PSY9511: Seminar 7

Deep learning for computer vision tasks

Esten H. Leonardsen

07.11.24

UNIVERSITY
OF OSLO

Outline

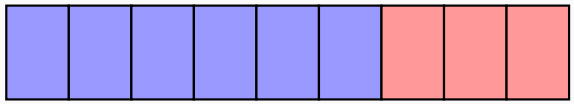
1. Exercise 4
2. Deep learning with artificial neural networks
3. Convolutional neural networks for computer vision

Weekly exercises

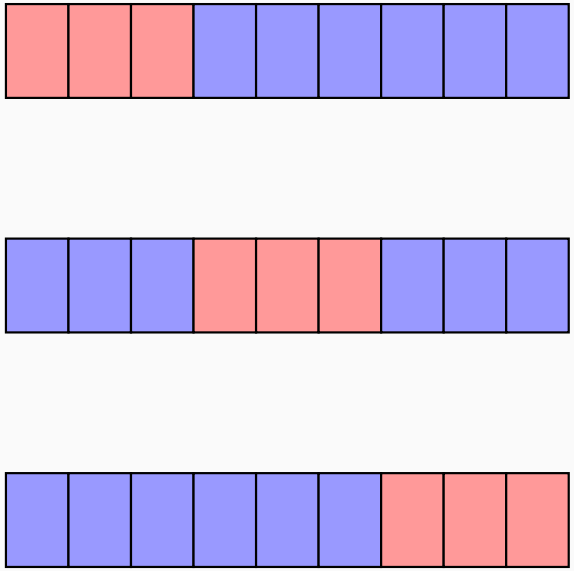
- The weekly exercises are **mandatory**
- The deadlines are **strict**

Validation procedures

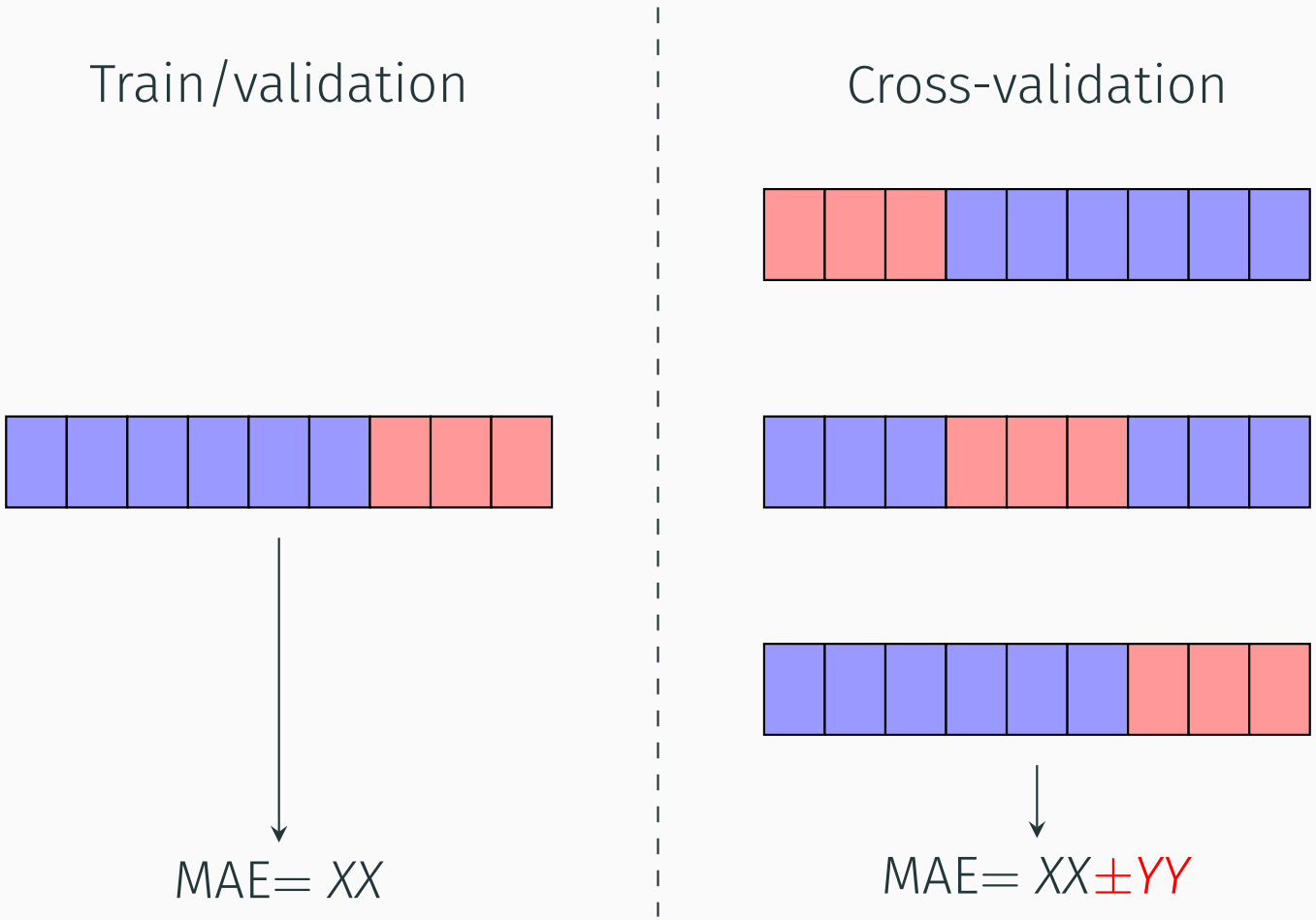
Train/validation



Cross-validation



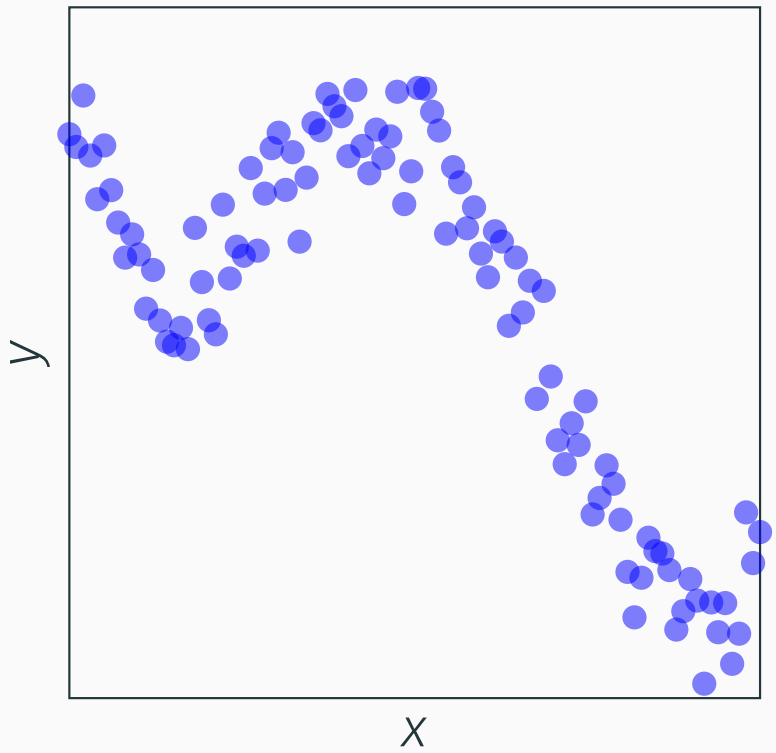
Validation procedures



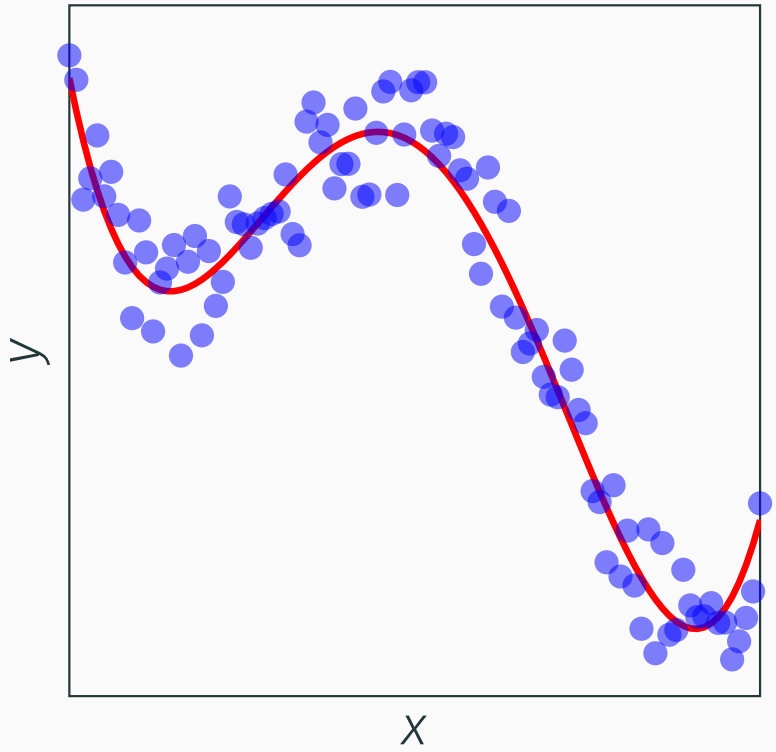
Deep learning

UNIVERSITY
OF OSLO

Deep learning: Motivation

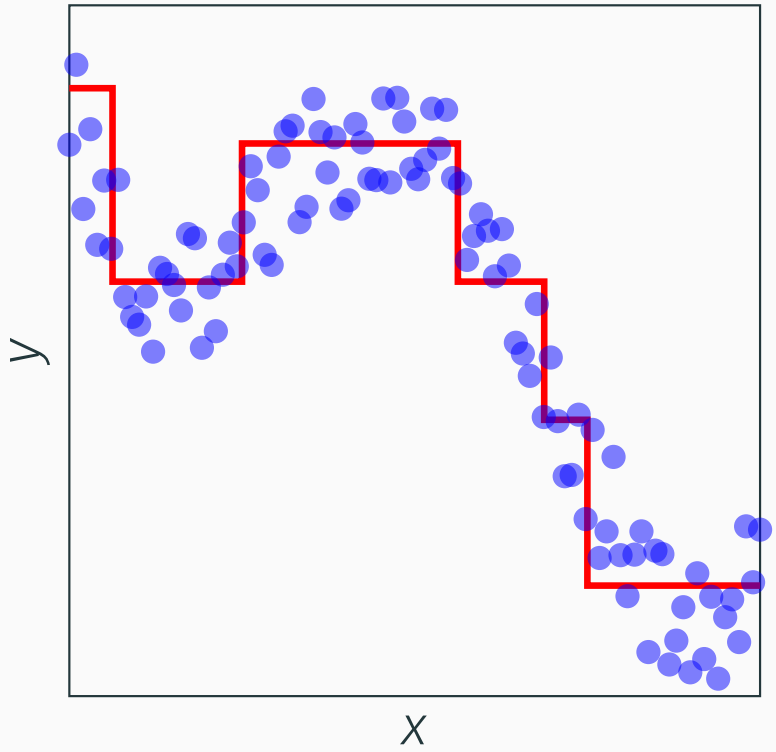


Deep learning: Motivation



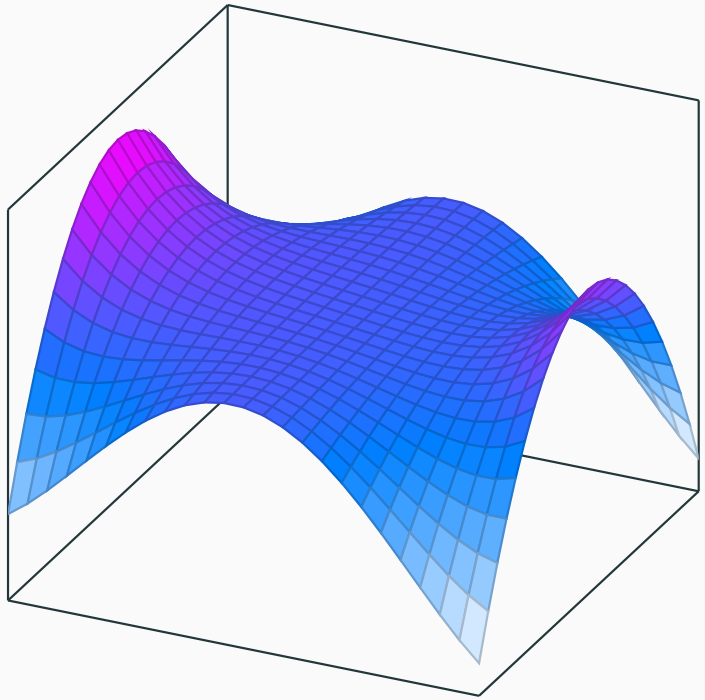
$$\hat{y} = s(x)$$

Deep learning: Motivation

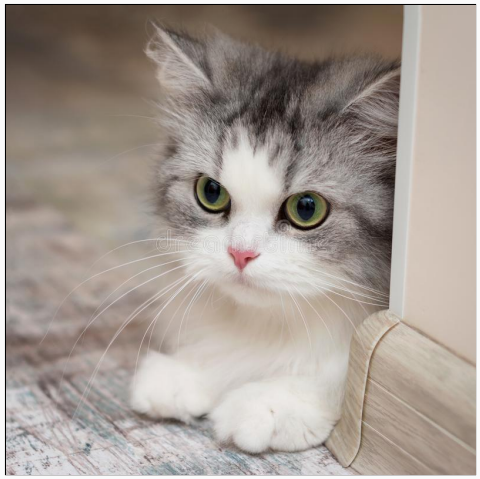


$$\hat{y} = \begin{cases} 4 & \cdots \\ 3 & 0.2 \leq x < 0.6 \\ 1.5 & \cdots \end{cases}$$

Deep learning: Motivation

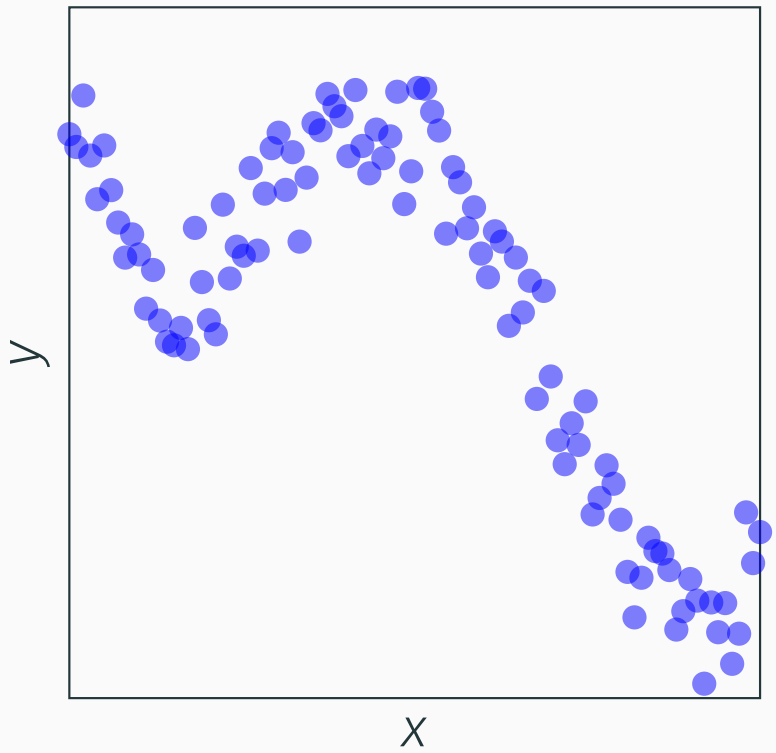


Deep learning: Motivation

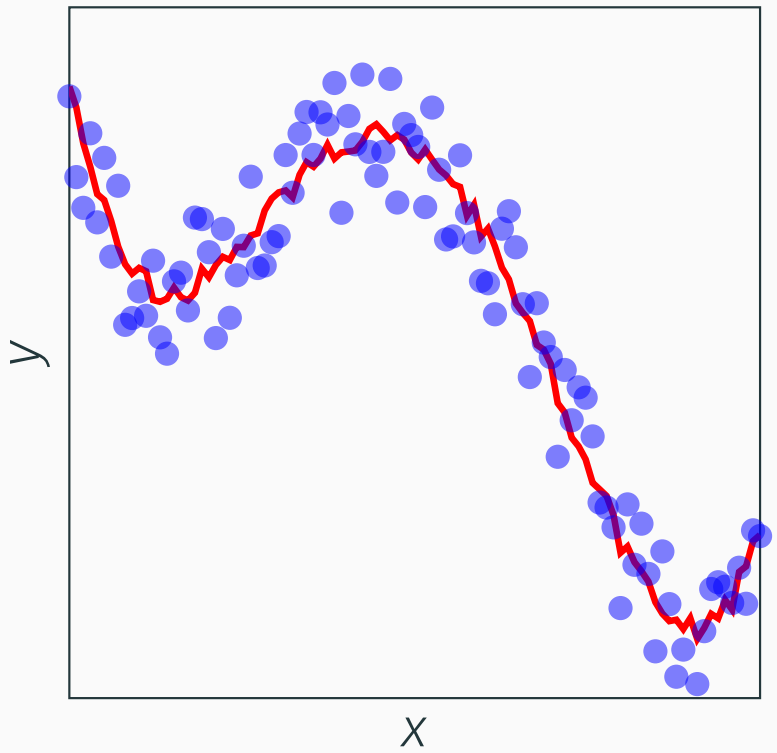


The cat wagged its tail

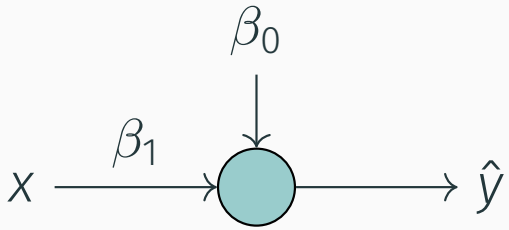
Deep learning: Motivation



Deep learning: Motivation

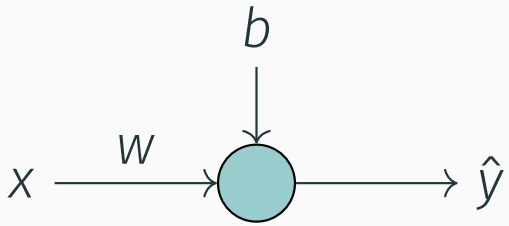


Deep learning: Artificial neural networks



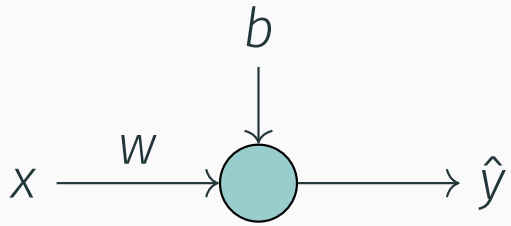
$$\hat{y} = \beta_0 + \beta_1 x$$

Deep learning: Artificial neural networks

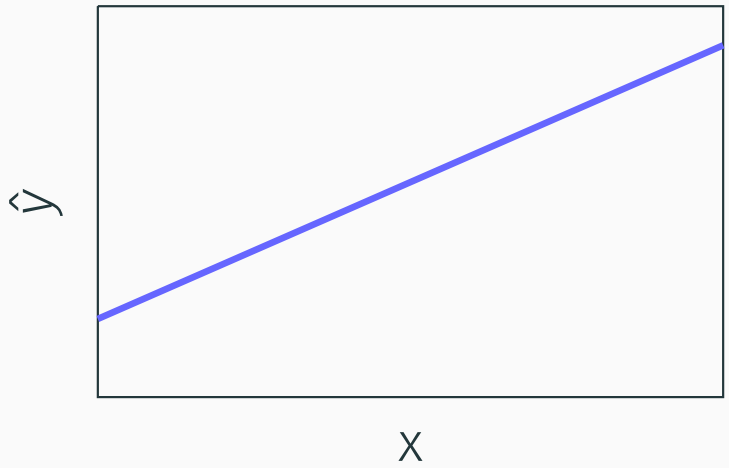


$$\hat{y} = wx + b$$

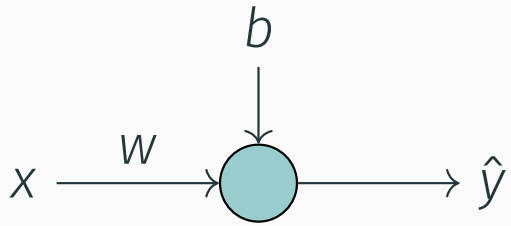
Deep learning: Artificial neural networks



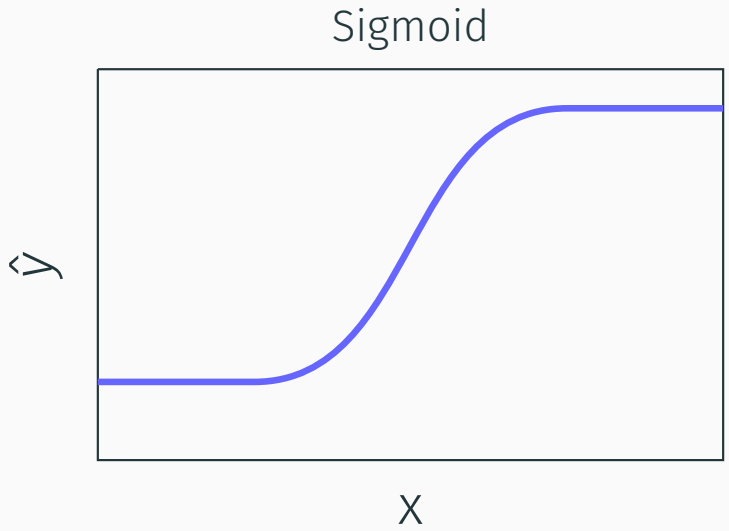
$$\hat{y} = wx + b$$



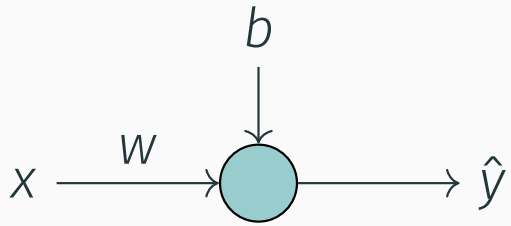
Deep learning: Artificial neural networks



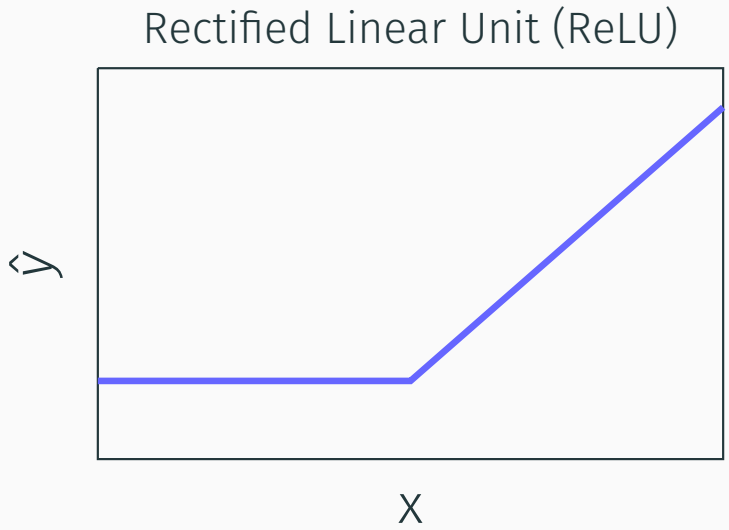
$$\hat{y} = \frac{e^{wx+b}}{1 + e^{wx+b}}$$



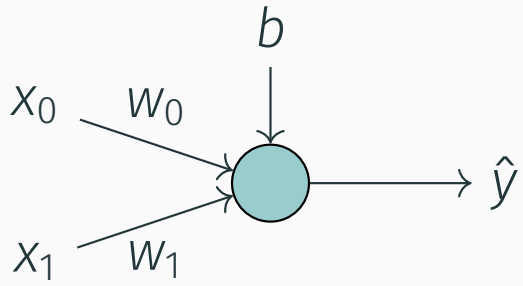
Deep learning: Artificial neural networks



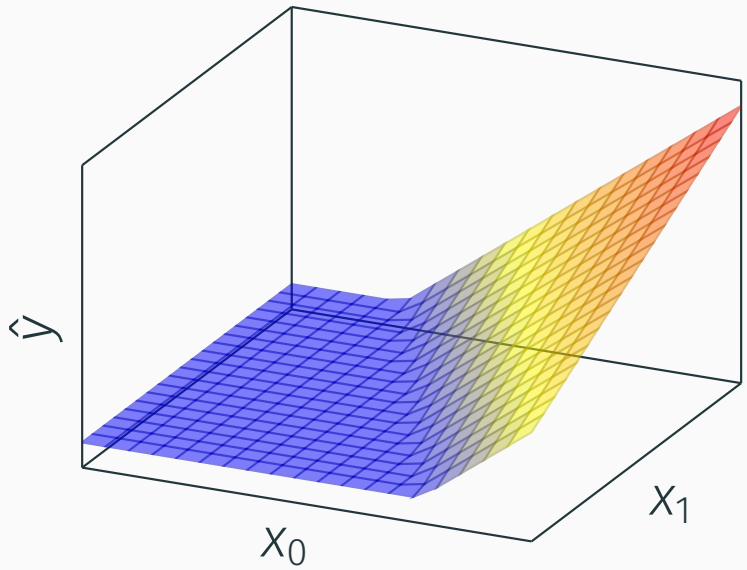
$$\hat{y} = max(0, wx + b)$$



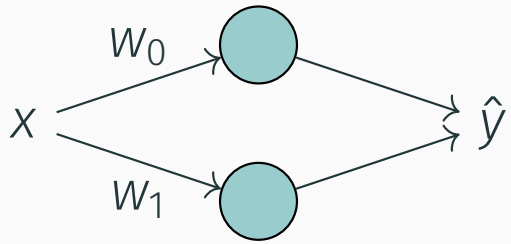
Deep learning: Artificial neural networks



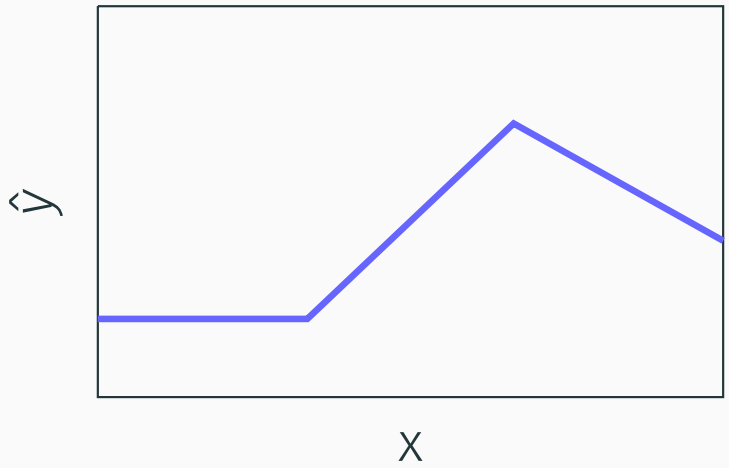
$$\hat{y} = max(0, w_0 x_0 + w_1 x_1 + b)$$



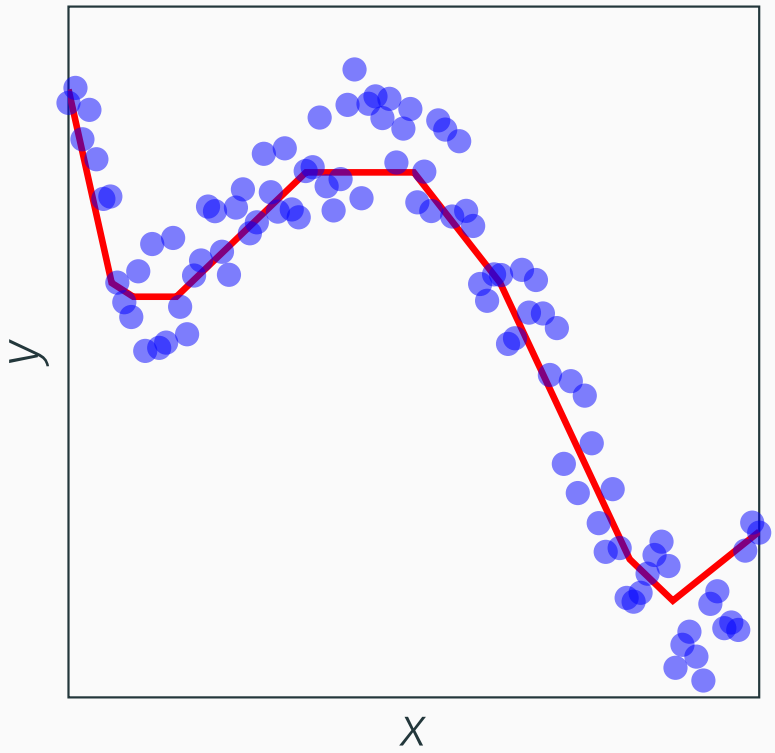
Deep learning: Artificial neural networks



$$\hat{y} = max(0, w_0 x + b_0) + max(0, w_1 x + b_1)$$



Deep learning: Artificial neural networks



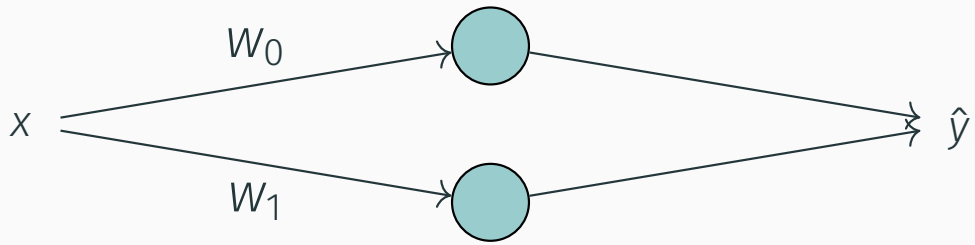
Piecewise linear function

Deep learning: Artificial neural networks

Universal approximation theorem:

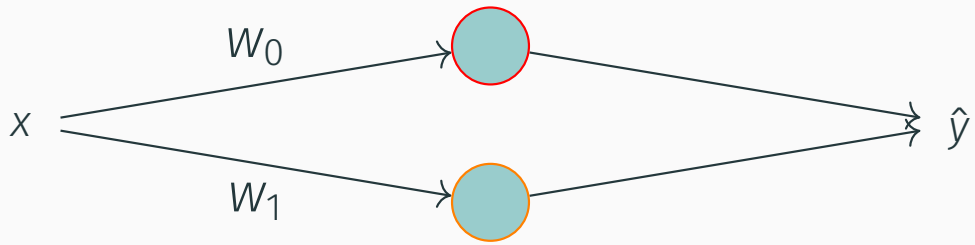
"Any relationship that can be described with a polynomial function can be approximated by a neural network with a single hidden layer."

Deep learning: Artificial neural networks



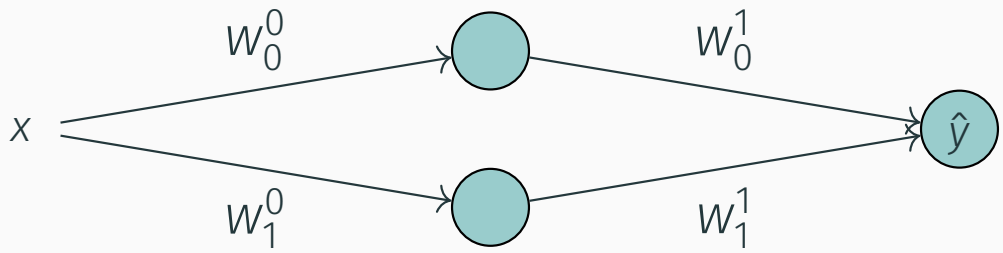
$$\hat{y} = max(0, w_0 x + b_0) + max(0, w_1 x + b_1)$$

Deep learning: Artificial neural networks



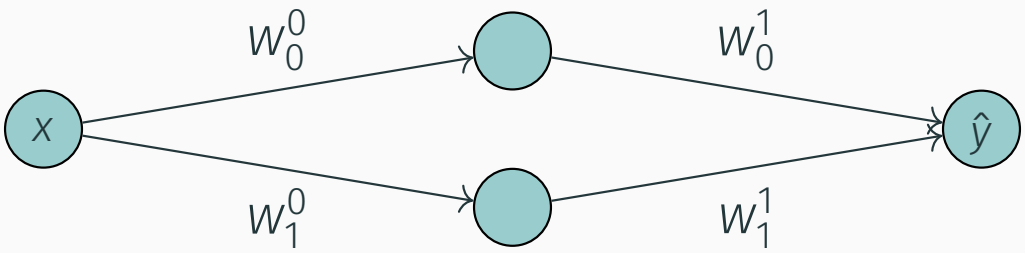
$$\hat{y} = max(0, w_0 x + b_0) + max(0, w_1 x + b_1)$$

Deep learning: Artificial neural networks



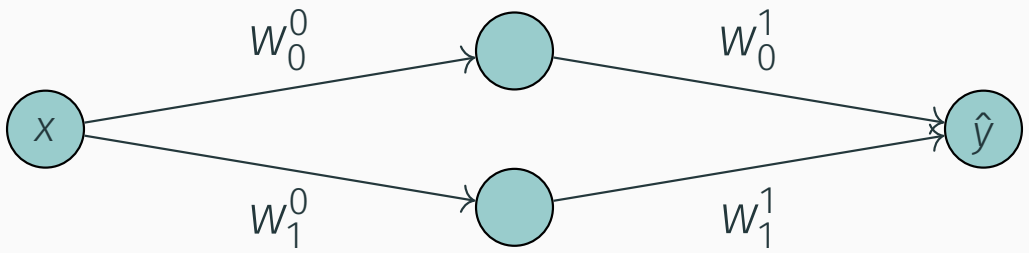
$$\hat{y} = max(0, w_0^1 * max(0, w_0^0 * x + b_0^0) + w_1^1 * max(0, w_1^0 * x + b_1^0) + b_0^1)$$

Deep learning: Artificial neural networks



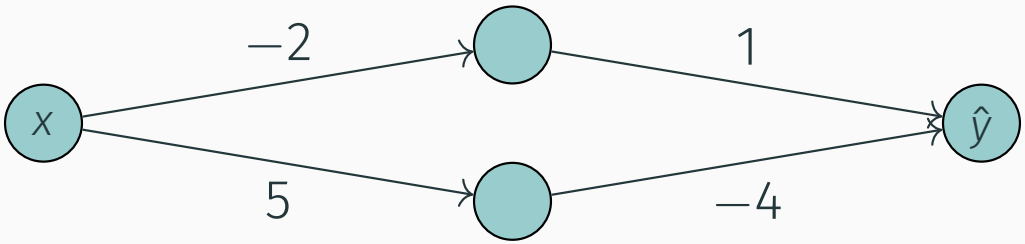
$$\hat{y} = max(0, w_0^1 * max(0, w_0^0 * x + b_0^0) + w_1^1 * max(0, w_1^0 * x + b_1^0) + b_0^1)$$

Deep learning: Artificial neural networks

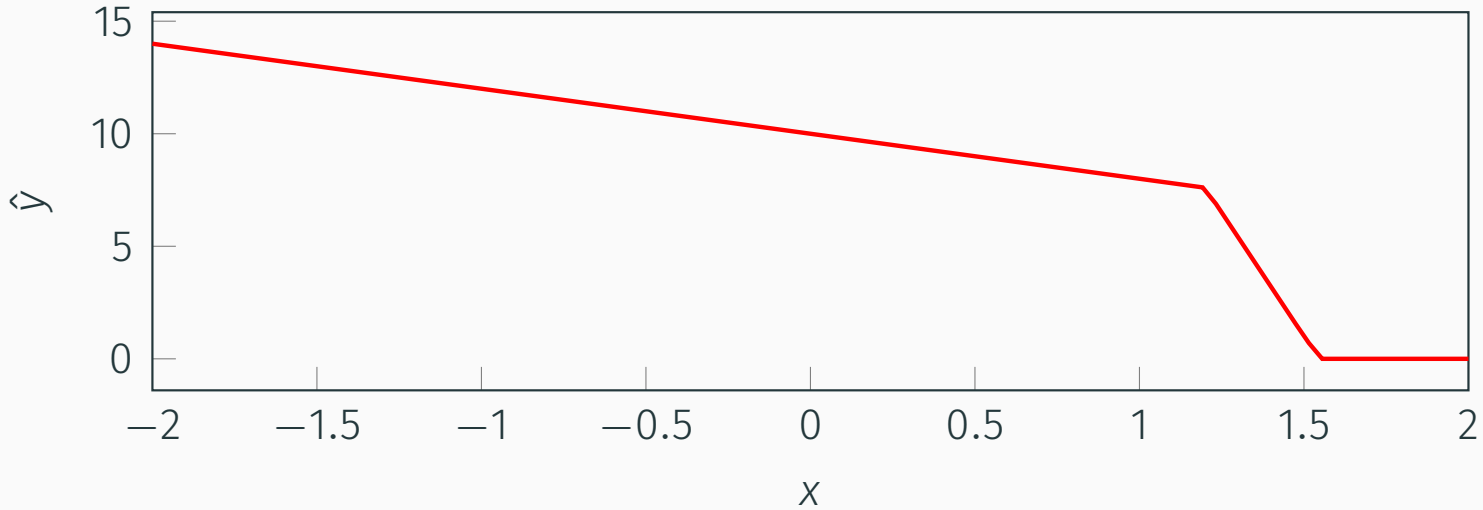


$$\hat{y} = max(0, w_0^1 * max(0, w_0^0 * x + b_0^0) + w_1^1 * max(0, w_1^0 * x + b_1^0) + b_0^1)$$

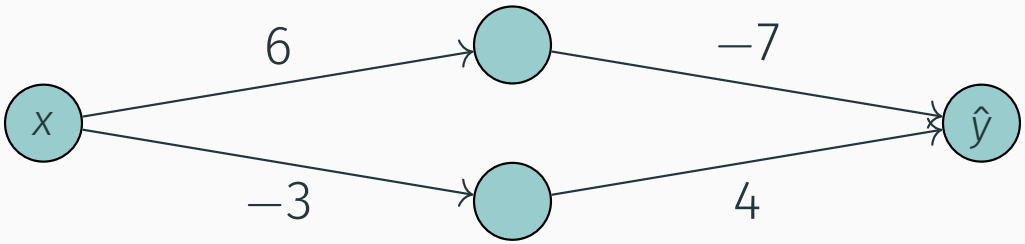
Deep learning: Artificial neural networks



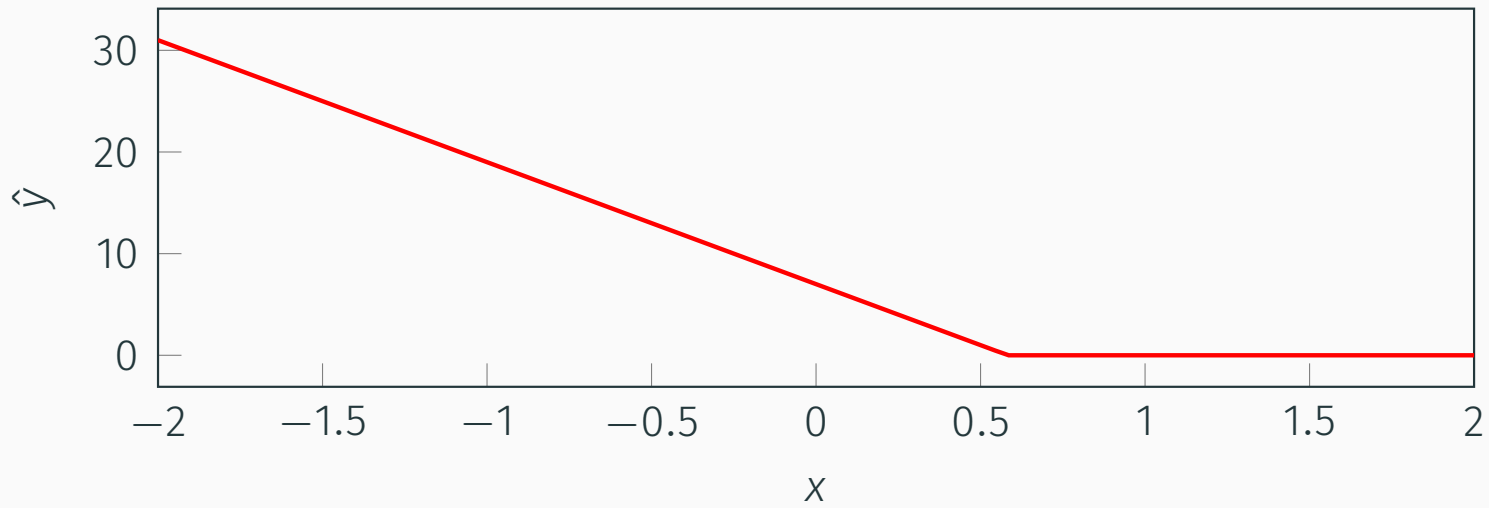
$$\hat{y} = max(0, 1 * max(0, (-2) * x + 3) + (-4) * max(0, 5 * x + (-6)) + 7)$$



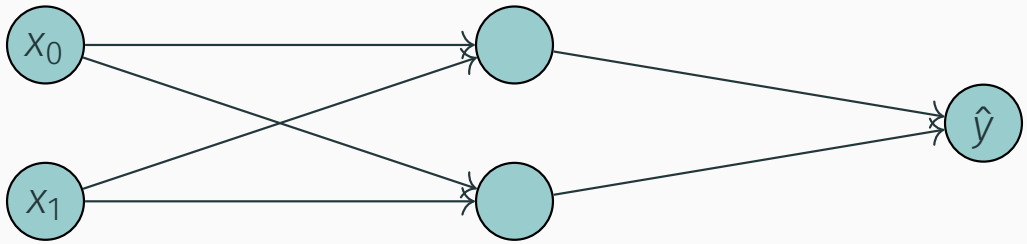
Deep learning: Artificial neural networks



$$\hat{y} = max(0, -7 * max(0, 6 * x + (-5)) + 4 * max(0, (-3) * x + 2) - 1)$$

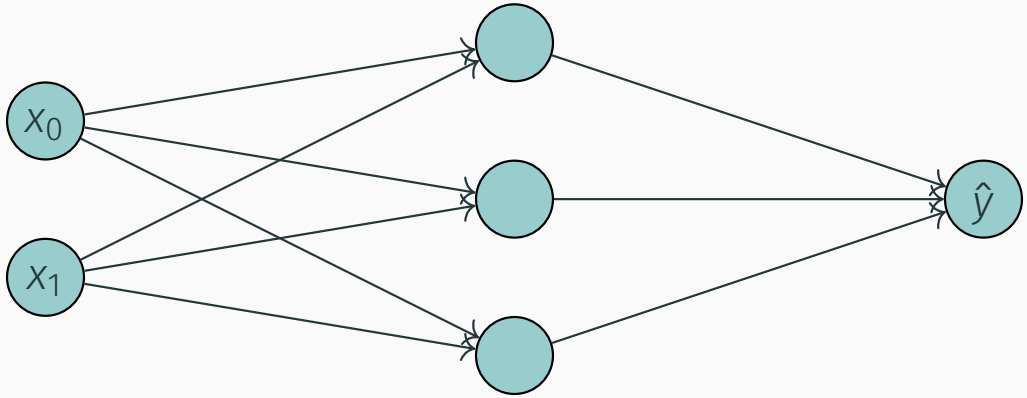


Deep learning: Artificial neural networks



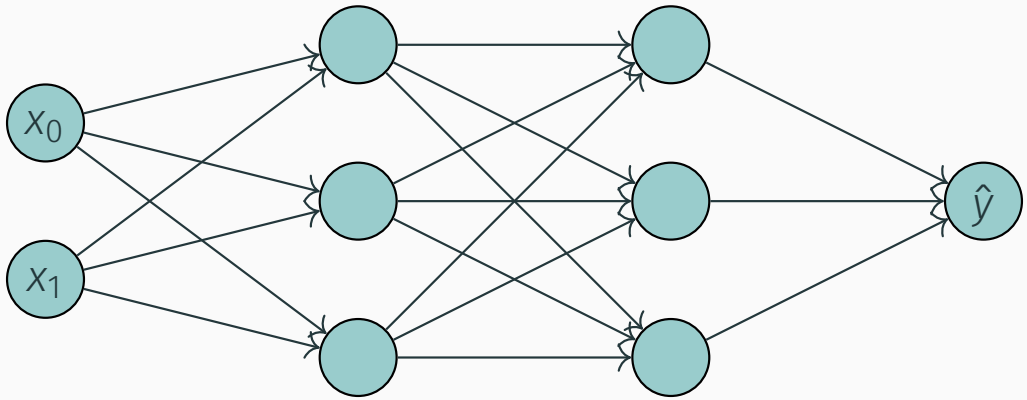
$$\hat{y} = max(0, w^1_{0,0} * max(0, w^0_{0,0} * x_0 + w^0_{1,0} * x_1 + b_{0,0}) + w^1_{1,0} * max(0, w^0_{0,1} * x_0 + w^0_{1,1} * x_1 + b_{0,1}) + b_1)$$

Deep learning: Artificial neural networks



$$\hat{y} = max(0, w^1_{0,0} * max(0, w^0_{0,0} * x_0 + w^0_{1,0} * x_1 + b_{0,0}) + w^1_{1,0} * max(0, w^0_{0,1} * x_0 + w^0_{1,1} * x_1 + b_{0,1}) + w^1_{2,0} * max(0, w^0_{0,2} * x_0 + w^0_{1,2} * x_1 + b_{0,2}) + b_1)$$

Deep learning: Artificial neural networks



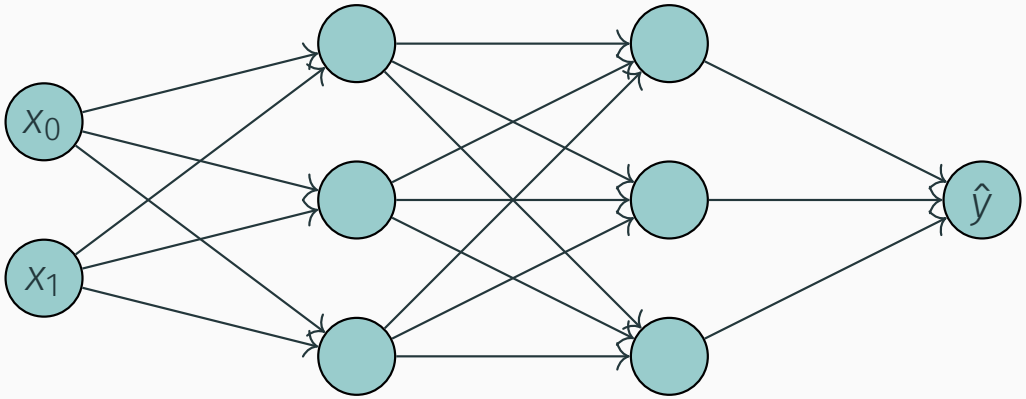
$$
\begin{aligned}
\hat{y} = max(0, & w^2_{0,0} * max(0, w^1_{0,0} * max(0, w^0_{0,0} * x_0 + w^0_{1,0} * x_1 + b_{0,0}) + \\
& w^1_{1,0} * max(0, w^0_{0,1} * x_0 + w^0_{1,1} * x_1 + b_{0,1}) + \\
& w^1_{2,0} * max(0, w^0_{0,2} * x_0 + w^0_{1,2} * x_1 + b_{0,2}) + \\
& b_{1,0}) + \\
& w^2_{1,0} * max(0, w^1_{0,1} * max(0, w^0_{0,0} * x_0 + w^0_{1,0} * x_1 + b_{0,0}) + \\
& w^1_{1,1} * max(0, w^0_{0,1} * x_0 + w^0_{1,1} * x_1 + b_{0,1}) + \\
& w^1_{2,1} * max(0, w^0_{0,2} * x_0 + w^0_{1,2} * x_1 + b_{0,2}) + \\
& b_{1,1}) + \\
& w^2_{2,0} * max(0, w^1_{0,2} * max(0, w^0_{0,0} * x_0 + w^0_{1,0} * x_1 + b_{0,0}) + \\
& w^1_{1,2} * max(0, w^0_{0,1} * x_0 + w^0_{1,1} * x_1 + b_{0,1}) + \\
& w^1_{2,2} * max(0, w^0_{0,2} * x_0 + w^0_{1,2} * x_1 + b_{0,2}) + \\
& b_{1,2}) + \\
& b_2)
\end{aligned}
$$

Deep learning: Artificial neural networks

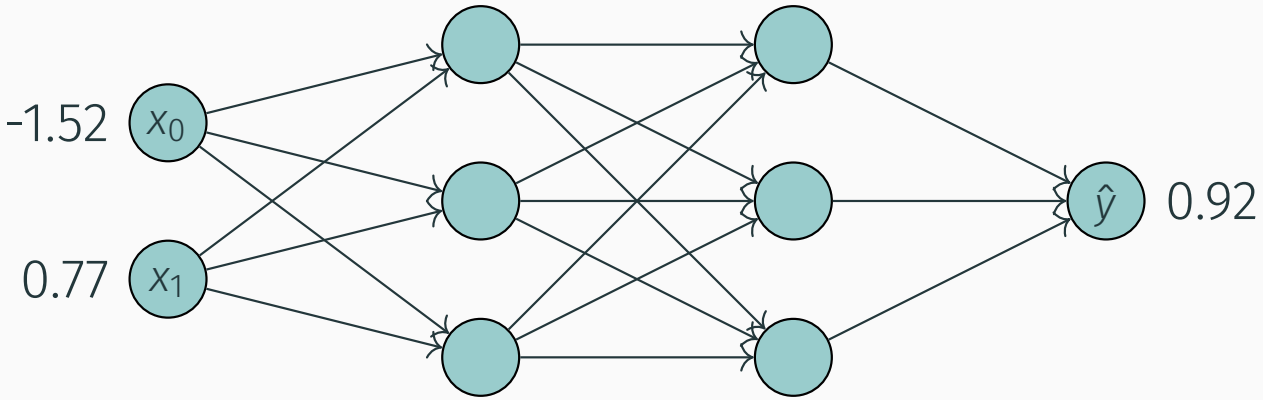
Artificial neural networks: Combines artificial neurons, simple computational units that compute a non-linear function of their inputs, in a computational graph

- Can approximate arbitrarily complex polynomial functions (given enough neurons)
- Organized in layers. We can expand a model in width (e.g. more neurons per layer) or depth (e.g. more layers)

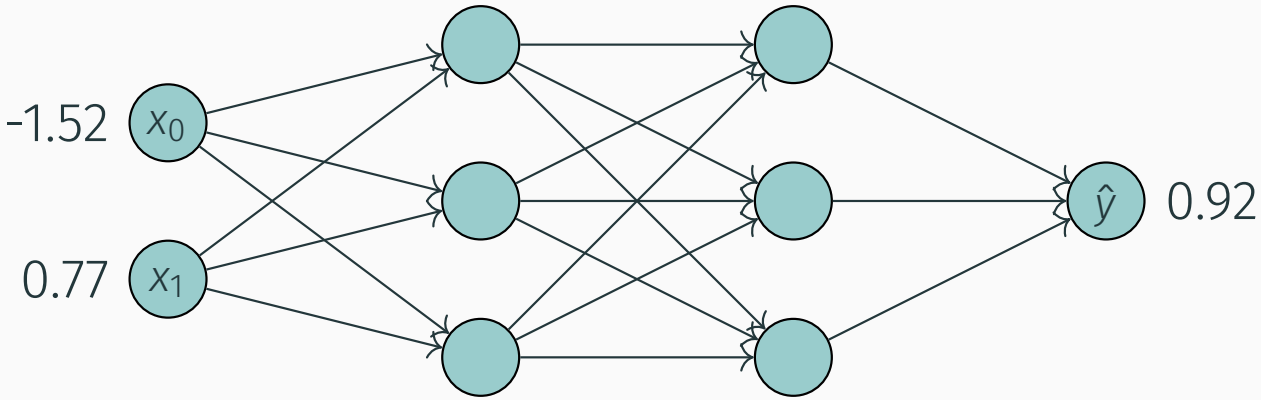
Deep learning: Loss functions



Deep learning: Loss functions

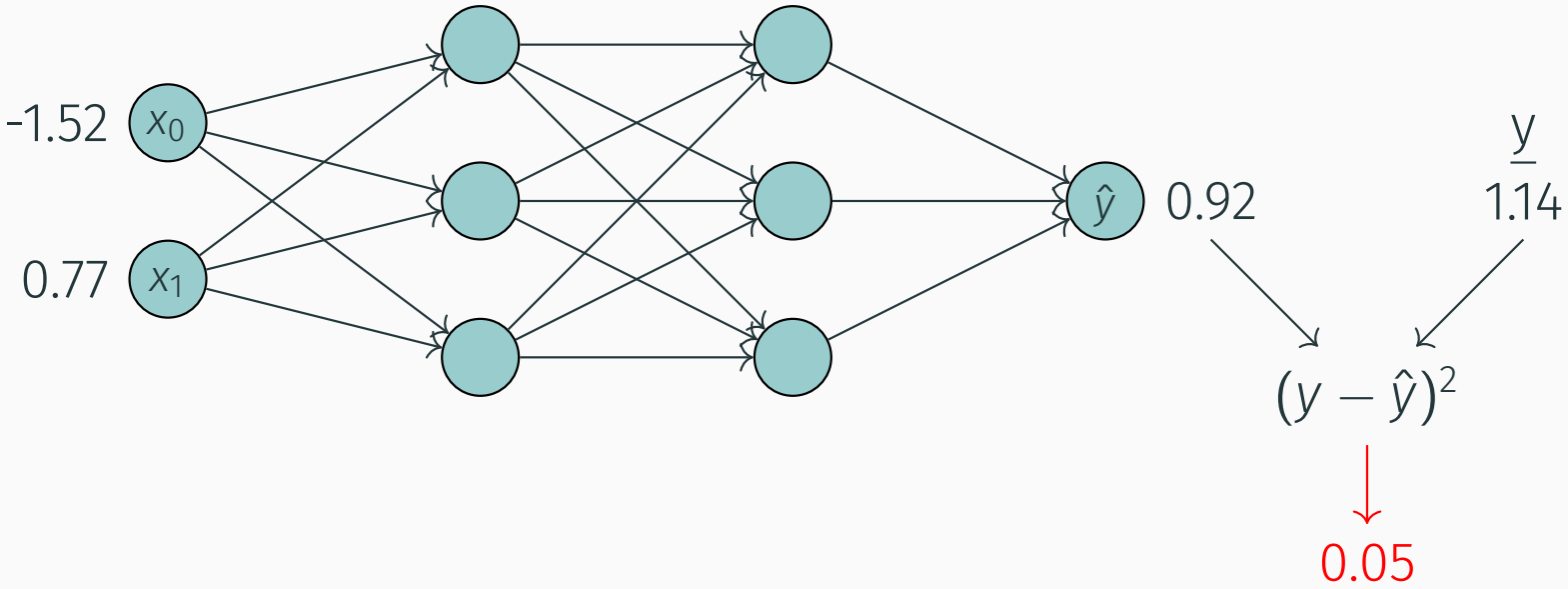


Deep learning: Loss functions

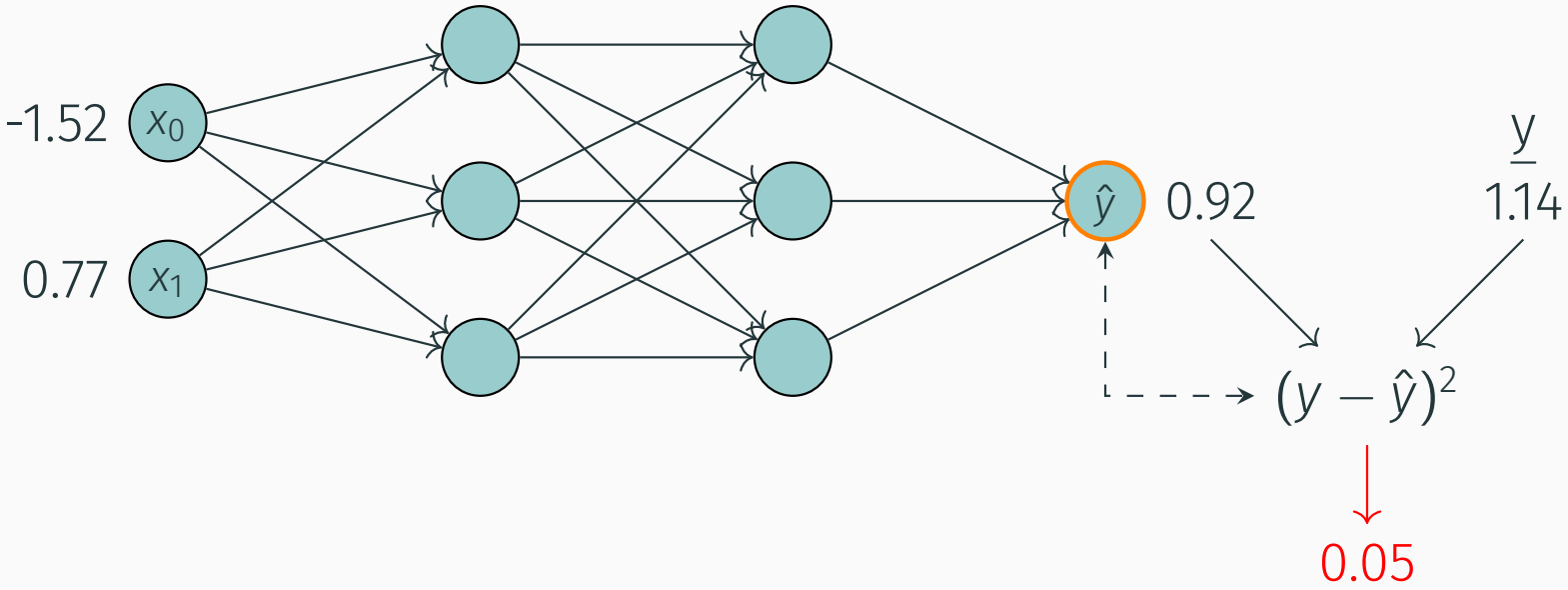


$$\underline{y}$$
1.14

Deep learning: Loss functions



Deep learning: Loss functions



Deep learning: Loss functions

In[1]:

```
from tensorflow.keras.layers import Input, Dense
from tensorflow.keras import Model

inputs = Input(shape=(2,))
hidden1 = Dense(units=3, activation='relu')(inputs)
hidden2 = Dense(units=3, activation='relu')(hidden1)
outputs = Dense(units=1, activation=?)(hidden2)

model = Model(inputs, outputs)
model.compile(loss=?)
```

Deep learning: Loss functions

In[1]:

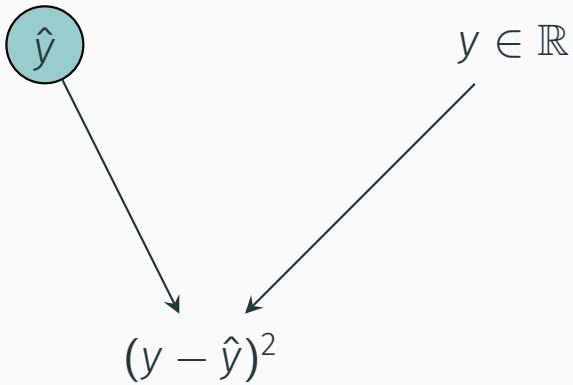
```
from tensorflow.keras.layers import Input, Dense
from tensorflow.keras import Model

inputs = Input(shape=(2,))
hidden1 = Dense(units=3, activation='relu')(inputs)
hidden2 = Dense(units=3, activation='relu')(hidden1)
outputs = Dense(units=1, activation=?)(hidden2)

model = Model(inputs, outputs)
model.compile(loss=?)
```

Deep learning: Loss functions

Regression

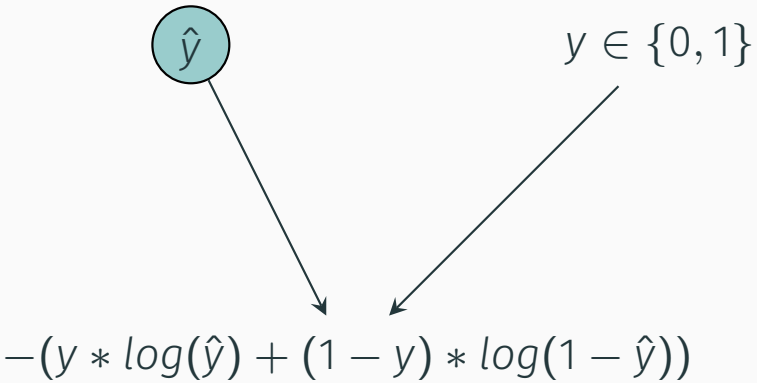


In[2]:

```
...
outputs = Dense(units=1, activation=None)(...)
...
model.compile(loss='mean_squared_error')
```

Deep learning: Loss functions

Binary classification



In[3]:

```
...
outputs = Dense(units=1, activation='sigmoid')(...)
...
model.compile(loss='binary_crossentropy')
```

Deep learning: Loss functions

Multiclass classification

$y \in \{cat, dog, bat\}$

Deep learning: Loss functions

Multiclass classification

x_0	y
	cat
	dog
	bat
	dog

Deep learning: Loss functions

Multiclass classification

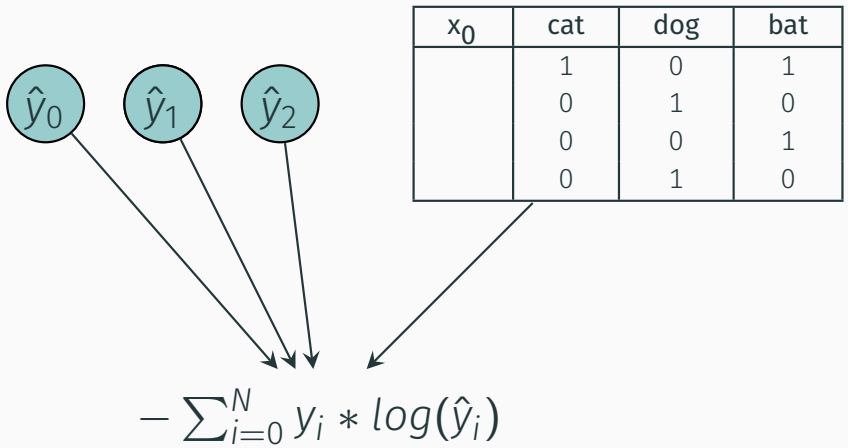
x_0	cat	dog	bat
	1	0	1
	0	1	0
	0	0	1
	0	1	0

Deep learning: Loss functions

Multiclass classification

x_0	cat	dog	bat
	1	0	1
	0	1	0
	0	0	1
	0	1	0

Deep learning: Loss functions



In[3]:

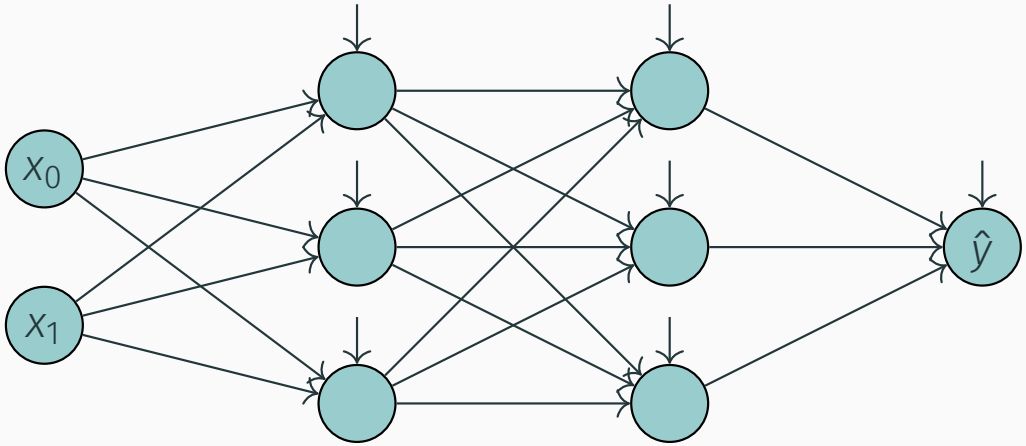
```
...
outputs = Dense(units=1, activation='softmax')(...)
...
model.compile(loss='categorical_crossentropy')
```

Deep learning: Loss functions

Loss functions: Behaves for neural networks as any other statistical learning model. However, important to **configure the final layer** correctly

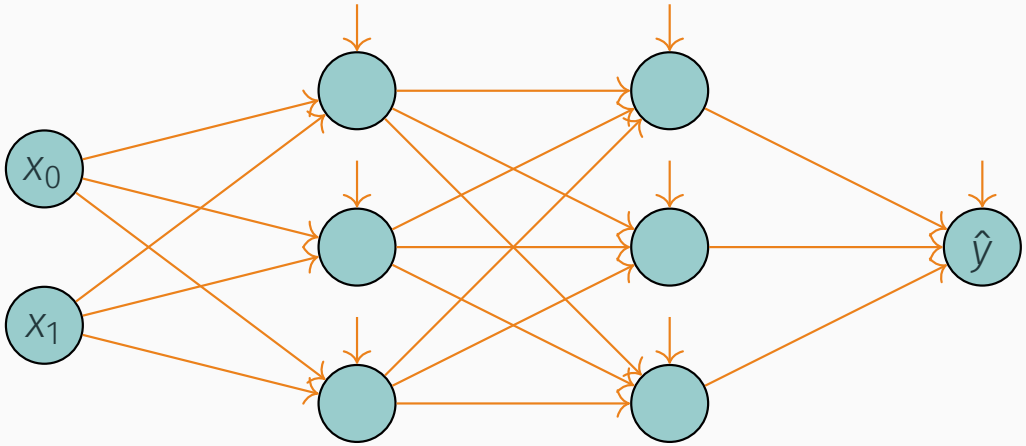
- Regression: Mean squared error
  - No activation
- Binary classification: Binary cross-entropy
  - Sigmoid activation
- Multiclass classification: Categorical cross-entropy
  - Softmax activation

Deep learning: Training



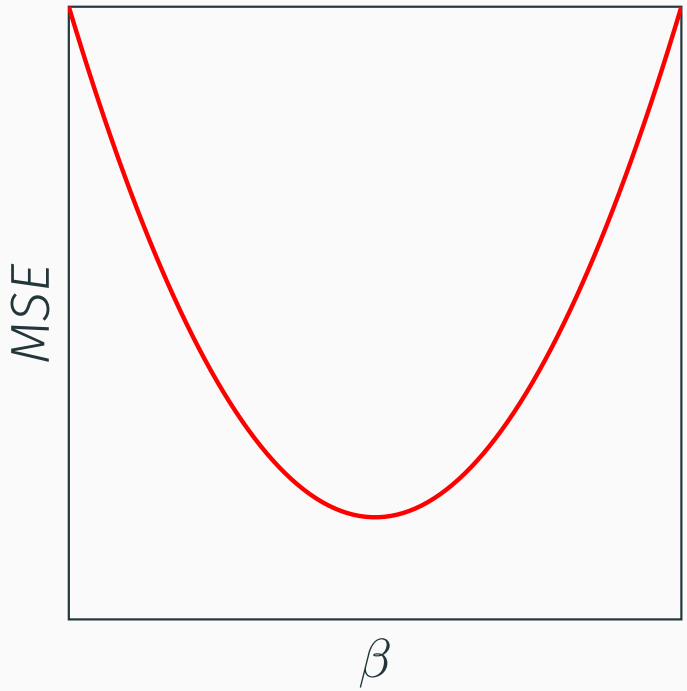
$$
\begin{aligned}
\hat{y} = max(0, & w^2_{0,0} * max(0, w^1_{0,0} * max(0, w^0_{0,0} * x_0 + w^0_{1,0} * x_1 + b_{0,0}) + \\
& w^1_{1,0} * max(0, w^0_{0,1} * x_0 + w^0_{1,1} * x_1 + b_{0,1}) + \\
& w^1_{2,0} * max(0, w^0_{0,2} * x_0 + w^0_{1,2} * x_1 + b_{0,2}) + \\
& b_{1,0}) + \\
& w^2_{1,0} * max(0, w^1_{0,1} * max(0, w^0_{0,0} * x_0 + w^0_{1,0} * x_1 + b_{0,0}) + \\
& w^1_{1,1} * max(0, w^0_{0,1} * x_0 + w^0_{1,1} * x_1 + b_{0,1}) + \\
& w^1_{2,1} * max(0, w^0_{0,2} * x_0 + w^0_{1,2} * x_1 + b_{0,2}) + \\
& b_{1,1}) + \\
& w^2_{2,0} * max(0, w^1_{0,2} * max(0, w^0_{0,0} * x_0 + w^0_{1,0} * x_1 + b_{0,0}) + \\
& w^1_{1,2} * max(0, w^0_{0,1} * x_0 + w^0_{1,1} * x_1 + b_{0,1}) + \\
& w^1_{2,2} * max(0, w^0_{0,2} * x_0 + w^0_{1,2} * x_1 + b_{0,2}) + \\
& b_{1,2}) + \\
& b_2)
\end{aligned}
$$

Deep learning: Training

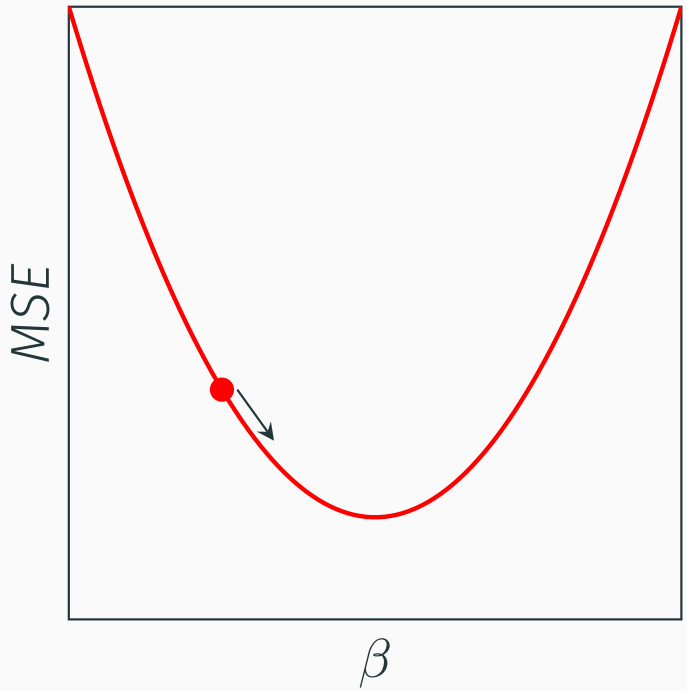


$$
\begin{aligned}
\hat{y} = max(0, & w^2_{0,0} * max(0, w^1_{0,0} * max(0,\ w^0_{0,0} * x_0 + w^0_{1,0} * x_1 + b_{0,0}) + \\
& w^1_{1,0} * max(0,\ w^0_{0,1} * x_0 + w^0_{1,1} * x_1 + b_{0,1}) + \\
& w^1_{2,0} * max(0,\ w^0_{0,2} * x_0 + w^0_{1,2} * x_1 + b_{0,2}) + \\
& b_{1,0}) + \\
& w^2_{1,0} * max(0, w^1_{0,1} * max(0,\ w^0_{0,0} * x_0 + w^0_{1,0} * x_1 + b_{0,0}) + \\
& w^1_{1,1} * max(0,\ w^0_{0,1} * x_0 + w^0_{1,1} * x_1 + b_{0,1}) + \\
& w^1_{2,1} * max(0,\ w^0_{0,2} * x_0 + w^0_{1,2} * x_1 + b_{0,2}) + \\
& b_{1,1}) + \\
& w^2_{2,0} * max(0, w^1_{0,2} * max(0,\ w^0_{0,0} * x_0 + w^0_{1,0} * x_1 + b_{0,0}) + \\
& w^1_{1,2} * max(0,\ w^0_{0,1} * x_0 + w^0_{1,1} * x_1 + b_{0,1}) + \\
& w^1_{2,2} * max(0,\ w^0_{0,2} * x_0 + w^0_{1,2} * x_1 + b_{0,2}) + \\
& b_{1,2}) + \\
& b_2)
\end{aligned}
$$

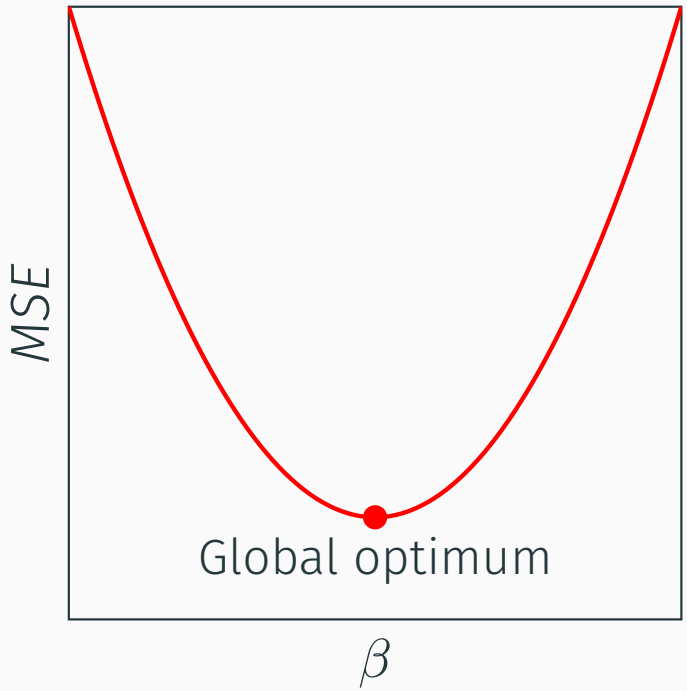
Deep learning: Training



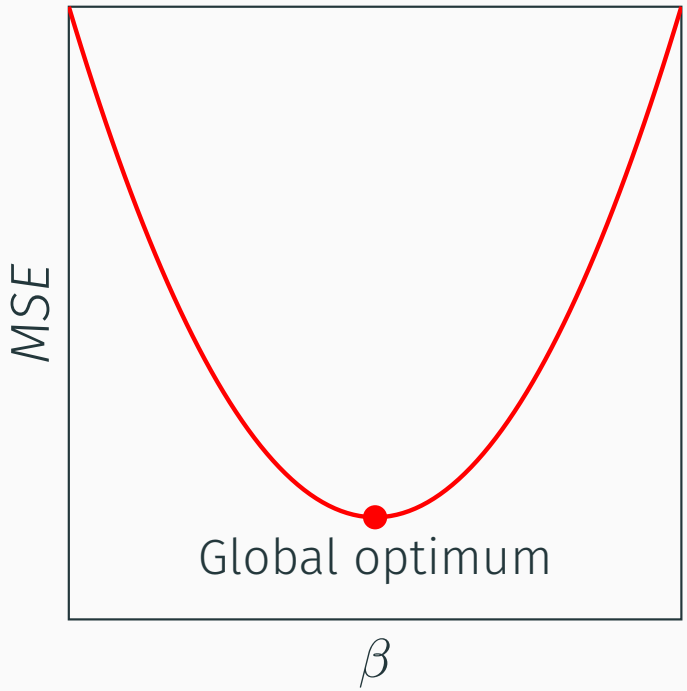
Deep learning: Training



Deep learning: Training



Deep learning: Training



- $|\beta| \rightarrow 10^6 - 10^{12}$
- $\beta_x \implies \beta_y$

Deep learning: Training

Learning representations by back-propagating errors

**David E. Rumelhart*, Geoffrey E. Hinton†
& Ronald J. Williams***

* Institute for Cognitive Science, C-015, University of California, San Diego, La Jolla, California 92093, USA
† Department of Computer Science, Carnegie-Mellon University, Pittsburgh, Philadelphia 15213, USA

We describe a new learning procedure, back-propagation, for networks of neurone-like units. The procedure repeatedly adjusts the weights of the connections in the network so as to minimize a measure of the difference between the actual output vector of the net and the desired output vector. As a result of the weight adjustments, internal 'hidden' units which are not part of the input or output come to represent important features of the task domain, and the regularities in the task are captured by the interactions of these units. The ability to create useful new features distinguishes back-propagation from earlier, simpler methods such as the perceptron-convergence procedure[1].

Deep learning: Training

Learning representations by back-propagating errors

David E. Rumelhart*, Geoffrey E. Hinton†
& Ronald J. Williams*

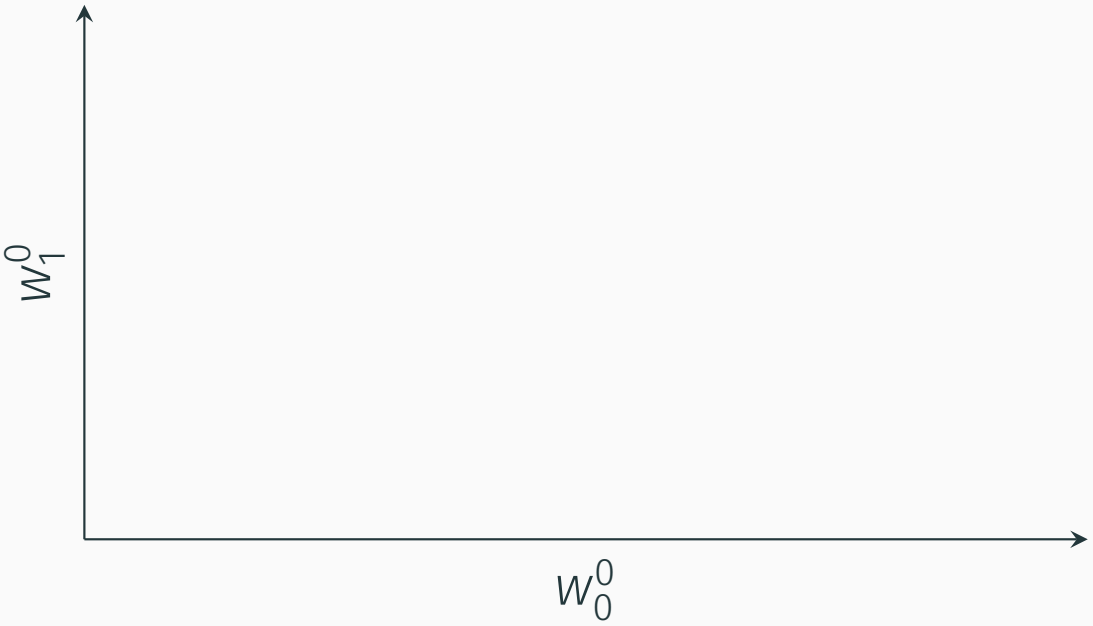
* Institute for Cognitive Science, C-015, University of California, San Diego, La Jolla, California 92093, USA
† Department of Computer Science, Carnegie-Mellon University, Pittsburgh, Philadelphia 15213, USA

We describe a new learning procedure, back-propagation, for networks of neurone-like units. The procedure repeatedly adjusts the weights of the connections in the network so as to minimize a measure of the difference between the actual output vector of the net and the desired output vector. As a result of the weight adjustments, internal 'hidden' units which are not part of the input or output come to represent important features of the task domain, and the regularities in the task are captured by the interactions of these units. The ability to create useful new features distinguishes back-propagation from earlier, simpler methods such as the perceptron-convergence procedure[1].

Deep learning: Training

$$\Delta R(\theta^m) = \left.\frac{\partial R(\theta)}{\partial \theta}\right|_{\theta=\theta^m}$$

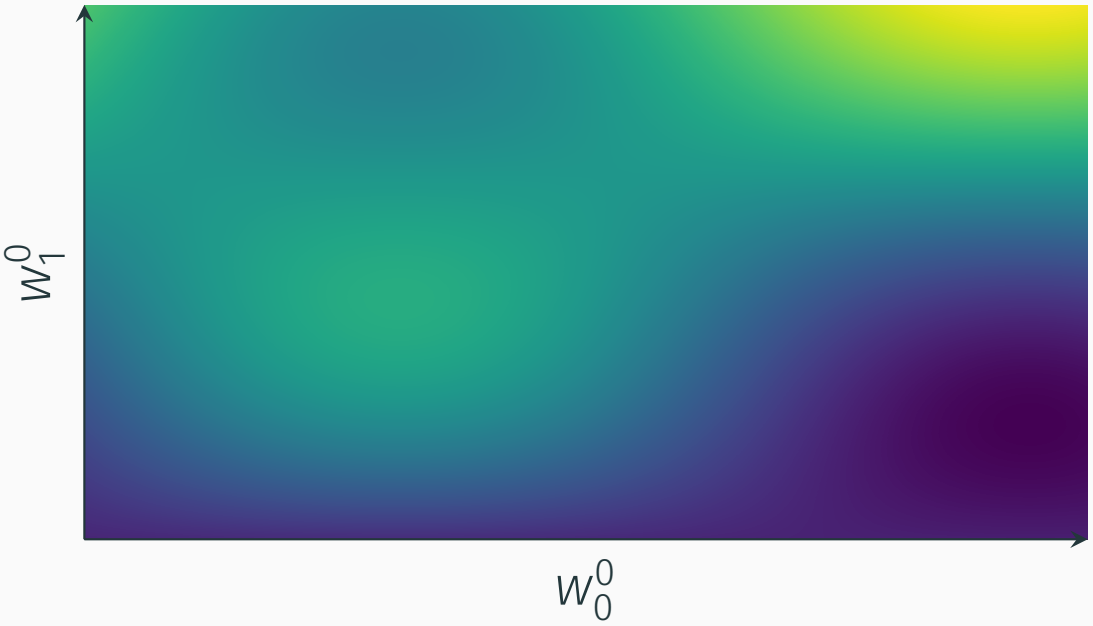
Deep learning: Training



$$\Delta R(\theta^m) = \left.\frac{\partial R(\theta)}{\partial \theta}\right|_{\theta=\theta^m}$$

- θ are the parameters of the model

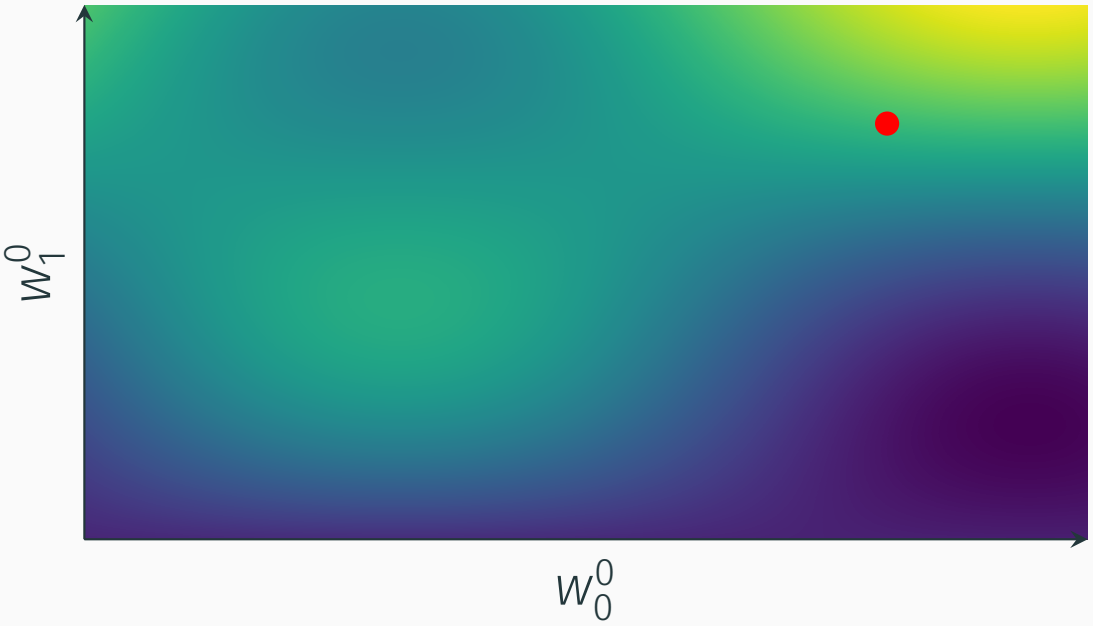
Deep learning: Training



$$\Delta R(\theta^m) = \left.\frac{\partial R(\theta)}{\partial \theta}\right|_{\theta=\theta^m}$$

- θ are the parameters of the model
- $R(\theta)$ is the loss as a function of the parameters

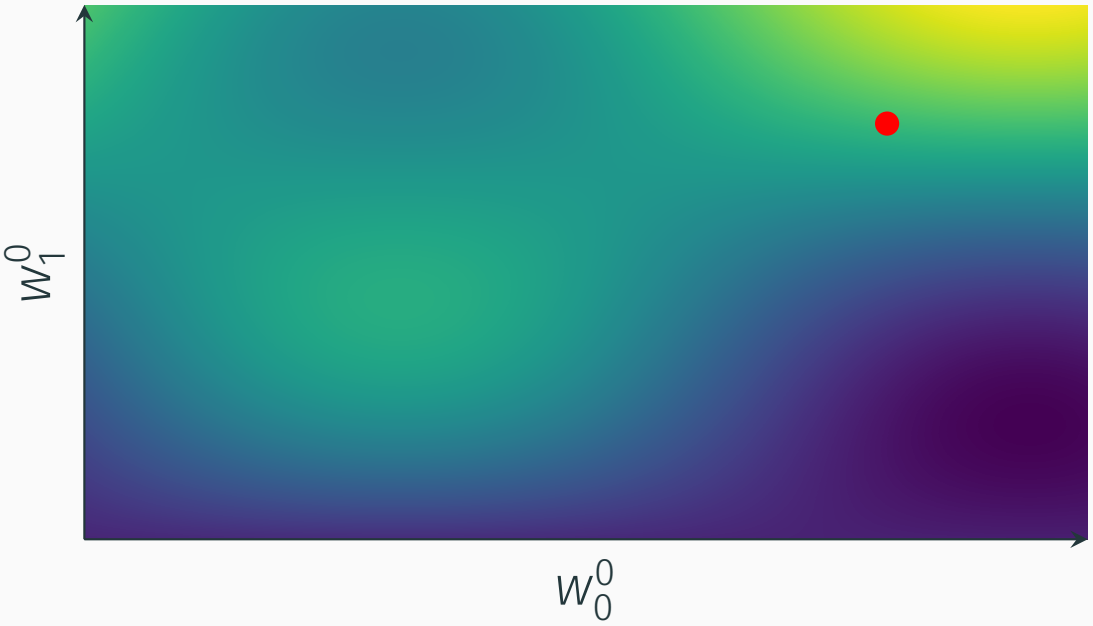
Deep learning: Training



$$\Delta R(\theta^m) = \left.\frac{\partial R(\theta)}{\partial \theta}\right|_{\theta=\theta^m}$$

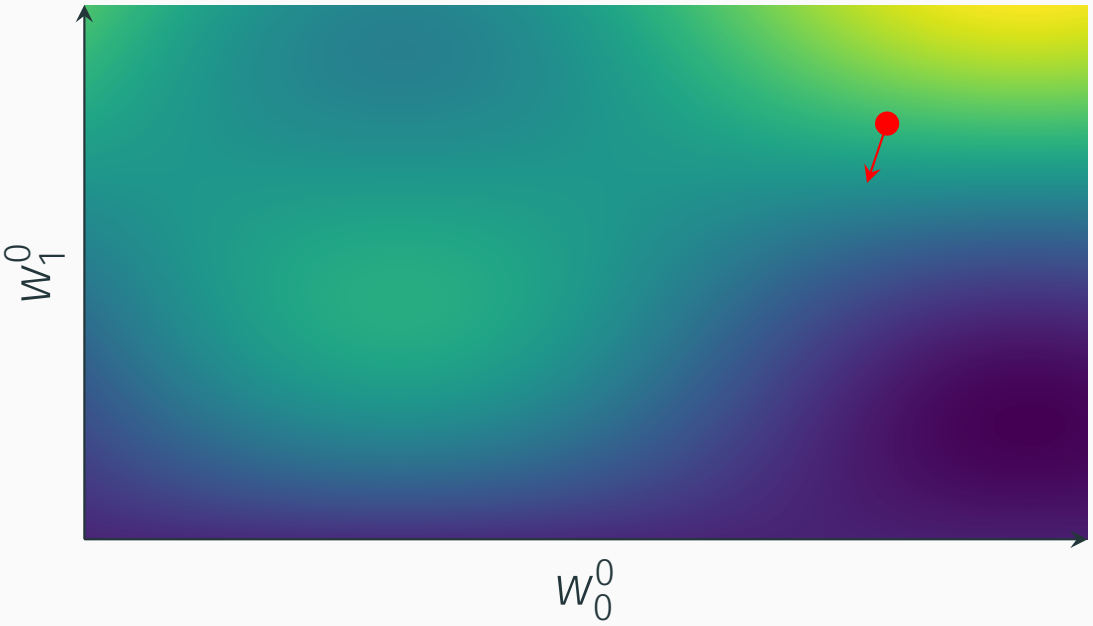
- θ are the parameters of the model
- $R(\theta)$ is the loss as a function of the parameters
- θ^m is a specific configuration of parameters

Deep learning: Training



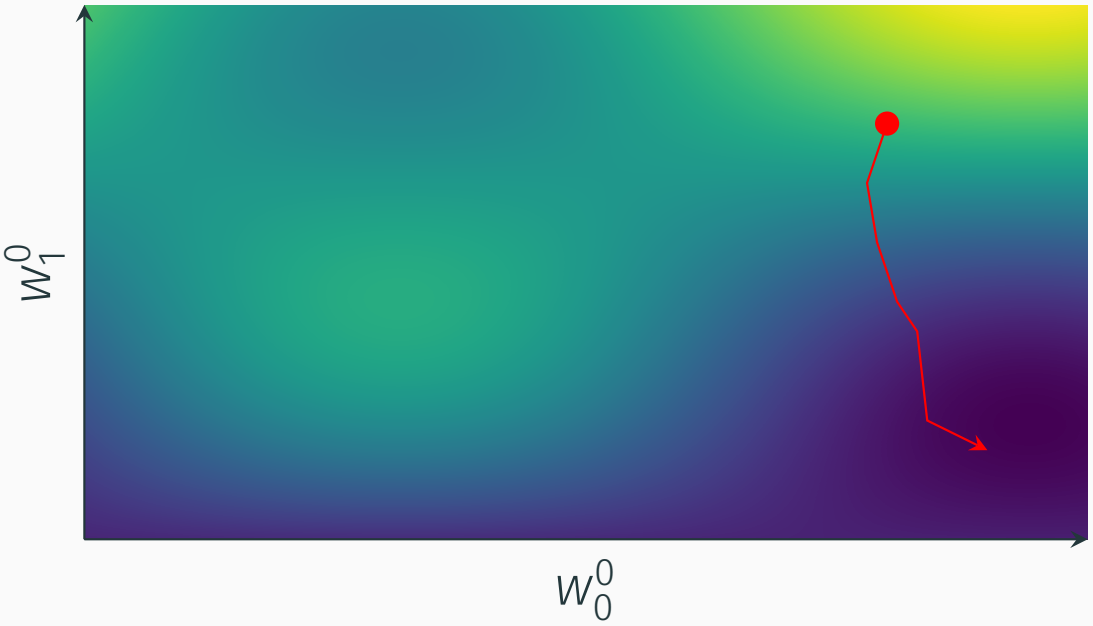
$$\frac{\partial R_i(\theta)}{\partial w_{jk}} = \frac{\partial R(\theta)}{\partial f_\theta(x_i)} \cdot \frac{\partial f_\theta(x_i)}{\partial g(z_{ik})} \cdot \frac{\partial g(z_{ik})}{\partial z_{ik}} \cdot \frac{z_{ik}}{w_{kj}}$$

Deep learning: Training



$$\frac{\partial R_i(\theta)}{\partial w_{jk}} = \frac{\partial R(\theta)}{\partial f_\theta(x_i)} \cdot \frac{\partial f_\theta(x_i)}{\partial g(z_{ik})} \cdot \frac{\partial g(z_{ik})}{\partial z_{ik}} \cdot \frac{z_{ik}}{w_{kj}}$$

Deep learning: Training



$$\frac{\partial R_i(\theta)}{\partial w_{jk}} = \frac{\partial R(\theta)}{\partial f_\theta(x_i)} \cdot \frac{\partial f_\theta(x_i)}{\partial g(z_{ik})} \cdot \frac{\partial g(z_{ik})}{\partial z_{ik}} \cdot \frac{z_{ik}}{w_{kj}}$$

Deep learning: Training

Backpropagation: Uses gradient descent to iteratively determine how the model weights should be updated to minimize the loss function

- **Gradient descent**: Calculate gradient based on all data points

Deep learning: Training

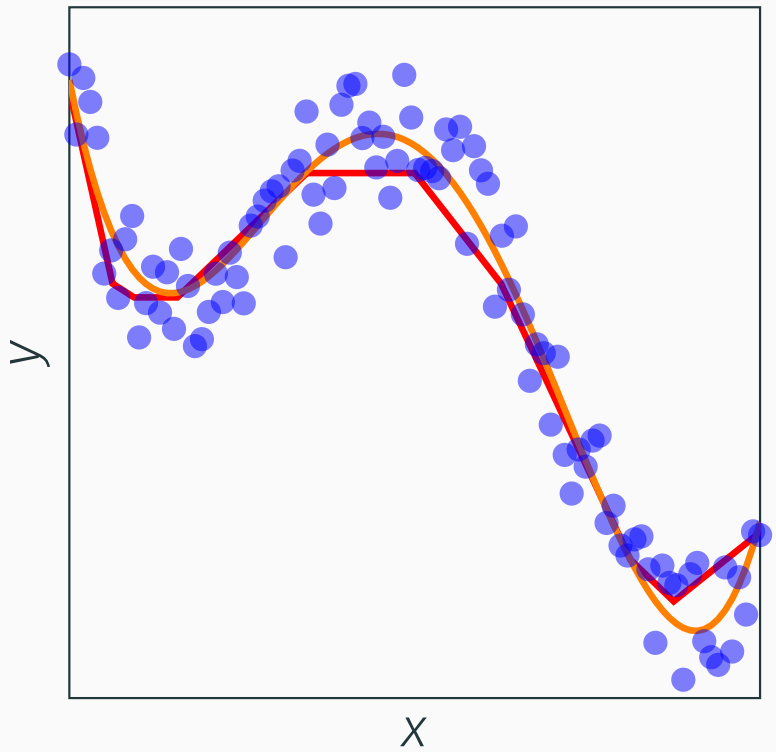
Backpropagation: Uses gradient descent to iteratively determine how the model weights should be updated to minimize the loss function

- **Gradient descent**: Calculate gradient based on all data points
- **Stochastic gradient descent**: Calculate gradient based on a batch of data points

Deep learning: The conundrum

Splines: A smooth curve implemented via piecewise polynomial functions

Neural networks: A piecewise linear function implemented as a hierarchy of artificial neurons



Deep learning: The conundrum

Splines: A smooth curve implemented via piecewise polynomial functions

- Requires us to carefully balance the complexity of the function

Neural networks: A piecewise linear function implemented as a hierarchy of artificial neurons

Deep learning: The conundrum

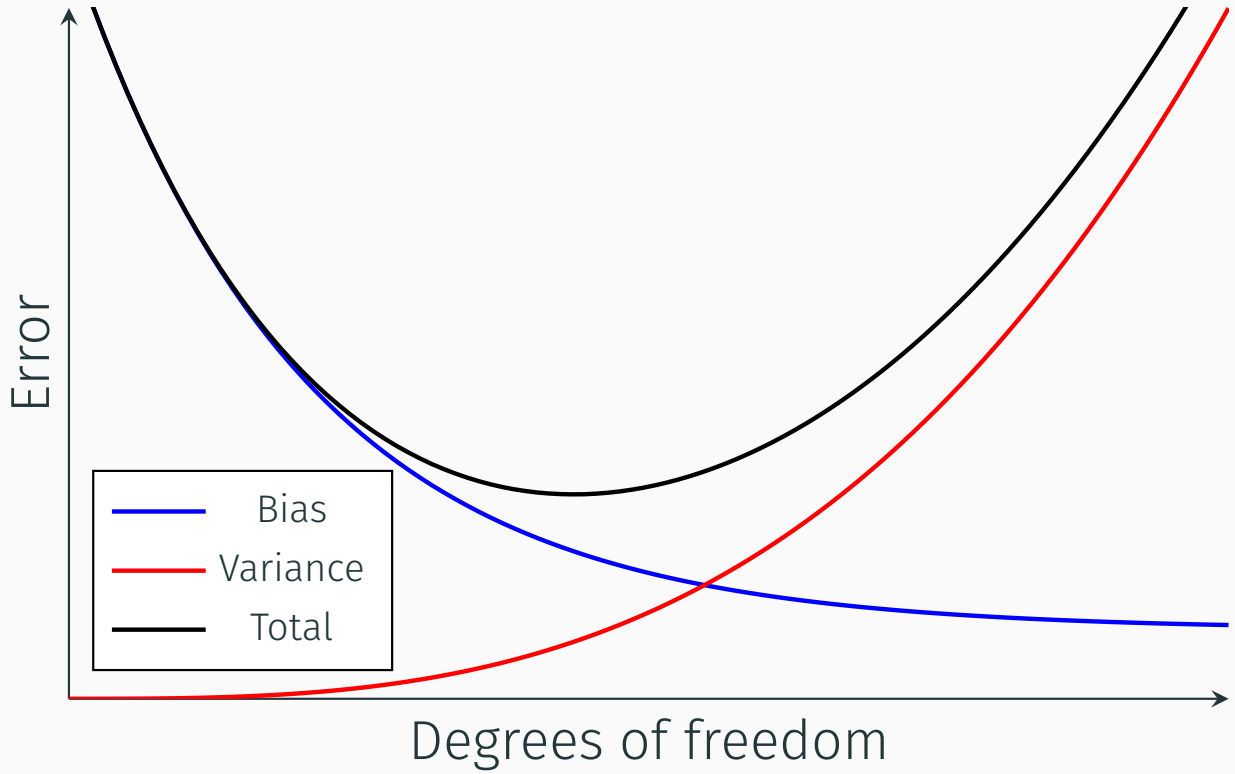
Splines: A smooth curve implemented via piecewise polynomial functions

- Requires us to carefully balance the complexity of the function

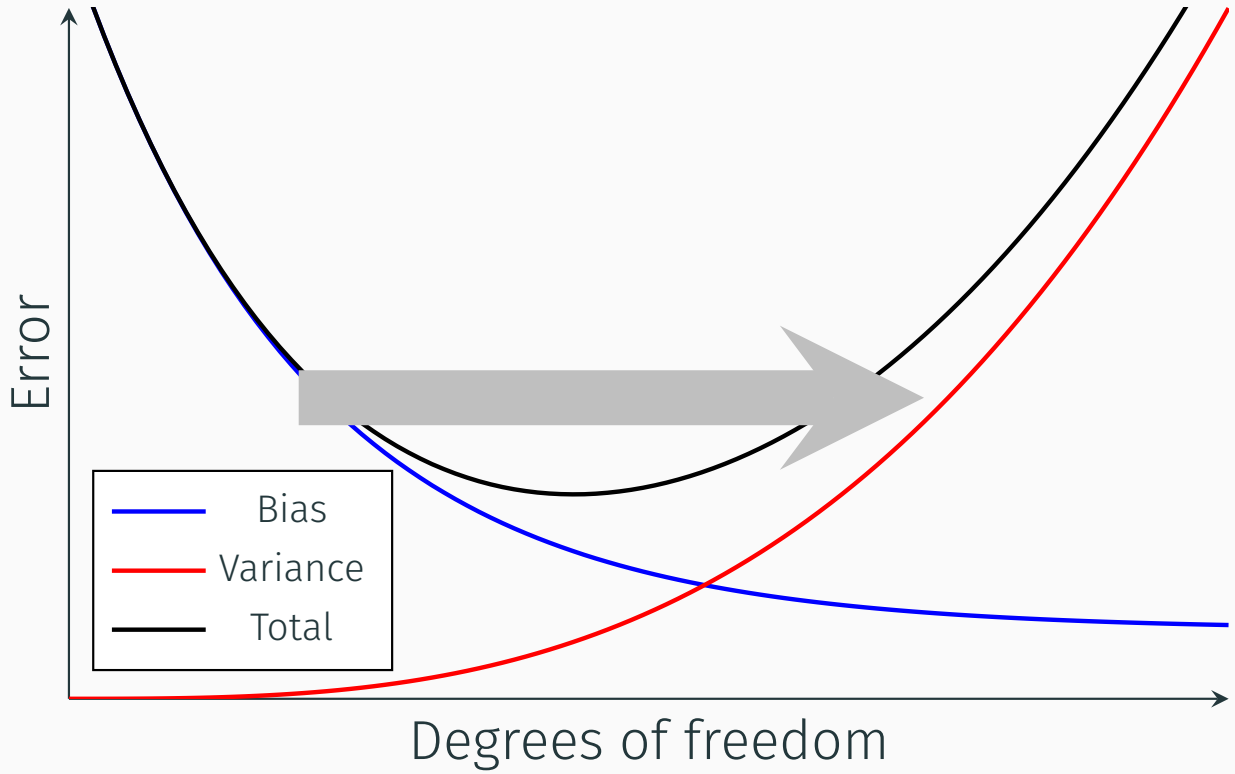
Neural networks: A piecewise linear function implemented as a hierarchy of artificial neurons

- Overparameterization 🥳

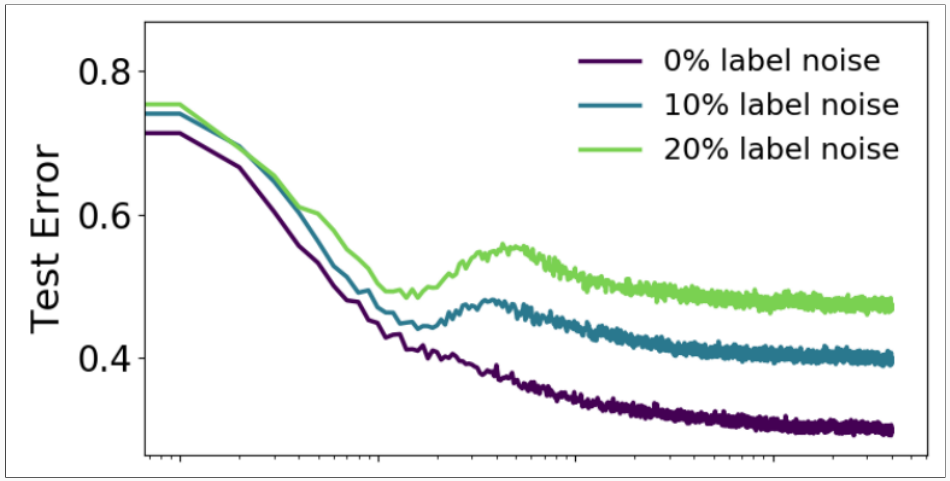
Deep learning: The conundrum

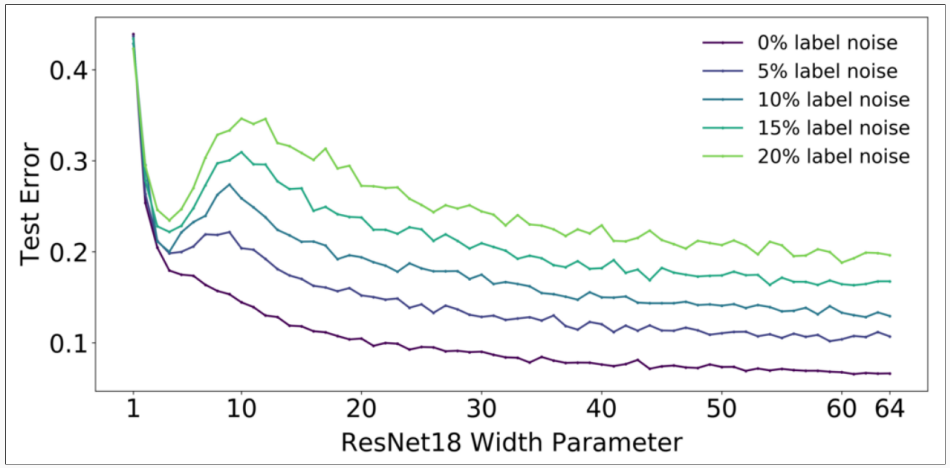


Deep learning: The conundrum

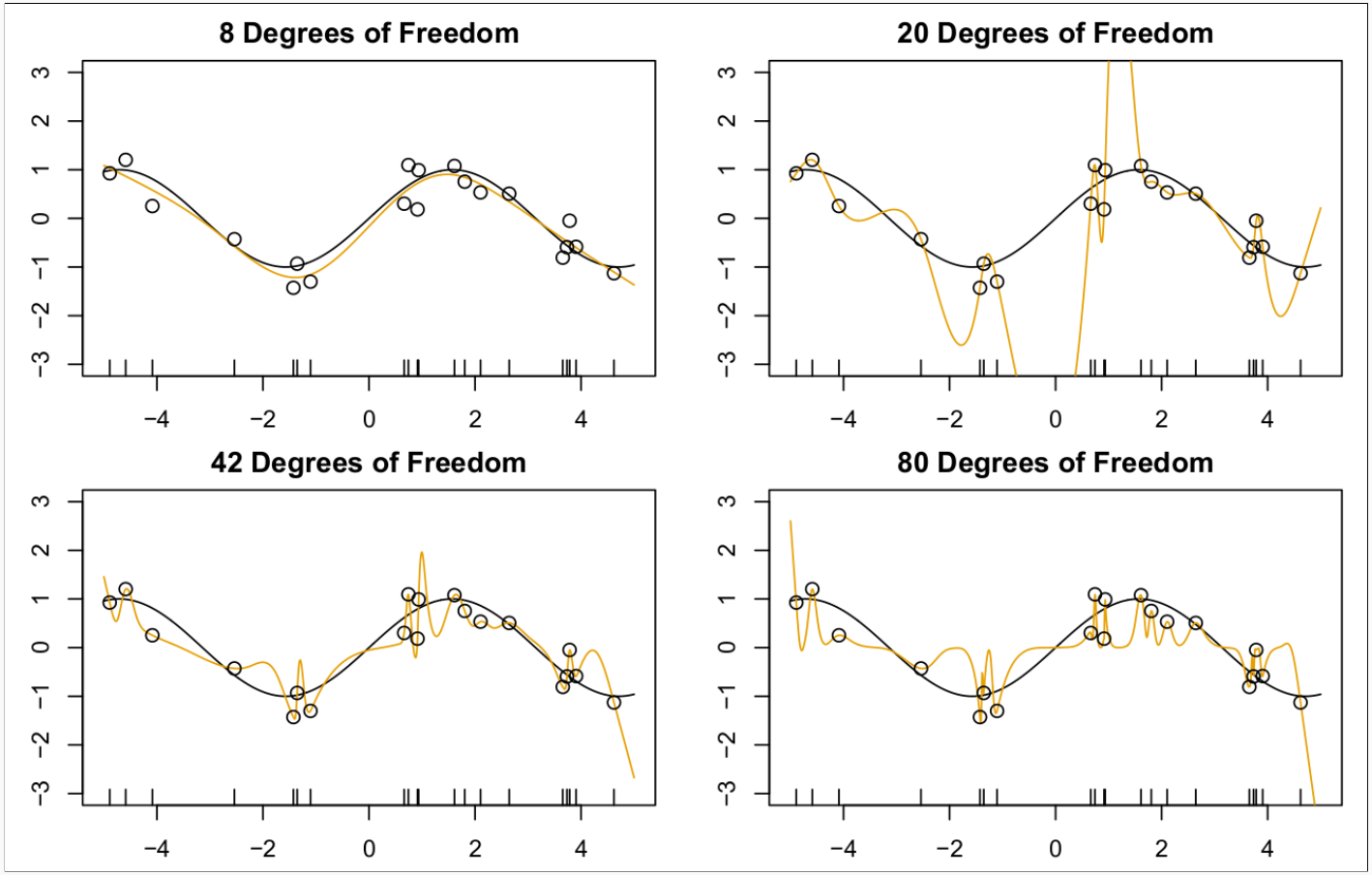


Deep learning: The conundrum





Deep learning: The conundrum



Deep learning: The conundrum

Overparameterization: Deep artificial neural networks generally have far more parameters than necessary (and often more than the number of data points)

- At face value, it is surprising that this does not yield severe overfitting
- However, it can be shown that neural networks, after perfectly fitting their training data, generally become more well-behaved and less wild

Deep learning: Regularization

- Weight decay: Applies an ℓ_2-penalty to the weights, similarly to ridge regression

  $R(\theta; \lambda) = R(\theta) + \lambda \sum \theta^2$

Deep learning: Regularization

- Weight decay: Applies an ℓ_2-penalty to the weights, similarly to ridge regression

  $R(\theta; \lambda) = R(\theta) + \lambda \sum \theta^2$

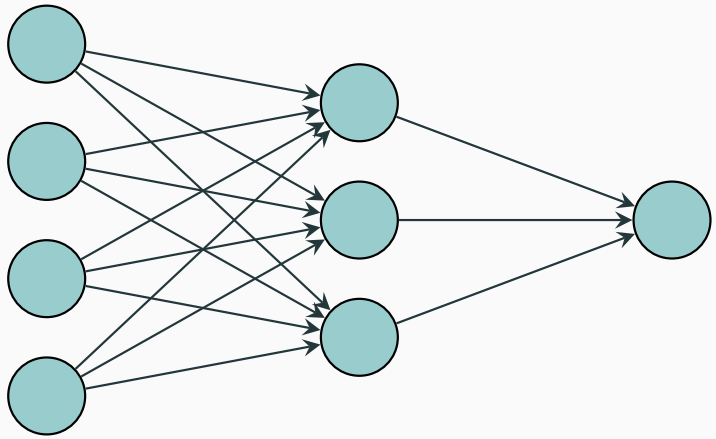
- Dropout: Randomly kills a fraction of the neurons during training

Deep learning: Regularization

- Weight decay: Applies an ℓ_2-penalty to the weights, similarly to ridge regression

  $R(\theta; \lambda) = R(\theta) + \lambda \sum \theta^2$

- Dropout: Randomly kills a fraction of the neurons during training

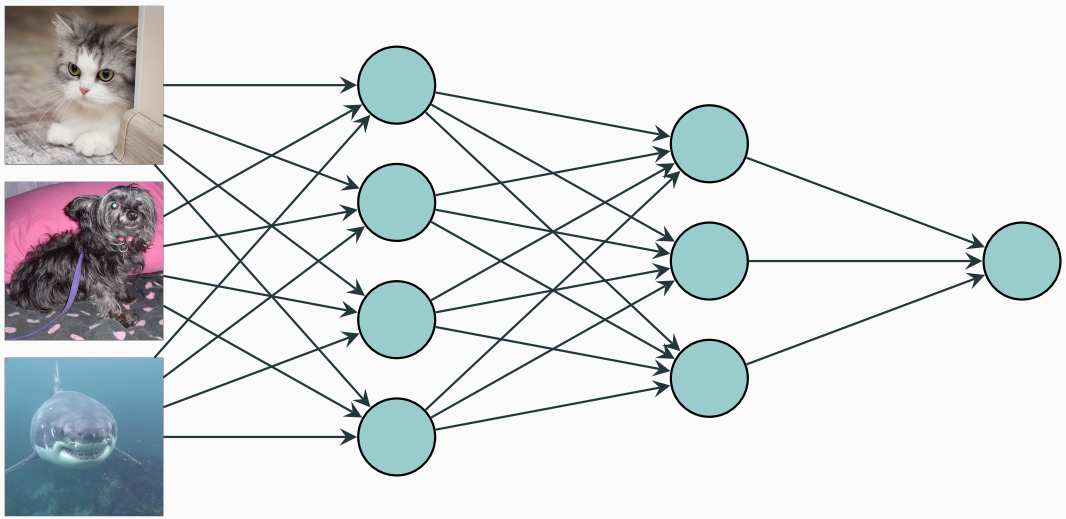


Deep learning: Regularization

- Weight decay: Applies an ℓ_2-penalty to the weights, similarly to ridge regression

  $R(\theta; \lambda) = R(\theta) + \lambda \sum \theta^2$

- Dropout: Randomly kills a fraction of the neurons during training

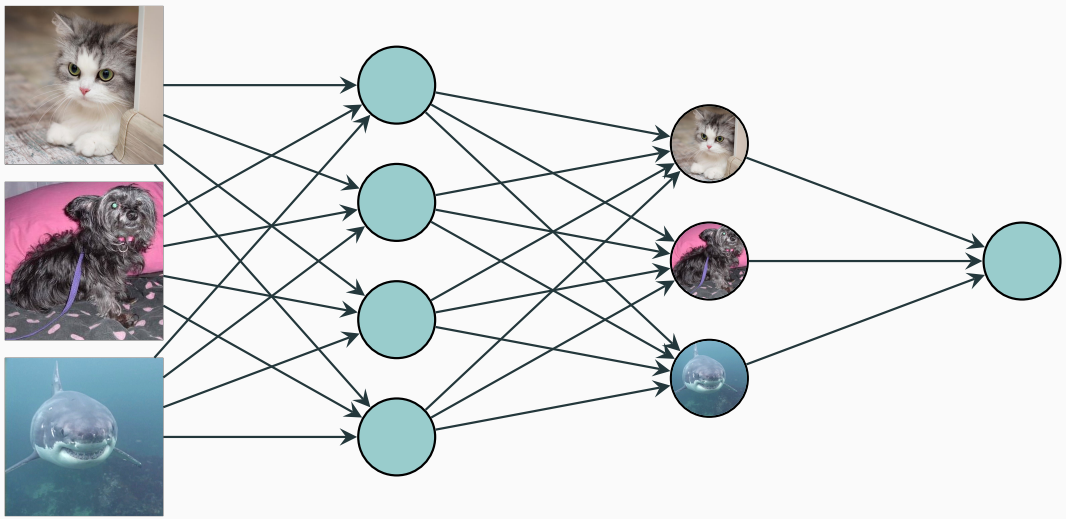


Deep learning: Regularization

- Weight decay: Applies an ℓ_2-penalty to the weights, similarly to ridge regression

  $R(\theta; \lambda) = R(\theta) + \lambda \sum \theta^2$

- Dropout: Randomly kills a fraction of the neurons during training

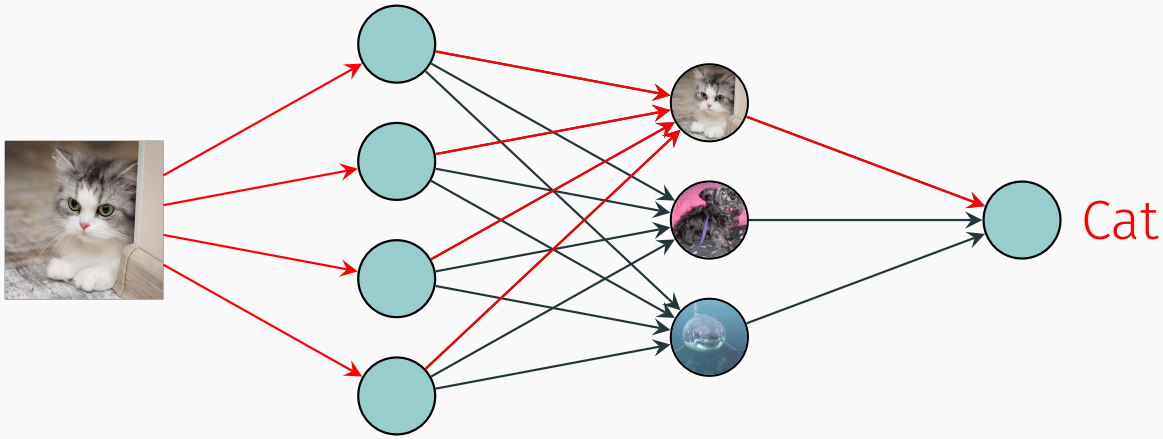


Deep learning: Regularization

- Weight decay: Applies an ℓ_2-penalty to the weights, similarly to ridge regression

  $R(\theta; \lambda) = R(\theta) + \lambda \sum \theta^2$

- Dropout: Randomly kills a fraction of the neurons during training

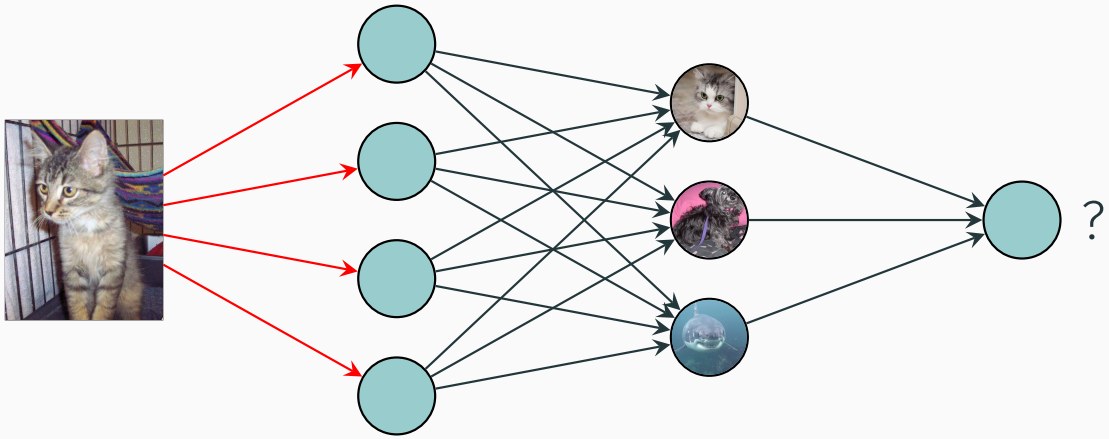


Deep learning: Regularization

- Weight decay: Applies an ℓ_2-penalty to the weights, similarly to ridge regression

  $R(\theta; \lambda) = R(\theta) + \lambda \sum \theta^2$

- Dropout: Randomly kills a fraction of the neurons during training

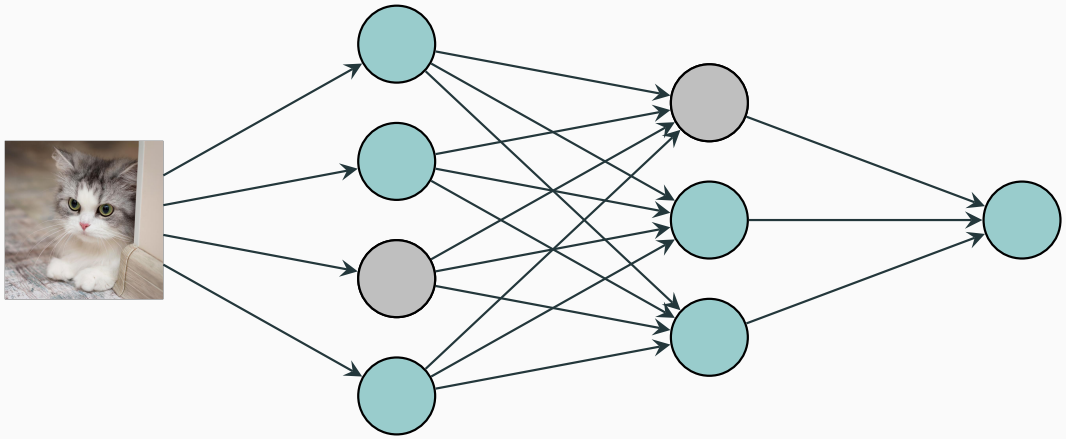


Deep learning: Regularization

- Weight decay: Applies an ℓ_2-penalty to the weights, similarly to ridge regression

  $R(\theta; \lambda) = R(\theta) + \lambda \sum \theta^2$

- Dropout: Randomly kills a fraction of the neurons during training

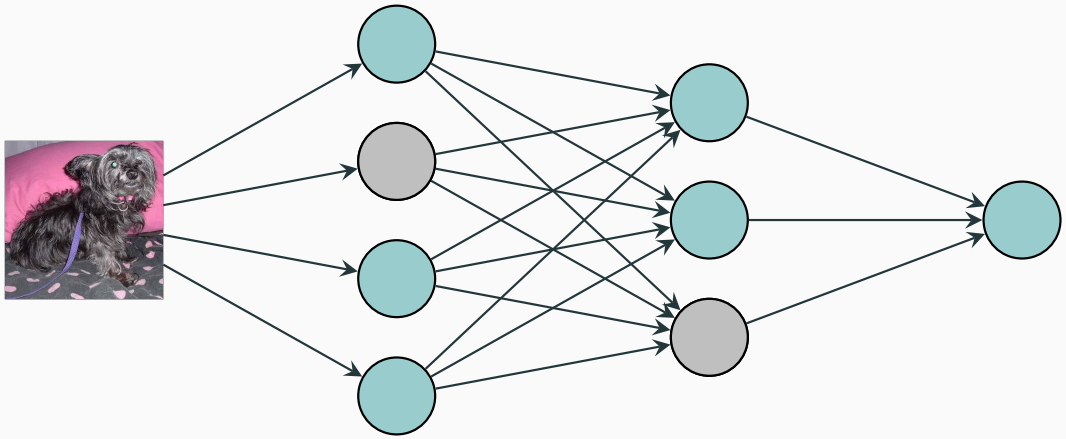


Deep learning: Regularization

- Weight decay: Applies an ℓ_2-penalty to the weights, similarly to ridge regression

  $R(\theta; \lambda) = R(\theta) + \lambda \sum \theta^2$

- Dropout: Randomly kills a fraction of the neurons during training



Deep learning: Regularization

- Weight decay: Applies an ℓ_2-penalty to the weights, similarly to ridge regression

  $R(\theta; \lambda) = R(\theta) + \lambda \sum \theta^2$

- Dropout: Randomly kills a fraction of the neurons during training
- Data augmentation: Attempts to generate more data

Computer vision

UNIVERSITY
OF OSLO

Computer vision: Background

Cat

Computer vision: Background


Sunflower


Ladybug

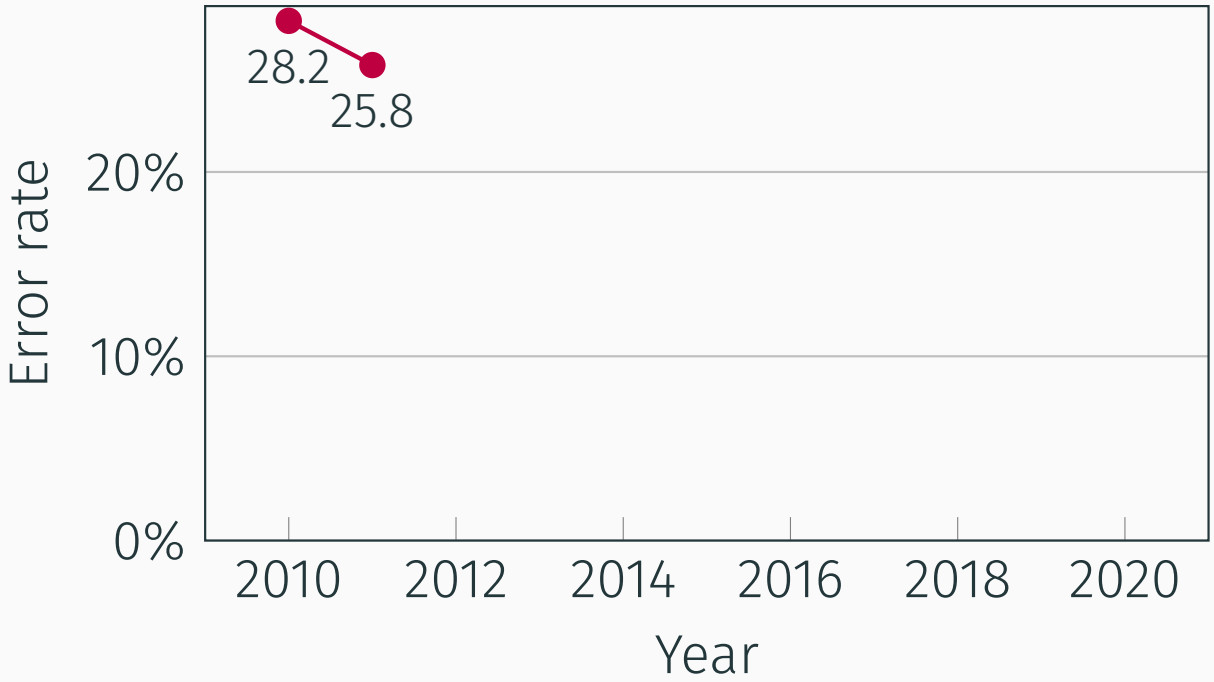

Cat


Airplane

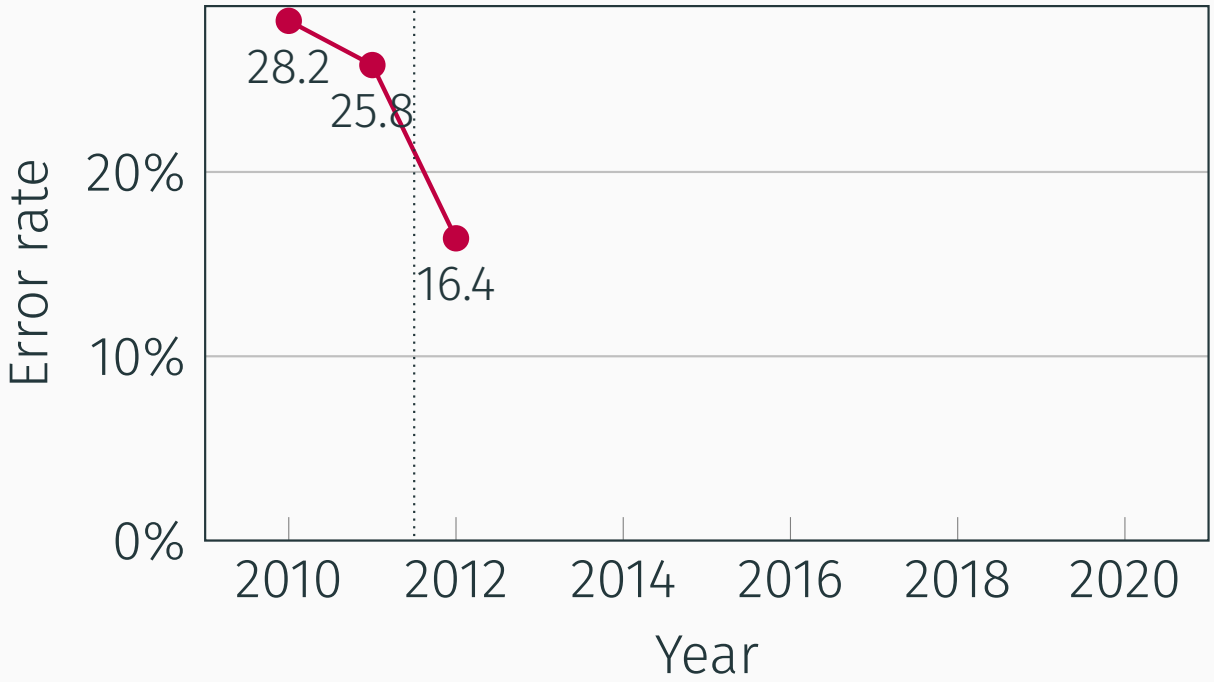

Shark

ImageNet: ∼14m images, ∼22k categories

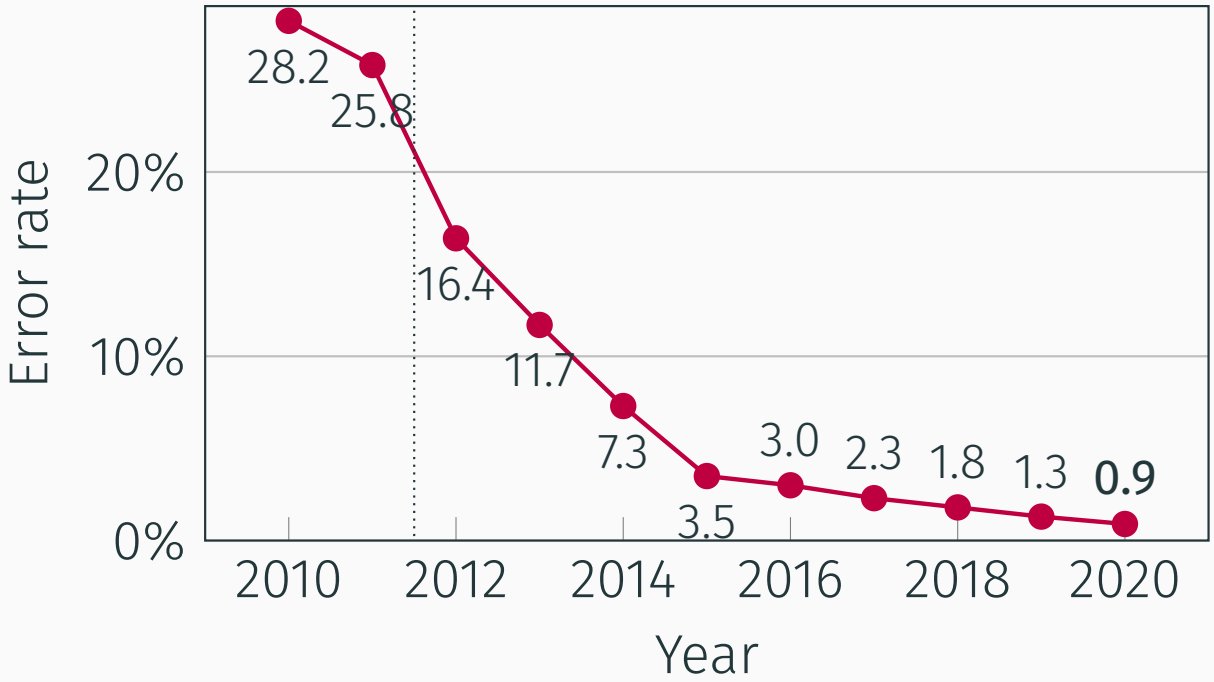
Computer vision: Background



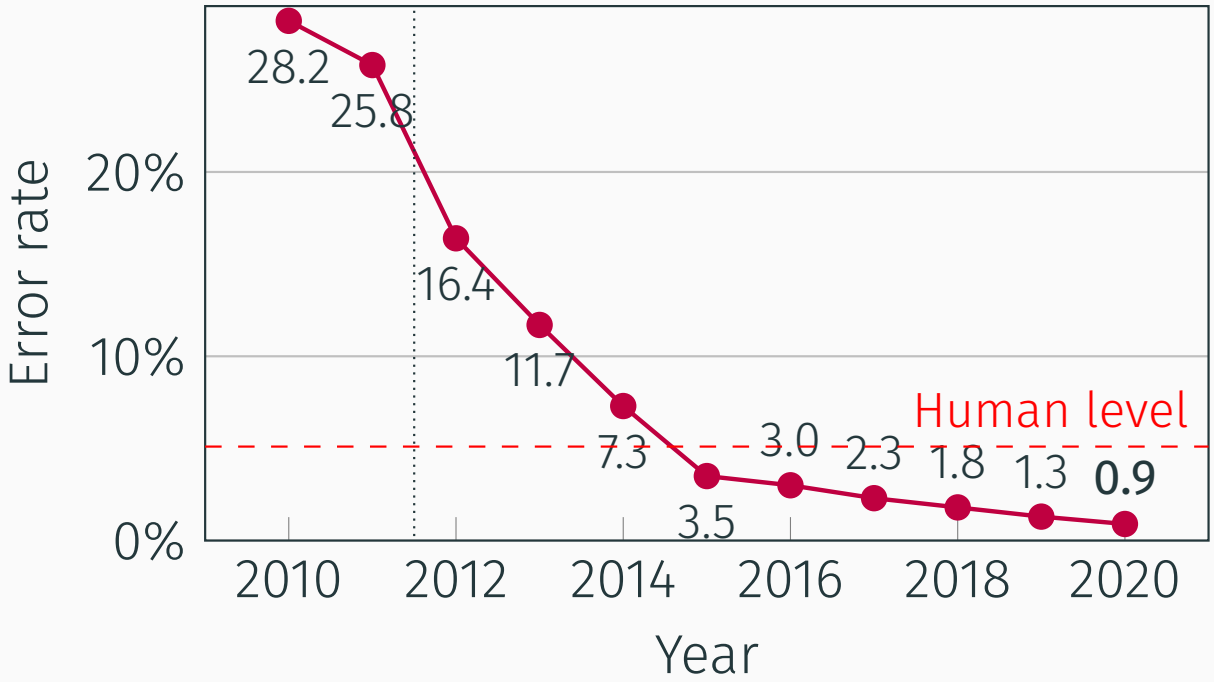
Computer vision: Background



Computer vision: Background



Computer vision: Background



Computer vision: Image data

Computer vision: Image data

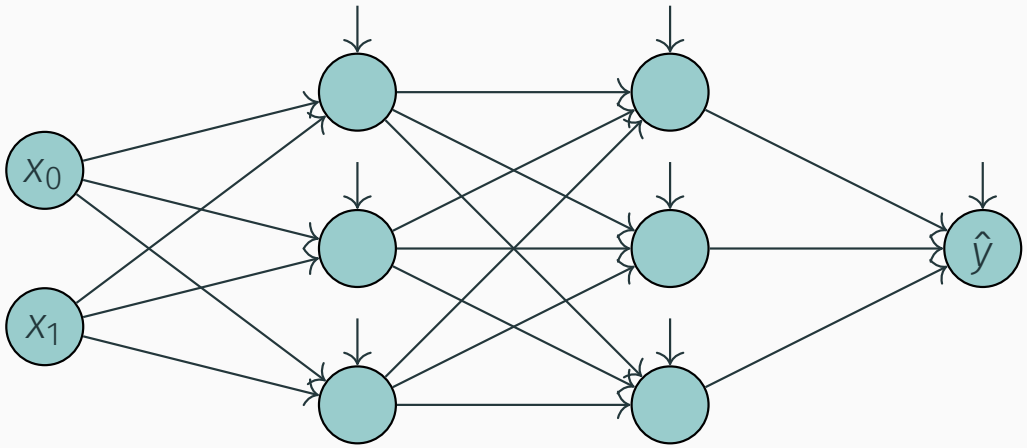
Computer vision: Image data

Computer vision: Image data

Computer vision: Image data

Computer vision: Image data

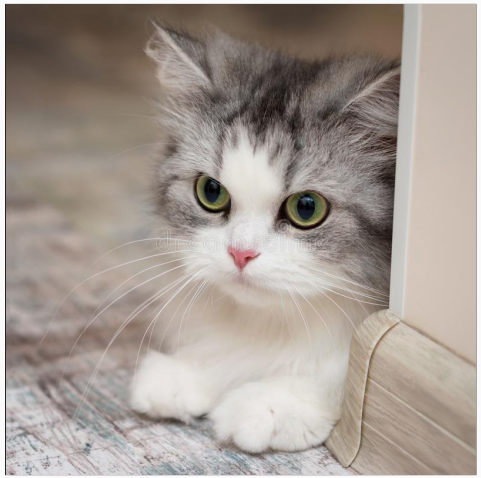
Convolutional neural networks: Inputs



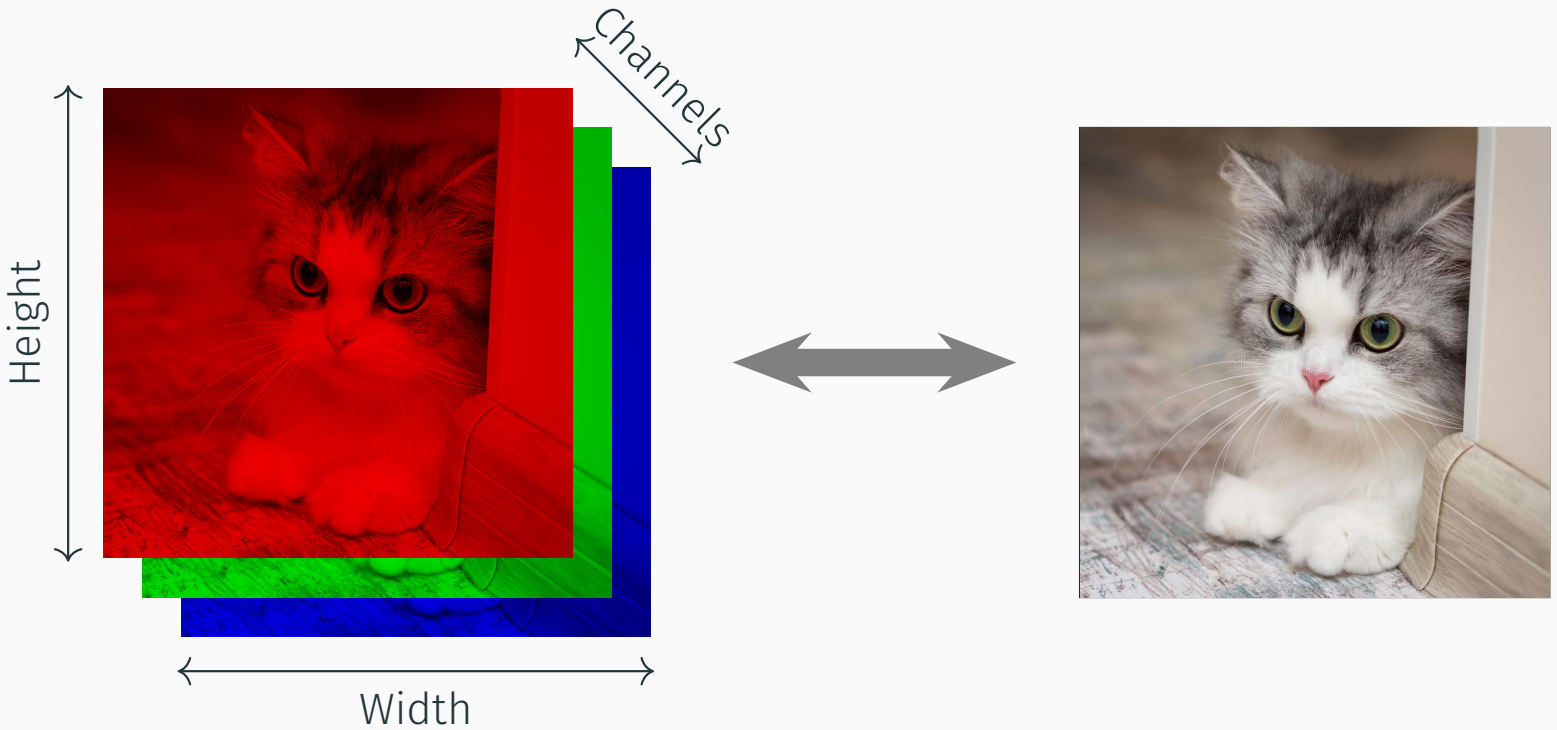
Convolutional neural networks: Inputs

Convolutional neural networks: Inputs

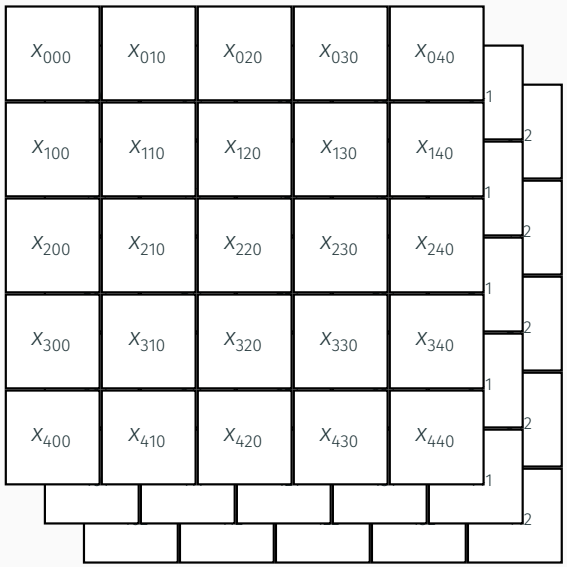
?

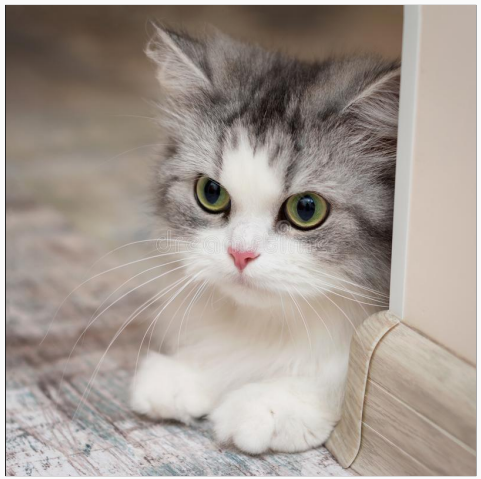


Convolutional neural networks: Inputs

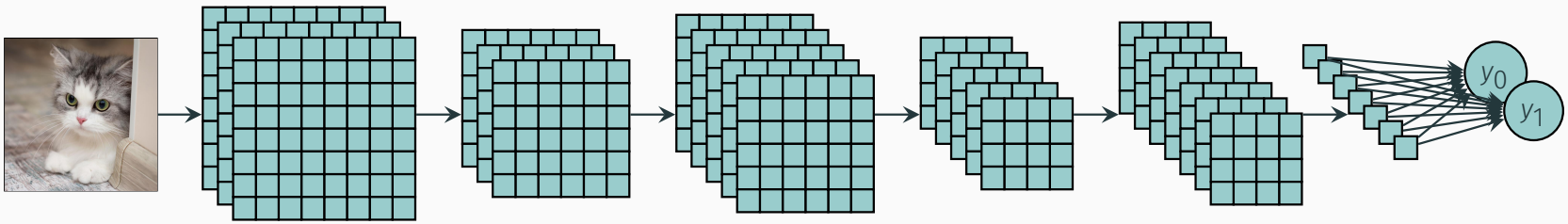


Convolutional neural networks: Inputs

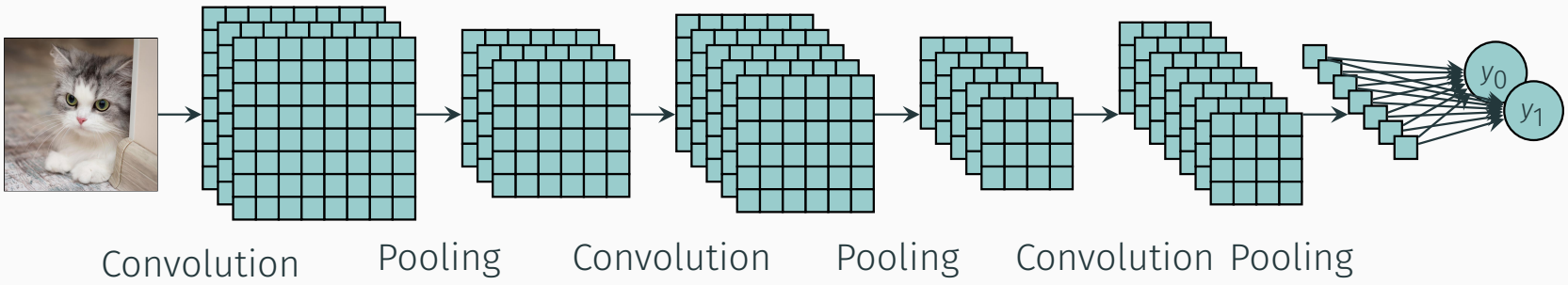




Convolutional neural networks: Architecture

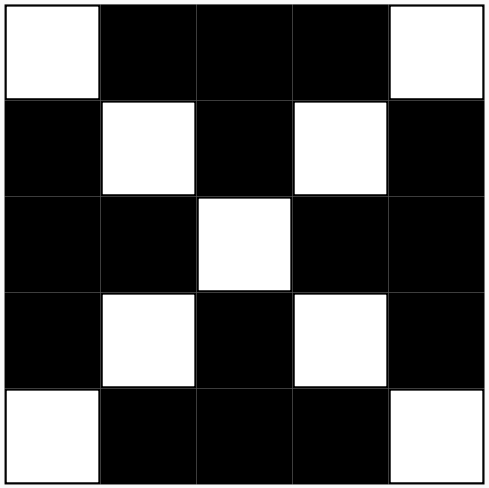


Convolutional neural networks: Architecture



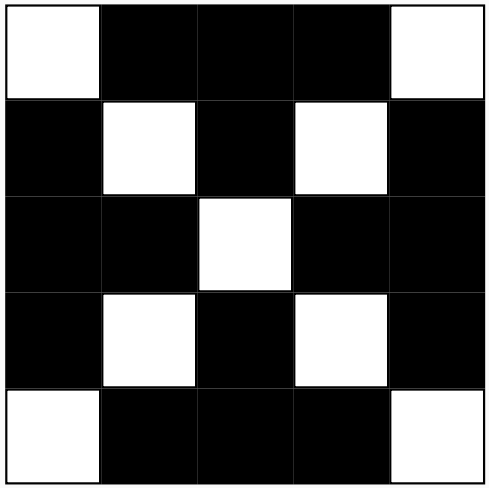
Convolutional neural networks: Convolution

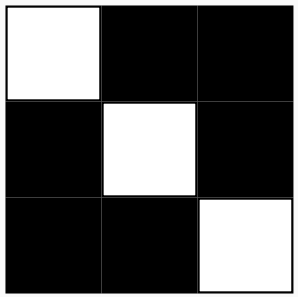
Image



Convolutional neural networks: Convolution

Image

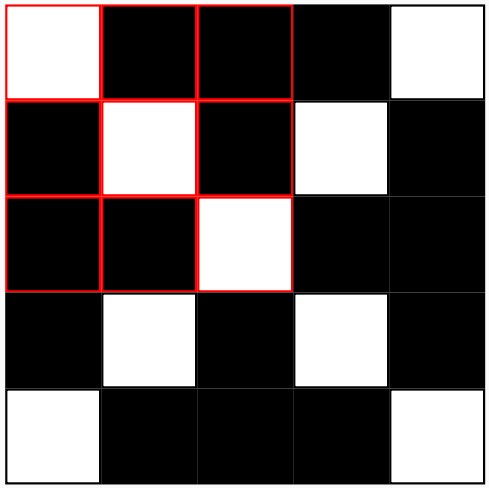




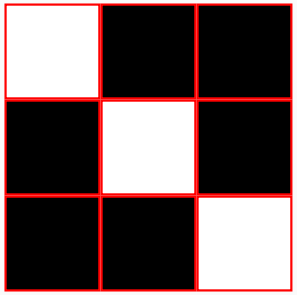
Pattern 1

Convolutional neural networks: Convolution

Image



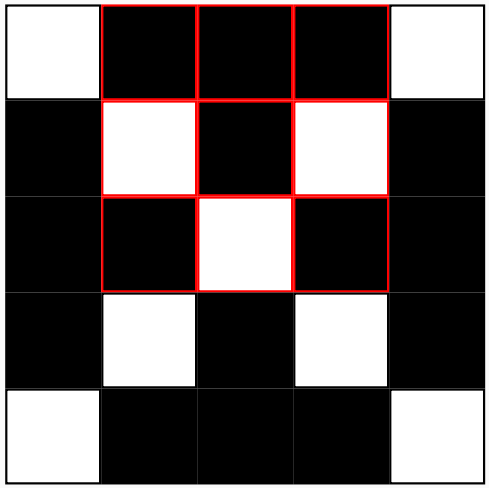
3

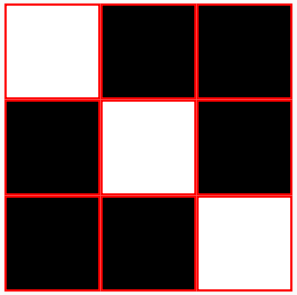


Pattern 1

Convolutional neural networks: Convolution

Image

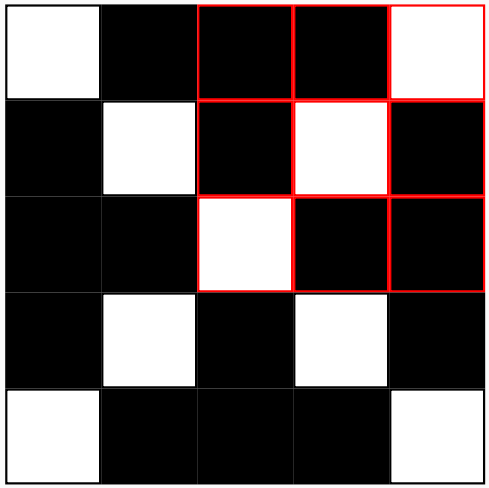


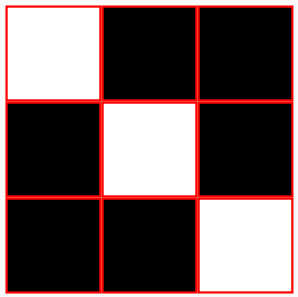


Pattern 1

Convolutional neural networks: Convolution

Image



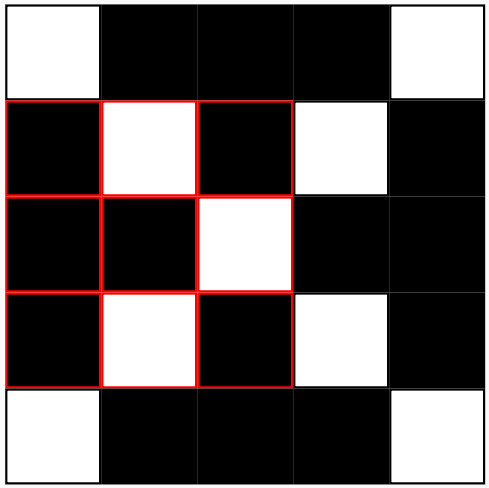


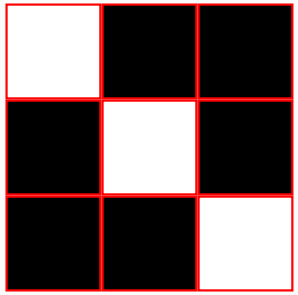
Pattern 1

3	0	1

Convolutional neural networks: Convolution

Image



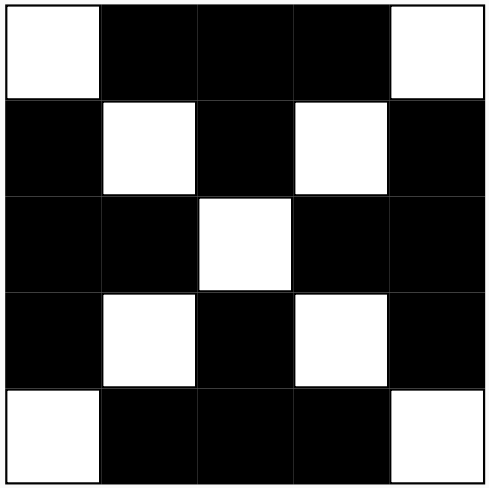


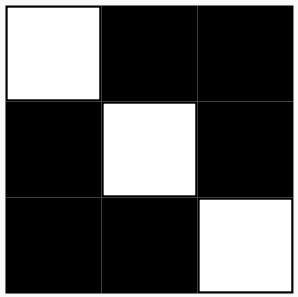
Pattern 1

3	0	1
0		

Convolutional neural networks: Convolution

Image



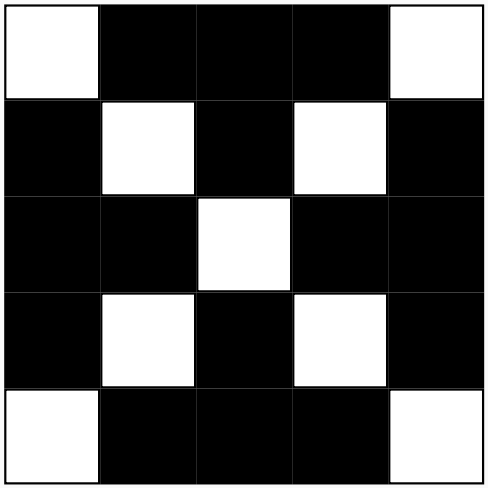


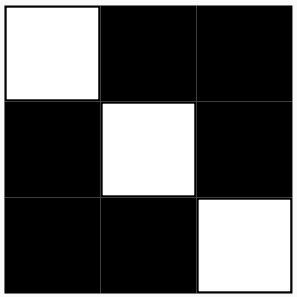
Pattern 1

3	0	1
0	3	0
1	0	3

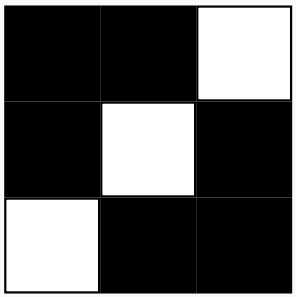
Convolutional neural networks: Convolution

Image

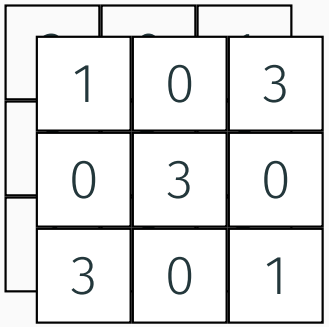




Pattern 1

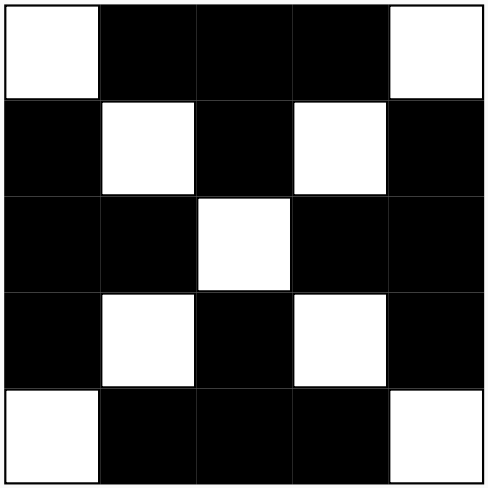


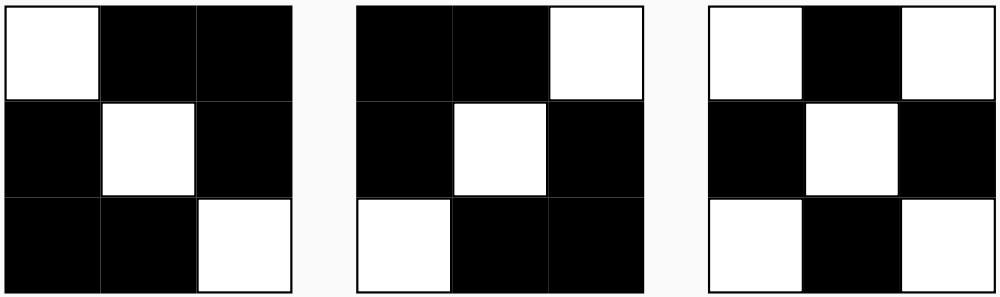
Pattern 2



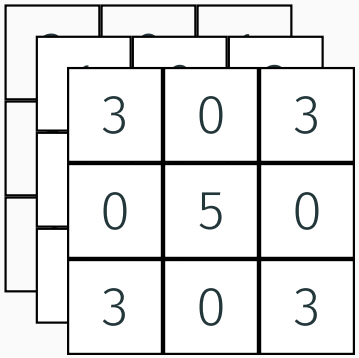
Convolutional neural networks: Convolution

Image



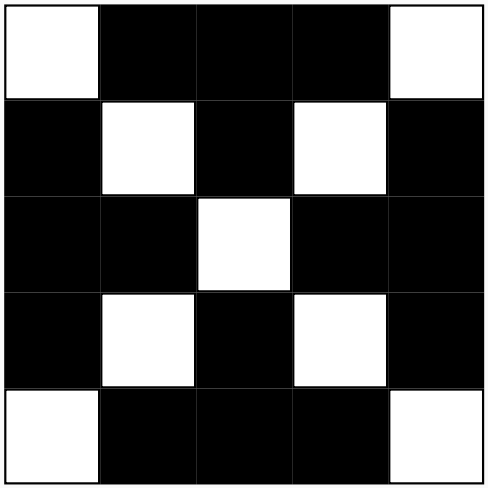


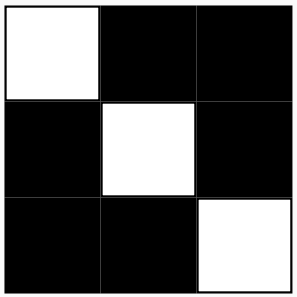
Pattern 1 Pattern 2 Pattern 3



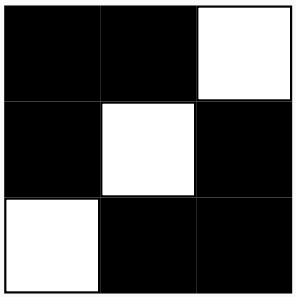
Convolutional neural networks: Convolution

Image

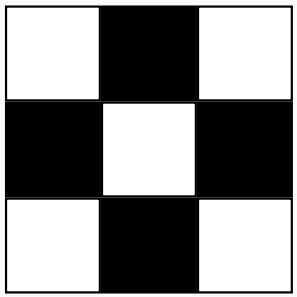




Pattern 1

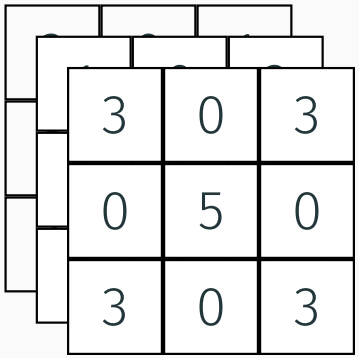


Pattern 2

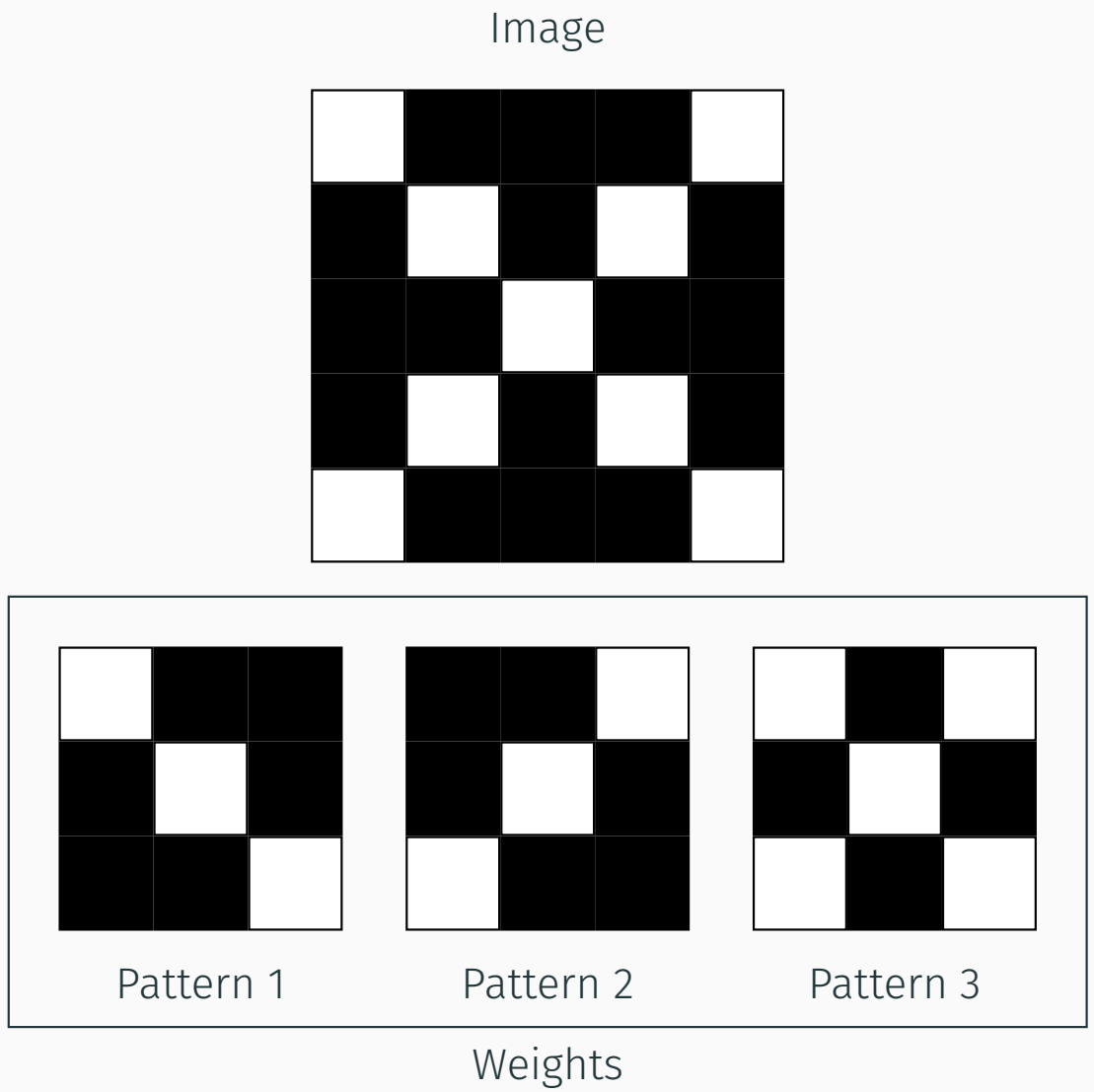


Pattern 3

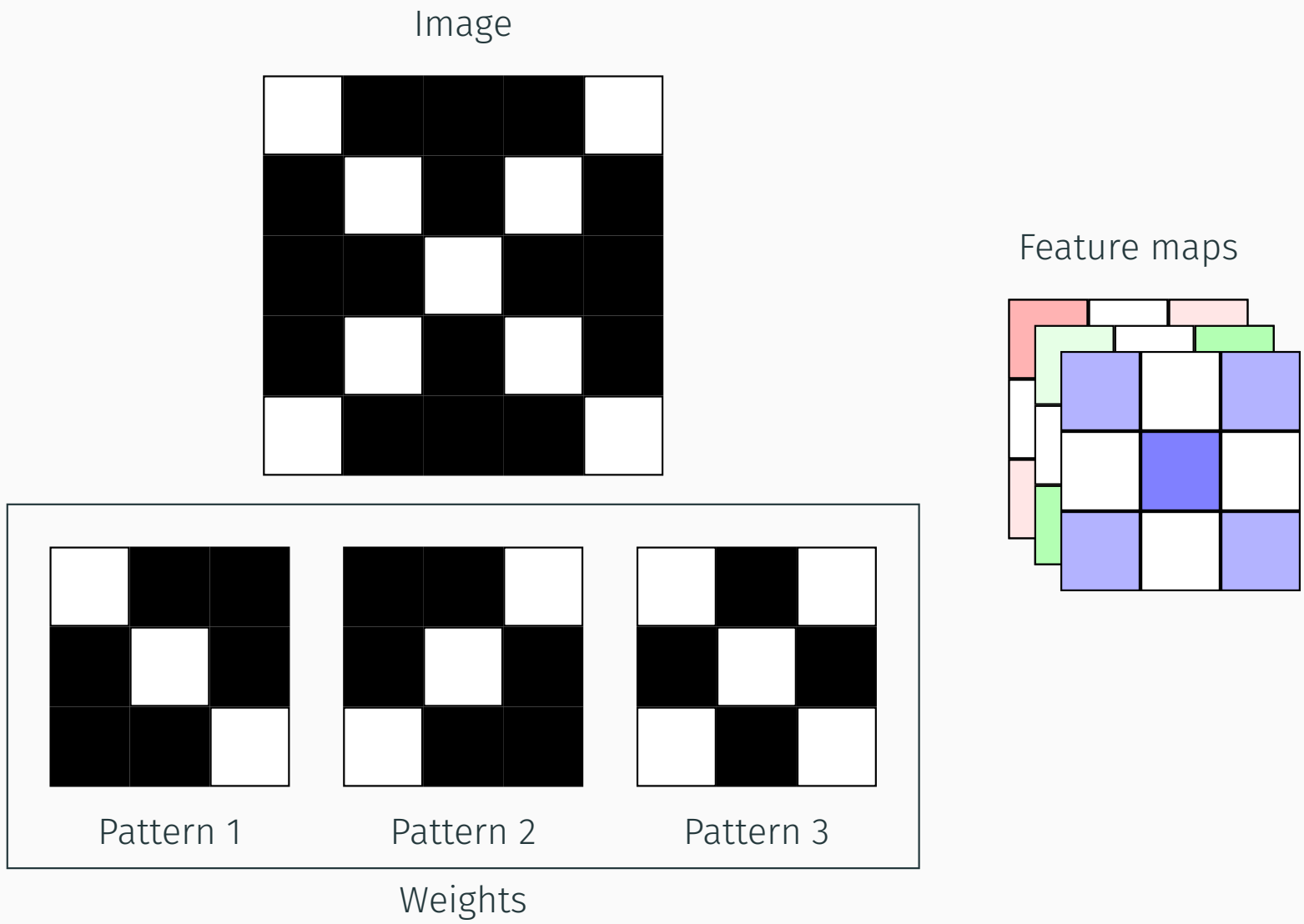
Feature maps



Convolutional neural networks: Convolution



Convolutional neural networks: Convolution



Convolutional neural networks: (Max-)Pooling

Feature map

0	1	2	3
4	5	6	7
8	9	10	1
12	13	14	15

Convolutional neural networks: (Max-)Pooling

Feature map

0	1	2	3
4	5	6	7
8	9	10	1
12	13	14	15

5

Convolutional neural networks: (Max-)Pooling

Feature map

0	1	2	3
4	5	6	7
8	9	10	1
12	13	14	15

5	7

Convolutional neural networks: (Max-)Pooling

Feature map

0	1	2	3
4	5	6	7
8	9	10	1
12	13	14	15

5	7
13	

Convolutional neural networks: (Max-)Pooling

Feature map

0	1	2	3
4	5	6	7
8	9	10	11
12	13	14	15

5	7
13	15

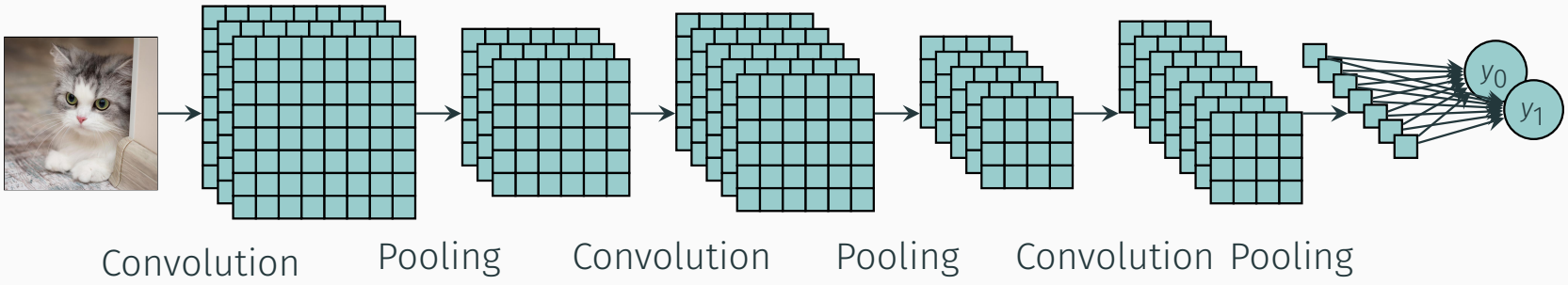
Convolutional neural networks: (Max-)Pooling

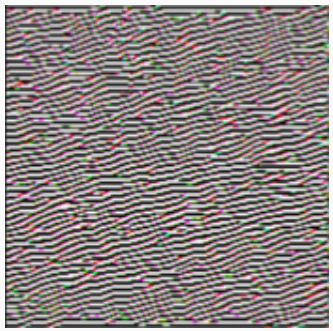
Feature map

0	1	2	3
4	5	6	7
8	9	10	1
12	13	14	15

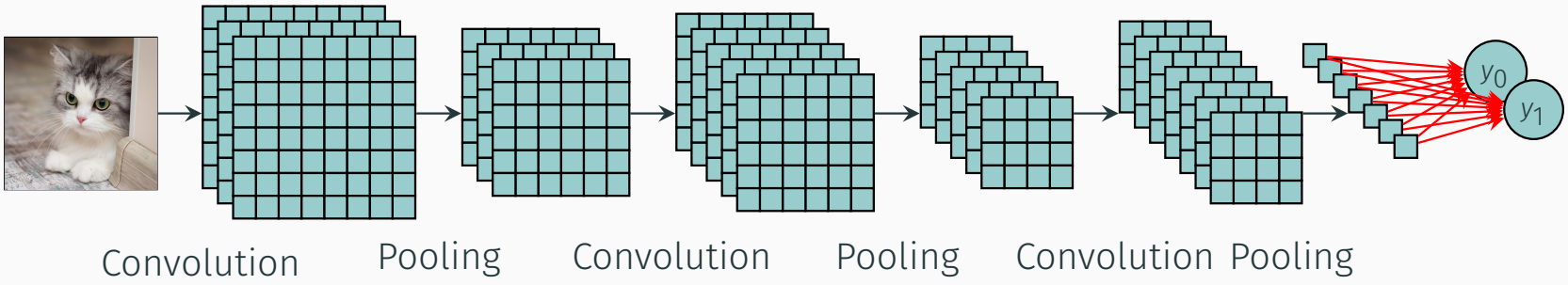
5	7
13	15

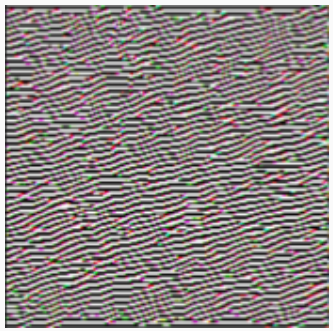
Convolutional neural networks: Overview



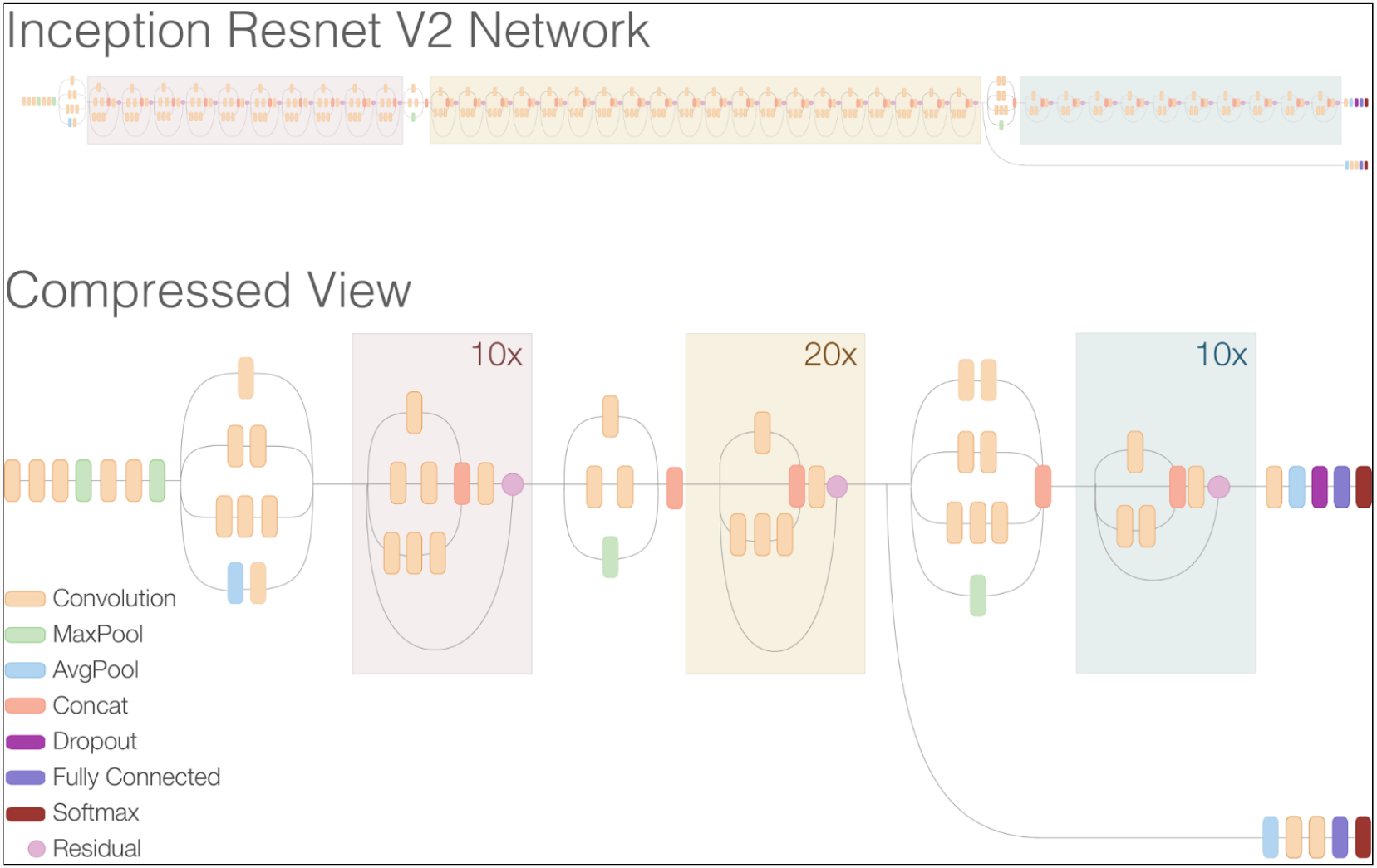


Convolutional neural networks: Overview





Convolutional neural networks: Overview

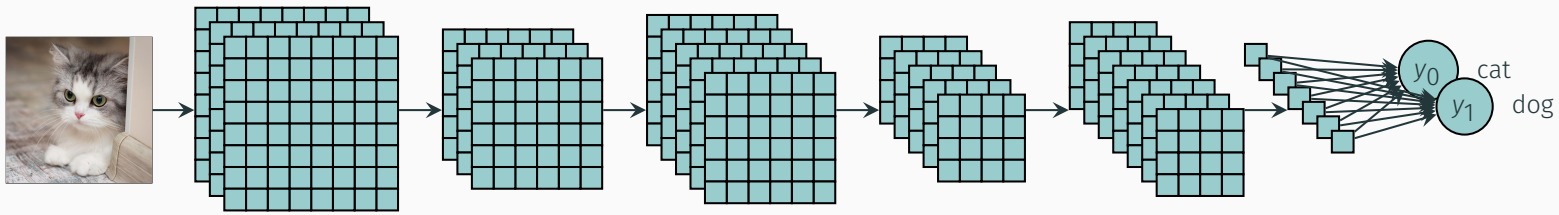


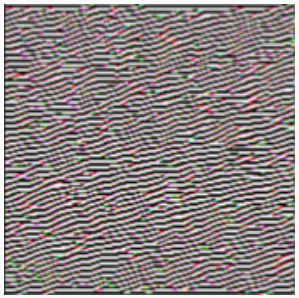
Convolutional neural networks: Overview

Convolutional neural networks (CNNs): Artificial neural networks tailored specifically for image data.

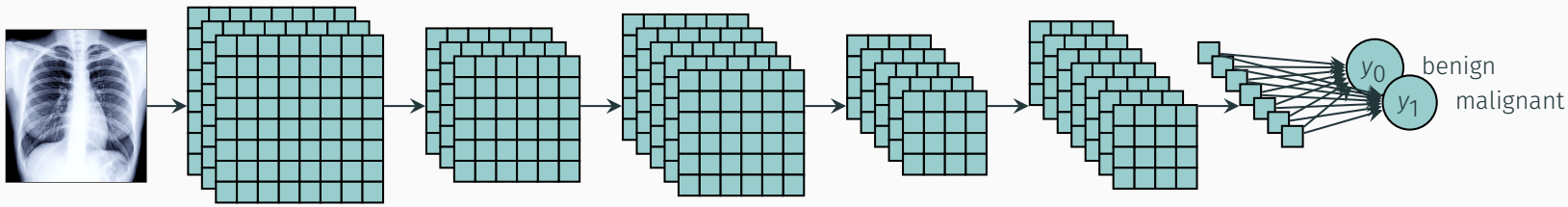
- Takes raw pixel data as input, e.g. arrays of size HxWxC
- Mainly consists of convolutions and pooling operations, which lets us recognize larger and more abstract patterns the deeper we get in the model
- The trainable parameters are the weights of the convolutional kernels, e.g. the patterns the model is looking for
- **New architectures extend beyond this basic formula, by employing residual connections, attention mechanisms etc.**

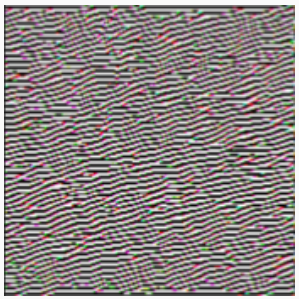
Computer vision: Transfer learning



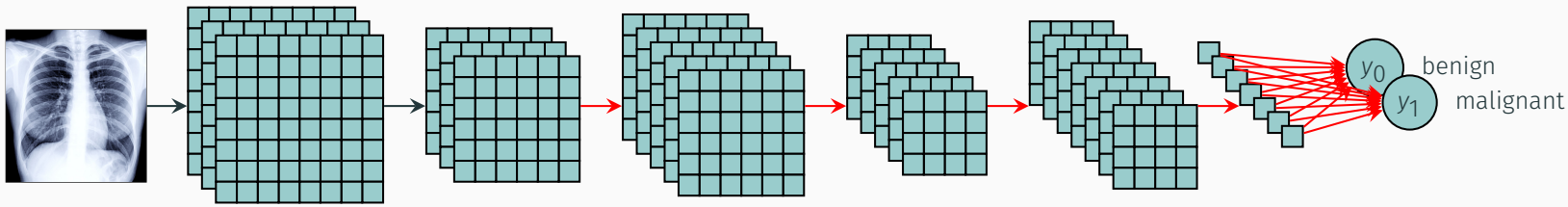


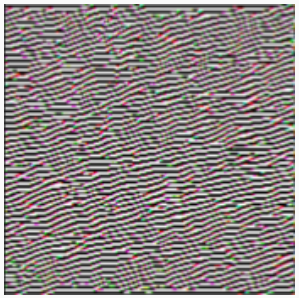
Computer vision: Transfer learning



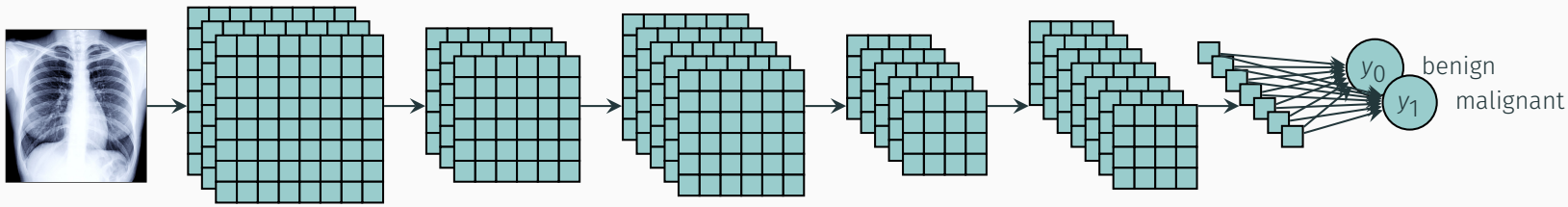


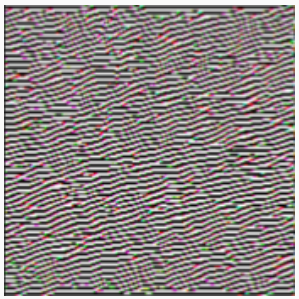
Computer vision: Transfer learning



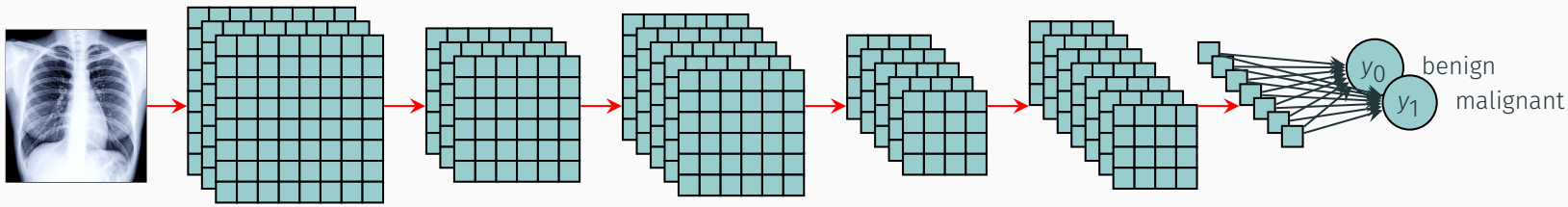


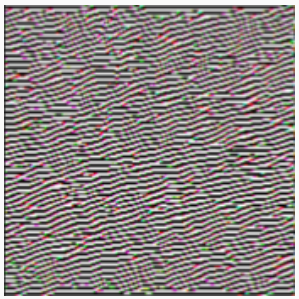
Computer vision: Transfer learning





Computer vision: Transfer learning





Computer vision: Transfer learning

Transfer learning: Utilizing pretrained models to solve new tasks.

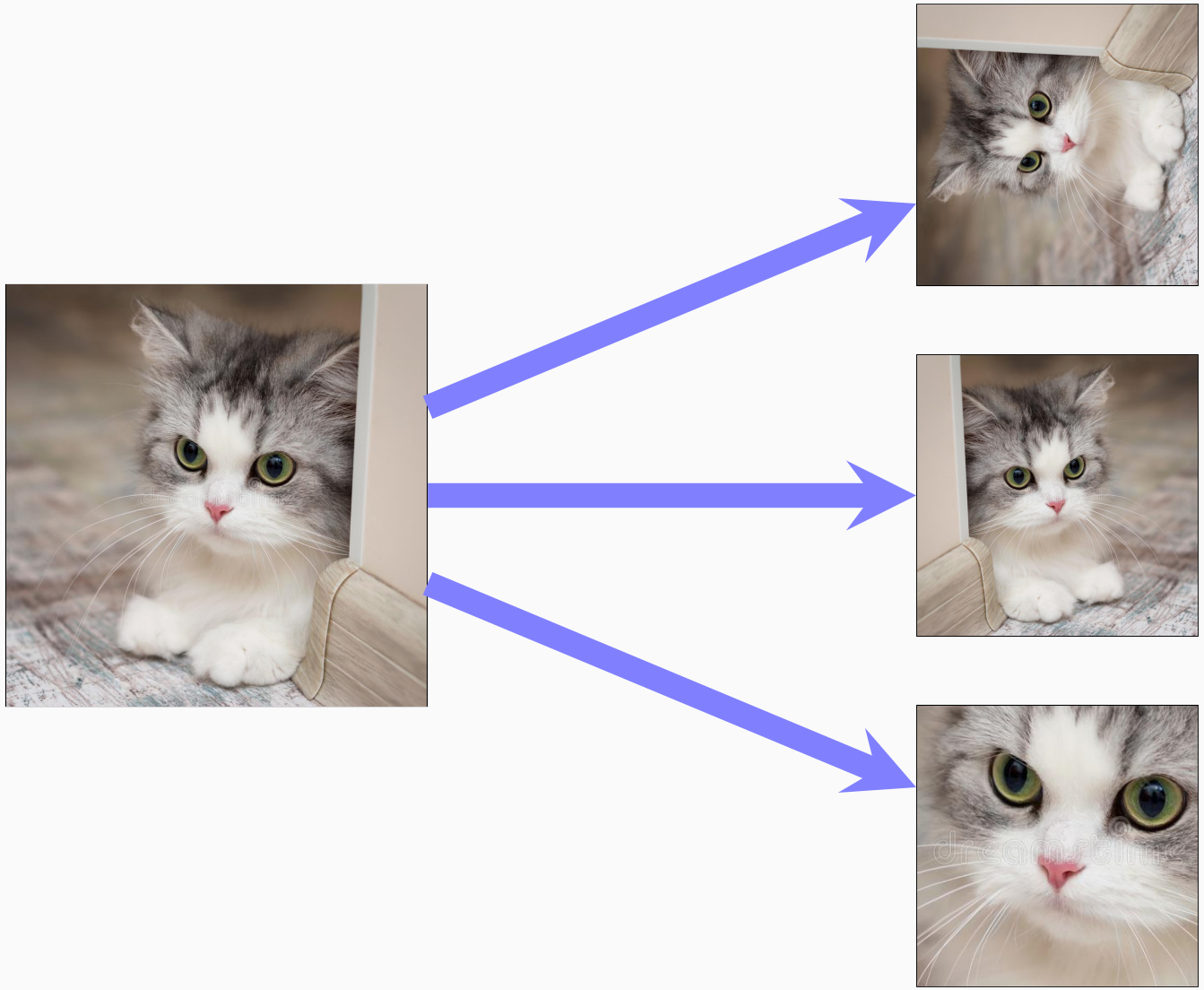
- Allows us to solve tasks where we don't have enough data to train a model from scratch
- Common to either freeze the weights of the convolutional part of pre-trained model and train a new classifier on top of them, or to finetune the entire model

Computer vision: Transfer learning

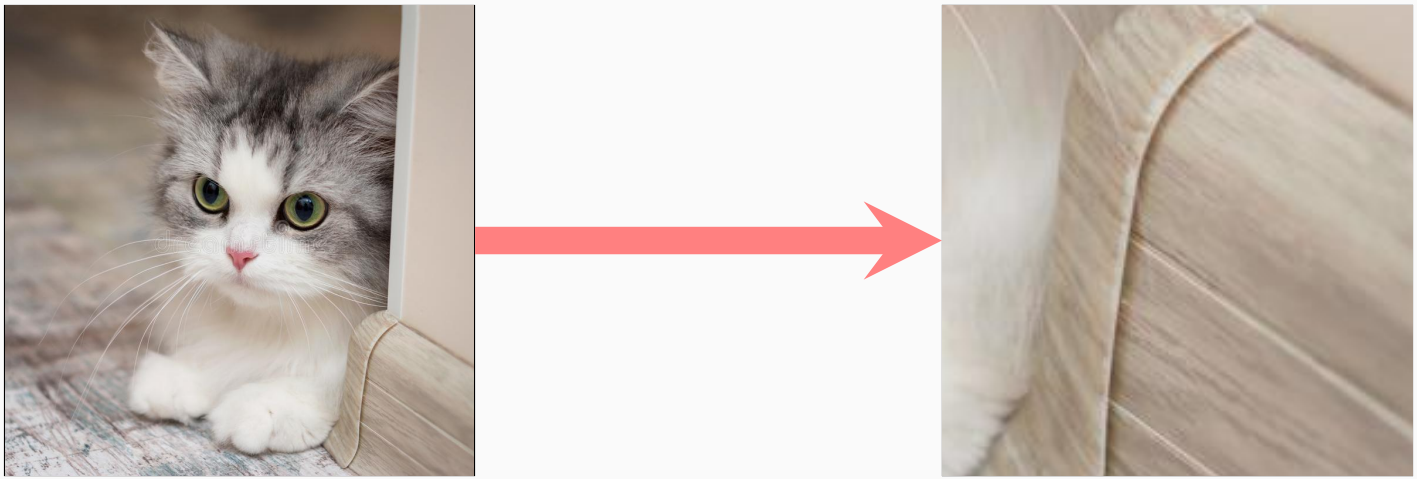
https://keras.io/api/applications/

Computer vision: Data augmentation

Computer vision: Data augmentation



Computer vision: Data augmentation



Computer vision: Data augmentation

https://albumentations.ai/

Computer vision: Tutorial

https://github.com/estenhl/flowers