# MNIST Training for BNN

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Design Your Own CPU - Design of Embedded Systems

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   - What is a neural network?
   - Training
   - Our Goal
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   - Layers
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3. **BNN Training Analysis**
   - Layer Analysis
   - Parameter Analysis

# What is a neural network?

## What is a neural network?

- The heart of deep learning

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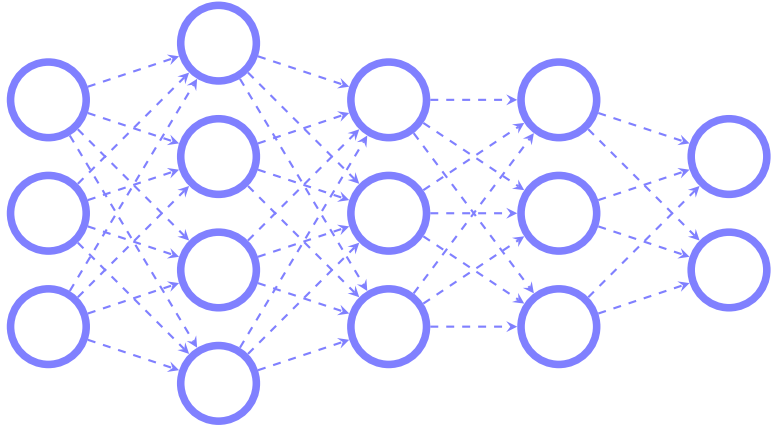
- Classify given data
  *e.g. speech or image recognition*

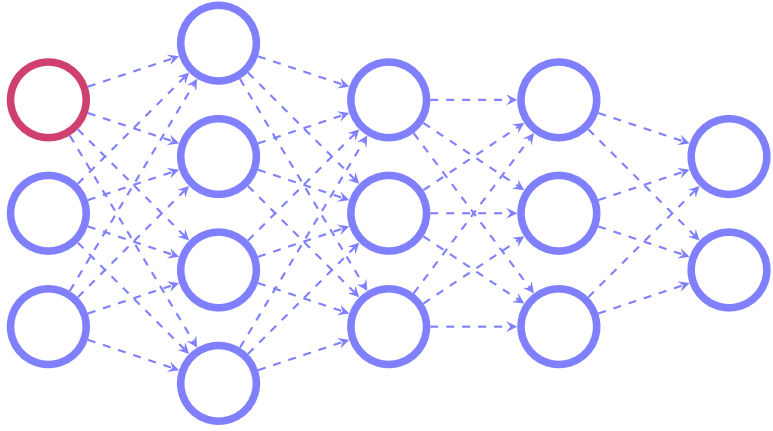
## What is a neural network?

- The heart of deep learning
- Classify given data
  *e.g. speech or image recognition*
- Rely on training data

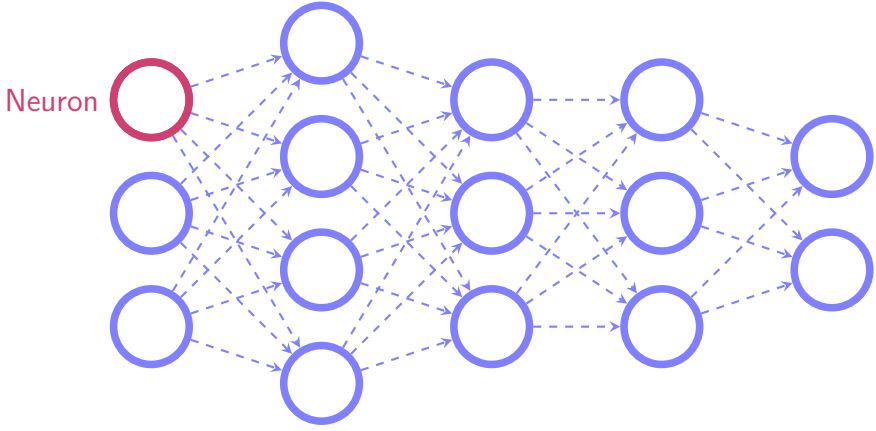
# What is a neural network?



# What is a neural network?



# What is a neural network?



## Neuron

- Holds a single value $v \in V_L$

Neuron

## Neuron

- Holds a single value $v \in V_L$
- Semantics depend on class of layer

Neuron

## Layer

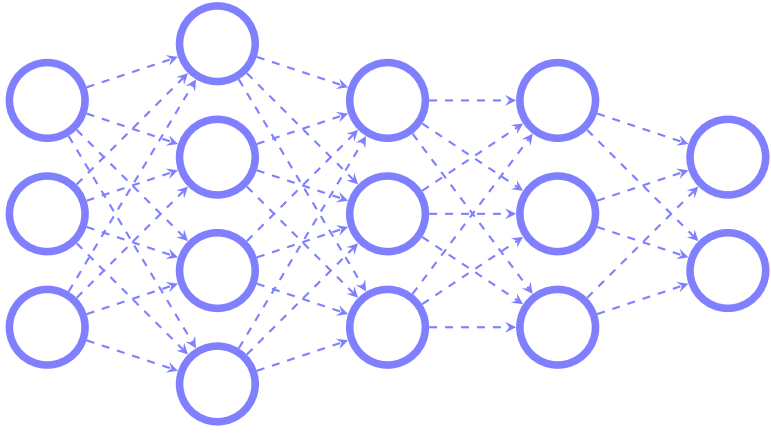
- Layer of neurons

## Layer

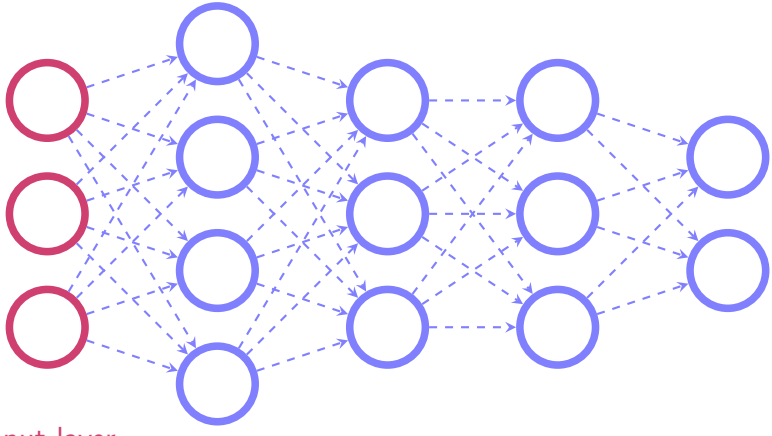
- Layer of neurons
- Three types:
  - Input layer: *Network input neurons*
  - Hidden layer: *Feature neurons*
  - Output layer: *Network output neurons*

Layer

## Classes of layers

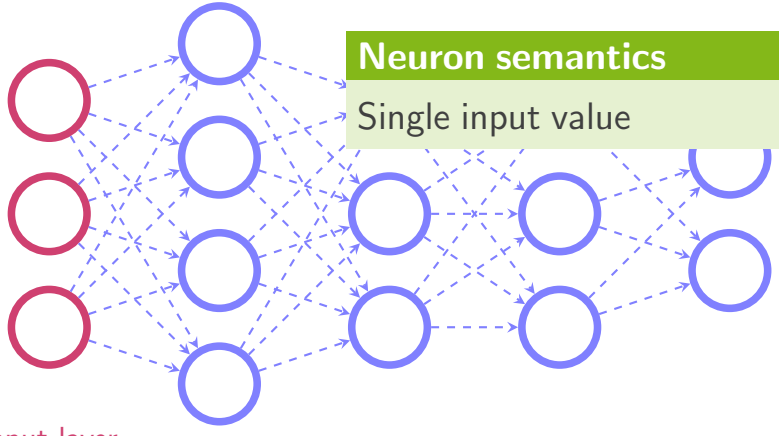


## Classes of layers

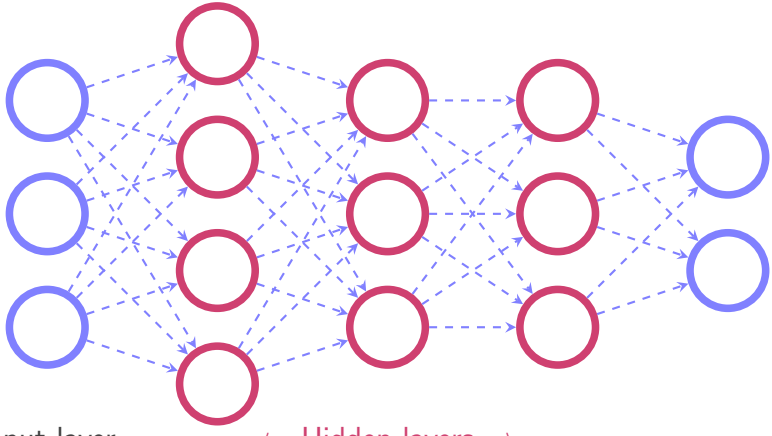


Input layer

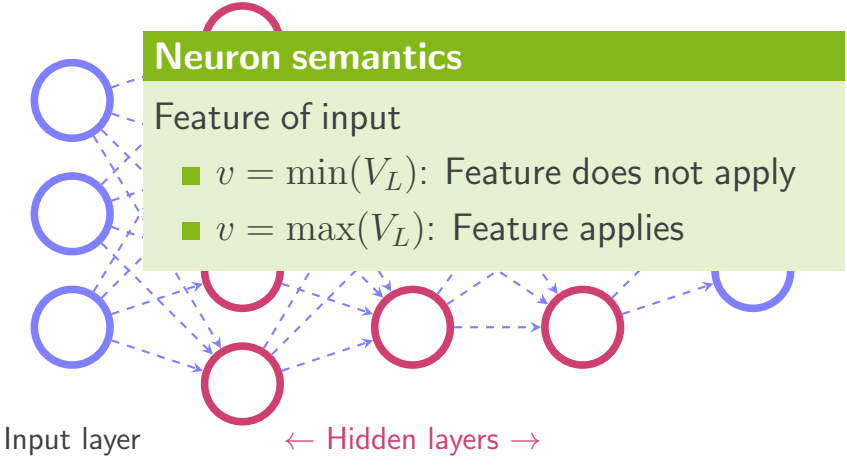
## Classes of layers



## Classes of layers



## Classes of layers

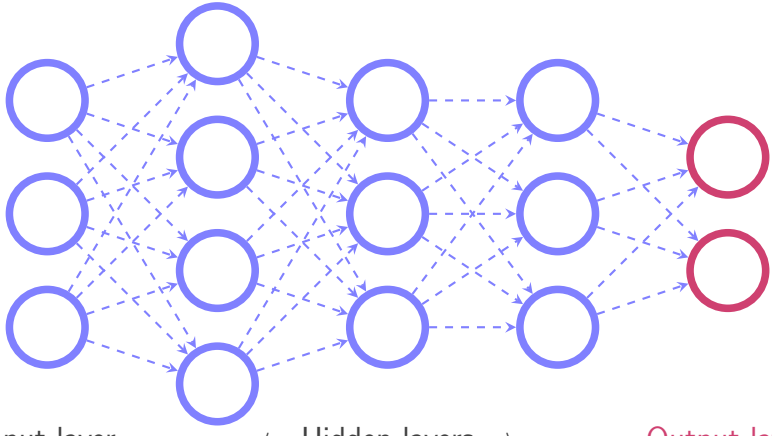



**Neuron semantics**

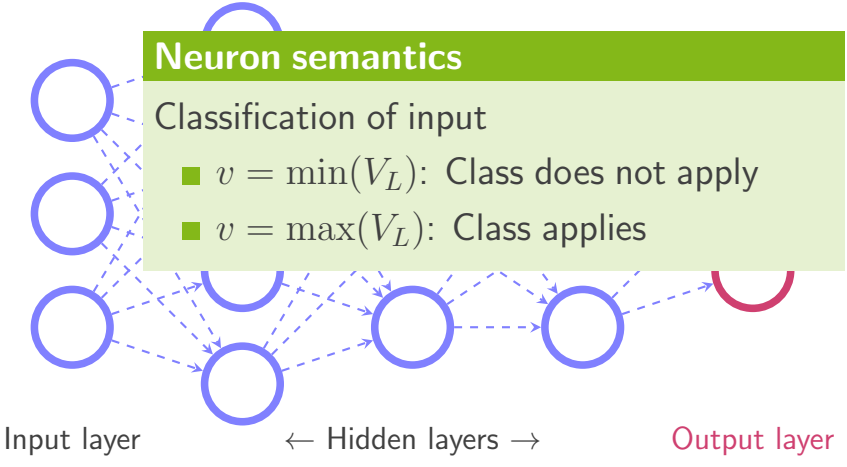
Feature of input

- $v = \min(V_L)$: Feature does not apply
- $v = \max(V_L)$: Feature applies

## Classes of layers



## Classes of layers

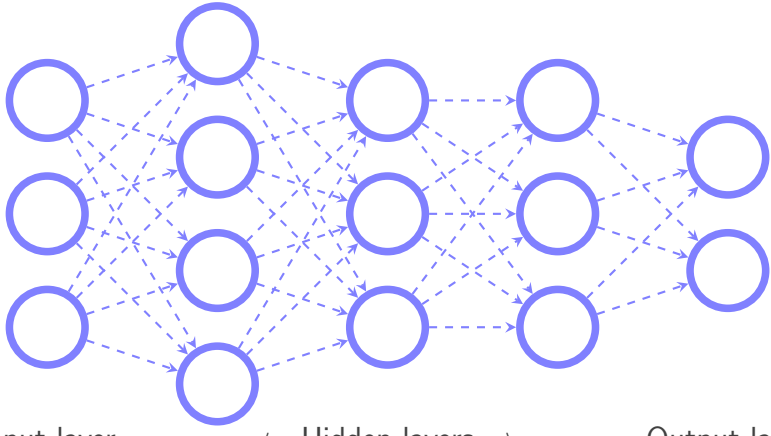



**Neuron semantics**

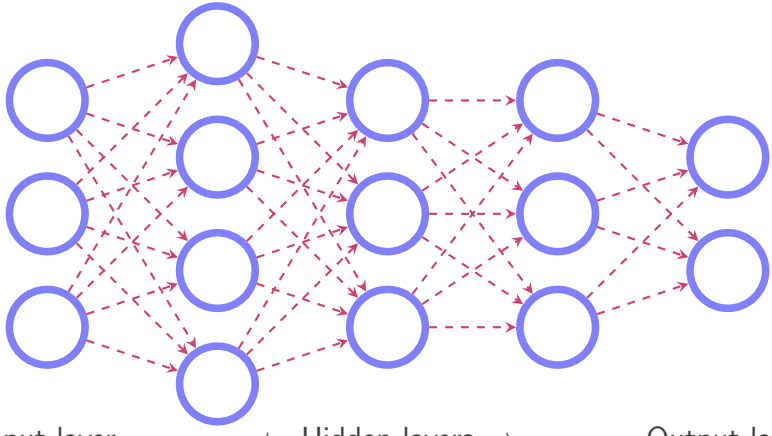
Classification of input

- $v = \min(V_L)$: Class does not apply
- $v = \max(V_L)$: Class applies

## Classes of layers

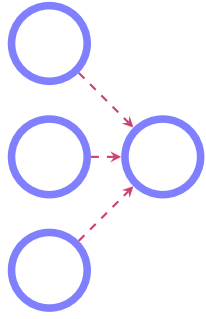


## Classes of layers



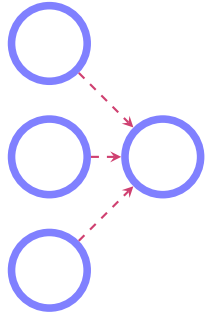
## Edges

- Connects all neurons between subsequent layers



## Edges

- Connects all neurons between subsequent layers
- Weighted



## Edges

- Connects all neurons between subsequent layers
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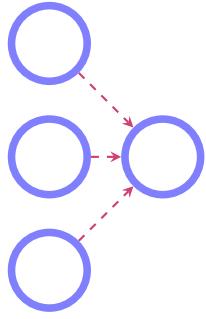
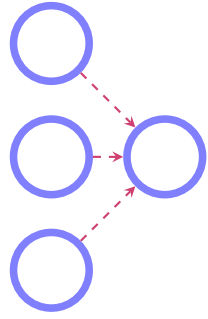
- Semantics:
  Higher weight
  $\rightarrow$ higher feature significance



## Edges

- Connects all neurons between subsequent layers
- Weighted
- Semantics:
  Higher weight
  $\rightarrow$ higher feature significance
- **Training: Optimize weights!**



# Training

## Training (Cycle)

1. Input data

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1. Input data
2. Run the network

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1. Input data
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3. Compare output with expected values
   $\rightarrow$ Calculate error ($|v - \text{expected}|$)

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1. Input data
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4. Run error back through network, adjust weights

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1. Input data ✓
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## Training (Cycle)

1. Input data ✓
2. Run the network?
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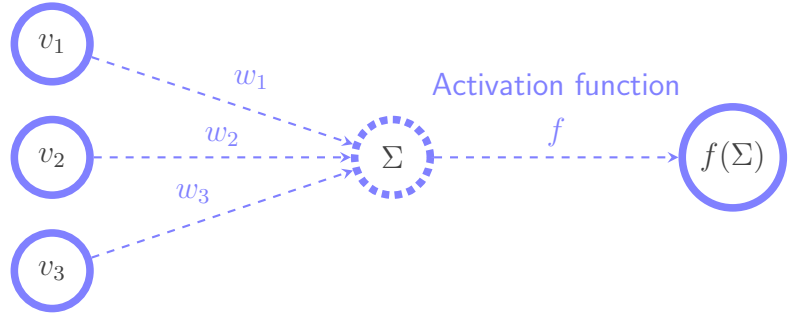
## Run the network



## Training (Cycle)

1. Input data ✓
2. Run the network ✓
3. Compare output with expected values
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## Training (Cycle)

1. Input data ✓
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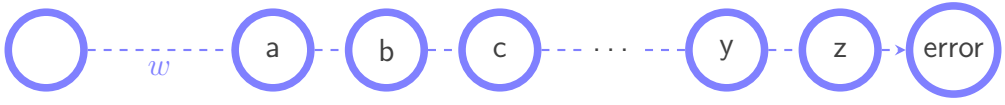
4. Run error back through network, adjust weights?

## Adjusting weights

### Backpropagation

Calculate change of error when adjusting some weight
$\rightarrow$ *Slope*



# Adjusting weights

## Backpropagation

Calculate change of error when adjusting some weight
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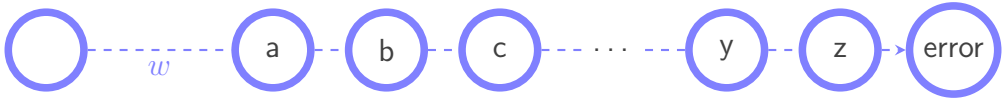



## Chain rule

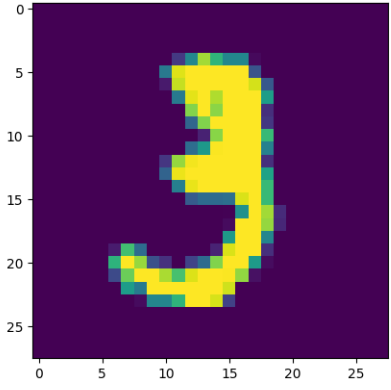
$$\frac{\delta \text{error}}{\delta w} = \frac{\delta a}{\delta w} \cdot \frac{\delta b}{\delta a} \cdot \frac{\delta c}{\delta b} \cdot \cdots \cdot \frac{\delta z}{\delta y} \cdot \frac{\delta \text{error}}{\delta z}$$

## Our Goal

- Create a BNN in PyTorch
- Image recognition on MNIST-Dataset

→ Keep an accuracy of at least 90%

- Export trained BNN

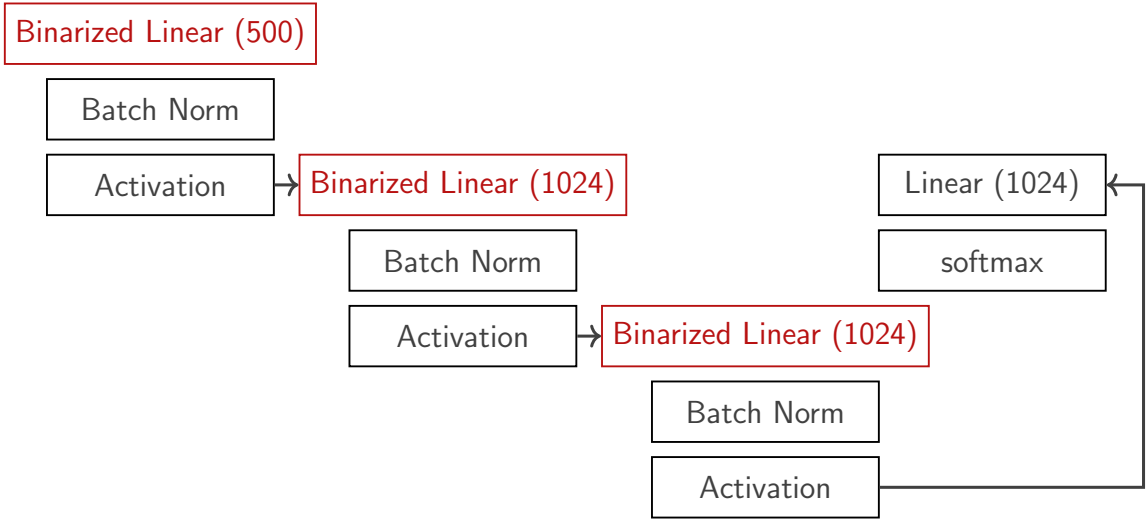


1. Neural Networks
   - What is a neural network?
   - Training
   - Our Goal

2. **BNN Design**
   - The Network
   - Layers
   - Binarization of Input data

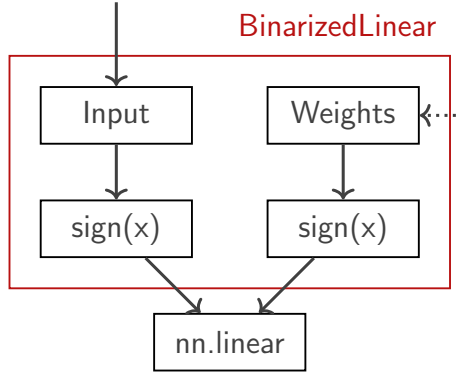
3. BNN Training Analysis
   - Layer Analysis
   - Parameter Analysis

## The Network


Binarized Linear (500)
Batch Norm
Activation
Binarized Linear (1024)
Batch Norm
Activation
Binarized Linear (1024)
Batch Norm
Activation
Linear (1024)
softmax

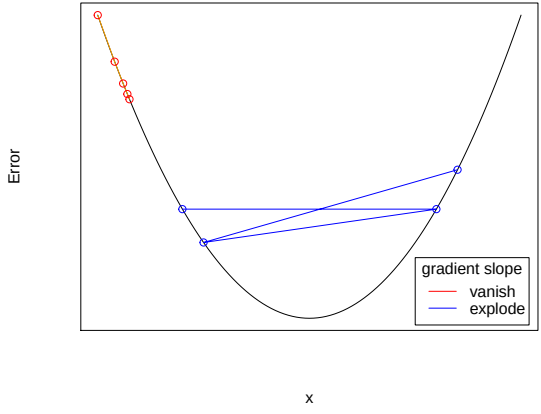
## Binarisation of Linear Layer

- binarisation of weights
- binarisation of input data for hidden layers
- calculation through *nn.linear*

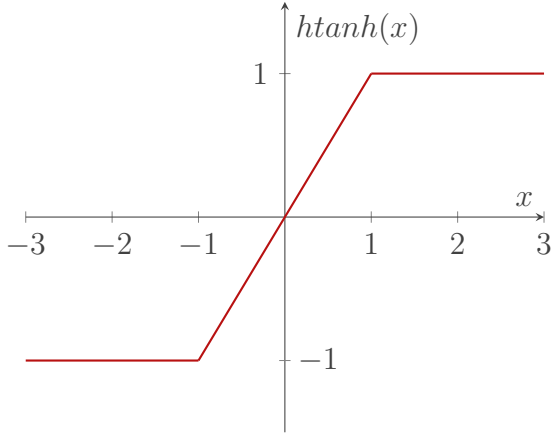


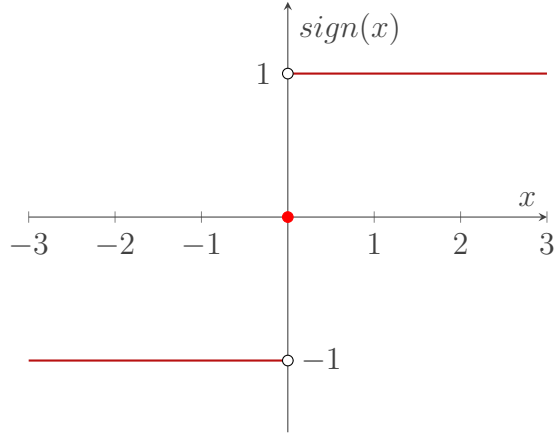
## Batch Norm (BN)

- Batches = data calculated in parallel
- In NN
  - normalize batches
  - mean 0
  - standard derivation 1
- In BNN
  - prevent *expolding gradient*



## Activation

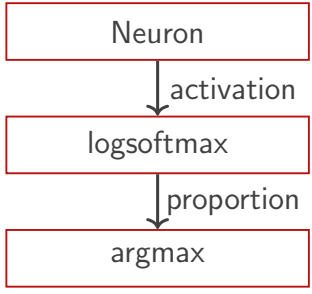


## Evaluation of last layer

- normalisation of activation
- decision of the network

$$LogSoftmax(x_i) = log(\frac{e^{x_i}}{\sum_j e^{x_j}})$$



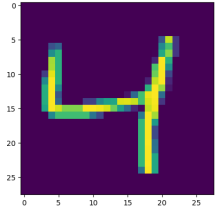
# Binarization of Input data

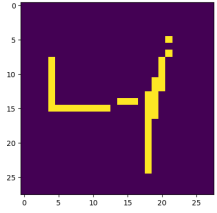
## Binarization of Input data

- Mapping 255 values to 0,1
- minimize accuracy losses
- 2 approaches
  - Threshold
  - Probability

## Threshold-Binarization

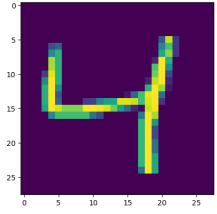
- define static threshold
- filter pixel-array via:
  pixel $>$ threshold

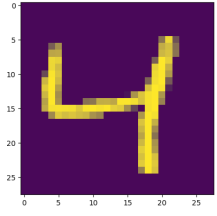


## Probability-Binarization

- each pixelvalue dictates its prob for being 1
- binarize same trainingset multiple times
  - Run each epoche with all trainingsets



## Comparison Threshold, Prob

- Threshold
  - Using integrated tensor-functions
  - 150ms per iteration
  - Convergence after approx. 100 epochs
- Probability
  - Iterate through tensor manually
  - 250ms per iteration
  - Convergence after approx. 20*30 iterations

## Evaluating Accuracy-Loss

| Run | Non-Binarized | threshold | prob |
|---|---|---|---|
| 1 | 91.99% | 89.24% | 92.52% |
| 2 | 91.99% | 89.24% | 91.82% |
| 3 | 91.99% | 89.24% | 92.56% |
| 4 | 91.99% | 89.24% | 91.02% |
| avg | **91.99%** | **89.24%** | **91.98%** |

- 600 epochs for threshold, default
- 20 epochs, 30 trainingsets for prob

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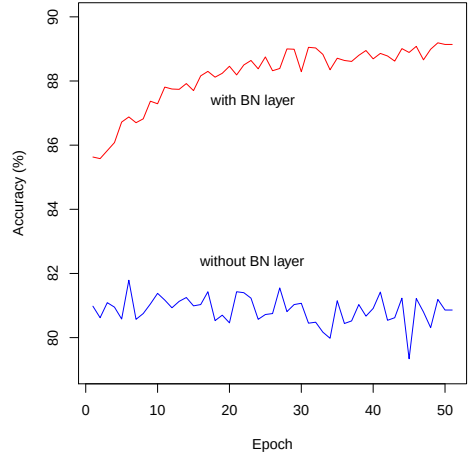
## Consequences of linear layer binarisation

| Run | binary | normal |
|---|---|---|
| 1 | **88.29**% | **97.43**% |
| 2 | 87.32% | 96.98% |
| 3 | 87.19% | 97.2% |

- training for 50 epochs
- mean loss of 9,6%
- loss in granularity

## Effect of Batch Norm

- 7.4% improved peak performance
- Less jitter with BN
- Reduced expolding gradient



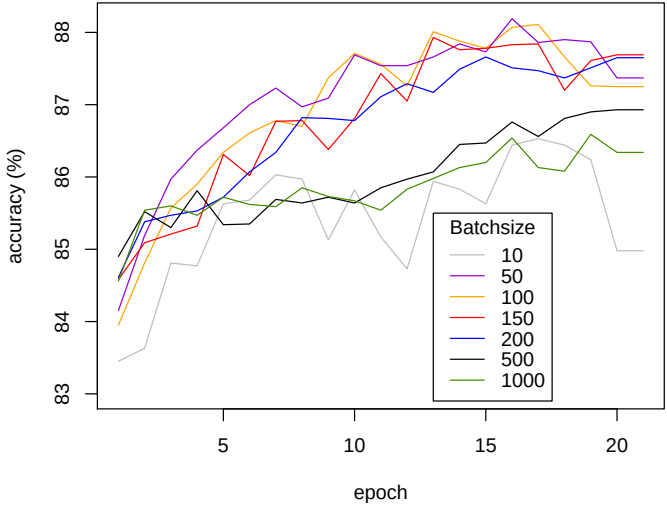
# Parameter Analysis

## Batch size

- frequency of error calculation
- normalisation though Batch Norm
- rate of parallelization

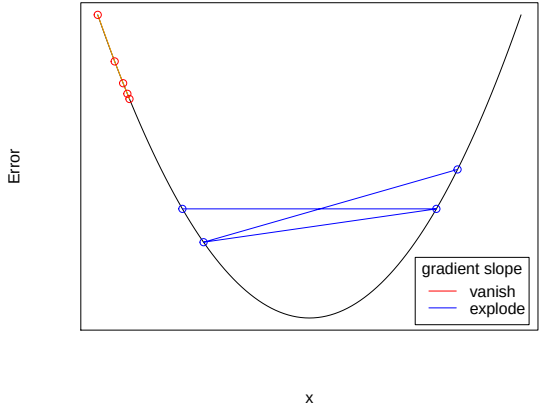
| Batchsize | Time (s) |
|---|---|
| 10 | 30,68 |
| 50 | 11,33 |
| 100 | 8,76 |
| 150 | 7,95 |
| 200 | 7,63 |
| 500 | 6,66 |
| 1000 | 6,39 |

# Evaluation of Batch size

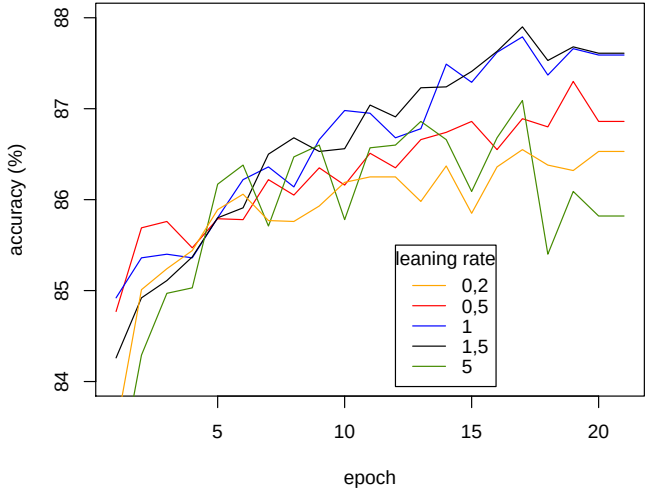


## Learning rate

- higher value $\rightarrow$ more weights are updated
- balance between vanishing- and exploding gradient



# Evaluation learning rate



# Thank you for your attention!