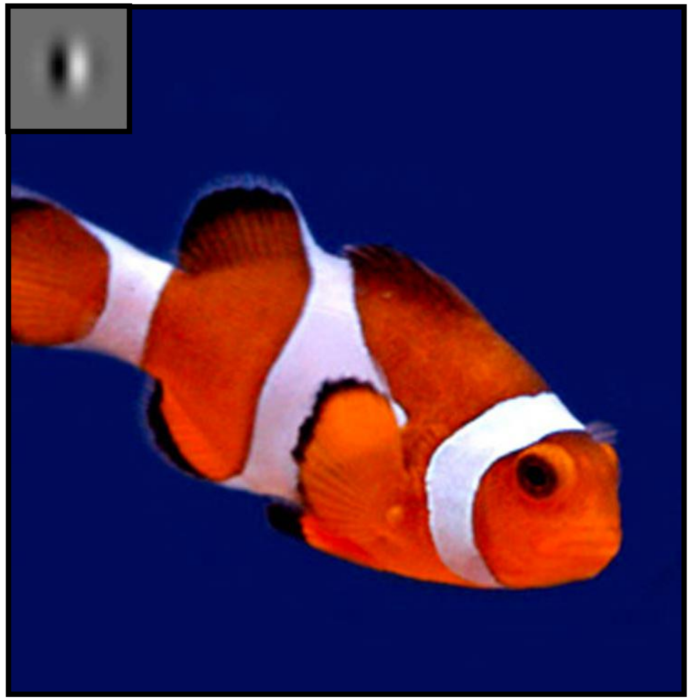
W computes a weighted sum of all pixels in the patch

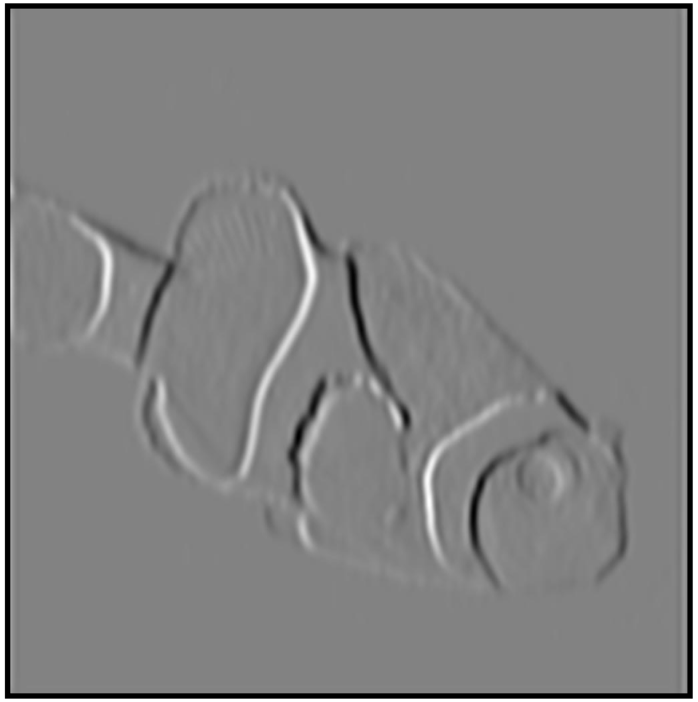




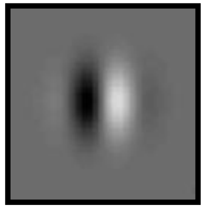
W is a convolutional kernel applied to the full image!

Convolution



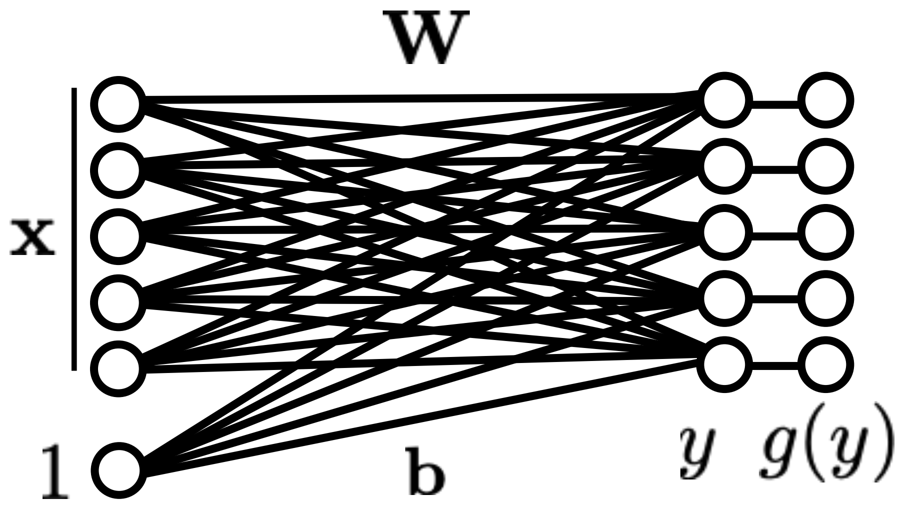


filter

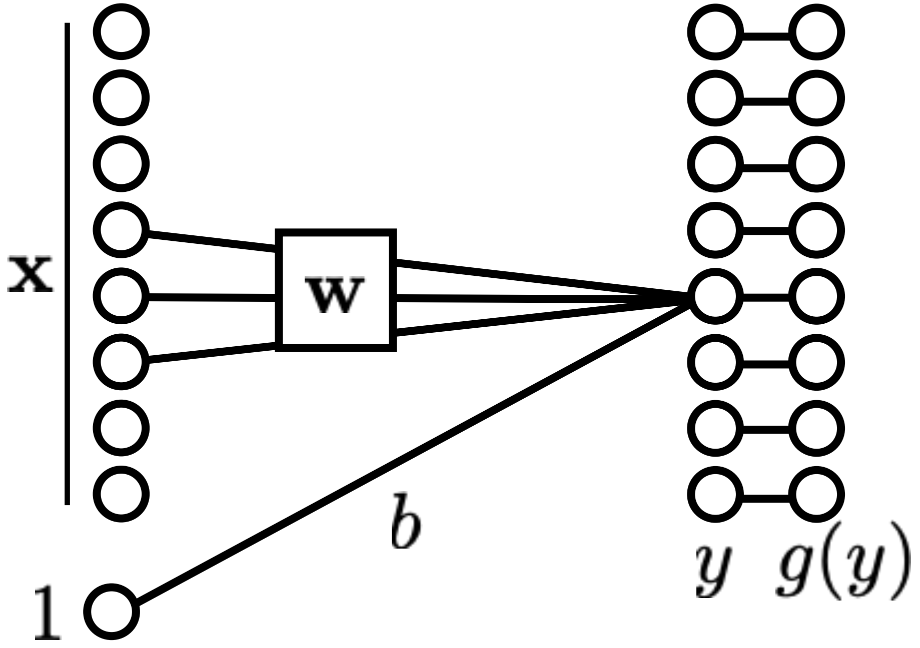


Fully-connected network

Fully-connected (fc) layer



Locally connected network

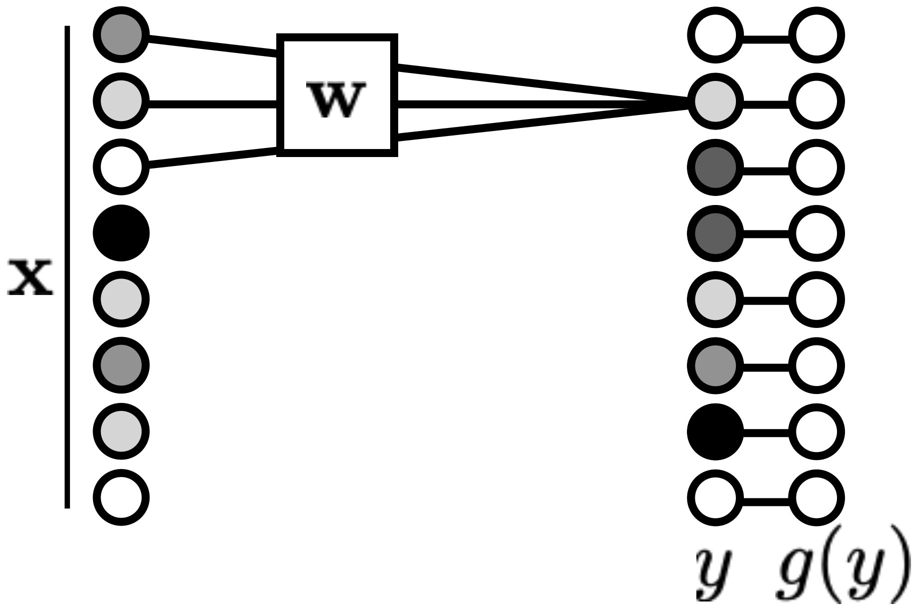


Often, we assume output is a **local** function of input.

If we use the same weights (**weight sharing**) to compute each local function, we get a convolutional neural network.

Convolutional neural network

Conv layer

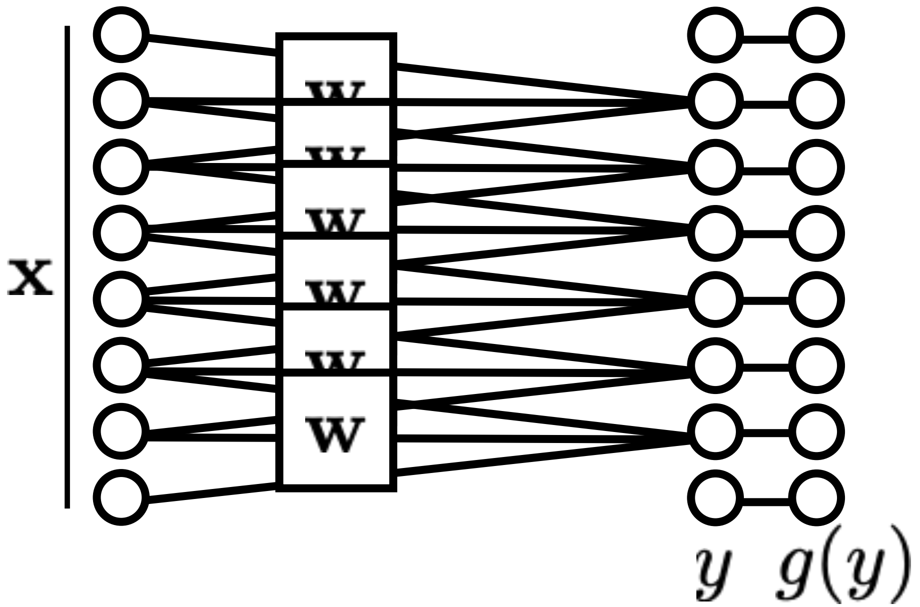


Often, we assume output is a **local** function of input.

If we use the same weights (**weight sharing**) to compute each local function, we get a convolutional neural network.

Weight sharing

Conv layer

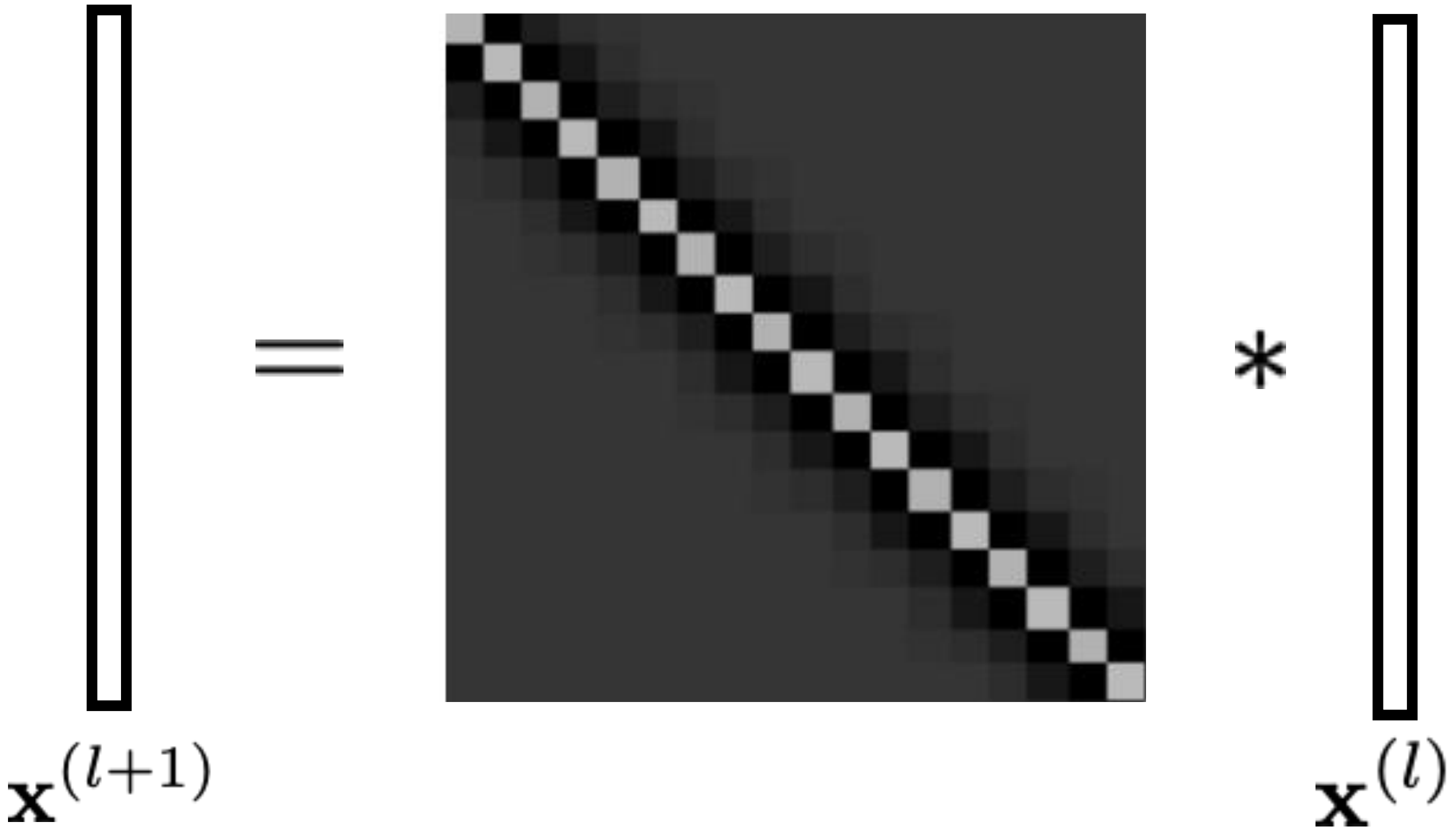


Often, we assume output is a **local** function of input.

If we use the same weights (**weight sharing**) to compute each local function, we get a convolutional neural network.

Toeplitz matrix

$$\begin{pmatrix} a & b & c & d & e \\ f & a & b & c & d \\ g & f & a & b & c \\ h & g & f & a & b \\ i & h & g & f & a \end{pmatrix}$$



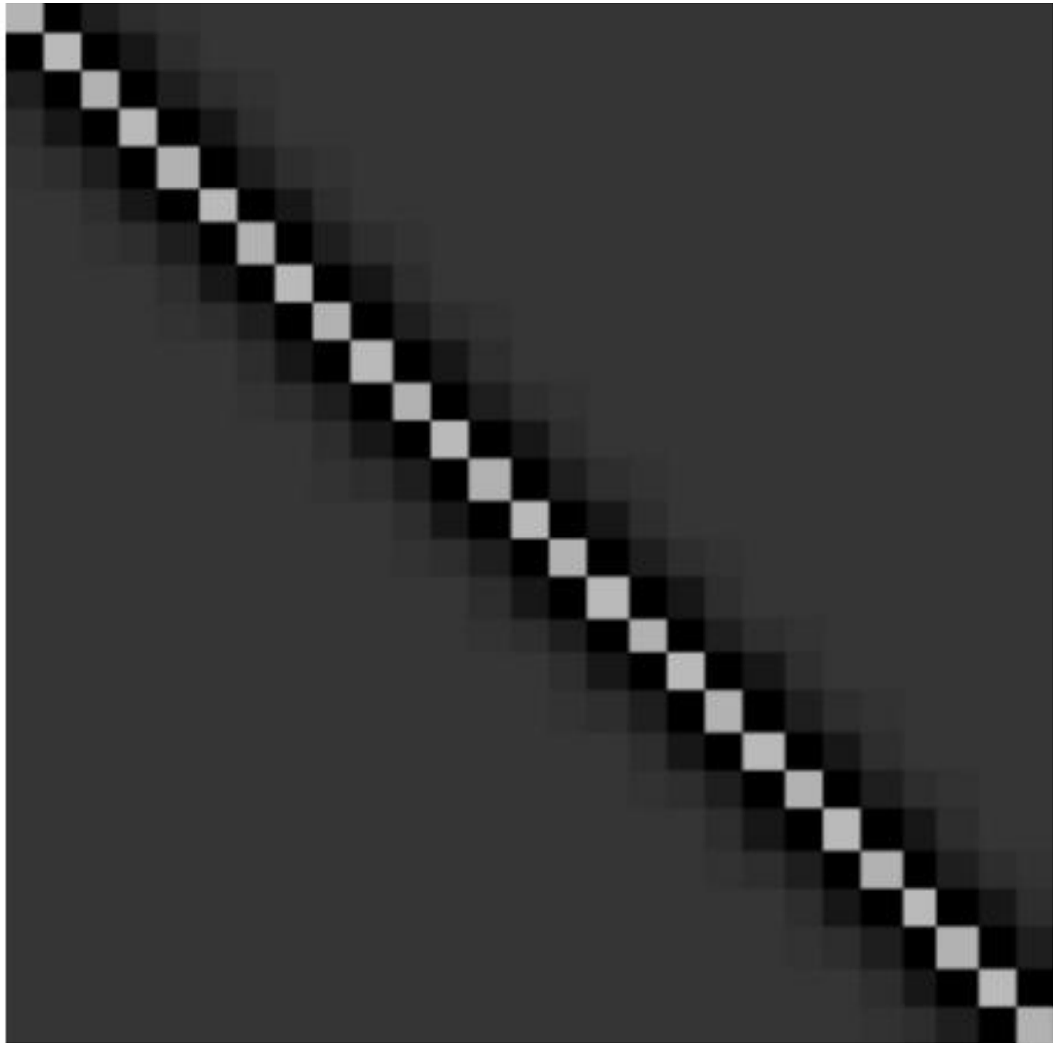
e.g., pixel image

- Constrained linear layer (infinitely strong regularization)
- Fewer parameters —> easier to learn, less overfitting

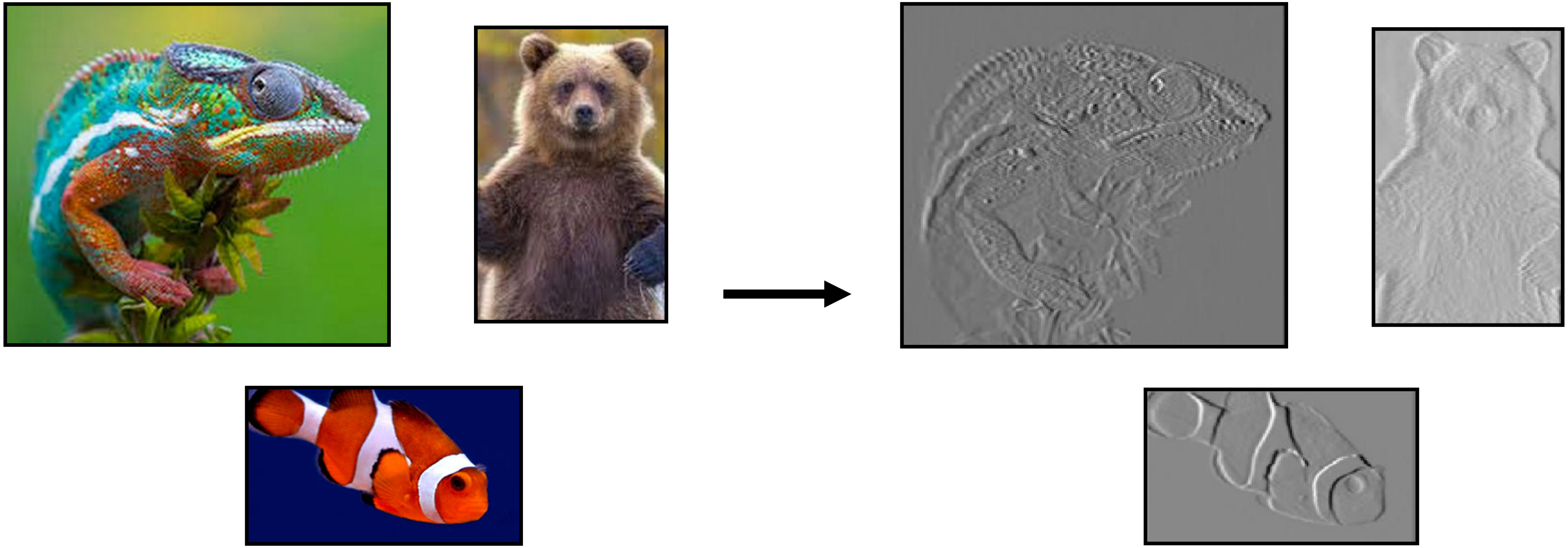
$$\mathbf{x}^{(l+1)} =$$

$$* \; \mathbf{x}^{(l)}$$

$\mathbf{x}^{(l+1)}$ $=$



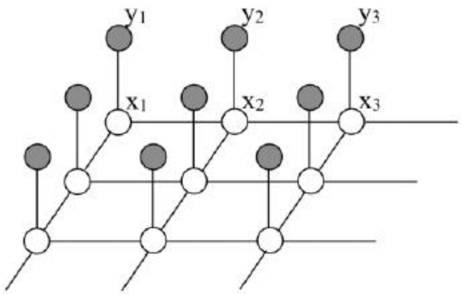
$*$ $\mathbf{x}^{(l)}$



Conv layers can be applied to arbitrarily-sized inputs

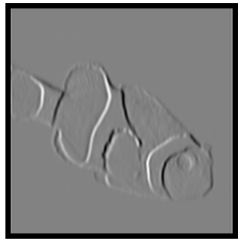
Five views on convolutional layers

1. Equivariant with translation (stationarity) $f(\mathtt{translate}(x)) = \mathtt{translate}(f(x))$

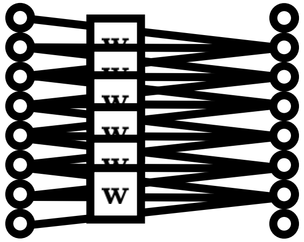


2. Patch processing (Markov assumption)

3. Image filter



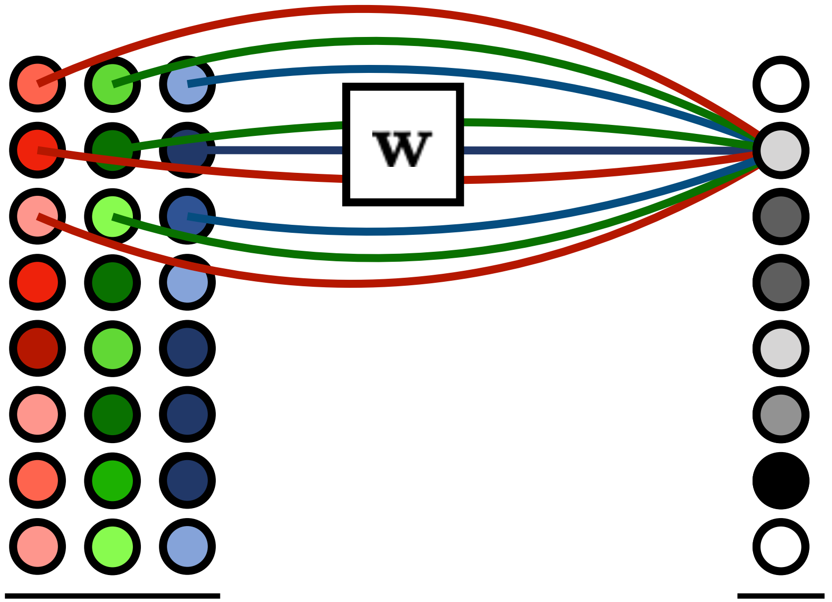
4. Parameter sharing



5. A way to process variable-sized tensors

Multiple channels

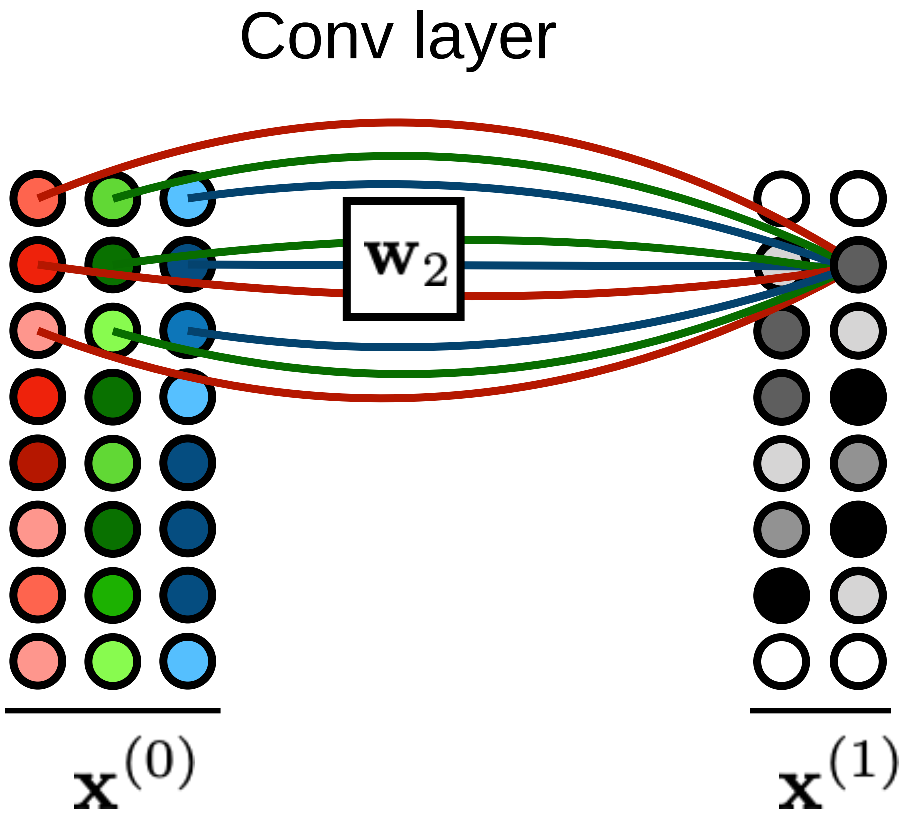
Conv layer



$\mathbf{x}^{(0)}$ $\mathbf{x}^{(1)}$

$$\mathbb{R}^{N \times C} \to \mathbb{R}^{N \times 1}$$

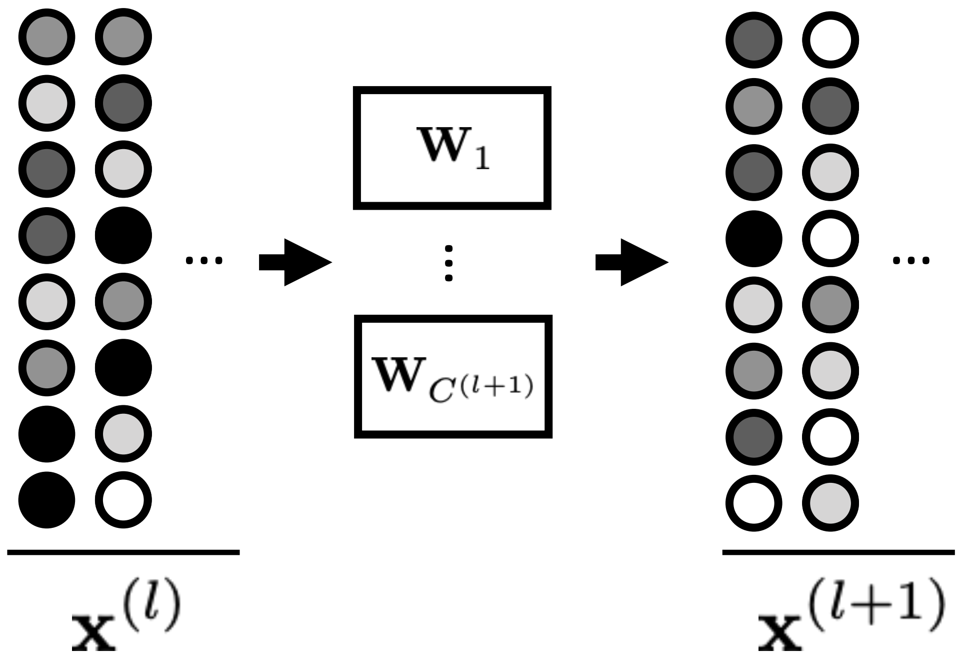
Multiple channels



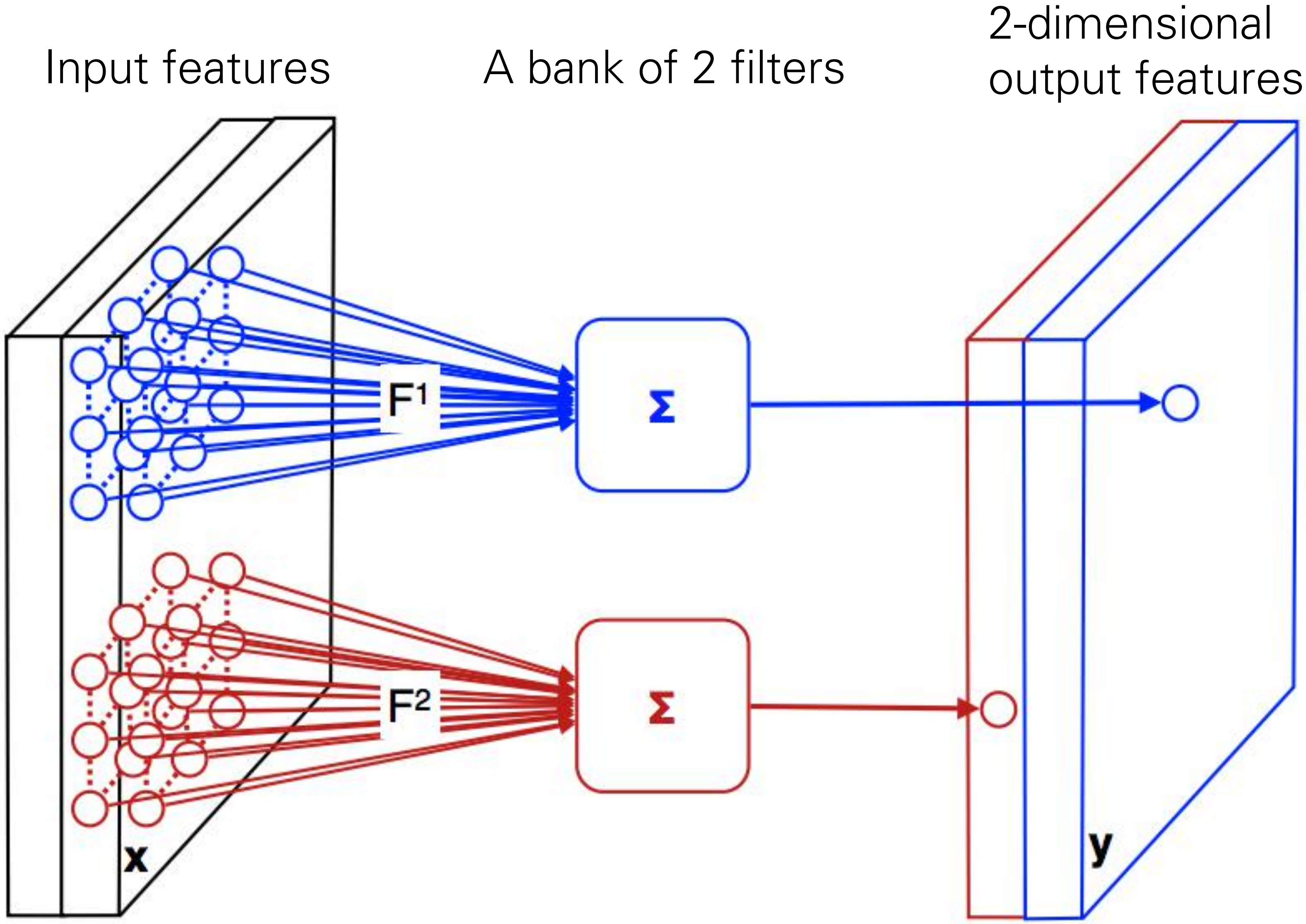
$$\mathbb{R}^{N\times C^{(0)}} \to \mathbb{R}^{N\times C^{(1)}}$$

Multiple channels

Conv layer



$$\mathbb{R}^{N \times C^{(l)}} \rightarrow \mathbb{R}^{N \times C^{(l+1)}}$$

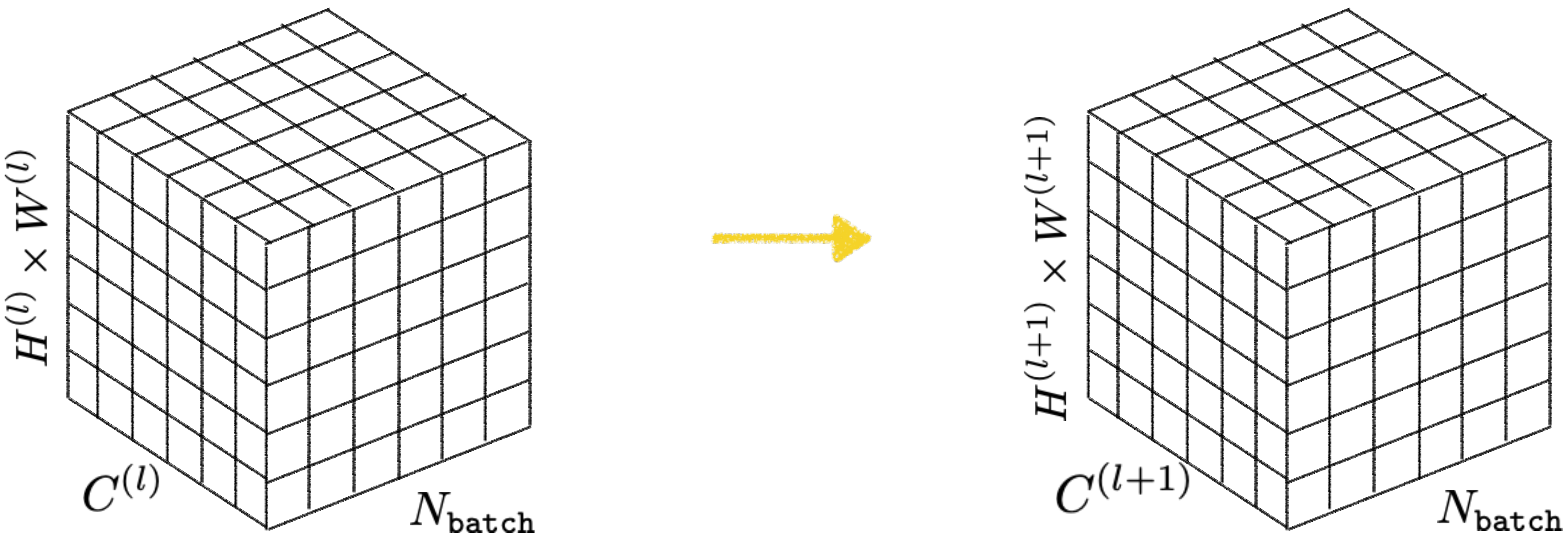


$$\mathbb{R}^{H \times W \times C^{(l)}} \rightarrow \mathbb{R}^{H \times W \times C^{(l+1)}}$$

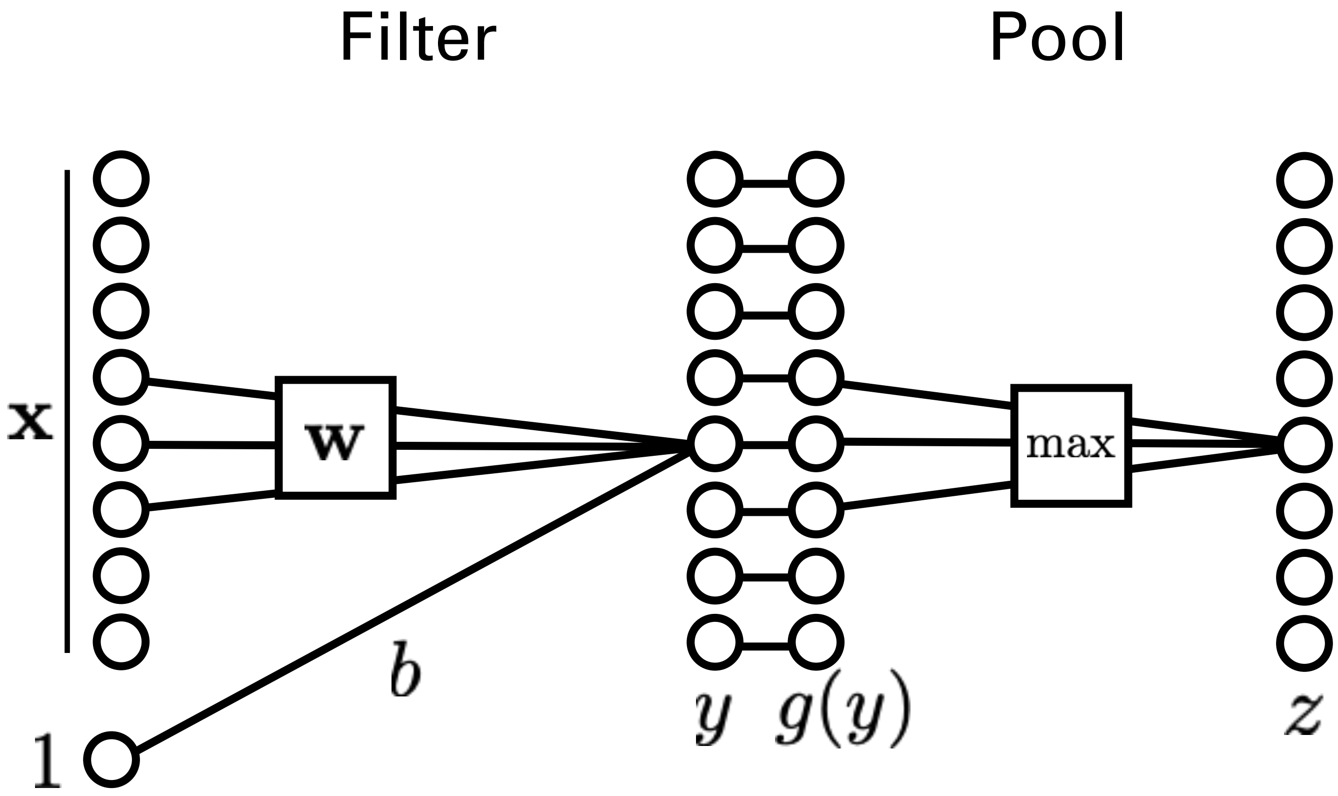
[Figure from Andrea Vedaldi]

"Tensor flow"

$\mathbf{x}^{(l)} \in \mathbb{R}^{N_{\texttt{batch}} \times H^{(l)} \times W^{(l)} \times C^{(l)}}$ $\mathbf{x}^{(l+1)} \in \mathbb{R}^{N_{\texttt{batch}} \times H^{(l+1)} \times W^{(l+1)} \times C^{(l+1)}}$



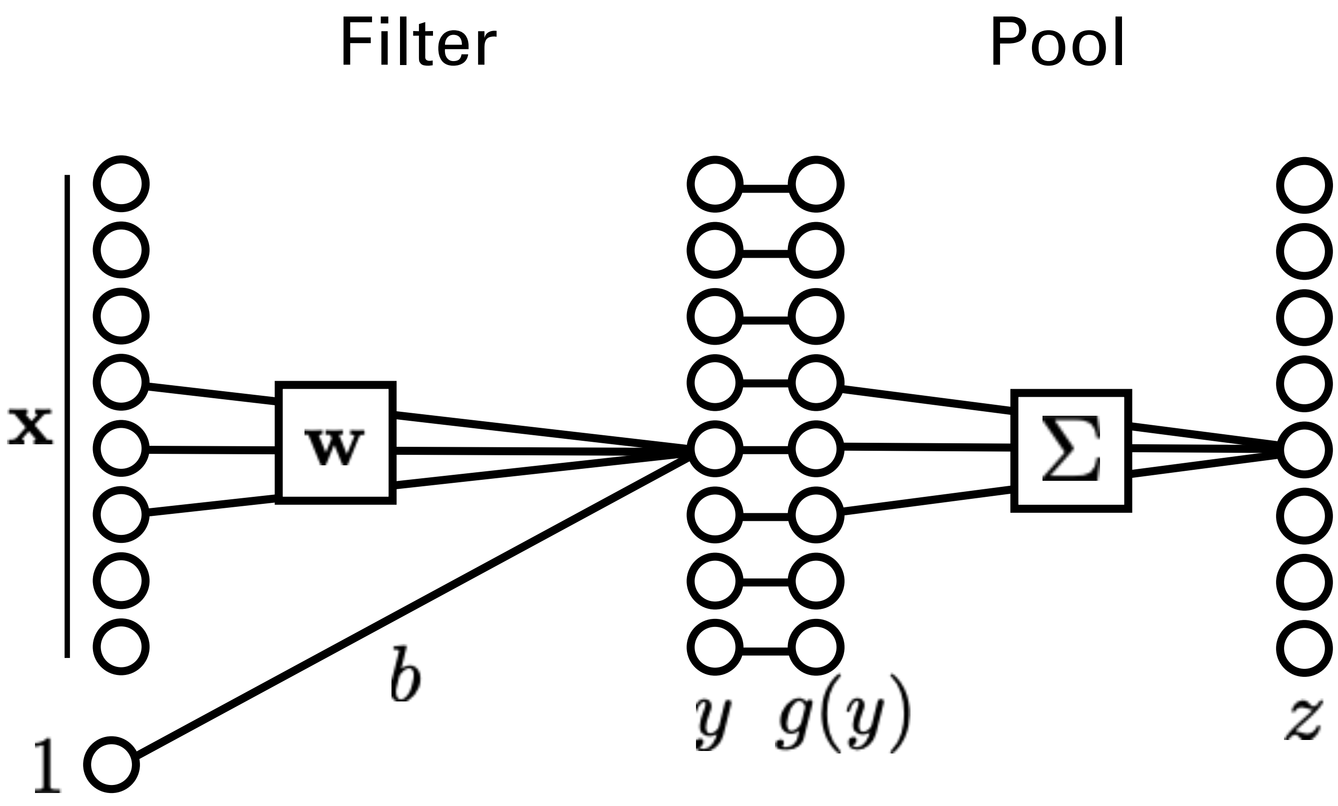
Pooling



Max pooling

$$z_k = \max_{j \in \mathcal{N}(j)} g(y_j)$$

Pooling



Max pooling

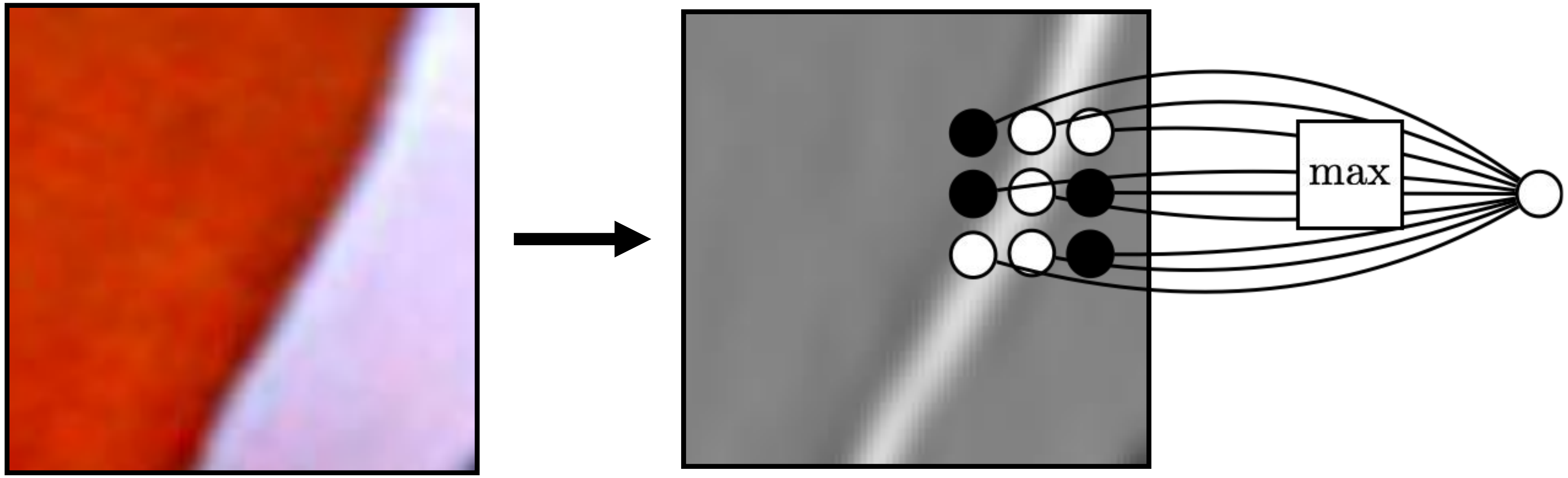
$$z_k = \max_{j \in \mathcal{N}(j)} g(y_j)$$

Mean pooling

$$z_k = \frac{1}{|\mathcal{N}|} \sum_{j \in \mathcal{N}(j)} g(y_j)$$

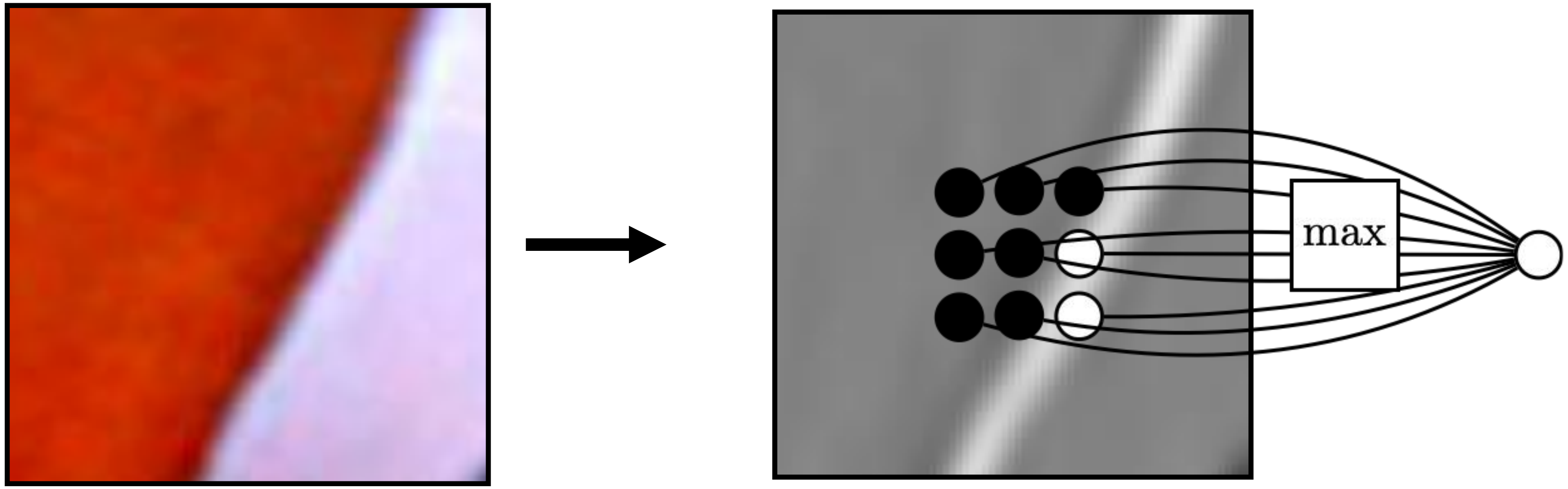
Pooling – Why?

Pooling across spatial locations achieves stability w.r.t. small translations:



Pooling – Why?

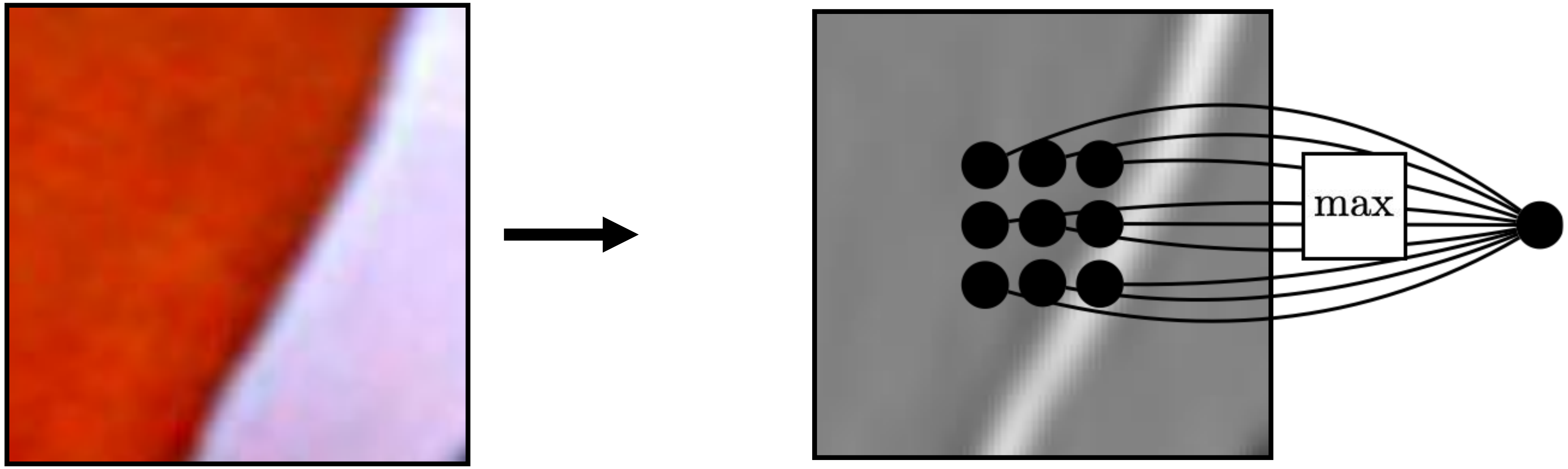
Pooling across spatial locations achieves stability w.r.t. small translations:



large response regardless of exact position of edge

Pooling – Why?

Pooling across spatial locations achieves stability w.r.t. small translations:



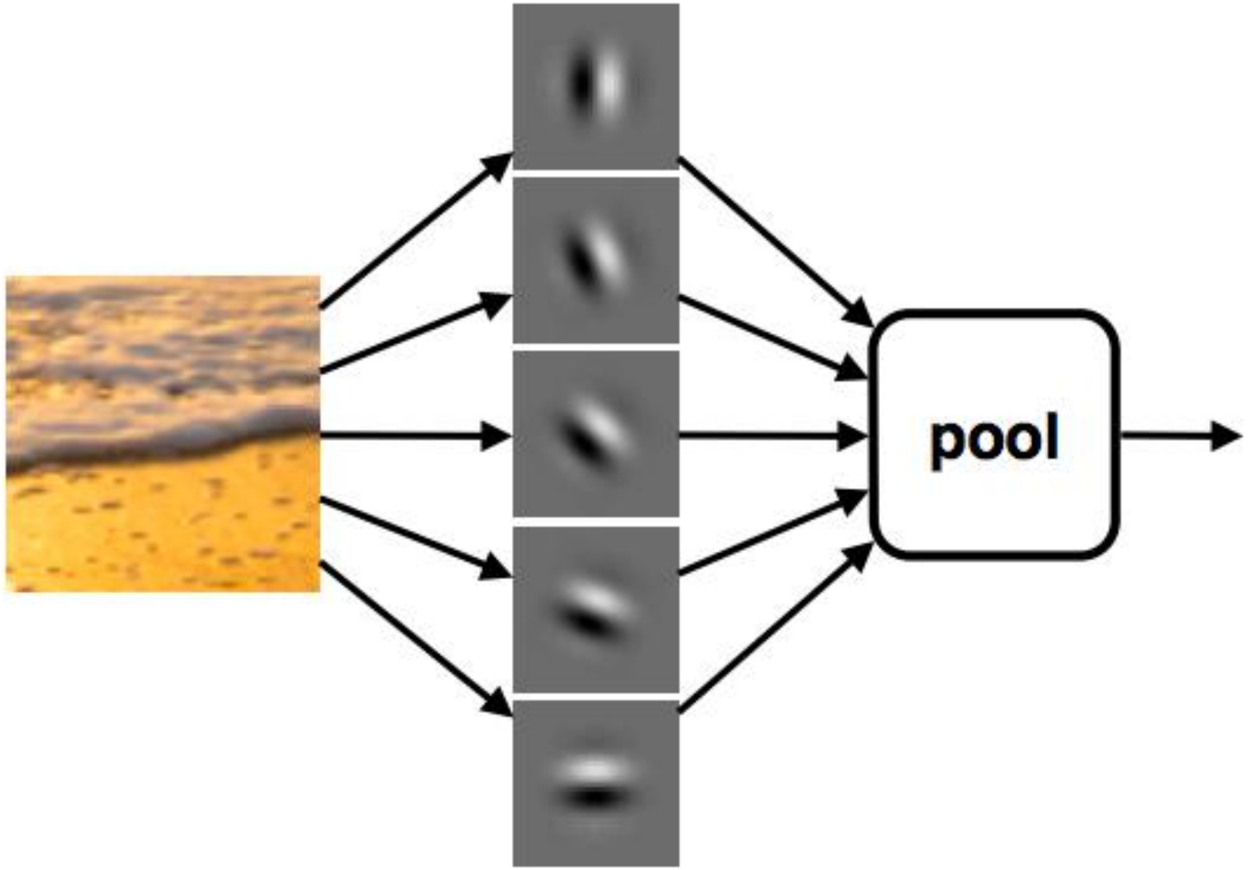
CNNs are stable w.r.t. diffeomorphisms

$\approx$

[“Unreasonable effectiveness of Deep Features as a Perceptual Metric”, Zhang et al. 201

Pooling – Why?

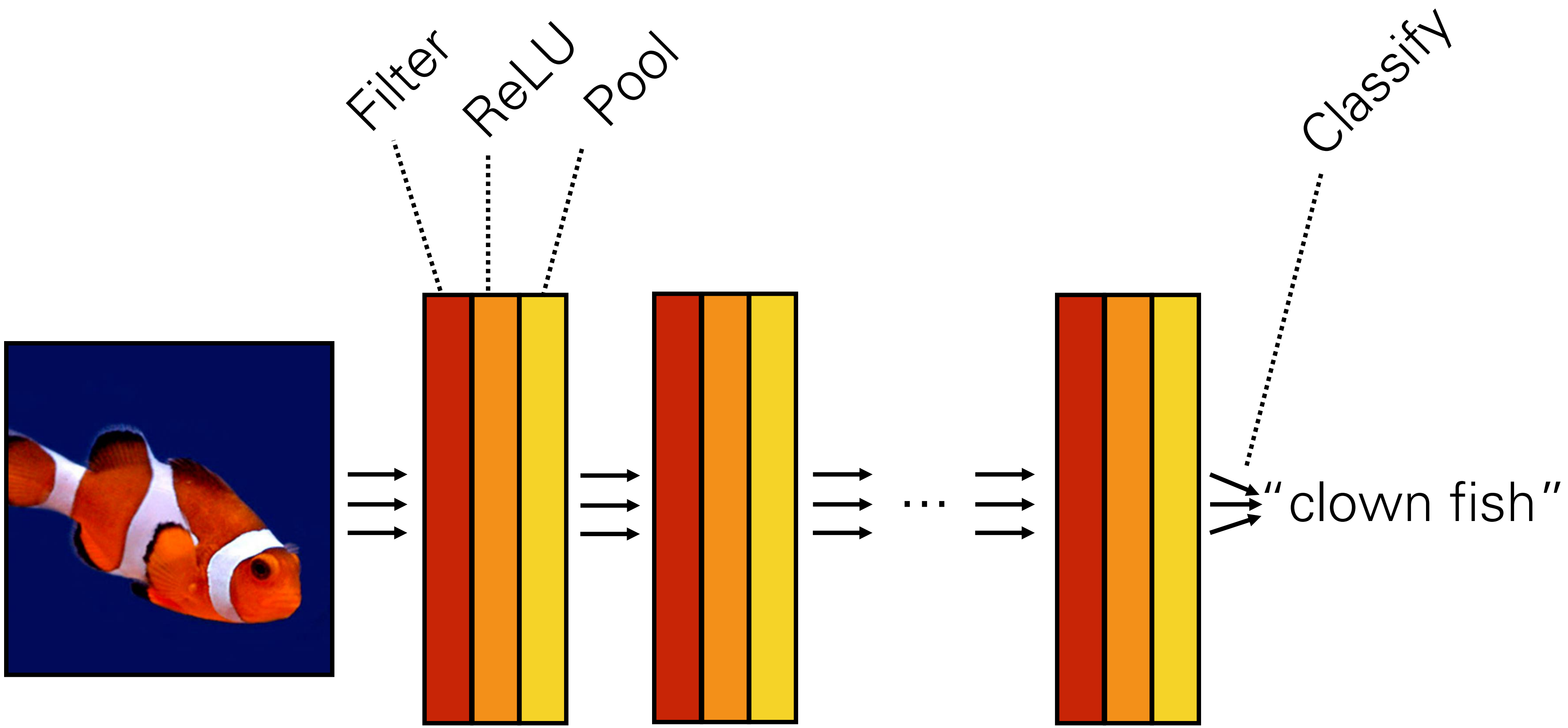
Pooling across feature channels (filter outputs) can achieve other kinds of invariances:



large response for any edge, regardless of its orientation

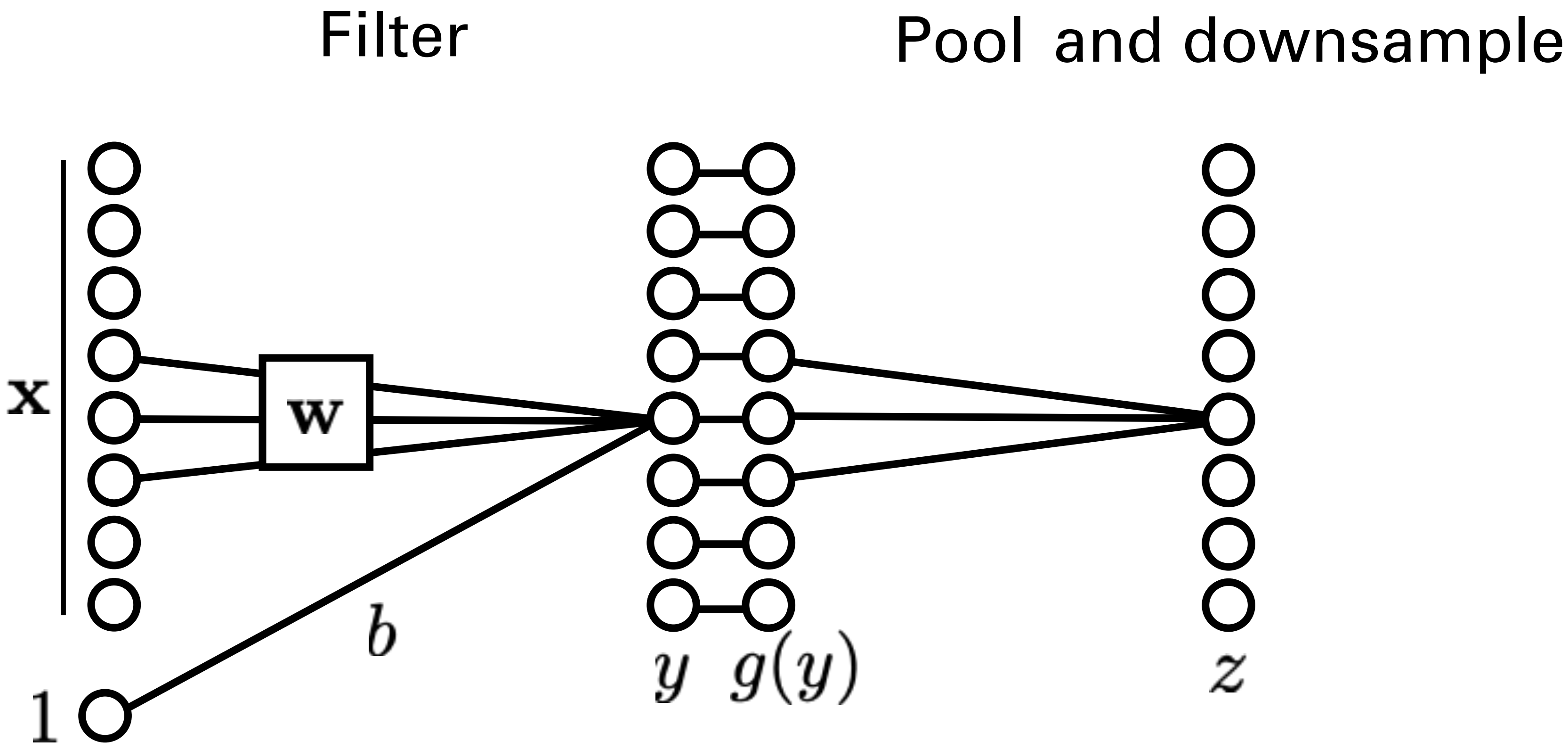
[Derived from slide by Andrea Vedaldi]

Computation in a neural net

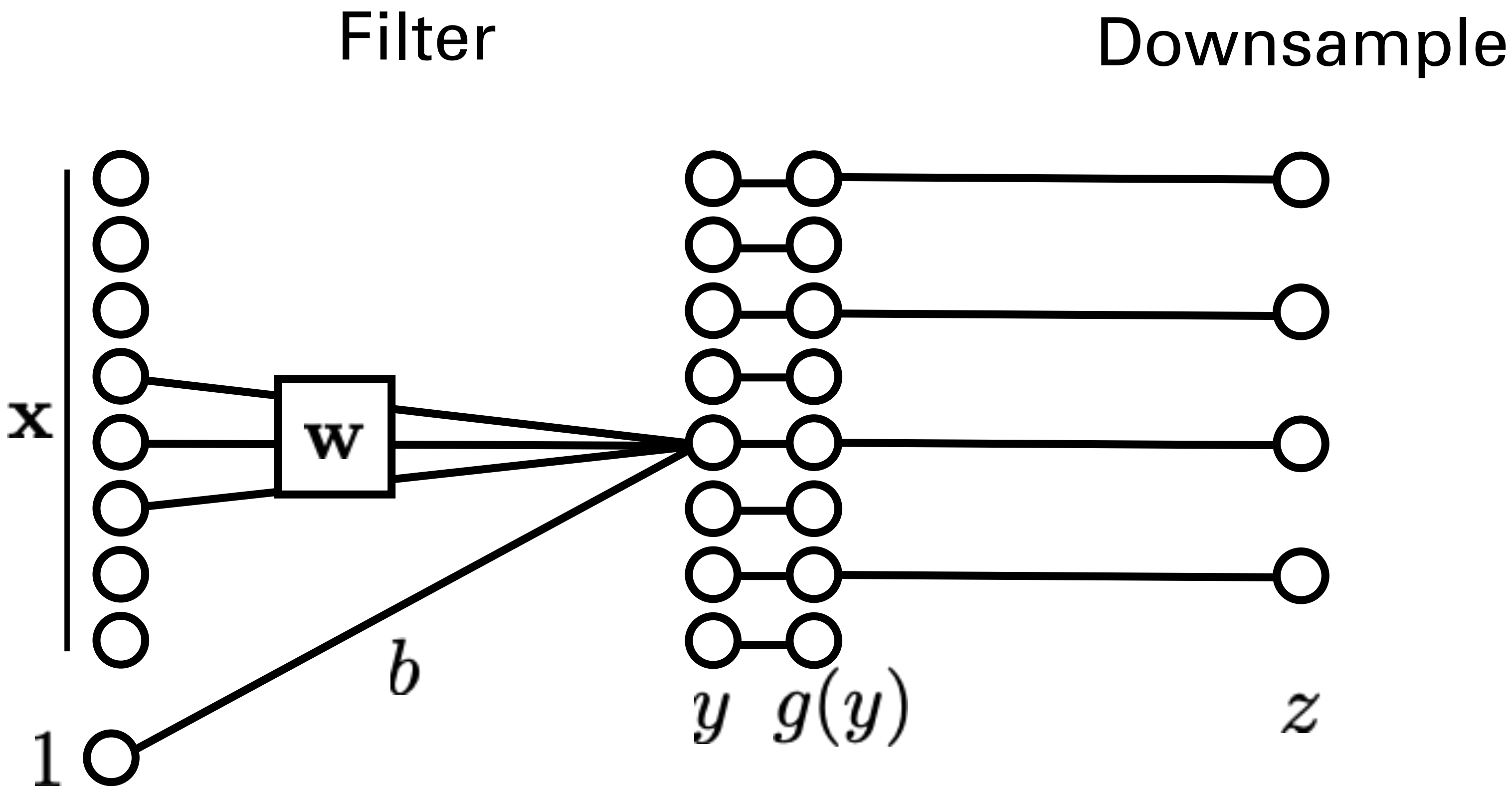


$$f(\mathbf{x}) = f_L(\dots f_2(f_1(\mathbf{x})))$$

Downsampling

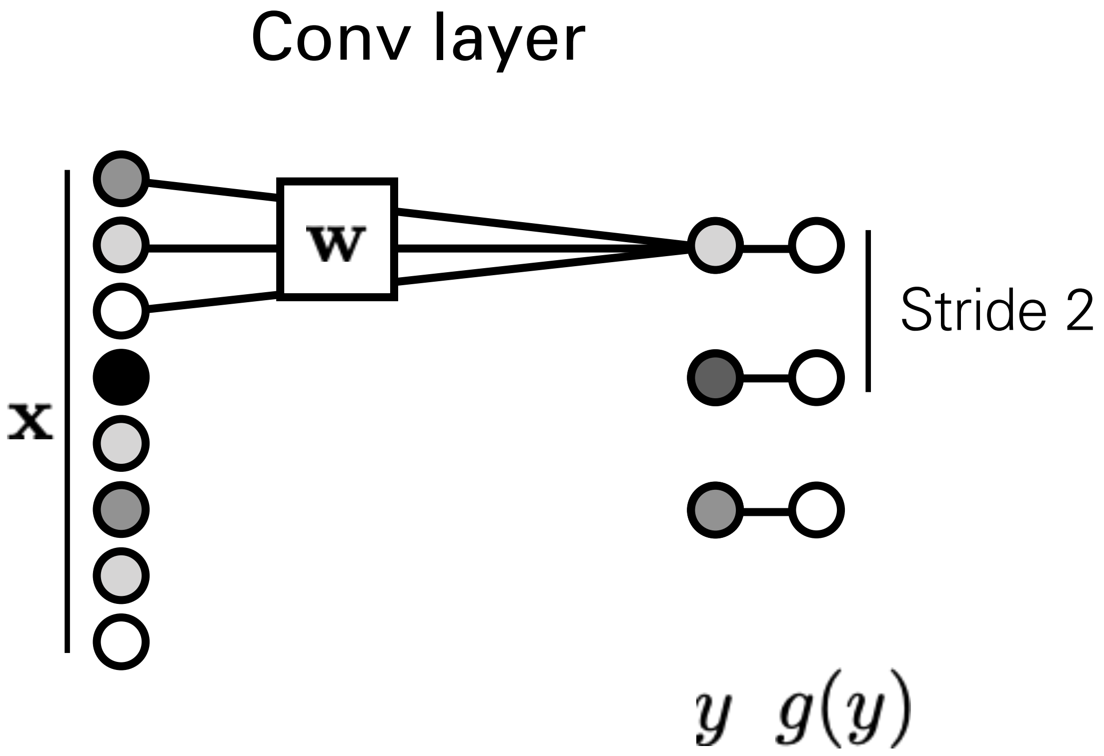


Downsampling



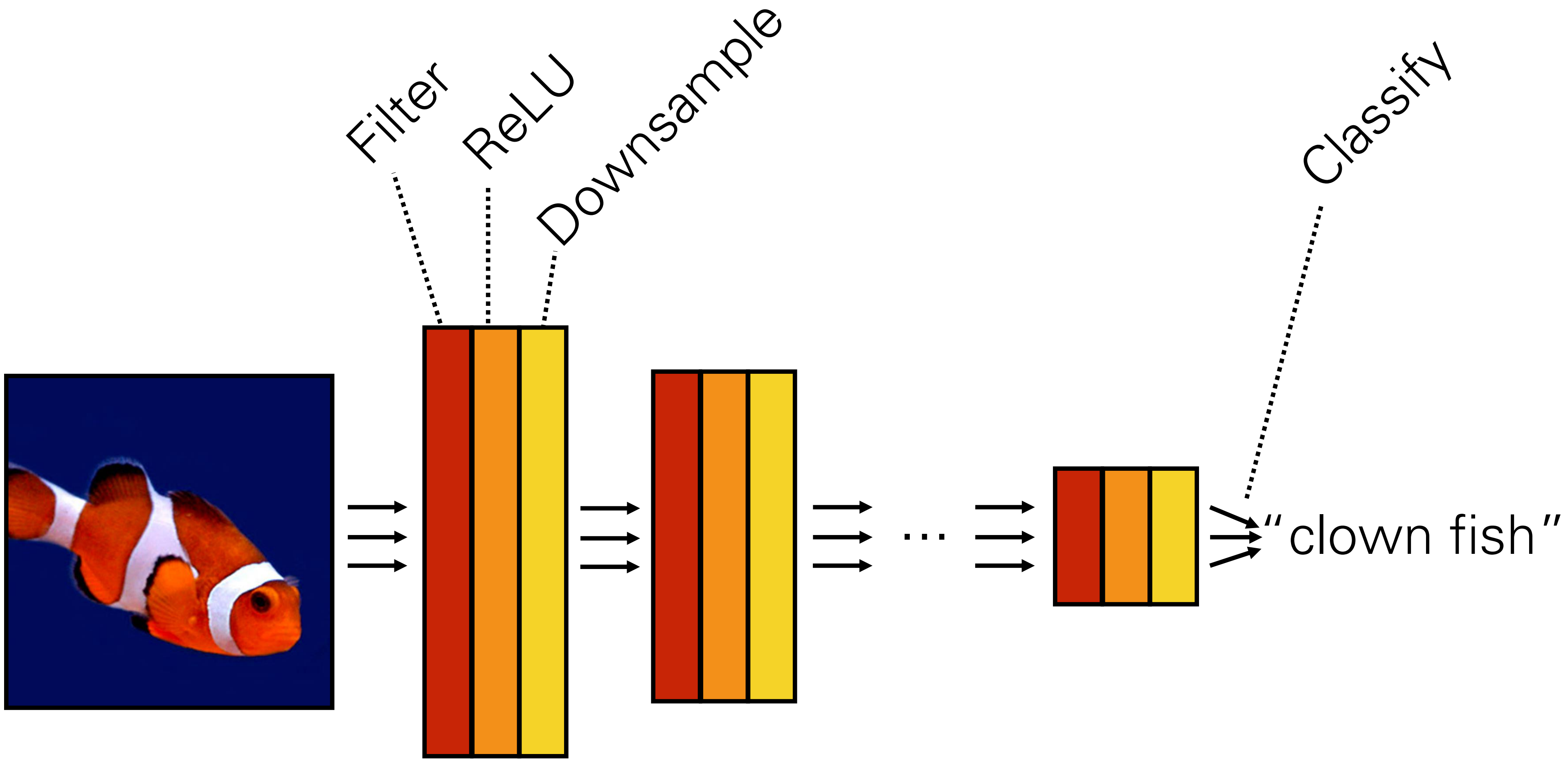
$$\mathbb{R}^{H^{(l)} \times W^{(l)} \times C^{(l)}} \to \mathbb{R}^{H^{(l+1)} \times W^{(l+1)} \times C^{(l+1)}}$$

Strided convolution



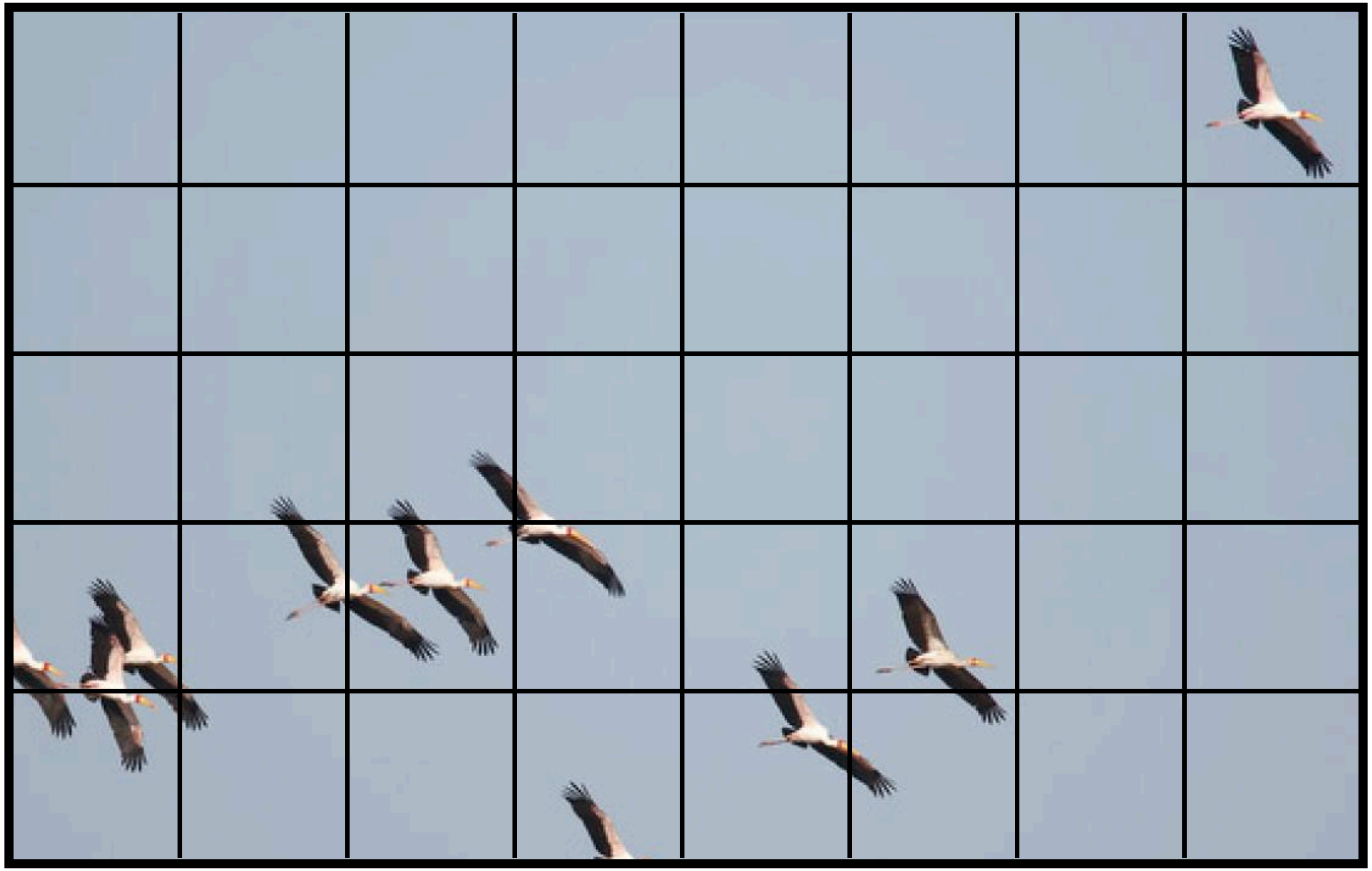
Strided convolutions combine convolution and downsampling into a single operation.

Computation in a neural net

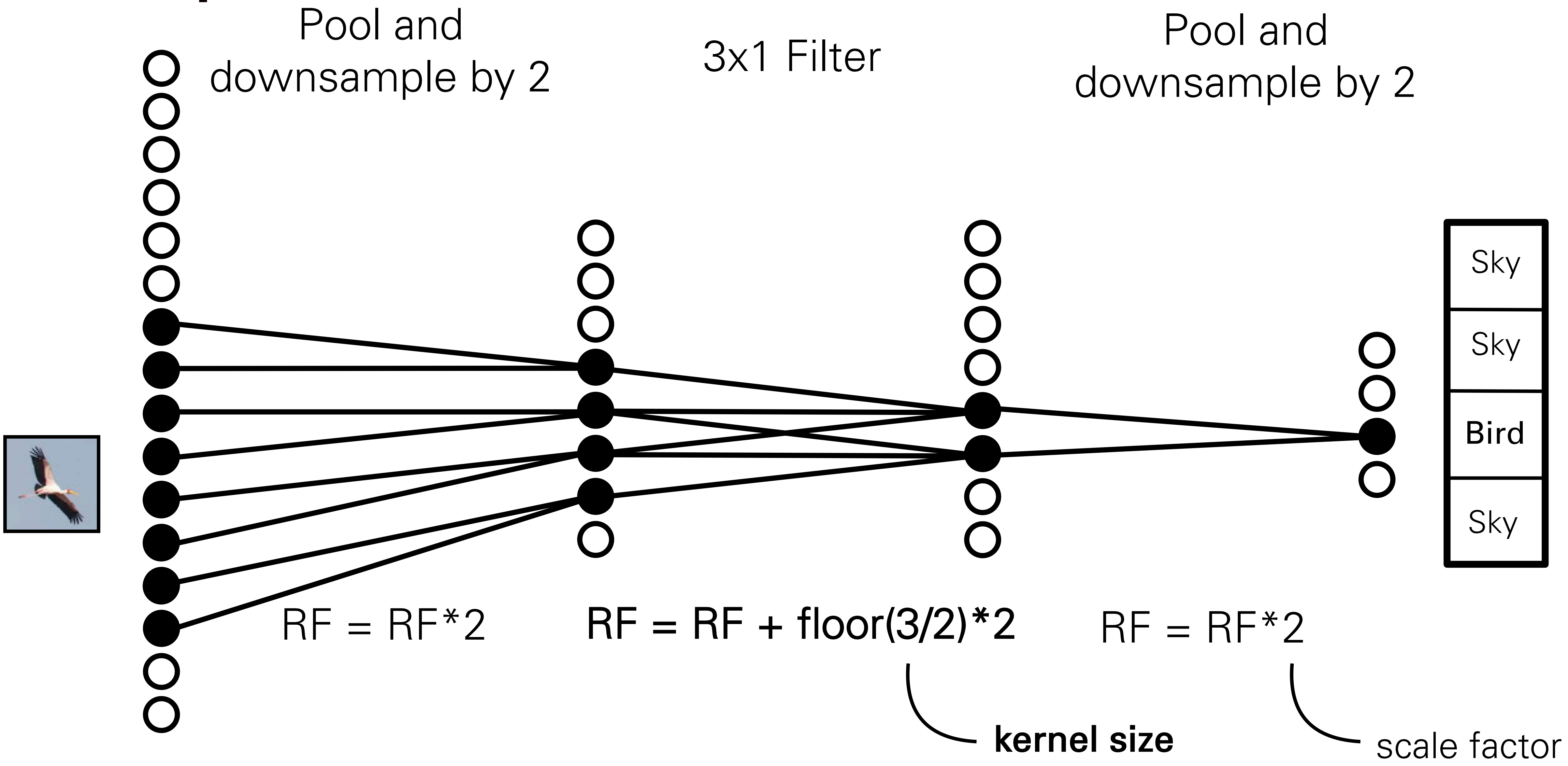


$$f(\mathbf{x}) = f_L(\dots f_2(f_1(\mathbf{x})))$$

Receptive fields

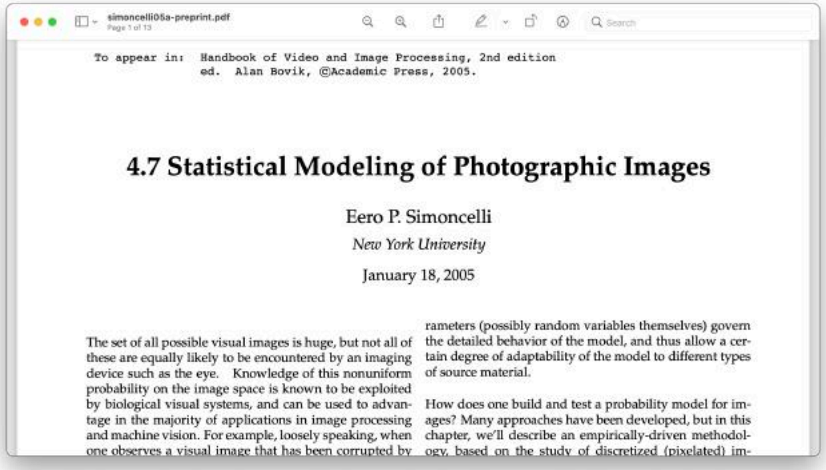


Receptive fields



[http://fomoro.com/tools/receptive-fields/index.html]

Why CNNs?



To appear in: Handbook of Video and Image Processing, 2nd edition
ed. Alan Bovik, ©Academic Press, 2005.

4.7 Statistical Modeling of Photographic Images

Eero P. Simoncelli
New York University

January 18, 2005

The set of all possible visual images is huge, but not all of these are equally likely to be encountered by an imaging device such as the eye. Knowledge of this nonuniform probability on the image space is known to be exploited by biological visual systems, and can be used to advantage in the majority of applications in image processing and machine vision. For example, loosely speaking, when one observes a visual image that has been corrupted by

rameters (possibly random variables themselves) govern the detailed behavior of the model, and thus allow a certain degree of adaptability of the model to different types of source material.

How does one build and test a probability model for images? Many approaches have been developed, but in this chapter, we'll describe an empirically-driven methodology, based on the study of discretized (pixelated) im-

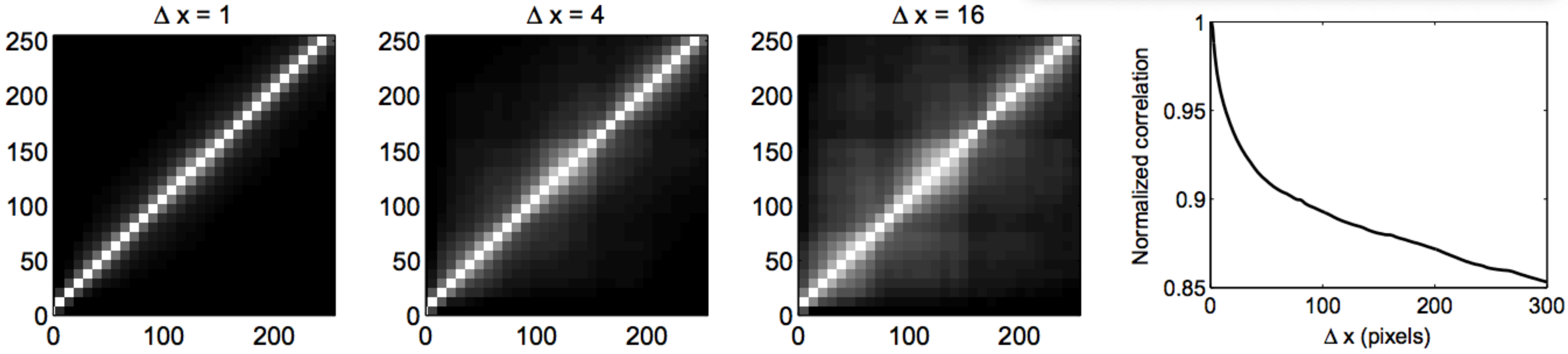


Fig. 1. (a) Scatterplots of pairs of pixels at three different spatial displacements, averaged over five examples images. (b) Autocorrelation function. Photographs are of New York City street scenes, taken with a Canon 10D digital camera, and processed in RAW linear sensor mode (producing pixel intensities are in roughly proportional to light intensity). Correlations were computed on the logs of these sensor intensity values [41].

[http://6.869.csail.mit.edu/fa18/notes/simoncelli2005.pdf]

Why CNNs?

Statistical dependences between pixels decay as a power law of distance between the pixels.

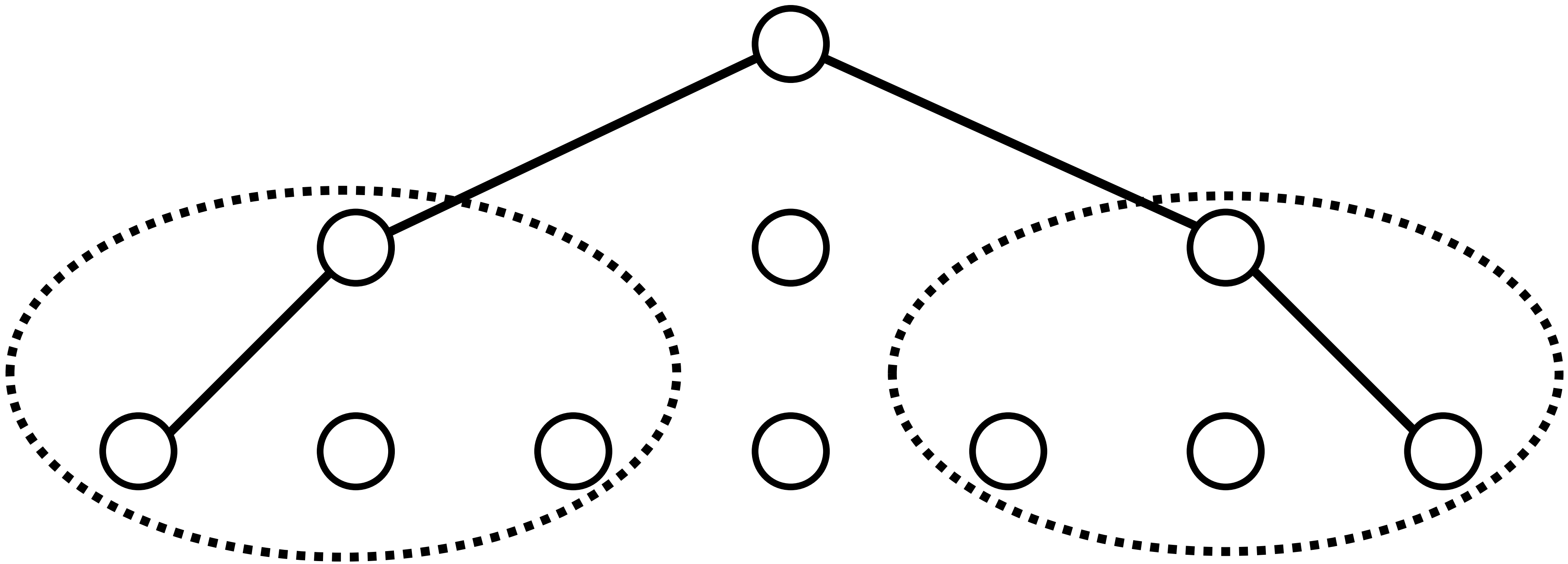
It is therefore often sufficient to model local dependences only. —> **Convolution**

More generally, we should allocate parameters that model dependences in proportion to the strength of those dependences. —> **Multiscale, hierarchical representations**

[For more discussion, see "Why does Deep and Cheap Learning Work So Well?", Lin et al. 2017]

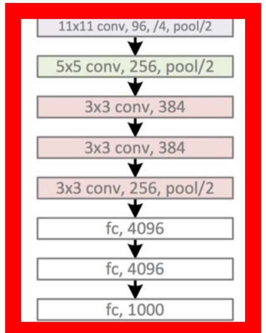
Why CNNs?

Capturing long-range dependences:



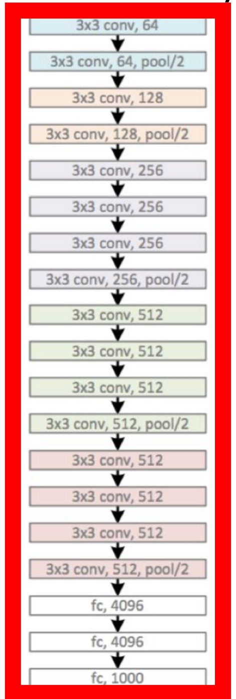
Deep Neural Networks for Visual Recognition

2012: AlexNet
5 conv. layers



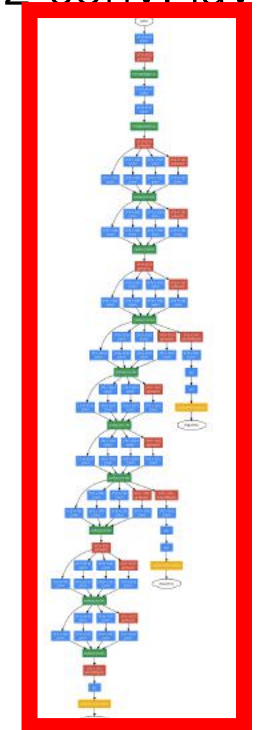
Error: 15.3%

2014: VGG
16 conv. layers

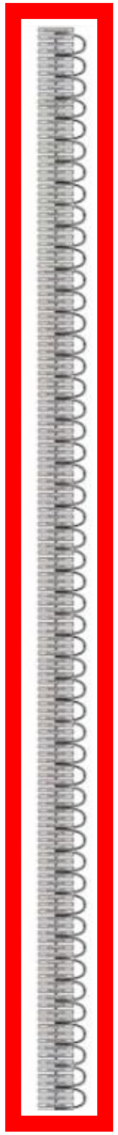


Error: 8.5%

2015: GoogLeNet
22 conv. layers



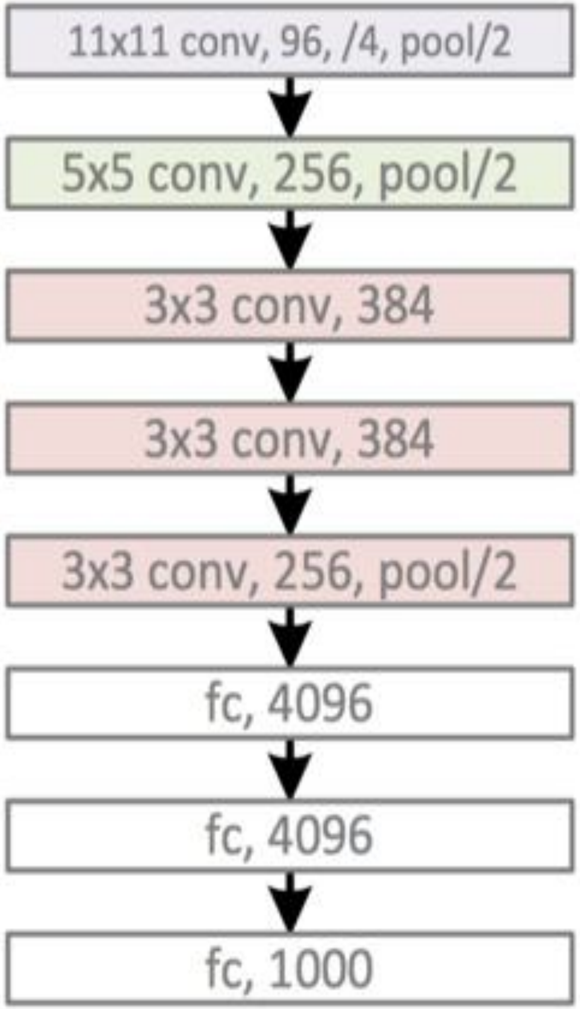
Error: 7.8%



2016: ResNet
>100 conv. layers

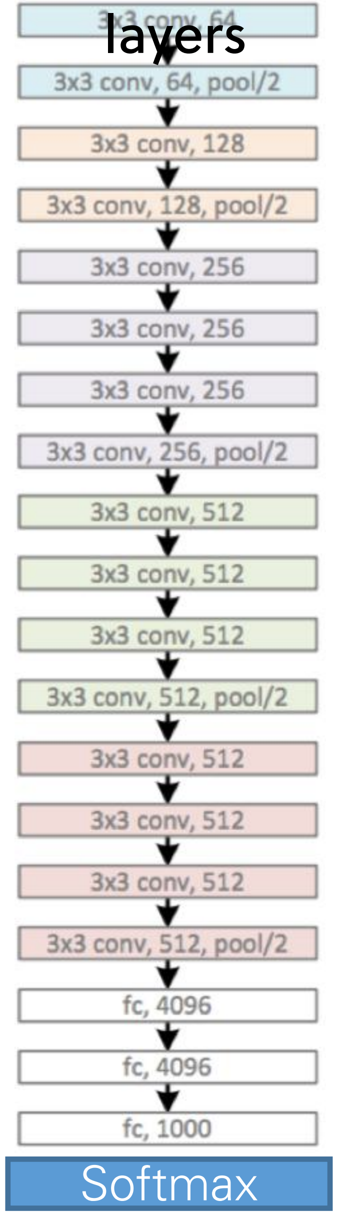
Error: 4.4%

2012: AlexNet
5 conv. layers



Error: 15.3%

2014: VGG 16 conv. layers

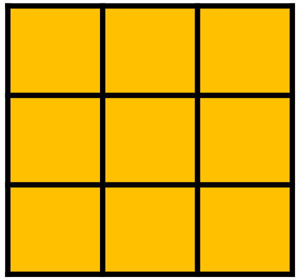


Error: 8.5%

VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION

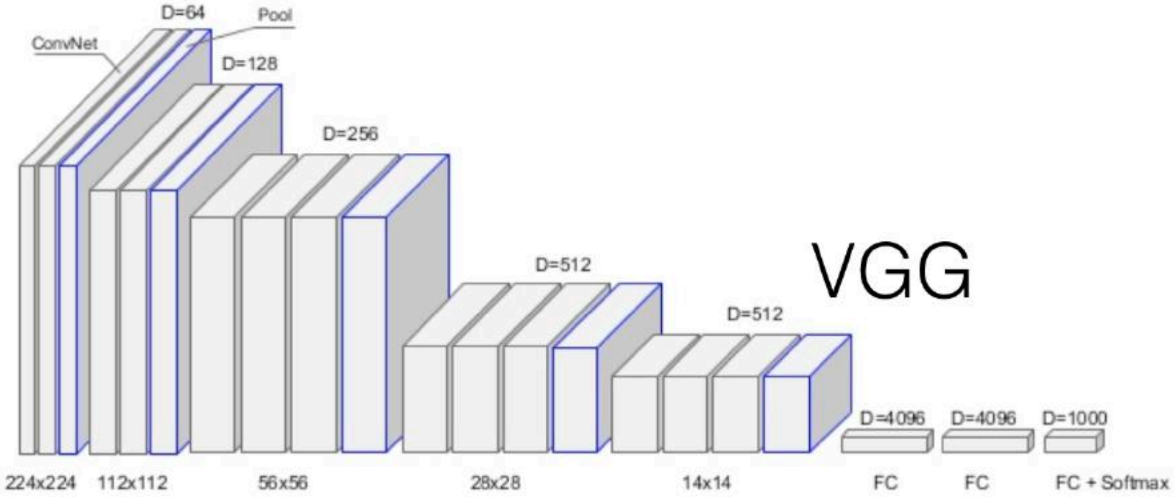
https://arxiv.org/pdf/1409.1556.pdf

Small convolutional kernels: 3x3

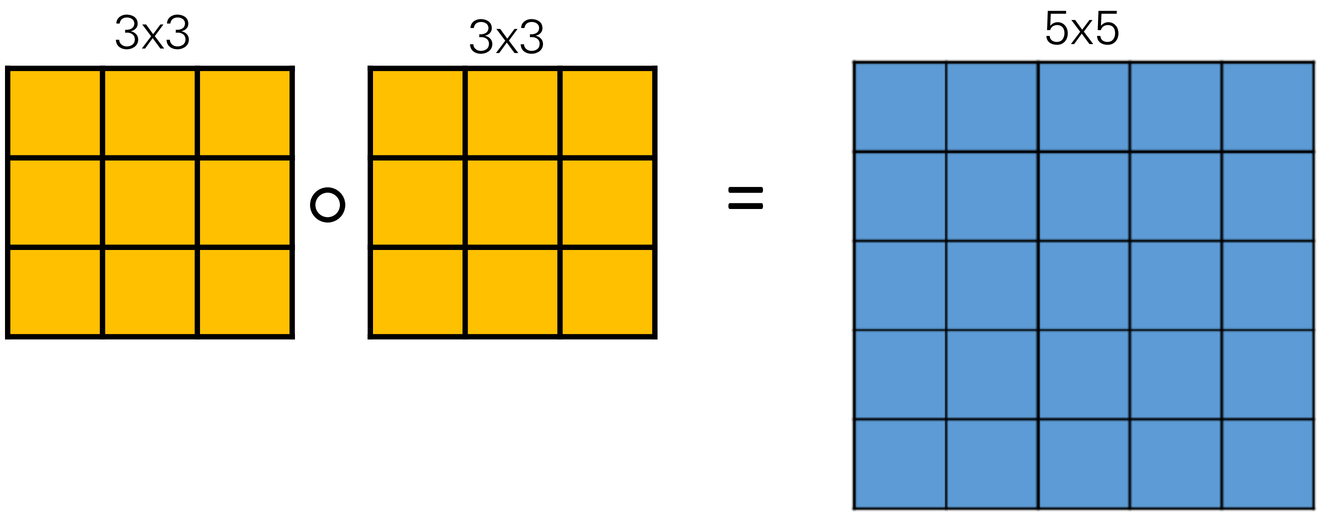


ReLu non-linearities

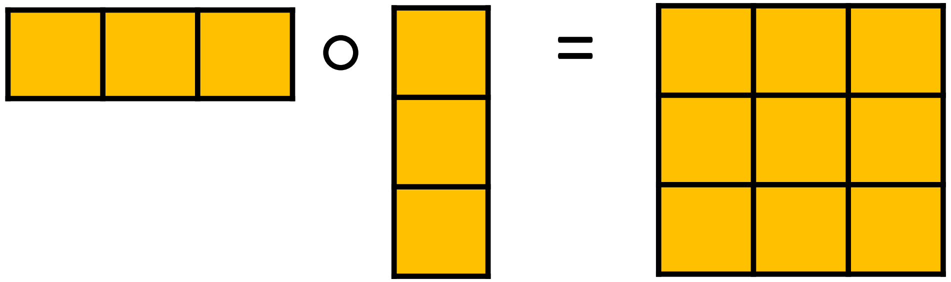
>100 million parameters.



Chaining convolutions

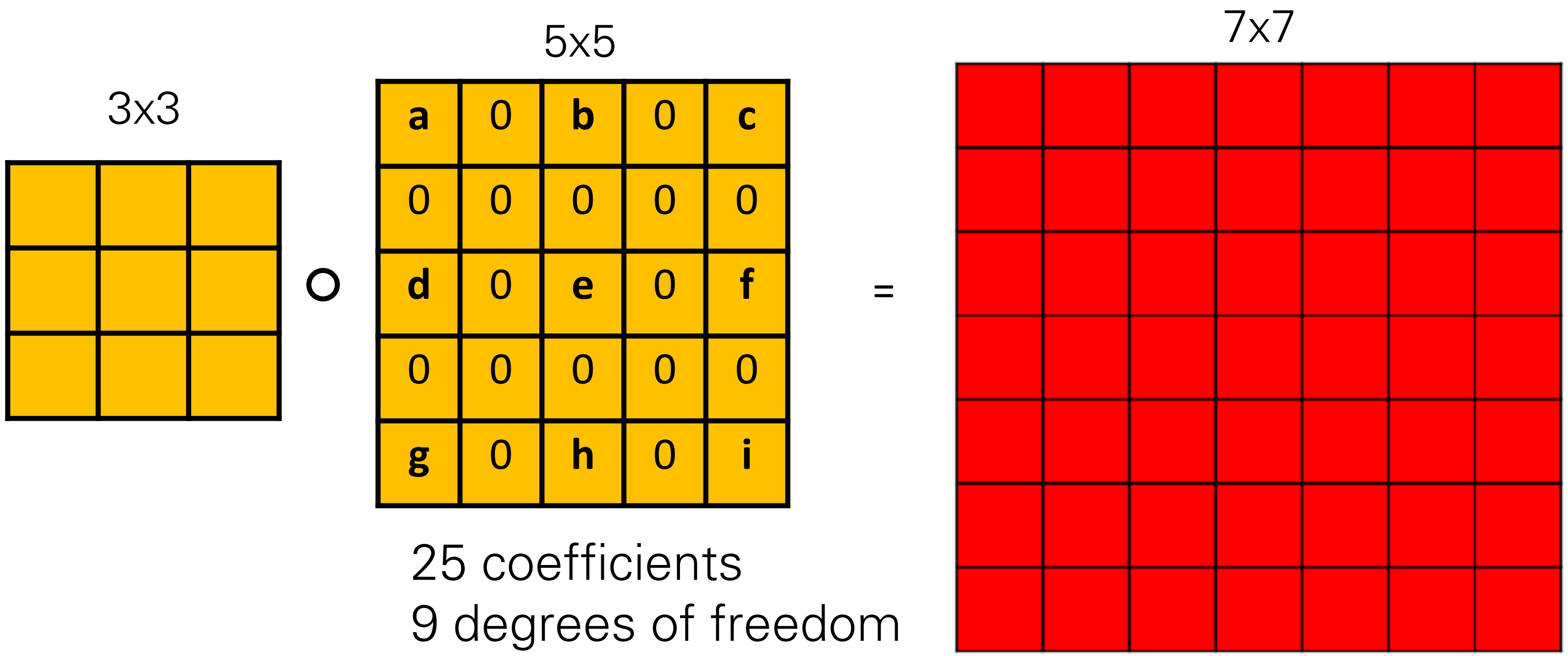


25 coefficients, but only
18 degrees of freedom



9 coefficients, but only
6 degrees of freedom.
Only separable filters… would this be enough?

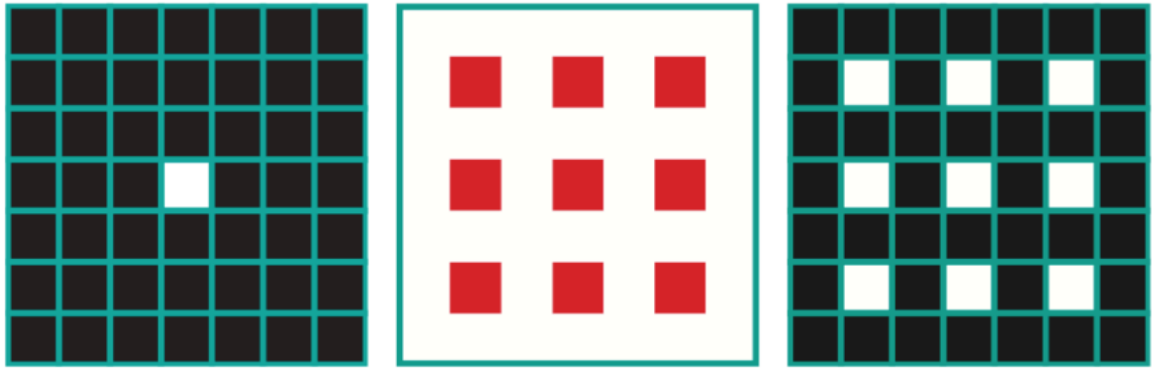
Dilated convolutions



25 coefficients
9 degrees of freedom

49 coefficients
18 degrees of freedom

What is lost?



(a) Input (b) Dilation 2 (c) Output

[https://arxiv.org/pdf/1511.07122.pdf]

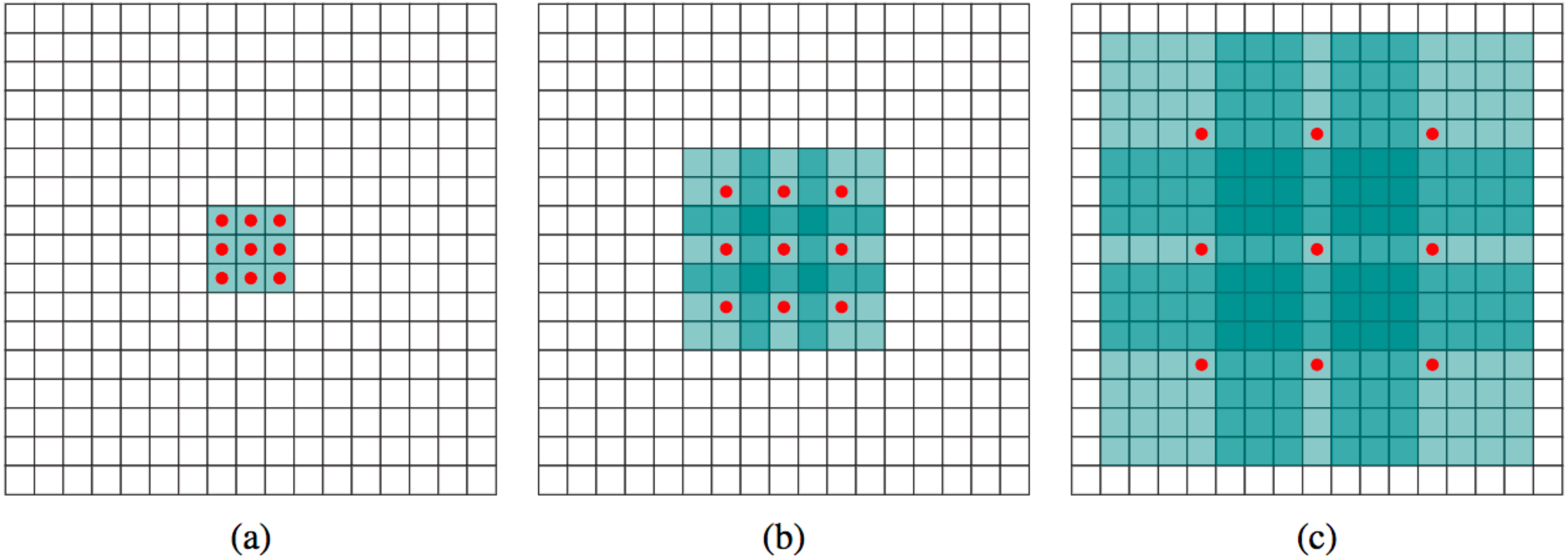


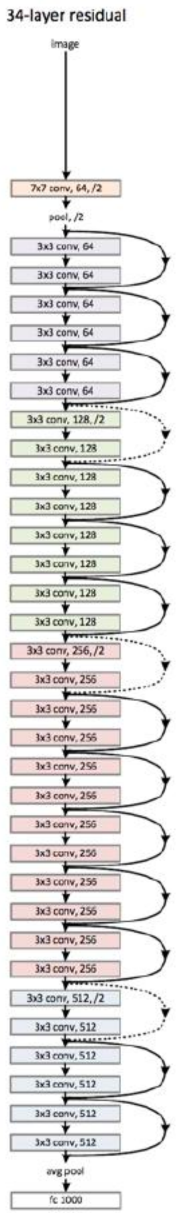
Figure 1: Systematic dilation supports exponential expansion of the receptive field without loss of resolution or coverage. (a) F_1 is produced from F_0 by a 1-dilated convolution; each element in F_1 has a receptive field of 3×3. (b) F_2 is produced from F_1 by a 2-dilated convolution; each element in F_2 has a receptive field of 7×7. (c) F_3 is produced from F_2 by a 4-dilated convolution; each element in F_3 has a receptive field of 15×15. The number of parameters associated with each layer is identical. The receptive field grows exponentially while the number of parameters grows linearly.

[https://arxiv.org/pdf/1511.07122.pdf]

2016: ResNet
>100 conv. layers

Deep Residual Learning for Image Recognition

https://arxiv.org/pdf/1512.03385.pdf



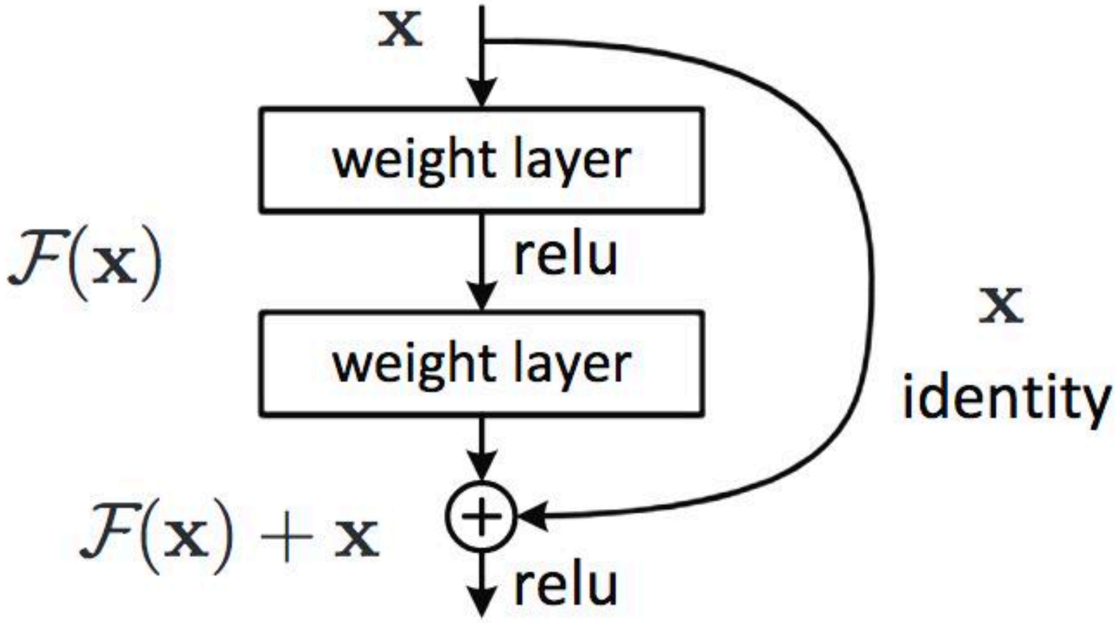
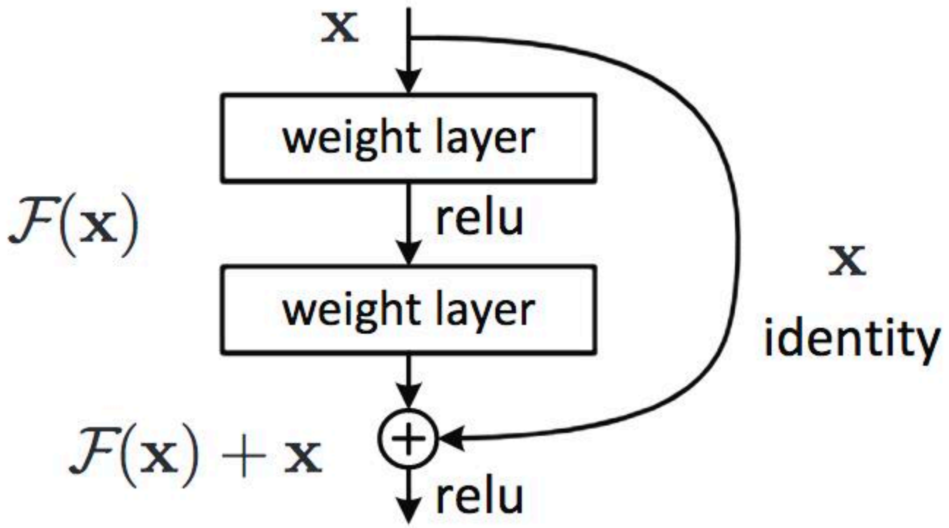


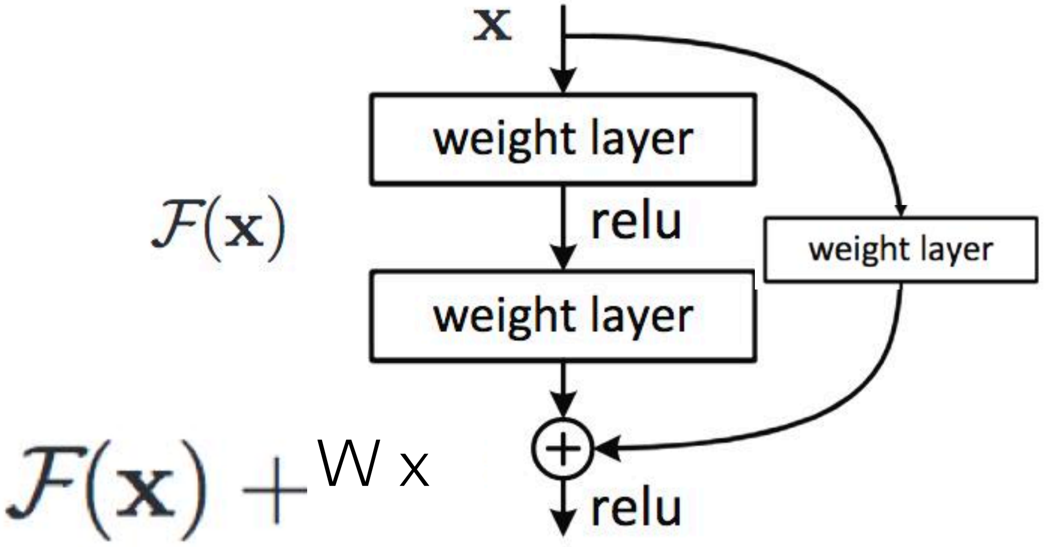
Figure 2. Residual learning: a building block.

Error: 4.4%

If output has same size as input:

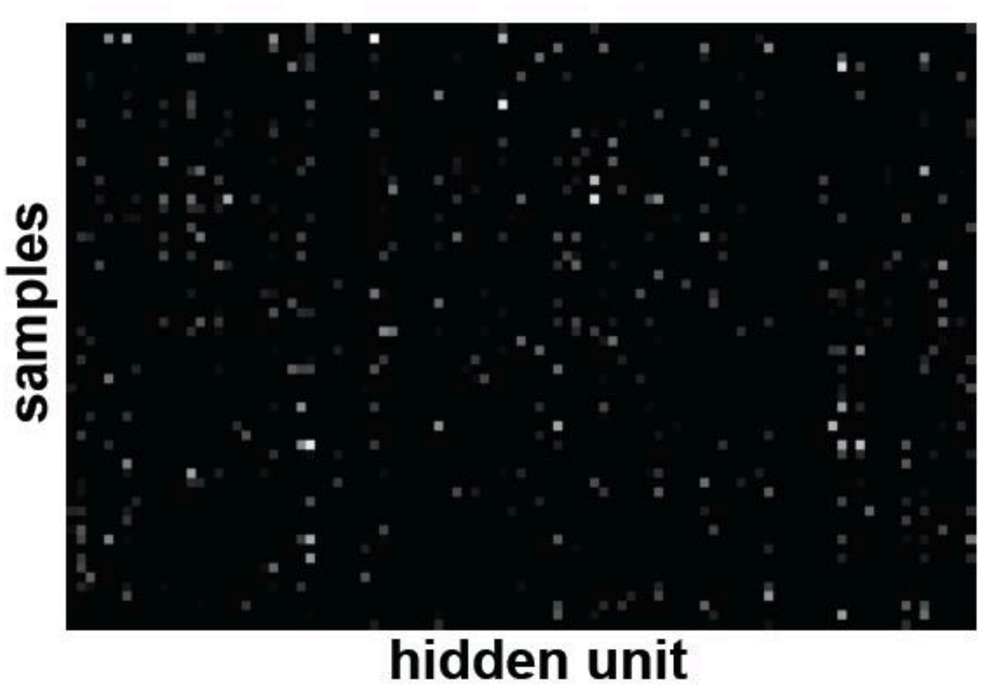


If output has a different size:



Other good things to know

- Check gradients numerically by finite differences
- Visualize hidden activations — should be uncorrelated and high variance

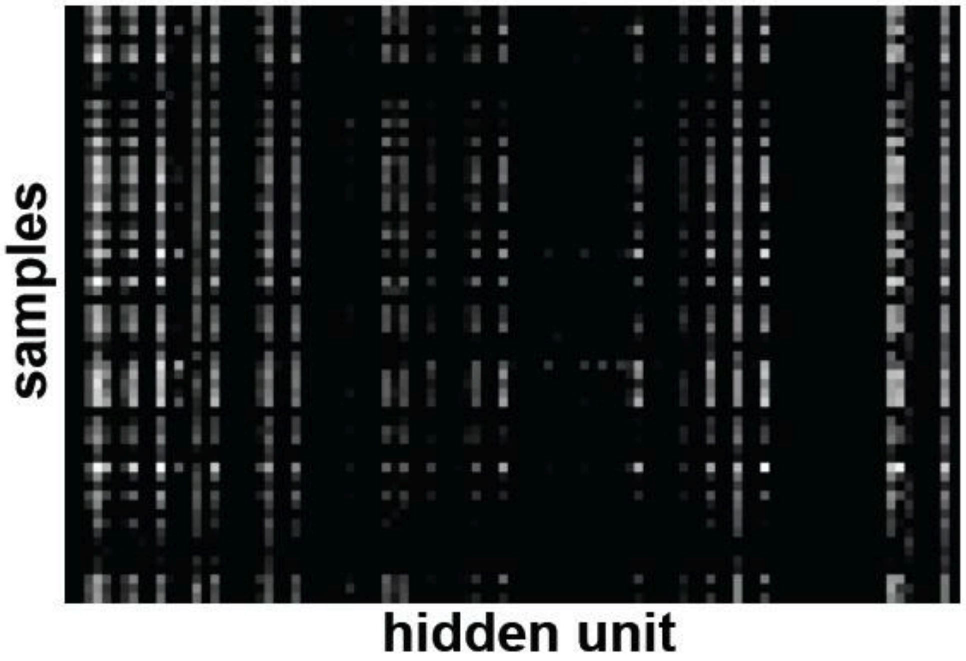


Good training: hidden units are sparse across samples and across features.

[Derived from slide by Marc'Aurelio Ranzato]

Other good things to know

- Check gradients numerically by finite differences
- Visualize hidden activations — should be uncorrelated and high variance

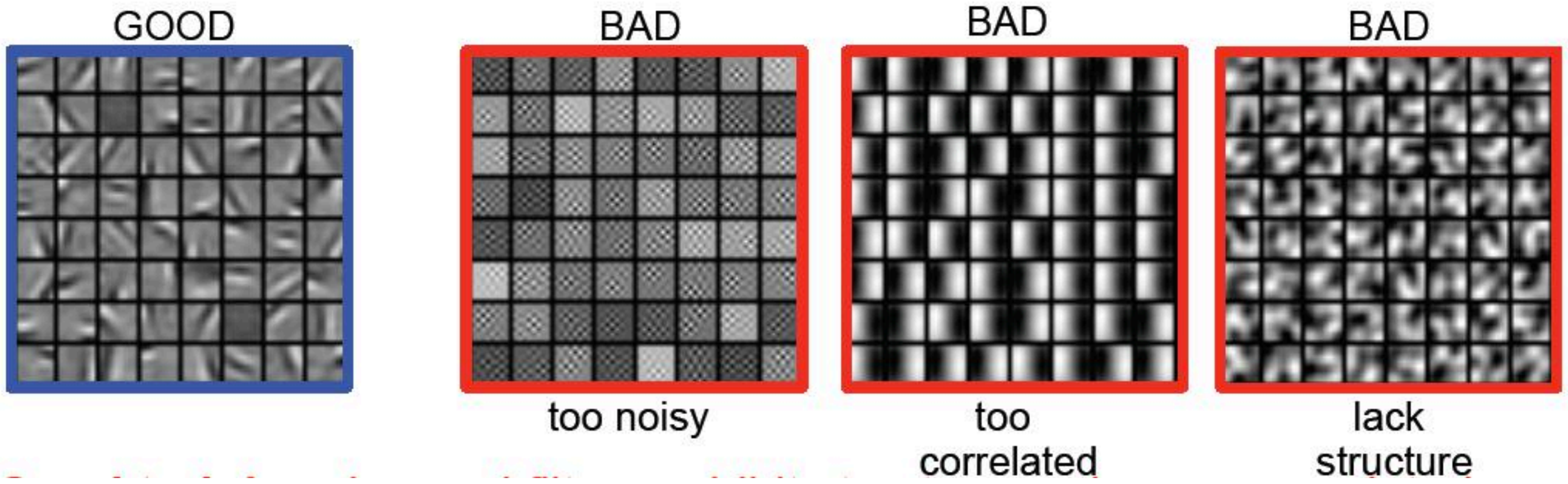


Bad training: many hidden units ignore the input and/or exhibit strong correlations.

[Derived from slide by Marc'Aurelio Ranzato]

Other good things to know

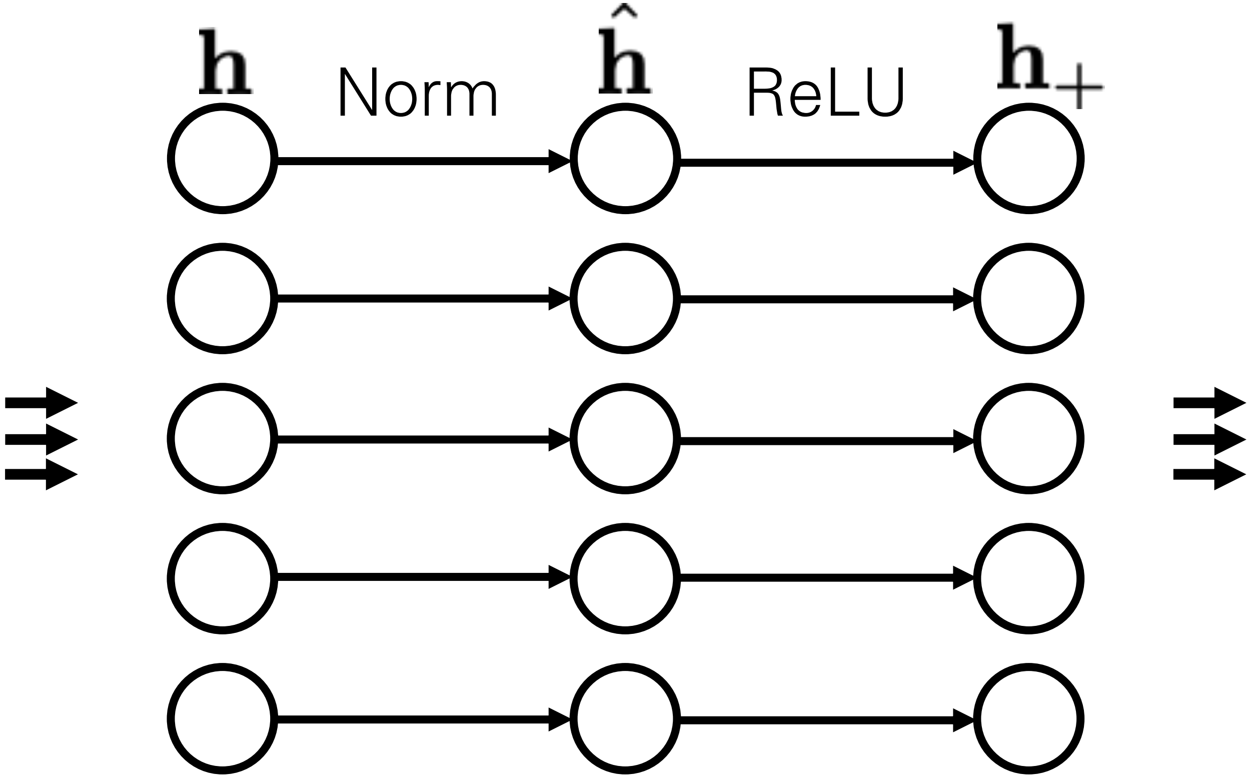
- Check gradients numerically by finite differences
- Visualize hidden activations — should be uncorrelated and high variance
- Visualize filters



Good training: learned filters exhibit structure and are uncorrelated.

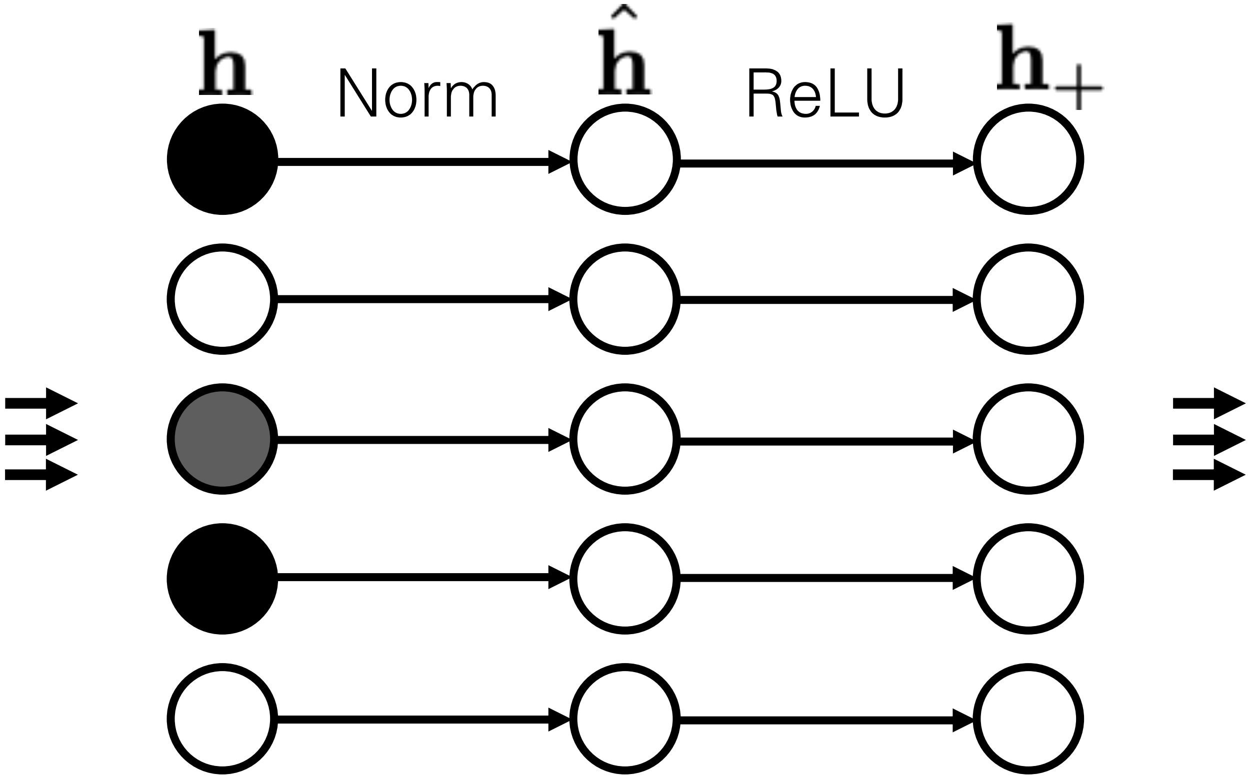
[Derived from slide by Marc'Aurelio Ranzato]

Normalization layers



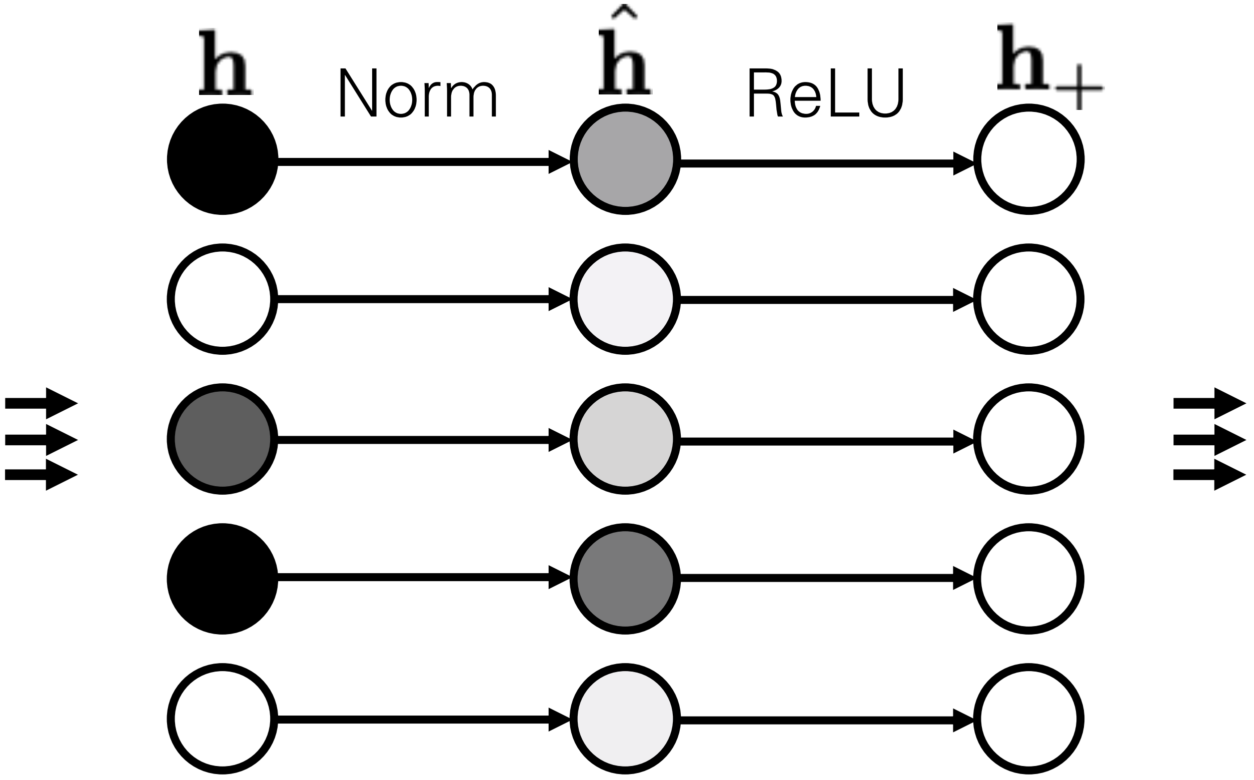
$$\hat{h}_k = \frac{h_k - \mathbb{E}[h_k]}{\sqrt{\mathtt{Var}[h_k]}}$$

Normalization layers



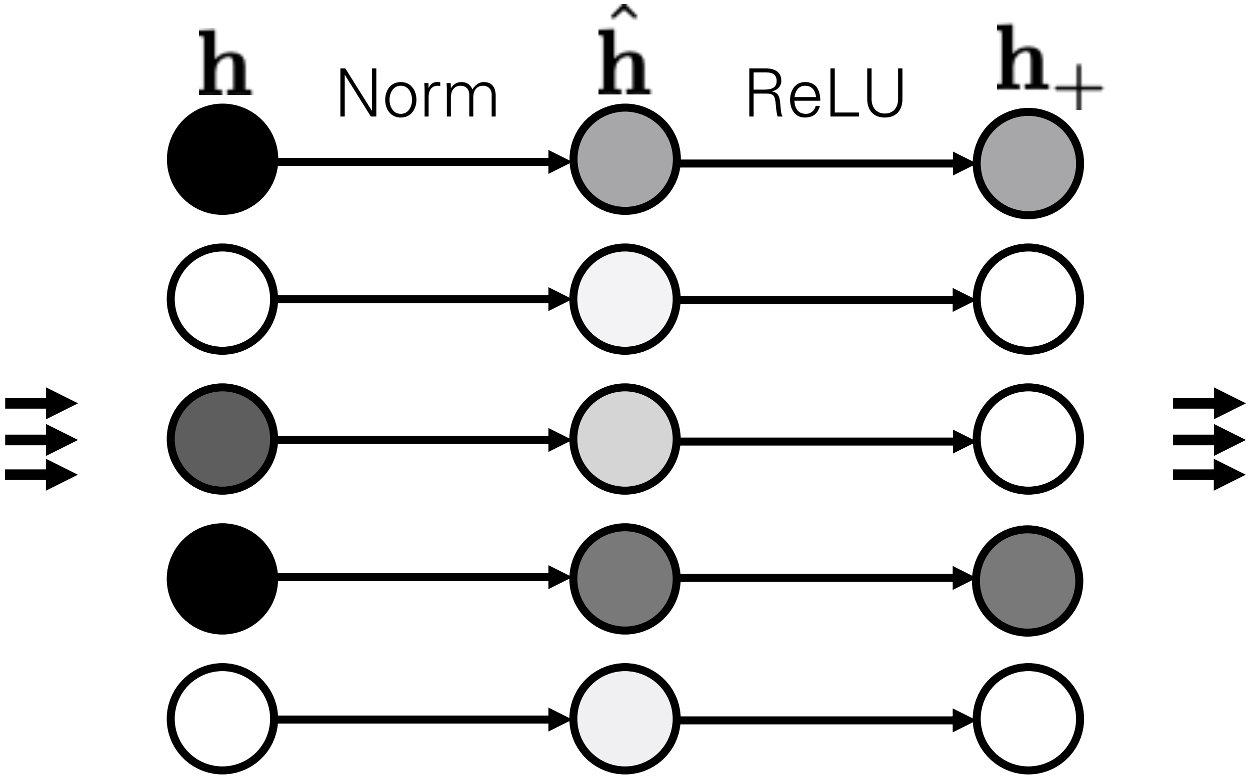
$$\hat{h}_k = \frac{h_k - \mathbb{E}[h_k]}{\sqrt{\mathtt{Var}[h_k]}}$$

Normalization layers



$$\hat{h}_k = \frac{h_k - \mathbb{E}[h_k]}{\sqrt{\mathtt{Var}[h_k]}}$$

Normalization layers



$$\hat{h}_k = \frac{h_k - \mathbb{E}[h_k]}{\sqrt{\mathtt{Var}[h_k]}}$$

Normalization layers

Keep track of mean and variance of a unit (or a population of units) over time.

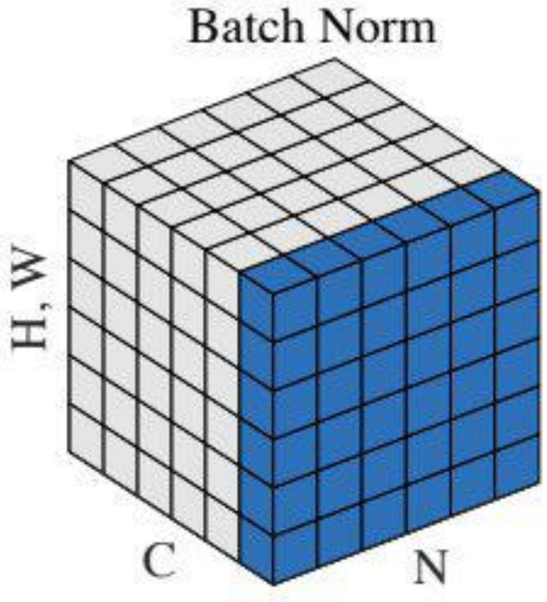
Standardize unit activations by subtracting mean and dividing by variance.

Squashes units into a **standard range**, avoiding overflow.

Also achieves **invariance** to mean and variance of the training signal.

Both these properties reduce the effective capacity of the model, i.e. regularize the model.

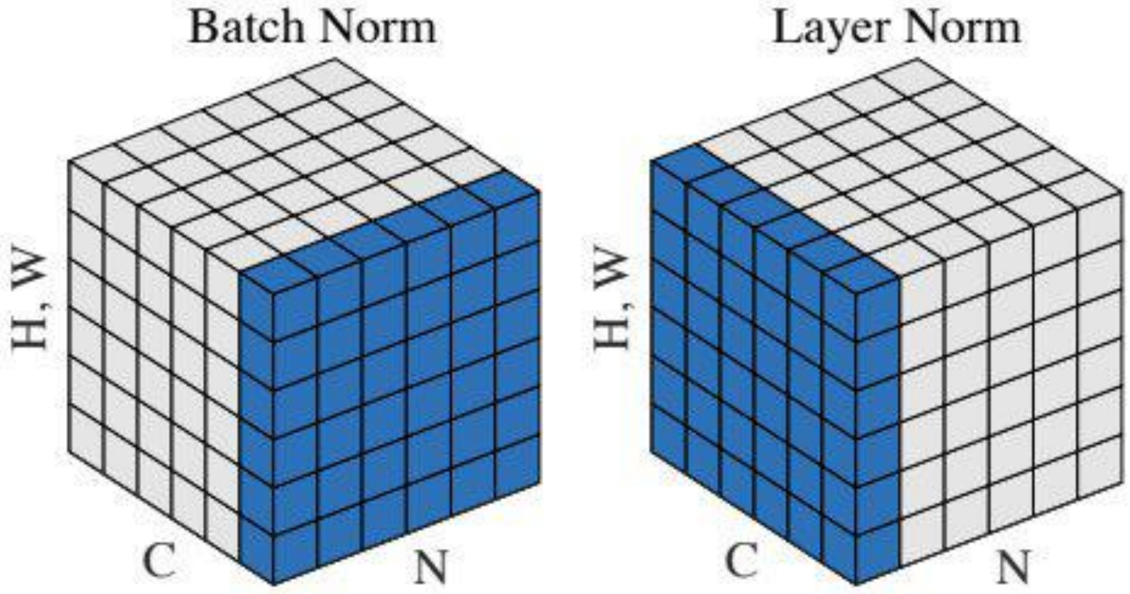
Normalization layers

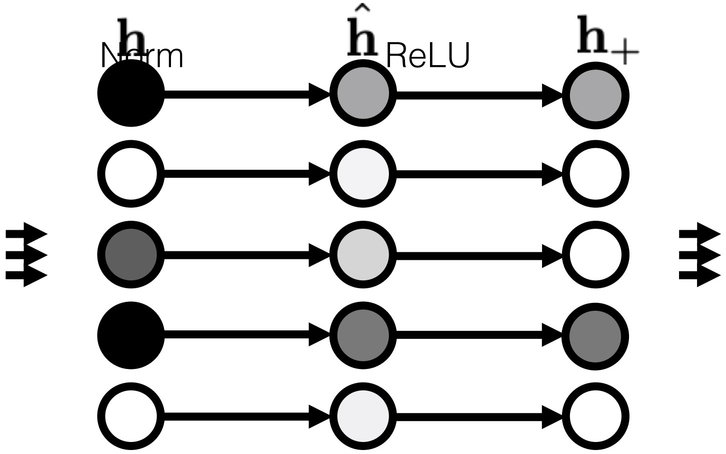


Normalize w.r.t. a single hidden unit's pattern of activation over training examples (a batch of examples).

[Figure from Wu & He, arXiv 2018]

Normalization layers

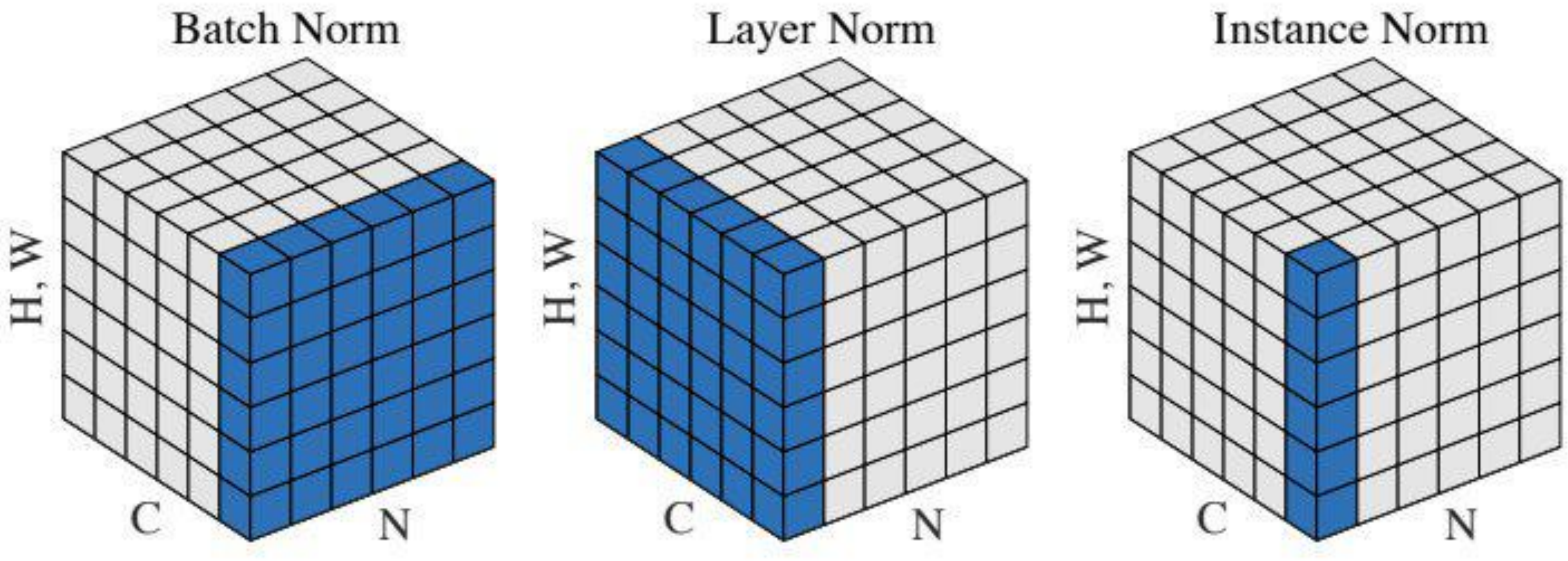




Normalize w.r.t. the mean and variance of the activations of all the hidden units (neurons) on this layer (c).

[Figure from Wu & He, arXiv 2018]

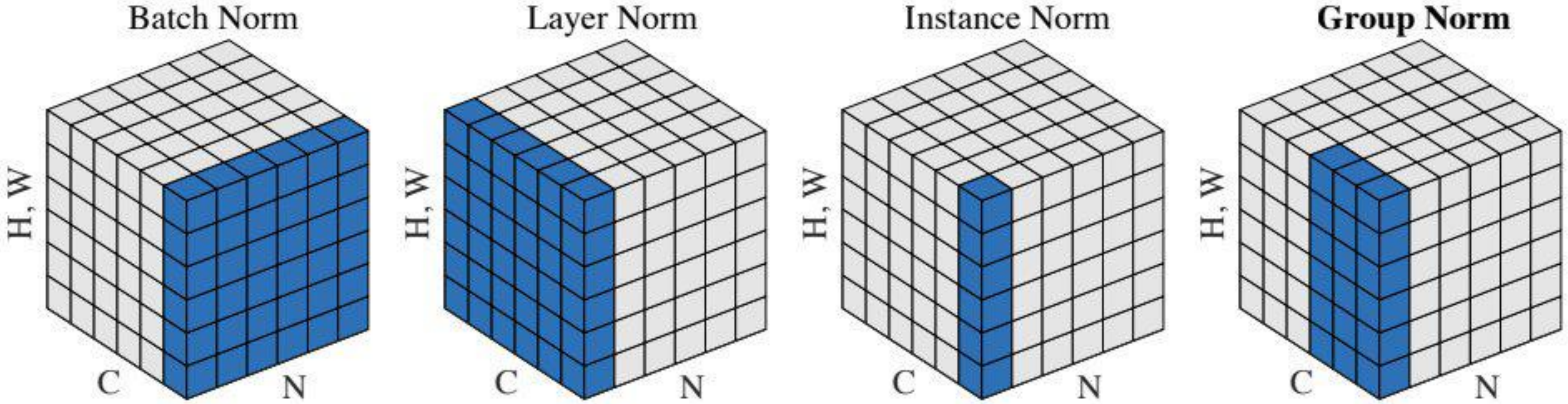
Normalization layers



Normalize w.r.t. the mean and variance of the activations of all the hidden units (neurons) on this layer (c) that process this particular location (h,w) in the image.

[Figure from Wu & He, arXiv 2018]

Normalization layers

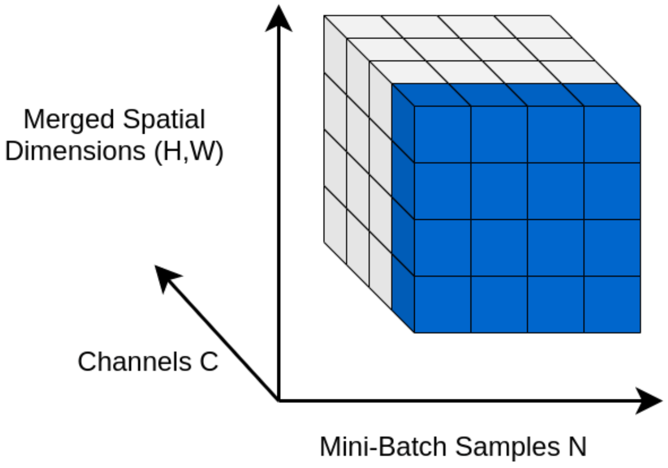


Might as well…

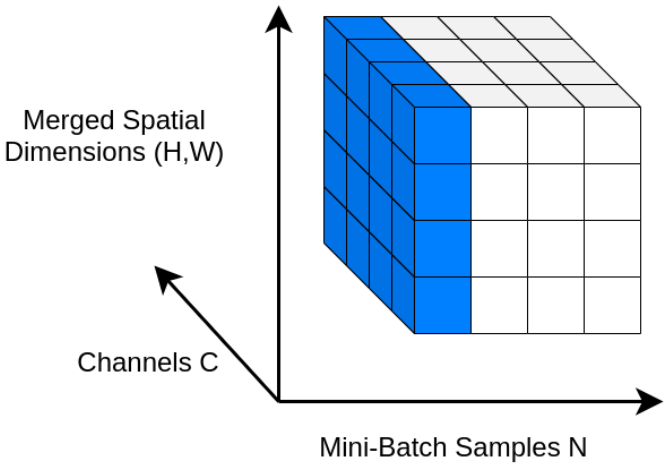
[Figure from Wu & He, arXiv 2018]

Normalization layers

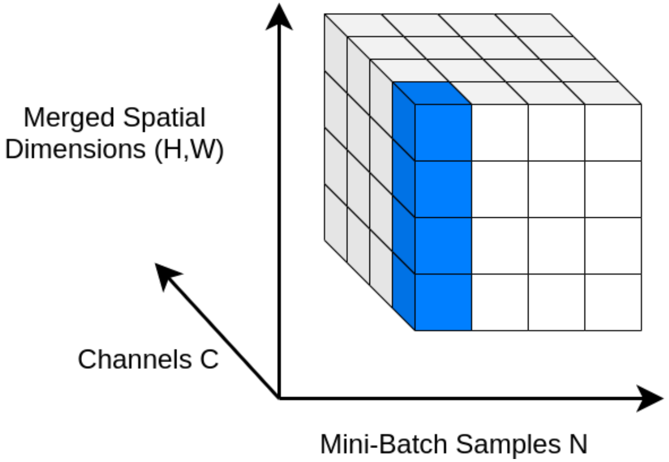
Batch Normalization (2015)



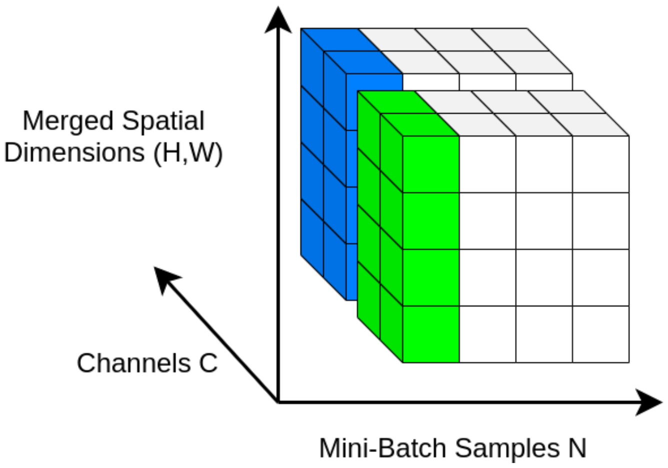
Layer Normalization (2016)



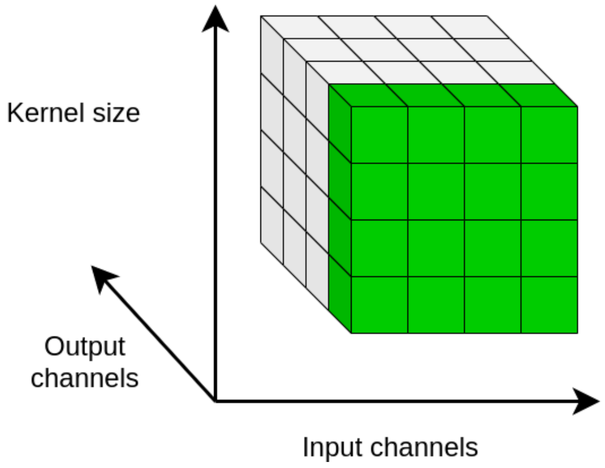
Instance Normalization (2016)



Group Normalization (2018)



Weight Standardization (2019)



[https://theaisummer.com/normalization]

No normalization layers

2101.08692.pdf
Page 1 of 30

Published as a conference paper at ICLR 2021

CHARACTERIZING SIGNAL PROPAGATION TO CLOSE THE PERFORMANCE GAP IN UNNORMALIZED RESNETS

Andrew Brock, Soham De & Samuel L. Smith
Deepmind
{ajbrock, sohamde, slsmith}@google.com

ABSTRACT

Batch Normalization is a key component in almost all state-of-the-art image classifiers, but it also introduces practical challenges: it breaks the independence between training examples within a batch, can incur compute and memory overhead, and often results in unexpected bugs. Building on recent theoretical analyses of deep ResNets at initialization, we propose a simple set of analysis tools to characterize signal propagation on the forward pass, and leverage these tools to design highly performant ResNets without activation normalization layers. Crucial to our success is an adapted version of the recently proposed Weight Standardization. Our analysis tools show how this technique preserves the signal in networks with ReLU or Swish activation functions by ensuring that the per-channel activation means do not grow with depth. Across a range of FLOP budgets, our networks attain performance competitive with the state-of-the-art EfficientNets on ImageNet.

1 INTRODUCTION

BatchNorm has become a core computational primitive in deep learning (Ioffe & Szegedy, 2015), and it is used in almost all state-of-the-art image classifiers (Tan & Le, 2019; Wei et al., 2020). A number of different benefits of BatchNorm have been identified. It smoothens the loss landscape (Santurkar et al., 2018), which allows training with larger learning rates (Bjorck et al., 2018), and the noise arising from the minibatch estimates of the batch statistics introduces implicit regularization (Luo et al., 2019). Crucially, recent theoretical work (Balduzzi et al., 2017; De & Smith, 2020) has demonstrated that BatchNorm ensures good signal propagation at initialization in deep residual networks with identity skip connections (He et al., 2016b;a), and this benefit has enabled practitioners to train deep ResNets with hundreds or even thousands of layers (Zhang et al., 2019).

However, BatchNorm also has many disadvantages. Its behavior is strongly dependent on the batch

2102.06171.pdf
Page 1 of 22

High-Performance Large-Scale Image Recognition Without Normalization

Andrew Brock [1] **Soham De** [1] **Samuel L. Smith** [1] **Karen Simonyan** [1]

Abstract

Batch normalization is a key component of most image classification models, but it has many undesirable properties stemming from its dependence on the batch size and interactions between examples. Although recent work has succeeded in training deep ResNets without normalization layers, these models do not match the test accuracies of the best batch-normalized networks, and are often unstable for large learning rates or strong data augmentations. In this work, we develop an adaptive gradient clipping technique which overcomes these instabilities, and design a significantly improved class of Normalizer-Free ResNets. Our smaller models match the test accuracy of an EfficientNet-B7 on ImageNet while being up to 8.7× faster to train, and our largest models attain a new state-of-the-art top-1 accuracy of 86.5%. In addition, Normalizer-Free models attain significantly better performance than their batch-normalized counterparts when fine-tuning on ImageNet after large-scale pre-training on a dataset of 300 million labeled images, with our best models obtaining an accuracy of 89.2%.[2]

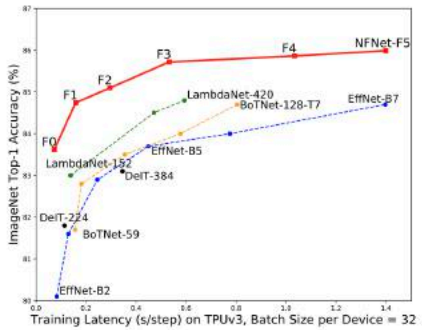


Figure 1. **ImageNet Validation Accuracy vs Training Latency.** All numbers are single-model, single crop. Our NFNet-F1 model achieves comparable accuracy to an EffNet-B7 while being 8.7× faster to train. Our NFNet-F5 model has similar training latency to EffNet-B7, but achieves a state-of-the-art 86.0% top-1 accuracy on ImageNet. We further improve on this using Sharpness Aware Minimization (Foret et al., 2021) to achieve 86.5% top-1 accuracy.

1. Introduction

The vast majority of recent models in computer vision are variants of deep residual networks (He et al., 2016b;a), trained with batch normalization (Ioffe & Szegedy, 2015).

However, batch normalization has three significant practical disadvantages. First, it is a surprisingly expensive computational primitive, which incurs memory overhead (Rota Bulò et al., 2018), and significantly increases the time required to evaluate the gradient in some networks (Gitman & Ginsburg, 2017). Second, it introduces a discrepancy between the behaviour of the model during training and at inference time (Summers & Dinneen, 2019; Singh & Shrivastava, 2019),

Next Lecture:
Sequential Processing with RNNs