Revisiting Multi-Step Nonlinearity Compensation with Machine Learning

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]

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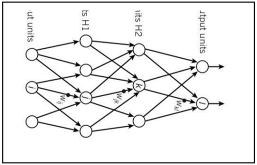
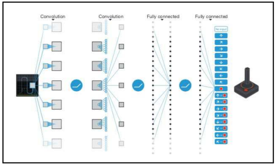
"Multi-layer" vs. "Multi-step"

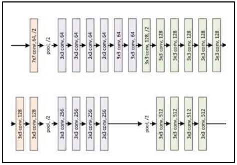
Deep Learning [LeCun et al., 2015]



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



ResNet [He et al., 2015]



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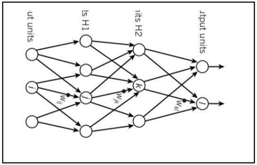
Multi-layer neural networks: impressive performance, countless applications

"Multi-layer" vs. "Multi-step"

Deep Learning [LeCun et al., 2015]



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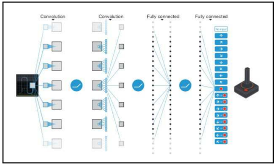

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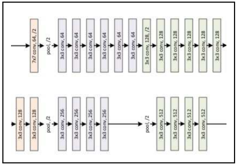

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Multi-layer neural networks: impressive performance, countless applications

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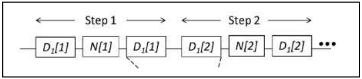
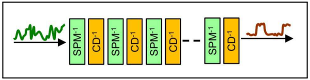


[Du and Lowery, 2010]



[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]

"Multi-layer" vs. "Multi-step"

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)

“Multi-layer” vs. “Multi-step”

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"Multi-layer" vs. "Multi-step"

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

“Multi-layer” vs. “Multi-step”

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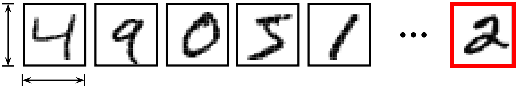
Complexity = Number of Steps × Complexity per Step

Outline

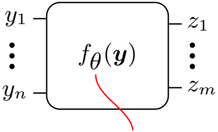
Outline

Supervised Learning

handwritten digit recognition (MNIST: 70,000 images)



28×28 pixels $\implies n = 784$

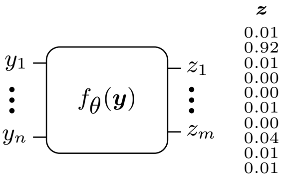


$\boldsymbol{z}$

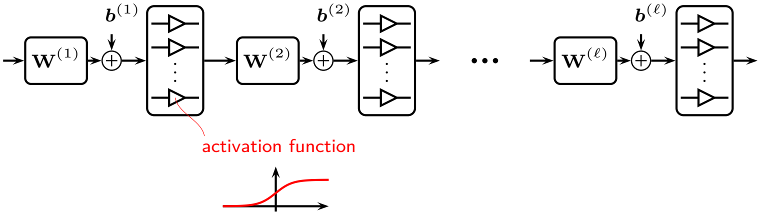
0.01
0.92
0.01
0.00
0.00
0.01
0.00
0.04
0.01
0.01

Supervised Learning

handwritten digit recognition (MNIST: 70,000 images)



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



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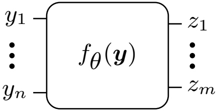

$\boldsymbol{z}$	$\boldsymbol{x}$
0.01	0
0.92	1
0.01	0
0.00	0
0.00	0
0.01	0
0.00	0
0.04	0
0.01	0
0.01	0

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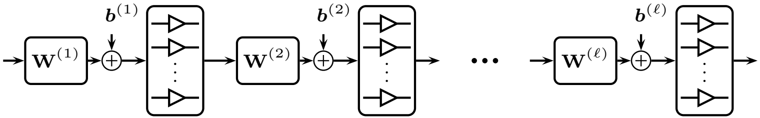


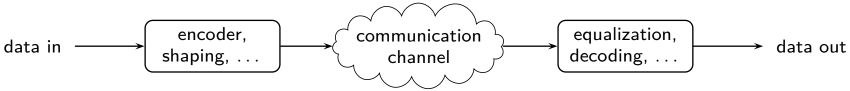
How to optimize $\theta = \{\boldsymbol{W}^{(1)}, \dots, \boldsymbol{W}^{(\ell)}, \boldsymbol{b}^{(1)}, \dots, \boldsymbol{b}^{(\ell)}\}$? Deep learning

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

mean squared error
cross-entropy, ...

stochastic gradient descent,
RMSProp, Adam, ...

Machine Learning for Physical-Layer Communications



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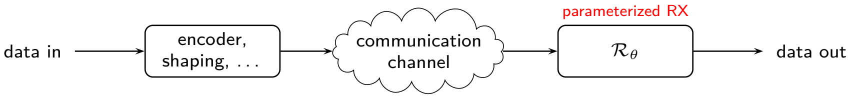

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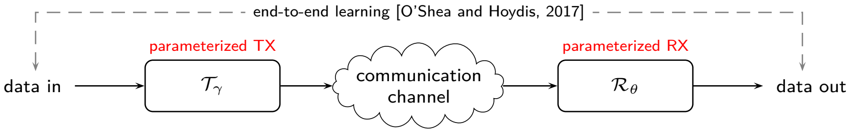

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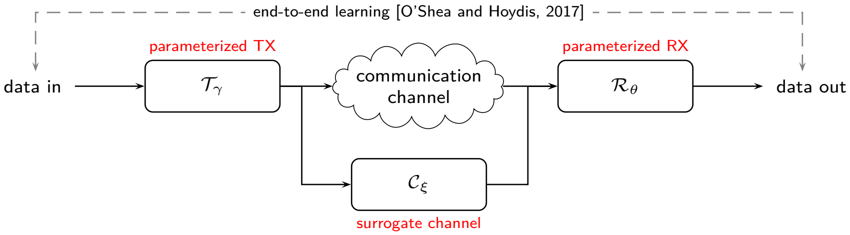

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[O'Shea et al., 2018], Approximating the void: Learning stochastic channel models from observation with variational GANs, (*arXiv*)
[Ye et al., 2018], Channel agnostic end-to-end learning based communication systems with conditional GAN, (*arXiv*)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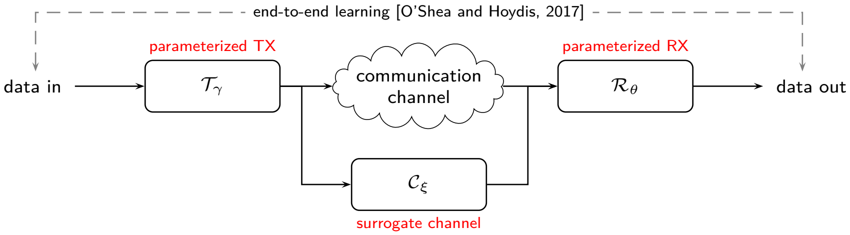
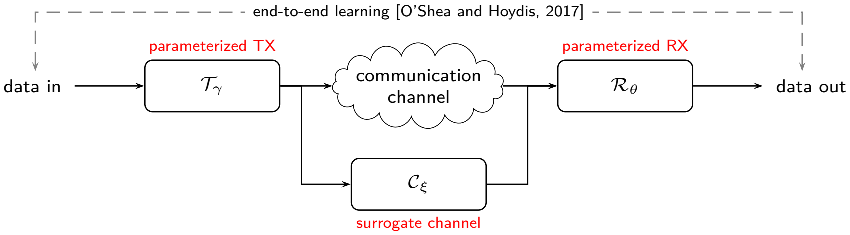
Machine Learning for Physical-Layer Communications



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

- 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 $\mathcal{T}_\gamma, \mathcal{R}_\theta, \mathcal{C}_\xi$

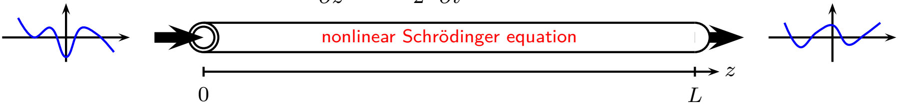
- How to choose network architecture (#layers, activation function)? ✗
- How to initialize parameters? ✗
- How to interpret solutions? Any insight gained? ✗
- ...

Model-based alternatives: sparse signal recovery [Gregor and Lecun, 2010], [Borgerding and Schniter, 2016], channel coding [Nachmani et al., 2016], ...

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

The Split-Step Method

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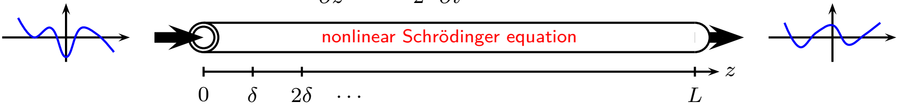
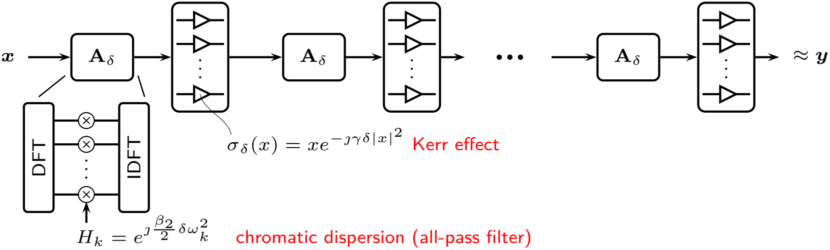
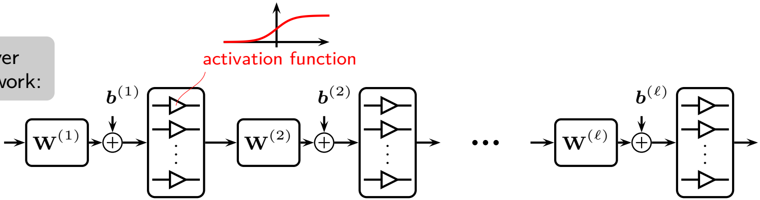


- Deterministic channel model: partial differential equation
- Split-step method with M steps ($\delta = L/M$):



Parameterizing the Split-Step Method

multi-layer neural network:



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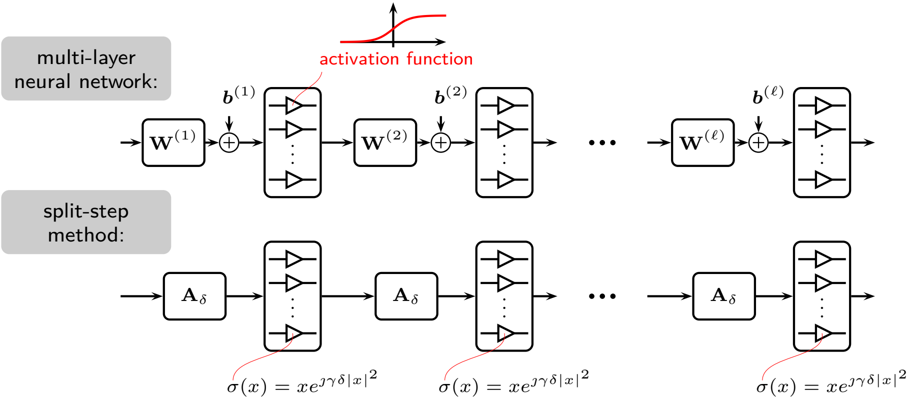

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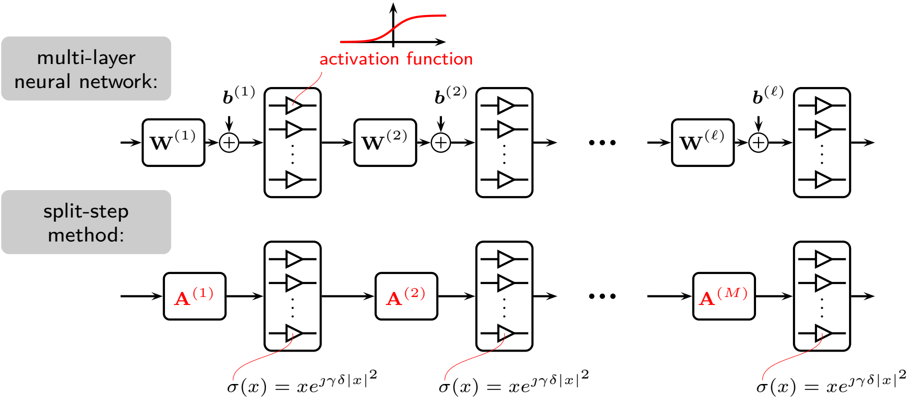

[Häger & Pfister, 2018], Nonlinear Interference Mitigation via Deep Neural Networks, *(OFC)*
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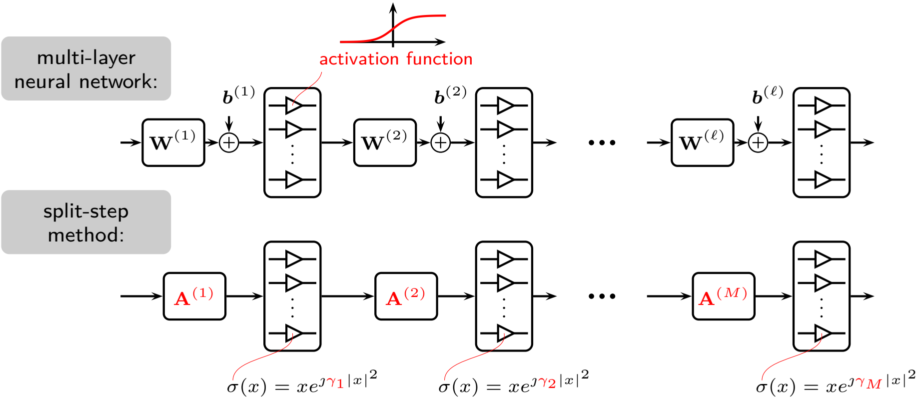

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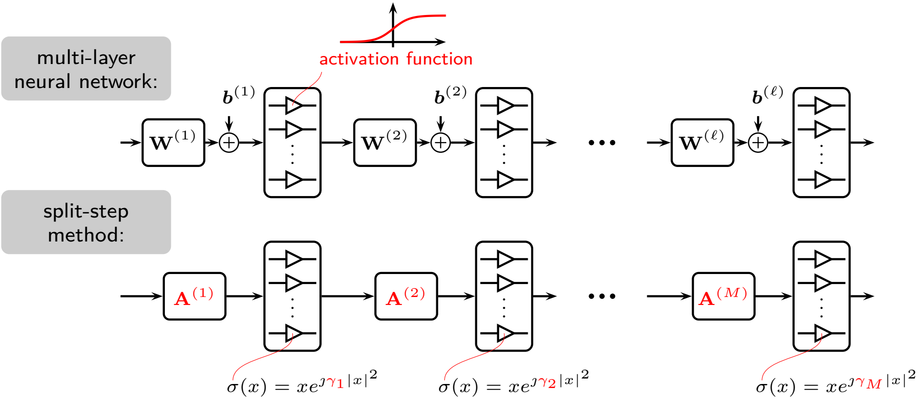
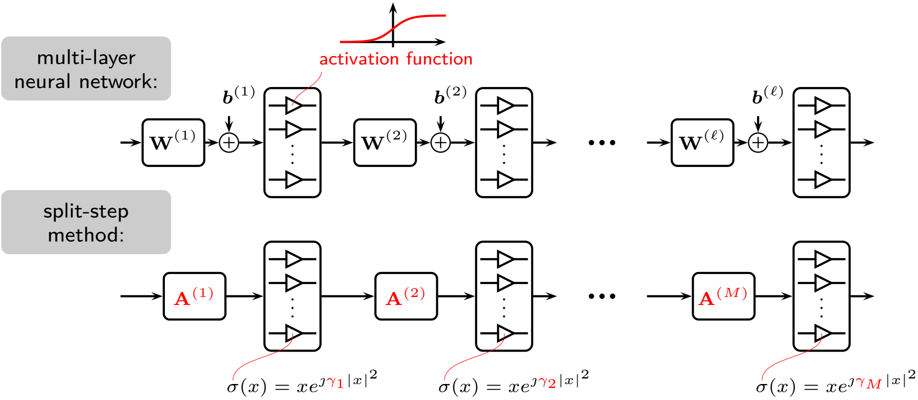


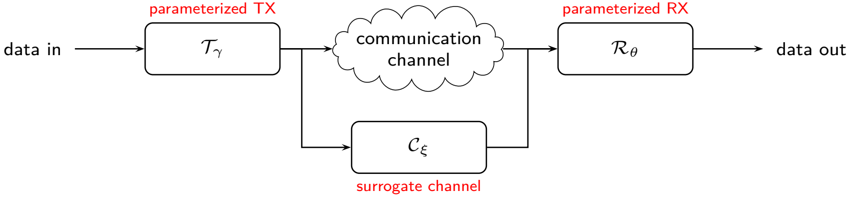
- Parameterized model f_θ with $\theta = \{\mathbf{A}^{(1)}, \ldots, \mathbf{A}^{(M)}, \gamma_1, \ldots, \gamma_M\}$

Parameterizing the Split-Step Method



- Parameterized model f_θ with $\theta = \{\mathbf{A}^{(1)}, \dots, \mathbf{A}^{(M)}, \gamma_1, \dots, \gamma_M\}$
- Includes as special cases: step-size optimization, "placement" of nonlinear operator, higher-order dispersion, matched filtering ...

Possible Applications



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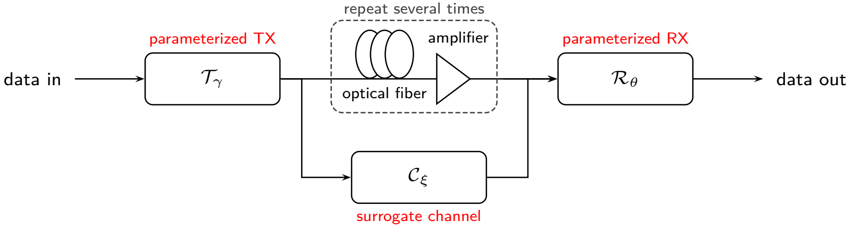

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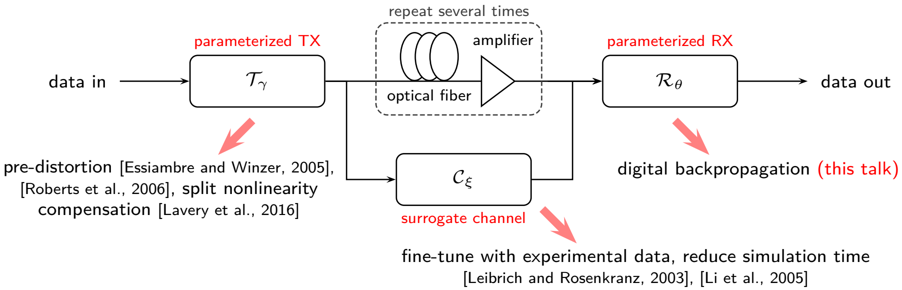

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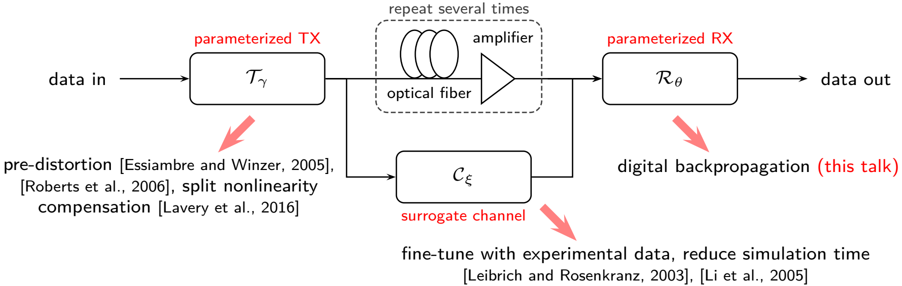
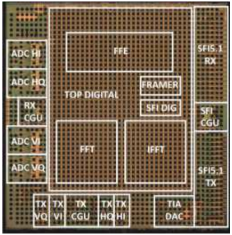


Model-based learning approaches

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

Outline

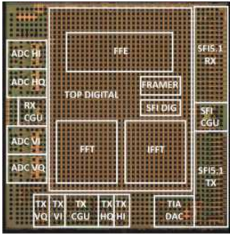
Real-Time Digital Backpropagation



[Crivelli et al., 2014]

- Invert a partial differential equation in real time ([Paré et al., 1996], [Essiambre and Winzer, 2005], [Roberts et al., 2006], [Li et al., 2008], [Ip and Kahn, 2008])

Real-Time Digital Backpropagation



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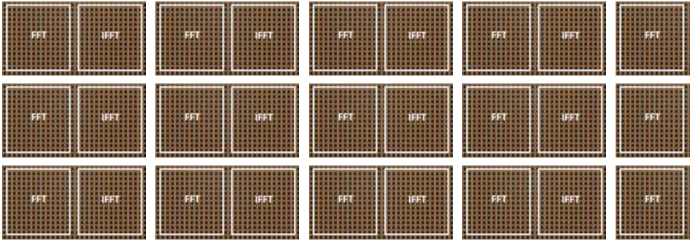

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- Widely considered to be impractical (too complex): linear equalization is already one of the most power-hungry DSP blocks in coherent receivers

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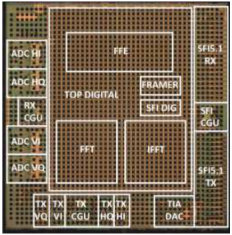

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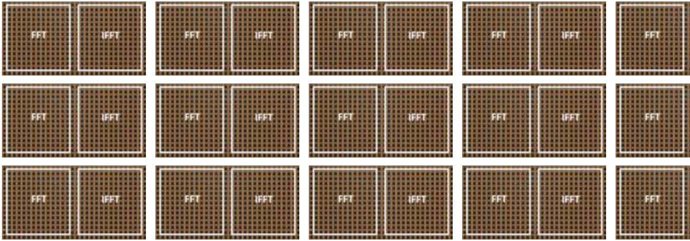

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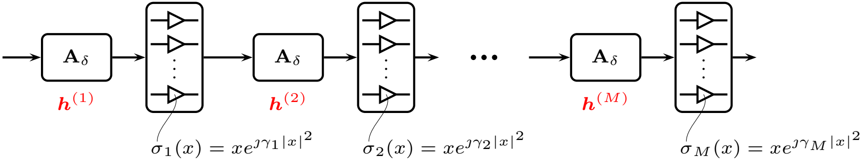
Our approach

Joint optimization, pruning, and quantization of all chromatic-dispersion filters leads to efficient digital backpropagation, even with many steps.

Learned Digital Backpropagation

Learned Digital Backpropagation

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



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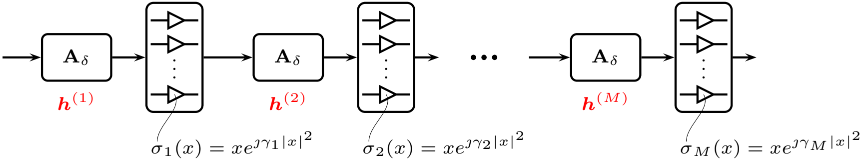

Deep learning of parameters $\theta = \{\boldsymbol{h}^{(1)}, \ldots, \boldsymbol{h}^{(M)}\}$:

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

mean squared error — Adam optimizer, fixed learning rate

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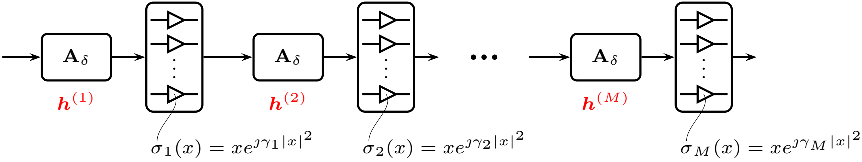

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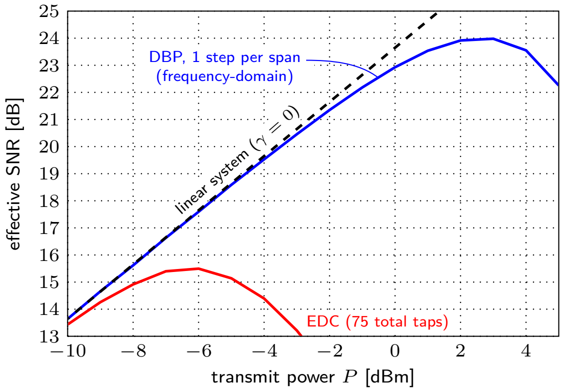
mean squared error — Adam optimizer, fixed learning rate

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

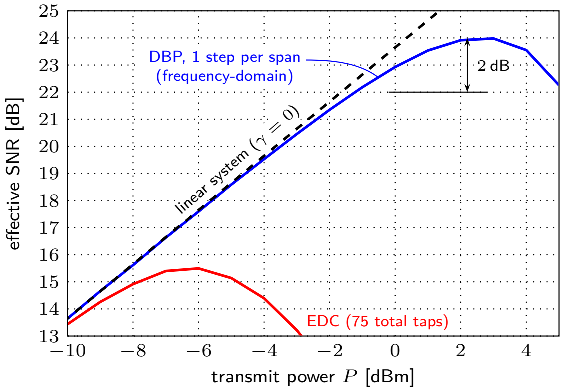
Revisiting Ip and Kahn (2008)



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.

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.

- $\gg 1000$ total taps (70 taps/step) $\implies$ $> 100\times$ complexity of EDC

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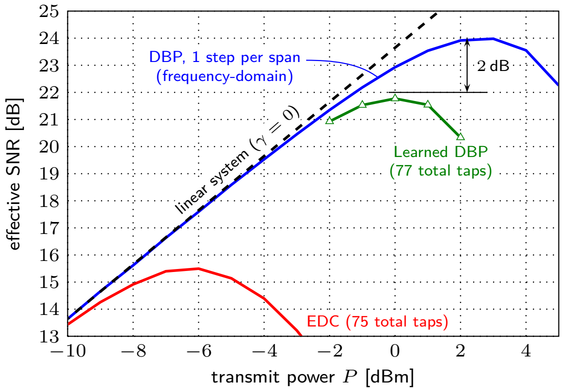

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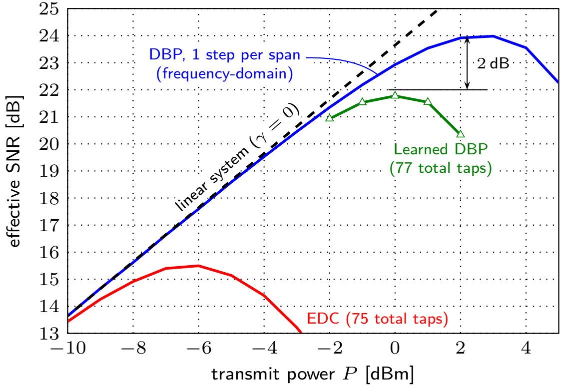

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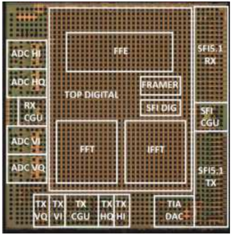
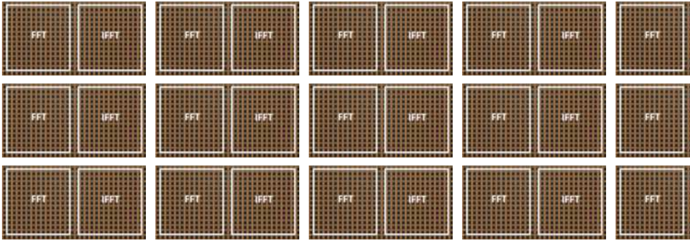
- Learned approach uses only 77 total taps: alternate 5 and 3 taps/step and use different filter coefficients in all steps [Häger and Pfister, 2018a]
- Can outperform "ideal DBP" in the nonlinear regime [Häger and Pfister, 2018b]

Real-Time ASIC Implementation



[Crivelli et al., 2014]



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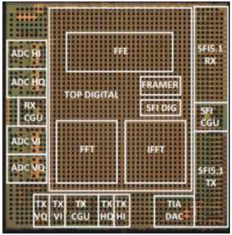

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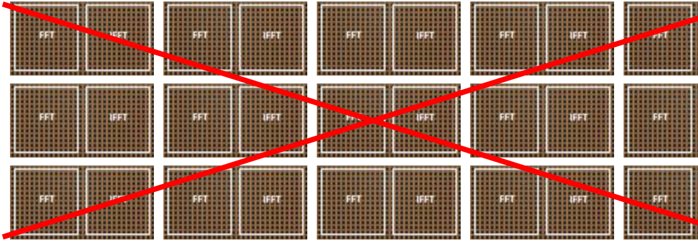

[Fougstedt et al., 2017], Time-domain digital back propagation: Algorithm and finite-precision implementation aspects, (*OFC*)
[Fougstedt et al., 2018], ASIC implementation of time-domain digital back propagation for coherent receivers, *(PTL)*
[Sherborne et al., 2018], On the impact of fixed point hardware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

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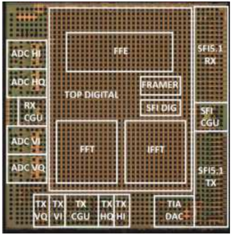

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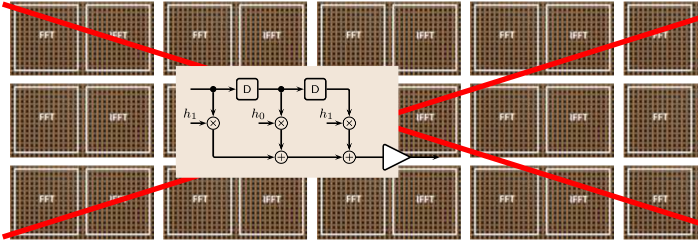

- Our linear steps are very short symmetric FIR filters (as few as 3 taps)

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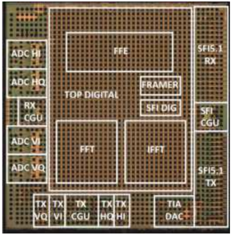

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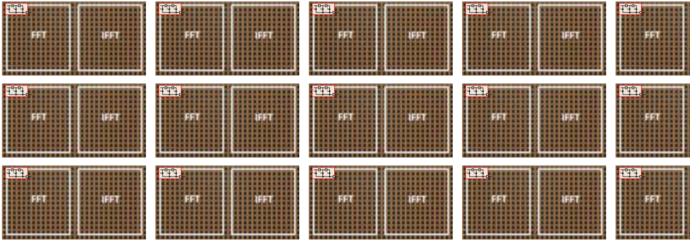

- Our linear steps are very short symmetric FIR filters (as few as 3 taps)
- 28-nm ASIC at 416.7 MHz clock speed (40 GHz signal)
    - Only 5-6 bit filter coefficients via learned quantization
    - Hardware-friendly nonlinear steps (Taylor expansion)
    - All FIR filters are fully reconfigurable

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

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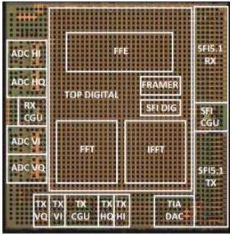

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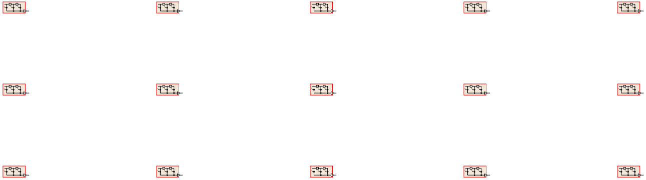

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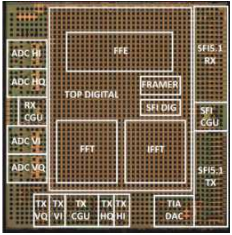

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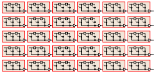

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- 28-nm ASIC at 416.7 MHz clock speed (40 GHz signal)
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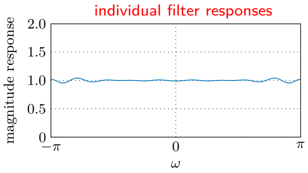
  - All FIR filters are fully reconfigurable
- $< 2\times$ power compared to EDC [Crivelli et al., 2014, Pillai et al., 2014]

[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"
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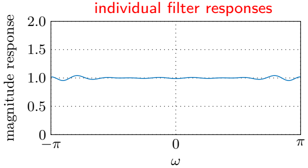

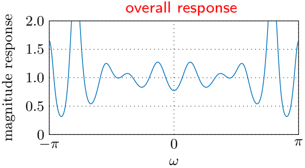

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The learning approach uncovered that there is no such requirement!

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

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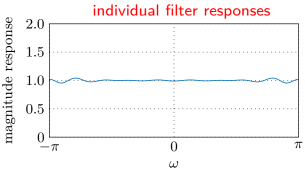
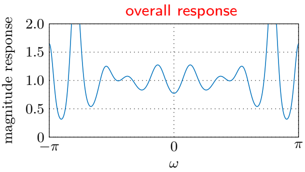
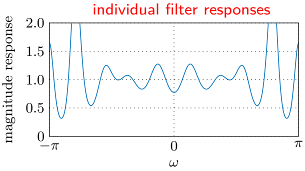
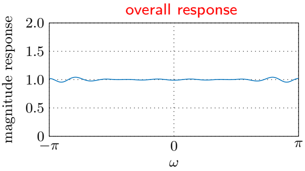




Sacrifice individual filter accuracy, but different response per step.

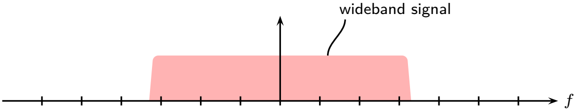
$\Longrightarrow$ Good overall response even with very short filters by joint optimization.





Outline

Wideband Signals and Subband Processing



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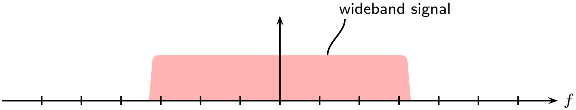
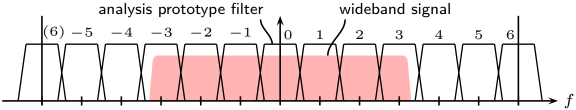


- Quadratic dependence of overall system memory on the backpropagated bandwidth $\implies$ problematic for time-domain DBP (#taps $\propto f^2$)

Wideband Signals and Subband Processing



- Quadratic dependence of overall system memory on the backpropagated bandwidth $\implies$ problematic for time-domain DBP (#taps $\propto f^2$)
- Subband processing: split received signal into N parallel signals

[Taylor, 2008], Compact digital dispersion compensation algorithms, *(OFC)*
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[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)*
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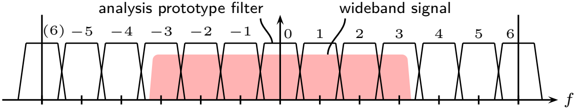

- Quadratic dependence of overall system memory on the backpropagated bandwidth $\implies$ problematic for time-domain DBP (#taps $\propto f^2$)
- Subband processing: split received signal into N parallel signals
- MIMO filter accounts for cross-phase modulation (XPM) between subbands [Leibrich and Rosenkranz, 2003]

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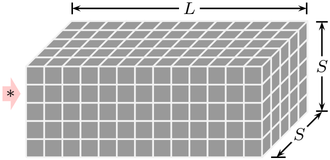
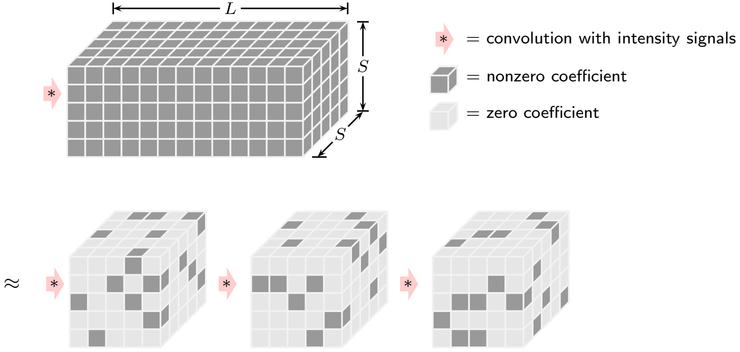


= convolution with intensity signals


= nonzero coefficient

= zero coefficient

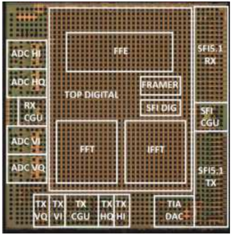
Wideband Signals and Subband Processing



- L_1-norm regularization applied to filter coefficients during gradient descent
- $\implies$ 92% of coefficients are zero with little performance penality

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

Polarization Mode Dispersion



[Crivelli et al., 2014]

- Modeling via PMD sections, $\mathbf{R}^{(i)}\mathbf{J}^{(i)}(\omega)$, in the split-step method:
  - $\mathbf{R}^{(i)}$: complex unitary rotation matrix with determinant one
  - $\mathbf{J}^{(i)}(\omega)$: first-order PMD matrix with differential group delay (DGD) τ_i, i.e.,

$$\mathbf{J}^{(i)}(\omega) = \begin{pmatrix} e^{-\jmath\omega\frac{\tau_i}{2}} & 0 \\ 0 & e^{\jmath\omega\frac{\tau_i}{2}} \end{pmatrix}$$

- PMD transfer matrix: $\mathbf{J}(\omega) = \prod_{i=1}^{M} \mathbf{R}^{(i)}\mathbf{J}^{(i)}(\omega)$ for large M

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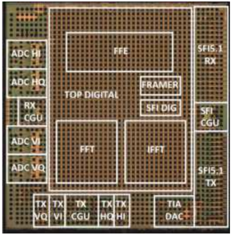

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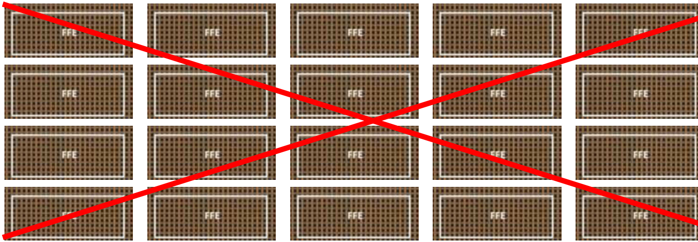

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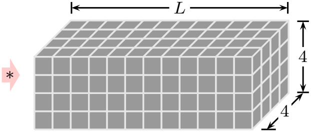
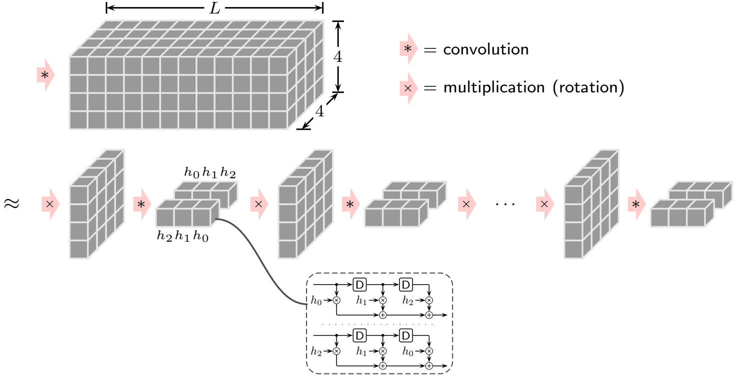
Adaptive PMD Compensation



= convolution

= multiplication (rotation)

Adaptive PMD Compensation



- Ongoing work: characterize optimization behavior (saddle points), integrate into digital backpropagation, . . .

[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)*

Conclusions

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- We have proposed a model-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
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Thank you!

FIBER-OPTIC COMMUNICATIONS RESEARCH CENTER

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