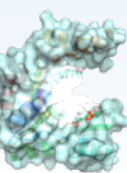


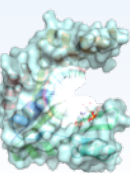


GRADIENT DESCENT

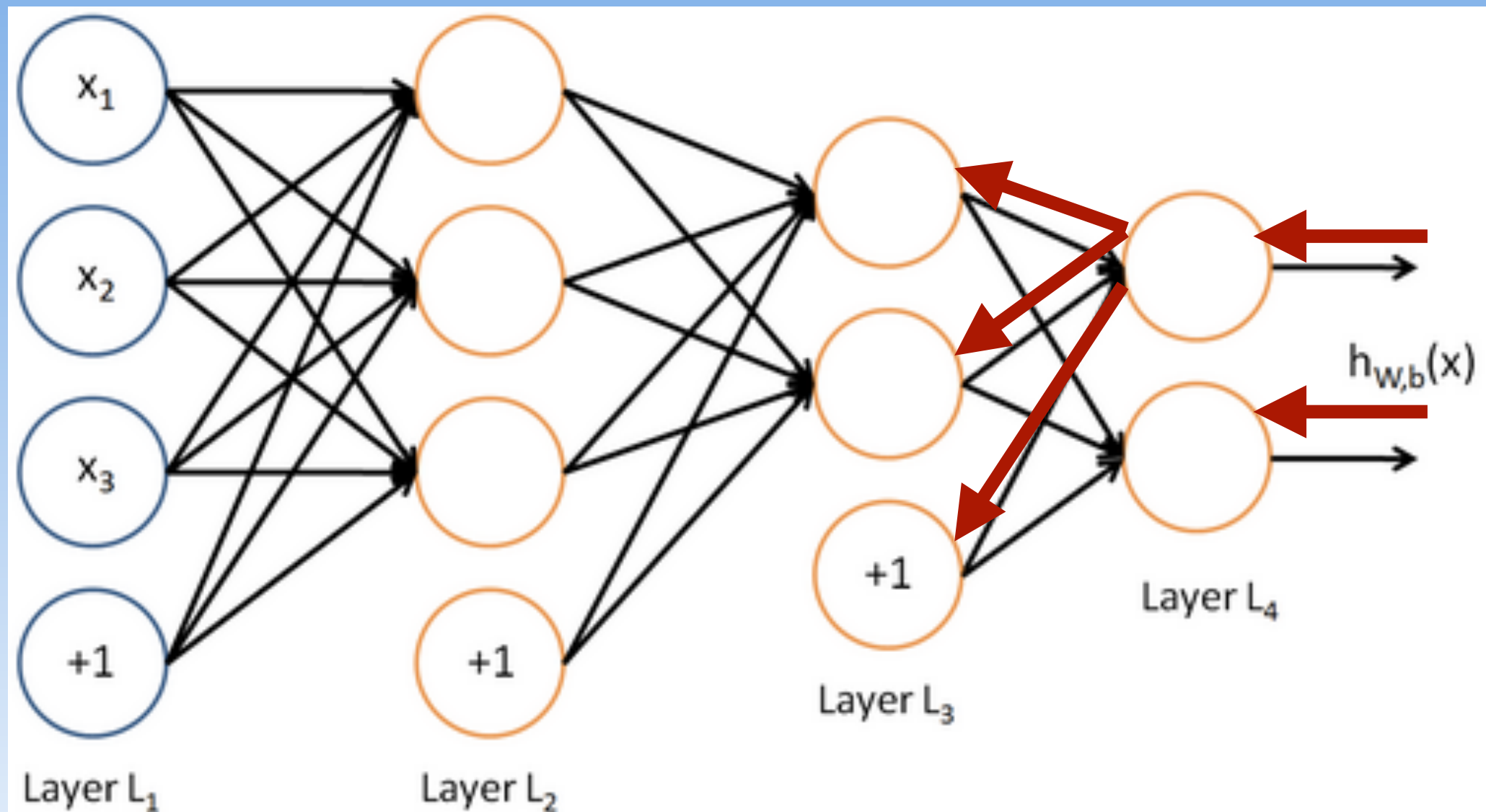


AGENDA

- * learning rate
- * loss function and its nonlinearity
- * local minima
- * backpropagation
- * effect of activation function on learning (gradients of the activation function)



BACKPROPAGATION



- Adjust weights using the error on value predicted by a node

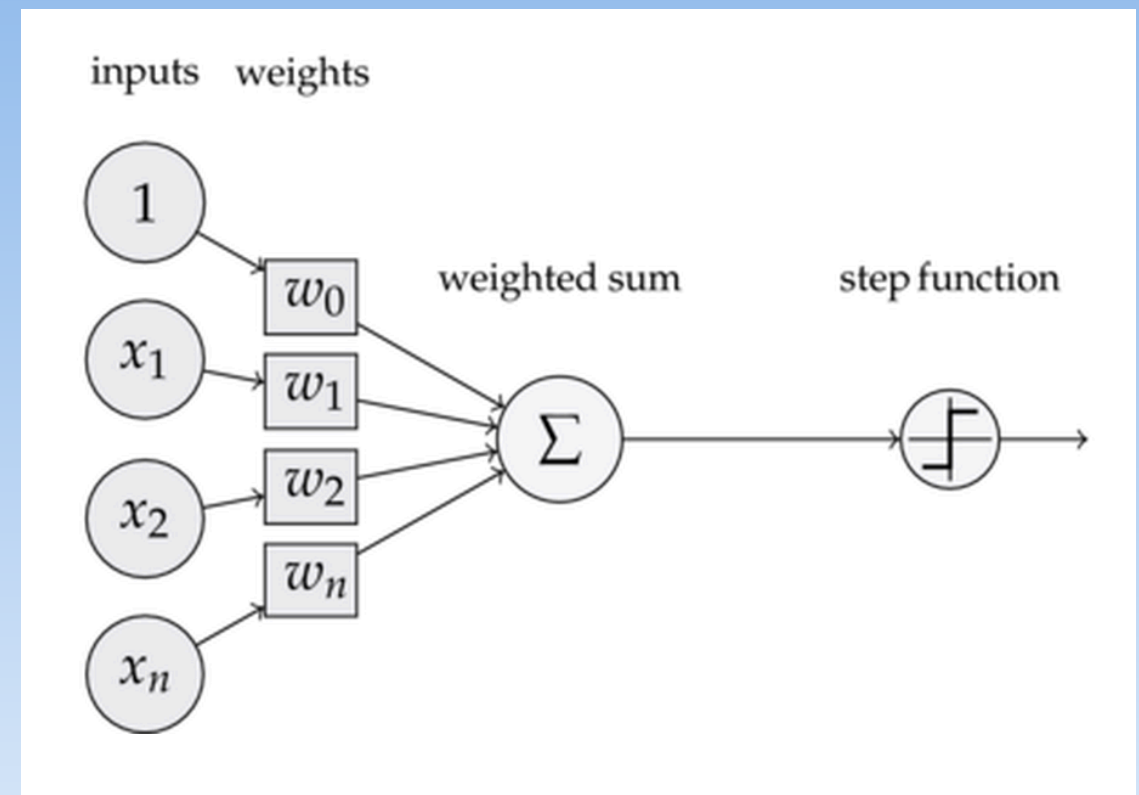
BACKPROPAGATION

Activation at node j:

$$\text{net}_j = \sum_i (o_i \times w_{ij})$$

Output at node j:

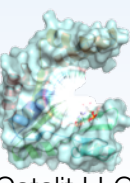
$$o_j = f(\text{net}_j) \text{ where } f(\text{net}_j) = 1 / (1 + e^{-\text{net}_j})$$



BACKPROPAGATION

Calculate the first derivative of the transfer function:

$$f'(\text{net}_j) = f(\text{net}_j) \times (1.0 - f(\text{net}_j))$$



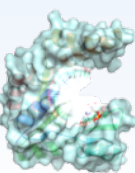
BACKPROPAGATION

Calculate the first derivative of the transfer function:

$$f'(\text{net}_j) = f(\text{net}_j) \times (1.0 - f(\text{net}_j))$$

and from that we can calculate the deltas (δ):

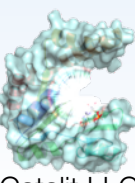
$$\delta = f'(\text{net}) \times (\text{received error})$$



BACKPROPAGATION

deltas for output node is:

$$\delta_{\text{output}} = f'(\text{net}) \times (t - o)$$



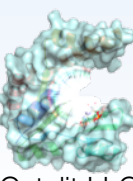
BACKPROPAGATION

deltas for output node is:

$$\delta_{\text{output}} = f'(\text{net}) \times (t - o)$$

delta for hidden node is:

$$\delta_j = f'(\text{net}_j) \times \sum_k (\delta_k \times w_{jk})$$



BACKPROPAGATION

deltas for output node is:

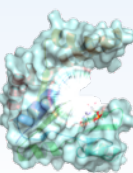
$$\delta_{\text{output}} = f'(\text{net}) \times (t - o)$$

delta for hidden node is:

$$\delta_j = f'(\text{net}_j) \times \sum_k (\delta_k \times w_{jk})$$

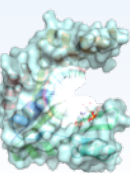
And the correction to apply to the weight is:

$$dw_{ij} = L \times o_i \times \delta_j$$



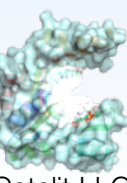
BACKPROP SUMMARY

- **Input:** Set activation for each node of input layer
- **Feedforward:** For each layer, calculate the output
- **Output error δ :** Compute loss function at output layer
- **Backpropagate:** output error back using **gradient**
- **Adjust weights:** At each stage apply correction to weights

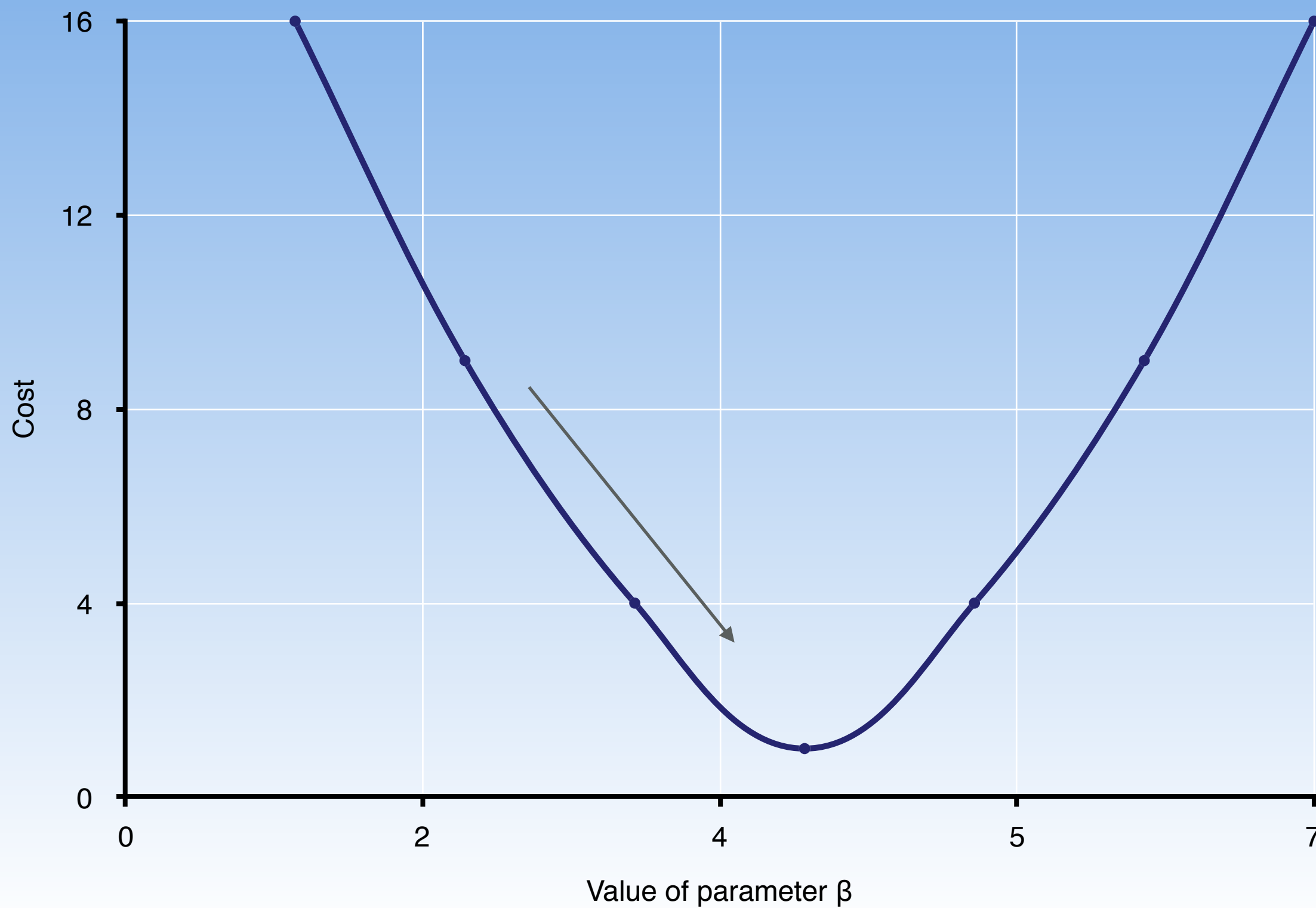


MAIN POINT

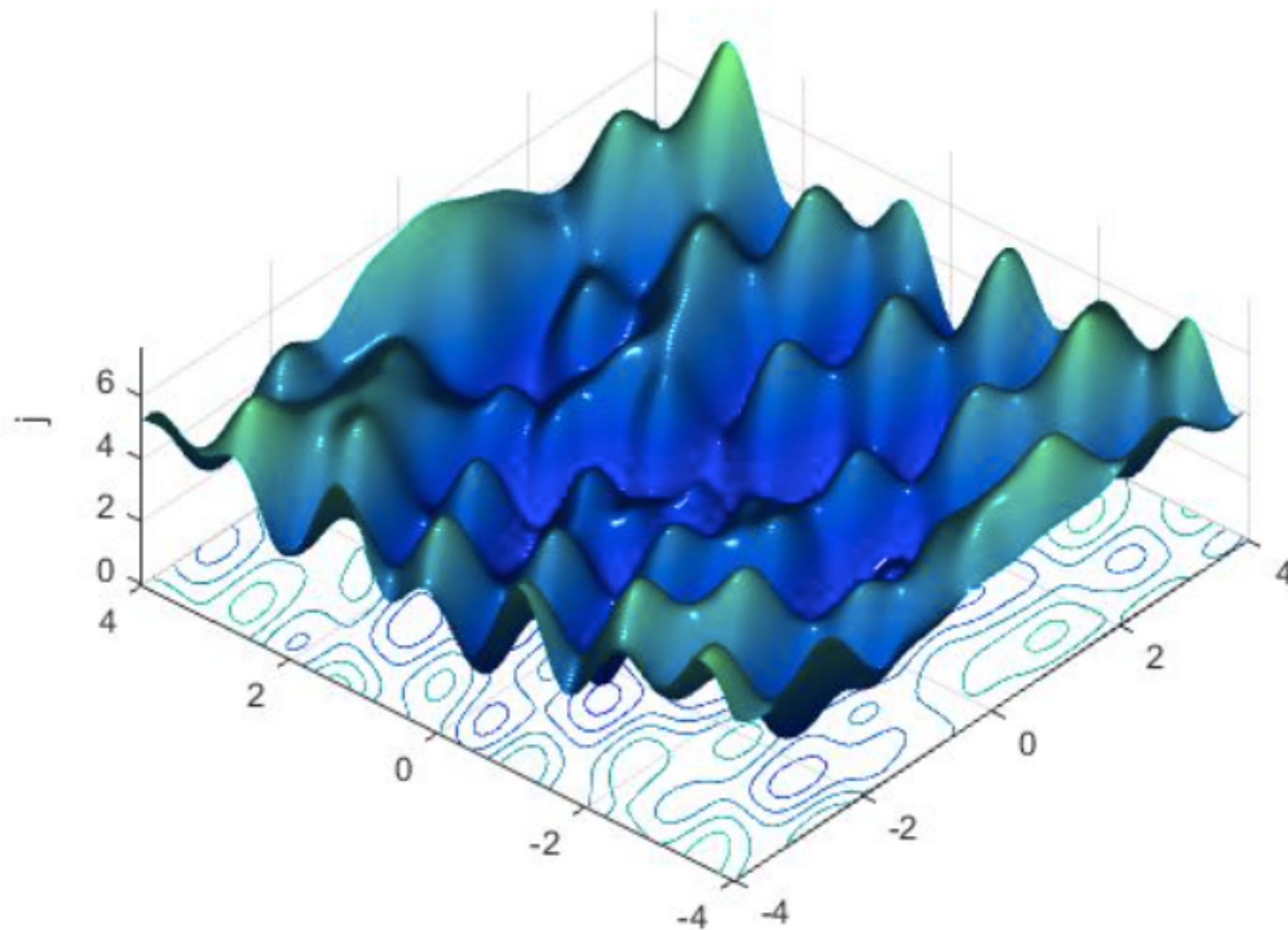
- Gradient \rightarrow allows to use error to correct the weights
- (NN is a differentiable graph)



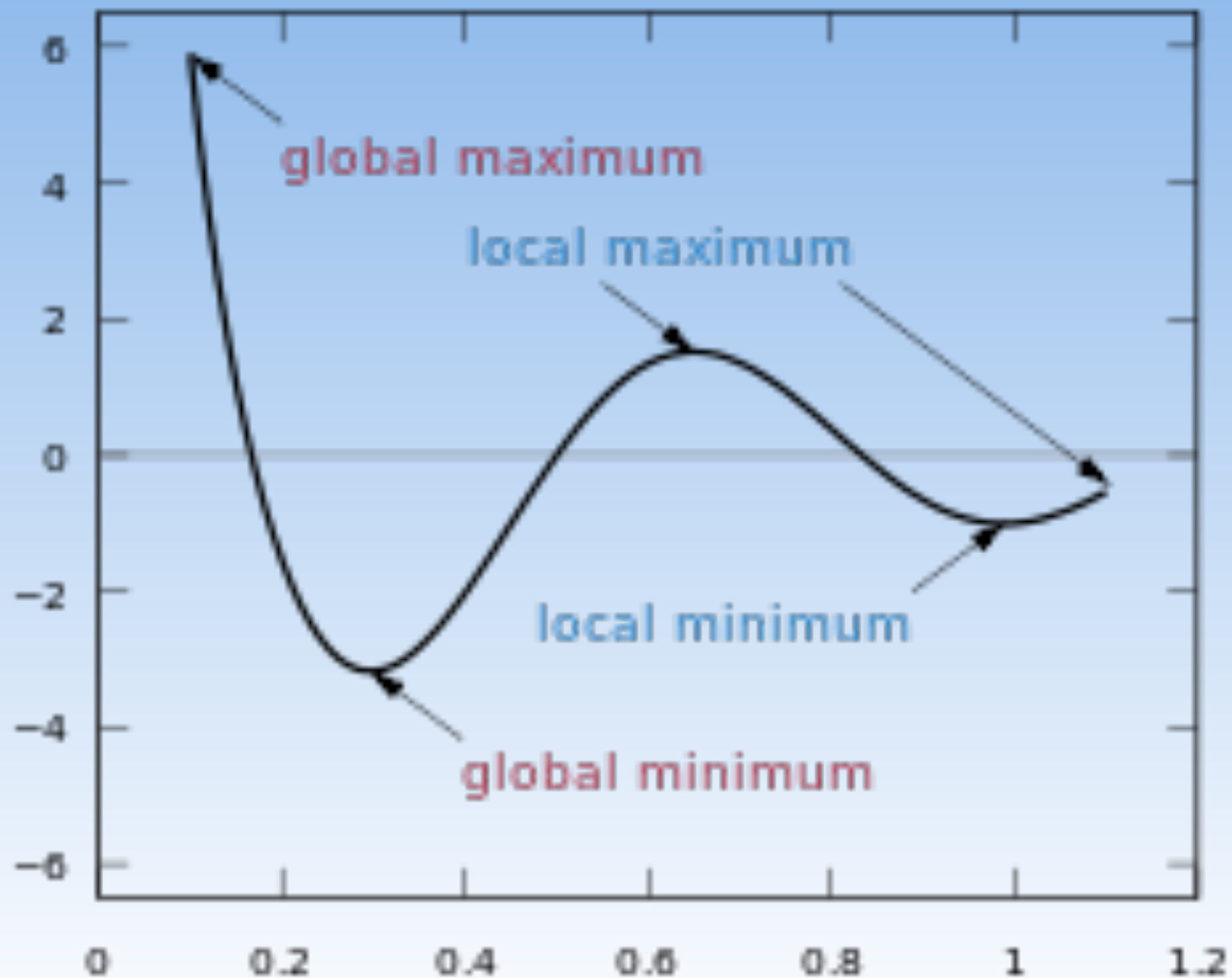
GRADIENT DESCENT



ACTUAL LOSS SURFACE

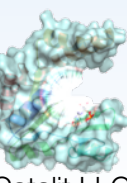


LOCAL MINIMA

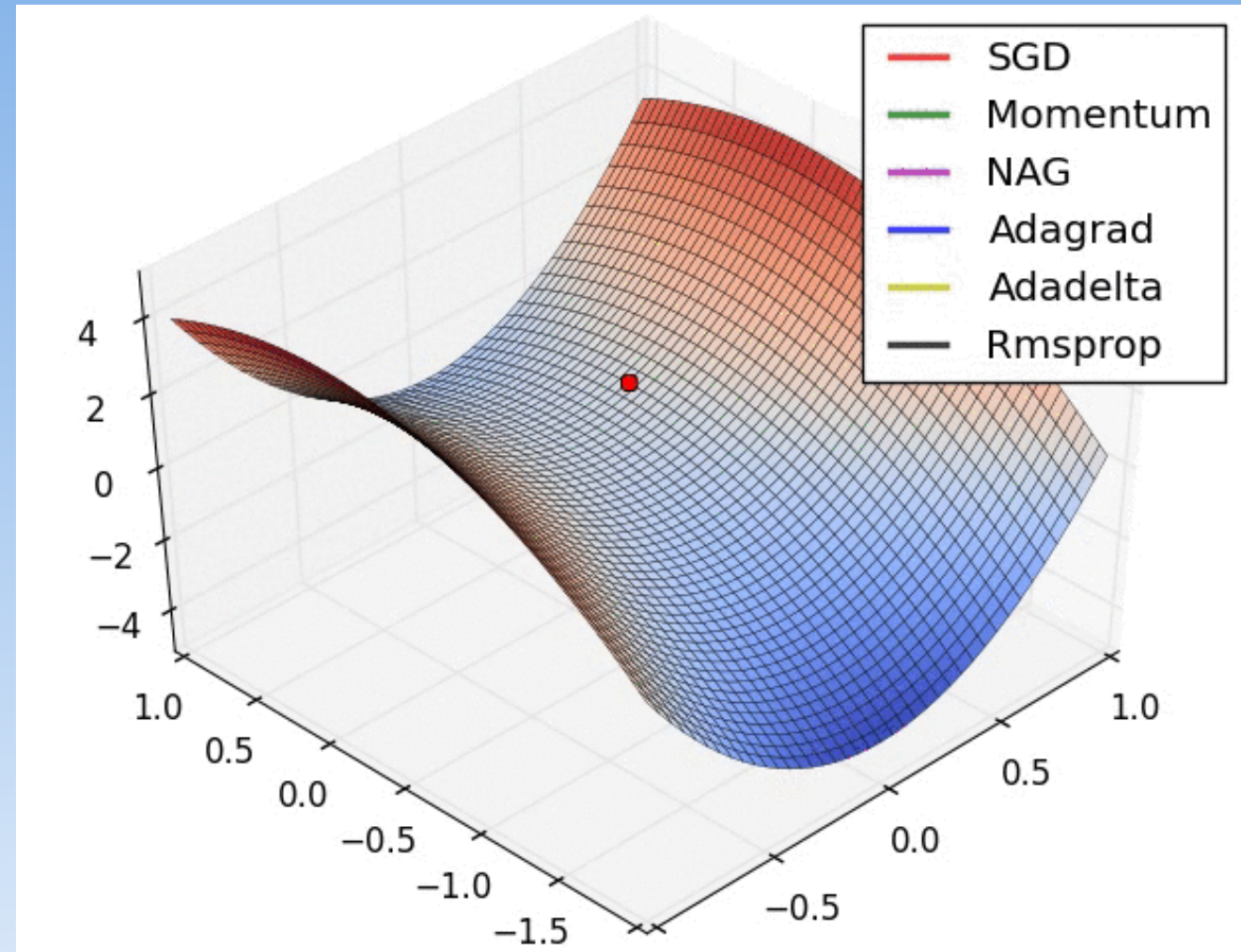
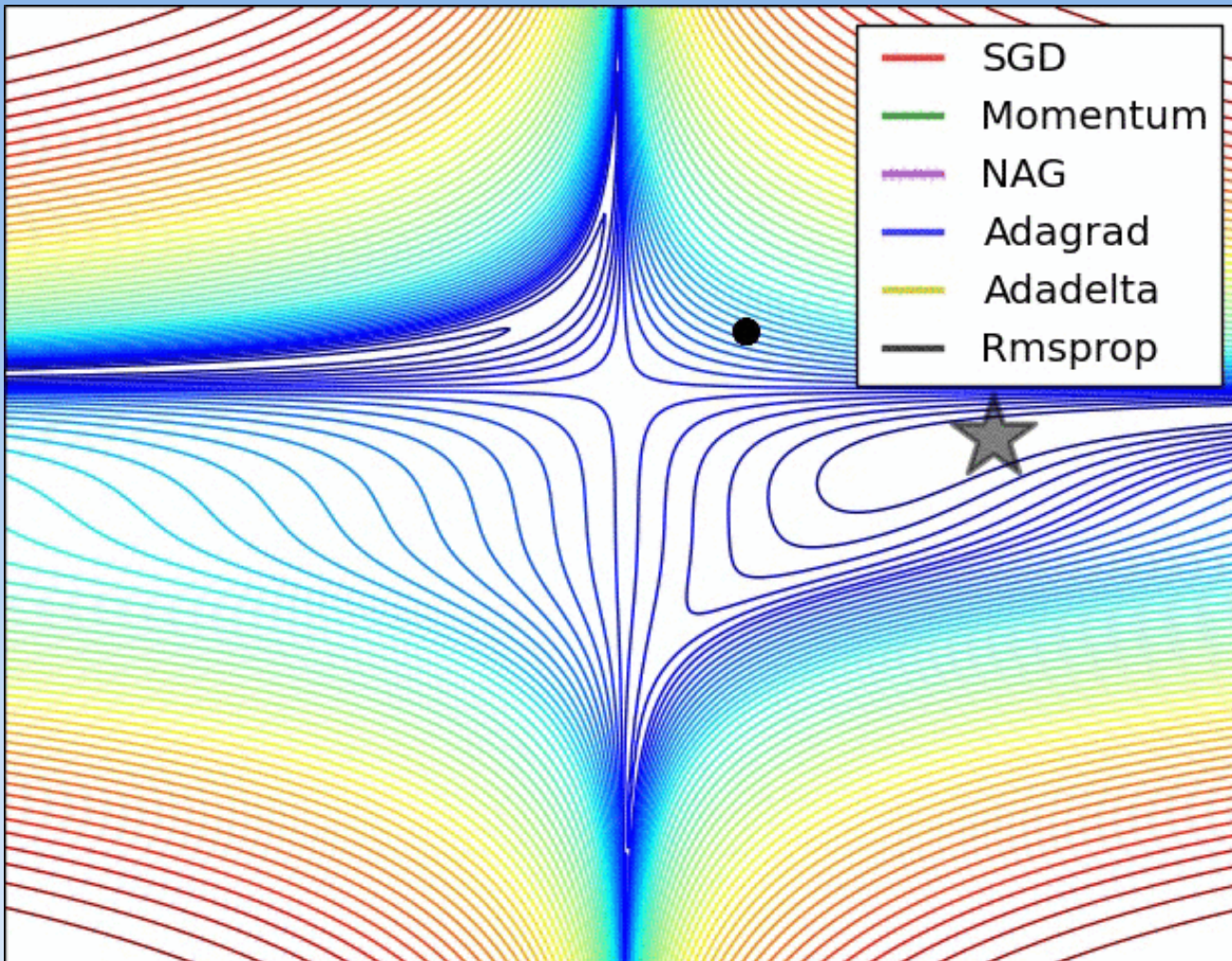


GRADIENT DESCENT

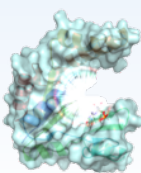
- Batch \Rightarrow Use whole dataset at each update
- Stochastic \Rightarrow Use 1 sample at each update
- Mini-batch \Rightarrow Use N samples at each update



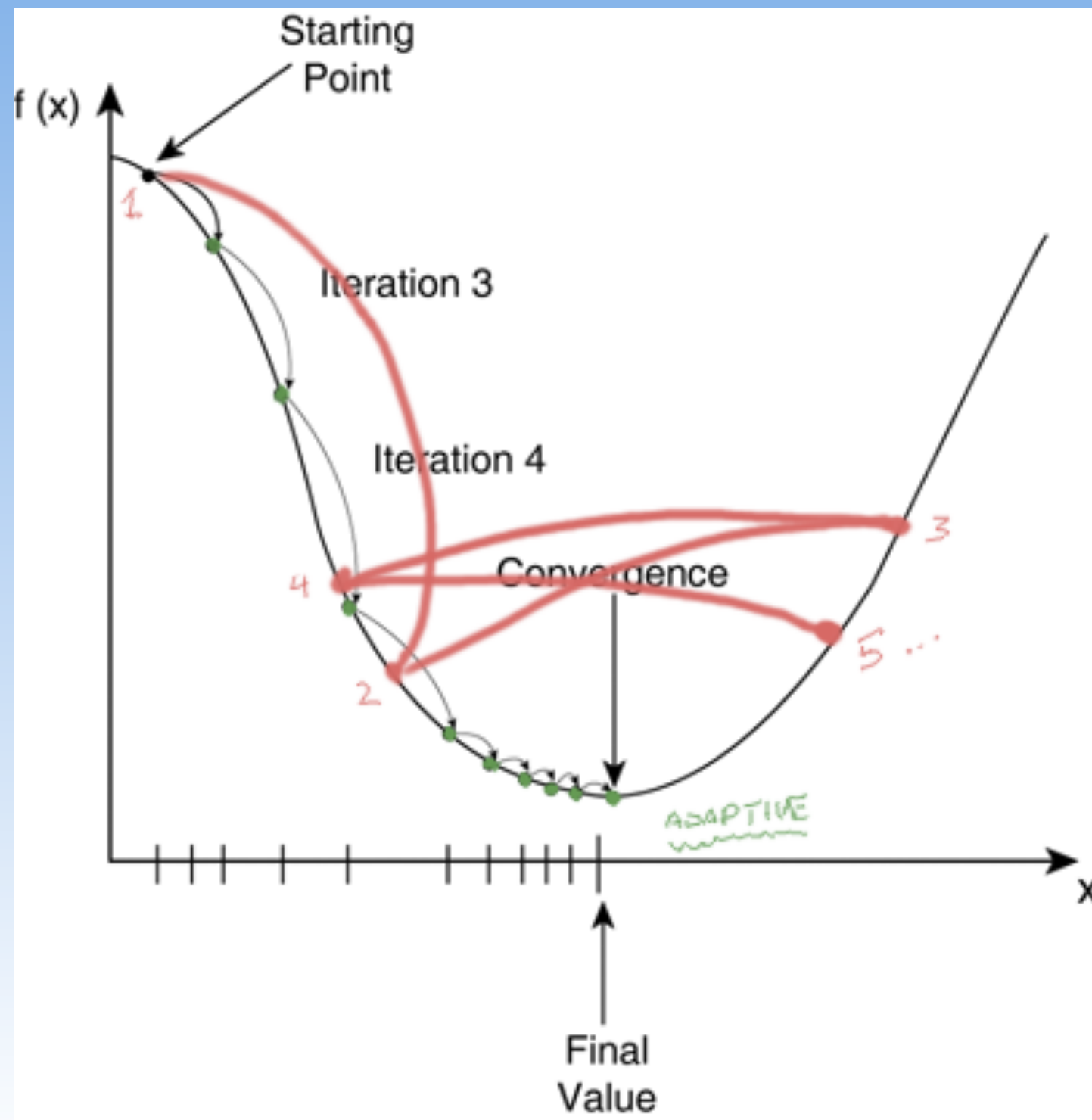
OPTIMIZERS



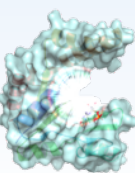
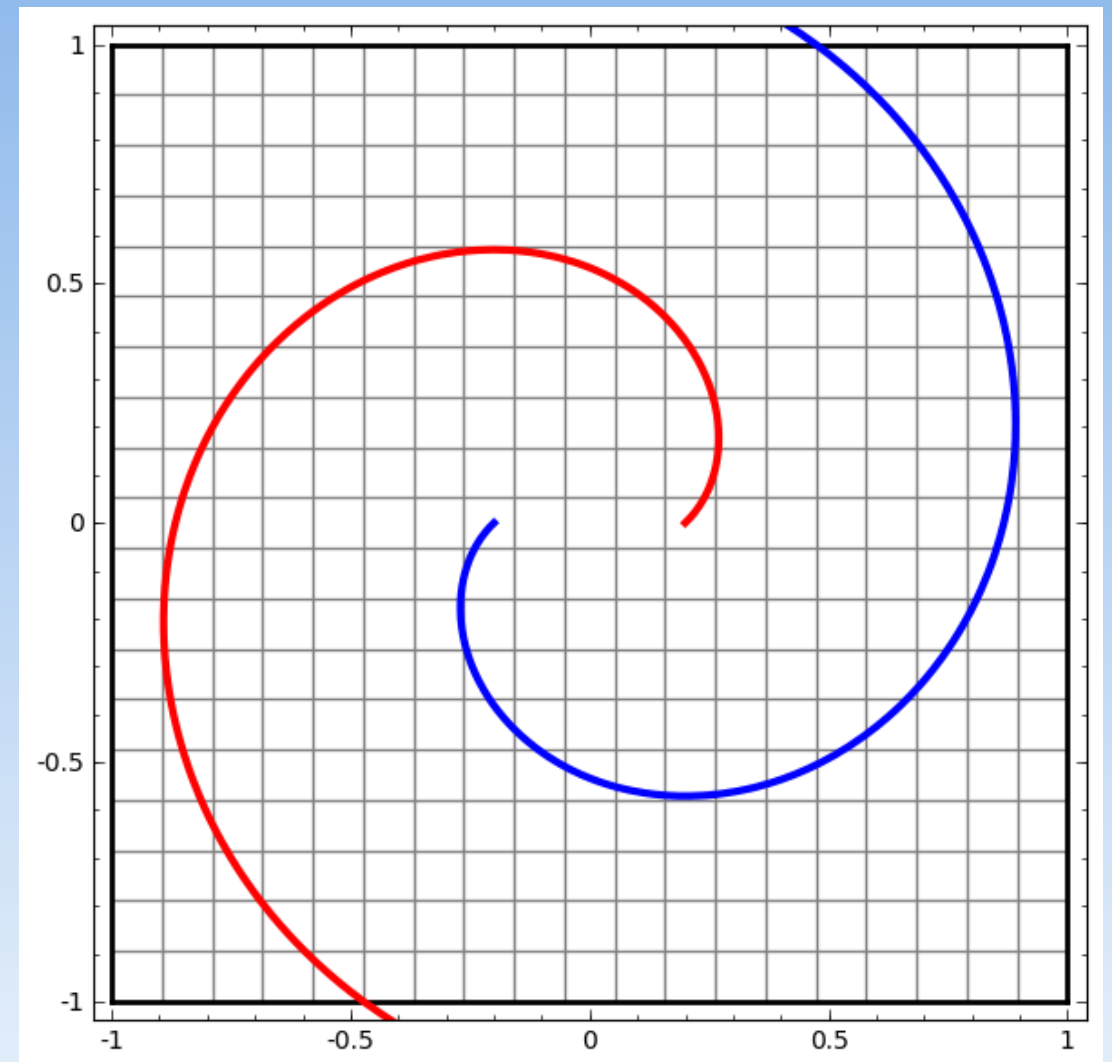
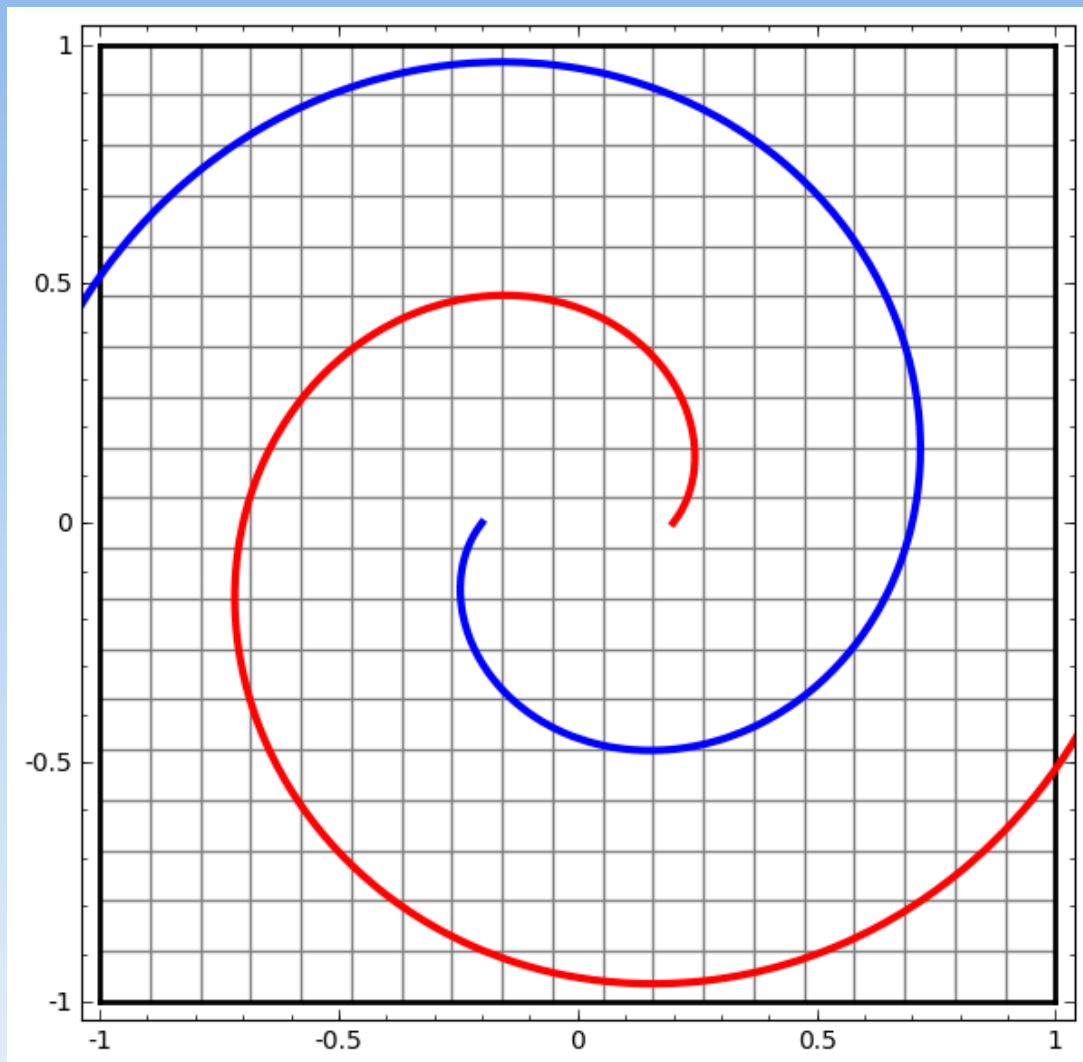
<http://sebastianruder.com/optimizing-gradient-descent/>



LEARNING RATE



ACTIVATION FUNCTION



LAB

