# ASIC Implementation of Digital Backpropagation with Deep-Learned Chromatic Dispersion Filters


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Joint work with: Christoffer Fougstedt[3], Lars Svensson[3], Henry D. Pfister[2], and Per Larsson-Edefors[3]

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# Outline

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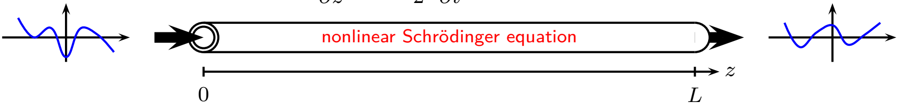
# Digital Backpropagation

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

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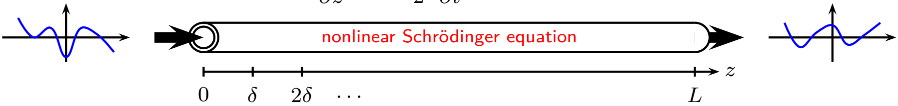
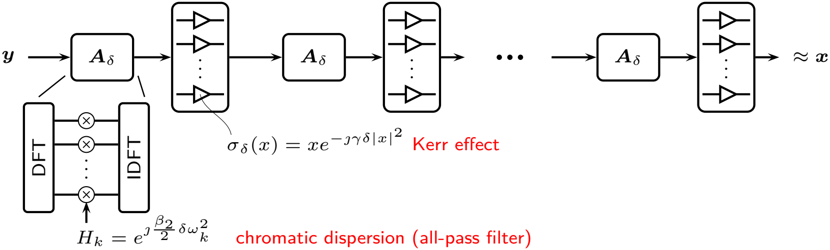



- Invert a partial differential equation in real time ([Paré et al., 1996], [Essiambre and Winzer, 2005], [Roberts et al., 2006], [Li et al., 2008], [Ip and Kahn, 2008])
- Split-step Fourier method with $M$ steps ($\delta = L/M$):



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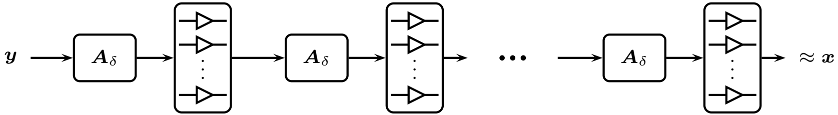
## Key ingredients

1. No FFT/IFFT: We use finite-impulse response (FIR) filters to compensate for CD-induced pulse broadening in each step.
2. Deep learning: The FIR filters are jointly optimized and quantized using machine-learning tools.
3. No step-reducing approaches: 64-step DBP (2 steps per span) would consume only marginally more power, not $2\times$ more.

# Outline

# Complexity-Reduced Digital Backpropagation



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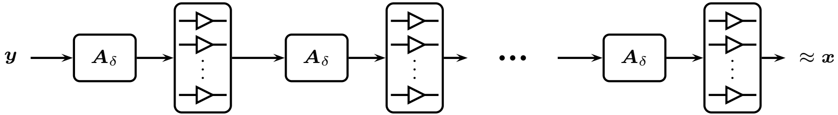


Extensive literature: [Du and Lowery, 2010], [Rafique et al., 2011], [Li et al., 2011], [Yan et al., 2011], [Napoli et al., 2014], [Secondini et al., 2016], . . .

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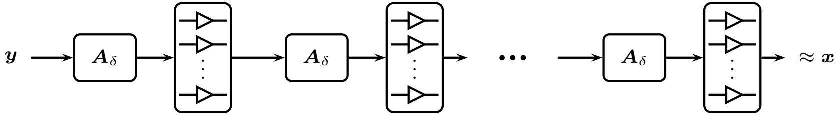


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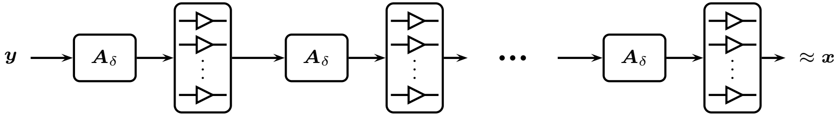


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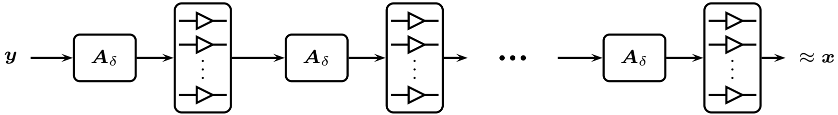


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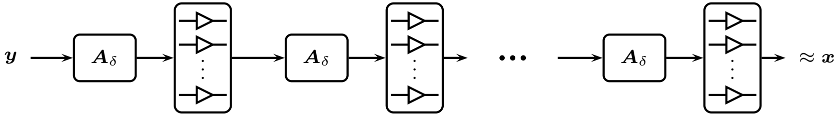


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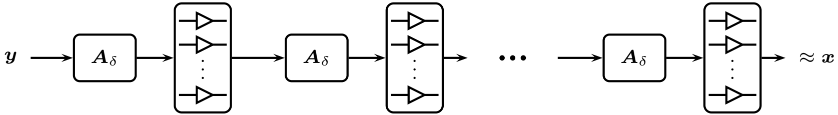
# Complexity-Reduced Digital Backpropagation

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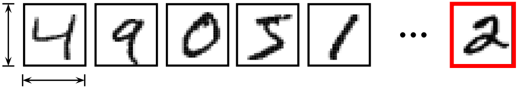
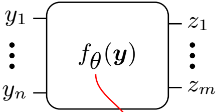
- Therefore, reduce $M$ as much as possible (step-reducing approaches)
- Intuitive, but . . .
- . . . this corresponds to flattening a deep (multi-layer) computation graph
- Machine learning: deep computation graphs work much better and are more parameter efficient than shallow ones

# Supervised Learning

handwritten digit recognition (MNIST: 70,000 images)



$28 \times 28$ pixels $\implies n = 784$




parameters
to be optimized/learned

$\boldsymbol{z}$

0.01
0.92
0.01
0.00
0.00
0.01
0.00
0.04
0.01
0.01

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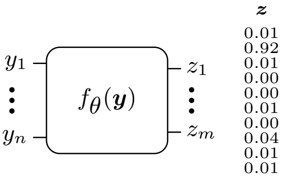
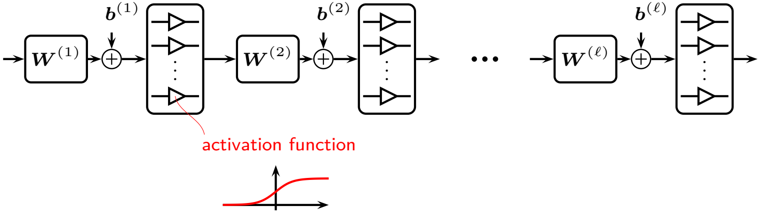



How to choose $f_\theta(\boldsymbol{y})$? Deep feed-forward neural networks



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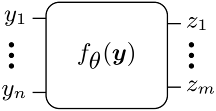


| $\boldsymbol{z}$ | $\boldsymbol{x}$ |
|---|---|
| 0.01 | 0 |
| 0.92 | 1 |
| 0.01 | 0 |
| 0.00 | 0 |
| 0.00 | 0 |
| 0.01 | 0 |
| 0.00 | 0 |
| 0.04 | 0 |
| 0.01 | 0 |
| 0.01 | 0 |

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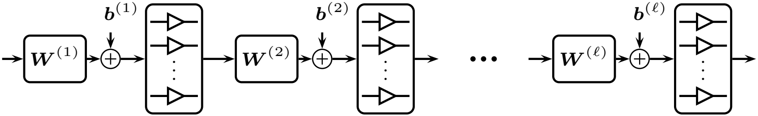


How to optimize $\theta = \{\boldsymbol{W}^{(1)}, \dots, \boldsymbol{W}^{(\ell)}, \boldsymbol{b}^{(1)}, \dots, \boldsymbol{b}^{(\ell)}\}$? Deep learning

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

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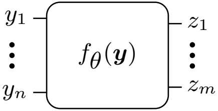


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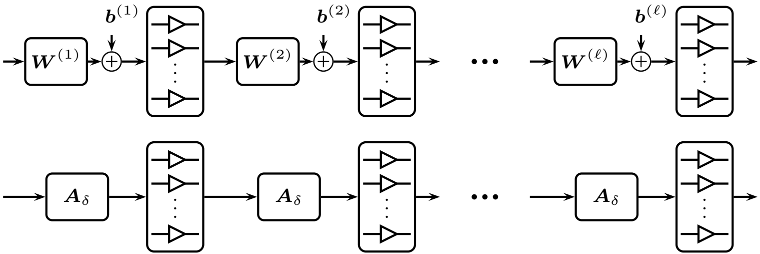

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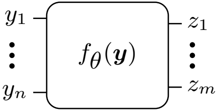


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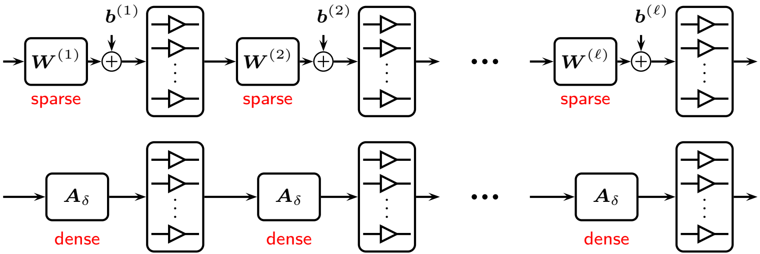
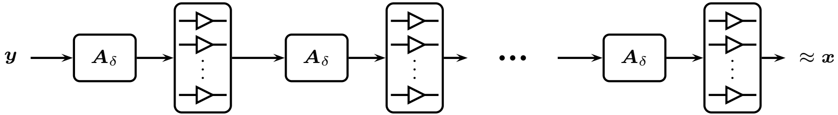


# Time-Domain Implementation and Truncation



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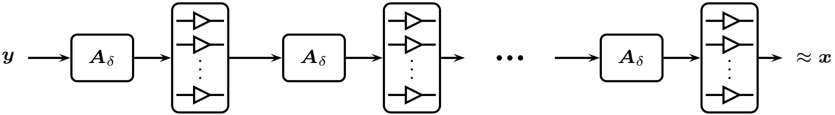


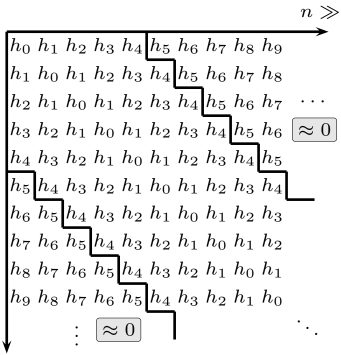

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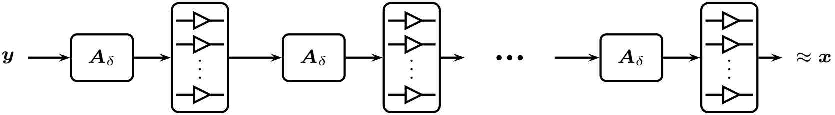
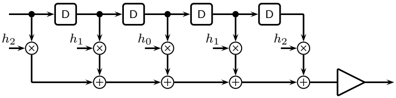
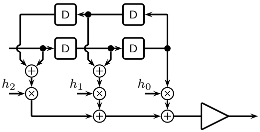



$n \gg 9$

$$\begin{array}{cccccccccc}
h_0 & h_1 & h_2 & h_3 & h_4 & 0 & 0 & 0 & 0 & 0 \\
h_1 & h_0 & h_1 & h_2 & h_3 & h_4 & 0 & 0 & 0 & 0 \\
h_2 & h_1 & h_0 & h_1 & h_2 & h_3 & h_4 & 0 & 0 & 0 & \cdots \\
h_3 & h_2 & h_1 & h_0 & h_1 & h_2 & h_3 & h_4 & 0 & 0 \\
h_4 & h_3 & h_2 & h_1 & h_0 & h_1 & h_2 & h_3 & h_4 & 0 \\
0 & h_4 & h_3 & h_2 & h_1 & h_0 & h_1 & h_2 & h_3 & h_4 \\
0 & 0 & h_4 & h_3 & h_2 & h_1 & h_0 & h_1 & h_2 & h_3 \\
0 & 0 & 0 & h_4 & h_3 & h_2 & h_1 & h_0 & h_1 & h_2 \\
0 & 0 & 0 & 0 & h_4 & h_3 & h_2 & h_1 & h_0 & h_1 \\
0 & 0 & 0 & 0 & 0 & h_4 & h_3 & h_2 & h_1 & h_0 \\
 & & \vdots & & & & & & & \ddots
\end{array}$$

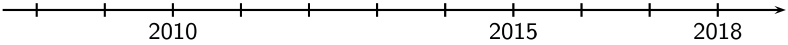



finite impulse response (FIR) filter




symmetric filter coefficients
$\Longrightarrow$ folded implementation

# Time-Domain Digital Backpropagation: Literature



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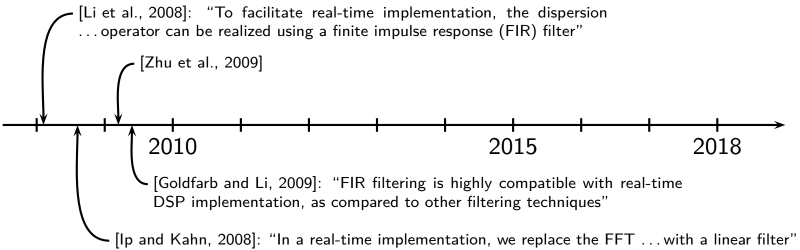

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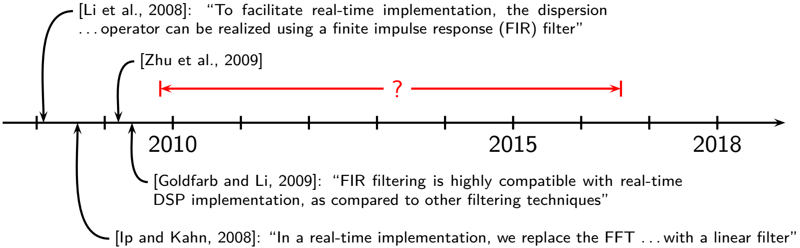

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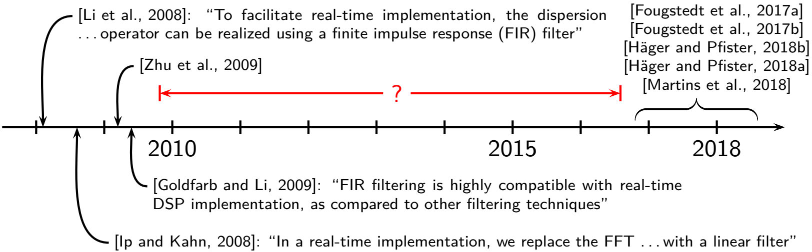

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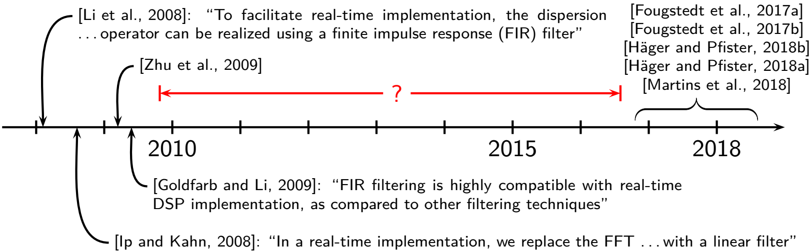


Nontrivial to achieve a good performance–complexity tradeoff!

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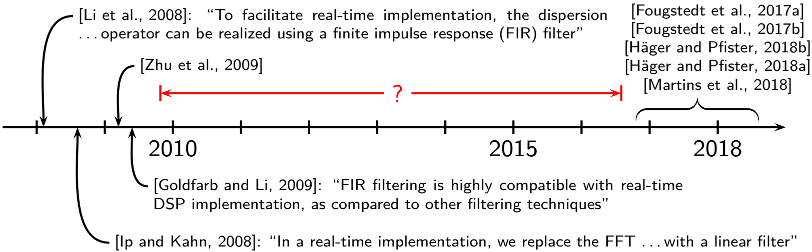


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Example for $R_{\text{symb}} = 10.7$ Gbaud, $L = 2000\,\text{km}$ [Ip and Kahn, 2008]

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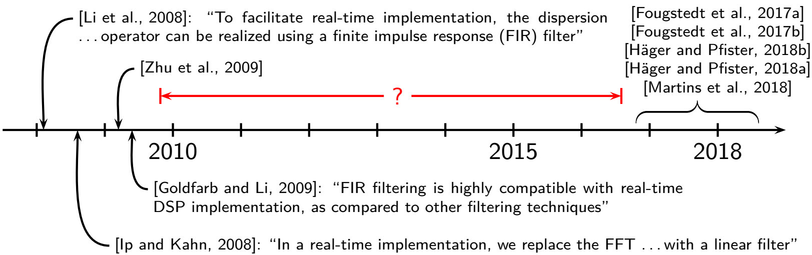
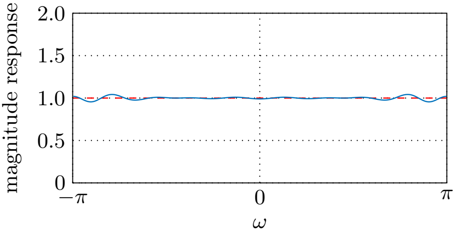



Nontrivial to achieve a good performance–complexity tradeoff!

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

- $\gg 1000$ taps required for good performance (70 taps per step)

# Problem: Truncation Errors




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

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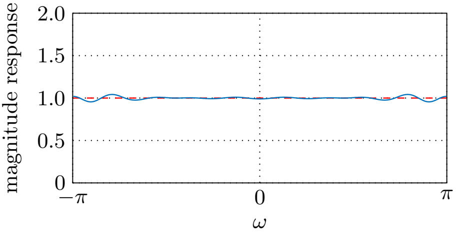


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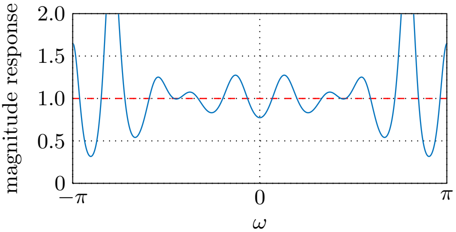


$$\boldsymbol{h}^{(1)} * \boldsymbol{h}^{(2)} * \cdots * \boldsymbol{h}^{(M)}$$

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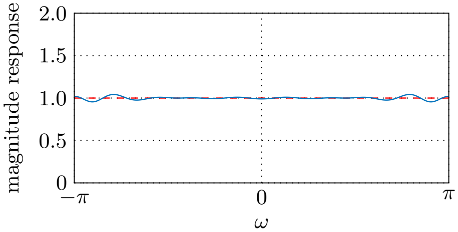


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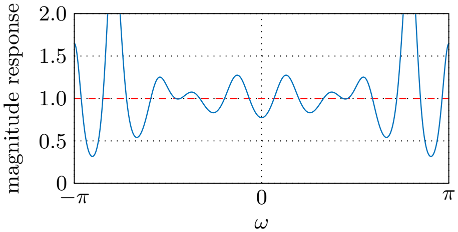


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Our approach:
Optimize all $M$ filters jointly

# Outline

# Joint Chromatic Dispersion Filter Optimization via Deep Learning

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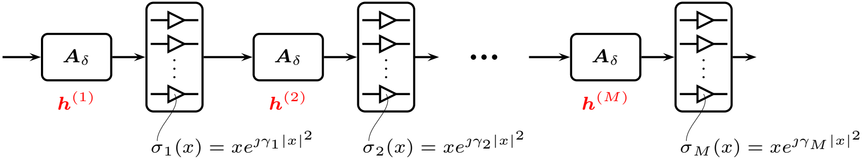
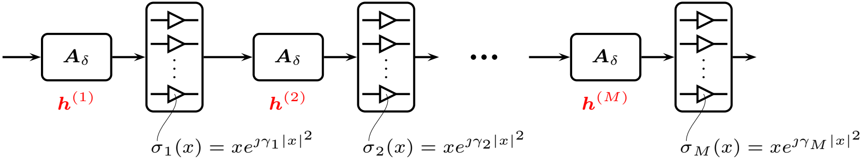
TensorFlow implementation of the computation graph $f_\theta(\boldsymbol{y})$:



# Joint Chromatic Dispersion Filter Optimization via Deep Learning

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




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

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

mean squared error

Adam optimizer, fixed learning rate

# Iterative Filter Tap Pruning

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

# Iterative Filter Tap Pruning

$$\xleftarrow{\qquad\qquad} \text{starting length } 2K'+1 \xrightarrow{\qquad\qquad}$$

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

# Iterative Filter Tap Pruning

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

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

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

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starting length $2K' + 1$

target length $2K + 1$

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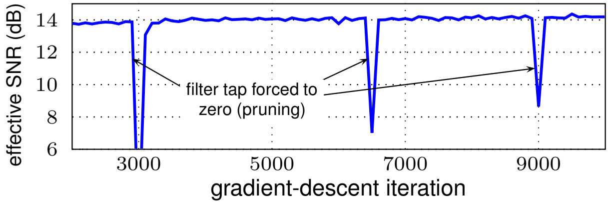
- Initially: constrained least-squares coefficients (LS-CO) [Sheikh et al., 2016]
- Typical learning curve:



# Outline

# Filter Coefficient Quantization

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DSP implementation requires quantized FIR filter coefficients.

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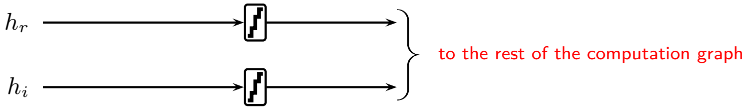
- Apply TensorFlow's "fake quantization" to each filter coefficient variable:



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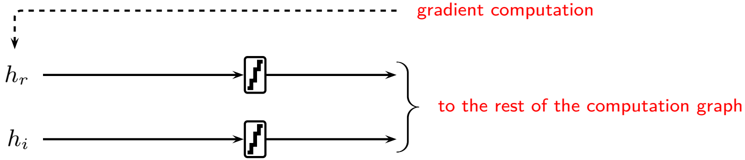


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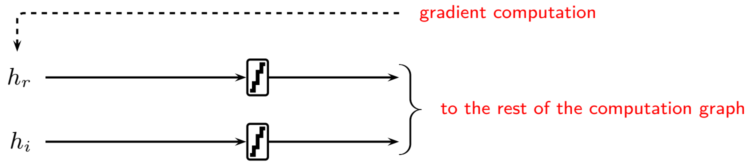


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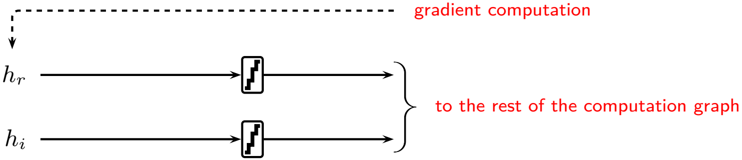


- Fake quantization: gradient computation and parameter updates are still performed in floating point
- Activate after the (floating-point) optimization has converged and continue training for few more iterations
- Joint optimization of quantized impulse responses $\Longrightarrow$ partial cancellation of quantization-induced frequency-response errors

# Hardware Model and Circuit Implementation

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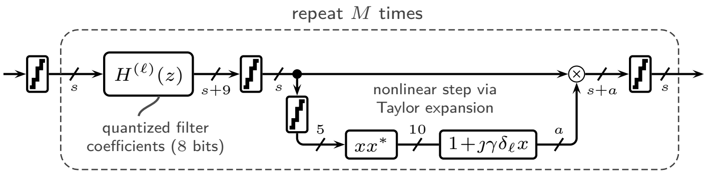

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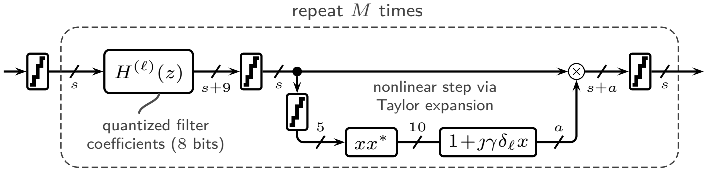


- Signal requantization to $s$ bits after each FIR filter and nonlinear step

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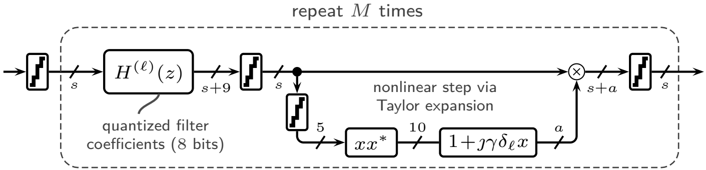


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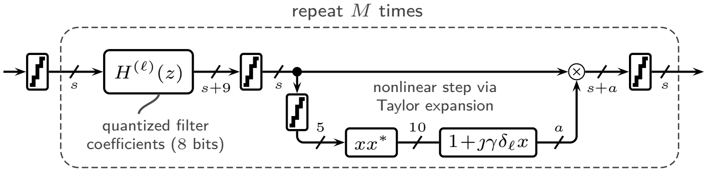


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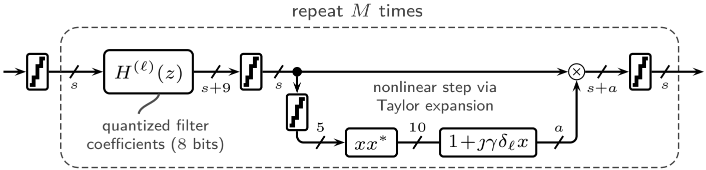


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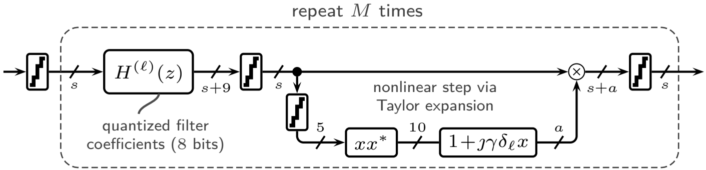


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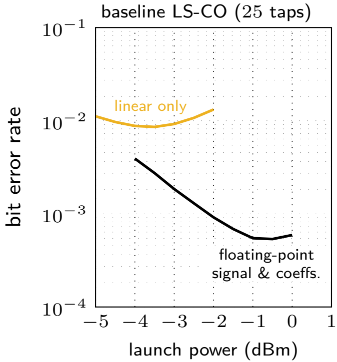
- Power estimation based on simulation of internal circuit switching statistics

# Outline

# Performance Results




System parameters:

- $32 \times 100$ km fiber
- 16-QAM single pol.
- RRC pulses (0.1 roll-off)
- 20 Gbaud
- 2 samples/symbol
- single channel

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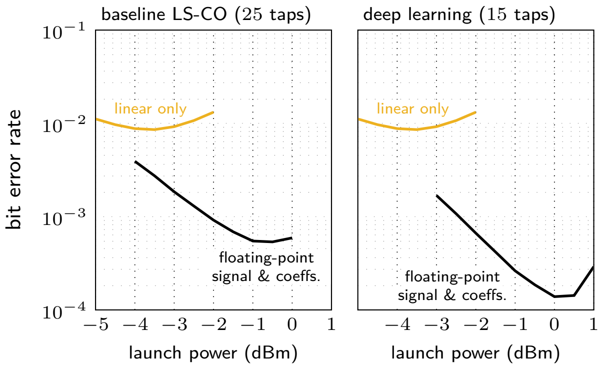


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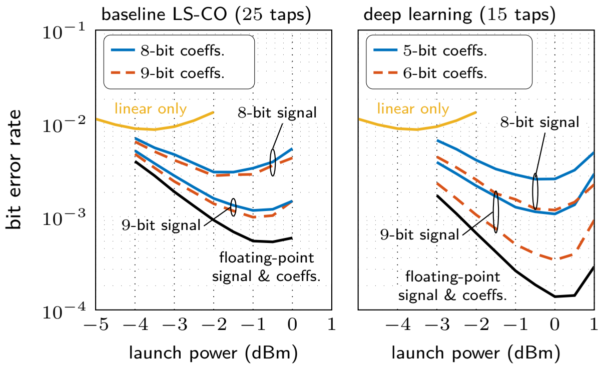


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- Deep learning gives 15-tap filters with better performance
- 8–9 signal bits required in both cases, depending on performance
- Deep learning leads to significantly fewer bits for the filter taps

# Power ($P$) and Chip Area ($A$) Results Per Step

| coeffs. & word length | filter taps | 8-bit signal $P$ (W) | 8-bit signal $A$ (mm$^2$) | 9-bit signal $P$ (W) | 9-bit signal $A$ (mm$^2$) |
|---|---|---|---|---|---|
| LS-CO 8-bit | 25 | 0.28 | 1.21 | 0.31 | 1.30 |
| LS-CO 9-bit | 25 | 0.34 | 1.38 | 0.37 | 1.54 |
| learned 5-bit | 15 | 0.15 | 0.61 | 0.18 | 0.69 |
| learned 6-bit | 15 | 0.17 | 0.69 | 0.20 | 0.81 |

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- $> 40\%$ power & area reduction for learned filters due to fewer taps and bits
- Estimate for 9-bit signal, 6-bit learned coefficients:
  - $33 \times 0.2$ W $= 6.6$ W or $\approx 83$ pJ/bit
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- Comparable to published results for static chromatic dispersion (CD) compensation
  - [Pillai et al., 2014]: $\approx 94$ pJ/bit for $2400$ km in $28$ nm
  - [Crivelli et al., 2014]: $\approx 221$ pJ/bit for $3500$ km in $40$ nm
  - [Crivelli et al., 2014]: entire RX chip is $75$ mm$^2$ with CD compensation occupying a relatively large fraction

# Conclusions

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Thank you!

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