Model-Based Machine Learning for Fiber-Optic Communication Systems

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Deep Learning [LeCun et al., 2015]  
Multi-layer neural networks: impressive performance, countless applications
Multi-layer neural networks: impressive performance, countless applications

Multi-step methods for solving the propagation equation in fiber-optics
In this talk, we ...
In this talk, we ...

1. show that multi-layer neural networks and the so-called split-step method in fiber-optics have the same functional form: both alternate linear and pointwise nonlinear steps
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1. show that multi-layer neural networks and the so-called split-step method in fiber-optics 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)
In this talk, we . . .

1. show that multi-layer neural networks and the so-called split-step method in fiber-optics 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. apply the proposed approach by revisiting hardware-efficient nonlinear equalization with deep-learning tools
Outline

1. Machine Learning and Neural Networks for Communications

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

3. Nonlinear Equalization: Learned Digital Backpropagation

4. Outlook and Future Work

5. Conclusions
Outline

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Supervised Learning

handwritten digit recognition (MNIST: 70,000 images)

28 × 28 pixels $\Rightarrow n = 784$

parameters to be optimized/learned
Supervised Learning

handwritten digit recognition (MNIST: 70,000 images)

How to choose $f_\theta(y)$? Deep feed-forward neural networks
Supervised Learning

handwritten digit recognition (MNIST: 70,000 images)

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

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

\[
\min_{\theta} \sum_{i=1}^{N} \text{Loss}(f_{\theta}(y^{(i)}), x^{(i)}) \triangleq g(\theta) \quad \text{using} \quad \theta_{k+1} = \theta_k - \lambda \nabla_{\theta} g(\theta_k) \quad (1)
\]
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)
[Zibar et al., 2016]. Machine learning techniques in optical communication, (J. Lightw. Technol.)
[Kamalov et al., 2018]. Evolution from 8qam live traffic to ps 64-qam with neural-network based nonlinearity compensation . . ., (OFC)

...
Machine Learning for Physical-Layer Communications

![Diagram of end-to-end learning](image)

- [Shen and Lau, 2011], Fiber nonlinearity compensation using extreme learning machine for DSP-based . . . , (OECC)
- [Giacoumidis et al., 2015], Fiber nonlinearity-induced penalty reduction in CO-OFDM by ANN-based . . . , (Opt. Lett.)
- [Zibar et al., 2016], Machine learning techniques in optical communication, (J. Lightw. Technol.)
- [Kamalov et al., 2018], Evolution from 8qam live traffic to ps 64-qam with neural-network based nonlinearity compensation . . . , (OFC)

- [Karanov et al., 2018], End-to-end deep learning of optical fiber communications (J. Lightw. Technol.)
- [Jones et al., 2018], Deep learning of geometric constellation shaping including fiber nonlinearities, (ECOC)
- [Li et al., 2018], Achievable information rates for nonlinear fiber communication via end-to-end autoencoder learning, (ECOC)

...
Machine Learning for Physical-Layer Communications

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end-to-end learning [O’Shea and Hoydis, 2017]

parameterized TX

\[ T_\theta \]

communication channel

parameterized RX

\[ R_\theta \]

surrogate channel

data in → data out

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

[Giacoumidis et al., 2015], Fiber nonlinearity-induced penalty reduction in CO-OFDM by ANN-based . . . , (Opt. Lett.)

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[Li et al., 2018], Achievable information rates for nonlinear fiber communication via end-to-end autoencoder learning, (ECOC)

[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)
Machine Learning for Physical-Layer Communications

Using neural networks for $T_\theta, R_\theta, C_\theta$

- 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

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

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

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], ...
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Fiber-optic systems enable **data traffic over very long distances** connecting cities, countries, and continents.
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- **Dispersion**: different wavelengths travel at different speeds (linear)
- **Kerr effect**: refractive index changes with signal intensity (nonlinear)
Channel Modeling

nonlinear Schrödinger equation

0

L

z
Channel Modeling

- Sampling over a fixed time interval $\implies F : \mathbb{C}^n \rightarrow \mathbb{C}^n$
Channel Modeling

\[ \frac{d u(z)}{d z} = A u(z) + j \gamma \rho(u(z)) \]

\( u(0) = x \)

Sampling over a fixed time interval \( \implies F : \mathbb{C}^n \rightarrow \mathbb{C}^n \)
Channel Modeling

\[ \frac{du(z)}{dz} = Au(z) + j\gamma \rho(u(z)) \]

\[ u(0) = x \quad \text{time-discretized nonlinear Schrödinger equation} \quad y = u(L) \]

- Sampling over a fixed time interval \( \implies \mathcal{F} : \mathbb{C}^n \to \mathbb{C}^n \)
- **Split-step method** with \( M \) steps (\( \delta = L/M \)):
Channel Modeling

\[ \frac{du(z)}{dz} = Au(z) \]

\[ u(0) = x \quad \text{time-discretized nonlinear Schrödinger equation} \]

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- Split-step method with \( M \) steps (\( \delta = L/M \)): 
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- Sampling over a fixed time interval \( \Rightarrow F : \mathbb{C}^n \rightarrow \mathbb{C}^n \)
- **Split-step method** with \( M \) steps \( (\delta = L/M) \):

\[ H_k = e^{j\frac{\beta_2}{2}\delta \omega_k^2} \quad \text{group velocity dispersion (all-pass filter)} \]
Channel Modeling

\[ \frac{du(z)}{dz} = \rho(x) = |x|^2 x \text{ element-wise} \]

\[ u(0) = x \quad \text{time-discretized nonlinear Schrödinger equation} \quad y = u(L) \]

- Sampling over a fixed time interval \( \Rightarrow \mathcal{F}: \mathbb{C}^n \rightarrow \mathbb{C}^n \)
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Channel Modeling

\[ \frac{du(z)}{dz} = + j\gamma \rho(u(z)) \quad \rho(x) = |x|^2 x \text{ element-wise} \]

\[ u(0) = x \quad \text{time-discretized nonlinear Schrödinger equation} \]

\[ y = u(L) \]

- Sampling over a fixed time interval \( \implies \mathcal{F} : \mathbb{C}^n \rightarrow \mathbb{C}^n \)
- **Split-step method** with \( M \) steps (\( \delta = L/M \)):

\[ H_k = e^{j \frac{\beta_2}{2} \delta \omega_k^2} \]

\[ \sigma_\delta(x) = xe^{j\gamma \delta |x|^2} \quad \text{Kerr effect} \]

\[ \text{group velocity dispersion (all-pass filter)} \]
Channel Modeling

\[ \frac{du(z)}{dz} = Au(z) + j\gamma \rho(u(z)) \]

\[ \rho(x) = |x|^2 x \text{ element-wise} \]

\[ u(0) = x \quad \Rightarrow \quad y = u(L) \]

- Sampling over a fixed time interval \( \Rightarrow F : \mathbb{C}^n \rightarrow \mathbb{C}^n \)
- Split-step method with \( M \) steps \( (\delta = L/M) \):

\[ H_k = e^{j\frac{\beta^2}{2}\delta \omega_k^2} \]

\[ \sigma_\delta(x) = xe^{j\gamma \delta |x|^2} \text{ Kerr effect} \]

\[ \text{group velocity dispersion (all-pass filter)} \]
Channel Modeling

\[ \frac{du(z)}{dz} = Au(z) + j\gamma \rho(u(z)) \]

\( \rho(x) = |x|^2 x \) element-wise

\[ u(0) = x \rightarrow \text{time-discretized nonlinear Schrödinger equation} \rightarrow y = u(L) \]

- Sampling over a fixed time interval \( \implies \mathcal{F} : \mathbb{C}^n \rightarrow \mathbb{C}^n \)
- **Split-step method** with \( M \) steps (\( \delta = L/M \)):

\[ \sigma_\delta(x) = xe^{j\gamma \delta |x|^2} \]

Kerr effect

\[ H_k = e^{j\frac{\beta_2}{2} \delta \omega_k^2} \]

group velocity dispersion (all-pass filter)
Deep Learning [LeCun et al., 2015]  

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

ResNet [He et al., 2015]

[Du and Lowery, 2010]  

[SpM, CD1, CD2, SPM, CD1, CD2]  

[Nakashima et al., 2017]
Parameterizing the Split-Step Method

multi-layer neural network:

\[
\begin{align*}
W^{(1)} & \quad b^{(1)} \\
& \quad \cdots \\
W^{(2)} & \quad b^{(2)} \\
& \quad \cdots \\
\cdots & \\
W^{(\ell)} & \quad b^{(\ell)}
\end{align*}
\]
Parameterizing the Split-Step Method

multi-layer neural network:

\[ W^{(1)} \rightarrow b^{(1)} \rightarrow W^{(2)} \rightarrow b^{(2)} \rightarrow \ldots \rightarrow W^{(\ell)} \rightarrow b^{(\ell)} \]

activation function

\[ \sigma(x) = x e^{i\gamma \delta |x|^2} \]

split-step method:

\[ A_\delta \rightarrow A_\delta \rightarrow A_\delta \rightarrow \ldots \rightarrow A_\delta \]

\[ \sigma(x) = x e^{i\gamma \delta |x|^2} \]
Parameterizing the Split-Step Method

multi-layer neural network:

\[ W^{(1)} b^{(1)} \rightarrow \ldots \rightarrow W^{(2)} b^{(2)} \rightarrow \ldots \rightarrow W^{(\ell)} b^{(\ell)} \]

activation function

\[ \sigma(x) = xe^{i\gamma \delta |x|^2} \]

split-step method:

\[ A^{(1)} \rightarrow \ldots \rightarrow A^{(2)} \rightarrow \ldots \rightarrow A^{(M)} \]

\[ \sigma(x) = xe^{i\gamma \delta |x|^2} \]

[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

multi-layer neural network:

\[ W^{(1)} \rightarrow b^{(1)} \rightarrow W^{(2)} \rightarrow \ldots \rightarrow W^{(\ell)} \rightarrow \ldots \rightarrow W^{(M)} \]

activation function:

\[ \sigma(x) = x e^{j\gamma \delta |x|^2} \]

split-step method:

\[ A^{(1)} \rightarrow \ldots \rightarrow A^{(2)} \rightarrow \ldots \rightarrow A^{(M)} \]

Parameterized model \( f_\theta \) with \( \theta = \{A^{(1)}, \ldots, A^{(M)}\} \)
Parameterizing the Split-Step Method

- Parameterized model $f_\theta$ with $\theta = \{A^{(1)}, \ldots, A^{(M)}\}$
- Includes as special cases: step-size optimization, “placement” of nonlinear operator, higher-order dispersion, matched filtering . . .
Possible Applications
Possible Applications

- Parameterized TX: \( \mathcal{T}_\theta \)
- Amplifier
- Optical fiber
- Parameterized RX: \( \mathcal{R}_\theta \)
- Surrogate channel: \( \mathcal{C}_\theta \)

Data in: \( \rightarrow \mathcal{T}_\theta \rightarrow \text{amplifier} \rightarrow \mathcal{R}_\theta \rightarrow \text{data out} \)
Possible Applications

Pre-distortion [Essiambre and Winzer, 2005], [Roberts et al., 2006], split nonlinear equalization [Lavery et al., 2016]

Fine-tune with experimental data, reduce simulation time [Leibrich and Rosenkranz, 2003], [Li et al., 2005]
Possible Applications

pre-distortion [Essiambre and Winzer, 2005], [Roberts et al., 2006], split nonlinear equalization [Lavery et al., 2016]

nonlinear equalization (this talk)

fine-tune with experimental data, reduce simulation time
[Leibrich and Rosenkranz, 2003], [Li et al., 2005]

Model-based learning approaches

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

\( \sigma_\delta(x) = xe^{j\gamma \delta |x|^2} \) Kerr effect

\[ H_k = e^{j\frac{\beta_2}{2} \delta \omega_k^2} \] group velocity dispersion (all-pass filter)
Digital Backpropagation

\( \sigma_\delta (x) = xe^{j\gamma (-\delta) |x|^2} \)  \text{Kerr effect}

\( H_k = e^{j \frac{\beta_2}{2} (-\delta) \omega_k^2} \)  \text{group velocity dispersion (all-pass filter)}
Digital Backpropagation

\[ \sigma_\delta(x) = xe^{j\gamma(-\delta)|x|^2} \]  
Kerr effect

\[ H_k = e^{j\frac{\beta_2}{2}(-\delta)\omega_k^2} \]  
group velocity dispersion (all-pass filter)

- Fiber with negated parameters \((\beta_2 \rightarrow -\beta_2, \gamma \rightarrow -\gamma)\) would perform perfect channel inversion [Paré et al., 1996] (ignoring attenuation)
Digital Backpropagation

\[
\sigma_\delta(x) = x e^{j\gamma(-\delta)|x|^2}
\]

Kerr effect

\[
H_k = e^{j\frac{\beta_2}{2}(-\delta)\omega_k^2}
\]

group velocity dispersion (all-pass filter)

- Fiber with negated parameters \((\beta_2 \rightarrow -\beta_2, \gamma \rightarrow -\gamma)\) would perform perfect channel inversion [Paré et al., 1996] (ignoring attenuation)

- Digital backpropagation: invert a partial differential equation in real time [Essiambre and Winzer, 2005], [Roberts et al., 2006], [Li et al., 2008], [Ip and Kahn, 2008]
Digital Backpropagation

\[ H_k = e^{j \frac{\beta_2}{2} (-\delta) \omega_k^2} \]

\[ \sigma_\delta(x) = xe^{j\gamma(-\delta)|x|^2} \]
Kerr effect

- Fiber with negated parameters \((\beta_2 \rightarrow -\beta_2, \gamma \rightarrow -\gamma)\) would perform perfect channel inversion [Paré et al., 1996] (ignoring attenuation)
- **Digital backpropagation**: invert a partial differential equation in real time [Essiambre and Winzer, 2005], [Roberts et al., 2006], [Li et al., 2008], [Ip and Kahn, 2008]
- Widely considered to be impractical (**too complex**): linear equalization is already one of the **most power-hungry DSP blocks** in coherent receivers
Real-Time Digital Backpropagation

[Crivelli et al., 2014]
Real-Time Digital Backpropagation

[Crivelli et al., 2014]
Real-Time Digital Backpropagation

[Crivelli et al., 2014]

Our approach: deep learning and model compression

- Joint optimization,
- pruning, and
- quantization

of all linear steps \(\Rightarrow\) hardware-efficient digital backpropagation
Learned Digital Backpropagation
Learned Digital Backpropagation

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

\[ h^{(1)} \]
\[ h^{(2)} \]
\[ \sigma_1(x) = xe^{\gamma_1|x|^2} \]
\[ \sigma_2(x) = xe^{\gamma_2|x|^2} \]
\[ \sigma_M(x) = xe^{\gamma_M|x|^2} \]
Learned Digital Backpropagation

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

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

$$\min_\theta \sum_{i=1}^N \text{Loss}(f_\theta(y^{(i)}), x^{(i)}) \triangleq g(\theta)$$

mean squared error

using $\theta_{k+1} = \theta_k - \lambda \nabla_\theta g(\theta_k)$

Adam optimizer, fixed learning rate
Learned Digital Backpropagation

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

$$h(1) = A_\delta$$
$$h(2) = A_\delta$$
$$...$$
$$h(M) = A_\delta$$

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

$$\min_\theta \sum_{i=1}^N \text{Loss}(f_\theta(y^{(i)}), x^{(i)}) \triangleq g(\theta)$$

mean squared error

using $\theta_{k+1} = \theta_k - \lambda \nabla_\theta g(\theta_k)$

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]:
- $25 \times 80$ km SSFM
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- $\gg 1000$ total taps (70 taps/step) $\Rightarrow > 100 \times$ complexity of EDC
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- $\gg 1000$ total taps (70 taps/step) $\implies > 100 \times$ complexity of EDC
- 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]
Revisiting Ip and Kahn (2008)

- **Parameters similar to [Ip and Kahn, 2008]:**
  - 25 × 80 km SSFM
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- **•** 
  - ≫ 1000 total taps (70 taps/step) \(\implies\) > 100× complexity of EDC

- 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]
Real-Time ASIC Implementation

[Crivelli et al., 2014]

[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)
Real-Time ASIC Implementation

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

- 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)
Real-Time ASIC Implementation

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Real-Time ASIC Implementation

- 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
- < 2× 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**.

⇒ 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”
- “Since backpropagation requires multiple iterations of the linear filter, amplitude distortion due to ringing accumulates (Goldfarb & Li, 2009)”
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- “We also note that [...] 70 taps, is much larger than expected”
- “This is due to amplitude ringing in the frequency domain”
- “Since backpropagation requires multiple iterations of the linear filter, amplitude distortion due to ringing accumulates (Goldfarb & Li, 2009)”

The learning approach uncovered that there is no such requirement!

[Lian, Häger, Pfister, 2018], What can machine learning teach us about communications? (ITW)
Why Does The Learning Approach Work?

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

⇒ **Good overall response** only possible with **very long** filters.

**Sacrifice individual filter accuracy,** but **different response per step.**

⇒ **Good overall response** even with **very short** filters by joint optimization.
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Wideband Signals and Subband Processing

wideband signal
Wideband Signals and Subband Processing

- Subband processing: split received signal into \( N \) parallel signals

---

[Taylor, 2008], Compact digital dispersion compensation algorithms, (OFC)
[Ho, 2009], Subband equaliser for chromatic dispersion of optical fibre, (Electronics Lett.)
[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)
[Oyama et al., 2015], Complexity reduction of perturbation-based nonlinear compensator by sub-band processing, (OFC)
...
Wideband Signals and Subband Processing

- Subband processing: split received signal into $N$ parallel signals
- Parameterizing the split-step method for coupled Schrödinger equations [Leibrich and Rosenkranz, 2003] $\Rightarrow$ low-complexity candidate for wideband processing [Häger and Pfister, 2018c]
- Similar structure as popular convolutional neural networks (alternating filter banks and nonlinearities)

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[Taylor, 2008], Compact digital dispersion compensation algorithms, (OFC)
[Ho, 2009], Subband equaliser for chromatic dispersion of optical fibre, (Electronics Lett.)
[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.)
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[Oyama et al., 2015], Complexity reduction of perturbation-based nonlinear compensator by sub-band processing, (OFC)

...
Polarization-Dependent Impairments

\[ L \times \star = \text{multiplication (rotation)} \]

\[ \star = \text{convolution} \]

[Crivelli et al., 2014]
Polarization-Dependent Impairments

- Combining digital backpropagation with compensation of polarization-mode dispersion

---

[Goroshko et al., 2016], Overcoming performance limitations of digital back propagation due to polarization mode dispersion, \textit{(CTON)}

[Czegledi et al., 2017], Digital backpropagation accounting for polarization-mode dispersion, \textit{(Opt. Express)}

[Liga et al., 2018], A PMD-adaptive DBP receiver based on SNR optimization, \textit{(OFC)}
Polarization-Dependent Impairments

- Combining digital backpropagation with compensation of polarization-mode dispersion
- Promising performance–complexity tradeoff using model-based factorization approach and machine learning [Häger et al., 2020]

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[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)
[Häger et al., 2020], Model-based machine learning for joint digital backpropagation and PMD compensation, (OFC)
Ongoing and Future Work

- **Experimental Demonstrations:** stay tuned . . .
- **How to integrate** into a standard coherent receiver DSP chain?
- **How to successfully train** in the presence of practical impairments (laser phase noise, transceiver noise, . . .)
- **How realistic is online learning** in custom DSP? (We only have “hundreds” of parameters, not “thousands” or “millions” like neural networks)
Conclusions
Conclusions

neural-network-based ML

universal function approximators

  good designs require
  experience and fine-tuning

  black boxes,
  difficult to “open”
## Conclusions

<table>
<thead>
<tr>
<th>neural-network-based ML</th>
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## Conclusions

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Thank you!
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