Reducing the Complexity of Digital Backpropagation with Machine Learning

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FIBER-OPTIC COMMUNICATIONS RESEARCH CENTER

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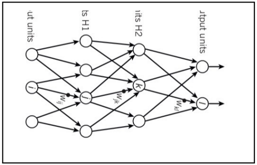
“Multi-layer” vs. “Multi-step”

Deep Learning [LeCun et al., 2015]



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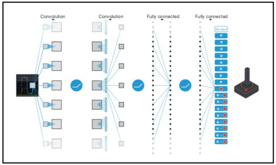

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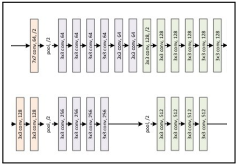

. . .

Multi-layer neural networks: impressive performance, countless applications

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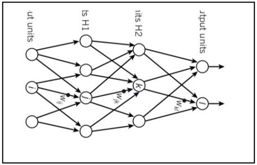

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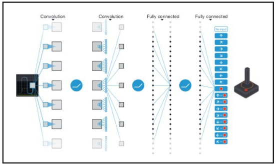

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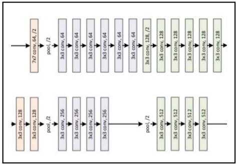

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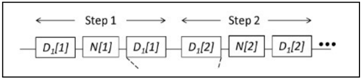
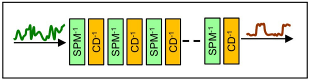


[Du and Lowery, 2010]



[Nakashima et al., 2017]

Conventional wisdom: Steps are inefficient $\Longrightarrow$ reduce as much as possible

- “with only four steps for the entire link . . . ” [Du and Lowery, 2010]
- “up to 80% reduction in required [. . .] steps” [Rafique et al., 2011]
- “it reduces 85% back-propagation stages [. . .]” [Yan et al., 2011]
- “considerably reduces the number of spans needed ” [Napoli et al., 2014]
- “single-step digital backpropagation” [Secondini et al., 2016]

Agenda

In this talk, we . . .

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Complexity $\overset{?}{\approx}$ Number of Steps

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Complexity = Number of Steps × Complexity per Step

Outline

1. Machine Learning and Neural Networks
2. Physics-Based Machine Learning for Fiber-Optic Communications
3. Learned Digital Backpropagation
4. Conclusions

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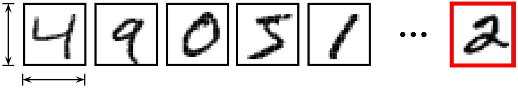
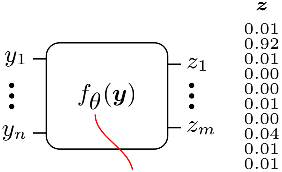
Supervised Learning

handwritten digit recognition (MNIST: 70,000 images)



28×28 pixels $\implies n = 784$



parameters
to be optimized/learned

Supervised Learning

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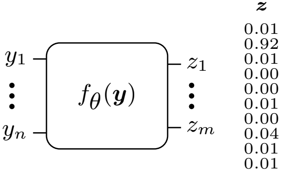
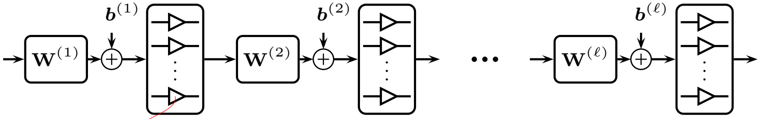
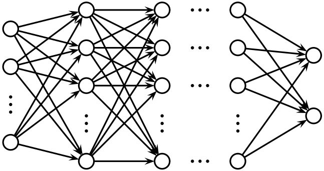


How to choose $f_\theta(\boldsymbol{y})$? Deep feed-forward neural networks



activation function



equivalent graph representation

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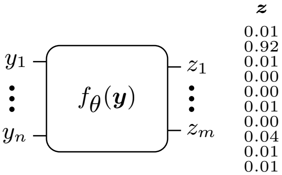

How to optimize $\theta = \{\boldsymbol{W}^{(1)}, \dots, \boldsymbol{W}^{(\ell)}, \boldsymbol{b}^{(1)}, \dots, \boldsymbol{b}^{(\ell)}\}$?

Supervised Learning

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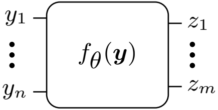

$\boldsymbol{z}$	$\boldsymbol{x}$
0.01	0
0.92	1
0.01	0
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0.00	0
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0.00	0
0.04	0
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Given a data set $\mathcal{D} = \{(\boldsymbol{y}^{(i)}, \boldsymbol{x}^{(i)})\}_{i=1}^{N}$, where $\boldsymbol{y}^{(i)}$ are model inputs and $\boldsymbol{x}^{(i)}$ are labels, we iteratively minimize

$$\frac{1}{|\mathcal{B}_k|} \sum_{(\boldsymbol{y},\boldsymbol{x}) \in \mathcal{B}_k} \mathcal{L}(f_\theta(\boldsymbol{y}), \boldsymbol{x}) \triangleq g(\theta) \qquad \text{using} \quad \theta_{k+1} = \theta_k - \lambda \nabla_\theta g(\theta_k)$$

stochastic gradient descent

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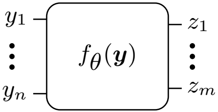

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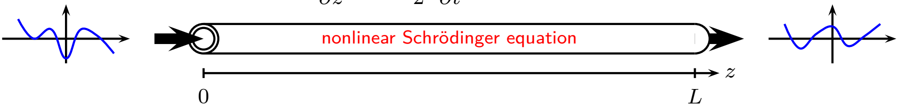
Are there other ways to design good f_θ?

Our contribution: designing "neural-network-like" models by exploiting the underlying physics of the propagation

Outline

The Split-Step Method

$$\frac{\partial u}{\partial z} = -\jmath \frac{\beta_2}{2} \frac{\partial^2 u}{\partial t^2} + \jmath \gamma u |u|^2$$



- Deterministic channel model: partial differential equation

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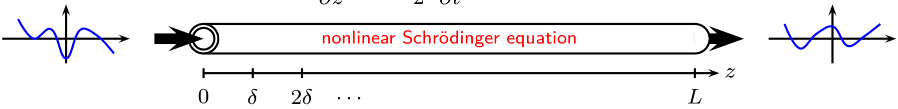
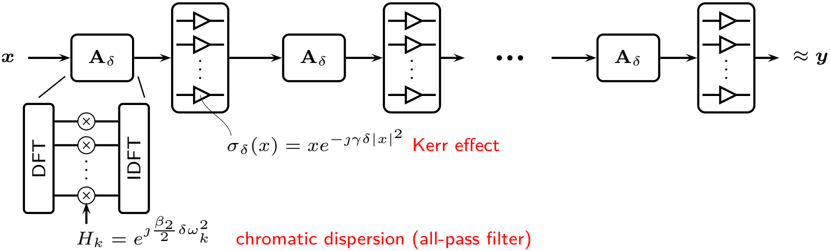


- Deterministic channel model: partial differential equation
- Split-step method with M steps ($\delta = L/M$):



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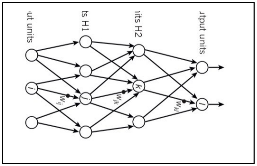

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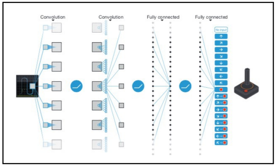

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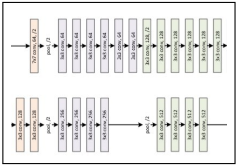

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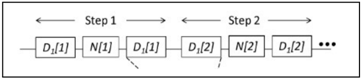

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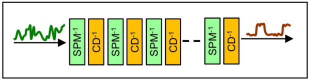
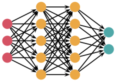
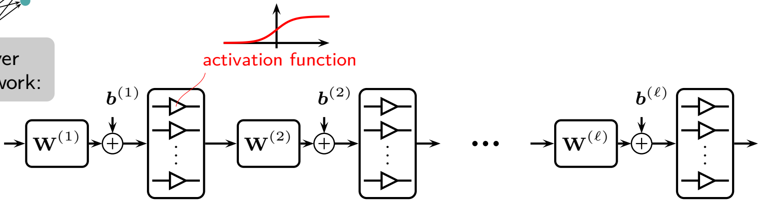


[Nakashima et al., 2017]

The Main Idea



multi-layer neural network:



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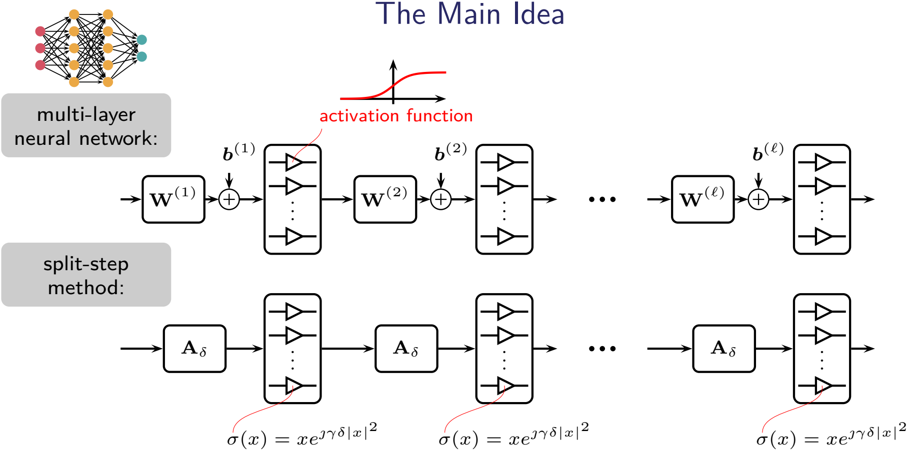

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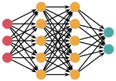
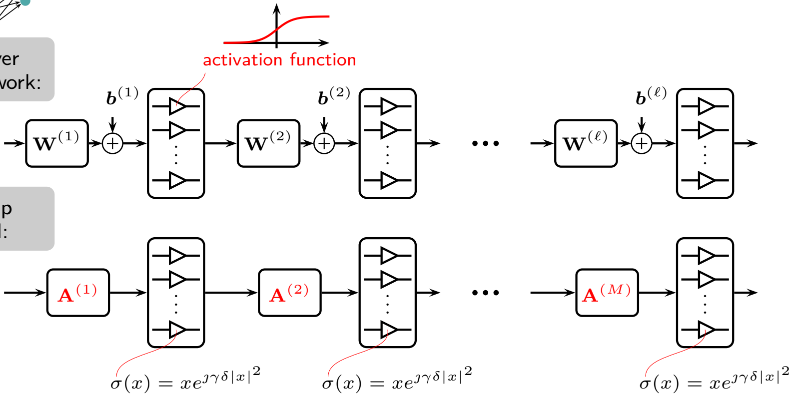


multi-layer neural network:

split-step method:



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[Häger & Pfister, 2018], Nonlinear Interference Mitigation via Deep Neural Networks, *(OFC)*
[Häger & Pfister, 2021], Physics-Based Deep Learning for Fiber-Optic Communication Systems, *IEEE J. Sel. Areas Commun.*

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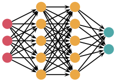

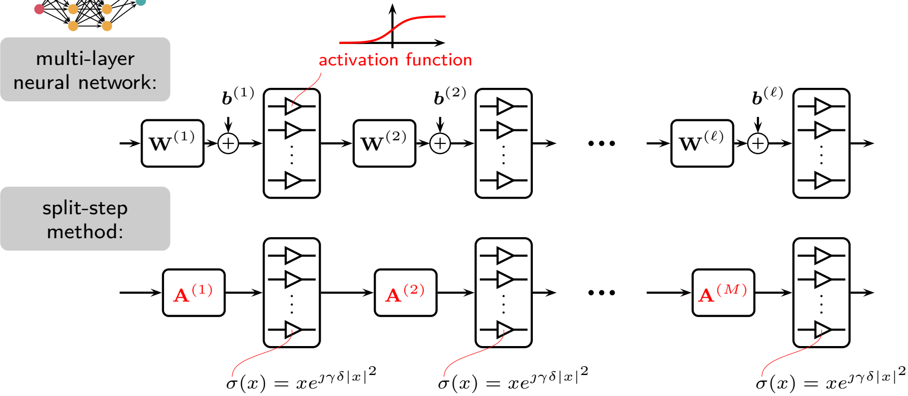

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- Special cases: step-size optimization, nonlinear operator "placement", ...

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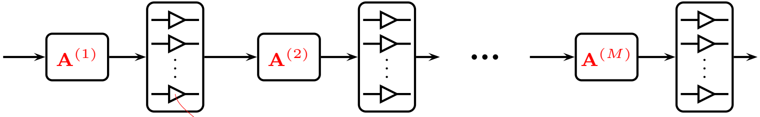
Potential Benefits



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

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

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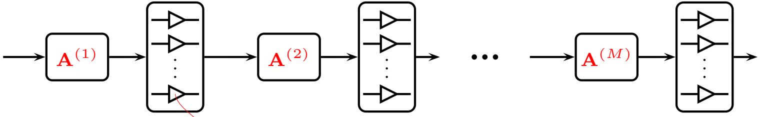

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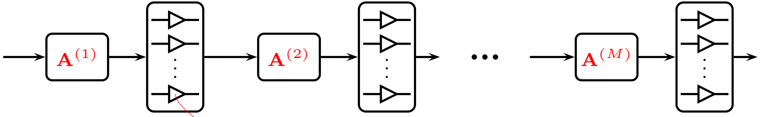

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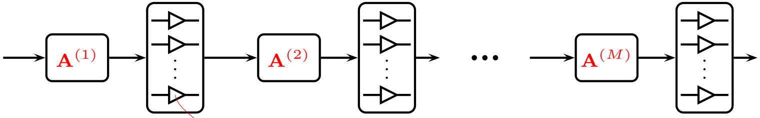

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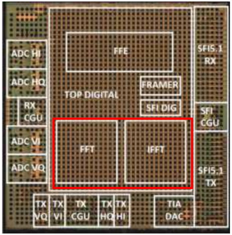
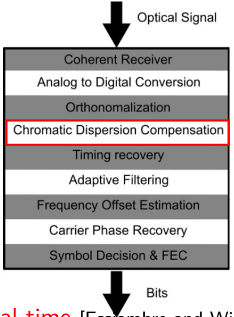
  - Learned parameter configurations are interpretable
  - Satisfactory explanations for benefits over previous handcrafted solutions

Outline

Real-Time Digital Backpropagation



[Crivelli et al., 2014]



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- Complexity increases with the number of steps M $\implies$ reduce M as much as possible (see, e.g., [Du and Lowery, 2010], [Rafique et al., 2011], [Li et al., 2011], [Yan et al., 2011], [Napoli et al., 2014], [Secondini et al., 2016], . . .)

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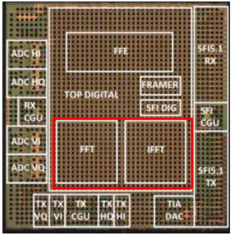

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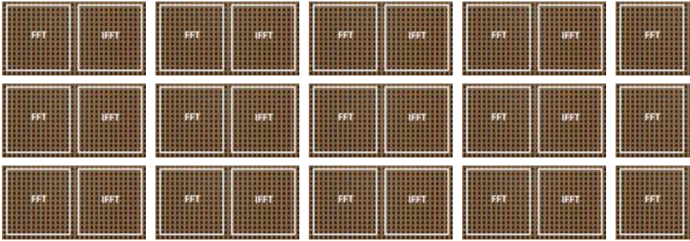

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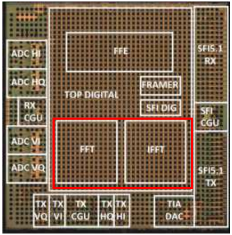

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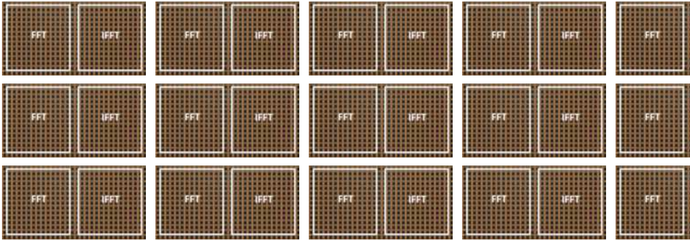

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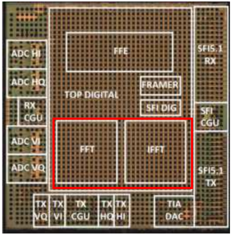

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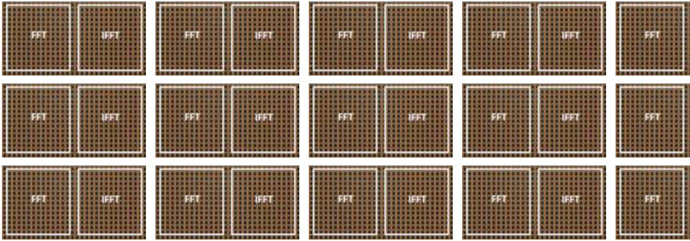

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- Intuitive, but . . .

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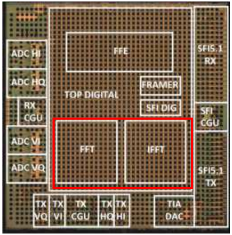

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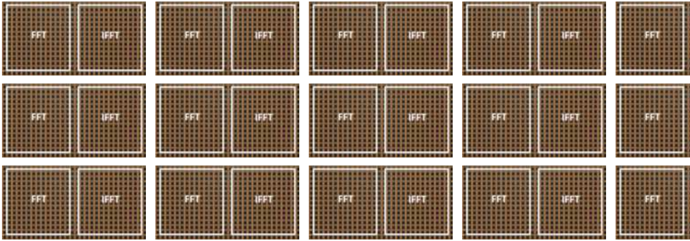
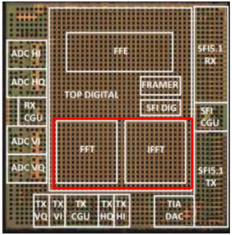
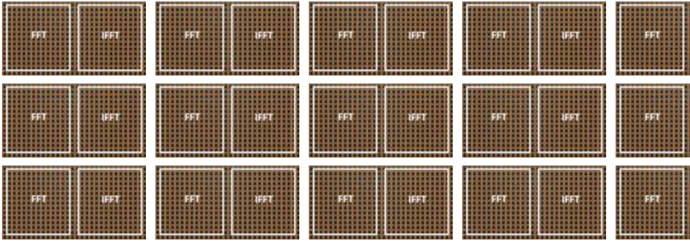


- Invert a PDE in real time [Essiambre and Winzer, 2005], [Roberts et al., 2006], [Li et al., 2008], [Ip and Kahn, 2008]: widely considered to be impractical
- Complexity increases with the number of steps M $\implies$ reduce M as much as possible (see, e.g., [Du and Lowery, 2010], [Rafique et al., 2011], [Li et al., 2011], [Yan et al., 2011], [Napoli et al., 2014], [Secondini et al., 2016], . . .)
- Intuitive, but . . . this flattens a deep (multi-layer) computation graph

Real-Time Digital Backpropagation



[Crivelli et al., 2014]



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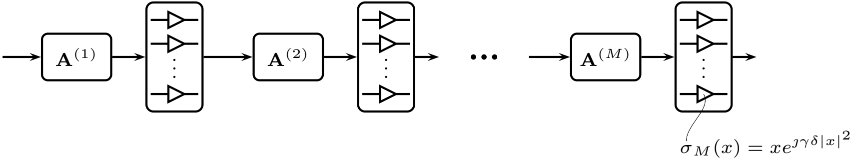
- Intuitive, but ... this flattens a deep (multi-layer) computation graph

Our approach: many steps but model compression

Joint optimization, pruning, and quantization of all linear steps

Learned Digital Backpropagation

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



Learned Digital Backpropagation

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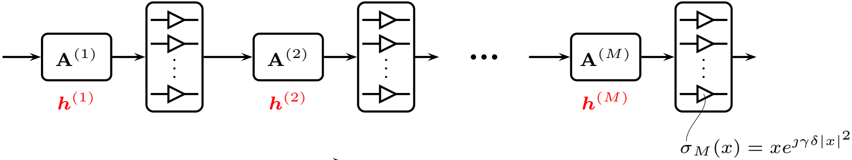
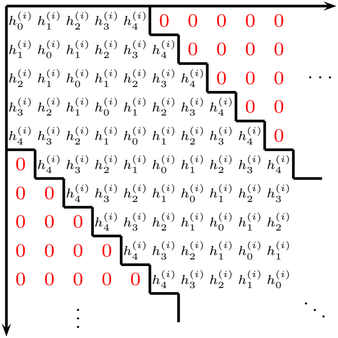
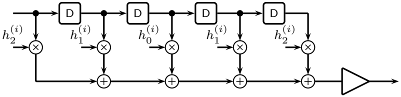


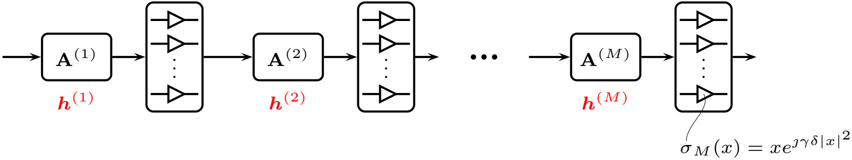




finite impulse response (FIR) filter
complex & symmetric coefficients

Learned Digital Backpropagation

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



Deep learning of all FIR filter coefficients $\theta = \{\boldsymbol{h}^{(1)}, \dots, \boldsymbol{h}^{(M)}\}$:

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

mean squared error

Adam optimizer, fixed learning rate

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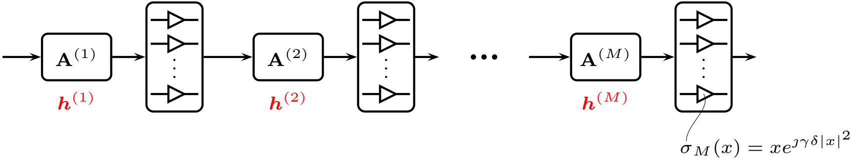
TensorFlow implementation of the computation graph $f_\theta(\boldsymbol{y})$:



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mean squared error — Adam optimizer, fixed learning rate

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

Iterative Filter Tap Pruning

$$\theta = \begin{cases} \boldsymbol{h}^{(1)} \\ \boldsymbol{h}^{(2)} \\ \vdots \\ \boldsymbol{h}^{(M)} \end{cases}$$

Iterative Filter Tap Pruning

$$\longleftarrow \text{starting length } 2K' + 1 \longrightarrow$$

$$\theta = \left\{ \begin{array}{lcccccccccccl} \boldsymbol{h}^{(1)} = (& h_{K'}^{(1)} & \cdots & h_{K}^{(1)} & \cdots & h_{1}^{(1)} & h_{0}^{(1)} & h_{1}^{(1)} & \cdots & h_{K}^{(1)} & \cdots & h_{K'}^{(1)} &) \quad \text{step } 1 \\ \boldsymbol{h}^{(2)} = (& h_{K'}^{(2)} & \cdots & h_{K}^{(2)} & \cdots & h_{1}^{(2)} & h_{0}^{(2)} & h_{1}^{(2)} & \cdots & h_{K}^{(2)} & \cdots & h_{K'}^{(2)} &) \quad \text{step } 2 \\ \vdots & \vdots & & & & & \vdots & & & & & \vdots & \\ \boldsymbol{h}^{(M)} = (& h_{K'}^{(M)} & \cdots & h_{K}^{(M)} & \cdots & h_{1}^{(M)} & h_{0}^{(M)} & h_{1}^{(M)} & \cdots & h_{K}^{(M)} & \cdots & h_{K'}^{(M)} &) \quad \text{step } M \end{array} \right.$$

Iterative Filter Tap Pruning

$\longleftarrow$ starting length $2K' + 1$ $\longrightarrow$

$$\theta = \begin{cases} \boldsymbol{h}^{(1)} = (\; h^{(1)}_{K'} \; \cdots \; h^{(1)}_{K} \; \cdots \; h^{(1)}_{1} \; h^{(1)}_{0} \; h^{(1)}_{1} \; \cdots \; h^{(1)}_{K} \; \cdots \; h^{(1)}_{K'} \;) & \text{step } 1 \\ \boldsymbol{h}^{(2)} = (\; h^{(2)}_{K'} \; \cdots \; h^{(2)}_{K} \; \cdots \; h^{(2)}_{1} \; h^{(2)}_{0} \; h^{(2)}_{1} \; \cdots \; h^{(2)}_{K} \; \cdots \; h^{(2)}_{K'} \;) & \text{step } 2 \\ \vdots \qquad \vdots \qquad \vdots \qquad \vdots & \\ \boldsymbol{h}^{(M)} = (\; h^{(M)}_{K'} \; \cdots \; h^{(M)}_{K} \; \cdots \; h^{(M)}_{1} \; h^{(M)}_{0} \; h^{(M)}_{1} \; \cdots \; h^{(M)}_{K} \; \cdots \; h^{(M)}_{K'} \;) & \text{step } M \end{cases}$$

- Initially: constrained least-squares coefficients (LS-CO) [Sheikh et al., 2016]

Iterative Filter Tap Pruning

$$\overleftarrow{\quad\text{starting length } 2K'+1\quad}\!\!\!\rightarrow$$

$$\overleftarrow{\quad\text{target length } 2K+1\quad}\!\!\!\rightarrow$$

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Iterative Filter Tap Pruning

starting length $2K' + 1$

target length $2K + 1$

$$\theta = \begin{cases} \boldsymbol{h}^{(1)} = (\; \cancel{h^{(1)}_{K'}} \; \cdots \; h^{(1)}_{K} \; \cdots \; h^{(1)}_{1} \; h^{(1)}_{0} \; h^{(1)}_{1} \; \cdots \; h^{(1)}_{K} \; \cdots \; \cancel{h^{(1)}_{K'}} \;) & \text{step } 1 \\ \boldsymbol{h}^{(2)} = (\; h^{(2)}_{K'} \; \cdots \; h^{(2)}_{K} \; \cdots \; h^{(2)}_{1} \; h^{(2)}_{0} \; h^{(2)}_{1} \; \cdots \; h^{(2)}_{K} \; \cdots \; h^{(2)}_{K'} \;) & \text{step } 2 \\ \vdots \qquad \vdots \qquad \vdots \qquad \vdots & \\ \boldsymbol{h}^{(M)} = (\; h^{(M)}_{K'} \; \cdots \; h^{(M)}_{K} \; \cdots \; h^{(M)}_{1} \; h^{(M)}_{0} \; h^{(M)}_{1} \; \cdots \; h^{(M)}_{K} \; \cdots \; h^{(M)}_{K'} \;) & \text{step } M \end{cases}$$

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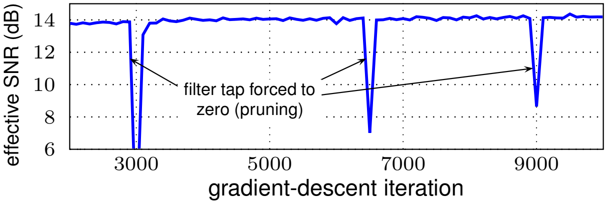
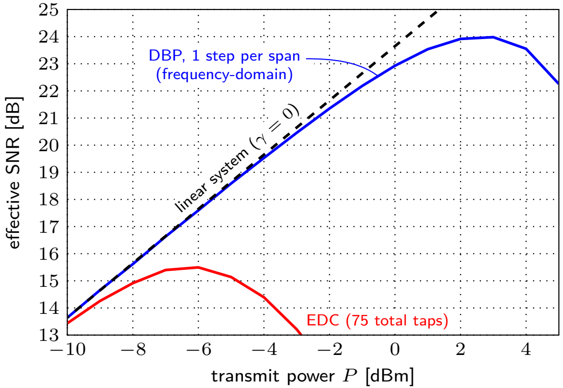
- Initially: constrained least-squares coefficients (LS-CO) [Sheikh et al., 2016]
- Typical learning curve:



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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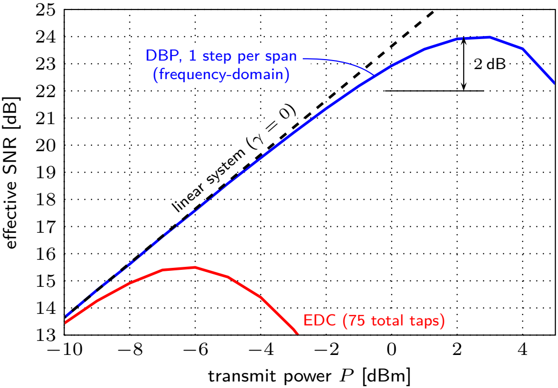

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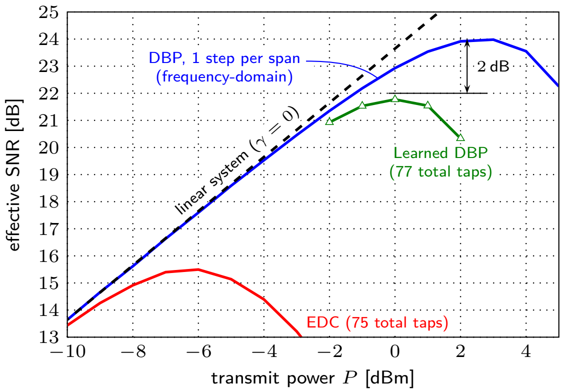

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- Learned approach uses only 77 total taps: alternate 5 and 3 taps/step and use different filter coefficients in all steps [Häger and Pfister, 2018a]

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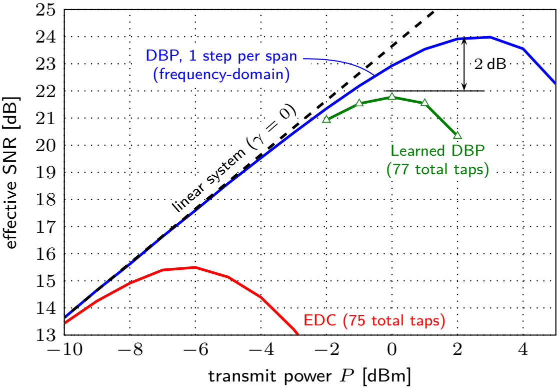

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- Learned approach uses only 77 total taps: alternate 5 and 3 taps/step and use different filter coefficients in all steps [Häger and Pfister, 2018a]
- Can outperform "ideal DBP" in the nonlinear regime [Häger and Pfister, 2018b]

Extensions & Experimental Investigations

Wideband & WDM signals

- [Häger and Pfister, 2018], Wideband time-domain digital backpropagation via subband processing and deep learning, *(ECOC)*

ASIC implementation & finite-precision aspects

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

Polarization-dependent Effects (PMD)

- [Bütler et al., 2021], Model-based Machine Learning for Joint Digital Backpropagation and PMD Compensation, *(J. Lightw. Technol.)*, see arXiv:2010.12313

Experimental demonstrations & implementation aspects (e.g., phase noise)

- [Oliari et al., 2020], Revisiting Efficient Multi-step Nonlinearity Compensation with Machine Learning: An Experimental Demonstration, *(J. Lightw. Technol.)*
- [Sillekens et al., 2020], Experimental Demonstration of Learned Time-domain Digital Back-propagation, *(Proc. IEEE Workshop on Signal Processing Systems)*
- [Fan et al., 2020], Advancing Theoretical Understanding and Practical Performance of Signal Processing for Nonlinear Optical Communications through Machine Learning, *(Nat. Commun.)*
- [Bitachon et al., 2020], Deep learning based Digital Back Propagation Demonstrating SNR gain at Low Complexity in a 1200 km Transmission Link, *(Opt. Express)*

Outline

Conclusions

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- We have proposed a physics-based machine-learning approach for fiber-optic communication systems
- We have revisited efficient multi-step digital backpropagation and shown that deep-learning tools can be used to
  - jointly optimize all linear substeps
  - prune filter taps to get very short filters
  - jointly quantize all filter coefficients
- Multi-step enables factorization into simple, elementary steps

[Häger & Pfister, 2020], "Physics-Based Deep Learning for Fiber-Optic Communication Systems", in *IEEE J. Sel. Areas Commun.* (to appear), see https://arxiv.org/abs/2010.14258

Code: https://github.com/chaeger/LDBP

Conclusions

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Thank you!

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