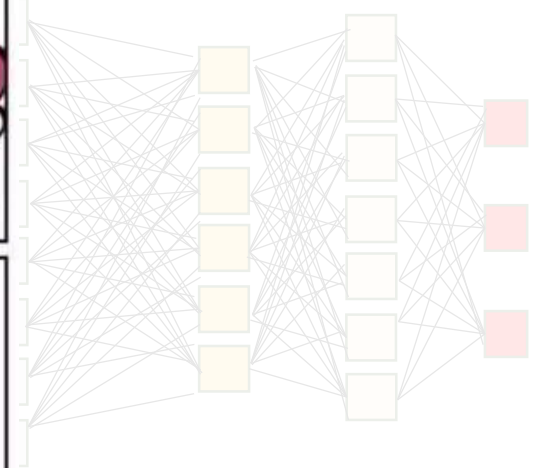
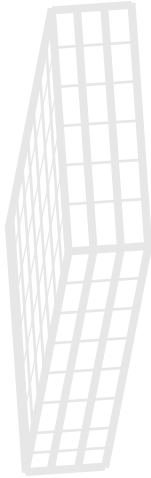
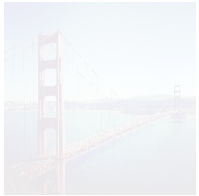


# Artificial Neural Networks in Python

*From Scratch!*





## outline

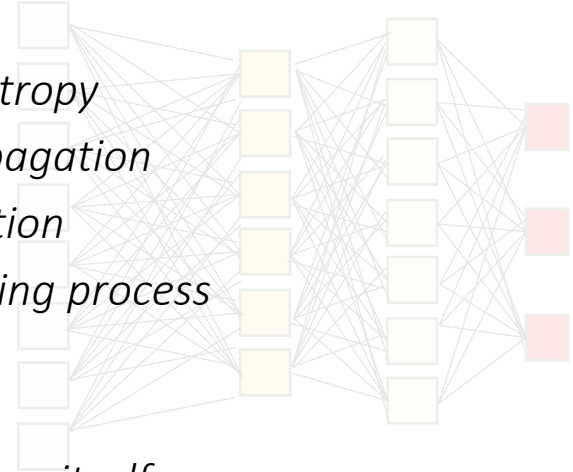
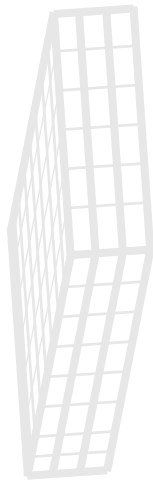
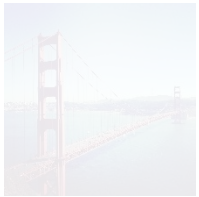
### 0 intro

#### I the core:

- a single neuron
- layers of neurons
- activation functions
- softmax
- loss & entropy
- backpropagation
- optimization
- the learning process

#### II convolution part:

- convolution itself
- pooling
- sigmoid
- flattening
- backpropagation - again
- testing the CNN & final remarks





## outline

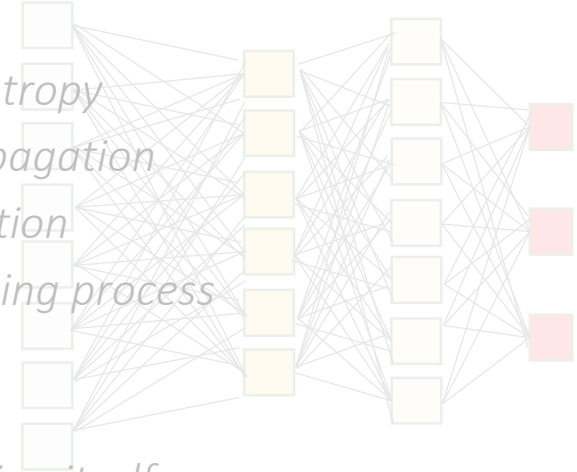
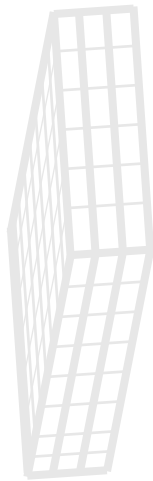
### 0 intro

I the core:

- a single neuron
- layers of neurons
- activation functions
- softmax
- loss & entropy
- backpropagation
- optimization
- the learning process

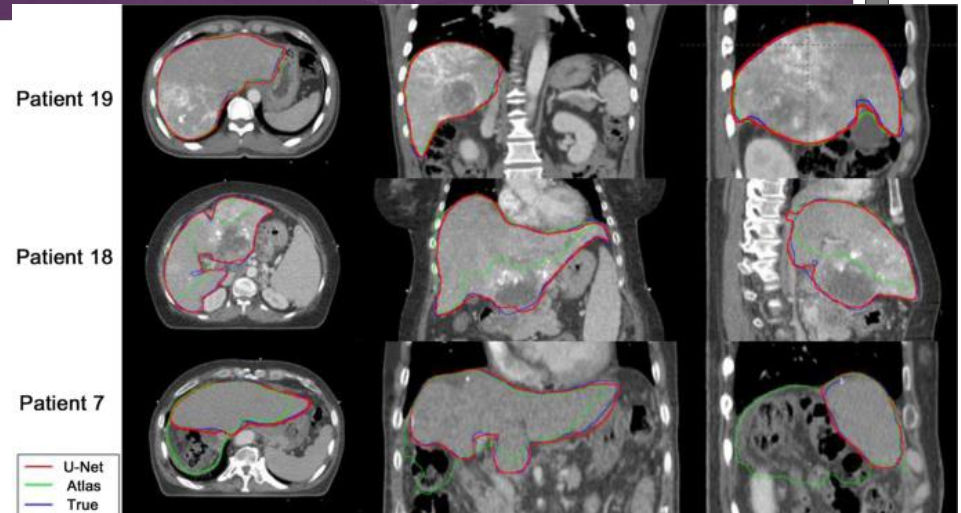
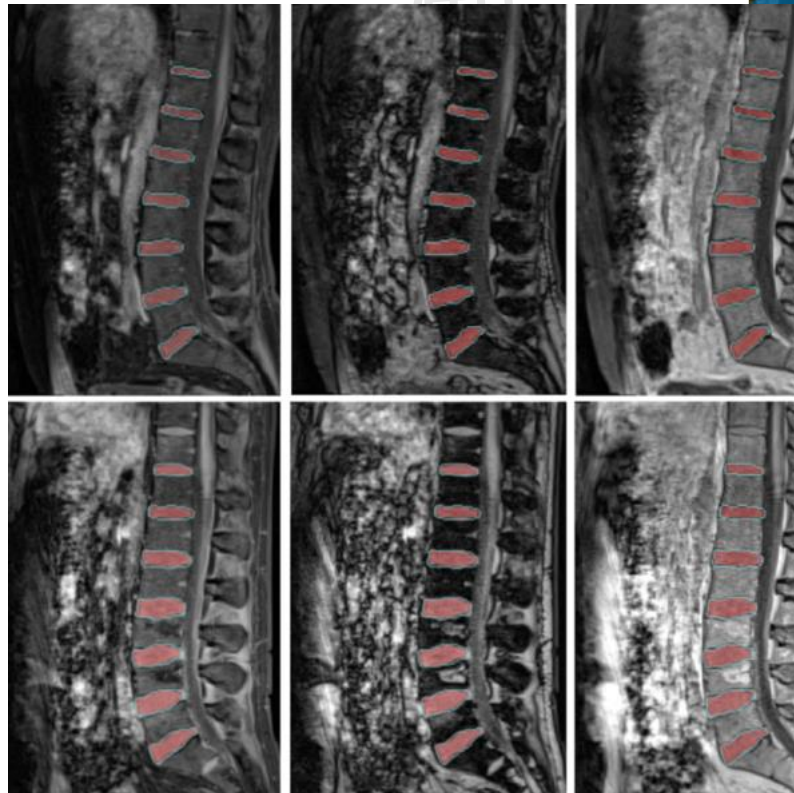
II convolution part:

- convolution itself
- pooling
- sigmoid
- flattening
- backpropagation - again
- testing the CNN & final remarks





## Why Artificial Neural Networks?



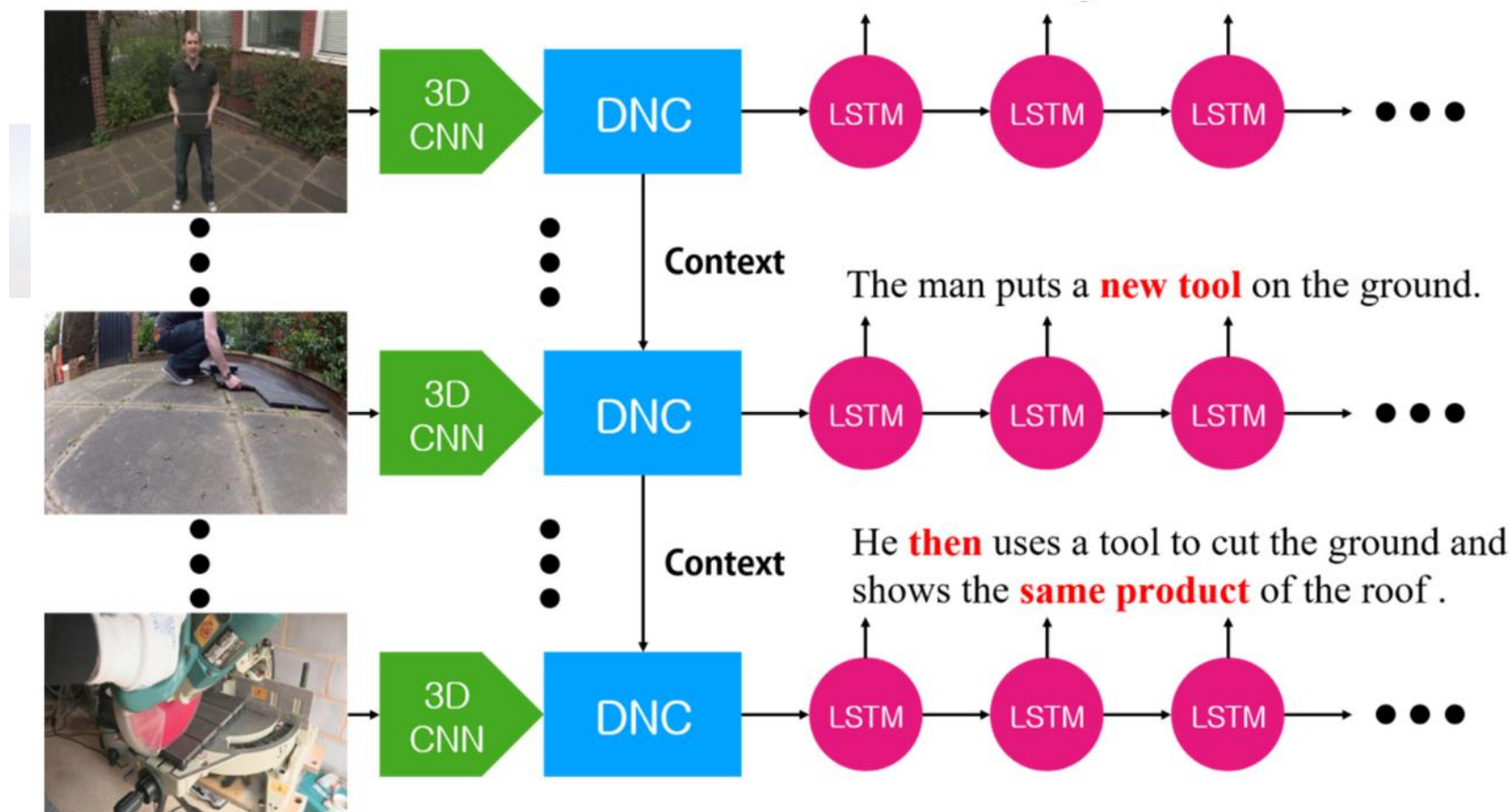


## Why Artificial Neural Networks?

**S:** 我<sup>3</sup> 就<sup>4</sup> 取<sup>5</sup> 钱<sup>6</sup> 给<sup>7</sup> 了<sup>7</sup> 她们  
i will get money to perf. them

**T:** <sup>2</sup>i <sup>1</sup>will <sup>0</sup>get the money to them

$P(\text{the} \mid \text{get, will, i, 就, 取, 钱, 给, 了})$







## Why Artificial Neural Networks?

Article

### DeepSOCIAL: Social Distancing Monitoring and Infection Risk Assessment in COVID-19 Pandemic

YOLOv4-based *Deep Neural Network* (DNN) model for automated people detection in the crowd in indoor and outdoor environments using common CCTV security cameras. The proposed DNN model in combination with an adapted inverse perspective mapping (IPM) technique and SORT tracking algorithm leads to a robust people detection and social distancing monitoring. The model has been trained against two most comprehensive datasets by the time of the research—the Microsoft Common Objects in Context (MS COCO) and Google Open Image datasets. The system has been

health authorities have set the 2-m physical distancing as a mandatory safety measure in shopping centres, schools and other covered areas. In this research, we develop a hybrid *Computer Vision* and YOLOv4-based *Deep Neural Network* (DNN) model for automated people detection in the crowd in indoor and outdoor environments using common CCTV security cameras. The proposed DNN model in combination with an adapted inverse perspective mapping (IPM) technique and SORT tracking algorithm leads to a robust people detection and social distancing monitoring. The model has been trained against two most comprehensive datasets by the time of the research—the Microsoft Common Objects in Context (MS COCO) and Google Open Image datasets. The system has been evaluated against the Oxford Town Centre dataset (including 150,000 instances of people detection)





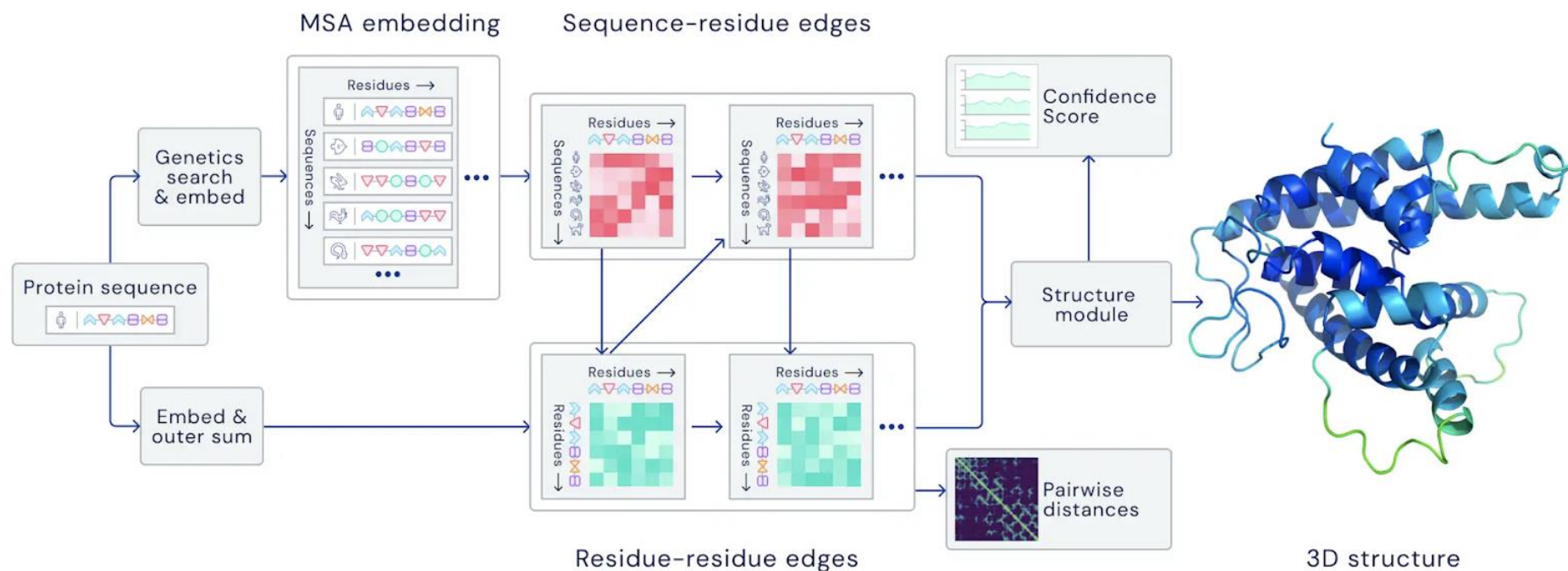
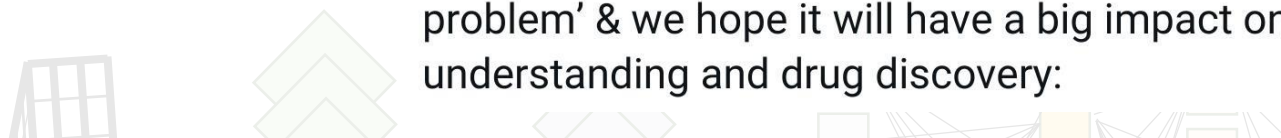
## Why Artificial Neural Networks?



Demis Hassabis ✓  
@demishassabis

...

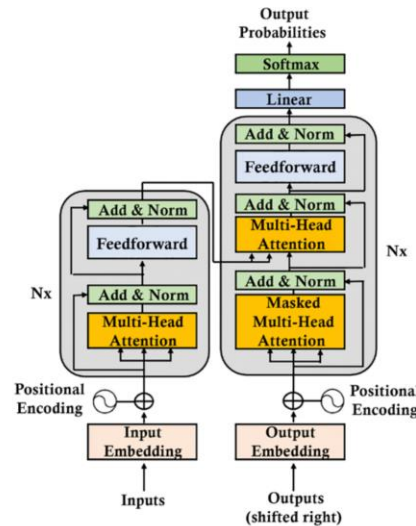
Thrilled to announce our first major breakthrough in applying AI to a grand challenge in science. [#AlphaFold](#) has been validated as a solution to the 'protein folding problem' & we hope it will have a big impact on disease understanding and drug discovery:







## Why Artificial Neural Networks?



language models  
“understanding” context



AI art

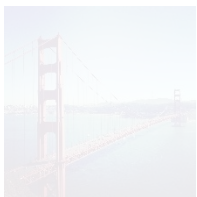




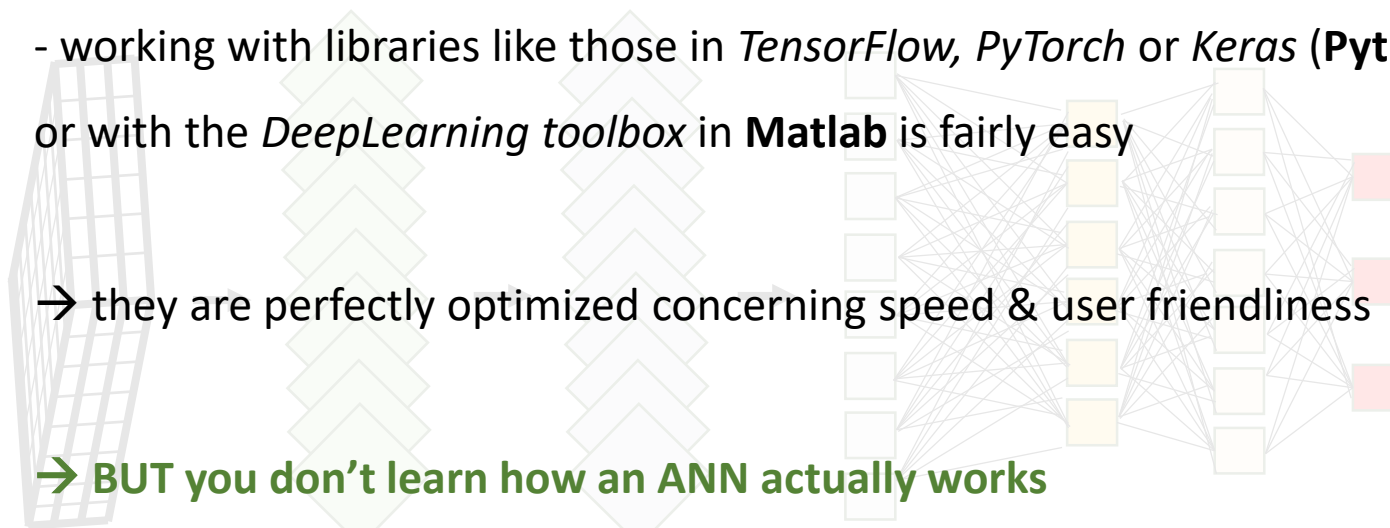
aim:

- creating a **simple**, but **fully functional convolutional ANN**, in Python
- **no use of external** ANN related **libraries** (only numpy!)

motivation:



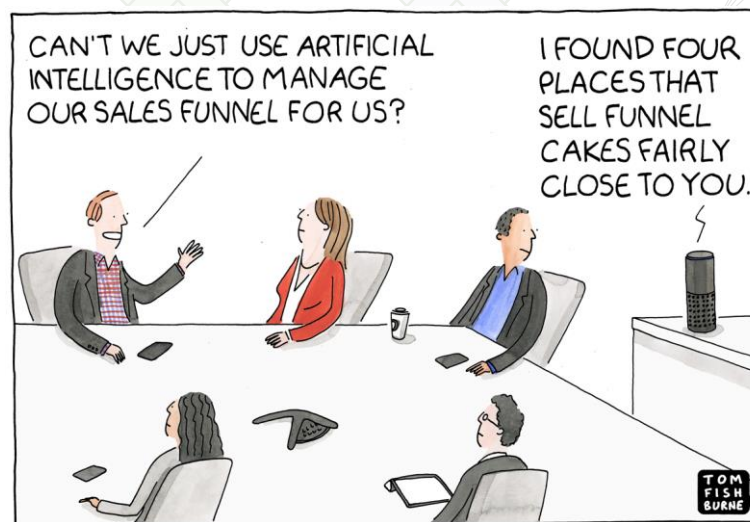
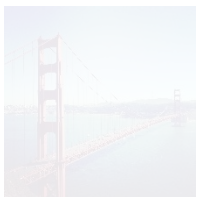
- working with libraries like those in *TensorFlow*, *PyTorch* or *Keras* (**Python**) or with the *DeepLearning toolbox* in **Matlab** is fairly easy
- they are perfectly optimized concerning speed & user friendliness
- **BUT you don't learn how an ANN actually works**
- **you can build it = you understand it!**
- **knowing how an ANN works exactly is a valuable skillset...**  
...and interesting anyway
- **we will see how somewhat abstract math turns into actual code**





- scope:**
- we won't get a code that is extremely fast and optimized concerning runtime
  - no nice graphical interface

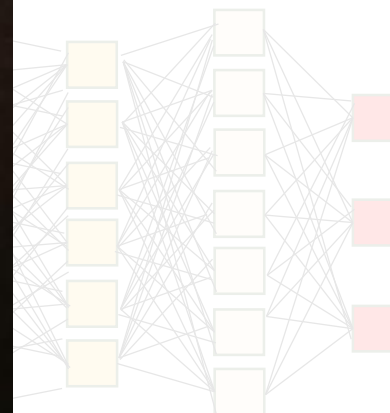
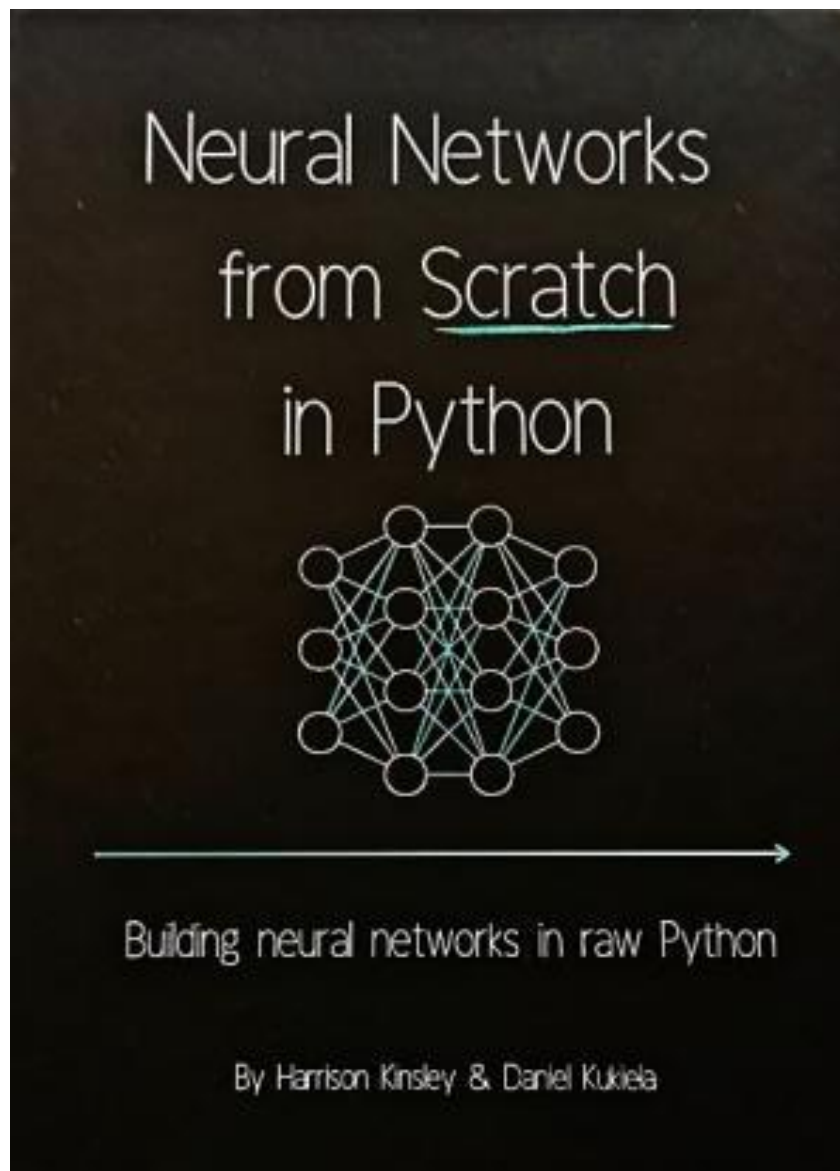
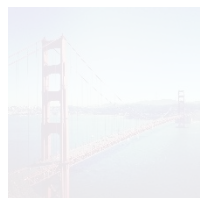
- prerequisites:**
- high school math:
    - o derivatives
    - o matrix and vector multiplication
    - o mean & variance
  - basic knowledge in Python or Matlab (syntax is similar)
- see my intro courses : )





**literature:**

this lecture us has been inspired by the book with the same name:





## outline

### 0 intro

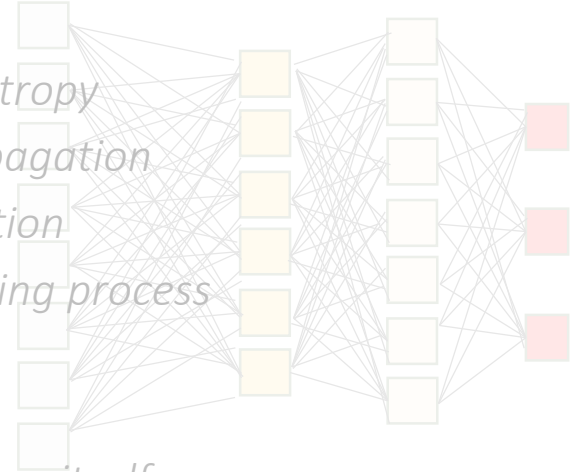
#### I the core:

##### - *a single neuron*

- *layers of neurons*
- *activation functions*
- *softmax*
- *loss & entropy*
- *backpropagation*
- *optimization*
- *the learning process*

#### II convolution part:

- *convolution itself*
- *pooling*
- *sigmoid*
- *flattening*
- *backpropagation - again*
- *testing the CNN & final remarks*





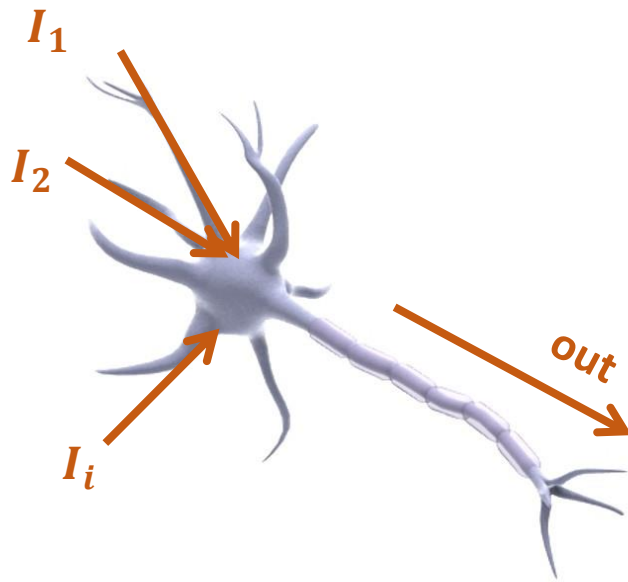


## what we know...

- inputs enter the neuron
- something happens inside the neuron
- neuron generates an output

## ...how we could model it

- inputs must be weighted (important vs unimportant input)
- **learning process: changing weights**
- output = sum of weighted inputs



$I_i$  input  $i$

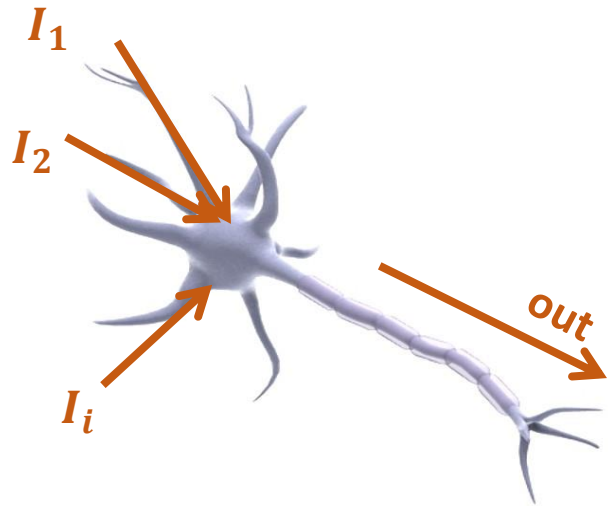
$w_i$  corresponding weight

$b$  bias (base potential)

$$o = \sum_i I_i \cdot w_i + b$$



**dot product**



$$o = \sum_i I_i \cdot w_i + b$$

$I_i$  input  $i$

$w_i$  corresponding weight

$b$  bias (base potential)

```
import numpy as np
```

```
def single_neuron(inputs):
```

```
    l = len(inputs)
```

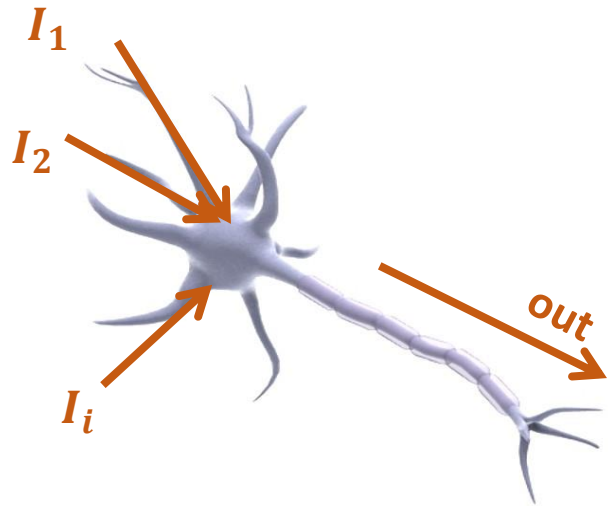
```
    weights = np.random.rand(1,l)
```

```
    bias     = np.random.rand(1,1)
```

```
    out      = np.dot(weights,inputs) + bias
```

```
    return(out)
```

save and run  
the function



$$o = \sum_i I_i \cdot w_i + b$$

$I_i$  input  $i$

$w_i$  corresponding weight

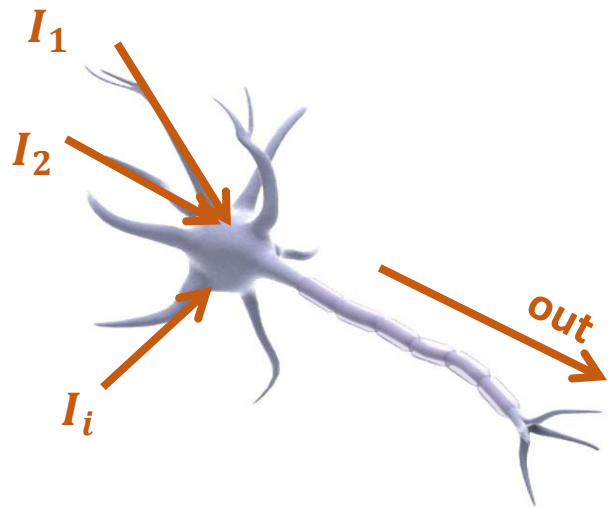
$b$  bias (base potential)

save and run  
the function

```
In [9]: I = [1,2,-4,5]
```

```
In [10]: out = single_neuron(I)
```

```
In [11]: print(out)  
[[2.54011995]]
```



$$o = \sum_i I_i \cdot w_i + b$$

$I_i$  input  $i$

$w_i$  corresponding weight

$b$  bias (base potential)

```
import numpy as np
```

```
def threeNeurons_OneLayer(inputs):
```

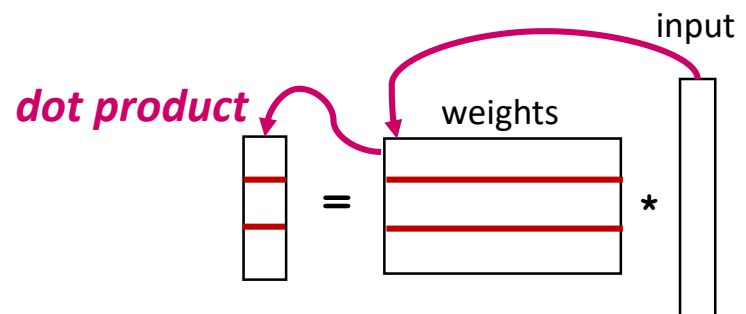
```
    l = len(inputs)
```

```
    weights = np.random.rand(3,1)
```

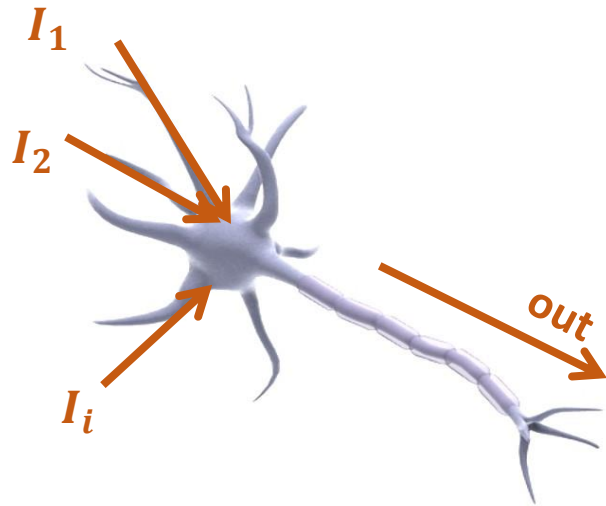
```
    bias    = np.random.rand(3)
```

```
    out     = np.dot(weights,inputs) + bias
```

```
    return(out)
```







$$o = \sum_i I_i \cdot w_i + b$$

$I_i$  input  $i$

$w_i$  corresponding weight

$b$  bias (base potential)

```
import numpy as np
```

```
def threeNeurons_OneLayer(inputs):
```

```
    l = len(inputs)
```

```
    weights = np.random.rand(3,1)
```

```
    bias     = np.random.rand(3)
```

```
    out      = np.dot(weights,inputs)
```

```
    return(out)
```

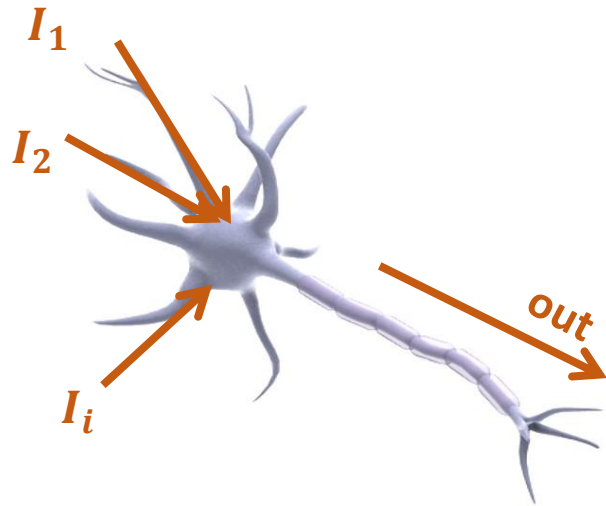
save and run  
the function

```
In [18]: I = [1,2,-4,5]
```

```
In [19]: out = threeNeurons_OneLayer(I)
```

```
In [20]: print(out)
```

```
[0.81383994 3.87728859 2.61411776]
```



$$o = \sum_i I_i \cdot w_i + b$$

$I_i$  input  $i$

$w_i$  corresponding weight

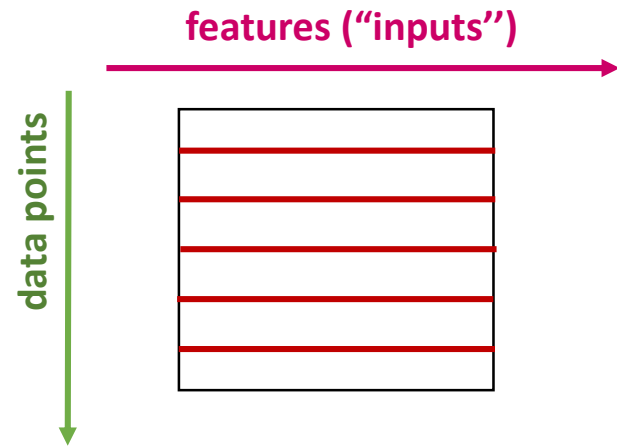
$b$  bias (base potential)

problem: - our input is actually a **matrix** /

- would like to link our neurons  
in a concise way

- passing on the information

→ layers





## outline

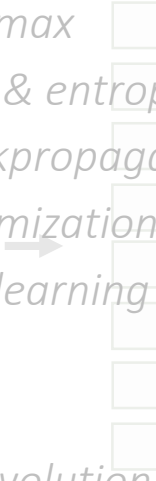
### 0 intro

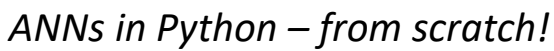
#### I the core:

- a single neuron
- **layers of neurons**
- activation functions
- softmax
- loss & entropy
- backpropagation
- optimization
- the learning process

#### II convolution part:

- convolution itself
- pooling
- sigmoid
- flattening
- backpropagation - again
- testing the CNN & final remarks





most convenient:

→ setting **weight**, **bias** and **output** as *attribute*

number of features per observation

number of neurons



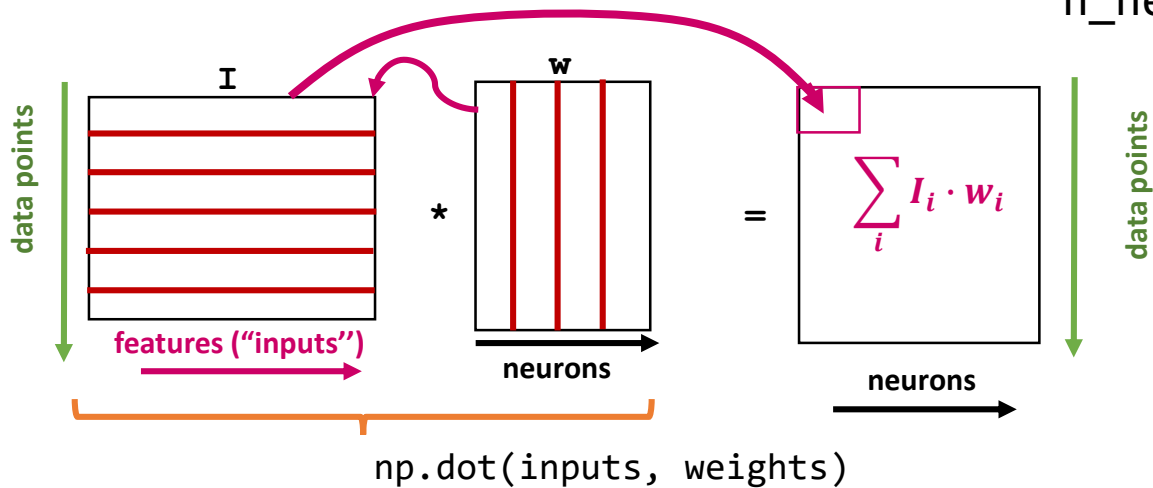




constructing a layer as **class**

→ setting **weight**, **bias** and **output** as *attribute*

n\_inputs: number of features  
per observation  
n\_neurons: number of neurons



**class** Layer\_Dense:

```
def __init__(self, n_inputs, n_neurons):  
    self.weights = np.random.rand(n_inputs, n_neurons)  
    self.biases = np.zeros((1, n_neurons))
```

initializing weights/biases

```
def forward(self, inputs):  
    self.output = np.dot(inputs, self.weights) + \  
        self.biases
```

as before: creating output; now as attribute



constructing a layer as **class**

→ setting **weight**, **bias** and **output** as *attribute*

n_inputs:	number of features per observation
n_neurons:	number of neurons

```
class Layer_Dense:

    def __init__(self, n_inputs, n_neurons):
        self.weights = np.random.rand(n_inputs, n_neurons)
        self.biases = np.zeros((1, n_neurons))

    def forward(self, inputs):
        self.output = np.dot(inputs, self.weights) + \
            self.biases
```

run e.g.

```
I = [[1, 3, 4, 5], [-2, -5, -6, 0]]
```

```
dense = Layer_Dense(4, 3)
dense.forward(I)
```

```
print(dense.output)
```



constructing a layer as **class**

→ setting **weight**, **bias** and **output** as *attribute*

n_inputs:	number of features per observation
n_neurons:	number of neurons

We can now easily link layers:

```
I      = [[1, 3, 4, 5], [-2, -5, -6, 0]]  
S      = np.shape(I)
```

```
dense1 = Layer_Dense(S[1], 3)
```

*n\_inputs* points to S[1] (3)  
*n\_neurons* points to 3

```
dense2 = Layer_Dense(3, 2)
```

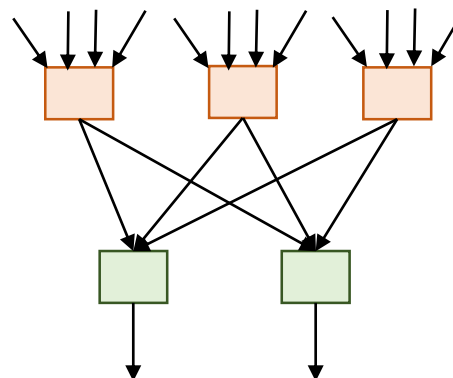
*defines the number of columns for next layer*  
*we will get two outputs per data point*

```
dense1.forward(I)
```

```
dense2.forward(dense1.output)
```

```
print(dense1.output)
```

```
print(dense2.output)
```





constructing a layer as **class**

→ setting **weight**, **bias** and **output** as *attribute*

n_inputs:	number of features per observation
n_neurons:	number of neurons

We can now easily link layers:

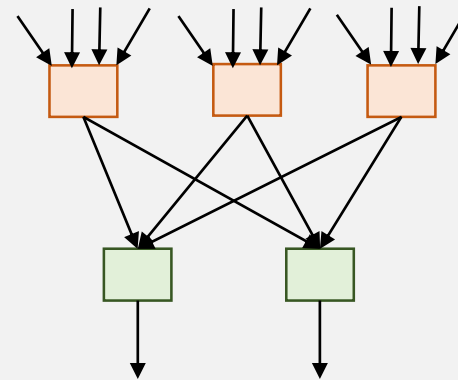
```
I      = [[1,3,4,5], [-2, -5, -6, 0]]  
S      = np.shape(I)
```

```
dense1 = Layer_Dense(S[1], 3)  
dense2 = Layer_Dense(3, 2)
```

defining layers

```
dense1.forward(I)
```

```
dense2.forward(dense1.output)
```



creating the actual network





## outline

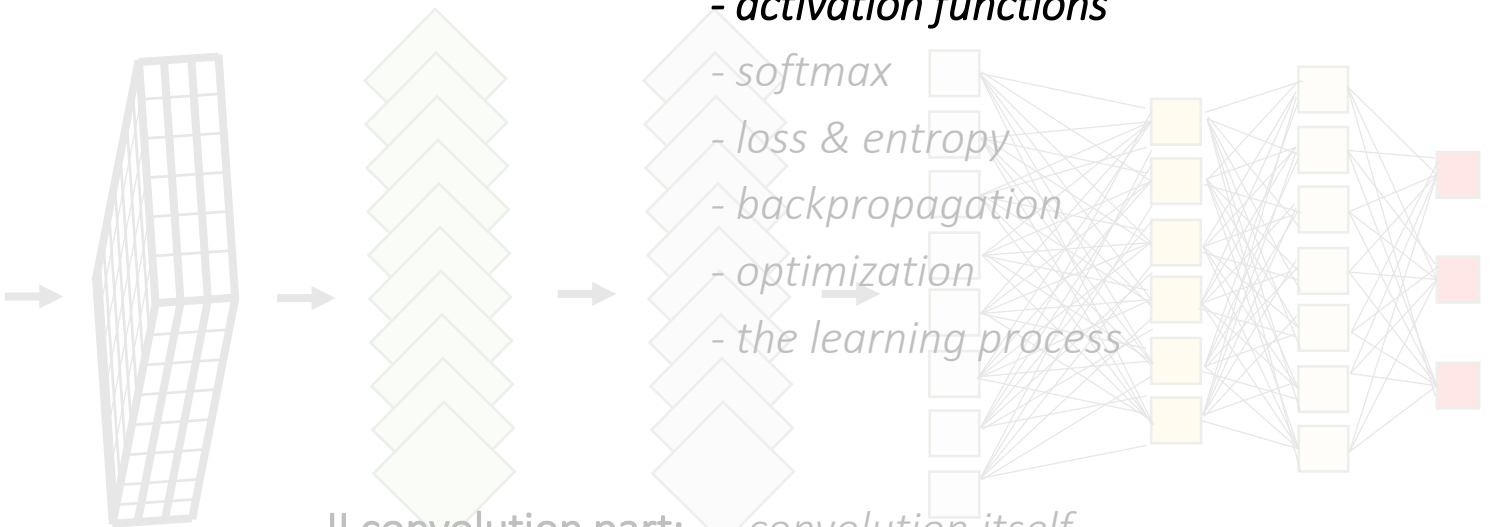
### 0 intro

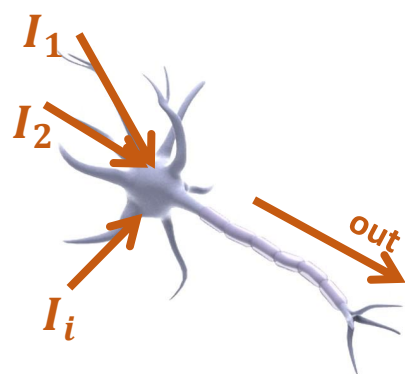
#### I the core:

- a single neuron
- layers of neurons
- **activation functions**
- softmax
- loss & entropy
- backpropagation
- optimization
- the learning process

#### II convolution part:

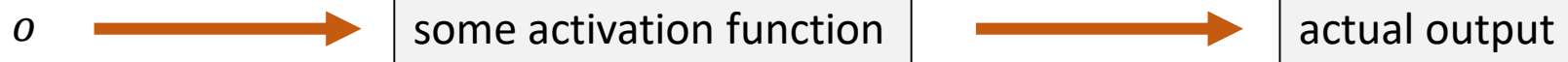
- convolution itself
- pooling
- sigmoid
- flattening
- backpropagation - again
- testing the CNN & final remarks



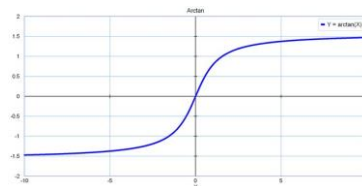


$I_i$  input  $i$   
 $w_i$  corresponding weight  
 $b$  bias (base potential)

$$o = \underbrace{\sum_i I_i \cdot w_i}_{\text{dot product}} + b$$

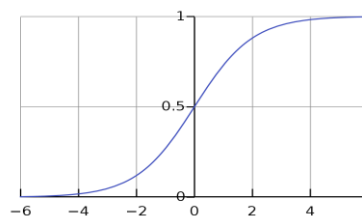


-  $y = \arctan(o)$



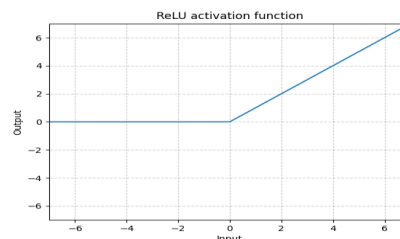
$(-\infty; +\infty) \rightarrow (-\pi/2; +\pi/2)$

-  $y = \text{sigm}(o)$



$(-\infty; +\infty) \rightarrow (0; 1)$

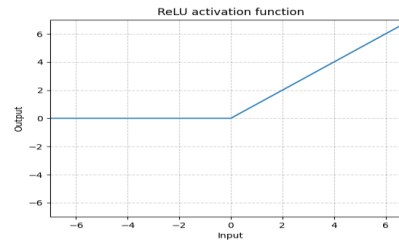
-  $y = \text{ReLU}(o)$   
 $= \max(0, o)$



$(-\infty; +\infty) \rightarrow (0; +\infty)$



$$y = \text{ReLU}(o) \\ = \max(0, o)$$



$$(-\infty; +\infty) \rightarrow (0; +\infty)$$

same idea as before:

```
class Activation_ReLU:
```

```
    def forward(self, inputs):  
        self.output = np.maximum(0, inputs)
```



```
I      = [[1,3,4,5], [-2, -5, -6, 0]]  
S      = np.shape(I)
```

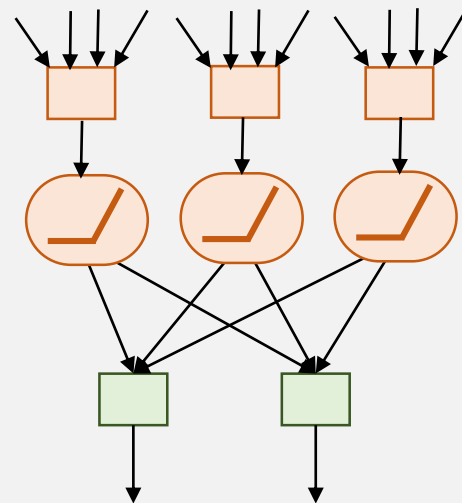
```
n_neu1 = 3  
n_neu2 = 2
```

```
dense1      = Layer_Dense(S[1], n_neu1)  
dense2      = Layer_Dense(n_neu1, n_neu2)  
activation1 = Activation_ReLU()
```

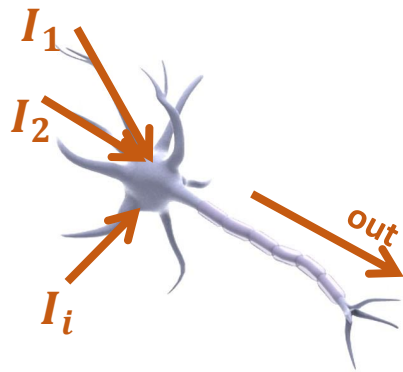
defining layers

```
dense1.forward(I)  
activation1.forward(dense1.output)  
dense2.forward(activation1.output)
```

```
print(dense1.output)  
print(activation1.output)  
print(dense2.output)
```



creating the actual network

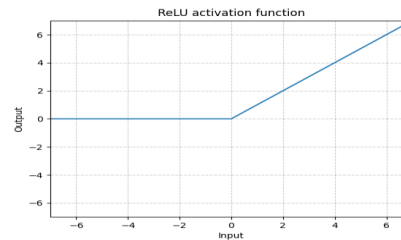


$I_i$  input  $i$   
 $w_i$  corresponding weight  
 $b$  bias (base potential)

$$o = \sum_i I_i \cdot w_i + b$$

dot product

-  $y = \text{ReLU}(o)$   
 $= \max(0, o)$



$(-\infty; +\infty) \rightarrow (0; +\infty)$

we can now create an arbitrarily complex network with any number of neurons

- the network is still **not able to learn**
- for that, we need a criteria, an **objective function**, to **optimize**
- for that, we need to compare the target output to the actual output  
(already ok for regression)
- for that we need a layer assigning **probabilities for classification**



## outline

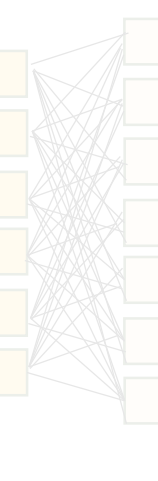
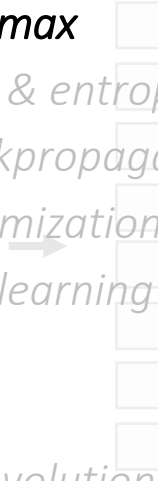
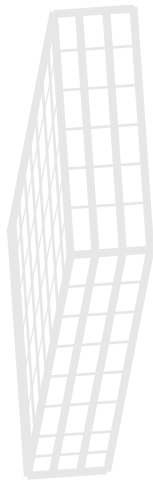
### 0 intro

### I the core:

- a single neuron
- layers of neurons
- activation functions
- **softmax**
- loss & entropy
- backpropagation
- optimization
- the learning process

### II convolution part:

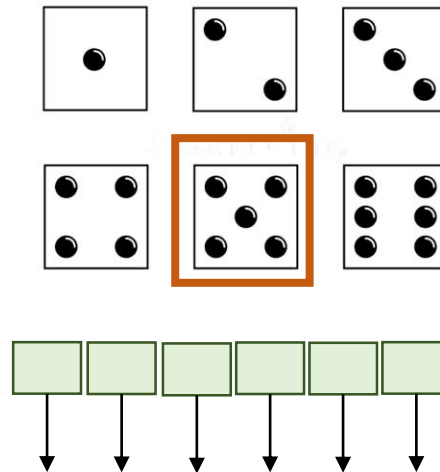
- convolution itself
- pooling
- sigmoid
- flattening
- backpropagation - again
- testing the CNN & final remarks



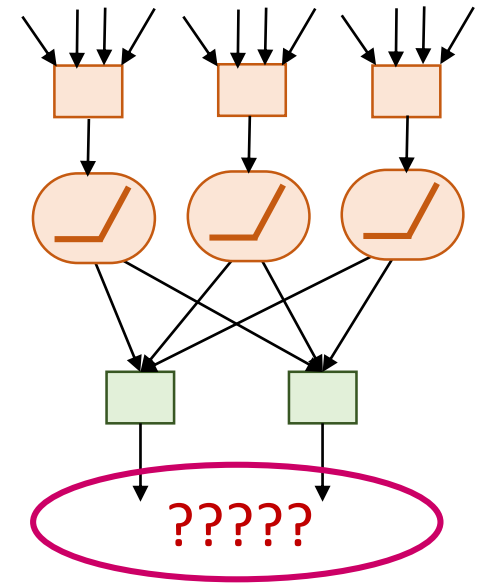




problem: how to assign probabilities to outputs?



real world  $p_i =$  0.05 0.1 0 0.05 0.7 0.1



→ entropy  $S$  is a good measure of the categorization quality (see next chapter)

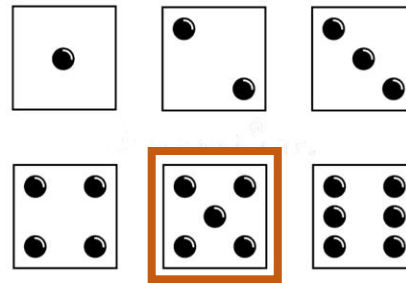
$$S = - \sum_i p_i \cdot \ln p_i$$

**note**: entropy has nothing to do with order  
→ it is a measure of the amount of information



problem: how to assign probabilities to outputs?

$$S = - \sum_i p_i \cdot \ln p_i$$



each output  $\varepsilon_i$  (that ranges from zero to  $+\infty$ )  
has to be mapped to  $p_i$  (that ranges from zero to 1)

$$\rightarrow p_i = p_i(\varepsilon_i) = ?$$

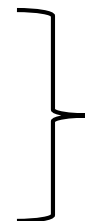
we know that:  $\sum_i p_i = 1$   
thus  $\sum_i p_i \varepsilon_i = \langle \varepsilon \rangle$   
where  $\varepsilon$  is a positive number

$\rightarrow$  **maximizing entropy** given these two constraints

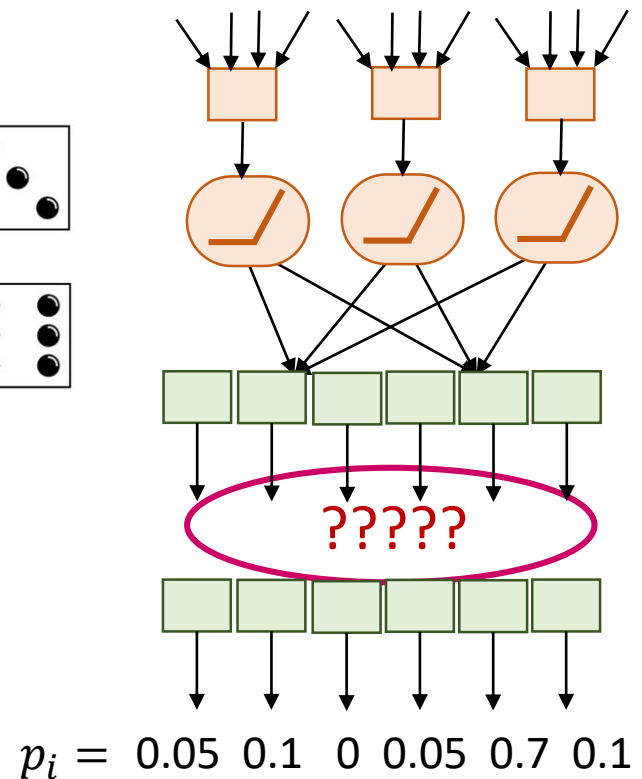
we know from stat physics,  
that this leads to the  
**Boltzmann distribution**  
(see Lagrangian multipliers)

$$p_i \sim \exp(\beta \varepsilon_i)$$

$$\sum_i p_i = 1$$



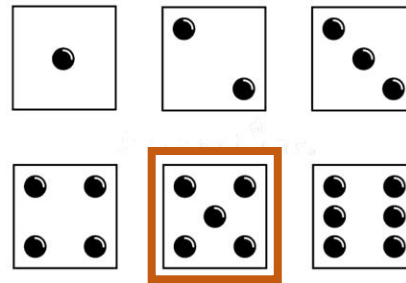
$$p_i = \frac{\exp(\beta \varepsilon_i)}{\sum_i \exp(\beta \varepsilon_i)}$$





problem: how to assign probabilities to outputs?

$$S = - \sum_i p_i \cdot \ln p_i$$



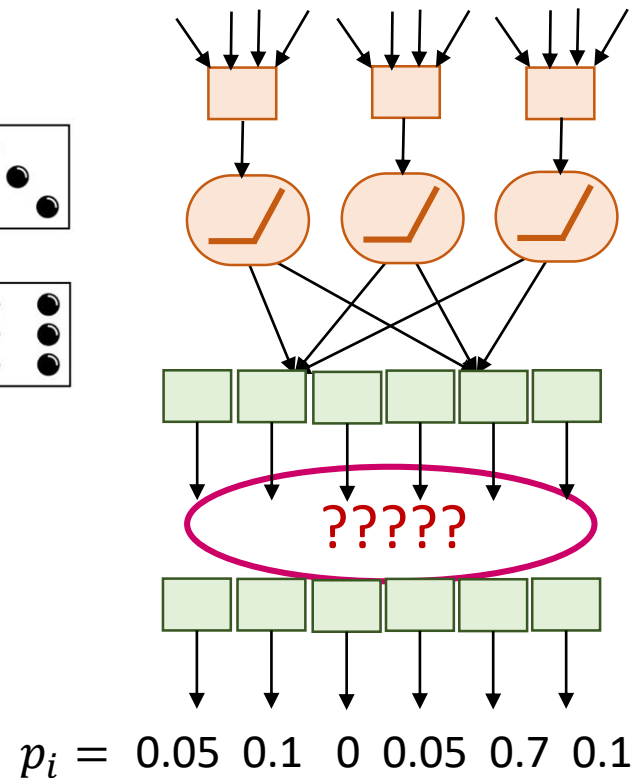
each output  $\varepsilon_i$  (that ranges from zero to  $+\infty$ )  
has to be mapped to  $p_i$  (that ranges from zero to 1)

$$\rightarrow p_i = p_i(\varepsilon_i) = ?$$

we know that:  $\sum_i p_i = 1$   
thus  $\sum_i p_i \varepsilon_i = \langle \varepsilon \rangle$   
where  $\varepsilon$  is a positive number

$\rightarrow$  **maximizing entropy** given these two constraints

check out **maximum entropy distributions** and **Lagrangian Multiplier**





problem: how to assign probabilities to outputs?

### ***Boltzmann distribution***

partition function

$\mathcal{Z}$  (normalization factor)

$$p_i = \frac{\exp(\beta \varepsilon_i)}{\sum_i \exp(\beta \varepsilon_i)}$$



$\beta$  unknown constant  $\rightarrow$  depending on context:

if  $\varepsilon_i$  is interpreted as energy  
 $\rightarrow \beta = -1/T$  with temperature  $T$   
(see reinforced learning)

here:  $\beta = 1$  (we don't have physical temperature  $\rightarrow$  unit system is arbitrary)

note: it's called ***softmax***, as contrast to a "hard max" like  $\operatorname{argmax}(\varepsilon_i)$



problem: how to assign probabilities to outputs?

**Boltzmann distribution**

$$p_i = \frac{\exp(\varepsilon_i)}{\sum_i \exp(\varepsilon_i)}$$

```
class Activation_Softmax:
```

```
    def forward(self, inputs):
```

```
        exp_values = np.exp(inputs - np.max(inputs))
```

adjusting in order to prevent overflow

```
        probabilities = exp_values/np.sum(exp_values, axis = 1,\
                                          keepdims = True)
```

```
        self.output = probabilities
```

→ lets add the new layer to the network



```
I      = [[1,3,4,5], [-2, -5, -6, 0]]  
S      = np.shape(I)
```

```
n_neu1 = 3  
n_neu2 = 2
```

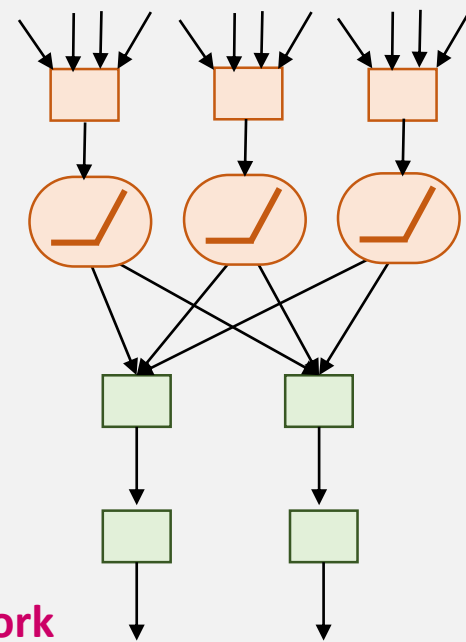
```
dense1      = Layer_Dense(S[1], n_neu1)  
dense2      = Layer_Dense(n_neu1, n_neu2)  
activation1 = Activation_ReLU()  
activation2 = Activation_Softmax()
```

defining layers

```
dense1.forward(I)  
activation1.forward(dense1.output)  
dense2.forward(activation1.output)  
activation2.forward(dense2.output)
```

```
print(activation2.output)  
print(np.sum(activation2.output,1))
```

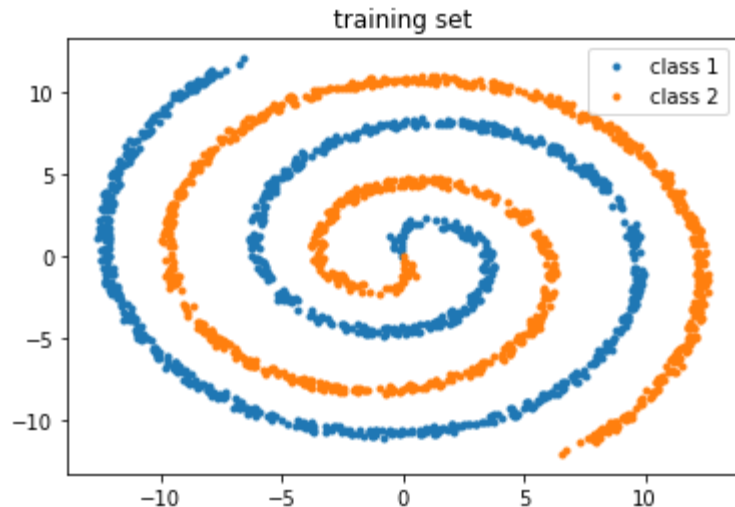
creating the actual network







the whole thing becomes more serious now → let us load a toy data set



### spiral data set

→ Spyder command prompt  
→ type: `pip install nnfs`

→ in Spyder  
→ type: `from nnfs.datasets import spiral_data`

```
[x, y] = spiral_data(samples = 200, classes = 3)
```

y: vector of classes, check:  
`print(np.unique(y))`

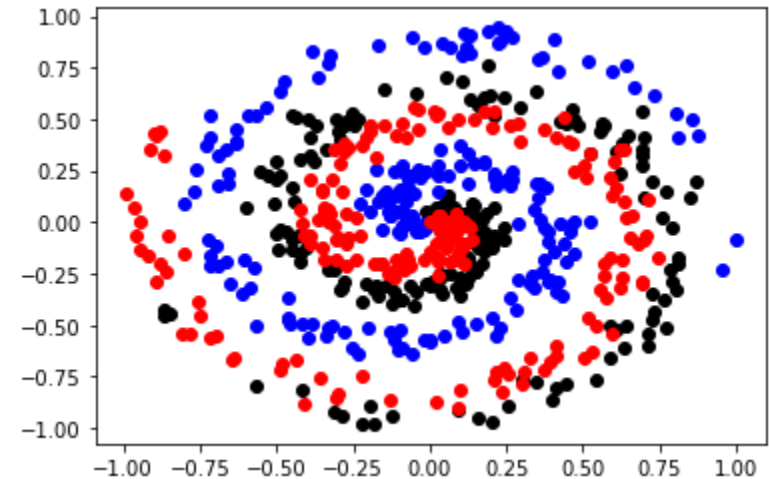
x: vector of **200 x 3** data points with two features,  
→ equivalent to **I** before, check:  
`print(x[0:5, :])`



the whole thing becomes more serious now → let us load a toy data set

```
import matplotlib.pyplot as plt
```

```
idx0 = np.argwhere(y==0)  
idx1 = np.argwhere(y==1)  
idx2 = np.argwhere(y==2)
```



```
plt.scatter(x[idx0,0],x[idx0,1], c = 'black')  
plt.scatter(x[idx1,0],x[idx1,1], c = 'blue')  
plt.scatter(x[idx2,0],x[idx2,1], c = 'red')
```

→ spiral shaped data is usually hard to analyze with common machine learning methods  
→ ANN



## outline

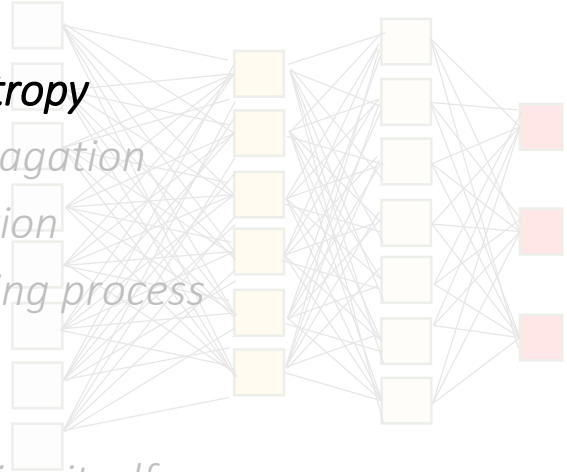
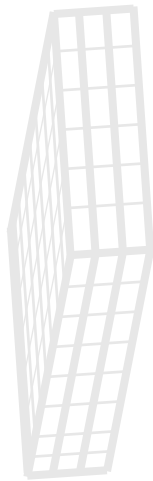
### 0 intro

#### I the core:

- a single neuron
- layers of neurons
- activation functions
- softmax
- **loss & entropy**
- backpropagation
- optimization
- the learning process

#### II convolution part:

- convolution itself
- pooling
- sigmoid
- flattening
- backpropagation - again
- testing the CNN & final remarks



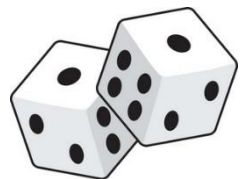


**Entropy is a mathematically precise measure of information!**

But what is entropy now – really?!

$$S = - \sum_{n=1}^N p_n \ln(p_n)$$

- entropy high  $\rightarrow$  information low
- entropy low  $\rightarrow$  information high



fair die: events are

1, 2, 3, 4, 5, 6

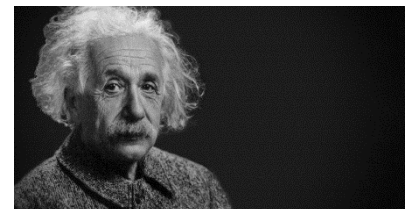
$p_n$  are

$p_1, p_2, p_3, p_4, p_5, p_6 = 1/6$  for all  $p_n$

Hi Eini: guess the  
number I rolled!



I have no idea, so all numbers are  
equally likely if it's a fair die.



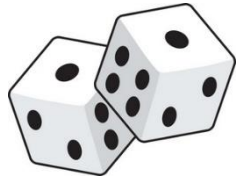


**Entropy is a mathematically precise measure of information!**

But what is entropy now – really?!

$$S = - \sum_{n=1}^N p_n \ln(p_n)$$

- entropy high  $\rightarrow$  information low
- entropy low  $\rightarrow$  information high



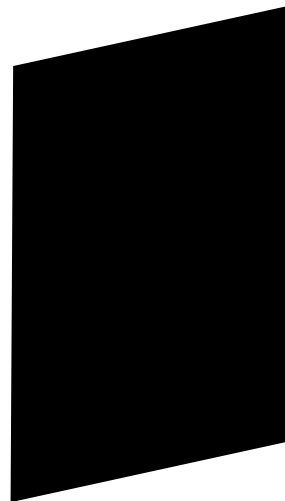
fair die: events are

1, 2, 3, 4, 5, 6

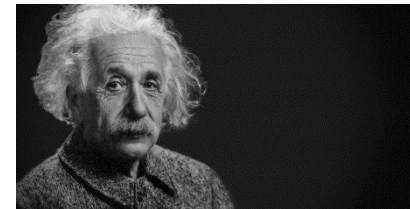
$p_n$  are

$p_1, p_2, p_3, p_4, p_5, p_6 = 1/6$  for all  $p_n$

Hi Eini: guess the  
number I rolled!



$$S = -\frac{1}{6} \ln\left(\frac{1}{6}\right) * 6 = 1.79 \dots$$



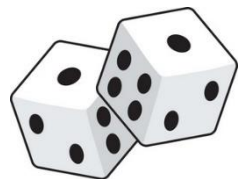


**Entropy is a mathematically precise measure of information!**

But what is entropy now – really?!

$$S = - \sum_{n=1}^N p_n \ln(p_n)$$

- entropy high  $\rightarrow$  information low
- entropy low  $\rightarrow$  information high



fair die: events are

1, 2, 3, 4, 5, 6

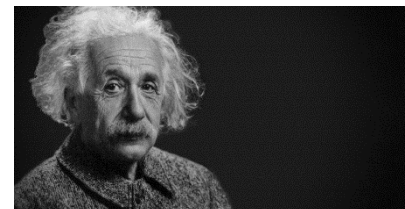
$p_n$  are

$p_1, p_2, p_3, p_4, p_5, p_6 = 1/6$  for all  $p_n$

Ok, I give you a  
hint: it is not a six.



Alright, so then  $p_6 = 0$  and all  
the other  $p_5 = 1/5$ .



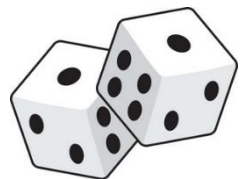


**Entropy is a mathematically precise measure of information!**

But what is entropy now – really?!

$$S = - \sum_{n=1}^N p_n \ln(p_n)$$

- entropy high  $\rightarrow$  information low
- entropy low  $\rightarrow$  information high



fair die: events are

1, 2, 3, 4, 5, 6

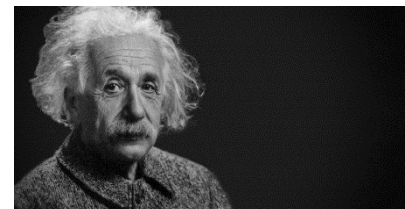
$p_n$  are

$p_1, p_2, p_3, p_4, p_5, p_6 = 1/6$  for all  $p_n$

Ok, I give you a  
hint: it is not a six.



Hence,  $S = -\frac{1}{5} \ln\left(\frac{1}{5}\right) * 5 =$   
1.61 ...





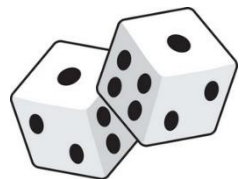


**Entropy is a mathematically precise measure of information!**

But what is entropy now – really?!

$$S = - \sum_{n=1}^N p_n \ln(p_n)$$

- entropy high  $\rightarrow$  information low
- entropy low  $\rightarrow$  information high



fair die: events are

1, 2, 3, 4, 5, 6

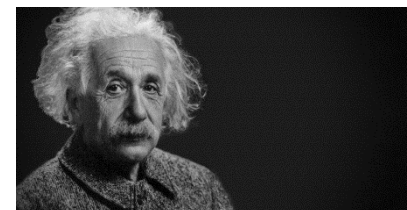
$p_n$  are

$p_1, p_2, p_3, p_4, p_5, p_6 = 1/6$  for all  $p_n$

Come on, don't be so nerdy. It is an odd number.



This helps a lot:  $p_2 = p_4 = p_6 = 0$   
and thus,  $p_1 = p_3 = p_5 = 1/3$





**Entropy is a mathematically precise measure of information!**

But what is entropy now – really?!

$$S = - \sum_{n=1}^N p_n \ln(p_n)$$

- entropy high  $\rightarrow$  information low
- entropy low  $\rightarrow$  information high



fair die: events are

1, 2, 3, 4, 5, 6

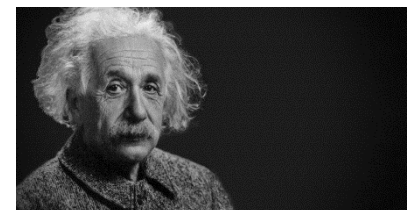
$p_n$  are

$p_1, p_2, p_3, p_4, p_5, p_6 = 1/6$  for all  $p_n$

Come on, don't be so nerdy. It is an odd number.



Hence,  $S = -\frac{1}{3} \ln\left(\frac{1}{3}\right) * 3 = 1.10 \dots$





**Entropy is a mathematically precise measure of information!**

But what is entropy now – really?!

$$S = - \sum_{n=1}^N p_n \ln(p_n)$$

- entropy high  $\rightarrow$  information low
- entropy low  $\rightarrow$  information high



fair die: events are

1, 2, 3, 4, 5, 6

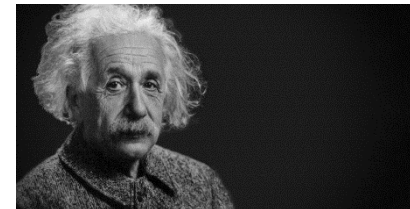
$p_n$  are

$p_1, p_2, p_3, p_4, p_5, p_6 = 1/6$  for all  $p_n$

I give up. It's a five.  
Next time I am gonna  
go to Schroedinger.



Fantastic! So all  $p_n = 0$  except for  
 $n=5$





**Entropy is a mathematically precise measure of information!**

But what is entropy now – really?!

$$S = - \sum_{n=1}^N p_n \ln(p_n)$$

- entropy high  $\rightarrow$  information low
- entropy low  $\rightarrow$  information high



fair die: events are

1, 2, 3, 4, 5, 6

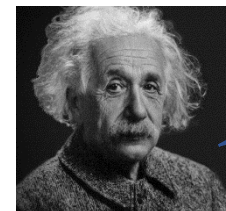
$p_n$  are

$p_1, p_2, p_3, p_4, p_5, p_6 = 1/6$  for all  $p_n$

I give up. It's a five.  
Next time I am gonna  
go to Schroedinger.



Hence,  $S = -0 \ln(0) * 5 - 1 * \ln(1) = 0$



But don't mention  
your cat!



$$S = - \sum_{n=1}^N p_n \ln(p_n)$$

- entropy high  $\rightarrow$  information low
- entropy low  $\rightarrow$  information high



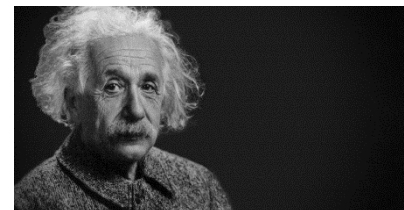
Information:

none (any number)

not a six

an odd number

the actual number



Entropy:

$S = 1.79$

$S = 1.61$

$S = 1.10$

$S = 0.00$



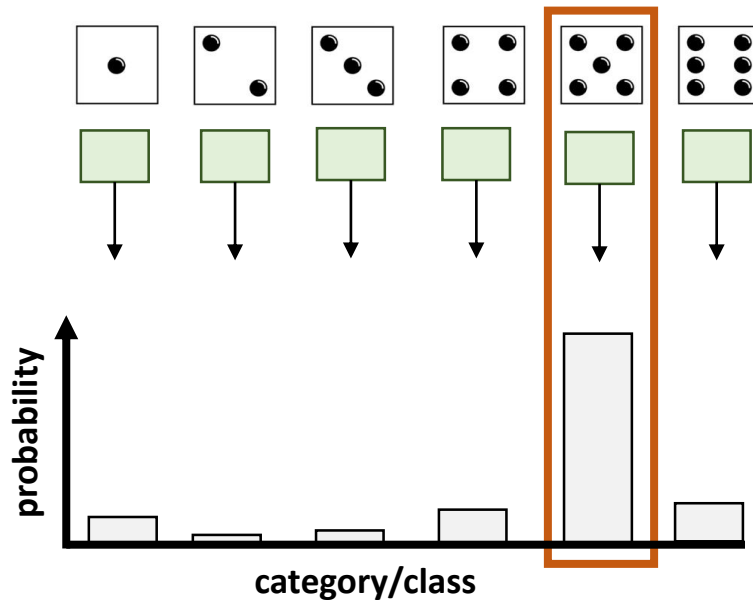
$y$  : the true class  
softmax  $\rightarrow$  predicts the learned class



we need to compare both quantities in order  
to determine the quality of our ANN

there are two things we are interested in:

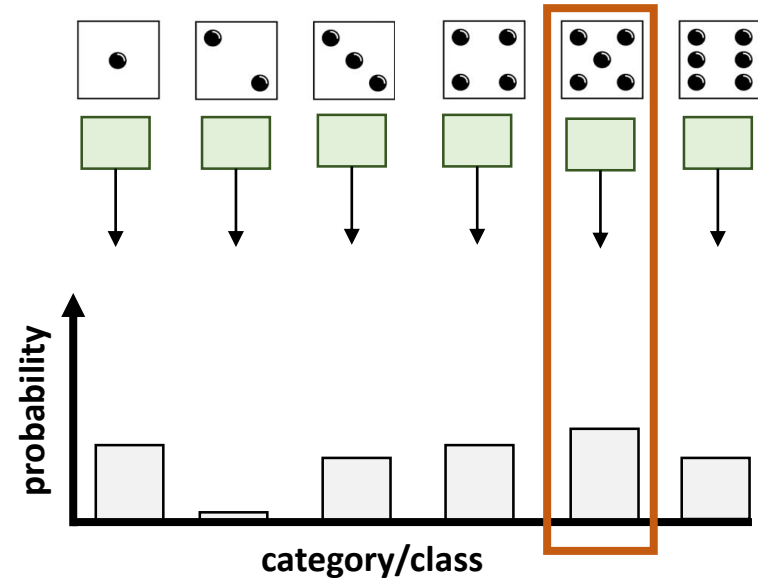
1) How *confident* is the ANN about its decision?



$$S \approx 0$$



$$S = - \sum_i p_i \cdot \ln p_i$$



$$S \approx \ln(\text{number of states})$$





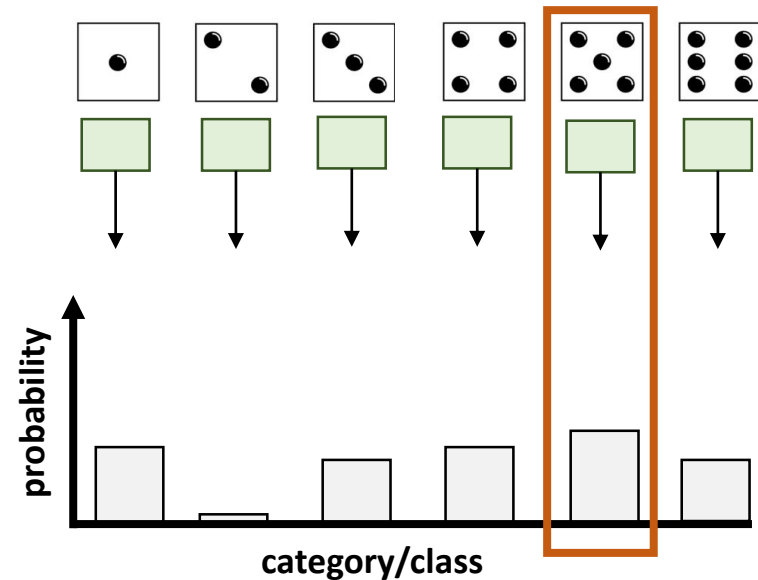
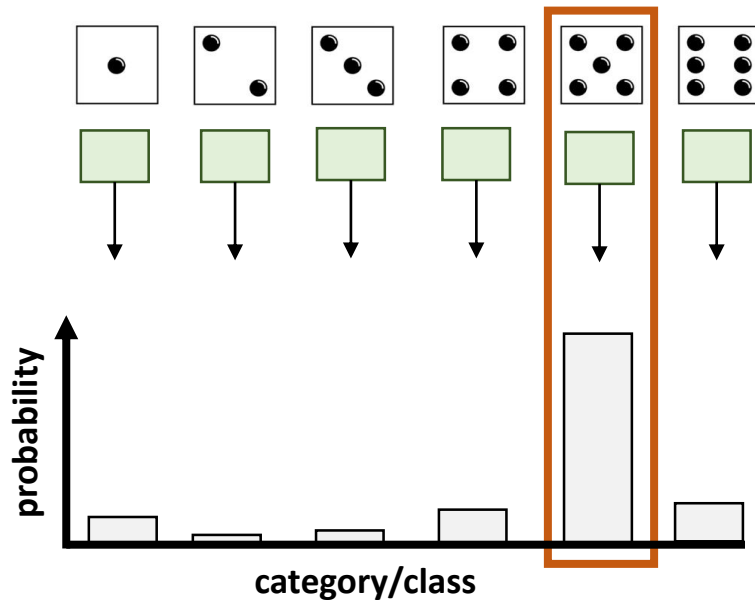
$y$  : the true class  
softmax  $\rightarrow$  predicts the learned class



we need to compare both quantities in order  
to determine the quality of our ANN

there are two things we are interested in:

2) How *often* did the ANN make the correct decision?

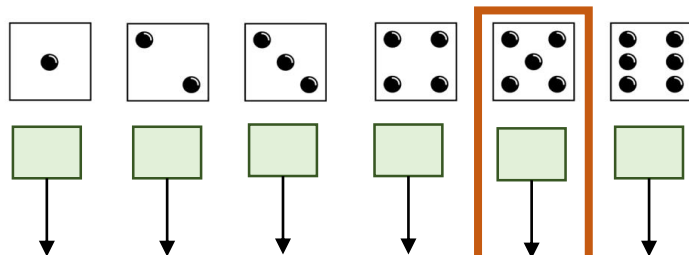






1) How *confident* is the ANN about its decision?

for each data point (after softmax layer)



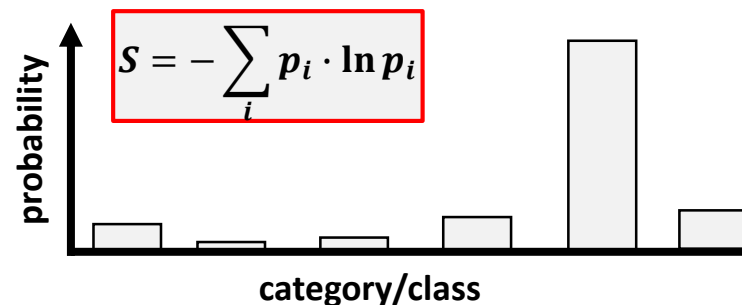
$$p_i = 0.1 \quad 0.05 \quad 0.2 \quad 0.0 \quad 0.45 \quad 0.2$$

$$p_{true_i} = 0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 0$$



$$S = - \sum_i p_{true_i} \cdot \ln p_i$$

calculating **cross entropy**  
for each sample



mean over all samples → total **Loss**

→ for categorization: mean of cross entropy

→ for regression: mean over RMSE

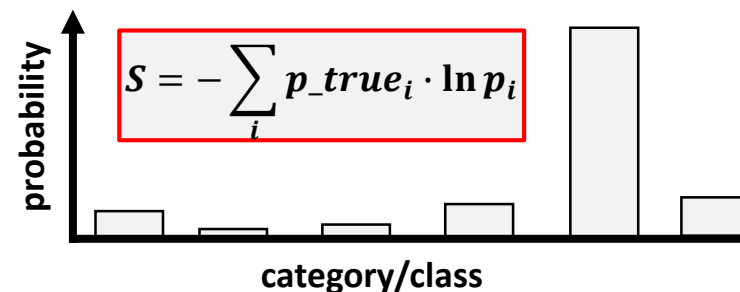
→ we'd like to keep the actual loss calculation separate  
from the total loss calculation

(in fact: we can turn most CNNs into regression networks  
by just removing the softmax layer and the cross entropy part)



1) How *confident* is the ANN about its decision?

mean over all samples → total *Loss*



```
class Loss:
```

```
    def calculate(self, output, y):
```



output here refers to the output from  
the softmax layer

```
        sample_losses = self.forward(output, y)
```



we are going to call *Loss* within another class later

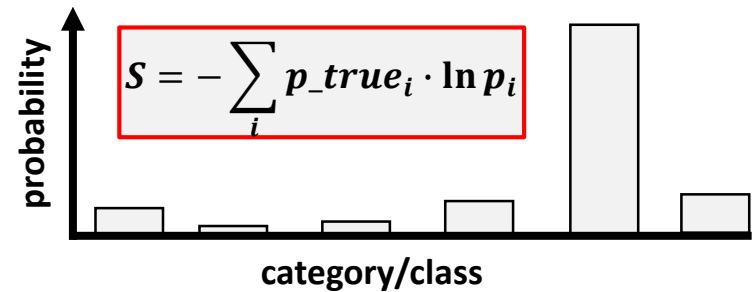
```
        data_loss = np.mean(sample_losses)
```

```
    return(data_loss)
```



1) How *confident* is the ANN about its decision?

now: calculating the cross entropy:



- `np.log`
  - will cause numerical issues for  $p_i \approx 0$
  - $p_i = 1$  not possible for numerical reasons (see softmax)
    - would be a numerical artefact

```
y_pred_clipped = np.clip(prob_pred, 1e-7, 1 - 1e-7)
```

the true y could be encoded in different ways → must be taken into account when calculating cross entropy

“one hot”

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

“sparse”

1
1
3
2



1) How *confident* is the ANN about its decision?

now: calculating the cross entropy:

	category/class			
				↓ samples
prob_pred =	0.8	0.1	0.1	
	0.9	0.05	0.05	
	0.1	0.15	0.75	
	0.2	0.7	0.1	
	...	...	...	

Nsamples = len(prob\_pred)

“sparse”

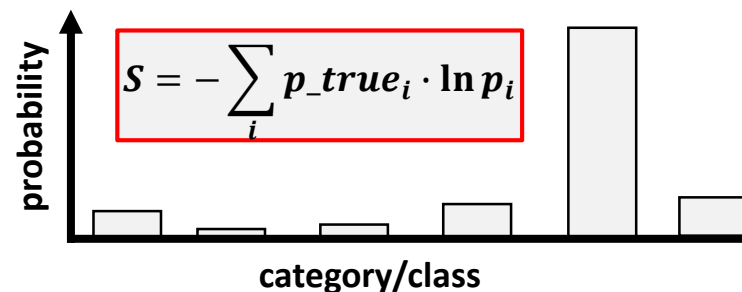
y\_true = 

1
1
3
2

```
if len(y_true.shape) == 1:  
    correct_confidences = \  
    y_pred_clipped[range(Nsamples), y_true]
```

checking if sparse (==1) or one hot (==2)

filters out the correct true class





1) How *confident* is the ANN about its decision?

now: calculating the cross entropy:

$$\text{prob\_pred} = \begin{matrix} & \xrightarrow{\text{category/class}} \\ \begin{pmatrix} \mathbf{0.8} & 0.1 & 0.1 \\ \mathbf{0.9} & 0.05 & 0.05 \\ 0.1 & 0.15 & \mathbf{0.75} \\ 0.2 & \mathbf{0.7} & 0.1 \\ \dots & \dots & \dots \end{pmatrix} & \downarrow \text{samples} \end{matrix}$$

Nsamples = `len(prob_pred)`

“one hot”

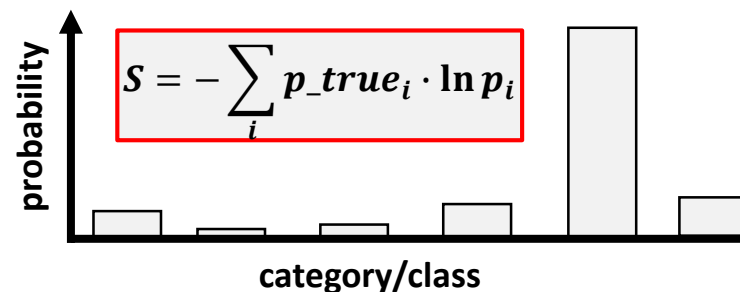
$$y_{\text{true}} = \begin{bmatrix} \mathbf{1} & \mathbf{0} & \mathbf{0} \\ \mathbf{1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{1} \\ \mathbf{0} & \mathbf{1} & \mathbf{0} \end{bmatrix}$$

checking if sparse (`==1`) or one hot (`==2`)

```
elif len(y_true.shape) == 2:
```

```
correct_confidences = \  
    np.sum(y_pred_clipped*y_true, axis = 1)
```

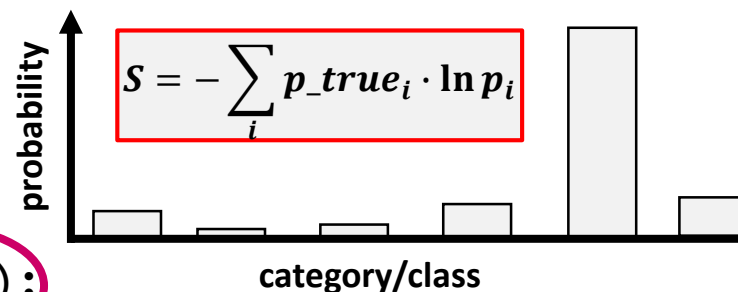
either ones or zeros → only correct true class contributes (axis = 1, summing across the columns)





1) How *confident* is the ANN about its decision?

now: calculating the cross entropy:



```
class Loss_CategoricalCrossEntropy(Loss):
```

```
    def forward(self, prob_pred, y_true):
```

```
        Nsamples = len(prob_pred)
```

```
        y_pred_clipped = np.clip(prob_pred, 1e-7, 1 - 1e-7)
```

```
        if len(y_true.shape) == 1
```

```
            correct_confidences = \
```

```
                y_pred_clipped[range(Nsamples), y_true]
```

```
        elif len(y_true.shape) == 2:
```

```
            correct_confidences = \
```

```
                np.sum(y_pred_clipped * y_true, axis = 1)
```

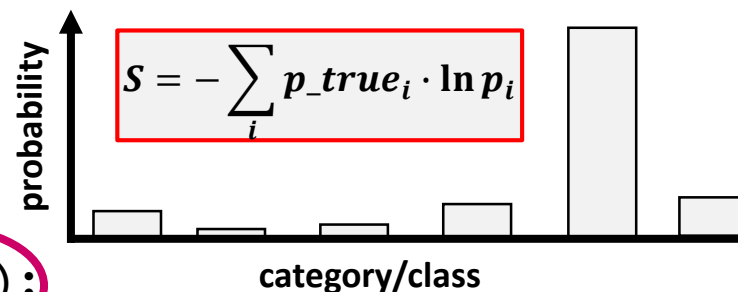
```
        negative_log_likelihoods = -np.log(correct_confidences)
```

```
        return(negative_log_likelihoods)
```



1) How *confident* is the ANN about its decision?

now: calculating the cross entropy:



```
class Loss_CategoricalCrossEntropy(Loss):
```

```
def forward(self, prob_pred, y_true):
```

= forward in *Loss*, returns *negative\_log\_likelihoods*

that's called *sample\_losses* in *Loss*. The *calculate* method has been inherited.

```
    Nsamples = len(prob_pred)
```

```
    y_pred_clipped = np.clip(prob_pred, 1e-7, 1 - 1e-7)
```

```
    if len(y_true.shape) == 1:
```

```
        correct_confidences = \
```

```
            y_pred_clipped[range(Nsamples), y_true]
```

```
    elif len(y_true.shape) == 2:
```

```
        correct_confidences = \
```

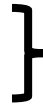
```
            np.sum(y_pred_clipped * y_true, axis = 1)
```

```
    negative_log_likelihoods = -np.log(correct_confidences)
```

```
    return(negative_log_likelihoods)
```



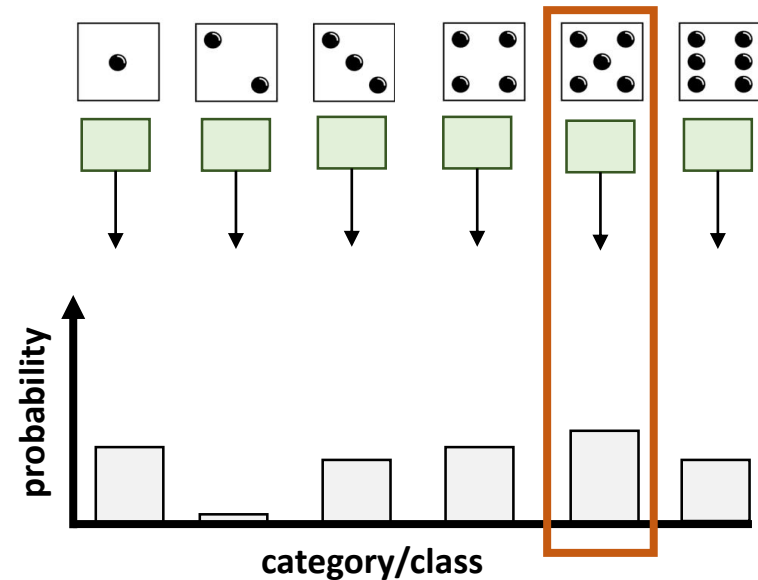
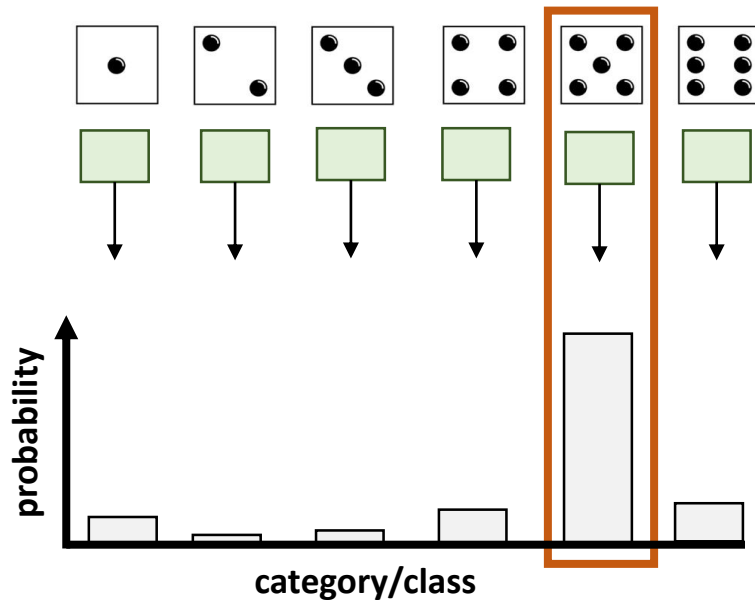
$y$  : the true class  
softmax  $\rightarrow$  predicts the learned class



we need to compare both quantities in order  
to determine the quality of our ANN

there are two things we are interested in:

2) How *often* did the ANN make the correct decision?

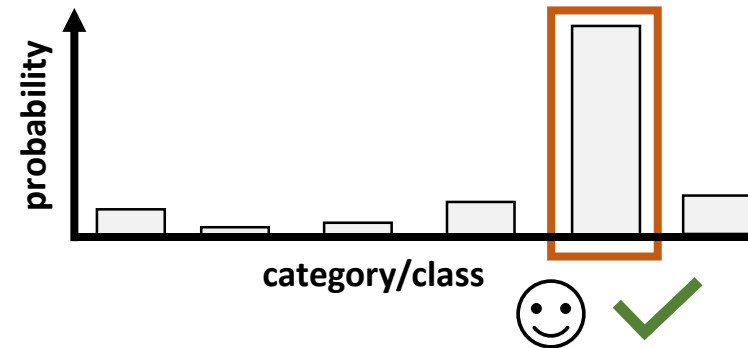






2) How often did the ANN make the correct decision?

category/class →			samples ↓
0.8	0.1	0.1	
0.9	0.05	0.05	
0.1	0.15	0.75	
0.2	0.7	0.1	
...	...	...	



output from softmax

```
predictions = np.argmax(activation2.output, axis = 1)
```

works already if y is sparse

```
if len(y.shape) == 2:
```

```
    y = np.argmax(y, axis = 1)
```

in case if y is one-hot

```
accuracy = np.mean(predictions == y)
```



```
nc      = 3
[x, y] = spiral_data(samples = 200, classes = nc)
S      = np.shape(x)
```

```
dense1      = Layer_Dense(S[1], 4 )
dense2      = Layer_Dense(4 , nc)
activation1  = Activation_ReLU()
activation2  = Activation_Softmax()
loss_function = Loss_CategoricalCrossEntropy()
```

defining layers

```
dense1.forward(x)
activation1.forward(dense1.output)

dense2.forward(activation1.output)
activation2.forward(dense2.output)

loss = loss_function.calculate(activation2.output, y)

predictions = np.argmax(activation2.output, axis = 1)
if len(y.shape) == 2:
    y = np.argmax(y, axis = 1)
accuracy = np.mean(predictions == y)
```

creating the actual network



## outline

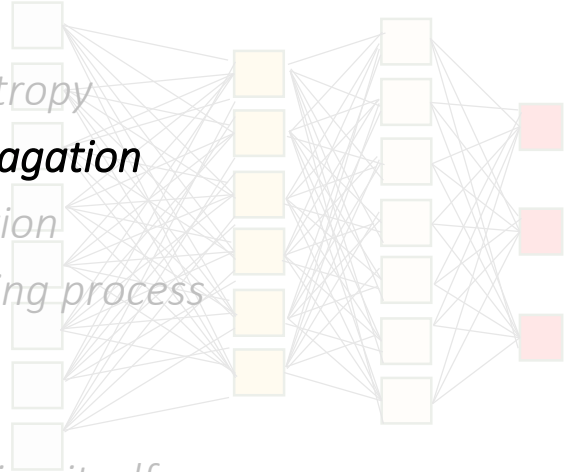
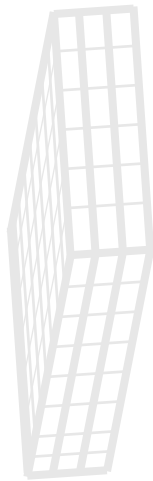
### 0 intro

### I the core:

- a single neuron
- layers of neurons
- activation functions
- softmax
- loss & entropy
- **backpropagation**
- optimization
- the learning process

### II convolution part:

- convolution itself
- pooling
- sigmoid
- flattening
- backpropagation - again
- testing the CNN & final remarks



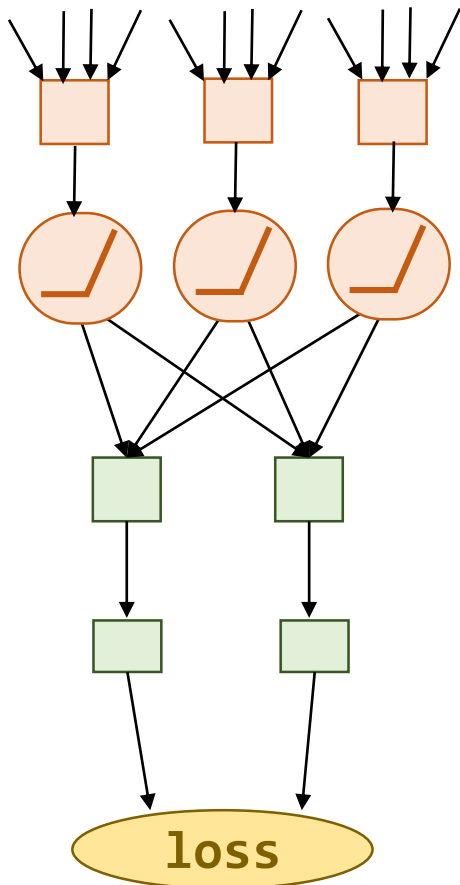


We have now an objective mathematical criterium of the classification quality of our ANN:

→ the **loss**

→ aim: minimizing the loss

input I   input I   input I



$$\sum_i I_i w_i + b$$

sum in a single neuron

$$A\left(\sum_i I_i w_i + b\right)$$

activation

$$\sum_j A\left(\sum_i I_i w_i + b\right)_j \omega_j + \beta$$

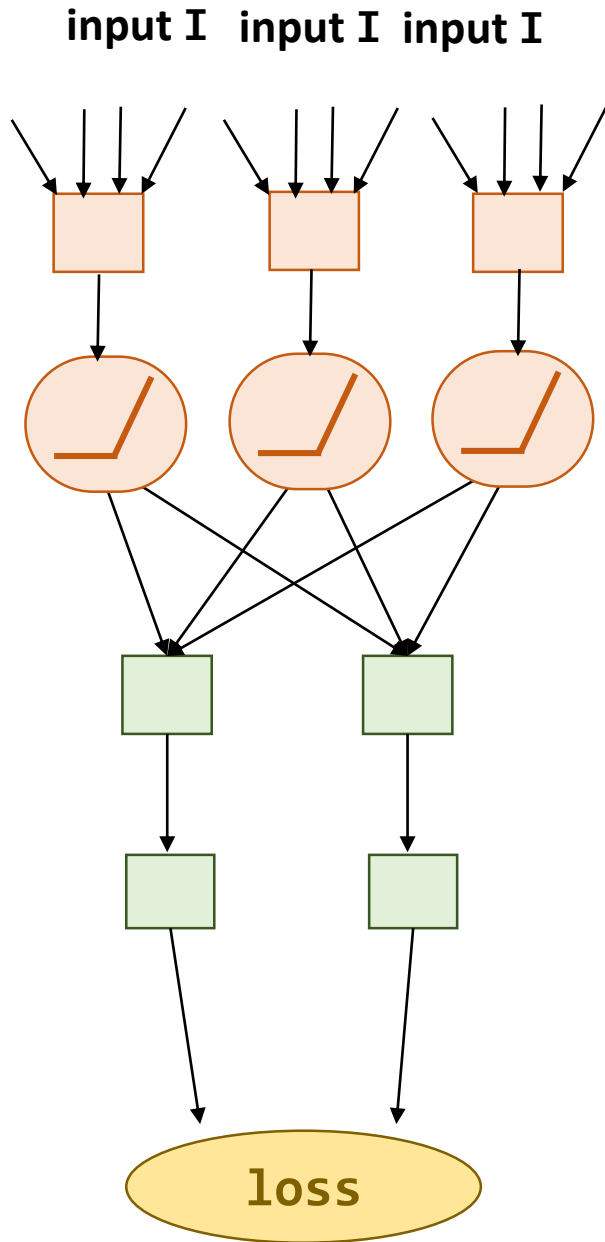
input of the next layer

$$p_m = \frac{\exp([\sum_j A(\sum_i I_i w_i + b)_j \omega_j + \beta]_k)}{\sum_k \exp([\sum_j A(\sum_i I_i w_i + b)_j \omega_j + \beta]_k)}$$

softmax

$$L_m = -\log(p_m)$$

loss calculation



## forward pass

sum in a single neuron

$$\sum_i I_i w_i + b$$

activation

$$A\left(\sum_i I_i w_i + b\right)$$

input of the next layer

$$\underbrace{\sum_j A\left(\sum_i I_i w_i + b\right)_j \omega_j + \beta}_{\zeta_j}$$

softmax

$$p_m = \frac{\exp([\sum_j A(\sum_i I_i w_i + b)_j \omega_j + \beta]_k)}{\sum_k \exp([\sum_j A(\sum_i I_i w_i + b)_j \omega_j + \beta]_k)}$$

loss calculation

$$L_m = -\log(p_m)$$

→ aim: minimizing the loss

## backpropagation

$$\frac{\partial \sum_i I_i w_i + b}{\partial w_i}$$

$$\frac{\partial A}{\partial \sum_i I_i w_i + b}$$

$$\frac{\partial \sum_j \zeta_j \omega_j + \beta}{\partial \zeta_j}$$

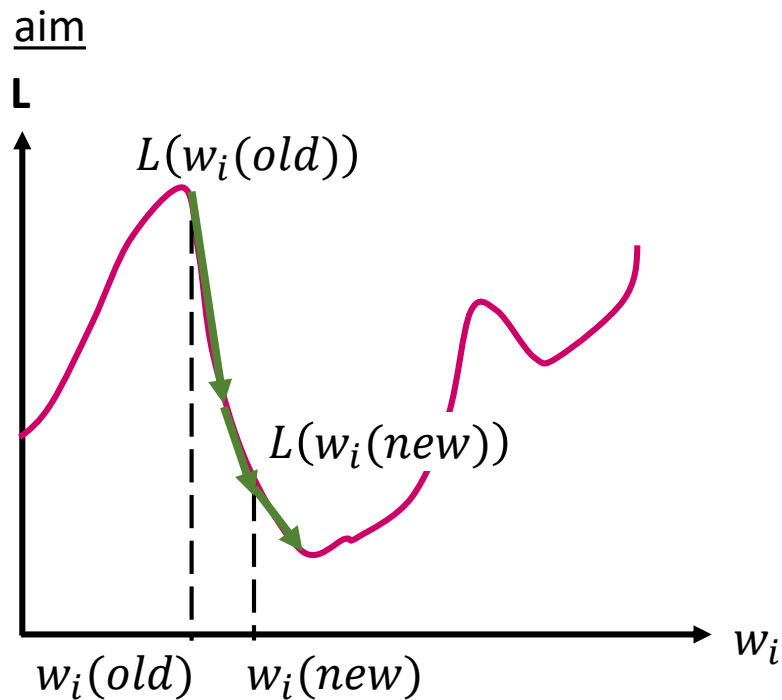
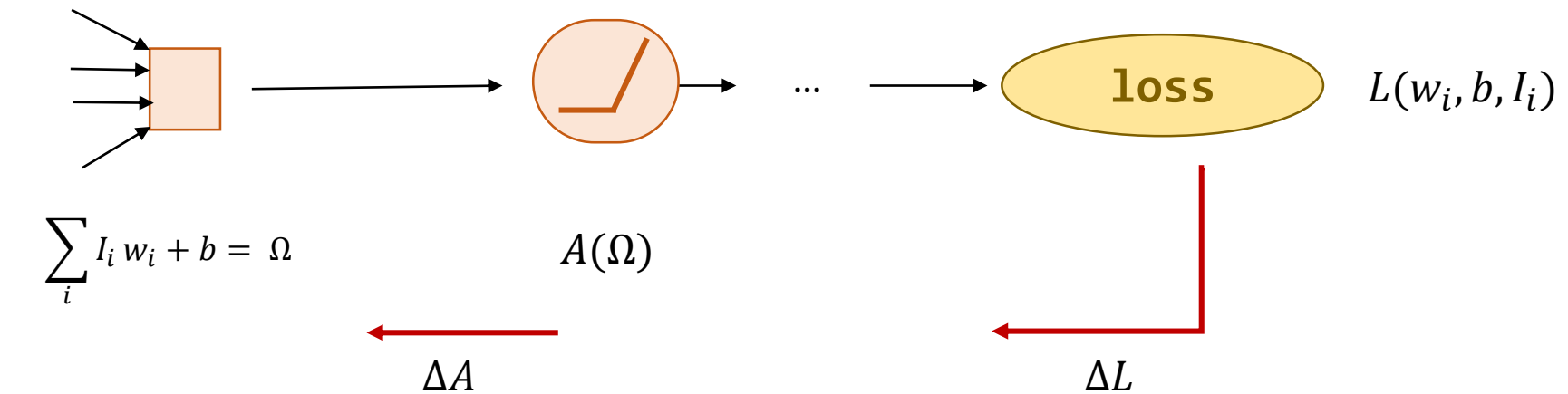
$$\frac{\partial \sum_j \zeta_j \omega_j + \beta}{\partial \omega_j}$$

$$\frac{\partial p_m}{\partial \epsilon_l}$$

$$\frac{\partial L_m}{\partial p_m}$$



Ok, that looks complicated, so let's understand it conceptually:



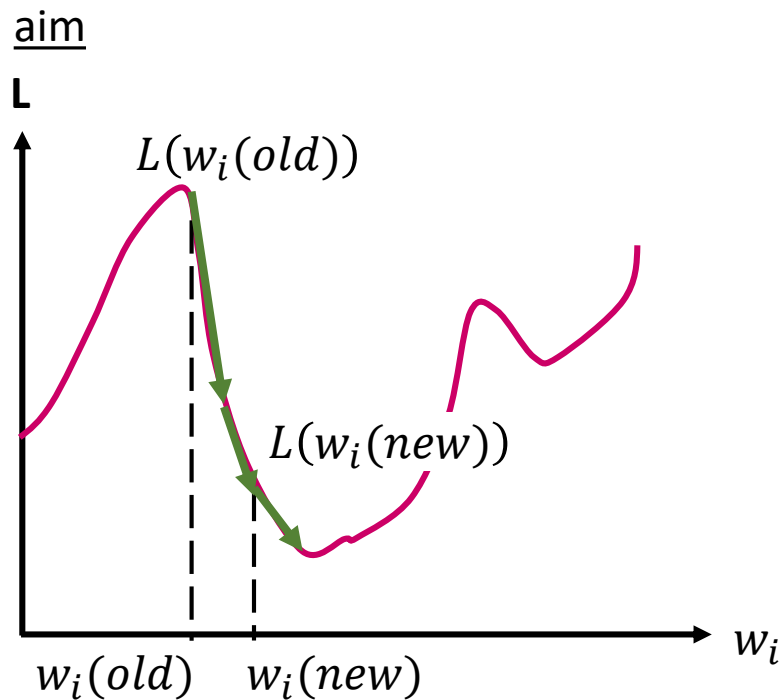
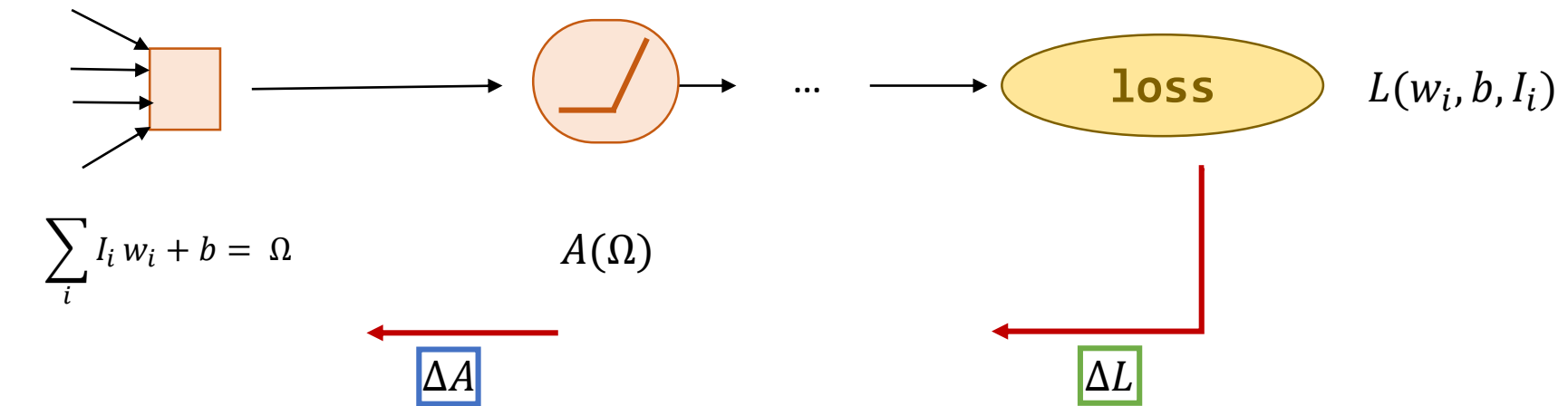
(gradient descent,  $\varepsilon = \text{const}$ ; see later)

$$w_i(new) = w_i(old) - \varepsilon \frac{\partial L}{\partial w_i}$$

$$\Delta w_i = -\varepsilon \frac{\partial L}{\partial w_i}$$



Ok, that looks complicated, so let's understand it conceptually:



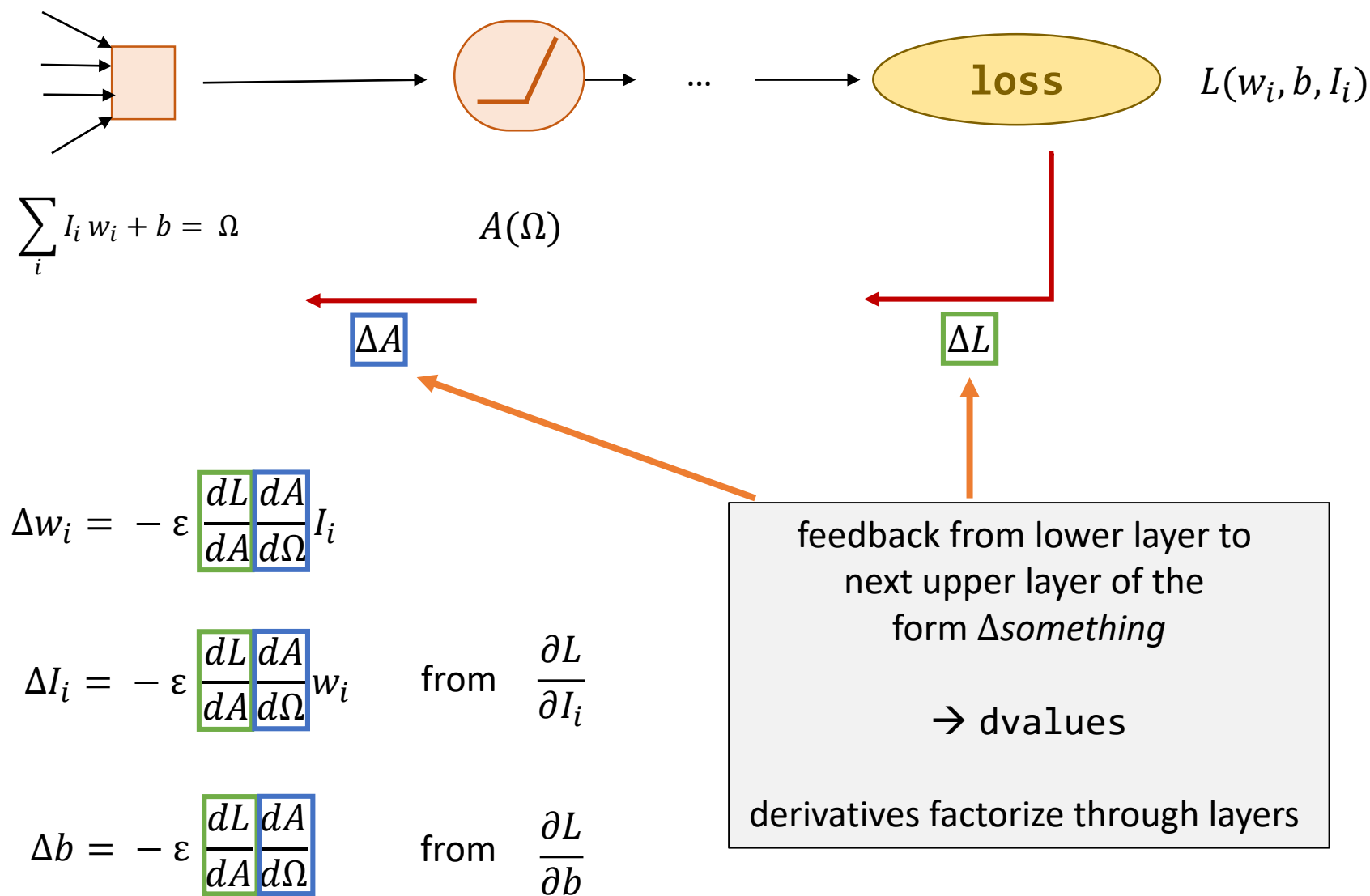
$$\Delta w_i = -\epsilon \frac{\partial L}{\partial w_i}$$

$$\Delta w_i = -\epsilon \frac{dL}{dA} \frac{dA}{d\Omega} \frac{\partial \Omega}{\partial w_i}$$

$$\Delta w_i = -\epsilon \frac{dL}{dA} \frac{dA}{d\Omega} I_i$$



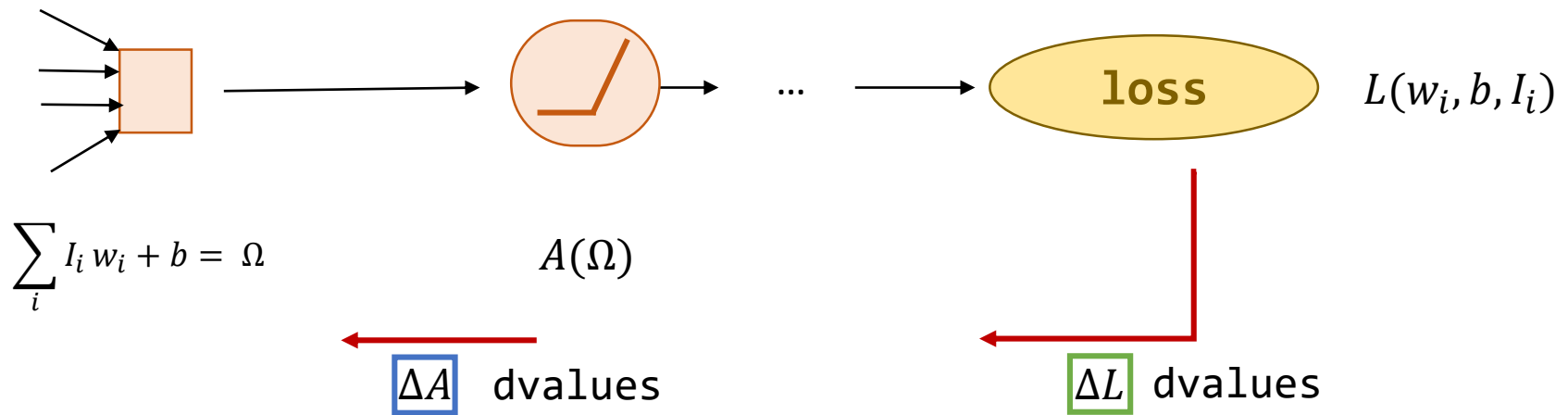
Ok, that looks complicated, so let's understand it conceptually:







Ok, that looks complicated, so let's understand it conceptually:



$$\Delta w_i = -\varepsilon \frac{dL}{dA} \frac{dA}{d\Omega} I_i$$

$$\Delta I_i = -\varepsilon \frac{dL}{dA} \frac{dA}{d\Omega} w_i$$

$$\Delta b = -\varepsilon \frac{dL}{dA} \frac{dA}{d\Omega}$$

hence, we need to include the following structure for backpropagation:

```
self.dweights = inputs * dvalues
self.dinputs = weights * dvalues
self.dbiases = 1 * dvalues
```



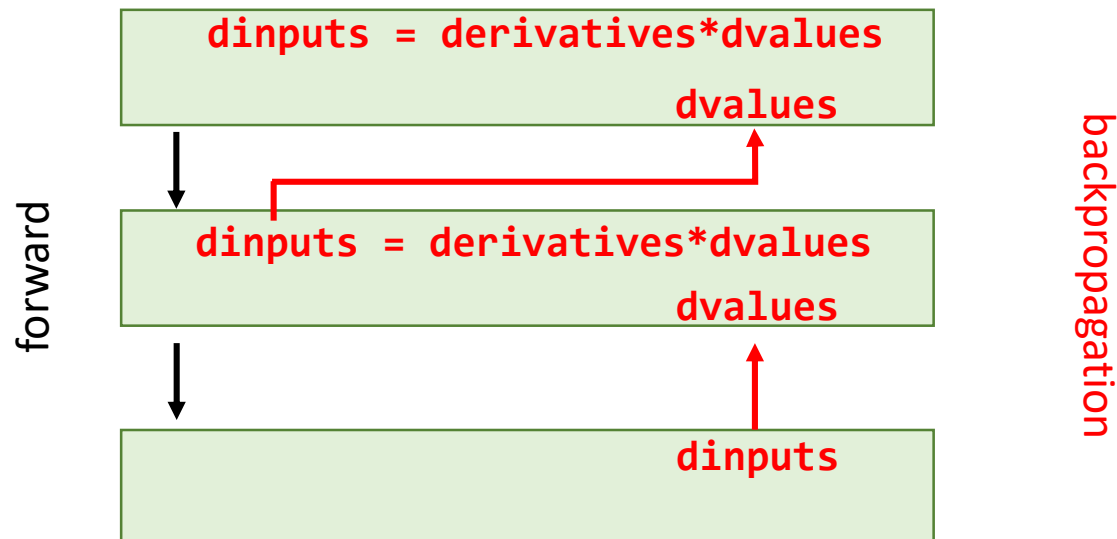
Apparently we need to apply the chain rule for derivatives throughout the network!

→ adding the method **backward** for the derivatives in each layer

→ we need to remember what the inputs were in **Layer\_Dense** for  $\frac{\partial I_i}{\partial w_i}$

→ we are passing on the derivatives from the lower layer to the next upper layer as **dvalues**

→ these derivatives are called **dinputs** in the lower layer





Apparently we need to apply the chain rule for derivatives throughout the network!

→ adding the method **backward** for the derivatives in each layer

→ we need to remember what the inputs were in **Layer\_Dense** for  $\frac{\partial l_i}{\partial w_i}$

→ we are passing on the derivatives from the next layer as **dvalues**

```
class Layer_Dense:
```

```
    def __init__(self, n_inputs, n_neurons):  
        ...
```

```
    def forward(self, inputs):  
        self.output = np.dot(inputs, self.weights) + self.biases  
        self.inputs = inputs
```

```
    def backward(self, dvalues):
```

**gradient wrt the weights → inputs are left**

```
self.dweights = np.dot(self.inputs.T, dvalues)
```

**gradient wrt the inputs → weights are left**

```
self.dinputs = np.dot(dvalues, self.weights.T)
```

**gradient wrt the biases → just ones are left**

```
self.dbiases = np.sum(dvalues, axis = 0, keepdims = True)
```



```
class Layer_Dense:
```

```
    def __init__(self, n_inputs, n_neurons):  
        self.weights = np.random.rand(n_inputs, n_neurons)  
        self.biases   = np.zeros((1, n_neurons))
```

```
    def forward(self, inputs):  
  
        self.output = np.dot(inputs, self.weights) + self.biases  
        self.inputs  = inputs
```

```
    def backward(self, dvalues):  
  
        self.dweights = np.dot(self.inputs.T, dvalues)  
        self.dinputs   = np.dot(dvalues, self.weights.T)  
        self.dbiases   = np.sum(dvalues, axis = 0, keepdims = True)
```

we are going to pass as dvalues for the previous layer



same procedure for the ReLU layer:

```
class Activation_ReLU:
```

```
    def forward(self,inputs):
```

```
        self.output = np.maximum(0,inputs)
        self.inputs = inputs
```

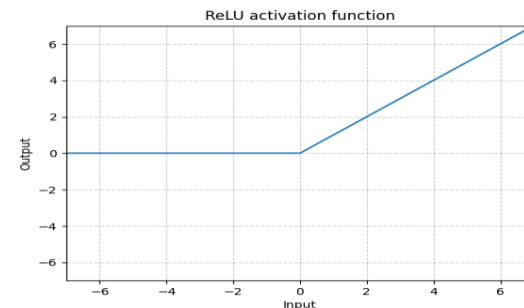
```
    def backward(self,dvalues):
```

```
        self.dinputs = dvalues.copy()
```

```
        self.dinputs[self.inputs <= 0] = 0
```

we are going to pass as dvalues for the previous layer

$$\text{ReLU}(y) = \max(0, y)$$





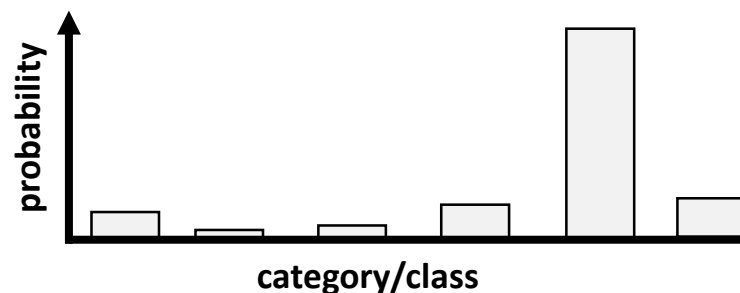
same procedure for calculating cross entropy:

$$S = - \sum_i p_{\text{true}_i} \cdot \ln p_i$$

$p_{\text{true}_i}$  either zero or one (= correct class/category  $i$ )  
 $p_i$  predicted probability of class/category  $i$

for each data point  $j$

$$S_j = - \sum_i p_{\text{true}_{ij}} \cdot \ln p_{ij}$$



$$\frac{\partial}{\partial p_{ij}} S_j = - \frac{p_{\text{true}_{ij}}}{p_{ij}}$$

**dvalues**

will come back from the next layer  
(e. g. softmax)

$$\text{grad}_p(S) = \begin{pmatrix} - \frac{p_{\text{true}_{i1}}}{p_{i1}} \\ - \frac{p_{\text{true}_{i2}}}{p_{i2}} \\ \vdots \\ - \frac{p_{\text{true}_{i3}}}{p_{i3}} \\ \vdots \end{pmatrix}$$

we will normalize by  
the sample size later  
→ optimizing for the  
entire gradient



same procedure for calculating cross entropy:

```
class Loss_CategoricalCrossEntropy(Loss):
```

```
    def forward(self, prob_pred, y_true):
```

```
        ...
```

```
    def backward(self, dvalues, y_true):
```

```
        Nsamples = len(dvalues)
```

```
        if len(y_true.shape) == 1:
```

```
            Nlabels = len(dvalues[0])
```

```
            y_true = np.eye(Nlabels)[y_true]
```

```
        self.dinputs = -y_true/dvalues/Nsamples
```

turning y\_true into a  
“one hot” structure

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

$$\frac{\partial}{\partial p_{ij}} S_j = - \frac{p_{true_{ij}}}{p_{ij}}$$



same procedure for softmax:

$$p_{ij} = \frac{\exp(\varepsilon_{ij})}{\sum_i \exp(\varepsilon_{ij})}$$

for each data point  $j$  and class/category  $i$

let us calculate the derivative wrt  $\varepsilon$  for a particular  $i = k$

$$\frac{\partial}{\partial \varepsilon_{kj}} p_{ij} = \frac{\partial}{\partial \varepsilon_{kj}} \frac{\exp(\varepsilon_{ij})}{\sum_i \exp(\varepsilon_{ij})}$$

**this part equals  
zero for  $i \neq k$**

$$= \frac{\exp(\varepsilon_{kj})}{\sum_i \exp(\varepsilon_{ij})} + \frac{\exp(\varepsilon_{ij})}{(\sum_i \exp(\varepsilon_{ij}))^2} \cdot (-1) \cdot \exp(\varepsilon_{kj})$$

$$= \frac{\exp(\varepsilon_{kj})}{\sum_i \exp(\varepsilon_{ij})} \left( 1 - \frac{\exp(\varepsilon_{ij})}{\sum_i \exp(\varepsilon_{ij})} \right)$$

$$= p_{kj}(1 - p_{ij}) \quad i = k$$

$$= -p_{kj}p_{ij} \quad i \neq k$$





same procedure for softmax:

$$p_{ij} = \frac{\exp(\varepsilon_{ij})}{\sum_i \exp(\varepsilon_{ij})}$$

for each data point  $j$  and class/category  $i$

we can write both cases as one equation using the **Kronecker** symbol  $\delta_{ik} = \begin{cases} 1 & i = k \\ 0 & i \neq k \end{cases}$

$$\left. \begin{array}{ll} \frac{\partial}{\partial \varepsilon_{kj}} p_{ij} = p_{kj}(1 - p_{ij}) & i = k \\ \frac{\partial}{\partial \varepsilon_{kj}} p_{ij} = -p_{kj}p_{ij} & i \neq k \end{array} \right\} \frac{\partial}{\partial \varepsilon_{kj}} p_{ij} = p_{kj}\delta_{ik} - p_{kj}p_{ij}$$

remember that  $p_{ij}$  is a matrix  $\rightarrow$  find a clever way how to include the **Kronecker** symbol in our code



for each data point  $j$  and  
class/category  $i$

same procedure for softmax:

$$\delta_{ik} = \begin{cases} 1 & i = k \\ 0 & i \neq k \end{cases}$$

$$\frac{\partial}{\partial \varepsilon_{kj}} p_{ij} = p_{kj} \delta_{ik} - \mathbf{p_{kj} p_{ij}}$$

$$p_{ij} = \frac{\exp(\varepsilon_{ij})}{\sum_i \exp(\varepsilon_{ij})}$$

let's say our  $p_{ij}$  is

$[0.3 \ 0.6 \ 0.1]$

for one particular  $j$

according to the above equations

→  $(\text{number of classes})^2$  derivatives (taking one  $i$ ,  
 $k$  goes from 1, 2, 3 ... to the number of classes)

$$\left\{ \frac{\partial}{\partial \varepsilon_{kj}} p_{ij} \right\}_j = \underbrace{\begin{pmatrix} 0.3 & 0 & 0 \\ 0 & 0.6 & 0 \\ 0 & 0 & 0.1 \end{pmatrix}}_{p_{kj} \delta_{ik}} - \underbrace{\begin{pmatrix} 0.09 & 0.18 & 0.03 \\ 0.18 & 0.36 & 0.06 \\ 0.03 & 0.06 & 0.01 \end{pmatrix}}_{\mathbf{p_{kj} p_{ij}}}$$



same procedure for softmax:

for each data point  $j$  and  
class/category  $i$

`softmax_output = [0.3 0.6 0.1]`

$$\left\{ \frac{\partial}{\partial \varepsilon_{kj}} p_{ij} \right\}_j = \underbrace{\begin{pmatrix} 0.3 & 0 & 0 \\ 0 & 0.6 & 0 \\ 0 & 0 & 0.1 \end{pmatrix}}_{p_{kj} \delta_{ik}} - \underbrace{\begin{pmatrix} 0.09 & 0.18 & 0.03 \\ 0.18 & 0.36 & 0.06 \\ 0.03 & 0.06 & 0.01 \end{pmatrix}}_{\mathbf{p}_{kj} \mathbf{p}_{ij}} \quad \left\{ \frac{\partial}{\partial \varepsilon_{kj}} p_{ij} \right\}_j \text{ is called } \mathbf{Jacobian} \text{ matrix (matrix of mixed derivatives)}$$

in Python, this reads:

```
jacobian_matrix = np.diagflat(softmax_output) - \
np.dot(softmax_output, softmax_output.T)
```

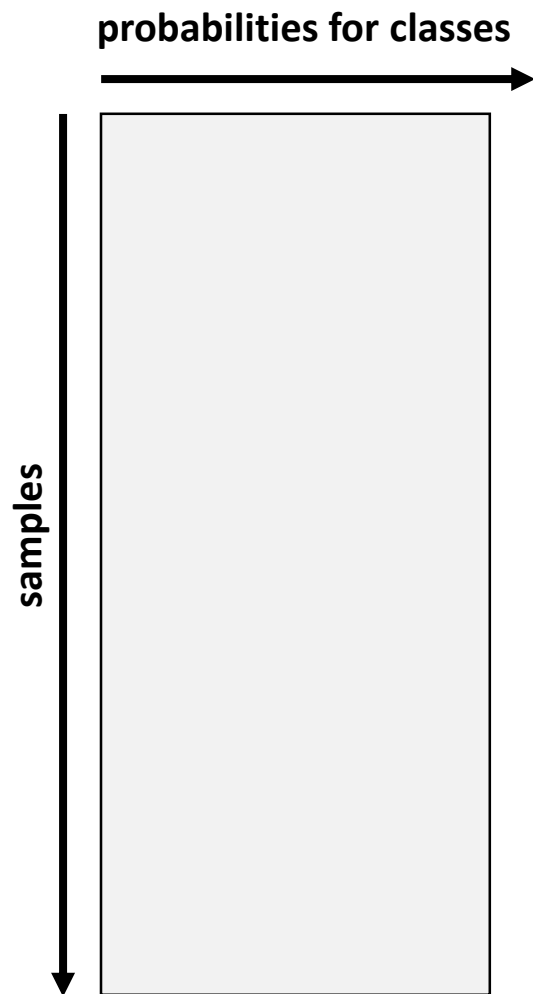
Hence, for each data point  $j$ , we are getting such a Jacobian matrix!




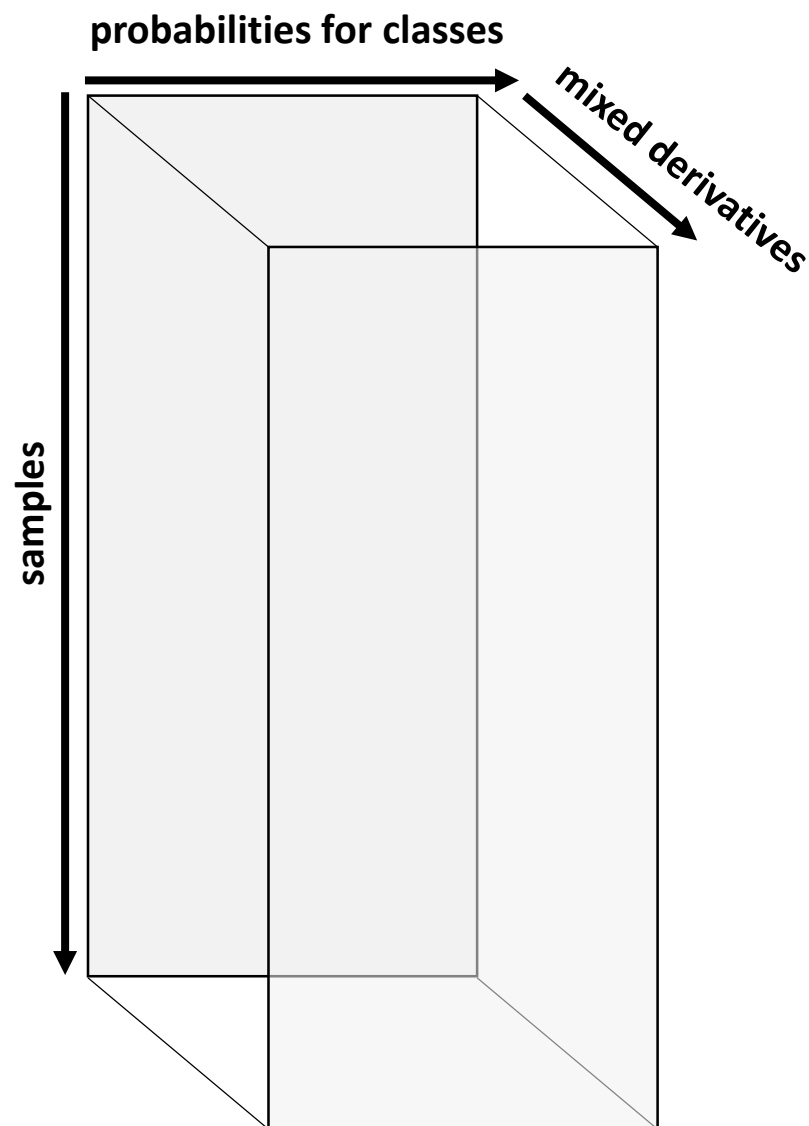
Hence, for each data point  $j$ , we are getting such a Jacobian matrix!

for each data point  $j$  and class/category  $i$

softmax\_output



$$\left\{ \frac{\partial}{\partial \varepsilon_{kj}} p_{ij} \right\}_j$$




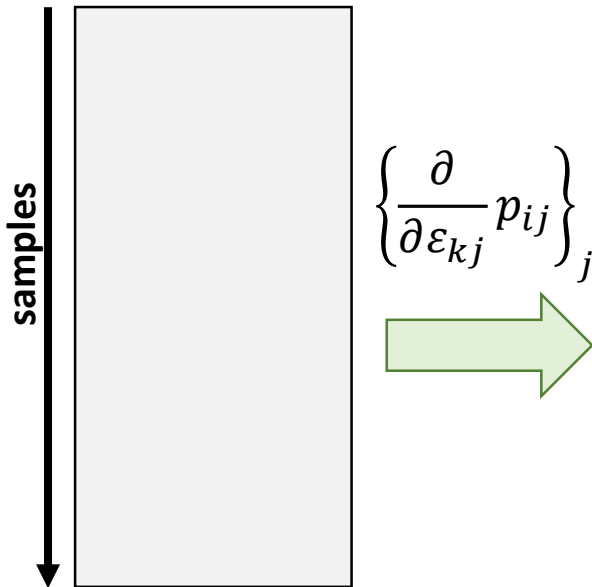


Hence, for each data point  $j$ , we are getting such a Jacobian matrix!

for each data point  $j$  and class/category  $i$

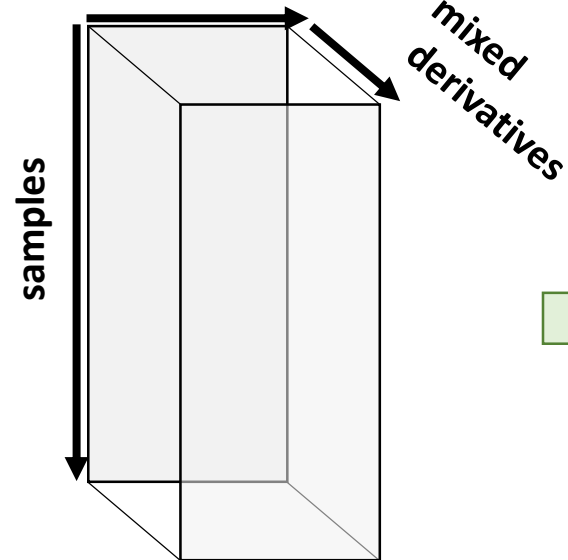
softmax\_output

probabilities for classes



$$\left\{ \frac{\partial}{\partial \varepsilon_{kj}} p_{ij} \right\}_j$$

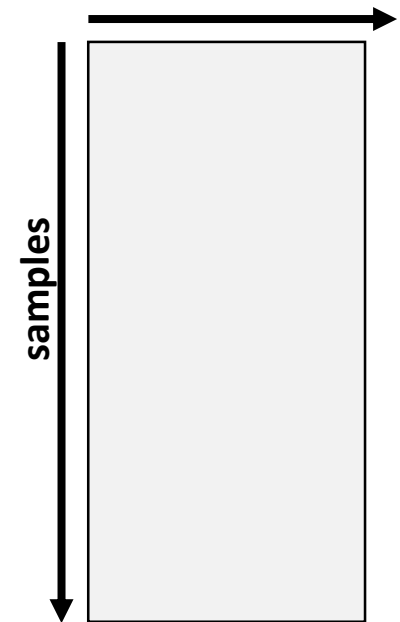
probabilities for classes



?

backprop denseLayer  
input

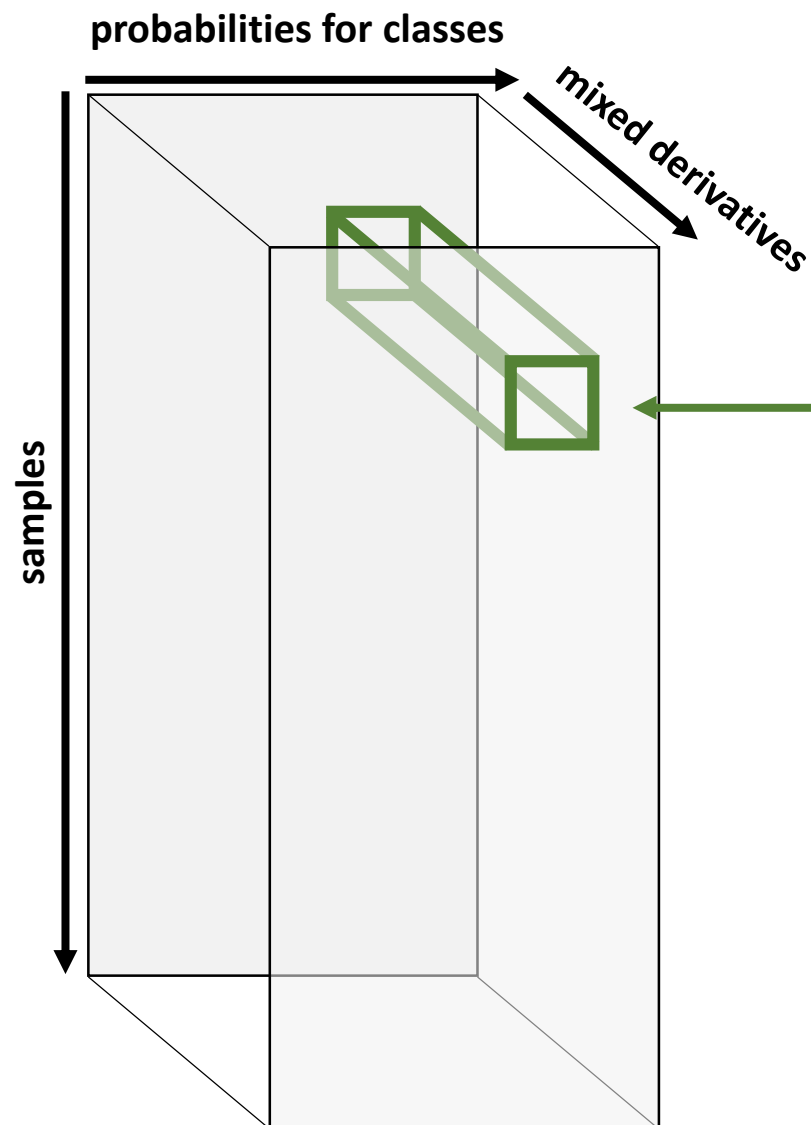
dinputs





Hence, for each data point  $j$ , we are getting such a Jacobian matrix!

for each data point  $j$  and class/category  $i$



$$p_{ij} = \frac{\exp(\varepsilon_{ij})}{\sum_i \exp(\varepsilon_{ij})}$$

- every  $p_i$  gets influenced by all the other  $i = 1, \dots, k, \dots$
- according to the chain rule: must get multiplied with dvalues from the loss function
- hence, multiplying two columns resulting in a number  $\rightarrow$  `np.dot`

`np.dot(jacobian_matrix, dvalues)`  
(but for each of these columns)



## class Activation\_Softmax:

```
def forward(self, inputs):  
    self.inputs = inputs  
    exp_values = np.exp(inputs - np.max(inputs, axis = 1, \  
                                         keepdims = True))  
    probabilities = exp_values / np.sum(exp_values, axis = 1, \  
                                         keepdims = True)  
    self.output = probabilities
```

```
def backward(self, dvalues):
```

```
    self.dinputs = np.empty_like(dvalues)
```

running the whole procedure for the entire data set in a loop

```
    for i, (single_output, single_dvalues) in \  
        enumerate(zip(self.output, dvalues)):
```

```
        single_output = single_output.reshape(-1, 1)
```

jacobian for each single data point

```
        jacobMatr = np.diagflat(single_output) - \  
                    np.dot(single_output, single_output.T)
```

multiplying jacobian column wise with dvalues from single data point (chain rule)

```
        self.dinputs[i] = np.dot(jacobMatr, single_dvalues)
```



```
class Activation_Softmax:
```

```
    def forward(self, inputs):
        self.inputs = inputs
        exp_values = np.exp(inputs - np.max(inputs, axis = 1, \
                                           keepdims = True))
        probabilities = exp_values / np.sum(exp_values, axis = 1, \
                                           keepdims = True)
        self.output = probabilities
```

```
    def backward(self, dvalues):

        self.dinputs = np.empty_like(dvalues)

        for i, (single_output, single_dvalues) in \
            enumerate(zip(self.output, dvalues)):

            single_output = single_output.reshape(-1, 1)
            jacobMatr = np.diagflat(single_output) - \
                        np.dot(single_output, single_output.T)

            self.dinputs[i] = np.dot(jacobMatr, single_dvalues)
```





$\varepsilon_{ij}$  from the last dense layer

softmax

$$p_{ij} = \frac{\exp(\varepsilon_{ij})}{\sum_i \exp(\varepsilon_{ij})}$$

loss

$$L_m = -\log(p_m)$$

returns total loss

calculating  
total loss

$$\begin{pmatrix} 0.20 & \mathbf{0.70} & 0.10 \\ \mathbf{0.90} & 0.05 & 0.05 \\ \mathbf{0.60} & 0.10 & 0.30 \\ 0.15 & 0.05 & \mathbf{0.80} \\ \dots & \dots & \dots \end{pmatrix} \text{ vs } \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \\ \dots & \dots & \dots \end{pmatrix}$$

CalcSoftmaxLossGrad

calculating gradient



```
class CalcSoftmaxLossGrad:
```

```
    def __init__(self):  
        self.activation = Activation_Softmax()  
        self.loss        = Loss_CategoricalCrossEntropy()
```

```
    def forward(self, inputs, y_true):  
        self.activation.forward(inputs)           calculating softmax  
        self.output = self.activation.output      saving softmax output
```

```
        return(self.loss.calculate(self.output, y_true))  
                                                    returning total loss  
                                                    see Loss()
```

**predicted probabilities for each class from softmax**

```
    def backward(self, dvalues, y_true):  
        Nsamples = len(dvalues)  
  
        if len(y_true.shape) == 2:  
            y_true = np.argmax(y_true, axis = 1)  
            self.dinputs = dvalues.copy()
```

**calculating the gradient of the probabilities**

```
            self.dinputs[range(Nsamples), y_true] -= 1  
            self.dinputs = self.dinputs/Nsamples
```



## class CalcSoftmaxLossGrad:

```
def __init__(self):
    self.activation = Activation_Softmax()
    self.loss = Loss_CategoricalCrossEntropy()

def forward(self, inputs, y_true):
    self.activation.forward(inputs)
    self.output = self.activation.output

    return(self.loss.calculate(self.output, y_true))

def backward(self, dvalues, y_true):
    Nsamples = len(dvalues)

    if len(y_true.shape) == 2:
        y_true = np.argmax(y_true, axis = 1)
        self.dinputs = dvalues.copy()

        calculating the gradient of the probabilities
        self.dinputs[range(Nsamples), y_true] -= 1
        self.dinputs = self.dinputs/Nsamples
```

$$\begin{pmatrix} 0.20 & \mathbf{0.70} & 0.10 \\ \mathbf{0.90} & 0.05 & 0.05 \\ \mathbf{0.60} & 0.10 & 0.30 \\ 0.15 & 0.05 & \mathbf{0.80} \\ \dots & \dots & \dots \end{pmatrix} \text{ vs } \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \\ \dots & \dots & \dots \end{pmatrix}$$



```
nc      = 3
[x, y] = spiral_data(samples = 200, classes = nc)
S       = np.shape(x)
```

```
dense1      = Layer_Dense(S[1], 4)
dense2      = Layer_Dense(4, nc)
activation1  = Activation_ReLU()
```

```
loss_function = CalcSoftmaxLossGrad()
```

defining layers

```
dense1.forward(x)
activation1.forward(dense1.output)

dense2.forward(activation1.output)

loss = loss_function.forward(dense2.output, y)

predictions = np.argmax(loss_function.output, axis = 1)
    if len(y.shape) == 2:
        y = np.argmax(y, axis = 1)
accuracy = np.mean(predictions == y)
```

creating the actual network



```
dense1.forward(x)
activation1.forward(dense1.output)

dense2.forward(activation1.output)

loss = loss_function.forward(dense2.output,y)

predictions = np.argmax(loss_function.output, axis = 1)
    if len(y.shape) == 2:
        y = np.argmax(y,axis = 1)
accuracy = np.mean(predictions == y)
```

creating the actual network

```
loss_function.backward(loss_function.output,y)
dense2.backward(loss_function.dinputs)
activation1.backward(dense2.dinputs)
dense1.backward(activation1.dinputs)
```

backpropagation



## We are done with the backpropagation now

→ let's run the code on the spiral data set in order to make sure that it works so far

→ also check:

```
print('loss:', loss)
print('accuracy:', accuracy)

print(dense1.dweights)
print(dense1.dbiases)

print(dense2.dweights)
print(dense2.dbiases)

print(loss_function.dinputs)
```

**The gradients are propagating through our network now.**

→ minimizing the gradient in a automated fashion → that's how the ANN learns



## outline

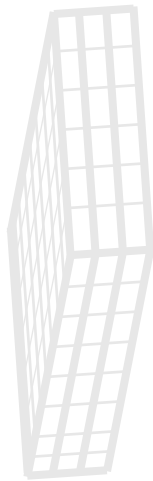
### 0 intro

### I the core:

- a single neuron
- layers of neurons
- activation functions
- softmax
- loss & entropy
- backpropagation
- **optimization**
- the learning process

### II convolution part:

- convolution itself
- pooling
- sigmoid
- flattening
- backpropagation - again
- testing the CNN & final remarks



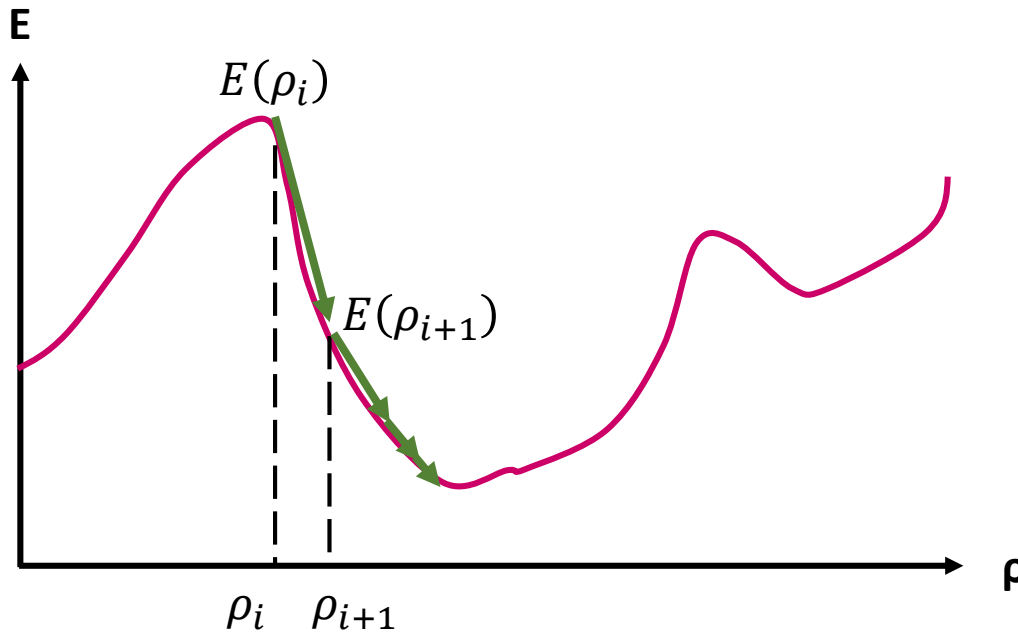


The gradients are propagating through our network now.

→ minimizing the gradient in a automated fashion → that's how the ANN learns

## Gradient Descent

cost function  $E$  depending on parameter  $\rho$



$$\text{grad}(E)_{\rho_i} \approx \frac{E(\rho_{i+1}) - E(\rho_i)}{\rho_{i+1} - \rho_i}$$

$$\rho_{i+1} = \rho_i - \alpha \cdot \text{grad}(E)_{\rho_i}$$

learning rate  $\alpha$

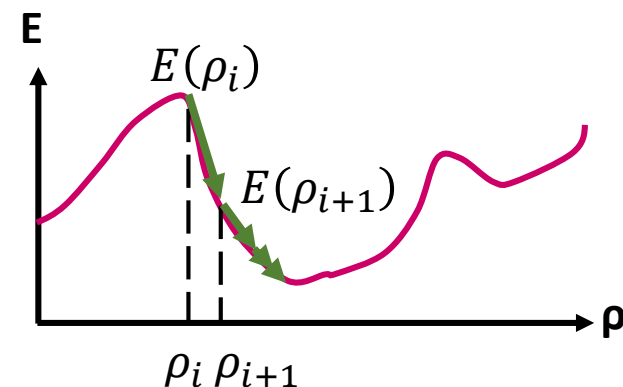




## Gradient Descent

$$\rho_{i+1} = \rho_i - \alpha \cdot \text{grad}(E)_{\rho_i}$$

learning rate  $\alpha$



- could get stuck in a local minimum

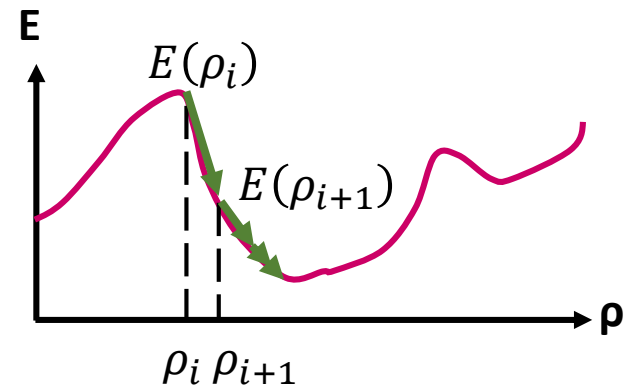
- learning rate  $\alpha$  is a *hyper parameter* we have to give
- we need to update weights and biases according to the above equation  
→ derivatives  $\cdot \alpha$
- writing a class that accesses the layers and performs the update  
**“Optimizer\_SGD”**  
Stochastic **G**radient **D**escent
- **Optimizer\_SGD** is updating the parameter values  
→ running the whole thing in a loop over N iterations



## Gradient Descent

$$\rho_{i+1} = \rho_i - \alpha \cdot \text{grad}(E)_{\rho_i}$$

learning rate  $\alpha$



```
class Optimizer_SGD:
```

default learning rate is 0.1

```
def __init__(self, learning_rate = 0.1):  
    self.learning_rate = learning_rate
```

```
def update_params(self, layer):  
    layer.weights += -self.learning_rate * layer.dweights  
    layer.biases += -self.learning_rate * layer.dbiases
```

the code so far

```
nc      = 3
[x, y] = spiral_data(samples = 200, classes = nc)
S       = np.shape(x)
```

```
dense1      = Layer_Dense(S[1], 4)
dense2      = Layer_Dense(4, nc)
activation1  = Activation_ReLU()
loss_function = CalcSoftmaxLossGrad()
```

```
optimizer    = Optimizer_SGD()
```

```
dense1.forward(x)
activation1.forward(dense1.output)
dense2.forward(activation1.output)
loss = loss_function.forward(dense2.output, y)
```

```
predictions = np.argmax(loss_function.output, axis = 1)
if len(y.shape) == 2:
    y = np.argmax(y, axis = 1)
accuracy = np.mean(predictions == y)
```

```
print('Loss:', loss)
print('accuracy:', accuracy)
```

```
loss_function.backward(loss_function.output, y)
dense2.backward(loss_function.dinputs)
activation1.backward(dense2.dinputs)
dense1.backward(activation1.dinputs)
```

```
optimizer.update_params(dense1)
optimizer.update_params(dense2)
```

**run this part in a loop**

**for epoch in range(10000):**



let us watch how the ANN learns: print the **loss** within the loop, each 100<sup>th</sup> epoch

```
if not epoch % 100:  
    print(f'epoch: {epoch}, ' +  
          f'accuracy: {accuracy:.3f}, ' +  
          f'loss: {loss:.3f}')
```

Console 1/A		
epoch: 0, accuracy: 0.413	loss: 0.148	
epoch: 100, accuracy: 0.4		
epoch: 200, accuracy: 0.5		
epoch: 300, accuracy: 0.5		
epoch: 400, accuracy: 0.5		
epoch: 500, accuracy: 0.5		
epoch: 600, accuracy: 0.5		
epoch: 700, accuracy: 0.5		
epoch: 800, accuracy: 0.5		
epoch: 900, accuracy: 0.5		
epoch: 1000, accuracy: 0.		
epoch: 1100, accuracy: 0.		
epoch: 1200, accuracy: 0.		
epoch: 1300, accuracy: 0.		
epoch: 1400, accuracy: 0.		
epoch: 8500, accuracy: 0.763	loss: 0.683	
epoch: 8600, accuracy: 0.765	loss: 0.681	
epoch: 8700, accuracy: 0.767	loss: 0.679	
epoch: 8800, accuracy: 0.767	loss: 0.677	
epoch: 8900, accuracy: 0.767	loss: 0.675	
epoch: 9000, accuracy: 0.768	loss: 0.673	
epoch: 9100, accuracy: 0.770	loss: 0.672	
epoch: 9200, accuracy: 0.772	loss: 0.670	
epoch: 9300, accuracy: 0.772	loss: 0.668	
epoch: 9400, accuracy: 0.772	loss: 0.666	
epoch: 9500, accuracy: 0.773	loss: 0.665	
epoch: 9600, accuracy: 0.772	loss: 0.663	
epoch: 9700, accuracy: 0.770	loss: 0.661	
epoch: 9800, accuracy: 0.770	loss: 0.660	
epoch: 9900, accuracy: 0.772	loss: 0.658	



We also want to plot **loss** and **accuracy**

```
Nsteps = 10000  
Monitor = np.zeros((Nsteps, 2))
```

```
for epoch in range(Nsteps):
```

```
    ...
```

```
    Monitor[epoch, 0] = accuracy  
    Monitor[epoch, 1] = loss
```

```
    ...
```

```
fig, ax = plt.subplots(2, 1)  
ax[0].plot(np.arange(Nsteps), Monitor[:, 0])  
ax[0].set_ylabel('accuracy [%]')  
ax[1].plot(np.arange(Nsteps), Monitor[:, 1])  
ax[1].set_xlabel('epoch')  
ax[1].set_ylabel('loss')
```



We also want to plot **loss** and **accuracy**

```
Nsteps = 10000  
Monitor = np.zeros((Nsteps, 2))
```

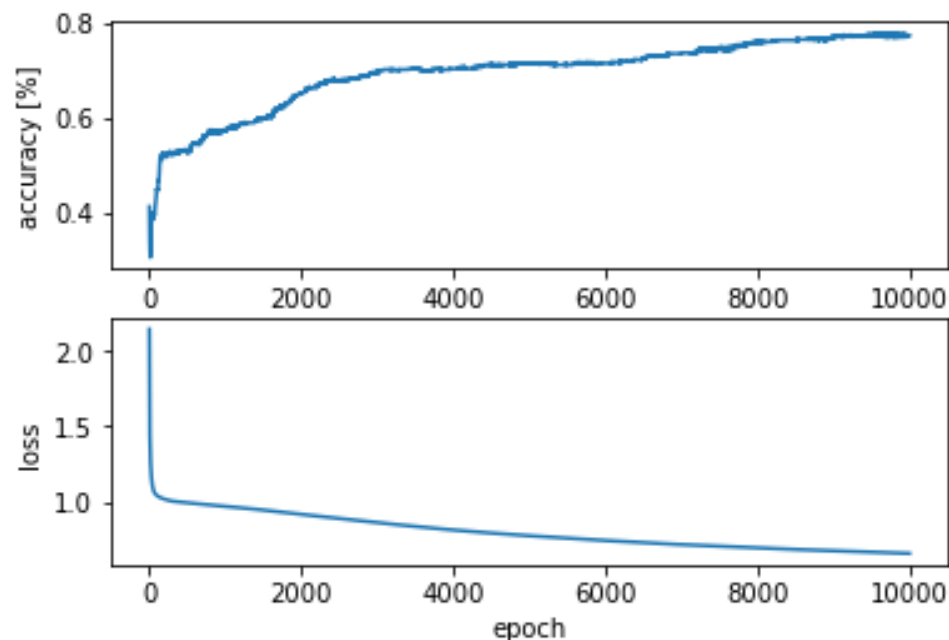
```
for epoch in range(Nsteps):
```

```
    ...
```

```
    Monitor[epoch, 0] = accuracy  
    Monitor[epoch, 1] = loss
```

```
    ...
```

```
fig, ax = plt.subplots(2, 1)  
ax[0].plot(np.arange(Nsteps), Monitor[:, 0])  
ax[0].set_ylabel('accuracy [%]')  
ax[1].plot(np.arange(Nsteps), Monitor[:, 1])  
ax[1].set_xlabel('epoch')  
ax[1].set_ylabel('loss')
```

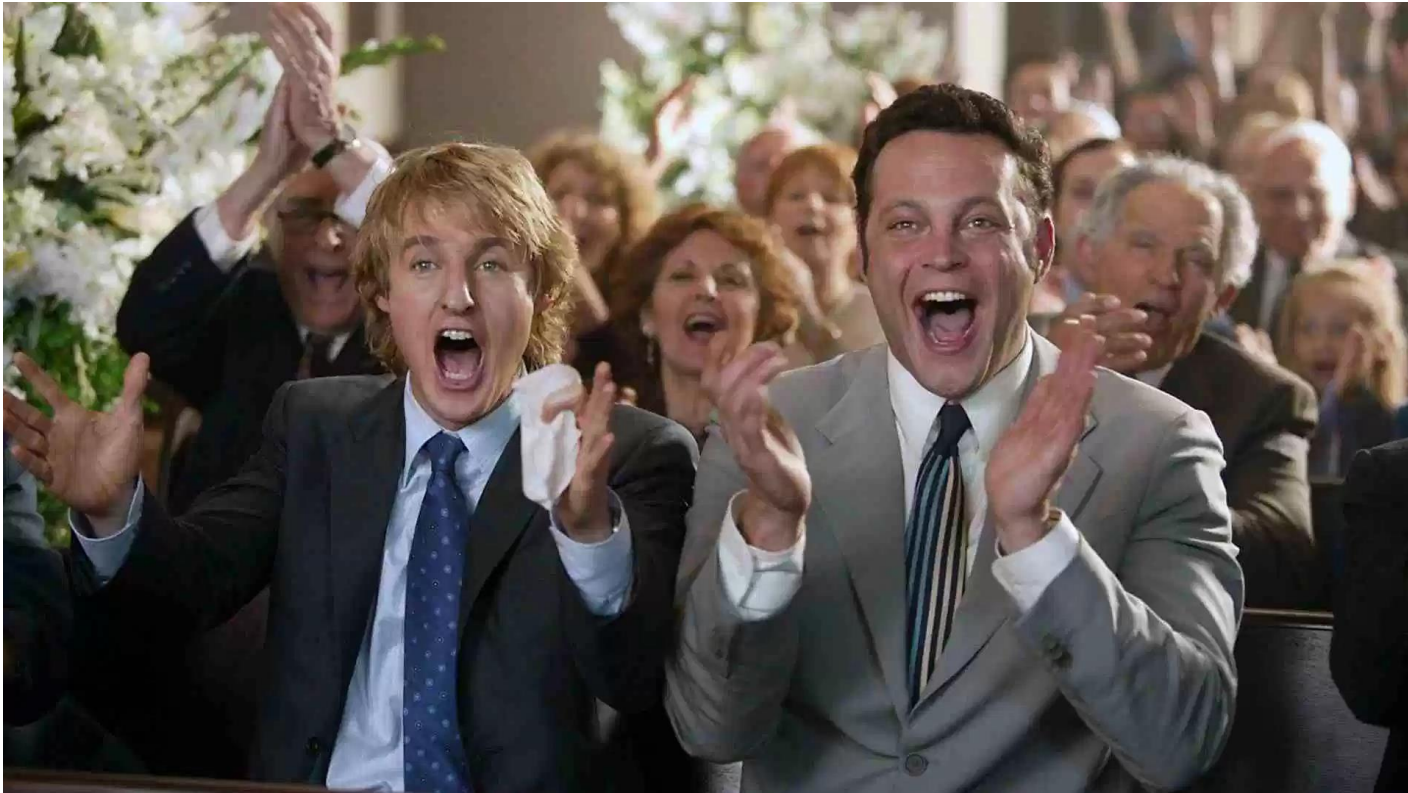






**We have created a fully functional ANN from scratch!**

*Congratulations*





## outline

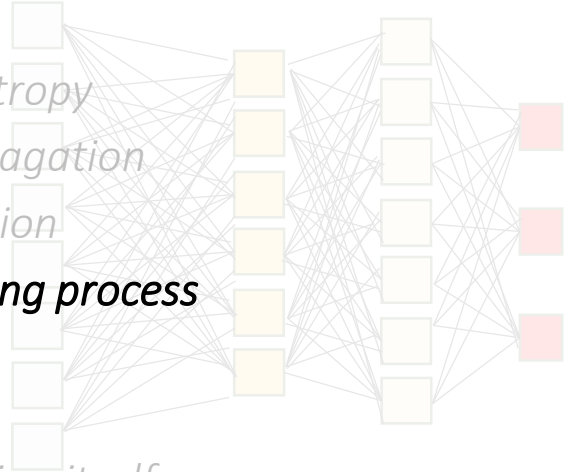
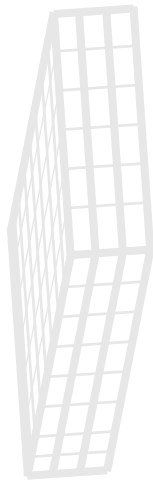
### 0 intro

### I the core:

- a single neuron
- layers of neurons
- activation functions
- softmax
- loss & entropy
- backpropagation
- optimization
- **the learning process**

### II convolution part:

- convolution itself
- pooling
- sigmoid
- flattening
- backpropagation - again
- testing the CNN & final remarks







## Aim in this section: improving how the ANN can learn

problem:

- if  $\alpha$  is too large: we could miss a minimum
- if  $\alpha$  is too small: learning is slow or we could get stuck in a local minimum

solution:

- ***learning rate decay***
- taking “shape” of gradient parameter space into account (passing local minima by using the ***momentum***)

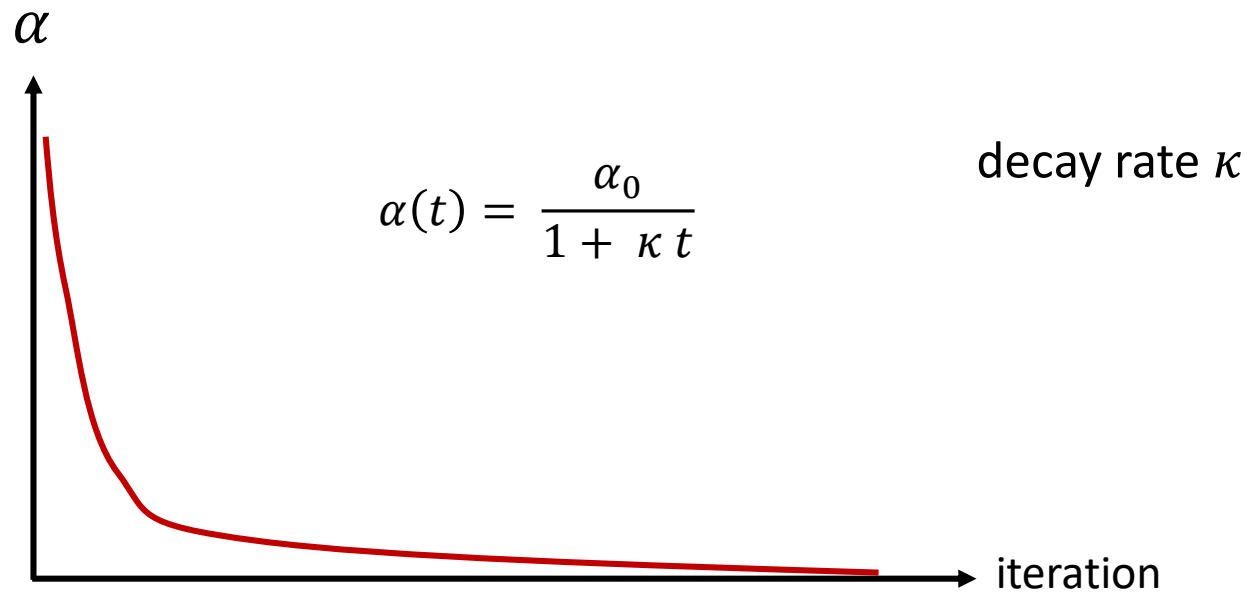
There is way more one could do:

- penalizing large weights and biases  
***(L1 & L2 regularization)***
- ***adaptive gradient*** (different learning rates per parameter)
- ***drop out***
- ....



**Aim in this section: improving how the ANN can learn**

solution: → *learning rate decay*





learning rate decay:

```
class Optimizer_SGD:
```

```
    def __init__(self, learning_rate = 0.1, decay = 0):  
        self.learning_rate      = learning_rate  
        self.decay              = decay  
        self.current_learning_rate = learning_rate  
        self.iterations        = 0
```

```
    def pre_update_params(self):  
        if self.decay:  
            self.current_learning_rate = self.learning_rate * \
```

$$\alpha(t) = \frac{\alpha_0}{1 + \kappa t}$$

```
            (1 / (1 + self.iterations * self.decay))  
  
    def update_params(self, layer):  
        layer.weights += -self.current_learning_rate * layer.dweights  
        layer.biases  += -self.current_learning_rate * layer.dbiases  
  
    def post_update_params(self):  
        self.iterations += 1
```

learning rate decay:

let us now include the decay and run the code again:

```
optimizer      = Optimizer_SGD(decay = 0.02)
```

```
Nsteps         = 10000
```

```
Monitor        = np.zeros((Nsteps, 3))
```

```
for epoch in range(Nsteps):
```

```
    ...
```

```
    Monitor[epoch, 2] = optimizer.current_learning_rate
```

```
    ...
```

```
    optimizer.update_params(dense1)
```

```
    optimizer.update_params(dense2)
```

```
    ...
```

```
ax[2].plot(np.arange(Nsteps), Monitor[:, 2])
```

```
ax[2].set_ylabel(r'$\alpha$')
```

```
ax[2].set_xlabel('epoch')
```

← calculating current  $\alpha$

← counting iterations

learning rate decay:

let us now include the decay and run the code again:

```
optimizer      = Optimizer_SGD(decay = 0.02)
```

```
Nsteps         = 10000
```

```
Monitor        = np.zeros
```

```
for epoch in range(Nste
```

```
    ...
```

```
    Monitor[epoch,2] = (
```

```
        ...
```

```
        optimizer.pre_update
```

```
        optimizer.update_pa
```

```
        optimizer.update_pa
```

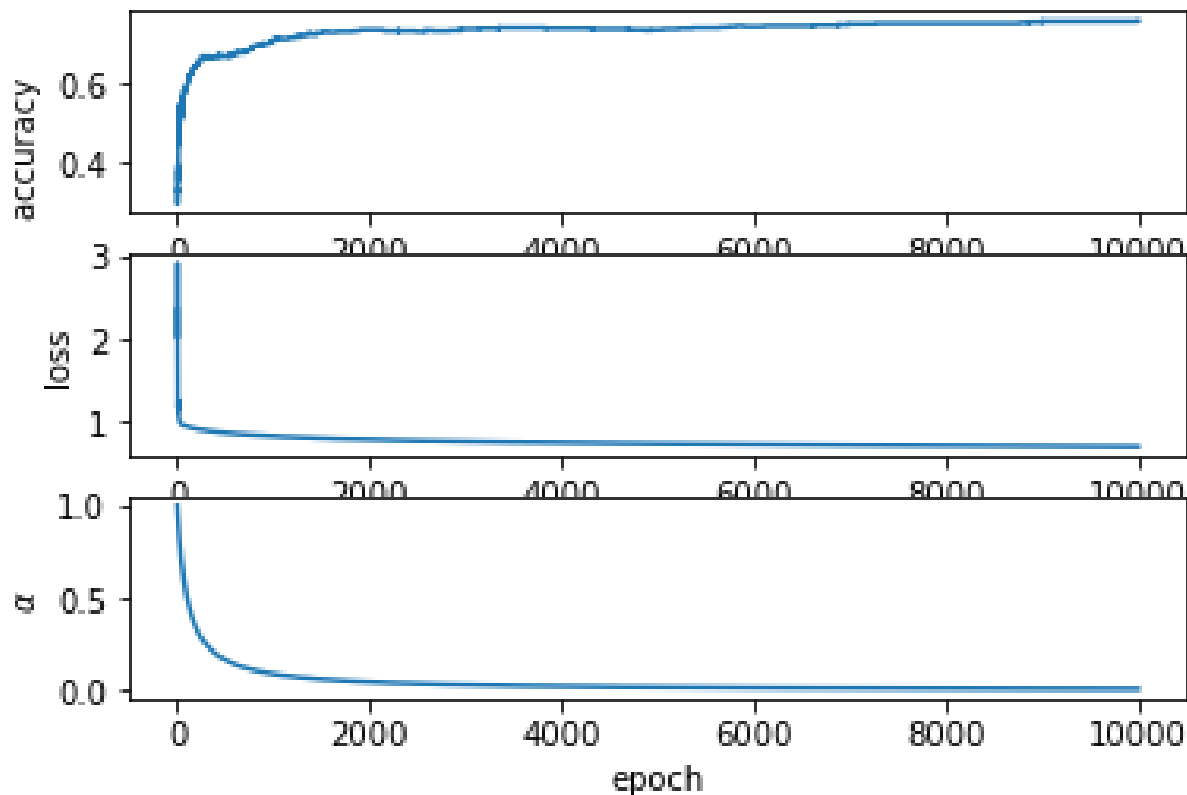
```
        optimizer.post_updat
```

```
    ...
```

```
ax[2].plot(np.arange(Nsteps), Monitor[:,2])
```

```
ax[2].set_ylabel(r'$\alpha$')
```

```
ax[2].set_xlabel('epoch')
```





momentum: using the **rolling average** over the gradient  
→ makes it more likely to pass a small local minimum (like a “hole”)

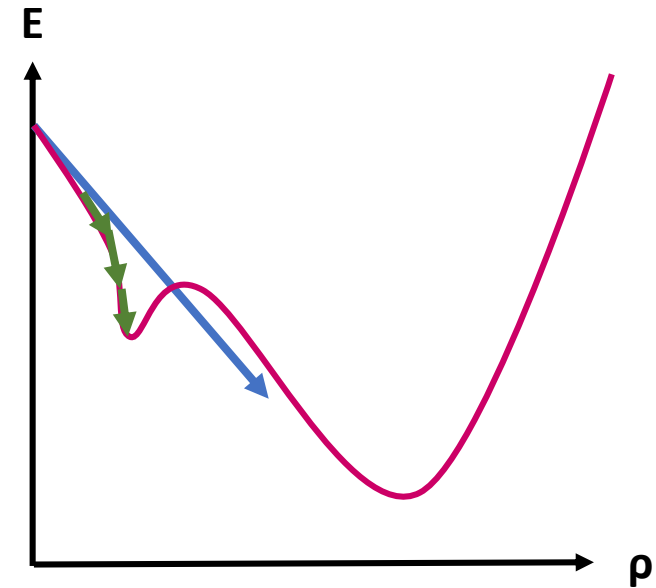
$$\rho_{i+1} = \rho_i - \alpha \cdot \text{grad}(E)_{\rho_i}$$

**average**:

$$\langle \text{grad}(E)_{\rho_i} \rangle = \frac{1}{n} \sum_{k=i-n}^i \text{grad}(E)_{\rho_k}$$

but we want to **weight** the contributions  
of the gradients  
→ the more distant, the less the influence  
(*rolling average*)

$$\langle \text{grad}(E)_{\rho_i} \rangle = \sum_{k=i-n}^i \mu_k \text{grad}(E)_{\rho_k}$$





momentum: using the **rolling average** over the gradient  
→ makes it more likely to pass a small local minimum (like a “hole”)

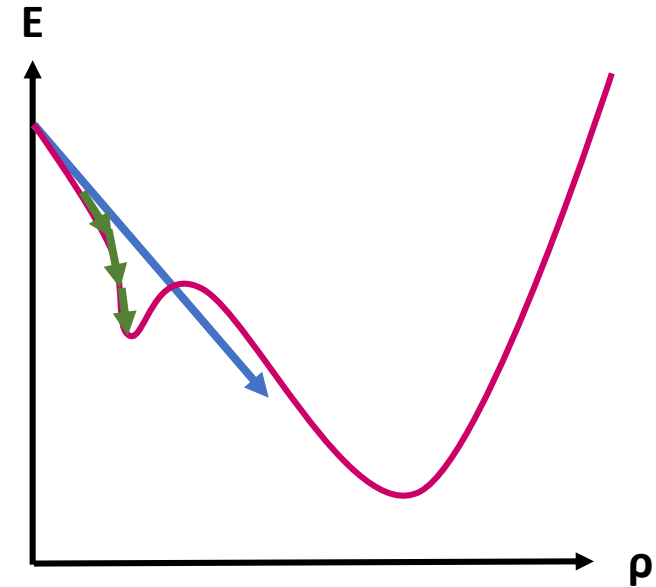
$$\rho_{i+1} = \rho_i - \alpha \cdot \text{grad}(E)_{\rho_i}$$

**average:**

$$\langle \text{grad}(E)_{\rho_i} \rangle = \sum_{k=i-n}^i \mu_k \cdot \text{grad}(E)_{\rho_k}$$

$$\langle \text{grad}(E)_{\rho_i} \rangle = \sum_{k=0}^i \mu_k \cdot \text{grad}(E)_{\rho_k}$$

has to decrease with  $(i - k)$





momentum: using the **rolling average** over the gradient  
→ makes it more likely to pass a small local minimum (like a “hole”)

$$\rho_{i+1} = \rho_i - \alpha \cdot \text{grad}(E)_{\rho_i}$$

**average:**

$$\langle \text{grad}(E)_{\rho_i} \rangle = \sum_{k=0}^i \mu_k \cdot \text{grad}(E)_{\rho_k}$$

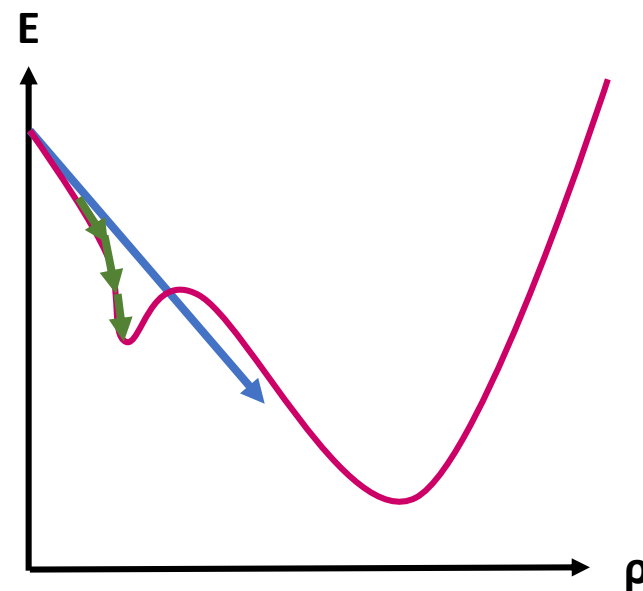
$$\langle \text{grad}(E)_{\rho_0} \rangle = \text{grad}(E)_{\rho_0} \quad \mu_0 = (0,1)$$

$$\langle \text{grad}(E)_{\rho_1} \rangle = \text{grad}(E)_{\rho_1} + \mu_0 \cdot \text{grad}(E)_{\rho_0}$$

$$\langle \text{grad}(E)_{\rho_2} \rangle = \text{grad}(E)_{\rho_2} + \mu_0 [\text{grad}(E)_{\rho_1} + \mu_0 \text{grad}(E)_{\rho_0}]$$

$$\langle \text{grad}(E)_{\rho_3} \rangle = \text{grad}(E)_{\rho_3} +$$

$$\mu_0 [\text{grad}(E)_{\rho_2} + \mu_0 [\text{grad}(E)_{\rho_1} + \mu_0 \cdot \text{grad}(E)_{\rho_0}]]$$







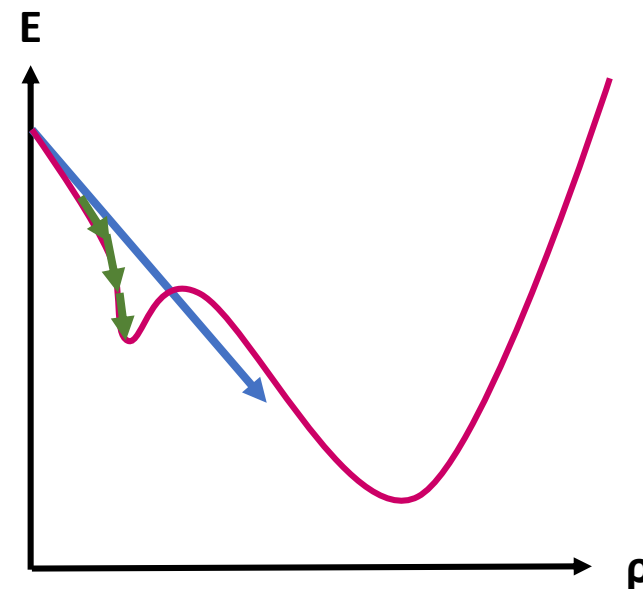
momentum: using the **rolling average** over the gradient  
→ makes it more likely to pass a small local minimum (like a “hole”)

$$\rho_{i+1} = \rho_i - \alpha \cdot \text{grad}(E)_{\rho_i}$$

**average:**

$$\langle \text{grad}(E)_{\rho_i} \rangle = \sum_{k=0}^i \mu_k \cdot \text{grad}(E)_{\rho_k}$$

$$\mu_0 = (0,1)$$



$$\begin{aligned} \langle \text{grad}(E)_{\rho_3} \rangle &= \text{grad}(E)_{\rho_3} + \\ &\quad \mu_0 \left[ \text{grad}(E)_{\rho_2} + \mu_0 \left[ \text{grad}(E)_{\rho_1} + \mu_0 \cdot \text{grad}(E)_{\rho_0} \right] \right] \end{aligned}$$

$$\mu_k = \mu_0^k$$

add this part to gradient descent



momentum: using the **rolling average** over the gradient  
→ makes it more likely to pass a small local minimum (like a “hole”)

so far:  $\rho_{i+1} = \rho_i - \alpha \cdot \text{grad}(E)_{\rho_i}$

now:  $\rho_{i+1} = \rho_i + \mu \cdot \mu_i - \alpha \cdot \text{grad}(E)_{\rho_i}$  momentum  $\mu$

$$\mu_{i+1} = \mu \cdot \mu_i - \alpha \cdot \text{grad}(E)_{\rho_i}$$

$$\rho_{i+2} = \rho_{i+1} + \mu \cdot \overbrace{[\mu \cdot \mu_i - \alpha \cdot \text{grad}(E)_{\rho_i}]}^{\mu_{i+1}} - \alpha \cdot \text{grad}(E)_{\rho_{i+1}}$$

$$\mu_{i+2} = \mu \cdot \mu_{i+1} - \alpha \cdot \text{grad}(E)_{\rho_{i+1}}$$

and so on...



momentum:

```
class Optimizer_SGD:
```

```
    def __init__(self, learning_rate = 0.1, decay = 0, momentum = 0):  
        self.learning_rate      = learning_rate  
        self.decay               = decay  
        self.current_learning_rate = learning_rate  
        self.iterations          = 0  
        self.momentum            = momentum
```



momentum:

```
class Optimizer_SGD:
```

```
    ...
```

```
    def update_params(self, layer):
```

```
        if self.momentum:
```

**we attach the momentum to the layer  
in order to remember the rolling average**

```
            if not hasattr(layer, 'weight_momentums'):
```

```
                layer.weight_momentums = np.zeros_like(layer.weights)
```

```
                layer.bias_momentums   = np.zeros_like(layer.biases)
```

$$\mu_{i+1} = \mu \cdot \mu_i - \alpha \cdot \text{grad}(E)_{\rho_i}$$

```
weight_updates = self.momentum * layer.weight_momentums - \
                  self.current_learning_rate * layer.dweights
layer.weight_momentums = weight_updates
```

```
bias_updates = self.momentum * layer.bias_momentums - \
                self.current_learning_rate * layer.dbiases
layer.bias_momentums = bias_updates
```

```
    else:
```



momentum:

```
class Optimizer_SGD:
    ...

    def update_params(self, layer):

        if self.momentum:

            ...

        else:

            same as before

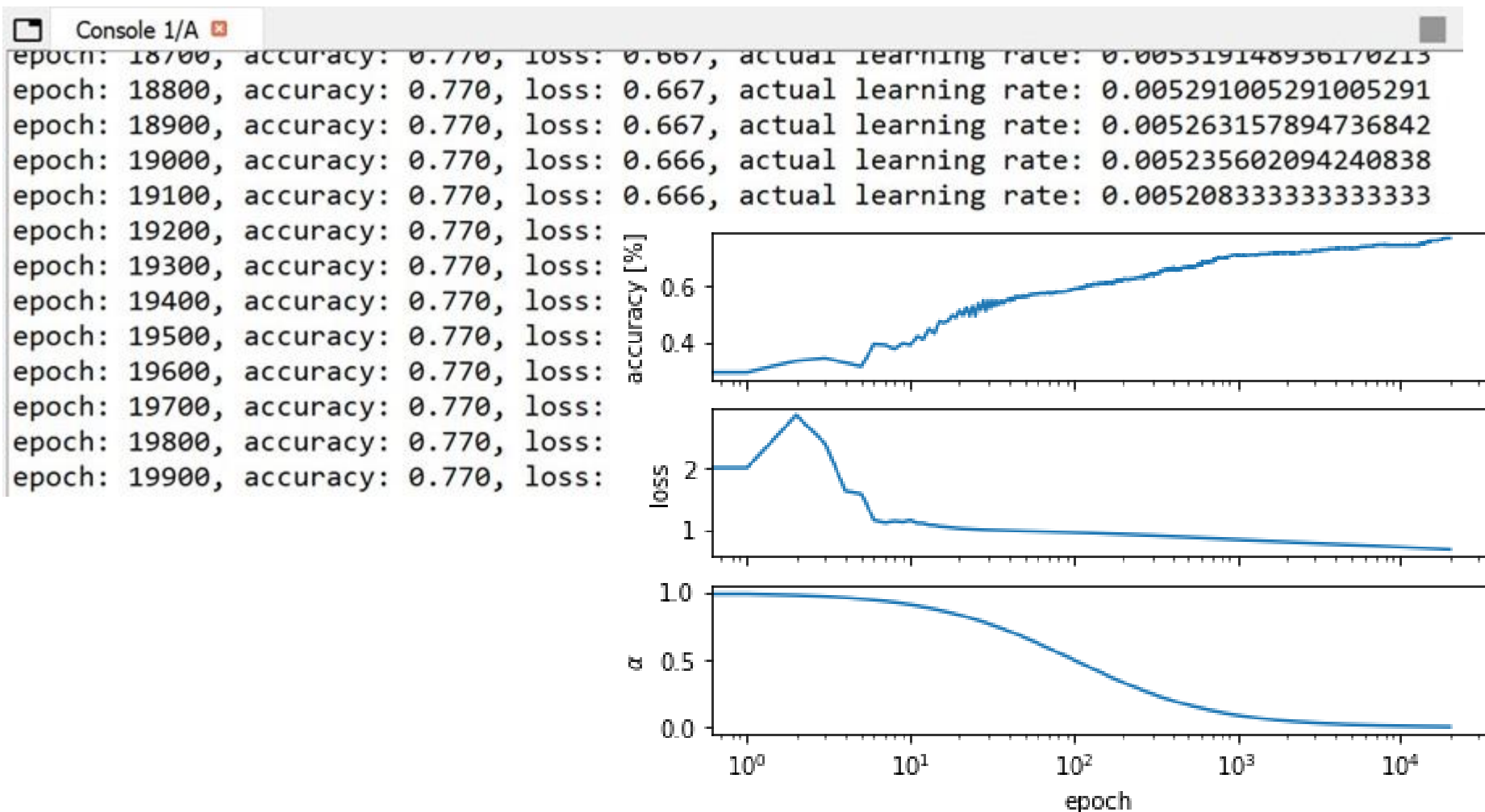
            weight_updates = -self.current_learning_rate * layer.dweights
            bias_updates    = -self.current_learning_rate * layer.dbiases

            layer.weights += weight_updates
            layer.biases  += bias_updates
```

momentum:

run the code with eg

```
optimizer= Optimizer_SGD(decay = 0.01, momentum = 0.1)
```

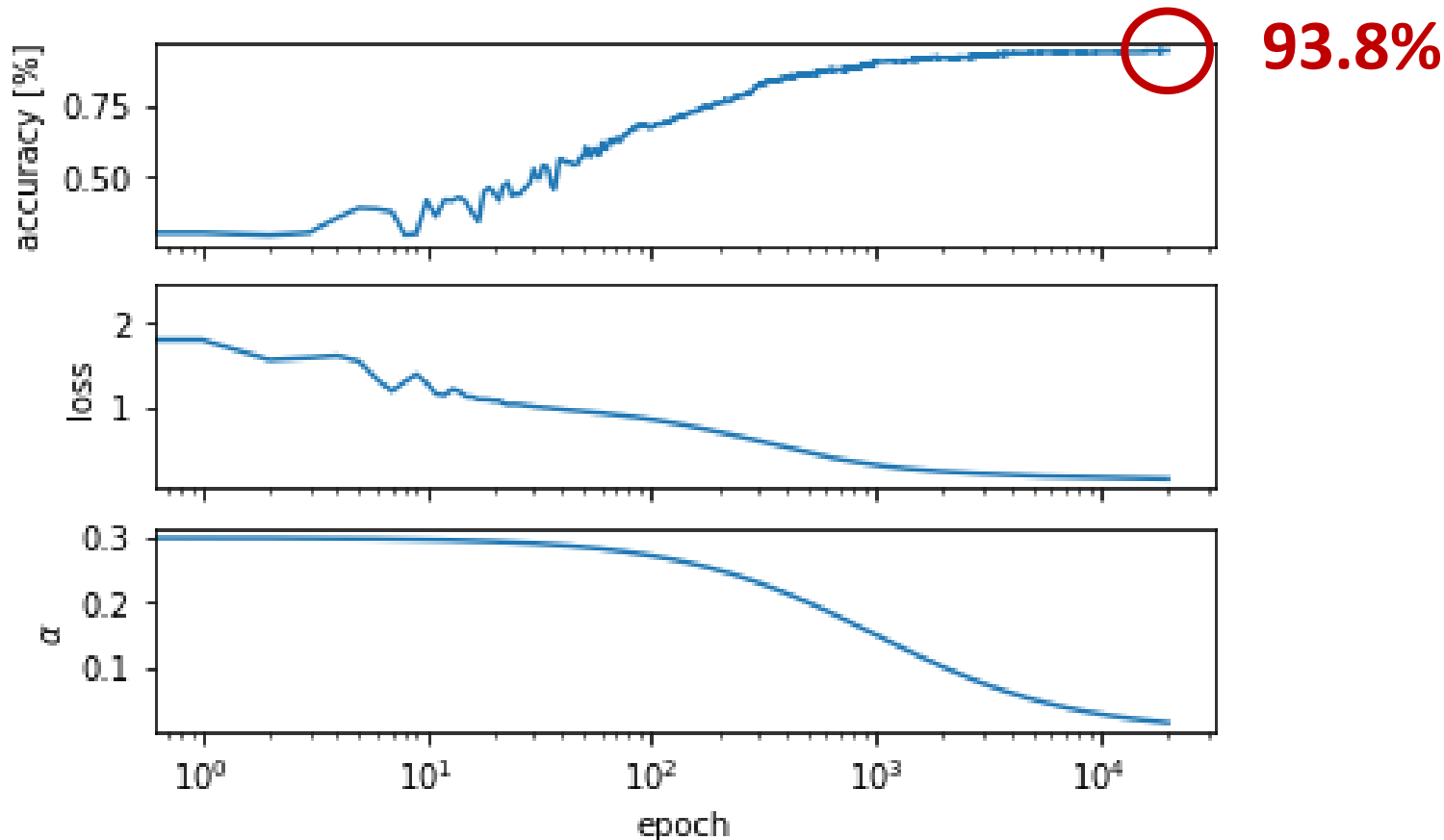




momentum:

run the code with eg

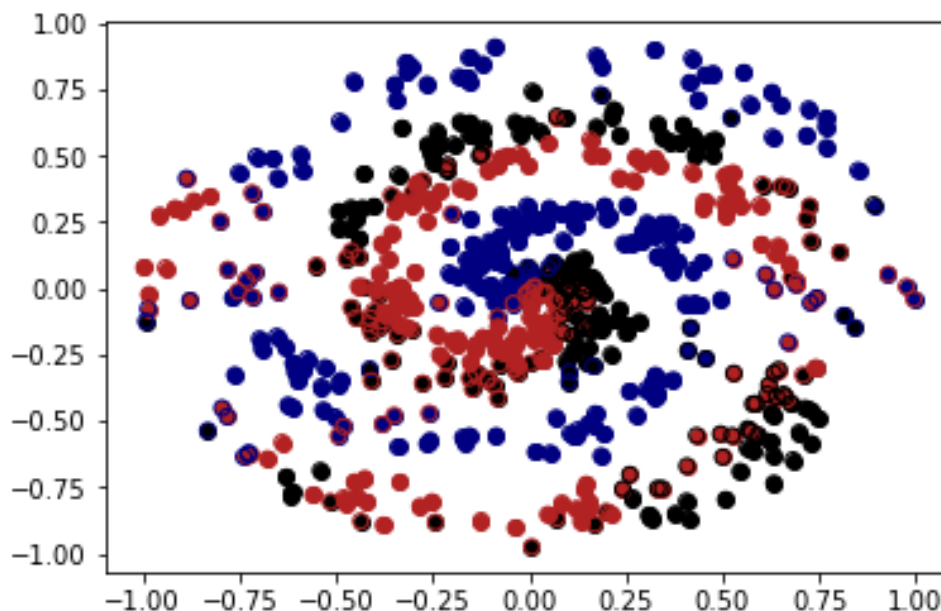
```
optimizer = Optimizer_SGD(learning_rate = 0.2, decay = 0.001, \  
                           momentum = 0.9)
```





before we are done:

- running the code is still a bit clumsy → calling ANN externally
- creating a function that runs the actual ANN incl plots
- checking predicted classes visually
- extracting the weights for actual application







before we are done:

- running the code is still a bit clumsy → calling ANN externally
- creating a function that runs the actual ANN incl plots
- checking predicted classes visually
- extracting the weights for actual application

We want to create a function, that runs the ANN and creates the plot

→ removing the

- plotting part
- the loop over the different epochs
- part where we initialize the layers and set up the network structure

and copy it into a new function we call **RunMyANN**



before we are done:

- running the code is still a bit clumsy → calling ANN externally
- creating a function that runs the actual ANN incl plots
- checking predicted classes visually
- extracting the weights for actual application

```
import matplotlib.pyplot as plt
import numpy as np
import nnfs #run "pip install nnfs" first
from nnfs.datasets import spiral_data

def RunMyANN():

    #creating the actual data:
    #x: 3x200 data points (2D)
    #y: corresponding classes
    [x, y] = spiral_data(samples = 200, classes = 3)

    nnfs.init()
```



before we are done:

- running the code is still a bit clumsy → calling ANN externally

- creating a function that runs the actual ANN incl plots

- checking predicted classes visually

- extracting the weights for actual application



calling the ANN

```
from MyANN import *
```

```
def RunMyANN():
```

```
    dense1          = Layer_Dense(2, 64)
    activation1      = Activation_ReLU()
    optimizer        = Optimizer_SGD(decay = 0.01, momentum = 0.1)
    dense2           = Layer_Dense(len(dense1.biases.T), 3)
    loss_activation  = CalcSoftmaxLossGrad()
```

```
    Nsteps   = 20000
    Monitor  = np.zeros((Nsteps, 3))
```

```
    for epoch in range(Nsteps):
        ...
```



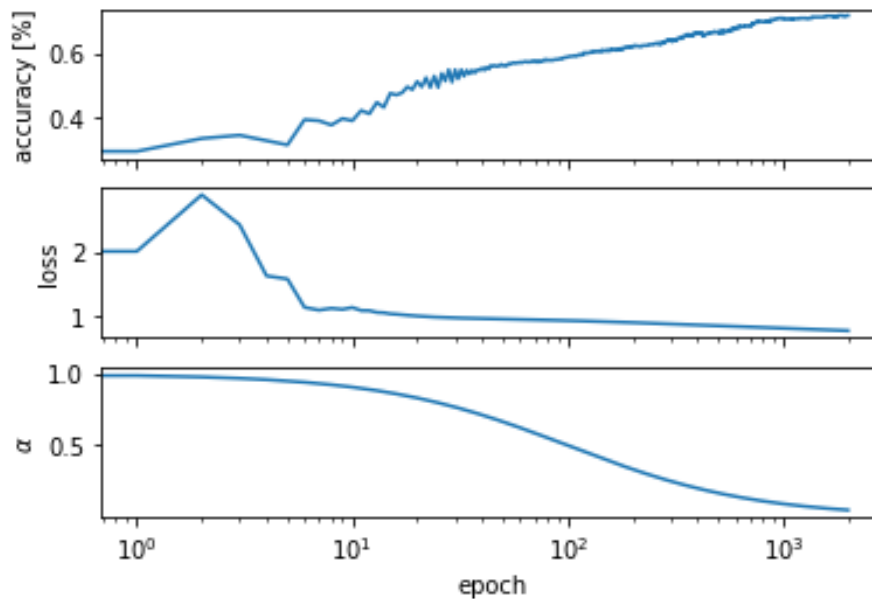
← as before



before we are done:

- running the code is still a bit clumsy → calling ANN externally
- creating a function that runs the actual ANN incl plots
- checking predicted classes visually
- extracting the weights for actual application

compile & test – run the function **RunMyANN.py**





before we are done:

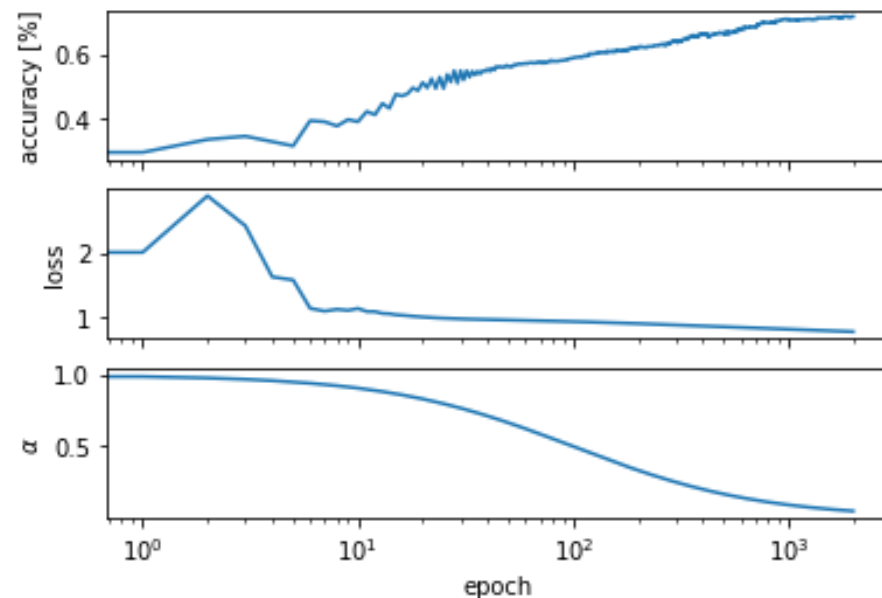
- running the code is still a bit clumsy → calling externally
- creating a function that runs the actual ANN incl plots
- checking predicted classes visually
- extracting the weights for actual application

go to the very end of **RunMyANN.py**

```
fig1, ax = plt.subplots(3, 1, sharex=True)
ax[0].plot(np.arange(Nsteps), Monitor[:,0])
ax[0].set_ylabel('accuracy [%]')
ax[1].plot(np.arange(Nsteps), Monitor[:,1])
ax[1].set_ylabel('loss')
ax[2].plot(np.arange(Nsteps), Monitor[:,2])
ax[2].set_ylabel('$\alpha$')
ax[2].set_xlabel('epoch')
plt.xscale('Log', base=10)
```

**plt.show()**

needed in order to show new plot  
in different window





## before we are done:

- running the code is still a bit clumsy → calling ANN externally
- creating a function that runs the actual ANN incl plots
- checking predicted classes visually
- extracting the weights for actual application

go to the very end of **RunMyANN.py**

```
...  
plt.xscale('Log', base=10)  
plt.show()  
  
idx0 = np.argwhere(y==0)  
idx1 = np.argwhere(y==1)  
idx2 = np.argwhere(y==2)  
  
idxp0 = np.argwhere(predictions==0)  
idxp1 = np.argwhere(predictions==1)  
idxp2 = np.argwhere(predictions==2)
```

extracting actual  
classes and predicted  
classes

before we are done:

- running the code is still a bit clumsy → calling ANN externally
- creating a function that runs the actual ANN incl plots
- checking predicted classes visually
- extracting the weights for actual application

go to the very end of **RunMyANN.py**

...

```
idx0 = np.argwhere(y==0)
idx1 = np.argwhere(y==1)
idx2 = np.argwhere(y==2)
```

```
idxp0 = np.argwhere(predictions==0)
idxp1 = np.argwhere(predictions==1)
idxp2 = np.argwhere(predictions==2)
```

```
plt.scatter(x[idx0,0], x[idx0,1], color = 'black')
plt.scatter(x[idx1,0], x[idx1,1], color = [0, 0, 0.5])#nice blue
plt.scatter(x[idx2,0], x[idx2,1], color = [0.7, 0.13, 0.13])#nice red
```

actual classes

```
plt.scatter(x[idxp0,0], x[idxp0,1], marker = 'o', \
            facecolors = 'none', edgecolors = 'black')
plt.scatter(x[idxp1,0],x[idxp1,1], marker = 'o', \
            facecolors = 'none', edgecolors = [0, 0, 0.5])
plt.scatter(x[idxp2,0],x[idxp2,1], marker = 'o', \
            facecolors = 'none', edgecolors = [0.7, 0.13, 0.13])
```

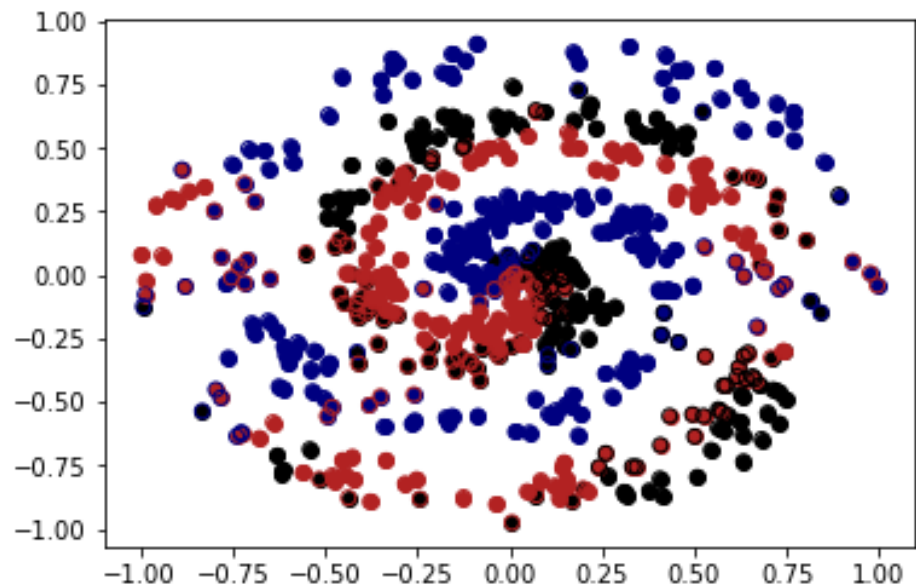
predicted classes

before we are done:

- running the code is still a bit clumsy → calling ANN externally
- creating a function that runs the actual ANN incl plots
- checking predicted classes visually
- extracting the weights for actual application

go to the very end of **RunMyANN.py**

```
...  
idx0 = np.argwhere(y==0)  
idx1 = np.argwhere(y==1)  
idx2 = np.argwhere(y==2)  
  
idxp0 = np.argwhere(predictions==0)  
idxp1 = np.argwhere(predictions==1)  
idxp2 = np.argwhere(predictions==2)  
  
plt.scatter(x[idx0,0], x[idx0,1], color = 'black')  
plt.scatter(x[idx1,0], x[idx1,1], color = [0, 0, 0.5])  
plt.scatter(x[idx2,0], x[idx2,1], color = [0.7, 0.13,  
  
plt.scatter(x[idxp0,0], x[idxp0,1], marker = 'o', \  
            facecolors = 'none', edgecolors =  
plt.scatter(x[idxp1,0],x[idxp1,1], marker = 'o', \  
            facecolors = 'none', edgecolors =  
plt.scatter(x[idxp2,0],x[idxp2,1], marker = 'o', \  
            facecolors = 'none', edgecolors =
```





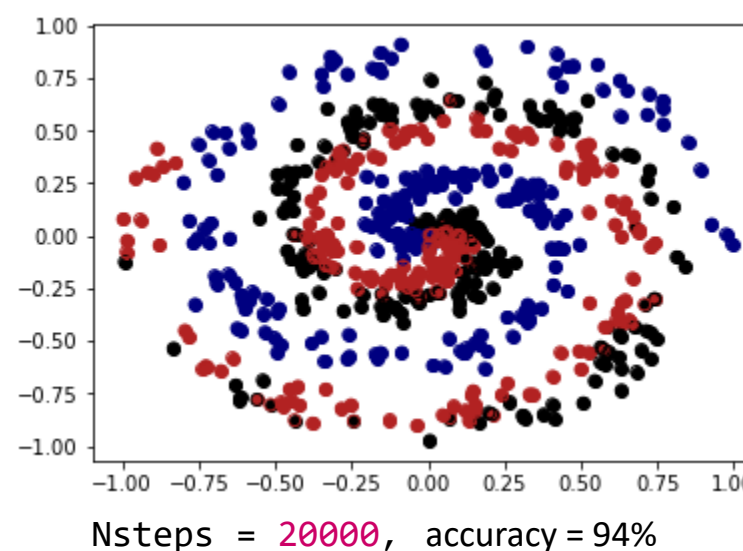
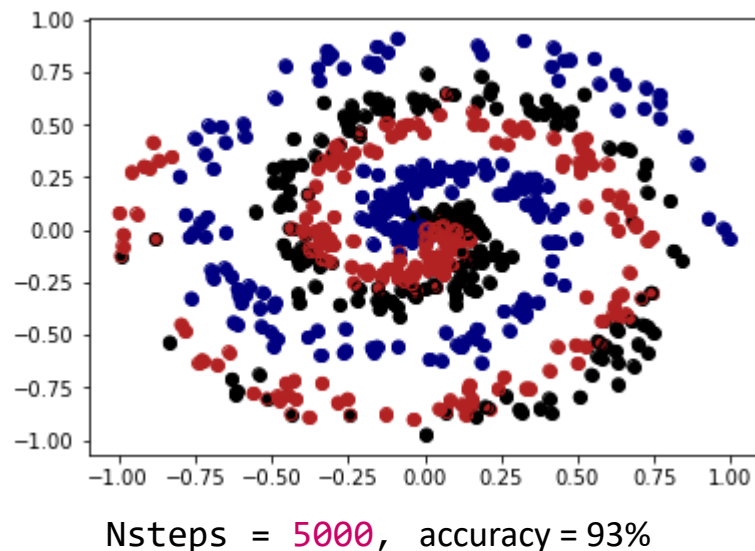
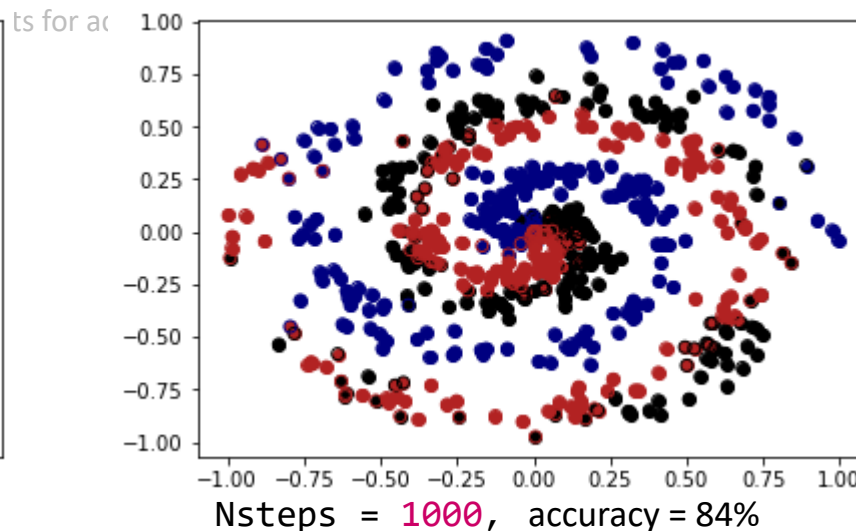
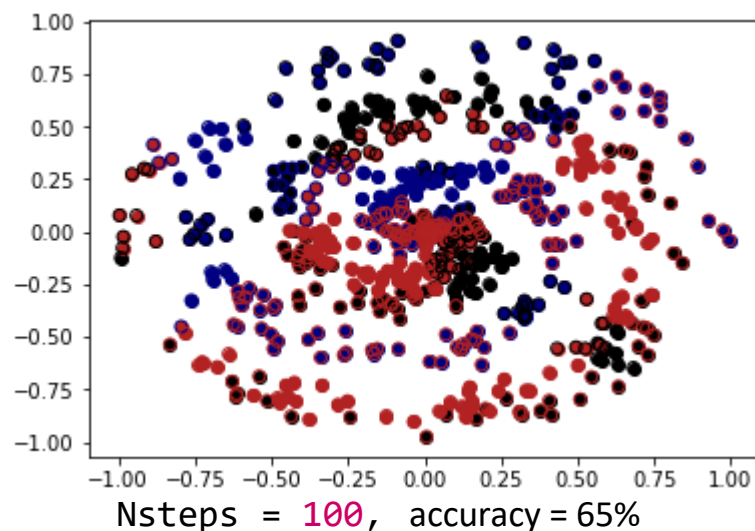


before we are done:

- running the code is still a bit clumsy → calling ANN externally
- creating a function that runs the actual ANN incl plots

the training process:

- checking predicted classes visually





## before we are done:

- running the code is still a bit clumsy → calling ANN externally
- creating a function that runs the actual ANN incl plots
- checking predicted classes visually
- extracting the weights for actual application

Since we have trained our ANN,  
we can use its memory hence  
the weights for classification!

go to **RunMyANN.py**  
and add lines at the very end  
to save the weights and biases

```
np.save('weights1.npy', dense1.weights)
np.save('weights2.npy', dense2.weights)

np.save('bias1.npy', dense1.biases)
np.save('bias2.npy', dense2.biases)
```

before we are done:

- running the code is still a bit clumsy → calling ANN externally
- creating a function that runs the actual ANN incl plots
- checking predicted classes visually
- extracting the weights for actual application

We are now creating a new file `ApplyMyANN.py` that calls the saved weights when applying the ANN to new data

```
import numpy as np
import WithOptimizationLearningRateDecayMomentum as MyANN
```

```
def ApplyMyANN(x_new):
```



new data with unknown classes

```
#loading saved weights & biases
```

```
w1 = np.load('weights1.npy')
```

```
w2 = np.load('weights2.npy')
```

```
b1 = np.load('bias1.npy')
```

```
b2 = np.load('bias2.npy')
```

before we are done:

- running the code is still a bit clumsy → calling ANN externally
- creating a function that runs the actual ANN incl plots
- checking predicted classes visually
- extracting the weights for actual application

```
def ApplyMyANN(x_new):
```

```
w1 = np.load('weights1.npy', dtype = float)
w2 = np.load('weights2.npy', dtype = float)

b1 = np.load('bias1.npy', dtype = float)
b2 = np.load('bias2.npy', dtype = float)
```

```
#creating network structure
```

```
s      = w1.shape
nrow   = s[0]
ncol   = s[1]
```

```
nCat = 3
```

```
dense1      = MyANN.Layer_Dense(nrow, ncol)
activation1  = MyANN.Activation_ReLU()
dense2      = MyANN.Layer_Dense(len(dense1.biases.T), nCat)
```



before we are done:

- running the code is still a bit clumsy → calling ANN externally
- creating a function that runs the actual ANN incl plots
- checking predicted classes visually
- extracting the weights for actual application

**def ApplyMyANN(x\_new):**

*#creating network structure*

```
s = w1.shape
nrow = s[0]
ncol = s[1]
```

```
nCat = 3
```

```
dense1 = MyANN.Layer_Dense(nrow, ncol)
activation1 = MyANN.Activation_ReLU()
dense2 = MyANN.Layer_Dense(len(dense1.biases.T), nCat)
```

*#transferring weights & biases*

```
dense1.weights = w1
```

```
dense2.weights = w2
```

```
dense1.biases = b1
```

```
dense2.biases = b2
```

*#feeding the network*

```
dense1.forward(x_new)
```

```
activation1.forward(dense1.output)
```

```
dense2.forward(activation1.output)
```

```
result = dense2.output
```

We need to maintain  
the structure of the ANN  
we have used for training

before we are done:

- running the code is still a bit clumsy → calling ANN externally
- creating a function that runs the actual ANN incl plots
- checking predicted classes visually
- extracting the weights for actual application

**def ApplyMyANN(x\_new):**

```
#transferring weights & biases
dense1.weights = w1
dense2.weights = w2

dense1.biases = b1
dense2.biases = b2

#feeding the network
dense1.forward(x_new)
activation1.forward(dense1.output)
dense2.forward(activation1.output)
result = dense2.output
```

Again, we are using the Boltzmann distribution for calculating the probabilities

```
exp_values = np.exp(result - np.max(result, axis = 1,\
                                   keepdims = True))
probabilities = exp_values/np.sum(exp_values, axis = 1,\
                                   keepdims = True)
```

```
predictions = np.argmax(probabilities, axis = 1)
```

```
return(predictions)
```

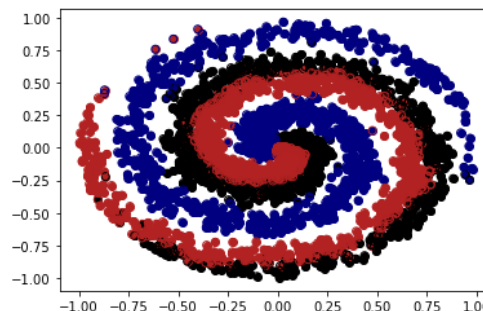
before we are done:

- running the code is still a bit clumsy → calling ANN externally
  - creating a function that runs the actual ANN incl plots
  - checking predicted classes visually
- extracting the weights for actual application

now we are done → performing two steps for using the ANN:

1) training (data set as large and diverse as possible, ideally needed to be done only once)

RunMyANN()



2) application (to new, yet unclassified data)

```
predClass = ApplyMyANN(x_new)
```

the actual analysis

```
idxp0 = np.argwhere(predClass==0)
```

```
idxp1 = np.argwhere(predClass==1)
```

```
idxp2 = np.argwhere(predClass==2)
```

```
plt.scatter(x[idxp0,0],x[idxp0,1], color = 'black')
```

```
plt.scatter(x[idxp1,0],x[idxp1,1], color = [0, 0, 0.5])
```

```
plt.scatter(x[idxp2,0],x[idxp2,1], color = [0.7, 0.13, 0.13])
```

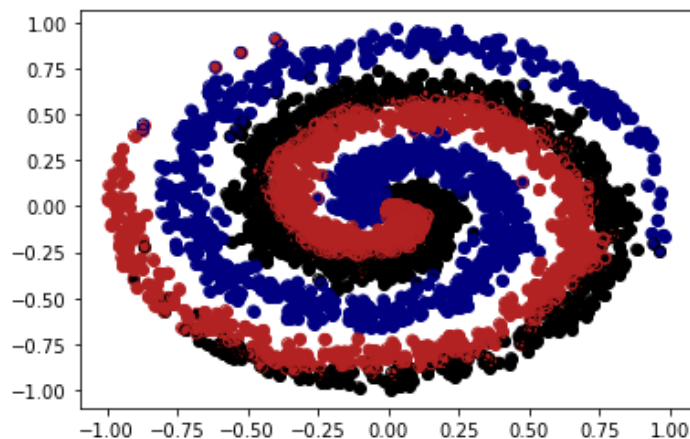
visualization



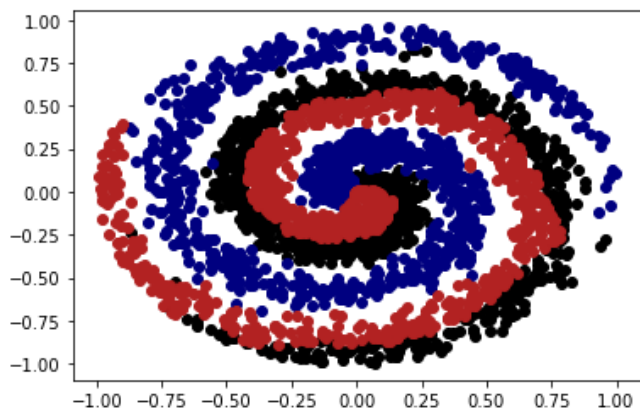
## before we are done:

- running the code is still a bit clumsy → calling ANN externally
- creating a function that runs the actual ANN incl plots
- checking predicted classes visually
- extracting the weights for actual application

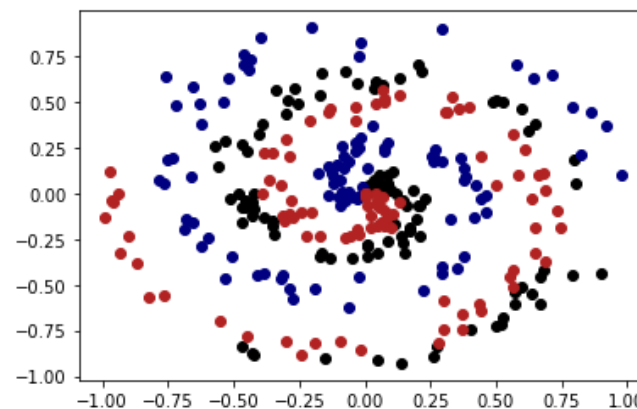
training result for sample size 1000



applied to 1000  
data points



applied to 100  
data points







our code works now sufficiently well 😊

→ part I is done



**part II:**

- we want the code to be able to ***categorize images*** (cats/ dogs etc)
- therefore it needs to understand features in an image  
→ **convolution**