FRIEDRICH-ALEXANDER-UNIVERSITÄT ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Neural Networks

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Flexibility vs. Abstraction

Low level → High level

cuDNN

- Linear Algebra operations
- Bare metal

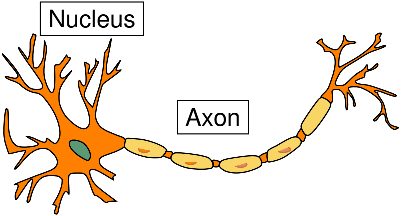
TensorFlow

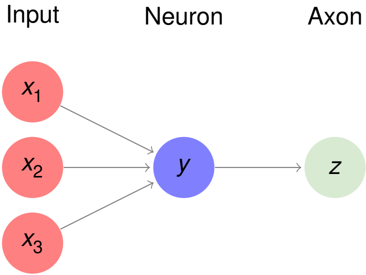
- Compiles graphs of Tensor operations
- High flexibility

K

- Stacks together elementary layers
- Reduced flexibility

Artifical Neural Networks





$$\mathbf{y} = f\left(\sum_{i}^{N} w_i x_i\right)$$

Neural Network

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- is responsible for holding a **graph of layers**, whereas a "layer" represents a function (e.g. ReLU) or operation (e.g. convolution)
  - we allow only extremely simple graphs
  - with a list of layers
  - and only one data source
  - and one loss function

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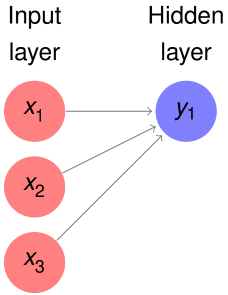
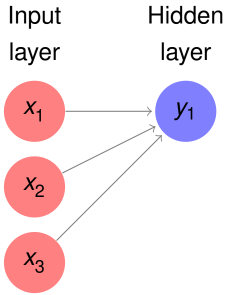
- **recursively calls backward** on its layers passing the error
- in our case stores the loss over iterations, while in other frameworks this is commonly separated into an optimizer class

Fully Connected Layer

Forward



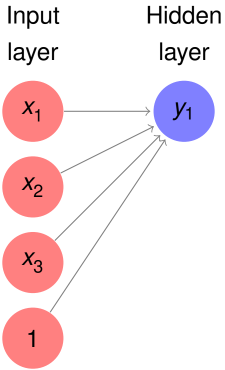
Forward



$$\begin{pmatrix} w_1 \\ \vdots \\ w_n \end{pmatrix}^T \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} + w_{n+1} = \hat{y}$$

$$\mathbf{w}^T \mathbf{x} = \hat{y}$$

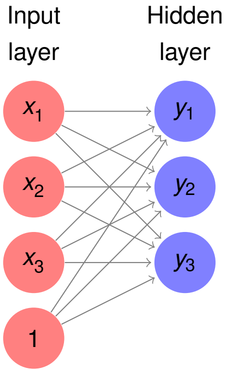
Forward



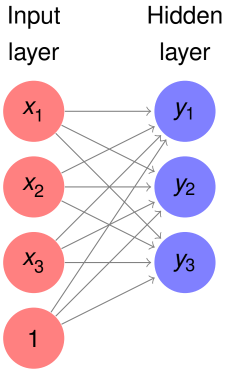
$$\begin{pmatrix} w_1 \\ \vdots \\ w_n \\ w_{n+1} \end{pmatrix}^T \begin{pmatrix} x_1 \\ \vdots \\ x_n \\ 1 \end{pmatrix} = \hat{y}$$

$$\mathbf{w}^T\mathbf{x} = \hat{y}$$

Forward



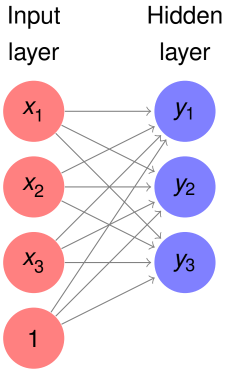
Forward



$$\begin{pmatrix} w_{1,1} & \cdots & w_{1,m} \\ \vdots & \ddots & \vdots \\ w_{n,1} & \cdots & w_{n,m} \\ w_{n+1,1} & \cdots & w_{n+1,m} \end{pmatrix}^T \begin{pmatrix} x_1 \\ \vdots \\ x_n \\ 1 \end{pmatrix} = \begin{pmatrix} \hat{y}_1 \\ \vdots \\ \hat{y}_m \end{pmatrix}$$

$$\mathbf{W}\mathbf{x} = \hat{\mathbf{y}}$$

Forward



$$\begin{pmatrix} w_{1,1} & \cdots & w_{1,m} \\ \vdots & \ddots & \vdots \\ w_{n,1} & \cdots & w_{n,m} \\ w_{n+1,1} & \cdots & w_{n+1,m} \end{pmatrix}^T \begin{pmatrix} x_{1,1} & \cdots & x_{1,b} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \cdots & x_{n,b} \\ 1 & \cdots & 1 \end{pmatrix}$$

$$\mathbf{WX} = \hat{\mathbf{Y}} \tag{1}$$

Backward

- Return gradient with respect to **X**:

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$$\mathbf{E}_{n-1} = \mathbf{W}^{\mathbf{T}}\mathbf{E}_n \tag{2}$$

- $\mathbf{E_n}$: **error_tensor** passed downward

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- Update **W** using gradient with respect to **W**:

- $\mathbf{E_n}$: **error_tensor** passed downward

Backward

- Return gradient with respect to **X**:

$$\mathbf{E}_{n-1} = \mathbf{W}^{\mathbf{T}}\mathbf{E}_n \tag{2}$$

- Update **W** using gradient with respect to **W**:

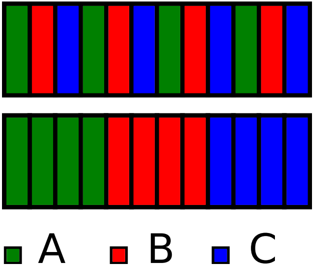
$$\mathbf{W}^{t+1} = \mathbf{W}^{t} - \eta \cdot \mathbf{E_n}\mathbf{X}^{T} \tag{3}$$

  Note: Dynamic programming part of Backpropagation

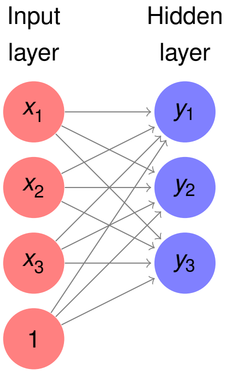
- $\mathbf{E_n}$: **error_tensor** passed downward
- η: learning rate

Memory Layout

- Numpy uses C ordering by default
- Wrong ordering will cause strided data access
- We want the batch size to be the outermost loop
  $\rightarrow$ We have to adjust our formulas for the implementation



Forward - Our Memory Layout



$$\begin{pmatrix} x_{1,1} & \dots & x_{1,b} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \dots & x_{n,b} \\ 1 & \dots & 1 \end{pmatrix}^T \begin{pmatrix} w_{1,1} & \dots & w_{1,m} \\ \vdots & \ddots & \vdots \\ w_{n,1} & \dots & w_{n,m} \\ w_{n+1,1} & \dots & w_{n+1,m} \end{pmatrix}$$

$$\mathbf{X}'\mathbf{W}' = \hat{\mathbf{Y}}' \tag{4}$$

with

$$\mathbf{X}' = \mathbf{X}^{\mathsf{T}},\ \mathbf{W}' = \mathbf{W}^{\mathsf{T}},\ \hat{\mathbf{Y}}' = \hat{\mathbf{Y}}^{\mathsf{T}} \tag{5}$$

$$\hat{\mathbf{Y}}^{\mathsf{T}} = (\mathbf{W}\mathbf{X})^{\mathsf{T}} = \mathbf{X}^{\mathsf{T}}\mathbf{W}^{\mathsf{T}} \tag{6}$$

Backward - Our Memory Layout

- Return gradient with respect to **X**:

$$\mathbf{E}'_{\mathbf{n-1}} = \mathbf{E}'_{\mathbf{n}}\mathbf{W}'^{\mathbf{T}} \quad (7)$$

- Update $\mathbf{W}'$ using gradient with respect to $\mathbf{W}'$:

$$\mathbf{W}'^{t+1} = \mathbf{W}'^{t} - \eta \cdot \mathbf{X}'^{\mathbf{T}}\mathbf{E}'_{\mathbf{n}} \quad (8)$$

Note: Dynamic programming part of Backpropagation

- $\mathbf{E}'_{\mathbf{n}}$: **error_tensor** passed downward
- η: learning rate

Basic Optimization

SGD

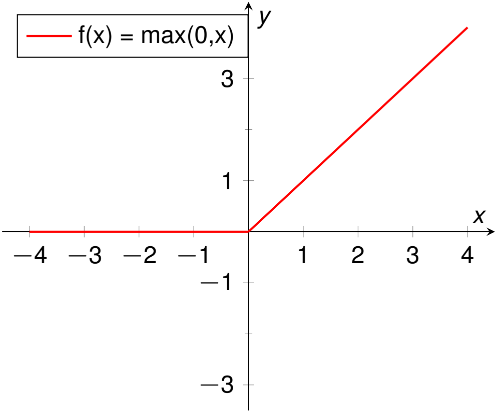
- In order to perform the aforementioned weight update we make use of a dedicated optimizer.
- In the first exercise we implement the Stochastic Gradient Descent Algorithm

$$\mathbf{w}^{(k+1)} = \mathbf{w}^{(k)} - \eta \underbrace{\nabla L(\mathbf{w}^{(k)})}_{\textit{Gradient}}$$

where η denotes the learning rate.

ReLU Activation Function

Forward



Backward

ReLU is not continuously differentiable!

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$$e_{n-1} = \begin{cases} 0 & \text{if } x \leq 0 \\ e_n & \text{else} \end{cases} \tag{9}$$

Note: DP part of Backpropagation yet again

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Note: DP part of Backpropagation yet again

- The scalar e is because activation functions operate elementwise on $\mathbf{E}$
- If you wonder about e_n instead of 1 consider that this is $\underbrace{\frac{\partial L}{\partial \hat{\mathbf{y}}}}_{\mathbf{E}} \cdot \underbrace{\frac{\partial \hat{\mathbf{y}}}{\partial \mathbf{x}}}_{\text{ReLU}}$

SoftMax Activation Function

Forward

Labels as N-dimensional **one hot** vector $\mathbf{y}$: $\begin{pmatrix} \vdots \\ 1 \\ \vdots \end{pmatrix}$

Forward

Labels as N-dimensional **one hot vector y**: $\begin{pmatrix} \vdots \\ 1 \\ \vdots \end{pmatrix}$

- Activation(Prediction) $\hat{\mathbf{y}}$ for every element of the batch of size B:

$$\hat{y}_k = \frac{\exp(x_k)}{\sum_{j=1}^{N} \exp(x_j)} \tag{10}$$

Numeric

- If $x_k > 0 \rightarrow e^{x_k}$ might become very large
- To increase numerical stability x_k can be shifted
- $\tilde{x}_k = x_k - \max(\mathbf{x})$
- This leaves the scores unchanged!

$$\frac{\exp(\tilde{x}_k)}{\sum_j \exp(\tilde{x}_j)} = \frac{\exp(x_k) \cdot \cancel{\exp(-x_{max})}}{\sum_j \exp(x_j) \cdot \cancel{\exp(-x_{max})}} \checkmark$$

Backward

- Compute for every element of the batch:

$$\mathbf{E}_{n-1} = \hat{y}\left(\mathbf{E}_n - \sum_{j=1}^{N} \mathbf{E}_{n,j}\hat{y}_j\right) \tag{11}$$

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- All operations are element-wise

Backward

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- All operations are element-wise
- Notice the similarity to the sigmoid gradient $\hat{y}(1 - \hat{y})$

Cross Entropy Loss

Forward

$$loss = \sum_{b=1}^{B} - \ln\left(\hat{y}_k + \epsilon\right) \ \textbf{where } y_k = 1 \tag{12}$$

- ϵ represents the smallest representable number. Take a look into *np.finfo.eps*
- ϵ increases stability for very wrong predictions to prevent values close to $log(0)$

Forward

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- ϵ represents the smallest representable number. Take a look into *np.finfo.eps*
- ϵ increases stability for very wrong predictions to prevent values close to $log(0)$
- Notice: the Cross Entropy Loss requires predictions to be greater than 0,
- thus the Cross Entropy Loss works most stable with SoftMax predictions.

Backward

$$\mathbf{E}_n = -\frac{y}{\hat{y}} \tag{13}$$

- ϵ cancels out due to derivation. An additional ϵ would distort the gradient dramatically!
- The gradient prohibits predictions of 0 as well.

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- The gradient prohibits predictions of 0 as well.
- Notice that this does **not** depend on an error $\mathbf{E}$.
  $\rightarrow$ it's the starting point of the recursive computation of gradients.

Thanks for listening.

Any questions?