# Fast Convolutional Neural Network Training and Classification on CUDA GPUs

Master Thesis in Computer Science

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# Overview

- The Goal
- A Review of Neural Networks
- Convolutional Neural Networks
- Implementation
- Benchmarks and Results
- Applications of CNNs
  - Convolutional Face Detector
  - Handwritten Digit Recognition
- Conclusion and Future Work

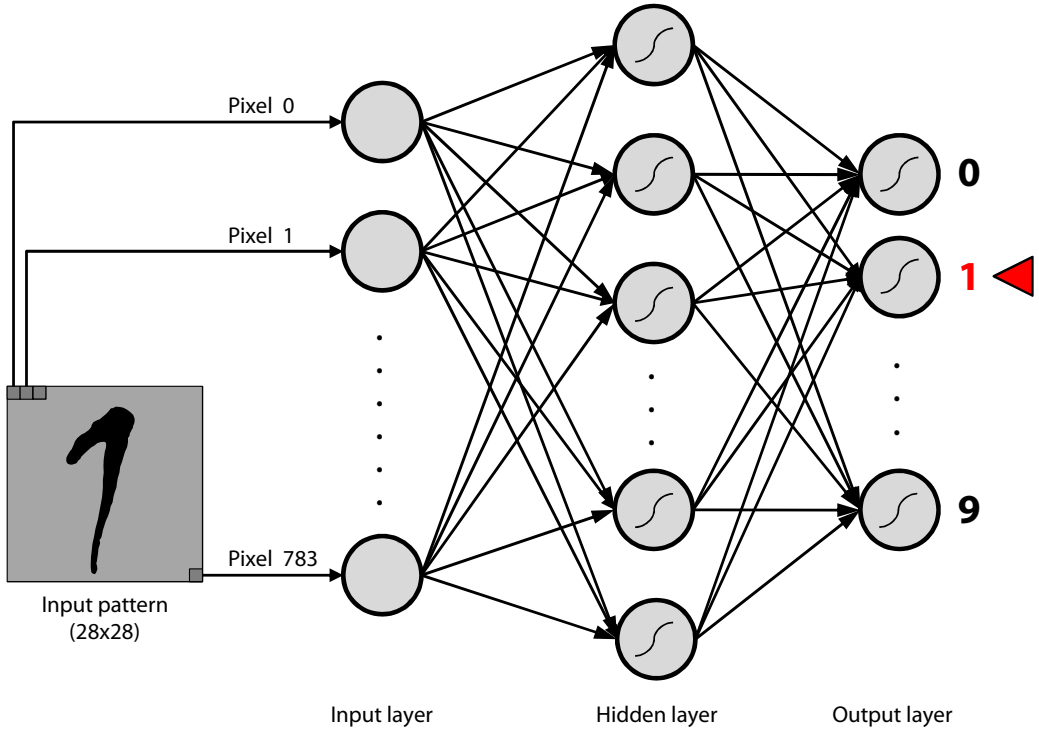
# The Goal

Our goal was to demonstrate the performance and scalability improvement that can be achieved by shifting the computation-intensive tasks of a convolutional neural network to the GPU using NVIDIAs CUDA architecture.

# A Review of Neural Networks

# Neural Networks (NNs)

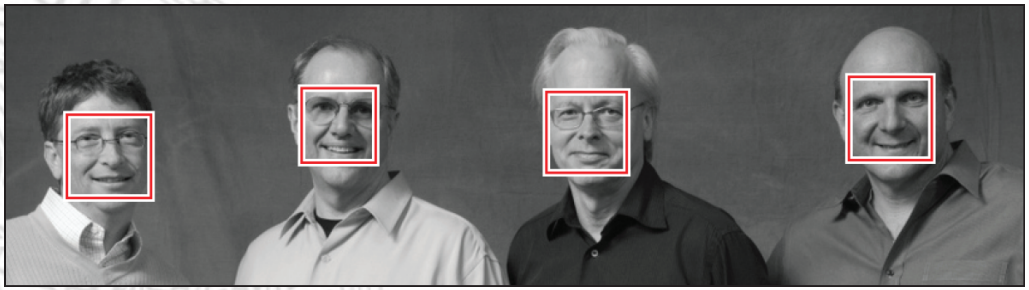
- Kind of machine learning algorithm which has to be trained.
- Are trained using a preclassified dataset.
- Often used for pattern recognition/classification tasks.
- Consist of many neurons which are organized in several layers.
- Have weighted connections between the single neurons.
- Training consists of forward- and backpropagation.

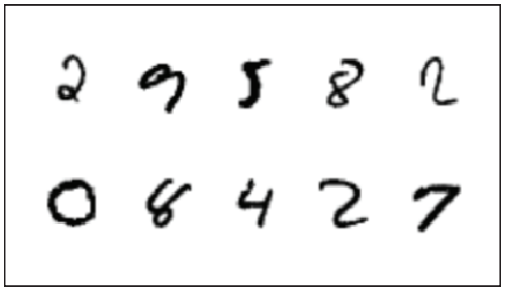


# Convolutional Neural Networks

## Convolutional Neural Networks (CNNs)

- Invented by Yann LeCun in the early 1990s [1].
- Special kind of neural networks, optimized for 2D problems.
- Can operate on raw images without separate feature extractor.
- Offer a certain invariance to shifting, scaling, and other forms of distortion.
- Are trained via the gradient decent method using error backpropagation.
- Successfully applied to handwriting recognition [2, 3], face detection [4], etc.

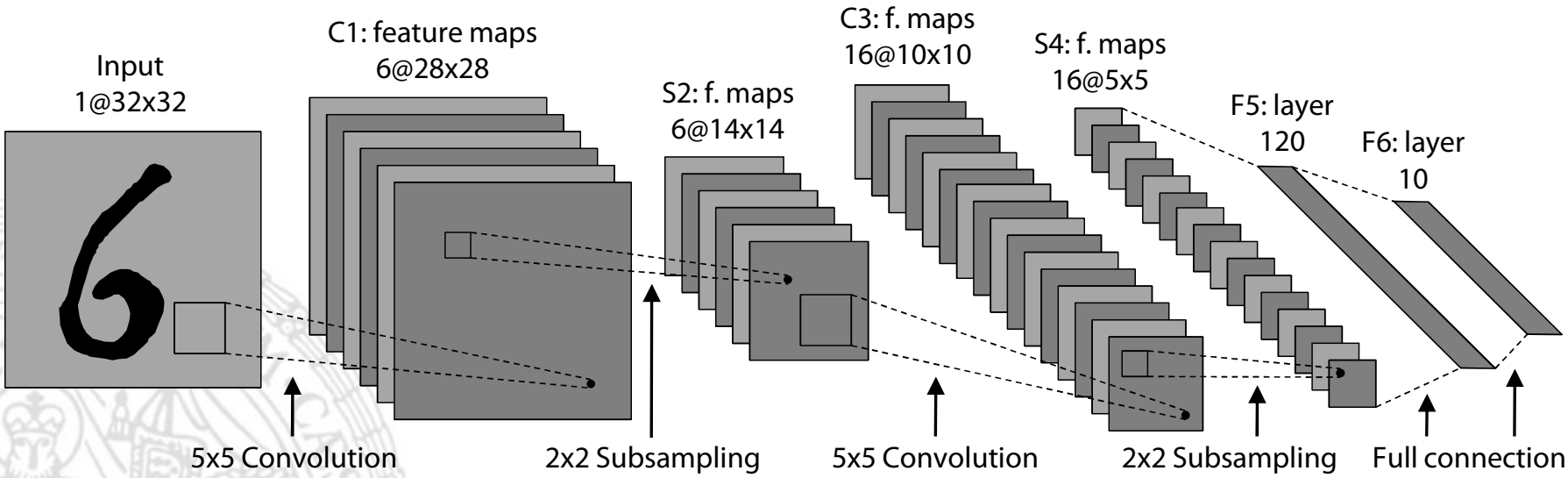




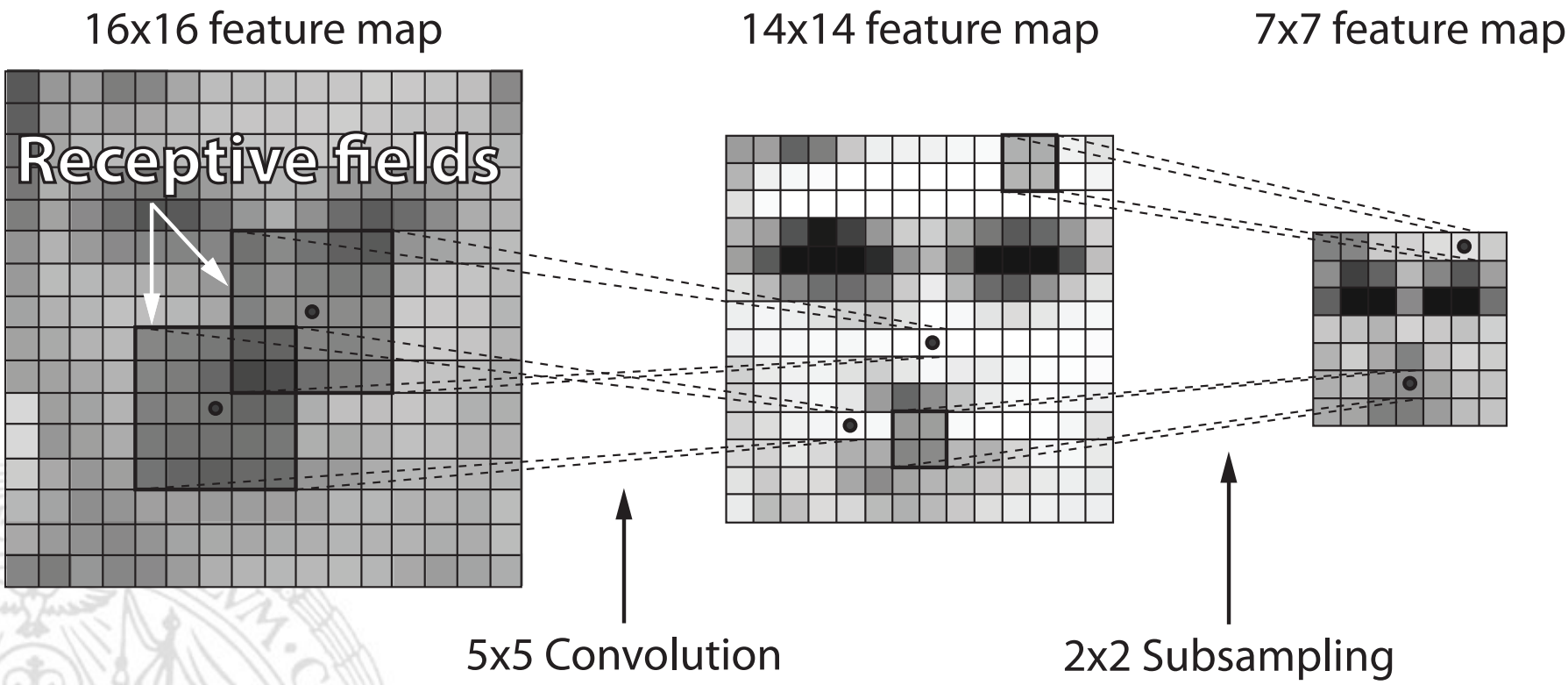
# CNN Topology

Feed-forward network, composed of three different types of layers:

- Convolution Layer (2D): feature extraction
- Subsampling Layer (2D): shift and distortion insensitivity
- Fully Connected Layer (1D): classification



# Convolution and Subsampling in Detail



## Drawbacks of CNNs

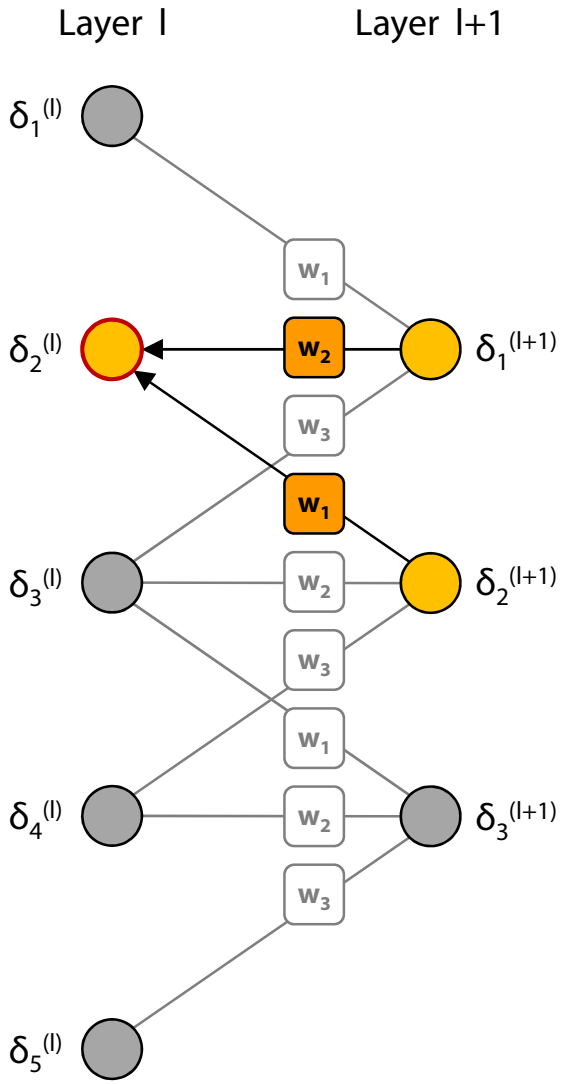
- Complex implementation
- Computational expensive
- Long training time
- Large number of configurable parameters which can only be determined by evaluating and testing:
  - Network topology
  - Number of feature maps/neurons inside the layers
  - Training parameters
  - ...

$\Longrightarrow$ High-performance library which shortens the training time using GPGPU computing and hides complexity from the developer.

# Implementation

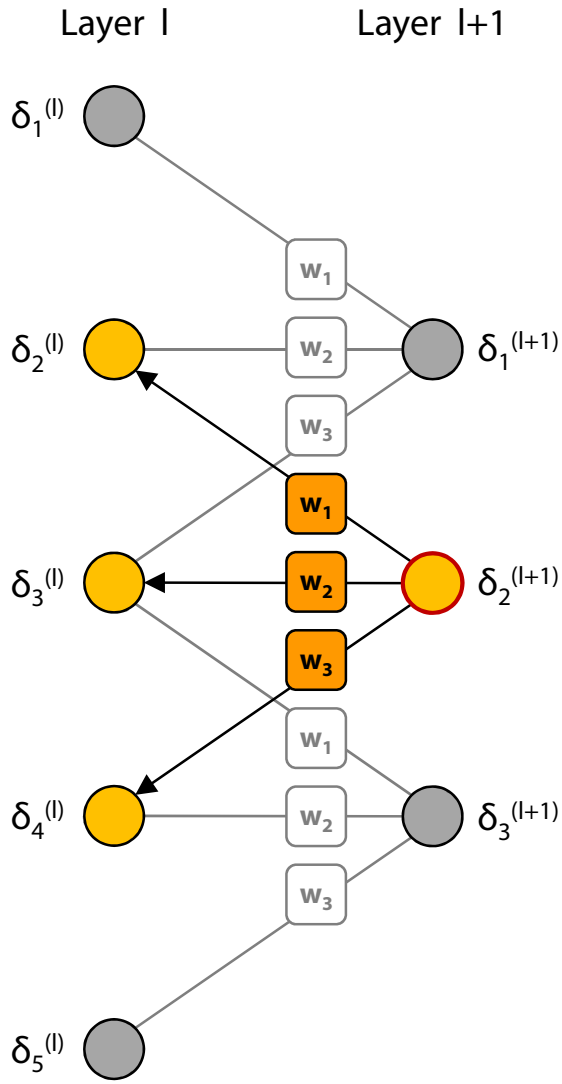
## Making CNNs simpler

- Traditional approach "pulls" the error back from the following layer during training phase.
- To calculate the error gradient each neuron needs the error of all neurons in the following layer $l + 1$ which are connected to it.
- This requires knowledge about the following layer $l + 1$.



## Making CNNs simpler – cont.

- Instead of pulling the error from the neurons in layer $l+1$ this layer could "push" the needed information back to layer $l$, providing one value for each neuron in it.
- Pushing the error back does not require any additional information about neighboring layers and results in a more regular structure.



## Making CNNs faster

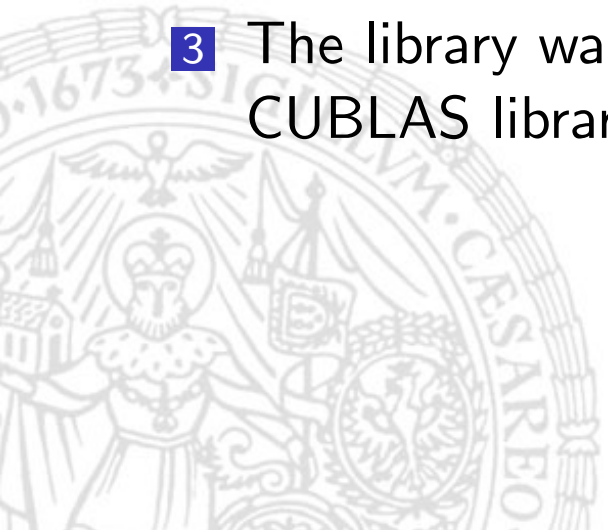
- Convolutions are not easy to optimize because of their irregular memory access pattern.
- To make the convolution more regular and easier to optimize one can "unfold" the convolution [5].

$\Longrightarrow$ Convolution can be implemented as a simple matrix-matrix product (see Appendix).

## Implementation Procedure

We implemented a high performance but still flexible library in C++ and CUDA to accelerate the training and classification process of arbitrary CNNs:

1. We started with a straight forward implementation without any manual parallelization or vectorization ($\mathrm{CPU}_{\mathrm{triv.}}$).
2. This implementation was optimized using functions from Intel's Performance Libraries IPP and MKL ($\mathrm{CPU}_{\mathrm{opt.}}$).
3. The library was ported to CUDA-enabled GPUs using the CUBLAS library and manually implemented functions (GPU).

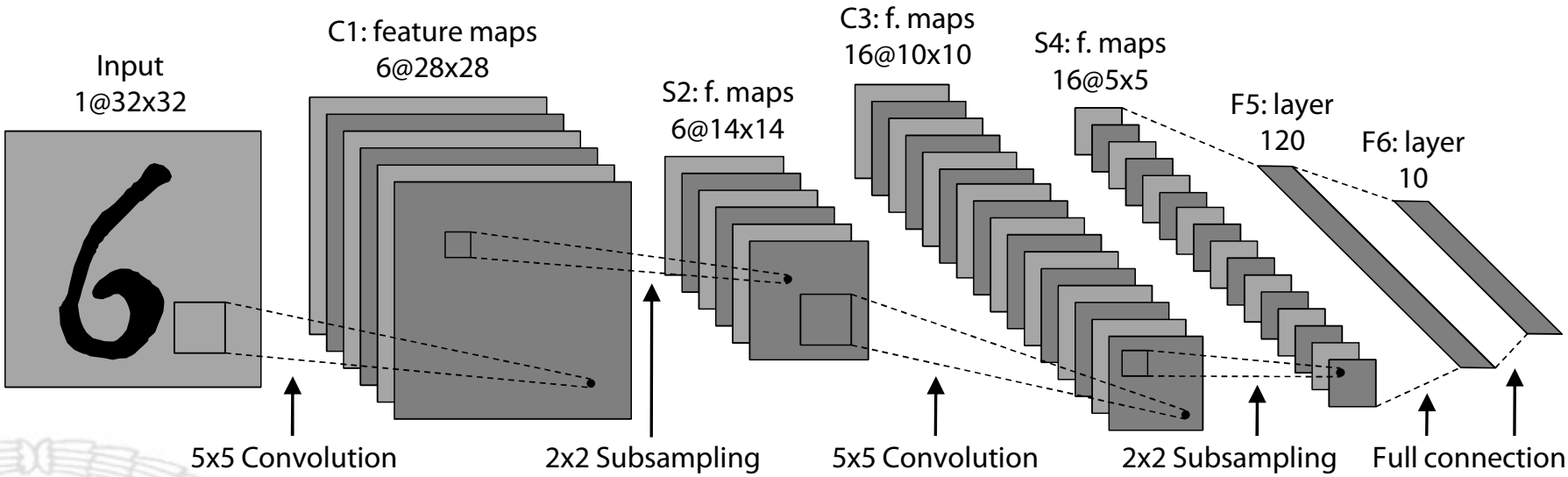


# Benchmarks and Results

**All benchmarks in our work were performed**

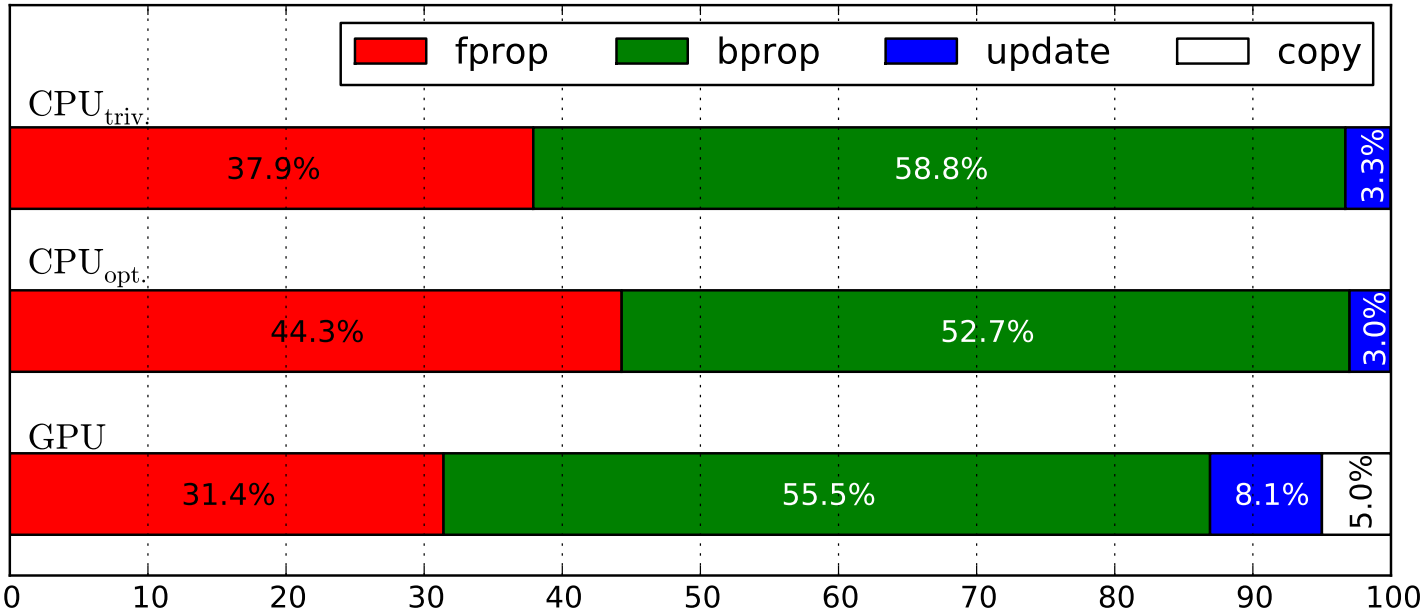
- on a PC equipped with an Intel Core i7 860 and a NVIDIA GeForce GTX 275,
- using the GNU C++ compiler for the CPU code and the NVIDIA NVCC compiler to generate the GPU code,
- in floating-point single precision (32-bit),
- measuring the execution time of 1,000 (online) training iterations using patterns form the MNIST database [6].

# Benchmarks on the LeNet5*




* Proposed by Yann LeCun in [3].

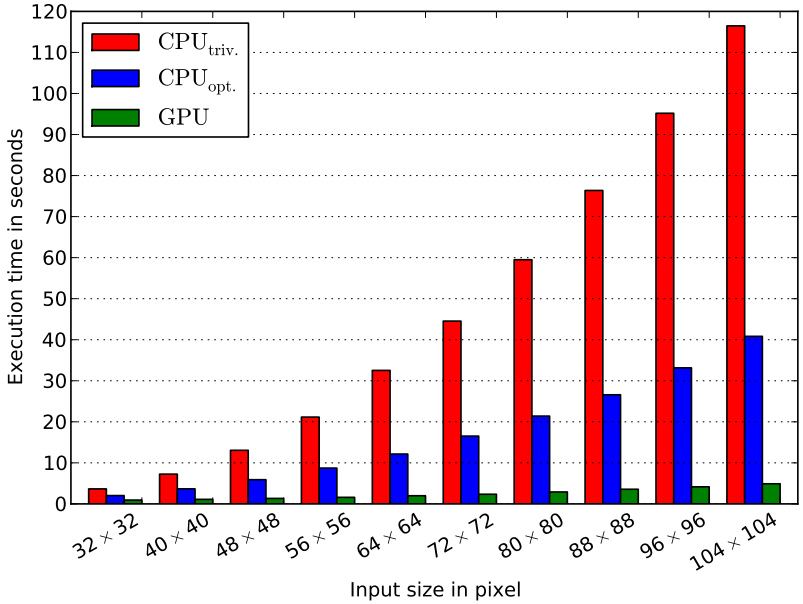
# Composition of Execution Time



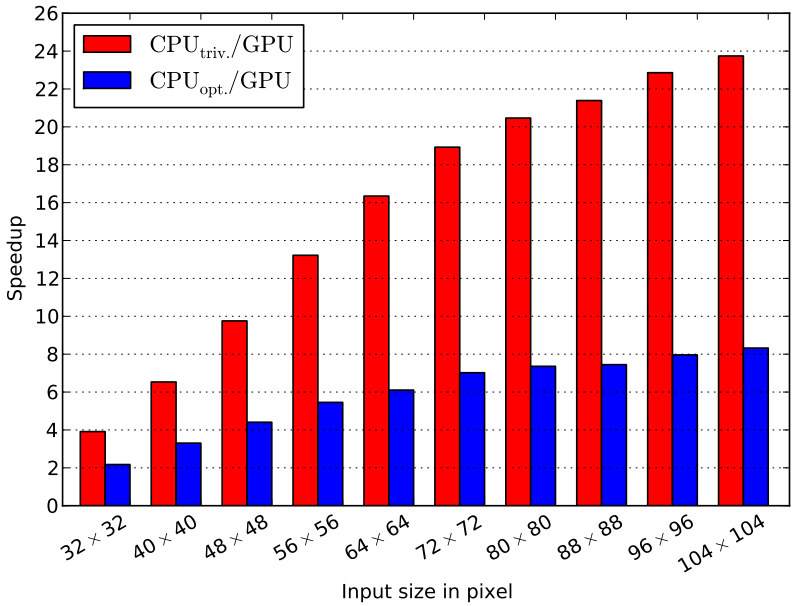

| | |
|---|---|
| **fprop** | Forward propagation of a pattern through the network. |
| **bprop** | Backward propagation of the error to obtain the gradient. |
| **update** | Adaption of the weights according to the gradient descent method. |
| **copy** | Transferring data from the CPU to the GPU and vice versa. |

# Scaling the Input Size of a LeNet5

## Execution Time




## Speedup

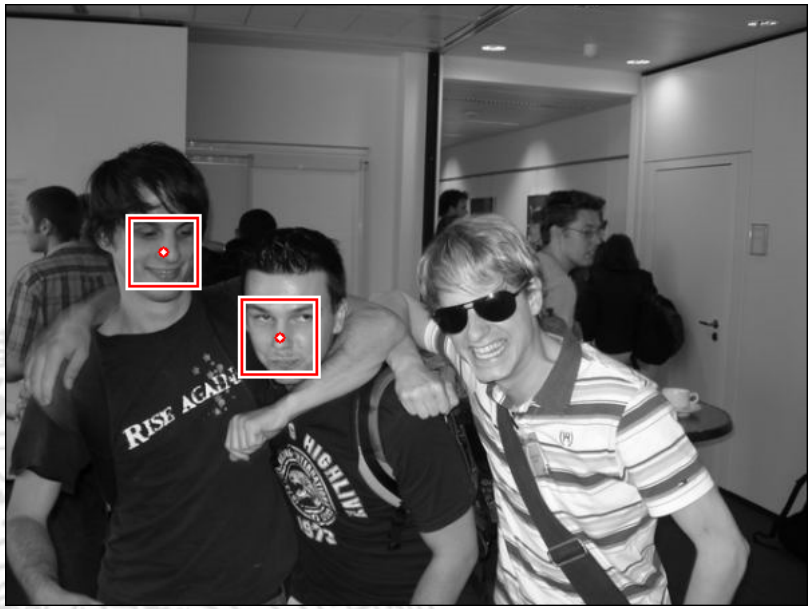


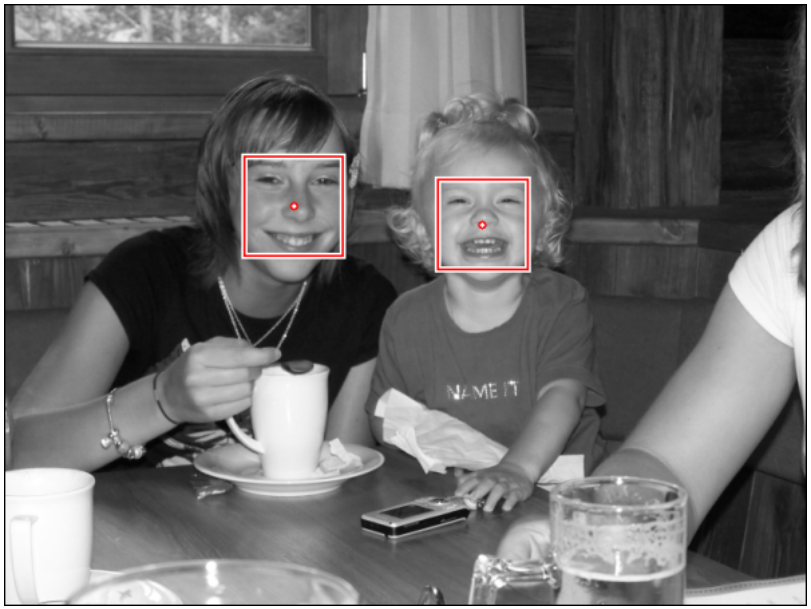

Execution time and corresponding speedup of the three different implementations performing 1,000 learning iterations of a LeNet5.

# Applications of CNNs

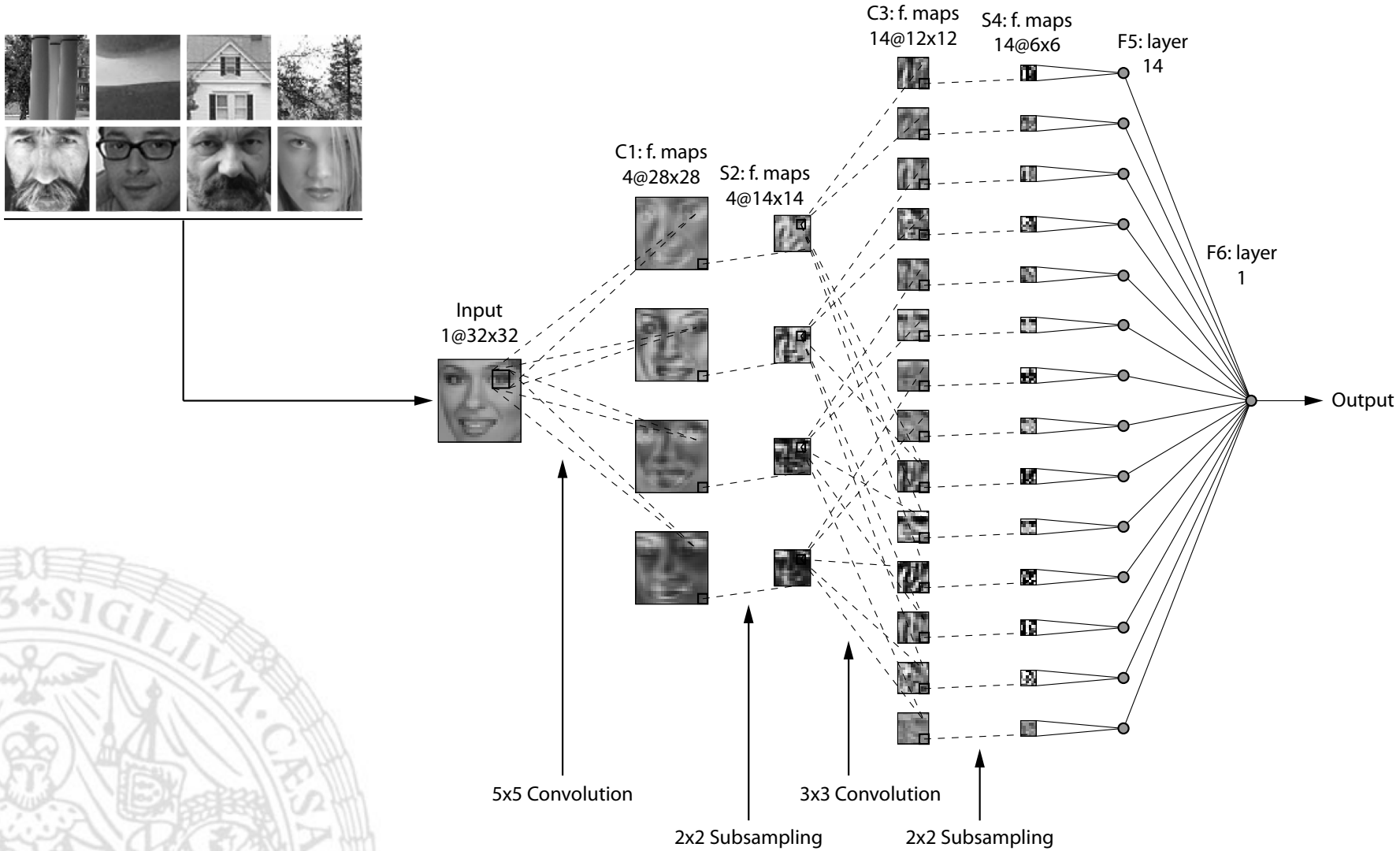
## Convolutional Face Detector

*Determine whether or not there are any faces in an image and, if present, return the image location and region of each face.*

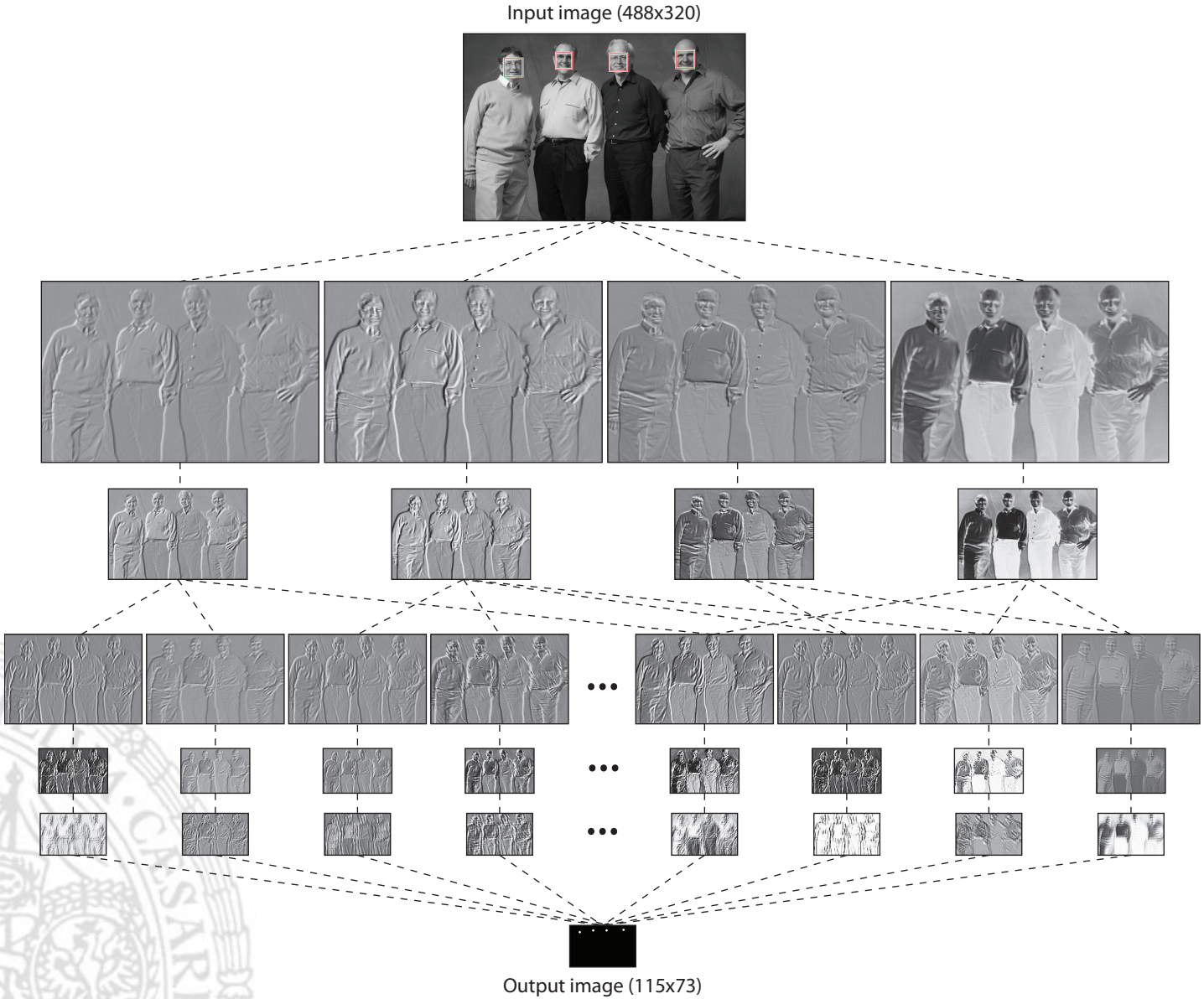


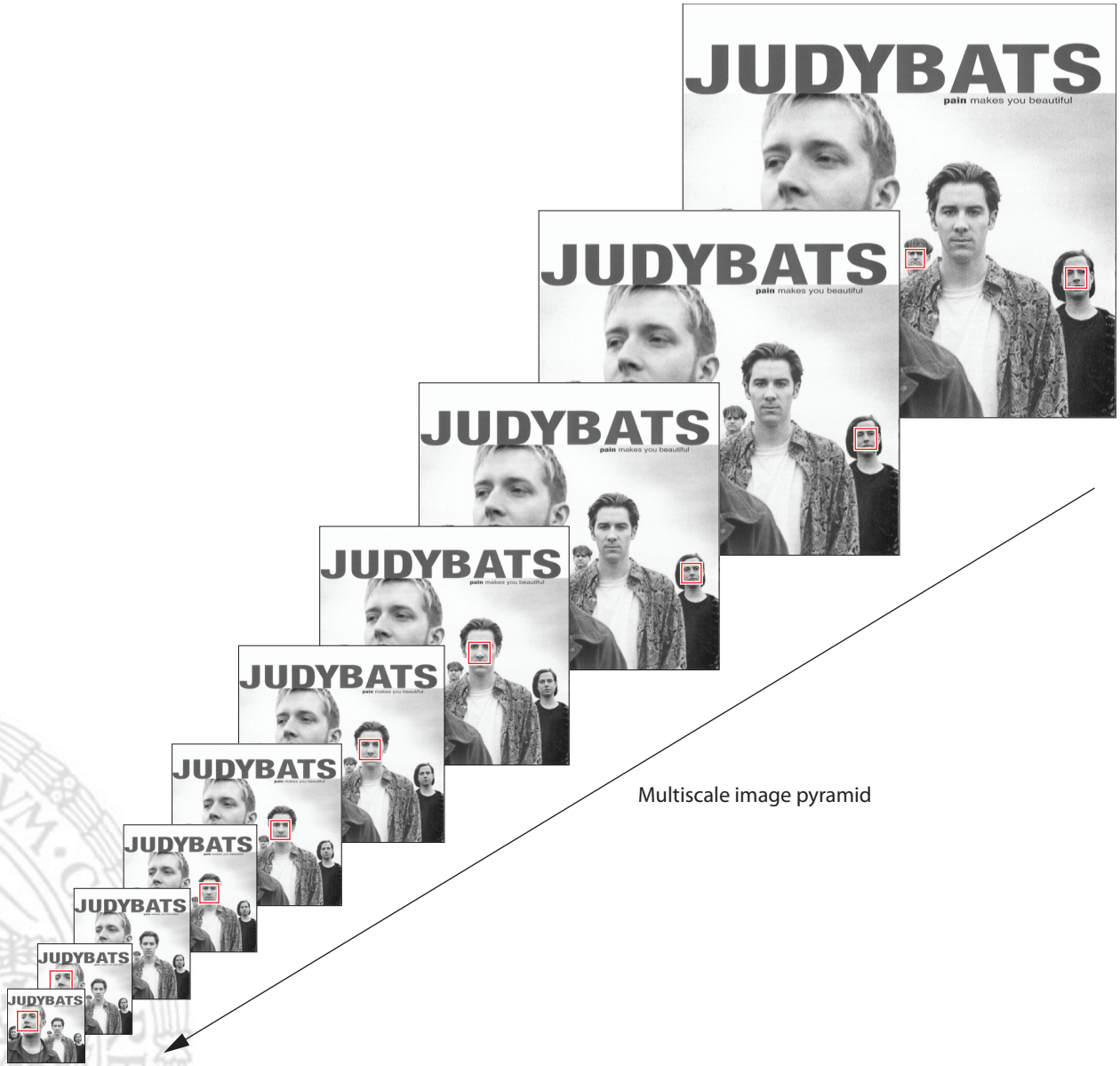
# Network Architecture [4]



# Face Localization



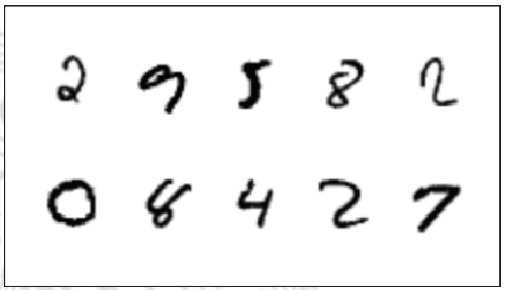
# Face Localization – cont.




2 face(s)
1 [1.00]
2 [1.0
LIVE ORF 1
Land der Hämmer, zukunftsreich

## Optical Character Recognition

- The MNIST database was used for evaluation.
- The first 54,000 patterns of the training set were used to train the network.
- The last 6,000 patterns of the training set were used as validation set for the early stopping algorithm.
- The test set, containing 10,000 patterns, was used to determine the network's classification performance.

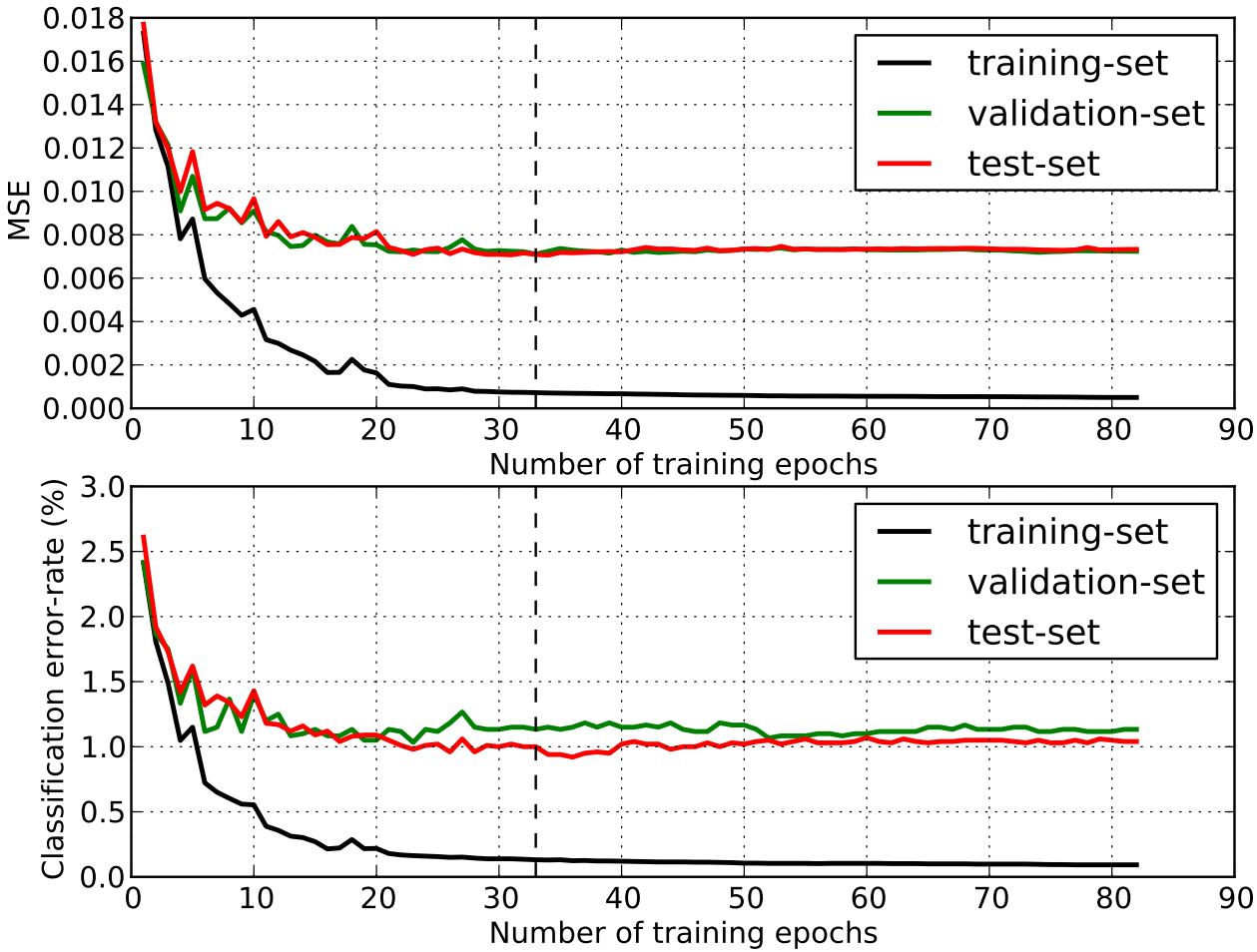


**MNIST Handwritten Digit Database**

- Provided by Yann LeCun and Corinna Cortes.
- Images of handwritten digits $(0, 1, \ldots, 9)$.
- Each of size $28 \times 28$ pixels with 256 gray levels.
- Contains 60,000 training and 10,000 test patterns.

# LeNet5 Classification Performance

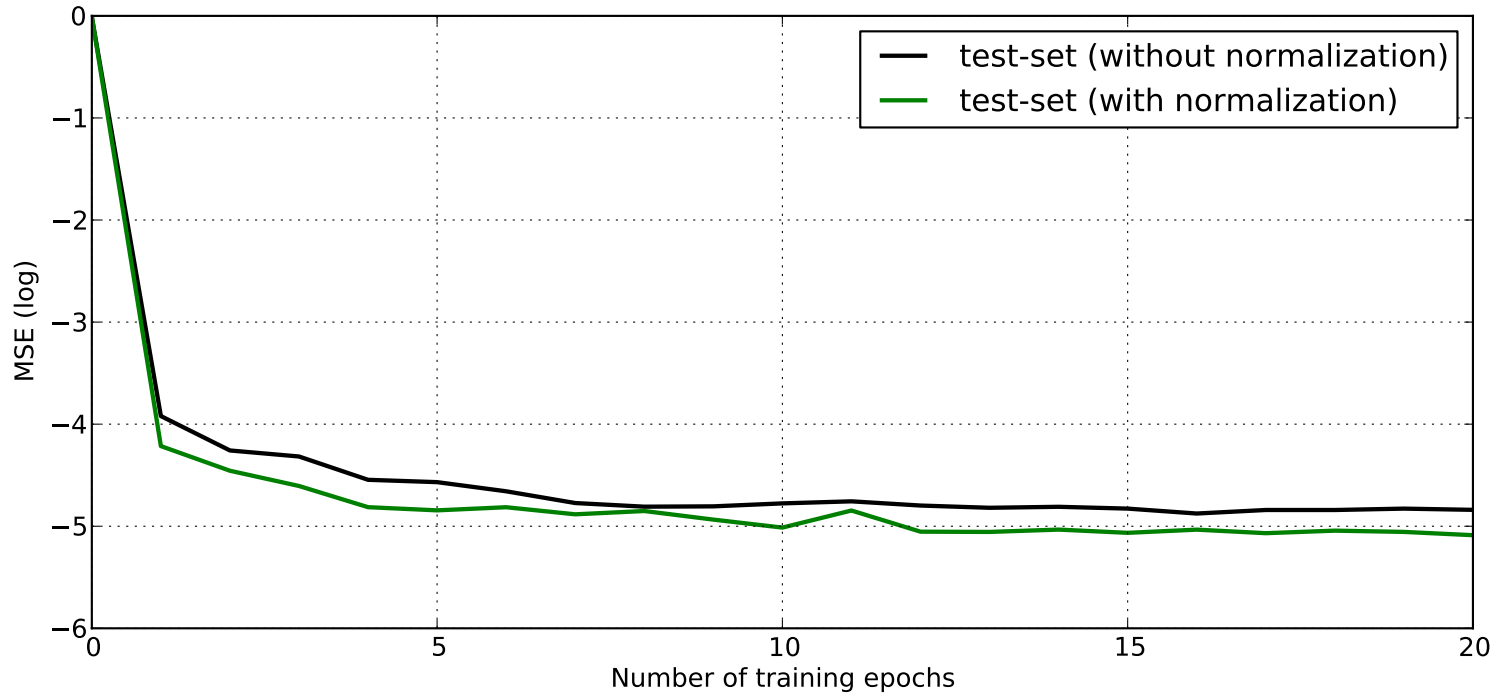
Avg. Classification Rate: 98,91%




Development of the error on all three datasets during the learning of the MNIST database by a LeNet5. The dashed line indicates the epoch with the best performance on the validation set.

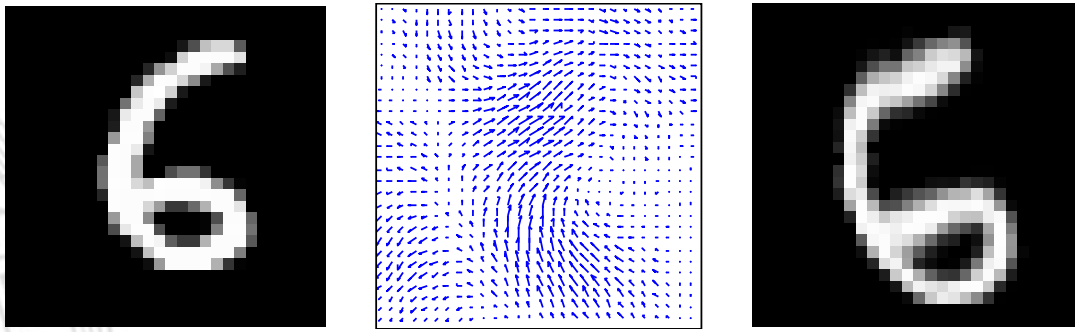
# Enhancing Classification Result by Normalization

- The input data is preprocessed so that the mean of the whole dataset is 0 and its standard deviation is 1.
- To achieve this we calculate the mean and the standard deviation of the whole training dataset.
- Before a pattern is fed into the network the mean is subtracted from it and the result is divided by the standard deviation.
- Classification rate improves by approximately 0.05 - 0.1%.



## Enlarge Training Dataset by Elastic Distortions

- More training data often improves the accuracy of a neural network.
- Therefore we enlarge the training dataset using elastic distortions:
  - For every existing training pattern we generate 9 virtual ones using 9 different displacement fields.
  - The newly generated patters are used for training along with the label of their original pattern.
  - Those displacement fields are regenerated in every training epoch.
  - Classification rate improves by approximately 0.3 - 0.6%.



# Conclusion and Future Work

## Conclusion

- GPUs work quite well for convolutional neural networks.
- The GPU implementation scales much better than the CPU implementations with increasing network size.
- The shorter training time allows more network evaluations which often lead to better results.
- The modifacitons applied to the training data and network improved the network's accuracy.

## Future Work

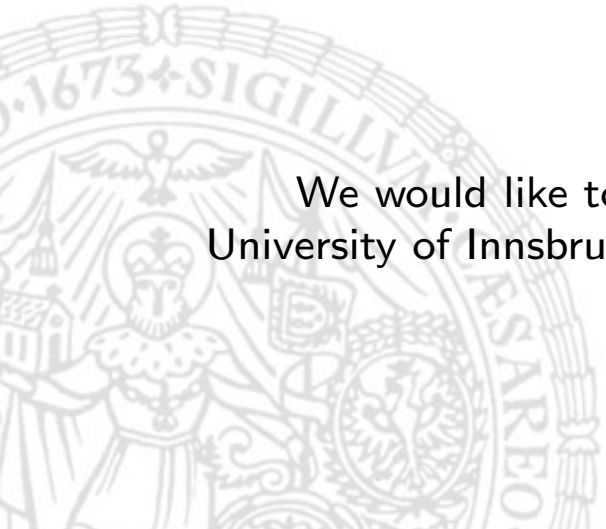
- Accomplish complex experimental tests with different network topologies and parameter settings using our fast GPU implementation.
- Analyze and compare the power consumption of our CPU implementation to our GPU versions.

# Thanks for your attention!

Questions?

According to the statements from Sonnenburg et al. in [7] which emphasis
the need for open source software in machine learning
we make our library [8] public available:

http://cnnlib.sourceforge.net (coming soon)



**Acknowledgments**

We would like to thank Dr. Alfred Strey for his helpful comments and the University of Innsbruck who supported this work with the "Förderungsstipendium".

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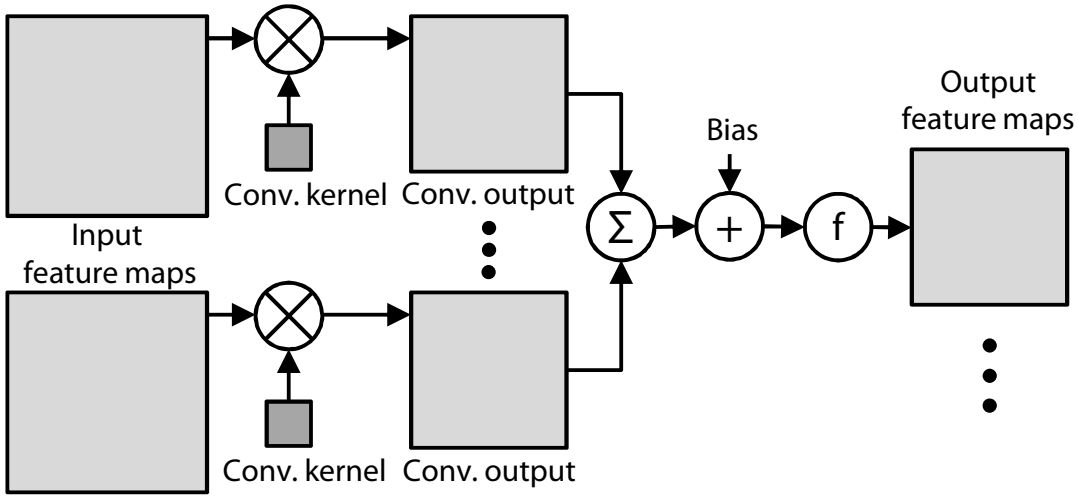
# Appendix

# Illustration of the operating principle of a convolutional and subsampling layer inside a CNN:

## Convolutional Layer




## Subsampling Layer

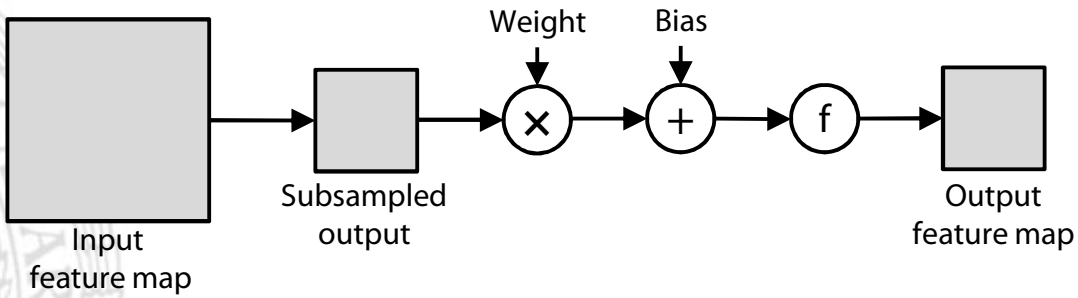
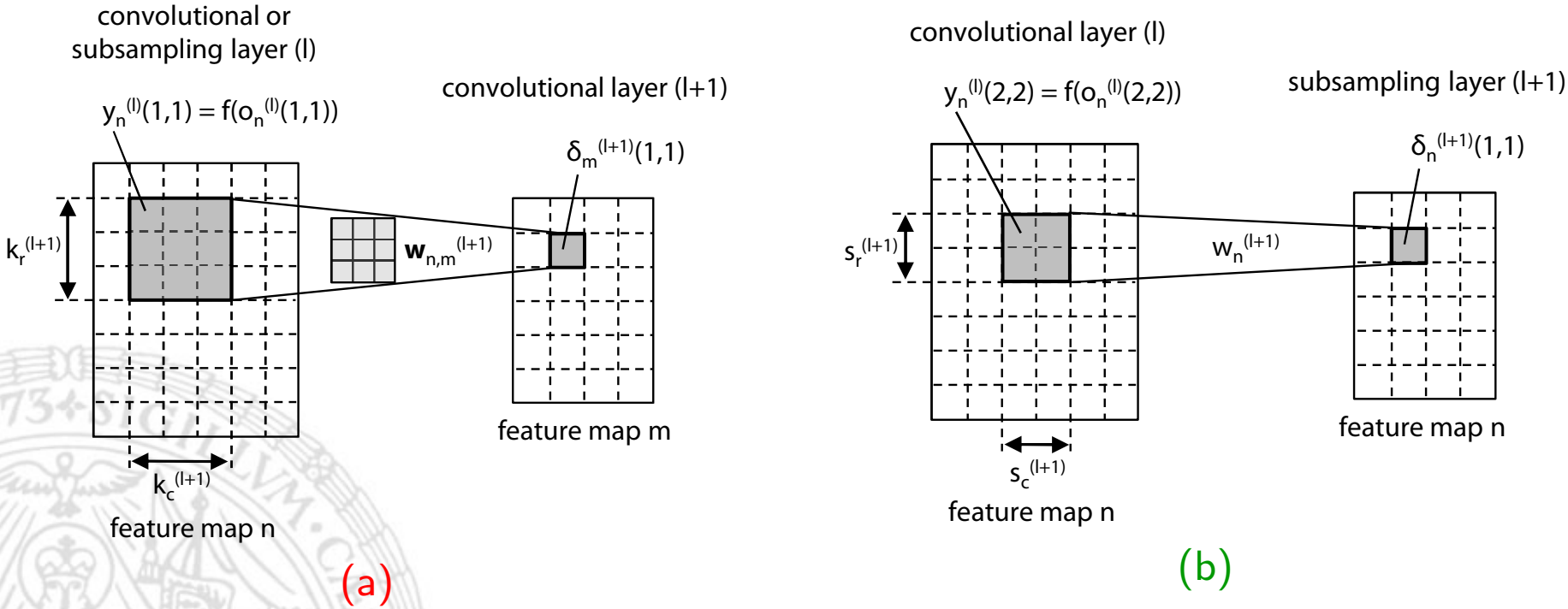
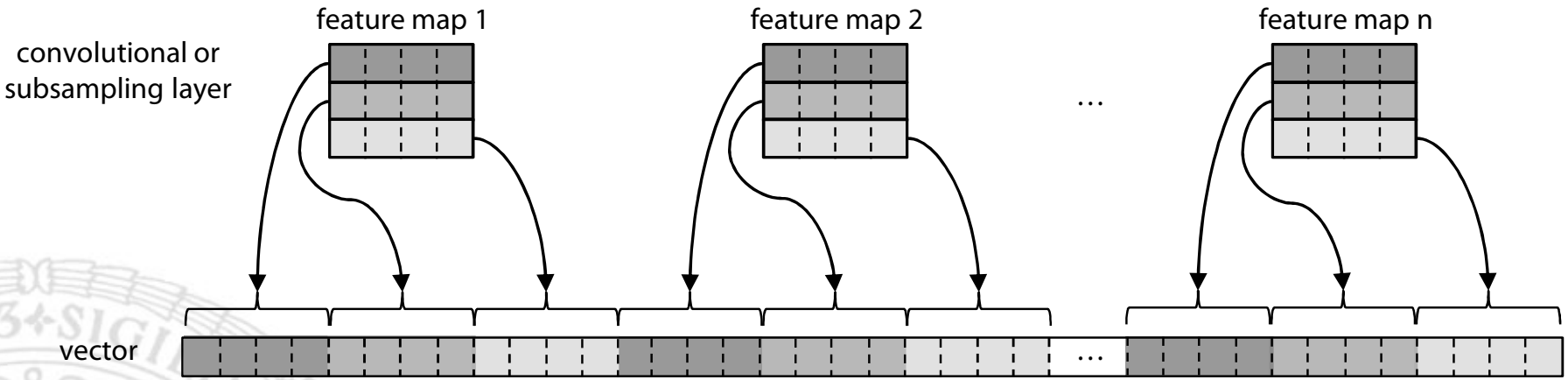


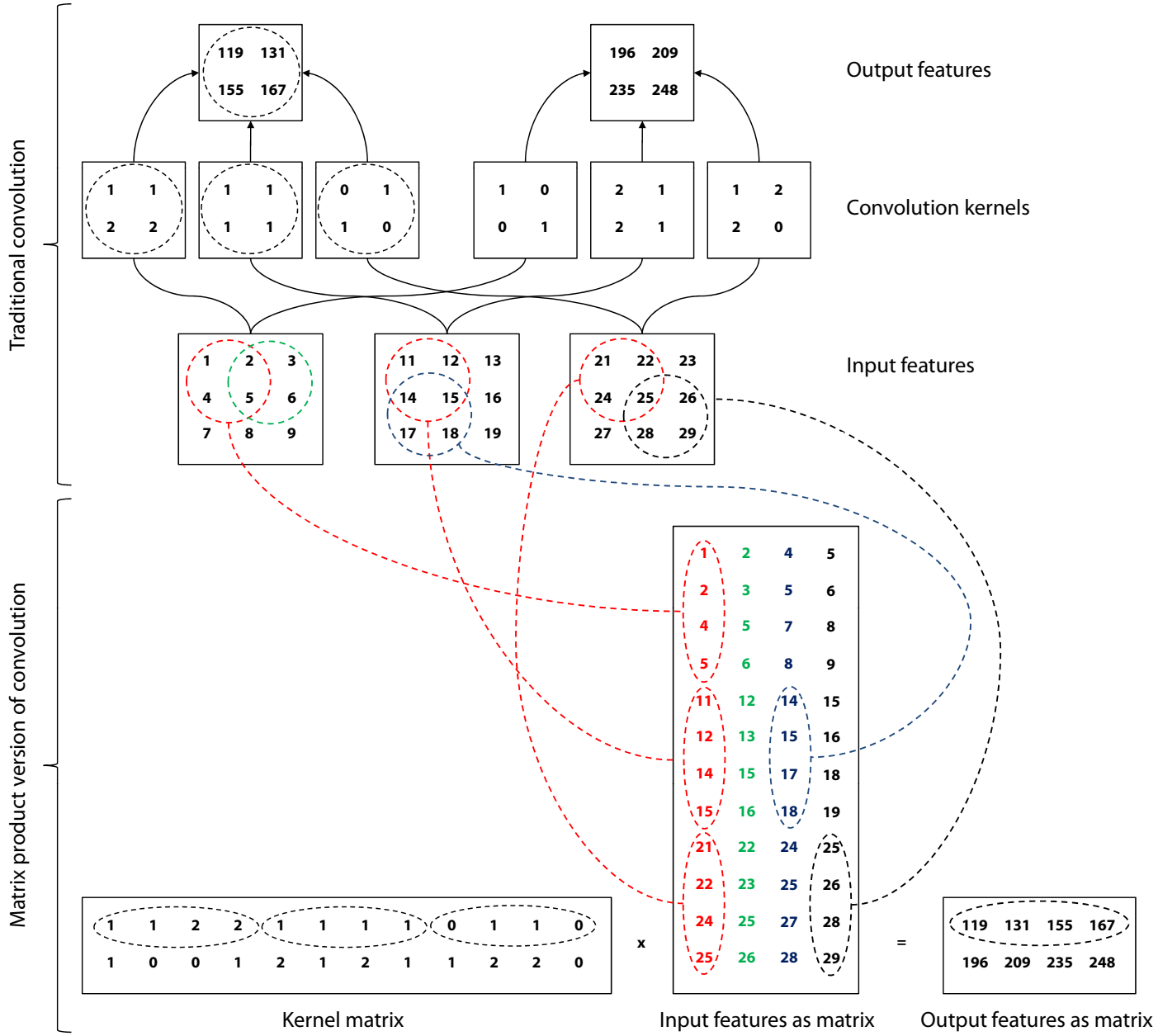
**Illustration of the error backpropagation for a convolutional layer followed by a subsampling layer (a) and a convolutional or subsampling layer followed by a convolutional layer (b):**



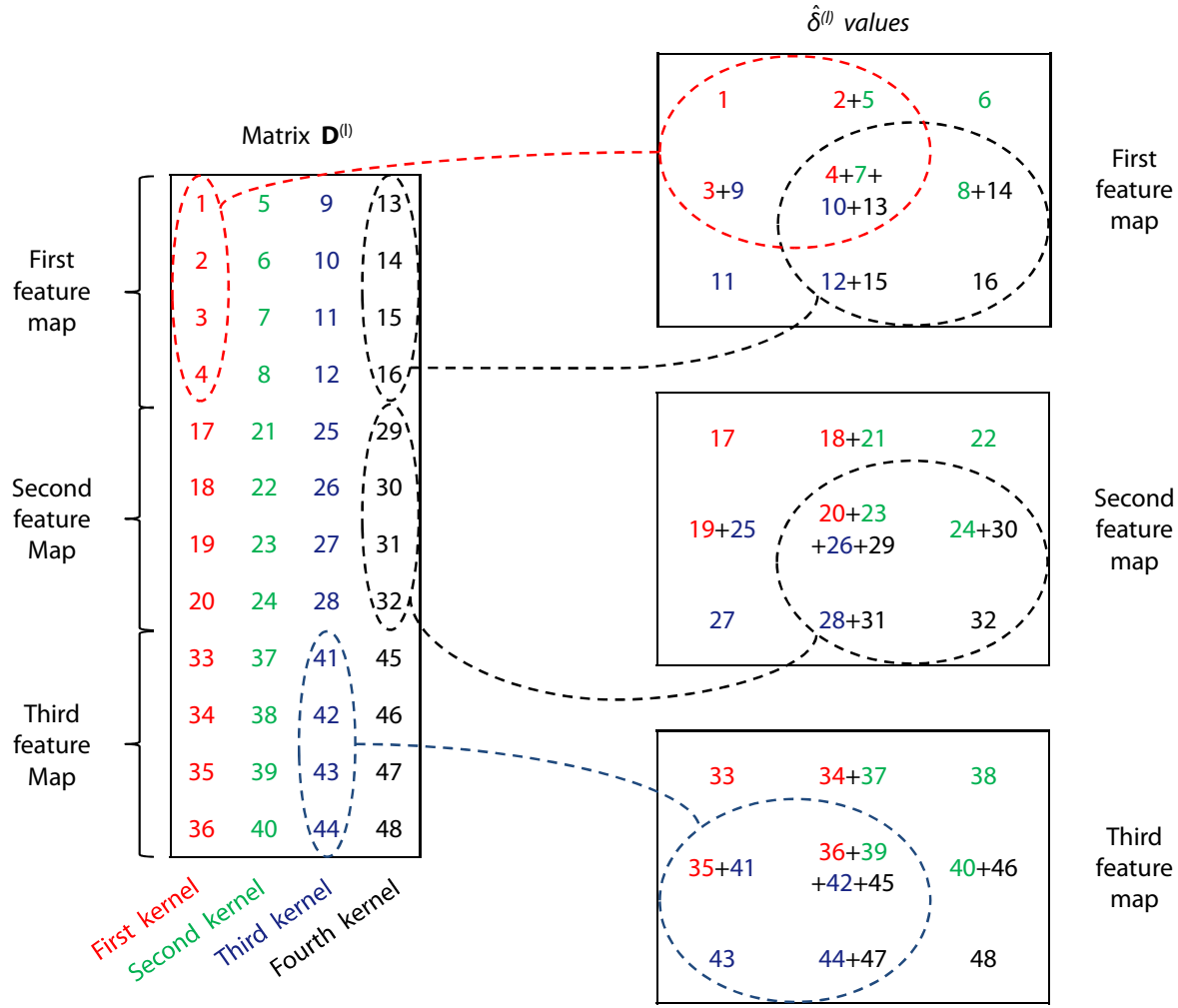
**Rearrangement of the feature maps of a convolutional or subsampling layer into a single vector, so that it can be used in the succeeding (1D) fully connected layer:**



# Unfolding the Convolution



# Backfolding



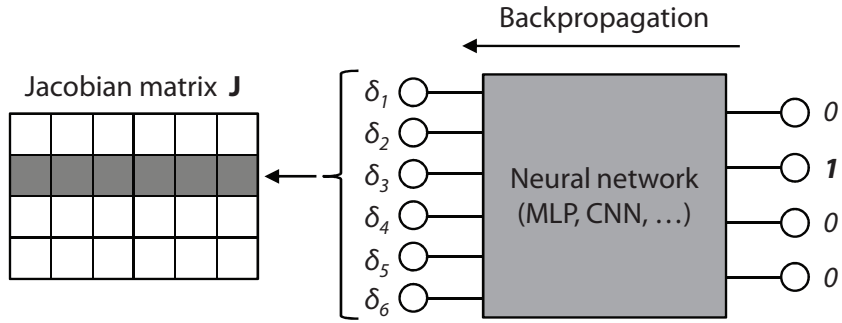
## Numerical Differentiation

$$\frac{\partial E}{\partial w^{(l)}(i,j)} = \frac{E_{\left[w^{(l)}(i,j)+\epsilon\right]} - E_{\left[w^{(l)}(i,j)-\epsilon\right]}}{2 \cdot \epsilon} \tag{1}$$

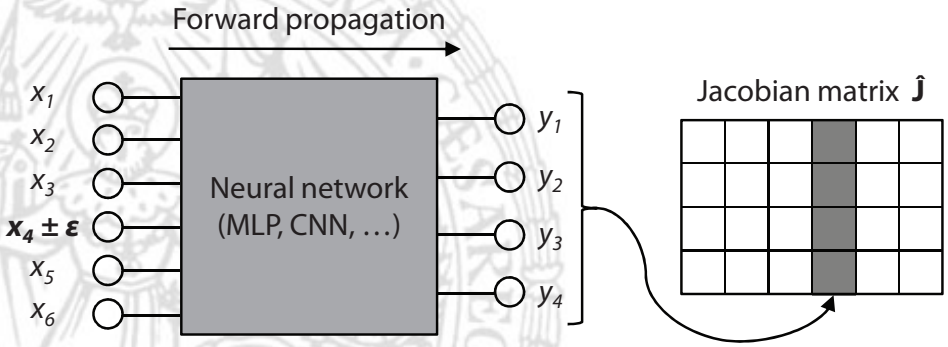
# Jacobian Matrix

$$J(i,j) = \frac{\partial y^{(L)}(j)}{\partial x(i)} \tag{2}$$

Constructing the Jacobian matrix **J** using the backpopagation function:



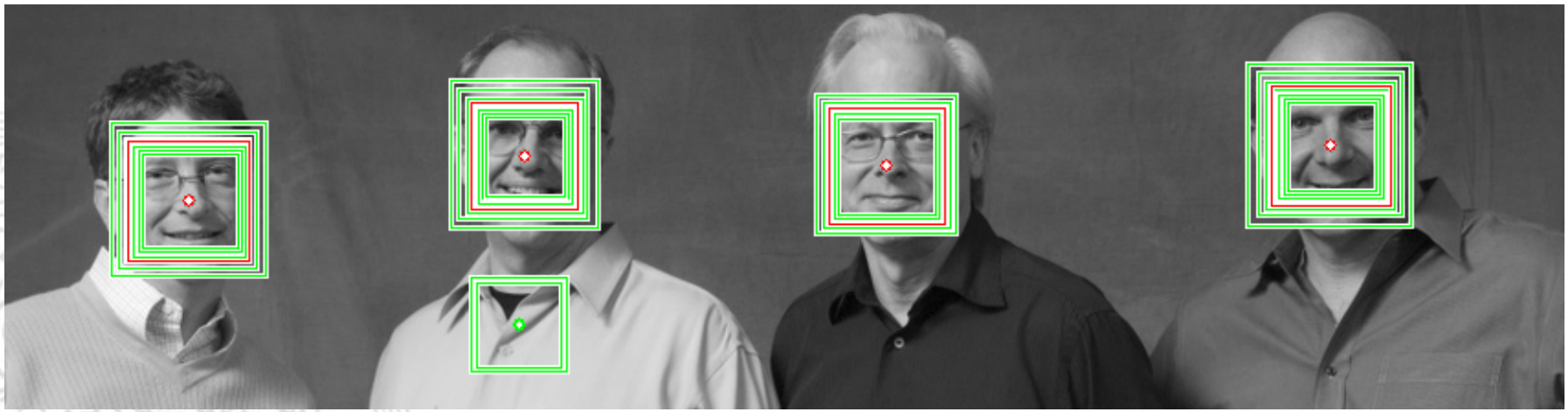

Constructing an approximation $\hat{\mathbf{J}}$ of the Jacobian matrix using the forward propagation function:



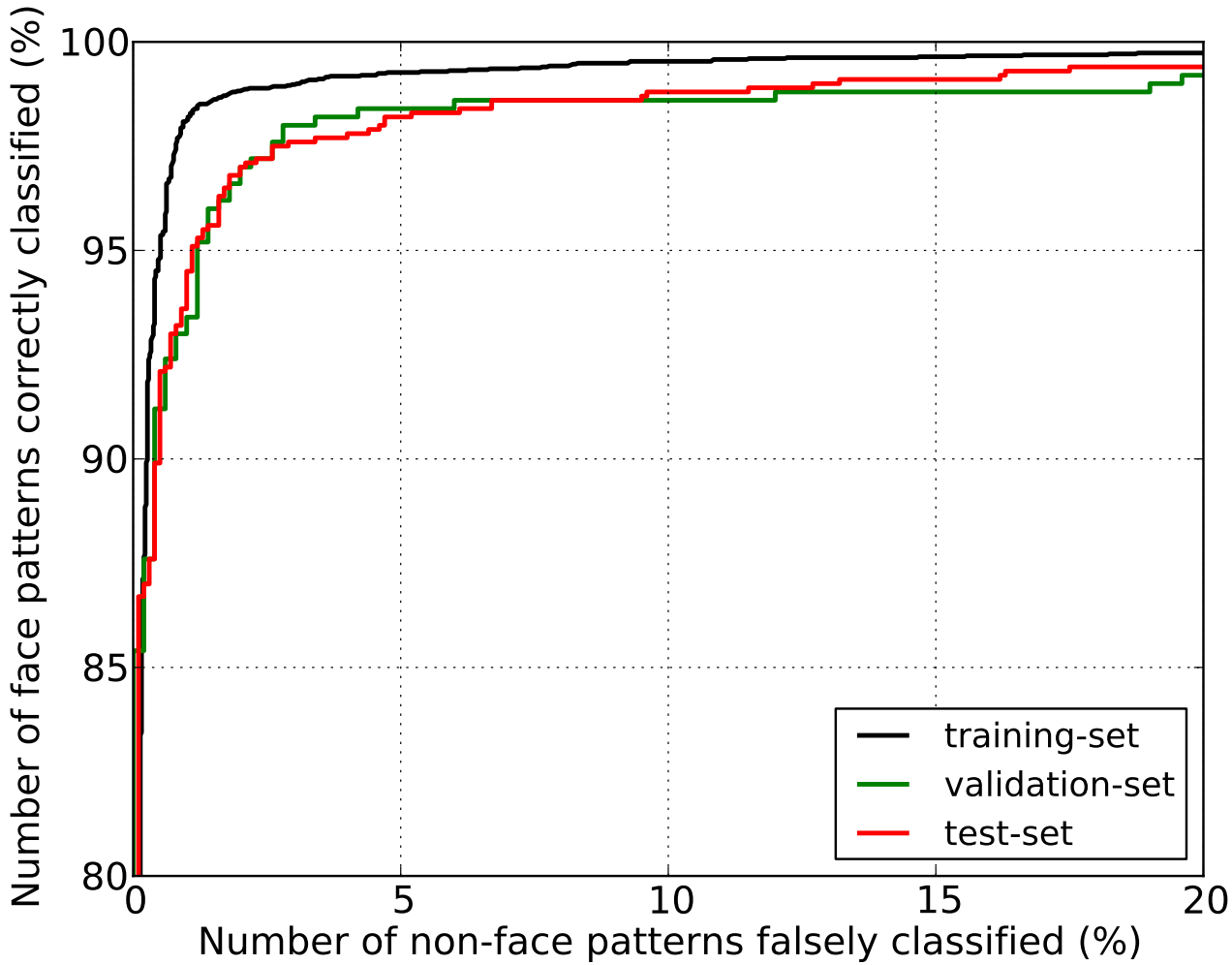

$$\hat{J}(i,j) = \frac{y^{(L)}_{[x(i)+\epsilon]}(j) - y^{(L)}_{[x(i)-\epsilon]}(j)}{2 \cdot \epsilon} \tag{3}$$

**Additional verification step to reduce the number of false detections:**

1. Each face candidate is tested at six scales in the original input image, ranging from 0.7 to 1.3 of the detected size.
2. At each scale the presence of a face is evaluated and compared to a threshold.
3. True faces will give high network responses in a certain number of consecutive scales, while non-faces don't.



**ROC curves of the trained GarciaNet applied to the training, validation, and test dataset:**



## Input Data Normalization

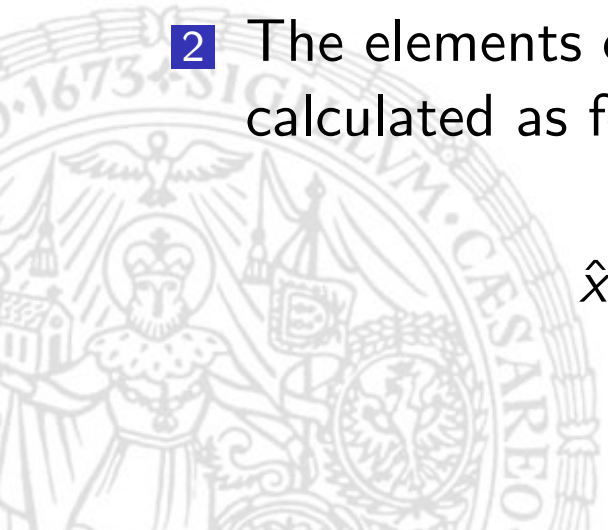
1. First of all the mean $m$ of the entire training set $S$ and its standard derivation $\sigma$ have to be calculated as follows:

$$m = \frac{1}{|S|} \cdot \sum_{x \in S} \frac{1}{|x|} \cdot \sum_{i=0}^{|x|-1} x(i) \tag{4}$$

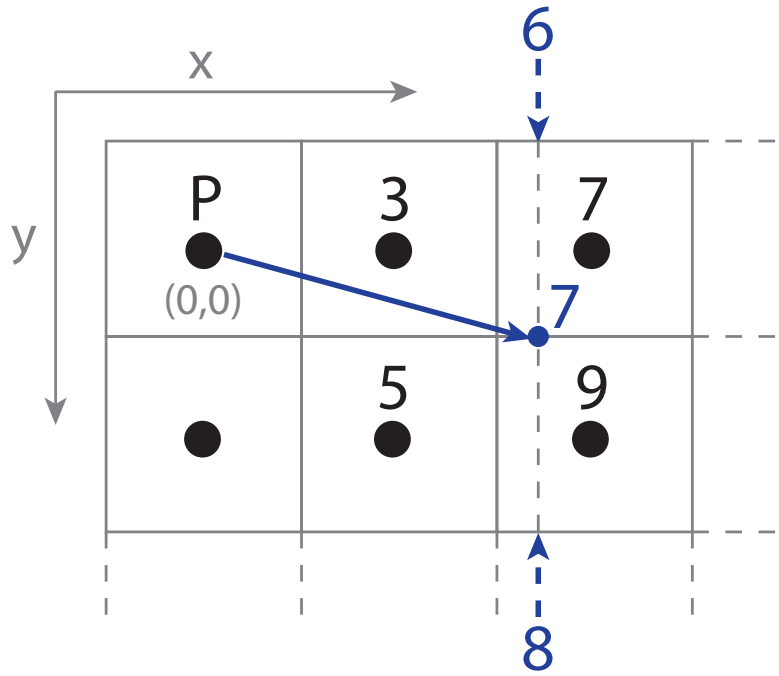
$$\sigma = \sqrt{\frac{1}{|S|} \cdot \sum_{x \in S} \frac{1}{|x|} \cdot \sum_{i=0}^{|x|-1} (x(i) - m)^2} \tag{5}$$

2. The elements of the normalized input vector $\hat{\mathbf{x}}$ can then be calculated as follows:

$$\hat{x}(i) = \frac{x(i) - m}{\sigma}, \quad i = 0, 1, \ldots, |x| - 1 \tag{6}$$

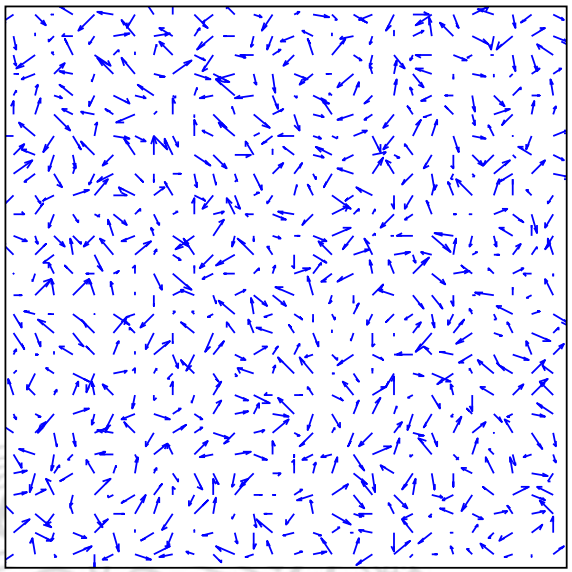


## Bilinear Interpolation for $\Delta x = 1.75$ and $\Delta y = 0.5$:

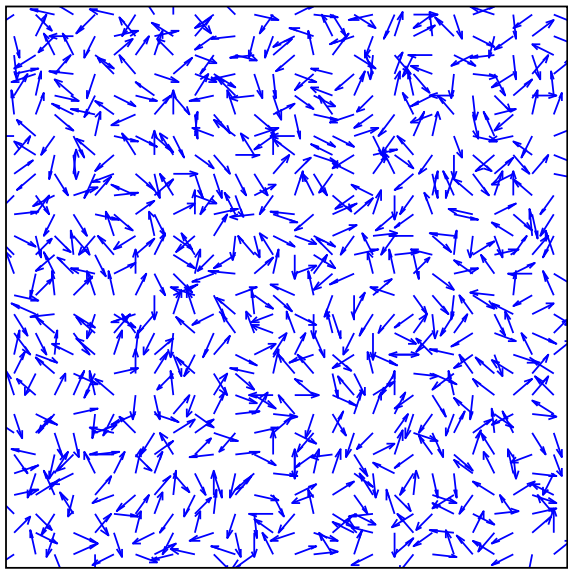



$$P_{x_1} = 3 + 0.75 \cdot (7 - 3) = 6$$
$$P_{x_2} = 5 + 0.75 \cdot (9 - 5) = 8$$
$$P = 6 + 0.5 \cdot (8 - 6) = 7 \tag{7}$$

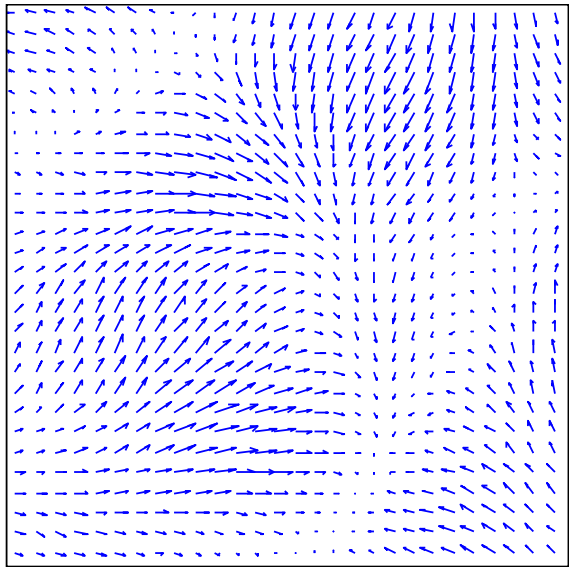
**Illustration of the single steps to generate a displacement field for elastic deformations:**



after initialization

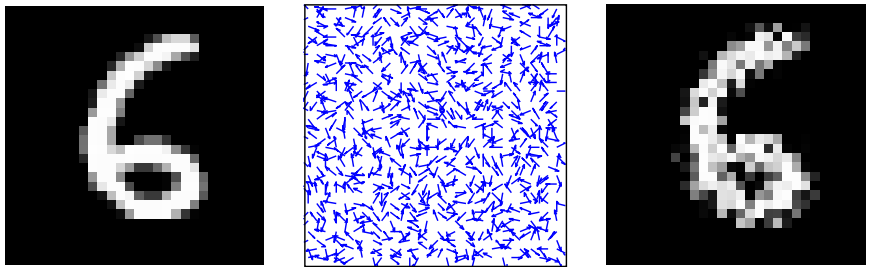


after normalization

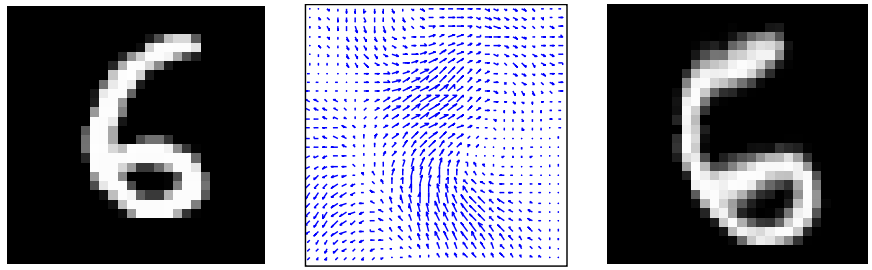


after Gaussian ($\sigma = 4$)

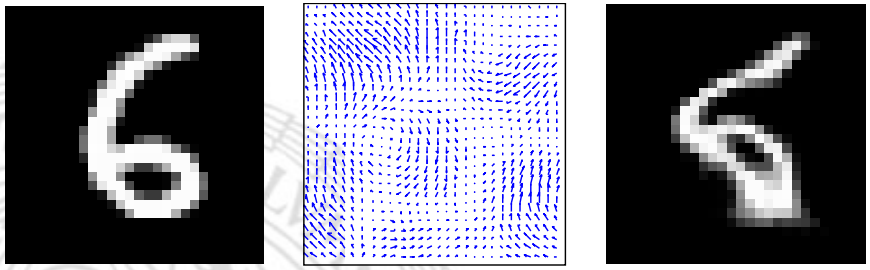
## Effects of $\sigma$ and $\alpha$:



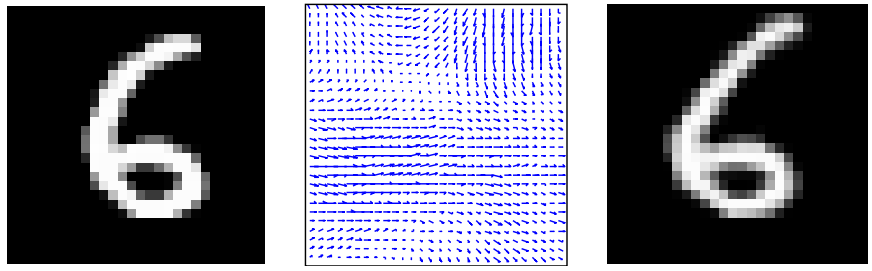
$\sigma = 0.1$ and $\alpha = 1$



$\sigma = 4$ and $\alpha = 34$



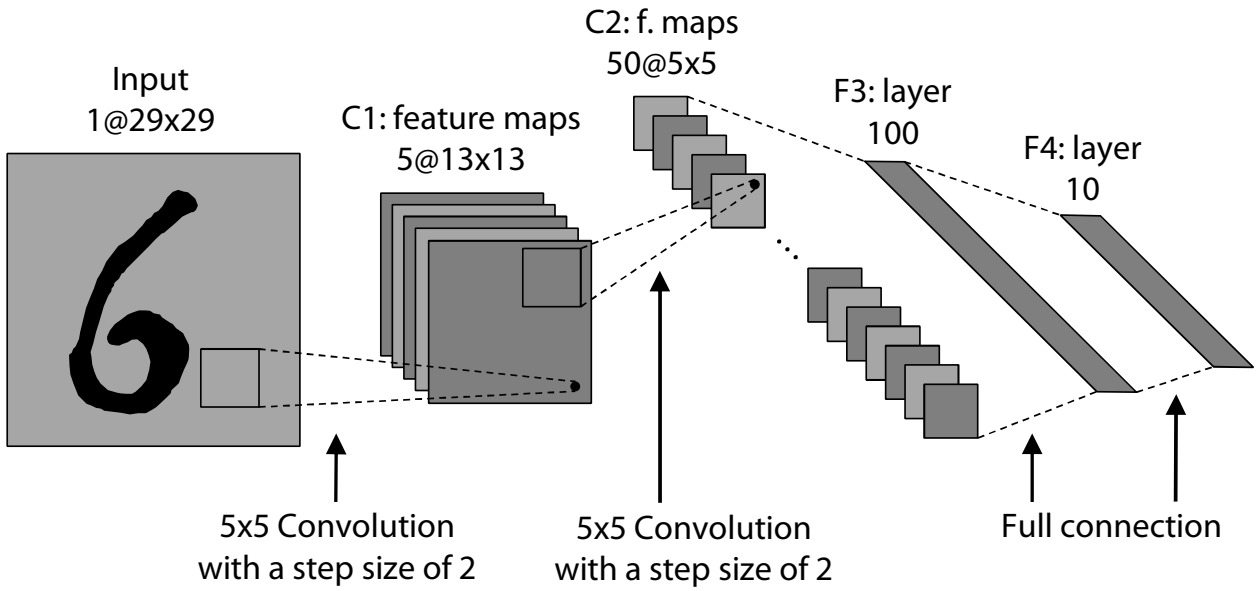
$\sigma = 3$ and $\alpha = 30$



$\sigma = 6$ and $\alpha = 22$

| **Properties** | **LeNet5** | **JahrerNet** |
|---|---|---|
| Structure | 5 Layer (C1 S2 C3 S4 F5 F6) | 5 Layer (C1 S2 C3 S4 C5 F6) |
| Connection S2 to C3 | Sparse, predefined | Random, probability 0.14 |
| Connection S4 to C5/F5 | Full | Random, probability 0.20 |
| # neurons | 8,010 | 21,160 |
| # connections | 51,046 | $\sim$ 100,000 |
| # trainable parameters | 331,114 | $\sim$ 770,000 |
| Rel. execution time (CPU) | 1 | $\sim$ 2.95 |
| Rel. execution time (GPU) | 1 | $\sim$ 1.06 |

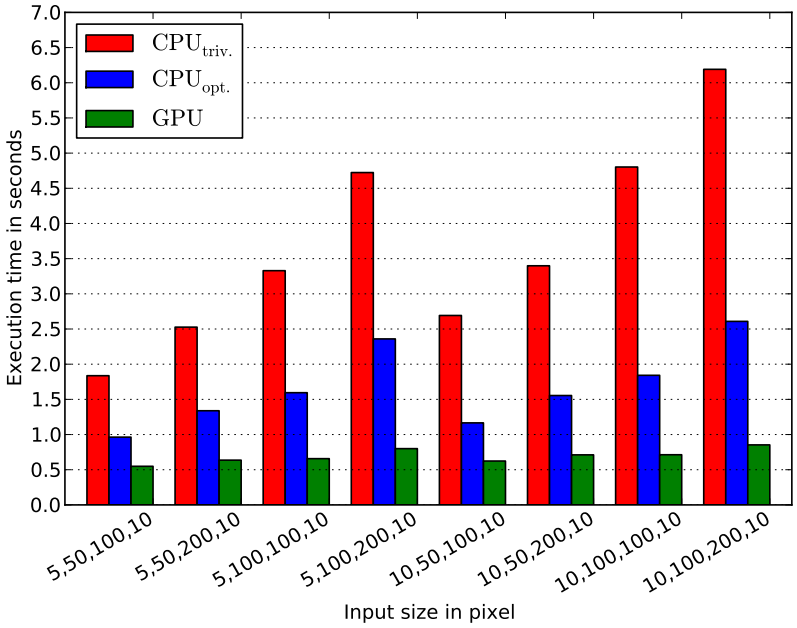
# Benchmarks on the SimardNet*



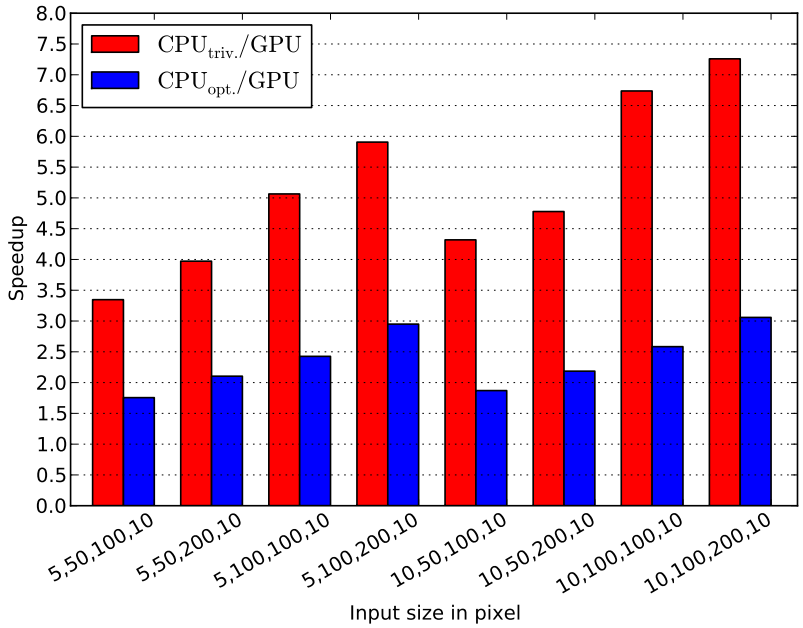

* Proposed by Simard et al. in [2] (one of the best performing networks on the MNIST database).

# Scaling Feature Maps and Inner Neurons of a SimardNet

## Execution Time

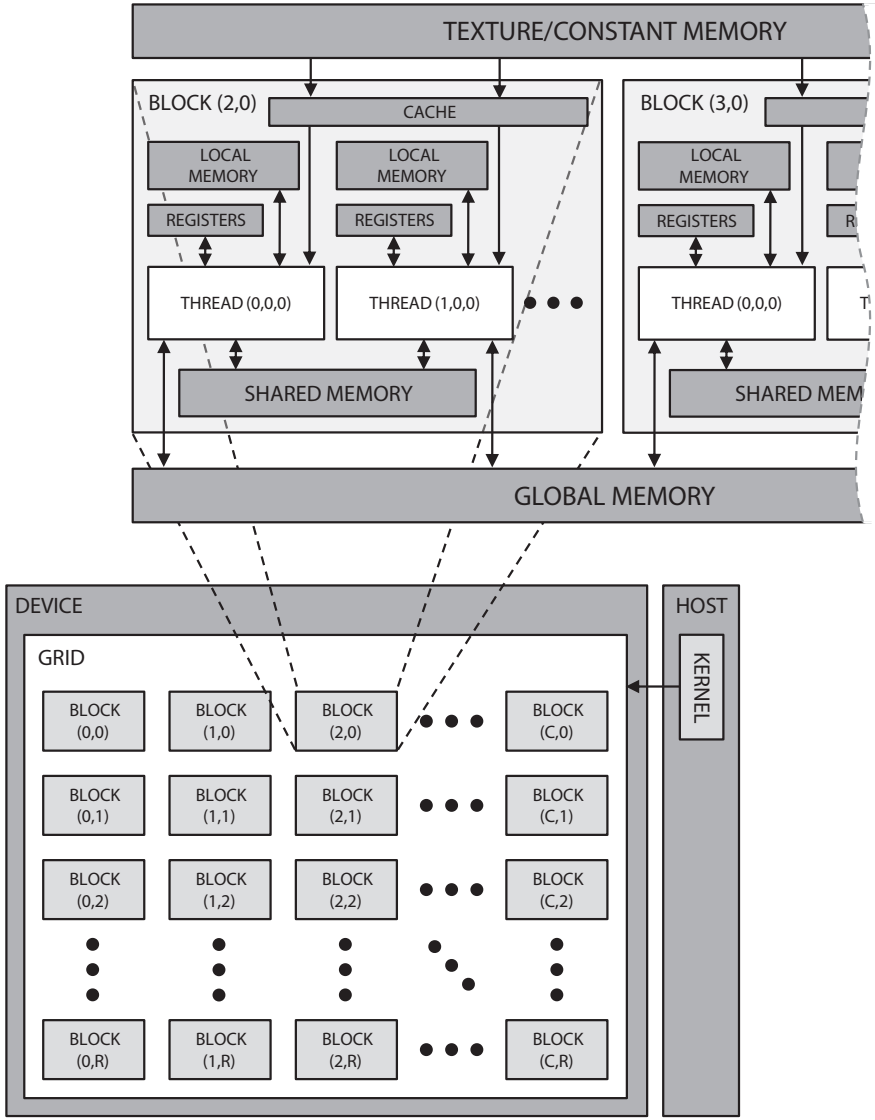



## Speedup

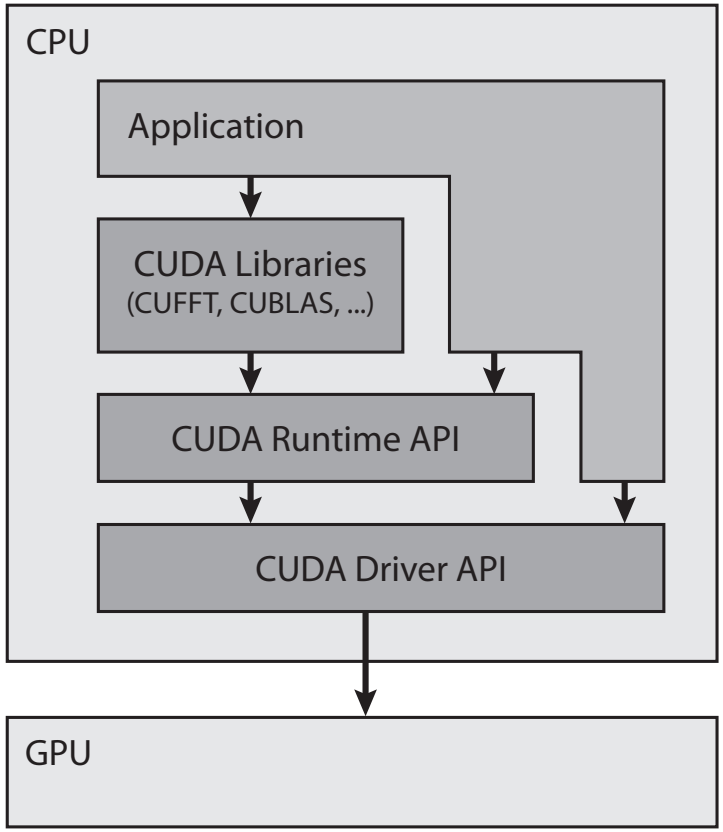



Execution time and corresponding speedup of the three different implementations performing 1,000 learning iterations of a SimardNet.

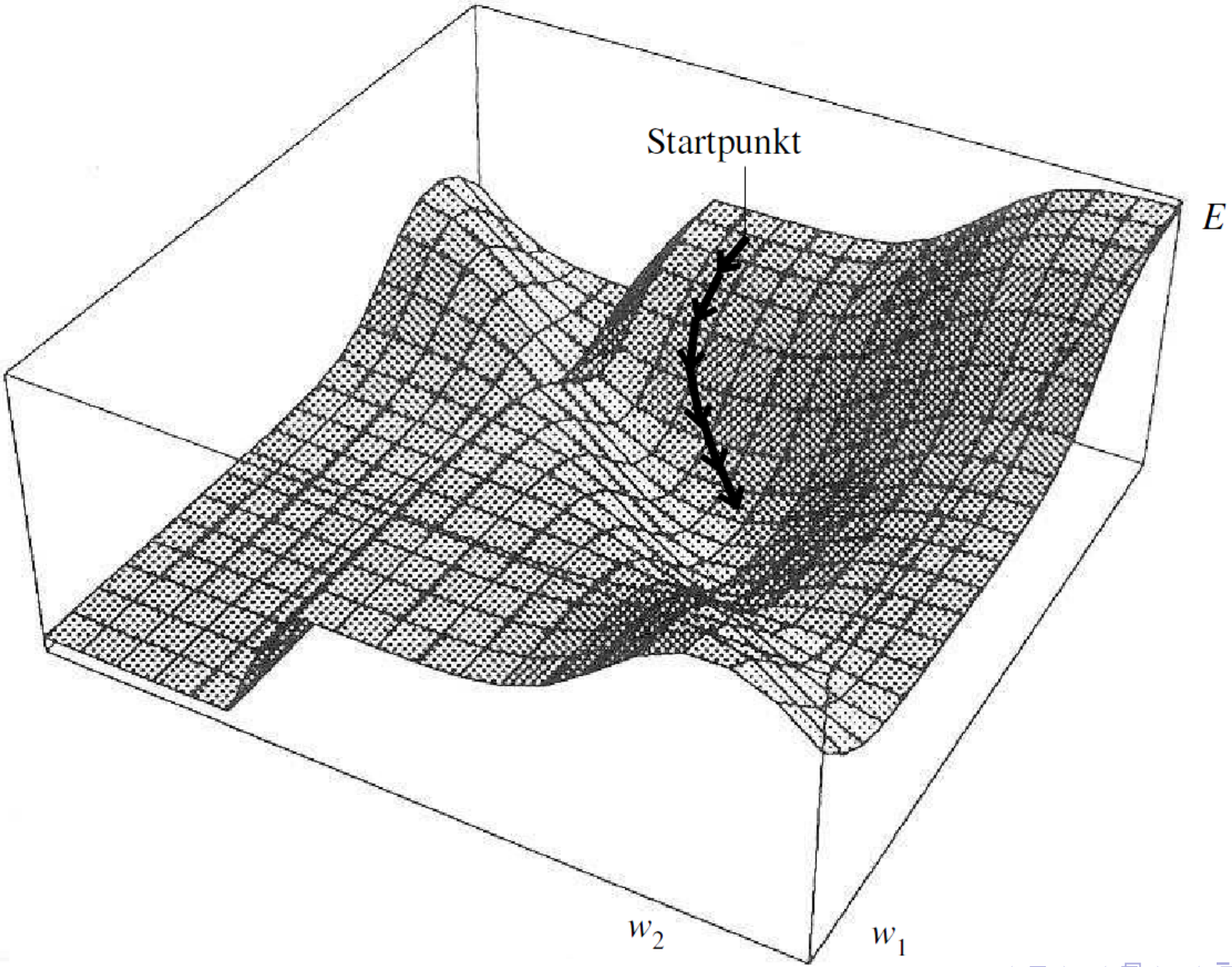
# CUDA Threading and Memory Topology



# CUDA Software Stack



# Gradient Descent Method



## CNNs using Random Connections

- Sparse connections break the symmetry of the network and can improve the network's performance.
- Michael Jahrer [9] advanced this approach by introducing random connections:
  - The connections between feature maps of consecutive layers are generated randomly at network initialization.
  - The used connection probability is around 0.1 - 0.2. Therefore a much larger network is needed to unveil its potential.
  - Using a large network with sparse random connections improves the network's accuracy but leads to a longer execution time.
  - Without modification of the dataset this network reaches a classification rate on the MNIST database of 99.15%.