# Introduction to Neural Network

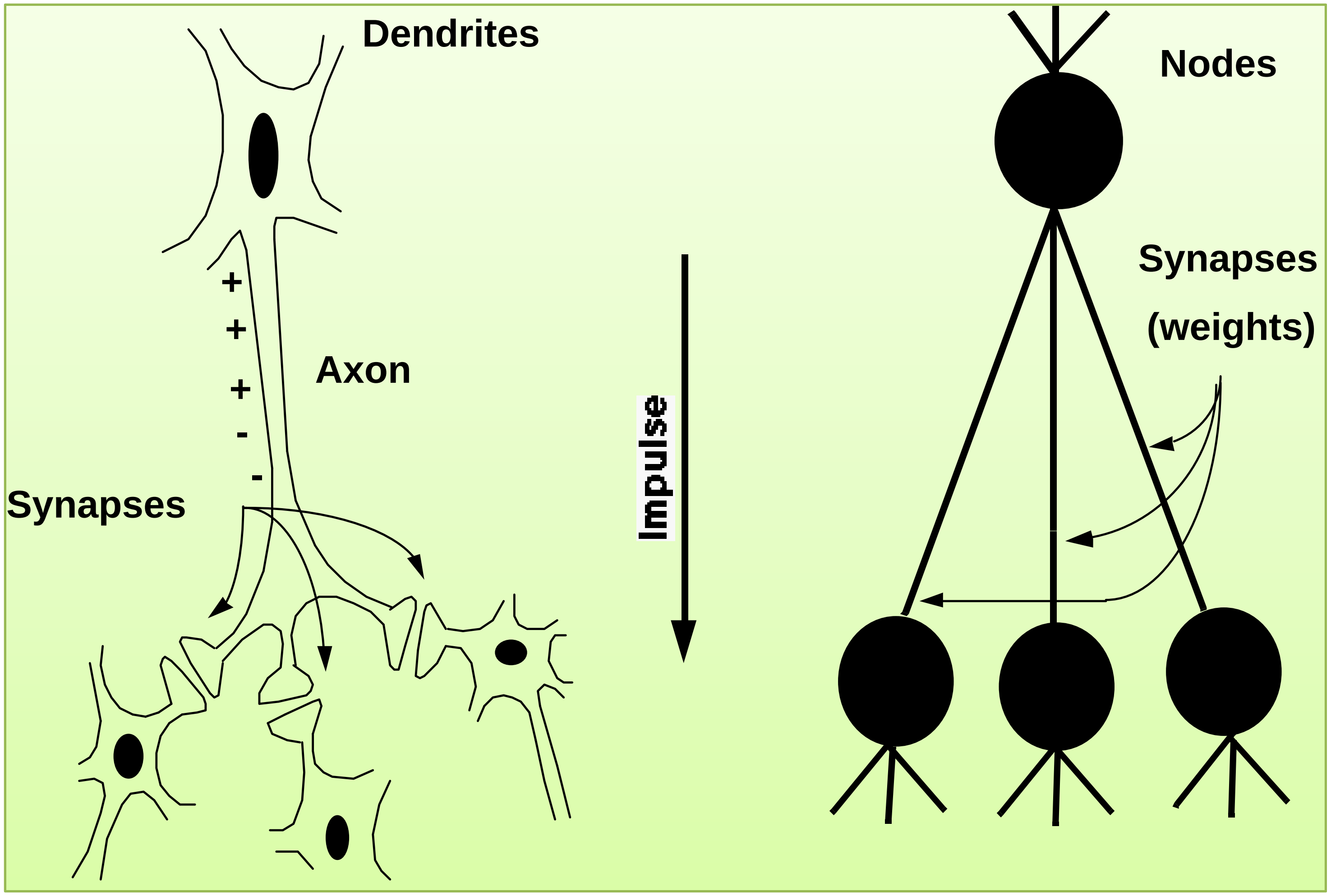
## Lecturer outline

- Neural network definition
- Biological analogy
- Potential application
- Why neural networks
- Limitations of neural networks
- Network architectures
- Neuron/node/perceptron
- Learning/training Types & Rules
- Developing Neural Networks
- Practical aspect of neural computing
- Neural networks performance
- Performance factors
- References

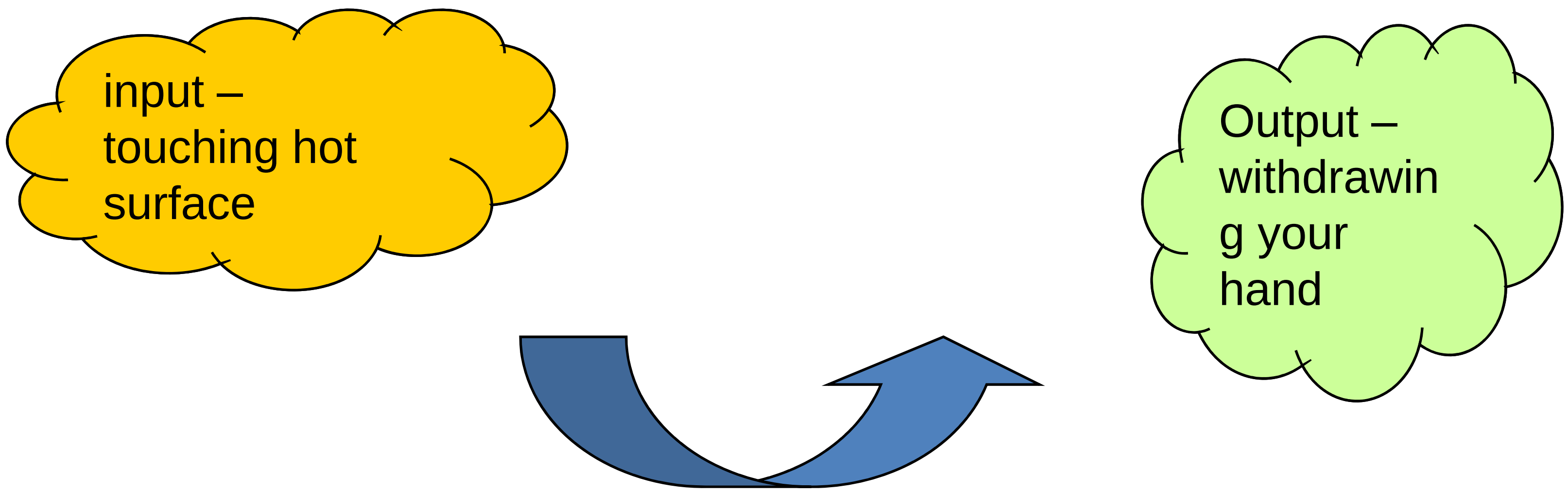
## Neural network definition

- NN is a computing sys. consists of a number of simple, highly interconnected nodes (processing elements) that process information
- A concept that try to mimic how human brain functions

# Biological Analogy



# Example



The processing in your brain that led from one to the other remains hidden

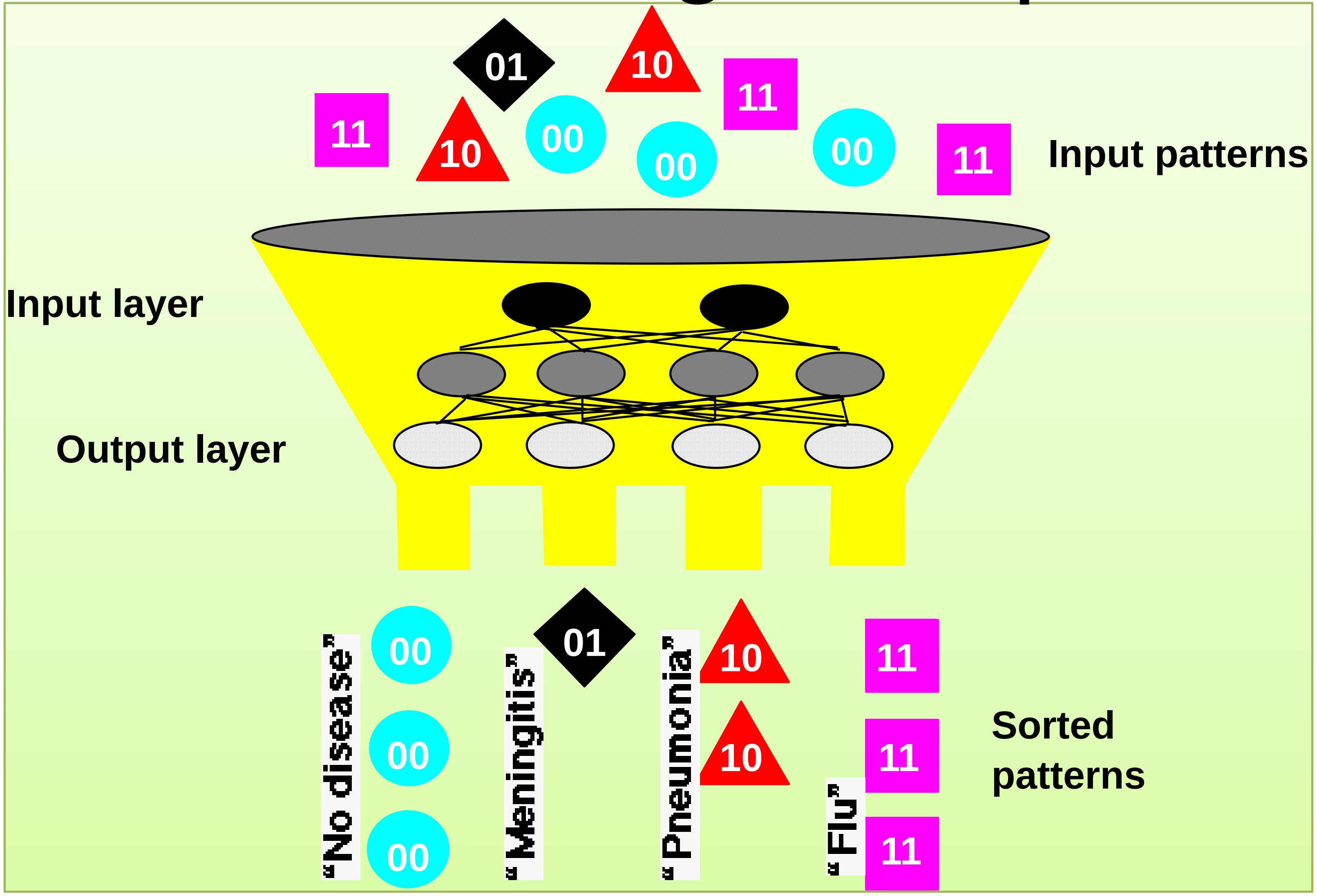
## Potential Applications

- Classification-given symptoms, determine the most likely disease, speech analysis, fault diagnosis
- Prediction-given wind velocity and humidity, predict evaporation rate
- Pattern association-retrieve an image from corrupted one

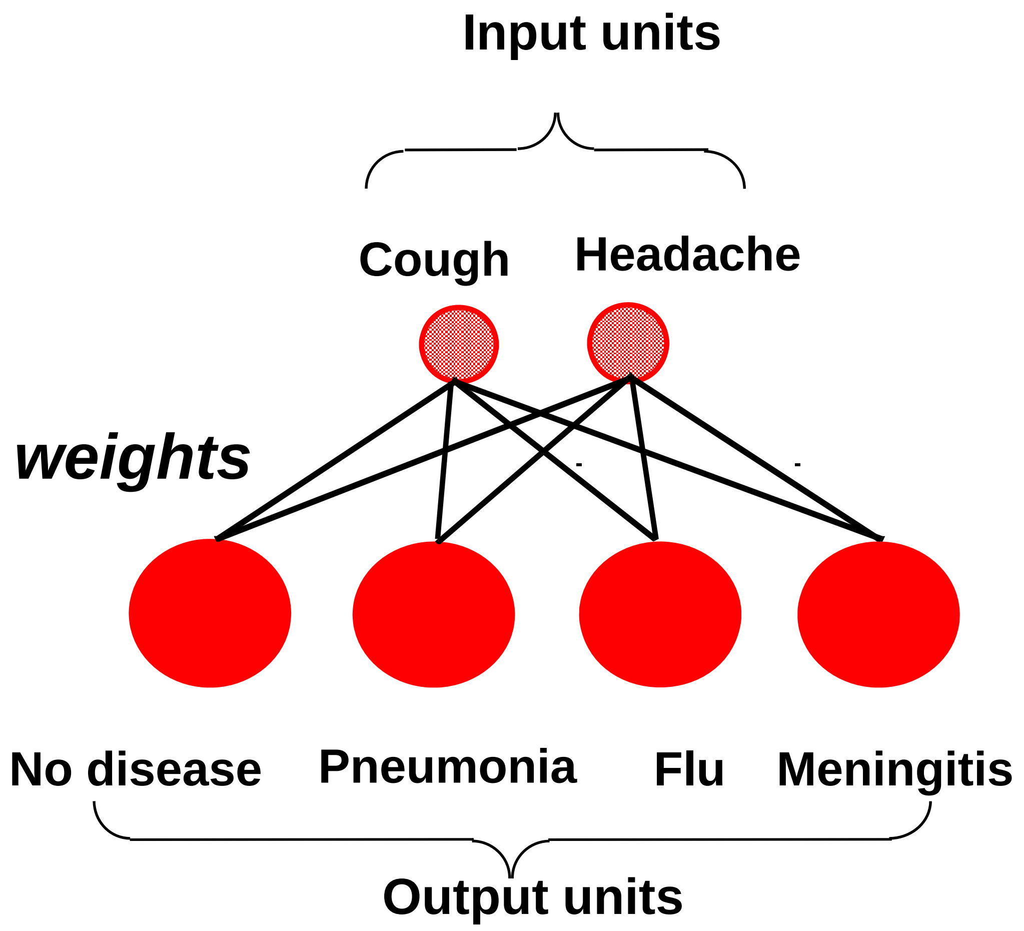
## Potential Applications

- Data conceptualization-cluster data with many attributes
- Data filtering-smooth input signal
- Optimization-optimize the settings of process controllers, thus feeding the correct amount of additives

# Clustering example



## classification example



**Δ rule**
*change weights to decrease the error*

- what we got
what we wanted
*error*

## Why neural networks?

- Compare to empirical model (curve fitting), NN model performs better for noisy or incomplete data. Better generalization

## Why neural networks?

- Compare to theoretical/mechanistic model, NN model is easier to develop especially for complex, nonlinear and uncertain syst.
- Potential for online use because a trained network may take less than a second to calculate results

## Limitations of Neural Networks

- Large amount of data – broad-based data set or experimental design is essential
- Long training times – however as computers become more powerful, time requirements are less

## Network architectures

- Three different classes of network architectures

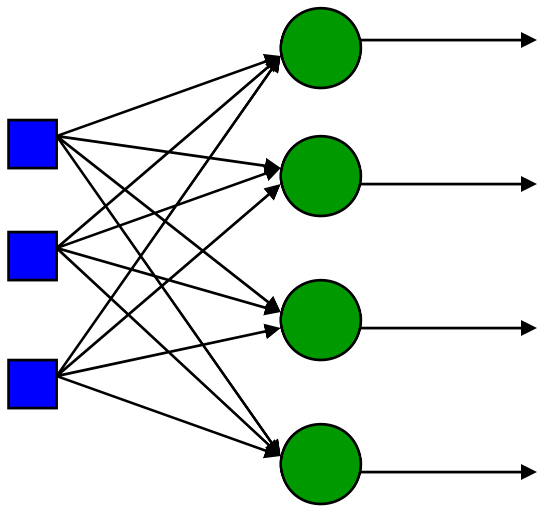
  single-layer feed-forward    neurons are organized
  multi-layer feed-forward    in acyclic layers
  recurrent

- The architecture of a neural network is linked with the learning algorithm used to train

## Single Layer Feed-forward

(one processing layer – the output layer)

***Input layer of source nodes***

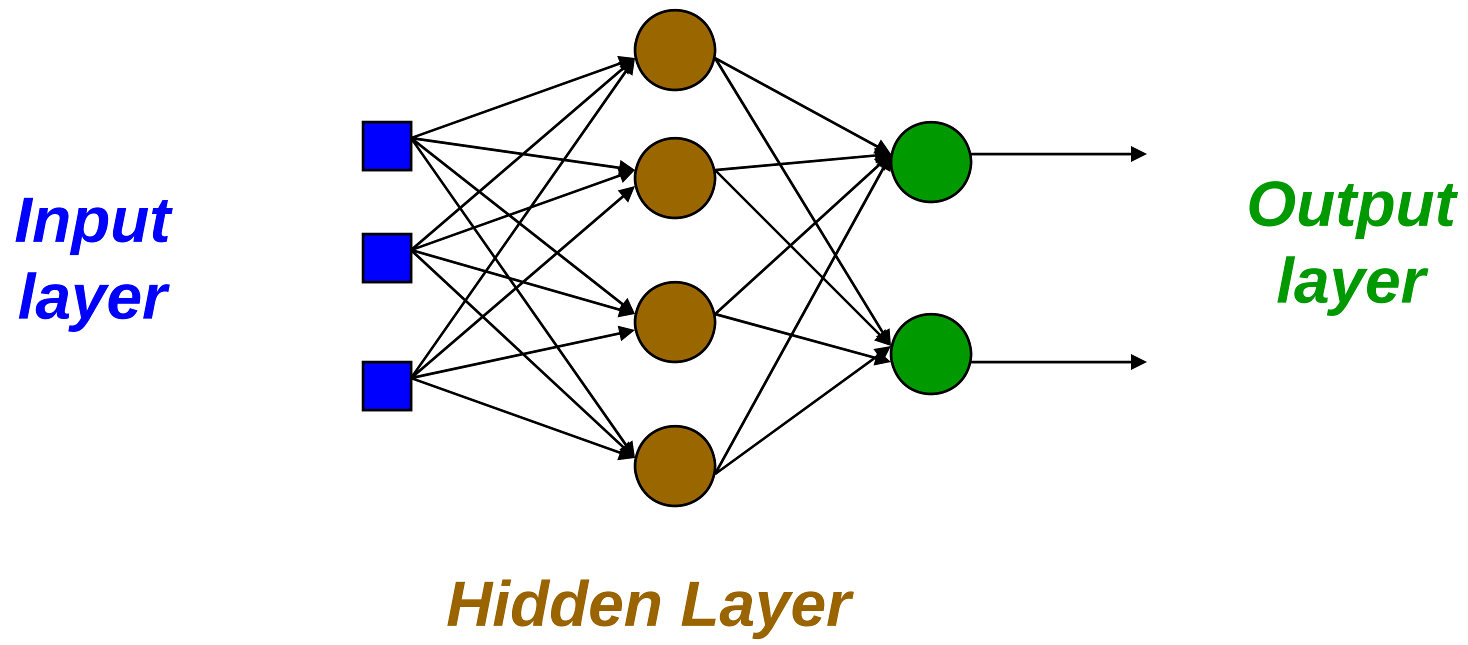


***Output layer of neurons***

## Multi layer feed-forward

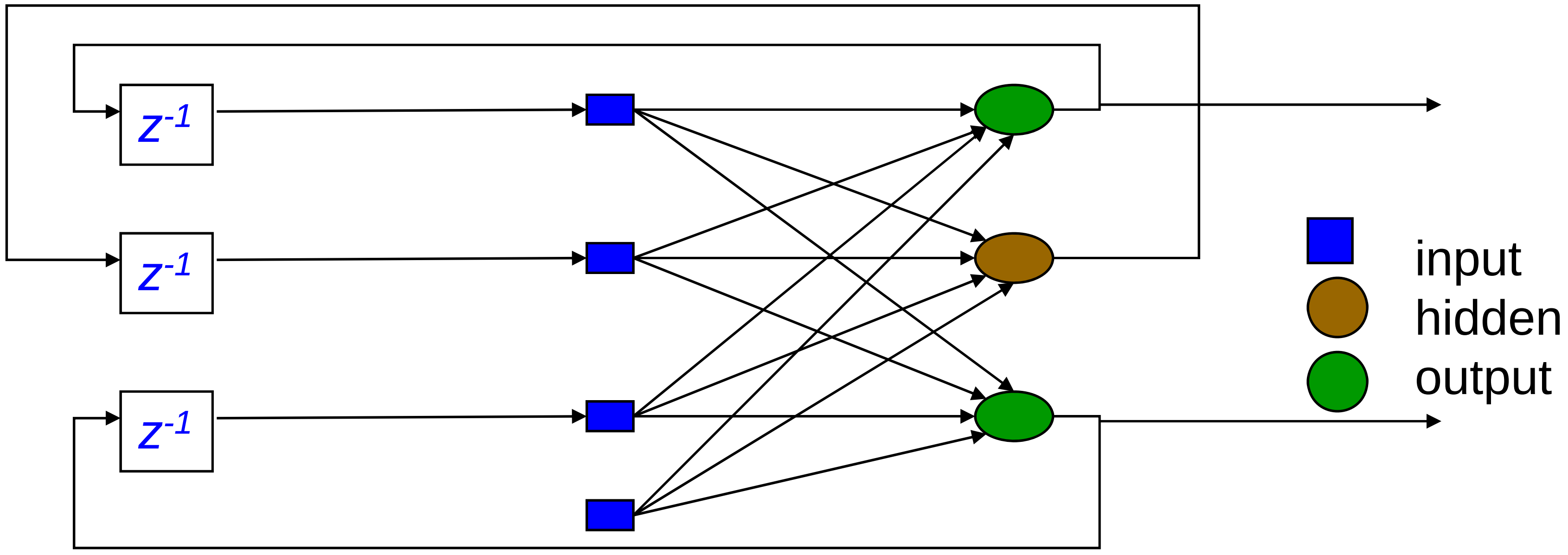
(several processing layers – hidden and output layers

3-4-2 Network



# Recurrent network

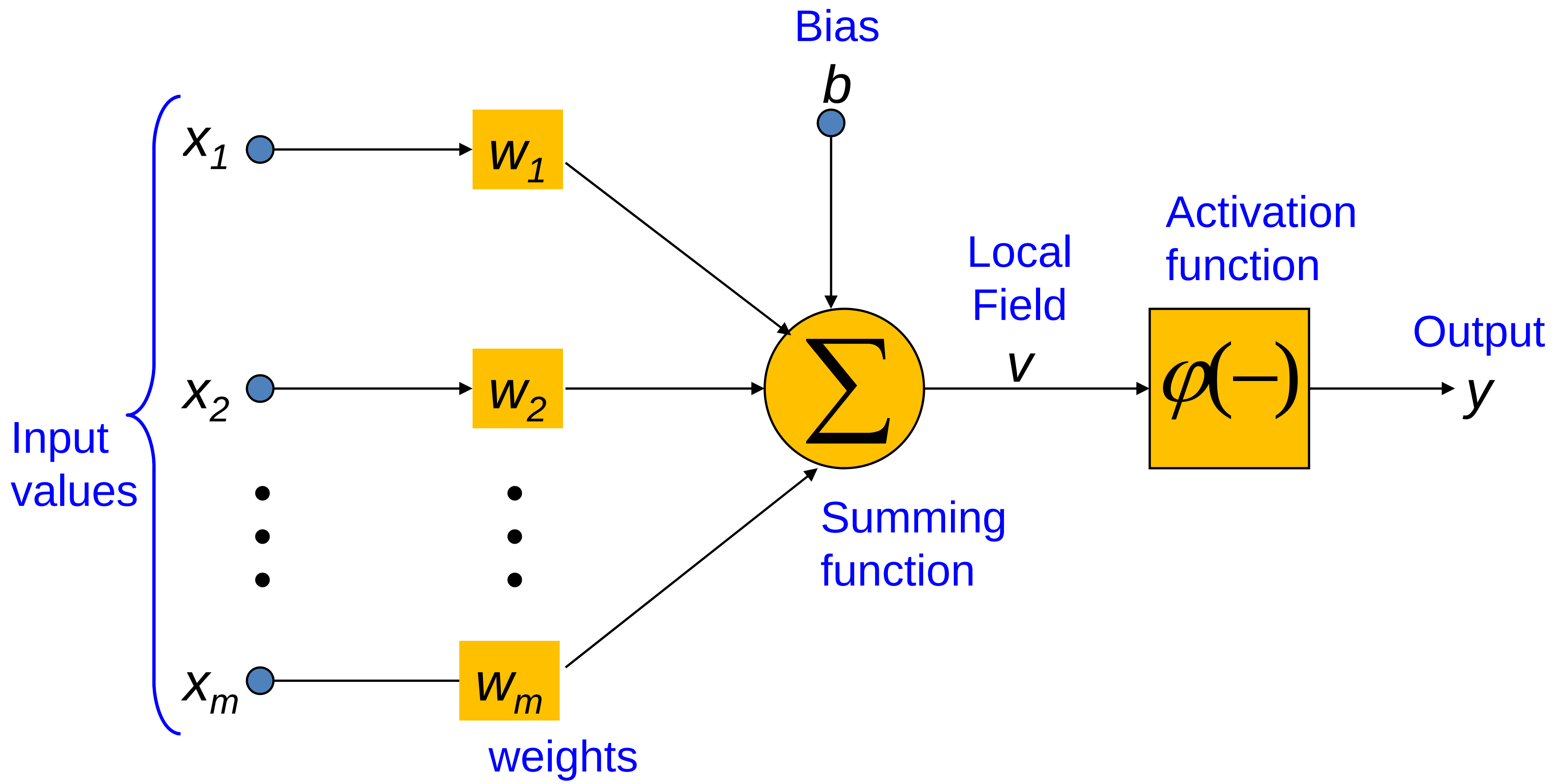
Recurrent Network with *hidden neuron*: unit delay operator $z^{-1}$ is used to model a dynamic system



## The Unit of a Neural Network

- The unit of a neural network is modeled on the biological neuron
- The unit combines its inputs into a single value, which it then transforms to produce the output; together these are called the activation function

## Neuron/node: perceptron



## Neuron

The neuron is the basic information processing unit of a NN. It consists of:

A set of links, describing the neuron inputs, with weights $W_1$, $W_2$, …, $W_m$

An adder function (linear combiner) for computing the weighted sum of the inputs (real numbers):

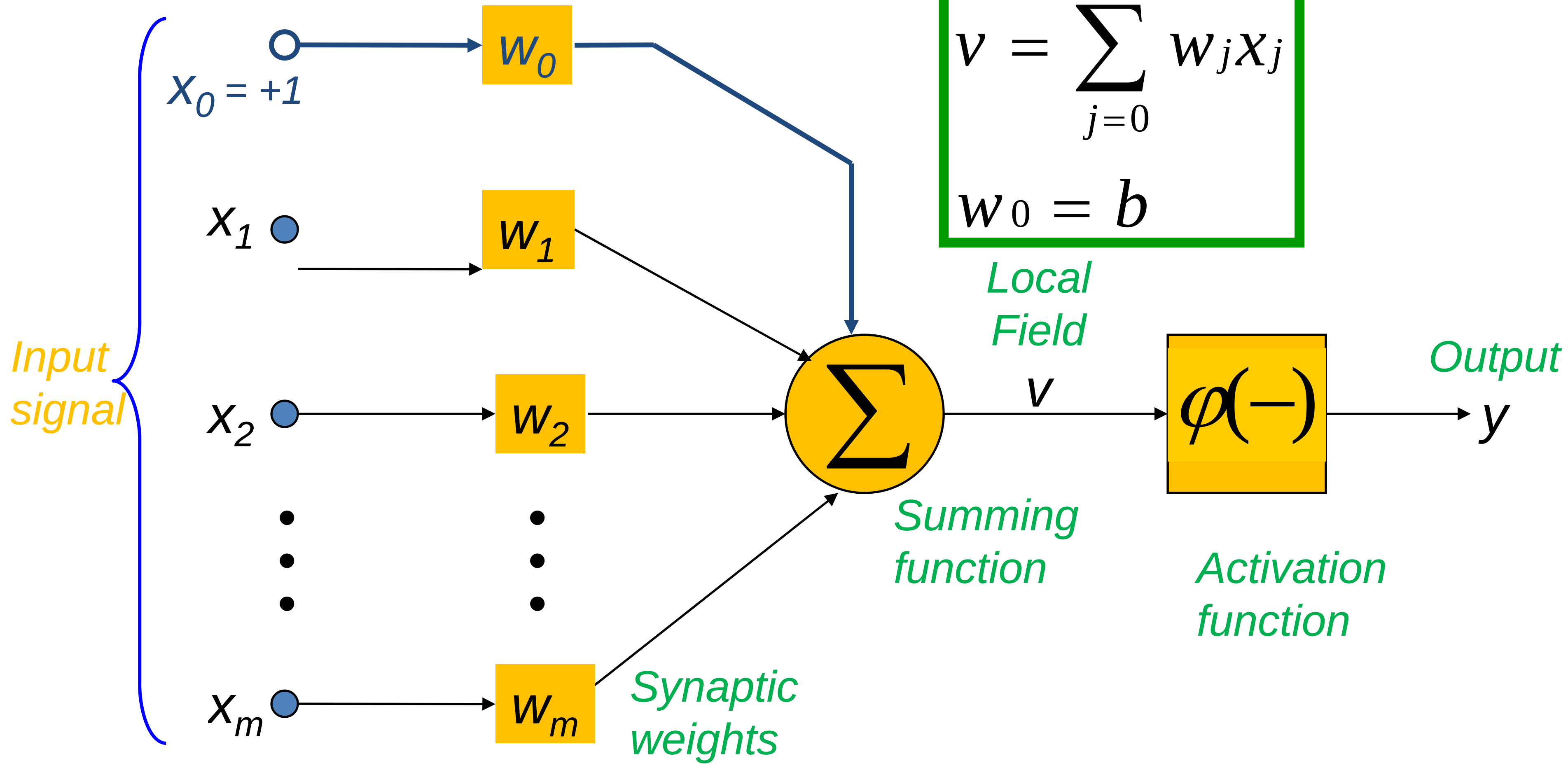
$$v = \sum_{j=1}^{m} w_j x_j$$

Activation function (squashing function) $\varphi$ for limiting the amplitude of the neuron output.

$$y = \varphi(v + b)$$

# Bias as extra input

- The bias is an external parameter of the neuron. *It* can be modeled by adding an extra input.



$$v = \sum_{j=0}^{m} w_j x_j$$

$$w_0 = b$$

# Neuron Models

- The choice of $\varphi$ determines the neuron model. Examples:
- step function:

$$\varphi(v) = \begin{cases} a & \text{if } v < c \\ b & \text{if } v > c \end{cases}$$

- ramp function:

$$\varphi(v) = \begin{cases} a & \text{if } v < c \\ b & \text{if } v > d \\ a + ((v-c)(b-a)/(d-c)) & \text{otherwise} \end{cases}$$

- sigmoid function:

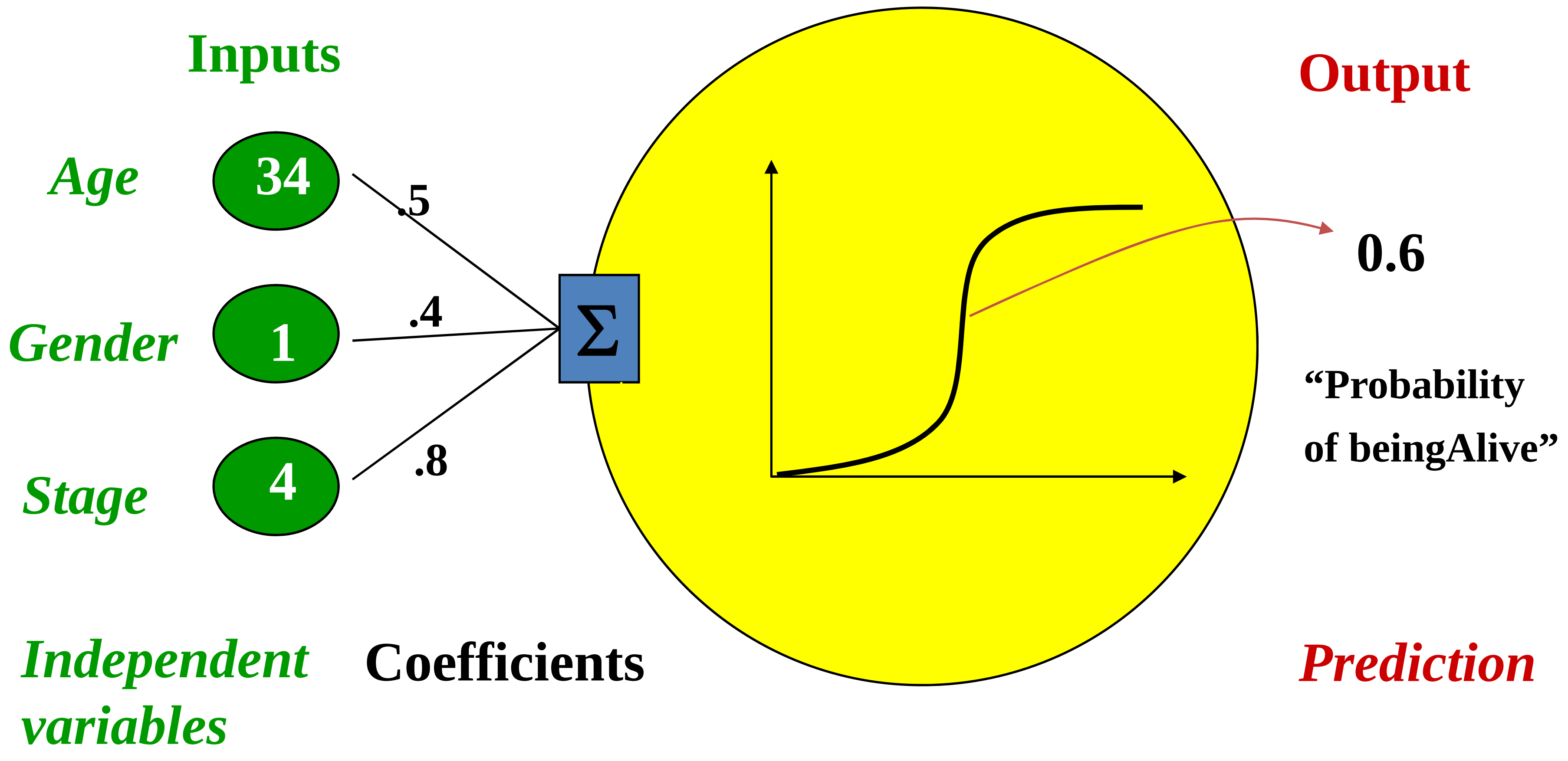
with z,x,y parameters

$$\varphi(v) = z + \frac{1}{1 + \exp(-xv + y)}$$

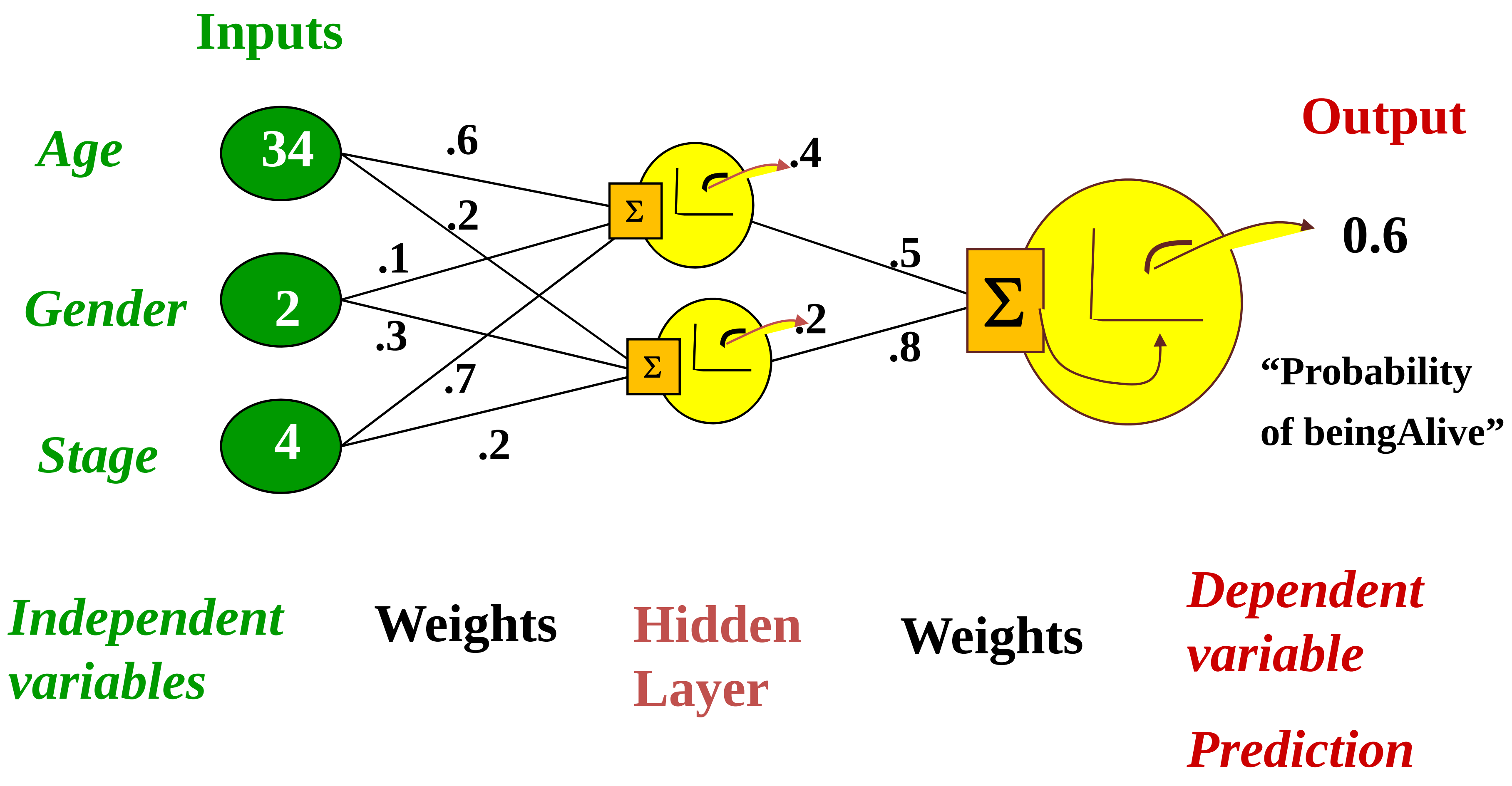
- Gaussian function:

$$\varphi(v) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left( -\frac{1}{2} \left( \frac{v-\mu}{\sigma} \right)^2 \right)$$

## Logistic function



# Neural Network Model



- How to calculate the output y
- How to update or adjust weights w? Depend on type of training algorithm use

$$v = \sum_{j=1}^{m} w_j x_j \Rightarrow y = \varphi(v + b)$$

## Learning/training Types

- Supervised learning – require input & desired output data
- Unsupervised learning – normally for pattern analysis – discover patterns or features, learning from observation, blur or corrupted images
- Reinforcement learning – the output can be correct or incorrect, do not know what the correct answer is.  Example: chess game – reward right moves and punish wrong ones

## Learning Rules/Algorithms

- Gradient or steepest Descent - Backprop
- Widrow-Hoff (Least Mean Square)
- Generalized Delta
- Error-Correction
- Scaled Conjugate gradient
- Levenberg-Marquardt
- Kohonen
- Hebbian
- Etc.

## Developing Neural Networks

- Requires 3 phases:
  - Training or learning phase – update/adjust the weights using learning/training algorithm, time consuming and the critical phase
  - Recall phase – access outputs deviation from target response using the calculated weight factors, biases and training data
  - Generalization phase – subject the network to new input patterns and known output data, where the system hopefully performs properly

## NN Training –supervised learning

- Training -process of setting/determining the best weights on the edges connecting all the units in the network
- The goal is to use the training set to calculate weights where the output of the network is as close to the desired output as possible for as many of the examples in the training set as possible

## Neural Network Training

- *Back propagation has been used since the 1980s to adjust the weights (other methods are now available):*

  Calculates the error by taking the difference between the calculated result and the actual result

  The error is fed back through the network and the weights are adjusted to minimize the error

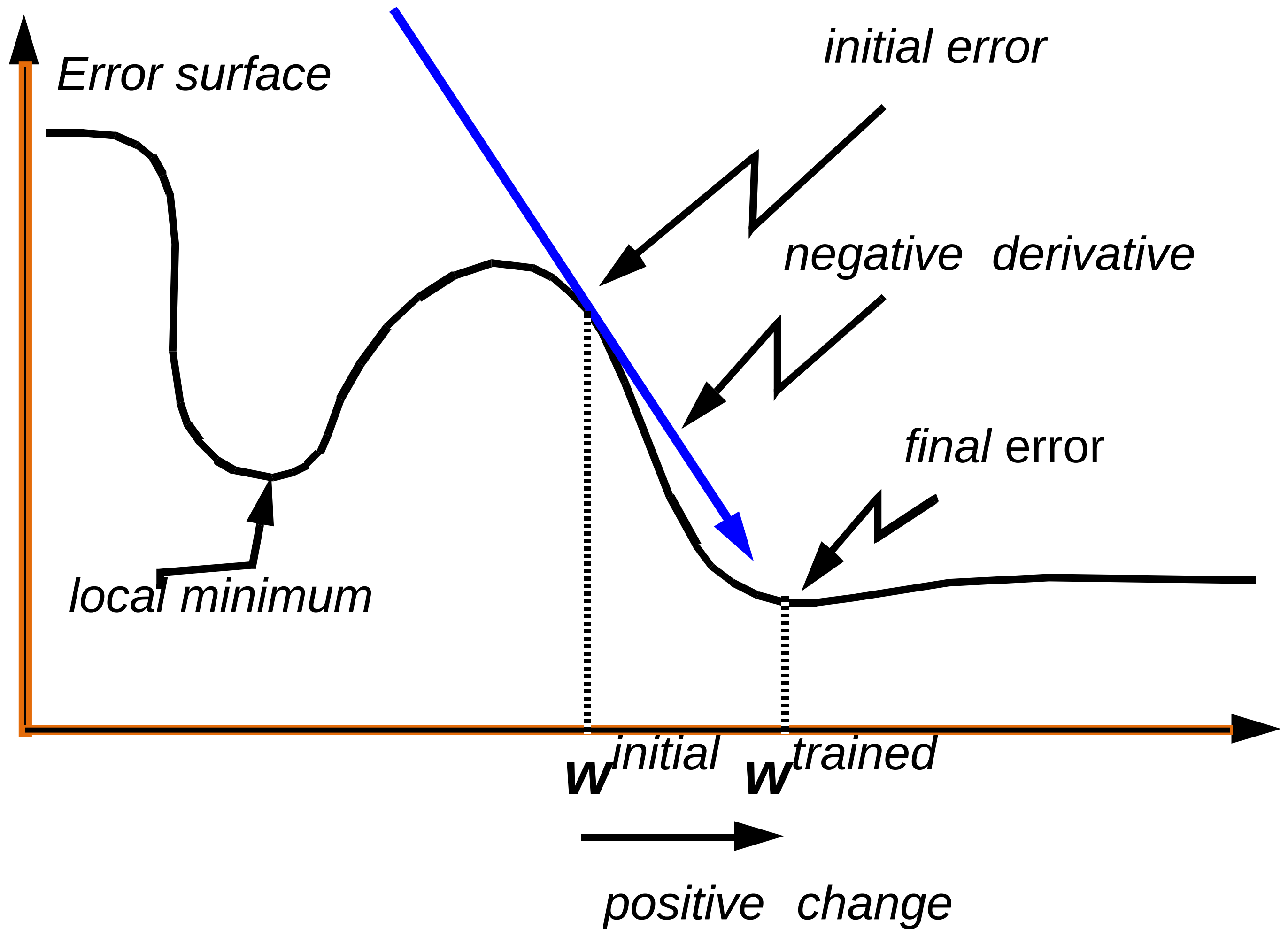
## Practical aspect of neural computing

- Selecting number of hidden layers
- Normalizing input and output data sets
- Initializing the weights
- Setting learning rate and momentum coefficient – depend on training algorithm use
- Selecting proper transfer function
- Generating and using a network learning curve

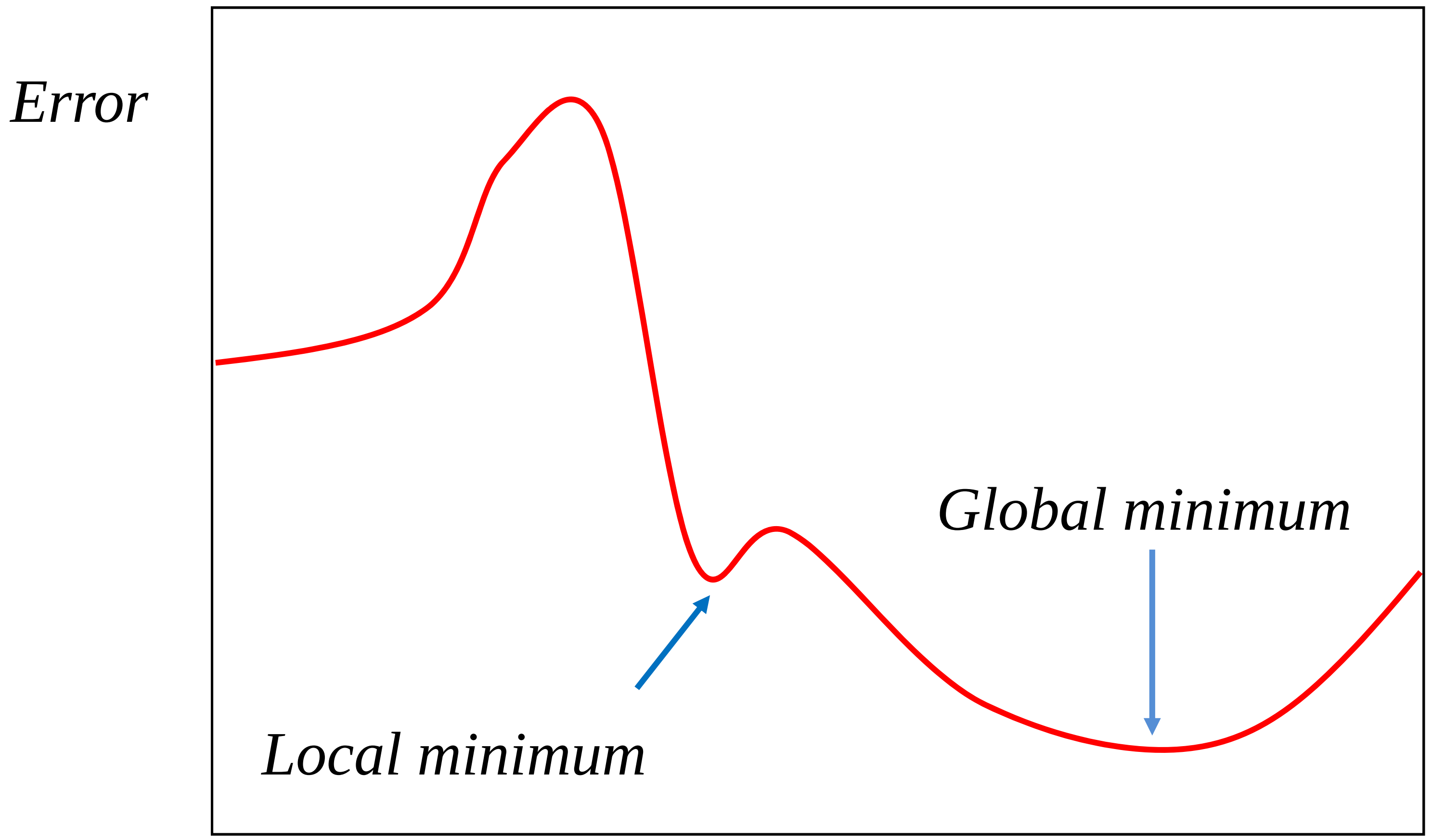
## Neural networks performance

- Accuracy – MSE, SSE, EI, overfitting
- Complexity of a model
- Convergence

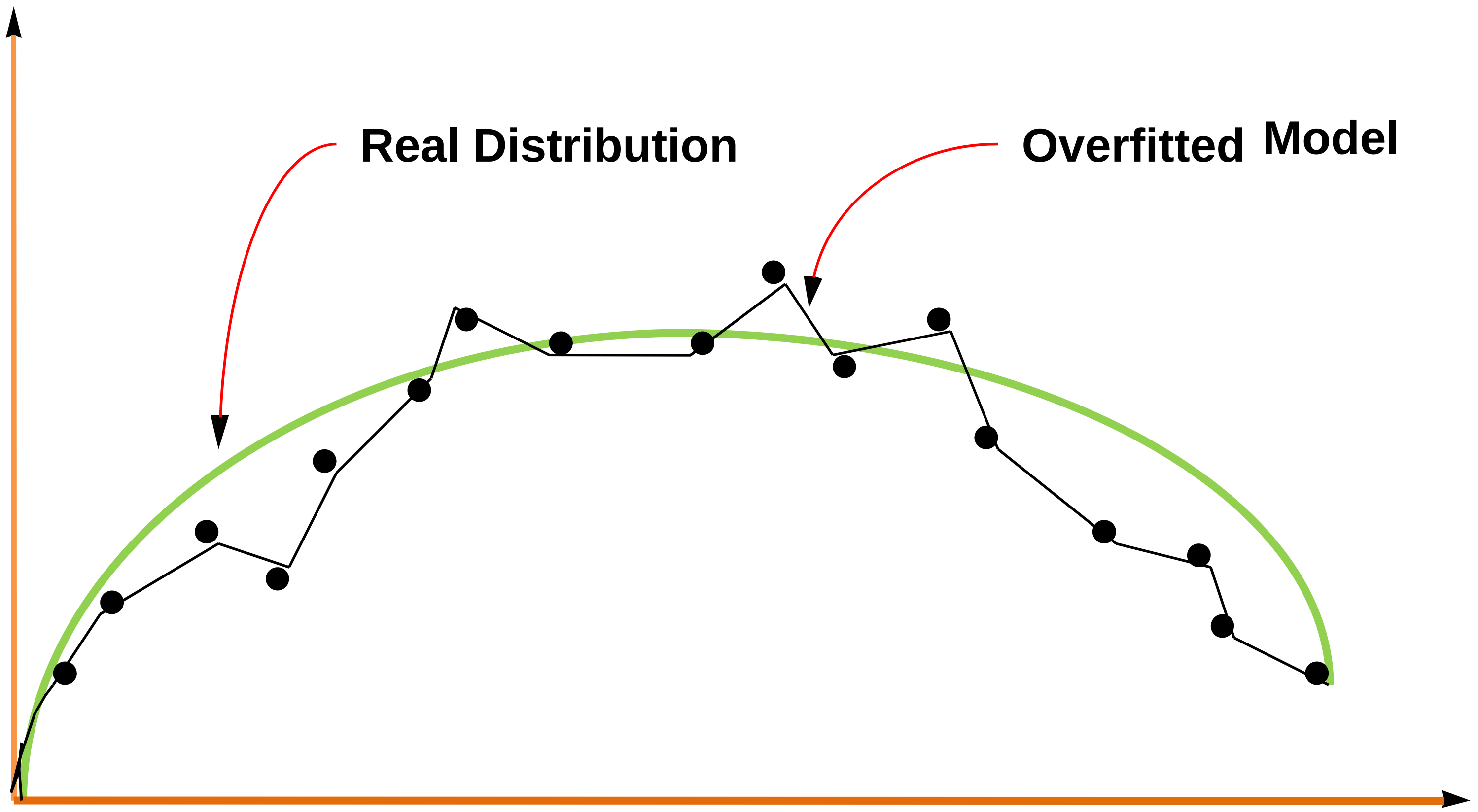
# Minimizing the Error



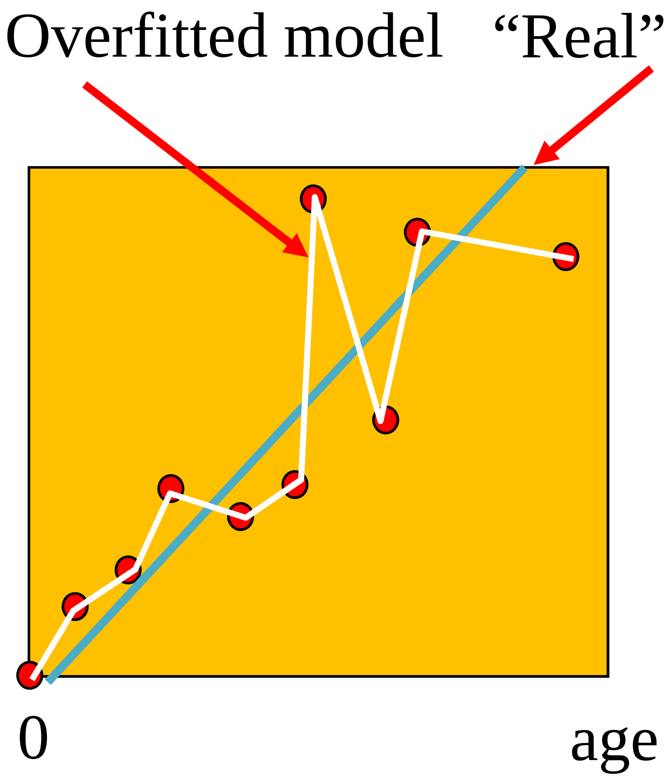
# Gradient descent

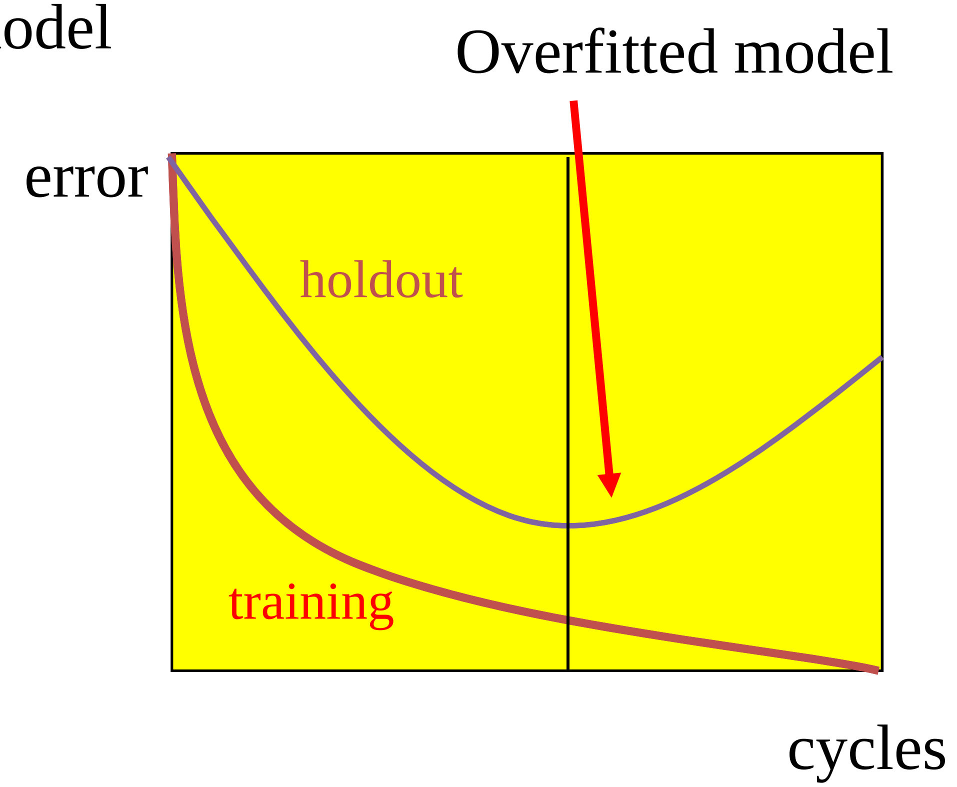


## Over fitting



# Over fitting in Neural Nets





## Performance factors

- Data Preparation
- Weight Initialization
- Learning rate and momentum
- Optimization method
- Architecture selection
- Activation functions
- Active Learning

## Some References

Introductory Textbooks

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