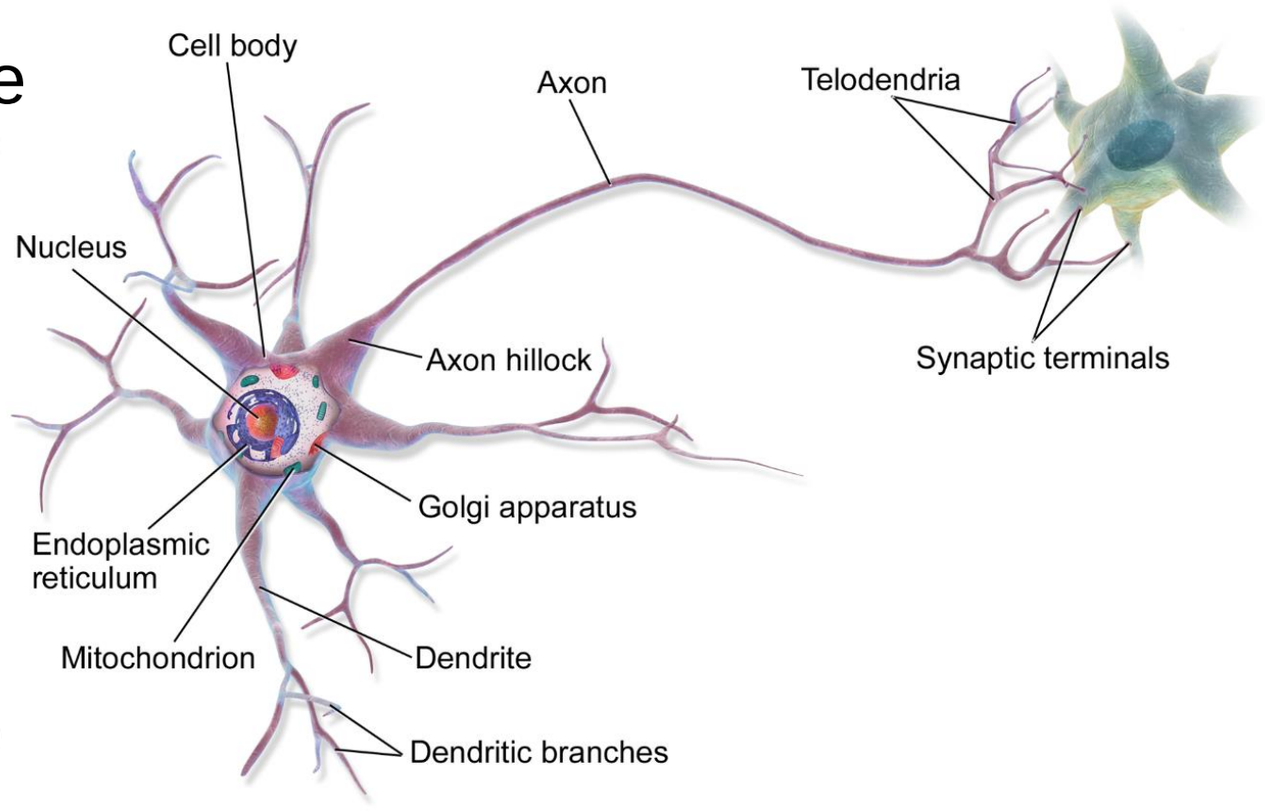
Neural Networks

Artificial Neural Networks

- Vaguely inspired by the biological neural networks that constitute animal brains

- The human brain is made of close to 100 billions of neurons interconnected by synapses.



- A neuron processes and transmits information through electrical and chemical signals that are carried via the synapses

- Neurons can connect to each other to form neural networks – each neuron can be connected with about 5,000 other neurons

Artificial NNs Vs Biological NN

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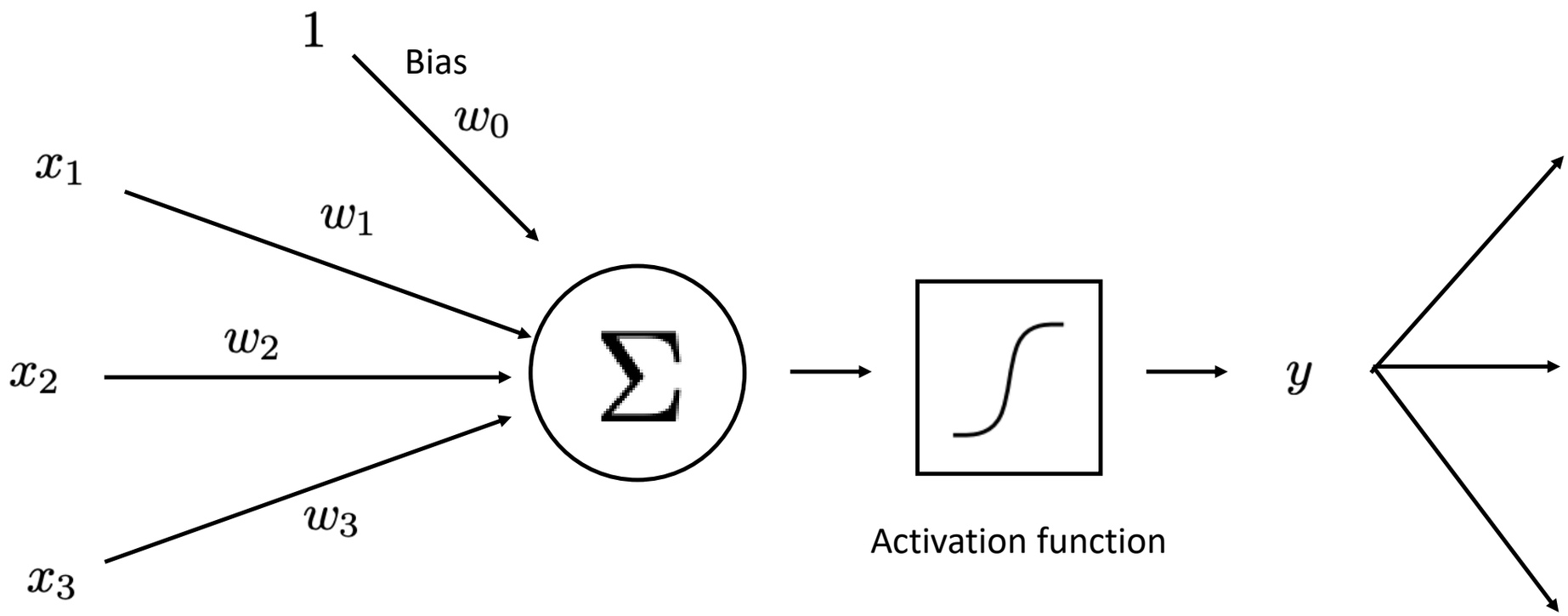
	ANN	BNN
Size	10-1000 Neurons & 1000's of synapses	86 Billion Neurons & >100 Trillion synapses
Topology	Usually Feed-forward, that is computed Layer by Layer	Complex Network that is computed asynchronously
Calculation Speeds	nano seconds	milli seconds
Power	100 watts (~100Watts)	20 watts
Others	Not Fault Tolerant, Learning	Fault Tolerant, Learning?

Applications

- Neural Nets have done exceptionally well at tasks like
  - Image Recognition, Character Recognition, Face Recognition
  - Feature Extractions, Finger print processing, Signature matching
  - Speech Recognition
- Other modest successes in: Stock market predictions, Combinatorial optimization, Medicine etc.

The Perceptron

- Perceptron: The main building block

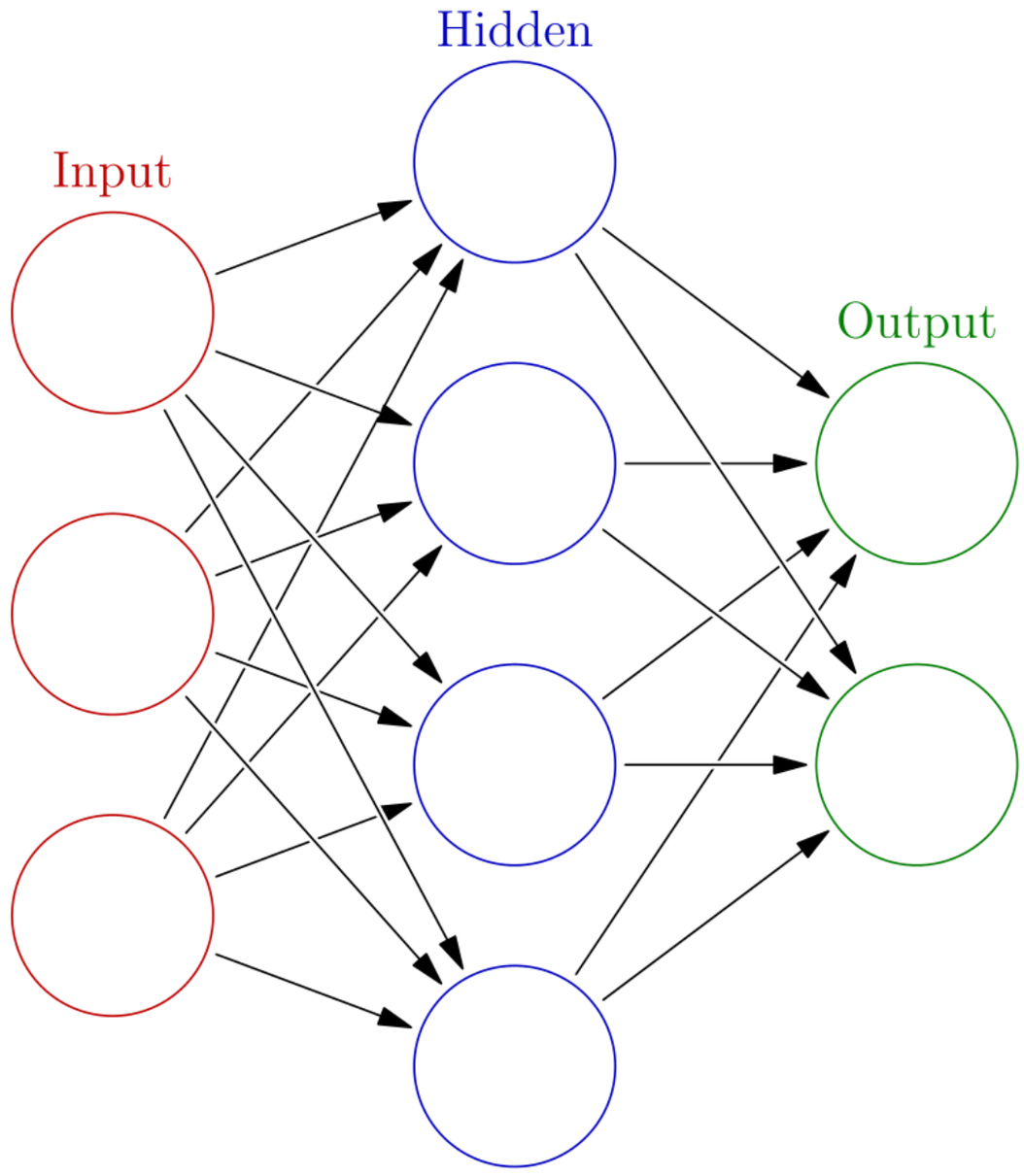


$$y = f\left(\sum w_i x_i\right)$$

Activation function

The Artificial Neural Net

- Number of Layers
  - Single Vs
  - Multi Layer
- Number of Nodes in each Layer
- Weights/connections
- Activation or Transfer function



Examples of Activation functions

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- ReLu (with Softmax/Linear)
- Sigmoid (Logistic)
- Hyperbolic Tangent (tanh)
- Step function (Heaviside)
- Softmax (Generalized Logistic)
- Linear

- Which one do we use?
  - There is no set procedure/Rule
  - ReLu has become very popular

An Example

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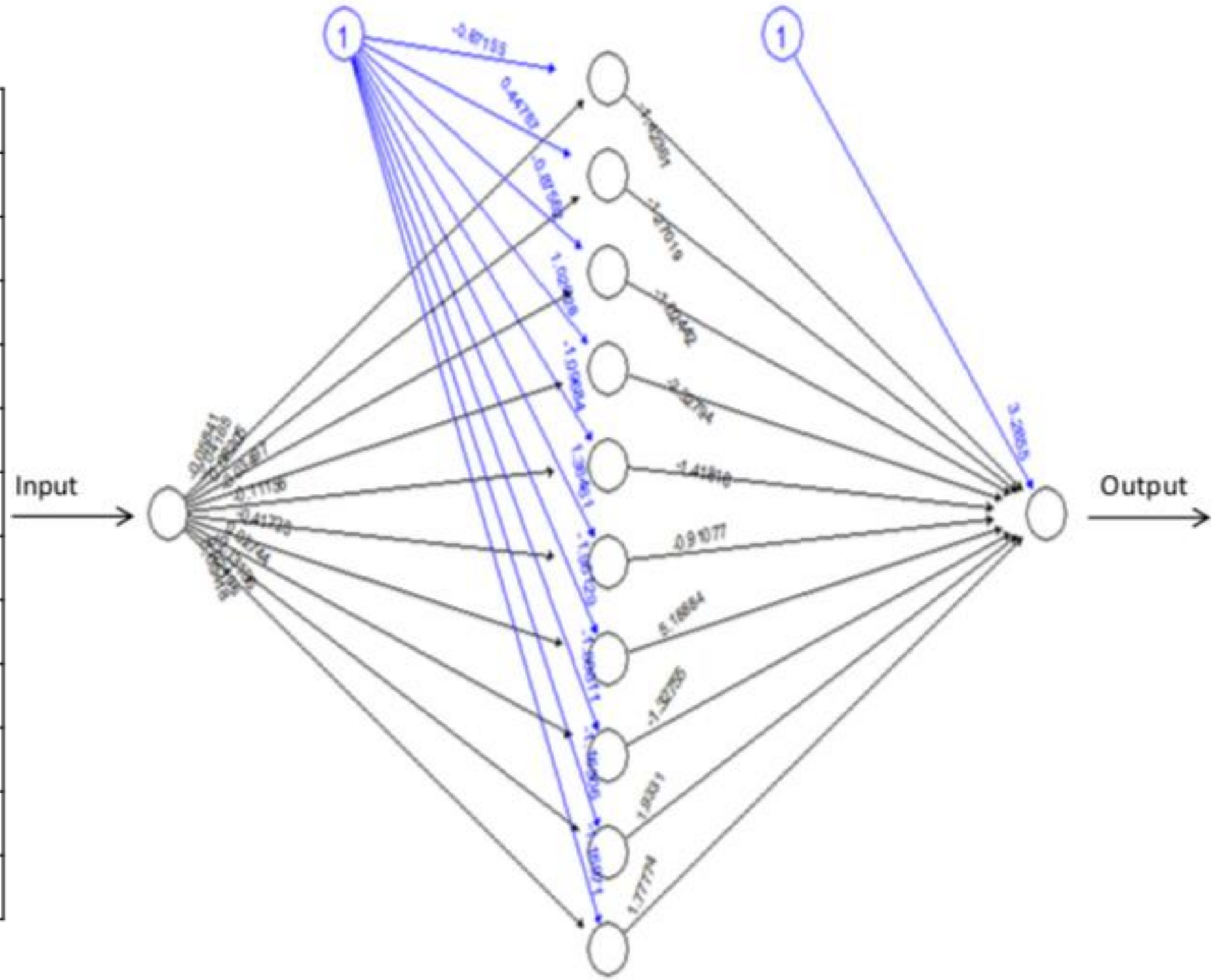
Training Data	
Input	Output
1.0	1.0
4.0	2.0
9.0	3.0
90.25	9.5
57.74	7.6
14.44	3.8
23.04	4.8
5.29	2.3
3.61	1.9
5.76	2.4
13.69	3.7



Learning

- How to determine the weights?
  - Start with guess values for weights
  - Calculate outputs from inputs
  - Compare outputs to desired outputs: Calculating errors
  - Training algorithms update the weights in a way to minimize the errors (cost functions)
- Cost (loss) functions: measures how close an output is to the desired output. Preferably:
  - Non-negativity
  - Globally continuous and differentiable

Training Also: Back Propagation

- Back propagation of errors, is a common algorithm to train artificial neural networks used in conjunction with an optimization method such as gradient descent.
- The method calculates the gradient of a loss function with respect to all the weights in the network.
- The gradient is fed to the optimization method which in turn uses it to update the weights, in an attempt to minimize the loss function.

Gradient Descent

- A first-order optimization algorithm.
- Essentially equivalent to falling down on a slope to eventually find the minimum (lowest point in the valley).
- To find a minimum (valley) of a function, take a small step along the steepest direction. And keep iterating.
- For finding maximums we'd do gradient ascent.

$$w_i^{new} = w_i - \eta \frac{\partial E}{\partial w_i}$$

Learning rate

- Choosing the Learning rate (η)
  - Too small, we will need too many iterations for convergence
  - Too large, we may skip the optimal solution
- Adaptive Learning Rate : start with high learning rate and gradually reduce the learning rate with each iteration

$$\eta_n = \frac{\eta_1}{n}$$

- Can also be chosen by Trial & Error – Use a range of learning rate (1, 0.1, 0.001, 0.0001) and use the results as a guide

Epochs, Batch size, Iterations

- When dataset is too large, passing all the data through a Neural net before we make weight updates is computationally expensive
- Instead we would create data batches with smaller batch size.
- After each batch is passed and weights updated, we will count it as one iteration.
- When an entire dataset is passed forward and backward (weights updated) through the neural network, we will count it as one epoch.
  - Too few epochs: under fitting, Too many: overfitting
  - Batch training: All of the training samples pass through the neural net, before weights are updated
  - Sequential training: Weights are updated after each training vector is passed through the neural net.

Scaling

- Scaling the Variables
  - The non-linearities in the activation function and the numerical rounding errors make input scaling quite important
  - Scaling can accelerate learning and improve performance

Overfitting

- Neural Network Models are susceptible to overfitting
  - Large number of weights and biases
  - Excessive learning (Epocs) on training data

- Ways to avoid Overfitting
  - Increase sample size
  - Early stopping
  - Reduce Network Size
  - Regularization

Regularization (weight decay)

- Regularization is a technique used to avoid this overfitting problem.
- The idea behind regularization is that models that overfit the data are complex models that have for example too many parameters.
- Regularization penalizes the usual loss function by adding a complexity term that would give a bigger loss for more complex models.
- Types of Regularization
  - LASSO
  - Ridge
- Optimal value of λ, the decay rate or penalty coefficient, is determined through cross-validation

Hyper parameters and tuning

- Hyper parameters are the variables which determines the network structure and the variables which determine how the network is trained
  - Number of hidden layers
  - Number of neurons in hidden layers
  - Decay factor
  - Number of Epoch
  - Learning Rate
  - The Activation Function
- Tuning these to ensure that you don’t overfit is an art.