MNIST Training for BNN

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Design Your Own CPU - Design of Embedded Systems

Content

What is a neural network?

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- The heart of deep learning

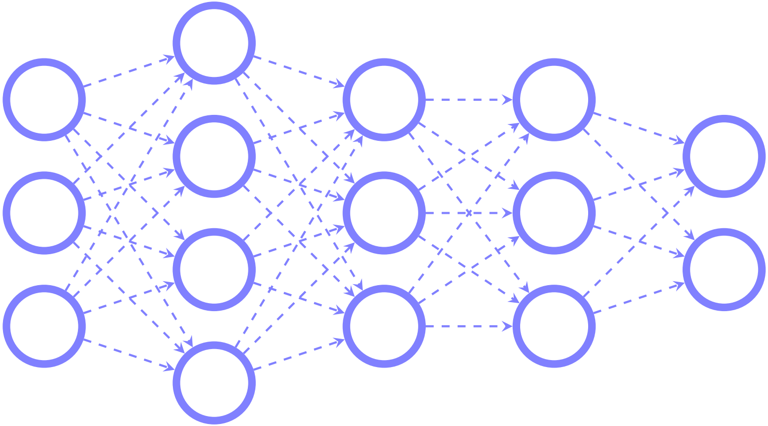
What is a neural network?

- The heart of deep learning
- 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?



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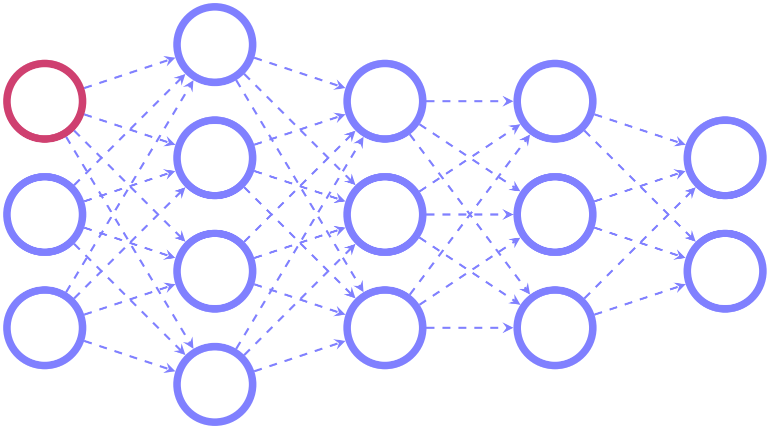
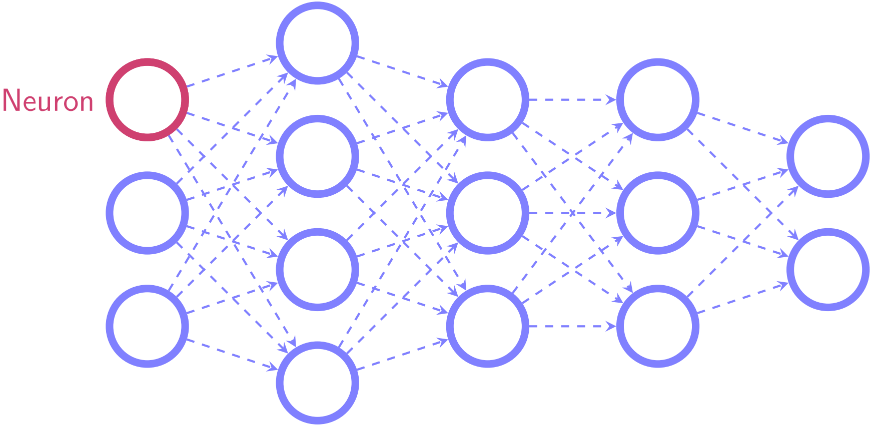


What is a neural network?

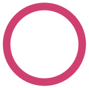


Neuron

- Holds a single value $v \in V_L$

Neuron

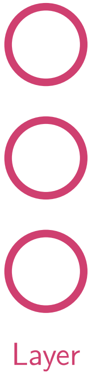
- Holds a single value $v \in V_L$
- Semantics depend on class of layer



Neuron

Layer

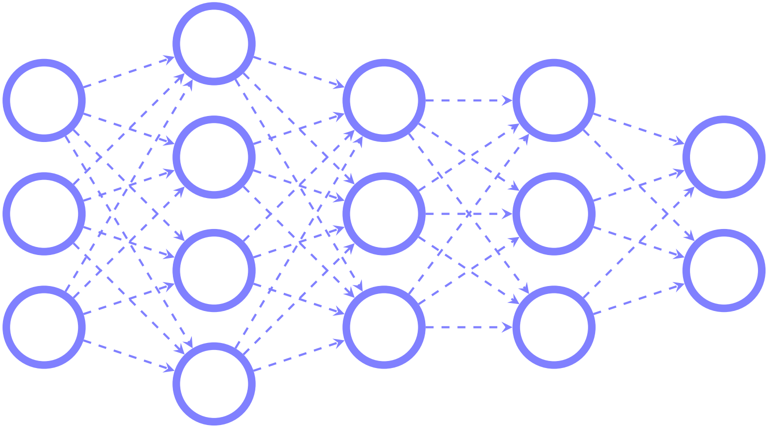
- Layer of neurons



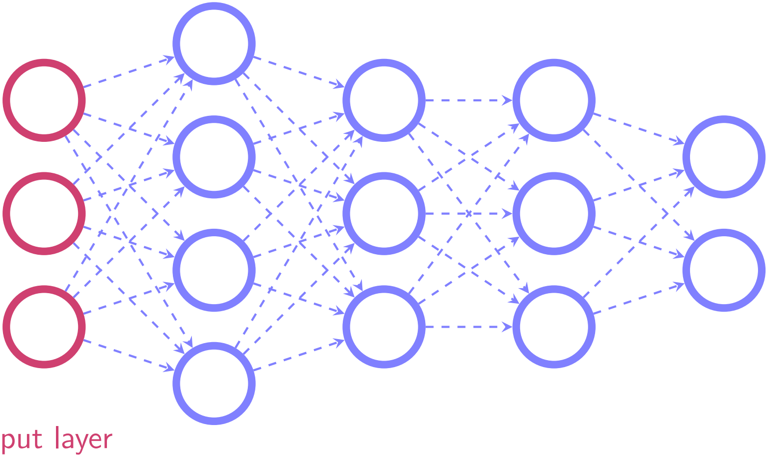
Layer

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

Classes of layers



Classes of layers



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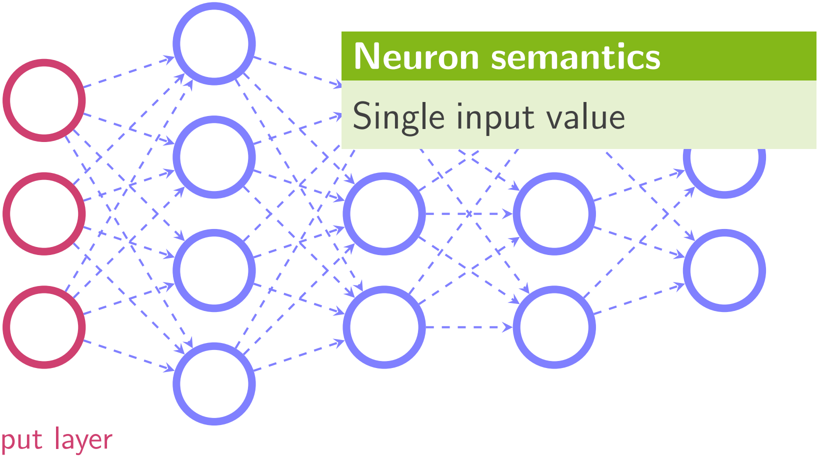
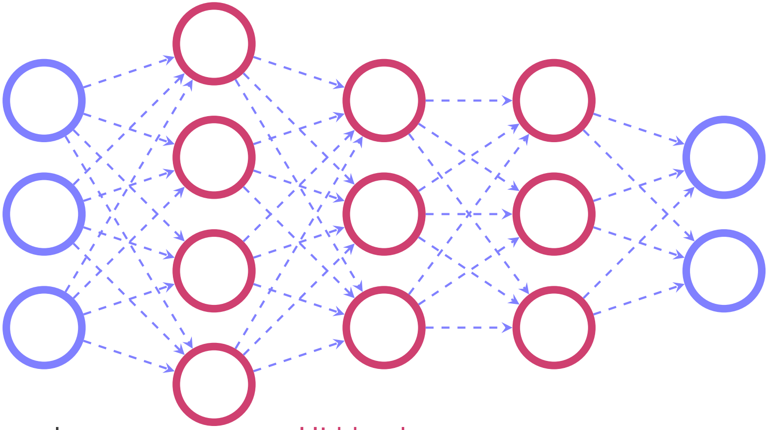
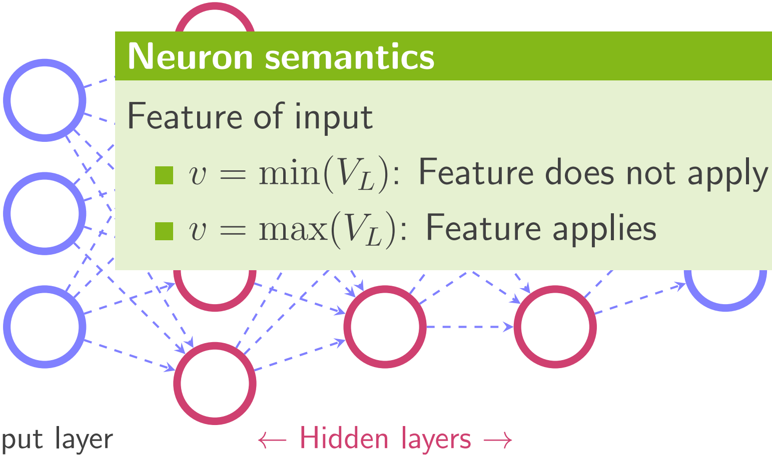


Classes of layers



Classes of layers

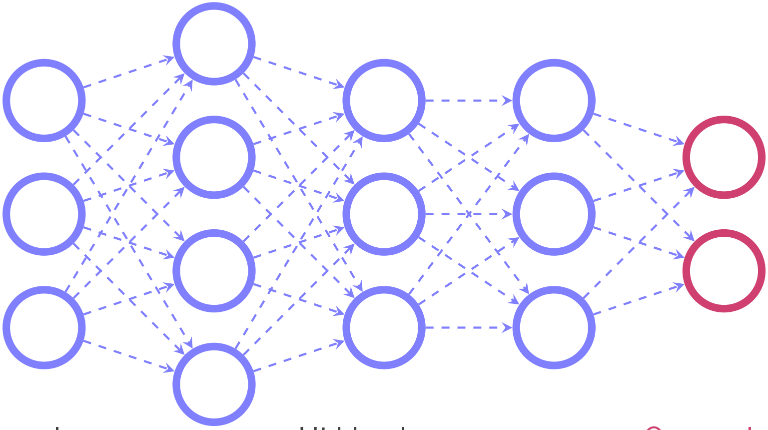


Neuron semantics

Feature of input

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

Classes of layers



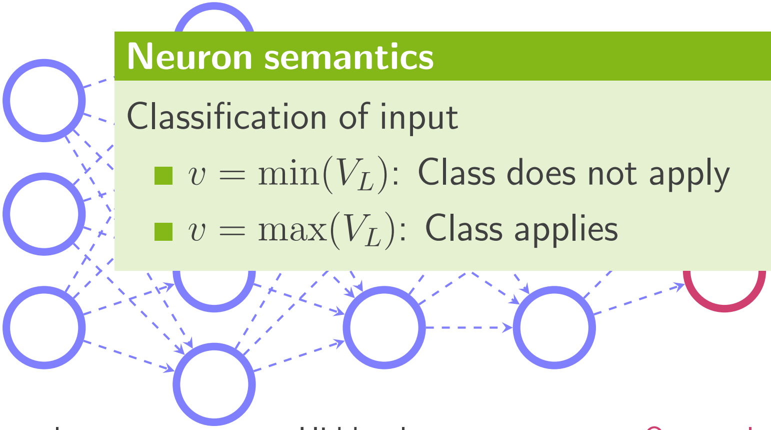
Input layer ← Hidden layers → Output layer

Classes of layers

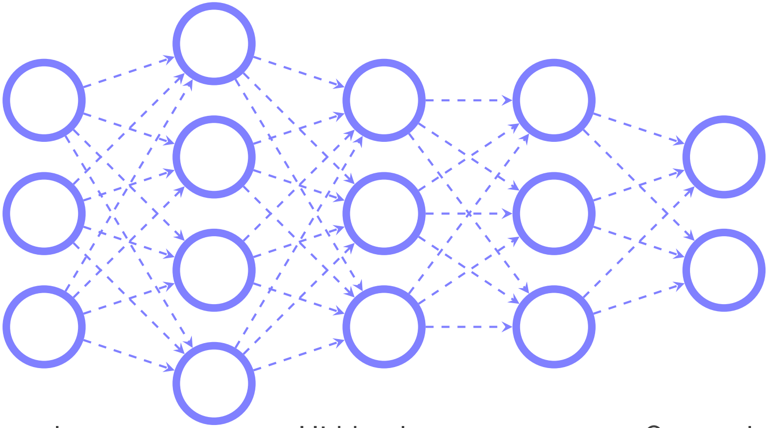
Neuron semantics

Classification of input

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



Classes of layers



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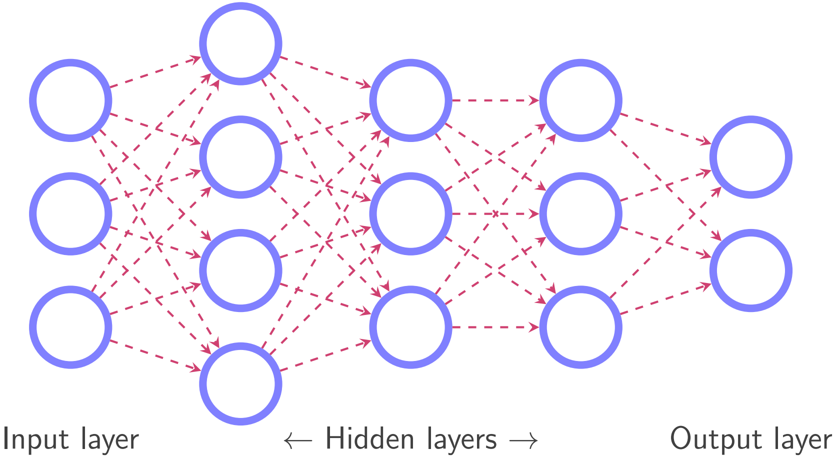
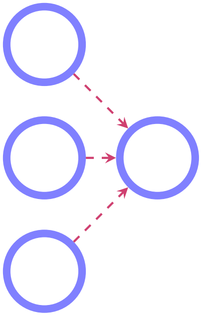
Classes of layers



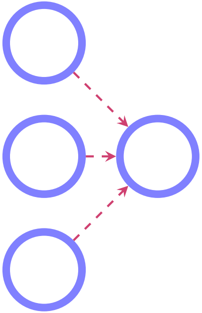
Edges

- Connects all neurons between subsequent layers



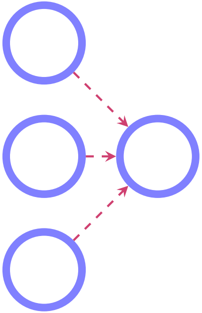
Edges

- Connects all neurons between subsequent layers
- Weighted



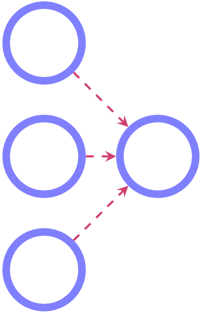
Edges

- Connects all neurons between subsequent layers
- Weighted
- 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

Training (Cycle)

1. Input data
2. Run the network

Training (Cycle)

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

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4. Run error back through network, adjust weights

Training (Cycle)

1. Input data ✓
2. Run the network
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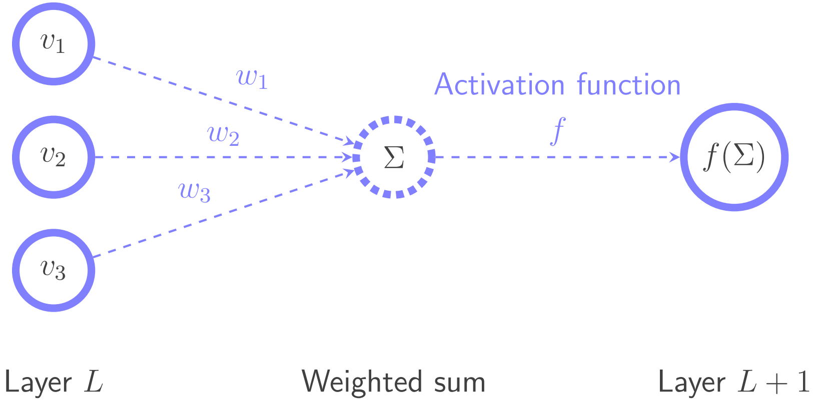
Training (Cycle)

1. Input data ✓
2. Run the network?
3. Compare output with expected values
   $\rightarrow$ Calculate error ($|v -$ expected$|$)
4. Run error back through network, adjust weights

Run the network



Training (Cycle)

1. Input data ✓
2. Run the network ✓
3. Compare output with expected values
   $\rightarrow$ Calculate error ($|v$ − expected$|$)
4. Run error back through network, adjust weights

Training (Cycle)

1. Input data ✓
2. Run the network ✓
3. Compare output with expected values
   $\rightarrow$ Calculate error ($|v -$ expected$|$) ✓
4. Run error back through network, adjust weights

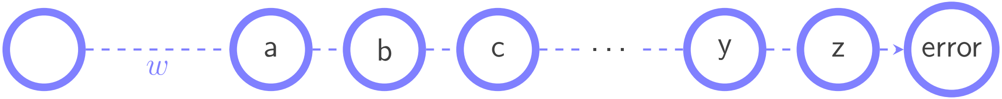
Training (Cycle)

1. Input data ✓
2. Run the network ✓
3. Compare output with expected values
   $\rightarrow$ Calculate error ($|v - \text{expected}|$) ✓
4. Run error back through network, adjust weights?

Adjusting weights

Backpropagation

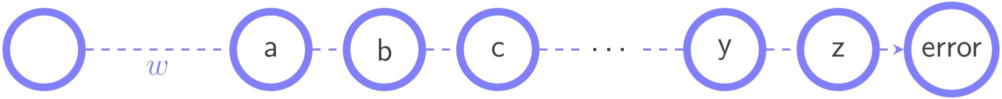
Calculate change of error when adjusting some weight
$\rightarrow$ *Slope*



Adjusting weights

Backpropagation

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



Chain rule

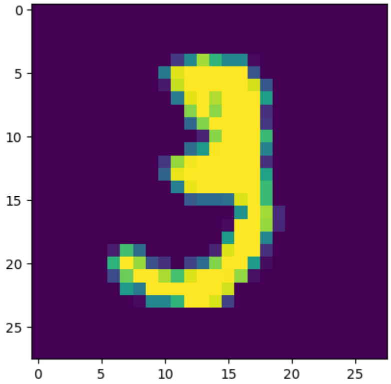
$$\frac{\delta \text{error}}{\delta w} = \frac{\delta a}{\delta w} \cdot \frac{\delta b}{\delta a} \cdot \frac{\delta c}{\delta b} \cdot \ldots \cdot \frac{\delta z}{\delta y} \cdot \frac{\delta \text{error}}{\delta z}$$

Our Goal

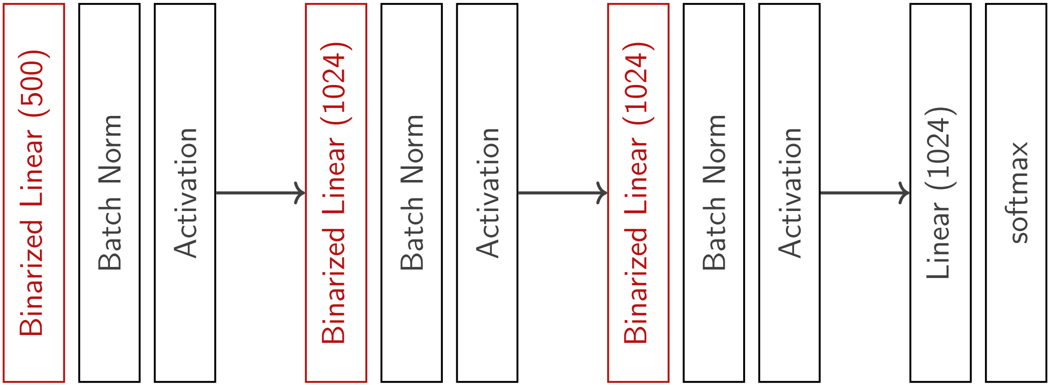
- Create a BNN in PyTorch
- Image recognition on MNIST-Dataset

→ Keep an accuracy of at least 90%

- Export trained BNN

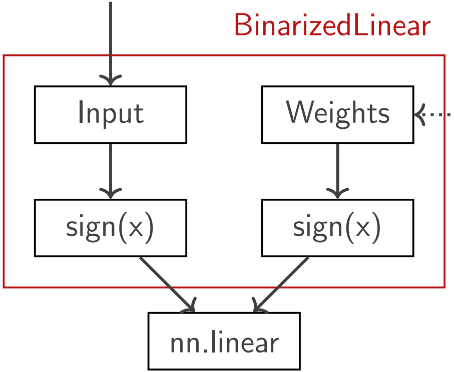


The Network


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

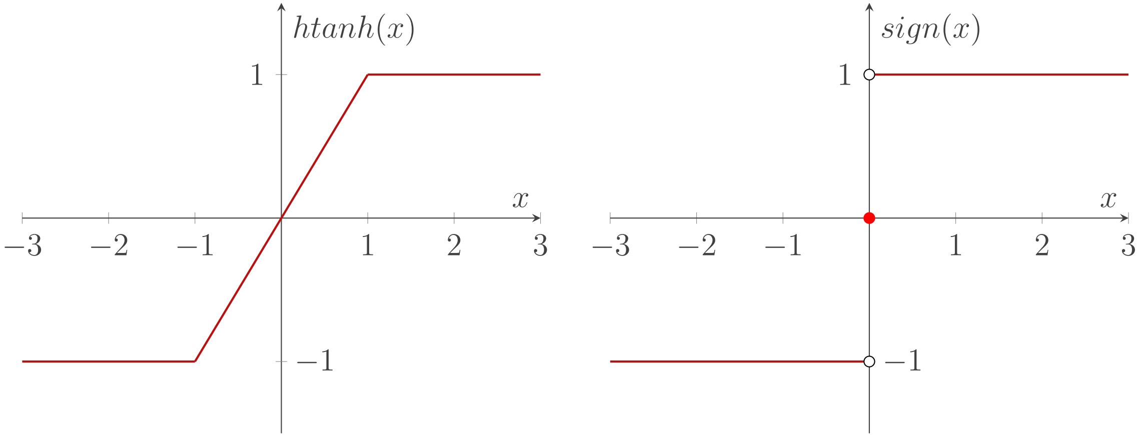
- binarisation of weights
- binarisation of input data for hidden layers
- calculation through *nn.linear*



Batch Norm (BN)

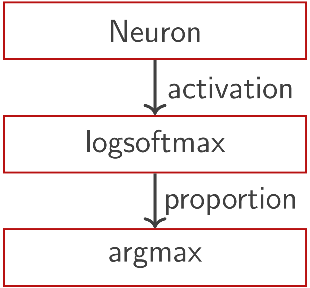
- In NN
  - normalize batches
  - mean 0
  - standard derivation 1
- In BNN
  - prevent *expolding gradient*

Activation



Evaluation of last layer

- normalisation of activation
- decision of the network



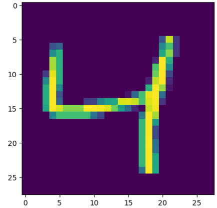
Binarization of Input data

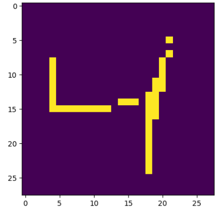
Binarization of Input data

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

Threshold-Binarization

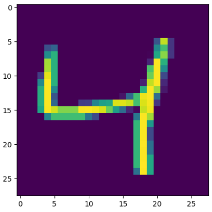
- define static threshold
- filter pixel-array via:
  pixel $>$ threshold

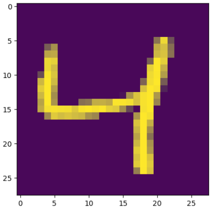




Probability-Binarization

- 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

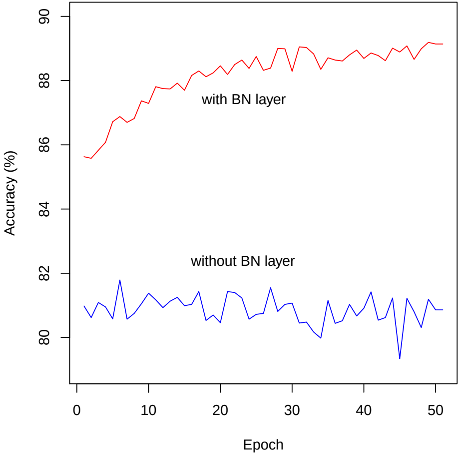
Consequences of linear layer binarisation

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

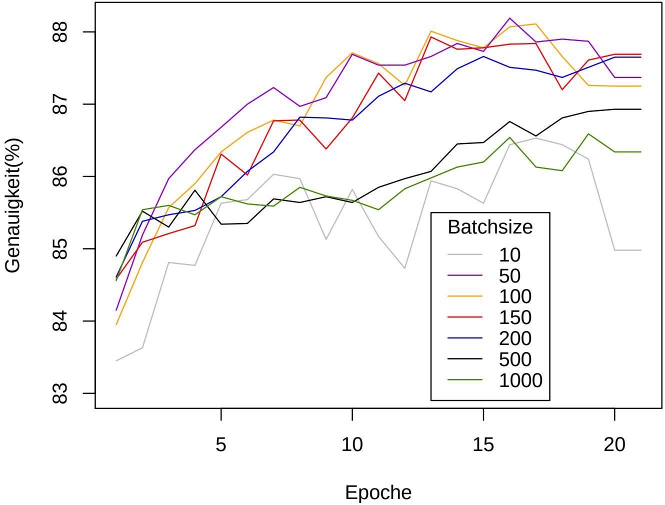


Batch size

- frequency of error calculation
- rate of parallelization

Batchgröße	Zeit (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 → more weights are updated
- balance between over- and underfitting

evaluation learning rate