



# Grundlagen der Programmierung

Praktikum  
2. Plenartermin

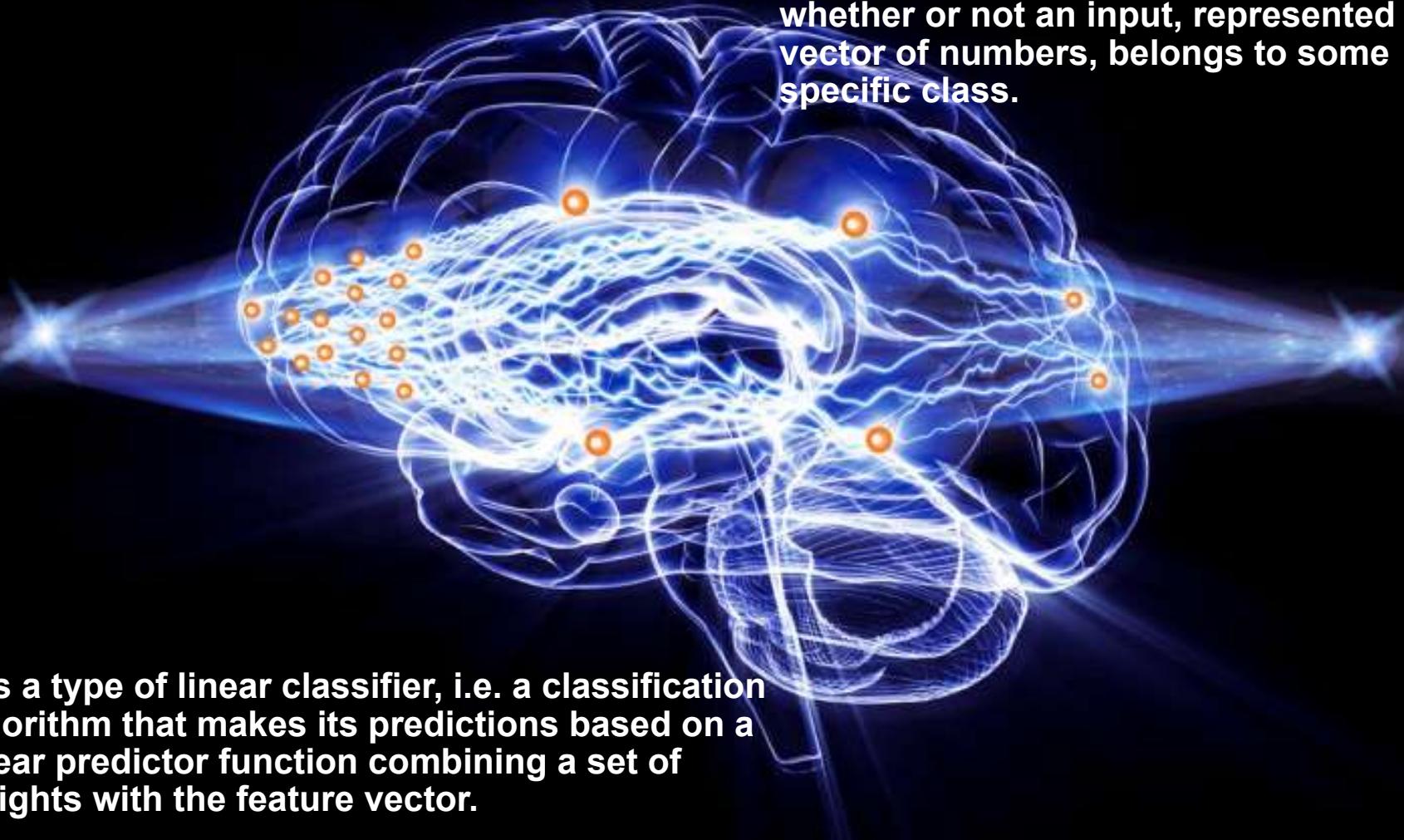
Artemiy Belousov, Ivan Kisel, Grigory Kozlov, Martin Parnet

# Abgabe Milestone 1

Heute um 23:59

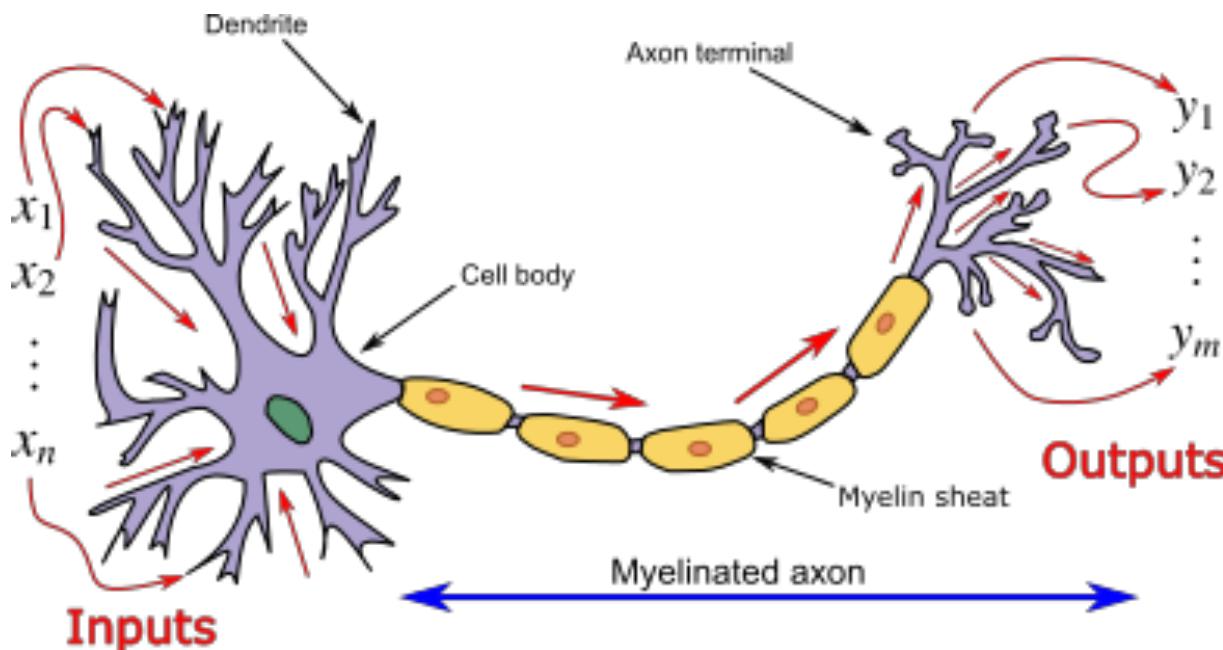
# Perceptron neural net

**Perceptron** is an algorithm for supervised learning of binary classifiers. A binary classifier is a function which can decide whether or not an input, represented by a vector of numbers, belongs to some specific class.



It is a type of linear classifier, i.e. a classification algorithm that makes its predictions based on a linear predictor function combining a set of weights with the feature vector.

# Neuron

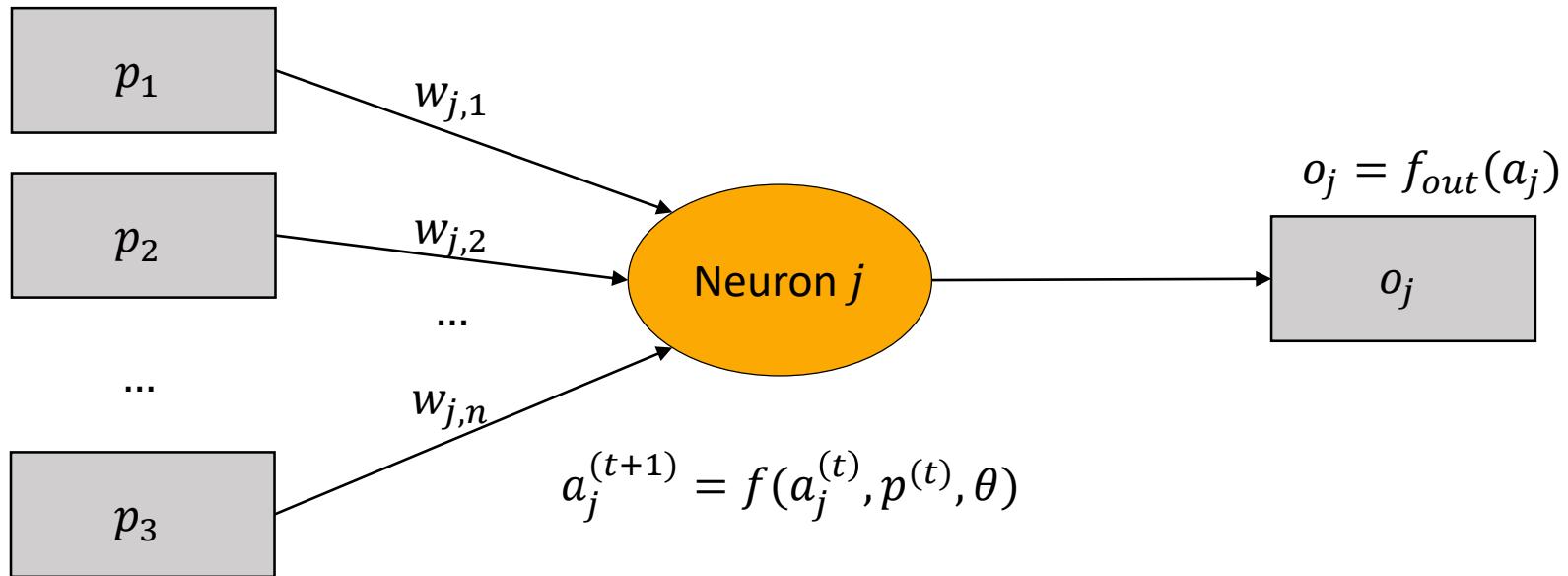


- Computation
  - Hodgkin Huxley equations
  - FitzHugh-Nagumo model

The **Hodgkin–Huxley model**, or **conductance-based model**, is a mathematical model that describes how action potentials in neurons are initiated and propagated. It is a set of nonlinear differential equations that approximates the electrical characteristics of excitable cells such as neurons and cardiac myocytes. It is a continuous time model.

The FHN Model is an example of a relaxation oscillator because, if the external stimulus exceeds a certain threshold value, the system will exhibit a characteristic excursion in phase space, before the variables relax back to their rest values.

# Neuron

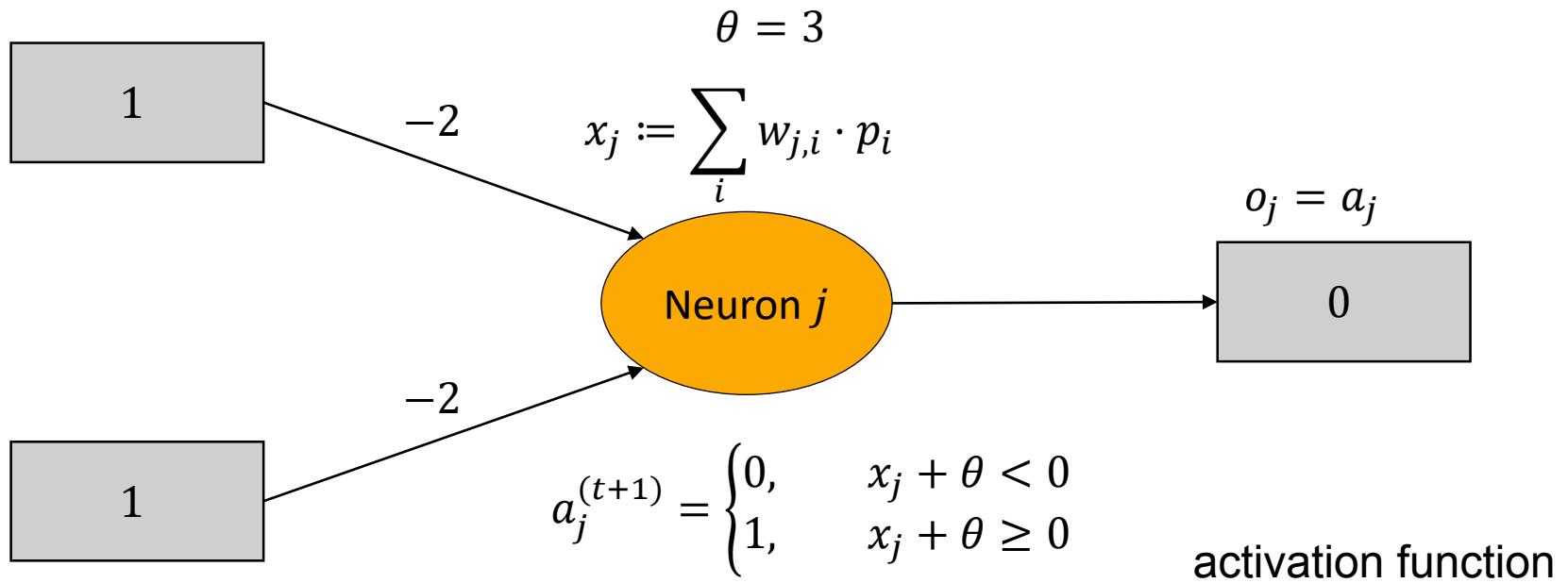


$p_i$	inputs
$w_{j,i}$	weights
$o$	output

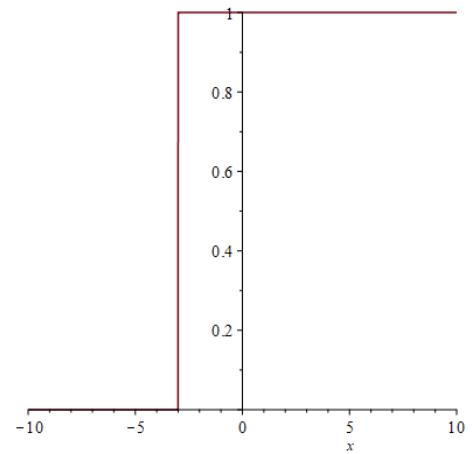
$\theta$	threshold
$f$	activation function
$a$	activation state

$f_{out}$	output function
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# Neuron - example



- Inputs and outputs: 0 or 1
- Threshold moves activation function
- Activation function produces 0 or 1



# Neuron characteristics

- Inputs and outputs
- Changing the state

$$x_j = \sum_i w_{j,i} \cdot p_i^{(t)}$$

$$a_j^{(t+1)} = f(x_j - \theta)$$

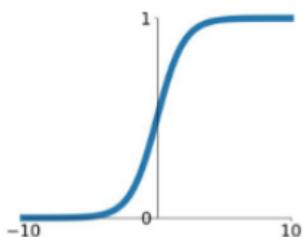
- $f$  is activation function ( $\frac{1}{1+e^{-x}}, \frac{1}{2} \tanh \frac{x}{2} + \frac{1}{2}, \frac{\sqrt{x}}{\sqrt{1+x^2}} \dots$ )
- $f$  is differentiable (important for backpropagation)
- $\theta$  is represented by extra neuron (optional)

# Activation functions



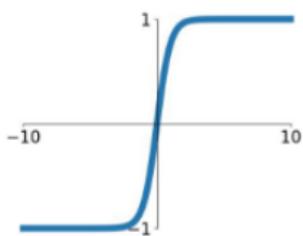
## Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



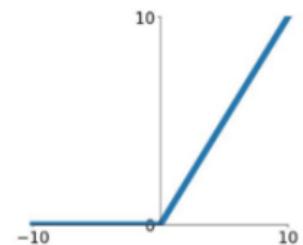
## tanh

$$\tanh(x)$$



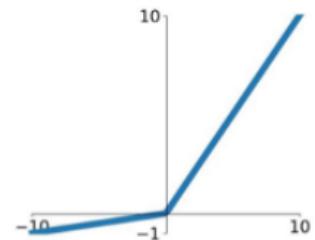
## ReLU

$$\max(0, x)$$



## Leaky ReLU

$$\max(0.1x, x)$$

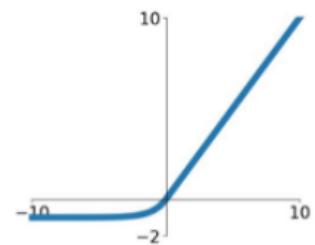


## Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

## ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



# Activation function: Softmax

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}}$$

$\mathbf{z}$  is a vector of the inputs to the output layer (if you have 10 output units, then there are 10 elements in  $\mathbf{z}$ ). And  $j$  indexes the output units, so  $j = 1, 2, \dots, K$



The softmax function squashes the outputs of each unit to be between 0 and 1, just like a sigmoid function. But it also divides each output such that the total sum of the outputs is equal to 1

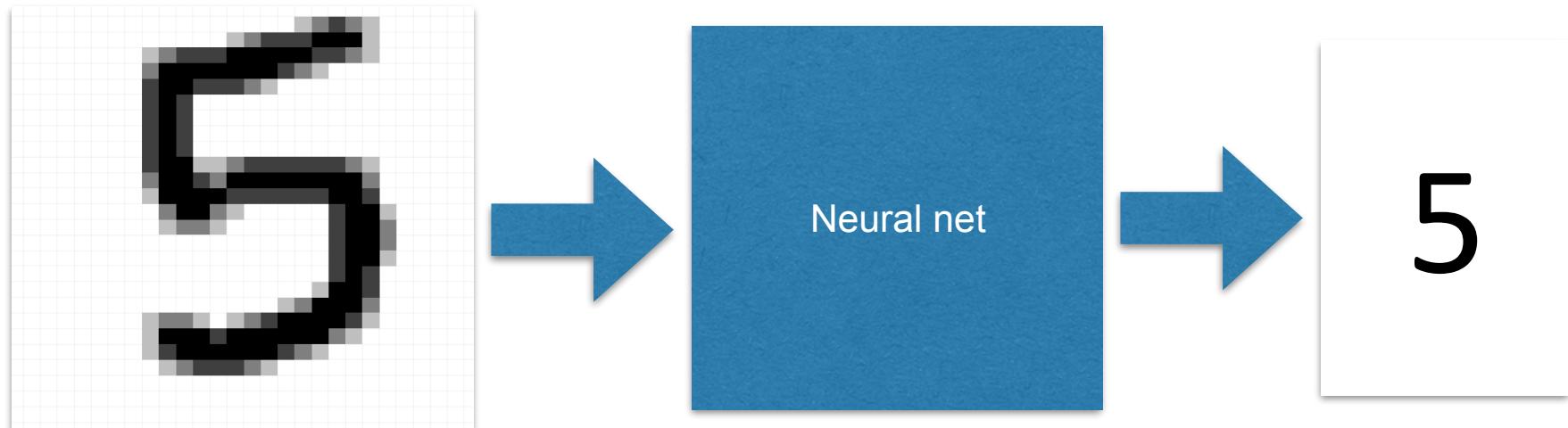
# Neural net



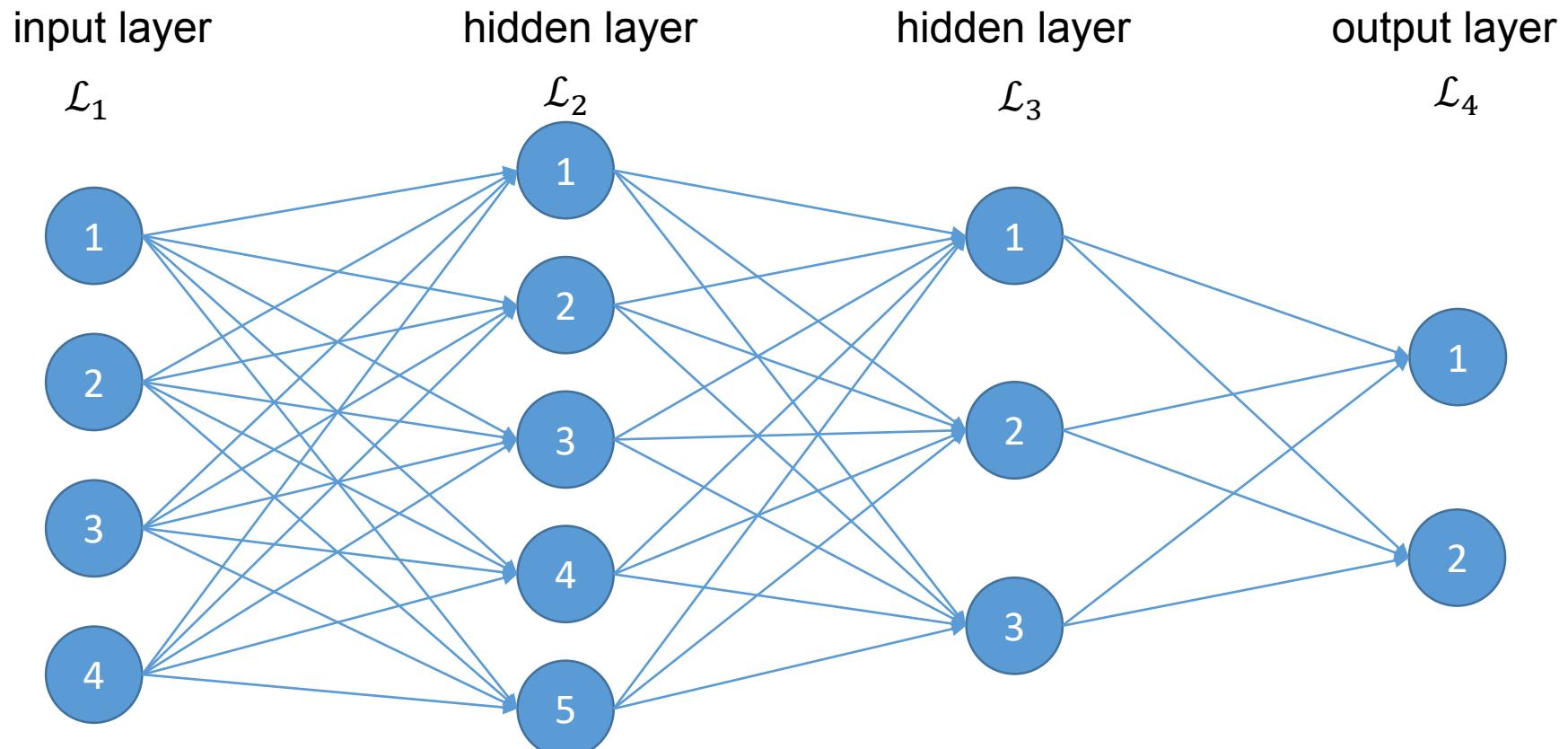
input

processing

output



# Neural net



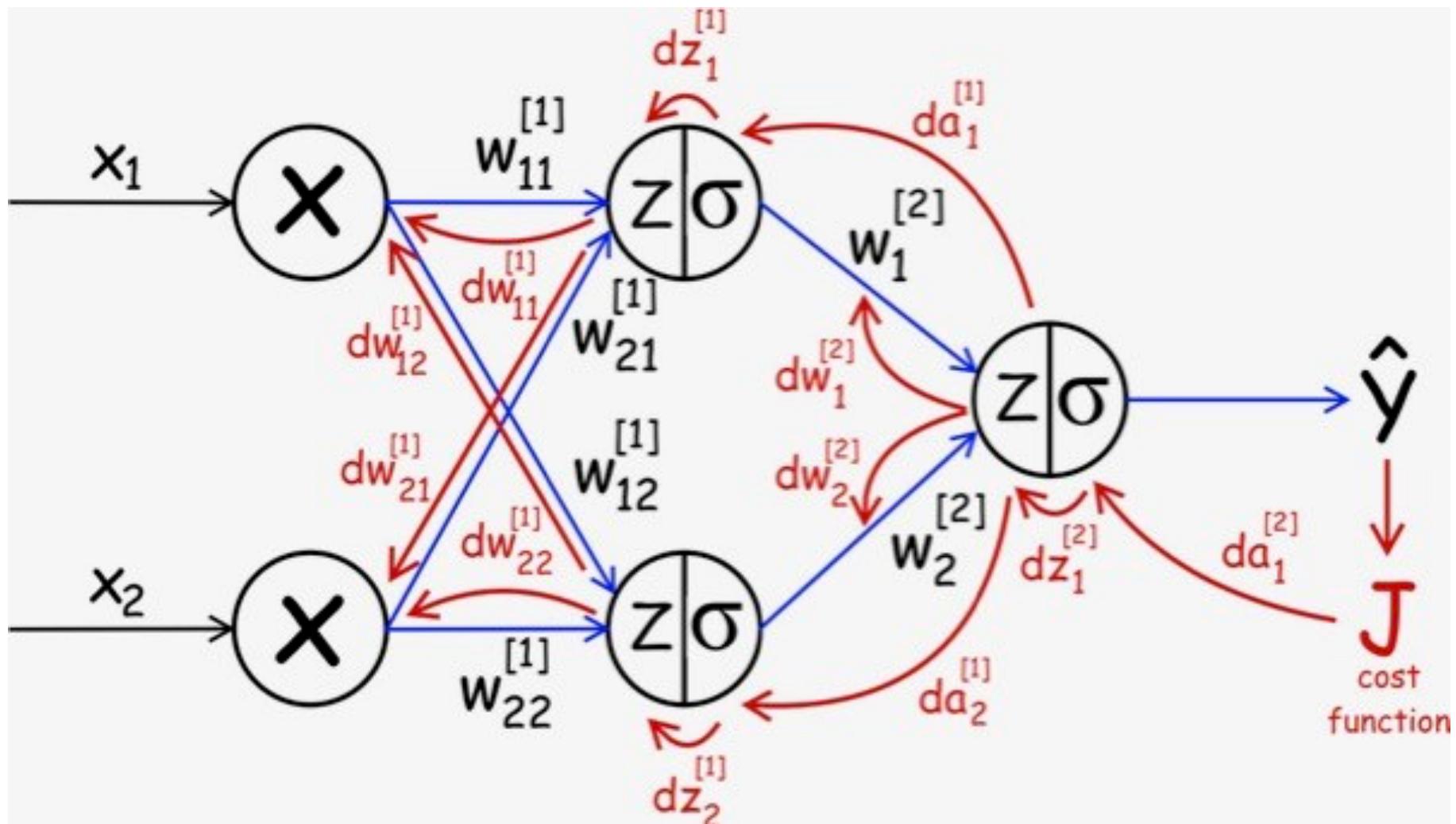
- Topology :  $\{5, 3, 2\}$  (without  $\theta$ -neuron)
- Feedforward network

# Training



- Optimization method
- Adjusting weights and bias
- Different algorithms online / offline
- Subset with data
  - Mini batches
- Back propagation
- Reinforcement learning (AlphaZero)

# Back propagation

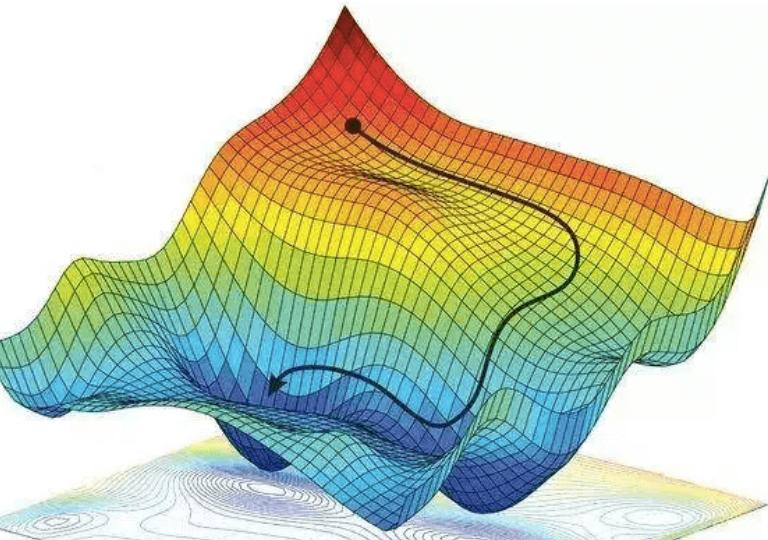


# Loss function

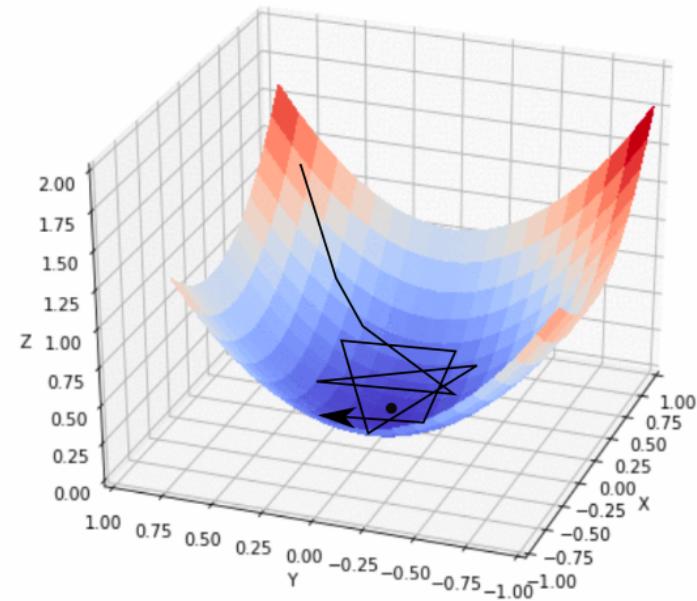


- **Loss function** is used for parameter estimation, and the event in question is some function of the difference between estimated and true values for an instance of data.
- **Loss function** helps in optimizing the parameters of the neural networks.
- The loss is calculated using **loss function** by matching the target(actual) value and predicted value by a neural network.
- Then we use the **gradient descent** method to update the weights of the neural network such that the loss is minimized.
- **Objective:** to minimize the loss for a neural network by optimizing its parameters(weights).

# Learning rate $\eta$



$$\Delta w_{n,j} = -\eta \frac{\partial E}{\partial w_{n,j}}$$



- Controls the speed of convergence
- Adaptive adjustment depending on the error rate
- Typically 0.001 as lower barrier
- Upper barrier 10



# Gradients

**Output layer gradient:**

$$\sigma_m = (\textcolor{red}{t_m} - f(x_m)) \cdot f'(x_m)$$

**Hidden layer gradient:**

$$\sigma_n = \sum_{p \in \mathcal{L}_N} (t_p - f(x_p)) \cdot f'(x_p) \cdot w_{p,n} \cdot f'(x_n)$$

**Softmax derivative:**

$f'(x) = S \cdot (1 - S)$ ; where  $S$  is activation function Softmax

**LReLU derivative:**

$$f'(x) = \begin{cases} 1 & , x > 0 \\ 0.01 & , x < 0 \end{cases}$$

# Adaptive Moment Estimation (Adam)

Computes adaptive learning rates for each parameter.

- Compute the decaying averages of past and past squared gradients

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

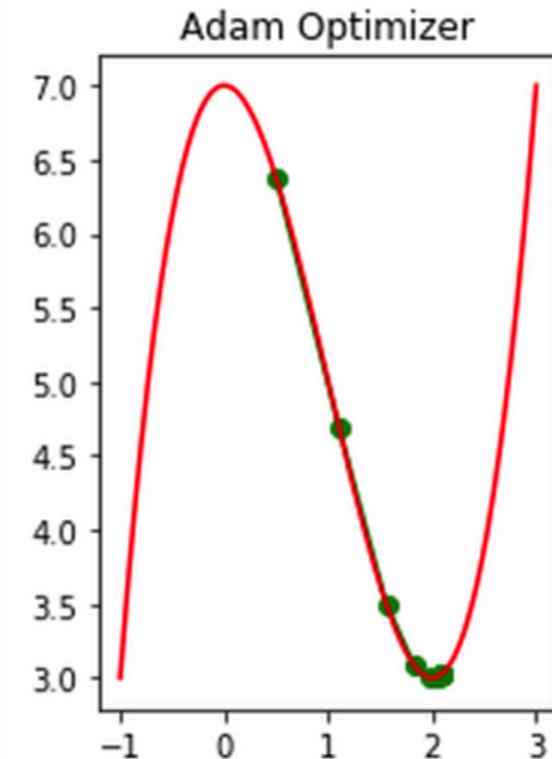
- Correct for bias

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

- Update weights

$$\theta_{t+1} = \theta_t + \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t$$



$$\beta_1 = 0.9; \beta_2 = 0.999; \epsilon = 10^{-8}$$

# Artificial Neural Network



In Qt the Neural Network is implemented as a separate file with:

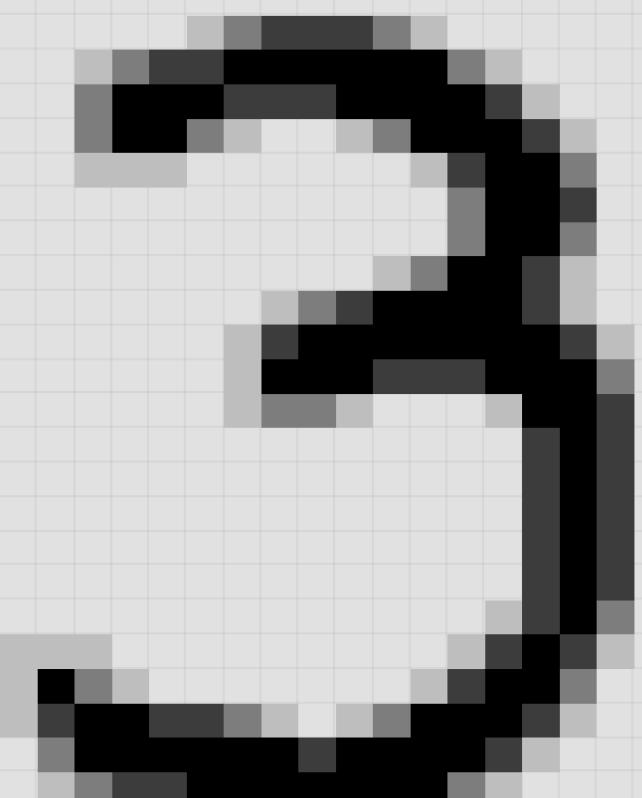
- Class Neuron with Perceptron parameters.
  - calculation output gradients
  - calculation hidden gradients
  - random weights
  - activation function
  - updating input weights
- Class Net - include variables and functions for the Neural Network:
  - std::vector <Layer> of neurone layers - parameters of every perceptrons.
  - calculations of Weights, gradients, input/output values etc.
  - realisation of training and validation Neural Network.

# Artificial Neural Network - running ANN



Neural Networks

Game of Life    Elastic Net    **Neural Net**



Identify

Load Weights    Save Weights

Load Images    Load Labels

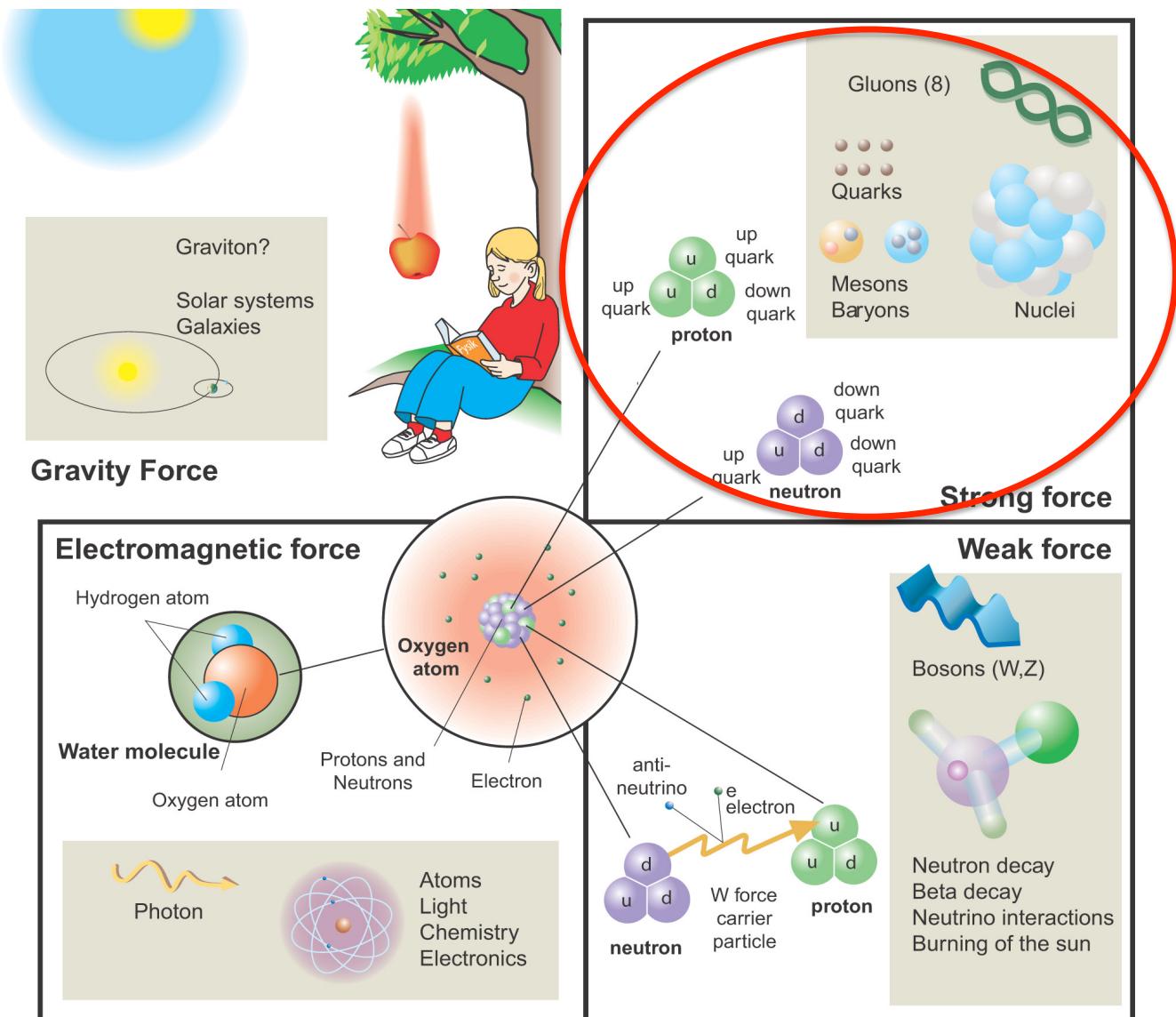
10000    Training

0    Draw MNIST

Clear

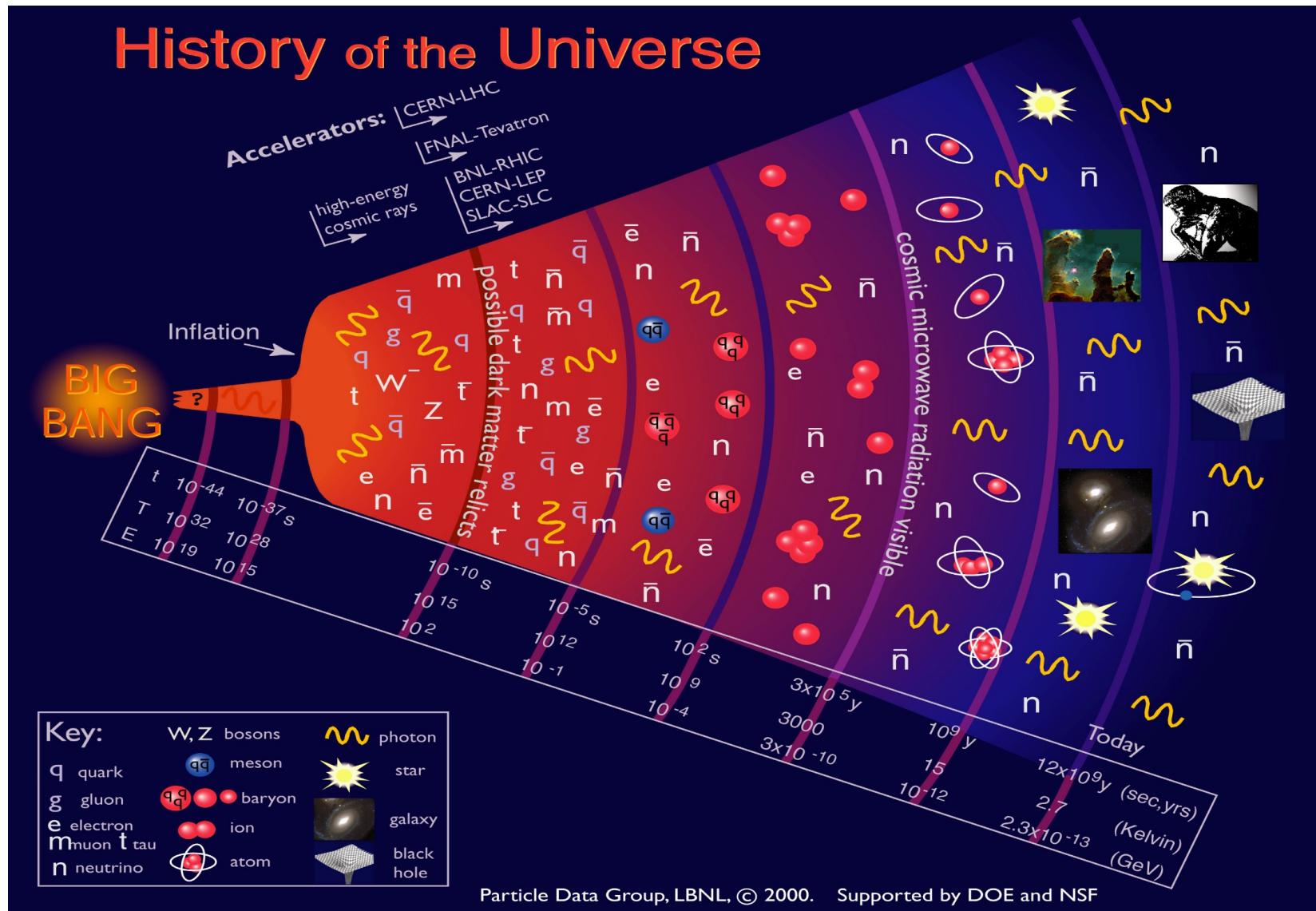
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# Fundamental Interactions





# Quarks and Gluons in the Universe



# Constituents of Matter

FERMIONS			matter constituents spin = 1/2, 3/2, 5/2, ...		
Leptons spin = 1/2			Quarks spin = 1/2		
Flavor	Mass GeV/c <sup>2</sup>	Electric charge	Flavor	Approx. Mass GeV/c <sup>2</sup>	Electric charge
$\nu_e$ electron neutrino	$<1 \times 10^{-8}$	0	u up	0.003	2/3
e electron	0.000511	-1	d down	0.006	-1/3
$\nu_\mu$ muon neutrino	$<0.0002$	0	c charm	1.3	2/3
$\mu$ muon	0.106	-1	s strange	0.1	-1/3
$\nu_\tau$ tau neutrino	$<0.02$	0	t top	175	2/3
$\tau$ tau	1.7771	-1	b bottom	4.3	-1/3

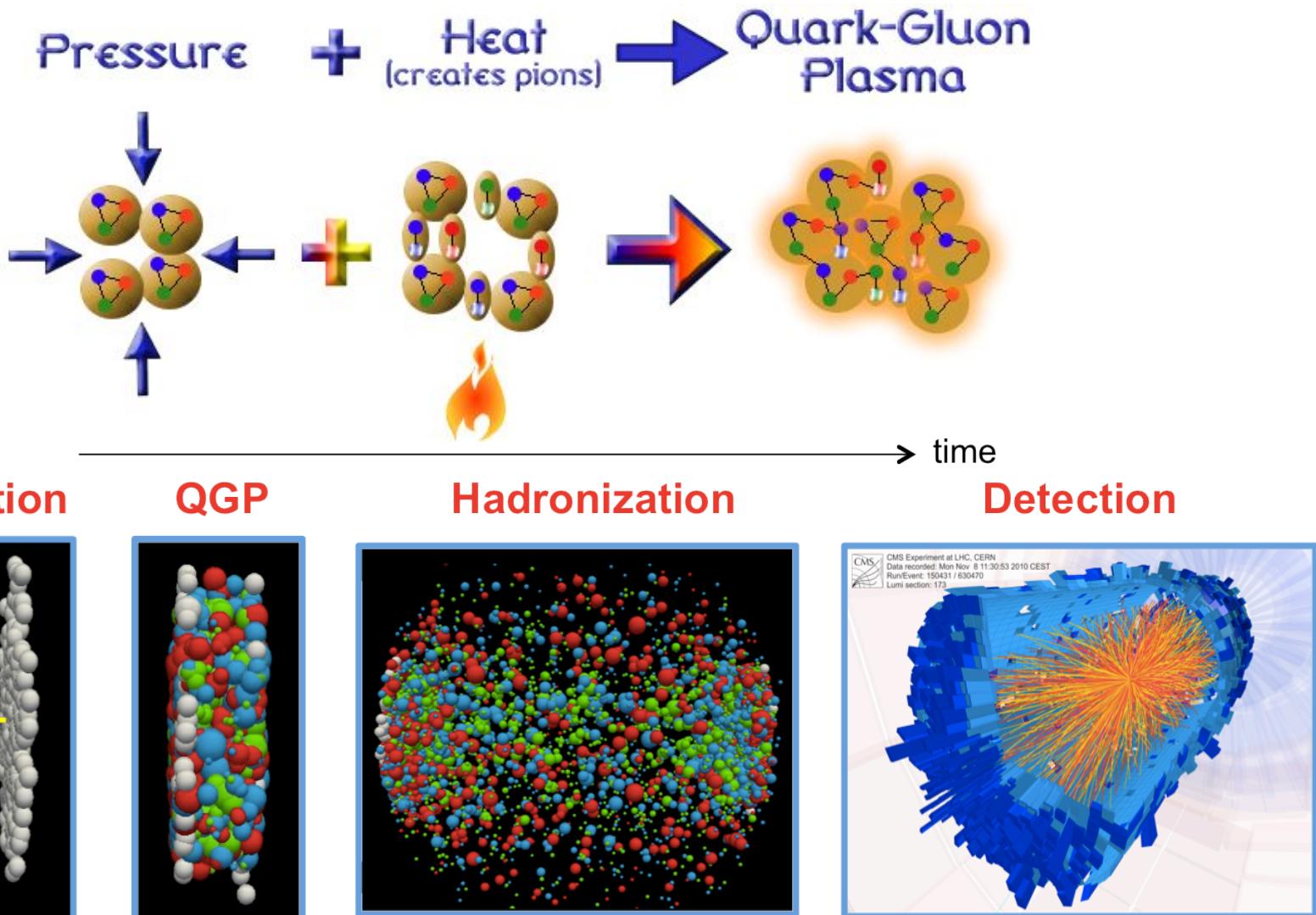
  

BOSONS			force carriers spin = 0, 1, 2, ...		
Unified Electroweak spin = 1			Strong (color) spin = 1		
Name	Mass GeV/c <sup>2</sup>	Electric charge	Name	Mass GeV/c <sup>2</sup>	Electric charge
$\gamma$ photon	0	0	g gluon	0	0
$W^-$	80.4	-1			
$W^+$	80.4	+1			
$Z^0$	91.187	0			

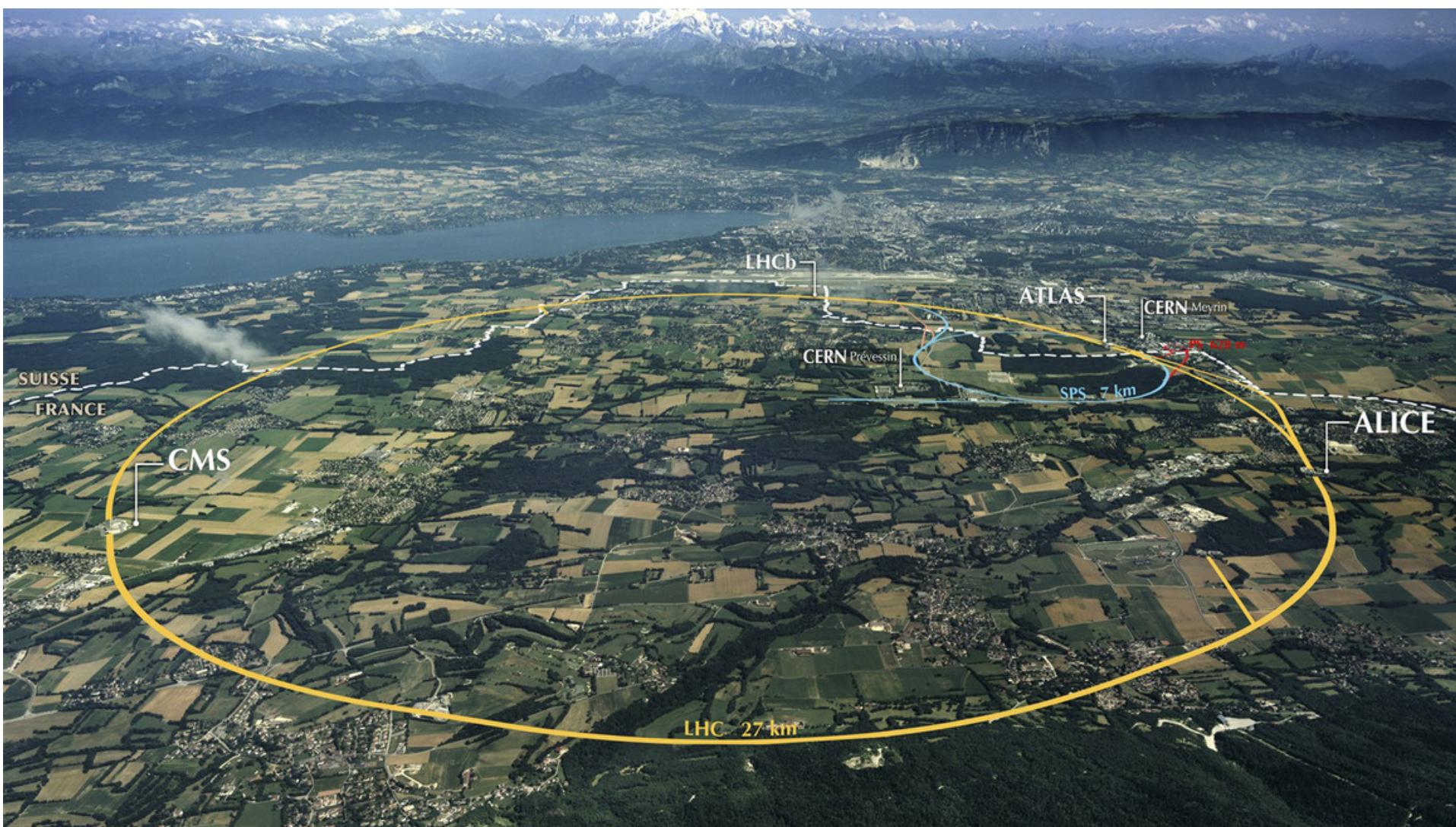
Basic ingredients of nuclear matter

Heavy quarks appear in hot nuclear matter

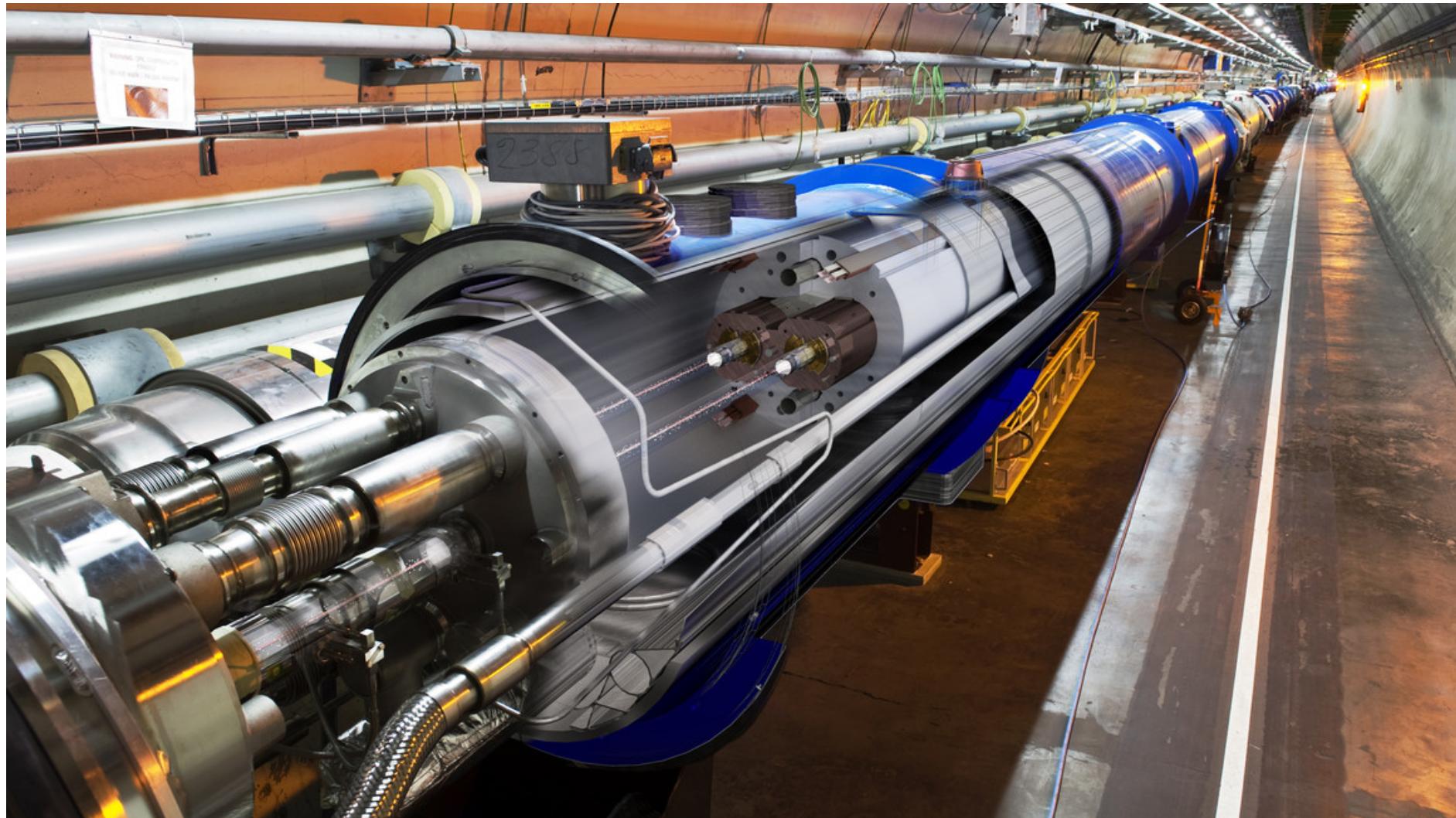
# QGP: Quark-Gluon Plasma



# Large Hadron Collider at CERN

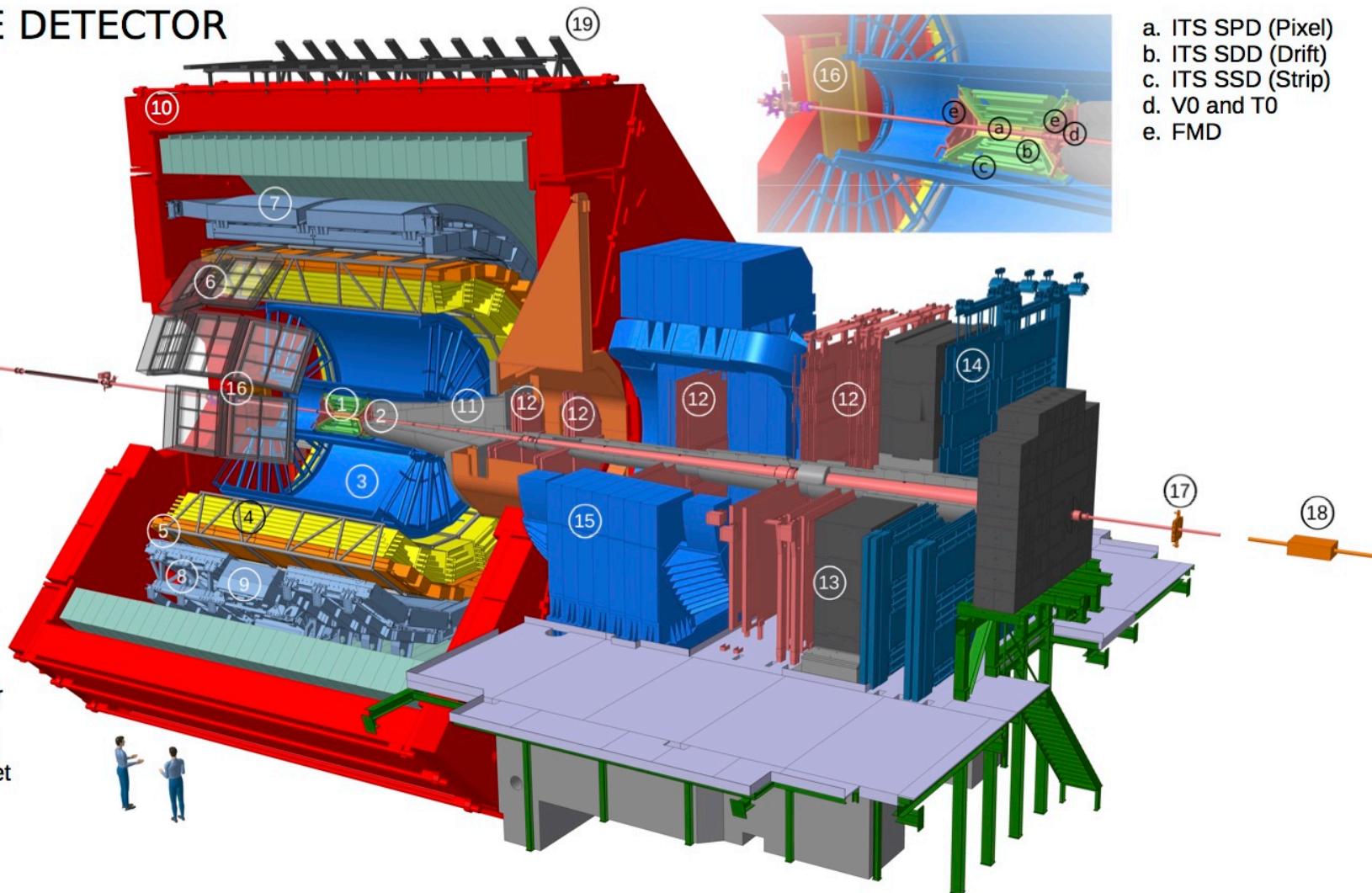


# Large Hadron Collider at CERN



# ALICE: A Large Ion Collider Experiment

## THE ALICE DETECTOR

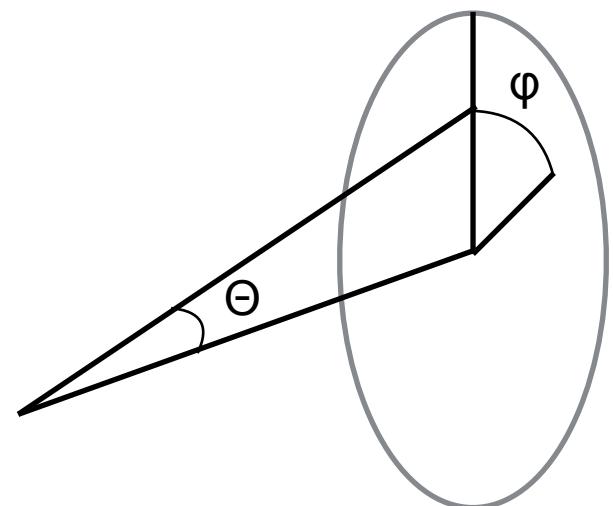


# ANN for QGP



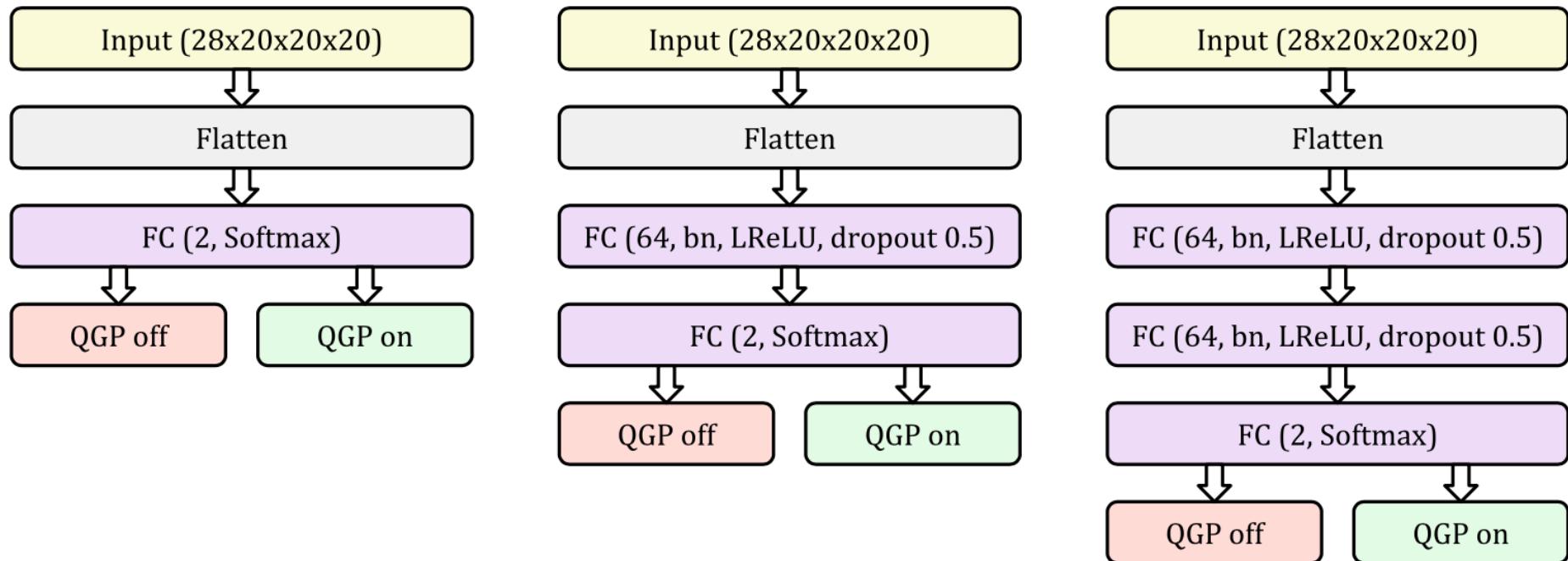
## Input data:

- 10000 simulated events (5000 with QGP and 5000 without QGP)
- central AuAu collisions at 31.2 GeV
- 1 event consist information about ~1500 particles
- particles are distributed into 4D matrix:
  - 28 bins - particle types;
  - 20 bins with log scale - particles momentum;
  - 20 bins - inclination angle  $\Theta$ ;
  - 20 bins - azimuth angle  $\varphi$ ;
- 4D matrix is flatten into 1D array

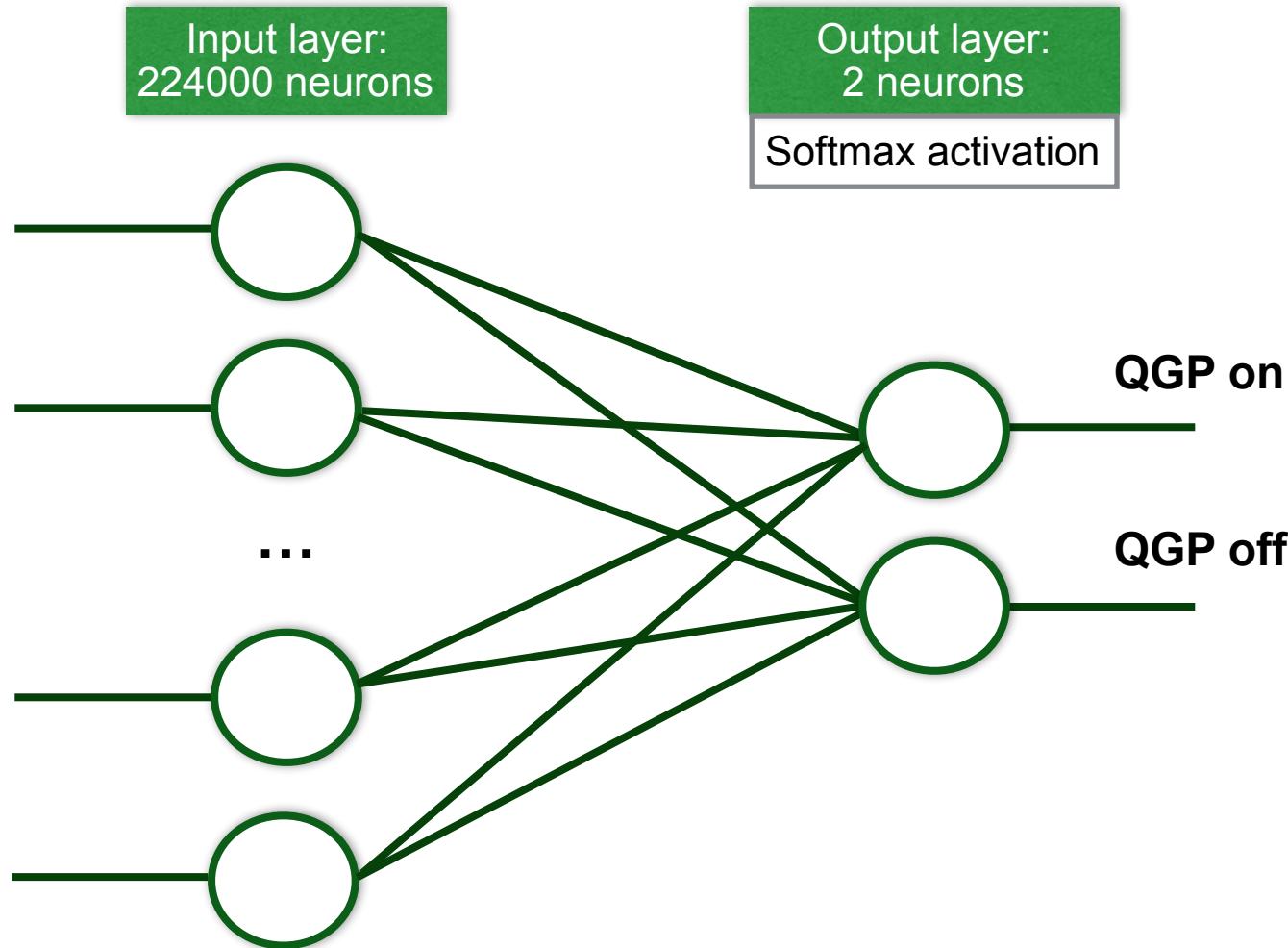


**ANN input layer:** 224000 neurons

# ANN for QGP



# ANN for QGP



# ANN for QGP



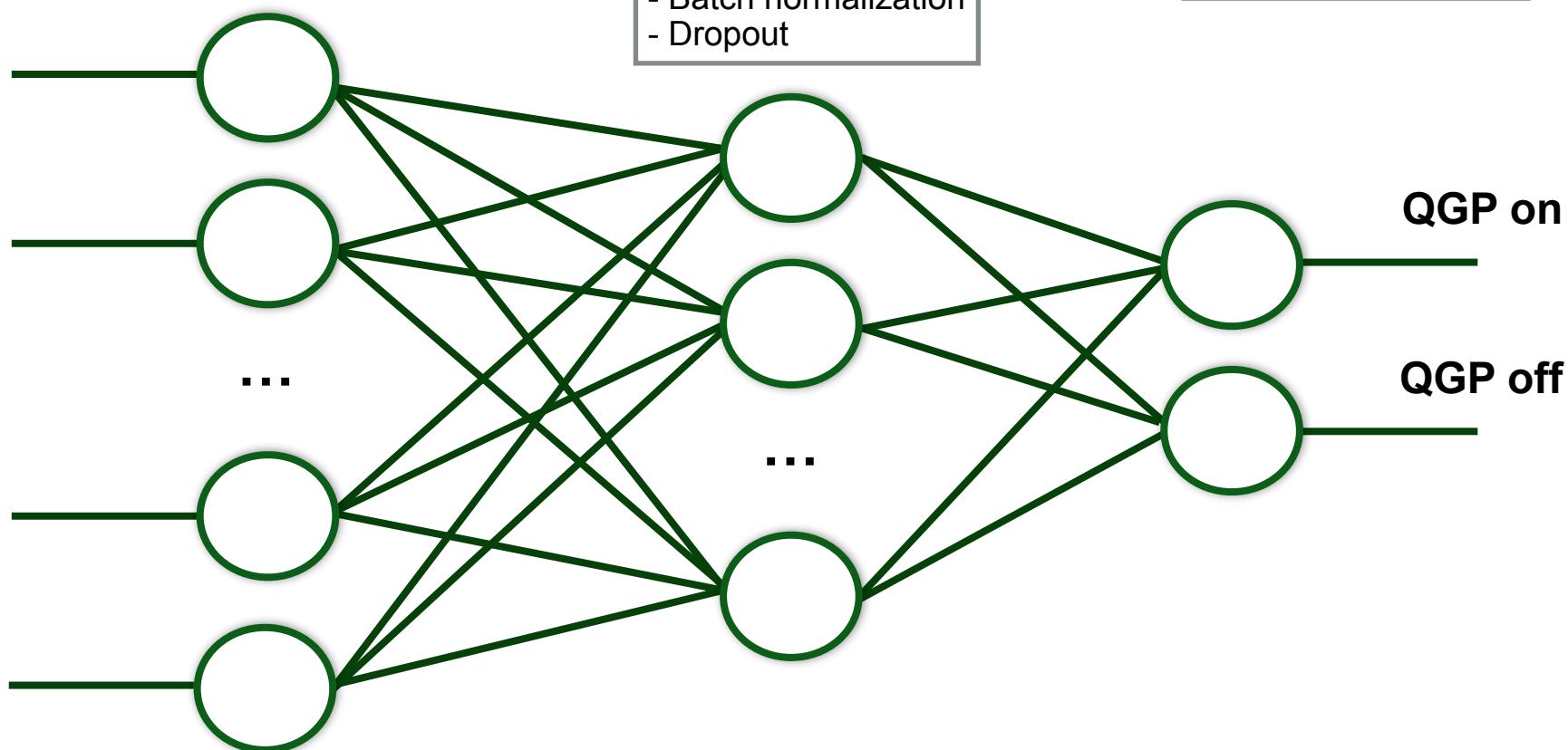
Input layer:  
224000 neurons

Hidden layers:  
64 neurons

- LReLU activation
- Batch normalization
- Dropout

Output layer:  
2 neurons

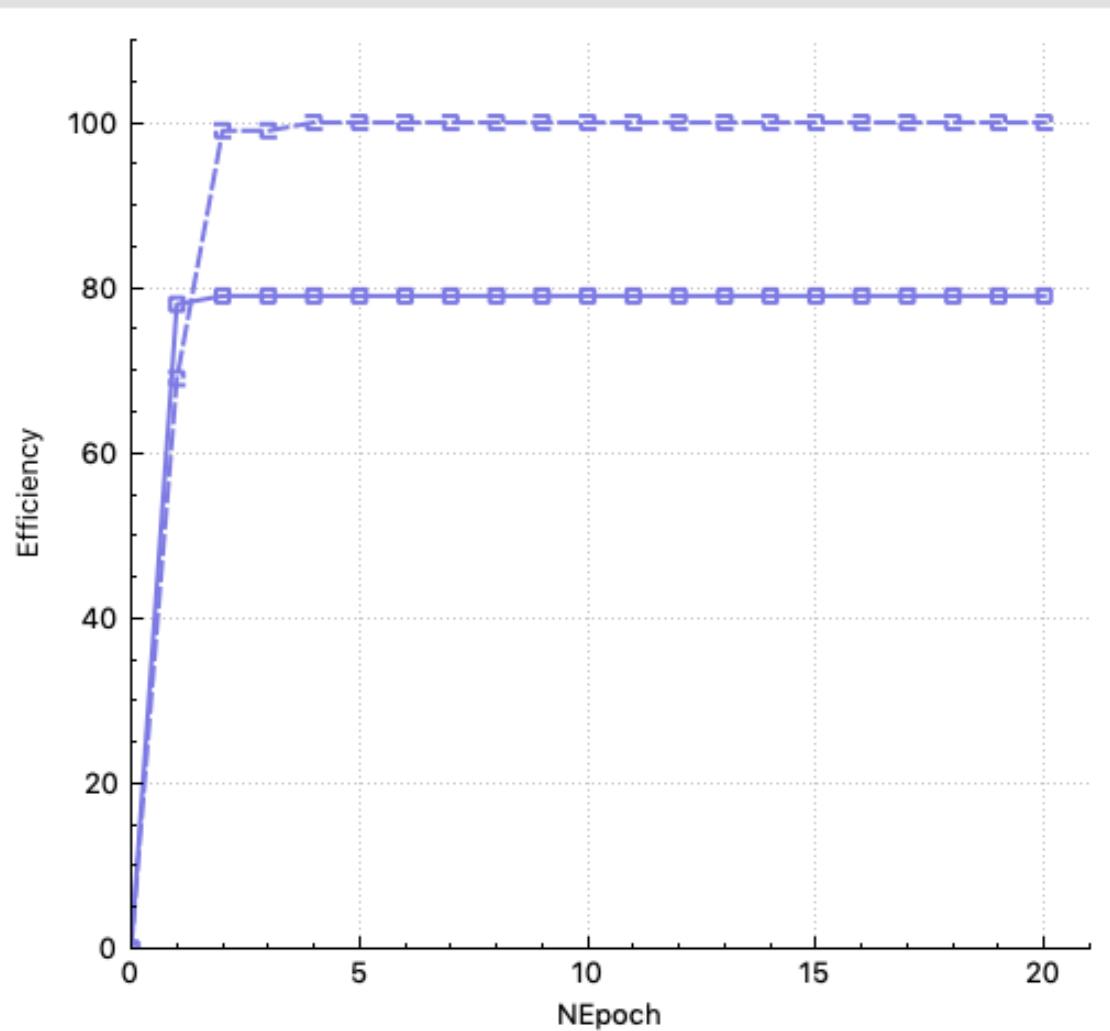
Softmax activation





# ANN for QGP

Neural Net



Load Data

Analyze

4000 Events for Training

1000 Events for Test

20 Quantity of Epochs

1 Batch size

FC(2,Softmax) Neural Net Mode

Training/Test Draw

# Abgabe Milestone 2

11.12.2019 um 23:59 über OLAT



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