Model-Based Machine Learning for Fiber-Optic Communication Systems

Christian Häger[(1)]

Joint work with: Henry D. Pfister[(2)], Rick M. Bütler[(3)], Gabriele Liga[(3)], Alex Alvarado[(3)], Christoffer Fougstedt[(4)], Lars Svensson[(4)], and Per Larsson-Edefors[(4)]

[(1)] Department of Electrical Engineering, Chalmers University of Technology, Sweden
[(2)] Department of Electrical and Computer Engineering, Duke University, USA
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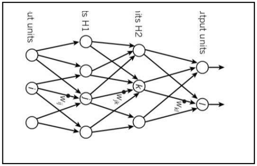
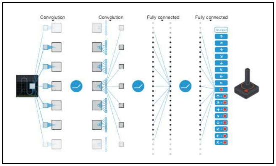
[(4)] Department of Computer Science and Engineering, Chalmers University of Technology, Sweden

Van der Meulen Seminar, December 13, 2019

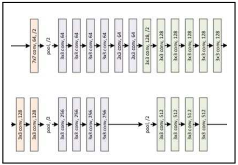
Deep Learning [LeCun et al., 2015]



Deep Q-Learning [Mnih et al., 2015]



ResNet [He et al., 2015]



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Multi-layer neural networks: impressive performance, countless applications

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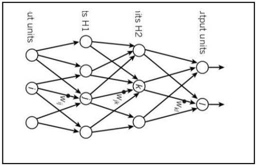

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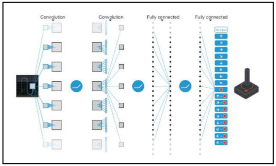

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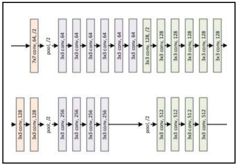

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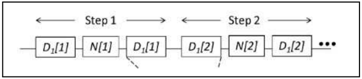
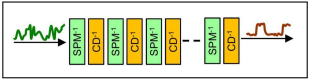


[Du and Lowery, 2010]



[Nakashima et al., 2017]

Multi-step methods for solving the propagation equation in fiber-optics

Agenda

In this talk, we . . .

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2. propose a model-based machine-learning approach based on parameterizing the split-step method (no black-box neural networks)

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In this talk, we . . .

1. show that multi-layer neural networks and the so-called split-step method in fiber-optics have the same functional form: both alternate linear and pointwise nonlinear steps
2. propose a model-based machine-learning approach based on parameterizing the split-step method (no black-box neural networks)
3. apply the proposed approach by revisiting hardware-efficient nonlinear equalization with deep-learning tools

Outline

1. Machine Learning and Neural Networks for Communications
2. Model-Based Machine Learning for Fiber-Optic Systems
3. Nonlinear Equalization: Learned Digital Backpropagation
4. Outlook and Future Work
5. Conclusions

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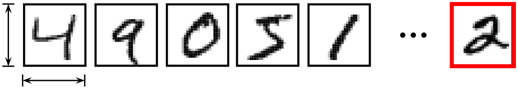
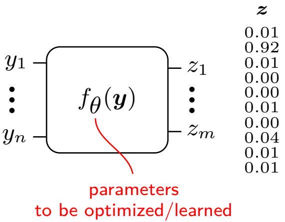
Supervised Learning

handwritten digit recognition (MNIST: 70,000 images)



28×28 pixels $\implies n = 784$



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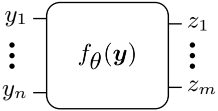
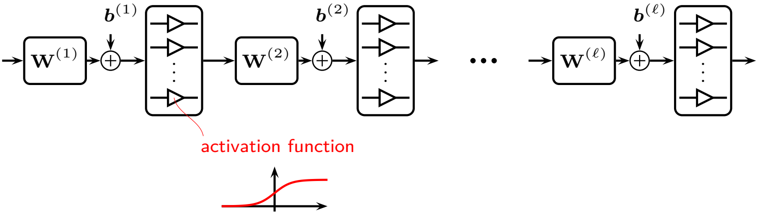


$\boldsymbol{z}$

0.01
0.92
0.01
0.00
0.00
0.01
0.00
0.04
0.01
0.01

How to choose $f_\theta(\boldsymbol{y})$? Deep feed-forward neural networks



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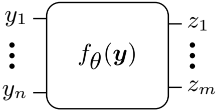

$\boldsymbol{z}$	$\boldsymbol{x}$
0.01	0
0.92	1
0.01	0
0.00	0
0.00	0
0.01	0
0.00	0
0.04	0
0.01	0
0.01	0

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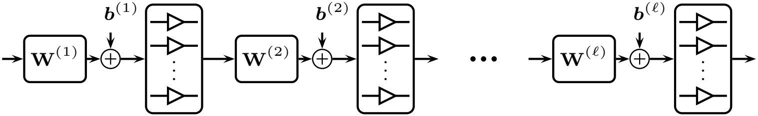


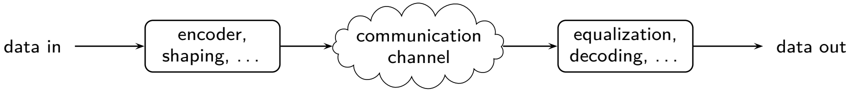
How to optimize $\theta = \{\boldsymbol{W}^{(1)}, \dots, \boldsymbol{W}^{(\ell)}, \boldsymbol{b}^{(1)}, \dots, \boldsymbol{b}^{(\ell)}\}$? Deep learning

$$\min_\theta \sum_{i=1}^{N} \text{Loss}(f_\theta(\boldsymbol{y}^{(i)}), \boldsymbol{x}^{(i)}) \triangleq g(\theta) \qquad \text{using} \quad \theta_{k+1} = \theta_k - \lambda \nabla_\theta g(\theta_k) \tag{1}$$

mean squared error
cross-entropy, ...

stochastic gradient descent,
RMSProp, Adam, ...

Machine Learning for Physical-Layer Communications



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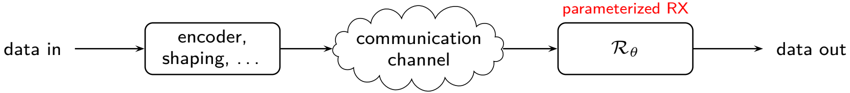

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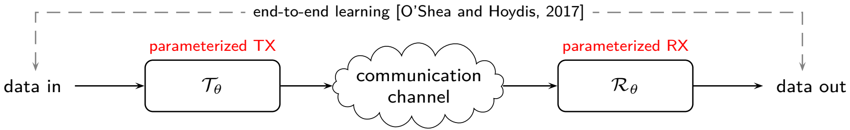

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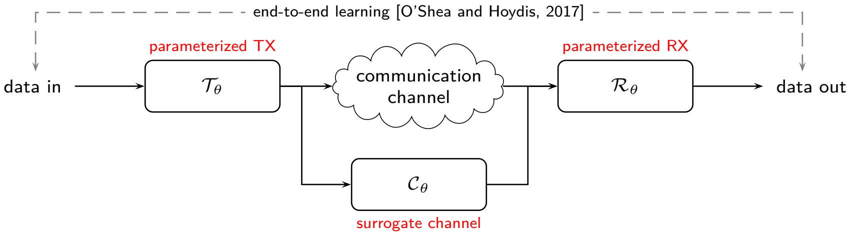

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[O'Shea et al., 2018], Approximating the void: Learning stochastic channel models from observation with variational GANs, (*arXiv*)
[Ye et al., 2018], Channel agnostic end-to-end learning based communication systems with conditional GAN, (*arXiv*)
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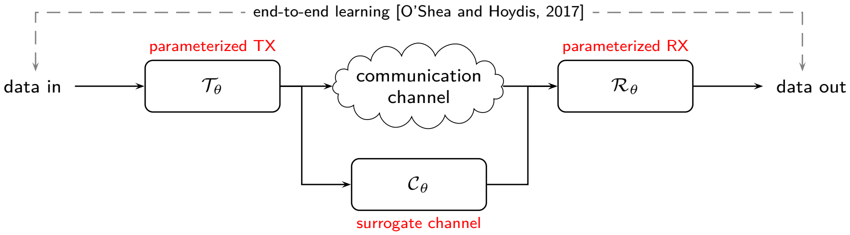
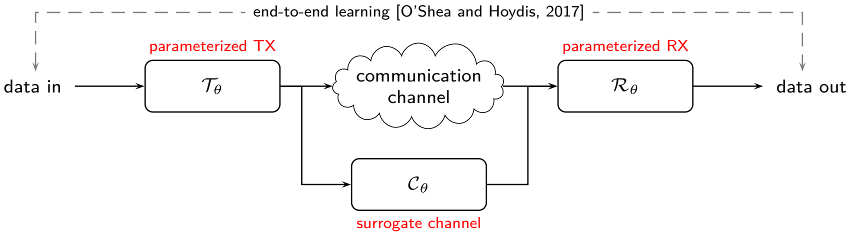


Using neural networks for $\mathcal{T}_\theta, \mathcal{R}_\theta, \mathcal{C}_\theta$

- How to choose network architecture (#layers, activation function)?
- How to initialize parameters?
- How to interpret solutions? Any insight gained?
- ...

Machine Learning for Physical-Layer Communications



Using neural networks for $\mathcal{T}_\theta, \mathcal{R}_\theta, \mathcal{C}_\theta$

- How to choose network architecture (#layers, activation function)? ✗
- How to initialize parameters? ✗
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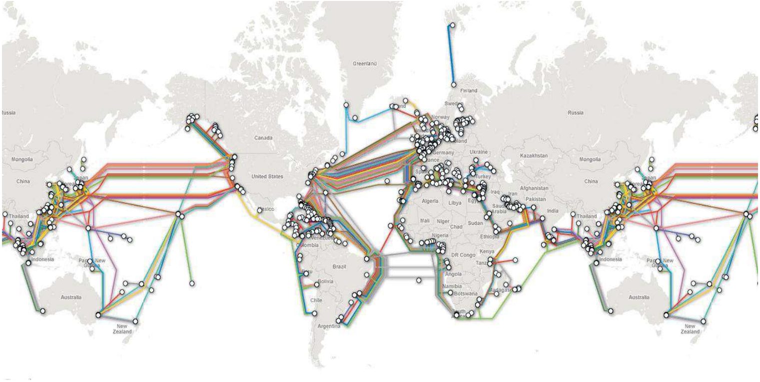
- . . .

Model-based learning: sparse signal recovery [Gregor and Lecun, 2010], [Borgerding and Schniter, 2016], neural belief propagation [Nachmani et al., 2016], radio transformer networks [O'Shea and Hoydis, 2017], . . .

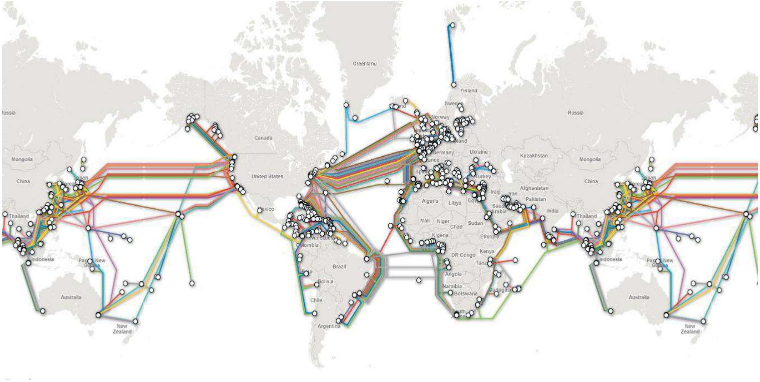
Outline

Fiber-Optic Communications



Fiber-optic systems enable data traffic over very long distances connecting cities, countries, and continents.

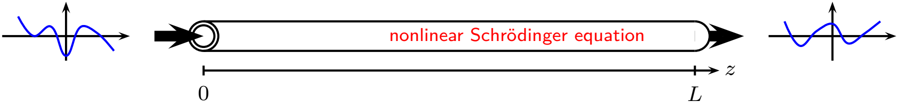
Fiber-Optic Communications



Fiber-optic systems enable data traffic over very long distances connecting cities, countries, and continents.

- Dispersion: different wavelengths travel at different speeds (linear)
- Kerr effect: refractive index changes with signal intensity (nonlinear)

Channel Modeling



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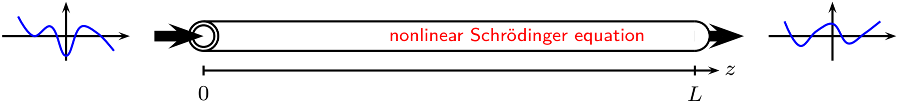
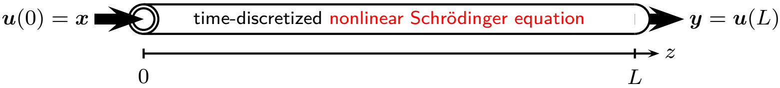


- Sampling over a fixed time interval $\implies \mathcal{F}: \mathbb{C}^n \to \mathbb{C}^n$

Channel Modeling

$$\frac{\mathrm{d}\boldsymbol{u}(z)}{\mathrm{d}z} = \mathbf{A}\boldsymbol{u}(z) + \jmath\gamma\boldsymbol{\rho}(\boldsymbol{u}(z))$$



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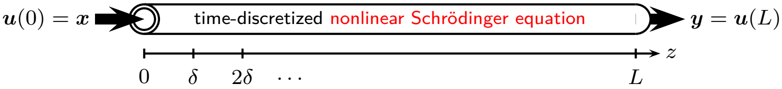

- Sampling over a fixed time interval $\implies \mathcal{F} : \mathbb{C}^n \to \mathbb{C}^n$
- Split-step method with M steps ($\delta = L/M$):

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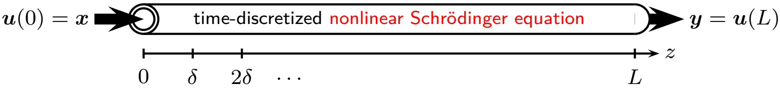

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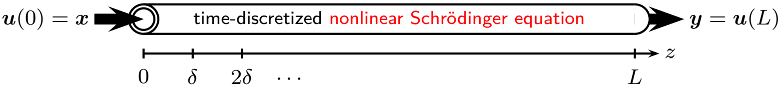

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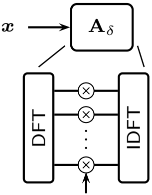
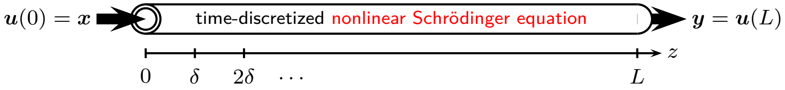


$H_k = e^{\jmath \frac{\beta_2}{2} \delta \omega_k^2}$ group velocity dispersion (all-pass filter)

Channel Modeling

$$\frac{\mathrm{d}\boldsymbol{u}(z)}{\mathrm{d}z} = \qquad + \jmath\gamma\boldsymbol{\rho}(\boldsymbol{u}(z)) \qquad \rho(x) = |x|^2 x \text{ element-wise}$$



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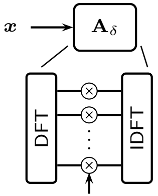

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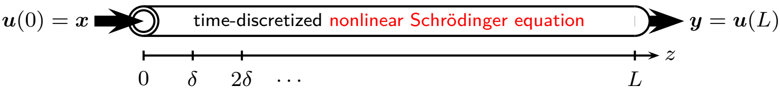

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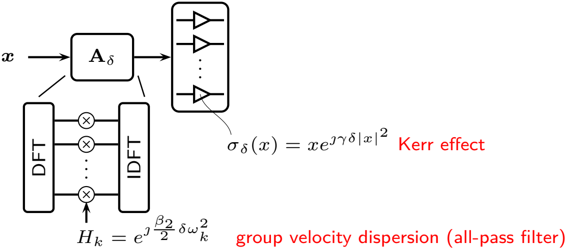

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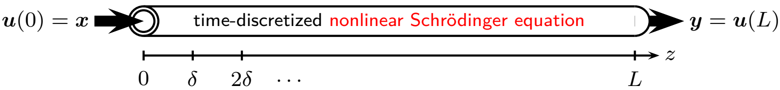

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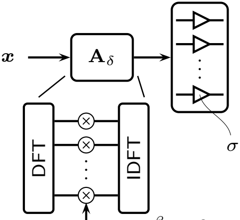

$\sigma_\delta(x) = x e^{\jmath\gamma\delta|x|^2}$ Kerr effect

$H_k = e^{\jmath \frac{\beta_2}{2} \delta \omega_k^2}$ group velocity dispersion (all-pass filter)

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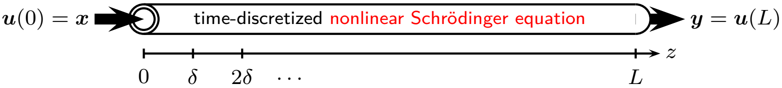

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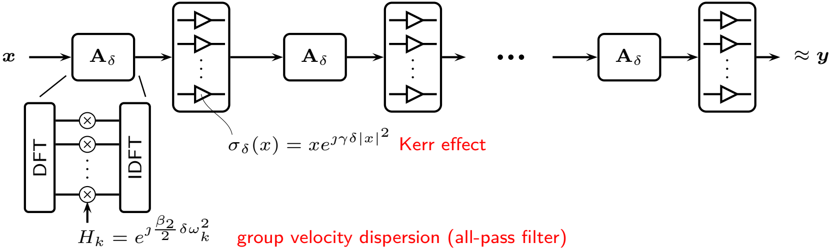

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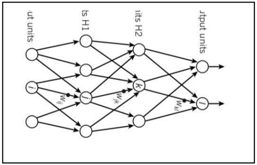

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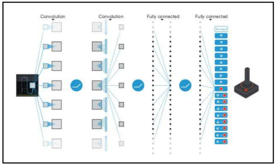

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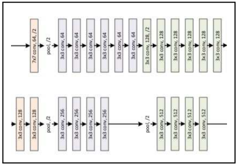

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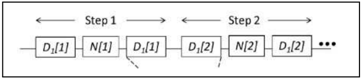

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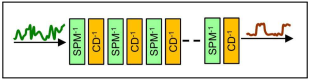
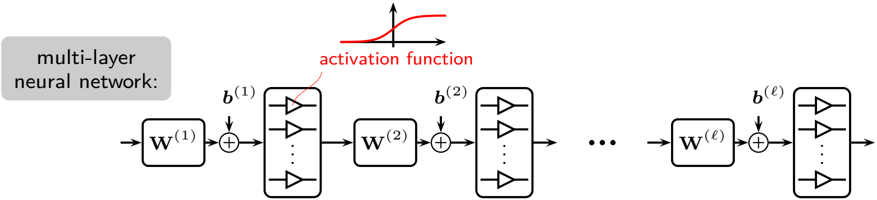


[Nakashima et al., 2017]

Parameterizing the Split-Step Method



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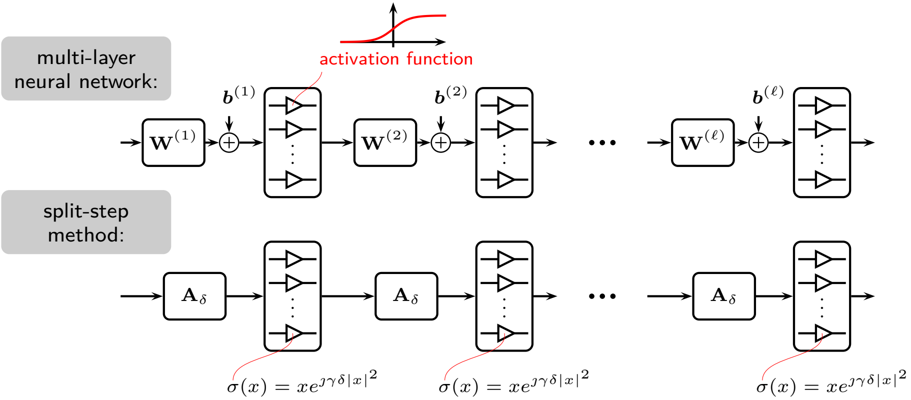

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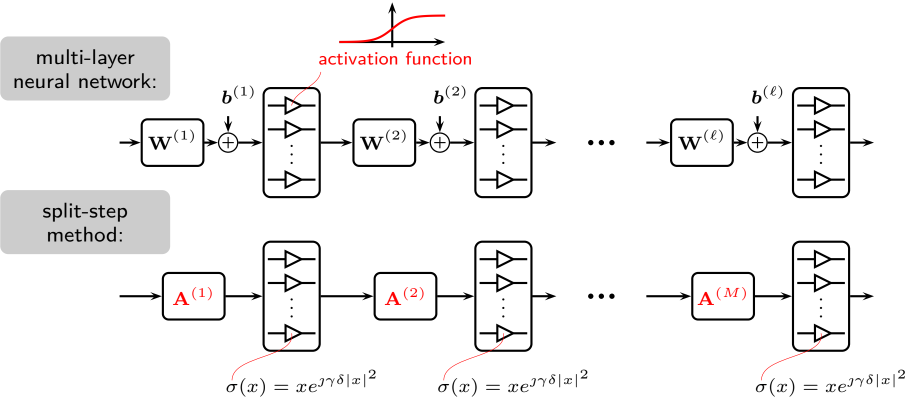
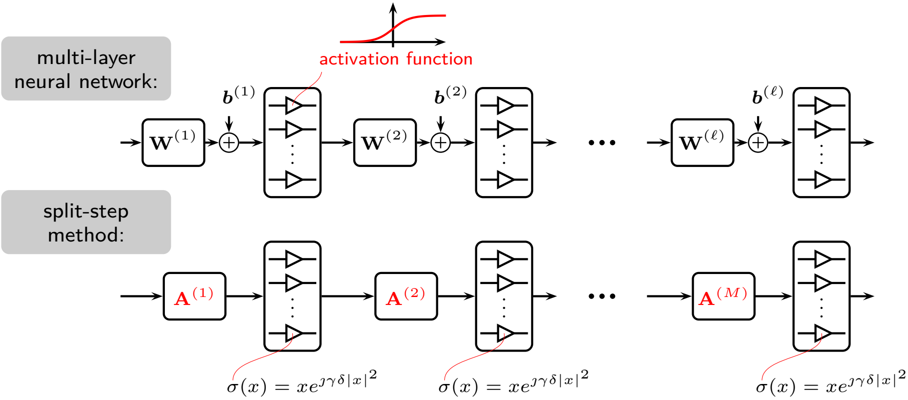


[Häger & Pfister, 2018], Nonlinear Interference Mitigation via Deep Neural Networks, *(OFC)*
[Häger & Pfister, 2018], Deep Learning of the Nonlinear Schrödinger Equation in Fiber-Optic Communications, *(ISIT)*

Parameterizing the Split-Step Method



- Parameterized model f_θ with $\theta = \{\mathbf{A}^{(1)}, \ldots, \mathbf{A}^{(M)}\}$

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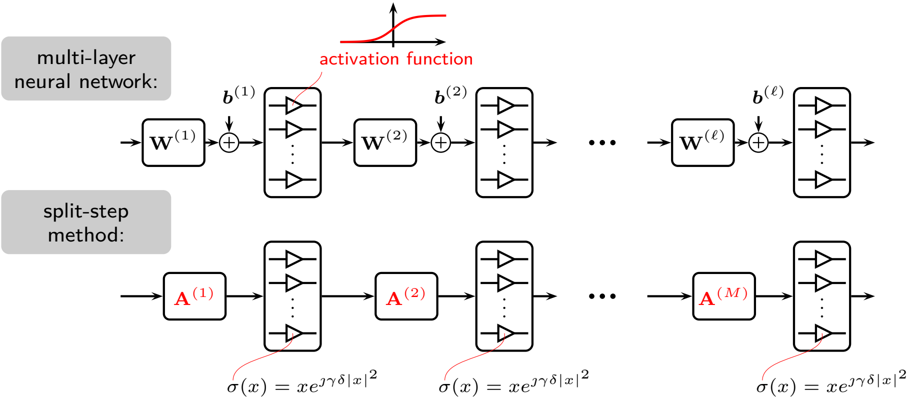
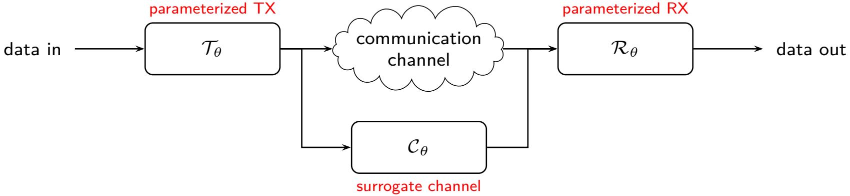
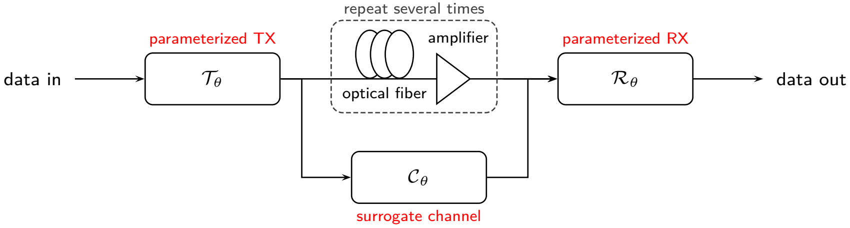


- Parameterized model f_θ with $\theta = \{\mathbf{A}^{(1)}, \ldots, \mathbf{A}^{(M)}\}$
- Includes as special cases: step-size optimization, "placement" of nonlinear operator, higher-order dispersion, matched filtering . . .

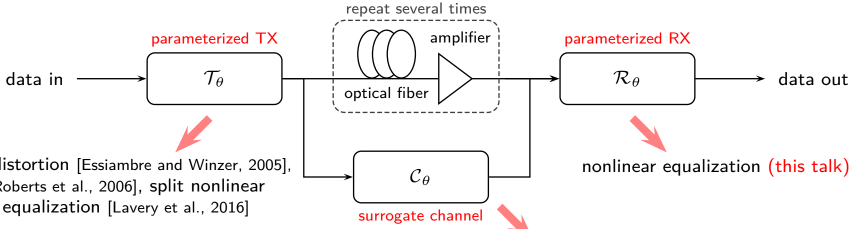
Possible Applications



Possible Applications



Possible Applications

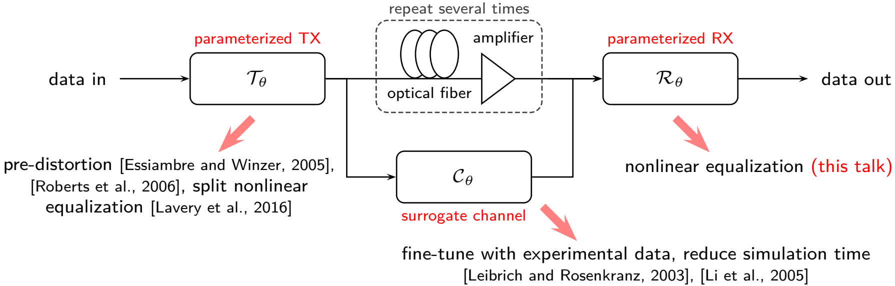


pre-distortion [Essiambre and Winzer, 2005], [Roberts et al., 2006], split nonlinear equalization [Lavery et al., 2016]

nonlinear equalization (this talk)

fine-tune with experimental data, reduce simulation time [Leibrich and Rosenkranz, 2003], [Li et al., 2005]

Possible Applications



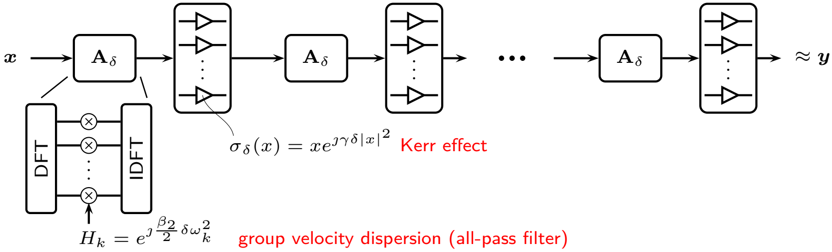
Model-based learning approaches

- How to choose network architecture (#layers, activation function)? ✓
- How to initialize parameters? ✓
- How to interpret solutions? Any insight gained? ✓

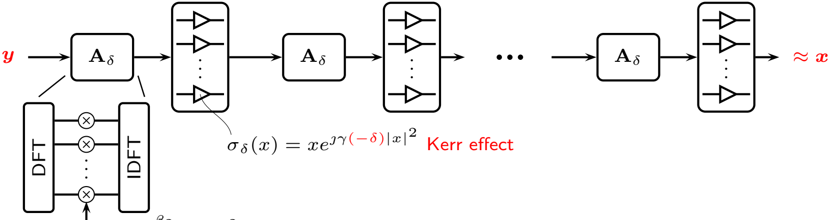
Outline

1. Machine Learning and Neural Networks for Communications
2. Model-Based Machine Learning for Fiber-Optic Systems
3. Nonlinear Equalization: Learned Digital Backpropagation
4. Outlook and Future Work
5. Conclusions

Digital Backpropagation



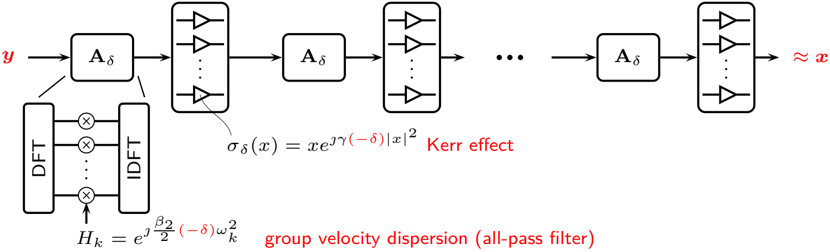
Digital Backpropagation



$\sigma_\delta(x) = x e^{\jmath \gamma (-\delta) |x|^2}$ Kerr effect

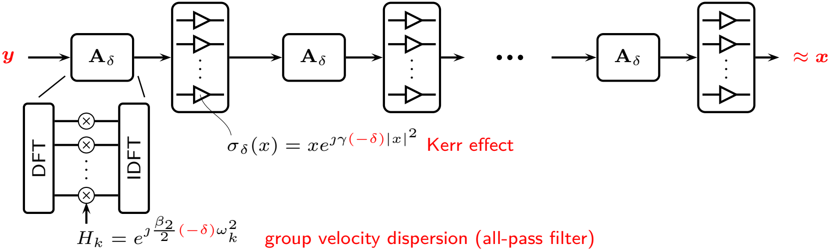
$H_k = e^{\jmath \frac{\beta_2}{2} (-\delta) \omega_k^2}$ group velocity dispersion (all-pass filter)

Digital Backpropagation



- Fiber with negated parameters ($\beta_2 \to -\beta_2$, $\gamma \to -\gamma$) would perform perfect channel inversion [Paré et al., 1996] (ignoring attenuation)

Digital Backpropagation



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- Digital backpropagation: invert a partial differential equation in real time [Essiambre and Winzer, 2005], [Roberts et al., 2006], [Li et al., 2008], [Ip and Kahn, 2008]

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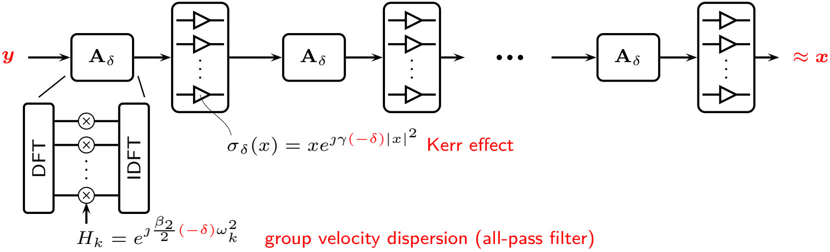
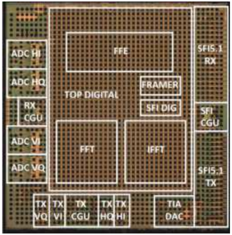


- Fiber with negated parameters ($\beta_2 \to -\beta_2$, $\gamma \to -\gamma$) would perform perfect channel inversion [Paré et al., 1996] (ignoring attenuation)
- Digital backpropagation: invert a partial differential equation in real time [Essiambre and Winzer, 2005], [Roberts et al., 2006], [Li et al., 2008], [Ip and Kahn, 2008]
- Widely considered to be impractical (too complex): linear equalization is already one of the most power-hungry DSP blocks in coherent receivers

Real-Time Digital Backpropagation



[Crivelli et al., 2014]

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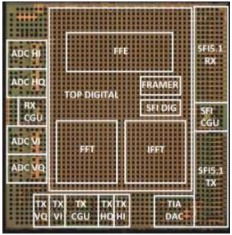

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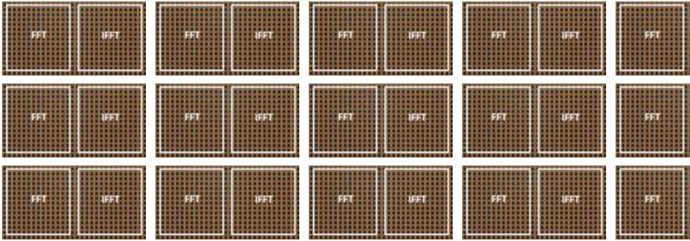

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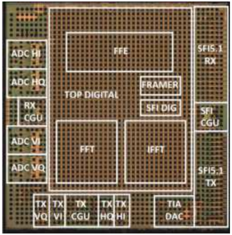

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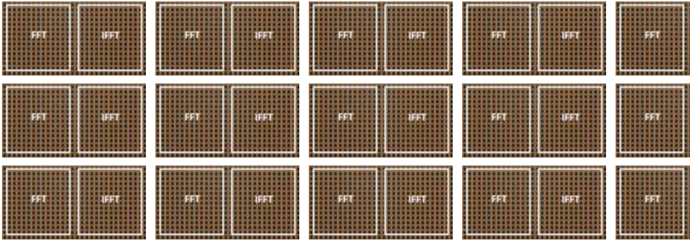


Our approach: deep learning and model compression

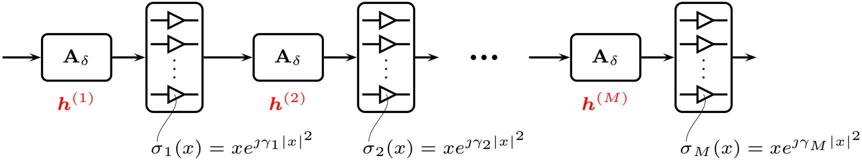
- Joint optimization,
- pruning, and
- quantization

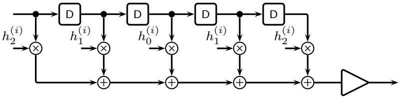
of all linear steps $\implies$ hardware-efficient digital backpropagation

Learned Digital Backpropagation

Learned Digital Backpropagation

TensorFlow implementation of the computation graph $f_\theta(\boldsymbol{y})$:





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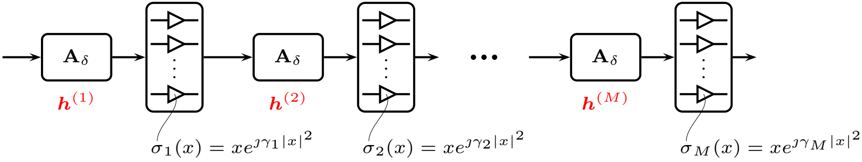

Deep learning of parameters $\theta = \{\boldsymbol{h}^{(1)}, \dots, \boldsymbol{h}^{(M)}\}$:

$$\min_\theta \sum_{i=1}^{N} \underbrace{\text{Loss}(f_\theta(\boldsymbol{y}^{(i)}), \boldsymbol{x}^{(i)})}_{\text{mean squared error}} \triangleq g(\theta) \qquad \text{using} \quad \underbrace{\theta_{k+1} = \theta_k - \lambda \nabla_\theta g(\theta_k)}_{\text{Adam optimizer, fixed learning rate}}$$

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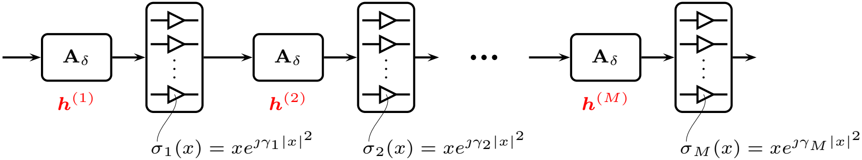

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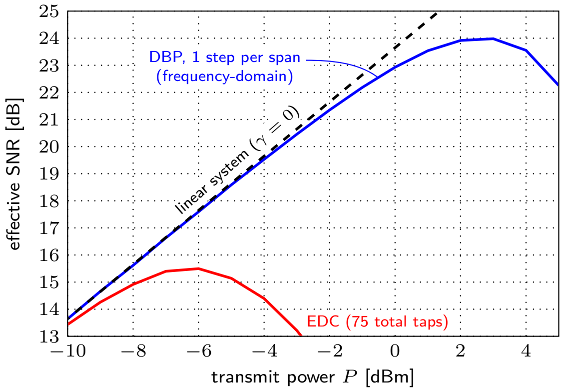
Iteratively prune (set to 0) outermost filter taps during gradient descent

Revisiting Ip and Kahn (2008)



Parameters similar to [Ip and Kahn, 2008]:

- 25×80 km SSFM
- Gaussian modulation
- RRC pulses (0.1 roll-off)
- 10.7 Gbaud
- 2 samples/symbol processing
- single channel, single pol.

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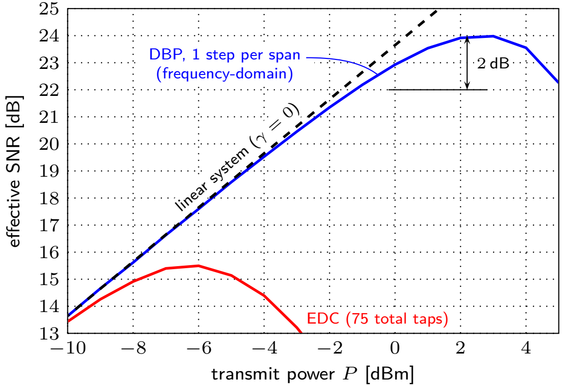

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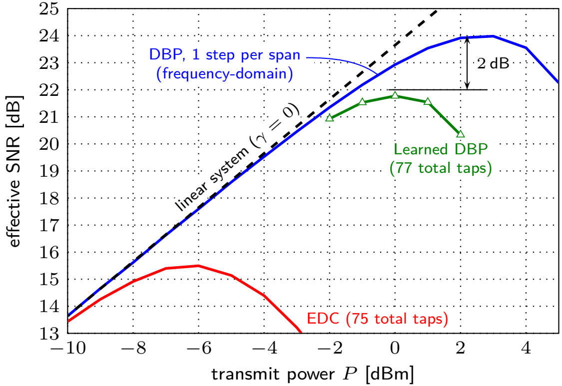

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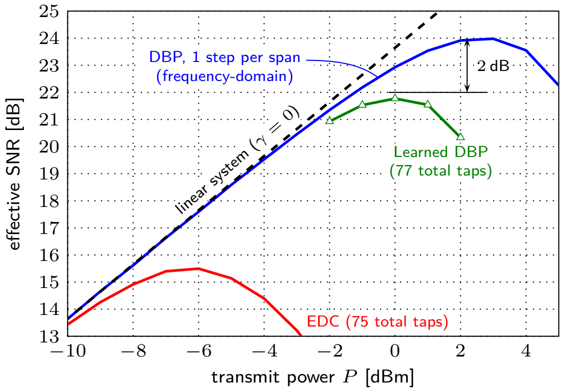

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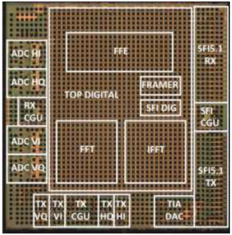
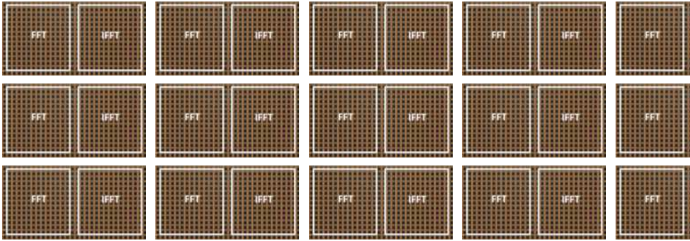
- Can outperform "ideal DBP" in the nonlinear regime [Häger and Pfister, 2018b]

Real-Time ASIC Implementation



[Crivelli et al., 2014]



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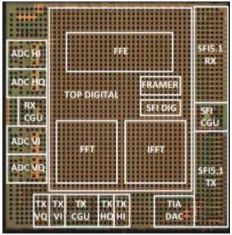

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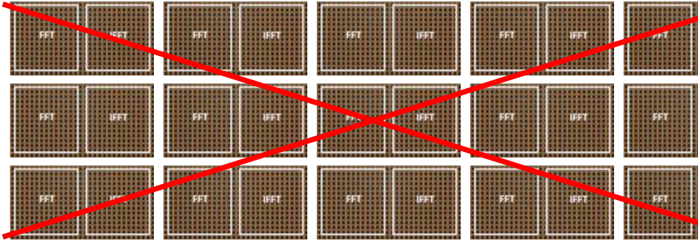

[Fougstedt et al., 2017], Time-domain digital back propagation: Algorithm and finite-precision implementation aspects, (*OFC*)
[Fougstedt et al., 2018], ASIC implementation of time-domain digital back propagation for coherent receivers, *(PTL)*
[Sherborne et al., 2018], On the impact of fixed point hardware for optical fiber nonlinearity compensation algorithms, (*JLT*)

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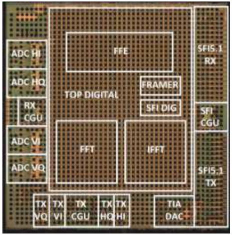

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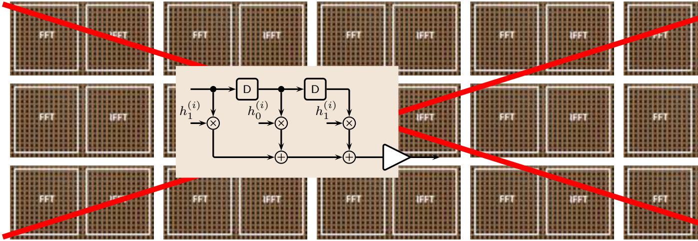

- Our linear steps are very short symmetric FIR filters (as few as 3 taps)

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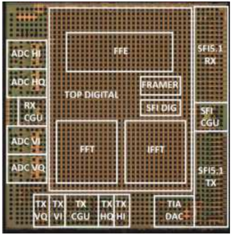

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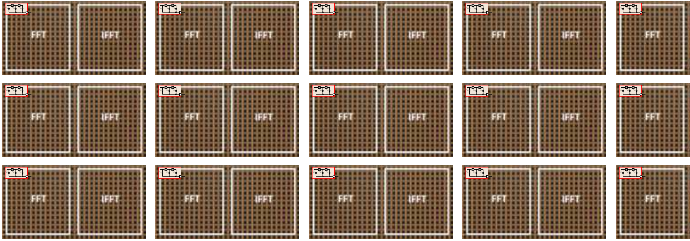
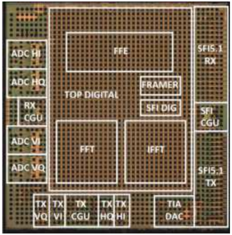


- Our linear steps are very short symmetric FIR filters (as few as 3 taps)
- 28-nm ASIC at 416.7 MHz clock speed (40 GHz signal)
  - Only 5-6 bit filter coefficients via learned quantization
  - Hardware-friendly nonlinear steps (Taylor expansion)
  - All FIR filters are fully reconfigurable

[Fougstedt et al., 2018], ASIC implementation of time-domain digital backpropagation with deep-learned chromatic dispersion filters, *(ECOC)*

Real-Time ASIC Implementation



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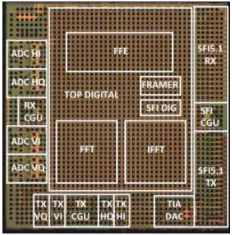

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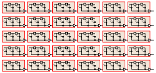

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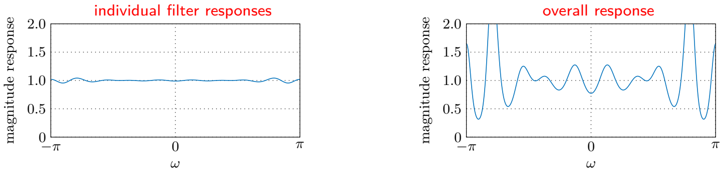
  - Only 5-6 bit filter coefficients via learned quantization
  - Hardware-friendly nonlinear steps (Taylor expansion)
  - All FIR filters are fully reconfigurable
- $< 2\times$ power compared to EDC [Crivelli et al., 2014, Pillai et al., 2014]

[Fougstedt et al., 2018], ASIC implementation of time-domain digital backpropagation with deep-learned chromatic dispersion filters, *(ECOC)*

Why Does The Learning Approach Work?

Previous work: design a single filter or filter pair and use it repeatedly.

$\Longrightarrow$ Good overall response only possible with very long filters.



From [Ip and Kahn, 2009]:

- "We also note that [. . .] 70 taps, is much larger than expected"
- "This is due to amplitude ringing in the frequency domain"
- "Since backpropagation requires multiple iterations of the linear filter, amplitude distortion due to ringing accumulates (Goldfarb & Li, 2009)"

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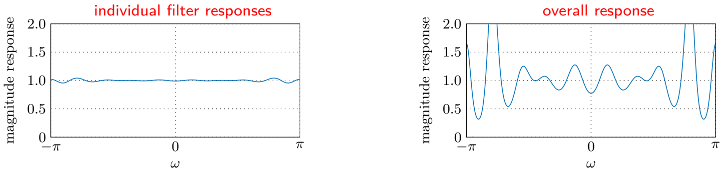

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The learning approach uncovered that there is no such requirement!

[Lian, Häger, Pfister, 2018], What can machine learning teach us about communications? (*ITW*)

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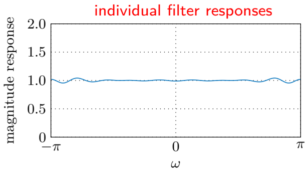
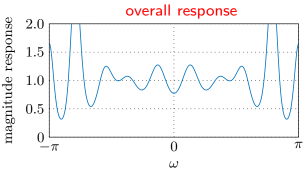
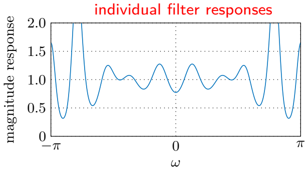
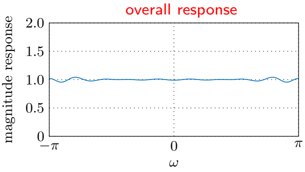




Sacrifice individual filter accuracy, but different response per step.

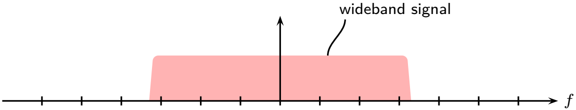
$\Longrightarrow$ Good overall response even with very short filters by joint optimization.





Outline

Wideband Signals and Subband Processing



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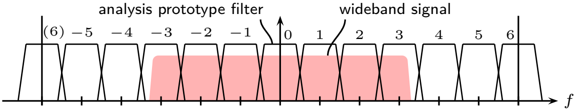
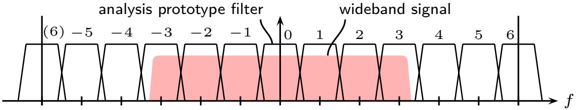


- Subband processing: split received signal into N parallel signals

[Taylor, 2008], Compact digital dispersion compensation algorithms, *(OFC)*
[Ho, 2009], Subband equaliser for chromatic dispersion of optical fibre, *(Electronics Lett.)*
[Slim et al., 2013], Delayed single-tap frequency-domain chromatic-dispersion compensation, *(PTL)*
[Nazarathy and Tolmachev, 2014], Subbanded DSP architectures based on underdecimated filter banks . . . , *(Signal Proc. Mag.)*
[Mateo et al., 2010], Efficient compensation of inter-channel nonlinear effects via digital backward . . . , *(Opt. Express)*
[Ip et al., 2011], Complexity versus performance tradeoff for fiber nonlinearity compensation . . . *(OFC)*
[Oyama et al., 2015], Complexity reduction of perturbation-based nonlinear compensator by sub-band processing, *(OFC)*
. . .

Wideband Signals and Subband Processing



- Subband processing: split received signal into N parallel signals
- Parameterizing the split-step method for coupled Schrödinger equations [Leibrich and Rosenkranz, 2003] $\Longrightarrow$ low-complexity candidate for wideband processing [Häger and Pfister, 2018c]
- Similar structure as popular convolutional neural networks (alternating filter banks and nonlinearities)

[Taylor, 2008], Compact digital dispersion compensation algorithms, *(OFC)*
[Ho, 2009], Subband equaliser for chromatic dispersion of optical fibre, *(Electronics Lett.)*
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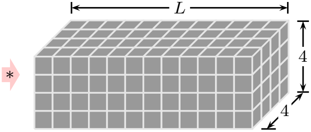
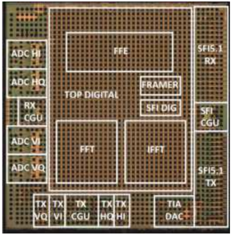
Polarization-Dependent Impairments



* = convolution

× = multiplication (rotation)



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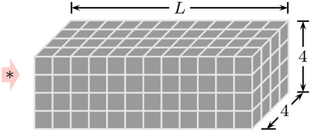

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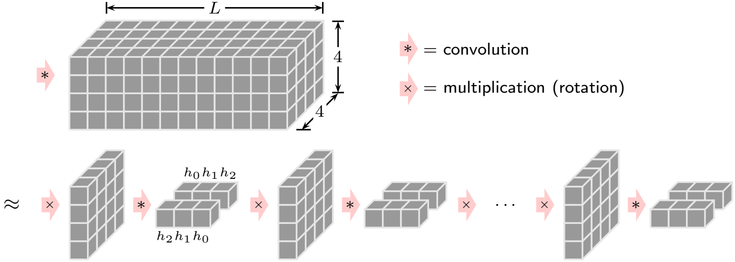
- Combining digital backpropagation with compensation of polarization-mode dispersion

[Goroshko et al., 2016], Overcoming performance limitations of digital back propagation due to polarization mode dispersion, *(CTON)*
[Czegledi et al., 2017], Digital backpropagation accounting for polarization-mode dispersion, *(Opt. Express)*
[Liga et al., 2018], A PMD-adaptive DBP receiver based on SNR optimization, *(OFC)*

Polarization-Dependent Impairments



- Combining digital backpropagation with compensation of polarization-mode dispersion
- Promising performance–complexity tradeoff using model-based factorization approach and machine learning [Häger et al., 2020]

[Goroshko et al., 2016], Overcoming performance limitations of digital back propagation due to polarization mode dispersion, *(CTON)*
[Czegledi et al., 2017], Digital backpropagation accounting for polarization-mode dispersion, *(Opt. Express)*
[Liga et al., 2018], A PMD-adaptive DBP receiver based on SNR optimization, *(OFC)*
[Häger et al., 2020], Model-based machine learning for joint digital backpropagation and PMD compensation, *(OFC)*

Ongoing and Future Work

- Experimental Demonstrations: stay tuned ...
- How to integrate into a standard coherent receiver DSP chain?
- How to successfully train in the presence of practical impairments (laser phase noise, transceiver noise, ...)
- How realistic is online learning in custom DSP? (We only have “hundreds” of parameters, not “thousands” or “millions” like neural networks)

Conclusions

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neural-network-based ML
universal function approximators
good designs require experience and fine-tuning
black boxes, difficult to "open"

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neural-network-based ML	**model-based ML**
universal function approximators	application-tailored
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black boxes, difficult to "open"	familiar building blocks (e.g., FIR filters) can enable interpretability

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Thank you!

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