Introduction to Neural Networks Operations and Distributed Training

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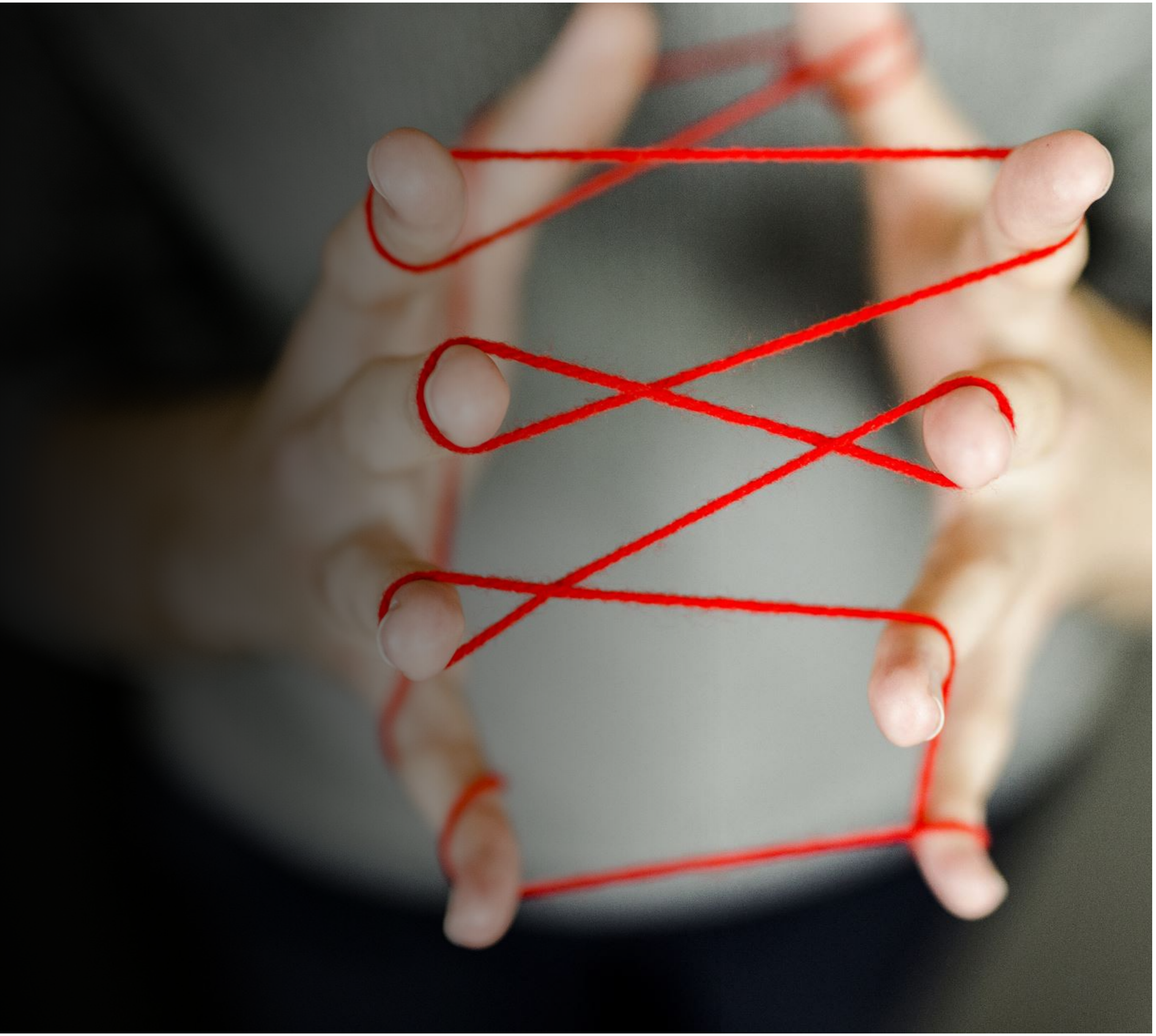
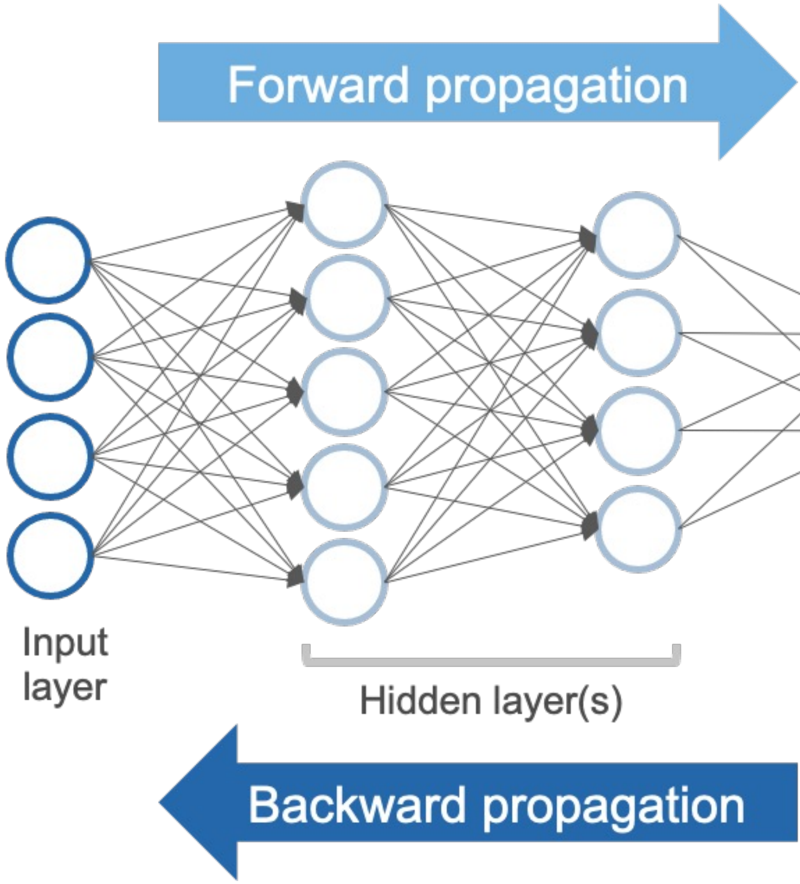
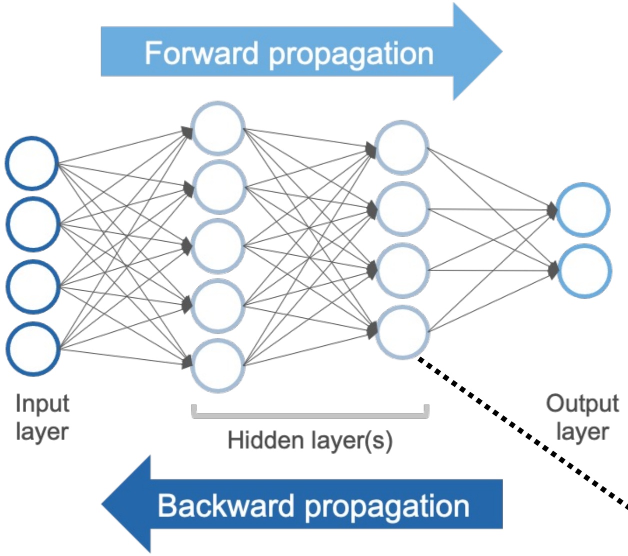
Deep Learning and GPU Programming Workshop @ 14.7.2022

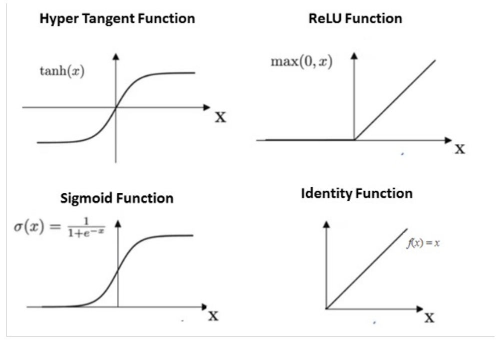


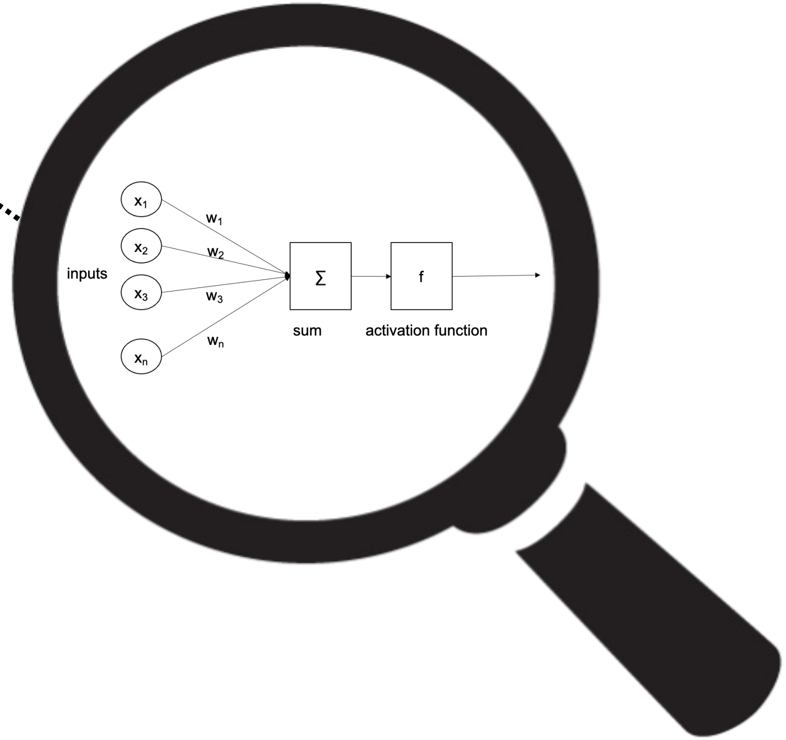
Machine Learning with (deep) Neural Networks



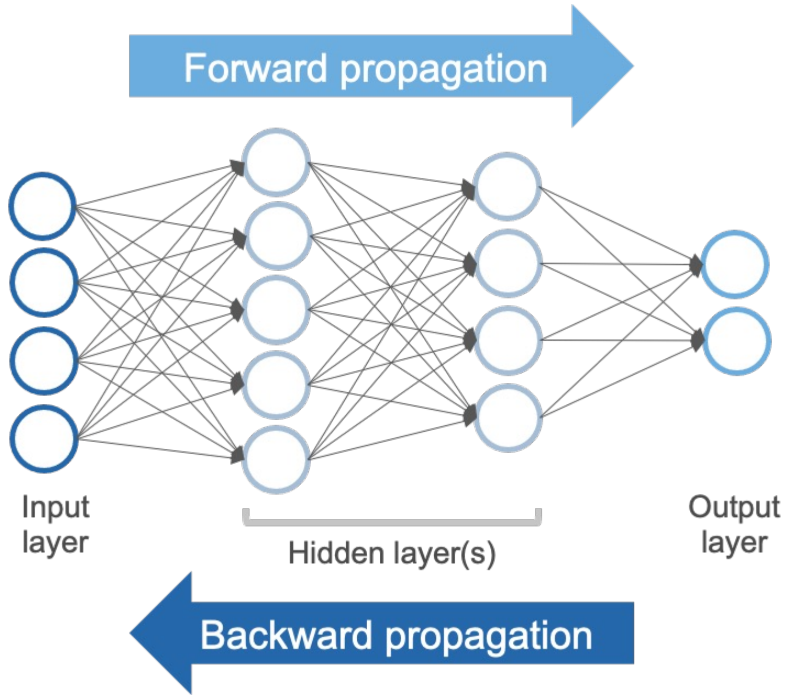
Machine Learning with (deep) Neural Networks







Machine Learning with (deep) Neural Networks



Loss function

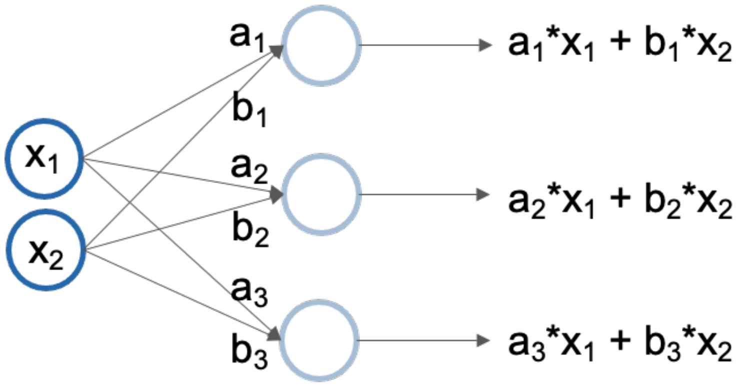
$$l = MSE = \frac{\sum_{i=1}^{n}(y_i - y_i^{p})^2}{n}$$

Optimizer SGD

$$\theta_t \leftarrow \theta_{t-1} - n_t * g(\theta_t;\ B_t)$$

$$g(\theta_t;\ B_t) = \frac{1}{|B_t|}\sum_{z \in B_t} \nabla l(\theta_t; z)$$

Forward Operations



Matrix Multiplication Operation

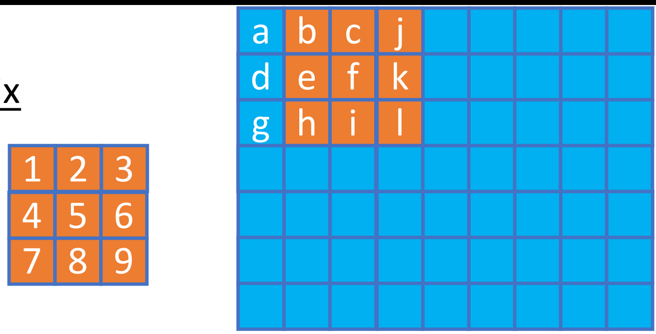
$$\begin{pmatrix} a_1 & b_1 \\ a_2 & b_2 \\ a_3 & b_3 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} a_1*x_1 + b_1*x_2 \\ a_2*x_1 + b_2*x_2 \\ a_3*x_1 + b_3*x_2 \end{pmatrix}$$

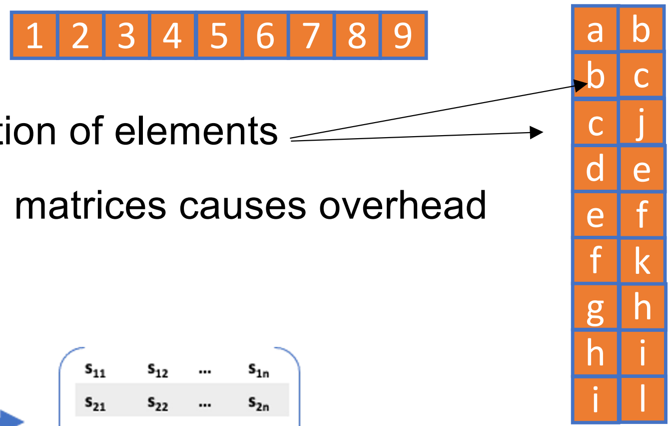
$$\begin{pmatrix} a_1 & b_1 \\ a_2 & b_2 \\ a_3 & b_3 \end{pmatrix} \begin{pmatrix} x_1 & y_1 \\ x_2 & y_2 \end{pmatrix} = \begin{pmatrix} a_1*x_1 + b_1*x_2 & a_1*y_1 + b_1*y_2 \\ a_2*x_1 + b_2*x_2 & a_2*y_1 + b_2*y_2 \\ a_3*x_1 + b_3*x_2 & a_3*y_1 + b_3*y_2 \end{pmatrix}$$

batch of two inputs

Forward Operations

<u>Convolutions as Matrix Multiplication</u>

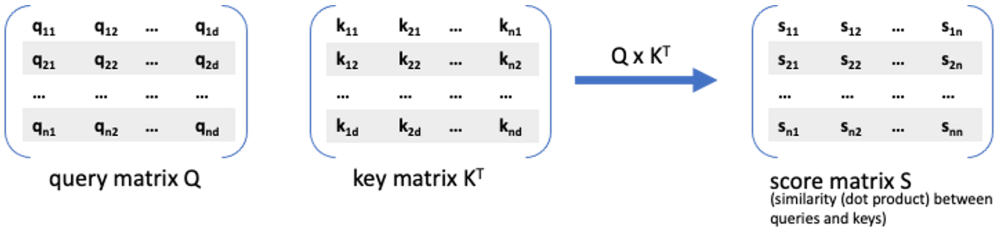


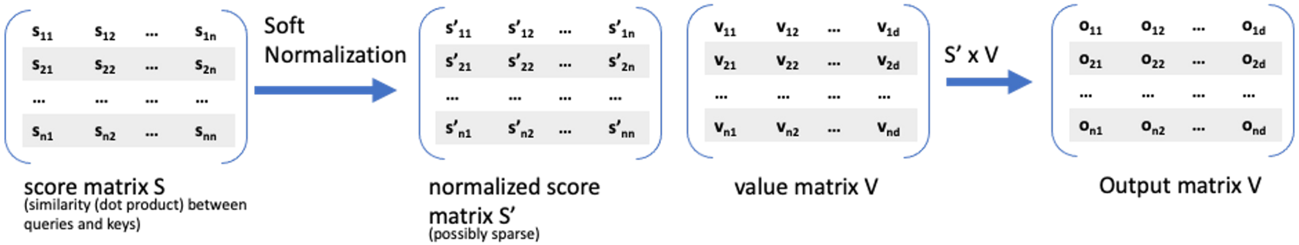


Duplication of elements

Built of special matrices causes overhead

<u>Attention Layers are also Matrix Multiplications</u>

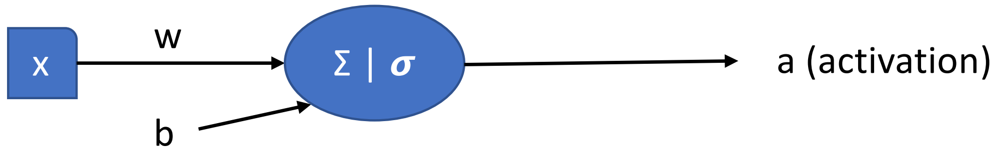




Back Propagation and Gradient Descent

- Linear regression y = w * x + b (I.e., a NN of a single neuron, and identity, f(x) = x, as activation function)

$\boldsymbol{\sigma}$ (w * x + b) = $\boldsymbol{\sigma}$ (z) if we define z as w * x + b

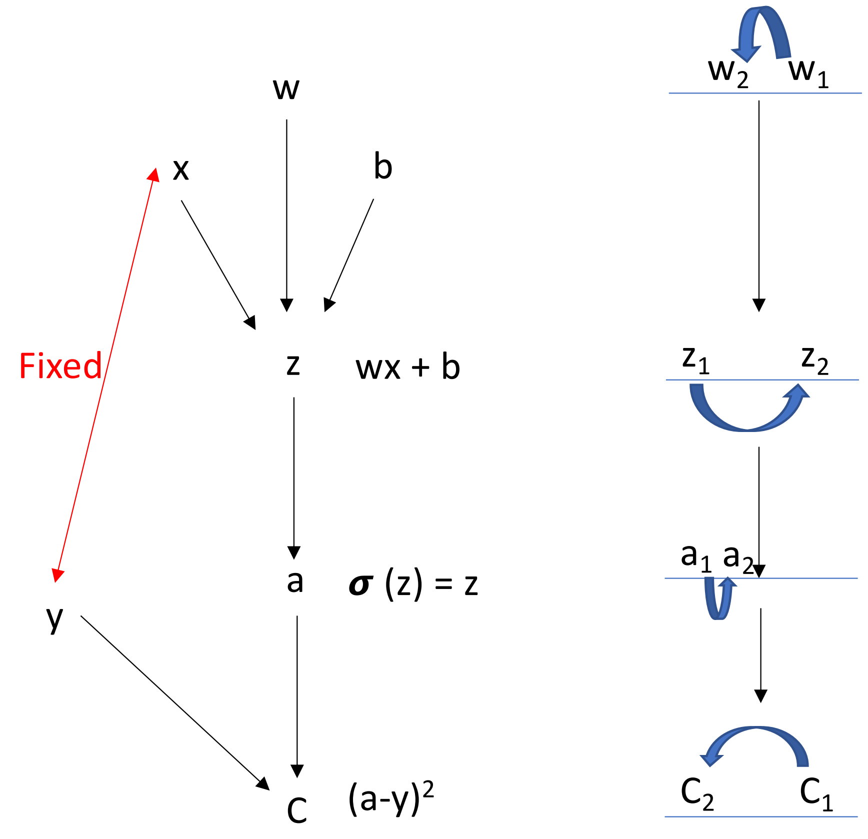


- Loss function defined as C = (a – y)2

- How does C change with w and b variations?
  - compute the ratio at with C changes with changes in w and b
  - use this ratio to modify then w and b in order to move C towards a minimum

Computing the Gradient

Gradient with a single input, that generates prediction a



$$\frac{\partial C}{\partial w} = \frac{\partial z}{\partial w}\frac{\partial a}{\partial z}\frac{\partial C}{\partial a} = 2x(a-y)$$

$$\frac{\partial z}{\partial w} = \text{x}$$

$$\frac{\partial a}{\partial z} = 1$$

$$\frac{\partial C}{\partial a} = 2(\text{a-y})$$

$$\frac{\partial C}{\partial b} = \frac{\partial z}{\partial b}\frac{\partial a}{\partial z}\frac{\partial C}{\partial a} = 2(a-y)$$

$$\frac{\partial z}{\partial b} = 1$$

$$\frac{\partial a}{\partial z} = 1$$

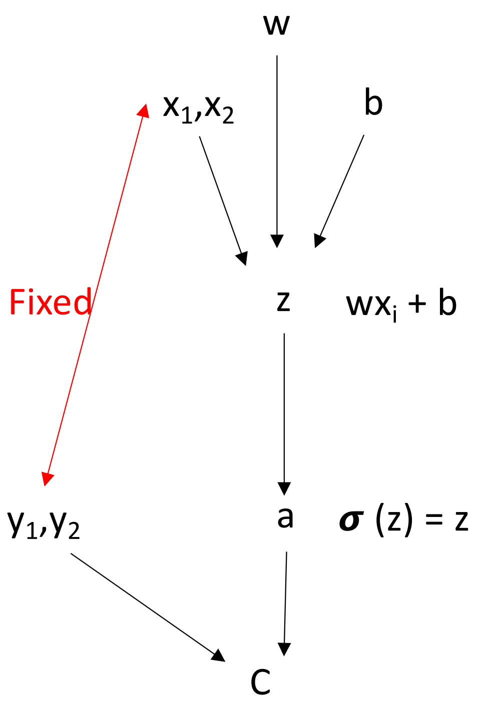
$$\frac{\partial C}{\partial a} = 2(\text{a-y})$$

Gradient Vector

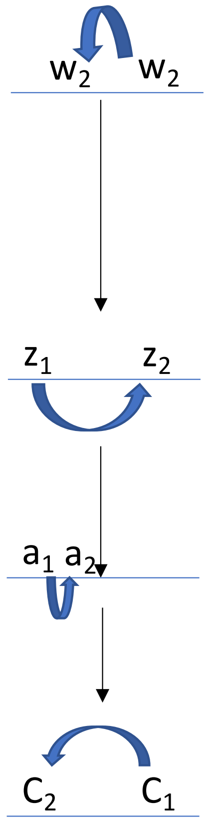
$$\begin{pmatrix} \dfrac{\partial C}{\partial w} \\ \dfrac{\partial C}{\partial b} \end{pmatrix} = \begin{pmatrix} 2x(a-y) \\ 2(a-y) \end{pmatrix}$$

Computing the Gradient

Gradient with two inputs that generates predictions: a and b



$\frac{1}{2} * ((a - y_2)^2 + (b - y_2)^2)$



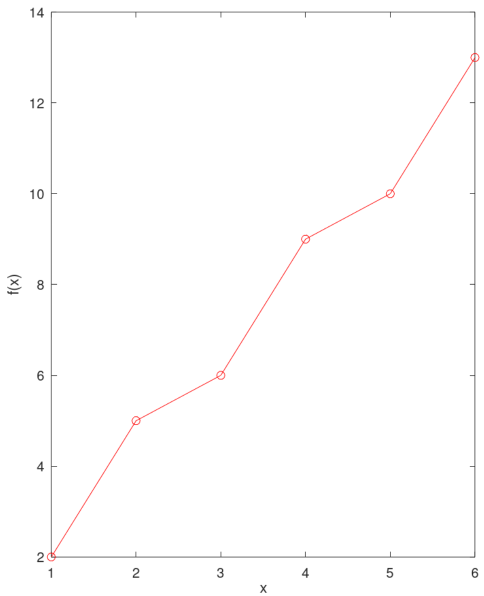
$$\frac{\partial C}{\partial w} = \frac{1}{2} * (2x(a - y_1) + 2x(b - y_2))$$

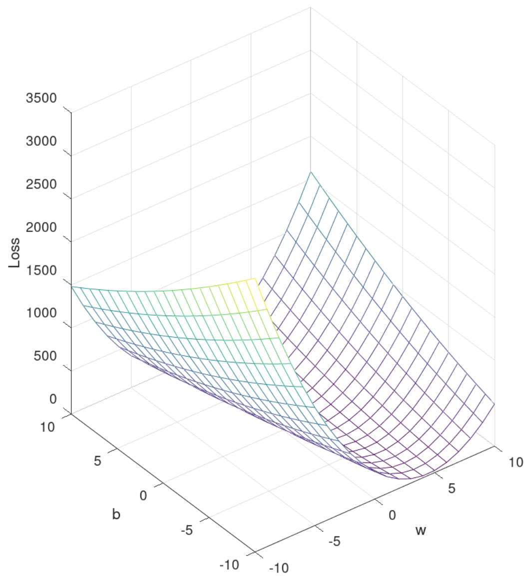
$$\frac{\partial C}{\partial b} = \frac{1}{2} * (2(a - y_1) + 2(b - y_2))$$

Gradient Vector

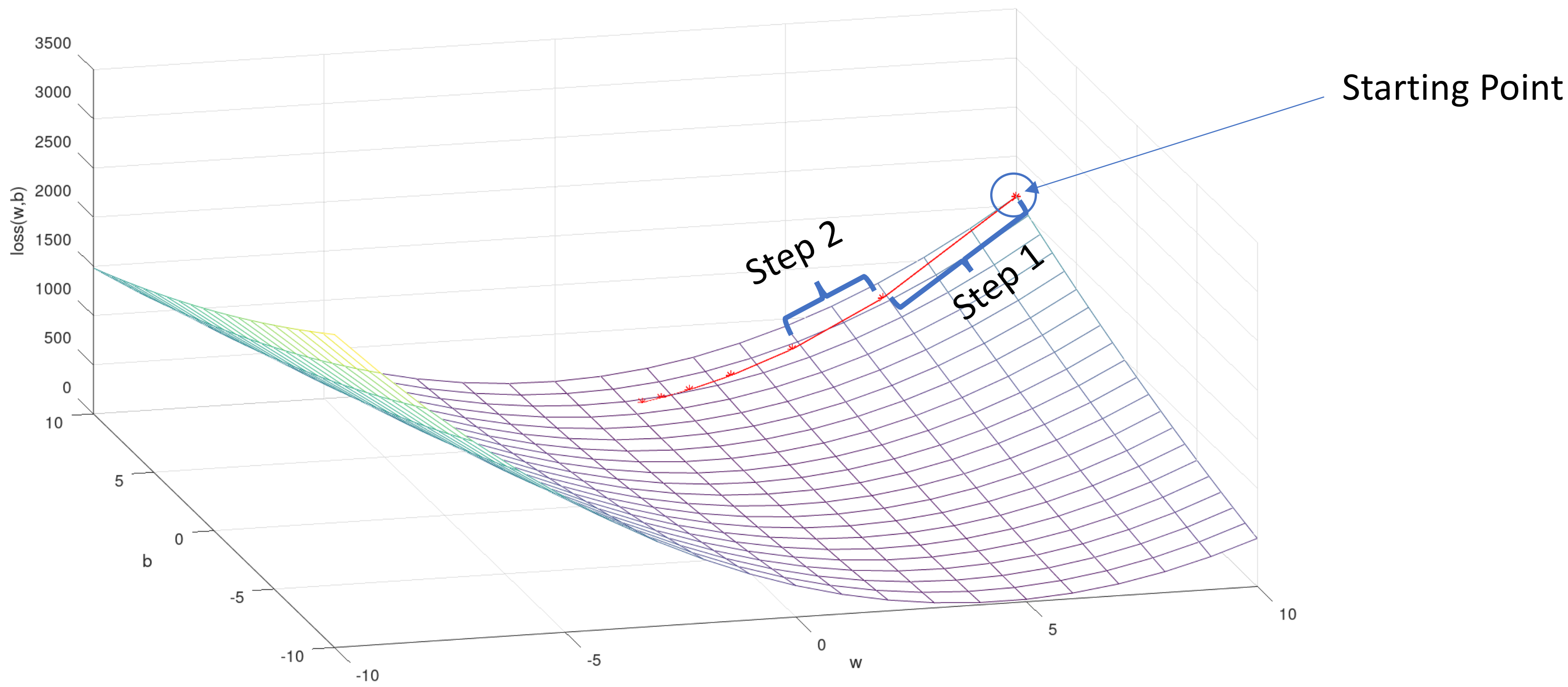
$$\begin{pmatrix} \frac{\partial C}{\partial w} \\ \frac{\partial C}{\partial b} \end{pmatrix} = \begin{pmatrix} \frac{1}{2} * (2x(a - y_1) + 2x(b - y_2)) \\ \frac{1}{2} * (2(a - y_1) + 2(b - y_2)) \end{pmatrix}$$

Back Propagation and Gradient Descent





Back Propagation and Gradient Descent



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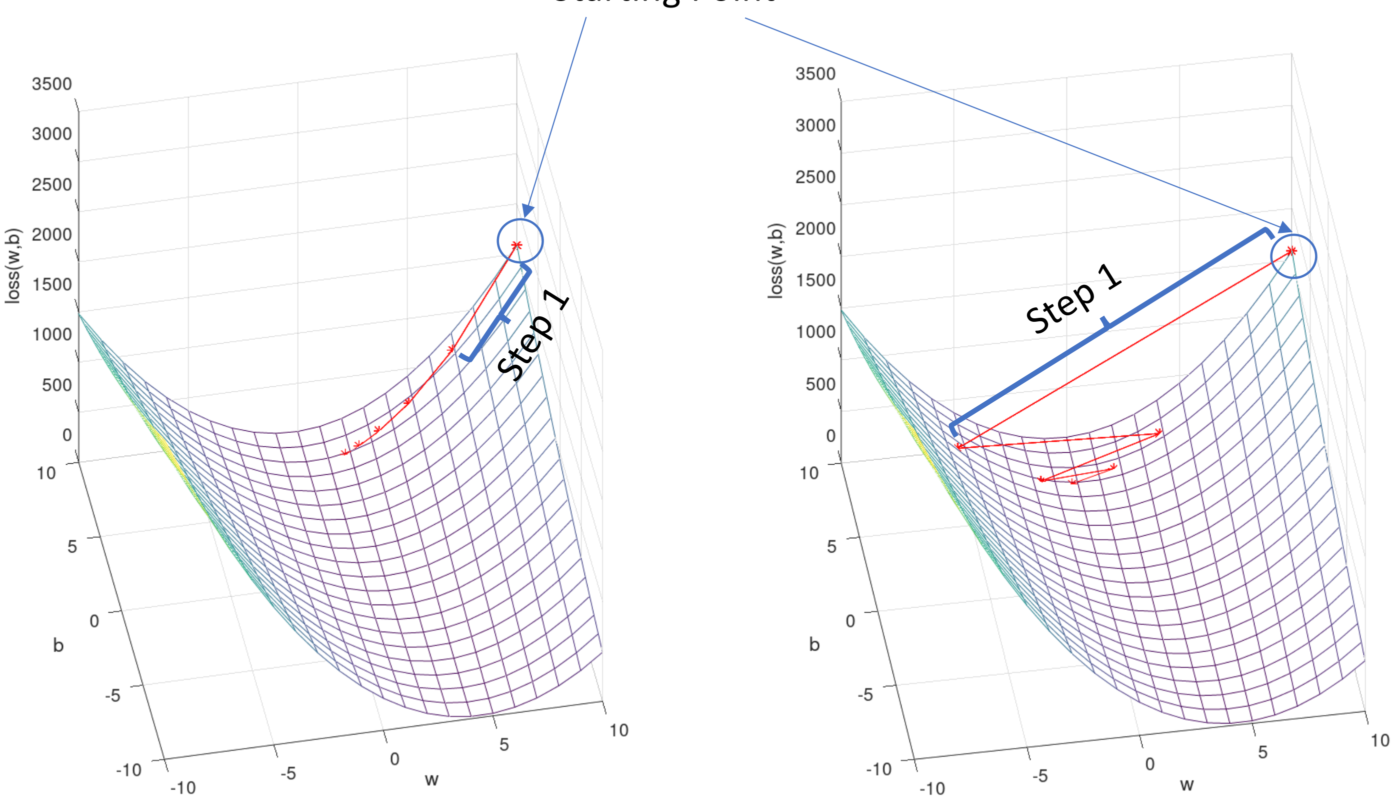
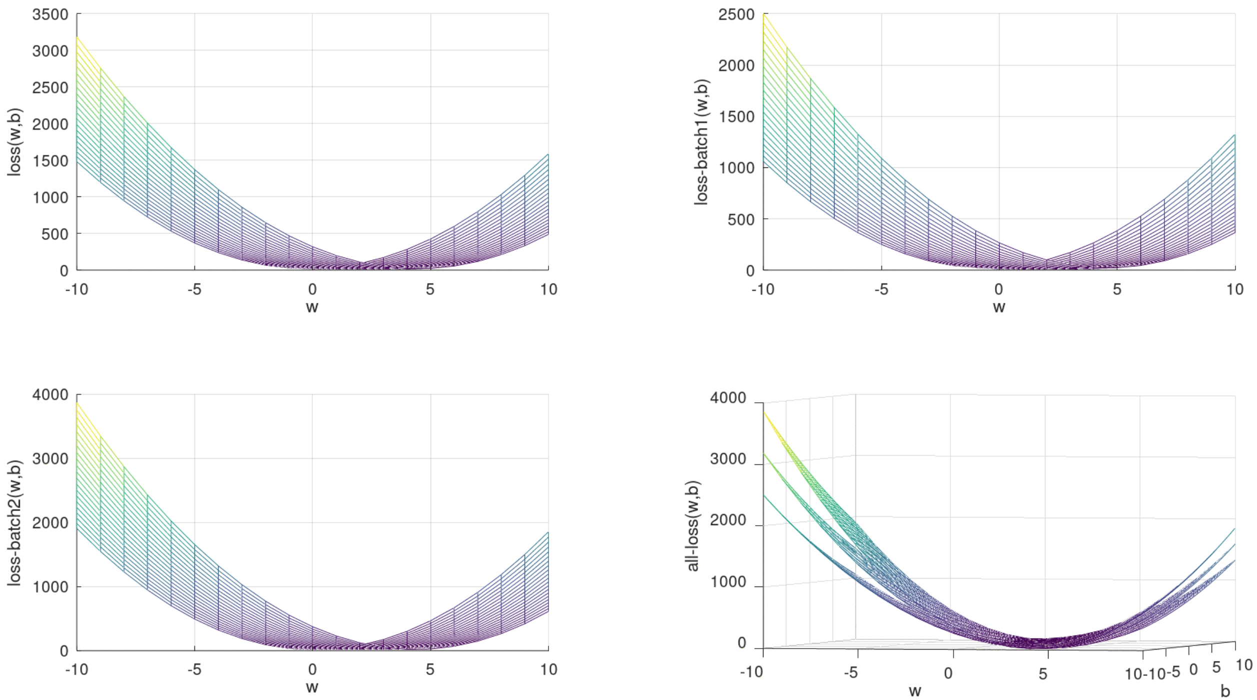


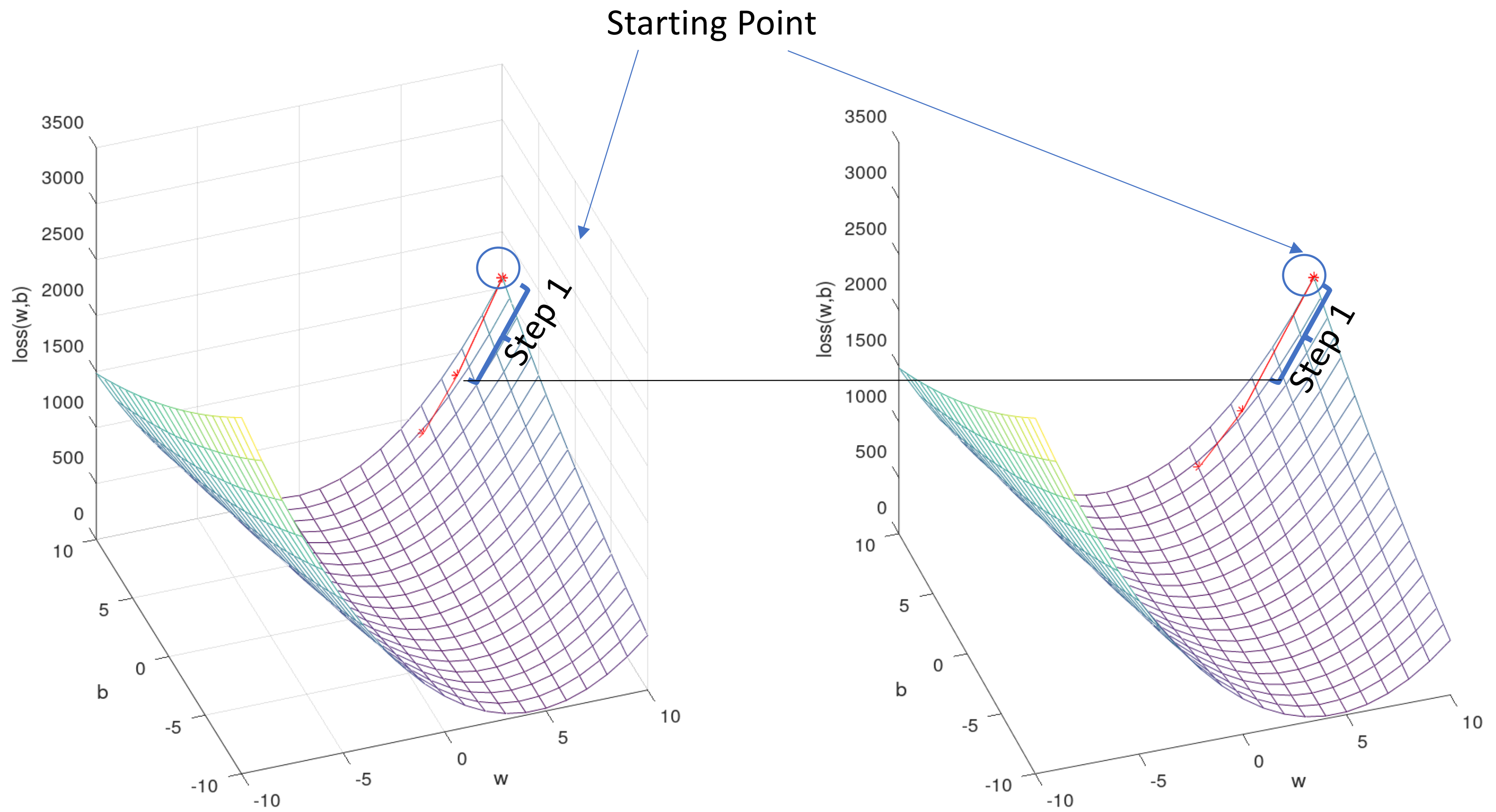
smaller learning rate

larger learning rate

Back Propagation and Gradient Descent

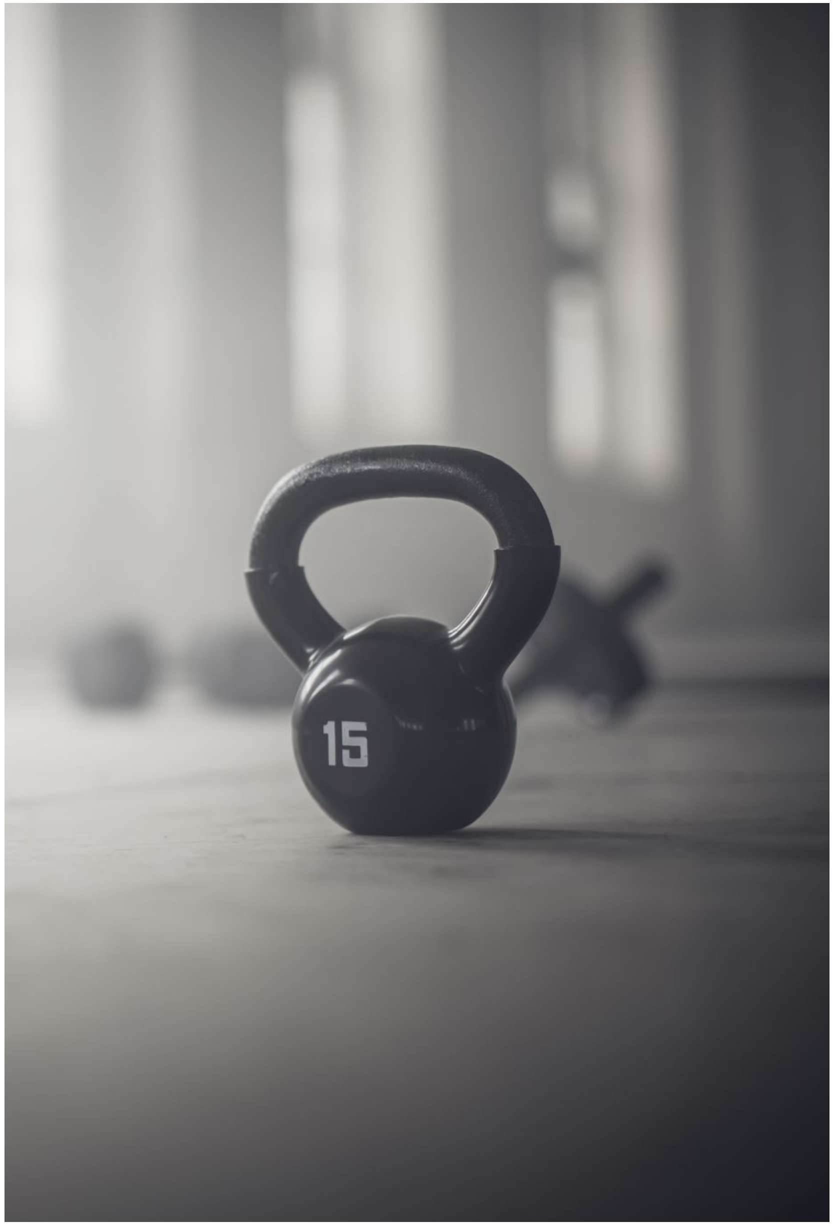


Back Propagation and Gradient Descent



gradient with batch 1

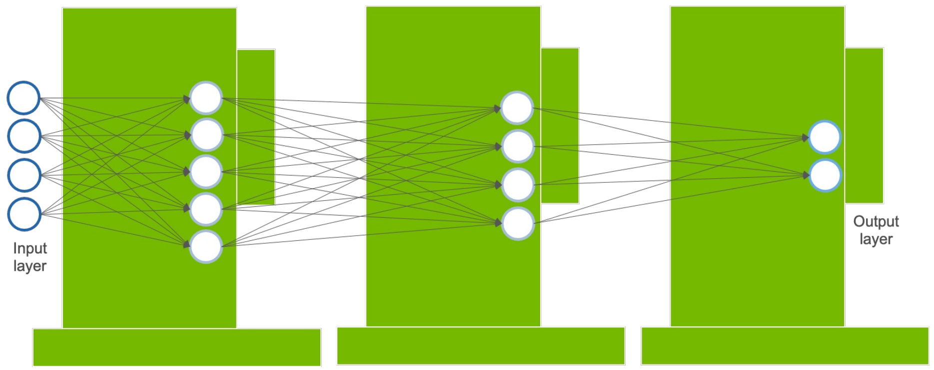
gradient with batch 2



Back Propagation and Gradient Descent

- Batch size implications
  - Smaller batches imply more steps per epoch:
    - More updates to weights --> More updates to the net
  - Smaller batches do not imply larger/smaller gradients

Parallel/Distributed ML Training



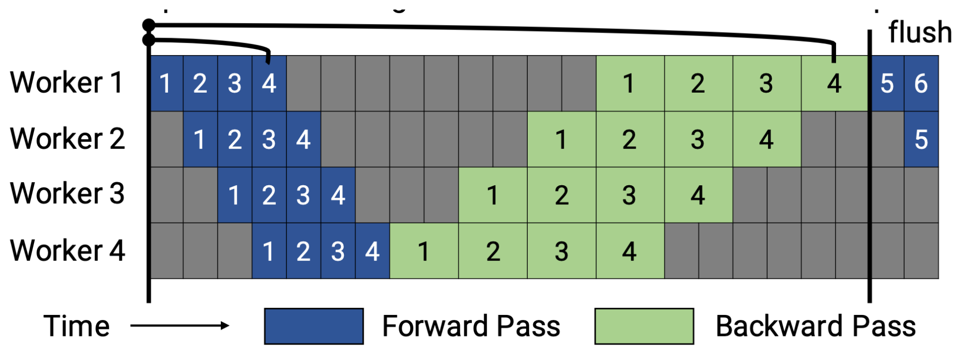
1. Model Parallelism: Memory usage and computation of a model distributed across devices

Two main variants:

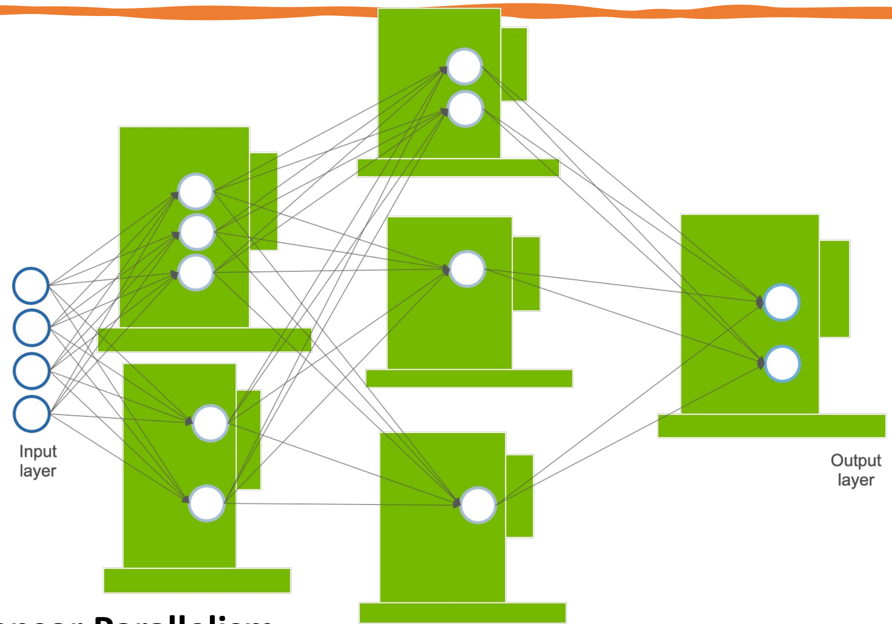
a) Pipeline parallelism
b) Tensor parallelism

Pipeline Model

- Complete layer per device
  - Weights stay within device
- Activations are communicated between GPUs
- Non efficient implementations may lead to inefficient usage of resources
  - Research area



Parallel/Distributed ML Training



1. Model Parallelism: Memory usage and computation of a model distributed across devices

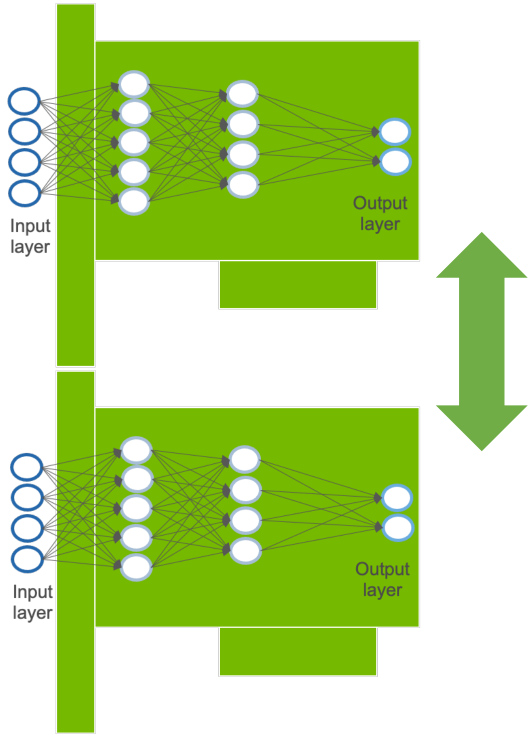
Two main variants:

a) Pipeline parallelism
b) Tensor parallelism

Tensor Parallelism

- Tensor operations (e.g., computing a layer output) distributed across device
    - Allows larger, more computationally expensive models
- Activations are communicated between GPUs
- Further points for inefficiencies
    - A device might depend on the activations computed by more than one device

Parallel/Distributed ML Training



2. Data Parallelism: Training mini-batch is split across devices

- Model must fit into the memory of a single device
- Weights are the same in each device
  - Gradients are communicated across all devices (all-to-all)