Deep Learning for Language Analysis

Deep Learning Introduction – Neural Network Basics

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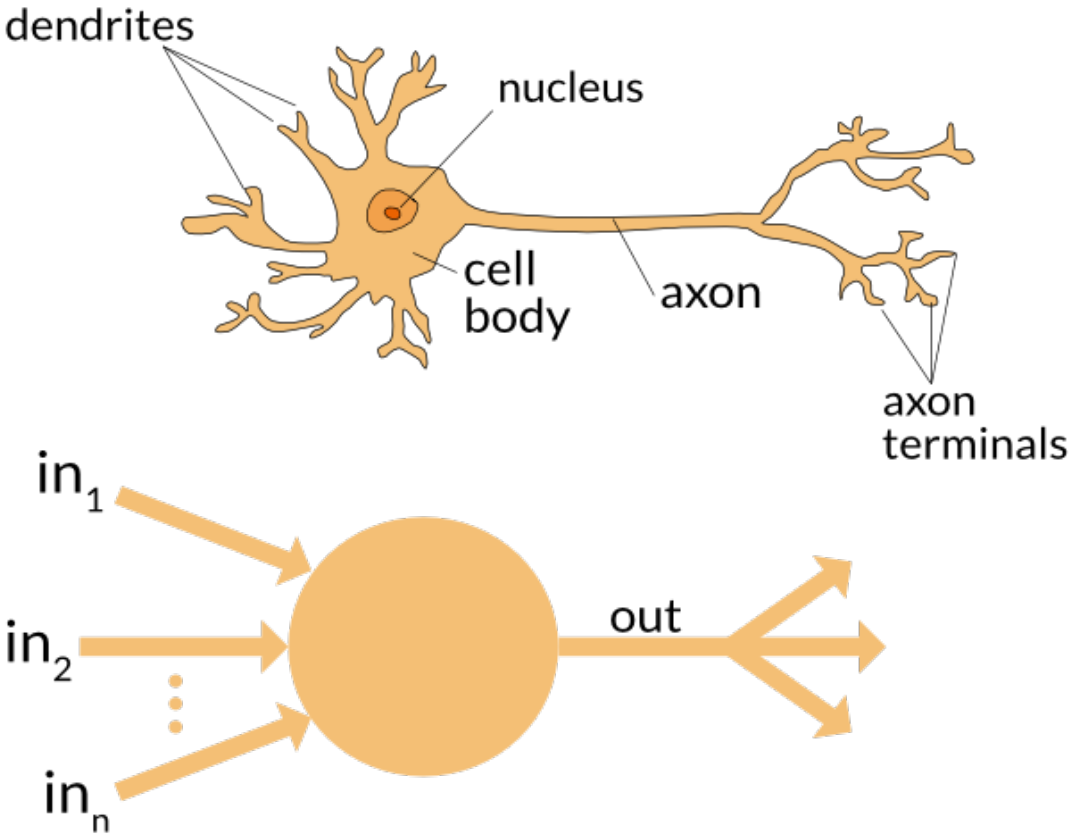
Biological Inspiration



Source: https://towardsdatascience.com/the-differences-between-artificial-and-biological-neural-networks-a8b46db828b7

Brief History

- 1943 First Perceptron Model developed
- 1960s AI was considered to replace all human activity
- But too less data and low hardware stopped early progression
- 1990s starting to grow again due to more available data, better hardware and more efficient networks

- Is this only the next hype of AI?
- We‘ll see...

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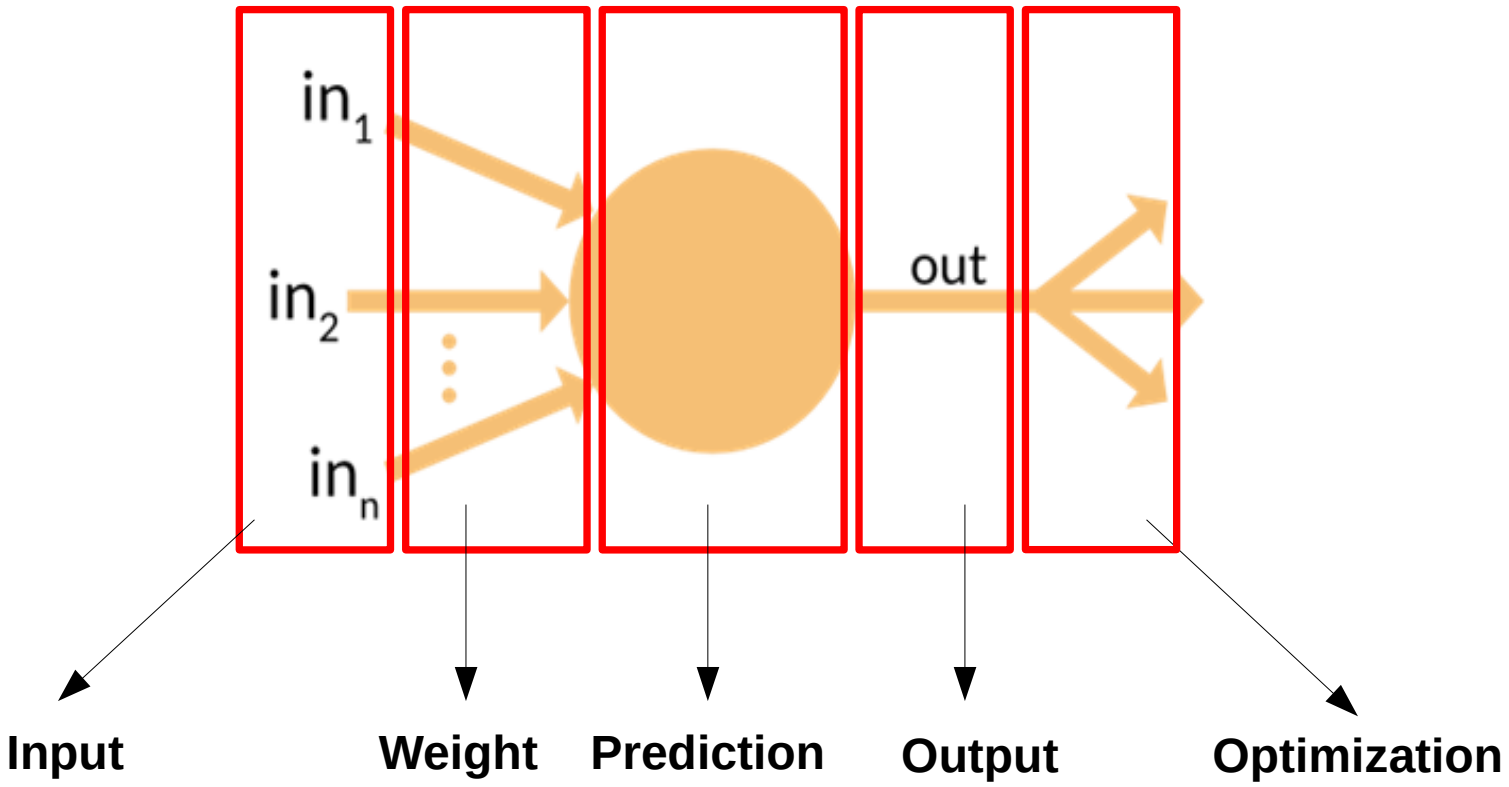
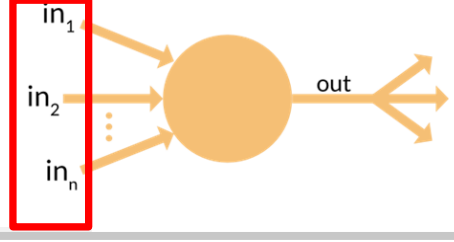
Perceptron

Components



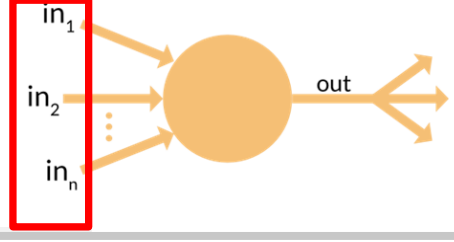
Perceptron



INPUT – General

- Inputs must be numerical values
- If data is not represented as numerical values they must be transformed into numbers
- In order to train the Perceptron the class is needed for every data
- Most of the time each entry is eventually represented as vector with different values

Perceptron



INPUT – Example

- Perceptron should learn if a patient has illness based on blood values, i.e. binary classification problem (sick or not sick)

- **Blood values of a patient:**

  Input_1 = Amount of Iron

  Input_2 = Amount of White Blood Cells

  Input_3 = Amount of Sugar

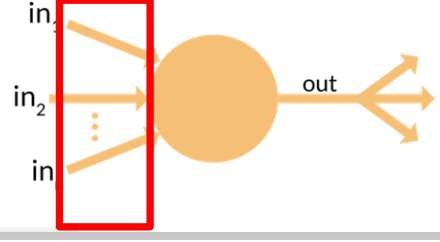
  Vector Components: { Input_1, Input_2, Input_3 }

- **Train Data** could be as following:

  Patient_1 = { 1, 0, 1 } => Class 1 (sick)

  Patient_2 = { 1, 1, 1 } => Class 0 (not sick)

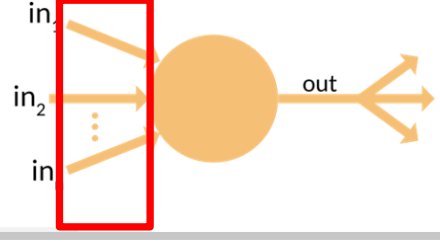
  …



WEIGHTS – General

- Each input type has its own weight
- The weights are used to calculate the output class
- They are also represented as vector
- If weights lead to wrong class then they need to be adjusted
- The adjustment will go on until the correct output class for a vector is calculated

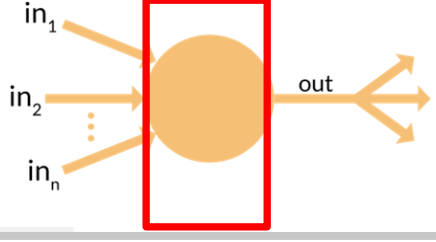
- But what are the intial values?
- Most of the time semi-randomly generated



WEIGHTS – Example

- Input types are blood values of patients (Input_1, Input_2, Input_3)
- Each input type is connected to one weight

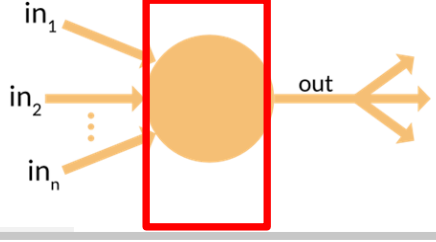
- 3 input types => 3 different weights



PREDICTION – General

- The calculation is based on the dot product of the input vector and the weights vector
- The result is something between 0 and 1

Perceptron



PREDICTION - Example

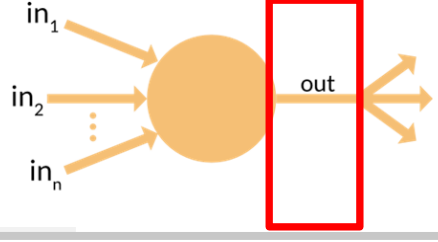
- Patient_1 has following blood values:

  Input_1 = 2 (Amount of Iron)

  Input_2 = 3 (Amount of White Blood Cells)

  Input_3 = 2 (Amount of Sugar)

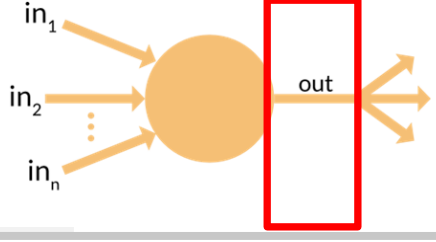
- **Vector** = { 2, 3, 2 }
- **Intial weights** = { 0.5, -0.2, 0.1 } (randomly generated)
- **Calculation** = 2 * 0.5 + 3 * (-0.2) + 2 * 0.1 = 0.6



OUTPUT – General

- The output is the result of the dot product and an activation function.
- Determines the class
- Activation functions can be super simple functions, e.g. thresholds or more complex ones, e.g. Sigmoid

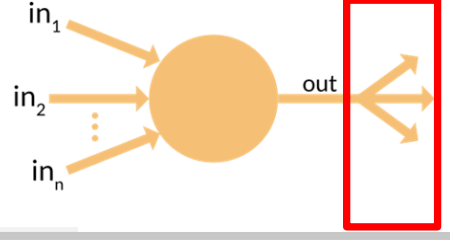
Perceptron



OUTPUT – Example

- **Vector** = { 2, 3, 2 }
- **Intial weights** = { 0.5, -0.2, 0.1 } (randomly generated)
- **Calculation** = 2 * 0.5 + 3 * (-0.2) + 2 * 0.1 = 0.6
- **Threshold** = 0.5

- **Class predicted is** = 0.6 > 0.5 => 1 (patient is sick)



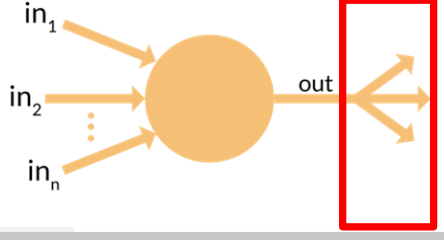
OPTIMIZATION - General

- If calculation of prediction outputs a wrong class
- Then the weights have to be adjusted in order to calcuate the correct class

- If the predicted class > actual class, then decrease weights
- If the predicted class < actual class, then increase weights

- Optimizer functions can also be simple, e.g. Hebbian Learn Rule or very complex

Perceptron



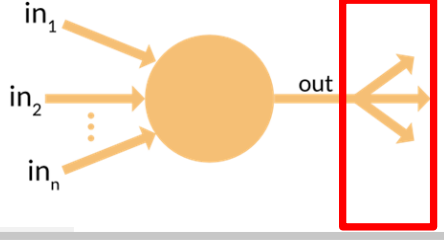
OPTIMIZATION - Training

- **Hebbian Learn Rule:**
  *Weight Adjustment = Learning Rate * Input Value * Error*

- Learning Rate is a Hyperparameter
- The higher the rate the faster the perceptron adapts to new values but forgets faster already learned insights

- Error is calculated as the following:
  Error = Target Class – Predicted Class

Perceptron



OPTIMIZATION – Example

- **Vector** = { 2, 3, 2 }
- **Intial weights** = { 0.5, -0.2, 0.1 } (randomly generated)
- **Calculation** = 2 * 0.5 + 3 * (-0.2) + 2 * 0.1 = 0.6
- **Threshold** = 0.5
- **Class predicted is** = 0.6 > 0.5 => „1“ (patient is sick)
- **Target class is** = „0“ (patient is not sick)
- **Error** = 0 (Target) – 1 (Result) = -1
- **Learning Rate** = 0.02

- **Adjustment for Input_1 and Weight_1** = 0.02 * 2 * (-1) = -0.04
- **New Weight_1** = 0.5 (Old weight) – 0.04 (Adjustment) = 0.46

- **Weights before:** { 0.5, -0.2, 0.1 }
- **Weights after:** { 0.46, -0.26, 0.06 }

Multi Class Perceptron

Multi Class Problem

> Previously only two classes: „0“ or „1“ (Sick – Not Sick, Spam – No Spam, etc.)

Example for Multi Class Problem:

> Image Recognition

> Each picture (dog, cat, mouse, etc.) equals to one class

Multi Class Perceptron

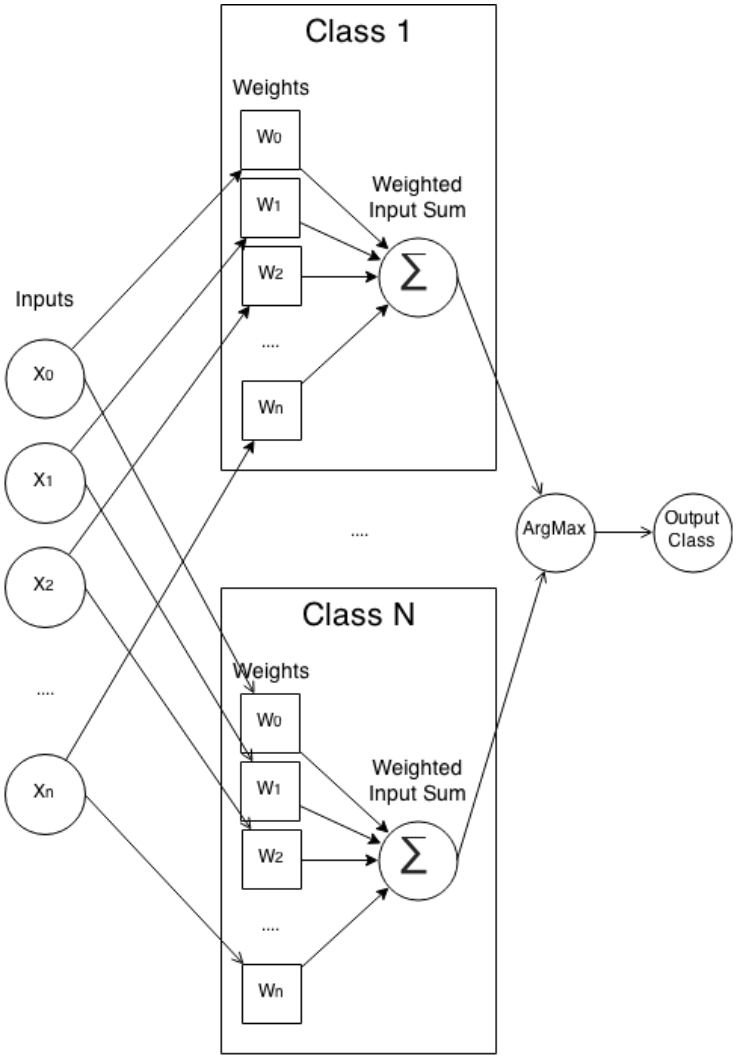
From Binary to Multi?

> Is it possible to use perceptrons for multiple classes?

> If not, what could we change to make it work?

Multi Class Perceptron

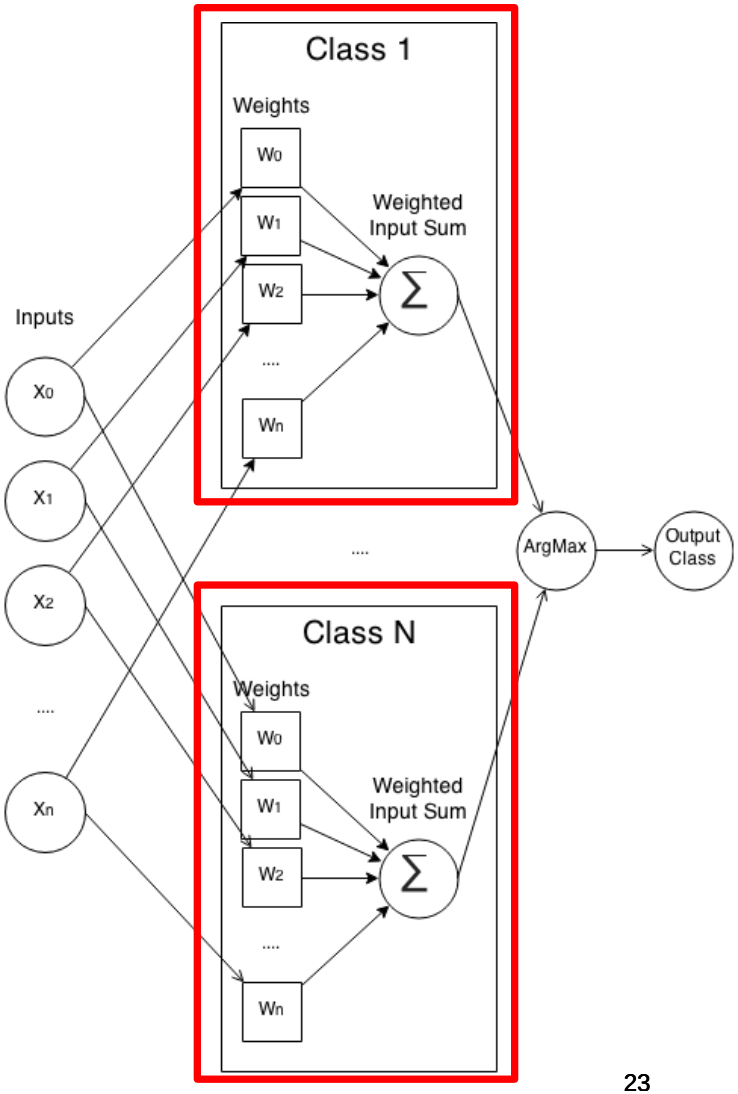
General



Multi Class Perceptron

CALCULATION

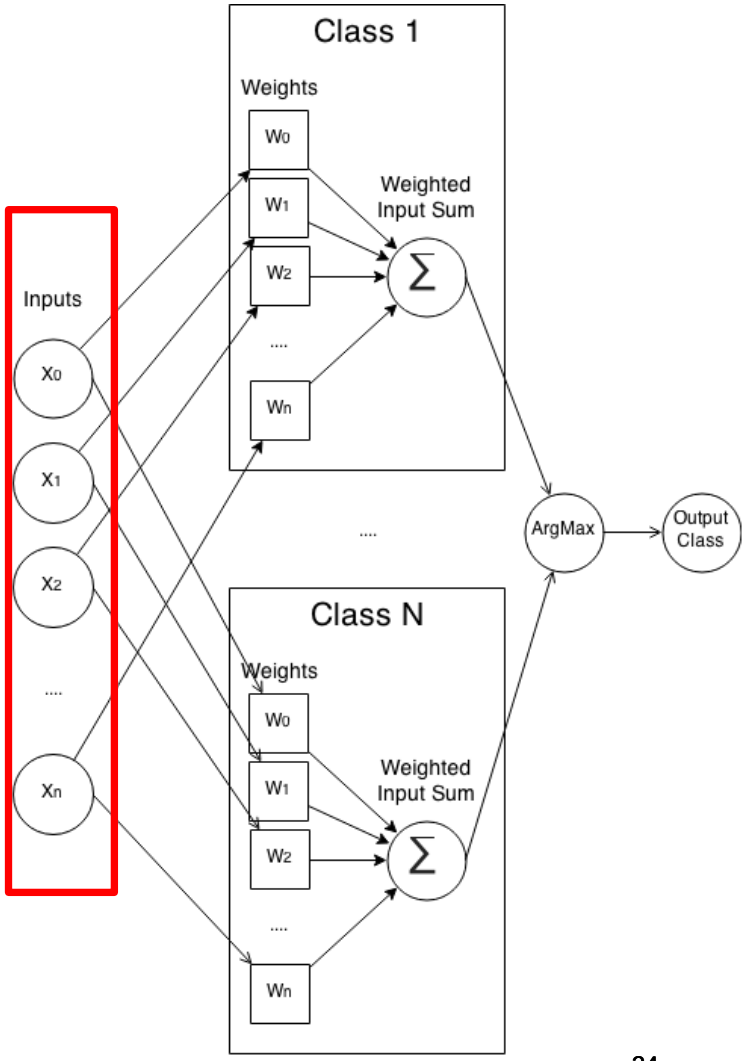
- Each class is one perceptron and will be trained separately
- That is, each class/perceptron has its own set of weights to train
- Calculation remains the same



Multi Class Perceptron

INPUT

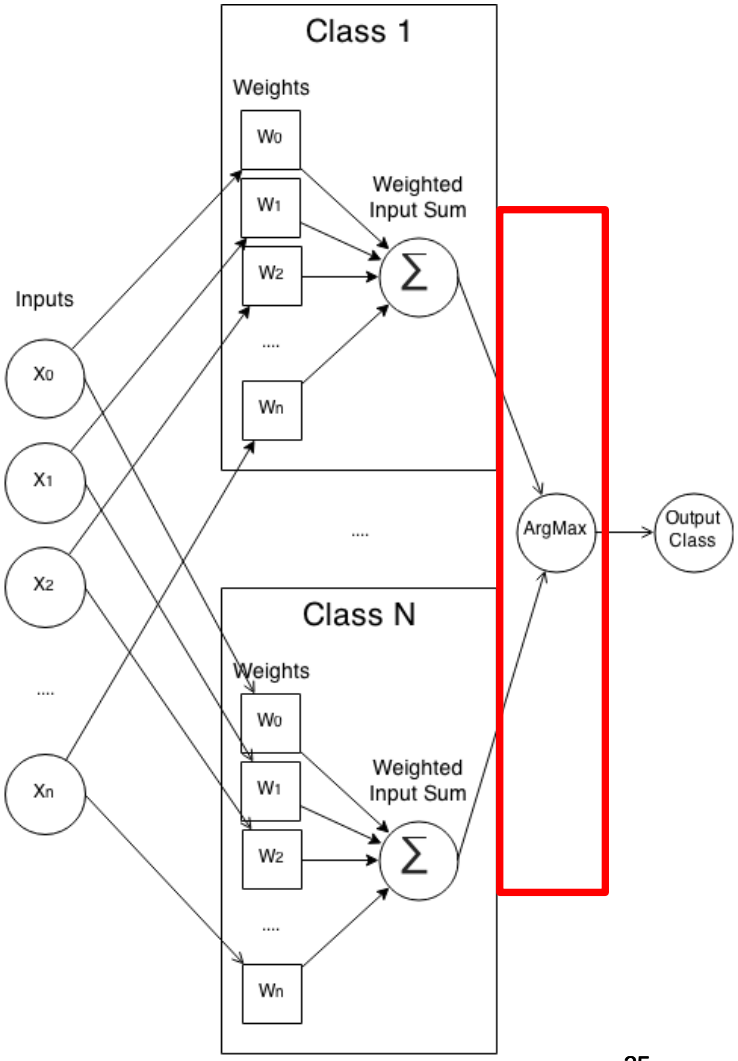
> The whole input will be trained with each class weight set



Multi Class Perceptron

PREDICTION

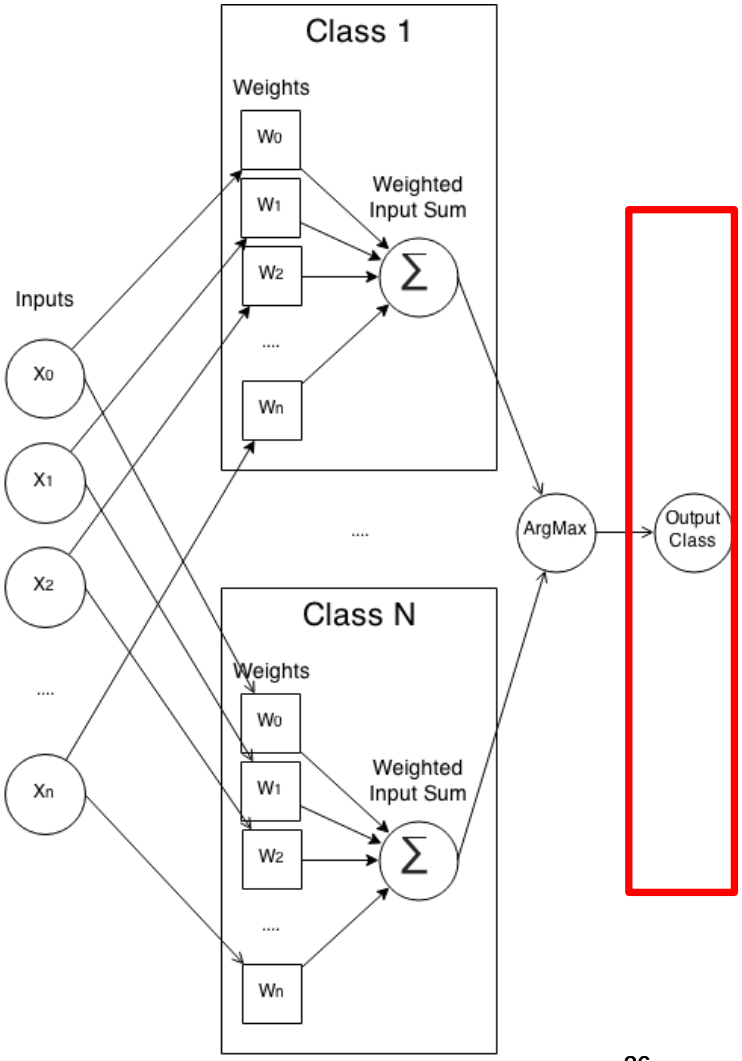
- Results of each class weight calculation will be compared
- The class with the highest calculation is the class of prediction (ArgMax Function)



Multi Class Perceptron

TRAINING

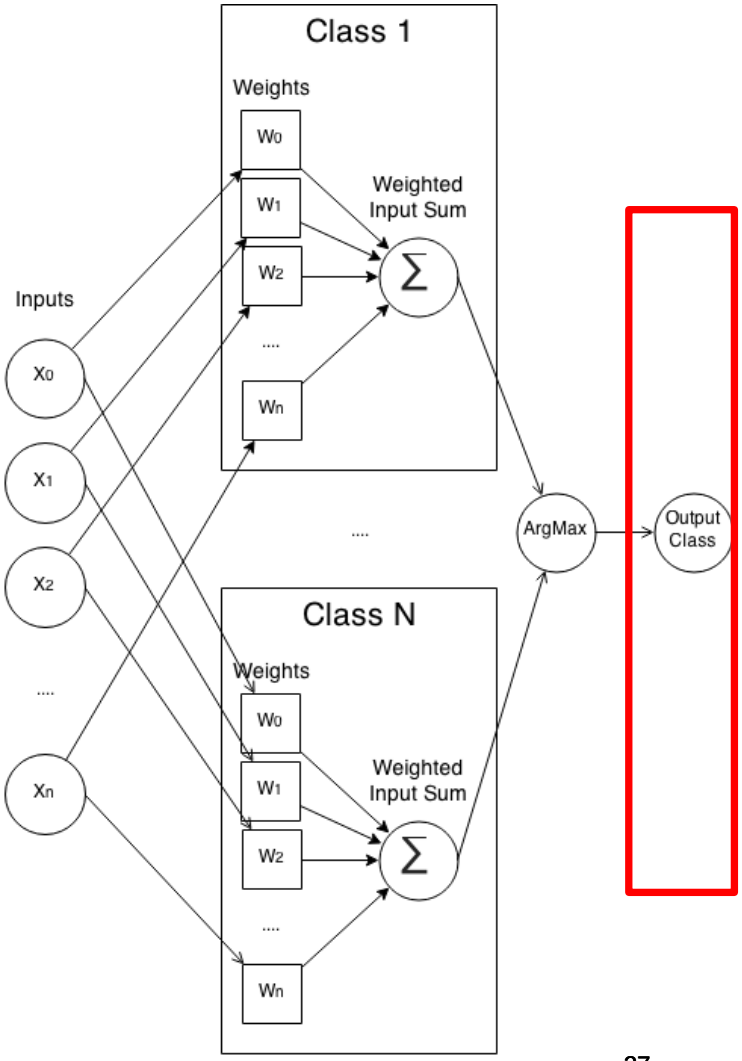
> But how do we train now?



Multi Class Perceptron

TRAINING

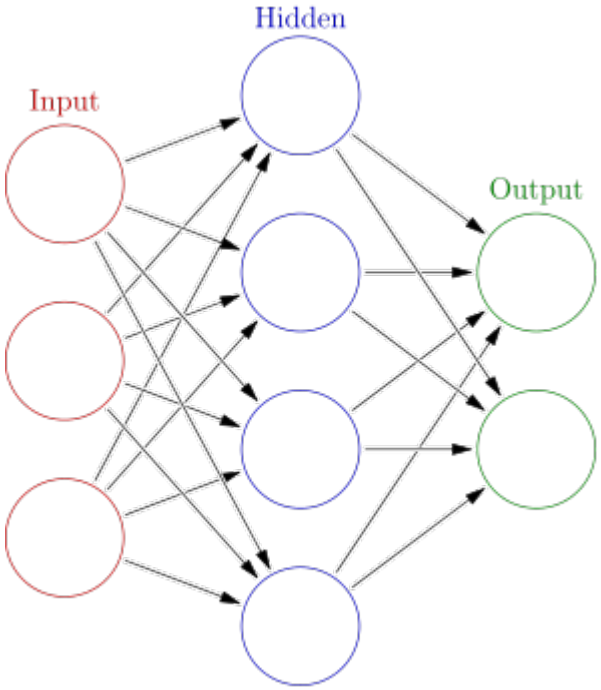
- If the prediction is wrong, the weights of the predicted class have to be decreased for the particular input
- Weights of correct (but not predicted) class have to be adjusted upwards



Muli Layer Perceptrons

Structure of Multi Layer Perceptrons (aka Neural Networks)

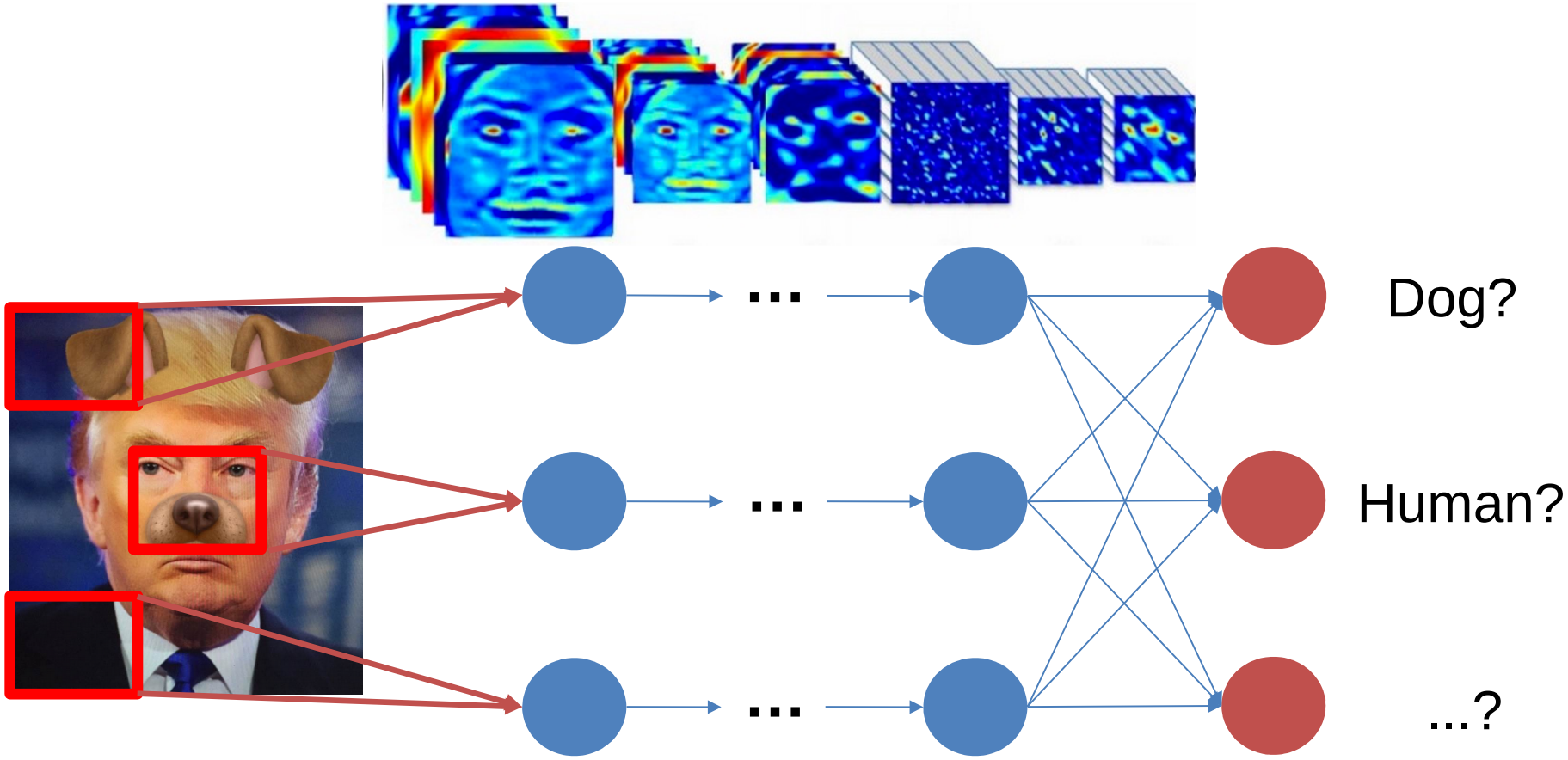
- Multi Class Perceptrons have one hidden layer where all the calculations is done
- For more complex problems neural networks with several layers have been developed (and nowadays called „deep“)



Source: https://en.wikipedia.org/wiki/Artificial_neural_network

Muli Layer Perceptrons

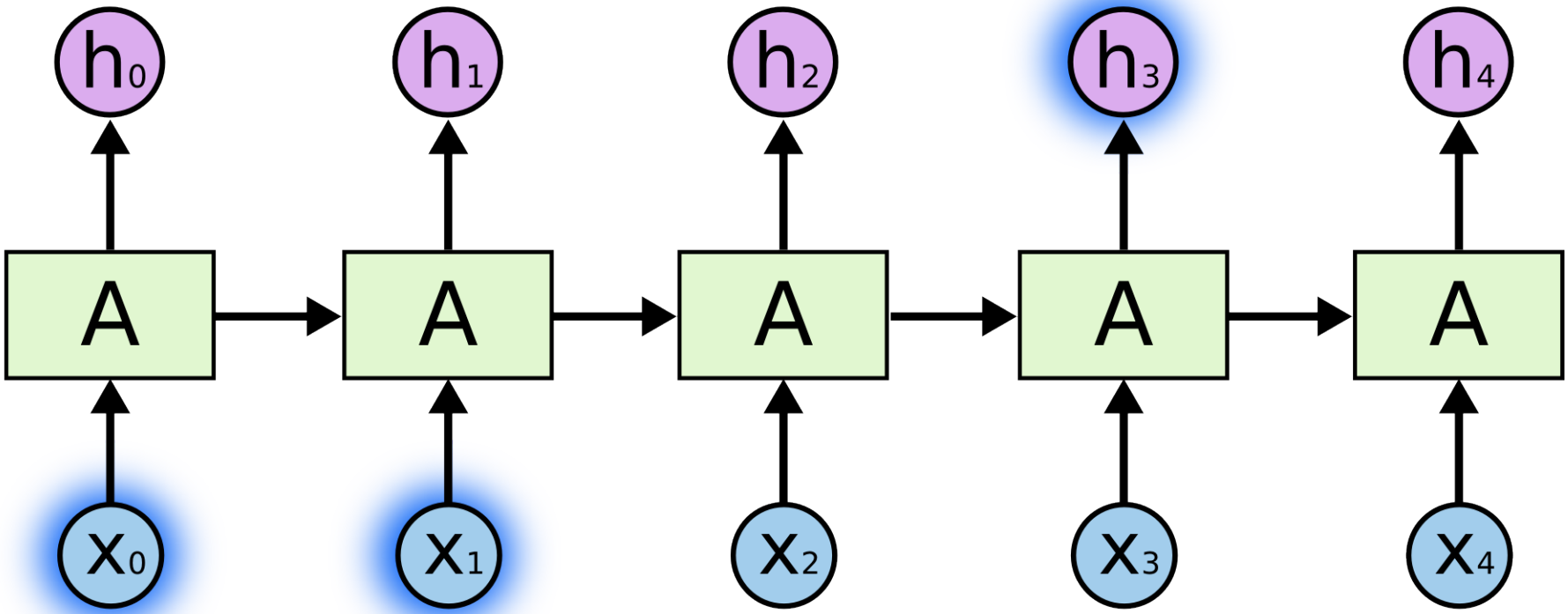
Example for Deep Learning – Convolutional Neural Network



Recurrent Neural Network

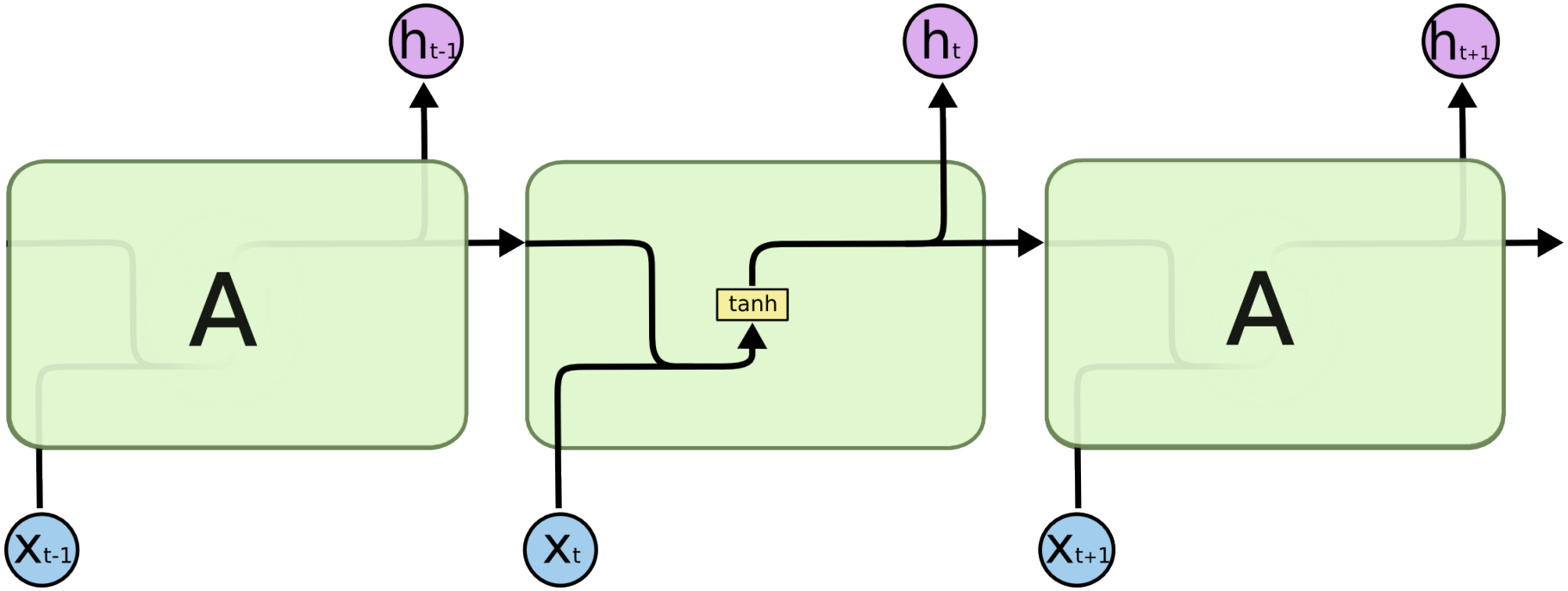
- Recurrent Neural Network (RNN) as model
- RNNs have a „memory“
- Takes not only input into calculation for each neuron but also the result of previous neurons
- Much more like the human brain (reading, speaking, etc.)

Recurrent Neural Network – Remember previous



Source: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Recurrent Neural Network – Internal Calculation



Summary and terms

- **Input:** Numerical vectors or matrices
- **Activation:** Can be a threshold or other functions to determine if Neuron fires or not („0“ or „1“)
- **Learning rate:** Determines how fast an algorithm should adjust to new data. A high learning rate adjusts better and faster to new data but also discards learned insights
- **Optimizer:** Function to optimize model (i.e. weights)
- **Epochs:** An epoch is a whole iteration of than one iteration of all data to have an optimal model for the given problemall input data. Algorithms need more
- **Batches:** Sometimes data is too big to put fully into RAM. Then it needs to be processed into data slices (aka batches).
- **Overfitting**: If model adapts perfectly on training data but not on new unseen data, then we talk of overfitting. It is like remebering by heart
- **Regularization:** Goal is to use as less variables for a model as possible to prevent overfitting, e.g. by dropping out a fixed number of neurons