A Deep Learning Approach to Structured Signal Recovery

Seminarvortrag

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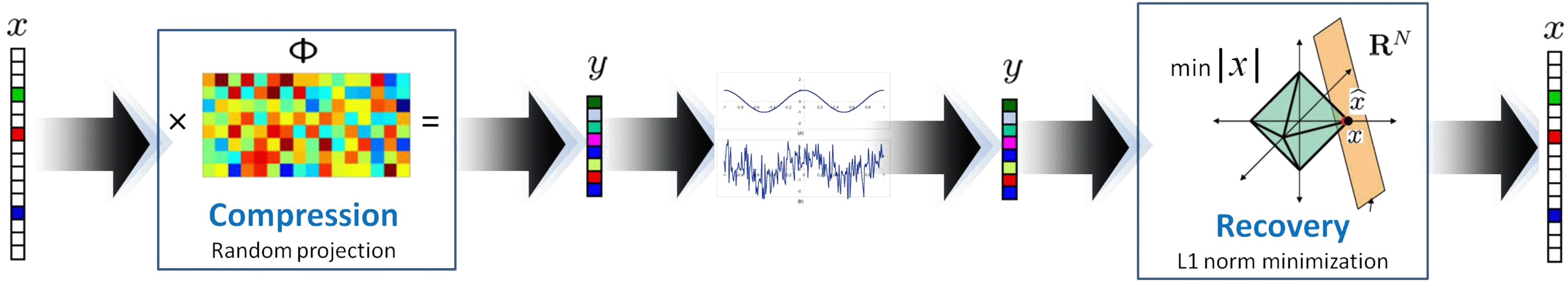
Introduction: Compressive Sensing

System Overview



Compress signal with a (random) measurement matrix

Transmission of compressed signal

Reconstruction of original signal

Source: https://www.ti.rwth-aachen.de/research/applications/cs.php

Agenda

Introduction

- Problem Statement
- Research Goals

Background

- Compressive Sensing
- Deep Learning

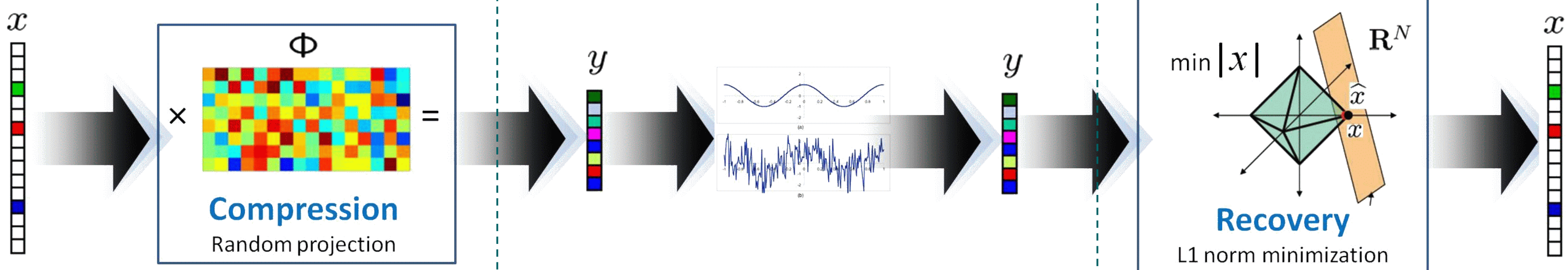
Review

- Using Autoencoders for reconstruction and measurements

Outlook

- Improving the architecture with convolutional networks

Research Questions

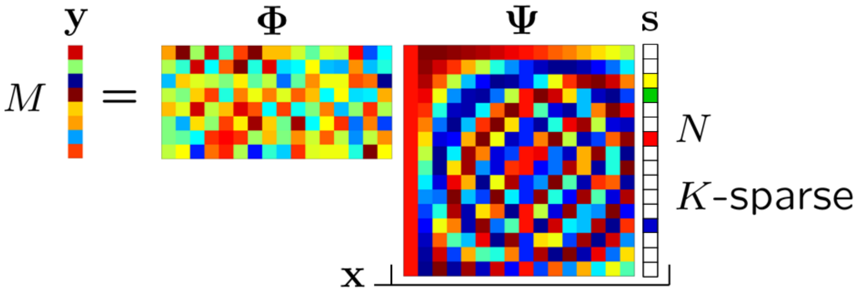


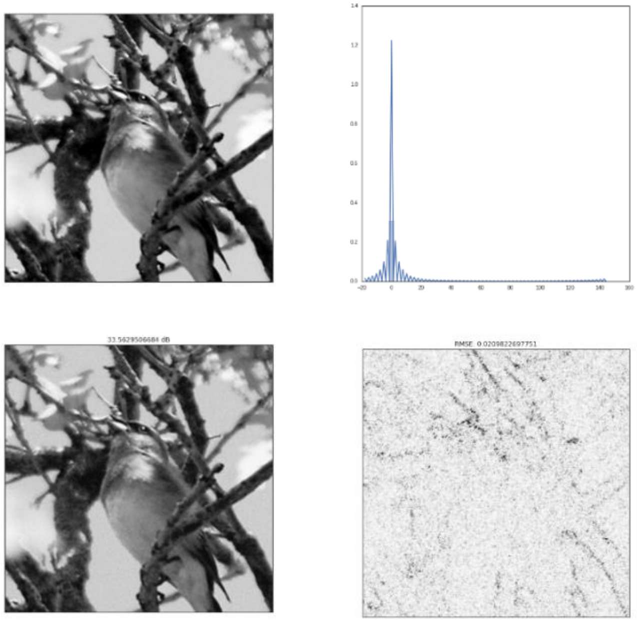
1. How to choose the measurement matrix?

2. Which algorithm for reconstruction?

Source: https://www.ti.rwth-aachen.de/research/applications/cs.php

Problem: Natural Signals are usually not sparse in the target domain



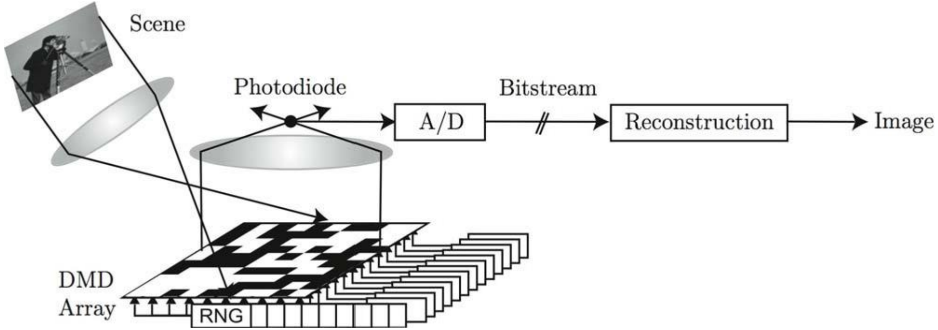


Examples: Images, Audio Signals

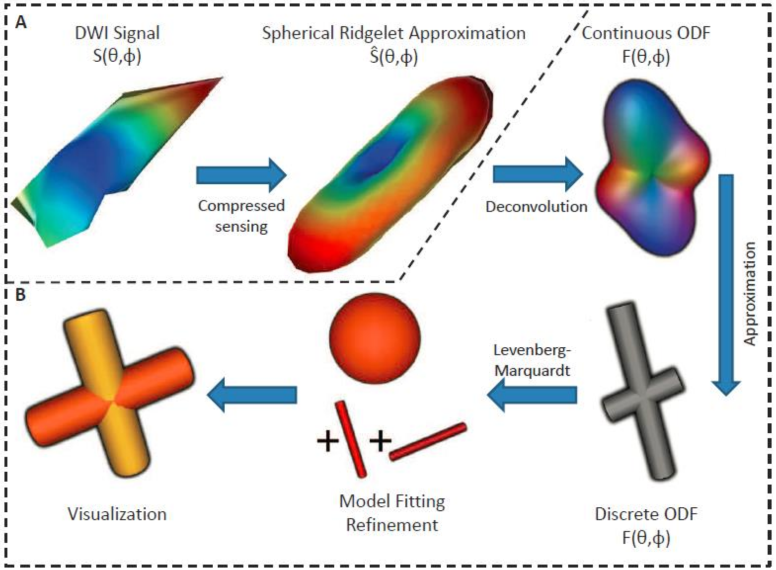
Solution: Wavelet Transformations

Proof of Concept: Compressive Sensing for Image Acquisition

- Use of inexpensive Hardware (e.g. CCD with lower spatial resolution)
- Shorter time for signal acquisition

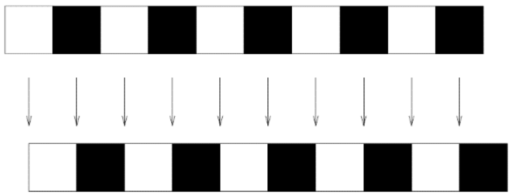


Example Usage: MRI



Source: Koppers et al., Spherical Ridgelets for Multi-Diffusion-Tensor Refinement - Concept and Evaluation. In: *Bildverarbeitung für die Medizin 2015* (2015)

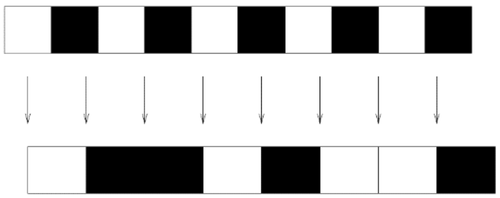
Image Sampling



Nyquist Sampling

$$f_{\mathrm{B}} = \frac{1}{2}$$

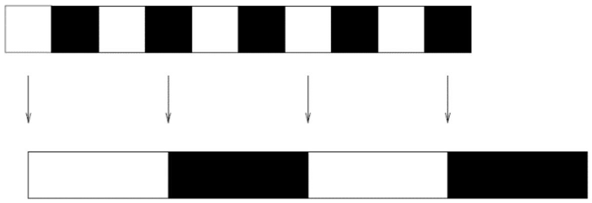
$$r = 1 = f_{\mathrm{Nyquist}}$$



Pixel Errors

$$f_{\mathrm{B}} = \frac{1}{2}$$

$$r = \frac{4}{5} < f_{\mathrm{Nyquist}}$$



Aliasing

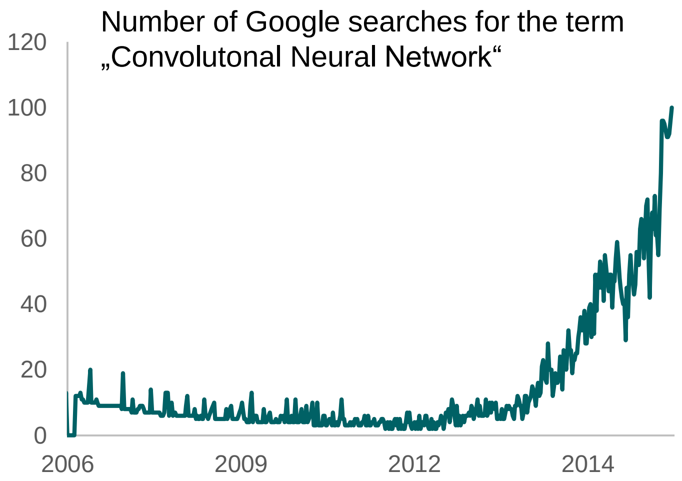
$$f_{\mathrm{B}} = \frac{1}{2}$$

$$r = \frac{1}{3} < f_{\mathrm{Nyquist}}$$

Source: Image Processing, Chapter 3

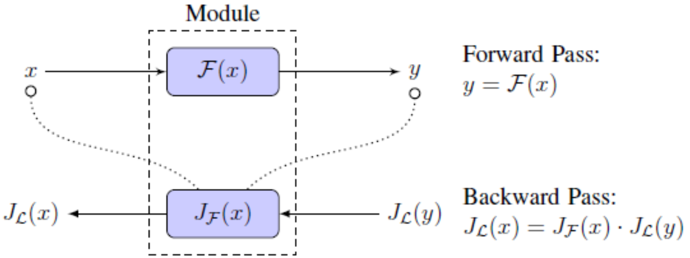
CNNs ermeged as the State-of-the-Art in Image Processing

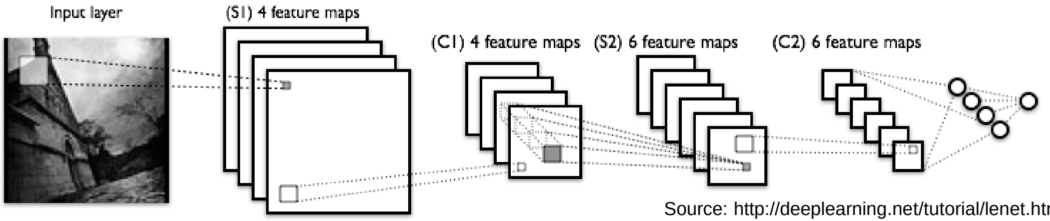
- 1957: Perceptron Learning, Rosenblatt
- 1969: Minsky & Papert showed downsides of perceptrons
- 1980s: Backpropagation Algorithm
- 1995: Alternatives where developed, e.g. SVMs
- since 2005: Training of deep neural networks → RBMs, Deep Belief Networks
- **2012: Outstanding performance of CNN in ImageNet Large Scale Visual Recognition Challenge (ILSVRC)** (AlexNet)



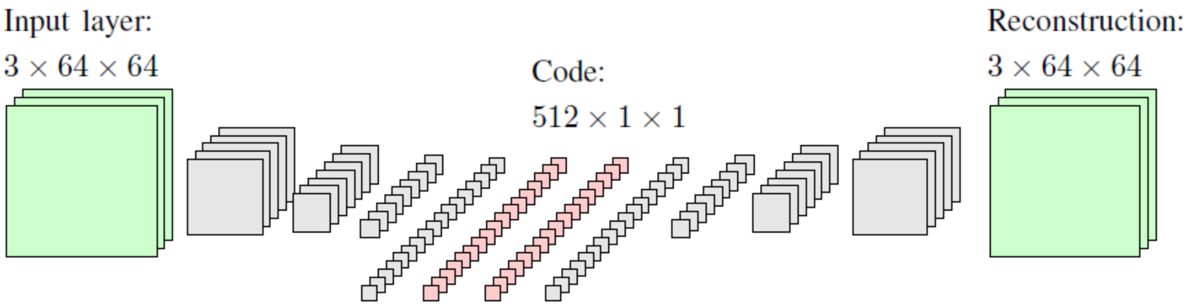
Quelle: Google Trends, abgerufen 02.05.16

Deep Neural Networks



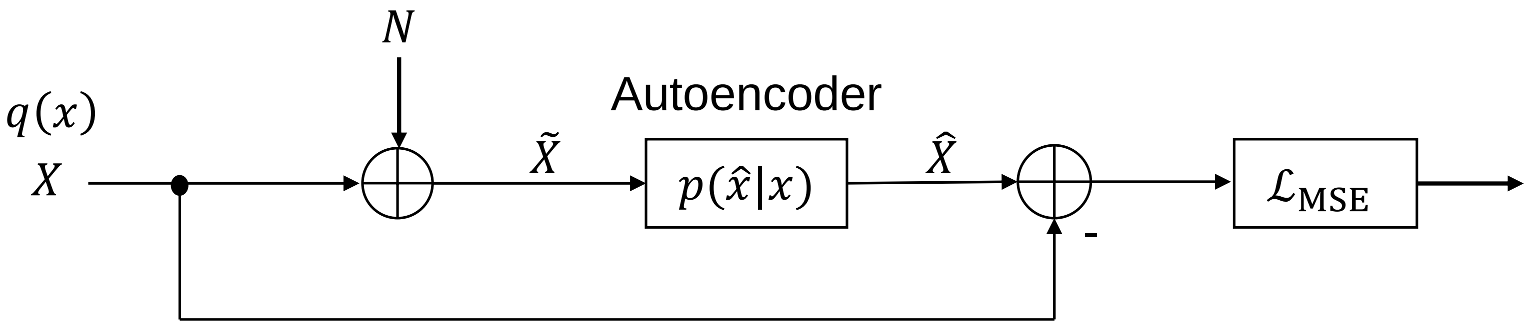


Source: http://deeplearning.net/tutorial/lenet.html

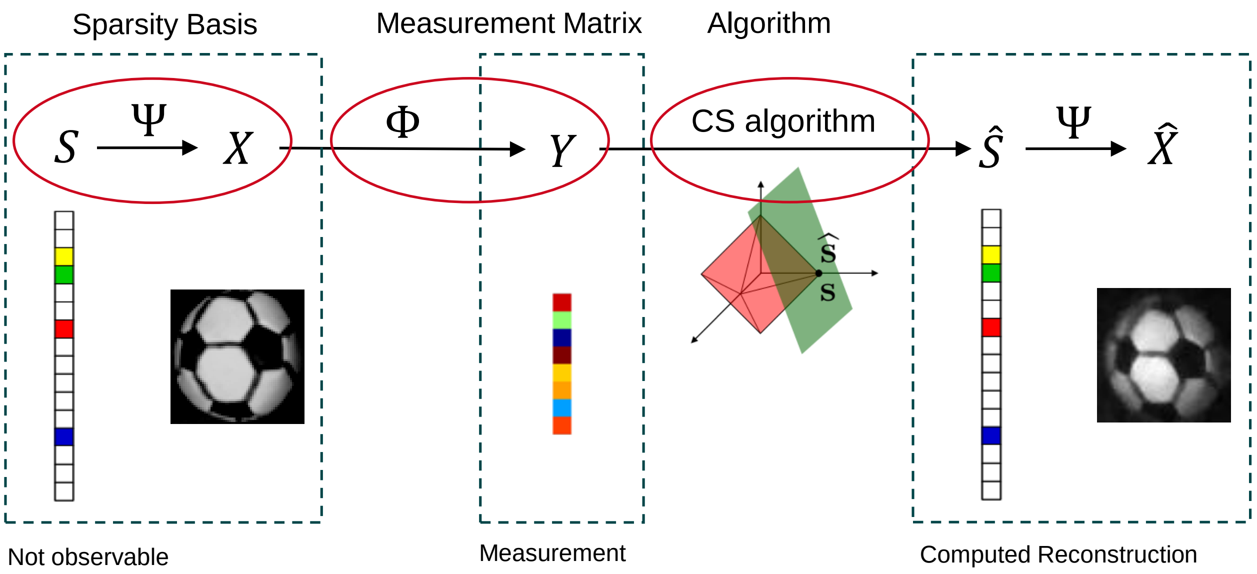


Unsupervised Learning

Modell: $p(\hat{x}|x) = \text{Normal}(\hat{x}|\mu = x, \Sigma)$



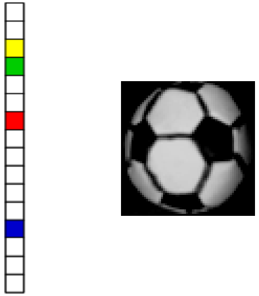
Compressive Sensing Pipeline for Non-Sparse Data



Compressive Sensing: Sparsity Transform

Sparsity Basis

$$S \xrightarrow{\Psi} X$$



Not observable

$$S \xrightarrow{\Psi} X \xrightarrow{\Psi'} \hat{S}$$

DCT $\quad \Psi_{\mathrm{n}}^{k} = \cos\left(\frac{\pi}{N}\left(n + \frac{1}{2}\right)k\right)$

DFT $\quad \Psi_{\mathrm{n}}^{k} = e^{-\frac{2\pi i\, kn}{N}}$

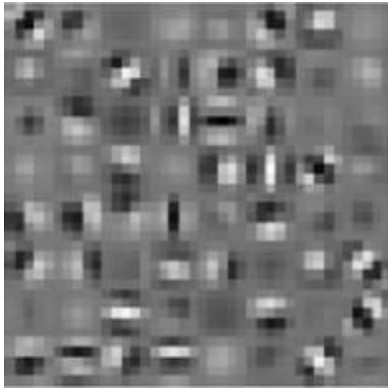
Gabor Wavelets

Learned: PCA, Autoencoder

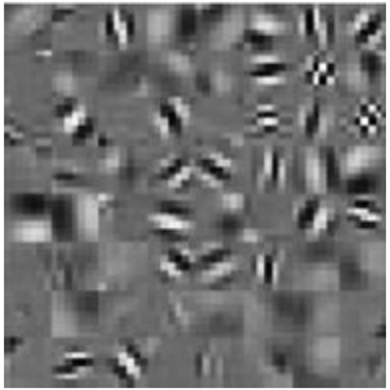
Building kernels for M-dimensional Data

$$\Psi_{\mathrm{n}_1,\ldots,\mathrm{n}_\mathrm{M}}^{k_1,\ldots,k_M} = \prod_{i=1}^{M} \Psi_{n_i}^{k_i}$$

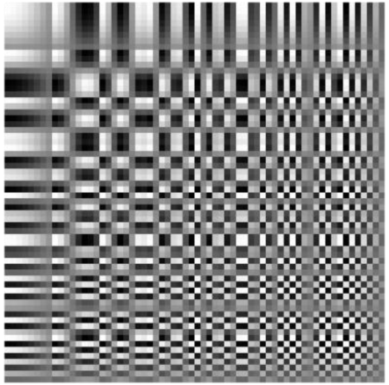
Connection between DCT and Neural network weights



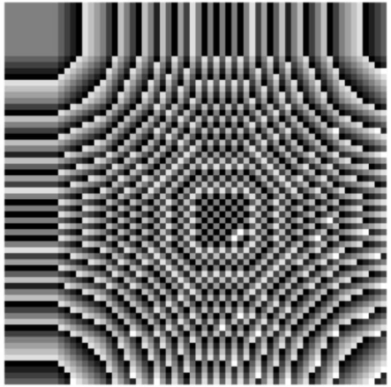
VGGNet



GoogLeNet



DCT



DFT (angle)

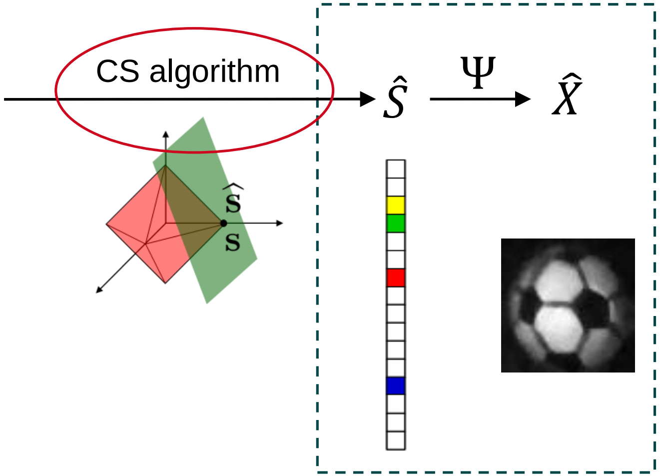
Learned by neural networks
(RGB weights converted to gray scale)

$$\Psi_{\mathrm{n}}^{k} = \cos\left(\frac{\pi}{N}\left(n+\frac{1}{2}\right)k\right)$$

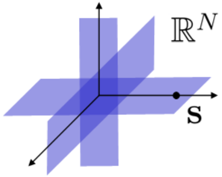
$$\Psi_{\mathrm{n}}^{k} = e^{-\frac{2\pi i\,kn}{N}}$$

Weights adapted from: VGGNet (Zisserman et. al), GoogLeNet

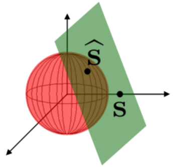
Compressive Sensing Pipeline for Non-Sparse Data



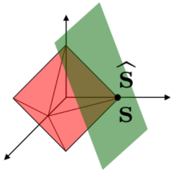
Computed Reconstruction



$$\hat{s} = \arg\min_{s^*} \|s^*\|_0 \ \text{s.t.}\ \Phi(\Psi\hat{s}) = y$$ NP-hard

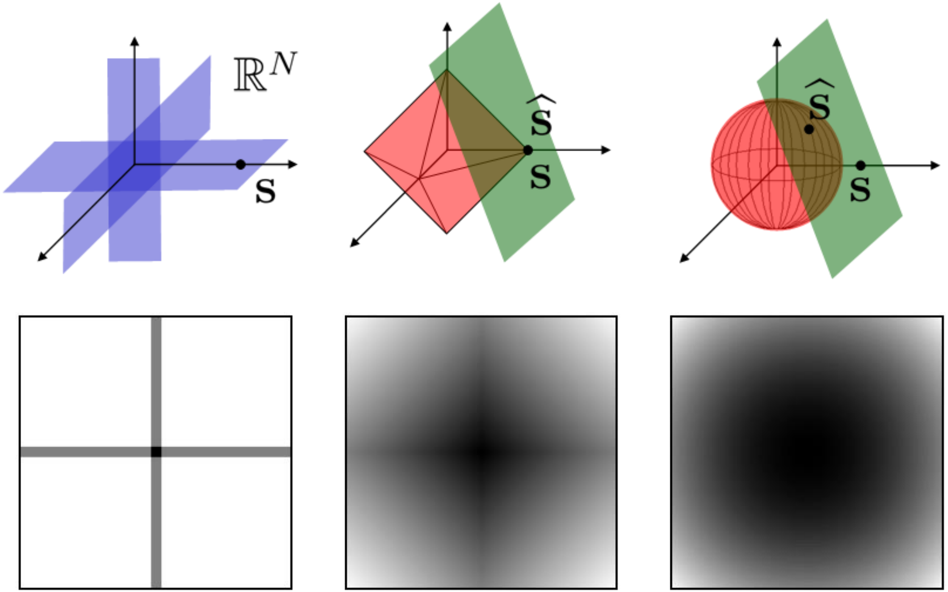


$$\hat{s} = \arg\min_{s^*} \|s^*\|_2 \ \text{s.t.}\ \Phi(\Psi\hat{s}) = y$$ Not sparse!



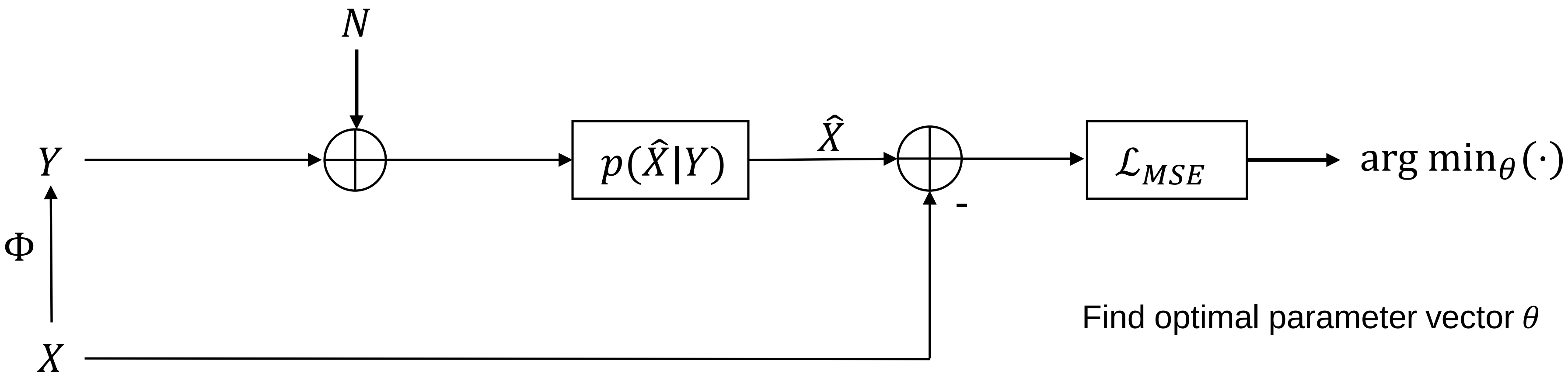
$$\hat{s} = \arg\min_{s^*} \|s^*\|_1 \ \text{s.t.}\ \Phi(\Psi\hat{s}) = y$$ **Sparse result**

Sparsity in Reconstruction



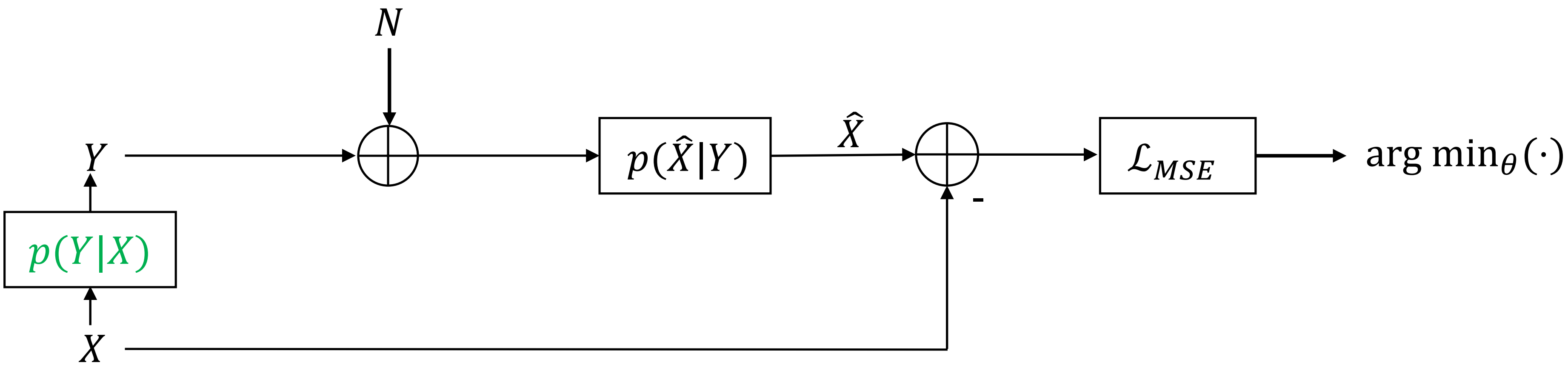
Adapted from:
Baraniuk, Richard: Compressive Sensing. *Lecture Notes in IEEE Signal Processing Magazine, Volume 24, July 2007*

Learning Reconstruction with Random Measurements

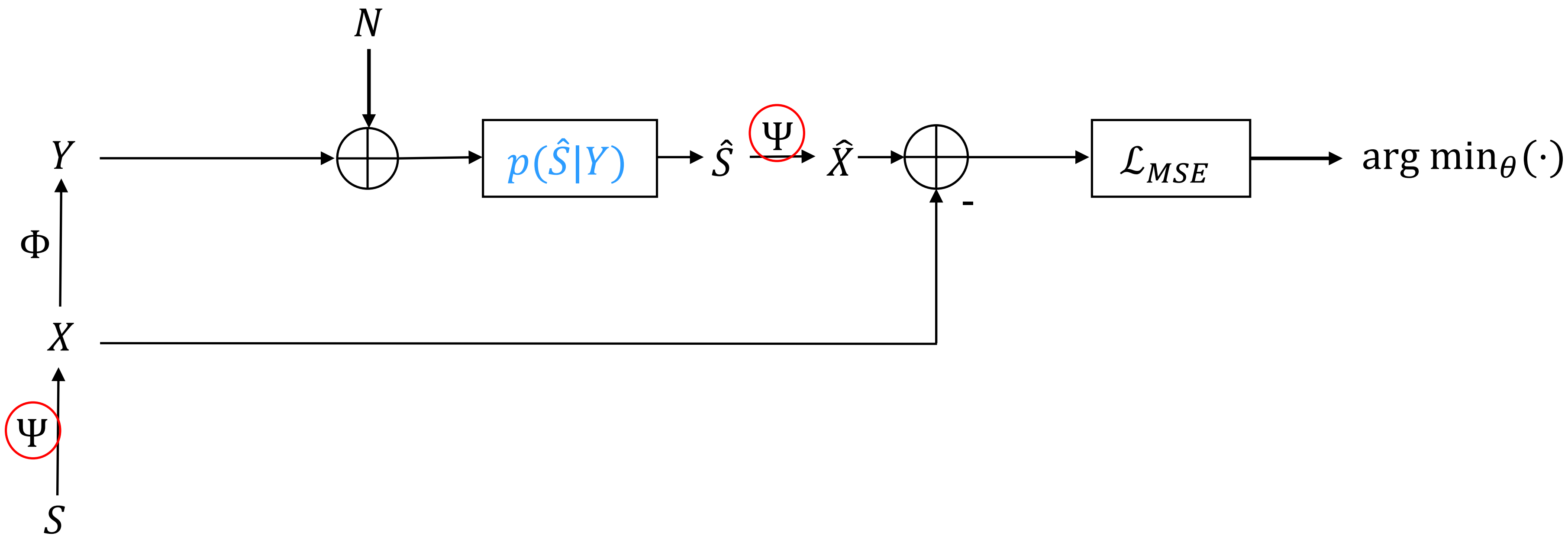


Find optimal parameter vector θ

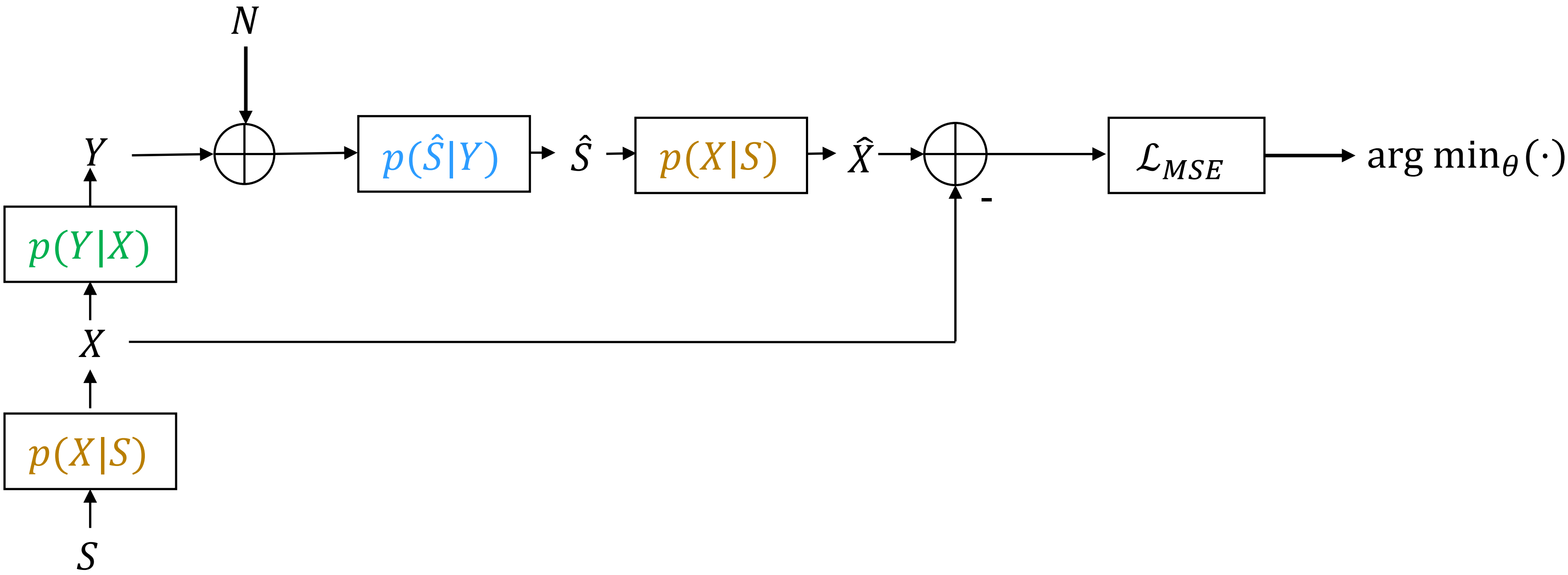
Learning Measurement and Reconstruction



Learning the Sparsity Basis with Random Measurements

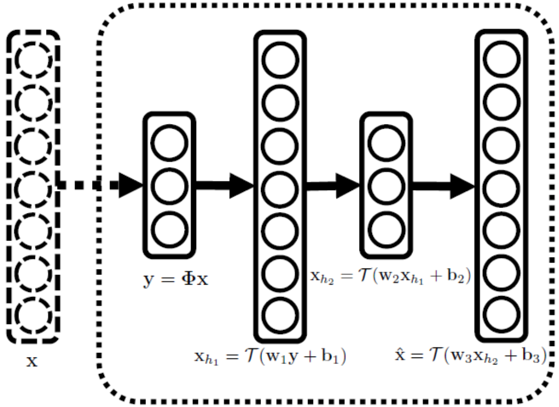


Learning Measurements and the Sparsity Basis

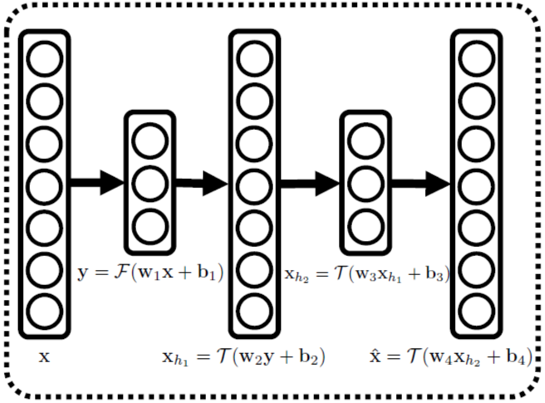


Stacked Autoencoder architectures for Compressive Sensing

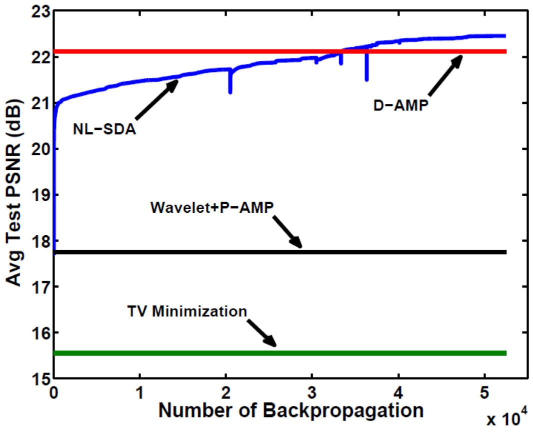
SDA for signal reconstruction



SDA for reconstruction and adaption of the measurement matrix

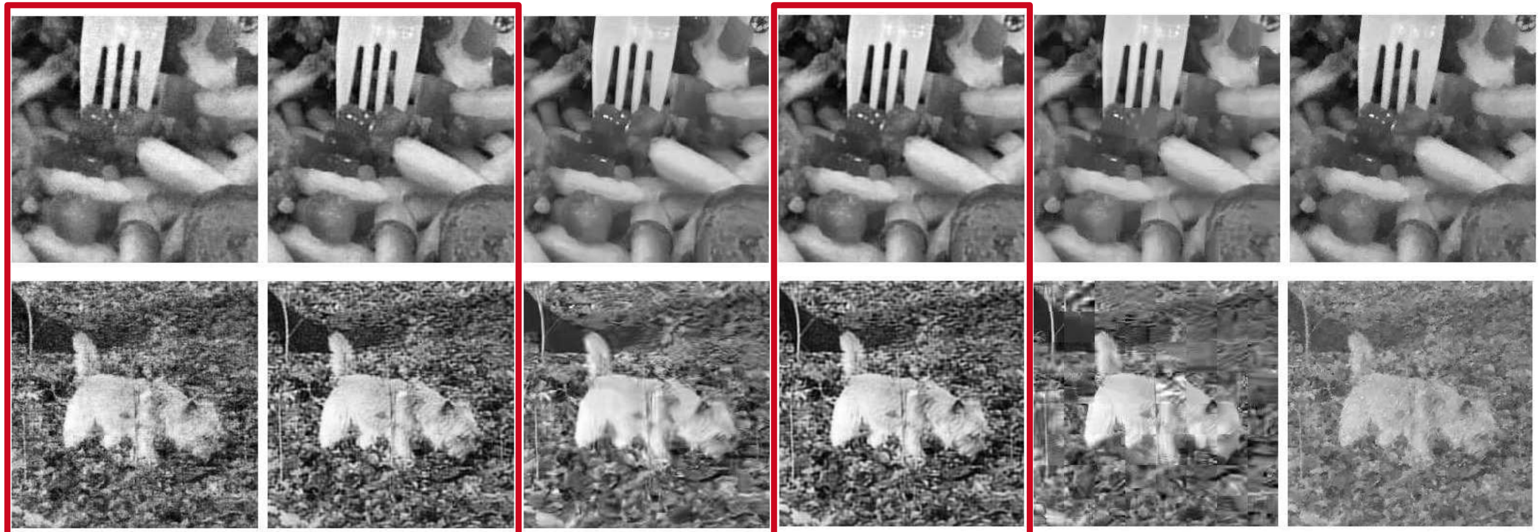


Training results



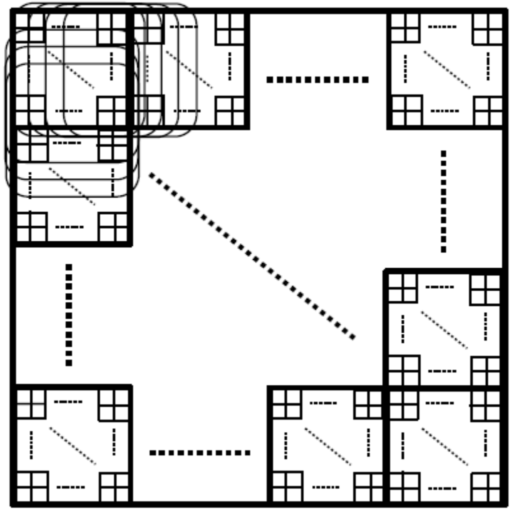
Source: Mousavi, Ali et al., A Deep Learning Approach to Structured Signal Recovery

Comparison of different CS algorithms



Algorithm	SDA+Linear Measurements	SDA+Nonlinear Measurements	D-AMP	SDA, overlap, measurments	Tiled D-AMP	TV
PSNR	29.45 dB	31.79 dB	31.90 dB	**32.46 dB**	30.57 dB	25.16 dB
	20.19 dB	21.27 dB	20.25 dB	21.88 dB	18.54 dB	14.68 dB

Introducing Convolutions



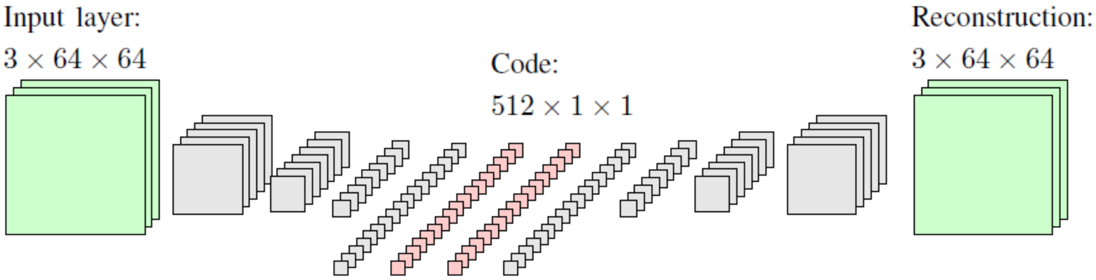
Source: Mousavi, Ali et al., A Deep Learning Approach to Structured Signal Recovery

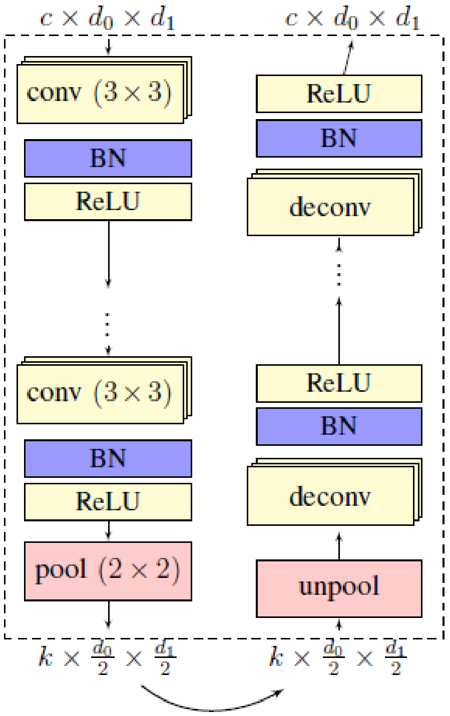
- Until now, „fully connected“ architectures were used on NxN blocks of the image with an overlap
- This corresponds to the convolution operation:

$$(x * y)_s\,(m,n) = \sum_{u,v} x(sm-u, sn-v)\;y(u,v)$$

- Fully-connected network can now be trained directly on arbitrary large images!

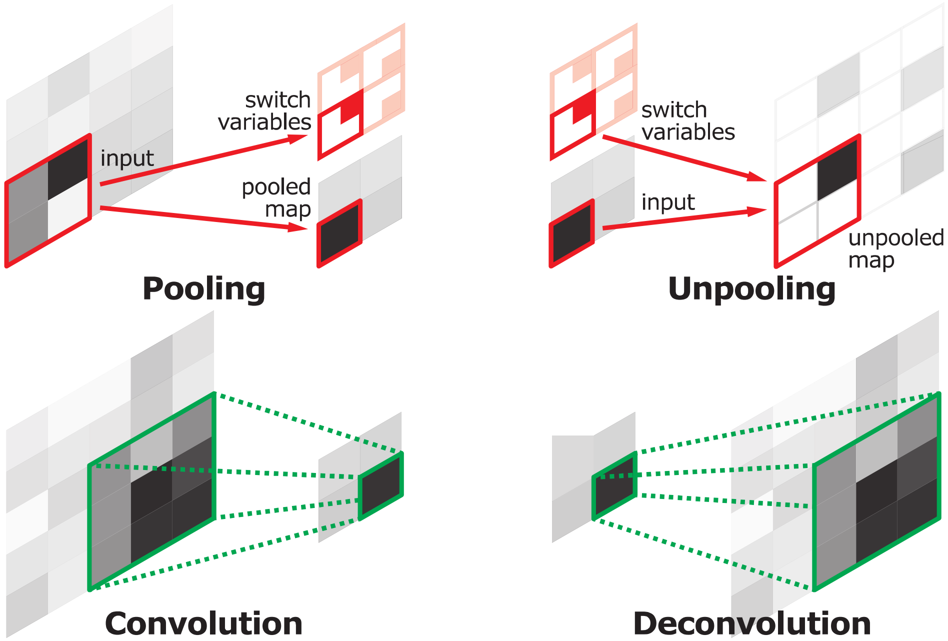
Convolutional Autoencoder for Image Processing





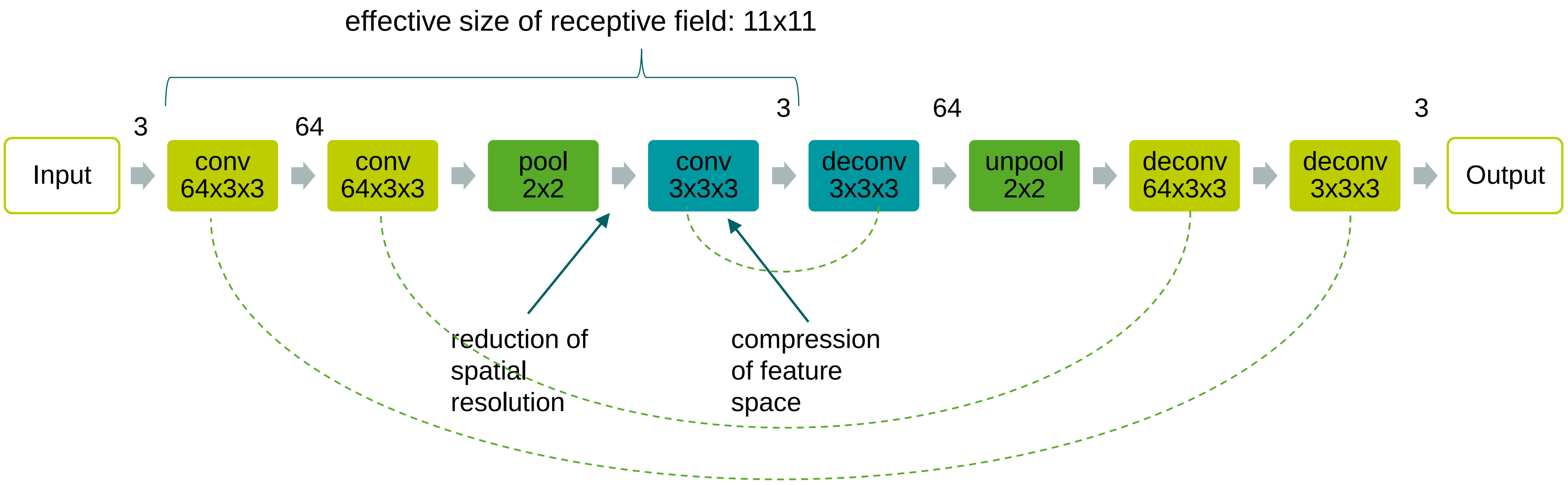
Outlook

Deconvolution und Unpooling



Source:
Zeiler et al., Deconvolutional Networks

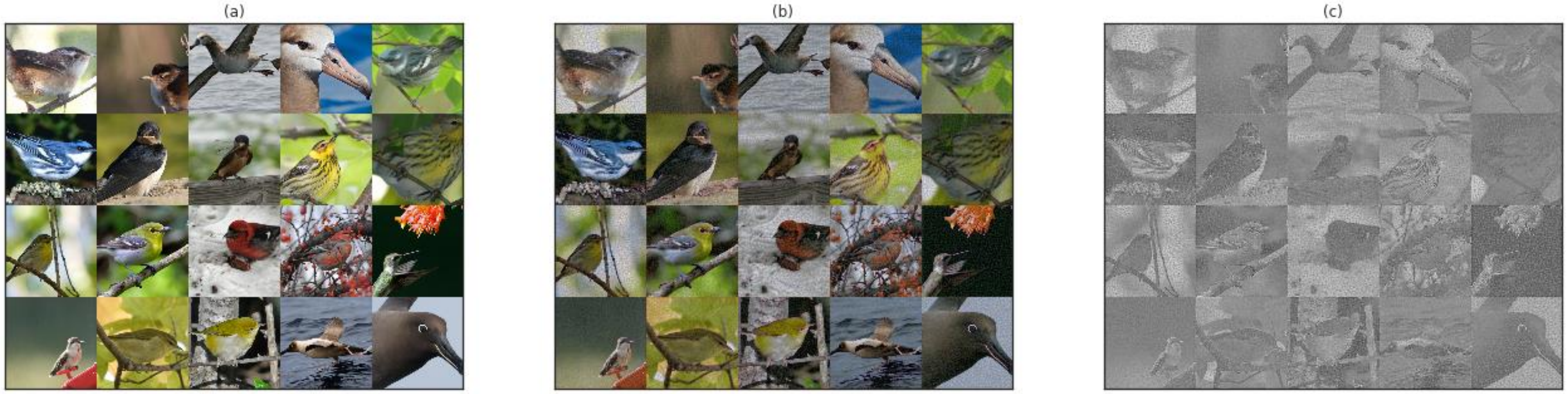
Proposed Architecture



Data compression by 75%

Decoder with tied weights upsamples the measurement

Convolutional Autoencoder on CalTech Birds Dataset



Original Images | Reconstructions (PSNR 19.3 dB) | Residuums

$M/N = 0.25$

Much smaller receptive field, nevertheless promising results

Vielen Dank
für Ihre Aufmerksamkeit