Deep Learning of the Nonlinear Schrödinger Equation in Fiber-Optic Communications

Christian Häger[1,2] Henry D. Pfister[2]

[1] Department of Electrical Engineering, Chalmers University of Technology, Gothenburg

[2] Department of Electrical and Computer Engineering, Duke University, Durham

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FIBER-OPTIC COMMUNICATIONS RESEARCH CENTER

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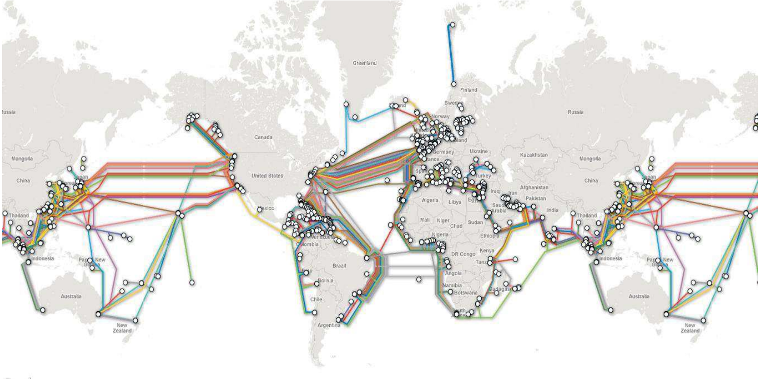
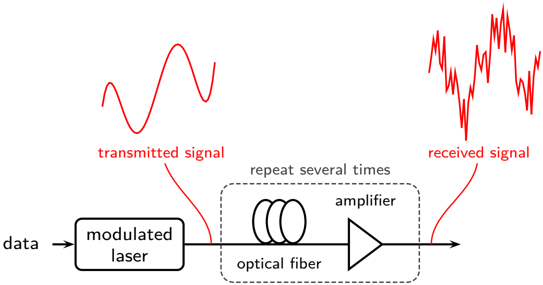
Fiber-Optic Communications



Fiber-optic communication systems enable high-speed data traffic (100 Gbit/s per channel or higher) over very long distances.

Fiber-Optic Communications



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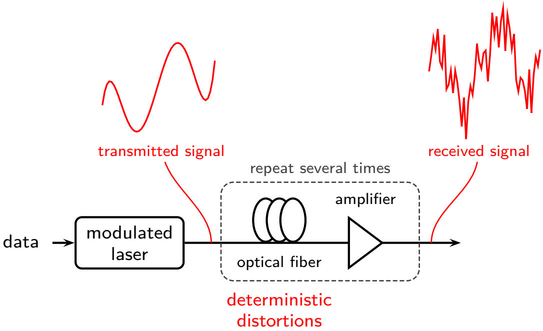
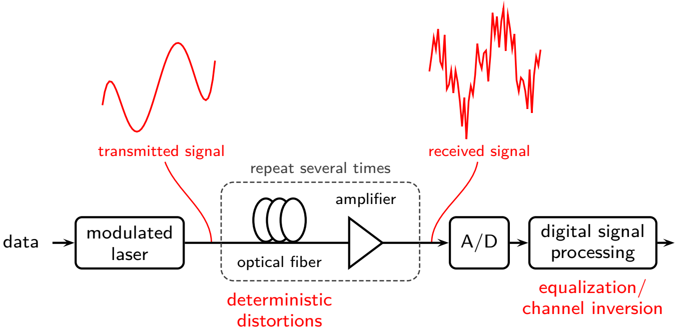


- Dispersion: different wavelengths travel at different speeds (linear)
- Kerr effect: refractive index changes with signal intensity (nonlinear)

Fiber-Optic Communications



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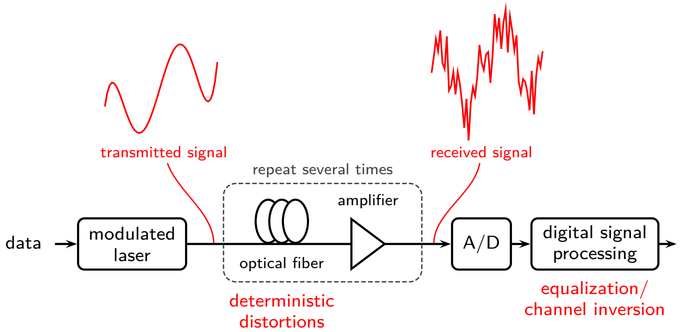

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- Key challenge: complexity constraints due to very high data rates

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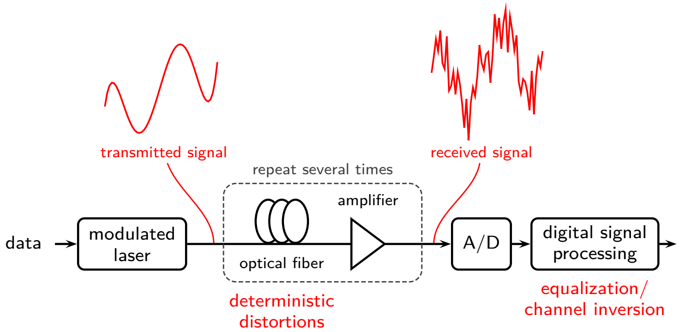

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This talk

Machine learning for low-complexity real-time channel inversion

Outline

1. Channel Modeling and the Nonlinear Schrödinger Equation
2. Connection to Deep Learning
3. Joint Filter Optimization and Pruning
4. Results
5. Conclusions

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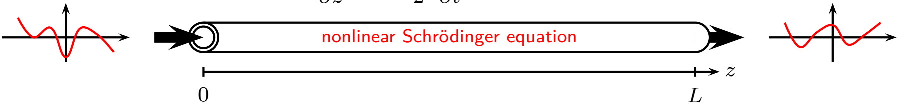
Channel Modeling and Digital Backpropagation

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



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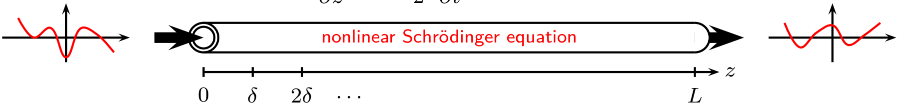
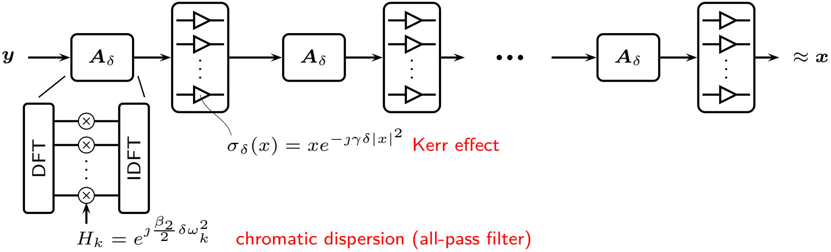
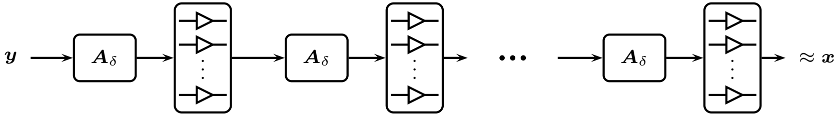


- Invert a partial differential equation in real time ([Paré et al., 1996], [Essiambre and Winzer, 2005], [Roberts et al., 2006], [Li et al., 2008], [Ip and Kahn, 2008])
- Split-step Fourier method with M steps ($\delta = L/M$):



Real-Time Digital Backpropagation



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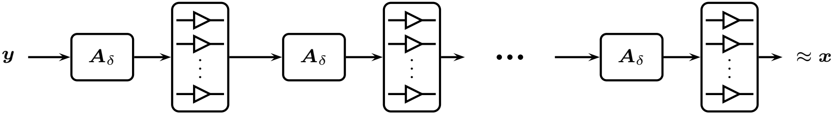

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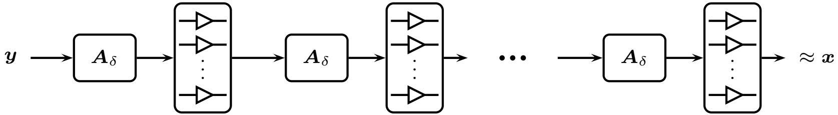

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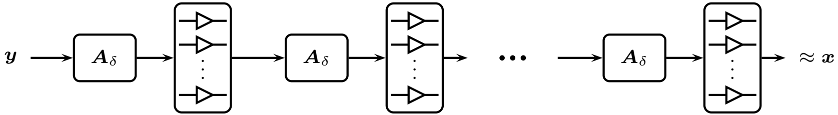

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- Intuitive, but ...

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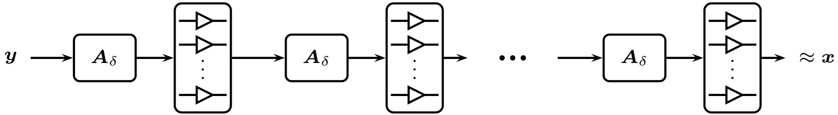

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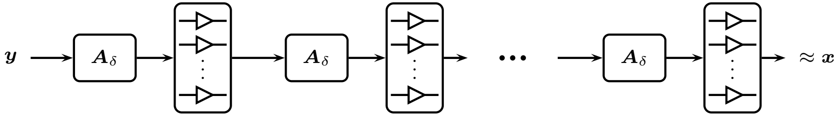

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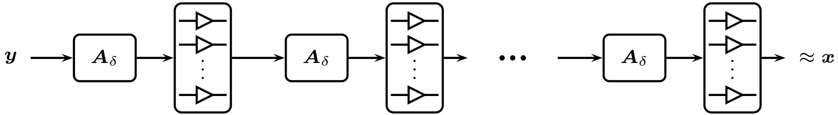

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Main contribution

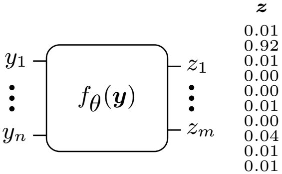
- Joint optimization of all linear steps leads to efficient channel inversion
- Power consumption comparable to published results for linear equalization

Outline

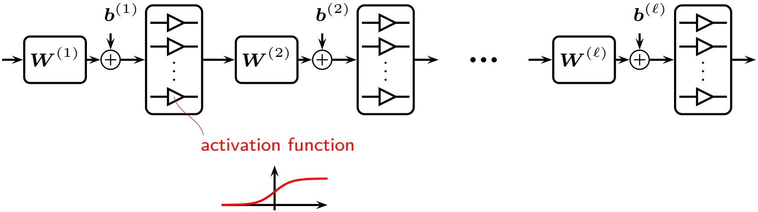
Supervised Learning

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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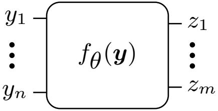

$\boldsymbol{z}$	$\boldsymbol{x}$
0.01	0
0.92	1
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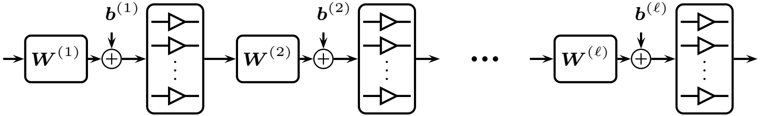

How to optimize $\theta = \{\boldsymbol{W}^{(1)}, \ldots, \boldsymbol{W}^{(\ell)}, \boldsymbol{b}^{(1)}, \ldots, \boldsymbol{b}^{(\ell)}\}$? Deep learning

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Supervised Learning

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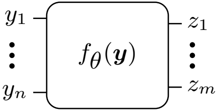

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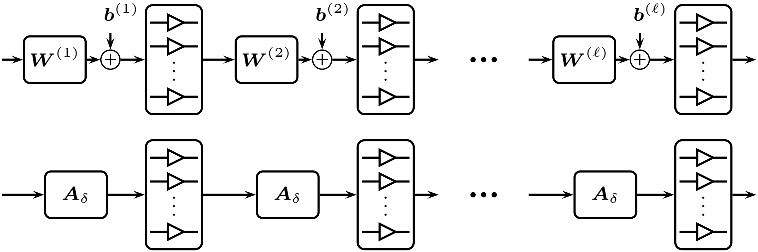

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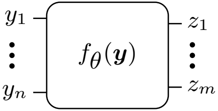

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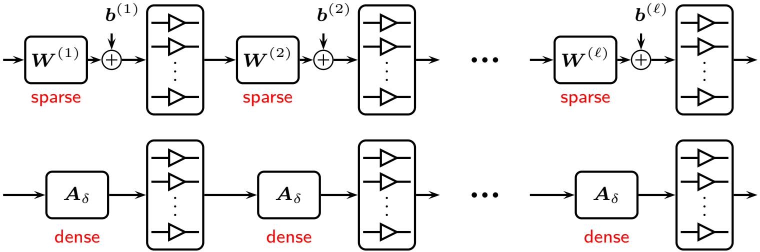
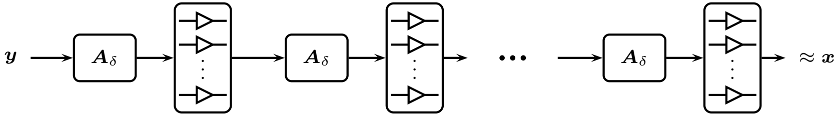


Time-Domain Implementation and Truncation



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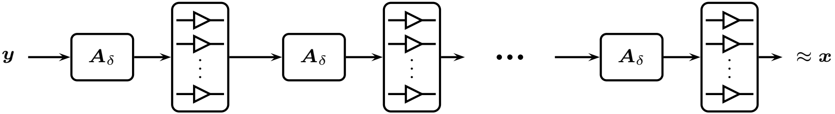

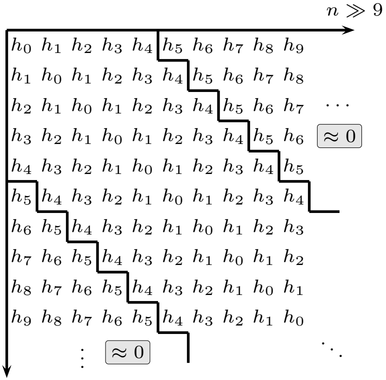

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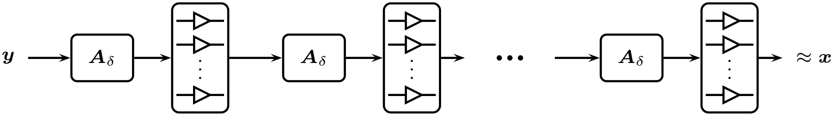
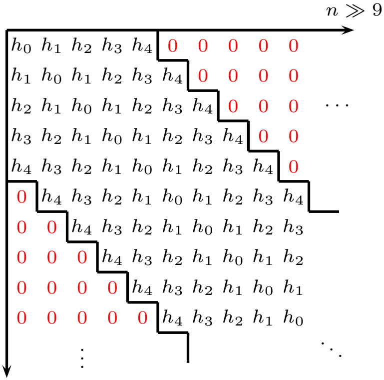
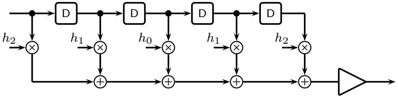
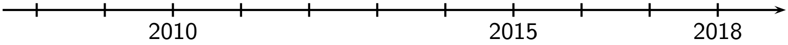






finite impulse response (FIR) filter

Time-Domain Implementation and Truncation



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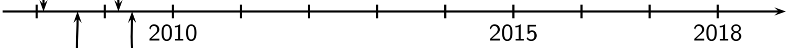
Time-Domain Implementation and Truncation

[Li et al., 2008]: "To facilitate real-time implementation, the dispersion . . . operator can be realized using a finite impulse response (FIR) filter"

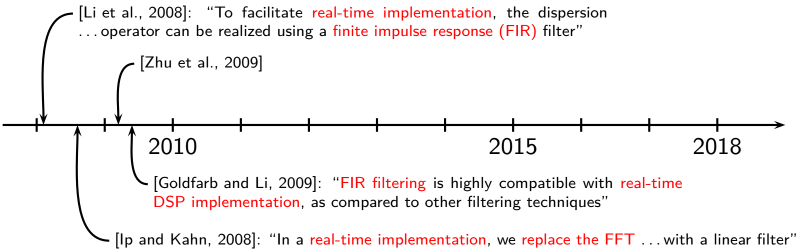
[Zhu et al., 2009]



[Goldfarb and Li, 2009]: "FIR filtering is highly compatible with real-time DSP implementation, as compared to other filtering techniques"

[Ip and Kahn, 2008]: "In a real-time implementation, we replace the FFT . . . with a linear filter"

Time-Domain Implementation and Truncation



Nontrivial to achieve a good performance–complexity tradeoff!

Example for $R_{\text{symb}} = 10.7$ Gbaud, $L = 2000$ km [Ip and Kahn, 2008]

- $\gg 1000$ total filter taps required for good performance

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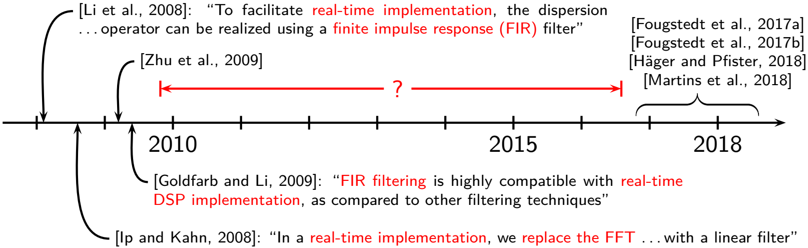

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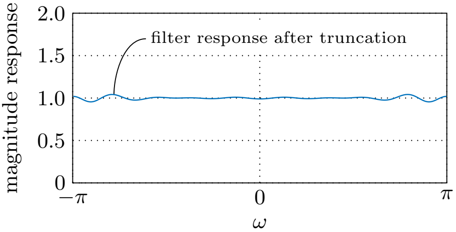
Problem: Truncation Errors



$$\boldsymbol{h}^{(1)} = \boldsymbol{h}^{(2)} = \cdots = \boldsymbol{h}^{(M)}$$

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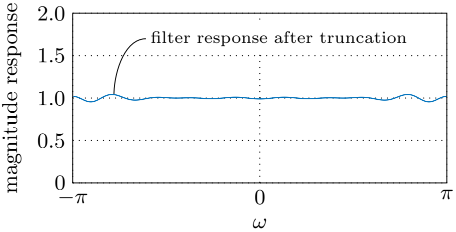

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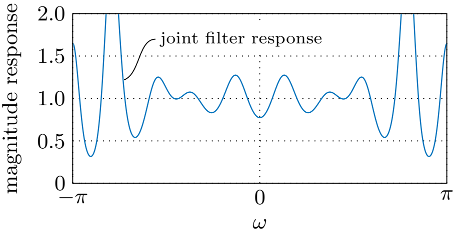

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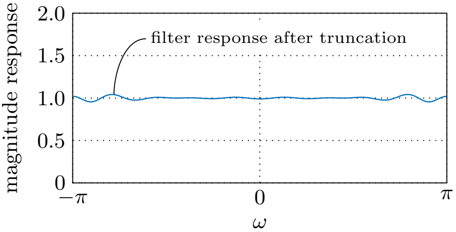

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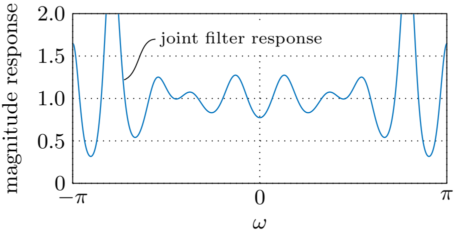

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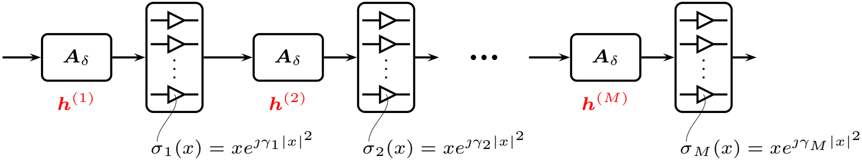
Our approach:
Optimize all M filters jointly

Outline

Joint Filter Optimization

Joint Filter Optimization

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



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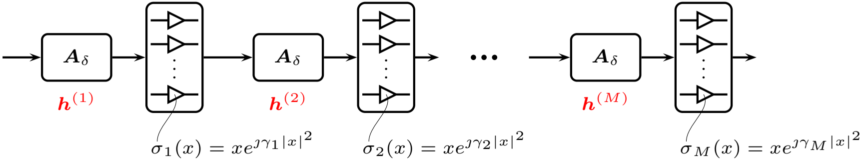

Deep learning of parameters $\theta = \{\boldsymbol{h}^{(1)}, \dots, \boldsymbol{h}^{(M)}\}$:

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mean squared error — Adam optimizer, fixed learning rate

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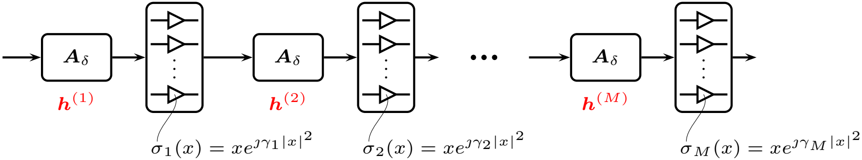

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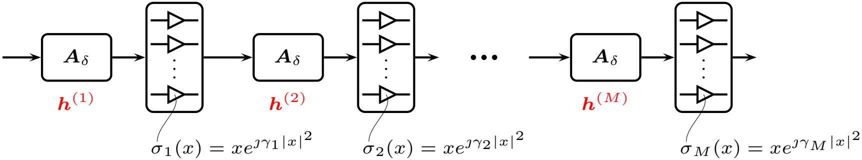

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mean squared error — Adam optimizer, fixed learning rate

- How to choose the starting point θ_0 and get short filters?
- Pre-optimization possible via multi-objective optimization problem

Iterative Filter Tap Pruning

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

Iterative Filter Tap Pruning

starting length $2K' + 1$

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

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

Iterative Filter Tap Pruning

$$\overbrace{\hspace{10em}}^{\text{starting length } 2K'+1} \quad \overbrace{\hspace{6em}}^{\text{target length } 2K+1}$$

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

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

Iterative Filter Tap Pruning

starting length $2K' + 1$

target length $2K + 1$

$$\theta = \begin{cases} \boldsymbol{h}^{(1)} = (\; h_{K'}^{(1)} \; \cdots \; h_K^{(1)} \; \cdots \; h_1^{(1)} \; h_0^{(1)} \; h_1^{(1)} \; \cdots \; h_K^{(1)} \; \cdots \; h_{K'}^{(1)} \;) & \text{step } 1 \\ \boldsymbol{h}^{(2)} = (\; h_{K'}^{(2)} \; \cdots \; h_K^{(2)} \; \cdots \; h_1^{(2)} \; h_0^{(2)} \; h_1^{(2)} \; \cdots \; h_K^{(2)} \; \cdots \; h_{K'}^{(2)} \;) & \text{step } 2 \\ \vdots \\ \boldsymbol{h}^{(M)} = (\; h_{K'}^{(M)} \; \cdots \; h_K^{(M)} \; \cdots \; h_1^{(M)} \; h_0^{(M)} \; h_1^{(M)} \; \cdots \; h_K^{(M)} \; \cdots \; h_{K'}^{(M)} \;) & \text{step } M \end{cases}$$

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$$\theta = \begin{cases} \boldsymbol{h}^{(1)} = (\; \cancel{h_{K'}^{(1)}} \; \cdots \; h_K^{(1)} \; \cdots \; h_1^{(1)} \; h_0^{(1)} \; h_1^{(1)} \; \cdots \; h_K^{(1)} \; \cdots \; \cancel{h_{K'}^{(1)}} \;) & \text{step } 1 \\ \boldsymbol{h}^{(2)} = (\; \cancel{h_{K'}^{(2)}} \; \cdots \; h_K^{(2)} \; \cdots \; h_1^{(2)} \; h_0^{(2)} \; h_1^{(2)} \; \cdots \; h_K^{(2)} \; \cdots \; \cancel{h_{K'}^{(2)}} \;) & \text{step } 2 \\ \vdots \qquad \vdots \qquad \vdots \qquad \vdots & \\ \boldsymbol{h}^{(M)} = (\; h_{K'}^{(M)} \; \cdots \; h_K^{(M)} \; \cdots \; h_1^{(M)} \; h_0^{(M)} \; h_1^{(M)} \; \cdots \; h_K^{(M)} \; \cdots \; h_{K'}^{(M)} \;) & \text{step } M \end{cases}$$

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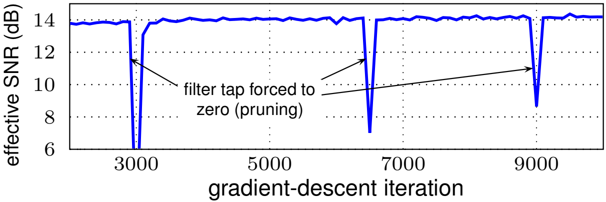
Iterative Filter Tap Pruning

starting length $2K'+1$

target length $2K+1$

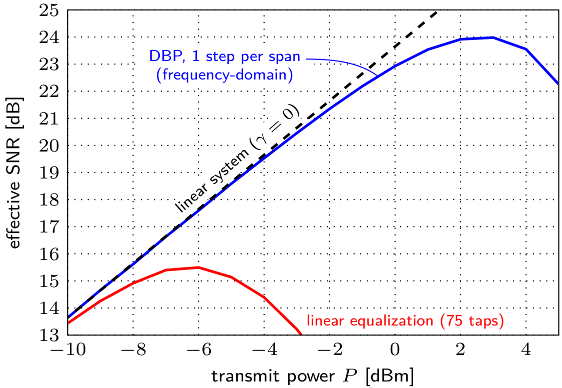
$$\theta = \begin{cases} \boldsymbol{h}^{(1)} = (\cancel{h^{(1)}_{K'}} \; \cdots \; h^{(1)}_{K} \; \cdots \; h^{(1)}_{1} \; h^{(1)}_{0} \; h^{(1)}_{1} \; \cdots \; h^{(1)}_{K} \; \cdots \; \cancel{h^{(1)}_{K'}}) & \text{step } 1 \\ \boldsymbol{h}^{(2)} = (\cancel{h^{(2)}_{K'}} \; \cdots \; h^{(2)}_{K}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

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



Outline

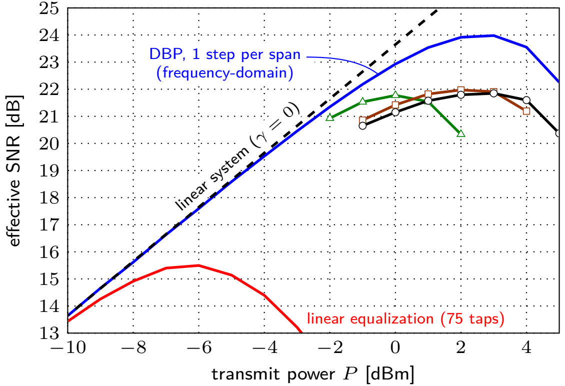
Optimization Results



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.

Optimization Results



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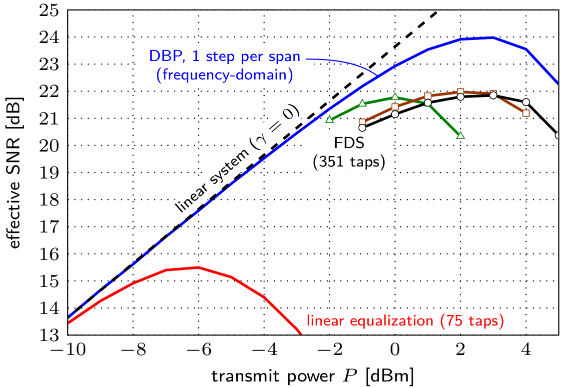
Optimization Results



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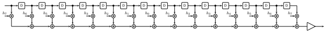
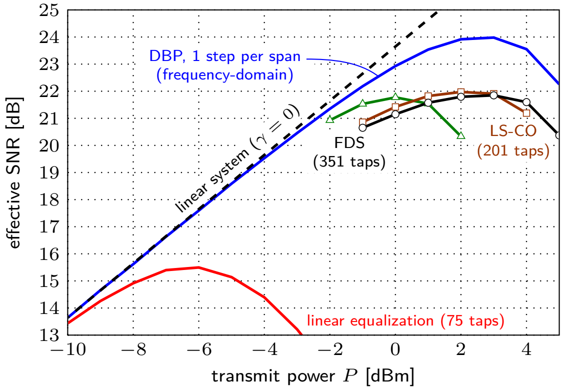
FDS  · · · frequency-domain sampling (15 taps per step)

Optimization Results



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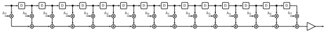
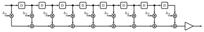
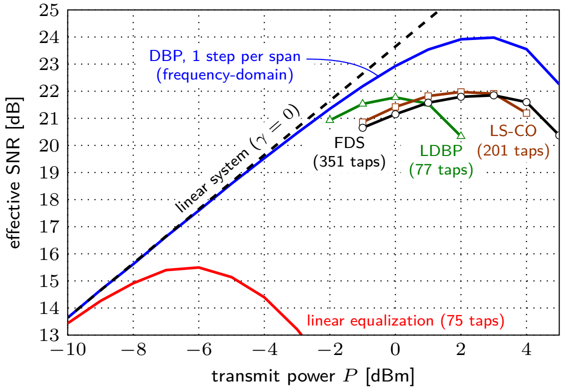
FDS  · · · frequency-domain sampling (15 taps per step)

LS-CO  · · · constrained least-squares [Sheikh et al., 2016] (9 taps per step)

Optimization Results



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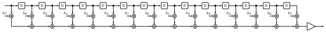
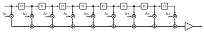
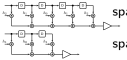
FDS  · · · frequency-domain sampling (15 taps per step)

LS-CO  · · · constrained least-squares [Sheikh et al., 2016] (9 taps per step)

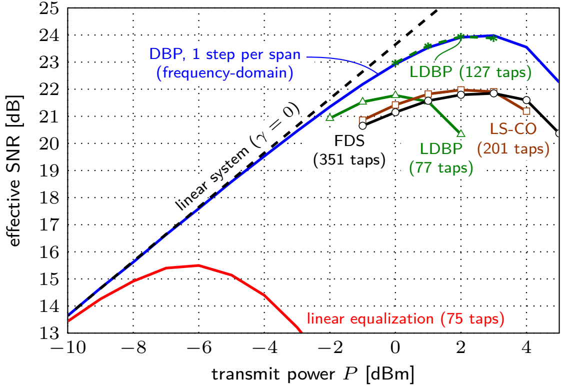
LDBP 

span 1, 3, . . .

span 2, 4, . . .

deep learning and pruning (alternate 5 and 3 taps and use different coefficients in all steps)

Optimization Results



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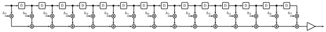
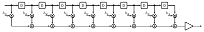
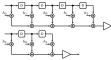
FDS  . . . frequency-domain sampling (15 taps per step)

LS-CO  . . . constrained least-squares [Sheikh et al., 2016] (9 taps per step)

LDBP 
span 1, 3, . . .
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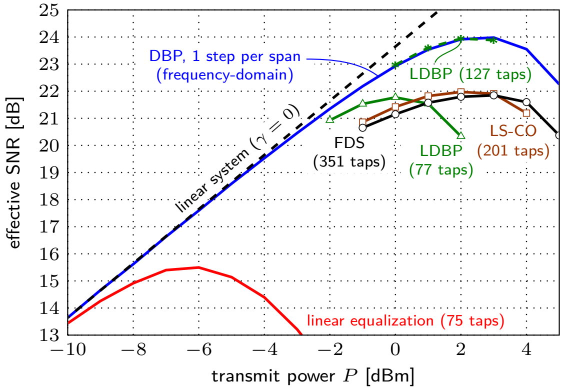

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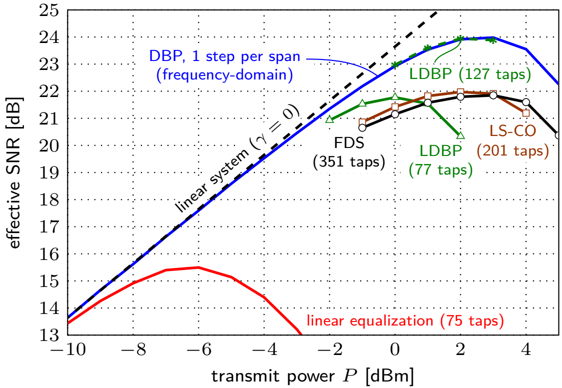

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- 28-nm CMOS synthesis results show $\approx$ 2-fold power and area reduction compared to baseline filters (slightly different system parameters)

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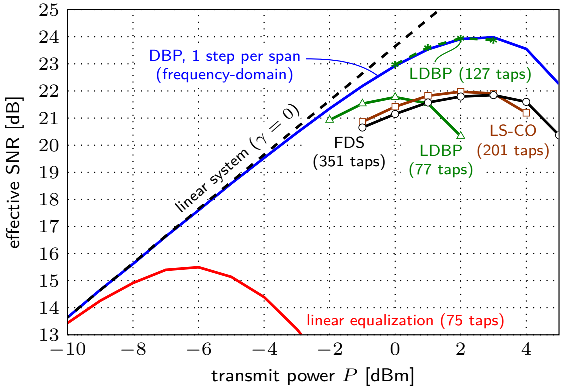

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- 28-nm CMOS synthesis results show $\approx$ 2-fold power and area reduction compared to baseline filters (slightly different system parameters)
- Power consumption comparable to linear equalization in [Pillai et al., 2014],[Crivelli et al., 2014]
- Nonlinearities consume $< 20\%$ of the total power

Conclusions

Conclusions

- We have addressed the problem of inverting the nonlinear Schrödinger equation for fiber-optic systems in real time
- Established numerical method (split-step Fourier method) leads to a computation graph reminiscient of a deep feed-forward neural network
- Deep learning in the resulting computation graph can be interpreted as a joint filter (i.e., linear propagator) optimization problem
- This approach requires significantly fewer parameters than previous methods $\implies$ less complexity and power consumption

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Thank you!

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