Model-Based Machine Learning for Joint Digital Backpropagation and PMD Compensation

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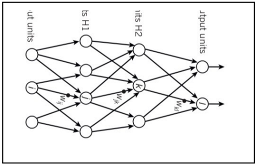
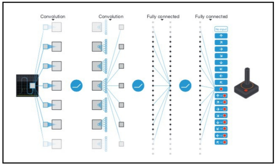
Deep Learning [LeCun et al., 2015]



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



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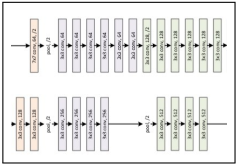

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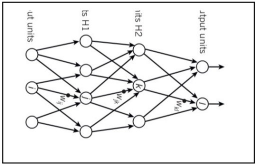
Multi-layer neural networks: impressive performance, countless applications

Deep Learning [LeCun et al., 2015]



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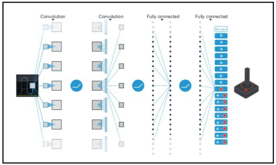

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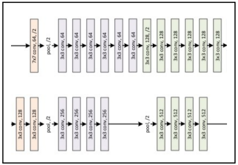

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Multi-layer neural networks: impressive performance, countless applications

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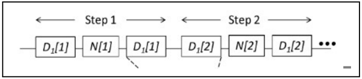
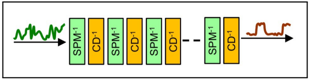


[Du and Lowery, 2010]



[Nakashima et al., 2017]

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

Agenda

In this talk, we . . .

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In this talk, we . . .

1. show that multi-layer neural networks and the split-step method have the same functional form: both alternate linear and pointwise nonlinear steps
2. propose a model-based machine-learning approach based on parameterizing the split-step method (no black-box neural networks)
3. revisit hardware-efficient digital backpropagation combined with distributed compensation of polarization mode dispersion

Outline

1. Machine Learning and Neural Networks for Communications

2. Model-Based Machine Learning for Fiber-Optic Communications

3. Learned Digital Backpropagation

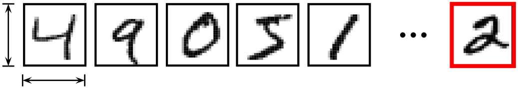
4. Polarization-Dependent Effects

5. Conclusions

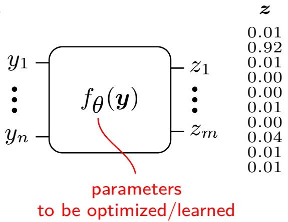
Outline

Supervised Learning

handwritten digit recognition (MNIST: 70,000 images)



28×28 pixels $\implies n = 784$



Supervised Learning

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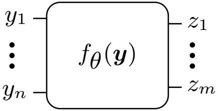
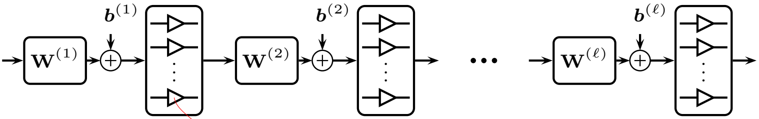


$\boldsymbol{z}$

0.01
0.92
0.01
0.00
0.00
0.01
0.00
0.04
0.01
0.01

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



activation function

Supervised Learning

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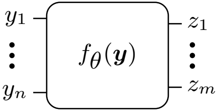
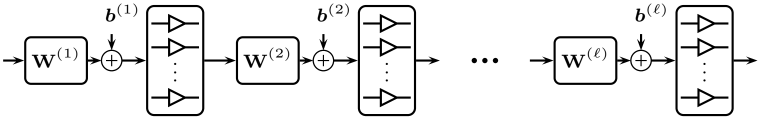


$\boldsymbol{z}$	$\boldsymbol{x}$
0.01	0
0.92	1
0.01	0
0.00	0
0.00	0
0.01	0
0.00	0
0.04	0
0.01	0
0.01	0

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



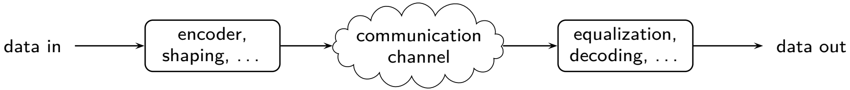
How to optimize $\theta = \{\boldsymbol{W}^{(1)}, \dots, \boldsymbol{W}^{(\ell)}, \boldsymbol{b}^{(1)}, \dots, \boldsymbol{b}^{(\ell)}\}$? Deep learning

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

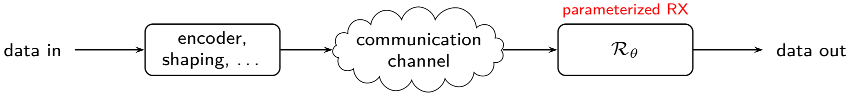
mean squared error
cross-entropy, ...

stochastic gradient descent,
RMSProp, Adam, ...

Machine Learning for Physical-Layer Communications



Machine Learning for Physical-Layer Communications



[Shen and Lau, 2011], Fiber nonlinearity compensation using extreme learning machine for DSP-based . . . , (*OECC*)
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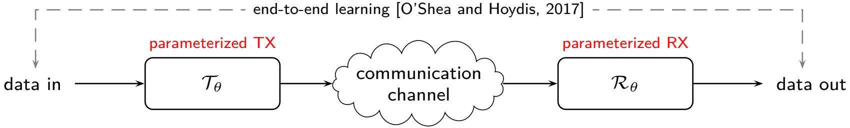

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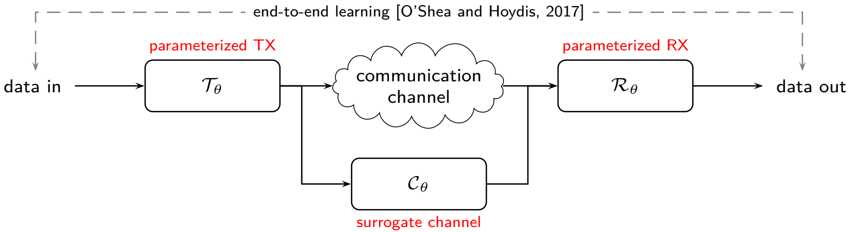

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[O'Shea et al., 2018], Approximating the void: Learning stochastic channel models from observation with variational GANs, (*arXiv*)
[Ye et al., 2018], Channel agnostic end-to-end learning based communication systems with conditional GAN, (*arXiv*)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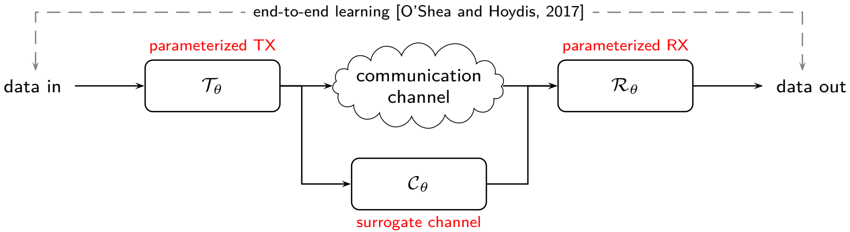
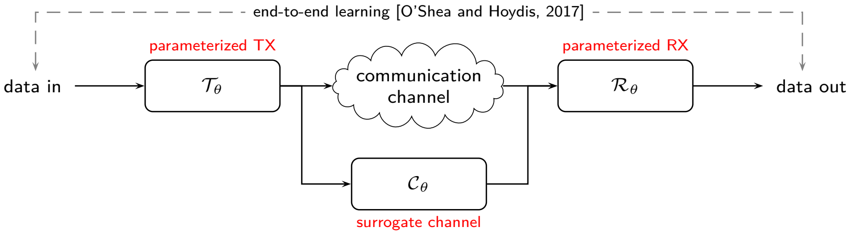


Using neural networks for $\mathcal{T}_\theta, \mathcal{R}_\theta, \mathcal{C}_\theta$

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

Machine Learning for Physical-Layer Communications



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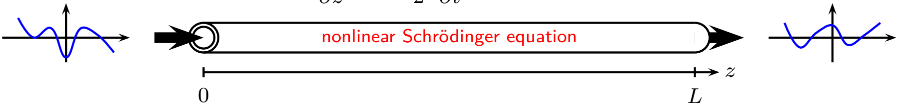
- ...

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

Outline

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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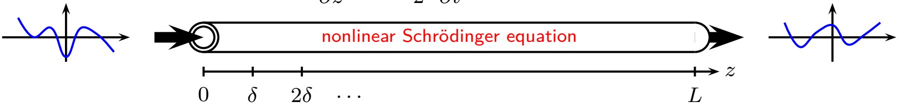
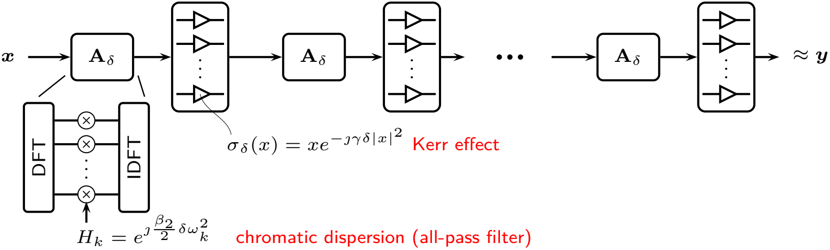
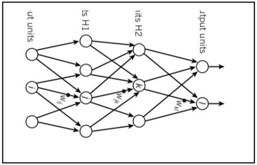


- Deterministic channel model: partial differential equation
- Split-step method with M steps ($\delta = L/M$):



Deep Learning [LeCun et al., 2015]



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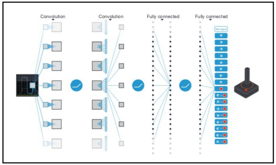

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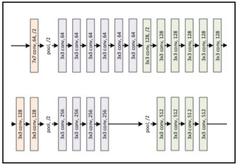

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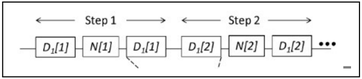

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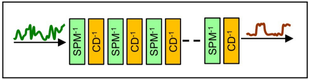
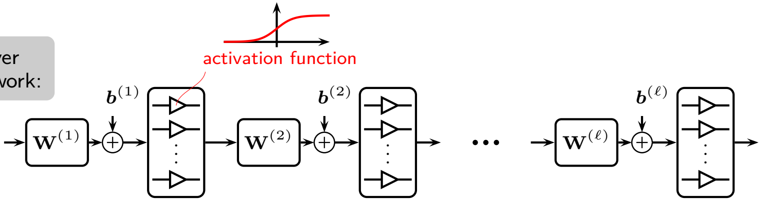


[Nakashima et al., 2017]

Parameterizing the Split-Step Method

multi-layer neural network:



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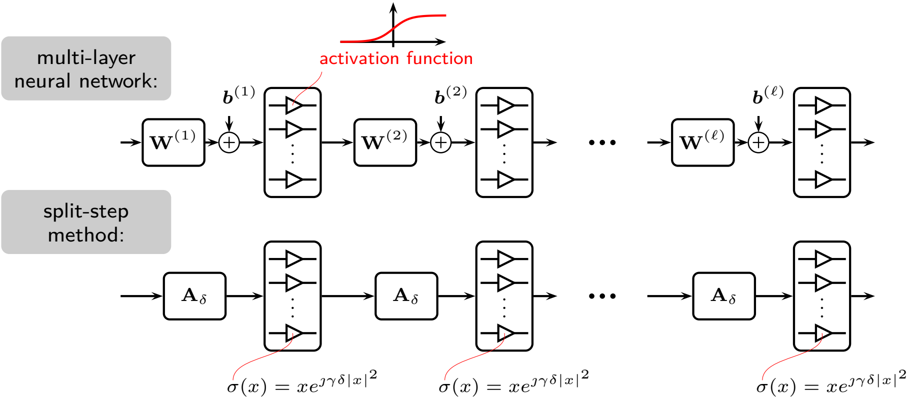

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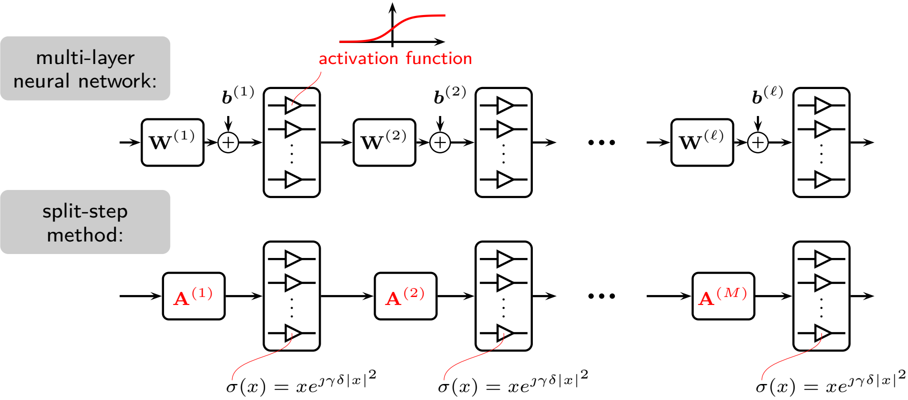
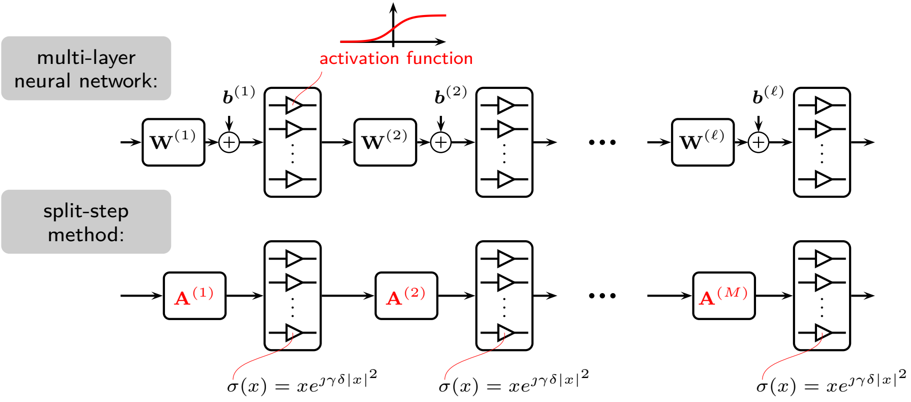


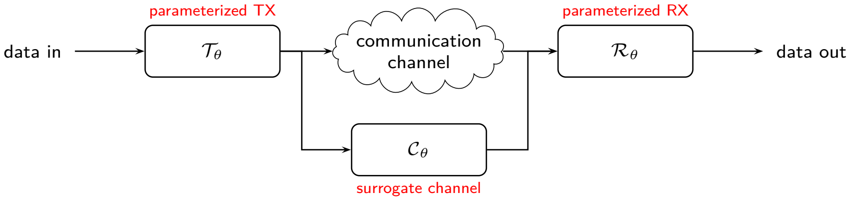
[Häger & Pfister, 2018], Nonlinear Interference Mitigation via Deep Neural Networks, *(OFC)*
[Häger & Pfister, 2018], Deep Learning of the Nonlinear Schrödinger Equation in Fiber-Optic Communications, *(ISIT)*

Parameterizing the Split-Step Method



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

Possible Applications



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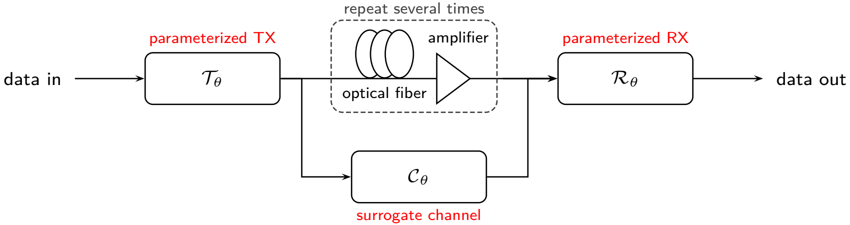

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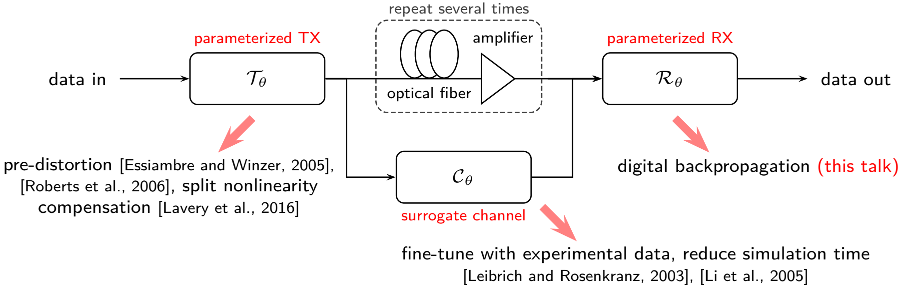

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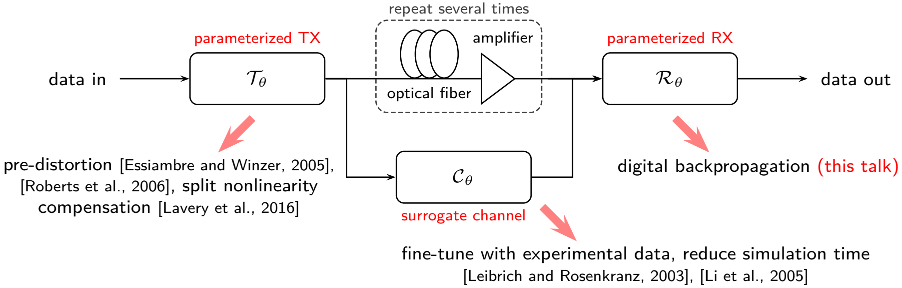
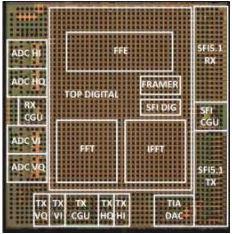


Model-based learning approaches

- 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])

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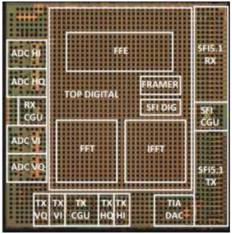

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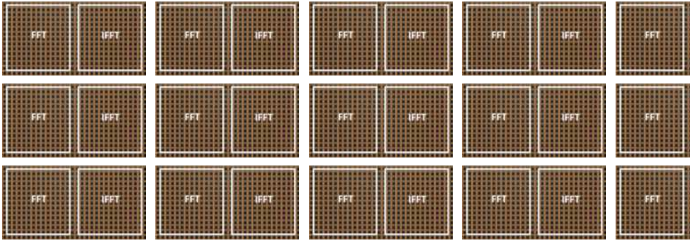

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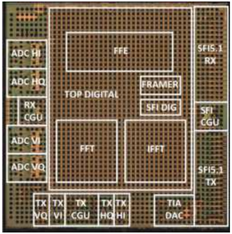

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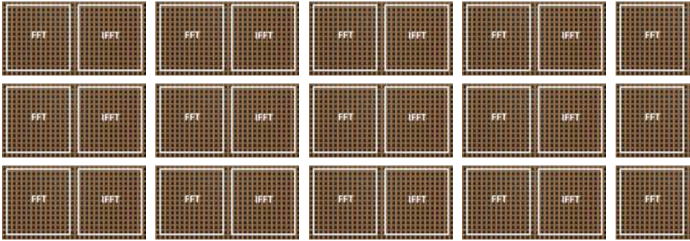

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Our approach

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

Learned Digital Backpropagation

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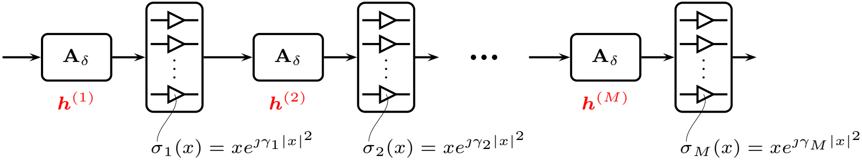
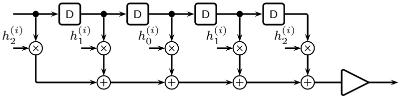
TensorFlow implementation of the computation graph $f_\theta(\boldsymbol{y})$:





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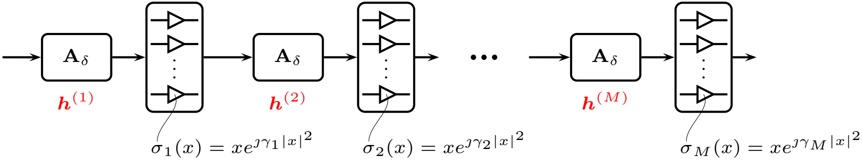

Deep learning of parameters $\theta = \{\boldsymbol{h}^{(1)}, \dots, \boldsymbol{h}^{(M)}\}$:

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

mean squared error — Adam optimizer, fixed learning rate

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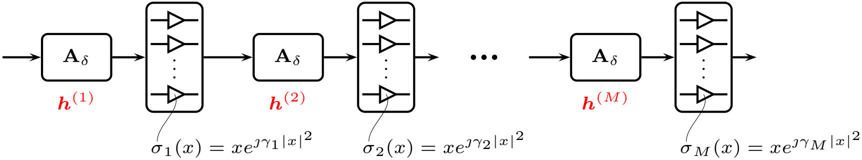

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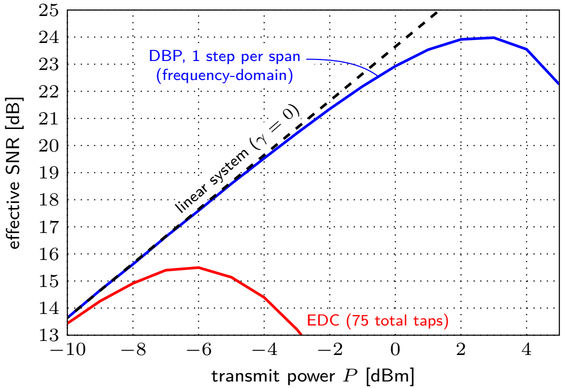
Iteratively prune (set to 0) outermost filter taps during gradient descent

Revisiting Ip and Kahn (2008)



Parameters similar to [Ip and Kahn, 2008]:

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

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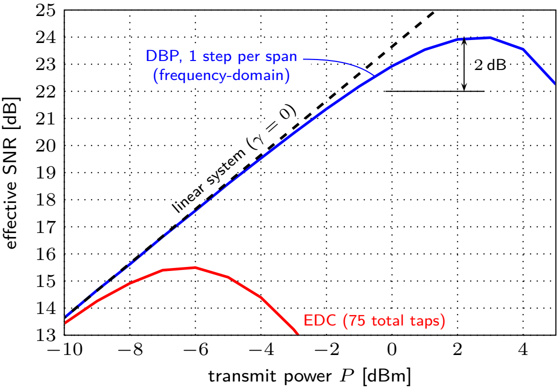

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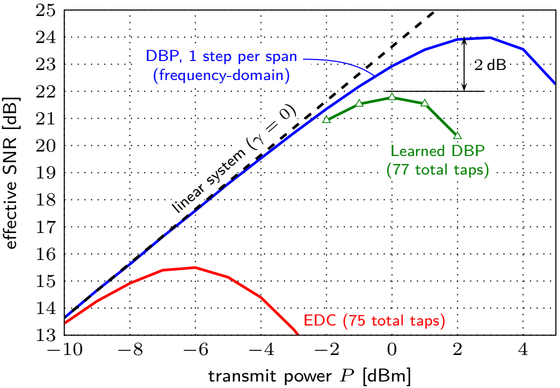
- $\gg 1000$ total taps (70 taps/step) $\implies$ $> 100\times$ complexity of EDC

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
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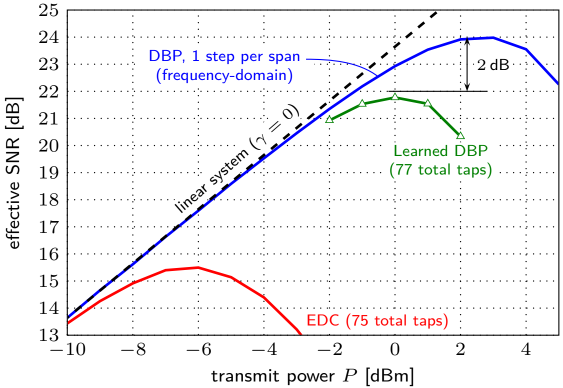

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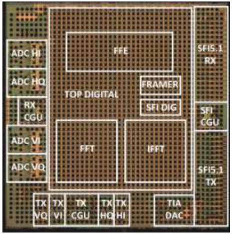
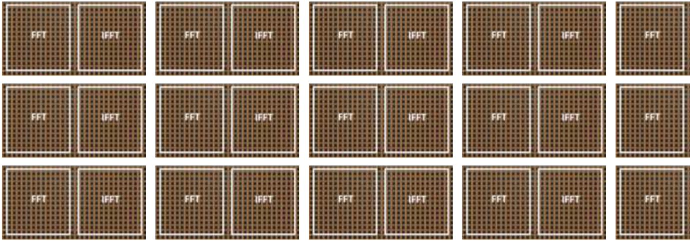
- Can outperform "ideal DBP" in the nonlinear regime [Häger and Pfister, 2018b]

Real-Time ASIC Implementation



[Crivelli et al., 2014]



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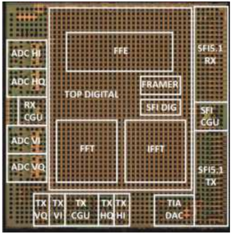

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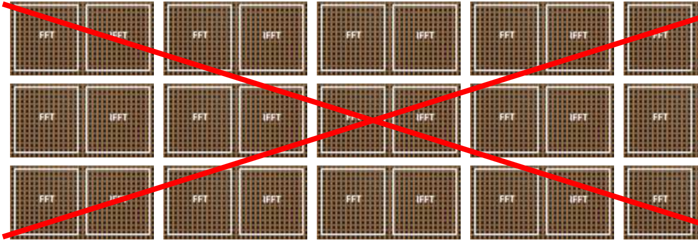

[Fougstedt et al., 2017], Time-domain digital back propagation: Algorithm and finite-precision implementation aspects, (*OFC*)
[Fougstedt et al., 2018], ASIC implementation of time-domain digital back propagation for coherent receivers, *(PTL)*
[Sherborne et al., 2018], On the impact of fixed point hardware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

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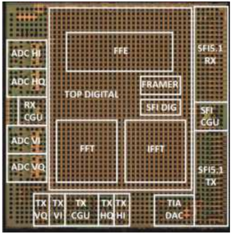

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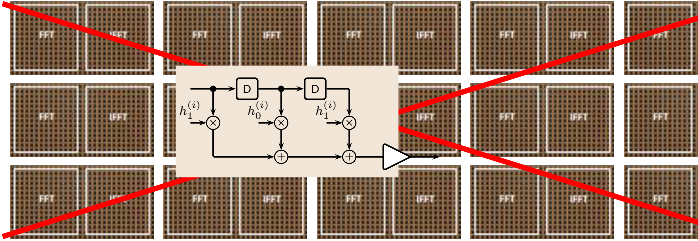

- Our linear steps are very short symmetric FIR filters (as few as 3 taps)

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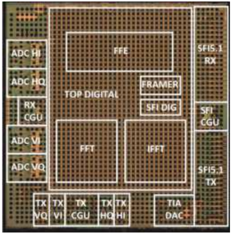

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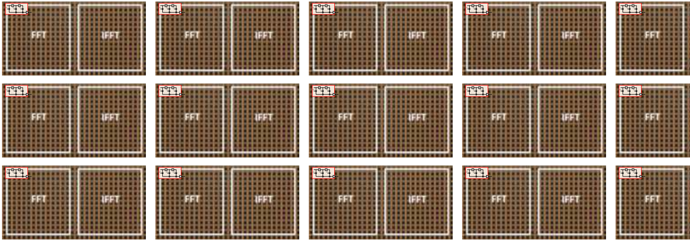

- Our linear steps are very short symmetric FIR filters (as few as 3 taps)
- 28-nm ASIC at 416.7 MHz clock speed (40 GHz signal)
  - Only 5-6 bit filter coefficients via learned quantization
  - Hardware-friendly nonlinear steps (Taylor expansion)
  - All FIR filters are fully reconfigurable

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

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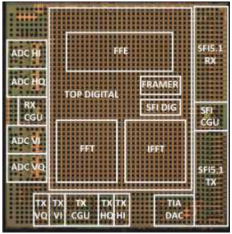

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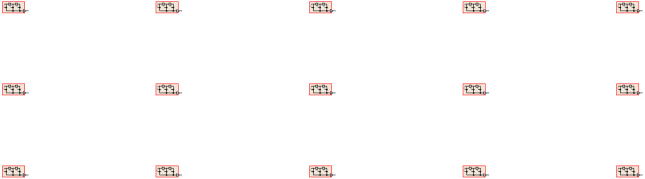

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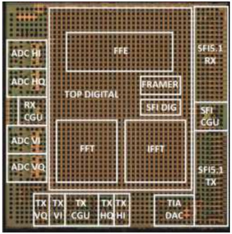

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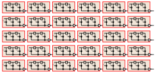

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- $< 2\times$ power compared to EDC [Crivelli et al., 2014, Pillai et al., 2014]

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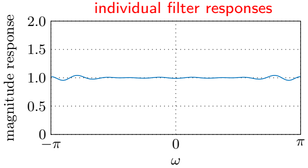
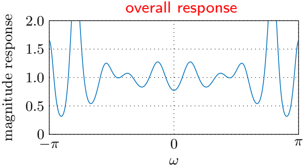
Why Does The Learning Approach Work?

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

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





From [Ip and Kahn, 2009]:

- "We also note that [...] 70 taps, is much larger than expected"
- "This is due to amplitude ringing in the frequency domain"
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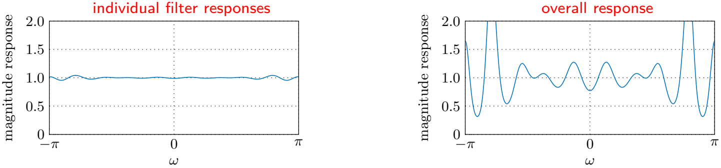

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The learning approach uncovered that there is no such requirement!

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

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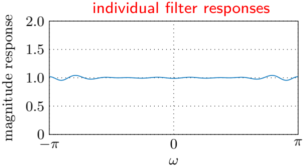
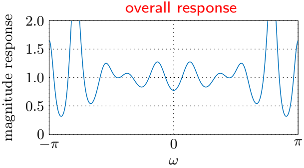
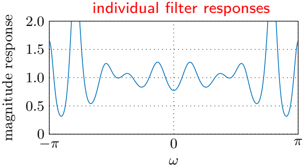
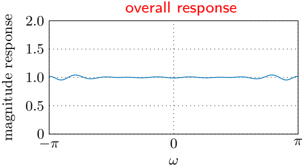




Sacrifice individual filter accuracy, but different response per step.

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

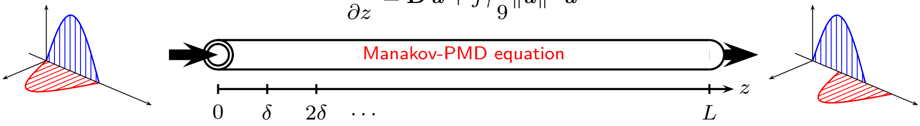




Outline

Evolution of Polarization-Multiplexed Signals

$$\frac{\partial \boldsymbol{u}}{\partial z} = \hat{\mathbf{D}}\,\boldsymbol{u} + \jmath\gamma\frac{8}{9}\|\boldsymbol{u}\|^2\,\boldsymbol{u}$$



- Jones vector $\boldsymbol{u} \triangleq (u_1(t,z), u_2(t,z))^\top$ with complex baseband signals
- linear operator $\hat{\mathbf{D}}$: attentuation, chromatic & polarization mode dispersion

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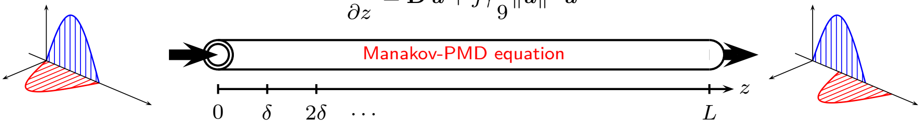
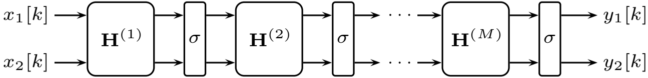
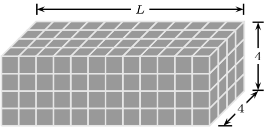


- Jones vector $\boldsymbol{u} \triangleq (u_1(t,z), u_2(t,z))^\top$ with complex baseband signals
- linear operator $\hat{\mathbf{D}}$: attentuation, chromatic & polarization mode dispersion
- Split-step method: alternate linear and nonlinear steps $\sigma(\boldsymbol{x}) = \boldsymbol{x}e^{\jmath\gamma\frac{8}{9}\delta\|\boldsymbol{x}\|^2}$

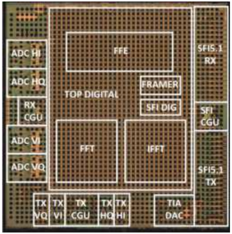


$e^{\delta\hat{\mathbf{D}}} \approx$



2×2 complex or
4×4 real MIMO filters $\Longrightarrow$ complexity!

Real-Time Compensation of Polarization Impairments



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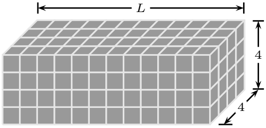

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- $\implies$ adaptive filtering (via stochastic gradient descent) required

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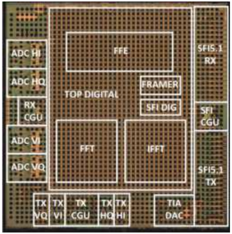

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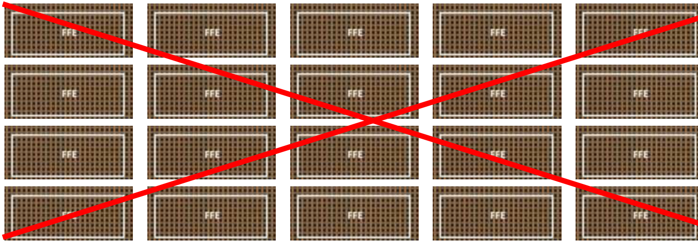

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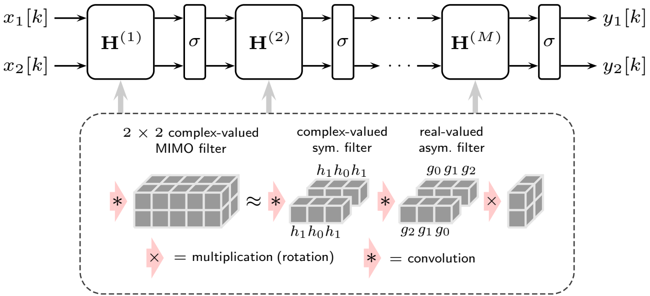
Using (and updating) full MIMO filters in each step is not feasible.

Our approach: Factorize each MIMO Filter



- 5-tap real-valued filters to approximate first-order PMD (DGD)
- Memoryless rotations $\begin{pmatrix} a & -b^* \\ b & a^* \end{pmatrix}$, where $a, b \in \mathbb{C}$ (4 real parameters)

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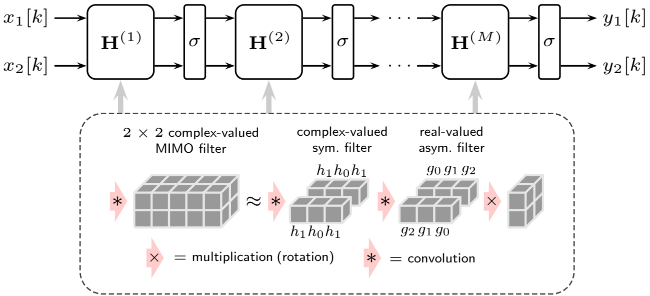
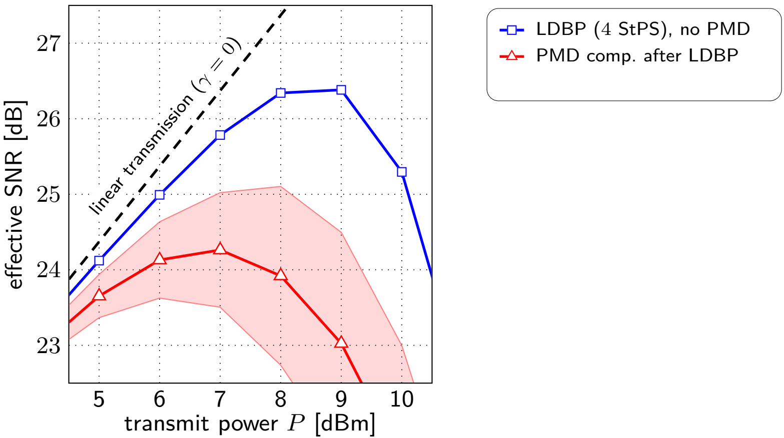


- 5-tap real-valued filters to approximate first-order PMD (DGD)
- Memoryless rotations $\begin{pmatrix} a & -b^* \\ b & a^* \end{pmatrix}$, where $a, b \in \mathbb{C}$ (4 real parameters)
- Assumes no knowledge about PMD realizations or accumulated PMD
- FIR-filter based! Avoids frequency-domain (FFT-based) filtering

[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)*

Results (32 Gbaud, 10×100 km, 0.2 ps/$\sqrt{\text{km}}$ PMD)



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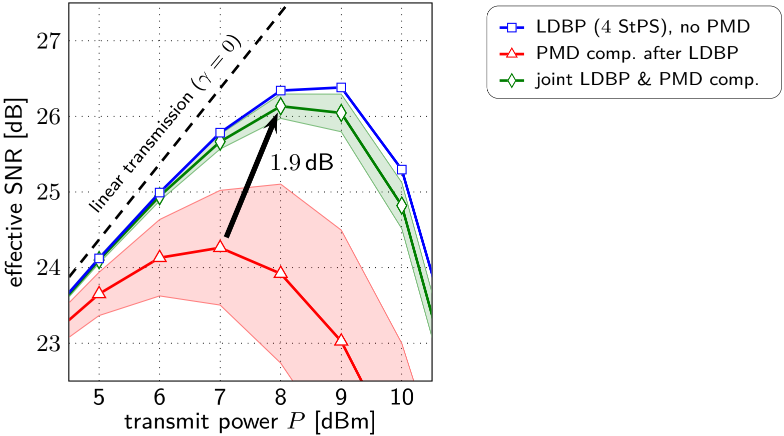

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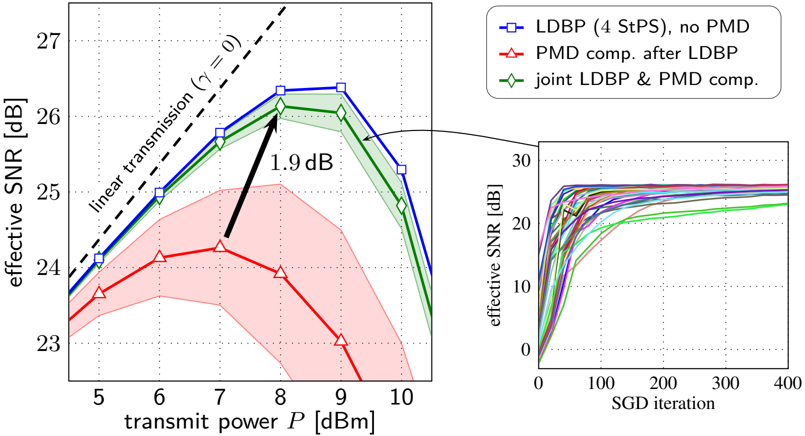


- Similar parameters & simulation setup compared to [Czegledi et al., 2016], results averaged over 40 PMD realizations
- Reliable convergence "from scratch" + only 9 real parameters per step

Related and Recent Works

Learned digital backpropagation

- [Häger & Pfister, 2018], Nonlinear Interference Mitigation via Deep Neural Networks, *(OFC)*
- [Häger & Pfister, 2018], Deep Learning of the Nonlinear Schrödinger Equation in Fiber-Optic Communications, *(ISIT)*
- [Lian, Häger, Pfister, 2018], What can machine learning teach us about communications? (*ITW*)
- [Häger et al., 2019], Revisiting multi-step nonlinearity compensation with machine learning (*ECOC*)

Wideband & WDM signals (alternating filter banks and nonlinearities)

- [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)*

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

- [Sillekens et al., 2020], Experimental demonstration of learned time-domain digital back-propagation, *(arXiv)*
- [Bitachon et al., 2020], Deep learning based digital back propagation with polarization state rotation & phase noise invariance, *(OFC)*

The Bigger Picture

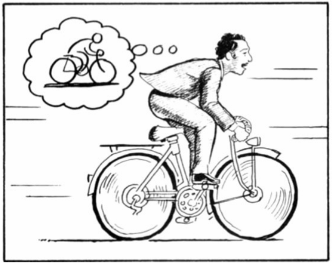
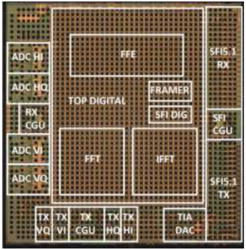


Figure 1. A World Model, from Scott McCloud's *Understanding Comics*. (McCloud, 1993; E, 2012)



[Crivelli et al., 2014]

- Optical receivers build models of their "environment"

Ha and Schmidhuber, 2018, "World Models", arXiv:1803.10122 [cs.LG]

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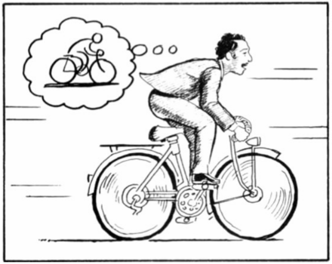

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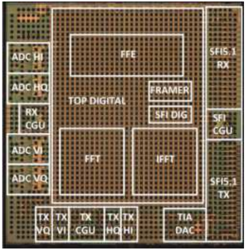

[Crivelli et al., 2014]

- Optical receivers build models of their "environment"
- Currently these models are linear and/or rigid (non-adaptive)
- Interpretable physics-based “multi-layer” models for machine learning can be obtained by exploiting our existing domain knowledge

Ha and Schmidhuber, 2018, "World Models", arXiv:1803.10122 [cs.LG]

Conclusions

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neural-network-based ML
universal function approximators
good designs require experience and fine-tuning
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neural-network-based ML	model-based ML
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Thank you!

FIBER-OPTIC COMMUNICATIONS RESEARCH CENTER

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